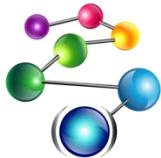


Knowledge Graphs with LLMs: Neuro-Symbolic AI

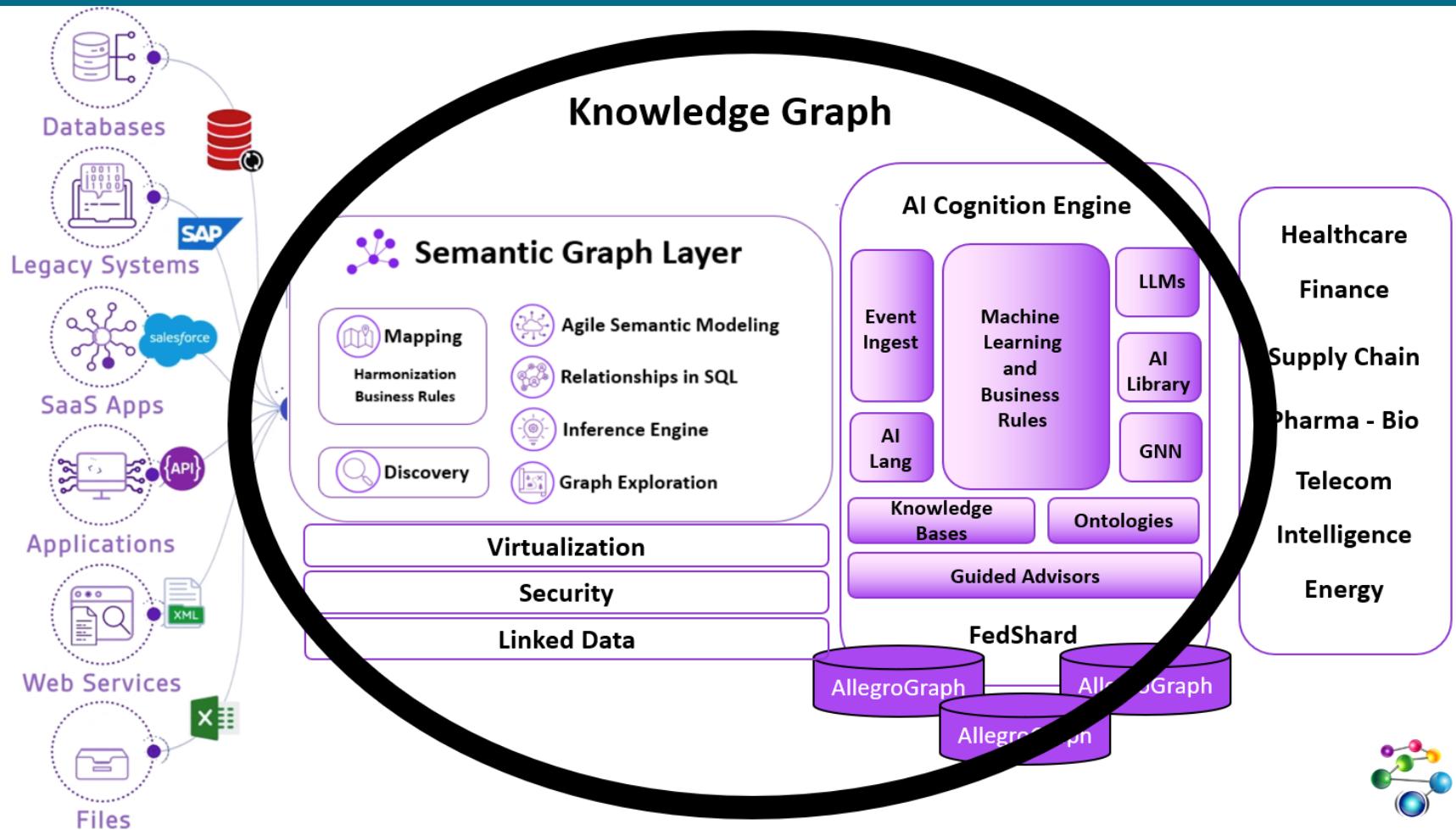
An introduction

January 2024



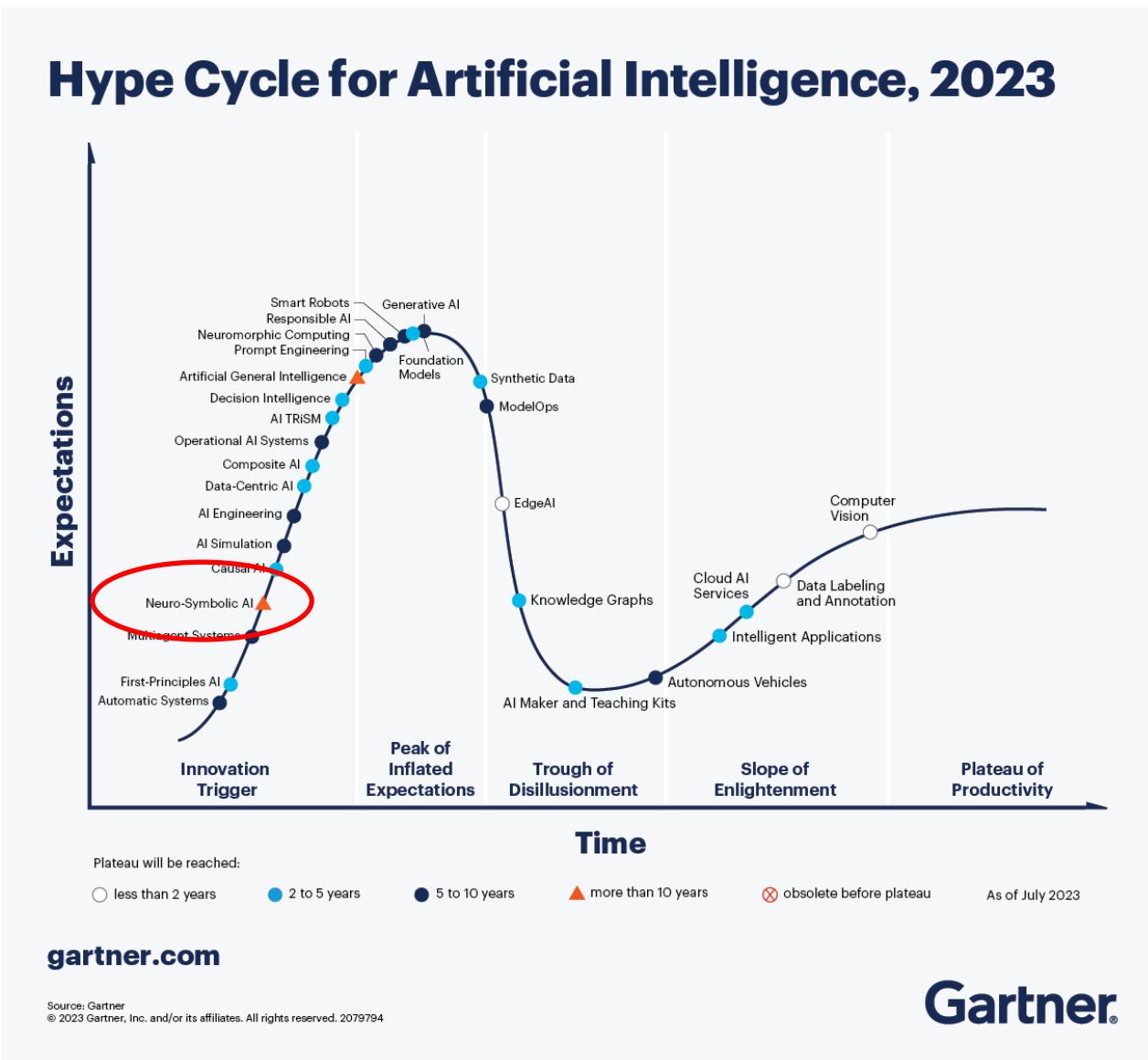
We are a Knowledge Graph Company

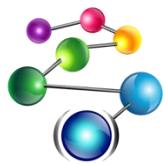
AllegroGraph Platform





2023: Neuro-Symbolic AI is on the Rise





Enterprise Drivers for Neuro-Symbolic AI

Trust

Limitations of AI models that rely purely on machine learning techniques that focus on correlation over understanding and reasoning. LLMs sometimes give factually incorrect answers or produce unexpected results (hallucinations)

Explainability

The need for explanation and interpretability of AI outputs that are especially important in the regulated industry use cases and in systems that use private data.

Semantics

The need to move toward semantics over syntax in systems that deal with real-world entities in order to ground meaning to words and terms in specific domains.

Future-proof Systems

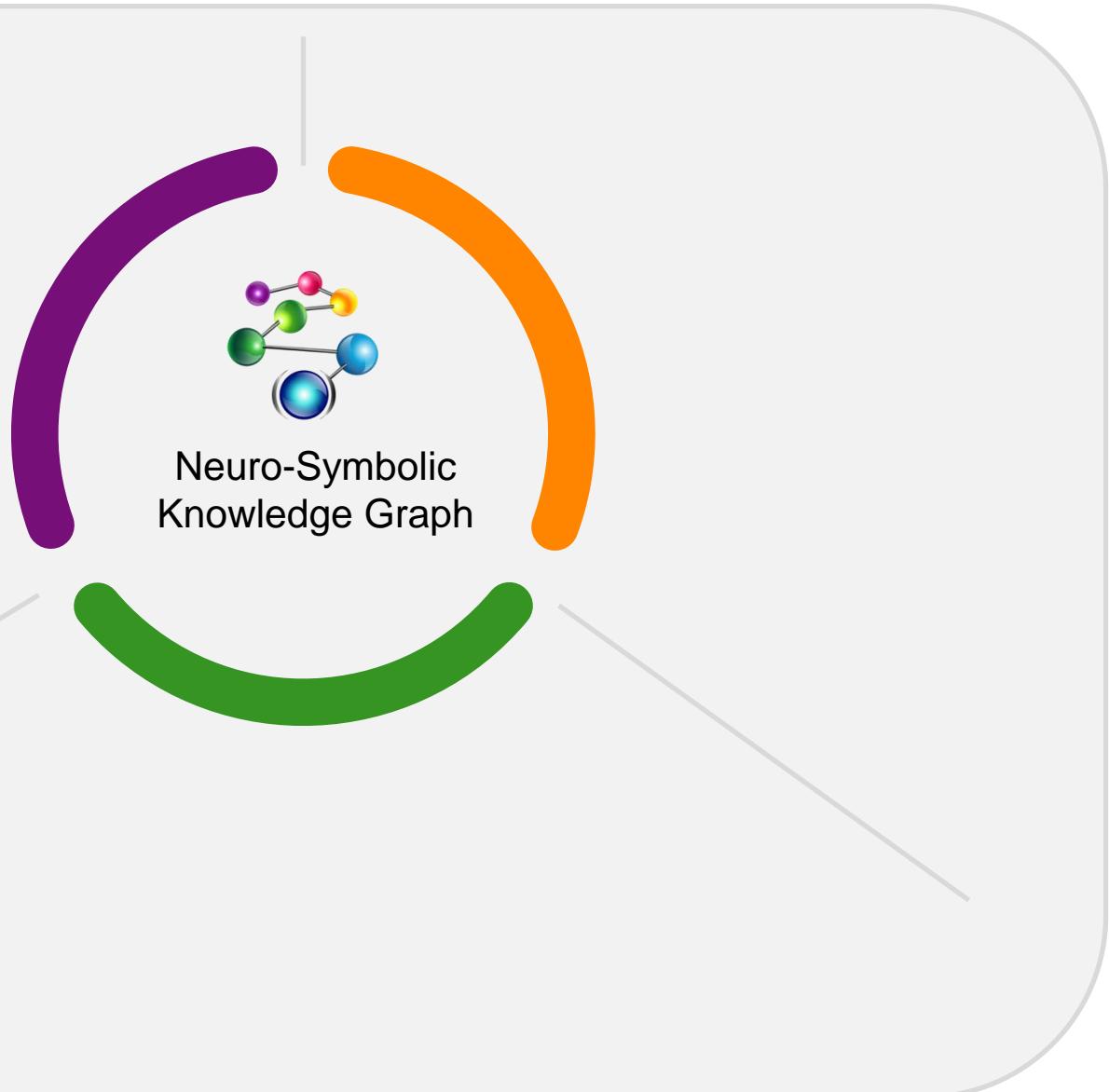
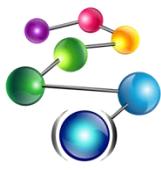
The integration of multiple reasoning mechanisms necessary to provide agile AI systems eventually leading to adaptive AI systems.

Composite AI Tooling

The set of tools available to combine different types of AI models is increasing and becoming easier to use for developers, data scientists and end users.

