**Metaphor detection and interpretation**

by

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**Abstract**

The ubiquity of metaphor in our daily life makes the computational realization of metaphor identification and interpretation become a crucial segment in the NLP translation field. This introduction and literature review of this thesis provides the basic theory of metaphor computation, discusses the related work of the state-of-the-art models for metaphor detection and interpretation, introduces three widely used datasets. We design an integration machine to get a metaphorical sentence as input and output a sentence with a literal interpretation. In metaphor detection, since the current novel neural network metaphor detection models ignored the impact of the word concreteness factor and word belonging element, our model combines the factors. On top of that, Graph Convolution Network is a new variation of the classic CNN that perform the convolution on the nodes, which is also applied in our model. In metaphor interpretation, we design the interface between the WordNet knowledge and the similarity different to find the most suitable attribute to replace the metaphorical words. Our model is still in the developing process and waits for a later update.

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# *Chapter 1* Introduction

## 1.1 Background

Metaphor expressions appear pervasively in daily life as well as in many literary works. According to relevant statistics research, metaphorical usage occurs on average once in every three sentences in typical corpora. People use metaphor frequently since metaphor expression furnish vivid explanations for abstract experience and perception. Meantime, our cognitive system and ways of thinking are based on metaphors aiming to understand our world better. The cognitive and rhetorical phenomena make metaphors active in all kinds of natural language communication scenarios, while a large number of implicit metaphorical expressions have become a problematic task in natural language processing. The computational realization of metaphor identification and interpretation therefore plays a crucial role in the NLP translation field.

## 1.2 Basic linguistic theory in metaphor

Traditional metaphor theory asserts that metaphor is merely a rhetorical method, and only provides an ordinary describing function for expression. In terms of Aristotle's poetics, metaphor is the similarity between objects. This theory emphasizes the feature differences between literal and metaphorical words.

As the development of cognitive science, in light of modern linguistic theories, Lakoff and Johnson [1] assert the conceptual metaphor theory, arguing that metaphor is systematic reasoning from a concrete conceptual source domain to an abstract target domain. Normally, we use a concrete expression to describe the abstract theory. For instance (Figure 1), the metaphorical sentence "She devoured his novels" utilizes the verb "devour" to describe a sense of greedy reading rather than literally swallowing a novel.

Figure 1 "devoured" in the first sentence is literal usage, and in the second sentence is metaphorical usage, the "devoured" is the source word in the second sentence.

There is another modern linguistic theory in metaphor derives from Steen et al. [2], namely Metaphor Identification Procedure (MIP): a metaphor is identified if the literal meaning of a word contrasts with the meaning that word takes in this context. Like the previous example, the word "devour" is unusual in the context of 'novel'. A novel cannot be devoured. The contextual meaning contrasts with the literal meaning of the word. Additionally, another similar metaphor theory is SPV. The intuition of the theory is that metaphoricity is identified by detecting the incongruity between a target word and its context.

Moreover, Gentner [3] 's structural mapping theory proposed that the process of structural mapping is the analogous transfer, which seeks for structural similarity by matching different objects, and then extracts the relationship in the source problem through schema induction to solve the problem of the target domain. It is concluded that the process of metaphor mapping is essentially the matching process of the relationship structure between the source domain and the target domain.

In the 1990s, Fauconnier and Turner extended the conceptual metaphor theory and proposed a conceptual integration model [4]. Besides, other theories like basic metaphor theory and characteristic significance imbalance theory have laid a solid theoretical foundation for the metaphorical computing task.

## 1.3 Research Subject of Metaphor Computing

The metaphor computation task mainly focuses on two aspects. One is how to use a computational method to detect and classify metaphorical expressions in a typical corpus. The other task is to let the computer understand and metaphorical meaning and then interpret it into the most suitable demotic word through word context.

Metaphor detection can be seen as a classification task, which is to identify a target work if it is a metaphor expression. Various approaches have been implemented by word embedding level to sentence level. When a sentence contains words such as "as" and "like", it is readily to be detected. Whereas without such words, the difficulty of detection highly rises. In word level, machine learning methods, including SVM and random forest or word embedding methods like GloVe are developed based on the concreteness difference of the target word and source word. By measuring the cosine similarity of the components in the phrase, metaphor can be effectively detected. Metaphor detection can also be seen as a sequence labeling task, which is labelling the target word in a sentence. In sentence level, the neural network method has been widely applied for the NLP field for semantic modelling and context modelling. Beginning with the pretraining work embedding vectors, to multi-level processing algorithms, also along with neural network method in deep learning and large-scale corpus language models, novel methods are continually lifting the performance of metaphor detection result.

The task for metaphor interpretation aims to let the model understand the implicit literal meaning of a metaphorical expression. How to precisely replaced metaphorical expression has been a problematic issue for long. For instance, we need to interpret the sentence "Time is money", the computer will replace the metaphorical word "money" as its literal meaning "previous". Human beings generally understand metaphor through association with knowledge, providing ideas for the construction of a metaphor interpretation model. However, many difficulties and problems are waiting to overcome, such as considering culture and including novel knowledge base.

# *Chapter 2* Research Background

Our task incorporates two parts: first is for innovation on metaphor detection, which is identifying the existence of metaphor among various sorts of words. Afterwards, the second task is for metaphor interpretation, which is transferring the metaphor word into the most suitable demotic word through word context.

## 2.1 Metaphor detection

In the first task, in order to raise the performance of the previous work, we initially tend to use a neural network method containing modules like CNN, BiLSTM, CRF or combinations of the above and augment essential detailed process like emotional analysis into it. If possible, consider more on the linguistic part of the metaphor theory for advancement. Then restructure the model based on the previous work.

After constructing our model, we will set our training and test dataset as the three widely used metaphor datasets: VUA, MOH-X, TroFi. We may set the results of the state-of-the-art model like Mao et al. (2019) as the baselines for comparison.

If the output result is less than expectation, we will change the aspect of thinking, think about innovation points, restructure our model, adjust the learning parameters or augment new modules in our model.

## 2.2 Metaphor interpretation

In this task, we tend to follow the previous work and do some innovations. We tend to utilize the cooperation mechanism of the source domain and the target domain. On one side, we may append one of the knowledge bases, let each word contains more knowledge information, including emotion and environment. On the other side, we may add a process after the selection, which is checking if the replaced word in the context is suitable by CBOW.

After constructing our model, we may set our training and test dataset as the same as the Su et al. (2018) works. Furthermore, set the results of the state-of-the-art model as the baselines for comparison.

