## How Knowledgeable Are LLMs?

Xin Luna Dong

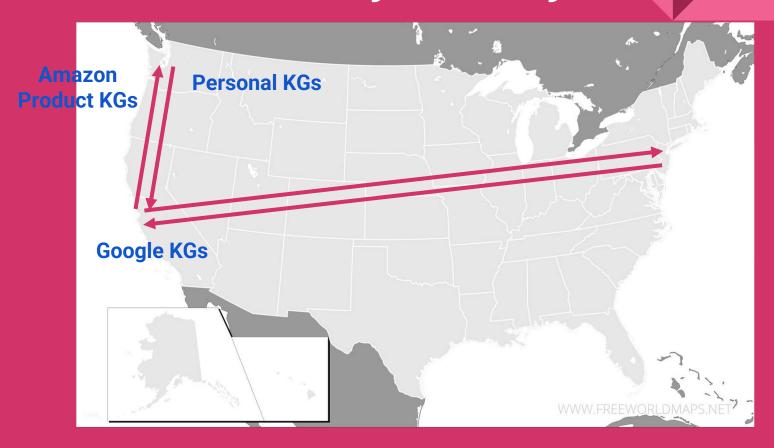
8/2023

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

## About Me: My Journey

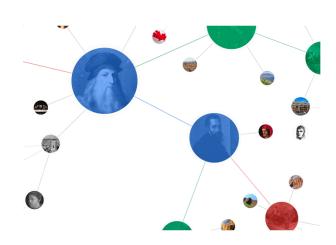


## **About Me: KGs in My Journey**



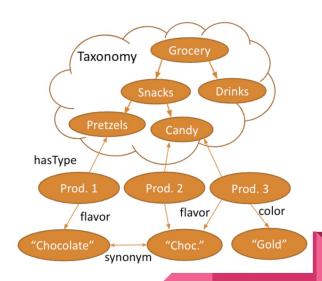
## **Generations of Knowledge Graphs**

#### 1. Entity-Based KGs



**Google Generic KGs** 

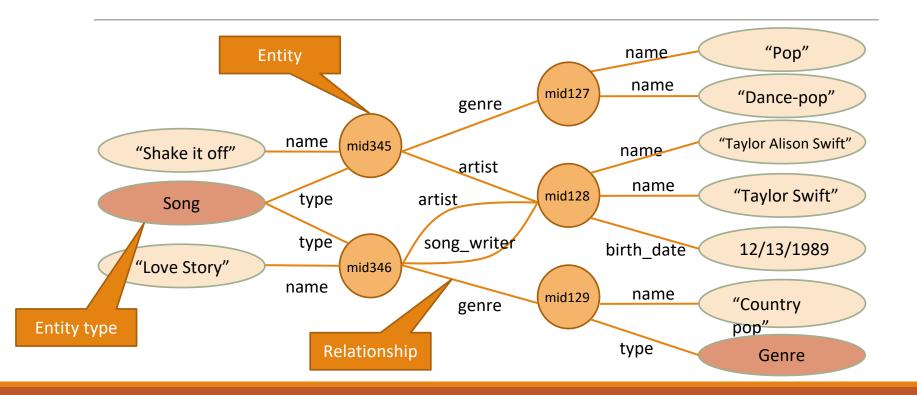
#### 2. Text-Rich KGs



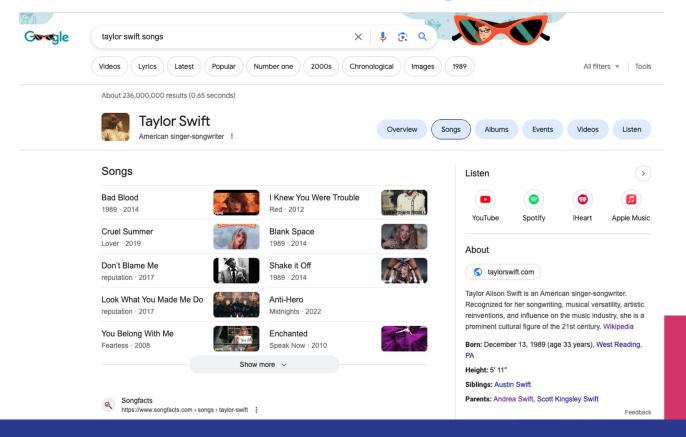
**Amazon Product KGs** 

# **Generation #1: Entity-Based Knowledge Graphs**

## **Entity-Based KG Example**



## Google KG Shows in 25% Google Search in 2015



## **Entity-Based KGs**

#### **Characteristics**

- Ontology (types, relationships) manually defined w. clear semantics
- Entities are named-entities, w. no overlap

