Towards A Friendly Online Community: 
An Unsupervised Style Transfer Framework for Profanity Redaction

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Abstract

Offensive and abusive language is a pressing problem on social media platforms. In this work, we propose a method for transforming offensive comments, statements containing profanity or offensive language, into non-offensive ones. We design a RETRIEVE, GENERATE and EDIT unsupervised style transfer pipeline to redact the offensive comments in a word-restricted manner while maintaining a high level of fluency and preserving the content of the original text. We extensively evaluate our method’s performance and compare it to previous style transfer models using both automatic metrics and human evaluations. Experimental results show that our method outperforms other models on human evaluations and is the only approach that consistently performs well on all automatic evaluation metrics.

1 Introduction

Despite the undeniably positive impact social media has on facilitating communication, it is also a medium that can be used for abusive behavior. Many social media platforms do not restrict the language users use, leading to an overflow of strong language that might not be appropriate for children (Duggan, 2014; Rieder, 2010). Verbal abuse and cyber-bullying is also a common problem on social media. Such phenomena are harmful to the victims, the online community, and in particular adolescents who are more susceptible and vulnerable in such situations (Patchin and Hinduja, 2010; Pieschl et al., 2015). To mitigate such problems, recent studies have focused on developing machine learning models for detecting hate speech (Davidson et al., 2017; Xiang et al., 2012; Djuric et al., 2015; Waseem and Hovy, 2016; Chen et al., 2012; Xiang et al., 2012; Founta et al., 2019). However, little progress has been made regarding the task of transforming hateful sentences into non-hateful ones, a potential next-step after detecting the hateful content. dos Santos et al. (2018) propose an extension of a basic encoder-decoder architecture by including a collaborative classifier. To the best of our knowledge, this is the only approach dealing with abusive language redaction.

Unsupervised text style transfer is an important area in text generation that has recently received a lot of attention. Generally speaking, text style transfer is the task of rewriting sentences in a source style to a target style while preserving the original sentences as much as possible. In the context of the paper, we define a corpus to be stylistic if every sample in the corpus shares a common style. Most style transfer approaches are developed and validated on bi-stylistic datasets (Shen et al., 2017; Hu et al., 2017; Li et al., 2018; Prabhumoye et al., 2018; Tian et al., 2018; He et al., 2019; Wu et al., 2019), which require stylistic features on both source and target samples. Some common bi-stylistic datasets for text style transfer are the (negative-positive) Yelp restaurant reviews (Shen et al., 2017) & Amazon product reviews (He and McAuley, 2016), (democratic-republican) Political slant (Prabhumoye et al., 2018), (male-female) Gender (Reddy and Knight, 2016) and (factual-romantic-humorous) Caption (Gan et al., 2017). Models training on these datasets are not normally suitable for being trained and validated on uni-stylistic datasets, where only the source or the target set is stylistic (e.g., offensive to normal text). Recently, Madaan et al. (2020) introduce a uni-stylistic Politeness dataset along with a tag-and-generate approach, in which a generator model learns style phrases from the target samples to fill in tagged positions (cannot be generalized to our case where the target sentences are not stylistic).
In this work, we propose a novel RETRIEVE, GENERATE and EDIT framework to solve the task of transferring offensive sentences into non-offensive ones. For validation, we use three criteria for assessing the performance of our model, namely, content preservation, style transfer accuracy and fluency. We perform an extensive comparison with prior style transfer work on both objective and subjective ratings.

2 Methodology

2.1 Problem Formulation

Given a vocabulary of restricted words \( V_r \) and a corpus of labeled sentences \( D = \{ (x_1, l_1), \ldots, (x_n, l_n) \} \) where \( x_i \) is a sentence and \( l_i = \text{“offensive”} \) if there exists an offensive word \( v_i (v_i \in V_r) \) in \( x_i \), otherwise \( l_i = \text{“non-offensive”} \). For \( (x_i, l_i) \) where \( l_i = \text{“offensive”} \), we re-generate \( x_i^* \) such that it does not contain any words from \( V_r \), preserves as much content from \( x_i \) as possible, and is grammatical and fluent. Unlike dos Santos et al. (2018), who handle general hateful and offensive content detected by Davidson et al. (2017)’s offensive language and hate speech classifier, we focus our work on profanity removal.

