



IJCAI/2023 MACAO



IJCAI

International Joint Conferences on
Artificial Intelligence Organization

Open-Environment Knowledge Graph Construction and Reasoning: Challenges, Approaches, and Opportunities

<https://openkg-tutorial.github.io/>

Ningyu Zhang¹, Meng Wang², Tianxing Wu³, Shumin Deng^{4✉}



19, Aug, 2023

Why Do We (Still) Need Knowledge Graph in the Era of LLMs?

GPT-4 visual input example, École Polytechnique Exam Question:

User Answer question I.1.a. Think step-by-step.

I. Principe de la détection de rayonnement avec un bolomètre

Comme illustré sur la figure 1 un bolomètre est constitué d'un absorbeur qui reçoit le rayonnement que l'on désire détecter. Sa température T , supposée uniforme, est mesurée à l'aide d'un thermomètre incorporé, constitué d'un matériau conducteur dont la résistance $R(T)$ varie avec la température T ; cette variation est caractérisée par le coefficient $\alpha = \frac{1}{R} \frac{dR}{dT}$. L'ensemble possède la capacité thermique C_B .

Un barreau, conducteur thermique, homogène, de longueur L , de section S et de conductivité thermique λ et sans échanges thermiques latéraux, relie le bolomètre à un thermostat de température T_b fixe.

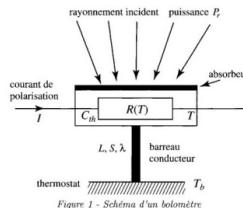


Figure 1 - Schéma d'un bolomètre

I.1. Dans cette première partie, on étudie le comportement du bolomètre en régime stationnaire, à la température de fonctionnement $T = T_0$.

I.1.a) Exprimer la température $T(x)$ en tout point du barreau conducteur repéré par son abscisse x ; on prendra $T(0) = T_0$ et $T(L) = T_b$.

GPT-4 To answer question I.1.a, we need to express the temperature $T(x)$ in every point of the conductive bar, which is characterized by the abscissa x . We are given that $T(0) = T_0$ and $T(L) = T_b$.

For a stationary regime, the heat equation for the one-dimensional heat conduction in the bar is:

$$d^2T/dx^2 = 0$$

Integrating once, we get:

$$dT/dx = C_1$$

Integrating a second time:

$$T(x) = C_1x + C_2$$

To determine the constants C_1 and C_2 , we use the boundary conditions:

$$T(0) = T_0, \text{ which gives } C_2 = T_0$$

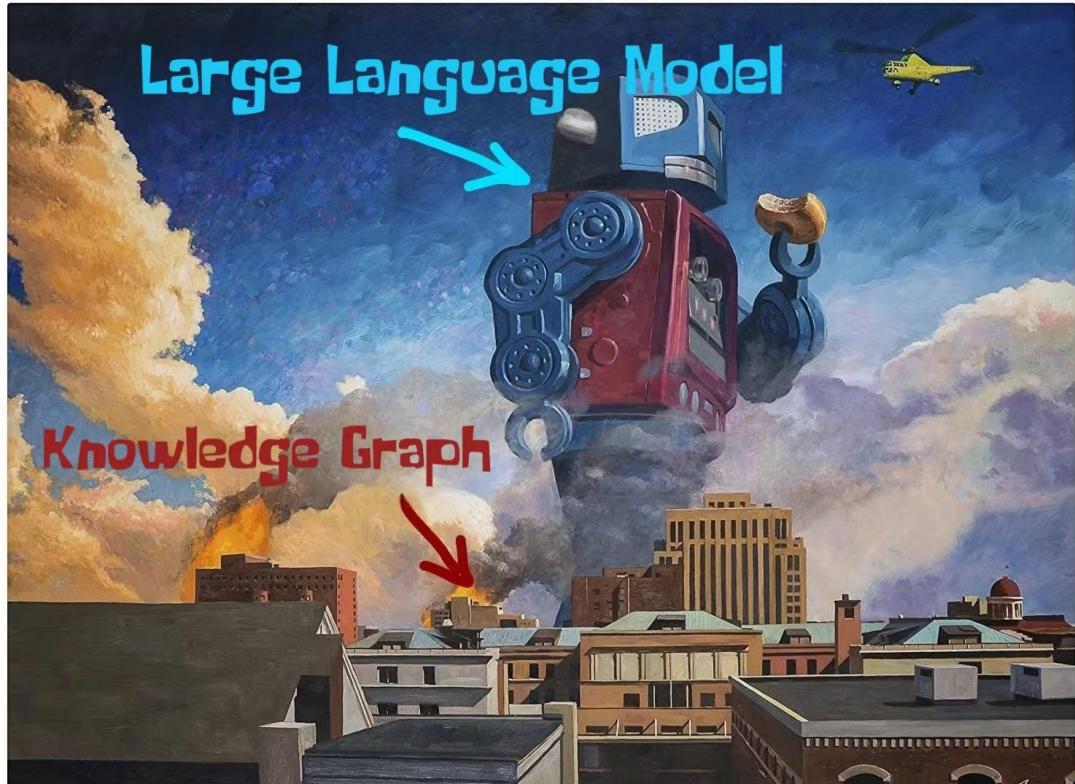
$$T(L) = T_b, \text{ which gives } C_1 = (T_b - T_0)/L$$

Finally, the expression for $T(x)$ is:

$$T(x) = (T_b - T_0) * (x/L) + T_0$$

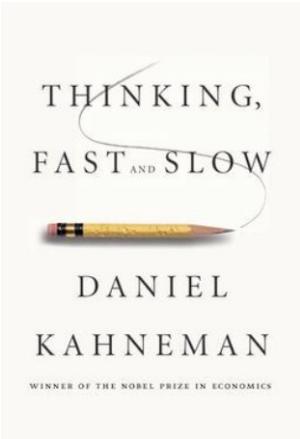
This represents a linear temperature profile along the conductive bar, with a slope of $(T_b - T_0)/L$.

Table 15. Example prompt demonstrating GPT-4's visual input capability. The prompt consists of a question which requires understanding a physics problem with a diagram written in French and solving it using chain-of-thought prompting.



Why Do We (Still) Need Knowledge Graph in the Era of LLMs?

- Deep Learning for **System II Processing**, as proposed by **Yoshua Bengio**
- Language models need sensory grounding for **meaning** and **understanding**, as argued by **Yann LeCun**



EL How many World Cup championships has Messi won?

Lionel Messi has not won any World Cup championships with the Argentina national team. He has played in three World Cup tournaments (2006, 2010, and 2014), and his team finished as runners-up in the 2014 World Cup.

W1 a story about a boy and a girl choosing their subjects for university

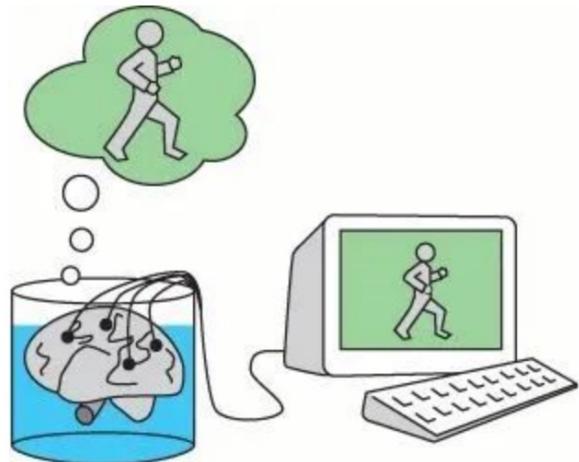
Once upon a time, there was a boy and a girl who were about to finish high school and embark on their university journey. They were both very excited but also nervous about choosing their subjects for the next four years.

The boy had always been interested in science and technology. He was particularly passionate about robotics and had even built his own robot at home. So, he knew that he wanted to study engineering in university. He researched different universities and their engineering programs, looking at their curriculum and facilities. He also talked to his science teachers and mentors for advice and guidance.

The girl, on the other hand, had a love for the arts. She was an avid writer and painter, and had always enjoyed expressing herself through creativity. She wasn't quite sure what she wanted to study yet, but knew it had to be something that allowed her to be imaginative and explore her artistic side. She attended university fairs, talked to art professors and alumni, and looked at different universities' fine arts programs.

Why Do We (Still) Need Knowledge Graph in the Era of LLMs?

- ❑ Symbol Grounding
- ❑ Common Sense: The Dark Matter of Language and Intelligence
- ❑ Objective-Driven AI



Given a set of rules and facts, you have to reason whether a statement is true or false. Here are some facts and rules:

The bear likes the dog.
The cow is round.
The cow likes the bear.
The cow needs the bear.
The dog needs the squirrel.
The dog sees the cow.
The squirrel needs the dog.
If someone is round then they like the squirrel.
If the bear is round and the bear likes the squirrel then the squirrel needs the bear.
If the cow needs the dog then the cow is cold.

Does it imply that the statement "The cow likes the squirrel." is True?

Given a set of rules and facts, you have to reason whether a statement is true or false.

Here are some facts and rules:

The e4 likes the e5.
The e14 is e2.
The e14 likes the e4.
The e14 needs the e4.
The e5 needs the e26.
The e5 sees the e14.
The e26 needs the e5.
If someone is e2 then they like the e26.
If the e4 is e2 and the e4 likes the e26 then the e26 needs the e4.
If the e14 needs the e5 then the e14 is e1.

Does it imply that the statement "The e14 likes the e26." is True?

Presenters



IJCAI/2023 MACAO



Ningyu Zhang



Meng Wang



Tianxing Wu



Shumin Deng



- Introduction to KG Construction and Reasoning (Ningyu Zhang, 30 Min)
- **Low-resource** KG Construction and Reasoning (Shumin Deng, 40 Min)
- **Multimodal** KG Construction and Reasoning (Meng Wang, 40 Min)
- **Uncertain** KG Construction and Reasoning (Tianxing Wu, 40 Min)
- Discussion on Main Issues & Opportunities (Ningyu Zhang, 30 Min)
- QA & Discussion



IJCAI/2023 MACAO



IJCAI
International Joint Conferences on
Artificial Intelligence Organization

Introduction to KG Construction and Reasoning

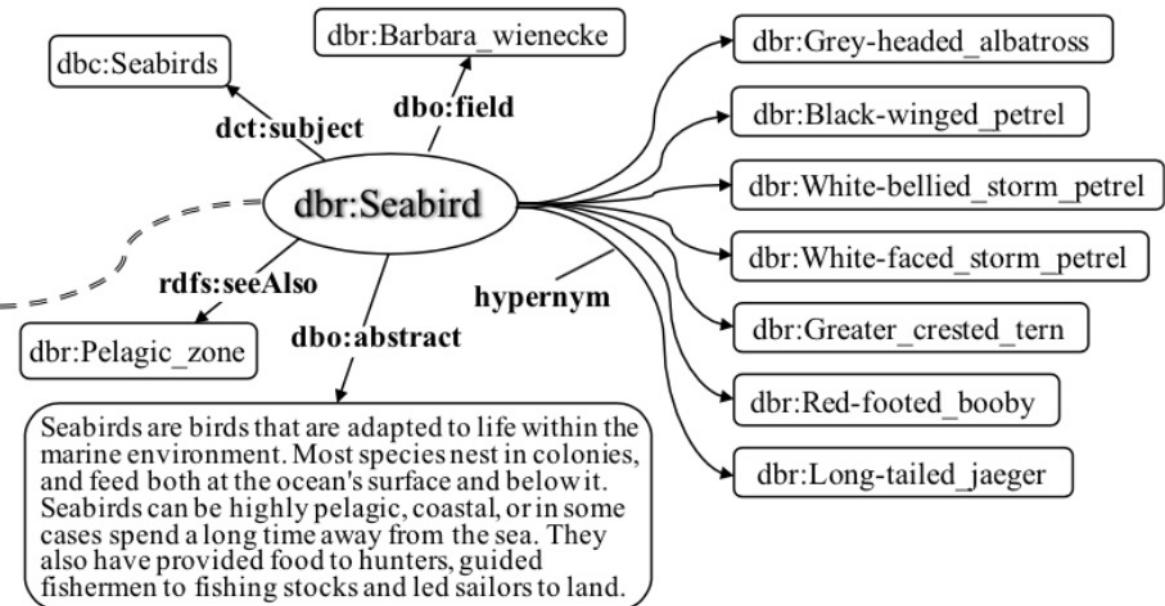
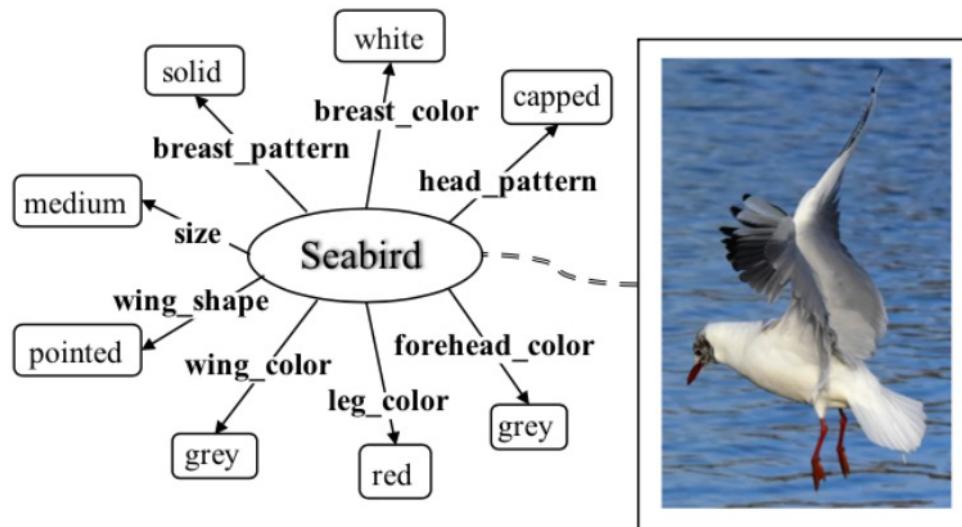
<https://openkg-tutorial.github.io/>

Ningyu Zhang
Zhejiang University

19, Aug, 2023

Knowledge Representation

- Knowledge representation is a **surrogate for the essence of things**
 - justice, fairness, cube
- Knowledge representation is an **ontological commitment**
 - Iron: knowledge represents differently for Physicists, Chemists, Recyclers



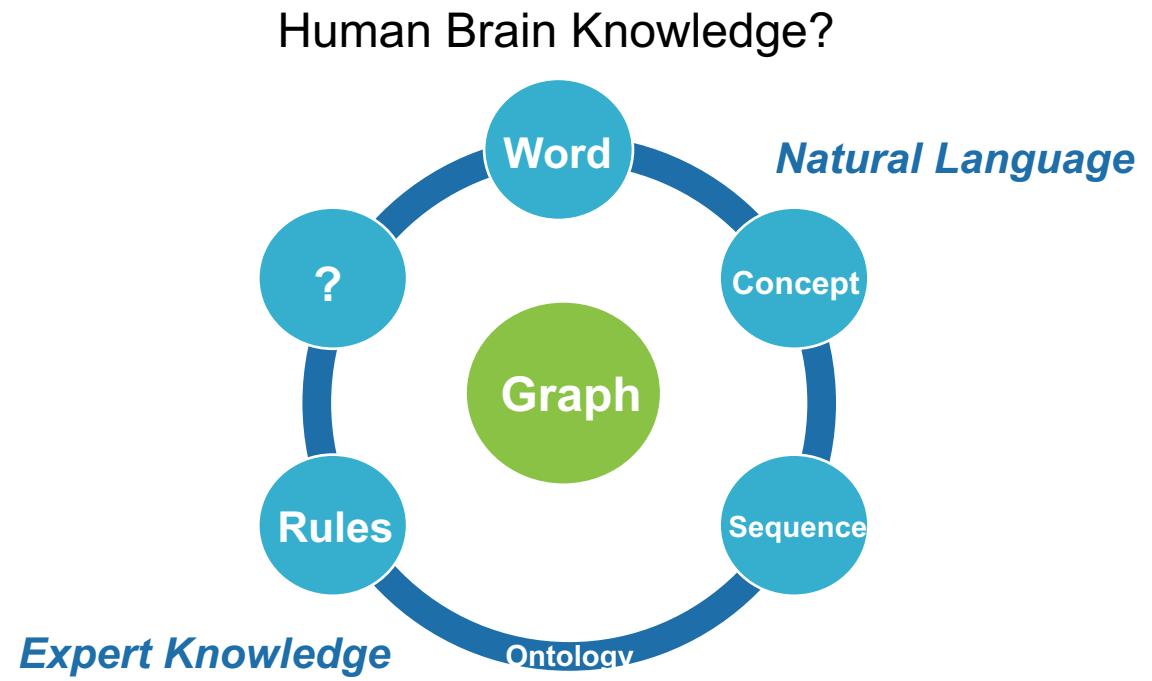
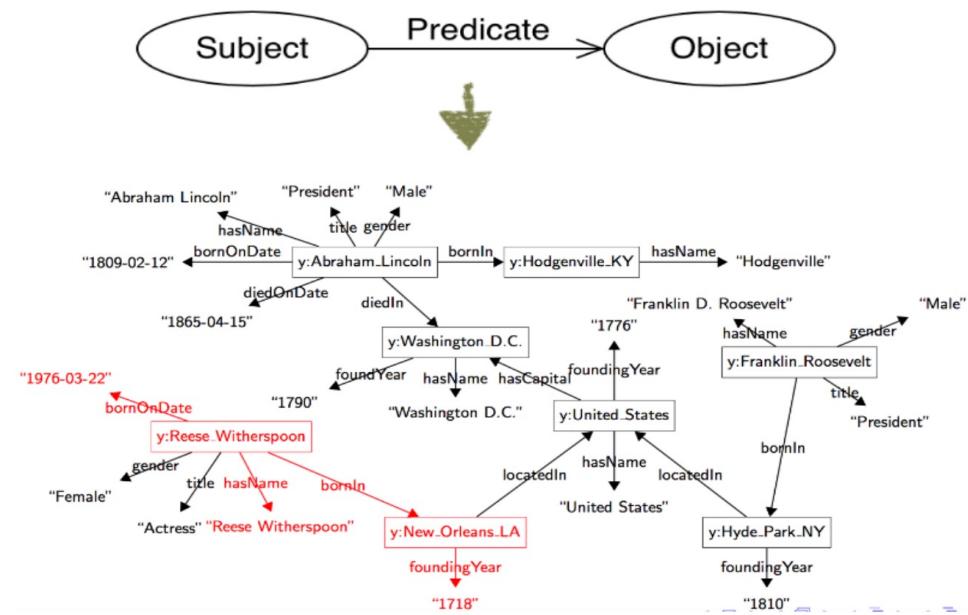
Knowledge Structure and Abstraction

- *"In coming to understand the world—in learning concepts, acquiring language, and grasping causal relations—our minds make inferences that appear to go far beyond the data available"*
- Large Language Models Are **NOT** Abstract Reasoners



KG = Textual Semantics + Structural Knowledge

A triple (S,P,O) encodes a statement — a simple *logical expression*, or claim about the world



Language \neq Knowledge

Representation Type	Interpretability	Type of Knowledge	Computability
<i>Natural Language</i>	<i>Understandable by humans</i>	<i>Explicit knowledge</i>	<i>Not easily computationally processed</i>
<i>Knowledge Graphs</i>	<i>Understandable by humans</i>	<i>Explicit knowledge + Implicit knowledge</i>	<i>Relatively easy to computationally process</i>
<i>Language Models</i>	<i>Not understandable by humans</i>	<i>Implicit knowledge</i>	<i>Easily computable and processable</i>

Knowledge Graph and Applications (General)

Google's search result for the query “J. R. R. Tolkien”

J. R. R. Tolkien

Writer : Overview Books Videos



The Tolkien Society

Biography - The Tolkien Society

Who was Tolkien? ... John Ronald Reuel Tolkien (1892–1973) was a major scholar of the English language...

Died September ... Spouse Edith Tolkien (m. 1916–1971)

Books >



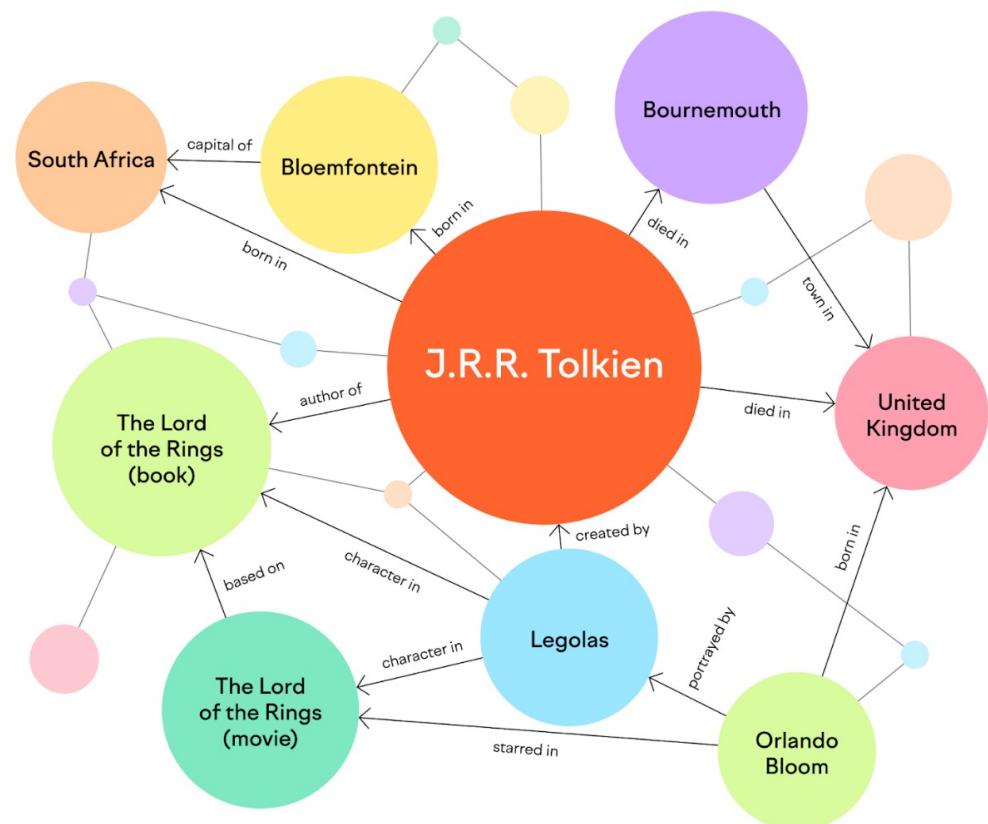
The Lord of the Rings 1954
The Hobbit 1937
The Silmarillion 1977
Beren and Lúthien 2017
The Fellowship of the Ring 1954
Unfinished Tales of... 1980

About

John Ronald Reuel Tolkien CBE FRS was an English writer and philologist. He was the author of the high fantasy works *The Hobbit* and *The Lord of the Rings*. From 1925 to 1945, Tolkien was the Rawlinson and Bosworth Professor of Anglo-Saxon and a Fellow of Pembroke College, both at the University of Oxford. [Wikipedia](#)

Born: January 3, 1892, Bloemfontein, South Africa

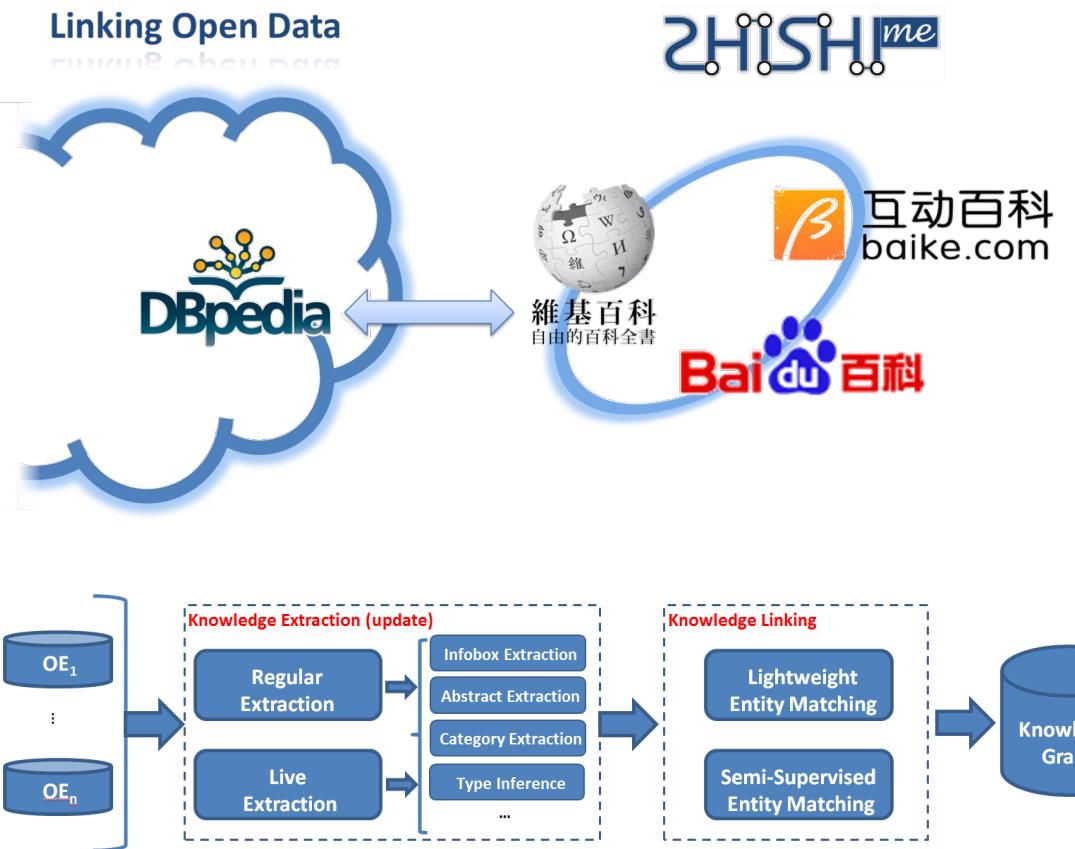
Died: September 2, 1973, Bournemouth, United Kingdom



Knowledge Graph and Applications (Chinese)

Zhishi.me

Linking Open Data

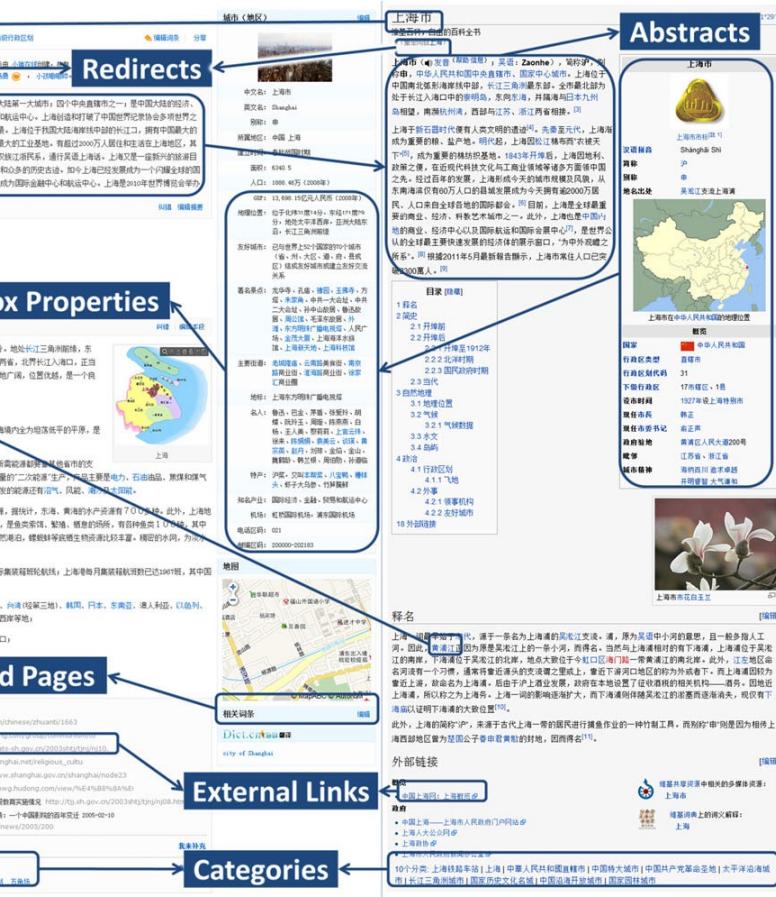


- [1] Knowledge graph construction from multiple online encyclopedias. World Wide Web 2020
- [2] Zhishi.me - Weaving Chinese Linking Open Data. ISWC 2011

Baidu



Hudong



Zh-Wikipedia



上海白玉兰

Jim

Knowledge Graph and Applications (Chinese)



The screenshot shows the homepage of OpenKG.CN. At the top, there is a navigation bar with links: 问答 (FAQ), 数据 (Data), 工具 (Tools), 模型 (Models), cnSchema, 注册 (Register), OpenKG工作组 (OpenKG Working Group), CIPS SIGKG, and a user profile icon. Below the navigation bar, there is a row of seven circular icons representing different categories: data storage, tools, models, members, classification, users, and information. The background features a blue sky with white clouds. In the center, the OpenKG.CN logo (a stylized white cloud-like shape) is displayed next to the text "OpenKG.CN" and "中文开放知识图谱". Below this, there are six data statistics with corresponding icons: 280 (data), 63 (tools), 4 (models), 110 (members), 18 (classification), and 367 (articles). At the bottom right, there is a QR code with the text "请关注openkg公众号" (Please follow the openkg WeChat public account).

问答 数据 工具 模型 cnSchema 注册 OpenKG工作组 CIPS SIGKG

☰

280  数据

63  工具

4  模型

110  成员

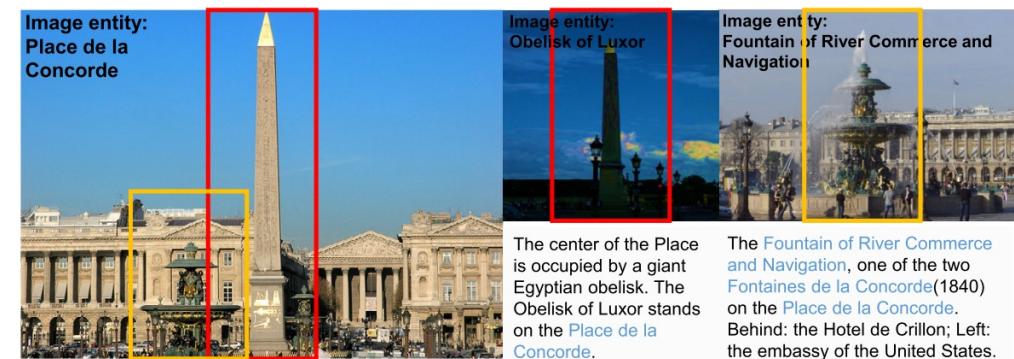
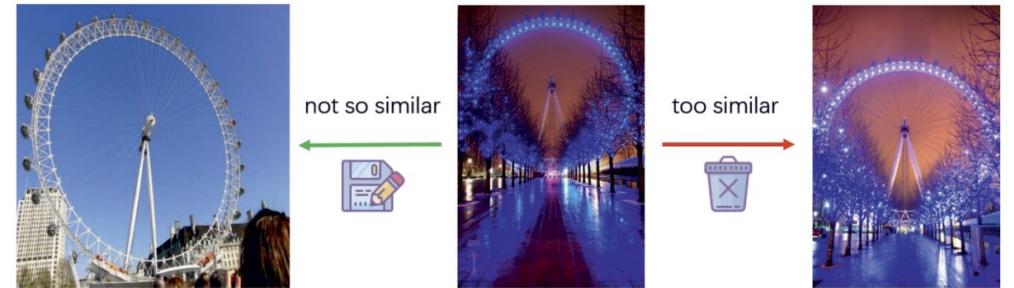
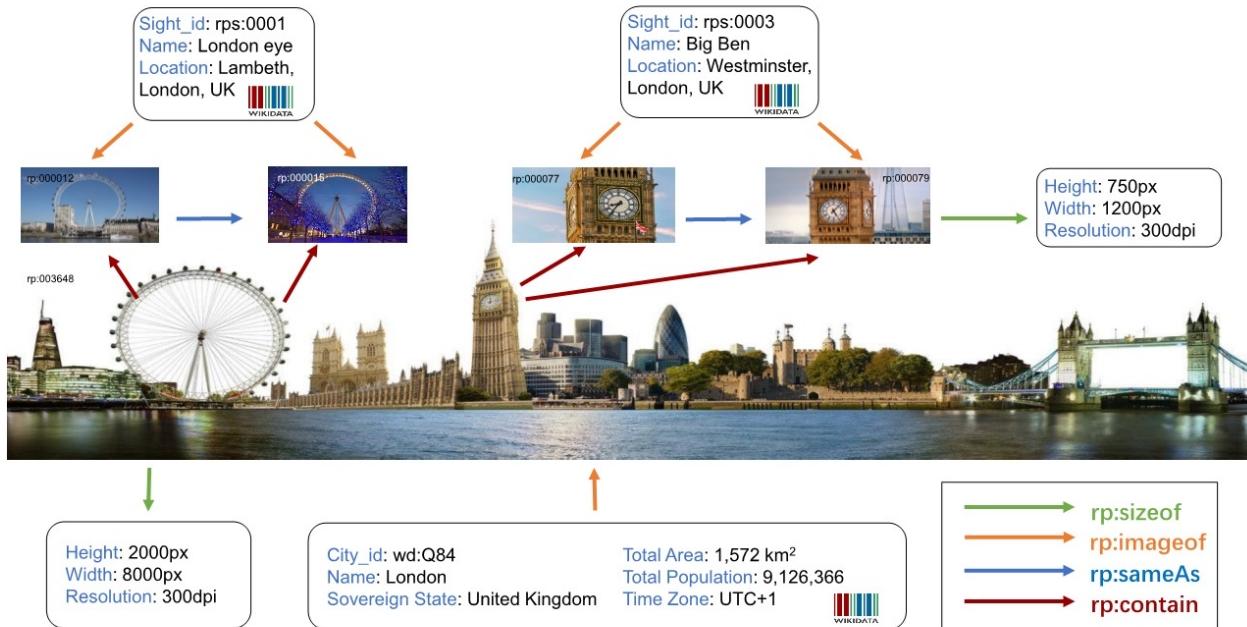
18  分类

367  文章

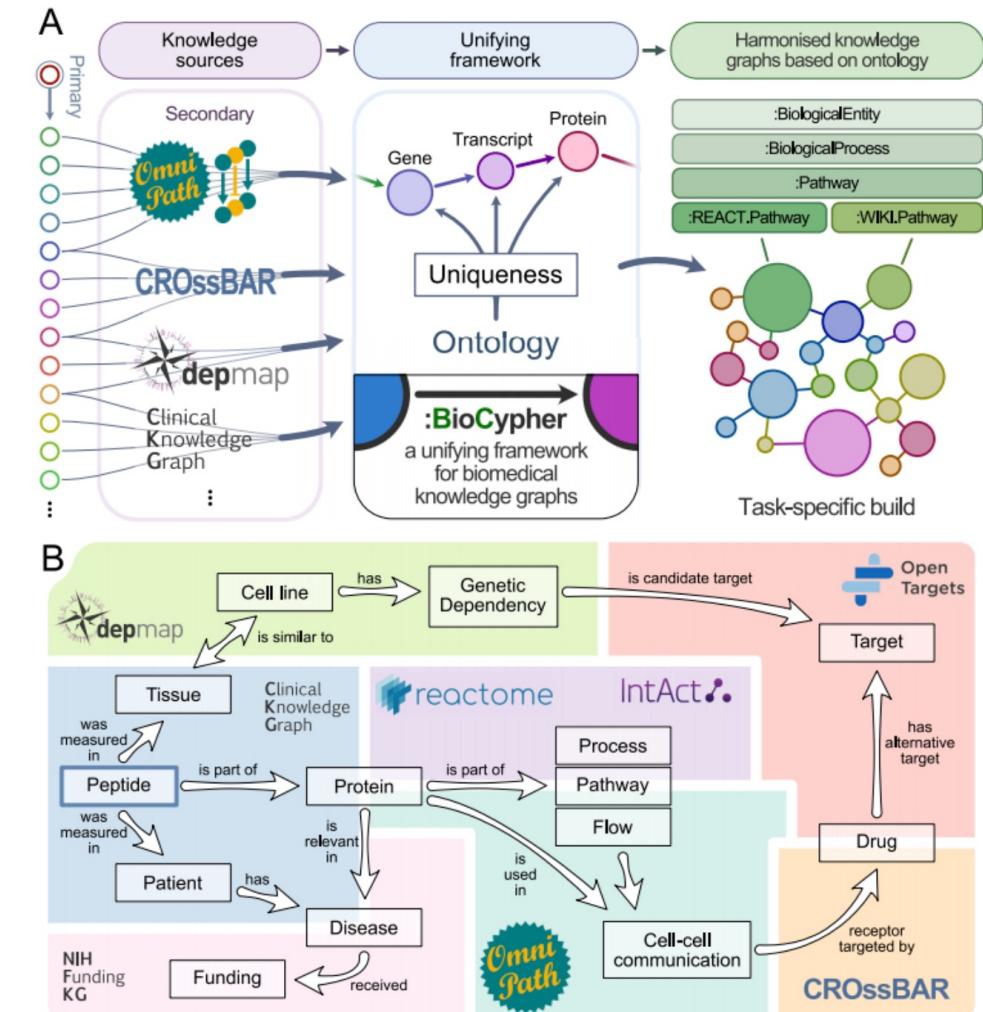
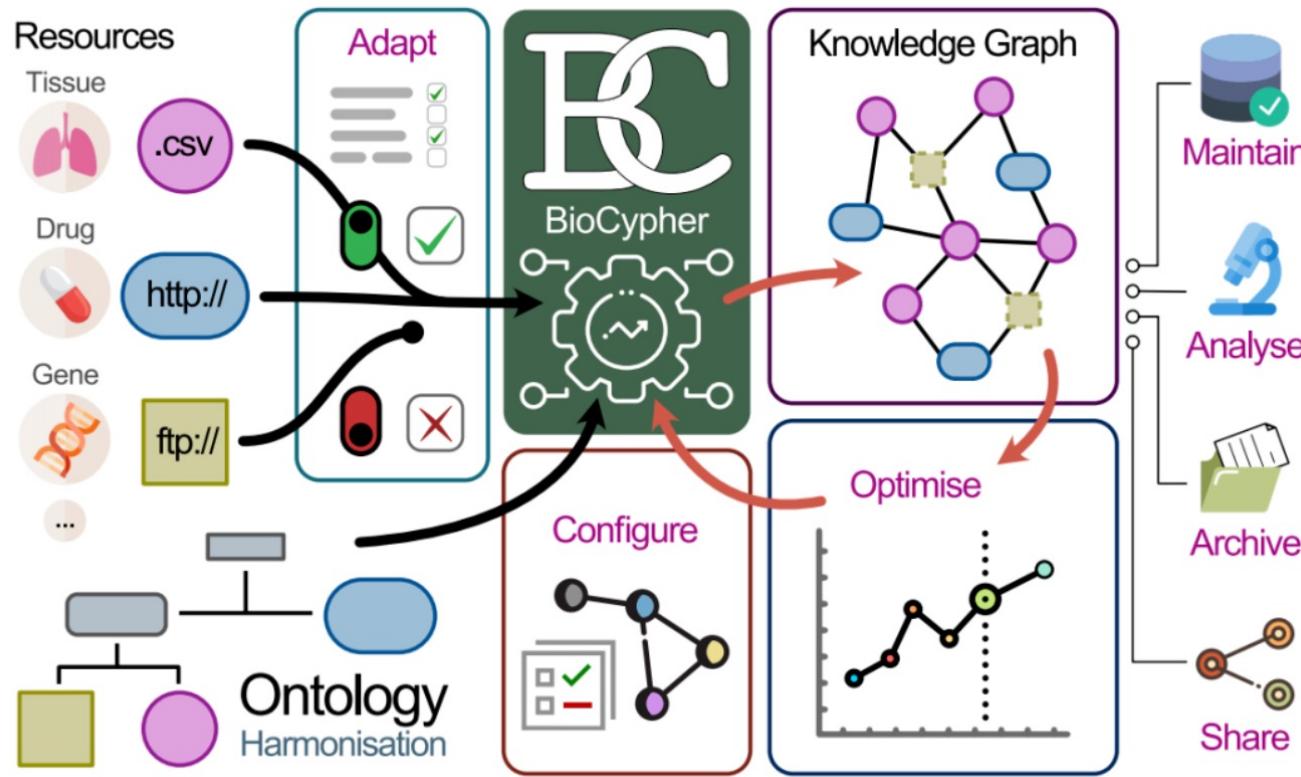
请关注openkg公众号



