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Modeling Causality in Law

(Modélisation de la causalité en droit)

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Résumé

L'intérêt en apprentissage machine pour étudier la causalité s'est considérablement accru ces dernières années. Cette approche est cependant encore peu répandue dans le domaine de l’intelligence artificielle (IA) et du droit. Elle devrait l'être. L'approche associative actuelle d’apprentissage machine révèle certaines limites que l'analyse causale peut surmonter. Cette thèse vise à découvrir si les modèles causaux peuvent être utilisés en IA et droit.

Nous procédons à une brève revue sur le raisonnement et la causalité en science et en droit. Traditionnellement, les cadres normatifs du raisonnement étaient la logique et la rationalité, mais la théorie duale démontre que la prise de décision humaine dépend de nombreux facteurs qui défient la rationalité. À ce titre, des statistiques et des probabilités étaient nécessaires pour améliorer la prédiction des résultats décisionnels. En droit, les cadres de causalité ont été définis par des décisions historiques, mais la plupart des modèles d’aujourd’hui de l'IA et droit n'impliquent pas d'analyse causale. Nous fournissons un bref résumé de ces modèles, puis appliquons le langage structurel de Judea Pearl et les définitions Halpern-Pearl de la causalité pour modéliser quelques décisions juridiques canadiennes qui impliquent la causalité.

Les résultats suggèrent qu'il est non seulement possible d'utiliser des modèles de causalité formels pour décrire les décisions juridiques, mais également utile car un schéma uniforme élimine l'ambiguïté. De plus, les cadres de causalité sont utiles pour promouvoir la responsabilisation et minimiser les biais.

Mots-clés : Causalité, Raisonnement, Droit, Modèle causale, Modèle structural, Apprentissage automatique, Intelligence artificielle, DAG, SCM, IA et droit

Abstract

The machine learning community's interest in causality has significantly increased in recent years. This trend has not yet been made popular in AI & Law. It should be, because the current associative ML approach reveals certain limitations that causal analysis may overcome. This research paper aims to discover whether formal causal frameworks can be used in AI & Law.

We proceed with a brief account of scholarship on reasoning and causality in science and in law. Traditionally, normative frameworks for reasoning have been logic and rationality, but dual theory has shown that human decision-making depends on many factors that defy rationality. As such, statistics and probability were called for to improve prediction of decisional outcomes. In law, causal frameworks have been defined by landmark decisions but most of the AI & Law models today do not involve causal analysis. We provide a brief summary of these models, and then attempt to apply Judea Pearl's structural language and the Halpern-Pearl definitions of actual causality to model a few Canadian legal decisions that involve causality.

Results suggest that it is not only possible to use formal causal models to describe legal decisions, but also useful because a uniform schema eliminates ambiguity. Also, causal frameworks are helpful in promoting accountability and minimizing biases.

Keywords: Causality, Reasoning, Law, Structural Causal Model, Actual Causality, DAG, SCM, ML, AL, AI & Law

Table of Abbreviations

AGI	Artificial General Intelligence
AI	Artificial Intelligence
ALICE	Automated Learning and Intelligence for Causation and Economics
AR	Argument Retrieval
BN	Bayesian Network
BOW	Bag-Of-Words
CBR	Case-Based Reasoning
CC	Cognitive Computing
CLS	Critical Legal Studies
CPM	Conditional Plausibility Measure
DAG	Directed Acyclic Graph
DES	Diethylstilbestrol
DL	Deep Learning
DLP	Default Logic Paradigm
DNA	Deoxyribonucleic Acid
DNN	Deep Neural Network
DT	Decision Tree
EEG	Scalp Electroencephalography
ERP	Einstein-Podolsky-Rosen
ERP	Enterprise Resource Planning
F1	F function at value 1
FAccT	Fairness Accountability and Transparency
fMRI	Functional Magnetic Resonance Imaging
FN	False Negative
FP	False Positive
GREBE	GeneratoR of Exemplar-Based Explanations
HP	Halpern-Pearl
IBP	Issue-Based-Prediction
IE	Information Extraction
k-NN	k-Nearest Neighbor
LES	Legal Expert System
LSAT	Law School Admission Test
LUIMA	Legal Unstructured Information Management Applications
MCI	Material Contribution to Injury
MCR	Material Contribution to Risk of harm
ML	Machine Learning
NESS	Necessary Element of a Sufficient Set
NLP	Natural Language Processing

PEL	Pure Economic Loss
POGG	Peace, Order, and Good Government
POS	Part-Of-Speech
QA	Question Answering
RBR	Rule-Based Reasoning
RCM	Rubin Causal Model
RCT	Randomized Controlled Trial
RegEx	Regular Expression
RF	Random Forest
RL	Reinforcement Learning
SCM	Structural Causal Model
SEM	Structural Equation Model
SVM	Support Vector Machine
TF-IDF	Term Frequency–Inverse Document Frequency
TN	True Negative
TP	True Positive
UIMA	Unstructured Information Management Applications
VAF	Value-based Argument Framework
VJAP	Value Judgment-based Argumentative Prediction
Word2vec	Word to Vector
WYSIWYG	What You See Is What You Get

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INTRODUCTION

Many law schools insist on a minimum cut-off score on the Law School Admission Test (LSAT) as part of a student candidate's admission requirement. Below is the first question of Section I on the June 2007 exam.[1]

> *A company employee generates a series of five-digit product codes in accordance with the following rules: The codes use the digits 0, 1, 2, 3, and 4, and no others. Each digit occurs exactly once in any code. The second digit has a value exactly twice that of the first digit. The value of the third digit is less than the value of the fifth digit.*
>
> *If the last digit of an acceptable product code is 1, it must be true that the*[2]
>
> *(A) first digit is 2*
> *(B) second digit is 0*
> *(C) third digit is 3*
> *(D) fourth digit is 4*
> *(E) fourth digit is 0*

Two out of the five sections on the LSAT examine the student's aptitude in logical and analytical reasoning. It suggests that reasoning skills are considered essential for the study and the practice of law. Indeed, not only the law, our ability to think and reason is our only window to understanding the world. Particularly, this paper is interested in causal reasoning, which identifies relationships between cause and effect. Causal reasoning is primarily inductive logic,[3] a branch of logical reasoning.[4] Both reasoning and causality have been fascinating scholars of all disciplines for many centuries. For example, Aristotle in *Metaphysics*,[5] René Descartes in *Passions*,[6] David

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[1] Law School Admission Council, "The official LSAT PREPTEST®, June 2007", online:<https://www.lsac.org/sites/default/files/legacy/docs/default-source/jd-docs/sampleptjune.pdf>
[2] The corrected answer is (A). The product code is necessarily 24031.
[3] John Stuart Mill, *A System of Logic, Ratiocinative and Inductive*, people's edition ed (New York: Longmans, Green, and Co., 1893) at 401.
[4] Jo Reichertz, "Induction, Deduction, Abduction" in *SAGE Handb Qual Data Anal* (1 Oliver's Yard, 55 City Road, London EC1Y 1SP United Kingdom: SAGE Publications Ltd, 2014) 123.
[5] Andrea Falcon, "Aristotle on Causality" in Edward N Zalta, ed, *Stanf Encycl Philos*, spring 2019 ed (Metaphysics Research Lab, Stanford University, 2019).
[6] René Descartes, "The Passions of the Soul" in John Cottingham, Robert Stoothoff & DugaldTranslators Murdoch, eds, *Philos Writ Descartes* (Cambridge University Press, 1985) 325.

Hume in *A Treatise of Human Nature*,[7] and Immanuel Kant in *Critique of Pure Reason*,[8] just to name a few.

To appreciate the relevance of reasoning and causal thinking, consider the following four situations and what they have in common:

1. A woman approaching menstruation
2. A person with a brain tumour
3. A person having eaten a lot of junk food
4. A person injected with anabolic steroid

All four have been used successfully in courts of law to explain murder. In the first situation, two women walked free from British criminal courts after pleading that premenstrual tension had made them act out of character.[9] As for brain tumours, a jury from the Connally Commission concluded that the Charles Whitman's mass killings[10] were in part due to a tumour in his brain.[11] Today, brain imaging can be admissible in courts under the Federal Rules of Evidence in the United States.[12] In the case of junk food, the famous "Twinkie defence" of Dan White in the Harvey Milk murder claimed diminished capacity due to depression evidenced by his junk food habit. The defence reduced his conviction from first-degree murder to manslaughter.[13] Finally, bodybuilders' "dumbbell defence" from anabolic steroid consumption has been used in legal cases in the United States since 1988.[14]

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7 William Edward Morris & Charlotte R Brown, "David Hume" in Edward N Zalta, ed, *Stanf Encycl Philos*, spring 2020 ed (Metaphysics Research Lab, Stanford University, 2020).

8 Graciela De Pierris & Michael Friedman, "Kant and Hume on Causality" in Edward N Zalta, ed, *Stanf Encycl Philos*, winter 2018 ed (Metaphysics Research Lab, Stanford University, 2018).

9 "British Legal Debate: Premenstrual Tension and Criminal Behavior", *N Y Times* (29 December 1981), online: <https://www.nytimes.com/1981/12/29/science/british-legal-debate-premenstrual-tension-and-criminal-behavior.html>.

10 "Texas Tower shooting of 1966 - The shooting | Britannica", online: <https://www.britannica.com/event/Texas-Tower-shooting-of-1966/The-shooting>.

11 JoAnn Ponder, "From the Tower shootings in 1966 to Campus Carry in 2016: Collective trauma at the University of Texas at Austin" (2018) 15:4 Int J Appl Psychoanal Stud 239–252.

12 Dean Mobbs et al, "Law, responsibility, and the brain." (2007) 5:4 PLoS Biol e103.

13 Gregg Barak, *Battleground: Criminal Justice [2 volumes]* (ABC-CLIO, 2007) at 663.

14 Bruce Maycock & Andrea Beel, "Anabolic Steroid Abuse and Violence" (1997) BOCSAR NSW Crime Justice Bull 8.

As we have seen, understanding causality has far reaching legal implications. Whether an act carried out by a person attracts legal responsibility hinges on the perceived causation between the act and the consequence;[15] and this perception evolves over time. For instance, epilepsy used to be perceived as "demonic" behaviour[16] and harm caused to others during an epileptic attack was considered a form of assault. Today, it is considered a neurological disorder, and automatism may be used as a defence against harm caused to others during epileptic seizures.[17]

Thus, the law changes as a result of acquired scientific knowledge; scientific progress slowly influences the way we understand causality and culpability. Empirical science collects data based on which we make hypotheses,[18] and we test these hypotheses by conducting experiments.[19] Where we do not have enough data to support a given hypothesis, we use statistics to infer its likelihood (probability). As we deal with growing data sets and approach Big Data, computers are becoming essential in performing these complex and tedious statistical calculations at a large scale.

With the advent of Artificial Intelligence (AI), the machine not only performs these calculations efficiently, it also automates the formulation of equations, which is the basis of Machine Learning (ML). ML is a technique in computer science that aims to achieve AI. It is the practice of using algorithms to improve prediction or performance by learning from input data or environment without being explicitly programmed. Rather than receiving "instructions", the machine is given an architecture and is "trained", using large amounts of data to perform the desired task.

Since 2015, the breakthrough in Computer Vision[20] using Deep Learning[21] techniques put AI back in the spotlight.[22] As Deep Learning is commonly associated with Deep Neural Networks, Neural

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[15] See Art 1457 CCQ; Also see Jean-Louis Baudouin, Patrice Deslauriers et Benoît Moore, *La responsabilité civile*, 8e éd. (2014),

[16] Matthew 17:14-18 (New International Version)

[17] *R* v *Parks*, [1992] 2 SCR 871; *R* v *Bohak*, (2004) MJ No 172 .

[18] Jan-Willem Romeijn, "Philosophy of Statistics" in Edward N Zalta, ed, *Stanf Encycl Philos*, spring 2017 ed (Metaphysics Research Lab, Stanford University, 2017).

[19] *Ibid* s 3.

[20] Computer vision is a field of artificial intelligence that trains computers to interpret and understand the visual world using image recognition techniques.

[21] Deep Learning is family of machine learning methods based on artificial neural networks. More details will be discussed further in this paper.

[22] John Markoff, "A Learning Advance in Artificial Intelligence Rivals Human Abilities", *N Y Times* (10 December 2015), online: <https://www.nytimes.com/2015/12/11/science/an-advance-in-artificial-intelligence-rivals-human-vision-abilities.html>.

Networks are getting most of the attention. This is the reason why “Artificial Intelligence”, “Machine Learning”, “Deep Learning” and “Neural Network” are often used interchangeably, causing confusion. Strictly speaking, they are not the same thing. Below is a simple diagram depicting the relationships of these terms commonly used in mass media:

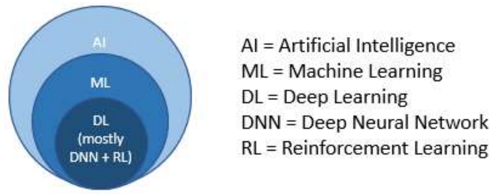


Figure 1: Relationship between AL, ML, and DL

A more nuanced illustration is given below:

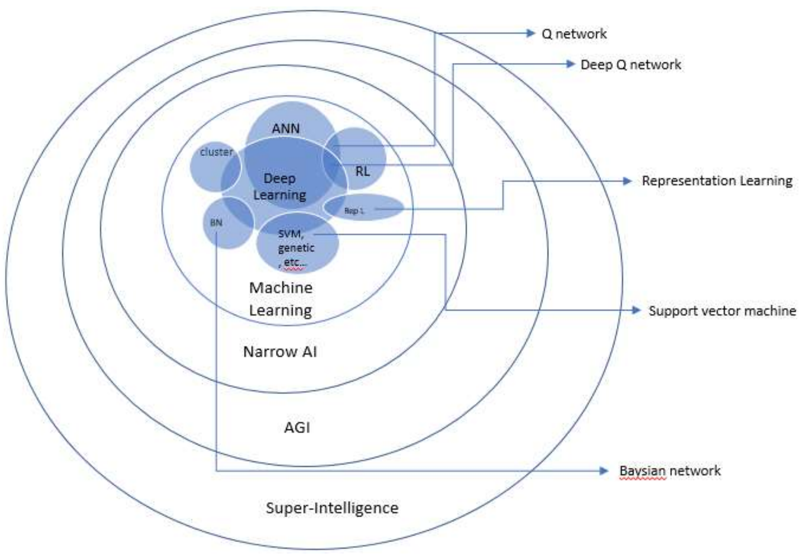


Figure 2: Relationships between various AI techniques

The AI realm is composed of Narrow AI, Strong AI, and Superintelligence. Narrow AI (also known as Weak AI) refers to a machine’s ability to reproduce a specific human behaviour. The machine does not have human cognitive ability or consciousness. Still, narrow AI is a powerful tool to automate specific tasks using algorithms. Strong AI (also known as AGI or General AI) refers to the ability for a machine to reproduce human intelligence fully, including abstraction, contextual adaption, and so on. Strong AI would think, learn, and have emotions like a human can.[23] Superintelligence refers to the stage beyond Strong AI, where a machine is more intelligent than the intelligence of all humans combined.[24] Strong AI and Superintelligence have captured our imagination, but today's AI is still Narrow AI.[25]

ML techniques excel in finding the "fit" to the data. That is, we provide the data, and let the machine find the best function *f(x)* that describes the data set, by degree of probability. This method of "fitting function to data" relies on the correlation of data. Judea Pearl refers to this statistical inference as the associative approach[26] but it cannot inform us about causal relationships.[27]

Since the mid 1990s, the field of computer science has gone through a major shift of focus from mathematical-logic tools to probability-theory tools.[28] As a result, causal analysis has been somehow "abandoned" by the AI community for two to three decades.[29] The abandonment is likely due to the overwhelming success of Bayesian networks.[30] With the breakthrough in computer vision and natural language processing, the machine is now capable of doing marvelous things, outperforming humans to the point we feel threatened. But there are two fundamental differences between statistical inference (association) and causal inference in AI.

First, statistical inference is by association: what is the distribution of Y given that the observable X, $P(Y|X)$? To answer this question, data is observed from a sample of the population. This observational finding is what we aim to estimate in machine learning. $P(Y|X)$ and $P(X|Y)$ give us the correlations between X and Y, and correlations form the basis of most of today's AI

[23] Kai-Fu Lee, *AI Superpowers: China, Silicon Valley, and The New World* (Boston: Houghton Middlin Harcourt, 2018). Page number is unavailable as the source of reference is in Kindle format. It is in Chapter 6.
[24] Superintelligence is often referred to as "Singularity".
[25] Wim Naudé & Nicola Dimitri, "The race for an artificial general intelligence: implications for public policy" (2019) AI Soc, online: <https://doi.org/10.1007/s00146-019-00887-x>.
[26] Judea Pearl & Dana Mackenzie, *The Book of Why: The New Science of Cause and Effect* (Basic Books, 2018) c 1, Google-Books-ID: 9H0dDQAAQBAJ.
[27] *Ibid* c 10.
[28] Eyal Amir, "Reasoning and decision making" in Keith Frankish & William MEditors Ramsey, eds, *Camb Handb Artif Intell* (Cambridge University Press, 2014) 191 at 209.
[29] Pearl & Mackenzie, *supra* note 26 c 1.
[30] *Ibid* c 3.

techniques.[31] However, correlations are limiting in that they tell us nothing about whether *X* causes *Y*, *Y* causes *X*, something else causes both *X* and *Y*, or they are sheer coincidence.[32]

Causal inference, on the contrary, dives into their relationship. In addition to knowing *X* and *Y* are correlated, we want to know the direction of influence, that is, whether *X* is influencing *Y* or *vice versa*. To answer the question, we conduct experiments to intervene in the data generating process – this is part of a broader family of machine learning methods, based on artificial neural networks – by artificially forcing the variable X, thus discovering the distribution of Y if we wiggle X: *P(Y|do(X)*.[33] The important detail is that the distribution of *Y* if one *observes X* is not the same as the distribution of *Y* if one *intervenes* on *X*.

$$P(Y|do(X) \neq P(Y|X)$$

The second fundamental difference between the two types of inference is that statistical inference involves studying a sample of the population and inducing knowledge about the entire population, and "hoping" that the sampled population is representative of the whole. But we could have extended the sample and studied more cases. On the other hand, causal inference studies individual cases of the population but there is no way to study "more". Even if we have data about the entire population, we could not have known the counterfactual outcome because we have no access to the parallel universe.

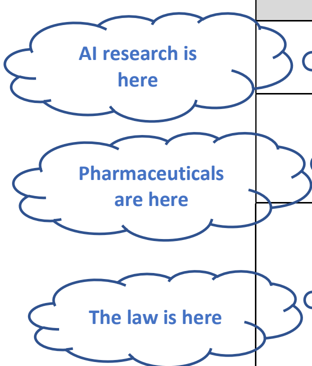
Therefore, Big Data will render statistical inference less and less useful because having large amount of data will no longer be a problem thanks to reduced cost of storage and processing power.[34] The arrival of Big Data means that associative ML will eventually hit a wall with statistical inference. In other words, we must find another way to overcome the limits of probabilistic inference, and causal inference may be the solution.

Judea Pearl has been innovating in the field of causal inference for the past three decades. After having worked on Bayesian networks, Pearl understands the probabilistic approach and its limits.

[31] An exception is perhaps reinforcement learning where the training of behaviour is not based on correlation, but rather on system of reward.
[32] Pearl & Mackenzie, *supra* note 26 c 3.
[33] *Ibid* c 4.
[34] *Ibid* c 10.

To make machines truly intelligent, he advocates that we get past the first step (Association) and move towards the second and third steps (Intervention and Counterfactuals) on the "Ladder of Causality".[35] Pearl unified three existing causal models into a structural causal model (SCM) and developed "do-calculus" to support causality analysis.[36] He collaborated with Joseph Y. Halpern to solidify and prove the Halpern-Pearl (HP) definitions of actual causality[37] that will be discussed in the last chapter of this paper.

Table 1: Judea Pearl's Ladder of Causality



Level of Causal Hierarchy	Name	Activity	Questions
1	Association $P(Y\|X)$	Seeing	What is going on? How are X and Y related?
2	Intervention $P(Y\|do(X), Z)$	Doing	If I wiggle X, will Y change? I have a headache. What happens if I take Aspirin?
3	Counterfactuals $P(Y_x\|X', Y')$	Imagining	What if? But-for test. Had I not wiggled X, would Y have changed? Had I not taken Aspirin, would the headache have gone away?

The ML community's interest in causality has significantly increased in recent years.[38] AI & Law has made progress with probabilistic ML for some time. Now, the question is whether AI & Law will follow this new causal trend. Before answering this question, perhaps the first step is to find out whether it is possible, and useful, to include causal ML in AI & Law, which is the central question of this thesis. We proceed with a brief history of scholarship on reasoning and causality in science and in law, and key concepts deriving from them; and then a summary of different AI & Law models in the last few decades, followed by an attempt to construct causal models for legal cases.

[35] See Table 1.
[36] Judea Pearl, Madelyn Glymour & Nicholas P Jewell, *Causal inference in statistics : a primer* (West Sussex: John Wiley and Sons Ltd., 2016) c 2.
[37] Joseph Y Halpern, *Actual Causality* (The MIT Press, Cambridge, Massachusetts, 2016).
[38] Bernhard Schölkopf, "Causality for Machine Learning" (2019) ArXiv191110500 Cs Stat, online: <http://arxiv.org/abs/1911.10500>, arXiv: 1911.10500.

This paper is organized in the following manner. Part A is dedicated to reasoning and causality. Within Part A, Chapter 1 focuses on reasoning and causality in science and philosophy; and Chapter 2 on reasoning and causality in law. Chapter 1 explores the different types of reasoning including logic, rational choice, dual theory, and probability, and how they form the building blocks of argumentation. We will also explore how humans form judgements and make decisions. We travel a journey from Aristotle's logic, David Hume's fork, Newtonian physics, through Einstein's theory of special relativity and the time machine, to the Monty Hall TV show and Simpson's paradox.

Then, the concepts from Chapter 1 will be revisited through the lens of the law in Chapter 2. We begin by looking at Formalists' case-based reasoning and rule-based reasoning, and then at other relevant considerations that affect judgement, such as cognition and emotion. Schools of thought like Legal Realism, Critical Legal Studies, and Law and Economics bring interdisciplinary concepts into the discussion. Following legal theories, we summarize the causality frameworks in Canadian law, using examples of common law torts, contracts, civil law responsibilities, and criminal law.

Part B of this paper is dedicated to the application of AI to law. A new research area, AI & Law, has emerged in the field of computer science since the 1980's.[39] Chapter 3 summarizes the efforts made so far by researchers, from legal reasoning models, outcome prediction, argumentation models, to text analytics and cognitive computing. The lack of causal analysis in AI in the last few decades is evidenced in this chapter.

Many publications in AI & Law are written in foreign countries and with statutes and case law from those countries; but whenever possible, an attempt is made to illustrate their models using examples in Canadian law. However, where it is impossible to use Canadian examples due to lack of data, foreign examples are used.

Finally, Chapter 4 is a hands-on exercise to construct legal models using Halpern and Pearl's formal mathematical frameworks, and to evaluate the values and challenges of doing so. This

[39] Kevin D Ashley, *Artificial Intelligence and Legal Analytics: New Tools for Law Practice in the Digital Age* (Cambridge: Cambridge University Press, 2017) at 3.

modelling exercise will answer the central question of this chapter, which is, whether it is possible or useful to include causal analysis in AI & Law; and if so, what the next step should be.

PART A: REASONING AND CAUSALITY

The workings of the brain and the mind[40] give us our only foray into understanding the universe, whether it is an observable phenomenon, or one at the atomic level that is invisible to the naked eye. How do we think? What is consciousness? These are questions that have baffled philosophers[41] and the common mass alike. Empirical research on the brain and on the mind dates to the 1800's and has come a long way in the last few decades.[42] In its infancy, researchers began with perception, attention, and memory. By the mid 1900's, studies of amnesia, split brain, and blindsight paved the way for the current wave of research on consciousness.[43] Today, advanced imaging techniques[44] allow us to literally see what the brain is doing while we are thinking or experiencing emotions. These studies have revealed the importance of our frontal lobe in nearly every aspect of mental and cognitive functioning[45] to the point where some begin to question whether "free will" indeed exists.[46] The answers that these studies aim to find have direct implications in the law, because legal causation requires voluntary execution of our acts. As such, the more we understand cognition, and what causes our actions, the blurrier the line between wilfulness and automatism becomes.[47]

In this part, we discuss reasoning and causality generally, and their applications in law in Chapter 2. We are going to see that traditional reasoning frameworks like logic and rationality are gradually being supplemented by a dual theory of decision-making. In terms of causality, we are going to highlight the main criteria for causality as well as the important distinction between correlation and causal relationship. These scientific concepts reappear in the analysis of legal decisions.

[40] Cartesian dualism separates the brain and the mind into two different entities. The brain is the physical organ while the mind encompasses mental properties such as consciousness, intentionality, and intelligence.
[41] Plato, Aristotle, René Descartes, John Locke, Thomas Hobbes, John Stuart Mills and so on.
[42] Joseph E LeDoux, Matthias Michel & Hakwan Lau, "A little history goes a long way toward understanding why we study consciousness the way we do today" (2020) 117:13 Proc Natl Acad Sci 6976–6984.
[43] *Ibid*.
[44] Electroencephalogram (EEG) and Functional magnetic resonance imaging or functional MRI (fMRI) are examples of imaging techniques that measure brain activities.
[45] Brian Levine & Fergus I.M. Craik, *Mind and the frontal lobes : cognition, behavior, and brain imaging* (New York: Oxford University Press, 2012).
[46] Joshua Greene & Jonathan Cohen, "For the law, neuroscience changes nothing and everything" (2004) 359:1451 Philos Trans R Soc Lond B Biol Sci 1775–1785.
[47] Brigitte Vallabhajosula, *Murder in the courtroom : the cognitive neuroscience of violence*, American Psychology-Law Society series (2015).

Before diving into the details, it is perhaps useful to consider upfront some differences between legal reasoning and scientific reasoning. First, the pursuit of science is meant to conduct empirical experiments to illuminate the question but the option is closed to legal actors.[48] Instead, the law deals with issues using conclusions already drawn from science. Second, legal reasoning demands a definitive conclusion (sometimes after appeal) while scientific reasoning need not lead to any conclusion;[49] even if a scientific conclusion is reached, it may be rebutted years later. Third, legal decisions are bound by the rule of law even if rules are erratic or unjust. However, science is only bound by the laws of physics. Also, legal decisions can be made by vote while scientific conclusions must be based on axioms and proven concepts. Finally, legal reasoning encourages categorical thinking[50] (e.g., guilty or not guilty). Science, on the other hand, embraces probabilistic thinking.[51]

These differences are by no means exhaustive. After all, legal thinking as a social science can be more an art than a science at times. Different frameworks and vocabularies continue to be developed over the years to describe the human condition from two different disciplines; thus, distinctions are bound to grow.

[48] Phoebe Ellsworth, "Legal Reasoning and Scientific Reasoning" (2011) 63:1 Ala Law Rev 895–918 at 907.
[49] *Ibid* at 908.
[50] *Ibid* at 913.
[51] *Ibid* at 915.

Chapter 1: Reasoning and Causality in Science

Reasoning at large is the process of thinking about something or drawing conclusions in a sensible way.[52] The ability to reason is a prerequisite for argumentation, learning, and judgement. [53] Several normative theories dominate the study of reasoning; they are logic, rational choice, dual theory, and probability. Logic and rational choice posit that humans are logical and rational beings,[54] but dual theory and probabilistic logic may convince us otherwise.[55]

After exploring different theories of reasoning, we will then zero in on causality, a necessary element in many legal actions.[56] The notion of cause is also at the core of the theory of induction,[57] thus making causality the main pillar of the inductive branch of logical reasoning.

1.1. Reasoning

Logic is often understood as the *modus ponens* (if-then) mechanics in reasoning, but that is only a small part. Formal logics have been developed for thousands of years in India, China, and Greece. But it was not until Aristotle that logic became a fully systematic discipline.[58] One of Aristotle's contributions was the synthesis of the logical inquiry of his predecessors. The *Organon*, "instrument" in Greek, is the standard collection of Aristotle's six works on logic.[59] Aristotle's branch of logic is called "term logic" where relationships are studied between categories (terms). Term logic has wide application and acceptance in Western science and mathematics.[60] Later, the Stoics began the development of propositional (true/false) logic and predicate (first-order quantifier) logic.[61]

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52 "Reason", online: *Encycl Br* <https://www.britannica.com/topic/reason>.
53 "Definition of Reasoning", online: *Merriam-Webster* <https://www.merriam-webster.com/dictionary/reasoning>.
54 E McCready, "Chapter 13 - Rational Belief and Evidence-Based Update" in T -W Hung & T J Lane, eds, *Rationality* (San Diego: Academic Press, 2017) 243.
55 Daniel Kahneman, *Thinking, Fast and Slow* (New York: Farrar, Straus, Giroux, 2013).
56 See Jean-Louis Baudouin, Patrice Deslauriers et Benoît Moore, *La responsabilité civile*, 8e éd. (2014), Chapter 4.
57 Mill, *supra* note 3 at 400.
58 Susanne Bobzien, "Ancient Logic" in Edward N Zalta, ed, *Stanf Encycl Philos*, summer 2020 ed (Metaphysics Research Lab, Stanford University, 2020).
59 Robin Smith, "Aristotle's Logic" in Edward N Zalta, ed, *Stanf Encycl Philos*, summer 2019 ed (Metaphysics Research Lab, Stanford University, 2019).
60 *Ibid*.
61 Susanne Bobzien, "Ancient Logic" in Edward N Zalta, ed, *Stanf Encycl Philos*, summer 2020 ed (Metaphysics Research Lab, Stanford University, 2020).

Today, it is commonly accepted that logical reasoning is divided into the following three branches: deduction, induction, and abduction.[62]

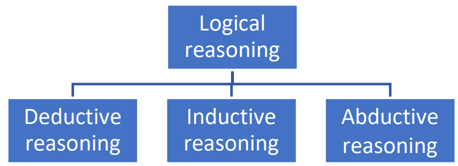

Figure 3: Three branches of logical reasoning

Deduction

Deductive reasoning is the paradigm of mathematical reasoning, and its logic is identified with the classical notion of inference.[63] Deductive logic is to arrive at a conclusion given certain premises in a top-down and reductive flow. The classic form (Aristotle's form) of deductive logic is syllogism,[64] in which a conclusion is drawn, whether valid or not, from two assumed propositions, each of which shares a term with the conclusion, and shares a common term that is not present in the conclusion.[65]

For example:

1. All swans are **white** (proposition).
2. **Daisy** is a swan (proposition).
3. It follows that **Daisy** is **white** (conclusion).

Note that the conclusion may or may not be valid if one of the premises is false:[66]

1. All swans are **white** (proposition).
2. **Donald** is a swan (false proposition: Donald is a duck.)
3. Therefore, **Donald** is **white** (conclusion may be true or false).

Deductive reasoning is the foundation of science and engineering, but it is easy to fall into logic traps. A mistake in the premise (e.g., Donald is a swan) may lead to invalid conclusion. Besides, it is difficult to teach deductive thinking to a machine. Consider below a programmer's nightmare:

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[62] Reichertz, *supra* note 4.
[63] Atocha Aliseda, *Abductive reasoning: logical investigations into discovery and explanation*, Synthese library v 330 (Dordrecht, The Netherlands: Springer, 2006) at 56.
[64] Paul Tomassi, *Logic* (London; New York: Routledge, 1999) at 23.
[65] *Ibid* at 20.
[66] *Ibid* at 30.

1. All grass gets wet when it **rains**.
2. **Water** the lawn, the grass gets wet.
3. **Water** the lawn, it **rains**.

Computer science must conquer this type of challenge in order to teach the machine deductive logic.

In law, syllogism is the basis of the formal case-based reasoning known as Formalism or Legalism, which we will discuss in Chapter 2. Legal syllogism is in a nutshell:

1. Law finding (proposition)
2. Fact finding (proposition)
3. Apply law to fact (conclusion).

In characterizing contract, the Supreme Court reaffirms the importance of logic in reasoning, "conclusion must arise from structured syllogism, and not from intuition, instinct, or any individualistic sense of what seems fair in a particular situation."[67]

Indeed, a flawed syllogism proposed by counsel will be rejected. In a real estate contract case, the Supreme Court declared:[68]

> *"…the Association's reasoning is as follows: since it has been given the responsibility under s. 74(17) of the Act to determine… the content of the mandatory form, and since the parties are required to use the form provided…, it follows that the form's provisions are mandatory clauses of the contract. In my view, this is a false syllogism."*

[67] *Churchill Falls (Labrador) Corp v Hydro-Québec*, 2018 SCC 46, [2018] 3 SCR 101 at para 146.

[68] *Association des courtiers et agents immobiliers du Québec v Proprio Direct inc*, 2008 SCC 32 (CanLII), [2008] 2 SCR 195 at para 51.

Induction

Opposite of deduction, inductive logic is a bottom-top approach.[69] If a phenomenon has been observed repeatedly, induction generalizes these observations into a rule.[70]

For example:

1. Daisy is a **swan** and she is **white** (observation).
2. Felix is a **swan** and he is **white** (observation).
3. Every **swan** we see so far is **white** (generalization).
4. **All swans** must be **white** (presumed rule).

Nevertheless, there is no guarantee that the presumed rule is valid: all it takes is one exception (e.g., a black swan) for the rule to be squashed. We could say that induction is a probabilistic approach to reasoning.[71] To be more confident about the validity of the rule, we make a lot of observations such that a guess with well-supported evidence becomes an "educated guess".

The problem of induction is that inferring the truth of a theory from a series of successful tests is not completely reliable. Bertrand Russell illustrated this point with a chicken's (or a turkey's) reasoning: "The man who has fed the chicken every day throughout its life at last wrings its neck instead, showing that more refined views as to the uniformity of nature would have been useful to the chicken."[72]

The question that Russell raised, whether any number of cases of a rule being fulfilled in the past afford evidence that it will be fulfilled in the future, is especially relevant in the current AI approach to causal inference. Currently, AI learns the rule based on many past experiences, but an observation repeated many times does not guarantee the validity of a rule in the future.

Despite the problem of inductivism, Wesley Salmon is deeply convinced that it is indispensable in reasoning.[73] He maintained that there is a crucial sense in which the logic of science is inevitably inductive, and that a justification of induction is essential to a full understanding of the logic of

[69] Tomassi, *supra* note 64 at 7.
[70] Mill, *supra* note 3 at 354.
[71] Tomassi, *supra* note 64 at 8.
[72] Bertrand Russell, *The problems of philosophy*, A Galaxy Book; GB 21 (New York: Oxford University Press, 1959) c VI.
[73] Maria Carla Galavotti, "Wesley Salmon" in Edward N Zalta, ed, *Stanf Encycl Philos*, fall 2018 ed (Metaphysics Research Lab, Stanford University, 2018).

science.[74] We will see further in the paper how he solved the problem of induction using probability.

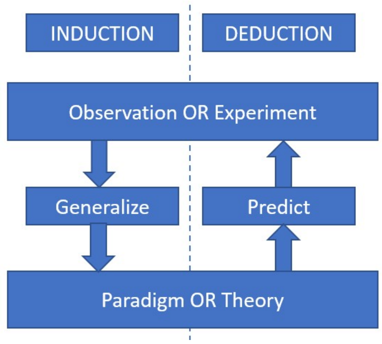

Figure 4: Opposites of Induction and Deduction

Abduction

Although deduction and induction seem like opposite roads towards each other, both branches of reasoning rely on scientific data, contrary to the ad hoc approach of abductive logic. Abduction seeks to find the simplest and most likely explanation for the observations.[75] In other words, abduction is "explanatory reasoning".[76] But we really do not know and there may be no way of validating the logic flow.

More difficulties arise as explanation is not always straightforward. There are several types of explanation, such as mechanistic explanation, functional explanation, and formal explanation.[77] Consider the question, "Why is a tire round?" The mechanical explanation is that it is the most effective way to make it; the functional explanation is that it rolls nicely on the road; and the formal explanation is that it is a tire.[78] As shown, explanations require a variety of cognitive processes and may lead to different abductive outcomes.

[74] *Ibid*.
[75] Igor Douven, "Abduction" in Edward N Zalta, ed, *Stanf Encycl Philos*, summer 2017 ed (Metaphysics Research Lab, Stanford University, 2017).
[76] Aliseda, *supra* note 63 at 35.
[77] Tania Lombrozo, "Explanation and Abductive Inference" in *KJ Holyoak RG Morrison Eds Oxf Handb Think Reason* Oxford Library of Psychology (Oxford University Press, 2012).
[78] *Ibid*.

Abductive thinking is difficult to grasp; the following illustration may look like deduction, but not quite:

1. All swans we see so far are white (generalization).
2. This thing is white (observation).
3. Therefore, this thing must be a swan (conclusion).

Meanwhile, abduction can also be illustrated by the elephant test. The elephant refers to situations in which an idea "is hard to describe, but instantly recognizable when spotted", and has been used in legal decisions when an issue is open to interpretation.

In *Cadogan Estates Ltd* v *Morris*,[79] Lord Justice Stuart-Smith invoked the "well-known elephant test. It is difficult to describe, but you know it when you see it". Similarly, in *Ivey* v *Genting Casinos*,[80] Lord Hughes opined "like the elephant, it is characterised more by recognition when encountered than by definition."

Judge Potter Stewart also used the elephant test to describe hard-core pornography in *Jacobellis* v *Ohio*.[81] On the definition of pornography, he said, "I shall not today attempt further to define the kinds of material I understand to be embraced within that shorthand description; and perhaps I could never succeed in intelligibly doing so. But I know it when I see it, and the motion picture involved in this case is not that."

Abduction appears speculative as the process of forming an explanatory hypothesis cannot be logically reconstructed;[82] yet, it is used often to complement what deduction cannot do. Take Bayesian probability as an example: a speculation is taken as a prior probability distribution (a "prior")[83] and then predictions are made about the likelihood of an outcome, "posterior probability distribution" by manipulating the priors.[84] In fact, Bayesian inference has found applications in a

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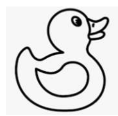
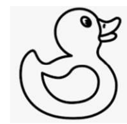
[79] *Cadogan Estates Ltd* v *Morris*, [1998] EWCA Civ 1671, [1999] 1 EGLR 59.
[80] *Ivey (Appellant)* v *Genting Casinos (UK) Ltd t/a Crockfords (Respondent)*, [2017] UKSC 67.
[81] *Jacobellis* v *Ohio*, 378 US 184 (1964).
[82] Aliseda, *supra* note 63 at 56.
[83] Scott Michael Lynch, *Introduction to applied Bayesian statistics and estimation for social scientists*, Statistics for social science and public policy (New York: Springer, 2007) at 48.
[84] *Ibid* at 49.

wide range of disciplines, including statistics, engineering, and medicine. Abduction is now mainstream computer science.[85] We will explore more of probabilistic inference later in this paper.

