LLMIDxAdvis: Resource-Efficient Index Advisor Utilizing Large Language Model

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ABSTRACT

Index recommendation is essential for improving query performance in database management systems (DBMSs) through creating an optimal set of indexes under specific constraints. Traditional methods, such as heuristic and learning-based approaches, are effective but face challenges like lengthy recommendation time, resource-intensive training, and poor generalization across different workloads and database schemas. To address these issues, we propose LLMIDXADVIS, a resource-efficient index advisor that uses large language models (LLMs) without extensive fine-tuning. LLMIDxADvis frames index recommendation as a sequence-tosequence task, taking target workload, storage constraint, and corresponding database environment as input, and directly outputting recommended indexes. It constructs a high-quality demonstration pool offline, using GPT-4-Turbo to synthesize diverse SQL queries and applying integrated heuristic methods to collect both default and refined labels. During recommendation, these demonstrations are ranked to inject database expertise via in-context learning. Additionally, LLMIDXADVIS extracts workload features involving specific column statistical information to strengthen LLM's understanding, and introduces a novel inference scaling strategy combining vertical scaling (via "Index-Guided Major Voting" and Bestof-N) and horizontal scaling (through iterative "self-optimization" with database feedback) to enhance reliability. Experiments on 3 OLAP and 2 real-world benchmarks reveal that LLMIDXADVIS delivers competitive index recommendation with reduced runtime, and generalizes effectively across different workloads and database schemas.

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The source code, data, and/or other artifacts have been made available at https://github.com/XinxinZhao798/LLMIdxAdvis.

1 INTRODUCTION

Index recommendation aims to generate an optimal set of indexes under constrained conditions (e.g., storage budget or a maximum number of indexes) based on the key columns of the target workload. This process facilitates efficient data retrieval by reducing the need for full table scans, which is critical for performance optimization in database management systems (DBMSs). Traditionally, database administrators (DBAs) manually recommend indexes based on the target workload. However, this problem has been shown to be NP-complete [36] due to the vast search space combined with the complexities of constrained optimization. These challenges are further exacerbated in sophisticated analytical workloads, making manual index recommendation increasingly difficult for DBAs. To address this, researchers have developed automated solutions using heuristic methods [19] and learning-based approaches [5, 20, 50, 55]. These methods treat the index recommendation process as a pipeline comprising three key components. For a given workload, the pipeline starts with (1) the Candidate Generation Component, which constructs the initial search space. Next, (2) the Index Selection Component navigates this search space to recommend indexes, iteratively refining the optimal set with guidance from (3) the Benefit Estimation Component. This process continues until a stopping criterion is reached or no additional performance improvements can be achieved.

Limitations of Existing Methods. Although existing methods are capable of generating satisfactory results, they still contend with the challenges such as lengthy recommendation time or resource-intensive demands. For *heuristic methods*, these approaches explore the search space—constructed from candidate indexes—in a greedy manner to generate optimal results. However, under complex database schemas with numerous columns, the vast search space may leads to extended recommendation time. For instance, heuristic methods require an average of 1,897 seconds to generate recommendations for JOB benchmark. For *learning-based methods*, these are generally resource-intensive due to prolonged model training process, which can also be considered as an online recommendation process tailored to the target workload. For instance, methods utilizing reinforcement learning require an average training time

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of 13,615 seconds for JOB benchmark. Moreover, defining a unified model for varying workload compositions or database schemas remains a significant challenge for learning-based methods. This difficulty arises from differences in the action space, which is primarily composed of index candidates generated based on the target workload. As a result, learning-based methods require retraining for each workload with newly generated index candidates, even under the same database schema, which leads to both resource inefficiency and the lack of generalization capability.

Motivation. Given the above limitations, we are inspired to explore whether it is possible to develop a method for efficient index recommendation while minimizing training resource requirements. Motivated by the exceptional performance of large language models (LLMs) in various natural language processing (NLP) tasks [1, 15, 52], LLMs present a promising solution for index recommendation. A natural approach would be to retain the conventional pipeline—candidate generation and index selection via benefit estimation—but replace the index selection component with an LLM. However, this approach remains inefficient due to the costly candidate generation and numerous iterative explorations.

To address this, we depart from the traditional pipeline and instead use an LLM as a sequence-to-sequence model, taking workloads as input and directly outputting recommended indexes. Recent research [35] has explored this direction by fine-tuning the T5 language model [39] to recommend indexes for a given SQL. However, this approach is still resource-intensive, requiring substantial fine-tuning data. To overcome these challenges, we intend to develop a resource-efficient LLM-based method for index recommendation, reducing the reliance on extensive fine-tuning while maintaining satisfactory performance.

Challenges of Exploring LLM for Index Recommendation. Some preliminary attempts indicate that providing only superficial information, such as the original queries in the workload, as input to an LLM fails to produce the expected indexes. This is likely due to the rarity of such scenarios during the LLM's pre-training process [13, 51]. Therefore, the first challenge is how to address the lack of database expertise in general LLMs (C1). To enable a resource-efficient, fine-tuning-free LLM for index recommendation, the key is to design prompts that describe the task effectively with precise guidance for the optimal index recommendation. This objective drives us to create database-aware prompts, enabling the LLM to infer the pattern that identify which indexes are optimal.

The second challenge is how to enable the LLM to understand the given workload (C2). Existing methods often focus on generating index candidates based on the relevant columns' name while disregarding workload features due to the limitations of their approaches. However, workload features are crucial and must be carefully addressed. On one hand, the superficial information in the workload may include index-irrelevant details that could interfere with the LLM's understanding. On the other hand, intrinsic statistical information about specific columns, which is crucial for index creation, cannot be directly extracted from the workload alone. Thus, understanding the workload comprehensively from the perspective of index management remains a significant challenge.

The third challenge is *how to improve the reliability of recommendations generated by LLM.* **(C3)**. Without fine-tuning, the reliability

of LLM-recommended indexes is limited. Existing research on LLMs proposes several strategies to enhance inference performance, including techniques such as major voting [16, 49] (which involves voting across n samples), Best-of-N [10, 26, 45] (which selects the best result among n samples), and running multiple iterations of inference to progressively refine the output [14, 48]. These strategies could potentially enhance the performance of fine-tuning-free methods. However, index recommendation is database-aware and requires interaction with the database to obtain feedback. Therefore, these existing inference scaling strategies must be adapted to suit the specific requirements for index recommendation.

Our Proposal. To address the above challenges, we propose a resource-efficient index recommendation pipeline, named LLMIDX-ADVIS, which enables flexible index recommendations for various workloads across different database schemas. The core idea is to leverage prompt engineering on LLMs, focusing on constructing appropriate demonstrations and integrating comprehensive workload features to guide the LLM in optimizing indexes without fine-tuning, while producing effective recommendations via inference scaling.

Specifically, we first construct a high-quality demonstration pool offline to facilitate online index recommendation. To achieve this, we utilize GPT-4-Turbo [32] to synthesize diverse SQL queries for workload generation. For each workload, we determine optimal indexes through generating all possible sets using multiple heuristic methods and performing benefit estimation. Significantly, we construct two different types of labels: "default label" with optimal set, and "refined label" that require refinement (e.g., creating new indexes or dropping existing ones) to support the subsequent LLM inference scaling strategy. During the recommendation process, LLMIDXADVIS performs similarity matching to select the appropriate demonstrations for the given workload, enabling in-context learning to inject database expertise into LLM without additional need for resource-intensive fine-tuning (for C1).

