Auto-Cypher: Improving LLMs on Cypher generation via LLM-supervised generation-verification framework

Aman Tiwari[*], **Shiva Krishna Reddy Malay**[*], **Vikas Yadav**,
Masoud Hashemi, **Sathwik Tejaswi Madhusudhan**

ServiceNow Research

{aman.tiwari, shivakrishnareddy.ma, vikas.yadav,
masoud.hashemi, sathwikt.madhusudhan}@servicenow.com

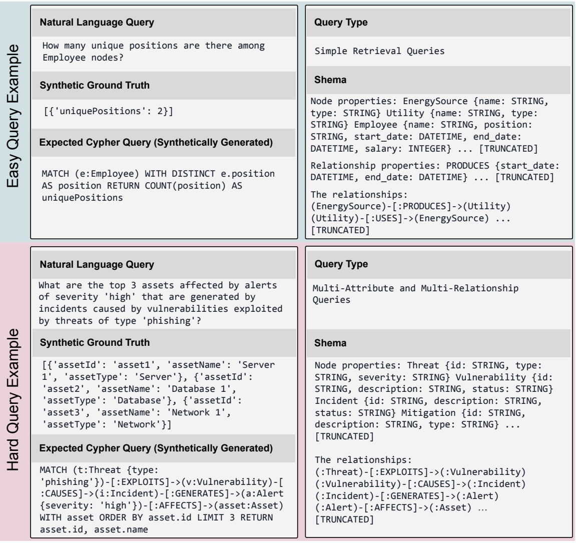
Abstract

Graph databases like Neo4j are gaining popularity for handling complex, interconnected data, over traditional relational databases in modeling and querying relationships. While translating natural language into SQL queries is well-researched, generating Cypher queries for Neo4j remains relatively underexplored. In this work, we present an automated, LLM-Supervised, pipeline to generate high-quality synthetic data for Text2Cypher. Our Cypher data generation pipeline introduces LLM-as-Database-Filler, a novel strategy for ensuring Cypher query correctness, thus resulting in high quality generations. Using our pipeline, we generate high quality Text2Cypher data, `SynthCypher`, containing 29.8k instances across various domains and queries with varying complexities. Training open-source LLMs like LLaMa-3.1-8B, Mistral-7B, and QWEN-7B on `SynthCypher` results in performance gains of up to 40% on the Text2Cypher test split and 30% on the SPIDER benchmark, adapted for graph databases.

Keywords: Synthetic Data, Text2Cypher, Large Language Models, Graph Databases, Cypher Query Generation, Knowledge Graphs, Neo4j, Natural Language Interfaces.

1 Introduction

As the use of graph databases like Neo4j (neo, 2024) grows, converting natural language into Cypher queries (Text2Cypher) is becoming increasingly important. Cypher (Francis et al., 2018), designed for querying and analyzing graph data, is well-suited for applications such as social networks, recommendation systems, and knowledge graphs (Ji et al., 2021). However, generating Cypher queries from natural language poses challenges due to the complexity of graph structures, which surpasses that of relational databases. Large language models (LLMs) have shown promise in Text2Cypher tasks. However, unlike Text2SQL, which benefits from extensive datasets and benchmarks (Deng et al., 2021; Li et al., 2023; Shi et al., 2024), resources for training LLMs to generate accurate Cypher queries are limited.


Easy Query Example
Hard Query Example

Natural Language Query

```
How many unique positions are there among
Employee nodes?
```

Synthetic Ground Truth

```
[{'uniquePositions': 2}]
```

Expected Cypher Query (Synthetically Generated)

```
MATCH (e:Employee) WITH DISTINCT e.position
AS position RETURN COUNT(position) AS
uniquePositions
```

Query Type

```
Simple Retrieval Queries
```

Shema

```
Node properties: EnergySource {name: STRING,
type: STRING} Utility {name: STRING, type:
STRING} Employee {name: STRING, position:
STRING, start_date: DATETIME, end_date:
DATETIME, salary: INTEGER} ... [TRUNCATED]

Relationship properties: PRODUCES {start_date:
DATETIME, end_date: DATETIME} ... [TRUNCATED]

The relationships:
(EnergySource)-[:PRODUCES]->(Utility)
(Utility)-[:USES]->(EnergySource) ...
[TRUNCATED]
```

Natural Language Query

```
What are the top 3 assets affected by alerts
of severity 'high' that are generated by
incidents caused by vulnerabilities exploited
by threats of type 'phishing'?
```

Synthetic Ground Truth

```
[{'assetId': 'asset1', 'assetName': 'Server
1', 'assetType': 'Server'}, {'assetId':
'asset2', 'assetName': 'Database 1',
'assetType': 'Database'}, {'assetId':
'asset3', 'assetName': 'Network 1',
'assetType': 'Network'}]
```

Expected Cypher Query (Synthetically Generated)

```
MATCH (t:Threat {type:
'phishing'})-[:EXPLOITS]->(v:Vulnerability)-[
:CAUSES]->(i:Incident)-[:GENERATES]->(a:Alert
{severity: 'high'})-[:AFFECTS]->(asset:Asset)
WITH asset ORDER BY asset.id LIMIT 3 RETURN
asset.id, asset.name
```

Query Type

```
Multi-Attribute and Multi-Relationship
Queries
```

Shema

```
Node properties: Threat {id: STRING, type:
STRING, severity: STRING} Vulnerability {id:
STRING, description: STRING, status: STRING}
Incident {id: STRING, description: STRING,
status: STRING} Mitigation {id: STRING,
description: STRING, type: STRING} ...
[TRUNCATED]

The relationships:
(:Threat)-[:EXPLOITS]->(:Vulnerability)
(:Vulnerability)-[:CAUSES]->(:Incident)
(:Incident)-[:GENERATES]->(:Alert)
(:Alert)-[:AFFECTS]->(:Asset) …
[TRUNCATED]
```

Figure 1: Example showing an input *Natural Language Query* converted to *Cypher Query* for the given *Schema*. The example on top shows an easy retrieval question while the bottom example shows complex Multi-Attribute and Multi-Relationship Query.

