SkIn: Skimming-Intensive Long-Text Classification Using BERT for Medical Corpus

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Abstract

BERT is a widely used pre-trained model in natural language processing. However, since BERT is quadratic to the text length, the BERT model is difficult to be used directly on the long-text corpus. In some fields, the collected text data may be quite long, such as in the healthcare field. Therefore, to apply the pre-trained language knowledge of BERT to long text, in this paper, imitating the skimming-intensive reading method used by humans when reading a long paragraph, the Skimming-Intensive Model (SkIn) is proposed. It can dynamically select the critical information in the text so that the sentence input into the BERT-Base model is significantly shortened, which can effectively save the cost of the classification algorithm. Experiments show that the SkIn method has achieved superior accuracy than the baselines on long-text classification datasets in the medical field, while its time and space requirements increase linearly with the text length, alleviating the time and space overflow problem of basic BERT on long-text data.

1. Introduction

A large number of comment texts are generated on social media every time, and in some fields, some of these texts have long lengths. Especially in the medical field\cite{4, 5, 25}, the text describing the disease, the treatment effect, etc., may have a considerable length. Mining the opinions and sentiments contained in these comments helps track people’s attitudes and behaviors\cite{26}, look for similar patients and provide advice to new patients\cite{27, 28}, improve the survivorship of patients\cite{29}, identify potential disease hazards\cite{30}, collect statistical data to help scientific research in the medical field\cite{4}, and prevent potential drug adverse effects and medical accidents\cite{27, 31}. However, manual classification of such massive data will cost a lot\cite{32}, so we need to find an automatic way. However, because of the length of these texts, such tasks are quite challenging.

In the Natural Language Processing (NLP) field, pre-trained models can introduce a priori language knowledge, accelerating and optimizing the model training. BERT\cite{1} performs to some extent among the pre-trained language models, so it is widely used in NLP tasks\cite{2}. However, BERT is based on Transformer structure\cite{3}, which requires the time and space to the level of quadratic power of the input length for the intermediate results. This problem poses a challenge for applying the BERT model in long-text corpus.

When reading a long text, humans sometimes skim the full text quickly and then pay more attention to a critical segment for intensive reading. Therefore, with the inspiration of such skimming-intensive reading skill, we propose the Skimming-Intensive method (SkIn). We first use a classification algorithm with lower accuracy but a cheap cost to classify roughly, and then we select the most crucial segment through the classification process. Finally, we input the selected segment into a more precise classification model. In order to select the most crucial segment of a sentence, we propose the self-adaptive attention method to judge the importance of each segment.
We apply this method to Corpora for Medical Sentiment (CMS) [5], a long-text classification dataset in the medical field. Compared with the basic BERT model, SkIn achieves a improvement of accuracy while significantly reducing the cost of time and space. The increase of the cost of SkIn is much more slower than the basic BERT model. It saves up to more than 90% of the space cost compared with the baselines.

2. Background

BERT pre-trained language model [1], which stands for Bidirectional Encoder Representations from Transformers, is based on the Transformer encoder architecture. It embeds tokens into word vectors and then uses the multi-head self-attention layers to integrate the relevant information in the whole sentence, for which some scholars call it "contextual embedding" [4, 6]. Due to space limitation of this paper, please refer to reference [3] for a detailed description of the multi-head self-attention and Transformer. We can briefly describe a single self-attention mechanism layer applied in BERT by Eq. (1), where $K \in \mathbb{R}^{L \times d_k}$, $L$ is the length of the input and $d_k$ is the embedding dimension. If the number of the attention layers in BERT is recorded as $N$, BERT has $O(N d_k L^2)$ time & space cost. The BERT-Base model, the most versatile and popular one among BERT, has an embedding dimension of 768 and 12 layers of attention [1], which makes the GPU memory overflow easily during the training when $L$ is large. Even though reducing the batch size can save the GPU memory, the training time with reduced batches will be incredibly prolonged. Therefore, BERT sets an input length limit of 512 tokens to avoid the overflow problem, but it does not solve the problem essentially.

