

# What Does This Word Mean?

## Explaining Contextualized Embeddings with Natural Language Definition

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### Abstract

Contextualized word embeddings have boosted many NLP tasks compared with traditional static word embeddings. However, the word with a specific sense may have different contextualized embeddings due to its various contexts. To further investigate what contextualized word embeddings capture, this paper analyzes whether they can indicate the corresponding sense definitions and proposes a general framework that is capable of explaining word meanings given contextualized word embeddings for better interpretation. The experiments show that both ELMo and BERT embeddings can be well interpreted via a readable textual form, and the findings may benefit the research community for a better understanding of what the embeddings capture<sup>1</sup>.

## 1 Introduction

Contextualized word embeddings, such as ELMo, BERT, and OpenAI GPT, GPT-2 (Peters et al., 2018; Devlin et al., 2018; Radford et al., a,b) have been shown to yield richer representations of meaning and boosted many NLP tasks. To understand what contextualized word embeddings capture, Schuster et al. (2019) recently visualized the representations of ELMo and showed that 1) embeddings of the same word in different contexts can form a cluster, and 2) when a word has multiple senses, the embeddings can be separated into multiple distinct groups, one for each meaning. To further investigate the meanings contextualized word embeddings indicate, this paper focuses on analyzing whether a contextualized embedding is sense-informative enough to indicate the corresponding sense definition given a (target word, context) pair. We train and evaluate our model on

the online Oxford dictionary dataset released by Chang et al. (2018).

To analyze if the embeddings are sense-informative, our work focuses on learning a mapping between the semantic space of contextualized word embeddings and the space of definition embeddings. Specifically, a better mapping indicates richer sense-specific cues in the contextualized word embedding.

Different from the definition modeling in the prior work (Noraset et al., 2017; Gadetsky et al., 2018; Chang et al., 2018), we reformulate the task from natural language generation (NLG) to classification, i.e., selecting the most reasonable definition according to the target word and its contexts. As recent work has shown the great success in encoding lexical resources into consistent representations (Tissier et al., 2017; Bahdanau et al., 2017; Bosc and Vincent, 2018), in this paper, we leverage pretrained sentence encoder (Cer et al., 2018) to project all definitions in the Oxford dictionary to a consistent embedding space, supporting our reformulation which requires to learn a mapping transforming from the contextualized word embedding space to the definition embedding space. Therefore, we can avoid some predicaments in NLG, such as troubles in generating fluent sequences, the exposure bias problem (Ranzato et al., 2015) and the difficulties in evaluation (Stent et al., 2005).

## 2 Methodology

The goal of this paper is to analyze whether we can distill sense-specific information from the pretrained contextualized word embeddings such as ELMo and BERT for better interpretation. Specifically, given the embedding of a (word, context) pair, our model learns a non-linear mapping network  $f : X \rightarrow Y$  to project it into the desired

<sup>1</sup>The source code and the trained models are publicly available at <https://github.com/MiuLab/GenDef>.