To address these limitations, we introduce an automated data generation pipeline specifically designed for Text2Cypher tasks. Our proposed pipeline generates high-quality synthetic Cypher queries to enable supervised fine-tuning of LLMs for Text2Cypher task, ensuring more precise natural language to Cypher translation. The pipeline begins by generating diverse graphical schemas across a wide range of domains and complexity. For these schemas, we generate natural language questions covering substantial taxonomies (such as simple retrieval, complex aggregation, path-finding,

[*] Co-first authors with equal contribution.

The dataset used in this work is available at: https://huggingface.co/datasets/ServiceNow-AI/SynthCypher.

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etc.), which are then used to create corresponding Cypher queries. A key feature of our pipeline is the LLM-as-Database-Filler which generates synthetic Neo4j databases. Finally, in the validation step only executable queries that produce correct results are retained. This results in SynthCypher, a robust and diverse dataset for Text2Cypher tasks.

Using SynthCypher, we trained LLMs including Qwen 2.5 (Hui et al., 2024), Llama 3.1 (Van Der Maaten et al., 2024), and Mistral (Jiang et al., 2023), along with their code-specialized versions. Moreover, due to the lack of a widely accepted benchmark for Cypher, we adapted the SPIDER (Deng et al., 2020) benchmark, originally designed for Text2SQL, to serve as a benchmark for graph databases.

Our contributions are threefold: (1) We introduce a pipeline for Cypher code generation that ensures valid queries via robust validation, producing the high-quality dataset SynthCypher with 29.8k training and 2k test samples, covering 109 query taxonomies and 700 domains. The LLM-as-Database-Filler method generates synthetic Neo4j databases to verify query correctness. (2) We fine-tune state-of-the-art LLMs (Qwen, Llama 3.1, Mistral) on text2Cypher tasks. Models fine-tuned with SynthCypher show up to 40% accuracy improvement on 7B & 8B models and 30% on a modified SPIDER benchmark. (3) We adapt the SPIDER benchmark for Cypher query generation, addressing the lack of Cypher benchmarks.

2 Related Work

Prior works on natural language querying of knowledge graphs using Cypher has mostly focused on traditional NER based extraction (Liang et al., 2021; Hains et al., 2023) or manual annotation (Guo et al., 2022) approaches which make them both limited in scope, and cumbersome to write. LLMs have shown promising potential for Text2Cypher task where recently, Neo4j Labs published a GPT-4o generated dataset (tom, 2024), initiating first efforts on Text2Cypher data generation. Importantly, this Text2Cypher data without any validation steps on a limited domain set, with only 6 query types on HuggingFace (Wolf et al., 2019) results only in 50% correctly executable cyphers. Concurrent (peer-reviewed unpublished) Synth2C (Zhong et al., 2024) generates Cyphers using GPT-4o similar to Neo4j Labs as well as a templatized pipeline with traditional NLP techniques and llm-as-judge to validate generated cypher descriptions against original questions. However, this technique again does not check for execution correctness and is furthermore limited only to Medical domain (with datasets not publicly available).

The Text2SQL problem has been extensively studied in the literature, with numerous benchmarks and datasets (Zhong et al., 2017; Deng et al., 2020; Li et al., 2024; Chang et al., 2023; Yu et al., 2018b; Deng et al., 2022). Among these, SPIDER (Deng et al., 2020) is specially a prominent dataset covering a broad range of real-world scenarios. However, its real-world applicability remains uncertain, as evidenced by the SPIDER-V2 (Cao et al., 2024) benchmark, where GPT-4 achieves only a 6% pass@1.

3 Data Generation Pipeline

Synthetic data generation (Xu et al., 2023; Luo et al., 2023; Ouyang et al., 2022) have proven highly effective. We use LLMs such as Llama 3.1 70B (Van Der Maaten et al., 2024), Mixtral 8x22B (Jiang et al., 2024), and GPT-4 (OpenAI, 2023) to automatically generate diverse domains, schemas, natural language queries, and Cypher queries. Our pipeline covers a broad range of domains and query types, ensuring diversity across topics and difficulty. From data generation to validation, all steps are autonomously managed by models and scripts, allowing the process to run at scale. Generated Cypher queries are executed and validated against expected results to ensure quality.

Step 1: Schema Generation: We begin by random selection of the seed domains (e.g., e-commerce, inventory management) from Neo4j (neo, 2024) example databases. We then use Mixtral to expand these domains to cover 700 distinct domains. A skeleton schema is generated for each domain, outlining the nodes and relationships (Block 1 in Figure 2). These schemas are validated with GPT-4 for correctness and manually reviewed for coherence and real-world utility in 25% of cases. See Appendix B for more details on schema generation.

Step 2: Natural Language Question and Ground Truth Generation For each schema, we generate questions based on 109 predefined query types, such as “Simple Retrieval” or “Sub-Graph Queries” (Block 2 in Figure 2). A dummy ground truth answer for each query is also generated. In the next stage, we fill the database with entries including this dummy answer as the right answer for the

