Short Text Classification via Knowledge powered Attention with Similarity Matrix based CNN

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ABSTRACT
Short text is becoming more and more popular on the web, such as Chat Message, SMS and Product Reviews. Accurately classifying short text is an important and challenging task. A number of studies have difficulties in addressing this problem because of the word ambiguity and data sparsity. To address this issue, we propose a knowledge powered attention with similarity matrix based convolutional neural network (KASM) model, which can compute comprehensive information by utilizing the knowledge and deep neural network. We use knowledge graph (KG) to enrich the semantic representation of short text, specially, the information of parent-entity is introduced in our model. Meanwhile, we consider the word interaction in the literal-level between short text and the representation of label, and utilize similarity matrix based convolutional neural network (CNN) to extract it. For the purpose of measuring the importance of knowledge, we introduce the attention mechanisms to choose the important information. Experimental results on five standard datasets show that our model significantly outperforms state-of-the-art methods.

1 INTRODUCTION
With the development of the Internet, some platforms such as Twitter, WeChat, and Facebook have become an important way of information dissemination. As an important step in further research, short text classification is widely used in public opinion analysis [12], sentiment analysis [2], human-machine dialogue [5], etc. Compared with long text (document, paragraph), short text is sparser and more difficult to disambiguate. The existing work of short text classification is mainly divided into two categories: explicit representation, implicit representation.

Explicit representation. For explicit representation, short texts are processed by traditional steps: segmentation, POS tagging and syntactic analysis. Then, the text features are extracted from many aspects, such as TF-IDF, Dependency Parsing and KG. Although explicit approaches can represent text from many features, ambiguity is still not solved. Otherwise, POS tagging can consume a large amount of manpower. The sparsity of explicit representation also leads to its infeasibility. In the short text I want to eat a hamburger, if the word hamburger is not in KG, the explicit model will fail.

Implicit representation. In terms of implicit representation, the short text is usually mapped into hyperspace by neural network. The implicit representation model does well in capturing more abundant semantic information from contexts and words based on deep neural network. However, it ignores the relations in the KG, such as Is_a and Has_instance_of. For instance, the short text Warrior won the NBA Championship, Warrior is the name of a basketball team, but the implicit model may regard Warrior as a person or a new word, because this model can not comprehend Warrior is a polysemous word. So we need new knowledge out of the text to fill this gap.

In this paper, we propose a novel deep neural network that combines explicit and implicit representation for short text classification. We use the extended knowledge to enrich the semantic representation of short text, such as Freebase [3], Wikidata [40]. This way needs to obtain the relevant concepts of short text by retrieving the KG, and uses symbolic method to obtain entity information. Specially, in order to enhance the semantic representation of the text, we introduce the parent-entity information to text. In the end, we incorporate these entity information into deep neural network.

Although we feed hierarchical information into neural network (it may improve the accuracy of classification by enriching the semantic representation), there are still two problems need to be settled. First, not all words or entities have the same attention...
weight when training. For instance, short text C: Steve Jobs is the CEO of Apple. The label of C is Human; Steve Jobs should have the biggest weight, because Steve Jobs is a person, and it has the biggest impact on the label Human. Prior works [13, 19] use knowledge graph to enrich the semantic representation of sentence, but they ignore this issue. Second, a few studies [27, 43] considered the relevant information between short text and its label. They unilaterally express semantics. Text W: something is off. This text is regarded as negative by the word off, so there is a close relation between W and label negative. Based on this elaboration, we argue that this relevance can enhance the performance of classification. To solve

![Figure 1: In the Wikidata, symbol is used to indicate exact semantics. The concept apple is a polysemous word, it has many self-entities that refer to different things, such as symbol Q312 refers to Apple Computer Inc, symbol Q4781117 refers to American automobile. However, these two self-entities are both called apple in the literal. Moreover, we introduce the parent information of entity by relation Has_instance_of (P31) in our model, for instance, the parent-entity of Q312 is Q4830453. Green circles refer to self-entities. Blue circles refer to parent-entities.](image)

the above issues, we introduce the attention mechanisms and similarity matrix to our model. The attention mechanism is mainly used to acquire the weight about different vectors, it is widely used in machine translation [1], question answer [9], etc. CNN is good at extracting position in variant features and dealing with spatially related data, so it is already used in many natural language processing (NLP) scenes. For the first problem, we use self-entity attention and parent-entity attention to assign the different weights to the entities. In Figure 2, short text Xiao likes eating apple, its right self-entities are \{Q3249878, Q2134499, Q89\}, its right parent-entities are \{Q8171, Q35120, Q1364\}, our model can assign a larger weight to Q3249878 and Q8171, because their semantics match the text expression best. For the second problem, we construct a similarity matrix based on CNN, which detects the interaction information between the words in short text and the words in the representation of label, a convolutional layer over CNN is used to obtain abundance matching patterns between them. We regard this information as a kind of knowledge, and integrate it into semantics of text.

