Literature Survey on Aspect Based Sentiment Analysis using Deep Learning techniques

1 Abstract

We shall discuss he techniques mentioned in recent works in the field of aspect level sentiment analysis, we will proceed by understanding the works of these authors which are ‘Exploiting BERT for End-to-End Aspect-based Sentiment Analysis’, ‘Aspect-Based Sentiment Analysis Using BERT’ and ‘A Challenge Dataset and Effective Models for Aspect-Based Sentiment Analysis’.

2 Deep Learning based A.B.S.A.

2.1 A Hybrid Approach for Aspect-Based Sentiment Analysis Using a Lexicalized Domain Ontology and Attentional Neural Models [Wallaart and Frasincar, 2019]

The authors of this paper deal with the domain of Aspect Based Sentiment Analysis for the Restaurant domain. They develop a technique to outperform the erstwhile state of the art model on SEMEVAL-16 Task 5 dataset. The authors predict sentiment using domain ontology and a neural network with a rotatory attention mechanism. They use two steps which they call extensions to change the order in which the roatory attention is employed, then running over the rotatory mechanisms for several iterations.

The approach is elaborated in the following points:

- The ontology they use consists of three main classes : SentimentValue indicating the positive or negative sentiment associated with the expression, AspectMention links the word to it’s parent concept and SentimentMention devides the sentiment bearing words into 3 categories, a word falls into the first category if the word expresses the same sentimet for every aspect, if the word is relevant for a few aspects and not a sentiment bearing word for the other aspects and the word fals into the last category if it does not belong to any of the above mentioned categories.

- In the second step the authors try to capture the words in the target phrase, most relevant to the context provided.

- The authors then train their deep learning based hybrid model in a two step approach.The mehod proposed by the authors first uses the ontology to predict a positive or negative sentiment. If the ontology is not able to provide an accurate result, the algorithm will use the LCR-Rot algorithm as a backup method.

The author present their results as follows:

	SemEval-2015				SemEval-2016			
	out-of-sample	in-sample	cross-validation		out-of-sample	in-sample	cross-validation	
	acc.	acc.	acc.	st. dev.	acc.	acc.	acc.	st. dev.
Ont	65.8%	79.7%	79.7%	0.0183	78.3%	75.3%	75.3%	0.0152
BoW	76.2%	91.0%	87.9%	0.0311	83.2%	89.3%	84.5%	0.0254
CABASC	76.6%	85.8%	87.1%	0.0138	84.6%	79.2%	84.0%	0.0218
LCR-Rot	**78.4%**	86.2%	88.0%	0.0144	86.9%	92.9%	85.8%	0.0214
LCR-Rot-inv	77.1%	85.2%	88.1%	0.0146	86.5%	93.9	85.5%	0.0161
LCR-Rot-hop	**78.4%**	88.6%	87.6%	0.0181	**87.7%**	86.3	85.6%	0.0169
Ont+BoW	79.5%	86.9%	83.5%	0.0308	85.6%	86.7%	85.7%	0.0329
Ont+CABASC	79.6%	84.3%	83.2%	0.0138	85.9%	82.3%	85.5%	0.0298
Ont+LCR-Rot	**80.6%**	84.5%	83.7%	0.0144	87.0%	88.3%	86.3%	0.0323
Ont+LCR-Rot-inv	79.9%	89.0%	83.7%	0.0146	86.6%	88.7%	86.2%	0.0296
Ont+LCR-Rot-hop	**80.6%**	85.7%	83.5%	0.0298	**88.0%**	86.7%	86.2%	0.0308

Figure 1: Results[1]

2.2 Exploiting BERT for End-to-End Aspect-based Sentiment Analysis [Li et al., 2019]

In this paper, the authors focus on aspect based sentiment analysis and frame the problem as a sequence labeling task.They use the BERT model for their experiment, The input is a sentence form SemEval ABSA dataset, which is fed to a BERT[Devlin et al., 2019a] model, the model then produces contextualized representation of the input sentence. They add a linear classification layer on top of the BERT representations and they use this task-specific layer to predict the tag sequence of the input tokens. The tags are B-POS,NEG,NEU, I-POS,NEG,NEU, E-POS,NEG,NEU, S-POS,NEG,NEU or O, denoting the beginning of aspect, inside of aspect, end of aspect, single-word aspect, with positive, negative or neutral sentiment respectively, as well as outside of aspect.They wish to show with

[1] `https://personal.eur.nl/frasincar/papers/ESWC2019/eswc2019.pdf`

the experimental results the effectiveness of BERT-based models on aspect-based sentiment analysis task and BERT's ability to avoid overfitting.

2.3 Aspect-Based Sentiment Analysis Using BERT [Hoang et al., 2019]

The authors of this paper have also used a pre-trained BERT model on the SemEval aspect level annotated dataset for their work, they us the BERT model for two purposes:

- To predict if a given aspect category is present in a model or not.
- To predict the aspect level sentiment associated with a given review.

The authors create three models using BERT[Devlin et al., 2019a] which are:

- An aspect classifier: The authors tokenize the input sentences and take the aspect for the sentence from the training data, combine both of them by using a special token and ask the model to predict if the given aspect is present in the sentence or not.
- A aspect level sentiment classifier: The authors feed the tokenized sentence and the aspect associated with the sentence to the BERT model and add a classification layer on top of the representation BERT produces, they use this linear classifier to classify the aspect level sentiment for the input sequence; which is one out of three classes (negative,neutral,positive).
- A combined classifier: The authors combine the two models discussed above in a way that the input tokens are fed into the aspect classifier along with the aspect to be tested for it's presence, if the model predicts that the aspect is absent from the input sequence then the model output is unrelated otherwise the sentence and the aspect are forwarded to the second BERT based classifier, which predicts the sentiment for that aspect in the input sequence, the authors train both the models jointly in this case.

The authors wished to show the effectiveness of BERT and that of the jointly trained combined-BERT based model for aspect level sentiment analysis.

3 A Challenge Dataset and Effective Models for Aspect-Based Sentiment Analysis [Jiang et al., 2019]

The authors of this work also work on the aspect level sentiment analysis task, the authors of this work make contributions in the form of a new aspect level annotated dataset called MAMS and a new machine learning architecture for aspect level sentiment analysis by using a capsule network; We shall define both the works:

- The authors created a new dataset called MAMS for aspect-based sentiment analysis in which each sentence contains multiple aspects unlike SemEval aspect based sentiment analysis data, this was done in order to stop aspect-level classification to simplify into sentence -level sentiment prediction.
- For better aspect level sentiment prediction the authors propose a CapsNet-BERT architecture by combining both BERT and capsule network they do this by replacing the embedding layer and encoding layer of CapsNet with pre-trained BERT.This modified novel architecture takes“[CLS] sentence [SEP] aspect [SEP]” as its input just like the previous model, computes the representation of the input sequence using the pre-trained BERT and feed the representations into the capsule layers for sentiment value prediction.

4 Summary

We discussed three works utilizing pre-trained BERT models for performing aspect level sentiment analysis task, we saw how all the three models used BERT representations in three different ways by using it for different objectives, showing the capacity of BERT.