

# From Local to Global: A GraphRAG Approach to Query-Focused Summarization

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## Abstract

The use of retrieval-augmented generation (RAG) to retrieve relevant information from an external knowledge source enables large language models (LLMs) to answer questions over private and/or previously unseen document collections. However, RAG fails on global questions directed at an entire text corpus, such as “What are the main themes in the dataset?”, since this is inherently a query-focused summarization (QFS) task, rather than an explicit retrieval task. Prior QFS methods, meanwhile, do not scale to the quantities of text indexed by typical RAG systems. To combine the strengths of these contrasting methods, we propose *GraphRAG*, a graph-based approach to question answering over private text corpora that scales with both the generality of user questions and the quantity of source text. Our approach uses an LLM to build a graph index in two stages: first, to derive an entity knowledge graph from the source documents, then to pre-generate community summaries for all groups of closely related entities. Given a question, each community summary is used to generate a partial response, before all partial responses are again summarized in a final response to the user. For a class of global sensemaking questions over datasets in the 1 million token range, we show that GraphRAG leads to substantial improvements over a conventional RAG baseline for both the comprehensiveness and diversity of generated answers.

## 1 Introduction

Retrieval augmented generation (RAG) (Lewis et al., 2020) is an established approach to using LLMs to answer queries based on data that is too large to contain in a language model’s *context window*, meaning the maximum number of *tokens* (units of text) that can be processed by the LLM at once (Kuratov et al., 2024; Liu et al., 2023). In the canonical RAG setup, the system has access to a large external corpus of text records and retrieves a subset of records that are individually relevant to the query and collectively small enough to fit into the context window of the LLM. The LLM then

generates a response based on both the query and the retrieved records (Baumel et al., 2018; Dang, 2006; Laskar et al., 2020; Yao et al., 2017). This conventional approach, which we collectively call *vector RAG*, works well for queries that can be answered with information localized within a small set of records. However, vector RAG approaches do not support *sensemaking* queries, meaning queries that require global understanding of the entire dataset, such as “What are the key trends in how scientific discoveries are influenced by interdisciplinary research over the past decade?”

*Sensemaking* tasks require reasoning over “connections (which can be among people, places, and events) in order to anticipate their trajectories and act effectively” (Klein et al., 2006). LLMs such as GPT (Achiam et al., 2023; Brown et al., 2020), Llama (Touvron et al., 2023), and Gemini (Anil et al., 2023) excel at sensemaking in complex domains like scientific discovery (Microsoft, 2023) and intelligence analysis (Ranade and Joshi, 2023). Given a sensemaking query and a text with an implicit and interconnected set of concepts, an LLM can generate a summary that answers the query. The challenge, however, arises when the volume of data requires a RAG approach, since vector RAG approaches are unable to support sensemaking over an entire corpus.

In this paper, we present **GraphRAG** – a graph-based RAG approach that enables sensemaking over the entirety of a large text corpus. GraphRAG first uses an LLM to construct a knowledge graph, where nodes correspond to key entities in the corpus and edges represent relationships between those entities. Next, it partitions the graph into a hierarchy of communities of closely related entities, before using an LLM to generate community-level summaries. These summaries are generated in a bottom-up manner following the hierarchical structure of extracted communities, with summaries at higher levels of the hierarchy recursively incorporating lower-level summaries. Together, these community summaries provide global descriptions and insights over the corpus. Finally, GraphRAG answers queries through map-reduce processing of community summaries; in the map step, the summaries are used to provide partial answers to the query independently and in parallel, then in the reduce step, the partial answers are combined and used to generate a final global answer.

The GraphRAG method and its ability to perform global sensemaking over an entire corpus form the main contribution of this work. To demonstrate this ability, we developed a novel application of the LLM-as-a-judge technique (Zheng et al., 2024) suitable for questions targeting broad issues and themes where there is no ground-truth answer. This approach first uses one LLM to generate a diverse set of global sensemaking questions based on corpus-specific use cases, before using a second LLM to judge the answers of two different RAG systems using predefined criteria (defined in Section 3.3). We use this approach to compare GraphRAG to vector RAG on two representative real-world text datasets. Results show GraphRAG strongly outperforms vector RAG when using GPT-4 as the LLM.

GraphRAG is available as open-source software at <https://github.com/microsoft/graphrag>. In addition, versions of the GraphRAG approach are also available as extensions to multiple open-source libraries, including LangChain (LangChain, 2024), LlamaIndex (LlamaIndex, 2024), NebulaGraph (NebulaGraph, 2024), and Neo4J (Neo4J, 2024).

## 2 Background

### 2.1 RAG Approaches and Systems

RAG generally refers to any system where a user query is used to retrieve relevant information from external data sources, whereupon this information is incorporated into the generation of a response to the query by an LLM (or other generative AI model, such as a multi-media model). The query and retrieved records populate a prompt template, which is then passed to the LLM (Ram et al., 2023). RAG is ideal when the total number of records in a data source is too large to include in a single prompt to the LLM, i.e. the amount of text in the data source exceeds the LLM’s context window.

In canonical RAG approaches, the retrieval process returns a set number of records that are semantically similar to the query and the generated answer uses only the information in those retrieved records. A common approach to conventional RAG is to use text embeddings, retrieving records closest to the query in vector space where closeness corresponds to semantic similarity (Gao et al., 2023). While some RAG approaches may use alternative retrieval mechanisms, we collectively refer to the family of conventional approaches as *vector RAG*. GraphRAG contrasts with vector RAG in its ability to answer queries that require global sensemaking over the entire data corpus.

GraphRAG builds upon prior work on advanced RAG strategies. GraphRAG leverages summaries over large sections of the data source as a form of "self-memory" (described in [Cheng et al. 2024](#)), which are later used to answer queries as in [Mao et al. 2020](#)). These summaries are generated in parallel and iteratively aggregated into global summaries, similar to prior techniques ([Feng et al., 2023](#); [Gao et al., 2023](#); [Khattab et al., 2022](#); [Shao et al., 2023](#); [Su et al., 2020](#); [Trivedi et al., 2022](#); [Wang et al., 2024](#)). In particular, GraphRAG is similar to other approaches that use hierarchical indexing to create summaries (similar to [Kim et al. 2023](#); [Sarthi et al. 2024](#)). GraphRAG contrasts with these approaches by generating a graph index from the source data, then applying graph-based community detection to create a thematic partitioning of the data.

## 2.2 Using Knowledge Graphs with LLMs and RAG

Approaches to knowledge graph extraction from natural language text corpora include rule-matching, statistical pattern recognition, clustering, and embeddings ([Etzioni et al., 2004](#); [Kim et al., 2016](#); [Mooney and Bunescu, 2005](#); [Yates et al., 2007](#)). GraphRAG falls into a more recent body of research that use of LLMs for knowledge graph extraction ([Ban et al., 2023](#); [Melnyk et al., 2022](#); [OpenAI, 2023](#); [Tan et al., 2017](#); [Trajanoska et al., 2023](#); [Yao et al., 2023](#); [Yates et al., 2007](#); [Zhang et al., 2024a](#)). It also adds to a growing body of RAG approaches that use a knowledge graph as an index ([Gao et al., 2023](#)). Some techniques use subgraphs, elements of the graph, or properties of the graph structure directly in the prompt ([Baek et al., 2023](#); [He et al., 2024](#); [Zhang, 2023](#)) or as factual grounding for generated outputs ([Kang et al., 2023](#); [Ranade and Joshi, 2023](#)). Other techniques ([Wang et al., 2023b](#)) use the knowledge graph to enhance retrieval, where at query time an LLM-based agent dynamically traverses a graph with nodes representing document elements (e.g., passages, tables) and edges encoding lexical and semantical similarity or structural relationships. GraphRAG contrasts with these approaches by focusing on a previously unexplored quality of graphs in this context: their inherent *modularity* ([Newman, 2006](#)) and the ability to partition graphs into nested modular communities of closely related nodes (e.g., Louvain, [Blondel et al. 2008](#); Leiden, [Traag et al. 2019](#)). Specifically, GraphRAG recursively creates increasingly global summaries by using the LLM to create summaries spanning this community hierarchy.

## 2.3 Adaptive benchmarking for RAG Evaluation

Many benchmark datasets for open-domain question answering exist, including HotPotQA ([Yang et al., 2018](#)), MultiHop-RAG ([Tang and Yang, 2024](#)), and MT-Bench ([Zheng et al., 2024](#)). However, these benchmarks are oriented towards vector RAG performance, i.e., they evaluate performance on explicit fact retrieval. In this work, we propose an approach for generating a set of questions for evaluating global sensemaking over the entirety of the corpus. Our approach is related to LLM methods that use a corpus to generate questions whose answers would be summaries of the corpus, such as in [Xu and Lapata \(2021\)](#). However, in order to produce a fair evaluation, our method avoids generating the questions directly from the corpus itself (as an alternative implementation, one can use a subset of the corpus held out from subsequent graph extraction and answer evaluation steps).

