



# Unsupervised Adverse Drug Event related document detection with Bert-based model

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# UNSUPERVISED ADVERSE DRUG EVENT RELATED DOCUMENT DETECTION WITH BERT-BASED MODEL

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## 1. Motivation

- The post-marketing pharmacovigilance (PhV) practice aims at detecting, monitoring, characterizing and preventing adverse drug events (ADEs) in the medical reports.
- Identification of ADEs relies on the well-trained health professionals, while there are still an enormous amount of documents waiting to be reviewed.
- Annotating such electronic health records (EHRs) is very expensive.

## 2. Problems

We defined firstly "block" (noted as  $b$ ), as the basic unit of textual content to analyse, which can be either a whole document, a paragraph, a sentence or some pieces of sentences, etc. An ADE involves a drug  $d$ , a symptom  $s$  in a kind of textual block  $b$  with the description containing the two entities, which can be represented as:

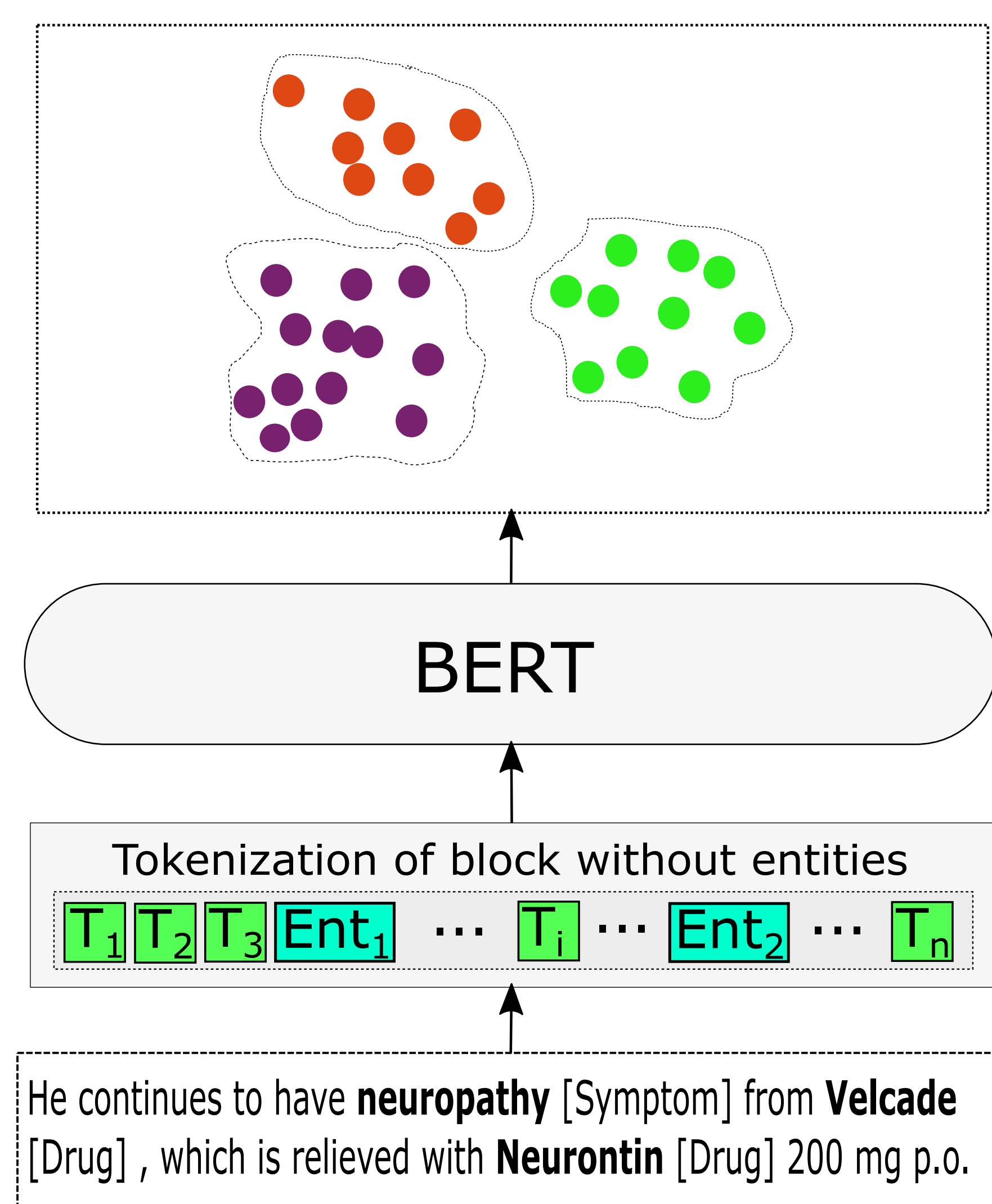
$$(relation) r(d, s, b) = \mathbf{ADE}(d, s, b)$$