We could summarize the three branches of logical reasoning by the following illustration.

Table 2: Logics of Deduction, Induction, and Abduction

DEDUCTION	INDUCTION	ABDUCTION
 All swans are white.  Daisy is a swan. Therefore, Daisy is white.	 Daisy is a swan and is white.  Felix is a swan and is white.  Donald is a “swan” (but it’s a duck!) and is white. Therefore, all swans are white (wrong!).	 All swans are white.  Donald is white. Therefore, Donald must be swan (wrong!)

The use of logic helps us reach conclusions from premises by providing a consistent standard of reasoning paths. Endowed with logic, one is ready to make arguments, an essential skill in a complex world. More precisely, an argument is broken down to a “claim” (a conclusion in need of support), “evidence” (facts that are used to support the claim), and “warrants” (reasons used to justify the connections between evidence and claim).[86]

A normative framework for argumentation is dialectic. Dialectic is a discourse between two opposing points of views and can takes different forms.[87] Debate is a frequent form of dialectic. As a counterpart to dialectic, rhetoric,[88] is a mixture of reasoning techniques to persuade by

[85] Aliseda, *supra* note 63 at 40.
[86] Frans H van Eemeren et al, “Toulmin’s Model of Argumentation” in Frans H van Eemeren et al, eds, *Handb Argum Theory* (Dordrecht: Springer Netherlands, 2014) 203.
[87] Bobzien, *supra* note 61 s 8.
[88] Christof Rapp, “Aristotle’s Rhetoric” in Edward N Zalta, ed, *Stanf Encycl Philos*, spring 2010 ed (Metaphysics Research Lab, Stanford University, 2010) s 3.

discovery. In Aristotle's view, the work of rhetoric is to discover the available means of persuasion,[89] sometimes with an appeal to emotion.[90]

One argumentation technique, *reductio ad absurdum*, or argument by contradiction, is to disprove a claim by reducing the proposition to absurdity.[91] Like, "If it is true, then pigs can fly." It is a technique found repeatedly in Aristotle's prior analytics logic. To argue, then, is to bring about an inference objection or a counter argument to contradict the claim.[92]

However, not all argumentation techniques are sound. For instance, some fallacious arguments are based on false beliefs or facts, or connecting propositions that do not logically connect; "slippery slope"[93] is a type of false argument that resembles this: "if we legalize gay marriage, what comes next, people want to marry their pets." In a criminal trial, the Supreme Court rejected counsel's "slippery slope" argument for extending too far a challenge for cause in the Canadian jury selection process to a proportionately representative jury roll for the sake of "a guard against racism".[94]

Another notorious argument type is circular argument,[95] which is a form of begging the question. "If A, therefore A." "God exists because the Bible says so." "A tire has got to be round." The Supreme Court reckons that "bootstrapping" where parties looking to other evidence to confirm the reliability of evidence is a circular argument.[96]

Judgment and Rationality

Being bombarded with different arguments, the next step is to decide which argument is most convincing, like judges must reach a verdict in the courtroom. Outside the courtroom, individuals make countless decisions everyday, from what one should eat for lunch to whether one should go to university. Besides practical decisions of what one should do, we also make moral judgement

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[89] *Ibid* s 2.
[90] *Ibid* s 5.
[91] Tomassi, *supra* note 64 at 89.
[92] *Ibid* at 31.
[93] Hans Hansen, "Fallacies" in Edward N Zalta, ed, *Stanf Encycl Philos*, summer 2020 ed (Metaphysics Research Lab, Stanford University, 2020).
[94] *R v Kokopenace*, 2015 SCC 28 (CanLII), [2015] 2 SCR 398 at paras 84–88.
[95] Hansen, *supra* note 93.
[96] *R v Khelawon*, 2006 SCC 57 (CanLII), [2006] 2 SCR 787 at para 100.

of good and evil. Research has uncovered systematic regularities in how people make decisions and judgement.

Traditionally, the rational theory of choice posits that people have orderly preferences that obey a few intuitive axioms. When faced with choices, it is assumed that we gauge each alternative's subjective utility and choose one with the highest return.[97] In economics, the mainstream model is based on the same principle, that humans naturally calculate a utility function and opt for maximum reward.[98]

Critics of the rational model say that there are factors that put constraints on different human resources, such as short attention span and poor memory capacity, as well as finite time. Therefore, it is unreasonable to expect decision makers to exhaustively compute each option's expected utility.[99] In addition, there is a growing body of literature that supports the idea that decision-making involves not only cognition, but also emotion and intuition.[100]

Tversky and Kahneman discovered additional factors in decision-making that defy rationality.[101] One factor is "heuristics and biases". Heuristics and biases are individual beliefs of the likelihood of an event,[102] which may be misconceptions of chance.[103] For instance, tossing a coin gives us either Head (H) or Tail (T). We tend to think that the probability of a fair coin turning HHTHT is more likely than HHHHH, because the latter does not appear random. But statistically, every flip of the coin is an independent event, so the probability of HHTHT is equal to that of HHHHH.[104]

Consider also, a person's chance of winning the lottery. We may think that a person who won the lottery is less likely to win it again. It turns out that, statistically, winning the lottery today and winning it again next week are independent events. Thus, a person who has never won the lottery

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[97] McCready, *supra* note 54 at 247.
[98] Ejan Mackaay, *Law and economics for civil law systems* (2013) at 40.
[99] Kahneman, *supra* note 55 c 2.
[100] Grant Soosalu, Suzanne Henwood & Arun Deo, "Head, Heart, and Gut in Decision Making: Development of a Multiple Brain Preference Questionnaire": (2019) SAGE Open, online: <https://journals.sagepub.com/doi/10.1177/2158244019837439>.
[101] Amos Tversky & Daniel Kahneman, Daniel Kahneman & Amos Tversky, *Choices, values, and frames* (New York : Cambridge, UK: Russell Sage Foundation ; Cambridge University Press, 2000).
[102] Amos Tversky & Daniel Kahneman, "Judgment under Uncertainty: Heuristics and Biases" (1974) 185:4157 Science 1124–1131.
[103] *Ibid*.
[104] *Ibid*.

has the same chance of winning as someone who has won at least once.[105] But our subjective sense of chance blinds us from rational inference, exposing us to heuristics and biases.

Another factor that influences our judgement is "framing". For example, having to choose between a 50% chance of losing $100 or a 70% chance of losing $50; or between a 25% chance of winning $30 and a 20% chance of winning $45, changes our way of perceiving the choices available to us.[106] Given only apple and mango, if a person's favourite fruit is orange, this person may feel that her need is not met and does not purchase anything. However, if she is given 24 different kinds of fruit, she might not buy anything either as she is "choice-overloaded". Humans tend to engage in choice when given the right number and combination of options.

There is also the "decoy" effect that is used widely in marketing.[107] Consider, a person chooses A when offered {A, B, C} but chooses B from the options {A, B}. This behaviour is a response to a contraction (reduced) condition. Choosing A, when offered either {A, B} or {A, C}, but not choosing A when offered {A, B, C} is a response to an expansion (added) condition. This type of adding or removing options introduces the idea of asymmetric dominance.[108] Asymmetric dominance is also described as the attraction effect which refers to the fact that in a choice between options {A, B}, a third option C that is clearly inferior to A (but not to B) can be added, thereby increasing the choice likelihood of A.

Another factor that defies rational choice is "priming". Priming is a technique in which the introduction of one stimulus influences how a person responds to a subsequent stimulus.[109] It taps into humans subconscious association in thinking. For example, the word "eat" primes "soup", and the word "wash" primes "soap".[110] Priming explains why we tend to impulse buy when shopping for groceries with an empty stomach. The marketing industry also takes advantage of this human condition.

[105] Donald J Koosis, *Statistics*, Wiley classics library (New York: Wiley, 1972) at 22.
[106] Benedetto De Martino et al, "Frames, Biases, and Rational Decision-Making in the Human Brain" (2006) 313:5787 Science 684–687.
[107] Maurits C Kaptein, Robin Van Emden & Davide Iannuzzi, "Tracking the decoy: maximizing the decoy effect through sequential experimentation" (2016) 2:1 Palgrave Commun 1–9.
[108] Ian J Bateman, Alistair Munro & Gregory L Poe, "Decoy Effects in Choice Experiments and Contingent Valuation: Asymmetric Dominance" (2008) 84:1 Land Econ 115–127.
[109] Kahneman, *supra* note 55 c 4.
[110] *Ibid*.

Furthermore, one's ability to hold off instant gratification also affects decision-making. In child development research, children are asked to respond to the marshmallow test. A child must decide between one marshmallow immediately or two marshmallows tomorrow. Children who choose delayed but greater reward are believed to have higher chance of success in their future.[111]

All the above factors prompted new ways of understanding reasoning. The psychology of reasoning was dominated by the deduction paradigm from around 1960 to 2000.[112] Since the new millennium, research has gravitated around a dual theory,[113] that humans use two fundamental ways of thinking in decision-making. There are many names for the dual: implicit and explicit, or system 1 and system 2. Daniel Kahneman calls it fast and slow thinking.[114]

Dual theory observes that the first type of thinking, system 1, is unconscious or preconscious, rapid, and automatic while the second type, system 2, tends to be conscious, slow, and controlled.[115] System 1 is associative, intuitive, contextualized, and prone to cognitive biases, while system 2 is rule-based, deliberate, abstract, and uses normative reasoning. As a result, system 2 thinking demands more effort from our working memory; so, humans have a lower capacity for system 2 than for system 1 thinking.[116] But the line between system 1 and system 2 is not clear cut. In other words, both systems could be working at the same time, and their roles can be reversed.[117] The interplay between the two systems is complex and depending on the individual, some may invoke system 2 in a given circumstance, but some may not. This means that the dual reasoning pattern is not uniform across individuals.[118]

We have only begun to understand our biology in the last few decades. For example, scientists used to think that human brain cells do not regenerate after we reach adulthood. But neuroplasticity

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[111] Louise Twito et al, "The Motivational Aspect of Children's Delayed Gratification: Values and Decision Making in Middle Childhood" (2019) 10 Front Psychol, online: <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6684787/>.
[112] Keith J Holyoak, Robert G Morrison & Jonathan St B T Evans, *Dual-Process Theories of Deductive Reasoning: Facts and Fallacies* (Oxford University Press, 2012).
[113] *Ibid*.
[114] Kahneman, *supra* note 55.
[115] *Ibid* cs 2–3.
[116] *Ibid*.
[117] *Ibid* c 8.
[118] *Ibid* c 5.

shows that new pathways can be built even in old age.[119] Also, scientists used to think that our DNA predetermines the person we become. But epigenetics suggests that DNA expressions may not depend on DNA sequencing.[120] This means that other factors may turn on or off the genes we inherit, which effectively ends the debate between nature and nurture. The complexity of human cognition requires combining the studies of psychology, neuroscience, and molecular genetics, into new fields such as cognitive neurogenetics.[121] Moreover, with neuroimaging techniques, like scalp electroencephalography (EEG) and functional magnetic resonance imaging (fMRI), researchers can now elucidate relationships between brain area and behaviour.[122]

In addition, our decision-making is influenced by social rules as well.[123] For instance, deontic philosophy believes that social norms form the basic concept on which inferences operate. Therefore, a person may act based on a social rule, independent of what the person may think is the "rational" choice. Deontic reasoning is often about obligation and duty, but can be used in non-ethical problem solving as well.[124] Moreover, culture also influences our way of reasoning. For example, rationality is shown to be adaptive because some cultures (e.g., Eastern cultures) tend to tolerate "apparent contradiction",[125] which gives the impression that Western cultures gear towards analytical thinking and Eastern cultures gear towards holistic thinking.

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[119] Joyce Shaffer, "Neuroplasticity and Clinical Practice: Building Brain Power for Health" (2016) 7 Front Psychol, online: <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4960264/>.
[120] Carrie Deans & Keith A Maggert, "What Do You Mean, 'Epigenetic'?" (2015) 199:4 Genetics 887–896.
[121] Adam E Green & Kevin N Dunbar, "Mental Function as Genetic Expression: Emerging Insights From Cognitive Neurogenetics" in *KJ Holyoak RG Morrison Eds Oxf Handb Think Reason* (2012).
[122] Brigitte Vallabhajosula, "The Basics of Neuroimaging" in *Murd Court* (New York: Oxford University Press, 2015) s 3.9, 3.1.
[123] Sieghard Beller, "Deontic reasoning reviewed: psychological questions, empirical findings, and current theories" (2010) 11:2 Cogn Process 123–132.
[124] *Ibid*.
[125] N Y Louis Lee, "Chapter 4 - Cross-Cultural Differences in Thinking: Some Thoughts on Psychological Paradigms" in T -W Hung & T J Lane, eds, *Rationality* (San Diego: Academic Press, 2017) 61 at 70.

Probability

Choice under uncertainty, together with heuristics and biases, make it difficult to predict outcome accurately; but fortunately, Bayes' theorem, and its application, Bayesian inference[126] come to rescue. The Bayesian view of causality is related to degree of belief. Specifically, Bayesian modelling allows the prediction of a reasonable outcome based on prior knowledge or belief (abduction). To do so, it uses Bayes' theorem to update the probability for a hypothesis as more evidence becomes available. To understand the origin of Bayes' theorem, consider $P(A|B)$, the probability that A is true, given that B is true. Then, the joint probability $P(A,B)$, that both A and B are true, is the probability that B is true, $P(B)$ multiplied by the probability that A is true given that B is true, $P(A|B)$. That is,

$$P(A,B) = P(A|B)P(B)$$

By symmetry, it follows that

$$P(B|A)\,P(A) = P(A|B)P(B)$$

Dividing both sides by $P(A)$ gives the equation of Bayes' theorem:[127]

$$P(B|A) = \frac{P(A|B)P(B)}{P(A)}$$

Why is it important? Because often $P(A|B)$ is known, but the converse, $P(B|A)$ is unknown. With Bayes' theorem, the unknown can be derived from the known. This revelation means that an outcome can be predicted given known and unknown distributions.[128] Indeed, Bayesian inference is such an important technique in science and engineering that it also lays the foundation of some branches of machine learning.

To conclude the first half of the chapter, traditional frameworks of reasoning involve logic and rational theory of choice. Gradually, a dual theory is developed to explain the complexity of human

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[126] Although it was statistician Thomas Bayes who first formulated the theorem, it was not until mathematician Pierre-Simon Laplace further developed and popularised it that we have what is now called Bayesian probability.
[127] Pearl, Glymour & Jewell, *supra* note 36 at 12.
[128] *Ibid*.

thinking. And since we still do not absolutely understand how we make decisions, Bayesian probability has been helpful in describing and predicting decisional outcomes.

1.2. Causality

Causality belongs to the inductive branch of reasoning;[129] it studies the relationship between cause and effect. The function of causality is two-fold: to account for what happened (backward-looking);[130] and to predict the consequence of action to achieve goals (forward-looking).[131] Work on causality goes back to Aristotle,[132] and David Hume modernized it with empirical methods.[133] Causality finds wide application in medicine, physics, law, among others.

With respect to the criteria for medical causation, the authority goes to Sir Austin Bradford Hill, who demonstrated the connection between cigarette smoking and lung cancer.[134] In his guidelines for investigating causality in epidemiological studies, Sir Bradford Hill listed the following nine factors: strength, consistency, specificity, temporality, biologic gradient (directional), plausibility (explainable), coherence (without conflict), experimental evidence, and analogy (insight).

Strength, consistency, and specificity speak to the relationship between the assumed cause and effect; Temporality means that the cause must precede the effect; Biological gradient means that the relationship is directional: that the cause causes the effect and not the other way around; Plausibility means that there is a reasonable pathway to link outcome to exposure; Coherence: consistent results; Experimental evidence: backed by data; and Analogy: result with some kind of insight.[135]

Sir Bradford Hill mentioned that not all the criteria must be met but the conclusion is drawn from the totality of evidence. To demonstrate causation, his criteria may be summarised into three

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[129] Mill, *supra* note 3 at 401.
[130] Halpern, *supra* note 37.
[131] Patricia W Cheng & Marc J Buehner, "Causal Learning" in *KJ Holyoak RG Morrison Eds Oxf Handb Think Reason* Oxford Library of Psychology (Oxford University Press, 2012).
[132] Halpern, *supra* note 37.
[133] *Id*.
[134] Austin Bradford Hill, "The Environment and Disease: Association or Causation?" (1965) 58:5 Proc R Soc Med 295–300.
[135] *Ibid*.

conditions: 1) association, 2) temporality,[136] and 3) non-spuriousness. In the language of AI, the three conditions mean 1) correlation between features X and Y; 2) X occurs before Y; and 3) the relationship is directional and non-confounding. Non-confounding means that there does not exist another factor A that is the cause of both X and Y.

For causality generally, the inductive canons of John Stuart Mill are an important body of work. In *A System of Logic*,[137] Mill described the cause of an effect as something that is "antecedent invariably and unconditionally".[138] Unconditional here is in the sense of necessity: that but for the cause, the effect cannot be. Today, this but-for concept is prevalent in dealing with causation in law, to be discussed in Chapter 2. Mill also contemplated the "lasting or ceasing effect" of a cause: "A *coup de soleil* gives a man a brain fever: would the fever go off as soon as he is moved out of the sunshine? A sword is run through his body: must the sword remain in his body in order that he may continue dead?"[139] This "lasting or ceasing effect" is the equivalent of the *de novo* or intervening concept in law (Chapter 2). Then, Mill further clarified, "The conditions which are necessary for the first production of a phenomenon, are occasionally also necessary for its continuance; but more commonly its continuance requires no condition except negative ones."[140]

Moreover, Mill pointed out the subtle but important distinction between correlation and causality. Some of his ideas would baffle researchers for years to come. He studied William Whewell and Auguste Comte, and made the most relevant remark in causality:

> *"…the distinction between those constant relations of succession or coexistence which Mr. Whewell terms Laws of Phenomena, and those which he terms, as I do, Laws of Causation, is grounded… upon a real difference. It is no doubt with great injustice that Mr. Whewell… assumes that M. Comte has overlooked this fundamental distinction, and that by excluding the investigation of causes, he excludes that of all the most general truths."*[141]

This distinction is the main divide between the two fundamental approaches to causal discovery in computer science today, to be discussed in the next few pages.

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[136] Note that temporality is a condition that may be argued in quantum physics.
[137] Mill, *supra* note 3.
[138] *Ibid* at 222.
[139] *Ibid* at 224.
[140] *Ibid*.
[141] *Ibid* at 209.

Mill ascertained that the laws of cause and effect are the main business of induction.[142] He articulated that a causal relationship must be unconditional (i.e. necessary) but not absolutely one-to-one. That is, an effect can be caused by multiple causes; or a cause can produces multiple effects; This means that causality can be a combination of these varieties, thus producing a many-to-many relationship. Mill also considered the cancelling effects of causality, as well as joint and separate effects:

> *"A stream running into a reservoir at one end tends to fill it higher and higher, while a drain at the other extreme tends to empty. Now, in such cases as these, even if the two causes which are in joint action exactly annul one another, still the laws of both are fulfilled; the effect is the same as if the drain had been open for half an hour first, and the stream had flowed in for as long afterwards. Each agent produced the same amount of effect as if it had acted separately, though the contrary effect which was taking place during the same time obliterated it as fast as it was produced."*[143]

These concepts are relevant in legal cases when multiple tortfeasors are involved.

Fast forward to the present, epidemiologist Kenneth Rothman reckoned that concepts of causal inference are "largely self-taught",[144] and since philosophers agree that causal propositions cannot be proven, the roles of logic, belief and observation in evaluating the propositions have not been settled neither.[145] Indeed, we contradict our own causal theories often. For example, scientists used to think that vitamin E has antioxidant effects but only realized later that whereas natural foods rich in vitamin E have antioxidant effects, vitamin E pills do not.[146] This phenomenon may be explained by a mediator,[147] to be discussed soon.

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142 *Ibid* at 247.
143 *Ibid* at 244.
144 Kenneth J Rothman, Sander Greenland & C Stat, "Causation and Causal Inference in Epidemiology" (2005) 95 Am J Public Health 25.
145 *Ibid*.
146 Cheng & Buehner, *supra* note 131.
147 Pearl & Mackenzie, *supra* note 26 c 9.

The road to causal discovery may be grouped into two main approaches which are not mutually exclusive:[148]

1. Associative approach; and
2. Causal approach

Associative Approach

The associative approach is closely related to David Hume's rule of causal inference and statistics. Hume was a devoted empiricist with a probabilistic version of inductivism.[149] In other words, Hume saw every phenomenon of cause and effect as a probability between 0 and 1, but never 0 or 1. He would not admit that taking Aspirin causes headache to stop. If he were alive, he would explain it as such: "In the past, taking Aspirin has relieved my headache; therefore, I believe that taking Aspirin would probably relieve my headache now. But my inference is based on the Aspirin's superficial sensible qualities, which have nothing to do with headache relief. Even if I assume that the Aspirin has "secret powers" that are doing the heavy lifting in relieving my headache, they cannot be the basis of my inference, since these "secret powers" are unknown…"[150]

Embracing science only with a probabilistic approach, Hume divided knowledge acquisition into two prongs: relations of ideas and matters of fact. The distinction between the two prongs is known as "Hume's fork".[151] Relations of ideas are analytic, necessary, and knowable *a priori* while matters of fact are synthetic, contingent, and knowable *a posteriori*.[152] Therefore, ideas are acquired rationally, "in the mind"; while facts are acquired empirically through observational science. But they do not intersect; that is, knowledge is either statement of idea or statement of fact. Thus, causality for Hume could only be inferred using observable evidence.

Later, this view would be contested by Immanuel Kant, who infused rationalism and empiricism in the acquisition of knowledge.[153] But many scholars stand by Hume, including Hans

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[148] Some may be more inclined to divide them as chance vs determinism; however, the causal approach can be probabilistic, as will be explained later.
[149] Morris & Brown, *supra* note 7 s 4.
[150] *Ibid* s 5.
[151] *Ibid*.
[152] *Ibid*.
[153] Michael Rohlf, "Immanuel Kant" in Edward N Zalta, ed, *Stanf Encycl Philos*, spring 2020 ed (Metaphysics Research Lab, Stanford University, 2020).

Reichenbach,[154] who developed an account of probability appropriate for scientific inference.[155] Reichenbach thought that "it would be illusory to imagine that the terms 'true' or 'false' ever express anything else than high or low probability values."[156] Working in the tradition of Hume, Wesley Salmon also developed a sophisticated version of empiricism by combining probability[157] and realism[158] in order to deal with the problem of induction.

The probabilistic view of causality sees causality as an expression between 0 and 1. Specifically, the strength of the relation between cause X and effect Y is determined by their contingency or probabilistic contrast, the difference between the probabilities of Y in the presence and absence of X.[159]

$$\Delta P = P(Y^+|X^+) - P(Y^+|X^-)$$

If the strength ΔP, is positive, then X causes Y. In contrast, if ΔP is negative, X does not cause Y; furthermore, X prevents Y. Finally, if ΔP is close to zero, there is no causal effect. Thus, the associative approach to causality relates to the correlation between cause and effect whose strength is expressed in probability. Association is accurate in degrees but informs no direction. For as far as association is concerned, strong causal influence may happen by coincidence.

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[154] Clark Glymour & Frederick Eberhardt, "Hans Reichenbach" in Edward N Zalta, ed, *Stanf Encycl Philos*, winter 2016 ed (Metaphysics Research Lab, Stanford University, 2016) s 2.
[155] H Reichenbach, F Eberhardt & CN Glymour, *The Concept of Probability in the Mathematical Representation of Reality*, Full Circle, Publications of the archive of scientific philosophy (Open Court, 2008).
[156] Paolo Parrini, Wesley C. Salmon & Merrilee H. Salmon, Paolo Parrini, Wesley C Salmon & Merrilee H Salmon, *Logical empiricism : historical & contemporary perspectives* (Pittsburgh: University of Pittsburgh Press, 2003) at 283.
[157] Galavotti, *supra* note 73 s 3.
[158] *Ibid* s 6.2.
[159] Cheng & Buehner, *supra* note 131.

Causal Approach

In contrast, the second approach to causality, the causal approach, is closely related to (and often confused[160] with) determinism.[161] Determinism is the view that given *X*, the outcome *Y* must or must not result as a matter of law.[162] But the causal approach described here does not necessarily take the deterministic view. The causal approach is about finding the direction of influence. For instance, we know that the rooster crows before sunrise, but it is the sunrise that causes the crowing, not the other way around. Humans intuitively understand the directions of causal inference, rather than see the world merely in probabilistic association.

In order to investigate the direction of influence, causal analysis requires intervention. Intervention is merely another word for experimentation.[163] We intervene to be sure that *X* causes *Y*, as opposed to, *Y* happens in presence of *X*. Mathematically, $P(Y|do(X))$, as opposed to, $P(Y|X)$. In practice, the causal approach conducts experiment with randomized controlled trials (RCT).[164] For example, in an Aspirin experiment, half the participants would be given real Aspirin, while the other half would be given Aspirin look-alike sugar pills. If participants who took real Aspirin experience no more headache while those who took fake ones still have a headache, we can say confidently (assuming all things being constant) that Aspirin causes the headache to stop. As demonstrated, there is a fundamental difference between observation (correlation) and intervention (causation), as Mill had noticed hundreds of years ago.[165]

Judea Pearl has been advocating for the use of causal thinking in AI research.[166] He developed a mathematical framework for causal inference by combining graphical representation, called

[160] Confusion of causality and determinism is particularly acute in quantum mechanics. Quantum mechanics is largely understood as probabilistic, as many believe that one cannot predict with certainty the manner of radioactive decay. But there has not been consensus on the definition of quantum mechanics; and depending on the definition, causality in quantum mechanics can be deterministic or probabilistic. Interested reader may inquire about the "wave" and "particle" properties of atoms, Schrödinger's wave equations, and the problem of measurement.
[161] Carl Hoefer, "Causal Determinism" in Edward N Zalta, ed, *Stanf Encycl Philos*, spring 2016 ed (Metaphysics Research Lab, Stanford University, 2016) s 4.4.
[162] *Ibid* s 1.
[163] Judea Pearl, *Causality : models, reasoning, and inference* (Cambridge, U.K.: Cambridge University Press, 2000) c 2.
[164] Pearl, Glymour & Jewell, *supra* note 36 at 53.
[165] Mill, *supra* note 3 at 209.
[166] Pearl, Glymour & Jewell, *supra* note 36.

directed acyclic graph (DAG), structural equations, and probabilistic paths.[167] As mentioned in the Introduction, Pearl's main criticism of today's AI approach is our obsession with correlation. In associative analysis, researchers understood that we cannot infer a causal relationship from a data set by observation, unless there is substantial prior knowledge about the mechanisms that generated the data.[168] A correlation tells us that every time the light is on, the light switch is at the "on" position. But to demonstrate that the light switch turns the light on, and the light does not turn the switch on, we need intervention.

An emphasis must be made that the associative approach and the causal approach are not mutually exclusive. One way to combine them is to establish direction of influence with a probabilistic qualifier. That is why causal inference is not necessarily deterministic.

$$X \xrightarrow{P(Y|X)} Y$$

Figure 5: X causes Y with a Probability P

Pearl illustrates the three stages of causality inference using "The Ladder of Causality":[169]

1. Association (There exists a correlation of Aspirin intake and headache disappears.)
2. Intervention (Take Aspirin and see what happens.)
3. Counterfactuals (Without Aspirin, would headache have disappeared anyway?)

A few more concepts must be introduced before further discussing causality. One important concept is a confounder variable. A confounder has two definitions.[170] One is "declarative", which is inaccurate:[171] "any variable that is correlated with both exposure *X* and outcome *Y*." This definition refers to correlation and does not inform us about cause and effect. The other definition is "procedural", which is accurate: [172] "adjusting for the variable and seeing if it is a confounder."

[167] Pearl, *supra* note 163.
[168] Pearl & Mackenzie, *supra* note 26.
[169] *Ibid*.
[170] *Ibid* c 4.
[171] It is used in Alfredo Morabia's "Epidemiology: An epistemological perspective".
[172] It is used in Sven Hernberg's "Significance testing of potential confounders and other properties of study groups -- misuse of statistics".

The procedural definition knows that the variable is related to X and Y, but causality needs to be established.

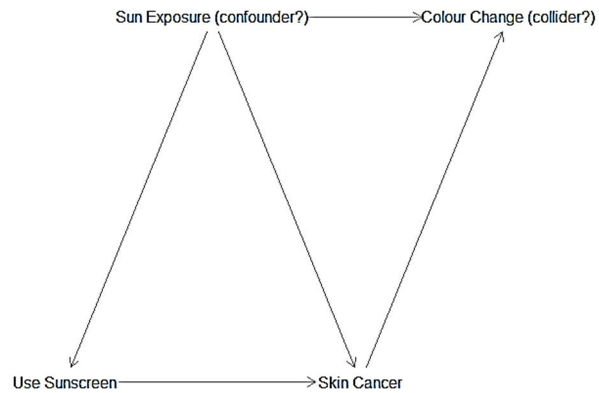

Figure 6: Sun exposure and skin cancer

For example, sun exposure is closely associated with the use of sunscreen (*X*) and skin cancer (*Y*). To find out if sun exposure is a confounder, we need to study the effect of sun exposure on sunscreen use and skin cancer. The opposite of a confounder is a collider, which is being influenced by a suspected cause and effect.[173] In this example, sun exposure increases the use of sun screen and the risk of skin cancer, suggesting a confounder; and both sun exposure and skin cancer change the colour of the skin, suggesting a collider.

Finally, an equally important concept is the mediator variable.[174] Moeller's disease, known commonly as scurvy, is a disease that causes a gruesome death with gum problems and bleeding from the skin. Scurvy was responsible for more deaths at sea than storms, shipwrecks, combat, and all other diseases combined.[175] Scottish doctor James Lind discovered that citrus fruit cured scurvy. But today, we know that vitamin C, rather than citrus fruit, is responsible for healthy connective tissue.

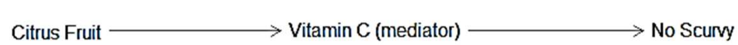

Figure 7: Vitamin C is a mediator between citrus fruit and healthy tissue

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[173] Pearl, Glymour & Jewell, *supra* note 36 at 40.
[174] *Ibid* at 75.
[175] Catherine Price, "The Age of Scurvy", (14 August 2017), online: *Sci Hist Inst* <https://www.sciencehistory.org/distillations/the-age-of-scurvy>.

Paradoxes in Causality

In statistics, there exist many baffling paradoxes. These paradoxes are even more fascinating through the lens of causality. Below are three paradoxes that may change the way we think about causal inference.

The first one is the Monty Hall paradox. Monty Hall is the original host of an American television show *Let's Make a Deal*.[176] In the show, the contestant was giving three doors. Behind each door is either a car or a goat. There is one car and two goats. So, we can say that each contestant has 1/3 chance of winning the car.

Table 3: Probabilities of winning a car by door

Door 1	Door 2	Door3
1/3	1/3	1/3

Suppose the contestant chooses Door 1. Then, the host reveals that behind Door 3 is a goat. Now, the question is, should the contestant stay with Door 1 or switch to Door 2?

Most people, especially mathematicians, would say it does not matter because the chance of winning the car was 1/3 and now the chance of winning is 1/2. But it is not that simple.

Imagine that the host opened Door 1. Then the contestant lost and there was no need to ask any more question. Imagine that the host opened Door 2. Then the contestant also lost and there was no need to ask any more question. But the host opens Door 3, and at this point, the contestant has not won or lost. The host opens Door 3 after the contestant chooses Door 1. So, we could say that the contestant's choice of Door 1 and that the car is behind Door 2 cause the host to open Door 3.

Table 4: Another way to see the probabilities

Door 1	Door 2 or Door3
1/3	1/3 + 1/3 = 2/3

Now, we know the car is not behind Door 3. But the chance of car behind Door 2 and Door 3 remains 2/3. That means that the probability of the car behind Door 2 is double of that of the car behind any door.

[176] There are many versions of the problem. For other explanations, go to https://www.montyhallproblem.com/.

Table 5: Probabilities of winning after door 3 is opened

Door 1	Door 2
1/3	2/3 + 0/3 = 2/3

The Monty Hall problem teaches us that our analysis depends not only on the data (what is behind which door) but also the data generation process (the rule of the game). This lesson is important because it reveals the limitation of probabilistic inference without causal analysis.

Another paradox is Berkson's,[177] which was discovered in a hospital. Consider two independent diseases, Disease X and Disease Y, both require hospitalization. Suppose 7.5% of the general population gets Disease X, but among the hospitalized people with Disease Y, 25% would have Disease X. Mathematically, the conditional probability of X given (X or Y) is greater than the conditional probability of X given both (X or Y) and Y:

$$P(X|X \cap Y) > P(X|X \cap Y, Y)$$

The surge in percentage is a statistical bias. Berkson's bias is a special case of collider bias, as a result of conditioning incorrectly on a common effect (hospitalization) of at least two causes.[178] This is the reason why Pearl warns that adjusting for a collider is not allowed,[179] because doing so creates collider bias or the "explain-away" effect.[180] We will explain conditioning in Chapter 4.

We could understand Berkson's paradox as a selection bias: when two independent variables contribute to overall result, the variables compensate each other. For example, if restaurants are rated by the taste of food (X) and decorations (Y), which are independent, then between two five-star restaurants, the restaurant with ugly decorations will probably have better tasting food.

Finally, the most well-known paradox in statistics is Simpson's paradox,[181] which describes a situation in which a relationship is observed in separate groups of data, but the relationship disappears when these groups are combined. Consider that a population of patients is divided into

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[177] Joseph Berkson, "Limitations of the Application of Fourfold Table Analysis to Hospital Data" (1946) 2:3 Biom Bull 47–53.
[178] Daniel Westreich, "Berkson's bias, selection bias, and missing data" (2012) 23:1 Epidemiol Camb Mass 159–164.
[179] Pearl & Mackenzie, *supra* note 26 c 3.
[180] *Ibid* c 6.
[181] Gary Malinas & John Bigelow, "Simpson's Paradox" in Edward N Zalta, ed, *Stanf Encycl Philos*, fall 2016 ed (Metaphysics Research Lab, Stanford University, 2016) s 1.1.

two age groups and each group is treated with two different brands of drugs. The following results reflect Simpson's paradox.

Table 6: Statistics on effectiveness of drugs by age groups

Age Group	Drug A effective	Drug B effective
18-40	**88%** (70/80)	84% (228/270)
41-65	**67%** (180/270)	63% (50/80)
Total	71% (250/350)	**83%** (278/350)

In both age groups, Drug A is more effective than Drug B but together Drug B is more effective. This phenomenon can be explained by the fact that more young people were treated with Drug B and more old people were treated with Drug A, but the total is summed without the weighted average. Thus, when combined into one group, the faithfulness condition[182] is lost.[183]

The above three paradoxes are excellent ways to illustrate two things: that the human brain is not wired for probabilistic thinking; and that reasoning and causal thinking are subjective, leading to different hypotheses even though reality remains constant. These revelations are pertinent in constructing causal models (Chapter 4); it explains why the same situation can be reflected in different causal models.

The Timing of Cause and Effect and the Unreliability of Science

Another aspect of causal reasoning is temporality. Consider Billy is about to throw a stone at a window. The window does not shatter until Billy throws the stone. However, this rule of temporality may be true only in classical physics, where the condition of "cause first, effect after" is consistent with the belief that matters cannot travel faster than the speed of light.

Causal systems are defined as systems that depend only on current and/or past events.[184] Systems that are not causal are "acausal",[185] out of which "anti-causal systems" depend solely on future

[182] A causal graph is "unfaithful" when two variables may be independent in subpopulations but dependent in a combined population.
[183] Peter Spirtes, Clark Glymour & Richard Scheines, *Causation, Prediction, and Search, 2nd ed.* (1993) at 38, journalAbbreviation: Causation, Prediction, and Search.
[184] AV Oppenheim, AS Willsky & SH Nawab, *Signals and Systems*, Prentice-Hall signal processing series (Prentice Hall, 1997) at 46.
[185] Kyu-Young Whang et al, *Advances in Knowledge Discovery and Data Mining: 7th Pacific-Asia Conference, PAKDD 2003. Seoul, Korea, April 30 - May 2, 2003, Proceedings* (Springer, 2003) at 237, Google-Books-ID: nWtrCQAAQBAJ.

events. So long as nothing travels faster than light, all systems are causal; but it does not mean that anti-causal systems cannot exist. In modern physics, this question is put to the test, as the notion of causality is more flexible.

The insights of the theory of special relativity[186] by Albert Einstein confirmed the temporality of causality, but the concept of "simultaneity" in time applies only to observers who are in physical proximity. In other words, to the proximate observers, events are separated by time-interval,[187] and Newton's kinematics of rigid bodies hold,[188] so that cause precedes its effect. In a time-interval, a point can only travel at a velocity equal to or slower than the speed of light.[189] Yet, if signals could move faster than light, they would violate the principle of causality because effect could precede cause. The Grandfather paradox, which asks what happens if a time traveler kills his own grandfather before he ever meets the time traveler's grandmother, addresses the absurdity. Thus, under the theory of special relativity, time travel remains a subject of fiction.

But later, in Einstein's theory of general relativity, the concept of causality is also generalized. The principle of locality holds that objects are directly influenced only by immediate surroundings. However, whether it is true hinges on the existence of quantum entanglement.[190] The Einstein-Podolsky-Rosen (EPR) paradox raised the question[191] but experiments at the time had been inconclusive. Einstein did not believe in entanglement and called it "spooky action at a distance",[192] as it would violate the speed limit on the transmission of information implicit in relativity theory. However, recently, the existence of particle entanglement has been inferred by researchers.[193] This finding opens the door to acausal systems: that effect could precede cause.

