Intermediate Training on Question Answering Datasets Improves Generative Data Augmentation

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Abstract

Manually annotating datasets requires domain experts to read through many documents and carefully label them, which is often expensive. Recently, pre-trained generative language models (GLMs) have demonstrated exceptional abilities in generating text which motivates to leverage them for generative data augmentation. We improve generative data augmentation by formulating the data generation as context generation task and use question answering (QA) datasets for intermediate training. Specifically, we view QA to be more as a format than of a task and train GLMs as context generators for a given question and its respective answer. Then, we cast downstream tasks into question answering format and adapt the fine-tuned context generators to the target task domain. Finally, we use the fine-tuned GLM to generate relevant contexts, which is further used as synthetic training data for their corresponding tasks. We perform extensive experiments, case studies, and ablation studies on multiple sentiment and topic classification datasets and demonstrate substantial improvements in performance in few-shot, zero-shot settings. Remarkably, on the SST-2 dataset, intermediate training on SocialIQA dataset achieves an improvement of 40% on Macro-F1 score. Through thorough analyses, we observe that QA datasets that requires high-level reasoning abilities (e.g., abstractive and common-sense QA datasets) tend to give the best boost in performance in both few-shot and zero-shot settings.

1 Introduction

Recent advances in NLP demonstrate exceptional capabilities of generative language models in generating text (Radford and Narasimhan, 2018; Radford et al., 2019; Lewis et al., 2020; Brown et al., 2020). Prior work (Kumar et al., 2020; Anaby-Tavor et al., 2020; Mekala et al., 2021) leverage them for generative data augmentation that usually involves prepending the target label to training sample, fine-tuning the GLM and generating synthetic data by prompting the GLM with the target label.

However, it is not evident that the model parameters learnt during pre-training or fine-tuning should support data generation using such unintuitive formulation with label tokens as prompt. In limited data regimes like few-shot, the fine-tuning can be unstable (Devlin et al., 2019) and it relies on the pre-trained encoder parameters to be reasonably ideal for the target task (Phang et al., 2018). Therefore, for diverse target task domains that are different than pre-training domain, such formulation may result in poor performance.

To address this challenge, we propose to use QA formulation to prompt the GLM for synthetic data. To enable this formulation, we use QA datasets for intermediate training to obtain high quality data generators. Specifically, we view QA more as a format and train GLMs to be context generators for a given question and answer (Gardner et al., 2019). Then, we adapt it to the target domain by continuously training it further on the few-shot supervision, resulting in target-domain data generator.

As illustrated in Figure 2, our method consists of two steps. The first step is QAC fine-tuning, where we fine-tune a pre-trained language model on QA dataset to obtain a general context generator that is capable of generating context for a given question and answer. We view QA as a format rather than a task i.e. instead of frequently used context-question-answer format to solve QA task (Radford and Narasimhan, 2018; Radford et al., 2019;
Raffel et al., 2020), we view the QA dataset in question-answer-context format to train context generators. Then, we adapt the general context generator to the target domain. Inspired from recent work in converting several NLP tasks into a common format (McCann et al., 2018; Raffel et al., 2020), we format the target tasks into a question-answer schema. For example, as shown in Figure 1, topic classification and sentiment analysis data can be formatted into question-answer-context format with its respective label as answer and text as context. We adapt the context generator to the target task domain by further continuously training on target task few-shot supervision, resulting in target task context generator. Finally, we generate synthetic training data for the target dataset by generating context for questions and answers pertaining to the respective dataset. Then, we augment the generated samples to the few-shot supervision and train a target task model on the augmented data.

Note that, our method differs from generic intermediate task fine-tuning (Phang et al., 2018) in terms of the usage of the fine-tuned language model. In our method, the GLM fine-tuned on an intermediate QA dataset is used to generate synthetic training data whereas in intermediate task fine-tuning, the fine-tuned model is directly plugged into the target task. It also differs from (Vu et al., 2021) in terms of the generated data, where they consider NLI as auxiliary task and generate synthetic samples in target-domain for NLI task irrespective of the target task and perform intermediate task fine-tuning. Our method formats target tasks into question-answer format and directly generates the samples relevant for target task.

We perform experiments on multiple sentiment analysis and topic classification datasets with several abstractive, extractive, and common-sense reasoning QA datasets. Through rigorous experiments and analysis, we observe that QA datasets that require high-level reasoning abilities such as abstractive and common-sense QA datasets suit the best for generating high-quality data.

