

Credits also to:



Mark Granroth-Wilding



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EQT
MOTHER BRAIN

Knowledge Graph in Private Equity: LLM-enhanced Construction, Contextual Retrieval, and Reasoning



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EQT & Motherbrain

- EQT: Private Equity Fund
 - Global investment fund w €200Bn+ AUM
 - Buys, grows & sells companies
 - Venture Capital, Buyout, Infrastructure, etc.
- Motherbrain: Data & Machine Learning Platform
 - Support investment professionals globally
 - Merging and enriching data using AI (on GCP)
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Agenda

Motivation

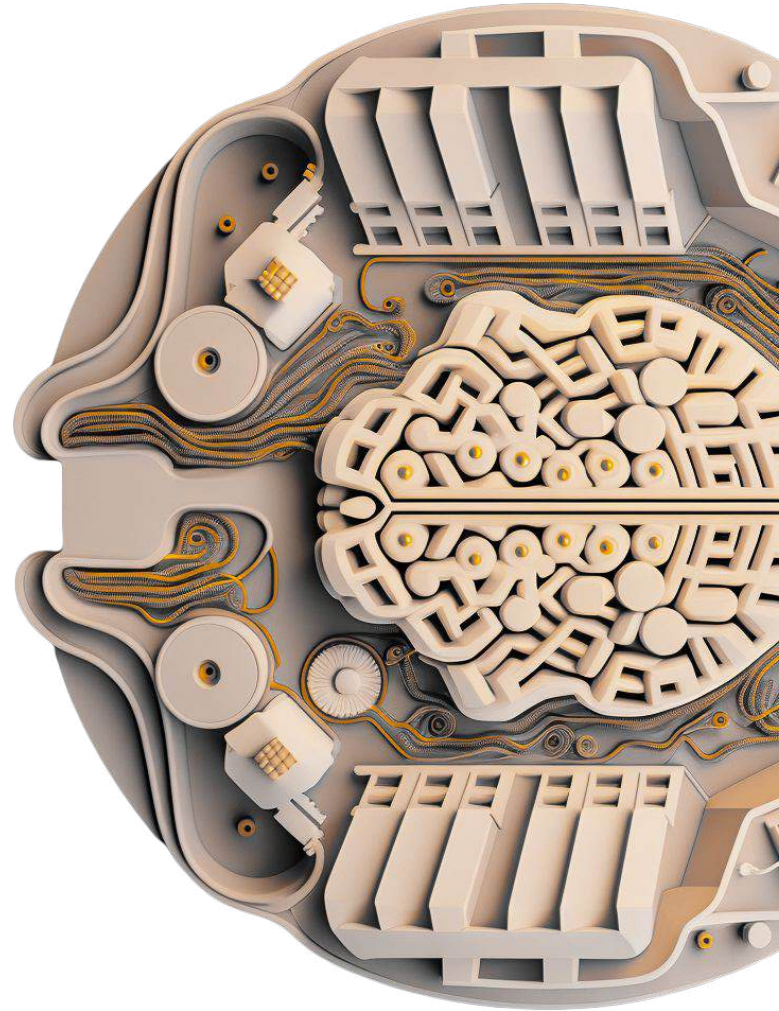
Approach

KG Construction

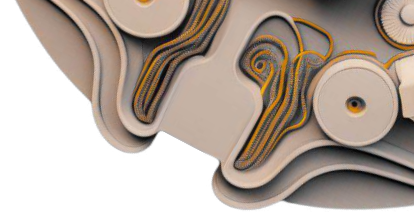
Contextual Retrieval

Reasoning

Summary



Motivation: a simplified view of deal process



Sourcing

- Which companies exist within my mandate?
- How do I make sure to spend time on interesting opportunities?
- What does the market look like around a deal?



Due Diligence

- What are the risks and attractions in this opportunity?
- What is the full potential this company can achieve?
- Who do we know we can ask for insights?



Holding

- How can we make sure to fulfil the full potential plan?
- What are the potential disruptions and market trends?
- How are we actually tracking on the plan?



Exit

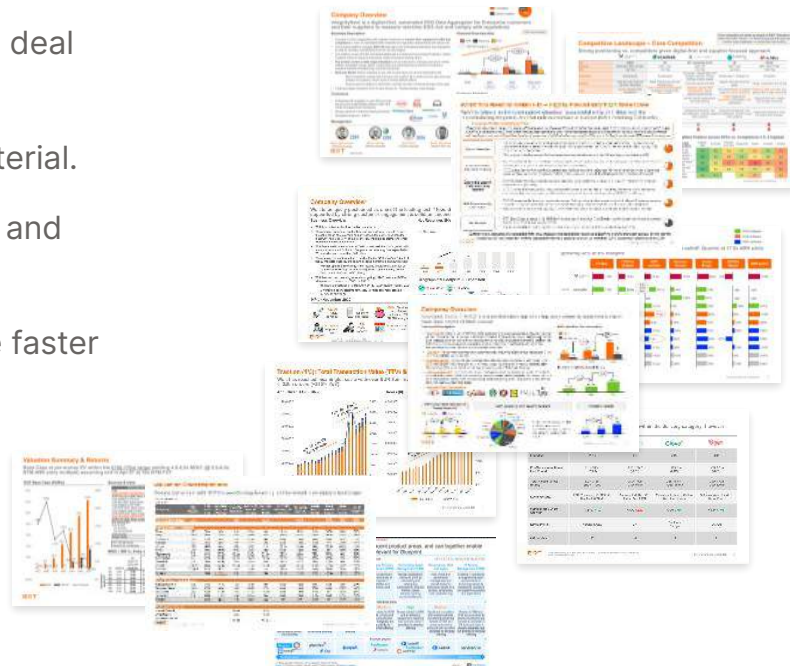
- How do we position the deal up for a successful sale?
- How can we make sure the company is in good health and can continue to grow?
- Which bankers and advisors should I talk to?



Motivation: leverage proprietary knowledge

Proprietary Knowledge

- So much interesting information is gathered throughout a deal process.
- EQT has been doing this since 1994... there is a lot of material.
- Reading through material is pretty intense as most decks and market reports are very dense. And long...
- But understanding historical deals is very important to be faster and smarter in future deal assessments.



Motivation: leverage third-party knowledge

Third-party Knowledge

- External experts and consultants often provide valuable insights that are not available internally.
- Leverage industry specialists can bring in-depth market analyses and fresh perspectives.
- Third-party data sources can offer objective viewpoints, free from internal biases.
- Most subscription-based sources are structured, hence easier to integrate.



 PitchBook  crunchbase

Agenda

Motivation

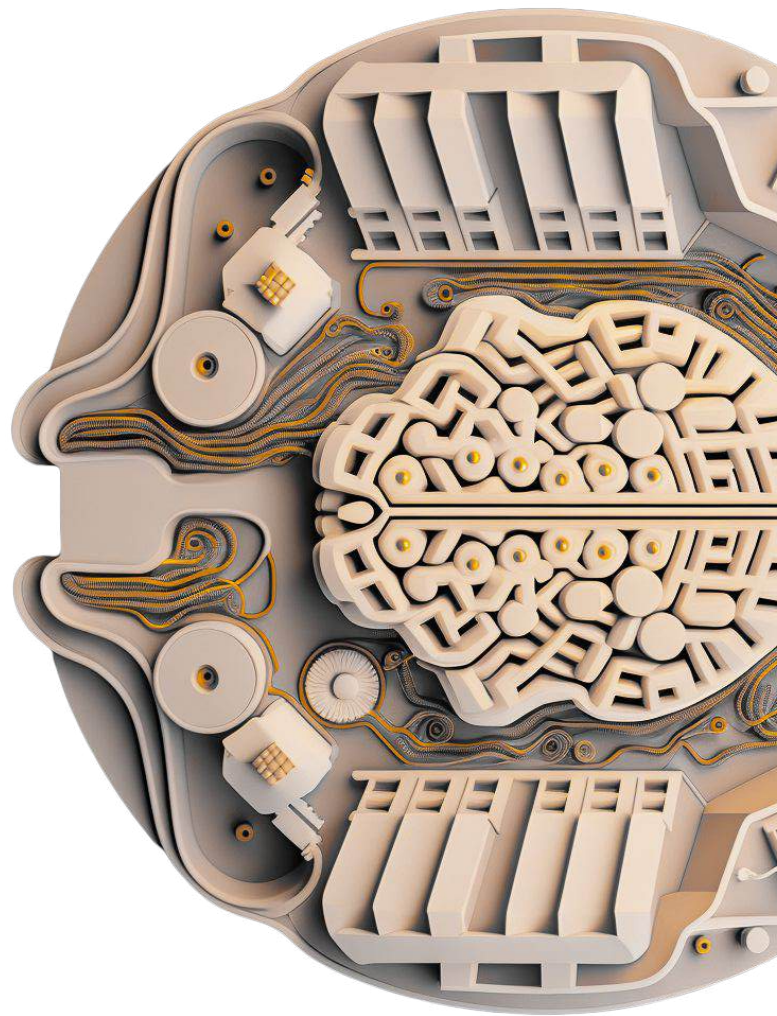
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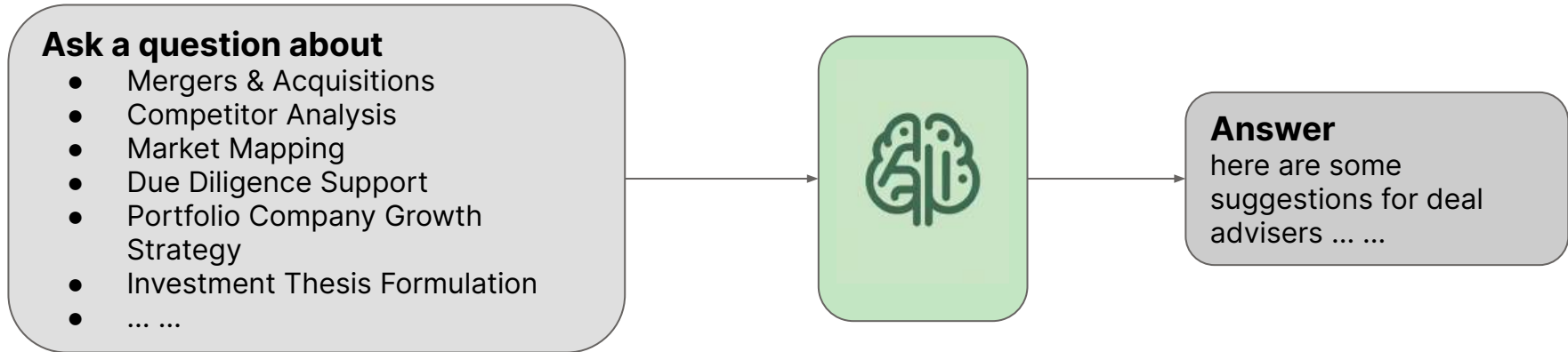
Reasoning

Summary



Approach: objective and applications

Develop an **Intelligent and Knowledgeable Agent/Service** to help deal professionals in many applications:



Approach: a concrete example

Develop an **Intelligent and Knowledgeable Agent/Service** to help deal professionals in many applications:

Ask a question

We are looking at a deal of a company named ManyPets (manypets.com). Can you suggest some deal experts in related sectors and also some direct competitors in EU?



