LitMind Dictionary: An Open-Source Online Dictionary

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Abstract

Dictionaries can help language learners to learn vocabulary by providing definitions of words. Since traditional dictionaries present word senses as discrete items in predefined inventories, they fall short of flexibility, which is required in providing specific meanings of words in particular contexts. In this paper, we introduce the LitMind Dictionary (https://dictionary.litmind.ink), an open-source online generative dictionary that takes a word and context containing the word as input and automatically generates a definition as output. Incorporating state-of-the-art definition generation models, it supports not only Chinese and English, but also Chinese-English cross-lingual queries. Moreover, it has a user-friendly front-end design that can help users understand the query words quickly and easily. All the code and data are available at https://github.com/blcuicall/litmind-dictionary.

1 Introduction

Helping language learners understand words in doubt is an important topic in the field of Intelligent Computer-Assisted Language Learning (ICALL) (Segler et al., 2002; Enayati and Gilakjani, 2020; Lolita et al., 2020). Most dictionaries present word senses as discrete items in predefined inventories to help language learners understand new words. Nevertheless, this form is suffering from several limitations and may bring users inconveniences in many cases. First, many commonly used words are polysemous, and it’s difficult for language learners to distinguish different word senses because of the cognitively inaccurate nature of discrete sense boundaries (Rosch and Mervis, 1975; Kilgarriff, 1997; Tyler and Evans, 2001). As Kilgarriff (2007) argued, there are no decisive ways of identifying where one sense of a word ends and the next begins.

In addition, the predefined inventories need to be updated manually by lexicographers, which is time-consuming and causes dictionaries to lag behind the ever-changing language usage. For example, many new words have emerged along with the change in people’s lifestyles, such as tweet (make a post on Twitter) and geekery (enthusiasm for a subject). However, these words and senses didn’t appear in traditional dictionaries until they were used for a long time.

We overcome these limitations by developing LitMind Dictionary,1 an open-source online generative dictionary. It takes a word and the context containing the word as input and provides automatically generated definitions for the word. In this way, the word’s definition in current context can be given directly, saving users from selecting from a variety of senses. This approach breaks away from the limitation of predefined inventories, with potential to generate correct definitions of new words according to the contexts.

In LitMind Dictionary, the context-aware definitions are generated using a range of NLP and machine learning techniques mainly based on our previous work of definition modeling (Yang et al., 2020; Fan et al., 2020; Kong et al., 2020). The proposed dictionary uses improved versions of these models, and incorporates some engineering tricks to handle extreme cases. Moreover, the dictionary

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1LitMind is derived from The Literary Mind and the Carving of Dragons, which is the first systematic literary theory work in China, written around 502 BC.
supports Chinese and English queries as well as Chinese-English cross-lingual queries, all of which are realized in a generative fashion for the first time. Finally, the user-friendly interface design can help users understand the query words as quickly and easily as possible.

2 Related Work

Our work is related to the task of definition modeling, which aims at automatic definition generation. This task is first introduced by Noraset et al. (2017). They used word embeddings as encoded information and a two-layer LSTM as the decoder.

However, their method failed to account for polysemous words, and subsequent work proposed different solutions for this problem. Gadetsky et al. (2018) released a dataset containing example sentences and computed the AdaGram vector (Bartunov et al., 2016) of input words, which is a non-parametric Bayesian extension of skip-gram capable to learn numbers of representations at desired semantic resolution. Chang et al. (2018) proposed to project the given words to high-dimensional sparse vectors, and picked different dimensions for different meanings. Mickus et al. (2019) implemented a self-attention based model, and proposed several masking strategies for the input words and example sentences. Li et al. (2020) explicitly decomposed the meaning of words into semantic components, and modeled them with discrete latent variables. Yang et al. (2020) explored definition modeling for Chinese and incorporated sememes (Dong and Dong, 2006), minimal semantic units, as part of the representation of given words. Zheng et al. (2021) proposed to enhance the definition generation with word formation features in parataxis languages like Chinese. Besides, Ishiwatari et al. (2019) extended this task to describe unknown phrases. They replaced the target word in context with a placeholder, and used a character-level CNN together with static embedding for word representation.

