Is GPT-3 a Good Data Annotator?

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Abstract

GPT-3 (Generative Pre-trained Transformer 3) is a large-scale autoregressive language model developed by OpenAI, which has demonstrated impressive few-shot performance on a wide range of natural language processing (NLP) tasks. Hence, an intuitive application is to use it for data annotation. In this paper, we investigate whether GPT-3 can be used as a good data annotator for NLP tasks. Data annotation is the process of labeling data that could be used to train machine learning models. It is a crucial step in the development of NLP systems, as it allows the model to learn the relationship between the input data and the desired output. Given the impressive language capabilities of GPT-3, it is natural to wonder whether it can be used to effectively annotate data for NLP tasks. In this paper, we evaluate the performance of GPT-3 as a data annotator by comparing it with traditional data annotation methods and analyzing its output on a range of tasks. Through this analysis, we aim to provide insight into the potential of GPT-3 as a general-purpose data annotator in NLP.

1 Introduction

Large language models, like GPT-3 (Brown et al., 2020), have shown impressive performance on multiple NLP tasks. However, the direct use of GPT-3 for inference in a production setting is not practical due to its large size, which leads to slow inference and challenges in scaling due to its high cost. Moreover, such large language models often lack the flexibility of local deployment, since their parameters are usually not publicly available. As a result, it is often more feasible to use smaller language model models, such as BERT_{BASE} (Devlin et al., 2019), in production environments.

Though large language model-based prompt learning has attracted increasing interest in recent years, training/fine-tuning base-sized or even smaller models on human annotated data is still the most prevalent approach in practice for production. Data annotation is the process of labeling data to help machine learning models better understand the purpose of any given task (Liu et al., 2016; Rogers, 2021), recognize patterns and make predictions (Tan et al., 2022). There are many different approaches of data annotation, including assigning numerically values to data instances, categorizing data into predefined classes, providing additional context or information about the data (Sang and Meulder, 2003; Zhang et al., 2015; Ding et al., 2021a), and so on. Annotated data plays a critical role in a wide range of downstream tasks, including natural language processing (Deng et al., 2009; Ardila et al., 2019), image and video recognition (Russakovsky et al., 2014; Agrawal et al., 2015), and self-driving cars (Sun et al., 2019). By providing high-quality annotated data, researchers and developers can help machine learning models make more accurate and reliable predictions.

However, data annotation can be a costly endeavor, particularly for individuals or small and medium-sized enterprises (SMEs). The cost of data annotation typically includes the labor costs associated with the labeling process, as well as the time and resources required to hire, train and manage annotators. Additionally, there may be costs associated with the annotation tools and infrastructure needed to support the annotation process. Individuals or SMEs may have limited resources/budgets for data annotation, which can make it challenging to invest in the necessary labor and technology.

GPT-3 (Brown et al., 2020) is a powerful large language model developed by OpenAI. Its knowledge can be transferred to downstream tasks through knowledge distillation (Kim et al., 2022). Evaluations show that GPT-3 has gained a surpris-

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ingly wide range of domain-specific knowledge through its pretraining on massive corpus. Some examples are presented in Appendix A.1. Meanwhile, due to the model architecture and pretraining tasks designed for auto-regressive generation, GPT-3 is capable of generating human-like text and performing a wide range of NLP tasks, such as machine translation, summarization, and questionanswering. Thus, we would like to explore the potential of using GPT-3 to democratize artificial intelligence (AI) for individuals and SMEs. One way that GPT-3 might help individuals or SMEs is by enabling them to annotate data for machine learning model training, without requiring specialized in-domain knowledge. This could enable more individuals or SMEs to benefit from the advances of AI. Additionally, GPT-3 could help significantly reduce the time and resources required for data annotation, which could allow individuals or SMEs to focus more the key business problems. Democratizing AI (Garvey, 2018) through the development of large language models like GPT-3 can level the playing field for individuals or SMEs, giving them the opportunity to harness the power of AI to drive their businesses forward.

In this paper, we conduct extensive experiments to evaluate the performance, time and cost-effectiveness of 3 different GPT-3 based data annotation approaches for both text and token-level NLP tasks. Our main contributions can be summarized as follows:

- To the best of our knowledge, we are the first to conduct comprehensive analysis on the feasibility of leveraging GPT-3 for data annotation.
- We study 3 different GPT-3 based data annotations approaches, and then conduct extensive experiments both text and token-level NLP tasks to evaluate their performance.
- We find generation-based methods are more costeffective to utilize GPT-3 compared with directly annotating unlabeled data.