2.2 Data Collection

We construct the list of 1,580 restricted words \( V_r \) from various sources. For Corpus \( D \), we extract a total of 12M comments from 2 highly controversial subreddits (6M from each): r/The_Donald and r/politics from January 2019 to December 2019 using BigQuery. We extract sentences that have between 5 and 20 words from the comments. We further remove sentences containing URL, number, email, emoticon, date and time using the Ekphrasis text normalization tool (Baziotis et al., 2017). The remaining sentences are then labeled as either “offensive” or “non-offensive”, as defined, resulting in 350K “offensive” sentences and 7M “non-offensive” sentences.

2.3 Framework

As shown in Figure 1, our RETRIEVE-GENERATE-EDIT framework first retrieves possible Part-of-Speech (POS) tagging sequences, which are then used as the templates for generating candidates in the GENERATE module and corrected by the EDIT module.

Retrieve We first perform POS tagging on both the labelled 350K offensive and 7M non-offensive comments using the Stanza POS tagger (Qi et al., 2020). We replace the POS tags of the offensive terms in \( V_r \) with a [BW] token. Then, given an offensive sentence \( x_i \) and its POS sequence \( p_i \), we use the Lucene search engine (TF-IDF based) to find the set of 10 most similar POS sequences \( \{ p_i' \} \) that belong to sentences in the non-offensive set.

https://www.noswearing.com/dictionary
https://www.cs.cmu.edu/~biglou/resources/bad-words.txt
https://cloud.google.com/bigquery
https://lucene.apache.org/core/
Generate  
After getting $x_i$, $p_i$ and \{$p'_i$\}, the **GENERATE** module creates a set of sentences $C_i$ containing no offensive words. The module achieves this by “matching” words in $x_i$ into possible positions in each $p'_i$ to generate new sentences. The positions that are unable to be matched are “filled” by a pretrained language model. The pseudocode for the algorithm can be found in Algorithm 1.

**Algorithm 1: Candidate set generation.**

\[
\text{Input:} \quad x_i, p_i, p'_i, V_r \\
\quad T_i - \text{set of unique POS tokens in } p_i \\
\quad T'_i - \text{set of unique POS tokens in } p'_i \\
\quad F - \text{pretrained mask-filling model} \\
\text{Output:} \quad \text{Set of candidate sentences } C_i. \\
\text{Definition: } P^n_k := \text{Value of the } k\text{-permutations of } n. \\
T_{\text{shared}} \leftarrow T_i \cap T'_i \\
c_0 \leftarrow [\text{MASK}]_1[\text{MASK}]_2 \ldots [\text{MASK}]_{|p'_i|} \\
C_i \leftarrow \{c_0\} \\
\text{foreach token } t_k \in T_{\text{shared}} \text{ do} \\
\quad \mathcal{W}_k \leftarrow \text{set of words in } x_i \text{ tagged with } t_k \\
\quad S_k \leftarrow \text{list of } t_k \text{'s positions in } p'_i \\
\quad \mathcal{A}_k \leftarrow \text{list of possible assignments of words in } \mathcal{W}_k \text{ to positions } S_k \\
\quad \triangleright \mathcal{O}(\max(|\mathcal{W}_k|, |S_k|)) \\
\quad \text{foreach candidate } c_j \in C_i \text{ do} \\
\quad \quad C_i.\text{remove}(c_j) \\
\quad \quad \text{foreach assignment } a \in \mathcal{A}_k \text{ do} \\
\quad \quad \quad c'_j \leftarrow \text{ASSIGN}(a, c_j) \\
\quad \quad \quad C_i.\text{add}(c'_j) \\
\quad \end{foreach} \\
\text{return } \{\mathcal{F}(c_j)\}_{j=0,1,\ldots,|C_i|} \\
\]

