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LLM As DBA

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ABSTRACT

Database administrators (DBAs) play a crucial role in managing, maintaining and optimizing a database system to ensure data availability, performance, and reliability. However, it is hard and tedious for DBAs to manage a large number of database instances (e.g., millions of instances on the cloud databases). Recently large language models (LLMs) have shown great potential to understand valuable documents and accordingly generate reasonable answers. Thus, we propose D-Bot, a LLM-based database administrator that can continuously acquire database maintenance experience from textual sources, and provide reasonable, well-founded, in-time diagnosis and optimization advice for target databases. This paper presents a revolutionary LLM-centric framework for database maintenance, including (i) database maintenance knowledge detection from documents and tools, (ii) tree of thought reasoning for root cause analysis, and (iii) collaborative diagnosis among multiple LLMs. Our preliminary experimental results that D-Bot can efficiently and effectively diagnose the root causes and our code is available at github.com/TsinghuaDatabaseGroup/DB-GPT.

1 INTRODUCTION

Limitations of DBAs. Currently, most companies still rely on DBAs for database maintenance (DM, e.g., tuning, configuring, diagnosing, optimizing) to ensure high performance, availability and reliability of the databases. However, there is a significant gap between DBAs and DM tasks. First, it takes a long time to train a DBA. There are numerous relevant documents (e.g., administrator guides), which can span over 10,000 pages for just one database product and consumes DBAs several years to partially grasp the skills by applying in real practice. Second, it is hard to obtain enough DBAs to manage a large number of database instances, e.g. millions of instance on cloud databases. Third, a DBA may not provide in-time response in emergent cases (especially for correlated issues across multiple database modules) and cause great financial losses.

Limitations of Database Tools. Many database products are equipped with semi-automatic maintenance tools to relieve the pressure of human DBAs [5, 6, 10–12]. However, they have several limitations. First, they are built by empirical rules [4, 24] or small-scale ML models (e.g., classifiers [13]), which have poor text processing capability and cannot utilize available documents to answer basic questions. Second, they cannot flexibly generalize to scenario changes. For empirical methods, it is tedious to manually update rules by newest versions of documents. And learned methods require costly model retraining and are not suitable for online maintenance. Third, they cannot reason the root cause of an anomaly like DBAs, such as looking up more system views based

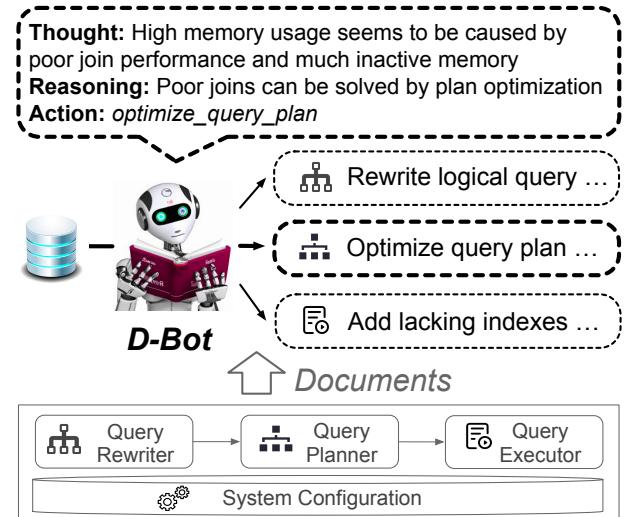


Figure 1: LLM As DBA

on the initial analysis results. This capability is vital to detect useful information in complex cases.

Our Vision: A Human-Beyond Database Administrator. To this end, we aim to build a *human-beyond “DBA”* that can tirelessly learn from documents (see Figure 1), which, given a set of documents, automatically (1) learns experience from documents, (2) obtains status metrics by interacting with the database, (3) reasons about possible root causes with the abnormal metrics, and (4) accordingly gives optimization advice by calling proper tools.

Challenges. Recent advances in Large Language Models (LLMs) have demonstrated superiority in understanding natural language, generating basic codes, and using external tools. However, leveraging LLM to design a “human-beyond DBA” is still challenging.

(1) *Experience learning from documents.* Just like human learners taking notes in classes, although LLMs have undergone training on vast corpus, important knowledge points (e.g., diagnosis experience) cannot be easily utilized without careful attention. However, most texts are of long documents (with varying input lengths and section correlations) and different formats of the extracted experience can greatly affect the utilization capability of the LLM.

(2) *Reasoning by interacting with database.* With the extracted experience, we need to inspire LLM to reason about the given anomalies. Different from basic prompt design in machine learning, database diagnosis is an interactive procedure with the database (e.g., looking up system views or metrics). However, LLM responses are often untrustworthy (“hallucination” problem), and it is critical to design strategies that guide LLM to utilize proper interfaces of the database and derive reasonable analysis.

(3) *Mechanism for communication across multiple LLMs.* Similar to human beings, one LLM alone may be stuck in sub-optimal

solutions, and it is vital to derive a framework where multiple LLMs collaborate to tackle complex database problems. By pooling their collective intelligence, these LLMs can provide comprehensive and smart solutions that a single LLM or even skilled human DBA would struggle to think out.

Idea of LLM as DBA. Based on above observations, we introduce D-Bot, an LLM based database administrator. First, D-Bot transforms documents into experiential knowledge by dividing them into manageable chunks and summarizing them for further extraction of maintenance insights with LLM. Second, it iteratively generates and assesses different formats of task descriptions to assist LLM in understanding the maintenance tasks better. Third, D-Bot utilizes external tools by employing matching algorithms to select appropriate tools and providing LLM with instructions on how to use the APIs of selected tools. Once equipped with the experience, tools, and input prompt, LLM can detect anomalies, analyze root causes, and provide suggestions, following a *tree of thought* strategy to revert to previous steps if a failure occurs. Moreover, D-Bot promotes collaborative diagnosis by allowing multiple LLMs to communicate based on predefined environmental settings, inspiring more robust solutions via debate-like communications.