Our contributions are summarized as follows:

• We propose to use QA datasets for training generative language models to be context generators for a given question and answer.
• We format sentiment analysis and topic classification tasks into question answer format and model synthetic training data generation for these tasks as context generation.
• Extensive experiments on multiple sentiment analysis and topic classification datasets demonstrate the effectiveness of our method in zero-shot and few-shot settings.

Reproducibility. We will release the code and datasets on Github\(^1\).

2 Problem Formulation

For a given task \( T \), the input in a few-shot setting contains (1) a very small labeled dataset \( \mathcal{L}_T = \{(D_1, l_1), (D_2, l_2), \ldots, (D_j, l_j)\} \) and (2) \( m \) target classes \( C = \{C_1, C_2, \ldots, C_m\} \). Our method also requires user to provide a question per dataset that is representative of the task and the dataset. Our aim is to build a model for the task \( T \) using

\[^1\]https://github.com/dheeraj7596/QAGen
these inputs, that assigns a label $C_j \in C$ to each document $D_i$.

3 QAC Fine-tuning: Intermediate Training on Question-Answering Datasets

A question-answering dataset $Q$ contains triplets of question $q$, answer $a$, and context $c$. Question-answering datasets can be divided into two types based on the type of answers: (1) extractive datasets and (2) abstractive datasets. The answers in extractive QA datasets can be found as a contiguous span in the context. Therefore, extractive datasets also contain the span information of the answer in context. In an abstractive QA datasets, the answer is generated in natural language without necessarily relying on the vocabulary of the question or context. All common-sense QA datasets are abstractive in nature. Since we aim to train a context generator, we don’t require span information and only consider questions, answers, and contexts for all QA datasets.

We use the question-answering as a format and transform the QA dataset $Q$ into training data $D_{QAC}$ for fine-tuning the GLM. Each sample with the triplet $(q, a, c)$ where $q$ is question, $a$ is answer, and $c$ is context is converted into a training sample by appending “question:” prefix before the question, “answer:” prefix before the answer, and “context:” prefix before the context and all separated by the new line character. For example, given a question $q = \textit{“when did battle of plassey happen?”}$, answer $a = \textit{“23 June 1757”}$, and context $c = \textit{“the battle of plassey was a decisive victory of the british east india company over the nawab of bengal and his french allies on 23 June 1757.”}$, we create a training document for GLM in the following format:

```
question: when did battle of plassey happen?
answer: 23 June 1757
context: the battle of plassey was a decisive victory of the british east india company over the nawab of bengal and his french allies on 23 June 1757.
```

Similarly, we convert the QA dataset $Q$ into training data $D_{QAC}$. Once we create $D_{QAC}$, we fine-tune a pre-trained GLM $G$ on $D_{QAC}$ to obtain a General Context Generator $G_Q$ using language modeling objective to maximize the log-likelihood of the $(q, a, c)$ triplet. Mathematically, for a given question $q_i$, answer $a_i$, and context $c_i$, we learn parameters $\Theta$ by maximizing $\mathcal{L}$ where:

$$\mathcal{L} = \sum_i \log(P(q_i, a_i, c_i; \Theta))$$

$$= \sum_i \log(p(c_i|q_i, a_i; \Theta))$$

One can view our formulation as asking the question $q_i$ and answer $a_i$ to play the role of prompt and the context $c_i$ to be the continuation, thus facilitating conditional context generation. We call this step QAC fine-tuning.

4 Domain Adaptation and Synthetic Training Data Generation

Once we obtain the general context generator $G_Q$ from QAC fine-tuning step, we adopt it to the target domain by fine-tuning it further on the few-shot supervision. To preserve its context generating ability, we choose to perform QAC fine-tuning instead of the usual language model fine-tuning. We enable QAC fine-tuning by transforming the few-shot supervision into question-answer-context format. First, we manually design one question per dataset that is representative of the task and the dataset. Furthermore, following (Schick and Schütze, 2021a), we define a verbalizer as a mapping $v: C \rightarrow V$ that maps each label in $C$ to a word from $G_Q$’s vocabulary $V$. Finally, for every document $D_i$ and its respective label $l_i$ in few-shot supervision, we consider the verbalizer mapping of the label, $v(l_i)$, as answer and the text $D_i$ as context. For example, a negative review “I hate this movie” from IMDb dataset is transformed as follows:

```
question: is the movie good or bad?
answer: bad
context: i hate this movie.
```

