Words are not enough! Short text classification using words as well as entities

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Zusammenfassung

Textklassifizierung, auch als Textkategorisierung bezeichnet, ist eine klassische Aufgabe in der natürlichen Sprachverarbeitung. Ziel ist es, Textdokumenten eine oder mehrere vordefinierte Klassen oder Kategorien zuzuordnen. Die Textklassifizierung hat eine Vielzahl von Anwendungsszenarien.

Herkömmliche Probleme bei der Klassifizierung von Binär- oder Mehrklassentexten wurden in der Maschinelles Lernen Forschung intensiv untersucht. Wenn jedoch Techniken des Maschinelles Lernenes auf kurze Texte angewendet werden, haben die meisten Ansätze der Standardtextklassifizierung die Probleme wie Datensparsamkeit und unzureichende Textlänge. Darüber hinaus sind kurze Texte aufgrund fehlender Kontextinformationen sehr mehrdeutig. Infolgedessen können einfache Textklassifizierungsansätze, die nur auf Wörtern basieren, die kritischen Merkmale von Kurztexten nicht richtig darstellen.

In dieser Arbeit wird ein neuartiger Ansatz zur Klassifizierung von Kurztexten auf der Basis neuronaler Netze vorgeschlagen. Wir bereichern die Textdarstellung, indem wir Wörter zusammen mit Entitäten verwenden, die durch den Inhalt des gegebenen Dokuments repräsentiert werden. Tagme wird zuerst verwendet, um benannte Entitäten aus Dokumenten zu extrahieren. Wir verwenden dann das Wikipedia2Vec Modell, um Entitätsvektoren zu erhalten. Unser Modell wird nicht nur auf vortrainierte Wortvektoren, sondern auch auf vortrainierte Entitätsvektoren trainiert. Wir vergleichen die Leistung des Modells mit reinen Wörtern und die Leistung des Modells mit Wörtern und Entitäten. Der Einfluss verschiedener Arten von Wortvektoren auf die Klassifizierungsgenauigkeit wird ebenfalls untersucht.

Abstract

Text classification, also known as text categorization, is a classical task in natural language processing. It aims to assign one or more predefined classes or categories to text documents. Text classification has a wide variety of application scenarios.

Traditional binary or multiclass text classification problems have been intensively studied in machine learning research. However, when machine learning techniques applied to short texts, most of the standard text classification approaches have the problems such as data sparsity and insufficient text length. Moreover, due to the lack of contextual information, short texts are highly ambiguous. As a result, simple text classification approaches based on words only, can not represent the critical features of short texts properly.

In this work, a novel neural network based approach of short text classification is proposed. We enrich text representation by utilizing words together with entities represented by the content of the given document. Tagme is first utilized to extract named entities from documents. We then utilize Wikipedia2Vec model to get entity vectors. Our model is trained not only on top of pre-trained word vectors, but also on top of pre-trained entity vectors. We compare the performance of the model using pure words and the model using words as well as entities. The impact of different kinds of word vectors on the classification accuracy is also studied.

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Abkürzungsverzeichnis

BERT Deep Bidirectional Encoder Representations from Transformers.

BoW Bag-of-Words.

CBOW Continuous Bag of Words.

CharCNN Character-level Convolutional Neural Network.

CNN Convolutional Neural Network.

DBOW Distributed Bag of Words.

DCNN Dynamic Convolutional Neural Network.

DMN Dynamic Memory Network.

EL Entity Linking.

ELMo Embeddings from Language Models.

EntCNN Convolutional Neural Network for Text Classification with Entities.

FLOPs Floating Point Operations.

FN False Negative.

FP False Positive.

GloVe Global Vectors for Word Representation.

GPT Generative Pre-Training model.

GPU Graphics Processing Unit.

GRU Gated Recurrent Unit.

HAN Hierarchical Attention Network.

ICA Independent Component Analysis.

KB Knowledge Base.

K-NN K-Nearest Neighbors.

LDA Latent Dirichlet Allocation.

LSA Latent Semantic Analysis.

LSTM Long Short-Term Memory.

NED Named Entity Disambiguation.

NEL Named Entity Linking.

NER Named Entity Recognition.

NLP Natural Language Processing.

NMT Neural Machine Translation.

OOV Out-of-vocabulary.

PCA Principal Component Analysis.

RCNN Recurrent Convolutional Neural Network.

ReLU Rectified Linear Unit.

RNN Recurrent Neural Network.

SGD Stochastic Gradient Descent.

sLDA Spatial Latent Dirichlet Allocation.

SVM Support-Vector Machine.

TextCNN Convolutional Neural Network for Text Classification.

TextRNN Recurrent Neural Network for Text Classification.

TF-IDF Term Frequency–Inverse Document Frequency.

TN True Negative.

TP True Positive.

TPU Tensor Processing Unit.

VDCNN Very Deep Convolutional Neural Network.

VSM Vector Space Model.

WSD Word Sense Disambiguation.

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1 Introduction

1.1 Motivation

The advent of the World Wide Web (WWW) and the digitization of all areas of our lives have led to an explosive growth of globally available data in recent decades. Among these resources, text data has the largest quantity. How to automatically classify, organize and manage the vast data has become a research topic with important purposes. Natural language processing (NLP) refers to the analysis and processing of human natural language by computers. It's an interdisciplinary subject between computer science and linguistics. Text classification, also known as text categorization, is a classical task in NLP. It aims to assign one or more predefined classes or categories to text documents. Text classification has a wide variety of application scenarios, for instance:

News filtering and organization. News websites contain a large number of articles. Based on the content of the articles, they need to be automatically classified by subjects. For example, news can be divided into politics, economics, military, sports, entertainment, etc.

Sentiment analysis and opinion mining. On the e-commerce websites, after clients have completed transactions, the products are positively commented or negatively commented. The merchants need to collect customer feedback to obtain an advice of what is working well about the product or service and what should be done to make experience better.

Email classification and spam filtering. It is often desirable to classify email in order to determine either the subject or to determine junk email from numerous emails in an automated way. This can significantly improve the experience of mailbox users.

Document organization and retrieval. The media receives a large number of submissions every day. We rely on text categorization technology to automatically review articles and mark erotic, violent, junk advertisement and other illegal content.

Traditional binary or multiclass text classification problems have been intensively studied in machine learning research[6][29]. However, when machine learning techniques are applied to short texts, most of the standard text classification approaches have the problems such as data sparsity and insufficient text length. Moreover, due to the lack of contextual information, short texts are highly ambiguous. As a result, simple text classification ap-

proaches based on words only, can not represent the critical features of short texts properly.

In this work, to overcome the mentioned shortness and sparsity problem of short texts, we enrich text representation by utilizing words together with entities represented by the content of the given document. Additionally, we compare the performance of the model using pure words and the model using words as well as entities.

1.2 Contribution

In this work a novel neural network based approach of short text classification is proposed. We utilize and modify the convolutional neural network for sentence classification proposed by Kim (2014)[28]. Our model is not only trained on top of pre-trained word vectors, but also on top of pre-trained entity vectors. Tagme implemented by Ferragina et al. (2010) [20] is first used to extract named entities from documents. We then utilize Wikipedia2Vec model developed by Yamada et al. (2018)[57] to get entity vectors. The impact of different kinds of word vectors on the classification accuracy is also studied in this work. Comprehensive experiments have been carried out to explore the classification performance of different neural network architectures.

1.3 Thesis Structure

The next chapter provides some background knowledge so we are able to gain a basic understanding of the process of text classification. Chapter 3 introduces previous work of short text classification and text classification with entities which is similar to our work. Especially, various deep learning approaches for text classification, their advantages and disadvantages are discussed. Chapter 4 introduces Wikipedia2Vec model and its submodels because Wikipedia2Vec is utilized to get entity vectors in our work. Our main contribution of this work is presented in chapter 5, convolutional neural network for text classification with words and entities. Chapter 5 explains the basics of recurrent neural network and long short-term memories. Our investigated experiments, evaluation and analysis of the utilized models can be found in chapter 7. Finally we conclude with chapter 8, which summarizes important aspects of this work and briefly discusses some possible future work.

2 Background

2.1 Text Classification

Text classification application

Text classification can be used in a wide variety of real world applications.
Basically speaking there are four different types of classification tasks. Binary classification is the task of classifying texts of a given set into two classes. For example, when given two labels we just need to figure out is the email spam or not spam, or is the customer review positive or negative. In multi-class classification where we have a set of classes that a particular document can have, we need to identify which class it is. For example, is the news sports, scientific or politics. Multilabel classification is an extension of the previous type where a given text can have multiple labels so it could not just be part of one class but part of multiple classes. Finally when we try to group a bunch of documents, we do not know their labels, so we need to learn the structure of the given documents, and this is called clustering.

Text classification type

There are three different types of methods that we can use to classify documents. Manual classification by hand, we try to figure out which category it should be. This method has its own merits in the sense that it is quite accurate and it would be consistent in terms of its classification results assuming it is done by experts in that domain. The downside is that it is pretty slow and expensive. Rule-based classification is very accurate if the rules are suitable to our tasks. The shortcoming is that we need to manually build and maintain a rule-based system, if we want to add a new criteria we need to come up with a new rule for that. The main idea of statistical classification methods is that we automatically learn how to classify the documents. It can scale well, can be accurate if we set it well and it is automatic because it is done by computers. The disadvantage is that it requires lots of training data so we need the documents which we want to classify as well as the labels and classes which are not associated with the documents. The weakness is obviously that it requires a lot of data, sometimes a huge amount of data, which is normally hard to get and thus can be a serious problem.

Text classification definition

Statistical classification is that we assume some texts are represented by t and some corresponding classes c. We want to learn the probability of t being of class c, that is:

$$P(c|t) \tag{2.1}$$

We can think of text classification tasks as a two stage process. Text representation is we process text into some (fixed) representation given documents. It is about how we can learn t. Text classification is that we want to classify this document given previous representation. It's about how to learn $P(c|t)$.

Short text classification

Short texts usually refer to texts that are relatively short in length and generally do not exceed 160 characters, such as tweets, chat information, news topics, opinion comments, question texts, mobile phone text messages, and document summaries.

2.2 Text Representation (Feature Engineering)

Feature engineering is often not only the most labor-intensive and time-consuming in machine learning, but also is extremely important. Feature engineering is different from classifiers and does not have wide versatility. It often needs to be combined with the understanding of a specific task. The NLP domain to which the text classification problem belongs naturally also has its own way of dealing with features. Most work of the traditional classification tasks is also carried out here.

As shown in Figure 2.1, text feature engineering can be divided into three parts: text preprocessing, feature extraction and feature selection.

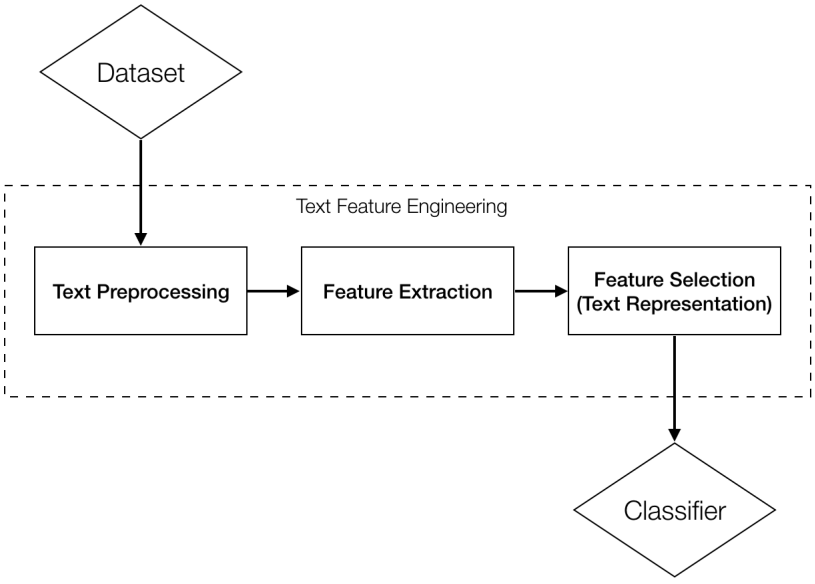


Figure 2.1: Text Classification Process

Text preprocessing

Most text data in their raw format aren not well structured and contain lots of unnecessary information such as misspelled words, stop-words, punctuations and emojis, etc. Especially, word segmentation is considered to be a quite important first step for Chinese NLP tasks, because unlike English and any other Indo-European languages, Chinese words can be composed of multiple characters with no spaces appearing between them. Text preprocessing involves a variety of techniques to convert raw text data into cleaned and standardized sequences, which can further improve the performance of classifiers. Detailed preprocessing methods will be discussed in our experiments. Table 1 and 2 are two Chinese to English translations with different word segmentation methods.

中外	科学	名著	
chinese and foreign	scientific	masterpiece	✔
中	外科学	名著	
mid	surgery	masterpiece	✘

Table 1: Chinese to English translation of 中外科学名著 with different word segmentation methods

北京	大学生	前来	应聘	
Peking	undergraduates	come to	apply for jobs	✔
北京大学	生前	来	应聘	
Peking university	while living	come to	apply for jobs	✘

Table 2: Chinese to English translation of 北京大学生前来应聘 with different word segmentation methods

Feature extraction and text representation

The purpose of text representation is to convert preprocessed texts into a form which computer can process. It's the most important part which determines the quality of text classification. Traditional feature extraction techniques include syntactic word representations such as n-gram, weighted words such as bag-of-words (BoW), and semantic word representations (word embeddings) such as word2vec, GloVe, etc. Note that vector space model (VSM)[49] refers to the data structure for each document and BoW refers to what kind of information we can extract from a document. They are different aspects of characterizing texts.

BoW is a simple but powerful model to represent text documents. What we need is just to convert text documents into vectors. Only the uni-gram words are extracted, no

syntax, no semantics and no word position information. Each document is converted into a vector which represents the frequency of all distinct words that present in the document vector space.

Here are two simple text documents:

```
(1) I don't like this type of movie, but I like this one.
(2) I like this kind of movie, but I don't like this one.
```

The uni-grams of these two text documents are:

```
I, don't, like, this, type, of, movie, but, I, like, this, one
I, like, this, kind, of, movie, but, I, don't, like, this, one
```

Each bag-of-words can be represented as:

```
BoW1 = {I:2, don't:1, like:2, this:2, type:1, of:1, movie:1, but:1, one:1}
BoW2 = {I:2, like:2, this:2, kind:1, of:1, movie:1, but:1, don't:1, one:1}
```

The document vector space is:

```
{I, don't, like, this, type, of, movie, but, one, kind}
```

The corresponding document vectors are:

```
[2, 1, 2, 2, 1, 1, 1, 1, 1, 0]
[2, 1, 2, 2, 0, 1, 1, 1, 1, 1]
```

The biggest shortcoming of this representation is that it ignores text contexts. Every word is independent of each other and thus can not represent the semantic information of texts. We can find that these two document vectors are extremely similar in the above example, which demonstrates that the two sentences have very likely the same meaning. However they mean the exact opposite. In general, the lexicon in real world applications is at least one million in size, so BoW model has two serious problems: high dimension and high sparsity. BoW is the basis of vector space model, so in vector space model we can reduce the dimension by using feature selection methods and increase the density by calculating feature weighting factors.

Some algorithms are used to reduce dimensionality, such as principal component ana-

lysis (PCA), independent component analysis (ICA), linear discriminant analysis (LDA), and latent semantic analysis (LSA), etc. The textual representations using these machine learning methods are generally considered to be deep representations of the documents. In addition, distributed semantic word representations are seen as the foundation of deep learning methods.

Feature selection
When doing the task of text categorization, it is often necessary to extract features from the documents. Normally we train the model using part of the features which are useful for learning, rather than using all the features which will eventually lead to curse of dimensionality[8] problems.

The feature selection process includes the selection of extracted features and the calculation of feature weights.

The basic idea of feature selection is to rank the original features independently according to an evaluation metric, we then select some features with the highest score, and filter out the remaining features. Commonly used supervised feature selection methods include Relief, Fisher score and Information Gain[35] based methods, etc.[16] Note that feature selection methods should be distinguished from feature extraction techniques. Feature extraction is that we create new features from the original datasets, whereas feature selection returns a subset of the initial features. Feature weight calculation mainly refers to the classic statistical method, term frequency–inverse document frequency (TF-IDF) method and its extensions.

2.3 Text Classification (Classifiers)

Discriminative methods which directly estimate a decision boundary, such as logistic regression and support vector machine (SVM), generative models which build a generative statistical model such as naïve bayes, and instance based classifiers which use observations directly, such as k-nearest neighbor (K-NN), are more traditional but still commonly used machine learning classification approaches. Tree-based classification algorithms, such as decision tree and random forests are fast and accurate for text classification.

Deep learning has a significant influence in the fields of image processing, speech recognition, and NLP. The influence of deep learning on NLP and especially on text classification is mainly reflected in the following aspects.

End-end training

In the past, when doing statistical natural language processing, experts need to define various features and need a lot of domain knowledge. Sometimes it is not easy to find a good feature. But with end-to-end training, as long as there are pairs of inputs and outputs (input-output), what we need to do is just labeling the output corresponding to the input in order to form a training data set. The learning system can be then established through automatic training using neural networks, without artificial settings and carefully designed features. This has changed the development of many NLP technologies and greatly reduced the technical difficulties of NLP. This means that as long as we have enough computational resources (GPU, TPU) and labeled data, we can basically implement the NLP model and get really good results, which promotes the popularity of NLP technologies.

Semantic representation (word embeddings)

One of the commonly used semantic representations is context-free embedding, which means that the representation of a word is fixed (represented by a multi-dimensional vector) regardless of its context. The other representation depends on the context of different sentences, the meaning of the same word might be different, so its embeddings are also accordingly different. Now using models like BERT and GPT, we can train and obtain the dynamic embedding of a word based on its context.

Pre-trained model

We know that neural networks need to be trained with data, they extract information from data and convert them into corresponding weights. These weights can be then extracted and transfered to other neural networks. Because we've transfered these learned features, when we try to solve a similar problem, we don't need to train a new neural network model from scratch, instead we can start with models that have been trained to solve similar problems. By using pre-trained models which are previously trained with massive amounts of data, we can apply the corresponding structures and weights directly to the problems we are facing. This process is called `Transfer Learning`. Since the pre-trained models have been well trained, we don't need to modify too many weights, what we need to do is just modifying some parameters. And this is called `Fine Tuning`. As a result, the pre-trained model can significantly reduce the training time.

Sentence encoding methods (CNN/RNN/LSTM/GRU/Transformer)

For a sentence of variable length, it can be encoded with RNN, LSTM, GRU or Transformer. Although these several encoding methods for sentences are feasible, recently we tend to use Transformer to encode sentences. We can apply the encoded sentences in various

NLP applications such as machine translation, question answering, language modeling, sentiment analysis, text classification and so on.

