

Generative Data Augmentation using LLMs improves Distributional Robustness in Question Answering

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Abstract

Robustness in Natural Language Processing continues to be a pertinent issue, where state of the art models under-perform under naturally shifted distributions. In the context of Question Answering, work on domain adaptation methods continues to be a growing body of research. However, very little attention has been given to the notion of domain generalization under natural distribution shifts, where the target domain is unknown. With drastic improvements in the quality and access to generative models, we answer the question: How do generated datasets influence the performance of QA models under natural distribution shifts? We perform experiments on 4 different datasets under varying amounts of distribution shift, and analyze how "in-the-wild" generation can help achieve domain generalization. We take a two-step generation approach, generating both contexts and QA pairs to augment existing datasets. Through our experiments, we demonstrate how augmenting reading comprehension datasets with generated data leads to better robustness towards natural distribution shifts.

1 Introduction

Natural language processing has seen substantial progress over the last few years owing to the emerging abilities of pre-trained language models. In many benchmarks, large pre-trained models adapted to a target dataset reach or even surpass human performance. However, very often these models fail to generalize to changing test distributions.

Through this work, we perform a systematic study of how "in-the-wild" generation can affect the distributional robustness of question-answering models trained on the popular Stanford Question Answering Dataset (SQUAD) (Rajpurkar et al., 2016). Synthetic data generation is a widely

adopted method for domain adaptation in QA systems (Shakeri et al., 2020) (Yue et al., 2021) (Yue et al., 2022). However, domain adaptation methods have access to unlabelled/labelled data belonging to the target domain, and do not account for unseen natural distribution shifts. Our work studies the effect of generated data on distribution shifts where the target domain is unseen.

The conception of a dataset has undergone significant evolution in recent times. This transformation has been catalyzed by the advent of generative models trained 'in-the-wild', such as those described in (Brown et al., 2020), (Bubeck et al., 2023), and (Touvron et al., 2023). These models, which utilize vast and diverse datasets across a range of domains, have facilitated the infusion of the web with synthesized data of high calibre, applicable to an extensive array of conceptual topics. Interestingly, these models are not merely confined to generation based on a pre-established distribution; they possess the capacity for repeated prompting, resulting in the creation of markedly diverse data. In the context of this emerging model paradigm, our research investigates the following query: How do generated datasets affect the distributional robustness of Question Answering models? Specifically, we focus on *Natural Distribution Shifts*, where the test distribution is naturally occurring (Wang et al., 2021), where robustness can be defined around model's performance under distribution shift.

We present an overview of our generation setup in Figure 1. For generating data, utilize GPT-3.5 (Brown et al., 2020), and create a question-answering dataset using questions provided in the SQUAD (Rajpurkar et al., 2016) dataset. We use a dual generation approach, by first prompting the language model to generate a context for a question given in the SQUAD dataset, and then generating question-answer pairs for the newly generated context.

As the prevalence of generative AI continues to

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grow, it is anticipated that vast quantities of synthesized data will be utilized directly for machine learning model training. It is crucial to acknowledge, however, that there currently exists a scarcity of standardized evaluation and critique methods for such datasets. The generation of data unveils an array of unique opportunities and obstacles, thus warranting a more comprehensive evaluation process. Therefore, as a key part of our research, we present SQUAD-G, a question-answering dataset derived from generated data. This dataset will be made accessible to the public, facilitating straightforward and replicable benchmarking, alongside the assessment of the utility and critique of generated datasets, thus ensuring reliable and trustworthy natural language processing.

OUR CONTRIBUTIONS

- ▶ We propose a framework to improve the distributional robustness of reading comprehension models in the presence of natural distribution shifts.
- ▶ Through a thorough quantitative evaluation, we evaluate the capabilities of LLMs to generate high quality synthetic data for question answering tasks.
- ▶ We release a new dataset to benchmark further work on evaluating models trained on generated data.

2 Related Work

2.1 Distribution Shift in NLP

(Ramponi and Plank, 2020) provide a comprehensive survey of domain adaptation and generalization problems in NLP, dividing methods into *data centric* and *model centric*. In our work, we adopt a data centric approach towards domain generalization. (Wang et al., 2022) note that there is often a significant overlap in test-train data for QA models, and SOTA models often fail to perform well on questions that cannot be memorized from training data. This motivates our work to create diverse datasets for training and evaluation. This work also highlights the scarcity of research done for generalization in QA models, especially for natural distribution shifts. (Arora et al., 2021) outline the several different kinds of out-of-distribution data in NLP, and highlight the need to better benchmark performance on these samples.