*Adaptive benchmarking* refers to the process of dynamically generating evaluation benchmarks tailored to specific domains or use cases. Recent work has used LLMs for adaptive benchmarking to ensure relevance, diversity, and alignment with the target application or task ([Yuan et al., 2024](#); [Zhang et al., 2024b](#)). In this work, we propose an adaptive benchmarking approach to generating global sensemaking queries for the LLM. Our approach builds on prior work in LLM-based persona generation, where the LLM is used to generate diverse and authentic sets of personas ([Kosinski, 2024](#); [Salminen et al., 2024](#); [Shin et al., 2024](#)). Our adaptive benchmarking procedure uses persona generation to create queries that are representative of real-world RAG system usage. Specifically, our approach uses the LLM to infer the potential users would use the RAG system and their use cases, which guide the generation of corpus-specific sensemaking queries.

## 2.4 RAG evaluation criteria

Our evaluation relies on the LLM to evaluate how well the RAG system answers the generated questions. Prior work has shown LLMs to be good evaluators of natural language generation, including work where LLMs evaluations were competitive with human evaluations ([Wang et al., 2023a](#); [Zheng et al., 2024](#)). Some prior work proposes criteria for having LLMs quantify the quality of

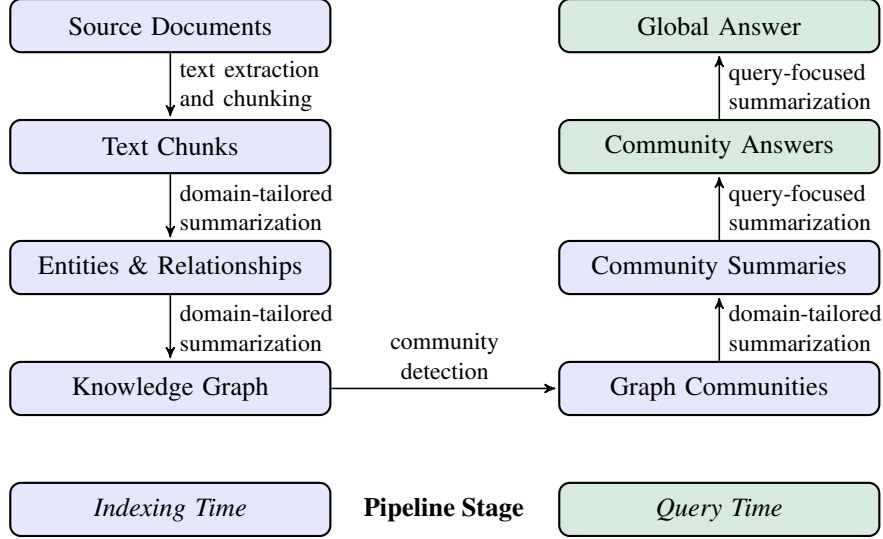


Figure 1: Graph RAG pipeline using an LLM-derived graph index of source document text. This graph index spans nodes (e.g., entities), edges (e.g., relationships), and covariates (e.g., claims) that have been detected, extracted, and summarized by LLM prompts tailored to the domain of the dataset. Community detection (e.g., Leiden, Traag et al., 2019) is used to partition the graph index into groups of elements (nodes, edges, covariates) that the LLM can summarize in parallel at both indexing time and query time. The “global answer” to a given query is produced using a final round of query-focused summarization over all community summaries reporting relevance to that query.

generated texts such as “fluency” (Wang et al., 2023a). Some of these criteria are generic to vector RAG systems and not relevant to global sensemaking, such as “context relevance”, “faithfulness”, and “answer relevance” (RAGAS, Es et al. 2023). Lacking a gold standard for evaluation, one can quantify relative performance for a given criterion by prompting the LLM to compare generations from two different competing models (LLM-as-a-judge, (Zheng et al., 2024)). In this work, we design criteria for evaluating RAG-generated answers to global sensemaking questions and evaluate our results using the comparative approach. We also validate results using statistics derived from LLM-extracted statements of verifiable facts, or “claims.”

### 3 Methods

#### 3.1 GraphRAG Workflow

Figure 1 illustrates the high-level data flow of the GraphRAG approach and pipeline. In this section, we describe the key design parameters, techniques, and implementation details for each step.

##### 3.1.1 Source Documents → Text Chunks

To start, the documents in the corpus are split into text chunks. The LLM extracts information from each chunk for downstream processing. Selecting the size of the chunk is a fundamental design decision; longer text chunks require fewer LLM calls for such extraction (which reduces cost) but suffer from degraded recall of information that appears early in the chunk (Kuratov et al., 2024; Liu et al., 2023). See Section A.1 for prompts and examples of the recall-precision trade-offs.

##### 3.1.2 Text Chunks → Entities & Relationships

In this step, the LLM is prompted to extract instances of important *entities* and the *relationships* between the entities from a given chunk. Additionally, the LLM generates short descriptions for the entities and relationships. To illustrate, suppose a chunk contained the following text:

NeoChip’s (NC) shares surged in their first week of trading on the NewTech Exchange. However, market analysts caution that the chipmaker’s public debut may not reflect trends for other technology IPOs. NeoChip, previously a private entity, was acquired by Quantum Systems in 2016. The innovative semiconductor firm specializes in low-power processors for wearables and IoT devices.

The LLM is prompted such that it extracts the following:

- The entity NeoChip, with description “NeoChip is a publicly traded company specializing in low-power processors for wearables and IoT devices.”
- The entity Quantum Systems, with description “Quantum Systems is a firm that previously owned NeoChip.”
- A relationship between NeoChip and Quantum Systems, with description “Quantum Systems owned NeoChip from 2016 until NeoChip became publicly traded.”

These prompts can be tailored to the domain of the document corpus by choosing domain appropriate few-shot exemplars for in-context learning (Brown et al., 2020). For example, while our default prompt extracts the broad class of “named entities” like people, places, and organizations and is generally applicable, domains with specialized knowledge (e.g., science, medicine, law) will benefit from few-shot exemplars specialized to those domains.

The LLM can also be prompted to extract *claims* about detected entities. *Claims* are important factual statements about entities, such as dates, events, and interactions with other entities. As with entities and relationships, in-context learning exemplars can provide domain-specific guidance. Claim descriptions extracted from the example text chunk are as follows:

- NeoChip’s shares surged during their first week of trading on the NewTech Exchange.
- NeoChip debuted as a publicly listed company on the NewTech Exchange.
- Quantum Systems acquired NeoChip in 2016 and held ownership until NeoChip went public.

See [Appendix A](#) for prompts and details on our implementation of entity and claim extraction.

### 3.1.3 Entities & Relationships → Knowledge Graph

The use of an LLM to extract entities, relationships, and claims is a form of abstractive summarization – these are meaningful summaries of concepts that, in the case of relationships and claims, may not be explicitly stated in the text. The entity/relationship/claim extraction processes creates multiple instances of a single element because an element is typically detected and extracted multiple times across documents.

In the final step of the knowledge graph extraction process, these instances of entities and relationships become individual nodes and edges in the graph. Entity descriptions are aggregated and summarized for each node and edge. Relationships are aggregated into graph edges, where the number of duplicates for a given relationship becomes edge weights. Claims are aggregated similarly.

In this manuscript, our analysis uses exact string matching for *entity matching* – the task of reconciling different extracted names for the same entity (Barlaug and Gulla, 2021; Christen and Christen, 2012; Elmagarmid et al., 2006). However, softer matching approaches can be used with minor adjustments to prompts or code. Furthermore, GraphRAG is generally resilient to duplicate entities since duplicates are typically clustered together for summarization in subsequent steps.

### 3.1.4 Knowledge Graph → Graph Communities

Given the graph index created in the previous step, a variety of community detection algorithms may be used to partition the graph into communities of strongly connected nodes (e.g., see the surveys by Fortunato (2010) and Jin et al. (2021)). In our pipeline, we use Leiden community detection (Traag et al., 2019) in a hierarchical manner, recursively detecting sub-communities within each detected community until reaching leaf communities that can no longer be partitioned.

Each level of this hierarchy provides a community partition that covers the nodes of the graph in a mutually exclusive, collectively exhaustive way, enabling divide-and-conquer global summarization. An illustration of such hierarchical partitioning on an example dataset can be found in [Appendix B](#).

### 3.1.5 Graph Communities → Community Summaries

The next step creates report-like summaries of each community in the community hierarchy, using a method designed to scale to very large datasets. These summaries are independently useful as a way to understand the global structure and semantics of the dataset, and may themselves be used to make sense of a corpus in the absence of a specific query. For example, a user may scan through community summaries at one level looking for general themes of interest, then read linked reports at a lower level that provide additional details for each subtopic. Here, however, we focus on their utility as part of a graph-based index used for answering global queries.