We calculate a weighted sum of the self-entity vectors to produce the self-entity representation A2, the parent-entity representation A3 is formed by the same way. By using explicit entity (symbol) to represent text information can make the semantic expression of text more clearer. Meanwhile, we obtain the interaction information A4 by similarity matrix based CNN. Besides, we make full use of word level feature A1 of short text and employ A2, A3 and A4 to generate the short text representation S. Finally, we classify the short text based on S. Our main contributions are presented as follows:

(1) We propose Short Text Classification via Knowledge powered Attention with Similarity Matrix based CNN. As far as we all know, this is the first model which combines explicit entity (symbol) in KG with interaction information between short text and its representation of label to short text classification.

(2) We propose two types of attention mechanism to measure the importance of each entity related to short text and use similarity matrix based CNN to obtain the interaction information. Moreover, we introduce the parent-entity information to our model.

(3) In the last part of our experiment, we compared three types word embedding in our model.

(4) We experimented on five standard datasets, and the results show that our model significantly outperforms state-of-the-art methods.

2 PROBLEM FORMULATION

In this section, we will formally define some related concepts which will be used in this paper.

Definition 1 (Knowledge graph): A knowledge graph is a semantic network where the entities and their relations are represented by nodes and edges. Specifically, \( \{h, r, t\} \) is represented as a fact in knowledge graph, \( r \) refers to a relation between entity \( h \) and entity \( t \). Each entity can also contain additional information, such as entity description and alias. In this paper, we use the Wikidata [40] as our knowledge graph, which has more than 58248460 entities and has been applied to many NLP tasks. In the Wikidata, the entity is represented by symbol which has the exact semantics, for example, Earth (Q2) – the third planet from the Sun in the Solar System.

Definition 2 (Concept and entity): Intuitively, in Figure 1, apple is an abstract concept, it can refer many items, in order to solve the problem of polysemy, the entity is introduced, entity Q26944932 refers to a family name, entity Q4830453 refers to Apple Computer Inc, they both have the same name apple in the literal.

Definition 3 (Knowledge graph embedding): It encodes each entity and relation in KG into continuous low dimensional vector space. In recent years, several knowledge graph embedding methods have been proposed, there are two main categories: translation based models such as TransE [4], TransC [28], TransA [16], etc., and semantic matching models such as RESCAL [31], DisMult [45] and HolE [30]. In this paper, we utilize the most widely used model TransE, for the following reasons: 1) TransE has a geometric interpretation which can explain the relation in every triple (head, relation, tail); 2) TransE is easy to train; 3) In the Wikidata, there are 54020000 triples, TransE is very efficient on training in this scale dataset. We use the tool provided by OpenKE [15] to obtain the \( d_t \)-dimensional graph embedding Matrix \( CE, d_t=100 \).
Definition 4 (Entity linking): In NLP, entity linking is a task which confirms the identity of entity. Based on the Wikidata, we developed a tool Searcher to link the short text to KG, this tool can only be used for obtaining the relevant concepts about short text, for example, short text $E$: *Eating a poisonous pear is good for Alice*. After entity linking, the concepts of $E$ are \{poisonous, pear, alice\}.

Definition 5 (Symbolic method): It is used to obtain the entity about the text, each identity of entity is only one. In Figure 1, by retrieving the KG, the self-entities about concept “apple” are \{Q312, Q26944932, Q4781117, etc.\}. Moreover, we obtain their parent-entities \{Q101352, Q1420, Q4830453, etc.\} by the relation $P31$.

Definition 6 (Label’s representation): We introduce the interaction information between short text and its label into the semantic representation of text. In general, a label is a symbol, such as HUM and TEC. It’s difficult to extract the information of label literally. These labels also have a phenomenon of polysemy. To solve the above problems, we extend these labels and clarify the true meaning of them by manual, and then we use the description (representation) of label which store in the Wikidata to describe its information, for instance, (label: HUM) $\implies$ (label extention: Human) $\implies$ (the representation of HUM: common name of Homo sapiens, unique extant species of the genus Homo).