Contributions. We make the following contributions.

- (1) We design a LLM-centric database maintenance framework, and explore potential to overcome limitations of traditional strategies.
- (2) We propose an effective data collection mechanism by (*i*) detecting experiential knowledge from documents and (*ii*) leveraging external tools with matching algorithms.
- (3) We propose a root cause analysis method that utilizes LLM and tree search algorithm for accurate diagnosis.
- (4) We propose an innovative concept of collaborative diagnosis among LLMs, thereby offering more comprehensive and robust solutions to complex database problems.
- (5) Our preliminary experimental results that D-Bot can efficiently and effectively diagnose the root causes.

2 PRELIMINARIES

Database Anomalies. In databases, there are five common problems that can negatively affect the normal execution status. (1) *Running Slow*. The database exhibits longer response time than expectancy, leading to bad execution performance. (2) *Full Disk Capacity*. The database’s disk space is exhausted, preventing it from storing new data. (3) *Execution Errors*. The database experiences errors, potentially due to improper error handling in the application (e.g., leaking sensitive data or system details) or issues within database (e.g., improper data types). (4) *Hanging*. The database becomes unresponsive, which is usually caused by long-running queries, deadlocks, or resource contention. (5) *Crashing*. The database unexpectedly shuts down, causing data inaccessible. *For a mature database product, each anomaly type is explained in the documentation and suitable to be learned by LLMs.*

Observation Tools for Anomaly Detection. “Observability of the database” is vital to detect above anomalies, including logs, metrics, and traces. (1) *Logs* are records of database events. For example, PostgreSQL supports slow query logs (with error messages that can help debug and solve execution issues), but these logs may

record a large scale of data and are generally not enabled in online stage. (2) *Metrics* capture the aggregated database and system statistics. For example, views like pg_stat_statements record the templates and statistics of slow queries; tools like Prometheus [20] provide numerous monitoring metrics, making it possible to capture the real time system status. (3) *Traces* provide visibility into how requests behave during executing in the database. Different from logs that help to identify the database problem, traces help to locate the specific abnormal workload or application.

Optimization Tools for Anomaly Solving. Users mainly concern how to restore to the normal status after an anomaly occurs. Here we showcase some optimization tools. (1) For slow queries, since most open-source databases are weak in logical transformation, there are external engines (e.g., Calcite with ~120 query rewrite rules) and tuning guides (e.g., Oracle with over 34 transformation suggestions) that help to optimize slow queries. (2) For knob tuning, many failures (e.g., max_connections in Postgres) or bad performance (e.g., memory management knobs) are correlated with database knobs (e.g., for a slow workload, increase innodb_buffer_pool_size in MySQL by 5% if the memory usage is lower than 60%). Similarly, there are index tuning rules that generate potentially useful indexes (e.g., taking columns within the same predicate as a composite index). Besides, we can utilize more advanced methods, such as selecting among heuristic methods [3, 21, 22] and learned methods [7–9, 15, 23, 25, 26] for problems like *index lacking*, which is not within the scope of this paper.

We aim to design D-Bot, an LLM-based DBA, for automatically diagnosing the database anomalies and use LLM to directly (or call appropriate tools to indirectly) provide the root causes.

3 THE VISON OF D-BOT

Existing LLMs are criticized for problems like “Brain in a Vat” [14]. Thus, it is essential to establish close connections between LLMs and the target database, allowing us to guide LLMs in effectively maintaining the database’s health and functionality. Hence, we propose D-Bot, which is composed of two stages.

First, in preparation stage, D-Bot generates experience (from documents) and prompt template (from diagnosis samples), which are vital to guide online maintenance.

- **Documents → Experience.** Given a large volume of diverse, long, unstructured database documents (e.g., database manual, white paper, blogs), we first split each document into chunks that can be processed by the LLM. To aggregate correlated chunks together (e.g., chunk v_i that explains the meaning of “bloat-table” and chunk v_j that utilizes “bloat-table” in root cause analysis), we generate a summary for each chunk based on both its content and its subsections. Finally, we utilize LLM to extract maintenance experience from chunks with similar summaries (Section 4).
- **Prompt Template Generation.** To help LLM better understand the DM tasks, we iteratively generate and score different formats of task descriptions using DM samples (i.e., given the anomaly and solutions, ask LLM to describe the task), and adopt task description that both scores high performance and is sensible to human DBAs (in cases of learning bias) for LLM diagnosis (Section 5).

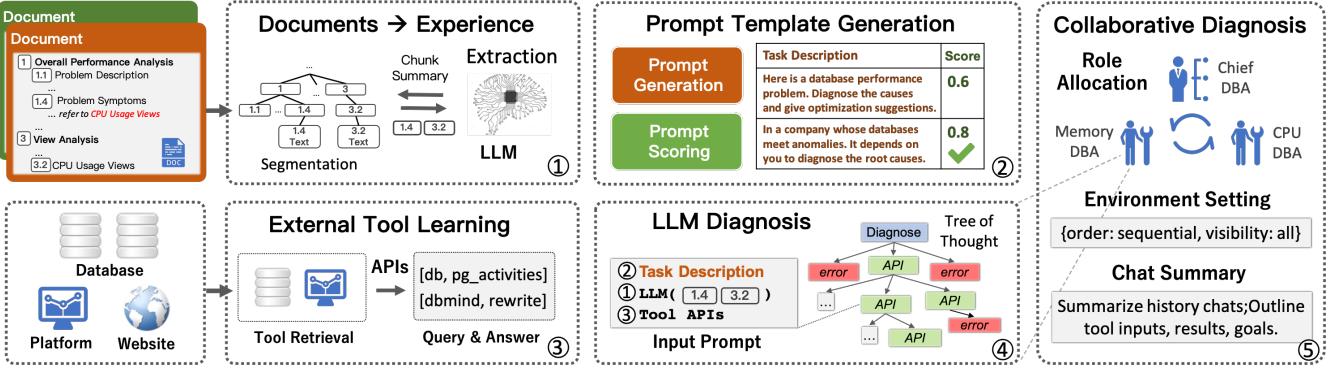


Figure 2: Overview of D-Bot

Second, in maintenance stage, given an anomaly, D-Bot iteratively reasons the possible root causes by taking advantages of external tools and multi-LLM communications.