After transforming the few-shot supervision, we fine-tune $G_Q$ on the converted few-shot supervision data to obtain Target Task Context Generator $G_T$. Synthetic Training Data Generation. As mentioned previously, we have a question $q$ for every dataset that is representative of the task and the dataset and all possible labels $C$. Therefore, for every distinct label $C_j$, we create a question-answer prompt with $q$ as question, $v(C_j)$ as answer and let the Target Task Context generator $G_T$ generate the context $c_{gen}$. Specifically, given question $q$ and
Table 1: QA Dataset statistics. Common-sense QA datasets are also abstractive in nature that require common-sense reasoning to answer the questions.

| Dataset       | Type       | # Samples | Training Context        |
|---------------|------------|-----------|-------------------------|
| SQuAD         | Extractive | 87600     | Wikipedia               |
| NewsQA        | Extractive | 76560     | News                    |
| TweetQA       | Abstractive| 10692     | News Tweets             |
| SocialIQA     | Common-sense| 33410    | Crowdsourcing           |
| CosmosQA      | Common-sense| 21448    | Blogs                   |

answer \(v(C_j)\), we conditionally generate \(c_{gen}\) using \(P(c_{gen}|q, a)\) probabilities from \(G_T\):

\[
c_{gen} = \arg \max_c P(c|q, a)
\]

The generated context \(c_{gen}\) and label \(C_j\) is considered as a synthetic training sample. We generate \(n\) such samples to create synthetic training data denoted by \(D_{gen}\).

Once we generate synthetic training data \(D_{gen}\), we train the target task model on combined \(D_{gen}\) and few-shot supervision data. We use this trained target-task model during inference.

5 Experiments

In this section, we evaluate our method against several data augmentation and few-shot methods on sentiment analysis and text classification tasks.

5.1 QA Datasets

We consider several extractive, abstractive, and common-sense QA datasets. Common-sense QA datasets are also abstractive datasets that require common-sense reasoning to answer the questions. The QA dataset statistics are provided in Table 1. The details of these datasets are as follows:

- **SQuAD**: (Rajpurkar et al., 2016, 2018) is a collection of questions and answers based on Wikipedia articles.
- **NewsQA**: (Trischler et al., 2017) is a challenging QA dataset in News domain where a crowdworker was shown a news article’s headline and summary, and was asked to formulate a question about the article without accessing its full content. Therefore, some of the questions don’t have answers. Since we need answers for QAC fine-tuning, we consider only those questions that have answers.
- **TweetQA**: (Xiong et al., 2019) is a QA dataset made from a collection of tweets sampled from two major news websites CNN, NBC.
- **SocialIQA**: (Sap et al., 2019) is QA dataset that tests social common-sense intelligence. The data is made of common phrases from stories and books.
- **CosmosQA**: (Huang et al., 2019) is a commonsense-based reading comprehension task formulated as multiple-choice questions. Answering questions require reasoning not only based on the exact text spans in the context, but also abstractive commonsense reasoning.

5.2 Target Task Datasets

We evaluate our method on three English sentiment analysis: IMDb reviews (Maas et al., 2011), Yelp reviews\(^2\), SST-2 (Socher et al., 2013) and three English topic classification tasks datasets: Yahoo (Zhang et al., 2015), The New York Times (NYT), AGNews (Zhang et al., 2015). The statistics of the target task datasets, dataset-representative questions, and their respective verbalized labels are mentioned in Table 2. The details of the datasets is mentioned in Appendix A.2.

5.3 Compared Methods

We compare with a wide range of intermediate-task fine-tuning (ITFT) and data augmentation methods described below:

- **BERT-FT** trains the BERT-base-uncased classifier (Devlin et al., 2019) on the few-shot supervision.
- **ITFT-X** (Phang et al., 2018) first trains a model on dataset X and fine-tunes it further on the target task. We compare with ITFT-MNLI and ITFT-SQuAD fine-tuned immediately on MNLI (Williams et al., 2018) and SQuAD datasets respectively.
- **BackTranslation** (Sennrich et al., 2016) augments samples by translating them into non-English language and translating them back to English. We translate them to French, Spanish, and Portuguese thereby augmenting three synthetic samples for every sample.