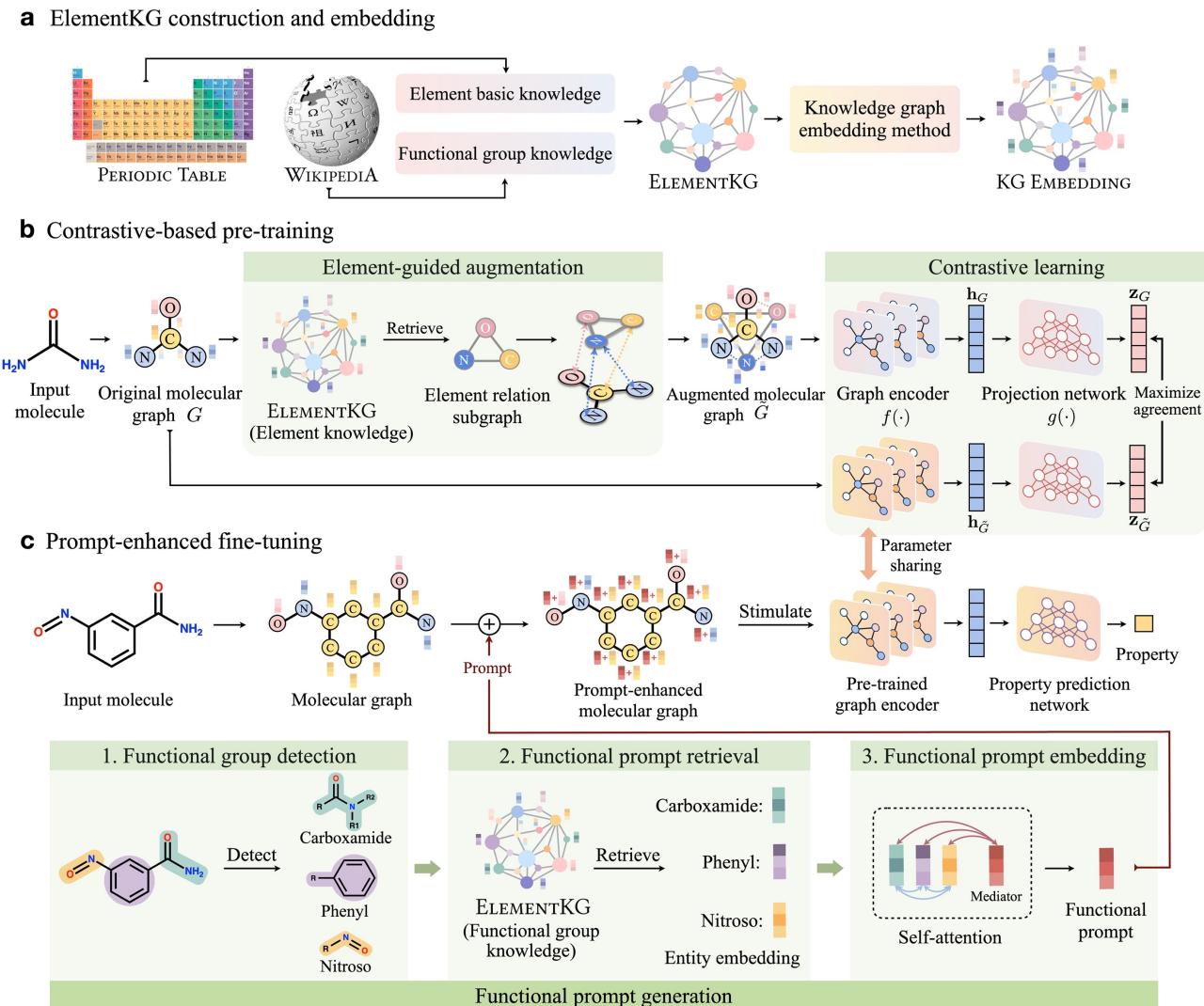
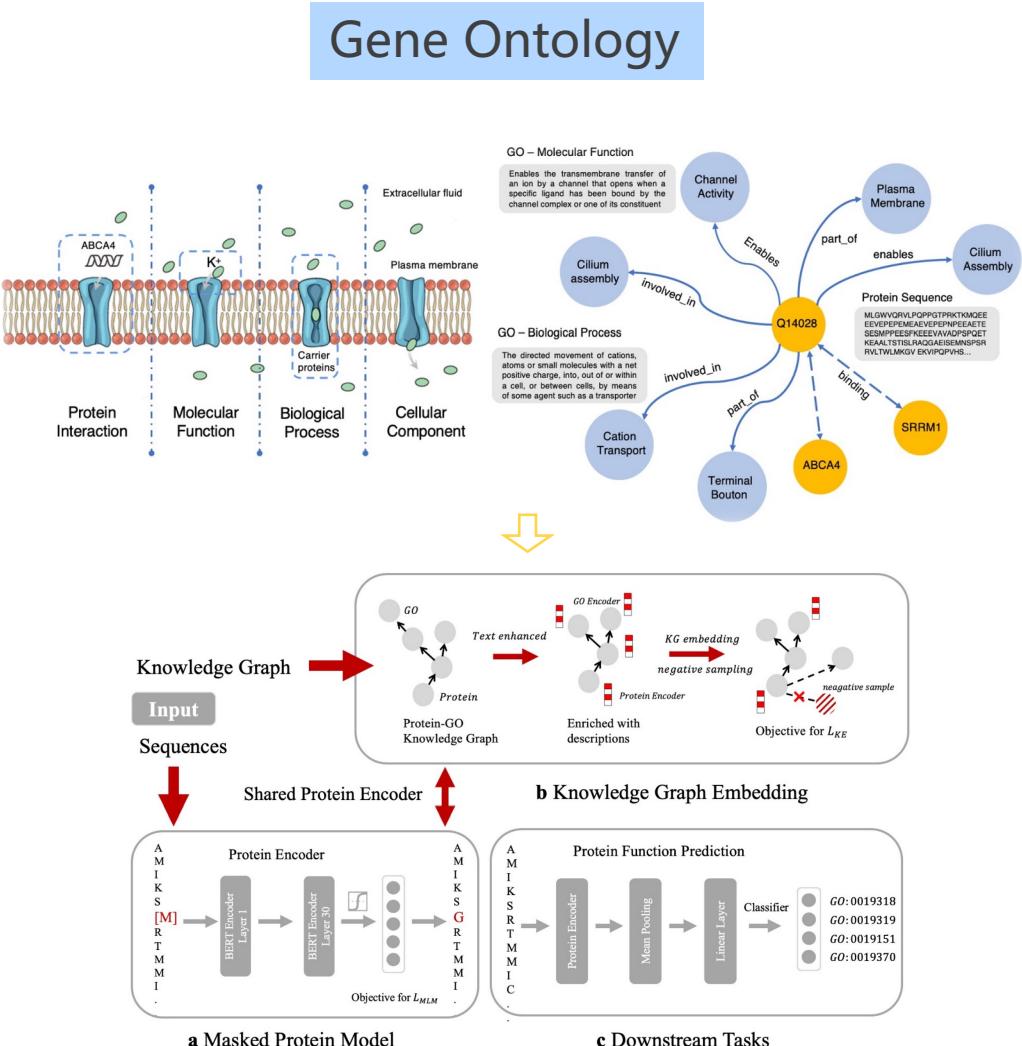
Knowledge Graph and Applications (Multimodal)



Knowledge Graph and Applications (Biomedical)



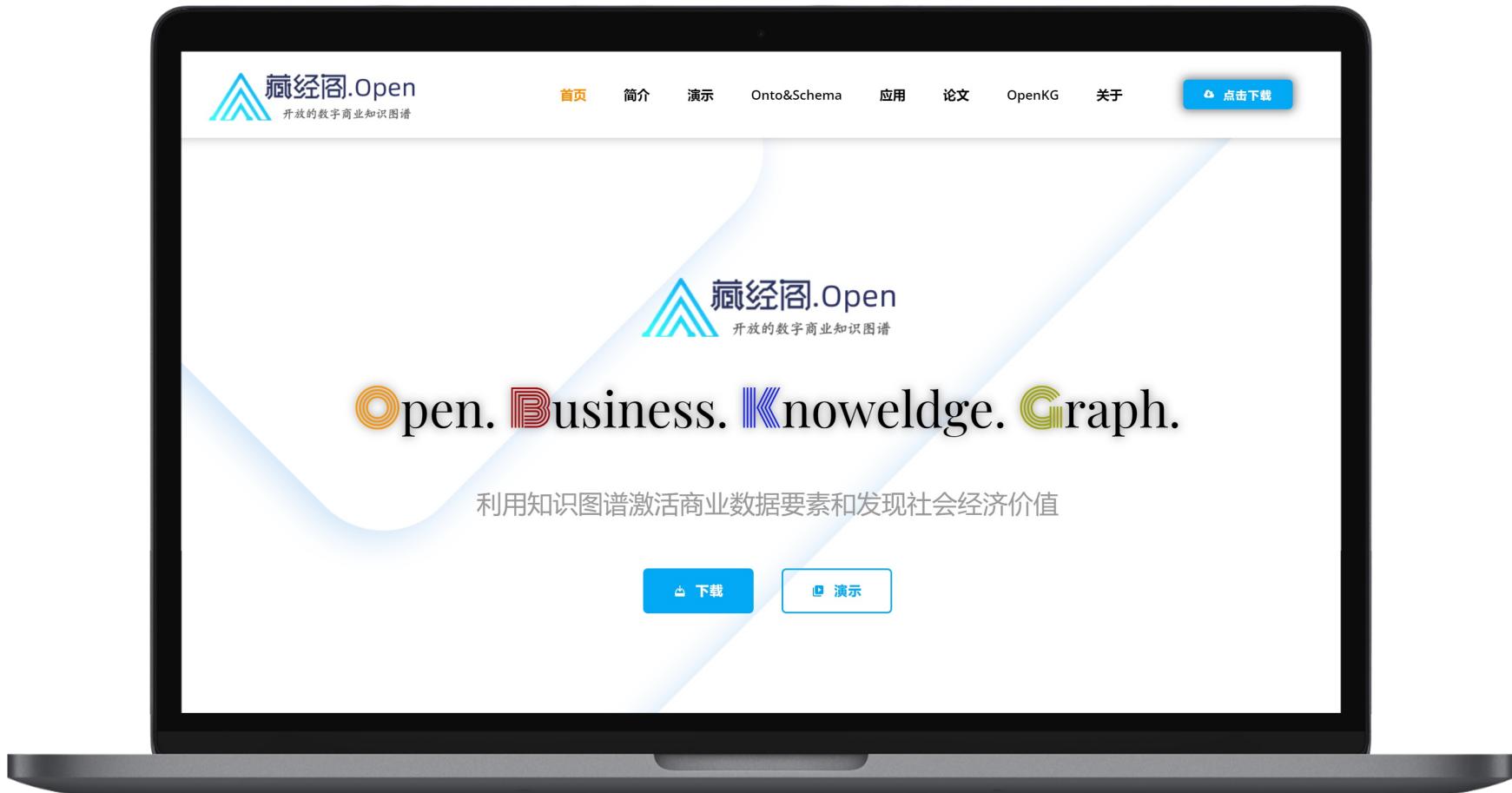
Knowledge Graph and Applications (Biomedical)



[1] OntoProtein: Protein Pretraining With Gene Ontology Embedding (ICLR 2022)

[2] Knowledge graph-enhanced molecular contrastive learning with functional prompt (Nature Machine Intelligence 2023)

Knowledge Graph and Applications (E-commerce)

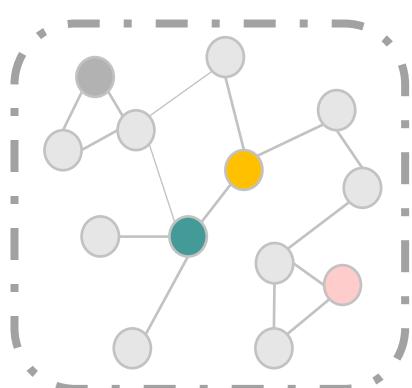


<https://kg.alibaba.com/>

- [1] Billion-scale pre-trained e-commerce product knowledge graph model (ICDE2021)
- [2] Construction and Applications of Billion-Scale Pre-trained Multimodal Business Knowledge Graph (ICDE2023)

KG Construction

The process of populating (or building from scratch) a KG with new knowledge elements (e.g., entities, relations, events)



KG

Named Entity Recognition (NER)

Relation Extraction (RE)

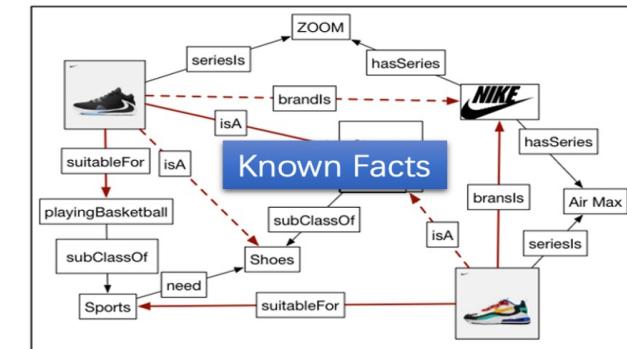
Event Extraction (EE)

Entity Linking (EL)

.....

KG Reasoning

The process of utilizing existing knowledge to derive new knowledge from a KG through logical reasoning, associative inference, or machine learning methods



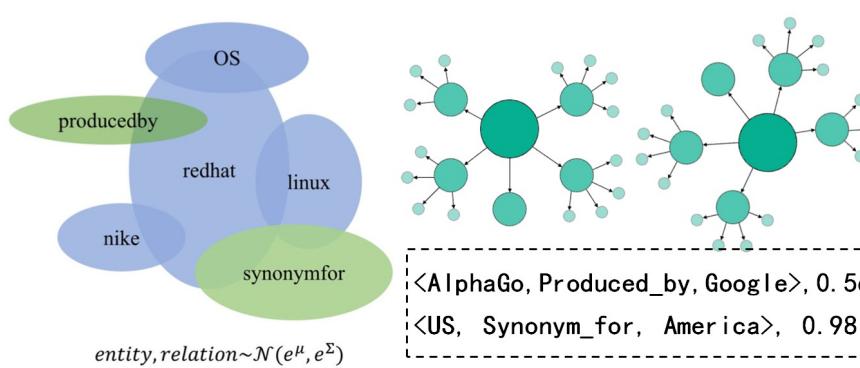
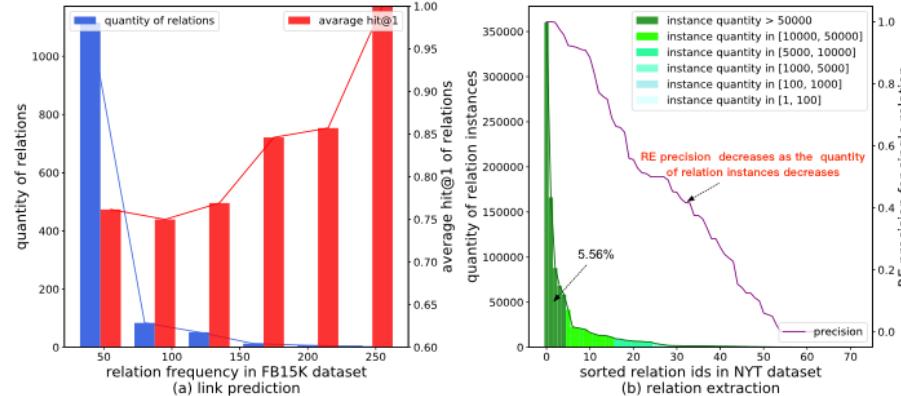
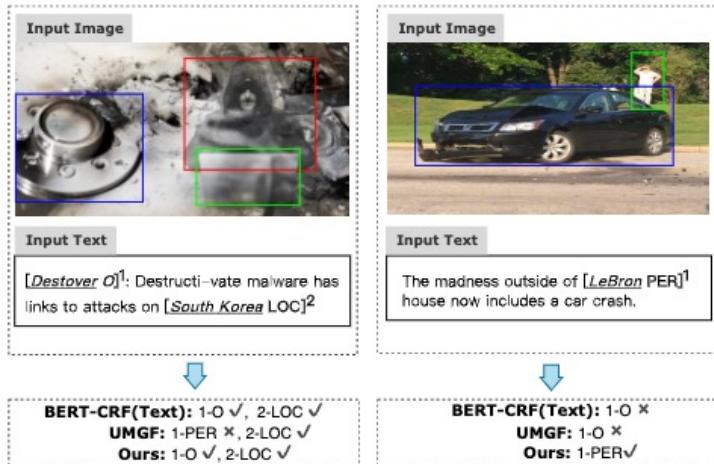
New Facts
New Relations
New Axioms
New Rules

Challenges for Open-environment KG Construction and Reasoning

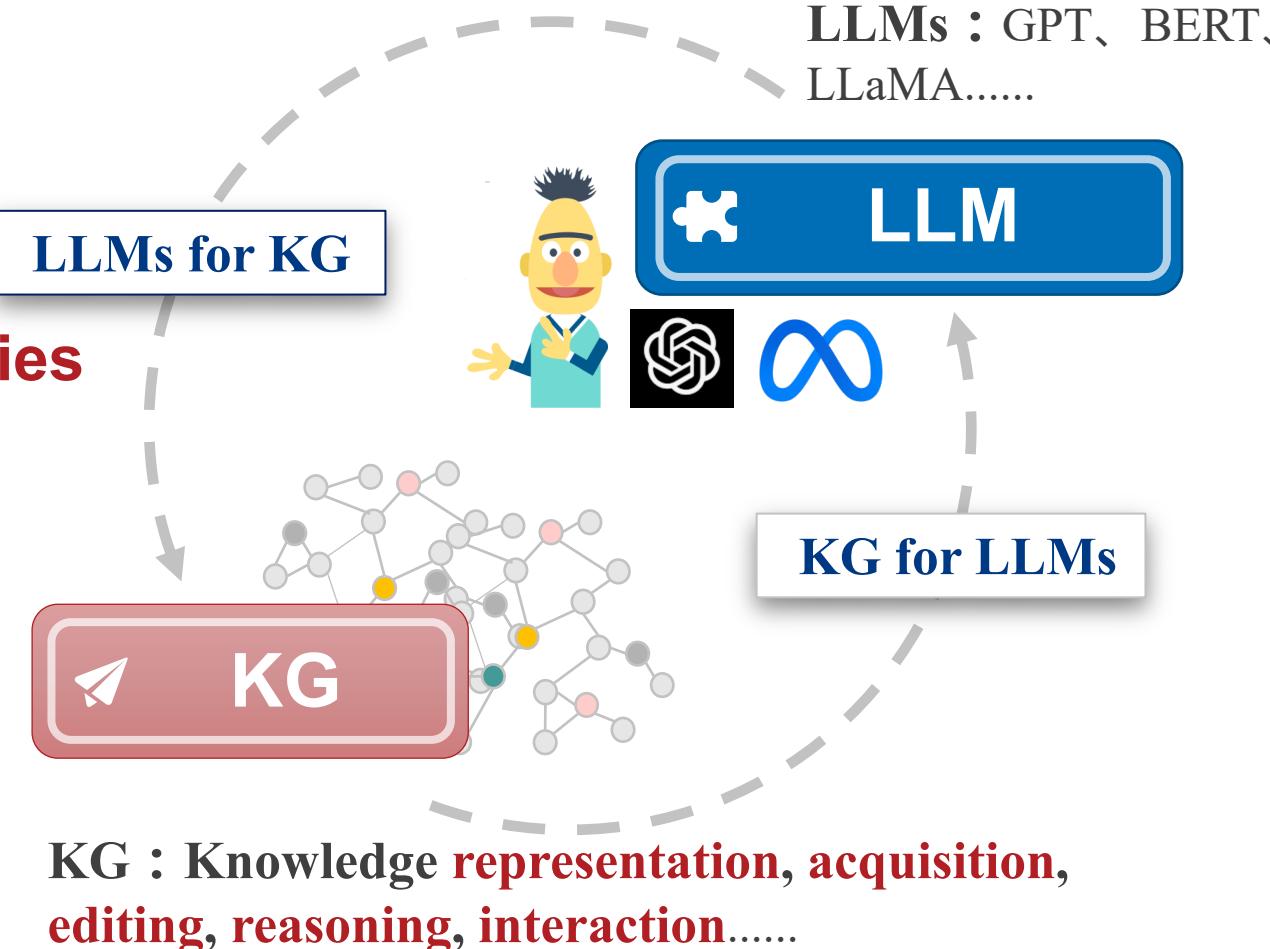


IJCAI/2023 MACAO

- ❑ Low-resource
- ❑ Multimodal
- ❑ Uncertain
- ❑ More Opportunities



- Low-resource
- Multimodal
- Uncertain
- More Opportunities





IJCAI/2023 MACAO



IJCAI
International Joint Conferences on
Artificial Intelligence Organization

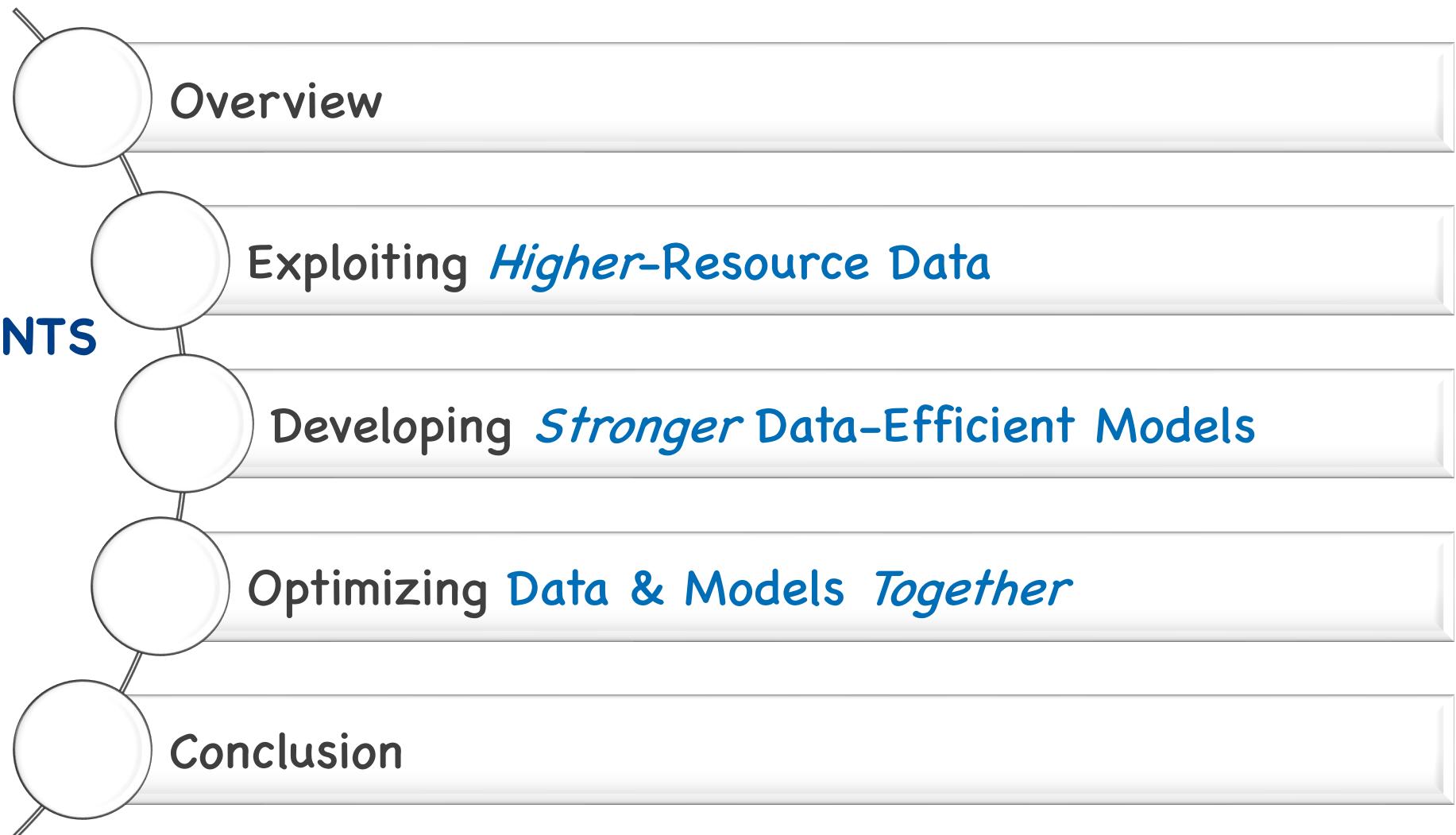
Low-resource KG Construction and Reasoning

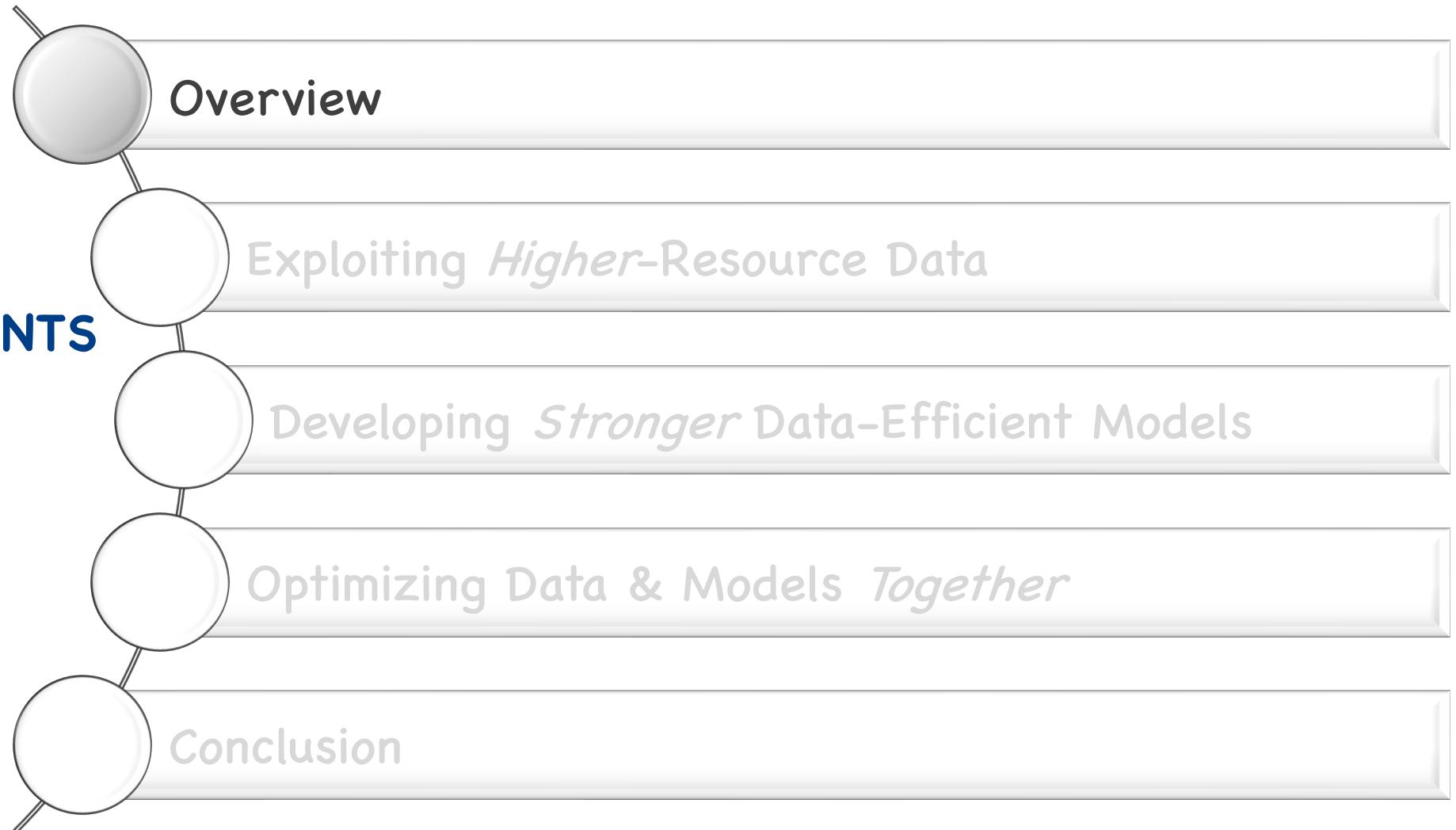
<https://openkg-tutorial.github.io/>

Shumin Deng

National University of Singapore

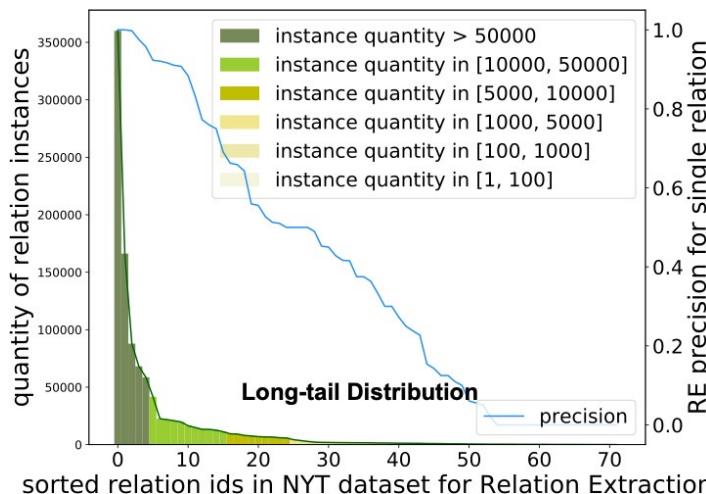
19, Aug, 2023



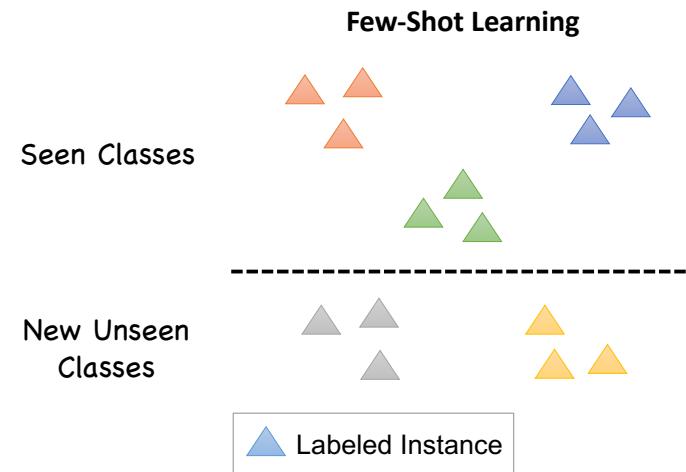


Low-resource Scenarios

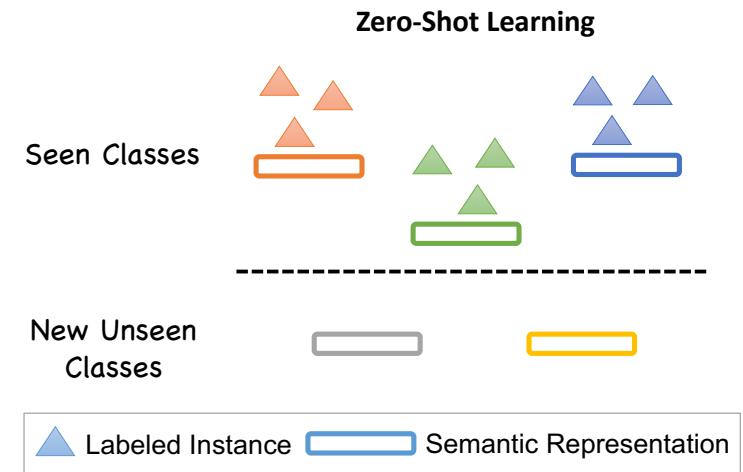
- In the slides, low-resource refers to **low-data-resource**
- Considering **maldistribution of samples** & **new unseen classes**, we systematically categorize low-resource scenarios into three aspects



Long-tail Scenario



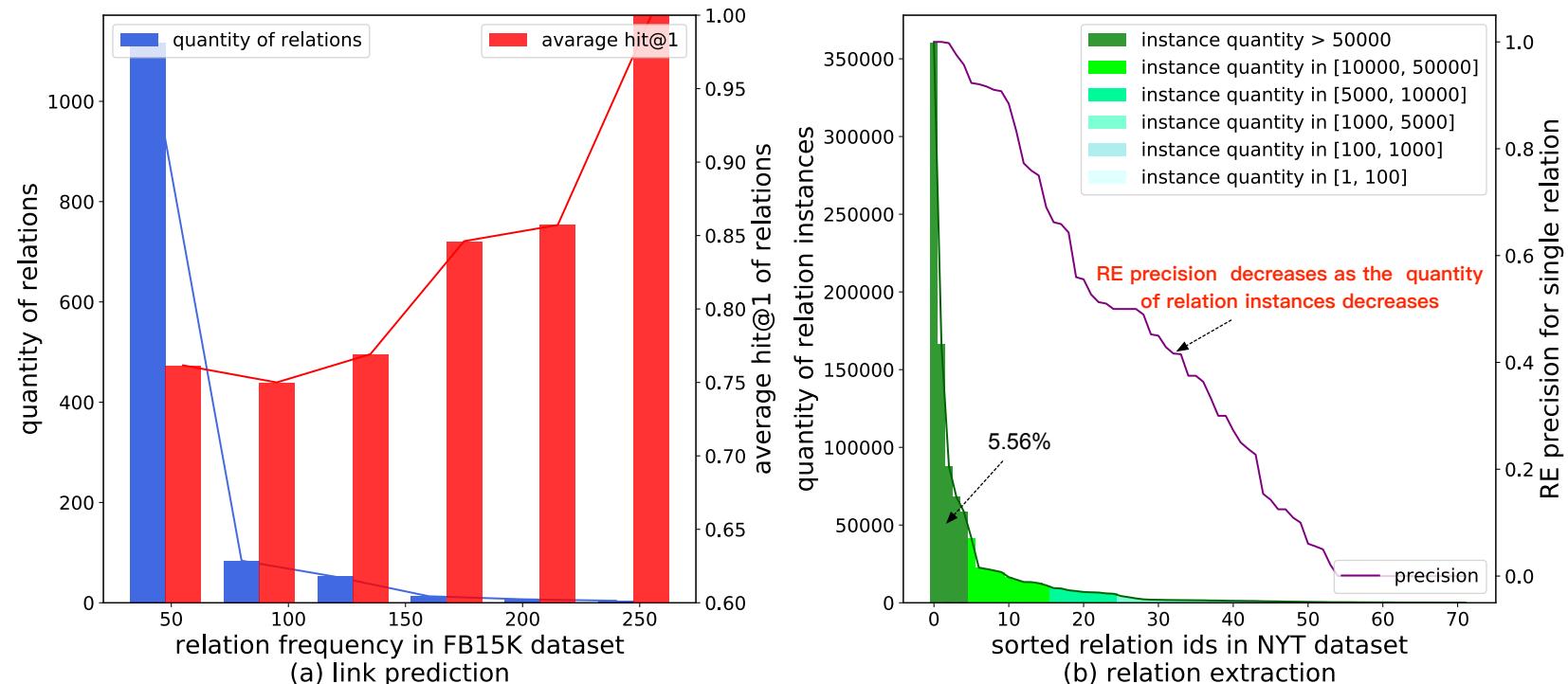
Few-shot Scenario



Zero-shot Scenario

Low-resource Scenarios

- In the slides, low-resource refers to **low-data-resource**
- In most cases, the KG construction (KGC) and KG Reasoning (KGR) **performance** are in positive correlation with **quantity of samples**



Relation Adversarial Network for Low Resource Knowledge Graph Completion (WWW 2020)

KG Construction

Named Entity Recognition (NER)

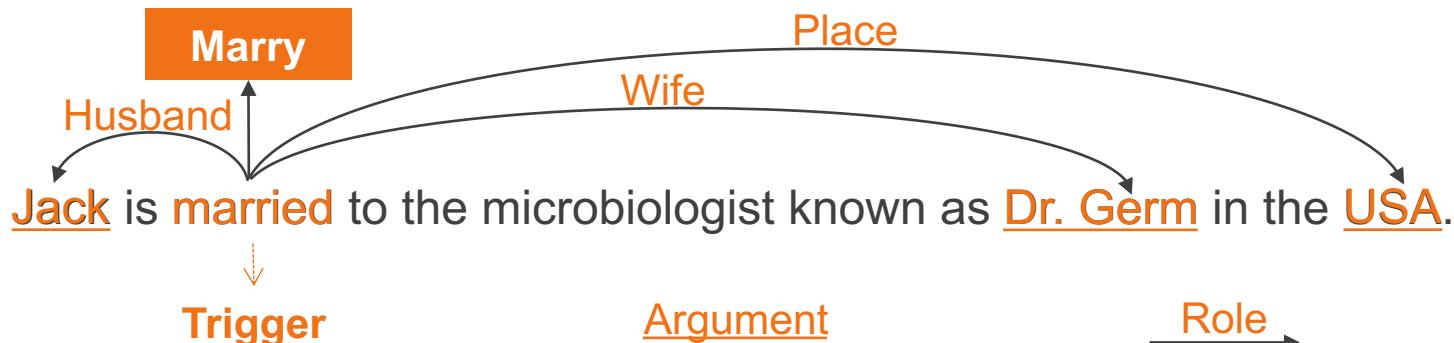
Jack is married to the microbiologist known as Dr. Germ in the USA.

