Experiments with adversarial attacks on text genres

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Abstract

Neural models based on pre-trained transformers, such as BERT or XLM-RoBERTa, demonstrate SOTA results in many NLP tasks, including non-topical classification, such as genre identification. However, often these approaches exhibit low reliability to minor alterations of the test texts. A related problem concerns topical biases in the training corpus, for example, the prevalence of words on a specific topic in a specific genre can trick the genre classifier to recognize any text on this topic in this genre. In order to mitigate the reliability problem, this paper investigates techniques for attacking genre classifiers to understand the limitations of the transformer models and to improve their performance. While simple text attacks, such as those based on word replacement using keywords extracted by tf-idf, are not capable of deceiving powerful models like XLM-RoBERTa, we show that embedding-based algorithms which can replace some of the most “significant” words with words similar to them, for example, TextFooler, have the ability to influence model predictions in a significant proportion of cases.

1 Introduction

Non-topical text classification concerns a wide range of problems that are aimed at predicting a text property that is not connected directly to the text topic, for example, at predicting its genre, difficulty level, the age or the first language of its author, etc. Unlike topical text classification, non-topical text classification needs a model that predicts a label on the basis of its stylistic properties. Automatic genre identification is one of the standard problems of non-topical text classification, as it is useful in many areas such as information retrieval, language teaching or basic linguistic research (Santini et al., 2010).

An early comparison of various datasets, models and linguistic features for genre classification (Sharoff et al., 2010) shows that traditional machine learning models, for example, SVM, can be very accurate in genre classification on their native dataset, but suffer from a dataset shift. Since then, many new approaches to text classification have emerged. In particular, BERT (Bidirectional Encoder Representations from Transformers) is an efficient pre-trained model based on the Transformer architecture (Devlin et al., 2018). It achieves the state-of-the-art results for various NLP tasks, including text classification. In this study we use XLM-RoBERTa (Conneau et al., 2019) is an improved variant of BERT. It has the same architecture, but uses bigger and more genre diverse corpora and an updated pre-training procedure. In addition, XLM-RoBERTa is a multilingual model trained on Common Crawl data in comparison to multilingual BERT only trained on Wikipedia.

One of the most significant problems in genre classification concerns topical shifts (Petrenz and Webber, 2010). If in the training corpus a specific topic is more frequent for a specific genre, then many classification models can be biased towards indicating this genre by the keywords of this topic. This becomes especially problematic in the case of data shift between the training and testing corpora (Petrenz and Webber, 2010). For this reason, they check reliability of their genre classifiers by testing on datasets from different domains. We test this in our study too.

There have been numerous attempts to attack NLP models by making minor changes to a text which lead to different predictions. An overview of different methods is presented in (Huq and Pervin, 2020). These techniques help to reveal the flaws of the NLP models and to find out what are the features in the texts that are taken into account by the models. TextFooler (Jin et al., 2019) sorts the words of texts under attack by their impact on the target class probability and tries to replace the most important words with their closest neighbours with the similarity defined as the dot
product between the corresponding word embeddings. BertAttack (Li et al., 2020) has a similar algorithm, but instead of using word embeddings it relies on Bert token embeddings. Because of this, BertAttack processes the whole words and subword tokens in different ways, while trying to find suitable words to replace subword tokens.

Until now, there have been no reports of successful attempts of attacking genre classifiers or non-topical classification in general using neural methods, even though it is important to understand their reliability and to find ways for improving their robustness. In this study, we test two methods to attack text genre classifiers. The first method is based on swapping the keywords which are found with tf-df extraction, while the second method applies a modified TextFooler algorithm. Moreover, we try to improve the performance of the original classifiers by adding a set of texts broken by TextFooler to the training corpus. In this paper we perform the following steps to investigate attacking techniques and to improve the reliability of the genre classifier:

1. training a baseline classifier using XLM-RoBERTa (Section 2.1);
2. attacking the XLM-RoBERTa classifier by swapping topical keywords between the genres (Section 3.1);
3. attacking the XLM-RoBERTa classifier with TextFooler (Section 3.2);
4. performing targeted attacks on the XLM-RoBERTa classifier (Section 3.3);
5. training a new XLM-RoBERTa classifier by using the original training corpus combined with the successfully attacked texts (Section 3.4).