\(^2\)https://www.yelp.com/dataset/
• **PEGASUS** (Zhang et al., 2019) is a state-of-the-art paraphrasing model. We paraphrase the input text and consider it as a synthetic sample and augment it to the training set.

• **EDA** (Wei and Zou, 2019) generates synthetic samples by synonym replacement, random insertion, random swap, and random deletion and augment them to the training set.

We denote our method as QAGen, which includes QAC fine-tuning, domain adaptation, synthetic samples generation, and training the target task classifier. QAGen-X represents that the QAC fine-tuning of GLM is performed on QA dataset X. We also compare with BERT-GPT2 where we don’t perform QAC fine-tuning and directly fine-tune GLM on target dataset.

5.4 Experiment Settings

We consider two low-data regimes: (1) Few-shot and (2) Zero-shot. Following (Vu et al., 2021), we consider 8 annotated samples per label in the few-shot setting. In the zero-shot setting, we skip domain adaptation step and use $G_Q$ for synthetic training data generation and train the target task model only on generated synthetic training data. We use GPT2-Medium (Radford et al., 2019) as our GLM and we fine-tune it for 3 epochs in QAC-fine-tuning and domain adaptation steps. While generating synthetic training samples, we use top-$k$ sampling with $k = 20$, maximum length to 200, and generate $n = 450$ synthetic samples per label. We use BERT-base-uncased (Devlin et al., 2019) as target task classifier. We feed [CLS] representation into the classification head and train all the parameters on the downstream target tasks. Following (Devlin et al., 2019), we fix the number of epochs of target task BERT classifier training to 4 unless mentioned otherwise. We perform 3 random restarts and report the mean and standard deviation. We use Transformers library (Wolf et al., 2020) for our experiments.

We generate the same number of samples as QAGen i.e. 450 per label for all data augmentation baselines. We use BERT-base-uncased as the target task classifier for all baselines. While training the target task classifier, since the number of training samples for baselines like BERT-FT, ITFT are different than data augmentation baselines and our method QAGen, we set the number of epochs for all baselines such that the number of update steps remain the same for fair comparison.

5.5 Results & Discussion

We present evaluation results of few-shot setting in Table 3 and zero-shot setting in Table 4. We use micro and macro-f1 as evaluation metrics. We discuss the effectiveness of our method below.

**QAGen vs Baselines.** In the few-shot setting, QAGen with abstractive and common-sense based datasets out-perform all baselines in most of the datasets, beating the best baseline in five out of six datasets. QAGen performs better than BERT-FT on all datasets, achieving upto 14% improvement on SST-2 dataset. Although ITFT performs better than vanilla fine-tuning, QAGen demonstrates better performance than ITFT on all datasets. For example, QAGen-TweetQA shows 11% improvement over ITFT-SQuAD on AG-News dataset. QAGen demonstrates higher performance than data-augmentation baselines on all datasets except NYT. NYT is relatively easier dataset that results in near supervised performance (94% micro f1) with BERT-FT on just 8 samples per label. We attribute the superior performance of QAGen to the context-generating ability acquired during QAC fine-tuning that is efficiently leveraged by generating synthetic samples which are augmented to the training set.

**Abstractive vs Extractive QA Datasets.** We observe that the performance of QAGen with abstractive QA datasets is significantly better than QAGen with extractive QA datasets in both few-shot and zero-shot settings. For example, QAGen-TweetQA has an improvement of 20% over QAGen-SQuAD on IMDb dataset in few-shot setting. This is because of the intrinsic nature of extractive QA datasets i.e. answer being present in context as a contiguous span. We observe that the generative language model fine-tuned on an extractive QA dataset retains the ability to generate context that encompasses the answer. Note that, while generating synthetic training samples, the answer in the prompt is its respective topic. For example, out of 500 generated samples by QAGen-SQuAD for Yelp dataset, 213 samples contain at least one occurrence of its corresponding verbalized label whereas it is only 73 for QAGen-CosmosQA. Thus, many synthetic samples generated contain their corresponding label in text. Therefore, a classifier trained on synthetic samples that have their corresponding labels in the text, gets overfit on the label tokens and doesn’t generalize on unseen test data.
Table 3: Few-Shot Evaluation Results. Micro and Macro-f1 are used as evaluation metrics. All experiments are repeated with three random seeds. Mean and standard deviation (in the subscript) are reported. The best baseline for each dataset is underlined and all results of QAGen that performs better than the best baseline are in bold.

