Detection of Propaganda Techniques in News Articles (Team-Titans)

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Abstract

Propaganda is commonly defined as information of a biased or misleading nature, possibly purposefully shaped, to promote an agenda or a cause. In this project we are trying to build machine learning system for the Detection of Propaganda Techniques in News Articles. There are two subtasks to be solved as part of this project which are Span Identification and Technique Classification. As a baseline architecture we used a Bi-directional LSTM model for the span identification task. For the technique classification task, we tried different models like logistics regression, random forest model out of which the random forest model performed the best. For the final phase we used transformer based model like BERT, RoBERTa, for both the tasks, we have seen significant improvement in the F1 scores as part of the final phase and we are able to secure position 17 on leader board in SI Task and Position 18 in TC Task.

1 Introduction

Propaganda detection in the news Articles is incredibly essential since they impact people's mindsets to forward a certain goal. Text-based propaganda employs a variety of propaganda strategies. The propaganda detection pipeline includes two sub tasks

1.1 Task-1 Span Identification (SI):

1.1.1 Problem Statement

Given a plain-text document, identify those specific fragments which are propagandistic. (Binary(P/NP) sequence tagging task).

1.1.2 Proposed Solution

For span identification we makes use of a state-of-the-art language model enhanced by tagging schemes for token level classification with BIOE encoding scheme.

1.2 Task-2 Technique Classification (TC):

1.2.1 Problem Statement

Given a text fragment identified as propaganda and its document context, identify the applied propaganda technique in the fragment. (14 class Classification Task)

1.2.2 Proposed Solution

For the technique classification model, we use BERT language model to get the contextual sequence representation for the propaganda span and its context to perform classification.

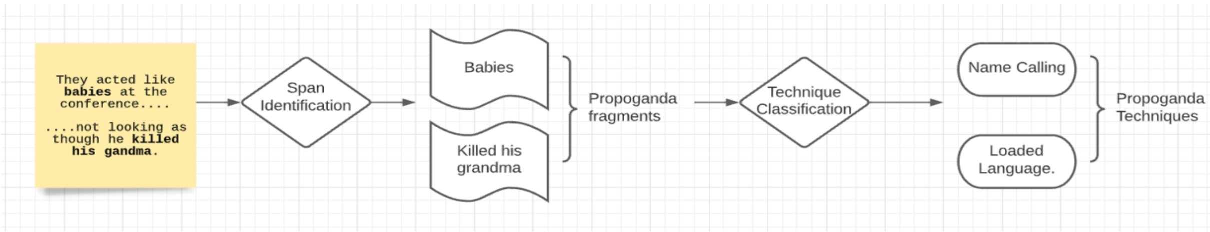


Figure 1: Problem Description Flow Diagram

2 Related Work

2.1 Literature Survey

After reading several paper we came across below mentioned paper have given some good insights on the problem statements. Below are the details of the papers as part of the literature survey.

1. Paper1 - newsSweeper at SemEval-2020 Task 11: Context-Aware Rich Feature Representations For Propaganda Classification Paramansh Singh, Siraj Sandhu, Subham Kumar, Ashutosh Modi `https://arxiv.org/abs/2007.10827`

   The approach discussed in this paper are as follows:

   (a) SI task - Use of pre-trained BERT language model enhanced with tagging techniques developed for the task of Named Entity Recognition (NER), to develop a system for identifying propaganda spans in the text.

   (b) TC task - Incorporated contextual features in a pre-trained RoBERTa model for the classification of propaganda techniques

2. Paper2 - Li, W., Li, S., Liu, C. et al. Span identification and technique classification of propaganda in news articles. Complex Intell. Syst. (2021). `https://doi.org/10.1007/s40747-021-00393-y`. The approach discussed in this paper are as follows:

   (a) SI task – BERT-based binary classifier, with optimized sampling process, combined EDA(easy data augmentation techniques) to prevent the overfitting. Also adopted the sentence-level feature concatenating (SLFC), so that model can learn characteristics better.

   (b) TC task - BERT-based architecture with a dimensionality reduction Full Connected (FC) layer and a linear classifier.