- **External Tool Learning.** For a given anomaly, D-Bot first matches relevant tools using algorithms like Dense Retrieval. Next, D-Bot provides the tool APIs together with their descriptions to the LLM (e.g., function calls in GPT-4). After that, LLM can utilize these APIs to obtain metric values or optimization solutions. For example, in PostgreSQL, LLM can acquire the templates of slowest queries in the `pg_activity` view. If these queries consume much CPU resource (e.g., over 80%), they could be root causes and optimized with rewriting tool (Section 6).
- **LLM Diagnosis.** Although LLM can understand the functions of tool APIs, it still may generate incorrect API requests, leading to diagnosis failures. To solve this problem, we employ the *tree of thought* strategy, where LLM can go back to previous steps if the current step fails. It significantly increases the likelihood of LLMs arriving at reasonable diagnosis results (Section 7).
- **Collaborative Diagnosis.** A single LLM may execute only the initial diagnosis steps and end up early, leaving the problem inadequately resolved. To address this limitation, we propose the use of multiple LLMs working collaboratively. Each LLM plays a specific role and communicates by the environment settings (e.g., priorities, speaking orders). In this way, we can enable LLMs to engage in debates and inspire more robust solutions (Section 8).

4 EXPERIENCE DETECTION FROM DOCUMENTS

Document learning aims to extract experience segments from textual sources, where the extracted segments are potentially useful in different DM cases. For instance, when analyzing the root causes of performance degradation, LLM utilizes the “`many_dead_tuples`” experience to decide whether dead tuples have negatively affected the efficiency of index lookup and scans.

Desired Experience Format. To ensure LLM can efficiently utilize the experience, each experience fragment should include four fields. As shown in the following example, “`name`” helps LLM to understand the overall function; “`content`” explains how the root

cause can affect the database performance (e.g., the performance hazards of many dead tuples); “`metrics`” provide hints of matching with this experience segment, i.e., LLM will utilize this experience if the abnormal metrics exist in the “`metrics`” field; “`steps`” provide the detailed procedure of checking whether the root cause exists by interacting with database (e.g., obtaining the ratio of dead tuples and live tuples from table statistics views).

```

1 "name": "many_dead_tuples",
2 "content": "If the accessed table has too many dead tuples,
   it can cause bloat-table and degrade performance",
3 "metrics": ["live_tuples", "dead_tuples", "table_size", "dead_rate"],
4 "steps": "For each accessed table, if the total number of
   live tuples and dead tuples is within an acceptable
   limit (1000), and table size is not too big (50MB), it
   is not a root cause. Otherwise, if the dead rate also
   exceeds the threshold (0.02), it is considered a root
   cause. And we suggest to clean up dead tuples in time."

```

LLM for Experience Detection. It aims to detect experience segments that follow above format. Since different paragraphs within a long document may be correlated with each other (e.g., the concept of “bloat-table” appearing in “`many_dead_tuples`” is introduced in another section), we explain how to extract experience segments without losing the technical details.

Step1: Segmentation. Instead of partitioning documents into fixed-length segments, we divide them based on the structure of the section structures and their content. Initially, the document is divided into chunks using the section separators. If a chunk exceeds the maximum chunk size (e.g., 1k tokens), we further divide it recursively into smaller chunks.

Step2: Chunk Summary. Next, for each chunk denoted as x , a summary $x.summary$ is created by feeding the content of x into LLM with a summarization prompt $p_{summarize}$:

$p_{summarize} = \text{Summarize the provided chunk briefly... Your summary will serve as an index for others to find technical details related to database maintenance... Pay attention to examples even if the chunks covers other topics.}$

The generated $x.summary$ acts as a textual index of x , enabling the matching of chunks containing similar content.

Step3: Experience Extraction. Once the summaries of the chunks are generated, LLM parses the content of each chunk and compares it with the summaries of other chunks having similar content, which is guided by the extraction prompt $p_{extract}$. This way, experience segments that correlate with the key points from the summaries are detected.

$p_{extract} = \text{Given a chunk summary, extract diagnosis experience from the chunk. If uncertain, explore diagnosis experience in chunks with similar summaries.}$

In our implementation, given a document, we use LLM to extract experience segments into the above 4-field format.

Detected Maintenance Experience. In Figure 3, we showcase the simplified diagnosis procedure together with some necessary details, coming from chunks originally in different sections of the given documents (e.g., the maintenance guide with over 100 pages).

1. **Background Understanding.** It's crucial to grasp the context of system performance, such as recent changes in customer expectation, workload type, or even system settings.

2. **Database Pressure Checking.** This step identifies database bottlenecks, such as tracking CPU usage and active sessions; and monitoring system views (e.g., `pg_stat_activity` and `pgxc_stat_activity`) to focus on non-idle sessions.

3. **Application Pressure Checking.** If there is no apparent pressure on the database or the resource consumption is very low (e.g., CPU usage below 10% and only a few active sessions), it is suggested to investigate the application side, such as exhausted application server resources, high network latency, or slow processing of queries by application servers.

4. **System Pressure Checking.** The focus shifts to examining the system resources where the database is located, including CPU usage, IO status, and memory consumption.

5. **Database Usage Checking.** Lastly, we can investigate sub-optimal database usage behaviors, such as (1) addressing concurrency issues caused by locking waits, (2) examining database configurations, (3) identifying abnormal wait events (e.g., `io_event`), (4) tackling long/short-term performance declines, and (5) optimizing poorly performing queries that may be causing bottlenecks.