$$Self\, Attention(K) = \text{softmax}(\frac{K K^T}{\sqrt{d_k}})K$$  

Once BERT was proposed, it broke the best scores on several NLP tasks, and its pre-training can introduce rich language knowledge into our next processing model. Because of this advantage, we still try to find ways to apply it despite the difficulty of lengthy text. Google\footnote{https://github.com/google-research/bert} provides open-source pre-trained BERT models with different complexities. For example, the BERT-Tiny model, a concise version of BERT-Base, has an embedding dimension of 128 and 2 layers of attention. The BERT pre-trained models used in this paper are all provided by Google.

Related works. Some scholars solved this problem by truncating the input in fixed ways [7, 8]. Chen et al. [8] extracted two sentences shorter than a certain length, the one from the beginning, and the other from the end of the text. Then they input them into the BERT-Base model for classification. Nevertheless, this kind of method suffers from a loss of information that could help understand the sentence [9].

Another method is segmenting the text into many short segments, then using a downstream network to establish semantic associations between different segments [7, 4, 10]. Pappagari et al. [10] proposed a slide-window model, where the text is segmented into fixed length blocks and input into BERT. Then, an LSTM [11] network or Transformer is used to fuse the output of different blocks into a global feature. This method seems to avoid the information loss of the truncation method, but experiments show that it has no significant improvement in accuracy, and still has a quadratic memory cost (see §5.3 Time & Memory Cost).

Some scholars [12, 13, 14] choose to optimize the Transformer. Beltagy et al. [13] used local windowed attention for shortening the length of sentences to be processed simultaneously by attention. By such methodology, the cost of the Transformer can be saved, while the upper length limit of BERT can be increased. However, such an increment is often limited and accompanied by the loss of information that may contain essential information.
Min et al. [15] proved that there is a critical segment in almost all long text by human reading experiment, and the information obtained in this segment is similar to the whole text. With this idea, they divided a paragraph into sentences and proposed a method to select the critical sentences using the encoder-decoder architecture. Ding et al. [16] proposed a method called MemRecall to give a score to each part to select the key segment. Their methods achieved excellent results in several Q&A and classification datasets. Fiok et al. [9] also proposed the Text Guide method to select the key segment. Selecting the critical segment significantly reduces the algorithm overhead without losing essential information. This paper also follows the idea of key-segment selection.

3. Methodology & Model

Problem definition. Given the input text \( s \in \mathbb{R}^L \), the model is expected to predict the sentence classification \( \hat{y} \) posteriorly. Where the number of classes is \( U \), in other words, \( \hat{y} \in \{1, 2, \ldots, U\} \).

Methodology. Inspired by the previous work [16], we also assume that there is a key segment \( s^+ \subset s \), which can be classified similarly to \( s \) by a certain Classifier as Eq.(2):

\[
\text{Classifier}(s^+) \approx \text{Classifier}(s)
\]  

Therefore, how to find this key segment is an essential problem. An intuitive way is to tag the key segment manually and train a Sequence Labeling [17] model to segment the text. However, such manual tagging is not only tedious but also affected by subjective factors easily. So to calculate the importance of each segment without additional labeling, we propose the Self-adaptive Attention mechanism (SaA).

![Figure 1: The architecture of SkIn model.](image-url)
Model summary. As shown in Figure 1, we first divide the long text $s$ into $n$ segments of length $l$, that is $(s^{(1)}, s^{(2)}, \ldots, s^{(n)})$. Then, the skimming method, called Previous Classification and Self-adaptation Attention (PrC-SaA) is used to quickly generate a weight for each segment and a previous classification result related to this weight. The classification result is used for training the PrC-SaA while the score is used for selecting the key segment. We select the segment $s^{(k)}$ with the highest score and its context as the key segment $s^{+}$. Then we input $s^{+}$ into the intensive method called Key Segment Classification (KSC) for precise classification. The PrC-SaA is to imitate the skimming reading of human, and the KSC is the intensive reading, for which our model is called Skimming-Intensive Model (SkIn).

