# Learning Discrete Word Embeddings to Achieve Better Interpretability and Processing efficiency 

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# Learning Discrete Word Embeddings to Achieve Better Interpretability and Processing efficiency 

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## Résumé

L'omniprésente utilisation des plongements de mot dans le traitement des langues naturelles est la preuve de leur utilité et de leur capacité d'adaptation a une multitude de tâches. Cependant, leur nature continue est une importante limite en terme de calculs, de stockage en mémoire et d'interprétation. Dans ce travail de recherche, nous proposons une méthode pour apprendre directement des plongements de mot discrets. Notre modèle est une adaptation d'une nouvelle méthode de recherche pour base de données avec des techniques dernier cri en traitement des langues naturelles comme les Transformers et les LSTM. En plus d'obtenir des plongements nécessitant une fraction des ressources informatiques nécéssaire à leur stockage et leur traitement, nos expérimentations suggèrent fortement que nos représentations apprennent des unités de bases pour le sens dans l'espace latent qui sont analogues à des morphèmes. Nous appelons ces unités des sememes, qui, de l'anglais semantic morphemes, veut dire morphèmes sémantiques. Nous montrons que notre modèle a un grand potentiel de généralisation et qu'il produit des représentations latentes montrant de fortes relations sémantiques et conceptuelles entre les mots apparentés.
Mots clés: plongements, discret, binaire, Transformer, LSTM, sémantique, morphème, Search Data Structure Learning, Multi-Bernouilli Regression Search, généralisation, interprétabilité

## Abstract

The ubiquitous use of word embeddings in Natural Language Processing is proof of their usefulness and adaptivity to a multitude of tasks. However, their continuous nature is prohibitive in terms of computation, storage and interpretation. In this work, we propose a method of learning discrete word embeddings directly. The model is an adaptation of a novel database searching method using state of the art natural language processing techniques like Transformers and LSTM. On top of obtaining embeddings requiring a fraction of the resources to store and process, our experiments strongly suggest that our representations learn basic units of meaning in latent space akin to lexical morphemes. We call these units sememes, i.e., semantic morphemes. We demonstrate that our model has a great generalization potential and outputs representation showing strong semantic and conceptual relations between related words.
Keywords: embeddings, discrete, binary, Transformer, LSTM, semantic, morpheme, Search Data Structure Learning, Multi-Bernouilli Regression Search, generalization, interpretability

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## Liste des sigles et des abréviations

| DNN | Deep Neural Network |
| :--- | :--- |
| NMT | Neural Machine Translation |
| GEC | Grammatical Error Correction |
| NLP | Natural Language Processing |
| NLM | Neural Language Model |

BiLM Bidirectional Language Model

LM Language Model

MBRS Multi-Bernouilli Regression Search

BiLSTM Bidirectional Long Short-Term Memory
H.D. Hamming Distance

POS Part of Speech

XOR Exclusive OR (bit operation)
$k$-NN $\quad k$ Nearest Neighbors

## Introduction

Natural language processing has evolved considerably in recent years. It went from using complex statistical methods to using various deep neural network (DNN) architectures. This methodology shift introduced an increasing need for training data to a point where the minimum amount required for acceptable results became hardly achievable in a lot of downstream tasks. One way to mitigate that need was to add a pre-training step allowing the use of abundant raw text in a given language to get adequate prior knowledge about how the words in the vocabulary relate to each other. The result of this pre-training step are word embeddings that can be directly used in tasks such as neural machine translation (NMT) and grammatical error correction (GEC). Further ways to lessen this need for data were also used depending on the task to solve. For example, NMT and GEC use synthetic corpora generation such as using Back-Translation $[\mathbf{1 1}, \mathbf{4 3}, \mathbf{2 0}]$ or direct corpora generation from versioned text [23]. Although these proved to help performance, they are not useful for other tasks and there is still a limit to the amount of useful synthetic samples that can be generated.

Word representations were first being learned implicitly as part of a DNN aimed at solving an NLP task (e.g. Neural Language Model [2]). Then, they started to be considered as an independent task $[\mathbf{2 7}, \mathbf{3 1}]$. The resulting embeddings proving to be useful, other works moved from the single vector representation to propose deeper combinations of vectors which could then be fine-tuned to the required task afterwards $[32,33,34,9]$. All these techniques commonly use continuous vectors for the embeddings. This allows for greater precision, but the usual large vocabularies that are used consenquently make it so that significantly more compute resources are required to store and process them. The continuous nature also prohibits the interpretability of an embedding in isolation, limiting their use to potential downstream tasks only. In this work, we propose a technique to learn binary (i.e. discrete) word embeddings, which we argue can encode what we call semantic morphemes representing language independent latent discrete units of meaning analogous to lexical morphology. We also argue that this can provide similar performance while achieving greater interpretability and computation efficiency. This achieved level of interpretability also suggests the resulting embeddings are not only useful as intermediate representations. Our contribution is the
adaptation of the Multi-Bernouilli Regression Search [10] technique to learn binary word embeddings directly by training our model end-to-end. The learned embeddings are 40 bits wide, greatly reducing the required resources, while still encoding rich semantic information. Our experimentation also shows our architecture having great generalization potential.

In chapter 1, we first present more detailed insight on the motivation that led us to want discrete representations. We then present related work in chapter 2 to provide a better background. In chapter 3, we define our technique and describe our training methodology. Finally, in chapter 4, we present the results of our experimentations.

## Chapter 1

## Motivation

### 1.1. Towards an Intelligent Vocabulary

As much as NLP models evolved, a common problem remained present with each different iteration and still is to this day. This problem is tokenization, or how should the text be presented. For example, should the word don't be kept as is? Should it be split as do $\cdot$ n't or $d o n \cdot$ ' $t$ to explicitly present to a model that this is a contraction of do and not. The former would lead to a more complex problem as the vocabulary would grow quickly. On the other hand, the latter seems to be more intuitive and also allows for a smaller vocabulary because other contractions like won't would share a common token. Then, if splitting common word contractions can lead to a more compact and intelligent vocabulary, why not use an even finer granularity for the tokenization by exploiting the compositionality of the english language. The different morphemes and the different parts of compound words could be considered individually. Table 1.1 shows how prefixes and suffixes can be extracted as independent tokens. Such a granularity would allow models to learn more specific representations for each token. In other words, if we consider the tokens cat and cats, two different representations would need to be learned even though each token represents the same entity with a different quantity. By using the split $c a t \cdot s$, this unnecessary overlapping is avoided.

| Word | Tokenization |
| :--- | :--- |
| cats | cat $\cdot s$ |
| canadian | canad $\cdot$ ian |
| countdown | count $\cdot$ down |
| considered | consider $\cdot$ ed |
| liberate | liber $\cdot$ ate |
| devalue | $d e \cdot$ value |

Table 1.1. Examples of tokenization based on morphemes

| Word | Tokenization | Meaning |
| :--- | :--- | :--- |
| cats | $c a t \cdot s$ | More than one cat |
| dogs | $d o g \cdot s$ | More than one dog |
| canadian | canada $\cdot$ ian | Belonging to Canada |
| italian | italy $\cdot$ ian | Belonging to Italy |
| french | france $\cdot$ ian | Belonging to France |

Table 1.2. Examples of ideal tokenization
Morphology brings a better separation of concerns, yet the english grammar has a lot of irregularities that make this unusable in practice. A great amount of cases are not trivial. Should the word ate be split into eat • ed or kept as is? Should bound morphemes (i.e. morpheme without meaning by themselves) like canad in table 1.1 really be considered as a token? Even under the assumption that every word we encounter is written correctly, there is no clear good way to properly split raw text for optimal processing. Multiple data-driven techniques $[\mathbf{2 1}, \mathbf{3 4}, \mathbf{3 5}, \mathbf{4 2}]$ were explored, but again, they are based on the underlying characters. So, we decided to move our focus from finding an optimal way to tokenize words and instead tried to exploit latent semantic features since we believed they were more consistent.

### 1.2. Semantic Morpheme

The many inconsistencies with regular languages previously described led us to hypothesize that a word could be translated to an intermediate, language independent, representation based on what we call semantic morphemes (sememes). Analogous to lexical morphemes, we intended to represent words by the composition of discrete latent semantic units. Table 1.2 illustrates how the meaning could be split in sememes (e.g. Belonging to and More than one could be sememes) and how it could be achieve with what we consider an ideal tokenization. This reiterates the complexities of using text while showing how the meaning does not depend on the actual spelling. This also shows why we think of semantics as a more consistent basis. To emphasize this idea, there is another way of visualizing our intuition. If we take for example the words : cat, dog, bite and claw. They have no grammatical relation (i.e. they do not share any morpheme), but these four words clearly share common sememes, i.e., they have a common latent relation based on their meaning.

### 1.3. Embeddings Interpretability

The use of real valued vector for word embeddings is almost ubiquitous in state of the art models for NLP. One problem is that they embed information in a way that is not usable as is. Each dimension of the vectors having an infinite number of possible values makes it that
no features or patterns can really be observed directly．Like it was presented in［28］and［31］， there exist interesting relations between these vectors such as the linear subtructures that arise with similar concepts（e．g．difference between king and queen is similar to the difference between man and woman），but the interpretation can only come from the comparison with other vectors and cannot be extracted by simply observing their values independently．

One of our inspirations for this work are the chinese hanzis（i．e．characters）．They can be seen as a unit between morphemes and our sememes．For example，the word communism is translated as 共产主义 in mandarin．A nice property of hanzis is that this word can be understood without even knowing what it is．By examining each characters separately，we can extract the following meaning ：shared（共）＋production（产）＋main（主）＋righteous－ ness（义）．One could argue that the same could be achieved by looking at the etymology of the word，which is ：common（belonging equally to）+ ism（a distinctive doctrine）${ }^{1}$ ．Yet，as we previously explained in section 1.1 and illustrated in table 1.2 ，we would have to extract common from the morpheme commun which is not necessarily trivial as there are a lot of exceptions in the english language．So，we believed that by learning discrete（i．e．binary） word embeddings，we would be able to observe a similar phenomenon by looking at the se－ memes learned，which could make them interpretable as is and could be used in other areas of research like linguistics．

[^0]
## Chapter 2

## Related Work

### 2.1. Continuous Word Embeddings

Pre-trained continuous word embeddings predominate the natural language processing literature. Various methods to learn them have been proposed, all stemming from Firth's statement : "You shall know a word by the company it keeps" [13]. Referred as distributional semantics, this concept is based on the co-occurences of words. One of the first mentions of this idea used for NLP was in [2]. In their work, they indirectly learn word embeddings by training a Neural Language Model (NLM). The word sequences probabilities are jointly learned with what they call the distributed word feature vectors (i.e. the embeddings) which are simply vectors of free parameters used as the input for the NLM instead of onehot encoded vectors. This allowed for a great dimensionality reduction as the input didn't have to be as wide as the vocabulary. Also, the NLM could now encode word distribution information separately for each word.

Following this, further work was done to explicitly learn the embeddings before using them in a downstream task. With this new pre-training step, the models for these tasks could directly use the distributional information instead of learning it jointly, hence reducing the complexity of the problem. Two popular shallow learning methods stood out in the literature : Word2Vec [27] and GloVe [31]. Word2Vec proposed two local context methods : Skip-Gram, where the model has to predict the surrounding word window using the middle word ;and CBOW, where the model needs to predict the middle word using the surrounding window. Both of these are simple, but they have one major drawback which is their inherent locality preventing them from using the word co-occurence statistics efficiently. GloVe tries to circumvent this by using the co-occurences data of the whole corpus. In their work, they observed that comparing the ratio of the co-occurence probabilities of words in a common context helps to distinguish relevant and irrelevant relations. This idea can be interpreted in vector space as the difference between the vectors. So, the embeddings are learned by
minimizing a least squares regression model based on the pre-computed co-occurences and weighted on the frequencies of the words to mitigate the noise from under-represented words.

Even though these shallow models allowed for downstream tasks to perform better, a single vector representation contrains the learning potential. Words can have multiple meanings and different semantic and syntactic contexts that all must be compressed into a single vector. Deeper representations hence came to be used, such as ELMo [32]. Similar to [2], they pre-trained an $L$-layer bidirectional LSTM network as a language model (BiLM). To allow for more accurate representations, embeddings are not static as opposed the the previous methods presented. They actually are a function of the sentence in which they are. Input sentences are processed by the pre-trained BiLM and the final word embedding is a learned weighted combination of the $L$ hidden layers. The next big leap in deep word representations came with the Transformer [41] architecture. GPT [33] and GPT-2 [34] use a Transformer decoder to pre-train a fowards-only language model and then finetune on downstream tasks. Another popular pre-training method is BERT [9] which, on the other hand, does not train as a LM. It pre-trains bidirectional representations by using a Transformer encoder to predict masked words and the next sentences, which, similarly to ELMo, incorporates the whole sentence in the representation of a single word. Finetuning layers can then be added on top of the pre-trained model to use it with downstream tasks.

This progress managed to achieve better performance at the expense of greatly increased complexity. Consequently, the interpretation of the learnt features and of the resulting representions is not trivial, which contrains their generalization potential and their degree of reusability.

### 2.2. Non-distributional Word Embeddings

The problem with the lack of interpretability in word embeddings has also been raised in [12]. Instead of learning latent representations, they craft sparse binary vectors from the different linguistic aspects of a word : part of speech, hypernyms, hyponyms, holonymes, semantic categories, lexical and predicate-argument semantics, emotion, sentiments, colors, synonyms and antonyms. These properties are taken from existing resources like WordNet $[\mathbf{2 9}]^{1}$. Competitive results on many NLP tasks were obtained when compared with distributional embeddings like Word2Vec and GloVe. This method is highly dependent on availability of linguistic data and manual adaptation of this data, which greatly limits the degree to which it can generalize to unseen words. Although there are a lot of downsides, it still hints towards the fact that discrete and interpretable representations can be learned and that they can be a viable alternative.

[^1]
### 2.3. Binarization as Compression

In other works, the discretization of word embeddings was considered as a lossless compression problem. One of the motivations for this is that continuous representations account for a significant amount of parameters in a model, which can be a limiting factor if the required resources are not available (e.g. embedded systems). Similar to the VQ-VAE architecture [30] used for image processing, a fixed length codebook of continuous vectors can be learned and then indexed appropriately. This is what [38] did in their work. They actually use $M$ codebooks of $K$ continuous vectors and then learn how to combine a vector from each codebook together to get a final embedding. An auto-encoder architecture is used with the Gumbel-softmax trick [25] to have dfferentiable indexing. Even though downstream models will use the combined continuous embeddings, the discrete indexes can be used to understand what the model learns as related word will index similar vectors.

Another way to achieve compression is by applying a hard threshold on the latent representations to obtain binary representations. As opposed to the previous technique, these discrete features are not indexes. They are analogous to their continuous counterpart. In order to use gradient based learning with this method, [40] uses an auto-encoder where the decoder is simply the transposed weight matrix of the encoder. The binarized output of the encoder is used as the decoder's input. To counteract the loss of semantic information from the thresholding operation in latent space, they also added an orthogonality constraint on the shared encoder/decoder weights in order to discourage correlation between binary features. Also using an auto-encoder, [37] applies either deterministic or stochastic binarization on the encoder's output. The encoder and the decoder have separate parameters and the gradient flows through using Straight-throught estimation [3]. Instead of using orthogonality regularization, they add a semantic preservation loss. This means that the relative distance between a triple of words must be similar in the input space and in the latent space.

These approaches all achieve a reduction in memory usage and better interpretability without sacrificing a significant amount of performance. They also share the same caveat, which is that they depend on pre-trained continuous embeddings. This bounds their results on the quality of the source vectors used.

## Chapter 3

## Learning Binary Embeddings

As opposed to what was presented in the related work, we do not compress pre-trained embeddings, rather we learn binary word embeddings directly. To do so, we adapted the Multi-Bernouilli Regression Search with the proposed F-beta loss in [10]. In section 3.1, we will present the formalism of this adaptation and in section 3.2 the neural models used around this technique.

### 3.1. Multi-Bernouilli Regression Search with F-Beta optimization

The Multi-Bernouilli Regression Search (MBRS) is a family of models for the Search Data Structure Learning (SDSL) proposed in [10]. SDSL is meant as a generalization of database searching where the query entities, the database entities and their relations are not constrained (e.g. using an image patch as a query to search for related images in a database like CIFAR-10). What is meant by unconstrained relations is that the relevance of a query to an entity (e.g. $k$-NN or subset) is not explicitly defined but rather implicitly defined by the data.

Let $q$ be a query and $d$ be a document ${ }^{1}$. Let $f_{\theta_{1}}^{Q}(q)=\boldsymbol{\pi}^{q}$ and $f_{\theta_{2}}^{D}(d)=\boldsymbol{\pi}^{d}$ be parametric functionals for the query and document. Here, both functionals are implemented as independent neural networks (see 3.2). Both $\boldsymbol{\pi}^{q}$ and $\boldsymbol{\pi}^{d}$ are the parameters for a Multi-Bernouilli ${ }^{2}$ distribution such that $\boldsymbol{\pi}=\left(\pi_{1}, \pi_{2}, \ldots, \pi_{n}\right) \in[0,1]^{n}$. Also, assume there is a relation $R$ function (i.e. matching function) such that $F_{R}: \Omega_{Q} \times \Omega_{D} \rightarrow[0,1]$ predicts the probability of a relation between the queries domain $\Omega_{Q}$ and the documents domain $\Omega_{D}$. In the case of MBRS, we need a matching function to determine if a match between both domains has

[^2]occured. We define it as,
\[

$$
\begin{equation*}
M\left(f_{\theta_{1}}^{Q}(q), f_{\theta_{2}}^{D}(d)\right)=\prod_{i=1}^{n} \pi_{i}^{q} \pi_{i}^{d}+\left(1-\pi_{i}^{q}\right)\left(1-\pi_{i}^{d}\right) \tag{3.1.1}
\end{equation*}
$$

\]

With this formulation, each Bernouilli parameter represents a different bit. This means $f_{\theta_{1}}^{Q}(q)$ and $f_{\theta_{2}}^{D}(d)$ only match if the bits at each position are equal. This definition also allows the gradient to flow to both $f_{\theta_{1}}$ and $f_{\theta_{2}}$, so it can be trained end-to-end. The explicit binarization is obtained by using a hard threshold on $\boldsymbol{\pi}$ after training. As opposed to the hard-thresholding used in the compressing algorithms presented in 2.3, the multi-bernouillis are implicitly binarized during training by pulling each parameter $\pi_{i}$ towards 1 or 0 .

To train this matching function, we use an approximation of the F-Beta score as our loss function. We first define the precision as

$$
\begin{equation*}
p=P(R \mid M)=\frac{P(M \mid R) P(R)}{P(M)}=\frac{r \cdot q_{R}}{m}, \tag{3.1.2}
\end{equation*}
$$

where $M$ represents a match, $r$ is the recall, $q_{R}$ is the relation marginal probability and $m$ is the matching marginal probability. We then obtain the following F-Beta formulation:

$$
\begin{equation*}
F_{\beta}=\frac{\left(1+\beta^{2}\right) p r}{\beta^{2} p+r}=\frac{\left(1+\beta^{2}\right) \frac{r q_{R}}{m} r}{\beta^{2} \frac{r q_{R}}{m}+r}=r \cdot g(m), \text { where } g(x)=\frac{\left(1+\beta^{2}\right) q_{R}}{\beta^{2} q_{R}+x} \tag{3.1.3}
\end{equation*}
$$

where $\beta$ is a hyper-parameter. As explained in the original work, unbiased estimates can be obtained for $r$ and $m$. A naive estimator for $p$ can be obtained, but it would be biased. This is why this formulation was favored. To improve the sampling and implementation efficiency, we reformulate $m$ as

$$
\begin{equation*}
m=P(M)=P(R) P(M \mid R)+P(\neg R) P(M \mid \neg R)=q_{R} \cdot r+\left(1-q_{R}\right) \cdot s \tag{3.1.4}
\end{equation*}
$$

where $s$ is the fallout. Assuming we can sample from $P(Q, D \mid R)$ and from $P(Q, D \mid \neg R)$, estimators can be obtained with empirical averages. Let $X$ be samples from $P(Q, D \mid R)$ and $Y$ samples from $P(Q, D \mid \neg R)$, then our estimators are :

$$
\begin{align*}
& \hat{r}_{\theta}=\frac{1}{|X|} \sum_{q_{x}, d_{x} \in X} M_{\theta}\left(f_{\theta_{1}}^{Q}\left(q_{x}\right), f_{\theta_{2}}^{D}\left(d_{x}\right)\right)  \tag{3.1.5}\\
& \hat{s}_{\theta}=\frac{1}{|Y|} \sum_{q_{y}, d_{y} \in Y} M_{\theta}\left(f_{\theta_{1}}^{Q}\left(q_{y}\right), f_{\theta_{2}}^{D}\left(d_{y}\right)\right)  \tag{3.1.6}\\
& \hat{m}_{\theta}=q_{R} \cdot \hat{r}_{\theta}+\left(1-q_{R}\right) \cdot \hat{s}_{\theta} . \tag{3.1.7}
\end{align*}
$$

The final cost function we are trying to maximize is (the log is taken to provide numerical stability)

$$
\begin{equation*}
J_{\theta}=\log F_{\beta_{\theta}}=\log \left(\left(1+\beta^{2}\right)\right)+\log \left(\hat{r}_{\theta}\right)-\log \left(q_{R} \beta^{2}+\hat{m}_{\theta}\right) . \tag{3.1.8}
\end{equation*}
$$

In their work, Duchesneau et al. propose a redifinition of $\log \left(\hat{r}_{\theta}\right)$ where the $\log$ is moved inside the sum (see 3.1.5). The gradient of the initial formulation will be near zero for samples that are matching. Since we are trying to match between two domains, it is important that the model receives a good training signal for that case. By using this alternate estimator, a bigger gradient flows through the model when a match should occur. The adjusted cost function then becomes :

$$
\begin{equation*}
J_{\theta}=\log F_{\beta_{\theta}}=\log \left(\left(1+\beta^{2}\right)\right)+\rho_{\theta}-\log \left(q_{R} \beta^{2}+\hat{m}_{\theta}\right) \tag{3.1.9}
\end{equation*}
$$

where $\rho_{\theta}=\frac{1}{|X|} \sum_{q_{x}, d_{x} \in X} \log M_{\theta}\left(f_{\theta_{1}}^{Q}\left(q_{x}\right), f_{\theta_{2}}^{D}\left(d_{x}\right)\right)$. In section 3.2, we explain how we adapted our problem to this formulation.

### 3.2. Neural Models Architectures

Similar to what we presented in 2.1, we want to extract our binary representations from the word co-occurence statistics. One way to approximate them while easily integrating the required sampling is to consider local context windows of odd length. For a certain word, we consider that both the sequence of words before and after are as important. The odd length makes it so that we can have an equal context surrounding a particular word. We can then define the domain for $Q$ as the middle words and the domain for $D$ as this surrounding context. This formulation makes it easy to see how the data implicitly defines the relation R between both domains. It is also trivial to sample from $P(Q, D \mid R)$ and $P(Q, D \mid \neg R)$. We first sample $n$ middle words $q_{i}$ from the unigram probabilites of the vocabulary. Then, for each $q_{i}$, we uniformly sample an associated window $d_{i}$. This constitutes our samples $\left(q_{i}, d_{i}\right) \sim P(Q, D \mid R), i \in\{1,2, \ldots, n\}$. By reusing the middle words with the other contexts we can obtain our $P(Q, D \mid \neg R)$ samples at the same time. Formally, this means :

$$
\left(q_{i}, d_{j}\right) \sim \begin{cases}P(Q, D \mid R), & \text { if } i=j  \tag{3.2.1}\\ P(Q, D \mid \neg R), & \text { if } i \neq j\end{cases}
$$

The implementation of $f_{\theta_{1}}^{Q}$ and $f_{\theta_{2}}^{D}$ could be resource intensive, so doing it like this avoids unecessary processing since the computed $\boldsymbol{\pi}_{i}^{Q}$ and $\boldsymbol{\pi}_{i}^{D}$ can be reused. Figure 3.1 shows how we implemented both neural networks for $f_{\theta_{1}}$ and $f_{\theta_{2}}$. Since $Q$ only represents the middle words, the implementation is a $|V| \times k$ continuous embedding matrix, where $|V|$ is the vocabulary size and $k$ is the discrete embedding size. Even though the data is continuous during training, we refer to $k$ as the discrete size since at the end, a hard threshold is applied
directly on that matrix. In this case, because we are using a sigmoid before the matching function, the elementwise threshold function is

$$
\operatorname{bin}(x)= \begin{cases}1, & \text { if } x>0  \tag{3.2.2}\\ 0, & \text { otherwise }\end{cases}
$$

We use a combination of bidirectional LSTM and Transformer to process the contexts in $D$. The rationale behind this architecture is that we wanted to add self-attention on top of the LSTM to provide better focus on important words to the model (e.g. weighting nouns more than determinants). We first tried implementing an architecture like in [24], which uses additive attention similar to [1], but the results were not impressive. Inspired by [26], we then tried replacing the attention layer by a single layer Transformer encoder since this new architecture was proving to boost performance in a variety of NLP tasks. We also thought the multi-head attention would allow the model to capture more complex relations (e.g. different meaning for different context). As opposed to the original paper, we do not use the positional embeddings at the input of the Transformer. As input, we are using the LSTM's output which should provide implicit positional information in its latent representation. The input embeddings for the LSTM are the same as the one used for $f_{\theta_{1}}$ (i.e. $\theta_{1} \subset \theta_{2}$ ). Our intuition was that whether a word appears in the context before or after has a significant impact. This is why we process the before and after context separately (using the same LTSM and Transformer layer) and then combine them before trying to match them with MBRS. We believe that with this methodology, the self-attention will focus more on words that would impact significantly the meaning of the context.

Our cost function also requires the marginal probability for a relation (i.e. $q_{R}$ ). Since we defined our queries domain $\Omega_{Q}$ as the middle words in the windows, this allowed us to reformulate this term as :

$$
\begin{equation*}
q_{R}=P(R)=\sum_{q \in \Omega_{Q}} P(R \mid Q=q) P(Q=q)=\sum_{q \in \Omega_{Q}} P(Q=q)^{2} . \tag{3.2.3}
\end{equation*}
$$

This uses the fact that, in our case, a word always has a context, so the following equality holds :

$$
P(R \mid Q=q)=P(Q=q)
$$

This term being constant across training, we computed it once using the unigram probabilities of the training vocabulary.


Fig. 3.1. Our implementation of MBRS. $f_{\theta}^{Q}$ is simply the embeddings. It receives the index for the middle word of a window. $f_{\theta}^{D}$ is a BiLSTM with a single Transformer layer on top which receives the before and after window context separately (i.e. the after context can't attend to the before context and vice versa). The final representations of the before and after context are then concatenated and projected to the desired discrete embedding size. Both the result of $f_{\theta}^{Q}$ and $f_{\theta}^{D}$ are passed through a sigmoid to obtain $\boldsymbol{\pi}^{Q}$ and $\boldsymbol{\pi}^{D}$ which are used to optimize the cost function defined in 3.1.9. The embeddings are shared between both sub-models.

### 3.3. Experimental Setup

### 3.3.1. Dataset

We built our corpus by combining BookCorpus [44] and the whole english Wikipedia ${ }^{3}$. The original BookCorpus contained compilations, which means that certain books were duplicated as their stand-alone version was also present. To avoid a bias in the word probabilities, we removed these stand-alone versions so that no sentences appeared twice unnaturally.

We padded the beginning and end of each document to avoid windows overlapping between them. Documents refer to either a full book or a Wikipedia article. We tokenized the whole corpus with SpaCy $[\mathbf{1 7}]$ to standardize the input text. We did not apply any encoding like Byte Pair Encoding (BPE) [36] or SentencePiece [21]. Even though these techniques are useful for other NLP tasks like Language Understanding [9, 33, 34], Machine Translation

[^3]$[11,39,22]$ and Grammatical Error Correction $[\mathbf{2 0}, 5,16,14,7,8]$, they split words based on their characters, which we argued might not be optimal and is not the focus of this work. Also, their data-driven nature leads to word splits which are not necessarily proper morphemes (e.g. banana could split in $b a \cdot n a n a)$ and this defeats our goal of interpretability. We finally converted everything in lowercase.

In table 3.1, we summarize the final corpus properties. To limit the memory footprint ${ }^{4}$ of the embeddings and to allow us to analyze the quality of each embedding more efficiently, we limit our vocabulary to the 50,000 most frequent words with at least a frequency of 2 (this boundary is not reached in our case). All other words are replaced by an $<u n k>$ token.

| Corpus Information |  |
| ---: | ---: |
| Num. of words | $3,213,438,722$ |
| Num. of documents | $6,012,332$ |
| Doc. Train/Valid split | $20 \%$ |
| Original vocab. size | $8,375,078$ |
| Restricted vocab. size | 50,000 |

Table 3.1. Final properties after combining both raw corpora and preprocessing them.

