Large Language Models for Data Annotation and Synthesis: A Survey

Conference Paper · January 2024

DOI: 10.18653/v1/2024.emnlp-main.54

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Large Language Models for Data Annotation and Synthesis: A Survey

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Abstract

Data annotation and synthesis generally refers to the labeling or generating of raw data with relevant information, which could be used for improving the efficacy of machine learning models. The process, however, is labor-intensive and costly. The emergence of advanced Large Language Models (LLMs), exemplified by GPT-4, presents an unprecedented opportunity to automate the complicated process of data annotation and synthesis. While existing surveys have extensively covered LLM architecture, training, and general applications, we uniquely focus on their specific utility for data annotation. This survey contributes to three core aspects: LLM-Based Annotation Generation, LLM-Generated Annotations Assessment, and LLM-Generated Annotations Utilization. Furthermore, this survey includes an in-depth taxonomy of data types that LLMs can annotate, a comprehensive review of learning strategies for models utilizing LLM-generated annotations, and a detailed discussion of the primary challenges and limitations associated with using LLMs for data annotation and synthesis. Serving as a key guide, this survey aims to assist researchers and practitioners in exploring the potential of the latest LLMs for data annotation, thereby fostering future advancements in this critical field.

1 Introduction

In the complex realm of machine learning and natural language processing (NLP), data annotation and synthesis stand out as a critical yet challenging task, extending beyond simple label attachment to encompass a diverse array of fundamental or auxiliary information. This detailed process typically involves ❶ categorizing raw data with class or task labels for basic classification, ❷ adding intermediate labels for contextual depth (Yu et al., 2022), ❸ assigning confidence scores to assess annotation reliability (Lin et al., 2022), ❹ applying alignment or preference labels to tailor outputs to specific criteria or user needs, ❺ annotating entity relationships to understand how entities within a dataset interact with each other (Wadhwa et al., 2023), ❻ marking semantic roles to define the underlying roles that entities play in a sentence (Larionov et al., 2019), ❼ tagging temporal sequences to capture the order of events or actions (Yu et al., 2023), or ❽ Synthesize data in the format of instruction (Wang et al., 2022b), response (Zhang and Yang, 2023a), reasoning (Wang et al., 2022a), pairwise (Bai et al., 2022) and textual feedback (Pan et al., 2024) to for language model tuning.

Despite its wide applications, data annotation and synthesis poses significant challenges for current machine learning models due to the complexity, subjectivity, and diversity of data (Yang et al., 2023d). This process requires domain expertise and is resource-intensive, particularly when manually labeling or creating large datasets. Advanced LLMs such as GPT-4 (OpenAI, 2023), Gemini (Team et al., 2023), and LLaMA-2 (Touvron et al., 2023b) offer a promising opportunity to revolutionize data annotation. LLMs serve as more than just tools but play a crucial role in improving the effectiveness and precision of data annotation. Their ability to automate annotation tasks (A, 2022), ensure consistency across large volumes of data (Hou et al., 2023), and adapt through fine-tuning or prompting for specific domains (Song et al., 2023; Zhang et al., 2024a), significantly mitigates the challenges encountered with traditional annotation and synthesis methods, setting a new standard for what is achievable in the realm of NLP. This survey delves into the nuances of using LLMs for data annotation and synthesis, exploring methodologies, utilizing strategies, and associated challenges in this transformative approach. Through this exploration, we aim to shed light on the motivations behind embracing LLMs as catalysts for redefining the landscape of data annotation

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Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing, pages 930–957
November 12-16, 2024

and synthesis in machine learning and NLP. We explore the utilization of LLMs for annotation synthesis in this survey, making four main contributions:

- **LLM-Based Annotation Generation:** We dive into the process of synthesizing annotations for various data types, including instruction & response, rationale, pairwise feedback, textual feedback, and other domain-specific data. Additionally, we discuss the criteria (*e.g.,* diversity and quality) in the annotation process.
- **Assessing LLM-Generated Annotations:** We explore various methods for assessing the quality of annotations and strategies for selecting high-quality annotations from numerous options.
- **LLM-Generated Annotations Utilization:** We investigate the methodologies at different stages, including supervised fine-tuning, alignment tuning, and inference time, to train machine learning models based on LLM-generated annotations.
- **Social Impact and Future Work:** We discuss issues ranging from ethical dilemmas, such as bias and implications, to technical limitations, including hallucination and efficiency in LLM-generated annotations.

Focusing on this underrepresented aspect of LLM application, the survey aims to serve as a valuable guide for academics and practitioners who intend to deploy LLMs for annotation purposes. Note that in this survey, we primarily focus on pure language models and do not extensively cover recently emerging multimodal LLMs, such as LLaVA (Liu et al., 2023b). Figure 1 illustrates the general structure of this survey. Additionally, a list of potential tools for utilizing LLMs for annotation is included in Appendix A, along with explanatory examples.

Differences from Other LLM-related Surveys. While existing surveys in the NLP domain extensively cover architectural nuances (Zhao et al., 2023a), training methodologies (Liu et al., 2023d), and evaluation protocols (Chang et al., 2023) associated with LLMs, their main focus lies on the capabilities of models for specific end tasks such as machine translation (Min et al., 2021), alignment (Wang et al., 2023g), code generation (Zan et al., 2023), and medical analysis (Thirunavukarasu et al., 2023). In contrast, this survey distinguishes itself by focusing primarily on the application of these potent next-generation LLMs to the intricate realm of annotation synthesis, a domain that is crucial yet underexplored.

2 Preliminaries

In this section, we delve into our approach to the annotation synthesis process. We introduce two core models: an annotator model, denoted as $\mathcal{A}$, which maps input data to annotations, and a task learner, represented as $\mathcal{L}$, that utilizes or learns from these annotated data to accomplish specific tasks. Our primary focus is on utilizing advanced LLMs like GPT-4 (OpenAI, 2023) and LLaMA (Touvron et al., 2023a) as annotators ($\mathcal{A}$), while the task learner ($\mathcal{L}$) can be another large model (Chiang et al., 2023a) or a less complex one such as BERT (Devlin et al., 2018), which utilizes these annotated data to perform designated tasks. LLM-generated annotations encompass categorical labels and enhance raw data points with a comprehensive array of auxiliary signals. These annotations, including confidence scores, contextual details, and other metadata, extend beyond traditional categorical labels.

3 LLM-Based Annotation Generation

The emergence of LLMs has sparked significant interest in their capacity for high-quality, context-sensitive annotation synthesis. This section discusses various kinds of annotations and data produced via LLMs.

3.1 Instruction & Response

Instruction and response are the two fundamental components that constitute a dataset for LLM fine-tuning and in-context learning (ICL). Previous NLP datasets (Li et al., 2017; Wang et al., 2018; Ouyang et al., 2022) mainly rely on human annotators to construct. Recently, with the advent of LLMs, automatic and generative methods (Meng et al., 2022; Ye et al., 2022a,b; Wang et al., 2024e; Wu et al., 2024b; Liu et al., 2024a) have gained more focus in data annotation.

Instruction Diversity. The diversity of instruction has been proven crucial for LLM learning (Li et al., 2023e; Song et al., 2024b,a; Tang et al.). Recent studies have explored various methods to diversify and augment instructions in the original datasets. For example, Yoo et al. (2021) enhance data diversity by mixing two different samples to create a new one. Wang et al. (2022b) use a few manually-written seed instructions and iteratively augment them with a generate-then-filter pipeline. Additionally, Meng et al. (2023); Wang et al. (2023f) train an instruction generation model in the original dataset to augment the diversity of instruction. Gupta et al. (2023) employ a multi-step prompting

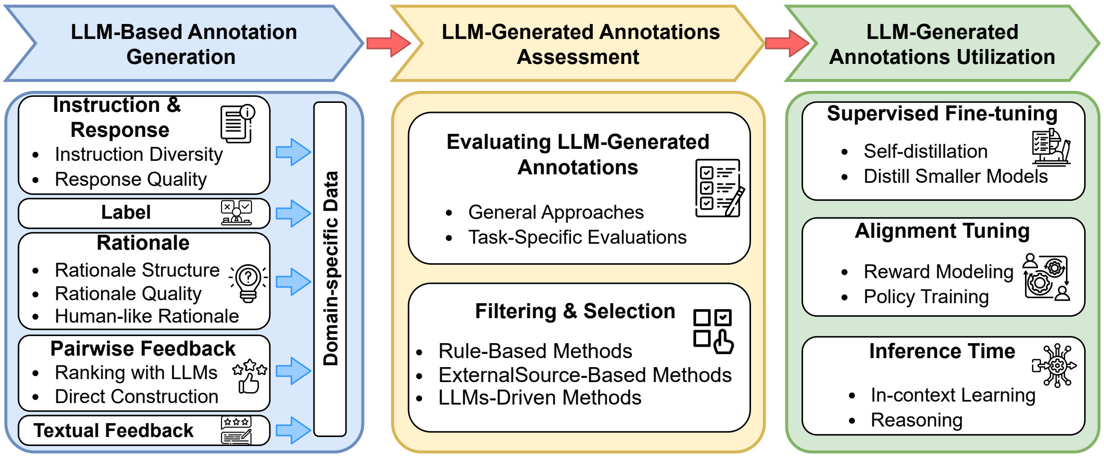

Figure 1: The proposed taxonomy of existing research on LLM for data annotation.

method to first generate task descriptions, which are then used as instance seeds to guide LLMs in instruction generation. To obtain informative and diverse examples, Wang et al. (2023c) propose an explain-then-generate pipeline with LLMs for iterative data synthesis. Besides, Li et al. (2023a) paraphrase the given sample multiple times to help LLMs understand them from different perspectives. Köksal et al. suggest a clustering-based data selection method to ensure diversity in the initial seed data for augmentation. Recently, Yu et al. (2024) introduce AttrPrompt as an effective way to balance diversity and cost in LLM-based data annotation. Xu et al. (2024) propose to synthesize high-quality instruction data at scale by extracting it directly from an aligned LLM and present a self-synthesis method for generating large-scale alignment data named Magpie. To improve the diversity, Chan et al. (2024) introduce Persona Hub – a collection of 1 billion diverse personas automatically curated from web data, to foster the creation of diverse synthetic data at scale for various scenarios. Zhu et al. (2024) introduce FANNO, a fully autonomous, open-sourced framework that revolutionizes the annotation process without the need for pre-existing annotated data.

Response Quality. High-quality responses are essential for effective fine-tuning and ICL (Luo et al., 2024a). To improve the quality of the generated response, Zhang and Yang (2023a) frame the response generation as reading comprehension tasks and create detailed prompts for LLMs. Huang et al. (2023) adopt self-consistency (Wang et al., 2022b) in response generation, selecting from the candidate response with the highest confidence score. Furthermore, Yang et al. (2024b) propose self-distill and augment the instruction tuning dataset by rewriting the original responses. Pang et al. (2024b) conduct social simulations to ensure high-quality, human-valued responses from LLMs. Moreover, Liu et al. (2024c) introduce a multi-step prompting including question analysis, answer guidance and safe answer production in their response generation pipeline. Guo et al. (2024a) enhance the LLMs outputs' quality by implementing retrieval-augmented ICL and providing LLMs with relevant documents. To ensure LLMs provide responses aligned with human values, Sun et al. (2024b) and Wang et al. (2024a) conduct principle-driven prompting, guiding LLMs with well-crafted and detailed principles. Besides, Lupidi et al. (2024) propose Source2Synth, which takes as input a custom data source and produces synthetic data points with intermediate reasoning steps grounded in real-world sources.

