Abstract

This work describes the participation of the Skoltech NLP group team (Sk) in the Toxic Spans Detection task at SemEval-2021. The goal of the task is to identify the most toxic fragments of a given sentence, which is a binary sequence tagging problem. We show that fine-tuning a RoBERTa model for this problem is a strong baseline. This baseline can be further improved by pre-training the RoBERTa model on a large dataset labeled for toxicity at the sentence level. While our solution scored among the top 20% participating models, it is only 2 points below the best result. This suggests the viability of our approach.

1 Introduction

Toxicity and offensive content is a major concern for many platforms on the Internet. Therefore, the task of toxicity detection has attracted much attention in the NLP community (Wulczyn et al., 2017; Hosseini et al., 2017; Dixon et al., 2018). Until recently, the majority of research on toxicity focused on classifying entire user messages as toxic or safe. However, the surge of work on text detoxification, i.e., editing of text to keep its content and remove toxicity (Nogueira dos Santos et al., 2018; Tran et al., 2020), suggests that localizing toxicity within a sentence is also useful. If we know which words of a sentence are toxic, it is easier to “fix” this sentence by removing or replacing them with non-toxic synonyms. Mathew et al. (2020) make human labelers annotate the spans as rationales for classifying a comment as hateful, offensive, or normal. They show that using such spans when training a toxicity classifier improves its accuracy and explainability and reduces unintended bias towards toxicity targets.

This year the SemEval hosts the first competition on toxic spans detection, namely, SemEval-2021 Task 5 (Pavlopoulos et al., 2021). It provides training, development, and test data for English. As far as we know, it is the first attempt to explicitly formulate toxicity detection as sequence labeling instead of classification of sentences.

Multiple NLP tasks recently benefited from transfer learning — transfer of probability distributions learned on some task to another model solving a different task. The most common example of transfer learning is the use of embeddings and language models pre-trained on unlabeled data (e.g. ELMo (Peters et al., 2018), BERT (Devlin et al., 2019) and its variations, T5 (Raffel et al., 2020), etc.) on other tasks (e.g. He et al. (2020); Wang et al. (2020) inter alia use pre-trained BERT models to perform tasks from the GLUE benchmark (Wang et al., 2018)).

Word-level toxicity classification can be formulated as a sequence labeling task, which also actively uses the pre-trained models mentioned above. BERT comprises the versatile information on words and their context, which allows to successfully use it for sequence labeling tasks of different levels: part-of-speech tagging and syntactic parsing (Koto et al., 2020), named entity recognition (Hakala and Pyysalo, 2019), semantic role labeling (He et al., 2019), detection of Machine Translation errors (Moura et al., 2020).

This diversity of applications suggests that word-level toxicity detection can also benefit from pre-trained models. Besides that, toxicity itself has been successfully tackled with BERT-based models. Research on sentence-level toxicity extensively used BERT and other pre-trained models. Both language-specific and multilingual BERT models were used to fine-tune toxicity classifiers (Leite et al., 2020; Ozler et al., 2020). This shows that BERT has information on toxicity.
Thus, we follow this line of work. Namely, we fine-tune a RoBERTa model (Liu et al., 2019) to perform a sequence labeling task. Besides that, we train a model for sentence classification on the Jigsaw dataset of toxic comments and use the information from this model to detect toxicity at the subsentential level. This helps us overcome the insufficient data size.

This is in line with previous work, which has shown that sentence-level labels can be used in combination with token labels (Rei and Søgaard, 2019) or completely substitute them (Rei and Søgaard, 2018; Schmaltz, 2019).

In our experiments, we test the hypothesis that the sentence-level toxicity labeling can be used for a sequence labeler that recognizes toxic spans in text. We suggest three ways of incorporating this data: as a corpus for pre-training, pseudo-labeling, and for joint training of sentence-level and token-level toxicity detection models. Our experiments show that the latter method yields the best result. Moreover, we show that using sentence-level labels can dramatically improve toxic span prediction when the dataset with token-level labels is small.

The contributions of this work are the following:

- We successfully use the dataset labeled for toxicity at the sentence level for token-level toxicity labeling,
- We propose a model for joint sentence- and token-level toxicity detection,
- We analyze the performance of our models, showing their limitations and reveal the ambiguities in the data.

2 The task

The training data of the task comprises 7,940 English comments with character-level annotations of toxic spans. The labeling was performed manually by crowd workers.

The spans labeled as toxic often contain rude words: “Because he’s a moron and a bigot. It’s not any more complicated than that.” (toxic spans are underlined). Other toxic spans consist of words that become toxic in context: “Section 160 should also be amended to include sexual acts with animals not involving penetration”. Borders of some toxic spans fall in the middle of a word; we treat such cases as markup errors.

