# PromAssistant: Leveraging Large Language Models for Text-to-PromQL

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With the increasing complexity of modern online service systems, understanding the state and behavior of the systems is essential for ensuring their reliability and stability. Therefore, metric monitoring systems are widely used and become an important infrastructure in online service systems. Engineers usually interact with metrics data by manually writing domain-specific language (DSL) queries to achieve various analysis objectives. However, writing these queries can be challenging and time-consuming, as it requires engineers to have high programming skills and understand the context of the system. In this paper, we focus on PromQL, which is the metric query DSL provided by the widely used metric monitoring system Prometheus. We aim to simplify metrics querying by enabling engineers to interact with metrics data in Prometheus through natural language, and we call this task text-to-PromQL. Building upon the insight, this paper proposes PromAssistant, a Large Language Model-based text-to-PromQL framework. PromAssistant first uses a knowledge graph to describe the complex context of an online service system. Then, through the synergistic reasoning of LLMs and the knowledge graph, PromAssistant transforms engineers' natural language questions into PromQL queries. To evaluate PromAssistant, we manually construct the first text-to-PromQL benchmark dataset which contains 280 metric query questions. The experiment results show that PromAssistant is effective in text-to-PromQL and outperforms baseline approaches. To the best of our knowledge, this paper is the first study of text-to-PromQL, and PromAssistant pioneered the DSL generation framework for metric querying and analysis.

CCS Concepts:  $\bullet$  Software and its engineering  $\rightarrow$  Domain specific languages;  $\bullet$  Computing methodologies  $\rightarrow$  Artificial intelligence.

Additional Key Words and Phrases: Metrics, PromQL, Online Service Systems, Large Language Models, Knowledge Graph, AIOps

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#### 1 Introduction

In recent years, online service systems represented by search engines, online shops, and social networks have become increasingly popular and important in our daily life. Moreover, with the development of technologies such as cloud computing, containers, and microservices, these online service systems have become increasingly complex and large [53]. Industrial online service systems may contain tens to hundreds of nodes, hundreds to thousands of services, and deployed on multiple data centers. For such a complex system, it is crucial to observe and understand its state and behavior [6, 32].

Therefore, metric monitoring systems are widely used in online service systems and have become an important infrastructure [6, 32]. Metrics are measurements of resource usage or behavior that can be observed and collected throughout the system. Monitoring systems enable engineers to collect, store, query, and visualize metrics in real-time. Engineers usually set multiple types of metrics for each type of component in the system (e.g., nodes, service instances, services, APIs, etc.) [6], e.g., CPU and memory usage of nodes, QPS and response latency of APIs. Modern online service systems usually includes a large number of metrics, which is because the whole system usually collect dozens to hundreds types of metrics, and each type of metric will generate many metric instances according to their associated system components. Engineers usually achieve fault diagnosis, performance optimization, and other objectives by analyzing these metrics.

To help engineers interact with the massive metric data, most monitoring systems provide query interfaces based on domain-specific languages (DSL). Engineers can query and analyze metric data by manually writing DSL queries. For example, Prometheus provides PromQL [39], InfluxDB provides Flux [18], and Microsoft Azure provides Kusto [5]. In this paper, we focus on Prometheus [38], one of the most widely used metric monitoring systems in modern online service systems, and it has been recognized as the de facto standard in the field of cloud-native-based online service system monitoring. The query language provided by Prometheus is called PromQL [39] (Prometheus Query Language), which enables engineers to query and analyze the metric data in Prometheus.

Manually writing PromQL queries is usually a challenging task. It requires the engineer to understand not only the syntax of PromQL but also the context of the target system related to the query. Specifically, first, a PromQL query can be very complex in real online service systems, which consist of multiple metric names, metric labels, metric values, operators, functions, etc. It requires engineers have an depth understanding of the systax of PromQL and extensive experience in writing PromQL queries, which brings a large learning cost. Second, the large scale and complexity of modern online service systems make it difficult for engineers to understand the full context of the system. This makes engineers may spend a lot of time to search the system context knowledge when writing PromQL queries. As the example shown in Figure 2, the engineer wants to write a PromQL query to find which node has the most available memory among the nodes where the order service is deployed. In order to write this PromQL query correctly, the engineer needs to know the correct metric name, the correct metric label, and where the order service (which may have dozens of service instances deployed on different nodes) is deployed. Engineers usually acquire the above knowledge by searching through the various platforms and tools in the system, which is usually time consuming.

In order to simplify the process of metrics querying, in this paper we wanted to design an approach that enables engineers to simply interact with metric data in Prometheus through natural language. Specifically, we would like engineers just to provide query requirements described in natural language, and then the approach can generate the corresponding PromQL queries. We named this task as text-to-PromQL. This kind of approach has been proven efficient in improving the productivity of engineers, such as the widely used techniques: code generation [25, 49] and text-to-SQL [21, 22]. However, as shown in the example in Figure 2, metrics queries are tightly tied to a specific system context, making it significantly different from the the usage scenarios of code and SQL. Therefore, these existing techniques are difficult to apply to text-to-PromQL tasks. A recent study [19] uses LLMs and few-shot learning to recommend metric queries related to an incident in cloud systems. However, this approach only recommends metric queries based on specific incidents and cannot generate metrics queries on demand, which limits its usage scenarios.

To address the preceding challenges, this paper presents PromAssistant, an LLM-based text-to-PromQL framework. PromAssistant can convert users' natural language questions into PromQL queries that match the context of a specific system, thus simplifying the process of metrics querying and analysis. The main idea of PromAssistant is to describe the complex context of a specific system (e.g., metric information, component dependencies) through a knowledge graph, and then transform natural language questions into PromQL queries through the synergistic reasoning of knowledge graph and LLMs. Specifically, PromAssistant first parses the input natural language question to understand the user intent and obtains the key information in the question. Then it retrieves metric knowledge and system component knowledge related to the question on the knowledge graph. Finally, the retrieved knowledge is fed to the LLMs as context to help LLMs generate accurate PromQL queries. Note that, although PromAssistant is implemented based on Prometheus, it can be applied to other similar monitoring systems with minor modifications.

To evaluate the effectiveness of PromAssistant, we manually construct the first text-to-PromQL benchmark dataset based an open-source microservice benchmark system. Then we conduct a series of experimental studies on this dataset. The results demonstrate the effectiveness of PromAssistant in text-to-PromQL. When using GPT-4-Turbo as the backbone LLM, PromAssistant achieves an accuracy of 69.1% in generating PromQL queries. Moreover, the experimental result confirms that PromAssistant is accurate in retrieving metric knowledge and system component knowledge. To the best of our knowledge, this paper is the first study of text-to-PromQL.

In summary, this paper makes the following main contributions:

- We propose PromAssistant, a text-to-PromQL framework based on synergistic reasoning of knowledge graph and LLMs.
- We manually construct the first text-to-PromQL benchmark dataset.
- We conduct a series of experimental studies to validate the effectiveness of PromAssistant.

## 2 Background and Motivation

In this section, we first introduce the background about Prometheus and PromQL, then motivate our work with an example.

# 2.1 Background

Metric monitoring systems have become an important infrastructure for modern online service systems for understanding system behaviors and states [6, 32]. Metric monitoring systems usually collect various metrics to observe the system state, and provide visualization and query functions to help engineers use the metrics data. In general, metrics are numerical measurements of the system state over a period of time, commonly used metrics include CPU usage, requests per second, request



Fig. 1. An Example of the Metric Data in Prometheus

error rate, etc. Modern online service systems usually includes a large number of metrics, which is because the whole system usually collect dozens to hundreds types of metrics, and each type of metric will generate many metric instances according to their associated system components. By observing and analyzing metrics data, engineers can detect system failures, identify root causes, and make operational decisions.

In recent years, Prometheus[38] has become the de facto standard in the field of cloud-native-based online service systems monitoring, because of its usability, scalability, and ecosystem. Prometheus is an open-source monitoring and alerting toolkit, which is also one of the core projects of Cloud Native Computing Foundation[9]. Prometheus provides a multi-dimensional metrics data model, an easy-to-use metrics query language, an efficient time series database, and the ability to integrate with a wide range of third-party systems and tools. Many organizations have used Prometheus to build their monitoring systems, and cloud providers such as AWS[4], Azure[5], and Alibaba Cloud[2] also offer Prometheus cloud services.

The data model is the foundation of the metric monitoring system. In Prometheus's data model, a metric record will contain three parts of information: metric name, labels, and sample. The metric name is usually a string that uniquely identifies a metric and briefly describes its monitoring object. Labels are sets of label value pairs that help categorize and differentiate the different dimensions of a metric. A sample contains a timestamp and a value, which records the value at a particular time. Given a metric name and a set of label-value pairs, a specific time series can be identified, which is the basic form that Prometheus stores data. Figure 1 shows an example of various time series derived from a metric. <code>http\_requests\_total</code> is the name of the metric, which monitors the total number of HTTP requests. In the example, the labels method and instance are used, method represents the HTTP request method and instance represents the service instance that receives the request. With different label values paris, four time series are obtained and each time series contains multiple samples.