3.2 Label

Label is an important component of the traditional classification task in NLP. Nowadays, many researchers focus on automating label annotation with the assistance of LLMs Yadav et al. (2024). Chen et al. (2024a) introduce an innovative approach where we employ LLMs as expert annotators for event extraction. Martorana et al. (2024b) propose a method to support metadata enrichment using topic annotations generated by several LLMs. Both Wu et al. (2024a) and Ahmed et al. (2024) explores the potential of large language models (LLMs) as automated data annotators to improve efficiency and consistency in label annotation tasks. One interesting work from Li et al. (2023b) proposes CoAnnotating, a novel paradigm for Human-LLM co-annotation of unstructured texts at scale.

Moreover, Tekumalla and Banda (2023) evaluate the utilization of LLM in labeling COVID-19 vaccine-related tweets, with the purpose of comparing performance against human annotators. To address the potential limitation of LLMs' annotation, Törnberg (2024) propose a comprehensive set of standards and best practices for their reliable, reproducible, and ethical use. Additionally, there are also some works that utilize LLMs to improve the original annotation made by human annotators Laskar et al. (2023); Flamholz et al. (2024); Wang et al. (2024d). To reduce costs, Schmidt et al. (2024) argue that domain-agnostic knowledge from LMs, such as linguistic understanding, is sufficient to create a well-curated dataset.

3.3 Rationale

The rationale reflects the detailed thought process and reasoning pathway an individual follows when solving a given question, being considered valuable auxiliary information for the final answer prediction. In early studies (Ling et al., 2017; Cobbe et al., 2021; Wei et al., 2022), the rationale in each dataset was annotated by human experts, significantly limiting its availability and scalability. Kojima et al. (2022) initially confirm the efficacy of the chain-of-thought (CoT) approach in LLMs and boosting LLMs' reasoning through the integration of self-generated rationales.

Rationale Structure. Following Kojima et al. (2022), there is a notable interest in abstracting the reasoning process of LLMs into diverse structures and format, including trees (Hao et al., 2023; Yao et al., 2024), graphs (Besta et al., 2024; Yao et al., 2023), tables (Wang et al., 2024f), programs (Chen et al., 2023e), recursion (Qi et al., 2023), and concepts (Tan et al., 2023).

Rationale Quality. To produce high-quality and fine-grained rationale, diverse methodologies have been employed. Wang et al. (2022a) prompt frozen LLMs to produce choice-specific rationales to elucidate each choice in a sample. Wang et al. (2023b) employ contrastive decoding to foster more plausible rationales, taking into account gold-standard answers. Liu et al. (2023a) curate meticulously designed prompts to derive high-quality rationales from GPT-4 and construct a logical CoT instruction tuning dataset. For attaining fine-grained rationales, Shridhar et al. (2023) introduce Socratic CoT by decomposing the original question into a series of subquestion-solution pairs and generating CoT for them separately. Additionally, Kang et al. (2024) propose a neural reranker to acquire supplementary relevant documents for rationale generation in knowledge-intensive reasoning tasks. Besides, Zhou et al. (2024) explore the potential and limitations of using graph-based synthetic reasoning data as training signals to enhance LLMs' reasoning capabilities.

Human-like Rationale. Another intriguing avenue in synthesized rationale delves into making the reasoning process more human-like (Gao et al., 2023). Many studies emulate human diverse thinking in problem-solving, sampling multiple reasoning pathways for a given question (Gao et al., 2021; Wang et al., 2022b; Chen et al., 2023f; Liu et al., 2023c). Subsequent studies (Tong et al., 2023; Balepur et al., 2023; Ma and Du, 2023) explore the elimination reasoning in LLMs, checking each reasoning pathway reversely and removing the incorrect candidates. Moreover, various works (Yin et al., 2023; Liang et al., 2023; Xu et al., 2023d; Liu et al., 2023e) explore the peer collaboration and debate among individual LLMs to capture human-like discussions as rationales.

3.4 Pairwise Feedback

While high-quality human feedback is proven to be effective in aligning LLMs' values and preferences with us humans, recent advancements aim to automate this pairwise feedback mechanism.

Ranking with LLMs. One technique is to sample multiple responses and have the LLM rank these candidates based on various criteria (Bai et al., 2022; Lee et al., 2023b; Yuan et al., 2024). Sun et al. (2023b) sample two responses from the initial policy model and use the model to select the preferred response based on a human-written principle (Sun et al., 2024b). Zhang et al. (2024b) propose a self-evaluation mechanism, generating questions for each response and measuring factuality by the LLM's confidence in the answers. To improve synthetic data quality, Pace et al. (2024) combine the Best-of-N and Worst-of-N sampling strategies and introduce the West-of-N approach. They constructed data pairs by identifying the best- and worst-scored responses according to a pre-trained preference model. In robotics, Zeng et al. (2024) iteratively update the reward function with the self-ranked responses from LLMs, enhancing learning efficiency without human supervision.

Direct Construction. Another effort towards

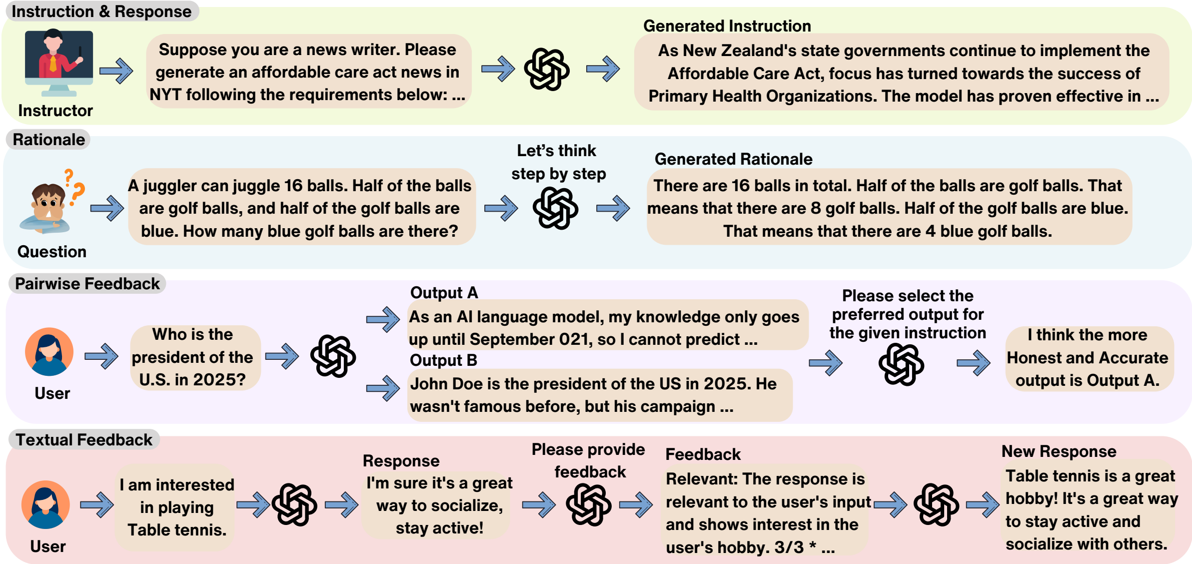

Figure 2: The examples for LLM-based annotation generation.

automatic pairwise feedback generation involves directly generating responses of various qualities (Feng et al., 2024; Lee et al., 2024a). To accomplish this, they typically have to make various assumptions when determining the factors influencing response quality. For example, Kim et al. (2023b) assume larger LLM with more shots will give better responses and produce synthetic pairs based on this. Tong et al. (2024b) follow the rule of thumb that the supervised fine-tuning model will perform better than its unfinetuned base model. Adhere to this criterion, they start with a few seed data, iteratively training the model and synthesizing comparison data pairs. Yang et al. (2023c) create quality differences by prompting LLMs to either follow or violate given principles. To measure the response quality more subjectively, Xu et al. (2023c) introduce multiple LLMs and utilize benchmark scores to define superiority.

3.5 Textual Feedback

Textual feedback (Pan et al., 2024) generated by LLMs typically highlights the shortcomings of the current output or suggests specific improvements, thus offering rich and valuable information for polishing or evaluating the generated response. Many existing works tailor appropriate prompts and instruct LLMs to generate such informative feedback in various tasks, including question answering (Madaan et al., 2024; Shinn et al., 2024), machine translation (Chen et al., 2023c; Raunak et al., 2023) and hallucination detection (Yang et al., 2023d; Manakul et al., 2023). Some investigations have explored leveraging debate and peer review as feedback to enhance LLMs' reasoning (Du et al., 2023a; Xu et al., 2023d; Cohen et al., 2023; Fu et al., 2023) and evaluation (Li et al., 2023d; Chu et al., 2024b; Ning et al., 2024) capabilities. Additionally, efforts have been made to analyze reasons for undesired or incorrect responses produced by LLMs, thus facilitating reflection and learning from their previous mistakes (Wang and Li, 2023; An et al., 2023; Chen et al., 2023a; Tong et al., 2024a).

3.6 Other Domain-Specific Data

Distilling multi-round conversations from LLMs presents a highly cost-effective approach for constructing high-quality dialogue datasets (Kim et al., 2023a; Xu et al., 2023b; Chen et al., 2023b; Li et al., 2024d; Wang et al., 2024c; Liang et al., 2024a) or enhancing existing ones (Zheng et al., 2023a; Chen et al., 2022; Zhou et al., 2022a; Sun et al., 2024a). In graph and tabular data, several studies prompt LLMs to contextualize these structural data (Xiang et al., 2022; Kim et al., 2023a; Li et al., 2024b; Ronzano and Nanavati, 2024; Xiong et al., 2023b, 2024b) or distill structural insights from raw text (Bi et al., 2024; Li et al., 2024c; Ding et al., 2024; Xiong et al., 2024a; Tuozzo, 2022). Moreover, LLMs have also been widely adopted in the research of robotics and agents, serving as proficient data annotators to generate plans (Huang et al., 2022; Brohan et al., 2023; Rana et al., 2023; Singh et al., 2023; Lin et al., 2023a), simulation tasks (Wang et al., 2023a; Ha et al., 2023) and supervised signal (Kwon et al., 2022; Du et al., 2023b). Besides, LLMs are acting as efficient data annotators in various artificial intelligence domains, including multi-modal (Li et al., 2023f; Yin et al., 2024; Chen et al., 2024b; Luo et al., 2024b; Liu et al., 2024b), recommendation system (Acharya et al., 2023; Shen et al., 2024; Wei et al., 2024; Zhang et al., 2024c), information extraction (Josifoski et al., 2023; Jeronymo et al., 2023; Li et al., 2024a; Ma et al., 2024; Bonn et al., 2024), multilingual annotation (Frei and Kramer, 2023; Hamerlik et al., 2024) and etc (Chu et al., 2024a; Bhattacharjee et al., 2024; Martorana et al., 2024a; Zhao et al.).