# *Chapter 3* Literature Review

## 3.1 Metaphor detection

### 3.1.1 Word level based metaphor detection

#### 3.1.1.1 Abstractness for metaphor detection

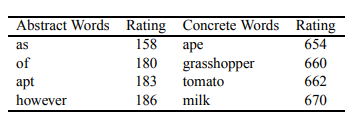
In light of the conceptual metaphor theory, Turney et al. [5] first implemented a method for identifying metaphors. Their approach to the problem of distinguishing literal and metaphorical senses is based on an algorithm for calculating the degree of abstractness of words by MRC Psycholinguistic Database (Figure 2). For instance, time is a word with a high relative abstract attribute. It therefore has a high value in using in metaphor.

Figure 2 examples for abstract words and concrete words in MRC database

Turney constructs the set of abstract words and concrete words. Then calculate the abstractness in terms of the semantic distance between the target words and the pre-designed word set. Finally, the model produces the possibility of if a word is used in metaphor or literal hinge on the word abstractness.

This model provides a new way of thinking for metaphor detection. However, the consideration of just abstractness is not a complete solution to the problem.

#### 3.1.1.2 Metaphor Detection with broader consideration on word

In 2014, Tsvetkov et al. [6] provide a broader view of metaphor detection on different languages besides English. They design three main feature categories:

(1) Abstractness and imageability: Abstractness is always concerned as the critical feature for metaphor. Imageability is not a redundant property. The majority of abstract words are hard to visualize.

(2) Supersenses: Supersenses are coarse semantic categories from WordNet. It classifies nouns and verbs into 45 classes. For instance, noun.animal, noun.body. This model also uses 13 classes adjective supersenses for addition.

(3) Vector space word representation: The model employ a 64-dimensional vector-space word representation where synonyms have similar vectors.

To make classification, the model uses a random forest classifier to consider the three features simultaneously. The classifier learns from independent subsamples of the training data. For input, each tree classifier gives the probability of each label, and those probabilities are averaged to the ensemble. Additionally, it usually performs logistic regression rather than linear results. If this probability is above a threshold, the relation will be viewed as metaphoric; otherwise, it is literal.

This model considers the word level on a higher aspect and combines them with a random tree method. However, the restriction on the input form of the phrase (Subject-Verb-Object or Adjective-Noun) limits the view for further progress.

#### 3.1.1.2 Word Embedding and WordNet for metaphor detection

In 2018, Mao et al. [7] propose an unsupervised learning method that can directly identify and interprets metaphors at word-level without any preprocessing. Their model is based on the Continuous Bag of Words (CBOW) and Skip-gram.

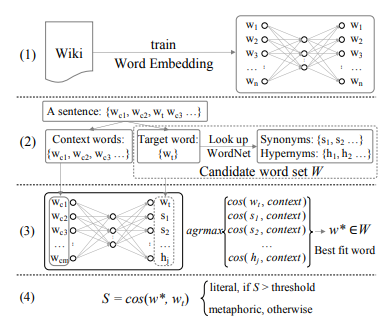
CBOW means given the context of a word, predict its center word, which has the highest probability. Skip-gram is the reverse of CBOW aiming to maximize the probability of predicting each context word given a center word.

Figure 3: word embedding based model structure

In Figure 3, it shows the structure of the entire model. First, input training word embeddings based on Wikipedia dumps for obtaining input and output word vectors. Afterwards, for a sentence, separate its target word and its context word. Furthermore, set Target words set for all the possible senses. Also, eliminate auxiliary verbs since these words contain less contextual meaning. Look up to the WordNet to get the Synonyms and Hypernyms of the Target words set and augment to Candidate word set W. In the next step, identify the best-fit word for the replacement of the target words given its context. Eventually, compute the cosine similarity between the target words the best-fit word. For S, if S is over a threshold, it will be considered as literal; otherwise, it is metaphoric.

This model makes use of the word vectors and its spatial relationship to provide a new way of thinking and directly contribute to the integration of metaphor recognition and metaphor understanding.

### 3.1.2 Neural network based metaphor detection

In sentence level, researchers find that metaphorical usage appears in a specific context. Without context, it is difficult to find the differences between metaphorical and literal expression. Therefore, constructing the interaction relation between target word and context, then discovering the connection between the two becomes a new field of thinking. The neural network method has been widely applied for the NLP field for semantic modelling and context modelling.

The main idea of the current neural network based method is to construct a semantic model for the target words and to the context of the target words. If the target word has a big difference with the context of semantics, the target word then can be considered as a metaphor; otherwise, it is not a metaphor. Many neural network models rely on the use of various semantic coding method to achieve different performance.

#### 3.1.2.1 Word Embedding and WordNet for metaphor detection

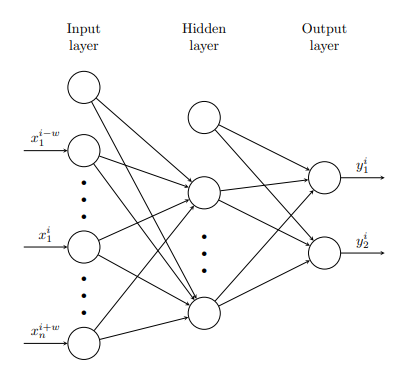
In 2016, Do Dinh and Gurevych [8] first implemented a neural network method on the metaphor detection task. The metaphor detection is treated as a tagging problem without any manual labelling. They experiment with the multilayer perceptrons with connected feedforward neural network.

Figure 4: multilayer perceptron with one hidden layer

As in Figure 4, this neural network incorporates an input layer, several hidden layers and an output layer. The output layer utilizes a softmax function to calculate the prediction result. Here is an instance of one hidden layer neural network of multilayer perceptron, the model use input x for a token which positions at I concatenate word embedding vectors to . Here w is the given window for the context size. Additional features enrich the input vector x by concatenation. The output layer utilizes logistic regression to calculate the and , which are the probability for metaphorical and literal usage. This work initially explored the application of neural networks on metaphor detection and somehow required to do more extension on the model.

#### 3.1.2.1 Word Embedding and WordNet for metaphor detection

Gao et al. [9] intend to resolve two problems: given a target verb and classify it whether the word is metaphorical or literal and detect all the metaphorical words in a sentence. The model utilizes a standard architecture based on bi-directional LSTMs (BiLSTM) augments with contextualized word embedding performing surprisingly well on the tasks.

For both sequence labelling and classification encoding, the model uses to represent each token by pre-trained word embedding from GloVe (Global Vectors for Word Representation) and the concatenation of ELMo (Embeddings from Language Model) vector . The combination of the two effectively reduces the word sense disambiguation.

