Improving Interpretability of Word Embeddings by Generating Definition and Usage

Haitong Zhang, Yongping Du*, Jiaxin Sun, Qingxiao Li
Faculty of Information Technology, Beijing University of Technology, Beijing, 100124, China

Abstract

Word Embeddings, which encode semantic and syntactic features, have achieved success in many natural language processing tasks recently. However, the lexical semantics captured by these embeddings are difficult to interpret due to the dense vector representations. In order to improve the interpretability of word vectors, we explore definition modeling task and propose a novel framework (Semantics-Generator) to generate more reasonable and understandable context-dependent definitions. Moreover, we introduce usage modeling and study whether it is possible to utilize distributed representations to generate example sentences of words. These ways of semantics generation are a more direct and explicit expression of embedding’s semantics. Two multi-task learning methods are used to combine usage modeling and definition modeling. To verify our approach, we construct Oxford-2019 dataset, where each entry contains word, context, example sentence and corresponding definition. Experimental results show that Semantics-Generator achieves the state-of-the-art result in definition modeling and the multi-task learning methods are helpful for two tasks to improve the performance.

Keywords: Word Embeddings Interpretability, Definition Modeling, Definition Generation, Usage Modeling, Usage Generation

1. Introduction

Word embeddings (Turian et al., 2010), capturing the semantic and syntactic relations among words, have been exploited to obtain superior performance in many NLP tasks (Huang et al., 2014; Tai et al., 2015; Yang et al., 2016). However, the dense representations of word embeddings make their interpretability limited inherently. Previous works, such as word similarity (Landauer and Dumais, 1997; Downey et al., 2007) and word analogy (Mikolov et al., 2013), can only evaluate the lexical information captured by embeddings indirectly.

Recently, Noraset et al. (2017) introduces a more transparent way to interpret an embedding’s semantics by directly generating the textual definition of the corresponding word. They propose definition modeling which is a task that estimates the probability of the definition given a target word embedding. Gadetsky et al. (2018) solves the ambiguity problem in definition modeling by incorporating the context of the defined word to generate context-dependent definitions.

In this work, we focus on improving the interpretability of word embeddings by semantic generation. We design a novel architecture based on encoder-decoder framework. The encoder maps the context into a sentence embedding and Scaled Dot-Product Attention (Vaswani et al., 2017) is used for the interaction between defined word and its context to encode context-aware semantic representation. Then the decoder generates context-dependent definition for a target word. During the decoding process, a gated mechanism is adopted to control the influence of both semantic information and current word information at each time step. Moreover, we introduce usage modeling to generate the example sentences of corresponding words. Two multi-task approaches are investigated to combine usage modeling and definition modeling, which share the representations at different levels.

Our contributions are as follows: (1) A new model is proposed and it can generate fluent and understandable context-dependent definitions, which achieves the state-of-the-art result compared with the previous definition models regardless of considering context or not. Further, the character-level and contextual word embeddings are used to compensate for the drawbacks of traditional word embeddings. (2) We introduce usage modeling task, and investigate two kinds of multi-task models that combine usage modeling and definition modeling by parallel-shared model and hierarchical-shared model respectively. To the best of our knowledge, our work is the first study that try to make example sentences by neural networks. (3) We construct a large dictionary dataset, which provides a wealth of dictionary resources that can be leveraged in different NLP tasks.

*Corresponding author.

Email addresses: z962630523@gmail.com (Haitong Zhang), ypdu@bjut.edu.cn (Yongping Du), sjx7252240163.com (Jiaxin Sun), lqx_bjut@163.com (Qingxiao Li)
2. Related Work

The early works focus on extracting and organizing the lexical knowledge from the dictionary resources. Chodorow et al. (1985) and Klavans and Whitman (2001) extract the implicit semantic and syntactic information in dictionary definitions to construct the taxonomy of words automatically. Dolan et al. (1993) constructs a lexical knowledge base which is based on the semantic information extracted from the dictionaries. These works create rich lexicon resources for many natural language processing tasks.

Recently, many works utilize dictionary definitions to learn or improve word embeddings. Wang et al. (2015) incorporates dictionary as a lexicographic knowledge to learn embeddings. Hill et al. (2016) explores the representations of phrases and sequences by training neural network to produce a target embedding for a word given its definition. Bosc and Vincent (2018) improves word embeddings with an auto-encoder structure that begins from the target word embedding and backs to the definition. Scheepers et al. (2018) utilizes the definitions to tune word embeddings towards better compositionality.