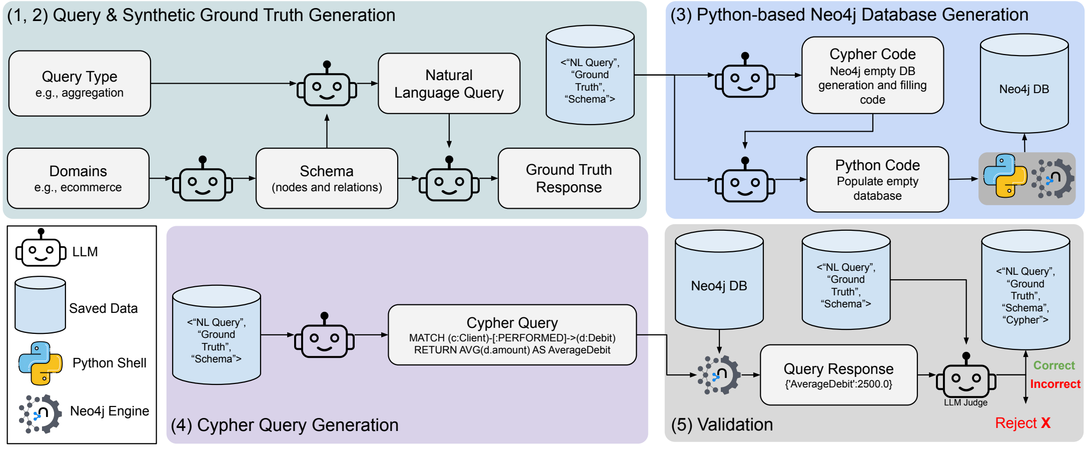
(1, 2) Query & Synthetic Ground Truth Generation
Query Type
e.g., aggregation
Natural Language Query
<"NL Query", "Ground Truth", "Schema">
Domains
e.g., ecommerce
Schema
(nodes and relations)
Ground Truth Response
(3) Python-based Neo4j Database Generation
Cypher Code
Neo4j empty DB generation and filling code
Neo4j DB
Python Code
Populate empty database
LLM
Saved Data
Python Shell
Neo4j Engine
<"NL Query", "Ground Truth", "Schema">
Cypher Query
MATCH (c:Client)-[:PERFORMED]->(d:Debit) RETURN AVG(d.amount) AS AverageDebit
(4) Cypher Query Generation
Neo4j DB
<"NL Query", "Ground Truth", "Schema">
<"NL Query", "Ground Truth", "Schema", "Cypher">
Query Response
{'AverageDebit':2500.0}
LLM Judge
Correct
Incorrect
Reject X
(5) Validation

Figure 2: Overview of the SynthCypher data generation pipeline, illustrating domain and schema creation, query and ground truth generation, database population, Cypher query generation, and validation steps.

question. See Appendix C for further details on question generation and query types.

Step 3: Neo4j Database Population An empty Neo4j database for each question is created which is populated with synthetic data that fits the schema, question, and ground truth. Python-based code, generated by GPT-4, is used to create and populate the database with nodes, relationships, and data, ensuring consistency between the schema and ground truth (Block 3 in Figure 2). To the best of our knowledge, this strategy of filling the database conditioned on a arbitrarily chosen dummy ground truth has not been explored in literature before. Reverse filling the database in this way enables execution of Cypher queries to check for execution success and Cypher-code correctness. Appendix E(8,9) provides more details on the data population process.

Step 4: Cypher Query Generation Next, the LLM generates Cypher queries for each question (Block 4 in Figure 2). Following latest work in inference time scaling, we allow the LLM to amply reason through various aspects of the Cypher query, such as relevant nodes, relationships, properties, nuances of the question as well as best coding practices. This iterative chain-of-thought reasoning process coupled with execution checks against the synthetically filled database ensures only the highest quality data is generated. See Appendix F for details on query generation.

Step 5: Validation of Cypher Queries To ensure accuracy, we validate the generated Cypher queries by executing them on the synthetic Neo4j database from Step-3 (Block 5 in Figure 2). The results are compared to the expected ground truth, and only queries that return correct results are retained and others retried up to 5 times before discarding. GPT-4 is used as a judge to validate the retrieved data against the ground-truth and ensure correctness of the Cypher query (Prompt 14 in appendix).

At the end of this process, we have a high-quality dataset, SynthCypher, that includes schema, Neo4j database, natural language questions, Cypher queries, and execution results. This dataset can be used for training and evaluating models aimed at converting natural language into Cypher code.

Split	Dataset	Count	Schema	Validation
Train	Ours	29,838	528	✓
Train	Neo4j Labs	7,735	15	×
Test	Ours	2,000	165	✓
Test	Neo4j Labs	-	-	-

Table 1: Comparison of datasets across training and testing splits

4 Experimental Setup

Data Setup: We used our dataset consisting of 25.8k samples spanning 109 query types and 528 schemas (Table 1) for training. The 109 query types in our SynthCypher represent diverse real-world Cypher use cases. For testing, we employed a separate dataset of 4k samples, covering all 109 query types across 165 schemas not included in train. This split ensures that the model is evaluated on a broad range of query complexities and schema variations. As an additional test dataset, we also adapt the popular SPIDER-SQL (Yu et al., 2018a) for Text2Cypher by modeling each table as a node and foreign key relationships.[1]

[1] Junction tables where all columns are foreign keys are still modeled as nodes for ease of data filling.

Setup	Model	SynCy-test	SPIDER
Base IFT	Llama-3.1-8B	30.9	30.8
	Mistral v0.2 7B	31.1	38.3
	Qwen2-7B	14.6	16.6
	Code-Llama-7B	38.5	37.3
	Code-Qwen-2.5	50.85	57.3
Instruct	Llama-3.1-8B	40.2	37.9
	Mistral v0.2 7B	27.7	25.2
	Qwen2-7B	29.2	33.5
	Code-Llama-7B	34.0	32.8
	Code-Qwen-2.5	29.2	50.8
	GPT-4o*	71	73.3
Base + SynCy (Ours)	Llama-3.1-8B	**71.4**	**62.2**
	Mistral v0.2 7B	69.4	61.3
	Qwen2-7B	67.1	55.2
	Code-Llama-7B	67.1	61.2
	Code-Qwen-2.5	70.1	62.1

Table 2: Last block shows Finetuning when our SynthCypher SFT data is mixed with UltraChat for text models/MagiCoder for code models. *gpt4o-2024-08-01-preview

Experiment Setup: We begin our experimentation by analysing the capabilities of the current state of the art 7B/8B models on Text2Cypher. We initially fully finetune three general base models, i.e. Llama 3.1 model(Van Der Maaten et al., 2024), Mistral-v0.2-7B(Jiang et al., 2023) and Qwen-2-7B(Hui et al., 2024), along with two code based models CodeLlama-7B and QwenCoder-2.5-7B. We use UltraChat-200K(Ding et al., 2023) for instruction-finetuning (IFT) the general models and MagiCoder-117K(Luo et al., 2023) for finetuning code models. These instruction finetuned model would highlight effectiveness of existing IFT datasets on Text2Cypher task. Next, we also benchmark off-the-shelf instruct versions of these models on both SynthCypher and SPIDER-Cypher.