To help engineers easily work with metric data, metric monitoring systems usually provide query interfaces based on domain-specific languages(DSL). Prometheus has implemented its own query language called PromQL[39] (Prometheus Query Language). PromQL is a domain-specific language built upon Go, which is similar to SQL for managing databases, GraphQL for query graph databases, etc. Using PromQL engineers can query and extract valuable insights from the time series in Prometheus. PromQL supports string, scalar, range vector, and instant vector data types, where range Vector and Instant Vector are specifically designed by Prometheus for retrieving time series. PromQL also provides many binary and aggregation operators and several functions to help engineers operate the data, such as add, subtract, sum, group, absolute values, etc. For example, query  $sum(rate(http\_requests\_total[5m]))$  calculates the sum of the per-second rate of the HTTP requests over the last 5 minutes. In this example,  $http\_requests\_total[5m]$  is a range vector that represents the HTTP requests number time series over the last 5 minutes. rate is a function used to

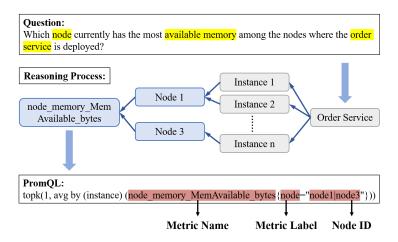


Fig. 2. A Motivation Example

calculate the per-second average rate of the time series, and *sum* is an aggregation operator used to calculate the sum over dimensions. Readers can refer to [39] for more details of the PromQL.

#### 2.2 Motivation

In practice, engineers may write PromQL queries to query metric data for different purposes, such as observing resource consumption trends, locating root causes, etc. These PromQL queries can be complex, and writing them requires a sufficient understanding of the syntax of PromQL and the context of the system (e.g., the deployment of service instances). This makes writing PromQL queries a time-consuming task. In this paper, we aim to design an approach that can transform engineers' natural language questions into PromQL queries. In this way, it helps engineers write the required PromQL query faster and reduces learning barriers and time costs.

Figure 2 shows an example of a natural language question and the corresponding PromQL query. In this example, the engineer wants to know which node has the most available memory among the nodes where the order service is deployed, so that he can decide the subsequent deployment strategy. The corresponding PromQL query uses *topk* operator to analyze the available memory metric of the corresponding node to achieve this purpose. Since LLMs exhibit promising natural language understanding and code generation capabilities, it is straightforward to implement the approach based on LLMs. However, we found it still has the following challenges:

First, LLMs lack knowledge of the metrics and components in the real system, which makes it difficult to generate the correct PromQL query directly based on the question. It can be seen from the example that in order to generate this PromQL query, LLMs first need to know the syntax of PromQL and the operators and functions provided by PromQL. LLMs have learned these knowledge through the public corpus during model training. However, as shown in the red segment of the PromQL query in Figure 2, generating this PromQL query also requires knowing the metrics name, metrics label, and Node ID, which is usually different in different systems. Both the metric name and label name can be customized by the engineer, and the node ID is represented differently in different systems. Therefore, directly using LLMs to generate a PromQL query is likely to get the PromQL query which is syntactically correct, but with the wrong context information.

Second, approaches based on fine-tuning or few-shot learning from historical Q&A samples are not suitable for text-to-PromQL. Fine-tuning and few-shot learning have been widely used in a

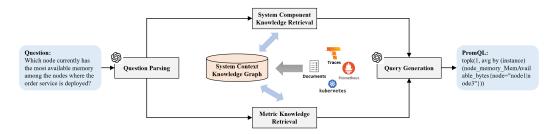


Fig. 3. Overview of PromAssistant

variety of tasks, but in our task, generating PromQL queries often require knowledge of system components (e.g., containers, pods, services). However, in modern online service systems (typically based on microservices architecture and deployed on the cloud), these system components are often dynamically changing. As the example shown in Figure 2, the nodes where the order service is deployed may change dynamically due to service scaling. Therefore, the knowledge of system components in historical data may be difficult to match with the current system state. Moreover, in real systems, only historical PromQL query statements can be easily collected, constructing high-quality Q&A pairs still requires a lot of work from engineers, which is expensive and difficult.

Third, generating PromQL queries often involves a multi-hop reasoning process, which cannot be met by a simple RAG strategy. Because of the complexity of modern online service systems, it is difficult for engineers to know the real-time status of all the components in the system. Therefore, the questions posed by engineers often do not contain all the information needed for writing PromQL queries. As the example shown in Figure 2, the reasoning process for writing this PromQL query is an obvious multi-hop reasoning process. In the question, the engineer only provides the name of the service, but what it wants to know is the metrics of all the nodes that have deployed the service. In order to find those nodes, it needs to first find all the service instances of that service and on which nodes those service instances are deployed. It can be seen that it is difficult to obtain these multi-hop knowledge with a simple retrieval or matching method based on the information contained in the question.

Through the above analysis, we can find that in order to generate the PromQL query based on the natural language question, we need to provide knowledge of the metrics and system components related to the question to LLMs on demand. At the same time, we need to be able to support multi-hop reasoning and retrieval to overcome the problem of insufficient original information. Therefore, we use a knowledge graph to describe the complex context of a system. Then, we achieve text-to-PromQL through the synergistic reasoning of knowledge graph and LLMs.

# 3 Approach

#### 3.1 Overview

In this work, we present a text-to-PromQL framework PromAssistant, which takes a natural language question as input and outputs the corresponding PromQL query of the question through synergistic reasoning with LLMs and knowledge graph. The main idea of PromAssistant is to describe a specific system's context (e.g., metrics information, component dependencies) through a knowledge graph, and then adopt a knowledge graph-enhanced RAG paradigm for accurate PromQL query generation.

An overview of PromAssistant is shown in Figure 3, the whole process includes two phases, i.e., system context knowledge graph construction and PromQL query generation from natural

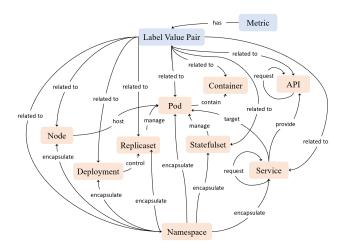


Fig. 4. Schema of the System Context Knowledge Graph

language questions. In order to provide the system context needed for LLMs to generate PromQL queries, we first construct a system context knowledge graph based on system documents, traces, and metadata from Kubernetes and Prometheus. Based on the system context knowledge graph, we convert natural language questions into PromQL queries through four steps, i.e., question parsing, system component knowledge retrieval, metric knowledge retrieval, and query generation. Given a natural language question as input, PromAssistant first extracts the metrics and system components information from the question. Then, based on the extracted metrics and component information, PromAssistant retrieves the system component knowledge and metric knowledge required to answer the question from the system context knowledge graph. Finally, PromAssistant feeds both the initial natural language question and the retrieved knowledge into the LLMs to obtain the corresponding PromQL query.

# 3.2 System Context Knowledge Graph

In this section, we introduce the definition of the system context knowledge graph and how we automatically construct the knowledge graph. The knowledge graph proposed in this paper is designed for the current commonly used Kubernetes-based system architecture. Nevertheless, it can be applied to systems with different architectures with minor modifications.

3.2.1 Schema of the System Context Knowledge Graph. Online service systems usually contain a variety of system components such as nodes, services, APIs, etc, and there are different relationships between these components. Each monitoring metric may also be associated with one or more system components through different labels. We want to describe the above relationships through the system context knowledge graph. Therefore, we design the schema of the knowledge graph as shown in Figure 4, where rounded rectangles indicate different types of entities in the knowledge graph and arrows represent the relationships between different types of entities. In particular, the schema contains two kinds of entity types, system component entities (i.e., orange rectangles) and metric data entities (i.e., blue rectangles).

The system component entities include nine entity types, i.e., *Node, Deployment, Namespace, Relicaset, Pod, Statefulset, Service, Container, API.* These entity types are derived from the resources defined by Kubernetes [24] and the common concepts in microservice systems. Relationships

between different entity types have different practical meanings, for example: dependencies between resources, such as a pod containing multiple containers; hierarchical relationships between concepts, such as a service providing multiple APIs; and invocations relationships, such as one service requesting another.

The metric data entities include two entity types, i.e., *Label-Value Pair, Metric.* These two entity types are derived from the data model in Prometheus [38]. The metric entity is only connected to the label-value pair entity, whereas the label-value pair entity may be linked to specific system components. With these two types of entities, we can identify one or more time series that we want to analyze.