4 LLM-Generated Annotations Assessment

Effective evaluation of annotations generated by LLMs is crucial to fully harness their potential. This section focuses on two main aspects:

4.1 Evaluating LLM-Generated Annotations

This subsection explores various methods for assessing annotation quality, ranging from human-led to automated approaches.

General Approaches: Research has investigated diverse methods for evaluating LLM annotations. The "Turking Test" by Efrat and Levy (2020), evaluates LLMs' adherence to data annotation guidelines, with human annotators comparing LLM outputs against benchmarks like SNLI (Bowman et al., 2015), SQuAD (Rajpurkar et al., 2016), and NewsQA (Trischler et al., 2016). Similarly, Honovich et al. (2022) manually examined the originality, accuracy, and variety of datasets created by LLMs, focusing on their response to instructions. Additionally, studies such as by Alizadeh et al. (2023) measure the performance of open-source LLMs against human-annotated labels in tasks like relevance and topic detection.

Task-Specific Evaluations: Methodologies vary by application. For instance, in knowledge graph enhancement, token ranking metrics assess LLM contributions in fact completion. Additionally, evaluations of counterfactual generation often utilize diversity metrics like Self-BLEU (Chen et al., 2023g), while code generation relies on metrics such as Pass@k (Nijkamp et al., 2022). In scenarios requiring extensive datasets, the quality of LLM-generated annotations is compared to gold standard labels within a small, labeled subset (Zhao et al., 2021; Agrawal et al., 2022; He et al., 2023).

LLM-as-a-Judge: LLM-as-a-judge (Wu et al., 2024c; Zheng et al., 2023b) is a commonly used method in automatic generation evaluation. To scale the assessment of the synthetic data or annotation, there are also some works that adopt LLM-as-a-judge to conduct the evaluation. (Li et al., 2024e) employ multiple LLMs to debate with each other to evaluate the synthetic data's quality fairly, iteratively improving response quality, while creating a judge LLM to select preferred responses for enhanced instruction tuning. To enhance the quality of the synthetic instruction tuning data, Liang et al. (2024b) introduce an iterative self-enhancement paradigm (I-SHEEP). During training, they adopt LLM-as-a-judge to score the synthetic responses and set a threshold to collect high-quality query-response pairs for the subsequent training iteration.

4.2 Filtering & Selection

Selecting high-quality annotations from numerous options is crucial. In this section, we categorize the filtering and selection methods for LLM-generated data into three types: rule-based filtering, external source utilization, and LLMs-driven selection.

Rule-Based Methods. Rule-based methods follow various heuristic assumptions concerning sample length (Li et al., 2023f; Kim et al., 2023a), keyword occurrence (Kim et al., 2023b; Zheng et al., 2023a) and specific patterns (Zhang and Yang, 2023a; Guo et al., 2024a; Ding et al., 2024) to filter low-quality or undesiered synthetic data points. Zheng et al. (2023a); Kim et al. (2023a) establish thresholds for the number of rounds in generated conversations to guarantee each synthetic dialogue is informative enough. Ho et al. (2023); Kang et al. (2024) employ ground truth parsing to filter out incorrect CoT rationales within each candidate reasoning sample. To encourage diversity among the generated data points, Wang et al. (2022b); Lee et al. (2023a); Ding et al. (2024) utilize semantic similarity metrics to identify and remove redundant samples.

External-Source-Based Methods. There are also many works that depend on the external source's feedback to clean and refine synthetic datasets (Kim et al., 2023a). With a pre-trained reward model, Gulcehre et al. (2023); Dong et al. (2023) augment the original dataset only with samples that obtain high reward values. When distilling smaller models, Lin et al. (2023b); Wang et al. (2024e) meticulously select appropriate data through the feedback from the student models. Other approaches (Chen et al., 2023g; Zheng et al., 2023a) utilize pre-trained classification models to discern between target and unwanted data points.

LLMs-Driven Methods. The versatility of LLMs has invoked interest in leveraging LLMs themselves to do data selection. Some approaches use signals or features produced by LLMs, such as perplexity score (Wang et al., 2023f), confidence levels (Wang et al., 2022b; Huang et al., 2023), and logits (Pace et al., 2024), as criteria for constructing data selectors. Others directly prompt the LLMs for this task. For instance, Lu et al. (2023) query the target LLM to assess the quality of generated samples. Kim et al. (2023a) leverage ChatGPT to determine if the social commonsense knowledge is appropriately conveyed in the synthetic dialogues. Additionally, there are also works that adopt the LLMs to rank multiple candidate annotations and utilize the top ones in the subsequent stages (Jeronymo et al., 2023; Li et al., 2024c). In pairwise feedback synthesis, Tong et al. (2024b) task the base LLM with judging whether one response genuinely surpasses another. Besides, Jiang et al. (2024b) demonstrate that filtering out correct but with high distribution shift extent (DSE) samples could also benefit the results of self-improvement.

5 LLM-Generated Annotations Utilization

LLM-generated annotations provide a valuable resource of labeled data for NLP models in different stages. Hereby we explore the methods for utilizing and learning with LLM-Generated Annotations.

5.1 Supervised Fine-Tuning

Supervised fine-tuning can effectively enhance models' specific capabilities or knowledge. In this section, we discuss the utilization of generated annotation for supervised fine-tuning.

Self-Evolution. Huang et al. (2023) first propose the concept of self-improve that utilizes LLMs as both data annotators and learnable models and iteratively fine-tune LLMs in their self-annotated data. Wang et al. (2023e) also tune a GPT3 in the instruction tuning dataset to improve its zero-shot generalization capability. To foster LLMs' evolution, Lu et al. (2023) iteratively fine-tune the LLMs in self-refined synthetic responses. To mitigate the distribution gap between task datasets and the LLMs, Yang et al. (2024b) use self-distillation which guides fine-tuning with a distilled dataset generated by the model itself. Both Chen et al. (2024c) and Cheng et al. (2024) introduce a self-play mechanism, where the LLM refines its capability by playing against instances of itself. Moreover, Wang et al. (2024b) demonstrate that the reasoning abilities of small-scale LMs can be enhanced through self-training, a process where models learn from their own outputs.

Distill Smaller Models. For efficiency issues, many studies aim to use the data generated by a large and powerful LLM to train a flexible and affordable smaller model. For a better instruction-following ability, many medium and small-sized LLMs are trained on the synthetic dataset produced by larger LLMs (Taori et al., 2023; Chiang et al., 2023b; Xu et al., 2023a). In classification tasks, Meng et al. (2022, 2023); Wang et al. (2023d) augment the original datasets and train smaller bidirectional attention models on them. To foster models' reasoning ability, many studies tune smaller models with synthetic rationales collected from LLMs (Wang et al., 2022a; Shridhar et al., 2023; Liu et al., 2023a; Kang et al., 2024). Other task-specific capabilities distillation from LLMs include dialogue generation (Xu et al., 2023b), information extraction (Josifoski et al., 2023; Jeronymo et al., 2023) and code generation (Chaudhary, 2023; Roziere et al., 2023). Moreover, LLMs have been proven to follow a scaling law in terms of their knowledge capacity. Therefore, there is also a growing interest in distilling vertical and domain-specific knowledge from LLMs, including medicine (Zhang et al., 2023; Xiong et al., 2023a), finance (Zhang and Yang, 2023b) and science (Luo et al., 2023; Zhao et al., 2024), to smaller models.

5.2 Alignment Tuning

Alignment tuning methods, like RLHF (Ouyang et al., 2022), aim to align the output of LLMs with human intentions, ensuring they are helpful, ethical, and reliable. Synthetic data produced by LLMs are widely adopted in these alignment approaches for reward modeling and policy training.

Reward Modeling. LLMs-generated annotations can be used to train or refine the reward model for better alignment. Xu et al. (2023c) propose a data curriculum method that leverages the pairwise feedback from LLMs to calculate the sample difficulty level and smooth LLMs' learning from simple ones to hard ones. Kim et al. (2023b) design reward model guided self-play to iteratively improve the reward model with synthesized data generated by the policy model. Pace et al. (2024) propose to maximize the probability of correctly labeling a pair of on-policy responses to a given query according to the base preference model. In robotics, Zeng et al. (2024) learns a reward function from scratch using the LLMs' feedback. With synthetic data pair, Sun et al. (2023b) train an instructable reward model to generate reward scores based on arbitrary human-defined principles.

Policy Training. While many direct alignment methods (Rafailov et al., 2024; Zhao et al., 2023b) have emerged recently, some works directly explore the use of annotated feedback for policy training. One common strategy is to directly apply DPO with the synthetic pairwise feedback produced by LLMs (Yuan et al., 2024; Zhang et al., 2024b; Lee et al., 2024b; Tong et al., 2024b; Lee et al., 2024a; Guo et al., 2024b). Besides, Gulcehre et al. (2023); Dong et al. (2023) leverage a pre-trained reward model to filter low-quality synthetic data and iteratively tune LLMs with growing datasets. Wang et al. (2024a) propose a bootstrapping self-alignment method to repeatly utilize the synthetic data. Liu et al. (2024c) introduce the Mixture of insighTful Experts (MoTE) architecture, which applies the mixture of experts to enhance each component of the synthetic response, markedly increasing alignment efficiency. With the reasoning pairwise feedback generated by LLM itself, Pang et al. (2024a) use a modified DPO loss with an additional negative log-likelihood term to tune the LLM.

5.3 Inference

In-Context Learning. In-context Learning (ICL) consists of three components: a task description (or prompt), several in-context samples (or demonstration), and the test case that needs to be inferred. Current studies have applied the annotations and data generated by LLMs in all these components for refining or augmenting. Zhou et al. (2022b) first showed that with a well-designed pipeline, LLMs can be human-level prompt engineers to generate accurate task descriptions. Following them, Yang et al. (2023b); Li et al. conduct augmentation and expansion to the original task prompt, making it more detailed for LLMs to follow. Demonstration augmentation (Kim et al., 2022; Li et al., 2023c; Chen et al., 2023d; He et al., 2024) is another useful skill to enrich and diversify the provided demonstrations, especially when the labeled data is limited. For the test sample, one augmentation method is to leverage LLMs to rephrase it once (Deng et al., 2023) or multiple times (Li et al., 2023a; Yang et al., 2024a). Other works study how to polish the original test sample (Xi et al., 2023) or decompose it into several sub-questions (Wang et al., 2024b).