3 OUR MODEL

In this section, we will describe our model–KASM which is shown in Figure 2, it mainly includes four components: (1) a method to choose the right entity, it is described as yellow box E in Figure 2; (2) a word encoding method for mining the potentially semantic information of word, this progress is described as PART1 in Figure 2, we input short text to neural network to obtain the word feature representation; (3) a knowledge (entity) encoding model for obtaining the precise semantics of text, this progress is described as PART2 in Figure 2, in the first, we use entity linking, symbolic method and model E to obtain the self-entity set and parent-entity set, in the last, we input these sets to our neural network to obtain the entity feature representation; (4) an interaction information detection model for capturing connection information between short text and the representation of its label, as shown in Figure 2–PART3, we input the similarity matrix to CNN and finally get the interaction information. By these components, we can get the information representation of text, then use it to classify short text. The following section will look at the process in more detail.

3.1 Choose the Right Entity

A concept usually has many entities (as shown in Figure 1), it means concept has different meanings in KG, but in sentence, the meaning of concept must be one. By definition 5, we can get the entities set of concept, then we need to remove the noise in entity set and retain the right entities. Many prior works \[6, 17\] use attention mechanism to make it. But when we introduced it in our work, we found this mechanism does not result in improvements during training, simple cosine is better in this task. The main reason is that there is a “extreme” phenomenon: the concept Yi has 5114 self-entities in the Wikidata, however, the concept limerick has only one self-entity, if they are in one sentence, attention mechanism may assign a smaller weight to the self-entities of limerick. It is wrong, limerick has only one meaning. Next, we will introduce our method about how to choose the right entity. Firstly, we can get the entity description $D_l$ ($l$ is the number of entities for every concept) of concept by retrieving the Wikidata. Secondly, the short text vector representation $S$ and the vector representation $D_l$ of $D_l$ can be captured by Google’s $d_0$-dimensional pre-trained vectors \[29\], $d_0=300$. The main operation is as bellow,

$$T = \text{Max}(C(S, D_1), C(S, D_2), ..., C(S, D_l))$$

In function 1, C refers to cosine function, the entity corresponding to T is the right entity, in Figure 3, it is Q89. By the same way, we can get the self-entity set $C$ and parent-entity set $F$ of the sentence.

3.2 Input Embedding

This section only describes the embedding in Figure 2 (PART1 and PART2). The input of these two parts consists of three parts: short text’s word set $S$ of size $l$, self-entity set $C$ of size $m$ and parent-entity set $F$ of size $n$. We use two kinds of embedding in this module, word embedding and KG embedding. Word and KG embedding layer map each word and entity to a high-dimensional vector space. We use Google’s $d_0$-dimensional pre-trained vectors to obtain the word embedding and use $d_1$-dimensional CE (it is shown in definition 3) to obtain the entity embedding.

3.3 Word Feature Representation

The function of this module is to produce word feature representation $A_l$, given a short text $s$ which has length $l$, each word in the text is transformed to its word embedding $X = \{x_1, x_2, ..., x_l\}, X \in \mathbb{R}^{l \times t}$, where $t$ is the dimension of word embedding matrix. And then we use Bi-GRU \[8\] to get hidden representations $H_{o,t} = \{h_0, ..., h_t\}$ (each $h_l$ represents bi-directional information at time $l$). In sentence, each word pays different attention to the label, the greater the extent of the attention, the greater the importance of word. Thus, the word feature representation $A_l$ of sentence is calculated as:

$$u_j = \text{tanh}(W_u h_j + b_u) ; T$$

$$\eta_j = \text{softmax}(u_j ; U_w)$$

$$A_l = \sum_{j=1}^{l} \eta_j h_j$$

we first get $u_j$ as the hidden presentation of $h_j$ by function 2, and then we calculate word’s weight $\eta_j, A_l$ is obtained by summarizing words’ weight. $W_u^{o,T}$ ($o$ is the hidden size of $H, o$ is the attention layer size from word level), $U_w^{o,1}$ and $v^n$ are stochastic matrix, they join learning during training progress.

