How Vulnerable Are Automatic Fake News Detection Methods to Adversarial Attacks?

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Abstract

As the spread of false information on the internet has increased dramatically in recent years, more and more attention is being paid to automated fake news detection. Some fake news detection methods are already quite successful. Nevertheless, there are still many vulnerabilities in the detection algorithms. The reason for this is that fake news publishers can structure and formulate their texts in such a way that a detection algorithm does not expose this text as fake news. This paper shows that it is possible to automatically attack state-of-the-art models that have been trained to detect Fake News, making these vulnerable. For this purpose, corresponding models were first trained based on a dataset. Then, using TextAttack, an attempt was made to manipulate the trained models in such a way that previously correctly identified fake news was classified as true news. The results show that it is possible to automatically bypass Fake News detection mechanisms, leading to implications concerning existing policy initiatives.

1 Introduction

The spreading of disinformation throughout the web has become a serious problem for a democratic society. The dissemination of fake news has become a profitable business and a common practice among politicians and content producers. A recent study entitled “Regulating disinformation with artificial intelligence” (Marsden and Meyer, 2019), examines the trade-offs involved in using automated technology to limit the spread of disinformation online. Based on this study, this paper discusses the social and technical problems of Automatic Content Moderation (ACM) poses to freedom of expression. Although AI and Natural Language Generation have evolved tremendously in the last decade, there are still concerns regarding the potential implications of automatically using AI to moderate content. One problem is that automatic moderation of content on social networks will accelerate a race in which AI will be created to counter-attack AI. Adversarial machine learning is an technique that attempts to fool models by exploiting vulnerabilities and compromising the results. For example, by changing particular words - e.g., from “Barack” (Obama) to “b4r4ck” - it is possible to mislead classifiers and overpass automatic detection filters. Recent works (Zhou et al., 2019) show the state-of-the-art machine learning models are vulnerable to these attacks.

This study relies on state-of-the-art techniques to attack and dive deep into the fake news detection vulnerabilities. The goal is to experiment with adversarial attacks to discover and compute the vulnerabilities of fake news classifiers. Therefore, this work aims to answer the following research question: How vulnerable is fake news detection to adversarial attacks?

The remainder of this paper is organized as follows. Section 2 discusses the background and previous related works. Section 4 describes the design of our experiments, and Section 5 presents the results and discussion. Section 6 summarizes our conclusions and presents future research directions.

2 Related Work

2.1 Fake News Detection

Fake news are used to manipulate general opinions of readers about a certain topic (Zhou and Zafarani, 2019). Unlike typical “clickbait” articles, which use misleading and eye-catching headlines, fake
news are usually quite long and wordy, consisting of inaccurate or invented plots (Chakraborty et al., 2016). This gives rise to the assumption of a well-researched and factually correct article. The reader, thus, does not notice how their personal opinion about a certain topic is deliberately manipulated.

Fake news detection refers to any kind of identification of such fake news. Due to the speed at which digital news is produced today, effective, automated fake news detection requires the use of machine learning tools. Previous research has mainly focused on fake news in social media and fake news in online news articles (Ghanem et al., 2021). There are various models of the machine detection of fake news, which are based on different heuristics.

For example, Ghanem et al. (Ghanem et al., 2021) discuss the effectiveness of the “FakeFlow” model, which incorporates both word embedding and affective information such as emotions, moods or hyperbolic words, based on four different datasets. The model receives several small text segments as input instead of an entire article. The result of the study was that this model is more effective than most state-of-the-art models. It generated similar results with less resources.

Another study (Woloszyn et al., 2021) investigates the possibility of using artificial intelligence for the automatic generation of Claim-Review. Claim-Review is the web markup introduced in 2015 that allows search engines to access fact-checked articles. The basic idea of the so-called “fact check” is that journalists and fact checkers identify misinformation and prevent it from spreading. Accordingly, it is important that fact-checked articles are highlighted and shared by users.

Furthermore, research is currently looking at when and why a news article is identified as fake news and when it is not (Shu et al., 2019). This research on “explainable fake news detection” aims to improve the detection performance of the algorithms. For this purpose, both news content and user comments are used as data input.