Answer

here are some suggestions for deal advisers in the pet insurance sector, as well as some direct competitors in the EU:
...

Approach: LLM prompting

Ask a question

We are looking at a deal of a company named ManyPets (manypets.com). Can you suggest some deal experts in related sectors and also some direct competitors in EU?

LLMs
ChatGPT
LLaMA
Gemini
Mistral
Claude
...

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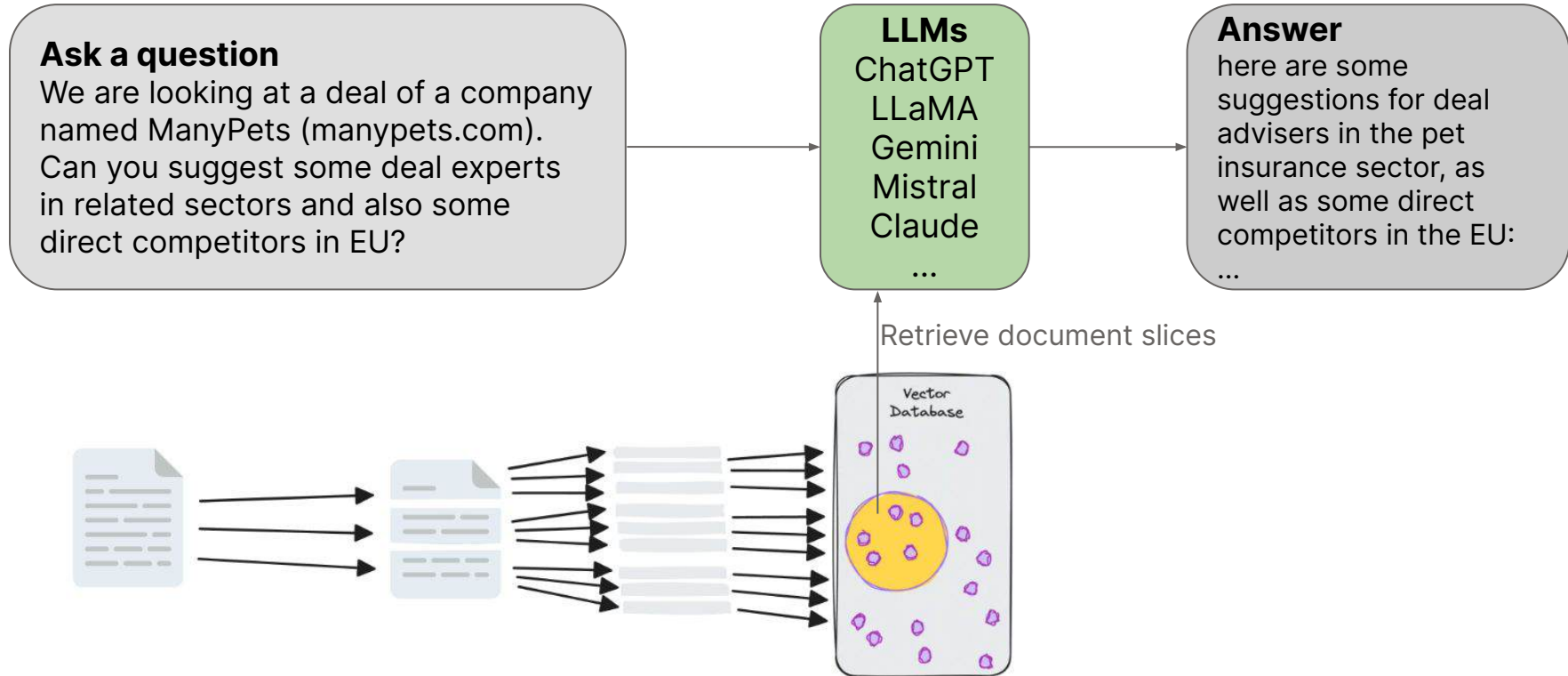
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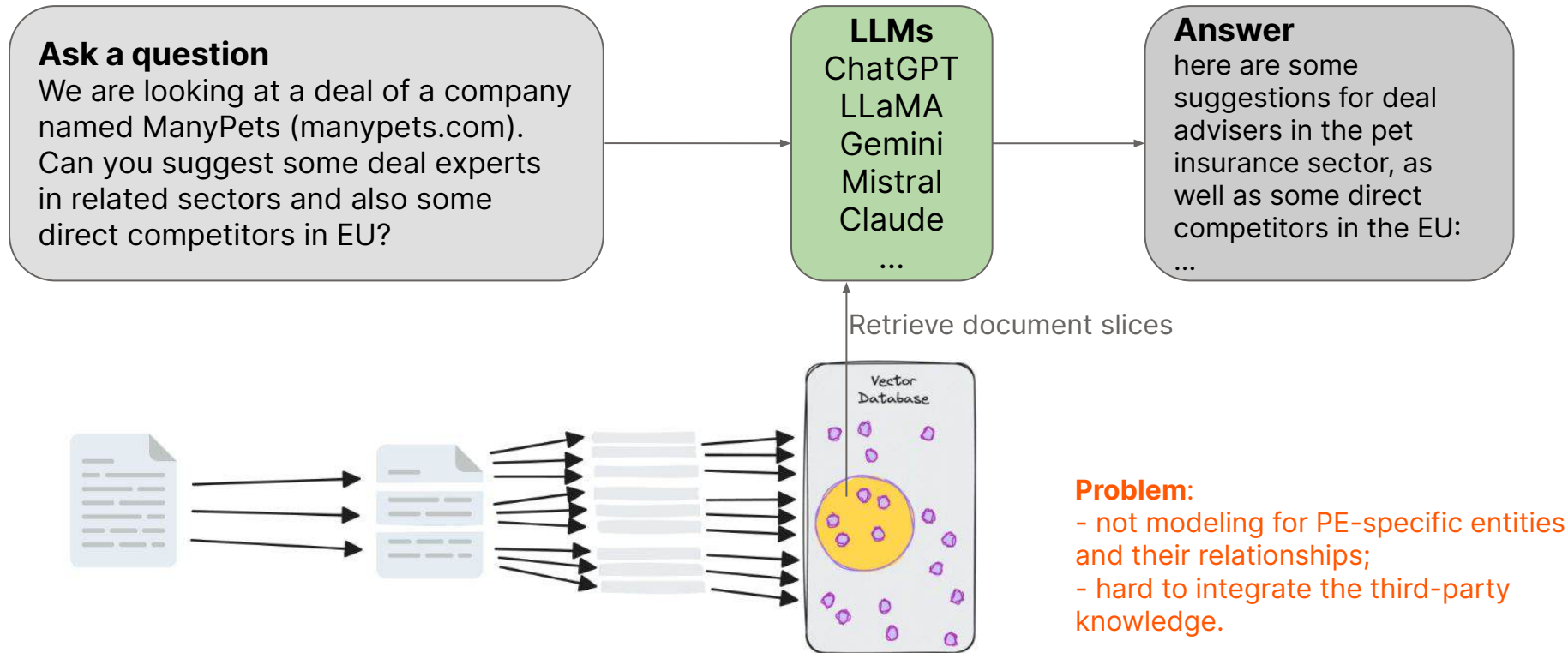


Problem: Lack domain-specific and up-to-date knowledge.

Approach: RAG - retrieval augmented generation



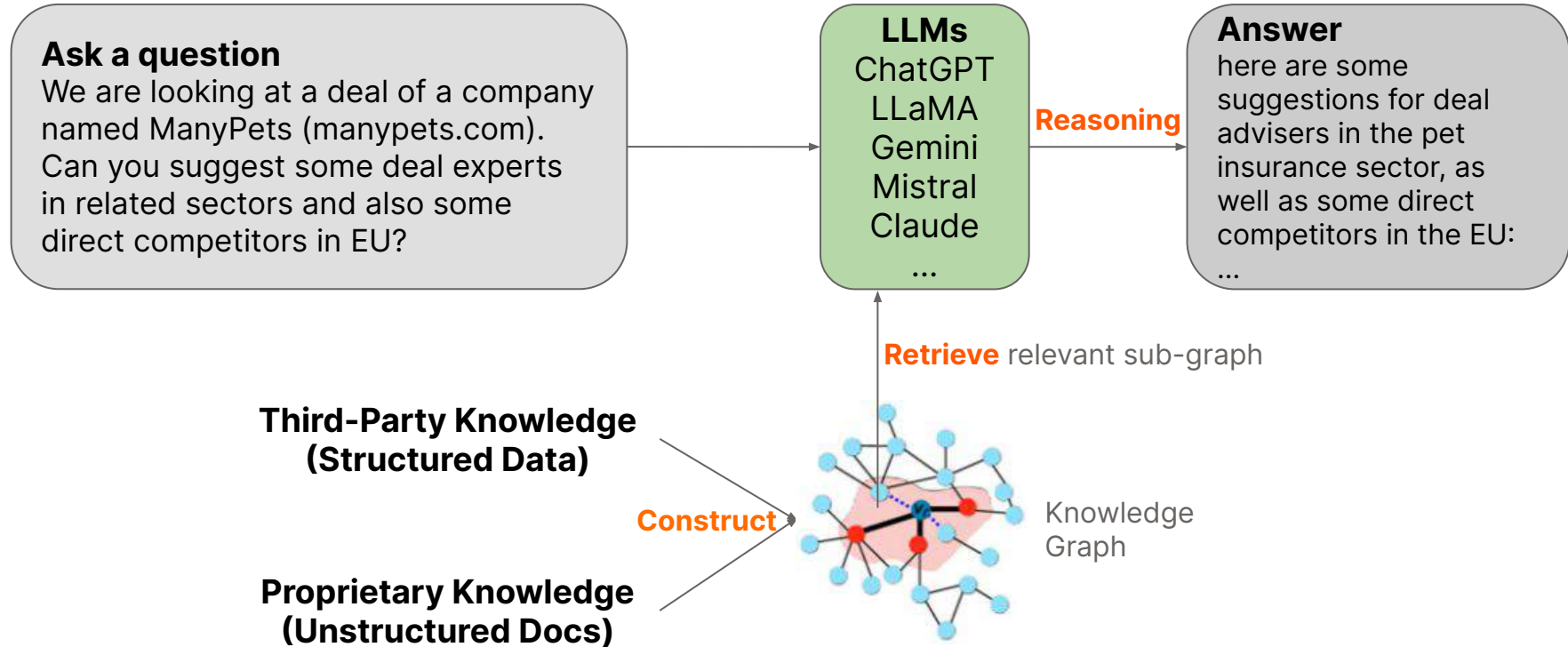
Approach: RAG - retrieval augmented generation



Problem:

- not modeling for PE-specific entities and their relationships;
- hard to integrate the third-party knowledge.

