D-Bot: Database Diagnosis System using Large Language Models

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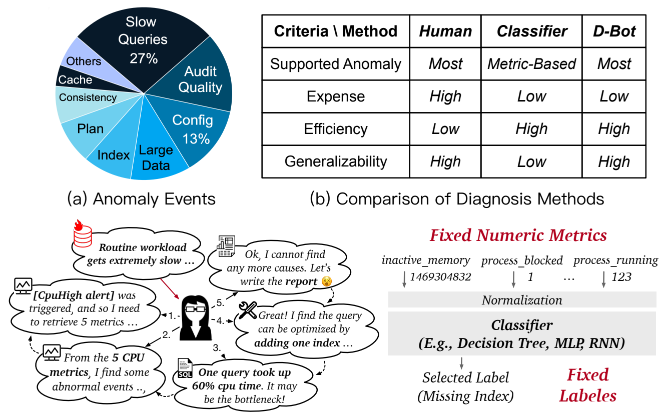
ABSTRACT

Database administrators (DBAs) play an important role in managing, maintaining and optimizing database systems. However, it is hard and tedious for DBAs to manage a large number of databases and give timely response (waiting for hours is intolerable in many online cases). In addition, existing empirical methods only support limited diagnosis scenarios, which are also labor-intensive to update the diagnosis rules for database version updates. Recently large language models (LLMs) have shown great potential in various fields. Thus, we propose *D-Bot*, an LLM-based database diagnosis system that can automatically acquire knowledge from diagnosis documents, and generate reasonable and well-founded diagnosis report (i.e., identifying the root causes and solutions) within acceptable time (e.g., under 10 minutes compared to hours by a DBA). The techniques in *D-Bot* include (*i*) offline knowledge extraction from documents, (*ii*) automatic prompt generation (e.g., knowledge matching, tool retrieval), (*iii*) root cause analysis using tree search algorithm, and (*iv*) collaborative mechanism for complex anomalies with multiple root causes. We verify *D-Bot* on real benchmarks (including 539 anomalies of six typical applications), and the results show that *D-Bot* can effectively analyze the root causes of unseen anomalies and *significantly outperforms traditional methods and vanilla models like GPT-4.*

PVLDB Artifact Availability:
The source code, data, technical report, and other artifacts have been made available at https://github.com/TsinghuaDatabaseGroup/DB-GPT.



Criteria \ Method	*Human*	*Classifier*	*D-Bot*
Supported Anomaly	*Most*	*Metric-Based*	*Most*
Expense	*High*	*Low*	*Low*
Efficiency	*Low*	*High*	*High*
Generalizability	*High*	*Low*	*High*

(a) Anomaly Events (b) Comparison of Diagnosis Methods

(c) Diagnosis by Human (d) Classifier for Fixed Scenario

Figure 1: Database diagnosis is a complex problem mainly handled by human expertise – (a) example root causes of anomalies in a database vendor; (b) comparison of diagnosis methods; (c) toy example of diagnosing by human DBA; (d) example of diagnosing by machine learning classifier.

1 INTRODUCTION

Database diagnosis aims to detect, analyze, and resolve anomaly events in database systems, thereby ensuring high data availability and workload performance. However, database anomalies are remarkably diverse, making it impossible to comprehensively cover them with predefined rules [18]. As shown in Figure 1 (a), a database vendor encountered over 900 anomaly events in three months, most of which spanned various facets of database and system modules (e.g., slow query processing, locking mechanisms, improper configurations). Furthermore, these modules exhibit complex correlations with system metrics (e.g., high CPU usage may result from concurrent commits or massive calculations). So it requires to explore different reasoning strategies (e.g., investigating different system views) before identifying the potential root causes.

As a result, database diagnosis is a challenging problem, where *"the devil is in the details"* [11, 62]. Many companies rely on the expertise of human database administrators (DBAs) to undertake diagnosis tasks. Here we present a simplified example (Figure 1 (c)): *(1) Anomaly Notification.* The database user notifies an anomaly, e.g., "routine queries ... is 120% slower than the norm ..."; *(2) Alert Detection.* Upon receiving the user's notification, the DBA first investigates the triggered alerts. For instance, the DBA discovers a "CPU High" alert, indicating the total CPU usage exceeded 90% for 2 minutes; *(3) Metric Analysis.* Next the DBA delves deeper to explore more CPU-related metrics (e.g., the number of running or blocked processes, the number of query calls). By analyzing these metrics, the DBA concludes the issue was caused by some resource-intensive queries. *(4) Event Analysis.* The DBA retrieves the statistics of top-k slow queries (query templates) from database views, and finds one query consumed nearly 60% of the CPU time. *(5) Optimization Advice.* The DBA tries to optimize the problematic query (e.g., index update, SQL rewrite) by experience or tools.

The above diagnosis process is inherently iterative (e.g., if the DBA fails to find any abnormal queries, she may turn to investigate I/O metrics). Besides, the DBA needs to write a diagnosis report[1] to facilitate the user's understanding, which includes information like root causes together with the detailed diagnosis processes.

However, there exists a *significant gap between the limited capabilities of human DBAs and the daunting diagnosis issues.* Firstly, training a human DBA demands an extensive amount of time, often ranging from months to years, by understanding a large scale of relevant documents (e.g., database tuning guides) and the necessity for hands-on practice. Secondly, it is nearly impossible to employ sufficient number of human DBAs to manage a vast array of database instances (e.g. millions of instances on the cloud). Thirdly, a human DBA may not provide timely responses in urgent scenarios, especially when dealing with correlated issues across multiple

[1]Over 100 diagnosis reports are available on the website *http://dbgpt.dbmind.cn/.*

database modules, which potentially lead to significant financial losses. Thus, *if typical anomalies can be automatically resolved, it will relieve the burden of human DBAs and save resources.*

Driven by this motivation, many database products are equipped with semi-automatic diagnosis tools [20, 22, 29, 30, 32]. However, they have several limitations. First, they are built by empirical rules [11, 62] or small-scale ML models (e.g., classifiers [34]), which have poor scenario understanding capability and cannot utilize the diagnosis knowledge. Second, they cannot be flexibly generalized to scenario changes. For empirical methods, it is tedious to manually update and verify rules by newest versions of documents. And learned methods (e.g., XGBoost [8], KNN [17]) require to redesign the input metrics and labels, and retrain models for a new scenario (Figure 1 (d)). Third, these methods have no inference ability as human DBAs, such as recursively exploring system views based on the initial analysis results to infer the root cause.

To this end, we aim to build an *intelligent diagnosis system* with three main advantages [65]. ***(1) Precise Diagnosis.*** First, our system can utilize tools to gather scenario information (e.g., query analysis with flame graph) or derive optimization advice (e.g., index selection), which are necessary for real-world diagnosis. However, that is hardly supported by traditional methods. Second, it can conduct basic logical reasoning (i.e., making diagnosis plans). ***(2) Expense and Time Saving.*** The system can relieve human DBAs from on-call duties to some extent (e.g., resolving typical anomalies that rules cannot support). ***(3) High Generalizability.*** The system exhibits flexibility in analyzing unseen anomalies based on both the given documents (e.g., new metrics, views, logs) and past experience.

Recent advances in Large Language Models (LLMs) offer the potential to achieve this goal, which have demonstrated superiority in natural language understanding and programming [42, 43, 64, 67]. However, database diagnosis requires extensive domain-specific skills and *even the GPT-4 model cannot directly master the diagnosis knowledge (lower than 50% accuracy).* This poses three challenges.

(C1) How to enhance LLM's understanding of the diagnosis problem? Despite pre-trained on extensive corpora, LLMs still struggle in effectively diagnosing without proper prompting[2] (e.g., unaware of the database knowledge). The challenges include (i) extracting useful knowledge from long documents (e.g., correlations across chapters); (ii) matching with suitable knowledge by the given context (e.g., detecting an alert of high node load); (iii) retrieving tools that are potentially useful (e.g., database catalogs).

(C2) How to improve LLM's diagnosis performance for single-cause anomalies? With knowledge-and-tool prompt, LLM needs to judiciously reason about the given anomalies. First, different from many LLM tasks [12], database diagnosis is an interactive procedure that generally requires to analyze for many times, while LLM has the early stop problem [13]. Second, LLM has a "hallucination" problem [46], and it is critical to design strategies that guide LLM to derive in-depth and reasonable analysis.

(C3) How to enhance LLM's diagnosis capability for multi-cause anomalies? From our observation, within time budget, a single LLM is hard to accurately analyze for complex anomalies (e.g., with multiple root causes and the critical metrics are in finer-granularity). Therefore, it is vital to design an efficient diagnosis mechanism where multiple LLMs can collaboratively tackle complex database problems (e.g., with cross reviews) and improve both the diagnosis accuracy and efficiency.

To tackle above challenges, we propose *D-Bot*, a database diagnosis system using large language models. First, we extract useful knowledge chunks from documents (summary-tree based knowledge extraction) and construct a hierarchy of tools with detailed usage instructions, based on which we initialize the prompt template for LLM diagnosis (see Figure 3). Second, according to the prompt template, we generate new prompt by matching with most relevant knowledge (key metric searching) and tools (fine-tuned SentenceBert), which LLM can utilize to acquire monitoring and optimization results for reasonable diagnosis. Third, we introduce a tree-based search strategy that guides the LLM to reflect over past diagnosis attempts and choose the most promising one, which significantly improves the diagnosis performance. Lastly, for complex anomalies (e.g., with multiple root causes), we propose a collaborative diagnosis mechanism where multiple LLM experts can diagnose in an asynchronous style (e.g., sharing analysis results, conducting cross reviews) to resolve the given anomaly.

