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TüKaPo at SemEval-2020 Task 6: Def(n)tly not BERT: Definition Extraction using pre-BERT Methods in a post-BERT World

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Abstract

We describe our system (TüKaPo) submitted for Task 6: DeftEval, at SemEval 2020. We developed and evaluated multiple neural network models based on CNNs and LSTMs to perform binary classification of sentences containing definitions. Our final model achieved a F1 score of 0.6851 in subtask 1.

1 Introduction

Definition detection and extraction has been a well-researched topic in NLP research for over a decade.

2 Background

The DeftEval shared task is based around the English-language DEFT (Definition Extraction From Texts) corpus (Spala et al., 2019). It consists of annotated text extracted from the following semi-structured and free-text sources: 2017 SEC contract filings from the US Securities and Exchange Commission EDGAR database[1], and open-source textbooks from OpenStax CNX[2]. The latter encompasses topics from areas of biology, history, physics, psychology, economics, sociology, and government. Compared to similar existing definition corpora such as WCL (Navigli and Velardi, 2010) and W00 (Jin et al., 2013), the data offered by the DEFT corpus is larger in size (23,746 sentences; 11,004 positive annotations) while also providing finer-grained feature annotations (c.f figure 1[3]).

The shared tasks consists of three subtasks: 1) Sentence Classification (classify if a sentence contains a definition or not), 2) Sequence Labeling (label each token with BIO tags according to the corpus specification), and 3) Relation Classification (label the relations between each tag according to the corpus specification). We participated in the first subtask.

Training and development data is common for all three subtasks. It is presented in a tab-delimited CONLL-2003-like (Sang and De Meulder, 2003) format where each line represents a token and its features:

$$[TOKEN]\ [SOURCE]\ [START\_CHAR]\ [END\_CHAR]\ [TAG]\ [TAG\_ID]\ [ROOT\_ID]\ [RELATION]$$

SOURCE is the source text file, START_CHAR and END_CHAR are the character index boundaries of the token, TAG is the BIO label of the token, TAG_ID is the ID associated with the TAG, ROOT_ID is the ID associated with the root of this relation (if any), and RELATION is the relation tag of the token.

The test data for the first subtask is presented in the following CONLL-2003-like format: $[SENTENCE]$ $[BIN\_TAG]$. BIN_TAG is 1 if SENTENCE contains a definition, 0 otherwise. During the

[1] https://www.sec.gov/

[2] https://cnx.org/

[3] Additionally, relationships between terms and definitions are also annotated.

Tag	Description
Term	Primary term
Alias Term	Secondary, less common name for the primary term
Ordered Term	Multiple inseparable terms that have matching sets of definitions
Referential Term	NP reference to a previously mentioned term
Definition	Primary definition of a term
Secondary Definition	Supplemental information crossing a sentence boundary that could be part of the definition
Ordered Definition	Multiple inseparable definitions that have matching sets of terms
Referential Definition	NP reference to a previously mentioned definition
Qualifier	Specific date, location, or condition under which the definition holds

Table 1: DEFT Tag Schema

training for the first subtask, the training and development datasets were converted into the same format was the test dataset using a script provided with the corpus. A positive label was associated with every sentence that contained tokens with `B-Definition` or `I-Definition` tags; all other sentences were associated with a negative label.

2.1 Related Work

In the early days of definition extraction, rule-based approaches leveraging linguistic features showed promise. Westerhout (2009) used a combination of linguistic information (n-grams, syntactic features) and structural information (position in sentence, layout) to extract definitions from Dutch texts. Such approaches, however, were found to be dependent on language and domain and scale poorly. Later research incorporated machine learning methods to encode lexical and syntactic features as word vectors (Del Gaudio et al., 2014). Noraset et al. (2017) tackled the problem as a language modelling task over learned definition embeddings. Espinosa-Anke et al. (2015) derive feature vectors from entity-linking sources and sense-disambiguated word embeddings. More recently, Anke and Schockaert (2018) use convolutional and recurrent neural networks over syntactic dependencies to achieve state-of-the-art results on the WCL and W00 datasets (Navigli and Velardi, 2010; Jin et al., 2013).

3 System Overview

3.1 Baseline Experiments

We developed and iterated over both LSTM-based (Hochreiter and Schmidhuber, 1997) recurrent and convolutional (O'Shea and Nash, 2015) neural network models. Our baseline RNN architecture is a network of a single bidirectional LSTM layer followed by two feed-forward layers (w/t Dropout) and a final sigmoid-activated read-out layer. This architecture is implemented by model *BL-RNN* whose input layer accepts sequences of features vectors. Our baseline hybrid-CNN architecture is implemented by model *BL-CNN* that is based on the work by Anke and Schockaert (2018). It accepts feature vector sequences that are passed through a one-dimensional convolutional filter and a max-pooling layer, followed by a BiLSTM and read-out layer. The intuition behind combining convolutional and recurrent layers is to leverage the implicit local feature-extraction performed by the convolutional layers to refine the final representation passed to the recurrent layer, which then accounts for global features.