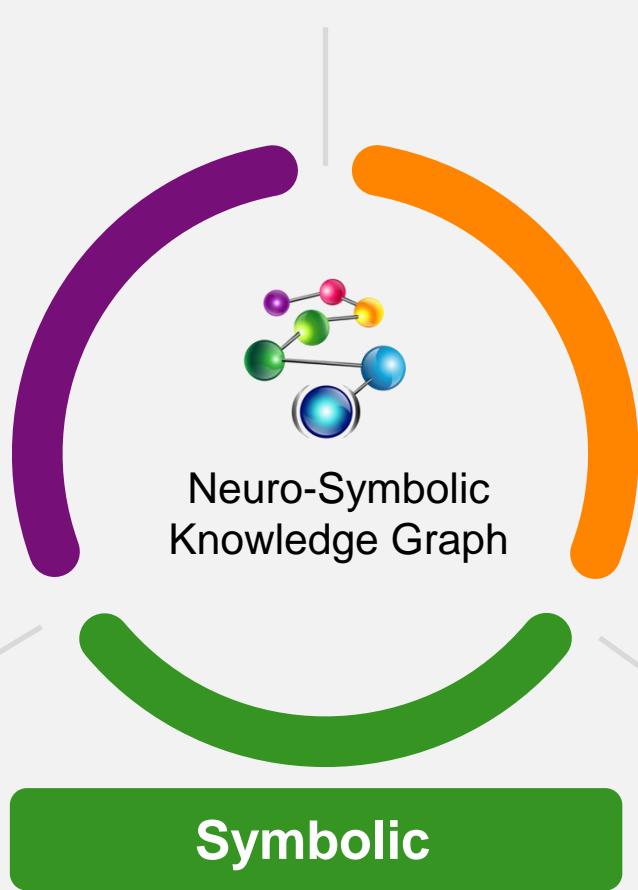
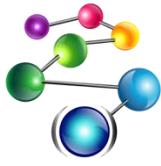
Neuro-Symbolic AI

Knowledge Graph Architecture



Neuro-Symbolic AI

Knowledge Graph Architecture

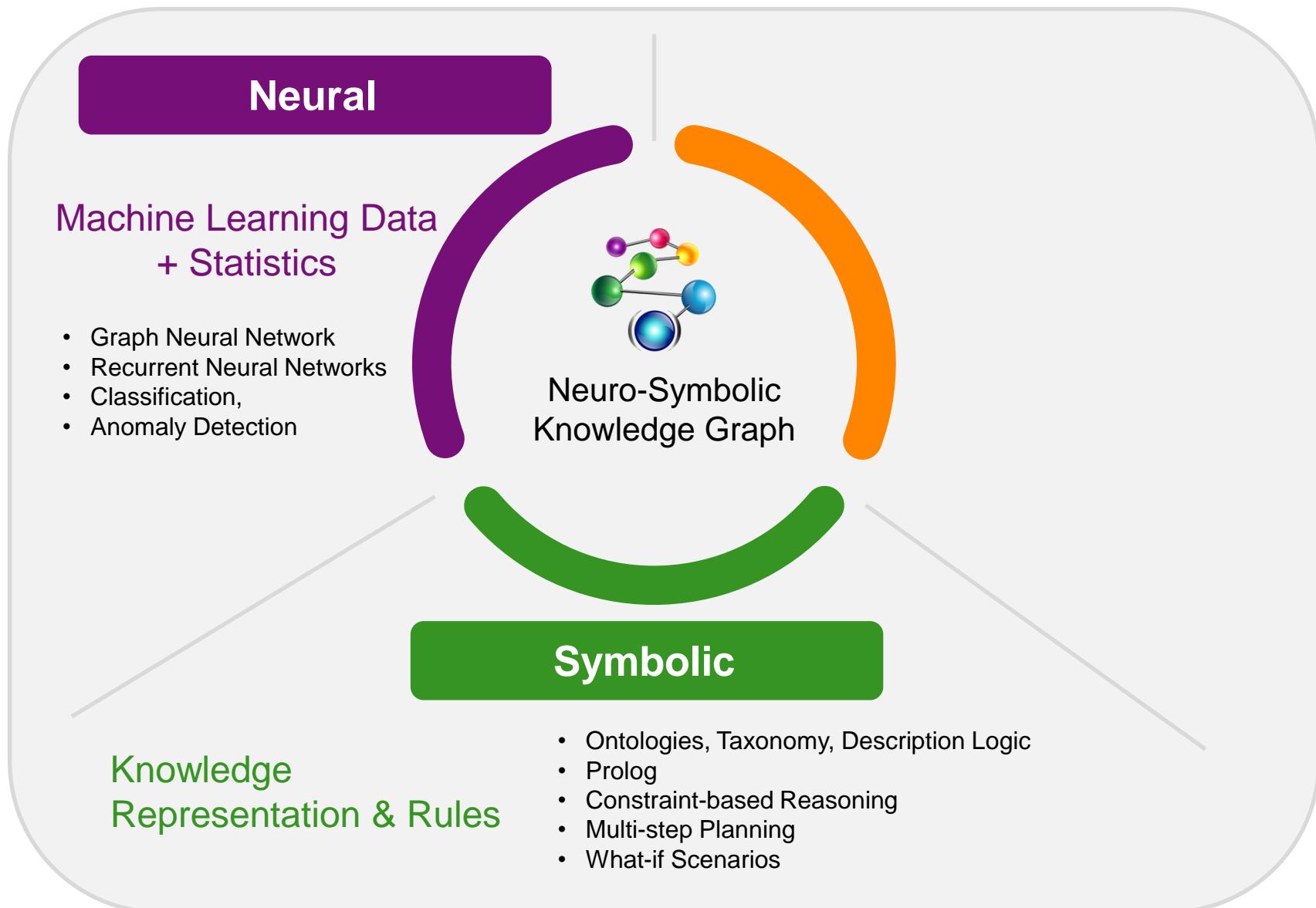
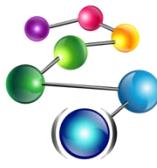


Knowledge
Representation & Rules

- Ontologies, Taxonomy, Description Logic
- Prolog
- Constraint-based Reasoning
- Multi-step Planning
- What-if Scenarios

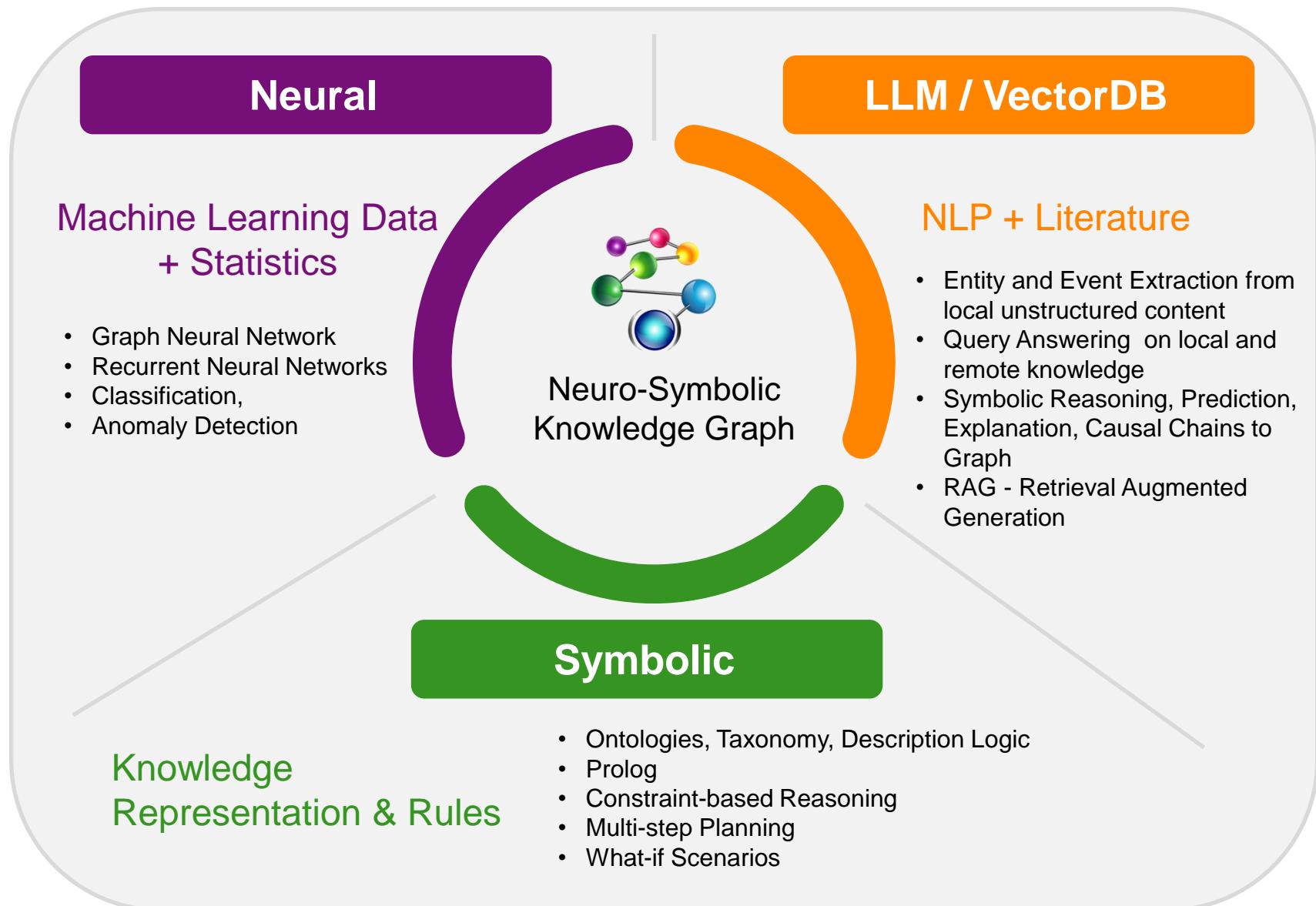
Neuro-Symbolic AI

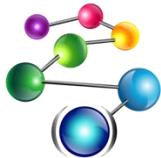
Knowledge Graph Architecture



Neuro-Symbolic AI

Knowledge Graph Architecture





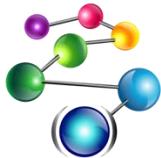
Symbolic – Logic, Reasoning, Rules

Strengths

- **Precision & Consistency**
 - Diagnoses, classifications, predictions are repeatable
- **Transparency & Explainability**
 - Clear insight into how conclusions are reached
- **Reliable in well-understood domains**

Weaknesses

- **Complexity & Maintenance**
 - Need continuous updates
- **Limited Flexibility**
 - Need more rules if novel cases come up
- **Dependent on Experts**
 - Need domain experts that understand their own rules and knowledge and can explain to rule-builder



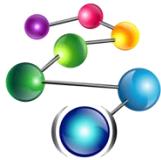
Neural - Machine Learning, Statistics

Strengths

- **Adaptability**
 - Learn and adapt from new data without writing rules
- **Pattern Recognition**
 - Identify patterns and correlations in large data sets
- **Efficiency in Data Handling**
 - Handle enormous amounts of data

Weaknesses

- **Black Box Problem**
 - Hard to explain recommendations and predictions. Trust issue
- **Data Quality and Quantity**
 - Insufficient, inaccurate or biased data leads to poor decision making
- **Ethical and Privacy Concerns**
 - For good results, you need to see ALL the data - potential for Personal Information Leakage



LLM – Vector, RAG

Strengths

- **Natural Language Understanding**
 - At a level we have never seen before. Reasoning is impressive
- **All the knowledge in the world**
 - LLMs integrate knowledge from many different sources and domains
- **Up-to-date**
 - With the latest from OpenAI and Google we now have up-to-date info

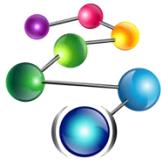
Weaknesses

- **Reliability and Accuracy**

Never trust any LLM conclusion, prediction, or recommendation.
- **Contextual understanding**

Lacks human embodiment for true understanding of the physical world
- **Ethical and Privacy Concerns**

Will this LLM train on my data?
Are the results acceptable from an ethical point-of-view



This talk has three parts

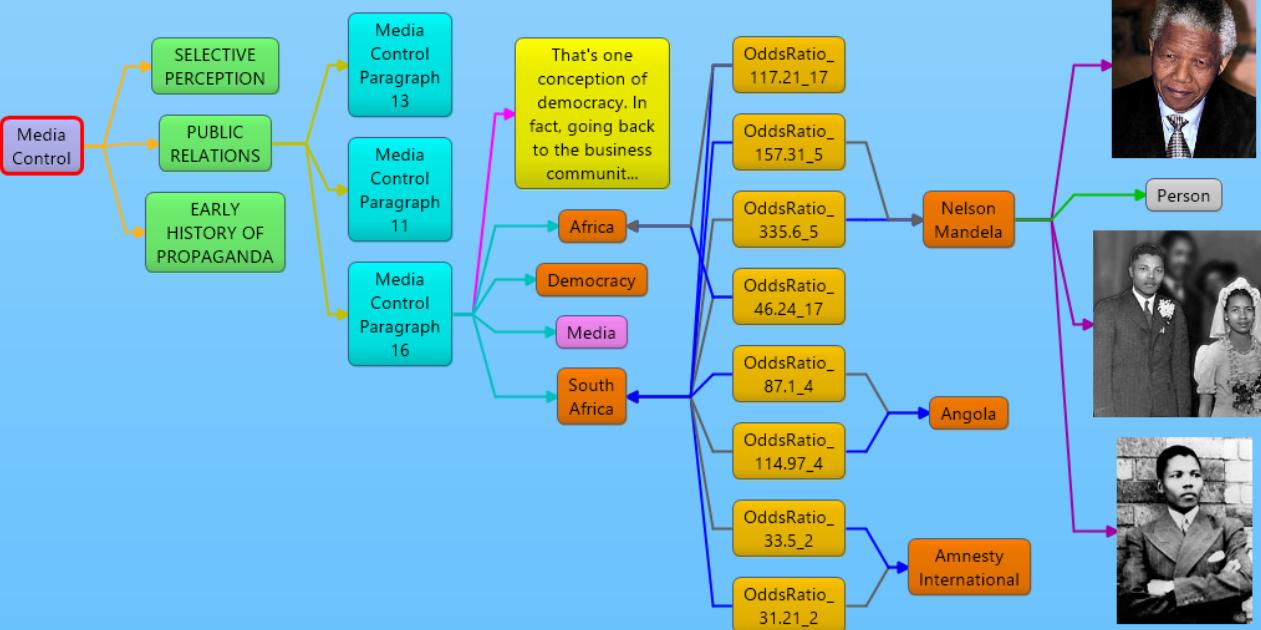
- A little bit about graphs and graph visualization
- Some examples of how to use LLMs with Knowledge Graphs
- A higher level discussion about NeuroSymbolic AI
- One or two examples