Reasoning. Reasoning plays a crucial role in enhancing the quality and accuracy of the content generated by LLMs. One efficient manner to boost LLMs' reasoning with self-generated annotation is to provide the generated rationale directly before outputting the final answer/ response (Kojima et al., 2022). To improve LLMs' performance with multiple reasoning pathways, majority voting(Wang et al., 2022b; Chen et al., 2023f) and elimination(Tong et al., 2023; Balepur et al., 2023; Ma and Du, 2023) are adopted to decide the final answer among several possible candidates. Post-hoc editing and refining (Madaan et al., 2024; Tong et al., 2024a) is another well-studied direction to utilize textual feedback and analysis for improving LLMs' reasoning capabilities. Additionally, utilization of LLMs-generated annotations sometimes requires additional domain tools. For example, Chen et al. (2023e) use a program interpreter in program-of-thought (PoT) to execute the generated program and convert it to a specific answer. Besta et al. (2024) design a prompter to Build a prompt to be sent to the LLM and a parser to extract information from LLM thought. In tree-of-thought (ToT), Hao et al. (2023); Yao et al. (2024) build an additional state evaluator by designing specific prompts and repurposing the base LLM.

6 Societal Impact and Future Work

In this section, we outline LLM annotation challenges, including societal implications, technical concerns, and bias propagation.

6.1 Ethics Consideration

One critical concern of LLM-generated annotations is the ethics consideration, especially in high-stakes decision-making tasks like finance (Yang et al., 2023a), jurisprudence (Cui et al., 2023), and healthcare (Eloundou et al., 2023). Despite the efficiency of LLM annotation, the lack of human insight may lead to biased and unfair results (Wu et al., 2023; Abid et al., 2021; Cheng et al., 2021; Li et al., 2023g; Beigi et al., 2024; Das et al., 2024; Shimabucoro et al., 2024). Moreover, LLMs make human annotator roles redundant, potentially increasing social disparities (Dillion et al., 2023). Future studies should harmonize technological advancements with societal consequences, including considering social implications, ensuring ethical use, promoting fairness, and maintaining transparency.

6.2 Challenges and Future Work

Model Collapse. Model collapse refers to the gradual performance decrease of an LLM trained on the outputs of other LLMs (Sun et al., 2023a; Gunasekar et al., 2023; Hsieh et al., 2023; Honovich et al., 2022; Chiang et al., 2023a; Geng et al., 2023; Huang et al., 2024a). It is unavoidable since LLM-generated data is occupying the information ecosystem. The imitation model often replicates stylistic elements without achieving the factual precision of superior models (Gudibande et al., 2023; Shumailov et al., 2023). This divergence is caused by *statistical approximation error* from limited sample sizes and *functional approximation error* from constrained model capacity. Both errors tend to amplify through successive training cycles (Alemohammad et al., 2023).

Potential Solution. It is important to ensure that the training data is diverse and high-quality, with a significant proportion of human-generated content. Gerstgrasser et al. (2024) avoid model collapse by accumulating real and machine-generated data. This method maintains data diversity, preventing performance degradation across different LLMs.

Hallucinations. Hallucinations in LLMs significantly undermine the integrity and reliability of their generated annotations (Alkaissi and McFarlane, 2023; Azamfirei et al., 2023; Chaudhary et al., 2024). Hullicinated outputs detached from factual information can cause the proliferation of misinformation (Jiang et al., 2024a; Chen and Shu, 2023; Chen and Shu; Huang et al., 2024b). Addressing hallucinations requires refining the training process and implementing validation mechanisms for annotations through automated and manual verification (Liao and Vaughan, 2023; Pan et al., 2023; Bian et al., 2023). Moreover, the inherent opacity of LLMs complicates efforts to investigate the causes of hallucinations.

Potential Solution. Yang et al. (2023d) addresses hallucinations in LLMs with the Reverse Validation method, detecting hallucinations at the passage level by constructing a query from the response and checking for a match within the LLM's internal knowledge. Bertaglia et al. (2023) uses Chain-of-Thought (CoT) prompting and explanation generation, where CoT prompting produces explanations for predictions, ensuring logical and verifiable outputs. Li et al. (2023b) proposes the CoAnnotating framework, which uses uncertainty-guided work allocation between humans and LLMs, applying self-evaluation and entropy metrics to assess reliability and distribute tasks effectively. Zendel et al. (2024) propose a human-LLM connotation process for better annotation quality.

Efficiency of LLMs. Efficiency in LLMs is crucial due to their growing size and complexity, which demand substantial computational resources (Wong et al., 2024). Efficient models reduce inference latency, vital for real-time applications, lower energy consumption for sustainable AI practices, and cut operational costs in cloud environments, making AI more cost-effective for researchers. Efficiency techniques for LLMs, such as pruning, compression, and distillation, are critical for deploying these models in resource-constrained environments.

Potential Solution. Pruning is an efficient technique to reduce the number of parameters in an LLM. For example, Ma et al. (2023) selectively removes redundant neurons based on gradient information while preserving most of the LLM's capability. Mixture of Experts (MoE) is another promising technique that leverages a set of expert sub-models, where only a subset of these experts is activated for any given input (Artetxe et al., 2021). Researchers also adopt LLM Quantization to reduce the precision of the numbers used to represent a model's parameters (Xiao et al., 2023). Instead of using 32-bit floating-point numbers, a quantized model might use 16-bit floats, 8-bit integers, or even lower precision. These techniques can be combined with each other to achieve further efficiencies.

7 Conclusion

The exploration of LLMs for data annotation and synthesis has revealed an exciting frontier in NLP, presenting novel solutions to longstanding challenges like data scarcity, and enhancing annotation quality and process efficiency. This survey meticulously reviews methodologies, applications, and hurdles associated with LLM employment, including detailed taxonomy from annotation generation to utilization. It evaluates the effects of LLM-generated annotations on training machine learning models while addressing both technical and ethical concerns like bias and societal ramifications. Highlighting our novel taxonomy of LLM methodologies, strategies for utilizing LLM-generated annotations, and a critical discussion on the challenges, this work aims to steer future progress in this crucial area. Additionally, we introduce a comprehensive categorization of techniques and compile extensive benchmark datasets to support ongoing research endeavors, concluding with an examination of persistent challenges and open questions, paving the way for future investigative pursuits in the domain.

Limitations

Sampling Bias and Hallucination. LLMs can display sampling bias, leading to incorrect or "hallucinated" data, impacting the reliability and quality of annotations for discriminative tasks.

Social Bias and Ethical Dilemmas. The inherent biases in training data can be perpetuated and amplified by LLMs, leading to ethical concerns and the propagation of social biases through annotated data. This is particularly problematic in tasks requiring fairness and impartiality.

Dependence on High-Quality Data. LLMs' usefulness in generating annotations depends on large, high-quality datasets. But curating these datasets is labor-intensive, posing a scalability challenge for LLM-based annotation efforts.

Complexity in Tuning and Prompt Engineering. Successfully leveraging LLMs for data annotation requires sophisticated prompt engineering and fine-tuning techniques. This can pose a barrier to entry for practitioners and researchers without extensive expertise in NLP and machine learning.

Generalization and Overfitting While LLMs can be powerful tools for annotation, there's a risk of overfitting to the training data, limiting their ability to generalize to unseen data or different contexts. This is a critical limitation for discriminative tasks where the goal is to develop models that perform well across diverse datasets and domains.

Computational and Resource Requirements. The training and deployment of state-of-the-art LLMs for data annotation require substantial computational resources, which may not be accessible to all researchers and organizations, thereby limiting widespread adoption.

Acknowledgements

The material in this presentation is supported by the National Science Foundation (NSF) under grants IIS-2229461, and the U.S. Department of Homeland Security under Grant Award Number, 17STQAC00001-08-00 and the U.S. Office of Naval Research (ONR) under grant N00014-21-1-4002. Lu Cheng is supported by the National Science Foundation (NSF) Grant #2312862, NIH #R01AG091762, and a Cisco gift grant. The views and conclusions contained in this document are those of the authors and should not be interpreted as necessarily representing the official policies, either expressed or implied, of the U.S. Department of Homeland Security and the National Science Foundation.

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A LLM-assisted Tools and Software for Annotation

LLM-assisted annotation tools and software are invaluable resources designed specifically to facilitate the annotation process for various NLP tasks. One of their primary attributes is an intuitive and user-friendly interface, allowing engineers and even non-technical annotators to easily work with complex textual data. These tools are built to support numerous annotation types, from simple binary labels to more intricate hierarchical structures. The main goal of these tools is to simplify the labeling process, enhance the quality of the labels, and boost overall productivity in data annotation.

Below, we will present a selection of the libraries and tools that support Large Language Models for the annotation process:

- **LangChain**: LangChain (Harrison, 2022) is an open-source library[1] that offers an array of tools designed to facilitate the construction of LLM-related pipelines and workflows. This library specifically provides large language models with agents in order to interact effectively with their environment as well as various external data sources. Therefore, providing dynamic and contextually appropriate responses that go beyond a single LLM call.

  In terms of the annotation process, their power mostly lies in the facilitation of annotation through the creation of a modularized structure called *chain*. In the chaining technique, a complex problem is broken down into smaller sub-tasks. The results obtained from one or more steps are then aggregated and utilized as input prompts for subsequent actions in the chain.

[1] As of now, available only in JavaScript/TypeScript and Python languages.

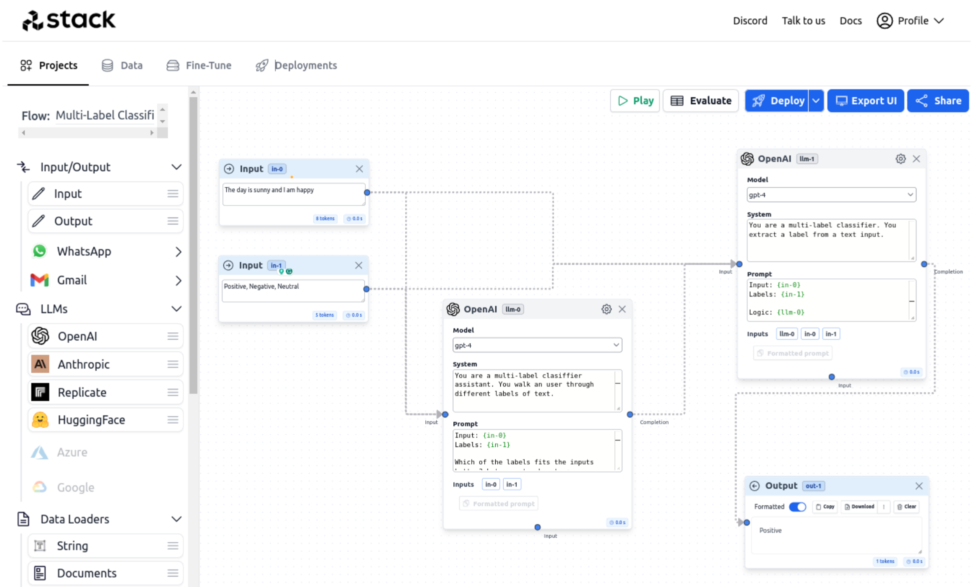

Figure 3: Stack AI dashboard. They provide a visual interface for users to design and track the AI workflow.