3.4 Entity Feature Representation

We regard entity information as a kind of knowledge, which can help decide the class label when given a short text. Given a self entity set $C$ of size $m$, denotes as \{c_1, ..., c_m\}, by graph embedding matrix CE and deep neural network, we can get its hidden vector representation $E = \{e_1, ..., e_m\}, e_m$ is the m-th self-entity vector. In the same way, parent-entity set $F = \{f_1, ..., f_n\}$, its hidden vector representation is $K = \{k_1, ..., k_n\}$. In $C$ and $F$, every entity has not an equivalent effect on text representation, in the next, we will
introduce two attention mechanisms to pay attention to important entities.

self-entity attention We propose self-entity attention based on vanilla attention [1] to measure the importance of self-entity in short text, the self-entity feature representation \( A^2 \) is calculated as:

\[
\alpha_j = \text{softmax}(\tanh(W^T e_j + b_j)U^T) \tag{5}
\]

\[
A^2 = \sum_{j=1}^{m} \alpha_j e_j \tag{6}
\]

Here, \( \alpha_j \) denotes the weight of every entity in \( C \), a large \( \alpha_j \) means \( j \)-th self-entity is more similar to the short text in semantic level. \( W^i \in \mathbb{R}^{i \times e} \) (\( i \) is the hidden size of \( E \), \( e \) is the size of self-entity attention layer) and \( U^j \in \mathbb{R}^{e \times 1} \) are the weight matrix and need to be learned during the training, \( b^j \) is the offset.

parent-entity attention In \( C \), every self-entity is represented by the symbol, and a self-entity has only one parent-entity, because symbol’s semantic information is unique. In practice, statistical methods (Deep Learning, Machine Learning, etc.) are uncertain and stochastic, so it cannot assign the right weight to each entity. We can not say that self-entity \( b \) has the largest weight, its parent-entity \( q \) has the largest weight too. To solve this issue, we propose the

parent-entity attention based on self-attention [26]. The parent-entity feature representation \( A^3 \) is calculated as:

\[
\beta_j = \text{softmax}(\tanh(W^T k_j + b_t)U^T) \tag{7}
\]

\[
A^3 = \sum_{j=1}^{n} \beta_j k_j \tag{8}
\]

Here, \( \beta_j \) denotes the weight of every parent-entity in \( F \), a large \( \beta_j \) means \( j \)-th parent-entity is more similar to the short text in semantic level. \( W^m \in \mathbb{R}^{m \times n} \) (\( m \) is the hidden size of \( K \), \( n \) is the size of parent-entity attention layer) and \( U^{n \times 1} \) are the weight matrix and need to be learned during the training, \( b^t \) is the offset.

3.5 Interaction Information

In this section, we will introduce the interaction information. By definition 6, we can get label’s representation \( L \) of length \( d \), \( L = \{l_1, ..., l_d\} \) and use the same way as section 3.2 to get \( L \)’s embedding \( S = \{s_1, ..., s_g\} \), \( s_g \) means the \( g \)-th word vector. Now, we have the representation of short text and label from literal level. When we considered the interaction information over literal level, inspired by [35], we found that although some texts express the same meaning, their words have different orders. Such as “Where is Barack Obama’s hometown?” and “Where was president Obama born?” These texts have different expressions (order or synonym), but they all refer to one topic – Location. Many encoder models can not catch these interaction information, such as RNN, although it considers the word information by order, if two sentences have different word order, their semantic information will be different. So we construct a similarity matrix based on CNN, its convolutional kernels can extract these interaction information and solve the above problems. Next we will describe it in detail.

We first construct a similarity matrix, it is calculated as,

\[
M_{gl} = \text{cosine}(s_g, x_l) \tag{9}
\]
We need to use a fully connected layer to produce the final interaction information. After that, we use softmax and cross entropy as our training loss, and all the parameters need to be optimized from a set of parameters.

Above four calculations, we get four features, 

\[ A_1(x_1), A_2(x_2), A_3(x_3), A_4(x_4) \]

to be optimized from a set of parameters. We used 80% for train, 20% for test.

\[ P_k = \phi(W^{k}W_{hl} + b_k) \]  

where, \( P_k \) is the output of max-pooling layer.

We used 9 state-of-the-art methods as our compared models.

To verify the effectiveness of our model, we conducted experiments on five datasets: MR, TREC, SST-1, SST-2, AG New. In this section, we will describe these datasets in detail and show them in Table 1.

1. **MR**: It’s a movie reviews dataset from web, there are two classifications: positive reviews and negative reviews [32]3. We used 80% for train, 20% for test.
2. **TREC**: It’s a question classification dataset [25]4, which has the question class definitions, the training and test question sets.
3. **SST-1**: Stanford Sentiment Treebank [37]5, a dataset for predicting the sentiment of movie reviews, it has a finer granularity than MR, there are five classifications: very negative, negative, neutral, positive, very positive.
4. **SST-2**: Same as SST-1, we removed neutral reviews, so there are two classifications: positive and negative.
5. **AG-new**: The original dataset [43]6 consists of four types article: World, Sports, Business, Sci/Tec. Every article includes title and its description. In our work, we only use the title as the dataset.