### 3.3.2. Model Configuration and Training

We set the embedding dimensionality to 40 and used windows of 51 words. The LSTM's hidden size and the feed-forward layer in the Transformer encoder were both set to 100. We used a single Transformer layer with 8 attention heads, a ReLU activation and the default dropout rate of 0.1 . For MBRS, we used a $\beta$ of $2^{-15}$ with a group size (gs) of 200 . We used the Adam optimizer [19] with a learning rate of 0.0001 and no weight decay. We used a batch size (bs) of 16. Following [10], we exponentially increased $\beta$ to avoid bit saturation by linearly increasing $\log _{2} \beta$ from -100 to our desired -15 in 1000 steps. We also use their regularization on the outputs of $f_{\theta}^{Q}$ and $f_{\theta}^{D}$, which is

$$
\begin{align*}
\gamma & =\frac{\sum_{i}^{k}\left(z_{f_{\theta}^{Q}}^{i}\right)^{2}}{k}+\frac{\sum_{i}^{k}\left(z_{f_{\theta}^{D}}^{i}\right)^{2}}{k}  \tag{3.3.1}\\
\lambda & =\tau * \frac{J_{\theta}}{\gamma} \tag{3.3.2}
\end{align*}
$$

where $k$ is the embedding dimensionality and $\tau$ is a hyper-parameter ( 0.001 in our case). The complete cost function is then

$$
\begin{equation*}
J=J_{\theta}+\lambda * \gamma \tag{3.3.3}
\end{equation*}
$$

[^4]The model was trained for 455,000 steps and the hard threshold (see 3.2.2) was applied to the embedding weights to obtain the final representations.

The group size refers to the $P(Q, D \mid R)$ and $P(Q, D \mid \neg R)$ samples used in equation 3.2.1. Since we are reusing samples for efficiency, the group size is equal to the number of $P(Q, D \mid R)$ samples. This means that, with our configuration, a single batch has $200^{2}$ estimators for the MBRS matching. This is achieved with only gs $*$ bs windows that needs to be in memory (i.e. 3200). The model was trained on a single GTX1080 and 3200 windows was the maximum that would fit in memory. From our experimentation, a bigger group size compared to the batch size was favorable, so this is why gs $\gg$ bs. This also follows from the fact that the recall and fallout are empirical estimates and that having more samples allows the model to have a better estimation of the real word distributions.

The $\beta$ was chosen to be this low to weight precision way more than recall. If the value was too high, the model always ended up collapsing every embeddings to the same value. If the value was too low, than the precision constraint was too important for the model to learn any meaningful representations. The same goes for the restrained capacity of the model, which is really small compared to the language understanding state of the art BERT for example. If the model had too much capacity, it would also collapse the embeddings to a single representation. If it had too little, the learning potential was too limited. With the current configuration, a good precision/recall balance was achieved.

## Chapter 4

## Results

### 4.1. Embedding Neighborhoods

To establish the quality of our embeddings, we explored the neighborhoods of each words in the binary latent space. In 4.1.1, we look at the closest words in terms of hamming distance and compare them with continuous and binary GloVe embeddings. In 4.1.2, we use unsupervised clustering to try to reveal more complex hidden relationships.

### 4.1.1. Nearest Neighbors

The first qualitative evaluation we did was to manually look at the nearest neighbors for common words. This allowed us to use common knowledge as an informal baseline (e.g. it is assumed to be common knowledge that computer belongs to the family of electronics). The hamming distance was used as our distance measure. It is analogous to the cosine similarity which is often used with continuous vectors. It also has a performance advantage since it is adapted for binary representations and the computation is inherently simple. To have a baseline, we wanted embeddings with known good results, so we used GloVe. We trained our own vectors using their public implementation ${ }^{1}$ and our training corpus. The vector dimension was set to 256 and distance weighting was disabled. Since we do not explicitly weight co-occurences by their distance, we assumed it would make the available context for each word more akin to ours. We used the same window size of 51 . All other parameters were left at their default value and we trained the model for 100 iterations. As presented in the related work, [40] proposes a simple model to compress continuous embedding to binary representations. To have a more comparable baseline, we used this technique to compress our trained GloVe embeddings. We set the compressed dimensionality to 40 and trained until convergence using a $\lambda_{\text {reg }}$ of 1 .

[^5]We present in table 4.1 some neighborhoods we analyzed. One characteristic that is quickly observable is that our model seems to group based on semantic similarities, which is comparable to both the compressed and continuous GloVe embeddings. The basis of our methodology being distributional semantics, this was the expected behaviour. One novel property that we observed is that our groupings also include grammatical similarities (e.g. same POS). This behaviour is apparent with the words computer and computers. Both representations were still grouped with other related words (e.g. laptop, workstation, programming). However, most of the closest words to computer are singular and most of the closest words to computers are plural, which is not true when looking at GloVe. Similar inflectional relations are exposed when looking at the verbs eat, ate, eats and eating. In section 4.2 , we explore the interpretability of this behaviour by looking at the bits used by the model for different grammatically related words.

Table 4.1 lists the words in ascending order of hamming distance (cosine similarity for the continuous embeddings). Based only on this distance measure, the embeddings from our work appear to put more emphasis on grammatical properties when compared with both GloVe counterparts. To get a more accurate interpretation, we evaluated our results on two similarity datasets. Similar to [40], we used : MEN [4], for word similarity; and SimVerb [15], for verb similarity. We compiled the spearman rank-order correlation coefficients in table 4.2. According to this, continuous GloVe vectors are grouped by their meaning significantly more than the other methods. One caveat is that they require $\approx 200$ times more memory (assuming 4 bytes floating point numbers) than our work. To see if this performance was due to their higher precision, we compressed them to 256 bits using the same method previously explained. The results were really close to the originals ${ }^{2}$, meaning the training methodology has more importance. At 40 bits, our work is better than compressed GloVe. A quick qualitative evaluation of the neighbors of the verb eat and its inflections in table 4.1 seems to indicate that the opposite was expected. From common knowledge, eaten, meal, lunch and eating are more related to the verb eat than fly, choose, explode and steal. Although, this only takes into account the word itself. If we consider the context in which the word might appear, these grammatical properties speak to the semantics of that context. Whether I eat or I am eating has different meaning when considering the sentences in which each would be present. At no point is character-level information provided to our model, meaning this apparent correlation with the morphology of nearest neighbors is the manifestation of a common semantic marker. In consequence, our view of what a sememe might represent might have been too narrow. Another factor we considered is that the low dimensionality of our embeddings forces the model to learn features as a combination of multiple bits. By only looking at the hamming distance, the closest neighbors will have most of the same bits, hence most of the same features. Assuming the model makes a distinction between

[^6]|  | computer | computers | eat | ate | eats | eating |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| This Work | laptop mainframe competency workstation graphical webcam pc space computing microphone smartphone competency macro encryption programming | hardware <br> printers <br> laptops <br> gadgets <br> processors <br> workstations <br> plugins <br> cpus <br> calculators <br> apps <br> notebooks <br> drinks <br> ipad <br> modules <br> machines | fly choose explode steal enjoy skim smelled mew dat birthdays lili crave breathe infect consume | bathed whistled <br> chattered hid woke simmered palmed craved paled imagined consumed searched toasted clapped retorts | stirs sucks <br> dissolves treats clears withdraws fills fakes ignores stings lowers begs assembles distinguishes shrugs | watering chewing hoarding feeding drinking smoking tagging pruning packing roasting cooking healthy nesting washing hatching |
| $\frac{\text { Compressed }}{\underline{\text { GloVe }}}$ | laboratory lab labs web <br> handled <br> laboratories <br> telephone console software computing processing devices modeling controlling electronic | database <br> modules <br> software <br> computing <br> labs <br> simulation <br> electronics <br> automated <br> input <br> user <br> micro <br> simpler <br> interface <br> environments feedback | eaten <br> meal <br> lunch <br> eating <br> meat <br> bread <br> potatoes <br> soup <br> biscuits <br> happened <br> drink <br> beef <br> sauce <br> chewing <br> hungry | drink <br> dressed <br> hang <br> fancy <br> drank <br> quietly <br> smiled <br> meal <br> stuck <br> eyed <br> drinks <br> mouthed <br> glance <br> sight <br> clothes | mashed tart jerky spiced sweets garlic gravy iced spaghetti rooster biscuits morgue sunflower rhiannon donut | meal <br> chasing <br> cooking <br> eat <br> meat <br> believe <br> eats <br> soup <br> dishes <br> eaten <br> chewing <br> sour <br> ate <br> food <br> lunch |
| GloVe | computers software computing technology electronic electronics systems <br> lab <br> digital <br> user <br> hardware internet data information ibm | computer software computing devices hardware systems ibm laptops machines mainframe desktop interface laptop pc electronics | eating ate eaten meal hungry food bite meat eats bread cooked breakfast chicken drink dinner | eat meal eaten eating drank hungry cooked delicious sandwiches breakfast bite bread chewed lunch wandered | consumes <br> eat <br> sleeps eaten feeds bites eating consume forgets ate cleans tosses hates drags sucks | eat ate eaten meal food meat hungry feeding bite cooked chicken drink consumed diet drinking |

Table 4.1. Five words and their 15 closest neighbors in ascending order of hamming distance for this work and for binary embeddings of the same dimension obtained by compressing pretrained GloVe continuous embeddings. The 15 closest words based on cosine similarity are also included using our trained GloVe embeddings.
grammatical and semantical properties, then encoding grammatical features might require more information, so the closest words are more likely to have these same features, explaining the apparent emphasis on morphological similarities over semantic ones. It is hard to say from these preleminary results only if the model makes this distinction or if grammatical properties can actually be mapped to semantical units. Either way, our conclusion from this is that this distance measure might not be optimal to properly understand and evaluate the relations that were learned. We tried several similarity and distance measures from [6], but the results didn't differ in any meaningful way (see table 4.4), which also supports our multi-bit encoding hypothesis. We also present more in depth experimentations based on this in section 4.2.

Even with a constrained embedding width, our model was able to learn more complex features than simply compressing from a good pre-trained model. Seeing how even compressed at 256 bits GloVe manages to still encode better semantic information, pushing the number of bits in our embeddings higher might greatly improve their quality. It would also still require significantly less memory compared to continuous vectors with the same number of dimensions. Their binary nature would make computations faster, but it would also allow the use of hardware acceleration by using vector instructions ${ }^{3}$ [40]. This avenue and the use of a potentially better distance measure is left for future work.

| Dataset |  | This work | GloVe - Bin | GloVe - Con | GloVe - Bin |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Name | Coverage | (40 bits) | $(40 \mathrm{bits})$ | $(256 \mathrm{dim})$. | $(256 \mathrm{bits})$ |
| MEN | $99.0 \%$ | 53.9 | 48.2 | $\mathbf{7 3 . 8}$ | 71.6 |
| SimVerb | $94.0 \%$ | 12.8 | 5.6 | $\mathbf{1 6 . 6}$ | 15.6 |

Table 4.2. Spearman rank-order correlation coefficient for the word similarity dataset MEN [4] and for the verb similarity dataset SimVerb [15]. Since we limit our vocabulary to 50k, we include the coverage of the dataset. If either word in a pair is unknown, we ignore it. The 256 bits version of the compressed GloVe embeddings were trained similarly to the 40 bits version.

### 4.1.2. Unsupervised Clustering

The second qualitative evaluation we did was to cluster our results to have a broader view of how our latent space behaved. To do so, we used $k$-Modes [18], an extension of the popular $k$-Means algorithm that more adequately clusters categorical values. We used 300 clusters with 12 random initializations ${ }^{4}$. This amount of clusters was chosen to obtain easily

[^7]interpretable word lists although it leads to some redundancy. Some are showed in table 4.3. Again, they seem to be predominantly grouped around a specific grammatical property. Cluster 7 contains adverbs; 16 the present participle inflection of verbs; 18 the third person inflection of verbs; 44 the past inflection of verbs; 55 the plural form of nouns; and 108 different adjectives. Semantic similarities are still present. In cluster 55, the words all seem to pertain to the concept of buildings or structures in particular. Similar behaviour can also be observed for names, years, integers and floating point numbers. The same conclusions as in 4.1.1 can be made regarding the interpretation of this behaviour and how this apparent grammatical clustering might relate to semantics.

| Clusters |  |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 6 | 7 | 16 | 18 | 31 | 37 | 44 | 55 | 119 | 180 |
| classical | brilliantly | sending | proclaims | revisit | 12.8 | went | walls | 69 | 90th |
| representational | moderately | discarding | expects | uncover | 15.7 | signaled | gates | 59 | 81st |
| esoteric | somewhat | retrieving | interprets | bestow | 11.9 | changed | pillars | 47 | 74th |
| meditative | largely | delivering | observes | clarify | 16.7 | came | rooftops | 43 | 80th |
| hindustani | predominantly | relinquishing | relates | discuss | 19.8 | boomed | panels | 54 | 75th |
| medieval | uniformly | disregarding | proves | recreate | 13.1 | reverted | shelves | 56 | 39th |
| rabbinic | remarkably | interrogating | resembles | criticise | 5.2 | hacked | façades | 105 | 46th |
| utilitarian | characteristically | locating | recalls | contemplate | 23.3 | transferred | headstones | 58 | 87th |
| symbolist | vastly | executing | ceases | rehearse | 20.1 | ventured | columns | 62 | 30th |
| gothic | tremendously | revising | inspires | acknowledge | 18.8 | continued | beams | 159 | eighteenth |
| dialectic | noticeably | holding | resumes | applaud | 19.2 | proceeded | spheres | 103 | 48th |
| renaissance | undeniably | exercising | declares | awaken | 12.0 | ensues | eaves | 102 | seventeenth |
| rococo | perfectly | halting | mimics | remember | 8.3 | offered | hangings | 76 | 55th |
| symbolic | universally | inciting | foresaw | rearrange | 22.2 | transitioned | mists | 61 | 84th |
| egalitarian | hitherto | examining | begs | criticize | 19.5 | switched | fundamentals | 202 | 49th |
| cubist | proportionally | boosting | believes | ignore | 9.5 | flipped | lamps | 107 | 91st |
| confucian | doubly | protecting | confirms | imitate | 14.1 | strayed | ramparts | 57 | 67th |
| contemplative | uniquely | assigning | applies | appreciate | 9.6 | redirected | doorways | 53 | 25th |
| alchemical | comparatively | compensating | succeeds | discern | 9.8 | forwarded | marbles | 66 | twentieth |
| literary | virtually | securing | explains | conceal | 23.5 | beckoned | rings | 46 | 10th |
| sociological | highly | pursuing | pretends | reunite | 12.4 | shifted | strata | 51 | 50th |
| contemporary | less | propelling | dislikes | broaden | 12.1 | presented | runes | 77 | 41st |
| pedagogical | strikingly | forging | absorbs | confirm | 12.2 | agreed | shards | 127 | 70th |
| postcolonial | wonderfully | investigating | acknowledges | illustrate | 0.50 | conveyed | panelling | 52 | fifteenth |
| pictorial | decidedly | renewing | favours | amus | 17.0 | amounted | facies | 119 | 61st |
| neoclassical | oddly | dialing | attaches | reject | 6.8 | appealed | molars | 452 | 37th |
| bureaucratic | distinctly | choosing | arises | avert | 23.7 | agreeing | shackles | 366 | 59th |
| patriarchal | finely | removing | contends | confide | 17.8 | consigned | perils | 291 | 36th |
| humanistic | densely | extracting | feels | forestall | 25.1 | returned | bricks | 205 | 60th |
| linguistic | nicely | hoisting | thinks | offend | 22.7 | turned | stacks | 168 | 40th |
| italic | reasonably | spurring | settles | compose | 19.3 | reacted | papyrus | 183 | 31st |
| gregorian | mildly | surrendering | resolves | indulge | 18.4 | vanished | corridors | 483 | 64th |
| secular | hugely | seizing | emerges | absorb | 21.9 | confined | moons | 492 | 65th |
| sentimental | infinitely | resisting | considers | improvise | 18.3 | declined | torches | 471 | 79th |
| psychoanalytic | sufficiently | sealing | presents | rethink | 8.4 | inserted | slabs | 419 | twelfth |
| monumental | excessively | installing | merges | recognise | 32.8 | rang | bulkheads | 522 | 32 nd |
| poetic | mathematically | taking | asserts | explore | 8.6 | confessed | gables | 384 | 27th |
| pentecostal | marginally | lifting | renders | forgo | 24.5 | paused | vents | 326 | 88th |
| realist | vividly | constructing | precedes | portray | 8.7 | communicated | partitions | 209 | 22nd |

Table 4.3. Subset of 10 word clusters taken from the 300 computed using $k$-Modes. The chosen 40 words for each are in ascending order of hamming distance from the centroid of their respective cluster.


### 4.2. Relations in Bit Differences

Part of our goal was to achieve interpretability. To see if any concepts could easily be linked to learnt features, we examined how bits differed between embeddings of words with known properties. Semi-automatic word lists were built (see appendix A) around these four inflections : plurals, past, third person and present participle. Another similar experiment was done with a manual list of 27 countries and their associated nationality. Then, for each of these lists, we used a bitwise XOR between the embeddings of each word pair and summed the results to get the probability of each bit to be different. We did this process with our embeddings and with the compressed GloVe embeddings from 4.1.1 as a comparative. In 4.2.1, we explain how certain patterns emerged and in 4.2 .2 we explore the interpretability of these patterns.

### 4.2.1. Emergence of patterns

Our assumption was that if a feature has a high probability to differ between words with a known property (e.g. past inflection), then it must be indicative of this property. Using our vectors, we looked at the probabilities of bit being different for the five word lists. In all five cases, unique sets of bits seem to expose the desired property. Figure 4.1 shows that about 6 bits have a high chance of changing between a singular word to a plural word. From our assumption, this means that the concept of plurality would be encoded using these 6 bits by the model. Similarly for past inflections, figure 4.2 shows that at least 8 bits are strongly involved. For present participle inflections, figure 4.3 also shows at least 8 bits are involved. This phenomenon is not as evident for the third person inflections, but from figure 4.4 we can see at least 4 significant bits. As for the countries and their nationality, figure 4.5 shows that 4 bits are heavily involved and 5 are not involved at all. Bits that always stay the same could aslo be indicative of a property, but we leave this for future work. Our compressed GloVe embeddings do not seem to capture the same relations. In all of the cases, except maybe for the nationalities, the probabilities are very similar. If we look at the standard deviation (see table 4.5), we can see that for the compressed version there is an average of $5.6 \%$ deviation from the mean as opposed to an average deviation of $15.2 \%$ for our work. In other words, from our representation, we can observe that some bits either have a significant chance to differ for a relation or a significant chance to be the same. This can't be concluded for the compressed GloVe embeddings. This correlates with the nearest neighbors experiments (see 4.1) where grammatical features seemed to be encoded. These sets of bit could be considered as semantic morphemes, i.e., they seem to be indicators of common meaning modifiers. See appendix B for the un-ordered version of the probabilities to see exactly which bits are more involved. These results only indicate that certain patterns are exposed. In the next section, we try to gain insight on potential practical applications for them.

Sorted bit difference probabilities between nouns in their base form and plural form


Fig. 4.1. The ordered probabilities of a certain bit being different between the embedding of the base form of a noun and the embedding of its plural form. A semi-automatic list of 4948 nouns present in the vocabulary was used (see appendix A.1.1). Here the ordered bits do not necessarily match between both techniques (see appendix B. 1 for an unordered version of this graph).

Sorted bit difference probabilities between verbs in their base form and past form


Fig. 4.2. The ordered probabilities of a certain bit being different between the embedding of the base form of a verb and the embedding of its past form. A semi-automatic list of 1638 verbs present in the vocabulary was used (see appendix A.1.2). Here the ordered bits do not necessarily match between both techniques (see appendix B. 2 for an unordered version of this graph).

Sorted bit difference probabilities between verbs in their base form and p.p. form


Fig. 4.3. The ordered probabilities of a certain bit being different between the embedding of the base form of a verb and the embedding of its present participle form. A semi-automatic list of 1366 verbs present in the vocabulary was used (see appendix A.1.3). Here the ordered bits do not necessarily match between both techniques (see appendix B. 3 for an unordered version of this graph).

Sorted bit difference probabilities between verbs in their base form and 3rd person form


Fig. 4.4. The ordered probabilities of a certain bit being different between the embedding of the base form of a verb and the embedding of its third person form. A semi-automatic list of 934 verbs present in the vocabulary was used (see appendix A.1.4). Here the ordered bits do not necessarily match between both techniques (see appendix B. 3 for an unordered version of this graph).

Sorted bit difference probabilities between countries and associated nationalities


Fig. 4.5. The ordered probabilities of a certain bit being different between the embedding of a country and the embedding of its associated nationality. A manual list of 27 countries present in the vocabulary was used (see appendix A.2.1). Here the ordered bits do not necessarily match between both techniques (see appendix B. 5 for an unordered version of this graph).

| Bit diff. probabilities | Standard Deviation |  |
| :--- | :---: | :---: |
|  | This Work | Comp. GloVe |
| Base $\leftrightarrow$ Plural | 0.1084 | 0.0283 |
| Base $\leftrightarrow$ Past | 0.1309 | 0.0287 |
| Base $\leftrightarrow$ P.P. | 0.1428 | 0.0253 |
| Base $\leftrightarrow 3 . P$. | 0.1208 | 0.0543 |
| Country $\leftrightarrow$ Nationality | 0.2583 | 0.1420 |

Table 4.5. Standard deviation in the bit difference probabilities for our embeddings and the compressed GloVe embeddings from 4.1.1.

### 4.2.2. Interpretability

In our motivation, we mentionned how we believed the representation of a word should ideally be mostly the same between its root and its inflected forms. We also argued that using morphology is not appropriate to achieve this. It was established that certain bit patterns seem to encode semantical properties, which points to this behaviour having been learned by the model without explicit tokenization (e.g. cats split into cat $\cdot s$ ). To try to confirm this conjecture, we first took the 10 bits $^{5}$ that were most likely to be different for a

[^8]specific word list (e.g. for singular to plural, figure B. 1 shows these to be: 26, 7, 17, $\ldots, 11$ ). For each of these bits, we computed the probability that it flipped to 1 and the probability that it flipped to 0 . If the probability of flipping to a 1 was bigger, we assumed we must force this specific bit to 1 to represent the property (e.g. plurality). The opposite process was applied if the probability of flipping to 0 was bigger. We then took the embedding of the base form of a word and modified it by forcing the 10 bits pattern we just computed and leaving the other 30 bits untouched. We did not simply flip the bits blindly. An example of this is again for singular to plural, when bit 26 is flipped, it is most likely flipped to a one. If the embedding we are modifying already has a 1 for this bit position, it will not be flipped to a 0 , it will stay the same.

The closest neighbors for these adjusted embeddings were then computed using the hamming distance. Results are presented for plurality in table 4.6 and for present participle in 4.7. The results are similar for the other inflections. In both cases, the closest words of the adjusted representation expose the desired property, but the neighborhood is not close to the expected neighborhood, that is to say simply adjusting the base embedding does not yield the inflected embedding. Lets assume the bit patterns represent our proposed sememe formulation. Each pattern is considered as a single semantic unit in this asusmption, thus forcing this pattern on an embedding is comparable to altering part of the latent meaning of a word. Both the car and the eat examples validate this. By analyzing the nearest neighbors of the adjusted embeddings, all the related words expose the desired semantical characteristic. The adjusted vector for car seems to be closer to the actual vector of cars compared to eat and eating. This correlates with the neighborhoods in table 4.1 where the nouns computer and computers were closer to word semantically similar to them individually and where the verb eat and its inflected forms seemed to be closer to words sharing more of a contextual semantic similarity. This goes to show that the separation between what we consider to be latent basic units of meaning is not as well-defined as we would have hoped, but they are present. This supports our earlier hypothesis that features are encoded as multiple bits, hence navigating the latent space is not trivial. As in 4.1.1, it also hints that a bigger vector size might have a big impact. Bigger and smaller embeddings were tried, but no results seemed to encode as much information as this configuration (which was chosen arbitrarily). Since tuning the hyper-parameters for our implementation was relatively difficult, we focused on analyzing these good results to understand what the model was learning and we let the exploration of different dimensionalities and the extraction of discrete latent units for future work.

| car |  | car (adjusted) |  | cars |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Relation | H.D. | Relation | H.D. | Relation | H.D |
| car | 0 | envelopes | 4 | cars | 0 |
| truck | 3 | tires | 5 | automobiles | 1 |
| suv | 3 | accessories | 5 | trucks | 2 |
| pickup | 4 | suvs | 5 | motorcycles | 3 |
| brake | 4 | dials | 5 | scooters | 3 |
| luggage | 4 | pallets | 6 | electronics | 4 |
| hovercraft | 4 | handguns | 6 | vehicles | 4 |
| motor | 4 | cables | 6 | bikes | 4 |
| vehicle | 4 | machines | 6 | machines | 4 |
| tractor | 5 | bumpers | 6 | elevators | 4 |
| wagon | 5 | wheels | 6 | streetcars | 5 |
| drugstore | 5 | strips | 6 | cabs | 5 |
| motorcycle | 5 | wires | 6 | accessories | 5 |
| shotgun | 5 | stickers | 6 | tires | 5 |
| windshield | 6 | vendors | 6 | tractors | 5 |

Table 4.6. Lists of closest words based on their hamming distance (H.D.). The middle column represents the base form embedding adjusted with the computed 10 bits pattern representing the plurality feature.

| eat |  |  | eat (adjusted) |  |  | eating |  |
| :--- | :---: | :--- | :--- | :---: | :--- | :--- | :--- |
| Relation | H.D. |  | Relation | H.D. |  | Relation | H.D |
|  | eat | 0 |  | modifying | 5 |  | eating |
| eat | 0 |  |  |  |  |  |  |
| ly | 6 |  | selecting | 5 |  | watering | 2 |
| choose | 6 |  | dispatching | 5 |  | chewing | 3 |
| explode | 7 |  | encountering | 5 |  | hoarding | 3 |
| steal | 7 |  | including | 5 | feeding | 4 |  |
| enjoy | 7 |  | intercepting | 5 |  | drinking | 4 |
| skim | 8 | possessing | 5 |  | smoking | 4 |  |
| smelled | 8 | affording | 5 |  | tagging | 5 |  |
| mew | 8 |  | capturing | 6 | pruning | 5 |  |
| dat | 8 |  | evading | 6 | packing | 5 |  |
| birthdays | 8 |  | destroying | 6 |  | roasting | 5 |
| lili | 8 |  | eliminating | 6 |  | cooking | 5 |
| crave | 8 |  | transporting | 6 |  | healthy | 5 |
| breathe | 8 | inspecting | 6 | nesting | 5 |  |  |
| infect | 8 |  | accessing | 6 | washing | 5 |  |

Table 4.7. Lists of closest words based on their hamming distance (H.D.). The middle column represents the base form embedding adjusted with the computed 10 bits pattern representing the present participle feature.

### 4.3. Generalization

As explained in 3.3.1, we limited our vocabulary to the 50,000 most frequent words. This only represents $0.5 \%$ of the whole training corpus vocabulary. This is a limiting factor if we want to use the embeddings in any downstream task. Assuming the model has a good grasp on the relations between words, we should be able to collect windows for unknown words and generate a new embedding. We can take advantage of the fact that we defined our training methodology as a matching problem between the middle words (i.e. the embeddings) and their surrounding context. By processing these new contexts with our trained model, we obtain a latent representation that matches the representation that the new middle word should have. This flexibility gives our work a lot of potential. Embeddings could be generated on new corpora with a lot of emerging words (e.g. sup for what's up). Technical and rare words could get comparable embeddings by gathering a few context windows to facilitate their understanding. Another application could be the easy identification of unknown named entities by training a classifier based on the binary embeddings. These are currently only conjectures and further reasearch would need to be done, but the results that we will present are favorable to these practical applications.

Formally, like the training phase, we collected windows of 51 words in a new corpus and then we used $f_{\theta}^{D}$ (fig. 3.1) to get a representation for each window. We averaged all the computed latent vectors for a single word and then applied a hard threshold (see eq. 3.2.2) to get the final binary representation. The source corpus was the complete SimpleWiki dump of September 20th $2020^{6}$ and only the unknown words with at least 10 windows were kept. The same text preprocessing as in 3.3.1 has been used. We processed the words in descending order of their windows count. As soon as an embedding was computed, the word was now considered known, which meant that if it appeared in the context of any subsequent word to process, its new representation was used instead of the $<u n k>$ token's embedding.