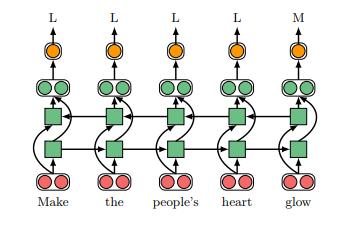
The first task refers to the Sequence Labeling Model. As shown in Figure 5, the model set the word representation to BiLSTM as input. Afterwards, the BiLSTM produces a result of contextualized representation for each token. The model then predicts a label for each word from by using a feedforward neural network.

Figure 5: A sequence labelling model for metaphor detection

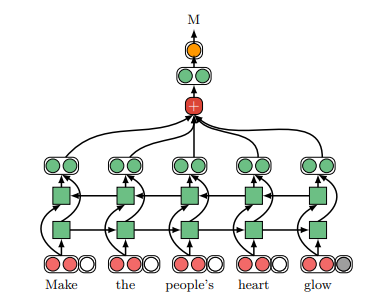
Furthermore, the classification model (Figure 6) of metaphor detection also concatenates an index embedding which indicating whether if it is the target word. Therefore, the word representation as input also produces a contextualized representation to . When computing the weight for each token , the model also utilizes the attention layer. Then compute the result as the weighted sum of the output of BiLSTM, here and are the learning parameters.

Figure 6: A classification model for metaphor detection

This model proves that sentence with context may provide abundant information. The BiLSTM may better capture the crucial information in the sentence and output a better performance.

**3.1.2.3 Neural Metaphor Detecting with CNN-LSTM Model**

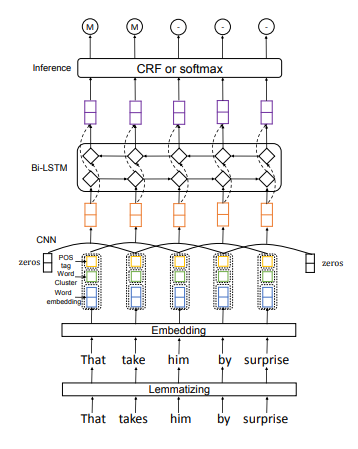
On the 2018 VUA metaphor detection sharing task, an extensive range of neural network methods are implemented containing RNN, LSTM, CNN or the combination of different neural network models. Wu et al. [10] performs the best result in the sharing task, which utilize the pre-trained word vector for input, then use the combination of CNN and BiLSTM for processing. CNN is to capture the local context information; BiLSTM is to capture the global context information. Finally, full-connected CRF or softmax layer is for prediction. This model will be detailed introduced from bottom to top in Figure 7.

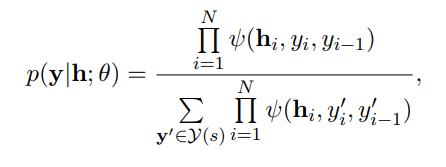
Figure 7: The structure for CNN-LSTM Model

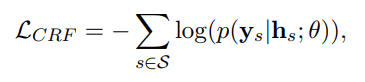
The model initially uses lemmatization to let the verb in the sentence transfer from different forms into one by the following strategy from Klebanov et al. (2016). In this way, the lemmatized word can simplify the semantic information and reduce the word number.

The next layer is a word embedding layer. The sequences of words in the sentence are converted into low-dimension vectors via a lookup table. The weight of words utilized pre-trained word2vec and is fine-tuned during model training. The model contains one-hot POS (Part Of Speech) tags as additional feature augmented into word embedding as well. K-means method is used to resolve the case that similar words may incorporate similar metaphor information.

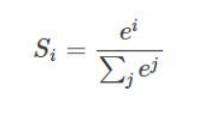
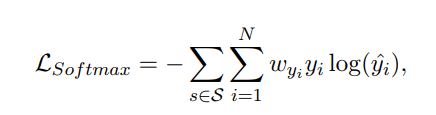
The third layer is the multiple kernel convolutional neural network for capturing local contextual information with different windows size for modelling. Afterwards, the fourth layer is the BiLSTM layer aiming to extract long-range contextual information from the CNN features map. This layer synthesizes the previous and future context information to output the hidden state at time .

The last layer implements two alternatives for inference, which are CRF and softmax. The two alternatives both produce better in the different test cases.

**CRF**: This is for prediction of the labels for each word. Given the matrix of hidden layer , the probability for the output sequence is:

Here is the parameter and is the set of all possible label sequence. And is for the potential function.

W and T mean the linear transformation parameter. Moreover, the CRF loss function is the negative log function for all the training samples. and are for hidden states.

**Softmax**: The loss function for softmax is also a negative log function. is the metaphor label for word and predict score as . The model sets larger loss weight on positive class due to the larger quantity of non-metaphorical words.

This model tactfully uses a combination of the two neural modules to add the necessary features to improve the performance, which is a very effective method. However, the model does not effectively use the metaphor theory to optimize the results.

**3.1.2.3 Sequential Metaphor Identification Inspired by Linguistic Theories**

As this review mentioned before, the two linguistic theory in metaphor SPV (Selectional Preference Violation) and MIP (Metaphor Identification Procedure) have not been emphasized before. Mao et al. [11] explored the two theory to implementation in 2019. Their model has the best result until now.

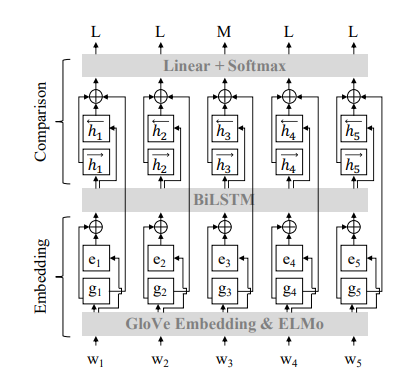
 Figure 8 shows the implementation on MIP: a metaphor expression is classified by the contrast between a word's contextual and literal meanings. For the basis word encoding, the author continues to use the concatenation of ELMo vector and GloVe word vector. Since the model requires the contextual meaning, BiLSTM that can effectively capture contextual information will be set as the hidden states. The result of each token will be outputted as label probability, which is L (literal) or M (metaphorical). The probability of a label prediction for a target word at position , which is a contextual and literal meaning representation of the target word.

