ABSTRACT

This paper discusses the effectiveness of various text processing techniques, their combinations, and encodings to achieve a reduction of complexity and size in a given text corpus. The simplified text corpus is sent to BERT (or similar transformer based models) for question and answering and can produce more relevant responses to user queries. This paper takes a scientific approach to determine the benefits and effectiveness of various techniques and concludes a best-fit combination that produces a statistically significant improvement in accuracy.

Keywords: BERT, QnA model, Stanford CoreNLP, LexNLP, spaCy, document similarity, document processing, misspelled Words, phonetic matching, Soundex, information retrieval

1 Introduction

In today’s world, BERT [Devlin et al., 2018] is one of the most popular models used to build question and answering systems. BERT generally needs additional training (with large relevant text corpus) to maintain relevance when presented with large complex documents (such as regulations, federal or institutional policies, and domain-specific documents). This shortcoming becomes clear when dealing with a complex sentence structure and can be alleviated by using innovative text pre-processing techniques on the text corpus and fine-tuning the model.

Why is this needed:

- Fine-tuned BERT QnA model can handle sequence length of 384 tokens at once. When the input context has more than 384 tokens, context gets divided into multiple chunks (length of each chunk can be set by user) and this is popularly known as sliding window approach.
- Each chunk is then processed along with question by BERT model giving answer text and probability as output, final answer text will be considered based on highest probability criteria.
- We observed that sliding window approach fails to provide correct answers when document size was over 1000 tokens, as BERT model was trained on data with smaller contexts.

This led us to explore possibilities of reducing complexity of input text and finding most relevant text from large context before passing on to BERT for inference. This paper explores the possibility of using text processing techniques to reduce the complexity of text sending to BERT and hence improve BERT’s accuracy on answering questions for complex documents without lots of extra training. The limitations of each techniques are also discussed in this paper.
2 Methodology

To improve the performance on BERT, we implemented a couple of techniques, such as Definition Tokenization, Dependency Tokenization, Paragraph Splitting, Relevant Paragraph Ranking, and BERT Fine-tuning. The entire flow for text processing and BERT question and answering system we tried to propose is as below:

![Figure 1: Proposed Text Processing Flow for BERT QnA](image)

2.1 Definition Tokenization

One of our tokenization strategies is Definition Tokenization. We replace the specific terms used in the document with a single token. First, we identify definition sentences mentioned in the document via keyword search such as "mean" and "define". For example, "Common ownership means a relationship between two companies" is a definition sentence. Second, we identify the subject (including the noun and its modifiers) in the definition sentences through Stanford CoreNLP's dependency annotation [Manning et al., 2014]. "Common ownership" in this case, and tokenize the subject as XnXn (where n is a number, X can be any capitalized characters). The result of tokenization is as below:

| Original                                                                 | Definition Tokenization |
|-------------------------------------------------------------------------|-------------------------|
| Common ownership means a relationship between two companies.             | X1X1 means a relationship between two companies. |

LexNLP [Bommarito II et al., 2018] is also used to help us tokenize compound nouns outside of the definition sentences. LexNLP is trained on financial domains and is able to recognize some specific terms in the domain. The result is as below:

| Original                                                                 | Definition Tokenization |
|-------------------------------------------------------------------------|-------------------------|
| Financial Institution needs to submit a suspicious activity report.      | X1X2 needs to submit a suspicious activity report. |

Finally, we replace all the definition subject with correspondent tokens over the document.

With this approach, we are able to reduce a couple of words into one token, and thus reduce the amount of text in the sentences.

The limitations of this approach include the following:

- Variant amount of tokenization: highly dependent on how often the definition terms are used across the document and how many terms are defined
- Customization of the definition keywords for different documents: each document may have different keyword for identifying a definition sentence

2.2 Dependency Tokenization

The other tokenization strategy we use is Dependency Tokenization that uses Stanford CoreNLP’s dependency annotation to tokenize words. We first identify the verb in a sentence. Then we group the subjects and modifiers and tokenize them. We also do the same for objects. Below is the result:

| Original                                                                 | Definition Tokenization |
|-------------------------------------------------------------------------|-------------------------|
| Bank and insurance company need to submit a suspicious activity report.  | X1X3 need to submit X1X4. |
In this example, “AIJbank” and “AIJcompany” are subjects of “AIJneed”, and “AIJinsurance” is the modifier of “AIJcompany”, so we tokenize them all together. “AIJreport” is the object in this case, “AIJa”, “AIJsuspicious”, “AIJactivity” are its modifiers. Complex sentences usually involve a lot of subjects, objects, and modifiers. With this approach, we can simplify such sentences to a great extent.