In table 4.8, we can see that the model is able to generate new embeddings that are related to similar words. We observed that new words tend to have a neighborhood composed of mostly other new words. Same thing for the words used in the original vocabulary (e.g. covid19, evaporates, canadian and updated). This is not a problem, since the closest words are still semantically related. In some cases (e.g. broadcasted and tables), the new words integrate seamlessly into the already existing vocabulary. This makes our idea of translating to a language independent representation really promising and further supports our observations on the seemingly presence of latent discrete units of meaning. The words evaporates and platypus are examples of predicted representations collapsing to the same vector. This could be explained as the model not being precise enough, hence requiring more capacity, but even

[^9]| covid-19 | (1293 win.) |  | evaporates | (61 win.) |  | $\begin{gathered} \hline \text { broadcasted } \\ \hline \text { Relation } \end{gathered}$ | (46 win.) |  | platypus <br> Relation | (74 win.) |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Relation | H.D. | New |  | H.D. | New |  | H.D. | New |  | H.D. | New |
| leukaemia | 3 | $\checkmark$ | hardens | 0 | $\checkmark$ | screened | 5 |  | seahorse | 0 | $\checkmark$ |
| ebola | 3 |  | collides | 2 | $\checkmark$ | play | 5 |  | ibises | 0 | $\checkmark$ |
| hcv | 4 | $\checkmark$ | hibernates | 2 | $\checkmark$ | performed | 5 |  | artiodactyls | 0 | $\checkmark$ |
| barbiturates | 4 | $\checkmark$ | circulates | 2 | $\checkmark$ | spawned | 6 |  | tapir | 0 | $\checkmark$ |
| lsd | 4 |  | condenses | 2 | $\checkmark$ | filmed | 6 |  | cassowary | 0 | $\checkmark$ |
| eas | 4 |  | diffuses | 3 | $\checkmark$ | redone | 6 |  | peafowl | 1 | $\checkmark$ |
| rubella | 4 | $\checkmark$ | ejaculates | 3 | $\checkmark$ | produced | 6 |  | marsupial | 1 | $\checkmark$ |
| dbs | 5 | $\checkmark$ | dries | 3 |  | choreographed | 6 |  | mastiff | 1 | $\checkmark$ |
| gsr | 5 | $\checkmark$ | melts | 3 |  | arranged | 6 |  | bullfrog | 1 | $\checkmark$ |
| ivf | 5 |  | germinates | 3 | $\checkmark$ | commenting | 6 |  | orangutan | 1 | $\checkmark$ |
| flu | 5 |  | corrodes | 4 | $\checkmark$ | streamed | 6 |  | dhole | 1 | $\checkmark$ |
| mortality | 5 |  | preys | 4 | $\checkmark$ | sung | 6 |  | ornithischia | 1 | $\checkmark$ |
| rhinovirus | 5 | $\checkmark$ | chews | 4 | $\checkmark$ | sang | 6 |  | dugong | 1 | $\checkmark$ |
| beeswax | 5 | $\checkmark$ | vibrates | 4 | $\checkmark$ | serialization | 6 |  | honeyeater | 1 | $\checkmark$ |
| suffocation | 5 | $\checkmark$ | dissolves | 4 |  | scripted | 6 |  | quokka | 1 | $\checkmark$ |
| table |  |  | cana | dian |  | updat |  |  | do |  |  |
| Relation | H.D. | New | Relation | H.D. | New | Relation | H.D. | New | Relation | H.D. | New |
| staves | 3 | $\checkmark$ | australian | 4 |  | facelifted | 2 | $\checkmark$ | labradoodle | 3 | $\checkmark$ |
| accompaniments | 4 | $\checkmark$ | norwegian | 5 |  | discontinued | 5 |  | toddler | 3 |  |
| slots | 4 |  | tasmanian | 5 |  | restarted | 5 |  | hound | 3 |  |
| booths | 4 |  | gambian | 6 |  | overhauled | 5 |  | dachshund | 3 | $\checkmark$ |
| hangings | 4 |  | banff | 6 |  | serviced | 5 |  | horseman | 3 |  |
| frets | 4 | $\checkmark$ | fivb | 6 |  | ported | 5 |  | sheepdog | 3 | $\checkmark$ |
| settings | 4 |  | faroese | 6 |  | trademarked | 5 |  | goat | 3 |  |
| columns | 5 |  | tiwi | 6 | $\checkmark$ | configured | 5 |  | shorthair | 3 | $\checkmark$ |
| wristbands | 5 | $\checkmark$ | estonian | 6 |  | reopened | 5 |  | whale | 4 |  |
| files | 5 |  | soweto | 6 |  | shipped | 6 |  | bobtail | 4 | $\checkmark$ |
| shelves | 5 |  | cbc | 6 |  | available | 6 |  | lop | 4 | $\checkmark$ |
| whiteboards | 5 | $\checkmark$ | kenyan | 6 |  | retrofitted | 6 |  | thylacine | 4 | $\checkmark$ |
| scopes | 5 |  | zimbabwean | 6 |  | 07 | 6 |  | elephant | 4 |  |
| imprints | 5 |  | swedish | 6 |  | resold | 6 |  | sylph | 4 | $\checkmark$ |
| polonaises | 5 | $\checkmark$ | batavian | 6 |  | deprecated | 6 |  | squirrel | 4 |  |

Table 4.8. Lists of closest words based on their hamming distance (H.D.). The top row are words that were computed from new windows from SimpleWiki with the amount of windows used. The bottom row are words that were already in the vocabulary. The New column indicates whether the word was added from SimpleWiki or not.
this constrained model does not suffer significantly from this problem. In table 4.9, we also show that the amount of windows used does not need to be important. Even with only 10 windows to generate their embedding, the first three of these examples manage to have a representation that is related to other entities with similar properties. However, a problem appears when we look at the new word s10. To put in context, this refers to the Galaxy S10 phone from Samsung. From the closest neighbors, we can see that the model focuses on both galaxy (e.g. hipparcos, extrasolar, eon) and s10/samsung (e.g. s5, s6, s12). The small amount of windows makes it hard for the model to make the distinction. Although we mention this as a problem, it is hard to really affirm that it is an unwanted behaviour. It seems our method uses adequate language cues to produce proper embeddings. Also, from
our discussion in section 4.1.1, the hamming distance might not fully represent the quality of the learned features. Further research should be done to better understand the relations captured by the model and to see if the generalization is in fact adequate.

| dinghies | (10 win.) |  | rockhole | (10 win.) |  | memoirist | (10 win.) |  | s10 | (10 win.) |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Relation | H.D. | New | Relation | H.D. | New | Relation | H.D. | New | Relation | H.D. | New |
| competitors | 3 |  | liana | 4 | $\checkmark$ | sexologist | 2 | $\checkmark$ | s5 | 2 | $\checkmark$ |
| belts | 5 |  | solanaceae | 4 | $\checkmark$ | ethnologist | 3 | $\checkmark$ | hipparcos | 3 | $\checkmark$ |
| podiums | 5 |  | protea | 4 | $\checkmark$ | humorist | 3 |  | extrasolar | 4 | $\checkmark$ |
| snowboarders | 5 | $\checkmark$ | frog | 4 |  | ethnographer | 4 | $\checkmark$ | 1987a | 4 | $\checkmark$ |
| floats | 5 |  | ruminant | 4 | $\checkmark$ | logician | 4 | $\checkmark$ | eon | 4 |  |
| substitutes | 5 |  | goat | 5 |  | japanologist | 4 | $\checkmark$ | s6 | 4 | $\checkmark$ |
| darts | 5 |  | gracilis | 5 |  | caricaturist | 4 | $\checkmark$ | s12 | 4 | $\checkmark$ |
| favourites | 5 |  | cappella | 5 |  | moviemaker | 4 | $\checkmark$ | extragalactic | 4 | $\checkmark$ |
| racers | 5 |  | mimosa | 5 | $\checkmark$ | frontiersman | 4 | $\checkmark$ | f4 | 4 |  |
| openers | 5 |  | prostitute | 5 |  | neuroscientist | 5 | $\checkmark$ | quasar | 4 |  |
| kayaks | 6 |  | jacaranda | 5 | $\checkmark$ | grammarian | 5 | $\checkmark$ | animated | 4 |  |
| spots | 6 |  | subtribe | 5 | $\checkmark$ | comedienne | 5 | $\checkmark$ | hikari | 4 | $\checkmark$ |
| sleds | 6 | $\checkmark$ | toddler | 5 |  | neurobiologist | 5 | $\checkmark$ | pulsar | 4 |  |
| gunsmiths | 6 | $\checkmark$ | sophora | 5 | $\checkmark$ | speechwriter | 5 | $\checkmark$ | f2 | 5 |  |
| mmorpgs | 6 | $\checkmark$ | amborella | 5 | $\checkmark$ | bureaucrat | 5 |  | antares | 5 | $\checkmark$ |

Table 4.9. Lists of closest words based on their hamming distance (H.D.) for new words from SimpleWiki with a limited amount of windows. The New column indicates whether the word was added from SimpleWiki or not.

### 4.4. Learned Bit Templates

In 4.1, it was established that similar words are close in embedding space, but no specific bit patterns were found that we could associate to a specific known concept. From our results in 4.2 , we got the intuition that maybe some exist, but that they are not as explicit as we would have hoped. To confirm this, in 4.4.1 we try to identify bit templates from manual lists of words we judged similar (e.g. months of the year) and in 4.4.2 we try to identify bit templates by training a classifier on WordNet lexical categories.

### 4.4.1. From Manual Word Lists

The first technique we used was more systematic. We manually built lists of words we judged related to a common concept (e.g. months of the year). Then, from the embeddings in these lists, we computed the entropy for each bit position. We extracted a bit template by adding bits in ascending order of entropy. Each time we added a feature, we built a list of words matching the template exactly. We repeated this procedure until the group of words was mostly related to the desired concept.

Table 4.10 contains some of these concepts we were able to associate to a specific template. The resulting groups do not necessarily contain all possible related words from the
vocabulary. Some interesting phenomenons can be observed. One is that all the months can be identified by a single template. This is important as it means this model has the potential to provide embeddings with humanly recognizable features. Another is that most of these groups represent their associated concept really well. Almost no unrelated words are present as the ones that we consider inadequate is relative to our judgment (e.g. in the Movie Directors word group, all the names in bold are not directly linked to the label we gave it but they still had a role in cinema or television). These results prove to be promising although they affirm our doubt about the unexpected complexity of our latent representations as previously stated.

### 4.4.2. From WordNet Lexical Groups

The second technique we used to learn bit templates is more flexible. We used the fact that WordNet categorizes all the words by their different POS and meaning (see appendix C.2). This allowed us to train a model to predict the possible categories for a word based only on its binary embedding.

We first extracted all the words from our vocabulary that could be associated with at least one category from WordNet (see appendix D). Then we converted our embeddings to contain values in $\{-1,1\}$ instead of $\{0,1\}$. This gave an equal importance to the absence of a bit. The inputs were the adjusted embeddings $E \in\{-1,1\}^{k}$, where k is the embedding size, and the outputs were Multi-Bernouilli ${ }^{7}$ vectors $C \in[0,1]^{l}$, where $l$ is the number of categories. Each $C_{i}, i \in\{1,2, \ldots, l\}$ represents the probability of a word belonging to the i-th WordNet category. In this experiment, we assumed a $100 \%$ probability if the word could be matched, otherwise $0 \%$. Consequently, $C$ is equivalent to a binary vector. We trained a single layer feed-forward network with a sigmoid output that we paired with a Binary Cross Entropy loss. Using Adam as the optimizer with an initial learning rate of 0.0001, we trained until convergence, reducing the learning rate by a factor of 10 every 100 steps without improvement. No regularization was used. The results were the weight matrix $W \in \mathbb{R}^{k \times l}$, where each row represented the influence of a bit for predicting a particular cartegory, and the bias terms $b \in \mathbb{R}^{l}$, which we ignored for interpretation. With more data, we could have empirical estimates for $C$, which would more accurately weight a bit in relation to each category. This is left for future work.

The adjustment performed on the input allowed us to consider positive values in $W$ to favor the presence of a bit (i.e. translates to a 1) and negative values to favor the absence of a bit (i.e. translates to a 0 ). For each row, we sorted in descending order each element by their absolute value. Starting by the bit that had the biggest influence, we gradually added bits to our template based on their sign until the amount of words ${ }^{8}$ with an embedding matching

[^10]| Concept | Words Following the Template |
| :--- | :--- |
| Months | may march september january june october july august april november december february |
| Uncountable | water oil coffee wine snow sand sugar rice meat cotton corn powder wheat livestock beef <br> lumber liquor tar malaria foam munitions opium barley mosquito dynamite vodka steak <br> mustard sausage sugarcane popcorn groceries cabbage vinegar biscuit sunflower hemp <br> firewood fumes kerosene geiger lettuce manure snowball mussels tanning molasses <br> harvester moonshine guano tofu veal creams lard nightshade walnuts scurvy slush blackouts |
|  | director wife artist writer firm teacher agent engineer poet painter actors soldier ceo critic <br> producers merchant reporter expert businessman citizen girlfriend worker physician farmer <br> widow lover employee specialist photographer servant administrator monk instructor bride <br> sculptor researcher novelist entrepreneur explorer employer dealer mistress playwright <br> economist filmmaker educator screenwriter operative commentator sailor curator builder <br> contractor apprentice banker thief tutor illustrator seller psychologist troupe butcher |
| mechanic clown collaborator trader magician practitioner heroine salesman ensign |  |
| cartoonist prostitute examiner broker heiress gardener millionaire blacksmith geologist |  |
| navigator anthropologist traveler proprietor industrialist nanny biologist billionaire laird |  |
| traveller bully goldsmith tailor baroness squire seaman theorist foe classmate aviator |  |
| sociologist registrar dentist engraver magnate animator turk enthusiast prodigy robber |  |
| financier adventurer schoolteacher aristocrat essayist pharmacist tycoon dramatist |  |
| businesswoman publicist entomologist gambler strategist shoemaker overseer socialite |  |
| rancher coo storyteller midwife informer centurion forester archivist wanderer texan |  |
| horseman scotsman janitor custodian innovator dutchman sorceress housemate djinn |  |
| irishman gunslinger philologist statistician laborer assessor playmate grocer innkeeper |  |
| hairdresser journeyman cfo respondent delinquent postman yeoman draftsman sportscaster |  |
| retainer pundit prospector draughtsman restaurateur plumber sportswriter seamstress |  |
| ecologist villager zealander bookkeeper whaler realtor machinist pediatrician humorist |  |
| bureaucrat handyman shipbuilder colonist cto satirist conservator cobbler leaguer |  |
| watchmaker ophthalmologist newsreader educationist astrophysicist showman newscaster |  |
| egyptologist joiner |  |

Table 4.10. Word lists (ordered by corpus frequency) that contain a manually defined bit pattern associated with known concepts. The words that we deemed unrelated are in bold.
perfectly the current template was really low $(<30)$. This usually led to a very specific list of words related to the desired concept. To account for inaccuracies during training, we also relaxed the matching constraint to allow for a margin of $n$ bits of error (e.g. for a 6 bits template, we would consider embeddings having at least $6-n$ matched bits).

From the preliminary results in table $4.11,4.12$ and 4.13 , the same conclusion as in 4.4.1 can be made, which is that conceptual connections seem to be encoded in our embeddings, especially for nouns. One of our initial hypotheses for this work was that a word could be translated to a series of language independent sememes. Basically, the representation of a word would be based on units of meaning we call sememes rather than grammatical units. For these 3 example categories, different sememes seem to comprise the extracted templates. By allowing a certain margin of error in our matching, one or more of these sememes changes, but most of them stay the same, which in theory should change the meaning slightly while still essentially representing the same thing ${ }^{9}$. We say that one or more sememe changes because we did not experiment enough to affirm how many bits are used to represent each of these latent units (e.g. in section 4.2, it appears multiple bits are involved). Empirical observations follow this application of the theory. For noun.body, most of the words can be related to the human body (e.g. chest, lips), but some words refer to the body of an animal (e.g. shell, snout), which is still highly related to the template. For noun.animal, multiple aspects of this concept are matched like specific species (e.g. dog, wasp), food (e.g banana, chestnut, leaf) and location (e.g. sea, mariana ${ }^{10}$, marine). For noun.time, specific years are matched (e.g. 1707, 2010), different months (e.g. september, june, october), seasons (e.g. autumn, summer) and even actions often related to time or a time span (e.g. meal, prom, intermission).

We also did the same experiment with related verbs. The results are shown in table 4.14 and 4.15 . In both cases, the definition giving by WordNet is vague when looking at the words they categorize in these lexical groups (see appendices D. 4 and D.5), so we will evaluate the templates based on the category name as it seems to correlate better. If we look at the body related verbs, our pattern appears to be made up of sememes representing an action that could be done with our body. Obvious examples are shrug, grin, sneeze or spasm. More indirect examples could be : scare, by using your arm; knit, using your hands; or abduct, by carrying someone. Patterns learned for other verb groups were unfortunately not as relevant. One example is for verbs related to consumption. No interesting pattern emerges in the matching words. This could be caused by the ambiguity of the definition or simply because the amount of training words was low compared to other categories.

[^11]Margin Words fitting the template for noun.body:
$* 01 * 1 * * 011 * * 1 * * * * 1 * * * * 0 * 000 * 001 * * * * * * * * 1$

| 0 | jaw forearm |
| :---: | :---: |
| 1 | teeth cheek bone chin costa wrist spine fin thigh tooth abdomen snout torso calf paw nape $\mathrm{ni}^{* *}$ les thorax pelvis cartilage suture cytoplasm tibia ligaments vertebra ventricle epidermis sternum testicles humerus fibula callus |
| 2 | body lips chest shoulder neck finger tongue belt shell tail knee forehead muscle muscles skull hips tissue belly streak fork receptor eyebrow limbs tissues fingertips substrate limb cavity jaws aura posture $\mathrm{h}^{*}$ ps muzzle lashes lobe groin streaks colon insides ligament medial strides scalp sheath microscope hardness seam embryo paws $\mathrm{c}^{*}$ ck saliva eyelashes spindle tendon nipples vagina forearms biceps intestine collarbone strut forties gash allele uterus underparts $\mathrm{n}^{* *}$ ples forefinger moustache mandible rosette ovary femur fingertip carapace extremities hemoglobin chromatin cilia tendons acidity gums cheekbone columella atrophy colouration prefrontal ovaries bicep pouches $\mathrm{cl}^{*} \mathrm{t}$ reticulum fossa aorta ketone mucosa septum lamina pigmentation crustal dentition solute jawline umbilicus lithosphere follicle cuticle reuptake undersides armpit esophageal doublet orifice |

Table 4.11. Incremental list of words that fit the template within margin bits of error. By WordNet's definition, the template should represent : nouns denoting body parts. See appendix D. 2 for a list of words used for training.

For both the nouns and the verbs, potential human interpretable bit codes exist. By inspecting certain bit positions, it seems that it can be established whether a word represents a certain concept or not. It is clear that interpretability is better than any continuous counterpart, but again, more research needs to be done to better understand how features are exposed. With greater dimensionality, maybe a 1-to-1 relation could exist between a single bit and our proposed sememe unit.

Margin Words fitting the template for noun.animal:
**** $1 * 10 * * 0110 * * 01 * * 00 * 1 * * 0 * * * * 1 * 11 * * 101$
0 wasp sable gull vesper
sea dog y giant beetle snail mare turtle canary leopard moose pigeon elk dolphin camel
troll herring mosquito mammal mariana guillermo tuna rook antelope zebra grizzly pelican cyclops padre spiny kiwi kingfisher aster lemur tern algarve darter mako kestrel longbow coos vole cocos tricolor occidentalis amundsen humpback sancti
<unk> mountain males marine bear bird sub wolf douglas juan dragon ghost leaf volunteers muscle spider tiger warrior lion snake beast egg deer lance powder hawk frog raven fe cow dwarf snails jade scarlet whale kidney skeleton hector torch insect thief herd lizard shin predator banana chestnut worm verde feather hare capsule julio mole samurai stout ramon squirrel stallion mal axel sparrow myrtle alfredo toad viper wasps mace otter horseshoe flanks buff félix talon lynx scorpion ángel bony parrot heron paw cub yun jaya hen gall ryu mangrove gills trident pea fina eels saber robber stryker rocco newt rodent rodrigues surfer hiro bulldog cuckoo sunflower dung condor breeder tortoise salamander stag sturgeon ob whiting toddler sickle álvaro grasshopper elegans terrier puma dragonfly yew alonzo pygmy lichen pinkish martel rufous raptor woolly pixie pups nom rhinoceros kowalski cheetah keita ngāti falco conus amphibian otters stork hummingbird hoof sedge arrowhead niko starling rattlesnake sitter osprey jethro 2 simplex esperanza canis gazelle grouse phalanx j.r. albatross bunting hawkeye foal dill gunter harrier peralta melo thrush reiner pheasant banshee starfish miki trapper swordsman mueang burg tir ez mchugh bumblebee rhododendron petiole josep appleby chino gros cay weser coughlin grasshoppers toa scavenger walrus dorn corky pizarro grandes anemone bowser kenner mig mussel ficus homeworld gopher trapdoor mackerel trak haller rucker aran bobcat pitcairn posey taiga dingo alfalfa bachman iguana reptilian mallard emitter chia harpoon pumas parra aru palos orca catawba bivalve shredder plover nettle sagebrush neely tarantula ketone tycho tetrahedral testes kanda dimer cormorant ponderosa iceman japonica manatee armadillo feliciano gracilis hummingbirds zook maples último tartar hin merino griffon venter mino gantry yeager stanislas niebla adder hock bonin 100-metre gagarin flamingos karman matos putra a-1 lyase proboscis jäger limpets minnow bruiser roadrunners stingrays opossum arbuthnot lioness dimaggio parakeet camellia vermillion atacama 0.39 brahe lannister cormorants celestino riddick

Table 4.12. Incremental list of words that fit the template within margin bits of error. By WordNet's definition, the template should represent : nouns denoting animals. See appendix D. 1 for a list of words used for training.

| Margin | Words fitting the template for noun.time: |
| :---: | :--- |
|  | $* * * 10 * * 01 * * * 1 * 00 * * * 111 * * * * * * * 10 * * 0 * * * * * *$ |
| 0 | night summer previous morning wake occasions nights autumn easter daytime supper mornings midday |
| afternoons jeopardy millennia lunchtime jan. summertime $8: 30$ weeknight |  |

Table 4.13. Incremental list of words that fit the template within margin bits of error. By WordNet's definition, the template should represent : nouns denoting time and temporal relations. See appendix D. 3 for a list of words used for training.

## Margin Words fitting the template for verb.body: <br> * $010 * * * 0 * 0 * 0 * 1 * 0 * * * * * * * 1 * * 0 * * * * 001 * 01 * 1 *$

$0 \quad$ scare shrug absorb decipher inhale
gaze handle smell grin burn sigh reveal monitor punch hug cure dig heal glare temper gasp freeze wipe spill shiver expose moan consume chuckle rub smirk wink giggle gag wander summon verify conceal cough tease transplant stain scowl chew massage grunt murmur comprehend jolt vomit bandage boil implant undo confuse arenâ t prick grimace emit sniff conceive soak eradicate exhale yawn squeal ${ }^{* *}$ sy beep relish mourn unravel stun elicit mumble tickle impart underestimate yelp blindfold tempt annoy topple lurch clot scoot bellow meds cleanse divulge tantrum untie croak taint coughs confiscate gulping grumble brighten fasten sneeze stirs snore smother
'm feel sound smile phone review kill breath watch kiss, ve damn worry softly realize calm knife breathing smoke prove memories expect grip shake admit tape load stare mess bite laughter scream whisper tear sweat infection fix spare suffer smiles eyebrows healing solve wash possess bleeding dante facilitate pump embrace forgive beard stole snap idiot swallow thread squeeze frown whispers tattoo spray cries extract instinct spit adjust ache tasted curb groan depict suppress growl clutch orgasm slap headache lump distract jar invade calculate $\mathrm{c}^{* *} \mathrm{k}$ blush interrupt stab transmit rot calf slit tolerate sob sighs scarf toxicity eats choking grins donkey ecstasy twitch shudder hiss clit compliment furiously shrugs knit coughing caress tremble disclose gulped erase chuckles uncover reassure yank antibody chop i- reset scans flinch weave recreate provoke spoil stitch infiltrate ass**le addict workout pu**y moans gulp snort mutter imitate sling infect fling crank rattling shave restrain exert clutches poke symbolize shatter awaken

2 evoke stubble symbolizes growls caffeine clap puffed magically soothe discern twinkle clench wrench smear pry whimper pant liberate dictate ascertain contemplate delete appease invoke illuminate overload lessen slumber handshake graze wield sneer overwhelm juices disable wail expertly nibbled retort transfusion wailed throb deftly nudge apologise taunt wiggle avert perish flailing cellphone revulsion arse pout injure smirks undress slurred abort fetish replenish despise savor memorize dismantle dimple simmering dissipate rectify conjure edema bustle refill reap stupor spasm stiffen bothers deduce fingernail snag ailment squint banish rinse coax sew dispel humiliate conditioner oblige drool faucet hurl methodically befriend lotion beeped confide compress cramp $\mathrm{cl}^{*} \mathrm{t}$ blurt secrete implantation churn eject exhaling hasnâ t recycle ointment leer concoction wheezing ulcer crutch lightening snot â youâ ve startle skim abduct placate crushes err germinate cuddle heaviness contraceptives kneading earpiece irritate aundy negate withdraws appreciates know?â fart whoop holler twirl finalize puss supplementation unwind shudders broach squeals scold sharpen dampen reciprocate

Table 4.14. Incremental list of words that fit the template within margin bits of error. By WordNet's definition, the template should represent : verbs of grooming, dressing and bodily care. See appendix D. 4 for a list of words used for training.

| Margin | Words fitting the template for verb.consumption: |
| :---: | :--- |
|  | $* * * 0 * 0 * * * 0 * * * * * * * * * 1 * 0 * 1 * 0 * * * 1 * 0011 * 1 * 1 *$ |

have go want care food provide security trade hold try train pass reach pay trust walk vote horse watch share wind safety remain risk traffic save boat protect receive ' ve coffee trail shop pull express drink bear gain check buy sell maintain reduce poverty spend feed choose throw hide cook hunt waste smoke strip hat kick lift defend stick burn bet shower retreat mess swing deliver pitcher monitor blame bike slide encourage rope retain introduce recover navigation toll acquire rent generate lease steal prefer resist alert tide swim flee feast concentrate possess reward pump $f^{* *} k$ refuse ham buck divide wage harvest wrap crane tap submit cart sandwich recruit warn heal click flip boost drift pray grocery tire declare arrange canoe haul adjust dial blockade herd float wipe famine skate expose tub educate slice absorb weigh behave translate glove punish render shove dye bump foam bait evolve tuck pinch splash transmit rot wander donate pasture shortages feeder restrict trolley snack paddle donkey raft drown whisky inherit lifeboat bleed stimulate piracy peanut massage steak batter booster cheat seduce adhere

2 glide timbers inhibit shrink smack flex soaking grind jolt yank disperse divert brew shovel deter await vomit dispose mitigate commute hog cider trickle gulp gully rein drip infect restrain wildcat buffet fuss awaken coldest upkeep bake curfew dedicate sniff inflict discern forfeit weep relinquish booze hover emigrate liberate cling frighten jog upload soak kneel illuminate buggy welcomes deteriorate postpone unload beep disable fleece deflection partake kayak motivate inject grate stow mobilize nurture ration stun duffel barricade rationing hump graces subscribe apologise erode analyse roost elicit regenerate crave tickle vibrate wiggle sow trespassing visualize congratulate pout enrich recharge preside ebb aspire abort underestimate buoy smuggle blindfold despise dismantle displace dissipate conjure bustle heave refill lunge vagrant tern whirl sauna amplify radiate lurch overpower colonize humiliate conditioner stagger oblige browse drool faucet raiser cleanse adorn dredge bugger divulge pellet secrete purify jeopardize snowmobile imprison gape congregate refuel temp stopover untie cob skim cleave taint err backcountry cuddle whiz confiscate corkscrew perk know?â twirl seabird babble brag swish unwind amass catamaran disengage payday smother flatten

Table 4.15. Incremental list of words that fit the template within margin bits of error. By WordNet's definition, the template should represent : verbs of eating and drinking. See appendix D. 5 for a list of words used for training.

## Conclusion

In this work, we propose a novel method for training binary word embeddings inpired by Search Data Structure Learning. Instead of solving a compression problem using pre-trained continuous vectors, we implement a Multi-Bernouilli Regression Search to solve a matching problem between two domains : middle words and surrounding context for given windows of words. Our method has the advantage of learning the discrete representations directly, meaning the model can be trained end-to-end.

Our experiments strongly suggest that the semantical information of each word relative to itself and its surrounding context is encoded in an almost humanly interpretable way. It appears as if our initial idea of sememe, i.e., latent discrete units of meaning, applies to our resulting representations, although not as well-defined as expected. Certain combinations of bits can be associated to known grammatical properties such as different morphological inflections which in turn can be interpreted as contextual semantic markers. Known concepts can also be attributed to manually built or learnt bit templates. Furthermore, our method exhibits promising generalization capabilities by generating binary vectors for unknown words that can integrate seamlessly with the base vocabulary embeddings. Even though continuous GloVe embeddings obtained better similarity scores and it could be argued that their word clusters are more semantically related, our work requires up to 200 times less memory and allows for efficient vector operations to be used such as a XOR operation to compute the hamming distance. The low dimensionality and the discrete nature of our resulting embeddings also display better interpretability that opens up their use in linguistics research and not only as input to another downstream task.

Our extensive qualitative evaluation suggests that our method has a good potential for improvement. Many of our experimentation settings were chosen arbitrarily and much more configurations such as vector dimensionality and model capacity can be tried. Further exploration of these configurations and other potential applications are left for future work.

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## Appendix A

## Word Lists

## A.1. Semi-Automatic

These lists were generated from our 50,000 words training vocabulary. To be more accurate and to take into account irregular inflections (e.g. eat and ate), we processed about 8 million sentences with spaCy $[\mathbf{1 7}]$ to count POS tags for every word (see app. C.1). We used the whole corpus (i.e. not only the train split), which gave us statistics for 43,240 words out of 50,000 . We only considered POS tags if their count represented at least $5 \%$ of the occurences for the associated word in order to filter out false positives. From this, we looked for every word with inflected forms (i.e. plurals, past, third person and present participle) and extracted their lemma. If both words were in our vocabulary, we added the pair to the appropriate word list. These lists were not validated completely. A brief examination showed they were sufficient and contained very few errors. Hence, it would have no significant impact on our results.