Approach: RAG over KG (knowledge graph)



Approach: RAG over KG (knowledge graph)

Three Key Components:

1. **KG Construction** - Extract relevant entities, relations, and attributes from **proprietary documents** and **third-party data**.
2. **Contextual Retrieval** - According to the context provided by the query/question, retrieve the relevant sub-KG for LLM to reason about.
3. **Reasoning** - With the query/question and the retrieved sub-KG, generate the response/answer.

Agenda

Motivation

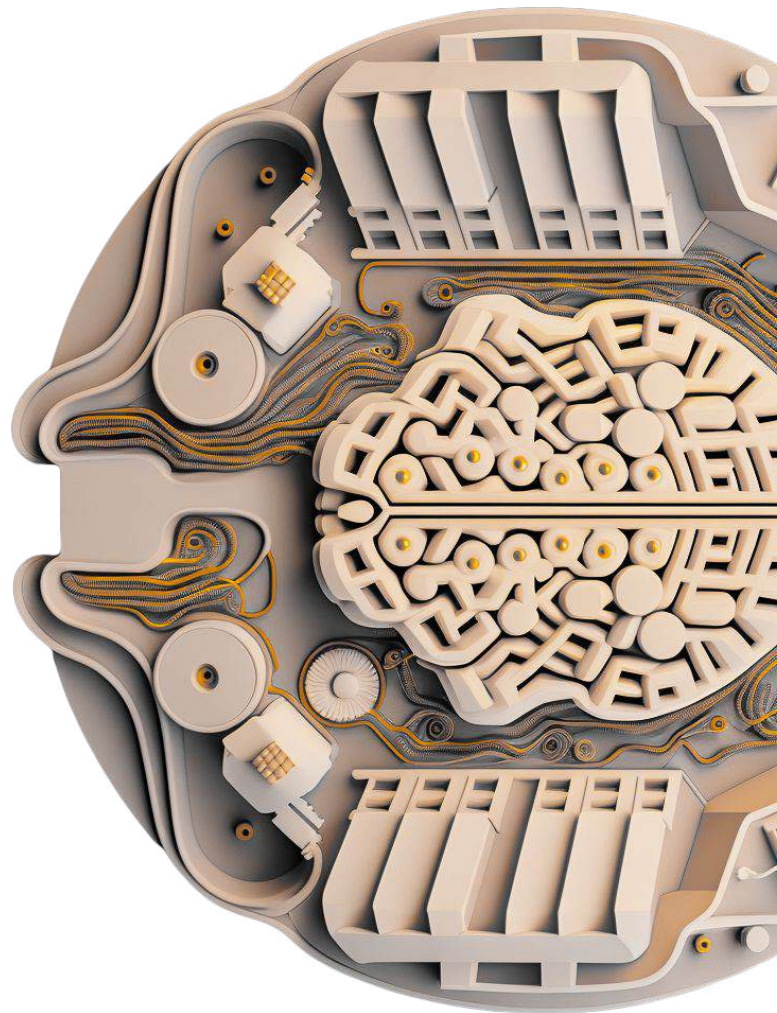
Approach

KG Construction

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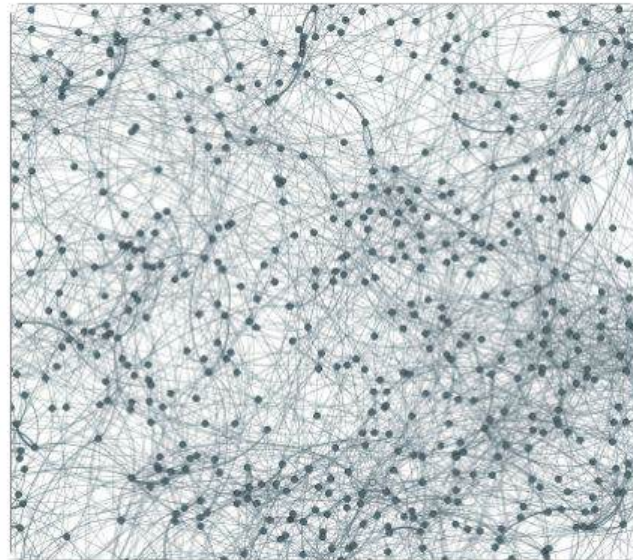
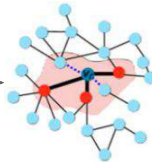


KG Construction: CompanyKG

- **Purpose:** quantify similarities among companies.
- **Example use cases:**
 - Market mapping
 - Competitor analysis
 - Mergers and Acquisitions (M&A)
- **Data source:** mostly third-party structure data, such as Pitchbook, Crunchbase, etc.

Third-Party Knowledge
(Structured Data)

Construct



A fraction of the entire graph

KG Construction: CompanyKG

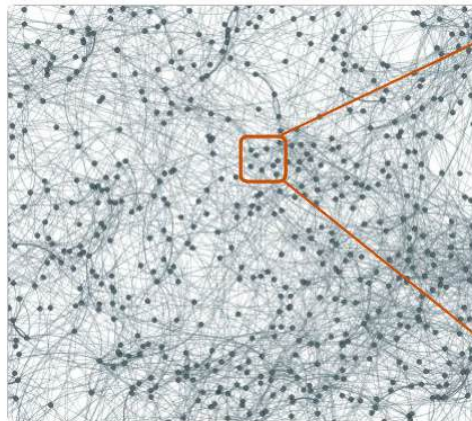
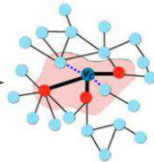
Relations: 15 relation types in 6 categories

- competitive landscape
- industry sector
- M&A transactions
- people's affiliation
- news/event engagement
- and product positioning

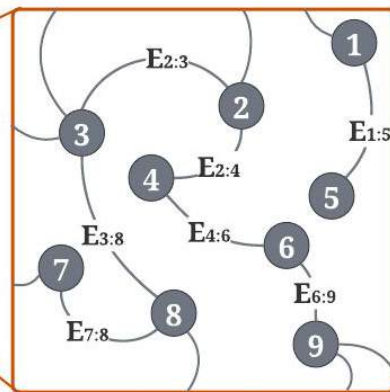
51.06 million weighted edges

Third-Party Knowledge
(Structured Data)

Construct



A fraction of the entire graph



A zoomed-in view of a minimal subgraph for illustrative purposes

Edge weights: 15-dim vector, where the i -th dimension is the weight of the i -th edge type (ET_i)

$E_{1:5} [0.0, 1.0, 0.0, 2.0, \dots, 5.1, 0.0, 1.6] \in \mathbb{R}^{15}$

$E_{2:3} [0.0, 1.0, 1.0, 0.0, \dots, 0.0, 0.0, 2.3] \in \mathbb{R}^{15}$

\vdots

KG Construction: CompanyKG

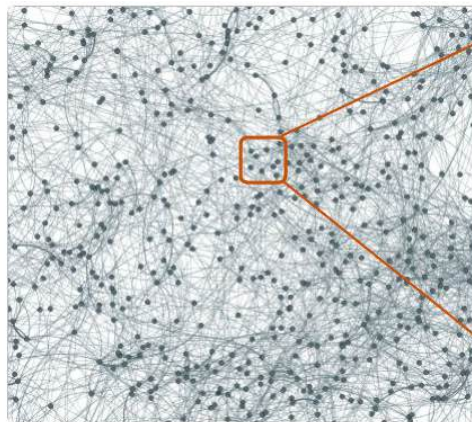
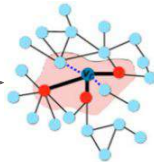
Nodes: 1.17 million companies

Node feature: description/keywords embeddings:

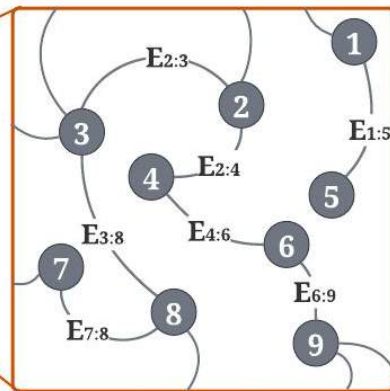
- multilingual BERT
- ADA2 (GPT3.5)
- SimCSE
- <https://doi.org/10.18653/v1/2021.emnlp-main.552>
- PAUSE
- <https://doi.org/10.18653/v1/2021.emnlp-main.791>

Third-Party Knowledge
(Structured Data)

Construct



A fraction of the entire graph



A zoomed-in view of a minimal subgraph for illustrative purposes

Node features: company description embeddings
from 4 language models

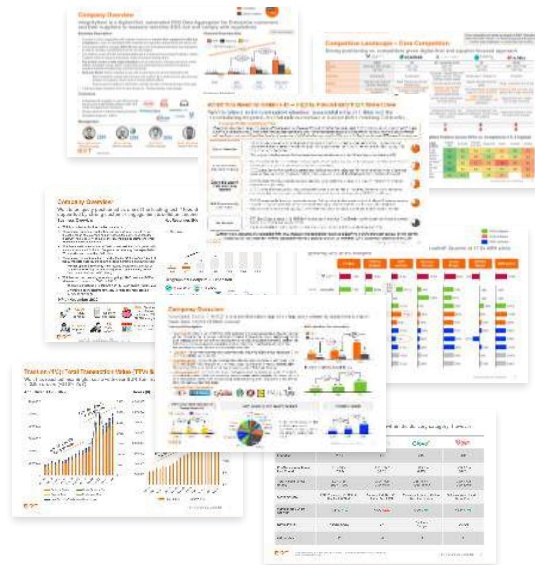
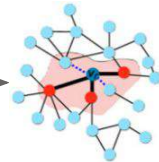
1	mSBERT: [0.32, 0.01, ... -0.49] $\in \mathbb{R}^{512}$
	ADA2: [0.05, 0.20, ... 0.35] $\in \mathbb{R}^{1536}$
	SimCSE: [0.29, 0.16, ... -0.24] $\in \mathbb{R}^{768}$
	PAUSE: [0.02, 0.73, ... 0.88] $\in \mathbb{R}^{32}$
2	mSBERT: [0.90, 0.53, ... 0.05] $\in \mathbb{R}^{512}$
	ADA2: [0.44, -0.10, ... 0.35] $\in \mathbb{R}^{1536}$
	SimCSE: [0.83, 0.01, ... 0.54] $\in \mathbb{R}^{768}$
⋮	PAUSE: [-0.22, 0.06, ... 0.90] $\in \mathbb{R}^{32}$

KG Construction: PEKG

- **Purpose:** Construct Knowledge Graph for EQT's PE deals.
- **Data source:** EQT's proprietary deal related documents. Each document is about a specific company (a.k.a., target company) in scope.