Relation Extraction (RE)

isSpouseOf

Jack is married to the microbiologist known as Dr. Germ in the USA.
→ Entity Pair ←

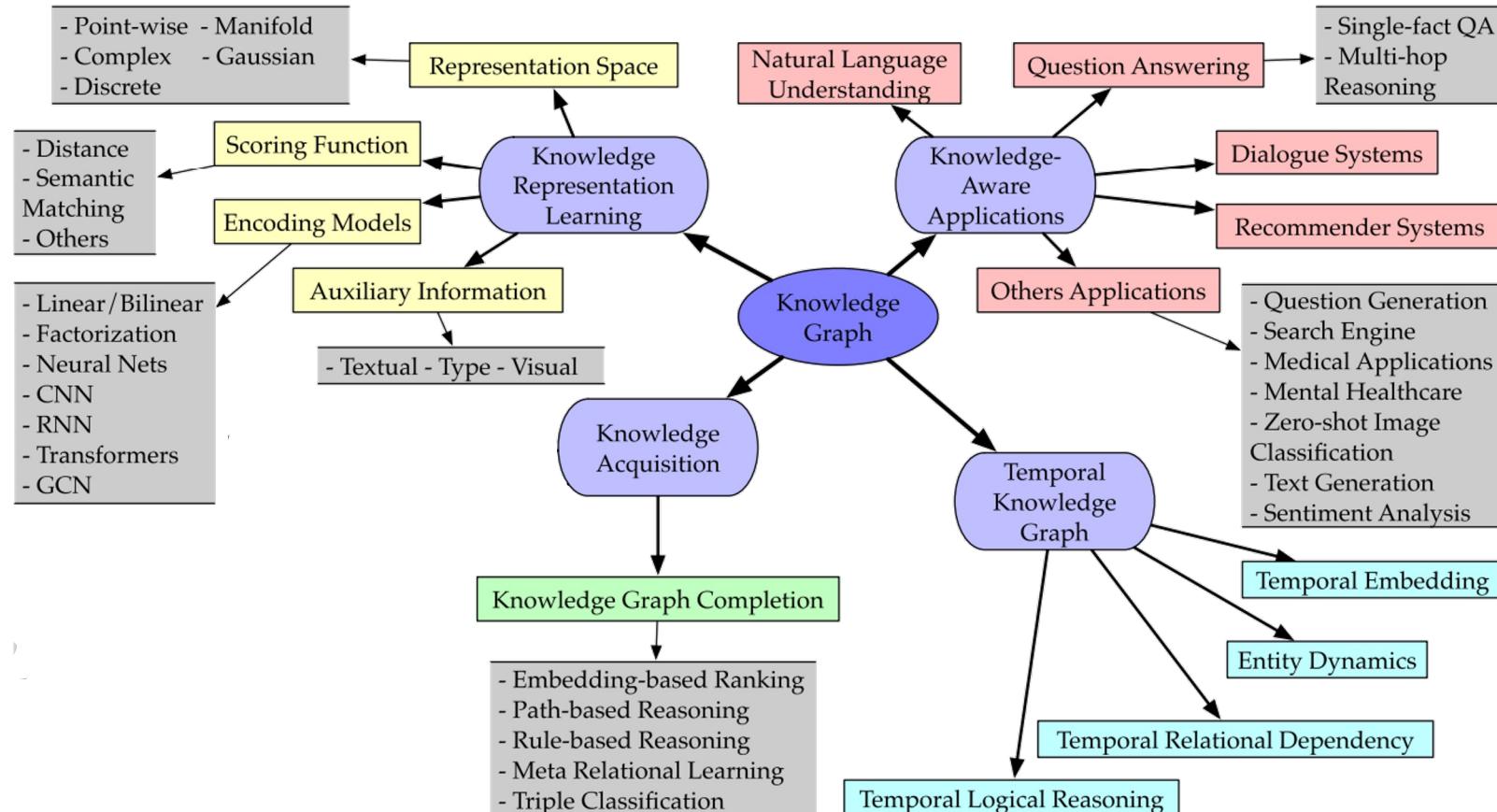
Event Extraction (EE)



Knowledge Extraction in Low-Resource Scenarios: Survey and Perspective (2023) [work in progress]

KG Reasoning

- KG Completion, Knowledge Representation Learning, Knowledge-aware Applications, and so on ...



A Survey on Knowledge Graphs: Representation, Acquisition, and Applications (TNNLS, 2021)

Exploiting Higher-resource Data



Weakly Supervised Augmentation

Multi-modal Augmentation

Multi-lingual Augmentation

Auxiliary Knowledge Enhancement

Developing Stronger Data-Efficient Models



Meta Learning

Transfer Learning

Prompt Learning

Optimizing Data and Models Together



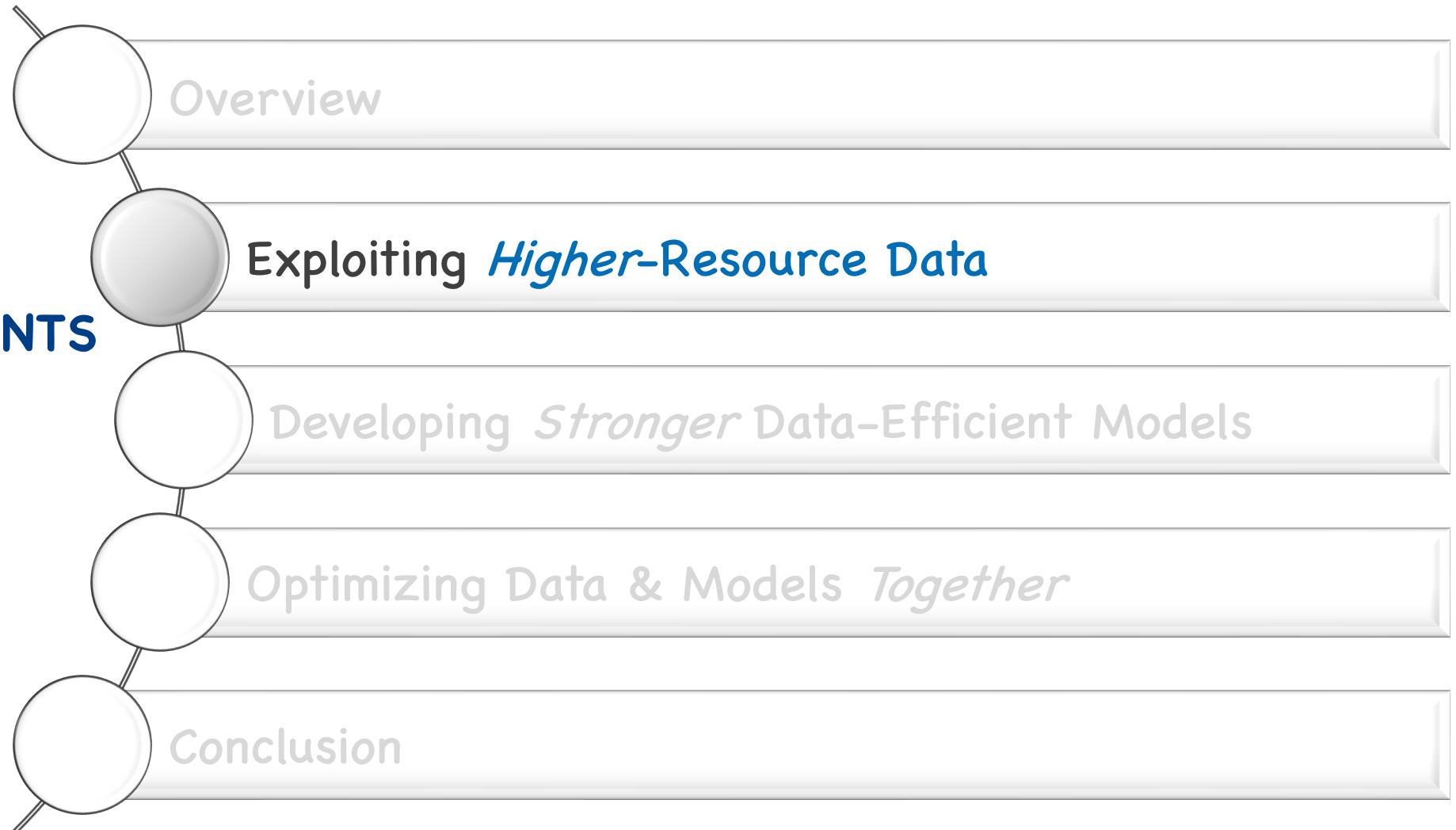
Multi-task Learning

Retrieval Augmentation

Task Reformulation



CONTENTS



Exploiting Higher-Resource Data

- To utilize **additional samples or knowledge (prior knowledge)** via endogenous generation or exogenous import
 - Objective: obtaining **more enriched and representative samples; more precise semantic representations**

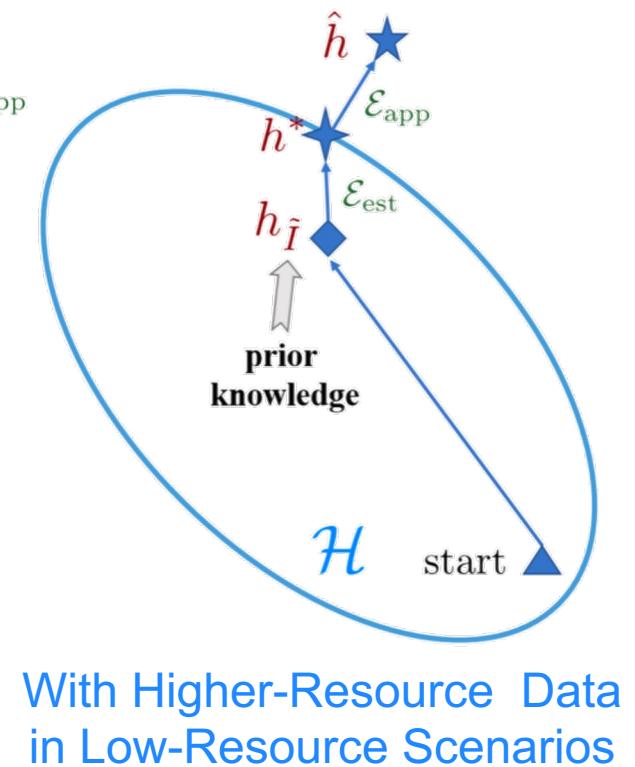
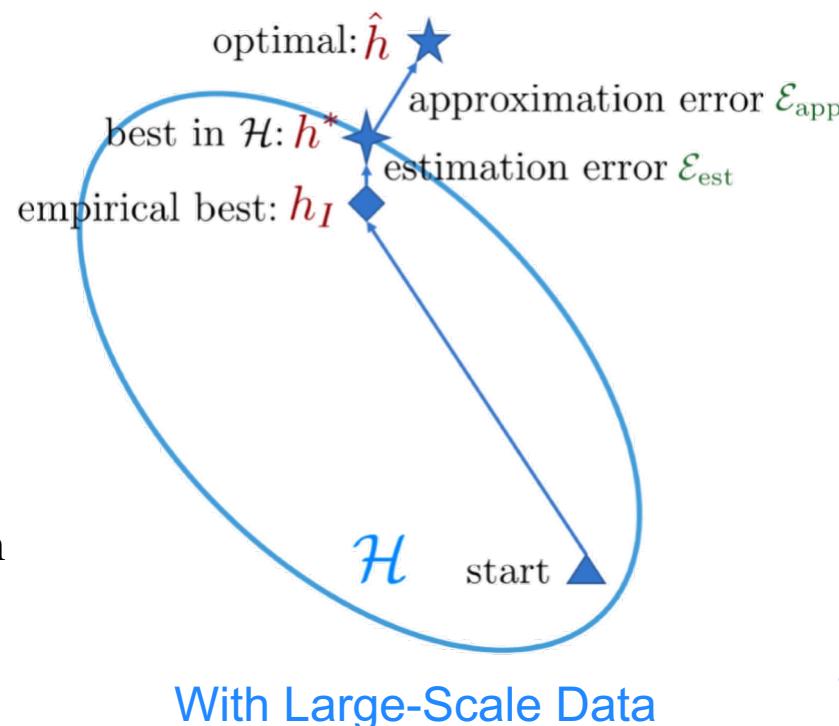
Given a hypothesis \hat{h} , we want to minimize its expected risk R

$\hat{h} = \arg \min_h R(h)$: the function that minimizes the expected risk

$h^* = \arg \min_{h \in \mathcal{H}} R(h)$: the function in \mathcal{H} that minimizes the expected risk

$h_I = \arg \min_{h \in \mathcal{H}} R_I(h)$: the function in \mathcal{H} that minimizes the empirical risk

\mathcal{H} : hypothesis space

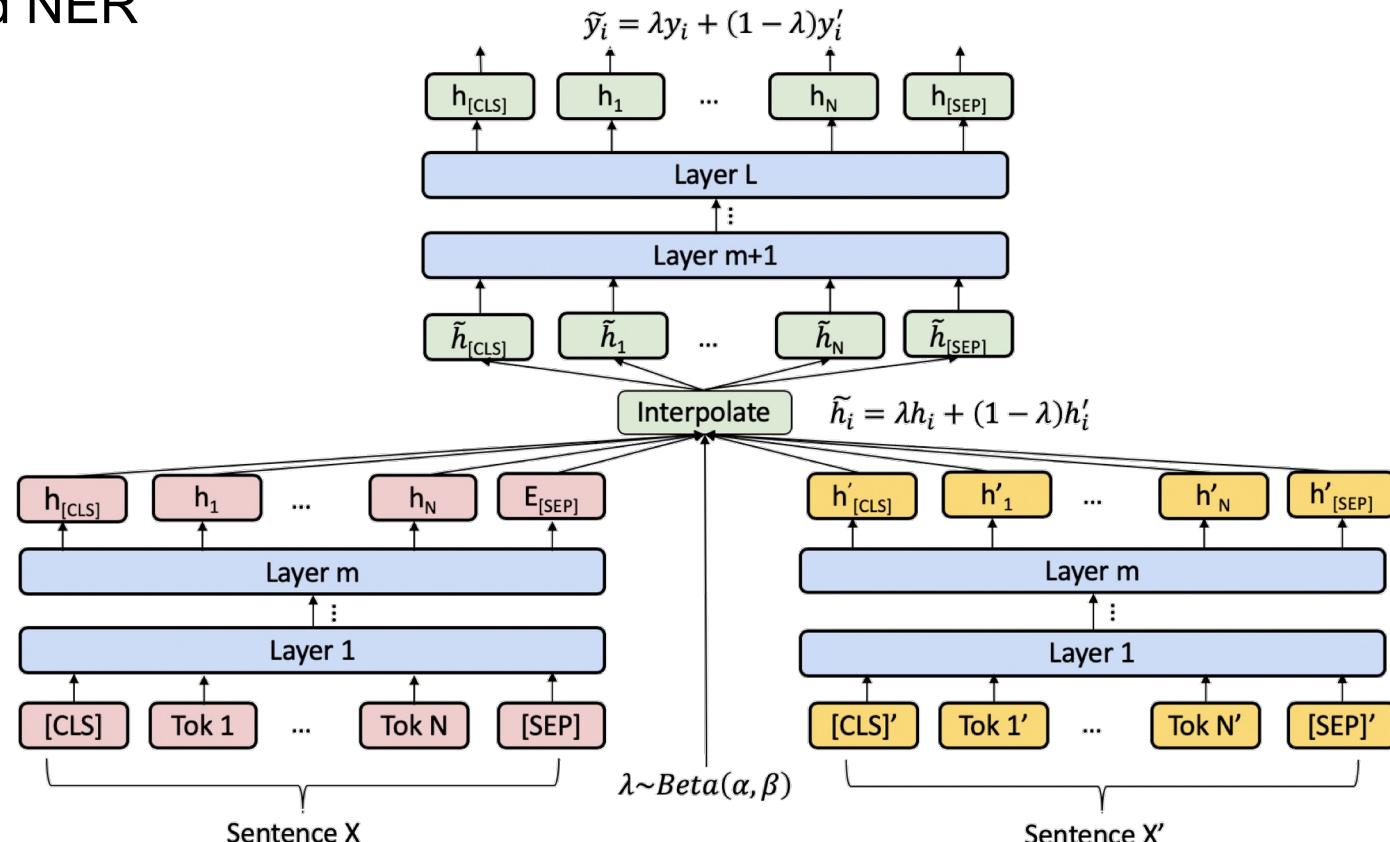


Generalizing from a Few Examples: A Survey on Few-shot Learning (ACM Computing Surveys, 2020)

Weakly Supervised Augmentation

□ Creating More Samples

- To create virtual samples by interpolating sequences close to each other for Semi-supervised NER

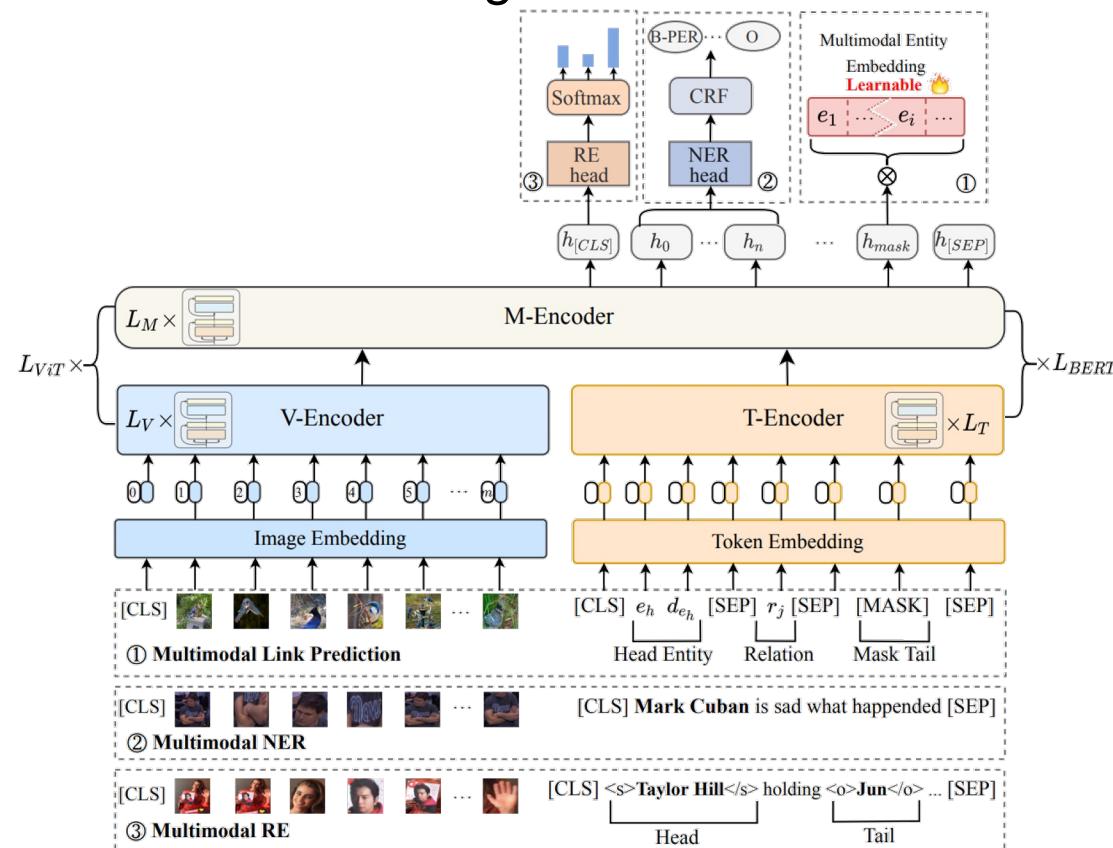


Local Additivity Based Data Augmentation for Semi-supervised NER (EMNLP 2020)

Multimodal Augmentation

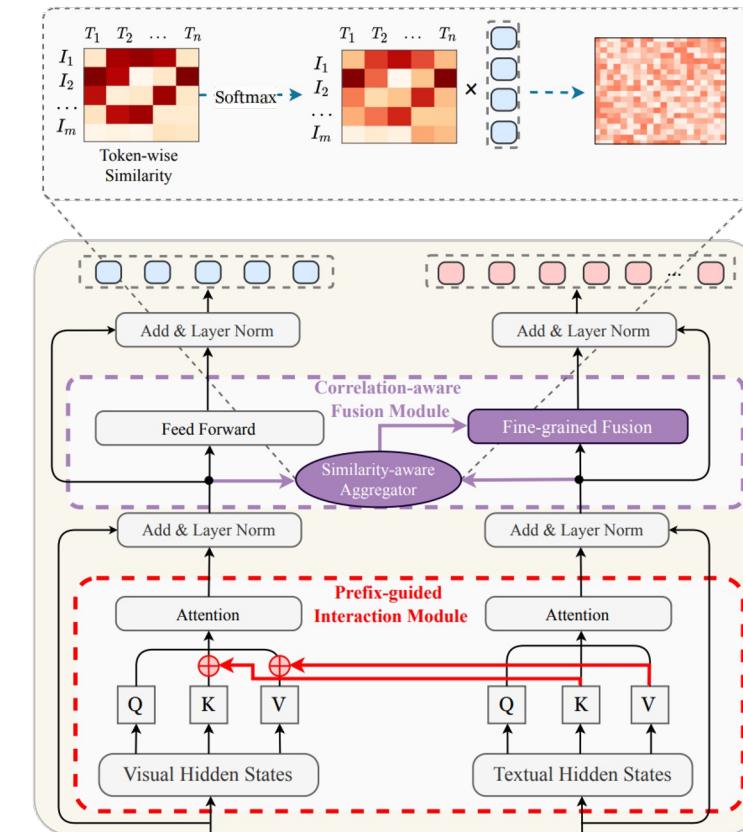
❑ Leveraging Multimodal Knowledge

❑ Multimodal Knowledge Fusion



(a) Unified Multimodal KGC Framework.

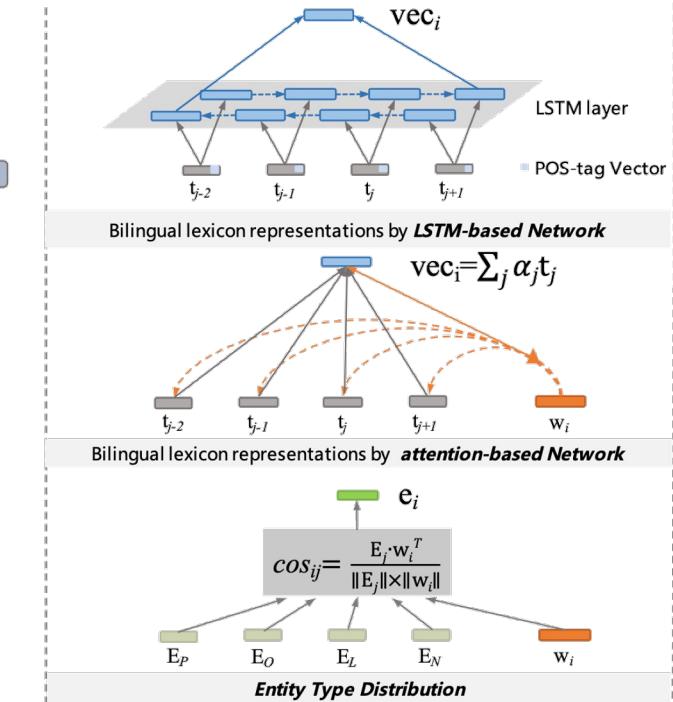
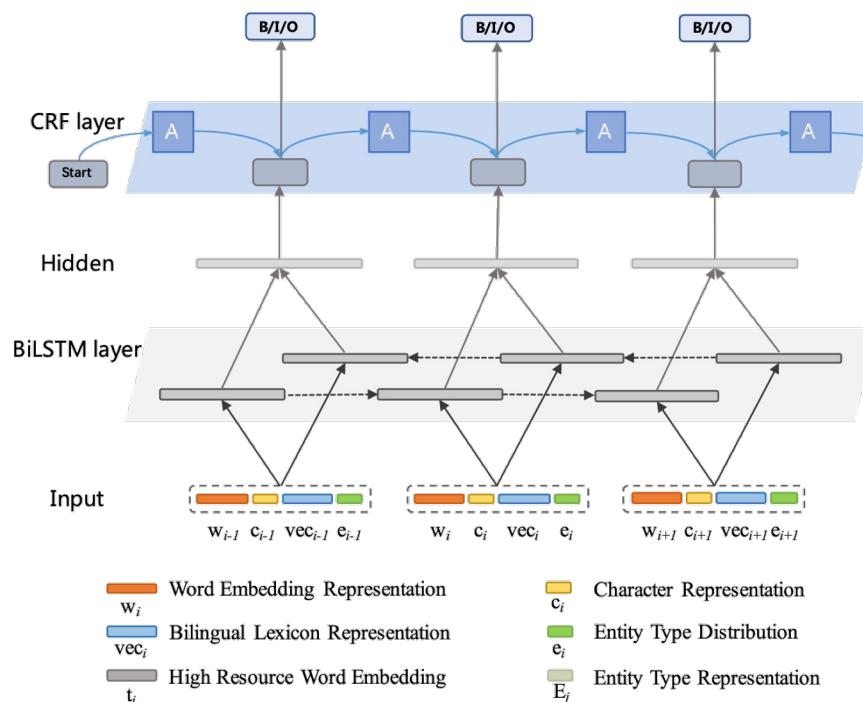
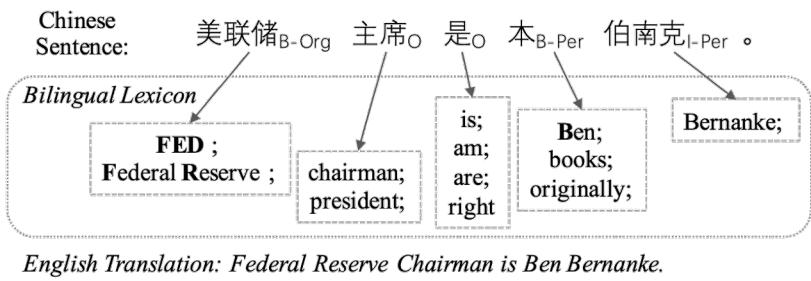
Hybrid Transformer with Multi-level Fusion for Multimodal Knowledge Graph Completion (SIGIR 2022)



(b) Detailed M-Encoder.

Multi-lingual Augmentation

- Leveraging Multi-lingual Knowledge
- Cross-lingual Knowledge Transfer

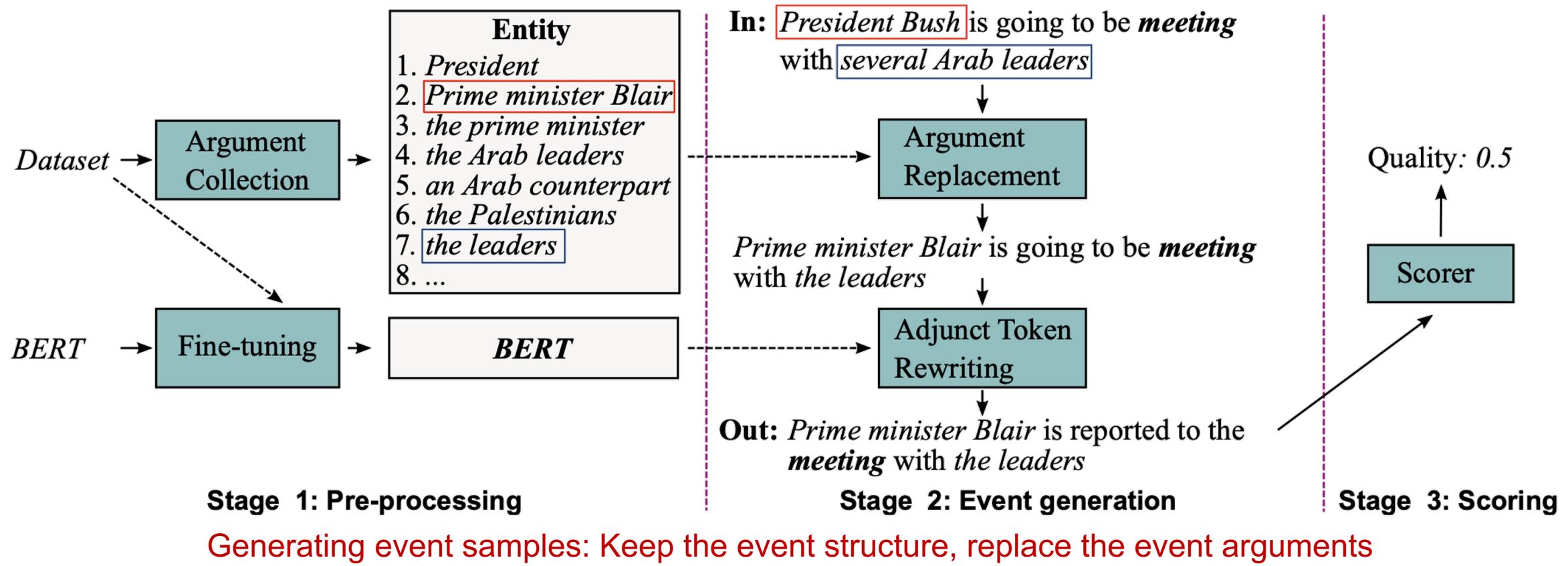


Improving Low Resource Named Entity Recognition using Cross-lingual Knowledge Transfer (IJCAI 2018)

Auxiliary Knowledge Enhancement

❑ Augmenting More Knowledge with Relevant Text

❑ Sample Augmentation



Exploring Pre-trained Language Models for Event Extraction and Generation (ACL 2019)

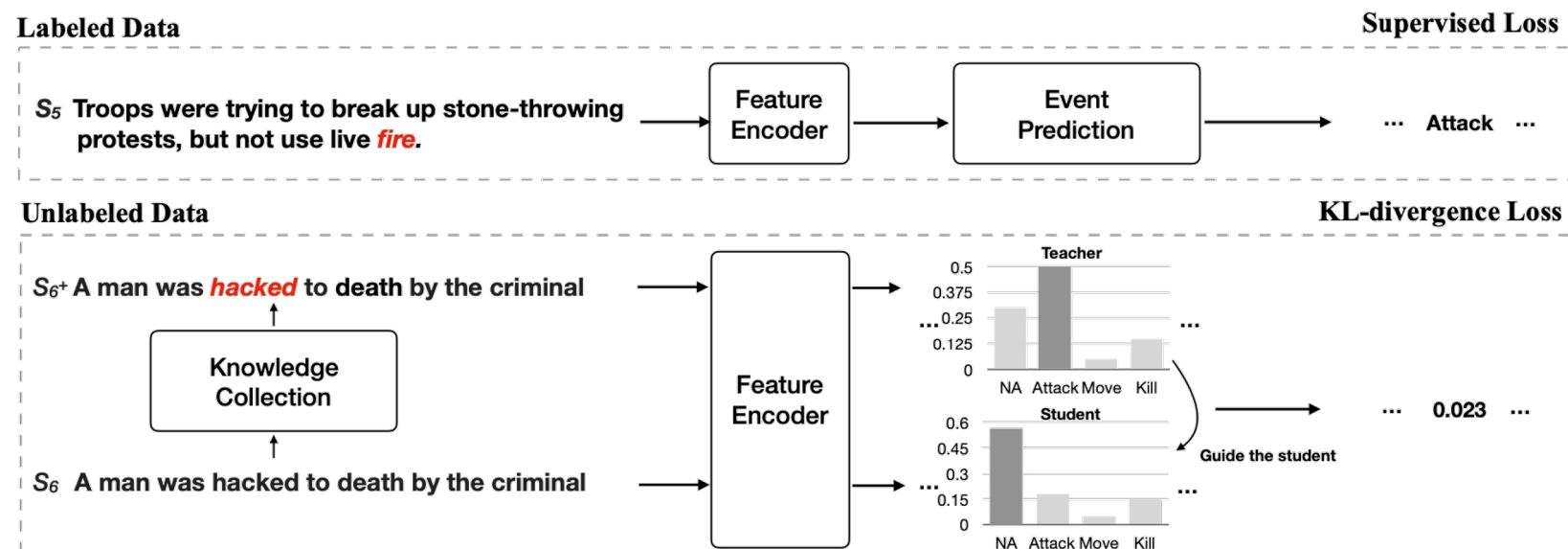
Auxiliary Knowledge Enhancement

- Augmenting More Knowledge with Relevant Text
 - Task Knowledge Augmentation

prone to overfitting & perform poorly



Figure 1: Examples of ED. *fire* is the densely labeled trigger for *Attack* event in ACE2005. *Hacked* and *intifada* are the unseen/sparingly labeled triggers in the training corpus. The red ones illustrate the triggers identified by open-domain trigger knowledge.



To provide extra semantic support on unseen/sparingly labeled trigger words

Auxiliary Knowledge Enhancement

❑ Augmenting More Knowledge with KG

- ❑ Enhancing sample features with KG triples
- ❑ E.g., Similar event schema in FrameNet & ACE05

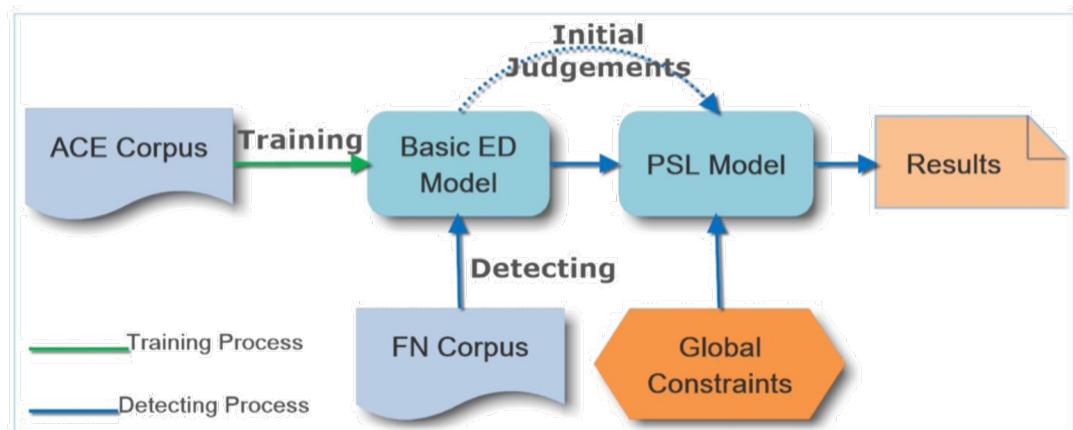


Figure 1: Our framework for detecting events in FN (including training and detecting processes).

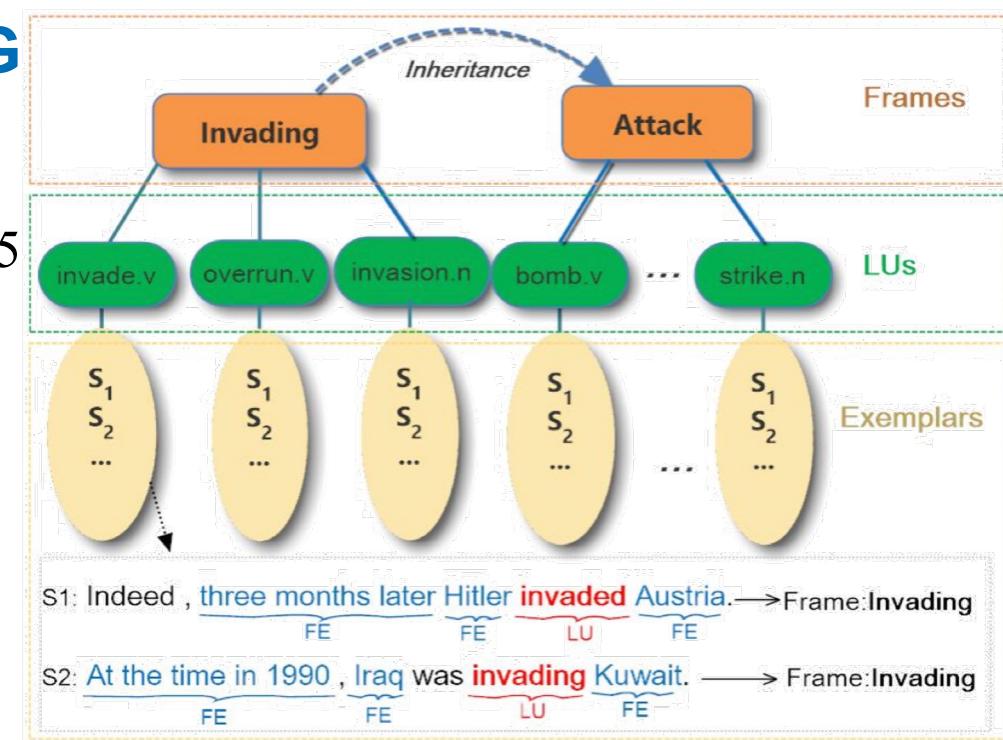
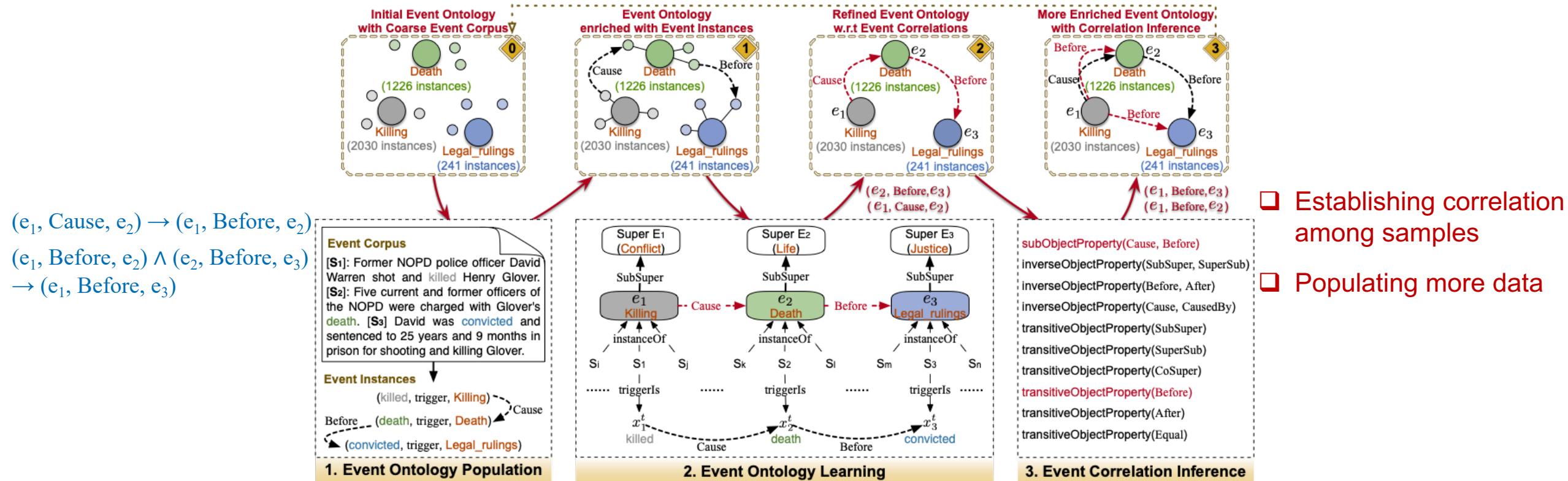


Figure 2: The hierarchy of FN corpus, where each S_k under a LU is a exemplar annotated for that LU. *Inheritance* is a semantic relation between the frames *Invading* and *Attack*.

Auxiliary Knowledge Enhancement

□ Augmenting More Knowledge with Ontology & Logical Rules



Step 1: Event Detection (Ontology Population) connect event types with instances, given the initial event ontology with coarse corpus.

Step 2: Event Ontology Learning establish correlations among event types, given the event ontology enriched with instances.

Step 3: Event Correlation Inference induce more event correlations based on existing event-event relations.

