BERT Masked Language Modeling for Co-reference Resolution

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Abstract

This paper explains the TALP-UPC participation for the Gendered Pronoun Resolution shared-task of the 1st ACL Workshop on Gender Bias for Natural Language Processing. We have implemented two models for mask language modeling using pre-trained BERT adjusted to work for a classification problem. The proposed solutions are based on the word probabilities of the original BERT model, but using common English names to replace the original test names.

1 Introduction

The Gendered Pronoun Resolution task is a natural language processing task whose objective is to build pronoun resolution systems that identify the correct name a pronoun refers to. It’s called a co-reference resolution task. Co-reference resolution tackles the problem of different elements of a text that refer to the same thing. Like for example a pronoun and a noun, or multiple nouns that describe the same entity. There are multiple deep learning approaches to this problem. NeuralCoref\(^1\) presents one based on giving every pair of mentions (pronoun + noun) a score to represent whether or not they refer to the same entity. In our current task, this approach is not possible, because we don’t have the true information of every pair of mentions, only the two names per entry.

The current task also has to deal with the problem of gender. As the GAP researchers point out (Webster et al., 2018), the biggest and most common datasets for co-reference resolution have a bias towards male entities. For example the OntoNotes dataset, which is used for some of the most popular models, only has a 25% female representation (Pradhan and Xue, 2009). This creates a problem, because any machine learning model is only as good as its training set. Biased training sets will create biased models, and this will have repercussions on any uses the model may have.

This task provides an interesting challenge specially by the fact that it is proposed over a gender neutral dataset. In this sense, the challenge is oriented towards proposing methods that are gender-neutral and to not provide bias given that the data set does not have it.

To face this task, we propose to make use of the recent popular BERT tool (Devlin et al., 2018). BERT is a model trained for masked language modeling (LM) word prediction and sentence prediction using the transformer network (Vaswani et al., 2017). BERT also provides a group of pre-trained models for different uses, of different languages and sizes. There are implementations for it in all sorts of tasks, including text classification, question answering, multiple choice question answering, sentence tagging, among others. BERT is gaining popularity quickly in language tasks, but before this shared-task appeared, we had no awareness of its implementation in co-reference resolution. For this task, we’ve used an implementation that takes advantage of the masked LM which BERT is trained for and uses it for a kind of task BERT is not specifically designed for.

In this paper, we are detailing our shared-task participation, which basically includes descriptions on the use we gave to the BERT model and on our technique of ‘Name Replacement’ that allowed to reduce the impact of name frequency.

2 Co-reference Resolution System Description

2.1 BERT for Masked LM

This model’s main objective is to predict a word that has been masked in a sentence. For this exper-
cise that word is the pronoun whose referent we’re trying to identify. This one pronoun gets replaced by the [MASKED] tag, the rest of the sentence is subjected to the different name change rules described in section 2.2.

The text is passed through the pre-trained BERT model. This model keeps all of its weights intact, the only changes made in training are to the network outside of the BERT model. The resulting sequence then passes through what is called the masked language modeling head. This consists of a small neural network that returns, for every word in the sequence, an array the size of the entire vocabulary with the probability for every word. The array for our masked pronoun is extracted and then from that array, we get the probabilities of three different words. These three words are: the first replaced name (name 1), the second replaced name (name 2) and the word none for the case of having none.

This third case is the strangest one, because the word none would logically not appear in the sentence. Tests were made with the original pronoun as the third option instead. But the results ended up being very similar albeit slightly worse, so the word none was kept instead. These cases where there is no true answer are the hardest ones for both of the models.

We experimented with two models.

Model 1 After the probabilities for each word are extracted, the rest is treated as a classification problem. An array is created with the probabilities of the 2 names and none ([name 1, name 2, none]), where each one represents the probability of a class in multi-class classification. This array is passed through a softmax function to adjust it to probabilities between 0 and 1 and then the log loss is calculated. A block diagram of this model can be seen in figure 1.

Model 2 This model repeats the steps of model 1 but for two different texts. These texts are mostly the same except the replacement names name 1 and name 2 have been switched (as explained in the section 2.2). It calculates the probabilities for each word for each text and then takes an average of both. Then finally applies the softmax and calculates the loss with the average probability of each class across both texts. A block diagram of this model can be seen in figure 2.

2.2 Name Replacement
The task contains names of individuals who are featured in Wikipedia, and some of these names are uncommon in the English language. As part of the pre-processing for both models, these names are replaced. They are replaced with common English names in their respective genders2. If the pronoun is female, one of two common English female names are chosen, same thing for the male pronouns. In order to replace them in the text, the following set of rules are followed.