GraphRAG generates community summaries by adding various element summaries (for nodes, edges, and related claims) to a community summary template. Community summaries from lower-level communities are used to generate summaries for higher-level communities as follows:

- *Leaf-level communities.* The element summaries of a leaf-level community are prioritized and then iteratively added to the LLM context window until the token limit is reached. The prioritization is as follows: for each community edge in decreasing order of combined source and target node degree (i.e., overall prominence), add descriptions of the source node, target node, the edge itself, and related claims.
- *Higher-level communities.* If all element summaries fit within the token limit of the context window, proceed as for leaf-level communities and summarize all element summaries within the community. Otherwise, rank sub-communities in decreasing order of element summary tokens and iteratively substitute sub-community summaries (shorter) for their associated element summaries (longer) until they fit within the context window.

### 3.1.6 Community Summaries → Community Answers → Global Answer

Given a user query, the community summaries generated in the previous step can be used to generate a final answer in a multi-stage process. The hierarchical nature of the community structure also means that questions can be answered using the community summaries from different levels, raising the question of whether a particular level in the hierarchical community structure offers the best balance of summary detail and scope for general sensemaking questions (evaluated in [section 4](#)).

For a given community level, the global answer to any user query is generated as follows:

- *Prepare community summaries.* Community summaries are randomly shuffled and divided into chunks of pre-specified token size. This ensures relevant information is distributed across chunks, rather than concentrated (and potentially lost) in a single context window.
- *Map community answers.* Intermediate answers are generated in parallel. The LLM is also asked to generate a score between 0-100 indicating how helpful the generated answer is in answering the target question. Answers with score 0 are filtered out.
- *Reduce to global answer.* Intermediate community answers are sorted in descending order of helpfulness score and iteratively added into a new context window until the token limit is reached. This final context is used to generate the global answer returned to the user.

## 3.2 Global Sensemaking Question Generation

To evaluate the effectiveness of RAG systems for global sensemaking tasks, we use an LLM to generate a set of corpus-specific questions designed to assess high-level understanding of a given corpus, without requiring retrieval of specific low-level facts. Instead, given a high-level description of a corpus and its purposes, the LLM is prompted to generate personas of hypothetical users of the RAG system. For each hypothetical user, the LLM is then prompted to specify tasks that this user would use the RAG system to complete. Finally, for each combination of user and task, the LLM is prompted to generate questions that require understanding of the entire corpus. Algorithm 1 describes the approach.



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**Algorithm 1: Prompting Procedure for Question Generation**

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- 1: **Input:** Description of a corpus, number of users  $K$ , number of tasks per user  $N$ , number of questions per (user, task) combination  $M$ .
  - 2: **Output:** A set of  $K * N * M$  high-level questions requiring global understanding of the corpus.
  - 3: **procedure** GENERATEQUESTIONS
  - 4:   Based on the corpus description, prompt the LLM to:
    1. Describe personas of  $K$  potential users of the dataset.
    2. For each user, identify  $N$  tasks relevant to the user.
    3. Specific to each user & task pair, generate  $M$  high-level questions that:
      - Require understanding of the entire corpus.
      - Do not require retrieval of specific low-level facts.
  - 5:   Collect the generated questions to produce  $K * N * M$  test questions for the dataset.
  - 6: **end procedure**
- 

For our evaluation, we set  $K = M = N = 5$  for a total of 125 test questions per dataset. Table 1 shows example questions for each of the two evaluation datasets.

### 3.3 Criteria for Evaluating Global Sensemaking

Given the lack of gold standard answers to our activity-based sensemaking questions, we adopt the head-to-head comparison approach using an LLM evaluator that judges relative performance according to specific criteria. We designed three target criteria capturing qualities that are desirable for global sensemaking activities.

Appendix F shows the prompts for our head-to-head measures computed using an LLM evaluator, summarized as:

- *Comprehensiveness.* How much detail does the answer provide to cover all aspects and details of the question?
- *Diversity.* How varied and rich is the answer in providing different perspectives and insights on the question?
- *Empowerment.* How well does the answer help the reader understand and make informed judgments about the topic?

Table 1: Examples of potential users, tasks, and questions generated by the LLM based on short descriptions of the target datasets. Questions target global understanding rather than specific details.

Dataset	Example activity framing and generation of global sensemaking questions
Podcast transcripts	<i>User:</i> A tech journalist looking for insights and trends in the tech industry <i>Task:</i> Understanding how tech leaders view the role of policy and regulation <i>Questions:</i> <ol style="list-style-type: none"><li>1. Which episodes deal primarily with tech policy and government regulation?</li><li>2. How do guests perceive the impact of privacy laws on technology development?</li><li>3. Do any guests discuss the balance between innovation and ethical considerations?</li><li>4. What are the suggested changes to current policies mentioned by the guests?</li><li>5. Are collaborations between tech companies and governments discussed and how?</li></ol>
News articles	<i>User:</i> Educator incorporating current affairs into curricula <i>Task:</i> Teaching about health and wellness <i>Questions:</i> <ol style="list-style-type: none"><li>1. What current topics in health can be integrated into health education curricula?</li><li>2. How do news articles address the concepts of preventive medicine and wellness?</li><li>3. Are there examples of health articles that contradict each other, and if so, why?</li><li>4. What insights can be gleaned about public health priorities based on news coverage?</li><li>5. How can educators use the dataset to highlight the importance of health literacy?</li></ol>

Furthermore, we use a “control criterion” called *Directness* that answers “*How specifically and clearly does the answer address the question?*”. In plain terms, directness evaluates the concision of an answer in a generic sense that applies to any generated LLM summarization. We include it to behave as a reference against which we can judge the soundness of results for the other criteria. Since directness is effectively in opposition to comprehensiveness and diversity, we would not expect any method to win across all four criteria.

In our evaluations, the LLM is provided with the question, the generated answers from two competing systems, and prompted to compare the two answers according to the criterion before giving a final judgment of which answer is preferred. The LLM either indicates a winner; or, it returns a tie if they are fundamentally similar. To account for the inherent stochasticity of LLM generation, we run each comparison with multiple replicates and average the results across replicates and questions. An illustration of LLM assessment for answers to a sample question can be found in [Appendix D](#).

## 4 Analysis

### 4.1 Experiment 1

#### 4.1.1 Datasets

We selected two datasets in the one million token range, each representative of corpora that users may encounter in their real-world activities:

**Podcast transcripts.** Public transcripts of *Behind the Tech with Kevin Scott*, a podcast featuring conversations between Microsoft CTO Kevin Scott and various thought leaders in science and technology ([Scott, 2024](#)). This corpus was divided into  $1669 \times 600$ -token text chunks, with 100-token overlaps between chunks ( $\sim 1$  million tokens).

**News articles.** A benchmark dataset comprised of news articles published from September 2013 to December 2023 in a range of categories, including entertainment, business, sports, technology, health, and science ([Tang and Yang, 2024](#)). The corpus is divided into  $3197 \times 600$ -token text chunks, with 100-token overlaps between chunks ( $\sim 1.7$  million tokens).

#### 4.1.2 Conditions

We compared six conditions including GraphRAG at four different graph community levels (**C0**, **C1**, **C2**, **C3**), a text summarization method that applies our map-reduce approach directly to source texts (**TS**), and a vector RAG “semantic search” approach (**SS**):

- **C0.** Uses root-level community summaries (fewest in number) to answer user queries.
- **C1.** Uses high-level community summaries to answer queries. These are sub-communities of C0, if present, otherwise C0 communities projected downwards.
- **C2.** Uses intermediate-level community summaries to answer queries. These are sub-communities of C1, if present, otherwise C1 communities projected downwards.
- **C3.** Uses low-level community summaries (greatest in number) to answer queries. These are sub-communities of C2, if present, otherwise C2 communities projected downwards.
- **TS.** The same method as in [Section 3.1.6](#), except source texts (rather than community summaries) are shuffled and chunked for the map-reduce summarization stages.
- **SS.** An implementation of vector RAG in which text chunks are retrieved and added to the available context window until the specified token limit is reached.

The size of the context window and the prompts used for answer generation are the same across all six conditions (except for minor modifications to reference styles to match the types of context information used). Conditions only differ in how the contents of the context window are created.

The graph index supporting conditions **C0-C3** was created using our generic prompts for entity and relationship extraction, with entity types and few-shot examples tailored to the domain of the data.



### 4.1.3 Configuration

We used a fixed context window size of 8k tokens for generating community summaries, community answers, and global answers (explained in [Appendix C](#)). Graph indexing with a 600 token window (explained in [Section A.2](#)) took 281 minutes for the Podcast dataset, running on a virtual machine (16GB RAM, Intel(R) Xeon(R) Platinum 8171M CPU @ 2.60GHz) and using a public OpenAI endpoint for gpt-4-turbo (2M TPM, 10k RPM).

We implemented Leiden community detection using the graspolologic library ([Chung et al., 2019](#)). The prompts used to generate the graph index and global answers can be found in [Appendix E](#), while the prompts used to evaluate LLM responses against our criteria can be found in [Appendix F](#). A full statistical analysis of the results presented in the next section can be found in [Appendix G](#).

