

# Where Are We in the Journey to A Knowledgeable Assistant?

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12/2024

This talk does not represent the company's point of view

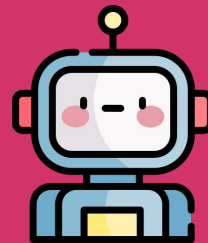


**Human beings have a natural craving for information**

**Providing the Right Information  
at the Right Time**

# Known Unknowns—Question Answering (QA)

What are visa requirements for visiting Santiago?



Visitors to Chile must obtain a visa from one of the Chilean diplomatic missions unless they come from one of the visa exempt countries.

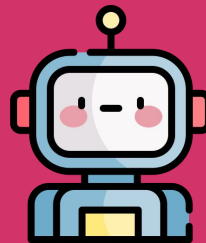
## Right Information

- Relevant: provide relevant info w. right specificity
- Trustworthy: correct, precise, up-to-date, attribution



# Known Unknowns—Recommendations

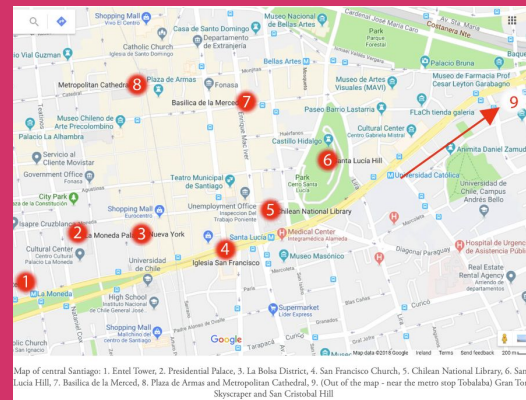
Where should I visit in Santiago?



If you only have one or two days in Santiago - stay in the central area. Most of the worth seeing places are located there with the exception of the famous Gran Torre skyscraper

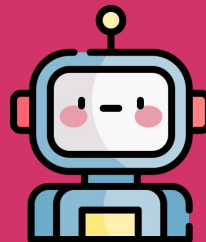
## Right Information

- Relevant: provide relevant info w. right specificity
- Trustworthy: correct, precise, up-to-date, attribution
- **Recomm:** Good ranking of items in a list and diversity
- **Multi-modal** output



# Known Unknowns—Multi-modal QA

Tell me about this building?  
When is it built?



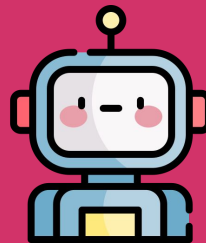
This is La Moneda Palace, the seat of the President of the Republic of Chile. It was completed in 1805, initially constructed to house the colonial mint.

## Right Information

- Relevant: provide relevant info w. right specificity
- Trustworthy: correct, precise, up-to-date, attribution
- Recomm: Good ranking of items in a list and diversity
- **Multi-modal input & output**

# Known Unknowns—Personalized QA

What are visa requirements for visiting Santiago?



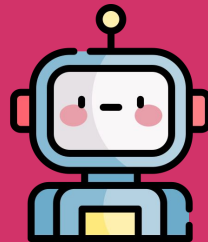
Citizens of the United States do not need a visa to visit Chile for up to 90 days for tourism or business if they have a valid passport.

## Right Information

- Relevant: provide relevant info w. right specificity
- Trustworthy: correct, precise, up-to-date, attribution
- Recomm: Good ranking of items in a list and diversity
- Multi-modal input & output
- **Personalized for the user**

# Known Unknowns—Personalized Recomm

Where should I visit in Santiago?



For a traveler who enjoys natural views, architecture, and history, Santiago offers a rich variety of attractions that cater to these interests.

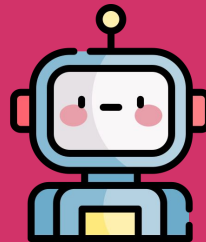
## Right Information

- Relevant: provide relevant info w. right specificity
- Trustworthy: correct, precise, up-to-date, attribution
- Recomm: Good ranking of items in a list and diversity
- Multi-modal input & output
- **Personalized for the user**

<b>Morning</b>	
9:00 AM - Breakfast in Barrio Lastarria	
• Start your day with a leisurely breakfast at a café in Barrio Lastarria. This neighborhood is known for its charming streets and vibrant atmosphere.	
10:00 AM - Cerro Santa Lucía	
• Walk to Cerro Santa Lucía, a nearby hill with beautiful gardens, fountains, and panoramic views of the city. Spend about an hour exploring and enjoying the scenery.	
<b>Late Morning</b>	
11:30 AM - Plaza de Armas and Metropolitan Cathedral	
• Head to Plaza de Armas, the historical center of Santiago. Visit the Metropolitan Cathedral to appreciate its stunning architecture and historical significance.	
<b>Afternoon</b>	
12:30 PM - Lunch in Barrio Lastarria	
• Return to Barrio Lastarria for lunch at one of its many delightful restaurants. Take your time to enjoy the local cuisine.	
2:00 PM - Museo Chileno de Arte Precolombino	
• After lunch, take a short walk to the Museo Chileno de Arte Precolombino. Spend around an hour exploring the impressive collection of pre-Columbian art and artifacts.	
<b>Late Afternoon</b>	
3:30 PM - La Moneda Palace	
• Visit La Moneda Palace and, if time allows, watch the Changing of the Guard ceremony or take a guided tour. Explore the nearby Centro Cultural Palacio de La Moneda if you're interested in more cultural exhibits.	
<b>Early Evening</b>	
5:00 PM - Cerro San Cristóbal	
• Take a short trip to Cerro San Cristóbal. You can take the funicular up to the summit for beautiful views of Santiago and the Andes. Spend a relaxing time at the top, enjoying the sunset.	
<b>Evening</b>	
7:00 PM - Dinner in Bellavista	
• Head to the Bellavista neighborhood for dinner. Choose from a variety of restaurants offering both local and international cuisine. After dinner, take a leisurely stroll around the colorful streets and soak in the lively atmosphere.	

# Known Unknowns—Contextualized Recomm

What are good restaurants nearby?



There are a variety of excellent dining options suitable for a group lunch. Here are some recommended restaurants nearby:

## Right Time

- Contextualized: answers suitable for the time, location, etc.

### 1. Tiramisu

- Cuisine: Italian
- Description: A popular spot known for its delicious pizzas, pastas, and salads. The atmosphere is lively, making it a great choice for groups.
- Address: Av. Isidora Goyenechea 3141, Las Condes

### 2. Pinpiln pausha

- Cuisine: Basque
- Description: Offers a wide range of Basque and Chilean dishes with an elegant yet welcoming atmosphere. Perfect for a leisurely group lunch.
- Address: Av. Isidora Goyenechea 2900, Las Condes

### 3. Cuervovaca

- Cuisine: Steakhouse
- Description: Known for its high-quality meats and extensive wine list. Ideal for meat lovers and a more substantial meal.
- Address: Av. Nueva Costanera 3960, Vitacura (a short drive from the hotel)

### 4. Aquí Está Coco

- Cuisine: Seafood
- Description: Famous for its seafood dishes and sustainable practices. The restaurant has a unique decor and a spacious layout suitable for groups.
- Address: La Concepción 236, Providencia (a short drive from the hotel)

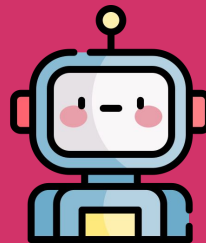
### 5. Piegari

- Cuisine: Italian and Argentine
- Description: Offers a mix of Italian and Argentine cuisine with a focus on quality ingredients. The spacious interior is great for accommodating larger groups.
- Address: Av. Isidora Goyenechea 3000, Las Condes



# Implicit Known Unknowns—Proactive Recomm

Where should I visit in Santiago?



... If you have a few more days, there are plenty of fantastic destinations in Chile that offer beautiful natural views for a June visit. Here are some recommendations:

## Right Time

- Contextualized: answers suitable for the time, location, etc.
- Proactive: provide related information proactively

### 1. Atacama Desert

The Atacama Desert is an incredible destination year-round, including June. Its dry climate ensures pleasant weather for exploration.

#### San Pedro de Atacama

##### • Highlights:

- **Valle de la Luna (Valley of the Moon):** Marvel at the unique rock formations and enjoy stunning sunset views.
- **El Tatio Geysers:** Visit these impressive geysers early in the morning.
- **Laguna Chaxa:** See flamingos and the striking landscape of the salt flats.
- **Laguna Cejar:** Float in the high-salinity waters of this stunning lagoon.
- **Travel:** Fly from Santiago to Calama (about 2 hours) and then drive or take a shuttle to San Pedro de Atacama (about 1.5 hours).
- **Activities:** Stargazing, exploring salt flats, visiting geysers, and discovering ancient archaeological sites.

### 2. Lake District

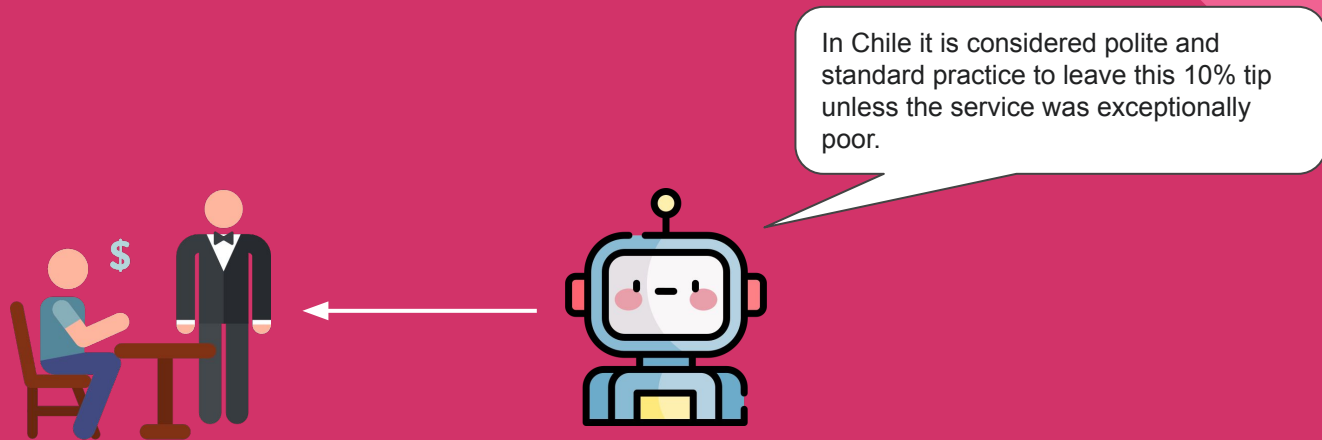
The Lake District remains beautiful in June, with its picturesque landscapes and charming towns.

#### Puerto Varas and Surroundings

##### • Highlights:

- **Puerto Varas:** Enjoy the charming town on the shore of Lake Llanquihue with views of Osorno Volcano.
- **Frutillar:** Discover this town known for its German heritage and scenic beauty.
- **Vicente Pérez Rosales National Park:** Visit Petrohué Waterfalls and explore trails with views of Osorno Volcano.
- **Travel:** Fly from Santiago to Puerto Montt (about 1.5 hours) and then drive to Puerto Varas (about 30 minutes).
- **Activities:** Hiking, sightseeing, visiting museums, and enjoying local cuisine.

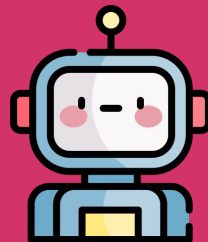
# Unknown Unknowns—Proactive Recomm



## Right Time

- Contextualized: answers suitable for the time, location, etc.
- Proactive: provide related information proactively
- **Timing: provide relevant info w/o being asked**

# Unknown Unknowns—Proactive Recomm

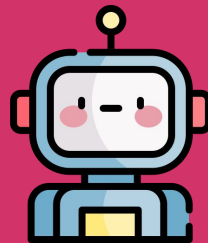


Would you like to hear about some famous figures from Santiago or Chilean history?

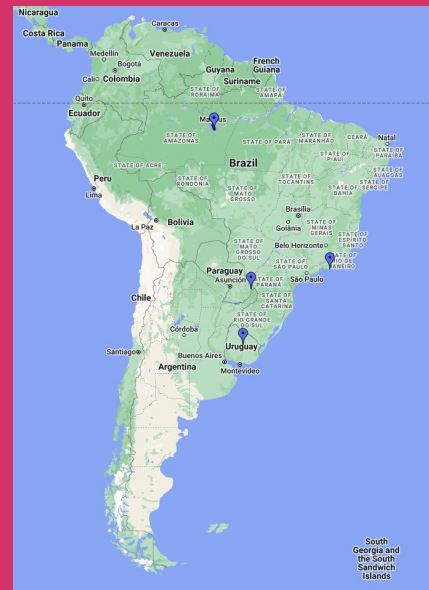
## Right Time

- Contextualized: answers suitable for the time, location, etc.
- Proactive: provide related information proactively
- Timing: provide relevant info w/o being asked
- **Inspiring: inspiration, relevant but not distractive**

# Personal Memory



You visited South America 3 times in the past.