Our basic assumption is that "the ADE relation lies in the contexts of the target entities". More specifically, we assume there exists a short text  $z$  in  $b$  around the entity pair  $(d, s)$  which is sufficient for the representation of ADE.

$$\mathbf{ADE}(d, s, b) \simeq \mathbf{ADE}(d, s, z)$$

## 3. Unsupervised BERT based ADE detection

We chose sentence as our "block"  $b$  together with its entity annotations as basic element to analyse and used Bidirectional Encoder Representation from Transformers (BERT) as well as its two modifications: Sentence-BERT and BioBERT, to encode each given textual context  $z$  into vectors of the same size. Finally A clustering algorithm is used for creating clusters of similar sentences.



### Modified BERT model

- **Sentence-BERT**, applying a siamese fine-tuning structure on basic BERT model to capture features in semantic space.
- **BioBERT**, pre-trained and fine-tuned in a traditional way but on the medical corpora.

## 4. The data

We used data in MADE challenge, whose corpora are only electronic health records with annotations of their entities. The granularity of corpus was set to sentence.

- **made\_sent\_all** All examples that contains only drugs or only symptoms were removed and thus we got a dataset where each block has at least one drug and one symptoms.
- **made\_sent\_1d1s** For the dataset above, we extract then those who has exactly one drug and one symptom, which called "1d1s" as "perfect situation".

## 5. What we found firstly

We have chosen a fully supervised approach (Bag of Words + Logistic Regression Classifier) as the baseline, which provided us a vision about the upper bound of our method. While the Bag of words with dummy classifier clarifies the lower bound.

made\_sent\_1d1s

Category	Exp	Precision	Recall	F1 Score	F2 Score
Supervised	BOW+LR	0.7862	0.7064	0.7438	0.7685
Supervised	BOW+Dummy	0.5294	0.5143	0.5217	0.5263
Unsupervised	BERT+Clustering	0.5200	0.6393	0.5735	0.5402
Unsupervised	BioBERT+Clustering	0.7467	0.6829	0.7134	0.7330
Unsupervised	S-BERT+Clustering	0.5200	0.7358	0.6094	0.5524

made\_sent\_all

Category	Exp	Precision	Recall	F1 Score	F2 Score
Supervised	BOW+LR	0.8372	0.8105	0.8234	0.8316
Supervised	BOW+Dummy	0.4946	0.5236	0.5087	0.5002
Unsupervised	BERT+Clustering	0.4538	0.5315	0.4896	0.4675
Unsupervised	BioBERT+Clustering	0.6923	0.7087	0.7004	0.6955
Unsupervised	S-BERT+Clustering	0.6154	0.6349	0.6250	0.6192

- Comparing to the basic BERT-based method, the Sentence-Bert-based method has an advantage in semantic meaning representation.
- Comparing to the other two BERT-based method, the BioBERT-based one shows a relatively good performance in both f1 and f2 score, especially for the "made\_sent\_1d1s" data, which is quite close to the supervised results. This may due to the domain specific vocabulary dictionary from the BioBERT model.

## 6. Perspectives

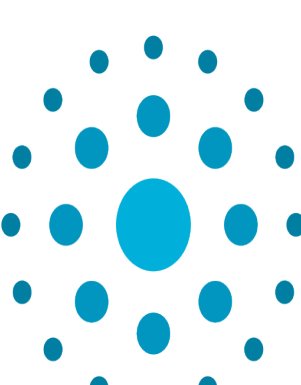
- Sentence-BioBERT may be more useful in this scenario
- cluster topic analysis
- improve for inner-block relations
- deal with inter-block problem

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