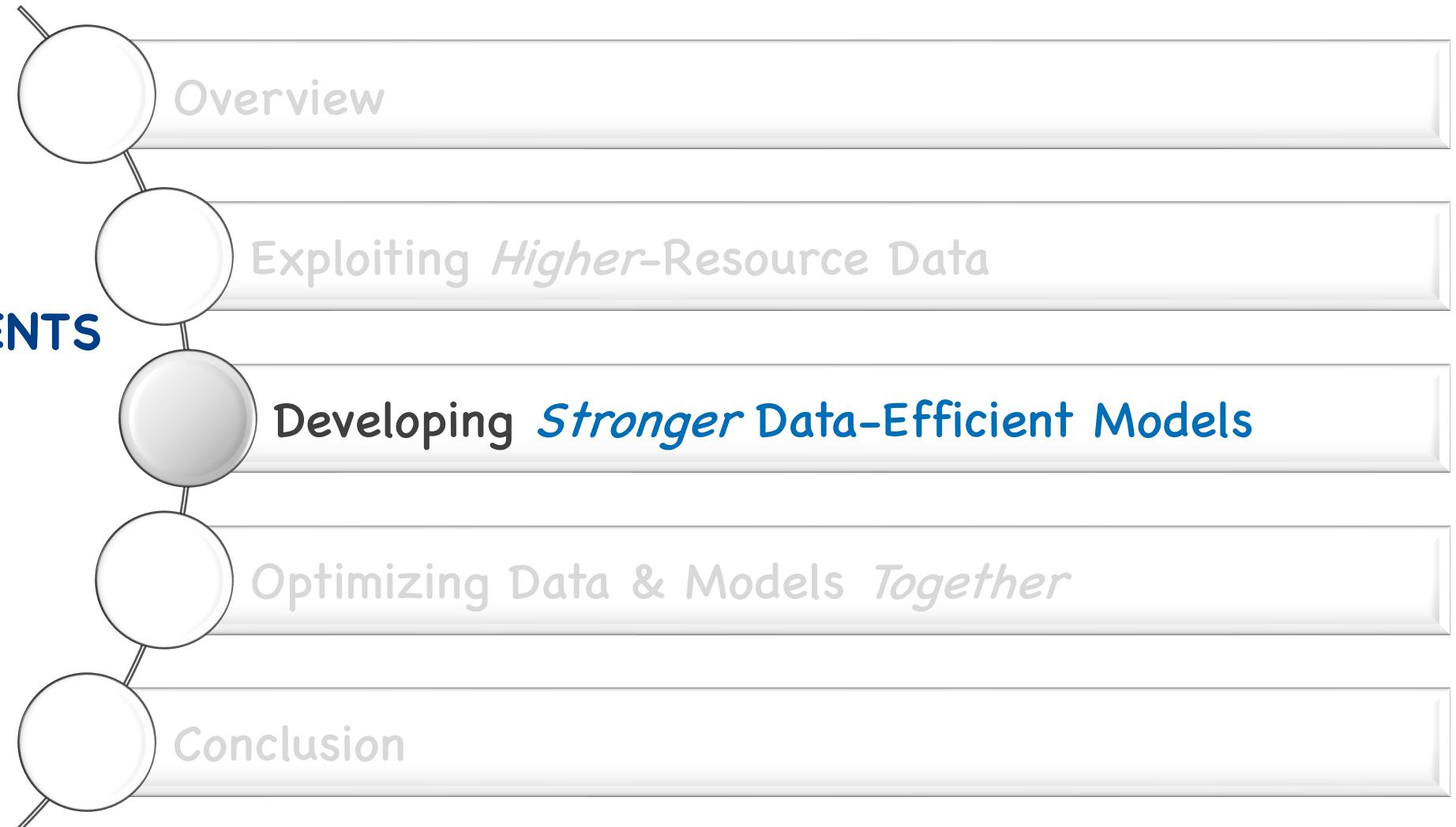
OntoED: Low-resource Event Detection with Ontology Embedding (ACL 2021)



What if higher-resource data are not always available ?



CONTENTS



Developing *Stronger* Data-Efficient Models

- To establish **robust models** to learn with low-resource data
 - Improving model learning abilities so as to make full use of existing sparse data and reduce dependence on samples

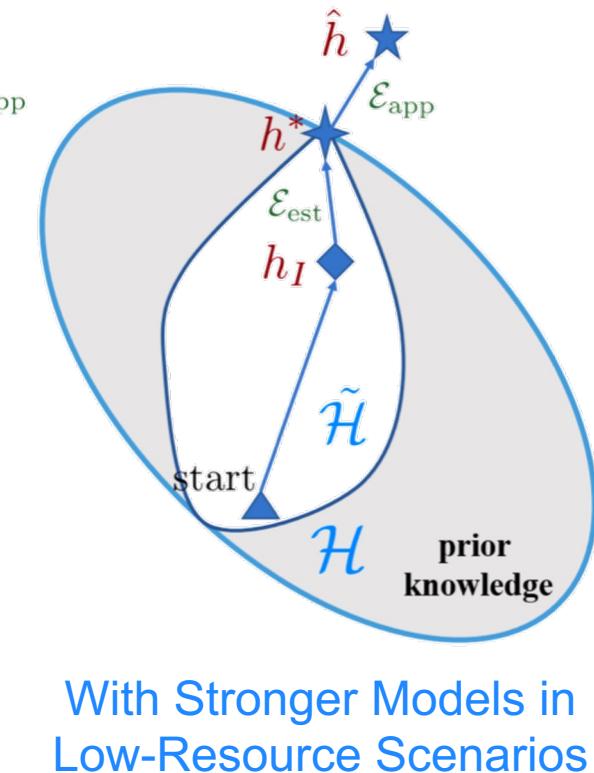
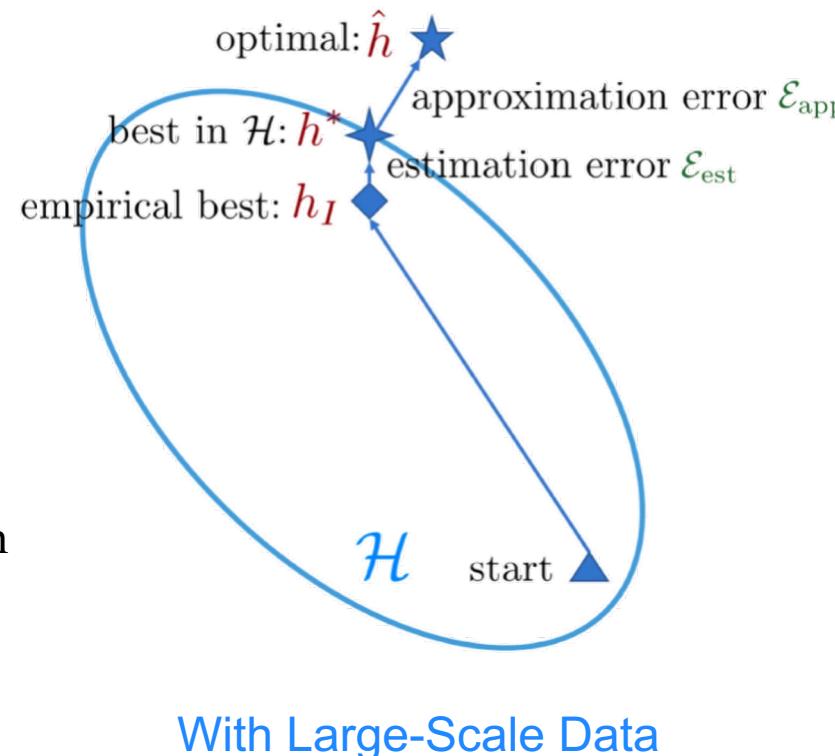
Given a hypothesis \hat{h} , we want to minimize its expected risk R

$\hat{h} = \arg \min_h R(h)$: the function that minimizes the expected risk

$h^* = \arg \min_{h \in \mathcal{H}} R(h)$: the function in \mathcal{H} that minimizes the expected risk

$h_I = \arg \min_{h \in \mathcal{H}} R_I(h)$: the function in \mathcal{H} that minimizes the empirical risk

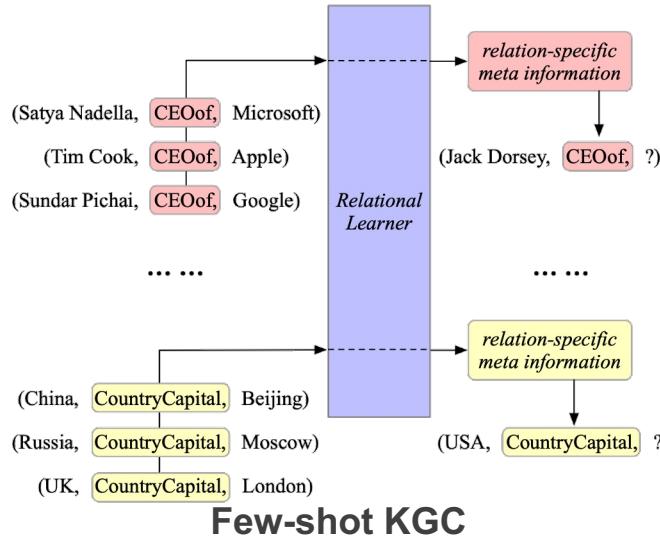
\mathcal{H} : hypothesis space



Generalizing from a Few Examples: A Survey on Few-shot Learning (ACM Computing Surveys, 2020)

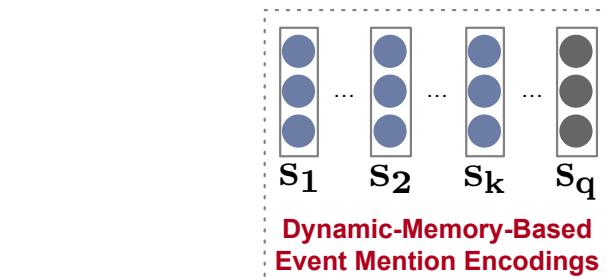
Meta Learning

□ Meta Knowledge Learner



Class-specific meta knowledge

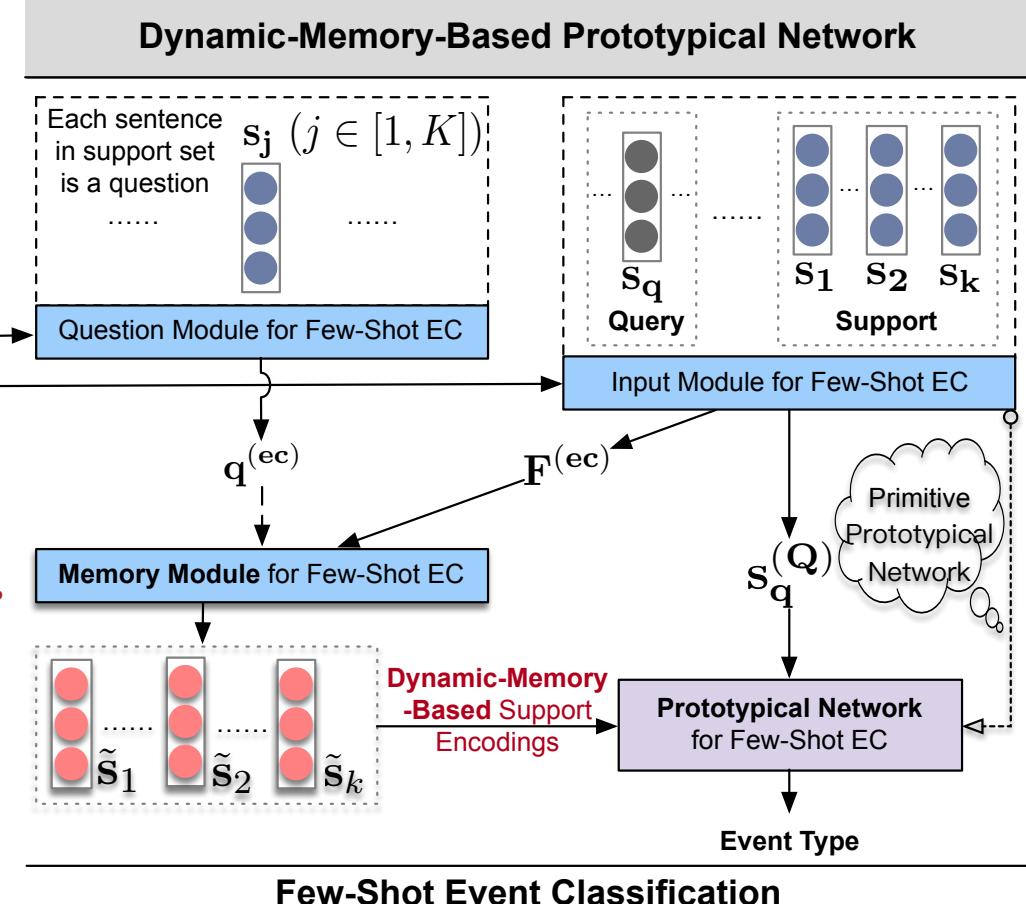
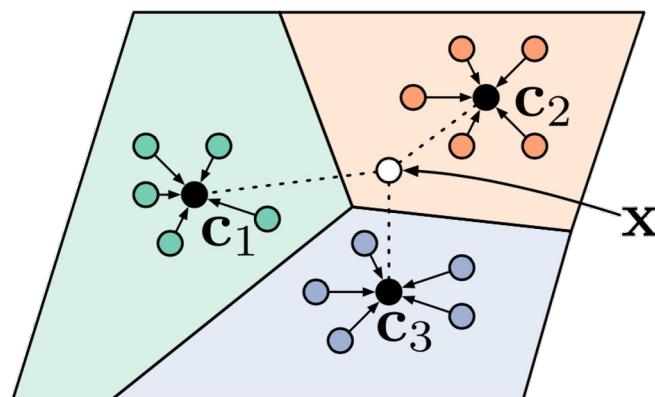
- Distinguish
- E.g., CEO_Of & Capital_Of



How does this event mention contribute to event prototype learning?

Class-general meta knowledge

- Induce
- E.g., Marry & Divorce



Meta Relational Learning for Few-Shot Link Prediction in Knowledge Graphs (EMNLP 2019)

Meta-Learning with Dynamic-Memory-Based Prototypical Network for Few-Shot Event Detection (WSDM 2020)

Meta Learning

□ Prompt-Based Meta Learning

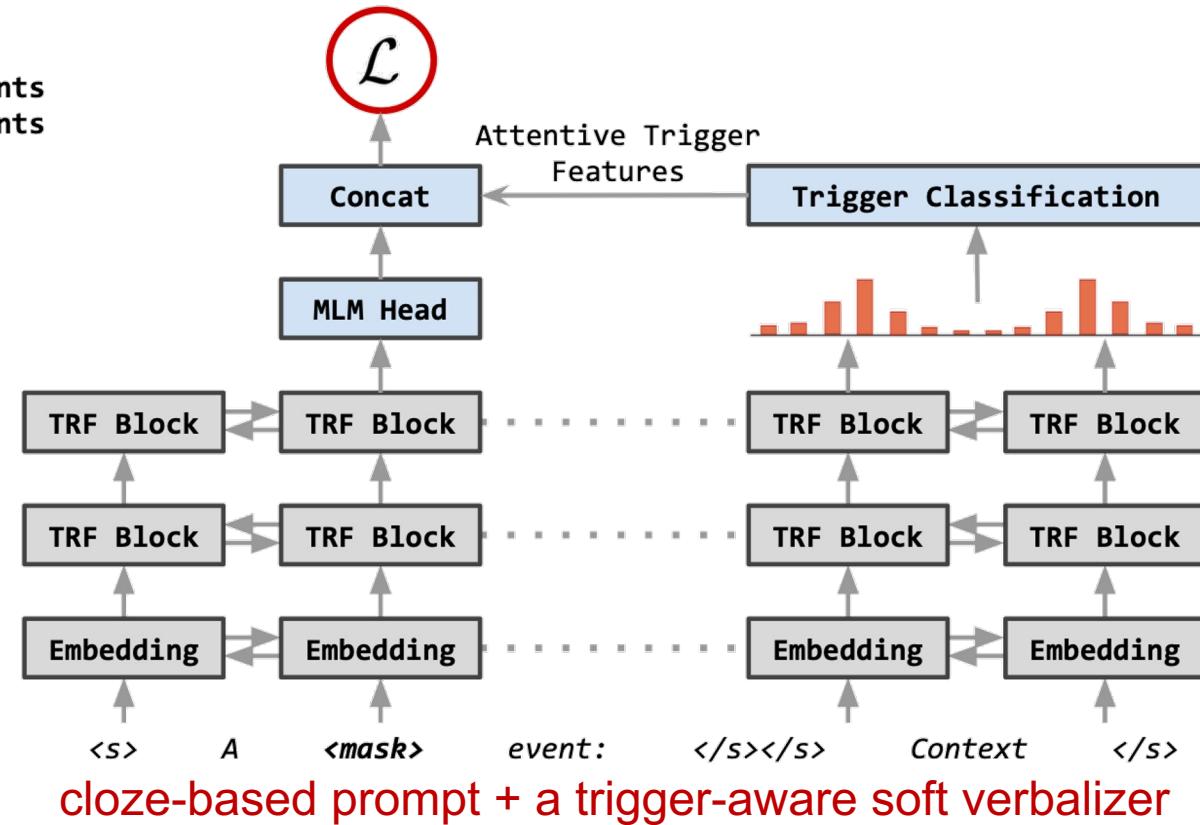
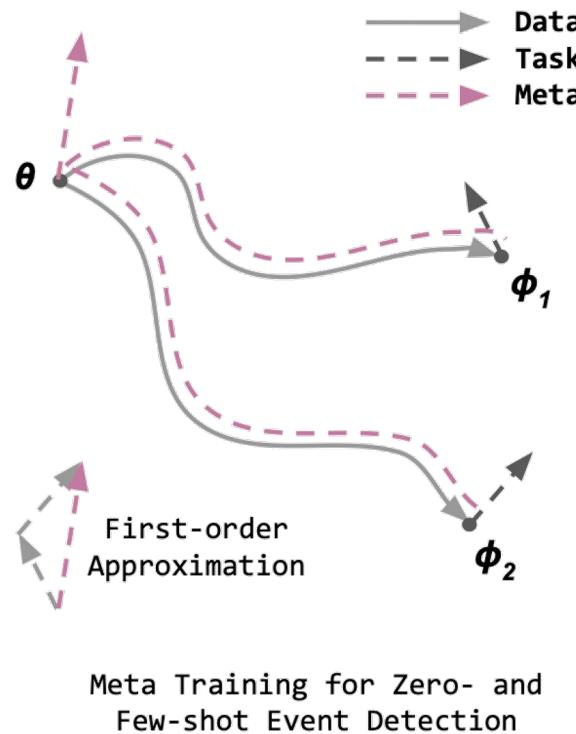
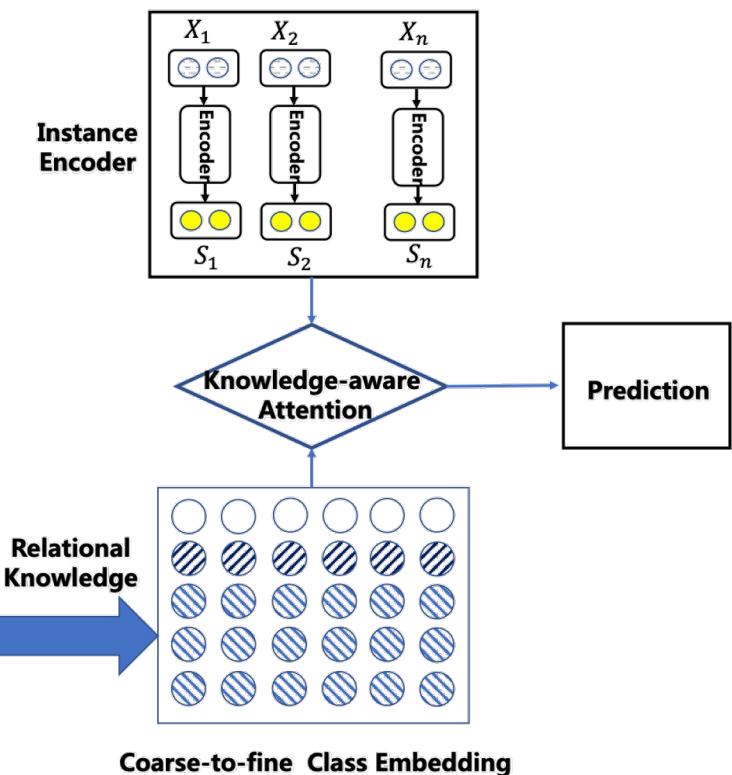
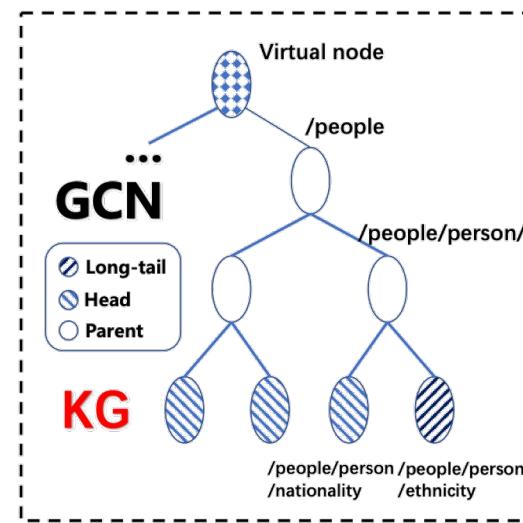
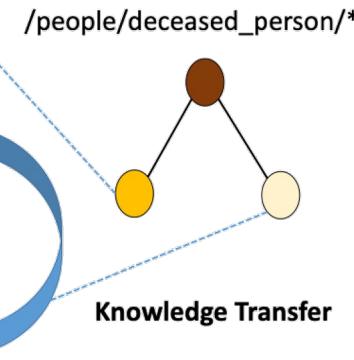
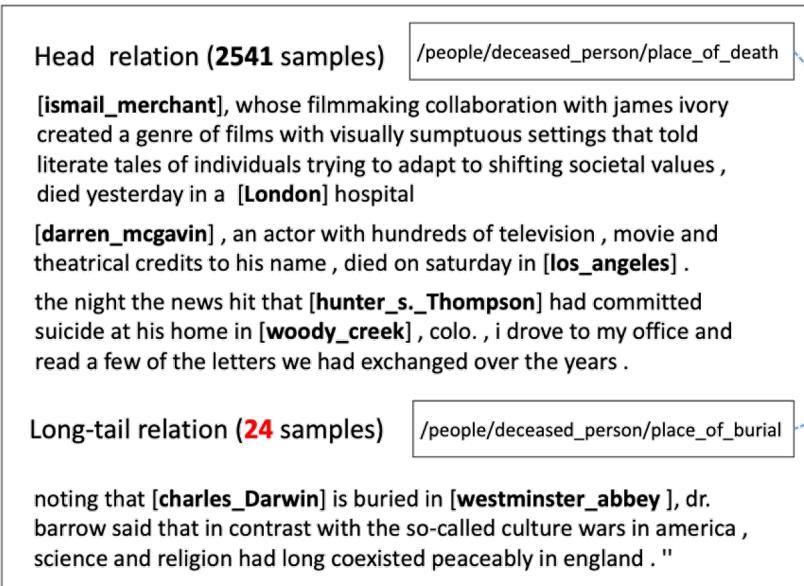


Figure 2: The proposed MetaEvent. The left subfigure illustrates the optimization process w.r.t. the initial parameter set θ with meta learning, and the right subfigure describes the proposed event detection model in MetaEvent.

Zero- and Few-Shot Event Detection via Prompt-Based Meta Learning (ACL 2023)

Transfer Learning

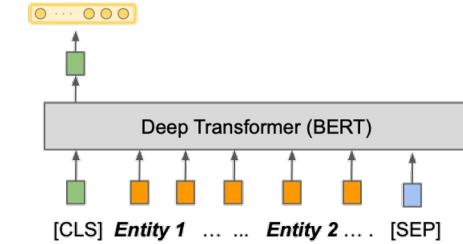
□ Transferring Class-related Semantics



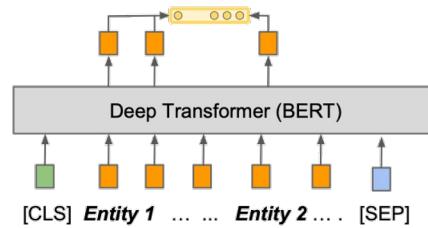
Long-tail Relation Extraction via Knowledge Graph Embeddings and Graph Convolution Networks (NAACL 2019)

Transfer Learning

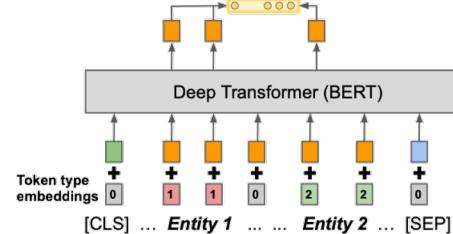
□ Transferring Pre-trained Language Representations



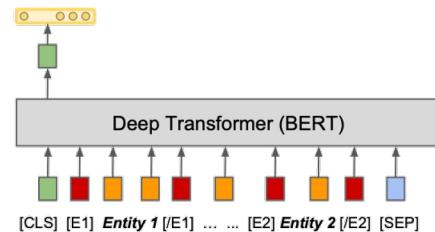
(a) STANDARD – [CLS]



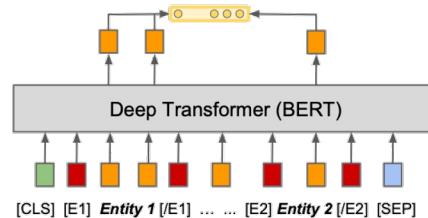
(b) STANDARD – MENTION POOLING



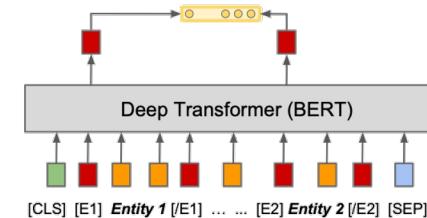
(c) POSITIONAL EMB. – MENTION POOL.



(d) ENTITY MARKERS – [CLS]



(e) ENTITY MARKERS – MENTION POOL.



(f) ENTITY MARKERS – ENTITY START

Figure 3: Variants of architectures for extracting relation representations from deep Transformers network. Figure (a) depicts a model with STANDARD input and [CLS] output, Figure (b) depicts a model with STANDARD input and MENTION POOLING output and Figure (c) depicts a model with POSITIONAL EMBEDDINGS input and MENTION POOLING output. Figures (d), (e), and (f) use ENTITY MARKERS input while using [CLS], MENTION POOLING, and ENTITY START output, respectively.

Matching the Blanks: Distributional Similarity for Relation Learning (ACL 2019)

Prompt Learning

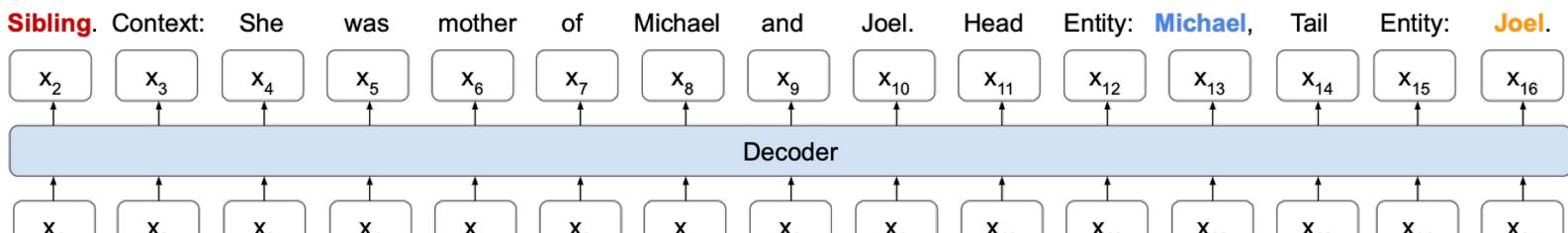
❑ Vanilla Prompt Learning

Input	Template Example	Relation: <Label>.
		Relation: Military Rank .
Output	Template Example	Context: <Sentence>. Head Entity: <Subject>, Tail Entity: <Object>.
		Context: Their grandson was Captain Nicolas Tindal. Head Entity: Nicolas Tindal , Tail Entity: Captain .

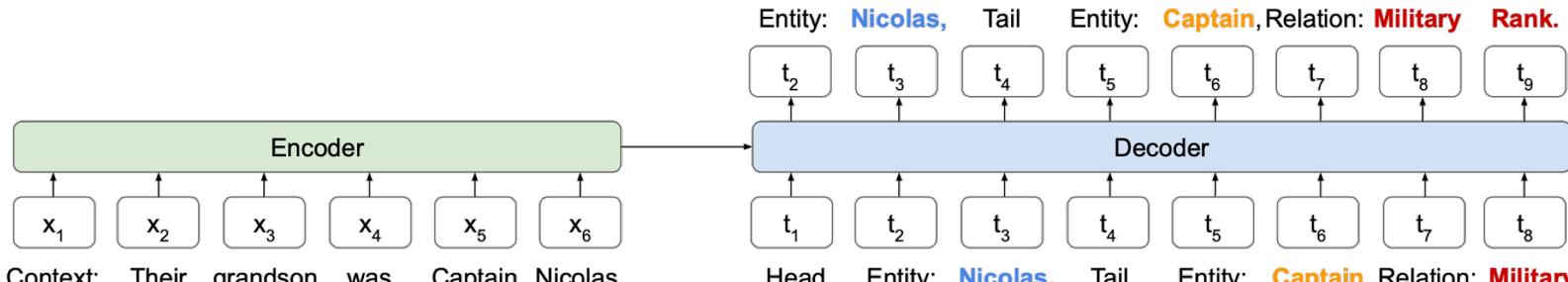
(a) Structured template for relation generator.

Input	Context: <Sentence>.
Example	Context: Their grandson was Captain Nicolas Tindal.
Output	Template Example
	Head Entity: <Subject>, Tail Entity: <Object>, Relation: <Label>.
	Head Entity: Nicolas Tindal , Tail Entity: Captain , Relation: Military Rank .

(b) Structured template for relation extractor.



(a) Training process for relation generator.



(b) Training process for relation extractor.

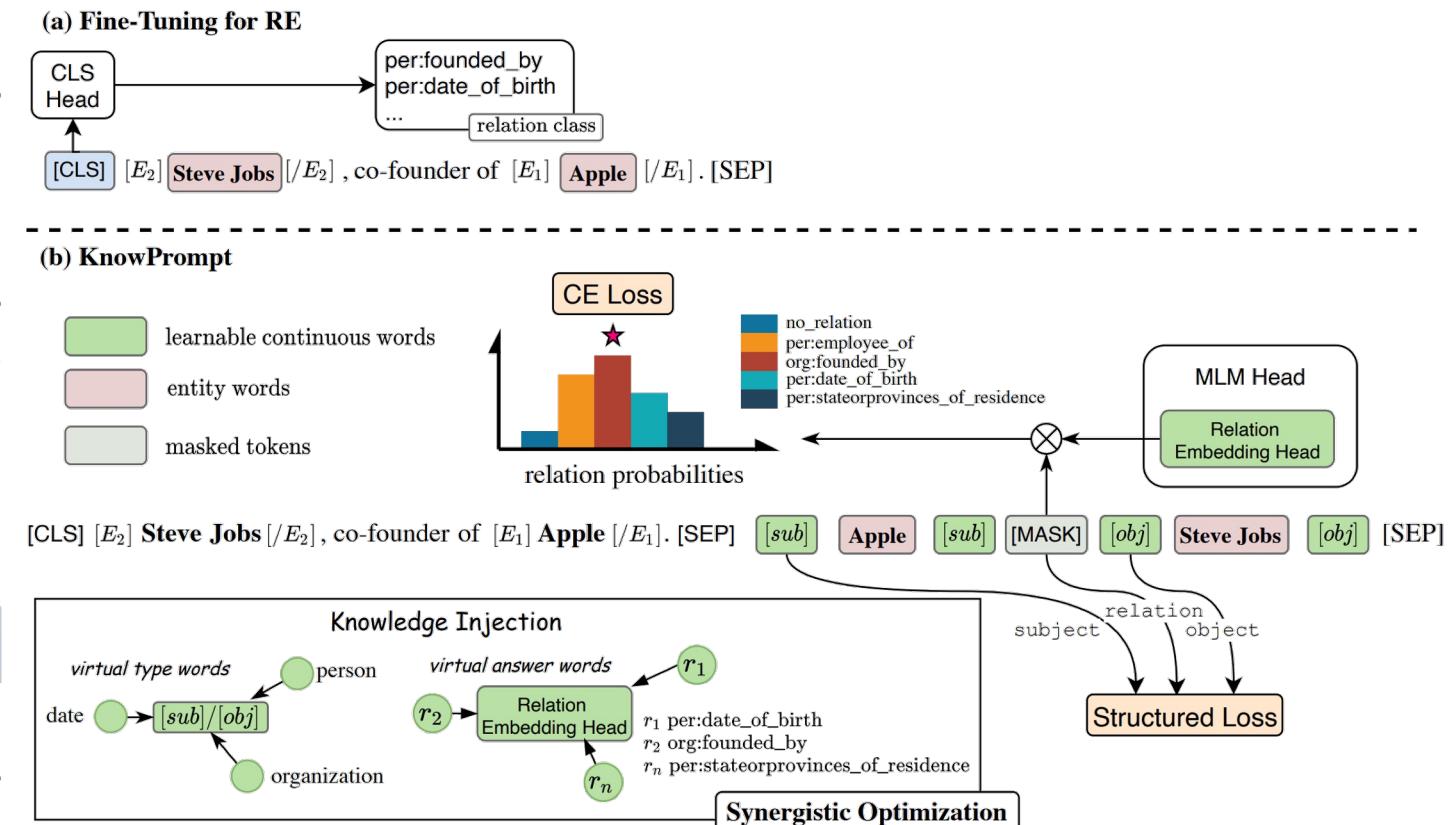
RelationPrompt: Leveraging Prompts to Generate Synthetic Data for Zero-Shot Relation Triplet Extraction (ACL 2022, Findings)

Prompt Learning

❑ Augmented Prompt Learning

❑ Schema Knowledge (virtual)

	[CLS] The cast is uniformly excellent and relaxed . [SEP]	
Prompt for Text Classification	It is [MASK]. [SEP] 	(a)
KnowPrompt for Relation Extraction	[CLS] [E1] Hamilton [/E1] is the first [E2] British [/E2] champion. [SEP] 	(b) (c)



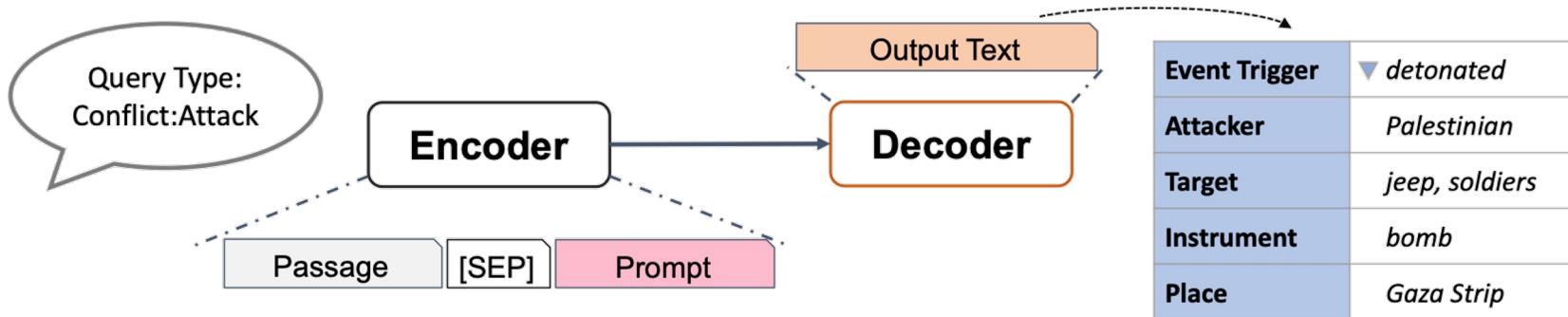
Knowledge-aware Prompt-tuning

KnowPrompt: Knowledge-aware Prompt-tuning with Synergistic Optimization for Relation Extraction (WWW 2022)

Prompt Learning

❑ Augmented Prompt Learning

❑ Schema Knowledge (manually design, textual)



Passage: Earlier Monday , a 19-year-old Palestinian riding a bicycle detonated a 30-kilo (66-pound) bomb near a military jeep in the Gaza Strip , injuring three soldiers.

Prompt	
Event Type Description	<i>The event is related to conflict and some violent physical act.</i>
Event Keywords	<i>Similar triggers such as war, attack, terrorism.</i>
E2E Template	<i>Event trigger is <Trigger>. \n some attacker attacked some facility, someone, or some organization by some way in somewhere.</i>
Output Text	
<i>Event trigger is detonated. \n Palestinian attacked jeep and soldiers by bomb in Gaza Strip.</i>	

Task-Specific Prompt

DEGREE: A Data-Efficient Generation-Based Event Extraction Model (NAACL 2022)

Prompt Learning

❑ Augmented Prompt Learning

❑ Instances & Schema Knowledge (automatically, pluggable)

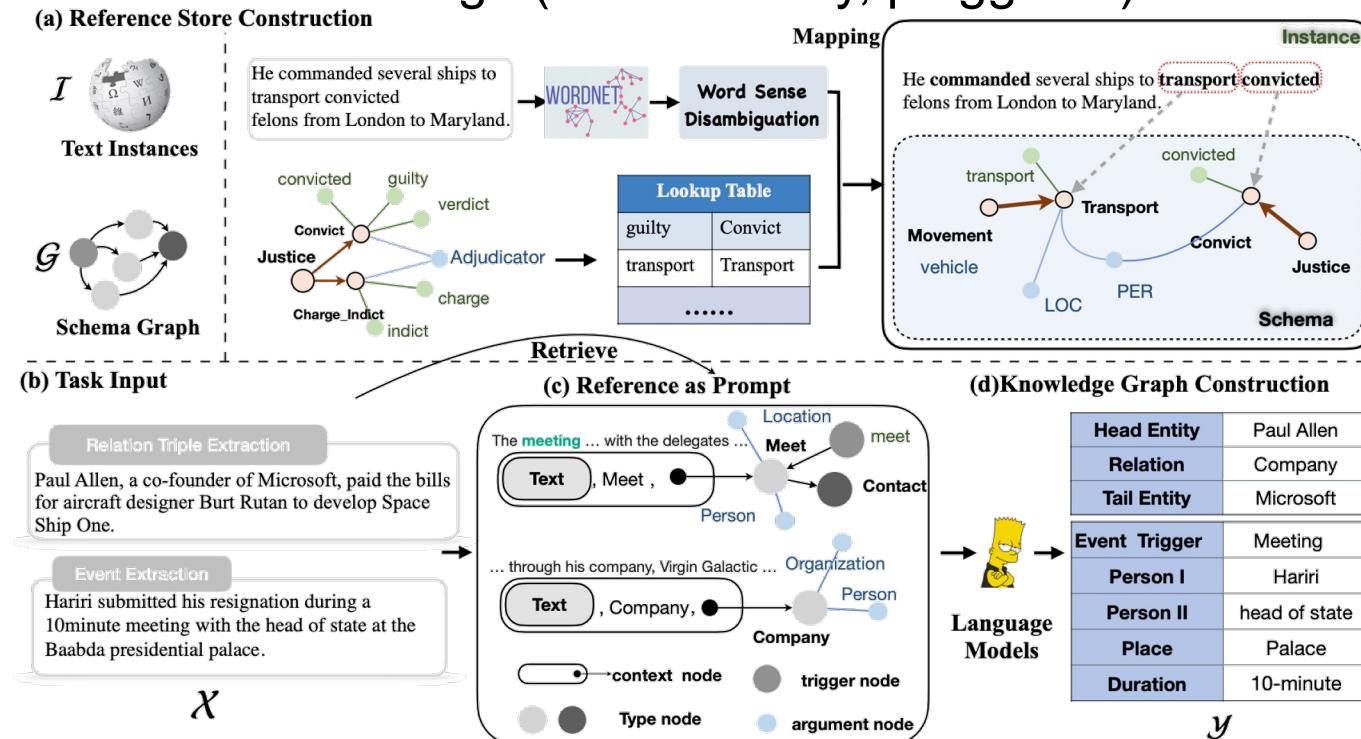


Figure 2: The architecture of schema-aware Reference As Prompt (RAP), which is model-agnostic and is readily pluggable into many existing KGC approaches TEXT2EVENT [34], DEGREE [18], PRGC [57], RELATIONPROMPT [12] and so on.

