Abstract
This paper compares BERT-SQuAD and Ab3P on the Abbreviation Definition Identification (ADI) task. ADI inputs a text and outputs short forms (abbreviations/acronyms) and long forms (expansions). BERT with reranking improves over BERT without reranking but fails to reach the Ab3P rule-based baseline. What is BERT missing? Reranking introduces two new features: charmatch and freq. The first feature identifies opportunities to take advantage of character constraints in acronyms and the second feature identifies opportunities to take advantage of frequency constraints across documents.

1 Introduction: Opportunities
Transformers such as BERT (Devlin et al., 2019) and ERNIE (Sun et al., 2019) have been extremely successful on a wide range of tasks. Nevertheless, there are opportunities to improve BERT on numbers (Wallace et al., 2019), negation (Ettinger, 2020), and more.

This paper compares BERT to Ab3P on the Abbreviation Definition Identification (ADI) task described in Section 1.1. ADI inputs texts and outputs pairs of short forms (SFs) and long forms (LFs). A number of ADI systems were developed more than a decade ago; some use rules (Sohn et al., 2008; Schwartz and Hearst, 2002) and others machine learning (Kuo et al., 2009).

Section 1.2 discusses similarities between ADI and question answering (QA). The QA dataset, SQuAD (Rajpurkar et al., 2016), includes many types of questions, some of which are similar to ADI: What does X stand for? X is a SF (abbreviation) and the answer is a LF (expansion). A simple program based on BERT-SQuAD performs remarkably well on ADI benchmarks, though not as well as Ab3P, a strong rule-based baseline.

Ab3P uses a set of 17 rules to extract SF-LF pairs. Rules were created iteratively. Each iteration finds a rule that reduces the majority of missing cases. The iteration stops when the desired recall has been achieved. One of these rules favors pairs with matching characters. That is, it is common for each character in an acronym to match each word in the expansion.

Why is BERT not doing better? What is BERT missing? Section 2.1 uses a reranking approach to improve BERT by adding two features that are easy to interpret:

1. charmatch compares the first letter of LF to the first letter of SF, and
2. freq counts instances of “LF (SF)” in a corpus of PubMed abstracts.

It has been suggested that deep nets are so powerful that feature engineering is no longer necessary. Reranking suggests this may not be correct, especially for tasks like ADI where rule-based systems outperform BERT.

1.1 The ADI Task
Abbreviations and acronyms are especially common in technical writing such as PubMed and arXiv (Veyseh et al., 2020), though they can be found in many other corpora such as Wikipedia. The first time a SF is used in a paper, there is usually a definition that connects the dots between the SF and the LF. It is more common for definitions to parenthesize the SF, though both types of definitions are common:

1. LF (SF): heat shock protein (HSP)
2. SF (LF): HSP (heat shock protein)
The ADI task takes a text as input, and outputs pairs of SFs and LFs that are defined in the input text. Four benchmarks have become standard in the ADI literature: Ab3P (Sohn et al., 2008), BIOADI (Kuo et al., 2009), MEDSTRACT (Wren et al., 2005) and SH (Schwartz and Hearst, 2002). Standard train, validation and test splits are available for download. All of these benchmarks are based on PubMed abstracts in ASCII without markup.

1.2 Related Work, Tasks & Tools

The ADI task is similar to a number of other tasks such as Question Answering (QA), Named Entity Recognition (NER), Acronym Disambiguation (AD), etc. SQuAD (Rajpurkar et al., 2016) is a popular benchmark for QA systems. SQuAD examples consist of questions, answers and contexts. There are many types of questions, including some that are similar to ADI such as:

1. Question: What does AFC stand for?
2. Context: The American Football Conference (AFC) champion Denver Broncos defeated the National Football Conference (NFC) champion Carolina Panthers 24–10 to earn their third Super Bowl title.

Systems output a span, a substring of the context that answers the question such as: American Football Conference. This example suggests BERT-SQuAD may be a more modern alternative to older rule-based approaches to ADI such as Ab3P.

Other studies have applied QA-like technology to a number of other tasks such as: event extraction (Du and Cardie, 2020; Liu et al., 2020; Feng et al., 2020; Sun et al., 2020), NER (Li et al., 2020), entity linking (Gu et al., 2021), coreference resolution (Wu et al., 2020), and more. These studies suggest that a QA model with fine-tuning can achieve state-of-the-art (SOTA) results on a range of tasks.

