Knowledge Management for Automobile Failure Analysis Using Graph RAG

1st Yuta Ojima
Department of System Innovation
School of Engineering
The University of Tokyo
Tokyo, Japan
y_ojima@m.sys.t.u-tokyo.ac.jp

2nd Hiroki Sakaji
Faculty of Information Science
and Technology
Hokkaido University
Hokkaido, Japan
sakaji@ist.hokudai.ac.jp

3rd Tadashi Nakamura
Chasis Engineering Dept. No.1
Isuzu Motors Limited
Tokyo, Japan
Tadashi_A_Nakamura@isuzu.com

4th Hiroaki Sakata
Chasis Engineering Dept. No.1
Isuzu Motors Limited
Tokyo, Japan
Hiroaki_Sakata@isuzu.com

5th Kazuya Seki
Quality Assurance Dept.
Isuzu Motors Limited
Tokyo, Japan
Kazuya_Seki@isuzu.com

6th Yuu Teshigawara
Quality Assurance Dept.
Isuzu Motors Limited
Tokyo, Japan
Yuu_Teshigawara@isuzu.com

7th Masami Yamashita
Technology Strategy Dept.
Isuzu Motors Limited
Tokyo, Japan
Masami_Yamashita@isuzu.com

8th Kazuhiro Aoyama
Department of System Innovation
School of Engineering
The University of Tokyo
Tokyo, Japan
aoyama@race.t.u-tokyo.ac.jp

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***Abstract*—This paper presents a knowledge management system for automobile failure analysis using retrieval-augmented generation (RAG) with large language models (LLMs) and knowledge graphs (KGs). In the automotive industry, there is a growing demand for knowledge transfer of failure analysis from experienced engineers to young engineers. However, failure events are phenomena that occur in a chain reaction, making them difficult for beginners to analyze them. While knowledge graphs, which can describe semantic relationships and structure information is effective in representing failure events, due to their capability of representing the relationships between components, there is much information in KGs, so it is challenging for young engineers to extract and understand sub-graphs from the KG. On the other hand, there is increasing interest in the use of Graph RAG, a type of RAG that combines LLMs and KGs for knowledge management. However, when using the current Graph RAG framework with an existing knowledge graph for automobile failures, several issues arise because it is difficult to generate executable queries for a knowledge graph database which is not constructed by LLMs. To address this, we focused on optimizing the Graph RAG pipeline for existing knowledge graphs. Using an original Q&A dataset, the ROUGE F1 score of the sentences generated by the proposed method showed an average improvement of 157.6% compared to the current method. This highlights the effectiveness of the proposed method for automobile failure analysis.**

***Index Terms*—Graph RAG, Large Language Model, Knowledge Graph, Knowledge Management, Automobile Failure**

I. Introduction

In the Japanese automotive industry, especially truck industry, the necessity of knowledge transfer of failure analysis has been increasing in recent years, specifically from experienced engineers to young engineers. There are two main reasons for this. The first reason is that failure analysis in automobiles is complex and challenging to address without sufficient experience. Vehicles are generally recognized as systems composed of multiple parts, meaning that a failure in one part can potentially lead to a chain of failures in other components. Therefore, understanding relationships of parts is crucial to find out the causal of failure, but this knowledge is mainly gained by experience not by lectures or textbooks.

The second one is that compared to the past, young engineers now need to address a broader and more specialized range of failure issues. Japan is currently facing to a problem of declining birthrate and an aging population, resulting in a reduced number of young engineers compared to the past. Moreover, there is growing complexity of automobile technologies owing to innovations such as CASE (Connected, Automated, Shared, Electric), Mobility as a Service (MaaS), and Electric Vehicles, so the burden on each young engineer has increased.

To address these challenges, a truck company issues and archives ”***failure documents***” each time a failure occurs to ensure the transfer of failure analysis expertise. These doc-

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uments contain details about the conditions of malfunctioning vehicles, repair methods, dates, and circumstances, each organized in separate columns and written in Japanese. For effective knowledge transfer, it is necessary for young engineers to understand these documents. However, because they are written in natural language, it is difficult to comprehend the relationships between critical components in failure analysis.

To facilitate understanding of the connections between components, it is reasonable to represent these documents in the form of a knowledge graph (KG), which can describe semantic relationships and store structured information and is used for tackling problems in various domains [1]. Hara et al. [2] has constructed ***failure KG*** from *failure documents*, but due to the vast amount of data within *failure documents*, *failure KG* also becomes complex and challenging for young engineers to comprehend.

