

# Data Management For Large Language Models: A Survey

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## Abstract

Data plays a fundamental role in the training of Large Language Models (LLMs). Effective data management, particularly in the formulation of a well-suited training dataset, holds significance for enhancing model performance and improving training efficiency during pretraining and supervised fine-tuning phases. Despite the considerable importance of data management, the current research community still falls short in providing a systematic analysis of the rationale behind management strategy selection, its consequential effects, methodologies for evaluating curated datasets, and the ongoing pursuit of improved strategies. Consequently, the exploration of data management has attracted more and more attention among the research community. This survey provides a comprehensive overview of current research in data management within both the pretraining and supervised fine-tuning stages of LLMs, covering various noteworthy aspects of data management strategy design: data quantity, data quality, domain/task composition, etc. Looking toward the future, we extrapolate existing challenges and outline promising directions for development in this field. Therefore, this survey serves as a guiding resource for practitioners aspiring to construct powerful LLMs through effective data management practices. The collection of the latest papers is available at [https://github.com/ZigeW/data\\_management\\_LLM](https://github.com/ZigeW/data_management_LLM).

## 1 Introduction

Large Language Models (LLMs) have shocked the natural language processing (NLP) community with their strong performance and emergent abilities (OpenAI, 2023; Touvron et al., 2023a; Wei et al., 2022). According to previous studies (Kaplan et al., 2020; Hoffmann et al., 2022), LLMs' achievements depend heavily on self-supervised

pretraining over processed vast volumes of text data. Recent research (Zhou et al., 2023a; Ouyang et al., 2022) further enhances LLMs' instruction-following ability and performance on downstream tasks through supervised fine-tuning on deliberately curated instruction datasets.

Constructing a well-suited training dataset, which we define as data management, is vitally important and challenging in both the pretraining and supervised fine-tuning (SFT) stages of LLMs. In the pretraining stage, constructing datasets with high-quality and the most useful data is essential for efficient training (Jain et al., 2020; Gupta et al., 2021). To equip LLMs with general abilities, heterogeneous dataset composition with mixtures of domains is also required (Gao et al., 2020; Longpre et al., 2023b; Shen et al., 2023). However, many prominent LLMs do not enclose (Anil et al., 2023; OpenAI, 2023) or only document which procedures are chosen (Brown et al., 2020; Workshop et al., 2022; Touvron et al., 2023a) in the construction of their pretraining data, leaving the reason behind it absent. In the SFT stage, the performance and instruction-following abilities of LLMs are largely evoked by carefully designed instruction datasets (Sanh et al., 2022; Ouyang et al., 2022). Although a handful of instruction datasets/benchmarks have been proposed with human annotations (Wang et al., 2022; Köpf et al., 2023), self-instruct (Wang et al., 2023c; Taori et al., 2023) or collection of existing datasets (Si et al., 2023; Anand et al., 2023), practitioners still find it confusing about the effect of instruction datasets on the performance of fine-tuned LLMs, leading to difficulties in choosing proper data management strategies in LLM fine-tuning practices.

To address these challenges, A systematic analysis of data management is required regarding the rationale behind management strategy selection and its consequential effect, the evaluation of curated training datasets, and the pursuit of improved