Second, leveraging the flexibility of LLMs in accepting diverse input features, we implement a comprehensive feature extraction mechanism to include various features derived from the columns, predicates, and specific statistics via querying database engines. This approach eliminates the limitations of existing methods, which are often constrained in incorporating workload features (for C2).

Third, since the LLM remains untuned, we introduce a database-aware inference scaling strategy to enhance the reliability of the recommendations, which operates from two facets: (1) Vertical Scaling: We sample multiple candidate index sets and an integrated index set using "Index-Guided Major Voting". These candidate sets are ranked based on their estimated costs, and the best-performing set (Best-of-N) is selected as the optimal result. (2) Horizontal Scaling: We design a "self-optimization" mechanism that allows LLM to iteratively refine its own index recommendations. During each optimization iteration, indexes are created virtually based on current optimal result, and the remaining storage capacity and cost reduction are calculated with the updated existing indexes to guide the LLM for reflection and refinement. This "self-optimization" process involves interaction with the database engine to obtain feedback, distinguishing it from traditional pure NLP tasks (for C3).

In summary, the proposed LLMIDXADVIS offers several advantages over traditional methods as shown in Table 1:

Table 1: Characteristics of different index recommendation methods. *Data Preparation* means, e.g., the time for index candidates generation or feature extraction. *Flexibility* means whether there are restrictions on the type of index (e.g., the number of columns in the index).

	Heuristic Methods	Learning-based Methods	LLMIDxAdvis
Performance	Optimal	Poor	Medium
Algorithm Runtime	Medium	Poor	Optimal
Data Preparation	Medium	Poor	Optimal
Flexibility	×	×	✓
Generalization	\checkmark	×	✓

- Performance: Maintains effective performance improvement.
- Efficiency: Recommends indexes with fewer LLM inferences, reducing algorithm runtime.
- Lightweight Data Preparation: Eliminates the need for tedious index candidate preparation, which require enumerating all index combinations even calculating the potential benefits in advance.
- Flexibility: Removes the limit on the number of index columns.
- Generalization: Adapts to various workloads across different databases due to the inherent generalization capabilities of LLMs.

Contributions. Our main contributions are as follows:

- LLM-Based Index Recommendation Pipeline: We propose
 an efficient and lightweight LLM-based pipeline for index recommendation, featuring a high-quality demonstration pool and comprehensive workload feature extraction. The demonstration pool
 uses GPT-4-Turbo to synthesize diverse SQL queries for workload generation and identify different types of labels through
 integrated heuristics, enabling in-context learning without finetuning. Feature extraction captures diverse workload attributes,
 facilitating LLM to fully understand the target workload.
- Inference Scaling Strategy: To achieve high performance without fine-tuning, we introduce a database-aware inference scaling strategy, including vertical scaling, which samples, ranks, and selects the optimal index set using an "Index-Guided Major Voting" and Best-of-N, and horizontal scaling, which iteratively refines indexes through a "self-optimization" process with database engine feedback. This ensures reliable and effective index recommendations during inference.
- Comprehensive Experimental Evaluation: We conduct an
 extensive experimental study, comparing LLMIDXADVIS against
 11 baselines across 3 OLAP benchmarks and 2 real-world benchmarks, which demonstrates that LLMIDXADVIS can efficiently recommends promising indexes. Furthermore, we validate LLMIDXADVIS in a cross-database schema setting, highlighting its ability
 to generalize across diverse workloads and databases.

2 RELATED WORK

2.1 Index Advisor

We categorize existing studies into three main types: heuristic-based methods, reinforcement learning (RL)-based methods, and other approaches [53].

Heuristic-based methods. Heuristic-based methods [19] gradually explore the candidates in a greedy manner under the instruction of benefit estimation to generate the recommended indexes until the stop criterion is satisfied. According to the definition of the initial index set, there are two search strategies for index candidates: (1) Bottom-Up strategy [2, 7, 40], which iteratively adds indexes to an empty initial index set, and (2) Top-Down strategy [4, 8], which iteratively removes indexes from an initial set with numerous index candidates. Although some rules such as splitting indexes into shared and residual columns or prefixing indexes by removing redundant columns [4] are used to refine the search space more precisely, these methods still present extremely long execution time while facing more sophisticated database schemas. Meanwhile, the optimization process of these methods is typically fixed due to the pre-defined search mode, which tends to fall into a local optimum.

RL-based methods. RL-based methods [20, 31, 50] focus on using reinforcement learning algorithms for index recommendation. Given the workload feature as the state representation, these methods select an action from the action space constructed by index candidates through the policy model. After updating the current state through the execution of the selected action, the benefit is evaluated using the reward function to guide the next iteration. This process iteratively refines both the policy model and the reward function, improving the decision-making process over time. However, RL-based methods often require several hours of training time to achieve stable performance, and due to the discrepancies in action spaces between different workloads or database schemas, it is difficult to train a unified model for diverse application scenarios or transfer a well-trained model to unseen workload environments.

Other methods. There are still some approaches that adopt other strategies for index recommendation. AutoIndex [55] utilizes Monte Carlo Tree Search to make incremental recommendations based on existing indexes. MFIX [5] employs a Bayesian optimization approach [34] utilizing a probabilistic random forest as surrogate model and an expected improvement with constraints as acquisition function, which leverages an optimal balance between exploitation and exploration. However, these methods still face similar challenges, such as suboptimal solutions or lengthy runtime.

Although existing methods are capable of achieving optimal performance, they still require substantial time or incur significant training costs, while learning-based methods simultaneously lack the ability to generalize across different scenarios. Therefore, we propose an efficient and lightweight pipeline that leverages pretrained LLMs with minimal domain-specific data injection instead of intensive training to address the aforementioned issues.

2.2 Large Language Models for Databases

Recently LLMs have gained significant prominence due to their extraordinary performance across various tasks. Meanwhile, growing research has emerged exploring the application of LLMs in the database, such as text-to-SQL [23, 24, 38], SQL rewrite [25], knob tuning [17, 21], and database diagnosis [54, 56].

IdxL [35] introduces an index recommendation approach that fine-tunes the T5 language model [39] using massive (SQL, indexes) training pairs. However, except the resource-intensive drawback, IdxL is unsuitable for workload-level index recommendation due

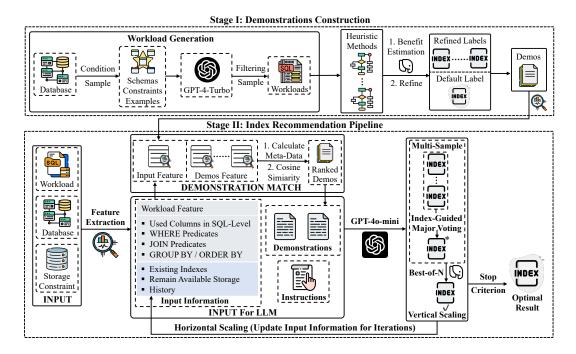


Figure 1: Overview of LLMIDXADVIS (Detailed in Section 3.2), involving the Demonstration Construction (Detailed in Section 4) and the Index Recommendation Pipeline (Detailed in Section 5).

to the lack of considering the relationship between recommended indexes for individual SQLs. To overcome these limitations, LLMIDX-ADVIS exploits the long-context capabilities of LLMs to provide a tuning-free workload-level index advisor, representing the first LLM-based index recommendation method.