## Right Time

- Contextualized: answers suitable for the time, location, etc.
- Proactive: provide related information proactively
- Timing: provide relevant info w/o being asked
- Inspiring: inspiration, relevant but not distractive
- **Memoir: connecting to personal memory for emotion needs**



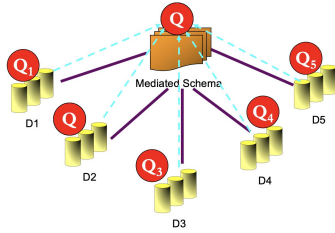
Providing the Right Information

***Where are we in this journey?***

# Integrating and Accessing All Valuable Data



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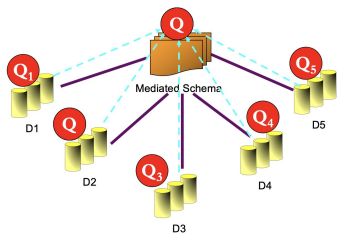
v1.0 Web Search &  
Runtime Data Integration

**2000's**  
**Runtime Integ.**

## Challenges:

- Answer summarization
- Heterogeneity
- Conflict resolution
- Latency

# Integrating and Accessing All Valuable Data

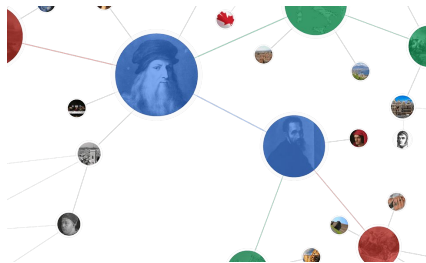


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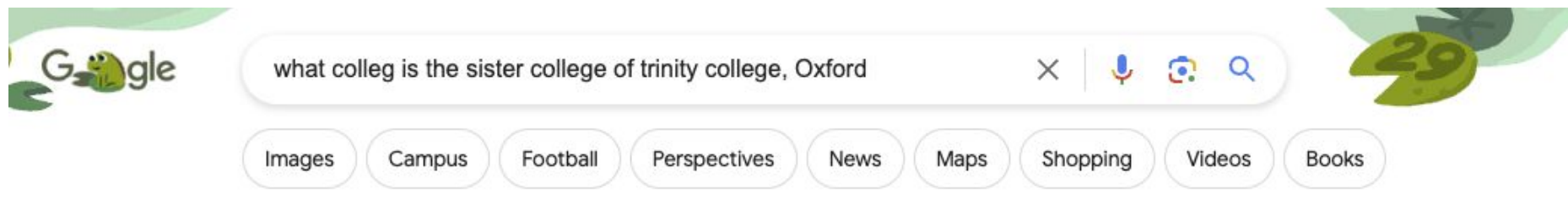
v2.0. KG  
-based QA

**2010's**  
**Offline Integ.**

## Challenges:

- KG construction
- Limited coverage
- Constrained expressive power
- Complex QA

# An Example



what colleg is the sister college of trinity college, Oxford

Images Campus Football Perspectives News Maps Shopping Videos Books


About 3,880,000 results (0.46 seconds)

Showing results for **what college** is the sister college of trinity college, Oxford  
Search instead for **what colleg** is the sister college of trinity college, Oxford

Trinity's sister college is ~~Christ Church, Oxford~~. Trinity has been linked with Westminster School since the school's re-foundation in 1560, and its Master is an ex officio governor of the school.

Wikipedia  
[https://en.wikipedia.org/wiki/Trinity\\_College,\\_Cam...](https://en.wikipedia.org/wiki/Trinity_College,_Cambridge)

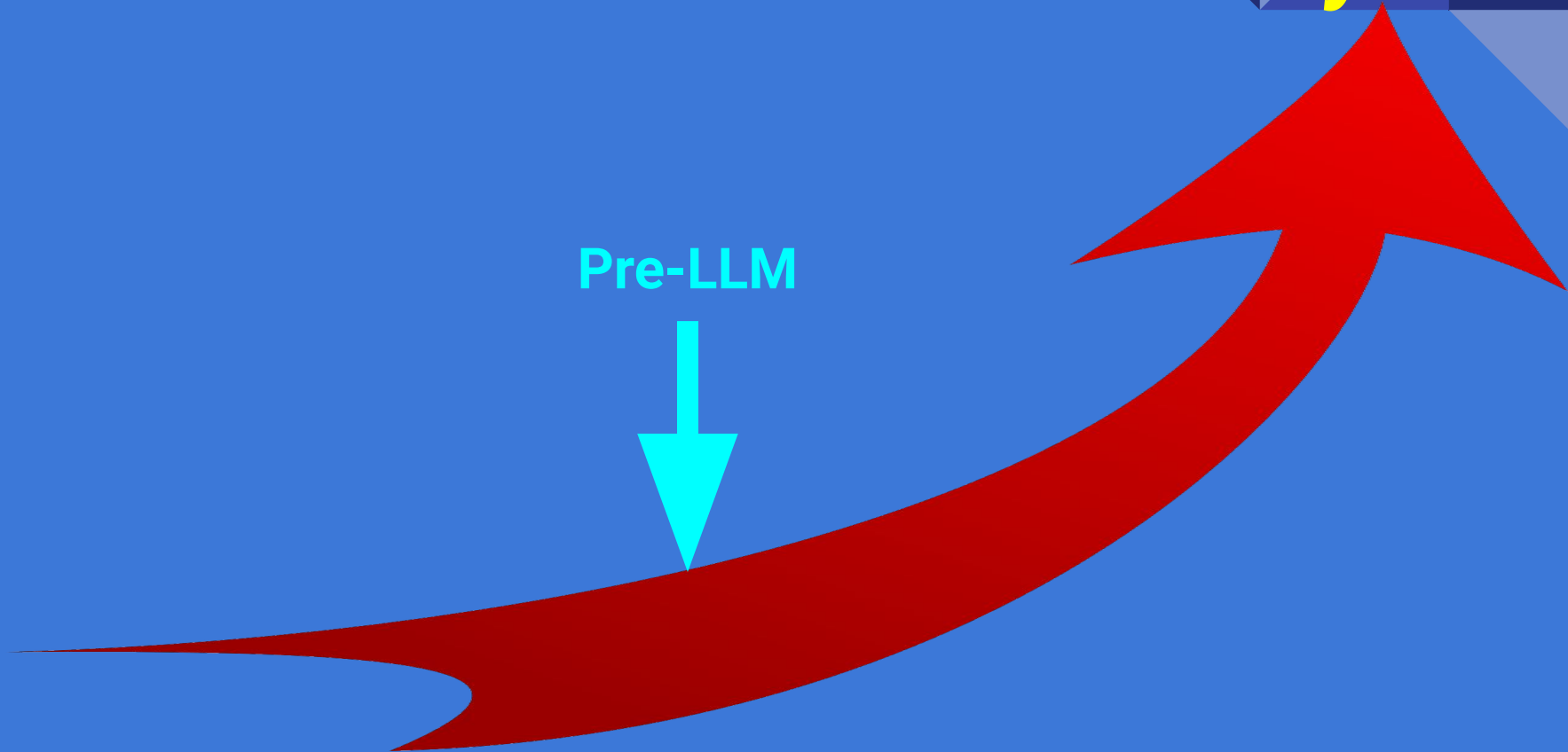
Trinity College, **Cambridge** - Wikipedia





# ***Where Are We in This Journey?***

Pre-LLM





***Meme 1. LLMs Have Solved the Problem***

# An Example



You

what college is the sister college of Trinity College, Oxford?



ChatGPT

The sister college of Trinity College, Oxford, is ~~St John's College, Cambridge~~. This relationship is part of the tradition of "sister colleges" between Oxford and Cambridge universities, where certain colleges at Oxford are twinned with certain colleges at Cambridge.



You

what college is the sister college of Trinity College, Oxford?



ChatGPT

The sister college of Trinity College, Oxford, is ~~Trinity College, Cambridge~~. The term "sister colleges" is used in the Oxbridge system to denote a form of informal relationship between colleges at Oxford and Cambridge with similar names, histories, or other connections. Both Trinity Colleges are part of their respective universities and share a name, but they are independent institutions with their own administration and traditions.

Cambridge ↕	Oxford ↕
King's College	New College
Queens' College	Pembroke College
Pembroke College	The Queen's College
Trinity Hall	All Souls College University College
Trinity College	Christ Church
Churchill College	Trinity College

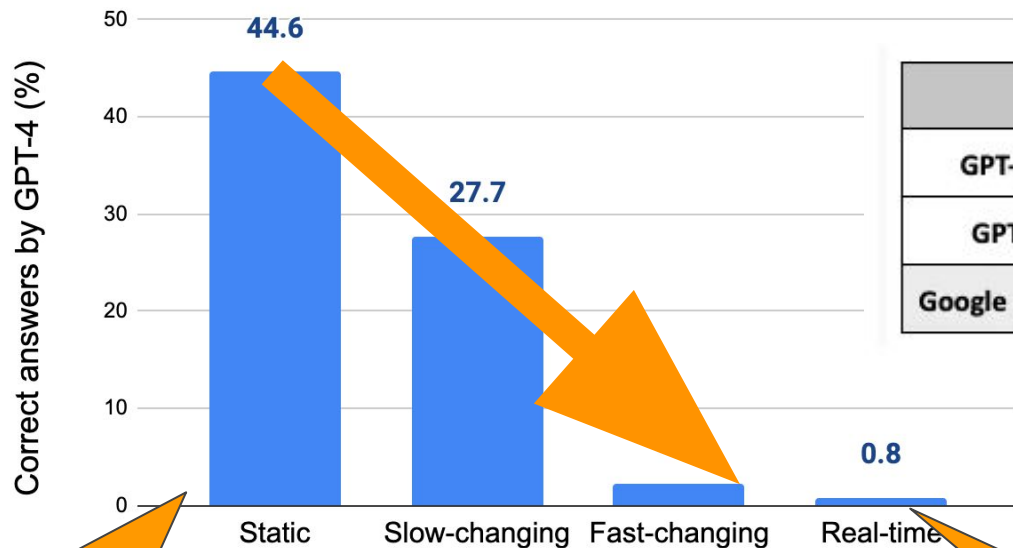
Ground truth

# How Knowledgeable are LLMs?

- How ***reliable*** are LLMs in answering factual questions?
- Do LLMs perform ***equally well*** across different types of factual knowledge?
- What are ***key factors*** that affect LLM factuality?



# LLM QA for Facts of Different Dynamisms



	Never	Slow	Fast
GPT-3.5	59%	15%	4%
GPT-4	64%	4%	12%
Google Search	68%	46%	32%

Low accuracy even for static facts

Very low accuracy for fast changing facts

# Simple Static Questions

---

Answer the following questions in as few words as possible. Say "unsure" if you don't know.

Question: What is the capital of China?

Answer: Beijing

Question: What is the capital of Wernythedia?

Answer: unsure

Question: {QUESTION}

Answer:

---

# Head-to-Tail Benchmark

	IMDb		Goodreads	DBpedia
	Title	Person	Book	-
<b>Head</b>	767 ( 0.01)	34,903 ( 0.48)	3,150 ( 2.31)	103,564 ( 1.30)
<b>Torso</b>	4,113 ( 0.05)	87,645 ( 1.21)	7,304 ( 5.35)	1,255,113 (15.77)
<b>Tail</b>	7,536,482 (99.94)	7,111,496 (98.31)	126,134 (92.35)	6,600,206 (82.93)

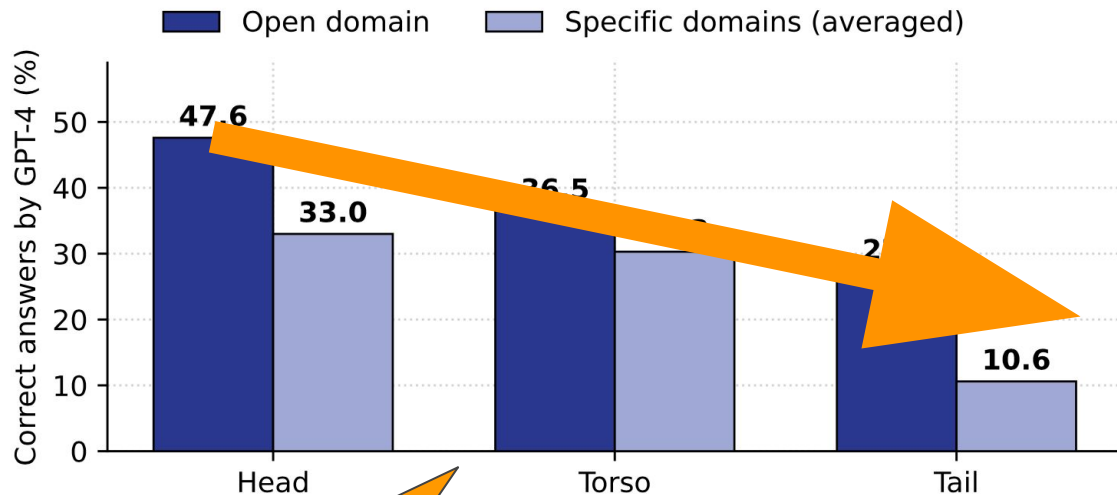
  

	MAG		DBLP
	Article	Conference	Scholar
	1,827,710 ( 0.70)	257 ( 1.63)	79,521 ( 2.44)
	9,386,034 ( 3.60)	965 ( 6.12)	500,778 (15.36)
	249,311,539 (95.70)	14,550 (92.25)	2,680,704 (82.20)

When counted by popularity, majority of entities are long-tail

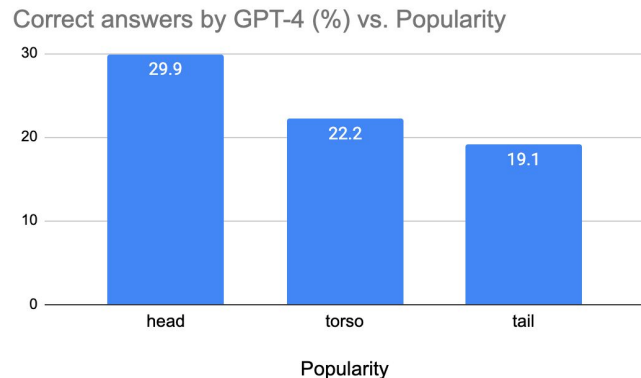
# LLM QA for Entities of Different Popularities