Interpreting word embeddings is often conducted through non-negative and sparse coding (Faruqui et al., 2015; Luo et al., 2015; Kober et al., 2016), and regularization (Sun et al., 2016). In addition, Park et al. (2017) applies rotation algorithms based on exploratory factor analysis (EFA) to embedding spaces for obtaining interpretable dimensions in an unsupervised manner. Their approach relies on solving complex optimization problems, while we focus on improving the interpretability by semantics generation. The most related work to this paper is definition modeling (Noraset et al., 2017) which is a task that estimates the probability of dictionary definition based on the defined word and its embedding. They propose several RNN-based definition models, which are trained on the dictionary definitions corpus and then used to generate the corresponding definitions of the words that are not seen during training. This approach is a more explicit demonstration of the semantics captured by word embeddings. However, they treat all of the words as monosemic words which brings the problem of word ambiguity. To address the polysemy issue, Gadetsky et al. (2018) extends the context information of the defined word into definition modeling. They propose two definition models that incorporate context information, and one of them is based on Adaptive Skip-gram vector representations (Bartunov et al., 2016) that provides different word embeddings according to its contexts, the other uses soft attention mechanism to extract the components of word embedding relevant to corresponding meaning. Chang et al. (2018) incorporate a sparse vector extractor to select sense-specific representation of the target word, which aim to provide a more explainable model for definition generation. In addition, Yang et al. (2019) incorporates sememes into Chinese definition modeling.

3. Contextualized Self-Interpretability by Usage Generation

3.1. Usage Modeling

Usage generation is similar to definition generation but with some differences. For definition generation, words other than the defined word are used to express the meaning of the target word. While, for usage generation, the model must understand how to use target word in the context. This is a more profound and more complex lexical semantic representation, and we call it Contextualized Self-Interpretability.

We introduce usage modeling for further improve the interpretability of word embeddings. Usage modeling estimates the probability of words in example sentence $U = \{w_1, \ldots, w_N\}$ given a target word $w^\ast$. The corresponding context $C$ is also considered to avoid the problem of ambiguity. The joint probability is decomposed into separate conditional probabilities as:

$$p(U|w^\ast, C) = \prod_{t=1}^{N} p(w_t|w_{<t}, w^\ast, C) \quad (1)$$

Note that the target word should be included in usage sentence. Similarly, usage modeling is a special case of language modeling, and the performance can be measured by the perplexity of test data. Below is an example entry from the Oxford English Dictionary.

**Soldier**: A person who serves in an army.

**example sentence**: He zoomed in on the view of one of the soldiers under his command.

Dictionary definitions are usually comprised of **genus** and **differentiae** (Chodorow et al., 1985; Montemagni and Vanderwende, 1992), where the **genus** is the hypernym of the defined word and the **differentiae** distinguishes the hypernym from defined word. The word “soldier” in the above example is defined as “a person who serves in an army”, where the “person” is genus and the rest is differentiae. However, the example sentences do not have a specific structure like definitions and there are a wide variety of tenses and lexical forms in sentences such as the word in the example above, from singular “soldier” to plural “soldiers”. These make usage modeling more complicated than definition modeling and a deeper understanding of semantics and syntax is needed.

3.2. A New Oxford-2019 Dataset

Rich dictionary resources are accessible online, such as WordNet, Wiktionary and Merriam-Webster Dictionary. However, most of them are short of example sentences compared with Oxford Dictionary. Gadetsky et al. (2018) collected a dataset utilizing Oxford Dictionary resources. But we find their data having some noise, and the data format is messy where the defined word contains **Arabic numerals, Non-English alphabets and Special symbols**. Moreover, some example sentences do not contain the target...
word which makes the context useless. To make up for
these deficiencies and explore usage modeling, we collect a
new Oxford-2019 dataset by Oxford Dictionaries API
1

We sample the most common 65,000 tokens in WikiText-
103 dataset (Merity et al., 2016), removing duplicate words,
function words and stop words, keeping only the words
that consist of pure letters as our vocabulary. We use the “sentences” returned by Oxford Dictionaries API as contexts while the “examples” as example sentences, so that we can model example sentence and distinguish corresponding meaning by the context. Here, “sentences” are extracted from corpora, using richer vocabulary and longer sentences than “examples”. Each specific definition includes three different context sentences and one example sentence. We split the collected data into train, valid, and test sets by specific meaning of words so that the same definition for a given word will not appear in different data sets.