3 LLMIDXADVIS OVERVIEW

In this section, we define the index selection problem with relevant preliminaries (Section 3.1) and present an overview of our proposed method, LLMIDXADVIS (Section 3.2).

3.1 Problem Formulation

Index recommendation refers to the process of searching for an optimal set of indexes from the index candidates generated based on the target workload while satisfying the constraint condition such as storage budget or maximum number of indexes.

Definition 1. Index Selection Problem (ISP). Given a workload $W = \{q_1, ..., q_m\}$ referred to a set of m queries, index candidates $I = \{i_1, i_2, ..., i_n\}$ constructed based on the columns appearing in workload W, and a storage constraint S_c , the ISP aims to find an optimal set of indexes $I^* \subseteq I$ that minimizes the estimated cost C:

$$I^* = \arg\min_{I \subseteq I} C(W, I),$$

s.t. $S(I^*) \le S_C.$ (1)

Here, $S(I^*) = \sum_{i \in I^*} s_i$ represents the total storage of the indexes in the optimal set, where s_i is the storage of the index i. $C(W, I) = \sum_{i=1}^{m} cost(q_i, I)$ represents the total estimated cost of the workload through executing the EXPLAIN command for each query under

the condition of index creation and obtaining the total cost from the query plan.

Since managing the physical indexes is time-consuming due to the modification of the indexes in the database engine, it is crucial to efficiently estimate the benefit of the recommended indexes. To address this, we introduce an additional plugin to optimize the index benefit estimation process described in this paper.

What-If Caller. Some database management systems (DBMSs) provide what-if callers [6] for hypothetical index management (e.g., HypoPG [18] extension in PostgreSQL [37]), which can simulate the process of index creation and deletion without actually modifying the data in the database engine. Meanwhile, it could calculate the index required storage, and update the estimated total cost of the query plan utilizing database statistics.

Definition 2. LLM-based Index Recommendation Problem (LLM-based IRP). Given a workload W, a database D and a storage constraint S_C , the LLM-based IRP aims to recommend the optimal index set I^* directly using LLM without additional fine-tuning.

$$LLM(Instruction, Feature(W, D), I(D), S_c) \rightarrow I^*.$$
 (2)

Here, *Instruction* denotes the task-specific instructions of LLM, which can be either relevant or irrelevant to the input information. $Feature(\cdot)$ denotes the function used to extract features from the target workload W in its corresponding database $D.I(\cdot)$ denotes the retrieval of the current existing indexes state in the database. $LLM(\cdot)$ denotes the pre-trained LLM without additional fine-tuning requirements. According to this definition, LLMIDXADVIS deviates from the conventional framework, and aims to realize an efficient and lightweight index recommendation pipeline.

3.2 System Overview

Figure 1 illustrates the overview of LLMIDXADVIS, which can be divided into two main stages.

Stage 1: Demonstration Construction (Section 4). In the first stage, we construct a high-quality demonstration pool consisting of diverse workloads paired with corresponding labels (default label and refine label), which are primarily designed for different existing indexes states. For workload generation, we synthesize analytical SQL queries using GPT-4-Turbo, incorporating both diversity and quality control, for workload generation. For label collection, multiple promising index sets under various storage constraints are recommended via a platform [19] that ensembles heuristics, and we thoroughly consider all the possible candidates, performing benefit estimation to identify the optimal set. To accommodate different initial states of existing indexes, we define two types of labels based on optimal set: the "default label" for the initial state without any indexes, and the "refined label" for the initial state containing existing indexes. Default label is the optimal set, while refined label is synthesized based on other suboptimal sets.

Stage 2: Index Recommendation Pipeline (Section 5). To optimize performance while minimizing data requirements, we leverage a pre-trained LLM with in-context learning (ICL) for index recommendation instead of fine-tuning an open-source model. Given a workload, its associated database, and storage constraints, LLMIDxADVIS first performs feature extraction, parsing the workload into specific characteristics (e.g., column information, WHERE, JOIN, GROUP BY, and ORDER BY conditions) and retrieving environment information (e.g., the existing indexes). Based on workload feature, demonstration match is performed for ICL knowledge injection, and the input-comprising the extracted features, selected demonstrations, and a fixed instruction—is then fed into the LLM to generate recommended index sets. To further improve the reliability of LLM's recommendation, we introduce a database-aware inference scaling strategy, enhancing result quality from vertical and horizontal dimensions. Specifically, vertical scaling primarily optimizes the recommendation through an "Index-Guided Major Voting" combined with Best-of-N, while horizontal scaling implements a "self-optimization" mechanism, enabling the LLM to iteratively improve its own recommendations based on the demonstrations with "refined label" in a database-aware manner.

4 DEMONSTRATION CONSTRUCTION

We propose using GPT-4-Turbo to generate workloads and collecting their labels through multiple heuristic methods.

4.1 Workload Generation

Considering that existing benchmarks provide several templates with fixed structure, which indicates that similar columns will appear in the workload with the same templates, it is necessary to synthesize diverse SQL queries beyond using these fixed templates to ensure high-quality data, avoiding overlap with test data. Given that OLTP benchmarks are primarily used to emulate concurrent real-time transactions in commercial environments through executing several simple queries repeatedly, it is easier to generate the optimal result due to fewer candidate indexes (e.g., there are

only two candidate columns per table on average for the Twitter database in OLTP-bench [11]). In this paper, we mainly focus on index recommendation for OLAP benchmarks.

Due to the complexity of analytical queries involving multiple operations like filter and join, referring to [17], we utilize GPT-4-Turbo [32] to synthesize complicated SQL queries with the prompt consisting of the system instruction, the database schema, the constraint conditions such as columns' values and the SQL dialect, and output format. We ensure the validity and diversity of generated SQL queries by carefully designing the input prompt and postprocessing the raw output. Specifically, diversity is controlled by randomly sampling tables, column values, and benchmark queries to guide the generation process each time, leading to varied query generation. To ensure data validity, we execute the EXPLAIN command to detect syntax errors in queries and resolve them through GPT-4-Turbo. To prevent data leakage, we perform data filtering based on its similarity to the standard benchmark after completing aforementioned data processing. Considering that individual slow queries of the workload have a significant impact on the optimization space, additional detailed time-out filtering is performed, and synthetical workloads are constructed through random sampling from the generated queries.

4.2 Label Collection

After workload generation, it is essential to identify the reliable label of each workload for demonstration construction. Since synthetic data does not have fixed templates so that the dimension of candidate indexes for demonstrations' workload is varied, it is infeasible to collect labels through learning-based methods due to the heavy training process. To minimize resource-intensive requirements, we implement a platform [19] that integrates multiple heuristic methods and generate index recommendations as label candidates under the initial state without any indexes for each workload and the given storage constraint.

Default Label Generation. Based on label candidates under corresponding storage constraint, we perform benefit estimation to select the optimal set as the default label. During benefit estimation, we observe that the recommendations from heuristic methods exhibit an unusual phenomenon, where the performance improvements derived from the results generated under low storage constraints are likely to surpass those generated under high storage constraints. We speculate that heuristic methods are limited by the fixed search pattern, tending to fall into local optimum. Therefore, we refine label candidates under specific storage constraints through extending candidates under lower storage. Then, we utilize what-if caller to select the optimal set among extended candidates for default labels generation, which only consist of index creation statements.