#### Key idea

Create a graph of entities and relationships to represent the world

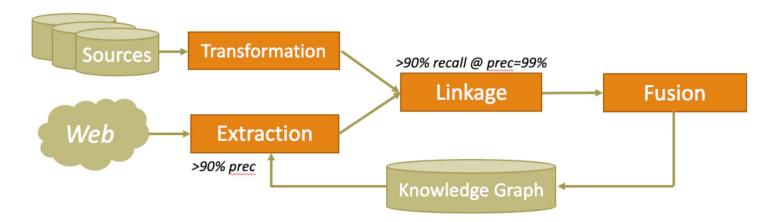
## Challenges: Heterogeneous Data Everywhere



Are "Born" and "date of birth" the same? → Schema Alignment
Are they the same person? → Entity Linkage
Why "May 14, 1982" vs "7 November 1983"? → Data fusion
Heterogeneity, Heterogeneity, Heterogeneity

## **Constructing Entity-Based KGs**

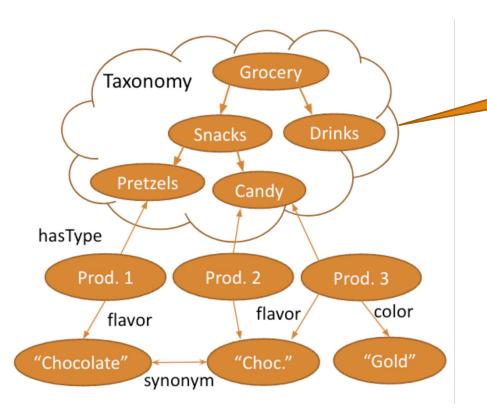
#### **Framework:**



Examples: Google KG (500B facts), Bing Satori, Alexa KG, Yago, DBPedia.

# Generation #2: Text-Rich Knowledge Graphs

## **Text-Rich KG Example**



Taxonomy

#### Other domains:

Bioinformatics, Health, Geography, Local business, Events, etc.

#### Example: Providing Structured Product Information



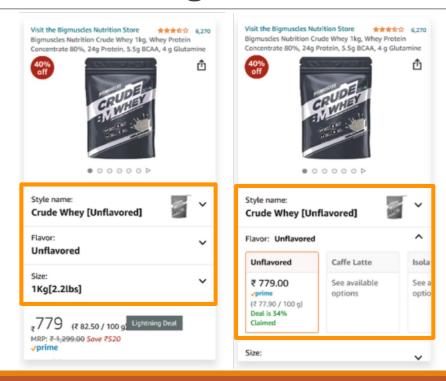
Roll over image to zoom in

**Brand** Cetaphil Ingredients Water, Cetyl Alcohol, Propylene Glycol, Iodopropynyl Butylcarbamate, 2-Bromo-2-Nitropropane-1, 3-Diol, Sodium Lauryl Sulfate, Stearyl Alcohol, Methylparaben, Propylparaben, Sodium Citrate, Butylparaben, Allantoin, Zinc Gluconate. Scent Fragrance free Non-Comedogenic, Fragrance-Additional Item free. Natural Information **Skin Type** Sensitive

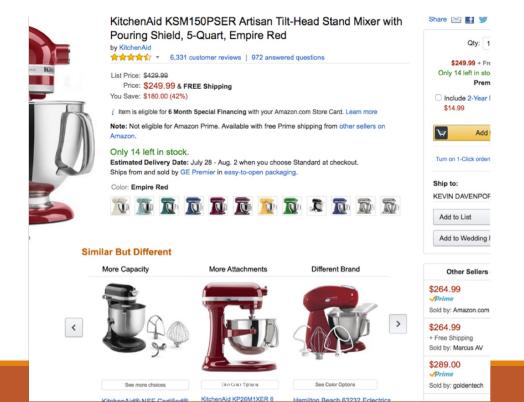
#### **About this item**

- Gentle for everyday use; Cetaphil gentle skin cleansing cloths will leave your skin feeling clean, refreshed and balanced after every use
- Removes makeup & dirt: Thoroughly remove makeup and dirt, leaving skin clean
- Mild & non irritating: Soap free formulation won't strip skin of its natural protective oils and emollients