| Method            | IMDB  | Yelp  | SST-2  | NYT    | Yahoo | AGNews |
|-------------------|-------|-------|--------|--------|-------|--------|
| QAGen-SQuAD       | 53.9±3| 45.9±2| 37.9±7| 83.7±6| 81.3±6| 81.3±6 |
| QAGen-NewspQA     | 57.9±5| 55.3±4| 36.4±1| 56.0±1| 50.6±7| 79.6±5 |
| QAGen-TweetQA     | 75.3±3| 74.5±5| 42.9±1| 42.0±1| 67.4±1| 67.5±2 |
| QAGen-SocialQA    | 79.5±1| 79.5±1| 39.4±1| 32.1±4| 77.5±4| 71.3±6 |
| QAGen-CosmosQA    | 77.0±2| 76.4±7| 42.3±1| 37.5±1| 67.4±6| 66.9±2 |

Table 5: Ablation Study

| Method            | IMDB  | Yelp  | SST-2  | NYT    | Yahoo | AGNews |
|-------------------|-------|-------|--------|--------|-------|--------|
| BERT-GPT2         | 70.9±7| 70.0±8| 32.4±7| 19.8±2| 52.9±6| 41.8±9 |
| QAGen-SQuAD       | 53.3±2| 42.7±1| 30.2±5| 21.4±6| 52.4±7| 47.3±1 |
| QAGen-NewspQA     | 53.4±6| 47.4±0| 32.8±1| 23.3±6| 51.6±7| 46.2±6 |
| QAGen-TweetQA     | 72.4±0| 70.6±1| 38.0±4| 37.0±2| 61.2±9| 56.5±4 |
| QAGen-SocialQA    | 78.8±3| 77.6±1| 36.9±2| 37.1±1| 76.2±2| 76.1±2 |
| QAGen-CosmosQA    | 75.9±2| 75.5±3| 37.4±5| 35.1±7| 69.6±4| 60.6±5 |

Table 5: Ablation Study

| Method            | IMDB  | Yelp  | SST-2  | NYT    | Yahoo | AGNews |
|-------------------|-------|-------|--------|--------|-------|--------|
| QAGen-SQuAD       | 53.9±3| 45.9±2| 37.9±7| 83.7±6| 81.3±6| 81.3±6 |
| QAGen-NewspQA     | 57.9±5| 55.3±4| 36.4±1| 56.0±1| 50.6±7| 79.6±5 |
| QAGen-TweetQA     | 75.3±3| 74.5±5| 42.9±1| 42.0±1| 67.4±1| 67.5±2 |
| QAGen-SocialQA    | 79.5±1| 79.5±1| 39.4±1| 32.1±4| 77.5±4| 71.3±6 |
| QAGen-CosmosQA    | 77.0±2| 76.4±7| 42.3±1| 37.5±1| 67.4±6| 66.9±2 |

Comparison with BERT-GPT2. QAGen performs better than BERT-GPT2 in both few-shot and zero-shot settings attaining improvement up to 40% and 42% respectively in macro-f1 on SST-2 dataset. This demonstrates that the context generating abilities are learnt and reinforced during the QAC fine-tuning which is efficiently utilized by generating synthetic samples.

Zero-shot Performance. The zero-shot performance of QAGen follows similar trend as few-shot performance. The performance of QAGen with abstractive and common sense reasoning QA datasets is better than QAGen with extractive datasets and BERT-GPT2. This demonstrates that our method results in high quality context generators that are able to generate artificial training data that results in high performance without any human annotated data.

5.6 Ablation Study

To understand the impact of domain adaptation and the few-shot samples, we compare with its two ablated versions in Table 5: (1) QAGen-DA represents our method without domain adaptation i.e. generating synthetic data using $G_Q$ and training the classifier on combined few-shot supervision and synthetic data generated by $G_Q$. (2) QAGen-Few Shot represents the classifier is trained only on the generated samples by $G_T$. We also present results of our complete pipeline QAGen for reference. QAGen performs better than QAGen-Few shot in almost all the cases, demonstrating the importance of including few-shot samples to the training set for classifier. The comparison between QAGen and QAGen-DA suggests that fine-tuning the language model further on target dataset helps in some scenarios but doesn’t always improve the performance. This is in line with previous research findings (Du et al., 2021; Vu et al., 2021; Pryzant et al., 2022).