All code, data, and materials to fully reproduce the experiments are openly available[1]

2 Baseline

2.1 Training data

For training the genre classifiers, we use existing FTD datasets in English and in Russian (Sharoff, 2018). Each of them contains more than 1,500 texts from a wide range of sources annotated with 10 genre labels, see Table 1. The dataset is relatively balanced with the most common categories being Argumentation and Promotion. For validation of the success of attacking models at the last stage (see the next section) we reserve a small portion of this dataset obtained by stratified sampling (columns Val in Table 1), which is not used in the training and attacking pipelines.

It is known that genre classifiers are often not robust when applied to a different corpus with the same labels (Sharoff et al., 2010), therefore we use independently produced test sets to simulate out-of-domain performance on large collections coming from a smaller number of sources. This makes them different from the training datasets, which came from a much wider range of sources.

For the Russian test set we use posts from LiveJournal, a social media platform popular in Russia.

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Table 1: Training and testing corpora

| Genre label | Prototypes | FTD EN | FTD RU | Natural annotation EN | LJ RU |
|-------------|------------|--------|--------|------------------------|------|
| Argument    | Expressing opinions, editorials | 276 | 77 | 207 | 77 | 400 | 481 | (Kiesel et al., 2019) |
| Fiction     | Novels, songs, film plots | 69 | 28 | 62 | 23 | 400 | 199 | BNC&Brown |
| Instruction | Tutorials, FAQs, manuals | 141 | 50 | 59 | 17 | 400 | 384 | StackExchange |
| News        | Reporting newswires | 114 | 37 | 379 | 103 | 400 | 1518 | Giga News |
| Legal       | Laws, contracts, T&C | 56 | 17 | 69 | 13 | 400 | 14 | UK and US legal codes |
| Personal    | Diary entries, travel blogs | 72 | 19 | 126 | 49 | 400 | 513 | ICWSM |
| Promotion   | Adverts, promotional postings | 218 | 66 | 222 | 85 | 400 | 68 | promo sites |
| Academic    | Academic research papers | 59 | 23 | 144 | 49 | 400 | 20 | arxiv.org |
| Information | Encyclopedic articles | 131 | 38 | 72 | 33 | 400 | 171 | Wikipedia |
| Review      | Product reviews | 48 | 22 | 107 | 34 | 400 | 185 | Amazon reviews |
| Total       | 1184 | 377 | 1447 | 483 | 4000 | 3553 |

[1] https://github.com/MikeLepekhin/TextGenresAttack
Table 2: Examples of English keywords extracted with tf-idf

| Genre    | Keywords                                                                 |
|----------|--------------------------------------------------------------------------|
| Argument | united, nations, reconciliation, international, development, people, security, countries |
| Fiction  | said, would, one, could, little, man, came, like, went, upon              |
| Instruction | tap, device, screen, email, tab, select, settings, menu, contact, message |
| News     | said, million, committee, disarmament, kongo, report, program, also, budget, democratic |
| Legal    | shall, article, may, paragraph, court, person, order, department, party, state |
| Personal | church, one, like, people, could, really, congo, time, years, would       |
| Promotion| viagra, cialis, online, writing, posted, service, levitra, business, buy, essay |
| Academic | system, quantum, fault, data, software, image, node, faults, application, fig |
| Information | committee, convention, parties, secretariat, iran, meeting, shall, mines, states, conference |
| Review   | google, home, new, like, star, paul, one, shoes, pro, art                 |

Table 3: Successful attacks with keyword replacement

| Replaced | 10%  | 50%  | 100%  |
|----------|------|------|-------|
| EN       | 14 (1.1%) | 31 (2.5%) | 196 (15.5%) |
| RU       | 22 (1.5%) | 44 (3.0%) | 148 (10.0%) |

3 Genre attacks

The genre attack task is to make minimal alterations to a target text with the aim to change its prediction by an existing classifier. If a test text can be altered to change the label predicted by the classifier, and if this can be achieved within a fixed limit of alterations, the text is counted as “broken”. We can try untargeted and targeted attacks:

- **untargeted** these are attacks that intend to force the classifier to change its correct prediction on a test set text to produce any incorrect label from our set of labels;
- **targeted** the opposite attack direction when we attack texts for which the classifier makes a mistake by making alterations to force the classifier to predict the correct label.