Currently, there are some experienced engineers who can easily search the necessary information from the documents, and they can provide the information to young engineers. However, the average age of these engineers is not low, and the numbers of them are expected to decline in the future. Additionally, truck failures cause substantial losses to both Japanese freights transportation, where trucks transport 91.4% of the total weight of goods moved[1], and truck drivers, so the company have to deal with the failures quickly. Therefore, anticipating the retirement of experienced engineers, it is essential to develop a system that can quickly identify the causes of failures without relying on their experience. Specifically, it is desirable to construct a system that can critically present the causes when the fault conditions are inputted.

Large Language Models (LLMs), like ChatGPT [3], demonstrate remarkable capabilities in various natural language processing tasks [4], and can response quickly, so they are expected to be effective for knowledge management of failure analysis. However, since a vanilla LLM does not retain domain- or organization-specific information, an approach called Retrieval-Augmented Generation (RAG) is needed. This method answers user questions based on external information resources, and Graph RAG [5], which is a type of RAG that combines LLMs and KGs, enables responses to users' queries based on the information within those graphs. However, current implementation of Graph RAG faces challenges in adapting to existing KGs.

In this study, we propose a novel Graph RAG system that can be applied to existing KGs. In the following section, we introduce related work, methodology—including current challenges—and the experiment using ROUGE [6]. Main contributions of this research are summarized as follows.

- We propose a Graph RAG system that is independent of the query representation in knowledge graph databases.
- The text generated by the proposed method achieved a higher ROUGE F1 score compared to those generated by the current Graph RAG and ChatGPT, demonstrating its effectiveness.

II. Related Work

A. Failure Knowledge Graph

Hara et al. [2] employed text mining techniques based on syntactic analysis, including the extraction of co-occurrence and dependency relations, as well as causal relation extraction using the algorithm proposed by Sakaji et al [7]. They constructed *failure KG*, a knowledge graph of failure information. A portion of *failure KG* is shown in Fig. 1.

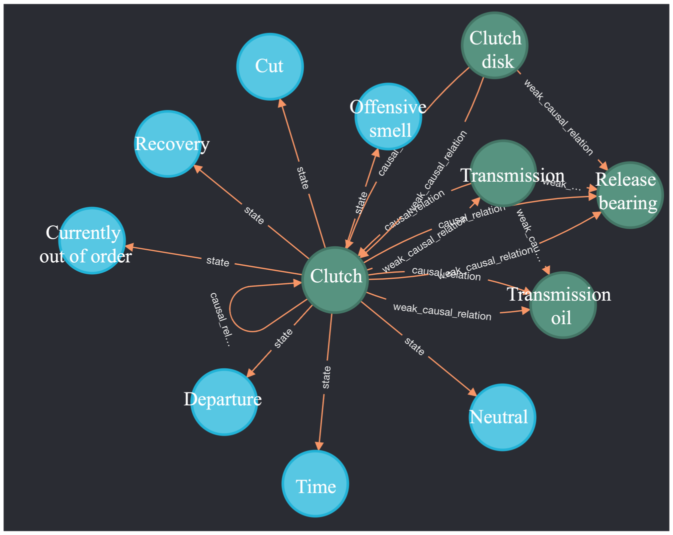


Fig. 1. *Failure KG* [2]. This figure illustrates the nodes related to the clutch node. The original graph was created in Japanese, and the displayed excerpts are translated into English. In this representation, the blue labels represent the states of the system, while green labels denote the components involved.

Each node is labeled as a system, component, part, status, or other categories by experienced engineers. The meaning of each node is validated through human involvement. The relationships obtained from each syntactic analysis are categorized as weak causal and status relations for co-occurrence, hierarchical relations for dependencies, and causal relations for causal relation extraction.

While they demonstrated the ability to extract the interrelations of parts involved in a failure, challenges remain in understanding the resulting network especially for young engineers, due to vast amount of data. Therefore, it is essential to implement the constructed knowledge graph in an application that can extract important sub-graphs from the KGs and generate answers for the question from young engineers.