3 Model architecture

3.1 Span Identification Task

3.1.1 Data Preprocessing

In the baseline approach we tagged each token using P/NP tags. We take this approach forward and tagged each token using BIOE scheme. B represents the Beginning of propaganda text I means Inside propaganda text, E represents the End of propaganda text, and O means outside the propaganda text i.e., non-propaganda text. Length of the articles are too long and because of that we cannot feed it directly to the state-of-the-art transformer model. We split the articles into sentences and capture the BIOE encoding at the sentence level. If the span present across multiple sentences, then the whole sentence is considered.

3.1.2 Training Setup

We pass the input sequence to the transformer based pretrained model. We used pyTorch Framework provided by the hugging face library for the pretrained transformer model. We used BertForTokenClassification, RobertaForTokenClassification and DistilbertForTokenClassification model. This model has token classification head on top, allowing it to make predictions at the token level, rather than the sequence level. Due to a smaller number of examples in the training data, most of the models were overfitting and failed to generalize. We used the BertForTokenClassification system for our final test set submission. The hyperparameter for the final system is Optimizer= Adam, lr= 3xe-5, batchsize=10 and epoch=4

3.1.3 Post processing

While Preparing Spans B, I and E are taken as propaganda token. By providing dependencies between the many tokens in a propaganda span, Begin and End tags assist to properly define the concept of spans and treat it as a span identification problem rather than a token classification task. The following strategy is used to form the span:

1. For the sequences which has only B tags we take the 5 tokens after the B tag and make the span.
2. For the sequences which has only E tags we take the 5 tokens before the E tag and make the span.
3. For the span having B and E tags if it has, I tokens in between them we make it a span ignoring the length of span otherwise if I is not there then we made span only if less than 5 tokens are present between B and E tags.

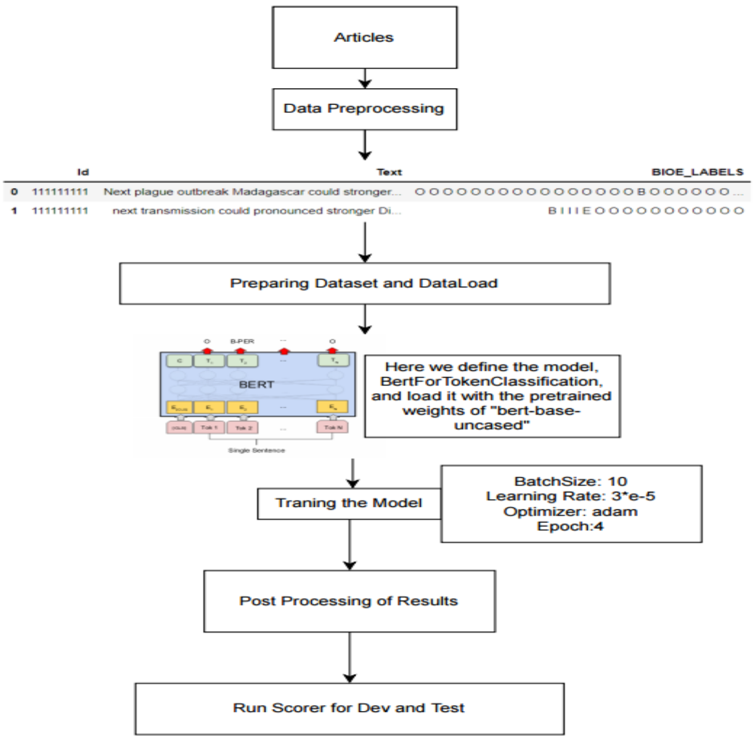


Figure 2: Span Identification Task End to End Flow Diagram

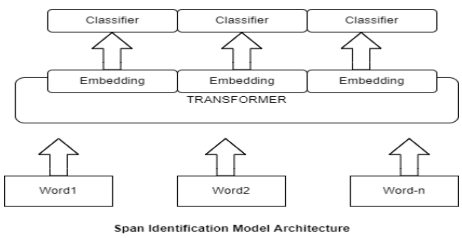


Figure 3: Span Identification Task Model Architecture

3.2 Technique Classification Task

3.2.1 Data Prepossessing

For the technique classification task, we divided the news article into context and the propaganda span. For the context we considered the sentence in which the span is present. This to avoid influence of lot of contexts to the span where the propaganda is present.