Refined Label Generation. To support index recommendation under various initial states of existing indexes, we construct refined labels using all suboptimal results. These labels are utilized in the subsequent LLM's "self-optimization" process of our pipeline (detailed in Section 5.2.2). Each suboptimal result represents an initial state of existing indexes, and refined labels are generated by performing index creation or deletion operations. This refined labeling can be considered a form of incremental index management.

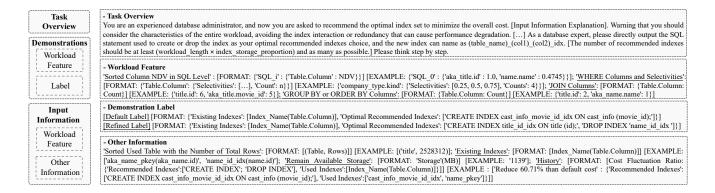


Figure 2: Illustration of LLMIDxADvIs's prompt. Due to the space constraints, we have abbreviated the specific content.

Upon finishing label collection in different initial states, we extract key information from *<workload*, *database*, *label>* triplets to construct demonstration pool. For workload and database, we retrieve database statistics and obtain core information of workload through comprehensive feature extraction (detailed in Section 5.1.1). For labels, default label includes only "CREATE INDEX" statements for recommendation, while refined label includes both "CREATE INDEX" and "DROP INDEX" statements.

5 INDEX RECOMMENDATION WITH LLM

With the demonstration pool ready, LLMIDXADVIS uses the LLM for index recommendation. It retrieves workload features (Section 5.1.1) and selects the most effective demonstrations for in-context learning (ICL) (Section 5.1.2) to create the LLM input (Section 5.1.3). To enhance the reliability of LLM inference, LLMIDXADVIS applies an index-guided scaling strategy from both vertical (Section 5.2.1) and horizontal perspectives (Section 5.2.2).

5.1 LLM Input

5.1.1 Workload Feature. Since existing methods' models are challenging to handle specific workload features (e.g., statistical information for specific column), which are essential for index management, instead, they simply consider the columns relevant to the workload for index candidates generation, leading to lengthy process for optimal result exploration. Therefore, we frame index recommendation as a sequence-to-sequence task, and leverage LLMs' flexibility of handling diverse inputs to overcome above limitations.

Considering that the primary purpose of indexes is reducing lengthy entire table scans to accelerate data retrieval, especially for larger tables, we generally adhere to following principles to recommend indexes for a given workload:

- Principle 1: Columns that appear in WHERE predicates tend to be the candidates for index construction, especially preferring those which retain fewer rows after conditional filtering.
- Principle 2: Columns involved in JOIN, GROUP BY, or ORDER BY conditions are typically regarded as potential candidates for indexing, which could avoid additional value retrieval or sorting from scanning entire table.

 Principle 3: Columns with a higher number of distinct values (NDV) are generally more suitable for index creation, as they are more likely to directly locate target rows through index due to the uniqueness of data value.

To obtain the above information, it is essential to accurately extract specific details of the workload. Therefore, we implement a comprehensive feature extraction mechanism capable of handling complex analytical SQL queries, which can extract columns under different conditional clauses based on SQL statement. For a given workload and corresponding database, we perform workload feature extraction as follows:

- Used Column Information in SQL-Level: Columns appearing
 in each SQL of the workload, along with their corresponding
 NDV, number of rows and data type. The specific information of
 the columns can be retrieved from the database statistics.
- "WHERE" Predicates and Corresponding Selectivity: All WHERE predicates appearing in the workload, along with their corresponding selectivity, which is defined as the ratio of rows that satisfy the condition to the total number of rows. Considering the uncertainty caused by the number of parallel workers used in specific node of query plan for the SQL, we construct a simple SQL query for each predicate formed as "SELECT * FROM [table] WHERE [predicate]", and obtain total rows from query plan as the number of rows satisfying the condition by executing the EXPLAIN command.
- "JOIN" Columns: Columns appearing in all JOIN conditions within the workload, along with their frequencies of occurrence.
- "GROUP BY" and "ORDER BY" Columns: Columns appearing
 in all GROUP BY or ORDER BY conditions within the workload,
 along with their frequencies of occurrence.

5.1.2 In-Context Learning. Considering the lack of database specific knowledge in general LLMs, except detailed feature extraction, we utilize in-context learning [3, 12, 30] to balance model performance with resource efficiency, which can utilize in-context demonstrations without extensive fine-tuning to adapt the model to a new domain.

Based on the constructed demonstration pool, it is essential to select demonstrations which are most effective for the given workload. In this regard, we primarily extract schema-independent

statistics from the workload as the meta-feature of a demonstration to support demonstration matching across different database schemas. The meta-feature involves the frequencies of the columns appearing in the workload as well as their NDVs, formatted as $[(f_1, ndv_1), ..., (f_k, ndv_k)]$. Specifically, we apply normalization and subsequently sort them in descending order based on the above two features as the ultimate workload meta-feature.

To accurately identify the most effective demonstrations, we explored the following three strategies for demonstration matching:

- Random Sample: Select demonstrations randomly from the demonstration pool.
- Cosine Similarity Ranking: Calculate the cosine similarity between workload meta-features and sort them in descending order.
- **K-Means Clustering [43]:** Use the k-means clustering algorithm [27] to determine *k* cluster centers, and select the matching cluster through calculating the Euclidean distance between the cluster centers and the meta-feature of the input workload, then randomly sample demonstrations from the matched cluster.

According to the experimental results (detailed in Section 6.5.3), the cosine similarity ranking is chosen as the final strategy for demonstration match. During LLM's inference, we inject top 2 demonstrations into LLM's input, and update them iteratively during "self-optimization" process (detail in Section 5.2.2).

- *5.1.3 Prompt Engineering.* As shown in Figure 2, the prompt of LLM is mainly composed of three components:
- **Fixed System Instruction** includes the task overview, the format of input and output information, as well as some simple suggestions, such as the requirements for recommended indexes order. Additionally, to avoid misleading LLM with the limited number of recommended indexes in demonstrations, we impose an additional condition that suggests recommending at least " $m \times S_p$ " indexes during the first inference. Here, m denotes the length of the workload, and S_p denotes the percentage of database size occupied by index storage constraint.
- Demonstrations are selected using the strategy discussed in Section 5.1.2, updating progressively according to their ranking during iterations to provide more information for effective refinement. Demonstrations' label will be determined based on the current state of existing indexes, choosing default label for the initial state without any existing indexes or refined label otherwise to enable incremental index management.
- Input Information primarily involves workload features mentioned in Section 5.1.1, used table rows, as well as additional characteristics such as existing indexes, remain available storage, and historical information, which will be updated throughout "self-optimization" process. Specifically, historical information includes the cost fluctuation with its recommended indexes and the indexes appeared in query plans (i.e., used indexes).