In our last setup, we concatenate our generated SynthCypher data with UltraChat for finetuning the general LLMs (LLaMa and Mistral) and with MagiCoder for finetuning the code LLMs (CodeLLaMa and QwenCoder). We use learning rate of 1e-05, batch size of 128 over three epochs for training and take the best one based on a sub-sampled validation set. To the best of our knowledge, there is only one other dataset for this task, i.e. Tomasnjo_gpt4o(tom, 2024) which is a created by naively prompting GPT-4o and checking only the cypher produces *some* results. The authors indicate that only 50% of the cypher passed the test cases on a small (27 samples) human generated benchmark. We show comparison of Tomasnjo_gpt4o with our subsampled SynthCypher data (to match the training size of 7.7K instances) in fig. 3. We chose our best performing base LLM (LLaMa-3.1-8B) for this comparison.

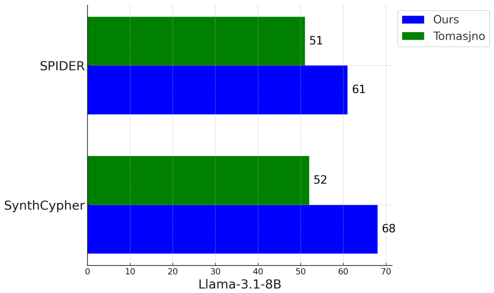

Figure 3: Evaluation on SynthCypher and SPIDER test splits from Llama3.1-8B fine-tuned with equal train size of down-sampled SynthCypher (ours) data and Neo4j Text2Cypher data.

Metric: We use an LLM-as-a-Judge variant of Exact Match (prompt 14), where GPT-4o assigns a score of 1 if all requested information in the question is present in the execution results, and 0 otherwise.

5 Results

As shown in Table-2, our SynthCypher dataset leads to significant improvements on both benchmarks across models. We draw several key observations:

(1) Need of Text2Cypher datasets - Both off-the-shelf instruct LLMs and our finetuned LLMs on base IFT datasets achieve very low performance. Thus, highlighting lack of Text2Cypher alignment of code LLMs and need of more Text2Cypher IFT datasets.

(2) Effectiveness of SynthCypher - LLMs finetuned with IFT data mix containing SynthCypher achieve 40% absolute improvement over the base IFT datasets and 30% over off-the-shelf instruct LLMs. These encouraging improvements highlight effectiveness of SynthCypher and directions for future works.

(3) SynthCypher pipeline - Comparison shown in fig. 3 clearly highlights effectiveness of our pipeline and SynthCypher over other existing dataset generated using GPT-4o. This highlights benefits of step-by-step controlled data generation for Text2Cypher.

6 Conclusion

In this work, we highlight and address the Text2Cypher gap in current open source models, and introduced a novel pipeline to automatically generate and validate high quality Text2Cypher data. Our presented dataset SynthCypher from our pipeline leads to substantial performance improvements across multiple LLMs. We also provide two evaluation benchmarks for future works in this direction.

7 Limitations

While synthetic data generation strategies have played a crucial role in open source LLM models, these strategies may pose risks in terms of reinforcing model biases, thereby resulting in a data distribution that may not model real world scenarios, or worse yet, cause real world harm (especially when applied to social graph networks). Furthermore, we have limited this research to smaller models and it is not clear if the same strategy would work on larger models.

SPIDER test dataset has been publicly released as of Feb-2024 and it is not clear if any of that data went into the pre-training of base models or the Instruct models we considered.

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A Appendix-1

B Schema Generation Process

We start with a seed list of 10 domains (e-commerce, IT Management, finance etc) as well as the domains in the Neo4J example databases on their website (neo, 2024). Then we prompt a Mixtral-822B model with higher temperature (0.8) to generate more such domains. Pooled together this yeilds 693 schemas which are split into Train and Test as shown in Table-1.

B.1 Nodes and Relationships

We start of by contructing a skeleton schema which includes the nodes and relationships that are *plausible* in the given domain. We elicit responses by conditioning on varying number of nodes and relationships, as well as various query taxonomies to cover a wide range of complexity in the graph as shown in Figure-4

B.2 Final Schema

Once we obtain the nodes and relationships sets, we come up with the full schema along with datatypes, properties and directed edges as shown in Figure-5. We elicit the model to reason through matching the nodes with the generated relationships and obtain a final schema. We manually vet 25% of the schemas to ensure diversity, coherence and real world usefulness.

C Question Generation

For every schema, 20 elicit questions at a time from Mixtral-8*22B by sequentially conditioning it on a randomly selected 7 query types. This ensured a diverse question set covering all domains and query types. We pass these questions through an simple LLM validation to ensure they are not too vague, for.e.g *"How many employees report to 'John Doe'?* rather than *How many employees report to a specific manager?*

D Synthetic Ground Truth Generation

For each question, we generate a dummy ground truth, which is of the expected structure, data-type and is plausibly true for that question. The prompt for the same is given in Figure-7 For e.g.

Question: "What is the total sales in USD for Apples in the California market and who made the most sales?"

Dummy answer: {"total_sales_usd": 10000, "employee": "John Doe"}

E Database Infilling

To fill the database with in such a way that the dummy answer is the right answer for the question, we come up with both positive (relevant to the question, and dummy answer) and negative data points (irrelevant to the question). The prompt is given in Figure-8 and Figure-9. A full example is given as well.