B. Large Language Model and RAG

The release of ChatGPT by OpenAI [3] has demonstrated the vast potential of LLMs to generate sentences. These models can engage in continuous conversations with users based on chat context and perform complex tasks such as coding and academic writing [4]. While LLMs can handle a wide range of questions, making them valuable for knowledge management, they often lack company-specific knowledge and may occasionally output incorrect information. Consequently, there is a growing need for the development of LLMs tailored

[1] https://jta.or.jp/wp-content/themes/jta_theme/pdf/yusosangyo2023.pdfs

for specific companies. However, unlike previous encoder-only language models like BERT [8], pre-training LLMs with specific domain knowledge or up-to-date information has become impractical owing to the significant amount of data, training time, and computational resources required, leading to extremely high costs. Additionally, contemporary LLMs, like ChatGPT, are generally offered solely as APIs, rendering pre-training unfeasible.

As a result, attention has shifted to Retriever-Augmented Generation (RAG) techniques. Fig. 2 provides an overview of RAG. This method involves retrieving necessary information from external data sources, such as document databases, based on the user's prompt and integrating this relevant information into the LLM's prompt. This effectively allows the LLM to incorporate the latest knowledge from specific domains [9]. When using LLMs offered as APIs, RAG enables the integration of information without being limited by the amount of data held, while also reducing computational resource requirements.

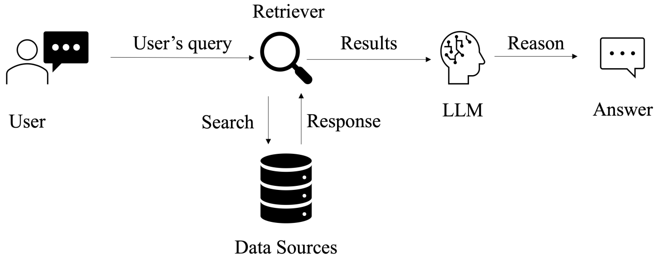


Fig. 2. Overview of RAG

C. Graph RAG

Microsoft has proposed a Graph RAG system as a RAG framework that utilizes knowledge graphs [5]. As Fig. 3 provides, this system consists of two steps.

1) *Constructing the Knowledge Graph*: Source documents containing the information to be provided to the LLM are converted into a KG using the LLM and prompts. After constructing the KG, the LLM forms graph communities, or clusters, from the entire graph based on the number of relationships derived from the document. This process can be viewed as labeling each node.
2) *RAG with LLM and KG*: First, the Retriever LLM generates a database query to extract information from the knowledge graph's database based on the user's query. The LLM then generates an answer using the retrieved response and the user's query.

Graph RAG can be viewed as executing a task categorized into Knowledge Graph-based Question Answering (KGQA), which focuses on providing answers to user-posed questions based on the KGs [10]. There are two main approaches to KGQA: the **Semantic Parsing** (SP) and **Information Retrieval** (IR) based methods [10]. The SP method involves converting natural language questions posed by users into search queries for the knowledge graph, specifically into logical symbols, and then generating answers based on the results obtained from these queries [10]. On the other hand, the IR method involves extracting an understandable sub-graph from the knowledge graph that is related to the question, reasoning based on this sub-graph, and generating the answer [10].

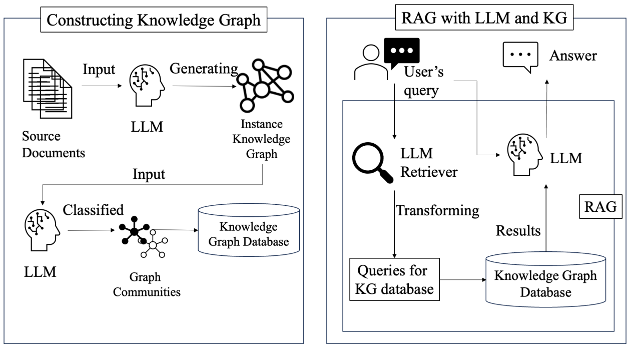


Fig. 3. Overview of the Graph RAG

In this process, the user's question is converted into a searchable query by the LLM, which is then sent to the knowledge graph database. The LLM generates an answer based on the information retrieved from the knowledge graph database.

Additionally, the combination of KGs and LLMs has been reported to generate more consistent answers and suppress the generation of misinformation, commonly referred to as ”hallucinations”, compared to other RAG approaches [9].