Attention

Encoder-Decoder model[52], or sequence to sequence (seq2seq) model, was first introduced in 2014 by Google. In an Encoder-Decoder neural network, a set of RNNs / LSTMs / GRUs encode an input sequence into a fixed-length internal representation, another set of RNNs / LSTMs / GRUs read this internal representation and decodes it into an output sequence. The length of the input and output sequences might differ. This Encoder-Decoder architecture has achieved excellent results on a wide range of NLP tasks, such as question answering and machine translation. Nevertheless, this approach suffers from the problem that neural networks are forced to compress all the necessary information of an input sequence into a fixed-length internal vector, which makes it difficult for neural networks to deal with longer sequences, especially those in the test set which are longer than the sequences in the training set.[7] First, the internal semantic vector cannot fully represent the information of the entire input sequence. Second, the pre-existent information will be overwritten by the newly input messages.

The attention mechanism is a way to free the Encoder-Decoder structure from fixed-length internal representations. It maintains the encoder's intermediate outputs from each step of the input sequences, and then trains the model to learn how to selectively focus on the inputs and relate them to the items in the output sequences. In other words, each item in the output sequence depends on the selected item in the input sequence.[1]

Although this mechanism increases the model's computational complexity, it is able to result in a better performance, even state-of-the-art. Additionally, the model can also show how to pay attention to input sequences when predicting output sequences. Unlike the situation in computer vision, where several approaches for understanding and visualizing CNNs have been developed, it's normally pretty hard to visualize and understand what neural networks in NLP have learned.[5] Thus this mechanism helps us to understand and analyze what the model is focusing on and how much it focuses on a particular input-output pair. Further attention visualization examples can be found in machine translation[7], text summarization[48], speech recognition[13] and image descriptions[56], etc.

3 Related Work

A central study in text classification is feature representation, which is commonly based on the bag-of-words (BoW) model. Besides, feature selection methods, such as TF-IDF model, LSA, sLDA, are applied to select more discriminative features. The major classifiers in the traditional machine learning era are mainly based on naïve bayes, maximum entropy, k-nearest neighbor (K-NN), decision tree and support-vector machine (SVM). Traditional machine learning algorithms for text classification are well summarized in [6][29].

3.1 Text Classification

Text categorization escapes the process of artificial feature design, text similarity comparison and distance definitions in the era of deep learning, but still can not escape the choice of text preprocessing, feature extraction, model selection, parameter optimization, coding considerations (one-hot, n-gram, etc.) and time cost trade-off.

In summary, there are six main types of deep learning models:

(1) Vector representation of words: word2vec, GloVe, FastText, BERT, GPT, ELMo, etc.

(2) Convolutional neural network feature extraction: TextCNN, CharCNN, DCNN, VD-CNN, etc.

(3) Pre-training & multi-task learning: BERT, GPT, ELMo, etc.

(4) Context mechanism: TextRNN, BiRNN, RCNN, etc.

(5) Memory storage mechanism: EntNet, DMN, etc.

(6) Attention mechanism: HAN, etc.

In the following paragraph we will get into a little details of the above models and get a global picture of the application and development of deep learning in text classification in recent years.

3.1.1 Vector Representation of Words

FastText[25], which is not much innovative in academics but has very outstanding performance, was proposed by Mikolov's team in Facebook in 2016. FastText (shallow network)

can often achieve the accuracy comparable to deep network in text classification, but is many orders of magnitude faster than deep network in training time. The core idea of FastText is to superimpose the word and n-gram vectors of the whole document to obtain a document vector, then we use this document vector to do softmax multiclassification. There are two techniques involved: character-level n-gram features and hierarchical softmax classification. Hierarchical softmax is first introduced in word2vec which we will discuss in the next chapter, so here we only focus on character-level n-gram.

Word2vec treats each word in the corpus as atomic. For each word it generates a vector, which ignores the words' internal morphological features. For example, "country" and "countries", these two words have many characters in common, in other words, they have similar internal forms. However, in traditional word2vec model, such words lose this internal information when converted to different IDs. To overcome this problem, FastText uses character-level n-grams to represent a word. For word "country", assuming that the value of n is 3, then its trigram are as follows:

<co, cou, oun, unt, ntr, try, ry>

where < indicates a prefix and > indicates a suffix. So we can use these trigrams to represent word "country". Furthermore, we can stack and add up the vector of these seven trigrams to represent word "country".

This brings two benefits: First, it will generate better word vectors for low frequency words, because their n-grams can be shared with other words. Second, for out-of-vocabulary (OOV) words, we can still produce their word vectors by superimposing their character-level n-gram vectors. Whereas in word2vec OOV words are either zero or randomly initialized.

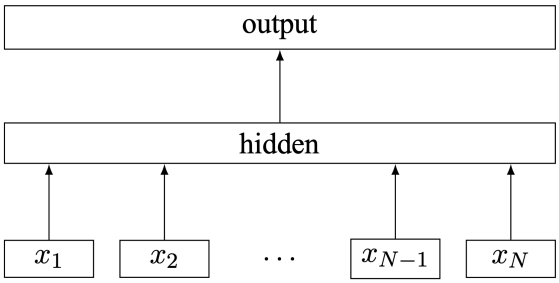


Figure 3.1: Model architecture of `FastText` for a sentence with N ngram features $x_1, ..., x_N$. The features are embedded and averaged to form the hidden variable.

As we can see in Figure 3.1, like Continuous Bag of Words (CBOW), FastText has three layers: input layer, hidden layer and output layer (hierarchical softmax). They have something in common. Their input are words represented by multiple vectors; they have a specific target value; the hidden layers are averages of multiple superimposed word vectors. The difference is that the input of CBOW is the context of the target word whereas the input of FastText is multiple words and their character-level n-gram features, which are used to represent a single document; the input words of CBOW are one-hot vectors whereas the input of FastText are embedded vectors; the output of CBOW is the target word where the output of FastText is the class label corresponding to the document.
In a word, FastText is a pretty simple but violent classification model. For paragraph reasons, global vectors for word representation (GloVe) will not be discussed here.

3.1.2 Convolutional Neural Network Feature Extraction

TextCNN[28], which has become a classical deep learning model in text categorization, was proposed by Kim in 2014.

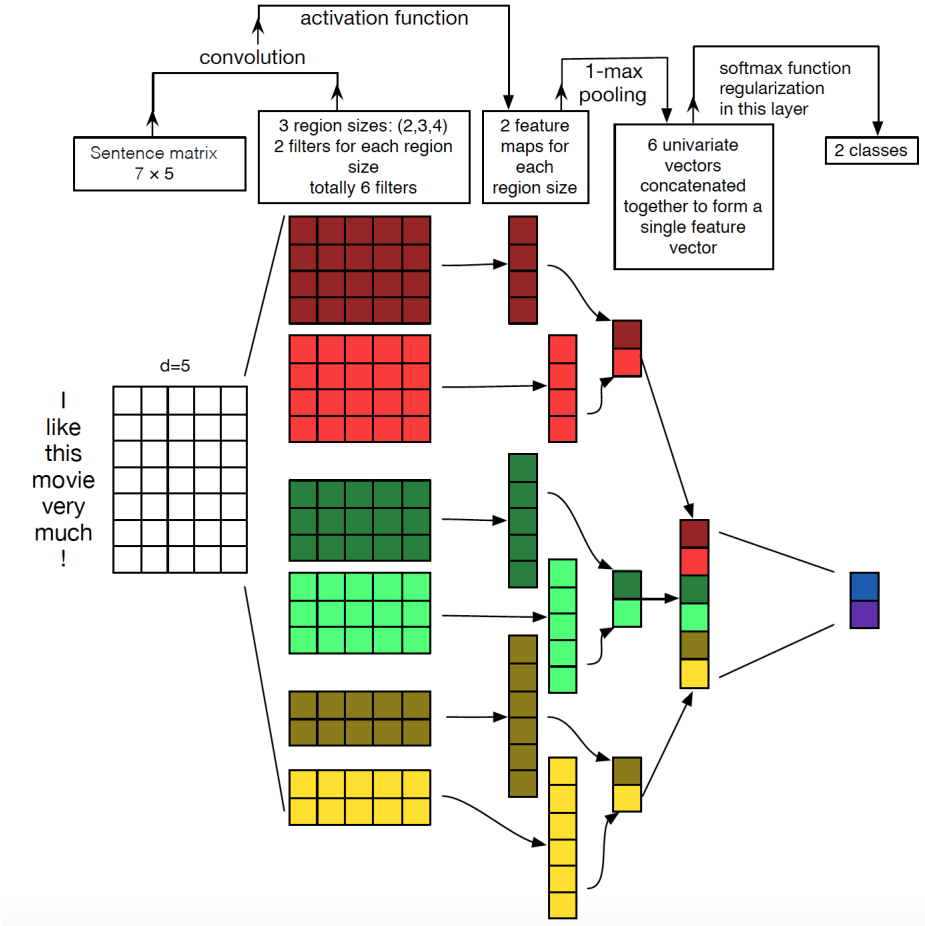


Figure 3.2: CNN architecture for sentence classification (adopted from Zhang 2014 [63])

As shown in Figure 3.2, the input layer is a 7×5 matrix. 5 is the word vector dimension and the sentence length is 7. The second layer uses 3 sets of convolution kernels with width of 2, 3 and 4, each size has 2 kernels. Each of the convolution kernels slides over the whole sentence to generate a feature map. In the figure, the kernel does not use padding during the sliding process. The convolution kernel with width of 4 slides over the sentence of length 7, we can get a feature map of length 4. 1-max pooling is performed over each map. Thus a univariate feature vector is generated from all the 6 maps, and these 6 features are concatenated to form one final feature vector. The final output layer receives this feature vector as input and uses it to classify the sentence.

Over the last several years deep learning methods especially convolutional neural networks (CNN) have been shown to outperform previous state-of-the-art machine learning techniques in computer vision. But when CNN is first used in NLP, we're faced with different problems.

The max pooling operation in CNN has advantages: it has feature's position and rotation invariant characteristics, because no matter where the feature appears in a sentence, it can be extracted regardless of its position. Besides, max pooling can reduce the number of model parameters, which is beneficial to reduce the model over-fitting problem. However in NLP this advantage isn't necessarily a good thing, because in many NLP applications the location information of the features is very important, for example, negative words appear in different positions, resulting in completely different sentence meanings:

```
I don't like this type of movie, but I like this one.
I like this kind of movie, but I don't like this one.
```

So for TextCNN the completely loss of feature's location information is its Achilles' heel. In summary, in TextCNN convolution is used to extract key information similar to n-grams. We are able to capture features between multiple consecutive words and share weights and biases when calculating the same type of features.

The overall performance of TextCNN is good, but there are problems. The local receptive field size (filter size) is fixed, it is difficult to determine the filter size. The ability to model longer sequence is limited. Most importantly, the feature's location information is lost.

Based on CNN, some models are proposed recently. Especially, due to the above problems, several works have been done.

Kalchbrenner and Blunsom et al. (2014)[27] introduced dynamic convolutional neural

network (DCNN). It uses dynamic k-max pooling, where the result of pooling isn't a maximum value, but the k-maximum values, which is a subsequence of the original input. This brings several benefits. The dynamic k-max pooling better preserves multiple important information in a sentence. The number of extracted features varies according to the length of the sentence. Besides, it preserves the relative positions between words and the word position information. It also takes into account the semantic information between words which are far away in a sentence.

Zhang et al. (2015)[63] conducted a variety of very good comparative experiments on CNN models mentioned in [28], and provide us with some CNN architecture and hyper-parameter setting advice.

Zhang and LeCun (2015)[62] proposed character-level convolutional neural network (Char-CNN) which is also an effective model. The most important point of their experimental conclusion is that this model can classify text without using words, which strongly suggests that the human language can also be considered as a signal that is no different from any other type of signals.

Conneau and Lecun et al. (2016)[14] first used very deep convolutional neural network (VDCNN) in NLP. Prior to their work, normally very shallow CNNs are used in text categorization. In their work they utilize 29 convolution layers to improve the accuracy of text classification. They get some important discoveries by exploring deep architectural approaches: VDCNN performs better on big datasets; deeper network depth can improve the model performance; etc.

Zhang and LeCun (2017)[61] did an interesting experiment which shows that FastText model has better results in character-level encoding for Chinese, Japanese, and Korean texts (CJK language), and better results in word-level encoding for English texts.

3.1.3 Pre-training & Multi-task Learning

Pre-training is a conventional method in computer vision since deep learning has become popular. We already know that for hierarchical CNN structure, neurons of different layers can learn different types of image features. For example, if we have a face recognition task, after having trained the network, we visualize the features learned by each layer of neurons, we will see that the lowest hidden layer of neurons learn has learned features such as colors and lines, the second layer facial organ, and the third layer facial contour. The lower the layer, the more basic the features. The upper the layer, the more related to the task the extracted features. Because of this, the pre-trained network parameters, espe-

cially the features extracted from the bottom layers, are more independent of the specific task, and more general. This is why we normally initialize new models with pre-trained parameters of bottom layers.

What about NLP? The general choice for pre-training in NLP is to use language models. The neural probabilistic language model introduced by Bengio et al. (2003)[9] can not only predict the next word given the last few words, but also obtain a by-product, a matrix, which is actually the word embedding matrix. Ten years later, the word2vec model proposed by Mikolov et al. (2013)[40], which simply aims to obtain word embeddings, has become more and more popular.

So what is pre-training in NLP? Given a NLP task, such as text classification or question answering, each word in a sentence is one-hot encoded as input, then multiplied by the learned word embedding matrix, so we get the words' corresponding embeddings. This seems to be a looking-up operation, but in fact, the word embedding matrix is actually the network parameter matrix which maps the one-hot layer to the embedding layer. So in other words, the network from one-hot layer to embedding layer is equivalently initialized with this pre-trained embedding matrix.

However the most serious problem with previous word embedding models is they can not deal with polysemy. We know that polysemy is a phenomenon that often occurs in human languages. What's the negative impact of polysemous words on word embeddings? For example:

`He jumped in and swam to the opposite bank.`
`My salary is paid directly into my bank.`

As shown above, "bank" has two meanings, but when we encode this word, the word embedding model can't distinguish between these two meanings. Despite the fact that the contextual words of these two sentences are different, when the model being trained, it will always predict the same word "bank". The same word "bank" occupies the same word embedding space (the same line in the matrix) of the model, which causes two different context information encoded into the same parameter space. As a result, word embeddings can't distinguish the different semantics of polysemous words.

Researchers have made an astonishing and huge progress in NLP in 2018. Large-scale pre-trained language models like OpenAI GPT and BERT perform quite well on various NLP tasks using generic model architectures. The idea is similar to pre-training in computer vision that we have discussed previously. But even better than that, the newly

proposed approaches do not require labeled data for pre-training. They make use of unlabeled data, which is obviously inexhaustible in real world, allowing us to extract a large amount of linguistic knowledge and encode them into the models. Integrating linguistic knowledge as much as possible will naturally enhance the generalization ability of the models, especially when we have limited amount of data. And introducing priori linguistic knowledge has always been one of the main purposes of NLP, especially in deep learning scenarios.

Deep contextualized word representations (ELMo) proposed by Peters et al. (2018)[44] dynamically adjust word embedding based on current context. The core idea of ELMo is that, we first learn word embeddings after we have trained language model, at this time the polysemous words still can not be distinguished. But when we actually use word embeddings, the words already have a specific context. Then we can adjust the word embedding according to the semantics of the word. The adjusted word embedding can better express the specific meaning in its context, which cleverly solve the problem of polysemy.

ELMo has a typical two-phase process. The first step is the use of language models for pre-training, called feature-based pre-training. The second step is to extract the word embedding of the corresponding word in each layer of the pre-trained model. Each word in a sentence can get three embeddings: in the bottom layer we get word embedding; the embedding in the first layer of long short-term memory (LSTM) captures word's syntactic information; the embedding in the second layer of LSTM captures word's semantic information. We then combine the extracted embeddings together as a new feature in the downstream NLP tasks. ELMo can improve its performance in 6 different NLP tasks.

Generative pre-training model (OpenAI GPT) introduced by Radford et al. (2018)[45] also has a two-phase training process, see Figure 3.3. In the first phase we use the language model for pre-training and in the second phase we fine-tune the model to solve downstream tasks. Despite of the similarity between GPT and ELMo, GPT has two major differences from ELMo. The first difference is that in GPT's second step, we need to fine-tune the same base model so that we can use it in the following downstream tasks. We also need substantial task-specific architecture modifications. The second difference between GPT and ELMo is that GPT uses Transformer as its feature extractor. Transformer, introduced by Vaswani et al. (2017)[54], which is first used in neural machine translation (NMT), is a novel neural network architecture based on a self-attention mechanism. Why do we use Transformer here? Because Transformer is currently the best feature extractor. Transformer outperforms recurrent neural network (RNN) because RNN can not be parallelized. Transformer also outperforms CNN because it can capture long-distance features. Additionally, in the pre-training step of GPT, although we still use the language model as

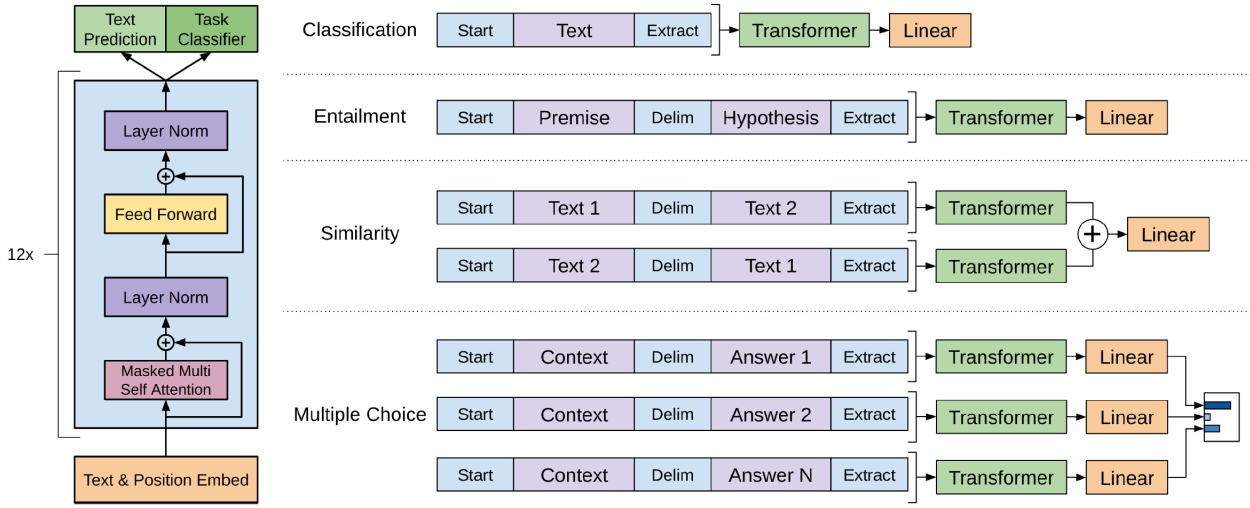


Figure 3.3: (**left**) `Transformer` architecture and training objectives used in `GPT`. (**right**) Input transformations for fine-tuning on different tasks. We convert all structured inputs into token sequences to be processed by the pre-trained model, followed by a linear+softmax layer. (adopted from [45])

target task, we adopt a single-direction language model. That is, one limitation with GPT is that it is only trained to predict the future left-to-right context, without right-to-left context. The result of GPT is very amazing. It achieves the best results in 9 out of 12 NLP tasks.