3.2.2 Training setup

The input sequence is prepared by concatenating the context and the span. Context and span are separated with a special token [SEP]. We used transformer-based tokenizer which provide (tokenTypeIds) that provide different tokens context and span. This helped the model to differentiate between context and span. We used BERT and Roberta for getting the vector for the input sequence. The vector is then fed to the hidden layer and then to softmax layer for multiclass classification. Due to data imbalance f1-score for the minority classes was coming as zero. We used the Bert(bert-base-uncased) system for our final test set submission. The hyperparameter for the final system is Optimizer= Adam, lr= 3xe-5, batchsize=8 and epoch=3.

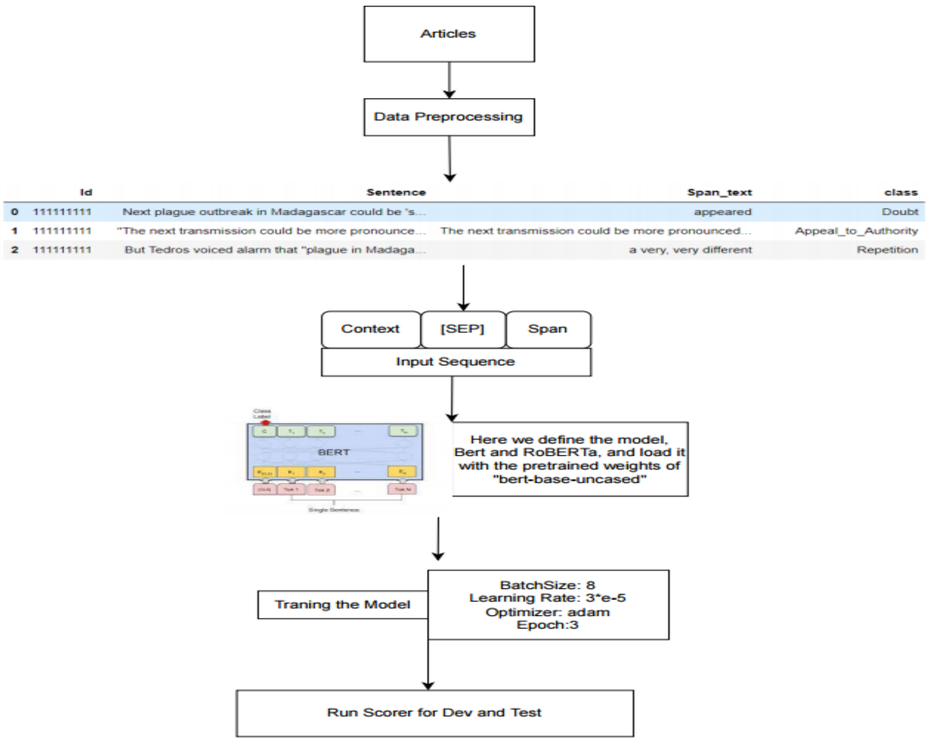


Figure 4: Technique Classification Task End to End Flow Diagram

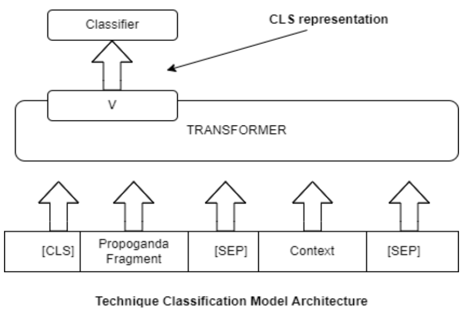


Figure 5: Technique Classification Task Model Architecture

4 Results

4.1 Result Comparison of Baseline Model and Final Model for Span Identification Task

The scores for different models on official development set trained with 80 percent training data have been reported in below Table.