5.2 LLM Inference Scaling

Given that the inference process is essentially predicting the probability distribution of next token based on preceding tokens, some differences may occur in multiple outputs with the same input information, resulting in the instability of recommendation results.

```
Multi-Sampling from LLM (Options)
CREATE INDEX lineitem_1_orderkey_1_suppkey_idx ON lineitem (1_orderkey, 1_suppkey)
CREATE INDEX nation_n_name_idx ON nation (n_name);
DROP INDEX orders o orderdate idx:
CREATE INDEX lineitem_l_orderkey_idx ON lineitem (l_orderkey);
CREATE INDEX nation_n_name_idx ON nation (n_name);
DROP INDEX orders o orderdate idx:
CREATE INDEX lineitem_1_orderkey_1_suppkey_idx ON lineitem (1_orderkey, 1_suppkey) ;
CREATE INDEX nation n name n regionkey idx ON nation (n name, n regionkey);
DROP INDEX lineitem_1_shipdate_idx;
                                    Aggregating
                                  Candidate Indexes
DROP INDEX orders o orderdate idx; [Count : 2]
DROP INDEX lineitem_l_shipdate_idx; [Count : 1]
CREATE INDEX nation_n_name_idx ON nation (n_name); [Count : 2]
CREATE INDEX lineitem_l_orderkey_idx ON lineitem (l_orderkey); [Count: 1]
CREATE INDEX lineitem_l_orderkey_l_suppkey_idx ON lineitem (l_orderkey,l_suppkey)
CREATE INDEX nation_n_name_n_regionkey_idx ON nation (n_name, n_regionkey);
                                      Merging
                                   Potential Option
DROP INDEX orders_o_orderdate_idx;
CREATE INDEX lineitem 1_orderkey_1_suppkey_idx ON lineitem (1_orderkey, 1_suppkey);
CREATE INDEX nation n na
                             me idx ON nation (n name)
```

Figure 3: Illustration of "Index-Guided Major Voting".

However, using greedy search method (i.e., setting the temperature as 0) for LLM inference to ensure stability may significantly degrade workload performance due to insufficient exploration of search space. Therefore, we introduce an index-guided inference scaling strategy to further enhance LLM's reliability while improving performance, involving vertical scaling and horizontal scaling.

5.2.1 Vertical Scaling. Specifically, we set LLM's hyperparameter of temperature as 0.6, and the number of samples as 8, performing multiple-sampling to enhance the diversity of LLM inference. For each sample, we treat it as a option for optimal set, and we observe that the indexes in these options exhibit some overlap, while their performances present significant variation during benefit estimation. Drawing inspiration from the major voting strategy [16, 49], we hypothesize that indexes recommended more frequently are likely to boost workload performance more effectively. Aiming to enhance the effectiveness of the current recommendations, we propose an "Index-Guided Major Voting" strategy to construct a potential option, and an illustration is presented in Figure 3.

Firstly, the candidate indexes are aggregated from the existing options and sorted based on their recommended frequency, involving both "CREATE INDEX" and "DROP INDEX" statements. Then, we perform the merging process to construct the potential option. For "DROP INDEX" statements, we retain statements with more than one recommendation, and append them into the potential option, releasing more space for index creation while mitigating the impact of occasional recommendation. For "CREATE INDEX" statements, we prioritize retaining all the single-column index recommendations to minimize storage. Considering multi-column indexes are more likely to be used but require more storage, we choose to retain those with more than one recommendation. If an index in potential option serves as the prefix of a multi-column index (e.g., the index "lineitem_l_orderkey_idx" is the prefix of the index "lineitem_l_orderkey_idx" in Figure 3), we keep

Table 2: Database information and workload statistics. For the statistics in SQL level, we present the "MIN / MAX / AVG" value of each clause in the standard benchmarks (left) and constructed demonstrations (right).

Database	Size	# Tables	# Demonstrations	# Queries	# WHERE Predicates per SQL	# JOIN Predicates per SQL	# GROUP BY / ORDER BY Columns per SQL
TPC-H [47]	7.2GB	8	192	19 745	1 / 4 / 2.11 0 / 8 / 1.47	0 / 7 / 2.87 2 / 13 / 4.11	0 / 7 / 1.95 2 / 7 / 2.06
JOB [22]	6.9GB	21	198	113 950	1 / 14 / 1.72 0 / 8 / 1.66	5 / 24 / 11.84 1 / 12 / 3.28	0 / 0 / 0.0 0 / 6 / 1.52
TPC-DS [46]	2.3GB	24	200	90 1003	1 / 14 / 1.98 0 / 25 / 2.34	0 / 21 / 6.13 0 / 14 / 3.2	0 / 17 / 4.88 0 / 15 / 3.74
SSAG	58GB	13	-	6	3 / 8 / 4.5	0 / 2 / 0.83	0 / 5 / 2.33
AMPS	14GB	6	-	95	0 / 3 / 0.77	0 / 1 / 0.03	0 / 1 / 0.16

the multi-column index, and accumulate the count of its prefix index for re-ranking. This process continues until all the multi-column indexes are considered.

After constructing all candidates for optimal set, we perform benefit estimation to identify the optimal set. Since the candidates are independent of each other, we can evaluate each result simultaneously using what-if caller, and the result with the minimum cost will be chosen as current optimal index set.

5.2.2 Horizontal Scaling. LLMIDxADVIS utilizes multi-step inference to implement a "self-optimization" mechanism, interacting with database engine to iteratively refine its recommendation.

After generating optimal set through vertical scaling, what-if caller is used to manage recommended indexes virtually, updating initial state of existing indexes for refinement. Before LLM inference in next iteration, LLM's input requires to be updated, involving demonstrations and input information. For demonstrations, we replace existing demonstrations with new ones according to previous ranking, skipping those that have already been presented to provide more reference information. Demonstrations' labels are updated based on current state of existing indexes, choosing refined label under the condition that exists indexes or default label otherwise. For input information, existing indexes, remain available storage, and historical information can be calculated after virtual index creation by what-if caller. The optimization process continues until the performance is no longer improved or the maximum number of iterations is reached, and the indexes with the optimal performance are selected as the final recommended result.

6 EXPERIMENTS

In this section, we conduct comprehensive experiments to evaluate the performance of the proposed LLMIDXADVIS, answering the following questions:

- RQ1: How does LLMIDXADVIS perform compared with the existing methods across various database schemas and a broad range of storage constraints?
- RQ2: Given that the optimization objective in the recommendation process is the estimated cost calculated by what-if caller, can these indexes effectively enhance the actual execution performance of the workload?
- **RQ3:** Is the proposed pipeline in LLMIDXADVIS strongly associated with the underlying LLM, that is, whether it is still effective when migrating to other LLM backbones?
- **RQ4:** Considering that LLMIDXADVIS consists of multiple components, how do they enhance the overall performance of the index recommendation pipeline?

 RQ5: Could LLMIDXADVIS be transferred to other scenarios beyond the in-context demonstrations? Here, we primarily investigate its generalization capability under varying storage constraints and database schemas.

6.1 Experimental Settings

6.1.1 Environments. We perform all the experiments in PostgreSQL 12.2 database system on a server equipped with an Intel(R) Xeon(R) CPU E5-2650 v4 @ 2.20GHz featuring 12 cores and 24 threads, along with 64GB of RAM. To support the cost estimation for the given workload, we implement the what-if caller through HypoPG extension [6] to simulate the process of creating or dropping index and obtain the estimated cost of a SQL query with the consideration of virtual indexes through executing the EXPLAIN command.