- **Matching** For each $p'_i$, we first create a set $T_{\text{shared}}$ of unique shared tokens in $p_i$ and $p'_i$. We initialize sentence $c_0$ of length $|p'_i|$ filled with [MASK] tokens to store the sentence generated according to $p'_i$. For a token $t_k$ in $T_{\text{shared}}$, we try to fill all its corresponding positions in $c_0$ using words in $x_i$ that are tagged with $t_k$. Suppose there are $N$ words and $M$ positions, then there are at most $\max(\frac{N!}{(N-M)!}, \frac{M!}{(M-N)!})$ possible permutations. We find the number to be 9.42 on average for 5K randomly sampled offensive sentences. We add each newly generated sentence $c'_j$ into $C_i$ and repeat for each $t_k$ on all sentences in $C_i$ until all their masked positions correspond to tokens not in $T_{\text{shared}}$.

- **Filling** For each resulting candidate sentence in $C_i$, we use the pretrained RoBERTa-base model (Liu et al., 2019) to fill in remaining [MASK] tokens. To enhance content preservation, we insert the original sentence $x_i$ before each of the generated sentences with a [SEP] token in between. We replace each [SEP] token with the most probable word predicted by RoBERTa that is not in $V_r$. The unmasked sentences after [SEP] are the outputs of the GENERATE module.

Edit  
We use an **EDIT** module to correct the problems of the output sentences from the GENERATE module, mostly related to wrong word orderings due to the permutation generation in the MATCHING step or low fluency due to a bad retrieved POS sequence from the RETRIEVE module. We first randomly sample 60K English-only non-offensive sentences and apply the RETRIEVE and GENERATE modules on the chosen sentences (dotted red arrows in Figure 1). In the RETRIEVE module, we retrieve POS sequences \{$p^N_i$\} from the non-offensive set and drop the first retrieved sequence, which is the original query sequence $y_i$ itself. We then form a parallel corpus using the generated candidates $C^N_i$ as the source dataset while having the original non-offensive sentences as the target dataset, resulting in 780K source-
target pairs. In this study, we finetune the pretrained T5-small model (Raffel et al., 2019) as our editing sequence-to-sequence model using the generated parallel corpus. We call the edited candidate set $C'_{i}$.

**Selection** We add a **SELECT** module to select the candidate of highest quality $x^*_i$ from $C'_{i}$. We first remove any candidate with words in $V_r$. Then, each generated candidate is assigned a content preservation score (BLEU score (Papineni et al., 2002) between the source and the candidate sentences) and a fluency score (perplexity estimated by the pretrained GPT-2 model with 117M parameters (Radford et al., 2019)). The content preservation and fluency scores are then normalized to $[0, 1]$ by MinMaxScaler. The candidate with the highest sum of content preservation and fluency scores is chosen.

### 3 Experimental Results

#### 3.1 Baselines

We compare our framework ($R+G+S$ and $R+G+E+S$) against 8 existing style transfer methods. These methods are: cross-alignment CA (Shen et al., 2017), back-translation BT (Prabhumoye et al., 2018), delete-only DL and delete-retrieve-generate DRG (Li et al., 2018), mask-and-infill MLM (Wu et al., 2019), auto-encoder with POS information preservation constraint AEC (Tian et al., 2018), deep latent sequence model DLS (He et al., 2019) and the tag-and-generate model TG (Madaan et al., 2020). We also compare our method with the removal approach REM, which simply removes offensive terms from sentences.

For all baselines methods, we replicate the experimental setups described in their papers. Since some of the baseline models’ performance are susceptible to unbalanced classes during training (Li et al., 2018; Wu et al., 2019; Tian et al., 2018), we subsample the non-offensive sentences from 7M to 350K sentences, resulting in a balanced dataset. We then split the offensive and non-offensive datasets into train (320K), validation (25K) and test (5K) sets. Implementation details can be found in Appendix A.