Contributions. We make the following contributions.

(1) We design an LLM-based database diagnosis framework to achieve precise diagnosis (see Section 3).

(2) We propose a context-aware diagnosis prompting method that empowers LLM to perform diagnosis by (i) matching with relevant knowledge extracted from documents and (ii) retrieving tools with a fine-tuned embedding model (see Sections 4 and 5).

(3) We propose a root cause analysis method that improves the diagnosis performance using tree-search-based algorithm that guides LLM to conduct multi-step analysis (see Section 6).

(4) We propose a collaborative diagnosis mechanism to improve the diagnosis efficiency, which involves multiple LLMs concurrently analyzing issues by their domain knowledge (see Section 7).

(5) Our experimental results demonstrate that *D-Bot* can accurately identify typical root causes within acceptable time (see Section 8).

2 PRELIMINARIES

2.1 Database Performance Anomalies

Database Performance Anomalies refer to the irregular or unexpected issues that prevent the database from meeting user performance expectations [35, 45], such as excessively high response time. Figure 2 show four typical database performance anomalies[3].

(1) Slow Query Execution. The database experiences longer response time than expectancy. For example, the slow query causes significant increase in CPU usage (system load) and query duration time, but the number of active processes remains low.

(2) Full Resource Usage. Some system resource is exhausted, preventing it accepting new requests or even causing errors (e.g., insert failures for running out of memory). For example, the high concurrency workload can not only cause great CPU and memory usage, but significantly increases the number of active processes.

[2] Prompting is to add additional information into LLM input. Although LLMs can memorize new knowledge with fine-tuning, it may forget previous knowledge or generate inaccurate or mixed-up responses, which is unacceptable in database diagnosis.

[3] Anomalies on the application/network sides and non-maintenance issues like database kernel debugging and instance deployment fall outside the scope of this work.

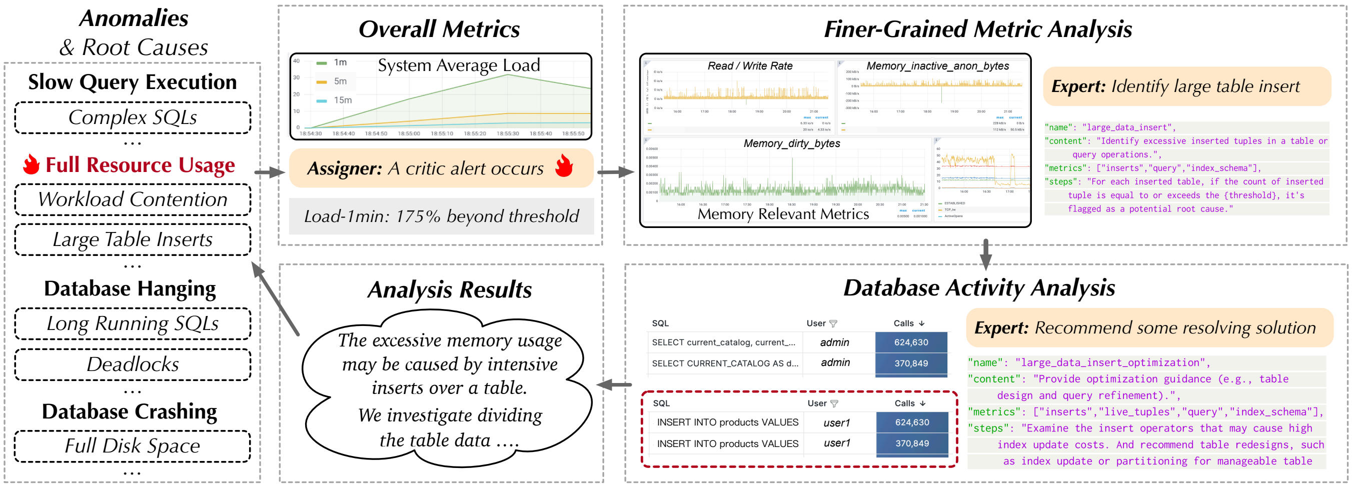


Figure 2: Example of Database Diagnosis.

(3) Database Hanging. The database becomes unresponsive, which is usually caused by long-running queries, deadlocks, or resource contention. For example, abnormal waits in submitted transactions cause great CPU consumption like the *full resource usage* anomaly, but it also involves frequent process interrupt and switching.

(4) Database Crashing. The database unexpectedly shuts down, causing data to become inaccessible. A typical root cause is full disk space, which leads to an inability to write new data or perform necessary operations, ultimately resulting in database failure and releasing the acquired resources.

2.2 Database Performance Diagnosis

Database Performance diagnosis refers to the process of analyzing and resolving above performance anomalies (usually in the form of a series of anomaly alerts) that occur within the database system. The primary objective of database diagnosis is to pinpoint the underlying *root causes*. Here we showcase some example root causes in standalone databases:

(1) Concurrency Workloads: Problems characterized by severe workload contention, where multiple database operations compete for system resources, leading to performance degradation.

(2) Query Operator Issues: Problems like inserting large tables, fetching large volumes of data, and executing complex predicates, which can strain the database system's processing capabilities.

(3) Planning and Execution: Root causes in this category involve abnormal planning times and prolonged database wait times, indicating inefficiencies in query planning and execution processes.

(4) Data-specific Issues: Problems like data corruption and dead tuples (rows that are no longer needed but remain in the physical storage) may lead to performance problem.

(5) Database Schema and Settings: These issues related to database schema (e.g., indexes) and configuration settings. Examples include missing indexes and small shared buffer sizes, which can impact query optimization and memory management.

(6) Harmful Background Tasks: Some database maintenance tasks, like "vacuum" for storage space reclamation, can become problematic when invoked too frequently (these tasks will compete system resources with user queries).

Once the root causes are identified, a set of *optimization actions* can be proposed to resolve these issues and restore normal database operations. Here we showcase some optimization tools.

(1) Query Rewrite Tools. Since most databases are weak in logical transformations [55] (e.g., complex predicate simplification), there are external rewrite tools (e.g., around 120 rules in Calcite [4]) that help to optimize slow queries.

(2) Knob Tuning Tools. Improper knob values may cause database failures (e.g., exceeding the maximal connection number) or bad performance (e.g., allocated working memory is too small). Thus, there are tools that utilize rules to provide tuning suggestions [3, 53]. For instance, it increases the value of innodb_buffer_pool_size in MySQL by 5% if the memory usage is lower than 60%.

(3) Index Tuning Tools. Similarly, there are index tuning rules that generate potentially useful indexes [7, 25, 54, 57, 66], such as creating composite index with columns in the same predicate.

Example 1. As shown in Figure 2, given an anomaly alert indicating high memory usage, we first examine the system load (e.g., node_memory_total for memory usage) during the anomaly time. The data confirms an abnormal memory utilization (over 90%). To understand this, we further obtain the relevant memory metrics (e.g., node_memory_inactive_anon_bytes). Analysis of these metrics suggests that the excessive memory usage may be caused by an intensive workload that inserts data into a table. To address this, we investigate if optimization strategies could help with reducing the memory consumption (e.g., dividing table data into partitions).

2.3 Large Language Models

Next, we introduce the fundamental concepts of Large Language Models (LLMs), including LLM architecture, LLM Prompting, and LLM Fine-tuning, which are pivotal for harnessing their capabilities in database diagnosis.

Transformer-Based LLMs. Existing LLMs mainly adopt the Transformer architecture, distinguished by its attention mechanism and feed-forward neural networks. Attention mechanism dynamically weighs elements in the input, allowing the model to focus on different parts of the text, i.e., the attention scores are computed

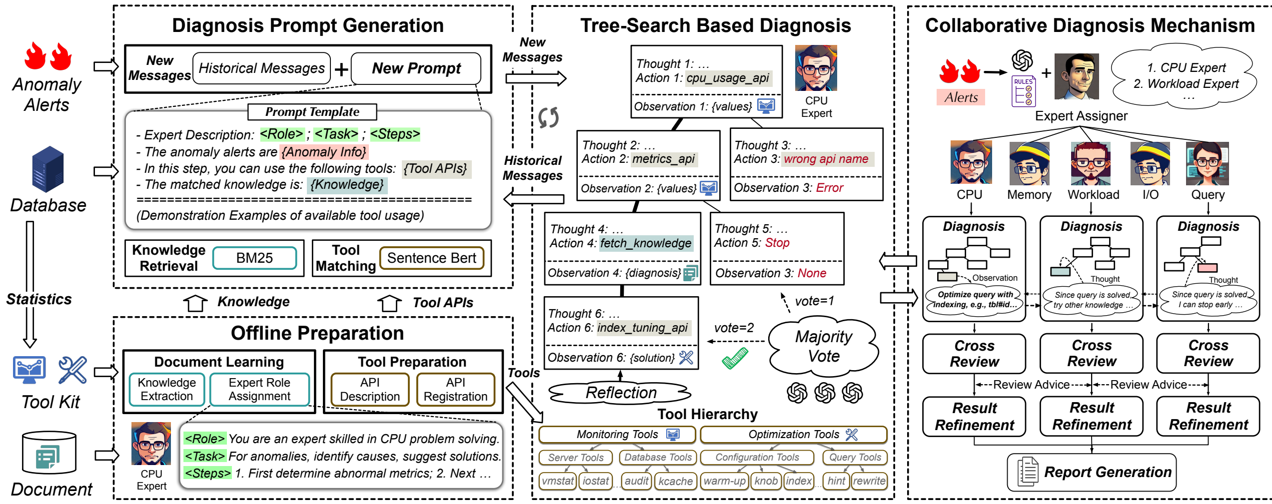


Figure 3: Database Diagnosis in *D-Bot*.

as $Attention(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$, where Q (queries), K (keys), and V (values) represent different aspects of the text, and d_k is the dimension of the keys. In addition, LLMs include feed-forward neural networks in each layer, which apply position-wise linear transformations to the output of the attention layer. This combination of attention and feed-forward networks facilitate accurate predictions of subsequent text elements.