3.1 Skimming: Previous Classification and Self-adaption Attention

The PrC-SaA consists of a Lite Encoder and a SaA module.

**Lite Encoder** quickly encodes all the input segments into semantic vectors with a lightweight model. It outputs a semantic vector $p^{(i)} \in \mathbb{R}^{d_g}$ for each segment $s^{(i)}$ with embedding dimension $d_g$ as shown in Eq.(3):

$$p^{(i)} = \text{LiteEncoder}(s^{(i)})$$  \hspace{1cm} (3)

In our model, the BERT-Tiny pre-trained model which is much cheaper than the BERT-Base, and a global average pooling layer are used as the Lite Encoder, as shown in Eq.(4) and (5), where $v^{(i)} \in \mathbb{R}^{l \times d_g}$ is the embedding matrix generated by BERT-Tiny of $s^{(i)}$.

$$v^{(i)} = \text{BERT}_{\text{Tiny}}(s^{(i)})$$  \hspace{1cm} (4)

$$p^{(i)} = \frac{\sum_{j=1}^{l} v^{(i)}_j}{l}$$  \hspace{1cm} (5)

**Self-adaptive Attention** (SaA) gives weight to each segment’s encoding vector $p^{(i)}$ and averages them into a global semantic vector by the given weight as shown in Eq.(7) and Eq.(8). Previously, each $p^{(i)}$ from the lite encoder layer is merged into the global encoding matrix $p \in \mathbb{R}^{n \times d_g}$ as shown in Eq.(6).

$$p = [p^{(1)}; p^{(2)}; \ldots; p^{(n-1)}; p^{(n)}]$$  \hspace{1cm} (6)

Then, the self-adaptive attention is used as Eq.(7) and (8). Unlike the general attention mechanism[18], SaA uses a trainable model parameter $W_{a} \in \mathbb{R}^{1 \times n}$ as one of the inputs of the attention mechanism. So the SaA is more like a dense layer than an attention layer. $g \in \mathbb{R}^{n}$ holds the weight score given to each segment, $r_{g} \in \mathbb{R}^{d_g}$ is the global semantic vector. Although the factor $1/\sqrt{d_g}$ will reduce the variance of the result of $softmax$, it can put the intermediate result $W_{a}p^{T}$ in a suitable range and avoid potential overflow and gradient problems[3].

$$g = softmax\left(\frac{W_{a}p^{T}}{\sqrt{d_g}}\right)$$  \hspace{1cm} (7)

$$r_{g} = gp$$  \hspace{1cm} (8)

To train the PrC-SaA, the skimming part, $r_{g}$ is input into a dense layer activated by $softmax$ to generate a vector $o_{pre} \in \mathbb{R}^{U}$ that contains the probability of the sentence belongs to each category as Eq.(9). Where $W_{op} \in \mathbb{R}^{U \times d_g}$ and $b_{op} \in \mathbb{R}^{U}$ are the model parameters.
\[ o_{pre} = \text{softmax}(W_{op}r_g + b_{op}) \] (9)

Therefore, we can use \( o_{pre} \) to train the PrC-SaA, which can judge the segment with the most significant importance, only through the labels of the original dataset without manually marking the most important segments.

3.2 Key Segment Selection

After the training of the skimming model, we input each long text in the dataset into PrC-SaA and get its weight vector \( g \), then select its key segment \( s^{+} \) by Algorithm 1.