The statistics of Oxford-2019 dataset are shown in Table 1. It contains example sentences with more contexts, and the size is much larger than that provided by Gadetsky et al. (2018). The domain information that may provide knowledge of the proper genus and POS tag of the word are also included, which could be utilized by other NLP tasks for further research.

| Split       | train | valid | test |
|-------------|-------|-------|------|
| #Words      | 32,066| 7,359 | 7,322|
| #Entries    | 231,949| 29,275| 29,241|
| #Tokens     | 2,595,561| 323,700| 322,915|
| Definition AL | 11.05 | 11.06 | 11.04 |
| Example AL  | 11.30 | 11.28 | 11.31 |
| Context AL  | 21.48 | 21.43 | 21.43 |

Table 1: The basic statistics of the new Oxford-2019 dataset. The average length of the contexts is much longer (>10) than the example sentences. AL means average length.

4. Models

We introduce the proposed definition model Semantics-Generator as shown in Figure 1. Further, two kinds of multi-task models are proposed combining usage modeling and definition modeling.

---

11https://developer.oxforddictionaries.com/

---

4.1. Semantics-Generator: Semantic Generative Network for Word Embedding

Context Encoder. The context encoder takes the context sentence as input and generates a meaningful sentence embedding of fixed-dimensions. We use BiGRU with a max pooling layer as context encoder (Conneau et al., 2017).

Firstly, given a context containing T words \{w_t\}_{t=1,...,T}, GRU computes a set of T vectors \(C_t = \{h_t\}_T\) that each \(h_t \in (h_1, \ldots, h_T)\) is the concatenation of feed-forward direction and back-forward direction respectively:

\[
\overrightarrow{h}_t = \overrightarrow{GRU}_t (w_1, \ldots, w_T)
\]
\[
\overleftarrow{h}_t = \overleftarrow{GRU}_t (w_1, \ldots, w_T)
\]

\[
h_t = [\overrightarrow{h}_t, \overleftarrow{h}_t]
\]

Then, a max pooling layer is used to select the maximum value over the hidden units for each dimension to get a vector \(V_c\) with the same dimensions as \(h_t\), which is used as the embedded representation of the context.

Interaction between Word and Context. Scaled Dot-Product Attention \(\text{Vaswani et al.}(2017)\) maps a query and a set of key-value pairs to an output. It is much faster
and more space-efficient in practice and improves the performance of many NLP tasks. We utilize it to compute the context-aware word embedding components. Given the target word embedding \(v^*\) with dimension \(d_v\) and its context’s key-value pairs with dimension \(d_k\), we compute the dot products of the target word with all keys of context, divided each by \(\sqrt{d_k}\), and apply a softmax function to obtain the weights on the values, which is computed according to the following equation:

\[
\text{Att}(V^*, C_k, C_v) = \text{softmax} \left( \frac{V^* \cdot C_v^T}{\sqrt{d_k}} \right) C_v
\]

where

\[
V^* = \sigma(W_d \cdot v^* + b_d)
\]

\[
C_k = \sigma(W_k \cdot C_v + b_k)
\]

\[
V^* \in \mathbb{R}^{1 \times d_v}, \quad C_k \in \mathbb{R}^{m \times d_v}, \quad C_v \in \mathbb{R}^{m \times d_v} \quad \text{and} \quad \sigma \text{ is the RELU activation function. The result } a^* = \text{Att}(V^*, C_k, C_v) \text{ by equation 3 is the context-aware semantic representation of word embedding, which is used to provide relevant meaning to the decoder at each time step.}

**Semantics Decoder.** The decoder uses GRU [Cho et al. 2014] as the recurrent unit. For Neural Machine Translation and Image Caption task, the encoder reads the source sentence or picture and transforms it into a fixed length vector representation which is the initial hidden state of the decoder RNN. Inspired by that, we assign the concatenation of the target word embedding \(v^*\) and its context embedding \(V_c\) to the initial hidden state of GRU,

\[
h_0 = [v^*; V_c]
\]

which can provide more comprehensive and explicit signal of the target word and context for decoder to generate smooth and consistent context-dependent definitions.