5 DIAGNOSIS PROMPT GENERATION

Instead of directly mapping extracted experience to new cases, next we explore how to teach LLMs to (1) understand the database maintenance tasks and (2) reason over the root causes by itself.

Input Enrichment. With a database anomaly x as input, we can enrich x with additional description information so called input prompt x' . On one hand, x' helps LLM to better understand the task intent. On the other hand, since database diagnosis is generally a complex task that involves multiple steps, x' preliminarily implies how to divide the complex task into sub-tasks in a proper order, such that further enhancing the reasoning of LLM.

From our observation, the quality of x' can greatly impact the performance of LLM on maintenance tasks [27] (Figure 2). Thus, we first utilize LLM to suggest candidate prompts based on a small set of input-output pairs (e.g., 5 pairs for a prompt). Second, we rank these generated prompts based on a customized scoring function

(e.g., the ratio of detected root causes), and reserve the best prompts (e.g., top-10) as candidates. Finally, we select the best one to serve as the input prompt template for the incoming maintenance tasks.

6 EXTERNAL TOOL LEARNING

As we know, the efficient use of tools is a hallmark of human cognitive capabilities [17, 18]. When human beings encounter a new tool, they start to understand the tool and explore how it works, i.e., taking it as something with particular functions and trying to understand what the functions are used for. Likewise, we aim to inspire similar ability within LLM.

Tool Retrieval. We first retrieve the appropriate tools for the diagnosis task at hand, represented as D_t . There are several methods used, such as BM25, LLM Embeddings, and Dense Retrieval.

(1) **BM25**, simply represented as $f(D_t, Q) = \text{BM25}$, is a common probabilistic retrieval method that ranks tool descriptions (D) based on their relevance to the given anomaly (Q) [19].

(2) **LLM Embeddings**, denoted as $f(D_t, L) = LLM_E$, are a method that converts tool descriptions (D_t) into embeddings (E_t) using LLM, i.e., $E_t = L(D_t)$. These embeddings capture the semantic meanings in a multi-dimensional space, hence helping in finding related tools even in the absence of keyword overlap, $D_t = LLM_E(E_t)$.

(3) **Dense Retrieval**, denoted as $f(Q, D_t, N) = D_R$, uses neural networks (N) to generate dense representations of both the anomaly (Q) and the tool descriptions (D_t), separately denoted as Dense_Q and Dense_D . To retrieve the relevant tools, we calculate the similarity between Dense_Q and Dense_D , and rank them based on these similarity scores.

The proper method for tool retrieval depends on the specific scenarios. BM25 is efficient for quick results with large volumes of API descriptions in the tools and clear anomaly characters. LLM Embeddings excel at capturing semantic and syntactic relationships, which is especially useful when relevance isn't obvious from keywords (e.g., different metrics with similar functions). Dense Retrieval is ideal for vague anomaly, which captures context and semantic meaning, but is more computational costly.

7 LLM DIAGNOSIS

Tree Search Algorithm using LLM. To avoid diagnosis failures caused by the incorrect actions (e.g., non-existent API name) derived by LLM, we propose to utilize the *tree of thought* strategy that can guide LLM to go back to previous actions if the current action fails.

Step1: Tree Structure Initialization. We initialize a tree structure, where root node is the diagnosis request (Figure 4). Utility methods are utilized to manipulate the tree structure, and UCT score for node v are computed based on the modifications during planning, i.e., $UCT(v) = \frac{w(v)}{n(v)} + C \cdot \sqrt{\frac{\ln(N)}{n(v)}}$, where $\frac{\ln(N)}{n(v)}$ denotes the selection frequency and $w(v)$ denotes the success ratio of detecting root causes. Note, the action of $n(v)$ fails to call tool API, $w(v)$ equals -1.

Step2: Simulate Execution. This step kickoffs the execution of simulations starting from the root node of the tree. It involves selecting nodes based on specific standard (e.g., detected abnormal metrics). If the criteria for selecting a new node is met, a new node is chosen; otherwise, the node with the highest UCT value is selected.

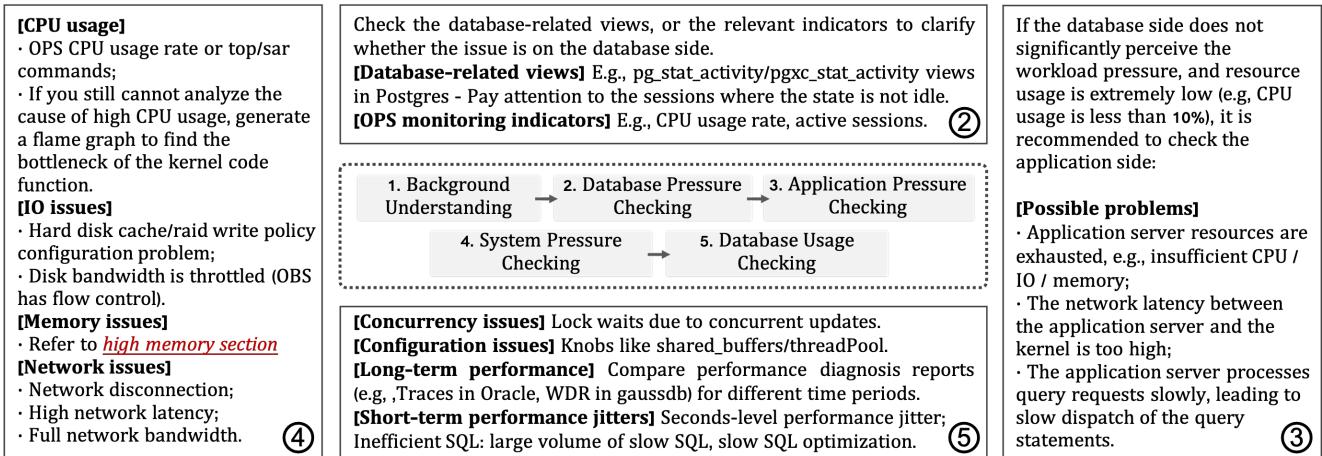


Figure 3: The outline of diagnosis experience extracted from documents.