## Simple questions



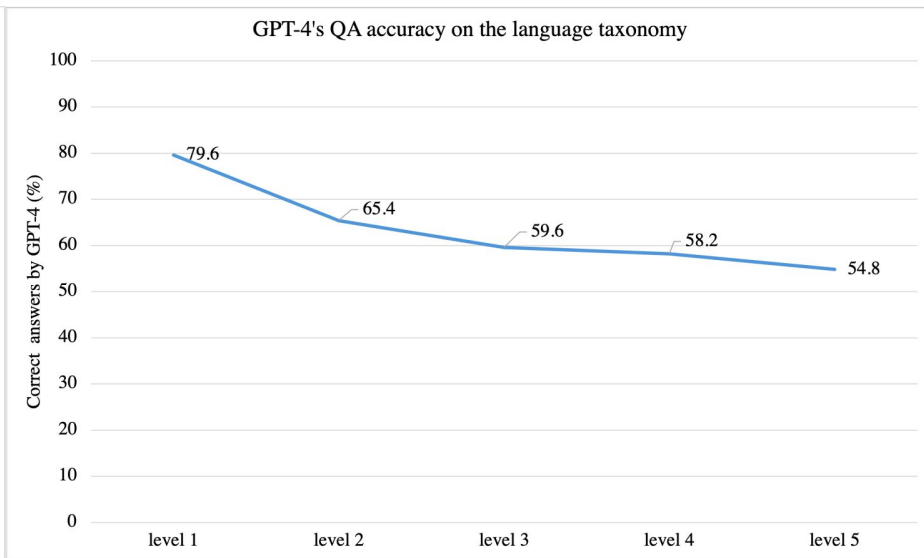
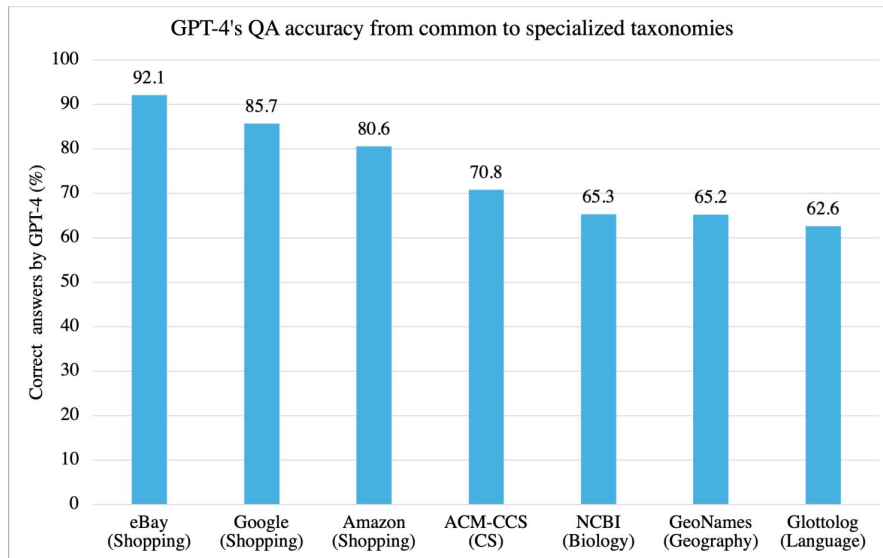
Low accuracy even for popular entities

## General questions





# LLM QA for Taxonomies

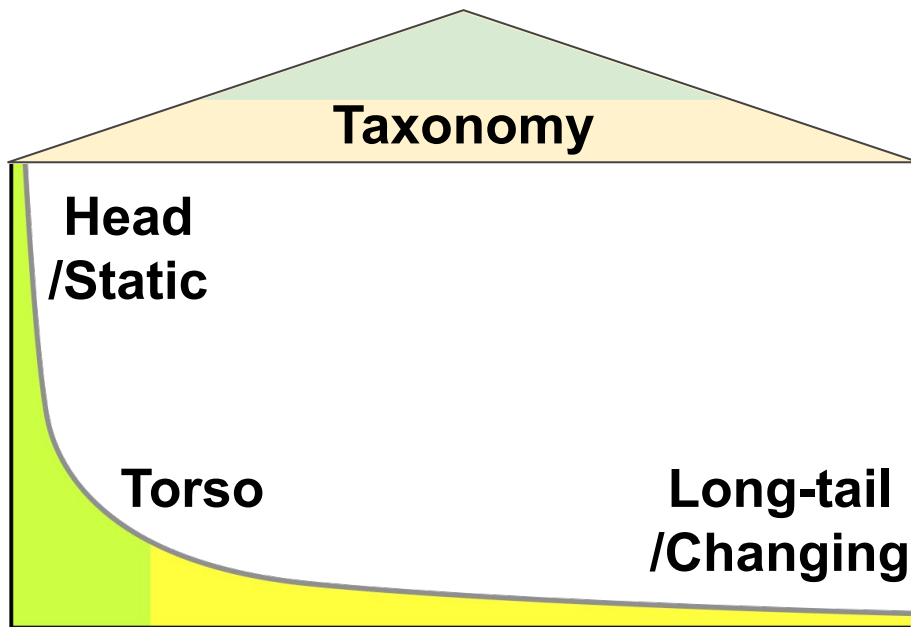


High quality for common taxonomies, medium-to-low quality for specialized taxonomies

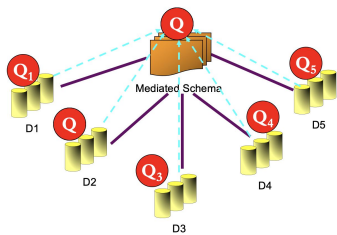
Quality dropping slightly from top to bottom in the taxonomy hierarchical tree

# How Knowledge Are LLMs?

**Training Data!!**



# Integrating and Accessing All Valuable Data

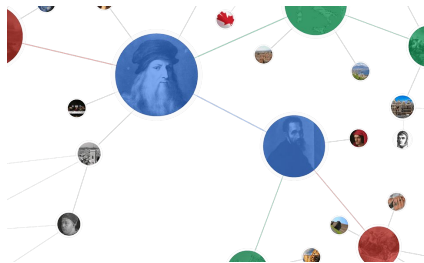


v1.0 Web Search &  
Runtime Data Integration

**2000's**  
**Runtime Integ.**

## Challenges:

- Answer summarization
- Heterogeneity
- Conflict resolution
- Latency



v2.0. KG  
-based QA

**2010's**  
**Offline Integ.**

## Challenges:

- KG construction
- Limited coverage
- Constrained expressive power
- Complex QA



v3.0. LLM

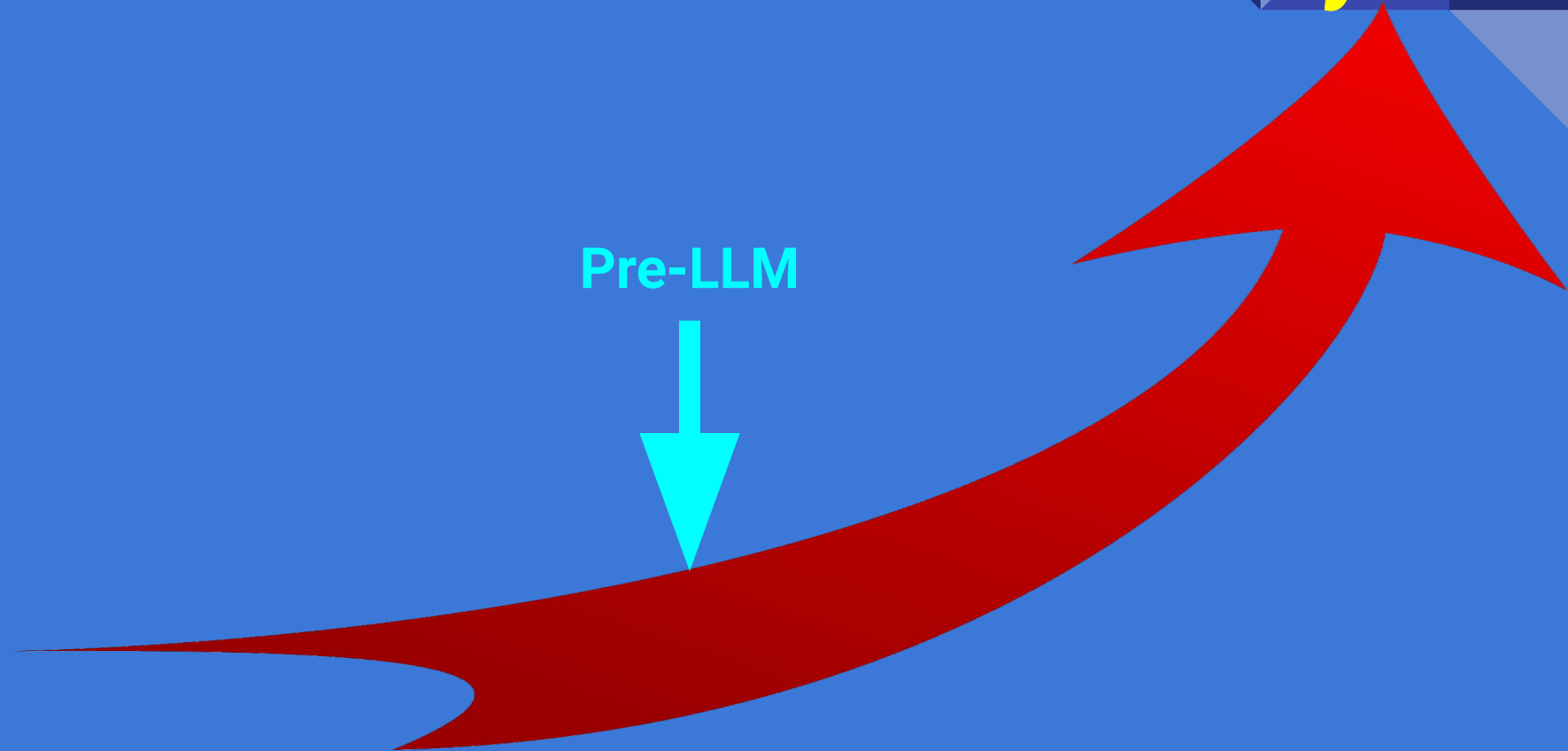
**2020's Knowl**  
**internalization**

## Challenges:

- Hallucinations

# ***Where Are We in This Journey?***

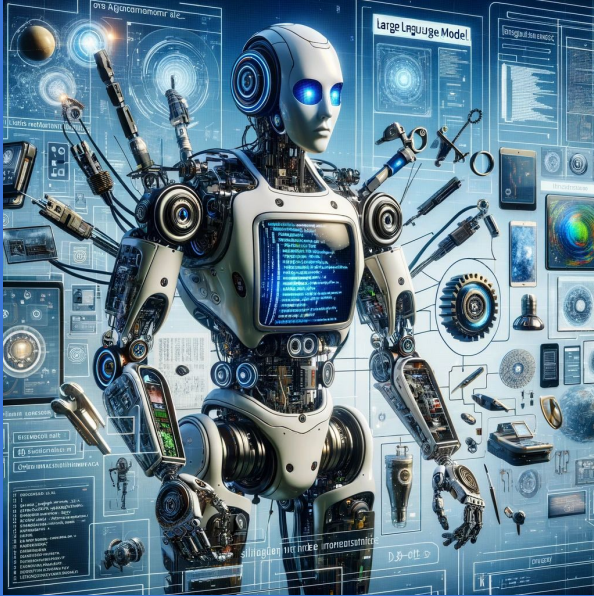
Pre-LLM



# ***Where Are We in This Journey?***

LLM





**Tool LLM**

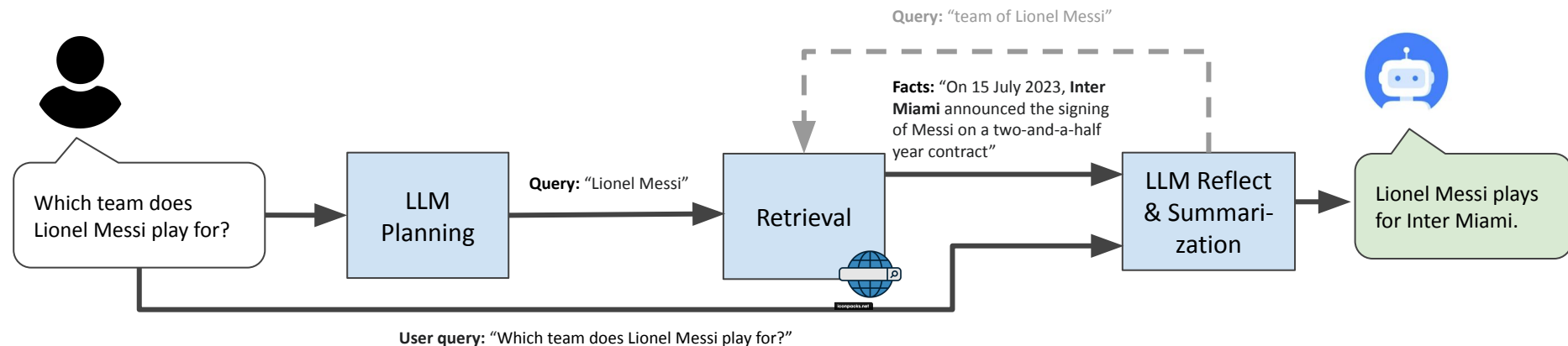


**RAG (Retrieval  
Augmented Generation)**



***Meme 2. RAG (LLM+Web Search)  
has solved the problem***

# RAG through Web Search





# RAG through Web—An Example



**You**

search the web and tell me what college is the sister college of Trinity College, Oxford?