Now we finally come to the new language representation model, deep bidirectional encoder representations from transformers (BERT), proposed by Devlin et al. (2018)[18], which obtains new state-of-the-art results in 11 NLP tasks including text classification. BERT has the same two-phase process as GPT. It is designed to pre-train deep bidirectional representations by jointly conditioning on both left and right context in all layers. The pre-trained BERT representations can be fine-tuned with just one additional output layer. They also proposed masked language model and next-sentence prediction method in order to pre-train the model in both forward and backward directions. BERT input representations are the sum of the token embeddings, the segmentation embeddings and the position embeddings.

There is a close relationship between the above 3 models, see Figure 3.4. If we change GPT model in the pre-training phase by using bidirectional language model, then we will get BERT. If we replace ELMo's feature extractor LSTM with Transformer, we will also get BERT.

In summary, inductive transfer learning consists of two steps: pre-training, in which the

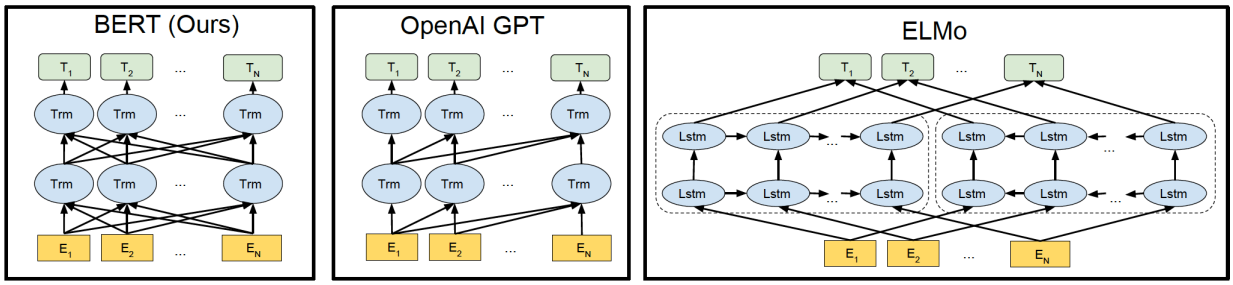


Figure 3.4: Differences in pre-training model architectures. `BERT` uses a bidirectional Transformer. `OpenAI GPT` uses a left-to-right Transformer. `ELMo` uses the concatenation of independently trained left-to-right and right-to-left LSTM to generate features for downstream tasks. Among three, only `BERT` representations are jointly conditioned on both left and right context in all layers. (adopted from [18])

model learns a general-purpose representation of inputs by using a specific feature extractor (RNN, LSTM, Transformer), and adaptation, in which the representation is transferred to a new task.[43] As we discussed previously, there are two main paradigms for adaptation: feature ensemble (ELMo) and fine-tuning (GPT, BERT). For ELMo, we extract contextual representations of the words from all layers by feeding the input sentence into pre-trained bidirectional LSTM network. During adaptation, we learn a linear weighted combination of word embeddings in all layers which is then used as input to a task-specific architecture in downstream tasks. In contrast, for GPT and BERT, after obtaining the pre-trained model, during fine-tuning (adaption), we still adopt the same model, use part of the training data of the downstream task, train on the same model to correct the network parameters obtained during the pre-training stage. We only need a task-specific output layer. So which paradigm is better? Peter et al. (2019)[43] did some research to empirically compare feature ensemble with fine-tuning approaches across diverse datasets. They come to a conclusion that the relative performance of two approaches depends on the similarity of the pre-training and target tasks. So for BERT, we would better fine-tune the model.

3.1.4 Context Mechanism

We know that the nature of convolution is to extract features. Deep learning is about feature representation learning. But documents or sentences are sequences, that is, the previous input is related to the subsequent input. So thinking about to use RNN to deal with texts seems to be reasonable. Recurrent neural network for text classification (TextRNN) proposed by Liu et al. (2016)[37], whose architecture is similar to TextCNN, is the first RNN model to classify documents. RNN and its variants can capture variable-length and bidirectional n-gram information. But it has disadvantages. As far as I'm concerned,

this model is not recommended because the training speed of RNN is very slow. RNN is also a biased model, in which later words are more dominant than earlier words.

Recurrent convolutional neural network (RCNN) which was introduced by Lai et al. (2016)[33] is a combination of CNN and RNN. They employ a bidirectional RNN to capture the contexts and learn the word representations. They also employ max-pooling to automatically determine which feature plays a more important role in text classification. This model runs faster than RNN and gets a good result in three of the four commonly used datasets.

3.1.5 Memory Storage Mechanism

Typical Encoder-Decoder model's performance is limited by the size of its memory, especially when dealing with longer sequences. This limitation can be solved by a strategy called attention mechanism which was proposed by Bahdanau et al. (2014)[7]. We can also refine the attention mechanism by adding a separate, readable and writable memory component. Dynamic memory networks (DMN) which was proposed by Kumar et al. (2016)[32] has four modules: input module, question module, episodic memory module and answer module. Here the input is a list of sentences, the question module is equivalent to the gated units which uses the attention mechanism to selectively store the input information in the episodic memory module. Then the output of episodic memory is answered by the answer module. The DMN obtains state-of-the-art results on several types of tasks and datasets including text classification.

3.1.6 Attention Mechanism

Hierarchical attention network (HAN) proposed by Yang et al. (2016)[59] is another model in which attention mechanism is introduced. The basic idea of HAN is that we first consider the hierarchical structure of documents: a sentence is a group of words, a document consists of several sentences. So we can divide documents hierarchy into three layers, that is: words, sentences and texts. We use two bidirectional LSTMs to model word-sentence and sentence-document. Second, different words and sentences contain different information thus they can not be treated equally. The attention mechanism is introduced in each model to capture longer dependencies. From this we derive the importance of different words and sentences when constructing sentences and texts accordingly.

The HAN model structure is very consistent with the human understanding process: word $\rightarrow$ sentence $\rightarrow$ document. The most important thing is that the attention layers can be well visualized when providing us with better classification accuracy. At the same

time, we can find that the attention part has a great influence on the expression ability of the model.

3.2 Short Text Classification

Traditional machine learning methods for short text classification are mainly based on widely used machine learning models, such as SVM, etc. Next we focus on deep learnings methods for short text classification which has dominated in research in recent years.

Wang et al. (2017)[55] introduced knowledge from a knowledge base and combine words with associated concepts to enrich text features. They also use character level information to enhance word embeddings. They finally build a joint CNN model to classify short texts. Our work is similar to their work, the difference is that we enrich word embeddings with entities while they utilize concepts. We also adopt the same datasets they used in the experiments.

Zeng et al. (2018)[60] proposed topic memory networks which jointly explore latent topics and classify documents in an end-to-end system.

3.3 Text Classification using Named Entities

There is not much research work about text classification using named entities. Kral (2014)[30] compared five different approaches to integrate named entities using naïve bayes classifier on Czech corpus in his work. The experimental results show that entity features do not significantly improve the classification performance over the baseline word-based features. The improvement is maximum 0.42%.

4 Wikipedia2Vec and Doc2Vec

One of our main concerns is to get good entity vectors. Our entity vectors are generated by using Wikipedia2Vec and Doc2Vec. Wikipedia2Vec, which is implemented by Yamada et al. (2018)[57], is an open source tool used for obtaining vector representations of words and entities from large corpus Wikipedia. This tool enables us to learn both the vectors of words and entities simultaneously and thus places similar words and entities close to each other in a high dimensional continuous vector space. Compared with existing embedding tools such as Gensim[46], FastText[25] and RDF2Vec[47], this tool has been proved to be the state-of-the-art NLP model in the named entity disambiguation (NED) task.

4.1 Word2vec and Skip-gram

The word2vec model, which was proposed by Mikolov et al. (2013)[40], has caught researchers a numerous amount of attention in recent years. The core idea of word2vec is to characterize one word through the neighbors of this word with prediction between every word and its context words. The word vector representations produced by the model have been proven to carry semantic features and can be subsequently used in many natural language processing applications and further research.

Word2vec actually contains two algorithms, that is, skip-gram, which predicts context words given target; continuous bag of words (CBOW), which predicts target word from bag-of-words context. The model also contains two moderately efficient training methods, hierarchical softmax and negative sampling[39].

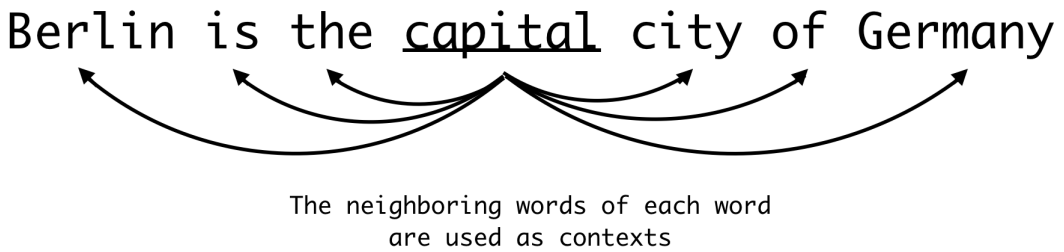


Figure 4.1: Word based skip-gram model

We now focus on skip-gram algorithm. Given a sentence of T words w_1, w_2, ..., w_T, for each word $t = 1 \ldots T$, we predict surrounding words in a window of "radius" m of every word. Here m is the size of the context window, w_t denotes the center word and w_{t+j} is its

context word. The objective function is to maximize the probability of any context word given the current center word. We want to maximize the following objective function:

$$J'(\theta) = \prod_{t=1}^{T} \prod_{\substack{-m \le j \le m \\ j \neq 0}} P(w_{t+j}|w_t; \theta) \tag{4.1}$$

Machine learning likes minimizing things so we add minus. T represents the normalization per word, so the objective function does not depend on the length of the sentence.

$$J(\theta) = -\frac{1}{T} \sum_{t=1}^{T} \sum_{\substack{-m \le j \le m \\ j \neq 0}} \log P(w_{t+j}|w_t) \tag{4.2}$$

So we minimize the negative log probability where θ represents all variables we will optimize.
For the conditional probability $P(w_{t+j}|w_t)$, the simplest formulation is:

$$P(o|c) = \frac{\exp(\boldsymbol{u}_o^{\mathrm{T}} \boldsymbol{v}_c)}{\sum_{w=1}^{V} \exp(\boldsymbol{u}_w^{\mathrm{T}} \boldsymbol{v}_c)} \tag{4.3}$$

where o is the outside (or output) word index, c is the center word index, v_c and u_o are "center" and "outside" vectors of indices c and o, V is a set containing all the words in the vocabulary. Note we have two vectors for each word because it makes math much easier. This softmax function uses word c to obtain probability of word o. We use softmax function because it's sort of a standard way to turn numbers into a probability distribution.

We now compute derivatives of equation 4.3 to work out minimum.

$$\frac{\partial}{\partial \boldsymbol{v}_c} \log \frac{\exp(\boldsymbol{u}_o^{\mathrm{T}} \boldsymbol{v}_c)}{\sum_{w=1}^{V} \exp(\boldsymbol{u}_w^{\mathrm{T}} \boldsymbol{v}_c)} = \frac{\partial}{\partial \boldsymbol{v}_c} \log \exp(\boldsymbol{u}_o^{\mathrm{T}} \boldsymbol{v}_c) - \frac{\partial}{\partial \boldsymbol{v}_c} \log \sum_{w=1}^{V} \exp(\boldsymbol{u}_w^{\mathrm{T}} \boldsymbol{v}_c) \tag{4.4}$$

For the left part of the formula, we have

$$\frac{\partial}{\partial \boldsymbol{v}_c} \log \exp(\boldsymbol{u}_o^{\mathrm{T}} \boldsymbol{v}_c) = \frac{\partial}{\partial \boldsymbol{v}_c} (\boldsymbol{u}_o^{\mathrm{T}} \boldsymbol{v}_c) = \boldsymbol{u}_o \tag{4.5}$$

For the right part of the formula, by using chain rule we have

$$\begin{aligned}
\frac{\partial}{\partial \boldsymbol{v}_c} \log \sum_{w=1}^{V} \exp(\boldsymbol{u}_w^{\mathrm{T}} \boldsymbol{v}_c) &= \frac{1}{\sum_{w=1}^{V} \exp(\boldsymbol{u}_w^{\mathrm{T}} \boldsymbol{v}_c)} \cdot \frac{\partial}{\partial \boldsymbol{v}_c} \sum_{x=1}^{V} \exp(\boldsymbol{u}_x^{\mathrm{T}} \boldsymbol{v}_c) \\
&= \frac{1}{\sum_{w=1}^{V} \exp(\boldsymbol{u}_w^{\mathrm{T}} \boldsymbol{v}_c)} \cdot \left(\sum_{x=1}^{V} \frac{\partial}{\partial \boldsymbol{v}_c} \exp(\boldsymbol{u}_x^{\mathrm{T}} \boldsymbol{v}_c) \right) \\
&= \frac{1}{\sum_{w=1}^{V} \exp(\boldsymbol{u}_w^{\mathrm{T}} \boldsymbol{v}_c)} \cdot \left(\sum_{x=1}^{V} \exp(\boldsymbol{u}_x^{\mathrm{T}} \boldsymbol{v}_c) \frac{\partial}{\partial \boldsymbol{v}_c} (\boldsymbol{u}_x^{\mathrm{T}} \boldsymbol{v}_c) \right) \\
&= \frac{1}{\sum_{w=1}^{V} \exp(\boldsymbol{u}_w^{\mathrm{T}} \boldsymbol{v}_c)} \cdot \left(\sum_{x=1}^{V} \exp(\boldsymbol{u}_x^{\mathrm{T}} \boldsymbol{v}_c) \boldsymbol{u}_x \right)
\end{aligned} \tag{4.6}$$

Combining formula 4.5 with 4.6 we get the final derivative of conditional probability $P(w_{t+j}|w_t)$, that is

$$\begin{aligned}
\frac{\partial}{\partial \boldsymbol{v}_c} \log(P(o|c)) &= \boldsymbol{u}_o - \frac{1}{\sum_{w=1}^{V} \exp(\boldsymbol{u}_w^{\mathrm{T}} \boldsymbol{v}_c)} \cdot \left(\sum_{x=1}^{V} \exp(\boldsymbol{u}_x^{\mathrm{T}} \boldsymbol{v}_c) \boldsymbol{u}_x \right) \\
&= \boldsymbol{u}_o - \sum_{x=1}^{V} \frac{\exp(\boldsymbol{u}_x^{\mathrm{T}} \boldsymbol{v}_c)}{\sum_{w=1}^{V} \exp(\boldsymbol{u}_w^{\mathrm{T}} \boldsymbol{v}_c)} \cdot \boldsymbol{u}_x \\
&= \boldsymbol{u}_o - \sum_{x=1}^{V} P(x|c) \cdot \boldsymbol{u}_x
\end{aligned} \tag{4.7}$$

Besides, we can observe that the minuend in formula 4.7 is an expectation, which is an average over all the context vectors weighted by their probability. The above formula is just the partial derivatives for the center word vector parameters. Similarly, we also need to compute the partial derivatives for the output word vector parameters. Finally, we have derivatives with respect to all the parameters and we can minimize the cost(loss) function using gradient descent algorithm.

4.2 Wikipedia2Vec

Wikipedia2Vec iterates over the entire Wikipedia pages. It extends the conventional word vector model (i.e., skip-gram model) by using two submodels: Wikipedia link graph model and anchor context model. It then jointly optimizes these three models.

4.2.1 Wikipedia Link Graph Model

Wikipedia link graph model[58] is a model which learns entity vectors by predicting neighboring entities in Wikipedia's link graph. Wikipedia's link graph is an undirected graph

whose nodes represent entities and edges represent links between entities in Wikipedia.

Entity linking (EL) is the task of recognizing (named entity recognition NER) and linking (named entity disambiguation NED) a named-entity mention to an instance in a knowledge base (KB), typically Wikipedia-derived resources like Wikipedia, DBpedia and YAGO.[12]

NED in NLP is a task to determine the identity of entities which are mentioned in documents. For example, given the sentence "Washington is the capital city of the United States", here we aim to determine that Washington refers to "Washington, D.C." and not to "George Washington", the first President of the United States. EL requires a KB that contains entities. Wikipedia2Vec is obviously based on Wikipedia, in which each page is regarded as a named entity. For example the page of Washington, D.C. in Wikipedia has a link to the page of United States, so there is an edge between this pair of entities. There are also some other cases, for example, Berlin has a link to Germany, Germany has a link to Berlin, both of the entities are linked to each other.

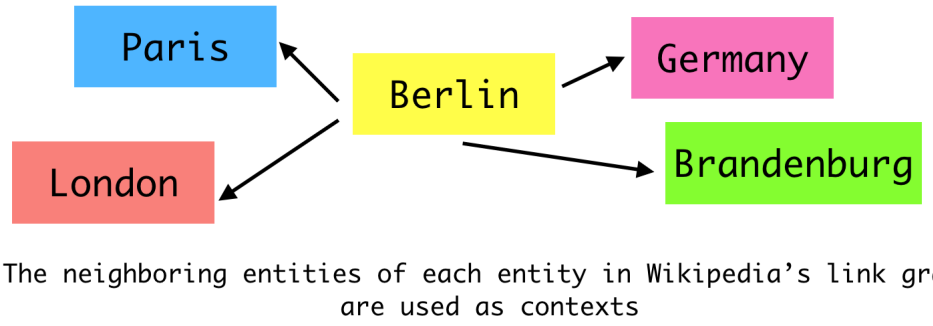


Figure 4.2: Wikipedia link graph model

Given a set of entities e_1, e_2, ..., e_n, for each entity e_i, we compute the probability of every entity in the set that is linked to this entity e_i. Here E denotes the set of all the entities in KB and S_e is the set of entities which has a link to entity e. We want to maximize the probability of any entity that has a link to entity e given this entity e. So we need to minimize this following objective function:

$$J_e = -\sum_{e_i \in E} \sum_{e_o \in S_{e_i}, e_i \neq e_o} \log P(e_o|e_i) \tag{4.8}$$

For the conditional probability $P(e_o|e_i)$, we compute it using the following softmax function:

$$P(e_o|e_i) = \frac{\exp(\boldsymbol{u}_{e_o}^{\mathrm{T}} \boldsymbol{v}_{e_i})}{\sum_{e \in E} \exp(\boldsymbol{u}_{e}^{\mathrm{T}} \boldsymbol{v}_{e_i})} \tag{4.9}$$

4.2.2 Anchor Context Model

So far we have learned entity vectors using entities and word vectors using words. We obtain these vectors by training two different models, so the words and entities are mapped into different vector spaces. We hope to map them into the same vector space so we introduce anchor context model[58] which learns entity vectors and word vectors simultaneously by predicting the context words given an entity.