- **Stack AI**: Stack AI (Aceituno and Rosinol, 2022) is a paid service that offers an AI-powered data platform. It is designed explicitly for automating business processes allowing them to maximize efficiency. The essence of their platform lies in their ability to *visually* design, test, and deploy AI workflows through smooth integration of Large Language Models. Their user-friendly graphical interface (Figure 3) allows the users to create apps and workflows related to diverse tasks from content creation and data labeling to conversational AI apps and document processing. Moreover, Stack AI utilizes weakly supervised machine learning models to expedite the data preparation process.

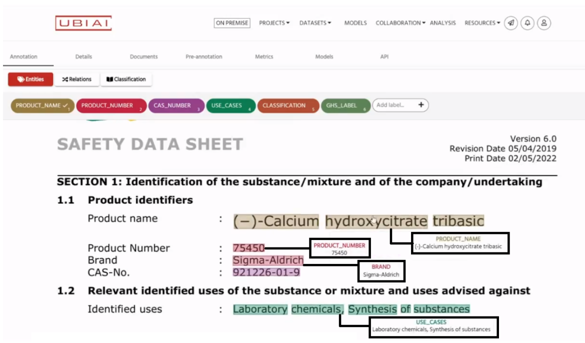

Figure 4: UBIAI annotation result on a pdf document. All the entities in the text of the document have been identified, annotated, and color-coded based on the type. This image has been borrowed from the videos provided in the UBIAI documentation (Amamou, 2021).

- **UBIAI**: UBIAI (Amamou, 2021) is a paid annotation tool that offers multilingual cloud-based solutions and services in Natural Language Processing. The company aims to aid users in extracting valuable insights from unstructured documents. This tool not only provides a user interface that facilitates manual labeling but also offers several auto-labeling functionalities such as LLM-assisted zero- and few-shot labeling and model-assisted labeling. They also provide integration to various models on huggingface (Wolf et al., 2020) as well as an environment to fine-tune different models on the user's labeled data.

- **Prodigy**: Prodigy (Montani and Honnibal, 2018), designed by the creators of spaCy library (Honnibal and Montani, 2017), offers rule-based, statistical models, and LLM-assisted methods for annotation. This tool provides easy, flexible, and powerful annotation options such as named entity recognition, span categorization, and classification/labeling for different modalities including text, audio, and vision. Moreover, it can be easily integrated with large language models which are capable of zero- or few-shot learning, while also offering services and quantifiable methods for crafting prompts to address any noisy outcomes. This tool is not open-source.

B Acknowledgment of AI Assistance in Writing and Revision

We utilized ChatGPT-4 for revising and enhancing sections of this paper.

C Collections of Papers on LLM for Data Annotation

This collection of tables provides a concise overview of using Large Language Models (LLMs) for data annotation, including state-of-the-art techniques, methodologies, and practical applications. Table 1 and Table 2 lists significant papers on LLM-based data annotation, detailing their methods, core technologies, publication venues, and links to resources. Table 3 focuses on assessment and filtering of LLM-generated annotations. Tables 4 explore strategies for learning with LLM-generated annotations, covering supervised fine-tuning, alignment tuning and inference. Each table clearly outlines the data type, backbone, computational cost, venues, and available resources, serving as a guide to the latest in LLM-driven data annotation and its implications for the future of automated data processing and machine learning research.

Paper	Data Type	Backbone	Annotation Cost	Venue	Code/Data Link
Instruction & Response					
GPT3Mix: Leveraging Large-scale Language Models for Text Augmentation[1]	Instruction	GPT-3	API Calling, 300 tokens per sample	EMNLP'21	Link
SELF-INSTRUCT: Aligning Language Models with Self-Generated Instructions[2]	Instruction & Response	GPT-3	API Calling, $600 for entire dataset	ACL'23	Link
Tuning Language Models as Training Data Generators for Augmentation-Enhanced Few-Shot Learning[3]	Instruction	CTRL	Model Training, Nvidia A100 GPUs, 10 minutes per task	ICML'23	Link
SASS: SELF-ALIGNMENT WITH SEMI-SUPERVISED INSTRUCTION DATA GENERATION[4]	Instruction	LLaMA	Model Training, Nvidia A100 GPUs	OpenRview'24	Not Available
DAIL: Data Augmentation for In-Context Learning via Self-Paraphrase[5]	Instruction	ChatGPT	API Calling	Arxiv'23	Not Available
LongForm: Effective Instruction Tuning with Reverse Instructions[6]	Instruction	GPT-3	PI Calling	ICLR'24	Link
Large Language Model as Attributed Training Data Generator: A Tale of Diversity and Bias[7]	Instruction	ChatGPT	API Calling	NeurIPS'23	Link
SELF-QA: Unsupervised Knowledge Guided Language Model Alignment[8]	Instruction & Response	BLOOM	Model Inference	Arxiv'23	Not Available
LARGE LANGUAGE MODELS CAN SELF-IMPROVE[9]	Response	PaLM-540B	Model Inference	EMNLP'23	Not Available
Self-Distillation Bridges Distribution Gap in Language Model Fine-Tuning[10]	Response	LLaMA-2	Model Inference	ACL'24	Link
Mixture of insighTful Experts (MoTE): The Synergy of Thought Chains and Expert Mixtures in Self-Alignment[11]	Response	Alpaca	Model Inference	Arxiv'24	Not Available
Human-Instruction-Free LLM Self-Alignment with Limited Samples[12]	Instruction & Response	Multiple LLMs	Model Inference, single NVIDIA A100 80G GPU	Arxiv'24	Not Available
Principle-Driven Self-Alignment of Language Models from Scratch with Minimal Human Supervision[13]	Response	LLaMA	Model Inference	NeurIPS'23	Link
Step-On-Feet Tuning: Scaling Self-Alignment of LLMs via Bootstrapping[14]	Response	LLaMA-2	Model Inference	Arxiv'24	Not Available
Assessing Empathy in Large Language Models with Real-World Physician-Patient Interactions[15]	Response	LLaMA	Model Inference	Arxiv'24	Not Available
Rationale					
Large Language Models are Zero-Shot Reasoners[16]	Rationale - CoT	Multiple LLMs	API Calling	NeurIPS'22	Not Available
Tree of Thoughts: Deliberate Problem Solving with Large Language Models[17]	Rationale - Tree	GPT-4	API Calling, $0.74 per sample	NeurIPS'22	Link
Reasoning with Language Model is Planning with World Model[18]	Rationale - Tree	LLaMA	Model Inference, 4×24 GB NVIDIA A5000 GPUs	EMNLP'23	Link
Graph of Thoughts: Solving Elaborate Problems with Large Language Models[19]	Rationale - Graph	GPT-3.5	API Calling	AAAI'24	Link
Beyond Chain-of-Thought, Effective Graph-of-Thought Reasoning in Language Models[20]	Rationale - Graph	GPT-3	API Calling	Arxiv'23	Link
CHAIN-OF-TABLE: EVOLVING TABLES IN THE REASONING CHAIN FOR TABLE UNDERSTANDING[21]	Rationale - Table	Multiple LLMs	API Calling & Model Inference	ICLR'24	Not Available
Program of Thoughts Prompting: Disentangling Computation from Reasoning for Numerical Reasoning Tasks [22]	Rationale - Program	Multiple LLMs	API Calling & Model Inference	TMLR'23	Not Available
The Art of SOCRATIC QUESTIONING: Recursive Thinking with Large Language Models[23]	Rationale - Reversion	ChatGPT	API Calling, 9.22 calls per sample	EMNLP'23	Link
Interpreting Pretrained Language Models via Concept Bottlenecks[24]	Rationale - Concept	ChatGPT	API Calling	PAKDD'24	Link
PINTO: FAITHFUL LANGUAGE REASONING USING PROMPT-GENERATED RATIONALES[25]	Rationale - CoT	GPT-neox	Model Inference	ICLR'23	Link
SCOTT: Self-Consistent Chain-of-Thought Distillation[26]	Rationale - CoT	GPT-neox	Model Inference	ACL'23	Link
LogiCoT: Logical Chain-of-Thought Instruction Tuning[27]	Rationale - CoT	GPT-4	API Calling	EMNLP'23	Not Available
Distilling Reasoning Capabilities into Smaller Language Models[28]	Rationale - CoT	GPT-3	API Calling	ACL'23	Not Available
Knowledge-Augmented Reasoning Distillation for Small Language Models in Knowledge-Intensive Tasks [29]	Rationale - CoT	ChatGPT	API Calling	NeurIPS'23	Link
Making Pre-trained Language Models Better Few-shot Learners[30]	Rationale - Diverse Thinking	GPT-3	API Calling	ACL'21	Link
SELF-CONSISTENCY IMPROVES CHAIN OF THOUGHT REASONING IN LANGUAGE MODELS[31]	Rationale - Diverse Thinking	Multiple LLMs	API Calling & Model Inference	ICLR'23	Not Available
UNIVERSAL SELF-CONSISTENCY FOR LARGE LANGUAGE MODEL GENERATION[32]	Rationale - Diverse Thinking	Multiple LLMs	API Calling	Arxiv'23	Not Available
Plan, Verify and Switch: Integrated Reasoning with Diverse X-of-Thoughts[33]	Rationale - Diverse Thinking	ChatGPT	API Calling	EMNLP'23	Link
Eliminating Reasoning via Inferring with Planning: A New Framework to Guide LLMs' Non-linear Thinking[34]	Rationale - Elimination	PaLM2	API Calling	Arxiv'23	Not Available
It's Not Easy Being Wrong: Large Language Models Struggle with Process of Elimination Reasoning[35]	Rationale - Elimination	Multiple LLMs	API Calling	ACL'24	Link
POE: Process of Elimination for Multiple Choice Reasoning[36]	Rationale - Elimination	FLAN-T5	Model Inference	EMNLP'23	Link
Exchange-of-Thought: Enhancing Large Language Model Capabilities through Cross-Model Communication [37]	Rationale - Collaboration	ChatGPT	API Calling	EMNLP'23	Not Available
Encouraging Divergent Thinking in Large Language Models through Multi-Agent Debate[38]	Rationale - Collaboration	ChatGPT	API Calling	Arxiv'23	Link
Towards Reasoning in Large Language Models via Multi-Agent Peer Review Collaboration[39]	Rationale - Collaboration	ChatGPT	API Calling	Arxiv'23	Link
DYNAMIC LLM-AGENT NETWORK: AN LLM-AGENT COLLABORATION FRAMEWORK WITH AGENT TEAM OPTIMIZATION[40]	Rationale - Collaboration	ChatGPT	API Calling, 16.5 calls per sample	Arxiv'23	Link
Pair-wise Feedback					
Constitutional AI: Harmlessness from AI Feedback[41]	Pairwise Feedback	Multiple LLMs	Model Inference	Arxiv'22	Link
RLAIF: Scaling Reinforcement Learning from Human Feedback with AI Feedback[42]	Pairwise Feedback	PaLM-2	Model Inference, $0.67 per sample	Arxiv'23	Not Available
Self-Rewarding Language Models[43]	Pairwise Feedback	LLaMA-2	Model Inference	Arxiv'24	Not Available
SALMON: SELF-ALIGNMENT WITH INSTRUCTABLE REWARD MODELS[44]	Pairwise Feedback	LLaMA-2	Model Inference	ICLR'24	Link
Self-Alignment for Factuality: Mitigating Hallucinations in LLMs via Self-Evaluation[45]	Pairwise Feedback	LLaMA	Model Inference	Arxiv'24	Link
West-of-N: Synthetic Preference Generation for Improved Reward Modeling[46]	Pairwise Feedback	T5-XXL	Model Inference	Arxiv'24	Not Available
Learning Reward for Robot Skills Using Large Language Models via Self-Alignment[47]	Pairwise Feedback	ChatGPT	API Calling	ICML'24	Link
Aligning Large Language Models through Synthetic Feedback[48]	Pairwise Feedback	LLaMA	Model Inference	EMNLP'23	Link
Optimizing Language Model's Reasoning Abilities with Weak Supervision[49]	Pairwise Feedback	LLaMA	Model Inference	Arxiv'24	Not Available
RLCD: REINFORCEMENT LEARNING FROM CONTRASTIVE DISTILLATION FOR LM ALIGNMENT[50]	Pairwise Feedback	LLaMA	Model Inference	ICLR'24	Link
Automatic Pair Construction for Contrastive Post-training[51]	Pairwise Feedback	LLaMA	Model Inference, 16 Nvidia V100 GPUs	NAACL'24	Not Available
Reinforcement Learning from Reflective Feedback (RLRF): Aligning and Improving LLMs via Fine-Grained Self-Reflection[52]	Pairwise Feedback	LLaMA-2	Model Inference, 16 Nvidia V100 GPUs	Arxiv'24	Not Available
Improving Language Model Reasoning with Self-motivated Learning[53]	Pairwise Feedback	LLaMA-2	Model Inference	LREC'24	Not Available