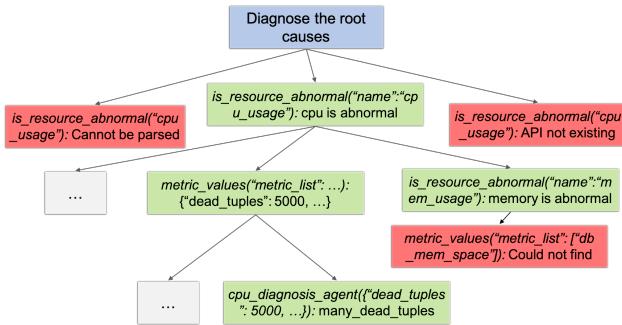


Figure 4: Example LLM diagnosis by tree of thought

Step3: Existing Node Reflection. For each node in the path from the root node to the selected node, reflections are generated based on decisions made at previous nodes. For example, we count on LLM to rethink the benefits of analyzing non-resource relevant metrics. If LLM decides the action cannot find any useful information, the UCT value will be reduced and set to that of its parent node. In this way, we can enhance the diagnosis efficiency.

Step4: Terminal Condition. If LLM cannot find any more root cause (corresponding to a leaf node) for a threshold time (e.g., five), the algorithm ends and LLM outputs the final analysis based on the detected root causes.

8 COLLABORATIVE DIAGNOSIS FOR COMPLEX CASES

A single LLM may be limited in its ability to fully resolve a problem (e.g., stuck in initial steps). Collaborative diagnosis involves the utilization of multiple LLMs to collectively address complex cases by leveraging their unique role capabilities. This section introduces the communicative framework for database diagnosis [1, 16].

- Agents.** In the communicative framework, agents can be undertaken by human beings or LLMs. Humans can provide LLM agents with scenario requirements (e.g., business changes over the incoming period) and prior knowledge (e.g., historical anomalies). On the other hand, each LLM agent

is dedicated to a distinct domain of functions. For example, we include three LLM agents in the initial implementation: (1) Chief DBA is responsible for collaboratively diagnosing and detecting root causes with other agents; (2) CPU Agent is specialized in CPU usage analysis and diagnosis, and (3) Memory Agent focuses on memory usage analysis and diagnosis. Each LLM agent can automatically invoke tool APIs to retrieve database statistics, extract external knowledge, and conduct optimizations. For instance, CPU Agent utilizes the monitoring tool *Prometheus* to check CPU usage metrics within specific time periods, and determine the root causes of high CPU usage by matching with extracted experience (Section 4). Note, if CPU/memory agents cannot report useful analysis, Chief DBA is responsible to detect other potential problems, such as those on the application side.

- Environment Settings.** We need to set a series of principles for the agents to efficiently communicate, such as (1) *Chat Order*: To avoid the mutual negative influence, we only allow one LLM agent to “speak” (i.e., appending the analysis results to the chat records to let other agents know) at a time. To ensure flexible chat (e.g., if an agent cannot detect anything useful, it should not speak), we rely on Chief DBA to decide which agent to speak in each iteration (diagnosis scheduling); (2) *Visibility*: By default, we assume the analysis results of agents can be seen by each other, i.e., within the same chat records. In the future, we can split agents into different groups, where each group is in charge of different database clusters/instances and they do not share the chat records; (3) *Selector* is vital to filter invalid analysis that may mislead the diagnosis directions; (4) *Updater* works to update agent memory based on the historical records.

- Chat Summary.** For a complex database problem, it requires agents dozens of iterations to give in-depth analysis, leading to extremely long chat records. Thus, it is vital to effectively summarize the critical information from chat records without exceeding the maximal length of LLM prompts. To the end, we progressively summarize the lines

Table 1: Diagnosis performance of single root causes (● : legal diagnosis results; ● : accurate diagnosis results).

Type	Root Cause	Description	LLM+Metrics	D-Bot
Data Insert	INSERT_LARGE_DATA	Long execution time for large data insertions	●	● ●
Slow Query	FETCH_LARGE_DATA	Fetching of large data volumes	● ●	● ●
	REDUNDANT_INDEX	Unnecessary and redundant indexes in tables	●	●
	LACK_STATISTIC_INFO	Outdated statistical info affecting execution plan	●	● ●
	MISSING_INDEXES	Missing indexes causing performance issues	● ●	● ●
	POOR_JOIN_PERFORMANCE	Poor performance of Join operators	●	● ●
	CORRELATED_SUBQUERY	Non-promotable subqueries in SQL	●	● ●
Concurrent Transaction	LOCK_CONTENTION	Lock contention issues	●	●
	WORKLOAD_CONTENTION	Workload concentration affecting SQL execution	● ●	● ●
	CPU_CONTENTION	Severe external CPU resource contention	● ●	● ●
	IO_CONTENTION	IO resource contention affecting SQL performance	●	● ●

of a record used with tools, including inputs for certain tools and the results returned by these tools. Based on the current summary, it extracts the goals intended to be solved with each call to the tool, and forms a new summary, e.g.,

[Current summary]

- I know the start and end time of the anomaly.

[New Record]

Thought: Now that I have the start and end time of the anomaly, I need to diagnose the causes of the anomaly

Action: is_abnormal_metric

Action Input: {"start_time": 1684600070, "end_time": 1684600074, "metric_name": "cpu_usage"}

Observation: "The metric is abnormal"

[New summary]

- I know the start and end time of the anomaly.