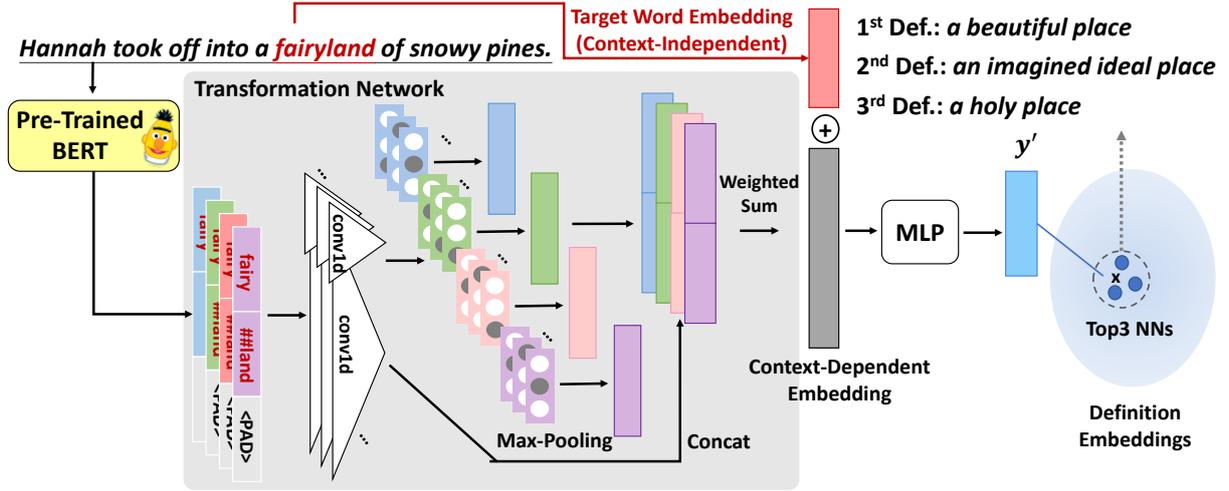


Figure 1: Illustration of the proposed model using contextualized embeddings from BERT as the context-dependent component. We use the one-dimensional convolution with its kernel sizes being 1 and 3.

definition space. Note that the mapping is many-to-one intrinsically because there exist some examples sharing the same definition, and their target words or contexts differ. This paper assumes that *contextualized word embeddings can be easily translated into their corresponding definitions if their semantics is well captured in the representations*. To validate the assumption, the following models are proposed for mapping the embeddings.

## 2.1 Model Objective

The whole framework of our proposed model is illustrated in Figure 1. Our goal is to learn the mapping that transforms contextualized word embeddings into their corresponding definition, which is to solve:

$$f^* = \arg \min_f \|f(\mathbf{x}) - \mathbf{y}\|_2, \quad (1)$$

where  $\mathbf{x} = (\mathbf{u}, \mathbf{v}) \in X$  consists of the target word embedding  $\mathbf{u}$ , which is context-independent and serving as the target word identity, and a context-dependent component  $\mathbf{v}$ , which could be either the context embedding or the contextualized target word embedding;  $\mathbf{y} \in Y$  is the embedding of the corresponding definition. Both the definition embedding and the context embedding are encoded by the pretrained transformer-based universal sentence encoder (Cer et al., 2018), and we utilize different types of contextualized word embeddings, such as ELMo, BERT-base, and BERT-large, by swapping the context-dependent component shown in the left part of Figure 1.

Note that though we model this task as a classification problem, we do not train a classifier that regards all definitions as discrete labels but learn a translation between two representation spaces, motivated by Lample et al. (2017, 2018), because different definitions may have semantic similarities. We first encode all ground truth definitions to a consistent embedding space and learn a mapping function  $f$ . During the inference stage, given a target word and its context, we retrieve the corresponding human-readable definitions of the top- $k$  nearest neighbors of our predicted embedding in the definition embedding space, with consideration of the whole 79,030 definition candidates in the Oxford dictionary. Note that the candidates for each word are not restricted to its existing definitions in the dictionary, considering that words may go through semantic shift, such as the word *gay* has shifted its meaning from *happy* to *homosexual*.

## 2.2 Mapping Architecture

Our mapping architecture consists of a transformation network followed by the 7-layer MLP, with batch normalization (Ioffe and Szegedy, 2015) and ReLU. In order to incorporate diverse context-dependent embeddings (such as ELMo and BERT), different transformation nets are proposed, whose common goal is to map the input features to a fixed-dimension representation. Three variants are described in detail.

- **Context Embedding:** the target word embedding and its context embedding encoded

by a pretrained sentence encoder are concatenated as the input to the transformation net, which is simply implemented as a fully-connected layer with the ReLU activation.

- **ELMo**: we apply a weighted sum over 3 extracted contextualized word embeddings, i.e., the output of character CNN and two LSTMs, getting a single context-dependent vector for concatenating with the target word vector.
- **BERT**: the target word is tokenized into word pieces, and we use one-dimensional convolution (conv1d) (Kim, 2014) and max-pooling to tackle the variable-lengthed features. We extract the last 4 layers from BERT and jointly learn softmax-normalized weights corresponding to each layer similar to ELMo.<sup>2</sup> Figure 1 illustrates the mapping model leveraging features from BERT, which expresses the best capability of carrying sense-specific explanation among all variants.