- 3.2.2 System Context Knowledge Graph Construction. To construct the knowledge graph, we automatically extract various entities and relationships from different sources and fuse them together. Specifically, we used four data sources to build the knowledge graph, and because these data are structured, we only need to design rules to enable their fusion and automate the whole process. The details of how each data source is used are as follows:
  - **Prometheus**: Metadata of the monitored metrics in the system is stored in the server of Prometheus, which serves as the source of metrics knowledge. Specifically, we obtain the metric name, metric description, metric type, label name, and label value through the API provided by Prometheus. These information are then used to construct the label-value pair entities and metric entities and their relations.
  - Kubernetes: Kubernetes stores the metadata about the resources it manages and provides
    APIs for querying the metadata. And the data model of Kubernetes already defines clear
    relations for the resources it manages. Therefore, we directly use these APIs get all the entities
    corresponding to Kubernetes resources and the relations between them.
  - Traces: A trace is the description of the detailed execution process of a request through the service instances in the system [35]. Through traces, we identify the services entities and APIs entities in the system and the request relations between them.
  - **Documents**: In online service systems, engineers usually write documents to describe the functions of the services and APIs. These descriptions can help us recognize the intent of users' questions. Therefore, we extract the service descriptions and API descriptions from the system's documents and use them as the attributes of the corresponding entities.

After all the knowledge (including entities and their relationships) has been extracted from different sources, we link them together following the schema in Figure 4. Also, we can update the knowledge graph through periodic queries or proactive notifications, making it consistent with the system status all the time. We store the constructed knowledge graph in a graph database for subsequent usage. Moreover, we also store the names and descriptions of metrics, services and APIs in Elasticsearch [13] to speed up the retrieval in subsequent steps.

#### 3.3 Question Parsing

As shown in the example in Figure 2, in order to write the corresponding PromQL query, we need to know the detailed information of the metric and the system components in the question (e.g., metric name, metric label, and node ID, etc.). We can see that all the required information is contained in the constructed system context knowledge graph. However the graph is too large to feed the entire graph into LLMs, thus we only retrieve knowledge related to the question in the graph. Specifically, we first parse the original question to obtain the raw information about the metrics and system components that the engineer queried. Then we use them as the input to retrieve the relevant knowledge from the knowledge graph. Note that because of the different characteristics of the metrics and system components, we parse and retrieve them separately.

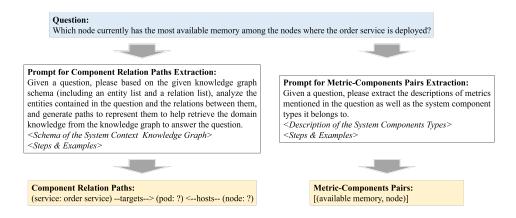


Fig. 5. Example of the Prompt and Result of Question Parsing

Specifically, PromAssistant uses LLMs for question parsing since LLMs exhibit a powerful natural language understanding capability. For each question PromAssistant prompts LLMs to extract components relation paths and metrics from the original question separately. We then explain the extraction process in detail.

3.3.1 Components Relation Paths Extraction. In the questions from the engineers, they usually do not directly mention the components used in writing the PromQL query, but instead describe the dependencies between the target component and other components. As shown in the example in Figure 2, instead of directly providing the ID of the target node, the engineer mentions that he is concerned with the node where the order service is deployed. Therefore, for more precise knowledge retrieval, we extract paths from the question to represent the entities and their relationships involved in the question, which we call components relation paths. Each components relation path is a sequence of entities and relationships  $W = [e_1, r_1, e_2, r_2, \dots, r_{n-1}, e_n]$ , where  $e_i$  denotes the i-th entity and  $r_i$  denotes the i-th relation in the relation path. For each entity  $e_i$ , we keep its entity type and name; when the entity name is not extracted, we use a placeholder (e.g., ?) to represent its name.

We design the prompt based on the Chain-of-Thought (CoT) [44] and few-shot learning [7] paradigm. Meanwhile, to enable the LLMs to recognize the predefined entities and relations, we incorporate the schema of the system context knowledge graph in the prompt. Figure 5 shows the designed prompt and an example of the extracted components relationship path. It can be seen that the engineer in the original question is concerned with the node where the order service is deployed, and the path we extracted is (service: order service) – targets – > (pod:?) < -host – (node:?). This is because the service is deployed to a node as the pod, thus the path we extracted contains two hops. Moreover, since the names of the pod and node are not mentioned in the question, they are represented as placeholders in the path. Note that we instruct the model not to output paths where the metric names are all empty, and for some complex questions, we may extract multiple components relation paths.

3.3.2 Metric-Component Pairs Extraction. In the questions from the engineers, they usually describe the metrics they want to query and the system components associated with those metrics. As shown in the example in Figure 2, the engineer wants to query the available memory of the node. Therefore, we extract the description of the metrics and the directly associated system components from the question. We represent the parsing result as a set of pairs of metric and component type

 $M = [(m_1, c_1), (m_2, c_2), \dots, (m_n, c_n)]$ , where  $m_i$  denotes the discription of the *i*-th metric and  $c_i$  denotes the component type directly associated with the *i*-th metric.

We also design the prompt based on the CoT and few-shot learning paradigm. Figure 5 shows the prompt template and an example. The pairs of metric and component type extracted from this question is [(available memory, node)]. This result indicates that the engineer wants to query the available memory at the node level. Note that if the model does not extract a metric description, we will use the whole sentence of the question as the metric description. If the component type that the metric belongs to is not extracted, we will set the component type as "ALL", which corresponds to all components in the system.

### 3.4 System Component Knowledge Retrieval

In this section, we introduce how PromAssistant uses the extracted components relation paths to retrieve question-related system component knowledge in the knowledge graph. Our main idea is to retrieve path instances in the knowledge graph that meet the requirements (including entities, and relations) of components relational paths, and we call them reasoning paths. This idea extends existing studies on KG-based LLMs reasoning [29, 42]. Specifically, given a set of components relation paths, PromAssistant uses the following steps to retrieve the reasoning paths.

First, we preprocess the components relation paths to ensure that each path starts with a specific entity. For the path with the first entity name is a placeholder, we look for the first entity in the path whose name is not a placeholder, and use this entity as the starting point to split the path into two paths. Moreover, since the entity names extracted from the original question may be different from the real entity names, we replace them with the real entity names by similarity search. Specifically, for each entity in the path with an entity name, we use BM25 algorithm [40] to retrieve the names of all entities of the same type as that entity in the knowledge graph, and then use the most similar entity name to replace it.

Then, for each preprocessed components relation path, we adopt a breadth-first search algorithm to retrieve the reasoning paths in the knowledge graph. The pseudocode of the algorithm is presented in Algorithm 1. The algorithm first initializes the reasoning path with the first entity of the components relation path. Then it iteratively extends each reasoning path by searching for eligible relations and entities. For entities whose entity name is a placeholder, all entities with the same entity type as the entity are used to extend the reasoning path. After all components relation paths are processed, we get a set of reasoning paths. For the example shown in Figure 2, we get two reasoning paths (service: order service) - targets - > (pod: pod1) < -host - (node: node1) and (service: order service) - targets - > (pod: pod2) < -host - (node: node3). It can be seen that these two reasoning paths demonstrate two real deployment relationships.

## 3.5 Metric Knowledge Retrieval

In this section, we introduce how PromAssistant uses the extracted metric-component pairs to retrieve the metrics and label-value pairs related to the question. Our main idea is to determine the range of candidate metrics by the component type of each metric in the metric-component pairs and select the most relevant metrics from them. Then we recognize the relevant label-value pairs based on the reasoning path retrieved in the previous step.

3.5.1 Metrics Retrieval. For each metric-component pair, we first retrieve all entities whose entity type is the same as the component type in the metric-component pair. Then, we search in the knowledge graph for all metrics entities that are reachable after two hops from these entities, i.e., all metrics which are associated through label-value pair entities. Subsequently, for these metrics, we use the BM25 algorithm [40] to compute and rank the correlation between the metric description in

Algorithm 1 Retrieve system component knowledge based on components relation path

```
Require: Knowledge Graph G, Components Relation Path P = [e_1, r_1, e_2, r_2, \dots, e_n]
Ensure: Reasoning Paths Paths
  1: Paths \leftarrow [[e_1]]
                                                                  ▶ Initialize paths with the start node
 2: for index \leftarrow 1 to length(P) - 1 step 2 do
        relation \leftarrow P[index]
 3:
        expectedEntity \leftarrow P[index + 1]
 4:
        newPaths \leftarrow []
 5:
        for path in Paths do
            currentNode \leftarrow path[-1]
 7:
            connectedNodes \leftarrow GetNodesByRelation(
 8:
            current Node, relation)
            for node in connectedNodes do
 9:
                if node = expectedEntity or
 10:
               expectedEntity.name ='?' then
                     newPath \leftarrow path + [relation, node]
 11:
                    newPaths.append(newPath)
 12:
                end if
 13:
            end for
 14.
        end for
 15.
        Paths \leftarrow newPaths
 17: end for
18: return Paths
```

the metric-component pair and the descriptions of these metrics themselves. And we treat the top k metrics (k=10 in this paper) among them as the candidate metrics. We choose multiple metrics because the user-queried metric may be derived from the computation of several real metrics, e.g., the request error rate is derived from the total number of requests and the number of request errors. Suppose that n metric-component pairs are obtained after question parsing, then we will obtain no more than nk candidate metrics in total. For some complex problems, we may get a large number of candidate metrics, which may make the final prompt exceed the token limit. Therefore, we prompt LLMs to select several most relevant metrics from the candidate metrics as the final retrieval result. And we adopt the same prompt design approach as in the question parsing phase.