### 3.6 Combination and Training

Above four calculations, we get four features, \( A_1, A_2, A_3, A_4 \), where \( A_1 \) denotes the word feature, \( A_2 \) and \( A_3 \) denote the entity feature, \( A_4 \) denotes the interaction information. After that, we use softmax and cross entropy as our training loss, and all the parameters need to be optimized form a set of parameters, specifically,

\[ y = softmax(M^T[A_1; A_2; A_3; A_4] + b) \]

\[ L = - \sum_d y^{*}_d \log(y_d, \delta) \]

where, \( d \) is the number of sentences, \( y^{*}_d \) is the target label. \( M \) is the weight matrix.

### 4 EXPERIMENTS

#### 4.1 Dataset

To verify the effectiveness of our model, we conducted experiments on five datasets: MR, TREC, SST-1, SST-2, AG New. In this section, we will describe these datasets in detail and show them in Table 1.

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#### 4.2 Compared Models

We used 9 state-of-the-art methods as our compared models.

1. **TF-IDF&Bayes** This is the standard baseline for short text classification. In this model, TF-IDF which based on Bags of Words is used for text representation, Bayes as a classifier. This baseline was implemented by scikit-learn7.
2. **TextCNN** This model uses Convolutional Neural Networks for text classification which was proposed by [22]. It uses multichannel for word embedding. All embeddings are randomly initialized by word2vec during training.
3. **Char-CNN** It was proposed by [43], they made a character level convolutional network and designed 6 convolutional layers and 3 fully-connected layers for text classification.

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1. https://www.cs.cornell.edu/people/pabo/movieview-data/
2. http://cogcomp.cs.illinois.edu/Data/QA/QC/
3. https://nlp.stanford.edu/sentiment/
4. https://github.com/ToneLi/Corpus/tree/master/AG_new
5. https://scikit-learn.org/

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**Table 1:** We show the five widely used datasets in five aspects: name, training/test data, Avg.Len (sentence’s average length), Class (the number of classification category) and Cla1-6 (the number of sentences in each category). MR (Cla1-positive, Cla2-negative), TREC (Cla1-ABBR, Cla2-LOC, Cla3-DESC, Cla4-NUM, Cla5-ENTRY, Cla6-HUM), SST-1 (Cla1-very negative, Cla2-negative, Cla3-neutral, Cla4-positive, Cla5-very positive), AG-new (Cla1-World, Cla2-Sports, Cla3-Business, Cla4-Sci/Tech)
Table 2: Accuracy of Composed Models on Different Datasets

| Model        | MR   | TREC | SST-1 | SST-2 | AG-new |
|--------------|------|------|-------|-------|--------|
| TF-IDF&Bayes | 0.7620 | 0.9040 | 0.3881 | 0.7930 | 0.8609 |
| TextCNN      | 0.8152 | 0.8933 | 0.4740 | 0.8810 | 0.8611 |
| CharCNN      | 0.7701 | 0.7600 | –     | –     | 0.7827 |
| RNTN         | –    | –    | 0.4570 | 0.8540 | –      |
| DCNN         | –    | 0.9300 | 0.4805 | 0.8680 | –      |
| MV-RNN       | 0.7900 | –    | 0.4440 | 0.8290 | –      |
| KPCNN        | 0.8325 | 0.9346 | –     | –     | 0.8836 |
| ULMFiT       | –    | 0.9640 | –     | –     | 0.9499 |
| BERT-Fit     | –    | 0.9720 | –     | –     | 0.9475 |
| KASM         | 0.9164 | 1.0   | 0.9136 | 0.9823 | 0.9750 |

(4) **MV-RNN** In this work [36], authors use Matrix Recursive Neural Network with parse trees to solve the classification task.

(5) **DCNN** This model [21] uses dynamic convolutional neural network and k-max pooling for classification. Specifically, it does not rely on parse tree, and it is applicable for any language.

(6) **RNTN** This method [37] introduces the Sentiment TreeBank and the Recursive Neural Tensor Network in classification task and has a good performance in this task.

(7) **KPCNN** It was proposed by [19]. This model first to combine the CNN and prior knowledge in short text classification, in order to enrich the text representation, authors used three embeddings: word embedding, concept embedding and character embedding.

(8) **ULMFiT** The authors proposed an effective transfer learning method [18] for text classification. Otherwise, they introduce three novel methods to retain the previous knowledge during the tuning progress: discriminative fine-tuning, slanted triangular learning rates, and gradual unfreezing.