In anchor context model, we want to predict the context words of an entity pointed to with target anchor.[58] Here A denotes the set of anchors in KB. Each anchor in A contains a referent entity e_i and a set of its context words S. The previous c and next c words of a referent entity are seen as its context words. The objective function is as follows:

$$J_a = -\sum_{(e_i,S) \in A} \sum_{w_o \in S} \log P(w_o|e_i) \tag{4.10}$$

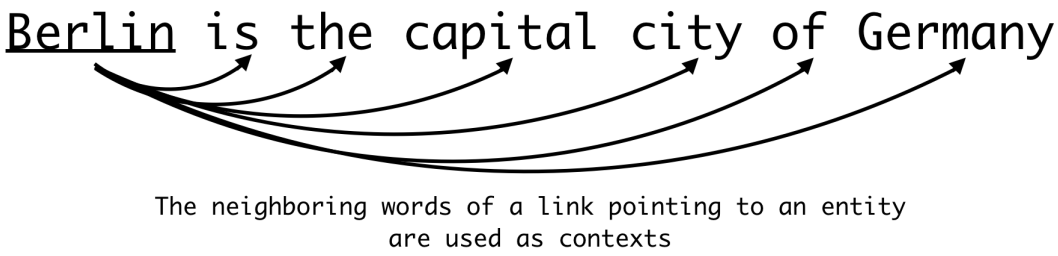


Figure 4.3: Anchor context model

For the conditional probability $P(w_o|e_i)$, we compute it using the following softmax function:

$$P(w_o|e_i) = \frac{\exp(\boldsymbol{u}_{w_o}^{\mathrm{T}} \boldsymbol{v}_{e_i})}{\sum_{w \in W} \exp(\boldsymbol{u}_{w}^{\mathrm{T}} \boldsymbol{v}_{e_i})} \tag{4.11}$$

4.3 Doc2Vec

Doc2Vec is proposed by Quoc Le and Tomas Mikolov in 2014.[34] Doc2Vec, also called Paragraph Vector, is an unsupervised algorithm, with which we are able to get fixed-length feature representations from variable-length documents. Doc2Vec can be used on text classification and sentiment analysis tasks.

Similar to word2vec, Doc2Vec also has two training algorithms, that is, distributed bag of words (DBOW) which is similar to skip-gram in word2vec, and distributed memory (DM) which is similar to continuous bag of words (CBOW) in word2vec. Especially, the input of DBOW is the paragraph vector. The model is trained to predict the words in a small window. In contrast to DBOW, in DM, the paragraph vector and local context word vectors are concatenated or averaged to predict the next word in a context.

Quoc Le also did experiments trained on Wikipedia which shows that the Paragraph Vector algorithms perform significantly better than other methods and embedding quality is enhanced.[15] So in our work, we train the Doc2Vec model on Wikipedia dump and use Doc2Vec to obtain better entity embeddings.

5 Convolutional Neural Network for Short Text Classification

In this section, we modify traditional convolutional neural network for text classification (TextCNN) and propose a new model called convolutional neural network with entities for text classification (EntCNN), using words as well as entities to extract more contextual information from texts. We first introduce the way to obtain entities and entity vectors from texts. Then we describe our model to show how to learn features from words and entities.

5.1 Entity Linking

The first step of our work is to detect named entities from texts. A named entity is, roughly speaking, anything that can be referred to with a proper name: a person, a location or an organization.[26] As we have mentioned in chapter 4, entity linking (EL) is the task of recognizing and disambiguating named entities to a knowledge base (KB). It is sometimes also known as named entity recognition and disambiguation. Why can we benefit from EL? By linking named entity mentions appearing in texts with their corresponding entities in a KB, we can make use of KB which contains rich information about entities to better understand documents. EL is essential to many NLP tasks, including information extraction, information retrieval, content analysis, question answering and knowledge base population.[50] Shen and Jiawei Han et al. (2014) wrote an outstanding survey about EL, see [50].

In our work, we utilize TagMe to extract entities and link them to Wikipedia entries. TagMe is an end-to-end system which has two major stages. First, we process a text to extract named entities (i.e. named entity recognition). Then we disambiguate the extracted entities to the correct entry in a given KB (i.e. named entity disambiguation). After having obtained entity entries in a KB, we use Wikipedia2Vec to get entity vectors. As we have discussed in the previous chapter, Wikipedia2Vec is a disambiguation-only approach. In contrast to end-to-end approach, this model takes standard named entities directly as input and disambiguates them to the correct entries in a given KB. In our work, we just need to query previously obtained entity entries on Wikipedia2Vec, then we can get entity vectors as output.

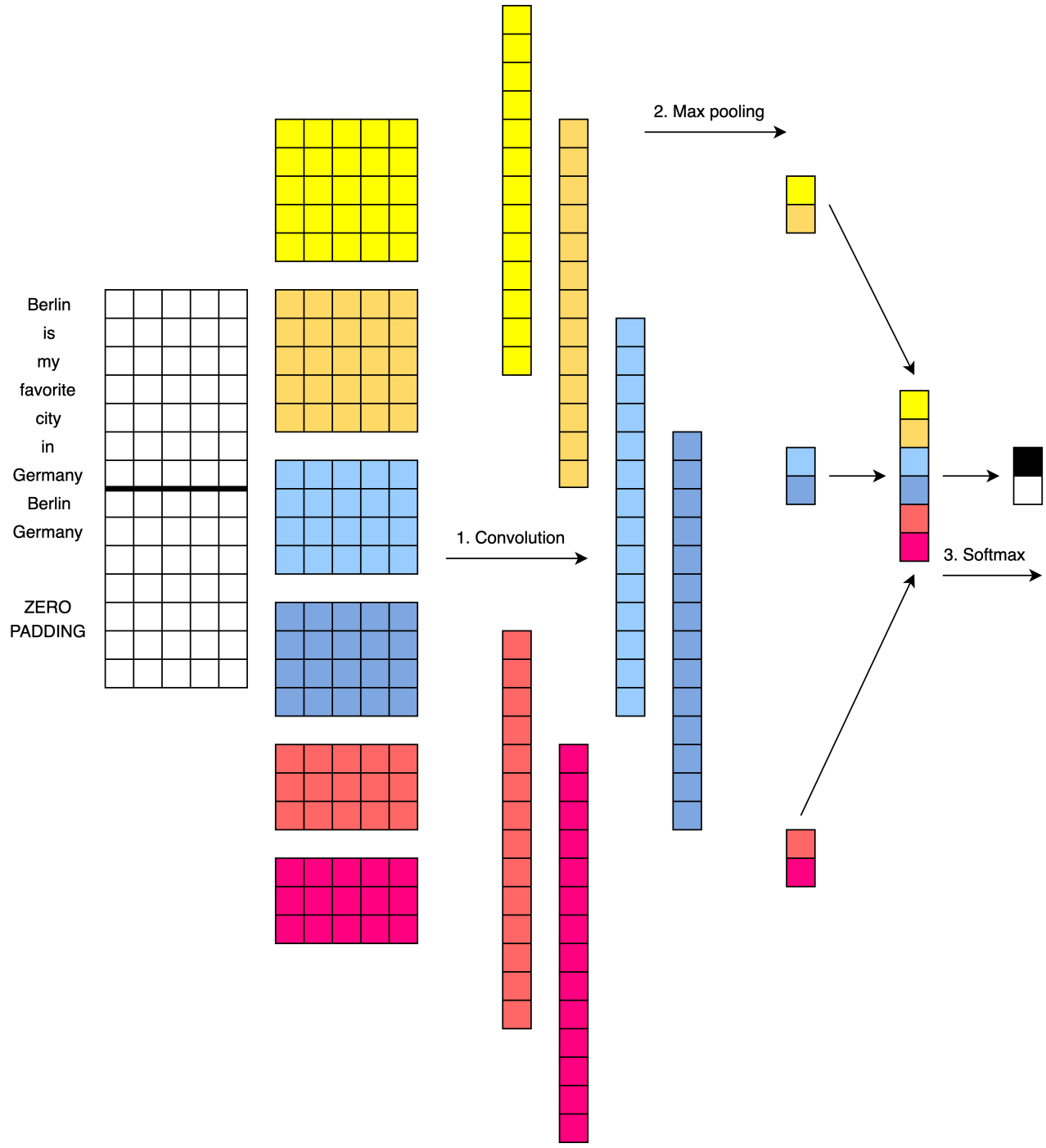


Figure 5.1: Convolutional neural network with words and entities for short text classification

5.2 Overall Architecture of EntCNN

As we have discussed in chapter 3, CNNs have achieved impressive results on text classification tasks. In our work, we focus on single layer CNN due to its outstanding empirical performance and use it as our baseline model.

We begin with a preprocessed sentence as Figure 5.1 shows: Berlin is my favorite city in Germany. The whole network contains input layer (embedding layer), convolution and max-pooling layer, dropout layer and output layer. The details are described in the following paragraph.

Embedding Layer
We first convert the preprocessed sentence to an embedding matrix. This word embedding matrix maps vocabulary word indices into low-dimensional vector representations. Each row of the matrix is a word vector representation. It's essentially a look-up table. Note that each sentence is zero-padded to the maximum sentence length of a document. We initialize word vectors with publicly available pre-trained word2vec or GloVe models. Vocabulary words which do not present in the set of pre-trained models are randomly initialized. Similarly, Our entity embedding matrix is initialized using Wikipedia2Vec. Note that entity embedding matrix should have the same length as word embedding matrix due to Tensorflow implementation reasons. But it turns out that this doesn't affect the final result because padded-zeros are finally ignored after max-pooling step. Note that not all entities have entity vectors. We also adopt the same zero-padding strategy for entities that don't have entity embeddings, i.e. they are zero-padded in the entity embedding matrix.

Assume the maximum sentence length of a given document is l. The dimensionality of word and entity vectors are denoted as d. So we can obtain the embedding matrix $\mathbf{W}$ by concatenating the embedding matrix of words and entities together: $\mathbf{W} = \mathbf{W}_w \oplus \mathbf{W}_e$. $\mathbf{W}_w$ and $\mathbf{W}_e$ denote the embedding matrix of words and entities respectively. $\oplus$ stands for concatenation operator. Thus given a sentence, its embedding matrix can be represented as:

$$\mathbf{W} = \mathbf{v}_1^w \oplus \mathbf{v}_2^w \oplus \cdots \oplus \mathbf{v}_l^w \oplus \mathbf{v}_1^e \oplus \mathbf{v}_2^e \oplus \cdots \oplus \mathbf{v}_l^e \tag{5.1}$$

Convolution and Max-Pooling Layer
Unlike convolution operations in computer vision where filter width can be one or any

other integers, filter width should be equal to the dimensionality of word and entity vectors (i.e. d) in text classification. It doesn't make any sense to operate on part of word vectors. For example, for word `example`, we can't recognize it when just seeing `xa` or `ampl`. Thus we just need to vary filter height f. Given a filter (convolution kernel) which has size $f \times d$, suppose we have a concatenation of words and entities $\mathbf{v}_i, \mathbf{v}_{i+1}, \ldots, \mathbf{v}_{i+j}$, denoted as $[\mathbf{v}_i : \mathbf{v}_{i+f-1}]$. A feature map is then generated from this window of words and entities by:

$$c_i = g(\mathbf{w} \cdot [\mathbf{v}_i : \mathbf{v}_{i+f-1}] + b) \tag{5.2}$$

where g is a non-linear activation function and b is a bias term. Various nonlinear activation functions are applied to introduce non-linearity into deep neural networks. Historically commonly used functions include sigmoid, hyperbolic tangent (tanh) and rectified linear unit (ReLU). In our work, we choose ReLU because it has characteristics such as simplicity, non-saturating nonlinearity which helps to avoid the vanishing gradient problem, and it has been observed to be able to accelerate the convergence of stochastic gradient descent (SGD).[31] For every possible window of words and entities in a sentence $\{\mathbf{x}_{1:f}, \mathbf{x}_{2:f+1}, \ldots, \mathbf{x}_{n-f+1:n}\}$, we use this filter to produce feature maps:

$$\mathbf{c} = [c_1, c_2, \ldots, c_{n-f+1}] \tag{5.3}$$

A max-over-time pooling function is then applied to this feature map to create a fixed length vector. Max-pooling is a strategy where we take the maximum value, reducing its dimensionality while capturing the most important features. Note that we use filters of different region sizes (heights). We also use multiple filters to learn different features for the same region size (height). Because each filter produces vectors of different shapes, we need to iterate through them, create a layer for each of them, adopt the same pooling scheme, and then merge the results into one big feature vector.

Dropout Layer

This big feature vector is then passed to a dropout layer. Dropout[51] is perhaps the most popular regularization method in CNN. The idea is quite simple. A dropout layer stochastically disables a fraction of its neurons during training by setting them to zero, which prevents neurons from co-adapting and forces them to learn individually useful features, thus significantly reduces overfitting. The output of dropout layer is denoted as h.

Softmax Layer

The feature vector from dropout layer is finally passed to a fully connected layer. We can generate label predictions by doing a matrix multiplication and picking the class with the highest score. We also apply a softmax function to convert raw scores into a probability distribution over labels.

$$\begin{aligned} p &= \text{softmax}(\mathbf{w} \cdot \mathbf{h} + b) \\ \hat{p} &= \arg\max(p) \end{aligned} \tag{5.4}$$

5.3 Training

Loss Function

Our goal of training is to minimize the loss function. The cross-entropy error is the standard loss function for categorization problems. Compared with cross-entropy error, the mean squared error (MSE) and classification error are not good loss functions for classification problem.

In binary classification, where the number of classes m equals 2, cross-entropy error can be calculated as:

$$\text{L} = -(y \log(p) + (1 - y) \log(1 - p)) \tag{5.5}$$

where p indicates the probability of the prediction is positive and y is the label of the observed sample, 1 is positive and 0 is negative. If $m > 2$ (i.e. multi-class classification), we calculate a separate loss for each class per observation and sum the result:

$$\text{L} = -\frac{1}{m} \sum_{i=1}^{m} y_i \log(p_i) \tag{5.6}$$

where m is the number of classes, $\boldsymbol{y} \in \mathbb{R}^m$ is the one-hot represented true label, $\boldsymbol{p} \in \mathbb{R}^m$ is the predicted probability for each class that observation is of class i after softmax calculation.

Regularization

L2 regularization is perhaps the most common regularization method to prevent overfitting. It can be implemented by penalizing the squared magnitude of all parameters directly in the objective function. That is, for every weight w in the network, we add the term $\frac{1}{2}\lambda w^2$ to the objective, where λ is the regularization strength. Now the new loss function becomes:

$$\mathrm{L}'(w) = \mathrm{L}(w) + \frac{1}{2}\lambda w_1^2 + \frac{1}{2}\lambda w_2^2 + \cdots \tag{5.7}$$

So we have the final loss function:

$$\mathrm{L}'(w) = -\frac{1}{m}\sum_{i=1}^{m} y_i \log(p_i) + \lambda \|w\|_2^2 \tag{5.8}$$

In [63], it's recommended to set the dropout rate to a small value ($0 \sim 0.5$) and a relatively large λ value (commonly used 3) for L2 regularization. Practically, we increase the number of feature maps to see if or not it helps to improve the performance. If not, we need a larger dropout rate.

Cross Validation

To avoid overfitting, a common practice is to use cross-validation approach. We randomly split the training set into n distinct subsets with approximately equal size, called folds. We then train and evaluate the model $n-1$ times, pick a different fold for evaluation each time and train on the other $n-1$ folds, yielding 1 score at last. The final result of cross-validation is summarized with the mean of the n scores. It has been shown empirically to have a good balance of bias and variance when we perform n-fold cross validation using $n = 5$ or $n = 10$.[24] Because most datasets are small in our experiments, we set n to 10.

6 Recurrent Neural Network for Short Text Classification

We know that fully connected neural networks and CNNs can only process individual inputs. The previous input and the following input are completely unrelated. However, in some tasks we need to be able to better process the sequences, where the previous input and the subsequent input are related. For example, if we want to understand a sentence, it's not enough to understand each word separately. We need to understand a group of words or the entire sequence of words. So we need another very important neural network in deep learning: recurrent neural network (RNN).