Proprietary Knowledge
(Unstructured Docs)

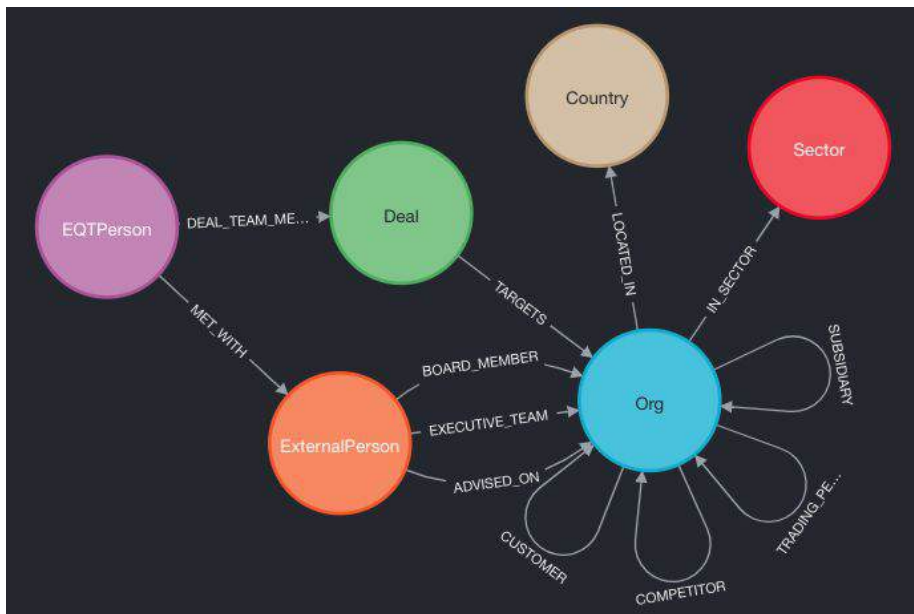
Construct



EQT's PE
deal docs

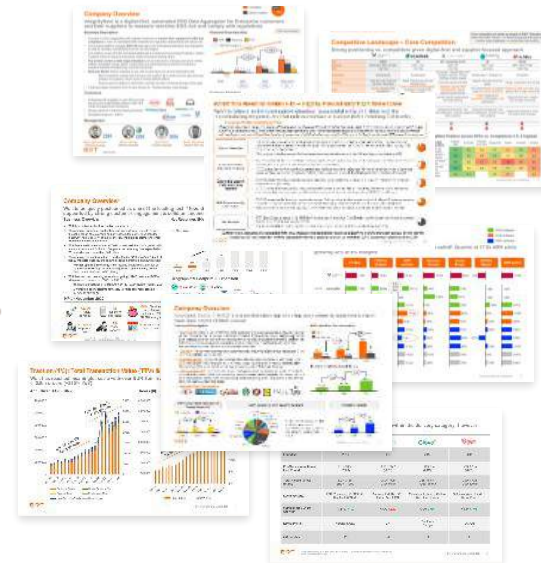
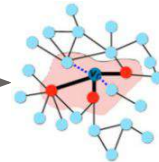
KG Construction: PEKG

- What **entities** and **relations** we extract and build into PEKG?



Proprietary Knowledge
(Unstructured Docs)

Construct

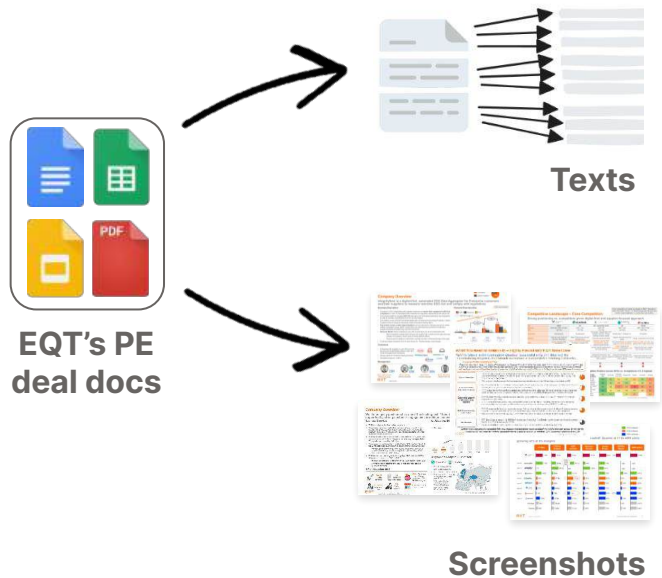


EQT's PE
deal docs

Extraction Guide
(Meta Graph)

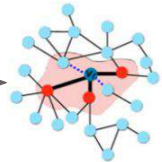
KG Construction: PEKG

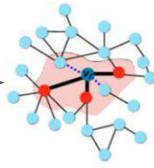
- How do we automate PEKG construction?



Proprietary Knowledge
(Unstructured Docs)

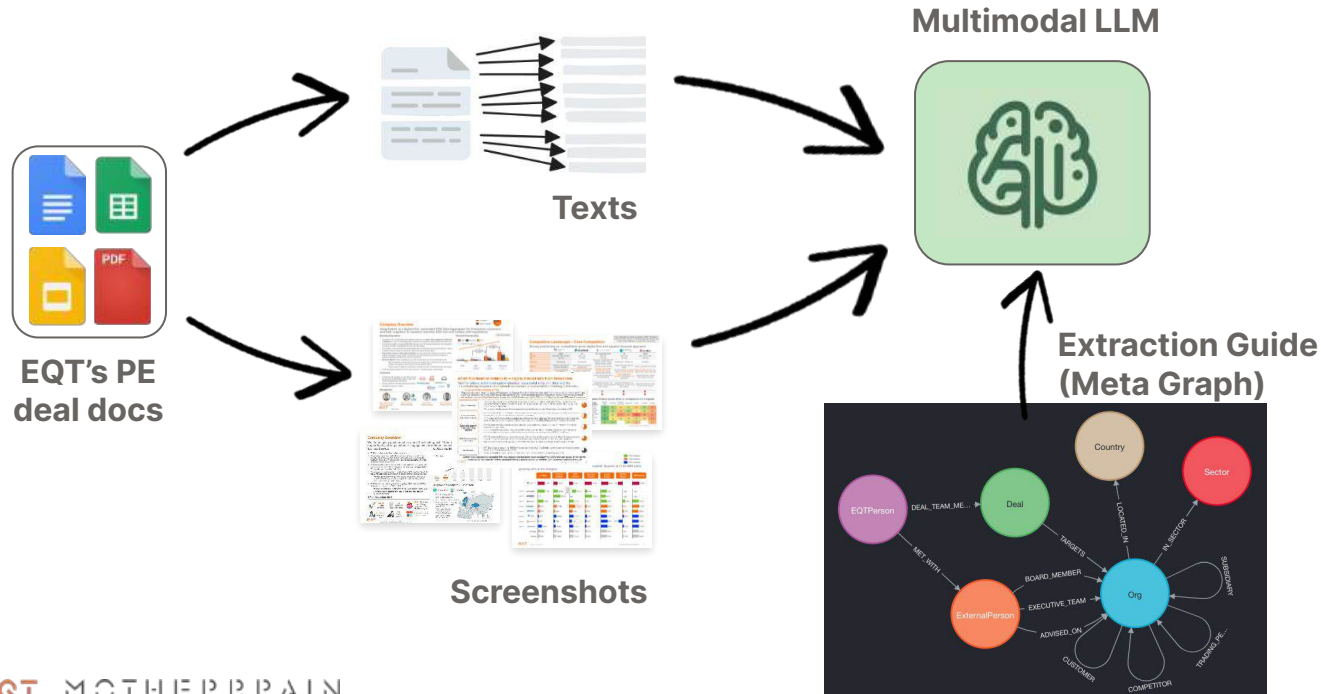
Construct





KG Construction: PEKG

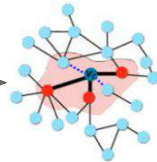
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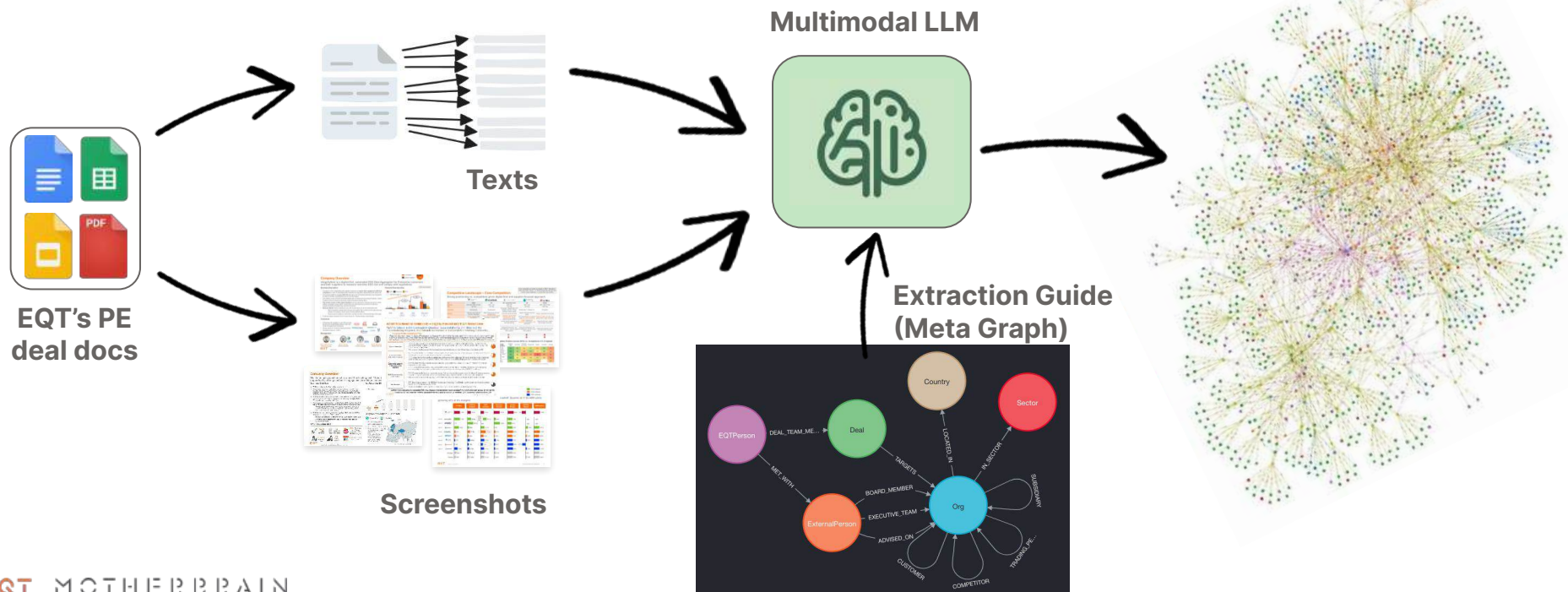
KG Construction: PEKG

Proprietary Knowledge
(Unstructured Docs)