(9) **BERT-Fit** This method was proposed by [38] which based on BERT [11]. The BERT uses multi-layer bidirectional Transformer to encode origin sentence to potentially semantic representation, in order to enhance the semantic feature, the token, segment and position embeddings are packed together into a word embedding. It breaks the record of text classification. However, it ignores the semantics of labels. In our work, we add the interaction information between text and its label’s information to our model. Experiments show that this information can improve model accuracy. Our model performs better on the dataset TREC and AG-new compared to ULMFiT, this model used unidirection-LSTM (ULSTM) as the basic compute unit. The whole process is divided into 3 steps: LM pre-training, LM fine-tuning and Classifier fine-tuning. In order to solve the problem about information dropout in ULSTM, this model puts the output of each moment together, and then did two operations, max-pooling and mean-pooling. However, we argue that this progress ignores the context information of a single semantic unit and the weight of each word in a sentence. To cure the above problems, we used GRU and CNN as the basic compute units and proposed two types attention mechanism to assign the weight for the word and entity.

By analysing the baseline models, we find that the CharCNN performs worse than TextCNN on accuracy. TextCNN has an accuracy of 0.89 in TREC, however CharCNN only has 0.76. The reason is that the text representation in char level can lose the semantic information of text, and it can not calculate the relation between two

### 4.3 Hyper Parameters and Settings

In our model, the batch size is 64. The learning rate is set to 0.0001, and learning rate decay is 0.9. The gradient clipping threshold is set to 5.0. We used Adam [23] as our optimizer. In word level, word embedding dimension is 300, the number of GRU’s hidden units is 300, the size of attention layer is 300. In self-entity level, self-entity embedding dimension is 100, the number of GRU’s hidden units is 300, the size of self-entity attention layer is 300. In parent-entity level, parent-entity embedding dimension is 100, the number of GRU’s hidden units is 600, the size of parent-entity attention layer is 600. In CNN interaction level, the word embedding dimensions are {10 (MR), 13 (TREC), 11 (SST1), 8 (SST2), 15 (AG)}, the filter numbers are {10 (MR), 13 (TREC), 11 (SST1), 8 (SST2), 15 (AG)}, filter windows are 3, 4, 5.

### 4.4 Results

In this section, we will show the overall results on five datasets. In addition, we analyze the effectiveness of parent-entity and interaction information. We also visualize attention weight, by this way, we can see how these attention models work.

The result of KASM and competing models on five datasets are summarized in Table 2. We can see that KASM significantly outperforms other approaches. It performs best on SST1, it can improve the accuracy by more than 50 percent in comparing DCNN. In TREC, our model obtains 2.8 percent accuracy improvement over the best model—BERT-Fit. BERT uses the multi-layer bidirectional Transformer to encode origin sentence to potentially semantic representation, in order to enhance the semantic feature, the token, segment and position embeddings are packed together into a word embedding. It breaks the record of text classification. However, it ignores the semantics of labels. In our work, we add the interaction information between text and its label’s information to our model. Experiments show that this information can improve model accuracy. Our model performs better on the dataset TREC and AG-new compared to ULMFiT, this model used unidirection-LSTM (ULSTM) as the basic compute unit. The whole process is divided into 3 steps: LM pre-training, LM fine-tuning and Classifier fine-tuning. In order to solve the problem about information dropout in ULSTM, this model puts the output of each moment together, and then did two operations, max-pooling and mean-pooling. However, we argue that this progress ignores the context information of a single semantic unit and the weight of each word in a sentence. To cure the above problems, we used GRU and CNN as the basic compute units and proposed two types attention mechanism to assign the weight for the word and entity.
adjacent words. So, in our model, we do not consider the character information.

DCNN performs better than CNN, because it uses different kernels in every convolutional layer. This method can help model capture more comprehensive information, so the accuracy can reach 0.93. RNTN needs sentment tree, it increases the uncertainty and complexity of the model, so it only gets 0.45 in SST-1. TF-IDF&Bayes computes the word vector based on word frequency, it cannot mine the semantic information of the text, it performs worse on most datasets. MV-RNN cannot assign the right weight for each word, which lead it perform worse in SST1, SST2 and MR. Otherwise, these models ignore the extend information, so in our model, we use entity information which store in KG and interaction information obtained by simialrity matrix to enhance the performance of classification, and let the machine to think more closely to humans.

In model KPCNN, although authors introduced knowledge information to text representation, they ignored that different words have the different impact to the label. Attention mechanism can solve this problem and MV-RNN’s issue as mentioned above, so we design two types attention model: self-entity attention model and parent-entity attention model to assign weight for every entity.