## **Example: Providing Choices**



## Example: Explaining Recommendations



#### **Text-Rich KGs**

#### **Characteristics**

- Ontology (types, relationships) very complex with overlaps and ambiguities; E.g., millions of product types
- Entities may not be named-entities, such as products
   E.g., "Onus 2 Colors Highlighter Stick, Shimmer Cream Powder Waterproof Light Face Cosmetics, creamy Self Sharpening Crayon STick Highlighter" vs. "Xin Luna Dong"
- Attribute values are oftentimes texts, with overlaps and ambiguities E.g., "Coffee" vs "Cappuccino" as icecream flavors

#### **Key Idea**

Finding structure and modeling ambiguity from text sources

### Do We Need Different Techniques?

Scott's Cakes Dark Chocolate Toffee Cream Filling Candies with Dark Blue Foils in a 1 Pound Red Roses Box by Scott's Cakes

Be the first to review this item

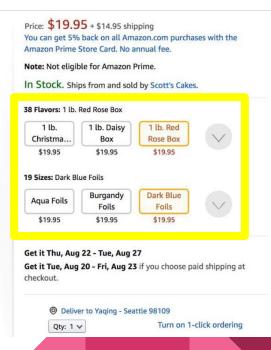








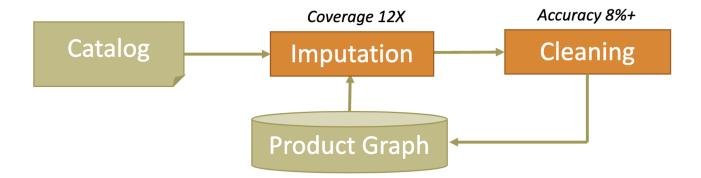




Different challenges: Unstructured and Noisy product

## **Constructing Text-Rich KGs**

#### Framework:



**Examples:** Amazon Product Graph (1B facts)

# Generation #3: ???

Will LCM Replace KGs?

#### An Example



Tell me about famous people named Michael Jordan. Be brief





Sure, here are brief descriptions of three famous individuals named Michael Jordan:

- Michael Jordan (Basketball Player): An American former professional basketball player, considered one of the greatest of all time. He led the Chicago Bulls to six NBA championships and won five MVP awards.
- Michael B. Jordan (Actor): An American actor known for his roles in TV series like "The Wire," "Friday Night Lights," and films such as "Fruitvale Station," "Creed," and "Black Panther."
- Michael I. Jordan (Researcher): An American scientist and professor specializing in machine learning, statistics, and artificial intelligence, currently teaching at the University of California, Berkeley.

#### **Another Example**



Tell me famous people named Xin Luna Dong. Be brief





Tell me famous people named Luna Dong. Be brief



scie

the (

play

How

Luna



Tell me famous people named Xin Dong. Be brief



As of my last training data up to September 2021, there are no notable or famous individuals named Xin Dong that stand out. Please note that this is a common name in Chinesespeaking regions, so there may be many individuals with this name who aren't widely recognized internationally. There might also be notable people with this name who have gained prominence after my last training cut-off in 2021.

#### **Another Example**



Tell me famous books for knowledge graphs



Sure, here are some popular books on the subject of knowledge graphs:

- "Knowledge Graph and Semantic Computing: Semantic, Knowledge, and Linked Big Data" by various authors. This book contains selected papers from leading researchers on the topic.
- "Knowledge Graphs: Methodology, Tools and Selected Use Cases" by Sherif Sakr and Marcin Wylot. This book provides an accessible, yet comprehensive introduction to the field of knowledge graphs.
- "Knowledge Graphs: Fundamentals, Techniques, and Applications" by Raghava Mutharaju, Sarasi Lalithsena, Pavan Kapanipathi. A comprehensive look into various aspects of knowledge graphs, including the technical aspects and practical applications.