## A.1.1. Plurals

## Singular form with associated plural modifications

year(s) state(s) eye(s) man(en) woman(en) child(ren) member(s) game(s) time(s) day(s) student(s) hand(s) other(s) work(s) service(s) thing(s) month(s) area(s) record(s) force(s) team(s) point(s) event(s) song(s) school(s) arm(s) word(s) player(s) medium(a) foot(eet) right(s) minute(s) book(s) art(s) family(ies) group(s) study(ies) hour(s) award(s) friend(s) country(ies) sport(s) show(s) film(s) part(s) datum(a) system(s) building(s) parent(s) place(s) championship(s) operation(s) run(s) unit(s) week(s) play(s) line(s) company (ies) artist(s) girl(s) issue(s) term(s) star(s) life(ves) lip(s) name(s) character(s) change(s) remain(s) activity(ies) match(es) program(s) result(s) goal(s) mile(s) island(s) plan(s) brother(s) house(s) problem(s) track(s) case(s) story (ies) finger(s) individual(s) form(s) troop(s) boy(s) city(ies) season(s) station(s) soldier(s) use(s) single(s) worker(s) $\operatorname{ship}(\mathrm{s})$ election(s) number(s) nation(s) lie(s) product(s) officer(s) male(s) condition(s) level(s) leave(s) element(s) resident(s) leg(s) tree(s) car(s) rule(s) household(s) appearance(s) project(s) race(s) wall(s) effect(s) look(s) effort(s) side(s) affair(s) leader(s) club(s) mountain(s) yard(s) source(s) facility(ies) type(s) second(s) offer(s) language(s) review(s) note(s) son(s) community(ies) way(s) party(ies) plant(s) critic(s) episode(s) role(s) relation(s) champion(s) one(s) animal(s) sale(s) $\operatorname{report}(\mathrm{s}) \operatorname{model}(\mathrm{s}) \operatorname{seat}(\mathrm{s})$ letter(s) resource(s) class(es) final(s) organization(s) question(s) law(s) field(s) piece(s) title(s)

## Singular form with associated plural modifications

position(s) representative(s) claim(s) figure(s) vote(s) site(s) attack(s) power(s) official(s) weapon(s) science(s) district(s) performance(s) cell(s) train(s) body(ies) authority(ies) region(s) thank(s) fan(s) material(s) cover(s) citizen(s) reason(s) gun(s) order(s) step(s) action(s) street(s) village(s) version(s) set(s) call(s) act(s) human(s) sound(s) attempt(s) turn(s) tear(s) end(s) article(s) tooth(eeth) vehicle(s) century(ies) copy(ies) start(s) method(s) town(s) shoulder(s) door(s) bird(s) metre(s) office(s) kid(s) institution(s) writer(s) picture(s) standard(s) idea(s) head(s) property(ies) studio(s) road(s) example(s) detail(s) thought(s) room(s) band(s) fund(s) lyric(s) communication(s) skill(s) structure(s) decade(s) scene(s) location(s) patient(s) flower(s) function(s) home(s) image(s) church(es) wing(s) pass(es) employee(s) teacher(s) win(s) guy(s) candidate(s) bank(s) light(s) date(s) inhabitant(s) painting(s) item(s) engine(s) user(s) ground(s) thousand(s) paper(s) lead(s) application(s) store(s) object(s) cause(s) value(s) good(s) sister(s) course(s) section(s) horse(s) cost(s) guard(s) interest(s) musician(s) river(s) university (ies) try (ies) winner(s) court(s) director(s) technique(s) war(s) owner(s) charge(s) vocal(s) degree(s) passenger(s) design(s) production(s) business(es) water(s) person(s) county(ies) document(s) scholar(s) return(s) card(s) operate(s) route(s) publication(s) duty(ies) daughter(s) hundred(s) purpose(s) age(s) stage(s) branch(es) division(s) actor(s) king(s) visitor(s) factor(s) subject(s) measure(s) recording(s) victim(s) blue(s) wood(s) concern(s) contribution(s) moment(s) feeling(s) prisoner(s) partner(s) her(s) difference(s) device(s) face(s) movement(s) stair(s) author(s) movie(s) $\operatorname{loss}(\mathrm{es}) \operatorname{matter}(\mathrm{s}) \operatorname{aspect}(\mathrm{s}) \operatorname{meter}(\mathrm{s}) \operatorname{rock}(\mathrm{s}) \operatorname{novel}(\mathrm{s}) \operatorname{test}(\mathrm{s}) \operatorname{instrument}(\mathrm{s}) \operatorname{policy}(i e s) \operatorname{adult}(\mathrm{s}) \operatorname{practice}(\mathrm{s}) \operatorname{rate}(\mathrm{s}) \operatorname{sign}(\mathrm{s})$ account(s) knee(s) drug(s) forest(s) market(s) industry(ies) couple(s) host(s) job(s) requirement(s) supply(ies) boat(s) network(s) competition(s) tool(s) round(s) move(s) agent(s) newspaper(s) component(s) meeting(s) park(s) master(s) medal(s) experience(s) collection(s) root(s) vessel(s) process(es) territory(ies) center(s) mission(s) list(s) bear(s) customer(s) injury(ies) color(s) producer(s) dream(s) lake(s) credit(s) circumstance(s) poem(s) farmer(s) ear(s) dollar(s) wave(s) supporter(s) scientist(s) border(s) share(s) occasion(s) relationship(s) dog(s) page(s) guest(s) engineer(s) style(s) video(s) exist(s) session(s) mill(s) concert(s) death(s) researcher(s) principle(s) statistic(s) opportunity(ies) participant(s) college(s) population(s) government(s) saint(s) stone(s) benefit(s) limit(s) agency(ies) theme(s) rank(s) province(s) ally(ies) channel(s) period(s) decision(s) judge(s) tribe(s) support(s) voice(s) reach(es) athlete(s) railway(s) god(s) shoe(s) driver(s) warrior(s) release(s) viewer(s) drum(s) trial(s) machine(s) voter(s) platform(s) category(ies) asset(s) regulation(s) lady(ies) bone(s) volume(s) link(s) technology(ies) crime(s) mine(s) settler(s) opponent(s) night(s) pattern(s) slave(s) stop(s) key(s) people(s) inch(es) enemy(ies) immigrant(s) photograph(s) volunteer(s) tie(s) option(s) magazine(s) ranger(s) cheek(s) fighter(s) festival(s) connection(s) space(s) tradition(s) playoff(s) acre(s) tank(s) municipality(ies) boundary(ies) origin(s) bar(s) bridge(s) settlement(s) shop(s) increase(s) coach(es) temperature(s) edition(s) wind(s) price(s) map(s) negotiation(s) battle(s) minister(s) file(s) tour(s) flight(s) reference(s) grade(s) protest(s) giant(s) lion(s) pupil(s) emotion(s) doctor(s) shot(s) locomotive(s) speaker(s) demand(s) shadow(s) score(s) topic(s) spot(s) department(s) basis(es) stake(s) muscle(s) talk(s) interview(s) pant(s) solution(s) coin(s) airline(s) ton(s) height(s) camp(s) column(s) campaign(s) pair(s) visit(s) taxis(es) crosse(s) influence(s) bus(es) symptom(s) restaurant(s) disease(s) bill(s) tower(s) lot(s) challenge(s) leed(s) control(s) protein(s) target(s) present(s) computer(s) table(s) league(s) angel(s) ability(ies) comment(s) board(s) experiment(s) enter(s) tournament(s) difficulty(ies) boot(s) quarter(s) answer(s) cut(s) seed(s) travel(s) writing(s) signal(s) walk(s) plate(s) ball(s) client(s) eagle(s) architect(s) approach(es) descendant(s) hero(es) colony(ies) message(s) theory(ies) veteran(s) hospital(s) reader(s) improvement(s) contract(s) range(s) assist(s) photo(s) wheel(s) pilot(s) amount(s) rebel(s) generation(s) adventure(s) kilometer(s) rider(s) reserve(s) exhibition(s) hope(s) pound(s) creature(s) vampire(s) lord(s) post(s) situation(s) runner(s) colleague(s) floor(s) society(ies) archive(s) organisation(s) reform(s) ring(s) expert(s) refugee(s) connect(s) rating(s) direction(s) farm(s) edge(s) circle(s) politician(s) love(s) estate(s) professional(s) programme(s) manufacturer(s) culture(s) casualty (ies) singer(s) arrangement(s) graphic(s) founder(s) lesson(s) journalist(s) instruction(s) flame(s) kind(s) aim(s) portion(s) temple(s) sample(s) crop(s) variation(s) concept(s) survivor(s) grant(s) composition(s) plain(s) statement(s) hole(s) follower(s) association(s) port(s) display(s) centre(s) pirate(s) threat(s) priest(s) broadcast(s) victory(ies) task(s) ruin(s) $\operatorname{army}$ (ies) development(s) touchdown(s) appeal(s) twin(s) chamber(s) relative(s) manage(s) consequence(s) venue(s) box(es) gene(s) bishop(s) chapter(s) segment(s) union(s) glass(es) library(ies) content(s) discover(s) camera(s) audience(s) rival(s) provision(s) stream(s) nomination(s) tourist(s) criterion(a) restriction(s) conference(s) journal(s) million(s) layer(s) suburb(s) lecture(s) committee(s) heart(s) sibling(s) deal(s) cardinal(s) fire(s) operator(s) investor(s) hotel(s) corner(s) cloud(s) procedure(s) panel(s) secret(s) finding(s) associate(s) alumnus(i) particle(s) chair(s) insect(s) brand(s) allegation(s) colour(s) servant(s) count(s) read(s) dragon(s) trustee(s) specimen(s) spirit(s) drawing(s) witness(es) holding(s) performer(s) heel(s) conflict(s) symbol(s) aire(s) activist(s) world(s) food(s) observation(s) demon(s) wish(es) wolf(ves) wound(s) strike(s) string(s) lawyer(s) workshop(s) cat(s) truck(s) mention(s) museum(s) reaction(s) developer(s) competitor(s) drive(s) publisher(s)

## Singular form with associated plural modifications

sheet(s) senator(s) bag(s) portrait(s) rise(s) scale(s) fact(s) estimate(s) deposit(s) smile(s) zone(s) firm(s) bond(s) rover(s) code(s) composer(s) variant(s) motor(s) investigation(s) ticket(s) drink(s) achievement(s) eyebrow(s) fee(s) trail(s) chain(s) environment(s) variety(ies) kilometre(s) fight(s) delegate(s) wicket(s) davy(ies) surface(s) sequence(s) compound(s) highway(s) poet(s) tactic(s) grave(s) repair(s) proposal(s) bed(s) incident(s) argument(s) murder(s) monument(s) capability (ies) proceeding(s) plane(s) mechanic(s) enterprise(s) interaction(s) dimension(s) discussion(s) monk(s) legend(s) slope(s) rebound(s) cap(s) kiss(es) short(s) entry(ies) merchant(s) habitat(s) foundation(s) battalion(s) responsibility(ies) strategy(ies) bit(s) ethic(s) ray(s) regiment(s) premise(s) chance(s) essay(s) gift(s) jet(s) apartment(s) ranking(s) bomb(s) fly(ies) manager(s) local(s) consumer(s) monster(s) being(s) roll(s) battery(ies) choice(s) agreement(s) lung(s) payment(s) national(s) exhibit(s) investment(s) trace(s) bomber(s) crew(s) mind(s) mechanism(s) governor(s) artifact(s) fragment(s) council(s) editor(s) contact(s) sculpture(s) molecule(s) raider(s) black(s) fear(s) label(s) ruler(s) complaint(s) soul(s) dancer(s) ceremony(ies) contestant(s) graduate(s) disorder(s) raid(s) factory(ies) cup(s) president(s) loan(s) row(s) sense(s) initiative(s) opinion(s) career(s) error(s) wife(ves) summer(s) dish(es) odd(s) ancestor(s) path(s) miner(s) genre(s) hunter(s) lane(s) fruit(s) sector(s) beat(s) vein(s) size(s) donation(s) setting(s) mother(s) expectation(s) pole(s) bat(s) curve(s) exercise(s) response(s) palm(s) shell(s) cave(s) tip(s) designer(s) tube(s) france(s) entity(ies) speed(s) parish(es) request(s) lap(s) sailor(s) missile(s) objective(s) classic(s) frame(s) risk(s) recommendation(s) commander(s) maker(s) variable(s) advance(s) mammal(s) neighbor(s) missionary(ies) remnant(s) patriot(s) profit(s) promise(s) fossil(s) squadron(s) bell(s) organism(s) lover(s) deputy (ies) carrier(s) prize(s) encounter(s) watt(s) saving(s) up(s) dynamic(s) toe(s) emission(s) back(s) conservative(s) statue(s) website(s) guideline(s) command(s) struggle(s) cowboy(s) reside(s) dispute(s) print(s) derive(s) coordinate(s) general(s) corporation(s) format(s) mode(s) bullet(s) blade(s) highland(s) highlight(s) exception(s) provider(s) intention(s) toy(s) gallery(ies) measurement(s) uniform(s) hectare(s) illustration(s) celebration(s) expense(s) quality(ies) theater(s) address(es) nurse(s) equation(s) villager(s) instance(s) pocket(s) sentence(s) similarity(ies) scheme(s) dance(s) masse(s) protester(s) guitar(s) rumor(s) depth(s) planet(s) nail(s) vegetable(s) baby (ies) defender(s) commissioner(s) suit(s) phase(s) third(s) translation(s) father(s) beach(es) spectator(s) celebrity(ies) pick(s) metal(s) religion(s) surrounding(s) ashe(s) nerve(s) rose(s) distance(s) gain(s) lock(s) bottle(s) tomato(es) parameter(s) penalty(ies) valley(s) expression(s) fist(s) holiday(s) talent(s) phone(s) winter(s) flag(s) damage(s) reporter(s) laboratory(ies) painter(s) survey(s) stamp(s) teaching(s) humanity(ies) kingdom(s) revenue(s) finish(es) sander(s) rat(s) shirt(s) gentleman(en) down(s) scot(s) tension(s) spell(s) regard(s) modification(s) sea(s) complication(s) conversation(s) quantity(ies) differ(s) discipline(s) inscription(s) prince(s) employer(s) sword(s) save(s) convention(s) security(ies) predator(s) tonne(s) attribute(s) executive(s) communist(s) riot(s) landscape(s) native(s) feather(s) chemical(s) advocate(s) telecommunication(s) screen(s) limitation(s) helicopter(s) wage(s) red(s) storm(s) white(s) criminal(s) acid(s) button(s) diamond(s) commercial(s) bull(s) panther(s) professor(s) personality (ies) councillor(s) shield(s) transaction(s) teammate(s) ride(s) classroom(s) angle(s) theatre(s) trait(s) rocket(s) snail(s) costume(s) attraction(s) possibility(ies) advantage(s) preparation(s) cop(s) chronicle(s) trader(s) formation(s) commission(s) ram(s) ingredient(s) peer(s) quarterfinal(s) remark(s) domain(s) cluster(s) airport(s) addition(s) inmate(s) liberal(s) mineral(s) chip(s) escape(s) soil(s) peasant(s) stay(s) meal(s) sponsor(s) companion(s) venture(s) mistake(s) guide(s) violation(s) accusation(s) pool(s) sketch(es) crowd(s) frequency(ies) township(s) demonstration(s) marriage(s) carman(en) outcome(s) pioneer(s) cycle(s) shift(s) teenager(s) suspect(s) watch(es) destroyer(s) trend(s) cousin(s) ghost(s) treatment(s) trick(s) sort(s) description(s) atom(s) strip(s) survive(s) holder(s) combine(s) accident(s) pipe(s) defense(s) dodger(s) affect(s) excavation(s) receptor(s) bay(s) arch(es) prayer(s) campus(es) grandchild(ren) possession(s) alien(s) ritual(s) shore(s) faction(s) dolphin(s) wrestler(s) moth(s) glove(s) rapid(s) destination(s) poll(s) concentration(s) patron(s) listener(s) success(es) observer(s) export(s) viking(s) partnership(s) devil(s) off(s) compete(s) snake(s) midland(s) whisper(s) keyboard(s) firearm(s) breast(s) tile(s) residence(s) debt(s) tone(s) barrier(s) standing(s) speech(es) meadow(s) disability(ies) arrow(s) weekend(s) fishery (ies) attitude(s) scream(s) minority(ies) teen(s) trouble(s) torre(s) installation(s) circuit(s) reinforcement(s) cliff(s) delay(s) stick(s) opera(s) marking(s) vision(s) fellow(s) exam(s) mutation(s) fortification(s) patent(s) cartoon(s) beam(s) pillar(s) tissue(s) tune(s) counterpart(s) debate(s) substance(s) tenant(s) locality (ies) advertisement(s) spark(s) stranger(s) joke(s) impact(s) feed(s) interval(s) transfer(s) wanderer(s) brave(s) bug(s) flood(s) implication(s) introduce(s) seal(s) span(s) bee(s) finalist(s) elder(s) patch(es) brigade(s) passage(s) appointment(s) investigator(s) trade(s) plantation(s) touch(es) decoration(s) isle(s) craft(s) flat(s) collector(s) sensor(s) defeat(s) sand(s) stretch(es) robot(s) privilege(s) explore(s) parson(s) permit(s) practitioner(s) doubt(s) brake(s) script(s) satellite(s) folk(s) brow(s) sack(s) expedition(s) tape(s) plot(s) spider(s) bean(s) colt(s) correspond(s) extension(s) habit(s) brick(s) assignment(s) pit(s) top(s) tributary(ies) reviewer(s) tire(s) examination(s) recruit(s) obligation(s) stroke(s) strikeout(s) constraint(s) beetle(s) crystal(s) falcon(s) air(s) notice(s)

## Singular form with associated plural modifications

wrist(s) wagon(s) node(s) renovation(s) patrol(s) check(s) mirror(s) genetic(s) infection(s) wine(s) offering(s) promotion(s) cry(ies) capital(s) electron(s) shade(s) recipient(s) fingertip(s) cd(s) spear(s) inform(s) duck(s) background(s) pressure(s) representation(s) complex(es) fort(s) poster(s) shareholder(s) witch(es) reply(ies) reception(s) knife(ves) bowl(s) sunday(s) package(s) explosive(s) colonist(s) charity(ies) square(s) steal(s) dock(s) ad(s) commentator(s) cigarette(s) rail(s) neuron(s) qualification(s) definition(s) commune(s) documentary(ies) ideal(s) current(s) major(s) monastery(ies) contest(s) migrant(s) combination(s) potato(es) failure(s) pig(s) behavior(s) cadet(s) blow(s) innovation(s) history(ies) doll(s) predecessor(s) obstacle(s) cable(s) buck(s) traveler(s) filmmaker(s) foreigner(s) dress(es) castle(s) scholarship(s) packer(s) amendment(s) administrator(s) interpretation(s) wire(s) identity(ies) captain(s) conclusion(s) enzyme(s) specification(s) ion(s) met(s) breath(s) disc(s) petal(s) license(s) railroad(s) prison(s) treaty(ies) sanction(s) roof(s) discovery(ies) specialist(s) clip(s) exchange(s) gas(es) server(s) defendant(s) ballot(s) clan(s) royal(s) candle(s) desire(s) terrorist(s) killing(s) yield(s) stock(s) barrel(s) strand(s) push(es) warship(s) contemporary(ies) hurt(s) phrase(s) wildcat(s) rope(s) mate(s) suggestion(s) finance(s) ridge(s) breed(s) defence(s) originate(s) zombie(s) fixture(s) fang(s) heir(s) attorney(s) resort(s) wetland(s) butterfly(ies) scar(s) reading(s) rain(s) manner(s) opening(s) glance(s) confront(s) analysis(es) retailer(s) alteration(s) nest(s) subscriber(s) linguistic(s) brain(s) dot(s) knot(s) landing(s) pack(s) adaptation(s) fisherman(en) knuckle(s) denote(s) dam(s) express(es) congregation(s) signature(s) hurricane(s) alternative(s) islander(s) propose(s) ant(s) deity(ies) margin(s) ministry(ies) over(s) tomb(s) pond(s) contributor(s) earning(s) elbow(s) close(s) builder(s) dwelling(s) stable(s) pier(s) contractor(s) monitor(s) $\operatorname{arrest}(\mathrm{s}) \operatorname{melody}(\mathrm{ies})$ interception(s) warning(s) clash(es) bush(es) senior(s) mask(s) weight(s) creator(s) establishment(s) jurisdiction(s) villain(s) denomination(s) vowel(s) container(s) pump(s) infant(s) calculation(s) intellectual(s) pathway(s) relic(s) evening(s) flyer(s) motion(s) grape(s) elevation(s) exit(s) import(s) shelter(s) fiber(s) deed(s) prospect(s) build(s) avenger(s) clue(s) switch(es) coat(s) meaning(s) businessman(en) gap(s) sight(s) trouser(s) canal(s) stare(s) nationalist(s) duke(s) utility(ies) curtain(s) dealer(s) selection(s) hostility(ies) objection(s) generator(s) dart(s) earthquake(s) care(s) crack(s) surgeon(s) worry(ies) participate(s) net(s) accessory(ies) loop(s) junior(s) derivative(s) 80(s) beginning(s) worm(s) slide(s) turtle(s) pill(s) scenario(s) fold(s) quote(s) elephant(s) donor(s) vendor(s) applicant(s) nominee(s) militant(s) buyer(s) accomplishment(s) blanket(s) cent(s) norm(s) commitment(s) fit(s) sleeve(s) entrepreneur(s) noise(s) assistant(s) suffer(s) photographer(s) cannon(s) affiliate(s) broadcaster(s) protocol(s) thief(ves) mystery(ies) mouth(s) purchase(s) continent(s) decrease(s) seminar(s) philosopher(s) smell(s) whale(s) search(es) press(es) valve(s) firework(s) rest(s) consideration(s) trap(s) danger(s) perspective(s) citation(s) assembly(ies) lyon(s) shelf(ves) organizer(s) portray(s) carriage(s) qualifier(s) entrance(s) killer(s) respect(s) comparison(s) hurdle(s) beast(s) drain(s) successor(s) jewel(s) invite(s) dune(s) bite(s) listing(s) virus(es) $\sin (\mathrm{s})$ analyst(s) jacket(s) wonder(s) fortune(s) ocean(s) invader(s) motive(s) convince(s) reservation(s) pilgrim(s) deliver(s) assumption(s) terminal(s) elector(s) pin(s) hat(s) attacker(s) thread(s) shout(s) tablet(s) birth(s) certificate(s) wizard(s) $\operatorname{archaeologist}(\mathrm{s})$ monkey(s) charger(s) cow(s) parallel(s) upgrade(s) flash(es) grain(s) mariner(s) taste(s) statute(s) morning(s) kit(s) prosecutor(s) cottage(s) joint(s) penguin(s) hearing(s) explanation(s) textile(s) presentation(s) sky(ies) fin(s) liberty(ies) preserve(s) disappear(s) defect(s) spy(ies) resolution(s) goat(s) offence(s) gang(s) icon(s) strain(s) vine(s) profile(s) processor(s) mural(s) myth(s) centimeter(s) belt(s) shrub(s) textbook(s) will(s) cookie(s) 90(s) diver(s) priority (ies) mount(s) woodland(s) hymn(s) strait(s) corridor(s) preference(s) database(s) criticism(s) actress(es) dinosaur(s) economy(ies) bike(s) $70(\mathrm{~s})$ faculty (ies) bead(s) ambassador(s) sediment(s) tent(s) marsh(es) filter(s) reject(s) advisor(s) landowner(s) justice(s) disaster(s) special(s) instinct(s) orchestra(s) register(s) swimmer(s) receiver(s) mayor(s) remember(s) emperor(s) motorcycle(s) automobile(s) reward(s) detective(s) intervention(s) suspicion(s) sacrifice(s) morale(s) future(s) amenity(ies) boiler(s) crusader(s) treasure(s) pop(s) beer(s) bubble(s) punch(es) owl(s) seller(s) explorer(s) partisan(s) minor(s) acquisition(s) depiction(s) needle(s) ambition(s) vector(s) average(s) bracket(s) cylinder(s) announce(s) rush(es) pitch(es) explosion(s) proportion(s) prefer(s) youth(s) hostage(s) stoke(s) lawsuit(s) recipe(s) subsidiary(ies) treat(s) offender(s) launch(es) bombing(s) chord(s) fault(s) split(s) reeve(s) educator(s) reflection(s) generate(s) trench(es) prototype(s) ecosystem(s) climb(s) lash(es) bath(s) coast(s) nutrient(s) bandit(s) diary(ies) mound(s) husband(s) convert(s) proponent(s) enthusiast(s) boxer(s) hang(s) musical(s) engagement(s) miracle(s) collaborator(s) simpson(s) crash(es) repeat(s) ferry(ies) headline(s) pot(s) thumb(s) sim(s) old(s) instructor(s) concession(s) brewer(s) spaniard(s) corpse(s) medicine(s) skirt(s) noun(s) bedroom(s) eyelid(s) capture(s) orbit(s) admission(s) energy(ies) rod(s) cyclist(s) pet(s) journey(s) gesture(s) comrade(s) salary(ies) apple(s) conviction(s) realm(s) interior(s) slot(s) cemetery(ies) fatality(ies) apostle(s) reptile(s) reef(s) supplier(s) prostitute(s) bid(s) axis(es) sex(es) socialist(s) slip(s) insurgent(s) oil(s) elevator(s) puzzle(s) twenty(ies) songwriter(s) crossing(s) insight(s) stall(s) deck(s) medication(s) tendency(ies) robe(s) vineyard(s) wedding(s) academy(ies) storyline(s) wait(s) breeder(s) abuse(s) echo(es) initial(s) assassin(s) policeman(en) surround(s) exploit(s) front(s) glacier(s)