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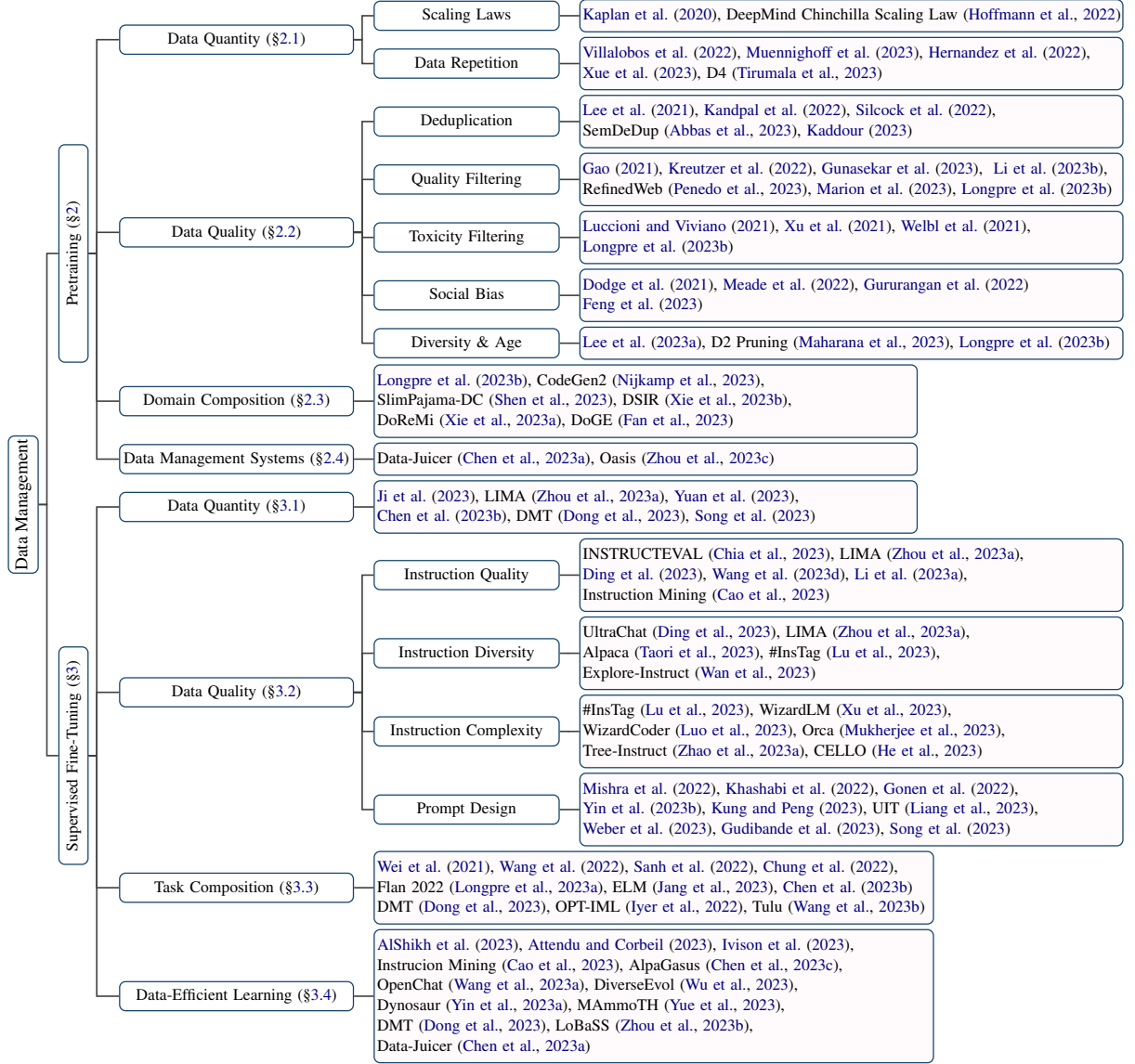


Figure 1: Taxonomy of research in data management for pretraining and supervised fine-tuning of Large Language Models (LLM).

strategies. Therefore, this survey aims to provide a comprehensive overview of current research in data management as shown in Figure 1. In Section 2, we focus on pretraining data management, including the research on data quantity, data quality, domain composition, and data management systems. In Section 3, we discuss the data quantity, data quality, task composition, and data-efficient learning in the SFT stage of LLMs. In Section 4, looking into the future, we present the existing challenges and promising future directions in training data management for LLMs. Through this survey, we are devoted to offering a guiding resource to practitioners attempting to build powerful LLMs with effective and efficient data management practices.

## 2 Pretraining of LLM

Data management is found to be important in the pretraining of many prominent LLMs (OpenAI, 2023; Touvron et al., 2023a; Wei et al., 2022). While most do not report their data management procedures or only report the strategies they adopted, the reason for choosing the specific strategy and the effects of data management strategies are crucial for building stronger LLMs. In this section, we first review the research studying training dataset scaling law with/without data repetition. Then, data quality regarding deduplication, quality filtering, toxicity filtering, social bias, and data diversity and age are explored. After that, domain composition and domain reweighting methods are

discussed. Finally, two recently proposed data management systems are introduced implementing the pretraining data management pipelines.

## 2.1 Data Quantity

The amount of data required for efficient pretraining of LLMs is an ongoing research topic in NLP communities. Scaling laws are proposed to depict the relationship between model size and training dataset size. With model size continuously increasing, exhaustion of text data draws researchers' attention to data repetition in the LLMs' pretraining.

### 2.1.1 Scaling Laws

Before the popularization of LLMs, the relationship between training dataset size and the performance of language models with Transformer architecture (Vaswani et al., 2017) had already attracted researchers' attention. Kaplan et al. (2020) study the empirical scaling laws for Transformer language model performance on the cross-entropy loss and find the model performance has a power-law relationship with training dataset size when not bottlenecked by model size and training computation budget. They also conclude that model performance improves predictably as long as model size and training dataset size are scaled up simultaneously, but encounters overfitting if either of them is fixed while the other increases. Their proposed prediction ratio of performance penalty shows that the model size should increase faster than the training dataset size.

Following the power-law relationship proposed by Kaplan et al. (2020), Hoffmann et al. (2022) conduct experiments on much larger language models and draw a different conclusion that model size and dataset size should scale at roughly the same rate with more compute budget.

### 2.1.2 Data Repetition

While Kaplan et al. (2020) and Hoffmann et al. (2022) focus on scaling law with unique data trained only for one epoch, Hernandez et al. (2022) address the issue about text overlap in the training dataset and study the scaling law with a small fraction of repeated data. They observe a strong *double descent phenomenon* (Nakkiran et al., 2021) where repeated data leads to test loss increase mid-way through the training process and find that a predictable range of repetition frequency leads to severe performance degradation.