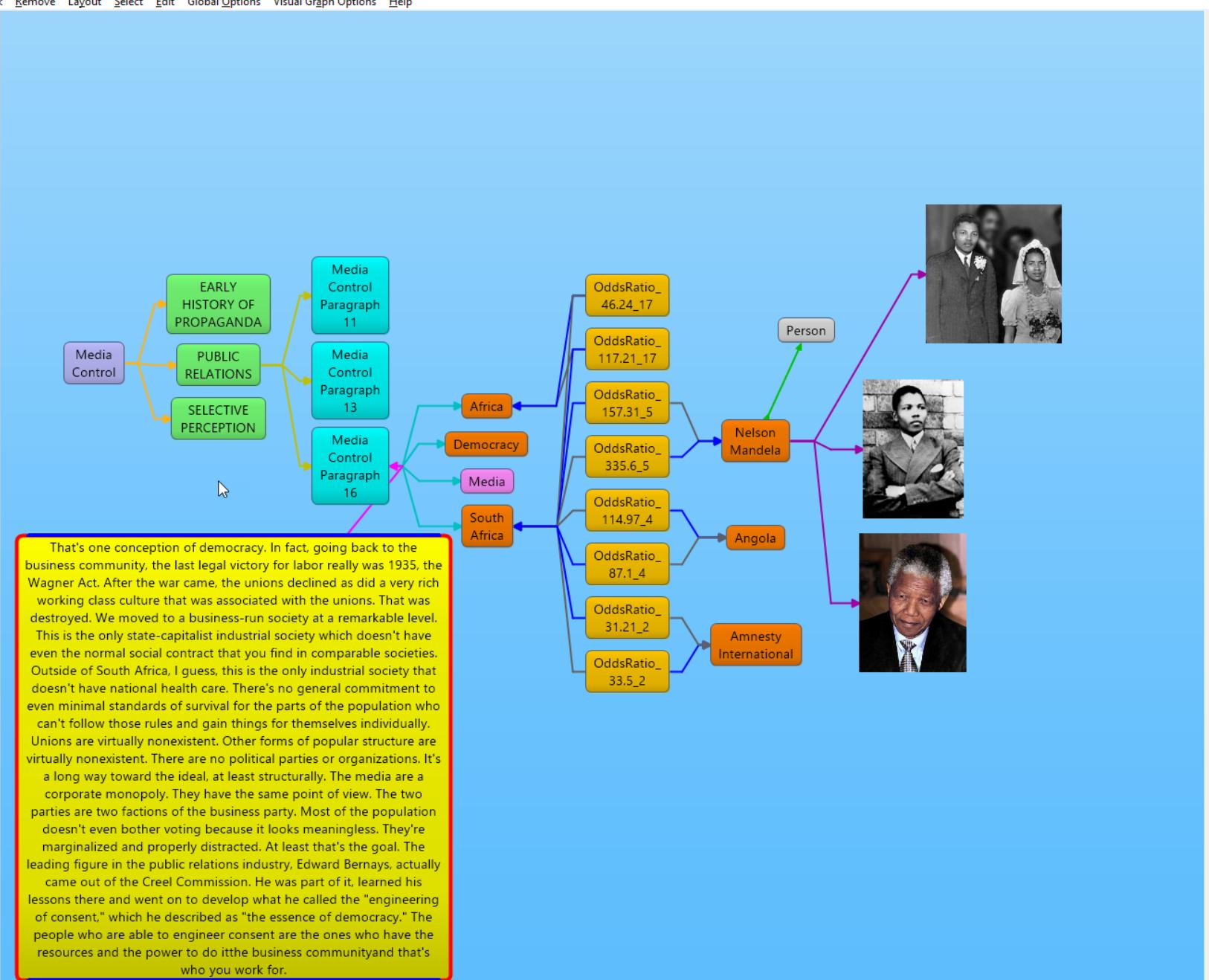
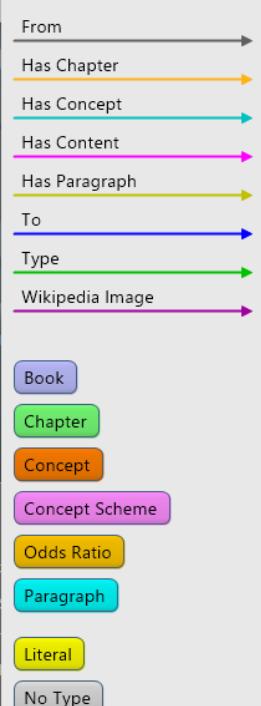
A knowledge graph for Noam Chomsky



- Initiated by the Chomsky Project to preserve Noam Chomsky's work
- Volunteers created extensive taxonomy of Chomsky related topics
- Volunteers collected books, interviews, papers and used markup to create systematic document structure
- We put all of that in a knowledge graph and allowed for semantic search
- And since the advent of vector stores and LLM we can talk to Chomsky without programming skills

- From →
- Has Chapter →
 - Has Concept →
 - Has Content →
 - Has Paragraph →
 - To →
 - Type →
 - Wikipedia Image →
- Book
- Chapter
- Concept
- Concept Scheme
- Odds Ratio
- Paragraph
- Literal
- No Type





Media Control Paragraph 16

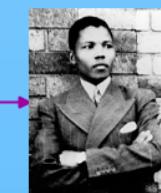
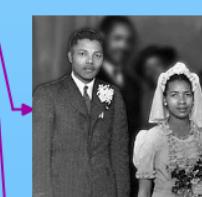
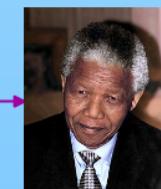
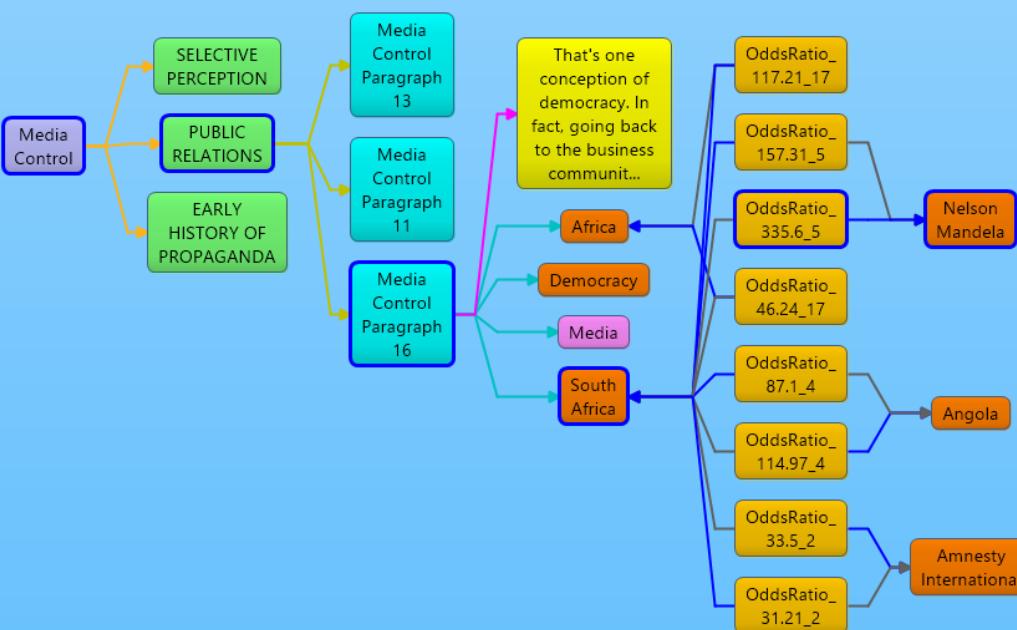
Revisit



Show All Triples

Property	Value
	Left-click a property to collapse or expand its rows. Shift-left-click to add a property's triples to the graph view. Control-left-click a property to make it a current predicate.
From Book	Media Control
From Chapter	PUBLIC RELATIONS
Gensim Similarity	Media Control Paragraph 11 Media Control Paragraph 19 Media Control Paragraph 5 Media Control Paragraph 6 Power Systems Answer 159 Power Systems Answer 293 Power Systems Answer 79 Requiem for the American Dream Paragraph 21 Requiem for the American Dream Paragraph 331 Requiem for the American Dream Paragraph 402
Has Abstractive Summary	In fact, going back to the business community, the last legal victory for labor really was 1935, the Wagner Act. After the war came, the unions declined as did a very rich working class culture that was associated with the unions. We moved to a business-run society at a remarkable level. Other forms of popular structure are virtually nonexistent.
Has Category	Politics Work
Has Concept	Africa Business Capitalism Class Democracy Health Care Industrial Sector Media Political Parties Public Relations Society South Africa War Working Class
Has Content	That's one conception of democracy. In fact, going back to the business community, the last legal victory for labor really was 1935, th
Has Extractive Summary	In fact, going back to the business community, the last legal victory for labor really was 1935, the Wagner Act. Outside of South Africa, I guess, this is the only industrial society that doesn't have national health care. The leading figure in the public relations industry, Edward Bernays, actually came out of the Creel Commission. After the war came, the unions declined as did a very rich working class culture that was associated with the unions. This is the only state-capitalist industrial society which doesn't have even the normal social contract that you find in comparable societies. It's a long way toward the ideal, at least structurally.

- From →
- Has Chapter →
 - Has Concept →
 - Has Content →
 - Has Paragraph →
 - To →
 - Type →
 - Wikipedia Image →
- Book
Chapter
Concept
Concept Scheme
Odds Ratio
Paragraph
Literal
No Type



SPARQL Prolog

Name Query

Revisit

Show Text Query

Run Query

 Full Cardinality REDUCED DISTINCT Limit

32

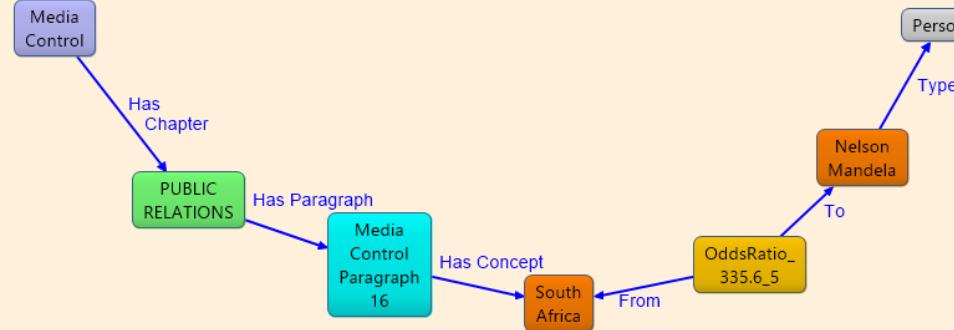
 Offset

0

FROM

FROM NAMED

Remember to right-click in this view.



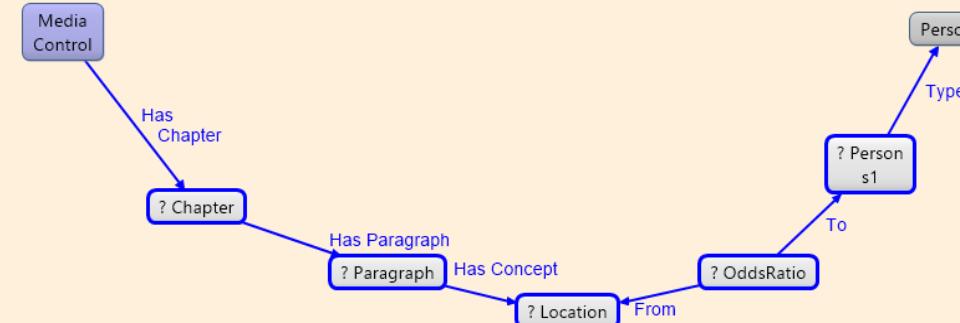
SPARQL Prolog Full Cardinality REDUCED DISTINCT Limit

32

 Offset

0

Remember to right-click in this view.