We conducted several experiments with the above two architectures and iterated over successful models. Training data was split into 90-10 train-test data splits. 10% of the train data split was used for validation. All models were trained for 100 epochs with an early-stopping mechanism that monitored the validation loss over the last 10 epochs. Batch size was set to 128, and ADAM (Kingma and Ba, 2014) was used as

Experiment	Model	Word Embeddings	Features	Precision	Recall	F1-Score
1. W/o Semantic Information	BL-RNN	-	POS + Deps	0.56	0.75	0.64
2. W/t Semantic Information	BL-RNN	Glove	Tokens + Deps	0.74	0.63	**0.68**
		w2v		0.71	0.60	0.65
	BL-CNN	Glove		0.72	0.62	**0.67**
		w2v		0.72	0.58	0.64
3. Effect of punctuation & dependency relations	BL-RNN	Glove	Tokens + POS	0.75	0.62	0.68
			Tokens + Deps + POS	0.76	0.58	0.66
			Tokens + POS + Punct	0.76	0.64	**0.69**
			Tokens + Deps + POS + Punct	0.76	0.62	0.68
	BL-CNN		Tokens + POS	0.74	0.65	0.69
			Tokens + Deps + POS	0.77	0.67	**0.71**
			Tokens + POS + Punct	0.77	0.64	0.70
			Tokens + Deps + POS + Punct	0.79	0.62	0.70
4. Final Model	FINAL-HYBRID	Glove	Tokens + POS + Punct	0.77	0.64	0.70
			Tokens + Deps + POS + Punct	0.75	0.70	**0.73**

Table 2: Results of experiments performed on the baseline & final models.

the binary cross-entropy optimizer. URLs were stripped from token sequences as a preprocessing step. The results of our experiments are listed in table 2. All experiments were carried out multiple times; the reported figures were averaged over three iterations.

Our initial experiments were premised on the hypothesis that neural definition extraction can be modelled on primarily morphosyntactic features while excluding or restricting the use of semantic and lexical information. By limiting the influence of semantics, we expected to train a model that generalized well over multiple domains by virtue of being less susceptible to lexical cues that could potentially act as distractors. To test this, we trained the RNN model on a concatenation of part-of-speech tag and dependency relation sequences. Similarly, two more RNN models were trained on word embedding and dependency relation sequences, their word embedding matrix initialized with 300-dimensional pre-trained GloVe (Pennington et al., 2014) and word2vec (Mikolov et al., 2013) embeddings respectively[4]. The results proved our hypothesis to be flawed, as the models enriched with semantic information provided by the word embeddings consistently out-performed our syntax-only model. This result also carried over to the hybrid-CNN models. Overall, we found that models trained with GloVe embeddings to be more performant than those trained with w2v.

Build upon the results of the previous experiments, we tested the effect of combining punctuation and part-of-speech tags. It was immediately evident that replacing the *PUNCT* POS tag with the punctuation character occurring at that position had a positive effect on the model's performance. Beyond the implicit increase in information offered by the actual character, it also reaffirms the importance of syntactic features in this task. The addition of dependency relation features, however, has a less immediately-obvious impact. The RNN model sees a reduction in performance while the hybrid-CNN model fares better. Upon further investigation, we determined that encoding dependency information at sentence-level as opposed to word-level yields better performance.

[4]The GloVe and w2v embeddings were trained on the Common Crawl and Google News corpora respectively.

3.2 Final Architecture

Our final architecture is informed by the results of our previous experiments. It accepts five inputs: At word-level, both token and part-of-speech tags (w/t punctuation) are used. Pre-trained GloVe embeddings are used for tokens, while embeddings for POS tags are learned on-the-fly. The concatenation of both embeddings is passed through two "feature extraction" units that consist of a BiLSTM (to target sequence/global information), and a 1D-Conv + MaxPool layer (to target local information). At sentence-level, dependency information is encoded as the concatenation of the embeddings of the head, modifier and dependency label of each relation. This is connected to two stripped-down "feature extraction" units without the BiLSTM layer, since dependency relations are sequentially independent. Finally, the extracted representations of both word- and sentence-level features are concatenated and connected to a feed-forward layer and a read-out layer.

The above architecture's separation of feature-extraction at token and sentential levels allows their information to be combined at a higher level in the network. And we indeed see a marked improvement when this model is trained with dependency information. The model achieved a best F1-score of 0.76 during development.

4 Evaluation & Results

5 Conclusion

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