ADI is also similar to NER. NER is used for a number of tasks that extract spans, substrings of input text, and labeling them with tags such as person, organization, location, etc. (Doddington et al., 2004), as in ACE. Some benchmarks use BIO tags to label spans. Each word in the input text is tagged as B (begins a span), I (inside a span) or O (otherwise). Some benchmarks introduce tags such as B-disease and B-chemical to distinguish disease entities from chemical entities. Lee et al. (2020) show BioBERT is effective on a number of such NER benchmarks: NCBI Disease (Doğan et al., 2014) i2b2/VA (Uzuner et al., 2011), BC5CDR (Li et al., 2016), BC4CHEMD (Krahling et al., 2015), BC2GM (Smith et al., 2008), JNLPBA (Kim et al., 2004), LINNAEUS (Gerner et al., 2010) and Species-800 (Pafilis et al., 2013), as well as related tasks such as relation extraction and QA.

PubMed annotations for millions of PubMed abstracts are available for download. PubMed identifies spans and tags them with six bioconcepts: genes, diseases, chemicals, mutations, species and cell lines. PubMed also links entities to ontologies such as MeSH. PubMed links the gene p53, for example, to different points in the ontology for different species: humans, mice, fruit flies, etc.

There have been concerns that work based on PubMed may not generalize well to other domains. Benchmarks based on arXiv will be used in competitions at AAAI-2021 for AI and AD tasks (Veyseh et al., 2020). The AI task uses NER-like labels with 5 tags: B-short, B-long, I-short, I-long and O, where B-short and I-short are used for SF spans, and B-long and I-long are used for LF spans.

This paper will use the ADI task which inputs definitions, as opposed to AI and AD tasks which include subsequent mentions taken out of context. Here is an example from the AI benchmark of a subsequent mention of MRC.

Using Google, we found the document. The definition of MRC appears a few sentences earlier.

The ADI task is based on word sense disambiguation (WSD). The input sentence contains a SF, such as
| Benchmark | Method  | Ab3P | BERT-SQuAD |
|-----------|---------|------|------------|
| Ab3P      |         | 0.889| 0.794      |
| BIOADI    |         | 0.838| 0.698      |
| MEDSTRACT |         | 0.943| 0.844      |
| SH        |         | 0.858| 0.769      |

Table 1: Ab3P has better F-scores on 4 benchmarks.

| Benchmark | Pr(correct|charm match)| not char match | char match |
|-----------|------------|---------------|---------------|
| Ab3P      | 0.15       | 0.96          |
| BIOADI    | 0.07       | 0.94          |
| MEDSTRACT | 0.18       | 0.98          |
| SH        | 0.10       | 0.94          |

Table 2: BERT-SQuAD does not capture charmatch.

The MRC technique employs a single copper loop of small radius both at the energy transmitter end and sensor node’s receiving end. The AD task is to choose the appropriate LF from a short list of candidates:

1. machine reading comprehension
2. maximal ratio combining
3. magnetic resonance coupling

More context would be helpful. With Google, we found the document; the definition, immediately before the input sentence, resolves the ambiguity.

2 BERT-SQuAD: An Alternative to Ab3P for ADI

The Ab3P method takes a text as input and outputs pairs of SFs and LFs that are defined in the input text. BERT-SQuAD takes a question and context as input, and outputs a span from the document that answers the question. For the comparisons in Table 1, we give BERT-SQuAD the SF from Ab3P output. These SFs are turned into questions of the form: What does <SF> stand for? Even with this unfair hint, BERT-SQuAD is less effective than Ab3P, as shown in Table 1.17

Many of the errors are “off-by-one,” where the candidate LF has one word too many or one too few, especially at the left edge of the LF. The right edge tends to be easier because the right edge of the LF is often delimited by a parenthesis between the LF and the SF.

2.1 Two More Features: Charmatch & Freq

What is BERT-SQuAD missing? Consider the example: healthy controls (HC). In this case, BERT-SQuAD drops the first word from the LF, returning controls instead of healthy controls. BERT’s candidate violates a constraint on characters, where the bold characters in healthy controls are likely to match the characters in the SF (HC). Ab3P uses old-fashioned rules to capture this constraint.