Another aspect of causal inference is the unreliability of scientific conclusions. Experimentation in empirical research may not be as impartial as one thinks. There are a few considerations. First,

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[186] Albert Einstein, "On the Electrodynamics of moving bodies" in *Collecred Pap Albert Einstein* (Princeton University Press) at 140.
[187] *Ibid* at 144.
[188] *Ibid* at 143.
[189] *Ibid* at 155.
[190] Quantum entanglement means that entangled particles can still influence each other even after they are separated.
[191] A Einstein, B Podolsky & N Rosen, "Can Quantum-Mechanical Description of Physical Reality Be Considered Complete?" (1935) 47:10 Phys Rev 777–780.
[192] Albert Einstein, *The Born-Einstein letters: correspondence between Albert Einstein and Max and Hedwig Born form 1916 to 1955* (London: MacMillan Press, 1971) at 158.
[193] C F Ockeloen-Korppi et al, "Stabilized entanglement of massive mechanical oscillators" (2018) 556:7702 Nature 478–482.

researchers are humans; the objectivity of research may be called to question due to error, bias, or misconduct.[194] Second, large volumes of scientific research are funded by powerful private corporations[195] whose goal is financial profit, rather than scientific discovery. Thus, large corporation have the power to politicize research. Third, the mere observation of the observer may influence the behaviour of the subject. Evidence of the observer effect has been found in social science[196] as well as physical science.[197] Therefore, we must be mindful that the knowledge we derive from scientific research has limits, and it is with these limits that decisions and policies are made in and outside the law. As a result, although we intend that justice be served, we cannot guarantee it.

In summary, causality is the inductive branch of reasoning. Many of its concepts find applications in science and engineering as well as in law. Causal discovery can be approached by two mainstream methods: associative inference and causal inference. Associative inference relies on observational data and probability to describe the likelihood of X causing Y; on the other hand, causal inference includes intervention and counterfactuals to establish direction of influence, and demands the understanding of concepts such as confounders, colliders, and mediators. These two methods are not mutually exclusive, and both rely on empirical research, which is not without limits.

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[194] David B Resnik, *The Ethics of Science: An Introduction*, taylor&francis e-library ed (New York: Routledge, 2005) c 5.

[195] Thomas Bodenheimer, "Uneasy Alliance — Clinical Investigators and the Pharmaceutical Industry" (2000) 342 N Engl J Med 1539–44; "Science's Worst Enemy: Corporate Funding", online: *Discov Mag* <https://www.discovermagazine.com/the-sciences/sciences-worst-enemy-corporate-funding>; "As Federal Research Funds Recede, the Private Sector is Filling the Gap", online: *Lab Manag* <https://www.labmanager.com/business-management/as-federal-research-funds-recede-the-private-sector-is-filling-the-gap-2182>.

[196] Jim McCambridge, John Witton & Diana R Elbourne, "Systematic review of the Hawthorne effect: new concepts are needed to study research participation effects." (2014) 67:3 J Clin Epidemiol 267–277.

[197] E Buks et al, "Dephasing in electron interference by a 'which-path' detector" (1998) 391:6670 Nature 871–874; "Quantum Theory Demonstrated: Observation Affects Reality", online: *ScienceDaily* <https://www.sciencedaily.com/releases/1998/02/980227055013.htm>.

Chapter 2: Reasoning and Causality in Law

To discuss reasoning in law, the first question to ask would be what kind of law. Positive law, unlike natural law, is predominately the law of the West. This paper focuses on the Canadian system of law, hence, positive law. Canada is a bijural country,[198] combining both the civil law tradition and the common law tradition. Despite efforts[199] to integrate indigenous legal traditions into Canadian law,[200] the scope of our *Constitution*[201] guarantees only the duty to consult,[202] and aboriginal and treaty rights are by no means absolute.[203] Therefore, customary law will be outside the scope of this paper.

It is noteworthy that there is no consensus on what the process of legal reasoning is. In the first half of this chapter, attempts are made to revisit some of the concepts in Chapter 1 in the eyes of the law. The reason this chapter cannot revisit all the concepts in Chapter 1 is that some of them are more scientific theories than practical doctrines. For example, the notion of temporality as a criterion of causality is debated only on the atomic and subatomic levels, but the law deals with conflicts in the classical Newtonian world, so we have not encountered an occasion for its legal debates. As for the paradoxes, the closest legal application related to the Simpson's paradox was a potential gender bias lawsuit against the University of California, Berkey by women, claiming men were favoured in admission. The lawsuit did not happen as mathematicians examined the departments separately and found that women had higher admission rates.[204]

This chapter reconsiders logical reasoning, judgement and rationality, and the but-for condition for causality. We will explore mainstream concepts such as case-based reasoning and rule-based reasoning, and then other relevant considerations that affect judgement. Theories like Legal

[198] *Bilingualism in Canada's Court System: The Role of the Federal Government*, by Marie-Ève Hudon, 2017-33-E (Library of Parliament, Ottawa, Canada).
[199] For example, the Justice Partnership and Innovation Program (JPIP) is a response to the "Making Progress on the Truth and Reconciliation Commission of Canada's Calls to Action".
[200] "Justice Partnership and Innovation Program", online: <https://www.justice.gc.ca/eng/fund-fina/jsp-sjp/pfo-pfc.html>.
[201] *Constitution Act, 1982,* being Schedule B to the Canada Act 1982 (UK), 1982, c 11.
[202] *Haida Nation v British Columbia (Minister of Forests)*, [2004] 3 SCR 511, 2004 SCC 73 ; *The Duty to Consult Indigenous Peoples*, by Isabelle Brideau, Zotero, 2019-17-E (Library of Parliament, Ottawa, Canada).
[203] *R* v *Sparrow*, [1990] 1 SCR 1075.
[204] P J Bickel, E A Hammel & J W O'Connell, "Sex Bias in Graduate Admissions: Data from Berkeley" (1975) 187:4175 Science 398–404.

Realism, Critical Legal Studies, and Law and Economics will be introduced to broaden the discussion. Then, the second half of this chapter will be focused on summarizing Canadian causality frameworks using examples of common law torts, contracts, civil law responsibilities, and criminal law.

2.1. Legal Reasoning

Legal reasoning is a method of thought and argument used by lawyers and judges in legal interactions. The "official" theory of judicial behaviour is Christopher Langdell's Formalism,[205] which is referred to as Legalism by Richard Posner,[206] and involves asserting a legal rule, citing authorities, and explaining that the rule applies. Some consider this inductive process circular, as the case decision follows the rule, but the rule is derived inductively from the cases.[207] Legal reasoning uses cognitive reasoning, but it is not quite common logic. Edward Levi claimed that legal reasoning has its own logic.[208] But whose logic? A lawyer and a judge do not have the same purpose in applying legal reasoning. A judge aims to arrive at an impartial and fair conclusion given the pleadings of both sides, while a lawyer representing a client tries to make the best arguments to convince the judge.

The role of the judge is slightly broader in common law than in civil law.[209] In civil law, the rule is in the statute,[210] and the judge interprets it. In common law, the judge follows decisions from higher courts. But in the absence of precedent, the judge makes law. The common law judge dictates the *ratio decidendi*, the legal rule, binding subsequent cases.[211] Even *obiter dictum* of a judge is authoritative, although not a legal rule. This difference between the two traditions makes the judge freer with case law than with statutory law. As such, the references of the reasoning are distinct between civil law and common law.

While the starting point of common law is case law, and the starting point of civil law is statute,[212] the "official" process of arriving at a judgement follows the same path:

1. Issue (What is the debate?)
2. Rules (What are the applicable rules?)

[205] Ellsworth, *supra* note 48.
[206] Richard A Posner, *How judges think* (Cambridge, MA: Harvard University Press, 2008) at 41.
[207] Thomas C Grey, "LANGDELL'S ORTHODOXY." (1983) 45 Univ Pittsburgh Law Rev 1–949 at 21.
[208] Edward Hirsch Levi, "An Introduction to Legal Reasoning" Univ Chic LAW Rev 75.
[209] Pierre-André Côté, *Interprétation des lois*, 4e édition. ed (Montréal: Éditions Thémis, 2009) at para 1658.
[210] *Ibid*.
[211] Brewer, Scott, *Philosophy of legal reasoning: Precedents, statutes, and analysis of legal concepts* (New York: Routledge 2011) at 21.
[212] Richard Posner, "Legal Formalism, Legal Realism, and the Interpretation of Statutes and the Constitution" (1986) Case West Reserve Law Rev 179 at 187.

3. Facts (What is the evidence?)
4. Analysis (How are facts applied to the rules?)
5. Conclusion (What is the verdict?)

This traditional approach uses the method of logical syllogism discussed in Chapter 1. Generally, case law resembles induction while statutory law resembles deduction. However, Posner disagrees with the traditional view that common law reasoning resembles induction and statutory interpretation, deduction.[213] He calls Legal Formalism decisions by deductive logic,[214] and its counterpart, Legal Realism, decisions by policy. In both cases, the essential step is interpretation, which is not a deductive process.[215] Although concepts are meaningful, Posner considers them unhelpful in the interpretation of the law.

We begin with traditional accounts of case-based reasoning and rule-based reasoning, followed by alternative decision-making patterns.

Case-based Reasoning

In case law, the basic pattern of legal reasoning is by example, also known as case-based reasoning (CBR). CBR is the process of solving new problems based on the solutions of past problems.[216] CBR is not a fixed method but an approach to solving problems and can be generally described as the following cycle:[217]

1. RETREIVE the most similar cases.
2. REUSE the knowledge if "identical".
3. REVISE the information if "similar"; make new rule.
4. RETAIN learned information for future.

Two key concepts may be derived from the above cycle: precedent and analogy. Precedent, or *stare decisis*, is where an earlier decision is applied in a later case if the two cases are "identical'.

[213] *Ibid* at 190.
[214] *Ibid* at 184.
[215] *Ibid* at 190.
[216] Janet L Kolodner, "An introduction to case-based reasoning" (1992) 6:1 Artif Intell Rev 3–34.
[217] Agnar Aamodt & Enric Plaza, "Case-Based Reasoning: Foundational Issues, Methodological Variations, and System Approaches" (1994) 7:1 AI Commun 39–59.

When two cases are found "identical", the analysis is no different from rule-based reasoning in which deductive logic is employed.

On the other hand, when facts at hand are not quite the same but "similar' to previous cases, that is, in distinguishing cases, analogy is applied. However, not everyone agrees. Larry Alexander thinks that a judge's analogical reasoning from case to case is illusory.[218] The outcome of so-called analogical processes derives simply from ordinary reasoning. He argues that a judge naturally draws moral and empirical conclusions through induction, deduced from authoritative rules, and then performs a balancing act, which requires no legal training at all.[219]

The common law *stare decisis* principle is that precedent is followed hierarchically. Higher court decisions are binding to lower courts, but courts of same level need not bind each other.[220] On one hand, the judge is not free to ignore the results of a great number of cases before him/her; on the other hand, the judge has a great deal of freedom to maneuver the facts to "bend" the rules.

This freedom is sometimes used for equity or for public policy. For example, although our society values the freedom to contract, it may be against public order to "contract out" certain liabilities, so the court will decide how to strike a balance between freedom and policy. Creativity in the interpretation of legal texts for good policy is justified by Legal Realists, to be discussed later.

CBR has some shortcomings. For instance, the *ratio decidendi* of a case is not always clearly spelled out in the text because judges often do not state the rule on which they decide cases. So, two persons reading the same case may derive different sets of rules from the text. In addition, case law has been described as "chaos with a full index",[221] in that there is no organized manner of arrangement, making it difficult to find a legal principle in its proper place.

Therefore, legal actors must master not only how to compare and distinguish cases, but also to efficiently find the relevant cases. We are lucky in this regard compared to lawyers in the days of Christopher Langdell, as AI has greatly facilitated legal research. Today, legal databases[222] return

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[218] Larry Alexander & Emily Sherwin, *Demystifying Legal Reasoning* (Cambridge: Cambridge University Press, 2008) at 104.
[219] *Ibid* at 130.
[220] John EC Brierley, *Stare Decisis* (The Canadian Encyclopedia. Historica Canada, 2006).
[221] Grey, *supra* note 207 at 13.
[222] Canlii, SOQUIJ, Westlaw, and so on.

relevant cases with statistics of subsequent affirmations and reversals. But we must question whether algorithms behind the AI are representative of what we expect them to do. For example, some factual similarities or differences, "features", are more relevant (e.g., the defendant's state of mind) than others (e.g., his name). As we train the machine, relevant features are given more weight while irrelevant ones are given less weight or no weight at all. If this annotation process is not performed correctly, the AI will not give accurate results.

The common law is developed through the process of CBR; but perhaps the notion of common law needs to be clarified. Originally, starting with the Norman conquest in the 11th century, common law rules were developed by royal courts (e.g., King's Bench). To bring an action, the plaintiff would purchase a writ in the office of Chancery. The head of the Chancery was the Lord Chancellor, who oversaw a group of Chancellors. Gradually, the King would delegate decision-making to Chancellors. Around the 14th century, Chancery was operating as a court. Since Chancellors were often well versed in canon law, equity as a body of law was developed in Chancery and was by now administered concurrently with the common law.[223]

At times when the English common law was too harsh,[224] the court of equity provided equalizing relief. But not everyone can access the court of equity: as one of the maxims goes, "He who comes into equity must come with clean hands."[225] The principle of equity provides relief for the worthy, but bars those guilty of improper conduct.[226]

Today, when we refer to the common law, we include both common law and equity.[227] But technically, common law *in rem* remedies, such as the right to damages, are contrasted with equitable *in personam* remedies, such as the right to an injunction;[228] and in case of conflict between the rules of common law and those of equity, the former prevails.[229]

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223 Sarah Worthington, *Equity* (OUP Oxford, 2006), Google-Books-ID: 4mtCAgAAQBAJ.
224 Clark, *Equity* (Indianapolis: The Bobbs-Merrill Company, Inc., 1954) at 4.
225 *Ibid* at 42.
226 *Tinsley* v *Milligan*, [1993] UKHL 3, House of Lords (UK) ; *D & Builders Ltd v Rees*, [1965] EWCA Civ 3.
227 Worthington, *supra* note 223.
228 Clark, *supra* note 224 at 11.
229 *Ibid* at 39.

Other than the twelve maxims to be applied in equity,[230] both common law and equity share the same reasoning methods, which is CBR.

Rule-based Reasoning

Statutory law is made up of rules. Each rule is a formula for decision-making.[231] The decision maker begins with a rule, whether a statute or a *ratio*, then applies it to a set of facts, and reaches a verdict. Specifically, a rule has at least three parts:

1. a set of elements, collectively called a test;
2. a result that occurs when all the elements are present (test is satisfied); and
3. a causal term that determines whether the result is mandatory, prohibitory, discretionary, or declaratory.[232]

Rule-based reasoning (RBR) is deductive reasoning. For example, if it is forbidden to sell liquor to minors (the rule) and Claude sells liquor to a minor (the fact), then Claude is guilty by syllogism (the verdict).

There are a few challenges in RBR. First, the facts to apply to the rule may be ambiguous; second, the text may not be clear; third, there may exist another provision that negates the current provision; fourth, the meaning of the rule is not what it says in black and white; and finally, the rule itself may be challenged.

Firstly, the text is the most important element of the legislative message[233] and, if it is clear, one needs not interpret[234] but simply applies the plain (literal) meaning.[235] But in practice, even if the text is clear, there are many ways in which ambiguity can creep into the apparently straightforward process of RBR. Like, there may be two versions of facts in the above example: Claude did not accept money from the minor. He simply gave the minor liquor in exchange of something else. Was there a sale? Also, there may also be more than one rule that is potentially applicable. For

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[230] *Ibid* at 28.
[231] Richard K Neumann, Ellie Margolis & Kathryn M Stanchi, *Legal reasoning and legal writing*, eighth edition ed, Aspen coursebook series (New York: Wolters Kluwer, 2017) at 9.
[232] *Ibid*.
[233] Côté, *supra* note 209 at para 980.
[234] *Ibid* at para 1069.
[235] *Ibid* at para 1080.

instance, in child support, if both parents live in Quebec, the Quebec calculation applies.[236] If the debtor parent lives outside of Quebec, the federal calculation applies. Difficulties then arise when the debtor parent equally shares residences "in" and "out" of the province.

Secondly, if the wording of a statute does not provide, one finds answers elsewhere, perhaps the dictionary, for ordinary meaning; or the *Interpretation Act,*[237] doctrine and case law. Interpretation of legislation is complex and involves many rules. Some basic rules include the "golden rule", which says to neglect ordinary means to ensure the consistency of the whole,[238] and the "mischief rule", which looks to the defect that the legislation is set out to remedy.[239] Other rules include *Noscitur a sociis,* getting meaning from accompanying words,[240] and *Ejusdem generis*, getting meaning from a class or a list.[241] In terms of doctrine and case law, for example, a child endowed with reason may be liable to damages in Quebec,[242] but the *Civil Code* does not tell us at what age a child is endowed with reason. According to jurisprudence,[243] the average age of a child to have developed a certain degree of reason is 6 years and 9 months old.[244] But in truth, every child's development is subject to heredity and environment, and would be considered accordingly.

Thirdly, while a valid rule is in force, there may exist another rule that, if present, defeats the effect of the current rule. For instance, provocation[245] is a partial defence to the charge of murder[246] in Canada.

Fourthly, even when the law is written in black and white, the meaning may be contrary to the text. For example, *art. 2847 CCQ* says in the second paragraph that a simple presumption may be rebutted by proof to the contrary, but a deemed presumption is absolute and irrebuttable. However, legal doctrine claims that the legislator made a mistake in using the word "deemed" in *art. 1632*, that the presumption is simple, not absolute, despite the written text.

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[236] *Divorce Act*, RSC 1985, c 3 (2nd Supp) s 2(1).
[237] *Interpretation Act*, RSC 1985, c I-21.
[238] Côté, *supra* note 209 at para 1200.
[239] *Ibid* at para 1408.
[240] *Ibid* at para 1177.
[241] *Ibid* at para 1182.
[242] Art 153, 164(2), 1462 CCQ
[243] *Ginn* c *Sisson*, (1968), [1969] CS 585.
[244] Jean-Louis Baudouin, Pierre-Gabriel Jobin & Nathalie Vézina, *Les obligations, 8e éd.* (2014) at para 1–111.
[245] *Criminal Code*, RSC 1985, c C-46 s 232.
[246] *Ibid* s 231.

While the meaning of a legislative rule may be clear, the application of the rule may nevertheless be problematic.[247] In the infamous *Vader* murder case,[248] Justice Thomas relied on *section 230* of the *Criminal Code*, the so-called "constructive murder" provision and convicted Travis Vader of second-degree murder. The provision says that causing death during the commission of a serious offence is murder even if the accused did not intend to cause or could not foresee death. However, the Supreme Court of Canada had declared *section 230* unconstitutional in *Martineau*[249] back in 1990. The *Criminal Code* was never updated up to *Vader*, causing the confusion; fortunately, *section 230* was eventually repealed in 2019.

Finally, even if a rule is clear, backed by case law, it may still be challenged. Consider Canada's division of federal and provincial powers. A complete set of legal reasoning tools have been developed to deal with it. They are analyses of validity, applicability, and operability of law.[250]

Validity analysis determines if the law enacted is *intra vires* or *ultra vires*, which is a logical test, completely detached from moral or effective standards. The analysis proceeds with the "pith and substance" test which asks what the "matter" of the law is, and then "fits" the matter into federal power (*section 91* of the *Constitution*) or provincial power (*section 92*).

In analysing the "matter" of the law, consideration must be given to a legislation's purpose, legal and practical effects.[251] A statute may contain an ill-intended purpose. In *Saumur*,[252] a by-law was enacted to stop citizens from passing leaflets. But the Supreme Court reasoned that the by-law has had a hidden or colourable purpose, which was to infringe the freedoms of speech and of religion entitled to members of Jehovah's Witness. As a result, the Court struck down the by-law.

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[247] Côté, *supra* note 209 at para 338.
[248] *R* v *Vader*, 2016 ABQB 505 (CanLII).
[249] *R* v *Martineau*, 1990 CanLII 80 (SCC), [1990] 2 SCR 633.
[250] Patrick Macklem et all, *Canadian constitutional law*, 4th ed. ed (Toronto: Emond Montgomery Publications, 2010) at 199.
[251] Côté, *supra* note 209 at para 1115; Macklem, *supra* note 250 at 218.
[252] *Saumur* v *City of Quebec*, [1953] 2 SCR 299.

The "pith and substance" analysis can be complex, taking into account principles like peace, order, and good government (POGG),[253] criminal power,[254] and trade and commerce,[255] each having their own tests. Moreover, federal and provincial powers can overlap.

One solution to deal with overlap, called "double aspect", has been developed which says that when federal and provincial aspects are of equal importance, neither should be ignored. In *Hodge*,[256] "subjects which in one aspect and for one purpose fall within *Sect. 92* may in another aspect and for another purpose fall within *Sect. 91*." But in *Bell*,[257] Justice Beetz warned that "double aspect" is to be used with "great caution" as concurrency expands situations where provincial law could be subordinate to federal law as an application of the doctrine of paramountcy.

In the case where one provision appears invalid, but the overall legislation is validly enacted, only the offending portion would be declared inoperable. To determine if a provision is invalid, different tests have been applied over the years: "rational and functional connection", "necessarily incidental", "truly necessary", and "integral part" collectively illustrated the "ancillary" doctrine. In *GM*,[258] the Supreme Court of Canada showed us how the reasoning is executed.

First, we must consider whether the impugned provision intrudes into the other head of power of government. If it does not, there is no issue. But if it intrudes, is it part of an otherwise overall valid scheme? If the overall scheme is invalid, it is the end of discussion. But if the provision is part of a valid scheme, then apply the "rational and functional connection" test if intrusion is minimal; otherwise, apply the "truly necessary" test.

The legislator is supposed to maintain, in all the laws adopted on a given subject, some consistency both in the formulation of the texts and in the policies that these texts implement.[259] But where a valid provincial law overreaches federal jurisdiction, the provincial law may be rendered inapplicable by the doctrine of interjurisdictional immunity.[260] Its analysis is a two-part test: Does

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[253] Macklem, *supra* note 250 c 9.
[254] *Ibid* c 11.
[255] *Ibid* c 10.
[256] *Hodge* v *The Queen (Canada)*, [1883] UKPC 59.
[257] *Bell Canada* v *Quebec (Commission de la Santé et de la Sécurité du Travail)*, [1988] 1 SCR 749 at para 38.
[258] *General Motors of Canada Ltd* v *City National Leasing*, [1989] 1 SCR 641.
[259] Côté, *supra* note 209 at para 1271.
[260] Macklem, *supra* note 250 at 250.

the challenged provincial law trench on the protected core of a federal power? If so, is its effect "sufficiently serious" to invoke the doctrine? Interjurisdictional immunity is becoming a thing of the past as its application does not address operative conflict or promote cooperation. In fact, the Supreme Court favours the application of paramountcy over interjurisdictional immunity in case of a double aspect.[261] As such, we see that statutory reasoning can evolve over time.

Paramountcy, or to be precise, federal paramountcy, is the doctrine to deal with operability of law in Canada.[262] The question of why not provincial paramountcy remains a valid but mysterious one. In a power overlap situation, three things can happen. First, federal and provincial powers are complementary in which case dual compliance is possible. We have seen that double aspect deals with this scenario. Second, powers duplicate one another, in which case there is not much of an issue.[263] Third, federal and provincial powers conflict in which case one law permits while the other prohibits.[264]

To determine whether a conflict exists between federal and provincial legislative enactments, the Supreme Court set out yet another analytical framework, known as the "frustration of purpose" test, in *Moloney*:[265] First, are both laws independently valid? If one is invalid, then there is no conflict. Second, does the operation of the provincial law frustrate the purpose of the federal enactment? If so, the inferior law remains in force but is inoperative to the extent it conflicts with the superior law. In other words, federal law prevails.

As shown, rule-based reasoning can have its own mechanics that are different from case-based reasoning. But rule-based reasoning and case-based reasoning are intertwined. They are both used, and often concurrently, by judges to reach a verdict.

It is worth noting that whichever form of reasoning is used, the decision-making process values efficiency. That is, if an issue of law has been dealt with in the past, the decision maker must follow the previous conclusion without going through the reasoning process again. For example, in

[261] *Law Society of British Columbia* v *Mangat*, 2001 SCC 67, [2001] 3 SCR 113.
[262] Macklem, *supra* note 250 at 272.
[263] *Ibid* at 279.
[264] *Multiple Access Ltd* v *McCutcheon*, 1982 CanLII 55 (SCC), [1982] 2 SCR 161.
[265] *Alberta (Attorney General)* v *Moloney*, 2015 SCC 51 (CanLII), [2015] 3 SCR 327.

administrative law, when a standard of review falls within one of the *Dunsmuir*[266] categories, there is no need to apply any test to determine whether the standard is one of correctness or reasonableness. Similarly, in tort, when a duty has been established in a relationship category, for example, manufacturers owe duty of care to consumers, the *Anns-Cooper*[267] test needs not to be applied.

Other Reasoning Considerations

There are considerations other than case law or statute affecting courtroom decisions. Judicial notice is one of them. Judicial notice is normally a concept in evidence. It embodies what everyone knows, including general principles such as the law of gravity or well-known societal phenomena. In fact, it requires no proof.[268] Some argue that judicial notice operates like a rule of law because it is backed by common sense and ordinary experience that judges take into the courtroom and decisions are made from them. For instance, Justice L'Heureux-Dubé's *obiter* in *Moge*[269] on the feminization of poverty has been taken up by lower courts and treated precedentially,[270] thus making judicial notice not significantly different from *stare decisis*.

Another consideration is policy. Decisions are made based on policies that promote well-being for society. For instance, in product liability cases, legal actors argued for strict liability because manufacturers could better spread the cost of injuries than consumers. In the 1970's, the Pinto vehicle manufactured by Ford tended to erupt in flames in rear-end collisions causing fatal fires. At the time, Ford was reluctant to modify the fuel system design because economic cost-benefit analysis showed that doing so would cost the manufacturer more than paying damages to victims. More than a hundred lawsuits were filed against Ford. The failure to consider social costs called for a policy-based reasoning to award large sums of punitive damages. In the end, Ford went ahead with a much-needed recall program.

[266] *Dunsmuir* v *New Brunswick*, 2008 SCC 9, [2008] 1 SCR 190.
[267] *Cooper* v *Hobart*, 2001 SCC 79, [2001] 3 SCR 537.
[268] Art 2806 CCQ
[269] Moge v *Moge*, [1992] 3 SCR 813.
[270] Susan Drummond, "Judicial Notice: The Very Texture of Legal Reasoning" (2000) Can J Law Soc Can Droit Société Vol 15 Issue 1 2000 P 1-38, online: <https://digitalcommons.osgoode.yorku.ca/scholarly_works/396>.

We see Posner's idea of "efficiency" at work in the Pinto example. Posner made two claims about economic efficiency in the law. First, he claimed that the law is in fact efficient; and second, that the law ought to be efficient.[271] To conduct an economic analysis, values must be expressed in monetary terms.[272] For instance, an algebraic equation was formulated by Judge Learned Hand of the United States.[273] The Hand Formula,

$$PL = B$$

governs the relation between investment in precaution (*B*) and the product of the probability (*P*) and magnitude (*L*) of harm resulting from the accident. In negligence, if *PL* exceeds *B*, then the defendant should be liable. Otherwise, if *B* equals or exceeds *PL*, then the defendant should not be held liable. However, in strict liability, the manufacturer is liable regardless of precaution.

Table 7: The Hand Formula

Regime	$PL > B$ (e.g. 10x5 > 25)	$PL < B$ (e.g. 10x5 < 100)
Negligence (Canada)	Liable (Defendant pays) Deterrence (cheaper to avoid harm)	Not Liable (Victim pays) No Deterrence (Precaution costly)
Strict Liability (U.S.)	Liable (Defendant pays) Deterrence (cheaper to avoid harm)	Liable (Defendant pays) No Deterrence (Precaution costly)

In the case where $PL < B$, that is, the prevention of harm is costly, the only difference between negligence regime and strict liability regime is who pays the victim, not deterrence. This means that a manufacturer may opt for compensating the victim rather than preventing harm, exactly as in the case of Pinto before punitive damages were imposed. In Canada, product liability takes the negligence model while the U.S. takes the strict liability model. Neither country's policy produces any causal effect on prevention; however, the U.S. strict liability model compensates the victim in the case of harm.

Posner's economic analysis can be used to explain the situation both before and after the punitive awards. Before punitive damages, human lives were not given a monetary value in the magnitude

[271] Mackaay, *supra* note 98 at 15.
[272] Richard A Posner, *Economic analysis of law*, 8th ed.. ed, Aspen casebook series (Austin, Tex. : New York: Wolters Kluwer Law & Business ; Aspen Publishers, 2011).
[273] *US* v *Carroll Towing*, 159 F2d 169 (2d Cir 1947).

of harm, *L*. The cost-benefit equation shows that the product of probability and compensation of harm, *PL*, is less than the cost in design change, *B*. In order to deter Ford's behaviour, the court attached a monetary representation to the social value of human lives, such that $PL > B$, making it no longer economical for Ford to let accidents happen. This solution is possible in the U.S. as the awarding of multi-million-dollar punitive damages is not uncommon.[274]

However, Canada's punitive damages are modest compared to the U.S.[275] *Whiten*,[276] in which the $1 million punitive award was restored in the Supreme Court was a rare occasion. In Quebec, the awarding of punitive damages is even more restrictive, only when provided by law.[277] Whether punitive damages could serve as deterrence is unclear in Canada.

In awarding damages, courts have said that it is "not an exact science", admitting the difficulties in using statistics in sentencing or victim compensation. In *Andrews*,[278] the Supreme Court of Canada speaks of the Court's doubt in the reliance on probability: "The apparent reliability of assessments provided by modern actuarial practice is largely illusionary, for actuarial science deals with probabilities, not actualities. This is in no way to denigrate a respected profession, but it is obvious that the validity of the answers given by the actuarial witness, as with a computer, depends upon the soundness of the postulates from which he proceeds. Although a useful aid, and a sharper tool than the 'multiplier-multiplicand' approach favoured in some jurisdictions, actuarial evidence speaks in terms of group experience. It cannot, and does not purport to, speak as to the individual sufferer."

In addition, some legal theories reject altogether the notion of legal reasoning in law. Contrary to the traditional belief of Legal Formalism that legal reasoning requires logic, Legal Realism emerged as a school of thought that challenged the "mechanical jurisprudence" of Formalists.[279] Oliver Holmes Jr. attacked the "official" theory of how common law judges decide cases with his

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274 Lewis N Klar, "The Impact of U.S. Tort Law in Canada Symposium: Does the World Still Need United States Tort Law - Or Did It Ever" (2010) 38:2 Pepperdine Law Rev 359–374.
275 *Ibid*.
276 *Whiten* v *Pilot Insurance Co*, 2002 SCC 18, [2002] 1 SCR 595.
277 Art 1621 *CCQ*; *A Comparative Look at Punitive Damages in Canada*, SSRN Scholarly Paper, by Stephane Beaulac, papers.ssrn.com, SSRN Scholarly Paper ID 2963334 (Rochester, NY: Social Science Research Network, 2002) at 357.
278 *Andrews* v *Grand & Toy Alberta Ltd*, 1978 CanLII 1 (SCC), [1978] 2 SCR 229.
279 *The Cambridge handbook of thinking and reasoning* (Cambridge: Cambridge University Press, 2005) at 690.

maxim: "The life of the law has not been logic; it has been experience". By "experience", Holmes meant a judge's subconscious intuition; while by "logic", he meant an attempt in vain to systematize developed law.[280]

Realists stipulate that judges determine the outcome of a lawsuit intuitively before reasoning out the conclusion with established legal principle. "That the law was a self-contained logical system providing for the scientific, deductive derivation of the right answer in new cases" is delusional.[281] Instead, the true basis of the decision was sometimes drawn from outside the law, in historical, social, cultural, political, economic, and psychological forces. As a result, two cases with the same rule and the same factual matrix may be decided differently.

For example, both *Microsoft*[282] and *Nabisco*[283] dealt with the territorial reach of U.S. law enforcement access to data but concluded opposite outcomes. In *Microsoft*, the Justice Department issued a warrant to the corporation on details of an email account of a suspected drug trafficker stored on a data center in Ireland. The Second Circuit Court agreed with Microsoft that the U.S. law does not apply extraterritorially even if the disclosure is domestic. Contrastingly, in *Nabisco*, the Justice Department issued subpoenas to compel U.S. banks to produce foreign-held banking records. The Court allowed the subpoenas as it relates to domestic conduct even though data is stored elsewhere.

In Microsoft, about which country's search and seizure rules apply to Microsoft's data center in Ireland: the U.S.'s or Ireland's. the SCA does not apply extraterritorially and the contents of the email account are stored in Ireland, the warrant would have unlawful extraterritorial reach.

Theories such as Critical Legal Studies (CLS), Law and Economics,[284] and Law and Society. Among them, CLS are considered progressive Realists while the other two relate to interdisciplinary social science. CLS argue that interpretation of the law is subjective, and they

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280 *The Life of the Law: What Holmes Meant*, SSRN Scholarly Paper, by Brian Hawkins, papers.ssrn.com, SSRN Scholarly Paper ID 1753389 (Rochester, NY: Social Science Research Network, 2012).
281 note 279 at 690.
282 *United States* v *Microsoft Corp*, 584 US (2018).
283 *RJR Nabisco, Inc* v *European Cmty*, 136 S Ct 2090 (2016).
284 We have already seen Law and Economics in the Hand Formula illustration.

emphasize even more strongly than the Realists the role of power and political ideology.[285] To them, decisions are based on personal and social values, not law. CLS accepts the critical aspect of Legal Realism but challenges its constructive program.[286] The Realists' constructive program contains three elements: understanding the consequences of legal decisions, abandoning abstract legal concepts as the basis for decision, and adopting the method of balancing in legal analysis.[287] But CLS offers no constructive program, only interminable critiques.[288] Duncan Kennedy, one of the founders of CLS, hypothesizes that a judge already decided how he wants the decision to come out and works himself back to reason it creatively.[289]

Law and Economics also brings additional considerations into legal decision-making. We have briefly discussed the idea of using economic concepts to understand the law in the Pinto case above. Using economics in law has been attempted by thinkers like Machiavelli, Hobbes, Locke, and Adam Smith.[290] But it was not until the 1960's that the school took off in American scholarship. Ejan Mackaay thinks that the current movement began with Ronald Coase's 1960 article on social cost.[291] Law and Economics assumes that given certain choices, people rationally assess their circumstances and do what will maximize their own welfare.[292] Skilled in economics, followers use formulas to calculate economic efficiency. They cleverly adhere to formulas with a constant utility function, *u*, which makes the overall theory quite fail-proof. But without precise definitions of *u*, the formulas may lack exactness. Interestingly, the notion of pure economic loss (PEL) is not a part of Law and Economics. PEL is a common law recovery of economic loss not accompanied by any physical damage to a person or property.[293]

Law and Society takes a multidisciplinary or an interdisciplinary approach to understanding the law.[294] They highlight social and political impacts on legal decision-making. Law does not exist

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[285] Mark Tushnet, "Critical Legal Studies: An Introduction to Its Origins and Underpinnings" (1986) 36:4 J Leg Educ 505.
[286] *Ibid* at 507.
[287] *Ibid*.
[288] *Ibid* at 516.
[289] Duncan Kennedy, "Freedom and Constraint in Adjudication: A Critical Phenomenology" (1986) 36 J Leg Educ 518.
[290] Mackaay, *supra* note 98 at 17.
[291] *Ibid* at 205.
[292] *Ibid* at 35.
[293] R Brown, *Pure Economic Loss in Canadian Negligence Law* (LexisNexis, 2011).
[294] Robert E Goodin & Lynn Mather, "Law and Society" in *Oxf Handb Polit Sci* (Oxford University Press, 2013).

in a vacuum; thus, the study of law and society rests on the belief that the law must be understood in context.[295] The understanding that the law is a construct to allow large groups of individuals to live "orderly" together brings society and culture into the forefront of legal decision-making. Political scientists today continue to use comparative approaches to research questions in the field.[296]

Furthermore, the study of psychoanalysis in legal decision-making has been made popular in recent years.[297] For instance, motivated reasoning is a process where desired justification is reached from emotionally biased reasoning rather than logical reasoning.[298] Human beings try to avoid cognitive dissonance, the mental discomfort we experience when confronted by contradictory information, especially on matters that directly relate to happiness and mental health. Rather than re-examining a contradiction, it is easier to simply dismiss it. The research posits that this cognitive process, prevalent in the mass society, is also extended to legal actors. Particularly, the effect of laughter during oral arguments was studied. The results indicate that incidents of laughter elicited by attorneys has a distinct influence on the justices' votes.[299]

In the AI age, patterns of decision-making can be picked out easily with machine learning methods. For example, legal analytics can automatically identify words and features in large volumes of legal text and make conclusions about them. In the past, research has shown that judges rule more leniently after a food break.[300] Research also demonstrates a correlation between judges' political affiliations and their voting.[301] This type of analysis opens doors to "judge-shopping" and is a controversial debate. The French Government banned the publication of all data analysis related to judges' rulings in the country and imposed a prison sentence of up to five years on those

[295] *Ibid*.
[296] *Ibid*.
[297] *Law and the Unconscious: A Psychoanalytic Perspective*, SSRN Scholarly Paper, by Anne C Dailey, papers.ssrn.com, SSRN Scholarly Paper ID 3065072 (Rochester, NY: Social Science Research Network, 2017).
[298] Thomas Pryor, *The Psychology of Legal Decision Making,* Retrieved from the University of Minnesota Digital Conservancy, http://hdl.handle.net/11299/185138.
[299] Dailey, *supra* note 297.
[300] Shai Danziger, Jonathan Levav & Liora Avnaim-Pesso, "Extraneous factors in judicial decisions" (2011) 108:17 Proc Natl Acad Sci 6889–6892.
[301] Adam Liptak, "Supreme Court Says Judges Are Above Politics. It May Hear a Case Testing That View.", *N Y Times* (16 September 2019), online: <https://www.nytimes.com/2019/09/16/us/politics/supreme-court-judges-partisanship.html>.

violating the law.[302] *Article 33* of the provision[303] is aimed at preventing legal technology companies from publicly revealing the pattern of judges' behaviours in relation to court decisions. Outside France, it is unclear whether judges have accepted AI scrutinizing their decisions or simply that they have not caught on regarding the implications.

In conclusion, formal legal reasoning is divided into two branches: case-based reasoning and rule-based reasoning. The traditional view is that case-based reasoning is induction thinking bound by precedent while rule-based reasoning is deductive thinking constrained by law. Considerations such as judicial notice and policy, and theories suggesting other factors of judicial decision-making, including psychoanalysis, and concepts from legal theories such as Realism, CLS, Law and Economics, as well as Law and Society, broaden the discussion on judicial behaviour.