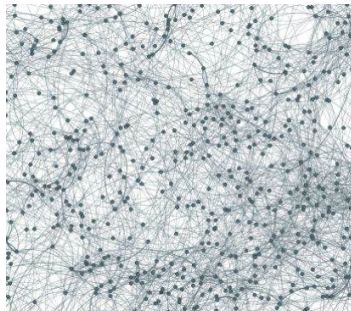
Construct



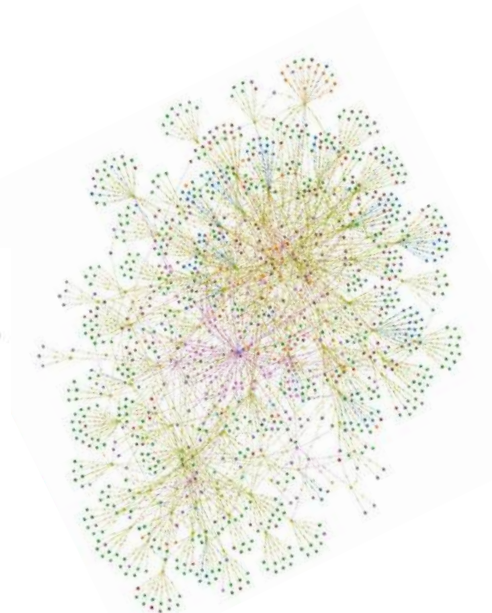
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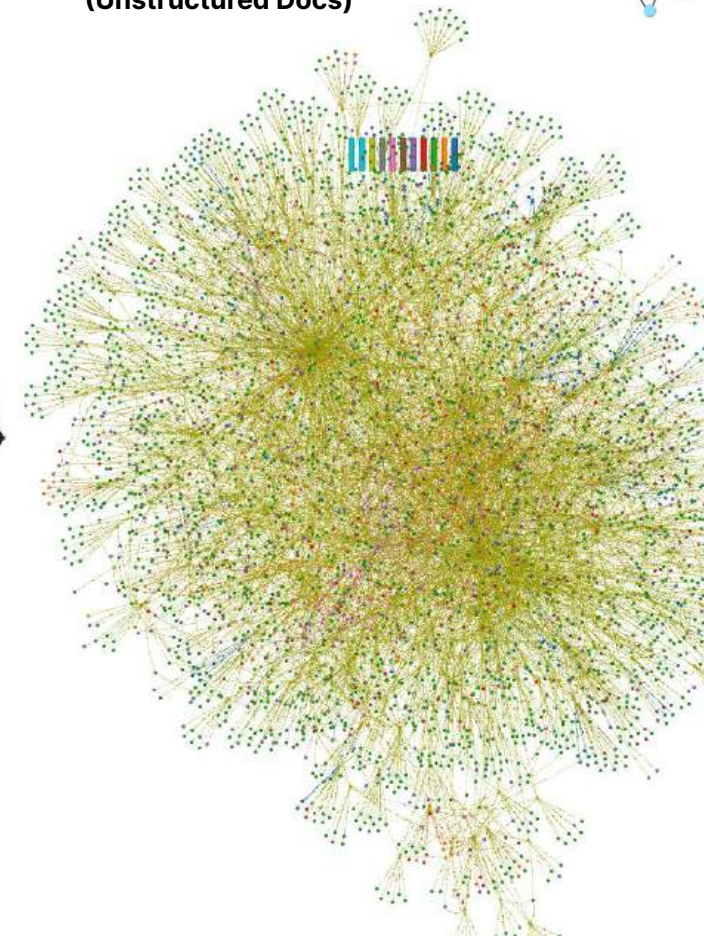
KG Construction: PEKG + CompanyKG



CompanyKG



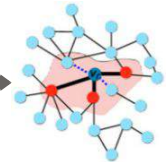
PEKG



Third-Party Knowledge
(Structured Data)

Proprietary Knowledge
(Unstructured Docs)

Construct



Agenda

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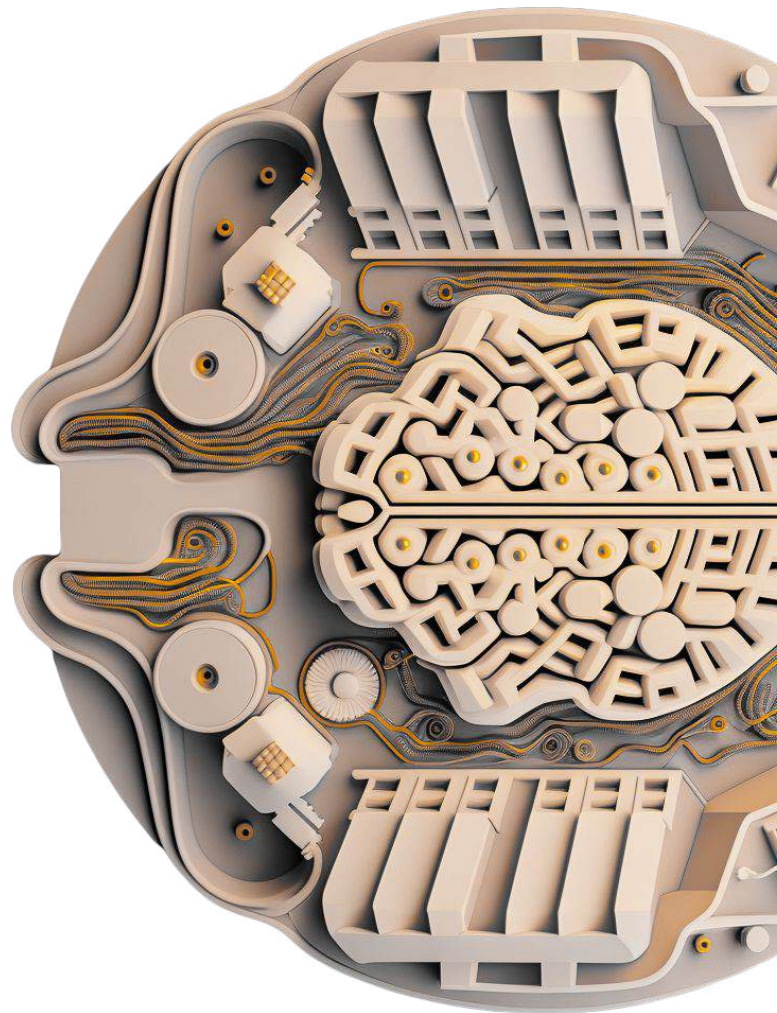
Approach

KG Construction

Contextual Retrieval

Reasoning

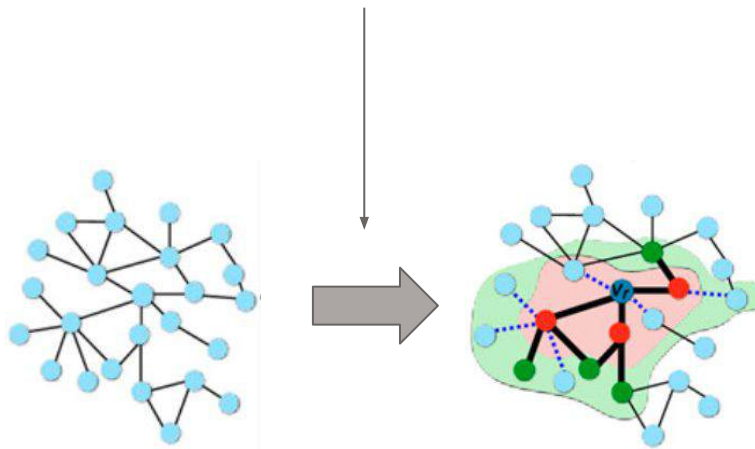
Summary



Contextual Retrieval

Objective: retrieve a sub-KG from the entire KG according to the context of the input query/question.

- The existing work mostly
 - assumes the availability of a contextual sub-KG, **which is not true in reality;**
 - or adopt a overly simplified approach, such as **randomly expand 2 steps from a center node.**

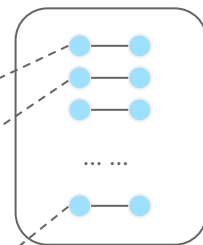


Contextual Retrieval: Semantic Triplets Search

Examples of “Triplet”s:

Start node	Relation	End node
● EQT	— is based in	● Stockholm
● Martin	— worked with	● Mark
...
● KTH	— belongs to	● University