#### 3.2 Evaluations

**Automatic Evaluations** Following most prior studies on text style transfer, we use 3 criteria to evaluate the generated outputs of the models: content preservation, style transfer accuracy and fluency. For content preservation, we report the BLEU-self (BL) (Papineni et al., 2002), ROUGE (RG) (Lin, 2004) and METEOR (MT) (Denkowski and Lavie, 2011). We calculate the style transfer accuracy (Acc.) as the percentage of generated sentences not containing any words in $V_r$. For fluency, we use the average perplexity (PPL) of generated sentences calculated by the pretrained GPT-2 model (Radford et al., 2019).

We show the performances of methods that have at least 60% accuracy in Table 1, while reporting the remaining ones in Appendix B. Our models are the only ones that consistently perform among the top in all 3 criteria. The perplexity of $R+G+E+S$ is lower than the perplexity of $R+G+S$ by 226 points, suggesting the effectiveness of the trained sequence-to-sequence model to edit the output candidates from the **GENERATE** module.

Although we do not compare the performance of our framework with (dos Santos et al., 2018), we use the same set of evaluation metrics reported in their work. On a training dataset of size 224K offensive sentences and 7M non-offensive Reddit sentences, dos Santos et al. (2018) report a content preservation

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*https://huggingface.co/gpt2*

[1] RETRIEVE, GENERATE, EDIT and SELECT. The EDIT module can be skipped.
score, proposed by [Fu et al. (2018)] of 0.933, a style transfer accuracy of 99.54% and a worse perplexity than CA’s outputs. For reference, our best performing model, R+G+E+S, achieves a Fu et al. (2018)’s content preservation score of 0.965, a style transfer accuracy of 99.6% and a better perplexity than CA.

Human Evaluations We ask 3 unbiased human judges to rate the outputs of our models, as well as MLM and DLS, which are the 4 best performing models according to the automatic evaluation metrics. Following [Li et al. (2018)], the annotators judge the generated sentences on content preservation (CP) and grammaticality (Gra.) on a scale from 1 to 5. From 5K offensive sentences in the test set, we randomly sample 100 offensive sentences and ask the annotators to rate the generated outputs of the 4 models on these chosen sentences. We report the style transfer success rate (Succ.) for each method, which is calculated as the number of sentences that do not contain any words from $V_r$ and receive an average CP and Gra. scores of at least 4. Table 2 shows the results of the manual evaluations, which demonstrates a significantly higher Succ. score of R+G+S and R+G+E+S in comparison with previously published models. Some generated samples of the 4 methods are available in Appendix C.

4 Conclusion

In this paper, we propose a novel RETRIEVE, GENERATE and EDIT text style transfer framework that redacts offensive comments on social media in a word-restricted manner. The experimental results on both automatic metrics and manual evaluations demonstrate the strong performance of our method over prior models for the given task. For future work, we envision the possibility of extending the framework by automatically detecting the restricted vocabulary set $V_r$. Such ability would enable the framework to be a robust style transfer method that is applicable to both uni-stylistic and bi-stylistic datasets.

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Appendix A. Implementation Details

We finetune the T5-small model in the EDIT module with a learning rate of $10^{-4}$, the Adam optimizer, cross-entropy loss function and a training batch size of 256 for 3 epochs. We set the max length of input/output sequences to be 30 and the beam size to be 5.

