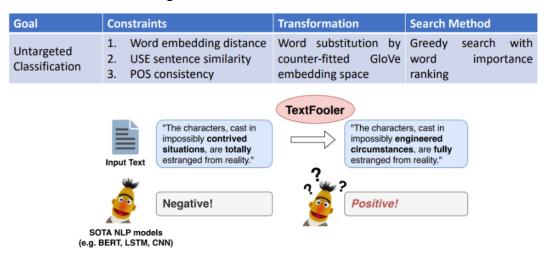
Team members:

- Gia Trong Nguyen
- Nikita Sergeev

Current progress:

Implementing attack algorithm from scratch

- Algorithm was taken from this <u>article</u>. In the previous week we used an implemented version of this algorithm by *textattack* python package, but it's not good to use the already implemented code, because it gives zero understanding. So, we decided to implement this algorithm from scratch for better understanding of nlp adversarial attack.
- Some information about this algorithm:



Algorithm look like this:

Evasion Attacks: TextFooler

```
· Algorithm
                                                                                                                      for c_k in Candidates do
                                                                                                                               \leftarrow Replace w_j with c_k in X_{adv}
                                                                                                             13:
              Algorithm 1 Adversarial Attack by TEXTFOOLER
                                                                                                             14:
                                                                                                                        if Sim(X', X_{adv}) > \epsilon then
              Input: Sentence example X = \{w_1, w_2, ..., w_n\}, the correspond-
                                                                                                                              Add c_k to the set FINCANDIDATES Y_k \leftarrow F(X')

P_k \leftarrow F_{Y_k}(X')
                                                                                                             15:
                    ing ground truth label Y, target model F, sentence similarity
                                                                                                             16:
                    function Sim(\cdot), sentence similarity threshold \epsilon, word embed-
                                                                                                             17:
                    dings Emb over the vocabulary Vocab.
                                                                                                                          end if
                                                                                                              18:
              Output: Adversarial example X_{\rm adv}

    Initialization: X<sub>adv</sub> ←

                                                                                                             20:
                                                                                                                       if there exists c_k whose prediction result Y_k \neq Y then
               2: for each word w_i in X do
                                                                                                             21:
                                                                                                                          In FINCANDIDATES, only keep the candidates c_k whose
                                                                                                                          prediction result Y_k \neq Y
c^* \leftarrow \underset{c \in \text{FinCandidates}}{\operatorname{argmax}} \quad \text{Sim}(X, X'_{w_j \to c})
X_{\text{adv}} \leftarrow \text{Replace } w_j \text{ with } c^* \text{ in } X_{\text{adv}}
   WIR
                       Compute the importance score I_{w_i} via Eq. (2)
                                                                                                             22:
                                                                                                             23:
               6: Create a set W of all words w_i \in X sorted by the descending
 constraint
                                                                                                             24:
                                                                                                                          return X_{\rm adv}
                   order of their importance score I_{w_i}.
                                                                                                             25:
                                                                                                                      else if P_{Y_k}(X_{adv}) > \min_{c_k \in FINCANDIDATES} P_k then

 Filter out the stop words in W.

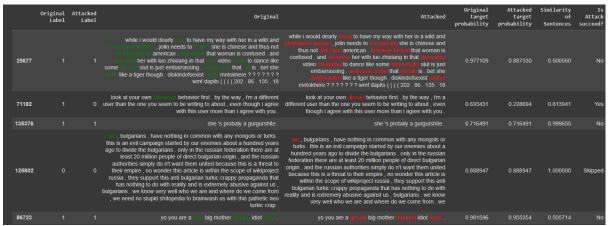
 Search
               8: for each word w_i in W do
                                                                                                                                 \operatorname{argmin}_{c_k \in \mathsf{FINCANDIDATES}} P_k
                                                                                                             26:
                       Initiate the set of candidates CANDIDATES by extracting the top N synonyms using CosSim(Emb_{w_j}, Emb_{word}) for
                                                                                                             27:
                                                                                                                          X_{\text{adv}} \leftarrow \text{Replace } w_j \text{ with } c^* \text{ in } X_{\text{adv}}
Transformation
                       each word in Vocab.
                                                                                                             28:
                                                                                                                      end if
                        Candidates \leftarrow POSFilter(Candidates)
                                                                                                             29: end for
                       FINCANDIDATES ← { }
                                                                                                             30: return None
```