2.2 Adversarial Attack

Adversarial attacks are part of adversarial machine learning, which has become increasingly important in the field of applied artificial intelligence in recent years. In an adversarial attack, the input data of a neural network is intentionally manipulated to test how resistant it is to deliver the same outputs. These manipulated input data is called “adversarial examples” (Zhixuan Zhou and Hsu, 2021). Such a neural network is described as a “fake news detector” in the context of this paper. The reason for research in the field of adversarial attacks is that more and more attempts are being made to outsmart fake news detectors on the internet. This can be done, for example, by changing the spelling of a word so that the word remains easily interpretable for humans but not for an algorithm (from “Barack” to “B4r4ck”). For this reason, the input data is always manipulated in such a way that a human hardly notices any differences from the non-manipulated input data. In the area of object recognition, for example, only individual pixels are slightly changed, which the human eye can hardly perceive.

Examples of adversarial examples in the field of fake news detection are:

- **Fact distortion**: Here, some words are changed or exaggerated. It can be about people, time or places.
- **Subject-object-exchange**: By exchanging subject and object in a sentence, the reader is confused as to who is the executor and who is the recipient.
- **Cause confounding**: Here, either false causal connections are made between events or certain passages of a text are omitted.

Up to now, vulnerabilities to adversarial attacks have been identified in all application areas of neural networks. Especially in the context of increasingly safety-critical tasks for neural networks (e.g., autonomous driving), methods for detecting false or distorted input data are becoming more and more relevant. (Morris et al., 2020).

2.3 Regulating disinformation with artificial intelligence

According to the study “Regulating disinformation with artificial intelligence” (Marsden and Meyer, 2019), disinformation is defined as ‘false, inaccurate, or misleading information designed, presented and promoted to intentionally cause public harm or for profit. This definition is based on the definition of “Final report of the High Level Expert Group on Fake News and Online Disinformation” (Comission, 2018), which additionally specifies that the term “disinformation” does not include fundamentally illegal content such as hate speech
or incitement to violence. Nor does it include mis-
information that is clearly not misleading, such
as satire or parody. As a further delimitation, the
paper defines the term “misinformation”, which
refers to any misinformation that is unintentionally
or accidentally false or inaccurate.

Marsden and Meyer explain the causes of disin-
formation in the online context and the responses
that have been formulated from a technological per-
spective. Furthermore they analyze the impact of
AI-disinformation initiatives on freedom of expres-
sion, media pluralism and democracy.

The issue of disinformation is a very long-term
historical problem with human society. It has just
got a global effect through automation, through the
internet and new technologies. Even in the past,
people faced the challenges of filtering out false
information or illegal content from newly emerging
media such as newspapers, radio or television. So,
on the one hand there is currently a desire within
the European Commission to take action against
illegal and unwanted content through online inter-
mediaries. On the other hand, the intervention and
regulation of content on the internet is also seen
critically, because this is against the basic concept
of the internet with its freedom of expression. How-
ever, to stop the global spread of disinformation, a
restriction of freedom of expression is necessary.
Accordingly, for measures to filter fake news, there
are three principles that must exist when restricting
freedom of expression (Marsden and Meyer, 2019):

- Measures must be established by law
- Measures must be legitimate and shown to be
  necessary
- Measures must be the least restrictive method
  of pursuing the goal

There are two different ways to detect and re-
move disinformation: The human and the technical
moderation by AI. Over time, AI solutions have
become increasingly effective in detecting and re-
moving illegal or unwanted content, but they also
raise the question of who is the judge in decid-
ing what is legal or illegal and what is wanted or
unwanted in society. The problem here is that nei-
ther law nor technology can be truly neutral. Both
reflect the values and priorities of those who de-
signed them. This principal is called “garbage in –
garbage out”. According to expert opinions, AI
can help to make an initial filtering, especially for
texts and articles, which is then checked by humans.
If AI is wrong, there is always the possibility to
reverse the decision. To do this, companies also
hire cheap subcontractors in remote countries to
remove content.

Policy initiatives in the past have focused on
making internet intermediaries more responsible
for reducing disinformation on their platforms.
While actual content creators were responsible for
their content in the past, now the platforms have to
take more and more responsibility for the content of
the individual actors. The reactions of intermediary
sites such as Facebook and YouTube are technolo-
gical initiatives that identify certain content and
remove it in different ways or do not publish it at
all. The three most popular initiatives are filtering,
blocking, deprioritisation:

Filtering is the most effective method. There
are 2 different types of filtering: ex-ante and ex-
post. This means filtering before a content goes
online and filtering after it has already been pub-
lished. With the exception of obviously illegal con-
tent (e.g. child abuse images or terrorist content)
or disruptive content (e.g. spam, viruses), the ex
post-removal is preferable. The reason for this is
that there is better legal justification for this. One
example of filtering is YouTube Content ID. With
YouTube Content ID, uploaded files are matched
against databases of works provided by copyright
holders. If a match is found, copyright owners can
decide whether to block, monetise or track a video
containing their work.