As a development set, we use the trial dataset of 690 texts provided by the task organizers. We evaluate our final models on the hidden test set of the task consisting of 2,000 texts.

3 Pre-training for toxic span detection

Here we give the motivation behind our models and describe their architecture and training setup.

3.1 Motivation

Our intuition is that the toxicity is often lexically-based, i.e., there are certain words that are considered offensive and make the whole sentence toxic. In this case, we expect that as we add extra data to our toxic span dataset, after some point, the vocabulary of toxic words in it will saturate and stop increasing. However, Figure 1 shows that the size of the toxic vocabulary linearly depends on the dataset size, which suggests that its size is insufficient for the task. In this case, the model will often need to label unseen words. To mitigate the lack of data, we leverage the additional dataset with toxicity information, namely, the Jigsaw toxic comments dataset which features 140,000 user utterances labeled as toxic or safe.

![Figure 1: Size of the toxic vocabulary as a function of the corpus size.](https://www.kaggle.com/c/jigsaw-toxic-comment-classification-challenge/data)
Jigsaw toxic comments dataset. We propose three ways of incorporating this data.

The first way is **pseudo-labeling** (Lee et al., 2013). We apply the **RoBERTa tagger** to predict the toxic spans in the Jigsaw dataset. We use these predictions to further train the model.

Another option is to use the Jigsaw data to fine-tune RoBERTa with it. We suggest two scenarios. The first is to fine-tune the model on the Jigsaw dataset for the sentence classification task, and then on the toxic spans dataset — this model is referred to as **RoBERTa classifier + tagger**. In this case, the model has different output layers for the two tasks, and other layers are shared.

Finally, we propose a novel architecture for joint token- and sentence-level classification, where the score $y$ for a sentence $x = \{x_1, x_2, ..., x_n\}$ is computed as the average of word-level scores:

$$
\hat{y} = \sigma \left( \alpha + \beta \frac{1}{n} \sum_{i=1}^{n} \hat{y}_i \right)
$$

where $\alpha$, $\beta$ and $\gamma$ are trainable parameters, and $\sigma$ is the logistic function. This model does not need to be trained on the data with token-level labeling but can get token-level toxicity information from sentence labels. We fine-tune this model both on Jigsaw and toxic spans datasets. The model is referred to as **tagging classifier**.

3.3 Working with spans

To reformulate toxic spans detection as a token classification problem, we label a token as toxic if at least one of its characters is toxic. When projecting the predicted token-level labels back to the character level, we try two strategies:

1. Consider a token to be toxic if its toxicity score is higher than the threshold, do not force the labels of tokens within a word to agree with each other.

2. Consider a word to be toxic if the aggregated toxicity score of all its tokens is higher than the threshold. We try four different aggregation functions: min, max, mean, and the simplified naive Bayes formula:

$$
\hat{x} = \frac{\prod_i x_i}{\prod_i x_i + \prod_i (1 - x_i)}.
$$

In both methods, we label a space character as toxic only if the characters both to the right and to the left of it are toxic.

4 Baselines

In this section, we present a set of common baseline approaches used for sequence tagging, such as CRF and LSTM with pretrained word embeddings. We implement them in order to analyze the performance of our methods in the context of other techniques.

**Word-based LogReg**  This is a vocabulary-based method: we label words as toxic if they appear in our toxic vocabulary. The vocabulary is created as follows. We create a set of toxic and safe phrases, where toxic phrases are toxic spans from our data and safe phrases are sentences from our data with removed toxic spans. We then train a binary logistic regression classifier of toxic and safe phrases using words as features. The by-product of this classifier is the list of weights for all words from the data. We consider words with weights greater than a threshold as toxic.

**Attention-based LogReg**  Another approach to represent words is to take their attention weights from a RoBERTa-based sentence-level toxicity classifier (we train it on the Jigsaw dataset). We assemble attention weights from all RoBERTa heads and layers in a single vector of dimension 144. These vectors are used as features in a logistic regression classifier. This approach is motivated by the fact that a RoBERTa model trained to recognize toxicity puts more emphasis on certain words associated with sentence-level toxicity. Surprisingly, this model underperforms the logistic regression classifier, which uses words as features.

**Conditional Random Fields**  We suggest that the toxicity level of a word can be context-dependent, so we also experiment with sequence labeling models. We try Conditional Random Fields (CRF) (Lafferty et al., 2001) model. It uses the following features: the word itself, the word’s part of speech, whether the word is a digit and consists of uppercase letters. Each word is represented with these features of the current, previous, and next words. The model performs closely to the attention-based classifier.

**Sequence labeling with LSTM**  Finally, we experiment with the LSTM architecture (Hochreiter and Schmidhuber, 1997). We implement a Bi-LSTM network and also train an LSTM tagger from the AllenNLP library.\(^3\) We do not use any pre-

\(^3\)https://github.com/allenai/allennlp
trained embeddings in the Bi-LSTM model and use
two versions of the AllenNLP LSTM: without pre-
trained embeddings and with GloVe embeddings
(Pennington et al., 2014).