III. Methodology

A. Problem Definition

When applying the current Graph RAG to automotive fault knowledge management, two major challenges emerge. The first challenge is the difficulty in adapting to existing knowledge graphs. As previously mentioned, the current Graph RAG is based on the SP method. It can be considered that executable queries can be generated without high-cost training, which is generally needed [10], as the same LLM is utilized both for converting a user query q from the natural language space to a query q for KG databases in logical symbol space, as well as for constructing KGs from documents. Therefore, while Graph RAG is effective for KGs constructed by LLM, it remains unclear whether it can be applied to existing KGs created using other methods. As stated in II-A, *failure KG* is difficult for beginners to comprehend, but it has been confirmed that the relationships between components during a failure can be partially extracted. Therefore, in this study, we want to focus on utilizing this KG as it currently exists. Additionally, the knowledge graphs in Graph RAG often lack human-validated meaning, making them insufficient for practical use.

The second challenge is that the relationships and structures described in the knowledge graph are rarely used in answer generation. Since Graph RAG operates using the SP method, the search typically targets the graph's nodes rather than its edges, i.e., the relationships. However, automobile failures involve chains and their structures, making it essential to use the information from entire sub-graphs containing the necessary information, rather than focusing on specific nodes.

These challenges primarily arise from the fact that the current Graph RAG constructs a pipeline based on the SP method. In response, we propose an **IR-based Graph RAG** that is applicable to existing knowledge graphs and is based on the IR method. While it has been mentioned that the IR method may lead to an increase in the number of extracted sub-graphs in response to complex queries, there is potential to resolve this issue using LLMs.

B. Proposed Method

The following outlines the pipeline of the IR-based Graph RAG. A schematic diagram is presented in Fig. 4.

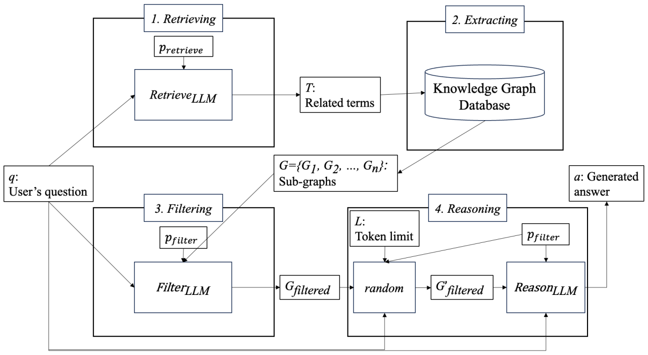


Fig. 4. Overview of the IR-based Graph RAG

1) *Retrieving*: Given a user query q, the LLM processes the input and retrieves a set of related terms T by identifying relevant automotive issues and faults. Mathematically, this can be expressed as below:

$$T = Retrieve_{LLM}(q, p_{retrieve}) \tag{1}$$

where $p_{retrieve}$ is the prompt instructing the retrieval of related words.

2) *Extracting*: Sub-graphs are extracted based on the retrieved words. This extraction involves generating a rule-based search query that is free from grammatical errors. For each word $t \in T$, a sub-graph G_t is defined as s set of relationships, including the node n_t corresponding to the target word t, along with the edges E_t and connected nodes N_t. Mathematically, the sub-graph G_t can be expressed as:

$$G_t = (n_t, N_t, E_t) \tag{2}$$

where n_t is the target word node, N_t is the set of nodes connected to n_t, and E_t is the set of edges connecting n_t to N_t, or N_t to n_t. In other words, these relationships form one-hop chain. Also, the sub-graph G_t is then represented as sets of text shown in Fig. 5.

3) *Filtering*: The LLM is used to filter the extracted sub-graphs, selecting candidates that are relevant to the user's question. This step is necessary because many edges are connected to specific words (such as "engine"), resulting in the extraction of numerous unrelated sub-graphs. By using the LLM, this step mitigates the conventional issue of an overwhelming number of extracted sub-graphs when adopting the IR-method for KGQA. Let $G = G_1, G_2, \ldots, G_n$ represent the set of extracted sub-graphs. The LLM applies a filtering function $Filter_{LLM}$ that selects a subset $G_{filtered} \subseteq G$ of sub-graphs relevant to the query q, which can be expressed as:

$$G_{filtered} = Filter_{LLM}(G, q, p_{filter}) \tag{3}$$

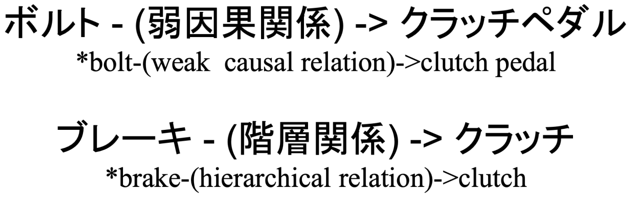
where p_{filter} is the prompt containing instructions to filter the sub-graphs.