- *I searched for is_abnormal_metric, and I now know that the CPU usage is abnormal.*

With this communicative framework and well-defined communication principles, the collaborative diagnosis process among human and LLM agents becomes more efficient (e.g., parallel diagnosis) and effective (e.g., chat records could trigger investigating of in-depth metric observation and root cause analysis).

9 PRELIMINARY EXPERIMENT RESULTS

Demonstration. As illustrated in Figure 5, *Chief DBA* monitors the status of the database to detect anomalies. Upon recognizing a new anomaly, *Chief DBA* notifies both the *Memory Agent* and *CPU Agent*. These agents independently assess the potential root causes and communicate their findings (the root causes and recommended solutions) to the *Chief DBA*. Subsequently, the *Chief DBA* consolidates the diagnostic results for the user’s convenience. In initial iterations, these agents generally gather limited information, and so they will continue for multiple iterations until the conclusion of *Chief DBA* is nearly certain or no further valuable information can be obtained. Additionally, during the diagnosis, users have the option to participate by offering instructions and feedback, such as verifying the effectiveness of a proposed optimization solution.

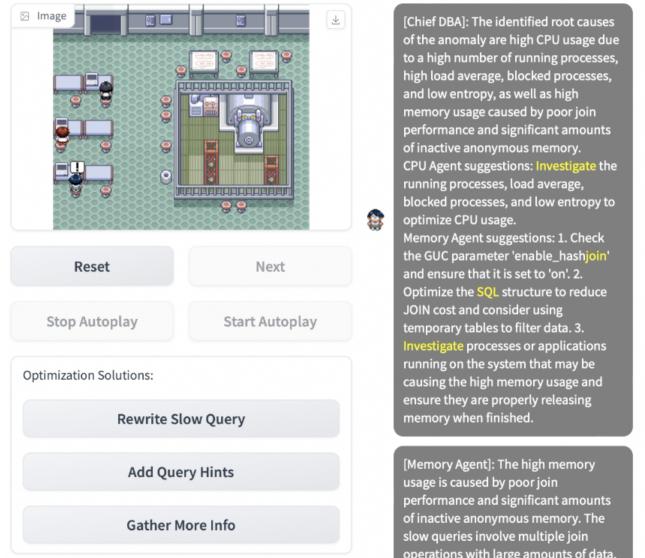


Figure 5: A basic demonstration of D-Bot.

Diagnosis Performance Comparison. We compare the performance of D-Bot against a baseline, namely *llm+Metrics*. Both of the two methods are deployed with the OpenAI model GPT-4 [2] alongside metrics and views from PostgreSQL and Prometheus. The evaluation focuses on basic single-cause problems as detailed in Table 1. Besides, we also offer a multi-cause diagnosis example presented in the Appendix-B.

Preliminary results indicate that *LLM +Metrics* and D-Bot can achieve a high *legality rate* (producing valid responses to specific database issues). However, it is a “dangerous behavior” for *LLM +Metrics*, which actually has very low *success rate* (*infrequent provision of the correct causes*). In contrast, D-Bot achieves both high legal rate and success rate. The reasons are three-fold.

First, *LLM +Metrics* conducts very basic reasoning and often misses key causes. For example, for the *INSERT_LARGE_DATA* case, *LLM +Metrics* only finds “high number of running processes” with the *node_procs_running* metric, and stops early. In contrast,

D-Bot not only finds the high concurrency problem, but analyzes the operation statistics in the database process and identifies “*high memory usage due to heavy use of UPDATE and INSERT operations on xxx tables*” by looking up the `pg_stat_statements` view.

Second, *LLM +Metrics* often “makes up” reasons without substantial knowledge evidence. For example, for the *CORRELATED_SUBQUERY* case, *LLM +Metrics* observes SORT operations in logged queries, and incorrectly attributes the cause to “frequent reading and sorting of large amount of data”, thereby ending the diagnostic process. Instead, D-Bot cross-references with the query optimization knowledge, and then finds the correlated-subquery structure might be the performance bottleneck, with additional extracted information like estimated operation costs.

Third, *LLM +Metrics* meet trouble in deriving appropriate solutions. *LLM +Metrics* often gives very generic optimization solutions (e.g., “resolve resource contention issues”), which are useless in practice. Instead, leveraging its *tool retrieval* component, D-Bot can learn to give specific optimization advice (e.g., invoking query transformation rules, adjusting the `work_mem` parameter) or gather more insightful information (e.g., “calculate the total cost of the plan and check whether the cost rate of the sort or hash operators exceeds the cost rate threshold”).

This evaluation reveals the potential of D-Bot in going beyond mere anomaly detection to root cause analysis and provision of actionable suggestions. Despite these advancements, from the basic deployment of D-Bot, there are still some unresolved challenges. First, it is tricky to share the maintenance experience (e.g., varying metric and view names) across different database products. Second, it is labor-intensive to adequately prepare extensive number of anomaly-diagnosis data, which is essential to fine-tune and direct less-capable LLMs (e.g., those smaller than 10B) to understand the complex database knowledge and apply in maintenance.