## Singular form with associated plural modifications

gig(s) schedule(s) traveller(s) equal(s) classmate(s) turret(s) fork(s) sphere(s) mosque(s) indicator(s) avenue(s) assessment(s) bench(es) gathering(s) capacity(ies) subdivision(s) headlight(s) impression(s) prediction(s) total(s) spike(s) weekday(s) consonant(s) bind(s) sum(s) pad(s) altitude(s) cabin(s) technician(s) marche(s) gear(s) rein(s) belonging(s) hamlet(s) hodge(s) buccaneer(s) reservoir(s) alliance(s) rabbit(s) creation(s) distribution(s) shortage(s) burst(s) collect(s) swing(s) mongol(s) trust(s) tornado(es) ensemble(s) incentive(s) lay(s) franchise(s) bicycle(s) economist(s) aesthetic(s) tumor(s) dose(s) periodical(s) strength(s) narrative(s) suite(s) interface(s) correction(s) waterway(s) audition(s) fluid(s) burial(s) fine(s) gut(s) gem(s) toilet(s) comedy(ies) aquatic(s) dungeon(s) believer(s) optic(s) bump(s) canon(s) forum(s) stereotype(s) protagonist(s) rally(ies) coefficient(s) basin(s) ace(s) 60(s) biography(ies) transmission(s) trophy(ies) out(s) ratio(s) skin(s) disagreement(s) bruise(s) galaxy(ies) assault(s) lesion(s) firefighter(s) tract(s) flaw(s) grass(es) favorite(s) shrine(s) chick(s) beverage(s) elf(ves) execution(s) construction(s) swamp(s) hormone(s) commentary(ies) baron(s) dynasty(ies) hint(s) trunk(s) trailer(s) projection(s) controller(s) cabinet(s) bengal(s) antiquity(ies) clock(s) oversee(s) convoy(s) commodity(ies) memorial(s) residue(s) pitcher(s) eat(s) invention(s) guarantee(s) boast(s) bolt(s) sermon(s) credential(s) notion(s) syllable(s) fool(s) fish(es) supervisor(s) burrow(s) pose(s) configuration(s) distributor(s) diplomat(s) compilation(s) hazard(s) orphan(s) grin(s) spread(s) transition(s) palace(s) grove(s) pain(s) progress(es) surprise(s) astro(s) carving(s) recount(s) laborer(s) voyage(s) fence(s) antibody(ies) ending(s) grenade(s) invasion(s) contrast(s) magistrate(s) reactor(s) padre(s) regent(s) virtue(s) spice(s) volcano(es) captive(s) email(s) orchard(s) devotee(s) robotic(s) bout(s) wasp(s) compare(s) trainer(s) freedom(s) pause(s) transform(s) cue(s) transformation(s) charter(s) independent(s) consultant(s) lobe(s) warehouse(s) gland(s) occupation(s) delivery(ies) labourer(s) garment(s) chapel(s) van(s) walker(s) aspiration(s) cartridge(s) passport(s) creditor(s) stress(es) tongue(s) cheer(s) radical(s) profession(s) crow(s) skull(s) sentiment(s) weakness(es) nucleus(i) weed(s) berry(ies) plaintiff(s) $\operatorname{snap}(\mathrm{s})$ balloon(s) assign(s) bow(s) frigate(s) superior(s) conductor(s) plea(s) reality(ies) helmet(s) matrix(ces) favor(s) outsider(s) maneuver(s) cumming(s) husky(ies) friar(s) skater(s) climate(s) appropriation(s) werewolf(ves) soundtrack(s) fresco(es) bearing(s) adviser(s) merit(s) implement(s) newscast(s) parasite(s) congress(es) hybrid(s) spore(s) suck(s) atrocity(ies) pursuit(s) shipment(s) secretary(ies) shrug(s) inside(s) pub(s) revelation(s) radio(s) expenditure(s) pension(s) original(s) realise(s) appliance(s) twist(s) fantasy(ies) republic(s) scripture(s) franc(s) cruise(s) furnishing(s) boss(es) convict(s) constituent(s) paint(s) newcomer(s) petition(s) confession(s) yell(s) illness(es) clause(s) half(ves) surname(s) runway(s) screening(s) tyre(s) perception(s) sandwich(es) banner(s) empire(s) confederate(s) juvenile(s) diocese(s) boulder(s) anthology(ies) siren(s) disturbance(s) comedian(s) illustrate(s) ornament(s) adjustment(s) airfield(s) legion(s) cake(s) printer(s) san(s) blog(s) mat(s) fountain(s) revision(s) pamphlet(s) designation(s) sixty(ies) thinker(s) badge(s) gibbon(s) routine(s) primary(ies) accolade(s) terrace(s) reduction(s) hornet(s) pearl(s) rehearsal(s) controversy(ies) replacement(s) sequel(s) royalty(ies) cancer(s) griffith(s) buy(s) advise(s) cast(s) moor(s) mutant(s) inhibitor(s) archer(s) pasture(s)
indication(s) footballer(s) pepper(s) airplane(s) idol(s) waterfall(s) tariff(s) offense(s) indoor(s) psychologist(s) antibiotic(s) astronaut(s) fleet(s) sensation(s) stadium(s) working(s) rollin(s) pulse(s) regular(s) fox(es) nationality(ies) decline(s) excuse(s) astronomer(s) stride(s) amateur(s) adherent(s) four(s) celtic(s) dealing(s) loser(s) integer(s) outlaw(s) crown(s) rescue(s) fry(ies) anchor(s) cavalier(s) shower(s) visual(s) neck(s) contender(s) loyalist(s) pharmaceutical(s) promoter(s) gospel(s) gator(s) seeker(s) craftsman(en) piston(s) fabric(s) regime(s) mall(s) parade(s) presenter(s) insult(s) widow(s) prophet(s) urge(s) grassland(s) classification(s) escort(s) striker(s) distinction(s) mushroom(s) pedestrian(s) announcement(s) simulation(s) disk(s) fairy(ies) analytic(s) scroll(s) dialogue(s) dome(s) choir(s) seizure(s) pronoun(s) mandate(s) skeleton(s) commando(s) keeper(s) laser(s) timber(s) vibration(s) leaflet(s) regret(s) cosmetic(s) packet(s) truth(s) civilization(s) quarry(ies) adolescent(s) detainee(s) budget(s) prop(s) highlander(s) chromosome(s) counter(s) elect(s) ribbon(s) banker(s) crisis(es) regulator(s) horror(s) fingernail(s) summon(s) thug(s) transmitter(s) northward(s) operative(s) revolution(s) breaker(s) gallon(s) clone(s) arrival(s) bend(s) staple(s) artisan(s) moon(s) collapse(s) brush(es) trojan(s) supplement(s) $\operatorname{pod}(\mathrm{s})$ intersection(s) demographic(s) racer(s) rapper(s) caste(s) accent(s) demonstrator(s) guerrilla(s) shooter(s) showcase(s) rodent(s) regulate(s) high(s) croat(s) submission(s) supermarket(s) marlin(s) legislature(s) militia(s) praise(s) spin(s) crane(s) bottom(s) formula(s) combatant(s) basic(s) afternoon(s) groove(s) detector(s) accommodation(s) billion(s) plastic(s) basket(s) tentacle(s) perpetrator(s) junction(s) chuckle(s) blessing(s) float(s) casino(s) learner(s) avoid(s) elite(s) planner(s) trooper(s) lodge(s) onion(s) vocalist(s) aggie(s) quaker(s) extra(s) charm(s) referee(s) drawer(s) hedge(s) taxpayer(s) grime(s) telescope(s) occurrence(s) $\operatorname{sink}(\mathrm{s})$ administration(s) fare(s) bulb(s) banknote(s) protection(s) exile(s) sculptor(s) clerk(s) polymer(s) horizon(s) guitarist(s) flavor(s) hire(s) comet(s) taxi(s) op(s) barge(s) finisher(s) eruption(s) cart(s) plaque(s) cascade(s) crater(s) mansion(s) excerpt(s) friday(s) barn(s) investigate(s) dane(s) merger(s) vaccine(s) conversion(s) introduction(s) puppet(s) hine(s) serial(s) rhyme(s) confine(s) react(s) accuse(s) transformer(s) batter(s) sabre(s) theorist(s) saxon(s) summit(s) extract(s) bundle(s) waiver(s) research(es) rent(s) principal(s) favourite(s) gunner(s) coyote(s) trigger(s)

## Singular form with associated plural modifications

cord(s) shard(s) translator(s) footprint(s) moral(s) collision(s) bribe(s) terminate(s) emergency(ies) inquiry(ies) stat(s) triangle(s) amphibian(s) curse(s) stint(s) seventy(ies) massacre(s) inspector(s) portal(s) buddy(ies) bonus(es) compartment(s) bodyguard(s) endeavor(s) sandal(s) eastward(s) jersey(s) fluctuation(s) blazer(s) engraving(s) theologian(s) gunman(en) $\operatorname{solid}(\mathrm{s}) \operatorname{starter}(\mathrm{s})$ receipt(s) slice(s) stocking(s) $\operatorname{cook}(\mathrm{s})$ herd(s) towel(s) italic(s) abnormality(ies) primate(s) fifty(ies) fracture(s) pen(s) decree(s) flashback(s) lease(s) programmer(s) gasp(s) expansion(s) commit(s) alloy(s) apology(ies) stitch(es) wavelength(s) drill(s) vent(s) scan(s) attendant(s) passion(s) storey(s) ape(s) vault(s) grocery(ies) robber(s) thirty(ies) detachment(s) mortal(s) chore(s) harmony(ies) beaver(s) affiliation(s) grip(s) byzantine(s) climber(s) illusion(s) fortress(es) torch(es) psalm(s) desert(s) grader(s) flap(s) dragoon(s) billing(s) fitting(s) grower(s) shooting(s) scandal(s) mast(s) subordinate(s) friendship(s) propeller(s) antique(s) tier(s) abortion(s) landlord(s) pigeon(s) carpet(s) tractor(s) feminist(s) miniature(s) maverick(s) pace(s) vertebrate(s) dweller(s) blast(s) cuff(s) mortar(s) booth(s) chef(s) airman(en) sweet(s) tap(s) commuter(s) income(s) mollusk(s) pea(s) output(s) shifter(s) amplifier(s) canton(s) conspirator(s) biscuit(s) sighting(s) chase(s) chunk(s) scissor(s) federation(s) inspection(s) brewery(ies) depart(s) hinge(s) shipyard(s) extreme(s) frown(s) shilling(s) index(ices) dagger(s) hypothesis(es) snack(s) clement(s) monday(s) cossack(s) swede(s) siding(s) barbarian(s) acquaintance(s) texture(s) eighty(ies) shock(s) pleasure(s) manifestation(s) punishment(s) spouse(s) invitation(s) raptor(s) conquest(s) rack(s) hunt(s) motivation(s) triple(s) still(s) giggle(s) embassy(ies) bearer(s) peanut(s) ration(s) bowler(s) explode(s) eel(s) youngster(s) playwright(s) administer(s) nickname(s) electrode(s) grouping(s) reformer(s) complete(s) earring(s) ban(s) gather(s) droplet(s) toll(s) buddhist(s) yourself(ves) sidewalk(s) therapy(ies) semantic(s) sortie(s) pixel(s) numeral(s) squirrel(s) slam(s) emigrant(s) organiser(s) moan(s) girlfriend(s) socket(s) symphony(ies) manual(s) relay(s) overlook(s) fringe(s) cage(s) yacht(s) stunt(s) surgery(ies) twig(s) dinner(s) recover(s) toxin(s) disadvantage(s) construct(s) synthesizer(s) stain(s) constant(s) calf(ves) bathroom(s) warrant(s) goddess(es) tit(s) comb(s) parody(ies) ditch(es) thrust(s) juror(s) noodle(s) blend(s) deficiency(ies) housemate(s) specialty(ies) tender(s) preview(s) entrant(s) crate(s) excursion(s) $\operatorname{activate}(\mathrm{s})$ henchman(en) messenger(s) font(s) nipple(s) immortal(s) precaution(s) nil(s) hub(s) probe(s) interrupt(s) mood(s) murderer(s) lesbian(s) roller(s) rag(s) discharge(s) clipper(s) animation(s) ordinance(s) spelling(s) stalk(s) frontier(s) signatory(ies) dictionary(ies) assure(s) canoe(s) facet(s) strut(s) cushion(s) vandal(s) fingerprint(s) partition(s) restraint(s) retreat(s) deficit(s) chant(s) weaver(s) launcher(s) duet(s) coil(s) pebble(s) befriend(s) pavilion(s) mentor(s) rebellion(s) thorn(s) pesticide(s) pyramid(s) parliament(s) niche(s) camel(s) byte(s) ideology(ies) superhero(es) linguist(s) departure(s) scorer(s) cooperative(s) dive(s) colonel(s) accountant(s) clutch(es) token(s) awaken(s) soloist(s) antagonist(s) condom(s) tanker(s) challenger(s) lad(s) orchid(s) glider(s) cutter(s) fat(s) broker(s) anarchist(s) subscription(s) dependency(ies) minion(s) shepherd(s) scratch(es) nose(s) forecast(s) cleric(s) mustang(s) pipeline(s) grievance(s) facade(s) pastor(s) debut(s) don(s) remedy (ies) mon(s) slack(s) empty (ies) telephone(s) photon(s) foe(s) 20(s) radar(s) density(ies) substitute(s) adjective(s) tee(s) bunker(s) hound(s) funeral(s) thunderstorm(s) interchange(s) badger(s) headache(s) mosaic(s) maid(s) simon(s) o'clock(' clock) brief(s) trainee(s) bandage(s) homosexual(s) cafe(s) meyer(s) portfolio(s) alarm(s) smartphone(s) $\operatorname{lid}(\mathrm{s})$ furnace(s) orange(s) captor(s) nightclub(s) neutron(s) blind(s) pajama(s) inhibit(s) equivalent(s) vacancy(ies) evaluation(s) premiere(s) garrison(s) trumpet(s) pancake(s) rune(s) licence(s) bet(s) blossom(s) delegation(s) forearm(s) hoof(ves) pan(s) chest(s) transcript(s) bower(s) sect(s) deployment(s) planter(s) pest(s) ruling(s) rivalry(ies) physicist(s) synagogue(s) liner(s) dye(s) skyscraper(s) click(s) millimeter(s) pointer(s) bicep(s) shutter(s) symbolize(s) flare(s) pollutant(s) subtitle(s) steamer(s) tug(s) shoal(s) dispatch(es) greeting(s) projectile(s) gamer(s) baptist(s) mountaineer(s) ware(s) desk(s) gown(s) roadway(s) idiot(s) paramedic(s) pursue(s) lieutenant(s) cater(s) talon(s) olive(s) installment(s) rupee(s) postcard(s) setback(s) commandment(s) scare(s) query(ies) recorder(s) piano(s) whaler(s) guild(s) growl(s) riff(s) exploration(s) rerun(s) shiver(s) achieve(s) jack(s) anomaly(ies) bang(s) housewife(ves) dan(s) recital(s) advertiser(s) philosophy(ies) precursor(s) flock(s) fur(s) princess(es) royalist(s) cathedral(s) cheekbone(s) pore(s) fate(s) romance(s) beneficiary(ies) incarnation(s) migration(s) arcade(s) altar(s) ensue(s) uprising(s) grizzly(ies) auction(s) marshal(s) outcrop(s) cube(s) entertainer(s) gangster(s) peach(es) crewman(en) $\operatorname{smith}(\mathrm{s}) \operatorname{may}(\mathrm{s})$ rooster(s) implant(s) due(s) tribute(s) quotation(s) enhancement(s) jury(ies) embrace(s) ballet(s) constitution(s) gladiator(s) suffix(es) potential(s) percentage(s) drag(s) anecdote(s) hallucination(s) gray(s) kidney(s) drummer(s) apologize(s) instruct(s) latitude(s) paratrooper(s) rocker(s) dormitory(ies) connector(s) manor(s) carpenter(s) traverse(s) iron(s) subgroup(s) slum(s) homeowner(s) steroid(s) flute(s) vulture(s) treatise(s) outpost(s) workman(en) slipper(s) medalist(s) quarterback(s) sympathy(ies) pope(s) pigment(s) liability(ies) $\operatorname{surfer}(\mathrm{s})$ coincide(s) declaration(s) acoustic(s) dissident(s) aide(s) parliamentarian(s) puppy(ies) meat(s) aristocrat(s) pro(s) overlap(s) scent(s) flake(s) traitor(s) fumble(s) amend(s) concentrate(s) math(s) vase(s) cereal(s) gust(s) crocodile(s) bulletin(s) signing(s) freak(s) expose(s) prophecy(ies) pie(s) winning(s) subset(s) fable(s) fifth(s) pedal(s) revolt(s) bride(s) editorial(s) cracker(s) mason(s) mosquito(es) correspondent(s) flip(s) admiral(s) probability(ies) canyon(s) scorpion(s)

## Singular form with associated plural modifications

throne(s) free(s) vassal(s) closure(s) chill(s) forty(ies) currency(ies) maroon(s) balcony(ies) friendly(ies) consultation(s) sideline(s) proposition(s) eater(s) cavern(s) edmond(s) gen(s) mixture(s) vamp(s) litre(s) feat(s) seam(s) counselor(s) mormon(s) superstar(s) bucket(s) rug(s) tutor(s) gunboat(s) intruder(s) bachelor(s) armament(s) umpire(s) alert(s) pat(s) $\operatorname{ladder}(\mathrm{s})$ hobby (ies) berth(s) incursion(s) concerto(s) burger(s) chieftain(s) sewer(s) breach(es) skier(s) compliment(s) mail(s) motorist(s) shutout(s) exemption(s) geologist(s) fraction(s) hull(s) pacer(s) bellow(s) ounce(s) reparation(s) constable(s) leopard(s) apprentice(s) insert(s) catalogue(s) proton(s) waste(s) fibre(s) masterpiece(s) architecture(s) anthropologist(s) sticker(s) hydrocarbon(s) reflex (es) plug(s) shipwreck(s) camper(s) balance(s) spectacle(s) biologist(s) billiard(s) fashion(s) scrap(s) briton(s) gull(s) magnet(s) connor(s) tre(s) smuggler(s) resume(s) axiom(s) plead(s) rape(s) critique(s) bobcat(s) filament(s) eliminate(s) census(es) coral(s) initiate(s) shopper(s) television(s) milestone(s) adversary(ies) bracelet(s) transistor(s) planting(s) longhorn(s) trademark(s) necessity(ies) impulse(s) resolve(s) depression(s) rental(s) rotation(s) dwarf(ves) directive(s) viewpoint(s) medium(s) affection(s) vitamin(s) privateer(s) hispanic(s) strive(s) fix(es) 30(s) comfort(s) western(s) cult(s) inventor(s) tragedy(ies) backer(s) golfer(s) dividend(s) quest(s) solvent(s) harbor(s) negative(s) gypsy(ies) welcome(s) doorway(s) fairground(s) edit(s) toss(es) whistle(s) glimpse(s) envelope(s) ambulance(s) grunt(s) grandson(s) aviator(s) claimant(s) stronghold(s) proprietor(s) buckeye(s) shingle(s) crusade(s) sentinel(s) contradiction(s) bandmate(s) pony(ies) gender(s) feast(s) methodology(ies) breech(es) whip(s) mortgage(s) staff(s) wednesday(s) stumble(s) robbery(ies) exposure(s) enclosure(s) lancer(s) kidnap(s) mutter(s) freedman(en) therapist(s) chaplain(s) brothel(s) censor(s) reappear(s) hank(s) confrontation(s) deacon(s) velocity(ies) procession(s) buttress(es) navy(ies) bark(s) airstrike(s) sonnet(s) pickup(s) tapestry(ies) lighthouse(s) gold(s) upland(s) wither(s) fundamental(s) calorie(s) shut(s) browser(s) freeze(s) expatriate(s) mare(s) sparrow(s) tribunal(s) rotate(s) metaphor(s) lender(s) watcher(s) pellet(s) railing(s) walkway(s) howitzer(s) pediatric(s) strawberry(ies) interpreter(s) main(s) steward(s) podcast(s) anger(s) wipe(s) commoner(s) willow(s) ancient(s) advancement(s) essential(s) tray(s) refinery(ies) riding(s) discourse(s) specific(s) breathe(s) tenet(s) rampart(s) catalyst(s) thermodynamic(s) goon(s) layout(s) on(s) oath(s) iris(es) laptop(s) stallion(s) fugitive(s) smoker(s) assurance(s) lick(s) lee(s) flop(s) aunt(s) slug(s) roommate(s) tab(s) coalition(s) fascist(s) bust(s) connotation(s) bully(ies) warlord(s) beggar(s) checkpoint(s) hood(s) hitter(s) adventurer(s) gradient(s) recollection(s) chemist(s) consume(s) alternate(s) mug(s) chorus(es) gardener(s) clump(s) juice(s) prime(s) canvas(es) oyster(s) wash(es) belle(s) islet(s) evil(s) wander(s) mystic(s) appendage(s) seminole(s) temptation(s) alley(s) allowance(s) squeeze(s) ailment(s) testimony(ies) admirer(s) cutting(s) feud(s) injection(s) rainforest(s) ass(es) deviation(s) fraternity(ies) persist(s) inspiration(s) gauge(s) great(s) staircase(s) marseille(s) spill(s) attachment(s) miller(s) gorge(s) hen(s) assertion(s) scrub(s) mangrove(s) reel(s) coating(s) announcer(s) throat(s) restroom(s) violate(s) melt(s) cellar(s) surveyor(s) convey(s) allusion(s) zealander(s) vacation(s) thunderbird(s) dio(s) chairman(en) methodist(s) musket(s) lagoon(s) batch(es) sitcom(s) inconsistency(ies) franciscan(s) ranch(es) dominion(s) constellation(s) ski(s) manifest(s) lecturer(s) goth(s) animator(s) marble(s) drift(s) volt(s) principality(ies) sacrament(s) gadget(s) reaper(s) coaster(s) dip(s) punt(s) coffin(s) souvenir(s) tremor(s) eclipse(s) reprint(s) portrayal(s) thesis(es) billboard(s) pencil(s) sergeant(s) attention(s) solicitor(s) spoil(s) malay(s) forensic(s) palisade(s) viper(s) sorrow(s) quit(s) extremist(s) tenth(s) formulation(s) playground(s) hoop(s) clown(s) pelican(s) streetcar(s) brace(s) skate(s) gay(s) locker(s) eyeball(s) galley(s) $\operatorname{rip}(\mathrm{s})$ analyze(s) rogue(s) trio(s) assassination(s) overhear(s) placement(s) seedling(s) discrepancy(ies) roster(s) incumbent(s) $\operatorname{potter}(\mathrm{s}) \operatorname{low}(\mathrm{s})$ endorsement(s) parrot(s) lily(ies) beginner(s) sooner(s) anthem(s) predate(s) gag(s) favour(s) grid(s) bye(s) proverb(s) condominium(s) salon(s) muse(s) suicide(s) cleaner(s) psychiatrist(s) forbid(s) cocktail(s) quartet(s) additive(s) railcar(s) collar(s) certification(s) otter(s) jockey(s) motorway(s) hacker(s) archbishop(s) mold(s) rancher(s) precinct(s) lifeboat(s) phantom(s) happening(s) magpie(s) pageant(s) iteration(s) pour(s) courtier(s) dessert(s) harrier(s) filly(ies) duct(s) terrier(s) brazilian(s) turnover(s) pledge(s) mist(s) addict(s) ethnicity(ies) coal(s) crest(s) aggregate(s) kidnapper(s) reconstruction(s) etching(s) prejudice(s) protector(s) chimpanzee(s) handler(s) venetian(s) prank(s) bumper(s) pal(s) emblem(s) suitcase(s) sprite(s) hoosier(s) ember(s) tory(ies) evoke(s) epic(s) saracen(s) grace(s) cymbal(s) platoon(s) gunshot(s) composite(s) allele(s) loyalty(ies) carbohydrate(s) samuel(s) corvette(s) swell(s) kiln(s) spire(s) reproduction(s) scanner(s) blogger(s) contraction(s) poison(s) gopher(s) cheese(s) zero(s) folly(ies) baker(s) pregnancy(ies) speculation(s) con(s) curator(s) behave(s) tick(s) prairie(s) goalkeeper(s) eight(s) winery(ies) index(es) capacitor(s) innocent(s) reunite(s) bra(s) beating(s) theorem(s) tweet(s) sniper(s) ore(s) voltage(s) sponge(s) sleeper(s) folder(s) garage(s) projector(s) helper(s) membership(s) councilor(s) sage(s) oscillation(s) safeguard(s) sheriff(s) fireplace(s) disguise(s) novelist(s) swear(s) sensibility (ies) complexity(ies) pianist(s) diagnostic(s) porch(es) biker(s) precede(s) lunch(es) truss(es) epistle(s) correlation(s) abstract(s) delusion(s) discount(s) ayer(s) revival(s) pear(s) fourth(s) shred(s) warhead(s) interruption(s) mimic(s) excess(es) feeder(s) illustrator(s) rookie(s) orbital(s) intestine(s) cadre(s) cheerleader(s) cure(s) congressman(en) industrialist(s) taunt(s)

## Singular form with associated plural modifications

pumpkin(s) crook(s) permutation(s) $\operatorname{kink}(\mathrm{s})$ distraction(s) riddle(s) saying(s) raft(s) accomplice(s) atheist(s) directory(ies) couch(es) reprisal(s) inductee(s) liar(s) novice(s) fertilizer(s) freemason(s) countryman(en) hatch(es) beacon(s) sprint(s) extremity (ies) liter(s) suitor(s) bias(es) foal(s) tilt(s) olympian(s) calculate(s) amazon(s) hon(s) lodging(s) harm(s) separatist(s) shotgun(s) sausage(s) commodore(s) crevice(s) st(s) pickle(s) vulnerability(ies) bitch(es) stud(s) password(s) oar(s) rendition(s) valuable(s) healer(s) template(s) chocolate(s) entertainment(s) ache(s) rim(s) gymnast(s) loom(s) paragraph(s) barricade(s) prescription(s) disparity(ies) replay(s) horde(s) grand(s) wildfire(s) progressive(s) correlate(s) chariot(s) bureaucrat(s) footnote(s) aerodynamic(s) sultan(s) glare(s) footpath(s) reverse(s) scribe(s) mage(s) frustration(s) heron(s) abbreviation(s) rotor(s) restoration(s) spiral(s) shove(s) complement(s) gorilla(s) errand(s) auxiliary(ies) victor(s) revolver(s) staffer(s) semiconductor(s) compatriot(s) upset(s) mussel(s) abbot(s) rarity(ies) watercolor(s) bristle(s) premium(s) nucleotide(s) ligament(s) courtyard(s) spoon(s) kicker(s) greet(s) auditor(s) rooftop(s) dyke(s) arie(s) disappearance(s) midwife(ves) templar(s) sanctuary(ies) intervene(s) hell(s) midshipman(en) instrumental(s) alter(s) fuse(s) soap(s) spitfire(s) handgun(s) endeavour(s) nick(s) beauty(ies) cohort(s) cherry(ies) forgive(s) penny(ies) assailant(s) cease(s) informant(s) borrow(s) donut(s) pawn(s) suspension(s) resist(s) lament(s) conception(s) bypass(es) drawback(s) babe(s) carcass(es) mep(s) intrigue(s) diner(s) gee(s) lifetime(s) nuance(s) deliberation(s) clam(s) flick(s) gatherer(s) pharmacy(ies) oscar(s) splinter(s) tavern(s) dressing(s) spinner(s) sinner(s) patriarch(s) pixie(s) attendance(s) silver(s) hollow(s) caricature(s) perk(s) naturalist(s) warbler(s) linebacker(s) saloon(s) toad(s) heroine(s) posting(s) vest(s) reagent(s) stool(s) porter(s) pastry(ies) enclave(s) rescuer(s) niece(s) medic(s) monologue(s) crutch(es) tendon(s) moss(es) tom(s) advert(s) fig(s) therapeutic(s) dial(s) superpower(s) genital(s) savage(s) diameter(s) capitalist(s) forget(s) magnate(s) outing(s) octave(s) exponent(s) first(s) virgin(s) lever(s) elm(s) jurist(s) stance(s) speculate(s) pagan(s) blueprint(s) wildflower(s) biographer(s) skit(s) caregiver(s) hog(s) freeway(s) rower(s) reminder(s) bystander(s) cuisine(s) uncertainty(ies) butcher(s) bass(es) enforcer(s) misunderstanding(s) mom(s) recess(es) sweat(s) booster(s) inspire(s) plume(s) carol(s) chandelier(s) environmentalist(s) majority (ies) chop(s) nursery(ies) suture(s) orientation(s) gum(s) caller(s) boom(s) converge(s) halt(s) barrow(s) cedar(s) spit(s) gateway(s) multiple(s) residency(ies) diagnosis(es) prohibition(s) puff(s) steppe(s) copyright(s) transcription(s) compromise(s) hesitate(s) life(s) registration(s) duel(s) battlefield(s) chancellor(s) goldsmith(s) pundit(s) examiner(s) rap(s) clearance(s) pharmacist(s) deduction(s) endowment(s) particular(s) manoeuvre(s) boutique(s) bronze(s) infrastructure(s) innovator(s) transplant(s) bot(s) six(es) best(s) democracy(ies) distortion(s) west(s) borrower(s) binding(s) spare(s) leaning(s) offensive(s) pheromone(s) increment(s) byrd(s) donkey(s) wallaby(ies) mascot(s) triplet(s) summary(ies) deflection(s) opposite(s) commence(s) benefactor(s) disagree(s) bible(s) bowel(s) payload(s) thruster(s) bogie(s) delight(s) necklace(s) bother(s) guess(es) hun(s) airship(s) affinity(ies) sauce(s) harvest(s) heater(s) allergy(ies) canine(s) stove(s) bookstore(s) medallion(s) dentist(s) disposal(s) outage(s) woe(s) grasshopper(s) persecution(s) snippet(s) mole(s) precedent(s) agenda(s) kernel(s) wharf(ves) earth(s) injustice(s) dodd(s) silhouette(s) disruption(s) girder(s) salad(s) completion(s) workplace(s) seagull(s) confide(s) cloth(s) bastion(s) linkage(s) prom(s) waiter(s) bounce(s) botanist(s) bookseller(s) huguenot(s) timer(s) spasm(s) mumble(s) checker(s) homer(s) haunt(s) druid(s) alias(es) amp(s) termite(s) dormer(s) alcohol(s) self(ves) fell(s) edict(s) verandah(s) fisher(s) exclaim(s) fender(s) approve(s) contingent(s) gargoyle(s) greenhouse(s) leftover(s) gambler(s) foster(s) computation(s) peg(s) clay(s) sayer(s) execute(s) withdrawal(s) bohemian(s) shriek(s) overture(s) cramp(s) shank(s) tiptoe(s) weave(s) oboe(s) dorm(s) englishman(en) sociologist(s) annotation(s) hierarchy(ies) emerald(s) showing(s) pylon(s) roar(s) alkaloid(s) intermediate(s) skeptic(s) thrill(s) dry(ies) educate(s) troupe(s) legacy(ies) ulcer(s) appointee(s) blotch(es) choreographer(s) bakery(ies) evangelist(s) tithe(s) hale(s) mennonite(s) retainer(s) lace(s) alignment(s) allocation(s) converter(s) conifer(s) turkey(s) prospector(s) diode(s) rambler(s) fleck(s) simulator(s) tense(s) purse(s) heal(s) marathon(s) cache(s) cartel(s) orphanage(s) observatory(ies) emissary (ies) ascend(s) contradict(s) mistress(es) birthday(s) millionaire(s) escalator(s) eyewitness(es) brochure(s) impairment(s) lemur(s) butter(s) serpent(s) were(s) cam(s) ravine(s) mover(s) alphabet(s) heartbeat(s) dissolve(s) ovary(ies) surge(s) bungalow(s) concubine(s) livelihood(s) workstation(s) booklet(s) purchaser(s) mint(s) vice(s) navigator(s) soup(s) swim(s) sentry(ies) perceive(s) wrong(s) sucker(s) mummy (ies) insider(s) quilt(s) airliner(s) analogue(s) houseguest(s) runaway(s) soybean(s) repository(ies) buffer(s) puddle(s) whore(s) pressing(s) sting(s) duchy(ies) cyst(s) tabloid(s) trajectory(ies) tracker(s) speck(s) insecurity(ies) griffin(s) dame(s) resin(s) potion(s) cargo(es) catcher(s) lemon(s) rainbow(s) refreshment(s) snatch(es) pilgrimage(s) scrape(s) loudspeaker(s) inclusion(s) levy(ies) forester(s) steamboat(s) newborn(s) podium(s) deadline(s) bison(s) napkin(s) intermediary (ies) coconut(s) tight(s) booking(s) parachute(s) interfere(s) fundraiser(s) convent(s) dependent(s) minefield(s) blister(s) byrne(s) diaper(s) spray(s) admire(s) evidence(s) homicide(s) martian(s) digger(s) cockroach(es) affirm(s) par(s) abolitionist(s) hive(s) antiquary(ies) blaster(s) inventory(ies) chronicler(s) covenant(s) clipping(s) trapper(s) axon(s)