Each word in the definition has a varying degree of dependency on the defined word. Moreover, the \(t\)th generated word \(w_t\) also depends on previous words \(w_1, \ldots, w_{t-1}\) variably. Note that the decoder is autoregressive during the generation process. In order to alleviate the influence of previous generated error words on the subsequent decoding process, we add a gated function to the input \(x_t\) at each decoding step as:

\[
x_t = g_t \odot [a^*; v_t; C^*; E^*]
\]

\[
g_t = \text{sigmoid}(W_a \cdot [a^*; v_t; C^*; E^*])
\]

\[
C^* = \text{CNN}(v^*)
\]

\[
E^* = \text{ELMo}(c^*)
\]

where \(\odot\) is the element-wise product, \(v_t\) denotes the word embedding of \(w_t\), and \(c^*\) is the context of the target word \(w^*\). \(C^*\) and \(E^*\) are the character-level information and the ELMo embeddings [Peters et al. 2018] of the target word, respectively, which we will explain in detail later. Unlike [Noraset et al. 2017], our gated function controls the influence of both the defined word and the current input at each time step. Then, the GRU updates the output of each time step by:

\[
h_t = g(x_t, h_{t-1})
\]

where \(g\) is recurrent nonlinear function.

**Character-Level Information.** Many words in English consist of root and affixes. For example, the English morpheme \texttt{re-} often refers to again as “reinforce” while \texttt{dis-} usually means opposite as “dislike”. These character-level morphological and semantic information have a certain impact on the meaning of the defined word, so we use character-level embeddings to capture these features. Following [Noraset et al. 2017], we utilize a character-level convolution neural network (CNN) followed by a max pooling layer to create these features [Kim et al. 2016] as \(C^*\).

Moreover, two-layer Highway Network [Srivastava et al. 2015]
Contextual Word Embeddings. Traditional word vectors only allow a single context-independent representation for each word which is difficult to represent the complex characteristics of a word and its varied semantics with different contexts. We use ELMo embeddings \cite{Peters:2018} of the context of the target word to supplement the contextualized word representation, denoted as $E^*$. ELMo are functions of the entire input sentence so that a word may have different representations depending on the corresponding contexts.

\subsection{Multi-Task Learning with Usage Modeling}

Multi-task sequence to sequence learning \cite{Luong:2015} has achieved better results on many sequence modeling tasks \cite{Niehues:2017,Clark:2018}. In order to further improve the interpretability of word embeddings, we investigate two kinds of multi-task models that combine usage modeling and definition modeling, which share the representations at different levels by parallel and hierarchical level respectively, as shown in Figure 2. For a given word and its context, our multi-task models can generate both definition and example sentence of target word. Since definition modeling and usage modeling are based on the same target word and context, the multi-task models have the same architecture as Semantics-Generator, with just one more decoder for usage modeling.

**Parallel-Shared Model.** In parallel-shared model, both definition modeling and usage modeling are supervised at the same-level layer. For each task, we use two separate task-specific semantics decoders while only share the embedding layer. Both decoders receive the concatenation of target word embedding $v^*$ and context embedding $V_c$ as the initial hidden state (Eq 7), and compute their outputs respectively as follows:

\begin{equation}
\begin{align}
\text{h}^{\text{definition}} &= \text{GRU}^{\text{definition}}(D) \tag{12} \\
\text{h}^{\text{usage}} &= \text{GRU}^{\text{usage}}(U) \tag{13}
\end{align}
\end{equation}

where $D = \{w_1, \ldots, w_T\}$ and $U = \{w_1, \ldots, w_N\}$ refer to the definition sequence and example sentence sequence, respectively.

**Hierarchical-Shared Model.** We also investigate two hierarchical multi-task models where definition modeling and usage modeling are supervised at different-level layers. \textit{Hir-Shared(DU)} supervises definition modeling at bottom layer while usage modeling at top layer and \textit{Hir-Shared(UD)} is the opposite. Follow \cite{Hashimoto:2016}, shortcut connection is used to prevent the catastrophic forgetting between tasks. The input of higher-level decoder is the concatenation between the lower layer decoder output and the words representations, and the outputs of two tasks are computed as follows:

\begin{equation}
\begin{align}
\text{h}^{\text{bottom}} &= \text{GRU}^{\text{bottom}}(X) \tag{14} \\
\text{h}^{\text{top}} &= \text{GRU}^{\text{top}}(X; \text{h}^{\text{bottom}}) \tag{15}
\end{align}
\end{equation}

where $X$ refer to the input sequence of the lower level or higher-level task.

\section{Experimental Setup}

\subsection{Datasets and Automatic Evaluation Metrics}

We train and evaluate our proposed definition model Semantics-Generator on both the original Oxford dataset constructed by \cite{Gadetsky:2018} and our new collected Oxford-2019 dataset. For the multi-task models, we report the performance on our new dataset.