**Algorithm 1: Key Segment Selection**

| Input | Weight vector \( g \); Long text \( s \); Number of segments \( n \); Length of each segment \( l \); |
|-------|---------------------------------------------------|
| Output: | Selected key segment \( s^{+} \); |
| 1   | Get the key index \( k = \text{Argmax}(g) \); |
| 2   | if \( k == 0 \) then |
| 3   | \( \text{return} \ s[0 : l + l/2] \) |
| 4   | else if \( k == n - 1 \) then |
| 5   | \( \text{return} \ s[l \times (n - 1) - l/2 : l \times n] \) |
| 6   | else |
| 7   | \( \text{return} \ s[l \times (k - 1) - l/4 : l \times k + l/4] \) |
| 8   | end |

Merging too much context may lead to irrelevant information and excessive overhead, while too little context may lead to losing essential information when key parts cross the edge of the segment. Therefore, by Algorithm 1, the length of each key segment is fixed at \( 1.5l \), which includes the content of the segment with the highest score. If the skimming model is correctly set and adequately trained, the selection of key segment can effectively prevent irrelevant information from entering the precise intensive model, and as a result, the model performance can be optimized (see §5.2 Result of SkIn).

3.3 Intensive: Key Segment Classification

Since the length of the key segment is significantly shorter than the original text, a heavy classification model with high accuracy can be used on shortened text. That is the KSC module.

The KSC consists of a Strong Encoder and a vector concatenation operation.

**Strong Encoder.** Similar to the Lite Encoder, the input key segment \( s^{+} \) is firstly encoded by a high-precision text encoding layer into a local semantic vector \( r_l \in \mathbb{R}^{d_l} \), where \( d_l \) is the embedding dimension of this encoder, as shown in Eq.(10).

\[ r_l = \text{StrongEncoder}(s^{+}) \] (10)

In our model, similar to the PrC-SaA, the BERT-Base pre-trained model and a global average pooling layer are used as the Strong Encoder, as shown in Eq.(11) and (12).

\[ e_l = \text{BERT}_{\text{Base}}(s^{+}) \] (11)
\[ r_l = \frac{\sum_{i=1}^{1.5l} e_{l,i}}{1.5l} \]  

**Vector concatenation.** In order to complete the part of global information, the local encoding vector \( r_l \) and the global encoding vector \( r_g \) generated in the PrC-SaA are concatenated as the final feature \( r \in \mathbb{R}^{d_g + d_l} \), as shown in Eq.(13).

\[ r = [r_l, r_g] \]  

This final feature is output via a dense layer similar with PrC-SaA, as shown in Eq.(14), where \( o \in \mathbb{R}^U \), whose content is the probability that the text belongs to each category, \( W_o \in \mathbb{R}^{U \times (d_g + d_l)} \) and \( b_o \in \mathbb{R}^U \) are the model parameters.

\[ o = \text{softmax}(W_or_g + b_o) \]  

### 3.4 Training Methodology

**Stage 1.** The PrC-SaA model is trained in advance, during which the \( o_{pre} \) is taken as the output, and the cross-entropy function characterizes the loss as Eq.(15).

\[ \text{Loss}_{PrC} = \text{CrossEntropy}(o_{pre}) \]  

**Stage 2.** After the previous training, for each long text in the dataset, PrC-SaA is used to predict a weight score, and then Algorithm 1 extracts its key segment.

**Stage 3.** After the whole dataset is segmented and selected, the joint training of the whole SkIn model is conducted. PrC-SaA still accepts the input of all segments \( s^{(1)}, s^{(2)}, \ldots, s^{(n)} \), while KSC accepts the input of key segment \( s^+ \). Instead of \( o_{pre} \), \( o \) is used as the output. The cross-entropy function characterizes the loss as Eq.(16).

\[ \text{Loss} = \text{CrossEntropy}(o) \]  

### 4. Experiment

To verify the effectiveness of SkIn model, we apply it to the CMS dataset collected by Yadav et al.[5]. Moreover, we measure its prediction accuracy and time & memory cost.