As the model size grows, according to the scaling law, more training data is required, raising concerns about running out of high-quality training data (Villalobos et al., 2022; Hoffmann et al., 2022). One straightforward way to overcome this issue is to train on data repeatedly. However, data repetition notoriously leads to performance degradation as discussed above. Motivated by this contradiction, several works study the consequence of pretraining on datasets repeatedly for multiple epochs. Muennighoff et al. (2023) find that with constrained data and fixed compute budgets, repeatedly training on the same data up to 4 epochs yields negligible changes to loss compared to training on unique data. They also propose a scaling law accounting for the diminishing of returns with more repetition and excess parameters. Xue et al. (2023) also observe a multi-epoch degradation in model performance and find that dataset size, model parameters, and training objectives are the key factors to this phenomenon. They further find that commonly used regularization techniques are not helpful in alleviating multi-epoch degradation, except for dropout. Questioning the previous findings, Tirumala et al. (2023) show that training on carefully chosen repeated data can outperform training on randomly selected new data, whilst training on randomly chosen repeated data cannot, suggesting a feasible way of repeating on intelligently selected data.

## 2.2 Data Quality

High-quality data is crucial in the training of machine learning tasks according to previous studies (Jain et al., 2020; Gupta et al., 2021). In the pretraining of LLMs, quality assurance techniques are also adopted and usually form a data management pipeline (Rae et al., 2021; Nguyen et al., 2023; Tirumala et al., 2023), including deduplication, quality filtering, and toxicity filtering. Other aspects like social bias, data diversity, and data age are also interesting topics in the research community.

### 2.2.1 Deduplication

Deduplication is widely used in data management procedures of many prominent LLMs and preprocessing of publicly available datasets (Brown et al., 2020; Workshop et al., 2022; Touvron et al., 2023a; Raffel et al., 2020). Lee et al. (2021) use N-gram similarity with MinHash (Broder, 1997) to detect duplications in training datasets and find that deduplication is beneficial in memorization mitigation, train-test overlap avoidance, and training efficiency

while keeping model perplexity. Kandpal et al. (2022) also show that deduplication can considerably lower the success rate of privacy attacks aiming at model memorization.

Among practices of deduplication, N-gram-and-hashing is the most commonly adopted technique (Lee et al., 2021; Borgeaud et al., 2022; Rae et al., 2021). Silcock et al. (2022) compare it with neural approaches, i.e. a contrastively trained bi-encoder, and a "re-rank" style approach combining a bi- and cross-encoder, and conclude that neural approaches can significantly outperform traditional N-gram-and-hashing methods. Abbas et al. (2023) propose *SemDeDup* to remove semantic duplicates that lie closely in the pre-trained model embedding space and apply clustering to reduce the searching computation. Similarly, Kaddour (2023) construct a subset of the Pile (Gao et al., 2020) called *MiniPile* by filtering out low-quality embedding clusters.

### 2.2.2 Quality filtering

Quality filtering is another key step in constructing a suitable pretraining dataset, since public datasets like Common Crawl<sup>1</sup> and multilingual datasets (Kreutzer et al., 2022) usually contain low-quality data that hampers the training of LLMs. Existing works usually perform quality filtering using a classifier (Brown et al., 2020; Gao et al., 2020; Du et al., 2022; Touvron et al., 2023a), hand-crafted heuristics (Yang et al., 2019; Raffel et al., 2020; Nijkamp et al., 2022) or threshold filtering using criterion like perplexity (Wenzek et al., 2020; Muennighoff et al., 2023).

Quality filtering is usually proven to be beneficial in model performance improvement (Longpre et al., 2023b), despite the reduction of training data quantity and variety. light-weight language model *phi-1* and *phi-1.5* with 1.3B parameters trained on carefully selected high-quality data and synthetically generated data show outstanding performance on code tasks and commonsense reasoning, respectively. Penedo et al. (2023) construct *RefinedWeb* dataset consisting of properly filtered and deduplicated high-quality web data, outperforming models trained on the Pile (Gao et al., 2020). Contradictory to the common conclusions, Gao (2021) find that aggressive filtering can lead to performance degradation on a wide range of tasks for GPT-like LLMs because the filtering objectives are not robust enough. Addressing this issue, Marion et al.

(2023) examines three data quality estimators, perplexity, Error L2-Norm (EL2N), and memorization factor through data pruning, and surprisingly find that pruning dataset based on perplexity performs far better than more complicated techniques like memorization.

### 2.2.3 Toxicity Filtering

Toxicity refers to the text content which is *rude, disrespectful, or unreasonable language that is likely to make someone leave a discussion* (Gehman et al., 2020; Welbl et al., 2021). As raw text corpora usually contain toxic text (Luccioni and Viviano, 2021; Longpre et al., 2023b), toxicity filtering aims to remove text with undesirable toxic text in the pre-training datasets, further preventing LLMs from generating toxic utterances. Similar to quality filtering, heuristic and rule-based filtering (Lees et al., 2022; Gargee et al., 2022; Friedl, 2023) and N-gram classifier (Raffel et al., 2020) are adopted as toxicity filters. Although effective in model detoxifying, Longpre et al. (2023b) discover that toxicity filtering reduces the risk of toxic generation with worse model generalization and toxicity identification ability. Moreover, Xu et al. (2021) and Welbl et al. (2021) both find that training dataset detoxification leads to the marginalization of minority groups like dialects and minority identity mentions.