3.5.2 Label-Value Pairs Retrieval. For each metric we retrieved, we further retrieval the label-value pairs that are relevant to the question. In real systems, the metric labels can be divided into two categories, the first is related to the system components, such as pod, service, etc., and the second is related to the semantic of the metric, such as method, mode, etc. We retrieve the two types of metric labels separately.

For the labels related to the system components, the reasoning paths we retrieved in the previous step already contain the components related to the question. Therefore, for each retrieved metric, we directly retrieve the paths that are starting with the metric and ends with the components in the reasoning paths, which are in the form of  $metric - > label - value\ pair - > component$ . We treat these paths as the knowledge of the component related labels and add them to the reasoning paths.

For the labels related to the semantic of the metric, we use LLMs to select the required labelvalue pairs. For each metric, we first obtain the labels related to the semantic of the metric from the knowledge graph, i.e., the labels corresponding to the label-value pair entities which are not

# **Prompt for PromQL Query Generation:** Task Description: You are an expert in writing PromQL. Your task is to write PromQL statements based on the specific question or query requirements expressed in natural language. Relevant metrics and domain knowledge (presented as triples) will be provided to assist you. <Steps & Examples> 1. Related Metrics: -kube statefulset status replicas current: type:gauge, description: The number of current replicas per StatefulSet. -kube statefulset status replicas ready: type: gauge, description: The number of ready replicas per StatefulSet. 2.Domain Knowledge - (metric: kube statefulset status replicas current) --has--> (metric label value: statefulset=nacosdb-mysql) - (metric label value: statefulset=nacosdb-mysql) -related to--> (statefulset: nacosdb-mysql) - (statefulset: nacosdb-mysql) --manages--> (pod: nacosdbmysql-0) - (statefulset: tsdb-mysql) --manages--> (pod: tsdb-mysql-2) 3.Ouestion

Fig. 6. An Example of the Prompt for PromQL Query Generation

<Question>

connected to any component entities. Then, we input the name, description, and type of each metric, and the name and example values of the labels into the LLMs. And we prompt the LLMs to identify the labels that are related to the question and to generate descriptions of the label values. Subsequently, based on the obtained descriptions of each label value, we use BM25 algorithm [40] to retrieve the relevant label-value pair entities and take the top m entities as the final result. We then represent the result as paths in the form of metric->label-value pair and add them to the reasoning paths.

#### 3.6 Query Generation

Based on the retrieved system component knowledge and metric knowledge, PromAssistant leverages LLMs to transform the natural language question into a PromQL query. An example of the prompt used for PromQL query generation is shown in Figura 6, which is also designed based on the CoT and few-shot learning paradigm. As shown in the example we incorporate the retrieved knowledge into the prompt as two parts. In the first part, there is the name, type, and description of the metrics we retrieved. In the second part, there are all the reasoning paths we retrieved. Note that since some of the knowledge is repeated in multiple reasoning paths, we split the reasoning paths into triples for representation. The constructed prompt is directly fed to LLMs to get the corresponding PromQL query.

#### 4 Evaluation

To evaluate PromAssistant we conduct a series of experiment studies to answer the following research questions:

- **RQ1:** How effective is PromAssistant in translating natural language question to metric query?
- RQ2: How accurate is PromAssistant in system component knowledge retrieval and metric knowledge retrieval?
- RQ3: How much does the different knowledge contribute to the effectiveness of PromAssistant?

#### 4.1 Dataset

To the best of our knowledge, there are no public datasets for the text-to-PromQL task. To fill this gap, we manually construct the first text-to-PromQL benchmark dataset based on an open-source microservice-based online service system. Our benchmark dataset contains 280 manually constructed question-PromQL query pairs. The most complex PromQL query in the dataset contains 47 tokens (including metric name, metric label, metric label value, operator, function, etc.). Meanwhile, we run the system for a week and include in the dataset the metrics data, trace data, and system deployment records generated during this period. Researchers can use these data to quickly restore the state of the system and perform metric queries, and we believe it is helpful for subsequent research.

4.1.1 Metric Collection. We use the medium-scale open-source microservice system TrainTicket [53, 54] to construct our benchmark dataset. TrainTicket is an online train ticket booking system and has been widely used in researches on microservice architecture [36], anomaly detection [51], and root cause analysis [26, 46, 50]. It contains more than 40 services implemented in different languages. We deploy the system to simulate a real metrics collection and query environment.

We first deploy TrainTicket on a Kubernetes cluster and use Prometheus to collect metrics data. The cluster contains six nodes, each of which has a 16-core 3.0GHZ CPU, 32GM RAM, and runs with Ubuntu 20.10. TrainTicket is deployed on these nodes for a total of 96 service instances. We use four exporters to collect metrics from different components of the system, including node-exporter[37], cadvisor[15], kube-state-metrics[23], and metrics-generator[17]. These exporters predefine various metrics and specify the name, type, label, and description of each metric. We also customize several metrics in addition to these predefined metrics. All the metrics are collected and stored by Prometheus. OpenTelemetry[35] and Grafana Tempo [16] are used as the distributed tracing framework to collect and store traces.

To produce metric data, we use the load generator provided by TrainTicket [53] to execute automated test cases to simulate user requests. The whole process lasts for 7 days. Then we collect all the metrics, traces, and Kubernetes deployment records generated during this period as the raw data of our benchmark dataset. In total, we collect 209 metrics, and each metric contains at least 4 labels and at most 16 labels. Table 1 shows the number of system components and metrics included in the dataset.

4.1.2 Question-Answer Pair Construction. In order to design realistic natural language query questions, we first investigate typical metric query usage scenarios. Specifically, we collected typical PromQL query cases from multiple sources, including 33 cases from official documentation, 38 cases from third-party tutorials, and 45 cases from Stack Overflow (filtered from 500 related questions). In addition, we also collect the top 200 distinct PromQL queries executed in a week

Name	Number	Name	Number
API	140	Metric	209
Pod	147	Label-Value Pairs	2,489
Container	163	Node	6
Deployment	140	Namespace	8
Service	77	Replicaset	55
Statefulset	7		

Table 1. Number of System Components and Metrics in the Dataset

from one of the teams at a world-leading Internet Service Provider (ISP). These cases contain both simple and complex PromQL queries.

Based on the collected typical cases, we ask two Ph.D students and a faculty member to analyse the cases and design the questions, all of whom had work or internship experience at world-leading ISPs. We first summarize the collected cases into different typical scenarios, where PromQL queries with similar intent would be considered as the same scenario. Then we summarize the natural language question for each scenario based on the description of the query in the collected documents or questions. Finally, each participant then instantiates these scenarios into different natural language questions and corresponding PromQL queries in our system based on his/her understanding of the system and the question. For each designed question, the other two participants will confirm its rationality. If a question is contentious, all participants will further discuss it until they reach a consensus. Moreover, we invite several engineers from a world-leading ISP to help us further confirm the soundness of the constructed questions. Finally, we have designed a total of 280 questions, and crafted the corresponding PromQL query for each question. Note that each question may have one or more corresponding PromQL queries, this is because PromQL queries using different operators or functions may achieve the same result. Researchers can also apply the questions in the dataset to their systems with slight modifications.

