Evaluation of Pretrained BERT Model by Using Sentence Clustering

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Abstract

For evaluation of pre-trained models like bidirectional encoder representations from transformers (BERT), task-based approaches are frequently adopted and there is a possibility that meta parameters for fine-tuning influence results of the evaluations. However, task-based approaches for languages, except English, have a problem—there is no common dataset for their evaluation. Hence, evaluating pre-trained models for these languages with task-based approaches is challenging. In this work, we evaluate Japanese pre-trained BERT models with CLS token. We input labeled sentences to models, get CLS token embeddings, and calculate scores from in-class and out-of-class dispersions, which can be calculated from embeddings and labels of sentences. Experiment results show that a model released by Laboro.AI Inc. is the best Japanese pre-trained BERT model. Meanwhile, the results of evaluation with sentence clustering are different from those of evaluations that are based on fill mask task.

1 Introduction

BERT (Devlin et al., 2019) is a high-performance pre-training model. It helped in the improvement of the performance of natural language processing tasks. Generally, task-based approaches were adopted for evaluating pre-training models like BERT. In English language, a dataset for task-based evaluation, such as the general language understanding evaluation (GLUE) (Wang et al., 2018), can be used, and it is easy to compare models. However, when a pre-trained model is fine-tuned for task-based evaluation, meta parameters for fine-tuning may influence scores of the model. Hence, task-based evaluation with fine-tuning has a possibility of biased evaluation. Also, there is no common task-based dataset for languages except English, so it is challenging to compare pre-trained models for other languages.

In this work, we evaluate Japanese pre-trained BERT models using CLS token embeddings in outputs of target models. CLS token embedding can be regarded as an input sentence embedding, and models can be rated with evaluating embeddings itself. However, how to evaluate sentence embeddings is also challenging. Here, we use clustering to evaluate sentence embeddings. Also, we prepare sets of sentences sorted by genre and use BERT models to get embeddings of each sentence. Then, we cluster those embeddings and evaluate models with clustering score.

2 Related Works

Generally, a task-based approach for evaluation is adopted to compare and evaluate pre-trained models like BERT. Although this simple method requires data for evaluation, it consists of the following 3 steps:

1. Solve a task with pre-trained model A and get its accuracy.
2. Solve this same task with pre-trained model B and get its accuracy.
3. Compare the accuracies and evaluate models A
and B.

The GLUE can be used for English, but there is no common dataset for other languages, so we have to prepare the dataset for evaluation ourselves.

There is a work that compared and evaluated some Japanese pre-trained BERT models. In this work, we evaluated three BERT models using document classification tasks with the Amazon dataset (Shibayama et al., 2019). However, BERT is a model for sentences, and there is no established method of document classification with BERT. Therefore, whether document classification is the right task to evaluate or not is questionable. We use a sentence as input of BERT and evaluate models using CLS token embeddings, which can be considered as sentence embeddings from outputs of BERT.

The approaches for evaluation of embeddings are task-based, but in the case of word embeddings from outputs of some method like word2vec (Mikolov et al., 2013), there is a viewpoint that embeddings represent the meaning of words. Also, there is a research that evaluated embeddings with correlation of similarities between words calculated from the similarity of embeddings and by hand (Sakaizawa and Komachi, 2016).

3 Evaluation of BERT

In Section 2, we mentioned that a task-based approach is frequently adopted to evaluate embeddings. Also, we mentioned that there is a viewpoint that embeddings represent the meaning of words. When this viewpoint is applied to clustering, we can say that a cluster can be represented by a group of embeddings in it. In what follows, we use this to evaluate pre-trained BERT models with sentence clustering.

3.1 Method of the Evaluation

Embeddings that were outputted from BERT model \( m \), were evaluated by the following 5 steps. Labels for sentences of model \( m \)’s input were required to do this evaluation.