### 2.2.4 Social Bias

Besides the marginalization of minority groups caused by data detoxifying, several works (Kurita et al., 2019; Nangia et al., 2020; Meade et al., 2022; Feng et al., 2023) find that pre-trained LLMs can capture social biases contained in the large amounts of training text. Evaluating the C4 (Raffel et al., 2020) dataset, Dodge et al. (2021) recommend documenting the social biases and representation harms as well as excluded voices and identities in large web text corpora. Using a new dataset of U.S. high school newspaper articles, Gururangan et al. (2022) also argue that quality filters used for GPT-3 prefer newspapers published by larger schools located in wealthier, educated, and urban ZIP codes, leading to a language ideology. Feng et al. (2023) conduct a comprehensive case study focusing on the effects of media political biases in pretraining corpus on the fairness of hate speech detection and misinformation detection w.r.t. partisan leanings and how it is propagated to language models even further to downstream tasks.

<sup>1</sup><https://commoncrawl.org/>, a large text corpus contains raw web page data, metadata extracts, and text extracts.



### 2.2.5 Diversity & Age

There are also works focusing on other aspects of data management in the pretraining stage of LLMs. For example, [Lee et al. \(2023a\)](#) show that the formal diversities of publicly available pretraining datasets are high when measured by the recently proposed Task2Vec diversity coefficient ([Miranda et al., 2022](#)). They also demonstrate that the coefficient is aligned with the intuitive properties of diversity and suggest using it in building more diverse datasets. [Maharana et al. \(2023\)](#) proposes a novel pruning method *D2 Pruning* to balance data diversity and difficulty in data selection by representing a dataset as an undirected graph with difficulty scores and adopting forward and reverse message passing strategy to select a coreset encapsulating both diverse and difficult regions of the dataset space.

[Longpre et al. \(2023b\)](#) explore the age of the evaluation dataset and draw conclusions that the temporal shift between evaluation and pretraining data will lead to inaccurate performance estimation and the temporal misalignment cannot be overcome by fine-tuning, especially for larger models.

## 2.3 Domain Composition

Public available pretraining datasets usually contain mixtures of data collected from multiple sources and domains, e.g. the Pile ([Gao et al., 2020](#)) contains web documents from Common Crawl, Wikipedia, Books, and collections from medical, academic, coding and math, legal, and social resources. Many prominent models are also trained on a mixture of data from different domains, e.g. LaMDA ([Thoppilan et al., 2022](#)) is trained on dialogs data from public forums, C4 data, code documents from programming-related Q&A sites and tutorials, Wikipedia (English), English web documents, and non-English web documents.

Efforts are made to explore the impact of domain mixtures on the pre-trained model performance. [Longpre et al. \(2023b\)](#) group the Pile ([Gao et al., 2020](#)) data into nine domains and conduct ablate-one-at-a-time experiments to show the impact of different domains. They draw conclusions that the domains with high quality (Books) and high diversity (Web) are broadly helpful, and it is beneficial to include as many data sources as possible even though they are less relevant to the downstream tasks. *SlimPajama-DC* ([Shen et al., 2023](#)) arrives at the same point that merging all domains typi-

cally yields better results than deliberately selected combinations, given that global deduplication is conducted to remove overlaps among different domain datasets. Both [Longpre et al. \(2023b\)](#) and [Shen et al. \(2023\)](#) agree that specific mixtures may excel in evaluation benchmarks for targeted tasks, but the former claim that the priority does not always exist compared to inclusion of diverse web domains. *CodeGen2* ([Nijkamp et al., 2023](#)) studies the impact of mixtures of programming and natural languages on model performance and finds that models trained with mixtures do not perform better than but closely to domain-matched models given the same compute budget.

Several methods are also proposed to find the proper domain composition weights. *DSIR* ([Xie et al., 2023b](#)) formulates the problem as selecting a subset of raw unlabeled datasets to match target distribution given some unlabeled target samples. Specifically, it leverages the classic importance resampling approach ([Rubin, 1988](#)) and estimates the importance weights using n-gram features and KL reduction. Without knowledge of downstream tasks, *DoReMi* ([Xie et al., 2023a](#)) trains a small proxy model using Group Domain Robust Optimization (Group DRO) ([Oren et al., 2019](#); [Sagawa et al., 2020](#)) to generate domain weights. It improves model performance on all domains by up-weighting domains with the largest loss gap between the evaluated model and a pre-trained reference model. Improved from *DoReMi* ([Xie et al., 2023a](#)), [Fan et al. \(2023\)](#) propose *DoGE* which reweights training domains to minimize the average validation loss across all training domains or on a specific unseen domain. The final generalization objective is accessed by a gradient-based generalization estimation function measuring the contribution of each domain to other domains. Then, domains contributing higher to learning other domains will receive larger weights.