## 4.2 Experiment 2

To validate the comprehensiveness and diversity results from Experiment 1, we implemented claim-based measures of these qualities. We use the definition of a factual claim from [Ni et al. \(2024\)](#), which is “a statement that explicitly presents some verifiable facts.” For example, the sentence “California and New York implemented incentives for renewable energy adoption, highlighting the broader importance of sustainability in policy decisions” contains two factual claims: (1) California implemented incentives for renewable energy adoption, and (2) New York implemented incentives for renewable energy adoption.

To extract factual claims, we used **Claimify** ([Metropolitansky and Larson, 2025](#)), an LLM-based method that identifies sentences in an answer containing at least one factual claim, then decomposes these sentences into simple, self-contained factual claims. We applied Claimify to the answers generated under the conditions from Experiment 1. After removing duplicate claims from each answer, we extracted 47,075 unique claims, with an average of 31 claims per answer.

We defined two metrics, with higher values indicating better performance:

1. **Comprehensiveness:** Measured as the average number of claims extracted from the answers generated under each condition.
2. **Diversity:** Measured by clustering the claims for each answer and calculating the average number of clusters.

For clustering, we followed the approach described by [Padmakumar and He \(2024\)](#), which involved using Scikit-learn’s implementation of agglomerative clustering ([Pedregosa et al., 2011](#)). Clusters were merged through “complete” linkage, meaning they were combined only if the maximum distance between their farthest points was less than or equal to a predefined distance threshold. The distance metric used was  $1 - \text{ROUGE-L}$ . Since the distance threshold influences the number of clusters, we report results across a range of thresholds.

## 5 Results

### 5.1 Experiment 1

The indexing process resulted in a graph consisting of 8,564 nodes and 20,691 edges for the Podcast dataset, and a larger graph of 15,754 nodes and 19,520 edges for the News dataset. [Table 2](#) shows the number of community summaries at different levels of each graph community hierarchy.

**Global approaches vs. vector RAG.** As shown in [Figure 2](#) and [Table 6](#), global approaches significantly outperformed conventional vector RAG (SS) in both comprehensiveness and diversity criteria across datasets. Specifically, global approaches achieved comprehensiveness win rates between 72-83% ( $p < .001$ ) for Podcast transcripts and 72-80% ( $p < .001$ ) for News articles, while diversity win rates ranged from 75-82% ( $p < .001$ ) and 62-71% ( $p < .01$ ) respectively. Our use of directness as a validity test confirmed that vector RAG produces the most direct responses across all comparisons.

**Empowerment.** Empowerment comparisons showed mixed results for both global approaches versus vector RAG (SS) and GraphRAG approaches versus source text summarization (TS). Using an LLM to analyze LLM reasoning for this measure indicated that the ability to provide specific exam-

### Podcast transcripts

	SS	TS	C0	C1	C2	C3		SS	TS	C0	C1	C2	C3		SS	TS	C0	C1	C2	C3		SS	TS	C0	C1	C2	C3			
SS	50	17	28	25	22	21		SS	50	18	23	25	19	19		SS	50	42	57	52	49	51		SS	50	56	65	60	60	60
TS	83	50	50	48	43	44		TS	82	50	50	50	43	46		TS	58	50	59	55	52	51		TS	44	50	55	52	51	52
C0	72	50	50	53	50	49		C0	77	50	50	50	46	44		C0	43	41	50	49	47	48		C0	35	45	50	47	48	48
C1	75	52	47	50	52	50		C1	75	50	50	50	44	45		C1	48	45	51	50	49	50		C1	40	48	53	50	50	50
C2	78	57	50	48	50	52		C2	81	57	54	56	50	48		C2	51	48	53	51	50	51		C2	40	49	52	50	50	50
C3	79	56	51	50	48	50		C3	81	54	56	55	52	50		C3	49	49	52	50	49	50		C3	40	48	52	50	50	50
Comprehensiveness								Diversity								Empowerment								Directness						

### News articles

	SS	TS	C0	C1	C2	C3		SS	TS	C0	C1	C2	C3		SS	TS	C0	C1	C2	C3		SS	TS	C0	C1	C2	C3			
SS	50	20	28	25	21	21		SS	50	33	38	35	29	31		SS	50	47	57	49	50	50		SS	50	54	59	55	55	54
TS	80	50	44	41	38	36		TS	67	50	53	45	44	40		TS	53	50	58	50	50	48		TS	46	50	55	53	52	52
C0	72	56	50	52	54	52		C0	62	47	50	40	41	41		C0	43	42	50	42	45	44		C0	41	45	50	48	48	47
C1	75	59	48	50	58	55		C1	65	55	60	50	50	50		C1	51	50	58	50	52	51		C1	45	47	52	50	49	49
C2	79	62	46	42	50	59		C2	71	56	59	50	50	51		C2	50	50	55	48	50	50		C2	45	48	52	51	50	49
C3	79	64	48	45	41	50		C3	69	60	59	50	49	50		C3	50	52	56	49	50	50		C3	46	48	53	51	51	50
Comprehensiveness								Diversity								Empowerment								Directness						

Figure 2: Head-to-head win rate percentages of (row condition) over (column condition) across two datasets, four metrics, and 125 questions per comparison (each repeated five times and averaged). The overall winner per dataset and metric is shown in bold. Self-win rates were not computed but are shown as the expected 50% for reference. All Graph RAG conditions outperformed naïve RAG on comprehensiveness and diversity. Conditions C1-C3 also showed slight improvements in answer comprehensiveness and diversity over TS (global text summarization without a graph index).

Table 2: Number of context units (community summaries for **C0-C3** and text chunks for **TS**), corresponding token counts, and percentage of the maximum token count. Map-reduce summarization of source texts is the most resource-intensive approach requiring the highest number of context tokens. Root-level community summaries (**C0**) require dramatically fewer tokens per query (9x-43x).

	Podcast Transcripts					News Articles				
	C0	C1	C2	C3	TS	C0	C1	C2	C3	TS
Units	34	367	969	1310	1669	55	555	1797	2142	3197
Tokens	26657	225756	565720	746100	1014611	39770	352641	980898	1140266	1707694
% Max	2.6	22.2	55.8	73.5	100	2.3	20.7	57.4	66.8	100

ples, quotes, and citations was judged to be key to helping users reach an informed understanding. Tuning element extraction prompts may help to retain more of these details in the GraphRAG index.

**Community summaries vs. source texts.** When comparing community summaries to source texts using GraphRAG, community summaries generally provided a small but consistent improvement in answer comprehensiveness and diversity, except for root-level summaries. Intermediate-level summaries in the Podcast dataset and low-level community summaries in the News dataset achieved comprehensiveness win rates of 57% ( $p < .001$ ) and 64% ( $p < .001$ ), respectively. Diversity win rates were 57% ( $p = .036$ ) for Podcast intermediate-level summaries and 60% ( $p < .001$ ) for News low-level community summaries. Table 2 also illustrates the scalability advantages of GraphRAG compared to source text summarization: for low-level community summaries (**C3**), GraphRAG required 26-33% fewer context tokens, while for root-level community summaries (**C0**), it required over 97% fewer tokens. For a modest drop in performance compared with other global methods, root-level GraphRAG offers a highly efficient method for the iterative question answering that characterizes sensemaking activity, while retaining advantages in comprehensiveness (72% win rate) and diversity (62% win rate) over vector RAG.

Table 3: Average number of extracted claims, reported by condition and dataset type. Bolded values represent the highest score in each column.

Condition	Average Number of Claims	
	News Articles	Podcast Transcripts
C0	<b>34.18</b>	32.21
C1	32.50	32.20
C2	31.62	<b>32.46</b>
C3	33.14	32.28
TS	32.89	31.39
SS	25.23	26.50

## 5.2 Experiment 2

Table 3 shows the results for the average number of extracted claims (i.e., the claim-based measure of comprehensiveness) per condition. For both the News and Podcast datasets, all global search conditions (**C0-C3**) and source text summarization (**TS**) had greater comprehensiveness than vector RAG (**SS**). The differences were statistically significant ( $p < .05$ ) in all cases. These findings align with the LLM-based win rates from Experiment 1.

Table 4 contains the results for the average number of clusters, the claim-based measure of diversity. For the Podcast dataset, all global search conditions had significantly greater diversity than **SS** across all distance thresholds ( $p < .05$ ), consistent with the win rates observed in Experiment 1. For the News dataset, however, only **C0** significantly outperformed **SS** across all distance thresholds ( $p < .05$ ). While **C1-C3** also achieved higher average cluster counts than **SS**, the differences were statistically significant only at certain distance thresholds. In Experiment 1, all global search conditions significantly outperformed **SS** in the News dataset – not just **C0**. However, the differences in mean diversity scores between **SS** and the global search conditions were smaller for the News dataset than for the Podcast dataset, aligning directionally with the claim-based results.