Schema-aware Reference as Prompt

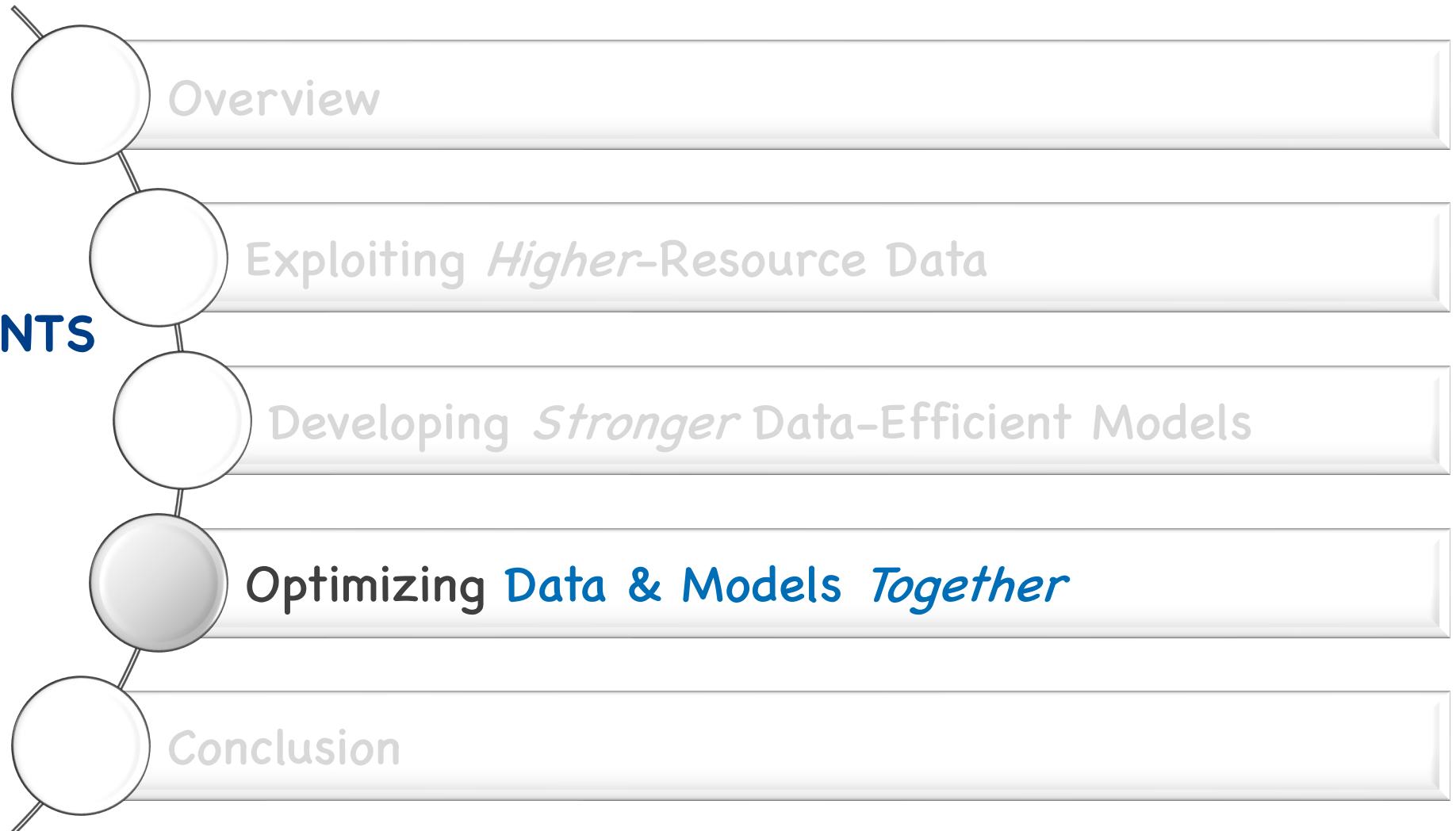
Schema-aware Reference as Prompt Improves Data-Efficient Relational Triple and Event Extraction (SIGIR 2023)



What if higher-resource data & stronger models are accessible?



CONTENTS



Optimizing Data & Models Together

- To integrate crucial data and robust models together in low-resource scenarios
 - Searching more **suitable strategies** for learning with existing sparse data

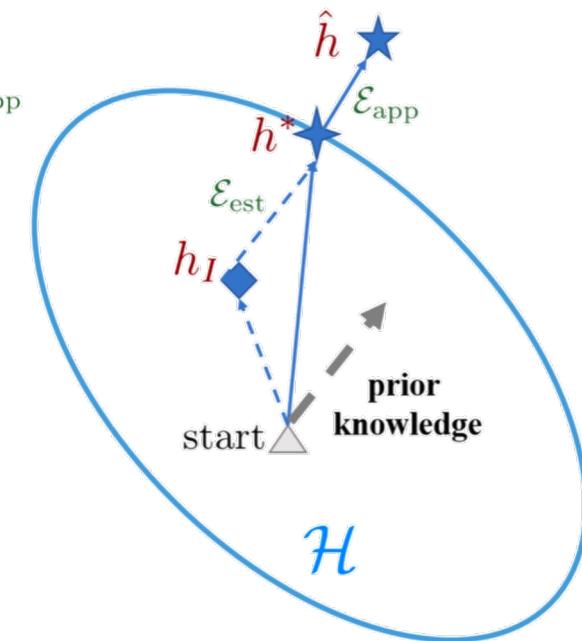
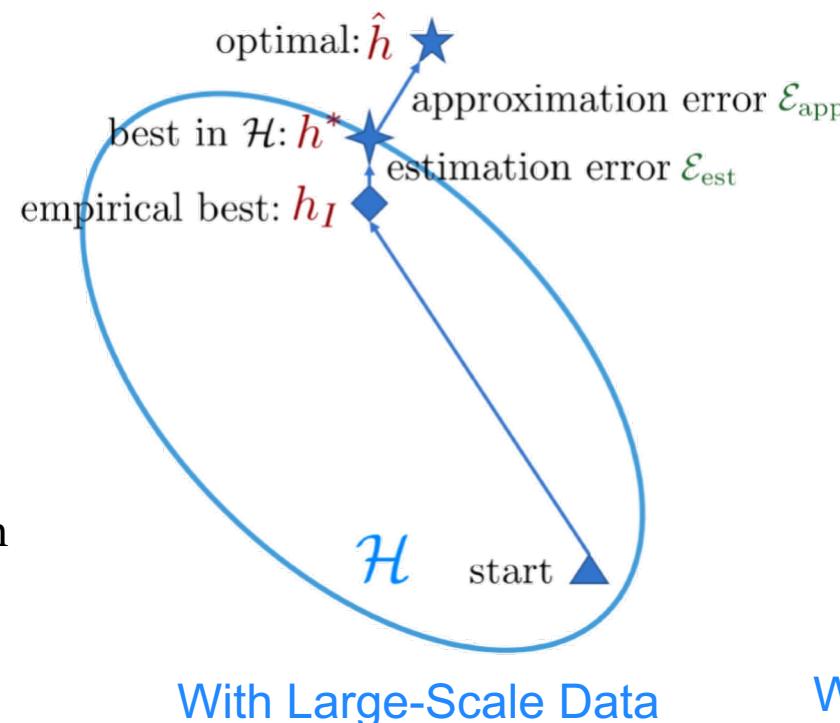
Given a hypothesis \hat{h} , we want to minimize its expected risk R

$\hat{h} = \arg \min_h R(h)$: the function that minimizes the expected risk

$h^* = \arg \min_{h \in \mathcal{H}} R(h)$: the function in \mathcal{H} that minimizes the expected risk

$h_I = \arg \min_{h \in \mathcal{H}} R_I(h)$: the function in \mathcal{H} that minimizes the empirical risk

\mathcal{H} : hypothesis space



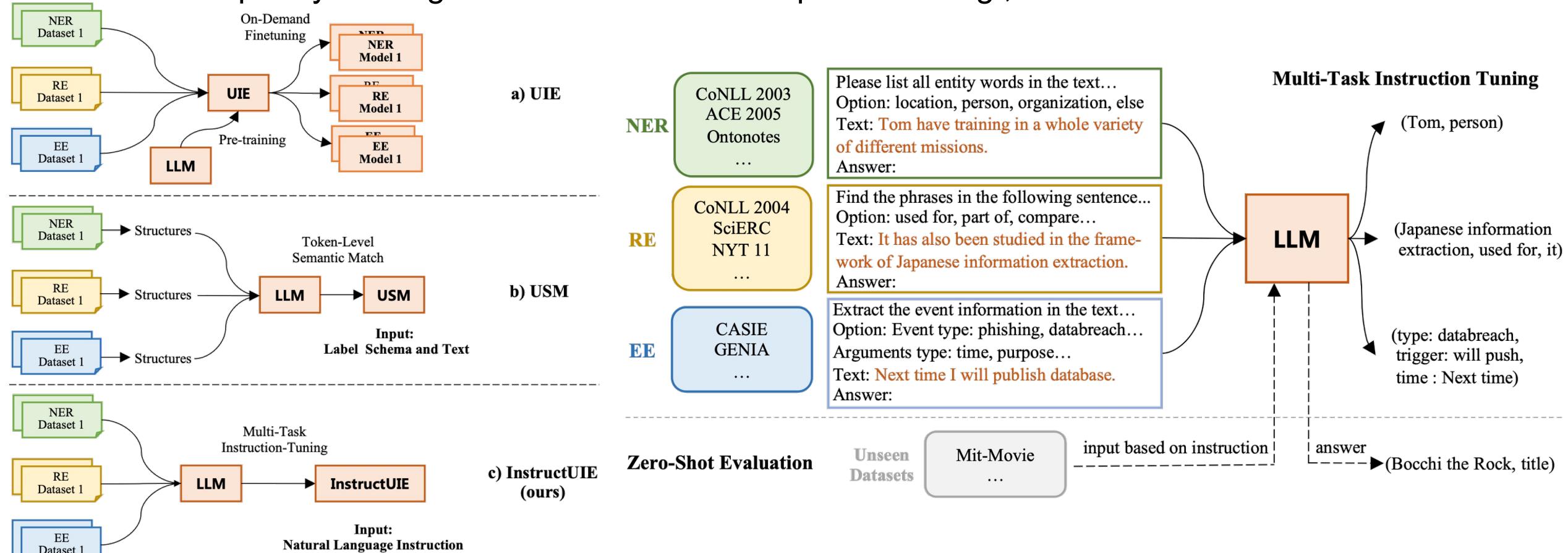
With Optimizing Data & Models
Together in Low-Resource Scenarios

Generalizing from a Few Examples: A Survey on Few-shot Learning (ACM Computing Surveys, 2020)

Multi-task Learning

□ Multi-task Instruction Tuning

- Implicitly leverage the correlation of multiple tasks. E.g., NER → RE → EE



InstructUIE: Multi-task Instruction Tuning for Unified Information Extraction (2023)

Retrieval Augmentation

☐ Retrieval Augmentation helps Decouple Knowledge from Memorization

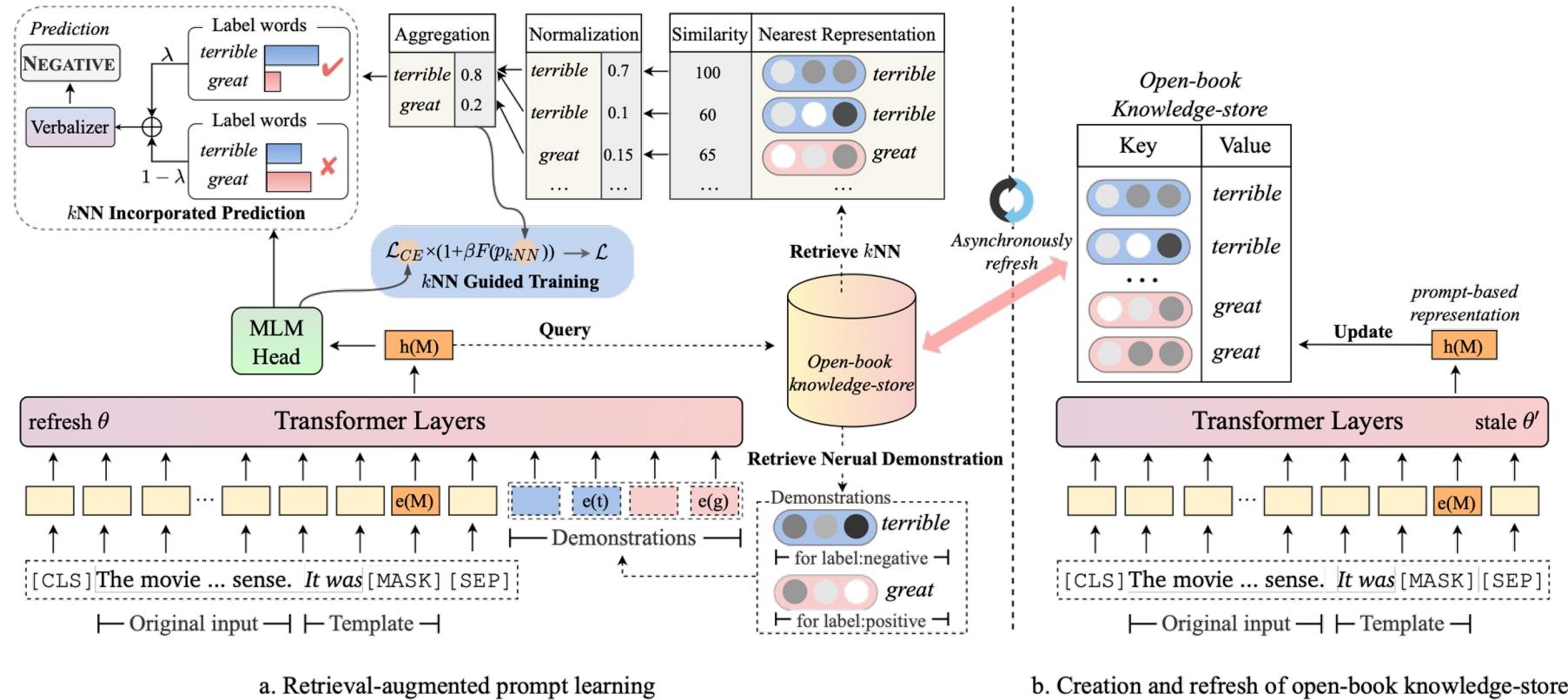
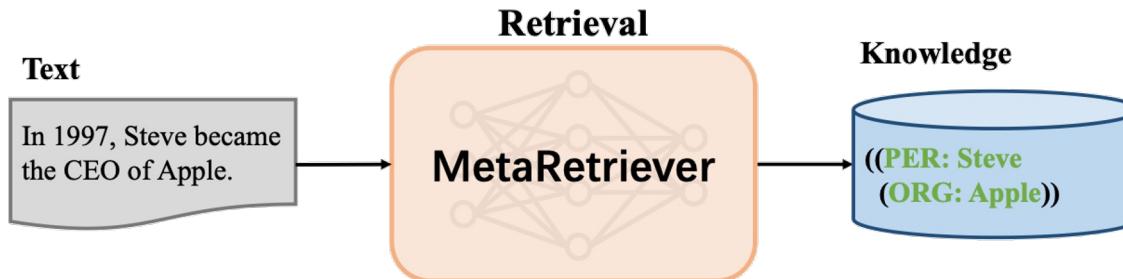


Figure 2: Overview of RETRO_PROMPT. Note that $e(\cdot)$ denotes word embedding function in the PLM \mathcal{M} , while “M”, “t” and “g” in $e(\cdot)$ specifically refers to “[MASK]”, “terrible” and “great”.

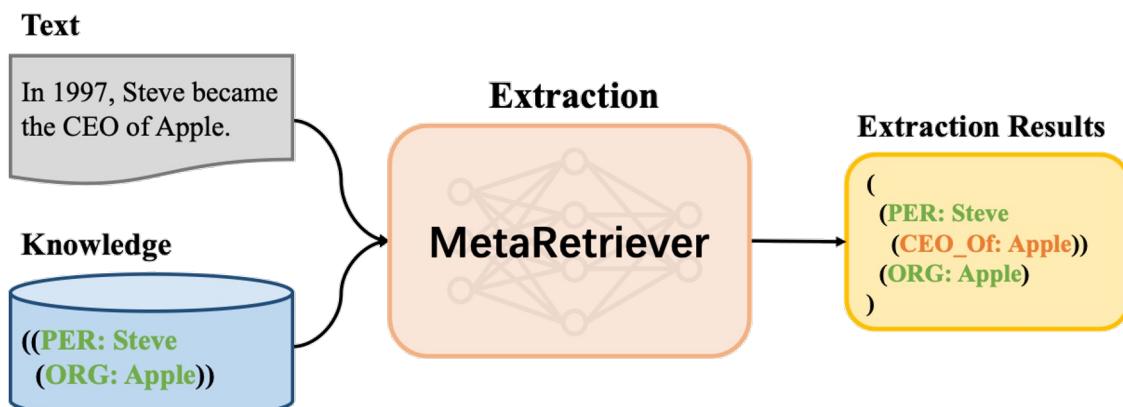
Decoupling Knowledge from Memorization: Retrieval-Augmented Prompt Learning (NeurIPS 2022)

Retrieval Augmentation

☐ Retrieve from PLM then Extract



(a) First: Retrieval task-specific knowledge from the model.



(b) Second: Extraction based on the retrieved knowledge.

Universal Information Extraction with Meta-Pretrained Self-Retrieval (ACL 2023)

Task Reformulation

□ KGC → QA/MRC

(a) Event Extraction

On Sunday, a protester stabbed an officer with a paper cutter.

↓ ↓ ↓ ↓
 Time Attacker Attack Target Instrument

(b) Machine Reading Comprehension

On Sunday, a protester stabbed an officer with a paper cutter.

- Q1: What instrument did the protester use to stab an officer?
- A1: A paper cutter
- Q2: When did the protest stab an officer?
- A2: (On) Sunday.

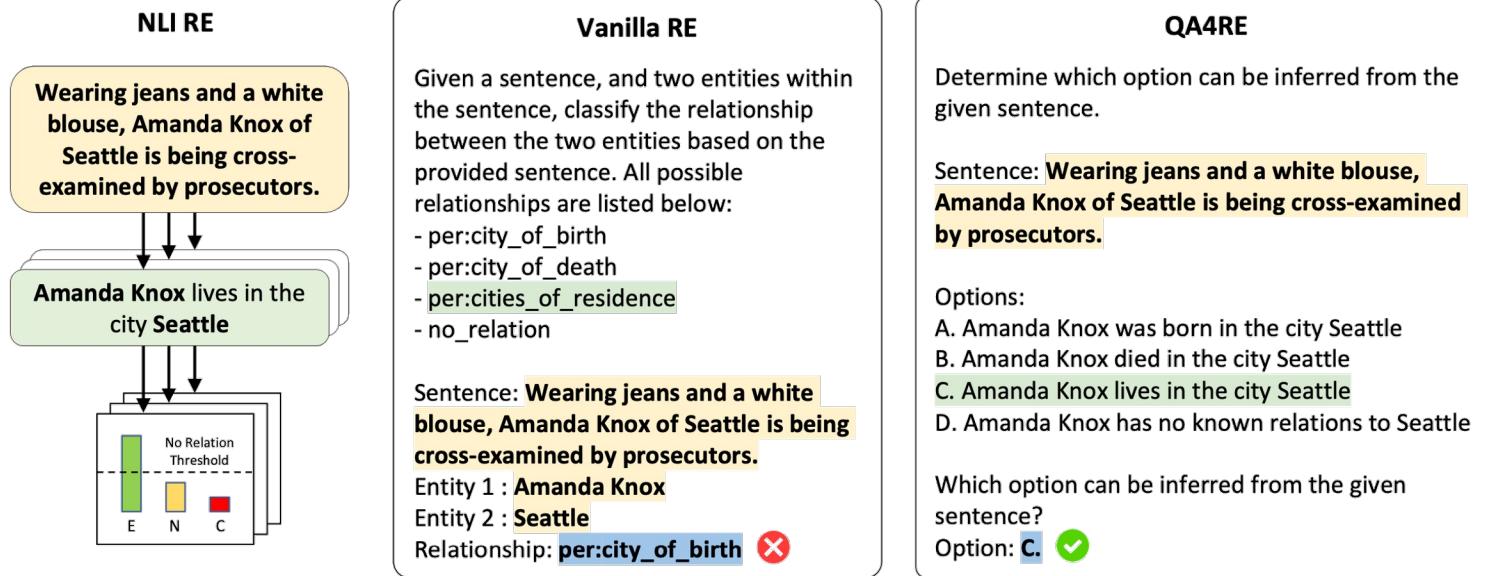
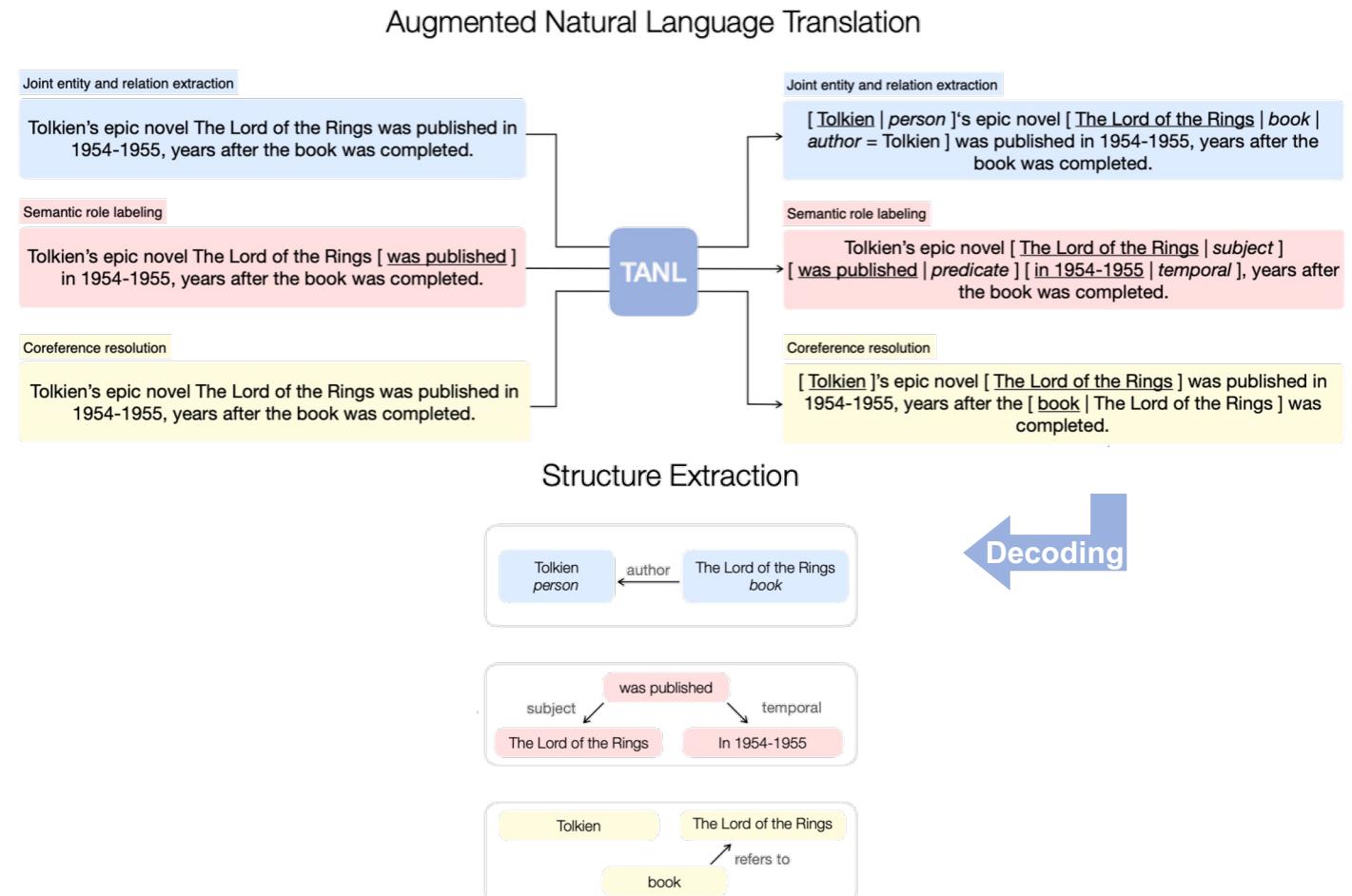
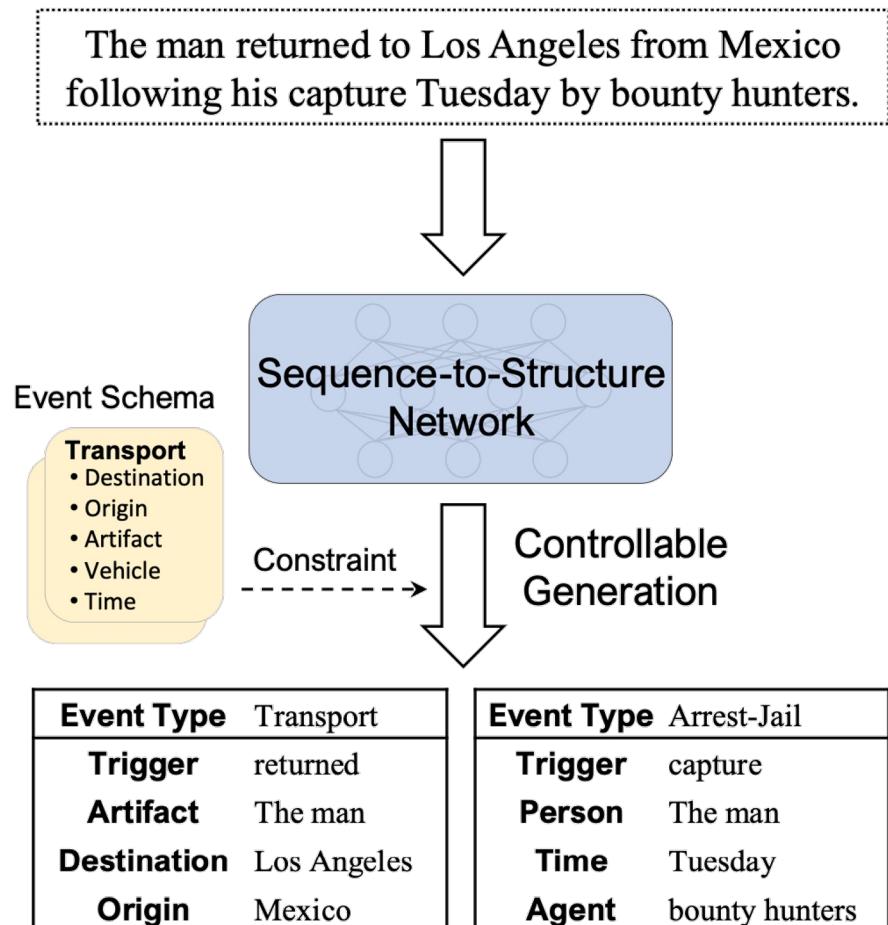


Figure 2: This figure shows a schematic of the SoTA NLI zero-shot framework in which each sentence must be compared with each relation template (left), the vanilla formulation for prompting GPT-3 for RE as done in Jimenez Gutierrez et al. (2022) (center) and our multiple-choice QA setting, in which each relation is transformed into a template and GPT-3 is expected to predict only a single letter (right).

Event Extraction as Machine Reading Comprehension (EMNLP 2020)
 Aligning Instruction Tasks Unlocks Large Language Models as Zero-Shot Relation Extractors (ACL 2023, Findings)

Task Reformulation

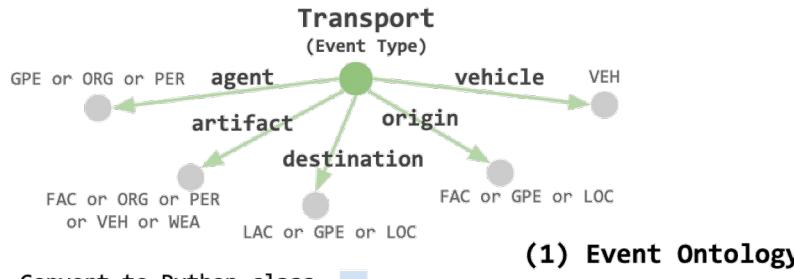
□ KGC → Text-to-Structure Generation



Text2Event: Controllable Sequence-to-Structure Generation for End-to-end Event Extraction (ACL 2021)
 Structured Prediction as Translation between Augmented Natural Languages (ICLR 2021)

Task Reformulation

□ KGC → Text-to-Structure Generation (with Code)



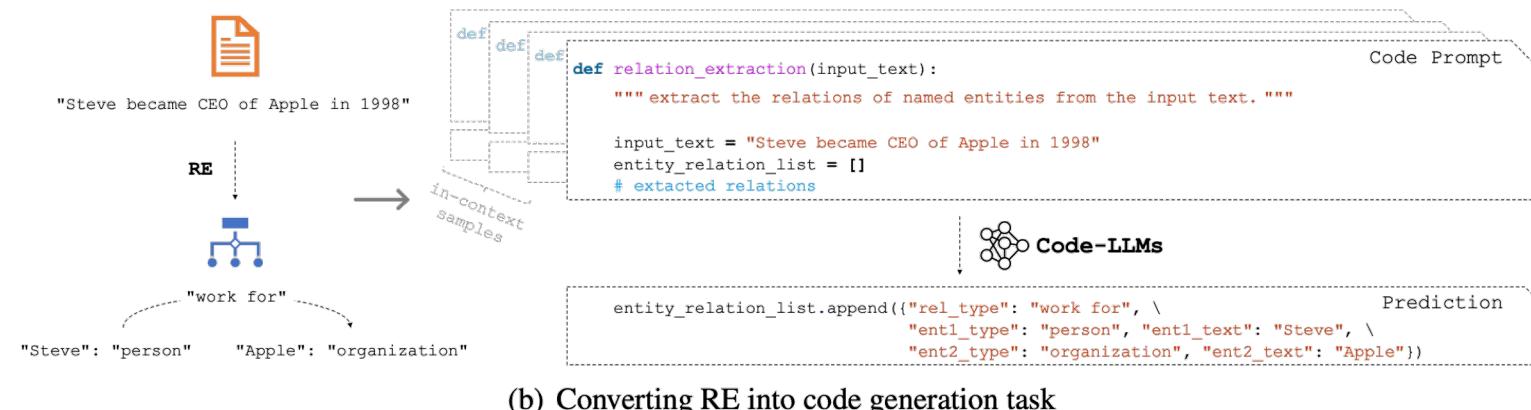
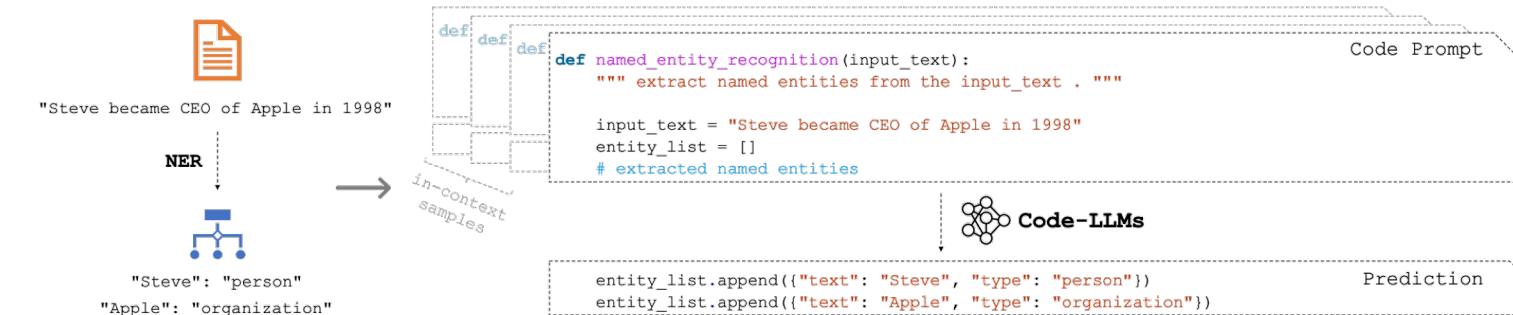
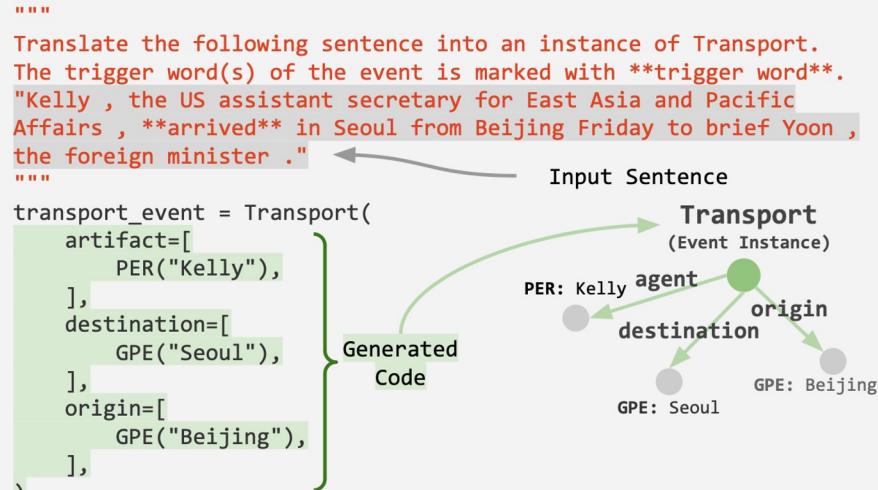
Convert to Python class

```
class Transport(Movement):
```

...

(2) Event Definition

Prompt LLM



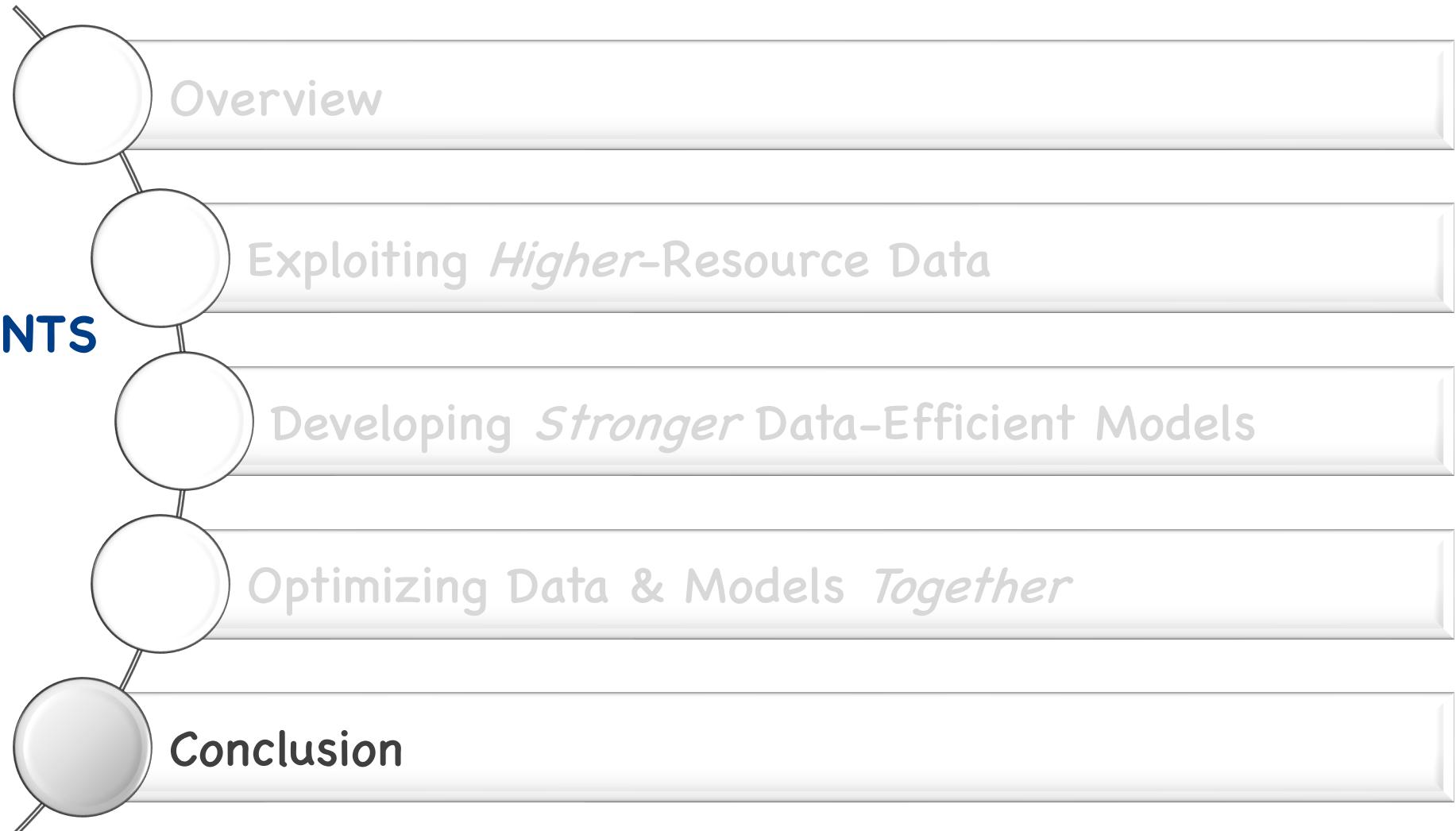
Code4Struct: Code Generation for Few-Shot Event Structure Prediction (ACL 2023)
CodeIE: Large Code Generation Models are Better Few-Shot Information Extractors (ACL 2023)



We are in the era of LLMs!