LLM Prompting. To provide LLM with specific instructions for guiding their response generation, we can prepend or append a prompt P to the input X to create a new input, denoted as $X' = P \oplus X$ or $X' = X \oplus P$. LLM then generates the output text based on this modified input. Note (i) prompting does not require any additional updates to the model parameters and (ii) prompts can be manually crafted or automatically learned from data [68].

LLM Fine-tuning involves adjusting the model parameters on a small and task-specific dataset (e.g., thousands of samples). Initially, the model parameters, denoted as θ, are inherited from the pre-training phase. Fine-tuning aims to minimize the loss function $\mathcal{L}$, tailored to the specific task (e.g., classification or regression), over the task-specific dataset $\mathcal{D}$. It is represented as $\theta_{\text{new}} = \theta_{\text{old}} - \alpha \cdot \nabla\mathcal{L}(\theta_{\text{old}}; \mathcal{D})$, where a small learning rate α is often used to ensure gradual parameter updates [63].

We rely on LLM prompting to guide close-sourced LLMs like GPT-4 to diagnose (see Section 5), and utilize LLM fine-tuning to prepare localized LLMs (see Section 8.6).

3 THE OVERVIEW OF *D-BOT*

We present the challenges and components in *D-Bot* (Figure 3).

(1) Offline Preparation. First, offline preparation equips *D-Bot* with essential knowledge and tools for database diagnosis, which involves three main steps: (i) *Document Learning:* We conduct document knowledge extraction by creating summary trees to represent document structures and extracting relevant information via tree traversal (e.g., identifying nodes with similar summaries). (ii) *Tool Preparation:* We set up diagnosis tools by detailing API descriptions and integrating these APIs into *D-Bot* for use during diagnosis. (iii) *Expert Role Description:* We generate the role descriptions (e.g., expert character, basic diagnosis steps, available tools) of LLM experts through the clustering of knowledge chunks, such that each LLM expert can handle a specific area of database problems.

(2) Diagnosis Prompt Generation. With all necessary knowledge and tools readily available, we create context-aware prompts to steer the diagnosis process. Each prompt integrates five main parts: (i) Role description, which outlines the expertise and duties of the LLM. (ii) Anomaly description that provides the details of triggered alerts (e.g., occurring time, anomaly summary, severity level). (iii) Diagnosis tools (e.g., monitoring, indexing, query optimization) matched to the diagnosis context through a fine-tuned Sentence-BERT model. (iv) Knowledge chunks pinpointed with keyword search methods (e.g., BM25). (v) Historical message that supply essential background information (e.g., previous tool calling results) to aid the following tree-search-based diagnosis.

(3) Tree-Search Based Diagnosis. LLM encounters challenges like hallucination and unstable LLM responses (e.g., inaccurate API requests, overly general analysis) that can cause diagnosis failures. To address this problem, we introduce a specialized tree-search strategy, which allows LLM to explore multiple possible reasoning chains and efficiently find the most beneficial chain (based on both the database feedback and LLM evaluations).

(4) Collaborative Diagnosis Mechanism. To manage the increasing complexity and resource demands of *Tree-Search Based Diagnosis*, we employ a *Collaborative Diagnosis Mechanism* that enhances diagnosis efficiency by engaging multiple LLM experts. This process involves (i) identifying relevant LLM experts for a given anomaly; (ii) conducting asynchronous diagnosis with these experts (using a more focused set of tools and knowledge chunks); (iii) refining diagnosis findings via cross-review and generating a comprehensive diagnosis report for the anomaly.

4 OFFLINE PREPARATION

In this section, we explain how to prepare necessary knowledge and tools for LLM diagnosis.

4.1 Document Learning

We first decide the knowledge format that is suitable to use in LLM prompting. Next, we introduce the extraction method to obtain such

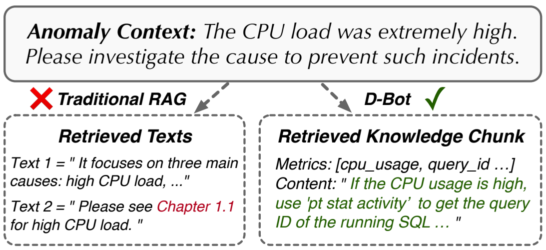


Figure 4: Comparison of knowledge extraction methods.

knowledge chunks from given documents. Finally, we showcase the obtained knowledge chunks and their clustering results.

4.1.1 Knowledge Format. Similar to the diagnosis evidence in Figure 2, given some documents, the desired knowledge chunk is composed of four parts: *(i) "Name"* helps LLM to understand the overall function; *(ii) "Content"* explains how the root cause can impact the database performance (e.g., performance degradation due to an excessive number of dead tuples); *(iii) "Metrics"* is a list of involved metric names, used for knowledge matching in prompt generation (Section 5.1); *(iv) "Steps"* provides the detailed procedure of analyzing with the relevant metrics. This allows the LLM to imitate and perform step-by-step analysis.

4.1.2 Knowledge Extraction. Next we explain how to extract such knowledge from documents. In database diagnosis, the relevant documents have two characters, i.e., (i) most documents are of long context involved diversified aspects (e.g., both resource and configuration issues are discussed in maintenance guide) and (ii) some paragraphs are correlated with each other. For example, the concept of "bloat-table" appearing in "many_dead_tuples" (like Chapter 3.2) is explained in another section (like Chapter 1.1.3). Existing document splitting and RAG approaches cannot divide diagnosis documents based on their semantic content. This often results in chunks that are either incomplete or entirely irrelevant, leading to erroneous diagnosis. For instance, traditional RAG erroneously retrieves incomplete chunk that merely refers to other chunks (e.g., *"see Chapter 1.1"* in Figure 4) and fails to give useful analysis.

Although there are already some long-context LLMs [2] that support long documents as input, they cannot ensure the quality of answered knowledge. For instance, recent studies [26] show that most existing LLMs cannot accurately complete tasks like line retrieval when processing documents containing tens of thousands of tokens, not to mention the processing of diagnosis materials with hundreds of thousands of tokens. Besides, they involve high computational cost. Thus, we propose an algorithm that extracts deterministic knowledge chunks from long-length documents.

Step1: Chapter Splitting. Instead of directly splitting documents into fixed-length segments, we divide them based on the chapter structures and their content (e.g., applications split by keywords like "tenant examples"). If a block exceeds the maximum block size (e.g., 4k tokens) that the LLM can handle, we further divide it recursively into smaller blocks. This allows LLMs to accurately summarize or extract the knowledge using appropriate prompts (e.g., "do not miss any details").

Step2: Summary Tree Construction. Next, based on the chapter relations, we initialize a tree structure, where the root node is the

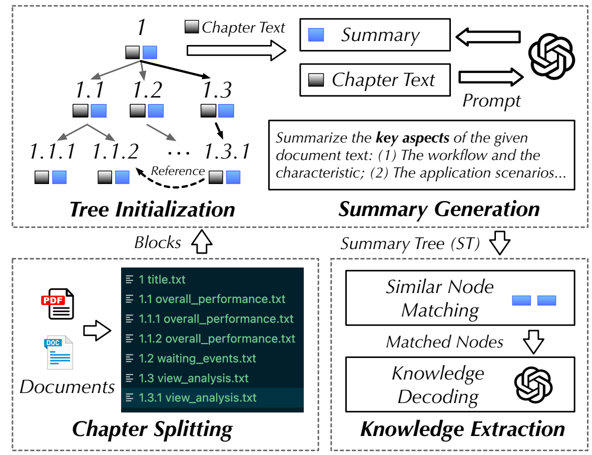


Figure 5: Summary tree based knowledge extraction.

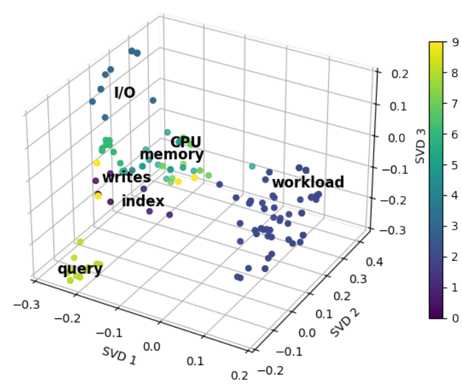


Figure 6: Clustering results of extracted knowledge.

document title and other nodes denote split document blocks. For each node i, its child node denotes a subsection of chapter i and node i includes two parts: (1) the content of chapter i and (2) the summary of chapter i, which is created by feeding the content into LLM with a summarization prompt, i.e., $p_{summarize}$ = *Summarize the provided chunk briefly ⋯ Your summary will serve as an index for others to find technical details related to database maintenance ⋯ Pay attention to examples even if the chunks cover other topics.*

The generated summary acts as a textual index of the node i, enabling the matching of blocks with similar content or relations like cross references.