1. Get CLS token’s embedding from the output of each sentence of model \( m \), and use the embedding as the sentence vector.
2. Check which class contains the sentence vector, and calculate \( g_{i}^{(m)} \): centroid of each class of model \( m \).
3. Calculate \( A_{m} \): in-class dispersion of each class from the following expression\(^1\).
   \[
   A_{m} = \sum_{i=1}^{N} \sigma_{i}^{2}
   \]
   where \( \sigma_{i}^{2} = \sum_{j \in C_{i}} (g_{i}^{(m)} - x_{i,j})^{2} \), \( C_{i} \) is class \( i \) and \( N \) is number of classes.
4. Calculate \( g^{(m)} \): average centroids of all classes and calculate \( B_{m} \): out-of-class dispersion from the following expression.\(^2\)
   \[
   B_{m} = \sum_{i=1}^{N} \sum_{j} ||g^{(m)} - g_{i}^{(m)}||^{2} (N = \text{Number of classes})
   \]
5. Calculate a degree of separation: \( M_{m} = \frac{A_{m}}{B_{m}} \), and use \( M_{m} \) as a score of model \( m \). This score becomes smaller when clustering with model \( m \) is performed properly.

Figure 1 summarizes the flow of the evaluation.

3.2 Re-evaluation by Using Fill Mask Task

We re-evaluated models with a fill mask task in order to verify the results of sentence clustering evaluation. The steps for the re-evaluation are as following:

1. Prepare a dataset- we prepared a dataset that contains sentences and which word to be masked in matching sentence as labels.
2. Predict masked word with model- we calculated percentages that mask token was the word in matching label which was defined in a dataset from outputs of models.
3. Average and comparison- we compared averages of percentages that were calculated in step 2.

\(^1\)We consider the second power of deviation as the dispersion in this work in order to calculate easily. So, true in-class dispersion can be calculated from \( \sigma_{i}^{2} \).

\(^2\)Also, we consider the second power of deviation of centroids of all classes as dispersion like \( A_{m} \).
Detailed information on the abovementioned comparison is in the next subsection.

3.3 Experimental Setups

Firstly, we explain common setups for evaluation with sentence clustering and fill mask task. We compared six models: a model which was released by Kurohasi & Murawaki Lab at Kyoto University (hereafter, Kyoto Univ. Ver.)\(^3\), Mr. Morinaga (hereafter, MeCab Ver.)\(^4\), Mr. Yohei Kikuta (hereafter, SP Ver.)\(^5\), Inui & Suzuki Lab at Tohoku University (hereafter, Tohoku Univ. Ver.)\(^6\), National Institute of Information and Communications Technology (NICT) (hereafter, NICT Ver.)\(^7\), and Laboro.AI Inc. (hereafter, Laboro Ver.)\(^8\). We did not fine-tune models for comparisons.

Table 1 summarizes the word tokenizer and pre-training corpus of pre-trained models. Model size of all models are base format of official BERT (Devlin et al., 2019): 12-layer, 768-hidden, and 12-heads. So sentence vectors we got in the evaluation with sentence clustering have 768 dimensions. Juman++ and MeCab are software for morphological analysis. Juman++ uses Recurrent Neural Network Language Model and MeCab uses bi-gram Markov model for analysing. SentencePiece is unsupervised text tokenizer and detokenizer, so model publishers which use SentencePiece as tokenizer release pre-trained SentencePiece model with their BERT model.

| Models           | Tokenizer (characteristic) | Pre-training corpus          |
|------------------|----------------------------|------------------------------|
| Kyoto Univ. Ver. | Juman++                    | Wikipedia                    |
| MeCab Ver.       | MeCab + NEologd (No subword tokenize) | Articles of business news |
| SP Ver.          | SentencePiece (do_lower_case = True) | Wikipedia                    |
| Tohoku Univ. Ver.| MeCab + NEologd            | Wikipedia                    |
| NICT Ver.        | MeCab + Jumandic           | Wikipedia                    |
| Laboro Ver.      | SentencePiece              | Texts on the Internet (12GB)|

In the evaluation with sentence clustering, we used Livedoor news corpus\(^9\). This dataset contains nine categories of articles and we used one hundred articles per category. We extracted titles from selected articles and regarded categories as classes. Then, we calculated scores with the method in Section 3.1 and compared these scores.

In the evaluation with fill mask task, we made a fill mask dataset from Japanese domain of Webis-
CLS-10 (Prettenhofer and Stein, 2010) and used it. The following two steps show how to make a fill mask dataset from Webis.