- "Linked Data: Structured Data on the Web" by David Wood, Marsha Zaidman, Luke Ruth,
  Michael Hausenblas. This book offers a practical introduction to linked data and how it's
  used in semantic web technologies, which are closely related to knowledge graphs.
- "Semantic Web for the Working Ontologist: Effective Modeling in RDFS and OWL" by Dean Allemang, Jim Hendler This book isn't specifically about knowledge graphs, but it provides foundational knowledge about semantic web technologies that are critical to understanding and working with knowledge graphs.
- "Foundations of Data Science" by John Hopcroft and Ravindran Kannan This one covers a broad range of data science topics, including knowledge graphs.
- "Graph Databases" by Ian Robinson, Jim Webber, Emil Eifrem. This book is all about graph databases, which provide the underlying technology for many knowledge graphs.

## Key Questions to Ask Regarding Hallucination

- How *reliable* are LLMs when answering factual questions?
- Do LLMs perform *equally well* across different types of factual knowledge?
- Do well-known LLM tricks work?
  - Increasing model size
  - Instruction tuning
  - Few-shot in-context learning

#### **Head-to-Tail Benchmark**

Domain	Sources	# Templates	# Instances
Movies	IMDb	13	3,093
Books	Goodreads	4	3,000
Sports	SR/Olympic Sports	7	3,150
Academics	MAG, DBLP	13	2,946
Open	DBpedia	393	9,132
Total		430	21,321

Table 2: The overall statistics of Head-to-Tail.

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Table 2: The overall statistics of Head-to-Tail.

#### 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 captical of Wernythedia?

Answer: unsure

Question: {QUESTION}

Answer:

## **Correctness Checking**

#### 3 categories

- Correct
- Incorrect
- Unsure

#### 3 metrics

- Accuracy=corr/all
- Hallucination rate= Incorr / all
- Missing rate= Unsure / all

You need to check whether the prediction of a question-answering system to a question is correct. You should make the judgment based on a list of ground truth answers provided to you. Your response should be "correct" if the prediction is correct or "incorrect" if the prediction is wrong.

Question: Who authored The Taming of the Shrew (published in 2002)?

Ground truth: ["William Shakespeare", "Roma Gill"]

Prediction: W Shakespeare

Correctness: correct

Question: Who authored The Taming of the Shrew (published in 2002)?

Ground truth: ["William Shakespeare", "Roma Gill"]

Prediction: Roma Shakespeare

Correctness: incorrect

Question: {QUESTION}

Ground truth: {GROUND\_TRUTH}

Prediction: {PREDICTION}

Correctness:

98% consistent w. human labels

#### Q1. How Reliable Are LLMs on Factual Questions?

Domain	$A_{LM}$	$\mathbf{H}_{\mathbf{LM}}$	Miss.
Specific Open	19.2 22.1	11.8 14.8	69.0 63.2
All	20.4	13.1	66.5

le 3: Performance of ChatGPT on Head-to-Tail. numbers are in percentage (%).

Similar for *specific* domains and *general* domains

Very low accuracy. High missing rate; hallucination rate reasonable

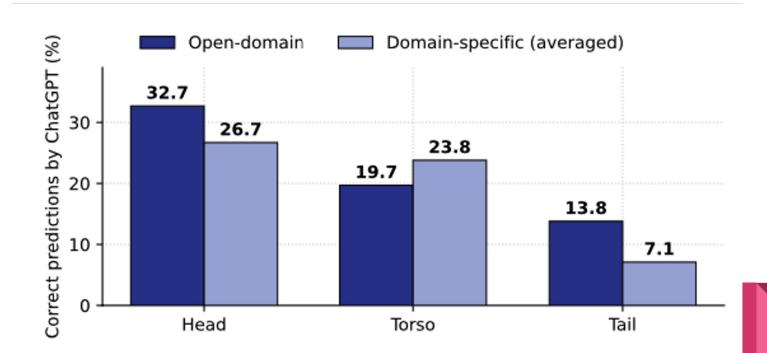
## **Entity Distributions**

	IM	Db	Goodreads	SR/Olympic Sports
	Title	Person	Book	Athlete
Head Torso Tail	767 ( 0.01) 4,113 ( 0.05) 7,536,482 (99.94)	34,903 ( 0.48) 87,645 ( 1.21) 7,111,496 (98.31)	847 ( 0.05) 13,118 ( 0.75) 1,723,765 (99.20)	3,150 ( 2.31) 7,304 ( 5.35) 126,134 (92.35)