5 Evaluation

5.1 Experimental Setting

For each transfer learning model, we use two-
stage fine-tuning. We first train only the output
layers of the models with the learning rate of
$10^{-3}$, and then the whole models with the learn-
ing rate of $10^{-5}$. In both cases, we use linear
learning rate warm-up for 3000 steps. We use the
AdamW optimizer (Loshchilov and Hutter, 2019)
and the batch size of 8, and early stopping to de-
termine the number of training steps. We use the transformers\(^4\) library for training.

For all the models which use the additional data
from Jigsaw, we apply this scheme twice. The
pseudo-label model is first fine-tuned on the origi-
nal toxic spans dataset, and then on the self-labeled
Jigsaw dataset, whereas the RoBERTa classifier
+ tagger and tagging classifier are first fine-tuned
on the Jigsaw dataset (as classifiers), and then on
the toxic spans dataset (as taggers).

5.2 Results

The scores of our models and the competing sys-
tems are shown in Table 1. Our best submitted sys-
tem (tagging classifier) had the $F_1$-score of 0.681
on the test set, while the best team over the whole
task got 0.708. This brings our team to the top
20% of the leaderboard. The pseudo-labeling ap-
proach was only marginally worse, scoring 0.674.
Simply fine-tuning RoBERTa only on the tagging
problem scored 0.668. On the other hand, none of
our baselines could approach this result. Our best
baseline is the word-based LogReg classifier. Ap-
parently, other models fail to learn even the toxic
vocabulary because their word representations are
not informative enough.

While our best-performing model is only 18th
best out of 92 participating systems, the results of
the top systems are fairly close to ours (the differ-
ce is less than 2.5%). The variation of deep
learning models often falls in this margin (Reimers
and Gurevych, 2017). For our models, the sample
standard deviation of the $F_1$-score is about 0.9%, so
the difference between their performance is likely
to be statistically insignificant.

\(\text{https://huggingface.co/transformers}\)

| Model                          | $F_1$ score |
|-------------------------------|-------------|
| Top-5 participants            |             |
| HITSZ-HLT                     | 0.708       |
| S-NLP                         | 0.707       |
| hitmi&t                       | 0.698       |
| L                             | 0.698       |
| YNU-HPCC                      | 0.696       |
| Our models                    |             |
| tagging classifier            | 0.683       |
| pseudo-labeling               | 0.682       |
| RoBERTa tagger                | 0.678       |
| RoBERTa classifier + tagger   | 0.670       |
| Our baselines                 |             |
| Word-based LogReg             | 0.556       |
| LSTM basic embeddings         | 0.538       |
| Bi-LSTM basic embeddings      | 0.530       |
| Attention-based Logreg        | 0.524       |
| CRF                           | 0.523       |
| LSTM Glove embeddings         | 0.497       |

Table 1: Performance of our models (baselines and
RoBERTa-based models) and their comparison with
the 5 best-performing participants. Models within each
section are sorted from best to worst.

An important hyper-parameter of the models is
the probability threshold. It is usually fine-tuned
on the development set. However, the development
set provided for the task is too small. The thresh-
old fine-tuned on it performs even worse than the
standard threshold of 0.5. Thus, during the evalua-
tion period of the competition, we tried submitting
models with different threshold values. While this
is not a completely fair practice because we indi-
rectly used the test for tuning a model parameter,
we suspect that many teams were overfitting to the
test set in a similar way. We suggest that in order to
make the evaluation fair, the results of the models
on the final test set should not be available before
the end of the competition, even in the indirect way
(i.e., in the form of teams ranking without scores
as it was done in this competition).

The best results which we report here were
achieved with the threshold of 0.6 (see Table 1).
We compare these results with those of the same
models with the default threshold of 0.5 in Table 3.
It shows that these scores are lower by up to 1%.

Another hyper-parameter of our models is
the method of converting token-level labels to

\(\text{https://huggingface.co/transformers}\)
| Aggregation Type | F₁ score |
|------------------|----------|
| No aggregation   | 0.685    |

| Aggregation of word-level scores | Score  |
|---------------------------------|--------|
| max token score                 | 0.673  |
| min token score                 | 0.641  |
| average token scores            | 0.670  |
| naive Bayes                     | 0.653  |

Table 2: Scores of the tagging classifier model with different token aggregation methods (computed on the development set).

| Model                             | threshold | F₁ score |
|-----------------------------------|-----------|----------|
| tagging classifier                 | 0.5       | 0.681    |
| pseudo-labeling                    |           | 0.674    |
| RoBERTa tagger                     |           | 0.668    |
| RoBERTa classifier + tagger        |           | 0.664    |

Table 3: F₁-scores of models with different probability thresholds.

character-level labels. We compare different methods on the development set (see Table 2). Surprisingly, the prediction of labels for each token individually with no aggregation works better than assigning labels to the whole words. This might happen because the attempts to decode words consistently lead to the propagation of wrongly predicted labels. Following this observation, we use the no-aggregation strategy for all models.