**ChatGPT**

Based on a [quick search](#), here's what I found.

The sister college of Trinity College, Oxford is ~~Christ Church, Oxford~~. Both colleges were founded in 1546 by King Henry VIII from existing institutions [\[1\]](#).

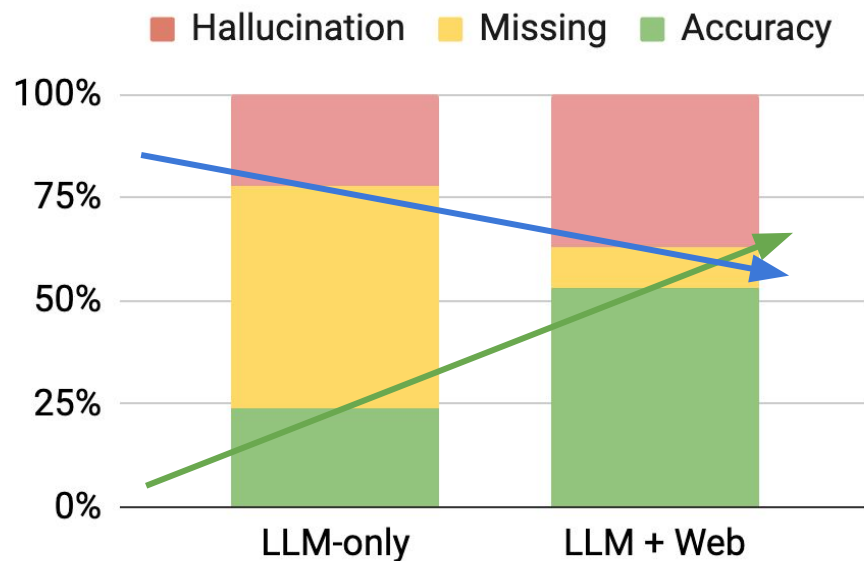


Cambridge	Oxford
King's College	New College
Queens' College	Pembroke College
Pembroke College	The Queen's College
Trinity Hall	All Souls College University College
Trinity College	Christ Church
Churchill College	Trinity College

Ground truth

# Baseline RAG Results

Initial experimental results



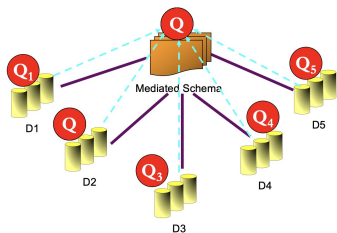
Accuracy  
increased

But more  
hallucinations

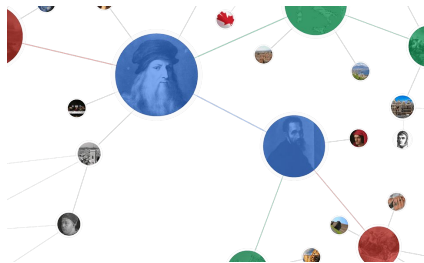
# Integrating and Accessing All Valuable Data



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v1.0 Web Search &  
Runtime Data Integration



v2.0. KG  
-based QA



v3.0. LLM

**2000's**  
**Runtime Integ.**

v1.5 Tool LLM &  
Web-augmented RAG

**2010's**  
**Offline Integ.**

**2020's Knowl**  
**internalization**

## Challenges:

- Answer summarization
- Heterogeneity
- Conflict resolution
- Latency



## Challenges:

- KG construction
- Limited coverage
- Constrained expressive power
- Complex QA

## Challenges:

- Hallucinations

Portrayed By GPT-4

# ***Where Are We in This Journey?***

LLM



# ***Where Are We in This Journey?***

**Web-based  
RAG**



## WORD OF THE YEAR

# hallucinate

verb [ huh-**loo**-suh-neyt ]

(of artificial intelligence) to produce false information contrary to the intent of the user and present it as if true and factual.



Dictionary.com



dictionarycom • Follow



dictionarycom You're not dreaming: today's #WordOfTheDay is also our 2023 #WordOfTheYear: "hallucinate."

Are you familiar with the AI sense of this word? Visit link in bio to learn more.

8w



c.b.bicknell Hallucinate means woke thinking.

7w Reply



prmrbs936 About 50 years late from LSD Beans Uppers Downers MESCI-choco

7w Reply

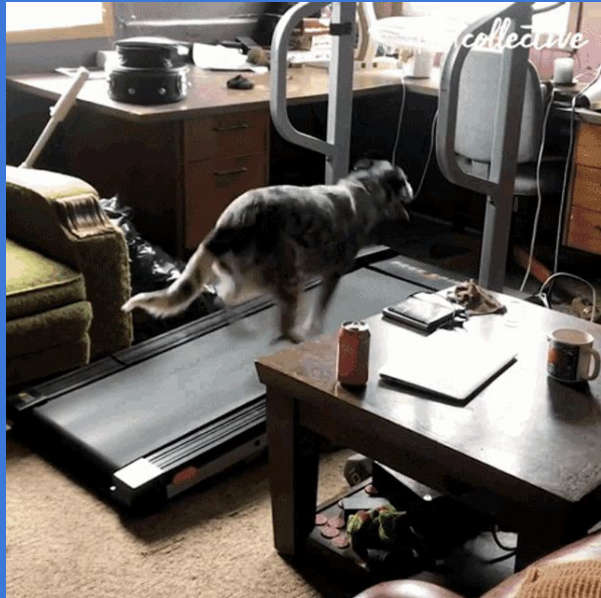


833 likes

December 12, 2023

Log in to like or comment.

# Providing The Right Information



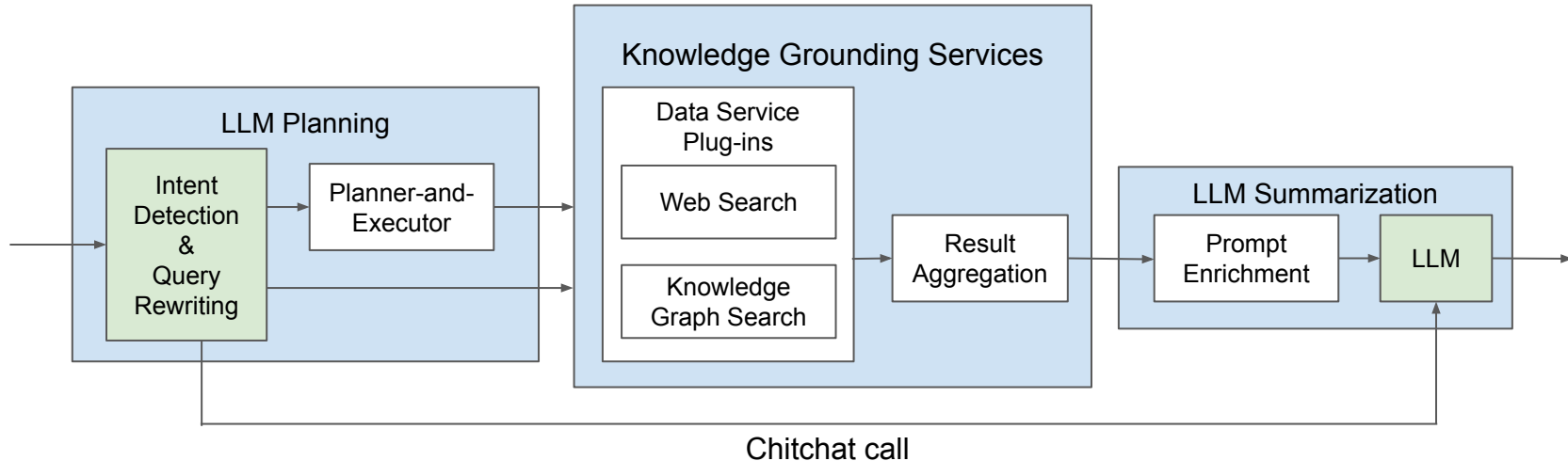
*Is Correct, Relevant  
Information Closer  
or Farther Away?*

# Our Solution: Federated RAG





# Federated RAG Architecture



**Planning:** Decide user intent and rewrite to web search query and/or KG search query

**Example:**

Input: "What was Meta's stock price yesterday?"

Intent: {domain=stock, factuality=factual}

Web search query: "Meta's stock price"

KG query: {  
company: "Meta",  
date/time: "yesterday",  
queried attribute: "price"}

**Knowledge Grounding:** Fetch information from web search, KG search, etc.

**Example (Cont'):**

KG Output: (w. KG output, we may early stop Web search to reduce latency)

"Symbol: META  
Current Price: 315.43  
Open Price: 301.44  
High Price: 316.31  
Low Price: 300.915 ....."

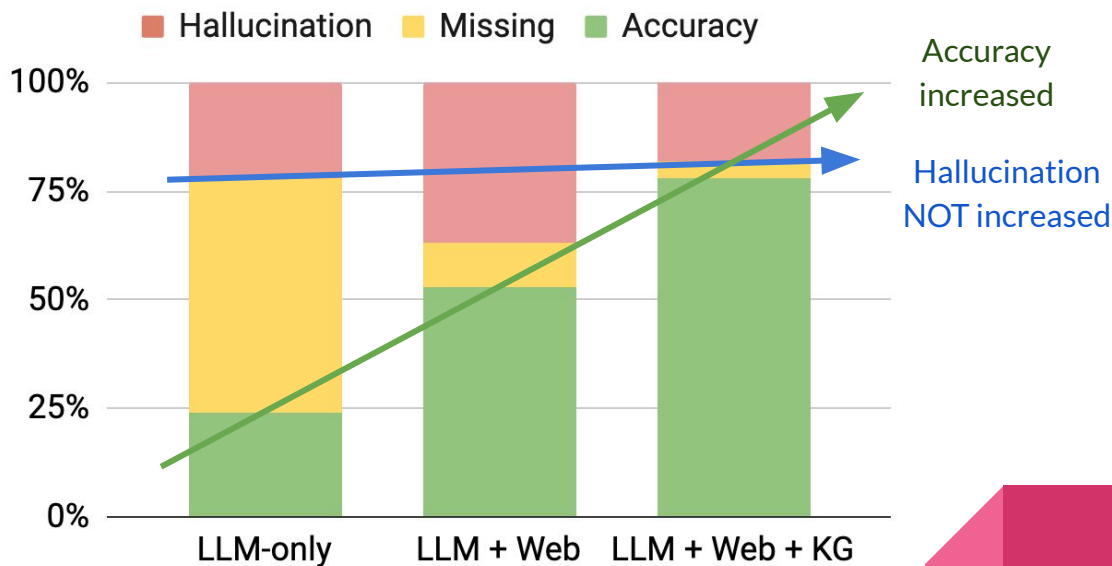
**LLM Summarization:** Summarize retrieved information and generate answers through LLM

**Example (Cont'):**

Output: Meta's stock price yesterday, Oct 20, 2023, opened at \$301.44 and closed at \$304.79. The stock price fluctuated between a high of \$316.31 and a low of \$300.915 throughout the day.