2.2 Robustness in Question Answering

(Longpre et al., 2019) performed one of the first experiments towards domain agnostic question answering using data augmentation techniques that

utilize pretrained models. (Miller et al., 2020) introduce three new datasets for QA models, constructed from New York Times articles, Reddit Posts, and Amazon Product Reviews. This is the first comprehensive study analyzing the effect of natural distribution shift on QA models. Our work builds on this by utilizing these datasets to evaluate our data augmentation method. Furthermore, (Miller et al., 2020) conduct an extensive evaluation of the robustness of different model and adaptation methods under 15 distribution shifts in question answering. However, they do not explore new methods that incorporate better generalization in QA models. (Liu et al., 2021) highlight similar challenges in open domain question answering, breaking down the root causes towards failure. Our work is grounded in extractive question answering, and aims to be the first study that studies the effects of creating datasets using large language models for downstream QA tasks.

2.3 Generalization using Generated Data

(Gowal et al., 2021) demonstrate how generated data conditioned on the training set can lead to adversarial robust models, while (Bartolo et al., 2021) create synthetic data to improve adversarial robustness in QA models. Our work confirms and extends this hypothesis for QA models specifically for natural distribution shifts. More recently, context generation has been used as a data augmentation for text classification (Mekala et al., 2022) and information retrieval (Su et al., 2022). Our work "instructs" (Wei et al., 2022) a GPT-3.5 model to generate a context for a given question. Along similar lines, (Bansal and Grover, 2023) demonstrate how Stable Diffusion¹ can be used to create diverse datasets for image classification. We leverage the generation capabilities of large language models to generate diverse datasets for downstream tasks, that can be inferred using smaller models.

3 Methodology

3.1 Context Generation

We first generate contexts by conditioning it on a question present in the SQUAD dataset. This allows the language model to generate a paragraph that can be used to generate question-answer pairs. Since the paragraph is generated using an existing question, the generated context is consistent with the informative trivia format of SQUAD-like

¹<https://github.com/CompVis/stable-diffusion>

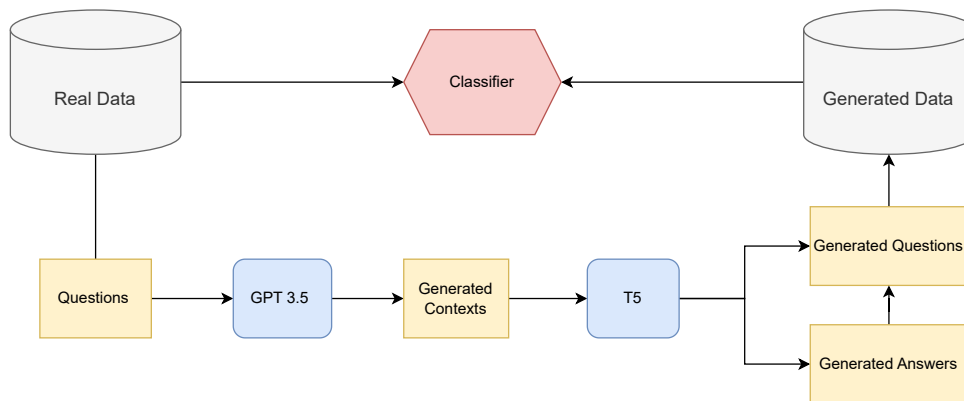


Figure 1: Overview of the generation system. Our method creates a generated dataset which is then augmented with the real dataset to train a question answering model.

datasets. To maintain further consistency, the generated context is clipped to be within 250 words, based on the average context length present in the SQUAD dataset. We prompt GPT 3.5 (gpt-3.5-turbo)² in the following manner: *Generate a paragraph which answers the following question: (question)*. Here the question is sampled from the SQUAD dataset. Figure 1 demonstrates the generation process. Additionally, the Appendix A contains examples from the generation process.

3.2 Question Answer Generation

After the context is created, the generated paragraph is used to create question-answer pairs. This is done by using a T5 based question generation model (Lopez et al., 2020) that is trained on the SQUAD dataset, which takes a paragraph as an input and returns a question-answer pair. We use the open source³ implementation for this model. Additionally we also filter out QA pairs based on round-trip consistency (Alberti et al., 2019).