### 4.2 Evaluation Setup

- 4.2.1 Studied LLMs. We select two LLMs in our experiments, i.e., GPT-4-Turbo [33], and DeepSeek-Coder-V2-236B [10], for the following reasons. First, these LLMs have been widely used in previous software engineering research (e.g., code generation [12, 47], AIOps [8, 19, 45]) and have shown advanced effectiveness. Second, these LLMs contain both generic LLM (GPT-4-Turbo) and code LLM (DeepSeek-Coder-V2-236B), which can provide a more comprehensive view of the effectiveness of PromAssistant and baseline approaches. We implement PromAssistant and all baseline approaches with each of the above LLMs.
- *4.2.2 Baselines.* To the best of our knowledge, there is no research specifically on text-to-PromQL. Therefore we follow the typical practice and use the following two approaches as baselines.
  - Basic Prompt: This approach directly queries LLMs for text-to-PromQL, with a prompt designed based on the Chain-of-Thought (CoT) [44] paradigm. The prompt is similar to the example prompt in Figure 6, but excludes the domain knowledge and examples. It indicates the basic capabilities of LLMs in text-to-PromQL.
  - Few-shot Learning [19]: This approach enhances the basic prompt with retrieval-based few-shot learning. We retrieve questions similar to the current question from the historical question-answer pairs, and include the similar question-answer pairs in the prompt. This approach is derived from Xpert [19], which uses few-shot learning to recommend queries

LLM	Approach	MetricAcc	SyntaxAcc	QueryAcc
GPT-4-Turbo	Basic Prompt	28.3%	86.1%	2.6%
	Basic Prompt + 1-shot	57.8%	96.1%	15.2%
	Basic Prompt + 3-shot	70.4%	96.1%	21.3%
	Basic Prompt + 10-shot	77%	96.5%	37.4%
	PromAssistant	91.3%	96.1%	69.1%
DeepSeek-Coder-V2-236B	Basic Prompt	39.6%	95.7%	5.2%
	Basic Prompt + 1-shot	74.3%	96.1%	25.2%
	Basic Prompt + 3-shot	77.4%	95.2%	33%
	Basic Prompt + 10-shot	81.3%	93%	42.6%
	PromAssistant	91.3%	95.7%	66.9%

Table 2. Effectiveness of PromAssistant and Baseline Approaches

related to the incident in online service systems, and we modify it to match the text-to-PromQL task. We use k-shot to represent this approach, where k represents the number of retrieved question-answer pairs (we set k as 1, 3 and 10 in the evaluation).

It should be noted that all the prompts used by PromAssistant are equipped with fixed examples, and historically similar question-answer pairs are not used. It makes PromAssistant significantly different from the few-shot learning-based approaches.

- *4.2.3 Evaluation Metrics.* We adopt the following three metrics to evaluate the effectiveness of PromAssistant and baseline approaches.
  - MetricAcc: The percentage of PromQL queries using the correct metrics out of all generated PromQL queries. We treat a PromQL query as using the correct metrics only if all the metrics in that query are the same as the ground truth.
  - **SyntaxAcc**: The percentage of syntactically correct PromQL queries out of all generated PromQL queries. A PromQL query is considered syntactically correct only if it passes Promtheus' syntax checking.
  - QueryAcc: The percentage of correct PromQL queries out of all generated PromQL queries. A PromQL query is considered correct only if the query is the same as the ground truth. Note that since a PromQL query may have multiple equivalent implementations, we consider all equivalent implementations as correct.

It should be noted that  $QueryAcc \leq MetricAcc$  and  $QueryAcc \leq SyntaxAcc$ , because a correct PromQL query requires both the syntax of the query and the metrics in the query are correct. Furthermore, to ensure the correctness of the results, we manually checked the evaluation results of all metrics.

4.2.4 Implementation. We implement PromAssistant using Python 3.10, Neo4j 5.14.0 [30], and ElasticSearch 8.11.0 [13]. We construct the system context knowledge graph based on the metric data, trace data, and deployment records in the dataset. And we use the wiki of TrainTicket as system documentation and extract API descriptions and service descriptions from it. The final knowledge graph contains 3,356 entities and 43,405 relations, and we store it in the graph database Neo4j. We set k in the metrics retrieval step as 10 and m in the label-value pairs retrieval step as 1. We randomly select 50 questions from the dataset as historical questions to implement the few-shot learning approach. The remaining 230 questions are used as the test set for all approaches.

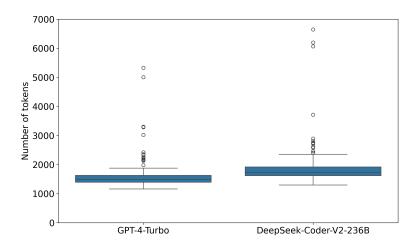


Fig. 7. Token Consumption Using Different LLMs

#### 4.3 RQ1: Effectiveness

Table 2 shows the effectiveness evaluation results of PromAssistant and baseline approaches. It can be seen that PromAssistant exhibits superior performance compared to all the baseline approaches, and achieves the highest MetricAcc (91.3%), and QueryAcc (69.1%).

It can be seen that although the code LLM DeepSeek-Coder-V2-236B has better code generation capability compared to GPT-4-Turbo, its performance is about the same as GPT-4-Turbo in our evaluation. Specifically, MeticAcc and SyntaxAcc of all approaches are close. And the QueryAcc for Basic Prompt and Few-shot Learning is slightly higher when using DeepSeek-Coder-V2-236B than when using GPT-4-Turbo. This may be due to the better code generation capability of DeepSeek-Coder-V2-236B. However, the QueryAcc of PromAssistant with DeepSeek-Coder-V2-236B (66.9%) is lower than that with GPT-4-Turbo (69.1%), which may be because the generic LLMs can better understand the contextual knowledge provided by PromAssistant.

The Basic Prompt shows the poorest performance among all approaches. We find that while its SyntaxAcc reaches a maximum of 95.7%, its QueryAcc only reaches a maximum of 5.2%. On the other hand, the MetricsAcc of the Basic Prompt reaches a maximum of 39.6%. This is because we use some open-source metric exporters when constructing the dataset, and the code and documents of these exporters may have been used for model training of the LLMs. Thus, LLMs can correctly use a part of the metrics without additional knowledge. The results of Basic Prompt demonstrate that the LLMs struggle to generate correct PromQL queries when lacking knowledge of metrics and system components.

As shown in the results, enhancing the Basic Prompt with few-shot learning improves the performance of generating PromQL queries. As the number of input historical examples increases, the QueryAcc also increases significantly, e.g., the QueryAcc increase from 5.2% to 42.6% when using DeepSeek-Coder-V2-236B. This indicates that retrieving more historical examples can help improve the performance of PromQL query generation. However, the performance of the approach based on few-shot learning is still lower than PromAssistant. This is because historical examples cannot provide all the knowledge related to the question. Especially for questions that have not appeared before, historical examples cannot help the LLMs to reason and generate the corresponding PromQL query. Moreover, it is important to note that PromAssistant achieves better performance without

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Approach	Avg Precision	Avg Recall	Avg F1-Score
PromAssistant (GPT-4-Turbo)	0.907	0.903	0.901
PromAssistant (DeepSeek-Coder-V2-236B)	0.857	0.882	0.864

Table 3. Accuracy of Metrics Retrieval

Table 4. Accuracy of Reasoning Paths Retrieval

Approach	Avg Precision	Avg Recall	Avg F1-Score
PromAssistant (GPT-4-Turbo)	0.691	0.908	0.741
PromAssistant (DeepSeek-Coder-V2-236B)	0.656	0.864	0.695

using historical examples. In practice, the performance of PromAssistant can be further improved through few-shot learning or fine-tuning.

Moreover, we find that the QueryAcc of all approaches shows a decrease compared to its MetricCcc and SyntaxAcc. For example, when using GPT-4-Turbo PromAssistant achieves 91.3% and 96.1% in terms of MetricAcc and SyntaxAcc, but only 69.1% in terms of QueryAcc. This is probably due to two reasons. First, in addition to using the correct metrics, generating the correct PromQL query requires knowledge of the metric labels and system components related to the question. Second, we found that even if all the required knowledge is provided to the LLMs, the genetated PromQL queries are not always correct. This is because LLMs also need to understand and use the provided knowledge properly, and this process may also cause errors.

For LLM-based approaches, the token consumption is critical. If too many tokens are input it may result in the prompt exceeding the context length limit, thus obtaining incorrect results. Therefore, as shown in Figure 7, we statistic the token consumption of PromAssistant when using different LLMs. It can be seen that in most test cases, the number of consumed tokens is less than 2000. Only a few test cases consume a higher number of tokens, but the maximum is less than 7000. DeepSeek-Coder-V2-236B consumes more tokens because its tokenizer produces more tokens for the same text than GPT-4-Turbo's tokenizer. The maximum context length of both GPT-Turbo and DeepSeek-Coder-V2-236B is 128k, it can be seen that in the experiments no test case exceeds the limit. Considering that our experiments are based on a medium-sized online service system (containing 147 pods and 77 services), it is reasonable to believe that PromAssistant can be used in larger scale systems in the industry.

In conclusion, PromAssistant is effective in translating natural language questions to PromQL queries and outperforms Basic Prompt and few-shot learning-based approaches. And PromAssistant does not consume a lot of tokens, which demonstrates the cost-effectiveness of PromAssistant. Compared to the baseline approaches, PromAssistant improved the QueryAcc from 37.4% to 69.1% and from 42.6% to 66.9% when using GPT-4-Turbo and DeepSeek-Coder-V2-236B, respectively.