We conjecture that domain adaptation is important when the structure of target task dataset is different than the QA dataset. For example, domain adaptation helps most of the QA datasets on SST-2
dataset because the text in SST-2 is single sentence where as most of the QA datasets have paragraphs as context. Moreover, it also depends on the number of samples the language model is fine-tuned on during domain adaptation. We observe that the more number of samples, the positive is the impact. For example, the number of few-shot samples are the highest in Yahoo compared to other datasets and domain adaptation positively contributes to the performance on Yahoo for all QA datasets.

5.7 Performance vs No. of Generated Samples

We fix the few-shot supervision size to 8 samples per label and vary the number of generated samples per label and plot the performance of QAGen-TweetQA and QAGen-SocialIQA on AGNews and IMDb datasets, shown in Figure 3. We repeat each setting with three different seeds and plot the mean performance. We observe that the performance increases and it stagnates after a while. This shows that synthetic training data can give a substantial boost to the few-shot training data, minimizing the human effort in manual annotations, however, it cannot replace the original training data completely as it requires more human annotated data to improve beyond some limit.

5.8 Performance vs Few-shot supervision size

We fix the number of generated samples to 450 per label and vary the number of annotated samples and plot the performance of QAGen-CosmosQA and QAGen-SocialIQA on Yahoo and SST-2 datasets in Figure 4. We also plot the performance of BERT-FT for reference. We repeat each experiment with three random seeds and plot the mean performance. We observe that the performance of QAGen increases with the size of supervision and the improvement over BERT-FT in the low-data regime is substantial. For example, with only 4 annotated samples per label in Yahoo dataset, the macro F1 of QAGen-CosmosQA is better than BERT-FT by 22%. However, we also observe that the performance gap between QAGen and BERT-FT decreases with increase in supervision size and gets stagnated after a while. As the size of supervision increases, the supervision by itself is sufficient for high performance, thus reducing the performance boost due to synthetic training data.

5.9 Case study: Evaluating Context Generator

We hypothesize that our method results in high-quality context generators that are capable of generating context for a given question and answer. To validate this hypothesis in in-domain and out-of-domain settings, we perform two experiments on QA task.

In-domain Analysis. In this experiment, we validate whether the context generator is capable of generating context for question, answer pairs belonging to the same domain as QA dataset used for QAC fine-tuning. We consider SQuAD dataset and partition it into training set with 1000 (question, answer, context) triplets, dev set of size 1700 with only (question, answer) pairs and a test set of size 6570. First, we consider GPT2-Medium as GLM and perform QAC fine-tuning on the training set. Then, we generate contexts for the dev set and augment the (question, answer, generated context) triplets to the training set. Finally, we train a BERT-base-uncased QA model on the augmented data. We compare it with the BERT model trained only on the original training set. We report F1 scores on test set in Table 6. We observe a boost of 4% using our synthetic training data, validating our hypothesis in the in-domain setting.

Out-of-domain Analysis. In this experiment, we
Table 6: Case Study: We evaluate our context generators in in-domain and out-of-domain settings. In both cases, we observe substantial improvement in the performance demonstrating the effectiveness of our method.

| Setting       | Model   | F1 score |
|---------------|---------|----------|
| In-domain     | BERT    | 32.11    |
|               | QAGen   | 36.74    |
| Out-of-domain | BERT    | 14.96    |
|               | QAGen   | 25.31    |

validate our hypothesis in the out-of-domain setting i.e. the domain of target dataset is different than the QA dataset used for QAC fine-tuning. We follow our proposed pipeline and consider SQuAD as the QA dataset for QAC fine-tuning and NewsQA as the target dataset. We partition NewsQA dataset into 1000 (question, answer, context) triplets for domain adaptation, 17000 (question, answer) pairs for context generation, and test on 10000 samples. We fine-tune GPT2-medium on SQuAD to obtain general context generator and adapt to the NewsQA domain by training it further on 1000 question, answer, context triplets from NewsQA. Using the target task context generator, we generate contexts for 17000 question, answer pairs, augment it to the training set, and train BERT-base-uncased QA model on the augmented data. From F1 scores reported in Table 6, we can observe more than 10% improvement in the performance, demonstrating the efficiency of our method in out-of-domain setting.

