An Empirical Exploration in Quality Filtering of Text Data

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Abstract

While conventional wisdom suggests that more aggressively filtering data from low-quality sources like Common Crawl always monotonically improves the quality of training data, we find that aggressive filtering can in fact lead to a decrease in model quality on a wide array of downstream tasks for a GPT-like language model. We speculate that this is because optimizing sufficiently strongly for a proxy metric harms performance on the true objective, suggesting a need for more robust filtering objectives when attempting to filter more aggressively. We hope this work leads to detailed analysis of the effects of dataset filtering design choices on downstream model performance in future work.

1 Introduction

As language models increase in size, the need for large, high-quality text datasets has increased as well. Recent work in dataset construction for large language models has centered largely on taking large internet corpora like Common Crawl and employing some method of filtering using some proxy for quality to extract a smaller, high quality training set (Wenzek et al., 2019; Brown et al., 2020; Raffel et al., 2020; Yang et al., 2020). In particular, we focus on shallow classifier-based quality filtering as in Brown et al. (2020) because it provides a simple, continuous, and quantifiable way to adjust the aggressiveness of filtering, and because this reflects the type of classifier used in prior work.

While intuitively it may seem like the more data is discarded the higher quality the remaining data will be, we find that this is not always the case with shallow classifier-based filtering. Instead, we find that filtering improves downstream task performance up to a point, but then decreases performance again as the filtering becomes too aggressive.

We speculate that this decrease in performance is due to Goodhart’s law (Goodhart, 1984), and specifically regressive Goodharting (Manheim and Garrabrant, 2019):

Goodhart’s Law. Any observed statistical regularity will tend to collapse once pressure is placed upon it for control purposes. (Goodhart, 1984)

In other words, optimizing a metric that is a proxy for a desired outcome tends to invalidate the proxy. By optimizing too strongly for the classifier’s score by discarding too many low-scoring documents, the documents that are kept are consistently biased towards the ones with features superficially resembling the high quality data in a way that satisfies the classifier, rather than truly high quality data.

The average is taken across all task accuracies, with each task weighted equally. The error bars in this plot represent standard error and are computed by $se_{\text{mean}} = \frac{1}{n} \sqrt{\sum se_i^2}$, where $se_i$ represents the standard error for each individual task.
2 Related work

The recent proliferation of ever larger language models has led to increasing demands on training data (Radford et al., 2018, 2019; Gokaslan and Cohen, 2019; Rosset, 2019; Shoeybi et al., 2019; Devlin et al., 2019; Liu et al., 2019; Raffel et al., 2020; Brown et al., 2020; Zeng et al., 2021). This data is increasingly derived from internet corpora like Common Crawl (Radford et al., 2019; Ortiz Suárez et al., 2019; Wenzek et al., 2020; Conneau et al., 2020; Brown et al., 2020; Gao et al., 2020; Raffel et al., 2020).

However, the quality of raw Common Crawl data is often insufficient to be directly used. To combat this, many existing works use some kind of proxy for quality, like a classifier between known high quality data and low quality data (Brown et al., 2020; Gao et al., 2020; Zeng et al., 2021), hand-crafted heuristics (Yang et al., 2020; Raffel et al., 2020), or keeping only documents with perplexity scores that fall in some middle quantile of an existing language model (Wenzek et al., 2020). Brown et al. (2020) in particular filter extremely aggressively using their classifier, discarding about 98.7% of their data.

Previous work has shown that models trained on heuristic-filtered datasets perform better on downstream tasks (Raffel et al., 2020). However, Gao et al. (2020) show that a perplexity-filtered CC-derived dataset actually performs worse than unfiltered CC on certain tasks. Brown et al. (2020) do not provide any detailed analysis, but claim better quality for filtered data as evaluated through loss on held out sets of “generative text samples.”

3 Downstream Evaluation Experiment

To evaluate the effect of different degrees of filtering, we create a series of training sets with a controlled filtering methodology but with different hyperparameter settings to result in varied filtering ratios. We filter using the same method used in Brown et al. (2020), with a Pareto-distribution thresholded filtering method and a shallow CommonCrawl-WebText classifier. In this method, rather than using a hard threshold, the threshold $\tau \sim \text{Pareto}(\alpha)$ is sampled from a Pareto distribution, such that each document is kept if $\tau > 1 - \text{score}$, where $\alpha$ is a hyperparameter that controls the permissivity of the filter (see Table 1).

| $\alpha$ | Fraction Discarded |
|---------|---------------------|
| 1       | 0.4107              |
| 2       | 0.6351              |
| 3       | 0.7610              |
| 4       | 0.8329              |
| 5       | 0.8761              |
| 6       | 0.9026              |
| 7       | 0.9198              |
| 8       | 0.9315              |

Table 1: Percentage of discarded documents of various settings using our classifier.

In effect, this relaxes the filter when compared to a hard threshold and allows some low-scoring data to be kept.

As none of the data or models used in Brown et al. (2020) has been made public, we instead use the same type of fasttext (Joulin et al., 2017) classifier between unfiltered Common Crawl and OpenWebText2 as used in Gao et al. (2020).

We use GPT-Neo (Black et al., 2021) to train a series of models on each training set and evaluate on downstream tasks using the EleutherAI LM evaluation harness (Gao et al., 2021). Each model is 1.3 billion parameters, has a GPT-2 architecture (Radford et al., 2019) with the same model hyperparameters as the GPT-3-XL setting in Brown et al. (2020), and is trained for 25k iterations with a batch size of 256.