F Cypher Generation

We do this in four detailed steps so as to give the model ample reasoning and planning tokens. These include

- Analysing the user's question - Figure-10
- Identifying the pertinent nodes, relationships, and properties for the question. Figure-11
- Recalling the best practices and coding guidelines for Cypher, including performance concerns. 12
- Generating the final Cypher query. 13

Skeleton Schema Generation

```
You are an expert in Neo4j databases. You are given a Neo4J database name. Your job is to come
      up with a possible list of nodes and relationships in the database. The nodes and
     relationships should be in such a way that they could exist in a real-world scenario
     based on the database name provided.

Database Name: {database_name}

INSTRUCTIONS:
You need to design {num_nodes} nodes and {num_relationships} relationships that could be
     present in the database.

Relationships should be in the format of "RELATIONSHIP_NAME", i.e. all uppercase with spaces
     replaced by underscores.

** The same relationship can be SHARED by different kinds of nodes. So you should design these
      relationships such that they can connect various pairs of nodes. **

The nodes and releationships should be in such a way that we can ask the following kinds of
     queries on them:

{taxonomies}

You MUST explain how the queries of the above taxonomies can be used in the context of the
     nodes and relationships you have provided.

Return your response as JSON with the following format:
{{
"nodes": {node_examples},
"relationships": {relationship_examples}
}}

Output your result as:

Explanation: <your explanation here>

Json response: <your json response here>
```

Figure 4: Skeleton schema generation step using Mixtral-8*22B

Complete Schema Generation

```
You are an expert in Neo4j databases. You are given a Neo4J database name.
Your job is to come up with a possible schema for nodes and relationships in
the database.

# Instructions:
- Note that the node and relationship properties can have any of the
following types:
BOOLEAN, DATE, DURATION, FLOAT, INTEGER, LIST, LOCAL DATETIME, LOCAL TIME,
POINT, STRING,
ZONED DATETIME, and ZONED TIME.

- It is important that the generated schema can be used to create queries
such as the following:
Taxonomies:
{taxonomies}
The nodes should be formatted as given in the example below.
Example: If the node is 'Person', you should write it as:
Person {{name: STRING, age: INTEGER, date_of_birth: DATETIME}}
The relationship properties should be formatted as given in the example
below.
Example: If the relationship is 'WORKS_AT', you should write it as:
WORKS_AT {{ employee_id: STRING, since: DATETIME, salary: INTEGER}}
The relationships should be formatted as given in the example below.
Example: If the relationship is 'WORKS_AT', you should write it as:
(:Person)-[:WORKS_AT]->(:Employer)

# Example:
Database Name: movies
NODES: [Movie, Person]
RELATIONSHIPS: [ACTED_IN, REVIEWED, DIRECTED, PRODUCED, WROTE, FOLLOWS]
Schema:
```
Node properties:
Movie {{title: STRING, votes: INTEGER, tagline: STRING, released: INTEGER}}
Person {{born: INTEGER, name: STRING}}

Relationship properties:
ACTED_IN {{roles: LIST}}
REVIEWED {{summary: STRING, rating: INTEGER}}

The relationships:
(:Person)-[:ACTED_IN]->(:Movie)
(:Person)-[:DIRECTED]->(:Movie)
(:Person)-[:PRODUCED]->(:Movie)
(:Person)-[:WROTE]->(:Movie)
(:Person)-[:FOLLOWS]->(:Person)
(:Person)-[:REVIEWED]->(:Movie)
```
# Task:
Database Name: {database_name}
NODES: [{nodes_list}]
RELATIONSHIPS: [{relationships_list}]

Explanation: <Explain how the nodes, releationships, and properties can be used to frame
    queries
as per the taxonomies provided>.
Schema:
```
Node properties:
<your node properties here>
Relationship properties:
<your relationship properties here>
The relationships:
<your relationships here>
```
MAKE ABSOLUTELY SURE THAT SCHEMA IS IN THE ABOVE FORMAT WITH ```<schema>``` tags.
```

Figure 5: Complete schema generation step using Mixtral-8*22B

Question Generation

```
You are an expert in Neo4j databases. I will provide you with a schema, and
your task is to generate 20 unique questions directly related to that
specific graph schema.

## Task:
Generate 20 questions that focus on the schema's nodes and relationships.

## Steps for Question Generation:
1. Analyze the Schema: Examine the provided schema and identify relevant
nodes and relationships.
Select Nodes and Relationships: Based on the query type, choose nodes and
relationships to form
the questions.
2. Generate Diverse Questions: Create 20 questions, each addressing
different  aspects of the schema. Ensure no two questions are similar.
3. Cover Key Aspects: Each question should focus on distinct parts
of the schema, such as relationships between nodes, node properties, or
node types.
4. Vary Complexity: Ensure the questions range from basic to advanced,
covering various levels of query complexity.
Random Selection: Randomly select nodes or relationships when forming
each question, ensuring diversity in the coverage.
5. Specific Values: When generating questions involving values like date,
time, money, name, or location, use appropriate placeholder values
(e.g., ”2024-01-01” for a date. ”John Smith” for name etc). Be creative!
6. Clarity and Relevance: All questions should be clear, unambiguous, and
reflective of what a human would ask.

Important:
* Ensure each question includes all the information necessary for a
meaningful answer.
* Generate exactly 20 questions, ensuring they cover different aspects
of the schema and that
none are repetitive.

Type of query for which questions need to be generated are:
{Query Type}

Schema:
{Schema}
```