SPARQL Prolog

Reindent

Name Query

Revisit

Graph View

Table View

Graphical Query View



```
select distinct ?OddsRatio ?Person ?Location ?Paragraph ?Chapter where
{ chomsky:Media_Control chomsky:hasChapter ?Chapter .
?Chapter chomsky:hasParagraph ?Paragraph .
?Paragraph chomsky:hasConcept ?Location .
?OddsRatio chomsky:To ?Person ;
    chomsky:From ?Location .
?Person rdf:type chomsky:Person .
}
limit 10
```

10 Results

Create Visual Graph

Add to Visual Graph

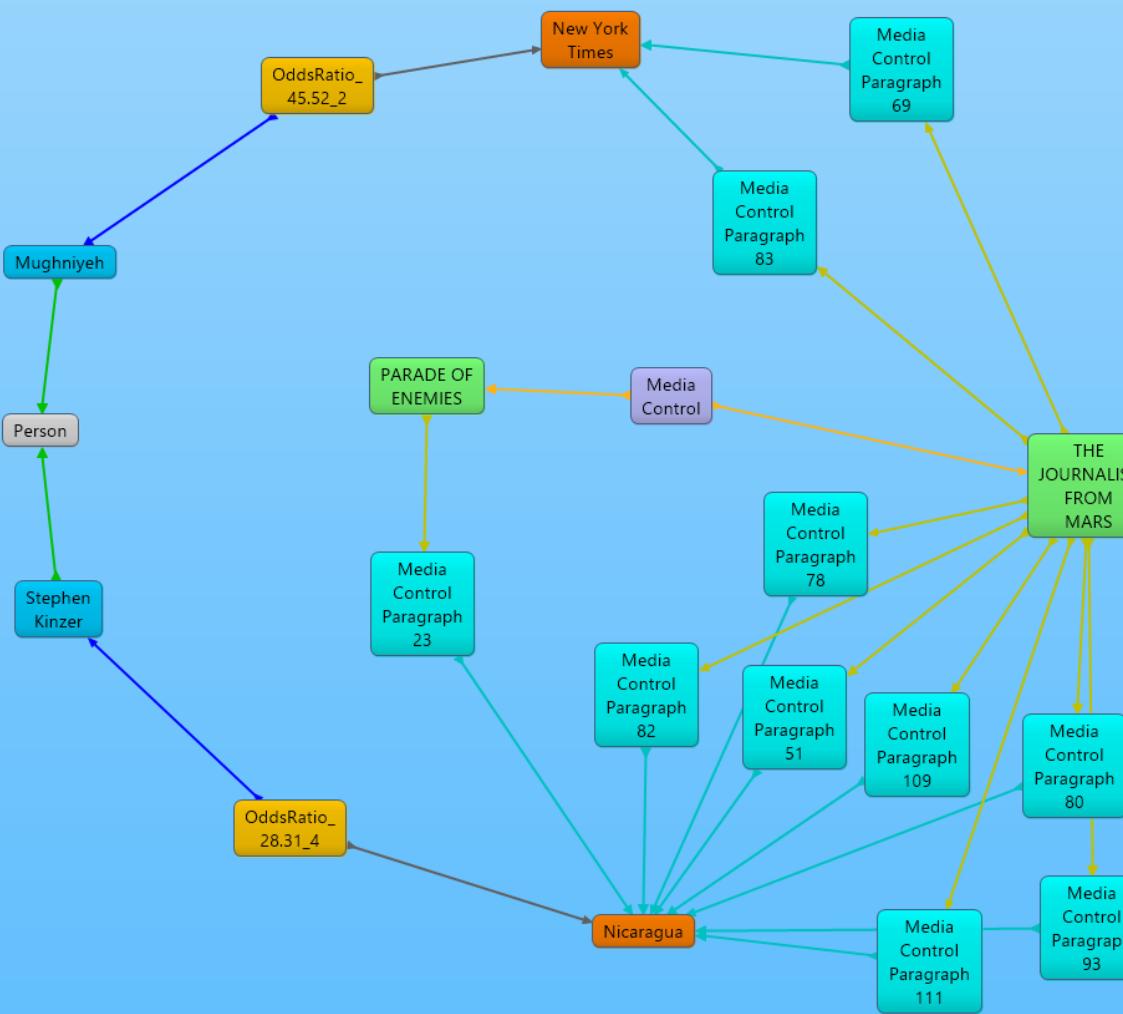
Write Text Report

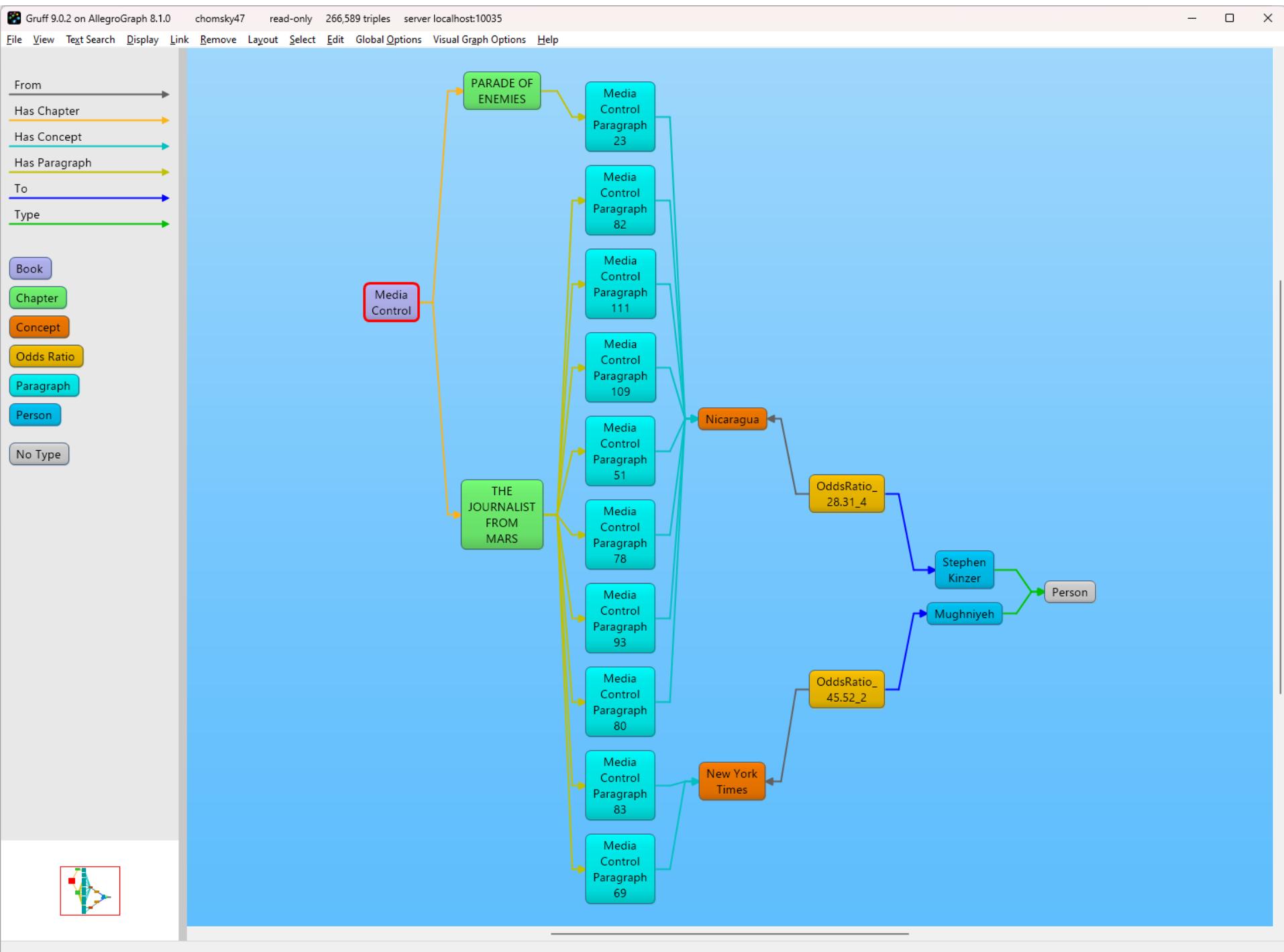
Save as CSV

?OddsRatio	?Person	?Location	?Paragraph	?Chapter
OddsRatio_28.31_4	Stephen Kinzer	Nicaragua	Media Control Paragraph 80	THE JOURNALIST FROM MARS
OddsRatio_28.31_4	Stephen Kinzer	Nicaragua	Media Control Paragraph 82	THE JOURNALIST FROM MARS
OddsRatio_28.31_4	Stephen Kinzer	Nicaragua	Media Control Paragraph 111	THE JOURNALIST FROM MARS
OddsRatio_28.31_4	Stephen Kinzer	Nicaragua	Media Control Paragraph 109	THE JOURNALIST FROM MARS
OddsRatio_28.31_4	Stephen Kinzer	Nicaragua	Media Control Paragraph 51	THE JOURNALIST FROM MARS
OddsRatio_28.31_4	Stephen Kinzer	Nicaragua	Media Control Paragraph 78	THE JOURNALIST FROM MARS
OddsRatio_28.31_4	Stephen Kinzer	Nicaragua	Media Control Paragraph 93	THE JOURNALIST FROM MARS
OddsRatio_28.31_4	Stephen Kinzer	Nicaragua	Media Control Paragraph 23	PARADE OF ENEMIES
OddsRatio_45.52_2	Mughniyah	New York Times	Media Control Paragraph 83	THE JOURNALIST FROM MARS
OddsRatio_45.52_2	Mughniyah	New York Times	Media Control Paragraph 69	THE JOURNALIST FROM MARS

From →
Has Chapter →
Has Concept →
Has Paragraph →
To →
Type →

Book
Chapter
Concept
Odds Ratio
Paragraph
Person
No Type





Select the Subject Nodes to Display

Matching Choices

Use Control+Click or Control+Space to select multiple values.

Subject	Types	Predicate	Object
Media Control	Book	Label	Media Control
MEDIA CONTROL The Spectacul...	Chapter	Label	MEDIA CONTROL The Spectacular Achievements of Propag...
Noam Chomsky: Can Civilization ...	News Article	Has Content	There is "capitalism" and then there is "really existing capital...
Tomgram: Noam Chomsky, The ...	News Article	Has Content	It didn't take long. In the immediate aftermath of the droppin...
WW"Perilously close to propaganda...	News Article	Has Content	It was no accident that the war in Iraq was the quintessential...
Failed States Paragraph 133	Paragraph	Has Content	In the most extensive media review of CPA practices, relying ...
Failed States Paragraph 376	Paragraph	Has Content	We thus have another demonstration of the Bush vision of d...
Failed States Paragraph 378	Paragraph	Has Content	There was much derision, along with sober expressions of ...
Failed States Paragraph 456	Paragraph	Has Content	That the Gaza pullout was in reality an expansion plan was h...
Failed States Paragraph 481	Paragraph	Has Content	The concern is not unfamiliar. The most prominent scholar ...
Failed States Paragraph 535	Paragraph	Has Content	Washington's isolation extends to other areas too. The Unite...
Hegemony or Survival Paragraph ...	Paragraph	Has Content	If the public escapes its marginalization and passivity, we fa...

Match Context for Media Control

Media Control

OK Cancel Hover Delay (milliseconds) 200

For help on any menu command, highlight the command and press F1.



Book

Select the Subject Nodes to Display

Matching Choices

Use Control+Click or Control+Space to select multiple values.

Subject	Types	Predicate	Object
Global Discontents Answer 162	Answer, Paragraph	Has Content	But ultimately the apartheid regime and their supporters cou...
Global Discontents Answer 28	Answer, Paragraph	Has Content	This is, incidentally, quite apart from the issue of the legitima...
Hegemony or Survival Paragraph ...	Paragraph	Has Content	Turning elsewhere, during the Reagan years Washington's ...
Hegemony or Survival Paragraph ...	Paragraph	Has Content	While Western powers and intellectuals were admiring the...
Nelson Mandela	Person, Concept	Pref Label	Nelson Mandela (en)
Power Systems Answer 138	Answer, Paragraph	Has Content	If you look at the record of who is designated a terrorist, it's s...
Who Rules the World Paragraph ...	Paragraph	Has Content	In this way, the honorable term "dissident" is used selectivel...
Who Rules the World Paragraph ...	Paragraph	Has Content	Cuban achievements in the liberation of Africa and the endin...