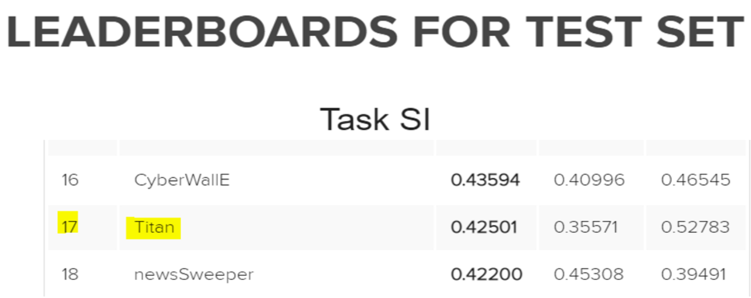
Span Identification Task(Dev Data-set)			
Model	Precision	Recall	F1
BILSTM (Baseline)	0.1862	0.3508	0.2433
BERT with NP Tagging (Final)	0.321	0.286	0.213
BERT with BIOE Tagging (Final)	**0.433**	**0.357**	**0.392**

4.2 Result Comparison of Baseline Model and Final Model for Technique Classification Task

The scores for different models on official development set trained with 80 percent training data have been reported in below Table.

Technique Classification Task(Dev Data-set)	
Model	F1
Logistic Regression (Baseline)	0.31
Random Forest (Baseline)	0.35
BERT (Final)	**0.57**
RoBERTa (Final)	0.44

4.3 Leader Board Ranking for Test Data Set



LEADERBOARDS FOR TEST SET

Task SI

16	CyberWallE	0.43594	0.40996	0.46545
17	Titan	0.42501	0.35571	0.52783
18	newsSweeper	0.42200	0.45308	0.39491

Figure 6: Leader Board Ranking for SI Task

Rank	Team	F1	F1 Appeal_to_Authority	F1 Appeal_to_fear-prejudice	F1 Bandwagon,Reductio_ad_h
17	DiSaster	0.56648	0.51163	0.35254	0.20408
18	Titan	0.55922	0.25806	0.36154	0.17857

Figure 7: Leader Board Ranking for TC Task

5 Discussion and Error Analysis

5.1 Span Identification Task

As can be observed from the result table 4.1, altering the tagging technique from P/NP to BIOE increased the score, maybe because BIOE captures the span nature of the output. It is observed that increasing the batch size resulted in reduced performance. High learning rate greater than 1*e-3 and more epoch was reducing the generalizability of model resulting in an overfit model.

5.2 Technique Classification Task

- We observed that for this task BERT outperforms other transformer model RoBerta and thus it is used to generate input representations.
- As can be seen in the below figure, the model shows reasonably good performance when predicting Loaded Language, Name Calling or Labeling. These classes are the most frequent ones. On the other hand, techniques Slogans and whatabotism, Straw_men, Red_Herring are among the hardest to identify. They are also among the least frequent ones.
- The BERT model training with finetuning only the last layer resulted in poor performance so we finetuned all the layers of BERT and run the model for a smaller number of epochs to avoid overfitting. As seen from the below figure model with large number of epoch and high learning rate has poor performance due to overfitting.

Figure 8: Comparison of Model Performance with different hyper parameters

6 Conclusion

We presented models for detecting propaganda spans in articles and categorizing the propaganda method utilized in a specific propaganda fragment. We demonstrate how cutting-edge language models can be effective for both subtasks. We demonstrated how the BIOE tagging technique can aid in the detection of spans. The span length analysis is used to forecast spans for the test dataset. We devised a data preparation approach to add context and propaganda span in an input sequence to a transformer-based model for classification. This approach resulted in a better performance and helped us move up the rankings on leaderboard. We secured Rank 18 for TC task and Rank 17 for SI task.

7 Work Distribution

The below table shows the work distribution among the team members.

Task Name	Team Member Name
Span Identification Task	Akash Deshmukh
Technique Classification Task	Rohit Nain
Report	Akash Deshmukh and Rohit Nain
Presentation	Akash Deshmukh and Rohit Nain

References

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