# Federated RAG Performance

Initial Experimental Results

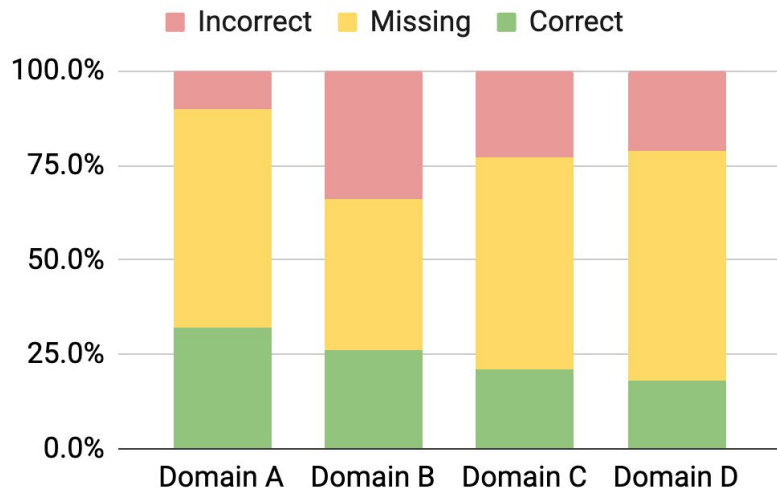


# Providing the Right Information

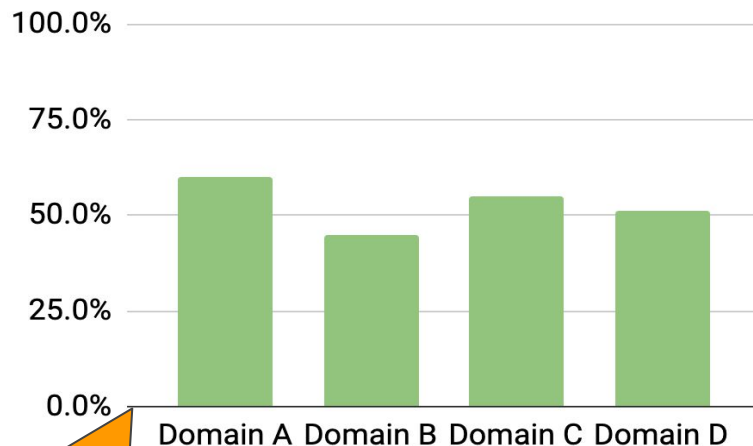
***Why did we succeed?—5 Learnings***

# Learning 1. Good Metrics Is Key to Quality

LLM only



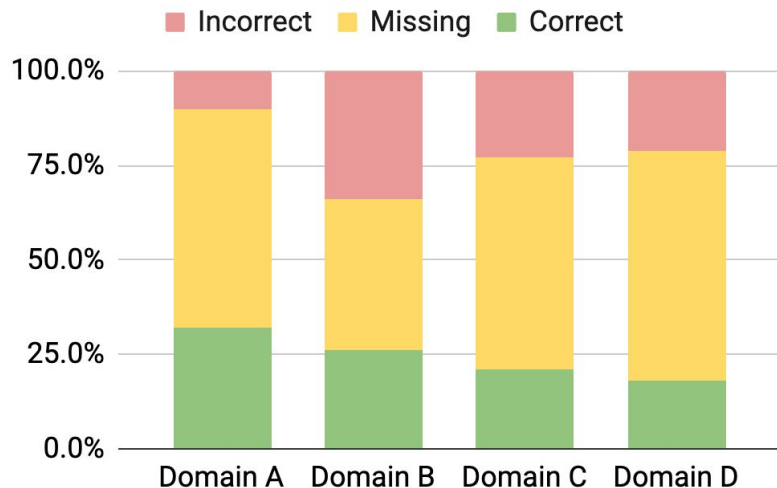
LLM + Web



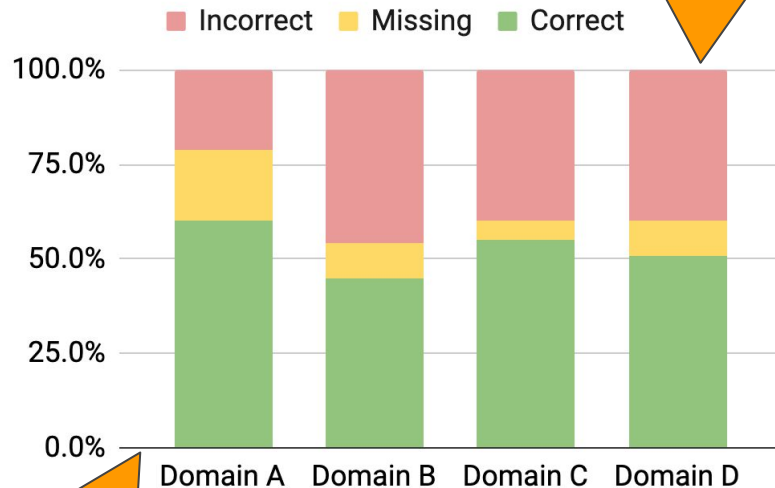
Much higher accuracy

# Learning 1. Good Metrics Is Key to Quality

LLM only



LLM + Web

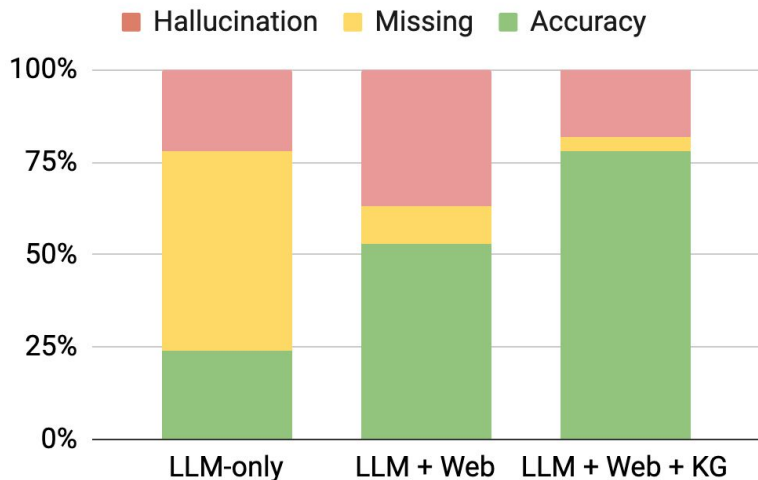


Much more hallucinations

Much higher accuracy

# Learning 1. Good Metrics Is Key to Quality

Initial Experimental Results



Factuality	2%	16%	59%
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- Accuracy is not binary, especially when multiple facts exist. We consider four levels:
  - Perfect
  - Acceptable
  - Missing
  - Incorrect
- **Factuality = Perfect + Acceptable \* 0.5 - Incorrect**
  - Penalize hallucinations
- In addition, we set constraints on critical metrics, like hallucination rate, latency, etc.

# Learning 2. KG Increases Accuracy & Reduces Latency

Contributions from Web vs. KG Retrieval

Sources	Web	KG	Union
Retrieval coverage	64%	38%	77%
Answer accuracy	91%	99%	92%
Latency	~1300 ms	~200ms	-

- KG retrieval results, when successful, are precise and concise, allowing >99% answer accuracy
- KG retrieval saves latency by >1 sec. An early stopping on web search can cut E2E latency significantly

# Learning 3. Easy Tasks Can Be Distilled to a Small LM

## In-context few-shot learning on 10 domains (single-turn)

	Llama2 7B	Llama2 70B	GPT4
Domain Categorization	76%	92%	91%
Query Rewriting	48%	68%	75%

In-context few-shot learning performs reasonably well for domain categorization, but does not work well for query rewriting (*aka., API call parameter generation*)

## Fine tuning on 3 domains with complex APIs

	Single-turn	Multi-turn	Latency (30 tokens)
Domain Categ. (Llama 1.4B)	99%	94%	~180ms
Query Rewriting (Llama 7B)	84%	-	200ms

Even with fine tuning, query rewriting is still hard → **Tool LLM** has a long way to go

**Long contexts** in multi-turn conversations reduces quality of results



# Learning 4. Summarization Plays A Critical Role in Reducing Hallucinations

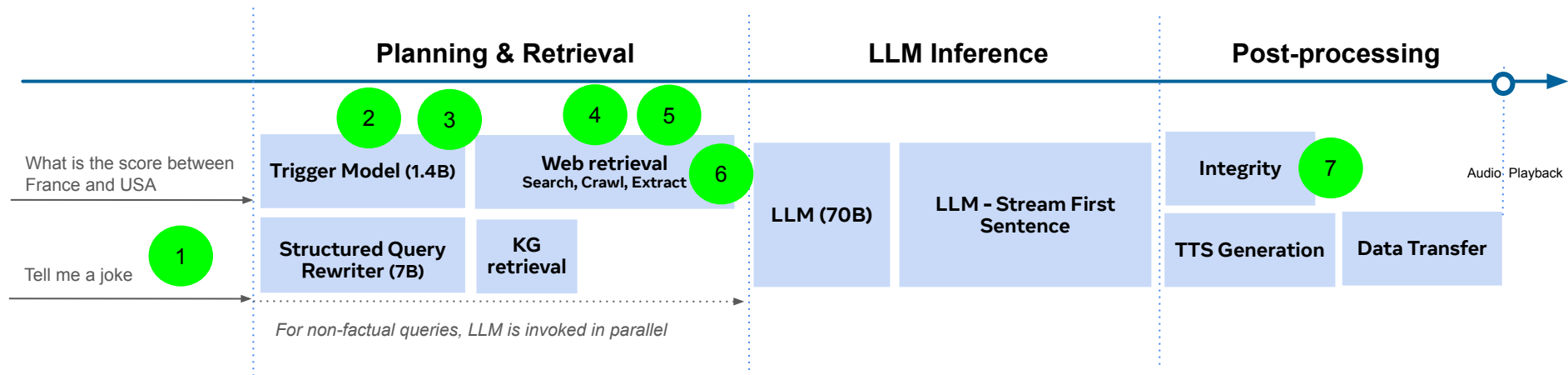
Fine-tuning for temporal and numerical summarization (60% errors) w. ~500 samples

	Zero-shot	Fine-tuned
Accurate	80%	81%
Missing	6%	11%
Hallucinated	14%	8%
Factuality	66%	73%

More than half of summarization errors happened for **time/dates** and **numerical** values; especially from **semi-structured websites**

Just 500 samples, with careful annotations, can significantly improve summarization quality

# Learning 5. Latency Requires Relentless Optimizations

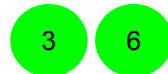


	p50 E2E latency
Brute force	~6 sec
Optimized	4 sec

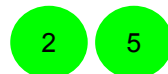
- Parallelization, even for dependent components



- Careful tradeoff of latency and quality

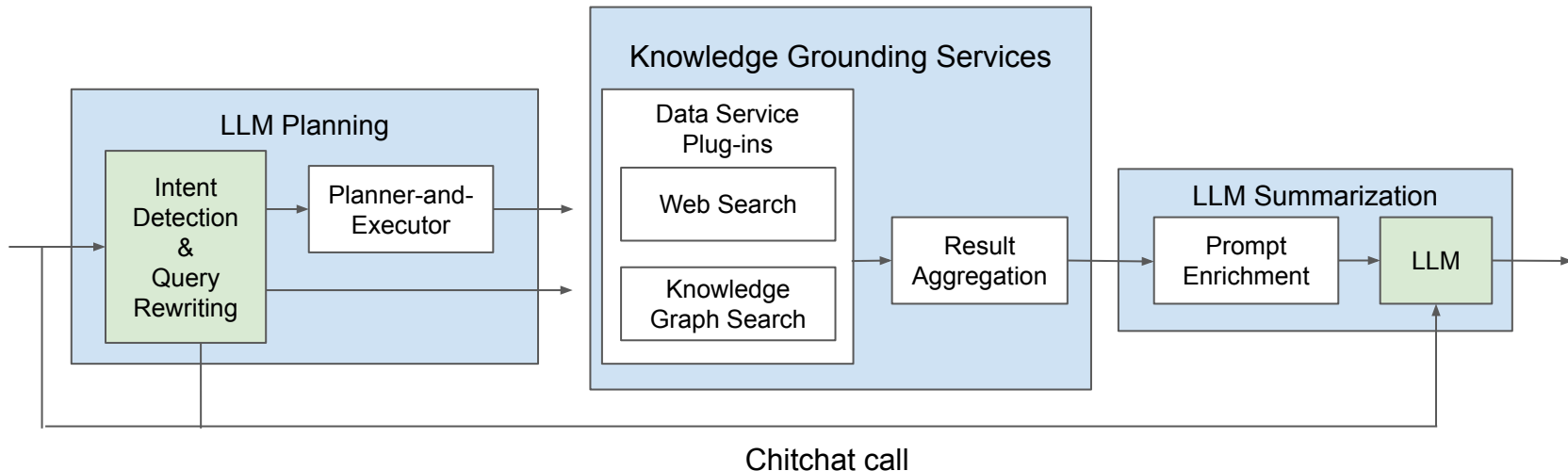


- Caching, load balancing, etc.



# Federated RAG Learning Summary

## #1. Good metrics is key to quality



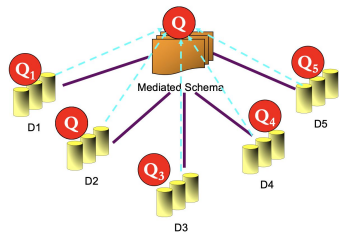
### #3. Easy tasks can be distilled to a small LM

## #2. KG increases accuracy & reduces latency

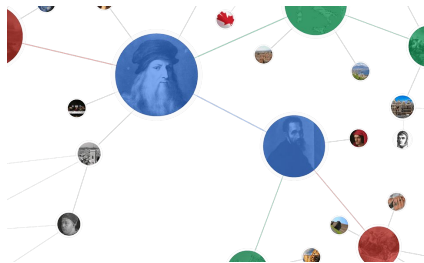
## #4. Summarization plays a critical role in reducing hallucinations

## #5. Latency requires relentless optimizations

# Integrating and Accessing All Valuable Data



v1.0 Web Search &  
Runtime Data Integration



v2.0. KG  
-based QA



v3.0. LLM

**2000's**  
*Runtime Integ.*

v1.5 Tool LLM &  
Web-augmented RAG

**2010's**  
*Offline Integ.*

v2.5 Federated  
RAG

**2020's Knowl**  
*internalization*

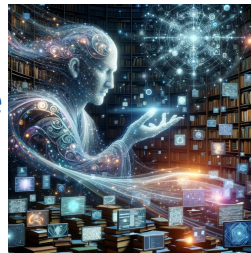
## Challenges:

- Answer summarization
- Heterogeneity
- Conflict resolution
- Latency



## Challenges:

- KG construction
- Limited coverage
- Constrained expressive power
- Complex QA



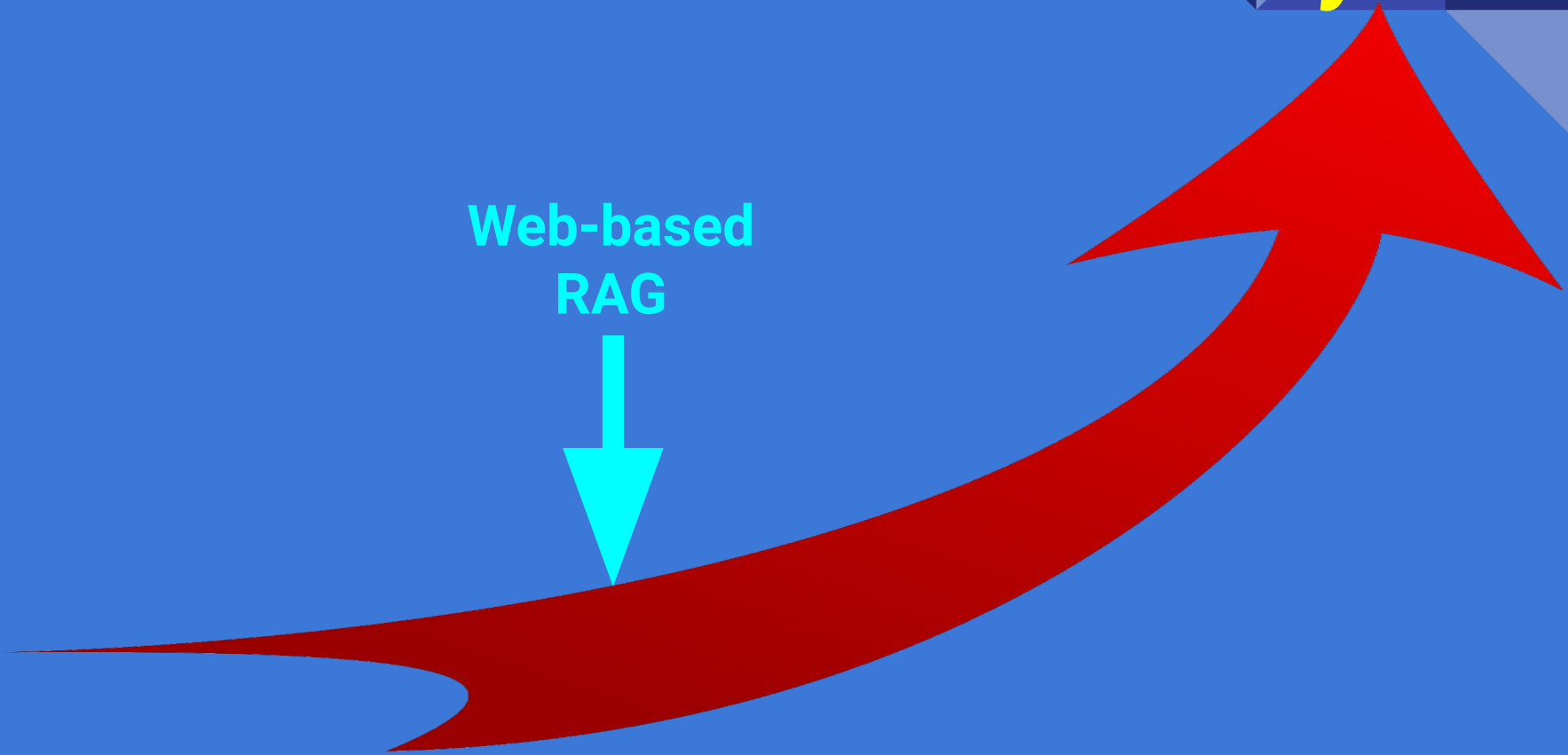
## Challenges:

- Hallucinations

Portrayed By GPT-4

# ***Where Are We in This Journey?***

**Web-based  
RAG**



# ***Where Are We in This Journey?***

Federated  
RAG



# Providing the Right Information

*Where Can We Further Improve?  
—5 Opportunities*

# Opportunity 1. Automatic Eval for Fast Iterations

	ChatGPT-3.5	ChatGPT-4	Llama-3.0 8B	Llama-3.0 70B	Llama-3.1 70B
CRAG benchmark [1]					
Correct answers	92.0%	96.7%	94.6%	98.9%	98.2%
Missing answers	100%	100%	100%	100%	100%
Incorrect answers	92.0%	94.3%	90.7%	97.9%	96.8%
Accuracy	94.5%	97.2%	95.3%	99.0%	98.4%

LLMs show big promise in auto-evaluation  
when ground truths are given



## Opportunity 2. New Mechanisms to Leverage KGs

	Retrieval Recall	Summarization Accuracy	Correct Answers
Relevant triples	43%	99%	43%
All triples for queried entity	93%	73%	68%
Full Wiki page for queried entity	98%	1%	1%

- Need the right balance between retrieval recall and answer generation accuracy
- KG query rewriting may not be the right approach

# Opportunity 3. (Semi-)Structured Data Need More Love



ChatGPT

Based on a [quick search](#), here's what I found.

The sister college of Trinity College, Oxford is ~~Christ Church, Oxford~~. Both colleges were founded in 1546 by King Henry VIII from existing institutions [1].



Cambridge	Oxford
King's College	New College
Queens' College	Pembroke College
Pembroke College	The Queen's College
Trinity Hall	All Souls College University College
Trinity College	Christ Church
Churchill College	Trinity College

Correct retrieval but wrong answers from the tabular data.

# Opportunity 4. Don't Forget—LLMs Have Internalized A Lot of Factual Knowledge

All of the following questions have a never-changing unique answer. Some are head (popular), others are tail (less popular). Decide if you can reliably answer the questions without resorting to external knowledge sources. Return yes for those you are confident to answer, and no for others. Here are the questions.

1. How tall is the Statue of Liberty
2. How many bones are in a human adult's body
3. When was George Washington. (US president born)
4. Who's the author of the book "Seed of Evil"



Metamate · GPT-4

2 steps >

1. Yes, the height of the Statue of Liberty is a well-known fact.
2. Yes, the number of bones in a human adult's body is a standard piece of knowledge.
3. Yes, George Washington's birth date is a widely known historical fact.
4. No, the author of the book "Seed of Evil" is not a commonly known fact.

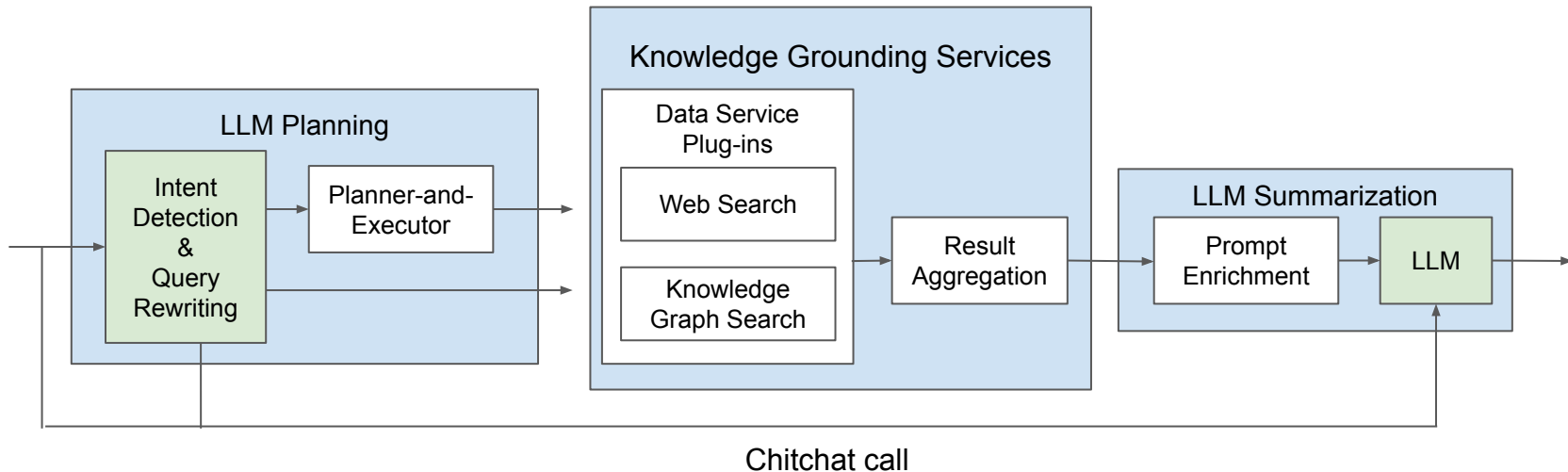
## Opportunity 5. High Quality? Low Latency? Both?

	Retrieval Recall	E2E Accuracy	Latency
Fastest 2 pages	59%	60%	Base
Top-2 pages	68%	63%	+1 sec
Top-5 pages	73%	59%	+1.5 sec

Search quality affects accuracy positively or negatively, but adds latency

# Federated RAG Opportunity Summary

## #1. Automatic eval for fast iterations



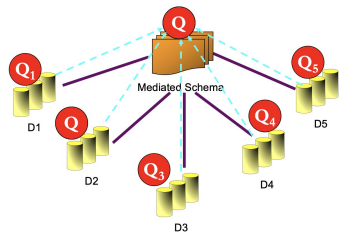
## #4. LLMs have internalized a lot of knowledge

## #2. New mechanisms to leverage KGs

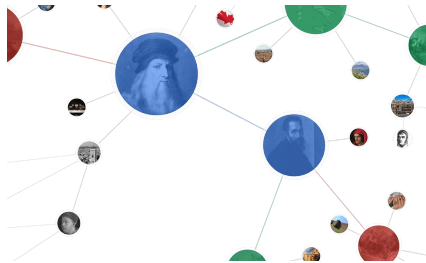
### #3. Semi-structured data need more love

## #5. High Quality? Low Latency? Both?

# Integrating and Accessing All Valuable Data



v1.0 Web Search &  
Runtime Data Integration



v2.0. KG  
-based QA



v3.0. LLM

**2000's**  
**Runtime Integ.**

v1.5 Tool LLM &  
Web-augmented RAG

**2010's**  
**Offline Integ.**

v2.5 Federated  
RAG

**2020's Knowl**  
**internalization**

v3.5 LLM w. Dual  
Neural Knowledge

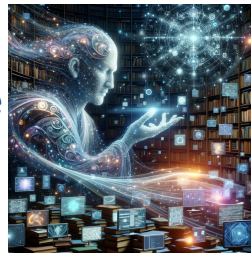
## Challenges:

- Answer summarization
- Heterogeneity
- Conflict resolution
- Latency



## Challenges:

- KG construction
- Limited coverage
- Constrained expressive power
- Complex QA



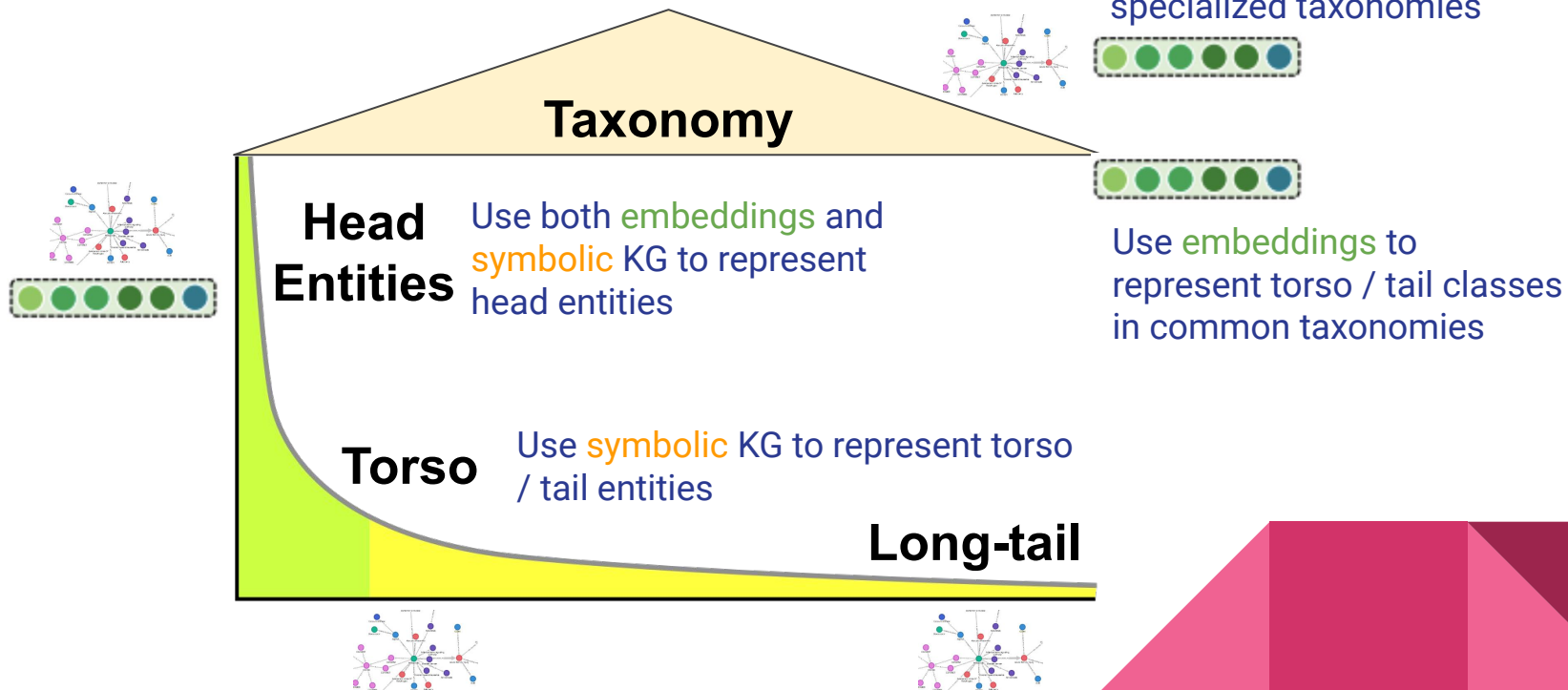
## Challenges:

- Hallucinations

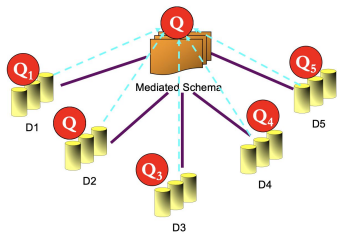


Portrayed By GPT-4

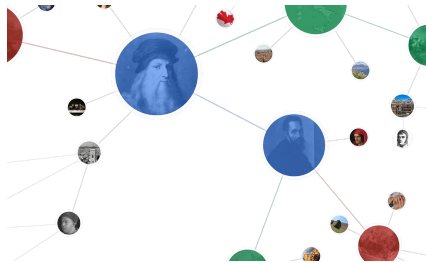
# KG Future: Dual Neural Knowledge



# Integrating and Accessing All Valuable Data



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Neural Knowledge

## Challenges:

- Answer summarization
- Heterogeneity
- Conflict resolution
- Latency



## Challenges:

- KG construction
- Limited coverage
- Constrained expressive power
- Complex QA



## Challenges:

- Hallucinations



Portrayed By GPT-4

# WE ARE FAR FROM THERE



# Providing the Right Information

A screenshot of a social media post, likely from LinkedIn, featuring a light blue background with a pattern of small, colorful icons. The post is for the "Meta KDD Cup 2024 CRAG: Comprehensive RAG Benchmark". At the top, there are several green status bars indicating progress: "Round 1: Completed", "Round 1b: Completed", and "Phase 2: Completed". Below these are several hashtag buttons: "#rag", "#ilm", "#knowledge\_retrieval", "#question\_answering\_systems", "#generative\_ai", and "#knowledge\_graph". The main text of the post reads "Meta KDD Cup 2024" followed by "CRAG: Comprehensive RAG Benchmark" in large, bold letters. Below the title, there is a trophy icon and the number "31,500". At the bottom, there is a row of statistics: "By Meta", "144.8k" views, "2596" likes, "384" comments, and "5644" shares. To the right of the statistics is a "Share" button. On the far right, there is a vertical stack of four shelves filled with colorful, geometric books. The overall design is clean and modern, with a focus on the benchmark's progress and engagement.

Round 1: Completed Round 1b: Completed Phase 2: Completed

#rag #ilm #knowledge\_retrieval #question\_answering\_systems #generative\_ai #knowledge\_graph

Meta KDD Cup 2024

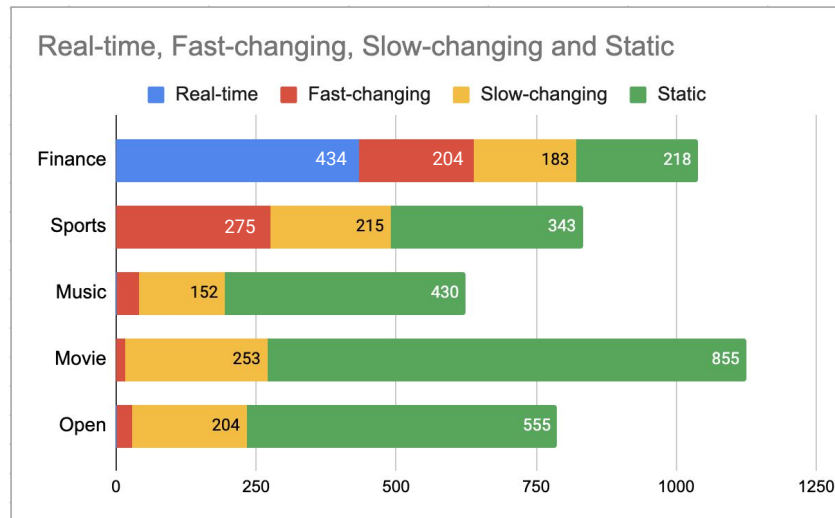
## CRAG: Comprehensive RAG Benchmark

31,500

By Meta 144.8k 2596 384 5644 85 Share

# Rich and Insightful Question-Answer Set

- 4400+ QA pairs from 5 domains (Finance, Sports, Music, Movie, Encyclopedia)
- Questions for *static*, *slow-changing*, *fast-changing*, and *real-time* information
- Questions for *head*, *torso*, and *tail* entities
- *Simple-fact* questions and *complex* questions



Total	Simple	Simple w. Cond	Set	Comparison	Aggregation	Multi-hop	Post-processing	False Premise
4409	1205	689	403	546	489	382	180	525

## Accessible Retrieval Content

- 220K webpages: 50 webpages for each question from BraveAPI web search
- Mock KG: 2.6M entities, 30:1 signal-to-noise ratio
- Mock APIs: 38 mock APIs

## Reliable Tasks and Evaluation

- Task 1: Answer generation over top-5 web search results—**Answer Summarization**
- Task 2: + Mock-KG Search API—**Structured Search, Answer Selection**
- Task 3: + 50 web search results—**Search Ranking**

# LLM-only vs. Straightforward RAGs

Domain	Solution	Accuracy	Hallucination	Missing	Factuality
Llama-3 (70B)	LLM Only	32%	29%	39%	3%
	Straightforward Task 3	41%	32%	28%	9%
GPT4 Turbo	LLM Only	34%	14%	53%	20%
	Straightforward Task 1	36%	28%	36%	8%
	Straightforward Task 2	41%	25%	34%	16%
	Straightforward Task 3	44%	30%	26%	14%

RAG may improve accuracy

KG w. crisper retrieval results helps

RAG may also bring more hallucinations

# KDD Cups Winning Solutions



**Big jump!!**

Tasks	Auto-eval			Manual-eval
	GPT-4	Llama 3	KDDCup Winning team	
Task 1	8%	5%	29%	30%
Task 2	16%	8%	30%	32%
Task 3	13%	9%	31%	36%

Xiao Yang, Kai Sun, Hao Xin, Yushi Sun, et al. CRAG–Comprehensive RAG Benchmark. NeurIPS, 2024.

Xiao Yang, Kai Sun, et al. KDD Cup CRAG competition: Systems, Findings and Learnings. IEEE Data Engineering Bulletin, 2024.

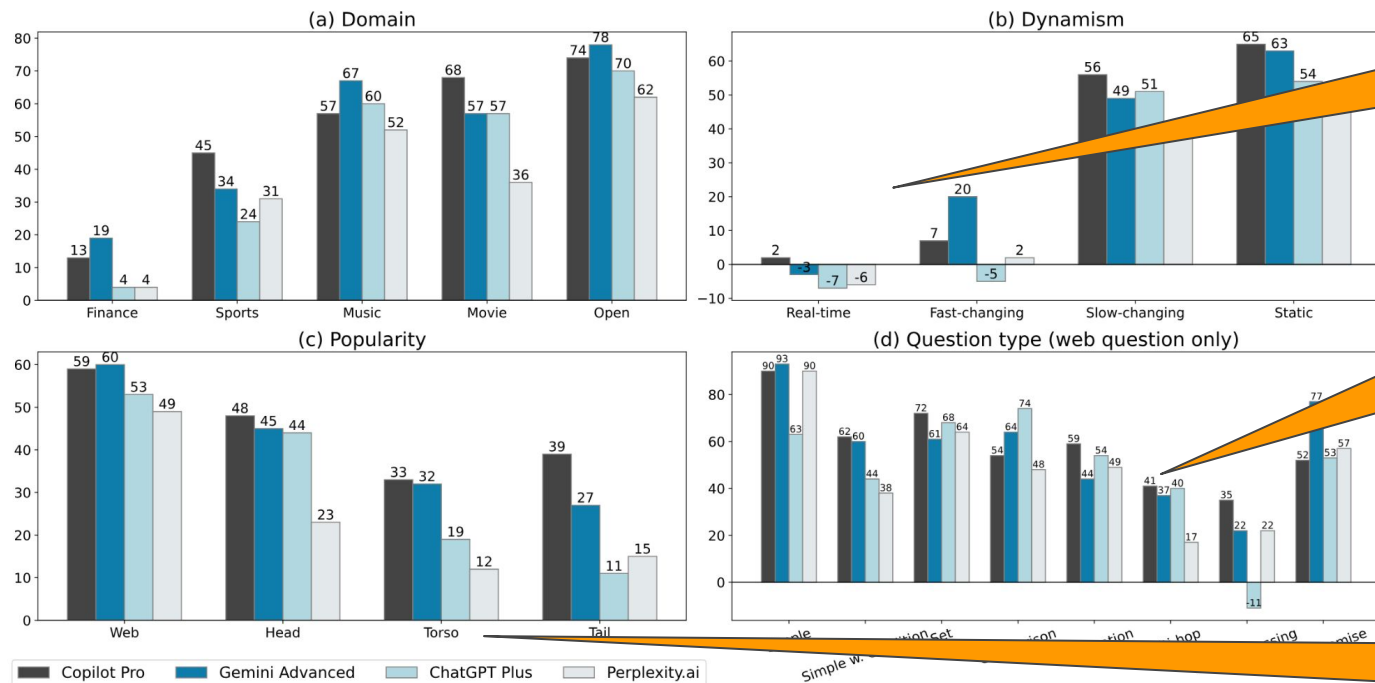
# State-of-the-Art Industry Solutions

System	Perfect	Acceptable	Incorrect	Missing	Factuality	Latency (s)
Copilot Pro	63%	12%	18%	8%	<b>50.4%</b>	11.6
Gemini Advanced	61%	10%	17%	13%	49.5%	5.2
ChatGPT Plus (4o)	60%	13%	25%	2%	42%	6.2
Meta Wearables	53%	10%	16%	22%	41%	<b>3.4</b>
Perplexity.ai	56%	9%	25%	10%	35%	4.6
Notes: 1. Manual annotations. 2. Retrieval by the SOTA solutions themselves.						

Perfect < 63%. Still a big gap to fill

Different latency-quality tradeoffs

# SOTA Industry Solutions on Diff Dimensions



Improvements needed for **fast-changing** facts

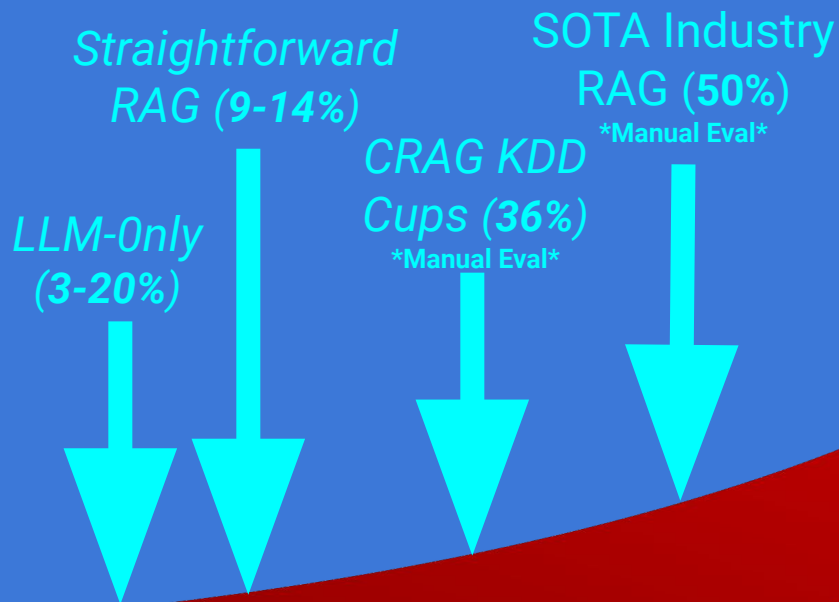
Improvements needed for **complex** questions

Improvements needed for **torso/tail** questions

Figure 3: SOTA systems human-eval scores (in percentage) across different dimensions.

# Where Are We in This Journey?

## —A Quantified Answer



Hugging Face

**Daily Papers**

by  AK





Putting Everything in Context

***Building Next-Generation Intelligent  
Assistants for Wearable Devices***

# Stages of Intelligent Assistants

## I. Chatbot

Text input



## II. Voice Asst

Voice input



## III. Wearable Asst

Voice + Visual + Context



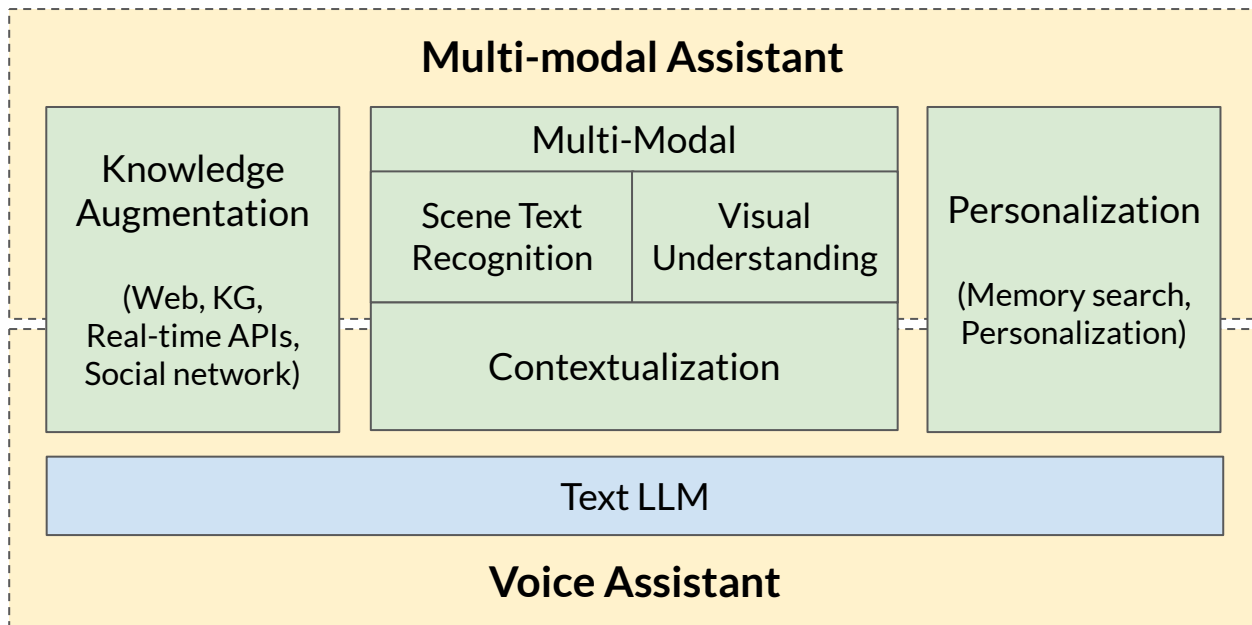
# What Is Different for A Wearable Assistant?