Step3: Knowledge Extraction. After generating the summary tree, LLM parses each document block i (with content from both node i and its child nodes) and compares it with the summaries of other blocks having similar content, which is guided by the extraction prompt, i.e., $p_{extract}$ = *"Given a chunk summary, extract diagnosis experience from the chunk. If uncertain, explore diagnosis experience in chunks from child nodes or chunks with similar summaries."*

This way, knowledge that correlates with the key points from the summaries are detected. For each detected knowledge C_i, we decide whether to keep C_i in a hybrid manner. Specifically, if LLM indicates a low likelihood that C_i is redundant (compared with existing knowledge), we will incorporate it. Otherwise, we will conduct a manual examination of C_i, where C_i can be kept if we discover any new insights, even though C_i has significant overlap with some existing knowledge. In this way, we can ensure *the inclusion of most diagnosis knowledge and reduce the potential for redundant information.*

4.1.3 Clustering Results of Extracted Knowledge. We showcase 188 knowledge chunks extracted from 81 pages of documents, including the general diagnosis guides, cases, and detailed reports[4]. To derive insights from this diverse set of knowledge chunks, we (i) convert the chunks into numerical vectors using a pre-trained embedding model (e.g., Ada-002 [2]); and (ii) apply the DBSCAN algorithm [23] to group knowledge chunks by the similarity of their text embeddings; and (iii) reduce the dimensionality of the text embeddings (to three dimensions) using Principal Component Analysis (PCA). In this way, we can visualize the knowledge extraction results in Figure 6, which illustrates that *the knowledge distribution largely aligns with the types of root causes* (Section 2.2).

It is evident that a knowledge chunk can be relevant to multiple topics (e.g., slow queries may get involved in both CPU and operator analysis). Thus, effective utilization and communication of these knowledge chunks (e.g., experts from different topics) are vital for the following diagnosis.

4.2 Tool Preparation

Apart from knowledge, human DBAs need to frequently interact with monitoring and optimization tools (e.g., database views, system commands, index tuning tools). To facilitate effective LLM diagnosis, it's essential to ensure LLM understand the complex API functions within available tools.

First, we establish a structured hierarchy to classify and organize "categories-tools-APIs", where "APIs" represent the specific functions of a tool. For example, an index selection tool would be categorized under "optimization", with "configuration tool" as its tool type, and "heuristic_index_selection" as an example API (Figure 3). This hierarchy aids in organizing and understanding the diverse range of database tools.

Second, for each tool function, we provide a detailed *utilization specification* (in the form of function comment). This includes the function's explanation, its parameters, and relevant use cases (for Section 5.2). For instance, the function explanation for "heuristic_index_selection" could be *"Automatically select cost-reduction indexes based on query patterns and workload. Arguments include query frequency, data volume, index storage constraints, ...".*

Finally, we dynamically register tool functions by iterating through APIs in the given tool modules, obtaining each API's function names along with their *utilization specifications.*

5 DIAGNOSIS PROMPT GENERATION

Next we explain how to automatically generate diagnosis prompts by matching with the extracted knowledge and tools.

5.1 Knowledge Retrieval

Apart from knowledge that offers general diagnosis processes (included in the prompt template), most knowledge chunks are only useful under specific context. such as the analysis of abnormal CPU metrics (Figure 7). Thus, for a given context (e.g., with 5 abnormal

[4]github.com/TsinghuaDatabaseGroup/DB-GPT/tree/main/doc2knowledge/docs

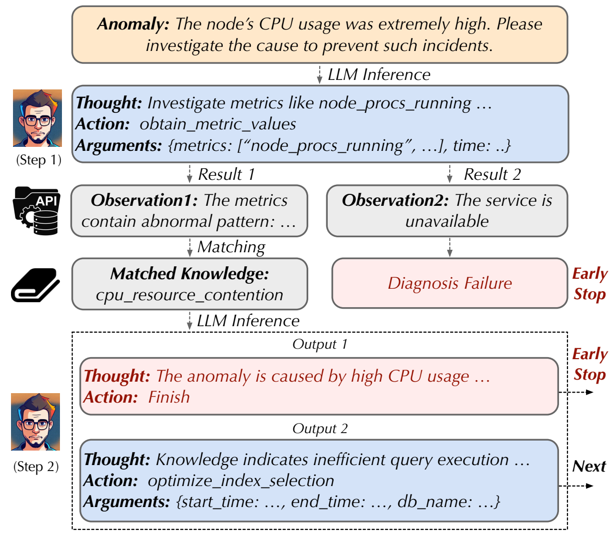


Figure 7: Example multi-step diagnosis by LLM.

CPU metrics), we adopt the approximate algorithm BM25 [48] to rank the most relevant knowledge chunks. Specifically, the BM25 algorithm ranks a set of knowledge chunks based on their "metrics" attribute, computed as:

$$\text{Score}(D, Q) = \sum_{i=1}^{n} \text{IDF}(q_i) \cdot \frac{f(q_i, D) \cdot (k_1 + 1)}{f(q_i, D) + k_1 \cdot (1 - b + b \cdot \frac{|D|}{\text{avgDL}})} \quad (1)$$

where D is a knowledge block, Q is a set of abnormal metrics (by anomaly detection algorithms like KS-Test [5]), $f(q_i, D)$ is the frequency of the metric q_i in D, avgDL is the average knowledge block length, k_1 and b are free hyper-parameters. IDF(q_i) is the inverse document frequency of the metric q_i, computed as:

$$\text{IDF}(q_i) = \ln\left(\frac{N - n(q_i) + 0.5}{n(q_i) + 0.5} + 1\right) \quad (2)$$

where N is the total number of extracted knowledge chunks, and $n(q_i)$ is the number of documents containing metric q_i.

The advantage of this approach is that we can match knowledge chunks even when the names or meanings of the metrics involved are not exactly the same and easily apply the extract knowledge across different monitoring tools or even systems.

5.2 Tool Matching

Different from *matching knowledge chunks with abnormal metrics*, database tools involve complex APIs and the API names may not be directly relevant to the context (e.g., APIs like *sort_remove* for slow queries). In this way, both the *BM25* algorithm and general embedding models [47] may have relatively high error rates. Thus, we propose to fine-tune a more powerful pre-trained Sentence-BERT model [47] that accurately matches suitable tools for an diagnosis context. This procedure includes two main steps, i.e., model fine-tuning and tool matching.

• *Sentence-BERT Fine-tuning:* Let $S = \{s_1, s_2, \ldots, s_n\}$ denote the set of diagnosis contexts, and $T = \{t_1, t_2, \ldots, t_m\}$ denote the set of database tools. We aim to fine-tune a pre-trained Sentence-BERT model to comprehend the relational context between anomalies and database tools. The fine-tuning process is performed with a labeled dataset $D = \{(s_i, t_j, y_{ij})\}_{i=1,j=1}^{n,m}$, where y_{ij} is the label indicating the relevance of tool t_j for a diagnosis context s_i. The objective function is computed by cross-entropy loss:

$$\mathcal{L} = -\sum_{i=1}^{n}\sum_{j=1}^{m} y_{ij}\log(p_{ij}) + (1 - y_{ij})\log(1 - p_{ij}), \tag{3}$$

where p_{ij} is the predicted probability that tool t_j is relevant for anomaly s_i, obtained by passing the concatenated embeddings of s_i and t_j through a sigmoid function. Note, since representative anomalies are hard to collect, we sample paths ("[Category]-[Tool]-[API]") from the tool hierarchy (Section 4.2) and generate diversified anomalies from each path.

• *Suitable Tool Matching:* After fine-tuning, the model is employed to match the appropriate database tools for a new diagnosis context s. The matching score between diagnosis context s and database tool t_j is computed as the cosine similarity between their embeddings, i.e.,

$$\text{sim}(s, t_j) = \frac{\text{emb}(s) \cdot \text{emb}(t_j)}{||\text{emb}(s)||_2 ||\text{emb}(t_j)||_2}, \tag{4}$$

where emb(.) denotes the embedding function of the fine-tuned Sentence-BERT model. The set of recommended database tools $\hat{T}$ for diagnosis context s is obtained by selecting the top-k tools with the highest matching scores:

$$\hat{T} = \arg\,\text{top}_k\{\text{sim}(s, t_j)\}_{j=1}^{m}. \tag{5}$$

Finally, the selected top-k tools are integrated into the prompt, including their names, function descriptions, and argument lists, based on which LLMs can generate calling requests and obtain tool execution results to enhance root cause diagnosis.

6 TREE SEARCH FOR LLM DIAGNOSIS

As shown in Figure 7, LLMs employing basic chain of thought methods [56, 60] are prone to mistakes such as (i) generating incorrect tool calling request or encountering request failures (e.g., service temporarily unavailable) and (ii) stopping diagnosis early without carefully examining the proposed root causes. Although there are some *tree of thought* methods [59], they have three limitations (Table 1). First, they only use the basic outputs of LLMs as tree nodes, without integrating diagnosis-specific tree nodes like knowledge-based analysis. Second, they generate new tree nodes arbitrarily, leading to unnecessary or useless explorations. Third, they rely on basic search algorithms like width-first search, which cannot flexibly expand the tree based on the diagnosis status of existing tree nodes, resulting in great computation wastes or incomplete diagnosis (given the constraints like time limit). Therefore, we aim to solve these problems through a tree-search based algorithm designed for diagnosis, allowing LLMs to reconsider previous actions if the current action fails or no valuable root causes are identified.

Step 1: Tree Initialization. We initiate by constructing a search tree starting with an "Action Input" root node, which contains the task's objectives (e.g., *"In each state, you first give some thought to analyze the situation now, together with some tool API calls to actually change the state to the next state. ..."*) and relevant input information, such as general knowledge (e.g., common diagnosis steps) and available tool APIs. This initial step guides LLM to explore potential actions, facilitating the addition of new tree nodes.