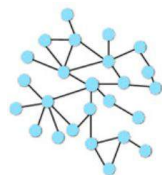
Triplet embedding



LLM

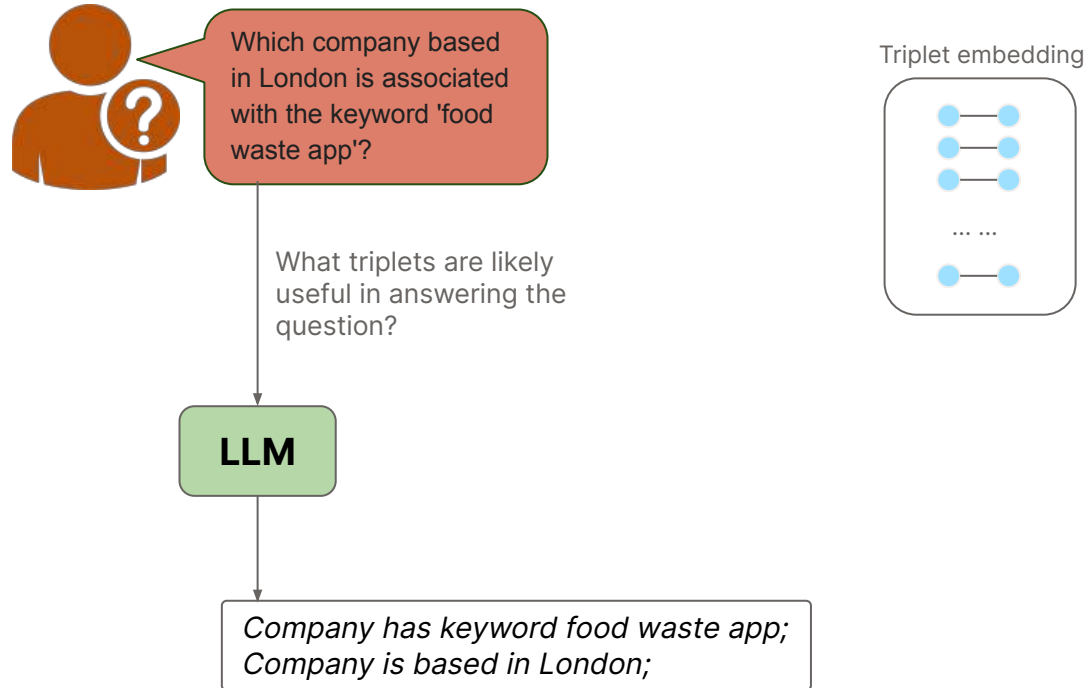


Embed triplets into
vector space

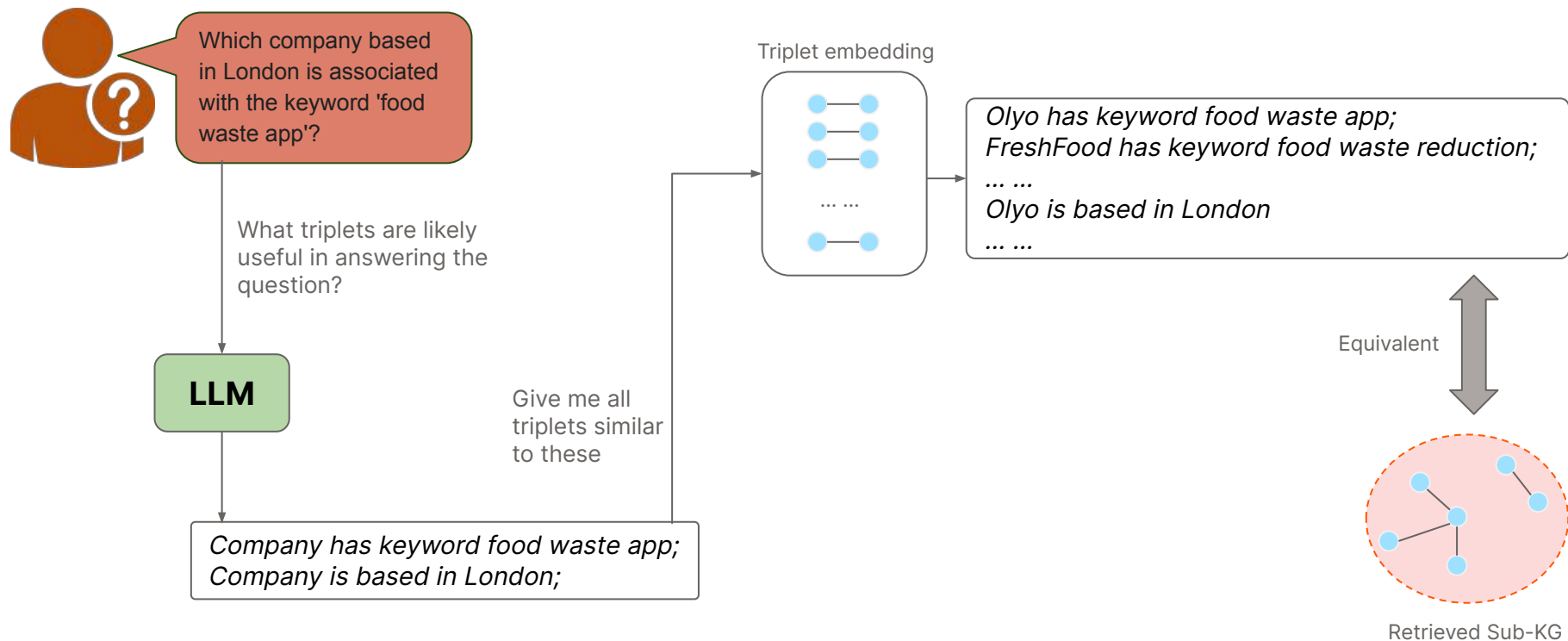


KG

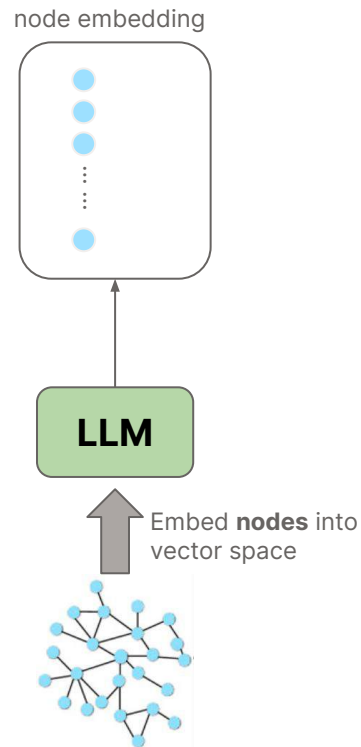
Contextual Retrieval: Semantic Triplets Search



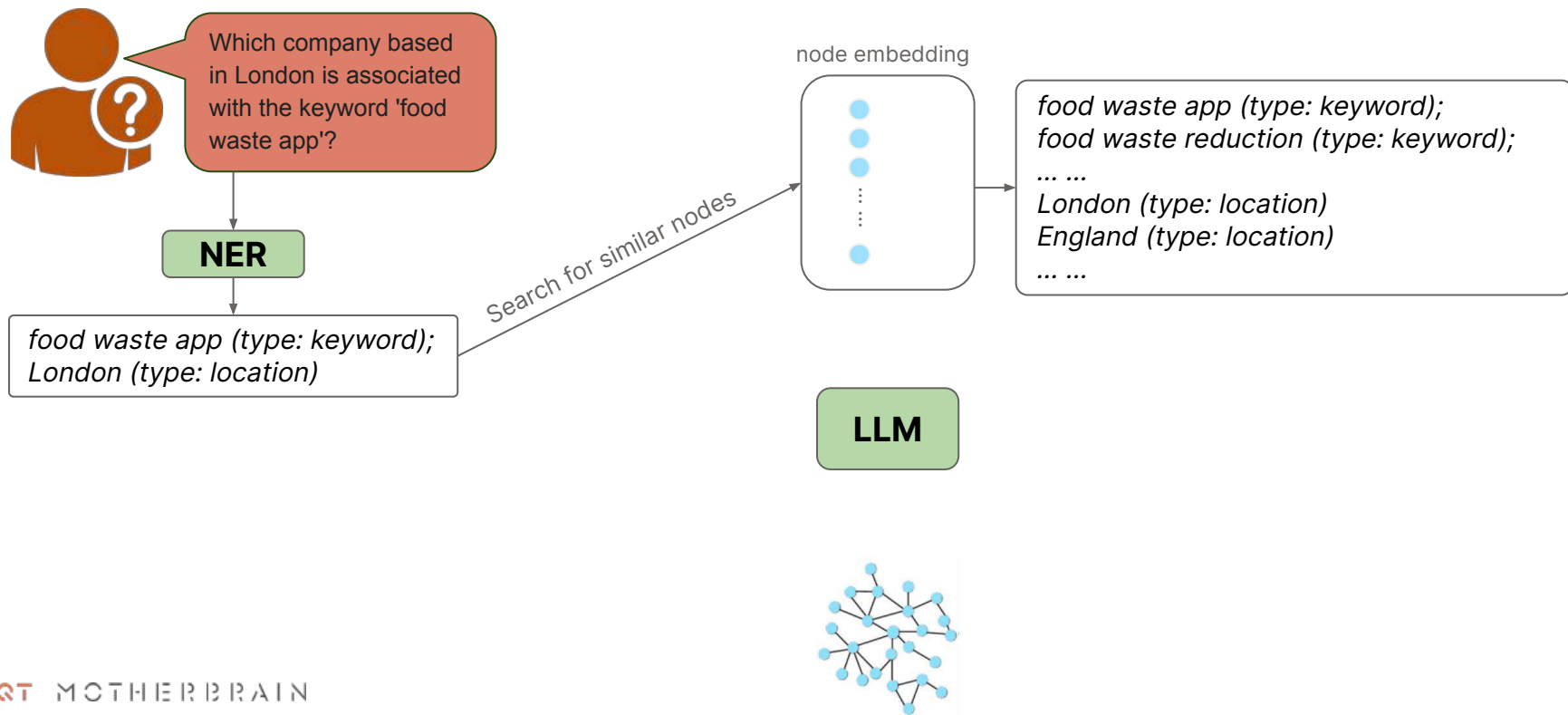
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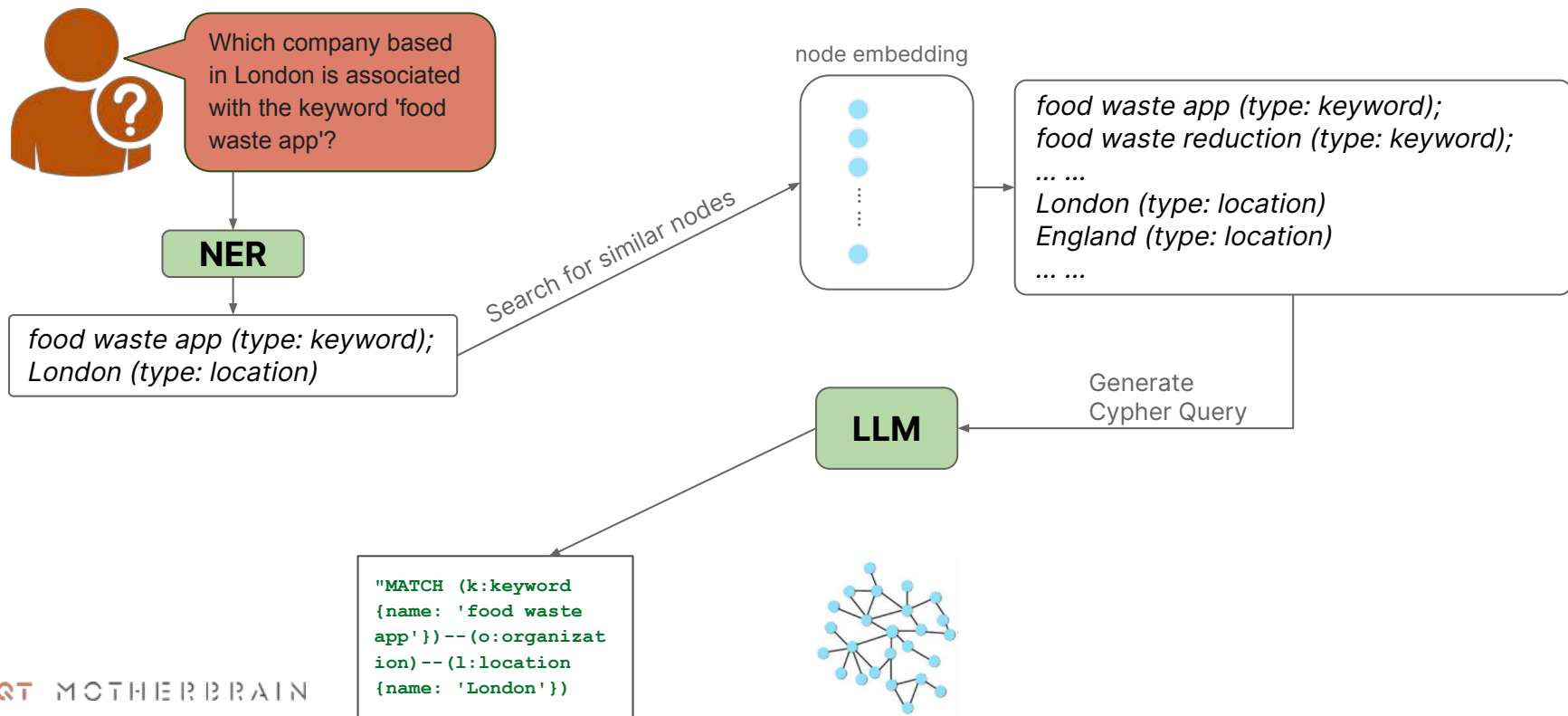
Contextual Retrieval: NER + Cypher