The genre attacks are conducted to achieve cross-validation for attacks without leaking information about the target texts to the classifier: we randomly shuffle the training dataset and make 5 iterations of the cross-validation mechanism: For every $i$ the texts with numbers from $0.2i \cdot |X|$ to $0.2(i + 1) \cdot |X| - 1$ are used as test texts to attack the classifier which has been trained on the remaining texts from the training corpus. Thus, we get five architecturally identical classifier models with slightly different weights, as well as a set of successfully attacked texts we can use our analysis below.

2.2 Training genre classifiers

We fine-tune the baseline XLM-RoBERTa classifiers following the same architecture as (Sun et al., 2019) using the training part of the FTD corpus for 10 epochs with the Adam optimiser with learning rate $= 5 \cdot 10^{-5}$ since these hyperparameters are used for fine-tuning in the original papers for several BERT-like models (Devlin et al., 2018; Liu et al., 2019).
3.1 Untargeted attack by swapping topical keywords

First, we test a simple text attack generator which is based on replacing keywords extracted for each genre by keywords extracted for other genres. The keywords are defined by their tf-idf scores within the genre texts. Table 2 lists the most significant keywords according to the tf-idf score. Some keywords correspond to their genres quite reasonably, for example, those from Fiction or Legal texts. However, most genres have fairly topical keywords, which indicates the prevalence of specific topics in the training corpus. For example, the keyword lists show that both Argument and News contain a lot of texts about international politics, while many Instruction texts refer to Internet services or communication devices.

Then the attack generator replaces a certain percentage of the keywords for a genre to a keyword of a random genre. We choose the following range of the keywords to be replaced: 10%, 50%, 100%. Contrary to our expectations concerning the prevalence of topic-specific keywords, our XLM-R classifier is reasonably robust to attacks on both English and Russian texts, as the rate of successfully broken texts is fairly low even when all tf-idf keywords are replaced, see Table 3.

3.2 Attacking with untargeted TextFooler

The original TextFooler algorithm has the following way:

\[ I_w = \begin{cases} F_Y(X) - F_Y(X_{\setminus w}), & \text{if } F(X) = F(X_{\setminus w}) = Y \\ (F_Y(X) - F_Y(X_{\setminus w})) + (F_Y(X_{\setminus w}) - F_Y(X)), & \text{if } F(X) = Y, F(X_{\setminus w}) = \bar{Y}, \text{ and } Y \neq \bar{Y}. \end{cases} \]

where \( F(X) \) is the predicted label for text \( X \), \( F_Y(X) \) is the predicted probability of the genre \( Y \) for the text \( X \), and \( X_{\setminus w} \) denotes a text with \( w \) removed. The intuition of the importance score is that removal of a more important word leads to greater distortion of the predicted probability.

Then for every word in the attacked text, \( k \) closest words are chosen by the value of the dot product of their embeddings with the embedding of the original word. These words are the candidates for replacing the original word. We iterate through the words \( w_i \) in the order of their importance and try to replace each of them with one of the candidates following rules in a set of filters. If we succeed in doing that, then the text replacement is considered as successful. Otherwise, we continue to iterate through the list of candidates. If we cannot find a candidate \( w_i \) for replacing the word \( w \), we try the word for which the classifier gives the minimal probability of the original class for the text with this replacement. If we have iterated all over the words \( w_i \), but the classifier still predicts the original label for the text, the attack is unsuccessful.