### 2.3 Reverse Mapping

In order to analyze what the mapping captures for better interpretation, we examine the reverse direction of our mapping after training, motivated by Yuan et al. (2016). Given a context-dependent embedding  $\mathbf{v}$  and its ground truth definition embedding  $\mathbf{y}$ , also the word embedding  $\mathbf{u}_w$  for each target word  $w$  in the vocabulary  $V$ , and a pretrained mapping  $\tilde{f}$ , the word that is the closest vector to the target definition after mapping is formulated as:

$$\arg \max_{w \in V} \cos(\tilde{f}(\mathbf{u}_w, \mathbf{v}), \mathbf{y}). \quad (2)$$

In our experiments, the word set corresponding to the top- $k$  highest cosine scores often contains the actual target word, also overlapping with a few synonyms provided by the Oxford dictionary. When applying to contextualized word embeddings from BERT-base, the model achieves the average recall of 23.7%, even though we do not incorporate any synonym information during training. This demonstrates that our models are capa-

<sup>2</sup>Note that our work focuses on analyzing the sense information encoded in the contextualized embeddings; thus, our model is stacked upon the frozen representations extracted from the pretrained BERT instead of fine-tuning them. More training details are given in the supplementary material.

ble of automatically capturing potential similarities. Examples of the generated synonyms can be found in the supplementary material.

## 3 Experiments

In order to examine whether the sense-specific information captured by contextualized word embeddings can be well disentangled, the following experiments are conducted.

### 3.1 Definition Retrieval

This is to analyze whether our proposed mapping indeed interprets the sense-specific definitions from contextualized word embeddings. Considering that the words can be seen and unseen, our experiments contain two levels of tasks (Chang et al., 2018).

- **Seen** is to test the pair with (*seen word, unseen context, seen definition*), including 151,306 pairs of instances containing 9,276 target words.
- **Unseen** is to test the pair with (*unseen word, unseen context*), including 15,959 pairs of instances corresponding to the 1,000 randomly selected target words held-out from training. Such a **zero-shot** setting challenges if the input feature is informative enough and if the mapping can generalize to the unseen but semantically consistent embeddings. Also, it is a practical and appealing task as many new words are coined every year.

We ensure both being polysemic tasks by sampling within instances whose target words have at least 3 definitions when building these two test sets.

#### 3.1.1 Results

We measure the performance of various proposed architectures with average precision (@1, @5, @10) as well as the average cosine distance between the predicted definition embedding and the ground truth embedding (lower is better). Two baselines without using contextualized embeddings as context-dependent input features are proposed, 1) using the target word embedding only, which entirely ignores the contexts and thus being a lower bound of this task and 2) leveraging the context embedding from the pretrained Transformer-based universal-sentence encoder as

Task	Methods	P@1	P@5	P@10	Cosine Dist
<b>Seen</b>	target word embedding	33.27 / 18.29	50.77 / 31.92	56.06 / 36.69	0.251
	+ context embedding	59.36 / 45.19	71.43 / 58.17	74.95 / 62.42	0.178
	+ ELMo	67.00 / 53.91	77.32 / 65.69	80.35 / 69.58	0.149
	+ BERT-base	<b>74.83 / 63.34</b>	<b>83.28 / 73.97</b>	<b>85.46 / 77.06</b>	<b>0.123</b>
	+ BERT-large	73.89 / 62.36	82.61 / 73.24	84.92 / 76.28	0.126
<b>Zero-Shot</b>	target word embedding	1.84 / 1.06	6.54 / 4.22	9.67 / 6.44	0.388
	+ context embedding	1.97 / 1.29	7.00 / 4.77	10.78 / 7.50	0.383
	+ ELMo	2.04 / 1.38	6.79 / 4.65	10.21 / 7.06	0.387
	+ BERT-base	3.27 / 2.28	9.59 / 7.41	14.44 / 11.44	0.344
	+ BERT-large	<b>3.50 / 2.52</b>	<b>10.47 / 8.17</b>	<b>15.58 / 12.35</b>	<b>0.339</b>

Table 1: Precision@K (average within examples sharing the same target words / average within examples sharing the same (target word, definition)) and cosine distance for models using various input features.

Methods	Tasks	
	Seen	Unseen
Noraset et al. (2017)	21.6 / 36.7	1.7 / 15.8
Chang et al. (2018)	24.9 / 41.0	2.0 / 15.9
target word embedding	28.4 / 36.9	4.6 / 17.2
+ context embedding	58.5 / 62.8	5.1 / 16.8
+ ELMo	66.5 / 71.6	4.8 / 17.2
+ BERT-base	<b>74.7 / 78.3</b>	<b>7.1 / 19.3</b>

Table 2: BLEU@4 / ROUGE-L:F scores of NLG-based models and various proposed architectures.

described in Section 2.2. Note that the naive baseline is randomly guessing among the whole 79,030 definitions, with P@1 lower than 0.0013%, showing the difficulty of this task.