## Singular form with associated plural modifications

daisy(ies) quarrel(s) grey(s) interrogation(s) midfielder(s) lobbyist(s) powder(s) confer(s) sportsman(en) meditation(s) enroll(s) imprint(s) woodpecker(s) homeland(s) wild(s) newsletter(s) moderate(s) goody(ies) tease(s) lander(s) pouch(es) adjust(s) farmhouse(s) clamp(s) ambush(es) frenchman(en) casting(s) forge(s) overall(s) transporter(s) purge(s) consort(s) maritime(s) substitution(s) reunion(s) mandible(s) debtor(s) swap(s) advisory(ies) blocker(s) lobster(s) clarinet(s) headliner(s) embankment(s) conqueror(s) ledge(s) dare(s) outburst(s) router(s) hose(s) calculator(s) siege(s) intrusion(s) scarf(ves) suv(s) inherit(s) canopy(ies) isolate(s) trombone(s) pinnacle(s) buckle(s) storefront(s) hike(s) integral(s) howl(s) pray(s) cape(s) screenwriter(s) helix (ces) hippie(s) dale(s) flashlight(s) candy(ies) reputation(s) failing(s) stork(s) scavenger(s) ink(s) mould(s) david(s) quark(s) thicket(s) going(s) harper(s) sweater(s) torture(s) gemstone(s) dash(es) conglomerate(s) abraham(s) long(s) gaul(s) furrow(s) cornice(s) subsystem(s) recovery(ies) identifier(s) symmetry(ies) breakdown(s) trope(s) resignation(s) lorry(ies) competency(ies) addiction(s) fury(ies) header(s) widower(s) unicorn(s) kidnapping(s) headstone(s) undertaking(s) steel(s) notation(s) supreme(s) financier(s) manipulation(s) ever(s) warm(s) disclosure(s) modality(ies) umbrella(s) magnitude(s) approximation(s) stag(s) firefly(ies) secretion(s) regional(s) aboriginal(s) bookshelf(ves) caution(s) mock(s) enquiry(ies) talkie(s) clap(s) emplacement(s) campaigner(s) evangelical(s) preside(s) postulate(s) knockout(s) luxury(ies) outcast(s) drinker(s) thunderbolt(s) imitation(s) daily(ies) aker(s) sorority(ies) slovak(s) mattress(es) jackal(s) peripheral(s) judgement(s) alchemist(s) campground(s) pogrom(s) silk(s) pun(s) supercar(s) shipbuilder(s) brownie(s) bun(s) toddler(s) hiss(es) saucer(s) superintendent(s) fed(s) pairing(s) shaker(s) sorcerer(s) suffering(s) snort(s) understanding(s) crawl(s) paddle(s) homestead(s) moore(s) paperback(s) remake(s) geometry(ies) swarm(s) perfume(s) conspiracy(ies) assay(s) trawler(s) reproduce(s) interlude(s) odor(s) heading(s) training(s) plague(s) atmosphere(s) blacksmith(s) geographer(s) chaser(s) typhoon(s) slayer(s) lineup(s) adapt(s) typeface(s) indictment(s) amulet(s) germ(s) monarchy(ies) lance(s) boil(s) covert(s) taylor(s) vial(s) petitioner(s) townhouse(s) wedge(s) coupon(s) panic(s) exporter(s) genealogy(ies) salamander(s) raine(s) tutorial(s) lintel(s) jain(s) tailor(s) livre(s) aquarium(s) bidder(s) piercing(s) chat(s) adventist(s) collage(s) efficiency(ies) tenement(s) tectonic(s) cybernetic(s) autograph(s) minuteman(en) foul(s) dude(s) alligator(s) tortoise(s) filing(s) raccoon(s) columnist(s) muppet(s) sub(s) preliminary(ies) caress(es) overcome(s) boulevard(s) platelet(s) scooter(s) levee(s) fake(s) private(s) thrower(s) spa(s) racehorse(s) crag(s) passer(s) reinforce(s) exterior(s) overseer(s) coup(s) pardon(s) barrister(s) absence(s) dub(s) lookout(s) steer(s) condemn(s) notch(es) hurry(ies) freighter(s) peril(s) dreamer(s)
coordinator(s) fen(s) voucher(s) buster(s) canister(s) aquifer(s) ruby(ies) formality(ies) gravestone(s) negotiator(s) banquet(s) antidepressant(s) dismissal(s) centurion(s) evacuation(s) crux(ces) forgery(ies) rectangle(s) raisin(s) devote(s) trapping(s) shear(s) theft(s) prefect(s) inlet(s) positive(s) foray(s) permission(s) exposition(s) vesper(s) verdict(s) picnic(s) snow(s) prelate(s) elective(s) ural(s) crush(es) flirt(s) flourish(es) supervise(s) cough(s) equate(s) spoke(s) harness(es) superstition(s) gnome(s) idiom(s) uncover(s) mobster(s) timeline(s) tub(s) collectible(s) generalization(s) faerie(s) archetype(s) writ(s) schooner(s) liaison(s) cannibal(s) nature(s) prism(s) obstruction(s) follicle(s) billionaire(s) covering(s) mature(s) intent(s) dummy (ies) sophomore(s) surrender(s) caption(s) sofa(s) supersonic(s) 10(s) rake(s) instrumentalist(s) intake(s) bulkhead(s) beet(s) ascent(s) compressor(s) harlequin(s) colonial(s) apparition(s) misconception(s) recognition(s) cheetah(s) lattice(s) accelerator(s) hydraulic(s) blonde(s) importer(s) shovel(s) thoroughfare(s) lumberjack(s) splash(es) tryout(s) panelist(s) $\operatorname{access}(e s) \operatorname{mag}(s)$ woolworth(s) inclination(s) misfortune(s) fil(s) pronunciation(s) fissure(s) strengthen(s) hallmark(s) assemblage(s) hanger(s) cipher(s) gully(ies) diesel(s) divorce(s) mediator(s) dwell(s) trolley(s) liberator(s) accelerate(s) repetition(s) buoy(s) palacio(s) hover(s) sprout(s) adapter(s) notification(s) sprinter(s) approval(s) glide(s) improvisation(s) loophole(s) sailboat(s) scoop(s) secure(s) landfill(s) oscillator(s) contraceptive(s) retire(s) inference(s) conquistador(s) passageway(s) more(s) elk(s) hummingbird(s) backpack(s) dick(s) transept(s) thrasher(s) timetable(s) warlock(s) couplet(s) fanatic(s) aqueduct(s) sloop(s) archeologist(s) diverge(s) neanderthal(s) refrigerator(s) ford(s) obituary(ies) philanthropist(s) seduce(s) dragonfly(ies) anxiety(ies) cream(s) lobby(ies) ballistic(s) briefing(s) gym(s) burner(s) playlist(s) intercept(s) hamburger(s) maple(s) queue(s) registry (ies) minstrel(s) meteor(s) coastline(s) finch(es) terror(s) taboo(s) crease(s) slate(s) racket(s) baptism(s) tyrant(s) antecedent(s) executor(s) trim(s) appreciate(s) leftist(s) waitress(es) spotlight(s) dad(s) dissertation(s) echelon(s) basement(s) basque(s) bunny(ies) casing(s) cask(s) wrapper(s) nettle(s) piper(s) ironclad(s) culprit(s) carnival(s) snapshot(s) bombardment(s) intensity (ies) sore(s) vigilante(s) pelt(s) oracle(s) snowflake(s) refinement(s) muffin(s) raman(en) platter(s) consult(s) cookbook(s) veil(s) coward(s) humanist(s) cistern(s) ghetto(s) recite(s) disposition(s) exhale(s) ornithologist(s) cucumber(s) pretender(s) ode(s) transcend(s) shin(s) paleontologist(s) skid(s) omission(s) capillary (ies) proclamation(s) irregular(s) sparkle(s) printing(s) hanging(s) questionnaire(s) yellow(s) yarn(s) gcse(s) mishap(s) width(s) atoll(s) locust(s) coincidence(s) slash(es) stairway(s) vapor(s) forerunner(s) shamrock(s) neurotransmitter(s) deduce(s) revert(s) granddaughter(s) pallet(s) boomer(s) walnut(s) barony(ies) awake(s) diversion(s)

## Singular form with associated plural modifications

insecticide(s) lottery(ies) offset(s) hermit(s) contemplate(s) scam(s) mixer(s) crossover(s) hack(s) quay(s) correspondence(s) upheaval(s) posture(s) shrink(s) belly(ies) thoroughbred(s) primitive(s) cloister(s) saxophone(s) curiosity (ies) traditionalist(s) snarl(s) linger(s) conform(s) veer(s) pizza(s) filling(s) canary(ies) watercourse(s) poke(s) modem(s) tumour(s) retort(s) blackmail(s) inquire(s) conservationist(s) opioid(s) phoenician(s) penetrate(s) chute(s) nonprofit(s) shopkeeper(s) perch(es) smack(s) tangle(s) bard(s) syndicate(s) lubricant(s) silence(s) stipulation(s) avalanche(s) courthouse(s) foundry(ies) dor(s) storyteller(s) rosette(s) ill(s) imbalance(s) calm(s) shack(s) hampton(s) abstraction(s) elaborate(s) litter(s) plum(s) tuck(s) wreath(s) taping(s) annual(s) viaduct(s) jacobite(s) exert(s) bab(s) conjecture(s) façade(s) searchlight(s) barb(s) transponder(s) herder(s) bestseller(s) engraver(s) baton(s) literature(s) drifter(s) codex(ices) courier(s) resistor(s) lapel(s) groom(s) enforce(s) dramatist(s) minaret(s) flicker(s) shudder(s) bree(s) wraith(s) parapet(s) creole(s) assemble(s) specialization(s) wheeler(s) refuge(s) radiator(s) aeroplane(s) memo(s) bassoon(s) plunge(s) transgression(s) equity(ies) epithet(s) prelude(s) grandfather(s) rowdy(ies) rom(s) cheque(s) carton(s) injunction(s) ease(s) blackout(s) perturbation(s) clearing(s) glade(s) vive(s) ale(s) dreadnought(s) rendering(s) shallow(s) squeal(s) elimination(s) lapse(s) imp(s) signer(s) caliph(s) leech(es) garland(s) allegiance(s) pastel(s) hitman(en) recruiter(s) parkland(s) tester(s) interceptor(s) stingray(s) scold(s) referral(s) three(s) utterance(s) bivalve(s) cobblestone(s) cartographer(s) coupling(s) parlor(s) tribune(s) fetus(es) vicar(s) grill(s) coffee(s) gutter(s) quad(s) tulip(s) backup(s) cancellation(s) moulding(s) weather(s) never(s) cour(s) clench(es) mythology(ies) nave(s) slur(s) dictator(s) fragrance(s) orchestration(s) roadblock(s) clove(s) trucker(s) stripper(s) violet(s) asylum(s) tenor(s) deformity(ies) progression(s) identification(s) primer(s) observance(s) borrowing(s) meme(s) revue(s) wrangler(s) overrun(s) asshole(s) nerd(s) opener(s) grocer(s) pottery(ies) mac(s) veterinarian(s) revive(s) anniversary(ies) cormorant(s) snipe(s) loaf(ves) sash(es) civic(s) phonetic(s) salute(s) vaccination(s) owing(s)

## A.1.2. Past

## Base form with past inflection modifications

be(was) have(d) be(were) say(id) do(id) make(de) use(d) become(ame) call(ed) take(ook) have('d) find(ound) release(d) play(ed) begin(an) leave(ft) hold(eld) win(on) locate(d) come(ame) go(went) build(t) receive(d) serve(d) move(d) start(ed) $\operatorname{ask}(\mathrm{ed}) \operatorname{die}(\mathrm{d}) \operatorname{look}(\mathrm{ed}) \operatorname{get}(\mathrm{ot}) \operatorname{publish}(\mathrm{ed}) \operatorname{lead}(\mathrm{d}) \operatorname{include}(\mathrm{d}) \operatorname{turn}(\mathrm{ed})$ open(ed) see(aw) want(ed) lose(t) work(ed) give(ave) establish(ed) feel(lt) return(ed) know(ew) continue(d) tell(old) produce(d) announce(d) join(ed) see(n) create(d) write(ote) describe(d) appear(ed) consider(ed) follow(ed) reach(ed) elect(ed) record(ed) form(ed) $\operatorname{sign}(\mathrm{ed})$ finish(ed) develop(ed) appoint(ed) bring(ought) send(t) remain(ed) decide(d) sell(old) add(ed) kill(ed) run(an) design(ed) meet(t) hear(d) perform(ed) complete(d) involve(d) try(ied) direct(ed) report(ed) need(ed) feature(d) change(d) stand(ood) replace(d) provide(d) award(ed) spend(t) live(d) allow(ed) pass(ed) seem(ed) introduce(d) end(ed) raise(d) keep(pt) enter(ed) attend(ed) score(d) force(d) defeat(ed) study(ied) walk(ed) fall(ell) represent(ed) note(d) require(d) cover(ed) stop(ped) help(ed) offer(ed) cause(d) launch(ed) happen(ed) manage(d) rise(ose) carry(ied) increase(d) believe(d) arrive(d) select(ed) fail(ed) retire(d) operate(d) mean(t) smile(d) support(ed) claim(ed) grow(ew) catch(ught) earn(ed) drop(ped) present(ed) refer(red) agree(d) compose(d) discover(ed) shake(ook) expect(ed) order(ed) acquire(d) propose(d) graduate(d) promote(d) plan(ned) remove(d) show(ed) construct(ed) issue(d) watch(ed) intend(ed) reveal(ed) transfer(red) fill(ed) pay(id) recognize(d) destroy(ed) accept(ed) divide(d) settle(d) participate(d) mention(ed) compare(d) combine(d) teach(aught) bury(ied) suggest(ed) purchase(d) organize(d) conduct(ed) assign(ed) occur(red) capture(d) declare(d) speak(oke) gain(ed) adopt(ed) suffer(ed) realize(d) draw(ew) buy(ought) push(ed) refuse(d) step(ped) pick(ed) estimate(d) stare(d) connect(ed) designate(d) focus(ed) reply(ied) nominate(d) result(ed) expand(ed) identify(ied) reduce(d) grant(ed) face(d) inspire(d) share(d) laugh(ed) lie(ay) confirm(ed) lay(id) mark(ed) define(d) love(d) attack(ed) succeed(ed) occupy(ied) obtain(ed) suppose(d) achieve(d) arrest(ed) whisper(ed) point(ed) attempt(ed) glance(d) visit(ed) learn(ed) stay(ed) approve(d) invite(d) explain(ed) abandon(ed) lean(ed) control(led) train(ed) employ(ed) grab(bed) consist(ed) contain(ed) oppose(d) seek(ought) lift(ed) influence(d) prove(d) convert(ed) derive(d) choose(se) hire(d) schedule(d) educate(d) contribute(d) admit(ted) cross(ed) engage(d) register(ed) maintain(ed) miss(ed) observe(d) collect(ed) express(ed) paint(ed) argue(d) remember(ed) regard(ed) throw(ew) strike(uck) survive(d) answer(ed) resign(ed) press(ed) merge(d) vote(d) attach(ed) conclude(d) improve(d) fix(ed)

## Base form with past inflection modifications

tie(d) rule(d) roll(ed) like(d) surround(ed) wait(ed) charge(d) accuse(d) distribute(d) deliver(ed) praise(d) protect(ed) separate(d) arrange(d) damage(d) accompany(ied) hope(d) threaten(ed) reject(ed) drive(ove) kiss(ed) approach(ed) dress(ed) mount(ed) wonder(ed) wear(ore) link(ed) enjoy(ed) repeat(ed) bind(ound) restore(d) translate(d) burn(ed) understand(ood) respond (ed) adapt(ed) shrug(ged) wrap(ped) exist(ed) sound(ed) touch(ed) fly (ew) disappear(ed) land(ed) criticize(d) date(d) treat(ed) shift(ed) indicate(d) emerge(d) save(d) act(ed) lock(ed) travel(ed) edit(ed) demand(ed) file(d) attract(ed) decline(d) promise(d) celebrate(d) deny(ied) expose(d) gather(ed) modify(ied) cite(d) jump(ed) sponsor(ed) command(ed) execute(d) print(ed) eliminate(d) aim(ed) preserve(d) pause(d) clear(ed) get(otten) portray(ed) talk(ed) dominate(d) fund(ed) recommend(ed) post(ed) recover(ed) comment(ed) suspend(ed) slip(ped) escape(d) donate(d) animate(d) erect(ed) flee(d) view(ed) discuss(ed) cease(d) contest(ed) attribute(d) snap(ped) wish(ed) demolish(ed) display(ed) tour(ed) generate(d) prefer(red) dismiss(ed) withdraw(ew) organise(d) shout(ed) characterize(d) assist(ed) rebuild(t) relocate(d) knock(ed) ignore(d) isolate(d) request(ed) fit(ted) deploy(ed) struggle(d) sail(ed) kick(ed) suspect(ed) initiate(d) trade(d) implement(ed) switch(ed) recall(ed) pitch(ed) rush(ed) cry(ied) decorate(d) climb(ed) demonstrate(d) recognise(d) manufacture(d) lower(ed) travel(led) depart(ed) submit(ted) hate(d) restrict(ed) ban(ned) twist(ed) cancel(led) insist(ed) review(ed) resume(d) fold(ed) inherit(ed) reflect(ed) exhibit(ed) figure(d) test(ed) convict(ed) spot(ted) permit(ted) check(ed) supply(ied) sweep(pt) warn(ed) orient(ed) collaborate(d) stretch(ed) depict(ed) deem(ed) commence(d) challenge(d) delay(ed) dissolve(d) collapse(d) remind(ed) scream(ed) compile(d) administer(ed) wave(d) scatter(ed) seize(d) trap(ped) disband(ed) relieve(d) revise(d) swallow(ed) update(d) recruit(ed) murmur(ed) document(ed) imprison(ed) perceive(d) prevent(ed) sustain(ed) abolish(ed) question(ed) encounter(ed) transform(ed) block(ed) load(ed) honor(ed) renew(ed) listen(ed) alter(ed) race(d) guide(d) proceed(ed) acknowledge(d) discontinue(d) plant(ed) toss(ed) enable(d) invent(ed) reform(ed) dub(bed) handle(d) accomplish(ed) crash(ed) practice(d) prompt(ed) divorce(d) pronounce(d) examine(d) drag(ged) slam(med) target(ed) absorb(ed) assemble(d) pursue(d) authorize(d) inhabit(ed) fear(ed) shove(d) squeeze(d) quote(d) count(ed) desire(d) brush(ed) reserve(d) possess(ed) imagine(d) advise(d) fade(d) transport(ed) impose(d) wipe(d) deal(t) govern(ed) activate(d) $\operatorname{avoid}(e d)$ interpret(ed) wake(oke) chuckle(d) endanger(ed) pack(ed) hesitate(d) assure(d) enhance(d) rest(ed) witness(ed) predict(ed) criticise(d) proclaim(ed) respect(ed) widen(ed) expel(led) curl(ed) interview(ed) specify(ied) render(ed) condemn(ed) trace(d) search(ed) decrease(d) eat(ate) flash(ed) tighten(ed) prove(n) revive(d) rescue(d) calculate(d) arise(ose) investigate(d) renovate(d) dry(ied) breathe(d) explore(d) stain(ed) resolve(d) park(ed) clench(ed) arch(ed) surrender(ed) allocate(d) groan(ed) suck(ed) strip(ped) invade(d) trust(ed) prohibit(ed) embark(ed) import(ed) remark(ed) consume(d) $\operatorname{sink}(u n k)$ slow(ed) induce(d) contract(ed) emigrate(d) flip(ped) reinforce(d) infect(ed) ruin(ed) match(ed) seal(ed) complain(ed) spell(ed) enclose(d) flood(ed) rip(ped) invest(ed) value(d) forget(ot) welcome(d) detect(ed) bat(ted) explode(d) tuck(ed) adjust(ed) comprise(d) glare(d) project(ed) reunite(d) dispute(d) highlight(ed) exchange(d) aid(ed) precede(d) tend(ed) blame(d) lie(d) endorse(d) reopen(ed) crack(ed) persuade(d) bless(ed) realise(d) crush(ed) anticipate(d) $\operatorname{appeal}(e d)$ lease(d) burn(t) enact(ed) protest(ed) regain(ed) double(d) drift(ed) reverse(d) enlarge(d) terminate(d) chart(ed) weaken(ed) transmit(ted) kidnap(ped) smell(ed) greet(ed) retreat(ed) piss(ed) vanish(ed) exclude(d) drain(ed) pave(d) $\operatorname{tap}(\mathrm{ped})$ borrow (ed) constitute(d) utilize(d) loan(ed) encode(d) garner(ed) shorten(ed) sue(d) displace(d) plead(ed) confine(d) guarantee(d) attain(ed) dance(d) rent(ed) summon(ed) tip(ped) deserve(d) peer(ed) pop(ped) label(ed) detach(ed) access(ed) migrate(d) cultivate(d) emphasize(d) ease(d) halt(ed) distract(ed) confront(ed) shatter(ed) tug(ged) align(ed) haunt(ed) survey (ed) appreciate(d) evacuate(d) assert(ed) straighten(ed) cancel(ed) annex(ed) amend(ed) fortify(ied) disturb(ed) owe(d) negotiate(d) slap(ped) admire(d) weigh(ed) bow(ed) finance(d) guess(ed) trigger(ed) insert(ed) pin(ned) judge(d) assess(ed) erupt(ed) repair(ed) track(ed) bother(ed) expire(d) scan(ned) breed(d) clean(ed) solve(d) stroke(d) pose(d) strengthen(ed) rejoin(ed) yank(ed) drown(ed) imply(ied) resist(ed) stress(ed) detain(ed) suppress(ed) spark(ed) lick(ed) tease(d) exile(d) reorganize(d) process(ed) discharge(d) testify(ied) violate(d) sanction(ed) account(ed) exceed(ed) dispatch(ed) anchor(ed) volunteer(ed) reconstruct(ed) chase(d) excavate(d) accumulate(d) fry(ied) haul(ed) presume(d) embrace(d) correct(ed) retrieve(d) moan(ed) whip(ped) speculate(d) reward(ed) accelerate(d) choke(d) postpone(d) devise(d) conceal(ed) confess(ed) doubt(ed) vacate(d) beg(ged) oblige(d) guard(ed) export(ed) pace(d) hook(ed) soak(ed) disperse(d) debate(d) flow(ed) prolong(ed) punish(ed) confer(red) intercept(ed) cool(ed) wander(ed) stir(red) bounce(d) flick(ed) shiver(ed) taste(d) dump(ed) lend(t) honour(ed) culminate(d) ensure(d) react(ed) neglect(ed) float(ed) leak(ed) waste(d) compel(led) illuminate(d) $\operatorname{copy}$ (ied) extract(ed) evaluate(d) scramble(d) rape(d) root(ed) spill(ed) hunt(ed) wink(ed) intensify(ied) discard(ed) hail(ed) enforce(d) dip(ped) flank(ed) analyze(d) pledge(d) reissue(d) mandate(d) pray(ed) roar(ed) concede(d) clutch(ed) darken(ed) assassinate(d) dream(ed) advertise(d) exit(ed) reprint(ed) grunt(ed) resemble(d) giggle(d) smash(ed) pound(ed) redesign(ed) confiscate(d) forge(d) propel(led) flatten(ed) slump(ed) denounce(d) snatch(ed) thank(ed) duck(ed)

## Base form with past inflection modifications

tune(d) substitute(d) deport(ed) overturn(ed) puzzle(d) matter(ed) dismantle(d) pretend(ed) consult(ed) circulate(d) harden(ed) yield(ed) fulfil(led) elongate(d) compress(ed) bestow(ed) omit(ted) tangle(d) coincide(d) screw(ed) besiege(d) abuse(d) flourish(ed) label(led) exercise(d) assault(ed) mask(ed) drape(d) sever(ed) reinstate(d) inflict(ed) endure(d) spawn(ed) delete(d) dare(d) scratch(ed) attest(ed) heal(ed) envision(ed) depend(ed) dart(ed) span(ned) offend(ed) depose(d) spare(d) stiffen(ed) research(ed) flare(d) exploit(ed) deprive(d) hang(ed) tremble(d) snarl(ed) convene(d) divert(ed) raid(ed) refurbish(ed) commemorate(d) persist(ed) grasp(ed) picture(d) ensue(d) scowl(ed) fuel(ed) apologize(d) lecture(d) differ(ed) grimace(d) dislike(d) facilitate(d) inhale(d) pierce(d) cede(d) exhale(d) boil(ed) skip(ped) stack(ed) tow(ed) wrinkle(d) wreck(ed) provoke(d) deteriorate(d) craft(ed) augment(ed) denote(d) stalk(ed) tempt(ed) categorize(d) conserve(d) poison(ed) slice(d) liberate(d) prevail(ed) soften(ed) notify(ied) scale(d) implicate(d) plunge(d) disrupt(ed) supplement(ed) improvise(d) popularize(d) practise(d) batter(ed) speed(d) mediate(d) fuse(d) poke(d) adorn(ed) function(ed) bark(ed) blush(ed) arouse(d) grumble(d) prop(ped) verify(ied) experiment(ed) $\operatorname{sip}(\mathrm{ped}) \operatorname{stall}(\mathrm{ed})$ ascend(ed) clarify(ied) intrigue(d) sample(d) intervene(d) await(ed) leap(ed) inject(ed) repeal(ed) glow(ed) twitch(ed) squint(ed) disclose(d) bolt(ed) blurt(ed) wrestle(d) amass(ed) inspect(ed) petition(ed) linger(ed) dash(ed) whirl(ed) glaze(d) articulate(d) venture(d) showcase(d) enslave(d) summarize(d) grit(ted) strap(ped) phase(d) shuffle(d) reign(ed) hamper(ed) rotate(d) cough(ed) subdue(d) convey(ed) fumble(d) flinch(ed)
bruise(d) blast(ed) spoil(ed) chew(ed) revoke(d) surge(d) sacrifice(d) reproduce(d) clash(ed) clap(ped) audition(ed) harvest(ed) bump(ed) hover(ed) finalize(d) discourage(d) entertain(ed) incur(red) recount(ed) excel(led) muster(ed) lunge(d) smoke(d) befriend(ed) nudge(d) tumble(d) recycle(d) cure(d) eject(ed) reclaim(ed) deepen(ed) peek(ed) awaken(ed) clamp(ed) recapture(d) resurrect(ed) correlate(d) penetrate(d) synthesize(d) pinch(ed) alert(ed) afford(ed) mess(ed) rattle(d) blind(ed) clip(ped) emit(ted) stamp(ed) shave(d) download(ed) encompass(ed) dissipate(d) rally(ied) worship(ped) swirl(ed) signal(ed) stroll(ed) dictate(d) smack(ed) trim(med) simulate(d) publicize(d) filter(ed) inquire(d) diversify(ied) reappear(ed) evict(ed) scrape(d) perish(ed) elaborate(d) calm(ed) revere(d) huddle(d) heave(d) stimulate(d) rebel(led) steer(ed) restart(ed) pluck(ed) $\operatorname{trip}(\mathrm{ped})$ repulse(d) dial(ed) strangle(d) compute(d) contemplate(d) caress(ed) cheat(ed) slaughter(ed) poise(d) drill(ed) communicate(d) peel(ed) defect(ed) muse(d) streak(ed) swell(ed) obscure(d) mock(ed) degrade(d) shriek(ed) recite(d) synchronize(d) hunch(ed) mobilize(d) radiate(d) relinquish(ed) correspond(ed) breach(ed) splash(ed) spearhead(ed) stock(ed) rig(ged) manifest(ed) erase(d) cramp(ed) sprawl(ed) disuse(d) retort(ed) glue(d) worsen(ed) escalate(d) loosen(ed) rumble(d) buzz(ed) tolerate(d) loot(ed) commute(d) lurch(ed) empower(ed) oust(ed) stomp(ed) encircle(d) remodel(ed) fuck(ed) stem(med) modernize(d) fasten(ed) harass(ed) rake(d) compliment(ed) trick(ed) stabilize(d) boost(ed) traverse(d) $\log ($ ged $)$ tackle(d) cringe(d) claw(ed) plot(ted) accommodate(d) wake(oken) slash(ed) hurl(ed) reconcile(d) resent(ed) forgive(n) recreate(d) chop(ped) lure(d) humiliate(d) bang(ed) harm(ed) compensate(d) shower(ed) retract(ed) drip(ped) sire(d) streamline(d) outlaw(ed) complement(ed) spray(ed) hinder(ed) contend(ed) tag(ged) thwart(ed) subside(d) hush(ed) revisit(ed) gape(d) patrol(led) interfere(d) whistle(d) behave(d) discipline(d) starve(d) detonate(d) flop(ped) censor(ed) materialize(d) freak(ed) spike(d) bathe(d) assimilate(d) extinguish(ed) swap(ped) shield(ed) customize(d) amplify(ied) undermine(d) hoist(ed) bellow(ed) falter(ed) repel(led) weld(ed) exert(ed) defer(red) squeal(ed) fool(ed) nail(ed) weep(pt) bombard(ed) mold(ed) graze(d) despise(d) whimper(ed) lash(ed) taint(ed) relay(ed) topple(d) restructure(d) profess(ed) emphasise(d) smuggle(d) infer(red) salvage(d) intimidate(d) smear(ed) pardon(ed) ram(med) lengthen(ed) swipe(d) rewrite(ten) roast(ed) revamp(ed) fare(d) optimize(d) applaud(ed) stifle(d) plunder(ed) dismount(ed) hack(ed) foster(ed) discount(ed) apprehend(ed) sag(ged) broaden(ed) sharpen(ed) tick(ed) analyse(d) levy(ied) chime(d) buckle(d) glide(d) massacre(d) sparkle(d) wage(d) torment(ed) hum(med) exempt(ed) rain(ed) mingle(d) fake(d) howl(ed) adore(d) ripple(d) revolve(d) avert(ed) enlighten(ed) tweet(ed) caution(ed) contradict(ed) wiggle(d) officiate(d) pant(ed) jog(ged) disapprove(d) scrub(bed) wrench(ed) replicate(d) deflect(ed) chant(ed) reckon(ed) forfeit(ed) moor(ed) vibrate(d) puff(ed) charm(ed) abort(ed) insure(d) scold(ed) dread(ed) skim(med) brew(ed) dodge(d) esteem(ed) grill(ed) creak(ed) comfort(ed) revolt(ed) deduce(d) propagate(d) solidify(ied) cherish(ed) adhere(d) thump(ed) relent(ed) bully(ied) lament(ed) hinge(d) wane(d) $\operatorname{roam}(\mathrm{ed})$ rehabilitate(d) whine(d) precipitate(d) herald(ed) seep(ed) defy(ied) dive(d) taunt(ed) reestablish(ed) evoke(d) $\operatorname{spy}$ (ied) tickle(d) evaporate(d) shrink(ank) entail(ed) cruise(d) rearrange(d) disintegrate(d) soothe(d) rescind(ed) implant(ed) chronicle(d) devour(ed) diverge(d) crop(ped) wedge(d) wield(ed) derail(ed) postulate(d) inhibit(ed) quicken(ed) trickle(d) quiver(ed) hatch(ed) allude(d) rehearse(d) zip(ped) imitate(d) crumble(d) rack(ed) signal(led) mould(ed) tax(ed) waver(ed) congratulate(d) deceive(d) duplicate(d) purify(ied) apologise(d) worship(ed) skid(ded) refute(d) ridicule(d) hone(d) snicker(ed) latch(ed) secrete(d) glitter(ed) disarm(ed) lapse(d) boycott(ed) colonize(d) dangle(d) crackle(d) subscribe(d) $\operatorname{snag}(\mathrm{ged})$ confide(d) flatter(ed) sketch(ed) mash(ed) shimmer(ed) legalize(d) gag(ged) recede(d) groom(ed) veer(ed) limp(ed) $\operatorname{prod}(\mathrm{ded})$ fuel(led) churn(ed) disregard(ed) replay(ed) steady(ied) splinter(ed) squat(ted) lessen(ed) bolster(ed) refit(ted) scout(ed) twirl(ed) moderate(d) chip(ped) interact(ed) tingle(d) stutter(ed) salute(d) warrant(ed) faint(ed) stitch(ed)