The limitations of this approach include the following:

- Highly dependent on the accuracy of NLP dependency parse: in very complicated sentences, the dependency results may not be correct and end up tokenizing wrong words, distorting the structure of the sentences.
- Computationally expensive: extracting dependency from each sentence requires a lot of computation.

2.3 Paragraph Splitting

The other text processing we do is to split the document into paragraphs and send the most relevant paragraphs with a question for BERT to answer. Since the document we are dealing with contains tens of thousands of words, BERT is not able to pick up the answer in a sea. Given the hierarchy of the regulation documents we deal with, we split the document into small paragraphs (which contain a piece of information about a specific regulation) using regular expression and spaCy’s sentence segmentation [Honnibal and Montani, 2017].

The limitations of this approach include the following:

- BERT not able to answer broader questions: after splitting into paragraphs, the information becomes more specific, and BERT cannot revert to high-level answer.
- Splitting strategy very subjective: developer needs to make judgement about how far the splitting should go. If the paragraph is too long, BERT will still have issue figuring out answer; however, if the paragraph is too short, you may not have enough information to match the question. The golden rule is that the split paragraph should contain complete piece of information.

| Original | 5 times the amount of the nonvoting capital stock of the Financing Corporation which is outstanding at such time; or the amount of capital stock of the Financing Corporation held by such remaining bank at the time of such determination; by the amounts added to reserves after December 31, 1985, pursuant to the requirement contained in the first 2 sentences of section 1436 of this title. | Number of Tokens: 66 |
|----------|-------------------------------------------------------------------------------------------------------------|---------------------|
| Definition and Dependency Tokenization | 5 times the amount of the Y1Y300 X1441 which is outstanding at Y1Y1416; or the amount of Y1Y1122 of the Y1Y415 held by such Y1Y1099 at the time of Y1Y651 X1393 added to reserves after December 31, 1985, pursuant to the requirement contained in the first 2 sentences of section 1436 of this title. | Number of Tokens: 54 |

2.4 Relevant Paragraph Ranking

To narrow BERT’s search space and obtain more accurate answers, we build a similarity ranking model based on Doc2Vec [Le and Mikolov, 2014] and TF-IDF [Ramos et al., 2003] to locate the most relevant paragraphs given a question. We compare the similarity among the paragraphs and the question and send the top relevant paragraphs to BERT for an answer. The number of top paragraphs is a hyperparameter, depending on the size of the document, the larger the document, the more relevant paragraphs needed. Doc2Vec provides us the flexibility of the words used in the questions. User does not need to provide exact same words as appeared in the documents to get the answer, since the
sentences are vectorized and compared according to the context; while TF-IDF helps us identify the right paragraphs more accurately if user does provide the exact words.

Given the questions and the documents we had, we use the weight of 50-50 between Doc2Vec and TF-IDF.

The limitations of this approach include the following:

- The weight between Doc2Vec and TF-IDF is arbitrary: increase the weight of Doc2Vec if we want more flexibility in question’s wording, but we may lose accuracy
- The number of top relevant paragraphs varies: it depends on how specific the question is, how similar the paragraphs are in the document, and how huge the document is

2.5 Soundex Encoding

To overcome spelling mistakes in questions, we also implement Soundex Based Encodings [Koneru et al., 2016]. Soundex tries to encode the words in the form of phonetic sounds. Even if the spellings are wrong in the question, the phonetic encoding remains the same. E.g. Hello yields an encoding of H400 and Hallo also yields the encoding of H400. With TF-IDF the Soundex encoded terms are used that make it easier to find the relevant sections from the document. By default, Soundex uses encodings of length 4 (H400) but we decided to use encoding of length 6 (H40000) to accommodate more term varieties in our documents.

2.6 BERT Fine-tuning

We analyzed the performance of BERT model trained on SQUAD2.0 [Rajpurkar et al., 2018] and decided to fine tune it further with data distribution similar to FDIC documents since SQUAD2.0 dataset is observed to have simple structure as compared to sentence complexity structure in FDIC documents. The ones in FDIC spanned across multiple lines hence leading to increased complexity of structure. Since BERT is trained on SQUAD dataset, model was observed performing poor on FDIC documents even for simple “who/where” kind of questions.

