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Knowledge Graph Infused Natural Language to SQL with Domain Adapted LLM for Patient Data



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Agenda

- Introduction
 - Current challenges with data democratization
 - Challenges with traditional LLMs / RAG
- McKesson Compile's NL to SQL approach
- NL to SQL showcase
- Results and Metrics
- Conclusion

Current Challenges in Data Democratization

- Expertise limitations
 - Analyst required to query data using SQL
- Domain-specific complexities
 - Specialized nomenclature
 - Multiple diverse coding systems
 - Dilution of context from business user to analyst to SQL query
 - Diverse healthcare elements hosted on complex database models
- Limitations of traditional LLMs / RAG
 - Complex schematic understanding
 - Non-standard table and schema nomenclature
 - Low-precision retrieval due to lack of semantic knowledge

Challenges with Traditional LLMs / RAG

- Complex schematic understanding
- Non-standard table and schema nomenclature
- Low-precision/ Low-recall retrieval due to lack of semantic knowledge
- Lengthy prompts to guide through the intricacies of healthcare data analytics
 - Financial implications
- Ground-truth or the retrieved context do not capture the relationships in the data
- Co-pilots and task specific LLMs (NL to SQL) lack the required context of the domain and data elements

McKesson Compile's NL to SQL approach

The approach is broadly divided into 3 parts:

1. Data ingestion

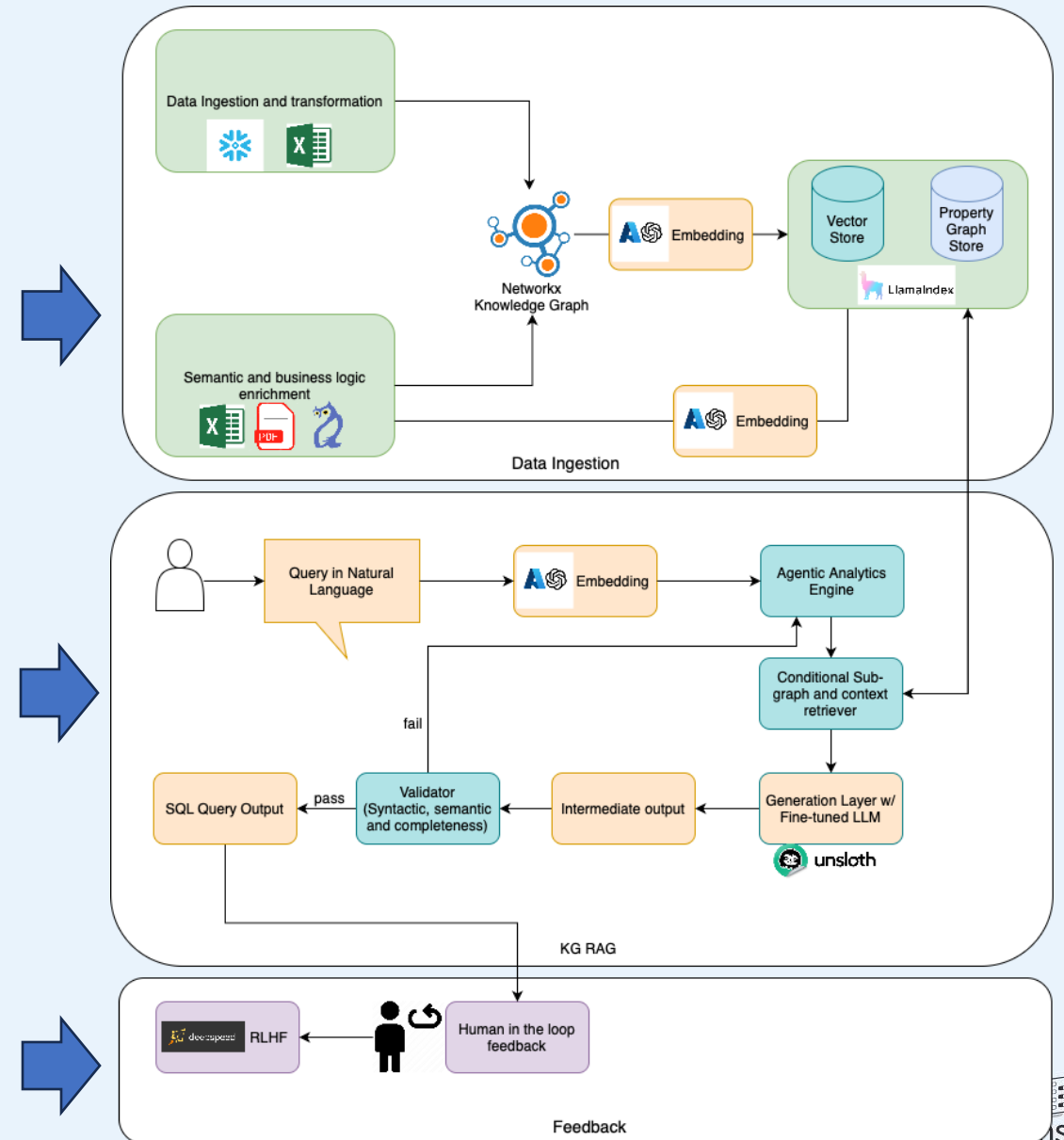
- Semantic and schematic knowledge ingestion