Blocking is probably the most widespread
method. It is used by users, email providers, search
engines, social media platforms and network and in-
ternet access providers. Similar to filtering, block-
ing can take place ex-ante or ex-post, i.e. after
knowledge, request or order. Blocking means that
the content is not completely removed but blocks
certain users from accessing the content. For this
reason, it provides one significant advantage: Con-
tent can be blocked depending on the provider’s
terms of use or the laws of a particular region. For
example, content may be blocked in certain places
but may be available in others, e.g. if some coun-
tries allow certain content by law while others do
not.

The last option is deprioritisation. In the con-
text of disinformation, deprioritisation means that
content is de-emphasized in users’ feeds. This
takes place when correct content from certain
providers is displayed side by side with incorrect content. Then the wrong information is identified and deprioritised so that it is displayed further down and not so prominently anymore.

3 Data Set

The data used in this paper was collected by a project called Untrue.News: A search engine designed to find fake stories on the internet (Woloszyn et al., 2020). It uses an open-source web crawler for searching fake news. This web crawler is connected to a natural language processing pipeline that uses automatic and semi-automatic strategies for data enrichment. In this way approximately 30,000 documents have been retrieved, dating back to the year 1995 (English documents). For our research we used 25,886 English sentences of these documents. More languages, that were not used for our project can be found at untrue.news. Woloszyn et al. (2020) use four categories to classify their documents:

- **TRUE**: completely accurate statements
- **FALSE**: completely false statement
- **MIXED**: partially accurate statements with some elements of falsity
- **OTHER**: special articles that do not provide a clear verdict or do not match any other categories

These can be found in (Tchechmedjiev et al., 2019) and are less than those found in the schema.org/ClaimReview markup. For performing the text attacks, we only used the TRUE and FALSE statements. In Table 2 classification results can be found for the models trained with all four categories.

4 Experiment Design

To understand the vulnerability of models trained to detect fake news we split our experiment into two steps. First training state-of-the-art machine learning models using the dataset described in Section 3 and second applying adverserial attacks on the dataset using TextAttack to manipulate the trained models to classify fake news as TRUE news.

4.1 Fake News Detection as a Classification Problem

Two types of classifiers were used. **Bin** a binary classifier, in which a positive class represents true news, and the negative not being true news and **Mult** a multiclass classifier, where each document is classified as either being true news, fake news, untrue news or other.

4.2 Pre-trained Models

In this subsection, we present the applied pre-trained models and BERT (Devlin et al., 2019) which two of the models are based on. In this context a token describes a single word of a given text and a segments describes a sequence of tokens. The trained models will later be attacked by the Text Attack recipes described in Section 4.4.

4.2.1 BERT

The BERT (Bidirectional Encoder Representations from Transformers) model was originally trained on two datasets: BookCoorpus (Zhu et al., 2015) and English Wikipedia.

The way BERT analyzes the text is by taking concatenations of two segments. The total length of the concatenation is bound by a parameter $T$ and is computed as one input with particular tokens in between describing the beginning and end of the sentence, as well as the separation point of the two segments.

During pretraining, BERT applies a Masked Language Model (MLM) and a Next Sentence Prediction (NSP). For MLM BERT selects 12% of input tokens and replaces them with a [MASK] token and another 1.5% with a random vocabulary token. It then proceeds with predicting the selected [MASK] tokens. With NSP BERT makes a binary prediction on whether two segments in a text are adjacent.

4.2.2 RoBERTa

The pre-trained RoBERTa (Robustly optimized BERT approach) (Liu et al., 2019) is an optimized version of the original BERT model. The authors use a total length of concatenation $T = 512$ (-longer than previously used) and expand the used datasets to: BookCoorpus, CC-News (Nagel, 2016), OpenWebText (Gokaslan and Cohen, 2019) and Stories (Trinh and Le, 2019). Furthermore, RoBERTa trains using a bigger batch size, removes NSP and changes the the masking for MLM each time a new input is given to the model therefore avoiding constant masking during different training epochs.