#### 4.1 Dataset

The CMS dataset is composed of two sub-datasets. One is the **Medical-Condition** dataset, composed of social media users’ comments on their clinical symptoms. As shown in Table 1, these comments are divided into three categories according to the progress of clinical symptoms: symptoms **Exist**, symptoms **Recover**, and symptoms **Deteriorate**. The other is the **Medication** dataset, which is composed of comments on the effects of medical treatment. As shown in Table 2, these comments are divided into three categories according to the effect of medical treatment: **Effective** treatment, **Ineffective** treatment, and **Serious Adverse Effect** (SAE).
Table 1: Examples of **Medical-Condition** dataset. The underlined are the basis for labeling.

| Label  | Example                                                                                           |
|--------|---------------------------------------------------------------------------------------------------|
| Exist  | Chest pains borking and thinking I’m going to die can someone help me to distract my thoughts so I can enjoy my holiday. |
| Recover| Tumor has not grown, but will be on meds and monitored. This is good news. Thanks for your comfort and prayer mission. |
| Deteriorate | I had a migraine with aura a couple of days ago. Since then my anxiety has been worse, feel panicky and low mood. Has anyone else experienced this? |

Table 2: Examples of **Medication** dataset. The underlined are the basis for labeling.

| Label      | Example                                                                                           |
|------------|---------------------------------------------------------------------------------------------------|
| Effective  | I have had nervous tics since I was very young. I’m now almost 60 years old & still have tics. They are only calmed by taking Clonazepam. |
| Ineffective| Propranolol isn’t helping and the GP’s and Psychiatrists won’t give me Benzo’s. Is there anything else that can help with crippling anxiety? |
| SAE        | Just switched from Cefalex to Effexor. My head feels spacey and dizzy. Is this normal and how long will it last? |

**Figure 2:** Distribution of sentence length in (A) **Medical-Condition** and (B) **Medication** datasets. The Length refers to the number of tokens in sequence generated by the standard BERT tokenizer[1].

The text of the datasets is tokenized by BERT tokenizer[1], and the length statistics of the token sequences are shown in Figure 2. The original datasets were not divided, so 30% of each dataset is randomly selected as the evaluate set. The distribution of the datasets after division is shown in Table 3. All texts in the dataset are intercepted to 1024 tokens.
Table 3: Statistics of labels in both datasets.

| Dataset       | Label | Train | Test | Total |
|---------------|-------|-------|------|-------|
|               | Medical-Condition |       |      |       |
|               | Exist     | 1662  | 734  | 2396  |
|               | Recover   | 501   | 202  | 703   |
|               | Deteriorate | 1468  | 621  | 2089  |
|               | Total     | 3631  | 1557 | 5188  |
|               | Medication |       |      |       |
|               | Effective | 337   | 125  | 462   |
|               | Ineffective | 436   | 117  | 553   |
|               | SAE       | 837   | 389  | 1226  |
|               | Total     | 1610  | 631  | 2241  |

4.2 Regularization

**L2 Normalization**[19] is one of the most common methods to prevent overfitting of deep neural networks. L2 normalization is to add the L2 norm of all the weight to the loss function as a penalty term. If the model parameters are recorded as $\theta$, the loss function with L2 normalization is shown below, where $r_{L2}$ is the normalization rate of L2, the hyperparameter of the training.

$$Loss_{L2} = Loss + r_{L2} \sum_{\theta} \|\theta\|_{L2}$$ (17)

**Dropout** layer[20] randomly discards the input tensor value with a probability $p_{dropout}$ during the training. The dropout layer has been proved to effect as data augmentation[21], which improves the robustness of neural networks, so it is widely used in deep learning.

**Label Smoothing** method[22] is an overfitting prevention method for classification tasks. It replaces 0 in the label one-hot vector to $\gamma$, and 1 to $1 - \gamma$ so that the input of softmax is much smoother to prevent overfitting for some unbalanced tags.