4) *Reasoning*: The final filtered sub-graphs, along with the user's question, are given to the LLM as a prompt to generate the final answer. If the number of selected sub-graphs is too large and exceeds the token limit L for the prompt, random sub-graphs are removed before included in the prompt. This can be expressed as:

$$G'_{filtered} = random(G_{filtered}, L, q, p_{reason}) \tag{4}$$

where p_{reason} is the prompt used to instruct the LLM to reason and generate the answer. This prompt is shown if Fig. 6. The final answer a is then generated by the LLM as expressed below:

$$a = Reason_{LLM}(G'_{filtered}, q, p_{reason}) \tag{5}$$



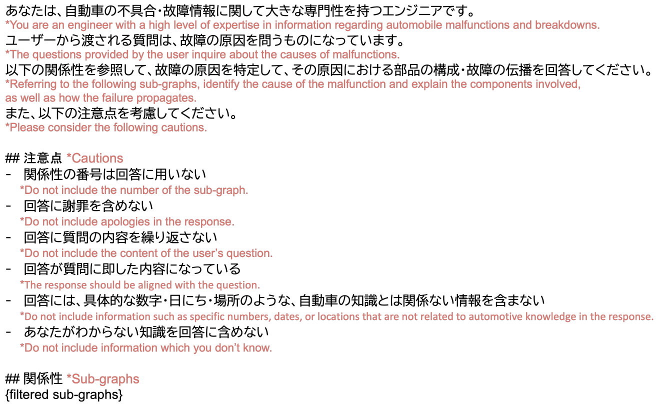
ボルト - (弱因果関係) -> クラッチペダル
*bolt-(weak causal relation)->clutch pedal

ブレーキ - (階層関係) -> クラッチ
*brake-(hierarchical relation)->clutch

Fig. 5. Examples of sub-graph representations

C. Evaluation

To evaluate the proposed method, we assess its validity by creating and using a Q&A dataset to measure the textual similarity between the responses generated by Graph RAG and the expected answers. The dataset is generated by providing the LLM with *failure documents* and specific instructions as prompts, resulting in a set of questions and answers related to malfunction or failure information. To make the content more practical, the dataset is designed so that the answers involve the actual component configurations and failure propagation processes typically analyzed during failure analysis. The sentences from *failure documents* are cleansed and converted into grammatically correct and meaningful sentences by the LLM.

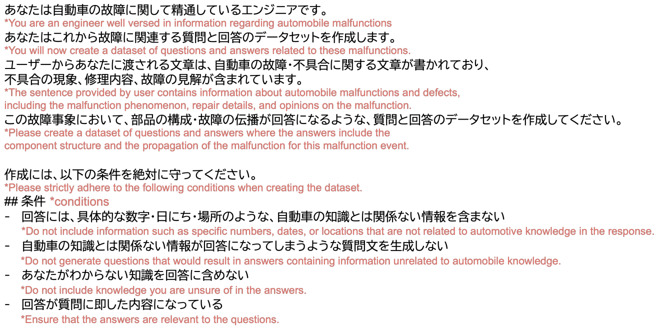


```
あなたは、自動車の不具合・故障情報に関して大きな専門性を持つエンジニアです。
*You are an engineer with a high level of expertise in information regarding automobile malfunctions and breakdowns.
ユーザーから渡される質問は、故障の原因を問うものになっています。
*The questions provided by the user inquire about the causes of malfunctions.
以下の関係性を参照して、故障の原因を特定して、その原因における部品の構成・故障の伝播を回答してください。
*Referring to the following sub-graphs, identify the cause of the malfunction and explain the components involved,
as well as how the failure propagates.
また、以下の注意点を考慮してください。
*Please consider the following cautions.

## 注意点 *Cautions
-  関係性の番号は回答に用いない
   *Do not include the number of the sub-graph.
-  回答に謝罪を含めない
   *Do not include apologies in the response.
-  回答に質問の内容を繰り返さない
   *Do not include the content of the user's question.
-  回答が質問に即した内容になっている
   *The response should be aligned with the question.
-  回答には、具体的な数字・日にち・場所のような、自動車の知識とは関係ない情報を含まない
   *Do not include information such as specific numbers, dates, or locations that are not related to automotive knowledge in the response.
-  あなたがわからない知識を回答に含めない
   *Do not include information which you don't know.

## 関係性 *Sub-graphs
{filtered sub-graphs}
```

