Abstract

This paper presents a combination of data augmentation methods to boost the performance of state-of-the-art transformer-based language models for Patronizing and Condescending Language (PCL) detection and multi-label PCL classification tasks. These tasks are inherently different from sentiment analysis because positive/negative hidden attitudes in the context will not necessarily be considered positive/negative for PCL tasks. The oblation study observes that the imbalance degree of PCL dataset is in the extreme range. This paper presents a modified version of sentence paraphrasing deep learning model (PEGASUS) to tackle the limitation of maximum sequence length. The proposed algorithm has no specific maximum input length to paraphrase sequences. Our augmented under-represented class of annotated data achieved competitive results among top-16 SemEval-2022 participants. This paper's approaches rely on fine-tuning pretrained RoBERTa and GPT3 models such as Davinci and Curie engines with extra-enriched PCL dataset. Furthermore, we discuss Few-Shot learning technique to overcome the limitation of low-resource NLP problems.

Keywords: Natural Language Processing, Transformers, Data Augmentation, RoBERTa, GPT-3, Curie and Davinci Engines.

1 Introduction

Natural Language Understanding (NLU) and Interpretation (NLI) is a branch of Natural Language Processing (NLP) in Artificial Intelligence (AI), which involves understanding and analyzing human language in-depth. Recent advances in Deep Neural Networks (DNNs) have enabled NLP research scientists to achieve state-of-the-art results for tasks that were extremely difficult, if not impossible Devlin et al. (2019), Lan et al. (2020). However, understanding human emotions, reactions, and uncovering hidden insights from unstructured text data such as news stories channel is still challenging.

Language attitudes and intentions extracting in response to the support for the marginalized and vulnerable communities is one of the emergent NLP applications. Patronizing and condescending language (PCL) is a type of behavior that projects a sense of superiority to vulnerable populations Pérez-Almendros et al. (2020). Furthermore, biases and discrimination can result from patronizing attitudes, causing some people to feel unfairly treated, inadequate, unintelligent, and possibly infuriated Saeedi et al. (2021).

Since raw text data extracting from web is a common data collection method, language models can learn different forms of harmful language Heidari and Jones (2020). The PCL understanding is inherently different from sentiment analysis because positive/negative hidden attitudes in the context will not necessarily be considered positive/negative for PCL tasks. It is difficult due to the fair amount of world knowledge and commonsense reasoning required to understand this kind of language Saeedi et al. (2020). The fine-grained idea of PCL detection towards vulnerable communities was presented by Pérez-Almendros et al. (2022). They evaluated baseline results of NLP techniques to detect the presence of PCL and classify PCL types at the text span level.

In this paper, we describe systems participating in the SemEval-2022, PCL detection competition, multiple tasks of language interpretation. The competition is divided into binary classification and multi-label categorization tasks. Data quality analysis led us to explore several NLP data augmentation techniques and state-of-the-art DNN architectures for these challenging tasks. Our attempts to improve the performance of previous
Figure 1: PCL data for binary and multi-label classification problems. Labels 0 and 1 are corresponding to not containing and containing PCL, respectively. "Authority voice" is the PCL category of paragraph. Training model on combined features as the concatenation of keyword and paragraph with RoBERTa separation token "</s>".

| Tasks          | Keyword | Paragraph                                      | labels | Combined Features                                       |
|----------------|---------|------------------------------------------------|--------|---------------------------------------------------------|
| PCL Binary     | Homeless| Housing Minister Grant Shapps added: 'The plight of homeless people should be on our minds all year round - not just at Christmas.' | 1      | Homeless</s>Housing Minister Grant Shapps added: 'The plight of homeless people should be on our minds all year round - not just at Christmas.' |
| PCL multi-label| Refugee | UNHCR gave a report on the state of refugees worldwide on Wednesday as World Refugee Day was marked. | 0      | Refugee</s>UNHCR gave a report on the state of refugees worldwide on Wednesday as World Refugee Day was marked. |

| Keyword | Paragraph                                      | PCL Category | Combined Features                                       |
|---------|------------------------------------------------|--------------|---------------------------------------------------------|
| Homeless| Housing Minister Grant Shapps added: 'The plight of homeless people should be on our minds all year round - not just at Christmas.' | Authority voice | Homeless</s>Housing Minister Grant Shapps added: 'The plight of homeless people should be on our minds all year round - not just at Christmas.' |

2 Tasks Definition and Dataset Analysis

As discussed, PCL competition consists of two classification tasks, each focused on the different objectives of PCL towards underprivileged communities. Figure 1 shows samples of data, their salient features, and annotated labels in training set for both tasks. The first task aims to classify a paragraph that contains PCL as an act of appearing kind or helpful but internally feeling superior to others. The second task is the investigation of the text categorization problem, where each PCL-containing paragraph may belong to several PCL categories.

2.1 Data Analysis of Binary Classification

For the PCL binary classification task, we had access to 10469 human-labeled paragraphs for training our models. Two annotators consider their disagreement on borderline cases as not containing PCL. Our exploratory data analysis reveals multi-label classification techniques commonly confused in the PCL categorization task.