## Base form with past inflection modifications

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## A.1.3. Present Participle

## Base form with present participle inflection modifications

be(ing) include(ing) follow(ing) go(ing) have(ing) make(ing) use(ing) work(ing) live(ing) play(ing) take(ing) look(ing) lead(ing) run(ning) try (ing) come(ing) begin(ning) do(ing) win(ning) leave(ing) get(ting) say (ing) move(ing) start(ing) stand(ing) become(ing) give(ing) hold(ing) serve(ing) feel(ing) remain(ing) think(ing) fight(ing) grow(ing) talk(ing) wait(ing) act(ing) sit(ting) lose(ing) operate(ing) feature(ing) return(ing) fly (ing) watch(ing) surround(ing) see(ing) turn(ing) walk(ing) speak(ing) score(ing) provide(ing) allow(ing) reach(ing) call(ing) result(ing) set(ting) perform(ing) exist(ing) create(ing) pass(ing) end(ing) kill(ing) wear(ing) tell(ing) support(ing) drive(ing) miss(ing) receive(ing) sell(ing) increase(ing) keep(ing)
know(ing) contain(ing) cause(ing) regard(ing) finish(ing) show(ing) develop(ing) carry(ing) represent(ing) produce(ing) join(ing) fall(ing) rise(ing) bring(ing) cross(ing) break(ing) lie(ying) help(ing) consist(ing) ask(ing) cover(ing) date(ing) face(ing) stare(ing) change(ing) put(ting) pull(ing) form(ing) study(ing) enter(ing) continue(ing) add(ing) close(ing) depend(ing) ride (ing) visit(ing) defeat(ing) burn(ing) involve(ing) appear(ing) hope(ing) dance(ing) replace(ing) survive(ing) beat(ing) seek(ing) compete(ing) graduate(ing) breathe(ing) raise(ing) shake(ing) smile(ing) send(ing) hang(ing) eat(ing) want(ing) sleep(ing) let(ting) consider(ing) defend(ing) listen(ing) claim(ing) die(ying) cut(ting) tour(ing) rule(ing) manage(ing) attend(ing) laugh(ing) earn(ing) hide(ing) arrive(ing) push(ing) connect(ing) happen(ing) force(ing) establish(ing) attempt(ing) stay(ing) complete(ing) travel(ing) concern(ing) search(ing) belong(ing) pay(ing) report(ing) deal(ing) promote(ing) throw(ing) describe(ing) refer(ring) contribute(ing) participate(ing) correspond(ing) hit(ting) wonder(ing) bear(ing) lean(ing) indicate(ing) breed(ing) attack(ing) fail(ing) focus(ing) save(ing) point(ing) reduce(ing) bind(ing) command(ing) drop(ping) cry (ing) release(ing) stop(ping) reside(ing) extend(ing) gain(ing) cite(ing) govern(ing) maintain(ing) rush(ing) emerge(ing) handle(ing) prepare(ing) struggle(ing) retire(ing) note(ing) strike(ing) climb(ing) feed(ing) relate(ing) suggest(ing) approach(ing) travel(ling) press(ing) require(ing) expand(ing) pick(ing) float(ing)

## Base form with present participle inflection modifications

scream(ing) believe(ing) kiss(ing) flow(ing) improve(ing) threaten(ing) reveal(ing) protect(ing) expect(ing) jump(ing) argue(ing) conduct(ing) rest(ing) collect(ing) slide(ing) cast(ing) comprise(ing) remove(ing) skate(ing) love(ing) buy(ing) occur(ring) direct(ing) spread(ing) mark(ing) lift(ing) measure(ing) demand(ing) oppose(ing) enjoy(ing) control(ling) realize(ing) destroy(ing) settle(ing) promise(ing) step(ping) explain(ing) match(ing) depict(ing) introduce(ing) ignore(ing) advance(ing) view(ing) shift(ing) sound(ing) spin(ning) check(ing) avoid(ing) achieve(ing) accompany(ing) prevent(ing) discuss(ing) organize(ing) present(ing) lay(ing) assume(ing) accept(ing) precede(ing) bleed(ing) reflect(ing) choose(ing) decide(ing) $\operatorname{sink}(\mathrm{ing})$ obtain(ing) owe(ing) count(ing) shine(ing) mix(ing) combine(ing) link(ing) apply(ing) investigate(ing) block(ing) wish(ing) grab(bing) generate(ing) capture(ing) curl(ing) refuse(ing) pursue(ing) engage(ing) steal(ing) pound(ing) stretch(ing) question(ing) secure(ing) enable(ing) dig(ging) launch(ing) cool(ing) knock(ing) hurl(ing) identify(ing) dress(ing) switch(ing) remember(ing) retain(ing) tremble(ing) glance(ing) need(ing) affect(ing) determine(ing) function(ing) succeed(ing) treat(ing) practice(ing) blow(ing) define(ing) address(ing) deliver(ing) purchase(ing) ensure(ing) shout(ing) exclude(ing) ensue(ing) celebrate(ing) chase(ing) incorporate(ing) care(ing) compare(ing) order(ing) declare(ing) recover(ing) decline(ing) examine(ing) acquire(ing) span(ning) announce(ing) ste(ing) charge(ing) experience(ing) demonstrate(ing) marry(ing) escape(ing) occupy(ing) slip(ping) express(ing) specialize(ing) rotate(ing) pretend(ing) post(ing) wave(ing) transfer(ring) discover(ing) fold(ing) recruit(ing) target(ing) assist(ing) freeze(ing) drag(ging) aim(ing) originate(ing) flee(ing) solve(ing) rebuild(ing) observe(ing) review(ing) hurt(ing) scout(ing) prove(ing) limit(ing) hire(ing) praise(ing) undergo(ing) wake(ing) respond(ing) render(ing) melt(ing) separate(ing) judge(ing) wander(ing) grant(ing) crash(ing) recognize(ing) implement(ing) issue(ing) comment(ing) ring(ing) signal(ing) beg(ging) flash(ing) pour(ing) fear(ing) attract(ing) lower(ing) employ(ing) eliminate(ing) preserve(ing) tie(ying) pump(ing) twist(ing) dream(ing) conclude(ing) yell(ing) graze(ing) sense(ing) construct(ing) brush(ing) mate(ing) $\log$ (ging) reign(ing) depart(ing) guide(ing) adopt(ing) weigh(ing) resemble(ing) stick(ing) descend(ing) pack(ing) divide(ing) invite(ing) consume(ing) convert(ing) expose(ing) pray(ing) culminate(ing) agree(ing) restore(ing) strengthen(ing) whisper(ing) compose(ing) repeat(ing) crush(ing) decrease(ing) merge(ing) await(ing) appeal(ing) fade(ing) mount(ing) bend(ing) portray(ing) pierce(ing) differ(ing) suck(ing) drown(ing) accuse(ing) disappear(ing) chart(ing) utilize(ing) intend(ing) lock(ing) commit(ting) impose(ing) fix(ing) deny(ing) dare(ing) drift(ing) clutch(ing) tap(ping) wipe(ing) supply(ing) request(ing) boil(ing) drip(ping) exceed(ing) preside(ing) ache(ing) restructure(ing) transport(ing) arise(ing) linger(ing) retreat(ing) satisfy(ing) worry(ing) invade(ing) concentrate(ing) project(ing) select(ing) crack(ing) proceed(ing) scatter(ing) rely(ing) dry(ing) preach(ing) like(ing) encode(ing) guard(ing) grind(ing) slam(ming) plead(ing) remind(ing) cheat(ing) squeeze(ing) negotiate(ing) admit(ting) possess(ing) carve(ing) mention(ing) prevail(ing) encompass(ing) seem(ing) oversee(ing) advocate(ing) trace(ing) collaborate(ing) confirm(ing) crawl(ing) inspire(ing) violate(ing) welcome(ing) glare(ing) complain(ing) distribute(ing) pant(ing) widen(ing) blink(ing) criticize(ing) compile(ing) bet(ting) invest(ing) arrange(ing) research(ing) coordinate(ing) kneel(ing) roar(ing) imagine(ing) shut(ting) chew(ing) shove(ing) commemorate(ing) highlight(ing) abandon(ing) pertain(ing) swell(ing) overlap(ping) echo(ing) distinguish(ing) thrive(ing) slow(ing) swirl(ing) imply(ing) award(ing) peer(ing) starve(ing) guess(ing) organise(ing) ban(ning) bother(ing) forget(ting) analyze(ing) draft(ing) evolve(ing) lick(ing) enhance(ing) rip(ping) stir(ring) protest(ing) adjust(ing) waste(ing) blaze(ing) honor(ing) prefer(ring) cling(ing) pose(ing) withdraw(ing) creep(ing) signal(ling) drain(ing) balance(ing) regulate(ing) yield(ing) calculate(ing) inform(ing) absorb(ing) reject(ing) propose(ing) assess(ing) plot(ting) murder(ing) taste(ing) spill(ing) fulfil(ling) interact(ing) glide(ing) weaken(ing) steam(ing) relax(ing) recall(ing) mock(ing) aspire (ing) specialise(ing) circulate(ing) exhibit(ing) communicate(ing) tighten(ing) swallow(ing) emphasize(ing) acknowledge(ing) integrate(ing) exit(ing) dangle(ing) sustain(ing) ascend(ing) debate(ing) injure(ing) supervise(ing) translate(ing) sweat(ing) bury(ing) insist(ing) cruise(ing) terminate(ing) seal(ing) stalk(ing) raid(ing) rename(ing) explode(ing) resign(ing) smash(ing) blind(ing) trust(ing) stumble(ing) sob(bing) resist(ing) speed(ing) free(ing) smell(ing) execute(ing) flirt(ing) escort(ing) scratch(ing) pop(ping) advise(ing) weld(ing) pause(ing) rescue(ing) dump(ing) evaluate(ing) collapse(ing) brake(ing) grasp(ing) drum(ming) burst(ing) aid(ing) permit(ting) chant(ing) sneak(ing) radiate(ing) flush(ing) embrace(ing) hum(ming) penetrate(ing) interfere(ing) glitter(ing) adapt(ing) spy(ing) filter(ing) cough(ing) click(ing) surpass(ing) educate(ing) flank(ing) relocate(ing) strain(ing) witness(ing) seize(ing) register(ing) commence(ing) blame(ing) influence(ing) forage(ing) facilitate(ing) shatter(ing) poke(ing) hack(ing) prohibit(ing) chat(ting) upgrade(ing) giggle(ing) slap(ping) scale(ing) rot(ting) leak(ing) sway(ing) assert(ing) soar(ing) gape(ing) repair(ing) appoint(ing) tumble(ing) unite(ing) detect(ing) tend(ing) spawn(ing) restrict(ing) strip(ping) interpret(ing) intersect(ing) intervene(ing) pin(ning) sprawl(ing) showcase(ing) exchange(ing) soak(ing) bang(ing) swear(ing) realise(ing) roam(ing)

## Base form with present participle inflection modifications

deteriorate(ing) loom(ing) react(ing) lodge(ing) enforce(ing) illustrate(ing) growl(ing) pave(ing) shimmer(ing) go(in') migrate(ing) howl(ing) ease(ing) moan(ing) calm(ing) whip(ping) figure(ing) cheer(ing) intimidate(ing) admire(ing) stem(ming) hate(ing) anticipate(ing) condemn(ing) quote(ing) knit(ting) interview(ing) scrape(ing) sip(ping) tingle(ing) spit(ting) tow(ing) loot(ing) reopen(ing) regain(ing) arrest(ing) distract(ing) whistle(ing) rain(ing) mentor(ing) trigger(ing) cope(ing) shield(ing) flourish(ing) reform(ing) administer(ing) crumble(ing) delay(ing) shuffle(ing) tip(ping) spot(ting) practise(ing) round(ing) exercise(ing) caress(ing) vibrate(ing) heave(ing) submit(ting) elect(ing) respect(ing) flutter(ing) resolve(ing) vanish(ing) induce(ing) encounter(ing) rig(ging) access(ing) scramble(ing) blast(ing) suppress(ing) hop(ping) restrain(ing) predict(ing) blush(ing) accelerate(ing) shrink(ing) risk(ing) reverse(ing) clench(ing) bow(ing) lecture(ing) assemble(ing) tuck(ing) concede(ing) import(ing) thump(ing) dazzle(ing) thank(ing) decorate(ing) opt(ing) dart(ing) ruin(ing) export(ing) donate(ing) foster(ing) deploy(ing) rattle(ing) assign(ing) probe(ing) illuminate(ing) straighten(ing) rent(ing) decay(ing) bypass(ing) churn(ing) rumble(ing) volunteer(ing) inspect(ing) sacrifice(ing) brood(ing) update(ing) smooth(ing) assault(ing) twitch(ing) proclaim(ing) reinforce(ing) spray(ing) flick(ing) diminish(ing) bulge(ing) crave(ing) shudder(ing) clap(ping) contest(ing) offend(ing) contact(ing) activate(ing) betray(ing) surrender(ing) constitute(ing) chuckle(ing) recommend(ing) irritate(ing) resume(ing) quit(ting) sniff(ing) reward(ing) bud(ding) forge(ing) punish(ing) prosecute(ing) yank(ing) deepen(ing) revive(ing) signify(ing) unfold(ing) grieve(ing) reel(ing) dub(bing) embark(ing) plunge(ing) thrash(ing) peel(ing) strive(ing) dissent(ing) recognise(ing) halt(ing) summon(ing) forbid(ding) taunt(ing) reunite(ing) accumulate(ing) flap(ping) peek(ing) tick(ing) extract(ing) combat(ing) accommodate(ing) dissolve(ing) rustle(ing) insert(ing) invent(ing) straddle(ing) remodel(ing) disrupt(ing) derive(ing) scare(ing) transition(ing) bloom(ing) abuse(ing) inhabit(ing) hatch(ing) fry(ing) behave(ing) torture(ing) stride(ing) attach(ing) shrug(ging) estimate(ing) crouch(ing) retrieve(ing) escalate(ing) specify(ing) dodge(ing) relieve(ing) recite(ing) screw(ing) remark(ing) dash(ing) enclose(ing) splash(ing) wane(ing) stock(ing) apologize(ing) harass(ing) whirl(ing) worsen(ing) wreck(ing) correct(ing) stain(ing) consolidate(ing) wade(ing) crackle(ing) clone(ing) compromise(ing) imitate(ing) persuade(ing) inflict(ing) do(in') dismantle(ing) inhibit(ing) anchor(ing) shorten(ing) empower(ing) navigate(ing) rejoin(ing) deserve(ing) groom(ing) conceal(ing) wince(ing) snarl(ing) denounce(ing) undermine(ing) wrench(ing) ripple(ing) traverse(ing) slug(ging) seep(ing) impress(ing) grapple(ing) minimize(ing) convey(ing) stress(ing) soften(ing) stomp(ing) authorize(ing) wail(ing) cultivate(ing) snore(ing) symbolize(ing) chatter(ing) benefit(ing) itch(ing) boost(ing) mistake(ing) twinkle(ing) surge(ing) confess(ing) nag (ging) fumble(ing) degrade(ing) overtake(ing) criticise(ing) craft(ing) stall(ing) taper(ing) commute(ing) spar(ring) slash(ing) overflow(ing) collide(ing) snowboard(ing) boast(ing) nominate(ing) harm(ing) affirm(ing) stifle(ing) reckon(ing) stroll(ing) bruise(ing) harden(ing) recount(ing) enlist(ing) classify(ing) duck(ing) flare(ing) savor(ing) grate(ing) incite(ing) fake(ing) defy(ing) designate(ing) rape(ing) stack(ing) skim(ming) liberate(ing) shriek(ing) associate(ing) rove(ing) stabilize(ing) decode(ing) suspect(ing) crunch(ing) blur(ring) ponder(ing) meander(ing) nurture(ing) mumble(ing) ration(ing) uphold(ing) revert(ing) endorse(ing) flex(ing) download(ing) divert(ing) twirl(ing) cease(ing) overpower(ing) displace(ing) amass(ing) tickle(ing) reproduce(ing) breach(ing) cascade(ing) isolate(ing) inject(ing) inherit(ing) erect(ing) renew(ing) fuel(ing) devour(ing) pry(ing) rehearse(ing) slay(ing) allude(ing) tamper(ing) mask(ing) swap(ping) officiate(ing) stamp(ing) guarantee(ing) squat(ting) enact(ing) smack(ing) adhere(ing) clinch(ing) spring(ing) snatch(ing) discharge(ing) fracture(ing) abide(ing) invoke(ing) dissipate(ing) scrub(bing) mingle(ing) shear(ing) formulate(ing) spiral(ing) sag(ging) swarm(ing) testify (ing) picture(ing) utilise(ing) roast(ing) shelter(ing) gallop(ing) alert(ing) sketch(ing) babble(ing) squirm(ing) rake(ing) venture(ing) reply(ing) omit(ting) massage(ing) recede(ing) evade(ing) sever(ing) spare(ing) wink(ing) clasp(ing) glaze(ing) conform(ing) neglect(ing) panic (king) rouse(ing) clip(ping) stink(ing) pinch(ing) rewrite(ing) nudge(ing) renovate(ing) trot(ting) tax (ing) sue(ing) suspend(ing) desire(ing) reclaim(ing) doubt(ing) audition(ing) clash(ing) cancel(ling) propagate(ing) amend(ing) fuse(ing) infect(ing) justify(ing) besiege(ing) expel(ling) analyse(ing) puff(ing) attribute(ing) steady (ing) arouse(ing) certify (ing) simulate(ing) intensify (ing) revise(ing) succumb(ing) trickle(ing) rebound(ing) rack(ing) shunt(ing) fling(ing) equip(ping) love(in') phrase(ing) honour(ing) vie(ying) divorce(ing) shower(ing) worship(ping) disable(ing) differentiate(ing) propel(ling) elevate(ing) root(ing) cock(ing) grumble(ing) stutter(ing) piss(ing) plunder(ing) contend(ing) trim(ming) deceive(ing) wage(ing) pledge(ing) fiddle(ing) ram(ming) streak(ing) conserve(ing) puzzle(ing) lag(ging) motivate(ing) wiggle(ing) marshal(ling) dispense(ing) intercept(ing) dispose(ing) inquire(ing) wither(ing) bust(ing) squeal(ing) lumber(ing) appreciate(ing) clarify(ing) drool(ing) replicate(ing) disregard(ing) paddle(ing) scoop(ing) erase(ing) endanger(ing) channel(ing) strangle(ing) furnish(ing) evacuate(ing) peck(ing) erupt(ing) comply(ing) confer(ring) damp(ing)
maximize(ing) mature(ing) slaughter(ing) obey(ing) resort(ing) speculate(ing) deprive(ing) batter(ing) prop(ping)

## Base form with present participle inflection modifications

reconstruct(ing) disclose(ing) converse(ing) obstruct(ing) disarm(ing) avenge(ing) discard(ing) emphasise(ing) allocate(ing) grit(ting) deem(ing) sum(ming) phase(ing) crop(ping) dispatch(ing) coax(ing) flatten(ing) duel(ing) exhale(ing) infiltrate(ing) rave(ing) dread(ing) indulge(ing) scold(ing) revolt(ing) contradict(ing) expire(ing) simplify(ing) gush(ing) diverge(ing) falter(ing) topple(ing) disseminate(ing) bleach(ing) blossom(ing) utter(ing) damn(ing) sharpen(ing) mitigate(ing) verify(ing) reciprocate(ing) faint(ing) clatter(ing) lighten(ing) swipe(ing) slump(ing) summarize(ing) relive(ing) disperse(ing) torment(ing) sow(ing) fetch(ing) perceive(ing) upload(ing) mediate(ing) complicate(ing) blackmail(ing) recuperate(ing) snort(ing) relay(ing) disintegrate(ing) bash(ing) snoop(ing) reconcile(ing) provision(ing) oust(ing) strap(ping) bait(ing) rebel(ling) intrude(ing) incur(ring) plow(ing) hinder(ing) bribe(ing) madden(ing) complement(ing) tread(ing) memorize(ing) conjure(ing) relish(ing) twine(ing) hoist(ing) catalog(ing) decompose(ing) discriminate(ing) exert(ing) cancel(ing) daydream(ing) petition(ing) tangle(ing) prescribe(ing) smother(ing) gag(ging) buckle(ing) diagnose(ing) emulate(ing) drape(ing) unravel(ing) trick(ing) impart(ing) confine(ing) adore(ing) interrogate(ing) reload(ing) bug(ging) redeem(ing) alienate(ing) optimize(ing) supplement(ing) convene(ing) cringe(ing) pivot(ing) object(ing) cuddle(ing) purge(ing) leverage(ing) mandate(ing) skid(ding) graft(ing) gauge(ing) distort(ing) squeak(ing) erode(ing) hoard(ing) fasten(ing) congratulate(ing) splinter(ing) zip(ping) replay(ing) disobey(ing) perpetuate(ing) kindle(ing) annex(ing) quake(ing) gossip(ing) reorganize(ing) ply(ing) extinguish(ing) immigrate(ing) worship(ing) corrupt(ing) quicken(ing) lunge(ing) plough(ing) afford(ing) elaborate(ing) manifest(ing) stray(ing) wrinkle(ing) rethink(ing) compost(ing) streamline(ing) prickle(ing) cede(ing) marvel(ing) sober(ing) consent(ing) masquerade(ing) plug(ging) peep(ing) overhear(ing) detonate(ing) $\operatorname{mop}($ ping $)$ fend(ing) imprison(ing) stunt(ing) spur(ring) revisit(ing) vent(ing)

## A.1.4. Third Person

## Base form with third person inflection modifications

be(is) have(s) do(es) work(s) force(s) point(s) include(s) study(ies) say(s) show(s) run(s) play(s) make(s) take(s) contain(s) change(s) remain(s) match(es) plan(s) come(s) form(s) use(s) appear(s) consist(s) provide(s) lie(s) leave(s) go(es) race(s) $\operatorname{look}(\mathrm{s})$ follow(s) give(s) tell(s) offer(s) seem(s) serve(s) continue(s) become(s) report(s) begin(s) claim(s) figure(s) vote(s) attack(s) get(s) train(s) cover(s) step(s) want(s) set(s) call(s) act(s) sound(s) attempt(s) turn(s) end(s) start(s) find(s) $\operatorname{occur}(\mathrm{s}) \operatorname{refer}(\mathrm{s}) \operatorname{pass}(\mathrm{es}) \operatorname{ask}(\mathrm{s}) \operatorname{win}(\mathrm{s})$ date(s) lead(s) object(s) cause(s) value(s) cost(s) try(ies) charge(s) return(s) operate(s) measure(s) represent(s) concern(s) face(s) suggest(s) matter(s) practice(s) account(s) require(s) round(s) move(s) park(s) experience(s) process(es) bear(s) feel(s) wave(s) share(s) exist(s) benefit(s) judge(s) write(s) support(s) reach(es) release(s) drum(s) $\operatorname{link}(\mathrm{s})$ decide(s) produce(s) stop(s) believe(s) tie(s) reveal(s) help(s) involve(s) increase(s) focus(es) protest(s) explain(s) think(s) demand(s) spot(s) talk(s) visit(s) influence(s) challenge(s) control(s) bring(s) present(s) comment(s) enter(s) answer(s) cut(s) travel(s) signal(s) walk(s) approach(es) sit(s) receive(s) assist(s) arrive(s) hope(s) pound(s) comprise(s) reform(s) ring(s) connect(s) love(s) aim(s) grant(s) display(s) extend(s) broadcast(s) argue(s) ruin(s) keep(s) appeal(s) die(s) manage(s) discover(s) rival(s) create(s) lecture(s) deal(s) maintain(s) depend(s) put(s) count(s) read(s) wish(es) strike(s) mention(s) drive(s) rise(s) estimate(s) deposit(s) smile(s) drink(s) fight(s) refuse(s) agree(s) rebound(s) kiss(es) add(s) fly(ies) roll(s) consider(s) exhibit(s) trace(s) fear(s) send(s) realize(s) graduate(s) reflect(s) beat(s) bat(s) exercise(s) seek(s) tip(s) speed(s) request(s) advance(s) profit(s) promise(s) encounter(s) command(s) struggle(s) reside(s) derive(s) coordinate(s) highlight(s) address(es) develop(s) dance(s) suit(s) pick(s) teach(es) gain(s) lock(s) damage(s) survey(s) stamp(s) apply(ies) finish(es) tend(s) spell(s) regard(s) differ(s) save(s) attribute(s) advocate(s) ride(s) imply(ies) lose(s) chronicle(s) ram(s) peer(s) remark(s) escape(s) stay(s) accept(s) sponsor(s) venture(s) guide(s) shift(s) enable(s) suspect(s) watch(es) employ(s) wear(s) strip(s) survive(s) combine(s) affect(s) arch(es) incorporate(s) reduce(s) compete(s) whisper(s) scream(s) promote(s) delay(s) stick(s) admit(s) debate(s) spark(s) joke(s) feed(s) transfer(s) conclude(s) flood(s) introduce(s) seal(s) span(s) trade(s) touch(es) defeat(s) stretch(es) explore(s) permit(s) raise(s) correspond(s) stroke(s) notice(s) check(s) cry(ies) inform(s) duck(s) reply(ies) steal(s) commune(s) blow(s) dress(es) exchange(s) desire(s) yield(s)