Match Context for Nelson Mandela

Nelson Mandela

OK Cancel Hover Delay (milliseconds) 200



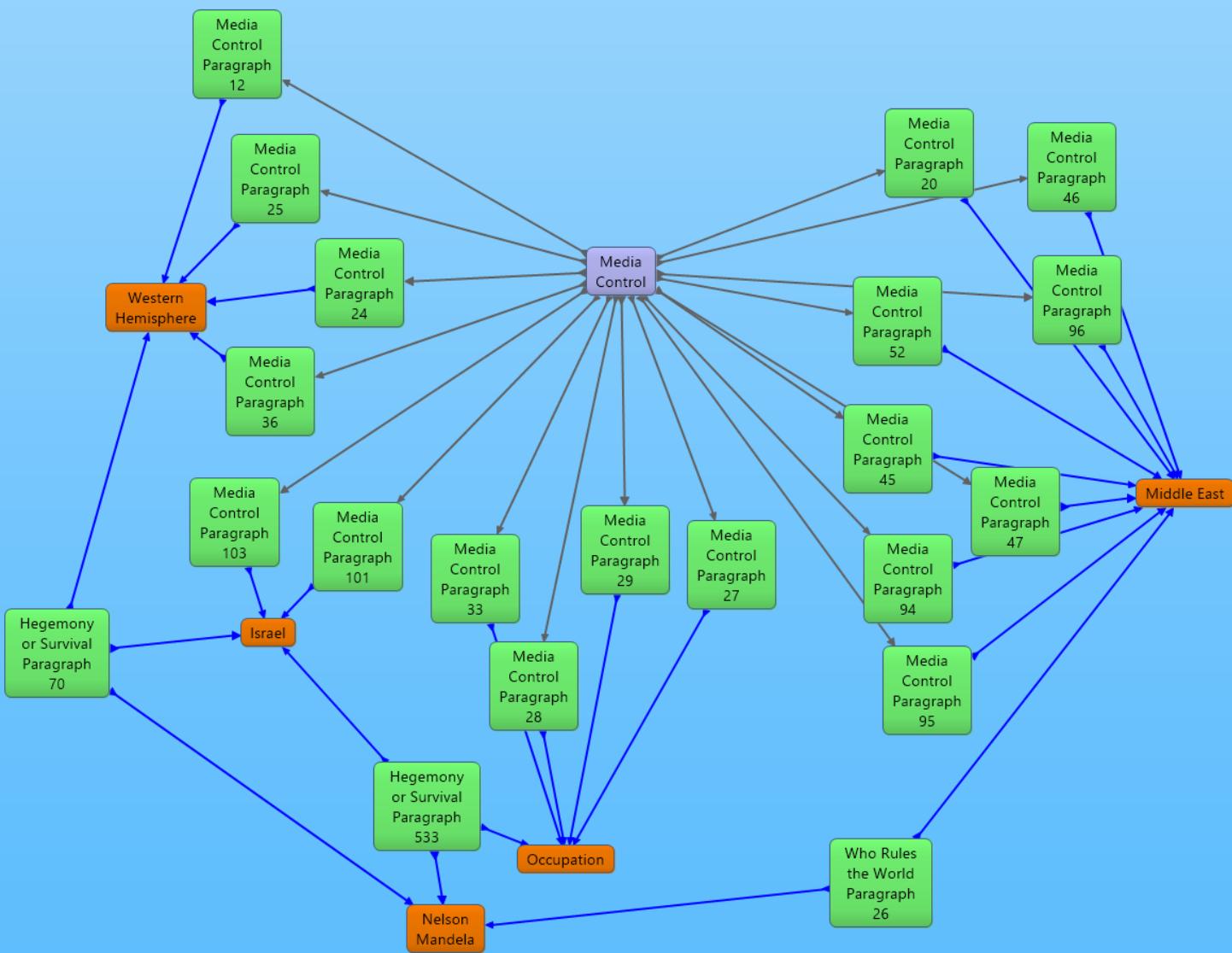
Book

Concept

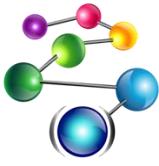
Media
ControlNelson
Mandela

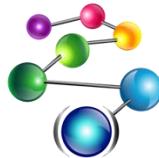
Has Concept →
Has Paragraph →

Book
Concept
Paragraph



Knowledge Graph can use LLM in many ways





Some SPARQL primitives (magic predicates)

1. Use all the knowledge in an LLM

- Ask a question and force LLM to return list of elements or JSON structures (llm:response)
- Turn strings into things (llm:node)
- Ask for a table all at once (llm:askForTable)

2. Use an LLM and vectorstore to query your private knowledge

- Query your text in your knowledge graph (llm:askMyDocuments & llm:nearestNeighbor)
- Create a chatbot for stateful interactions (llm:chatState)

3. Use an LLM to write queries against your knowledge graph



llm:response

Catalog
rootRepository
llm-playground-1Statements
0

TEST

0 - Hello, GPT X

```
1
2 SELECT ?response {
3   BIND (llm:response("Hello, GPT.") AS ?response)
4 }
```



▶ EXECUTE

1 ROW

DOWNLOAD RESULTS

QUERY INFORMATION

SEARCH

response

"Hello! How can I assist you today?"

Saved queries ^

0 - Hello, GPT [trash]1 - Entry lists [trash]2 - Resources [trash]3 - States [trash]4 - Borders [trash]5 - Ontology [trash]6 - Summar... [trash]

Query Templates ^

View triples

View quads

View classes

View predicates

>



llm:response returns lists

1 # This query demonstrates the use of `response` magic predicate.
2 # It generates a list of responses bound to the SPARQL variable `?entry`.
3
4 PREFIX llm: <http://franz.com/ns/allegrograph/8.0.0/llm/>
5 SELECT ?entry {
6 ?entry llm:response "List the most important types of threat actors in cyber security".
7 # Also try:
8 # ?entry llm:response "Suggest some names for a male cat."
9 # ?entry llm:response "Enumerate the causes of the American Civil War."
10 # ?entry llm:response "Name the colors of the rainbow."
11 }

▶ EXECUTE

10 ROWS

DOWNLOAD RESULTS

QUERY INFORMATION

SEARCH

entry

"Nation-states or Governments"

"Terrorists"

"Industrial Spies"

"Organized Crime Groups"

"Hacktivists"

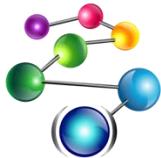
"Insiders"

"Competitors"

"Cybercriminals"

"Script Kiddies"

"Hactivists"



1 - Entry lists X

+ NEW QUERY

```
1 # This query demonstrates the use of `response` magic predicate.  
2 # It generates a list of responses bound to the SPARQL variable `?entry`.  
3  
4 PREFIX llm: <http://franz.com/ns/allegrograph/8.0.0/llm/>  
5 SELECT ?entry {  
6   ?entry llm:response "What are the top ten most frequent attacks by threat actors from a cyber security perspective".  
7   # Also try:  
8   # ?entry llm:response "Suggest some names for a male cat."  
9   # ?entry llm:response "Enumerate the causes of the American Civil War."  
10  # ?entry llm:response "Name the colors of the rainbow."  
11 }
```

► EXECUTE

10 ROWS

DOWNLOAD RESULTS

QUERY INFORMATION

SEARCH

entry

"Phishing attacks"

"Malware attacks"

"Ransomware attacks"

"Man-in-the-middle attacks"

"Denial-of-service attacks"

"SQL injection attacks"

"Zero-day exploit attacks"

"Cross-site scripting attacks"

"Password attacks"

"Drive-by attacks"



llm:response as magic predicate

AllegroGraph

Catalog Repository Statements

root llm-playground-1 0

?

TEST

0 - Hello, GPT × 1 - Entry lists ×

+

1
2 SELECT ?entry {
3 ?entry llm:response "List the US States.".
4 # Also try:
5 # ?entry llm:response "Suggest some names for a male cat."
6 # ?entry llm:response "Enumerate the causes of the American Civil War."
7 # ?entry llm:response "Name the colors of the rainbow."
8 }

EXECUTE

50 ROWS DOWNLOAD RESULTS QUERY INFORMATION SEARCH

entry

"Alabama"
"Alaska"
"Arizona"
"Arkansas"
"California"
"Colorado"

Saved queries

- 0 - Hello, GPT
- 1 - Entry lists
- 2 - Resources
- 3 - States
- 4 - Borders
- 5 - Ontology
- 6 - Summar...

Query Templates

- View triples
- View quads
- View classes
- View predicates



Infinitely composable

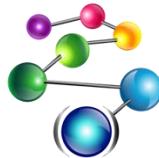
2 - Resources X 3 - States X +

```
9 PREFIX llm: <http://franz.com/ns/allegrograph/8.0.0/llm/>
10 SELECT ?state ?capital ?pop ?area ?admit ?gov ?celeb {
11   { SELECT ?state { ?state llm:response "List the US states.". } ORDER BY RAND() LIMIT 10 }
12   BIND (llm:response(CONCAT("Name the capital of the state of ", ?state, ". Return the city name only.")) AS ?capital).
13   BIND (llm:response(CONCAT("State the population of the state of ", ?state, ". Respond with a number only.")) AS ?pop).
14   BIND (llm:response(CONCAT("Tell me the square mile area of the state of ", ?state, ". Respond with a number only.")) AS ?area).
15   BIND (llm:response(CONCAT("In what year was ", ?state, " admitted to the Union?. Respond with a year only.")) AS ?admit).
16   BIND (llm:response(CONCAT("Who is the governor of the state of ", ?state, "? Respond with the governor's name only.")) AS ?gov).
17   BIND (llm:response(CONCAT("Who is the most famous celebrity from the state of ", ?state, "? Respond with the celebrity's name only.")) AS ?celeb).
18 }
19 ORDER BY ?state
```

▶ EXECUTE

10 ROWS DOWNLOAD RESULTS QUERY INFORMATION SEARCH

state	capital	pop	area	admit	gov	celeb
"Delaware"	"Dover"	"973764"	"2489"	"1787"	"John Carney"	"Aubrey Plaza"
"Idaho"	"Boise"	"1826913"	"83569"	"1890"	"Brad Little"	"Aaron Paul"
"Louisiana"	"Baton Rouge"	"4659978"	"51843"	"1812"	"John Bel Edwards"	"Louis Armstrong"
"Missouri"	"Jefferson City"	"6169.91"	"69704"	"1821"	"Mike Parson"	"Brad Pitt"
"New Mexico"	"Santa Fe"	"2117522"	"121590"	"1912"	"Michelle Lujan Grisham"	"Neil Patrick Harris"
"North Carolina"	"Raleigh"	"10439571"	"53819"	"1789"	"Roy Cooper"	"Michael Jordan"
"North Dakota"	"Bismarck"	"779094"	"70698"	"1889"	"Doug Burgum"	"Josh Duhamel"
"Ohio"	"Columbus"	"11.799 million"	"44826"	"1803"	"Mike DeWine"	"LeBron James"
"Pennsylvania"	"Harrisburg"	"12801989"	"46054"	"1787"	"Tom Wolf"	"Taylor Swift"
"Utah"	"Salt Lake City"	"3.206 million"	"84899"	"1896"	"Spencer Cox"	"Donny Osmond"



In many cases `askForTable` is easier 😊

States Table X

+ ▾

```
1 PREFIX llm: <http://franz.com/ns/allegrograph/8.0.0/llm/>
2
3 SELECT ?state ?capital ?pop ?area ?admitted ?governor ?celebrity {
4 (?state ?capital ?pop ?area ?admitted ?governor ?celebrity) llm:askForTable "Make a table of US States, their
capitals, population, area, year admitted to the Union, current governor and the most famous celebrity from that
state."}
```

▶ EXECUTE

51 ROWS

DOWNLOAD RESULTS

QUERY INFORMATION

SEARCH

state	capital	pop	area	admitted	governor	celebrity
"State"	"Capital"	"Population"	"Area (sq. mi)"	"Year Admitted"	"Governor"	"Famous Celebrity"
"Alabama"	"Montgomery"	"4,903,185"	"52,419"	"1819"	"Kay Ivey"	"Hank Aaron"
"Alaska"	"Juneau"	"731,545"	"665,384"	"1959"	"Mike Dunleavy"	"Sarah Palin"
"Arizona"	"Phoenix"	"7,278,717"	"113,990"	"1912"	"Doug Ducey"	"John McCain"
"Arkansas"	"Little Rock"	"3,017,804"	"53,179"	"1836"	"Asa Hutchinson"	"Bill Clinton"
"California"	"Sacramento"	"39,512,223"	"163,696"	"1850"	"Gavin Newsom"	"Arnold Schwarzenegger"
"Colorado"	"Denver"	"5,758,736"	"104,094"	"1876"	"Jared Polis"	"Tim Allen"
"Connecticut"	"Hartford"	"3,565,287"	"5,543"	"1788"	"Ned Lamont"	"Meryl Streep"
"Delaware"	"Dover"	"973,764"	"1,949"	"1787"	"John Carney"	"Joe Biden"
"Florida"	"Tallahassee"	"21,477,737"	"65,755"	"1845"	"Ron DeSantis"	"Dwayne Johnson"
"Georgia"	"Atlanta"	"10,617,423"	"59,425"	"1788"	"Brian Kemp"	"Julia Roberts"
"Hawaii"	"Honolulu"	"1,415,872"	"10,931"	"1959"	"David Ige"	"Bette Midler"
"Idaho"	"Boise"	"1,787,065"	"83,569"	"1890"	"Brad Little"	"Aaron Paul"
"Illinois"	"Springfield"	"12,671,821"	"57,914"	"1818"	"J.B. Pritzker"	"Barack Obama"
"Indiana"	"Indianapolis"	"6,732,219"	"36,418"	"1816"	"Eric Holcomb"	"Michael Jackson"
"Iowa"	"Des Moines"	"3,155,070"	"56,273"	"1846"	"Kim Reynolds"	"John Wayne"



Extract the graph of connecting US states



Catalog

root

Repository

llm-playground-1

Statements

646



TEST

4 - Borders X

```
21 PREFIX : <http://franz.com/>
22 INSERT {
23   ?stateNode rdfs:label ?state.
24   ?stateNode rdf:type :State.
25   ?stateNode :borders ?bordersNode.
26 } WHERE {
27   (?state ?stateNode) llm:response "List the US States.".
28   BIND (CONCAT("Write the states that border this state: ", STR(?state)) AS ?bordersPrompt).
29   (?borders ?bordersNode) llm:response ?bordersPrompt.
30 };
31 DELETE {
32   ?state1 :borders ?state2
33 } WHERE {
34   ?state1 :borders ?state2.
35   FILTER NOT EXISTS { ?state2 :borders ?state1 }
```