2 Related Work

Large Language Models Large Language Models (LLMs) have made significant progress on natural language processing tasks in recent years. These models are trained with self-supervision on large, general corpora and demonstrate excellent performance on numerous tasks (Brown et al., 2020; Rae et al., 2021; Taylor et al., 2022; Hoffmann et al.,

2022; Black et al., 2022; Zhang et al., 2022; Chowdhery et al., 2022; Thoppilan et al., 2022). LLMs possess the ability to learn in context through fewshot learning (Brown et al., 2020; Ouyang et al., 2022). Their capabilities expand with scale, and recent research has highlighted their ability to reason at larger scales with an appropriate prompting strategy (Lester et al., 2021; Wei et al., 2022; Chowdhery et al., 2022; Liu et al., 2021c; Kojima et al., 2022; Lewkowycz et al., 2022).

Prompt-Learning Prompt-Learning, also known as Prompting, offers insight into what the future of natural language processing (NLP) may look like (Lester et al., 2021; Liu et al., 2021c; Ding et al., 2021c). By mimicking the process of pre-training, prompt-learning intuitively connects pre-training and model tuning (Liu et al., 2021d). In practice, this paradigm has proven remarkably effective in low-data regimes (Scao and Rush, 2021; Gao et al., 2021). For instance, with an appropriate template, zero-shot prompt-learning can even outperform 32-shot fine-tuning (Ding et al., 2021b). Another promising characteristic of prompt-learning is its potential to stimulate large-scale pre-trained language models (PLMs). When applied to a 10B model, optimizing prompts alone (while keeping the parameters of the model fixed) can yield comparable performance to full parameter fine-tuning (Lester et al., 2021). These practical studies suggest that prompts can be used to more effectively and efficiently extract knowledge from PLMs, leading to a deeper understanding of the underlying principles of their mechanisms.

Data Augmentation There has been a significant amount of research in the natural language processing (NLP) community on learning with limited labeled data for various tasks, including unsupervised pre-training (Devlin et al., 2019; Peters et al., 2018; Yang et al., 2019; Raffel et al., 2019; Liu et al., 2021b), multi-task learning (Glorot et al., 2011; Liu et al., 2017), semi-supervised learning (Miyato et al., 2016), and few-shot learning (Deng et al., 2019; He et al., 2021; Qin and Joty, 2022). One approach to address the need for labeled data is through data augmentation(Chen et al., 2021; Feng et al., 2021), which involves generating new data by modifying existing data points using transformations based on prior knowledge about the problem's structure (Yang et al., 2020). The augmented data can be generated from labeled data (Ding et al., 2020; Liu et al., 2021a) and used directly in supervised learning (Wei and Zou, 2019) or employed in semi-supervised learning for unlabeled data through consistency regularization (Xie et al., 2019).

3 Methodology

We study 3 different approaches to utilize GPT-3 for data annotation: 1) prompt-guided unlabeled data annotation; 2) prompt-guided training data generation; 3) dictionary-assisted training data generation.

3.1 Prompt-Guided Unlabeled Data Annotation (PGDA)

The first approach involves the creation of prompts to guide GPT-3 in annotating unlabeled data. To this end, task-specific prompts are designed to elicit labels from GPT-3 for a given set of unlabeled data, which has been derived from human-labeled datasets by removing the existing labels. In cases where GPT-3 produces differing labels for the same unlabeled data, the labeling process is resolved through voting based on human labeling criteria. The resulting GPT-3-labeled data is then used to train a local model to predict human-labeled test data, with the performance of this model being evaluated. The cost of this method is monitored for comparison purposes.

3.2 Prompt-Guided Training Data Generation (PGDG)

The second approach is to utilize GPT-3 to autonomously generate labeled data for the specified task. This method involves the creation of prompts that guide GPT-3 to self-generate labeled data, which is subsequently utilized to train a local model to predict human-labeled test data for the purpose of evaluating performance. The cost of this approach is also monitored for the purpose of making a fair comparison.

3.3 Dictionary-Assisted Training Data Generation (DADG)

The third approach is similar to the second approach, with the primary distinction being the incorporation of Wikidata¹ to guide GPT-3 in generating labeled data within the corresponding domain. The

resulting Wikidata-guided GPT-3-generated data is then utilized to train a local model to predict human-labeled test data for the purpose of evaluating performance. As with the previous methods, the cost of this approach is also monitored for the purpose of making a fair comparison.