# 4.4 RQ2: Knowledge Retrieval Accuracy

The accuracy of knowledge retrieval is crucial to the effectiveness of PromAssistant. Therefore, in this section we evaluate the accuracy of PromAssistant in retrieving different knowledge. We first label the ground truth of the metrics and triples that are necessary in the query generation step for each question. Then we calculated the precision, recall, and F1-score for each question, based on its actual retrieved metrics and triples. Finally, we averaged the results from all questions to get the average precision, average recall, and average F1-score.

LLM	Approach	MetricAcc	SyntaxAcc	QueryAcc
GPT-4-Turbo	PromAssistant w/oMK	38.7%	90.9%	27.8%
	PromAssistant w/oSK	90.9%	95.2%	12.2%
	PromAssistant	91.3%	96.1%	69.1%
DeepSeek-Coder-V2-236B	PromAssistant w/oMK	39.6%	96.9%	26.5%
	PromAssistant w/oSK	87.4%	95.7%	10.4%
	PromAssistant	91.3%	95.7%	66.9%

Table 5. Evaluation of Contribution of Different Knowledge

Table 3 presents the result of the accuracy of PromAssistant in metrics retrieval. Note that we only statistics whether the correct metrics were retrieved (corresponding to the related metrics in Figure 6), without considering the metric labels. And retrieving the correct metrics does not mean that the metrics in the generated PromQL query are also correct. As shown in Table 3, all of the average F1-score exceed 0.86. In particular, when using GPT-4-Turbo the average precision and average recall exceed 0.9. This indicates that PromAssistant can effectively understand the intent of the question and retrieve the correct metrics.

Table 4 presents the result of the accuracy of PromAssistant in reasoning paths retrieval. Note that this result is obtained by statistics on the correctness of the retrieved triples, corresponding to the domain knowledge in Figure 6. Although the average precision in the results is relatively low (the highest only reaches 0.691), the average recall both exceed 0.86. This result is in line with the desired objective of our approach. PromAssistant has retrieved some knowledge that is not related to the question, but the vast majority of the required knowledge has been retrieved by PromAssistant. This retrieval result ensures that PromAssistant can generate the correct PromQL query.

In conclusion, PromAssistant is accurate in system component knowledge retrieval and metric knowledge retrieval. It achieves a high recall in both metrics retrieval (0.903) and reasoning paths retrieval (0.908).

# 4.5 RQ3: Ablation Study

We perform an ablation study to evaluate how different knowledge contributes to the effectiveness of PromAssistant. We derive two variants of PromAssistant called **PromAssistant w/oMK** and **PromAssistant w/oSK**. PromAssistant w/oMK removes the metric knowledge retrieval module from the approach, and only uses the system component knowledge to generate the PromQL query. PromAssistant w/oSK removes the component knowledge retrieval module from the approach, and only uses the metric knowledge to generate the PromQL query.

Table 5 shows the evaluation results of the contribution of the metric knowledge and system component knowledge. When metric knowledge is lacking, both MetricAcc and QueryAcc decrease significantly, with MetricAcc decreasing at most from 91.3% to 38.7% and QueryAcc decreasing at most from 69.1% to 27.8%. When system component knowledge is lacking, QuerayAcc also decreases significantly, at most from 69.1% to 12.2%. We can see that lack of metric knowledge or system component knowledge both result in a significant degradation in the performance of PromAssistant. The performance of PromAssistant is less degraded when lacking metric knowledge compared to when lacking system component knowledge, this is because some of the metrics in the dataset are from the open-source metric exporter. Therefore, for some questions, the LLM itself has knowledge about the metrics. The above results illustrate that both metrics knowledge and system component knowledge are important in the text-to-PromQL task. PromAssistant achieves

accurate retrieval of both metrics knowledge and system component knowledge, which leads to the precise generation of PromQL queries.

#### 4.6 Threats to Validity

4.6.1 Internal Threat. The threat to internal validity mainly lies in the implementation and configuration of baseline approaches. The basic prompt is simple to implement and no configuration is involved. There is no directly available open-source implementation of the few-shot learning-based approach. Therefore, we implement the approach by referring to the example of question answering using embeddings-based search provided in the OpenAI cookbook [34]. We carefully check the implementation and choose the optimal configuration.

*4.6.2 External Threat.* The threat to external validity mainly lies in the generalizability of our approach and the representativeness of the dataset.

The generalizability of our approach is under the threat of the knowledge graph schema in our approach. The knowledge graph schema in this paper is designed for Kubernetes-based online service systems and may be not suitable for all systems. However, it is also straightforward to migrate our knowledge graph construction method to other systems, such as service-mesh based systems. This is because our construction method only requires system documentation, deployment metadata, metrics metadata, and invocation relationships. This information can be easily obtained from the system's infrastructure.

Our experiments are conducted on the dataset we constructed. Because no publicly available dataset fits our task, we constructed the first text-to-PromQL dataset. The dataset are constructed based on the open-source microservice system TrainTicket, as there are no publicly available datasets from industrial. It is one of the largest open-source microservice systems and have been widely used in existing studies [26, 36, 46, 51]. It contains 96 service instances after deployment, which is close to some medium-sized microservice systems. Therefore, it is possible to simulate real metrics query scenarios. We don't use other open-source systems such as Sock Shop, because their scale is too small to model complex metrics query scenarios. Moreover, the questions in our dataset are carefully designed. When constructing the dataset we refer to official documents, questions on StackOverflow, and real cases from a world-leading ISP. We designed the questions based on these real-world cases. Therefore, the questions in our dataset are representative and can be used to evaluate the effectiveness of the text-to-PromQL approaches. And we will try to evaluate PromAssistant on more complex and diverse datasets in the future.

#### 5 Related Work

Natural Language to Domain-Specific Language: In recent years, deep learning and machine learning techniques have been widely used in text-to-DSL tasks, such as text-to-SQL [21, 22] and text-to-GraphQL [31]. These studies want to enable users to interact with domain-specific tools or data through natural language. Text-to-SQL has become one of the most popular research topics, as SQL is widely used for data querying and management. With the development of LLMs, there have been several studies in recent years exploring using LLMs to implement text-to-SQL [14, 27, 41]. Liu et al. [28] evaluate the text-to-SQL capability of ChatGPT under zero-shot setting, demonstrates the potential of LLMs for the task. Dong et al. [11] propose a ChatGPT-based zero-shot text-to-SQL apprach, which outperforms the performance of fine-tuning-based approaches through clear prompting, calibration with hints and consistent output. Sun et al. [43] enhance text-to-SQL performance of LLMs based on few-shot learning and instruction tuning. To the best of our knowledge, there is no research focusing on text-to-PromQL.

LLMs for AIOps To date, many efforts have been dedicated to the LLM-based AIOps, including root cause localization [1, 8, 52], log parsing [20, 45], and incident mitigation [3]. Ahmed et al. [1] uses historical fault records to fine-tune the LLMs for root cause localization and mitigation steps recommendation. Chen et al. [8] uses multi-source diagnostic information to model historical faults, and achieve root cause and fault category prediction based on few-shot learning. Zhang et al. [52] uses a similar idea to achieve automated root cause localization based on GPT-4. And Jiang et al. [20] and Xu et al. [45] use few-shot learning to achieve LLM-based log parsing results in promising performance. An et al. [3] implement automated incident mitigation based on the troubleshooting guides summarized by engineers by leveraging LLMs' ability to use tools and execute code. However, above works are based on historical fault cases and it is difficult to achieve good results when dealing with new faults. Some studies explore using LLMs to assist operation engineers in performing some operation tasks. Yu et al. [48] use LLMs to assist engineers in configuring metric monitor rules. Jiang et al. [19] used few-shot learning to recommend fault-related metric query statements for operation engineers. These studies are more practical than others, but they are also limited by historical data, which makes it difficult to achieve good generalizability. In this paper, we propose a text-to-PromQL approach that does not rely on historical data, which can help engineers query metrics in a simple and fast way.

#### 6 Conclusion

In this paper, we proposed PromAssistant, an LLM-based text-to-PromQL framework that enables engineers to interact with Prometheus metrics data through natural language. PromAssistant uses a knowledge graph to describe the complex context (e.g., metric names, metric labels, system component dependencies) of an online service system. Then, PromAssistant transforms the engineers' natural language questions into PromQL queries through the synergistic reasoning of knowledge graph and LLMs. To evaluate PromAssistant, we manually construct the first text-to-PromQL benchmark dataset based on an open-source microservice system. The experiment results demonstrate the effectiveness of PromAssistant in text-to-PromQL. When using GPT-4-Turbo as the backbone LLM, PromAssistant achieves an accuracy of 69.1% in generating PromQL queries. Moreover, the results confirm that PromAssistant is accurate in retrieving metric knowledge and system component knowledge. And we think PromAssistant has the potential to be applied to other metrics monitoring systems or metrics querying languages.