6 Limitations

One limitation of our approach is the synthetic training data generated can boost the performance upto an extent and beyond that it requires more annotated samples. So, the generated synthetic training data cannot replace the training data altogether but could minimize the annotation effort significantly.

7 Related Work

We review the literature of: (1) Few-shot Learning, (2) Data Augmentation, and (3) Language Model Fine-tuning.

Few-shot Learning: Our work is closely related to few-shot learning as we take few-annotated samples as supervision. (Bansal et al., 2020) proposes a self-supervised meta-learning approach for few-shot classification. (Schick and Schütze, 2021a) formulates input samples as cloze-style phrases and assigns pseudo-labels that are used for training the classifier and (Tam et al., 2021) improves it further without using any task-specific unlabeled data. (Lin et al., 2021) train multilingual autoregressive language models to enable few-shot learning in multiple languages. (Brown et al., 2020) introduce a new paradigm in-context learning to infer from large language models using few annotated samples. (Gao et al., 2021) converts smaller pre-trained language models to few-shot learners. We use QA datasets for intermediate training and generate synthetic training data to perform few-shot classification.

Data Augmentation: Data Augmentation has been an active research area to minimize the human annotation effort. (Wei and Zou, 2019) proposed a simple data augmentation method using synonym replacement, random insertion, random swap, and random deletion. (Sennrich et al., 2016) augments samples by translating them into foreign language and translating them back to English. (Du et al., 2021) computes task-specific query embeddings to retrieve sentences from unlabeled documents from the Internet. After rise in pre-trained generative language models, the generation capabilities of generative language models have been explored to generate synthetic data. (Anaby-Tavor et al., 2020; Kumar et al., 2020; Schick and Schütze, 2021b) generates labeled documents using the GLMs and (Yang et al., 2020) specifically for commonsense reasoning. (Puri et al., 2020) uses GLMs to synthesize questions and answers and improve performance on question answering task. (Vu et al., 2021) generates data for NLI task. Our method trains GLMs to be context generators that generates relevant context for a given question and answer.

Language Model Fine-tuning: Pre-trained language models are applied to downstream tasks by fine-tuning them using task-specific objective (Howard and Ruder, 2018). However, this process requires significant annotated downstream task data (Yogatama et al., 2019). Many methods have been proposed to address this challenge. (Gururangan et al., 2020) propose to continue training on unlabeled data from the target task domain. (Aghajanyan et al., 2021) propose pre-finetuning, a large-scale multi-task learning stage between language model pre-training and fine-tuning. (Gunel et al., 2021) introduce a contrastive learning objective for
the fine-tuning. (Mosbach et al., 2021) propose a strategy to make the fine-tuning of BERT-based models more stable. (Phang et al., 2018) introduced intermediate task fine-tuning which involves fine-tuning a language model on an auxiliary task before continuously training on the target task and achieves significant improvement on GLUE benchmark by intermediate fine-tuning on MNLI dataset. (Pruksachatkun et al., 2020) observes that the tasks requiring high-level inference and reasoning abilities are the best choice as intermediate tasks. (Vu et al., 2020) identifies the best auxiliary tasks for high performance on downstream tasks. (Vu et al., 2021) use NLI as auxiliary task to generate synthetic NLI data for intermediate fine-tuning. Our method is close to intermediate task fine-tuning, however, we use the fine-tuned generative language model to generate synthetic data instead of training directly for the downstream tasks.

8 Conclusion and Future Work

In this paper, we propose to train generative language models to be context generators for a given question and answer. To facilitate this, we use question answer as a format and utilize QA datasets for intermediate training of generative language models. We view sentiment and topic classification tasks in question-answer template and generate context using our fine-tuned generative language models. These generated contexts are used as synthetic training data and is augmented to the few shot supervision to train a classifier. Extensive experiments on multiple sentiment and topic classification datasets demonstrate superior performance of our method in few-shot and zero-shot settings. In the future, we are interested in extending it to other NLP tasks such as Natural language inference and Named entity recognition.

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A  Appendix

A.1 Experiments with a validation set

We perform experiments with a validation set. Since large validation sets are impractical in few-shot settings (Oliver et al., 2018), we consider the validation set to be of same size as the few-shot training set i.e. 8 annotated samples per label. In the experiments with validation set, we perform early stopping based on validation set performance. We present experimental results on few-shot setting with validation set in Table 7. We seldom observe significant improvement upon introducing the validation set. This is because a small validation set which is of same size as few-shot supervision is not large enough to tune the hyperparameters.