2.2. Causality in Law

How does causality in science and everyday life differ from causality in law? Science is interested in general causality (e.g., speeding kills) while the law is interested in specific causality (e.g., David was driving 150km/h when he hit a truck stopped on the road, killing himself.)[304] In addition, causality can also be defined explicitly and implicitly.[305] Explicit definitions of causality refer to what authoritative texts of law say causations are. And implicit definitions are to be teased out from usage of the concepts in legal doctrines making up the body of law.[306]

Implicit causation can be extracted from the usage of the legal concept of how causation is used in resolving problems. For example, when the law does not say explicitly, but it can be derived from case decisions that helping someone out of good heart can lead to liability. In *Zelenko* v *Gimbel Bros*,[307] a woman had collapsed in a department store and was carried to the store infirmary and left there unattended for several hours. She died. The court found the defendant liable, noting that

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[302] artificiallawyer, "France Bans Judge Analytics, 5 Years In Prison For Rule Breakers", (4 June 2019), online: *Artif Lawyer* <https://www.artificiallawyer.com/2019/06/04/france-bans-judge-analytics-5-years-in-prison-for-rule-breakers/>.
[303] LOI n° 2019-222 du 23 mars 2019 de programmation 2018-2022 et de réforme pour la justice - Article 33 https://www.legifrance.gouv.fr/eli/loi/2019/3/23/2019-222/jo/article_33
[304] Halpern, *supra* note 37 c 1.
[305] Michael Moore, "Causation in the Law" in Edward N Zalta, ed, *Stanf Encycl Philos*, winter 2019 ed (Metaphysics Research Lab, Stanford University, 2019) ss 2, 3.
[306] *Ibid* s 3.
[307] *Zelenko* v *Gimbel Bros, Inc*, 158 Misc 904 (NY Sup Ct 1935).

the department store owed the woman "no duty at all" and "could have let her be and die." However, by "meddling in matters with which legalistically it had no concern", they assumed a duty of reasonable care. The moral of the story: in common law, do not be a hero. While Quebec imposes a duty to rescue a person in peril,[308] none of the common law provinces demand such duty. The so-called "Good Samaritan" laws, such as Ontario's Good Samaritan Act and that of British Columbia, only provide relief of liability.

In the pages that follow, we will discuss causality using examples from common law tort, civil law liability, and criminal law in Canada.

In tort or civil liability, causation is to be proven on a balance of probabilities that the defendant's negligence contributed to the plaintiff's damage. Refer to Table 10. To succeed in action, the plaintiff has the burden of proof for all five elements in tort (left side of table) and all three elements in civil liability (right side).

Table 8: Common law tort and civil responsibility

Common law tort	Quebec civil responsibility
1. Duty of care	1. Fault
2. Standard of care	
3. Damages	2. Damages
4. Causation-in-fact	3. Causal link
5. Causation-in-law (Remoteness)	

Duty of care requires foreseeable harm and a relationship of sufficient proximity. The ancient test is the "Who is my neighbour?" test in *Donoghue*.[309] One should take reasonable care to avoid acts or omissions which can be reasonably foreseen to injure one's neighbour. Subsequent development gave birth to the 1977 *Anns* test in the U.K.,[310] which was adopted by Canada in *Cooper v Hobart*,[311] now referred to as the *Anns-Cooper* test. The *Anns-Cooper* test is a two-step test. The first step relates to foreseeability, and the second step proximity without any policy negation. Thus, these three elements are necessary:

[308] *Charte des droits et libertés de la personne*, C-12 s 2; art 1471 CCQ.
[309] *Donoghue* v *Stevenson*, [1932] UKHL 100.
[310] *Anns* v *Merton London Borough Council*, [1977] UKHL 4, [1978] AC 728.
[311] *Cooper v Hobart*, *supra* note 267.

1. Foreseeable harm (onus on plaintiff)
2. Prime facie proximity (onus on plaintiff)
3. No policy negation (onus on defendant)

Over the years, the *Anns-Cooper* test, as well as statutes, created several relationship categories not limited to the following:

1. Doctors owe duty to their patients.[312]
2. Professionals owe duty to their clients.[313]
3. Employers owe duty to their employees.[314]
4. Manufacturers owe duty to their consumers.[315]
5. Police owes duty to the accused.[316]
6. Police owes no duty to citizens.[317]
7. Accountants owe no duty to investors.[318]
8. The Crown owes no duty to smokers.[319]

The test for standard of care is the reasonable person test. In England, the reasonable person was introduced in *Vaughn* v *Menlove*.[320] The Supreme Court of Canada confirmed *Menlove* in *Ryan*,[321] saying that a reasonable person must exercise the standard of care that would be expected of an ordinary, reasonable and prudent person in the same circumstances.

Tests for causation are divided into bifurcated tests and unified tests.[322] In bifurcated tests, legal causation is constituted by two distinct components, cause-in-fact and cause-in-law. In Canada, cause-in-law is referred to as remoteness or legal cause. In the United States, it is called proximate

[312] C E Davies & R Z Shaul, "Physicians' legal duty of care and legal right to refuse to work during a pandemic" (2010) 182:2 Can Med Assoc J 167–170.
[313] Various professional codes of conduct.
[314] *Canada Labour Code*, RSC 1985, c L-2; *Code du travail*, RLRQ, c C-27.
[315] *Donoghue v Stevenson*, *supra* note 309.
[316] *Hill* v *Hamilton-Wentworth Regional Police Services Board 2007*, 2007 SCC 41, [2007] 3 SCR 129.
[317] *Ibid*.
[318] *Hedley Byrne & Co Ltd* v *Heller & Partners Ltd*, [1964] AC 465.
[319] *R* v *Imperial Tobacco Canada Ltd*, 2011 SCC 42, [2011] 3 SCR 45.
[320] *Vaughn* v *Menlove*, 1837 132 ER 490.
[321] *Ryan* v *Victoria (City)*, [1999] 1 SCR 201.
[322] Moore, *supra* note 305.

cause. In Quebec civil responsibility, tests for cause-in-fact and cause-in-law are combined into a unified test, the test for causal link ("*lien de causalité*") between fault and harm.

The standard test for cause-in-fact is the but-for test, as per *Snell.*[323] *Snell* is a Canadian decision based on the U.K. decision, *McGhee.*[324] Both cases deal with causation-in-fact and the inference of the causal link. But-for is a question of fact: "But for the negligence of the defendant, would the plaintiff's injuries not have occurred?" Also known as the "*sine qua non*" test, the but-for question is to be answered in a "robust and pragmatic approach".[325]

Before *Snell*, the causality test was already but-for. In 1960, in Toronto's TTC subway,[326] a plaintiff fell down the escalator along with others like dominoes. The plaintiff sued the TTC for inadequate handrail, but the Supreme Court found no causality between the handrails and the plaintiff's injury. Although the defendant was negligent in that it 1) had installed an untested handrail, and 2) had failed to provide supervision, it did not matter if the handrail was there since none of the victims even tried to grab it.

The plot thickens when there are concurrent tortfeasors and indivisible injury.

Where multiple tortfeasors are involved, the but-for analysis requires the following two conditional concepts:[327]

1. Necessary; and
2. Sufficient.

If a minimum score of 10 causes one harm, then:

[323] *Snell* v *Farrell*, [1990] 2 SCR 311.
[324] *McGhee* v *National Coal Board*, [1973] 1 WLR 1.
[325] *Ibid* at 569.
[326] *Kauffman* v *Toronto Transit Commission*, [1960] SCR 251.
[327] Mitchell McInnes, "Causation in Tort Law: Back to Basics at the Supreme Court of Canada" (1997) Alta Law Rev 1013–1013.

Causation	Remarks	Complexity	Liability
10 <= 4+4+4	Each 4 is necessary and insufficient. Together three 4s become sufficient.	Easy	Each 33%
10 <= 5+5+2	Each 5 is necessary and insufficient. Together two 5s become sufficient. 2 is unnecessary and insufficient.	Easy	50% for 5 0% for 2
10 <= 11+2	11 alone is necessary and sufficient. 2 is unnecessary and insufficient.	Easy	100% for 11 0% for 2
10 <= 11 + 12	11 alone is necessary and sufficient. 12 alone is necessary and sufficient.	Complex	*de novo*? Timing?

In *Athey*,[328] a victim with a history of back problems, suffered back and neck injuries from an accident, and then from a second accident resulting in a disc herniation. All defendants proceeded as one and admitted liability. The only issue was whether the accidents caused the disc herniation, or the pre-existing back condition did.

Where but-for causation is difficult or unworkable, courts have tried alternatives. In this case, attempts were made to identify a percentage of "materially contributing" negligence causing the harm. In the end, it was decided that the defendants contributed 25% to the plaintiff's harm, which was outside the *de minimis* range.

Athey created confusion. Many people, including judges, understood the material contribution test as an alternative to the but-for test.[329] Note that the material contribution test in *Athey* concerned material contribution to injury (MCI), while the material contribution test in *McGhee* concerned material contribution to risk of harm (MCR). They are two different concepts. MCI means the defendant played a causative role in the plaintiff's suffering while MCR denotes some role in increasing the likelihood of harm arising.[330]

A decade later, in *Hanke*,[331] where but-for causation is unprovable due to limits in scientific knowledge, the Supreme Court said material contribution should be used only in exceptional circumstances, and set out the following two criteria when it can be applied:

[328] *Athey* v *Leonati*, [1996] 3 SCR 458.
[329] David Mangan, "Confusion In Material Contribution" (2014) 91:3 Can Bar Rev, online: <https://cbr.cba.org/index.php/cbr/article/view/4308>.
[330] *Ibid*.
[331] *Resurfice Corp* v *Hanke*, 2007 SCC 7, 2007] 1 SCR 333.

First, it must be impossible for the plaintiff to prove that the defendant's negligence caused the plaintiff's injury using the but-for test. The impossibility must be due to factors that are outside of the plaintiff's control; for example, limits of scientific knowledge and usually with multiple tortfeasors.[332]

Second, it must be clear that the defendants breached a duty of care owed to the plaintiff, thereby exposing the plaintiff to an unreasonable risk of injury, and the plaintiff must have suffered that form of injury.[333]

Finally, in 2012, *Clements*[334] substantially narrowed the MCR, if not put it to sleep. In *Clements*, the wife sued her husband for speeding on a highway causing her injury when one of the motorcycle's tires hit a nail. She was unable to prove but-for causation because it is impossible to know whether the speeding or the nail contributed to the injury.

At this point, there was a lot of confusion about which test is the test for causation in multiple causes. The rule in *Hanke* still holds but the scope of "impossible to prove" must be clarified. The Supreme Court said that while MCR was available in multiple tortfeasor situations, the Court has never in fact applied it, not even in *Hanke*.[335] In other words, but-for is still the good old test.

The Court was reluctant to apply MCR as multiple wrongdoers would all point fingers at each other creating circular causation.[336] In addition, one may reason that MCR can infer a wrongdoer's wrongdoing even though it has not yet occurred. Inferring wrongdoing before it happens almost sounds like the premise of the movie *Minority Report*. In some ways, the notion of material contribution is merely an attempt to administer fairness.

Where scientific evidence is unable to verify a causal link between a defendant's creation of risk and a plaintiff's suffering, can a legal factfinder infer such a link? The Supreme Court thinks so,

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[332] *Ibid* at para 25.
[333] *Ibid*.
[334] *Clements* v *Clements*, 2012 SCC 32, [2012] 2 SCR 181.
[335] *Ibid* at para 28.
[336] *Ibid* at para 43.

in *Snell*.[337] Russel Brown, now Justice of the Supreme Court, referred to this causal inference as "inference causation",[338] and has convincingly argued for it.

But causal inference is tricky business, especially in medical malpractice cases; difficulties lie in limitation in scientific knowledge, even for medical experts. In *Snell*, Justice Sopinka quoted author David Harvey in *Medical Malpractice*: "Some courts have assumed an unrealistic posture in requiring that the medical expert state conclusively that a certain act caused a given result. Medical testimony does not lend itself to precise conclusions because medicine is not an exact science."

In *Snell*, the appellant surgeon was in the best position to observe and interpret the medical situation. By continuing the operation, he made it impossible for anyone else to detect the bleeding which allegedly caused the injury. In this situation, and with no evidence to rebut causation, the trial judge could have drawn causal inference.[339]

While *Snell* is not about reversed onus, in another joint tortfeasors' situation, the Court shifted the burden of proof, leaving each defendant to fend for himself. In *Cook*,[340] if both defendants are negligent towards the plaintiff but cause of harm cannot be proven between them, the onus shifts. In other words, only one of the defendants shot the plaintiff, but which one? Since both defendants are negligent, they are both liable.

The U.K. also innovated when causation was impossible. In *Fairchild*,[341] an employee got cancer from inhaling asbestos in the workplace but could not tell at which employer. Lord Bingham decided that it was better to be unfair to the employers than to be unfair to the employee.[342]

There is no shortage of legal innovation from courts worldwide to deal with infinitely many varieties of situations. In *Sindell*,[343] where Diethylstilbestrol (DES) drugs caused cancer in many

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[337] *Snell v Farrell*, *supra* note 323.
[338] Russell Brown, "The Possibility of 'Inference Causation': Inferring Cause-in-Fact and the Nature of Legal Fact-Finding" (2010) 55:1 McGill Law J Rev Droit McGill 1–45.
[339] The last fourth paragraph of the Supreme Court decision.
[340] *Cook* v *Lewis*, [1951] SCR 830.
[341] *Fairchild* v *Glenhaven Funeral Services Ltd*, [2002] UKHL 22.
[342] *Ibid* at para 114.
[343] *Sindell* v *Abbott Laboratories*, 26 Cal 3d 588, 163 Cal Rptr 132, 607 P2d 924 (1980).

babies over a few decades, the U.S. court ruled that allocation of liability should be proportionate to each defendant's market share.

In the U.S., "direct" causation is used to describe an uninterrupted situation where there is one cause for one effect; "overdetermination" describes a situation where there are two or more causes for the same effect; and "pre-emption" describes a situation where one event pre-empts the following event in causing the effect. Pre-emption is therefore the concept of *de novo* or intervening act in Canada. Canada's but-for test comprises both necessary and sufficient conditions, but American scholars refer to this necessary and sufficient test as Hart and Honoré's "necessary element of a sufficient set" (NESS) test,[344] which is an extension to the simple but-for counterfactual test. The NESS test states that an event is a cause of an effect if and only if it was a necessary element of a set of antecedent actual conditions that was sufficient for the occurrence of the consequence.[345] Therefore, it can be argued that the Canadian but-for test is in fact the American NESS test.

The second step of causality analysis is remoteness, or causation-in-law, the American proximate cause. There are two kinds of remoteness. The first kind is aimed at limiting the scope of liability: the plaintiff must establish that the causation proven in step one is not too remote. Remoteness is rather vague language. It speaks to the directness and the foreseeability of the cause; that is, the cause does not travel an outrageous causal route.

But where do we draw the line? Over the years, several tests of remoteness have been attempted. Below is the chronological development from strict to lax in Canada.

In *Wagon Mound No.1*,[346] "Was it foreseeable that this negligent conduct by the defendant will **probably** cause **this injury** to the plaintiff?"

In *Hughes*[347], "Was it foreseeable that this negligent conduct by the defendant will **probably** cause **this kind of injury** to the plaintiff?

[344] H L A Hart & Tony Honoré, *Causation in the Law* (OUP Oxford, 1985), Google-Books-ID: d7ZGAgAAQBAJ.
[345] Richard W Wright, "Causation in Tort Law" (1985) 73:6 Calif Law Rev 1735–1828.
[346] *Overseas Tankship (UK) Ltd* v *Morts Dock & Engineering Co (The Wagon Mound)*, [1961] AC 388.
[347] *Hughes* v *Lord Advocate*, [1963] UKHL 31.

In *Wagon Mound No. 2*[348], "Was it foreseeable that this negligent conduct by the defendant will **possibly** cause **this kind of injury** to the plaintiff?

In 2012, the Supreme Court settled the modern test for remoteness in a contract case, *Mustapha*.[349] The plaintiff saw a dead fly and part of another in an unopened bottle of drinking water. Obsessed with the event and its "revolting implications" for the health of his family, Mr. Mustapha developed a major depressive disorder, phobia and anxiety. Causation-in-fact has been proven, but is it too remote? Based on *Hadley,*[350] damages arising out of breach of contract are governed by the expectation of the parties at the time the contract was made. Thus, Chief Justice McLachlin concluded that the test in *Wagon Mound No.2* was too wide.[351] The degree of probability should go back to the test in *Wagon Mound No.1*. Thus, the modern test of remoteness in terms of foreseeability is the test of foreseeable probable precise harm: "Was the cause probable? If so, was the precise harm foreseeable?"

In addition, when the victim has pre-existing conditions, common law torts deal with remoteness using the thin skull doctrine and the crumbling skull doctrine.

The thin skull rule makes the defendant fully liable for the plaintiff's injuries even if the injuries are unexpectedly severe owing to a pre-existing yet stable condition. "The tortfeasor must take his or her victim as the tortfeasor finds the victim and is therefore liable even though the plaintiff's losses are more dramatic than they would be for the average person."[352]

On the other hand, the crumbling skull rule recognizes that the pre-existing condition was inherent in the plaintiff's original position. That is, the skull was crumbling anyway; so the defendant is liable only for the plaintiff's additional injuries.[353]

The second kind of remoteness deals with an intervening event, *novus actus interveniens*, that breaks the chain of events. In *Mckew*,[354] the plaintiff suffered from an accident that weakened his

[348] *Overseas Tankship (UK) Ltd* v *The Miller Steamship Co or Wagon Mound (No 2)*, [1967] 1 AC 617.
[349] *Mustapha* v *Culligan of Canada Ltd*, 2008 SCC 27, [2008] 2 SCR 114.
[350] *Hadley* v *Baxendale*, [1854] EWHC Exch J70.
[351] *Mustapha v Culligan of Canada Ltd.*, *supra* note 349 at para 13.
[352] *Athey v Leonati*, *supra* note 328 at para 34.
[353] *Ibid* at para 35.
[354] *McKew* v *Holland & Hannen & Cubitts (Scotland) Ltd*, [1969] 3 All ER 1621.

leg. Subsequently, the plaintiff climbed stairs without assistance and fell. Lord Reid ruled that the plaintiff knew that his leg was weakened by the first accident, therefore it was unreasonable for him to descend stairs without assistance. The intervening event liberated any previous negligence.

In common law contract, causation is also relevant, but its discussion is much less prominent. H. L. A. Hart offered three reasons. First, harm due to breach of contract is usually economic rather than physical; thus, the 'causal connection' between a breach of contract and economic loss is evident. Second, it is unnecessary to discuss standard and duty of care in contracts. Third, liability in contract is based on the assessment of risk.[355] As such, common law contract is sometimes viewed as a bad man's law.[356] Even the Supreme Court's new duty on contractual good faith, in *Bhasin*,[357] only goes so far as honesty during performance, and does not extend to duties of loyalty or of disclosing information.[358] So long as a party is ready to remedy the breach, one has no moral or positive duty to fulfil the contract, contrary to Quebec obligations. In Quebec, the good faith doctrine encompasses contract formation, performance and termination,[359] and proposes not only absence of bad faith, but also reasonableness, loyalty and honesty.[360]

We have thus concluded causality in private common law.

In Quebec, civil responsibility and contract are combined into the law of obligations. Moreover, unlike the common law, the civil law system does not recognize specific torts but organizes rather as a general and universal principle of civil responsibility. To succeed in a civil responsibility claim, the necessary elements are fault, damages, and causality.[361] If any one of the three elements is not proven, the action will fail. Refer to table 10.

As mentioned previously, fault requires mental capacity ("*être doué de raison*"). A person without such capacity, for example, a very young child or an incapacitated adult ("*majeur inapte*"),[362]

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[355] Hart & Honoré, *supra* note 344.
[356] Oliver Wendell Holmes, Jr, "The Path of the Law" (1897) 10:457 Harv Law Rev, online: <http://moglen.law.columbia.edu/LCS/palaw.pdf> at 4.
[357] *Bhasin* v *Hrynew*, 2014 SCC 71, [2014] 3 SCR 494.
[358] *Ibid* at para 86.
[359] Art 1375 CCQ
[360] Jean-Louis Baudouin, Pierre-Gabriel Jobin & Nathalie Vézina, *Les obligations, 7e éd.* (Cowansville: Ivon Blais, 2013) at 220.
[361] Art 1457 CCQ
[362] *Laverdure* c *Bélanger*, 1975 CS 612.

commits merely wrongdoing ("*faits fautifs*") but cannot be held legally liable. Also, fault can be intentional or gross fault.[363] And presumptions of fault or of responsibility can be found from *Art. 1459* to *Art. 1469* of the *Civil Code*.

Damages could be physical, material, or moral. They must be direct,[364] certain,[365] legitimate[366] and transferable[367] The remedy should be compensatory,[368] full and final.[369]

Causality as the third condition is a question of fact.[370] It is examined after fault (including presumption) and damages have been proven. Causality is the link between fault and damage; the link must be direct[371] and immediate,[372] both elements of foreseeability.[373]

Four principle theories were developed revolving around civil responsibility causality:

1. Equivalences of conditions (*équivalences des condition*)
2. Adequate causation (*causalité adequate*)
3. Immediate causation (*causalité immédiate*)
4. Reasonable anticipation of consequences (*prévision raisonnable des consequences*)

The theory of "equivalences of conditions" states that all the facts which contributed to the production of the harm must be retained equally as the legal causes of the damage, without any need to distinguish or prioritize them. This theory was used narrowly in medical malpractice but does not consider the proportional gravity of fault and was not welcome by the courts.

The theory of "adequate causation" says that facts contributing to damages are not necessarily legal causes, and may not necessarily be placed on equal footing, insofar as each has a different degree of involvement in the harm. It is then the judge to decide which fault, if any, plays a role,

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363 Art 1474 CCQ
364 Art 1607 CCQ
365 Art 1611(2), 1615 CCQ
366 Art 9 CCQ
367 Art 3, 1610 CCQ
368 Art 1611, 1621 CCQ
369 Art 1615, 1616(1), 1616 (2) CCQ
370 *Benhaim* v *St-Germain*, 2016 SCC 48, [2016] 2 SCR 352.
371 *Ibid*.
372 *Deguire Avenue Ltd* v *Adler*, [1963] BR 101.
373 Art 1613 CCQ

contributes materially and proportionally to the damage. In *Deguire*,[374] a painter lit a cigarette in an empty apartment which was not heated for weeks, causing fire. The judge decided that the painter lighting a cigarette and the concierge not heating the apartment each contributed 50% of the fire.

The theory of "immediate causation" illustrates the situation where an interrupting event *de novo* cuts prior faults or causes. It is the same concept as *novus actus interveniens* in the common law. In *Beaudoin*,[375] some children hoarded fireworks abandoned by the company after a firework display. The father of one of the children noticed this and confiscated the explosives. But instead of calling the appropriate authority which would have been the prudent thing to do, he negligently gave them to his own employee, a taxi driver, with instructions to get rid of the explosives. The driver then detonated the explosives with the children and the children were injured. It was ruled that the father's fault alone, *de novo*, liberated the negligence of the employee of the firework company having left the explosives on site in the first place.

The theory of "reasonable anticipation of consequences" is the foreseeability test in common law remoteness.

Despite all the theories, Quebec law adopts a pragmatic approach and does not follow any particular theory of causation, as long as fault can be shown as the direct and determining reason for the damage.[376] Jurisprudence demonstrated the adoption of adequate causation applied together with "reasonable anticipation". Refer to Table 9.

In terms of how civil law causality assists the award of damages, two situations come up. First, in the case where plaintiff and defendant share the fault, responsibility is divided *pro rata* between a victim's contributing fault and that of the defendant by function of their gravity of fault.[377] In *Bouliane*,[378] two girls aged 10 and 11 on a school outing descended a steep expert run in a toboggan, facing backwards, crashing into the scraper attached to a stopped snowmobile. While the school

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[374] *Deguire Avenue Ltd* v *Adler*, *supra* note 372.
[375] *Beaudoin* v *T W Hand Firework Co*, [1961] CS 709.
[376] Baudouin, Jobin & Vézina, *supra* note 244 at paras 1–697.
[377] Art 1478(2) CCQ
[378] *Drouin* c *Bouliane*, 1987 CanLII 705 (QC CA) ; *Bouliane* c *Commission scolaire de Charlesbourg*, (1984) CS 323, (1987) RJQ 1490 (CA).

committee was found negligent for having one supervisor (for 48 children on a hill with 15 toboggan tracks), and the sport centre employee negligent for having stopped the snowmobile where it was, the court also found the children imprudent to seat themselves backwards on the toboggan. As a result, the court allocated 10% victim's fault and 90% defendants' negligence.

Second, in a situation where multiple defendants exist, four scenarios arise:

1. Common fault (*la faute commune*):[379] where there is only one damage and contributing faults cannot be divided. The defendants are held liable solidarily.
2. So-called contributory faults (*les fautes dites contributoires*):[380] each defendant contributing to the cause of injury, held liable *pro rata*.
3. Successive faults (*les fautes successives*):[381] one fault after another in time. In *Lonardi*,[382] fifteen vehicles were vandalised. Each fault is distinct requiring separate analysis.
4. So-called simultaneous faults (*les fautes dites simultanées*):[383] can be used in a *force majeure* situation[384] where the defendant's fault occurs at the same time as the *force majeure* occurs. In such case, both causes are held liable solidarily.

Table 9: Causality, theory vs practice

Civil Law Causality	
Theories	Pragmatic Approach
Equivalences of conditions	Adequate causation
Adequate causation	
Immediate causation	Reasonable anticipation of consequences
Reasonable anticipation of consequences	

[379] Art 1526 CCQ
[380] Art 1478(1) CCQ
[381] Art 1457 CCQ
[382] *Montréal (Ville)* v *Lonardi*, 2018 SCC 29 (CanLII), [2018] 1 SCR 104.
[383] Art 1480, 1526 CCQ
[384] Art 1470 CCQ

Table 10: Civil responsibility in Québec

Civil responsibility as a result of causality				
Victim's fault One injury	Common fault One injury	Contributory faults One injury	Successive faults Multple injuries	Simultaneous faults One injury
Plaintiff v Defendant	Plaintiff v Defendants	Plaintiff v Defendants	Plaintiffs v Defendants	Plaintiff v Defendant and *force majeure*
Pro rata[385]	Solidarily[386]	*Pro rata*[387]	Distinct[388]	Solidarily[389]

As seen, Quebec also deals with the necessary and sufficient conditions where multiple causes and intervening acts arise, but in a more integrated manner.

We have thus concluded causality in Quebec civil responsibility and are now ready to proceed to the general principles of criminal causality in Canada.

True crimes, as opposed to regulatory offences, require that the offender commits *actus reus* along with the requisite *mens rea*. However certain offences in the *Criminal Code*[390] also require that the forbidden act cause a forbidden consequence.[391]

Offences where causation is an essential element include but are not limited to the following:[392]

- Homicide (Murder and Manslaughter)[393]
- Attempt to commit murder[394]
- Assault causing bodily harm[395]
- Aggravated Assault[396]
- Sexual assault causing bodily harm[397]

385 Art 1478(2) CCQ
386 Art 1526 CCQ
387 Art 1478(1) CCQ
388 Art 1457 CCQ
389 Art 1526 CCQ
390 *Criminal Code*, *supra* note 245.
391 *R* v *Nette*, 2001 SCC 78, [2001] 3 SCR 488 at para 44.
392 Peter Dostal, "Criminal Law Notebook", online: <http://criminalnotebook.ca/index.php/Criminal_Law_Notebook:About>.
393 *Criminal Code*, *supra* note 245 s 222.
394 *Ibid* s 239.
395 *Ibid* s 267(b).
396 *Ibid* s 268(1).
397 *Ibid* s 272(1)(c).

- Aggravated Sexual Assault[398]
- Dangerous Driving Causing Bodily Harm[399]
- Dangerous Driving Causing Death[400]
- Fraud[401]
- Defence of Person[402]

For these offences, criminal causality must be established in fact and in law. Factual causation is about the role of the accused in bringing about the forbidden consequence in a "medical, mechanical, or physical sense."[403] Similar to torts, the test for factual causation is the but-for test. However, in reading *Smithers*[404] and *Nette*,[405] it is not necessary for a judge to explain to a jury the distinction between legal causation and factual causation.[406] The jury needs only be instructed on deciding "whether the accused's actions significantly contributed to the victim's death."[407]

Legal causation is about the normative assessment of what the accused did to bring about the forbidden consequence. It is based on moral concepts of responsibility,[408] and it involves an assessment of whether the accused's involvement in bringing about the forbidden consequence is blameworthy enough to be considered legally responsible.[409] It has two elements: remoteness/foreseeability of harm and degree of participation.

Regarding remoteness/foreseeability of the harm, criminal law uses concepts of remoteness and foreseeability in assessing the accused's responsibility. The test for whether the forbidden consequence is too remote from the acts of the accused is whether the harm that results from the

[398] *Ibid* s 273.
[399] *Ibid* s 320(2).
[400] *Ibid* s 320(3).
[401] *Ibid* s 380.
[402] *Ibid* s 34.
[403] *R* v *Nette*, *supra* note 391 at para 44.
[404] *Smithers* v *R*, [1978] 1 SCR 506.
[405] *R* v *Nette*, *supra* note 391.
[406] *Ibid* s 46.
[407] *R* v *Sinclair (T) et al*, 2009 MBCA 71 at para 39.
[408] *R v Nette*, *supra* note 391 at para 83.
[409] *Ibid* at para 45.

accused's acts is reasonably foreseeable. However, the inference of foreseeability can be rebutted with evidence of intoxication.[410]

Regarding degree of participation, the question is whether the accused had a significant part in the criminal enterprise to assume responsibility. There are two sources of degree of participation tests: *Maybin*[411] and *Smithers*.[412]

The *Maybin* degree of participation[413] provides two different analytical tools, both centering around an intervening cause:

1. Reasonable foreseeability of intervening cause: The chain of causation may be "broken" by an unforeseeable non-human act.[414]
    a. Was the intervening act reasonably foreseeable at the time of the unlawful act?
    b. If so, was the forbidden consequence itself reasonably foreseeable at the time of the unlawful act?
2. Independent acts:[415] The chain of causation may be "broken" by another human's act.
    a. Did the accused's act trigger the actions of the other?[416]
    b. If so, was the accused's act still operating at the time of the forbidden consequence? If so, not too remote.
    c. If so, are the accused's acts of enough magnitude that they are not overwhelmed by the intervening acts?

The *Smithers* degree of participation test is much simpler compared to *Maybin*. It requires that the accused's act be a "significant contributing cause" of death beyond the *de minimus* range.[417]

The standard to prove causation is uniform in all homicide offences, including murder, manslaughter, and operation of a motor vehicle causing death.[418] But it appears that *Harbottle*

[410] *R* v *Seymour*, 1996 CanLII 201, [1996] 2 SCR 252 at para 23.
[411] *R* v *Maybin*, 2012 SCC 24, [2012] 2 SCR 30 at para 144.
[412] *Smithers v R*, *supra* note 404.
[413] *R v Maybin*, *supra* note 411 at para 34 et 38.
[414] Foreseeability of the intervening cause and not that of the harm.
[415] *R v Maybin*, *supra* note 411 at paras 50, 57, 59.
[416] If the intervening act was a natural act, was it "extraordinary", rather than "triggered".
[417] *Smithers v R*, *supra* note 404 at 519; *R v Nette*, *supra* note 391 at paras 71–72.
[418] *R* v *KL*, 2009 ONCA 141 at para 17.

requires a higher standard in first degree murder,[419] in which the Crown must prove that the accused's act was an "essential, substantial and integral part" of the cause of death.

In sum, causation in criminal law is like that in torts. It is a bifurcated test: the causation-in-law analysis is identical, while causation-in-law is slightly distinct. Legal causation in torts is a test of foreseeable probable precise harm, while legal causation in criminal law resolves around foreseeability of harm as well as degree of participation.

We have now concluded Chapter 2 by having examined legal reasoning patterns and laid down the causality frameworks in Canada using examples of common law torts, civil law responsibility, as well as criminal law.

[419] *R* v *Harbottle*, [1993] 3 SCR 306.

PART B: APPLYING AI TO LAW

As demonstrated in Part A of this thesis, reasoning and causality are complex notions both in science and in law. Human beings have a hard time understanding our own thinking patterns. To teach machines how to think would be an even bigger challenge,[420] as we cannot come to a consensus on how to define or measure human and artificial intelligence.[421]

Applying technology in law has been attempted since the Enlightenment period. Early work on this topic is attributed to Nicolaus I Bernoulli in his doctoral dissertation *De Usu Artis Conjectandi in Jure*, written in 1709.[422]

Then, Oliver Wendell Holmes, Jr. wrote in 1897, "For the rational study of the law the blackletter man may be the man of the present, but the man of the future is the man of statistics and the master of economics."[423]

In 1949, Lee Loevinger argued that the "inadequacy of socio-legal methods inherited from primitive ancestors to control a society" was in dire need of scientific investigation.[424] He compared, "The inescapable fact is that jurisprudence bears the same relation to a modern science of jurimetrics as astrology does to astronomy, alchemy to chemistry, or phrenology to psychology."

Since the 1980's, AI & Law has been a research field in computer science, which emerged from preceding ones. Before AI & Law, researchers explored functions such as question answering (QA), information extraction (IE), and argument retrieval (AR).[425] The software programs emerging up to that point were legal expert systems (LES).[426] LES are still widespread in the

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420 "What AI still can't do", online: *MIT Technol Rev* <https://www.technologyreview.com/2020/02/19/868178/what-ai-still-cant-do/>.

421 Paul Dumouchel, "Intelligence, Artificial and Otherwise" (2019) 24 Forum Philos.

422 A French translation of this dissertation is available in open access: Nicolas Bernoulli, *N. Bernoulli, L'usage de l'art de conjecturer en droit*, norbert meusnier ed (Departamento Lógica, Historia, Filosofía de la Ciencia (UNED), 1992), publisher: Norbert Meusnier.

423 Holmes, Jr., *supra* note 356.

424 Lee Loevinger, "Jurimetrics--The Next Step Forward" (1949) 33 Minn Law Rev, online: <https://scholarship.law.umn.edu/mlr/1796> at 455.

425 Ashley, *supra* note 39 at 3.

426 *Ibid* at 10.

commercial market today. But in the past decades, researchers have been gradually moving away from LES towards functions like legal text analytics and cognitive computing (CC).[427]

What follows is a dense history of how we have come from schematics and early computational models for legal reasoning, to the complex systems we have today.

[427] *Ibid* at 11.

Chapter 3: Existing Models in AI & Law

Without consistent forms of knowledge representation, human beings cannot communicate with each other any abstract or complex ideas, such as reasoning and causality. And as a result, there would be no talk of AI & Law or any technology in general. Thus, to be able to represent knowledge is crucial in understanding cognition and developing theories about it.

The format of knowledge representation is as important as the representation itself. For example, digital photography represents reality with 1 and 0 in a spatial framework. Also, alphabets and drawings are basic representations of everything in the world and their relationships.

3.1. Knowledge representation

The Hand Formula illustrated in the previous chapter is an example of using knowledge representation to describe legal liability. Choosing an appropriate knowledge representation for a legal system or application can lead to fruitful results. For example, a rule-based system is insufficient in analysing case-based reasoning, as we will demonstrate further in this chapter. Let us begin with the basics. Knowledge representation can be divided into three categories: mental spaces, featural representations, and structured representations.[428]

The first knowledge representation is mental spaces. We illustrate space with a map, often in two physical dimensions but sometimes also in three dimensions. Mathematically, the distance between two points is given by the formula below.

$$d(X,Y) = \left[\sum_{i=1}^{N}(X_i - Y_i)^r\right]^{1/r}$$

where r is the number of physical dimensions. Thus, the distance between two points $X(x_1,y_1)$ and $Y(x_2,y_2)$ on a two dimensional map is given by:

[428] Arthur B Markman, "Knowledge Representation" in *KJ Holyoak RG Morrison Eds Oxf Handb Think Reason* Oxford Library of Psychology (Oxford University Press, 2013).

$$d(X,Y) = \sqrt{(x_2 - x_1)^2 - (y_2 - y_1)^2}$$

Furthermore, humans' conceptual spaces for simple concepts like birds and animals can be mapped in a two-dimension plane.[429] The closer two points are together, the more similar the concepts are. The further the distance, the less similar. For instance, the figure below shows that a bird is closer to a goose than it is to a dolphin.[430]

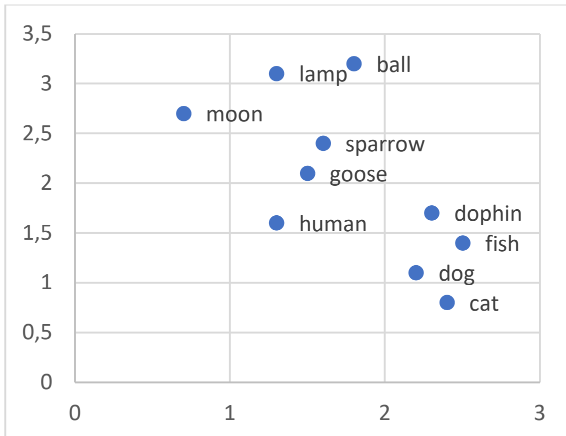

Figure 8: A spatial representation for purpose of illustration.

The advantages of spatial models are practicality and efficiency. As a result, spatial representations are often used when comparisons must be made among many items. But, the degree of proximity between points in semantic space has no obvious meaning.[431] For example, the moon is close to a ball because both are spheres. And the moon is close to a lamp because both are bright. But a ball and a lamp share no similarity. However, in spatial representation, the moon is close to a ball, and the moon is close to a lamp. These two conditions require that a ball be inevitably close to a lamp. Yet, this proximate distance created by the model does not reflect reality.

The second category of knowledge representation is featural representation, which addresses the weakness of spatial representation.[432] For example, dolphins have many features that are characteristic of fish, but they also have features of mammals. Only when we focus on the core

[429] Lance J Rips, Edward J Shoben & Edward E Smith, "Semantic distance and the verification of semantic relations" (1973) 12:1 J Verbal Learn Verbal Behav 1–20.
[430] Data is not to scale and does not reflect reality.
[431] Rips, Shoben & Smith, *supra* note 429.
[432] Markman, *supra* note 428.

characteristics of mammals is it possible to classify a dolphin correctly as a mammal. In other words, featural representation lets us pick the desired features to be presented in a spatial model. Had we chosen the characteristics of fish; we might have concluded that a dolphin is a fish.