The filters for choosing a suitable replacement can vary. First, we can keep the same part-of-speech tag (usually on the top level of tags, for example, NOUN→NOUN). Second, we can vary the lower limit threshold for the word similarity score for each candidate. In the original TextFooler algorithm, this threshold is fixed at 0.5. In our study the 20-80 percentile range for the embedding similarities between each word and
Table 5: Successful untargeted attacks with different USE thresholds

| USE  | Language | k=15   | k=30   | k=50   |
|------|----------|--------|--------|--------|
| 0.84 | EN       | 416 (32.9%) | 438 (34.7%) | 453 (35.8%) |
| 0.84 | RU       | 686 (47.4%) | 718 (49.6%) | 744 (51.4%) |
| 0.6  | EN       | 424 (33.5%) | 444 (35.1%) | 457 (36.2%) |
| 0.6  | RU       | 687 (47.5%) | 720 (49.8%) | 744 (51.4%) |
| 0.0  | EN       | 424 (33.5%) | 444 (35.1%) | 457 (36.2%) |
| 0.0  | RU       | 687 (47.5%) | 720 (49.8%) | 744 (51.4%) |

Table 6: Most common English word pairs amended with untargeted TextFooler attack

| Genre     | Words                                                                 |
|-----------|-----------------------------------------------------------------------|
| Argument  | people→residents (14), have→be (13), have→has (12), world→worldwide (8), be→have (8), social→societal (8), do→know (7), children→infants (7), people→individuals (7), nuclear→fissile (7) |
| Fiction   | had→has (12), had→have (10), will→wants (10), have→has (6), king→monarch (5), each→every (4), did→does (4), came→coming (4), come→happen (4), have→be (4) |
| Instruction | do→know (18), will→wants (12), be→have (10), have→be (10), should→ought (10), click→clicking (6), choose→choices (5), based→inspired (4), try→trying (4), example→examples (4) |
| News      | will→want (13), has→maintains (7), has→have (6), be→have (5), will→wants (5), have→be (5), said→stating (5), year→olds (4), new→ny (4), week→days (4) |
| Legal     | be→have (22), shall→hereof (18), shall→howsoever (11), terms→terminology (8), order→ordering (8), person→somebody (8), conditions→situations (5), contract→agreement (5), agreement→agreed (5) |
| Personal  | life→lives (6), do→know (5), think→suppose (5), wanted→want (5), felt→knew (4), people→individuals (3), started→begin (3), went→going (3), design→styling (2), so→because (2) |
| Promotion | be→have (6), new→ny (5), business→commerce (5), company→corporation (5), have→be (5), products→byproducts (4), opportunity→opportunities (4), help→aid (4), company→venture (4), model→models (4) |
| Academic  | scattering→scatter (8), have→be (5), findings→confirmatory (3), mathematical→dynamical (3), analysis→analyzed (3), show→showcase (3), idea→thought (3), computation→computing (3), be→have (3) |
| Information | system→integrator (4), number→numbering (4), has→have (3), system→mechanism (3), each→every (3), had→has (2), person→someone (2), little→scant (2), astronomy→ephemeris (2), ehc→liga (2) |
| Review    | google→yahoo (3), quality→dependability (2), review→reassessment (2), synth→synths (2), movie→movies (1), company→corporation (1), rescue→rescued (1), get→got (1), engadget→wired (1) |

its closest neighbour is 0.61–0.82 for English and 0.67–0.82 for Russian. If we take into account the top-15 most similar embeddings for each word embedding, the 20–80 percentile range for English is 0.49–0.66, for Russian it is 0.52–0.68. This limits the range of values for selecting the similarity threshold.

Finally, to preserve the meaning and the grammatical correctness of the attacked texts, we estimate the similarity between the original sentence and its attacked version with the Universal Sentence Encoder (Cer et al., 2018). The original TextFooler paper fixed the threshold of the minimal score to 0.84, we tried varying it in our study.