Figure 8: RNN\_HG model framework based on MIP

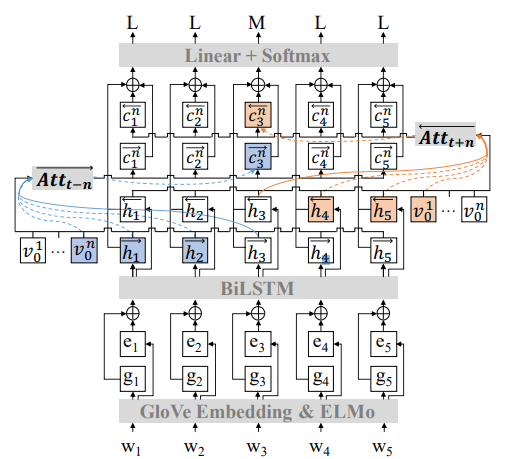
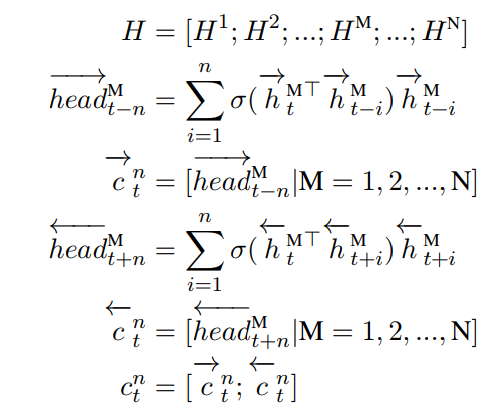
Figure 9 shows the implementation of SPV: metaphor expression can be identified by detecting the incongruity between a target word and its context. The model is RNN\_MHCA (Recurrent Neural Network Multi-Head Contextual Attention). The second model compares the target word (BiLSTM hidden state) with context . Notice that context incorporates two parts: left-side and right-side contextual attention representation. means the attention mechanisms on a window of context words.

Figure 9: RNN MHCA model framework based on SPV

Where is the hidden state of BiLSTM and is the number of head. The model employs a window size for contextual words. And is the hidden state for the target word. In this formula, consider the forward contextual information and past contextual information on both directions, effectively capture the information.

This model provides another aspect of thinking, which is linguistic advancement on the model. Previous neural models ignore the significance of different conceptual theory on the linguistic aspect. Therefore, linguistic consideration is a cardinal part for further work.

**3.1.2.4 Sequential Metaphor Identification by MWEs and GCNs**

Multiword Expression (MWEs) are general linguistic phenomena of semantic opacity. This kind of expression poses a difficulty to computational models. For instance, an expression like "take the bull by the horn", "go place", "kick the bucket" can be categorized as metaphorical Verb MWEs.

In order to address the detection of Multiword Expression, Rohanian et al. (2020) 's model utilizes the Graph Convolutional Network, which is a variation of the classic CNNs that performs the convolution operation on the nodes of a graph. And GCN can be defined as

Here W, X, A, b and GCN refers to the weight matrix, representation of the input sequence, adjacency matrix, bias term and the output of the convolution respectively. In GCN, there are also elements like Multi-head Self-attention and Attention Guided Adjacency.

This model modifies the origin GCNs and converts it into MWE-Aware GCN. In order to inform the model within the sentence and encode information about MWEs. The model utilizes two components in the MWE-Aware GCN are the dependency parse tree and token-level relations. The two components are fed into the separate GCNs and the output is the concatenation of the output from both components.

## 3.2 Metaphor interpretation

### 3.2.1 Widely used knowledge base

For metaphor interpretation, directly use the method like reasoning from context. This way seems possible, but the accuracy cannot assure. Consider the methodology that human being understands the metaphor. A man will remind of the previous knowledge he learned and extract the attribute in the word. For this, a knowledge base is necessary. Next, some crucial knowledge base for metaphor interpretation will be listed:

**WordNet**

WordNet is widely used in metaphor detection and metaphor interpretation for capturing the semantic information of words. It is an extensive English word database developed at Princeton University, where nouns, verbs, adjectives and adverbs are groups cognitively into synonyms for different concepts.

**VerbNet**

VerNet the biggest online verb word database. Every verb contains the subject description, parameter restriction and framework for semantic or syntax analysis. It is greatly useful for verb metaphor processing.

**FrameNet**

FrameNet is a framework semantics based word knowledge base. The majority of the word inside can be displayed by the semantic framework.

**HowNet**

Hownet is a semantic network based on word concepts, reflecting morpheme inclusion, morpheme equivalence, and domain-specific interactions between word concepts.

### 3.2.2 Knowledge based Metaphor interpretation

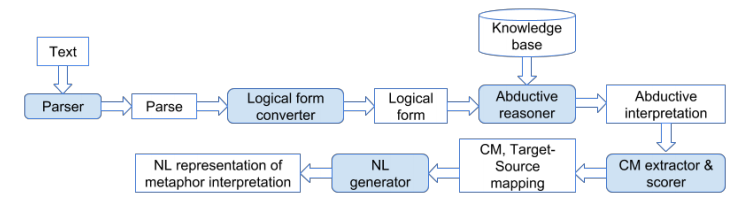
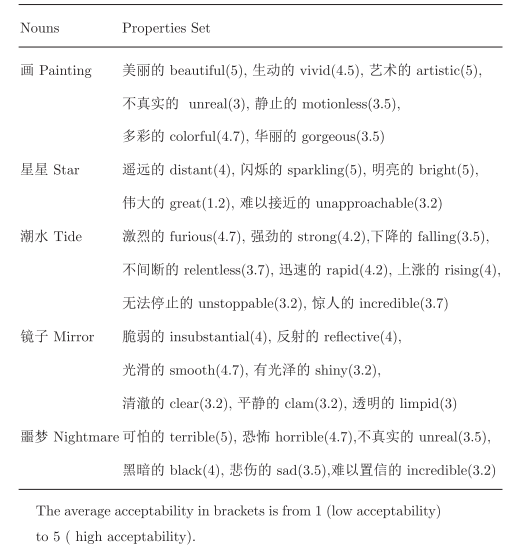
Ovchinnikova et al. [12] constructed a system of multilingual metaphorical understanding based on abductive reasoning (Figure 10). The system first analyzes the fragments containing the metaphorical text and generates the logical expression. The knowledge base is input into the inference system to get the inference result with the highest possibility, which is mapped into the conceptual metaphor. Finally, the conceptual metaphor is translated into logical predicates and translated into natural language expressions.

Figure 10: Abduction-based metaphor interpretation system

Shutova et al. [13] also proposed an unsupervised metaphorical comprehension system, which can change the metaphorical text into non-metaphorical text with the same meaning. The system trains the semantic similarity vector and the two meanings obtained by the UKWac corpus. The system mainly focused on subject-verb and verb-object types of metaphor, and the system accuracy reached 0.52.