4.2.3 BERTweet

The pre-trained BERTweet (Robustly optimized BERT approach) (Nguyen et al., 2020) is a pre-trained model that uses elements from both BERT and
RoBERTa. For instance, it’s architecture is taken from BERT, while the pre-training procedure is "copied" from RoBERTa. The main difference is the used dataset: the only used dataset consists of 850 English tweets together accumulating 80GB of memory.

4.2.4 Flair Embeddings

The main difference of Flair Embeddings (Akbik et al., 2018) to other models is their capturing of words which considers token as a sequence of characters. Furthermore, Flair Embeddings, also called contextual string embeddings, take contextual words into consideration, i.e. words that would appear consequently or previously. A word would therefore be embedded depending on the sequence of words. For our training we use the embeddings news-forward and news-backward, which were both trained on a 1 billion word corpus.

4.3 Parameterization

The training of each model runs for $E = 15$ Epochs each, since at the small amount of training samples all models start converging after approximately 7-8 epochs. The mini batch size is set to $b = 32$. For BERTweet and RoBERTa we specify the learning rate to $lr = 3 - e5$, while for Flair Embeddings to $lr = 0.1$. Finally, for Flair Embeddings we also set the anneal factor (describing the factor by which the learning rate is annealed) to $a_f = 0.5$ and the patience (the number of epochs without improvement until the learning rate would be annealed) to $p = 5$. $tp$ is the number of positive instances correctly classified as positive, $tn$ number of negative instances correctly classified as negative, $fp$ negative instances wrongly classified as positive, and $fn$ is the number of positive instances wrongly classified as negative. We defined positive instances as fake news websites and negative instances as reliable news websites.

4.4 Text Attack Recipes

The following attack recipes from TextAttack (Morriss et al., 2020) were applied on the dataset (described in Section 3) to manipulate the three introduced models to classify FALSE statements as TRUE, therefore misinterpreting fake news as true news.

- **DeepWordBug**: Generates small text perturbations in a black-box setting. It uses different types of character swaps (swapping, substituting, deleting and inserting) with greedy replace-1 scoring (Gao et al., 2018).
- **Pruthi**: Simulates common typos with a concentration on QWERTY keyboard. Uses character insertion, deletion and swapping (Pruthi et al., 2019).
- **TextBugger**: These attacks were optimized to perform with real world applications. They use space insertions, character deletion and swapping. Additionally they substitute characters with similar looking letters (ex. o with 0) and replace words with top nearest neighbor in context-aware word vector space (Li et al., 2019).
- **PSOZang**: Word level attack using a sememe-based word substitution strategy as well as particle swarm optimization (Zang et al., 2020).
- **PWWSRen2019**: These attacks focus on maintaining lexical correctness, grammatical correctness as well as semantic similarity by using synonym swap. Words for swap are prioritized on a combination of there saliency score and maximum word-swap effectiveness (Ren et al., 2019).
- **TextFoolerJin2019**: Word swap with their 50 closest embedding nearest neighbors. Optimized on BERT (Jin et al., 2020).
- **IGAWang**: Implemented as an adversarial attack defense method. Uses counter-fitted word embedding swap (Wang et al., 2021).
- **BAEGarg2019**: Uses a BERT masked language model transformation. It uses the language model for token replacement to best fit overall context (Garg and Ramakrishnan, 2020).
- **CheckList2020**: Inspired by the principles of behavioral testing. Uses changes in names, numbers and locations as well as contraction and extension (Ribeiro et al., 2020).
- **InputReductionFeng**: This attack concentrates on the least important words in a sentence. It iteratively removes the world with the lowest importance value until the model changes its prediction. The importance is measured by looking at the change in confidence of the original prediction when removing the
With exception of InputReductionFeng each recipe has three possible results for the attack on each sentence. Success means the text attack resulted in a wrong classification. Skipped mean that the model classified the sentence wrongly to begin with, therefore the sentence doesn’t need to be manipulated. Fail means the model still classified the sentence correctly. InputReductionFeng uses Maximized to indicate that the model uncertainty was maximized. A rubbish example is classified as correct with a higher accuracy than the original valid input. Skipped is used when the model classified the sentence wrongly to begin with, therefore the sentence doesn’t need to be manipulated.

5 Results and Discussion

The results discussed in this section can also be found in our Github repository (Schneider, 2021) including the respective implementations.

5.1 Training the Models

The first step of our experiment is to train state-of-the-art machine learning models to detect fake news. Since our dataset includes classes beyond TRUE and FALSE, we trained RoBERTa, BERTweet and Flair Embeddings both as binary and multi class classifier.