2. Knowledge graph (KG) RAG

- Proprietary retrieval mechanism from Graph and Vector stores
- Generational layer with domain adapted LLM

3. Feedback loop

- Human feedback capture mechanism for further model alignment with RLHF



Data | Data Understanding

Schematic data

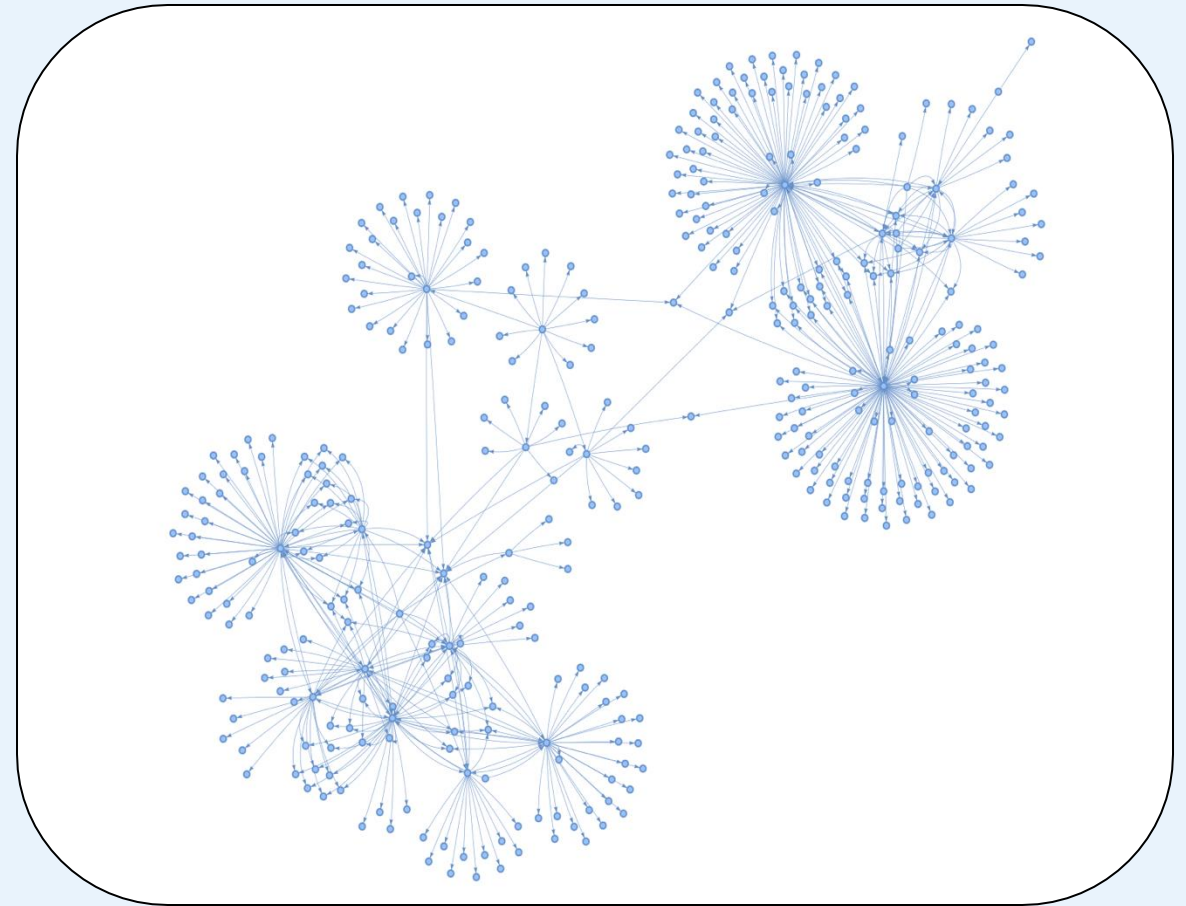
- Schema – table – column relationships
- Table – table relationships