Table 1: Comparison of Tree Search Methods

	Tree of Thought [59]	Tree Search (*D-Bot*)
Node Type	LLM's own outputs	Knowledge-based LLM Analysis / Tool Usage
Node Generation	Random Generation	Nodes derived from document experience / tools
Node Scoring	Pure LLM Voting	Database Feedback + Iterative Confidence Evaluation
Search Algorithm	Fixed Order Search	Scenario-based Search + Reflection

Step 2: Tree Node Scoring. To expand the initial search tree, we first assess the benefit scores of all existing leaf nodes based on three criteria: (i) instant benefit feedback from the database, (ii) long-term benefit using knowledge-augmented LLMs, and (iii) selection frequency.

(1) *Instant benefit* is calculated by, (i) when the node's output contains solutions, simulating anomalies in the database (see Section 8.2), deploying the proposed solutions (via optimization tools), and measuring the reduction in workload costs; and (ii) the *Instant Benefit* is set to zero otherwise.

(2) *Long-term benefit* is evaluated by LLMs with localized knowledge base. With existing leaf nodes as candidates, we prepare detailed prompt (e.g., *"You first analyze all the candidates. Then give your choice of the best candidate ..."*) to guide LLM evaluators in their assessment, focusing on (i) closeness to task completion (e.g., the presence of root causes or solutions), (ii) performance (e.g., the value of *instant benefit*), and (iii) efficiency (e.g., overlap rate with the analysis results of the ancestor nodes). Through multiple rounds of voting, the long-term benefit of a leaf node is quantified as the total number of valid votes.

(3) *Selection frequency* is computed as the maximum number of times an ancestor node has been selected, plus one. With these three criteria, we apply formulas like the UCT function [37] to calculate the overall benefit scores of leaf nodes.

Step 3: Tree Node Generation. Next, we expand new child nodes of one existing tree node with the highest benefit score (randomly selecting one if there are multiple tied ones). This involves prompting LLM with information from the selected node to suggest new and valid actions in four main sub-steps:

(1) *Action Generation:* With the information in the selected node as input, LLM generates a "new message" as suggested action.

(2) *Action Parsing And Validation:* We dissect the new message into segments (e.g., using "\n" as a delimiter), examine whether the first three segments separately starting with *"Thought", "Action", and "Action Input"*. If so, this message indicates a legal action. In contrast, this message is an illegal action and we require LLM to regenerate (e.g. for at most three times before switching to other nodes or terminating exploration).

(3) *Tree Node Creation:* We generate a new node, containing (i) the diagnosis state of its parent node, (ii) the message generated by LLM, and (iii) the outcome, either the execution result (for a tool node) or the knowledge retrieval result (for a knowledge node), derived from executing the command synthesized from the "Action" and "Action Input" segments.

(4) *Tree Expansion:* We append this new node as a child of the selected tree node, facilitating its expansion and the ongoing update of the search tree.

Step 4: Existing Node Reflection. For each node in the path from the root node to the selected node, we utilize LLM to reassess the benefits of taking the action (e.g., prompting with *"make some reflection to inherit to later trails"*), which are appended to the prompt of child node and affect LLM evaluation during benefit score computation. Nodes deemed to contain no useful information are marked as "pruned" to enhance diagnostic efficiency.

Step 5: Terminal Condition. We repeat the above Steps 2-4. If no new root causes (leaf nodes with valid actions) are identified for a set number of iterations (e.g., 20 steps), the algorithm terminates by outputting the root causes and solutions of the leaf node with the highest benefit score.

Table 2: Comparison of Multi-Agent Methods

	LLM agents	Cooperation Strategy	Cross Reviews	Local LLMs
MetaGPT [19]	Static	One-To-One Conversation	×	×
ChatDev [39]	Static	One-To-One Conversation	×	×
AgentVerse [10]	Static	One-To-Many Conversation	×	×
D-Bot	Dynamic	Asynchronous Communication	✓	✓

7 COLLABORATIVE DATABASE DIAGNOSIS

With tool learning and tree search algorithm, single LLM's diagnosis accuracy can be greatly improved. Nevertheless, we find single LLMs have trouble in resolving complex anomalies with multiple causes (e.g., looping over limited causes and struggling to find additional ones). Although there are some multi-agent frameworks [10, 19, 39], they (i) lack efficient communication strategies and (ii) do not support backwards feedback augmented by diagnosis knowledge. To address this, we propose a collaborative mechanism where multiple LLMs, each equipped with tools and tree search algorithms, work collectively to tackle complex cases [10].

Step1: Expert Preparation. We initialize 7 LLM experts by the knowledge clustering results (Section 4). Each expert is equipped with different knowledge and necessary tools in the prompt.

Step2: Expert Assignment. Next, to avoid resource waste and improve diagnosis efficiency, we assign appropriate experts to diagnose. That is, given an anomaly, we first generate a description of the anomaly (e.g., time period, alert types, severity level). Next, based on the anomaly description, *Expert Assigner* utilizes an LLM (e.g., GPT-4) to select a set of most relevant experts. For example, *CPU Expert* for the *Load_High* alert and *Memory Expert* for the *Out_of_Memory* alert. Note we adopt LLM rather than rules, which is more flexible to plugin new alert rules or expert roles.

Step3: Asynchronous Diagnosis. The chosen experts simultaneously diagnose (Section 6). Despite utilizing a common LLM, each expert is uniquely equipped with role-specific settings and domain knowledge. We enhance the diagnosis process with an asynchronous communication mechanism [24], which is built on the publish-subscribe model. That is, experts "publish" their findings or updates, which are then automatically "delivered" to other experts who have "subscribed" to these specific types of updates (e.g., all the reset selected experts).

This mechanism allows for the efficient and non-blocking information exchange (e.g., metric analysis, tool outputs, results) among LLM experts. For instance, the CPU Expert might post a finding about abnormal CPU load patterns of slow queries, triggering an event-driven notification to other experts. This event-driven approach enables the memory expert to promptly detect memory swap activities potentially caused by these slow queries.

Step4: Cross Review. Traditional multi-agent frameworks adopt a sequential pipeline, where one agent's mistakes cannot be corrected by the next. Instead, *D-Bot* introduces a cross-review mechanism. This allows all participating LLM experts spot and fix other's diagnosis errors and leads to more accurate diagnosis.

[Current summary s_{t-1}]
- I know the start and end time of the anomaly.

[New Record r_t]
Thought: Now that I have the start and end time of ...
Action: is_abnormal_metric
Action Input: {"start_time": 1684600070, ...}
Observation: "The metric is abnormal"

[New summary s_t]
- I know the start and end time of the anomaly.
- *I executed is_abnormal_metric, and CPU usage is abnormal.*

• *Incremental Message Summarization.* For an expert, it requires dozens of iterations to provide in-depth analysis, resulting in extensive analysis records. Therefore, it is crucial to effectively summarize the key information from these records. To achieve this, we progressively summarize the lines of a record (r_t), which includes inputs for specific tools and the corresponding results, or relevant knowledge. Specifically, for each step t, we maintain a running summary (s_{t-1}), encapsulating previous actions and outcomes. Upon generating the new record r_t, an LLM is assigned to incorporate the main idea of r_t into s_{t-1}, leading to the new summary s_t.

• *Review Advice.* Next, each expert gives the improvement advice based on the diagnosis results and summarized procedures of other experts. The review prompt is written like p_{review} = *"Please review the above diagnosis results, and give necessary advice to correct the incorrect analysis or unclear results."*

• *Diagnosis Refinement.* After the cross-review, each expert reevaluates their initial diagnosis and even conducts more inferences (e.g., calling tools to analyze more relevant metrics or settings). In this way, they can incorporate additional evidence, revising hypotheses, or overlooked aspects in the diagnosis results.

Step5: Report Generation. Based on the refined diagnosis results of selected experts, *Expert Assigner* generates detailed diagnosis report for the given anomaly, including (i) title (summary of the anomaly); (ii) anomaly date; (iii) detailed anomaly description (from alerts); (iv) root causes (within diagnosis results); (iv) solutions (within diagnosis results); (v) summarized diagnosis process.

8 EXPERIMENT RESULTS

With the carefully prepared micro benchmark, we conduct extensive experiments to evaluate the proposed techniques in *D-Bot*.

Table 3: Micro Benchmark Statistics. The applications cover ten typical root causes (introduced in Section 2.2).

Application	Sync Commits	Many Inserts	High Updates	Many Deletes	Index Missing	Redundant Indexes	Large Data Insert	Large Data Fetch	Poor Join	Correlated Subquery	Cases
Internet of Things	✓	×	×	×	×	×	×	×	×	×	83
E-Commerce	×	✓	✓	✓	✓	✓	✓	✓	✓	✓	211
Financial	✓	✓	×	×	×	✓	✓	✓	✓	×	31
Business Intel.	×	✓	✓	✓	✓	✓	✓	✓	✓	×	20
File Sharing	×	✓	✓	×	×	✓	✓	✓	✓	×	47
Social Meida	✓	×	×	×	×	×	×	×	×	✓	147

8.1 Environment Setup

Database. We implement *D-Bot* in PostgreSQL 12.5, using (*i*) the pg_stat_statements plugin for tracking frequent queries, and (*ii*) the hypopg plugin for creating hypothetical indexes [1].

LLMs. Prompt-based LLMs include GPT-4-0613 and gpt-3.5-turbo-16k [2], where the *temperature* is set to 0 in favor of reproduction. Fine-tuned LLMs include *Llama 2*, *CodeLlama* and *Baichuan 2*.