CONTENTS

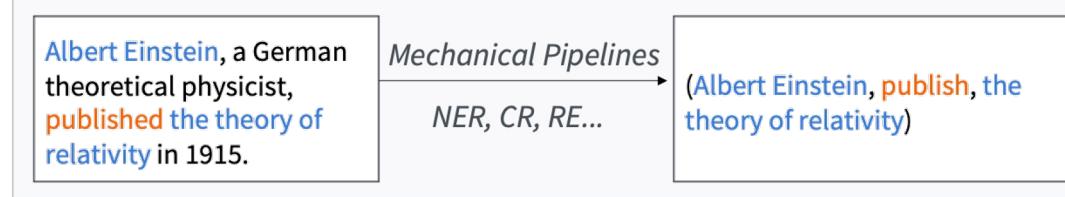


Knowledge & LM

Extracting Knowledge from Texts → Probing Knowledge from LMs

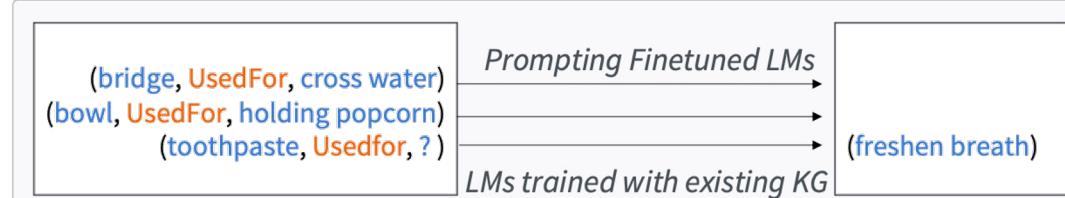
Factual knowledge extraction
from Texts

Text Mining



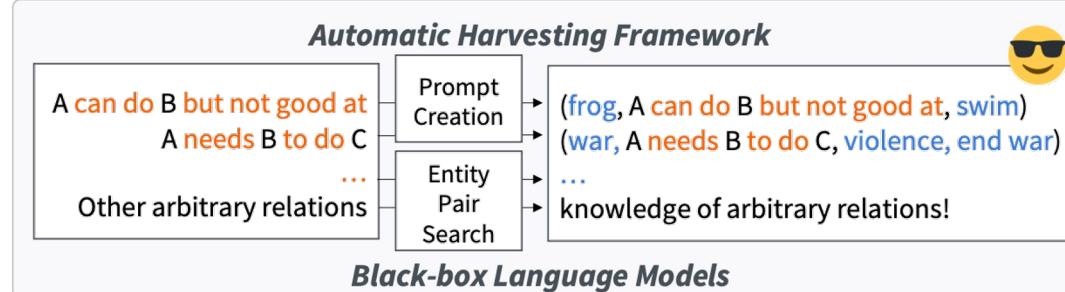
Factual knowledge query
from KB

KG Completion (COMET)



Factual knowledge probing
from LM

BertNet (Ours)



Knowledgeable or Educated Guess? Revisiting Language Models as Knowledge Bases (ACL 2021); A Review on Language Models as Knowledge Bases (2022)
BertNet: Harvesting Knowledge Graphs with Arbitrary Relations from Pretrained Language Models (ACL 2023, Findings)

Overview

Exploiting Higher-
Resource Data

Developing Stronger
Data-Efficient Models

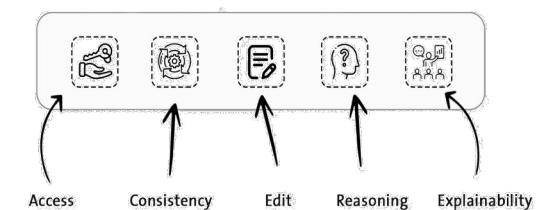
Optimizing Data &
Models Together

Conclusion

Require enough annotated
samples

Require schema engineering

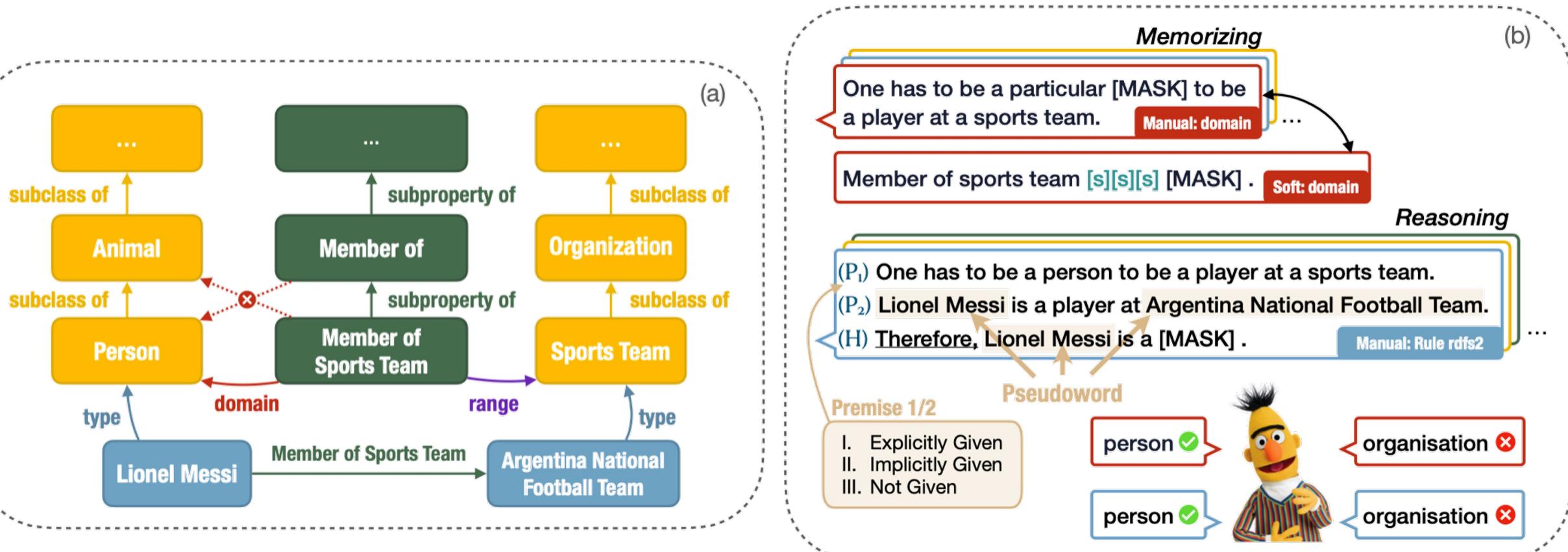
LMs-as-KBs



Support for open domain queries

Language Models as Knowledge Bases? (EMNLP 2019)

Factual Knowledge Probing → Ontological Knowledge Probing



An example of an ontological knowledge graph

Potential manual and soft prompts to probe the knowledge and corresponding semantics

LLMs for KG Construction and Reasoning

□ Empirical Study

Task	Dataset	BERT	RoBERTa	SOTA	ChatGPT
Entity Typing(ET)	BBN	80.3	79.8	82.2 (Zuo et al., 2022)	85.6
	OntoNotes 5.0	69.1	68.8	72.1 (Zuo et al., 2022)	73.4
Named Entity Recognition(NER)	CoNLL2003	92.8	92.4	94.6 (Wang et al., 2021)	67.2
	OntoNotes 5.0	89.2	90.9	91.9 (Ye et al., 2022)	51.1
Relation Classification(RC)	TACRED	72.7	74.6	75.6 (Li et al., 2022a)	20.3
	SemEval2010	89.1	89.8	91.3 (Zhao et al., 2021)	42.5
Relation Extraction(RE)	ACE05-R	87.5 63.7	88.2 65.1	91.1 73.0 (Ye et al., 2022)	40.5 4.5
	SciERC	65.4 43.0	63.6 42.0	69.9 53.2 (Ye et al., 2022)	25.9 5.5
Event Detection(ED)	ACE05-E	71.8	72.9	75.8 (Liu et al., 2022a)	17.1
	ACE05-E+	72.4	72.1	72.8 (Lin et al., 2020)	15.5
Event Argument Extraction(EAE)	ACE05-E	65.3	68.0	73.5 (Hsu et al., 2022)	28.9
	ACE05-E+	64.0	66.5	73.0 (Hsu et al., 2022)	30.9
Event Extraction(EE)	ACE05-E	71.8 51.0	72.9 51.9	74.7 56.8 (Lin et al., 2020)	17.0 7.3
	ACE05-E+	72.4 52.7	72.1 53.4	71.7 56.8 (Hsu et al., 2022)	16.6 7.8

KG Construction

Model	Knowledge Graph Reasoning / Question Answering			
	FB15K-237	ATOMIC2020	FreebaseQA	MetaQA
Fine-Tuned SOTA	32.4	46.9	79.0	100
Zero-shot				
text-davinci-003	16.0	15.1	95.0	33.9
ChatGPT	24.0	10.6	95.0	52.7
GPT-4	32.0	16.3	95.0	63.8
One-shot				
text-davinci-003	32.0	14.1	95.0	49.5
ChatGPT	32.0	11.1	95.0	50.0
GPT-4	40.0	19.1	95.0	56.0

Table 2: KG Reasoning(Hits@1 /blue1) and Question Answering (AnswerExactMatch).

KG Reasoning

LLMs for Knowledge Graph Construction and Reasoning: Recent Capabilities and Future Opportunities (2023)

Revisiting Relation Extraction in the era of Large Language Models (ACL 2023)

Evaluating ChatGPT's Information Extraction Capabilities: An Assessment of Performance, Explainability, Calibration, and Faithfulness (2023)

Overview

Exploiting Higher-Resource Data

Developing Stronger Data-Efficient Models

Optimizing Data & Models Together

Conclusion

LLMs for KG Construction and Reasoning

❑ Is KG Construction and Reasoning Solved by LLMs? **Not Really**

- ❑ [Difficulty of Samples] (measured by the confidence score of SLMs-based models)

Hard Samples: or , Easy Samples:

- ❑ [Complexity of Schema] (hard/easy tasks; large/small label types)

Complex Schema: , Simple Schema:

- ❑ [Quantity of Samples] Samples are extremely scarce:

Method	FewNERD			TACREV			ACE		
	5-shot	10-shot	20-shot	20-shot	50-shot	100-shot	5-shot	10-shot	20-shot
LLM CODEX	53.8 (0.5)	54.0 (1.4)	55.9 (0.5)	59.1 (1.4)	60.3 (2.4)	62.4 (2.6)	47.1 (1.2)	47.7 (2.8)	47.9 (0.5)
	53.6 (-)	54.6 (-)	57.2 (-)	60.1 (-)	58.3 (-)	62.7 (-)	52.9 (-)	52.1 (-)	49.3 (-)
SLM InstructGPT	59.4 (1.5)	61.4 (0.8)	60.7 (1.9)	62.4 (3.8)	68.5 (1.6)	72.6 (1.5)	55.1 (4.6)	63.9 (0.8)	65.8 (2.0)
	59.6 (1.7)	61.8 (1.2)	62.6 (1.0)	64.9 (1.5)	71.9 (2.2)	74.1 (1.7)	56.9 (4.7)	64.2 (2.1)	66.5 (1.7)
S+L + LLM Rerank	60.6 (2.1)	62.7 (0.8)	63.3 (0.6)	66.8 (2.6)	72.3 (1.4)	75.4 (1.5)	57.8 (4.6)	65.3 (1.7)	67.3 (2.2)
	61.3 (1.9)	63.2 (0.9)	63.7 (1.8)	68.9 (1.3)	74.8 (1.3)	76.8 (1.2)	59.5 (3.7)	65.3 (1.9)	67.8 (2.1)

Model	Knowledge Graph Construction			
	DuIE2.0	Re-TACRED	MAVEN	SciERC
Fine-Tuned SOTA	69.42	91.4	68.8	53.2
Zero-shot				
text-davinci-003	11.43	9.8	30.0	4.0
ChatGPT	10.26	15.2	26.5	4.4
GPT-4	31.03	15.5	34.2	7.2
One-shot				
text-davinci-003	30.63	12.8	25.0	4.8
ChatGPT	25.86	14.2	34.1	5.3
GPT-4	41.91	22.5	30.4	9.1

Large Language Model Is Not a Good Few-shot Information Extractor, but a Good Reranker for Hard Samples! (2023)

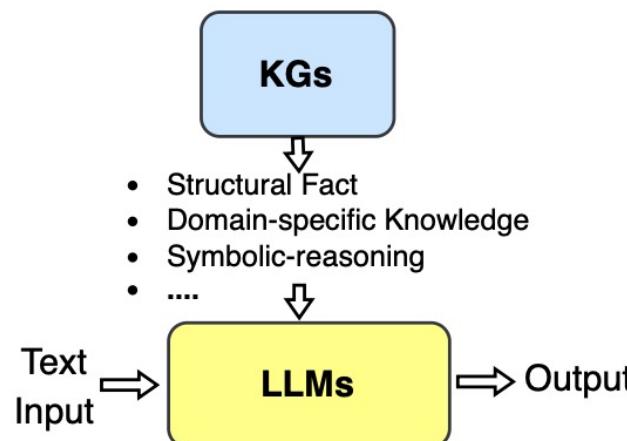
Exploring the Feasibility of ChatGPT for Event Extraction (2023)

Is Information Extraction Solved by ChatGPT? An Analysis of Performance, Evaluation Criteria, Robustness and Errors (2023)

Unifying LLMs and KGs

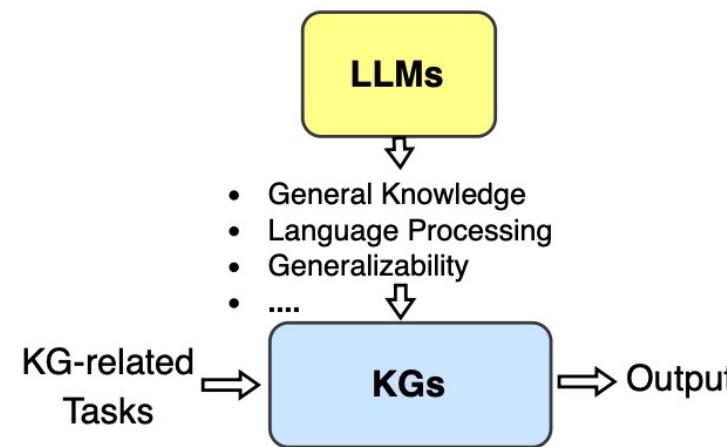
KGs and LLMs can fertilize each other

But the unifying should be correctly



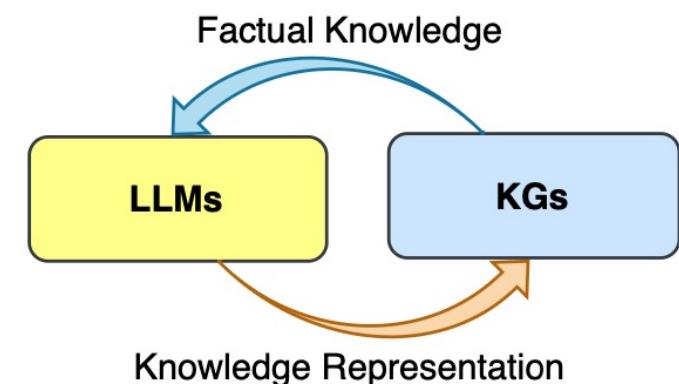
a. KG-enhanced LLMs

For KG Construction



b. LLM-augmented KGs

For KG Reasoning



c. Synergized LLMs + KGs

Jointly

Unifying Large Language Models and Knowledge Graphs: A Roadmap (2023)
Large Language Models and Knowledge Graphs: Opportunities and Challenges (2023)

Datasets & Toolkits

❑ Datasets

- ❑ Low-resource NER: [Few-NERD](#)
- ❑ Low-resource RE: [FewRel](#), [FewRel2.0](#), [LREBench](#), [Entail-RE](#)
- ❑ Low-resource EE: [FewEvent](#), [Causal-EE](#), [OntoEvent](#)

Also we can sample low-resource data from general full datasets, such as [Text2KG](#)

❑ Toolkits

- ❑ Traditional
 - ❑ [DeepKE](#), [OpenUE](#), [Zshot](#), [OpenNRE](#), [OmniEvent](#), [OpenKE](#), [NeuralKG](#), [NeuralKG-ind](#),
[DeepOnto](#), [PromptKG](#), ...
- ❑ LLM-based
 - ❑ [KnowLM](#), [AutoKG](#), [GPT4IE](#), [ChatIE](#), ...



IJCAI/2023 MACAO



IJCAI

International Joint Conferences on
Artificial Intelligence Organization

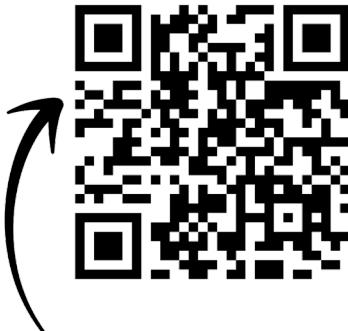
Thank You



Speaker: Shumin Deng



Date: 2023.08.19



Paper list on low-resource KGC



LLM-based toolkit for KGC



IJCAI/2023 MACAO



IJCAI

International Joint Conferences on
Artificial Intelligence Organization

Multimodal KG Construction and Reasoning

<https://openkg-tutorial.github.io/>

Meng Wang

XAI Lab

19, Aug, 2023

Multimodal Knowledge



Casinos on the Macanese skyline



Marina at [Macau Fisherman's Wharf](#)



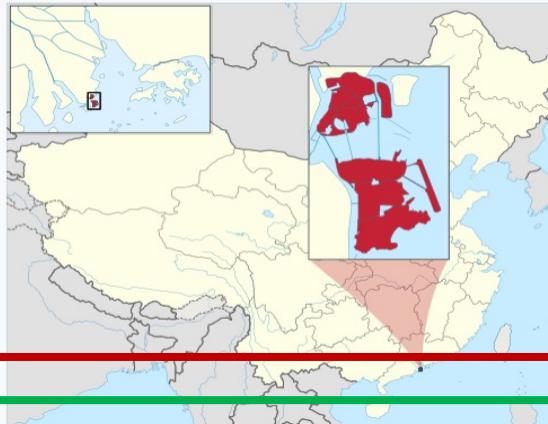
Tourism plays an important role in the economy of Macau, the people from Mainland China being the region's most prolific tourists.



Flag



Emblem



Location of Macau within China

Sovereign state	China
Portuguese lease	1557
Treaty of Peking	1 December 1887
Population	• 2022 estimate
	672,800
Transfer from Portugal	20 December 1999
Largest parish by population	Nossa Senhora de Fátima
Official languages	Chinese ^{[1][2][a]} . Portuguese ^{[1][2][b]}
Regional language	Cantonese ^[a] . Macanese

Image

Text

KG

Multimodal Knowledge



IJCAI/2023 MACAO

ESPN+ Watch Listen

SEP 30

Fri - 6:00 PM CT NBA TV Sat - 10:00 AM CT NBA TV

GS	0-0	MRC	0-0
WSH	0-0	LAC	0-0

NFL NCAAF NHL NBA MLB Soccer ...

Home Scores Schedule Standings Stats Teams Free Agency Players Sign Up: Fantasy Basketball Injuries More

NBA media days: The best quotes from around the league as teams kick off the 2022-23 season



Mini Christmas Tree, 22 Inch Small Christmas Tree with Lights Xmas Hat Tree Top and Mini Christmas Tree Ornaments Tabletop Artificial Xmas Tree for Christmas Decorations Indoor Home Decor

\$19⁹⁹

No Import Fees Deposit & \$18.22 Shipping to China [Details](#)

Coupon: Save an extra 20% when you apply this coupon [Terms](#)

Brand BSTCRAFT

Color Green

Material Polyvinyl Chloride

Item Weight 15.36 Ounces

Item Package 1

Quantity

Package Information 盒装

Occasion Thanksgiving

Special Light Up

Size: 6 ft | **Verified Purchase**

For the most part it was an easy assemble. I had to get the drift out since holes for bolts were not big enough and had to wrap tape around base of top layer since it was loose but that fixed the issue. Once up and fully expanded I was surprised to see how the tree came out. The multicolor lights that came with the tree are beautiful and with a few ornaments the Christmas Tree came out perfect.



Helpful

| Report abuse

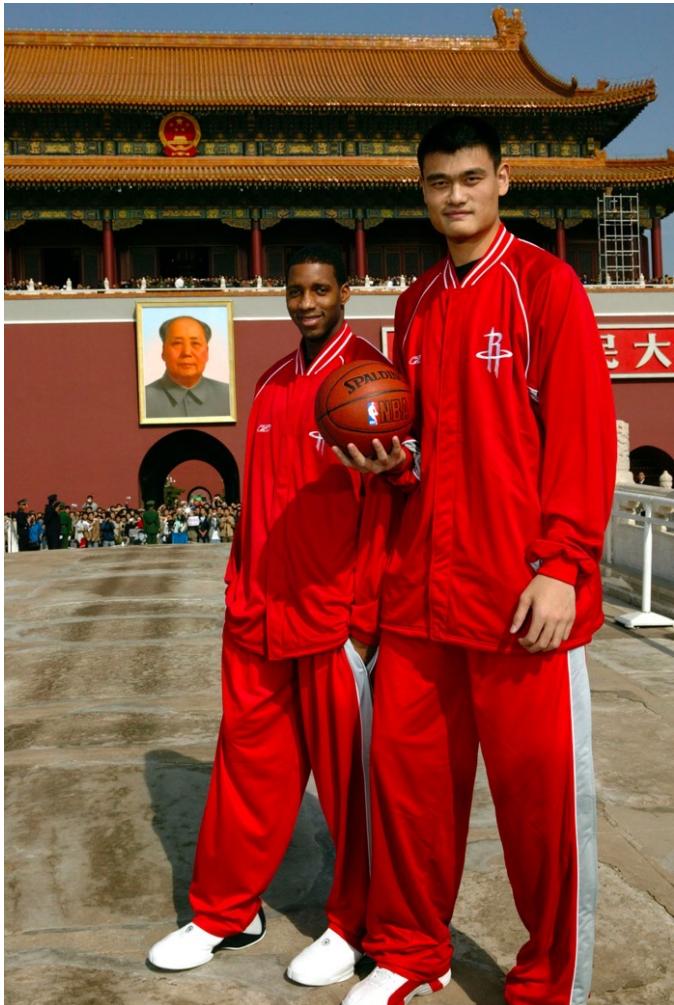
**Multimodal knowledge:
is an awareness or understanding of someone
or something in different multimodalities.**

**Why we need multimodality and
reasoning?**

Multimodal Knowledge



IJCAI/2023 MACAO



腾讯云

HOT 产品 解决方案 定价 文档 云市场 开发者 支持 合作与生态 客户

API 中心

文档中心 > API 中心 > 图像分析 > 图像理解相关接口 > 公众人物识别

公众人物识别

最近更新时间: 2019-08-22 19:41:50

1. 接口描述

接口请求域名: tiia.tencentcloudapi.com。

传入一张图片, 可以识别图片中包含的人物是否为公众人物, 如果是, 输出人物的姓名、

支持识别一 北京市东城区东交民巷 15号院内 15号院内 15号院内 15号院内 15号院内

默认接口请

Will Smith

American Actor

See all images

Result :
Yao Ming (100)
Will Smith (39)

...

Visual Entity Disambiguation

Multimodal Knowledge



IJCAI/2023 MACAO



刘欢

这是一个多义词，请在下列义项上选择浏览（共14个义项）

- 刘欢：中国内地流行音乐家
- 刘欢：广东省广州市中级人民法院助理审判员
- 刘欢：中国足球运动员
- 刘欢：长虹街道办事处副主任
- 刘欢：湖南发展研究中心研究员联络处副主任
- 刘欢：清华大学环境学院副教授
- 刘欢：清华大学教师
- 刘欢：象棋棋手
- 刘欢：矿大（北京）管院第十二届研究生会副主席
- 刘欢：苏州东吴队球员
- 刘欢：中国大陆男演员
- 刘欢：扣篮王刘欢
- 刘欢：全国技术能手

Liu Huan was met by fans in an American supermarket, bought \$8 bread and signed autographs for fans



基本信息

中文名	刘欢	毕业院校	国际关系学院法语文学专业
外文名	Liu Huan	经纪公司	百娱传媒股份有限公司
别 名	欢哥	代表作品	少年壮志不言愁、弯弯的月亮、心中的太阳、千万次的问、这一拜、好汉歌、从头再来、凤凰于飞
国 籍	中国	主要成就	CCTV MTV音乐盛典最受欢迎男歌手 《音乐风云榜》终身成就奖 北艺协会电视剧优秀音乐创作奖 第十届华语歌曲“榜中榜”之“评委特别奖” 第四届中国金唱片“最佳流行专辑”
民 族	汉族		
星 座	处女座		
血 型	O型		
身 高	173cm		
出生地	天津		
出生日期	1963年8月26日	生 肖	兔
职 业	歌唱家、音乐人、词曲创作人、大学音乐教授		

Huan Liu

Computer scientist



Huan Liu is a computer scientist at Arizona State University in Tempe, Arizona. He was named a Fellow of the Institute of Electrical and Electronics Engineers in 2012 for his contributions to feature selection in data mining and knowledge discovery. [Wikipedia](#)

Textual Entity Disambiguation

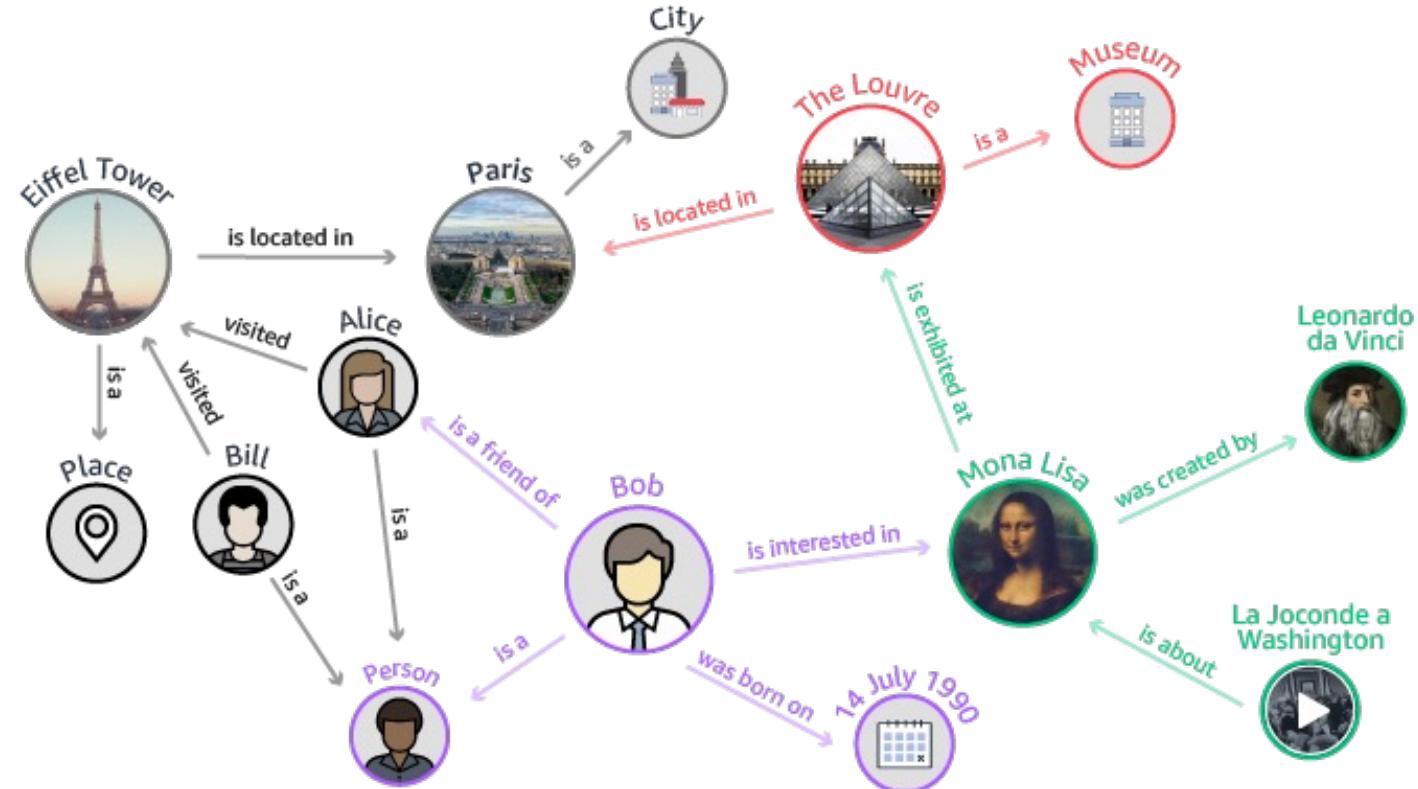
Multimodal Knowledge Graph

Node:

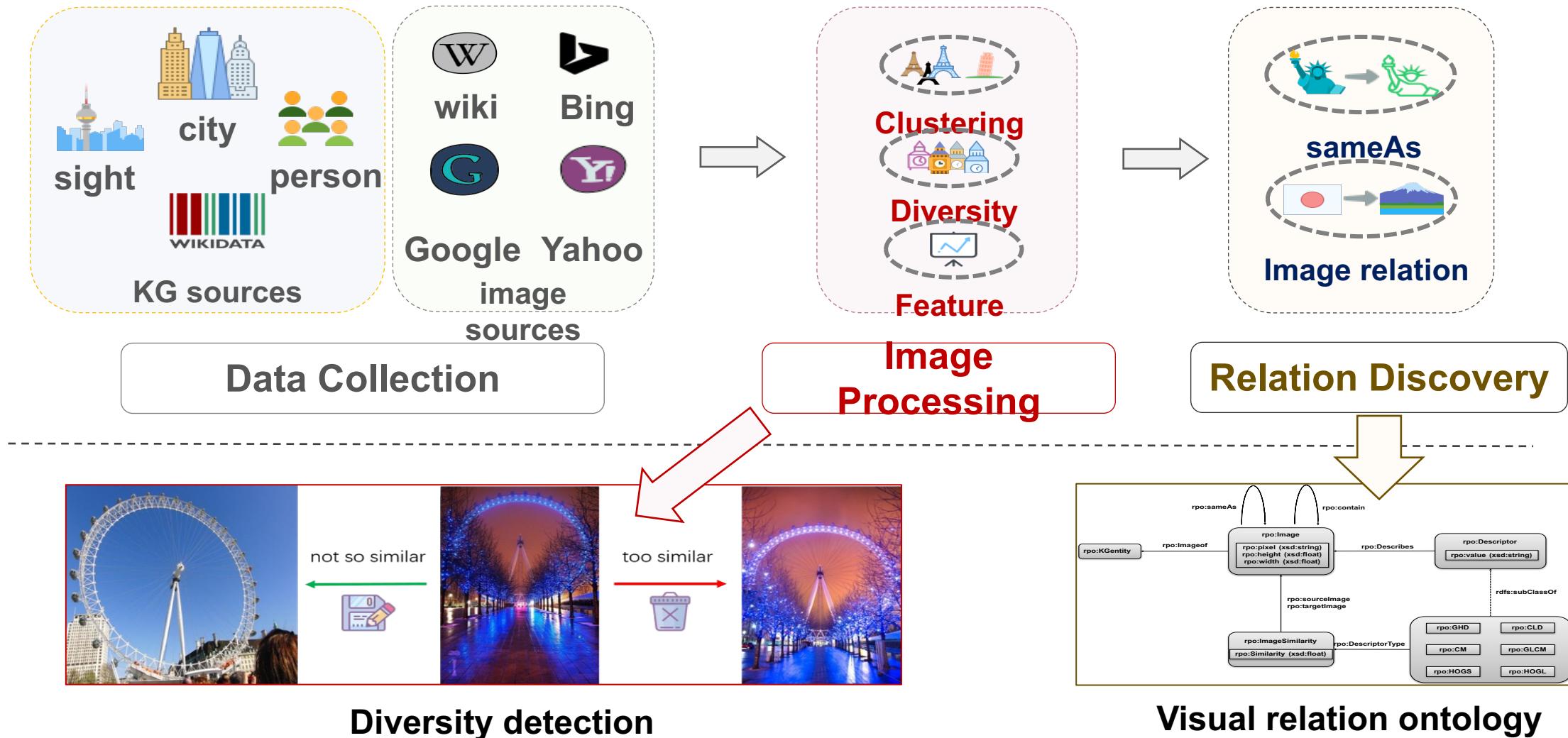
- Image entity
- Text entity
- Visual concept
- Textual concept

Relation:

- is-a
- has-visual-object
- meta-of
- has-tag
- co-locate-with



Multimodal Knowledge Graph



Richpedia: A Large-Scale, Comprehensive Multi-Modal Knowledge Graph. Big Data Research, 2020

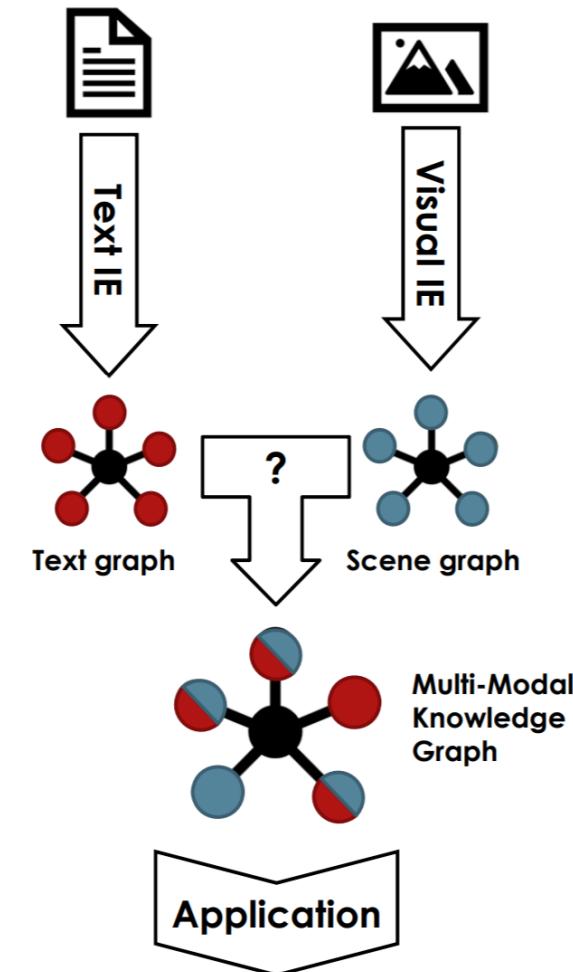
Multimodal Knowledge Graph

► Challenges:

- Parsing text to structured semantic graph
- Parsing images/videos to structures
- Grounding event/entities across modalities
- Multimodal argument role

► Applications

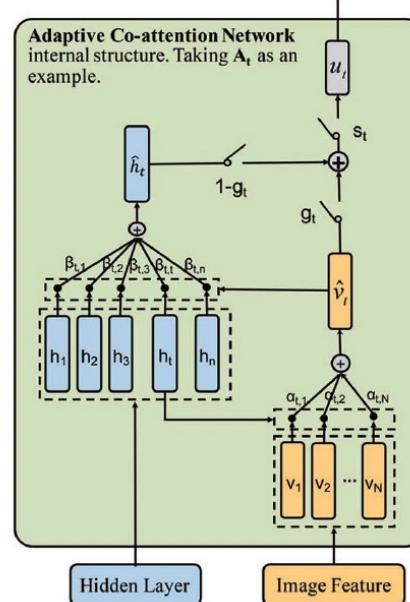
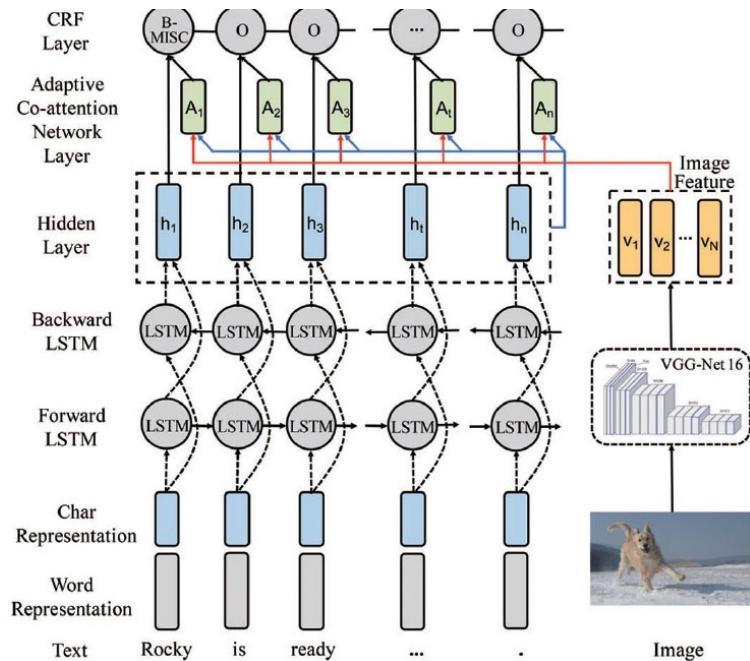
- Story Generation and Summarization
- Question Answering
- Commonsense Discovery



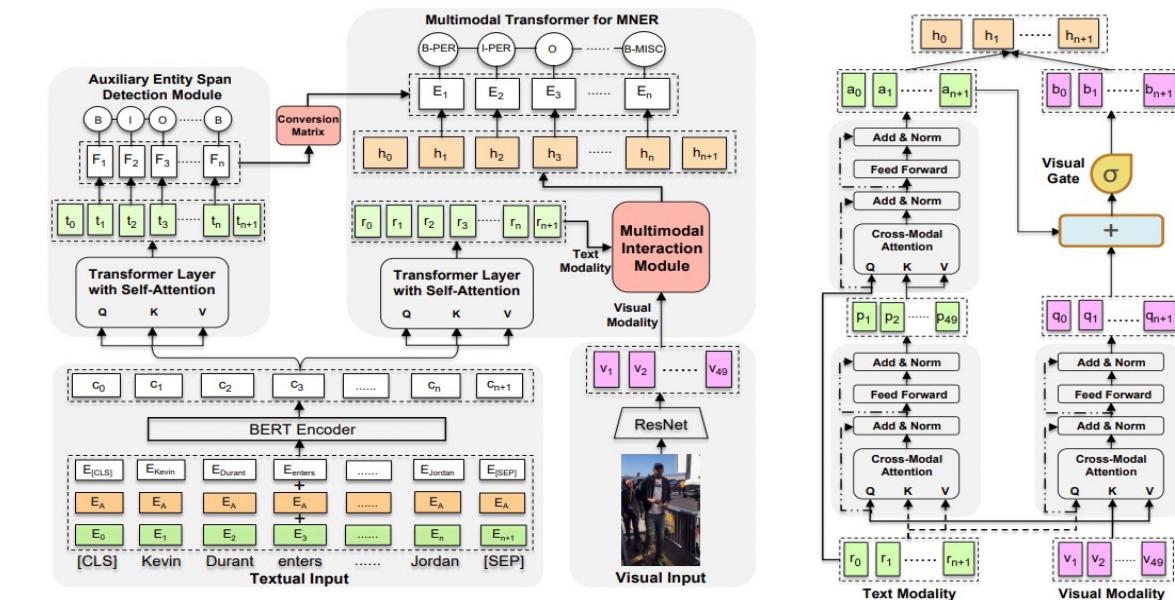
- **Multimodal Named Entity Recognition**
- **Multimodal Relation Extraction**
- **Multimodal Entity Alignment**

Multimodal KG Construction: MNER

Bi-directional LSTM network with CRF and an adaptive co-attention network



Leverage purely text-based entity span detection as an auxiliary module, and design UMT to guide the final predictions with the entity span predictions

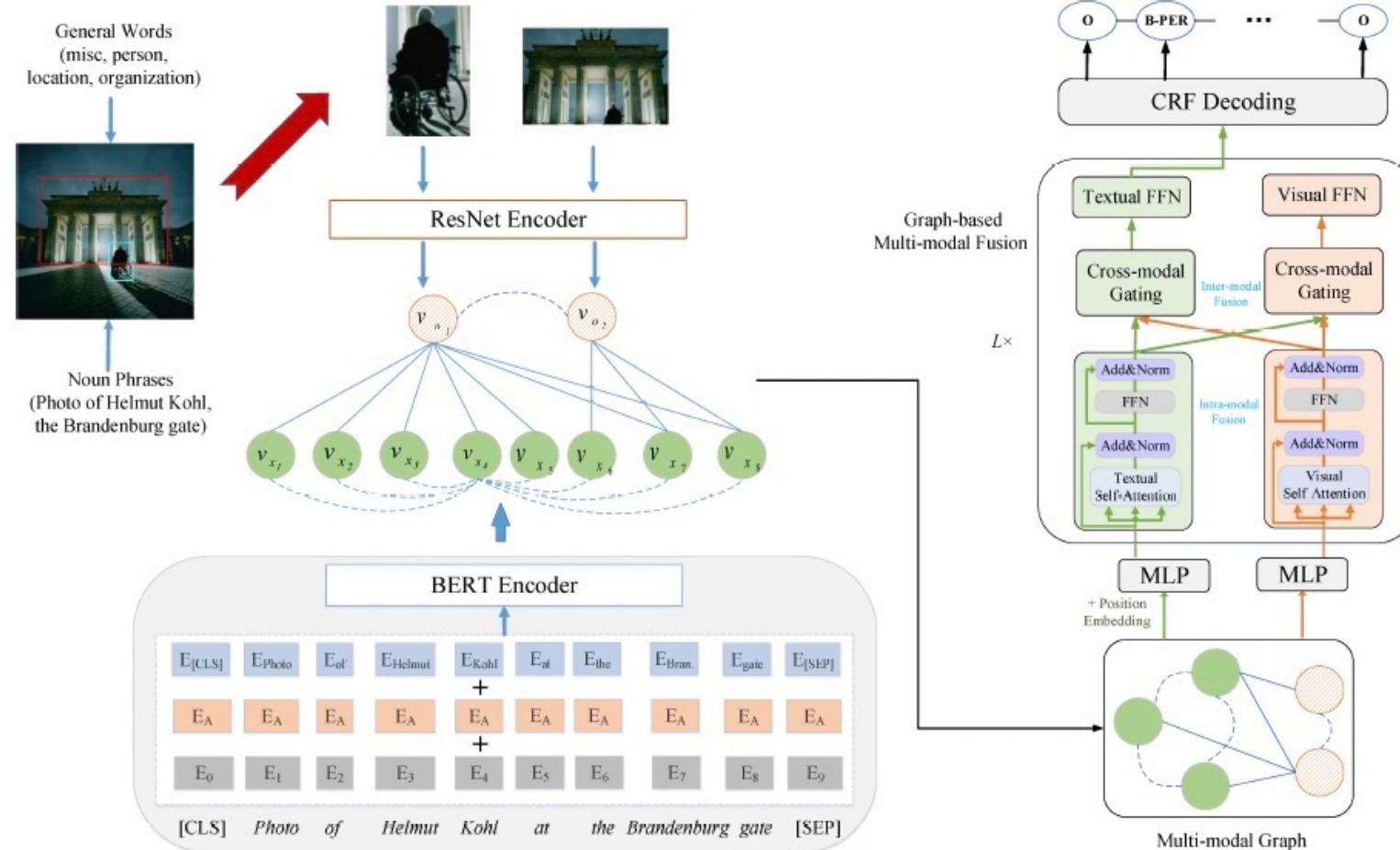


Adaptive Co-Attention Network for Named Entity Recognition in Tweets (AAAI 2018)