### 3.2.3 Word meaning theory based Metaphor interpretation

Su et al. [14] believed that the result of metaphor understanding is a cooperation between the source domain and the target domain, and the focus of metaphor understanding was to extract their similarities. They divide metaphor understanding into two steps: attribute extraction and attribute transfer. The system retrieves the source domain properties from the property database. The system then calculates the relationships between the attributes from the target domain and the source domain. Cosine similarity is used to measure the correlation based on the word vector model. The most relevant attributes are systematically selected as the best interpretation of the metaphor. Eventually, the model gets a decent result.

Figure 11: The properties of several nouns and the calculated acceptability

## 3.3 Widely used dataset

### 3.3.1 VUA

VUA (VU Amsterdam Metaphor Corpus) is the largest manually labelled figurative language Corpus among a various field that published in the Metaphor recognition task. It consists of four categories of texts, namely academic texts, novel texts, news texts and dialogue texts. The language contains over 2626 paragraphs, more than 16,000 sentences and about 200,000 words. This corpus is based on MIPVU metaphor recognition rules, and some texts are selected from BNC-baby for annotation.

|  |  |  |
| --- | --- | --- |
| Type | vocabulary | Segments quantity |
| Academic text | 49561 | 16 |
| Dialogue text | 48001 | 24 |
| Novel text | 44892 | 12 |
| News text | 45116 | 63 |
| Total | 187570 | 115 |

Table 1: vocabulary and segments quantity in VU Amsterdam Metaphor Corpus

### 3.3.2 MOH-X

The MOH-X corpus is a subset of the MOH corpus. The texts in the corpus are all from the WordNet dictionary, and the sentences in the corpus are generally of short length.

### 3.3.3 TroFi

TroFi Corpus came from The Wall Street Journal, in which 50 verbs were marked, including the literal and metaphorical usage of these words. The packet contains three fields. The first field is used to mark the position of the sample text in the Wall Street Journal; the second field is used to represent the label. It contains three values: L (Literal), N (Nonliteral), and U (Unannotated), and the third field is the sample text.

# *Chapter 4* Methodology

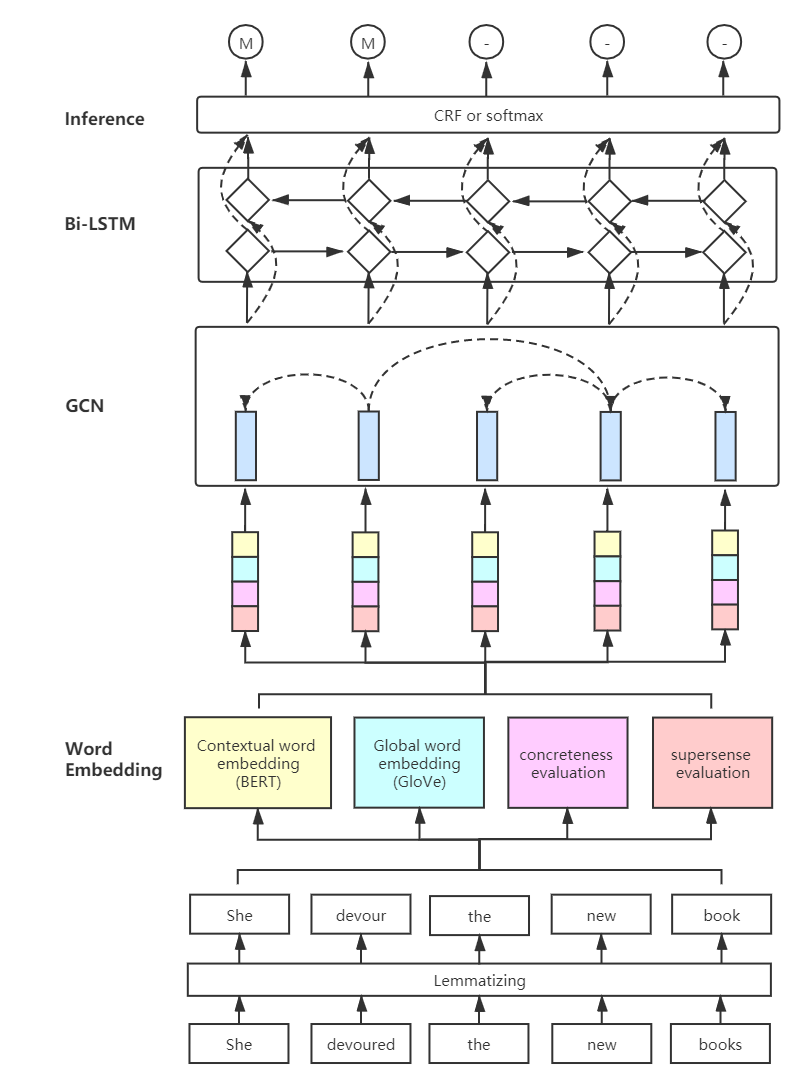
4.1 Initial model description

Figure 12: The initial model design

1) The first module is the lemmatization, which proposed by Klebanov et al. (2016). This module is for lemmatize the verb in the text. A sequence is set as input and output is the text with lemmatized words. Since verbs with different forms have the same semantic information, we use lemmatized verbs may simplify the semantic analysis process and provide a readily way for the model to understand. We will use the NLTK package for converting the verbs into lemmas.

2) The second layer is the word embedding layer. In this process, the model will turn each word in the sequence into a low-dimensional dense vector. Inspired by the concatenation process in Gao et al. (2018), we will also employ the concatenation of a contextual word embedding and a global word embedding. Nevertheless, considering BERT as the latest contextual word embedding method, we will use BERT or its variant like AlBERT or RoBERTa rather than ELMo.

On top of that, we may apply concreteness as additional layer by SVM classification. For each word, we obtain a real number estimation of concreteness from 0 to 5. Afterwards, concatenate it to the input vectors as the five different output class respectively.

Furthermore, inspired by Tsvetkov et al. (2014), we may also use supersenses of a word, which are coarse semantic categories from WordNet. It classifies nouns and verbs into 45 classes. We may apply the 45 classes for the concatenation of the input layer.

3) The third module is the GCN layer. Graph Convolutional Networks (GCN) is a variation of the classic CNNs that perform the convolution operation on nodes of a graph, making them suitable for capturing nonsequential inter-dependencies in the input.

4) The fourth module is the BiLSTM layer. LSTM is a useful tool to obtain the entire sequence information. Therefore, this layer is for capturing long-distance information. In this layer, it will combine the previous and future contextual information and produce the hidden state.