Semantic data

- Description of the node types
- Description of the node values
- Understanding the data types and data distribution
- Semantic tagging using the diverse node values and aliases
- Business logic

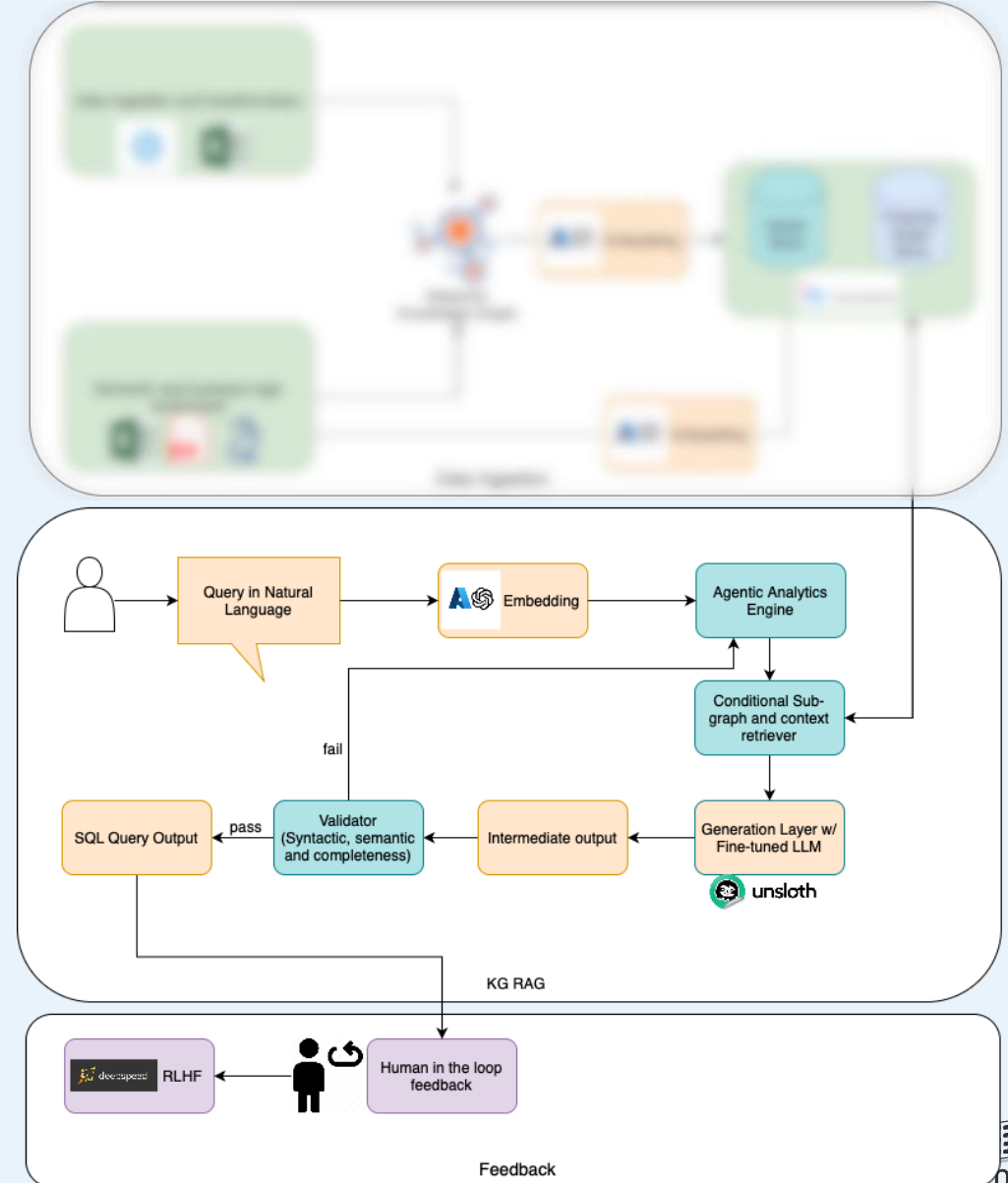
Embedded Knowledge Graph (KG)