For both comprehensiveness and diversity, across both datasets, there were no statistically significant differences observed among the global search conditions or between global search and **TS**.

Finally, for each pairwise comparison in Experiment 1, we tested whether the answer preferred by the LLM aligned with the winner based on the claim-based metrics. Since each pairwise comparison in Experiment 1 was performed five times, while the claim-based metrics provided only one outcome per comparison, we aggregated the Experiment 1 results into a single label using majority voting. For example, if **C0** won over **SS** in three out of five judgments for comprehensiveness on a given question, **C0** was labeled the winner and **SS** the loser. However, if **C0** won twice, **SS** won once, and they tied twice, then there was no majority outcome, so the final label was a tie.

We found that exact ties were rare for the claim-based metrics. One possible solution is to define a tie based on a threshold (e.g., the absolute difference between the claim-based results for condition A and condition B must be less than or equal to  $x$ ). However, we observed that the results were sensitive to the choice of threshold. As a result, we focused on cases where the aggregated LLM label was not a tie, representing 33% and 39% of pairwise comparisons for comprehensiveness and diversity, respectively. In these cases, the aggregated LLM label matched the claim-based label in 78% of pairwise comparisons for comprehensiveness and 69-70% for diversity (across all distance thresholds), indicating moderately strong alignment.

## 6 Discussion

### 6.1 Limitations of evaluation approach

Our evaluation to date has focused on sensemaking questions specific to two corpora each containing approximately 1 million tokens. More work is needed to understand how performance generalizes to datasets from various domains with different use cases. Comparison of fabrication rates, e.g., using approaches like SelfCheckGPT (Manakul et al., 2023), would also strengthen the current analysis.

Table 4: Average number of clusters across different distance thresholds, reported by condition and dataset type. Bolded values represent the highest score in each row.

Dataset	Distance Threshold	Average Number of Clusters					
		C0	C1	C2	C3	TS	SS
News Articles	0.5	<b>23.42</b>	21.85	21.90	22.13	21.80	17.92
	0.6	<b>21.65</b>	20.38	20.30	20.52	20.13	16.78
	0.7	<b>20.19</b>	19.06	19.03	19.13	18.62	15.80
	0.8	<b>18.86</b>	17.78	17.82	17.79	17.30	14.80
Podcast Transcripts	0.5	<b>23.16</b>	22.62	22.52	21.93	21.14	18.55
	0.6	<b>21.65</b>	21.33	21.21	20.62	19.70	17.39
	0.7	<b>20.41</b>	20.04	19.79	19.22	18.08	16.28
	0.8	<b>19.26</b>	18.77	18.46	17.89	16.66	15.07

## 6.2 Future work

The graph index, rich text annotations, and hierarchical community structure supporting the current GraphRAG approach offer many possibilities for refinement and adaptation. This includes RAG approaches that operate in a more local manner, via embedding-based matching of user queries and graph annotations. In particular, we see potential in hybrid RAG schemes that combine embedding-based matching with just-in-time community report generation before employing our map-reduce summarization mechanisms. This “roll-up” approach could also be extended across multiple levels of the community hierarchy, as well as implemented as a more exploratory “drill down” mechanism that follows the information scent contained in higher-level community summaries.

*Broader impacts.* As a mechanism for question answering over large document collections, there are risks to downstream sensemaking and decision-making tasks if the generated answers do not accurately represent the source data. System use should be accompanied by clear disclosures of AI use and the potential for errors in outputs. Compared to vector RAG, however, GraphRAG shows promise as a way to mitigate these downstream risks for questions of a global nature, which might otherwise be answered by samples of retrieved facts falsely presented as global summaries.

## 7 Conclusion

We have presented GraphRAG, a RAG approach that combines knowledge graph generation and query-focused summarization (QFS) to support human sensemaking over entire text corpora. Initial evaluations show substantial improvements over a vector RAG baseline for both the comprehensiveness and diversity of answers, as well as favorable comparisons to a global but graph-free approach using map-reduce source text summarization. For situations requiring many global queries over the same dataset, summaries of root-level communities in the entity-based graph index provide a data index that is both superior to vector RAG and achieves competitive performance to other global methods at a fraction of the token cost.

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## A Entity and Relationship Extraction Approach

The following prompts, designed for GPT-4, are used in the default GraphRAG initialization pipeline:

- [Default Graph Extraction Prompt](#)
- [Claim Extraction Prompt](#)

### A.1 Entity Extraction

We do this using a multipart LLM prompt that first identifies all *entities* in the text, including their name, type, and description, before identifying all *relationships* between clearly related entities, including the source and target entities and a description of their relationship. Both kinds of element instance are output in a single list of delimited tuples.

### A.2 Self-Reflection

The choice of prompt engineering techniques has a strong impact on the quality of knowledge graph extraction (Zhu et al., 2024), and different techniques have different costs in terms of tokens consumed and generated by the model. *Self-reflection* is a prompt engineering technique where the LLM generates an answer, and is then prompted to evaluate its output for correctness, clarity, or completeness, then finally generate an improved response based on that evaluation (Huang et al., 2023; Madaan et al., 2024; Shinn et al., 2024; Wang et al., 2022). We leverage self-reflection in knowledge graph extraction, and explore ways how removing self-reflection affects performance and cost.

Using larger chunk size is less costly in terms of calls to the LLM. However, the LLM tends to extract few entities from chunks of larger size. For example, in a sample dataset (HotPotQA, Yang et al., 2018), GPT-4 extracted almost twice as many entity references when the chunk size was 600 tokens than when it was 2400. To address this issue, we deploy a self-reflection prompt engineering approach. After entities are extracted from a chunk, we provide the extracted entities back to the LLM, prompting it to “glean” any entities that it may have missed. This is a multi-stage process in which we first ask the LLM to assess whether all entities were extracted, using a logit bias of 100 to force a yes/no decision. If the LLM responds that entities were missed, then a continuation indicating that “MANY entities were missed in the last extraction” encourages the LLM to detect these missing entities. This approach allows us to use larger chunk sizes without a drop in quality (Figure 3) or the forced introduction of noise. We iterate self-reflection steps up to a specified maximum number of times.



Figure 3: How the entity references detected in the HotPotQA dataset (Yang et al., 2018) varies with chunk size and self-reflection iterations for our generic entity extraction prompt with gpt-4-turbo.

## B Example Community Detection

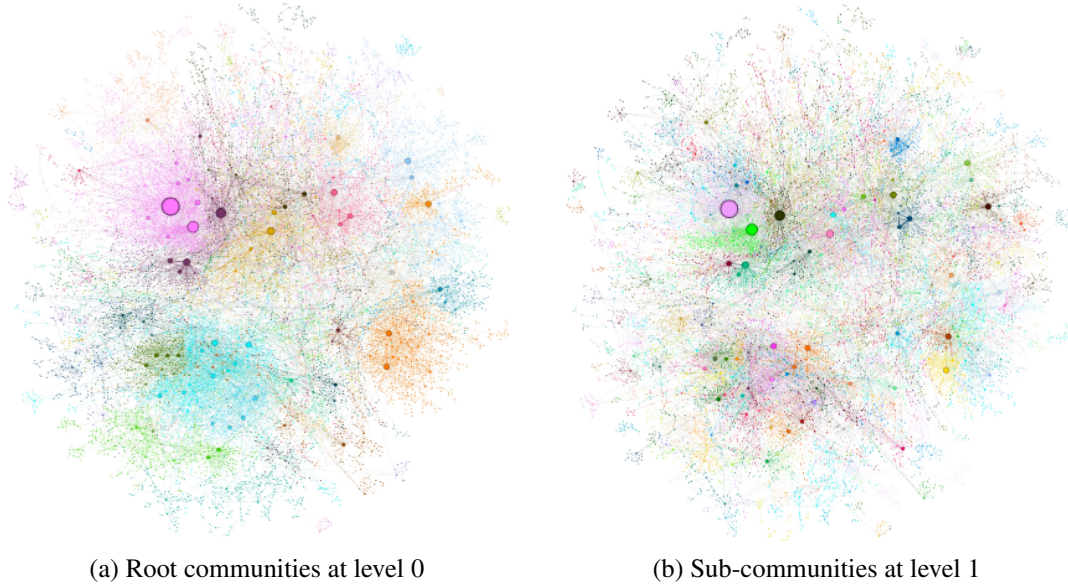


Figure 4: Graph communities detected using the Leiden algorithm (Traag et al., 2019) over the MultiHop-RAG (Tang and Yang, 2024) dataset as indexed. Circles represent entity nodes with size proportional to their degree. Node layout was performed via OpenORD (Martin et al., 2011) and Force Atlas 2 (Jacomy et al., 2014). Node colors represent entity communities, shown at two levels of hierarchical clustering: (a) Level 0, corresponding to the hierarchical partition with maximum modularity, and (b) Level 1, which reveals internal structure within these root-level communities.