4 Experiments

4.1 Setup

We train an extractive reading comprehension model using SQUAD V1.1, using the RoBERTA-Base model across all our experiments. We use a learning rate of $3e - 5$, a batch size of 16 and run our experiments for 3 epochs each. We use the implementation provided by HuggingFace, and run our models on a stand-alone Nvidia A100 GPU provided by Google Colab. We do not use GPT-3.5 as a baseline since the purpose of this study is to specifically measure the performance by smaller models.

²<https://platform.openai.com/docs/models>

³<https://github.com/patil-suraj/question-generation>

For all our experiments, we measure F1 and Exact Match scores to quantify performance on Natural Distribution Shift (NDS) datasets.

4.2 Datasets

We use the following datasets created by (Miller et al., 2020) to set up our test bed:

The **New Wikipedia** dataset contains newer QA pairs from wikipedia articles used by the SQUAD V1.1 dataset. Contains 7938 test samples from 48 contexts. The **New York Times** dataset contains articles from New York times which are then used to annotate QA pairs in the same format as SQUAD. It is ensured that the passage length statistics stay the same. Contains 10,065 test samples from 46 articles. **Reddit** dataset contains articles from Reddit where the authors concatenated each post’s title with its body. This dataset contains 9,803 test samples from 1969 posts. The **Amazon Product Reviews** dataset contains user generated product reviews from the "Home and Kitchen" category on Amazon. This data contains 9,885 test samples from 1909 reviews.

5 Results

5.1 Does generated data help with distributional robustness?

We evaluate the F1 and Exact Match scores of models trained with different datasets on natural distribution shifts (NDS) benchmarks. We note the average EM and F1 numbers across three random seeds in Table 1. The models are trained on an equal amount of real and generated data.

We find that the model, when trained on SQUAD, when subjected to natural distribution shift datasets, the model’s performance significantly deteriorates. A noteworthy observation was that exclusive train-

Dataset	SQUAD		NewWiki		NYT		Amazon		Reddit	
Metrics	F1	EM	F1	EM	F1	EM	F1	EM	F1	EM
Real data	90.4	83.0	89.4	79.2	86.4	76.1	79.9	66.4	80.1	67.1
Generated data	79.5	64.6	80.1	65.3	76.5	63.2	72.4	59.5	72.7	60.2
Real + Generated data	92.7	84.7	91.1	80.4	88.9	79.3	80.3	67.1	81.7	68.7

Table 1: Performance on natural distribution shift datasets.

Dataset	SQUAD		NewWiki		NYT		Amazon		Reddit	
Metrics	F1	EM	F1	EM	F1	EM	F1	EM	F1	EM
Real + 50% Generated data	91.4	81.1	90.4	82.2	87.4	77.1	79.7	65.4	80.3	67.4
Real + 100% Generated data	92.7	84.7	91.1	80.4	88.9	79.3	80.3	67.1	81.7	68.7
Real + 200% Generated data	92.9	84.8	91.3	80.7	88.5	79.1	80.9	67.3	80.8	68.1

Table 2: Performance on varying amounts of generated data.

ing on the generated data resulted in substandard performance on both the SQUAD and its Natural Distribution Shift (NDS) datasets. The inferior absolute performance could be potentially attributed to the distribution disparity between the source and the generated training datasets. Interestingly, we observe that for the model trained on the generated data, the performance gaps on the real validation dataset and its NDS datasets are low, which might be attributed to the benefits of training on diverse generated data.

Across all experiments, we note that the performance decrease is slightly less pronounced across the New York Times test set, which resembles the Wikipedia based training set in SQUAD most closely. Similarly, it is not surprising that the performance drop is substantial on user generated noisy datasets like Amazon Reviews and Reddit posts.

Finally, we expose our model to an evenly-distributed blend of real and generated datasets, with the goal of investigating the impact of generative augmentations. Our results reveal that the absolute performance of the model, when trained with a combination of real and generated data, either parallels or exceeds the performance of models trained exclusively on either real or generated datasets, across all naturally distributed datasets. This observation suggests that the incorporation of real data into the training process is indeed essential for attaining superior absolute performance.

To summarize, while using solely generated data improves robustness at the expense of absolute performance, a blend of real and artificially generated data presents the ideal balance for robust and precise training.

5.2 How much generated data is needed?

Here, we investigate how different combinations of the generated dataset can help the classifiers take advantage of the complementary strengths of the two data sources (Table 2).