We also made two experiments when the replacement of the stop words is allowed and not. We find that there is no big difference in the number of broken texts in either case. Furthermore, we experimented with various values of $k$ and the minimal USE score to find out how they affected the number of the attacked texts and the robustness of the XLM-RoBERTa model trained on them. Since the original TextFooler implementation in the TextAttack framework (Morris et al., 2020) does not contain embeddings for Russian, we used FastText embeddings for both English and Russian to make the experiments with both languages comparable.

Table 5 shows that the number of the successfully attacked texts is practically independent from the USE threshold when it varies from the default 0.84 to 0, so this filter is not particularly useful for genre attacks. At the same time, the proportion of the broken texts in-
In addition to the internet connection, you should also try to have at least 100 MB of free space available on your drive when you install Titan Poker.

Table 7: Example of deterioration of grammar in untargeted attack

| Genre      | English | Russian |
|------------|---------|---------|
| Argument   | 12.0    | 12.0    |
| Fiction    | 19.0    | 12.0    |
| Instruction| 16.5    | 23.5    |
| News reports| 10.0   | 21.0    |
| Legal      | 26.0    | 20.0    |
| Personal   | 18.0    | 6.0     |
| Promotion  | 12.0    | 25.0    |
| Academic   | 11.0    | 18.0    |
| Information| 5.5     | 5.5     |
| Review     | 3.0     | 3.5     |

Table 8: The median number of words per text for successful genre attacks

Table 9 lists for how many texts the classifier predictions can be improved by the attack mechanism. Targeted attacks are considerably harder than the untargeted.

3.3 Targeted attacks with TextFooler

For targeted attacks we use the same mechanism with TextFooler, but we choose the replacement candidate that maximises the probability of the true class. Table 9 lists for how many texts the classifier predictions can be improved by the attack mechanism. Targeted attacks are considerably harder than the untargeted.
3.4 Adding attacked texts to train new genre classifiers

In the next step we add broken texts with correct labels to train a new model and we test it on the validation portion of the original training corpus and also on test corpora. Table 12 lists the robust classifier performance on the test corpora. It shows that the XLM-RoBERTa classifier trained on the attacked texts attains higher accuracy than the baseline classifier. Table 13 shows, that for most genres the robust classifier achieves higher f1-score. The same is true for precision and recall.

Training XLM-RoBERTa on concatenation of the original and broken texts does not improve the classifier performance on the LiveJournal corpus but significantly increases the accuracy on the English genre corpus with natural annotation. Besides, the best result is attained when hyper-parameter value $k = 15$ is used. It shows that the quality of attack is more important than the number of the successfully attacked texts for boosting the classifier performance. In Table 10 we can see that the robust classifier performs better for most genres. In Table 11 the improvement in terms of the F1 score is limited, since for many genres improving recall implies deterioration of precision.

4 Related Work

Genre classification is not a new task, since non-topical classification is needed for many applications. There have been experiments with various architectures from linear discriminant analysis (Karlgren and Cutting, 1994) to SVM (Dowd and Cutting, 2001) to recurrent neural networks (Kumlovenskaya and Sharoff, 2019). Early work on robust genre classification across different training and testing corpora (Sharoff et al., 2010) reveals the problem of topical biases in the genre corpora available at the moment. In this paper we try to solve the problem indirectly by improving their robustness.

(Petrenz and Webber, 2010) investigate a very important idea concerning estimation of the reliability of genre classifiers via its validation on a corpus with different topical distributions but with the same genre labels. Our study continues this line of research when we use the datasets from natural annotation and LiveJournal to estimate the model accuracy on an out-of-domain testing corpus.