Figure 6: Question generation step using Mixtral-8*22B

Synthetic ground truth generation

~~~
You are an expert in Neo4j databases and creating test data. I have a Neo4j schema and a user
    query. I am creating a test dataset to validate my Neo4j Cypher queries. Your task is to
    analyze both the schema and the user question to determine which nodes, fields, and
    relationships are involved.

Based on your analysis, generate a dummy answer that closely mirrors what would be returned
    from a Neo4j query, without any post-processing. The fields in the dummy data should
    directly reflect the schema and be relevant to the user query.
**
Do not include fields unrelated to the question or absent from the schema.
**
The generated dummy data must:
- Be complete, concise, and accurate.
- Match the format returned by a Neo4j database.
- Use appropriate fields from the schema, without any unnecessary data.
- Reflect counts (votes, followers, etc.) as realistic and generally below
50, unless otherwise specified.
- Use correct ranges and units for numerical values
(e.g., convert "1 million" to "1000000").
- Ensure unique values for fields like IDs, timestamps,
or other attributes that require uniqueness in the database.

The output must be in valid, properly formatted JSON:
```json
{"Answer": <Dummy ANSWER>}
```
Before generating the answer, clearly define the nodes and relationships essential for
    covering the user question. If there are multiple records in the dummy data, ensure
    unique values for attributes such as IDs, timestamps, and steps.

Example user question:
Which Disney character laughed how many times, and what is their favorite color?

```json
{
  "Answer": [
    {
      "characterid": "b92",
      "characterName": "Mini",
      "laughed": 100,
      "favorite_color": "Red"
   },
   {
      "characterid": "d989",
      "characterName": "Jimmi",
      "laughed": 10,
      "favorite_color": "Blue"}]}
```
Schema:
{SCHEMA}

User Question:
{USER_QUESTION}
~~~

Figure 7: Synthetic ground truth generation step using Mixtral-8*22B

Code plan generation for database infilling

~~~
You are an expert in writing Python code. I am working on creating test data to validate Neo4j
     Cypher queries.
You will be provided with the Neo4j schema, a user question, and a ground truth answer.
Your task is to generate test case data that will populate an empty Neo4j database.

This will allow me to check if the Cypher query, based on the user's question, retrieves the
    correct result as per the ground truth answer. To ensure robust validation, the data you
    create must return the exact ground truth answer when queried, but the database should
    also include additional "negative" data points. These negative points must not interfere
    with the correct answer and will test the accuracy of the query.

Follow these steps:
Steps:
1. Analyze the User Question and Schema: Identify relevant nodes, relationships, and fields
    based on the schema and user question. Understand which entities are crucial to construct
     the ground truth answer.
2. Plan Data Population: Develop a structured plan that describes how the data will be
    populated. Include both the ground truth data and additional negative data points.
3. Write Cypher Queries:
   Provide the exact Cypher queries for:
   - Creating nodes and relationships for the ground truth answer.
   - Creating negative data points that do not match the answer but help ensure the test is
    comprehensive.
4. Comprehensive Negative Data: For the negative data points, ensure the information is random
    , and distinctly different from the ground truth. Include details like names, summaries,
    and other fields, making sure the negative data does not overlap with the ground truth.
5. Limit Negative Data Points: Do not create more than 5 negative data points. This ensures
    that the negative data is limited and doesn't overwhelm the test case.
6. Unique Fields for Negative Data: Fields like IDs, names, locations, or titles should be
    unique, especially in negative data points. Specify which fields require unique values,
    using UUIDs or similar approaches. Ensure this applies only to negative data; the ground
    truth must not use UUIDs.
7. UUID Usage in Negative Data: Assign UUIDs to variables before using them in the queries for
     negative data.
8. Relationship Creation: Create relationships between nodes using their IDs. Use the `MATCH`
    statement before creating relationships to ensure that the nodes exist and the correct
    connections are established.
9. Correct Range of Values: When populating fields like money, votes, or similar data, ensure
    they align with the question. For example, if the question mentions 1 million, use
    1000000; for 1.2 million, use 1200000.

Key Points to Remember:
- Order of Execution: Ensure that nodes are created before relationships.
- Use `MATCH` to verify node existence before establishing relationships.
- Correctness of Identifiers: Double-check that identifiers (like IDs) match between node
    creation and relationship creation queries. For instance, if a fruit node is created with
     `id = fruit1`; the same ID should be used in relationships.

For example:
```cypher
// Example for creating nodes and relationships
CREATE (fruit:Fruit {id: 'fruit1', name: 'apple'});
CREATE (juice:Juice {id: 'juice1', name: 'apple juice'});
MATCH (fruit:Fruit {id: 'fruit1'})
MATCH (juice:Juice {id: 'juice1'})
CREATE (fruit)-[:JUICED]->(juice);
```
- Ground Truth Accuracy: The ground truth answer must be present in the data.
This ensures the test works as expected, and only the ground truth will produce a valid answer
    .
- Proper Relationship Creation: Ensure relationships are established correctly by matching
    node IDs before creating the relationship.

Schema:
{SCHEMA}

User Question:
{USER_QUESTION}

Ground Truth Answer:
{SYNTHETIC_ANSWER_RESPONSE}
~~~