4.3 Experiment Settings

Table 4: Model and training hyperparameters.

| Hyperparameters          | Expression | Value |
|--------------------------|------------|-------|
| Global embedding dimension | $d_g$      | 128   |
| Local embedding dimension | $d_l$      | 768   |
| Number of labels         | $U$        | 3     |
| L2 regularization rate   | $r_{L2}$   | $1 \times 10^{-5}$ |
| Dropout probability      | $p_{dropout}$ | 0.3   |
| Segment length           | $l$        | 128   |
| Segments number          | $n$        | 8     |
| Total input length       | $l \times n$ | 1024  |
| Label smoothing factor   | $\gamma$   | 0.2   |
| Skimmed learning rate    | $\alpha_1$ | $1 \times 10^{-4}$ |
| Intensive learning rate  | $\alpha_2$ | $1 \times 10^{-5}$ |
| First moment factor      | $\beta_1$  | 0.9   |
| Second moment factor     | $\beta_2$  | 0.99  |
| Minibatch size           | $n_b$      | 32    |

**Training of PrC-SaA.** First, the unique token [CLS] and [SEP] of BERT, which is used to declare the classification task and the end of a sentence, are attached to the beginning and end
of the input text respectively. BERT-Tiny loads from Google pre-trained model. We use all three regularization methods above to reduce overfitting. Parameters were updated using Adam optimizer[23], which introduces three model hyperparameters: learning rate $\alpha_1$, momentum factor $\beta_1,\beta_2$.

**Training of SkIn.** After the previous training is finished, the trained PrC-SaA model is used to distill all the texts in datasets according to Algorithm 1. [CLS] and [SEP] are respectively added to the head and tail of the selected key segment, which are input into the KSC model, so that the whole SkIn model is jointly trained. BERT-Base loads from Google pre-trained model. We use all three regularization methods mentioned above to reduce overfitting too. Parameters were updated using Adam optimizer too, and the learning rate is adjusted to $\alpha_2$.

Table 4 shows all the model and training hyperparameters.

At the same time, the time & memory cost of SkIn under variable input length is measured. In the measurement of cost, SkIn model adopts two methods to adapt to the input length: (1) **SkIn-InvariableSegment** keeps the total number $n$ of segments fixed, and adjust the length $l$ of each segment in proportion to the increase of input length; (2) **SkIn-VariableSegment** keeps the length $l$ of each segment unchanged, and adjust the total number $n$ of segments in proportion to the input length.

### 4.4 Baselines

The experimental result of SkIn is compared with the following baseline models.

**BERT**[7] is shown in Figure 3-(A). The length of all texts is truncated or padded to the BERT’s upper limit of 512 tokens. After contextualized embedding using the pre-trained BERT-Base model, the global average pooling is performed, and the pooling result is output through a dense layer activated by $\text{softmax}$.

**CNN**[5] is shown in Figure 3-(B). The input tokens are embedded to 300-dimensional vectors and input into three 1D-CNNs activated by Rectified Linear Unit (ReLU)[24] with convolution kernel widths of 3, 4 and 5. Then, the convolution results are output to the global maximum pooling, and the pooling results are concatenated into the final feature vectors and input into a dense layer activated by $\text{softmax}$ for output.

**CNN-BERTemb** is similar to the CNN model as shown in Figure 3-(B). The embedding layer of CNN-BERTemb uses the embedding layer of the BERT-Base pre-trained model to generate 768-dimensional non-contextual word embedding vectors. The structure of the other parts of CNN-BERTemb is consistent with CNN model.

**BERT-128HT**[8] is shown in Figure 3-(C). Connect the 128 tokens at the beginning and 128 tokens at the end of the text with BERT’s unique token [SEP] (if the length is less than 128, pad it to 128). Input the connected sequence to BERT-Base for contextualized embedding, then perform global average pooling, and output the result through a dense layer activated by $\text{softmax}$.