Evaluated Methods. The evaluated methods include: (1) *HumanDBA*. A human DBA with 2 years working experience analyze the root causes. (2) *D-Bot (GPT-4)* is the version of *D-Bot* driven by GPT-4-0613 (within a limit of 8,192 tokens for each inference), which serves as 8 expert roles with different domain knowledge (Section 4.1.3). (3) *D-Bot (GPT-3.5)* is the version of *D-Bot* powered by the GPT-3.5 model. In case of exceeding the token limits, we use *gpt-3.5-turbo-16k* (a maximum of 16,385 tokens). (4) *DNN* utilizes a two-layer neural network with ReLU activation to classify the input abnormal metric vectors into one or multiple root causes [21]. (5) *DecisionTree* employs the decision tree algorithm to label the root causes for the input metric values [51]. (6) *Random Forest:* This model uses an ensemble of decision trees (10 trees) to balance between bias and variance. (7) *XGBoost:* This model applies gradient boosting that is effective for sparse data and is set up with 10 gradient boosted trees (n_estimators=10). (8) *KNN:* For the clustering-based method, we determine the optimal number of neighbors through cross-validation (testing up to 49 neighbors for best accuracy), and the selected best parameter (best_k=9) is used to predict on scaled test data. (9) *GPT-4* model that does not utilize the techniques in *D-Bot*, which (*i*) inputs suitable task description and demonstration examples and (*ii*) outputs the root causes. (10) *GPT-3.5*. Similarly, we test the performance of GPT-3.5 model without techniques in *D-Bot*.

Ablation Methods. We offer variants of *D-Bot* for ablation analysis: (1) *NoKnowledge* is *D-Bot (GPT-4)* that does not utilize the extracted knowledge. (2) *NoTreeSearch* is *D-Bot (GPT-4)* that adopts the chain-of-thought reasoning (e.g., LangChain [6]). (3) *SingleLLM* is *D-Bot (GPT-4)* that utilizes single LLM to diagnose.

8.2 Micro Diagnosis Benchmark

Based on works like [20, 31], we design a micro benchmark that offers (*i*) diversified anomaly scenarios (e.g., different applications, workloads, and anomaly types), (*ii*) executable scripts, (*iii*) clear scenario descriptions (e.g., *"In a database of an e-commerce platform, 91 users simultaneously perform searches ⋯ "*), together with (*iv*) evaluation metrics that can reflect the diagnosis performance.

Anomaly Cases. As shown in Table 3, we include a diverse set of simulated applications: (*i*) *Internet of Things (IoT)* applications mainly have the "highly commits" anomalies, caused by handling a lot of incoming data from sensors; (*ii*) *E-commerce* applications exhibit multiple anomalies (e.g., "highly updates" and "large data fetch"), possibly caused by concurrent updates to product databases and high volume data retrievals during sales; (*iii*) *Financial* applications involve anomalies like "poor joins", suggesting complex transactional operations; (*iv*) *Business Intelligence* applications mainly involve "redundant index" and "missing index" anomalies, emphasizing the importance of optimizing data access paths; (*v*) *File Sharing* applications (e.g., Dropbox, Google Drive) often encounter the "large data fetch" anomaly, caused by data retrievals of multimedia content. (*vi*) *Social Media* applications (e.g., MySQL originally for Twitter) predominantly face the "highly commits" anomaly when read and write data quickly. Different from *IoT*, they also involve complex queries that cause the "correlated subquery" anomaly.

Anomaly Distribution. There are 254 anomalies with single causes and 285 with multiple causes. Single-cause anomalies mainly result from "Missing Indexes". Other common causes include "Many Updates" and "Redundant Indexes", pointing to widespread inefficiencies in database operations and data schemas. Multi-cause anomalies are more diverse. The combination of "Sync Commits" and "Many Inserts" is the most frequent, occurring twice as often as any other combination like "Poor Join + Many Updates". Resolving these anomalies typically requires 13 to 16 actions in *D-Bot*, suggesting a moderate complexity in the diagnosis process.

Evaluation Metrics. We adopt two metrics for practical diagnosis evaluation. First, like works [28, 34], we use *Result Accuracy* (Acc) to quantify the precision of recommended root causes, i.e.,

$$\text{Acc} = \begin{cases} \frac{A_c - \sigma \cdot A_w}{A_a}, & \text{if } A_a > 0 \land A_c \geq \sigma \cdot A_w \\ 0, & \text{otherwise} \end{cases}$$

where A_c denotes the number of correct causes, A_a denotes the total number of causes, A_w denotes the number of wrongly detected causes, and σ is a hyper-parameter with 0.1 as the default value, because we identify *redundant causes is less harmful than missing causes* and restrict to at most 4 root causes for an anomaly.

Second, *Human Evaluated Accuracy* (HEval) shares the same equation as Acc. However, A'_c in HEval denotes number of causes that (*i*) are correctly detected and (*ii*) the analysis process also makes sense (human evaluation). HEval is *vital to provide reliable diagnosis for online usage.*

Table 4: Performance on different anomalies.

Diagnosis Method	Single Cause Anomaly		Multi-Cause Anomaly	
	Acc	HEval	Acc	HEval
HumanDBA	0.955	0.720	0.487	0.806
D-Bot (GPT-4)	0.754	0.500	0.655	0.669
D-Bot (GPT-3.5)	0.542	0.370	0.533	0.493
DNN	0.352	N/A	0.036	N/A
DecisionTree	0.331	N/A	0.086	N/A
GPT-4	0.351	0.39	0.105	0.151
GPT-3.5	0.266	0.2	0.144	0.130

8.3 Performance Comparison

We compare *D-Bot* with three types of baselines, including manual diagnosis (HumanDBA), existing machine learning methods (*DNN*, *DecisionTree*), and origin LLMs (GPT-4, GPT-3.5) across six applications. For each application, we sample ten testing anomalies from the micro benchmark. The remaining anomalies are used as the training samples for *DNN*, *DecisionTree*. The performance results are illustrated in Figures 8-9.

Diagnosis Performance. *D-Bot* achieves competitive performance as *HumanDBA*, such as outperforming *HumanDBA* with an accuracy of 80% (*D-Bot (GPT-3.5)*) for the Social Media application. *D-Bot* also demonstrates significant performance gains over the rest baselines (e.g., accuracy improvements ranging from 8% to 54% against *DNN* and *DecisionTree*). The reasons are three-fold.

First, *D-Bot* can judiciously utilize tools and provide informed diagnosis. For instance, It identifies specific problems such as *"high memory usage due to heavy use of UPDATE and INSERT operations over the same tables"* by querying the *pg_stat_statements* view. Conversely, the baselines struggle to detect the root causes, often defaulting to generic advice such as *"resolve resource contention issues"*, which lack the specificity needed for actionable improvements, rendering them less effective in practical applications. For the baselines, *Random Forest* achieves the highest accuracy among the baselines (57.1% in average), but still performs worse than *D-Bot* (e.g., 73.2% for *D-Bot (GPT-4)*). By constructing multiple trees and using their average predictions, Random Forest significantly reduces the risk of overfitting, making it much more robust across diverse samples. Besides, baselines like *Random Forest* are good at regression tasks involving numeric labels, beneficial for addressing hallucination issues observed in *GPT-4* and *GPT-3.5*.

Second, *D-Bot (GPT-4)* owns contextual comprehension (LLM) and tree-search reasoning capability. For instance, with the reflection mechanism, *D-Bot (GPT-4)* can follow the most beneficial chain of actions (e.g., calculating the total cost of a plan and deciding the optimization actions). In contrast, the baselines only input with basic abnormal metric values, perform general analysis, and often overlook underlying causes. For instance, in an *INSERT_LARGE_DATA* case, *GPT-4* merely identifies an increased count of running processes using the *node_procs_running* metric, resulting in an early diagnosis termination. Moreover, *DNN* and *DecisionTree* cannot leverage textual data, leading to their inability to resolve complex anomalies such as *Poor Join*.

Third, *D-Bot (GPT-4)* utilizes the document knowledge to learn the analysis of potential performance bottlenecks like correlated-subquery structure. We find *GPT-4* and *GPT-3.5* tend to make unsupported hypotheses, leading to inaccurate diagnostics. For example, upon detecting *SORT* operations in logged queries, *GPT-3.5* inaccurately attributes the bottleneck to *"frequent reading and sorting of large data volumes"*, missing query structure problems. Compared to *HumanDBA*, *D-Bot (GPT-4)* is more careful in capturing important details that help find the root causes. For example, in *Social Media*, *D-Bot (GPT-4)* does better than *HumanDBA* by collecting data from various sources (such as multiple system metrics and how query operators consume resources). This helps uncover problems like high I/O issues caused by concurrent inserts, which *HumanDBA* might ignore when focusing on a few slow queries.

Apart from the proposed Acc metric, we have compared the performance under standard precision, recall, F2 score metrics [16] and there are some new findings. First, *D-Bot (GPT-4)* has a higher recall but lower precision than *HumanDBA* due to its ability to use diverse knowledge bases but suffers from using inappropriate tools, causing more false positives. Second, *D-Bot* outperforms original LLMs by using specific diagnostic tools rather than vague tips, leading to higher recall and precision. Third, *D-Bot* achieves a better F2 score than other learning methods, balancing recall and precision well. In contrast, *DNN* creates too many potential causes, and *DecisionTree* misses many new anomalies.