We use BLEU \cite{Papineni:2002} and ROUGE \cite{Lin:2004} score as automatic evaluation metrics. Follow previous work \cite{Noraset:2017,Gadetsky:2018}, the average BLEU score is computed across all test entries by the sentence-BLEU binary in Moses library\footnote{http://www.statmt.org/moses/} for fair comparison. Moreover, we report the average F-measure of ROUGE-L which is calculated by Rouge package\footnote{https://github.com/pltrdy/rouge}.

\subsection{Baselines}

We compare our models with two types of baselines that consider contexts or not. The baselines that do not consider contexts \cite{Noraset:2017} are conditional RNN language models (RNNLM) based on the target word embedding. The target word is added at the beginning of the definition as a form of “seed” information \cite{Sutskever:2011}, then the RNNLM reads a word every time step and outputs a hidden representation used to generate next word one by one. The baseline with contexts includes AdaGram based model and Attention based model which are proposed by \cite{Gadetsky:2018}. We reimplement these models with the same settings on the datasets for fair comparison.

\subsection{Experimental Details}

All of our models utilize 2-layer GRU network as the RNN component of decoder, and word embeddings are initialized with pre-trained Word2Vec\footnote{https://code.google.com/archive/p/word2vec/} and fixed during training. We search the hyper-parameters based on the perplexity scores on the valid set. Both word embeddings and GRU hidden layers of decoder have 300 units. A one-layer BiGRU with 150 hidden units is used for fair comparison.

--

\begin{footnotesize}
\begin{enumerate}
\item \url{http://www.statmt.org/moses/}
\item \url{https://github.com/pltrdy/rouge}
\item \url{https://code.google.com/archive/p/word2vec/}
\end{enumerate}
\end{footnotesize}
### 6. Results and Discussion

#### 6.1. Overall Performance

**Automatic Evaluation** The performance of our definition model **Semantics-Generator** and all baselines (Model A-G) are reported in Table 2, and the experiments are implemented on both the Oxford dataset collected by Gadetsky et al. (2018) and our new Oxford-2019 dataset. Compared with our new dataset, the original Oxford dataset is small which contains fewer entries. It is noticed that these datasets are split by specific definition so that some test words may appear during training. We report the model performance on two different types of test data which are labeled as “Seen” and “Unseen” separately. The dataset with “Seen” label contains the target words with different meanings during training. On the contrary, the target words do not appear in the training set labeled as “Unseen”, which is more difficult to achieve the better performance. Among all of the baselines, the S+I-Adaptive model performs best on original small dataset (Model F). Although Noraset et al. (2017)’s methods (Model A-E) do not take into account the contexts, their models still perform strong. On the small dataset, their best model S+G+CH performs slightly lower in BLEU, but achieves the better ROUGE-L (Model E vs. F&G). Further, the performance of their work on our large dataset are improved and better than the baselines considering the contexts (Model A-E vs. F&G). The probable reason is that since dictionary definitions usually have inherent structure, generating the same definition for all contexts can still have some common expressions and it may reduce the errors introduced by the interaction between words and contexts. Our **Semantics-Generator** (Model H) gets significant improvement over the baselines by 3.31 BLEU, 4.79 ROUGE-L on the original dataset, and 0.74 BLEU, 1.53 ROUGE-L on our new dataset. In addition, it is found that pre-training can effectively improve the model performance on the small dataset. Figure 3 illustrates that the process of pre-training can help decrease perplexity and prevent overfitting. However, it does not work on our large dataset which shows that our model has ability of learning the general expression of dictionary definition when the data is enough even without pre-training (Model H vs. I).

![Figure 3: Perplexities of Semantics-Generator with or w/o pretraining on the Oxford dataset.](image)

#### Human Evaluation
In addition to automatic evaluations, we also leverage manual evaluations to enhance the reliability of the evaluations. We randomly select 100 entries from the test set of Oxford-2019 dataset and ask 5 students to annotate. Candidate definitions include the defi-
Table 3: Averaged human annotated scores on randomly sampled 100 entries from Oxford-2019 dataset.

| Model           | Quality | Readability |
|-----------------|---------|-------------|
| $S+G+CH$         | 2.03    | 3.33        |
| $S+I$-Attention | 2.23    | 3.37        |
| Semantics-Generator | 2.96   | 3.77        |

Table 3: Averaged human annotated scores on randomly sampled 100 entries from Oxford-2019 dataset.