Multimodal Named Entity Recognition for Short Social Media Posts (NAACL 2018)

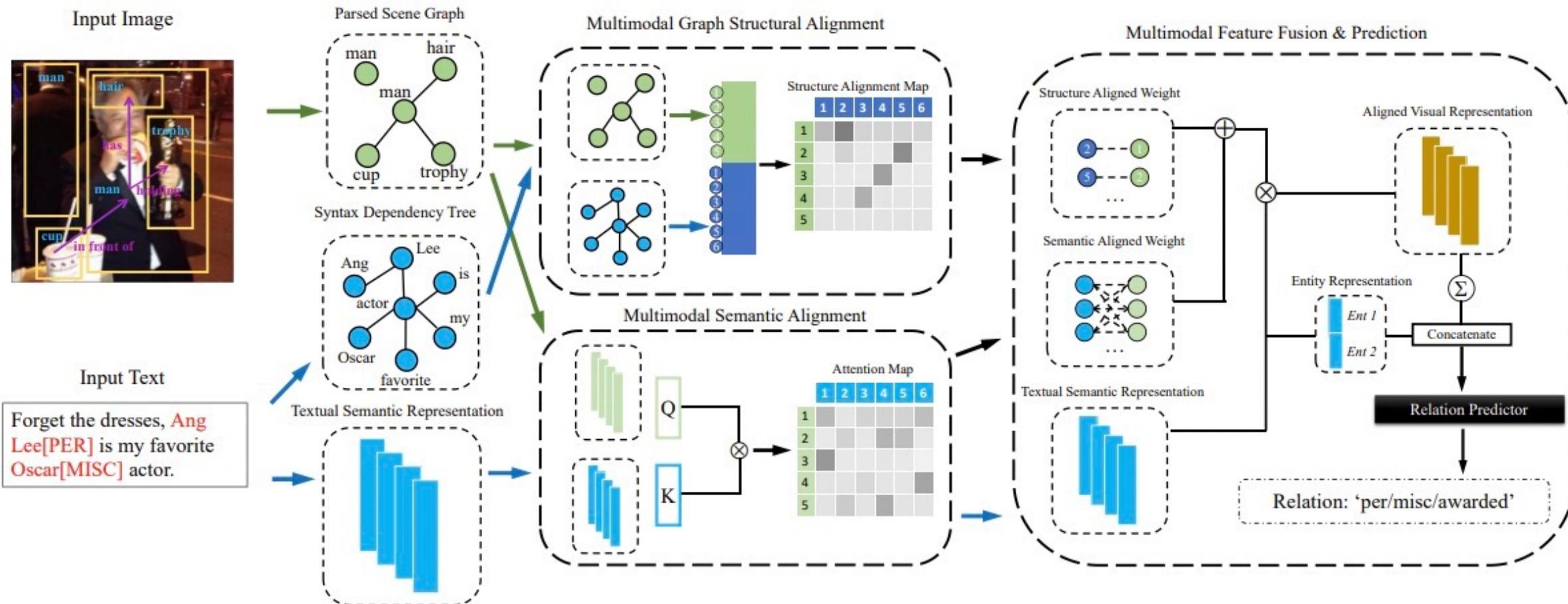
Multimodal KG Construction: MNER

Stack multiple graph-based multi-modal fusion layers that iteratively perform semantic interactions to learn node representations



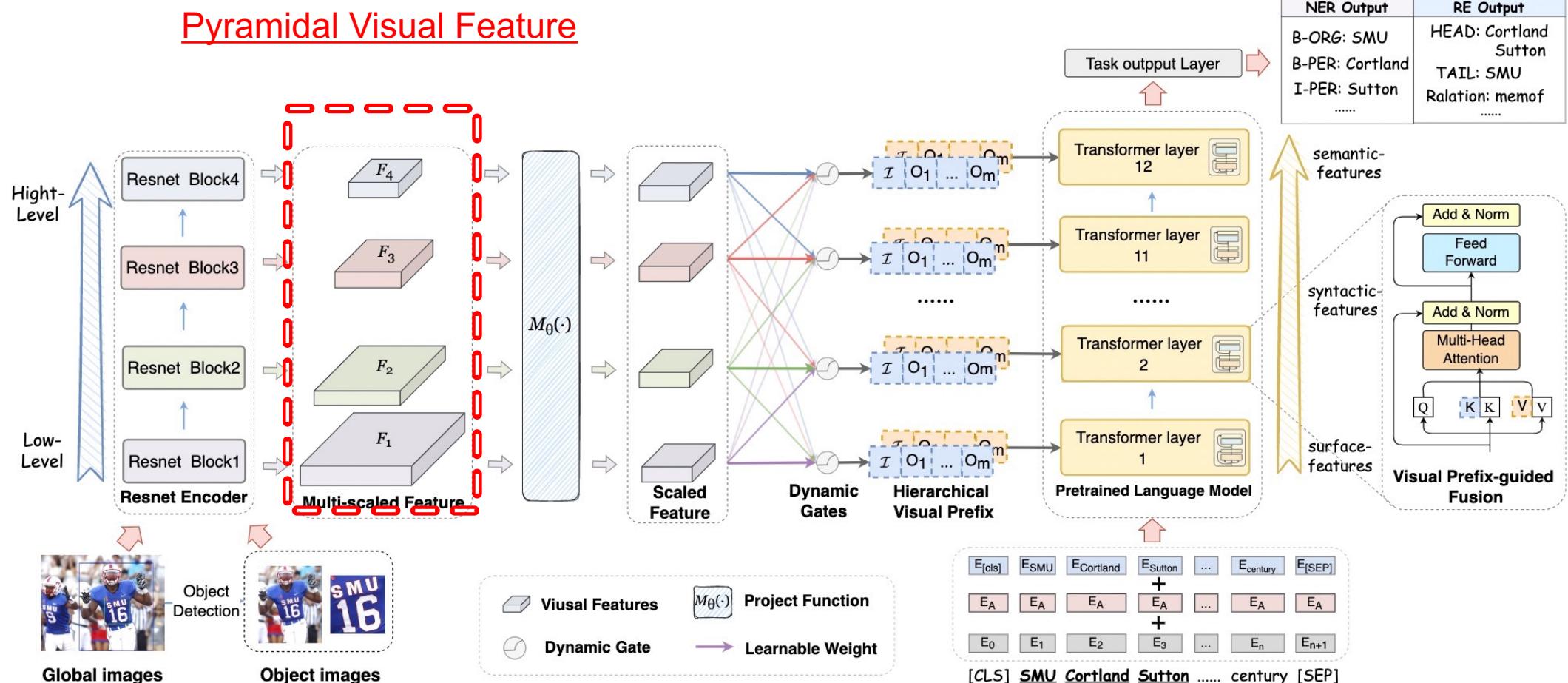
Multimodal KG Construction: MRE

Dual graph alignment method to capture this correlation for better performance



Multimodal KG Construction: MNER and MRE

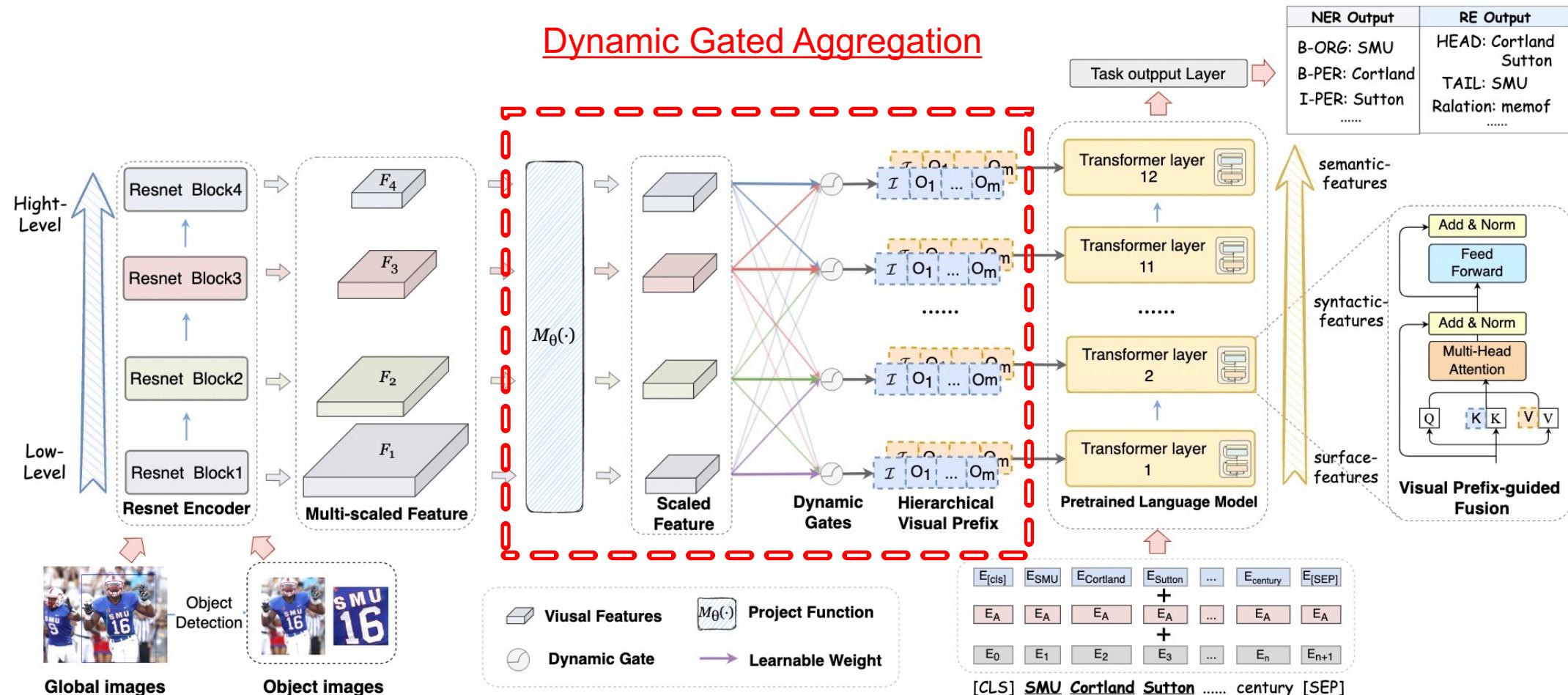
Hierarchical visual prefix fusion network



Good Visual Guidance Makes A Better Extractor:
Hierarchical Visual Prefix for Multimodal Entity and Relation Extraction (NAACL 2022 Findings)

Multimodal KG Construction: MNER and MRE

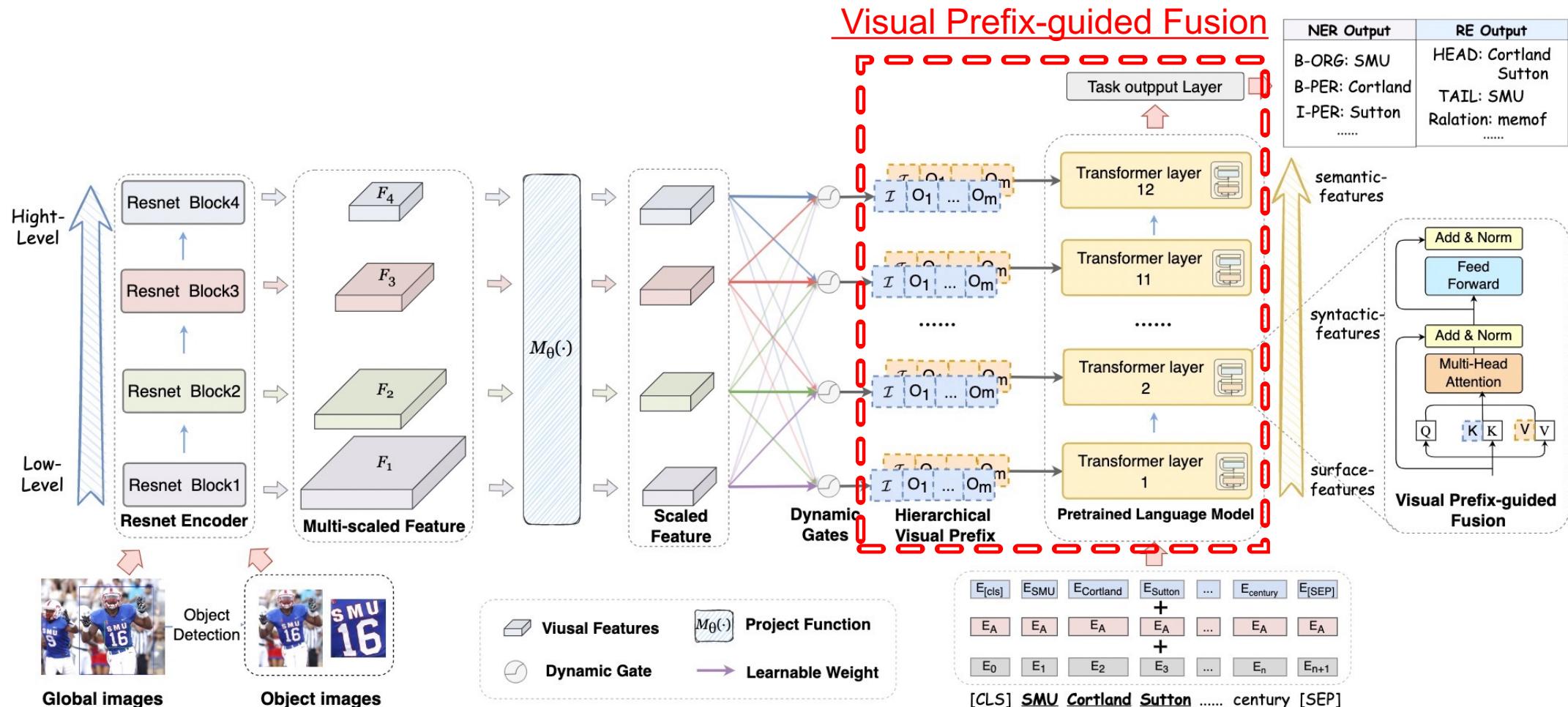
Hierarchical visual prefix fusion network



Good Visual Guidance Makes A Better Extractor:
Hierarchical Visual Prefix for Multimodal Entity and Relation Extraction (NAACL 2022 Findings)

Multimodal KG Construction: MNER and MRE

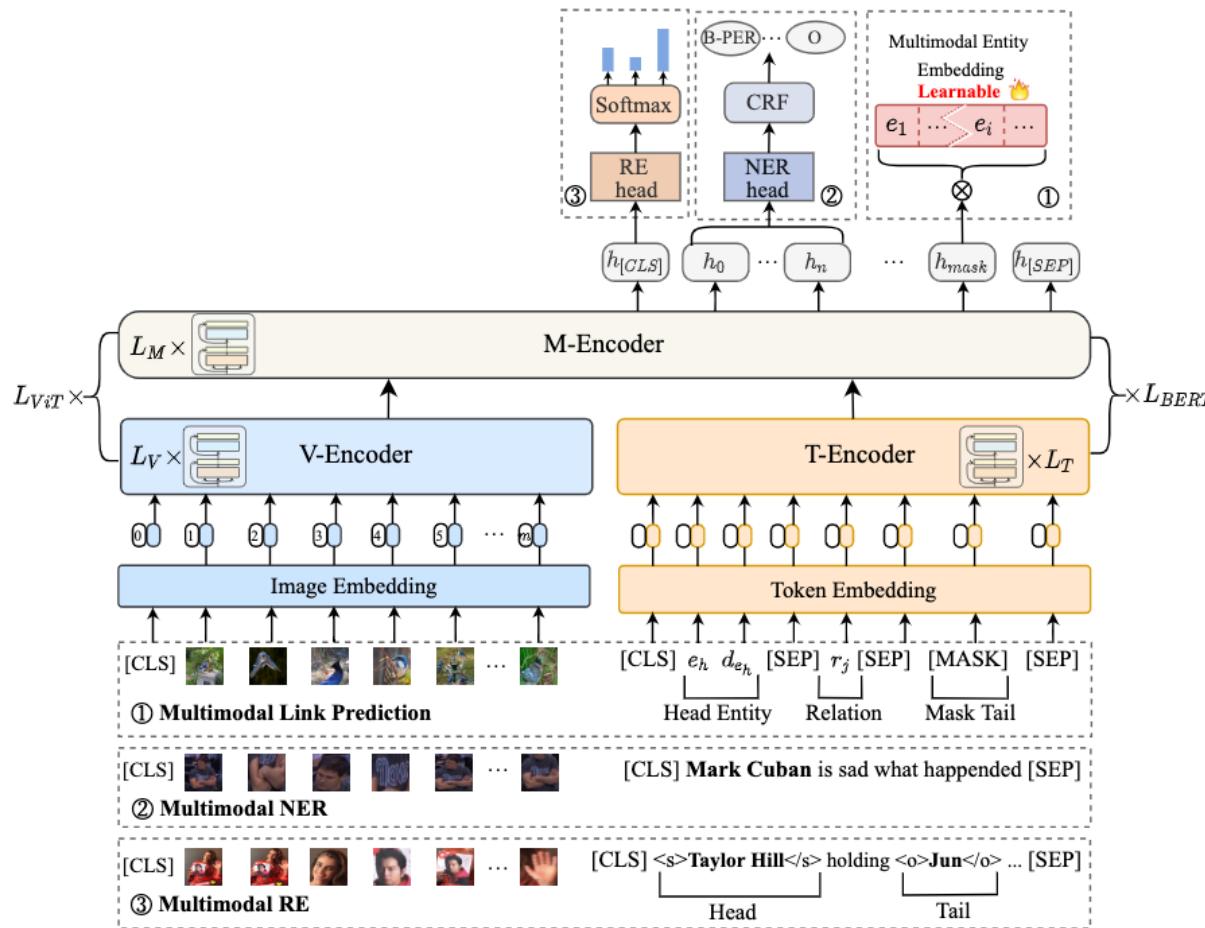
Hierarchical visual prefix fusion network



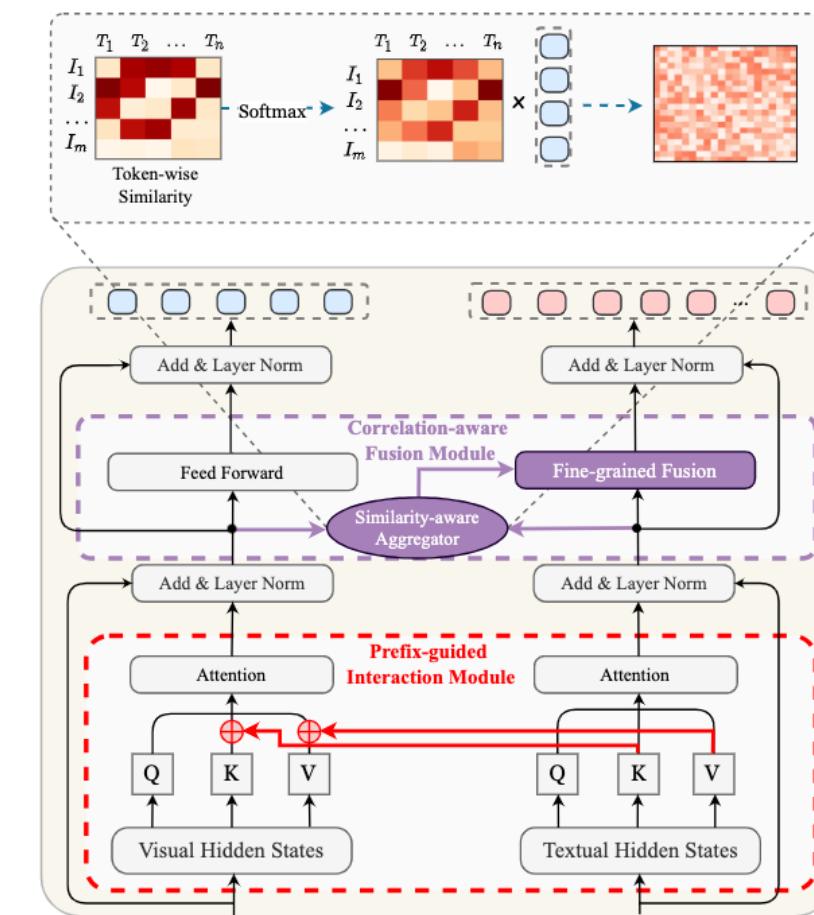
Good Visual Guidance Makes A Better Extractor:
Hierarchical Visual Prefix for Multimodal Entity and Relation Extraction (NAACL 2022 Findings)

Multimodal KG Construction: MNER and MRE

MKGformer, a hybrid transformer for unified multimodal knowledge discovery



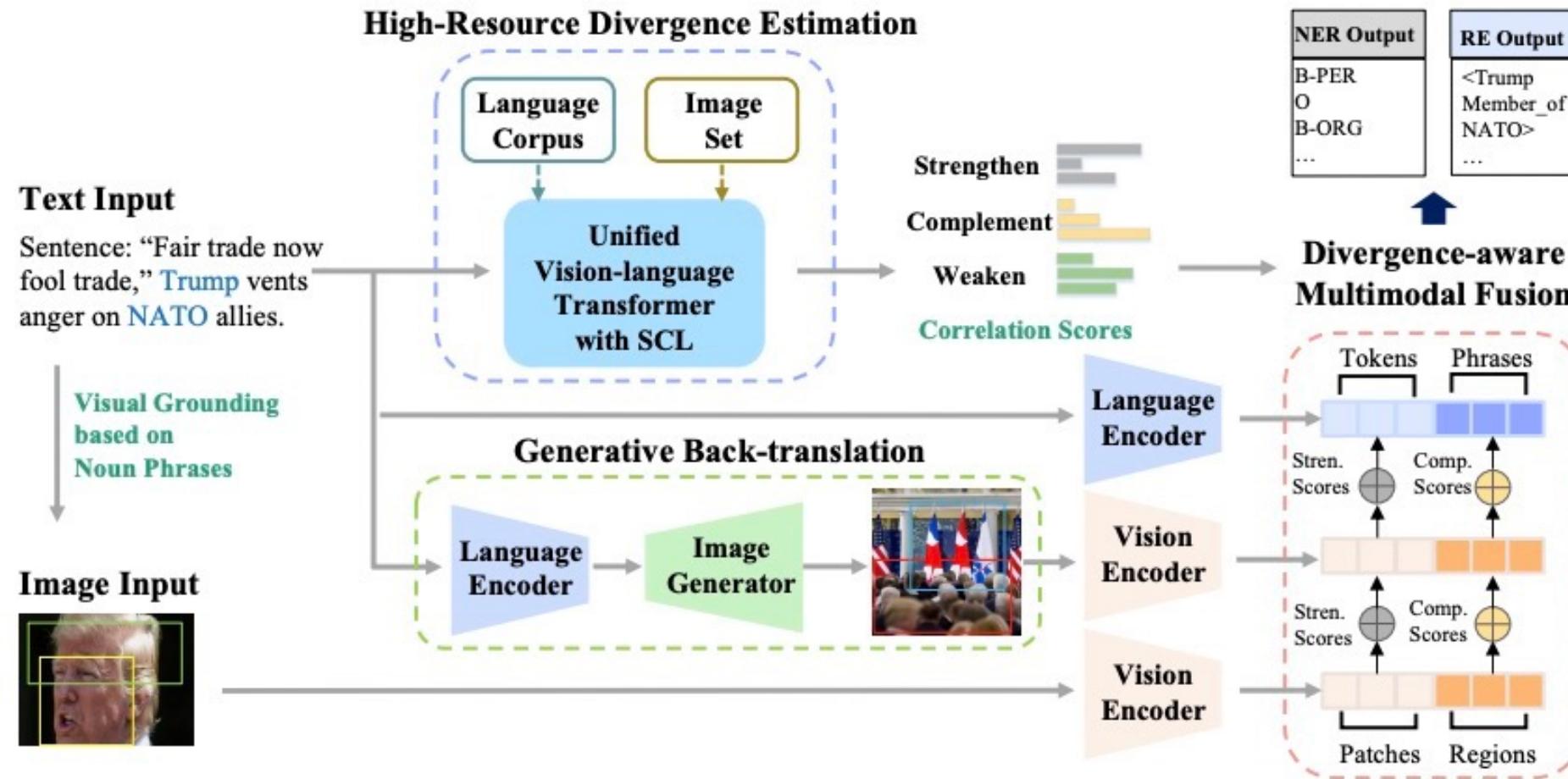
(a) Unified Multimodal KGC Framework.



(b) Detailed M-Encoder.

Multimodal KG Construction: MNER and MRE

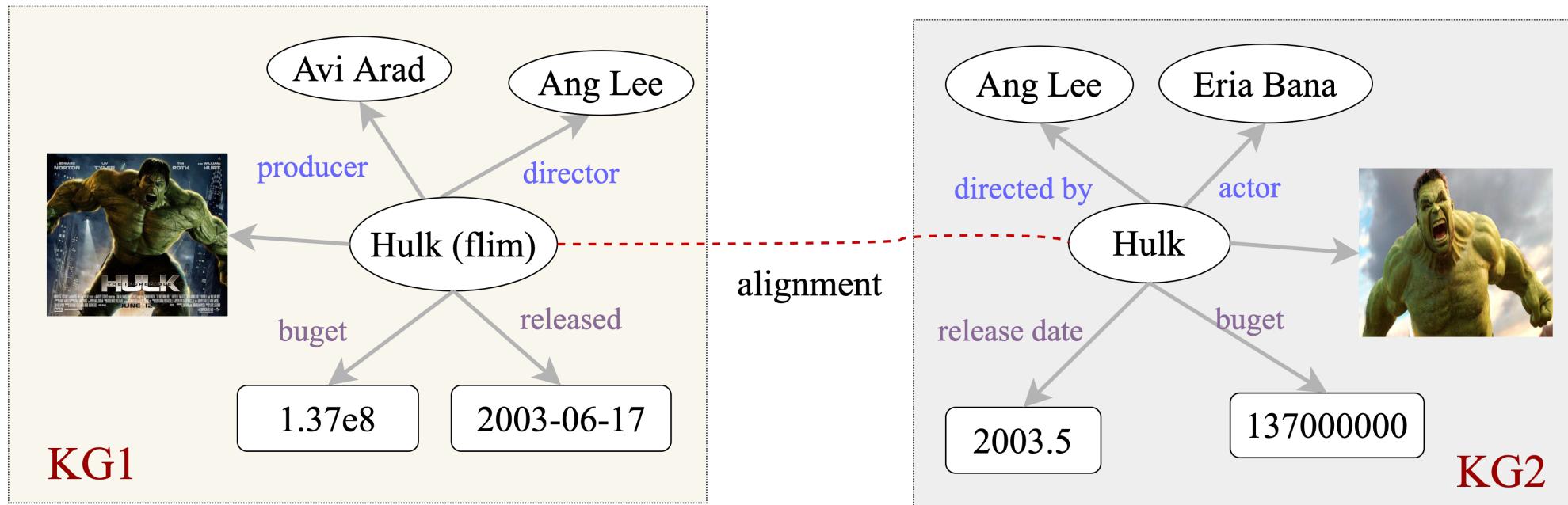
Motivated by the fact that the cross-modal misalignment is a similar problem of cross-lingual divergence issue in machine translation



Multimodal KG Construction: MMEA

Motivation: Multi-modal KGs usually contain images as the visual modality, like profile photos, or posters. Most KG are usually incomplete and often complementary to each other. Integrating multiple KGs into a unified one can enlarge the knowledge coverage.

Task: **Multi-modal entity alignment (MMEA)** aims to identify equivalent entities between two different multi-modal knowledge graphs, which consist of structural triples and images associated with entities.

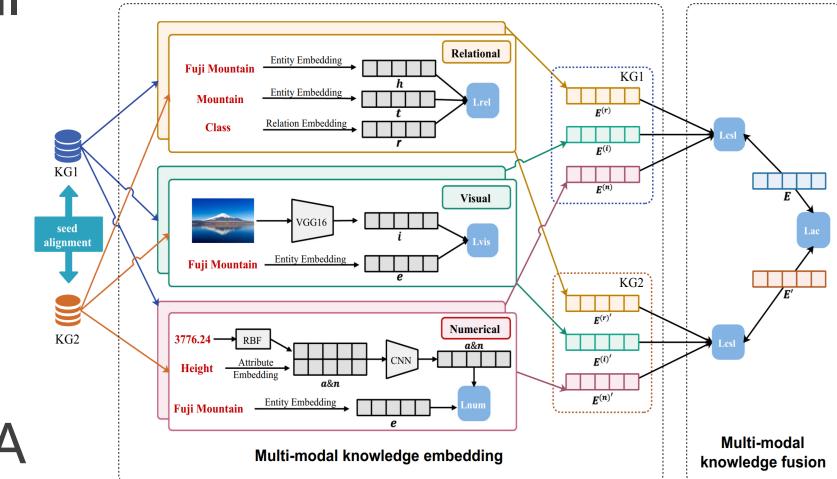


An example mapping of MMEA

Multimodal KG Construction: MMEA

Existing Models:

- **structure-based methods** that solely rely on structural information for aligning entities, e.g., BootEA, AliNet.
- **auxiliary-enhanced methods** that utilize auxiliary information (such as attributes, descriptions) to improve the performance, e.g., MultiKE, HMAN, BERT-INT.
- **multi-modal methods** that combine the multi-modal features to generate entity representations, e.g., MMEA, HMEA, EVA.



Gaps

- These methods focus on how to utilize and encode information from different modalities (views), **while it is not trivial to leverage multi-modal knowledge in entity alignment because of the modality heterogeneity**.
- These methods mainly utilize multi-modal representations to enhance the contextual embedding of entities, nevertheless, **customized entity representations for EA and inter-modal interactions are often neglected in modeling**.

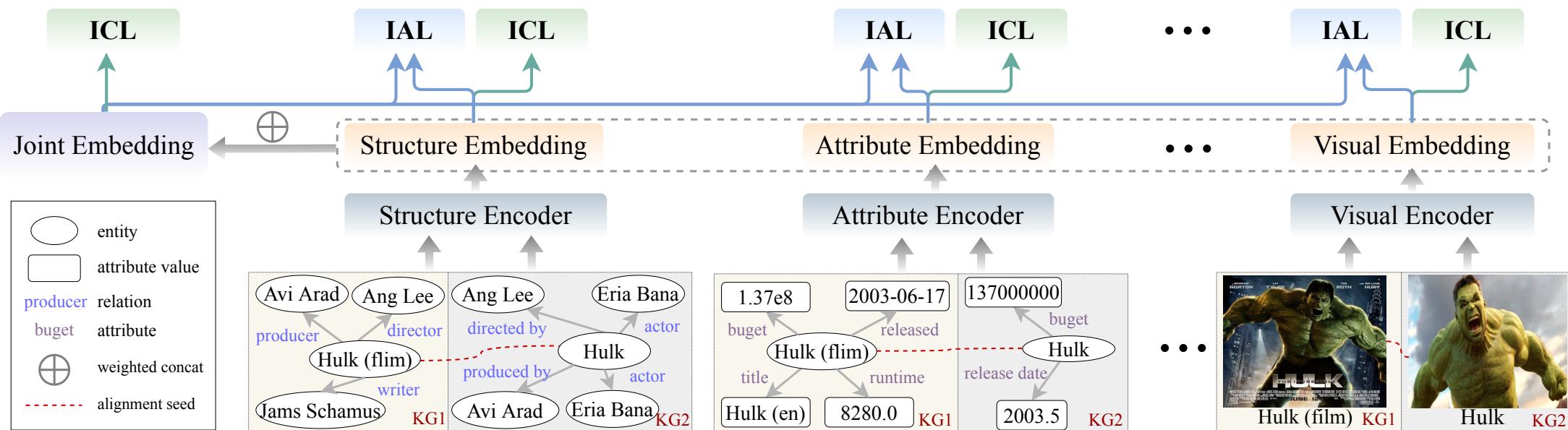
Multimodal KG Construction: MMEA

MCLEA, a **Multi-modal Contrastive Learning based Entity Alignment** model, which effectively integrates multi-modal information into joint representations for EA.

The proposed MCLEA consists of

➤ **Multi-Modal Embeddings**: learns modality-specific representations for each entity.

➤ **Contrastive Representation Learning**: jointly model intra-modal and inter-modal interactions.



ICL: Intra-modal Contrastive Loss, **IAL:** Inter-modal Alignment Loss

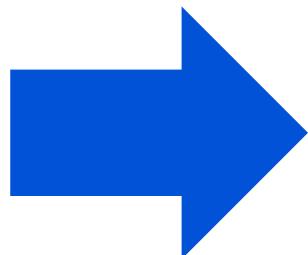
Multi-modal Contrastive Representation Learning for Entity Alignment. COLING 2022

Multimodal KG Construction: MMEA

different ratio seeds

Supervised setting on FB15K-DB15K/YAGO15K

MCLEA is basically superior to the previous **multi-modal methods** under different ratio of seeds, especially with only 20% training seeds

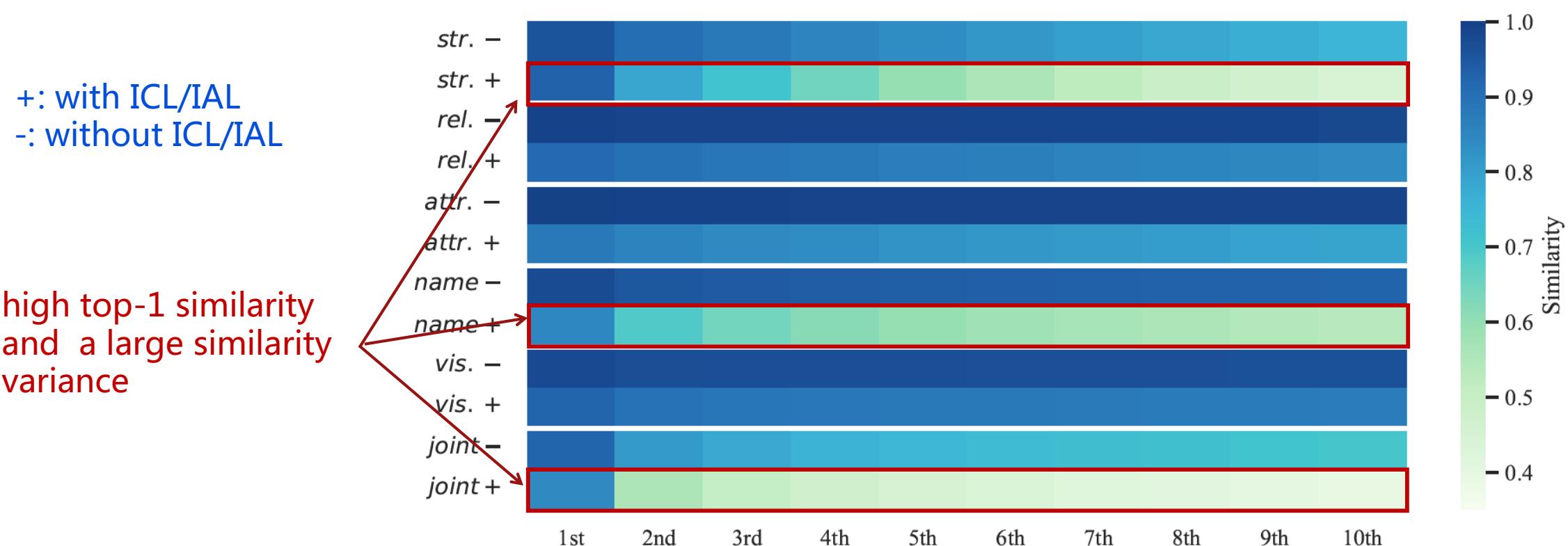


	Models	FB15K-DB15K			FB15K-YAGO15K		
		H@1	H@10	MRR	H@1	H@10	MRR
20%	PoE	.126	.251	.170	.113	.229	.154
	HMEA	.127	.369	—	.105	.313	—
	MMEA	<u>.265</u>	<u>.541</u>	<u>.357</u>	<u>.234</u>	<u>.480</u>	<u>.317</u>
	EVA*	.134	.338	.201	.098	.276	.158
	MCLEA (Ours)	.445	.705	.534	.388	.641	.474
50%	Improv. best %	67.9	30.3	49.6	65.8	33.5	49.5
	PoE	<u>.464</u>	<u>.658</u>	<u>.533</u>	<u>.347</u>	<u>.536</u>	<u>.414</u>
	HMEA	.262	.581	—	.265	.581	—
	MMEA	<u>.417</u>	<u>.703</u>	<u>.512</u>	<u>.403</u>	<u>.645</u>	<u>.486</u>
	EVA*	.223	.471	.307	.240	.477	.321
80%	MCLEA (Ours)	.573	.800	.652	.543	.759	.616
	Improv. best %	23.5	13.8	22.3	34.7	17.7	26.7
	PoE	<u>.666</u>	<u>.820</u>	<u>.721</u>	<u>.573</u>	<u>.746</u>	<u>.635</u>
	HMEA	<u>.417</u>	<u>.786</u>	—	.433	.801	—
	MMEA	<u>.590</u>	<u>.869</u>	<u>.685</u>	<u>.598</u>	<u>.839</u>	<u>.682</u>
	EVA*	.370	.585	.444	.394	.613	.471
	MCLEA (Ours)	.730	.883	.784	.653	.835	.715
	Improv. best %	9.6	1.6	8.7	9.2	-0.4	4.8

Multimodal KG Construction: MMEA

Similarity Distribution of Representations

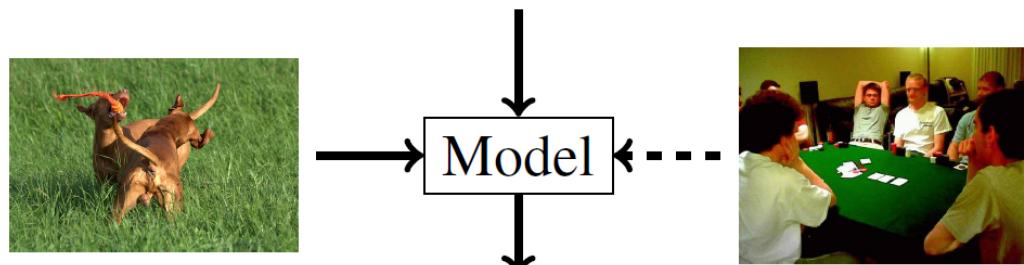
- It shows that contrastive learning (ICL and IAL) enable **more discriminative** entity learning in the joint representations.