Diagnosis Overhead. *(1) Diagnosis Time. HumanDBA* needs one to two hours to write a diagnosis report even for typical anomalies. This time is mainly consumed in devising solutions like indexing and query rewriting, even when the root cause is relatively straightforward. Instead, *D-Bot*, takes ten to several minutes to diagnose relatively complex anomalies (e.g., *5.38 minutes* for a composite anomaly k with two root causes). By testing across 15GB, 37GB, and 100GB databases, we find *D-Bot* performs well with low diagnosis overhead (separately with 4.33 / 5.89 / 4.93 minutes). Because *D-Bot* can efficiently interact with pre-equipped tools (context embedding) and enhance the efficiency (collaboration of multiple LLMs). And the utilized tools are plugins like hypopg (building hypothetical indexes rather than actually deploying them) and cost estimators, which are not sensitive to data scaling. However, an increase in query numbers will take up more LLM tokens to describe the workload information and cause high higher inference time (e.g., 22,000 queries for 24.8% more inference time). Traditional classifiers have lowest diagnosis time, as they simply map limited metrics to predefined causes. *(2) Diagnosis Expense.* Traditional classifiers and *D-Bot* are more economical than *HumanDBA*. *DNN* and *DecisionTree* require minimal system resources. And *D-Bot* can save much manpower at a minimal financial cost (e.g., 1.8 dollar for diagnosing the anomaly k with 40k LLM tokens).

> Finding 1. *D-Bot achieves a remarkable improvement over baselines (8% to 54%) due to its advanced contextual understanding and knowledge and tool utilization, and even competes closely with human expertise.*

Performance for Different Anomalies. *D-Bot (GPT-4)*, while having lower accuracy in single cause anomalies (0.754), shows a remarkable consistency in multi-cause anomalies with an accuracy of 0.655. This consistency is also reflected in the *HEval* scores (0.500 and 0.669, respectively), suggesting that *D-Bot (GPT-4)* maintains

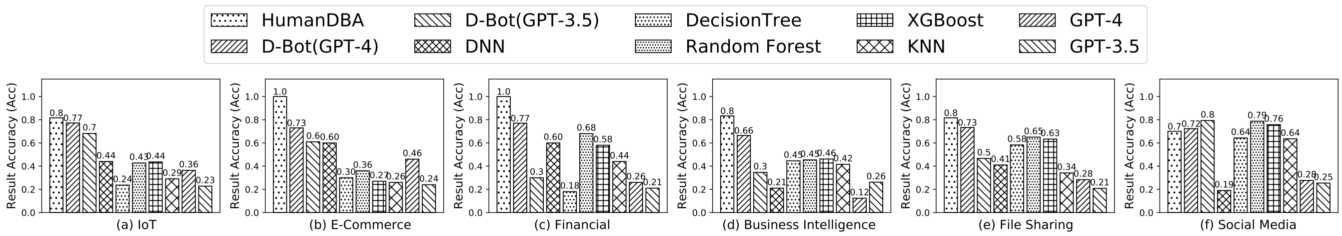


Figure 8: Performance Comparison (Result Accuracy).

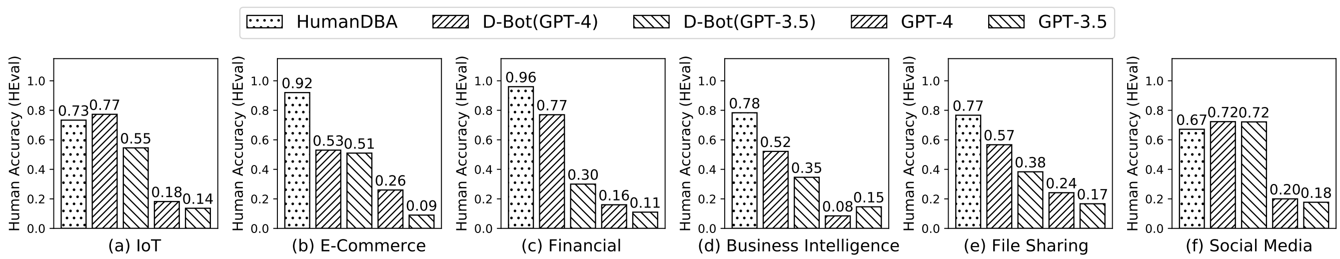


Figure 9: Performance Comparison (Human Evaluation). We do not include *DNN* and *DecisionTree* because they either have the black-box problem or fail to provide root cause analysis that is easy to understand by humans.

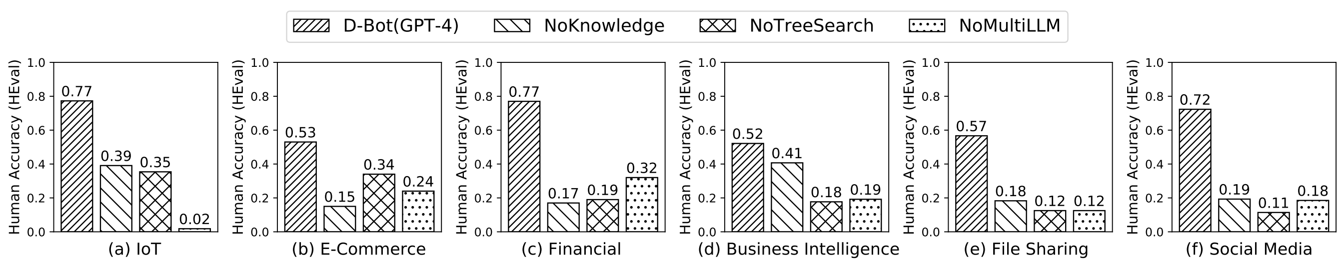


Figure 10: Ablation Study (Human Evaluation)

stable performance across different types of anomalies. *D-Bot (GPT-3.5)* and other methods like *DNN*, *DecisionTree*, *GPT-4*, and *GPT-3.5* show a general trend of lower performance in both *Acc* and *HEval*, especially in multi-cause anomalies, highlighting the complexity of these scenarios that require advanced diagnosis methods like *D-Bot*. Meanwhile, for *HumanDBA*, the *HEval* scores are relatively high for both single (0.720) and multi-cause anomalies (0.806), demonstrating the necessity of understanding human experience.

Finding 2. *D-Bot provides a more balanced and reliable performance across diverse and complex anomaly types.*

LLM Factors. The performance gap between *D-Bot (GPT-4)* and *D-Bot (GPT-3.5)* is significant, with *D-Bot (GPT-4)* outperforming *D-Bot (GPT-3.5)* by up to 30% in accuracy and stability in applications. *D-Bot (GPT-4)* excels in generating precise tool calling commands and comprehensive diagnosis summaries. For instance, it adeptly identifies complex queries involving large table fetches, a task where *D-Bot (GPT-3.5)* often falls short. In contrast, *D-Bot (GPT-3.5)* is prone to producing more generalized and sometimes inaccurate action commands, leading to less effective outcomes.

8.4 Ablation Study

As shown in Figure 10, we verify the effectiveness of three main components in *D-Bot*, i.e., document knowledge matching (*NoKnowledge*), tree-search-based reasoning (*NoTreeSearch*), and multi-agent diagnosis (*SingleLLM*).

8.4.1 Document Knowledge Matching. Without the relevant knowledge in the prompt, LLM experts mainly rely on expert settings (i.e., role, task, steps) to call tools and analyze root causes. When comparing *NoKnowledge* to *D-Bot*, we observe a decrease in diagnosis accuracy ranging from 19.2% to 64.1%. We have two observations. First, *NoKnowledge* produces significantly more redundant root causes (e.g., 2.05 times against *D-Bot (GPT-4)*), as it can't clearly tell apart relevant root causes using just the context. For instance, root causes like *"many inserts"* and *"large data insert"* both involve insert operations, but identifying them correctly requires specific knowledge about details like the number of insert operations and table sizes. Second, like the baselines, *NoKnowledge* often provides very general diagnoses (e.g., "abnormal patterns in CPU processes") and fails to accurately identify many anomalies. Moreover, we also find that, although LLMs like *GPT-4* are pre-trained on open corpora, they need external knowledge matching (fine-tuning is limited in updating knowledge) for specialized tasks like database diagnosis.

8.4.2 Tree Search Based Diagnosis. *NoTreeSearch* diagnoses less effectively than *D-Bot (GPT-4)*, showing a performance decrease by over 35.85%. It verifies that tree search plays an important role in correcting wrong knowledge matching or tool API callings (actions for extending child nodes), which significantly enhances the diagnosis accuracy, particularly for single-cause anomalies that involve various reasoning choices. For instance, in scenarios such as identifying specific query-related issues or optimizing database knobs, tree search enables *D-Bot (GPT-4)* to navigate through multiple potential solutions and pinpoint the most effective one.

8.4.3 Multi-Agent Diagnosis. Our analysis verifies the effectiveness of multi-agent mode (*D-Bot (GPT-4)*) over single-agent mode (single). For instance, in the IoT application, *D-Bot (GPT-4)* achieves a 77.27% success rate in identifying root causes, a substantial increase from the 75.45% success rate of *SingleLLM*. Besides, our tests on average diagnosis time revealed that *D-Bot* (multi-agent mode) is more efficient compared to *SingleLLM* (single-agent mode). The reasons are two-fold. First, *D-Bot* employs more than two experts in average (at most three), which utilize different metrics and domain knowledge to explore root causes and derive more root causes than *SingleLLM*. And these root causes are further examined, selected and refined during cross-review. Thus, *D-Bot* achieves higher diagnosis accuracy than *SingleLLM*. Second, although *D-Bot* takes time to select experts and conduct cross-reviews, the asynchronous mechanism reduces the iteration turns of tree-search algorithm in single experts, which generally take most diagnosis time. And so *D-Bot* is also more efficient than *SingleLLM* in diagnosis time.