4.5 Performance Analysis

In this section, we will evaluate the effect of different components used in our KASM, and compare the performance of KASM against its three variants, they are shown in the below.

1. **KASM without interaction information** To evaluate the effectiveness of interaction information, we make a variant of KASM, this model does not consider the interaction information between sentence and its label, but still retains the entity information and two types attention mechanism. By removing the interaction information, the model can not use the associated information between the sentence and label’s representation. We refer to this model as KASM – NII.

2. **KASM without attention** We use the same method as KASM-NII (removing one component [attention mechanism] in KASM). This model is not able to assign the different weights for words in sentence. So, each word in sentence has an equal impact on label. We refer to this model as KASM – NA.

3. **KASM without parent information and interaction information** This is a simple variant, which is used to verify the validity of parent-entity. In this model, we only consider the self-entity information and self-entity attention mechanism. By removing the parent information, the model can not use hierarchical information in KG, we refer to this model as KASM – simple.

As shown in Table 3, we perform the effect of KASM and its three variants. KASM-NA, KASM-NII and KASM-simple verify the effectiveness of attention, interaction information, and parent-entity information respectively. By analysing, we find the interaction information has the biggest impact on our model, that we believe this information can enhance the performance of classification. We can see that KASM-NII is slightly better than KASM-simple, the reason is that the information of entity is not enough in the Wikidata, many self-entities have not parent-entities in the condition of relation P31, such as entity Q19020713-ultimately, Q2106390-potboiler. If we use other relation, it can meet the same situation, therefore, a KG with high coverage and accuracy is very important.

By comparing KASM-NA and KASM, we can see that our attention mechanism can improve the accuracy of short text classification, this is because these mechanisms can focus on more important semantic units. In order to intuitively describe the effectiveness of the attention mechanism, we choose a sentence in AG to visualize its encoding progress. From Figure 4, these mechanisms always assign a bigger weight for the important semantic unit, such as in word level, oracle and data are important for label technology, so word attention assign a bigger weight for them. In self-entity level, Q185524 and Q42848 are more important than Q203872, P2139, etc. So self-entity attention assign a bigger weight for Q185524 and Q42848, we can see the same situation in the parent-entity level.

![Figure 4: We visualize the weights of three attention mechanisms. The more blue, the more important. The square means the weight for each word or entity.](image)

### Table 3: Performance of KASM and its variants

| Model        | MR     | TREC   | SST-1 | SST-2 | AG-new |
|--------------|--------|--------|-------|-------|--------|
| KASM-NII     | 0.7846 | 0.9580 | 0.4081| 0.8090| 0.7932 |
| KASM-simple  | 0.7794 | 0.9540 | 0.4036| 0.8029| 0.7365 |
| KASM-NA      | 0.9127 | 1.0    | 0.9122|       | 0.9884 | 0.9742 |
| KASM         | 0.9164 | 1.0    | 0.9136| 0.9823| 0.9750 |

4.6 Embedding in KASM

In this part, we will contrast three word embedding strategies in our model, they are random initialization, word2vec and BERT. In the training progress, the method of entity embedding remains unchanged.

1. **KASM-Random** The embedding matrix is randomly initialized by uniform distribution.

2. **KASM-Word2vec** The pre-trained embedding is computed by word2vec. It is based on the traditional neural network.

3. **KASM-BERT** The pre-trained embedding is computed by BERT.

BERT is a novel way for semantic representation of text, its context information is no longer just a few characters, but a longer context. The authors introduce the transformer in BERT, it has multi-head attention mechanism which can focus on more important information during the training. KASM-BERT uses BERT to
Table 4: KASM with different embedding strategies. KASM-R refers to KASM-Random, KASM-W refers to KASM-Word2vec, KASM-B refers to KASM-BERT.

| Model   | MR   | TREC | SST-1 | SST-2 | AG-new |
|---------|------|------|-------|-------|--------|
| KASM-R  | 0.9418 | 1.0  | 0.8654| 0.9862| 0.9505 |
| KASM-W  | 0.9164 | 1.0  | 0.9136| 0.9823| 0.9750 |
| KASM-B  | 0.8779 | 1.0  | 0.8913| 0.9724| 0.9676 |

compute the pre-trained embedding. As shown in Table 4, although BERT performs well in many tasks, BERT-embedding don’t help our model improve the accuracy. In contrast, the KASM-Word2vec which uses Word2vec is better. We think the reason is that BERT adds too much information to represent word vectors, such as position information, in our model, GRU can compute the position information word by word, we think using position information is unnecessary. To introduce the redundant information in our model will reduce the accuracy. We can see that KASM-Random performs poorly on AG-new and SST-1, but it shows better results on MR and SST-2 than KASM-Word2vec, the reason is that there are a lot of out-of-vocabulary words, i.e., some words are not in train dataset, but in test dataset. In the training progress, KASM-Random can use the initialized random matrix to learn a good embedding matrix.