#### References

- [1] Toufique Ahmed, Supriyo Ghosh, Chetan Bansal, Thomas Zimmermann, Xuchao Zhang, and Saravan Rajmohan. 2023. Recommending Root-Cause and Mitigation Steps for Cloud Incidents using Large Language Models. In 45th IEEE/ACM International Conference on Software Engineering, ICSE 2023. IEEE, 1737–1749. https://doi.org/10.1109/ICSE48619.2023.
- [2] Alibaba. 2024. Alibaba Cloud. Retrieved July 15, 2024 from https://www.alibabacloud.com
- [3] Kaikai An, Fangkai Yang, Liqun Li, Zhixing Ren, Hao Huang, Lu Wang, Pu Zhao, Yu Kang, Hua Ding, Qingwei Lin, Saravan Rajmohan, and Qi Zhang. 2024. Nissist: An Incident Mitigation Copilot based on Troubleshooting Guides. CoRR abs/2402.17531 (2024). https://doi.org/10.48550/ARXIV.2402.17531 arXiv:2402.17531
- [4] AWS. 2024. AWS. Retrieved July 15, 2024 from https://aws.amazon.com
- [5] Azure. 2024. Azure. Retrieved July 15, 2024 from https://azure.microsoft.com
- [6] Betsy Beyer, Chris Jones, Jennifer Petoff, and Niall Richard Murphy. 2016. Site Reliability Engineering: How Google Runs Production Systems (1st ed.). O'Reilly Media, Inc.
- [7] Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. Language Models are Few-Shot Learners. In Advances in Neural Information Processing Systems 33: Annual Conference on Neural Information Processing Systems 2020, NeurIPS 2020.

[8] Yinfang Chen, Huaibing Xie, Minghua Ma, Yu Kang, Xin Gao, Liu Shi, Yunjie Cao, Xuedong Gao, Hao Fan, Ming Wen, Jun Zeng, Supriyo Ghosh, Xuchao Zhang, Chaoyun Zhang, Qingwei Lin, Saravan Rajmohan, Dongmei Zhang, and Tianyin Xu. 2024. Automatic Root Cause Analysis via Large Language Models for Cloud Incidents. In Proceedings of the Nineteenth European Conference on Computer Systems, EuroSys 2024. ACM, 674–688. https://doi.org/10.1145/3627703.3629553

- [9] CNCF. 2024. CNCF. Retrieved July 15, 2024 from https://www.cncf.io/
- [10] DeepSeek-AI, Qihao Zhu, Daya Guo, Zhihong Shao, Dejian Yang, Peiyi Wang, Runxin Xu, Y. Wu, Yukun Li, Huazuo Gao, Shirong Ma, Wangding Zeng, Xiao Bi, Zihui Gu, Hanwei Xu, Damai Dai, Kai Dong, Liyue Zhang, Yishi Piao, Zhibin Gou, Zhenda Xie, Zhewen Hao, Bingxuan Wang, Junxiao Song, Deli Chen, Xin Xie, Kang Guan, Yuxiang You, Aixin Liu, Qiushi Du, Wenjun Gao, Xuan Lu, Qinyu Chen, Yaohui Wang, Chengqi Deng, Jiashi Li, Chenggang Zhao, Chong Ruan, Fuli Luo, and Wenfeng Liang. 2024. DeepSeek-Coder-V2: Breaking the Barrier of Closed-Source Models in Code Intelligence. CoRR abs/2406.11931 (2024). https://doi.org/10.48550/ARXIV.2406.11931
- [11] Xuemei Dong, Chao Zhang, Yuhang Ge, Yuren Mao, Yunjun Gao, Lu Chen, Jinshu Lin, and Dongfang Lou. 2023. C3: Zero-shot Text-to-SQL with ChatGPT. CoRR abs/2307.07306 (2023). https://doi.org/10.48550/ARXIV.2307.07306 arXiv:2307.07306
- [12] Xueying Du, Mingwei Liu, Kaixin Wang, Hanlin Wang, Junwei Liu, Yixuan Chen, Jiayi Feng, Chaofeng Sha, Xin Peng, and Yiling Lou. 2024. Evaluating Large Language Models in Class-Level Code Generation. In Proceedings of the 46th IEEE/ACM International Conference on Software Engineering, ICSE 2024. ACM, 81:1–81:13. https://doi.org/10.1145/3597503.3639219
- [13] Elastic. 2024. Elasticsearch. Retrieved July 15, 2024 from https://www.elastic.co
- [14] Dawei Gao, Haibin Wang, Yaliang Li, Xiuyu Sun, Yichen Qian, Bolin Ding, and Jingren Zhou. 2024. Text-to-SQL Empowered by Large Language Models: A Benchmark Evaluation. Proc. VLDB Endow. 17, 5 (2024), 1132–1145. https://www.vldb.org/pvldb/vol17/p1132-gao.pdf
- [15] Google. 2024. cadvisor. Retrieved July 15, 2024 from https://github.com/google/cadvisor
- [16] Grafana. 2024. Grafana Tempo. Retrieved July 15, 2024 from https://github.com/grafana/tempo
- [17] Grafana. 2024. metrics-generator. Retrieved July 15, 2024 from https://grafana.com/docs/tempo/latest/metrics-generator/
- [18] InfluxData. 2024. InfluxDB. Retrieved July 15, 2024 from https://www.influxdata.com/
- [19] Yuxuan Jiang, Chaoyun Zhang, Shilin He, Zhihao Yang, Minghua Ma, Si Qin, Yu Kang, Yingnong Dang, Saravan Rajmohan, Qingwei Lin, and Dongmei Zhang. 2024. Xpert: Empowering Incident Management with Query Recommendations via Large Language Models. In Proceedings of the 46th IEEE/ACM International Conference on Software Engineering, ICSE 2024. ACM, 92:1–92:13. https://doi.org/10.1145/3597503.3639081
- [20] Zhihan Jiang, Jinyang Liu, Zhuangbin Chen, Yichen Li, Junjie Huang, Yintong Huo, Pinjia He, Jiazhen Gu, and Michael R. Lyu. 2024. LILAC: Log Parsing using LLMs with Adaptive Parsing Cache. Proc. ACM Softw. Eng. 1, FSE (2024), 137–160. https://doi.org/10.1145/3643733
- [21] George Katsogiannis-Meimarakis and Georgia Koutrika. 2023. A survey on deep learning approaches for text-to-SQL. VLDB J. 32, 4 (2023), 905–936. https://doi.org/10.1007/S00778-022-00776-8
- [22] Hyeonji Kim, Byeong-Hoon So, Wook-Shin Han, and Hongrae Lee. 2020. Natural language to SQL: Where are we today? Proc. VLDB Endow. 13, 10 (2020), 1737–1750. https://doi.org/10.14778/3401960.3401970
- [23] Kubernetes. 2024. kube-state-metrics. Retrieved July 15, 2024 from https://github.com/kubernetes/kube-state-metrics
- [24] Kubernetes. 2024. Kubernetes. Retrieved July 15, 2024 from https://kubernetes.io/
- [25] Triet Huynh Minh Le, Hao Chen, and Muhammad Ali Babar. 2021. Deep Learning for Source Code Modeling and Generation: Models, Applications, and Challenges. *ACM Comput. Surv.* 53, 3 (2021), 62:1–62:38. https://doi.org/10.1145/3383458
- [26] Cheryl Lee, Tianyi Yang, Zhuangbin Chen, Yuxin Su, and Michael R. Lyu. 2023. Eadro: An End-to-End Troubleshooting Framework for Microservices on Multi-source Data. In 45th IEEE/ACM International Conference on Software Engineering, ICSE 2023. IEEE, 1750–1762. https://doi.org/10.1109/ICSE48619.2023.00150
- [27] Jinyang Li, Binyuan Hui, Ge Qu, Jiaxi Yang, Binhua Li, Bowen Li, Bailin Wang, Bowen Qin, Ruiying Geng, Nan Huo, Xuanhe Zhou, Chenhao Ma, Guoliang Li, Kevin Chen-Chuan Chang, Fei Huang, Reynold Cheng, and Yongbin Li. 2023. Can LLM Already Serve as A Database Interface? A BIg Bench for Large-Scale Database Grounded Text-to-SQLs. In Advances in Neural Information Processing Systems 36, NeurIPS 2023.
- [28] Aiwei Liu, Xuming Hu, Lijie Wen, and Philip S. Yu. 2023. A comprehensive evaluation of ChatGPT's zero-shot Text-to-SQL capability. CoRR abs/2303.13547 (2023). https://doi.org/10.48550/ARXIV.2303.13547 arXiv:2303.13547
- [29] Linhao Luo, Yuan-Fang Li, Gholamreza Haffari, and Shirui Pan. 2023. Reasoning on Graphs: Faithful and Interpretable Large Language Model Reasoning. CoRR abs/2310.01061 (2023). https://doi.org/10.48550/ARXIV.2310.01061 arXiv:2310.01061
- [30] Neo4j. 2024. Neo4j. Retrieved July 15, 2024 from https://neo4j.com/