Recent years have witnessed the application of pretrained language models in definition modeling (Chang and Chen, 2019). Reid et al. (2020) initialized encoders with BERT (Devlin et al., 2019) and employed variational inference for estimation and leverage contextualized word embeddings for improved performance. Bevilacqua et al. (2020) employed a novel span-based encoding scheme to fine-tune a pre-trained English Encoder-Decoder system to generate definitions. Huang et al. (2021) leveraged the T5 model (Raffel et al., 2019) for this task and introduced a re-ranking mechanism to model specificity in definitions.

Our approach follows previous work in using pretrained language models for two reasons: (1) due to the data scarcity in the definition modeling task, it’s difficult for other models to obtain better performance; (2) using contextual word embeddings can solve the ambiguity of polysemous words. Moreover, we employ cross-lingual pretrained language models (Lample and Conneau, 2019; Conneau et al., 2019) as an extension of the task to support Chinese-English queries.

3 System Description

Figure 1 shows an overview of the main functionality and architecture of LitMind Dictionary. In this section, we first describe its overall workflow, then we detail the definition generation model, and finally we introduce its user interface design.

3.1 Overall Workflow

The workflow of LitMind Dictionary is illustrated in Figure 2. When using the dictionary, a user needs to provide the query word and context. We require the word to appear in the context. If the query word refers to a named entity, the dictionary will directly retrieve the corresponding definition from a predefined list, such as Name, State or Province, Organization, etc. Otherwise, the dictionary will feed the query word and context into the monolingual or cross-lingual definition generation model, depending on the user’s selection.
3.2 Definition Generation Model

The definition generation model (DGM) shown in Figure 3 is the core component of LitMind Dictionary. It is used to automatically generate the definition of a given word. The whole model is a transformer (Vaswani et al., 2017) based encoder-decoder model, and we use pretrained language models to initialize the parameters in experiments.

For a given word $w$ and its corresponding context $c$, we segment them into subwords and use each subword as a token. To facilitate the word and context encoding, we concatenate them into a whole sequence $(w, [SEP], c)$. In order to represent the position of different tokens, we add a positional embedding and a segment embedding to each token as Vaswani et al. (2017)’s original setting. For the $i$-th token in the sequence, we add its token embedding $tok_i$, position embedding $pos_i$, and segment embedding $seg_i$, together as $x_i = tok_i + pos_i + seg_i$. We input the obtained embeddings into the definition generation model, and train the parameters by minimizing the cross-entropy loss between the generated definitions and the true distributions underlying the dataset:

$$\theta^* = \arg\max_{\theta} \sum_{d \in D} \log(P(d|x, \theta)),$$

where $\theta$ refers to all trainable parameters, and $d$ is the predicted definition.

3.3 Monolingual Mode

LitMind Dictionary supports English and Chinese monolingual modes (Yang et al., 2020; Fan et al., 2020). Monolingual refers to that the language of the definition is the same as that of the word. For English mode, users input English word and context, and our system will return English definitions $(<w^e, c^e> \rightarrow d^e)$.

3.4 Cross-lingual Mode

Now we introduce LitMind Dictionary in the cross-lingual scenario. The only difference from the monolingual mode is that the language of the input word and context is different from that of the output definition (Kong et al., 2020). In Chinese-English mode, the input word and context are in Chinese, and the output definition is in English $(<w^zh, c^zh> \rightarrow d^en)$.

As high quality Chinese-English dictionary resources are difficult to obtain, we don’t train the model on Chinese-English parallel dataset. Instead, we only train the model on English-English dataset, and then directly transfer the model to Chinese-English scenario in a zero-shot manner. Since multilingual PLMs is capable of encoding sequences in various languages, this zero-shot method shows effective results in our manual evaluation. In addition, this approach can be extended to other low-resource languages to help more language learners.

3.5 User Interface

As shown in figure 4, the interface of LitMind Dictionary is friendly designed and very easy to use. To make a query, users need to input a word and a sentence into the textboxes, and then click the search button. Our system will automatically generate and display the corresponding definition. Under the definition, some example sentences are listed to help users better understand the query word.