Table 4: The ablation study on the additional embeddings, experiments on original Oxford Dataset (BLEU / ROUGE-L).

| Model                  | Full       | Seen       | Unseen     |
|------------------------|------------|------------|------------|
| W2V+CH+ELMo            | 16.00/21.94| 16.53/21.98| 13.38/21.70|
| W2V+ELMo               | 15.93/21.38| 16.50/21.70| 13.01/20.99|
| W2V                    | 14.16/18.83| 14.55/18.72| 12.21/19.37|

Table 4: The ablation study on the additional embeddings, experiments on original Oxford Dataset (BLEU / ROUGE-L).

The effect of embeddings. To analyze whether additional embeddings have an impact on the performance of our model, we perform an ablation analysis on the tar-
check

| Word | Context | Model | Definition |
|------|---------|-------|------------|
| check | #1 We got our bill, paid the **check**, and made our way enthusiastically to Billy's bakery. | S+G+CH | a small quantity of something |
| check | #2 The mark is only awarded to organizations that pass regular quality **checks**. | S+G+CH | a small quantity of something |

Table 5: Generated definitions for word “check” in Oxford-2019 test set.

Figure 7: Influence of various parameters of the target word on BLEU scores of the generated definitions.

6.3. Discussion

Case Study We give a case in Table 5. From the result, it can be seen that the S+G+CH model generates the same definition for one target word. It does not consider the varied context information, so it can only generate one of its most common senses for a word. Our model **Semantics-Generator** and S+I-Attention are context-dependent, while our model can utilize context information better and generate more reasonable definitions. For example, it can generate “money” given context #1 with “bill” and “paid”. We will further analyze in the following.

How context information helps the models? Our model utilizes context information to 1) disambiguate the polysemy and 2) provide contextualized representation of target word. We analyze the impact of the number of senses of target words on definition generation in Oxford dataset. Figure 7(a) shows that the performance of the S+G+CH model is significantly degraded when the target word is more ambiguous (sense > 8), which illustrates the important role of context in the generation of polysemy definitions. The performance of our model **Semantics-Generator** is significantly better (3.83+BLEU) than S+I-Attention. But what happens if there is not enough context information? For example, the meaning of “utmost” given the context “he tried his utmost”. In this situation, only the embedding representation of the target word can help model understand the meaning. We analyze the impact of the context length on BLEU scores of generated definitions to verify our hypothesis. Figure 7(b) shows that our model is much stronger (10.8+BLEU) than the baseline models when the context is short (length < 10). This further illustrates that the contextualized vector representations (ELMo) can make up for the shortcomings of word vectors and provide better representations for target words to help the model understand the correct meaning.
**Table 6:** Some examples of definitions and usages generated by our multi-task models from Oxford-2019 test set.

| Word | Context | Definition | Usage |
|------|---------|------------|-------|
| order | Every person is hereby ordered to immediately evacuate the city of New Orleans. | make a formal or authoritative request to someone | He was ordered to leave the room. |
| order | The order of the knights templar was formed during the crusades when many knights and squires set out for the holy land. | a formal rule of law, especially in the roman catholic church | The order of the church. |
| skirt | She was wearing a knee-length dark blue jean skirt with a front slit and a blue backless top. | a garment worn in the upper part of the body | She wore a silk skirt. |
| skirt | Along the scenic route skirting the rim we stopped at every lookout to gaze at the fantastic scenery. | go over a wide area | The road was not to be skirted. |
| agreement | No provision was made in the agreements for time off, sick pay, or holidays. | the action of establishing a relationship between two or more parties | The agreement between the two countries. |
| gaze | I took my chair to the open corridor and sat there with my book, gazing at the sunset. | look at a place steadily | She gaze at the room. |

**Table 7:** The performance of our models on Oxford-2019 test set (PPL/ BLEU/ ROUGE-L). Here, * means multi-task model.

| Model                  | Oxford-2019 |        |        |
|------------------------|-------------|--------|--------|
|                        | Definition  | Usage  |        |
| Semantics-Generator    | 41.15/13.85/20.67 | 258.33/12.96/14.04 |        |
| Parallel-Shared*        | 40.42/13.96/20.81 | 237.64/13.49/14.32 |        |
| Hir-Shared(DU)*         | 42.67/13.57/20.41 | **227.71/13.51/14.47** |        |
| Hir-Shared(UD)*         | **39.67**/13.40/20.54 | 244.80/13.26/14.31 |        |