1. Pick twenty nouns that have the highest frequencies of occurrence from the test data of each domain: books, DVDs, and music.

2. Pick five sentences that contain matching selected words from test data of the matching domain randomly to each selected word.

3. Use nouns which were selected in step 1 as labels for matching sentences which were selected in step 2.

We replaced “selected nouns” which appeared for the first time in matching sentence with mask token. The following shows selected Japanese nouns for each domain.

**books:** 本, 人, 著者, 内容, 自分, 作品, 本書, 感じ, 文章, 主人公, 小説, 部分, 最後, 言葉, 読者, 作者, 人間, 物語, 他, 世界

**DVDs:** 映画, 作品, 人, シーン, 映像, 原作, 自分, ストーリー, 内容, ファン, 感じ, 主人公, 最後, アニメ, ドラマ, 物語, 人間, 世界, 子供, 部分

**music:** 曲, アルバム, 作品, 人, 音楽, 感じ, ファン, 音, バンド, 自分, 歌詞, 声, ギター, 歌, C D, 楽曲, サウンド, ライブ, シングル, 前作

We calculated percentages that mask token is the word in matching label with prepared dataset and each model. Then, we averaged percentages and compared these. The following shows notices of this comparison.

- We used transformers (Wolf et al., 2019) to solve the fill mask task.
- We replaced “C D” (Fullwidth form of CD) with CD (Halfwidth form of CD).
- We lowercased sentences when we used SP Ver. model. We did not lowercase sentences when we used SP Ver. model for the first time, and the model tokenized CD as token “C” and token “D”. We checked vocabulary file of the model and found the word “cd”, not “CD”. So we recognized we needed to activate lowercasing option.

4 Results

In this section, we show the results of the evaluations. First, we show the result of the evaluation with sentence clustering, and then the result of evaluation with fill mask task.

4.1 Result of Evaluation with Sentence Clustering

Table 2 summarizes $A_m$, $B_m$, and scores of evaluation with sentence clustering. Bigger $B_m$ is better, and smaller $A_m$ and score are better.

| Models               | $A_m$    | $B_m$   | Score  |
|----------------------|----------|---------|--------|
| Kyoto Univ. Ver.     | 240131.79| 337.83  | 710.81 |
| MeCab Ver.           | 97536.21 | 154.37  | 631.06 |
| SP Ver.              | 67744.36 | 104.05  | 651.06 |
| Tohoku Univ. Ver.    | 49991.31 | 65.64   | 761.58 |
| NICT Ver.            | 106698.11| 151.27  | 705.37 |
| Laboro Ver.          | 153378.22| 273.83  | 560.13 |

The following shows the results of comparing models by score, $A_m$, and $B_m$, and figure 2 is a bar graph of the results.

Table 3 shows scores of models except NICT Ver., and Laboro Ver. in previous work (Shibayama et al., 2020) and this work. According to this table, Scores of models except MeCab Ver. changes about 0.8–30 from results in previous evaluation (Shibayama et al., 2020). These changes did not influence the results of comparisons. Score of MeCab Ver. model became 100 or more higher than the previous result, but this change also did not influence results.
Table 3: Scores of previous work (Shibayama et al., 2020) and this work

| Models            | previous | this   |
|-------------------|----------|--------|
| Kyoto Univ. Ver.  | 710.88   | 710.81 |
| MeCab Ver.        | 458.19   | 631.06 |
| SP Ver.           | 668.92   | 651.06 |
| Tohoku Univ. Ver. | 792.34   | 761.58 |

4.2 Result of Re-evaluation with Fill Mask Task

Table 4 shows average of percentages that mask token is the word in matching label of all domains and three domains: books, DVDs, and music. Figure 3 shows a bar graph of column “All” in table 4.