> Finding 4. *Techniques proposed in D-Bot are crucial to boost diagnosis accuracy by reducing redundant root causes and enhancing precise anomaly identification.*

8.5 Evaluation on Hyper-Parameters

Next we evaluate the impact of hyper-parameters in *D-Bot*, including (i) the maximal number of retrieved knowledge chunks (denoted as *Knowledge chunk Numbers*), (ii) the maximal number of matched tool APIs (denoted as *Tool API Numbers*), and (iii) the maximal number of explored diagnosis paths during tree search, which a critical hyper-parameter that affects the diagnosis turns (denoted as *Tree Search Paths*).

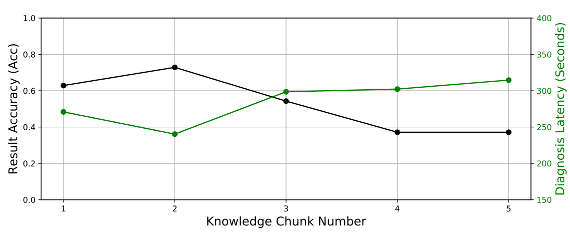


Figure 11: The Effectiveness of *chunk_num* parameter.

Knowledge Chunk Numbers. As shown in Figure 11, the diagnosis accuracy gets better when the knowledge chunk number increases from 1 to 2, but unexpectedly decreases when more than 2 chunks are used. There are two reasons. First, unlike RAG texts, the knowledge chunks in *D-Bot* are self-contained; each one provides a relatively complete analysis for an anomaly context (e.g., analyzing the root causes of severe CPU contention). Thus, 1 to 2 retrieved chunks are optimal for use in *D-Bot*. Second, to add additional knowledge chunks (e.g., 3 to 5), we need to loosen the threshold (e.g., from 0.4 to 0.5) for similarity search, which could lead to retrieving potentially irrelevant knowledge chunks. This increase in irrelevant information can mislead the diagnosis process (e.g., network analysis for a standalone database).

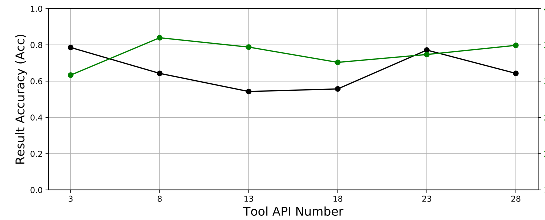


Figure 12: The Effectiveness of *tool_num* parameter.

Tool API Numbers. As show in Figure 12, there are no obvious performance or overhead gains with the increase of tool APIs. First, agents in *D-Bot* are designed to represent more specific, finer-grained diagnosis sub-areas, thereby eliminating the need to call many tools to complete a comprehensive diagnosis (e.g., 2 to 3 tools at most). Second, too many tools increase the risk of calling the useless tools, where the agent may not find the root causes within limited steps. Meanwhile, too few tools also may cause agents to make up some facts and cause diagnosis failures.

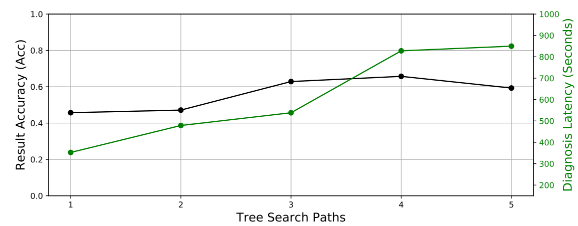


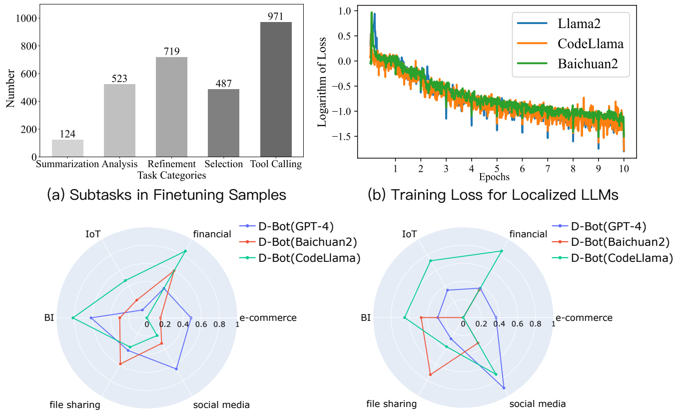
Figure 13: The Effectiveness of *search_paths* parameter.

Tree Search Paths. As shown in Figure 13, *D-Bot* achieves better performance with *search_paths* increasing from 1 to 4, but the diagnosis overhead also significantly increases after the *search_paths* is higher than 3. First, during tree search, higher *search_paths* means *D-Bot* can try out more diagnosis paths that potentially gain higher database benefits, which can increase the diagnosis success rate. However, in each path, the LLM agent can conduct at most 24 diagnosis steps, and thus is costly if the value of *search_paths* is too large. Thus, generally we set the *search_paths* as 2 or 3 for relatively complex anomalies.

8.6 Model Fine-tuning

Preparation. We first record the diagnosis processes of *D-Bot (GPT-4)* consisting of 5 sub-tasks (e.g., tool calling) and 2819 samples in total (see Figure 14(a)). We mix them together as a multi-task fine-tuning dataset. Specifically, the model input includes the prompt and historical messages, and we fine-tune LLMs to simulate the corresponding *D-Bot (GPT-4)* response (after cleansed). LLMs are implemented using PyTorch and BMTrain [63], trained on a machine with 503 GB RAM and 1 NVIDIA A100 GPU.

Training Procedure. We fine-tune three localized SOTA LLMs. As shown in Figure 14(b), all LLMs converge within 10 epochs. We



(a) Subtasks in Finetuning Samples

(b) Training Loss for Localized LLMs

(c) Testing Results (*Acc*)

(d) Testing Results (*HEval*)

Figure 14: Performance of Model Finetuning.

then manually select the best epoch checkpoints (i.e., 4th epoch for *Llama 2*, 1st epoch for *CodeLlama*, 10th epoch for *Baichuan 2*). Note *the obvious loss reduction does not mean increasing model performance*. We find many epoch checkpoints with low losses often over-fit the fine-tuning data (e.g., losing the text generation capabilities and tending to generate short confusing responses). Besides, *Llama 2* cannot generate reasonable diagnosis results (*Acc* equals 0 for most cases) even in the best epoch.

Performance Comparison. As shown in Figure 14(c)-(d), the demonstrated LLMs after fine-tuning achieve comparable performance to *GPT-4* in 27 test cases. We have several observations. First, *CodeLlama* performs best in financial, IoT and BI applications, because *CodeLlama* is specialized for code generation, which is more sensitive to metrics and queries. For instance, it can accurately identify *slow queries involving multiple JOINs as root cause*. Second, *Baichuan2* performs best for file application, which can assign suitable experts (e.g., Memory Expert), and analyze root causes in detail (e.g., pointing out disk I/O under-provisioned in the hardware configuration). However, the *HEval* performance of *Baichuan2* in financial application significantly degrades. For example, the model may list many root causes but does not give well-founded analysis. Third, *GPT-4* performs best for e-commerce and media applications, and shows *balanced performance across all applications*. Moreover, the localized LLMs show less generalizability to unfamiliar anomalies. For instance, the number of samples with *delete operations* as root causes is much smaller than others, causing the fine-tuned LLMs to often fail in these cases.

> Finding 5. *D-Bot using localized SOTA LLMs can achieve comparable diagnosis performance to* D-Bot (GPT-4)*, but their generalizability is greatly affected by the fine-tuning samples.*

9 RELATED WORK

Database Diagnosis. Existing works mainly rely on empirical rules and classification methods to analyze root causes. The ADDM tool [11] maintains a graph of database resource modules, based on which they estimate the query execution time and infer the bottlenecks. DBSherlock [62] utilizes a decision-tree-like method to construct predicates (in the form of $Attr > k$). ISQUAD [34] generates root causes by clustering queries with their metric vectors. However, these methods require great human intervention (e.g., designing rules, features, labels). Besides, they lack some critical capabilities (e.g., accepting new contextual information, analyzing query logs) for real-world diagnosis. Although there are some LLM-based methods that incorporate maintenance knowledge [31], they focus on general chatbot tools (e.g., Q&A exercises) and also fail to conduct scenario-specific diagnosis.

LLM Agents. Recent works have shown LLMs, when coupled with memory mechanisms and advanced tools, can imitate human-like interactions and decision-making in real world [41, 50, 59]. First, the augmentation of LLM agents with a variety of tools — ranging from web browser [36, 40] and wikipedia search [52, 61], to code interpreter [9, 15, 33] and multifaceted toolsets [44, 49] — has significantly enhanced LLM's adaptability. Besides individual agent skills, there is increasing interest in coordinating multiple LLM agents to utilize collective intelligence [14, 19, 27, 38, 58]. Notably, AgentVerse [10] shows that teamwork among multiple LLM agents can perform better than single agents in many tasks. *D-Bot* presents an *LLM-powered diagnosis system in the multi-agent paradigm.*

10 CONCLUSION

In this paper, we proposed a database diagnosis system leveraging large language models (LLMs). We conducted offline knowledge extraction from documents and prepared function APIs from existing tools. We matched with suitable knowledge and APIs into LLM prompt for online diagnosis, and we proposed a tree search-based algorithm to accurately and effectively utilize tools and conduct analysis with knowledge. We designed a collaborative diagnosis mechanism that improved the efficiency with the collaboration of multiple LLMs. Experimental results showed *D-Bot* achieved remarkable improvements over baselines and human DBAs.

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