6.1 Vanilla Recurrent Neural Network

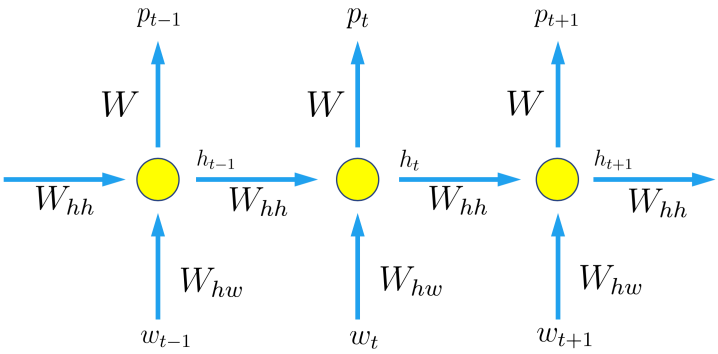


Figure 6.1: Recurrent neural network and the unfolding in time of the computation involved in its forward computation

Figure 6.1 shows a vanilla RNN being unfolded into a full network. By unfolding we mean that we write out the network for the complete sequence. The parameters in RNN are as follows: g and f are activation functions. w_t is the input at time step t. h_t is the hidden layer state at time step t. We can think of the hidden state h_t as the memory of the network. p_t is the output prediction at time step t. W_{hw} is the weight matrix from input layer to hidden layer. Here the first subscript h indicates that we want to work out the hidden layer. The second subscript implies that matrx W_{hw} multiplied by w_t. Accordingly W maps hidden layer to output layer. W_{hh} is the weight matrix between hidden layers. Note that a RNN shares the same set of parameters (W_{hw}, W_{hh} and W) across all time steps, thus greatly reducing the total number of parameters we need to learn.[3] At time t:

$$h_t = g(W_{hh}h_{t-1} + W_{hw}w_t + c) \tag{6.1}$$

$$p_t = f(Wh_t + b) \tag{6.2}$$

The above formulas define the forward propagation in RNN. We define $(W_{hh}h_{t-1}+W_{hw}w_t)$ as $V[h_{t-1}, w_t]$ to simplify the notations. We take the matrix W_{hh} and W_{hw}, put them side by side and stack them horizontally as follows: $[W_{hh} \vdots W_{hw}] = V$. Besides, $[h_{t-1}, w_t]$ indicates that we stack these two vectors vertically like $\begin{bmatrix} h_{t-1} \\ w_t \end{bmatrix}$. To make it clearly, we say h is 100 dimensional and w is 10,000 dimensional. Then W_{hh} will be $(100, 100)$ and W_{hw} will be $(100, 10000)$. When we stack these two matrices together, V will be a $(100, 10100)$ matrix. Correspondingly $\begin{bmatrix} h_{t-1} \\ w_t \end{bmatrix}$ will be a $(10100, 100)$ vector. So $[W_{hh} \vdots W_{hw}]$ multiplied by $\begin{bmatrix} h_{t-1} \\ w_t \end{bmatrix}$ we will get $(W_{hh}h_{t-1} + W_{hw}w_t)$. We rewrite the formula 6.1 and 6.2 as follows for simplicity:

$$h_t = g(V[h_{t-1}, w_t] + c) \tag{6.3}$$

$$p_t = f(Wh_t + b) \tag{6.4}$$

Exploding and vanishing gradients problems. We are interested in how the gradient propagates back in time in RNN:

$$\begin{aligned} \frac{\partial \text{cost}_N}{\partial h_1} &= \frac{\partial \text{cost}_N}{\partial p_N} \frac{\partial p_N}{\partial h_N} \left(\prod_{n \in \{N,\dots,2\}} \frac{\partial h_n}{\partial h_{n-1}} \right) \\ &= \frac{\partial \text{cost}_N}{\partial p_N} \frac{\partial p_N}{\partial h_N} \left(\prod_{n \in \{N,\dots,2\}} \frac{\partial h_n}{\partial z_n} \frac{\partial z_n}{\partial h_{n-1}} \right) \end{aligned} \tag{6.5}$$

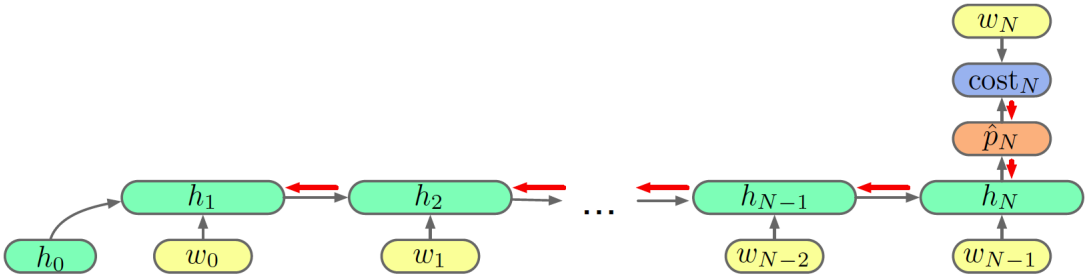


Figure 6.2: Problem of exploding and vanishing gradients in RNN (adopted from [2])

We define $(W_{hh}h_{t-1} + W_{hw}w_t + c)$ in Formula 6.1 as z_n. Then we get following derivatives:

$$\frac{\partial h_n}{\partial z_n} = \text{diag}(g'(z_n)) \tag{6.6}$$

$$\frac{\partial z_n}{\partial h_{n-1}} = W_{hh} \tag{6.7}$$

We rewrite the partial derivatives in Formula 6.5:

$$\frac{\partial h_n}{\partial h_{n-1}} = \frac{\partial h_n}{\partial z_n}\frac{\partial z_n}{\partial h_{n-1}} = \text{diag}(g'(z_n))\ W_{hh} \tag{6.8}$$

$$\begin{aligned}\frac{\partial \text{cost}_N}{\partial h_1} &= \frac{\partial \text{cost}_N}{\partial p_N}\frac{\partial p_N}{\partial h_N}\left(\prod_{n\in\{N,\dots,2\}}\frac{\partial h_n}{\partial h_{n-1}}\right) \\ &= \frac{\partial \text{cost}_N}{\partial p_N}\frac{\partial p_N}{\partial h_N}\left(\prod_{n\in\{N,\dots,2\}}\text{diag}(g'(z_n))\ W_{hh}\right)\end{aligned} \tag{6.9}$$

The core of the recurrent product is the repeated multiplication of W_{hh}. If the largest eigenvalue of W_{hh} equals 1, then gradient will propagate and it will be stable; if it is greater than 1, the product will grow exponentially as we multiply more and more times, the gradients will explode; if it is less than 1, the product will shrink exponentially, the gradients will vanish. These are problems in RNN: we will not be able to train the model if it explodes because the gradients will be infinite; if it vanishes, we will not be able to learn long range dependencies because we will get zero gradients after a few steps back in time.

Solutions to exploding and vanishing gradients problems. In general, gradient explosion is easier to handle. Our program will receive a NaN error when gradient explodes. We can also set a threshold, we can clip gradient values which exceed the preferred range when gradient exceeds this threshold.

Gradient vanishing problem is more difficult to handle. We can use other types of RNNs, such as LSTMs and gated recurrent unit (GRU), which is a most popular way and will be discussed in the flowing paragraph.

We can also use new activation functions rectified linear unit (ReLU) instead of Sigmoid and Tanh. See Table3.

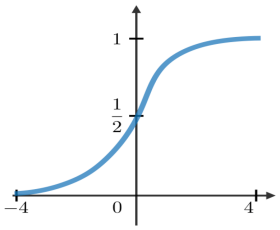
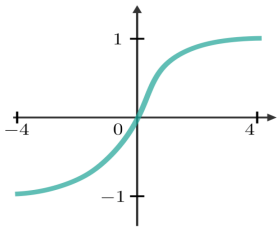
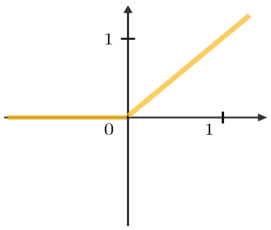
Sigmoid	**Tanh**	**ReLU**
$g(z) = \frac{1}{1+e^{-z}}$ 	$g(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}}$ 	$g(z) = \max(0, z)$ 

Table 3: Commonly used activation functions

6.2 Long Short-Term Memory

When the time interval is large, it's very difficult for simple RNNs to model long-distance dependencies, known as long-term dependencies problem.[22][10] Long short-term memory (LSTM)[23] which was proposed by Hochreiter and Schmidhuber in 1997 has cleverly solved this problem. LSTM networks – usually just called LSTMs, are a special kind of RNN, capable of learning long-term dependencies.[4]

In the following paragraph we'll step by step build a basic LSTMs model. Here we have two time steps and we're interested in how the hidden layer in the previous time step gets updated into the next time step. The update equation is as follows:

$$\boldsymbol{h}_n = g(V[w_{n-1}; \boldsymbol{h}_{n-1}] + \boldsymbol{c}) \tag{6.10}$$

Here $\boldsymbol{h}$ indicates hidden layers, w stands for input words and p is the output prediction. As Figure 6.3 presents, when we go from $\boldsymbol{h}_{n-1}$ to $\boldsymbol{h}_n$ we are going to pass the hidden layer $\boldsymbol{h}_{n-1}$ and the input w_{n-1} together through a linear transformation and a tanh non linearity. This is a simple RNN architecture.

$$\boldsymbol{h}_n = \tanh(V[w_{n-1}; \boldsymbol{h}_{n-1}] + \boldsymbol{c}) \tag{6.11}$$

In the hidden layer of the original RNN there is only one hidden state, which is very sensitive to short-term inputs. The next step is that we introduce an extra layer called cell state $\boldsymbol{c}$ and we can think of it as our memory, we use it to store our long-term state.

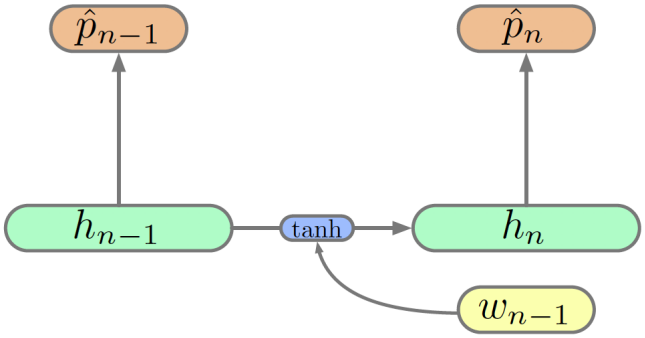


Figure 6.3: Basic RNN architecture (adopted from [2])

We then promote the hidden layer $\boldsymbol{h}$ to upper layer as Figure 6.4 shows. We update the cell state $\boldsymbol{c}_n$ by taking the previous cell state $\boldsymbol{c}_{n-1}$ and adding in a contribution from our hidden layer $\boldsymbol{h}_{n-1}$ with our input w_{n-1} which looks just like previous simple RNN. The difference is in this network we basically update cell states. And what really matters is these updates are additive. In the simple recurrent network as we go from one hidden layer to the next we are actually multiplying whereas in this network we do lots of sums. When we differentiate the sum rather than the product, the gradient can flow nicely back through the sum. The key thing in LSTMs is we replace multiplication with sum.

$$\boldsymbol{c}_n = \boldsymbol{c}_{n-1} + \tanh(V[w_{n-1}; \boldsymbol{h}_{n-1}] + \boldsymbol{b}_c) \tag{6.12}$$

$$\boldsymbol{h}_n = \tanh(V[w_{n-1}; \boldsymbol{h}_{n-1}] + \boldsymbol{c}) \tag{6.13}$$

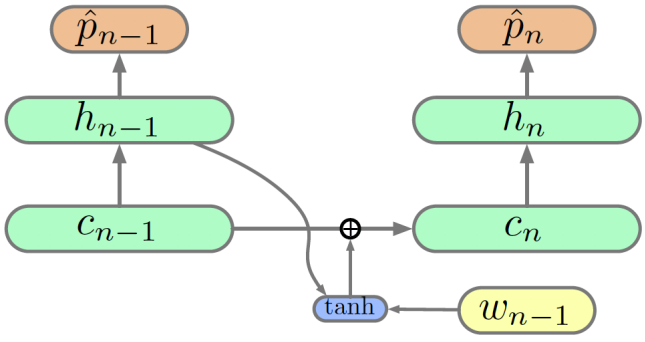


Figure 6.4: The cell state of LSTM (adopted from [2])

The next thing we need to do is called gating. The idea of gating in neural networks is just computing a non linearity which is bounded between 0 and 1 and we can think of it like a switch: if it is 1 we turn on the connection, if it is 0 we turn it off. The key thing

is that it is a continous function so we can differentiate it and do back propagation. The gate is actually a fully connected layer whose input is a vector and output is a vector between 0 and 1. Suppose W is the weight matrix of the gate and $\boldsymbol{b}$ is the bias term. The gate can be expressed as follows:

$$g(\boldsymbol{x}) = \sigma(W\boldsymbol{x} + \boldsymbol{b}) \tag{6.14}$$

As Figure 6.5 presents, here we introduce the **input gate** $\boldsymbol{i}$. We gate the contribution from the input and previous hidden layer. We then take a new linear transformation of the input w_{n-1} and the previous hidden layer $\boldsymbol{h}_{n-1}$, apply a sigmoid function to it and get a vector of gates. When observing formula 6.15, we can think of it in this way. If the gate is 1 then we will get a big contribution from our current input. If the gate is 0 then we will get no contribution from current input, cell state $\boldsymbol{c}_n$ is equal to cell state $\boldsymbol{c}_{n-1}$, so there is no update and model forgets nothing. If a gate is closed for many time steps, we will obtain long time dependencies. So input gate gives us the ability to ignore inputs.

$$\boldsymbol{c}_n = \boldsymbol{c}_{n-1} + \boldsymbol{i}_n \circ \tanh(V[w_{n-1}; \boldsymbol{h}_{n-1}] + \boldsymbol{b}_c) \tag{6.15}$$

$$\boldsymbol{i}_n = \sigma(W_i[w_{n-1}; \boldsymbol{h}_{t-1}] + \boldsymbol{b}_i) \tag{6.16}$$

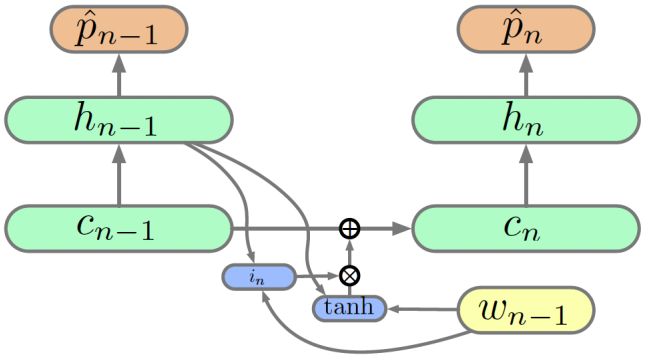


Figure 6.5: The input gate of LSTM (adopted from [2])

We have the ability either to include or ignore of the input but we do not have the ability to forget things what are in our cell state. Now we add a **forget gate** $\boldsymbol{f}$ as in Figure 6.6. As formula 6.19 shows, it is a sigmoid function of a new linear transformation of the input w_{n-1} and hidden layer $\boldsymbol{h}_{n-1}$. This forget gate is then multiplied by the previous cell state $\boldsymbol{c}_{n-1}$ to get a new cell state 6.17. Our new memory or new cell state is a mixture of the

previous cell state $\boldsymbol{c}_{n-1}$ weighted by the forget gate $\boldsymbol{f}_n$ and our new update from our input and the previous hidden layer weighted by the input gate $\boldsymbol{i}_n$. If all the forget gates are set to 0, we will forget all the memories. If all the input gates are set to 0, we will ignore all the inputs. So the model can choose between do I really propagate information forward perfectly and ignore inputs or do we forget what we have seen and introduce something new.

$$\boldsymbol{c}_n = \boldsymbol{f}_n \circ \boldsymbol{c}_{n-1} + \boldsymbol{i}_n \circ \tanh(V[w_{n-1}; \boldsymbol{h}_{n-1}] + \boldsymbol{b}_c) \tag{6.17}$$

$$\boldsymbol{i}_n = \sigma(W_i[w_{n-1}; \boldsymbol{h}_{t-1}] + \boldsymbol{b}_i) \tag{6.18}$$

$$\boldsymbol{f}_n = \sigma(W_f[w_{n-1}; \boldsymbol{h}_{t-1}] + \boldsymbol{b}_f) \tag{6.19}$$

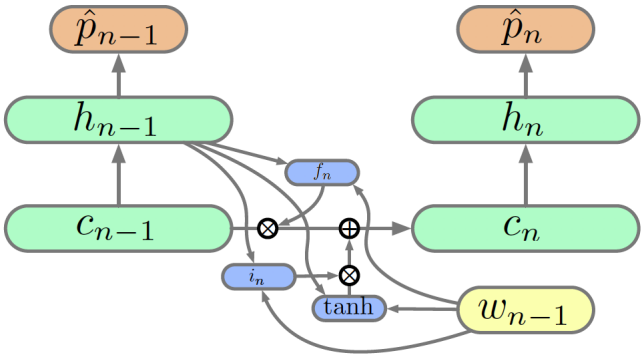


Figure 6.6: The forget gate of LSTM (adopted from [2])

Finally in LSTMs we always add a **output gate** $\boldsymbol{o}$ on the output from the cell state $\boldsymbol{c}_n$ to the hidden layer $\boldsymbol{h}_n$, as in Figure 6.7.

$$\boldsymbol{h}_n = \boldsymbol{o}_n \circ \tanh(W_h \boldsymbol{c}_n + \boldsymbol{b}_h) \tag{6.20}$$

$$\boldsymbol{c}_n = \boldsymbol{f}_n \circ \boldsymbol{c}_{n-1} + \boldsymbol{i}_n \circ \tanh(V[w_{n-1}; \boldsymbol{h}_{n-1}] + \boldsymbol{b}_c) \tag{6.21}$$

$$\boldsymbol{i}_n = \sigma(W_i[w_{n-1}; \boldsymbol{h}_{t-1}] + \boldsymbol{b}_i) \tag{6.22}$$

$$\boldsymbol{f}_n = \sigma(W_f[w_{n-1}; \boldsymbol{h}_{t-1}] + \boldsymbol{b}_f) \tag{6.23}$$

$$\boldsymbol{o}_n = \sigma(W_o[w_{n-1}; \boldsymbol{h}_{t-1}] + \boldsymbol{b}_o) \tag{6.24}$$

In summary, the hidden state h in RNN stores some historical information, which can be regarded as a kind of memory. In a simple RNN, the hidden state is rewritten at each time

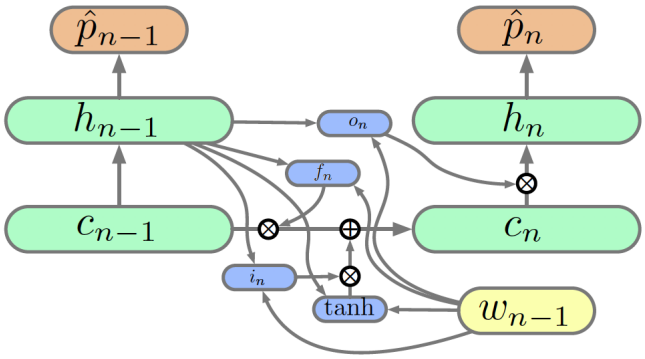


Figure 6.7: The output gate of LSTM (adopted from [2])

step, so it can be seen as a short-term memory. In contrast, long-term memory in neural networks can be seen as a network parameter, which is stored in the weight matrices. It contains the information learned from training data, and its update cycle is much longer than short-term memory.

In LSTMs, cell state c can capture some critical information and has the ability to keep it for a certain time. The life cycle of the stored information in cell state c is longer than short-term memory, but much shorter than long-term memory, so it is called long short-term memory (LSTM).