Figure 8: Code plan generation step using Gpt-4

Python code generation for database infilling

```
You are an expert in writing Python code. I am developing a test set of data to verify Neo4j
     Cypher queries. I will provide the Neo4j schema, user question, ground truth answer, and
     a code plan. Your task is to create test case data that populates an empty Neo4j database
      so that when
Cypher is executed based on the users question, it returns the correct answer from the
     database.

The data must ensure that querying the DB returns only the ground truth answer for the given
     question. Additionally, the database should contain negative data points that do not
     satisfy the query, ensuring the robustness of the test case. Follow these steps carefully:


Steps:
1. Analyze the schema and user question: Identify relevant nodes, fields, and relationships
     needed to answer the question.
2. Refer to the code plan: Follow the provided plan for structuring the data generation code.
3. Create relationships and nodes: Ensure all required relationships and nodes are generated
     in the database.
4. Write the Python code in a function `create_data()`: Return a list of Cypher queries that
     populate the DB to support the query validation.
5. No execution logic required: The function should return only the list of queries, not
     execute them.
6. Use real timestamps: Any fields like timestamps must reflect actual values.
7. Ground truth must satisfy the query: Ensure that only the ground truth data satisfies all
     conditions, and negative data does not.
8. Generate up to 5 negative data points: Each negative example should differ entirely from
     the ground truth (e.g., UUIDs, random names, summaries). Ensure negative data points are
     not more than five.
9. Use `MATCH` to ensure relationship correctness: Ensure relationships are created by
     matching node IDs before defining relationships.

Code Writing Suggestions:
- Avoid errors with f-strings by using string concatenation or `.format()` when needed.
- Assign UUIDs to variables before using them in queries to prevent errors.
- When creating relationships, first use `MATCH` to ensure nodes exist, then define the
relationships by their node IDs.

Key Points:
- Order of execution: Ensure nodes exist before creating relationships.
- Correctness of identifiers: Verify that `MATCH` statements correctly reference nodes created
      earlier.
- Consistency: Ensure the actual answer data perfectly satisfies the question, and negative
     examples do not match the query.

Example:
```
// Create fruit and juice nodes
CREATE (fruit:Fruit {id: 'fruit1', name: 'apple'});
CREATE (juice:Juice {id: 'juice1', name: 'apple juice'});

// Create the "Juiced" relationship
MATCH (fruit:Fruit {id: 'fruit1'})
MATCH (juice:Juice {id: 'juice1'})
CREATE (fruit)-[:JUICED]->(juice);
```
Important:
- Relationships: Ensure relationships are properly created by matching node IDs first.
- Correctness: Only the ground truth data should match the query conditions. Negative data
     should
never fulfill the query.
- Return format: Return the Python code wrapped in ```python  ``` tags.

Schema:
{SCHEMA}
User Question:
{USER_QUESTION}
Ground Truth Answer:
{SYNTHETIC_ANSWER_RESPONSE}
Code Plan:
{CODE_PLAN}
```

Figure 9: Python code generation step using Gpt-4

Cypher generation - Analyse user request

```
You are helpful and expert Neo4j and generating Cypher queries assistant.
You will be given
- Neo4j schema
- User question related to the given schema

<neo4jschema>
    {SCHEMA}
</neo4jschema>

<question>
    {USER QUESTION}
</question>

YOUR INSTRUCTIONS:-
You are a Neo4j expert. Follow these STEP BY STEP:

1. **Identify Nodes and Relationships**:

  - Examine the schema to identify the different types of nodes (entities) and relationships
  (edges) between them.

2. **Node Properties**:
  - Note the properties (attributes) of each node type.

3. **Relationship Properties**:
  - Note the properties of each relationship type.

4. **Indexes and Constraints**:
  - Check for any indexes or constraints that might be relevant for query optimization.

5. **Break Down User Question**:
  - Analyze the users  question step by step, using the provided schema as grounding.
  - Understand what the user needs, keeping in mind the eventual answer.
  - For units like 1 million or 1 dozen, convert them to their base forms (e.g., 1 million to
  1000000, 1 dozen to 12) when generating Cypher queries.

6. **Formulate the Response**:
  - Use the identified nodes, relationships, and their properties to inform your understanding
     of
  the users   question.
  - Ensure that any indexes and constraints are considered when formulating your response.
  - Formulate a clear breakdown of the user question and the analysis of the schema.
DO NOT GENERATE THE CYPHER QUERY, JUST FOLLOW THE GIVEN INSTRUCTIONS!
```

Figure 10: Cypher generation: Analyse question step using Gpt-4

Cypher generation - Relate user request to schema

```
You are helpful and expert Neo4j and generating Cypher queries assistant.
You will be given
- Neo4j schema
- User question related to the given schema
- Analysis of the Neo4j schema, the nodes and the relationships, entities between them, and
     the
user question.

<neo4jschema>
{SCHEMA}
</neo4jschema>

<question>
{USER QUESTION}
</question>

<schema_and_question_analysis>
{STEP 0 RESPONSE}
</schema_and_question_analysis>

YOUR INSTRUCTIONS:-
Follow these step by step:
1. Identify which nodes (entities) from the given schema are important in answering the user
question and forming the correct Cypher query. Keep track of these nodes. Whenever any kind of
      ID
is present in a node, make sure to add it so the final answer includes it along with other
important properties needed to answer the question. Do not make up any properties that are not
present in the schema.
2. For all identified important nodes, list all relationships related to those nodes and
     entities
individually. Do not create imaginary relationships; only consider the relationships that are
present in the schema.
3. For all identified important nodes and relationships, list and filter all properties
     related
to those nodes and entities individually. Do not create imaginary properties; only consider
     the
properties that are present in the schema. Whenever any kind of ID is present in a node, make
sure to add it as a property so the final answer includes it along with other important
properties needed to answer the question. Do not make up any properties that are not present
     in
the schema.
4. Identify and filter out only the nodes, relationships, and properties which are important
     and
relevant to answering the user's question and creating the correct Cypher query, given the
schema. List out all the important nodes, relationships, and properties that are required to
answer the user's question in the end. Whenever any kind of ID is present in a node, make sure
      to
add it as a property so the final answer includes it along with other important properties
     needed
to answer the question. Do not make up any properties that are not present in the schema.

DO NOT GENERATE THE CYPHER QUERY, JUST FOLLOW THE GIVEN INSTRUCTIONS!
```