To ensure that the effect is not confined to any specific task, we evaluate on a series of many downstream tasks. We use zero-shot prompting with no task-specific fine tuning and with prompting inspired by Brown et al. (2020) for many tasks. In total, we evaluate on ANLI Round 3 (Nie et al., 2020), BoolQ (Clark et al., 2019), CommitmentBank (de Marneffe et al., 2019), COPA (Gordon et al., 2012), Hellaswag (Zellers et al., 2019), LAMBADA (Paperno et al., 2016), MathQA (Amini et al., 2019), MultiRC (Khashabi et al., 2018), OpenbookQA (Mihaylov et al., 2018), PiQA (Bisk et al., 2019), PubmedQA (Jin et al., 2019), SciQ (Welbl et al., 2017), and Winograd (Sakaguchi et al., 2019). Error bars in all evaluation task plots indicate standard error with respect to instances of the evaluation task.

For the training data, we create 40 GB filtered
Figure 2: Plots of results for all downstream tasks explored in this paper. Higher is better on all metrics except LAMBADA perplexity (first plot in the third row), where lower is better.
chunks of the Common Crawl data for each value of \( \alpha \in \{1, 2, 3, 4, 5, 8\} \); in other words, different amounts of raw Common Crawl data are consumed for different \( \alpha \) to produce the same fixed 40GB size result. For reference, Brown et al. (2020) filter even more aggressively than we do, discarding about 98.7% of their data. The 40GB size is chosen because it is approximately the size of OpenWebText, which is representative of the amount of data usually used to train models of this size.

3.1 Results

Of the tasks evaluated, several tasks remained near chance or had very high variance, resulting in no clear trend. Of the remainder, an absolute majority exhibited an initial increase in performance and then a decrease in performance after the amount of documents discarded surpassed a threshold that varied by task. Additionally, for almost all tasks the most filtered model was not the best performing. Some tasks like BoolQ exhibit little clear trend. Not all tasks have the same optimal \( \alpha \)—compare PiQA and LAMBADA—and some tasks like PubmedQA show a much more sudden decrease in accuracy. For results on all tasks, see Figure 2.

3.2 Analysis

We hypothesize that this decline in performance is because of misalignment between the classifier objective, intended to be a proxy for quality, and actual document quality. For instance, a classifier to distinguish WebText2 from Common Crawl, as in GPT-3, would also exclude domains of text data not found as often in WebText2.

We also hypothesize that the difference in optimal \( \alpha \) between different tasks is because the characteristics of the different types of data that help the most with each task are over/underdiscarded to a different extent due to spurious correlations with the quality metric. As such, we do not expect the exact thresholds to transfer to other tasks, classifiers, or datasets. This is an expected consequence of Goodharting, because the degree to which different types of text data correlate with the features learned by the classifier is mostly spurious.

4 Domain Misalignment Experiment

To test the hypothesis that the misalignment of the objective leads to the exclusion of non-OpenWebText2-like data, we train a fasttext classifier to classify between BookCorpus2 (Gao et al., 2020) and OpenWebText (Gokaslan and Cohen, 2019), and compute the mean BookCorpus2-probability of each training set. If the classification model is favoring OpenWebText-like data over generally high-quality data, then as filtering increases in intensity, the proportion of BookCorpus2-like data should decrease as the data consists increasingly of OpenWebText-like text. Conversely, if the classification model is robustly favoring high quality text, then as filtering increases in intensity, the proportion of BookCorpus2-like data should increase, as low-quality text looks nothing like BookCorpus2. We also repeat this experiment for Pubmed Abstracts.

We chose BookCorpus2 and Pubmed Abstracts because of their similarity in distribution to LAMBADA and PubmedQA respectively, in the hopes of observing a similarity between the task evaluation curves and the data domain curves.

4.1 Results

As seen in Figure 3, the fraction of BookCorpus2-like data remains mostly constant until around 0.6, after which it declines sharply. A similar pattern is observed with Pubmed Abstracts, albeit with an earlier drop (Figure 4).

The BookCorpus2-like data curve’s drop precedes the LAMBADA performance drop by about 0.2. Similarly, the Pubmed Abstracts drop also precedes the PubmedQA’s main drop slightly.

4.2 Analysis

The decrease in Pubmed Abstracts and BookCorpus2 like data as filtering increases in aggressiveness supports the hypothesis that part of the problem is that text domains not similar to OpenWebText2 are being discarded.

Our main hypothesis for why the domain data content starts decreasing before the evaluation metric performance does is that these tasks are sufficiently different in distribution to the respective datasets.

5 Limitations

This work is intended to show that the common assumption that more aggressive data filtering is better is not always true, and thus focuses on one particular classifier used in the real world as an illustrative example. Depending on the type of
classifier, the training data used for the classifier, and the downstream task, this effect may not be relevant in certain settings. We leave an exhaustive exploration of the contribution of these various factors to future work.

6 Conclusion

In this paper, we explored the effect of filtering the training data using a shallow model trained on a proxy for quality on downstream language model performance. We showed that increasing the aggressiveness of filtering against this signal actually decreases model performance past a certain point, and speculate that this is due to Goodhart’s law, as the misalignment between proxy and true objective becomes more significant with increased optimization pressure. We hope that this work leads to more careful analysis of the effects of filtering in future language modeling work.

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