To do so, we assessed the average performance of models trained with three different input mixing combinations created by using 50%, 100%, and 200% of the generated dataset. We observed an increase in performance on shifted datasets as the size of the generated data increases while keeping the amount of real data fixed. However, when the proportion of the generated data increases twofold while keeping the proportion of the real data fixed, we observe that the performance gains are only marginal. Additionally, we note that using only half of the generated data does not provide enough meaningful signal in terms of diversity and does not lead to major performance improvements compared to training on real data.

Overall, we found that the ideal split between real and generated data is a 50-50 split where the two datasets are able to compliment each other, in terms of providing both diversity and in-domain samples at the same time.

6 Conclusion and Future Avenues

We created a framework that enhances the performance of reading comprehension models by supplementing real datasets with a diverse dataset generated by contemporary, real-world generative models. Our findings indicate that this training method yields superior results on test datasets and those with natural distribution shifts, due to the added

robustness from training on the generated data as opposed to traditional methods. We studied how varying amounts of generated data impact these patterns. We found that data generated by large, current language models prove more effective for developing sturdy models in Natural Language Processing (NLP). Our work also suggests a positive trend towards using high-quality synthetic data to train smaller, specialized models. In the future, we want to explore a more extensive comparison against question generation methods and how this paradigm fits into fine-tuning larger language models.

7 Limitations

The development of robust question answering models using synthetic data derived from modern large language models (LLMs) demonstrates a notable progression in the field of generative AI for trustworthy machine learning (ML). However, this study does not delve into other vital facets such as fairness and privacy. The primary focus of our methodology is to generate data from a large language model in a zero-shot fashion for topics that are adequately encapsulated within its range. Nonetheless, it becomes essential to fine-tune the base model for distributions that aren't sufficiently represented in its training data. In spite of these limitations, the central contributions of this paper continue to hold substantial value and offer key insights for advancing the positive influence in the realm of trustworthy ML.

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Frequently Asked Questions (FAQs)

* How are we sampling questions to generate paragraphs?

► One question is sampled per context in the original SQUAD dataset to condition the paragraph generation.

* Why don't we generate new contexts from scratch?

► This is done to create topically consistent datasets, and run a controlled experiment where only determine whether LLM generated contexts provide linguistic and stylistic diversity.

* Why don't we prompt GPT-3/3.5/4 to generate QA pairs as well?

► In our attempts to do so, we realised that GPT prompts do not generate outputs that stay faithful to the extractive nature of the SQUAD dataset. Furthermore, we wanted to limit our API usage.

A Appendix: Example Generations

This section provides supplementary material in the form of additional examples to bolster the reader’s understanding of the concepts presented in this work.

Original Context	The American bison is a large bovid which inhabited much of western North America prior to the 1800s, living on the prairies in large herds. However, the vast herds of bison attracted market hunters, who killed dozens of bison for their hides only, leaving the rest to rot. Thousands of these hunters quickly eliminated the bison herds, bringing the population from several million in the early 1800s to a few hundred by the 1880s. Conservation efforts have allowed the population to increase, but the bison remains near-threatened.
Sampled Question	"What type of creature is the American bison?"
Prompt	Generate a paragraph that answers the following question: "What type of creature is the American bison?"
Generated Context	The American Bison, often colloquially referred to as buffalo, is a North American species of bison that once roamed across the vast expanses of the continent in large herds. These colossal creatures are mammals, belonging to the family Bovidae, which includes other large, hooved mammals such as domestic cattle and goats. Adult bison are imposing creatures; they are known to stand up to 6.5 feet tall at the shoulder and can weigh over a ton, making them the heaviest land animals in North America. They have a robust body structure with a large, muscular hump over the shoulders and a shaggy, dark brown winter coat which gets lighter in the summer. Their large heads sport a pair of short, sharp horns, used both for defense and in fights for status within the herd. Despite their bulk, bison are surprisingly agile and fast, capable of reaching speeds up to 35 mph. The American Bison plays a crucial role in maintaining the health and biodiversity of the prairie ecosystem.
Generated Questions	Q: To which species does the term "buffalo" colloquially refer in North America? A: American Bison, Q: How does the American Bison use its horns? A: for defense and in fights for status within the herd

Table 3: Example #1 – Context, Question, and Answer Generation.