## Base form with third person inflection modifications

push(es) contribute(s) hurt(s) breed(s) originate(s) resort(s) demonstrate(s) choose(s) rain(s) glance(s) enjoy(s) confront(s) denote(s) express(es) prevent(s) spend(s) propose(s) close(s) intersect(s) arrest(s) clash(es) pump(s) insist(s) prove(s) exit(s) build(s) switch(es) stare(s) dart(s) care(s) crack(s) worry(ies) participate(s) recall(s) slide(s) fold(s) respond(s) quote(s) fit(s) suffer(s) purchase(s) decrease(s) smell(s) search(es) press(es) constitute(s) rest(s) attract(s) portray(s) respect(s) hurdle(s) drain(s) invite(s) bite(s) wonder(s) convince(s) deliver(s) conduct(s) pin(s) shout(s) revolve(s) upgrade(s) flash(es) taste(s) separate(s) preserve(s) disappear(s) strain(s) protect(s) mount(s) arise(s) filter(s) reject(s) assert(s) register(s) remember(s) declare(s) reward(s) deserve(s) pop(s) punch(es) announce(s) rush(es) pitch(es) prefer(s) treat(s) launch(es) split(s) reeve(s) generate(s) climb(s) lash(es) fill(s) convert(s) hang(s) crash(es) repeat(s) ferry(ies) capture(s) divide(s) bid(s) slip(s) puzzle(s) stall(s) wait(s) abuse(s) echo(es) surround(s) exploit(s) examine(s) bind(s) sum(s) burst(s) collect(s) swing(s) trust(s) lay(s) remove(s) interface(s) ensure(s) bump(s) utilize(s) rally(ies) assault(s) celebrate(s) organize(s) oversee(s) eat(s) guarantee(s) boast(s) fool(s) burrow(s) pose(s) replace(s) spread(s) surprise(s) recount(s) manufacture(s) compare(s) pause(s) transform(s) stress(es) snap(s) assign(s) bow(s) maneuver(s) exceed(s) merit(s) suck(s) shrug(s) realise(s) twist(s) direct(s) cruise(s) paint(s) engage(s) yell(s) illustrate(s) buy(s) advise(s) cast(s) decline(s) stride(s) rescue(s) anchor(s) improve(s) parade(s) insult(s) recommend(s) expand(s) escort(s) prohibit(s) mandate(s) regret(s) prop(s) elect(s) summon(s) bend(s) expect(s) staple(s) collapse(s) brush(es) showcase(s) regulate(s) praise(s) spin(s) crane(s) chuckle(s) float(s) avoid(s) lodge(s) sink(s) fare(s) hire(s) barge(s) cascade(s) investigate(s) acknowledge(s) react(s) accuse(s) batter(s) extract(s) facilitate(s) waiver(s) research(es) rent(s) trigger(s) terminate(s) curse(s) arrange(s) ignore(s) inhabit(s) slice(s) encode(s) cook(s) fracture(s) oppose(s) lease(s) commit(s) drill(s) scan(s) flap(s) lower(s) pace(s) dominate(s) blast(s) tap(s) chase(s) depart(s) hunt(s) giggle(s) blame(s) explode(s) administer(s) complete(s) ban(s) gather(s) toll(s) slam(s) moan(s) adopt(s) earn(s) relay(s) overlook(s) recover(s) stain(s) settle(s) warrant(s) comb(s) blend(s) activate(s) probe(s) interrupt(s) discharge(s) stalk(s) assure(s) strut(s) retreat(s) chant(s) befriend(s) pretend(s) dive(s) clutch(es) awaken(s) scratch(es) substitute(s) bandage(s) induce(s) blind(s) inhibit(s) specialise(s) dye(s) click(s) defend(s) symbolize(s) tug(s) dispatch(es) organise(s) pursue(s) cater(s) scare(s) query (ies) growl(s) shiver(s) achieve(s) bang(s) ensue(s) recognise(s) predict(s) embrace(s) persuade(s) drag(s) obtain(s) apologize(s) instruct(s) latitude(s) traverse(s) coincide(s) overlap(s) flake(s) fumble(s) concentrate(s) freak(s) expose(s) appoint(s) revolt(s) flip(s) scull(s) free(s) chill(s) exclude(s) alert(s) pat(s) breach(es) compliment(s) bellow(s) attain(s) insert(s) catalogue(s) waste(s) plug(s) balance(s) enhance(s) resume(s) plead(s) rape(s) acquire(s) critique(s) eliminate(s) initiate(s) resolve(s) strive(s) fix(es) comfort(s) welcome(s) collaborate(s) edit(s) toss(es) whistle(s) grunt(s) slow(s) feast(s) whip(s) stumble(s) kidnap(s) mutter(s) reappear(s) bark(s) shut(s) freeze(s) expatriate(s) rotate(s) govern(s) contend(s) wipe(s) breathe(s) lick(s) flop(s) slug(s) bust(s) bully(ies) consume(s) complain(s) wash(es) wander(s) squeeze(s) persist(s) characterize(s) spill(s) gorge(s) scrub(s) reel(s) violate(s) melt(s) convey(s) dio(s) manifest(s) drift(s) dip(s) punt(s) spoil(s) quit(s) brace(s) skate(s) rip(s) analyze(s) overhear(s) predate(s) gag(s) muse(s) forbid(s) mold(s) pour(s) pledge(s) evoke(s) telecast(s) swell(s) poison(s) behave(s) tick(s) reunite(s) emit(s) accommodate(s) safeguard(s) disguise(s) swear(s) precede(s) discount(s) abandon(s) mimic(s) cure(s) taunt(s) hatch(es) sprint(s) tilt(s) calculate(s) harm(s) separatist(s) ache(s) loom(s) replay(s) correlate(s) glare(s) reverse(s) spiral(s) shove(s) complement(s) upset(s) detect(s) bristle(s) greet(s) culminate(s) intervene(s) alter(s) fuse(s) endeavour(s) forgive(s) cease(s) borrow(s) resist(s) lament(s) bypass(es) intrigue(s) solve(s) clam(s) flick(s) restrict(s) evaluate(s) locate(s) perk(s) dial(s) forget(s) stimulate(s) speculate(s) inspire(s) chop(s) converge(s) halt(s) unite(s) spit(s) enlist(s) puff(s) compromise(s) hesitate(s) rap(s) manoeuvre(s) designate(s) spare(s) undertake(s) evolve(s) commence(s) disagree(s) bother(s) guess(es) retrieve(s) expire(s) restore(s) confide(s) betray(s) bounce(s) mumble(s) haunt(s) exclaim(s) approve(s) foster(s) execute(s) shriek(s) weave(s) roar(s) dry(ies) educate(s) heal(s) invest(s) ascend(s) contradict(s) deem(s) infect(s) dissolve(s) surge(s) swim(s) perceive(s) snatch(es) scrape(s) levy(ies) interfere(s) spray(s) admire(s) affirm(s) confer(s) enroll(s) imprint(s) moderate(s) tease(s) adjust(s) clamp(s) forge(s) purge(s) consort(s) swap(s) dare(s) inherit(s) isolate(s) buckle(s) hike(s) howl(s) pray(s) unlock(s) compose(s) torture(s) dash(es) furrow(s) warm(s) caution(s) mock(s) clap(s) preside(s) postulate(s) omit(s) prevail(s) snort(s) crawl(s) remake(s) reproduce(s) manipulate(s) adapt(s) boil(s) fulfill(s) wedge(s) panic(s) chat(s) caress(es) overcome(s) fake(s) reinforce(s) pardon(s) dub(s) steer(s) condemn(s) hurry(ies) devote(s) seize(s) crush(es) flirt(s) flourish(es) supervise(s) cough(s) equate(s) pertain(s) uncover(s) minimize(s) mature(s) surrender(s) rake(s) shovel(s) splash(es) tryout(s) access(es) strengthen(s) dwell(s) accelerate(s) hover(s) glide(s) scoop(s) secure(s) retire(s) correct(s) diverge(s) seduce(s) intercept(s) queue(s) trim(s) appreciate(s) donate(s) pelt(s) consult(s) recite(s) exhale(s) transcend(s) skid(s) sparkle(s) slash(es) deduce(s) revert(s) offset(s) contemplate(s) hack(s) shrink(s) snarl(s) linger(s) conform(s) veer(s) rejoin(s) disrupt(s) poke(s) retort(s) blackmail(s) inquire(s) penetrate(s) perch(es) smack(s) calm(s) elaborate(s) tuck(s) exert(s) enforce(s) flicker(s) shudder(s) assemble(s) plunge(s) simulate(s) ease(s) squeal(s) lapse(s) clean(s) submit(s) scold(s) grill(s) clench(es) distract(s) slur(s) undermine(s) overrun(s) revive(s) snipe(s) salute(s)

## A.2. Manual

This word list was generated manually by extracting arbitrary countries from the vocabulary and looking to see if the associated nationality was also present in the vocabulary. We stopped adding words when significant changes stopped being observed in our results.

## A.2.1. Countries and Nationalities

## Countr with nationality motifications

canada(ian) australia(n) russia(n) italy(ian) norway(egian) france(ench) hungary(ian) brazil(ian) austria(n) belgium(an) egypt(ian) iran(ian) croatia(n) palestine(ian) ukraine(ian) romania(n) serbia(n) armenia(n) bulgaria(n) albania(n) nigeria(n) malaysia(n) hawaii(an) colombia(n) ethiopia(n) bavaria(n) scandinavia(n)

## Appendix B

## Bit Differences - Unordered

## B.1. Plurals

Bit difference probabilities between nouns in their base form and plural form


Bits
【』 This Work \|u Compressed GloVe
Fig. B.1. The unordered probabilities of a certain bit being different between the embedding of the base form of a noun and the embedding of its plural form. A semi-automatic list of 4948 nouns present in the vocabulary was used (see appendix A.1.1)

## B.2. Past

Bit difference probabilities between verbs in their base form and past form


Bits
I』 This Work \|. Compressed GloVe
Fig. B.2. The unordered probabilities of a certain bit being different between the embedding of the base form of a verb and the embedding of its past form. A semi-automatic list of 1638 verbs present in the vocabulary was used (see appendix A.1.2)

## B.3. Present Participle

Bit difference probabilities between verbs in their base form and p.p. form


Fig. B.3. The unordered probabilities of a certain bit being different between the embedding of the base form of a verb and the embedding of its present participle form. A semi-automatic list of 1366 verbs present in the vocabulary was used (see appendix A.1.3)

## B.4. Third Person

Bit difference probabilities between verbs in their base form and 3rd person form


Fig. B.4. The unordered probabilities of a certain bit being different between the embedding of the base form of a verb and the embedding of its third person form. A semi-automatic list of 934 verbs present in the vocabulary was used (see appendix A.1.4)

## B.5. Countries and Nationalities

Bit difference probabilities between countries and associated nationalities


Bits
【 This Work $\mathbb{\square}$ ( Compressed GloVe
Fig. B.5. he unordered probabilities of a certain bit being different between the embedding of a country and the embedding of its associated nationality. A manual list of 27 countries present in the vocabulary was used (see appendix A.2.1)

## Appendix C

## Additional Vocabularies

## C.1. POS tags

| Complete list of POS tags considered |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
| $\$$ | AFX | JJ | NNPS | SP | VBZ |
| $"$ | CC | JJR | PDT | SYM | WDT |
| $"$ | CD | JJS | POS | TO | WP |
| , | DT | LS | PRP | UH | WP\$ |
| - LRB- | EX | MD | PRP $\$$ | VB | WRB |
| - RRB- | FW | NFP | RB | VBD | WRB |
| . | GW | NIL | RBR | VBG | XX |
| $:$ | HYPH | NN | RBS | VBN | SP |
| ADD | IN | NNP | RP | VBP | NNS |

## C.2. WordNet Lexical Categories

| Complete list of WordNet lexical categories |  |  |  |
| :---: | :---: | :---: | :---: |
| adj.all | noun.event | noun.quantity | verb.consumption |
| adj.pert | noun.feeling | noun.relation | verb.contact |
| adj.ppl | noun.food | noun.shape | verb.creation |
| adv.all | noun.group | noun.state | verb.emotion |
| cntlist | noun.location | noun.substance | verb.Framestext |
| noun.act | noun.motive | noun.time | verb.motion |
| noun.animal | noun.object | noun.Tops | verb.perception |
| noun.artifact | noun.person | verb.body | verb.possession |
| noun.attribute | noun.phenomenon | verb.change | verb.social |
| noun.body | noun.plant | verb.cognition | verb.stative |
| noun.cognition | noun.possession | verb.communication | verb.weather |
| noun.communication | noun.process | verb.competition |  |

## Appendix D

# WordNet Training Words 

## D.1. noun.animal

## Words from the noun.animal lexical group matching our vocabulary

world down head game hand young royal style blue hair female bay primary queen jack test male wing martin baby horse host tom emperor grade foot fish jersey scale cricket rail dog cancer throat ray fox adult grey bear bass bird turkey fly web flag investment arizona dam wolf giant lincoln morgan kid billy cat soldier moth argentina relative coat dragon shell tail ass hide welsh assault pan admiral lip runner robin jay layer hampshire sole cattle copper monster carrier eagle spider worker lucy tiger bull beetle cardinal lion drum breast pen poll sierra virus seal snake argentine bat hood hart horn drake prey egg sheep monitor deer chicken devon mouse belly armor ram hybrid dock permit brush pastor cannon fisher durham fur butterfly kit vector rod bitch swift dug spine pet chen tang bacteria duck boxer gastropod elbow amazon circus snail colt hawk rat raja bee livestock coral frog crest beard raven valve buck monarch roller swan fin rabbit elephant shark cow flank newfoundland salmon monkey citation crane crow tooth mollusk swallow wool survivor dove shire cock falcon cerambycidae pad mare pike omaha gill beef bug venus drill antenna vein whale saddle trout beaver arabian lamb turtle knot insect blackburn owl goat goose weaver secretariat ant lizard pomeranian vanessa racer sawyer stud predator skate stunt dinosaur panther mutant chestnut worm kitty snout chick sire spat penguin claw feather pony finch thoroughbred hare zeus cobra tick jaguar canary stray leopard phoebe mara hobby mole cornish cod pigeon wren maltese hind bunny viceroy elk affirmed crab orphan fang dolphin muzzle puppy greyhound drone vent lama squirrel ling shrimp camel peacock calf horseback python stallion doe pest wasp feeder mustang otis sparrow dominique roe parasite hereford flicker bison pembroke nanny viper kitten kangaroo galloway siren mule penelope roach beak ridley herring oyster otter perch liza mosquito rana hack filly racehorse kite coyote crocodile talon lynx wolverine mammal catfish pointer scorpion geometridae parrot noctuidae heron hound grunt ara guernsey eel fledgling slug boar pathogen sable bullock comb argus paw cub homo ox badger gorilla mammoth pinto tuna chow primate tortricidae partridge ape reeve helix hen sponge springer embryo nightingale ala pollard rattle vane mane spawn cisco lark squid sleeper octopus rudd gecko hackney rhea trumpeter primates brit maverick forewing sonora gnu fetus larva vulture flea brant hornet passerine rook carp hog sucker thorax lobster moray pup cochin chihuahua hydra ayrshire antelope emu manx newt canine rodent dobson cougar aix gelechiidae marlin wildcat caterpillar bulldog cuckoo alligator char gull zebra condor tortoise vertebrate reptile salamander weasel grizzly stag sturgeon redhead dun pelican woodpecker whiting castor quill bot hedgehog medusa warbler nestor guan grasshopper nit cocoon brahman terrier caribou jackal locust shrew boa uta cyclops barb charger swine silvia kelp dragonfly parr triton uma chameleon coney seaweed grenadier mya cairn nymph finisher

## Words from the noun.animal lexical group matching our vocabulary

peregrine leech mantis raccoon drosophila jellyfish withers waterfowl apis chinook mite ani cardigan teal clam gar schoolmaster mink beagle rhinoceros operculum kiwi passer longhorn firefly porcupine cheetah feline stifle marten falco quail kingfisher carabidae magpie gibbon tusk amphibian fawn arista skunk asp stork lhasa hummingbird columba broodmare trotter equine hoof watchdog selene starling milt rattlesnake tench osprey galleria carapace brill sow bongo arca whiff canis ibis gazelle agua grouse booby flamingo albatross ruff bunting hippocampus lycaenidae bantam buzzard tabby foal harrier stingray megachile blackbird thrush bronco carrion streptomyces slider weevil pheasant comma loon starfish ostrich snapper plankton steed lepidoptera vixen bluebird invertebrate nymphalidae lemur plasmodium giraffe chrysalis bumblebee tern dalmatian capuchin skink chimpanzee scavenger gelding smelt atticus walrus bighorn collie fluke scarab recombinant ferret mussel goldfish solitaire aquila sus tuft gopher crayfish mackerel pollack bobcat snipe cirrus nematode poodle diploid bovineshad roan darter mako margate roebuck mollie mongoose nutcracker coronet impala yolk dingo sloth halter capra gander anaconda whitefish midge hamster draco reticulum woodcock kestrel shiner mallard maja conch bos proteus stinger roadrunner setter basset jaeger cyanobacteria fossa petrel phytoplankton manta theropod hyena vermin cockroach gnat bacillus anguilla bivalve suckling wishbone flathead tachinidae plover harpy takin moa cob tarantula ewe creeper mullet termite haddock bristle kea mockingbird yearling loach gallus swordfish vole saki grub bulbul siphon herpes cormorant cockatoo tentacle thrasher teg manatee armadillo yak chlorophyll gosling pupa barracuda dory sweeper sunfish instar megachilidae merino griffon cotswold sphingidae retriever spitz shrike cichlid anas tetra walleye sula springbok sepia pseudomonas dodo placental adder seabird wallaby hock cygnus ermine salmonella largemouth koala pacer zooplankton mew songbird spaniel piranha chub escherichia chipmunk proboscis conspecific minnow humpback goby pug mus curculionidae hippopotamus haploid opossum llama lioness parakeet damselfly corvus staphylococcus irena centipede

## D.2. noun.body

## Words from the noun.body lexical group matching our vocabulary

a back part down head area right left side small hand system face body center heart middle person process hair blood mouth bridge wall arm structure b feature temple skin eye shoulder neck ball foot joint zone throat brain leg crown imperial bob wave quick chamber finger stomach gene nose tongue ear hip o plate ridge lap palm cheek passage vessel column index lip bone chin lock jaw knee organ flesh waist milk sole blade costa muscle root tube breast poll skull arch axis landmark tissue matrix radiation wrist tear trap fist belly thumb humor rod vegetation pot nerve brow lens pin elbow receptor membrane specimen bang pupil eyebrow ab lung beard liver valve os ankle bypass juice plaque thigh ink fold radius tooth iris fiber atlas plasma cock tract nucleus toe partition cone facial vein beaver heel kidney hemisphere corpus node abdomen gore apparatus marcel nail mantle shin groove chromosome pulp attic cortex limb nipple digit sac cavity sperm torso capsule artery afro antagonist hormone forearm keel hooks nasal calf penis rib serum abdominal lobe groin bulb palatine roach beak corona mohawk colon buff ponytail insulin flap pouch tensor socket stump ligament bladder scalp sheath duct gland whitehead stigma tunic appendix mummy queue marrow nape lambda bile ala mane atrium chop braid xx enamel cleavage saliva thorax spindle dorsum tendon canine pore chopper fascia vagina mons isthmus stubble adhesion mustache biceps secretion pelvis cartilage pectoral crotch intestine suture vestibule smear extremity hamstring retina molar sinus germ buttocks knuckle allele agonist uterus palate haircut cytoplasm collagen lymph graft semen filament navel bloodstream carina countenance genitalia ovary femur cunt xxx bosom fingertip capillary diaphragm shank tibia phalanx spleen arse hippocampus pons anus mucus chromatin haw pituitary aster epithelium dimple pate wattle suppressor hairline tarsus earlobe girdle fissure perspiration cheekbone lumen pancreas placenta fingernail fuzz clot beehive bursa plexus cusp peduncle vertebra clitoris thatch drool blister eyelid synapse pacemaker cornea ventricle axon reticulum epidermis sternum esophagus eyeball humerus snot aorta tiptoe amygdala ganglion foramen centrum septum underbelly lamina shunt gyrus rima hypothalamus cerebellum dentition venter goatee fibula larynx ribosome follicle exoskeleton cuticle rectum modifier trachea cadaver thalamus proboscis armpit vesicle sulcus orifice thumbnail

## D.3. noun.time

time over then may school while year now second season day life game end go march old september january june october july august april november december age century set february top death times history night point days half run period summer present today term past middle week leave moment festival turn beginning hours dead deep future morning date fall month youth chapter majority speed distance winter pass rate breath hour era spring prime window rule minute value watch sleep quarter evening birth bottom none generation christmas tonight bell sunday phase flow extension saturday decade anniversary afternoon cycle weekend tomorrow childhood reign occupation shift birthday frequency depression friday restoration absence holiday occasion pace flower grave eve minority tenure monday dawn calendar attendance midnight stretch trick renaissance presidency meal span reconstruction delay yesterday pulse duration wednesday interim thursday lease pause tuesday tide millennium baroque bout ab easter assumption sunset vacation snap threshold wartime overtime noon leisure inning shiva prohibition cease advent teens jubilee drought tempo tertiary jerk 1870s semester bloom deadline regency halloween 1860s lent twilight eternity centennial float 1900s thanksgiving 1850s incarnation antiquity maturity weekday acceleration cretaceous preseason termination wee 1840s halftime monsoon probation 1830s jurassic flux adulthood ascension twenties cradle sabbath honeymoon rag morrow immortality limitation infancy $9 / 11$ octave pleistocene sixties continuum epoch caliphate miocene afterlife 1820s olympiad triassic seventies fifties thirties adolescence annum cambrian blackout eighties spacing peacetime permian eocene fortnight kip devonian nineties curfew lapse forties puberty turnaround interlude epiphany carboniferous incubation bicentennial $24 / 7$ solstice lunchtime sabbatical gestation quaternary ramadan deathbed pinpoint boyhood respite bedtime ordovician enlistment moratorium prehistory annunciation hertz pliocene circumcision passover equinox holocene episcopate 1790s tiebreaker mesozoic silurian pentecost oligocene allegro paleozoic 1780s novitiate hospitalization checkout mississippian apogee precambrian 1770s airspeed 1760s tet eon cenozoic vespers trimester retardation transfiguration weeknight interregnum midterm paleocene clocking 1750s downtime sivan midweek embolism payday workday menopause

## D.4. verb.body

## Words from the verb.body lexical group matching our vocabulary

have make water play look help cup round act give feel call rest attack contract hold cut smile cover sun train break spring doctor hurt draw sleep entrance drug shirt labor bob wave condition nick tone pull dress drop trouble gain catch grow wear roll reduce laugh wet stream pale shock wake twin coat pack waste correct cry hat expect grin exercise blow leaf shake affect stare jacket shower nurse sigh treat beam soap comfort stretch harm bat nod shed breathe tear sweat breed joke torture faint suffer costume tense boot powder wash tan relax twist habit poison shoe hatch alter crane highlight soup heal frown gown lamb tire roar rouge barber freeze bundle shrug spit marcel exhaust slick blink relieve rack shiver wan stool spat gum chuckle clown razor smirk strap scrub manipulate pod vest perfume choke blush fracture groom litter wink giggle gag martyr remedy reproduce sob administer cough scarf tease nap kitten evacuate twitch bray hack bleed stimulate menace scowl massage purge bonnet comb cub brood lipstick overdose spawn puff vomit prank bandage stale snort infect grimace shave dung awaken vet tumble emit sniff perm clap soothe conceive pant wince hamstring shampoo inhale dope exhale yawn propagate optimize bathe presume sneer disable wail suction relapse inject fawn resurrect regenerate stub swagger refresh cripple pout injure undress foal corset abort animate dimple snuff sprout atrophy prim wanton squint crick cleanse recuperate salve farrow cramp secrete douche irritate quicken fart reek quack hock chloroform frock sneeze snore sedate snicker

## D.5. verb.consumption

Words from the verb.consumption lexical group matching our vocabulary
use go want play power need put board give hit range provide meet mine port drive serve fast horse host answer pop tax content receive drug carry trip wine drop drink address stomach eat tank wolf feed lap grass waste smoke enjoy cry kick lunch milk breakfast sample shower mess prey accommodate diet spare afford corn feast strain bolt raven sip swallow quarry drain delight fare picnic suck patronage gorge sustain consume toast exploit harness peck digest mainline cater chew avail huff plank smack crunch puff champ forage addict gulp spree exert quell dine dunk indulge inhale dope devour fodder starve gutter partake inject crave mumble ply browse abstain recycle brunch nibble repose overuse


[^0]:    ${ }^{1}$ As defined in WordReference Random House Unabridged Dictionary of American English © 2020．

[^1]:    ${ }^{1}$ Other sources omitted to be more concise.

[^2]:    ${ }^{1}$ The terms query and document are used to be comparable to the database searching literature, but in this context, they could represent any two domains to be matched.
    ${ }^{2}$ A Multi-Bernoulli random variable is a vector of independent but not identically distributed Bernoulli; the parameters of a Multi-Bernoulli is consequently a vector of probabilities.

[^3]:    ${ }^{3}$ The 2020/02/10 dump.

[^4]:    ${ }^{4}$ We designed a compact way to store the corpus so that it could be loaded in memory completely for faster sampling during training. It takes about 16 GB . If we loaded from persistent memory (e.g. hard-disk drive), we would have more memory headroom, thus allowing more embeddings to be trained.

[^5]:    ${ }^{1}$ https://github.com/stanfordnlp/GloVe.

[^6]:    ${ }^{2}$ The results presented in [40] are similar.

[^7]:    ${ }^{3}$ The dimensionality of the vectors must be compatible with the hardware registers' width for maximum performance optimization.
    ${ }^{4}$ As in $k$-Means, random centroids are initialized at the beginning of training. To ensure the best results, multiple model are fitted and the best one is kept.

[^8]:    ${ }^{5}$ We chose 10 because it empirically gave the best overall results.

[^9]:    ${ }^{6}$ https://dumps.wikimedia.org/simplewiki/latest/simplewiki-latest-pages-articles-multistream.xml.bz2-rss.xml.

[^10]:    ${ }^{7}$ See definition in 3.1.
    ${ }^{8}$ We used the whole vocabulary, not only the matching words used for training.

[^11]:    ${ }^{9}$ This is similar to our cat, dog, bite and claw example in 1.2 where there obviously is a shared latent representation.
    ${ }^{10}$ Most likely related to the Mariana Trench, the deepest oceanic trench where sea life was discovered.

[^12]:    hasten(ed) leave(d) repay(id) evade(d) croak(ed) redirect(ed) straddle(d) disembark(ed) discredit(ed) comb(ed) disseminate (d) rouse(d) signify (ied) pivot(ed) overhaul(ed) shun(ned) rust(ed) memorize(d) wail(ed) nip(ped) reprimand(ed) grate(d) consent(ed) refrain(ed) regroup(ed) redefine(d) redeem(ed) equate(d) untie(d) splatter(ed) decay(ed) query(ied) catalogue(d) buck(ed) consummate(d) patch(ed) elicit(ed) mimic(ked) solicit(ed) swivel(ed) refresh(ed) swoop(ed) annihilate(d) overlap(ped) knit(ted) coerce(d) plow(ed) stow(ed) bandage(d) recoil(ed) abdicate(d) minimize(d) marvel(ed) tutor(ed) stray (ed) rap(ped) elude(d) sneak(ed) emulate(d) parade(d) pry(ied) channel(ed) mislead(d) conjure(d) reel(ed) drum(med) broker (ed) gush(ed) stake(d) wobble(d) aspire(d) disgrace(d) peg(ged) dispense(d) bleach(ed) nurture(d) indulge(d) clone(d) mourn(ed) stoop(ed) pout(ed) bail(ed) clatter(ed) massage(d) stash(ed) mistake(ook) conjecture(d) ditch(ed) blindfold(ed) bulge(d) obstruct(ed) reload(ed) burden(ed) crunch(ed) camouflage(d) hike(d) remand(ed) impede(d) toast(ed) twinkle(d) bristle(d) intersect(ed) lighten(ed) flap(ped) triumph(ed) resonate(d) perk(ed) sprout(ed) refill(ed) fancy (ied) decompose(d) perpetuate(d) divest(ed) predate(d) reconsider(ed) dredge(d) eradicate(d) rinse(d) paste(d) fray (ed) incite(d) intrude(d) conjugate(d) splice(d) flirt(ed) hustle(d) rot(ted) spook(ed) instill(ed) impart(ed) ascertain(ed) fiddle(d) abstain(ed) envy(ied) visualize(d) swat(ted) sober(ed) blacklist(ed) cuddle(d) degenerate(d) relish(ed) sabotage(d) wade(d) saddle(d) ferry(ied) rebuke(d) secede(d) beep(ed) weave(d) ooze(d) itch(ed) revitalize(d) critique(d) herd(ed) cascade(d) pounce(d) whitewash(ed) blackmail(ed) squash(ed) dine(d) mitigate(d) deter(red) cleave(d) disjoint(ed) outweigh(ed) vent(ed) gallop(ed) spice(d) delve(d) cushion(ed) deviate(d) dampen(ed) rival(ed) negate(d) lag(ged) profit(ed) replenish(ed) benefit(ted) discern(ed) neutralize(d) overflow(ed) disobey(ed) rustle(d) catapult(ed) tack(ed) diffuse(d) dissent(ed) vomit(ed) whack(ed) email(ed) entice(d) revel(ed) tamper(ed) burrow(ed) exterminate(d) harness(ed) barricade(d) spiral(ed) prioritize(d) regenerate(d) conform(ed) stabilise(d) decode(d) pelt(ed) sizzle(d) stoke(d) scorn(ed) punt(ed) cleanse(d) dent(ed) vie(d) censure(d) reciprocate(d) misuse(d) videotape(d) rein(ed) paddle(d) buoy(ed) smudge(d) distrust(ed) quell(ed) dazzle(d) stereotype(d) endeavour(ed) merit(ed) twine(d) lead(ed) excise(d) butcher(ed) dissuade(d) rekindle(d) decipher(ed) barge(d) reboot(ed) congregate(d) alleviate(d) parachute(d) lumber(ed) keel(ed)