## 2.4 Data Management Systems

Addressing the difficulty in pretraining data management, integrated data management systems are necessary for LLM practitioners with different demands. [Chen et al. \(2023a\)](#) provides a data processing system *Data-Juicer* featuring the generation of diverse data recipes with over 50 versatile data management operators and dedicated tools targeting zero-code data processing, low-code customization, and off-the-shelf data processing components. A timely feedback loop at multiple development

stages of data recipes and LLMs is also supported. Zhou et al. (2023c) also propose a pretraining data curation and assessment system *Oasis* containing an interactive modular rule filter module, a debiased neural quality filter module, an adaptive document deduplication module, and a holistic data assessment module.

### 3 Supervised Fine-Tuning of LLM

Based on the general knowledge and capabilities learned in the pretraining stage, supervised fine-tuning (SFT) is proposed to further improve LLMs with instruction-following ability and alignment with human expectations (Wei et al., 2021; Sanh et al., 2022; Ouyang et al., 2022). Many efforts have been made to construct instruction data using human annotations (Wang et al., 2022; Köpf et al., 2023), self-instruct (Wang et al., 2023c; Taori et al., 2023) or collection of existing datasets (Si et al., 2023; Anand et al., 2023). Although LLMs fine-tuned with existing instruction datasets have achieved remarkable performance in various NLP tasks, the impacts of instruction data management on fine-tuned model performance are still under debate. Consistent with previous discussion regarding LLM pretraining, in this section, we summarize the research explorations in LLM SFT into data quantity, data quality including instruction quality, diversity, complexity, and prompt design, as well as task composition. Data-efficient SFT is also included to discuss current efforts on efficient SFT from the data aspect.

#### 3.1 Data Quantity

The explorations of the relationship between scaling instruction data quantity and fine-tuned model performance diverge in two directions. One branch of research focuses on scaling down the instruction data quantity to improve training efficiency. For example, LIMA (Zhou et al., 2023a) carefully curated 1,000 high-quality samples and experimentally justified their hypothesis that only limited instruction tuning data is needed to expose the knowledge and capabilities that the LLM has already acquired during pretraining. Chen et al. (2023b) observe that maybe only a single instruction is sufficient for single task-specific LLM fine-tuning, and 16K samples with 1.9M tokens may be sufficient to train a model specialized in the natural language inference (NLI) task. Another branch of research argues that scaling up the instruction data quantity is crucial

for success (Wei et al., 2021; Sanh et al., 2022).

Addressing this conflict, several works attempt to analyze the scaling pattern for different tasks or model abilities. Ji et al. (2023) conduct an empirical study on 12 major real-world online user cases and show that scaling up the instruction data leads to continuous improvement in tasks such as extraction, classification, closed QA, and summarization while leading to little improvement in tasks such as math, code, and chain-of-thought. Disagree with Ji et al. (2023), Dong et al. (2023) finds that general ability can be enhanced with about 1,000 samples and improves slowly after then, while mathematical reasoning and code generation improve consistently with the increasing of data amount. Similarly, Yuan et al. (2023) observes a log-linear relation between instruction data amount and models' mathematical reasoning performance, but stronger pre-trained models improve less with larger fine-tuning datasets. Song et al. (2023) conduct experiments covering ten distinct abilities and show that most abilities are consistent with data scaling. Still, each ability develops at different paces during instruction tuning with some abilities showing completely different patterns.

#### 3.2 Data Quality

Data quality is always a focal point in the SFT of LLMs, addressing instruction quality, diversity, complexity, and prompt design. Here we focus more on the management and analysis of existing instruction data instead of instruction generation methods which have been discussed in previous surveys (Zhang et al., 2023b; Wang et al., 2023e).

##### 3.2.1 Instruction Quality

Many researchers have found that the quality of instruction data is one of the most important factors in improving model performance (Chia et al., 2023; Zhou et al., 2023a; Ding et al., 2023). During the construction of instruction data, there is usually a filtering step to select high-quality instructions generated by models. Wang et al. (2023d) use perplexity as the index to select the most appropriate instructions from the pool of candidate instructions generated by open-source models. Li et al. (2023a) leverage the language model itself to assign quality scores to augmented instructions and iteratively improve model prediction. Cao et al. (2023) propose an automatic data selector *InstructionMining* to evaluate the quality of instruction data without manipulations from human experts.

They first hypothesize that the inference loss of a fine-tuned model on an evaluation set can serve as a proxy for data quality. Then, they introduce a set of natural language indicators to predict the inference loss without actually fine-tuning an LLM, i.e. the number of tokens in tokenized inputs and outputs, reward score (Köpf et al., 2023), perplexity, Measure of Textual Lexical Diversity (McCarthy and Jarvis, 2010), distance to approximate  $i$ -th nearest neighbors (Dong et al., 2011) in Sentence-BERT (Reimers and Gurevych, 2019) embedding space, and the naturalness, coherence, and understandability scores provided by UniEval dialogue model (Zhong et al., 2022).