For **Seen** experiments, Table 1 shows that the context-dependent component contains abundant sense-informative cues, where contextualized word embeddings, especially BERT, expresses the strong capability of producing corresponding definitions with about 15% enhancement of P@1 comparing to the second baseline. For **Unseen** results, the trend is similar: all models with context-dependent input features outperform the first baseline, and the variants with BERT reach the best scores among all metrics. The above results demonstrate rich sense-informative cues captured by the contextualized word embeddings.

Furthermore, we evaluate the definitions by their natural language surfaces using BLEU (Papineni et al., 2002) and ROUGE-L (Lin, 2004) scores. The results are in Table 2, where both Noraset et al. (2017) and the first proposed baseline generates or selects definitions depending merely on the static target word embedding, and all other

architectures are context-dependent. We initialize the target word embeddings for all models with pretrained *fasttext* (Joulin et al., 2016) on Wikipedia 2017, UMBC webbase corpus for a fair comparison. The results demonstrate that our mapping model can better explain the word representations than the prior work.

### 3.1.2 Analysis

An ablation study is conducted in which only the contextualized word embedding is used. While the scores of all 3 related variants drop dramatically due to the lack of the explicit, context-independent signal to the target word identity, the scores still outperform the first baseline by 7% (P@1) on the **Seen** task, showing the superiority of contextualized representations to their static counterparts. In addition, the reason about better performance of the models with contextualized embeddings compared to the one with context embeddings (the second baseline) is that two context embeddings sharing the same target word sense may differ a lot due to various words in the contexts, but they may have similar contextualized word embeddings produced from ELMo or BERT. This allows our proposed model to better interpret the sense information.

Despite the overall low performance under the zero-shot setting, it is found that all proposed models with context-dependent components are still able to disambiguate different senses. Table 3 shows a randomly-sampled example from the output of the BERT-base model. Although the model can only correctly answer the first definition of *draw*, which may be the most common usage so that it can be easily generated from the input embedding, we show that our model is still able to capture the other two very different word senses

Target	Contexts, Selected Definitions, Ground Truth
draw	The embodied capacity to write and <i>draw</i> seems to rule over the languid group of objects underneath. <b>1st Definition:</b> produce an image of someone or something by making lines and marks on paper <b>2nd Definition:</b> produce a picture or diagram by making lines and marks on paper with a pencil pen etc <b>3rd Definition:</b> compose or draw up something written or abstract <b>Ground Truth:</b> produce an image of someone or something by making lines and marks on paper
	When it came to the end of the day, though, I was more than happy to <i>draw</i> the curtains and shut the day out. <b>1st Definition:</b> arrange something carefully into a particular shape or position <b>2nd Definition:</b> arrange objects or parts in a zigzag formation or so that they are not in line <b>3rd Definition:</b> draw a circle round something especially to focus attention on it <b>Ground Truth:</b> pull curtains shut or open
	... hinders your ability to impart spin on the ball, reducing your ability to <i>draw</i> and fade the shot on command. <b>1st Definition:</b> put the ball in play by throwing it up between two opponents <b>2nd Definition:</b> strike the ball in the direction of ones followthrough so that it travels to the left ... <b>3rd Definition:</b> propel a ball with a bat racket stick etc to score runs or points in a game <b>Ground Truth:</b> hit the ball so that it deviates slightly usually as a result of spin

Table 3: The analysis of the top 3 selected definitions on the **Unseen** task.

Model	Accuracy (%)
Lee and Chen (2017)	52.14
Neelakantan et al. (2015)	54.00
Mancini et al. (2016)	54.56
Guo et al. (2019)	55.27
Chang et al. (2018)	57.00
Pilehvar and Collier (2016)	58.55
Proposed (BERT-base)	<b>68.64</b>

Table 4: The results on Word-in-Context (WiC) data.

according to the selected definitions. More output samples on both **Seen** and **Unseen** tasks can be found in the supplementary material.