A.2 Target Task Datasets

The details of target task datasets are as follows:

• IMDb: (Maas et al., 2011) is a movie review dataset with positive and negative as sentiments.

• Yelp: is a collection of reviews written by Yelp users with five fine-grained sentiment ratings.

• SST-2: (Socher et al., 2013) is a binary sentiment classification dataset with single sentence texts.

• Yahoo: (Zhang et al., 2015) is a topic classification dataset with question and answer pairs. Using these pairs, the task is to predict their corresponding topic.

• The New York Times (NYT): contains news articles written and published by The New York Times that are classified into 5 wide genres.

• AGNews: (Zhang et al., 2015) is a topic categorization dataset in news domain from AG’s corpus.

The size of test sets is mentioned in Table 8.

A.3 Examples of Generated Training Data

Table 9 shows a few examples of synthetic training data corresponding to IMDb and AGNews datasets generated by our method with all QA datasets.

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4https://www.yelp.com/dataset/
Table 7: Evaluation Results with validation set.

| Method               | IMDb    | Sentiment | SST-2    | NYT     | Yahoo   | AGNews  |
|----------------------|---------|-----------|----------|---------|---------|---------|
|                      | Mi-F1   | Ma-F1     | Mi-F1    | Ma-F1   | Mi-F1   | Ma-F1   |
| BERT-FT              | 68.7±0.6| 68.5±0.6 | 38.3±2   | 38.1±2  | 36.3±3  | 36.3±3  |
| ITFT-MNLI            | 66.2±3  | 64.6±3   | 35.3±7   | 35.3±7  | 33.3±5  | 33.3±5  |
| ITFT-SQuAD           | 61.1±0  | 59.7±0   | 34.0±3   | 34.0±3  | 31.4±4  | 31.4±4  |
| BackTranslation      | 67.4±0  | 66.9±0   | 36.4±4   | 36.4±4  | 34.6±4  | 34.6±4  |
| Pegasus              | 66.2±3  | 65.3±3   | 32.5±7   | 32.5±7  | 32.5±7  | 32.5±7  |
| EDA                  | 63.3±2  | 61.6±4   | 32.5±7   | 30.8±2  | 30.8±2  | 30.8±2  |
| BERT-GPT2            | 71.8±2  | 71.1±2   | 38.0±3   | 36.0±3  | 36.0±3  | 36.0±3  |

Table 8: Dataset statistics.

| Dataset  | # Test Examples |
|----------|-----------------|
| IMDb     | 25000           |
| Yelp     | 50000           |
| SST-2    | 2211            |
| Yahoo    | 60000           |
| NYT      | 10582           |
| AGNews   | 114000          |
| Dataset | Label | QA Dataset | Generated Text |
|---------|-------|------------|----------------|
| IMDb   | good  | SQuAD      | the film was first screened in the United Kingdom and Ireland in June 1985, where it received generally favourable reviews. |
|        |       | NewsQA     | I love that "Babylon 5" has a story in the form of an animated television show. When the first "Babylon" appeared on the VHS channel, I was a kid. |
|        |       | TweetQA    | This is a fantastic film, and I loved the trailer. You may know me and you may also know a friend of mine, so I can totally see the #JessicaLewis tweet. |
|        |       | SocialIQA  | Skylar went to the movies and saw a good movie. |
|        |       | CosmosQA   | This is one of my favorite movies of all time because the movie was made way back in the 80s and the dialogue is pretty hilarious. |
| AGNews | sports| SQuAD      | This document is about sports, and details the general aspects of the sport. It lays out the sport’s rules, and sets out the objectives and common grounds upon which the sport is based. |
|        |       | NewsQA     | (CNN) – When the Cincinnati Bengals and New England Patriots played at a stadium on Friday night, an audience of about 2 million people was in tow, and those people weren’t the only ones enjoying the game. |
|        |       | TweetQA    | It’s a football document and I want to make sure all our fans know #fbtampa. Thanks for the #baltimorebubnnnnnnnnn |
|        |       | SocialIQA  | Carson got the ball in their possession after scoring a goal in the soccer match. |
|        |       | CosmosQA   | We just played a nice game, and I thought we’d be better off if they could come up with a good plan to do it. We did have a little time, however, and we’d have a chance to score and give the ball back, but it just never worked out. |