### 3.2.2 Instruction Diversity

The intention and semantic diversity of instructions is another important factor that has shown a positive effect on model performance improvement (Zhou et al., 2023a; Ding et al., 2023; Taori et al., 2023). To better evaluate the instruction diversity of SFT datasets, *#InsTag* (Lu et al., 2023) is proposed as an open-set fine-grained tagger using ChatGPT<sup>2</sup>. Specifically, it first prompts ChatGPT to provide tags for given queries in an open setting, then performs a normalization procedure to deal with the noise in the raw tagging, including low-frequency filtering, rule aggregation, semantic aggregation with embedding clustering, and association aggregation merging associated tags together. With the generated tags, they quantify instruction diversity as the unique tag coverage rate for the overall tag set. They also analyze popular open-set SFT datasets and show that larger dataset size tends to be more diverse and induces higher performance.

Though important, diversity can be challenging in domain-specific tasks due to data constraints. Wan et al. (2023) propose an approach called *Explore-Instruct* to enlarge the data coverage through active exploration via LLMs. *Explore-Instruct* starts from representative domain user cases and searches the variations and possibilities by looking ahead into potential fine-grained sub-tasks and backtracking alternative branches widening the search space.

### 3.2.3 Instruction Complexity

The complexity of instructions also attracts researchers’ attention, especially in developing LLM with complex instruction-following and reasoning

abilities (Xu et al., 2023; Luo et al., 2023; Mukherjee et al., 2023). Several works endeavor to quantify and evaluate instruction complexity. Using aforementioned tags, *#InsTag* (Lu et al., 2023) quantifies complexity as the average tag number assigned to queries in a dataset. He et al. (2023) evaluate complex instruction with eight features, i.e. multi-tasking, semantics, formats, quantity constraints for task description, and multi-turn, length, noise, and heterogeneous information for input text.

To delve into the exploration of instruction complexity, Zhao et al. (2023a) propose *Tree-Instruct* to controllably enhance the complexity of instruction data. It treats the instruction as a semantic tree and constructs new complex instructions by adding nodes to the tree. Thus, the complexity of instruction can be controlled by adjusting the number of added nodes. Through experiments, they find that increased complexity can lead to sustained performance improvement. What’s more, the improvement does not come from the increased number of tokens, as a few complex instructions still outperform diverse but simple instructions under the same token budget. Curriculum instruction tuning ranging from easy to difficult might not be as helpful as expected, indicating the necessity of enhancing complexity. Another method of increasing complexity is also proposed. *Evol-Instruct* (Xu et al., 2023; Luo et al., 2023) rewrite instructions step by step with operations such as increasing reasoning, adding constraints, in-breadth evolving, deepening, and complicating input with code and table.

### 3.2.4 Prompt Design

Current instructions are either heuristically designed by human (Wang et al., 2022; Köpf et al., 2023) or synthetically generated by prominent models (Peng et al., 2023; Ding et al., 2023). However, the same intention and semantic meaning can be phrased into various prompts, and the choice of prompts can cause significant model performance variation (Gonen et al., 2022; Weber et al., 2023). Thus, what kinds of instruction prompts are better for LLM training might be vital yet have not been fully explored.

Early attempts include manual reformulation of prompts into the ones easier to follow for language models (Mishra et al., 2022), choosing prompts with the lowest perplexity to get the most significant gains in model performance (Gonen et al., 2022), and the surprising finding

<sup>2</sup><https://chatgpt.openai.com/>

that the discretized interpretation of continuous prompts is not always consistent with the discrete prompts describing the same task as heuristically expected (Khashabi et al., 2022). To know which parts of the instructions are most important in LLM fine-tuning, Yin et al. (2023b) and Kung and Peng (2023) both conduct ablation analysis removing contents in task definitions. Yin et al. (2023b) find that model performance only drops substantially without contents describing the task output, especially the label information, and 60% of tokens can be removed while maintaining or even improving model performance. Kung and Peng (2023) remove all semantic components in task definitions leaving only the output space information and delusive examples containing incorrect input-output mappings and achieve comparable model performance. Based on this finding, they cast doubts on the performance gain of fine-tuned models and state that the model may only pick up superficial patterns during instruction tuning. Addressing the issue of instruction format inconsistency, (Liang et al., 2023) develop a format transfer framework *UIT* to automatically transfer instructions from different datasets into unified formats.

Besides the choice of phrasing, the generation source of prompts is another factor in prompt design. Gudibande et al. (2023) raise questions on fine-tuning a weaker language model on outputs of a stronger model and find that the imitation model can only adapt to mimic the stronger model’s style but not its functionality, indicating the failure of closing the performance gap between open- and close-sourced through imitation instruction tuning. Similarly, (Song et al., 2023) also observe that human-designed data can outperform synthetically generated data from GPT-4 (OpenAI, 2023) to a large extent.