Moreover, unlike the prior work that required discrete token generation to interpret the pre-trained word embeddings (Noraset et al., 2017; Gadetsky et al., 2018; Chang et al., 2018), we reformulate the definition modeling task from an NLG problem to a classification problem via learning a mapping between two semantically continuous spaces, which greatly simplifies the hardness, making significant improvement as shown in Table 2. Specifically, as the input representations of Noraset et al. (2017) and the first proposed baseline are the same, i.e., they both are context-agnostic and utilize the same pretrained static word embeddings, the better performance of our model demonstrates the direct benefits of not requiring sequence generation.

### 3.2 Word Sense Selection in Context

We further examine if the captured sense-specific cues help word sense disambiguation via Word-in-Context data (WiC) (Pilehvar and Camacho-Collados, 2018), in which each instance contains a pair of two contexts sharing a target word, and

the task is to decide whether their word senses are the same.<sup>3</sup> To justify that the models are capable of selecting senses encoded in the embeddings, for each pair, our model outputs 10 candidate definitions (top-10 nearest neighbors), and we output TRUE if any definition occurs in both candidate sets, otherwise FALSE. Table 4 shows that the proposed model with contextualized word embeddings outperforms all previous models. We conclude that contextualized word embeddings indeed capture sense-informative cues and our proposed model is capable of interpreting the corresponding senses via definition.

## 4 Conclusion

This paper proposes a framework that can well interpret the contextualized word embeddings by human-readable sense definitions. The experiments demonstrate that contextualized word embeddings capture the sense-informative cues and the proposed model can better explain the semantics encoded in the representations.

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<sup>3</sup>To analyze the generalizability, we follow the experimental setting of Guo et al. (2019), where all baselines and the proposed model are pretrained and evaluated directly on the large WiC training set without fine-tuning.

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## A Experimental Details

**Hyperparameters Tuning** We have empirically found that simply using a linear layer as our mapping  $f$  fails to fit the training set well. In addition, for the model that utilizes contextualized embeddings extracted from BERT, replacing the conv1d and max-pooling with the simple average of all embeddings of the corresponding word pieces leads to worse results. The maximum number of word pieces is clipped to 3 considering not only statistics but also computational cost. In the one-dimensional convolution, we have tried different kernel sizes and eventually chose to use 256 filters with the kernel size equal to 3 in order to tackle all input word pieces, and the other 256 ones with the kernel size equal to 1 are incorporated with max-pooling, only considering the most activated word piece.

With adam as our optimizer, we let the learning rate be reduced by half if the loss on the validation set has stopped improving within 5 epochs. All hyperparameters are tuned on the hold-out validation set.

**Fine-Tuning Contextualized Embeddings** In order to further investigate the definition mapping task, we also conduct the experiments that allow the pretrained BERT model to be fine-tuned jointly when training our mapping. It is found that the results are much worse than the results of leveraging the frozen BERT representations shown in Table 1

no matter which architecture is used in our mapping. The relative worse performance on the training set may indicate that BERT suffers from catastrophic forgetting during fine-tuning in our task, despite our training set is large. We posit that it is because our task is much harder than others in the GLUE benchmark, where the model is required to disambiguate from near 80,000 definitions. More investigation is needed to address this issue.

**Details in Pretrained Representations** Both context embeddings and the definition embeddings are encoded by the Transformer-based universal sentence encoder<sup>4</sup>, with the dimension in  $\mathbb{R}^{512}$ . The dimension of representations from BERT-base<sup>5</sup>  $\in \mathbb{R}^{768}$ , while the ones from BERT-large and ELMo<sup>6</sup>  $\in \mathbb{R}^{1024}$ . The context-independent embeddings of all proposed variants are initialized with pretrained `fasttext` embeddings<sup>7</sup> in  $\mathbb{R}^{300}$ .

**Evaluation Metrics** The BLEU score has many variants. In our experiments, we apply the commonly-used corpus-level BLEU@4 without smoothing from the NLTK package. We also measure the ROUGE-L:F score, the longest common subsequence based statistics, with the python ROUGE package<sup>8</sup>.

## B Generated Synonyms

The examples of generated synonyms retrieved by reversing the mapping as referred in Section 2.3 are shown in Table 5. In more detail, we freeze the pretrained mapping and the context-dependent component, i.e., the contextualized representations from BERT, ELMo or the context embedding from the universal sentence encoder, and then probe through all target word embeddings in the training set to obtain the word that could maximize the cosine similarity between the predicted definition embedding and the ground truth one.