### 6.4. Single Task vs. Multi-Task Models

We report the performance of our multi-task models by perplexity, BLEU and ROUGE-L scores in Table 7. We train the single task model Semantics-Generator on definitions and example sentences respectively, and report their performance for comparison. The Parallel-Shared model can effectively improve the performance on both definition and usage modeling. This is reasonable because generating example sentence and definition are similar in some aspects, just like translating a kind of language into English and Spanish in machine translation. For usage modeling, the Hir-Shared(DU) performs better than the other models. Usage modeling task is more difficult which requires more complex syntax and semantic information, so supervising it at higher-level could have access to deeper representation transferred by the low-level definition modeling task. Table 6 shows some examples of generated definitions and usages. This result indicates that the semantic and syntactic information captured by the word embeddings have the ability to make example sentences for the target words.

### 7. Conclusion

Our work focuses on improving the interpretability of word embeddings by semantic generation. We explore the definition modeling task to generate dictionary definitions of words using pre-trained word embeddings. A novel framework Semantics-Generator is proposed to generate context-dependent definitions and it utilizes Scaled Dot-Product Attention mechanism to extract the specific meaning of target word with varied context. Moreover, additional character-level embeddings and ELMo embeddings are used to compensate for the drawbacks of traditional word embeddings. The proposed model outperforms other definition models on both the existing Oxford dataset and a newly collected Oxford-2019 dataset. The quantitative and qualitative analysis demonstrate the effectiveness of our model and indicate the importance of contextualized word representations when the target word is seen or lacking the context information.

In addition, we introduce usage modeling task, and try to utilize word embeddings to generate example sentences to further improve the interpretability of word vectors. Two kinds of multi-task approaches are investigated to combine usage modeling and definition modeling, which share the representations at different levels including parallel and hierarchical level. Our multi-task models can generate both definitions and example sentences of target words, and the experiment results show that it can take advantage of inductive transfer between tasks to achieve better performance on both definition modeling and usage modeling task.

In future work, we plan to utilize attention mechanism to focus on more relevant parts of the context at each generation step and combine multiple contexts to improve
our model. Moreover, generating example sentences based on word embeddings is an interesting but challenging task. We will focus on designing effective models with lexically constrained decoding to generate more reasonable example sentences.

Acknowledgements

This work is supported by the National Key R&D Program of China under grant no.2018YFC1900804, Research Program of State Language Commission under grant no. YB135-89.

References

Bartunov, S., Kondrashkin, D., Osokin, A., and Vetrov, D. (2016). Breaking sticks and ambiguities with adaptive skip-gram. In Artificial Intelligence and Statistics, pages 130–138.

Bosc, T. and Vincent, P. (2018). Auto-encoding dictionary definitions into consistent word embeddings. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 1522–1532.

Chang, T.-Y., Chi, T.-C., Tsai, S.-C., and Chen, Y.-N. (2018). xsense: Learning sense-separated sparse representations and textual definitions for explainable word sense networks. arXiv preprint arXiv:1809.03348.

Cho, K., Van Merriënboer, B., Gulcehre, C., Bahdanau, D., Bougares, F., Schwenk, H., and Bengio, Y. (2014). Learning phrase representations using rnn encoder-decoder for statistical machine translation. arXiv preprint arXiv:1406.1078.

Chodorow, M. S., Byrd, R. J., and Heidorn, G. E. (1985). Extracting semantic hierarchies from a large on-line dictionary. In Proceedings of the 23rd annual meeting on Association for Computational Linguistics, pages 299–304. Association for Computational Linguistics.

Clark, K., Luong, M.-T., Manning, C. D., and Le, Q. V. (2018). Semi-supervised sequence modeling with cross-view training. arXiv preprint arXiv:1809.08370.

Conneau, A., Kiela, D., Schwenk, H., Barrault, L., and Bordes, A. (2017). Supervised learning of universal sentence representations from natural language inference data. arXiv preprint arXiv:1705.02364.

Dolan, W., Vanderwende, L., and Richardson, S. D. (1993). Automatically deriving structured knowledge bases from on-line dictionaries. In Proceedings of the First Conference of the Pacific Association for Computational Linguistics, pages 5–14.

Downey, D., Schoenmackers, S., and Etzioni, O. (2007). Sparse information extraction: Unsupervised language models to the rescue. Technical report, WASHINGTON UNIV SEATTLE DEPT OF COMPUTER SCIENCE AND ENGINEERING.