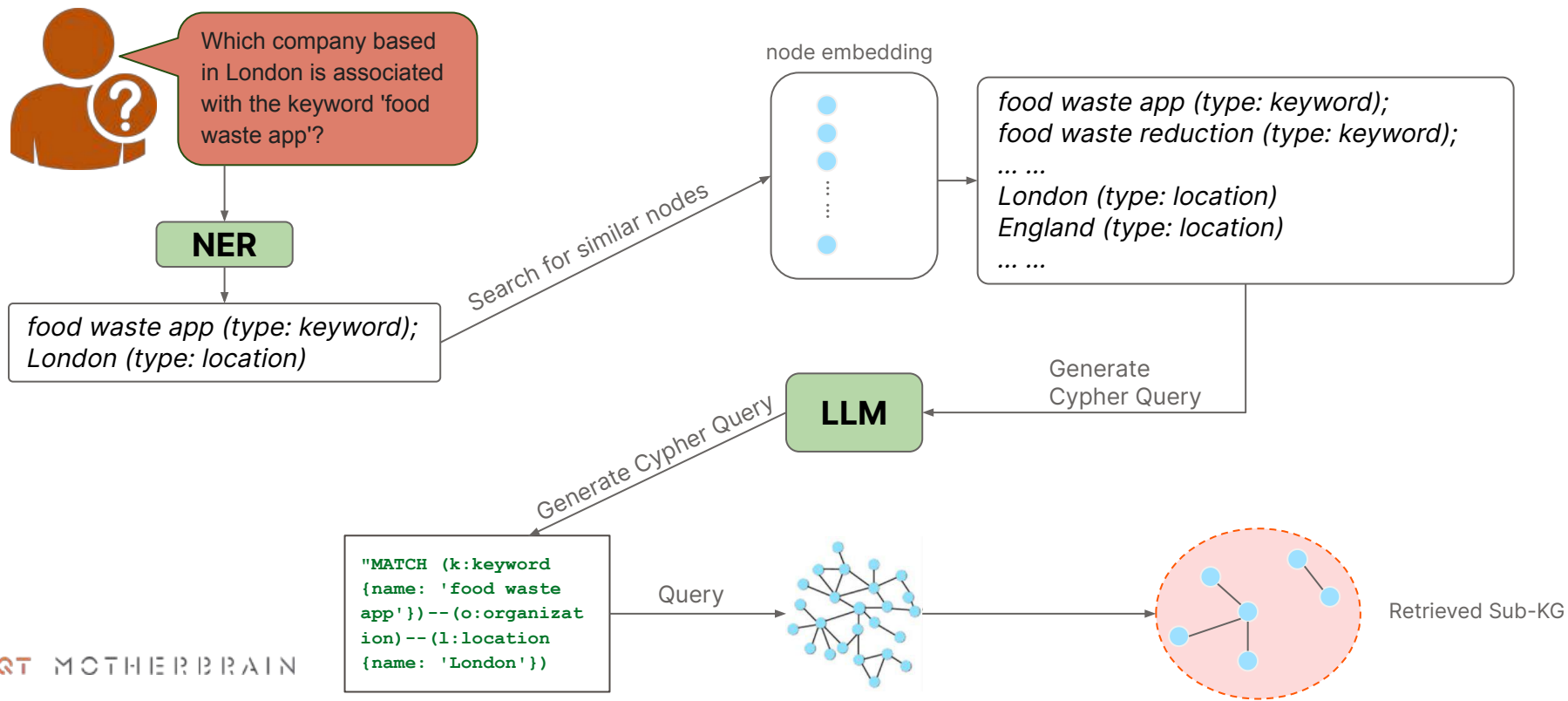
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Contextual Retrieval: NER + Cypher



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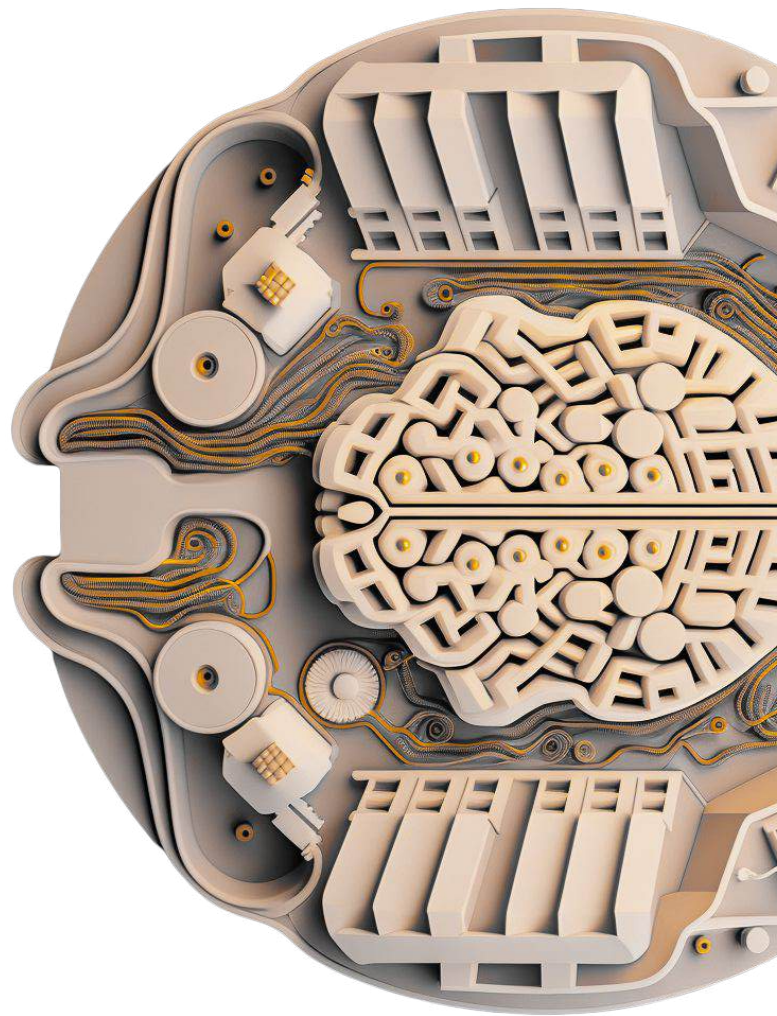
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Contextual Retrieval

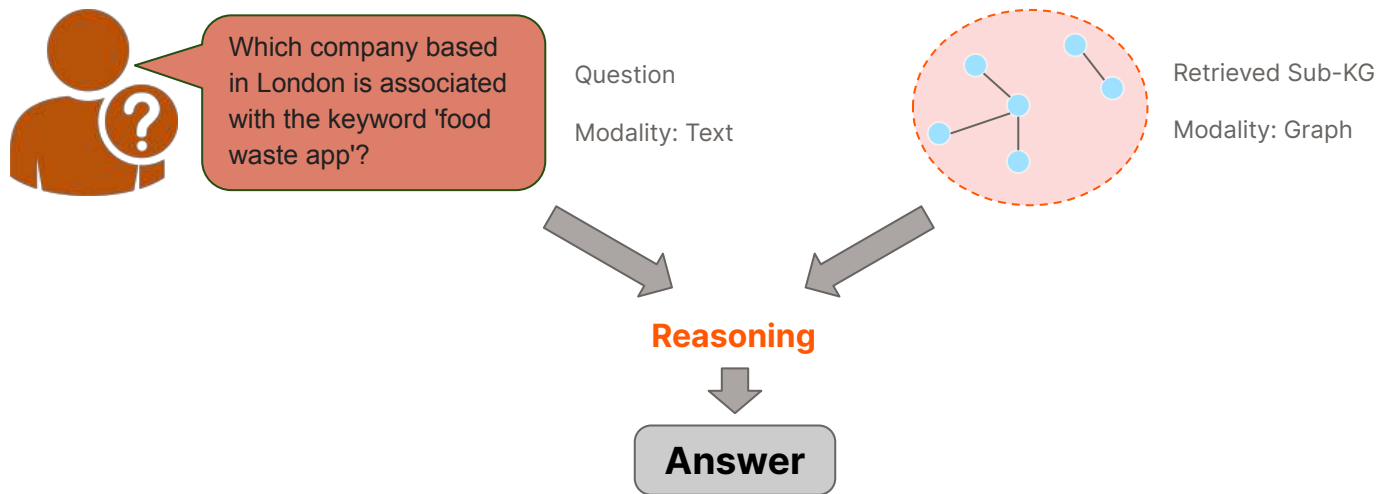
Reasoning

Summary



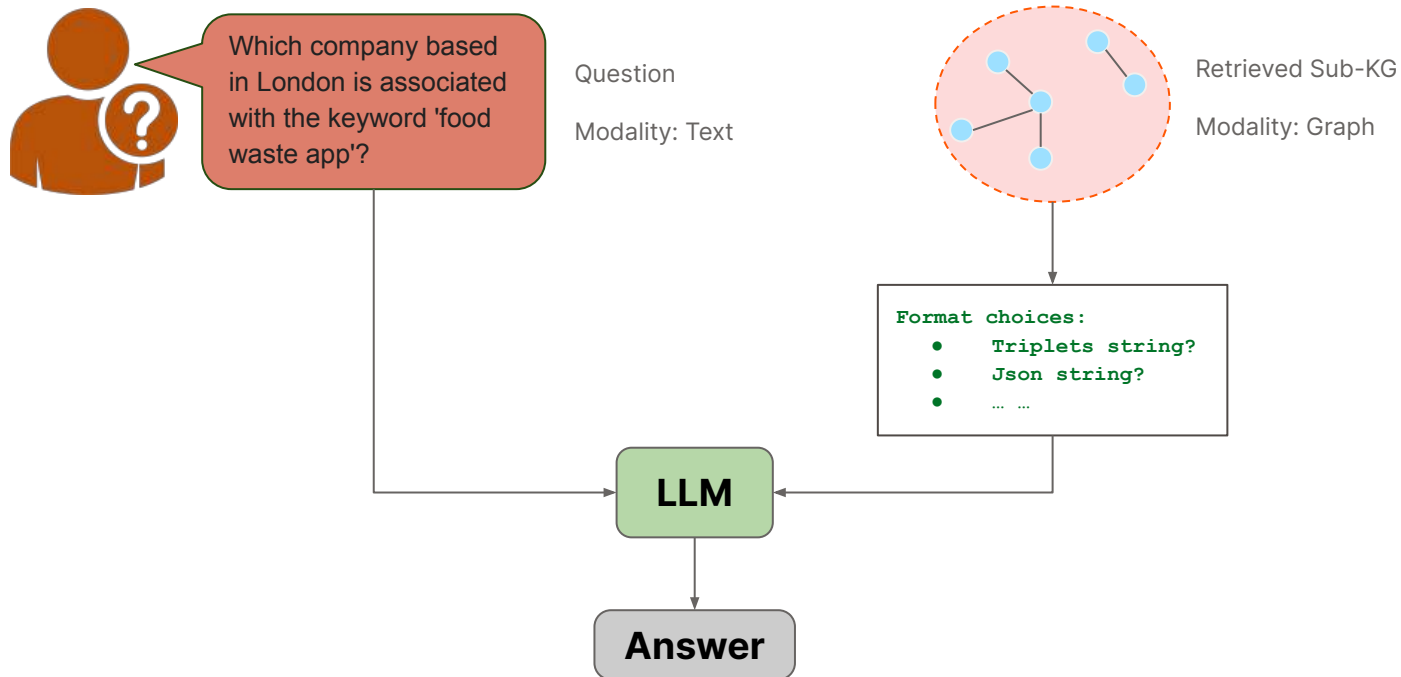
Reasoning

Objective: generate answer to the **textual question** using the retrieved **sub-KG** as input context.