Fig. 6. The prompt used for the Reasoning step. The original prompt is written in Japanese (in black), and the red text is its translation into English. To align with the expected responses in the dataset, the same instructions shown in Fig. 7 have been incorporated.



```
あなたは自動車の故障に関して精通しているエンジニアです。
*You are an engineer well versed in information regarding automobile malfunctions
あなたはこれから故障に関連する質問と回答のデータセットを作成します。
*You will now create a dataset of questions and answers related to these malfunctions.
ユーザーからあなたに渡される文章は、自動車の故障・不具合に関する文章が書かれており、
不具合の現象、修理内容、故障の見解が含まれています。
*The sentence provided by user contains information about automobile malfunctions and defects,
including the malfunction phenomenon, repair details, and opinions on the malfunction.
この故障事象において、部品の構成・故障の伝播が回答になるような、質問と回答のデータセットを作成してください。
*Please create a dataset of questions and answers where the answers include the
component structure and the propagation of the malfunction for this malfunction event.

作成には、以下の条件を絶対に守ってください。
*Please strictly adhere to the following conditions when creating the dataset.
## 条件 *conditions
-  回答には、具体的な数字・日にち・場所のような、自動車の知識とは関係ない情報を含まない
   *Do not include information such as specific numbers, dates, or locations that are not related to automotive knowledge in the response.
-  自動車の知識とは関係ない情報が回答になってしまうような質問文を生成しない
   *Do not generate questions that would result in answers containing information unrelated to automobile knowledge.
-  あなたがわからない知識を回答に含めない
   *Do not include knowledge you are unsure of in the answers.
-  回答が質問に即した内容になっている
   *Ensure that the answers are relevant to the questions.
```

Fig. 7. Excerpt from the prompt used for creating a dataset. The original prompt is written in Japanese (in black), and the red text is its translation into English. Some parts are modified.

This approach is similar to that of Balaguer et al [11]. Fig. 7 is the prompt used for generating dataset.

For the evaluation metric, we use the ROUGE F1 score [6]. We hypothesize that when questions generated from *failure documents* and the LLM are input into Graph RAG, which uses *failure KG* as the data source, the responses will be similar to those generated by *failure documents* and LLM. A higher ROUGE score indicates greater textual similarity with the dataset, suggesting that the generated response contains more of the required information. Therefore, we adopted this metric for this study.

IV. Experiment

A. Experiment Setting

In this study, we exclusively used ChatGPT as the LLM. Specifically, we employed the Azure OpenAI GPT-4o (2024-07-01) with the temperature parameter set to 0.

We compared three methods: the proposed method, ChatGPT, and the current Graph RAG. Both versions of Graph RAG use *failure KG*. Because the current Graph RAG adopts the SP method, we named it **SP-based Graph RAG**. Additionally, to implement SP-based Graph RAG, we used libraries supported by LangChain and Neo4j[2].

In the prompt for the SP-based Graph RAG, we include not only the reasoning prompt used in the IR-based Graph RAG but also an explanatory description of *failure KG*.

The SP-based Graph RAG was executed once, while the other two methods were run five times each to calculate the average score. This approach was chosen because of the variability in the generated text; when the token limit was exceeded, relationships are randomly deleted, leading to fluctuations in the scores.

For the evaluation, we used the F1 scores of ROUGE-1, ROUGE-2, and ROUGE-L. We computed the ROUGE F1 scores for each set in the dataset, summed them, and then divided the total by the number of sets.

B. Dataset

failure documents were provided by Isuzu Motors Limited. For the dataset, we used 43 sets of *failure documents* that included the term クラッチ (clutch) and contained all the necessary information for constructing *failure KG*. We instructed the LLM to create a dataset of questions and answers related to the chain of parts or failures. We used GPT-4 (1106-preview) provided by Azure OpenAI to construct the dataset, setting the temperature parameter to 0.

C. Results

The results are presented in Table I. For the SP-based Graph RAG, five sets of the dataset encountered errors and were excluded from the evaluation. All errors were attributed to syntax issues in the search queries generated for the KG, with successful query generation achieved for only ten sets.

The IR-based Graph RAG demonstrated an average score improvement of 157.6% compared to the current Graph RAG and an average improvement of 23.18% over ChatGPT. The IR-based Graph RAG consistently achieved the highest scores in all cases, indicating that it contained the most relevant information for the answers. Conversely, the SP-based Graph RAG produced very low scores, challenging to consider it a practical text. Furthermore, generating effective search queries proved to be challenging. Even when queries were successfully created, a significant number of syntax errors occurred, suggesting that this method may not be suitable for use with existing knowledge graphs.