Training data consists of 88 paragraphs/context along with multiple questions and answers for each paragraph in the SQUAD data format. Similarly test data consists of 50 paragraphs and validation data has got 15 paragraphs following the same format as described above for train data.

After experimenting with different set of hyperparameters, we finalized the one that used Adam as Optimizer [Kingma and Ba, 2014] with learning-rate=3e-5, train-batch-size=24 with other parameters having default values since this combination was proven to be optimized in terms of model accuracy when tested.

2.7 Experimental Result

Due to integration difficulties in tokenization, we tested BERT question and answer system with paragraph splitting and relevant paragraph ranking on three regulation documents, Suspicious Activity Reports, Fair Housing, and Appraisals, from the FDIC website.

We define two metrics to evaluate BERT performance:

- F1 score: We used the same approach as in SQUAD for evaluation. In this approach an answer was divided into tokens and confusion matrix was calculated based on the comparison of tokens between BERT’s answer and real answer. [Sokolova et al., 2006]

  True Positives (tp): the number of tokens shared between the actual answer and the predicted answer.
  False Positives (fp): the tokens in the prediction but not in the actual answer.
  False Negative(fn): the tokens in actual answer and not in the prediction.

  Precision: \[ \frac{tp}{(tp + fp)} \]

  Recall: \[ \frac{tp}{(tp + fn)} \]

1 https://www.fdic.gov/regulations/laws/rules/2000-6000.html
2 https://www.fdic.gov/regulations/laws/rules/2000-6000.html
3 https://www.fdic.gov/regulations/laws/rules/2000-4300.html
F1 Score:

\[ 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \]

- Quality score (Q score): We defined a scoring system and manually evaluate the quality of answers using the following standards.
  1: Unacceptable, if BERT does not cover the complete response
  2: Partial answered, if BERT covers the partially the complete response
  3: Complete answered, if BERT covers the complete response to the question

We compared the F1 score and quality score among BERT with entire document, BERT with manually selected paragraph, and BERT with text processing techniques. Figure 2-4 are the flows for each system.

We normalized the final score as

\[ \frac{(\text{Quality score} - 1)}{2} \]

to get a score ranging from 0 to 1 for better comparison.
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Figure 4: BERT with Text Processing

| Document                | Document size (words) | Number of Questions | Entire document | Manually selected paragraph | Text processing techniques |
|-------------------------|-----------------------|---------------------|-----------------|----------------------------|----------------------------|
|                        |                       |                     | F1 Score | Q Score | F1 Score | Q Score | F1 Score | Q Score |
| Suspicious Activity Report | 1420                | 27                  | 9.7%    | 3.7%    | 58.7%    | 79.5%    | 56.6%    | 74%     |
| Fair Housing            | 1780                 | 17                  | 8.2%    | 0%      | 44.6%    | 67.5%    | 41.3%    | 61.5%   |
| Appraisals              | 5367                 | 14                  | 6.42%   | 0%      | 62.1%    | 61%      | 51.7%    | 50%     |

Table 1: Test Results

Figure 5: F1 Score comparison
3 Conclusion

With text processing techniques such as paragraph splitting and relevant paragraph ranking, we can narrow down the content size and boost BERT accuracy on large documents by 30-50% in terms of F1 score. The upper bound of our BERT performance is BERT with manually selected paragraph since we directly provide the most relevant content. Compared to the upper bound, BERT with text processing techniques only sacrifice about 5-11% accuracy on F1 score.

Although Tokenization techniques also look promising for simplifying complex documents, during our development of the algorithm, we ran into the following issues to integrate this solution with our BERT QnA system:

- The handling of duplicate tokens: We should use the same tokens for the same phrases over the document.
- The matching of question and tokens: Dependency tokenization tokenized phrases in a more varied fashion (Adjective and Adverb are also tokenized with the noun), making it difficult to match with questions since user may not provide exact phrases as in the document. Although we tried to iterate through all the possible matching tokens, we were not able to determine which token should be taken since BERT could not provide us the absolute probability of an answer.

In the future, we will continue to improve our Tokenization algorithm, so it can fit into our BERT QnA system. One of the approaches to improve the tokenization algorithm is to determine the acronyms in the document and their meaning and linking the sections and their meaning in the documents. We will also continue to explore more text processing techniques to improve BERT’s performance.

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