This revelation flags a few kinds of dangers. The first danger is a researcher choosing the wrong features by mistake; hence, arriving at a wrong conclusion. The second danger is a researcher choosing the wrong features knowing what kind of conclusion is desired, producing unethical scientific results, as mentioned in Part A. Feature selection is especially important in AI as it is a foundational technique in machine learning.

Featural representations do a good job of representing the properties of items but a poor job at representing relationships. For example, poodles are a kind of dog. Saying that poodles are a kind of dog is true but saying that dogs are a type of poodle is not. That is to say, the way that items are connected to the relationship also matters. The indication of relationship of this type is called predicate (see Chapter 1). And the way items are connected to the relationships is called binding. So, a poodle is a dog can be represented as follows, where (is-a) is the binding.

$$\textbf{poodle} \xrightarrow{\textbf{(is-a)}} \textbf{dog}$$

The lack of relationship representation in featural representation makes this method merely associative, which is again, the main criticism of today's AI approach.

The third category of knowledge representation is structural representation which addresses the weakness of featural representation using predicates.[433] A predicate takes one argument called an attribute of an object. Thus, a red circle has at least two attributes or arguments: red and round. A bunch of these objects with their attributes would form a semantic network as follows. Note that each path between objects contains the kind of relationship (binding), such as "is-a" or "kind-of".

[433] *Ibid*.

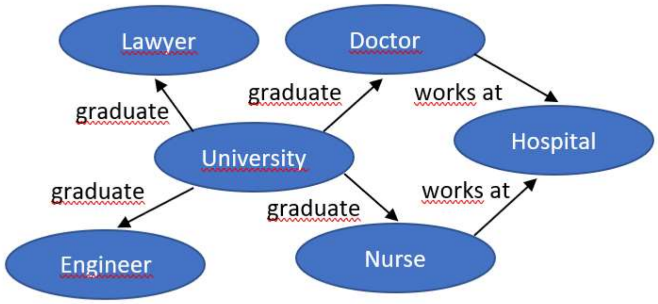

Figure 9: A structural representation

Thus, related objects would have similar attributes. Seeing the word "doctor" would semantically relate (bind) another word like "nurse".

This concept of "binding" is far-reaching because causal relationships can now be represented by symbols such as the following:

$$\mathbf{A} \xrightarrow{\textbf{(causes)}} \mathbf{B}$$

As seen, structural representation enables the causal approach to relate to causality. In fact, structural representation is the foundation of causal diagrams known as directed acyclic graphs (DAGs). A DAG is a component of Pearl's structural causal models (SCMs) invented by Pearl,[434] which will be discussed in Chapter 4.

More complex systems can be brought together by a semantic network such as the following:

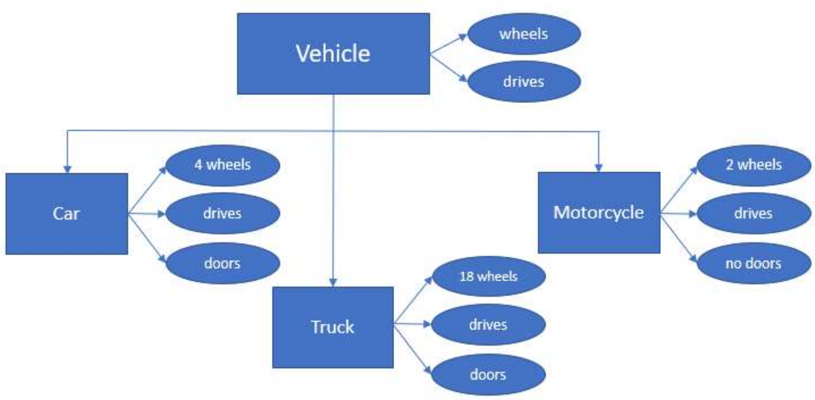

Figure 10: A semantic network

[434] Pearl, Glymour & Jewell, *supra* note 36 at 35.

A semantic network can look like object-oriented models[435] where data or objects have "inheritable" attributes and are related in categories or classes. For instance, a car is subset of a vehicle, and as such, inherits all the attributes of a vehicle: it has wheels and can be driven from point A to point B.

Why is a semantic network significant? Because it can help a machine understand sentences, and subsequently paragraphs, and then whole documents. A human understands that an elephant man is a fusion of an elephant and a man; but we know that a criminal lawyer is not a person who is a criminal and a lawyer. Yet a mermaid is a fish and a woman. A sophisticated semantic network can tell the machine these kinds of relationships by use of binding and structure.

From here, a sentence's meaning can be derived from the meaning of the words that compose them, guided by the sentence's grammar.[436] This type of analysis forms the basis of natural language processing (NLP), which is further evolved into other sophisticated types of linguistic models using statistics, machine learning and other techniques.

With the above three basic types of knowledge representation, we can now ascend to computational models of higher cognition. There are three basic types: traditional symbolic model, traditional connectionist model, and symbolic-connectionist model.[437]

Any representational system consists of representational elements and a set of rules for inferring new statements from existing statements, for example, nodes and arcs in a network. But what makes a traditional symbolic model is one that combines its basic representational elements into complex structures capable of expressing an open-ended set of relations.[438] The most common symbolic models are propositional notation and labeled graphs, which are sets of an infinite number of relational statements with a finite number of predicates and objects.[439]

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[435] The term "object-oriented" is specific in software engineering. The term encompasses principles which together characterise the object-oriented approach, including message-passing, encapsulation (hiding internal detail), inheritance (from class to subclass), and polymorphism (allowing different data types). The approach is being taught in mainstream software engineering curriculum.
[436] Rips, Shoben & Smith, *supra* note 429.
[437] Leonidas A A Doumas & John E Hummel, "Computational Models of Higher Cognition" in *KJ Holyoak RG Morrison Eds Oxf Handb Think Reason* Oxford Library of Psychology (Oxford University Press, 2012).
[438] *Ibid* at 52.
[439] *Ibid*.

For example, the labeled graph below where ovals represent relations and rectangles represent objects, and lines joining them together, is a traditional symbolic model.[440]

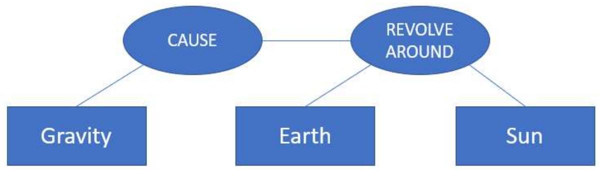

Figure 11: A traditional symbolic model

In addition to graphs, a symbolic model can also be production systems. For example, if *larger(A, B)* denotes A is larger than B. As such, if *larger(A, B)*, and *larger(B, C)*, then *larger(A, C)*.

Symbolic models are useful in describing relationship, but there are at least two limits. First, humans must input the relationship of the model manually, which creates a resource bottleneck. Second, a symbolic model lacks the capability of capturing shades of meaning and other subtleties associated with semantic content.

The second type of high cognition representations are traditional connectionist models which addressed certain limitations of symbolic models.[441] Traditional connectionists denote knowledge in units and patterns of activations. A unit could be a dog while patterns belonging to a dog would be living organism and mammal.

Table 11: Binary features per unit

Unit	Round shape	Living organism	Mammal	Speech
Moon	1	0	0	0
Dog	0	**1**	**1**	0
Dolphin	0	1	1	0
Fish	0	1	0	0
Human	0	1	1	1

Connectionist models provide a way to capture the similarities of different concepts. For example, a dog and a dolphin are closer to a human than a fish is. And the moon is quite different from a

[440] *Ibid* at 53.
[441] Doumas & Hummel, *supra* note 437 at 55.

human. Now, consider each of these units as an input, with multiple units and their patterns form a neural network:

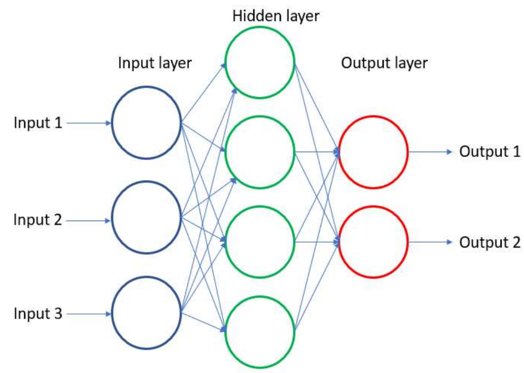

Figure 12: A neural network

This approach mimics biological neural networks, which is one of its strengths. In addition, if the number of layers of the pattern increases, and the system becomes too heavy for the human brain, computers can handle it. In fact, machine learning algorithms can be developed to enable connectionist networks to learn their own representations, both in the "hidden" layers of feed-forward and recurrent networks, and in unsupervised learning models.

Ironically, connectionist models have the "opposite" problem of symbolic models. Symbolic representations can handle directions. For example, *larger(A, B)* cannot mean *larger(B, A)*. In fact, it necessarily means the converse, *smaller(B, A)*. Although connectionist models can handle shades of gray, they have no sense of directions. Remember Hume's probabilistic inference, $P(A|B)$ gives us a degree of association but does not tell us anything about direction. Furthermore, every connectionist model must be trained individually.

To get the best of both worlds, the structure of traditional symbolic models and the distributed architecture of traditional connectionist models were combined to form the new symbolic-connectionist models. [442] The new model can represent semantic roles and their fillers. Symbolic-connectionist models are based on vectors, which consist of quantity having direction as well as magnitude.

[442] *Ibid* at 60.

Symbolic-connectionist models come in two general forms: those based on vector multiplication and those based on vector addition.[443] But models based on vector multiplication fail to capture the natural pattern of similarities among propositions. Both vector-based models have the potential to produce representations that support neural networks, and are semantically rich, flexible, and meaningfully symbolic.[444] Nevertheless, symbolic-connectionist models have not yet addressed aspects of human cognition including planning, quantification, negation, and language use.[445]

In summary, knowledge can be represented by mental spaces, featural representations, and structural representations in the basic level; then higher cognition can be represented by the traditional symbolic models and the traditional connectionist models, as well as the more recent symbolic-connectionist models.

3.2. Legal Reasoning Models

As discussed previously in Chapter 2, formal legal reasoning can be divided into case-based reasoning and rule-based reasoning. Similarly, formal legal reasoning models can be divided into case-based models and rule-based models. In computer science, rule-based models are more simplistic compared to case-based models.

Rule-based models translate or cross-reference legal rules into computer systems syntactically, semantically, and structurally. This translation from natural text into pseudocode is called normalization. Normalized texts resemble "if-then-else", and "and/or" propositions. For example, an individual is required by law to file a Canadian income tax return if this person is a Canadian resident within the meaning of the Canadian Income Tax Act.[446] Below is a simplified version of the normalized rules of determining if an individual is a Canadian resident.

```
If ordinarily resides in Canada OR has primary ties OR has secondary ties
  "ordinarily resident" – s.250(1)
Else
  If sojourned in Canada >= 183 days during tax year
    "deemed resident" – s.250(3)
  Else
```

[443] Doumas & Hummel, *supra* note 437.
[444] *Ibid*.
[445] *Ibid* at 63.
[446] *Income Tax Act*, RSC 1985, c 1 (5th Supp).

```
    If Canadian Forces OR servant or representative of Canada OR tax treaty
      If renounced right from tax treaty
        "non-resident" – s.250(5)
      Else
        "deemed resident" – s.250(3)
      End-if
    Else
      "non-resident"
    End-if
  End-if
End-if

If "ordinarily resident" or "deemed resident"
  required to file Canadian income tax return
End-if
```

Currently, normalization requires human intervention and can be cumbersome and time-consuming. Normalizing validity, applicability, and operability of constitutional analysis (Chapter 2) would be a daunting task. In addition, normalization is prone to problems of interpretation, and is limited to a given jurisdiction. Certain models combine various normalized statutes into statutory networks, which make it even more complex.[447] But once tried and tested, the algorithm is easy to understand and robust, until the law changes. Below is an example of a statutory network.

[447] Patricia Sweeney et al, "Social Network Analysis: A Novel Approach to Legal Research on Emergency Public Health Systems" (2013) 19 J Public Health Manag Pract JPHMP E38–E40.

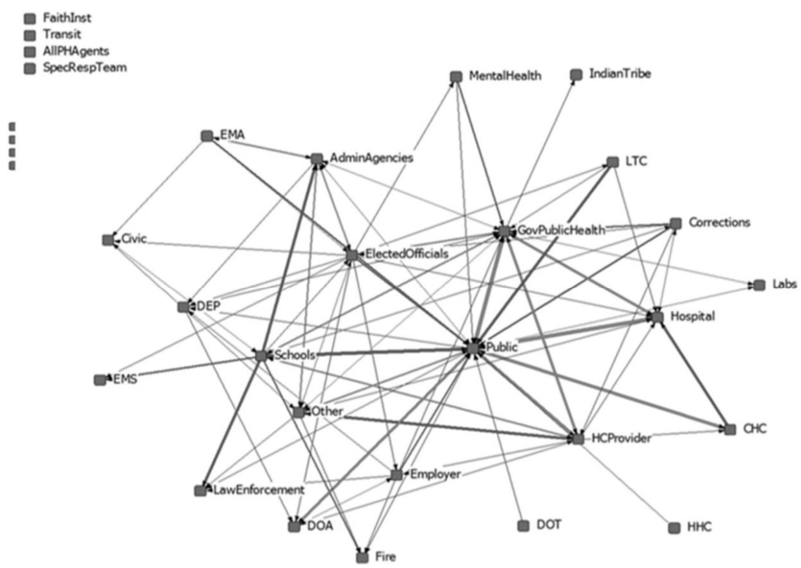

Figure 13: Legally Directed Agents for Infectious Disease Surveillance in New York State[448]

Rule-based legal reasoning models existed for decades. For instance, a program written in the Prolog programming language was used to determine British citizenship according to the *British Nationality Act* using approximately 150 normalized rules.[449] Another example is the TAXMAN program[450] written in the micro-PLANNER language to emulate sections of the *Internal Revenue Code* of 1954.[451] The flowchart-like algorithms used in these projects are not only useful in statutory reasoning, but also find wide applications in enterprise resource planning (ERP) and other business management processes.

On the other hand, case-based models are more sophisticated than ruled-based models because they can handle legal arguments in addition to legal rules. Case-based legal reasoning can be achieved with three basic models: 1) prototypes and deformations, 2) dimensions and legal actors, and 3) exemplar-based explanations.[452] None of these models extract legal texts automatically; instead, they use representations already constructed by humans.

[448] *Ibid*. Courtesy of the authors.
[449] Marek Sergot et al, "The British Nationality Act as a Logic Program" (1986) 29 Commun ACM 370–386; Ashley, *supra* note 39 at 47.
[450] L Thorne McCarty, "Reflections on 'Taxman': An Experiment in Artificial Intelligence and Legal Reasoning" (1977) 90:5 Harv Law Rev 837–893.
[451] *IRC §§ 354-356, 358, 361-362, 368*, (1954).
[452] Ashley, *supra* note 39 at 73.

The first type of CBR models, prototypes and deformations, focuses on how to decide a case by constructing legal concepts based on past decisions. Prototypes are precedents and hypotheticals with positive or negative legal concepts; and deformations are separate mappings for comparison.[453] For example, the Taxman II program[454] modelled the *Eisner*[455] case at the U.S. Supreme Court concerning whether a *pro rata* stock dividend resulting from a stock split was taxable income to the share holder under the relevant legislations.[456] The program had three prototypes and separate deformations that compared shareholder ownership ratios before and after distribution.[457]

Table 12: Taxman II program[458]

Case/Hypothetical	Prototype	+ve or -ve
Lynch	Distribution of corporation's cash was taxable income to shareholder.	positive
Peabody	Distribution by a corporation of another corporation's stock was taxable income to shareholder.	positive
Appreciation	Appreciation in value of stock without transfer was not taxable income.	negative

Naturally, the taxpayer would want to exclude positive prototypes in *Lynch* and *Peabody* but include the negative one in the Appreciation hypothetical. In contrast, the Internal Revenue Service (IRS) would want the opposite, to include positive prototypes in *Lynch* and *Peabody* and exclude the negative one in the Appreciation hypothetical.

Thus, Taxman II would try to find facts in *Eisner* linking to the Appreciation hypothetical by comparing the shareholder ownership ratio. Before the stock split, Mrs. Eisner owned 2,200 shares of the 500,000 shares in the corporation, which is the same ratio after the stock split, 3,300 shares of 750,000 shares. Therefore, the increase in number of shares should not result in taxable income as per the Appreciation hypothetical.

[453] L Thorne McCarty & N S Sridharan, *The Representation of an Evolving System of Legal Concepts: II. Prototypes and Deformations* (1980).
[454] The Taxman II program is not to be confused with the Taxman program which is a rule-based model.
[455] *Eisner* v *Macomber*, 252 US 189 (1920).
[456] M J Sergot et al, "The British Nationality Act as a Logic Program" (1986) 29:5 Commun ACM 370–386.
[457] Ashley, *supra* note 39 at 79.
[458] Data taken from the Taxman II program.

The concept behind prototypes and deformations is straightforward but its implementation involves numerous steps, even for a rather binary issue such as taxable income. In practice, a case is decided upon multiple arguments involving a wide variety of issues. Thus, computational models for legal reasoning for a real case can be resource heavy.

The second type of CBR models, dimensions and legal factors, aims to enable comparing similarity of favourable cases and distinguishing non-favourable ones. The first generation of these models is Hypo, followed by successors CABARET and CATO. [459]

Hypo was conceived to deal with trade secret misappropriation. The model represents legal factor by a dimension, which is a sliding scale. For example, one factor is secret-disclosure-to-outsiders. The more outsiders the trade secret was disclosed to, the higher the index is located on the sliding scale. Notice that the magnitude for each dimension is not to be confused with its weight. A factor high in magnitude may be weighted low as the factor may be not very important.

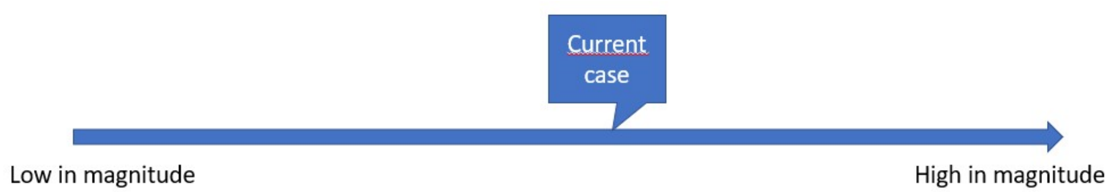

Figure 14: A dimension in Hypo model

Hypo retrieves all cases in the database that share the same dimensions. The program can then rank the cases by similarity and relevance, then liken or distinguish them. But Hypo does not address weight at all.

A successor model, CABARET,[460] improved Hypo by integrating a rule-based mechanism into case-based modelling. The subject of law in the model dealt with income tax home office deductions. The rule-based part works like the Canadian Income Tax example above but when the rules run out, the program resorts to Hypo type reasoning. How the program dedicates between rule-based logic and case-based logic can be defined using a separate algorithm.[461] The key

[459] Ashley, *supra* note 39 at 81.
[460] Edwina L Rissland & David B Skalak, "CABARET: rule interpretation in a hybrid architecture" (1991) 34:6 Int J Man-Mach Stud (Al and Legal Reasoning. Part 1) 839–887.
[461] Ashley, *supra* note 39 at 90.

improvement in CABARET is reasoning using a mixture of RBR and CBR, as judges do in most cases in court.

Another successor model, CATO,[462] improved Hypo by replacing dimensions with factors and by simplifying magnitude into binary representation. A legal factor either applies or it does not. So, each factor would be represented by 1 or 0, as opposed to a sliding scale. Moreover, CATO structures legal factors in hierarchy. This hierarchical structure allows downplaying or emphasizing a factor as it strengthens or weakens the claim.

The third type of CBR models, exemplar-based explanations, also aim to enable comparing similarity of favourable cases and distinguishing non-favourable ones. But instead of using dimensions as in Hypo, exemplar-based explanations use semantic networks.[463] A semantic network is a graph with nodes, that is, a symbolic model. Each node represents a concept or a fact, with arcs between them representing relationships.[464]

The GeneratoR of Exemplar-Based Explanations (GREBE) system[465] is an exemplar-based program that contains a database of semantic networks. It integrated RBR and CBR to determine and justify legal conclusions for cases in employment law. When given a factual matrix, the program tries to map the structures of the semantic net and matches relevant cases. Since the program cannot visually "see" the nets, the search algorithm is complex. Interestingly, GREBE did better in building arguments than students.[466] GREBE constructs legal arguments that look like natural English language.[467]

None of the above three types of CBR models provide any explanations. Instead, they "reason" by measuring, matching, and comparing, but they cannot "understand" the purpose or value underlying the legal rules. Take Taxman II as an example, the negative prototype of the

[462] Vincent Aleven, "Using background knowledge in case-based legal reasoning: A computational model and an intelligent learning environment" (2003) 150:1 Artif Intell (AI and Law) 183–237.
[463] L Karl Branting, "Building explanations from rules and structured cases" (1991) 34:6 Int J Man-Mach Stud (Al and Legal Reasoning. Part 1) 797–837.
[464] Semantic networks are sometimes referred to as structural and relational networks.
[465] Branting, *supra* note 463.
[466] Ashley, *supra* note 39 at 96.
[467] *Ibid* at 97.

Appreciation hypothetical was included to help the taxpayer based on a favourable outcome, but the computer does not understand why an unrealized gain was not taxable income.

A teleological model, one that supports explanation, would explain that an increase in share value that is not yet realized is not taxable income because it is not yet benefited by the shareholder (an underlying value). Also, it is possible that the stock price would decrease by the time the shareholder makes a transfer resulting in a loss (another underlying value). Therefore, assigning underlying values is the basis for theory construction.

A teleological model developed by Bench-Capon and Sarton[468] represents each legal rule by either pro-plaintiff, п, or pro-defendant, ʌ. Then, rules that have won are given higher preference than those that have not. Afterwards, theoretical value preference is given to the rule, such as NYGain, (for no gain yet) or MCash (for more cash).

Let us mimic the algorithm of this model by reproducing the *Eisner* case, with the taxpayer being the plaintiff π.

Table 13: The Eisner case in a teleological model

Steps	Instructions or Algorithm
Values	NYGain (no gain yet) MShare (more shares) MCash (more cash)
Factors – values	πCash (plaintiff got cash) – value MCash πShare (plaintiff got more shares) – value Mshare πApprec (plaintiff got share increase) – value NYGain
Cases and hypothetical	*Lynch*, πCash, п *Peabody*, πShare п Appreciation, πApprec, ʌ
Rules	If πCash, ʌ If πShare, ʌ If πApprec, п
Factor Preference	If πApprec, п > If pCash, ʌ If πApprec, п > If pCash, ʌ
Value Preference	NYGain > MCash NYGain > MShare

468 Giovanni Sartor, "Teleological arguments and theory-based dialectics" (2002) 10:1 Artif Intell Law 95–112.

In other words, a teleological model is a value-based model. Ranking is performed according to the underlying values of the legal factors rather than the legal factors themselves. However, this model is not more useful than the other CBR models because it assumes that judges apply values in past facts, and then apply them to current facts. But it is more likely that judges apply the values in the current circumstances and resolve conflict accordingly.[469] It is also not clear whether lawyers use underlying values in reasoning, thus, it is unclear if a teleological model is helpful to legal practitioners.

In addition, coming up with detailed values and factors requires human intervention; not only that, the code designed in each model is so specific to a case that they are only easy to understand to the programmers who wrote them. Therefore, the model is not easy to maintain.

To summarize CBR models, currently machines are not yet able to effectively and automatically extract concepts or meaning in the analysis section of cases, which means that human annotation is necessary in all these models. Even after manually extracting the concepts and inserting into the program, it is not clear that the algorithms are helpful in human decision-making.

3.3. Predictive Models

In addition to reasoning models, another type of model is one that can predict legal outcomes. Predictive models use either 1) CBR arguments, 2) machine learning (ML) algorithms, or 3) a combination of both.[470] Prediction using CBR models focuses on strength of argument; while prediction using ML algorithms learns correlation between feature X and outcome $Y = f(X)$.

Evaluation of prediction involves first identifying the true positives (TP), the true negative (TN), the false positives (FP) and the false negatives (FN).

[469] Ashley, *supra* note 39 at 103.
[470] *Ibid* at 107.

Table 14: A confusion matrix

		Reality	
		Positive	**Negative**
Prediction	Positive	TP	FP
	Negativ	FN	TN

Once statistics are collected, several formulas provide a reference of how well predictions do.

Table 15: Evaluation of predictive models

Evaluation	Formula	Remarks
Accuracy	$A = \frac{(TP + TN)}{(TP + TN + FP + FN)}$	Correct prediction over all prediction
Precision	$P = \frac{(TP)}{(TP + FP)}$	Correct positive over predicted positive
Recall	$R = \frac{(TP)}{(TP + FN)}$	Correct positive over correct prediction
F1 Score or F1 Measures	$F1 = 2\frac{(PR)}{(P + R)}$	Harmonized P and R (treating both P and R equally important)

Of ML algorithms, the k-Nearest Neighbor (k-NN) prediction is a similarity comparison (CBR) approach. Features of each precedent are weighted according to the case's outcome and a single point located on a graph is used to represent it. So, there are a cluster of "win" case points and a cluster of "lose" case points. Ideally, there will be clear division between the "win" cluster and the "lose" cluster. The location of the case at hand relative to the win/lose clusters will predict the likelihood of success. But when the win/lost points are blended, this method is unhelpful.

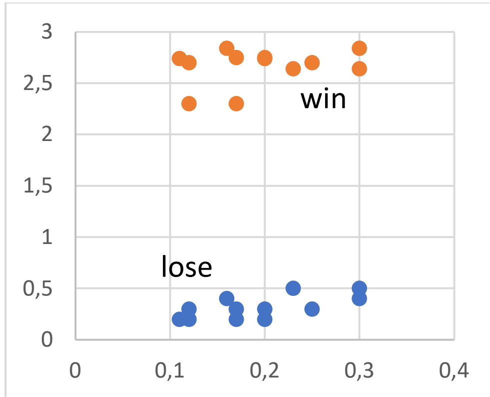

Figure 15: k-Nearest Neighbor clusters

Another ML technique is decision tree (DT). TreeAge Pro[471] is a DT software that is commercially available to legal counsel.[472] A DT is a hierarchical structure with leaves carrying target variables. Target variables can be acquired by manual input, or calculated in statistics, or by machine learning. Tree models where the target variable can take discrete (binary) values are called classification trees; those where the target variable can take floating values are called regression trees.

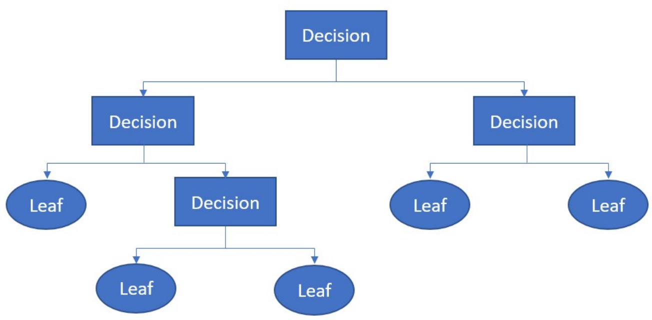

Figure 16: A decision tree

A DT is easy to understand but prone to "overfit" when the model memorises the data rather than learn the data, especially when the tree structure has many leaf nodes. Several techniques such as "pruning" and "early stopping" can reduce the complexity of trees.[473] Then, different aspects of

[471] Treeage.com

[472] Heather Heavin & Michaela Keet, *The Path of Lawyers: Enhancing Predictive Ability Through Risk Assessment Methods* (Edmonton: Canadian Institute for the Administration of Justice, 2016) at 26.

[473] University of Washington, *(OPTIONAL) Pruning decision trees to avoid overfitting - Preventing Overfitting in Decision Trees*, online: *Coursera* < https://www.coursera.org/lecture/ml-classification/optional-pruning-decision-trees-to-avoid-overfitting-qvf6v>.

the data can be combined into a collection of simpler trees to form a random forest (RF), and the final prediction can be arrived at through a process of voting.[474]

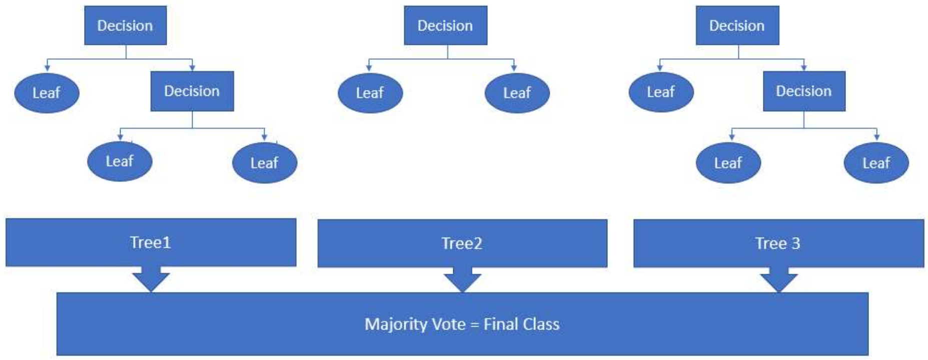

Figure 17: A random forest

A DT or a RF are some of the most transparent ML algorithms. Other ML models may look like a black box because of complex equations or hidden layers that are difficult to unpeel. We can illustrate how a black box comes to be by starting with a regression model. A regression algorithm is a target function that takes input, processes, and produces output.

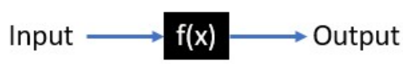

Figure 18: A system as a function of X

In predictive modeling, the goal is to find this target function, f, that best maps input variables x to an output variable $y = f(x)$ so that it can make accurate predictions of future y, given new input x. The function $f(x)$ can be a very simple story; for example, a single-variable linear regression with slope m and a constant coefficient c:

[474] Renu Khandelwal, "Decision Tree and Random Forest", (14 November 2018), online: *Medium* <https://medium.com/datadriveninvestor/decision-tree-and-random-forest-e174686dd9eb>.

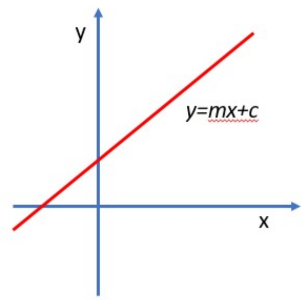

Figure 19: A linear regression

The function can be a slightly more complex story, for example, a neural network made up of multiple variables (features) and parameters (weights) arranged in layers:

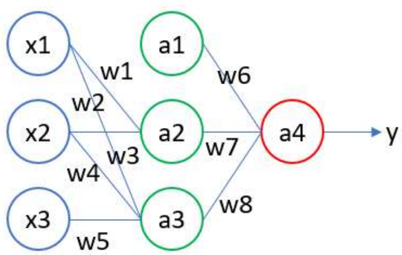

Figure 20: A neural network

And with many levels of nodes forms a complex neural network or "deep" neural network (DNN) consisting of hidden layers, making it difficult to understand, like a "black box".

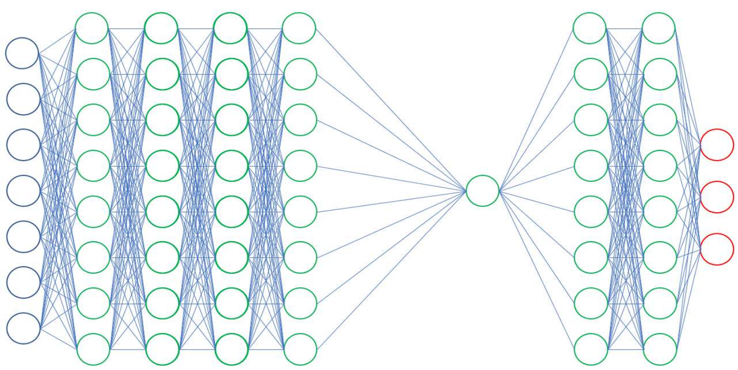

Figure 21: A complex neural network

The human brain may not be able to trace or unpeel the layers, but computers are excellent at it. However, regression models rely on the correlation of data, that is, the relationship between *x* and *y*. Therefore, no matter how sophisticated *f(x)* is, regression is merely "fitting the curve". In other words, regression cannot tell us anything about directions or causal relationships.

Compared to ML prediction, CBR prediction is more "explainable" because CBR models already contain arguments. Prediction of outcome is then extending from those arguments. There are two prediction methods within this category: CATO prediction and issued-based prediction (IBP).

We have seen CATO as a reasoning model; now we discuss it also as a predictive model.[475] Mentioned previously, CATO retrieves all relevant cases using factors; if cases exist and outcomes are consistent, the retrieved outcomes are the predictive outcome. Otherwise, there's no conclusion. Since cases are already in factor representations, CATO prediction merely piggybacks on them.

On the other hand, IBP improves CATO by replacing the factor hierarchy with a graph of "issues" that semantically connect the factors.[476] IBP identifies current issues; and for each issue, iteratively finds consistency in cases with related issue. If cases exist and outcomes are consistent, the retrieved outcomes are the predictive outcome; if cases exist but outcome are inconsistent, then there's no conclusion; if cases not found, widen the query to find cases and reiterate the process until exhausted.

IBP uses "issues" instead of factors, thus working at a deeper level of granularity. Results show that IBP is more accurate than CATO, DT and Hypo.[477] But most importantly, IBP's use of "issues" generates explanations that are intuitively accessible to lawyers.

The value-based teleological model by Bench-Capon and Sarton discussed earlier was also extended to a predictive model called AGATHA.[478] However, for the same doubt of whether using value preference is helpful in legal argument to lawyers, it is also unclear whether it is helpful in predictions.[479]

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[475] Aleven, "Using background knowledge in case-based legal reasoning", *supra* note 462.
[476] Stefanie Brüninghaus & Kevin Ashley, *Predicting Outcomes of Case-Based Legal Arguments.* (2003). Predicting Outcomes of Case-Based Legal Arguments. Proceedings of the International Conference on Artificial Intelligence and Law. 233-242. 10.1145/1047788.1047838.
[477] Ashley, *supra* note 39 at 119.
[478] Alison Chorley & Trevor Bench-Capon, "AGATHA: Using heuristic search to automate the construction of case law theories" (2005) 13:1 Artif Intell Law 9–51.
[479] Ashley, *supra* note 39 at 121.

3.4. Argumentation Models

Having seen reasoning models and predictive models, we now explore models that can "argue". As mentioned, RBR models are incapable of handling arguments; thus, we discuss only CBR models.

To model legal arguments, CBR models look to supporting or attacking a proposition. Simple models, such as Dung's[480] and ASPIC+,[481] represent arguments and attack relations between them. A more sophisticated model, Value-based Argument Framework (VAF), handles complex arguments with underlying "values", hence the name.[482] All three models are called "abstract" argument systems because they "abstract away" any structures of argumentation.[483]

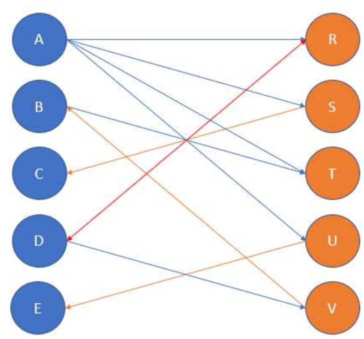

Figure 22: A Dungean argument model

Some argumentation models preserve the structure of arguments. For example, Carneades[484] represents each proposition as accepted (On) or not (Off).[485] A proposition is (On) if it is true given arguments up to that stage. Thus, the argumentation diagram provides a hierarchical structure that ascends to the conclusion from propositions that lead to it, much like a tree.

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[480] Phan Minh Dung, "On the acceptability of arguments and its fundamental role in nonmonotonic reasoning, logic programming and n-person games" (1995) 77:2 Artif Intell 321–357.
[481] Sanjay Modgil & Henry Prakken, "A general account of argumentation with preferences" (2013) 195 Artif Intell 361–397.
[482] Ashley, *supra* note 39 at 140.
[483] *Ibid* at 127.
[484] carneades.github.io
[485] *The Carneades Model of Argument Invention (2017) 14:2 SCRIPTed 168*, SSRN Scholarly Paper, by Douglas Walton & Thomas Gordan, papers.ssrn.com, SSRN Scholarly Paper ID 2097106 (Rochester, NY: Social Science Research Network, 2012) at 188.

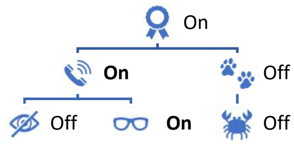

Figure 23: A Carneades argument model

In addition, the Carneades model can argue for both sides.

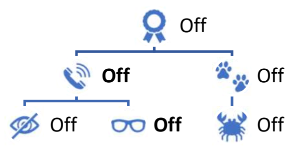

Figure 24: An adversary Carneades argument model

Up to this point, we are assuming perfectly proven evidence, which is hardly a reality. Various standards of proof, such as *de minimis*, *prime facie*, preponderance of evidence or beyond reasonable doubts are concepts that models would have to address.

Moreover, the examination of a witness in front of the judge is "real-time", not something that one can input to the model in advance. Also, legal procedures are often overlooked in models. The practice of law is as much the substance of law as the procedures; a practitioner must follow court procedures properly in order to succeed, or the action will fail. Consequently, legal arguments are only part of the picture, important nonetheless, but not the whole picture.

As "real-time" litigation involves uncertainties, probabilistic inference can be introduced to deal with them. Since the 1990's, Bayesian networks[486] (BN) seem to be the solution of choice.[487] Eugene Charniak demonstrated how causal graphs can be constructed with probabilistic paths.[488] His proposed models include directions, unlike Hume's inference which is based only on correlations. This nuance is important because a causal inference is one that combines probability and causal relationships, the best of both worlds. In Chapter 2, we mentioned that the two main

[486] Bayesian networks are a type of graphical model that uses Bayesian inference for probability computations.
[487] Eugene Charniak, "Bayesian Networks without Tears" (1991) 12:4 AI Mag, online: <https://www.aaai.org/ojs/index.php/aimagazine/article/view/918>.
[488] *Ibid*.

inferential approaches (associative and causal) can be combined; BN is such an example. In Chapter 4, we will discuss causal models in further details.