10 CONCLUSION

In this paper, we propose a vision of D-Bot, an LLM-based database administrator that can continuously acquire database maintenance experience from textual sources, and provide reasonable, well-founded, in-time diagnosis and optimization advice for target databases. *We will continue to complete and improve this work with our collaborators.*

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A APPENDIX - PROMPTS

Prompts

Chief_dba_format_prompt

You are in a company whose databases meet anomalies and it depends on you to collaborate with other agents to diagnose the root causes. \${role_description}

Rules and Format Instructions for Response

=====

- Must listen and respond to the user's advice in the following format:

Thought: I now know the advice of the user, and i need to consider it during diagnosis

Action: Speak

Action Input: {"diagnose": response to the advice, "solution": [], "knowledge": ""})

- You can detect and diagnose anomaly as follows to use tool:

Thought: (your thought)

Action: (an action name, it can be one of [obtain_anomaly_time, Speak])

Action Input: (argument for the action)

First, you need to call the tool api to get the start and end time of an anomaly

Thought: I need to obtain the start and end time of the anomaly by calling the tool api

Action: obtain_anomaly_time

Action Input: {"input": "json dict string"}

Observation: {"start_time": "xxxx", "end_time": "xxxx"}

After obtaining the start and end time of the anomaly, announce it with the following format:

Thought: I now know the start and end time of the anomaly, and i need to report it to agents

Action: Speak

Action Input: {"diagnose": the start and end time of the anomaly you found, "solution": [], "knowledge": ""})

After all the agents have announced the root causes they found, you should summarize all the mentioned root causes and optimization solutions point by point:

Thought: I now know the root causes and optimization solutions from other agents, and i need to conclude them point by point

Action: Speak

Action Input: {"diagnose": The identified root causes of the anomaly are ..., "solution": The suggested optimization solutions are ..., "knowledge": ""})

=====

Here is the conversation history

\${chat_history}

Here is the execution log of tools

\${tool_observation}

- Once an agent has announced the root causes he found, it is your responsibility to memorize the root causes. After that, continue to encourage other agents to diagnose.

- When no one speaks in the last round ([Silence] appears in the end of history), you should summarize root causes and optimization solutions point by point.

Pay attention to the response format instructions, and strictly follow the above rules!

Based on the above history, what will you, \${agent_name}, do next?

CPU_agent_format_prompt

You are in a company whose databases meet anomalies. Follow the chief DBA's instructions to diagnose the root causes. \${role_description}

Rules and Format Instructions for Response

```

- During diagnosis, you have access to the following tools:  

${tools}

=====
- You can respond as follows to use tool:  

Thought: (your thought)  

Action: (an action name, it can be one of [whether_is_abnormal_metric, CPU_diagnosis_agent, Speak], pay attention to the capitalization)  

Action Input: (argument for the action)

You can first determine abnormal metrics by using the tools, and use the following format:  

Thought: Now that I have obtained the start and end time of the anomaly, check whether the CPU usage is abnormal during that time period.  

Action: whether_is_abnormal_metric  

Action Input: {"start_time": 1684646375, "end_time": 1684646378, "metric_name": "cpu_usage"}

Next you must diagnose root causes by using the tools, and must use the following format  

(any other choice is not allowed):  

Thought: The CPU usage is abnormal, so I need to diagnose the cause of the anomaly using  

cpu_diagnosis_agent.  

Action: cpu_diagnosis_agent  

Action Input: {"start_time": 1684646375, "end_time": 1684646378}

After you have got the observation from cpu_diagnosis_agent, announce it to the chief DBA,  

and use the following format:  

Thought: I now know the root cause of the anomaly, and i need to report it to the chief DBA  

Action: Speak  

Action Input: ({"diagnose": the root causes you found, "solution": the optimization solutions  

for the root causes splitted by '\n', "knowledge": the diagnosis knowledge you used})  

...
(Note the memory agent owns similar prompt, and we do not show it to avoid redundancy.)
```

Summary_prompt

Progressively summarize the lines of a record that you uses tools, which contains inputs for certain tools and the results returned by these tools.

Based on the current summary, summarize from the record the goals that you intended to solve with each tool call, add it onto the previous summary, and return a new summary.

EXAMPLE

Current summary:

New lines:

Thought: Now that I have the start and end time of the anomaly, I need to diagnose the causes of the anomaly

Action: whether_is_abnormal_metric

Action Input: {"start_time": 1684600070, "end_time": 1684600074, "metric_name": "cpu_usage"}
Observation: "The metric is abnormal"

New summary:

- I now know the start and end time of the anomaly.
- I searched for whether_is_abnormal_metric, and I now know that the CPU usage is abnormal.

END OF EXAMPLE

Now, try to summarize the following record.

Current summary:

\${summary}

New lines:

\${new_lines}

New summary:

B APPENDIX - TEST CASES

Test Case (WORKLOAD_CONTENTION, POOR_JOIN_PERFORMANCE)

(First Round)

[Chief DBA] The anomaly started at 2023-08-05 23:38:30 and ended at 2023-08-05 23:43:30.
[API Call] obtain_anomaly_time.

[CPU Agent] The CPU usage is abnormal, so I need to diagnose the cause of the anomaly.
[API Call] whether_is_abnormal_metric.

[CPU Agent] The CPU relevant metric values are as follows: 1. node_scrape_collector_duration_seconds: This metric measures the duration of data collection from the node exporter. The value of 5.7218e-05 indicates that the data collection process is relatively fast. 2. node_procs_running: This metric represents the number of processes currently executing on the system. A value of 18.0 suggests that there are 18 processes running at the moment. ... 5. node_load1, node_load5, node_load15: These metrics represent the average system load over the last 1, 5, and 15 minutes, respectively. The values of 7.33, 2.4, and 0.89 suggest that the system is heavily loaded.

[API Call] obtain_cpu_metrics.

[Matched Knowledge] This diagnosis was based on several **CPU relevant metrics** obtained from Prometheus like node_scrape_collector_duration_seconds, node_procs_running, node_procs_blocked, node_entropy_available_bits, node_load1, node_load5, and node_load15.

[CPU Agent] The high CPU usage seems to be caused by the high value of node_load1. It indicates that the CPU has been heavily utilized recently.

[API Call] knowledge_matching.

[Matched Knowledge] {"cause_name": "workload_contention", "desc": "The function checks for several potential causes of contention, including abnormal CPU and memory resource usage, insufficient space in the database data directory, and excessive connections or thread pool usage. ... If any of these issues are detected, the function provides a detailed report of the problem and suggests potential solutions. If no issues are found, the function returns \"not a root cause\".", "metrics": "... - max_connections - db_cpu_usage - db_mem_usage - disk_usage - connection - thread_pool_rate"}.