## C Context Window Selection

The effect of context window size on any particular task is unclear, especially for models like gpt-4-turbo with a large context size of 128k tokens. Given the potential for information to be “lost in the middle” of longer contexts (Kuratov et al., 2024; Liu et al., 2023), we wanted to explore the effects of varying the context window size for our combinations of datasets, questions, and metrics. In particular, our goal was to determine the optimum context size for our baseline condition (SS) and then use this uniformly for all query-time LLM use. To that end, we tested four context window sizes: 8k, 16k, 32k and 64k. Surprisingly, the smallest context window size tested (8k) was universally better for all comparisons on comprehensiveness (average win rate of 58.1%), while performing comparably with larger context sizes on diversity (average win rate = 52.4%), and empowerment (average win rate = 51.3%). Given our preference for more comprehensive and diverse answers, we therefore used a fixed context window size of 8k tokens for the final evaluation.

## D Example Answer Comparison

Table 5: Example question, answers, and LLM-generated assessments for the News article dataset.

Question	Which public figures are repeatedly mentioned across various entertainment articles?
<b>Graph RAG</b>	<p>The entertainment industry is vast and diverse, encompassing film, television, music, sports, and digital media. Certain public figures stand out due to their significant contributions and influence across these sectors. The following summary highlights key individuals who are repeatedly mentioned in various entertainment articles, reflecting their impact and presence within the industry. <b>Actors and Directors [...]</b> <b>Public Figures in Controversy [...]</b> <b>Musicians and Executives [...]</b> <b>Athletes and Coaches [...]</b> <b>Influencers and Entrepreneurs [...]</b></p> <p>The repeated mention of these figures in entertainment articles signifies their ongoing relevance and the public’s interest in their work. Their influence spans across various aspects of entertainment, from shaping cultural narratives in film and television to driving trends in music and digital media. These individuals not only contribute to their respective fields but also influence the broader cultural landscape, often becoming central figures in social discussions and public discourse.</p>
<b>Naïve RAG</b>	<p>Public figures who are repeatedly mentioned across various entertainment articles include Taylor Swift, Travis Kelce, Britney Spears, and Justin Timberlake. These individuals have been highlighted for various reasons, ranging from their professional achievements to their personal lives. <b>Taylor Swift [...]</b> <b>Travis Kelce [...]</b> <b>Britney Spears [...]</b> <b>Justin Timberlake [...]</b></p> <p>These figures are frequently covered due to their high-profile status and the public’s interest in their careers and personal lives. Their activities, whether in music, sports, or personal relationships, have significant cultural and economic impacts, as evidenced by the media coverage and public reactions.</p>
<b>LLM Decision</b>	<p><b>Comprehensiveness: Winner=1 (Graph RAG).</b> Answer 1 is better because it provides a more comprehensive and detailed list of public figures from a wider range of entertainment sectors, including film, television, music, sports, gaming, and digital media. It also includes examples of their contributions and the impact they have on their respective fields, as well as mentions of controversies and their implications. Answer 2, while detailed in its coverage of a few individuals, is limited to a smaller number of public figures and focuses primarily on their personal lives and relationships rather than a broad spectrum of their professional influence across the entertainment industry.</p> <p><b>Diversity: Winner=1 (Graph RAG).</b> Answer 1 is better because it provides a more varied and rich response by covering a wide range of public figures from different sectors of the entertainment industry, including film, television, music, sports, gaming, and digital media. It offers insights into the contributions and influence of these figures, as well as controversies and their impact on public discourse. The answer also cites specific data sources for each mentioned figure, indicating a diverse range of evidence to support the claims. In contrast, Answer 2 focuses on a smaller group of public figures, primarily from the music industry and sports, and relies heavily on a single source for data, which makes it less diverse in perspectives and insights.</p> <p><b>Empowerment: Winner=1 (Graph RAG).</b> Answer 1 is better because it provides a comprehensive and structured overview of public figures across various sectors of the entertainment industry, including film, television, music, sports, and digital media. It lists multiple individuals, providing specific examples of their contributions and the context in which they are mentioned in entertainment articles, along with references to data reports for each claim. This approach helps the reader understand the breadth of the topic and make informed judgments without being misled. In contrast, Answer 2 focuses on a smaller group of public figures and primarily discusses their personal lives and relationships, which may not provide as broad an understanding of the topic. While Answer 2 also cites sources, it does not match the depth and variety of Answer 1.</p> <p><b>Directness: Winner=2 (Naïve RAG).</b> Answer 2 is better because it directly lists specific public figures who are repeatedly mentioned across various entertainment articles, such as Taylor Swift, Travis Kelce, Britney Spears, and Justin Timberlake, and provides concise explanations for their frequent mentions. Answer 1, while comprehensive, includes a lot of detailed information about various figures in different sectors of entertainment, which, while informative, does not directly answer the question with the same level of conciseness and specificity as Answer 2.</p>



## E System Prompts

### E.1 Element Instance Generation

```
---Goal---
Given a text document that is potentially relevant to this activity and a list of entity types, identify
all entities of those types from the text and all relationships among the identified entities.

---Steps---
1. Identify all entities. For each identified entity, extract the following information:
- entity_name: Name of the entity, capitalized
- entity_type: One of the following types: [{entity_types}]
- entity_description: Comprehensive description of the entity's attributes and activities

Format each entity as ("entity"{tuple_delimiter}<entity_name>{tuple_delimiter}<entity_type>{tuple_
delimiter}<entity_description>

2. From the entities identified in step 1, identify all pairs of (source_entity, target_entity) that
are *clearly related* to each other
For each pair of related entities, extract the following information:
- source_entity: name of the source entity, as identified in step 1
- target_entity: name of the target entity, as identified in step 1
- relationship_description: explanation as to why you think the source entity and the target entity are
related to each other
- relationship_strength: a numeric score indicating strength of the relationship between the source entity
and target entity

Format each relationship as ("relationship"{tuple_delimiter}<source_entity>{tuple_delimiter}<target_
entity>{tuple_delimiter}<relationship_description>{tuple_delimiter}<relationship_strength>)

3. Return output in English as a single list of all the entities and relationships identified in steps 1
and 2. Use **{record_delimiter}** as the list delimiter.

4. When finished, output {completion_delimiter}

---Examples---

Entity_types: ORGANIZATION,PERSON

Input:

The Fed is scheduled to meet on Tuesday and Wednesday, with the central bank planning to release its
latest policy decision on Wednesday at 2:00 p.m. ET, followed by a press conference where Fed Chair
Jerome Powell will take questions. Investors expect the Federal Open Market Committee to hold its
benchmark interest rate steady in a range of 5.25%-5.5%.

Output:

("entity"{tuple_delimiter}FED{tuple_delimiter}ORGANIZATION{tuple_delimiter}The Fed is the Federal Reserve,
which is setting interest rates on Tuesday and Wednesday)
{record_delimiter}
("entity"{tuple_delimiter}JEROME POWELL{tuple_delimiter}PERSON{tuple_delimiter}Jerome Powell is the chair
of the Federal Reserve)
{record_delimiter}
("entity"{tuple_delimiter}FEDERAL OPEN MARKET COMMITTEE{tuple_delimiter}ORGANIZATION{tuple_delimiter}The
Federal Reserve committee makes key decisions about interest rates and the growth of the United States
money supply)
{record_delimiter}
("relationship"{tuple_delimiter}JEROME POWELL{tuple_delimiter}FED{tuple_delimiter}Jerome Powell is the
Chair of the Federal Reserve and will answer questions at a press conference{tuple_delimiter}9)
{completion_delimiter}
```

...More examples...

---Real Data---

```
Entity_types: {entity_types}
Input:
{input_text}

Output:
```

### E.2 Community Summary Generation

```
---Role---
You are an AI assistant that helps a human analyst to perform general information discovery. Information
discovery is the process of identifying and assessing relevant information associated with certain
entities (e.g., organizations and individuals) within a network.
```

---Goal---

Write a comprehensive report of a community, given a list of entities that belong to the community as well as their relationships and optional associated claims. The report will be used to inform decision-makers about information associated with the community and their potential impact. The content of this report includes an overview of the community's key entities, their legal compliance, technical capabilities, reputation, and noteworthy claims.

---Report Structure---

The report should include the following sections:

- TITLE: community's name that represents its key entities - title should be short but specific. When possible, include representative named entities in the title.
- SUMMARY: An executive summary of the community's overall structure, how its entities are related to each other, and significant information associated with its entities.
- IMPACT SEVERITY RATING: a float score between 0-10 that represents the severity of IMPACT posed by entities within the community. IMPACT is the scored importance of a community.
- RATING EXPLANATION: Give a single sentence explanation of the IMPACT severity rating.
- DETAILED FINDINGS: A list of 5-10 key insights about the community. Each insight should have a short summary followed by multiple paragraphs of explanatory text grounded according to the grounding rules below. Be comprehensive.