TABLE I
The Experiment Results.

Method	ROUGE-1 F1	ROUGE-2 F1	ROUGE-L F1
ChatGPT	0.3305	0.1483	0.2364
SP-based	0.1538	0.06967	0.1185
IR-based	**0.4053**	**0.1845**	**0.2896**

Additionally, the proposed method outperformed ChatGPT, clearly demonstrating its capability to extract essential information from the *failure KG*. This indicates that the proposed

[2] https://python.langchain.com/v0.2/docs/integrations/graphs/neo4j_cypher/

approach is more effective for automotive failure knowledge management compared to existing technologies. Furthermore, when comparing the average number of tokens in the text generated by ChatGPT and the IR-based Graph RAG, the latter produces fewer tokens (as shown in Table II), suggesting that it generates more concise text. This may make it easier for beginners to understand.

TABLE II
THE AVERAGE TOKENS.

Method	Average Tokens
ChatGPT	530.2
IR-based	320.0

V. DISCUSSION

A. Cause Analysis about Missing Information

While the proposed method has demonstrated effectiveness, the evaluation metric scores remain low, raising concerns about its practicality. Possible reasons for this include missing information that should be stored in *failure KG* and the possibility that the method for extracting and describing sub-graphs is not appropriate. In this study, we conduct additional verification of the former issue.

To demonstrate that the amount of information recorded in *failure KG* is insufficient, we propose comparing the generated answers by adding sentences from *failure documents* that formed the basis of *failure KG* into the prompts. We hypothesize that including these sentences in the Reasoning step will improve the evaluation metrics, as they are expected to contain more information. Specifically, we add an evaluation method called IR-based Graph RAG with sentences (mentioned as ”With sentences” in Tables), where sentences from *failure documents* that generated the sub-graph are also extracted in the Filtering step and added as prompts alongside the sub-graphs during the Reasoning step. Thus, the following equation is added to the Filtering step:

$$S = Extract(G_{filtered}) \tag{6}$$

where S is the set of sentences extracted from *failure documents* that generated the sets of sub-graphs $G_{filtered}$.

Also, during the Reasoning step, these processes are executed:

$$G'_{filtered}, S' = random(G_{filtered}, S, L, q, p_{reason}) \tag{7}$$

$$a_{with\ sentences} = Reason_{LLM}(G'_{filtered}, S', q, p_{reason}) \tag{8}$$

where S' are randomly selected sentences to avoid exceed the token limit L, and $a_{with\ sentences}$ is the generated answer by this method, which was used for evaluation.

Additionally, we include a separate method called IR-based Graph RAG only sentences (mentioned as ”Only sentences” in Tables), in which sentences from *failure documents* are extracted during the Extracting step, similar to the IR-based Graph RAG with documents. However, in the Reasoning step, only these sentences are given as prompts. Therefore, adding to the pipeline of IR-based Graph RAG, (6) is executed during the Filtering step, and the following processes are executed in the Reasoning step:

$$S' = random(S, L, q, p_{reason}) \tag{9}$$

$$a_{only\ sentences} = Reason_{LLM}(G'_{filtered}, S', q, p_{reason}) \tag{10}$$

where $a_{only\ sentences}$ is the generated answer used for evaluation.

Each method was run five times, and the average ROUGE F1 score calculated for each run was used. The other experimental conditions remain the same as in the previously conducted experiments. The results are shown in Table III.

Based on the results, including both the sub-graphs and sentences from *failure documents* in the prompt during the Reasoning step leads to more accurate output. The scores of IR-based Graph RAG with sentences were the highest, showing an average improvement of 8.18% compared to the proposed method, which can be recognized as a significant difference. This suggests that the extracted sub-graph alone is insufficient and that there is missing information that should be described in *failure KG*.

TABLE III
RESULTS OF THE EXPERIMENT ABOUT MISSING INFORMATION.