Another argumentative model, the Value Judgment-based Argumentative Prediction model (VJAP) requires humans to assign legal factors, then from those factors, assign values.[489] The model then uses those values instead of factors to build the argument schemes.

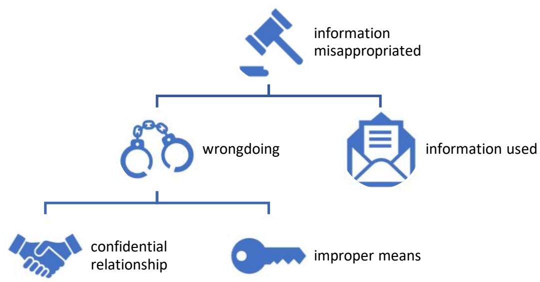

Figure 25: A VJAP illustration

Note that cases with the same values do not necessarily mean that they have the same factors. Like teleological models, VJAP operates on the deeper level of granularity. In terms of making predictions, VJAP builds on its argumentation model and adds "confidence propagations". A confidence propagation denotes a degree of confidence which is a weight value acquired automatically from previous cases. In sum, VJAP builds an argument scheme using values assigned by humans and predicts outcome with a degree of confidence. If the conclusion is favourable with a degree of confidence of greater than 50%, the case is predicted to "win". Otherwise, the other side wins.

Finally, Default Logic Paradigm (DLP)[490] is designed to model causation-in-fact based on evidence. It uses a statutory rule tree and connects evidentiary assertions into the rule conditions.

[489] Matthias Grabmair, *Predicting Trade Secret Case Outcomes Using Argument Schemes and Learned Quantitative Value Effect Tradeoffs* (New York, NY, USA: Association for Computing Machinery, 2017), event-place: London, United Kingdom.
[490] *A Default-Logic Paradigm for Legal Reasoning and Factfinding*, SSRN Scholarly Paper, by Vern R Walker, papers.ssrn.com, 06-14 SSRN Scholarly Paper ID 908626 (Rochester, NY: Social Science Research Network, 2006).

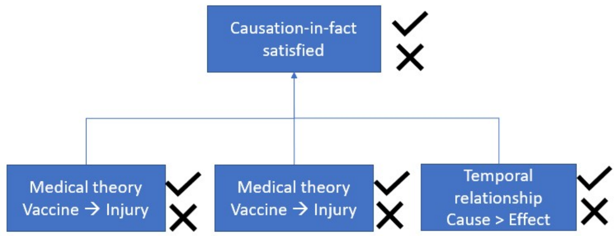

Figure 26: A DLP illustration

The argument diagram demonstrates only the route to success, but a separate fact finder is needed to assign the values to the conditions: values such as "true", "undecided" or "false". Continued development of this fact-finding approach can be found at the Research Laboratory for Law, Logic and Technology.[491]

For all the above models discussed so far, the manual process of acquiring factors, values, issues, and rules is cumbersome, time-consuming, and expensive. In addition, human-machine interface of these models is not elegant, relying on logic proposition rather than natural language.

3.5. Text Analytics

Natural language processing (NLP) and legal analytics can address current limitations in at least two major ways. First, NLP is enabling the use of natural language in input and output, providing a more elegant user experience. Second, legal analytics will enable understanding of legal concepts so that they can retrieve meaning from text, and perhaps one day, build argument models for us. Legal analytics will eliminate the resource bottleneck of human annotation.

Legal analytics is already greatly improving the efficiency of electronic discovery (eDiscovery) by predictive coding using keywords, Boolean and concept search to identify all kinds of legal documents.

Although gold standard annotation for models is still done by humans, machine learning techniques are being deployed rapidly to automatically extract relevant concepts within a large

[491] https://www.lltlab.org/

corpus of legal text. Today, commercial products such as SOQUIJ, WestlawNext and Lexis Advance Quicklaw can instantly return intuitive and helpful information when given keywords.

Text is commonly represented in ontologies and type systems, meaning categorizing or putting them in buckets. Legal text analysis is the process to collect, normalize, tokenize, and annotate from a large corpus legal text using supervised machine learning techniques. There is some usage of unsupervised learning as well, but it is more suitable for undefined or creative goals. The types of problems we need to solve in front of us here require supervised learning.

Some of the most used algorithms in text retrieval are bag-of-words (BOW), term frequency–inverse document frequency (TF-IDF), and part-of-speech (POS).[492] BOW indicates the frequency of words in a corpus. Normally, if a word appears many times in a document, it is probably an important word or closely related to the subject of the corpus. But BOW does not consider the "rareness" of a term, nor does it care about the order of words.

TF-IDF also reflects the importance of words in a document but it is smarter than BOW. The TF part, term frequency, is the same as BOW, but the IDF part reverses the rarity of a word, making it also important. Finally, POS, is a tagging method that tells us the importance of the word based on where it is in the sentence. For this reason, POS is also smarted than BOW. But it does not mean that BOW is useless. Sometimes, a simple solution is all one needs.

In addition to categorizing words, the program may be actively looking for certain words in a document. For example, to classify the conclusion part of the case, functions such as regular expression (regex) will look for and return the target paragraphs following "FOR THESE REASONS, THE COURT", or in French decisions, "POUR CES MOTIFS, LE TRIBUNAL".

Every language has its own way of forming sentences. Hence, training the machine on French texts requires a different set of algorithms. Supreme Court cases in Canada are delivered in both official languages but many cases on the provincial level are available only in French, such as decisions in Quebec and New Brunswick. Mining French text poses two additional challenges. One is that

[492] Gaining popularity is the use of Word2vec, which is a two-layer neural net that processes text by "vectorizing" words. Word2vec distinguishes between "Mary kills John" and "John kills Mary". Under BOW, the two would be given equal weight.

the language in data science is predominantly English. Not only is the programming language itself English, software libraries available are mostly English libraries. The other challenge is that less French legal texts are available for training machines compared to English legal texts.

Code-switching is a challenging NLP problem in bilingual places. Code-switching occurs when a document or a sentence is composed of more than one language. For example, a witness may testify “The man with the gun ran into the *dépanneur*” in “franglais”. Also, many court cases include both English and French quotes in the same text. Most current work in code-switching looks at bilingual pairs (multilingual pairs not yet emerging),[493] and several training strategies have been investigated.[494]

After text retrieval, the next task is to get some meaning from it, usually by classifying them into different types of corpora; for example, separating the corpus into different domains of law, such as business law, intellectual property law, or family law. This task of classification can be achieved by a colossal number of algorithms. Some of the common ones include Random Forest,[495] Support Vector Machine (SVM),[496] Naïve Bayes.[497] All of which help to “draw the line” between classifications. Some classifiers are discreet, and some are probabilistic.

Predictions with high accuracy have been achieved in 2017 for classifying legal domain (F1 score 96%), ruling (F1 98%) and estimation of date of ruling (F1 87%).[498] These predictions are good starts, but they are too simplistic for modelling arguments.

[493] Sunayana Sitaram et al, “A Survey of Code-switched Speech and Language Processing” (2019) ArXiv190400784 Cs Stat, online: <http://arxiv.org/abs/1904.00784>, arXiv: 1904.00784.
[494] Mohamed Menacer et al, *Machine Translation on a parallel Code-Switched Corpus* (Ontario, Canada, 2019).
[495] Seen previously, a Random Forest is classifier that includes multiple Decision Trees. Each Decision Tree is a flowchart-like structure in which each internal node represents a test on an attribute, each branch represents the outcome of the test, and each leaf node represents a label, all of which assist in reaching a decisional conclusion.
[496] A Support Vector Machine (SVM) is a supervised machine learning model that uses classification algorithms for two-group classification problems. It is claimed to perform well with a limited amount of data.
[497] Naïve Bayes are simple probabilistic classifiers based on applying Bayes' theorem with strong (naïve) independence assumptions between the features.
[498] Octavia-Maria Sulea et al, “Exploring the Use of Text Classification in the Legal Domain” (2017) ArXiv171009306 Cs, online: <http://arxiv.org/abs/1710.09306>, arXiv: 1710.09306.

Researchers in AI & Law are also working on separating case decisions into law, facts, and reasoning parts. The University of Montreal's JusticeBot project[499] made such an attempt in 2018 with promising initial results (76%). But to automatically extract legal factors or underlying values of factors is still far from reach.

Other than classification, researchers are also interested in similarity. The University of Ottawa offers a curriculum that teaches law students how to write programs to analyse similarities between international treaties. Below is a snapshot that indicates similar provisions (red means similar) between eight labour law treaties generated by libraries in R.

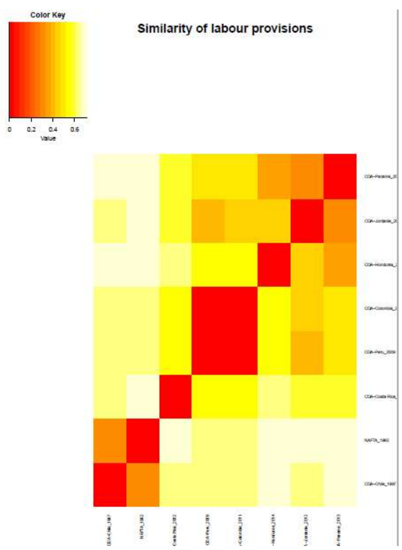

Figure 27: A similarity graph

Another milestone is the machine's ability to extract legal arguments automatically from decisions. Mochales' and Moen's model[500] detects argumentation from natural-language case law. The algorithm looks for features in a sentence, for instance, POS tags, verbs, punctuation pattern, complexity of sentence, surrounding sentences and so on. Then, the program uses Naïve Bayes, maximum entropy, and SVM to classify the sentence into argument or not.[501]

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[499] JusticeBot is a pilot project in partnership with Régie du logement du Québec (RLQ) and the Aide juridique de Montréal et Laval (AJML) on housing law that addresses social needs for tenants and landlords in Quebec. The JusticeBot program to be developed is a chatbot that aims to provide legal information to the public.
[500] Raquel Mochales & Marie-Francine Moens, *Study on the Structure of Argumentation in Case Law* (NLD: IOS Press, 2008).
[501] Ashley, *supra* note 39 at 291.

As the complexity of the software grows, numerous modules are required to achieve the desired results. For example, extracting arguments involves processing sentences into features, and then classifying the sentences based on the features. Each of these tasks could be performed by separate modules and assembled into a complex system.

LUIMA-Annotate is the annotation module of the complex LUIMA pipeline architecture.[502] LUIMA stands for "legal UIMA", an extension of UIMA type system for the legal domain. UIMA[503] analyze large volumes of unstructured information to discover knowledge that is relevant to end users.

In LUIMA, sentences are first divided into components. For instance, the logic below detects a mention of the plaintiff, an obligation, an optional "also" and three verbs that mean to prove.

```
If (PlaintiffMention MustRelationTerm "also"?("prove" | "show" | "establish"))
  MARK(LegalStandardFormulation);
End-if
```

So, the sentence "the plaintiff should also prove his costs" would be marked as belonging to the LegalStandardFormulation component. Then, sentences are further divided into different types.

As evidenced in the prototypes of LUIMA, we are still at information extraction (IE) and not yet at argument retrieval (AR). AR aims to retrieve concepts and relationships, enabling the forming of argument or the understanding of a human's argument. The goal of AR is to help humans solve legal problems by drawing useful concepts from legal text rather than simply keywords. NLP can help but AR is difficult because meanings are sometimes implicit in the text. Humans seem to have to an incredible ability to read what is not written in the text, but the machine is not so good at it.

3.6. Cognitive Computing

Since the 1980's, computer programs have been trying to retrieve information, answer questions, and perform legal reasoning. For example, Waterman's legal expert systems, the LDS and the SAL

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502 Matthias Grabmair et al, *Introducing LUIMA: an experiment in legal conceptual retrieval of vaccine injury decisions using a UIMA type system and tools* (San Diego, California: Association for Computing Machinery, 2015).
503 Apache's Unstructured Information Management Applications

on product liability, contain sets of if-then statements. The algorithm then arrives at conclusions by checking if the inquiry meets any if-statements. Alternatively, if a conclusion is sought, the inference engine can work its way back to criteria that must be met in order to arrive at the desired conclusion.

Legal expert systems have a few limitations. First, every jurisdiction has their own law. A legal expert system that works in one jurisdiction must be re-programmed to be used in another jurisdiction. Second, the law is full of ambiguous terms like "reasonable", "material contribution", and "*de minimis*", making the system's input and output imprecise. Third, even if the rules work perfectly, the system cannot help the lawyer with proving facts.

Despite their limitations, expert systems are still widely used today. For example, Neota Logic provides expert knowledge about bankruptcy and medical leave. Moreover, the Centre for Computer-Assisted Legal Instruction CALI [504] provides a web-based tool that allows non-programmers with legal skills to create expert system such as A2J Author®[505] that guides self-represented litigants throughout the legal process and generates legal documents for them.

However, these expert systems are primitive compared to the next aspiration of AI & Law, which is to achieve cognitive computing (CC). Although the term "cognitive" may suggest so, it does not mean that the computer is doing the thinking. Instead, CC means "computer teaming up with human" in solving problems. The machine is rational and analytic and has impeccable memory and enormous computing power. The human will provide expertise, judgement, intuition, empathy, moral compass, and creativity.[506] The computer is not meant to solve the problem, but rather, "understand" it and help the human choose a suitable solution.

As seen, researchers have come a long way since the 1980's. AI and legal analytics have improved information retrieval, expert systems, reasoning and outcome prediction to a great degree. However, we have not yet mastered legal argumentation and cognitive computing. In order to move forward, we must overcome a few challenges.

[504] https://www.cali.org/
[505] https://www.a2jauthor.org/
[506] Ashley, *supra* note 39 at 13.

One of the challenges of argumentation and cognitive computing is semantic annotation. As mentioned, information extraction (IE) is not argument retrieval (AR). IE is incomplete because it cannot retrieve "values" and concepts that are often implicit or "between the lines". On the other hand, AR is looking for domain specific relations, "values", preferences, and more.

Another challenge is the need to improve the human-machine interface. NLP must facilitate natural ways for humans to ask questions and comprehensive ways for human to receive answers. In addition, we must find a way to automate gold standard annotations, instead of relying on expensive human annotations.

Furthermore, predictive models are based solely on past data. CBR or ML techniques in prediction assume that the future follows the pattern in the past. But in law, this assumption is only partly true. The law evolves: statutes are updated regularly, and societal changes call for legal reform. For example, based on the same facts, *Carter*[507] unanimously struck down a twenty-one-year-old decision by the same Court, *Rodriguez*,[508] declaring physician-assisted dying no longer an indictable offence in Canada.

As well, the "living tree" doctrine (*théorie de l'arbre vivant*) has been deeply entrenched into Canadian constitutional law since the landmark *Persons Case*,[509] wherein Viscount Sankey stated, "The *British North America Act* planted in Canada a living tree capable of growth and expansion within its natural limits." This viewpoint is in contrast with the U.S. originalism, which interprets their constitution in a way that reflects the original meaning when it was written. Subsequently, the Supreme Court of Canada affirms the living tree doctrine and that the Constitution is organic and must be read in a broad and progressive manner to adapt it to changing times.[510] For these reasons, predictive models based solely on past data may be inadequate at times.

Finally, although powerful, ML is not the solution to all legal problems. Many legal AI systems that use ML also rely on conventional programming and architecture. Not to mention, some

[507] *Carter* v *Canada (Attorney General)*, 2015 SCC 5, [2015] 1 SCR 331.
[508] *R* v *Rodriguez*, [1993] 3 SCR 519.
[509] *Edwards* v *Law Society of Upper Canada*, AC 124, 1929 UKPC 86.
[510] *Reference re Same-Sex Marriage*, 2004 SCC 79, [2004] 3 SCR 698.

problems are better solved without ML. In the next chapter, we will explore solutions that may overcome current AI limits by introducing causal analysis.

Chapter 4: New Causal Models in AI & Law

Attempts to discuss causality with a formal language, "path coefficients", were made as early as 1921 by geneticist Sewall Wright.[511] Unfortunately, his causal questions were soon declared "unscientific", and for more than half a century, causal vocabulary was practically prohibited.[512] During that time, the method of path coefficient analysis could not be found in any conventional statistics textbooks.[513] As such, without the vocabularies, principles, methods, and tools were also stifled. Finally, and fortunately, Wright's scientific contributions were recognised in the 1980's.[514] Although delayed by six decades, it was better late than never. Today, path coefficients are indispensable in the development of AI.[515]

Evidently, causal analysis is not reserved for geneticists; jurists must analyse causality in the law to deal with a full spectrum of legal liability. We have seen in Chapter 2 a variety of frameworks devised by the court to test and infer causality. Although the ML community's interest in causality has significantly increased in recent years,[516] this trend has not yet been picked up in AI & Law. Despite a considerable number of computational models to date discussed in Chapter 3, the lack of causal analysis was noticeable.

The inclusion of causal analysis could be beneficial in overcoming some of the limitations of current AI's reliance on correlations. In this last chapter, we revisited some of Chapter 2's legal frameworks with a scientific vigour. Specifically, attempts are made to construct structural models to describe the facts and causations of selected decisions from that chapter, and then to provide some evaluations and learned insights after the exercise.

4.1. Formal Causal Frameworks

The gold standard for causation in the law is the but-for counterfactual test; however, this but-for test is too minimal for situations in which multiple, duplicate, or intervening causes pose additional

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[511] Sewall Wright, "Coefficients of Inbreeding and Relationship" (1922) 56:645 Am Nat 330–338.
[512] Pearl & Mackenzie, *supra* note 26 c 2.
[513] C.C. Li, "Method of Path Coefficients: A Trademark of Sewall Wright" (1991) 63:1 Hum Biol 1–17 at 5.
[514] Sewall Wright, "The Method of Path Coefficients" (1934) 5:3 Ann Math Stat 161–215.
[515] Path coefficients are used to describe the "weights" in linear regression models. The method of path coefficients can be used to calculate the mathematics of causal links between statistical variables in structural equations.
[516] Schölkopf, *supra* note 38.

complexity. H. L. A. Hart and Tony Honoré's NESS test,[517] later revised by Richard Wright,[518] defines "cause" as a "necessary element of a sufficient set of conditions". Independently, J. L. Mackie also proposed that a cause is at a minimum INUS condition, that is, "Insufficient but Non-redundant part of an Unnecessary but Sufficient" condition for its effects.[519]

However, the INUS test is no longer seen as adequate for pre-emptive situations, and it is unclear how and if judges have adopted the NESS test in decisions in other parts of the world. In Canada, the test for cause-in-fact is also the but-for test,[520] but the Canadian but-for test includes the notion of the "sufficient" condition when dealing with multiple potential causes.[521] Therefore, the Canadian but-for analysis is arguably identical to the American NESS test. It is important to note that the "sufficient" analysis, as part of the analysis for factual causation, is separate from the remoteness and policy analyses, which are cause-in-law considerations.[522]

Joseph Y. Halpern and Judea Pearl developed the Halpern-Pearl (HP) definitions of causality called "actual causality".[523] Actual causality provides a formal approach to causal analysis by combining the necessary and sufficient conditions, interventions and counterfactual reasoning. Particularly, the method of discovering causal relations through "interventions" is what distinguishes this approach from others. Later, Halpern and Hitchcock have extended the HP definitions, which allow the comparison of alternative explanations based on notions of normality, typicality, and defaults. Meanwhile, Pearl also invented a new branch of mathematics, do-calculus, to "do the math" in interventional causal models.

Halpern, Pearl and Hitchcock attempted not only to interpret their versions of the necessary and sufficient test, but also to formalize it in a structural language. Subsequently, Halpern has

[517] Hart & Honoré, *supra* note 344.
[518] Wright, *supra* note 345.
[519] John Leslie Mackie, *The Cement of the Universe: A Study of Causation* (Clarendon Press, 1974) at 62, Google-Books-ID: h38IAQAAIAAJ.
[520] *Resurfice Corp. v Hanke*, *supra* note 331 at para 25.
[521] *Athey* v *Leonati*, *supra* note 328; *Cook v Lewis*, *supra* note 340.
[522] Sufficient analysis, as part of the causation-in-fact analysis, is about a cause sufficient enough to contribute to the consequence. Both remoteness and policy belong to the causation-in-law analysis. Remoteness is about the foreseeability and the directness of the consequence while policy is about public order.
[523] Halpern, *supra* note 37.

published a "modified" (not to be confused with the "extended" version) HP definition.[524] Halpern also further discussed the considerations of responsibility and blame in actual causality.

Other attempts have been made to model causation in the law. For example, Richard Baldwin proposed a new structural definition of actual causation to avoid some of the issues in the (original) HP approach.[525] At the time, Baldwin claimed that the HP definitions failed to capture the NESS test. But since then, the HP definitions have been improved. In his latest book, Halpern also pointed out that there is no "right" model. How a model is constructed is as important as, if not more important than, the conclusions of the model. "The devil is in the details," so to speak.

In addition, a semi-formal framework for causal arguments[526] has been attempted to model arguments of a legal case. The vaccine injury case used in the semi-formal framework, *Althen*,[527] was also modelled by Vern Walker in the DLP framework[528] mentioned in Chapter 3. But the models are unrelated.

To simulate *Althen*'s arguments, the semi-formal framework first denotes *H(X)* as a factual proposition that X holds; *Sim(X,W)* as the propositional content of X similar to the propositional content of W; *EV(X)* as evidence of X, and *C(L,X, Y)* as the casual link between X and Y, where L is 1 or 2. 1 means X necessarily (always) causes Y, and 2 means X normally causes Y.

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[524] Joseph Y Halpern, "A Modification of the Halpern-Pearl Definition of Causality" (2015) ArXiv150500162 Cs, online: <http://arxiv.org/abs/1505.00162>, arXiv: 1505.00162.
[525] Richard A Baldwin & Eric Neufeld, *The Structure Model Interpretation of Wright's NESS Test* (Berlin, Heidelberg: Springer, 2003).
[526] Rūta Liepiņa, Giovanni Sartor & Adam Wyner, "Arguing about causes in law: a semi-formal framework for causal arguments" (2020) 28:1 Artif Intell Law 69–89; Ruta Liepina, Giovanni Sartor & Adam Wyner, *Causal Models of Legal Cases* (Cham: Springer International Publishing, 2018).
[527] *Althen* v *Secretary of Health and Human Services*, 418 F3d 1274 (Fed Cir 2005).
[528] Walker, *supra* note 490.

The semi-formal framework also defines two inference rules:
X1 . . . Xn → Y denotes strict rules,
X1 . . . Xn ⇒ Y denotes defeasible rules.

Furthermore, five general causal rules are defined.
Rule 1: $H(X) \wedge C(1,X,Y) \rightarrow H(Y)$
Rule 2: $H(X) \wedge C(2,X,Y) \Rightarrow H(Y)$
Rule 3: $Sim(X,W) \wedge C(L,X,Y) \Rightarrow C(L,W,Y)$
Rule 4: $EV(X) \Rightarrow H(X)$
Rule 5: $H(Y) \wedge C(1,X,Y) \Rightarrow H(X)$

Also, the converse of Rule 1 is true, such that if $H(X) \wedge C(1,X,Y) \rightarrow H(Y)$, that is , if X holds and X always causes Y, then Y holds; then it follows that $\neg H(Y) \wedge C(1,X,Y) \rightarrow \neg H(X)$, that is, if the same causal link holds and Y is not true, then X cannot be true.

TTV = tetanus toxoid vaccination being injected in the patient
ADEM = acute-disseminated encephalomyelitis illness
TCellAct = the chemical process of tetanus toxoid vaccination activating T cells
AntigDest = antigen cells destroyed (T cells should target this, wanted effect)
MlnDest = myelin cells destroyed (T cells should not target this, unwanted effect)
Symp(Mono) = monophasic symptoms occur.

Thus, Dr. Smith's reasoning can be modelled as follows:
1. *H(TTV)* – Assumption
2. *C(1, TTV, TCellAct)* – Claim
3. *H(TTV) ∧ C(1, TTV, TCellAct) →* ***H(TCellAct)***
4. *H(TCellAct)*
5. *C(1, TCellAct AntigDest)* – Claim
6. *Sim(AntigDest, MlnDest)* – Assumption ← refuted by Dr. Safran
7. *Sim(AntigDest, MlnDest) ∧ C(1, TCellAct AntigDest) ⇒* ***C(2, TCellAct, MlnDest)***
8. *C(2, TCellAct, MlnDest)*
9. *H(MlnDest)* – Assumption
10. *C(2, MlnDest, ADEM)* – Claim
11. *H(MlnDest) ∧ C(2, MlnDest, ADEM) ⇒* ***H(ADEM)***
12. *H(ADEM)*
13. *C(2, ADEM, Symp(Mono))* – Claim
14. *H(ADEM) ∧ C(2, ADEM, Syp(Mono)) ⇒* ***H(Symp(Mono))***

In the adversary, Dr. Safran simply put forth the following:
1. *¬ Sim(AntigDest, MlnDest)*

In other words, Dr. Safran refuted the causation by claiming that Dr. Smith's assumption (No.6) was wrong.

As a semi-formal framework, this method has not been recognised by the scientific community. Another reservation about this approach is that the causal conclusions are largely based on claims and assumptions, as opposed to facts.

We shall now turn to formal mathematical frameworks on causality developed by elite scientists over the past few decades; that is, Judea Pearl's structural causal model (SCM), combined with the HP definitions of actual causality.

Traditionally, there exist four types of causal models:

1. Graphical models by Pearl,[529] Lauritzen,[530] Spirtes, Glymour, and Scheines[531]
2. Potential-outcome (counterfactual) models (RCM/ Neyman–Rubin model)[532]
3. Sufficient-component cause models by Ken Rothman[533]
4. Structural-equation models (SEM) by Goldberger[534] and Duncan[535]

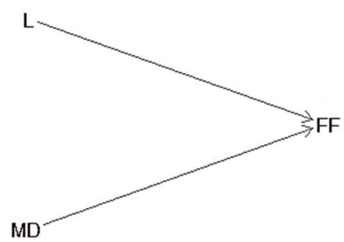
Judea Pearl has unified graphical models (1), potential-outcome (2), and SEM (4) into the structural causal model (SCM).[536] SCM uses the same fundamental tools in mathematics, such as variables, functions, and graphs. However, there are some additional concepts unique for causal modelling. For example, "exogenous" variables are variables exerting effects on others and "endogenous" variables are those being affected. If A causes B, then A is exogenous, and B is endogenous. In a diagram such as A → B, exogenous variables have arrows "going out" and endogenous variables have arrows "coming in". So, in A → B → C, B is both exogenous and endogenous. The rule is that only endogenous variables can be causes or be caused.[537] Therefore, if A is considered a cause of B, the model implies that U → A → B where U is some other cause of A that we are not interested in. But for simplicity, we could write A → B.

A directed acyclic graph (DAG) is the graphical component of an SCM. A DAG is a symbolic representation of exogenous variables, endogenous variables, and the paths that relate them. A

[529] Judea Pearl, "Graphical Models for Probabilistic and Causal Reasoning" in Philippe Smets, ed, *Quantified Represent Uncertain Imprecision* Handbook of Defeasible Reasoning and Uncertainty Management Systems (Dordrecht: Springer Netherlands, 1998) 367.
[530] Steffen L Lauritzen, *Graphical models* (Clarendon Press, 1996).
[531] Spirtes, Glymour & Scheines, *supra* note 183.
[532] Donald B Rubin, "Estimating causal effects of treatments in randomized and nonrandomized studies" (1974) 66:5 J Educ Psychol 688–701.
[533] K J Rothman, "Causes" (1976) 104:6 Am J Epidemiol 587–592.
[534] Arthur S Goldberger, "Structural Equation Methods in the Social Science" (1972) 40:6 Econometrica 979.
[535] Otis Dudley Duncan, *Introduction to Structural Equation Models* (Elsevier, 2014), Google-Books-ID: o5LOBQAAQBAJ.
[536] Pearl, *supra* note 163.
[537] Halpern, *supra* note 37 c 2.

variable in a DAG is also called a “node”, and although paths denote dependency relationships, they do not represent how or how much. For instance, the DAG below shows that L (lightning) and MD (match dropped) are causes of FF (forest fire). But it does not tell us whether they are conjunctive or disjunctive causes. Conjunctive causes are those that must be combined to necessarily cause an effect, while any disjunctive cause alone may cause the effect. This clarification is the reason an SCM consists of a DAG and structural equations. Hence, the SCM of forest fire is given by the structural equations and DAG below.

$FF = L \cap MD$ (conjunctive) or $FF = L \cup MD$ (disjunctive).



In terms of structural equations, a causal model *M*, is a pair *(S, F)*, where *S* is a signature, which explicitly lists the endogenous and exogenous variables and characterizes their possible values, and *F* defines a set of structural equations, relating the values of the variables. In turn, a signature *S* is a tuple *(U, V, R)*,[538] where *U* is a set of exogenous variables, *V* is a set of endogenous variables, and *R* associates with every variable Y $(Y \in U \cup V)$ a nonempty set *R(Y)* of possible values for *Y*.[539] In the case where we conduct an intervention, it would be useful to denote the assignment of a value to a variable as $X \leftarrow x$. As for uncertainties, we can represent them by probabilistic distribution.

The HP definition of actual causality is given by three conditions, AC1, AC2, and AC3. If the three conditions hold, then the $\vec{X}$ (collection of *X*) = $\vec{x}$ (collection of *x*) is the actual cause of effect φ in the causal setting of $(M, \vec{u})$. The expression $(M, \vec{u})$ refers to the fact that the model M is initialised by assigning a collection of values $\vec{u}$ to the exogenous variables $\vec{U}$.[540]

[538] A tuple is a finite ordered sequence.
[539] Halpern, *supra* note 37 c 2.1.
[540] *Ibid* c 2.2.

The three conditions and their evolution are summarized in the table below. As mentioned earlier, the HP definition underwent a few revisions. The first conditions AC1 and AC3 stay unchanged conceptually, but the second condition was originally consisted of AC2(a) and AC2(b), and then updated to AC2(a) and AC2(b^{u}), and finally modified to AC2(a^{m}).

Table 16: Evolution of the HP definitions of actual causality

Condition	**Notation and explanation**
AC1	$(M,\vec{u}) \models (\vec{X} = \vec{x})\ and\ (M,\vec{u}) \models \varphi$ Model holds and assigns that cause $(\vec{X} = \vec{x})$ happened; and the same model holds and assigns that effect φ happened.
AC2(a) Necessary condition	$(M,\vec{u}) \models [\vec{X} \leftarrow \vec{x}', \vec{W} \leftarrow \vec{w}]\neg\varphi$ Had the cause X not happened and other circumstances W happened, effect φ would not have happened.
AC2(b^{o}) AC2(b^{u}) Sufficient condition ~~AC2(c) strong causality~~	$(M,\vec{u}) \models [\vec{X} \leftarrow \vec{x}, \vec{W} \leftarrow \vec{w}, \vec{Z}' \leftarrow \vec{z}*]\ \varphi$ (Original 2001) $(M,\vec{u}) \models [\vec{X} \leftarrow \vec{x}, \boldsymbol{\vec{W}'} \leftarrow \vec{w}, \vec{Z}' \leftarrow \vec{z}*]\ \varphi$ (Updated 2005) The cause X would have produced its effect φ without alternative causes W or Z, but that perturbations (deviation paths) exist such that causes W and Z may be determined in the causal process being considered. Notice here that $\vec{W} \cap \vec{Z} = \varphi$ ~~$(M,\vec{u}) \models [\vec{X} \leftarrow \vec{x}, \vec{W} \leftarrow \vec{w^{n}}*]\ \varphi$~~ (considered but discarded) Same effect φ is achieved no matter what values of W are considered, intended to capture the intuitions behind sufficient causality. This condition never made it to the formal definitions.
AC2(a) and AC2(b^{u}) can be replaced by the simpler AC2(a^{m}) condition	
AC2(a^{m}) Combined necessary and sufficient condition	$(\boldsymbol{M},\boldsymbol{\vec{u}}) \models [\boldsymbol{\vec{X}} \leftarrow \boldsymbol{\vec{x}'}, \boldsymbol{\vec{W}} \leftarrow \boldsymbol{\vec{w}}*]\neg\boldsymbol{\varphi}$ **(Modified 2015)** The cause X would have produced its effect φ without alternative cause W. The need for a sufficiency condition arises only if we are considering contingencies that differ from the actual setting in AC2(a). Notice here that $\vec{Z}$ is integrated into $\vec{W}$ such that $\vec{W} = \varphi$
AC3	$\vec{X}$ is minimal. No subset of $\vec{X}$ satisfies conditions AC1 and AC2(a^{m}). This means that non-essential conditions are pruned from the model.

The key difference between the modified HP definition and the original/updated definitions is the insistence in AC2(a^{m}) that the contingency considered in AC2(a) be one where all the variables take their initial values. Doing so makes it clear that the sufficient conditions, AC2(b^{o}) or AC2(b^{u}), are needed only to handle cases where the variables in the contingency considered take on non-actual values.

Consider the following situation. Assassin is to put poison in Victim's soup. Bodyguard would put antidote to save Victim. What happened was that Assassin changed his mind and did not put poison in the soup. Bodyguard nonetheless put antidote in the soup. Victim of course did not die.

According the original and updated HP definitions, Bodyguard putting antidote is a cause for the contingency where Assassin puts in the poison, Victim survives if and only if Bodyguard puts in the antidote. On the other hand, according to the modified HP definition, Bodyguard putting in the antidote is not a cause, but is part of a cause (the other part being Assassin not putting poison in).[541]

In the remaining pages, we will consider the original, updated, and the modified definition as we see fit. Let us be clear that constructing a model does not by itself answer any causality questions. Constructing a model allows us to formulate the question, and then we may be able to manipulate the model to get some answers.

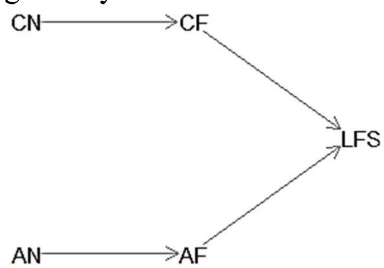
4.2. Modeling Canadian law

Let us start with *Cook*[542] discussed in Chapter 2. In *Cook*, two groups of hunters went looking for grouse in a clump of trees. Then, a grouse turned up. And two men, Mr. Cook and Mr. Akenhead, shot at the birds from different directions, hitting Mr. Lewis. Lewis lost an eye but was unable to proof whose bullet hit him.

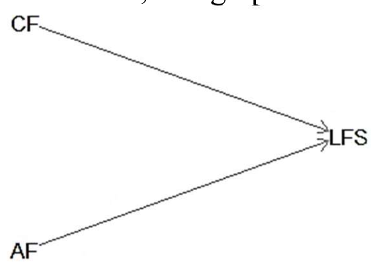
First, define the variables. [1 is true; 0 is false.] CN = 1; Cook was negligent. CF = 1; Cook fired. AN = 1; Akenhead was negligent. AF = 1; Akenhead fired. LFS = 1; Lewis got his face shot. Then, define structural equations. $M = (S, F)$ $S = (U, V, R) = (\{CN, AN\}, \{CF, AF, LFS\}, R(LFS)) = (\{1, 1\}, \{1, 1, 1\}, max(CF, AF))$ $F_{LFS}(CF, AF, CN, AN) = 1$ *iff (if and only if)* $max(CF, AF) = 1$

[541] *Ibid* c 3.4.2.
[542] *Cook v Lewis*, *supra* note 340.

The DAG of the current SCM is given by:



Since only endogenous nodes can be causes, this graph below also holds:



Explanations:
CF = CN = 1; Cook's negligence made him fire.
AF = AN = 1; Akenhead's negligence made him fire.
LFS = max(CF, AF) = CF ∪ *AF* [disjunctive model]

Lewis was shot if either Cook or Akenhead fired, or they both fired.
Scenario (1, 0) = Cook fired and Akenhead did not.
Scenario (0, 1) = Akenhead fired but Cook did not.
Scenario (1, 1) = Both Cook and Akenhead fired simultaneously.

LFS = max(CF, AF)
LFS = (CF, ¬AF) ∪ *(¬ CF, AF)* ∪ *(CF, AF)*
LFS = max(1, 0) ∪ *max(0, 1)* ∪ *max(1, 1) = 1*

In reality, both Cook and Akenhead fired:
LFS = max (1, 1) = 1

Counterfactual scenario:
LFS = max(0, 0) = 0
Lewis would not have been shot had neither Cook nor Akenhead fired.

Now, we perform the actual causality test for CF:
AC1: $(M, \vec{u}) \vDash (\vec{X} = \vec{x})\ and\ (M, \vec{u}) \vDash \varphi$
True, because CF happened and LFS happened.

AC2(a): $(M, \vec{u}) \vDash [\vec{X} \leftarrow \vec{x}', \vec{W} \leftarrow \vec{w}]\neg\varphi$
Failed. It is not but-for CF that LFS = 1. That is, if CF = 0, AF could have caused LFS.
Note that if we test the AC2(a^m) condition, the result is the same: condition is not met.
Therefore, CF is not the cause of LFS. By the same logic, AF is not the cause of LFS neither.

This conclusion is the same conclusion at trial, when the but-for test failed. In the absence of a finding that Lewis was shot by Cook or Akenhead, the victim was left uncompensated. But on appeal, the Court finds that both individuals breached the duty of care towards the injured, so they put the defendants together, *(CF ∪ AF)*.

So, let us perform causality test for *(CF ∪ AF)*:
AC1: $(M, \vec{u}) \vDash (\vec{X} = \vec{x})$ and $(M, \vec{u}) \vDash \varphi$
True, because *(CF ∪ AF)* happened and *LFS* happened.

AC2(a): $(M, \vec{u}) \vDash [\vec{X} \leftarrow \vec{x}, \vec{W} \leftarrow \vec{w}]\neg\varphi$
True, because it is but-for *(CF ∪ AF)*, *LFS* would not have happened.

AC2(b^u): $(M, \vec{u}) \vDash \left[\vec{X} \leftarrow \vec{x}, \overrightarrow{W'} \leftarrow \vec{w}, \vec{Z}' \leftarrow \vec{z}*\right] \varphi$
True, because *(CF ∪ AF)* alone is sufficient for *LFS*, not requiring other causes.

Alternatively, we can replace AC2(a) and AC2(b^u) by the modified AC2(a^m).
AC2(a^m): $(M, \vec{u}) \vDash [\vec{X} \leftarrow \vec{x}', \vec{W} \leftarrow \vec{w}*]\neg\varphi$
True, because it is but-for *(CF ∪ AF)* that *LFS*, and *(CF ∪ AF)* alone is sufficient for *LFS*.