		MAG		DBLP	DBpedia
	Article	Conference	Journal	Scholar	-
2	1,827,710 ( 0.70) 9,386,034 ( 3.60) 49,311,539 (95.70)	257 ( 1.63) 965 ( 6.12) 14,550 (92.25)	225 ( 0.46) 1,266 ( 2.58) 47,546 (96.96)	79,521 ( 2.44) 500,778 (15.36) 2,680,704 (82.20)	103,564 ( 1.30) 1,255,113 (15.77) 6,600,206 (82.93)

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

### Q2. Performance Similar for Head/Torso/Tail?



### Q2. Performance Similar for Head/Torso/Tail?

Domain	Не	Head Torso T		Torso		ail	
	$\overline{\mathbf{A}_{\mathbf{LM}}}$	$H_{LM}$	$\overline{\mathbf{A}_{\mathbf{LM}}}$	H <sub>LM</sub>	$\overline{\mathbf{A_{LM}}}$	$H_{LM}$	
Movies	51.3	11.5	46.4	16.6	6.4	11.8	
Books	20.1	26.3	22.5	29.2	8.0	19.2	
Sports	28.1	9.0	22.9	7.0	12.7	5.6	
Academics	5.9	3.0	2.3	1.7	0.8	0.9	
Open	32.7	20.8	19.7	13.3	13.8	10.2	
All	29.2	16.0	22.0	13.5	9.9	9.7	

Tail domains have lower accuracy

- Accuracy consistently dropping from head to torso to tail
- 2. Hallucination rate might be higher for torso

### Q2. Performance Similar for Head/Torso/Tail?

Model	Head &	Torso	Tail		
	$\overline{\mathbf{A_{LM}}}$	$\mathbf{H}_{\mathbf{LM}}$	$\overline{\mathbf{A_{LM}}}$	$\mathbf{H}_{\mathbf{LM}}$	
ChatGPT	18.6	14.2	22.3	14.8	

Table 5: Comparison of LLMs' knowledgeability about head, torso, and tail attributes in  $A_{LM}$  (%) and  $H_{LM}$  (%) using open-domain instances from Head-to-Tail.

Interestingly, not significant differences for head / torso / tail attributes

## Q3. Do Normal LLM Tricks Help?

Increasing model size does not appear to help significantly

Instruction-tuned counterparts have higher missing rate

Model	$A_{LM}$	$\mathbf{H}_{\mathbf{LM}}$	Miss.
LLaMA (7B)	14.9	78.3	6.7
LLaMA (13B)	16.7	82.1	1.1
LLaMA (33B)	20.5	78.0	1.5
LLaMA (65B)	20.0	79.7	0.3
Vicuna (7B)	11.9	78.6	9.5
Vicuna (13B)	11.7	63.3	25.0
Flan-T5 (3B)	3.6	16.8	79.7
Flan-T5 (11B)	6.8	18.4	74.8
Falcon (7B)	11.4	59.2	29.4
Falcon (40B)	12.6	43.4	44.0
Falcon-Instruct (7B)	8.1	57.9	34.0
Falcon-Instruct (40B)	10.4	36.0	53.7

## Q4. Would Few-Shot In-Context Learning Help?

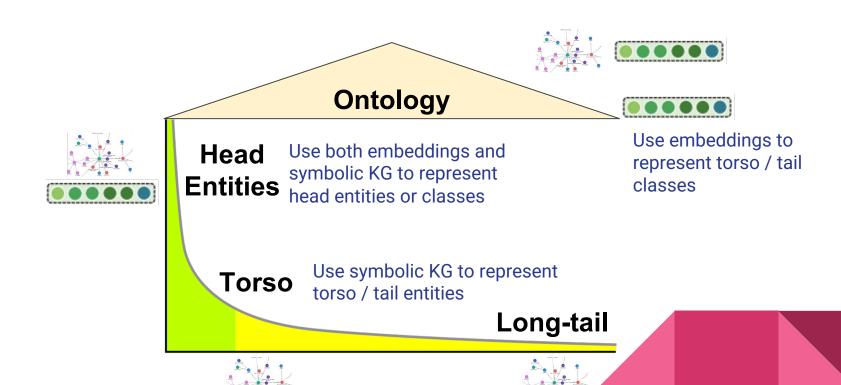
Zero-shot and Few-shot have similar performances