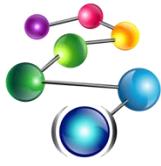
EXECUTE

RESULT

QUERY INFORMATION

SEARCH

No table results. See [QUERY INFORMATION](#) tab



The border graph

Gruff 9.0.0 on AllegroGraph 8.0.0 llm-playground-1 read / write 650 triples server 127.0.0.1:10035

File View Text Search Display Edit Global Options Query Options Table Options Help

SPARQL Prolog

Run Query Reindent Name Query Revisit

Graph View Table View Graphical Query View

Select All

Query

```
select ?s ?o where {
  ?s fr:borders ?o .
}
limit 1000
```

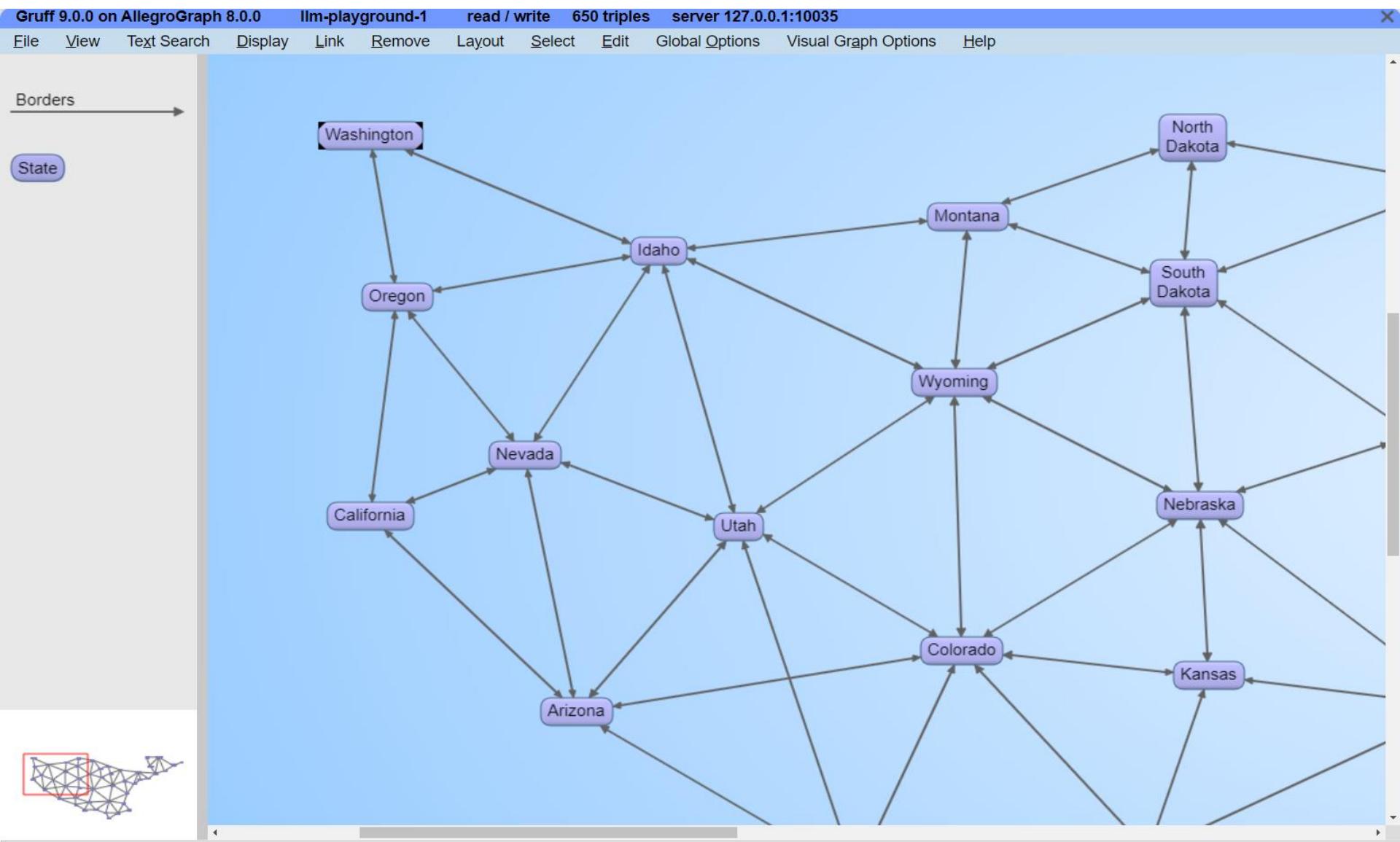
216 Results

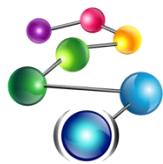
Create Visual Graph Add to Visual Graph Write Text Report Save as CSV

?s	?o
Wyoming	Idaho
Wyoming	Utah
Wyoming	Colorado
Wyoming	Nebraska
Wyoming	South Dakota
Wyoming	Montana
Wisconsin	Michigan
Wisconsin	Illinois
Wisconsin	Iowa
Wisconsin	Minnesota
West Virginia	Virginia
West Virginia	Pennsylvania
West Virginia	Ohio
West Virginia	Maryland
West Virginia	Kentucky
Washington	Idaho
Washington	Oregon
Virginia	West Virginia
Virginia	Tennessee
Virginia	North Carolina



The border graph visualized





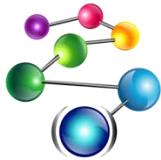
The border graph visualized

Gruff 9.0.0 on AllegroGraph 8.0.0 llm-playground-1 read / write 650 triples server 127.0.0.1:10035 X

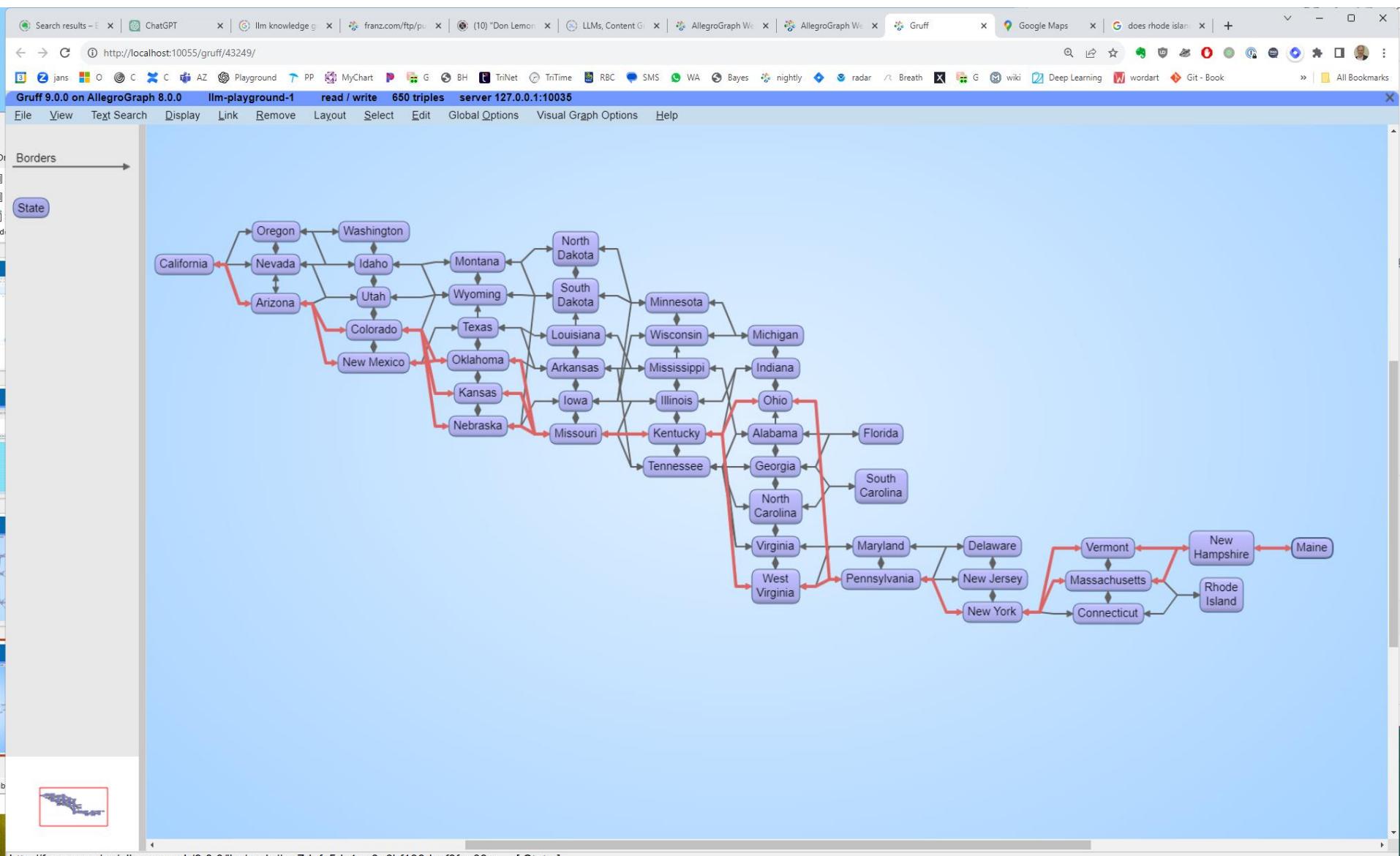
File View Text Search Display Link Remove Layout Select Edit Global Options Visual Graph Options Help

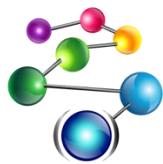
Borders →

State

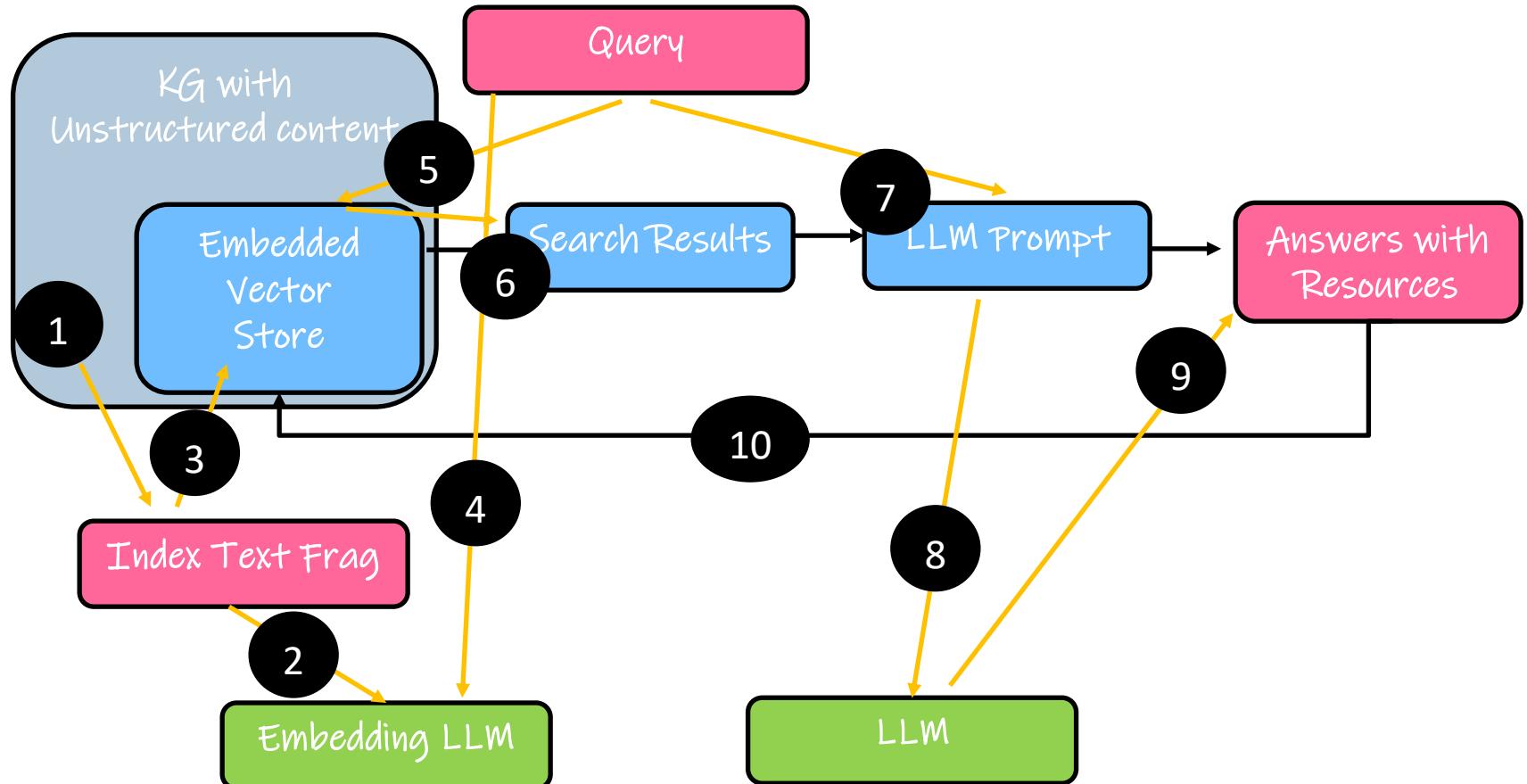


The border graph visualized





A vector store for search and RAG





Magic predicate: askMyDocuments

AskMyDocuments < ChatStream-1 < ChatStream-2 < Chat Bot-1 < Chat Bot-2 < Chat B > + NEW QUERY ▾

```
1 PREFIX llm: <http://franz.com/ns/allegrograph/8.0.0/llm/>
2
3 SELECT ?response ?citation ?score ?content {
4
5 bind("Briefly explain what you mean by 'Universal Grammar' as ?query")
6 (?response ?score ?citation ?content) llm:askMyDocuments (?query "chomsky47vecs" 10 0.0).
7
8 }
```