4 Experiments

4.1 Experiment Settings

In this study, we conducted thorough experiments on two crucial tasks: Text Classification (Sentence Level Task) and Named Entity Recognition (Token Level Task). For the Text Classification task, we selected the SST2 dataset (Socher et al., 2013), a well-known dataset comprising movie reviews. For Named Entity Recognition, we chose the AI domain split from the CrossNER dataset (Liu et al., 2020), which is the most difficult domain within the dataset and more closely mirrors real-world scenarios with its 14 entity types. To simulate the realworld scenario of using GPT-3 to annotate training data in the production setting, we assume that the user has access to the off-shelf GPT-3 API. In all our experiments, we use the latest GPT-3 model: text-davinci-003. In addition, we assume that the user uses BERT_{BASE} for production and has access to a few data points and Wikidata for each task. When evaluating the performance of different methods, we performed fine-tuning of BERT_{BASE} on the SST2 task with corresponding data for 32 epochs with early stopping, as well as on the Cross-NER task with corresponding data for 100 epochs with early stopping. After model fine-tuning, we evaluated the model on the human-labeled gold test data for each task to assess the quality of annotated data produced by the different approaches.

4.2 Sentence-Level Task

In this paper, the SST2 dataset is utilized for sentence-level text classification experiments. Future research will extend to more sentence-level tasks.

PGDA A subset of 10 gold data points was randomly selected from the train set of the SST2 dataset to construct a prompt template, as illustrated in Figure 2. The prompt was then utilized to guide the GPT-3 model in generating sentiment labels for unlabeled data, which were appended to the bottom of the prompt. Following post-processing to reformat the labeled data generated by GPT-3

Ihttps://www.wikidata.org/wiki/Wikidata:
Main_Page

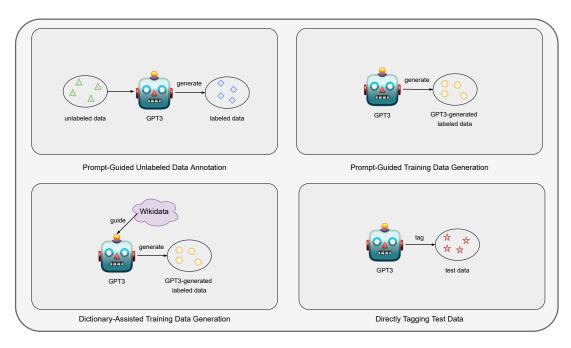


Figure 1: Illustration of proposed different methods.

Choose the sentiment of the given text from Positive and Negative.

Text: a feast for the eyes **Sentiment:** Positive

•••

Text: boring and obvious Sentiment: Negative
Text: [Unlabeled Data]

Sentiment:

Figure 2: An example of prompt-guided unlabeled data annotation for SST2.

into the SST2 format, a BERT $_{\rm BASE}$ model is then fine-tuned using the resulting data.

PGDG In this investigation, utilizing PGDG for the SST2 dataset is explored. The ability of GPT-3 to perform zero-shot generation is tested by providing a simple prompt for the model to generate sentences with a specified sentiment, as depicted in Figure 3. As with PGDA, the resulting data is then post-processed and reformatted into the SST2 format before being used to fine-tune a BERT $_{\rm BASE}$ model.

DADG In this investigation, utilizing DADG for the SST2 dataset is explored. The ability of GPT-3 to perform Wikidata-guided zero-shot generation is tested by providing several entities in Wikidata from the movie domain and a simple prompt for the model to generate sentences with a specified

Write 10 different movie reviews with positive sentiments with no more than 20 words.

Sentiment: Positive

Text:

Figure 3: An example of prompt-guided data generation for SST2.

Write a movie review with the given entity with negative sentiment in no more than 30 words.

Entity: [Movie Name] **Sentiment:** Negative

Text:

Figure 4: An example of dictionary-assisted data generation for SST2.

sentiment, as depicted in Figure 2. As with PGDA, the resulting data is post-processed and reformatted into the SST2 format before being used to fine-tune a $BERT_{BASE}$ model.

4.3 Token-Level Task

In this paper, the AI domain split in the CrossNER dataset is utilized for token-level task experiments. Future research will extend to more token-level tasks. The AI domain split has 14 entity types, namely product, field, task, researcher, university, programming_language, algorithm, misc, metrics, organisation, conference, country, location, person.

Researcher: A researcher in AI domain is an individual who conducts research and experiments related to Artificial Intelligence and its related fields, such as Machine Learning, Natural Language Processing and Computer Vision. AI researchers often use a variety of methods, such as computer simulations and mathematical models, to develop new algorithms and systems that can solve complex tasks. They also analyze and interpret data to gain insights and identify patterns, create prototypes and test out their theories and ideas in order to develop new AI applications.

Text: Advocates of procedural representations were mainly centered at MIT, under the leadership of Marvin Minsky and Seymour Papert.