5) The fifth module is the inference layer; we may implement it with CRF or Softmax. It finally outputs a prediction sequence with 1 or 0, like [1, 0, 0, 0, 1]. 1 indicates this word is the metaphorical word and 0 shows this word is the literal word.

## 4.2 Initial model evaluation

Initially, current models mainly discuss the variety of neural network implementation. However, most of the models have ignored the concreteness and belonging information. This kind of information is crucial for metaphor detection by machine learning methods. Also, BERT is a comparatively novel pre-trained model for contextual word embedding. BERT also has different further variants like AlBERT and RoBERTa performing better results. Therefore, our design of the model is state-of-the-art.

For the neural network, GCN is a variation of the old CNN model. GCN may get more context information than CNN. Therefore, it may provide great result on the performance. Additionally, since metaphorical information highly depends on the context, BiLSTM can store enough sequence contextual information from the past and future words.

# *Chapter 5* Project Schedule

1. Phase I – Preparation Phase

|  |  |  |
| --- | --- | --- |
| Literature review | 2020/5/24-2020/5/31 | Finished |
| task definition | 2020/5/24-2020/5/31 | Finished |
| Background research/study | 2020/5/24-2020/6/16 | Finished |
| Database preparation | 2020/6/15-2020/6/16 | Finished |
| Equipment acquisition | 2020/6/15-2020/6/16 | Finished |

1. Phase II – System Design Phase

|  |  |  |
| --- | --- | --- |
| Concatenation of the three models:  (Mao et al. 2019) RNN-BiLSTM-HG/MHCA  (Gao et al. 2018) Glove&Elmo-RNN-BiLSTM  (Wu et al 2018) CNN-BiLSTM-CRF | 2020/6/16-2020/6/21 | Finished |
| Design the word embedding method | 2020/6/16-2020/6/21 | Finished |
| Design the neural network processing | 2020/6/21-2020/6/24 | Finished |
| Design the full-connected layer | 2020/6/24-2020/6/27 | Finished |

1. Phase III – System Implementation Phase

|  |  |  |
| --- | --- | --- |
| Learning on Pytorch to practice building models like CNN/RNN/Bi-LSTM | 2020/6/10-2020/6/16 | Finished |
| Build Baseline implementation on Colab of  (Mao et al. 2019) RNN-BiLSTM-HG/MHCA  (Gao et al. 2018) Glove&Elmo-RNN-BiLSTM  (Wu et al 2018) CNN-BiLSTM-CRF | 2020/6/16-2020/6/21 | Finished |
| Try implementation on pure Bert with softmax | 2020/6/16-2020/6/21 | Finished |
| Try implementation with concatenation of several input:  Word2Vec/POS tagging/Glove/Elmo/Bert  Based on (Mao et al. 2019) RNN-BiLSTM-HG/MHCA | 2020/6/21-2020/6/27 | Finished |
| Fine tuning on the three metaphor detection models. | 2020/6/21-2020/6/27 | Future work |
| Add elements to our best modified model:   * Consider sentence emotion * Augment abstractness analysis | 2020/7/1-2020/7/14 | Future work |
| Build baseline of metaphor interpretation:   * (Mao et al. 2018) Word embedding and WordNet * (Su et al, 2019) Meaning theory | 2020/7/14-2020/7/21 | Future work |
| Make improvement on the interpretation model:  Consider emotion aspect and novel knowledge basis. | 2020/7/21-2020/7/28 | Future work |
| Make integration for both tasks, directly apply to the state-of-the-art machine translation. | 2020/8/1-2020/8/8 | Future work |

1. Phase IV – System Evaluation and Testing Phase

|  |  |  |
| --- | --- | --- |
| Fine tuning of our whole model | 2020/8/8-2020/8/16 | Finished |
| Evaluation and update | 2020/8/16-2020/8/24 | Finished |

# *Chapter 6* System Implementation

We use Pytorch on Google Colab to run our model.

1. Fine-tuning on BiLSTM from Gao et al. (2018)

Epoch = 20 batch = 16 hidden layer = 300 Dropout1 = 0.3 Dropout = 0.2 learning rate =2e-5

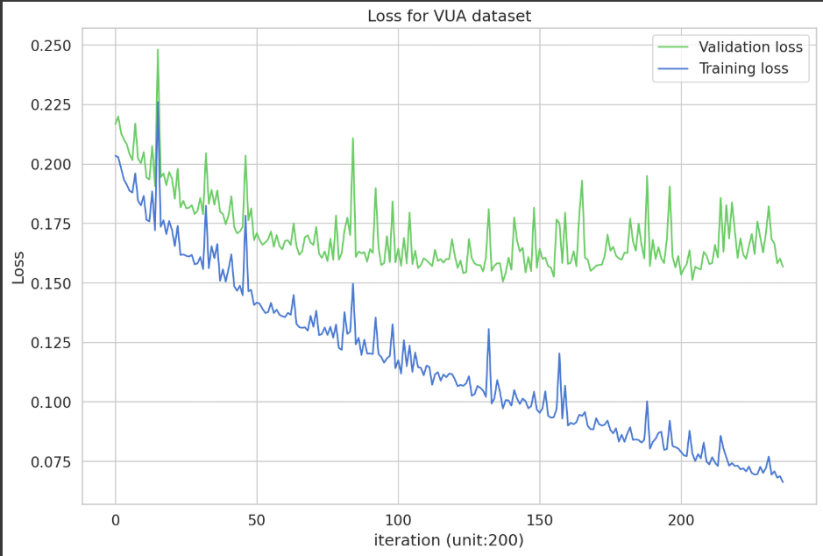
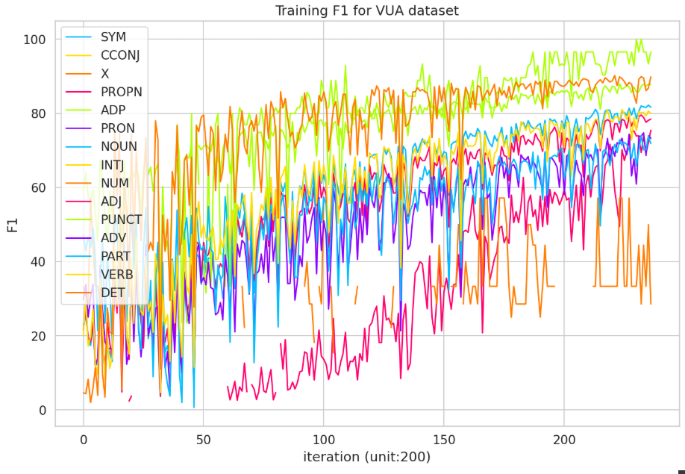
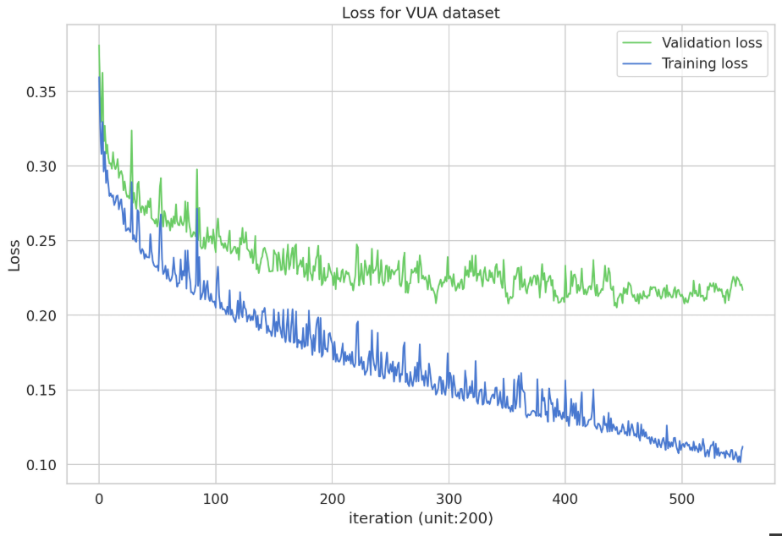
Result of Fine-tuning on Gao et al. (2018)