Figure 11: Cypher generation: Relate user request to the schema step using Gpt-4

Cypher generation - Incorporate Cypher best practices

```
You are helpful and expert Neo4j and generating Cypher queries assistant.
You will be given 1) Neo4j schema 2) User question related to the given schema 3) Analysis of
    the Neo4j schema, the nodes and the relationships, entities between them, and the user
    question.
- Filtered list of nodes, relationships, and properties which are important and relevant to
answering the user's question.
<neo4jschema>
{SCHEMA}
</neo4jschema>
<question>
{USER QUESTION}
</question>
<schema_and_question_analysis>
{STEP 0 RESPONSE}
</schema_and_question_analysis>
<important_nodes_relationships_properties>
{STEP 1 RESPONSE}
</important_nodes_relationships_properties>

YOUR INSTRUCTIONS:-
STRICTLY FOLLOWING THE GIVEN INFORMATION from <filtered_nodes_relationships_properties> and <
    convoluted_relationships>, think step by step out loud and create a explicit and detailed
     verbose STEP BY STEP "Cypher generation plan" for how a cypher query can be formulated
    to achieve what the user wants.
Make sure to explicitly mention nodes, relationships, conditions in your plan.
You MUST NOT WRITE CYPHER STATEMENTS, but instead verbally step by step generate a plan, which
     will help in forming the correct Cypher query.
During question analysis, for entites with shortforms, for example 1 million, or 1 dozen.
    Represent them in numbers, for e.g. 1000000 instead of 1 million and 12 instead of dozen.

Additionally, consider all of the following:
-- conditions which are required to filter the identified nodes and relationships (WHERE)
-- aggregation functions (COUNT, SUM, AVG, MIN, MAX, COLLECT, STDDEV, VARIANCE,
    PERCENTILE_CONT,
PERCENTILE_DISC, MODE, MEDIAN, ARRAY_AGG)
-- ordering (ORDER BY ASC, ORDER BY DESC)
-- limits (LIMIT, SKIP)
-- return statement, what should be returned. Avoid aggregation with RETURN statements. (
    RETURN,
DISTINCT, CASE, apoc.do.when)
-- matching patterns (MATCH, OPTIONAL MATCH)
-- creating nodes and relationships (CREATE, MERGE)
[Truncated]
-- conditional operations (CASE, FOREACH, WITH, apoc.do.when)
-- union operations (UNION, UNION ALL)
-- handling indexes and constraints (CREATE INDEX, CREATE CONSTRAINT, DROP INDEX,
DROP CONSTRAINT)
-- full-text search (CALL db.index.fulltext.queryNodes, CALL
db.index.fulltext.queryRelationships)
-- pagination (SKIP, LIMIT)
-- handling transactions (BEGIN, COMMIT, ROLLBACK)

ADDITIONAL CYPHER PRACTICES YOU MUST FOLLOW STRICTLY, so make sure this is followed in you
    cypher
generation plan:-
[Truncated.]
```

Figure 12: Cypher generation: Incorporate Cypher best practices step using Gpt-4

Cypher generation: Final cypher generation

```
You are helpful and expert Neo4j and generating Cypher queries assistant.
You will be given
- Neo4j schema
- User question related to the given schema
- Analysis of the Neo4j schema, the nodes and the relationships, entities between them, and
    the user question.
- Filtered list of nodes, relationships, and properties which are important and relevant to
    answering the user's question.
- A comprehensive Cypher generation plan, which will help you in forming the correct Cypher
    query.

<neo4jschema>
{SCHEMA}
</neo4jschema>

<question>
{USER QUESTION}
</question>

<schema_and_question_analysis>
{STEP 0 RESPONSE}
</schema_and_question_analysis>

<important_nodes_relationships_properties>
{STEP 1 RESPONSE}
</important_nodes_relationships_properties>

<cypher_generation_plan>
{STEP 2 RESPONSE}
</cypher_generation_plan>

YOUR INSTRUCTIONS:-
STRICTLY FOLLOWING THE GIVEN 'cypher_generation_plan' and other gathered given knowledge about
     required nodes and relationships, your task is to write me a detailed brief on the plan
    in way like what is question asking, what are the important details in schema, and other
    relevant info (Assume I don't have access to the plan so I will be relying on your
    writeup) and explain how you will generate the cypher then generate the syntactically
    correct final cypher query, which will give the desired result, in ansering the user's
    question.

Generated Cypher should be surrounded by ```cypher```.
For entites with shortforms, for example 1 million, or 1 dozen. Represent them in numbers, for
     e.g. 1000000 instead of 1 million and 12 instead of dozen.
```

Figure 13: Cypher generation: Final cypher generation step using Gpt-4

Execution Match - LLM-as-Judge

```
As an AI model, your task is to evaluate the student's answer based on the given question and
     the correct answer. The student's answer may not contain all the fields mentioned in the
     correct answer or vice versa, but it should address the specific elements asked in the
     question. If the main elements asked in the question are correctly answered, consider it
     correct.

For example:
    Example_Question: "Which employees earn more than 40K in salary that live in USA?"
    Example_Correct_Answer: [{{'name': 'John', 'employee_id': 1234, 'salary': 45K, 'country':
     'USA'}}, {{'name': 'Adam', 'employee_id': 2763, 'salary': 90K, 'country': 'USA'}}]
    Example_Student_Answer: [{{'emmployee_name': 'Adam'}}, {{'employee_name': 'John'}}]
In this example, student's answer is CORRECT because the question asks for employee and the
     student gave the employee names (which uniquely determine the employees). And all the
     values match. So the student's answer is correct.

For example:
    Example_Question: "Which employees earn more than 40K in salary that live in USA?"
    Example_Correct_Answer: [{{'name': 'John', 'employee_id': 1234, 'salary': 45K, 'country':
     'USA'}}, {{'name': 'Adam', 'employee_id': 2763, 'salary': 90K, 'country': 'USA'}}]
    Example_Student_Answer: [{{'emmployee_name': 'Adam'}}, {{'employee_name': 'John'}}, {{'
     employee_name': 'Victor'}}]
In this example, student's answer is INCORRECT because although the student gave the requested
      items, i.e, employee name, there is an additional value "Victor" which is incorrect.

Question:
{task}

Correct Answer:
{ground_truth}

Student's Answer:
{predicted}

Think step by step and finally return your final answer as: FINAL_ANSWER: CORRECT/INCORRECT
```

Figure 14: Execution Match - LLM-as-Judge