Researcher entity: Marvin Minsky; Seymour Papert;

Text: [Unlabeled Data]
Researcher entity:

Figure 5: An example of prompt-guided unlabeled data annotation for CrossNER.

PGDA In order to design the prompts for each entity type, we utilized the approach depicted in Figure 5. For each entity type, we initiated GPT-3 to generate its definition and provided a selection of data (no more than 10-shot) with entities belonging to the specified entity type in the prompt to assist GPT-3 in recognizing entities belonging to the same class within the unlabeled data. To obtain the unlabeled data, we removed all labels from the gold train data of the AI domain split in the CrossNER dataset. It was observed that the same entity may be labeled as different entity types with different prompts. Therefore, we also included an additional prompt, as illustrated in Figure 6, to determine the final entity type for each identified entity. The resulting data was post-processed and reformatted into the CrossNER format before being used to fine-tune a BERT $_{\rm BASE}$ model.

PGDG The process of generating training data for CrossNER using PGDG involves two steps. The first step involves prompting GPT-3 to generate entities for each entity type as shown in Figure 7. Noticed that we used no more than 200 entities for each entity type in our experiments. The sec-

Choose the right entity type from the candidate list for the given entity in the text context.

Text: Advocates of procedural representations were mainly centered at MIT, under the leadership of Marvin Minsky and Seymour Papert.

Entity: Marvin Minsky

Candidate List: product, task, researcher,

university, organisation, person

Entity Type: researcher

•••

Text: [Unlabeled Data]

Entity: [Entity]

Candidate List: [Entity_Type1, Entity_Type2,

Entity_Type3, ...]
Entity Type:

Figure 6: An example of prompt to determine the entity type of an entity.

ond step involves using these generated entities to generate sentences within a specific domain using GPT-3 as shown in Figure 8. In the process of generating sentences, we randomly select a few entities from the generated entities for each sentence. After this process, the resulting data is post-processed and formatted into the CrossNER format, which is then used to fine-tune a BERT $_{\rm BASE}$ model.

DADG Similar to PGDG, the process of generating training data for CrossNER using DADG involves two steps. The first step involves querying Wikidata to get the entities of each entity type. Similar to PGDG, we used no more than 200 entities for each entity type in our experiments. The second step involves using these generated entities to generate sentences within a specific domain using GPT-3 as shown in Figure 8. In the process of generating sentences, we randomly select a few entities from all the entities for each sentence. After this process, the resulting data is post-processed and formatted into the CrossNER format, which is then used to fine-tune a BERT_{BASE} model.

5 Results and Discussions

5.1 Sentence Level Task

In Table 1, the results of three different approaches are presented. Overall, the labeling approach PGDA demonstrated the highest level of performance among the three options. By labeling the

Researcher: A researcher in AI domain is an individual who conducts research and experiments related to Artificial Intelligence and its related fields, such as Machine Learning, Natural Language Processing and Computer Vision. AI researchers often use a variety of methods, such as computer simulations and mathematical models, to develop new algorithms and systems that can solve complex tasks. They also analyze and interpret data to gain insights and identify patterns, create prototypes and test out their theories and ideas in order to develop new AI applications.

Researcher: David Silver, Fei-Fei Li, Claude Shannon, Marvin Minsky, Ruslan Salakhutdinov Generate 15 different researchers in the AI domain.

Researcher:

- 1. David Silver
- 2. Fei-Fei Li
- 3. Claude Shannon
- 4. Marvin Minsky
- 5. Ruslan Salakhutdinov

6.

Figure 7: An example of prompting GPT-3 to generate entities for the type 'Researcher'.

Generate text with all the given entities in the AI domain.

Entities: Entity1_Type: Entity1; Entity2_Type: Entity2; ...
Text:

Figure 8: An example of prompt-guided data generation for SST2.

same 3,000 data points, PGDA achieved a score of 87.75, which was only 0.72 lower than the score of human-labeled data. However, the cost and time required for PGDA were significantly lower than those for human labeling. Utilizing the PGDA approach to annotate 6,000 data points resulted in better performance compared to the human-labeled 3,000 data points, while the cost was approximately 5% of the cost of human labeling. On the other hand, the zero-shot PGDG approach did not perform as well as either PGDA or human-labeled data, due to its lack of in-context learning. Additionally, the DADG approach, which involves generating data with in-domain entities, did not result in better performance. This is because enti-