Original Context	Exhibitions and annual horse shows in all districts and a national horse and cattle show at Lahore are held with the official patronage. The national horse and cattle show at Lahore is the biggest festival where sports, exhibitions, and livestock competitions are held. It not only encourages and patronises agricultural products and livestock through the exhibitions of agricultural products and cattle but is also a colourful documentary on the rich cultural heritage of the province with its strong rural roots.
Sampled Question	"What is Punjab’s biggest festival?"
Prompt	Generate a paragraph that answers the following question: "What is Punjab’s biggest festival?"
Generated Context	Punjab’s biggest festival is Baisakhi, also known as Vaisakhi, celebrated with great fervor and enthusiasm in the region. It’s a significant festival for the Punjabi people and is observed annually on the 13th or 14th of April. Baisakhi is not only a harvest festival, marking the time when farmers reap their rabi (winter) crops, but it also has deep religious significance, particularly for Sikhs. It commemorates the formation of the Khalsa Panth, a Sikh political and military group, by Guru Gobind Singh Ji in 1699. The day is marked by visiting gurdwaras, participating in processions, dancing the traditional Bhangra and Gidda, and sharing meals in the community. The joyous festival is a celebration of culture, heritage, and communal unity, encapsulating the vibrant spirit of Punjab.
Generated Questions	Q: When is Baisakhi observed? A: annually on the 13th or 14th of April, Q: Why is Baisakhi significant for farmers? A: a harvest festival, marking the time when farmers reap their rabi (winter) crops

Table 4: Example #2 – Context, Question, and Answer Generation.

Original Context	In Canada, the Royal Newfoundland Constabulary was founded in 1729, making it the first police force in present-day Canada. It was followed in 1834 by the Toronto Police, and in 1838 by police forces in Montreal and Quebec City. A national force, the Dominion Police, was founded in 1868. Initially the Dominion Police provided security for parliament, but its responsibilities quickly grew. The famous Royal Northwest Mounted Police was founded in 1873. The merger of these two police forces in 1920 formed the world-famous Royal Canadian Mounted Police.
Sampled Question	"When did Canada get its first police?"
Prompt	Generate a paragraph that answers the following question: "When did Canada get its first police?"
Generated Context	The first policing institution in Canada was established in the early 19th century. The Royal Newfoundland Constabulary, founded in St. John's, Newfoundland in 1729, is considered the oldest civil law enforcement body in North America. However, it primarily served as a paramilitary unit, dealing with the city's disorderly sailors and soldiers. Later, the North-West Mounted Police (NWMP), which is often seen as the direct predecessor to the current Royal Canadian Mounted Police (RCMP), was formed on May 23, 1873. The establishment of the NWMP marked a significant shift in the approach to law enforcement in Canada, transitioning from a military-style model to a community-focused approach. The NWMP, and later the RCMP, played a crucial role in establishing the rule of law across Canada, particularly in the west and north during the periods of rapid expansion and development in the late 19th and early 20th centuries.
Generated Questions	Q: What is the oldest civil law enforcement body in North America? A: The Royal Newfoundland Constabulary, Q: Which organization is seen as the direct predecessor to the Royal Canadian Mounted Police? A: the North-West Mounted Police

Table 5: Example #3 – Context, Question, and Answer Generation.

Original Context	The Earth of the early Archean (4,000 to 2,500 million years ago) may have had a different tectonic style. During this time, the Earth's crust cooled enough that rocks and continental plates began to form. Some scientists think because the Earth was hotter, that plate tectonic activity was more vigorous than it is today, resulting in a much greater rate of recycling of crustal material. This may have prevented cratonisation and continent formation until the mantle cooled and convection slowed down. Others argue that the subcontinental lithospheric mantle is too buoyant to subduct and that the lack of Archean rocks is a function of erosion and subsequent tectonic events.
Sampled Question	"During what time period was the Archean era?"
Prompt	Generate a paragraph that answers the following question: "During what time period was the Archean era?"
Generated Context	The Archean Eon, one of the four principal eons of Earth's geologic time scale, occurred approximately 4.0 to 2.5 billion years ago. It follows the Hadean Eon and precedes the Proterozoic Eon. The Archean era is divided into four geologic time periods, known as eras: the Eoarchean, Paleoarchean, Mesoarchean, and Neoarchean. This time period was crucial in Earth's history as it saw the formation of the planet's crust and the development of the earliest forms of life. Despite the extreme conditions, with high temperatures and a lack of oxygen, early life forms such as cyanobacteria began to emerge, which eventually played a role in shaping the Earth's atmosphere by producing oxygen through photosynthesis.
Generated Questions	Q: What eon follows the Hadean Eon and precedes the Proterozoic Eon? A: The Archean Eon, Q: Despite what conditions did early life forms begin to emerge during the Archean Eon? A: the extreme conditions, with high temperatures and a lack of oxygen

Table 6: Example #4 – Context, Question, and Answer Generation.