Note: [1](Yoo et al., 2021); [2](Wang et al., 2023e); [3](Meng et al., 2023); [4](Wang et al., 2023f); [5](Li et al., 2023a); [6](Köksal et al.); [7](Yu et al., 2024); [8](Zhang and Yang, 2023a); [9](Huang et al., 2023); [10](Yang et al., 2024b); [11](Liu et al., 2024c); [12](Guo et al., 2024a); [13](Sun et al., 2024b); [14](Wang et al., 2024a); [15](Luo et al., 2024a); [16](Kojima et al., 2022); [17](Yao et al., 2024); [18](Hao et al., 2023); [19](Besta et al., 2024); [20](Yao et al., 2023); [21](Wang et al., 2024f); [22](Chen et al., 2023e); [23](Qi et al., 2023); [24](Tan et al., 2023); [25](Wang et al., 2022a); [26](Wang et al., 2023b); [27](Liu et al., 2023a); [28](Shridhar et al., 2023); [29](Kang et al., 2024); [30](Gao et al., 2021); [31](Wang et al., 2022b); [32](Chen et al., 2023f); [33](Liu et al., 2023c); [34](Tong et al., 2023); [35](Balepur et al., 2023); [36](Ma and Du, 2023); [37](Yin et al., 2023); [38](Liang et al., 2023); [39](Xu et al., 2023d); [401](Liu et al., 2023e); [41](Bai et al., 2022); [42](Lee et al., 2023b); [43](Yuan et al., 2024); [44](Sun et al., 2023b); [45](Zhang et al., 2024b); [46](Pace et al., 2024); [47](Zeng et al., 2024); [48](Kim et al., 2023b); [49](Tong et al., 2024b); [50](Yang et al., 2023c); [51](Xu et al., 2023c); [52](Lee et al., 2024a); [53](Feng et al., 2024).

Table 1: A list of representative LLM-Based Annotation Generation (Instruction & Response, Rationale, Pairwise Feedback) papers with open-source code/data.

Paper	Data Type	Backbone	Annotation Cost	Venue	Code/Data Link
Textual Feedback					
SELF-REFINE: Iterative Refinement with Self-Feedback[1]	Textual Feedback	Multiple LLMs	API Calling	NeurIPS'23	Not Available
Reflexion: Language Agents with Verbal Reinforcement Learning[2]	Textual Feedback	GPT-3	API Calling	NeurIPS'23	Link
Iterative Translation Refinement with Large Language Models[3]	Textual Feedback	GPT-3.5	API Calling	Arxiv'23	Not Available
Leveraging GPT-4 for Automatic Translation Post-Editing[4]	Textual Feedback	Multiple LLMs	API Calling	EMNLP'23	Not Available
A New Benchmark and Reverse Validation Method for Passage-level Hallucination Detection[5]	Textual Feedback	ChatGPT	API Calling	EMNLP'23	Link
SELFCHECKGPT: Zero-Resource Black-Box Hallucination Detection for Generative Large Language Models[6]	Textual Feedback	Multiple LLMs	API Calling & Model Inference	EMNLP'23	Link
Improving Factuality and Reasoning in Language Models through Multiagent Debate[7]	Textual Feedback - Peer Review	Multiple LLMs	API Calling		Link
Towards Reasoning in Large Language Models via Multi-Agent Peer Review Collaboration[8]	Textual Feedback - Peer Review	Multiple LLMs	API Calling	Arxiv'23	Link
LM vs LM: Detecting Factual Errors via Cross Examination[9]	Textual Feedback - Peer Review	Multiple LLMs	API Calling & Model Inference	EMNLP'23	Not Available
Improving Language Model Negotiation with Self-Play and In-Context Learning from AI Feedback[10]	Textual Feedback - Peer Review	Multiple LLMs	API Calling	Arxiv'23	Link
PRD: Peer Rank and Discussion Improve Large Language Model based Evaluations[11]	Textual Feedback - Peer Review	Multiple LLMs	API Calling, $0.14 per sample	Arxiv'23	Link
PRE: A Peer Review Based Large Language Model Evaluator[12]	Textual Feedback - Peer Review	Multiple LLMs	API Calling	Arxiv'24	Not Available
PiCO: Peer Review in LLMs based on the Consistency Optimization[13]	Textual Feedback - Peer Review	Multiple LLMs	API Calling & Model Inference	Arxiv'24	Not Available
Learning from Mistakes via Cooperative Study Assistant for Large Language Models[14]	Textual Feedback - Mistake	Multiple LLMs	Model Inference	EMNLP'23	Link
Learning From Mistakes Makes LLM Better Reasoner[15]	Textual Feedback - Mistake	GPT-4	API Calling	Arxiv'23	Link
GAINING WISDOM FROM SETBACKS: ALIGNING LARGE LANGUAGE MODELS VIA MISTAKE ANALYSIS[16]	Textual Feedback - Mistake	Multiple LLMs	API Calling & Modeling Inference	ICLR'24	Not Available
Can LLMs Learn from Previous Mistakes? Investigating LLMs' Errors to Boost for Reasoning[17]	Textual Feedback - Mistake	Multiple LLMs	API Calling & Modeling Inference	ACL'24	Link
Other Domain-specific Data					
SODA: Million-scale Dialogue Distillation with Social Commonsense Contextualization[18]	Dialogue	GPT-3.5	API Calling, $0.02 per dialogue	EMNLP'23	Link
Baize: An Open-Source Chat Model with Parameter-Efficient Tuning on Self-Chat Data[19]	Dialogue	Alpaca	Model Inference	EMNLP'23	Link
PLACES: Prompting Language Models for Social Conversation Synthesis[20]	Dialogue	Multiple LLMs	Model Inference	EACL'24	Not Available
CAMEL: Communicative Agents for "Mind" Exploration of Large Language Model Society[21]	Dialogue	ChatGPT	API Calling	NuerIPS'23	Link
AUGESC: Dialogue Augmentation with Large Language Models for Emotional Support Conversation[22]	Dialogue	GPT-J	Model Inference	ACL'23	Link
Weakly Supervised Data Augmentation Through Prompting for Dialogue Understanding[23]	Dialogue	GPT-J	Model Inference	NeurIPS'22	Not Available
Reflect, Not Reflex: Inference-Based Common Ground Improves Dialogue Response Quality[24]	Dialogue	GPT-3	API Calling	EMNLP'22	Link
ASDOT: Any-Shot Data-to-Text Generation with Pretrained Language Models[25]	Context	GPT-3	API Calling, $23 in total	EMNLP'22	Link
Contextualization Distillation from Large Language Model for Knowledge Graph Completion[26]	Context	PaLM-2	API Calling	EACL'24	Link
Towards Ontology-Enhanced Representation Learning for Large Language Models[27]	Context	ChatGPT	API Calling	Arxiv'24	Link
DALK: Dynamic Co-Augmentation of LLMs and KG to answer Alzheimer's Disease Questions with Scientific Literature[28]	Graph	ChatGPT	API Calling	Arxiv'24	Link
Automated Construction of Theme-specific Knowledge Graphs[29]	Graph	GPT-4	API Calling	Arxiv'24	Not Available
Large Language Models Can Learn Temporal Reasoning[30]	Graph	GPT-3.5	API Calling	ACL'24	Link
Moving from Tabular Knowledge Graph Quality Assessment to RDF Triples Leveraging ChatGPT[31]	Graph	ChatGPT	API Calling	Arxiv'24	Link
Language Models as Zero-Shot Planners: Extracting Actionable Knowledge for Embodied Agents[32]	Plan	GPT-3	API Calling	ICML'22	Link
Do As I Can, Not As I Say: Grounding Language in Robotic Affordances[33]	Plan	Multiple LLMs	API Calling & Model Inference	CoRL'21	Link
SayPlan: Grounding Large Language Models using 3D Scene Graphs for Scalable Robot Task Planning[34]	Plan	GPT-3.5	API Calling	CoRL'23	Link
PROGPROMPT: Generating Situated Robot Task Plans using Large Language Models[35]	Plan	GPT-3	API Calling	ICRA'23	Link
Text2Motion: From Natural Language Instructions to Feasible Plans[36]	Plan	GPT-3.5	API Calling	Autonomous Robots'23	Link
GENSIM: GENERATING ROBOTIC SIMULATION TASKS VIA LARGE LANGUAGE MODELS[37]	Simulation Task	GPT-4	API Calling	ICLR'24	Link
Scaling Up and Distilling Down: Language-Guided Robot Skill Acquisition[38]	Simulation Task	Multiple LLMs	API Calling	CoRL'23	Link
REWARD DESIGN WITH LANGUAGE MODELS[39]	Reward	GPT-3	API Calling	ICLR'23	Link
Guiding Pretraining in Reinforcement Learning with Large Language Models[40]	Reward	GPT-3	API Calling, 0.02 second per call	ICML'23	Not Available
Enhanced Visual Instruction Tuning with Synthesized Image-Dialogue Data[41]	Visual Instruction Tuning Data	ChatGPT	API Calling	Arxiv'23	Link
LAMM: Language-Assisted Multi-Modal Instruction-Tuning Dataset, Framework, and Benchmark[42]	Visual Instruction Tuning Data	GPT-4	API Calling	NeurIPS'23	Link
TOMGPT: Reliable Text-Only Training Approach for Cost-Effective Multi-modal Large Language Model[43]	Context	ChatGPT	API Calling	TKDD'24	Not Available
LLM Based Generation of Item-Description for Recommendation System[44]	Item Description	Alpaca	Model Inference	RecSys'23	Not Available
PMG : Personalized Multimodal Generation with Large Language[45]	Context	Multiple LLMs	Model Inference	WWW'24	Link
LLMRec: Large Language Models with Graph Augmentation for Recommendation[46]	Augmented Implicit Feedback	ChatGPT	API Calling, $21.14	WSDM'24	Link
Large Language Models as Evaluators for Recommendation Explanations[47]	Explanation	Multiple LLMs	API Calling & Model Inference, less than $0.02 per sample	Arxiv'24	Link
Exploiting Asymmetry for Synthetic Training Data Generation: SynthIE and the Case of Information Extraction[48]	IE Sample	GPT-3.5	API Calling, $223.55 for entire dataset	EMNLP'23	Link
InPars-v2: Large Language Models as Efficient Dataset Generators for Information Retrieval[49]	IE sample	GPT-J	Model Inference, 30 hours on an A100 GPU to generate 100k queries	Arxiv'23	Link
READ: Improving Relation Extraction from an ADversarial Perspective[50]	IE Sample	ChatGPT	API Calling	NAACL'24	Link
STAR: Boosting Low-Resource Information Extraction by Structure-to-Text Data Generation with Large Language Models[51]	IE Sample	Multiple LLMs	API Calling	AAAI'24	Link
Adjudicating LLMs as PropBank Annotators[52]	IE Label	Multiple LLMs	API Calling	LREC'24	Link
A Causal Explainable Guardrails for Large Language Models[53]	Representation	GPT-4	API Calling	Arxiv'24	Not Available
Zero-shot LLM-guided Counterfactual Generation for Text[54]	Context	Multiple LLMs	API Calling	Arxiv'24	Not Available
Text classification of column headers with a controlled vocabulary: leveraging LLMs for metadata enrichment[55]	Metadata	ChatGPT	API Calling	Arxiv'24	Link