In-domain few-shot (positive examples) increases quality but also hallucination rate

	Domain	Domain Few-	-shot	Zero-shot		In-domain Few-shot	
	$A_{LM}$	$\mathbf{H}_{\mathbf{LM}}$	A <sub>LM</sub>	$\mathbf{H}_{\mathbf{LM}}$	$A_{LM}$	$\mathbf{H}_{\mathbf{LM}}$	
	Movies	51.3	11.5	51.1	12.5	54.7	7.1
	Books	20.1	26.3	16.5	17.8	18.4	42.4
ď	Sports	28.1	9.0	22.6	10.1	42.9	21.4
Head	Academics	5.9	3.0	8.4	7.2	20.4	15.9
	Open	32.7	20.8	32.6	24.7	45.0	27.8
	All	29.2	16.0	28.2	17.4	39.0	24.3

Table 7: Performance of ChatGPT with different prompts on Head-to-Tail. All numbers are in percentage (%).

#### **Next Generation of KG—Dual Neural KG**



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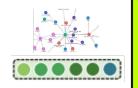
How to infuse head knowledge into LLMs to enable precise QA?











Head Entities

Use both embeddings and symbolic KG to represent head entities or classes

Use embeddings to represent torso / tail classes

Torso

Use symbolic KG to represent torso / tail entities

How to seamlessly plug-in external knowledge for QA regarding torso/tail knowl.?

Long-tail





#### Meta's Assistant

#### Empowering connection to people and experiences in your life





"Hey Facebook" (double press the button on your controller)

"Who's online?"--meet up with friends

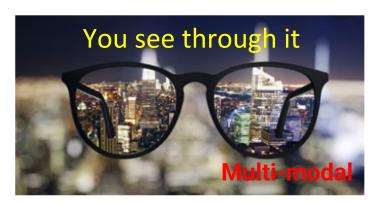
"Open Beat Saber"--jump straight in the game, and more.

#### Ray-Ban Stories



"Hey Facebook, take a picture" -capture moments hands-free "Hey Facebook"--call friends on Messenger, manage device settings, and more.

## **Building an AR/VR Smart Assistant**

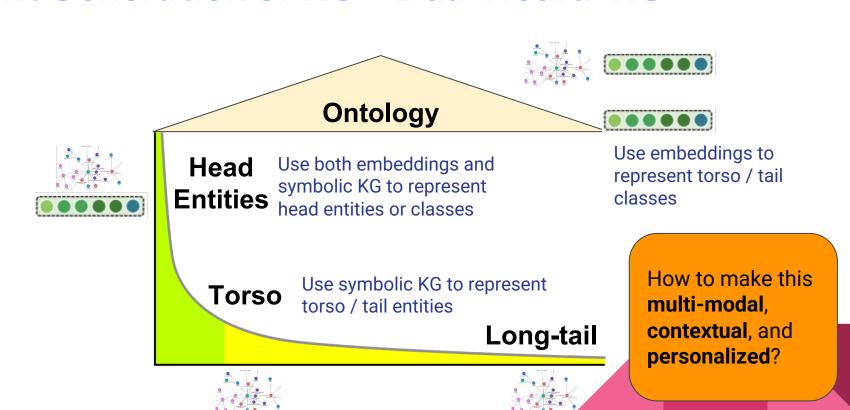








#### **Next Generation of KG—Dual Neural KG**



#### **Shameless Advertisement**

#### **Next-Generation Intelligent Assistants for AR/VR Devices**

Workshop "Multimodal Learning" 8/7 (Monday) 1:10pm, Room: 102A

**Tutorial: Towards Next-Generation Intelligent Assistants** 

leveraging LLM techniques

8/9 (Wednesday) 10am-1pm, Room: 202C

How to make this multi-modal, contextual, and personalized?

## Take-Aways. 3 Generations of KGs

#### 1. Entity-Based KGs

Resolving heterogeneity with entity linkage and web knowledge extraction

#### 2. Text-Rich KGs

Extractions and cleanings from sparse and noisy source data, and handling semantics ambiguities

#### 3. Dual Neural KGs

Knowledge infusion into LLMs, and seamless knowledge augmentation to facilitate LLMs

## Acknowledgement









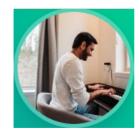












# **Thank You**

Q&A?