Return output as a well-formed JSON-formatted string with the following format:

```
{
  "title": <report.title>,
  "summary": <executive.summary>,
  "rating": <impact.severity.rating>,
  "rating_explanation": <rating.explanation>,
  "findings": [
    {
      "summary": <insight.1.summary>,
      "explanation": <insight.1.explanation>
    },
    {
      "summary": <insight.2.summary>,
      "explanation": <insight.2.explanation>
    }
  ]
}
```

---Grounding Rules---

Points supported by data should list their data references as follows:

"This is an example sentence supported by multiple data references [Data: <dataset name> (record ids); <dataset name> (record ids)]."

Do not list more than 5 record ids in a single reference. Instead, list the top 5 most relevant record ids and add "+more" to indicate that there are more.

For example:

"Person X is the owner of Company Y and subject to many allegations of wrongdoing [Data: Reports (1), Entities (5, 7); Relationships (23); Claims (7, 2, 34, 64, 46, +more)]."

where 1, 5, 7, 23, 2, 34, 46, and 64 represent the id (not the index) of the relevant data record.

Do not include information where the supporting evidence for it is not provided.

---Example---

Input:

Entities

id,entity,description

5,VERDANT OASIS PLAZA,Verdant Oasis Plaza is the location of the Unity March

6,HARMONY ASSEMBLY,Harmony Assembly is an organization that is holding a march at Verdant Oasis Plaza

Relationships

id,source,target,description

37,VERDANT OASIS PLAZA,UNITY MARCH,Verdant Oasis Plaza is the location of the Unity March

38,VERDANT OASIS PLAZA,HARMONY ASSEMBLY,Harmony Assembly is holding a march at Verdant Oasis Plaza

39,VERDANT OASIS PLAZA,UNITY MARCH,The Unity March is taking place at Verdant Oasis Plaza

40,VERDANT OASIS PLAZA,TRIBUNE SPOTLIGHT,Tribune Spotlight is reporting on the Unity march taking place at Verdant Oasis Plaza

41,VERDANT OASIS PLAZA,BAILEY ASADI,Bailey Asadi is speaking at Verdant Oasis Plaza about the march

43,HARMONY ASSEMBLY,UNITY MARCH,Harmony Assembly is organizing the Unity March

Output:

```

{{
  "title": "Verdant Oasis Plaza and Unity March",
  "summary": "The community revolves around the Verdant Oasis Plaza, which is the location of the Unity March. The plaza has relationships with the Harmony Assembly, Unity March, and Tribune Spotlight, all of which are associated with the march event.",
  "rating": 5.0,
  "rating-explanation": "The impact severity rating is moderate due to the potential for unrest or conflict during the Unity March.",
  "findings": [
    {{
      "summary": "Verdant Oasis Plaza as the central location",
      "explanation": "Verdant Oasis Plaza is the central entity in this community, serving as the location for the Unity March. This plaza is the common link between all other entities, suggesting its significance in the community. The plaza's association with the march could potentially lead to issues such as public disorder or conflict, depending on the nature of the march and the reactions it provokes. [Data: Entities (5), Relationships (37, 38, 39, 40, 41,+more)]"
    }},
    {{
      "summary": "Harmony Assembly's role in the community",
      "explanation": "Harmony Assembly is another key entity in this community, being the organizer of the march at Verdant Oasis Plaza. The nature of Harmony Assembly and its march could be a potential source of threat, depending on their objectives and the reactions they provoke. The relationship between Harmony Assembly and the plaza is crucial in understanding the dynamics of this community. [Data: Entities(6), Relationships (38, 43)]"
    }},
    {{
      "summary": "Unity March as a significant event",
      "explanation": "The Unity March is a significant event taking place at Verdant Oasis Plaza. This event is a key factor in the community's dynamics and could be a potential source of threat, depending on the nature of the march and the reactions it provokes. The relationship between the march and the plaza is crucial in understanding the dynamics of this community. [Data: Relationships (39)]"
    }},
    {{
      "summary": "Role of Tribune Spotlight", "explanation": "Tribune Spotlight is reporting on the Unity March taking place in Verdant Oasis Plaza. This suggests that the event has attracted media attention, which could amplify its impact on the community. The role of Tribune Spotlight could be significant in shaping public perception of the event and the entities involved. [Data: Relationships (40)]"
    }}
  ]
}}

```

---Real Data---

Use the following text for your answer. Do not make anything up in your answer.

Input:

{input.text}

...Report Structure and Grounding Rules Repeated...

Output:

### E.3 Community Answer Generation

---Role---

You are a helpful assistant responding to questions about a dataset by synthesizing perspectives from multiple analysts.

---Goal---

Generate a response of the target length and format that responds to the user's question, summarize all the reports from multiple analysts who focused on different parts of the dataset, and incorporate any relevant general knowledge.

Note that the analysts' reports provided below are ranked in the **descending order of helpfulness**.

If you don't know the answer, just say so. Do not make anything up.

The final response should remove all irrelevant information from the analysts' reports and merge the cleaned information into a comprehensive answer that provides explanations of all the key points and implications appropriate for the response length and format.

Add sections and commentary to the response as appropriate for the length and format. Style the response in markdown.

The response shall preserve the original meaning and use of modal verbs such as "shall", "may" or "will".

The response should also preserve all the data references previously included in the analysts' reports,

but do not mention the roles of multiple analysts in the analysis process.

Do not list more than 5 record ids in a single reference. Instead, list the top 5 most relevant record ids and add "+more" to indicate that there are more.

For example:

"Person X is the owner of Company Y and subject to many allegations of wrongdoing [Data: Reports (2, 7, 34, 46, 64, +more)]. He is also CEO of company X [Data: Reports (1, 3)]"

where 1, 2, 3, 7, 34, 46, and 64 represent the id (not the index) of the relevant data record.

Do not include information where the supporting evidence for it is not provided.

---Target response length and format---

{response\_type}

---Analyst Reports---

{report\_data}

...Goal and Target response length and format repeated...

Add sections and commentary to the response as appropriate for the length and format. Style the response in markdown.

Output:

## E.4 Global Answer Generation

---Role---

You are a helpful assistant responding to questions about data in the tables provided.

---Goal---

Generate a response of the target length and format that responds to the user's question, summarize all relevant information in the input data tables appropriate for the response length and format, and incorporate any relevant general knowledge.

If you don't know the answer, just say so. Do not make anything up.

The response shall preserve the original meaning and use of modal verbs such as "shall", "may" or "will".

Points supported by data should list the relevant reports as references as follows:

"This is an example sentence supported by data references [Data: Reports (report ids)]"

*Note: the prompts for SS (semantic search) and TS (text summarization) conditions use "Sources" in place of "Reports" above.*

Do not list more than 5 record ids in a single reference. Instead, list the top 5 most relevant record ids and add "+more" to indicate that there are more.

For example:

"Person X is the owner of Company Y and subject to many allegations of wrongdoing [Data: Reports (2, 7, 64, 46, 34, +more)]. He is also CEO of company X [Data: Reports (1, 3)]"

where 1, 2, 3, 7, 34, 46, and 64 represent the id (not the index) of the relevant data report in the provided tables.

Do not include information where the supporting evidence for it is not provided.

At the beginning of your response, generate an integer score between 0-100 that indicates how **helpful** is this response in answering the user's question. Return the score in this format: <ANSWER\_HELPFULNESS> score.value </ANSWER\_HELPFULNESS>.

---Target response length and format---

{response\_type}

---Data tables---

{context\_data}

...Goal and Target response length and format repeated...

Output:

## F Evaluation Prompts

### F.1 Relative Assessment Prompt

---Role---

You are a helpful assistant responsible for grading two answers to a question that are provided by two different people.

---Goal---

Given a question and two answers (Answer 1 and Answer 2), assess which answer is better according to the following measure:

{criteria}

Your assessment should include two parts:

- Winner: either 1 (if Answer 1 is better) and 2 (if Answer 2 is better) or 0 if they are fundamentally similar and the differences are immaterial.
- Reasoning: a short explanation of why you chose the winner with respect to the measure described above.