1. The names mentioned on the A and B columns are replaced.
2. Any other instances of the full name as it appears on the A/B columns are replaced.
3. If the name on the A/B column contains a first name and a last name. Instances of the first name are also replaced. Unless both entities share a first name, or the first name of one is contained within the other.
4. Both the name and the text are converted to lowercase

This name replacement has two major benefits. First, the more common male and female names work better with BERT because they appear more in the corpus in which it is trained on. Secondly, when the word piece encoding splits certain words the tokenizer can be configured so that our chosen names are never split. So they are single tokens (and not multiple word pieces), which helps the way the model is implemented.

Both models (1 and 2 presented in the above section) use BERT for Masked LM prediction where the mask always covers a pronoun, and because the pronoun is a single token (not split into word pieces), it’s more useful to compare the masked pronoun to both names, which are also both single tokens (not multiple word pieces).

Because the chosen names are very common in the English language, BERT’s previous training might contain biases towards one name or the other. This can be detrimental to this model where it has to compare between only 3 options. So the alternative is the approach in model number 2. In model 2 two texts are created. Both texts are basically the same except the names chosen as the

2https://www.ef.com/wwen/english-resources/english-names/
For example lets say we get the text:

"In the late 1980s Jones began working with Duran Duran on their live shows and then in the studio producing a B side single “This Is How A Road Gets Made”, before being hired to record the album Liberty with producer Chris Kimsey.”.

A is Jones and B is Chris Kimsey. For the name replacement lets say we choose two common English names like John and Harry. The new text produced for model 1 (figure 1) would be something like:

"in the late 1980s Harry began working with Duran Duran on their live shows and then in the studio producing a B side single “this is how a road gets made”, before being hired to record the album liberty with producer John.”

And for model 2 (figure 2) the same text would be used for the top side and for the bottom side it would have the harry and john in the opposite positions.
3 Experimental Framework

3.1 Task details

The objective of the task is that of a classification problem. Where the output for every entry is the probability of the pronoun referencing name A, name B or Neither.

3.2 Data

The GAP dataset (Webster et al., 2018) created by Google AI Language was the dataset used for this task. This dataset consists of 8908 co-reference labeled pairs sampled from Wikipedia, also it’s split perfectly between male and female representation. Each entry of the dataset consists of a short text, a pronoun that is present in the text and its offset and two different names (name A and name B) also present in the text. The pronoun refers to one of these two names and in some cases, none of them. The GAP dataset doesn’t contain any neutral pronouns such as it or they.

For the two different stages of the competition different datasets were used.

• For Stage 1 the data used for the submission is the same as the development set available in the GAP repository. The dataset used for training is the combination of the GAP validation and GAP testing sets from the repository.

• For Stage 2 the data used for submission was only available through Kaggle and the correct labels have yet to be released, so we can only analyze the final log loss of each of the models. This testing set has a total of 12359 rows, with 6499 male pronouns and 5860 female ones. For training, a combination of the GAP development, testing and validation sets was used. And, as all the GAP data, it is evenly distributed between genders.

The distributions of all the datasets are shown in table 1. It can be seen that in all cases, the None option has the least support by a large margin. This, added to the fact that the model naturally is better suited to identifying names rather than the absence of them, had a negative effect on the results.

3.3 Training details

For the BERT pre-trained weights, several models were tested. BERT base is the one that produced the best results. BERT large had great results in a lot of other implementations, but in this model it produced worse results while consuming much more resources and having a longer training time. During the experiments the model had an overfitting problem, so the learning rate was tuned as well as a warm up percentage was introduced. As table 2 shows, the optimal learning rate was $3 \times 10^{-5}$ while the optimal with a 20% warm up. The length of the sequences is set at 256, where it fits almost every text without issues. For texts too big, the text is truncated depending on the offsets of each of the elements in order to not eliminate any of the names or the pronoun.

| Learning Rate | Warmup | Accuracy mean | min | Loss mean | min |
|---------------|--------|---------------|-----|-----------|-----|
| 0.00003       | 0.0    | 0.840167      | 0.8315 | 0.559065  | 0.454225 |
| 0.00004       | 0.0    | 0.844444      | 0.8340 | 0.502667  | 0.442313 |
| 0.00005       | 0.0    | 0.822389      | 0.7970 | 0.556491  | 0.473528 |
| 0.00006       | 0.0    | 0.834000      | 0.7925 | 0.530862  | 0.456223 |
| 0.00007       | 0.1    | 0.745000      | 0.7435 | 0.660750  | 0.660750 |
| 0.00008       | 0.0    | 0.756333      | 0.7040 | 0.630707  | 0.544841 |
| 0.00009       | 0.2    | 0.802278      | 0.7465 | 0.587041  | 0.497051 |