6.1.2 Benchmarks and Datasets. We utilize 3 standard OLAP benchmarks consisting of complex analytical SQL queries to conduct the experimental evaluation, including TPC-H [47], Join Order Benchmark (JOB) [22], and TPC-DS [46]. The JOB benchmark involves 113 query templates based on data from the Internet Movie Database (IMDB), while the TPC-H and TPC-DS benchmarks involve 24 and 99 query templates respectively with synthetic data. Given that some of the SQL queries contribute significantly to the total execution time of the workload due to the complicated structure, refer to previous studies [19], we exclude these queries from the evaluation process. Specifically, we exclude the queries 4, 6, 9, 10, 11, 32, 35, 41, 95 in TPC-DS, and queries 2, 17, 20 in TPC-H.

Since LLMs have likely encountered queries from the above well-known benchmarks during their pre-training, we conduct extended experiments to evaluate LLMIDXADVIS without this influence. Specifically, we test LLMIDXADVIS on two real-world private commercial workloads from ByteDance: SSAG and AMPS, which should not be present in the pre-training corpus for LLMs. Among them, SSAG is an OLAP benchmark used for analyzing and managing slow SQL queries, including tasks like slow SQL identification and logical database analysis. AMPS, on the other hand, is an OLTP benchmark used in AI platform services, including transactions related to user management, permission control, algorithm management, model management, and task scheduling. These benchmarks are used exclusively as test sets in our evaluation. To explicitly observe the experimental results, all the pre-defined indexes except primary keys are removed before the index recommendation.

We utilize the method introduced in Section 4 to construct demonstrations for ICL, and the SQL queries generated with high similarity to the templates of standard benchmarks are filtered out to prevent data leakage. The detailed information is presented in Table 2, involving the database size, the number of tables in each database, the number of demonstrations, and the specific statistics

of the workloads in demonstrations and standard benchmarks (the number of distinct queries and the average number of query clause per type). For SSAG and AMPS, we treat them as complete testing benchmarks without additional demonstration construction. For the constructed demonstrations, statistical analysis indicates that the synthetic workloads not only exhibit a similar level of complexity as the standard benchmarks (refer to the specific statistics), but also offer a diverse set of query templates that surpass the standard benchmarks (refer to the # Queries).

Data Collection Cost. We briefly outline the cost involved in the demonstration construction process. For workload generation, we utilize GPT-4-Turbo sampling approximately 1,000 SQL queries per database, which takes nearly 17 hours with \$90 cost for 3 database schemas given an average GPT API's response time of around 20 seconds. We set the minimal scale factor to generate a small amount of data in the databases for filtering invalid queries, which takes only a few minutes. For label collection, we utilize multiple heuristic methods to generate the candidate labels for a workload under different storage constraints, and due to the different candidate numbers, this process takes an average of 2 min for each workload across all storage conditions on TPC-H, while it requires 1 hour per workload for JOB and TPC-DS. Considering that the virtual index management through what-if caller is independent across different database instances, the label generation can be performed concurrently for the three databases, and it takes approximately 8 days to sequentially generate the original labels for the constructed workloads on a single server. We speed up the label collection process through distributing it into 10 CPU servers.

6.1.3 Baselines. We compare both heuristic and learning-based existing methods with our proposed LLMIDXADVIS for extensive evaluations. For the heuristic methods which mainly utilize greedy search and its variants for index recommendation, we evaluate (1) Extend [40], (2) Relaxation [4], (3) DTA [2], (4) DB2Advis [44], (5) AutoAdmin [7], and (6) Drop [8]. For the learning-based methods, we evaluate (7) AutoIndex [55], which leverages Monte Carlo Tree Search for incremental index management; (8) DQN [31] and (9) SWIRL [20], which utilize reinforcement learning, specifically Deep Q-Network and the Proximal Policy Optimization (PPO) [42] algorithms, for index recommendation; (10) BALANCE [50], which leverages reinforcement learning similar to SWIRL with a transfer mechanism to adapt to dynamic workload scenarios; (11) MFIX [5], which utilizes Bayesian Optimization (BO) algorithm [34] for index recommendation.

Due to the fixed dimensions of trained models in learning-based methods [5, 20, 31, 50], which makes them infeasible to be applied for workloads with a different number of index candidates compared to the training workload, we adopt an online iterative approach for index recommendation in these methods instead of training them using the synthetic workloads. For the sake of fairness, we modify some of the existing methods [7, 8] to satisfy the index recommendation under the storage constraint.

6.1.4 Metrics. We evaluate the index advisors mainly from three aspects as follows. (1) **Relative Workload Cost Reduction** defines as the proportion of reduction in the workload estimated cost after virtually creating the recommended indexes, which can be

obtained in the query plan through executing the "EXPLAIN" command. A higher value signifies a better performance improvement. (2) **Algorithm Runtime** is the execution time of the algorithms to generate the index recommendation result, where lower value indicates better efficiency. (3) **Relative Workload Latency Reduction** defines as the proportion of reduction in the workload latency after creating the recommended indexes, which requires making actual modifications to the database to obtain accurate execution metrics. A higher value denotes a better performance improvement.

6.1.5 Evaluation Settings. We utilize GPT-40-mini [33] as the backbone of our pipeline, and primarily set up different experiments based on various storage constraints and application scenarios.

For storage constraint, given that the recommended index's size is related to the size of its associated database, we define it as the percentage of the corresponding database size. Specifically, the percentage can be calculated as: $\frac{index\ storage\ constraint\ (MB)}{database\ size\ (MB)}\times 100\%.$ We set up five different storage constraints in the evaluation of the workload's estimated cost, and after that, we primarily select the storage constraints of 30% and 60% to represent the lower and higher conditions for other experiments. In particular, we set up the experiment for 2 real-world benchmarks under only one representative storage constraint, as there is no significant performance improvement with higher storage owing to the small number of columns appeared in the workload.

For application scenarios, the evaluation of LLMIDXADVIS is conducted from two different settings: (1) In-Schema: We use all demonstrations for ICL matching to evaluate 3 OLAP benchmarks; (2) Cross-Schema: We use the demonstrations excluded the data in the test benchmark for ICL matching. Specifically, the real-world benchmarks are only evaluated under the cross-schema setting owing to no in-schema demonstration construction.

6.2 Evaluation of Workload Estimated Cost

To comprehensively evaluate LLMIDXADVIS's performance under different scenarios (RQ1), we conduct extensive experiments compared with 11 existing methods in 3 OLAP benchmarks under different storage constraints and 2 real-world benchmarks.

6.2.1 Standard Benchmark Evaluation. Experimental results in standard benchmarks are presented in Figure 4, and the main findings are as follows:

LLMIDxADVIS demonstrates an outstanding trade-off between efficacy and efficiency, accelerating the index recommendation process while identifying satisfactory indexes. Across all benchmarks and storage constraints, LLMIDxADVIS maintains high efficiency and recommends indexes with comparable performance to the state-of-the-art methods. We further analyze our method in terms of efficacy and efficiency as follows:

LLMIDxAdvis demonstrates comparable performance to most base-line methods. Experimental results indicate that LLMIDxAdvis (IS) surpasses the performance of learning-based methods in all benchmarks and achieves comparable results to heuristic methods in the TPC-H and JOB benchmarks. It only exhibits marginal performance degradation in the TPC-DS benchmark compared to heuristic methods, primarily due to the complexity of queries, which involve a large set of columns and result in an extensive candidate index

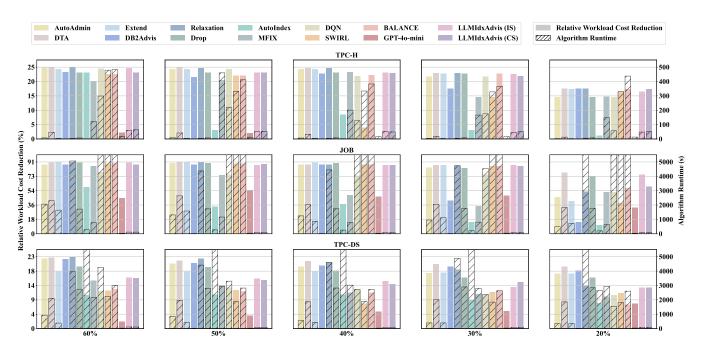


Figure 4: Workload cost evaluation across 3 OLAP benchmarks under different storage constraints.

set. This large search space presents challenges in recommending optimal results within fewer iterations and minimal direct feedback from the what-if caller.