6.3 Recurrent Convolutional Neural Network

In our work, we also experiment with recurrent convolutional neural network for text classification (RCNN) proposed by Lai (2015). To present a word meaning better and more precisely, we combine a word with its context. As shown in Figure 6.8, we use a bidirectional recurrent neural network to capture contexts. As shown in equation 6.25 and 6.26, $\boldsymbol{c}_l(w_i)$ denotes the left context of word w_i and $\boldsymbol{c}_r(w_i)$ denotes the right context of word w_i. $\boldsymbol{e}$ is a word embedding. $W^{(l)}$, $W^{(r)}$ are matrices used to transfer contexts into the next layer. $W^{(sl)}$, $W^{(sr)}$ are matrices used to combine the context of the current word with its left/right contexts.

$$\boldsymbol{c}_l(w_i) = f(W^{(l)}\boldsymbol{c}_l(w_{i-1}) + W^{(sl)}\boldsymbol{e}(w_{i-1})) \tag{6.25}$$

$$\boldsymbol{c}_r(w_i) = f(W^{(r)}\boldsymbol{c}_r(w_{i+1}) + W^{(sr)}\boldsymbol{e}(w_{i+1})) \tag{6.26}$$

Thus, the representation of word w_i can be defined as a concatenation of word embedding

$\boldsymbol{e}(w_i)$, its left context vector $\boldsymbol{c}_l(w_i)$ and its right context vector $\boldsymbol{c}_r(w_i)$.

$$\boldsymbol{x}_i = [\boldsymbol{c}_l(w_i); \boldsymbol{e}(w_i); \boldsymbol{c}_r(w_i)] \tag{6.27}$$

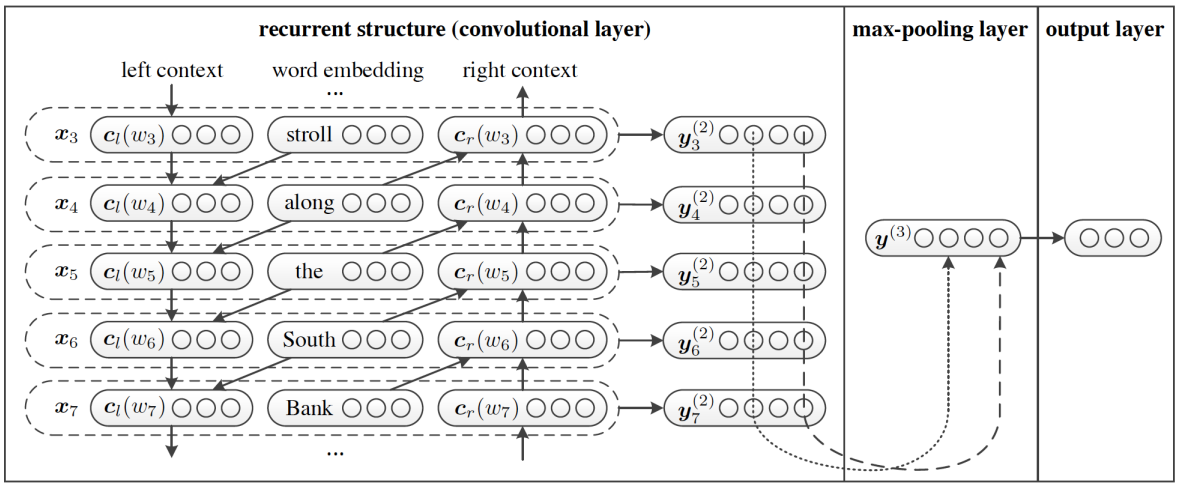


Figure 6.8: Recurrent convolutional neural network for text classification (adopted from [33])

After we calculate the representation of each word w_i, we can obtain the whole text representation using equation 6.28.

$$\boldsymbol{y}_i^{(2)} = \tanh(W^{(2)}\boldsymbol{x}_i + \boldsymbol{b}^{(2)}) \tag{6.28}$$

So how do we extract features from texts? We simply apply a max-pooling layer after all the word representations are calculated. Note that the max function is an element-wise function. That is, the k-th element of $\boldsymbol{y}^{(3)}$ is the maximum in the k-th elements of $\boldsymbol{y}_i^{(2)}$. Therefore, we can convert sentences of different lengths into a fixed length vector. Meanwhile, we are also able to capture the most important textual information of documents.

$$\boldsymbol{y}^{(3)} = \max_{i=1}^{n} \boldsymbol{y}_i^{(2)} \tag{6.29}$$

7 Experiments

7.1 Data

We conduct our experiments on four widely used datasets: TREC, Twitter, AG News and Movie Review. A summary of the datasets are listed in Table 4.

Datasets	c	l	m	train/test	$\|V\|$	$\|V_{pre}\|$
TREC	6	10	33	5452/500	8602	7223
Twitter	3	19	35	9684/3547	20755	12140
AG News	4	7	23	120000/7600	38916	25310
Movie Review	2	21	59	10662/CV	19897	16394

Table 4: Summary statistics of datasets. c: number of target classes, l: average sentence length, m: maximum sentence length, train/test: training/test set size, $|V|$: vocabulary size, $|V_{pre}|$: number of words present in the set of pre-trained word embeddings, CV: there is no standard train/test split, thus 10-fold cross validation is used.

TREC. TREC[1] is a question answering dataset. This dataset is adopted from [Li et al. 2002][36]. It includes six different kinds of questions. TREC class descriptions are shown in Table5. TREC details are listed in Table 6.

Abbreviation	abbreviation or expression abbreviated
Entity	food, animal, technique, language, plant, word, sport, etc.
Description	definition or description of something, etc.
Human	title or description of a person, etc.
Location	city, state, country, etc.
Numeric	count, date, size, weight, speed, temperature, distance, etc.

Table 5: Class descriptions of TREC dataset

Twitter. Twitter[2] is a dataset for a sentiment analysis competition. We need to predict three labels: positive, negative and neutral. Because tweets are noisy, they are specially preprocessed in our experiments, details can be seen in preprocessing part in this chapter. Twitter details are listed in Table 7.

[1] `http://cogcomp.cs.illinois.edu/Data/QA/QC/`

[2] `https://www.cs.york.ac.uk/semeval-2013/task2/`

Abbreviation	What is the full form of .com?
Entity	What's the second most used vowel in English?
Description	What is an annotated bibliography?
Human	Who is the founder of Scientology?
Location	What is the highest waterfall in the United States?
Numeric	How many people in the world speak French?

Table 6: Example sentences of TREC dataset

Positive	Good morning Becky! Thursday is going to be Fantastic!
	Taylor Swift is coming with Ed Sheeran June 29th, most perfect news I've heard all night.
Neutral	The heat game may cost a lot, plus I would rather see Austin Rivers play.
	November is an odd release date if true, but if it becomes big enough maybe she could sing it at Grammys.
Negative	Why is it so hard to find the @TVGuideMagazine these days? Went to 3 stores for the Castle cover issue. NONE. Will search again tomorrow...
	Just found a piece of candy that may have been injected with something.

Table 7: Example sentences of Twitter dataset

AG News. AG News is a collection of news articles. This dataset is adopted from [Zhang et al., 2015][62]. The original data consists of class index (1 to 4), news title and news description. We only use news title in our short text classification experiments. AG News details can be seen in Table 8.

Sci/Tech	IBM to hire even more new workers.
Sports	Capacity crowds at beach volleyball rock the joint.
World	US fighter squadron to be deployed in South Korea next month.
Business	Staples profit up, to enter china market.

Table 8: Example sentences of AG News dataset

Movie Review. Movie Review[3] is a dataset used in sentiment analysis experiments. This dataset is adopted from [Pang and Lee, 2005][42]. It contains sentences labeled with respect to their overall sentiment polarity (positive or negative). Movie Review does not have a standard test set. So for this dataset we randomly select 10% of the training data

[3] http://www.cs.cornell.edu/people/pabo/movie-review-data/

as the dev set. Movie Review details can be seen in Table 9.

Positive	If this movie were a book, it would be a page-turner, you can't wait to see what happens next.
	The film is faithful to what one presumes are the book's twin premises - - that we become who we are on the backs of our parents, but we have no idea who they were at our age; and that time is a fleeting and precious commodity no matter how old you are.
Negative	Too slow for a younger crowd, too shallow for an older one.
	The problem is not that it's all derivative, because plenty of funny movies recycle old tropes. The problem is that van wilder does little that is actually funny with the material.

Table 9: Example sentences of Movie Review dataset

7.2 Preprocessing

Text preprocessing is always the first step of a good NLP system, which provides the system with clean, easy to handle forms. The impact on the performance of commonly used text preprocessing methods with traditional machine learning classifiers has been investigated in a previous work[53], which shows that appropriate combinations of preprocessing methods depending on the domains and languages might result in a significant improvement of the accuracy, whereas inappropriate combinations might decrease the accuracy as well. A similar study with deep learning classifiers has also been conducted recently[11]. Therefore text preprocessing methods should be used and especially carefully selected.

In order to understand why text preprocessing really matters, we now consider the previously used sentences:

```
(1) I do not like this type of movie, but I like this one.
(2) I like this kind of movie, but I do not like this one.
```

We can clearly see that these two snippets represent completely opposite meanings. The question is in what ways text preprocessing might affect our sense of how different they are. To begin with, we calculate the cosine similarity of these two sentences, which is 0.90. The relevant document frequency matrix are shown in Table 10 when considered only lowercase words.

	i	do	not	like	this	type	of	movie	but	one	kind
(1)	2	1	1	2	2	1	1	1	1	1	0
(2)	2	1	1	2	2	0	1	1	1	1	1

Table 10: Document term matrix with stop words retained

We then remove stop-words according to the natural language tool kit's (NLTK) list of English stop-words. With those removed, as shown in Table 11, the two snippets now look less similar than before. In fact, the cosine distance between them decreases from 0.90 to 0.64. Thus, when asked how similar the two snippets are, our conclusions differ. And this does matter because text similarity calculation is the core and foundation of unsupervised learning techniques, such as clustering. Our observation of the above experiment makes it clear that using different text preprocessing methods will lead to different results.

	like	type	movie	one	kind
(1)	2	1	1	1	0
(2)	2	0	1	1	1

Table 11: Document term matrix with stop words removed

Next, the widely used text preprocessing techniques including lowercasing, tokenization, stop-words removal, stemming and lemmatizing are introduced.

Lowercasing

There are two case conversion approaches, lowercasing and uppercasing. Here we only focus on lowercasing, where all letters in all words of the document is converted completely to lowercase. The reason for doing this is that whether or not the first letter of a word is uppercase typically does not affect its meaning.[17] For example, "Computer" and "computer" all refer to the same type of machine which is able to be instructed to carry out sequences of arithmetic or logical operations automatically. So it is unnecessary to regard them as two different words in text analysis. Furthermore, it will lead to decline in the accuracy without lowercasing under such circumstances. However, there is not a general rule which demonstrates that lowercasing can always improve the performance. Especially when our corpus is in German, it would be more appropriate to retain the capitalization form of words since it is an important characteristic of German language. In English only proper nouns such as the names of people, cities, countries, nationalities, and languages, etc. are capitalized. From the following example we can notice that all

nouns are capitalized in German, wherever they appear in a sentence. This is a nearly unique feature in a contemporary language.

```
EN: A computer is a machine that can be instructed to carry out sequences
of arithmetic or logical operations automatically.
DE: Ein Computer ist eine Maschine, die angewiesen werden kann, Sequenzen
von arithmetischen oder logischen Operationen automatisch auszuführen.
```

Tokenization

Tokenization methods consist of sentence tokenization and word tokenization. Sentence tokenization is the process of splitting or segmenting text into individual sentences. Normally sentence tokenization is followed by word tokenization. Word tokenization is the process of splitting or segmenting sentence into a list of words. The resulting word tokens can be then used in further processing. Tokenization is important in NLP, especially in the operations where each word needs to be individually dealed with such as stemming and lemmatizing. In our work, we use NLTK library to tokenize words. Here is a word tokenization example.

```
Original text:
    He jumped in and swam to the opposite bank.
Tokenized text:
    [‘He’, ‘jumped’, ‘in’, ‘and’, ‘swam’, ‘to’, ‘the’, ‘opposite’, ‘bank’]
```

Removing stop-words

Sometimes some extremely commonly used words are unlikely to convey us much useful information, such as “the”, “the”, “and”, etc. These words are called stop-words. They can be removed from texts and excluded from the vocabulary we built. Removing stop-words has its benefit: we wouldn’t want the stop-words to take up too much space in our database or memory when processing large scale corpus. However it also has downsides, it might affect the accuracy. There is no standard stop-words list. NLTK has a list of stop-words in 16 different languages. We can also define our own stop-words list according to our needs in different domains and languages. In our experiments, stop-words are not removed.

Stemming and lemmatizing

Stemming and lemmatizing aims to reduce inflectional forms and sometimes derivationally related forms of a word to a common base form.[38] Stemming refers to the process of reducing a word to its most basic form. For instance, with removal of derivational affixes of the following words, the verb “to jump” may appear as: “jumped”, “jumping” and “jumps”,

we can obtain their common base form: jump.

Lemmatizing or lemmatization refers to the process of conducting morphological analysis to correctly return the base form for each word, which here we call it lemma. For instance, the verb 'to swim' may appear as: "swam", "swum", "swimming" and "swims", with lemmatizing we will obtain "swim" or "swimming" depending on the context, where "swimming" can be either the base form of a noun "swimming-pool" or of a verb "I swam in the river". Whereas with stemming we might obtain "swim". In fact, stemmer is typically easier to implement and runs faster than lemmatizer, because stemmer simply operates on a single word without any knowledge of the context but lemmatizer requires a dictionary look-up operation.

By observing the raw tweets we can find that it is a quite noisy corpus. The language used in tweets is very informal, with creative punctuation and spelling, misspellings, slang, new words and genre-specific terminology and abbreviations. Tweets also have lots of special characters such as emoticons, URLs, user-mentions, etc. as shown below. So we need some additional special preprocessing methods for tweets. In our work, we adopt the methods from a Kaggle twitter sentiment analysis competition[4].

```
#NowPlaying Michael Jackson - She's Out of My Life (Live At Wembley July
16. http://t.co/vxRYuADn L.O.V.E it! #MjTunes
```

URL

A uniform resource locator (URL), or web address in spoken English, is a reference to a web resource which specifies its location. In our daily lives we would love to share content such as URLs with friends or the public via Twitter. However URL in tweets doesn't provide us with any valuable information in text classification tasks. One feasible approach is removing all the URLs. Here we replace all the URLs in tweets with word `URL`. Note that all the links (URLs) posted in tweets will automatically be processed and shortened. The related regular expression used to match URLs is `((www\.[\S]+)|(https?://[\S]+))`.

User mention

Lots of tweets have an associated symbol `@`. For example, we would like to mention our friends with `@username` to share some funny posts or interesting ideas with them, or we just want to let someone else know that we are talking about them. User mention does not provide us with any useful information either. We replace all the user mentions in tweets with word `USER_MENTION`. The regular expression used to match user mention is

[4] `https://github.com/abdulfatir/twitter-sentiment-analysis`

`@[\S]+`.

Hashtag

A hashtag which is written with a # symbol, is used to index keywords or topics in tweets, allowing us to easily follow or mention topics we are interested in. We simply replace all the hashtags with the words with hash symbol #. For instance, `#KIT` is replaced with `KIT`. The regular expression used to match hashtags is `#(\S+)`.

Retweet

A retweet is a re-posting of a tweet. Sometimes we type `RT` at the beginning of a tweet to indicate that we are re-posting someone else's tweet. We remove `RT` from the tweets. The regular expression used to match retweets is `\brt\b`.

Emoticon

Emoticon is a set of characters used in social media to express emotion or active atmosphere, etc. They are textual portrayals of our moods or facial expressions. There is a list of commonly used emoticons on Wikipedia[5]. Exhaustively list and match all of the different emoticons that could possibly be used in tweets is obviously hard and impossible. In our work, we just match some widely used emoticons. We replace the matched emoticons with either `EMO_POS`, `EMO_NEG` or `EMO_NEU` depending on whether or not it's positive. The regular expressions used to match emoticons are listed in Table 12 and Table 13.

	Type	Emoticons
(1)	Smiley	`:), : ), :-), (:, ( :, (-:`
(2)	Laughing	`:D, : D, :-D, xD, x-D, XD, X-D, 8D, 8-D, =D, =3`
(3)	Sad	`:-(, : (, :(, ):, ) :, )-:`
(4)	Surprise	`:-O, :O, :-o, :o`
(5)	Kiss	`<3, :*`
(6)	Wink	`;-), ;), ;-D, ;D, (;, (-;`
(7)	Crying	`:,(, :'(, :"(`

Table 12: List of some widely used emoticons

Besides, we convert 2 or more letter repetitions to two letters. For instance, someone use tweets like "I looooooove it soooo much!" to emphasize the most significant words and express their strong feelings. Here we convert this sentence to "I love it so much!".

[5] `https://en.wikipedia.org/wiki/List_of_emoticons`

	Type	Regex	Replacement
(1)	Smiley	(:\s?\)|:-\)|\(\s?:|\(-:)	EMO_POS
(2)	Laughing	(:\s?D|:-D|x-?D|X-?D|8-?D|=D|=3)	EMO_POS
(3)	Sad	(:\s?\(|:-\(|\)\s?:|\)-:)	EMO_NEG
(4)	Surprise	(:-?O|:-?o)	EMO_NEU
(5)	Kiss	(<3|:*)	EMO_POS
(6)	Wink	(;-?\)|;-?D|\(-?;)	EMO_POS
(7)	Crying	(:,\(|:\'\(|:"\()	EMO_NEG

Table 13: List of regular expressions used to match emoticons

To have a better understanding of the preprocessing part, we select two original and preprocessed sampled sentences listed below:
Before: `@jackseymour11 I may have an Android phone by the time I get back to school! :)`
After: `USERMENTION i may have an android phone by the time i get back to school EMOPOS`

Before: `#NowPlaying Michael Jackson - She's Out of My Life (Live At Wembley July 16. http://t.co/vxRYuADn L.O.V.E it! #MjTunes`
After: `nowplaying michael jackson she is out of my life live at wembley july 16 URL love it mjtunes`

7.3 Evaluation Metrics

Binary classification
For a specific task, suppose we have a variety of machine learning or deep learning models on hand. The question is: which model should we choose from all these available models and apply it in the task? Actually all the machine learning algorithms consist of combinations of just three components: representation, evaluation and optimization.[19] So it's important to choose proper evaluation metrics that match our tasks. We compute our selected evaluation metric for multiple different models. Then we select the model with best value of evaluation metric.

An evaluation function, or objective function, or scoring function, is used to distinguish good classifiers from bad ones. Error rate and accuracy, they are two most commonly used evaluation metrics in binary and multiclass classification tasks. Error rate is the ratio of

the number of samples with wrong predictions to the total number of samples. Accuracy is the ratio of the number of samples with correct predictions to the total number of samples.

$$\text{Accuracy} = \frac{\#\text{correct predictions}}{\#\text{total instances}} \tag{7.1}$$

$$\text{Error rate} = \frac{\#\text{wrong predictions}}{\#\text{total instances}} \tag{7.2}$$

However, these two metrics sometimes can not provide us with any accurate information when the dataset has imbalanced classes, especially when greatly unbalanced. For instance, a dataset has 1000 randomly selected items in total, of which 990 are of class A and only 10 are of class B. We build a classifier to predict relevant items, and see that its accuracy on a test set is 99.0% which is amazingly good. But for comparison, suppose we have a dummy classifier that does not look at the features at all, and always just blindly predict the most frequent class (here class A). This dummy classifier's accuracy would also be 99.0%. It completely ignores the input data thus can not be used in practice.

For binary classification tasks, according to the combination of samples' real categories and our predicted categories, samples can be grouped into four classes: true positive (TP), false positive (FP), true negative (TN) and false negative (FN). The confusion matrix is shown in Table 14, where each row of the matrix represents the instances in an actual class, while each column represents the instances in a predicted class.

True Positive	`TP`	`FN`
True Negative	`FP`	`TN`
	Predicted Positive	Predicted Negative

Table 14: Confusion matrix of binary classification

Precision and recall are then defined as:

$$\text{precision} = \frac{TP}{TP + FP} \tag{7.3}$$

$$\text{recall} = \frac{TP}{TP + FN} \tag{7.4}$$

Generally speaking, it is common that when the value of precision is higher, recall is often lower. When the value of precision is lower, recall is often higher. For example, suppose we are in a supermarket buying strawberries. We can get good strawberries as many as

possible by increasing the number of picked strawberries. If all the strawberries are selected, then all the good strawberries must be selected, so precision would be lower. If we want the proportion of good ones in the selected strawberries as high as possible, we can only pick strawberries with most confidence, but this will inevitably leads to missing a lot of good strawberries, which makes recall lower. So there is always a trade-off between precision and recall. In the recommendation system, in order to disturb users as little as possible, it is more desirable that the recommended content is of users' interest, so precision is more important. In the fugitive information retrieval system, it is more desirable to miss the fugitives as little as possible, so recall is crucial. Text classification is a precision-oriented machine learning task, where we concern about how many positive predicted documents are really positive.