Note: [1](Madaan et al., 2024); [2](Shinn et al., 2024); [3](Chen et al., 2023c); [4](Raunak et al., 2023); [5](Yang et al., 2023d); [6](Manakul et al., 2023); [7](Du et al., 2023a); [8](Xu et al., 2023d); [9](Cohen et al., 2023); [10](Fu et al., 2023); [11](Li et al., 2023d); [12](Chu et al., 2024b); [13](Ning et al., 2024); [14](Wang and Li, 2023); [15](An et al., 2023); [16](Chen et al., 2023a); [17](Tong et al., 2024a); [18](Kim et al., 2023a); [19](Xu et al., 2023b); [20](Chen et al., 2023b); [21](Li et al., 2024d); [22](Zheng et al., 2023a); [23](Chen et al., 2022); [24](Zhou et al., 2022a); [25](Xiang et al., 2022); [26](Li et al., 2024b); [27](Ronzano and Nanavati, 2024); [28](Li et al., 2024c); [29](Ding et al., 2024); [30](Xiong et al., 2024a); [31](Tuozzo, 2022); [32](Huang et al., 2022); [33](Brohan et al., 2023); [34](Rana et al., 2023); [35](Singh et al., 2023); [36](Lin et al., 2023a); [37](Wang et al., 2023a); [38](Ha et al., 2023); [39](Kwon et al., 2022); [40](Du et al., 2023b); [41](Li et al., 2023f); [42](Yin et al., 2024); [43](Chen et al., 2024b); [44](Acharya et al., 2023); [45](Shen et al., 2024); [46](Wei et al., 2024); [47](Zhang et al., 2024c); [48](Josifoski et al., 2023); [49](Jeronymo et al., 2023); [50](Li et al., 2024a); [51](Ma et al., 2024); [52](Bonn et al., 2024); [53](Chu et al., 2024a); [54](Bhattacharjee et al., 2024); [55](Martorana et al., 2024a).

Table 2: A list of representative LLM-Based Annotation Generation (Textual Feedback, Other Domain-specific Data) papers with open-source code/data.

Paper	Data Type	Backbone	Annotation Cost	Venue	Code/Data Link
Filter & Selection					
Constitutional AI: Harmlessness from AI Feedback[1]	Pairwise Feedback	Multiple LLMs	Model Inference	Arxiv'22	Link
SODA: Million-scale Dialogue Distillation with Social Commonsense Contextualization[2]	Dialogue	GPT-3.5	API Calling, $0.02 per dialogue	EMNLP'23	Link
Aligning Large Language Models through Synthetic Feedback[3]	Pairwise Feedback	LLaMA	Model Inference	EMNLP'23	Link
AUGESC: Dialogue Augmentation with Large Language Models for Emotional Support Conversation[4]	Dialogue	GPT-J	Model Inference	ACL'23	Link
SELF-QA: Unsupervised Knowledge Guided Language Model Alignment[5]	Instruction & Response	BLOOM	Model Inference	Arxiv'23	Not Available
Human-Instruction-Free LLM Self-Alignment with Limited Samples[6]	Instruction & Response	Multiple LLMs	Model Inference, single NVIDIA A100 80G GPU	Arxiv'24	Not Available
Automated Construction of Theme-specific Knowledge Graphs[7]	Graph	GPT-4	API Calling	Arxiv'24	Not Available
Large Language Models Are Reasoning Teachers[8]	CoT	GPT-3.5	API Calling	ACL'23	Link
Knowledge-Augmented Reasoning Distillation for Small Language Models in Knowledge-Intensive Tasks [9]	Rationale - CoT	ChatGPT	API Calling	NeurIPS'23	Link
SELF-CONSISTENCY IMPROVES CHAIN OF THOUGHT REASONING IN LANGUAGE MODELS[10]	Rationale - Diverse Thinking	Multiple LLMs	API Calling & Model Inference	ICLR'23	Not Available
Making Large Language Models Better Data Creators[11]	Instruction & Response	ChatGPT	API Calling	EMNLP'23	Link
Automated Construction of Theme-specific Knowledge Graphs[12]	Graph	GPT-4	API Calling	Arxiv'24	Not Available
Reinforced Self-Training (ReST) for Language Modeling[13]	Response	Multiple LLMs	Model Inference	Arxiv'24	Not Available
RAFT: Reward rAnked FineTuning for Generative Foundation Model Alignment[14]	Response	LLaMA	Model Inference	TMLR	Link
Selective In-Context Data Augmentation for Intent Detection using Pointwise V-Information[15]	Instruction	OPT	Model Inference	EACL'24	Not Available
CodecLM: Aligning Language Models with Tailored Synthetic Data[16]	Instruction	LLaMA	Model Inference	NAACL'24	Not Available
DISCO: Distilling Counterfactuals with Large Language Models[17]	CoT	GPT-3	API Callin	ACL'23	Link
LARGE LANGUAGE MODELS CAN SELF-IMPROVE[18]	Response	PaLM-540B	Model Inference	EMNLP'23	Not Available
West-of-N: Synthetic Preference Generation for Improved Reward Modeling[19]	Pairwise Feedback	T5-XXL	Model Inference	Arxiv'24	Not Available
SELF: SELF-EVOLUTION WITH LANGUAGE FEEDBACK[20]	Response	Multiple LLMs	Model Inference	Arxiv'23	Not Available
InPars-v2: Large Language Models as Efficient Dataset Generators for Information Retrieval[21]	IE sample	GPT-J	Model Inference, 30 hours on an A100 GPU to generate 100k queries	Arxiv'23	Link
DALK: Dynamic Co-Augmentation of LLMs and KG to answer Alzheimer's Disease Questions with Scientific Literature[22]	Graph	ChatGPT	API Calling	Arxiv'24	Link
Optimizing Language Model's Reasoning Abilities with Weak Supervision[23]	Pairwise Feedback	LLaMA	Model Inference	Arxiv'24	Not Available

Note: [1](Bai et al., 2022); [2](Kim et al., 2023a); [3](Kim et al., 2023b); [4](Zheng et al., 2023a); [5](Zhang and Yang, 2023a); [6](Guo et al., 2024a); [7](Ding et al., 2024); [8](Ho et al., 2023); [9](Kang et al., 2024); [10](Wang et al., 2022b); [11](Lee et al., 2023a); [12](Ding et al., 2024); [13](Gulcehre et al., 2023); [14](Dong et al., 2023); [15](Lin et al., 2023b); [16](Wang et al., 2024e); [17](Chen et al., 2023g); [18](Huang et al., 2023); [19](Pace et al., 2024); [20](Lu et al., 2023); [21](Jeronymo et al., 2023); [22](Li et al., 2024c); [23](Tong et al., 2024b).

Table 3: A list of representative LLM-Generated Annotation Assessment papers with open-source code/data.