We also designed a feedback channel to collect real-world data. Users can click the feedback button to write the definition they think is appropriate. Besides, if users have overall suggestions for LitMind Dictionary, they can click the Make Suggestions button to give their advice.

4 Evaluation

In this section, we evaluate the performance of LitMind Dictionary. We conduct both monolingual (Chinese and English) and cross-lingual (Chinese-English) evaluations.
4.1 Datasets

For English monolingual experiments, we use the Oxford dataset published by Gadetsky et al. (2018) as training, validation and test dataset. The dataset has 97,855 entries in the training set, 12,232 entries in the validation set and test set respectively.

As for Chinese, we build a dataset from the Contemporary Chinese Learner’s Dictionary (CCLD), which is specially designed for Chinese learners. We first convert each page of the book into text using the optical character recognition (OCR) technology. We then recruit a group of annotators to proofread the text and correct the errors generated in the conversion process. Finally, we structure the text into the json format and extract words, example sentences and definitions and obtain the entire dataset of 6,284 words, 89,065 entries. The dataset is then split into three subsets as training set, validation set, and test set by the ratio of 8:1:1.

For the Chinese-English cross-lingual definition generation, we train the model using the above mentioned Oxford dataset. For evaluation, we randomly sampled 200 entries from the CCLD test set, and perform zero-shot generation on it. Since there are no golden English definitions in the test set, we organize manual evaluation to score the results generated by models.

| Dataset       | Words  | Entries | Exp. | Def.  |
|---------------|--------|---------|------|-------|
| Oxford        |        |         |      |       |
| Train         | 33,128 | 97,855  | 17.74| 11.02 |
| Valid         | 8,867  | 12,232  | 17.80| 10.99 |
| Test          | 8,850  | 12,232  | 17.56| 10.95 |
| CCLD-Mono     |        |         |      |       |
| Train         | 5,028  | 71,328  | 7.06 | 13.41 |
| Valid         | 628    | 8,700   | 6.89 | 13.43 |
| Test          | 628    | 9,037   | 7.37 | 13.47 |
| CCLD-Cross    |        |         |      |       |
| Test          | 163    | 200     | 7.19 | 14.38 |

Table 1: Statistics of the Oxford dataset, CCLD (Monolingual) dataset, and CCLD (Cross-lingual) dataset. The columns are the number of words and entries, the average length of example sentences and definitions.

Table 1 lists more detailed statistics of the above datasets.

4.2 Models

In this work, we mainly compare models of three different categories: non-pretrained model, pretrained masked LM, and pretrained encoder-decoder. We then present the detailed settings of these models.

**Non-Pretrained Model** We choose the LOG-CaD (Ishiwatari et al., 2019) model as a baseline for monolingual experiments. This model is an
encoder-decoder model proposed to describe unknown phrases, which can also be used to generate definitions for given words and contexts. The model has three different encoders, which are (1) a global context encoder to lookup pretrained embeddings of the given word; (2) a local context encoder (Bi-LSTM) to encode the context; (3) a CNN layer to encode character-level features of the given word. The decoder is a two-layer LSTM, which receives the above three encoded information and dynamically weighs them at each time step. We set the hyper-parameters exactly like the original paper for a fair comparison.

**Pretrained Masked LM** The masked LMs are pretrained by the MLM (Devlin et al., 2019) task, which aims to predict masked text pieces based on surrounded context. We use the masked LMs to initialize parameters in the transformer encoder. For monolingual experiments, we compare the BERT-Base and BERT-Large models. We only evaluate the effectiveness of English BERT-Large model since no Chinese model available. For cross-lingual experiments, we compare the mBERT and XLM-R-Large (Conneau et al., 2019) models. In practice, we randomly initialize a transformer decoder and feed the output of masked LMs into the cross-attention mechanism. The decoder architecture is set the same as Vaswani et al. (2017). We train the entire model in two phases. The first phase fix the parameters in the encoder and train the decoder from scratch by the learning rate of 1e-4. And the second phase use a smaller learning rate of 1e-5 to fine-tune the entire model. We report test results after the fine-tuning phase in Section 4.4.