LLMIDXADVIS significantly accelerates the index recommendation process, particularly on benchmarks with complex queries. Specifically, LLMIDxADVIS demonstrates higher efficiency than all learningbased methods across all benchmarks. Learning-based methods require extensive iterative training, resulting in time-consuming online recommendations. For example, learning-based methods take an average of 13,616 seconds for the JOB benchmark, while LLMIDxADvis completes the task in just 89 seconds, achieving a 99.3% improvement in efficiency $\left(\frac{13,616-89}{13.616} = 99.3\%\right)$. On the other hand, heuristic methods show varying efficiency across different benchmarks. In the TPC-H benchmark, which only includes 19 SQL queries with 8 tables, the index candidates amount to approximately one hundred entries, enabling heuristic methods to find the optimal result in an average of 10 seconds, whereas LLMIDxADvIs takes about 52 seconds. In contrast, for the complex JOB and TPC-DS benchmarks, heuristic methods require an average of 1,838 seconds, while LLMIDxADVIS completes the task in only 90 seconds, achieving a 95.1% efficiency improvement $\left(\frac{1,838-90}{1,838} = 95.1\%\right)$. Notably, DB2Advis [44], the fastest index recommendation method, avoids iterative evaluations by pre-ranking index candidates based on their benefits. However, it suffers significant performance degradation in certain scenarios, such as under 30% storage constraints in the TPC-H and JOB benchmarks.

Compared with the learning-based methods, LLMIDXADvis could leverage the unified pipeline recommending indexes across different database schemas. After utilizing LLM to model index recommendation as a NLP task. LLMIDXADVIS avoids the limitations of the learning-based methods which are incapable of training a unified model owing to the dimensionality discrepancy across different index candidates. Experimental results demonstrate that LLMIDXADVIS (CS) can still identify satisfactory recommendation indexes while retaining extraordinary recommendation efficiency, even surpassing the performance of LLMIDXADVIS (IS) in several scenarios. We speculate that is due to the inherent generalization capability of LLMs, which prevents the overfitting issues that may arise from task-specific supervised fine-tuning, thereby highlighting that LLMIDXADVIS could exhibit the satisfactory performance under resource-efficient requirements while enabling effective generalization across different database schemas.

LLMIDXADVIS'S elaborate designed pipeline significantly enhances the LLM's capability in index recommendation.To validate the efficacy of LLMIDXADVIS'S index recommendation pipeline, we conduct a comparative analysis utilizing GPT-40-mini for index recommendation solely based on the SQL statements of the target workload, which exhibits severe performance degradation compared with LLMIDXADVIS. We speculate that it is difficult for general LLMs to accurately extract the target workload's core information conducive for index creation due to their insufficient training in database expertise, further emphasizing the critical significance of LLMIDXADVIS'S database-specific knowledge augmentation framework.

6.2.2 Real-World Benchmark Evaluation. Considering the potential exposure of LLMs' pre-training process to the knowledge associated with the standard benchmarks, we additionally evaluate LLMIDX-ADVIS's performance under the real-world benchmarks keeping the entire demonstration pool as the cross-schema setting, and implement all the baseline methods in ByteDance private environment, with the results presented in Figure 5.

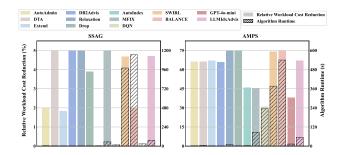


Figure 5: Workload cost evaluation across 2 real-world benchmarks under the storage constraint of 30%.

Under these private workload scenarios, LLMIDxADVIS could still recommend the second optimal indexes compared with the baseline methods, exhibiting its outstanding out-of-the-box capabilities. Due to the limited complexity of the database schema in these two workloads, the search space is comparable to or even smaller than that of the TPC-H benchmark. Thus heuristic methods exhibit high efficiency while LLMIDxADVIS maintains an average recommendation time of approximately 68 seconds, slightly lagging behind the heuristic methods. This suggests that LLMIDxADVIS is more advantageous for workloads with more complex queries and database schemas, where its faster search efficiency becomes more prominent in larger search spaces.

6.3 Evaluation of Workload Actual Latency

In addition to evaluating the estimated cost of the workload, we assess the average latency reduction during actual workload execution after applying the recommended indexes to verify their effectiveness in practical scenarios (RQ2). The results are shown in Figure 6.

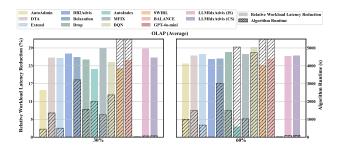


Figure 6: Average workload latency evaluation.

Compared to all baseline methods, LLMIDXADVIS demonstrates exceptional efficiency while maintaining comparable performance improvements. Unlike the estimated cost evaluations, heuristic methods show noticeable performance degradation during actual execution. We speculate that heuristic methods strictly follow whatif cost estimations to find the optimal result, which can sometimes inaccurately predict actual execution latency, leading to suboptimal outcomes. In contrast, LLMIDXADVIS, though it relies on some what-if cost estimations for self-optimization, uses its comprehensive feature extraction to capture critical workload statistics and

leverages LLMs' reasoning abilities to recommend suitable indexes. This approach reduces excessive dependence on what-if estimations and improves practical performance.

6.4 Evaluation of LLM Backbones

To validate the robustness of our index recommendation pipeline (RQ3), we replaced GPT-40-mini with various LLM base models, including the LLaMA [29] and Qwen [9] family, and primarily evaluate model performance under sophisticated JOB and TPC-DS benchmarks, as shown in Table 3. Experimental results demonstrate that LLMIDXADVIS's index recommendation pipeline can effectively adapt to various LLM base models, delivering promising results and underscoring the versatility of our framework.

Table 3: Relative workload cost reduction compared with different LLM backbones. Due to space limitation, we elaborate experimental results under partial storage constraints in complex database schemas, involving In-Schema (left) and Cross-Schema (right) settings. (Higher value is better)

	ЈОВ		TPC-DS	
	30%	60%	30%	60%
GPT-40-mini [33]	87.2 / 86.3	90.6 / 87.9	13.5 / 15.1	16.5 / 16.5
Meta-Llama-3.1-70B-Instruct [29]	83.0 / 85.8	86.5 / 89.8	15.9 / 17.1	18.3 / 17.8
Meta-Llama-3.1-8B-Instruct [29]	82.6 / 83.3	88.5 / 86.9	15.5 / 16.4	18.8 / 18.2
Qwen2.5-72B-Instruct [9]	19.8 / 52.4	86.2 / 87.9	16.0 / 16.2	16.6 / 17.7
Qwen2.5-7B-Instruct [9]	82.9 / 86.7	88.4 / 90.3	15.1 / 15.1	16.7 / 16.8
Qwen2.5-Coder-32B-Instruct [9]	57.3 / 58.5	89.8 / 86.7	15.3 / 15.5	18.9 / 17.8

6.5 Ablation Study

We conduct extensive ablation experiments to verify the effectiveness of different components in our method (RQ4).