Method	ROUGE-1 F1	ROUGE-2 F1	ROUGE-L F1
With sentences	0.4245	0.2106	0.3060
Only sentences	0.3940	0.1891	0.2825

While the additional experiment demonstrated that there was missing information that should have been included in *failure KG*. However, there was no significant difference observed between the IR-based Graph RAG and the IR-based Graph RAG only sentences. This can be explained by the proportion of information that LLMs can interpret. Generally, text of *failure documents* is considered to provide more information as a prompt compared to the sub-graphs. However, because *failure documents* are written in natural language, they likely contain a lot of information that could be considered noise. Therefore, the proportion of interpretable information from *failure documents* is likely smaller compared to that of the sub-graphs by the LLM. Additionally, the difference in the distribution of interpretable information between the sub-graphs and *failure documents* suggests that providing both sources of information in the prompt results in the highest score. In summary, these explanations can be represented as shown in Fig. 8.

B. Ablation Analysis about the Filtering step

To verify the effectiveness of the Filtering step in the proposed method, we conducted an ablation analysis. In this analysis, we removed the Filtering step from the pipelines and evaluated the ROUGE F1 score. We compare the vanilla IR-based Graph RAG, IR-based Graph RAG only sentences, and IR-based Graph RAG with sentences, and use the same

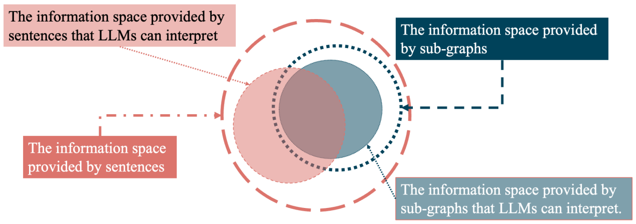

The information space provided by sentences that LLMs can interpret
The information space provided by sub-graphs
The information space provided by sentences
The information space provided by sub-graphs that LLMs can interpret.

Fig. 8. Comparison of the information space provided by sentences versus sub-graphs

experimental conditions as in the previous experiment, and the results are shown in Table IV.

TABLE IV
THE ABLATION ANALYSIS RESULTS OF THE IR-BASED GRAPH RAG.

Method	ROUGE-1 F1	ROUGE-2 F1	ROUGE-L F1
Vanilla	0.3882	0.1769	0.2809
Only sentences	0.3695	0.1713	0.2632
With sentences	0.3827	0.1885	0.2768

The results garnered indicate an average diminution of 7.077% relative to preceding scores, underscoring the indispensability of the filtering phase within the proposed methodology. This implies that the filtering stage in the proposed approach is not merely a procedural necessity, but a critical component, given that the selection of pertinent sub-graphs profoundly influences the precision of the outcomes. Additionally, it was found that filtering sub-graphs, which had been pointed out as a challenge in IR methods [10], can be performed on LLMs without requiring any special training.

C. Limitation and future works

This study has three major limitations. The first is the inadequacy of the sub-graph extraction method. In the context of failure events, chains of events are crucial, but this study extracts only one-hop chain. Future work should explore the introduction of an algorithm that can extract multi-hop chains. For example, it is a possible approach that embedding nodes or edges using an encoder model like BERT [8], and then determining which chains in KGs to use for reasoning based on cosine similarity to the query. This approach is similar to the method proposed by Saxena et al [12].

The second limitation concerns the evaluation method. In this study, the dataset was constructed using ChatGPT, and the evaluation was based on ROUGE F1. However, ROUGE is intended for use in scenarios where the target text is directly used, such as in extractive summarization, and its suitability for evaluating generated text remains questionable. To enhance the credibility of the evaluations, it is necessary to incorporate human evaluations as well.

The last one is that only a single round of interaction is conducted during the Reasoning step. In the experiments, there are some responses that simply include the names of components without providing deeper explanations. This is likely due to the attempt to generate an answer within a single interaction. Recent LLMs support agent systems, allowing them to act autonomously. These agents can analyze what information is needed to answer a given query, utilize provided tools (e.g., databases, web searches) to retrieve the required information, and perform reasoning based on it [13]. Depending on the prompt, they can autonomously execute multi-step processes, which enables them to generate more accurate and contextually appropriate responses.

VI. CONCLUSION

This study demonstrates that the proposed method, IR-based Graph RAG, is an effective system for knowledge management in automotive failure analysis. It suggests that providing information in the form of sub-graphs as prompts offers an interpretable format for LLMs. However, it is important to note that, that at this stage, it has not yet reached a level where it can be used directly, and we have identified issues specifically with the knowledge graph used in Graph RAG.

In the future, we intend to verify the practicality and validity for a wider range of events by increasing the size of the dataset. Additionally, we aim to improve the score accuracy through prompt engineering as part of our future work.

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