5 RELATED WORK

5.1 Short Text Classification

The short text contains a lot of useful information. Classification can help users to choose the information according to the category. The existing work of short text classification is mainly divided into two categories: explicit representation and implicit representation. Explicit representation generally uses artificial features for text representation, such as TFIDF, DF. [14] used ngram for text classification. [34] applied explicit and implicit information for sentence classification. [41] proposed Bayesian classifier for text classification based on unigram and bigram models. K Nearest Neighbors [46] and Support Vector Machine [20] have also been applied in text classification. The explicit model can represent text from many powerful features, however, these methods raise some problems: high feature dimension, data sparsity. Moreover, these features cannot save the semantic information of words. Implicit representation maps short text into implicit space by the neural network. In the next section, we will describe some works which used neural network model to solve this task.

5.2 Neural Network

With the great success of deep learning in computer vision and speech recognition, some researchers have tried to apply deep learning to short text classification. [22] proposed CNN multichannel model, which used two channels and three kernels to improve the accuracy of short text classification. [43] and [10] presented a model based on character-level convolutional neural network for short text classification. [27] proposed a recurrent neural network model for text classification and used three different mechanisms for sharing information. [18] presented an effective transfer learning method ULMFiT for text classification. By using neural network, implicit models do well in calculating the semantic information of words and sentences, but it ignores the prior knowledge stored in KG. In our model KASM, we consider the entity information which store in KG, it can help model improve the accuracy.

5.3 Knowledge Graph

A large amount of prior knowledge is stored in knowledge graph, by using knowledge graph to extend short text can improve the accuracy of short text classification. [19] first conceptualized sentence as some relevant concepts by using knowledge graph (Probate) [42]. [39] proposed a new method based on the Wikipedia, which overcame the problem of labeled data. [48] used knowledge guided convolutional neural networks for clinical text classification. These works have some limitations: they cannot solve the problem of polysemy in short text and ignore the importance of each concept. To solve these issues, we propose a “choose the right entity model” which is used to disambiguation, and use two types of attention mechanism to assign weight for each entity. Otherwise, we use parent-entity information to enrich the information of text.

5.4 Attention Mechanism

[1] first proposed attention mechanism which can be used in machine translation. [47] used hierarchical attention network (HAN) for document classification, this model includes sentence level attention layer and word level attention layer, so it can calculate the importance of word or sentence. [33] improved HAN, it proposed multilingual HAN to learn the structure of sentence. This model is good at full-resource and low-resource scenarios. [6] proposed the first classification model which combines self attention and prior knowledge in CN-probase [7]. [38] used BERT [11] for classification. The BERT’s structure is mainly Transformer which based on Multi-Head Attention. In this work, we use two types attention mechanism to obtain the important knowledge.

5.5 CNN in NLP Tasks

CNN has been widely used in NLP, [49] used CNN to extract position feature in sequence, and compared the difference between CNN and RNN in NLP. [21] introduced dynamic convolutional neural network (DCNN) to four NLP tasks, such as question classification and sentiment prediction. Its main idea is to use dynamic k max pooling over sequence. [49] proposed attention based convolutional neural network (ABCNN), which used attention mechanism to focus on the important feature in sentence. In [44], authors constructed an entity similarity matrix for semantics ranking, and used two types of pooling (query level max pooling) and bin pooling to extract the implicit features from matrix. [35] used similarity matrix based on CNN to calculate the interaction information between question and relation in the literal, this method is effective in question answer. [24] introduced multi-column convolutional neural networks (MCCNNs) to enrich the question information, these columns can calculate different aspects of information (answer path, answer context, answer type). In this work, we utilize CNN to catch the interaction information between short text and its
label. This is the first work to introduce this interaction information to text classification.

6 CONCLUSION

In this paper, we proposed a knowledge powered attention with similarity matrix based CNN classification model, we used knowledge graph to enrich the semantic representation of short text from two aspects: self-entity level and parent-entity level. To select the vital entity in sentence, we introduced two types of attention mechanisms: self-attention and parent-entity attention. Otherwise, we first use the interaction information between sentence and its label in short text classification. Specially, we constructed a similarity matrix based on CNN to calculate the interaction information. In the last, we verified the performance of three types word embeddings in our model. Our experiments show KASM is effective in short text classification.

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