6.5.1 Ablations on Input Features. As described in Section 5.1.1, we primarily extract the features for the target workload involving used columns information in SQL-level and specific condition information in workload-level (e.g., "WHERE" predicates and corresponding selectivity, columns in "JOIN", "GROUP BY" and "ORDER BY"). To validate the importance of this detailed feature extraction, we conducted an experiment (results in Table 4). The results show significant performance drops when using the raw workload or omitting parsed condition details, highlighting the critical role of comprehensive feature extraction in preserving key information for effective index creation.

6.5.2 Ablations on Demonstrations. To tackle the lack of database expertise in general LLMs, we construct a high-quality demonstration pool as presented in Section 4 using for in-context learning. We conduct the experiment reducing the number of demonstrations to validate its necessity (refer to "Demonstrations" in Table 4). In the zero-shot setting, no additional demonstrations are provided. As a result, we do not differentiate between in-schema and cross-schema scenarios for the zero-shot method, leading to a single performance measurement under a given storage constraint. We observe that the performance gradually decreases as the number of demonstrations reduces, supporting the observation that LLMs are deficient in database-specific knowledge.

Table 4: Ablation studies of LLMIDXADVIS. Here, we present the average of the relative workload cost reduction among 3 OLAP benchmarks under the settings of in-schema (left) and cross-schema (right). (Higher value is better)

	30%	60%
LLMIdxAdvis	41.4 / 39.9	44.3 / 42.8
Input Features		
- Raw Workload	38.3 / 38.8	41.0/ 41.7
- Only SQL-level Information	28.9 / 36.9	33.6 / 39.7
Demonstrations		
- zero-shot	29.9	40.7
- one-shot	37.8 / 37.8	42.7 / 42.2
Demonstrations Match Strategies		
- Random Sample	39.5 / 36.9	41.2 /41.6
- K-Means Clustering	37.1 / 37.9	42.4 / 41.9
LLM Hyperparameters		
- Temperature = 0	20.5 / 13.9	31.0 / 29.4
Inference Scaling Strategies		
- Sample 1 + IdxMV + Opt 4	30.1 / 26.3	37.6 / 37.1
- Sample 4 + IdxMV + Opt 4	36.2 / 37.2	42.8 / 41.0
- Sample 8 + Opt 4	37.1 / 36.1	43.4 / 42.8
- Sample 8 + IdxMV + Opt 1	36.3 / 36.9	42.7 / 40.6
- Sample 8 + IdxMV + Opt 2	37.5 / 37.8	42.7 / 40.9

6.5.3 Ablations on Demonstrations Match Strategies. After constructing the demonstrations, it is essential to pick up the most beneficial ones as discussed in Section 5.1.2. In this regard, we conduct an experiment comparing the different demonstration match strategies as presented in Table 4. We observe that the cosine similarity ranking strategy adopted in LLMIDXADVIS slightly outperforms the other two strategies: random sampling and K-Means clustering.

6.5.4 Ablations on LLM Hyperparameters. LLM inference process can control the diversity of the output content through adjusting the hyperparameter of temperature, which the higher value denotes generating more diverse results while reducing the reliability. We set the temperature as 0.6 in LLMIDXADVIS's original pipeline, and lowering it to 0 significantly degrades performance (refer to "LLM Hyperparameters" in Table 4), elucidating it infeasible to maintain the reliability of LLM through decreasing the hyperparameter of temperature.

6.5.5 Ablations on Inference Scaling Strategies. To improve the reliability and performance of our model, we introduce an index-guided inference scaling strategy (detailed in Section 5.2), which includes multi-sampling (abbreviated as Sample), an index-guided major voting strategy (abbreviated as IdxMV), and a self-optimization process (abbreviated as Opt). Ablation studies in Table 4 show significant performance drops when any of these components are removed, underscoring the importance of the complete strategy.

Specifically, integrating multiple inference strategies strengthens the generation of optimal indexes across different aspects: Multiple sampling increases the likelihood of producing the optimal result by expanding the pool of index candidates. Index-guided major voting ensures robust results for single inference by summarizing potential candidates in a database-aware manner. Self-optimization

leverages the reasoning ability of the model to refine the current optimal result based on previous outputs.

6.6 Generalization

Since the demonstrations cannot cover all scenarios, we conduct additional experiments (RQ5) to evaluate LLMIDXADVIS 's generalization across database schemas and storage constraints.

Table 5: Generalization to different storage constraints. We evaluate the relative workload cost reduction under two settings: in-schema (left) and cross-schema (right), with 30% and 60% storage constraints. (Higher value is better)

	30%		60%		
	In-Storage	Cross-Storage	In-Storage	Cross-Storage	
TPC-H	23.36 / 22.72	18.27 / 23.69	25.65 / 23.88	23.91 / 23.83	
JOB	87.17 / 86.33	86.68 / 86.42	90.58 / 87.95	88.59 / 88.71	
TPC-DS	13.45 / 15.07	13.54 / 13.27	16.54 / 16.5	16.11 / 16.94	

Figure 4 has already shown the cross-database schema generalization ability of LLMIDXADVIS. Table 5 highlights the generalization of LLMIDXADVIS across storage constraints. The results show smooth generalization across different storage constraints with minimal performance loss. In the in-schema setting, LLMIDXADVIS exhibits slight performance degradation under in-storage constraints compared to cross-storage constraints. We speculate that, in the in-schema setting, LLMs attempt to copy recommended indexes from demonstrations with the same schema. However, differences in storage constraints can prevent these indexes from achieving the expected performance. In the cross-schema setting, where demonstrations involve different schemas, LLMs cannot rely on the specific index information. Instead, they learn more generalizable strategies for index recommendation, resulting in performance similar to the in-schema setting.

7 CONCLUSION AND DISCUSSION

In this paper, we propose LLMIDXADVIS, an efficient and lightweight LLM-based pipeline for index recommendation that constructs a compact, high-quality demonstration pool for in-context learning and implement a comprehensive workload feature extractor, assisting the LLM to thoroughly comprehend the target workload. Meanwhile, an index-guided inference scaling strategy is designed involving both vertical and horizontal scaling to enhance the reliance and performance of our method.

Extensive experiments demonstrate that LLMIDxADVIS excels out-of-the-box, balancing efficacy, efficiency, and resource consumption. However, there still remains potential for further improvement. For efficacy, LLMIDxADVIS struggles to recommend optimal indexes for complex workloads (e.g., TPC-DS) due to the need for precise feature extraction under resource constraints. For efficiency, the iterative inference of the LLM significantly impacts recommendation time, suggesting that reducing inference steps could help. Additionally, minimizing resource usage leads to some trade-offs in performance. Fine-tuning an open-source LLM with diverse, high-quality data could further enhance performance across all aspects.

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