It appears this character constraint is missing from BERT-SQuAD. To test this hypothesis, we introduce a simple boolean feature, charmatch, that compares the first character of the SF to the first character of the candidate LF. Table 2 shows that candidates from BERT-SQuAD are more likely to be correct when these characters match.

In addition to charmatch, we identified another promising feature that we call freq. Consider the example: Latent herpes simplex virus (HSV) has been demonstrated in... Again, BERT-SQuAD is off by one, but this time, the candidate LF is too long: Latent herpes simplex virus. The freq feature takes advantage of the fact that many of these SFs are defined in thousands of PubMed abstracts. The freq feature uses suffix arrays (Manber and Myers, 1993) to count the number of matches of: SF + '(' + LF in PubMed. In this example, we found 6075 instances of “herpes simplex virus (HSV),” but only 8 instances of “Latent herpes simplex virus (HSV).” Of course, raw frequencies need to be normalized.

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14Ambiguity is more common across documents than within documents. MRC, for example, is unlikely to expand to two different LFs within the same document. In this respect, SFs obey a so-called “one sense per discourse” constraint like word senses (Gale et al., 1992). That is, the word bank is ambiguous. In one document, it may refer to a money bank, and in another document, it may refer to a river bank, but it is unlikely to be used both ways within the same document.

15https://arxiv.org/pdf/1805.07795.pdf

16The wireless transfer is performed by using the so called Magnetic Resonance Coupling (MRC) technique.

17BERT and Ab3P differ in many ways in addition to F-scores. BERT generalizes to many tasks, but it is bigger and slower and limited to inputs under 512 tokens.
Table 4: Coefficients for 12 logistic regression models:
\[ z = \beta_0 + \beta_1 \text{rank} + \beta_2 \text{charmatch} + \beta_3 \log(1 + \text{freq}) \]

| Feature | Benchmark |
|---------|-----------|
| Ab3P    | BIOADI    | MEDS. | SH |
| 1 (M 1-4) | 0.829 | 0.660 | 0.865 | 0.796 |
| 2 (M 5-8) | 0.908 | 0.787 | 0.945 | 0.901 |
| 3 (M 9-12) | 0.936 | 0.948 | 0.975 | 0.949 |

Table 5: Models with more features are more confident when they are correct. Models 1-4 use a single feature (rank). Models 5-8 add charmatch. Models 9-12 add freq. Confidence is estimated as median \( \sigma(z) \) for correct candidates.

appropriately because shorter strings tend to be more frequent than longer strings.

2.2 12 Models: Rank + Charmatch + Freq

To side-step difficult normalization and feature combination questions, we make use of reranking and machine learning. BERT-SQuAD was modified to output top-k candidates instead of just the top candidate. Table 3 shows there are more correct candidates in top position (rank 0), but there are also many correct candidates in other positions.

A dozen logistic regression models are used to rerank the top 5 candidates. Models 1-4 use eq (1), models 5-8 use eq (2) and models 9-12 use eq (3). \( y \) comes from the 4 gold sets: models 1, 5 & 9 use the Ab3P benchmark for \( y \), models 2, 6 & 10 use BIOADI, models 3, 7 & 11 use MEDSTRACT, and models 4, 8 & 12 use SH. Coefficients are shown in Table 4. All coefficients are significant. Reranking sorts candidates by \( z \), as defined in Table 4.

\[
\begin{align*}
  y & \sim \text{rank} \\
  y & \sim \text{rank} + \text{charmatch} \\
  y & \sim \text{rank} + \text{charmatch} + \log(1 + \text{freq})
\end{align*}
\]

3 Results

Scores for 12 BERT-SQuAD models and 4 benchmarks are shown in Figure 1. These results are summarized in Figure 2. Adding more features to BERT-SQuAD improves F-scores. Table 5 shows that models with more features are more confident.

4 Conclusions

This paper compared BERT-SQuAD to a rule-based baseline, Ab3P, on the ADI task. We proposed a reranking improvement to BERT that takes advantage of two features: charmatch and freq. F-scores for the proposed solution are better than BERT but worse than baseline, suggesting the two features shed light on opportunities for improving BERT-like models.
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