A measure which combines precision with recall is the traditional F-measure or balanced F-score. It is the harmonic mean of precision and recall.

$$F1 = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \tag{7.5}$$

It is a special case of the general $F(\beta)$ measure. $F(\beta)$-measure is the weighted harmonic mean of precision and recall.

$$F(\beta) = \frac{(1 + \beta^2) \times \text{precision} \times \text{recall}}{\beta^2 \times \text{precision} + \text{recall}} \tag{7.6}$$

Where $\beta > 0$ measures the relative importance of recall to precision. When $\beta = 1$, it degenerates into the standard $F1$ score, when $\beta > 1$, recall has a greater impact, when $\beta < 1$, precision has a greater influence.

Multiclass classification

The situation is different in multiclass classification tasks. Each combination of two categories has a corresponding confusion matrix. The evaluation metric of multiclass classification on N categories can be divided into N evaluation metrics of binary classification on 2 categories.

The final evaluation metrics are averages across classes. There are two possible ways that the metrics are averaged across all the classes. A straightforward approach is to first calculate the precision and recall score on each confusion matrix. We record them as $(P_1, R_1), (P_2, R_2), \ldots, (P_n, R_n)$, we then get the $F1_{macro}$ score by working out the average.

$$P_{macro} = \frac{1}{n}\sum_{i=1}^{n} P_i \tag{7.7}$$

$$R_{macro} = \frac{1}{n}\sum_{i=1}^{n} R_i \tag{7.8}$$

$$F1_{macro} = \frac{2 \times P_{macro} \times R_{macro}}{P_{macro} + R_{macro}} \tag{7.9}$$

We can also work out the averages of TP, FP, TN, FN on each confusion matrix, record them as $\overline{TP}$, $\overline{FP}$, $\overline{TN}$, $\overline{FN}$. Based on these averages, we can then calculate P_{micro}, R_{micro} and $F1_{micro}$.

$$P_{micro} = \frac{\overline{TP}}{\overline{TP} + \overline{FP}} \tag{7.10}$$

$$R_{micro} = \frac{\overline{TP}}{\overline{TP} + \overline{FN}} \tag{7.11}$$

$$F1_{micro} = \frac{2 \times P_{micro} \times R_{micro}}{P_{micro} + R_{micro}} \tag{7.12}$$

As a comparison, each class has equal weight in macro scores whereas in micro scores each instance has equal weight and largest classes have most influence. We compute metrics within each class, average resulting metrics across classes to get macro scores. We aggregrate outcomes across all classes, compute metrics with aggregate outcomes to obtain micro scores. So how should we make a choice between macro and micro scores? If the classes have about the same number of instances, macro and micro scores will be about the same. If some classes are much larger or have more instances than others, and we want to weight metric towards the largest ones, we use micro scores, if towards the smallest ones, use macro scores. In our work, we compute confusion matrices and obtain the above evaluation values with machine learning library for python called scikit-learn.

7.4 Computational Complexity

Here we consider the computational complexity of convolutional neural network for text classfication.

Time complexity

The time complexity, also called computational complexity, describes the amount of time it takes to run an algorithm. Time complexity is normally calculated by counting the

number of elementary operations performed by the algorithms. In scientific computations, the computational complexity of deep learning architectures such as TensorFlow or PyTorch is calculated by estimating the number of floating point operations (FLOPs) in the forward pass. Here elementary operation refers to FLOPs, which includes multiplication and accumulation. We ignore negligible costs such as non-linearities, dropout, and normalization layers. How do we estimate FLOPs? The dot product of vectors and matrices (matrix multiplication) is one of the most important operations in deep learning. Thus matrix multiplication and matrix transpose are basic operations. Matrix multiplication involves the accumulation of products or put it in another way, multiplier–accumulator (MAC) operations. The number of OPs/s (the number of operations per second) can be estimated by counting how many MACs can be completed per second. Each multiplication and accumulation is considered to be 1 OP, so 1 MAC is actually 2 OPs.

To compute the number of FLOPs, we assume convolution is implemented as a sliding window. For a standard convolutional kernel in a single layer we have:

$$\textbf{Time} \sim O\Big(2 \cdot K^2 \cdot M^2 \cdot C_{in} \cdot C_{out}\Big) \tag{7.13}$$

where M is the height and width of the output Feature Map, K is the Kernel width (assumed to be symmetric), C_{in} is the number of channels of the input feature maps or the number of output channels in the previous convolutional layer. C_{out} is the number of output channels or the number of output feature maps in this convolution layer.

To illustrate the above equation, we can analysis it in this way. We modify formula 7.4:

$$\textbf{Time} \sim O\left(\Big(2 \cdot C_{in} \cdot K^2\Big) \cdot M^2 \cdot C_{out}\right) \tag{7.14}$$

We first calculate the number of operations of one pixel in an output feature map. Then it is multiplied by $(M^2 \cdot C_{out})$ to be generalized to the entire output feature maps. The part in the parentheses can be divided into two steps as shown in equation 7.15, where the first item denotes we count the number of multiplications and the second denotes the number of accumulations. Because bias is not considered, we add 1 and finally get $(2 \cdot C_{in} \cdot K^2)$ as shown in formula 7.14.

$$(2 \cdot C_{in} \cdot K^2 - 1) = (C_{in} \cdot K^2) + (C_{in} \cdot K^2 - 1) \tag{7.15}$$

In addition, the size of output feature map M is determined by the size of input feature map X, kernel width K, padding and stride, which can be estimated as follows:

$$M = (X - K + 2 * \text{Padding})/\text{Stride} + 1 \tag{7.16}$$

The total time complexity of all convolutional layers is:

$$\textbf{Time} \sim O\left(2 \cdot \sum_{l=1}^{D} M_l^2 \cdot K_l^2 \cdot C_{l-1} \cdot C_l\right) \tag{7.17}$$

where l is the index of a convolutional layer, and D is the model depth or the number of convolutional layers. M_l is the spatial size of the output feature map. K_l is the spatial size (length) of the filter. C_l is the number of filters (width) or the output channels in the l-th layer. C_{l-1} denotes the number of input channels of the l-th layer or the number of output filters in the $(l-1)$-th layer.

The theoretical time complexity in above equations are simply the estimations of neural networks, rather than the actual running time. Because the actual running time are sensitive to implementations and hardwares.[21]

Space complexity

Space complexity is a measurement of the amount of working storage an algorithm needs. It means how much memory, in the worst case, is needed at any point in the algorithm. In practical deep learning, often the size of neural networks is bound by available memory. Sometimes there could possibly be a situation that can evolve where the memory can not hold so many model weights and intermediate variables that the program crashes. Therefore it is necessary to know how to calculate the size of the graphics card's memory occupied by the model that we design together with the intermediate variables. Then we will be comfortable with the memory of graphics card and the problems and bugs that it arises.

The space complexity in deep learning includes two parts: total parameters and output feature maps in each layers. Total parameters are the total weight parameters of the all layers where there are model parameters (the first part of the formula below). Feature maps are the output feature maps calculated in each layer of the model (the second part of the formula below).

$$\textbf{Space} \sim O\left(\sum_{l=1}^{D} K_l^2 \cdot C_{l-1} \cdot C_l + \sum_{l=1}^{D} M^2 \cdot C_l\right) \tag{7.18}$$

As we can see in formula 7.18, total parameters is only related to the spatial size of the kernel K, the number of channels C and the number of convolutional layers D, regardless of the input size (weight sharing). In fact, practical memory usage also depends on the implementations and platforms.

7.5 Entity Linking

We use TagMe[6] to extract and obtain useful named entities. TagMe[20] is a powerful system which has the ability to properly identify meaningful substrings (also called spots) in a plain-text and link each of them to a closely related Wikipedia[7] page fast and efficiently. Besides TagMe, there are also some other entity linking tools such as Dexter[8], Babelfy[9], etc. We choose to use TagMe in our work because it is reported to be one of the best entity linking tool in the scientific community. Most importantly, compared with existing tools, TagMe is able to annotate short texts such as tweets, search-engine results, news titles, etc.

An annotation is a pair (spot, entity), where spot (also mention) is a substring of the input text, and entity is a reference to the Wikipedia page that represents the meaning of the spot in that context. In a proper case, not only can the mention (spot) be linked to a named entity which contains the right mention in respect of named entity linking (NEL), but also solves the important and pervasive semantic problems across languages, ambiguity and polysemy, in the sense of word sense disambiguation (WSD).

We use RESTful API to obtain annotations provided by TagMe. We first send a text to the server for example. The response of the server includes all the annotations found in that text. TagMe associates an attribute with each annotation, called ρ. This ρ value, which estimates the goodness of the annotation with respect to other entities existing in the input text, should be used as a filter to discard annotations that are below a given threshold. A reasonable threshold is reported to be between 0.1 and 0.3. Note that ρ does not indicate the relevance of the entity in the input text, but is rather a confidence score assigned by TagMe to that annotation.

[6] `https://tagme.d4science.org/tagme/`
[7] `https://en.wikipedia.org/wiki/Main_Page`
[8] `http://dexter.isti.cnr.it/`
[9] `http://babelfy.org/`

For instance, consider the following sentence:

`On this day 24 years ago Maradona scored his infamous Hand of God goal against England in the quarter-final of the 1986.`

For this short text, the extracted annotations in JSON format are given below:


```
{
  "test": "5",
  "annotations": [
    {
      "spot": "On this day",
      "link_probability": 0.0014018691144883633,
      "rho": 0.0576556958258152,
      "title": "BBC News Online"
    },
    {
      "spot": "day",
      "link_probability": 0.0030609103851020336,
      "rho": 0.02183143049478531,
      "title": "Martin Day"
    },
    {
      "spot": "24 years",
      "link_probability": 0.0019907099194824696,
      "rho": 0.0009953549597412348,
      "title": "1986 FIBA World Championship"
    },
    {
      "spot": "Maradona",
      "link_probability": 0.15395480394363403,
      "rho": 0.2147175818681717,
      "title": "Diego Maradona"
    },
    {
      "spot": "infamous",
      "link_probability": 0.022769613191485405,
      "rho": 0.011384806595742702,
      "title": "Infamous (Motionless in White album)"
    },
    {
      "spot": "Hand of God goal",
      "link_probability": 0.8918918967247009,
      "rho": 0.582613468170166,
      "title": "Argentina v England (1986 FIFA World Cup)"
```

```
    },
    {
      "spot": "England",
      "link_probability": 0.2987603545188904,
      "rho": 0.27085503935813904,
      "title": "England national football team"
    },
    {
      "spot": "quarter-final",
      "link_probability": 0.014687774702906609,
      "rho": 0.1550503820180893,
      "title": "2010 FIFA World Cup knockout stage"
    }
  ]
}
```


The ρ value of the recognized spot "On this day" which links to Wikipedia page "BBC News Online" is 0.06. The ρ value of spot "Maradona" which links to entity "Diego Maradona" is 0.21. The latter annotation looks more reasonable in this sentence and thus should have and actually does have a higher ρ value. In fact, "Maradona", the well-known football player "Diego Maradona", is a partial name which have to be linked to the appropriate entity in a KB, such as Wikipedia or DBpedia.

In our work, we set ρ to 0.1. As a result, in this example, "Diego Maradona", "Argentina v England (1986 FIFA World Cup)", "England national football team" and "2010 FIFA World Cup knockout stage" are considered to be proper named entities and will be used in the next experimental steps.

In our experiments, we find that not all the sentences have extracted named entities. Not all the named entities have correlated entity embeddings in Wikipedia2Vec. To demonstrate that named entities can be a useful feature, some statistics are listed in Table 15.

We fisrt use TagMe to get named entities. From Table 15 we can know that about 92% sentences in TREC have entities. We then query these entities in Wikipedia2Vec to obtain entity embeddings. About 98% extracted named entities have corresponding entity embeddings in Wikipedia2Vec. Moreover, 92% sentences have at least one entity embedding, which means that only 8% sentences do not have features. These statistics make it clear that extracted named entities can be regarded as a new feature which will be utilized in our work. Feature statitics on the other datasets can be viewed in Appendix. For those entities which do not have entity embeddings, they are zero initialized.

TREC	Training Set	Test Set
#total sentences	5452	500
#sentences with entity	5031	460
#sentences without entity	421	40
percentage of sentences with entity	**92%**	**92%**
#total entities	12291	874
#average entities per sentence	2.44	1.90
#total entities with entity embedding in Wikipedia2Vec	12020	856
percentage of entities with entity embedding	**98%**	**98%**
#sentences which have at least 1 entity embedding	5000	460
percentage of sentences which have at least 1 entity embedding	**92%**	**92%**

Table 15: Feature statistics on TREC

7.6 Experimental Setup

Word Embeddings

The Word2Vec[10] model takes a document corpus as input and produces the word vectors as output. It is pre-trained on a very large unannotated corpus so we are able to achieve better generalization when given limited amount of training data. The pre-trained vectors of word2vec model are trained on part of Google News dataset which contains about 100 billion words. The model contains 300 dimensional vectors for 3 million words and phrases. Words which do not present in the set of pre-trained vectors are randomly initialized from a uniform distribution $[-0.25, 0.25]$.

The Wikipedia2Vec models are trained on an English Wikipedia dump. Available pre-trained models which have 100, 300 and 500 dimension words and entities can be found on the Wikipedia2Vec official page[11]. We can also train our own model using the latest English Wikipedia dump[12].

We can train the Doc2Vec model of the English Wikipedia dump. Detailed training introductions can be followed on this page[13]. In our work, the model size is set to 300 and epochs 5. We can improve the model accuracy with with more training epochs, such as 10 or 20 epochs, but it would take much more training time.

[10] `https://code.google.com/archive/p/word2vec/`
[11] `https://wikipedia2vec.github.io/wikipedia2vec/pretrained/`
[12] `https://dumps.wikimedia.org/enwiki/`
[13] `https://markroxor.github.io/gensim/static/notebooks/doc2vec-wikipedia.html`

Hyperparameters

Parameters	Values
filter sizes	lower:[3, 4, 5], upper:[3, 4, 5, 6]
number of filters	lower:16, upper:256
dropout rate	0.5
batch size	64
l2 regularization	3.0
embedding dimension	lower:100, upper:300
learning rate	0.005

Table 16: Experiment hyperparameters

Experimental Environment
In our work, all the experiments are accomplished on a workstation containing 3.60GHz Intel Xeon 4 Cores CPUs, 1 single NVIDIA GeForce GTX 1060 GPU with use of CUDA 10.0.130, cuDNN 7.3.0 and TensorFlow 1.3.

7.7 Results and Analysis

Our experimental results are listed in Table 17. All the experiments are repeated three to five times under the optimal hyperparameters. We then take an average of the results as final result. As we can see, our TextCNN implementation gets almost the same or better performance as our baseline. Our model EntCNN has higher accuracy with maximum 1.4% improvement than our baseline model TextCNN on all datasets. This conveys the information that entities do help to improve the performance of text classification.

The accuracy on Twitter 68.1% is much lower than three other datasets. It can be attributed to the following reasons. First, Twitter, which contains less than ten thousand sentences, is not a large corpus, especially for deep learning. Second, Twitter is a set of tweets which has three labels. Besides, it contains longer, more complicated and noisy sentences. When compared with TREC and AG News, it is obviously more difficult to analyze and label the sentences. Third, Twitter is a dataset used for sentiment analysis task but we do not conduct any similar analysis in our work. As reported in the original sentiment analysis competition paper [41], the best result of SemEval-2013 Task 2 subtask B is 69%, so our result appears to be reasonable.

Model	Twitter	TREC	Movie Review	AG News
Baseline(Word2Vec)	57.24	89.33	81.52	86.11
Word(Word2Vec)	68.1	89.4	**83.0**	87.4
Word(Word2Vec) + Entity(Wikipedia2Vec)	68.2	**90.4**	**83.0**	**87.9**
Word(Wikipedia2Vec) + Entity(Wikipedia2Vec)	**68.8**	89.8	82.8	**87.9**
Δ	+ 0.7	+ 1.0	-	+ 0.5
Word(Doc2Vec)	**69.3**	91.6	81.5	87.6
Word(Word2Vec) + Entity(Doc2Vec)	68.0	89.0	**82.0**	**88.1**
Word(Doc2Vec) + Entity(Doc2Vec)	**69.3**	**93.0**	81.3	87.4
Δ	-	+ 1.4	+0.5	+0.5
Entity(Wikipedia2vec)	46.4	61.4	51.8	79.3
Word(BERT)	69.3	90.2	79.3	87.4

Table 17: Classification results of different models on several different datasets. **Baseline**: we take the results reported in [55] as our baseline. **Word**: TextCNN(i.e. text classification using only words). **Word + Entity**: EntCNN(i.e. text classification using words and entities). **Entity**: text classification using only entities. All the words and entities are initialized from 300 dimensional pre-trained models Word2Vec, Wikipedia2Vec, Doc2Vec and 768 dimensional BERT respectively.

To verify the hypothesis that we can benefit from entities, we conduct an experiment where we use only entities to classify documents. The experimental results in Table 17 confirm that by using only entities, we are already able to achieve an accuracy that is better than randomly guessing (50% for binary classification and 33% for three-class classification).

From the confusion matrices shown in Figure 7.1 and Figure 7.2, we can find that our model EntCNN improves the classification accuracy on label `HUM` from 91% to 95%, `ENTY` from 73% to 77% respectively, and has overall higher accuracy than TextCNN. That is, named entities do help us to classify sentences on label `HUM` and `ENTY`. Another observation about the classification results is that labels `ABBR` and `ENTY` have much lower accuracy than other labels. One possible explanation is that label `ABBR` and `ENTY` are lack of enough training data. Confusion matrices on the other datasets can be seen in Appendix.

