# Data Augmentation for Improved Generalizability of Natural Language Processing Models

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### Abstract

A rapid data augmentation framework to improve the performance of natural language processing models. To augment data for a particular downstream task, we use DepCC, A Dependency-Parsed Text Corpus from Common Crawl. First, we take the Common Crawl data and index 35M documents using Apache Solr, a search engine that uses BM25 (Similar to TF-IDF) scoring model. Secondly, we prepare queries from the train/test dataset. After retrieving relevant documents using the query, we convert the documents into dense embeddings and apply K-nearest-neighbors to the candidate passages to rank the relevant documents. We augment data using various strategies. To show performance, we measure held-out accuracy.

### 1 Datasets

• ACL: Citation Intent Classification

• Hyper: HyperPartisan News Detection

• IMDb : Sentiment Classification

#### 1.1 Size of Datasets

| Task  | train set | $\operatorname{dev}$ set | test set | # of Classes |
|-------|-----------|--------------------------|----------|--------------|
| ACL   | 1688      | 114                      | 139      | 6            |
| Hyper | 516       | 64                       | 65       | 2            |
| IMDb  | 20000     | 5000                     | 25000    | 2            |

#### 1.2 Size of Augmented data

| Task  | Baseline | Strat. (i) | Strat. (ii) | Strat. (iii) |
|-------|----------|------------|-------------|--------------|
| ACL   | 1688     | 11005      | 10248       | 10621        |
| Hyper | 516      | 1496       | 2184        | 2184         |
| IMDb  | 20000    | 29492      | 67004       | 68666        |

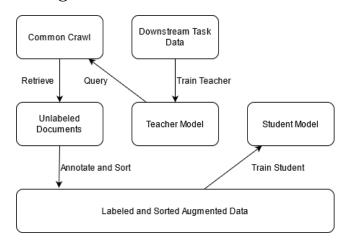
#### 2 Results

| Task  | ${f Baseline}$ | Strat. (i) | Strat. (ii) | Strat. (iii) |
|-------|----------------|------------|-------------|--------------|
| ACL   | 62.5           | 60.5       | 64.4        | 67.1         |
| Hyper | 85.2           | 90.2       | 88.7        | 86.7         |
| IMDb  | 93.8           | 92.4       | 91.9        | 92.3         |

### 3 Baseline models:

• An off-the-shelf RoBERTa model that has been finetuned to perform classification for each of the downstream tasks

# 4 Augmentation Model



# 5 Algorithm

- 1. Extract failed test examples from the baseline model
- 2. Retrieve passages/sentences from Common Crawl
- 3. Apply augmentation strategy (i)-(iii)
- 4. Augment all the labelled CC data to the training data
- 5. Retrain RoBERTa on the augmented training set

# 6 Augmentation Strategies

• Strategy (i)

Use baseline model (Teacher) to perform unsupervised labelling on retrieved CC data

• Strategy (ii)

Using a task specific binary classifier, filter out retrieved CC data that is "out-domain"

Use baseline model (Teacher) to perform unsupervised labelling on the filtered "in-domain"  ${\rm CC}$  data

• Strategy (iii)

Using a task specific binary classifier, filter out retrieved CC data that is "out-domain"

Use ground truth labels of failed test examples and assign labels to the filtered "in-domain" CC data

## 7 TBD

Modify Query and Retrival / oversampling / downsampling Perturb Query / Vary augmentation data / Measure Binary classifier