This paper is organized as follows. In Section 2, we introduce two PCL tasks, an in-depth analysis of their datasets, and the challenges of these tasks. In Section 3, we describe our different strategies to tackle discovered challenges of data quality. Next, we explore text augmentation methods to fine-tune the Transformer-based model for each individual task. In Section 4, we discuss our applied models, the experimental setup for fine-tuning models, and their performance. Finally, we conclude the paper in Section 5.
Words that might have positive connotations in sentiment analysis will not necessarily be considered positive in PCL.

Figure 2: Imbalanced data representation. This chart illustrates the number of observations per PCL category is not equally distributed because in the first task not containing PCL class can obviously discriminate the minority class.

2.2 Data Analysis of Multi-label Classification

For identifying PCL types, the number of manually labeled samples in the datasets is 2760, including all PCL positive data from the previous task. Each text span within the containing PCL paragraph can represent one or more PCL categories.

We were challenged to build a multi-label deep learning model capable of detecting different types of PCL. The unevenly distributed labels, also in the case of multi-label classification, could be problematic. Figure 2 illustrates the number of paragraphs associated with "unb" and "com" are the dominant categories. In Sections 3, we present different methods to combat these challenges, and we describe our efforts of training model on the proper distribution to handle imbalanced dataset in Section 4.

3 Tackling Data Imbalance

Taken together, these challenges led us to approach skewed class proportion problems in the PCL dataset with various Data Augmentation (DA) techniques in NLP Wei and Zou (2019). Like many other NLP techniques, DA is not an exact science, and understanding both dataset and task is essential. We conducted an ablation study to measure the impact of DA on the performance of the system.

We aimed to enhance the size of dataset to reduce the side effect of data imbalance. Before trying text augmentation methods, we preprocessed the data by removing HTML-tags and non-alphabetic characters. Then, we expanded English language contractions, e.g., from "you've" to "you have." The following subsections explain our DA methods.

3.1 Synonym Replacement

Synonym Replacement (SR) is a simple operation that randomly chooses some non-stop words from the sentence and replaces them with one of their synonyms chosen at random. We applied wordnet database from nltk library to identify synonyms of a given word within the paragraph Miller (1995). As SR is a lightweight and efficient way of performing DA, we tried to replace 1 to 3 words at a time to create diverse PCL samples. Table 1 illustrates scores achieved by training RoBERT\textsubscript{a}Large model on the augmented dataset. Regardless of the approach taken, the model performance did not spike as expected. As shown later, this approach has been mixed with other text augmentation methods in training models.

3.2 Oversampling

Since containing PCL samples are underrepresented, we considered oversampling (OS) Padurariu and Breaban (2019). Oversampling randomly duplicates data in the minority class by a factor of 8 and adds them to the PCL training dataset, so the number of samples in each class becomes almost equal. The performance of the training pre-trained model with augmented training data by far exceeded the baseline result. (See Table 1)

3.3 Back Translation

We applied back translation (BT) to treat the problem of underrepresented class and boost model performance. In this case, we used a powerful augmenter method of BT in nlpaug library and FairSeqMachineTranslation Wang et al. (2020) model from HuggingFace\footnote{https://huggingface.co/docs/transformers/model_doc/fsmt} Transformers. The aim was to generate more PCL samples and then train model on the true distribution. BT translates all PCL samples from English to German, then translates the previously translated text back into the source language. We reused our best-performing model on OS and SR methods. However, later experiments showed that this technique led the model heavily to overfit the augmented training data (Figure 3).
Note that we did no model validation using augmented data but did training with a mixture of OS, SR, and BT approaches. Although the improvement offered by BT is not so intelligible, statistical analysis is remarkable. The results are shown in Table 1.

![Accuracy per epoch](image)

Figure 3: 80% F1-score was achieved at epoch 3. We can see a clear sign of overfitting after this epoch.

### 3.4 PEGASUS Paraphrasing

Paraphrase generation was the last effort in DA. Paraphrase generation models (in an encoder-decoder form) learn to reconstruct the input using different words and retaining the same meaning while paraphrasing. Paraphrasing can act as a regularizer and reduce the overfitting during the training process Fu et al. (2020).

To leverage PCL dataset efficiently, we performed paragraph paraphrasing along with SR to come up with a less imbalanced dataset. PEGASUS (Pre-training with Extracted Gap-sentences for Abstractive Summarization) Zhang et al. (2020) is a self-supervised Transformer model that masks important sentences from the input and then generates them as one output sequence from the remaining sentences.