- Semantic knowledge embedding with schematic relationships
- Relationship prediction using semantic tagging
 - Useful for relevant sub-graph / community extraction
- High-precision retrieval and generation
 - Constrained sub-graph retrieval from KG
 - Less guidance required for complex problems through structured prompting
 - Fine-tuned LLM leveraging gisting approach for output generation



Query Synthesis & Continual Learning

- Agentic SQL generation
 - Iterative retrieval agent to ensure completeness in the answer through conditional retrieval
 - SQL Validation engine
 - Agent that ensures syntactical accuracy
 - Contextual relevance and completeness
 - Fine-tuned LLM leveraging gisting approach for output generation
- Feedback loop
 - Quick feedback through bucketized granular options
 - Specific feedback through free flow text
 - Maintaining output – feedback pairs for further fine-tuning of the LLM through RLHF



NL to SQL showcase: Example 1

Q: Extract Top 10 HCPs
(based on patient volume)
that are diagnosing patients
with Lung Cancer disease
(Diagnosis code: C34) for
the year of 2023

Filters and
transformations are
thoughtfully applied to
deliver precise and
concise answers to the
user's question

Identifies right tables and
columns of reference

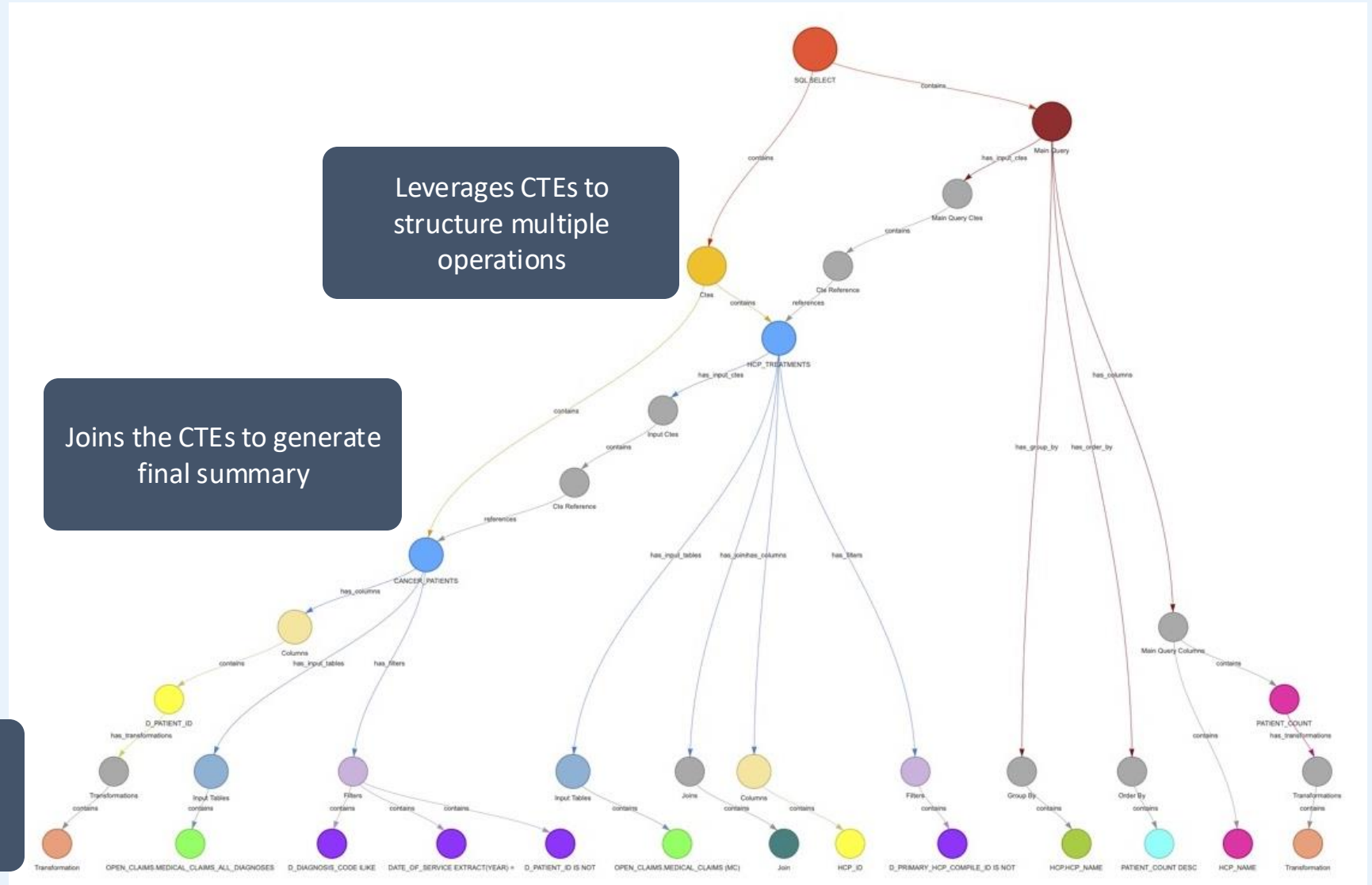


Figure: Visualization of SQL query generated by NL to SQL

NL to SQL showcase: Example 1 Output

Q: Extract Top 10 HCPs
(based on patient volume)
that are diagnosing patients
with Lung Cancer disease
(Diagnosis code: C34) for
the year of 2023