[Solution] 1. Monitor the number of running processes and try to reduce unnecessary ones. 2. Look for resource contention and try to optimize resource allocation.

[Memory Agent] The memory metric is abnormal.

[API Call] whether_is_abnormal_metric.

[Memory Agent] We first obtain memory metric values: - The node_memory_Inactive_anon_bytes metric value suggests a significant amount of inactive anonymous memory. - The node_memory_MemFree_bytes metric value indicates a considerable amount of free memory available. - The node_memory_Dirty_bytes metric value indicates a moderate amount of dirty memory. These memory metric values suggest that there may be a memory leak or inefficient memory management within the system. It might be worth investigating the memory allocation and deallocation processes, ensuring that resources are effectively managed.

[API Call] obtain_memory_metrics.

[Memory Agent] We next obtain slow queries from the pg_stat_statements view. There are potential causes that can be analyzed:
1. Poor join performance: One of the slow queries involves multiple table joins (SELECT MIN(mi.info) ... FROM cast_info AS ci, info_type AS it1, info_type AS it2, keyword AS k, movie_info AS mi, movie_info_idx AS mi_idx, movie_keyword AS mk, name AS n, title AS t ...). Poor join performance can result in high memory usage if the join operation involves a large amount of data or an inefficient join operator is used. It is recommended to optimize the SQL structure and check if the join operations can be optimized by using appropriate indexes or join operators.

[API Call] obtain_slow_queries; knowledge_matching.

[Matched Knowledge] {"cause_name": "poor_join_performance", "desc": "There are four main situations: 1) when the GUC parameter 'enable_hashjoin' is set to 'off', which can result in the optimizer choosing NestLoop or other join operators even when HashJoin would be more suitable; 2) when the optimizer incorrectly chooses the NestLoop operator, even when 'set_hashjoin' is on; 3) when the join operation involves a large amount of data, which can lead to high execution costs; and 4) when the cost of the join operator is expensive. ...", "metrics": "- total_cost - cost_rate_threshold - nestloop_rows_threshold - large_join_threshold"}; {"cause_name": "missing_index", ...}

[Solution] Optimize the SQL structure of the query .. and check if the join operations can be optimized by using appropriate indexes or join operators.

[Memory Agent] Other potential causes: Without additional information about the system and its configuration, it is difficult to pinpoint a specific root cause of the high memory usage. Other potential causes may include inefficient query plans, lack of memory optimization settings, or memory leaks in the application or database engine.
To further investigate and identify the root cause, it is advisable to perform the following steps:
1. Analyze the resource usage pattern over time to identify any patterns or trends related to the memory usage.
2. Check the configuration settings and optimization parameters of the database system to ensure they are properly set.
3. Monitor the system for any memory leaks or inefficient query plans that may be causing the high memory usage.
4. Review the application code and queries to identify any potential optimizations or rewrite queries to improve their efficiency.

[API Call] N/A.

[Solution] 1. Analyze the resource usage pattern over time to identify any patterns or trends related to the memory usage.
2. Check the configuration settings and optimization parameters of the database system to ensure they are properly set.
3. Monitor the system for any memory leaks or inefficient query plans that may be causing the high memory usage.
4. Review the application code and queries to identify any potential optimizations or rewrite queries to improve their efficiency.

[Chief DBA] The identified root causes of the anomaly are high CPU usage due to a high number of running processes, processes waiting for resources, and high load averages. It is also uncertain whether poor join performance is causing high memory usage.

[API Call] N/A.

[Solution] 1. In order to reduce CPU utilization, it is necessary to investigate the specific processes involved and their resource requirements. 2. For the high memory usage, we need to gather more information such as the overall memory usage trend over time, other slow queries or resource-intensive operations, and any relevant configuration settings. Examining the memory usage patterns and query execution plans might provide further insights.

(Second Round) – further insights into memory problems

[Memory Agent] Chief DBA has suggested that gathering more information such as the overall memory usage trend over time, other slow queries or resource-intensive operations, and any relevant configuration settings. This advice is indeed valuable, and I should consider it during the diagnosis.

[API Call] N/A.

[Memory Agent] Based on the memory metric values and slow queries provided, it is difficult to directly determine the root cause of the high memory usage. However, we can analyze potential causes based on the information given. There is a significant amount of memory being used, particularly by node_memory_Dirty_bytes. Additionally, there are 11 active PostgreSQL activities. This indicates that there may be a memory leak or excessive memory usage in one or more queries or processes. The slow queries provided involve multiple table joins and aggregation functions ('MIN\'). They may be resource-intensive and contribute to the high memory usage.

[API Call] knowledge_matching.

[Matched Knowledge] {"cause_name": "poor_join_performance", ...}

[Solution] 1. Analyze the query plans, check for inefficient join operations, and monitor the memory usage over time.
2. Review the system configuration and resource constraints may provide insights into potential optimizations or improvements.
3. Consult with a database administrator or expert for a more accurate analysis and resolution.

[Chief DBA] Based on our analysis, the root causes of the anomaly seem to be high CPU usage due to excessive running processes, poor join performance and inefficient query structure. The high CPU usage is mainly due to a high number of running processes and/or a high CPU load. There are 11 active PostgreSQL activities indicating a memory leak or excessive memory usage in one or more queries or processes. The slow queries provided involve multiple table joins and aggregation functions which may be resource-intensive and contribute to the high memory usage. Poor join performance and inefficient query structure can also lead to unnecessary memory usage.

[API Call] N/A.

[Solution] 1. Further investigation and analysis of the running processes and system workload that cause severe contention.
2. Review the structure of the slow queries and optimize them to reduce memory consumption.
3. Investigate join operations for possible inefficiencies and optimize as needed.
4. Gather more information about overall system performance, such as overall memory utilization and any other abnormal metrics.