Table 4: Average of percentages that mask token is true masked word

| Models            | books | DVDs  | music | All   |
|-------------------|-------|-------|-------|-------|
| Kyoto Univ. Ver.  | 11.53%| 11.18%| 9.24% | 10.65%|
| MeCab Ver.        | 11.24%| 13.62%| 7.62% | 10.83%|
| SP Ver.           | 7.36% | 9.86% | 6.41% | 7.88% |
| Tohoku Univ. Ver. | 14.04%| 12.76%| 10.81%| 12.54%|
| NICT Ver.         | 11.90%| 12.63%| 8.68% | 11.07%|
| Laboro Ver.       | 8.86% | 10.44%| 9.85% | 9.72% |

5 Discussion

In this section, we describe the results in Section 4, and why there is a difference between the results in Section 4.1 and Section 4.2.

We changed the tokenizer settings for MeCab Ver. model from previous evaluation not to use subword tokenize\(^{10}\). We think this influenced the score of MeCab Ver. model, which caused a difference from a previous work (Shibayama et al., 2020).

As mentioned earlier, we considered $A_m$ and $B_m$ as in-class and out-of-class dispersion, respectively, in order to calculate easily (see, footnotes of Section 3.1). Therefore, comparing $A_m$ means evaluating whether embeddings in the same class are close, and $B_m$ means evaluating differences of embeddings that are not in the same class. We can deduce the general tendencies of each model from the results in Section 4.1. The best model is Laboro Ver., which has the second-highest $B_m$ and about 100000 smaller $A_m$ than Kyoto Univ. Ver. model. MeCab Ver. model that has the best score in previous eval-

\(^{10}\)According to an article of MeCab Ver. model, we have to change scripts that use only MeCab as a tokenizer.
uation (Shibayama et al., 2020) is the second-best model. SP Ver. model is the third, which \( A_m \) of model is it of Tohoku Univ.Ver. model or more and it of MeCab Ver. model less. Tohoku Univ. Ver. model has the worst score, which has smallest \( A_m \) and \( B_m \). This means the dispersion of all embeddings is smaller than the other models.

However, the results in Section 4.1 are different from the results in Section 4.2. Thus, we could not conclude that the results of methods of evaluation with sentence clustering and fill mask task have the same tendency. We used the title of articles in evaluation with sentence clustering, but we used a sentence in product reviews (see synopsis of Webis-CLS-10 (Prettenhofer and Stein, 2010)) with fill mask task. This difference may have caused the differences between the results in Section 4.1 and Section 4.2.

6 Conclusion

We evaluated Japanese pre-trained BERT models using sentences that were labeled, and outputs of BERT that inputted those sentences. Then, we obtained the following result.

| Laboro Ver. | < MeCab Ver. | < SP Ver. | < NICT Ver. | < Kyoto Univ. Ver. | < Tohoku Univ. Ver. |

Also, we masked a specific noun in each sentence, calculated percentage that mask token is the word in matching label, and re-evaluated with averages of that percentage. However, we obtained the following result, and this is different from result of sentence clustering.

| Tohoku Univ. Ver. | > NICT Ver. | > MeCab Ver. | > Kyoto Univ. Ver. | > Laboro Ver. | > SP Ver. |

If we decrease the difference of type or domain of documents that are used in both experiments, there is a chance that the comparison results will be different from what we obtained in this work.

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A Basic Hyperparameters of Models We Evaluated

In this section, we show basic hyperparameters of pre-trained BERT models we evaluated. However, some parameters were not written in both config file of model and model publisher’s web site. Table 5 shows basic pre-training information of pre-trained models. “No Info” cell is a parameter that we could not found the correct value. Some publishers pre-trained the model with two step pre-training, and we
show those as Ph1 parameter and Ph2 parameter if there is differences.

Table 5: Basic pre-training information of BERT models

| Models          | Model Size | Whole Word Masking | Vocabulary Size max_seq_length |
|-----------------|------------|---------------------|--------------------------------|
| Kyoto Univ. Ver.| Base       | No                  | 32,000                          | 128                           |
| MeCab Ver.      | Base       | No                  | 32,000                          | No Info                       |
| SP Ver.         | Base       | No                  | 32,000                          | No Info                       |
| Tohoku Univ. Ver.| Base      | No                  | 32,000                          | 512                           |
| NICT Ver.       | Base       | No                  | 32,000                          | Ph1-128 Ph2-512               |
| Laboro Ver.     | Base       | No                  | 32,000                          | Ph1-128 Ph2-512               |