### 3.3 Task Composition

Since LLMs have shown surprisingly emergent abilities in handling various NLP tasks, multitask fine-tuning appears as a promising approach to further improve LLMs’ generalization performance on unseen tasks. The benefits of increasing the number of tasks in SFT have been experimentally proven on models with different sizes ranging from 3B (Wang et al., 2022), 11B (Sanh et al., 2022), 137B (Wei et al., 2021) to 540B (Chung et al., 2022) parameters.

Besides the scaling of the number of tasks, the mixture ratio of different instruction benchmarks

and task balancing is also found to be critical for effective instruction fine-tuning (Iyer et al., 2022; Longpre et al., 2023a). Dong et al. (2023) focus on task composition between mathematical reasoning, code generation, and general human-aligning abilities and find that model abilities are improved with low-resource mixed data but decreased with high-resource mixed data compared to those with individual source data, that is, conflicts among abilities are observed under high-resource settings. To further explain the conflicts, they vary the ratio of general and specialized data and conclude that when significant differences exist in task formats and data distributions between SFT tasks, the impact of data ratio is neglectable, on the contrary, when there exists some degree of similarities, the data ratio can cause noticeable variation of performance.

Different from compositing multiple tasks together, some works claim that LLM tuned on a single task data can outperform LLM tuned on multiple tasks (Jang et al., 2023; Chen et al., 2023b). Jang et al. (2023) state that the priority of training expert LLMs may lie in the avoidance of negative task transfer, prevention of catastrophic forgetting via continually learning new tasks without re-training, and compositional abilities emergent when merging individual experts together. Wang et al. (2023b) conduct analysis on factual knowledge, reasoning, multilinguality, coding, and open-ended instruction following abilities of models trained with 12 instruction datasets and show that different instruction datasets can unlock or improve specific abilities. In contrast, no single dataset of combinations can provide the best performance across all evaluations.

### 3.4 Data-Efficient Learning

Based on explorations of the impact of data quantity, data quality, and task composition on model performance discussed previously, many works propose to fine-tune LLM more efficiently with subset selection or learning strategy addressing different aspects of instruction data.

**Data Quantity** AlShikh et al. (2023) introduce a metric to detect LLMs’ ability to follow instructions, i.e. *Instruction Following Score (IFS)* defined as the percentage of responses classified as "answer-like" predicted by a binary classifier in the instruction dataset. They suggest using this metric as an early stopping criterion without tuning



on the full-sized dataset. Based on their observations of different scaling patterns for different abilities, Dong et al. (2023) propose *Dual-stage Mixed Fine-tuning (DMT)* strategy first to learn specialized abilities and then general abilities with a small proportion of specialized data to prevent forgetting.

**Instruction Quality** Several works focus on selecting a subset of instruction data with the highest quality. Cao et al. (2023) employ BlendSearch (Wang et al., 2020) to automatically search for the best subset. AlpaGasus (Chen et al., 2023c) adopts a data selection strategy that automatically identifies and filters out low-quality data using a strong LLM. Motivated by the computational overhead caused by data pruning prior to fine-tuning, Attenu and Corbeil (2023) propose a dynamic data pruning method that periodically filters out unimportant examples during SFT using extended versions of EL2N metric (Paul et al., 2021; Fayyaz et al., 2022). Without discarding data samples, OpenChat (Wang et al., 2023a) considers the general SFT data as a mixture of a small amount of expert data and a large amount of sub-optimal data without any preference labels. Then, *Conditioned-RLFT* strategy is proposed regarding different data sources as coarse-grained reward labels and fine-tuning the LLM as a class-conditioned policy to leverage complementary data quality information.

**Instruction Diversity** *DiverseEvol* (Wu et al., 2023) iteratively augments the training dataset using a data sampling technique that selects new data points most distinct from any existing ones in model embedding space to enhance the diversity in the chosen subsets.

**Task Composition** Given a small amount of target task data, Ivison et al. (2023) finds the relevant multitask subsets according to the similarity between the pre-trained model’s representations. Similarly, Dynosaur (Yin et al., 2023a) treats task selection based on instruction representations as a replay strategy in continual learning scenarios to mitigate catastrophic forgetting issues and improve generalization to unseen tasks. Yue et al. (2023) builds math generalist models *MAmmoTH* through instruction tuning on a unique hybrid of chain-of-thought and program-of-thought rationales in math.

**Others** Zhou et al. (2023b) introduce *learnability* as a new dimension of SFT data selection that

data can be learned more effectively by the model is preferable and data lacking informative content or excessively demanding for the model should be avoided. They also propose *LoBaSS* method to select SFT data using *learnability* as the principal criterion measured by the loss difference between fine-tuned and pre-trained models. *Data-Juicer* (Chen et al., 2023a) implements pipelines for LLM fine-tuning and operators for users to compose different data management recipes, as well as the evaluation of consequence model performance.

## 4 Challenges and Future Directions

The exploration of data management and its impact on LLM pretraining and SFT is still an ongoing task. In this section, we point out several challenges and corresponding future directions in training data management studies for LLMs.