### 4.3 Evaluation

For monolingual methods, we use the BLEU (Papineni et al., 2002) and NIST (Doddington, 2002) as automatic evaluation metrics. NIST focuses on content words by giving more weightage to them. This makes NIST more informative than solely assigning an equal weight to each n-grams as BLEU (Huang et al., 2021).

For cross-lingual methods, since there are no golden standard English definitions, we let 3 scorers to manually evaluate the generated results. We randomly shuffle a total of 600 definitions generated by 3 models and let scorers rate them independently. Specifically, each scorer evaluates a definition on two criteria of accuracy and fluency. Both criteria range from 1 to 5, with 1 being the lowest and 5 being the highest.

### 4.4 Results

Table 2 illustrates results of monolingual experiments. We observe that BART performs best among all the models. On the English test set, BART yields significantly better results than the other three methods. On the Chinese test set, although BART performs slightly worse on BLEU score, it still outperforms other model on NIST score significantly. Therefore, the LitMind Dic-
Table 4: Definition generation cases in three different modes.

| Word | Context | Reference |
|------|---------|-----------|
| prominence | By the close of the 1870s, Homer had achieved national prominence. | the state of being important, famous, or noticeable |
| LOG-CaD | the state of being protuberant or [unk] | the state or fact of being prominent |
| BERT-Base | the state or fact of being prominent | the quality or state of being recognized or prominent |
| BERT-Large | the state or fact of surpassing all others; superiority in rank or status | |

Table 4: Definition generation cases in three different modes.

| Word | Context | Reference |
|------|---------|-----------|
|惦记 (thinking about) | 我在这边过得很好，您别总惦记着。 (I have a good time here, don’t worry about it all the time.) | 因想念、担心、期盼而心里老想着 (Always thinking about sth. because of missing, worrying, looking forward to, etc.) |
| LOG-CaD | 用在名词或作品上 (Used in nouns or works.) | 无| |
| BERT-Base | 无法回忆起曾经发生过的事情；过去知道的事不记得了 | 心里记挂着某人或某事 (Keep thinking about sb. or sth.) |
| mBART | (with reference to the temperature) free from normal temperatures | the basic level of difficulty |
| XLM-R-L | (with reference to the temperature) free from normal temperatures | the base of something |

| Word | Context | Reference |
|------|---------|-----------|
|基础 (foundation) | 基础越高，基础越要坚实。 (The higher the building, the more solid the foundation.) | 地面以下用來支撐建築物的部分 (The part below the ground that supports a building.) |
| XLM-R-L | (with reference to the temperature) free from normal temperatures | the basic level of difficulty |
| mBART | the basic level of difficulty | the base of something |

4.5 Case Study

Table 4 shows the generated definitions in English, Chinese and Chinese-English modes. The models we chose to serve in LitMind Dictionary successfully generate accurate and fluent definitions.

For the English mode, LOG-CaD erroneously uses protuberant to explain prominence, and generates a special [unk] token. Both BERT-Base and BERT-Large use the given word in the definitions, and fail to explain the meaning. BART defines the given word as surpassing and superiority, which is more close to the reference semantically.

For the Chinese mode, LOG-CaD generates a completely irrelevant sentence and fails to explain the given word. Bert-Base generates the definition of 忘记 (forget) rather than 惦记 (thinking about), which basically have the opposite meanings. The mBART generates the most relevant definition compared to other models.

For the Cross-lingual mode, temperature generated by XLM-R-L has nothing to do with the given word foundation. The mBART generate a keyword of basic, but difficulty also fails to explain the meaning of given word. In contrast, the definition generated by mBERT is the most relevant.

5 Conclusion and Future Work

In this paper, we present LitMind Dictionary, an open-source online generative dictionary, which can generate context-aware definitions of a given word. Our system supports Chinese and English monolingual queries as well as Chinese-English cross-lingual queries, all of which are realized in a generative fashion for the first time. In the future, we will try to control the difficulty of the generated definitions to make it more suitable for language learners. We will also work on how to match more appropriate example sentences for the query words.
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