Format your response as a JSON object with the following structure:

```
{{
  "winner": <1, 2, or 0>,
  "reasoning": "Answer 1 is better because <your reasoning>."
}}
```

---Question---

{question}

---Answer 1---

{answer1}

---Answer 2---

{answer2}

Assess which answer is better according to the following measure:

{criteria}

Output:

### F.2 Relative Assessment Metrics

```
CRITERIA = {
  "comprehensiveness": "How much detail does the answer provide to cover all the aspects and details of the question? A comprehensive answer should be thorough and complete, without being redundant or irrelevant. For example, if the question is 'What are the benefits and drawbacks of nuclear energy?', a comprehensive answer would provide both the positive and negative aspects of nuclear energy, such as its efficiency, environmental impact, safety, cost, etc. A comprehensive answer should not leave out any important points or provide irrelevant information. For example, an incomplete answer would only provide the benefits of nuclear energy without describing the drawbacks, or a redundant answer would repeat the same information multiple times.",
  "diversity": "How varied and rich is the answer in providing different perspectives and insights on the question? A diverse answer should be multi-faceted and multi-dimensional, offering different viewpoints and angles on the question. For example, if the question is 'What are the causes and effects of climate change?', a diverse answer would provide different causes and effects of climate change, such as greenhouse gas emissions, deforestation, natural disasters, biodiversity loss, etc. A diverse answer should also provide different sources and evidence to support the answer. For example, a single-source answer would only cite one source or evidence, or a biased answer would only provide one perspective or opinion.",
  "directness": "How specifically and clearly does the answer address the question? A direct answer should provide a clear and concise answer to the question. For example, if the question is 'What is the capital of France?', a direct answer would be 'Paris'. A direct answer should not provide any irrelevant or unnecessary information that does not answer the question. For example, an indirect answer would be 'The capital of France is located on the river Seine'.",
  "empowerment": "How well does the answer help the reader understand and make informed judgements about the topic without being misled or making fallacious assumptions. Evaluate each answer on the quality of answer as it relates to clearly explaining and providing reasoning and sources behind the claims in the answer."
}
```

## G Statistical Analysis

Table 6: Pairwise comparisons of six conditions on four metrics across 125 questions and two datasets. For each question and metric, the winning condition received a score of 100, the losing condition received a score of 0, and in the event of a tie, each condition was scored 50. These scores were then averaged over five evaluation runs for each condition. Results of Shapiro-Wilk tests indicated that the data did not follow a normal distribution. Thus, non-parametric tests (Wilcoxon signed-rank tests) were employed to assess the performance differences between pairs of conditions, with Holm-Bonferroni correction applied to account for multiple pairwise comparisons. The corrected p-values that indicated statistically significant differences are highlighted in bold.

		Podcast Transcripts				News Articles				
	Condition 1	Condition 2	Mean 1	Mean 2	Z-value	p-value	Mean 1	Mean 2	Z-value	p-value
Comprehensiveness	C0	TS	50.24	49.76	-0.06	1	55.52	44.48	-2.03	0.17
	C1	TS	51.92	48.08	-1.56	0.633	58.8	41.2	-3.62	<b>0.002</b>
	C2	TS	57.28	42.72	-4.1	<b>&lt;0.001</b>	62.08	37.92	-5.07	<b>&lt;0.001</b>
	C3	TS	56.48	43.52	-3.42	<b>0.006</b>	63.6	36.4	-5.63	<b>&lt;0.001</b>
	C0	SS	71.92	28.08	-6.2	<b>&lt;0.001</b>	71.76	28.24	-6.3	<b>&lt;0.001</b>
	C1	SS	75.44	24.56	-7.45	<b>&lt;0.001</b>	74.72	25.28	-7.78	<b>&lt;0.001</b>
	C2	SS	77.76	22.24	-8.17	<b>&lt;0.001</b>	79.2	20.8	-8.34	<b>&lt;0.001</b>
	C3	SS	78.96	21.04	-8.12	<b>&lt;0.001</b>	79.44	20.56	-8.44	<b>&lt;0.001</b>
	TS	SS	83.12	16.88	-8.85	<b>&lt;0.001</b>	79.6	20.4	-8.27	<b>&lt;0.001</b>
	C0	C1	53.2	46.8	-1.96	0.389	51.92	48.08	-0.45	0.777
	C0	C2	50.24	49.76	-0.23	1	53.68	46.32	-1.54	0.371
	C1	C2	51.52	48.48	-1.62	0.633	57.76	42.24	-4.01	<b>&lt;0.001</b>
	C0	C3	49.12	50.88	-0.56	1	52.16	47.84	-0.86	0.777
	C1	C3	50.32	49.68	-0.66	1	55.12	44.88	-2.94	<b>0.016</b>
	C2	C3	52.24	47.76	-1.97	0.389	58.64	41.36	-3.68	<b>0.002</b>
Diversity	C0	TS	50.24	49.76	-0.11	1	46.88	53.12	-1.38	0.676
	C1	TS	50.48	49.52	-0.12	1	54.64	45.36	-1.88	0.298
	C2	TS	57.12	42.88	-2.84	<b>0.036</b>	55.76	44.24	-2.16	0.184
	C3	TS	54.32	45.68	-2.39	0.1	60.16	39.84	-4.07	<b>&lt;0.001</b>
	C0	SS	76.56	23.44	-7.12	<b>&lt;0.001</b>	62.08	37.92	-3.57	<b>0.003</b>
	C1	SS	75.44	24.56	-7.33	<b>&lt;0.001</b>	64.96	35.04	-4.92	<b>&lt;0.001</b>
	C2	SS	80.56	19.44	-8.21	<b>&lt;0.001</b>	70.56	29.44	-6.29	<b>&lt;0.001</b>
	C3	SS	80.8	19.2	-8.3	<b>&lt;0.001</b>	69.12	30.88	-5.53	<b>&lt;0.001</b>
	TS	SS	82.08	17.92	-8.43	<b>&lt;0.001</b>	67.2	32.8	-4.85	<b>&lt;0.001</b>
	C0	C1	49.76	50.24	-0.13	1	39.68	60.32	-3.61	<b>0.003</b>
	C0	C2	46.32	53.68	-1.5	0.669	40.96	59.04	-3.14	<b>0.012</b>
	C1	C2	44.08	55.92	-3.27	<b>0.011</b>	50.24	49.76	-0.22	1
	C0	C3	44	56	-2.6	0.065	41.04	58.96	-3.47	<b>0.004</b>
	C1	C3	45.44	54.56	-2.98	<b>0.026</b>	49.52	50.48	-0.01	1
	C2	C3	48.48	51.52	-0.96	1	50.96	49.04	-0.39	1
Empowerment	C0	TS	40.96	59.04	-4.3	<b>&lt;0.001</b>	42.24	57.76	-3.32	<b>0.012</b>
	C1	TS	45.2	54.8	-3.76	<b>0.002</b>	50	50	-0.12	1
	C2	TS	47.68	52.32	-2.2	0.281	49.52	50.48	-0.22	1
	C3	TS	48.72	51.28	-1.27	1	51.68	48.32	-1.2	1
	C0	SS	42.96	57.04	-3.71	<b>0.003</b>	42.72	57.28	-3.12	<b>0.022</b>
	C1	SS	47.68	52.32	-1.5	0.936	51.36	48.64	-0.84	1
	C2	SS	50.72	49.28	-0.55	1	49.84	50.16	-0.2	1
	C3	SS	48.96	51.04	-0.57	1	49.52	50.48	-0.08	1
	TS	SS	57.52	42.48	-4.1	<b>&lt;0.001</b>	52.88	47.12	-1.1	1
	C0	C1	48.72	51.28	-1.23	1	42.4	57.6	-3.9	<b>0.001</b>
	C0	C2	46.64	53.36	-2.54	0.12	44.8	55.2	-2.16	0.336
	C1	C2	49.28	50.72	-1.73	0.682	52	48	-1.45	1
	C0	C3	47.6	52.4	-1.78	0.682	44.32	55.68	-3.45	<b>0.008</b>
	C1	C3	50	50	0	1	51.44	48.56	-1.02	1
	C2	C3	50.72	49.28	-0.86	1	50.4	49.6	-0.22	1
Directness	C0	TS	44.96	55.04	-4.09	<b>&lt;0.001</b>	45.2	54.8	-3.68	<b>0.003</b>
	C1	TS	47.92	52.08	-2.41	0.126	46.64	53.36	-2.91	<b>0.04</b>
	C2	TS	48.8	51.2	-2.23	0.179	48.32	51.68	-2.12	0.179
	C3	TS	48.08	51.92	-2.23	0.179	48.32	51.68	-2.56	0.074
	C0	SS	35.12	64.88	-6.17	<b>&lt;0.001</b>	41.44	58.56	-4.82	<b>&lt;0.001</b>
	C1	SS	40.32	59.68	-4.83	<b>&lt;0.001</b>	45.2	54.8	-3.19	<b>0.017</b>
	C2	SS	40.4	59.6	-4.67	<b>&lt;0.001</b>	44.88	55.12	-3.65	<b>0.003</b>
	C3	SS	40.48	59.52	-4.69	<b>&lt;0.001</b>	45.6	54.4	-2.86	<b>0.043</b>
	TS	SS	43.6	56.4	-3.96	<b>&lt;0.001</b>	46	54	-2.68	0.066
	C0	C1	46.96	53.04	-2.87	<b>0.037</b>	47.6	52.4	-2.17	0.179
	C0	C2	48.4	51.6	-2.06	0.197	48.48	51.52	-1.61	0.321
	C1	C2	49.84	50.16	-1	0.952	49.28	50.72	-1.6	0.321
	C0	C3	48.4	51.6	-1.8	0.29	47.2	52.8	-2.62	0.071
	C1	C3	49.76	50.24	0	1	48.8	51.2	-1.29	0.321
	C2	C3	50	50	0	1	48.8	51.2	-1.84	0.262