▶ EXECUTE

5 ROWS

DOWNLOAD RESULTS

QUERY INFORMATION

SEARCH

response	citation	score	content
"Universal Grammar refers to the inherent ability in every human brain to learn language. It's the genetic basis of the language faculty, not a set of universal observations about language. While individual languages may seem different on the surface, they are believed to share basic structural principles, pointing to a universal language capability in humans."	Power_Systems_Answer_248	"8.8863415E-1"	"Well, that gets technical, but there's very exciting work going on refining the proposed principles of universal grammar. The concept is widely misunderstood in the media and in public discussions. Universal grammar is something different: it is not a set of universal observations about language. In fact, there are interesting generalizations about language that are worth studying, but universal grammar is the study of the genetic basis for language, the genetic basis of the language faculty. There can't be any serious doubt that something like that exists. Otherwise an infant couldn't reflexively acquire language from whatever complex data is around. So that's not controversial. The only question is what the genetic basis of the language faculty is."
"Universal Grammar refers to the inherent ability in every human brain to learn language. It's the genetic basis of the language faculty, not a s	Power_Systems_Answer_253	"8.8398063E-1"	"The goal of the study of universal grammar is to try to show that there is indeed something quite simple that can meet these various conditions. A plaus

AllegroGraph WebView | Snipping Tool Alternatives | Win | Previous Release Download Loc | meaning 'the advent of - Goog

kraken.franz.com:4000/webview/repositories/chomsky47/exec-query/chatBot/B4GwPoSlxsUgQw2nSRAwZ

Catalog Repository Statements

root chomsky47 266,707

?

T TEST

root

big-string-table

bigger

deletion-test

fedshard

java-catalog

replication

replsmall

stores

system

test-tla-dir

tests

translog

Repository

Query

Add, delete & import data

Namespaces

Repository control

Replication

Storage overview

Session

Scripts

Admin

Utilities

Learning Resources

Gruff

Traditional WebView

Pick a chat bot from the dropdown Chomsky

CLEAR HISTORY

Interviewer

Ich glaube das nicht

Chomsky

It's understandable if it's hard to believe. However, the evidence shows that poverty is both the cause and effect of defects in our democracy. It's a vicious cycle that needs concerted efforts to break, including measures to ensure prosperity for all.

Interviewer

Ja, je hebt gelijk

Chomsky

Thank you. Recognizing the problem is the first step towards addressing it. Policies aimed at wealth redistribution and strengthening of social safety nets can help break this cycle.

Interviewer

what did we recently talk about.

Chomsky

We recently discussed the main causes of poverty, which I stated were largely due to systemic factors that favor the wealthy and powerful. I also noted that poverty is both the cause and effect of defects in our democracy, requiring measures to ensure prosperity for all.

Write message to the bot here. Press enter to send or click the icon button on the right side.

Saved queries

AskMyDocument...

shortAMD

Query Templates

View triples

View quads

View classes

View predicates

View named graphs

Update triples

Query options

Limit to 1000 results

Reasoning

Cancel on warnings

Use MJQE

More query options...

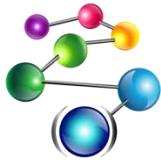
Display options

Full IRIs in results

Expand newlines

Short info in results

Copy query link



Two examples

- CallBrain
 - Analyzing sales call and give recommendations
- PatientGraph
 - Use many methods to predict

N3 Experience + Overview

Global partner with over a decade of generating significant revenue impact for leading technology and software clients

- Sales Skillset + Mindset + Culture
- Integrated End-To-End Sales Capabilities
- Technology + Software Focused (Cloud)
- Corporate + Partner Ecosystems Expertise
- Strategy + Design + Execution
- Proprietary Technology Platforms
- Atlanta (USA) HQ + 12 Global Offices
- SiriusDecisions Premier Partner
- 12+ year Track Record of Growth



Knowledge First Design For Dynamic Intelligent Contact Centers and Beyond

**May 4, 2022
EKG Conference NYC**

**Shannon Copeland, Managing Director,
Global Offering and Innovation Lead for Digital Inside Sales**

[with Dr Jans Aasman, CEO, Franz Inc]

CALL CENTER AI FOR INCREASED REVENUE AND PRODUCTIVITY



Prospect: ... so I need a gigabit router with 48 ports that can work in a Chemical Plant in N American, and can ship in 24 hours.

Agent: I work with your Industry everyday, and we have a sale going on for in-stock routers.



vPBX telephony



Speech to Text conversion

Public and Private LLM based Call Understanding and Insight Generation

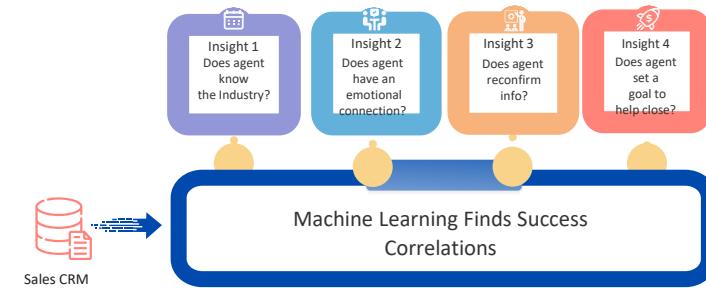


Success Correlation with AI Formulated Agent Recommendations

"Sally, you've got great industry knowledge, and I like how you use the current sale on routers for urgency and as a trial closing tool. Next time, I'd like to see you to try and reconfirm your assumptions with the prospect."

– Sally's Manager

Call Recordings



AI Generated Success Profile





CALL CENTER AI FOR INCREASED REVENUE AND PRODUCTIVITY



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Call Recordings

Knowledge Graph

Sales CRM

Machine Learning Finds Success Correlations

AI Generated Success Profile

- Insight 1 Does agent know the Industry?
- Insight 2 Does agent have an emotional connection?
- Insight 3 Does agent reconfirm info?
- Insight 4 Does agent set a goal to help close?



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AI Generated Success Profile

- Insight 1 Does agent know the Industry?
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- Insight 3 Does agent reconfirm info?
- Insight 4 Does agent set a goal to help close?

Feedback



Healthcare Needs Neuro-Symbolic AI

Entity Event Knowledge Graph for Powerful Health Informatics

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Abstract—This paper introduces the Entity-Event Knowledge Graph (EEKG) model for clinical data stored in graph databases. We describe how the EEKG model dramatically simplifies the representation of patient data, facilitates temporal queries, enables a 360 view of patients and promotes scalability by partitioning patient data into shards. We solved the practical problem that not all clinical data and life science knowledge can be sharded. The solution is to federate each individual shard with common shared data in a knowledge graph. One such shared data source is the UMLS (Unified Medical Language System) knowledge base, which contains genetic, drug clinical trials and Metathesaurus data that we link to individual patient records. We report on several use cases including EMR patient retrieval, matching patients with clinical trials, patient control group selection, and care quality measures.

Keywords—entity-event model, knowledge graph, distributed graph database, umls skos knowledge graph, clinical trials knowledge base

I. INTRODUCTION

We describe an EMR and Analytics data system based on the Entity-Event Knowledge Graph (EEKG) model where patient data is sharded into a distributed graph database and linked to knowledge bases that include facility, provider, payer, coding, as well as medical and scientific knowledge. The approach is primarily based on the earlier work of P. Mirhaji at Einstein Medical College and Montefiore Health System [1]. To provide as realistic a demonstration as possible without relying on confidential patient information, we utilized an open-source synthetic patient generator called Synthea to generate demographic, clinical and claims records for 1 million patients [2]. Using the automated sharding feature of the Allegrograph¹ Resource Description Framework (RDF) triple store, we sharded the patient data across a number of servers. We link the sharded patient data to a common knowledge base that also includes UMLS (Unified Medical Language System) and an NIH/NLM project that integrates

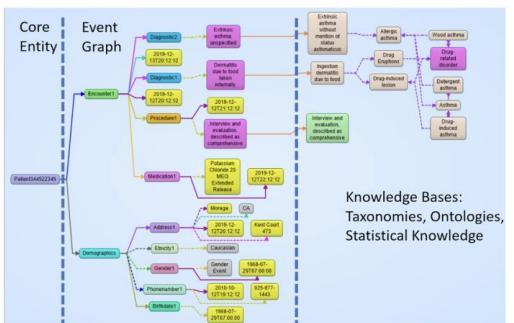
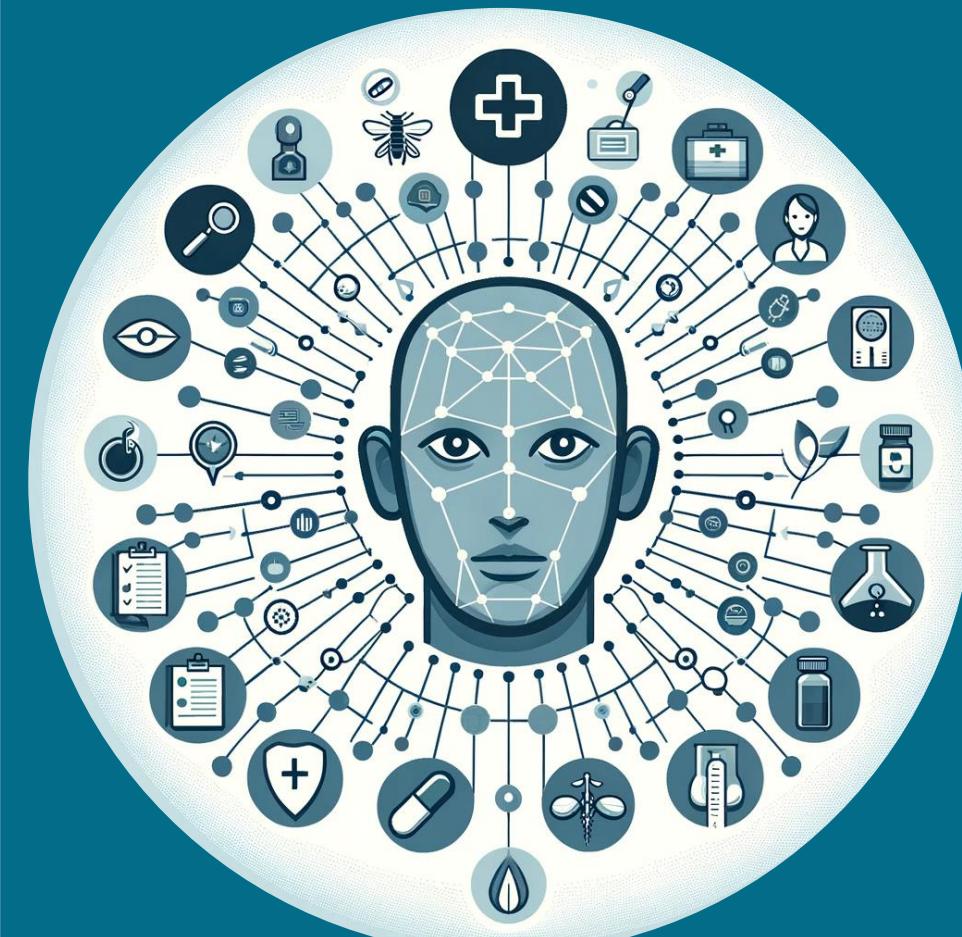
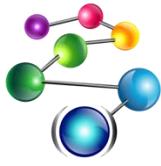


Figure 1 Patient health data and events represented as EE model linked to shared knowledge base