## C Sample Outputs

The randomly-sampled examples from the output of the proposed model with contextualized embed-

<sup>4</sup><https://tfhub.dev/google/universal-sentence-encoder-large/3>

<sup>5</sup><https://pypi.org/project/pytorch-pretrained-bert/>

<sup>6</sup><https://pypi.org/project/allennlp/0.8.4/>

<sup>7</sup><https://fasttext.cc/docs/en/english-vectors.html>

<sup>8</sup><https://pypi.org/project/rouge/0.3.1/>

Contexts, Generated Synonyms, Ground Truth
<p><b>Context:</b> Dressed <i>all</i> in black.  <b>Generated Synonyms:</b> all, altogether, strictly, totes, ferociously, bang exceedingly, completely, wholly, terribly, definitely, easily  <b>Ground Truth:</b> <i>all</i>, totally, outright, altogether, completely, absolutely, quite, wholly, fully, thoroughly, utterly, entirely</p>
<p><b>Context:</b> Worse <i>yet</i> concert goers with floor tickets had to remain outside in front of gate.  <b>Generated Synonyms:</b> yet, entirely, anyone, anywhere, still, ever  <b>Ground Truth:</b> <i>yet</i>, besides, even, additionally, further, still</p>
<p><b>Context:</b> If you have green eyes, <i>brighten</i> your eyes with a plum hue.  <b>Generated Synonyms:</b> brighten, flamboyant, embellish, lurid  <b>Ground Truth:</b> <i>brighten</i>, enhance, embellish, enrich</p>
<p><b>Context:</b> As the disease progresses the cone becomes more pronounced causing vision to become blurred and <i>distorted</i>.  <b>Generated Synonyms:</b> distorted, crooked, compressed, strained, stiffen slippage, sore, tuber, convoluted, recurrent  <b>Ground Truth:</b> <i>distorted</i>, crooked, twisted, awry, misshapen, deformed, bent, wry, malformed, irregular</p>
<p><b>Context:</b> The hospital trust shares its medical <i>expertise</i> in the field of blood diseases with the facility in India.  <b>Generated Synonyms:</b> expertise, prowess, knowhow, ustad, literacy  <b>Ground Truth:</b> <i>expertise</i>, skill, prowess, competence, proficiency</p>

Table 5: Samples of generated synonyms obtained by reversing the trained mapping.

Target Word	Contexts, Selected Definitions, Ground Truth
living	<p>The aim of the scheme is to improve the city environment and make better use of <i>living</i> space.  <b>1st Definition:</b> of a place used for living rather than working in  <b>2nd Definition:</b> a place regarded as giving access to another place  <b>3rd Definition:</b> denoting or relating to accommodation designed for occupation by more than one family  <b>Ground Truth:</b> of a place used for living rather than working in</p>
	<p>A <i>living</i> language both accumulates new words of value and preserves what is old and of value.  <b>1st Definition:</b> of a language still spoken and used  <b>2nd Definition:</b> of a language tending to have each element as an independent word without inflections  <b>3rd Definition:</b> of a form of a language as used in former or earliest times  <b>Ground Truth:</b> of a language still spoken and used</p>
	<p>But as I said I'm aware of the problems earning enough money to make a <i>living</i>.  <b>1st Definition:</b> an income sufficient to live on or the means of earning it  <b>2nd Definition:</b> give or bequeath an income or property to a person or institution  <b>3rd Definition:</b> of income or resources making it unnecessary to earn ones living  <b>Ground Truth:</b> an income sufficient to live on or the means of earning it</p>
push	<p>He patted me on the back and gave me a slight <i>push</i> to the door as if I should do it right now.  <b>1st Definition:</b> an act of pushing someone or something in order to move them away from oneself  <b>2nd Definition:</b> an act of moving on ones hands and knees or dragging ones body along the ground  <b>3rd Definition:</b> an act of pushing or shoving something  <b>Ground Truth:</b> an act of pushing someone or something in order to move them away from oneself</p>
	<p>The electric beds which can be raised and lowered at the <i>push</i> of a button will help give patients ....  <b>1st Definition:</b> an act of pressing a part of a machine or device  <b>2nd Definition:</b> a device which prevents or stops a specified thing  <b>3rd Definition:</b> a device used to prevent the operation or movement of a vehicle or other machine  <b>Ground Truth:</b> an act of pressing a part of a machine or device</p>
	<p>American Forces then embarked on the long <i>push</i> to Tokyo.  <b>1st Definition:</b> a military attack in force  <b>2nd Definition:</b> the action of returning a military attack counterattack  <b>3rd Definition:</b> a disorderly retreat of defeated troops  <b>Ground Truth:</b> a military attack in force</p>
view	<p>... I only have to lift my eyes by ten degrees and I have a sumptuous panoramic <i>view</i> of a building site.  <b>1st Definition:</b> a sight or prospect typically of attractive natural scenery ... by the eye from a particular place  <b>2nd Definition:</b> the ability to see something or to be seen from a particular place  <b>3rd Definition:</b> an object or feature of a landscape or town that is easily seen and recognized from a distance ...  <b>Ground Truth:</b> a sight or prospect typically of attractive natural scenery ... by the eye from a particular place</p>
	<p>Matisse's <i>view</i> of Collioure.  <b>1st Definition:</b> the distinctive nature or qualities of something  <b>2nd Definition:</b> an attribute quality or characteristic of something  <b>3rd Definition:</b> a tangible or visible form of an idea quality or feeling  <b>Ground Truth:</b> a work of art depicting a sight of natural scenery</p>
	<p>Members of the public can <i>view</i> these and other documents at the national archive.  <b>1st Definition:</b> inspect a house or other property with the intention of possibly buying or renting it  <b>2nd Definition:</b> show or provide something for consideration inspection or use  <b>3rd Definition:</b> examine and report on the condition of a building especially for a prospective buyer  <b>Ground Truth:</b> look at or inspect</p>