Faruqui, M., Tsvetkov, Y., Yogatama, D., Dyer, C., and Smith, N. (2015). Sparse overcomplete word vector representations. arXiv preprint arXiv:1506.02004.

Gadetsky, A., Yakubovskiy, I., and Vetrov, D. (2018). Conditional generators of words definitions. arXiv preprint arXiv:1806.10090.

Hashimoto, K., Xiong, C., Tsuruoka, Y., and Socher, R. (2016). A joint many-task model: Growing a neural network for multiple nlp tasks. arXiv preprint arXiv:1611.01587.

Hill, F., Cho, K., Korhonen, A., and Bengio, Y. (2016). Learning to understand phrases by embedding the dictionary. Transactions of the Association for Computational Linguistics, 4:17–30.

Huang, F., Ahuja, A., Downey, D., Yang, Y., Guo, Y., and Yates, A. (2014). Learning representations for weakly supervised natural language processing tasks. Computational Linguistics, 40(1):85–120.

Kim, Y., Jernite, Y., Sontag, D., and Rush, A. M. (2016). Character-aware neural language models. In Thirtieth AAAI Conference on Artificial Intelligence.

Kingma, D. P. and Ba, J. (2014). Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980.

Klavans, J. and Whitzman, B. (2001). Extracting taxonomic relationships from on-line definitional sources using lexing. In Proceedings of the 1st ACM/IEEE-CS joint conference on Digital libraries, pages 257–258. ACM.

Kober, T., Weeds, J., Reffin, J., and Weir, D. (2016). Improving sparse word representations with distributional inference for semantic composition. arXiv preprint arXiv:1608.06794.

Landauer, T. K. and Dumais, S. T. (1997). A solution to plato’s problem: The latent semantic analysis theory of acquisition, induction, and representation of knowledge. Psychological review, 104(2):211.

Lin, C.-Y. (2004). Rouge: A package for automatic evaluation of summaries. Text Summarization Branches Out.

Luo, H., Liu, Z., Luan, H., and Sun, M. (2015). Online learning of interpretable word embeddings. In Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing, pages 1687–1692.
Luong, M.-T., Le, Q. V., Sutskever, I., Vinyals, O., and Kaiser, L. (2015). Multi-task sequence to sequence learning. arXiv preprint arXiv:1511.06114.

Merit, S., Xiong, C., Bradbury, J., and Socher, R. (2016). Pointer sentinel mixture models. arXiv preprint arXiv:1609.07843.

Mikolov, T., Yih, W.-t., and Zweig, G. (2013). Linguistic regularities in continuous space word representations. In Proceedings of the 2013 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 746–751.

Montemagni, S. and Vanderwende, L. (1992). Structural patterns vs. string patterns for extracting semantic information from dictionaries. In COLING 1992 Volume 2: The 15th International Conference on Computational Linguistics, volume 2.

Niehues, J. and Cho, E. (2017). Exploiting linguistic resources for neural machine translation using multi-task learning. arXiv preprint arXiv:1708.00993.

Noraset, T., Liang, C., Birnbaum, L., and Downey, D. (2017). Definition modeling: Learning to define word embeddings in natural language. In Thirty-First AAAI Conference on Artificial Intelligence.

Papineni, K., Roukos, S., Ward, T., and Zhu, W.-J. (2002). Bleu: a method for automatic evaluation of machine translation. In Proceedings of the 40th annual meeting on association for computational linguistics, pages 311–318. Association for Computational Linguistics.

Park, S., Bak, J., and Oh, A. (2017). Rotated word vector representations and their interpretability. In Proceedings of the 2017 Conference on Natural Language Processing, pages 401–411.

Peters, M. E., Neumann, M., Iyyer, M., Gardner, M., Clark, C., Lee, K., and Zettlemoyer, L. (2018). Deep contextualized word representations. arXiv preprint arXiv:1802.05365.

Schepers, T., Kanoulas, E., and Gavves, E. (2018). Improving word embedding compositionality using lexicographic definitions. In Proceedings of the 2018 World Wide Web Conference on World Wide Web, pages 1083–1093. International World Wide Web Conferences Steering Committee.

Srivastava, R. K., Greff, K., and Schmidhuber, J. (2015). Highway networks. arXiv preprint arXiv:1505.00387.

Sun, F., Guo, J., Lan, Y., Xu, J., and Cheng, X. (2016). Sparse word embeddings using l1 regularized online learning.