Our experiments with using adversarial attacks for genre classification are novel. The most efficient adversarial attack techniques for classifiers (Jin et al., 2019; Li et al., 2020) are based on usage of word-level embeddings and finding for each word a fixed number of the most similar words as candidates for replacing with. Our genre attacks are based on the TextFooler (Jin et al., 2019) with a modification that we allow replacing of the stop-words and vary the USE threshold. TextFooler (Jin et al., 2019) was chosen as the basis for genre attacks in this study due to its efficiency and flexibility as it can be applied to various neural models. We also experimented with BertAttack, that differs from the TextFooler algorithm in its use of BERT token embeddings instead of pre-trained word-level embeddings. In our initial experiments we found it to be much slower than TextFooler and also somewhat less efficient for the genre attack task, for example, the percentage of the texts successfully broken by BertAttack is lower than 15% for English. Therefore, we only report the results with TextFooler here. A recent experiment on adversarial attacks on personal style, as another non-topical classification task, (Emmery et al., 2021) is the closest to our study. They attacked author profile predictions using similar methods. However, they have not investigated the question of attacks on genre predictions.

5 Conclusion

In this paper we show that the XLM-RoBERTa genre classifier is resistant to simple attack methods, such as replacement of tf-idf keywords, this is unlike traditional feature-based methods which are very sensitive to the
keywords. At the same time, even the XLM-RoBERTa classifier can be deceived by word-based adversarial attacks using mechanisms like TextFooler. In the case of the baseline classifier, more than 35% of English texts in the training corpus can be successfully broken, raising to more than 50% for Russian. The number of successfully attacked texts can be considered as an important metric for estimating the robustness of the classifiers – the lower the number of broken texts, the more difficult it is to break the classifier, which implies higher robustness. Also we find some important patterns in the attack results, in particular, the threshold for USE almost does not affect the number of the attacked texts; attacks are more efficient for the Russian language; the higher the number of replacing candidates, the less the difference in reliability of the robust classifier vs the original one.

Our experiments demonstrate the effectiveness of TextFooler at improving robustness of genre classifiers via adversarial attacks. For example, adding broken texts (with their original labels) improves the overall accuracy, while texts in the new collection cannot be broken by the same set of adversarial attacks, thus implying a more robust classifier. We also tried targeted attacks, but fewer text can be broken and the classifiers trained on the targeted attacked texts performed worse than those coming from the untargeted attack.

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Conneau, A., Khandelwal, K., Goyal, N., Vishrav, C., Wenzek, G., Francisco Guzman , E. G., Ott, M.,
| Corpus          | no attacked     | k=15            | k=30            | k=50            |
|-----------------|-----------------|-----------------|-----------------|-----------------|
| En, Natural     | 0.747 ± 0.026   | 0.796 ± 0.011   | 0.771 ± 0.01    | 0.776 ± 0.029   |
| Ru, LiveJournal | 0.76 ± 0.003    | 0.756 ± 0.008   | 0.755 ± 0.009   | 0.756 ± 0.005   |

Table 12: Accuracy of the XLM-RoBERTa classifier trained on the attacked texts

| Genre      | F1 Base | F1 Robust | Prec Base | Prec Robust | Rec Base | Rec Robust |
|------------|---------|-----------|-----------|-------------|----------|------------|
| Argument   | 0.566   | 0.732     | 0.534     | 0.724       | 0.603    | 0.740      |
| Fiction    | 0.914   | 0.929     | 0.951     | 0.913       | 0.88     | 0.945      |
| Instruction| 0.448   | 0.621     | 0.613     | 0.636       | 0.353    | 0.608      |
| News       | 0.689   | 0.856     | 0.529     | 0.784       | 0.988    | 0.943      |
| Legal      | 0.798   | 0.652     | 0.985     | 0.995       | 0.670    | 0.485      |
| Personal   | 0.658   | 0.702     | 0.580     | 0.681       | 0.760    | 0.725      |
| Promotion  | 0.502   | 0.885     | 0.802     | 0.915       | 0.365    | 0.858      |
| Academic   | 0.910   | 0.888     | 0.883     | 0.820       | 0.940    | 0.968      |
| Information| 0.944   | 0.847     | 0.917     | 0.753       | 0.973    | 0.968      |
| Review     | 0.752   | 0.777     | 0.933     | 0.865       | 0.630    | 0.705      |

Table 13: Comparison of the Base and the Robust XLM-RoBERTa results for the English natural annotation corpus

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