Table 6: Randomly sampled examples of the top 3 selected definitions on the **Seen** task.

Target Word	Contexts, Selected Definitions, Ground Truth
construction	There is, so far as I am aware, no authority on the true <i>construction</i> of this clause. <b>1st Definition:</b> a general statement or concept obtained by inference from specific cases <b>2nd Definition:</b> the precise terms of a statement or requirement the strict verbal interpretation <b>3rd Definition:</b> the action of making a statement or situation less confused and more comprehensible <b>Ground Truth:</b> an interpretation or explanation
	... intellectual predilection for stressing the active role of individuals in the social <i>construction</i> of social reality. <b>1st Definition:</b> the action of creating or preparing something <b>2nd Definition:</b> the process of analysing and developing an idea or principle in detail <b>3rd Definition:</b> the process of deciding or planning something <b>Ground Truth:</b> the creation of an abstract entity
	That tells us that the <i>construction</i> is an interrogative complement clause in each case. <b>1st Definition:</b> the arrangement of words and phrases to create wellformed sentences in a language <b>2nd Definition:</b> in systemic grammar a level of structure between clause and word ... <b>3rd Definition:</b> a single distinct meaningful element of speech or writing used with others ... <b>Ground Truth:</b> the arrangement of words according to syntactical rules
inflate	Unfortunately, the balloon refused to <i>inflate</i> properly and just dragged along on the surface of the sea. <b>1st Definition:</b> extend outwards beyond something else protrude <b>2nd Definition:</b> extending upwards over <b>3rd Definition:</b> become or make less wide <b>Ground Truth:</b> become distended with air or gas
	If there is one thing the Fed can do, they say, it is <i>inflate</i> the currency. <b>1st Definition:</b> make a slight reduction in the amount rate or price of <b>2nd Definition:</b> bring about a general reduction of price levels in an economy <b>3rd Definition:</b> exclude a nonnet amount such as tax when making a calculation in order to reduce the amount ... <b>Ground Truth:</b> bring about inflation of a currency or in an economy
	On his bicycle fitted with a luggage box ... a vacuum pump to <i>inflate</i> the cycle tyres whenever necessary. <b>1st Definition:</b> become or make less wide <b>2nd Definition:</b> squeeze or force into a small or restricted space <b>3rd Definition:</b> extend across or through <b>Ground Truth:</b> fill a balloon tyre or other expandable structure with air or gas so that it becomes distended

Table 7: More randomly sampled examples of the top3 selected definitions on the **Unseen** task.

dings from BERT-base on the **Seen** task are shown in Table 6, and the ones on the **Unseen** task are in Table 7.