5.1.1 Binary Classification

For the binary classification RoBERTa, BERTweet and FlairEmbeddings were only trained on TRUE and FALSE statements. Their precision, recall and F1-scores, depicted in Table 1, demonstrate that the BERT based models performed best with scores of > 80%. Overall, BERTweet had the best results, however the difference to RoBERTa is minimal even though the models were pre-trained on entirely different datasets. With an F1-score of 70% FlairEmbeddings received the worst score which could be traced back to the small size of the dataset.

| Model          | P   | R   | F1   |
|----------------|-----|-----|------|
| RoBERTa        | 0.827| 0.8264| 0.8260 |
| BERTweet       | 0.8382| 0.8376| 0.8373 |
| FlairEmbeddings| 0.7066| 0.7064| 0.7061 |

Table 1: These models were trained only with FALSE and TRUE statements. The scores indicate the Precision, the Recall and the F1-Score to the less complex classification in Section 5.1.1. FlairEmbeddings’ scores were affected the most and dropped to 50%.

| Model          | P   | R   | F1   |
|----------------|-----|-----|------|
| RoBERTa        | 0.7186| 0.7141| 0.7154 |
| BERTweet       | 0.7149| 0.7140| 0.7119 |
| FlairEmbeddings| 0.5298| 0.5055| 0.5026 |

Table 2: These models were trained only with all existing classes. The scores indicate the Precision, the Recall and the F1-Score

5.2 Adversarial Attacks

The next step is to apply adversarial attacks on the dataset using TextAttack. Approximately 40 FALSE statements were sampled from the dataset and attacked using the TextAttack recipes. Due to the poor multiclass classification performance we applied all attacks on the binary-trained models. The results can be found in Table 3 for BERTweet, in Table 4 for RoBERTa and in Table 5 for Flair. The tables contain the percentage of sentences predicted as Successful, Failed or Skipped. Table 6 shows the percentages obtained for InputReductionFeng for all three models and the mean value of score improvement over all sentences for each model. To see the distribution of word level and character level attacks, Table 7 was generated. It contains the mean value of the Success percentage that can be found in tables 3, 4 and 5.

BERTweet and RoBERTa both use document embeddings. They show similar results. For BERTweet the word level attack IGAWang had the highest success rate with 90%. CheckList2020 was the least successful with 20%. For RoBERTa the word level attack TextFoolerJin2019 was the most successful with 92.5% and CheckList2019 was the least successful with 7.5%. With the exception of IGAWang the recipes show the same order in
success rates. The character level attack DeepWordBug seems to be very successful for these two model, ranking place 2 for RoBERTa and 3 for BERTweet. This is surprising since in the overall ranking in Table 7 it only achieved place 7. This might be an indication that document embeddings are more vulnerable to character level attacks than word embeddings.

In comparison to BERT-based models Flair classified a lot more inputs wrongly, which is depicted in the higher percentage of skipped statements in Table 5. Nevertheless, it proved to be a lot less vulnerable towards adversarial attacks considering that the best performing recipe TextFoolerJin2019 only reached a success rate of 66% (vs 90% and 92.5%). Similar to the previous models, Checklist2020 performed worse, but this time with a success rate of only 2%. Both pure character level attack recipes failed most of their attacks with 48% (DeepWordBug) and 54% (Pruthi) fail rate. Overall, it appears that the contextualization used by Flair makes the model a lot robust towards the used word and character level based TextAttack recipes.

| Recipe            | Success (%) | Fail (%) | Skipped (%) |
|-------------------|-------------|----------|-------------|
| IGAWang           | 90          | 0        | 10          |
| TextFoolerJin2019 | 85          | 0        | 15          |
| DeepWordBug       | 77.5        | 7.5      | 15          |
| PWWSRen2019       | 77.5        | 7.5      | 15          |
| PSOZang           | 67.5        | 17.5     | 15          |
| BAEGarg2019       | 67.5        | 30       | 2.5         |
| TextBugger        | 57          | 28       | 15          |
| Pruthi            | 28          | 57       | 15          |
| Checklist2020     | 20          | 75       | 5           |

Table 3: Attack results for BERTweet.