Figure 13: Performance of Gao et al. (2018) on VUA

1. Fine-tuning on RNN-MHCA from Mao et al. (2019)

Epoch = 45 batch = 32 hidden layer = 300 Dropout1 = 0.3 Dropout = 0.2 learning rate =2e-5

Figure 14: Performance of Mao et al. (2019) on VUA

1. Build BERT-RNN-BiLSTM baseline

Epoch = 20 batch = 32 hidden layer = 1024 Dropout1 = 0.3 Dropout = 0.2 learning rate =2e-5

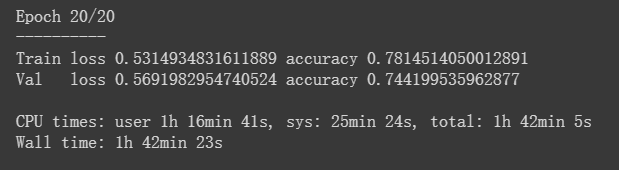


Figure 15: Performance of our BERT baseline on VUA

# *Chapter 7* Experimental Results

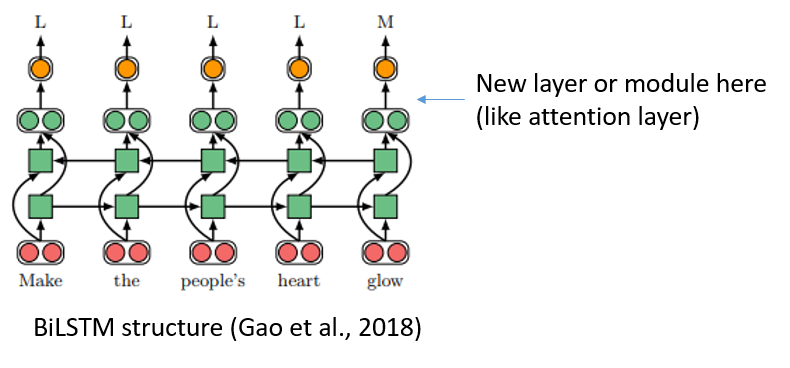
|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Models | VUA | | | |
| Acc | P | R | F1 |
| Gao et al. (2018)  RNN-HG (Mao et al., 2019)  RNN-MHCA (Mao et al., 2019) | 78.4 | 75.3 | 84.3 | 79.1 |
| 79.7 | 79.7 | 79.8 | 79.8 |
| 79.8 | 77.5 | 83.1 | 80.0 |
| BERT Baseline  Glove+BERT Baseline  Glove+BERT+CSE Baseline | 74.4 | 74.6 | 77.8 | 72.4 |
| 75.4 | 75.3 | 76.4 | 72.9 |
| ? | ? | ? | ? |
| GBC-BiLSTM  GBC-BiLSTM-GCN | ? | ? | ? | ? |
| ? | ? | ? | ? |

This section is waiting for an update.

# *Chapter 8* Future Works

Since this is the partial thesis, I will introduce all the innovation on current models. Here are several ideas.

### 4.1 Fine-tuning

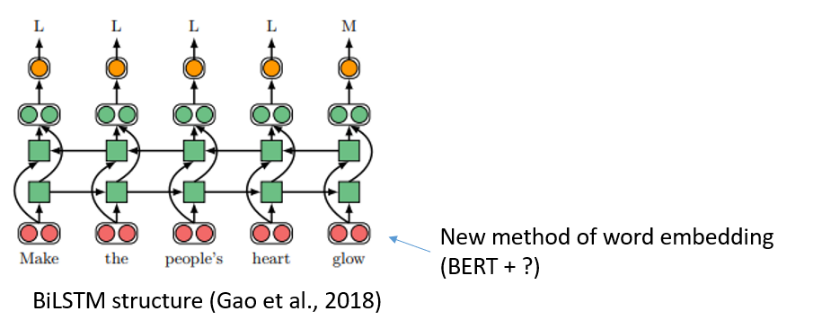
Take the BiLSTM structure (Gao et al., 2018) as the baseline. This model is a relatively contextual basic structure in metaphor detection. We may easily find out that later work RNN-HG and RNN-MHCA (Mao et al., 2019) uses the BiLSTM (Gao et al., 2018) and do fine-tune on the structure. We may also do fine-tuning on this basic BiLSTM structure and add a new layer on it.

### 4.1.2 Try new method for contextual embedding

Inspired from GloVe+ElMo embedding method (Gao et al., 2018), we may find out that different kinds of language representation concatenating together may perform a surprising excellent performance.

BERT as a Bidirectional Encoder Representation from Transformers, which is a state-of-the-art language representation. BERT is so novel that nearly no metaphor detection model currently utilizes it. In this way, we may use BERT as new ways for language representation. Also, a new representation is the ALBERT: A Lite BERT for Self-Supervised Learning of Language Representations. The lite version ALBERT may also be applied. Additionally, RoBERTa is a Robustly Optimized BERT Pretraining approach that may also be applied.