[31] Pin Ni, Ramin Okhrati, Steven Guan, and Victor Chang. 2024. Knowledge Graph and Deep Learning-based Text-to-GraphQL Model for Intelligent Medical Consultation Chatbot. *Inf. Syst. Frontiers* 26, 1 (2024), 137–156. https://doi.org/10.1007/S10796-022-10295-0

- [32] Sina Niedermaier, Falko Koetter, Andreas Freymann, and Stefan Wagner. 2019. On Observability and Monitoring of Distributed Systems - An Industry Interview Study. In Service-Oriented Computing - 17th International Conference, ICSOC 2019 (Lecture Notes in Computer Science, Vol. 11895). Springer, 36–52. https://doi.org/10.1007/978-3-030-33702-5\_3
- [33] OpenAI. 2024. GPT-4. Retrieved July 15, 2024 from https://platform.openai.com/docs/models/gpt-4-turbo-and-gpt-4
- [34] OpenAI. 2024. OpenAI Cookbook. Retrieved July 15, 2024 from https://cookbook.openai.com/
- [35] OpenTelemetry. 2024. OpenTelemetry. Retrieved July 15, 2024 from https://opentelemetry.io/
- [36] Xin Peng, Chenxi Zhang, Zhongyuan Zhao, Akasaka Isami, Xiaofeng Guo, and Yunna Cui. 2022. Trace analysis based microservice architecture measurement. In Proceedings of the 30th ACM Joint European Software Engineering Conference and Symposium on the Foundations of Software Engineering, ESEC/FSE 2022. ACM, 1589–1599. https://doi.org/10.1145/3540250.3558951
- [37] Prometheus. 2024. node-exporter. Retrieved July 15, 2024 from https://github.com/prometheus/node\_exporter
- [38] Prometheus. 2024. Prometheus. Retrieved July 15, 2024 from https://prometheus.io/
- [39] PromQL. 2024. PromQL. Retrieved July 15, 2024 from https://prometheus.io/docs/prometheus/latest/querying/basics/
- [40] Stephen E Robertson and Steve Walker. 1994. Some simple effective approximations to the 2-poisson model for probabilistic weighted retrieval. In SIGIR'94: Proceedings of the Seventeenth Annual International ACM-SIGIR Conference on Research and Development in Information Retrieval. Springer, 232–241.
- [41] Yewei Song, Saad Ezzini, Xunzhu Tang, Cedric Lothritz, Jacques Klein, Tegawendé F. Bissyandé, Andrey Boytsov, Ulrick Ble, and Anne Goujon. 2024. Enhancing Text-to-SQL Translation for Financial System Design. In *Proceedings of the 46th International Conference on Software Engineering: Software Engineering in Practice, ICSE-SEIP 2024.* ACM, 252–262. https://doi.org/10.1145/3639477.3639732
- [42] Jiashuo Sun, Chengjin Xu, Lumingyuan Tang, Saizhuo Wang, Chen Lin, Yeyun Gong, Heung-Yeung Shum, and Jian Guo. 2023. Think-on-Graph: Deep and Responsible Reasoning of Large Language Model with Knowledge Graph. CoRR abs/2307.07697 (2023). https://doi.org/10.48550/ARXIV.2307.07697 arXiv:2307.07697
- [43] Ruoxi Sun, Sercan Ö. Arik, Hootan Nakhost, Hanjun Dai, Rajarishi Sinha, Pengcheng Yin, and Tomas Pfister. 2023. SQL-PaLM: Improved Large Language Model Adaptation for Text-to-SQL. CoRR abs/2306.00739 (2023). https://doi.org/10.48550/ARXIV.2306.00739 arXiv:2306.00739
- [44] Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Brian Ichter, Fei Xia, Ed H. Chi, Quoc V. Le, and Denny Zhou. 2022. Chain-of-Thought Prompting Elicits Reasoning in Large Language Models. In Advances in Neural Information Processing Systems 35: Annual Conference on Neural Information Processing Systems 2022, NeurIPS 2022.
- [45] Junjielong Xu, Ruichun Yang, Yintong Huo, Chengyu Zhang, and Pinjia He. 2024. DivLog: Log Parsing with Prompt Enhanced In-Context Learning. In Proceedings of the 46th IEEE/ACM International Conference on Software Engineering, ICSE 2024. ACM, 199:1–199:12. https://doi.org/10.1145/3597503.3639155
- [46] Guangba Yu, Pengfei Chen, Yufeng Li, Hongyang Chen, Xiaoyun Li, and Zibin Zheng. 2023. Nezha: Interpretable Fine-Grained Root Causes Analysis for Microservices on Multi-modal Observability Data. In Proceedings of the 31st ACM Joint European Software Engineering Conference and Symposium on the Foundations of Software Engineering, ESEC/FSE 2023. ACM, 553–565. https://doi.org/10.1145/3611643.3616249
- [47] Hao Yu, Bo Shen, Dezhi Ran, Jiaxin Zhang, Qi Zhang, Yuchi Ma, Guangtai Liang, Ying Li, Qianxiang Wang, and Tao Xie. 2024. CoderEval: A Benchmark of Pragmatic Code Generation with Generative Pre-trained Models. In Proceedings of the 46th IEEE/ACM International Conference on Software Engineering, ICSE 2024. ACM, 37:1–37:12. https://doi.org/10.1145/3597503.3623316
- [48] Zhaoyang Yu, Minghua Ma, Chaoyun Zhang, Si Qin, Yu Kang, Chetan Bansal, Saravan Rajmohan, Yingnong Dang, Changhua Pei, Dan Pei, Qingwei Lin, and Dongmei Zhang. 2024. MonitorAssistant: Simplifying Cloud Service Monitoring via Large Language Models. In Companion Proceedings of the 32nd ACM International Conference on the Foundations of Software Engineering, FSE 2024. ACM, 38–49. https://doi.org/10.1145/3663529.3663826
- [49] Daoguang Zan, Bei Chen, Fengji Zhang, Dianjie Lu, Bingchao Wu, Bei Guan, Yongji Wang, and Jian-Guang Lou. 2023. Large Language Models Meet NL2Code: A Survey. In Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), ACL 2023. Association for Computational Linguistics, 7443–7464. https://doi.org/10.18653/V1/2023.ACL-LONG.411
- [50] Chenxi Zhang, Zhen Dong, Xin Peng, Bicheng Zhang, and Miao Chen. 2024. Trace-based Multi-Dimensional Root Cause Localization of Performance Issues in Microservice Systems. In Proceedings of the 46th IEEE/ACM International Conference on Software Engineering, ICSE 2024. ACM, 110:1–110:12. https://doi.org/10.1145/3597503.3639088
- [51] Chenxi Zhang, Xin Peng, Chaofeng Sha, Ke Zhang, Zhenqing Fu, Xiya Wu, Qingwei Lin, and Dongmei Zhang. 2022. DeepTraLog: Trace-Log Combined Microservice Anomaly Detection through Graph-based Deep Learning. In 44th IEEE/ACM 44th International Conference on Software Engineering, ICSE 2022. ACM, 623–634. https://doi.org/10.1145/

#### 3510003.3510180

[52] Xuchao Zhang, Supriyo Ghosh, Chetan Bansal, Rujia Wang, Minghua Ma, Yu Kang, and Saravan Rajmohan. 2024. Automated Root Causing of Cloud Incidents using In-Context Learning with GPT-4. In Companion Proceedings of the 32nd ACM International Conference on the Foundations of Software Engineering, FSE 2024. ACM, 266–277. https://doi.org/10.1145/3663529.3663846

- [53] Xiang Zhou, Xin Peng, Tao Xie, Jun Sun, Chao Ji, Wenhai Li, and Dan Ding. 2021. Fault Analysis and Debugging of Microservice Systems: Industrial Survey, Benchmark System, and Empirical Study. IEEE Trans. Software Eng. 47, 2 (2021), 243–260. https://doi.org/10.1109/TSE.2018.2887384
- [54] Xiang Zhou, Xin Peng, Tao Xie, Jun Sun, Chenjie Xu, Chao Ji, and Wenyun Zhao. 2018. Benchmarking microservice systems for software engineering research. In 40th International Conference on Software Engineering, ICSE 2018. ACM, 323–324. https://doi.org/10.1145/3183440.3194991