| Recipe                  | Success (%) | Fail (%) | Skipped (%) |
|-------------------------|-------------|----------|-------------|
| TextFoolerJin2019       | 92.5        | 5        | 2.5         |
| DeepWordBug             | 87.5        | 10       | 2.5         |
| PWWSRen2019             | 77.5        | 20       | 2.5         |
| TextBugger              | 75          | 22.5     | 2.5         |
| IGAWang                 | 70          | 10       | 20          |
| PSOZang                 | 70          | 20       | 10          |
| BAEGarg2019             | 60          | 37.5     | 2.5         |
| Pruthi                  | 37.5        | 60       | 2.5         |
| Checklist2020           | 7.5         | 90       | 2.5         |

Table 4: Attack results for Roberta.

| Model                | Maximized (%) | Skipped (%) | Score ↑φ |
|----------------------|---------------|-------------|----------|
| BERTweet             | 83            | 17          | +0.65    |
| Roberta              | 81            | 19          | +0.63    |
| Flair                | 75            | 25          | +0.64    |

Table 6: Attack results for InputReductionFeng. The result outputs of this attack are described in Section 4.4.

BERTweet seems to be the most vulnerable to InputReductionFeng attacks but the difference in score increasing is not very high (+0.01). Overall it seems that these attacks show similar results over all models.

| Recipe                  | Success (%) | Level |
|-------------------------|-------------|-------|
| TextFoolerJin2019       | 81.17       | word  |
| IGAWang                 | 70          | word  |
| PWWSRen2019             | 77.5        | word  |
| PSOZang                 | 68.33       | word  |
| BAEGarg2019             | 67.5        | word & character |
| DeepWordBug             | 63          | character |
| TextBugger              | 62.5        | word & character |
| Pruthi                  | 27.83       | character |
| Checklist2020           | 9.83        | word  |

Table 7: Mean Success Rates (all models).

Table 8 shows that the 4 top ranking attacks are word level attacks. It seems that the models are more vulnerable to word level attacks than to character level or mixed attacks (character & word).

Finally the Success Rate, for every model was calculated using formula 1:
\[ S_r = \frac{\sum_{i=1}^{a} s_i}{a} \]

with \( S_r \) being the success rate, \( s \) being the number of successful attacks, \( f \) being the number of failed attacks and \( a \) being number of attacks recipes.

| Model   | \( S_r \) (%) |
|---------|---------------|
| BERTweet| 72.45         |
| Roberta | 68.22         |
| Flair   | 54.77         |
| **Total Average** | **65.15%** |

Table 8: Success Rates.

The skipped statements were not taken into the calculation, as they are dependent on the model training and not on TextAttack. The skipped values show which statements were not predicted correctly by the model in the first place. Thus, they are depended on the model and reflect models accuracy. For the success rates we wanted to see TextAttack’s efficiency on statements that the model would correctly classify as fake news. Our results for the Success Rates underline the results seen in tables 3, 4 and 5, showing that Flair is less vulnerable to the attacks with \( S_r = 54.77\% \) than the other two models with \( S_r = \sim 70\% \). As an conclusion this gives us an Total Success Rate of 65.15\% for adversarial attacks on fake news detection using TextAttack.

6 Conclusion

This paper aimed to answers the question: how vulnerable are automatic fake news detection to adversarial attacks? We tested this by checking if automated augmentation of fake news sentences (FALSE statements) will lead to TRUE classification. This would allow them to bypass the fake news detection mechanisms. Our results show that using the python library TextAttack allows automated changing of classification for 65.15\% of the sentences. Flair, the only model using word-level embedding (contextual string embeddings), seems less vulnerable to attacks with a Success Rate of 54.77\%. The other two models using document embeddings show 72.45\% (BERTweet) and 68.22\% (Roberta). Furthermore, word-level swaps seem to be slightly more successful with an average of 76.87\% compared to character level or mixed swaps with average 55.21\%. Consequently, the models are more vulnerable to attacks using semantically correct sentences with changed meaning than to attacks using typos. Overall it seems that it is possible to bypass the classifier with these attacks. However, our results do not consider that a human will be able to see obvious spelling mistakes in sentences. Furthermore, a human will have a higher accuracy of recognizing unfitting words in sentences. Looking at the augmented sentences we think that many of them will be recognized as FALSE (TrOmp hsut down American airportA on 4 Jul 201B or Hollywood Action Star Christelle Chan Dead).

As a conclusion of these results we think that using the policy initiatives blocking and deprioritization, should be avoided if possible, as these methods don’t completely remove the fake news statements from the users feeds. This makes it easier to target these statements with automated attacks as shown in our research. A scenario would be to attack these sentences until they are unblocked or re-prioritized in a users feed. This would lead to dangerous spreading of Fake News in social networks.

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