5.3 Efficiency of pre-training

To understand the effect of the use of additional sentence-labeled data, we compare the performance of RoBERTa tagger (a model which uses only the toxic span dataset) and tagging classifier (a model which uses sentence-labeled Jigsaw data in addition to the toxic span dataset) models trained on subsets of the data of different sizes. We would like to see if the usefulness of additional sentence-labeled data reduces as we get more data with token-level labeling.

Figure 2 plots the F₁-scores of the two models trained on datasets of sizes between 10 and 7,940 sentences. It shows that when the training set size is between 10 and 1,000, pre-training with sentence-level annotations gives a considerable boost in performance. However, the effect of this pre-training becomes insignificant after the size of the data with word-level labeling reaches around 3,000. Thus, this pre-training strategy is efficient only in cases when the size of the data with word-level labeling is very small.

![Learning curves for two transfer learning models, with (tagging classifier) and without (RoBERTa tagger) additional sentence-level data.](image)

5.4 Error analysis

We analyze the errors of our best submitted system (tagging classifier) by comparing its predictions with the ground truth labels released after the end of the competition.

The vocabulary of false negative spans (527 unique tokens) is more diverse than that of false positives (275 unique tokens), while the number of false positives and false negatives in the test set is comparable (860 vs 813 tokens). It may indicate that the model is cautious and prefers to highlight only the hypotheses which have high confidence, while human annotators are more creative in their analysis. We give some examples of correct and incorrect labelings by our model in Table 4.

The most frequent false positive words characterize incompetence or lack of mental capacities: stupid, idiot, ignorant, moron, dumb, etc. Other frequent false positives are derogatory (pathetic, ridiculous, ass, garbage, loser, etc.), denounce particular misdeeds (liar, troll, racist, hypocrite, etc.), or express general negativity (damn, fuck, etc.). It is not obvious why human annotators label them as toxic in some cases, and as non-toxic in other cases. We suspect that inter-annotator agreement on such words is not very high.

The most frequent false negative words are function words: and, the, are, a, you etc. It happens because annotators sometimes label the whole text
Correct labeling
See a shrink you pathetic troll.
They’re not patriots. They’re vandals, thieves, and bullies.
Trudeau and Morneau are fiscally and economically inept and incompetent.

Incorrect labeling
That’s right. They are not normal. And I am starting from the premise that they are ABNORMAL. Proceed wth the typical racist, bigot, sexist rubbish. Thanks!
ADN is endorsing, without officially endorsing. Bunch of cowards!!!
Rabidly anti-Canadian troll.

Table 4: Examples of ground truth (underlined) and predicted (in bold) toxic spans

| Top 20 false positive words | Top 20 false negative words |
|-----------------------------|-----------------------------|
| stupid ass                  | and of                      |
| idiot liar                  | the have                    |
| ignorant garbage            | are loser                    |
| moron loser                 | a crap                      |
| dumb fools                  | ignorant all                |
| idiots troll                | racist chemical             |
| fool crap                   | you that                    |
| pathetic damn               | in not                      |
| stupidity fuck              | is bunch                    |
| ridiculous clown            | to dumb                     |

Table 5: The most common false positive and false negative words

or a large chunk of it as toxic. The more meaningful false negatives belong to the same classes as the false positives (ignorant, racist, loser, etc.). The most common false positive and false negative words are listed in Table 5.

In general, the performance on this task might be limited to 0.7 F1-score (the quality of the best-performing model) by the ambiguity of the annotations. In future work, it

6 Conclusions
We present a number of models for the detection of toxic spans within toxic sentences. All models are RoBERTa language models fine-tuned on the data with character-level labeling of toxic spans. In addition to that, we perform fine-tuning on an additional dataset with sentence-level toxicity labeling. This yields an improvement. However, our analysis shows that the effect of such pre-training is marginal when the main dataset size exceeds 1,000 samples. Therefore, substantial improvement is observed for small dataset sizes. Nevertheless, the models we propose can be useful in extremely low-resource scenarios.

Our model performs closely to the winning systems. We suggest that the differences between the 20 top models might be attributed to the variation of deep learning models and overfitting the test set. In addition to that, the error analysis shows that some errors in our model might be due to inconsistencies in the test data.

We release the code required to reproduce our experiments online.5

Acknowledgements
This work was conducted in the framework of the joint Skoltech-MTS laboratory.

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5https://github.com/skoltech-nlp/toxic-span-detection
Pseudo-label: The simple

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