We also compare the classification performance when we use different pre-trained word vector models. The entity vectors are initialized with Wikipedia2Vec or Doc2Vec. We do not use pre-trained Word2Vec model to initialize entity vectors because it is trained with Google News articles rather than Wikipedia dump, so pre-trained vectors do not be available for many Wikipedia entities. The word vectors of different models are initialized with Word2Vec, Wikipedia2Vec and Doc2Vec models respectively. From the results shown in Table 17, it is clear that the choice of pre-trained word vector models has an impact

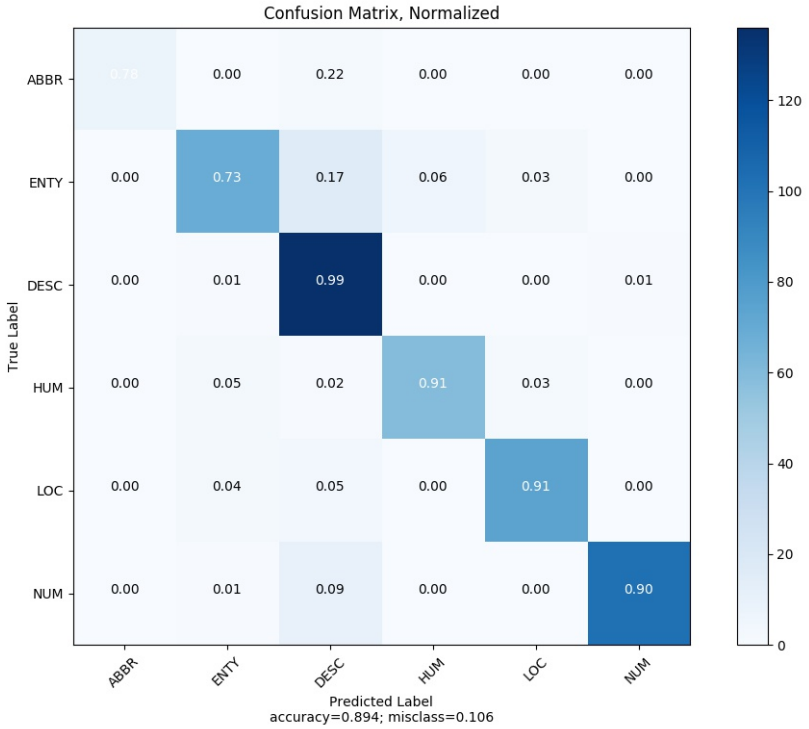


Figure 7.1: Baseline model (TextCNN) normalized confusion matrix on TREC

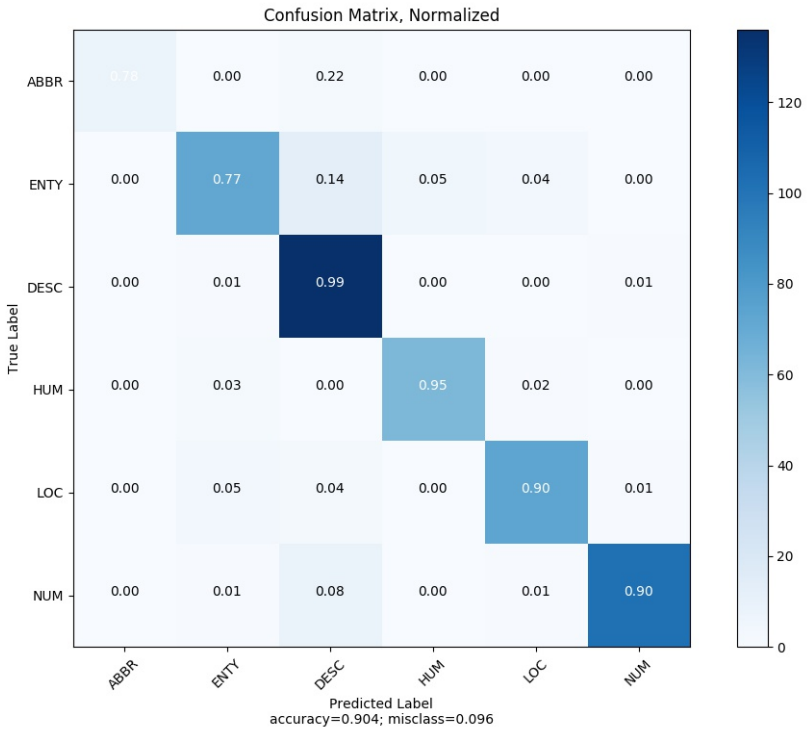


Figure 7.2: Our model (EntCNN) normalized confusion matrix on TREC

on performance, however different models perform better for different datasets. Doc2Vec works better for Twitter and TREC. Word2Vec and Wikipedia2Vec work better for Movie Review. All of them have good performance on AG News. So there is no single optimal choice for all datasets. Practically, our results suggest experimenting with different pre-trained word vectors for new datasets.

We also conduct an experiment where we initialize words from state-of-the-art model BERT. The word vetors in BERT have 768 dimensions. We obtain word vectors from an open toolkit bert-as-service[14]. The results demonstrate that we can not further improve the classification performance by just using word vectors from BERT.

To demonstrate that our preprocessing methods on Twitter do help us to improve the classification accuracy, we conduct an experiment with and without tweets specific preprocessing methods. By comparing the results shown in Table 18, we can clearly find that our preprocessing methods improve the classification accuracy by average 2% $\sim$ 3%. 2% is not a small number generally, especially when considering the fact that our model has an improvement of average 1%. This suggests that preprocessing is always the first step to consider and extremely important in NLP. When we conduct our experiments, we find that there is a performance difference when applying different preprocessing techniques on the same task.

Dataset	Without	With
Word(Word2Vec)	66.1	**68.1**
Word(Word2Vec) + Entity(Wikipedia2Vec)	66.1	**68.2**
Word(Wikipedia2Vec) + Entity(Wikipedia2Vec)	65.5	**68.8**

Table 18: Comparison between different preprocessing methods on Twitter. **Without**: classification without tweets specific preprocessing. **With**: classification with tweets specific preprocessing.

We also compare the performance of different text classification models, see Table 19. As we can see, TextCNN is already able to achieve pretty good performance, the models proposed later do not have much improvement. From evaluation scores on AG News and TREC listed in Tables at the end of this chapter, we can see on what labels the classification accuracy is improved.

[14] `https://github.com/hanxiao/bert-as-service`

To summarize our experimental results, our model EntCNN can improve the classification performance on four datasets, no matter they are traditional multi-class classification tasks or sentiment analysis tasks where we want to determine whether a sentence is positive or negative. Experimental results demonstrate that entities provide us with more contextual information and thus can help to classify documents.

Model	**Twitter**	**TREC**	**Movie Review**	**AG News**
TextCNN	68.1	89.4	83.0	87.4
RCNN	67.6	90.4	82.3	88.3
Bi-LSTM	63.6	88.4	83.7	88.2

Table 19: Comparison between different models. **TextCNN**: Convolutional Neural Network for sentence classification (Kim, 2014). **RCNN**: Recurrent Covolutional Neural Network for text classification (Lai, 2015). All words are initialized from 100 dimensional pre-trained model GloVe respectively.

Dataset	Precision	Recall	F1-Score
World	90.5	87.4	**88.9**
Sports	90.3	94.5	**92.3**
Business	84.9	85.2	**85.0**
Sci/Tech	86.5	85.1	**85.8**

Table 20: Evaluation of EntCNN on AG News

Dataset	Precision	Recall	F1-Score
World	91.5	85.7	88.5
Sports	89.0	95.2	92.0
Business	82.4	86.4	84.4
Sci/Tech	88.8	82.9	85.3

Table 21: Evaluation of TextCNN on AG News

Dataset	Precision	Recall	F1-Score
ABBR	100	77.8	87.5
ENTY	90.0	76.6	**82.8**
DESC	83.4	98.6	**90.4**
HUM	92.5	95.4	**94.0**
LOC	92.4	90.1	91.3
NUM	98.1	90.3	94.0

Table 22: Evaluation of EntCNN on TREC

Dataset	Precision	Recall	F1-Score
ABBR	100	77.8	87.5
ENTY	89.6	73.4	80.7
DESC	80.5	98.6	88.6
HUM	90.8	90.8	90.8
LOC	93.7	91.4	92.5
NUM	99.0	90.3	94.4

Table 23: Evaluation of TextCNN on TREC

8 Conclusion

8.1 Summary

Text classification has always been considered to be extremely important in NLP research and industry community. However, short text classification has not been a popular research topic. Thus, in our work, we explore the possibility to utilize named entities in neural network architectures to classify documents. Our key contribution is that we are the first to demonstrate that named entities help us to improve the performance of short text classification.

In our work, a novel neural network based approach of short text classification is proposed. We utilize and modify the convolutional neural network for text classification (TextCNN) proposed by Kim (2014)[28]. Our model is not only trained on top of pre-trained word vectors, but also on top of pre-trained entity vectors. Tagme is utilized to extract named entities from documents. We utilize Wikipedia2Vec and Doc2Vec to get entity vectors. Our feature statistics on four popular used NLP datasets demonstrate that the extracted named entities can be a feature for the following work. We compare the performance of our proposed model EntCNN with the baseline model TextCNN. By comparing our experimental results of different models on different datasets, we can conclude that entity vectors are helpful on mutil-class classification tasks. The impact of different kinds of pre-trained word vector representations on the classification accuracy is also studied in this work. The relative performance achieved using Word2Vec, Wikipedia2Vec, Doc2Vec and BERT depends on the dataset. Our results suggests that we experiment with different pre-trained word vectors for new NLP tasks. Additionally, our applied intensive preprocessing methods on tweets have been proven to show great improvement on the classification performance. Therefore, our experiment suggests that corpus specific preprocessing is always considered to be a crucial step in NLP.

8.2 Future Work

Our work is based on TextCNN proposed by Kim in 2014. This model achieves good classification performance across a wide range of text classification tasks and has become a standard baseline for text classification architectures since then. However fantastic progress has been achieved in NLP since last year in 2018. Large scale pre-trained language representation models like BERT, GPT and ELMo using the enormous amount of unannotated text on the web are proposed. These models can then be fine-tuned on small

amount of data NLP tasks and have been proven to be state-of-the-art models. BERT is a milestone in NLP and will have a lasting impact on subsequent NLP research and industrial applications. So in the following work, our efforts should be focused on these new SOTA models. Generative pre-trained language models together with task-specific fine-tuning should be considered to be a general NLP framework.

Due to time and compute resource reasons we did not explore fine-tuning BERT for text classification. Especially, according to our literature review, BERT for short text classification has not been studied yet. How to learn better pre-trained representations will continue to be a research popular point for some time. Pre-training on what size (word, sub-word, character etc.), what kind of language model (LSTMs, Transformer, etc.) to train, and how to adapt pre-trained models to specific tasks are interesting topics that still need to be explored.

When BERT involved in our work, we could explore the possibility to combine BERT input embeddings with entity embeddings. That is, BERT input representations are the sum of the token embeddings, the segmentation embeddings, the position embeddings and the entity embeddings.

A Feature Statistics

Table 24: Feature statistics on Movie Review

Movie Review	Positive	Negative
#total sentences	5331	5331
#sentences with entity	4517	4379
#sentences without entity	814	952
percentage of sentences with entity	**85%**	**82%**
#total entities	14171	13014
#average entities per sentence	3.14	2.97
#total entities with entity embedding in Wikipedia2Vec	13827	12677
percentage of entities with entity embedding	**98%**	**97%**
#sentences which have at least 1 entity embedding	4455	4328
percentage of sentences which have at least 1 entity embedding	**84%**	**81%**

Table 25: Feature statistics on AG News

AG News	Training Set	Test Set
#total sentences	120000	7600
#sentences with entity	110719	6989
#sentences without entity	9281	611
percentage of sentences with entity	**92%**	**92%**
#total entities	323517	20626
#average entities per sentence	2.92	2.95
#total entities with entity embedding in Wikipedia2Vec	316591	20204
percentage of entities with entity embedding	**98%**	**98%**
#sentences which have at least 1 entity embedding	110001	6942
percentage of sentences which have at least 1 entity embedding	**92%**	**91%**

Twitter	Training Set	Test Set
#total sentences	9684	3547
#sentences with entity	9219	3382
#sentences without entity	465	165
percentage of sentences with entity	**95%**	**95%**
#total entities	30551	10916
#average entities per sentence	3.31	3.23
#total entities with entity embedding in Wikipedia2Vec	28983	10278
percentage of entities with entity embedding	**95%**	**94%**
#sentences which have at least 1 entity embedding	9148	3345
percentage of sentences which have at least 1 entity embedding	**94%**	**94%**

Table 26: Feature statistics on Twitter

B Confusion Matrices

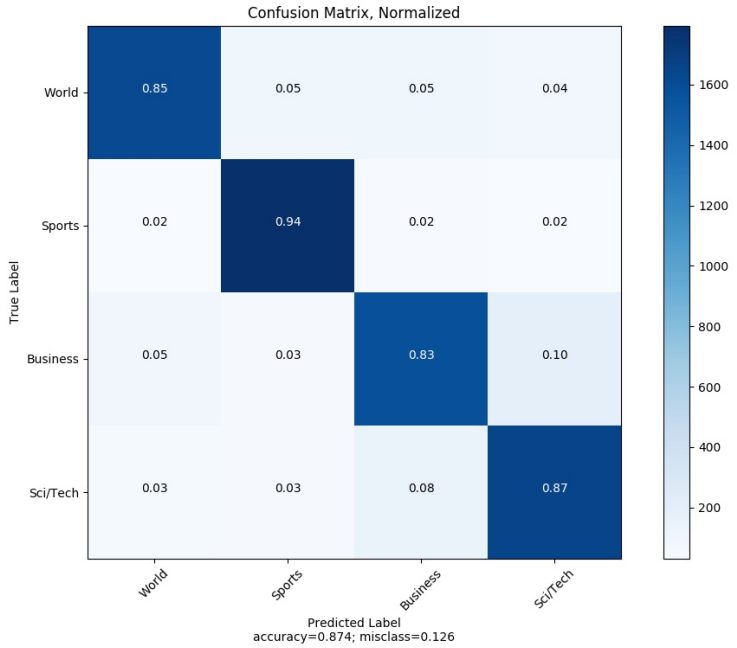


Figure B.1: Baseline model (TextCNN) normalized confusion matrix on AG News

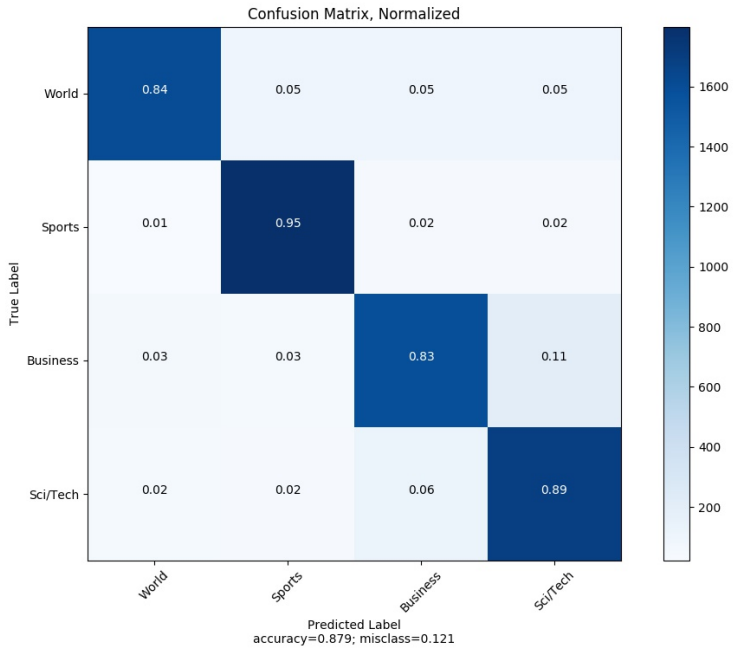


Figure B.2: Our model (EntCNN) normalized confusion matrix on AG News

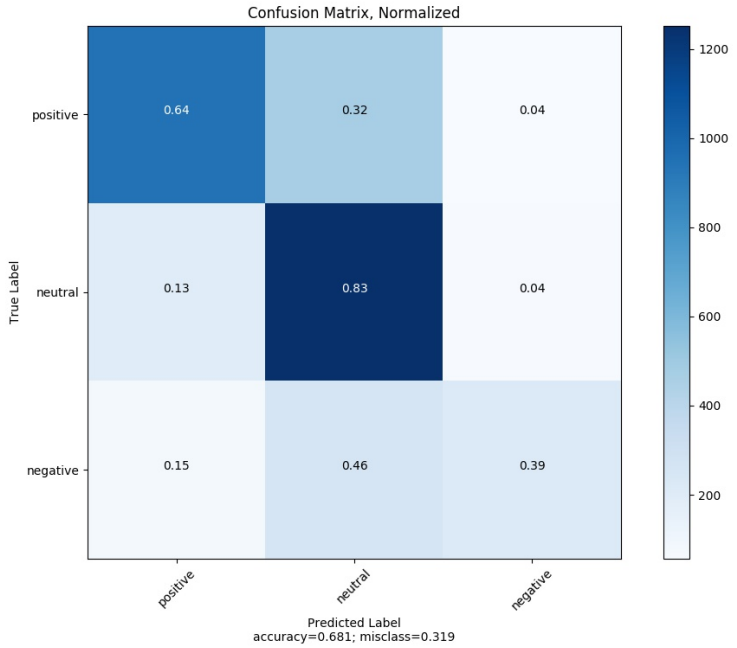


Figure B.3: Baseline model (TextCNN) normalized confusion matrix on Twitter

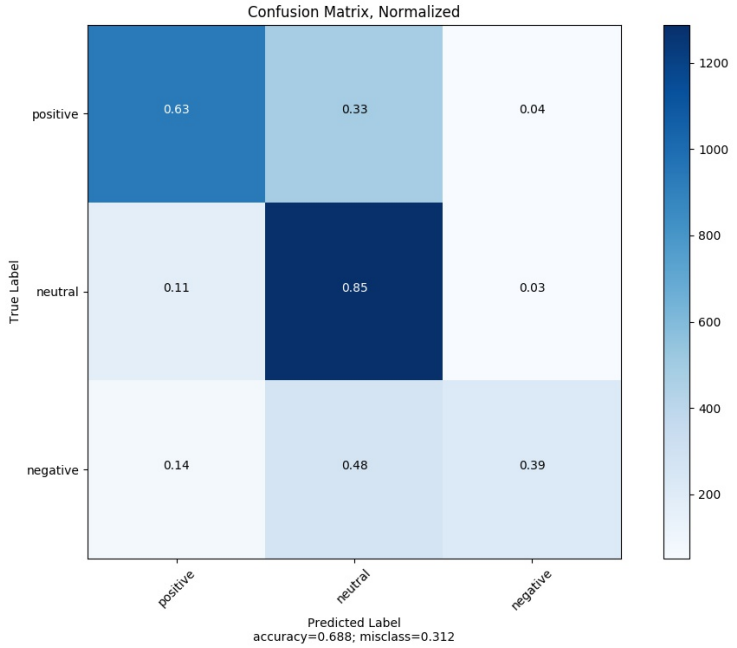


Figure B.4: Our model (EntCNN) normalized confusion matrix on Twitter

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Erklärung

Ich versichere wahrheitsgemäß, die Arbeit selbstständig verfasst, alle benutzten Hilfsmittel vollständig und genau angegeben und alles kenntlich gemacht zu haben, was aus Arbeiten anderer unverändert oder mit Abänderungen entnommen wurde sowie die Satzung des KIT zur Sicherung guter wissenschaftlicher Praxis in der jeweils gültigen Fassung beachtet zu haben.

Karlsruhe, 29. August 2019 QINGYUAN BIE