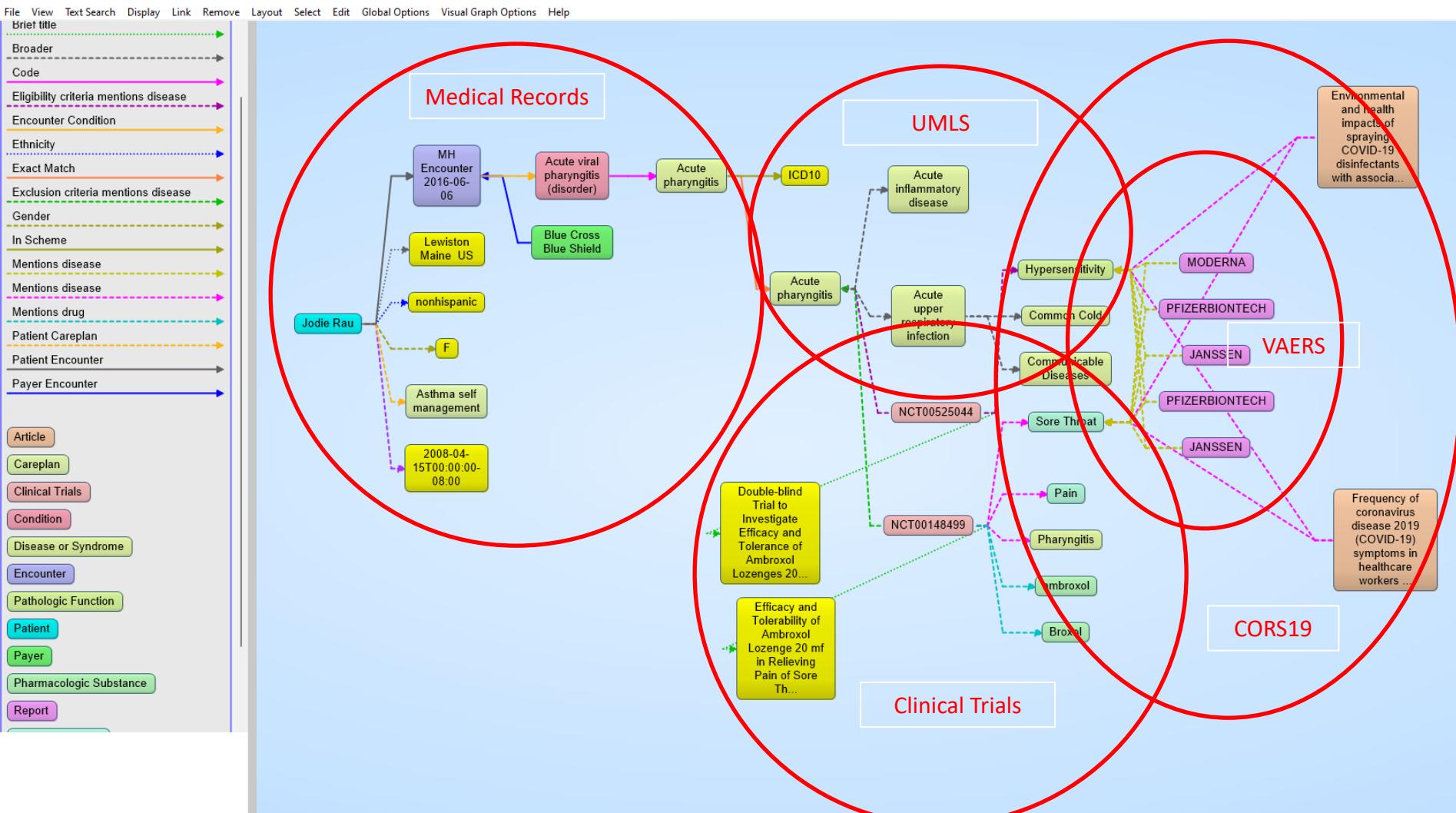
An event is anything associated with the entity that has a starting time and optionally, an ending time. The authors have used this approach in call centers, where the entities are customers and the events include calls and outcomes; in

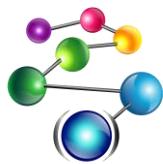
¹AllegroGraph is a Horizontally Distributed, Multi-model (Document and Graph), Entity-Event Knowledge Graph technology solution from Franz Inc.: <https://allegrograph.com/products/allegrograph/>



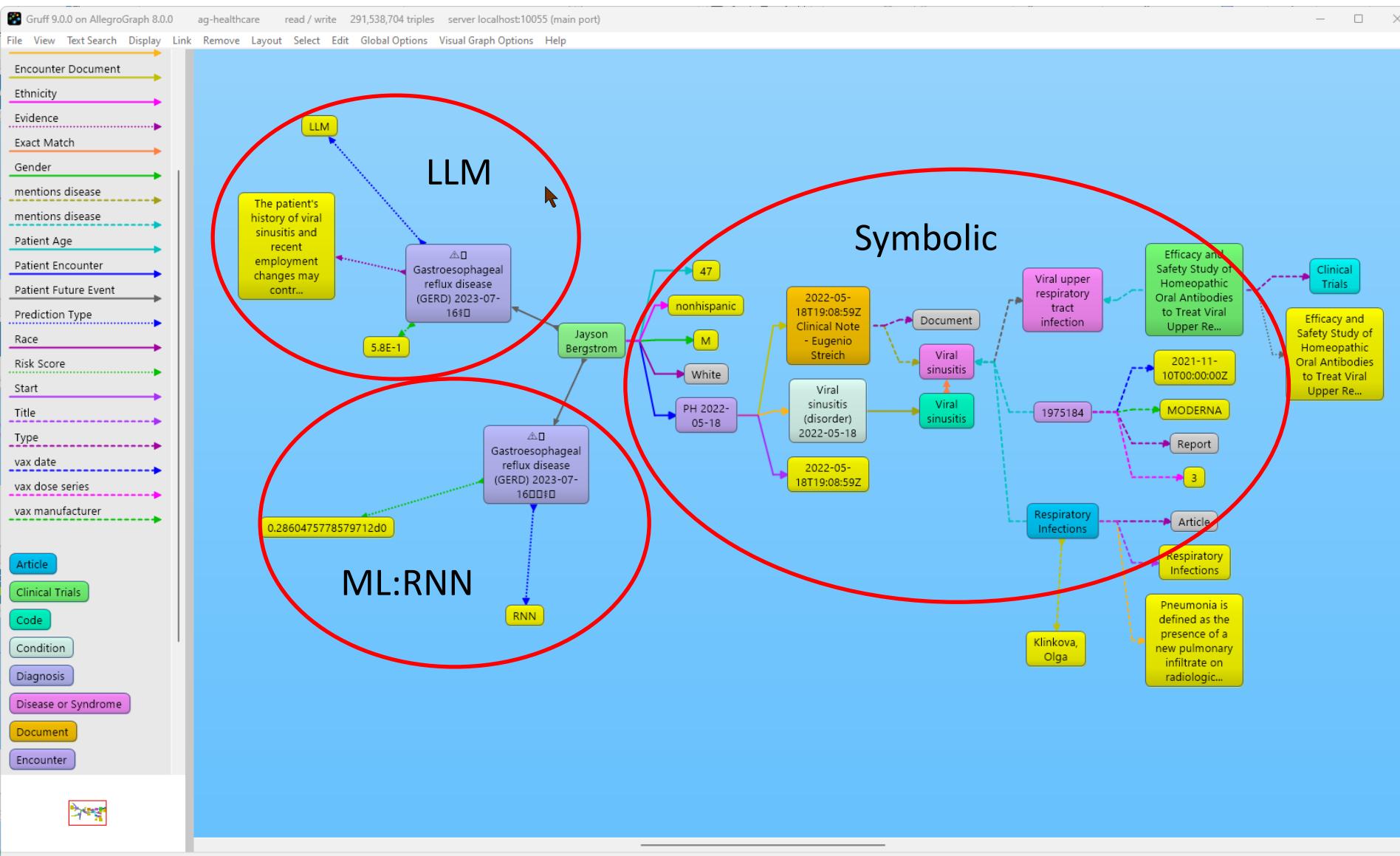


AllegroGraph Ties it All Together



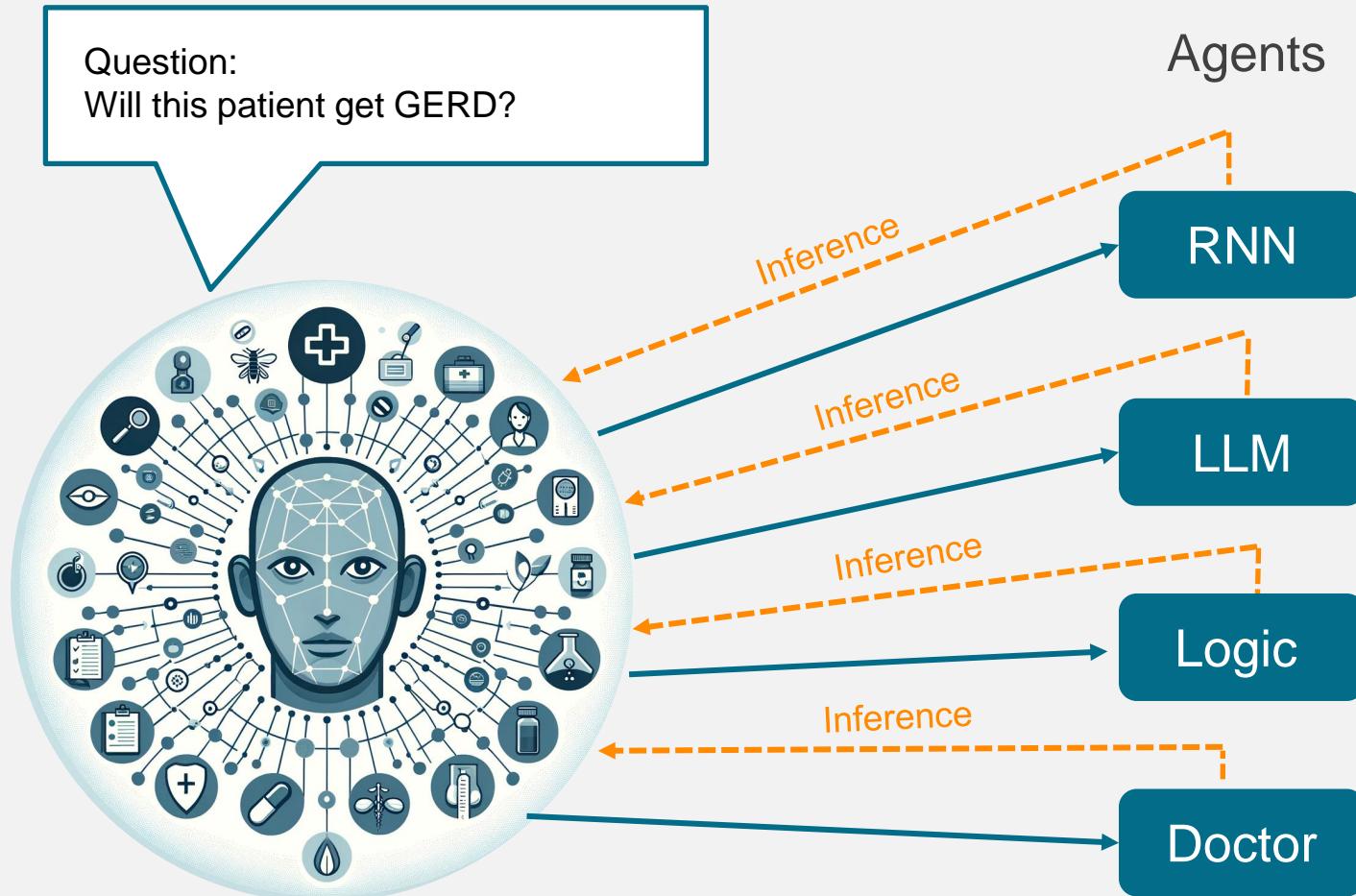


A patient with future events from LLM and RNN





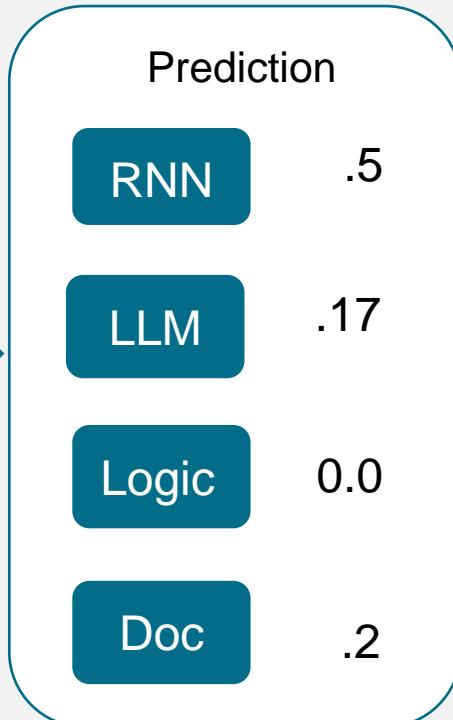
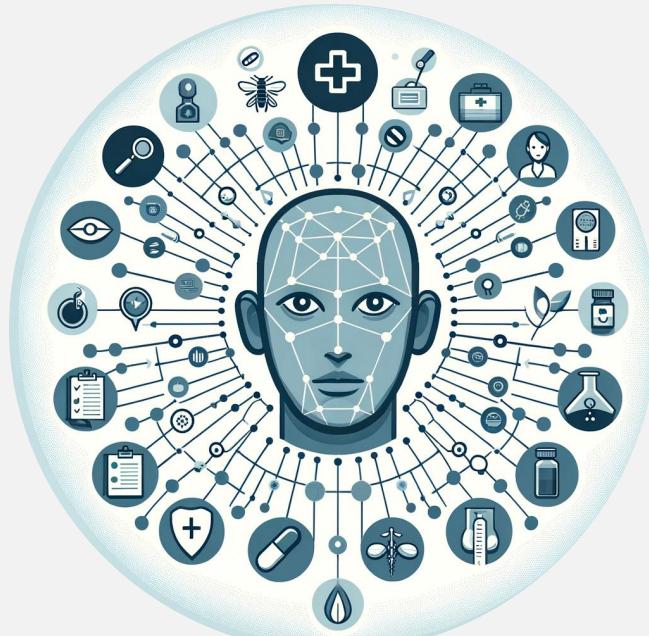
Neuro-Symbolic AI: Primary Inferencing



Neuro-Symbolic AI: Secondary Inferencing



Patient Knowledge Graph
with Events



Thank You

Dr. Jans Aasman, CEO of Franz Inc.

ja@franz.com