Appendix B. Full Automatic Evaluation Results

| Model                      | BL ↑ | RG ↑ | MT ↑ | FuCP ↑ | Acc. ↑ | PPL ↓  |
|----------------------------|------|------|------|--------|--------|--------|
| TG (Madaan et al., 2020)   | 66.1 | 76.3 | 45.4 | 0.960  | 23.4   | 3378.5 |
| DL (Li et al., 2018)       | 51.8 | 63.4 | 30.1 | 0.931  | 56.8   | 811.0  |
| DRG (Li et al., 2018)      | 47.9 | 59.6 | 28.3 | 0.927  | 57.2   | 1113.4 |
| CA (Shen et al., 2017)     | 18.3 | 36.2 | 11.9 | 0.907  | 65.0   | 747.7  |
| MLM (Wu et al., 2019)      | 49.7 | 63.3 | 40.8 | 0.983  | 65.5   | 798.6  |
| AEC (Tian et al., 2018)    | 46.7 | 56.3 | 25.9 | 0.912  | 90.2   | 3470.6 |
| BT (Prabhumoye et al., 2018)| 8.5  | 21.3 | 9.3  | 0.900  | 95.2   | 488.5  |
| DLS (He et al., 2019)      | 30.9 | 48.8 | 17.9 | 0.915  | 99.1   | 445.9  |
| R+G+S (Ours)               | 51.8 | 67.7 | 41.5 | 0.977  | 100.0  | 674.9  |
| R+G+E+S (Ours)             | 47.4 | 57.7 | 33.9 | 0.965  | 99.6   | 448.7  |
| REM (remove only)          | 81.3 | 87.9 | 49.0 | 0.986  | 100.0  | 1259.8 |

Table 1: Complete Automatic evaluation results. FuCP refers to the content preservation metric proposed by Fu et al. (2018).

Appendix C. Example Outputs
| Model   | Generated Output                                                                                                                                 |
|---------|-----------------------------------------------------------------------------------------------------------------------------------------------|
| **Original** | reap what you sow a*s clowns.                                                                         |
| DLS     | except what you believe us.                                                                           |
| MLM     | this is what you sow and amazing amazing.                                                               |
| R+G+S   | reap what you sow clowns.                                                                             |
| R+G+E+S | reap what you sow.                                                                                     |
| **Original** | the benghazi b*tch is going down.                                                                     |
| DLS     | the president cruz is going down.                                                                       |
| MLM     | the benghazi wall is going down.                                                                       |
| R+G+S   | the benghazi is down going down.                                                                        |
| R+G+E+S | the benghazi girl is going down.                                                                       |
| **Original** | put your head back up your a*s and stfu.                                                                    |
| DLS     | put your head back up your own and then.                                                                    |
| MLM     | stuff your smart back up your a*s and amazing great.                                                    |
| R+G+S   | put your head back up your back, and stfu.                                                                    |
| R+G+E+S | stfu and put your head back up.                                                                          |
| **Original** | the w*ore of babylon speaks.                                                                          |
| DLS     | the state of least run.                                                                                |
| MLM     | the house of babylon speaks.                                                                           |
| R+G+S   | babylon speaks the woman of babylon speaks.                                                             |
| R+G+E+S | the babylon speaks of it.                                                                              |
| **Original** | you obviously talking through your b*tt because you lack all sense of having a brain.                   |
| DLS     | you obviously talking on your own words because you want a lot of free.                                 |
| MLM     | you’re obviously talking all sense having through you lack all sense of a brain.                        |
| R+G+S   | you obviously lack all sense of having a brain through your mouth when talking.                         |
| R+G+E+S | you obviously lack all sense of having a brain.                                                         |
| **Original** | no one gives a d*mn about what your platform is because it has no merit.                                |
| DLS     | no one gives a about what your country is because it is no longer.                                      |
| MLM     | no one gives a flip about what your platform is because it has no merit.                                |
| R+G+S   | one cares about what one is doing because it has no merit.                                              |
| R+G+E+S | no one cares about what he is doing because it has no merit for.                                        |
| **Original** | i have no sympathy for that b*tch and i never will.                                                    |
| DLS     | i have no idea for that it would never will be.                                                       |
| MLM     | i have tremendous sympathy for that b*tch and i always will.                                           |
| R+G+S   | i have no sympathy for i will and never.                                                                |
| R+G+E+S | i have no sympathy for you and will never.                                                             |
| **Original** | war is h*ll and he deserves it.                                                                        |
| DLS     | war is cruz and he did it.                                                                             |
| MLM     | war is real and he knows it.                                                                           |
| R+G+S   | It is and he deserves it.                                                                               |
| R+G+E+S | it is war and he deserves it.                                                                           |

Table 2: Example outputs from our framework, DLS and MLM.