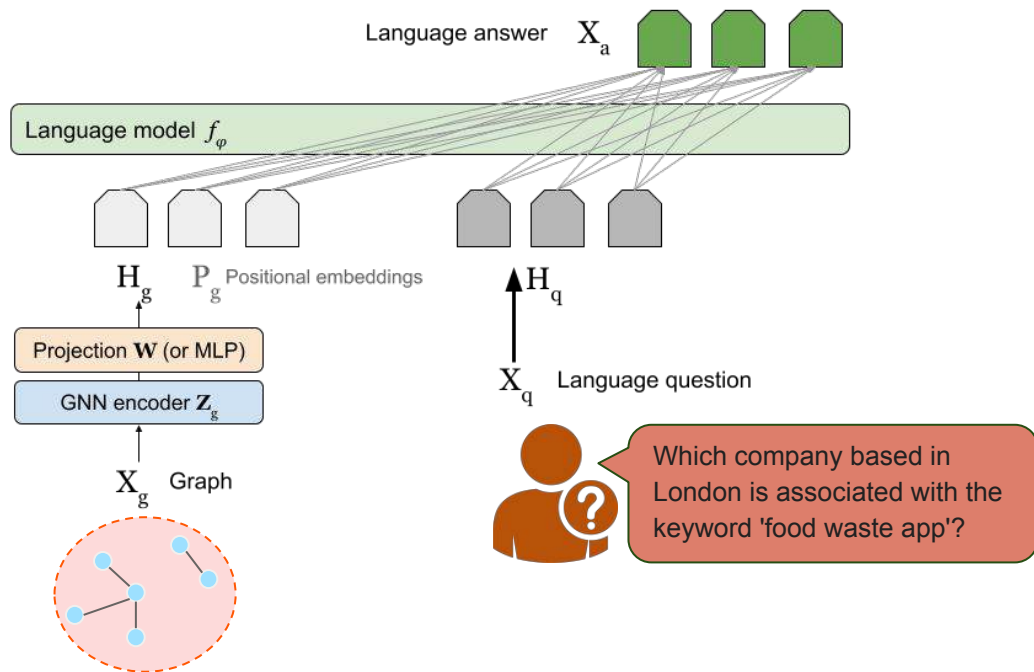
Reasoning: Zero-shot (simple option)

Zero-shot: transform the sub-KG into texts.



Reasoning: Cross-modal finetune (cool option)

Cross-modal finetune: jointly tune the word (text) and node (graph) into the same token space.



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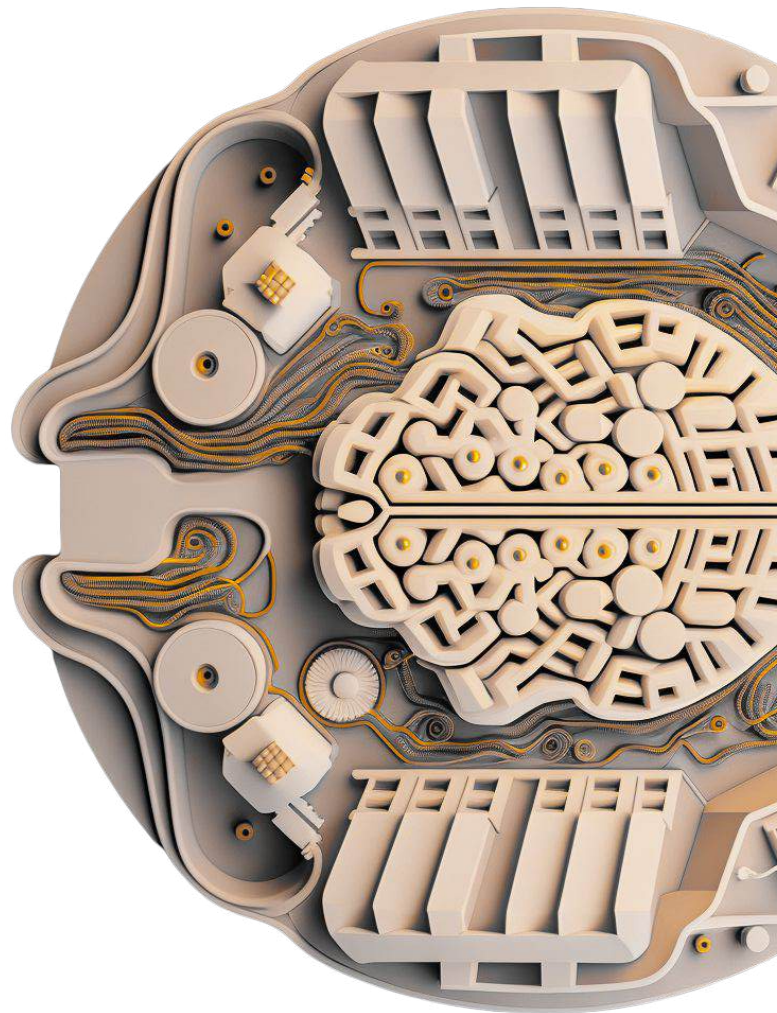
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KG Construction

Contextual Retrieval

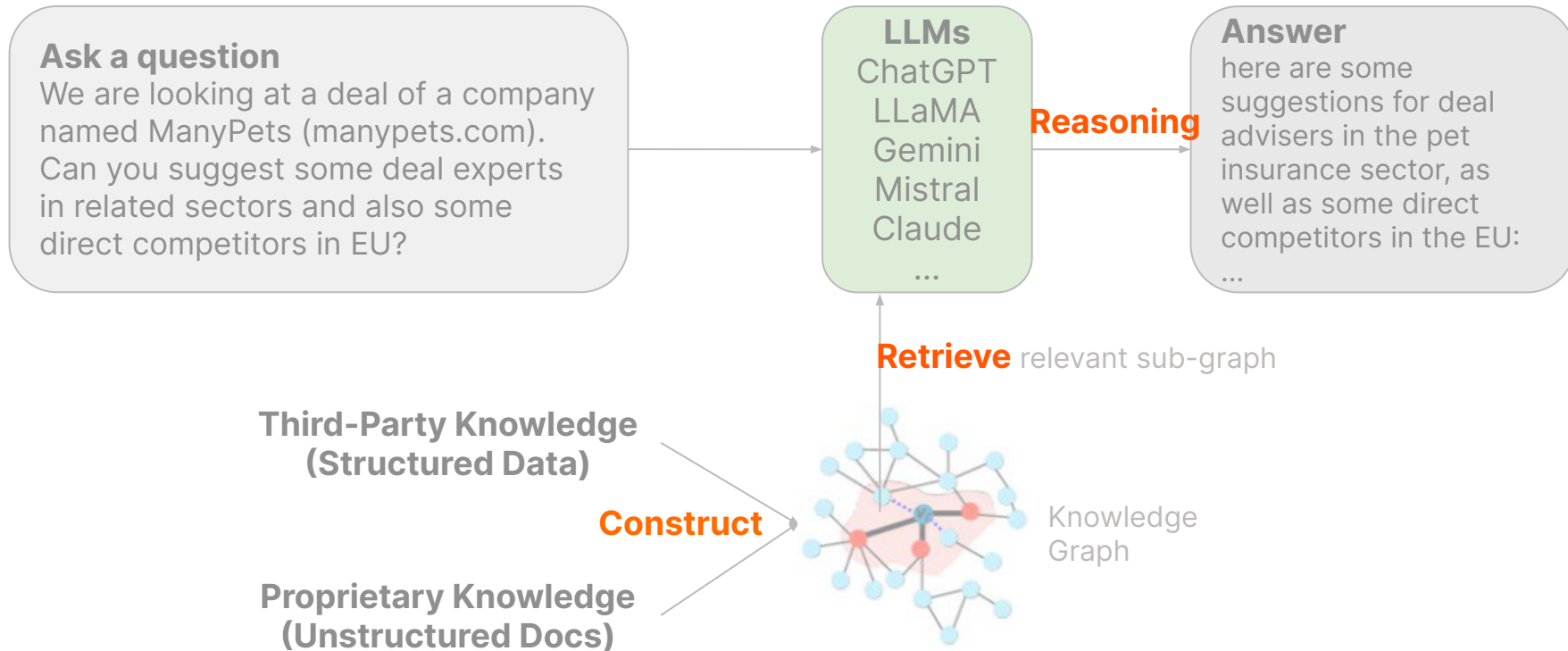
Reasoning

Summary



Summary

Knowledge Graph can empower LLM to facilitate PE investment activities.





Summary

Knowledge Graph can empower LLM to facilitate PE investment activities.

Reasoning

Retrieve

- Define the entities and relation first.
- Combine proprietary and 3rd-party data.
- Multimodal LLM enables automatic KG extraction.

Construct



Summary

Knowledge Graph can empower LLM to facilitate PE investment activities.

Reasoning

- Define the entities and relation first.
- Combine proprietary and 3rd-party data.
- Multimodal LLM enables automatic KG extraction.

Construct

Retrieve

- Identify named entities in question first.
- Graph database works better than vector database.
- Ask LLM to generate retrieval query.



Summary

Knowledge Graph can empower LLM to facilitate PE investment activities.

- Zero-shot is simple and performs OK!
- Cross-modal finetune is new and cool, yet will be challenging to do well.

Reasoning

- Define the entities and relation first.
- Combine proprietary and 3rd-party data.
- Multimodal LLM enables automatic KG extraction.

Construct

Retrieve

- Identify named entities in question first.
- Graph database works better than vector database.
- Ask LLM to generate retrieval query.

Thanks!

- For further interaction, feel free to ping me on LinkedIn:
www.linkedin.com/in/caolele
- Or, email us: tech_motherbrain-research@eqtpartners.com
- Learn more about EQT Motherbrain at:
<https://eqtgroup.com/motherbrain>
<https://motherbrain.ai/>