Consider as a comprehensive way, we may try employ the following ways for word embedding:

1. BERT
2. ALBERT
3. RoBERTa
4. GloVe+BERT (GloVe+ALBERT/ GloVe+RoBERTa)
5. ELMo+BERT (ELMo+ALBERT/ ELMo+RoBERTa)
6. GloVe+ELMo+BERT (GloVe+ELMo+ALBERT/ GloVe+ELMo+RoBERTa)

### 4.1.3 Apply modern linguistic theory

Recall that MIP (Metaphor Identification Procedure) and SPV (Selectional Preference Violation) are two fundamental linguistic theory that used for artificial metaphor classification. Mao et al. (2019) 's work implements two linguistic theory and performs a higher result.

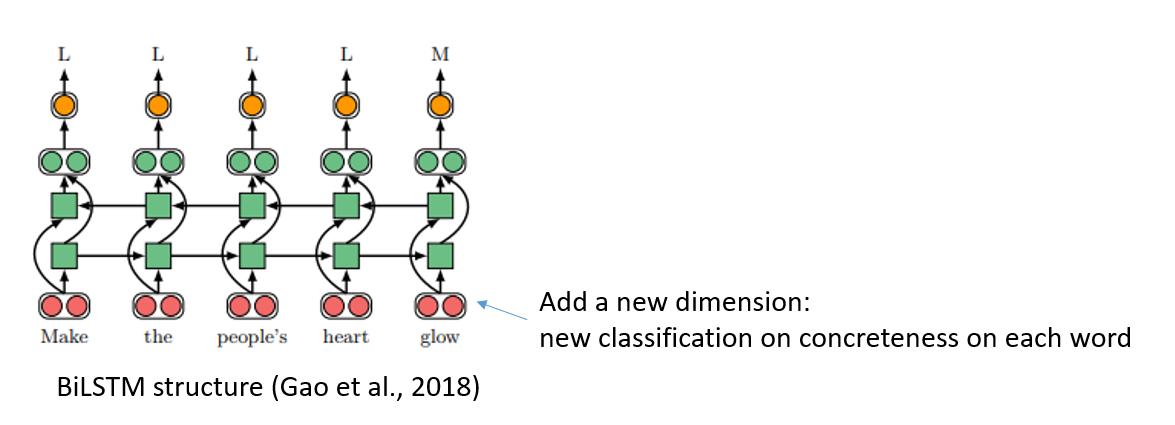
On top of that, Su et al. (2018) 's word relies on the interaction theory of metaphor and develops a new interaction network between the source domain and target domain. The model presents a robust performance.

Inspired by the two models, we need to find a different linguistic metaphor theory and implements in a new way. This would be extended later.

### 4.1.4 Consider word concreteness

Inspired from the conceptual metaphor theory, arguing that metaphor is systematic reasoning from a concrete conceptual source domain to an abstract target domain. The idea that a shift in concreteness within sentence indicates the presence of a metaphor has been around for a while.

Nevertheless, recent methods of detecting metaphor that have highly depends on deep neural models have ignored concreteness and psycholinguistic information. Augmenting Neural metaphor detection with concreteness may provide surprise result.

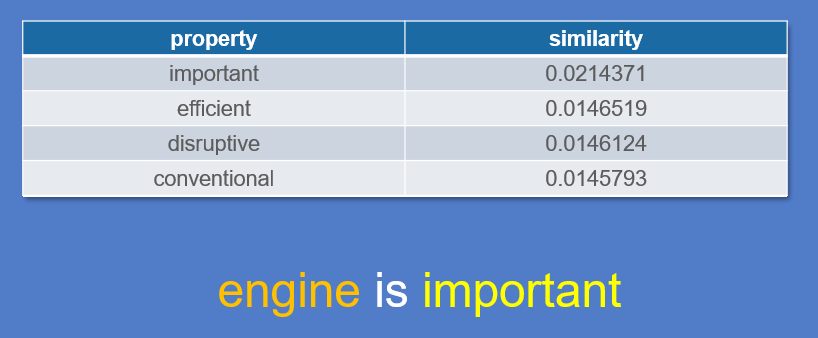
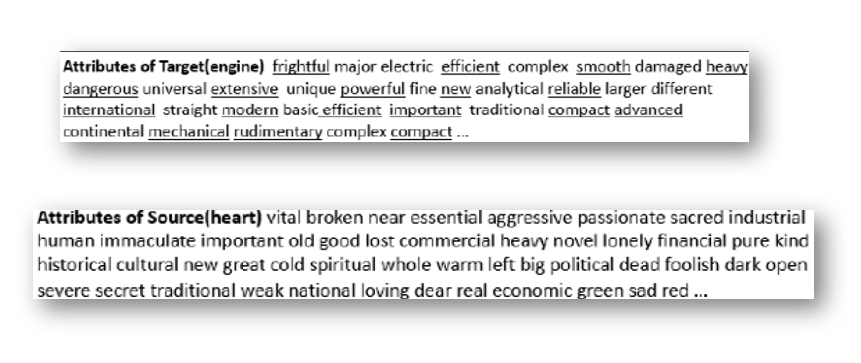
Therefore, based on Gao et al. (2018) 's sequence labeling model as the baseline and modify it to include a concreteness rating. We tend to add another concreteness classification to a new dimension of the word representation.

### 4.1.5 Consider word belonging

Inspired from the figurative language definition, one subject will be described by another word with different word belonging. Consider this sentence: "She devoured the book". Notice that "devoured" is a word to describe a lifeless subject, whereas "she" is a person. Therefore, Tsvetkov et al. (2014) 's work may be exceedingly useful for this innovation.

### 4.1.6 Apply knowledge base

Applying the knowledge base is widely used current metaphor interpretation models since the knowledge base provides sufficient attribute and semantic generalization classes for words. Such information is crucial for both metaphor detection and metaphor interpretation models.

For instance, look at the sentence "The aircraft's engine is regarded as the heart", the word "engine" and the "heart" has the similar attribute, if find the similar attribute, this sentence can be detected as metaphor and the metaphorical word can be replaced by the similar attribute for interpretation.

### 4.1.7 Consider sentence or word sentiment

Inspired from the impact of Figurative Language on Sentiment Analysis, we may find out that sentiment analysis may contribute to metaphor interpretation.

For instance, here is a sentence: "It is a thorny problem to solve since I feel so desperate about it." The entire sentence contains the emotion of despair. Since when we want to replace the metaphorical word "thorny", we need to choose the best literal meaning for this word, like we need to choose the meaning between "painful" and "perplex". We can find that "painful" has the nearest emotional information to the whole sentence emotion. Therefore, sentiment analysis may furnish a significant contribution.

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