Table 2: Results of the tuning for both models. Minimum and average Loss and Accuracy across all the tuning experiments performed.
| Parameter          | Value      |
|-------------------|------------|
| Optimizer         | Adam       |
| Vocabulary Size   | 28996      |
| Dropout           | 0.1        |
| Sequence Length   | 256        |
| Batch Size        | 32         |
| Learning Rate     | 3e−5       |
| Warm Up Steps     | 20%        |
| Stage 1:          | 81 — Stage 2: 148 |
| Epochs            | 1          |
| Gradient Accumulation Steps | 5 |

Table 3: Hyperparameters for the model training

4 Results

Tables 4 and 5 report results for models 1 and 2 reported in section 2.1 for stage 1 of the competition. Both models 1 and 2 have similar overall results. Also both models show problems with the None class, model 2 specially. We believe this is because our model is based on guessing the correct name, so the guessing of none is not as well suited to it. Also, the training set contains much less of these examples, therefore making it even harder to train for them.

|   | Precision | Recall | F1  | Support |
|---|-----------|--------|-----|---------|
| A | 0.83      | 0.87   | 0.85| 874     |
| B | 0.88      | 0.88   | 0.88| 925     |
| None | 0.64       | 0.52   | 0.57| 201   |
| Avg | **0.83** | **0.84** | **0.84** | **2000** |

Table 4: Model 1 results for the testing stage 1.

|   | Precision | Recall | F1  | Support |
|---|-----------|--------|-----|---------|
| A | 0.81      | 0.86   | 0.83| 874     |
| B | 0.88      | 0.78   | 0.82| 925     |
| None | 0.48       | 0.62   | 0.54| 201   |
| Avg | **0.81** | **0.80** | **0.80** | **2000** |

Table 5: Model 2 results for the testing stage 1.

4.1 Advantages of the Masked LM Model

As well as the Masked LM, other BERT implementations were experimented with for the task. First, a text multi class classification model (figure 4) where the [CLS] tag is placed at the beginning of every sentence, the text is passed through a pre-trained BERT and then the result from this label is passed through a feed forward neural network.

And a multiple choice question answering model (figure 5), where the same text with the [CLS] label is passed through BERT with different answers and then the result these labels is passed through a feed forward neural network.

These two models, which were specifically designed for other tasks had similar accuracy to the masked LM but suffered greatly with the log loss, which was the competition’s metric. This is because in a lot of examples the difference between the probabilities of one class and another was minimal. This made for a model where each choice had low confidence and therefore the loss increased considerably.

| BERT for Classification | Accuracy | Loss |
|------------------------|----------|------|
| 0.8055                 | 0.70488  |

| BERT for Question Answering | Accuracy | Loss |
|-----------------------------|----------|------|
| 0.785                       | 0.6782   |

| BERT for Masked LM | Accuracy | Loss |
|-------------------|----------|------|
| 0.838             | 0.44231  |

Table 6: Results for the tests with different BERT implementations.

4.2 Name Replacement Results

As table 2.2 shows, name replacement considerably improved the model’s results. This is in part because the names chosen as replacements are more common in BERT’s training corpora. Also, a 43% of the names across the whole GAP dataset are made up of multiple words. So replacing these with a single name makes it easier for the model to identify their place in the text.
Table 7: Results for the models with and without name replacement.

|                  | Accuracy | Loss  |
|------------------|----------|-------|
| Model 1 Original Names | 0.782    | 0.7021|
| Model 1 Name Replacement | 0.838    | 0.4423|

Table 8: Results for both models across both stages of the competition

|        | Model 1 | Model 2 |
|--------|---------|---------|
| Stage 1| 0.44231 | 0.49607 |
| Stage 2| 0.31441 | 0.30151 |

4.3 Competition results

In the official competition on Kaggle we placed 46th, with the second model having a loss around 0.301. As the results in table 8 show, the results of stage 2 were better than those of stage 1. And the second model, which had performed worse on the first stage was better in stage 2.

5 Conclusions

We have proved that pre-trained BERT is useful for co-reference resolution. Additionally, we have shown that our simple ‘Name Replacement’ technique was effective to reduce the impact of name frequency or popularity in the final decision.

The main limitation of our technique is that it requires knowing the gender from the names and so it only makes sense for entities which have a defined gender. Our proposed model had great results when predicting the correct name but had trouble with with the none option.

As a future improvement it’s important to analyze the characteristics of these examples where none of the names are correct and how the model could be trained better to identify them, specially because they are fewer in the dataset. Further improvements could be made in terms of fine-tuning the weights in the actual BERT model.

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