The original PEGASUS is limited by the length of text and does truncation on long texts input. The maximum length of PCL paragraphs is 5493 tokens, while the longest input of original PEGASUS model can be 60 tokens. Therefore, we need to handle the limitation of Transformers on the size of the text while training Liu et al. (2019). We proposed an algorithm, multi-sentence PEGASUS, to modify PEGASUS model for arbitrarily long document paraphrasing. This algorithm separates each paragraph into sentences, and then multi-sentence PEGASUS generates ten paraphrased sentences from each individual sentence. The main challenge is to retrieve the original paragraph, because the number of paraphrased sentences for each paragraph was different due to different number of sentences in each sample data. This algorithm can concatenate paraphrased sentences to get the original paragraph in efficient time (The implementation is available at our GitHub). Multi-sentence PEGASUS generates a new dataset containing PCL paragraph over ten times larger than the original containing PCL training data. The following example is a containing PCL data and its corresponding paraphrased context:

**Original Paragraph:** Shepherding in America has always been an immigrant’s job, too dirty, too cold and too lonely for anyone with options.

**PEGASUS Paraphrased:** In America, shepherding has always been an immigrant’s job, dirty, cold, and lonely.

After multi-sentence PEGASUS paraphrasing, two words in each generated text are replaced by their respective synonyms from wordnet corpus. The hyper-parameters values for PEGASUS model have been selected by trial and error. We set a number of times the model searches for the most optimal follow-up word within the text to 10 and played with the parameter that regulates the chances of appearance of high/low probability words.

### 4 Model Description

Our system is based on pre-trained transformers models on the augmented PCL dataset. We focused on exploiting superior performance of RoBERTa and GPT3 models.

#### 4.1 Fine-tuning RoBERTa

To simulate the baseline result, we first did regular fine-tuning RoBERTa for each PCL task on the concatenated features of dataset (keyword and paragraph). Submitted systems on the SemEval-2022 leaderboard were evaluated on the F1-score metric. The (73%) F1-score was achieved by training the model with parameter values of $1e^{-5}$, 2, 400 for learning rate, number of epochs, and warm-up steps, respectively while the baseline is 70.63% (See Table 1).

For the next step, we fine-tuned RoBERTa on the augmented datasets via each method mentioned
Table 1: Peg stands for PEGASUS paraphrasing. The training RoBERTa on the extra enriched dataset (SR/OS/BT/Peg) outperforms other DA methods. The learning process is controlled by setting hyper-parameters (Learning Rate (LR), Warm-up Steps (WS), and Number of Epochs) in the defined range. GPT3 model with Davinci and Curie engines yield good performance with small subset of PCL training dataset. Support parameter indicates the number of queries which is the same for both models. 100 queries in total, and 50 queries for each label.

4.2 GPT-3 Davinci and Curie

Limitation in the amount of available labeled data can be rectified with Few-Shot Learning technique by feeding the model a small amount of data at inference time. The OpenAI GPT3 Brown et al. (2020) language model uses this technique and also can be applied to PCL binary classification task. GPT3 has been trained on a huge text dataset from the open internet with billions of parameters.

In this scheme, we considered two offered models of GPT3 with different capabilities and price points. Davinci is the most capable in understanding the intent of a text, the motives of characters, and also the expensive engine. Also, Curie is quite faster and lower cost than Davinci and capable of tasks like sentiment classification.

We tried both models with Few-Shot learning technique by feeding the model a small amount of PCL training data (with an equal number of labels) as a prompt. The labeled examples were uploaded as a JSON file to OpenAI API for the purpose of classification. Davinci and Curie leverage a few labeled sets of examples without fine-tuning and enable to understand previously unseen data. We queried the model with a subset of training data to predict the most likely label for each query. In fact, Davinci and Curie engine classify specified queries using provided labeled data in a JSON file. These engines first search over the labeled data to select the most relevant for a particular query. Our implemented code is publicly available.

Table 1 illustrates the performance of Davinci and Curie models. OpenAI GPT3 prices are per tokens. Therefore, we just prompted Davinci and Curie by 1000 and 200 labeled data, respectively. They were evaluated on F1-score with 100 queries of even class distribution. Surprisingly, both models perform well without hyper-parameter tuning and on just a few examples of PCL. Davinci’s performance was the same as Curie’s result but with a slight edge in performance.
five times fewer labeled examples. OpenAI API offers the ability to fine-tune their model on the desired task, which is quite costly and time-intensive. An interesting future research direction can be exploring GPT3 applications for PCL detection and multi-label classification tasks, regardless of the cost to train the model.

5 Conclusion

This paper presented a system description for PCL detection and multi-label categorization tasks. Our exploratory data analysis revealed annotated PCL dataset is highly imbalanced. We enhanced data quality with a combination of data augmentation methods. We presented a modified version of sentence paraphrasing deep learning model, Multi-sentence PEGASUS, to tackle the limitation of maximum sequence length. The proposed algorithm has no specific maximum input length to paraphrase sequences. We evaluated the performance of the large pre-trained RoBERTa model on the extra enriched PCL dataset. We boosted the baseline performance and achieved competitive results among the top-16 SemEval-2022 participants. Furthermore, we tried two models of GPT3, Davinci and Curie with Few-Shot learning technique. Our investigation showed both models perform well without hyper-parameter tuning and on just a few examples of PCL. We believe these tasks have many potentials and challenges to further improve current results.

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