Paper	Data Type	Backbone	Annotation Cost	Venue	Code/Data Link
		Supervised Fine-tuning			
LARGE LANGUAGE MODELS CAN SELF-IMPROVE[1]	Response	PaLM-540B	Model Inference	EMNLP'23	Not Available
SELF-INSTRUCT: Aligning Language Models with Self-Generated Instructions[2]	Instruction & Response	GPT-3	API Calling, $600 for entire dataset	ACL'23	Link
SELF: SELF-EVOLUTION WITH LANGUAGE FEEDBACK[3]	Response	Multiple LLMs	Model Inference	Arxiv'23	Not Available
Self-Distillation Bridges Distribution Gap in Language Model Fine-Tuning[4]	Response	LLaMA-2	Model Inference	ACL'24	Link
Self-Play Fine-Tuning Converts Weak Language Models to Strong Language Models[5]	Response	zephyr	Model Inference	Arxiv'24	Link
Self-playing Adversarial Language Game Enhances LLM Reasoning[6]	Response	Multiple LLMs	Model Inference	Arxiv'24	Link
Stanford alpaca: An instruction-following llama model[7]	Response	GPT-3.5	API Calling	Arxiv'23	Link
Vicuna: An open-source chatbot impressing gpt-4 with 90%* chatgpt quality[8]	Response	GPT-4	API Calling	Arxiv'23	Link
Wizardlm: Empowering large language models to follow complex instructions[9]	Instruction	LLaMA	Model Inference	Arxiv'23	Link
Generating training data with language models: Towards zero-shot language understanding[10]	Instruction	CTRL	Model Inference	NeurIPS	Link
Tuning Language Models as Training Data Generators for Augmentation-Enhanced Few-Shot Learning[11]	Instruction	CTRL	Model Training	ICML'23	Link
Noise-Robust Fine-Tuning of Pretrained Language Models via External Guidance[12]	Response	ChatGPT	API Calling	EMNLP'23	Link
PINTO: FAITHFUL LANGUAGE REASONING USING PROMPT-GENERATED RATIONALES[13]	Rationale - CoT	GPT-neox	Model Inference	ICLR'23	Link
Distilling Reasoning Capabilities into Smaller Language Models[14]	Rationale - CoT	GPT-3	API Calling	ACL'23	Not Available
LogiCoT: Logical Chain-of-Thought Instruction Tuning[15]	Rationale - CoT	GPT-4	API Calling	EMNLP'23	Not Available
Knowledge-Augmented Reasoning Distillation for Small Language Models in Knowledge-Intensive Tasks[16]	Rationale - CoT	ChatGPT	API Calling	NeurIPS'23	Link
Baize: An Open-Source Chat Model with Parameter-Efficient Tuning on Self-Chat Data[17]	Dialogue	Alpaca	Model Inference	EMNLP'23	Link
Exploiting Asymmetry for Synthetic Training Data Generation: SynthIE and the Case of Information Extraction[18]	IE Sample	GPT-3.5	API Calling, $223.55 for entire dataset	EMNLP'23	Link
InPars-v2: Large Language Models as Efficient Dataset Generators for Information Retrieval[19]	IE sample	GPT-J	Model Inference, 30 hours on an A100 GPU to generate 100k queries	Arxiv'23	Link
Code alpaca: An instruction-following llama model for code generation[20]	Instruction & Response	Alpaca	Model Inferece	Arxiv'23	Link
Code llama: Open foundation models for code[21]	Instruction & Response	Multiple LLMs	Model Inference	Arxiv'23	Link
HuatuoGPT, Towards Taming Language Model to Be a Doctor[22]	Instruction & Response	ChatGPT	API Calling	Arxiv'23	Link
Doctorglm: Fine-tuning your chinese doctor is not a herculean task[23]	Response	ChatGPT	API Calling	Arxiv'23	Link
Xuanyuan 2.0: A large chinese financial chat model with hundreds of billions parameters[24]	Instruction & Response	BLOOM	Model Inference	CIKM'23	Not Available
Wizardmath: Empowering mathematical reasoning for large language models via reinforced evol-instruct[25]	Pairwise Feedback	ChatGPT	API Calling	Arxiv'23	Link
Gimlet: A unified graph-text model for instruction-based molecule zero-shot learning[26]	Instruction	ChatGPT	API Calling	NuerIPS'23	Link
		Alignment Tuning			
Automatic Pair Construction for Contrastive Post-training[27]	Pairwise Feedback	LLaMA	Model Inference, 16 Nvidia V100 GPUs	NAACL'24	Not Available
Aligning Large Language Models through Synthetic Feedback[28]	Pairwise Feedback	LLaMA	Model Inference	EMNLP'23	Link
West-of-N: Synthetic Preference Generation for Improved Reward Modeling[29]	Pairwise Feedback	T5-XXL	Model Inference	Arxiv'24	Not Available
Learning Reward for Robot Skills Using Large Language Models via Self-Alignment[30]	Pairwise Feedback	ChatGPT	API Calling	ICML'24	Link
SALMON: SELF-ALIGNMENT WITH INSTRUCTABLE REWARD MODELS[31]	Pairwise Feedback	LLaMA-2	Model Inference	ICLR'24	Link
Self-Rewarding Language Models[32]	Pairwise Feedback	LLaMA-2	Model Inference	Arxiv'24	Not Available
Self-Alignment for Factuality: Mitigating Hallucinations in LLMs via Self-Evaluation[33]	Pairwise Feedback	LLaMA	Model Inference	Arxiv'24	Link
Aligning Large Language Models by On-Policy Self-Judgment[34]	Response	LLaMA-2	Model Inference	Arxiv'24	Link
Optimizing Language Model's Reasoning Abilities with Weak Supervision[35]	Pairwise Feedback	LLaMA	Model Inference	Arxiv'24	Not Available
Reinforcement Learning from Reflective Feedback (RLRF): Aligning and Improving LLMs via Fine-Grained Self-Reflection[36]	Pairwise Feedback	LLaMA-2	Model Inference, 16 Nvidia V100 GPUs	Arxiv'24	Not Available
Direct language model alignment from online ai feedback[37]	Pairwise Feedback	PaLM-2	API Calling	Arxiv'24	Not Available
Reinforced Self-Training (ReST) for Language Modeling[38]	Response	Multiple LLMs	Model Inference	Arxiv'24	Not Available
RAFT: Reward rAnked FineTuning for Generative Foundation Model Alignment[39]	Response	LLaMA	Model Inference	TMLR	Link
Step-On-Feet Tuning: Scaling Self-Alignment of LLMs via Bootstrapping[40]	Response	LLaMA-2	Model Inference	Arxiv'24	Not Available
Mixture of insighTful Experts (MoTE): The Synergy of Thought Chains and Expert Mixtures in Self-Alignment[41]	Response	Alpaca	Model Inference	Arxiv'24	Not Available
Iterative reasoning preference optimization[42]	Pairwise Feedback	LLaMA-2	Model Inference	Arxiv'24	Not Available
		Inference Time			
Large Language Models are Human-Level Prompt Engineers[43]	Instruction	GPT-3.5	API Calling	ICLR'23	Link
Auto-ICL: In-Context Learning without Human Supervision[44]	Instruction	ChatGPT	API Calling	Arxiv'23	Link
Empowering Large Language Models for Textual Data Augmentation[45]	Instruction	ChatGPT	API Calling	Arxiv'24	Not Available
Self-generated in-context learning: Leveraging auto-regressive language models as a demonstration generator[46]	Instruction	GPT-J	Model Inference	NAACL'22	Link
Are Human-generated Demonstrations Necessary for In-context Learning?[47]	Instruction	Multiple LLMs	API Calling	Arxiv'23	Link
Self-ICL: Zero-Shot In-Context Learning with Self-Generated Demonstrations[48]	Instruction	Multiple LLMs	API Calling	EMNLP'23	Link
Self-Demos: Eliciting Out-of-Demonstration Generalizability in Large Language Models[49]	Instruction	ChatGPT	API Calling	NAACL'24	Link
Rephrase and respond: Let large language models ask better questions for themselves[50]	Instruction	GPT-4	API Calling	Ariv'23	Link
DAIL: Data Augmentation for In-Context Learning via Self-Paraphrase[51]	Instruction	ChatGPT	API Calling	Arxiv'23	Not Available
Just rephrase it! Uncertainty estimation in closed-source language models via multiple rephrased queries[52]	Instruction	Multiple LLMs	Model Inference	Arxiv'24	Not Available
Self-Polish: Enhance Reasoning in Large Language Models via Problem Refinement[53]	Instruction	GPT-3.5	API Calling	EMNLP'23	Link
Self-DC: When to retrieve and When to generate? Self Divide-and-Conquer for Compositional Unknown Questions[54]	Instruction	ChatGPT	API Calling	Arxiv'24	Not Available
Large Language Models are Zero-Shot Reasoners[55]	Rationale - CoT	Multiple LLMs	API Callinfg	NeurIPS'22	Not Available
SELF-CONSISTENCY IMPROVES CHAIN OF THOUGHT REASONING IN LANGUAGE MODELS[56]	Rationale - Diverse Thinking	Multiple LLMs	API Calling & Model Inference	ICLR'23	Not Available
UNIVERSAL SELF-CONSISTENCY FOR LARGE LANGUAGE MODEL GENERATION[57]	Rationale - Diverse Thinking	Multiple LLMs	API Calling	Arxiv'23	Not Available
Eliminating Reasoning via Inferring with Planning: A New Framework to Guide LLMs' Non-linear Thinking[58]	Rationale - Elimination	PaLM2	API Calling	Arxiv'23	Not Available
It's Not Easy Being Wrong: Large Language Models Struggle with Process of Elimination Reasoning[59]	Rationale - Elimination	Multiple LLMs	API Calling	ACL'24	Link
POE: Process of Elimination for Multiple Choice Reasoning[60]	Rationale - Elimination	FLAN-T5	Model Inference	EMNLP'23	Link
SELF-REFINE: Iterative Refinement with Self-Feedback[61]	Textual Feedback	Multiple LLMs	API Calling	NeurIPS'23	Not Available
Can LLMs Learn from Previous Mistakes? Investigating LLMs' Errors to Boost for Reasoning[62]	Textual Feedback - Mistake	Multiple LLMs	API Calling & Modeling Inference	ACL'24	Link
Program of Thoughts Prompting: Disentangling Computation from Reasoning for Numerical Reasoning Tasks [63]	Rationale - Program	Multiple LLMs	API Calling & Model Inference	TMLR'23	Not Available
Graph of Thoughts: Solving Elaborate Problems with Large Language Models[64]	Rationale - Graph	GPT-3.5	API Calling	AAAI'24	Link
Reasoning with Language Model is Planning with World Model[65]	Rationale - Tree	LLaMA	Model Inference, 4×24 GB NVIDIA A5000 GPUs	EMNLP'23	Link

Note: [1](Huang et al., 2023); [2](Wang et al., 2023e); [3](Lu et al., 2023); [4](Yang et al., 2024b); [5](Chen et al., 2024c); [6](Cheng et al., 2024); [7](Taori et al., 2023); [8](Chiang et al., 2023a); [9](Xu et al., 2023a); [10](Meng et al., 2022); [11](Meng et al., 2023); [12](Wang et al., 2023d); [13](Wang et al., 2022a); [14](Shridhar et al., 2023); [15](Liu et al., 2023a); [16](Kang et al., 2024); [17](Xu et al., 2023b); [18](Josifoski et al., 2023); [19](Jeronymo et al., 2023); [20](Chaudhary, 2023); [21](Roziere et al., 2023); [22](Zhang et al., 2023); [23](Xiong et al., 2023a); [24](Zhang and Yang, 2023b); [25](Luo et al., 2023); [26](Zhao et al., 2024); [27](Xu et al., 2023c); [28](Kim et al., 2023b); [29](Pace et al., 2024); [30](Zeng et al., 2024); [31](Sun et al., 2023b); [32](Yuan et al., 2024); [33](Zhang et al., 2024b); [34](Lee et al., 2024b); [35](Tong et al., 2024b); [36](Lee et al., 2024a); [37](Guo et al., 2024b); [38](Gulcehre et al., 2023); [39](Dong et al., 2023); [40](Wang et al., 2024a); [41](Liu et al., 2024c); [42](Chen et al., 2023c); [43](Zhou et al., 2022b); [44](Yang et al., 2023b); [45](Li et al.); [46](Kim et al., 2022); [47](Li et al., 2023c); [48](Chen et al., 2023d); [49](He et al., 2024); [50](Deng et al., 2023); [51](Li et al., 2023a); [52](Yang et al., 2024a); [53](Xi et al., 2023); [54](Wang et al., 2024b); [55](Kojima et al., 2022); [56](Wang et al., 2022b); [57](Chen et al., 2023f); [58](Tong et al., 2023); [59](Balepur et al., 2023); [60](Ma and Du, 2023); [61](Madaan et al., 2024); [62](Tong et al., 2024a); [63](Chen et al., 2023e); [64](Besta et al., 2024); [65](Hao et al., 2023).

Table 4: A list of representative LLM-Generated Annotation Utilization papers with open-source code/data.