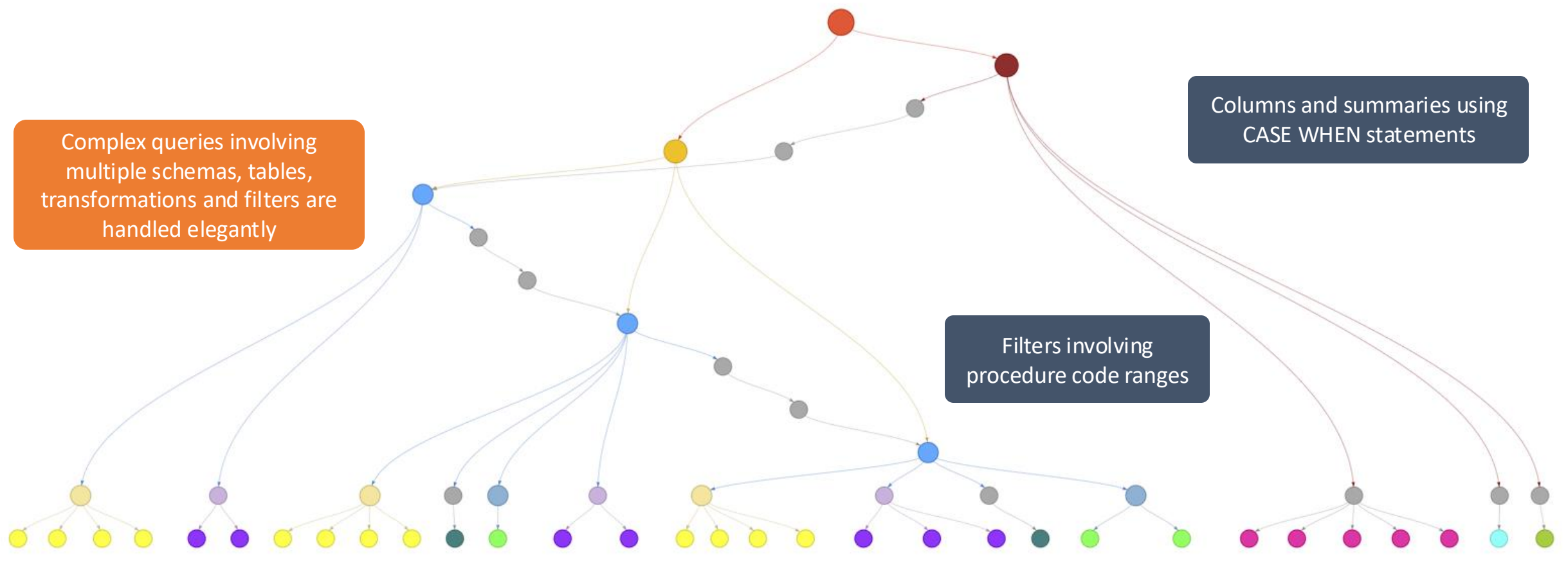
HCP	PATIENT_COUNT
HCP 1	3,123
HCP 2	2,513
HCP 3	2,441
HCP 4	2,158
HCP 5	1,578
HCP 6	1,555
HCP 7	1,503
HCP 8	1,496
HCP 9	1,460
HCP 10	1,431