SST2	Cost (USD)	Time	Results
PGDA (3000)	11.3	22 mins	87.75
PGDA (6000)	22.63	23 mins (multiprocess)	89.29
PGDG (3000)	0.7	7 mins (multiprocess)	78.25
PGDG (6000)	1.5	7 mins (multiprocess)	80.18
DADG (3000)	3.1	24 mins (multiprocess)	73.53
DADG (6000)	6.2	24 mins (multiprocess)	76.66
Human-labeled (3000)	428.6 - 857.1	360 mins	88.47
Directly Tagging	7.33	12 mins	95.77

Table 1: Cost, Time Spending and Results of SST2. 'multiprocess' means multiple threads.

ties are not typically key factors in the sentiment classification task, as most entities are neutral and do not provide additional information relevant to sentiment. Furthermore, since a large portion of the data in SST2 does not contain any entities, the sentences generated using DADG do not follow the same distribution as the test data in SST2, leading to poorer performance. For the purpose of comparison, the results of using GPT-3 to directly tag the test data are also presented. It is suggested that, for small-scale applications, it is practical to use GPT-3 to directly label unlabeled data.

5.2 Token Level Task

In Table 2, the results of three different approaches are presented. It was found that the train data labeling method using PGDA had the lowest performance among the three proposed methods, and it was also the most expensive option for this task. It should be noted that there are only 100 gold train data points in the AI domain split in the CrossNER dataset, and these same 100 data points were labeled using PGDA. However, the cost of labeling these 100 data points was higher than the cost of using the generation approaches to generate 3000 data points. It was observed that GPT-3 was effective at identifying entities in the text, but it may also identify entities that are not of the specified entity type, resulting in incorrect labeling. Additionally, GPT-3 may not accurately identify the boundaries of the entities. These two disadvantages make it impractical to use PGDA for labeling data for named entity recognition (NER) in a production setting, especially when there are multiple entity types.

The PGDG approach was able to achieve a result comparable to the 100 human-labeled gold train data at a lower cost. When utilizing Wikidata, the DADG approach was able to achieve a higher result than PGDG, likely due to its ability to leverage more unique entities and in-domain entities extracted from Wikidata. This shows that the ability to access in-domain entities is crucial for

CrossNER	Cost (USD)	Time	Results
PGDA (100)	15.39	21 mins	23.08
PGDG (1500)	7.78	17 mins (multiprocess)	42.63
PGDG (3000)	13.56	33 mins (multiprocess)	41.35
DADG (1500)	6.77	20 mins (multiprocess)	46.90
DADG (3000)	13.61	40 mins (multiprocess)	47.22
Human-labeled (100)	35.71 - 42.85	60 mins	42.00
Directly Tagging	63.23	20 mins (multiprocess)	46.65

Table 2: Cost, Time Spending and Results of Cross-NER. 'multiprocess' means multiple threads.

creating high-quality training data for NER.

6 Conclusions

In this study, we evaluated the effectiveness of GPT-3 as a data annotator on text classification and named entity recognition tasks using three main approaches. Our findings showed that GPT-3 performs best on text classification tasks when directly tagging test data due to its large-scale pre-training, but may not perform as well on more complex tasks like NER. Prompt-guided or dictionary-assisted training data generation may be more effective and cost-efficient for these tasks.

In future research, we plan to analyze the factors that impact the quality of data annotation using GPT-3 and explore whether there are more universal approaches that can be applied. We also intend to expand the scope of our study to include more challenging tasks such as relation extraction, natural language inference and question answering, and potentially investigate the use of GPT-3 for data annotation in natural language generation tasks and low-resource languages. Another potential direction is to compare the annotation ability between ChatGPT and GPT-3. Our overall goal is to better understand the capabilities and limitations of using LLM like GPT-3 for data annotation and identify potential areas for improvement in this field.

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A Appendix

A.1 Examples in Specific Domains

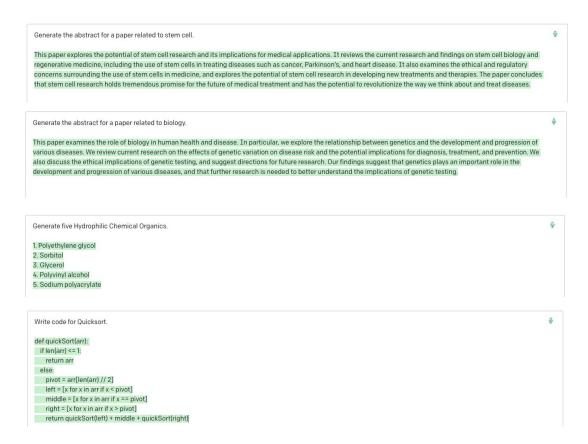


Figure 9: Some examples showing that GPT-3 has access to knowledge in specific domains.