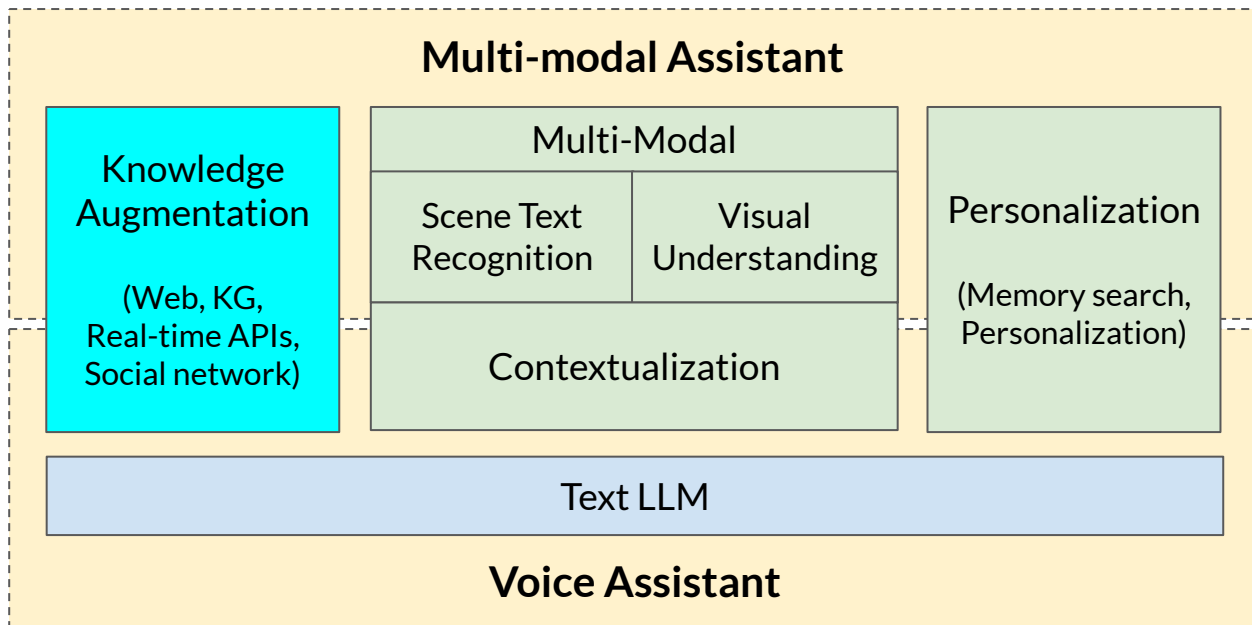
# Ray-ban Meta Video (0:24, 4:22)



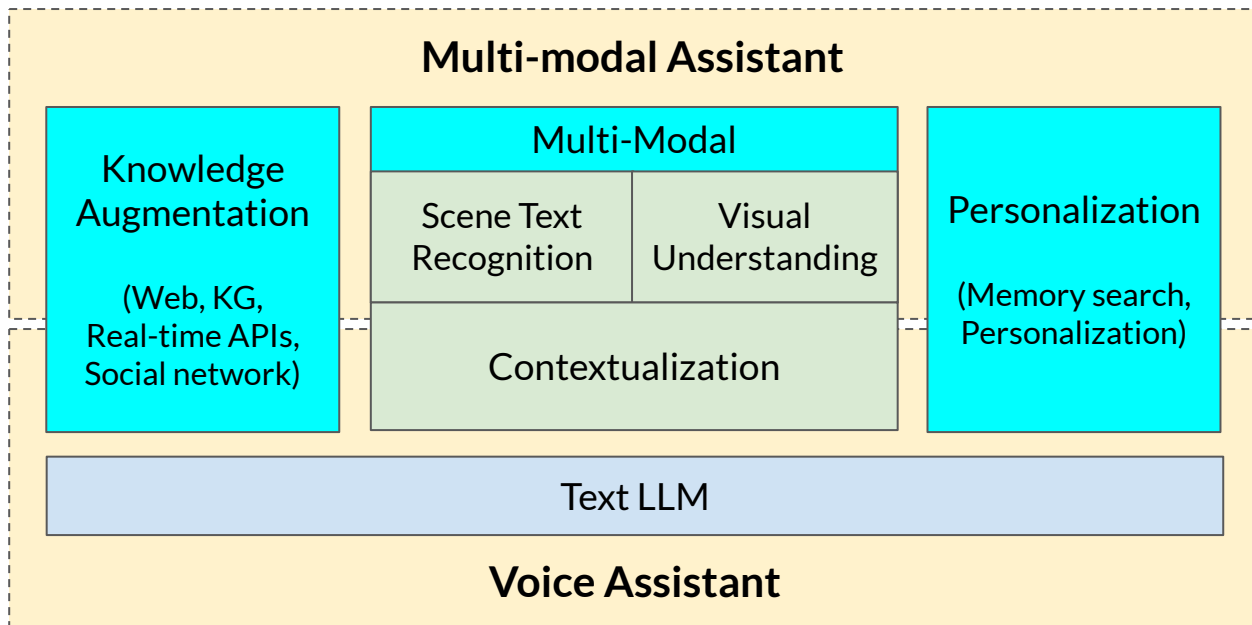
# Pillars for Next-Generation Assistant



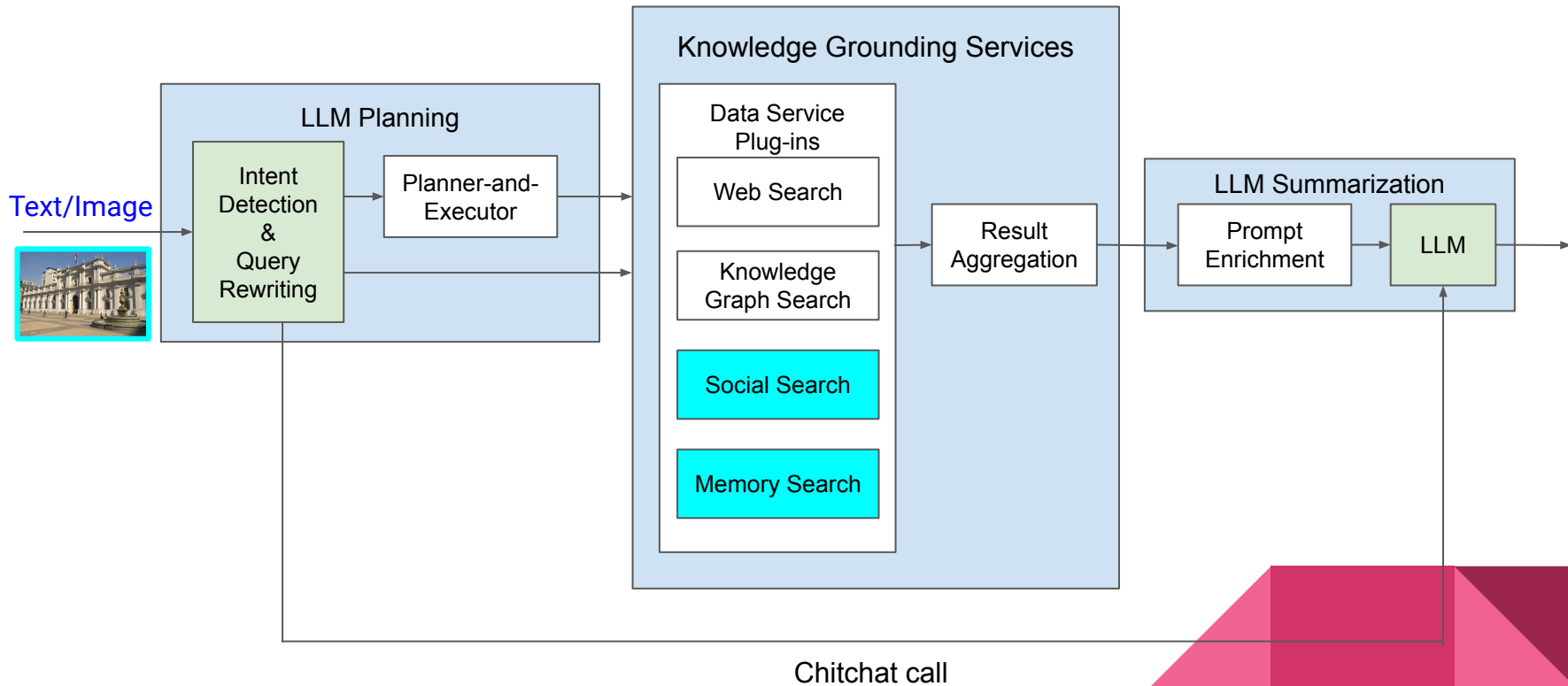
# Pillars for Next-Generation Assistant



# Similar Tech Extends to Other Pillars

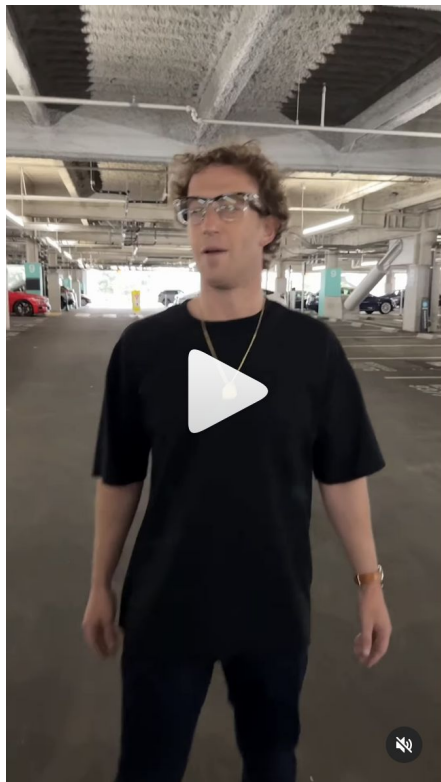


# Extending RAG for Memory & Public Search





# Latest Works Regarding Personal Memory

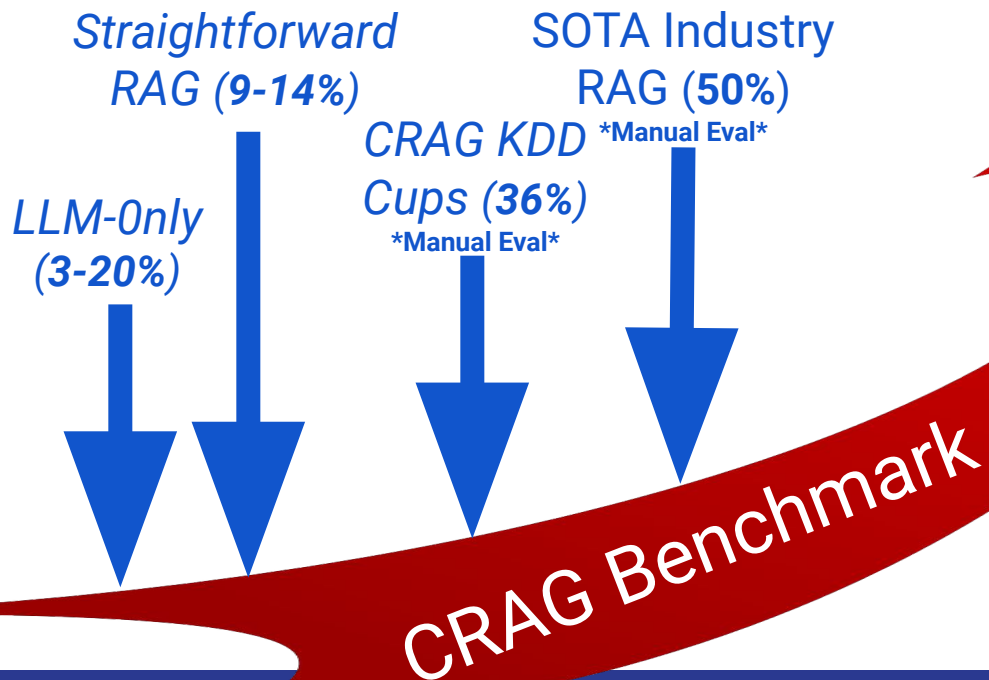


Recommendation



# Take-Aways

- **Mission:** *Providing the right information at the right time*
- **Our solution:** *Federated RAG*
- **Future KG:** *Dual Neural Knowledge*



# Acknowledgement



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Yushi Sun



Hao Xin



Nan Tang



Lei Chen

**HKUST:** Xiangsen Chen, Ziyu Jiang, Chenyu Yang