- Let's talk a little bit about constraints. As you can see, one of the steps of implementing is to implement constraints with cosine similarity. We need to define a corpus of synonym words. Our choice is the dataset from this <u>article</u>. Then we compute for every word top 50 synonyms. It was a hard part of our work, because we did not have a lot of resources. POS filter we do using *nltk* package. Stop words we also take from *nltk* package. To compute similarity of sentences we use <u>Universal</u>

 <u>Sentence Encoder</u>.
- Implementation of algorithm you can find in **TextFooler FROM SCRATCH** block in our notebook.
- We attack only toxic labels.

Get the result:

• To understand if our attack works or not we try to attack 5% of train and valid datasets. Then make the pandas dataframe to visualize the results. Here is an example:



Meaning of columns:

* *Original Label* - Label, which model predict

* *Attacked Label* - Label, after attacking

* *Original* - Original text

* *Attacked* - Attacked text

* *Original target probability* - Probability of Label, which model predict

* *Attacked target probability* - Probability of original Label, after attacking

```
* *Similarity of Sentences* - Cosine similarity, which show us semantic similarity of sentences

* *Is Attack succeed?* - Attack succeeded or not
```

• Some statistic:

5% of Train dataset and 5% of Val dataset

```
Yes 279
No 170
Skipped 51
Name: Is Attack succeed?, dtype: int64

No 22
Yes 21
Skipped 7
Name: Is Attack succeed?, dtype: int64
```

As you can see, our attack worked.

- * Yes Attack is success
- * No Attack is failed
- * Skipped Model predict toxic label as non-toxic

Train robust model (adversarial training)

• To train a robust model we add success attack samples to our original dataset and then we retrain the model.

• So, after the previous step we compare the *performance* of two models (Compute accuracy only for toxic label, exclude non-toxic samples).

```
Comparing performance of original and adversarial trained models on valid dataset with adversarial examples.
[ ] 1 from IPython.display import clear_output
     3 true, pred = evaluate(model, prepared_toxic_val_iterator, verbose=False)
     4 clear output()
     5 print(f"Accuracy score of the Original model: {accuracy_score(true, pred)}")
    Accuracy score of the Original model: 0.8349328214971209
[ ] 1 true, pred = evaluate(adversarial_model, prepared_toxic_val_iterator, verbose=False)
      2 clear output()
     3 print(f"Accuracy score of the Adversarial trained model: {accuracy_score(true, pred)}")
    Accuracy score of the Adversarial trained model: 0.9385796545105566
Conclusion: Here, as you can see, model, which not trained on adversarial examples give bad performance comparing with model trained on
adversarial attack
Comparing performance of original and adversarial trained models on valid original dataset.
[ ] 1 true, pred = evaluate(model, original_toxic_val_iterator, verbose=False)
     3 print(f"Accuracy score of the Original model: {accuracy_score(true, pred)}")
    Accuracy score of the Original model: 0.87
[ ] 1 true, pred = evaluate(adversarial_model, original_toxic_val_iterator, verbose=False)
     2 clear_output()
     3 print(f"Accuracy score of the Original model: {accuracy_score(true, pred)}")
    Accuracy score of the Original model: 0.938
```

• To evaluate *robustness* of two models we use this formula:

```
attack success rate = \frac{\# \text{ of successful attacks}}{\# \text{ of total attacks}}
```

```
Original model attack success rate: 0.621380846325167
Adverasarial trained model attack success rate: 0.4863157894736842
```

As we can see, adversarial trained model become more robust than the original one.

Each member contribution:

Gia Trong - Implementing main algorithm of adversarial attack, Train models, Evaluate the models, Write Report

Nikita - Compute top 50 synonyms of the corpus, Prepare data for training and evaluating processes.

Future work:

- Fixing some little bugs. Bring beauty.
- Try to use other methods of attack from textattack package
- Prepare presentation for defending project