AC3: $\vec{X}$ is minimal
True, because only essential conditions are considered (e.g., no other bullet, no high wind, or no supernatural phenomenon).

After combining the defendants, *(CF ∪ AF)*, the Court was able to establish causation in fact and in law and shifted the onus to them. In the event the defendants are unable to sort out blame between them, they are jointly liable.

Formally, actual causality does not include analysis of responsibility or of blame. But Halpern has discussed them.[543] The degree of responsibility of a cause X is given by $\frac{1}{(k+1)}$ if there is a witness *W*= *w* to *X* = *x* being a cause of φ in $(M, \vec{u})$, |*W*| = *k*. Here, a witness does not mean a "*témoin*", or a person who testifies. A witness here simply means another circumstance where *X* = *x* is not the cause of φ. Generally, the degree of responsibility = 1 for each participant in a conjunctive model, and ½ in a disjunctive model.

In *Cook*, a disjunctive model, the degree of responsibility of CF = $\frac{1}{(1+1)} = \frac{1}{2}$.
Similarly, the degree of responsibility of AF is also $\frac{1}{2}$.
Note that a degree of responsibility can be greater than 1 because it is not a probability.[544]

[543] Halpern, *supra* note 37 c 6.
[544] *Ibid*.

Halpern defined the degree of blame of X for φ relative to epistemic state (K, P) as below, where *dr* is the degree of responsibility.

$$\sum_{(M,\vec{u})\in K} dr((M,\vec{u}), \mathrm{X}=\mathrm{x}, \varphi) P((M,\vec{u}))$$

That is, the degree of blame of X for φ is the sum of all scenarios of (degree of responsibility *dr* multiplied by probability *P*) causing φ .

All scenario of (CF, AF) for LFS are represented by (1, 0), (0, 1), (1, 1).
Scenario 1 (1, 0): CF = 1, AF = 0, degree of responsibility of CF = 1
Scenario 2 (0, 1): CF = 1, AF = 1, degree of responsibility of CF = 0
Scenario 3 (1, 1): CF = 1, AF = 1, degree of responsibility of CF = $\frac{1}{2}$. (See above.)

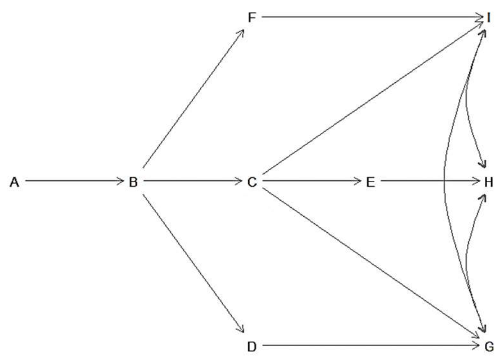
Therefore, the degree of blame of CF for LFS = $(1)\left(\frac{1}{3}\right) + (0)\left(\frac{1}{3}\right) + \left(\frac{1}{2}\right)\left(\frac{1}{3}\right) = \frac{1}{2}$.
Similarly, the degree of blame of AF for LFS = $(0)\left(\frac{1}{3}\right) + (1)\left(\frac{1}{3}\right) + \left(\frac{1}{2}\right)\left(\frac{1}{3}\right) = \frac{1}{2}$.

Notice that *Cook* distinguishes from the rock-throwing example where Suzy shattering the window would prevent ("pre-empt") Billy from being the cause of the window shattered, or *vice versa*. Cook and Akenhead fired at the same time, that is, pre-emption or causal chain are out of the question.

With the *Cook* exercise above, we may conclude that causality is relative to the causal model. Since a model is a representation of a reality, and as lawyers would know, there is no truth in court, only evidence. For this reason, A can be a cause of B in one model but not in another. So, two opposing lawyers can disagree about whether A is a cause of B even if they are both working with the HP definitions; they are simply using different models.

Remember also that we do not take many potential variables into account, such as the presence of high wind, moving target, or anything of the sort. Moreover, the case provides no evidence of whether Mr. Cook or Mr. Akenhead were "good" shooters. Had there been evidence, for example, that Mr. Cook never misses a shot and Mr. Akenhead is a lousy shooter, it may have created a higher probability of who indeed shot Mr. Lewis, depending on the positions of the parties and directions of gunfire. If these variables were provided, we could have constructed a more realistic model by using probabilistic path coefficients such as *P(LFS|CF)* or *P(LFS|AF)*.

In a realistic, and hence, complex model, Bayesian networks can be used to provide compact representations of probability distributions; they exploit (conditional) independencies between variables. The idea is to eliminate independent variables or conditionally dependent variables so that we are left with a more compact representation. Independent simply means the absence of causality. If X does not cause Y, then Y is independent of X. In graphic form, independent variables can be eliminated along with their arrows.

From a complex model	To a compact model
	

Now, we will briefly introduce the notion of HP's extension,[545] *M = (S, F, ⪰)* where ⪰ is a partial preorder or normality order.[546] The extension is designed to deal with normality. Imagine an alternate universe where certain attributes are unlike those on earth. For example, we take for granted that oxygen is in the atmosphere. "Taking it for granted" is an example of a partial preorder; that is, there is a partial preorder *s* over other worlds s'. Therefore, one way of interpreting partial preorder is $s \succcurlyeq s'$, that the world *s* is more likely than the other worlds s'. Thus, the but-for condition AC2+(a) can be expressed by: $s_{\vec{X}\leftarrow\vec{x},\vec{W}\leftarrow\vec{w},\vec{u}} \succcurlyeq s_{\vec{u}}$ and $(M,\vec{u}) \models [\vec{X} \leftarrow \vec{x}, \vec{W} \leftarrow \vec{w}]\neg\varphi$. That is, a clause is added to the AC2(a) requiring that $s_{\vec{X}\leftarrow\vec{x},\vec{W}\leftarrow\vec{w},\vec{u}} \succcurlyeq s_{\vec{u}}$ where *s* is the world that results by setting $\vec{X} \leftarrow \vec{x}'$ and $\vec{W} \leftarrow \vec{w}$ in context $\vec{u}$.

In this formulation, worlds that result from interventions on the actual world "are brought into play" in AC2+(a) only if they are at least as normal as the actual world. If we are using the modified HP definition, then AC2(a^m) is extended to AC2+(a^m) in the same way. The formulation describes

[545] HP's extension is not to be confused with HP's updated definition. The former deals with normality while the latter merely refined the original definition.
[546] Halpern, *supra* note 37 c 3.

with greater precision that in a world where there is normally oxygen in the atmosphere, we would not consider it a cause. But in a world where oxygen is not in the atmosphere, then having oxygen on scene would be considered a cause. Some other normality examples include: a doctor who is not the family doctor of a patient will not "normally" pay attention to him; or a victim with head trauma will "normally" have headaches.

Normality sounds useful, but how does one come up with a normality ordering in the first place? A lawyer who defends her client for causing a fire may not only have to disprove actual causality, but also raise the violation of normality. For instance, to defend an arsonist, the lawyer would have to raise that the humidity is abnormally low, and under a normal humidity index, a reasonable person would not have foreseen the possibility of fire.

Fortunately, Bayesian networks not only handle uncertainties, but also solve problems of partial preorder, as long as the representation can be expressed as an algebraic conditional plausibility measure (CPM).[547] Hence, the same way probability distributions eliminate independent variables, algebraic CPM applied to Bayesian networks can also achieve greater representational economy.

In what follows, we will ignore the extension to the HP definitions when constructing models, for simplicity, and for the fact that we have no access to the alternate universe.

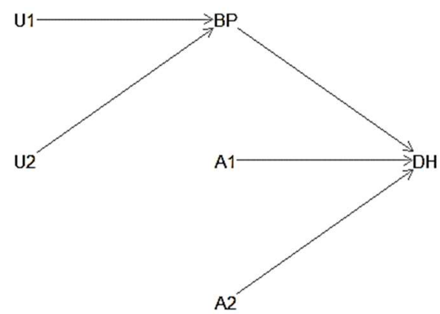
Now, let us model conjunctive causes. In *Athey*,[548] a victim with a history of back problems, suffered back and neck injuries in an accident, and then a second accident resulting in a disc herniation. Both defendants of the accidents admitted liability. The only issue was whether the accidents caused his disc herniation, or the pre-existing condition did.

First, define the variables. [1 is true; 0 is false.] *BP = 1*; Back problem existed. *A1 = 1*; First accident happened. *INJ = 1*; Injury occurred. *A2 = 1*; Second accident happened. *DH = 1*; Disc herniation resulted. Then, define structural equations. *M = (S, F)*

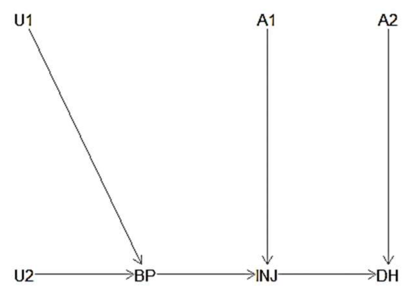
[547] *Ibid* c 5.2.1.
[548] *Athey v Leonati*, [1996] 3 SCR 458.

S = (U, V, R) = ({U1, U2}, {BP, A1, A2, DH}, R(DH)) = ({1, 1}, {1, 1, 1}, min(BP, A1, A2))
F_{DH} *(BP, A1, A2, U1, U2) = 1 iff min(BP, A1, A2) = 1*
F_{DH} is independent of exogenous variables *U1* and *U2*. As far as *U1* and *U2* go, they could be any reasons why Mr. Athey suffers from back problems in the first place, but we are not interested in that.

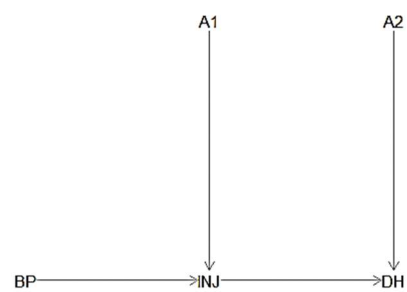
The DAG of the current SCM is given by:



We can improve the graph by keeping track of time, earliest time being on the left and latter time to the right:



Eliminating exogenous nodes, this graph below also holds:



DH = min(BP, A1, A2) = BP ∩ A1 ∩ A2 [conjunctive model]
Herniation is caused by first accident, second accident, and back problem

The two defendants for *A1* and *A2* proceeded as one and admitted liability. To simplify matter, let us consider both accidents as one denoted by *(A1+A2)*.

Now, perform causality test for *(A1+A2)*:

AC1: $(M,\vec{u}) \vDash (\vec{X} = \vec{x})$ and $(M,\vec{u}) \vDash \varphi$

True for (A1+A2) because both accidents happened, and disc herniation happened.

AC2(a): $(M,\vec{u}) \vDash [\vec{X} \leftarrow \vec{x}', \vec{W} \leftarrow \vec{w}]\neg\varphi$

True for *(A1+A2)*. It is but-for the accidents that disc herniation occurred.

Interestedly, the court also asked the counterfactual question, had the accidents not happened, would Mr. Athey still suffer from *DH* at some point. The court decided that this question was speculative and did not take it into account.

AC2(b^u): $(M,\vec{u}) \vDash \left[\vec{X} \leftarrow \vec{x}, \overrightarrow{W'} \leftarrow \vec{w}, \vec{Z}' \leftarrow \vec{z}*\right] \varphi$

Failed for *(A1+A2)*; but true for *(BP ∩ A1 ∩ A2)* combined.

(A1+A2) is necessary but insufficient alone to cause *DH*; However, together with *BP*, they are sufficient causes of *DH*.

Alternatively, performing the modified test AC2(a^m): $(M,\vec{u}) \vDash [\vec{X} \leftarrow \vec{x}', \vec{W} \leftarrow \vec{w}*]\neg\varphi$ would give the same result because actual values were unchanged. In other words, all of them, *BP*, *(A1+A2)* are parts of the cause for *DH*.

Without exact science to prove causation, the Supreme Court invented the material contribution to injury (MCI) test, and allocated causation factor 25% to *(A1+A2)*. Thus, disc herniation was caused by 75% *BP* ∩ 25% *(A1+A2)*.

Responsibility and blameworthiness:

The degree of responsibility of *BP* is $\frac{1}{(0+1)} = 1$. As there is no W; hence, k=0.

The degree of responsibility of *A1* is $\frac{1}{(0+1)} = 1$.

The degree of responsibility of *A2* is $\frac{1}{(0+1)} = 1$.

As there is only one scenario of *(BP, A1, A2)* for *DH*, that is *(1, 1, 1)*, the degrees of blame of *BP*, *A1*, and *A2* are also 1, 1, and 1 respectively.

The SCM shows that causal nodes are not transitive, which means that *BP* is a cause of *INJ*, and *INJ* is the cause of *DH*. But *BP* is not the cause of *DH*.

Causality: $BP \rightarrow INJ \rightarrow DH \neq BP \rightarrow DH$

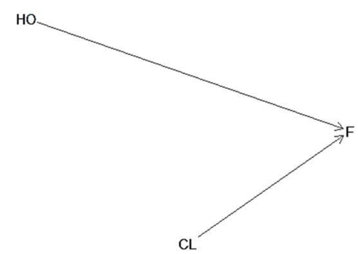
The precondition of back problems by itself does not mean it will induce disc herniation. Disc h~~H~~erniation occurred because a second accident occurred while Mr. Athey is still recovering from the injury. This property of non-transitivity is an important departure from logical inference, where A infers B, and B infers C, therefore, A infers C. In causality, there is no such deduction.

$$\text{Logical inference: } A \to B \to C = A \to C$$

Quebec civil law uses the same causal logic in conjunctive situations. In *Deguire*,[549] seen in Chapter 2, a painter lit a cigarette in an empty apartment which was not heated for weeks.

First, define the variables.
CL = 1; Cigarette was lit.
HO = 1; Heater was turned off.
F = 1; Fire resulted.

The SCM is given by:



F = min(CL, HO) = CL ∩ HO [conjunctive model]

The court decided that both the painter lighting a cigarette and the concierge not heating the apartment are necessary causes for the fire; and each contributed 50%.

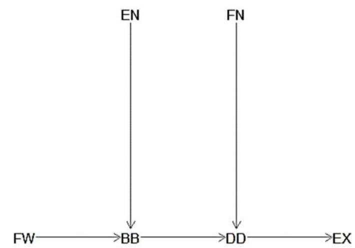
Now, let us progress to a causal chain with an intervening act. In *Beaudoin*,[550] also seen in Chapter 2, children hoarded fireworks abandoned by the company after a fireworks display. The father of one of the children noticed this and confiscated the bomb. But instead of calling the appropriate authority which would have been the prudent thing to do, he negligently gave them to his own employee, a taxi driver, with instructions to get rid of the bomb. The driver then detonated the bomb with the children and the children were injured.

FW = 1; Fireworks displayed.
EN = 1; Employee negligently left bomb in vicinity.
BB = 1; Bomb left in vicinity.
FN = 1; Father negligently gave bomb to driver.
DD = 1; Driver detonated bomb.

[549] *Deguire Avenue Ltd c Adler*, *supra* note 372.
[550] *Beaudoin c T. W. Hand Firework Co*, *supra* note 375.

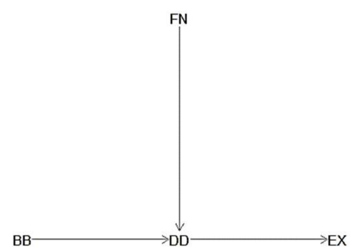
EX= 1; Explosion resulted.

Then, the SCM is given by:



EX = *DD*; and
DD = min(FN, BB) = FN ∩ *BB* [conjunctive]
BB = min(EN, FW) = EN ∩ *FW* [conjunctive]

The court founded the father's negligence so departed from reasonable standard that it liberated any responsibility from the part of the defendants. This finding makes FN an intervening cause of the explosion. Thus, the SCM is simplified to:



EX = *DD*; and
DD = min(FN, BB) = FN ∩ *BB* [conjunctive]

The court decided that the claim must fail because although the defendant was negligent in leaving the bomb behind, the victim's father demonstrated gross negligence, which is an intervening act that broke the chain of events. That is, the plaintiff's own fault liberated the defendant.

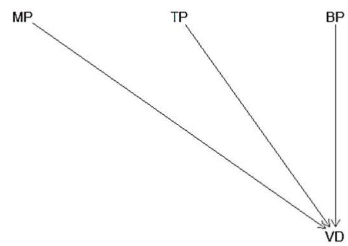
Lastly, let us model homicide with potential intervening acts. *Maybin*[551] is set in a busy bar late at night, where the accused brothers, T and M, repeatedly punched the victim in the face and head. T eventually struck a blow that rendered the victim unconscious. When the bouncer arrived on the scene, he struck the victim in the head. The medical evidence was inconclusive about which blow(s) caused death. At trial, the judge acquitted the accused after the facts failed the but-for test. On appeal, the judges affirmed causation-in-fact (that the accused contributed to the death) but were divided about whether the bouncer's punch was an intervening act. On final appeal, two questions

[551] *R v Maybin*, *supra* note 411.

were raised: could the accused have caused victim's death; and if so, was there an intervening act breaking the chain of legal causation.

First, define variables.
TP = 1; T punched victim repeatedly.
MP = 1; M punched victim repeated.
BP = 1; Bouncer gave the last punch.
VD = 1; Victim is dead.

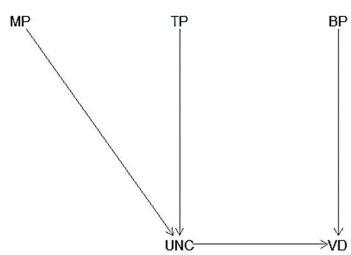
At trial, the SCM is given by:



$VD = (TP+MP) \cap BP$

The trial judge found that the brothers and the bouncer acted independently.[552] Therefore, the but-for test, AC2(a), failed. The accused were acquitted.

On appeal, the SCM changes:
UNC = 1; Victim became unconscious.



$VD = UNC \cap BP$
Since factual causation has been established, the remaining issue is a question of blame.

Recall that the degree of blame of X for φ is the sum of all scenarios of (degree of responsibility *dr* multiplied by probability *P*) causing φ .

All scenario of (UNC, BP) for VD are represented by (1, 0), (0, 1), (1, 1).
Scenario 1 (1, 0): UNC = 1, BP = 0, degree of responsibility of UNC = 1
Scenario 2 (0, 1): UNC = 1, BP = 1, degree of responsibility of UNC = 0 if bouncer intervening
Scenario 3 (1, 1): UNC = 1, BP = 1, degree of responsibility of UNC = $\frac{1}{2}$

[552] *Ibid* at para 325.

Therefore, the degree of blame of UNC for VD = $(1)\left(\frac{1}{3}\right)+(0)\left(\frac{1}{3}\right)+\left(\frac{1}{2}\right)\left(\frac{1}{3}\right)\ =\frac{1}{2}$.

Similarly, the degree of blame of BP for VD = $(0)\left(\frac{1}{3}\right)+(1)\left(\frac{1}{3}\right)+\left(\frac{1}{2}\right)\left(\frac{1}{3}\right)\ =\frac{1}{2}$.

Without more circumstantial evidence, it is a close call. The Supreme Court decided that the trial judge could have concluded that the bouncer's assault did not necessarily constitute an intervening act that severed the link between the accused's conduct and the victim's death, such that it would absolve them of moral and legal responsibility. In other worlds, the trial judge could have found that the accused's actions remained a material contributing cause of the death.

So far, we have seen SCMs where we intuitively know the directions of arrows, as we are looking in hindsight. However, scientific discovery of causality looks forward, without the benefit of hindsight. Currently, the link between greenhouse gases emission and climate change is a controversial one, not unlike cigarette smoking and lung cancer in the last century. Back in the 1950's, it was not obvious that smoking causes cancer. The chance of success was low in an action by the government against tobacco manufacturers for the recovery of health care expenditures incurred in treating individuals exposed to tobacco.[553]

As mentioned repeatedly, in a scenario where X and Y are highly related, the correlation cannot tell us about causality. So, how do we know X causes Y and not Y causes X? The answer is by intervention. Intervention is another way of saying "conducting experiments". Consider that we want to see if getting a certain vaccine will lead to a certain injury. We can physically inject the vaccine in various groups of people and see what happens. We change X and see if Y changes. If so, it maybe a cause, other things being held constant. And we change Y and see if X changes. If X is the cause of Y, then changing Y should not change X, unless it is a recursive cause. In addition, we can say that Y is dependent on X if changing X changes Y. Conversely, if X is not a cause of Y, then Y is independent on X.

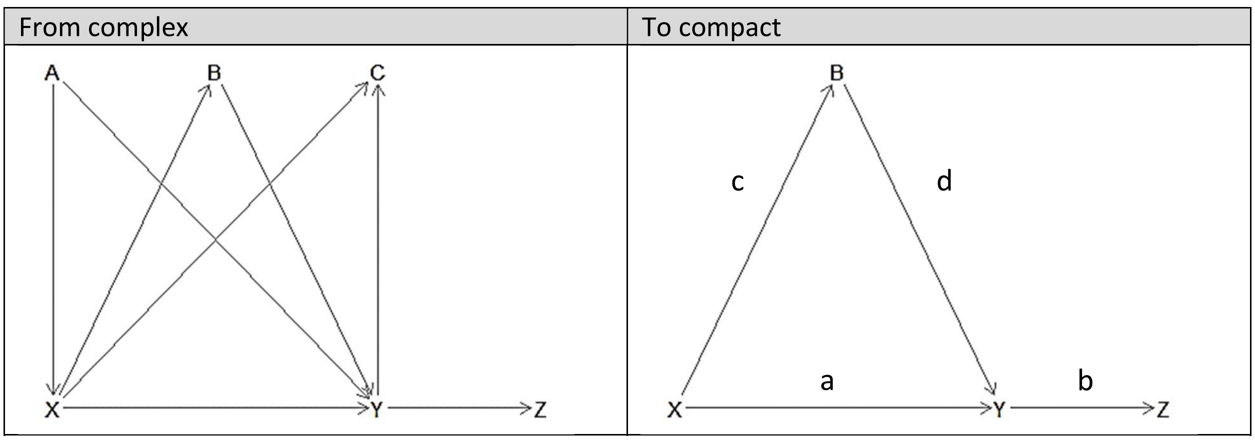
It is worth reiterating that while we change X, we must hold any other variables constant. That is, a patient who receives the vaccine should not change her habits, her diet, and so on.

Moreover, to ensure that the effect is not due to the placebo effect, we separate the trial population into two groups, one with real vaccine, and the other with a "fake" vaccine. This "fake" group is

[553] *British Columbia* v *Imperial Tobacco Canada Ltd*, 2005 SCC 49, [2005] 2 SCR 473.

called the control group and the study of which is called the random control trial (RCT). RCT goes back hundreds of years ago and is still the gold standard in empirical science today.

The purpose of conducting experiments is to “eliminate arrows”. In the complex model below on the left, A is called a confounder of X and Y, because A is influencing both X and Y. If A is a factor of age, we can compare X and control groups in every age group separately. Doing so is called “adjusting for” A or “controlling for” A. Adjusting for confounders prevents information about X from getting to Y or vice versa. This blockage of the pipeline is called d-separation. Thus, if we adjust for confounder A and the effect of X on Y remains constant, then X and Y are independent of A. Thus, the exercise of intervention is to discover as many independent variables as possible so we can eliminate them and be left with a simpler model, like the one on the right.



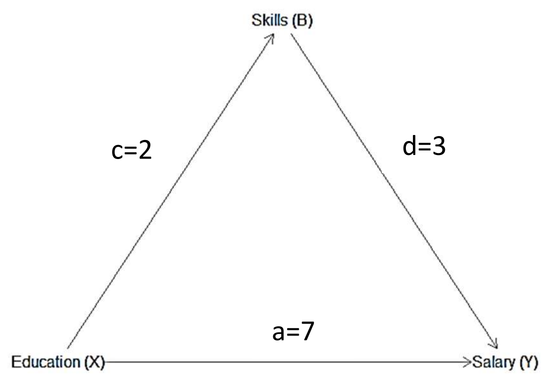
Contrastingly, C is called a collider because X and Y influence C. Since C blocks the association between X and Y, we could remove it and the arrows altogether without loss. But controlling for C will be a disaster! The reason it is forbidden to control for C is that doing so will create a non-causal association between X and Y, or “open the pipe”, therefore creating collider bias or Berkson’s paradox, as discussed in Chapter 1.

Moreover, if the relationship between X and Y is a linear regression $f(X) = Y = aX + b$, the path coefficient of X on Y is the strength, $R_{XY} = a$. By adjusting for the appropriate variables, we can find out the path coefficients, a, b, c, and d. For example, if X causes Y, and Y causes Z, Y being the mediator, as in the case below,

then the causal strength of X on Z is given by:

$$R_{XZ} = (R_{XY})(R_{YZ}) = ab$$

In the case where X causes Y directly and indirectly, shown in the case below, the total effect can be calculated.



$$Total\ Effect = Direct\ Effect + Indirect\ effect$$

$$R_{XY} + (R_{XB})(R_{BY}) = (7 \times 1) + (3 \times 2) = 13$$

If, rather than linear regression, the relationship between nodes is defined by a polynomial, like $f(X) = Y = aX^4 - bX^3 + cX^2 - dX + e$, we can still calculate the strength between nodes and determine dependencies. Of course, the mathematics will be more complex than illustrated here.

When we have thousands of variables, how can we effectively eliminate arrows? It turns out that there are some rules of thumb as well:

1. In X→B→Y, controlling for mediator B prevents information about X from getting to Y or vice versa. “Close the pipe partially”.
2. In X←A→ Y, controlling for confounder A prevents information about X from getting to Y or vice versa. “Close the pipe”.
3. In X→C←Y, controlling for collider C is not permitted. “Open the pipe”, a disaster.

Even if we identify a good variable to adjust for, we may not be able to adjust for it. The tobacco companies in the 1950's knew this and used it to their advantage. Clever executives came up with the idea of a confounding "smoking gene", that some people are born with a tendency to develop dependency on cigarettes (X) and they are born prone to cancer (Y). At that time, the technology to prove or disprove such a gene did not exist. Today, they would have to find another idea. Interestingly, the same tactic is now used to fend off any suggestion that humans are causing climate change.[554]

Sometimes, even if technology allows, intervention maybe impractical or unethical. For example, if we want to study the relationship between lack of touch in infants and their deaths, it would be naive to ask mothers not to touch their babies. Even if such a ridiculous proposition were possible, running an experiment could be costly. A situation like this one is where Pearl's do-calculus, a new branch of mathematics, becomes very useful.

Do-calculus calculates the effect of intervention by eliminating the "do" in $P(Y|do(X))$ so that we can rely on observational data $P(Y|X)$. Therefore, the purpose of do-calculus is to save us the trouble of conducting expensive or impossible experiments but still allow us to remove arrows.

In fact, do-calculus has gone mainstream. There are many software tools available that support SCM and do-calculus. Below is a non-exhaustive compilation:

1. R packages dagitty,[555] lavaan,[556] dagR,[557] and ggdag[558]
2. Compilations stremr, simcausal, MSMstructure, and DSA[559]
3. RStudio development environment[560]
4. DAGitty web application[561] and downloadable version
5. Shinydag web application[562]

[554] The book *Merchants of Doubt* by historians of science Naomi Oreskes and Erik M. Conway is recommended.
[555] https://CRAN.R-project.org/package=dagitty
[556] https://CRAN.R-project.org/package=lavaan
[557] https://CRAN.R-project.org/package=dagR
[558] https://CRAN.R-project.org/package=ggdag
[559] https://divisionofresearch.kaiserpermanente.org/projects/biostatistics/causalinferencesoftware
[560] https://rstudio.com
[561] http://www.dagitty.net/
[562] https://www.gerkelab.com/project/shinydag/

6. DoWhy Python library[563]
7. EconML Automated Learning and Intelligence for Causation and Economics (ALICE) project[564]
8. Causal Software suite[565]
9. GFORMULA 3.0 program[566]
10. Tetrad Project[567]
11. Python modules causalgraphicalmodels[568] and causalingerence[569]
12. DAG program[570]
13. Ecto hybrid C++/Python framework[571]

4.3. Evaluation

Scientific research models are generally evaluated by theoretical soundness, adequacy of sample size, and model fit, among others. As far as causal models go, evaluation techniques for modeling algorithms have remained somewhat primitive.[572] While there does not exist a "correct" model, we can talk of faithful or unfaithful models. A faithful model reflects causality more accurately than an unfaithful one. Based on observed data alone, it is impossible to verify the completeness of a causal diagram. However, certain conditional relationships between sets of variables can be tested empirically.[573] If relationships are not supported by data, the causal model is probably unfaithful. But a faithful model, together with smart intervention and sound do-calculus, may achieve full causal discovery, that is, inferring causality from empirical data.

What does this mean for legal actors? Judges do not dive deep into exact science to find factual causality. They use common sense whenever possible, and when the subject is highly technical,

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563 https://github.com/microsoft/dowhy
564 https://github.com/microsoft/econml
565 https://www.ccd.pitt.edu/tools/
566 https://www.hsph.harvard.edu/causal/software/
567 http://www.phil.cmu.edu/tetrad/
568 https://github.com/ijmbarr/causalgraphicalmodels
569 https://pypi.org/project/CausalInference/
570 https://epi.dife.de/dag/
571 https://plasmodic.github.io/ecto/index.html
572 Amanda Gentzel, Dan Garant & David Jensen, "The Case for Evaluating Causal Models Using Interventional Measures and Empirical Data" (2019) ArXiv191005387 Cs Stat, online: <http://arxiv.org/abs/1910.05387>, arXiv: 1910.05387.
573 *Ibid*.

they rely on expert opinions. This means that intervention and do-calculus are likely reserved for scientists. Nonetheless, SCMs are available to legal practitioners. Instead of arguing what one means by "cause", lawyers equipped with SCM vocabularies can discuss among each other why one cause is more likely than another. They can even perform HP causality tests, like AC2(a) or AC2(a^m), to determine if X is the cause of Y.

Practitioners can also construct SCMs and compare conclusions with court decisions. One advantage of using SCM is that it eliminates semantic ambiguity. SCM and HP definitions provide formal frameworks to interpret a legal case. When two lawyers look at a DAG with its structural equations, they are looking at WYSIWYG ("what you see is what you get") and nothing is confusing about it. They can proceed immediately to their legal arguments.

Going forward, if we collect and store SCMs and HP causality test results of precedents in a database, we can make predictions about future cases. Current AI & Law fellows have been working on legal outcome prediction for decades, but their models are based on associative or manual approaches. SCM and HP definitions will augment current AI with causal analysis. In addition, although humans may be more intuitive with simple causal models, when a model becomes highly complex, the machine will be better than humans at performing do-calculus.

Furthermore, legal reasoning does not have to be deterministic. We can include statistical (probabilistic) analysis into SCM and HP to handle uncertainty. This amalgamation of Newtonian determinism and Hume's probability allows directional relationship with probabilistic distribution on its path. That is, instead of saying "A causes B", we can say that "all being constant, the intervention of A highly induces the consequence of B". In addition to handling uncertainty, Bayesian networks can be used to handle normality ordering, blame, and any plausibility measures so long as they can be expressed in algebra.

Halpern's blame analysis gives rise to graded causality. For example, if two causes are isomorphic, one may be more blameworthy than the other. These concepts are omnipresent in the law. For example, a child incapable of telling right from wrong is considered less guilty or less liable in the eyes of the law. The extended HP definitions address responsibility and blame in these situations.

The functions of causal analysis are far reaching. For instance, before passing legislation, policy makers can perform causal simulations to save costs. Another function is to simulate changing societal values. Since an SCM can reveal the underlying values of legal factors, rather than merely legal factors, it "understands" a deeper level of granularity. Therefore, in a case where a behaviour was unacceptable yesterday but acceptable today, the model would still produce a sensible result. In this way, we can finally solve the problem of today's predictive AI, which is based on past observations at face value.

In addition, causality can ascribe to accountability. When disasters happen, we can study why they happened, so we can be smarter in the future. Also, causality is perfectly in line with the principles for responsible AI. A few years ago, AI communities came up with the "fairness, accountability and transparency" (FAccT) initiatives in machine learning development. Current critiques of AI & Law have been largely the non-explainability in algorithm and embedded bias in data. Causal analysis can respond to these critiques because the essence of causality inference is to explain the "why", and do-calculus can expose certain biases.

Imagine a database of legal causalities in which lawyers can query the best argument for the current case. The machine will not only provide what it calculates as the best argument that would lead to success, but also the reasons why, backed by SCMs. These benefits alone make causal studies worthwhile in AI & Law.

That said, causal analysis encounters some challenges. First, causality is relative to how the causal model is built. This flexibility is an advantage and a disadvantage at the same time. A lawyer may succeed in establishing causality, but the opposing lawyer can disagree by constructing a different causal model. Not to mention, pre-emption (Suzy throws rock pre-empting Billy from shattering the window) and overdetermination (Suzy and Billing both throw rocks shattering the window but only one of them could have shattered the window) are difficult to model as even humans have trouble grappling with these concepts.

Moreover, even a seasoned modeller may have difficulty deciding the appropriate number of variables. For instance, a factor may be a condition or a cause subject to different opinions. In the case of fire, the existence of oxygen in the atmosphere may be considered a cause by some, but a mere condition by others. This issue is important because using too few variables oversimplifies reality, yet having too many variables creates resource bottleneck. Thus, a complex causal model requires all the stars lined up: optimal variable selection, adequate assumptions, reasonable normality ordering, meticulous calculations, and so on.

Furthermore, intervention is sometimes impossible. Although do-calculus may replace it, there is no guarantee that it will lead to full causal discovery.

Finally, including mathematical causal frameworks in the practice of law creates extra burden on legal actors to learn the technology. It is the same argument that the use of smart contracts requires a lawyer's ability to understand coding, which may run into resistance.

CONCLUSION

At the beginning of this inquisitive journey, we set out a central question to be answered. That question was whether it is possible or useful to apply formal mathematical frameworks such as SCM and HP definitions of actual causality in legal reasoning. The answer is yes, we can use structural graphs and equations to describe a legal case and determine factual causation through HP's tests. Not only is it possible, it is useful to do so because a uniform language eliminates ambiguity. However, legal causation is more complicated than factual causation as it is subject to personal opinions such as foreseeability and degree of blameworthiness. Although not fully explored in this paper, the mathematical frameworks used here allow for representing normality and blame.[574] Thus, further research is needed to answer the question properly.

We travelled a journey of four chapters to arrive at the above conclusion.

Chapter 1 took us back to the origin of the human pursuits in understanding the universe through reasoning and causality. Aristotle's term logic put ancient endeavours in academic disciplines. Today, logical reasoning consists of three main branches; they are deduction, induction, and abduction. Logical reasoning enables us to make arguments. Normative frameworks for argumentation include dialectic and rhetoric. A common technique of argumentation is *reductio ad absurdum*; however, some techniques are fallacious, such as circularity and slippery slop.

In terms of judgement, research has uncovered systematic regularities in how people make decisions and judgement. The traditional rational theory of choice believes that humans naturally calculate a utility function and opt for maximum reward. But research in neuroscience and psychology suggests that our decision-making is influenced by our biology and our experience, and therefore, prone to biases. A new dual theory has emerged, in which humans employ two systems of thinking simultaneously, and decision is made from the interplay between the two systems that is unique to every individual. To deal with its complexity, researchers look to statistics and probability to model and predict our decision-making process.

[574] Halpern, *supra* note 37 c 6.

Causality is a special branch of reasoning where the relationship between cause and effect is studied. Aristotle contemplated it but it was David Hume who modernized the field with empirical methods. John Stuart Mill also laid down the inductive canons in which concepts such as necessity, continuance, and cancelling effects of causality were discussed. Mill's emphasis on the distinction between causation and correlation is especially relevant in today's AI development.

In addition, a criterion for causality, temporality, that cause must precede its effect, deserves special attention, as it seems to exist only in Newtonian physics. Recent experiments in particle entanglement suggests that effect may precede cause. Currently, the two main branches of causal discovery are statistical inference and causal inference. Statistical inference is achieved by probabilistic association and has gained tremendous success in AI. However, as Big Data progresses, this approach will hit a wall because 1) storage and processing huge amount of data is no longer problematic; and 2) data-driven correlations do not inform direction of influence. On the other hand, causal inference aims at examining the direction of influence through intervention, do-calculus and counterfactuals, and could be useful in AI & Law.

Chapter 2 revisited reasoning and causality through the lens of the law. According to the "official" theory, Formalism, legal reasoning is divided formally into case-based reasoning and rule-based reasoning. Case-based reasoning relies on *ratios* laid down by binding decisions while rule-based reasoning is driven by statutes. Although the references are different, both reasoning methods apply facts to legal rules. In addition to Formalism, legal theories such as Realism, Law and Economics, and Law and Society suggest alternative reasoning patterns in legal interactions.

The law is interested in specific causality (backward-looking) while science is interested in general causality (forward-looking).[575] Causality analysis in Canadian law is most relevant in civil responsibilities, common law torts, as well as criminal law. In torts, causality is bifurcated, separated into cause-in-fact and cause-in-law. The test for cause-in-fact is the but-for test, which includes the necessary and sufficient conditions. The test for cause-in-law is remoteness which examines the foreseeability of probable and precise harm. In Quebec, civil responsibility considered different causality theories but settled on the pragmatic approach. It is a unified analysis of adequate causation ("*causalité adequate*") and reasonable anticipation of consequences

[575] Halpern, *supra* note 37.

("*prévision raisonnable des conséquences*"). In criminal law, causality analysis is also divided into factual causation and legal causation. Factual causation is the but-for test, but the standard of proof is "beyond reasonable doubt", as opposed to "balance of probability" as would be in a civil trial. Legal causation is determined by remoteness/foreseeability of harm and degree of participation. Although the concepts are similar to those in torts and civil liabilities, criminal causality has its own frameworks of complicated tests formulated in *Nette*, *Maybin*, *Smithers*, and others.

The second part of this paper, Part B, was devoted to the application of AI in legal reasoning.

Chapter 3 gave an account of the efforts spent so far in the AI & Law field. Existing models focus on the task of question answering (QA), information extraction (IE), and argument retrieval (AR). However, most of these models require human annotations, which is extremely resource heavy. Increasingly, AI look to natural language processing (NLP) and machine learning (ML) in text analytics. The goal of AI & Law is to achieve cognitive computing (CC) in law. CC does not mean that the computer is doing the thinking; rather, it means that computer is helping humans in solving problems. On the legal commercial market, legal expert systems (LES) are still prevalent today, but more and more functions are being performed by "intelligent" algorithms, including legal research, eDiscovery, and outcome prediction.