![Figure 3: Baseline models.](image-url)

(A) BERT (B) CNN/CNN-BERTemb (C) BERT-128HT (D) BERT-SlideWindow
BERT-SlideWindow[7] is shown in Figure 3-(D). The length of each text is truncated or padded to 1024 tokens and then divided into 8 segments with equal lengths of 128. Each segment is embedded in BERT-Base and input into a global maximum pooling layer. After that, these pooling results are averaged, and the average result outputs through a dense layer activated by softmax.

5. Result

5.1 Result of PrC-SaA

The classification accuracy of PrC-SaA is shown in Table 6. The accuracy of PrC-SaA is not satisfactory, but we pay more attention to whether it can select the key segment correctly rather than the classification accuracy within the PrC-SaA stage.

Select a piece of text in the Medical-Condition test set, input it into PrC-SaA model, and make it generate scores for different segments of the text, as shown in Table 5. The true label of this text is Deteriorate, and the classification predicted by the PrC-SaA model is also Deteriorate.

As underlined in Table 5, the author emphasizes the deterioration of his symptoms in the second segment, so the PrC-SaA model gives it the highest score. This example can prove the effectiveness of the PrC-SaA in selecting the key segment from texts.

Table 5: Example of segmentation performance of PrC-SaA.

The [Pad] is the padding token used to pad the length of the input sequence. The underlined parts are the key sentences judged manually.

| Segment | Text                                                                 | Score/\% |
|---------|----------------------------------------------------------------------|----------|
| 1       | Hello, I just wanted to share my story really. I’m 24 now and I believe ever since I was a kid I’ve had anxiety. I was very shy and wouldn’t talk to anyone. I was and still am very selective over my friends. I was very sporty in school but I was unable to perform well with people I wasn’t comfortable with if that makes sense. I would just freeze in a way I wouldn’t perform as I know I could. Also occasionally it felt like I was in a daze. As I’ve got into my 20s my anxiety has worsened and got a lot more noticeable. | 18.52    |
| 2       | Saying that, there has been periods when I have felt okay such as when I was exercising daily and seeing my friends more. Now I have a lot less time for things like this as I have more responsibility now. (Management job, house, girlfriend, dog) My symptoms tend to come and go every 3 weeks or so. I would have 1/2 good weeks then maybe a bad month where I would feel demotivated, headaches, dizzy, health worries (even though I have no other health problems) bad stomachs, palpitations, worry, fatigue etc. It sucks really. I have found exercise and generally being busy... | 43.81    |
| 3       | ...has helped for me in the past which I have tried to do but sometimes I don’t even feel like leaving the house let alone anything else. I’m not on any meds but maybe I should be? I dunno I’m one of those people who would have a headache for a day, think I’m dying which then makes it worse. The headache would then go away but that would just repeat the next time. Same with heart and stomach related things. I consider myself lucky in life to be honest. I love my friends, family, girlfriend, pets etc. I’ve never had to deal with much grief... | 20.47    |
| 4       | ...yet which is lucky I think for being a 24 year old. Also I’m reasonably smart when anxiety doesn’t take over I’ve never really talked about this much to anyone apart from my girlfriend. Any advice for me? Would be appreciated Thanks Phil | 16.01    |
| 5       | [Pad]                                                               | 0.3      |
| 6       | [Pad]                                                               | 0.3      |
| 7       | [Pad]                                                               | 0.3      |
| 8       | [Pad]                                                               | 0.29     |

5.2 Result of SkIn

The classification performance scores of SkIn compared with the baseline model are shown in Table 6.
The results show that the SkIn model significantly improved in both datasets compared to the baseline model. Compared with the CNN model, the accuracy of the two datasets has improved by about 4% - 7%, and the F1 score about 5% - 8%. Compared with the PrC-SaA part, the results of joint training have been improved by 3% - 5% for both accuracy and F1 score, which shows the effectiveness of the intensive part of SkIn method.