**Comprehensive and Fine-grained Understanding** As discussed in previous sections, many efforts have been made to understand the impacts of data management on different training stages addressing different aspects. As current studies can serve as pieces of puzzles, there is still a lack of comprehensive understanding of the whole picture. Moreover, explorations using different datasets and models on different tasks may lead to contradictory conclusions, e.g., the trade-off between quality and toxicity filtering (Longpre et al., 2023b), detoxification v.s. debiasing (Xu et al., 2021; Welbl et al., 2021), fine-tuning with a few high-quality data (Zhou et al., 2023a; Chen et al., 2023b) v.s. data scaling (Wei et al., 2021; Sanh et al., 2022), task composition (Wang et al., 2022; Chung et al., 2022) v.s. expert models (Jang et al., 2023; Wang et al., 2023b), etc. Hence, more fine-grained understanding is required to solve these conflicts.

**General Data Management Framework** Although *Data-Juicer* (Chen et al., 2023a) and *Oasis* (Zhou et al., 2023c) propose data management systems to compose various data recipes in either the pretraining or SFT stage of LLM, practitioners still need to spend efforts on finding suitable datasets. Building upon the understanding of data management, constructing a general data management framework that is suitable for a broad range of applications is an urgent and worthy future direction in the development and promotion of LLMs.

**Hallucinations** Despite their strong power, LLMs are notorious for their hallucinations, i.e.

the generation of unexpected, irrelevant, or counterfactual output (Zhang et al., 2023c). Several works in hallucination trace down the occurrence of hallucination to the lack of pertinent knowledge and the internalization of false knowledge from the pretraining corpora (Li et al., 2022; McKenna et al., 2023; Dziri et al., 2022). To mitigate hallucination, the curation of pretraining corpora is adopted by many LLMs mainly focusing on the extracting of high-quality data, e.g., GPT-3 (Brown et al., 2020), Llama 2 (Touvron et al., 2023b), and Falcon (Penedo et al., 2023). The manually curated (Zhou et al., 2023a) and automatically selected (Chen et al., 2023c; Cao et al., 2023; Lee et al., 2023b) high-quality instruction data are also experimentally shown to be effective in reducing hallucination during the SFT stage. It can be seen from the previous research that data management in both the pretraining and SFT stages can be a promising solution to hallucination.

**Social Biases and Fairness** The problem of social biases and unfairness existing in current pretraining datasets and their impacts on pre-trained LLMs have been addressed in several works as discussed in Section 2.2.4. However, there is still a large gap between current prominent LLMs and ideal LLMs without social biases. Many questions are worth exploring, such as how to mitigate the potential biases in pretraining datasets, the existence of bias in the SFT datasets, and whether it is feasible to reduce social bias through SFT.

**Multimodal Data Management** Current research in data management mostly focuses on natural language processing. With the application of LLMs extending to multimodalities like vision, audio, and so on, the construction of multimodality datasets becomes more and more important. The proposed multi-modal LLMs usually construct their own instruction-tuning datasets based on manually designed (Dai et al., 2023; Zhu et al., 2023) or GPT-aided instructions (Liu et al., 2023; Zhao et al., 2023b) and data collected from benchmark adaptation (Zhang et al., 2023a; Gao et al., 2023) or self-instruction (Pi et al., 2023; Yang et al., 2023). It is interesting to see the impacts of multimodal data management on the performance of fine-tuned multimodal LLMs such as the data scaling law in multimodal instruction fine-tuning, the quality-control techniques in multimodal dataset construction, the impact of task balancing in multitask multimodal training, and so on.

## 5 Conclusions

This paper makes the first attempt to overview data management in the training of LLMs. We discuss the *pretraining* and *supervised fine-tuning* stage of LLM successively and summarize the up-to-date research efforts into *data quantity*, *data quality*, and *domain/task composition* for each stage. *Data management systems* in the pretraining stage and *Data-efficient learning* in the supervised fine-tuning stage are also discussed. Finally, we highlight several challenges and promising future directions for LLM training data management. We hope this survey can provide insightful guidance for practitioners and inspire further research in effective and efficient data management for the development of LLMs.

## Limitations

In this survey, we provide an overview of training data management for LLMs. Despite our best efforts, there may still be several limitations remaining in our work.

**Lack of Technical Details** The exploration of training data management expands across a wide range of datasets from different sources, models with different architectures and sizes, and tasks addressing the different abilities of LLMs. Due to the page limit, we do not discuss the technical details for each work, which may lead to certain confusion.

**Missing References** As the research of LLMs develops vigorously, works are published or preprinted at a rapid speed. We tried our best to cover the up-to-date works proposed in the recent two years, but some works may be inevitably missed in this survey. We will continue to pay attention to the research frontier and search for the latest efforts to supplement our work.

**Evaluation Data Management** In this work, we put our main efforts into the research of training data management for LLMs. However, the evaluation benchmark and data management are also important in the development of LLMs. We intend to include discussion in this field in our future work.

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