Chapter 4 attempted modelling causality of several Canadian decisions using SCM and HP definitions of actual causality. A few insights came out of the exercise. For example, using a uniform language eliminates ambiguity; however, causality is relative to the model, making the choice of model a point of debate. Also, a faithful causal model can infer causality by intervention, and by revealing which variables to control for. In the case where intervention is impossible, do-calculus can supplement. Furthermore, causal models respect the principles of responsible AI by way of explanation and exposing biases.

Today, we are aware of the limits of relying on correlations of observational data. In the future, associative AI will hit a wall as Big Data will render statistical inference unnecessary. This means that we must include causal analysis not only in AI & Law but also in AI generally. Fortunately, the trend has already started. The increasing volume of research publications on the subject as well as availability of software tools in recent years are evidential.

This paper demonstrated that there is a place for causal analysis in AI & Law. Modelling is only the tip of the iceberg. Once a model is built, the true potential lies in manipulating it so that it will lead us to causal discovery. Judea Pearl, the pioneer in causal reasoning, gave us seven tools, below, for the art of automated reasoning:[576]

1. Encoding causal assumptions: Transparency and testability.
2. Do-calculus and the control of confounding.
3. The algorithmicizing of counterfactuals.
4. Mediation analysis and the assessment of direct and indirect effects.
5. Adaptability, external validity, and sample selection bias.
6. Recovering from missing data.
7. Causal discovery.

For those who are interested in the subject, and brave enough to embark on the next journey, future research could be directed to the application of one or more of the tools above in AI & Law.

[576] Judea Pearl, "The seven tools of causal inference, with reflections on machine learning" (2019) 62:3 Commun ACM 54–60.

Table of Legislation

Canadian

Canada Labour Code, RSC 1985.

Constitution Act, 1982, being Schedule B to the *Canada Act* 1982 (UK), 1982, c 11.

Criminal Code, RSC 1985, c C-46.

Divorce Act, RSC 1985, c 3 (2nd Supp)

Income Tax Act, RSC 1985, c 1 (5th Supp).

Interpretation Act, RSC 1985, c I-21.

Quebec

Civil Code of Quebec, RLRQ c CCQ-1991.

Charte des droits et libertés de la personne, RLRQ c C-12.

Code du travail, RLRQ c C-27.

United States

Internal Revenue Code §§ 354-356, 358, 361-362, 368, (1954).

Table of Decisions

Canadian

Alberta (Attorney General) v *Moloney*, 2015 SCC 51 (CanLII), [2015] 3 SCR 327

Andrews v *Grand & Toy Alberta Ltd*, 1978 CanLII 1 (SCC), [1978] 2 SCR 229.

Association des courtiers et agents immobiliers du Québec v Proprio Direct inc, 2008 SCC 32 (CanLII), [2008] 2 SCR 195.

Athey v *Leonati*, [1996] 3 SCR 458.

Beaudoin c *T W Hand Firework Co*, [1961] CS 709.

Bell Canada v *Quebec (Commission de la Santé et de la Sécurité du Travail)*, [1988] 1 SCR 749.

Benhaim c *St-Germain*, 2016 SCC 48, [2016] 2 SCR 352.

Bhasin v *Hrynew*, 2014 SCC 71, [2014] 3 SCR 494.

Bouliane c *Commission scolaire de Charlesbourg*, (1984) CS 323, (1987) RJQ 1490 (CA).

British Columbia v *Imperial Tobacco Canada Ltd*, 2005 SCC 49, [2005] 2 SCR 473.

Carter v *Canada (Attorney General)*, 2015 SCC 5, [2015] 1 SCR 331.

Churchill Falls (Labrador) Corp v Hydro-Québec, 2018 SCC 46, [2018] 3 SCR 101 .

Clements v *Clements*, 2012 SCC 32, [2012] 2 SCR 181.

Cook v *Lewis*, [1951] SCR 830.

Cooper v *Hobart*, 2001 SCC 79, [2001] 3 SCR 537.

Deguire Avenue Ltd c *Adler*, [1963] BR 101.

Drouin c *Bouliane*, 1987 CanLII 705 (QC CA).

Dunsmuir v *New Brunswick*, 2008 SCC 9, [2008] 1 SCR 190.

Edwards v *Law Society of Upper Canada*, AC 124, 1929 UKPC 86.

General Motors of Canada Ltd v *City National Leasing*, [1989] 1 SCR 641.

Ginn c *Sisson*, (1968), [1969] CS 585.

Haida Nation v *British Columbia (Minister of Forests)*, [2004] 3 SCR 511, 2004 SCC 73.

Hill v *Hamilton-Wentworth Regional Police Services Board 2007*, 2007 SCC 41, [2007] 3 SCR 129.

Hodge v *The Queen (Canada)*, [1883] UKPC 59.

Kauffman v *Toronto Transit Commission*, [1960] SCR 251.

Laverdure c *Bélanger*, 1975 CS 612.

Law Society of British Columbia v *Mangat*, 2001 SCC 67, [2001] 3 SCR 113.

Moge v *Moge*, [1992] 3 SCR 813.

Montréal (Ville) c *Lonardi*, 2018 SCC 29 (CanLII), [2018] 1 SCR 104.

Multiple Access Ltd v *McCutcheon*, 1982 CanLII 55 (SCC), [1982] 2 SCR 161.

Mustapha v *Culligan of Canada Ltd*, 2008 SCC 27, [2008] 2 SCR 114.

R v *Bohak*, (2004) MJ No 172.

R v *Harbottle*, [1993] 3 SCR 306.

R v *Imperial Tobacco Canada Ltd*, 2011 SCC 42, [2011] 3 SCR 45.

R v *Khelawon*, 2006 SCC 57 (CanLII), [2006] 2 SCR 787 .

R v *KL*, 2009 ONCA 141.

R v *Kokopenace*, 2015 SCC 28 (CanLII), [2015] 2 SCR 398 .

R v *Maybin*, 2012 SCC 24, [2012] 2 SCR 30.

R v *Nette*, 2001 SCC 78, [2001] 3 SCR 488.

R v *Parks*, [1992] 2 SCR 871.

R v *Rodriguez*, [1993] 3 SCR 519.

R v *Seymour*, 1996 CanLII 201, [1996] 2 SCR 252.

R v *Sinclair (T) et al*, 2009 MBCA 71.

Reference re Same-Sex Marriage, 2004 SCC 79, [2004] 3 SCR 698.

Resurfice Corp v *Hanke*, 2007 SCC 7, 2007] 1 SCR 333.

Ryan v *Victoria (City)*, [1999] 1 SCR 201.

Smithers v *R*, [1978] 1 SCR 506.

Snell v *Farrell*, [1990] 2 SCR 311.

United States v Microsoft Corp, 584 US ___ (2018) .

Whiten v *Pilot Insurance Co*, 2002 SCC 18, [2002] 1 SCR 595.

United States

Althen v *Secretary of Health and Human Services*, 418 F3d 1274 (Fed Cir 2005).

Eisner v *Macomber*, 252 US 189 (1920).

Jacobellis v *Ohio*, 378 US 184 (1964).

RJR Nabisco, Inc v European Cmty, 136 S Ct 2090 (2016) .

Sindell v *Abbott Laboratories*, 26 Cal 3d 588, 163 Cal Rptr 132, 607 P2d 924 (1980).

US v *Carroll Towing*, 159 F2d 169 (2d Cir 1947).

Zelenko v *Gimbel Bros, Inc*, 158 Misc 904 (NY Sup Ct 1935).

United Kingdom

Anns v *Merton London Borough Council*, [1977] UKHL 4, [1978] AC 728.

Cadogan Estates Ltd v *Morris*, [1998] EWCA Civ 1671, [1999] 1 EGLR 59.

D & Builders Ltd v *Rees*, [1965] EWCA Civ 3.

Donoghue v *Stevenson*, [1932] UKHL 100.

Fairchild v *Glenhaven Funeral Services Ltd*, [2002] UKHL 22.

Hadley v *Baxendale*, [1854] EWHC Exch J70.

Hedley Byrne & Co Ltd v *Heller & Partners Ltd*, [1964] AC 465.

Hughes v *Lord Advocate*, [1963] UKHL 31.

Ivey (Appellant) v *Genting Casinos (UK) Ltd t/a Crockfords (Respondent)*, [2017] UKSC 67.

McGhee v *National Coal Board*, [1973] 1 WLR 1.

McKew v *Holland & Hannen & Cubitts (Scotland) Ltd*, [1969] 3 All ER 1621.

Overseas Tankship (UK) Ltd v *Morts Dock & Engineering Co (The Wagon Mound)*, [1961] AC 388.

Overseas Tankship (UK) Ltd v *The Miller Steamship Co or Wagon Mound (No 2)*, [1967] 1 AC 617.

Tinsley v *Milligan*, [1993] UKHL 3, House of Lords (UK).

Vaughn v *Menlove*, 1837 132 ER 490.

Bibliography

Monographs

Alexander, Larry & Emily Sherwin. *Demystifying Legal Reasoning* (Cambridge: Cambridge University Press, 2008).

Aliseda, Atocha. *Abductive reasoning : logical investigations into discovery and explanation*, Synthese library v 330 (Dordrecht, The Netherlands: Springer, 2006).

Ashley, Kevin D. *Artificial Intelligence and Legal Analytics: New Tools for Law Practice in the Digital Age* (Cambridge: Cambridge University Press, 2017).

Barak, Gregg. *Battleground: Criminal Justice [2 volumes]* (ABC-CLIO, 2007).

Baudouin, Jean-Louis, Pierre-Gabriel Jobin & Nathalie Vézina. *Les obligations, 7e éd.* (Cowansville: Ivon Blais, 2013).

Baudouin, Jean-Louis, Pierre-Gabriel Jobin & Nathalie Vézina. *Les obligations, 8e éd.* (2014).

Bernoulli, Nicolas. *N. Bernoulli, L'usage de l'art de conjecturer en droit*, norbert meusnier ed (Departamento Lógica, Historia, Filosofía de la Ciencia (UNED), 1992).

Brewer, Scott, *Philosophy of legal reasoning: Precedents, statutes, and analysis of legal concepts* (New York: Routledge 2011).

Brown, R. Pure Economic Loss in Canadian Negligence Law (LexisNexis, 2011).

Clark. *Equity* (Indianapolis: The Bobbs-Merrill Company, Inc.1954).

Côté, Pierre-André. *Interprétation des lois*, 4e édition. ed (Montréal: Éditions Thémis, 2009).

Duncan, Otis Dudley. *Introduction to Structural Equation Models* (Elsevier, 2014).

Einstein, Albert. *The Born-Einstein letters: correspondence between Albert Einstein and Max and Hedwig Born from 1916 to 1955* (London: MacMillan Press, 1971).

Halpern, Joseph Y. *Actual Causality* (The MIT Press, Cambridge, Massachusetts, 2016).

Hart, H L A & Tony Honoré. *Causation in the Law* (OUP Oxford, 1985).

Heavin, Heather & Michaela Keet. *The Path of Lawyers: Enhancing Predictive Ability Through Risk Assessment Methods* (Edmonton: Canadian Institute for the Administration of Justice, 2016).

Holyoak, Keith J, Robert G Morrison & Jonathan St B T Evans. *Dual-Process Theories of Deductive Reasoning: Facts and Fallacies* (Oxford University Press, 2012).

Kahneman, Daniel. *Thinking, Fast and Slow* (New York: Farrar, Straus, Giroux, 2013).

Kahneman, Daniel & Tversky, Amos, *Choices, values, and frames* (New York : Cambridge, UK: Russell Sage Foundation ; Cambridge University Press, 2000).

Koosis, Donald J. *Statistics*, Wiley classics library (New York: Wiley, 1972).

Lauritzen, Steffen L. *Graphical models* (Clarendon Press, 1996).

Lee, Kai-Fu. *AI Superpowers: China, Silicon Valley, and The New World* (Boston: Houghton Middlin Harcourt, 2018).

Levine, Brian & Craik, Fergus I M. *Mind and the frontal lobes : cognition, behavior, and brain imaging* (New York: Oxford University Press, 2012).

Lynch, Scott Michael. *Introduction to applied Bayesian statistics and estimation for social scientists*, Statistics for social science and public policy (New York: Springer, 2007).

Mackaay, Ejan. *Law and economics for civil law systems* (2013).

Mackie, John Leslie. *The Cement of the Universe: A Study of Causation* (Clarendon Press, 1974).

Macklem, Patrick et al. *Canadian constitutional law*, 4th ed. ed (Toronto: Emond Montgomery Publications, 2010).

Mill, John Stuart. *A System of Logic, Ratiocinative and Inductive*, people's edition ed (New York: Longmans, Green, and Co., 1893).

Neumann, Richard K, Ellie Margolis & Kathryn M Stanchi. *Legal reasoning and legal writing*, 8th edition, Aspen coursebook series (New York: Wolters Kluwer, 2017).

Oppenheim, AV, AS Willsky & SH Nawab. *Signals and Systems*, Prentice-Hall signal processing series (Prentice Hall, 1997).

Parrini, Paolo, Salmon, Wesley C & Salmon, Merrilee H. *Logical empiricism : historical & contemporary perspectives* (Pittsburgh: University of Pittsburgh Press, 2003).

Pearl, Judea. *Causality : models, reasoning, and inference* (Cambridge, U.K.: Cambridge University Press, 2000).

Pearl, Judea, Madelyn Glymour & Nicholas P Jewell. *Causal inference in statistics : a primer* (West Sussex: John Wiley and Sons Ltd., 2016).

Pearl, Judea & Dana Mackenzie. *The Book of Why: The New Science of Cause and Effect* (Basic Books, 2018).

Posner, Richard A. *Economic analysis of law*, 8th ed, Aspen casebook series (Austin, Tex. : New York: Wolters Kluwer Law & Business ; Aspen Publishers, 2011).

Posner, Richard A. *How judges think* (Cambridge, MA: Harvard University Press, 2008).

Pryor, Thomas. *The Psychology of Legal Decision Making* (2016), Retrieved from the University of Minnesota Digital Conservancy.

Reichenbach, H, F Eberhardt & CN Glymour. *The Concept of Probability in the Mathematical Representation of Reality*, Full Circle, Publications of the archive of scientific philosophy (Open Court, 2008).

Resnik, David B. *The Ethics of Science: An Introduction*, (New York: Routledge, 2005).

Russell, Bertrand. *The problems of philosophy*, A Galaxy Book; GB 21 (New York: Oxford University Press, 1959).

Spirtes, Peter, Clark Glymour & Richard Scheines. *Causation, Prediction, and Search,* 2nd ed., (The MIT Press, 1993).

Tomassi, Paul. *Logic* (London ; New York: Routledge, 1999).

Vallabhajosula, Brigitte. *Murder in the courtroom : the cognitive neuroscience of violence*, American Psychology-Law Society series (New York: Oxford University Press 2015).

Worthington, Sarah. *Equity* (OUP Oxford, 2006).

Articles

Aamodt, Agnar & Enric Plaza. “Case-Based Reasoning: Foundational Issues, Methodological Variations, and System Approaches” (1994) 7:1 AI Commun 39–59.

Aleven, Vincent. “Using background knowledge in case-based legal reasoning: A computational model and an intelligent learning environment” (2003) 150:1 Artif Intell (AI and Law) 183–237.

Amir, Eyal. “Reasoning and decision making” in Keith Frankish & William MEditors Ramsey, eds, *Camb Handb Artif Intell* (Cambridge University Press, 2014) 191.

Bateman, Ian J, Alistair Munro & Gregory L Poe. “Decoy Effects in Choice Experiments and Contingent Valuation: Asymmetric Dominance” (2008) 84:1 Land Econ 115–127.

Beller, Sieghard. “Deontic reasoning reviewed: psychological questions, empirical findings, and current theories” (2010) 11:2 Cogn Process 123–132.

Berkson, Joseph. “Limitations of the Application of Fourfold Table Analysis to Hospital Data” (1946) 2:3 Biom Bull 47–53.

Bobzien, Susanne. “Ancient Logic” in Edward N Zalta, ed, *Stanf Encycl Philos*, summer 2020 ed (Metaphysics Research Lab, Stanford University, 2020).

Bodenheimer, Thomas. “Uneasy Alliance — Clinical Investigators and the Pharmaceutical Industry” (2000) 342 N Engl J Med 1539–44.

Branting, L Karl. “Building explanations from rules and structured cases” (1991) 34:6 Int J Man-Mach Stud (Al and Legal Reasoning. Part 1) 797–837.

Brown, Russell. “The Possibility of ‘Inference Causation’: Inferring Cause-in-Fact and the Nature of Legal Fact-Finding” (2010) 55:1 McGill Law J Rev Droit McGill 1–45.

Buks, E et al. “Dephasing in electron interference by a ‘which-path’ detector” (1998) 391:6670 Nature 871–874.

Charniak, Eugene. “Bayesian Networks without Tears” (1991) 12:4 AI Mag, online: <https://www.aaai.org/ojs/index.php/aimagazine/article/view/918>.

Cheng, Patricia W & Marc J Buehner. “Causal Learning” in *KJ Holyoak RG Morrison Eds Oxf Handb Think Reason* Oxford Library of Psychology (Oxford University Press, 2012).

Chorley, Alison & Trevor Bench-Capon. “AGATHA: Using heuristic search to automate the construction of case law theories” (2005) 13:1 Artif Intell Law 9–51.

Danziger, Shai, Jonathan Levav & Liora Avnaim-Pesso. “Extraneous factors in judicial decisions” (2011) 108:17 Proc Natl Acad Sci 6889–6892.

Davies, C E & R Z Shaul. “Physicians’ legal duty of care and legal right to refuse to work during a pandemic” (2010) 182:2 Can Med Assoc J 167–170.

De Pierris, Graciela & Michael Friedman. “Kant and Hume on Causality” in Edward N Zalta, ed, *Stanf Encycl Philos*, winter 2018 ed (Metaphysics Research Lab, Stanford University, 2018).

Deans, Carrie & Keith A Maggert. “What Do You Mean, ‘Epigenetic’?” (2015) 199:4 Genetics 887–896.

Descartes, René. “The Passions of the Soul” in John Cottingham, Robert Stoothoff & DugaldTranslators Murdoch, eds, *Philos Writ Descartes* (Cambridge University Press, 1985) 325.

Doumas, Leonidas A A & John E Hummel. “Computational Models of Higher Cognition” in *KJ Holyoak RG Morrison Eds Oxf Handb Think Reason* Oxford Library of Psychology (Oxford University Press, 2012).

Douven, Igor. “Abduction” in Edward N Zalta, ed, *Stanf Encycl Philos*, summer 2017 ed (Metaphysics Research Lab, Stanford University, 2017).

Drummond, Susan. “Judicial Notice: The Very Texture of Legal Reasoning” (2000) Can J Law Soc Can Droit Société Vol 15 Issue 1 2000 P 1-38, online: <https://digitalcommons.osgoode.yorku.ca/scholarly_works/396>.

Dumouchel, Paul. “Intelligence, Artificial and Otherwise” (2019) 24 Forum Philos.

Dung, Phan Minh. “On the acceptability of arguments and its fundamental role in nonmonotonic reasoning, logic programming and n-person games” (1995) 77:2 Artif Intell 321–357.

Eemeren, Frans H van et al. “Toulmin’s Model of Argumentation” in Frans H van Eemeren et al, eds, *Handb Argum Theory* (Dordrecht: Springer Netherlands, 2014) 203.

Einstein, A, B Podolsky & N Rosen. “Can Quantum-Mechanical Description of Physical Reality Be Considered Complete?” (1935) 47:10 Phys Rev 777–780.

Einstein, Albert. “On the Electrodynamics of moving bodies” in *Collecred Pap Albert Einstein* (Princeton University Press).

Ellsworth, Phoebe. “Legal Reasoning and Scientific Reasoning” (2011) 63:1 Ala Law Rev 895–918.

Falcon, Andrea. "Aristotle on Causality" in Edward N Zalta, ed, *Stanf Encycl Philos*, spring 2019 ed (Metaphysics Research Lab, Stanford University, 2019).

Galavotti, Maria Carla. "Wesley Salmon" in Edward N Zalta, ed, *Stanf Encycl Philos*, fall 2018 ed (Metaphysics Research Lab, Stanford University, 2018).

Gentzel, Amanda, Dan Garant & David Jensen. "The Case for Evaluating Causal Models Using Interventional Measures and Empirical Data" (2019) ArXiv191005387 Cs Stat, online: <http://arxiv.org/abs/1910.05387>.

Glymour, Clark & Frederick Eberhardt. "Hans Reichenbach" in Edward N Zalta, ed, *Stanf Encycl Philos*, winter 2016 ed (Metaphysics Research Lab, Stanford University, 2016).

Goldberger, Arthur S. "Structural Equation Methods in the Social Science" (1972) 40:6 Econometrica 979.

Goodin, Robert E & Lynn Mather. "Law and Society" in *Oxf Handb Polit Sci* (Oxford University Press, 2013).

Green, Adam E & Kevin N Dunbar. "Mental Function as Genetic Expression: Emerging Insights From Cognitive Neurogenetics" in *KJ Holyoak RG Morrison Eds Oxf Handb Think Reason* (2012).

Greene, Joshua & Jonathan Cohen. "For the law, neuroscience changes nothing and everything" (2004) 359:1451 Philos Trans R Soc Lond B Biol Sci 1775–1785.

Grey, Thomas C. "LANGDELL'S ORTHODOXY." (1983) 45 Univ Pittsburgh Law Rev 1–949.

Halpern, Joseph Y. "A Modification of the Halpern-Pearl Definition of Causality" (2015) ArXiv150500162 Cs, online: <http://arxiv.org/abs/1505.00162>.

Hansen, Hans. "Fallacies" in Edward N Zalta, ed, *Stanf Encycl Philos*, summer 2020 ed (Metaphysics Research Lab, Stanford University, 2020).

Hill, Austin Bradford. "The Environment and Disease: Association or Causation?" (1965) 58:5 Proc R Soc Med 295–300.

Hoefer, Carl. "Causal Determinism" in Edward N Zalta, ed, *Stanf Encycl Philos*, spring 2016 ed (Metaphysics Research Lab, Stanford University, 2016).

Holmes, Jr, Oliver Wendell. "The Path of the Law" (1897) 10:457 Harv Law Rev, online: <http://moglen.law.columbia.edu/LCS/palaw.pdf>.

Kaptein, Maurits C, Robin Van Emden & Davide Iannuzzi. "Tracking the decoy: maximizing the decoy effect through sequential experimentation" (2016) 2:1 Palgrave Commun 1–9.

Kennedy, Duncan. "Freedom and Constraint in Adjudication: A Critical Phenomenology" (1986) 36 J Leg Educ 518.

Klar, Lewis N. "The Impact of U.S. Tort Law in Canada Symposium: Does the World Still Need United States Tort Law - Or Did It Ever" (2010) 38:2 Pepperdine Law Rev 359–374.

Kolodner, Janet L. "An introduction to case-based reasoning" (1992) 6:1 Artif Intell Rev 3–34.

LeDoux, Joseph E, Matthias Michel & Hakwan Lau. "A little history goes a long way toward understanding why we study consciousness the way we do today" (2020) 117:13 Proc Natl Acad Sci 6976–6984.

Lee, N Y Louis. "Chapter 4 - Cross-Cultural Differences in Thinking: Some Thoughts on Psychological Paradigms" in T -W Hung & T J Lane, eds, *Rationality* (San Diego: Academic Press, 2017) 61.

Levi, Edward Hirsch. "An Introduction to Legal Reasoning" Univ Chic LAW Rev 75.

LI, CC. "Method of Path Coefficients: A Trademark of Sewall Wright" (1991) 63:1 Hum Biol 1–17.

Liepiņa, Rūta, Giovanni Sartor & Adam Wyner. "Arguing about causes in law: a semi-formal framework for causal arguments" (2020) 28:1 Artif Intell Law 69–89.

Liptak, Adam. "Supreme Court Says Judges Are Above Politics. It May Hear a Case Testing That View.", *N Y Times* (16 September 2019), online: <https://www.nytimes.com/2019/09/16/us/politics/supreme-court-judges-partisanship.html>.

Loevinger, Lee. "Jurimetrics--The Next Step Forward" (1949) 33 Minn Law Rev, online: <https://scholarship.law.umn.edu/mlr/1796>.

Lombrozo, Tania. "Explanation and Abductive Inference" in *KJ Holyoak RG Morrison Eds Oxf Handb Think Reason* Oxford Library of Psychology (Oxford University Press, 2012).

Malinas, Gary & John Bigelow. "Simpson's Paradox" in Edward N Zalta, ed, *Stanf Encycl Philos*, fall 2016 ed (Metaphysics Research Lab, Stanford University, 2016).

Mangan, David. "Confusion In Material Contribution" (2014) 91:3 Can Bar Rev, online: <https://cbr.cba.org/index.php/cbr/article/view/4308>.

Markman, Arthur B. "Knowledge Representation" in *KJ Holyoak RG Morrison Eds Oxf Handb Think Reason* Oxford Library of Psychology (Oxford University Press, 2013).

Markoff, John. "A Learning Advance in Artificial Intelligence Rivals Human Abilities", *N Y Times* (10 December 2015), online: <https://www.nytimes.com/2015/12/11/science/an-advance-in-artificial-intelligence-rivals-human-vision-abilities.html>.

Martino, Benedetto De et al. "Frames, Biases, and Rational Decision-Making in the Human Brain" (2006) 313:5787 Science 684–687.

Maycock, Bruce & Andrea Beel. "Anabolic Steroid Abuse and Violence" (1997) BOCSAR NSW Crime Justice Bull 8.

McCambridge, Jim, John Witton & Diana R Elbourne. "Systematic review of the Hawthorne effect: new concepts are needed to study research participation effects." (2014) 67:3 J Clin Epidemiol 267–277.

McCarty, L Thorne. "Reflections on 'Taxman': An Experiment in Artificial Intelligence and Legal Reasoning" (1977) 90:5 Harv Law Rev 837–893.

McCready, E. "Chapter 13 - Rational Belief and Evidence-Based Update" in T -W Hung & T J Lane, eds, *Rationality* (San Diego: Academic Press, 2017) 243.

McInnes, Mitchell. “Causation in Tort Law: Back to Basics at the Supreme Court of Canada” (1997) Alta Law Rev 1013–1013.

Mobbs, Dean et al. “Law, responsibility, and the brain.” (2007) 5:4 PLoS Biol e103.

Modgil, Sanjay & Henry Prakken. “A general account of argumentation with preferences” (2013) 195 Artif Intell 361–397.

Moore, Michael. “Causation in the Law” in Edward N Zalta, ed, *Stanf Encycl Philos*, winter 2019 ed (Metaphysics Research Lab, Stanford University, 2019).

Morris, William Edward & Charlotte R Brown. “David Hume” in Edward N Zalta, ed, *Stanf Encycl Philos*, spring 2020 ed (Metaphysics Research Lab, Stanford University, 2020).

Naudé, Wim & Nicola Dimitri. “The race for an artificial general intelligence: implications for public policy” (2019) AI Soc, online: <https://doi.org/10.1007/s00146-019-00887-x>.

Ockeloen-Korppi, C F et al. “Stabilized entanglement of massive mechanical oscillators” (2018) 556:7702 Nature 478–482.

Pearl, Judea. “Graphical Models for Probabilistic and Causal Reasoning” in Philippe Smets, ed, *Quantified Represent Uncertain Imprecision* Handbook of Defeasible Reasoning and Uncertainty Management Systems (Dordrecht: Springer Netherlands, 1998) 367.

Pearl, Judea. “The seven tools of causal inference, with reflections on machine learning” (2019) 62:3 Commun ACM 54–60.

Ponder, JoAnn. “From the Tower shootings in 1966 to Campus Carry in 2016: Collective trauma at the University of Texas at Austin” (2018) 15:4 Int J Appl Psychoanal Stud 239–252.

Posner, Richard. “Legal Formalism, Legal Realism, and the Interpretation of Statutes and the Constitution” (1986) Case West Reserve Law Rev 179.

Rapp, Christof. “Aristotle’s Rhetoric” in Edward N Zalta, ed, *Stanf Encycl Philos*, spring 2010 ed (Metaphysics Research Lab, Stanford University, 2010).

Reichertz, Jo. “Induction, Deduction, Abduction” in *SAGE Handb Qual Data Anal* (1 Oliver’s Yard, 55 City Road, London EC1Y 1SP United Kingdom: SAGE Publications Ltd, 2014) 123.

Rips, Lance J, Edward J Shoben & Edward E Smith. “Semantic distance and the verification of semantic relations” (1973) 12:1 J Verbal Learn Verbal Behav 1–20.

Rissland, Edwina L & David B Skalak. “CABARET: rule interpretation in a hybrid architecture” (1991) 34:6 Int J Man-Mach Stud (Al and Legal Reasoning. Part 1) 839–887.

Rohlf, Michael. “Immanuel Kant” in Edward N Zalta, ed, *Stanf Encycl Philos*, spring 2020 ed (Metaphysics Research Lab, Stanford University, 2020).

Romeijn, Jan-Willem. “Philosophy of Statistics” in Edward N Zalta, ed, *Stanf Encycl Philos*, spring 2017 ed (Metaphysics Research Lab, Stanford University, 2017).

Rothman, K J. “Causes” (1976) 104:6 Am J Epidemiol 587–592.

Rothman, Kenneth J, Sander Greenland & C Stat. “Causation and Causal Inference in Epidemiology” (2005) 95 Am J Public Health 25.

Rubin, Donald B. “Estimating causal effects of treatments in randomized and nonrandomized studies” (1974) 66:5 J Educ Psychol 688–701.

Sartor, Giovanni. “Teleological arguments and theory-based dialectics” (2002) 10:1 Artif Intell Law 95–112.

Schölkopf, Bernhard. “Causality for Machine Learning” (2019) ArXiv191110500 Cs Stat, online: <http://arxiv.org/abs/1911.10500>.

Sergot, M J et al. “The British Nationality Act as a Logic Program” (1986) 29:5 Commun ACM 370–386.

Sergot, Marek et al. “The British Nationality Act as a Logic Program” (1986) 29 Commun ACM 370–386.

Shaffer, Joyce. “Neuroplasticity and Clinical Practice: Building Brain Power for Health” (2016) 7 Front Psychol, online: <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4960264/>.

Sitaram, Sunayana et al. “A Survey of Code-switched Speech and Language Processing” (2019) ArXiv190400784 Cs Stat, online: <http://arxiv.org/abs/1904.00784>.

Smith, Robin. “Aristotle’s Logic” in Edward N Zalta, ed, *Stanf Encycl Philos*, summer 2019 ed (Metaphysics Research Lab, Stanford University, 2019).

Soosalu, Grant, Suzanne Henwood & Arun Deo. “Head, Heart, and Gut in Decision Making: Development of a Multiple Brain Preference Questionnaire”: (2019) SAGE Open, online: <https://journals.sagepub.com/doi/10.1177/2158244019837439>.

Sulea, Octavia-Maria et al. “Exploring the Use of Text Classification in the Legal Domain” (2017) ArXiv171009306 Cs, online: <http://arxiv.org/abs/1710.09306>.

Sweeney, Patricia et al. “Social Network Analysis: A Novel Approach to Legal Research on Emergency Public Health Systems” (2013) 19 J Public Health Manag Pract JPHMP E38–E40.

Times, Special to the New York. “British Legal Debate: Premenstrual Tension and Criminal Behavior”, *N Y Times* (29 December 1981), online: <https://www.nytimes.com/1981/12/29/science/british-legal-debate-premenstrual-tension-and-criminal-behavior.html>.

Tushnet, Mark. “Critical Legal Studies: An Introduction to Its Origins and Underpinnings” (1986) 36:4 J Leg Educ 505.

Tversky, Amos & Daniel Kahneman. “Judgment under Uncertainty: Heuristics and Biases” (1974) 185:4157 Science 1124–1131.

Twito, Louise et al. “The Motivational Aspect of Children’s Delayed Gratification: Values and Decision Making in Middle Childhood” (2019) 10 Front Psychol, online: <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6684787/>.

Vallabhajosula, Brigitte. “The Basics of Neuroimaging” in *Murd Court* (New York: Oxford University Press, 2015).

Westreich, Daniel. “Berkson’s bias, selection bias, and missing data” (2012) 23:1 Epidemiol Camb Mass 159–164.

Wright, Richard W. “Causation in Tort Law” (1985) 73:6 Calif Law Rev 1735–1828.

Wright, Sewall. “Coefficients of Inbreeding and Relationship” (1922) 56:645 Am Nat 330–338.

Wright, Sewall. “The Method of Path Coefficients” (1934) 5:3 Ann Math Stat 161–215.

Internet Articles and Conference Papers

artificiallawyer. “France Bans Judge Analytics, 5 Years In Prison For Rule Breakers”, (4 June 2019), online: *Artif Lawyer* <https://www.artificiallawyer.com/2019/06/04/france-bans-judge-analytics-5-years-in-prison-for-rule-breakers/>.

Baldwin, Richard A & Eric Neufeld. *The Structure Model Interpretation of Wright’s NESS Test*, Yang Xiang & Brahim Chaib-draa, eds. (Berlin, Heidelberg: Springer, 2003).

Beaulac, Stephane. *A Comparative Look at Punitive Damages in Canada*, SSRN Scholarly Paper, by Stephane Beaulac, papers.ssrn.com, SSRN Scholarly Paper ID 2963334 (Rochester, NY: Social Science Research Network, 2002).

Brideau, Isabelle. *The Duty to Consult Indigenous Peoples*, by Isabelle Brideau, Zotero, 2019-17-E (Library of Parliament, Ottawa, Canada).

Brierley, John Ec. Stare Decisis (The Canadian Encyclopedia. Historica Canada, 2006).

Brüninghaus, Stefanie & Kevin Ashley. *Predicting Outcomes of Case-Based Legal Arguments.* (2003). Predicting Outcomes of Case-Based Legal Arguments. Proceedings of the International Conference on Artificial Intelligence and Law. 233-242. 10.1145/1047788.1047838.

Dailey, Anne C. *Law and the Unconscious: A Psychoanalytic Perspective*, SSRN Scholarly Paper, by Anne C Dailey, papers.ssrn.com, SSRN Scholarly Paper ID 3065072 (Rochester, NY: Social Science Research Network, 2017).

Dostal, Peter. “Criminal Law Notebook”, online: <http://criminalnotebook.ca/index.php/Criminal_Law_Notebook:About>.

Grabmair, Matthias et al. *Introducing LUIMA: an experiment in legal conceptual retrieval of vaccine injury decisions using a UIMA type system and tools* (San Diego, California: Association for Computing Machinery, 2015).

Grabmair, Matthias et al. *Predicting Trade Secret Case Outcomes Using Argument Schemes and Learned Quantitative Value Effect Tradeoffs* (New York, NY, USA: Association for Computing Machinery, 2017).

Hawkins, Brian. *The Life of the Law: What Holmes Meant*, SSRN Scholarly Paper, by Brian Hawkins, papers.ssrn.com, SSRN Scholarly Paper ID 1753389 (Rochester, NY: Social Science Research Network, 2012).

Hudon, Marie-Ève. *Bilingualism in Canada's Court System: The Role of the Federal Government*, by Marie-Ève Hudon, 2017-33-E (Library of Parliament, Ottawa, Canada).

Khandelwal, Renu. "Decision Tree and Random Forest", (14 November 2018), online: *Medium* <https://medium.com/datadriveninvestor/decision-tree-and-random-forest-e174686dd9eb>.

Liepina, Ruta, Giovanni Sartor & Adam Wyner. *Causal Models of Legal Cases*, Ugo Pagallo et al, eds. (Cham: Springer International Publishing, 2018).

McCarty, L Thorne & N S Sridharan. *The Representation of an Evolving System of Legal Concepts: II. Prototypes and Deformations* (1980).

Menacer, Mohamed et al. *Machine Translation on a parallel Code-Switched Corpus* (Ontario, Canada, 2019).

Mochales, Raquel & Marie-Francine Moens. *Study on the Structure of Argumentation in Case Law* (NLD: IOS Press, 2008).

Price, Catherine. "The Age of Scurvy", (14 August 2017), online: *Sci Hist Inst* <https://www.sciencehistory.org/distillations/the-age-of-scurvy>.

Rescher, Nicholas. *Reductio ad Absurdum*.

Walker, Vern R. *A Default-Logic Paradigm for Legal Reasoning and Factfinding*, SSRN Scholarly Paper, by Vern R Walker, papers.ssrn.com, 06-14 SSRN Scholarly Paper ID 908626 (Rochester, NY: Social Science Research Network, 2006).

Walton, Douglas & Thomas Gordan. *The Carneades Model of Argument Invention (2017) 14:2 SCRIPTed 168*, SSRN Scholarly Paper, by Douglas Walton & Thomas Gordan, papers.ssrn.com, SSRN Scholarly Paper ID 2097106 (Rochester, NY: Social Science Research Network, 2012).

Whang, Kyu-Young et al. *Advances in Knowledge Discovery and Data Mining: 7th Pacific-Asia Conference, PAKDD 2003. Seoul, Korea, April 30 - May 2, 2003, Proceedings* (Springer, 2003).

"As Federal Research Funds Recede, the Private Sector is Filling the Gap", online: *Lab Manag* <https://www.labmanager.com/business-management/as-federal-research-funds-recede-the-private-sector-is-filling-the-gap-2182>.

"Definition of Reasoning", online: Merriam-Webster <https://www.merriam-webster.com/dictionary/reasoning>.

"Justice Partnership and Innovation Program", online: <https://www.justice.gc.ca/eng/fund-fina/jsp-sjp/pfo-pfc.html>.

(OPTIONAL) Pruning decision trees to avoid overfitting - Preventing Overfitting in Decision Trees.

"Quantum Theory Demonstrated: Observation Affects Reality", online: *ScienceDaily* <https://www.sciencedaily.com/releases/1998/02/980227055013.htm>.

"Reason | Britannica", online: <https://www.britannica.com/topic/reason>.

“Science’s Worst Enemy: Corporate Funding”, online: *Discov Mag* <https://www.discovermagazine.com/the-sciences/sciences-worst-enemy-corporate-funding>.

“Texas Tower shooting of 1966 - The shooting | Britannica”, online: <https://www.britannica.com/event/Texas-Tower-shooting-of-1966/The-shooting>.

“What AI still can’t do”, online: *MIT Technol Rev* <https://www.technologyreview.com/2020/02/19/868178/what-ai-still-cant-do/>.