Table 6: Classification performance of baselines and our models. The best results are shown in bold.

| Model                | Medical-Condition | Medication |
|----------------------|-------------------|------------|
|                      | Acc./% F1/%       | Acc./% F1/%|
| BERT                 | 61.59 58.02       | 75.54 69.99|
| CNN                  | 57.29 53.04       | 75.69 70.18|
| CNN-BERTemb          | 61.72 55.78       | 77.56 72.64|
| BERT-128HT           | 63.01 60.09       | 76.41 72.17|
| BERT-SlideWindow     | 60.89 56.57       | 77.42 71.91|
| PrC-SaA              | 61.27 56.26       | 76.99 72.70|
| SkIn                 | **64.42 61.60**   | **79.45 75.74**|

5.3 Time & Memory Cost

We measure the time & memory cost of BERT, BERT-SlideWindow, and SkIn with both above-mentioned length adjustment methods on the Medical-Condition train set. With the increase of token length, similar to the SkIn-InvariableSegment, the BERT-SlideWindow model always divides the input into 8 segments, and the length of each segment increases in equal proportion. Due to the limitation of the algorithm and GPU memory, BERT cannot be trained when the token length is greater than 512, BERT-SlideWindow runs out of the GPU memory when the token length is greater than 1536, and SkIn-InvariableSegment reaches the maximum length of BERT when the length is greater than 2560. Therefore, the existing data are used for quadratic polynomial regression to predict the data when the model fails. The data is presented in Fig. 4.

As shown in Fig. 4, results (A) and (B) show that when the token length is from 128 to 2048, the cost of both BERT and BERT-SlideWindow show noticeable quadratic growth, and the cost of SkIn method in this range is much lower than the other two. Especially with a longer token length, SkIn saves up to more than 90% (from 162.0 GB to 14.03 GB) of the memory compared with BERT. Therefore, SkIn can significantly reduce the cost of BERT pre-trained model in long-text classification.

Results (C) and (D) show that if the number of segments is adjusted to fit the input while the length of each segment is unchanged, the SkIn method can reach a linear space-time complexity, but the division of segments will introduce additional time cost. Moreover, by changing the length of segments while the number of segments is maintained, the SkIn method still has a quadratic space-time complexity, but does not introduce additional time cost. Therefore, in actual use, the number of segments and the length of segments should be adjusted simultaneously according to the text length.

6. Conclusion and Discussion

Because of the benefits of opinion mining in medical comments mentioned before, we try to use the pre-trained BERT to accomplish the task. However, the comments in the medical corpus may be lengthy. BERT, which is quadratic to the sequence length, is hard to apply directly to the long text. So the main contribution of this paper is as follows:

1. **The self-adaptive attention (SaA) mechanism** is proposed to select the most critical segment by the classification process without additional dataset annotations. Based on the SaA and BERT, the Skimming-Intensive (SkIn) method for long text classification is proposed.
2. **Classification accuracy.** The classification accuracy of SkIn is evaluated on the CMS dataset[5]. The result shows that compared with the baselines, the accuracy of SkIn is improved.

![Figure 4](image)

**Figure 4:** (A)(C) memory and (B)(D) time cost with varying sentence length. The Length refers to the number of tokens in sequence generated by the BERT tokenizer. Hollow points represent the data predicted by quadratic polynomial regression. The data were measured using 1 NVIDIA Ampere A100 GPU (39GB) with batch size of 16.

3. **Cost.** SkIn and baselines methods are compared in terms of space-time cost. The result shows that SkIn saves considerable time and memory and reaches a linear time-space complexity.

The experiment results show that the SkIn method not only achieves better accuracy than the baseline model but also has a linear increase in space-time complexity on long-text datasets, which solves the overflow problem of basic BERT on long texts. The self-adaptive attention mechanism can effectively alleviate the problem of lengthy text processing laconically without extra annotations. This method that only uses an additional network to select the critical segment can be adapted to various NLP downstream models and may become a general paradigm for lengthy text processing. In future work, we will apply this methodology to complex downstream tasks such as aspect-based sentiment analysis and Q&A system.
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