Note: Data shown is for illustrative purposes only

NL to SQL showcase: Example 2

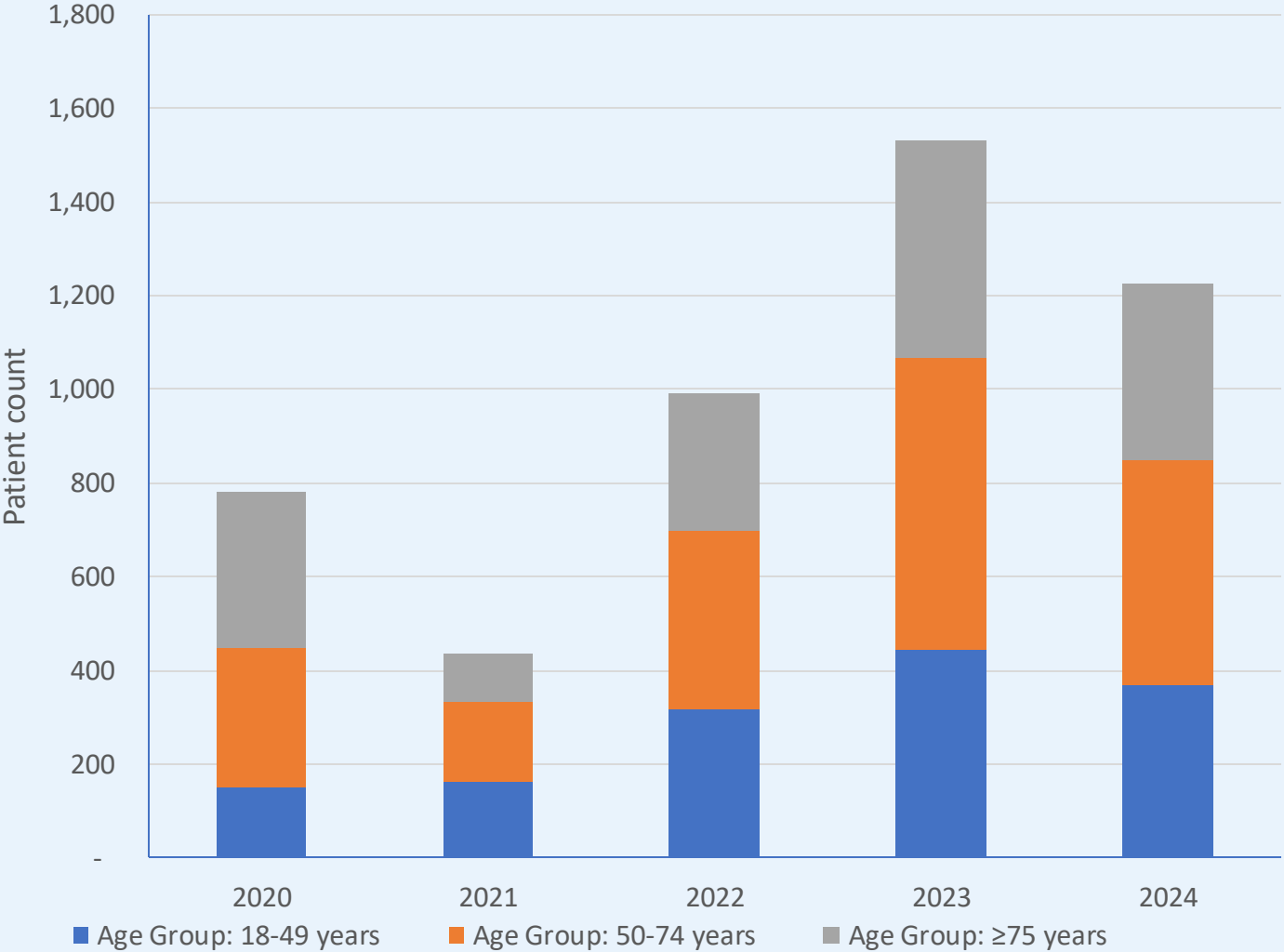
Q: Provide feasibility estimates (patient counts) by year from 2020 to 2024 in 25 year age group buckets for patients aged ≥ 18 years with a non-inpatient, non-diagnostic* claim and having an hMPV diagnosis.

**Non-diagnostic claims are claims without any procedures for Radiology, Venipuncture Pathology and Laboratory.*



NL to SQL showcase: Example 2 Outputs

METRIC	SERVICE_YEAR	PATIENT_COUNT
Age Group: 18-49 years	2020	149
Age Group: 18-49 years	2021	162
Age Group: 18-49 years	2022	318
Age Group: 18-49 years	2023	443
Age Group: 18-49 years	2024	368
Age Group: 50-74 years	2020	299
Age Group: 50-74 years	2021	169
Age Group: 50-74 years	2022	379
Age Group: 50-74 years	2023	623
Age Group: 50-74 years	2024	479
Age Group: ≥75 years	2020	334
Age Group: ≥75 years	2021	106
Age Group: ≥75 years	2022	295
Age Group: ≥75 years	2023	466
Age Group: ≥75 years	2024	379



Note: Data shown is for illustrative purposes only

Results Demonstrate a Reduction in 3 Key Areas

↓ 95%

Non-executable queries

- Schema misidentification & incorrect syntax
- Attributed to
 - SQL Validation agent
 - KG relationships

↓ 5x

Hallucinations

- Semantic / contextual relevance & completeness
- Attributed to
 - Agent orchestrator
 - Conditional retrieval agent

↓ 15x

Token count

- Attributed to
 - Fine-tuned LLM with gisting
 - Condensed context through KG relationships

Conclusions and Future Directions

- Real-world applications
 - Clinical decision intelligence
 - Analytical applications like feasibility analysis, cohort analysis, etc.
 - Advanced provider network analytics
 - Operational improvements
- Improved precision and recall in data democratization
- Cost-efficient GenAI application
- Strong foundation for NL to insights

Thank you for your attention

Questions?

Visit McKesson Compile at booth 212