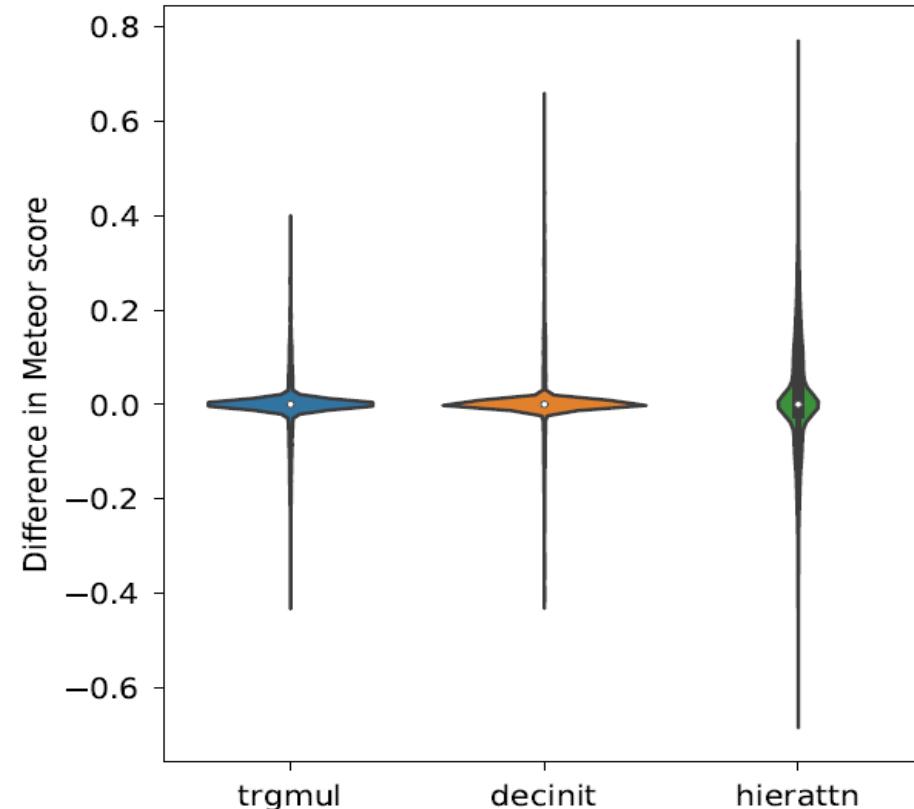
Similarity visualization of representations of test entities and their top-10 predicted counterparts

Is the multi-modal really helpful?

Two dogs play with an orange toy in tall grass.



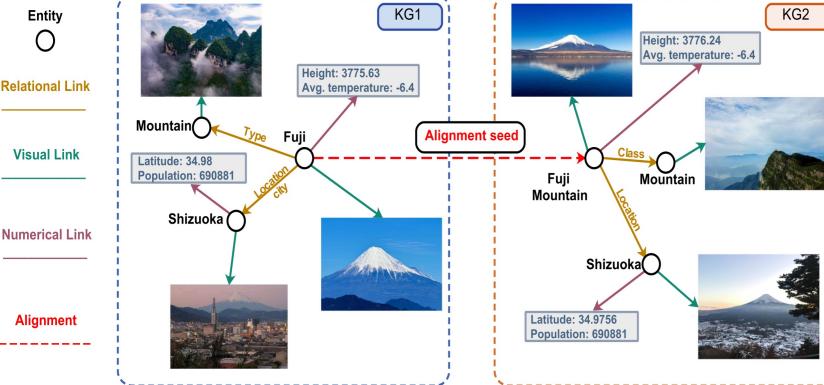
Zwei Hunde spielen im hohen Gras mit einem orangen Spielzeug.



Only needed for incorrect, ambiguous, and gender-neutral words

Adversarial Evaluation of Multimodal Machine Translation. EMNLP 2018

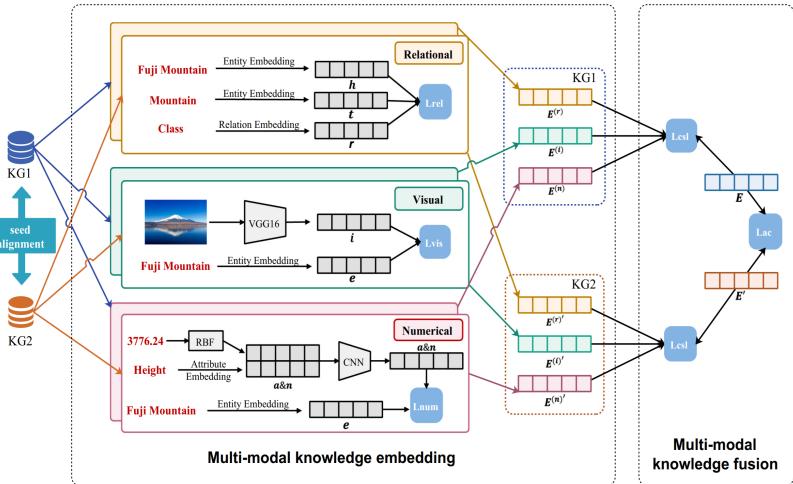
Is the multi-modal really helpful?



Datasets:
MMKG FB15K-DB15K and
FB15K-YAGO15K

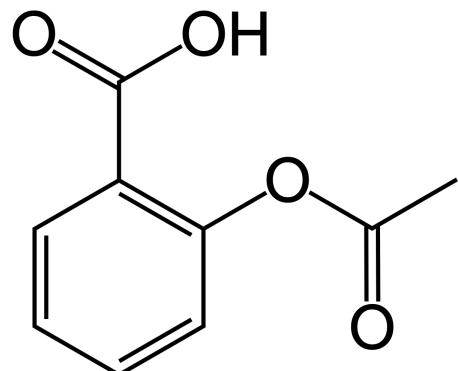
$$\mathcal{L} = - \sum_{t \in T} \log p(t \mid \theta_1, \dots, \theta_n).$$

Liu, Ye, et al. “MMKG: multi-modal knowledge graphs.” *European Semantic Web Conference (ESWC 2019)*.



$$L_{csl}(\mathbf{E}, \mathbf{E}^{(r)}, \mathbf{E}^{(i)}, \mathbf{E}^{(n)}) = \alpha_1 \|\mathbf{E} - \mathbf{E}^{(r)}\|_2^2 + \alpha_2 \|\mathbf{E} - \mathbf{E}^{(i)}\|_2^2 + \alpha_3 \|\mathbf{E} - \mathbf{E}^{(n)}\|_2^2,$$

Chen, Liyi, et al. “MMEA: Entity Alignment for Multi-modal Knowledge Graph.” *International Conference on Knowledge Science, Engineering and Management (KSEM 2020)*. (Best Paper)



Is the multi-modal really helpful?

Issue 1: Visual inconsistency between equivalent entities

Flag of *Oakland_(Californie)*



Skyline of *Oakland,_California*



Logo of *Little_Mix*



Little_Mix at a music festival



From French DBpedia

From English DBpedia

From French DBpedia

From English DBpedia

Issue 2: Incompleteness of visual data

30%-40% of 15k aligned entity pairs in DBP15K lack at least one image.

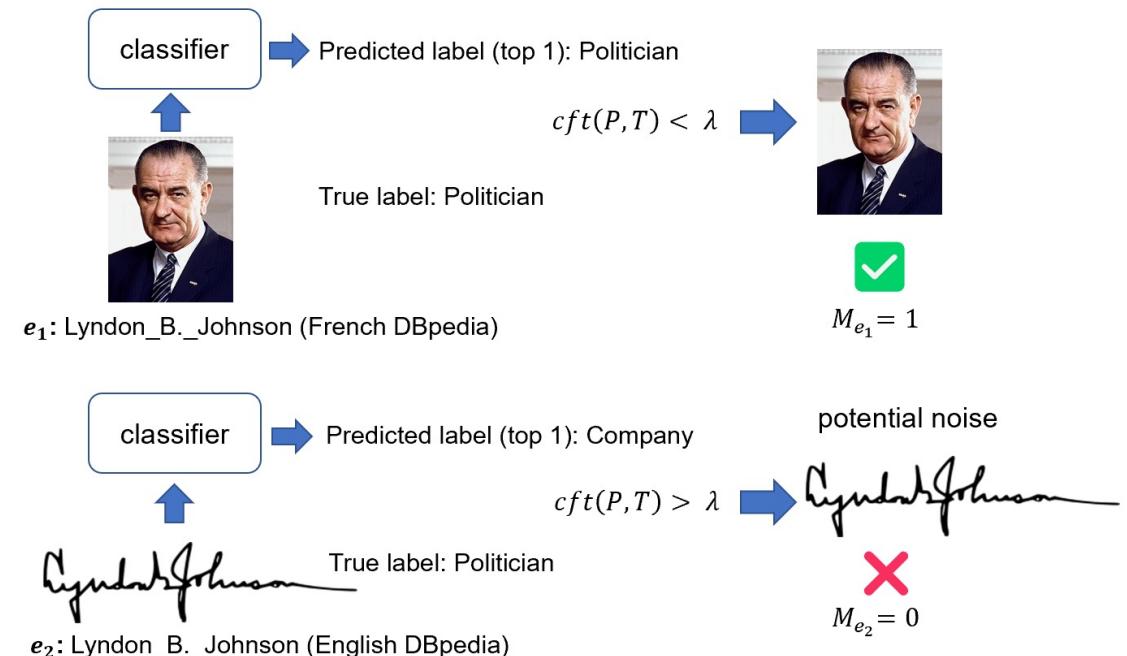
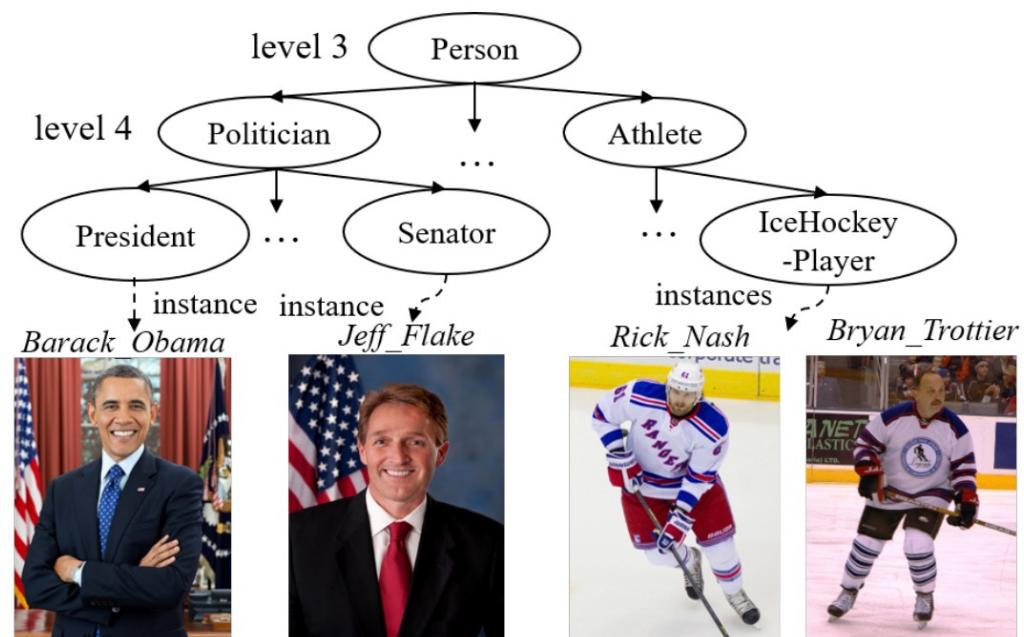
To what extent or under what circumstances is visual context truly helpful to the EA task? Is there a way to filter potential noises and better use entity images?

Probing the Impacts of Visual Context in Multimodal Entity Alignment[J]. Data Science and Engineering, 2023, 8(2): 124-134.

Is the multi-modal really helpful?

Method: Visual noises identification

1. Obtain entity types (classes) and define Inter-class conflicts.
2. Take entity types as the labels of corresponding images, and train classifiers.
3. Identity entity images which the top K predicted labels and their true labels are semantically distant.



Is the multi-modal really helpful?

Entity alignment results on

DBP15K.

Methods	FR-EN			JA-EN			ZH-EN		
	H@1	H@10	MRR	H@1	H@10	MRR	H@1	H@10	MRR
MTransE [4]	0.224	0.556	0.335	0.279	0.575	0.349	0.308	0.614	0.364
IPTransE [27]	0.333	0.685	0.451	0.367	0.693	0.474	0.406	0.735	0.516
JAPE [15]	0.324	0.667	0.430	0.363	0.685	0.476	0.412	0.745	0.490
GCN-Align [21]	0.373	0.745	0.532	0.399	0.745	0.546	0.413	0.744	0.549
SEA [14]	0.400	0.797	0.533	0.385	0.783	0.518	0.424	0.796	0.548
MuGNN [2]	0.495	0.870	0.621	0.501	0.857	0.621	0.494	0.844	0.611
HMAN [23]	0.543	0.867	-	0.565	0.866	-	0.537	0.834	-
AliNet [17]	0.552	0.852	0.657	0.549	0.831	0.645	0.539	0.826	0.628
MultiKE [24]	0.639	0.712	0.665	0.393	0.489	0.426	0.509	0.576	0.532
EVA [12]	<u>0.700</u> ±.005	<u>0.891</u> ±.005	<u>0.768</u> ±.004	<u>0.622</u> ±.004	<u>0.846</u> ±.008	<u>0.701</u> ±.005	<u>0.596</u> ±.007	<u>0.816</u> ±.008	<u>0.674</u> ±.007
SimpleEA	<u>0.504</u> ±.005	<u>0.826</u> ±.004	<u>0.616</u> ±.005	<u>0.505</u> ±.005	<u>0.797</u> ±.006	<u>0.608</u> ±.005	<u>0.479</u> ±.005	<u>0.772</u> ±.007	<u>0.582</u> ±.006
Masked-MMEA (λ_0)	<u>0.661</u> ±.007	<u>0.889</u> ±.004	<u>0.742</u> ±.006	<u>0.602</u> ±.004	<u>0.852</u> ±.006	<u>0.692</u> ±.004	<u>0.582</u> ±.006	<u>0.827</u> ±.008	<u>0.670</u> ±.007
Masked-MMEA (λ_1)	0.712 ±.005	0.901 ±.003	0.779 ±.004	0.627 ±.005	0.858 ±.005	0.711 ±.004	0.612 ±.006	0.837 ±.006	0.693 ±.005

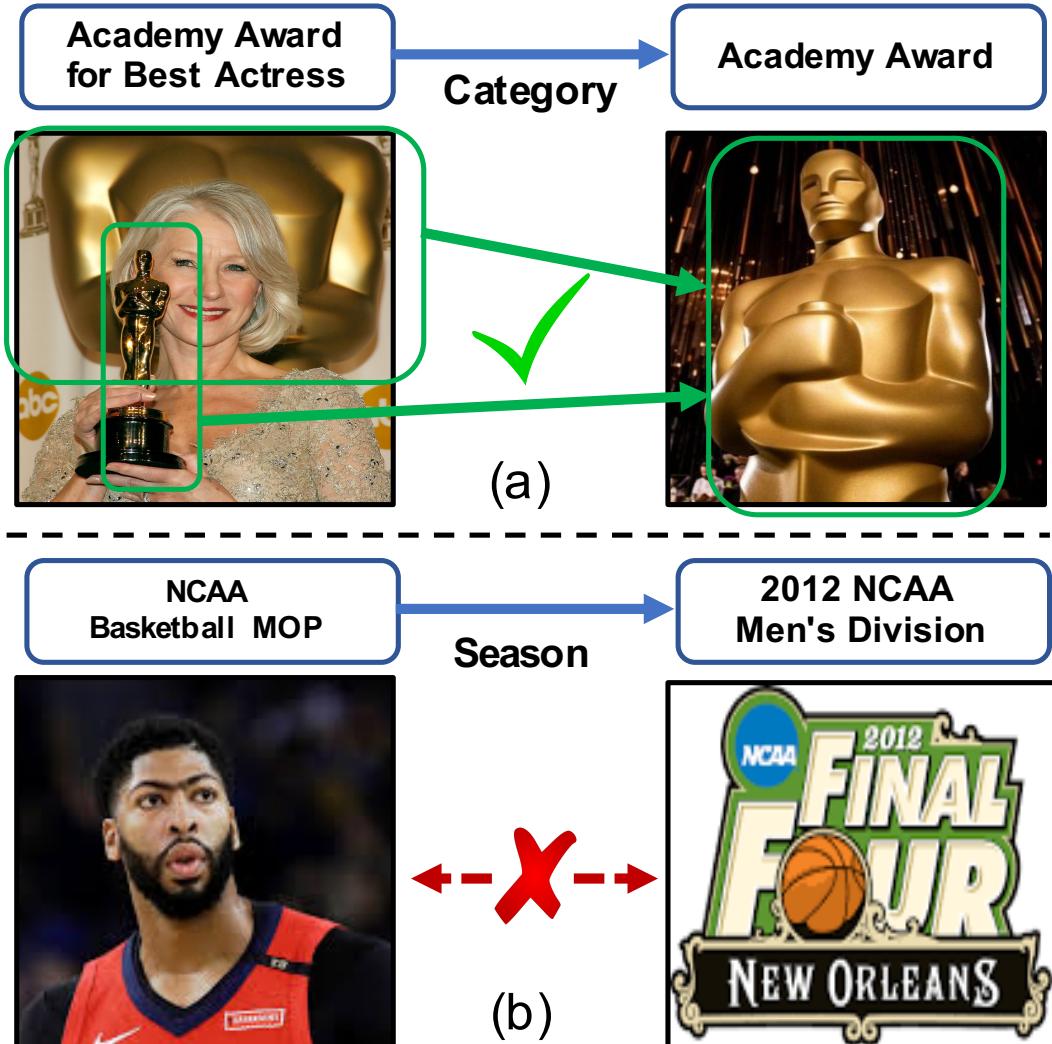
SimpleEA:
using only structural information

Masked-MMEA:
structural similarities + visual similarities

* The results of EVA are reproduced by only utilizing structural and visual context, as the setting of Masked-MMEA.

Probing the Impacts of Visual Context in Multimodal Entity Alignment[J]. Data Science and Engineering, 2023, 8(2): 124-134.

Is the multi-modal really helpful?



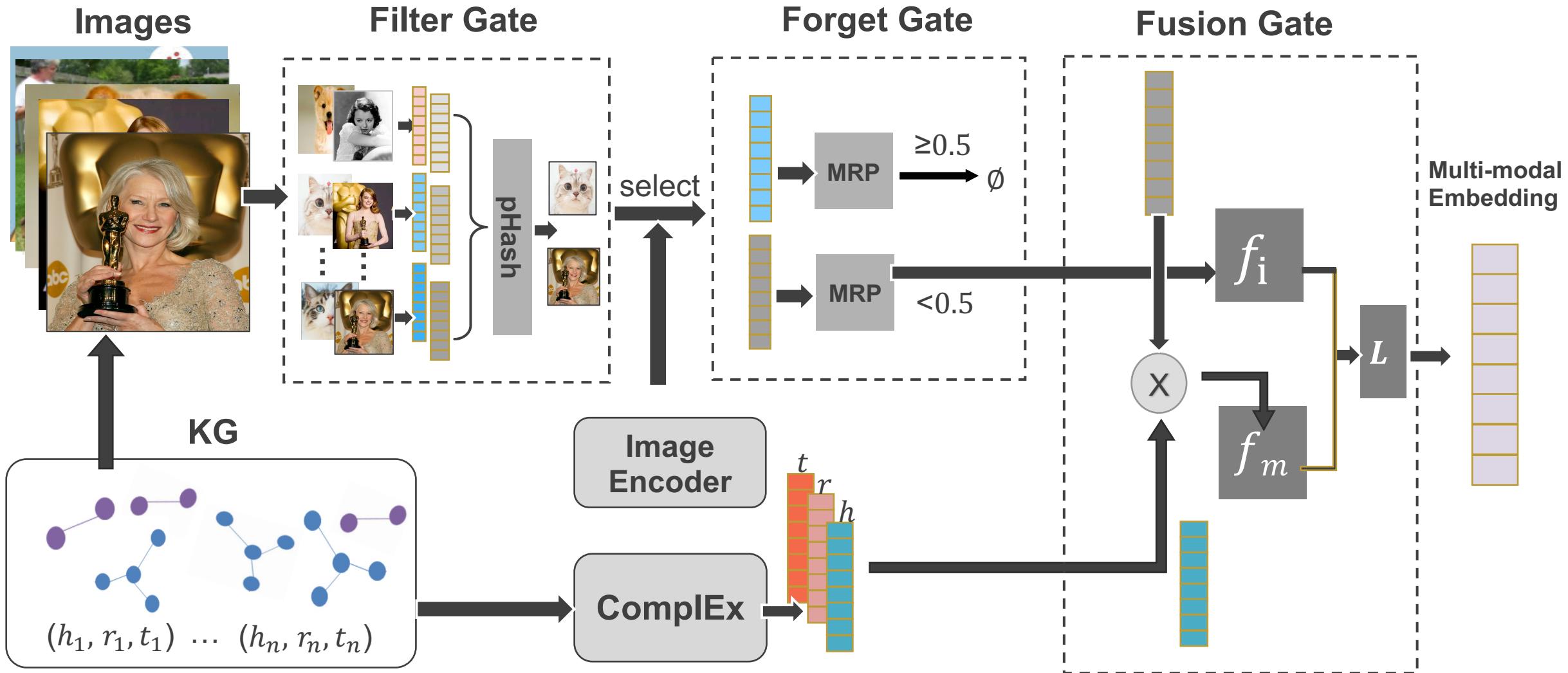
- What extent the visual context can improve the quality of knowledge graph tasks over unimodal models?

We argue that visual information is not always useful.

*maybe, the key is “**Relation**”*

- We also intend to probe the effect of different **visual feature encoders**.

Is the multi-modal really helpful?



Is the multi-modal really helpful?

Models	FB15K-IMG			
	MR	Hits@1	Hits@3	Hits@10
TransE [4]	-	0.247	0.534	0.688
DisMult [33]	-	0.218	0.404	0.582
ComplEx [27]	-	0.599	0.759	0.840
RotatE [26]	43	0.750	0.829	0.884
TorusE [7]	-	0.674	0.771	0.832
TransAE [30]	53	-	-	64.50
RSME(No Img)	37.18	0.724	0.824	0.885
RSME(VIT)	35.76	0.794	0.867	0.908
RSME(VIT+Forget)	25.48	0.802	0.881	0.924

Number of Triples	Image Effective Rate
0-50	0.715
50-100	0.794
100-500	0.802
500-1000	0.839
1000-2000	0.906

WN18-IMG-S		FB15K-IMG-S	
relationship	MPR	relationship	MPR
_hyponym	0.094	active_moiety	0.000
_hypernym	0.132	tennis_winner	0.000
_has_part	0.100	dog_breed/color	0.158
_part_of	0.117	river/mouth	0.280
_member_holonym	0.048	cause_of_death	0.557
_synset_domain_topic_of	0.146	religion	0.593
_derivationally_related_form	0.138	category	0.605
_member_of_domain_topic	0.084	judge	0.805
_member_meronym	0.076	country_of_origin	0.852
average MPR	0.104	average MPR	0.386

Is the multi-modal really helpful?

Results on real-world dataset

Model	Hits@1 ↑	Hits@3 ↑	Hits@10 ↑	MR ↓	MRR ↑
<i>Unimodal approach</i>					
TransE (Bordes et al., 2013)	0.150	0.387	0.647	118	0.315
TransH (Wang et al., 2014)	0.129	0.525	0.743	112	0.357
TransD (Ji et al., 2015)	0.137	0.532	0.746	110	0.364
DistMult (Yang et al., 2015)	0.060	0.157	0.279	524	0.139
ComplEx (Trouillon et al., 2016)	0.143	0.244	0.371	782	0.221
TuckER (Balazevic et al., 2019)	0.497	0.690	0.820	1473	0.611
KG-BERT (Yao et al., 2019)	0.092	0.207	0.405	61	0.194
StAR (Wang et al., 2021a)	0.176	0.307	0.493	79	0.280
<i>Multimodal approach</i>					
TransAE (Wang et al., 2019)	0.274	0.489	0.715	36	0.421
RSME (Wang et al., 2021b)	0.485	0.687	0.838	72	0.607
MKGformer (Chen et al., 2022)	0.448	0.651	0.822	23	0.575

Table 3: Results of the link prediction on OpenBG-IMG. The bold numbers denote the best results.

Dataset	# Ent	# Rel	# Train	# Dev	# Test
OpenBG-IMG	27,910 [†]	136	230,087	5,000	14,675
OpenBG500	249,743	500	1,242,550	5,000	5,000
OpenBG500-L	2,782,223	500	47,410,032	10,000	10,000
OpenBG (Full)	88,881,723	2,681	260,304,683	-	-
Wikidata5M	4,594,485	822	20,614,279	5,163	5,133
OGB-LSC	91,230,610	1,387	608,062,811	15,000	10,000

Table 2: Summary statistics of OpenBG datasets. [†]: there are 14,718 multi-modal entities in OpenBG-IMG. OpenBG (Full) do not have a train/dev/test split. OGB-LSC refers to the WikiKG90Mv2 in OGB-LSC.

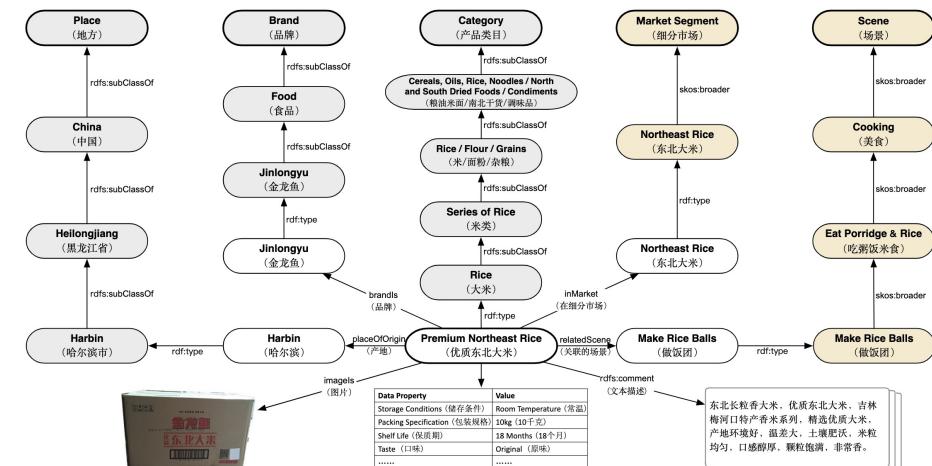
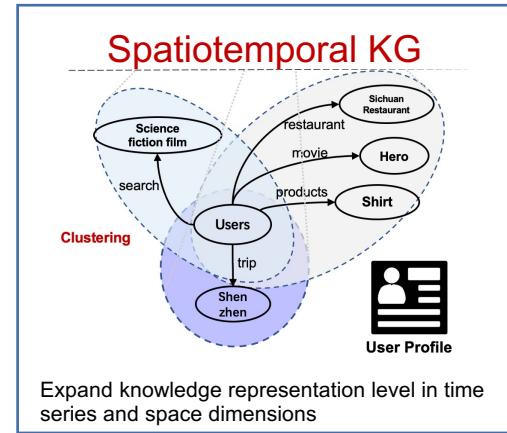
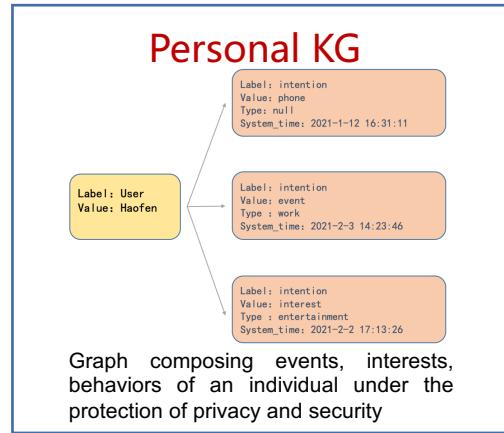
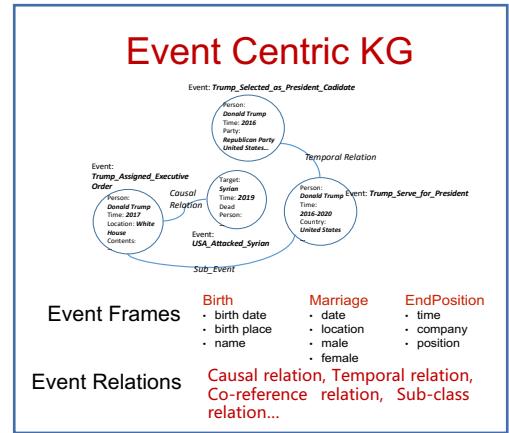
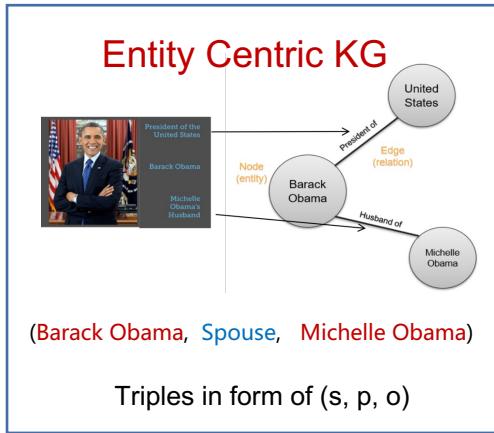
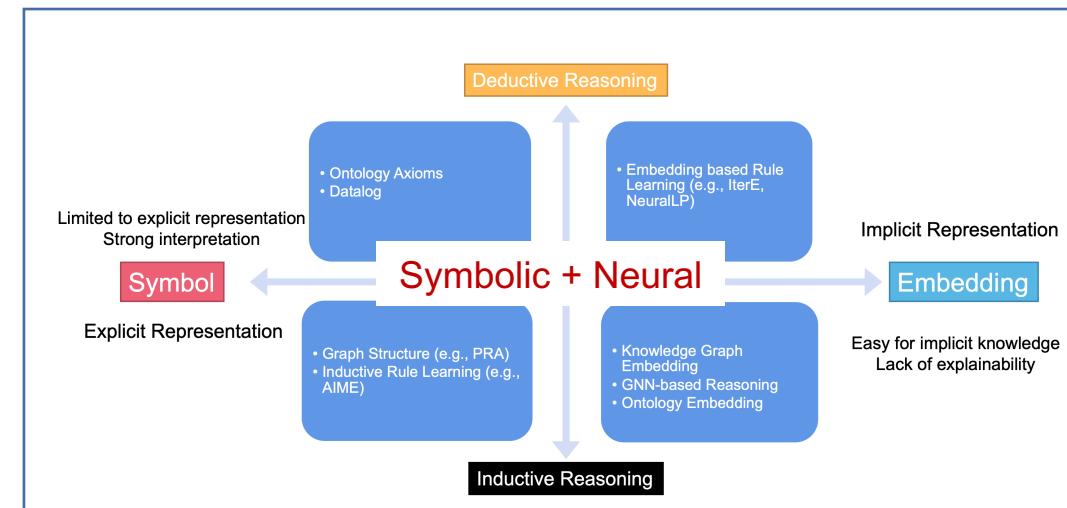
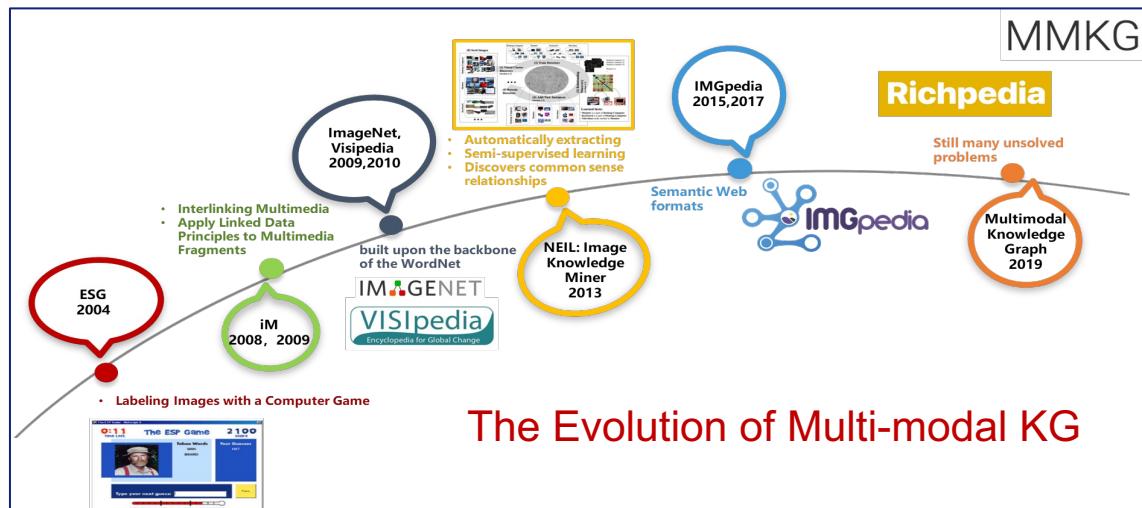


Figure 4: A snapshot of OpenBG.

Future “Multi-modal Opportunities”



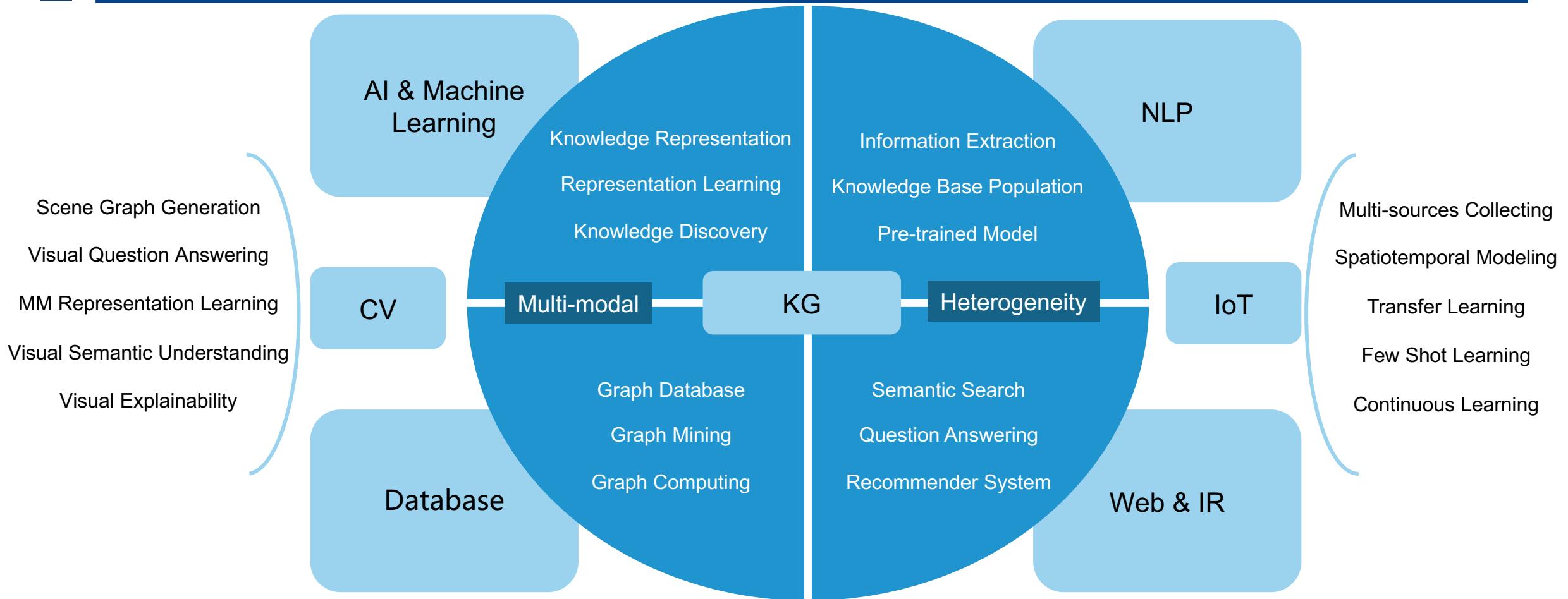
Knowledge types: simple -> complex, static -> dynamic, community -> personal, plain -> spatiotemporal



Challenges

Traditional symbolic knowledge representation methods are difficult to accurately represent complex knowledge such as **dynamics**, **processes**, and **cross-modalities**. At the same time, how to **combine symbolic reasoning** methods based on knowledge graphs and **neural reasoning** methods is extremely challenging.

Future “Multi-modal Opportunities”



The life cycle of KG construction: more types/sources, advanced techs, rapid updates, and widely used applications

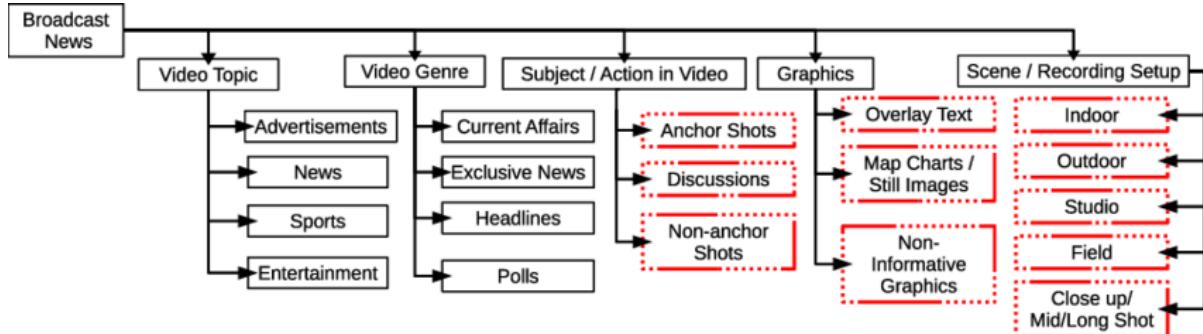
101

Challenges

The multi-scale, multi-modal, and multi-disciplinary characteristics of data have put forward new requirements for knowledge representation, collection, extraction, storage, computing, and application. Among them, it is necessary to overcome few shots, explainability, and domain adaptation issues. How to realize knowledge update at a low cost is also extremely challenging.

Future “Multi-modal Opportunities”: Representation

LSCOM



Large-Scale Concept Ontology for Multimedia , *IEEE Multimedia Magazine*, 13(3), 2006.

COMM

```

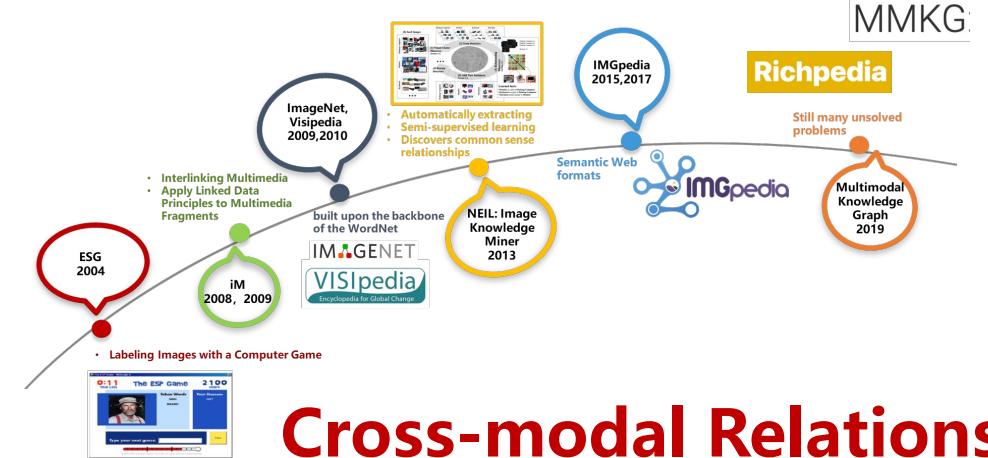
<?xml version="1.0" encoding="UTF-8"?>
<!DOCTYPE xmp>
<xmp>
  <Description xsi:type="ContentEntityType">
    <MultimediaContent xsi:type="ImageType">
      <Image id="IM01">
        <SpatialDecomposition>
          <StillRegion id="SR1">
            <Semantic>
              <Label><Name> Roosevelt </Name></Label>
            </Semantic>
          </StillRegion>
          <StillRegion id="SR2">
            <TextAnnotation> <!-- TextAnnotationType -->
              <KeywordAnnotation><Keyword> Churchill </Keyword></KeywordAnnotation>
            </TextAnnotation>
          </StillRegion>
          <StillRegion id="SR3">
            <Semantic>
              <Definition> <!-- Also TextAnnotationType -->
                <StructuredAnnotation><Who><Name> Stalin </Name></Who></StructuredAnnotation>
              </Definition>
            </Semantic>
          </StillRegion>
        ...
      </MultimediaContent>
    </Description>
  </xmp>

```



B

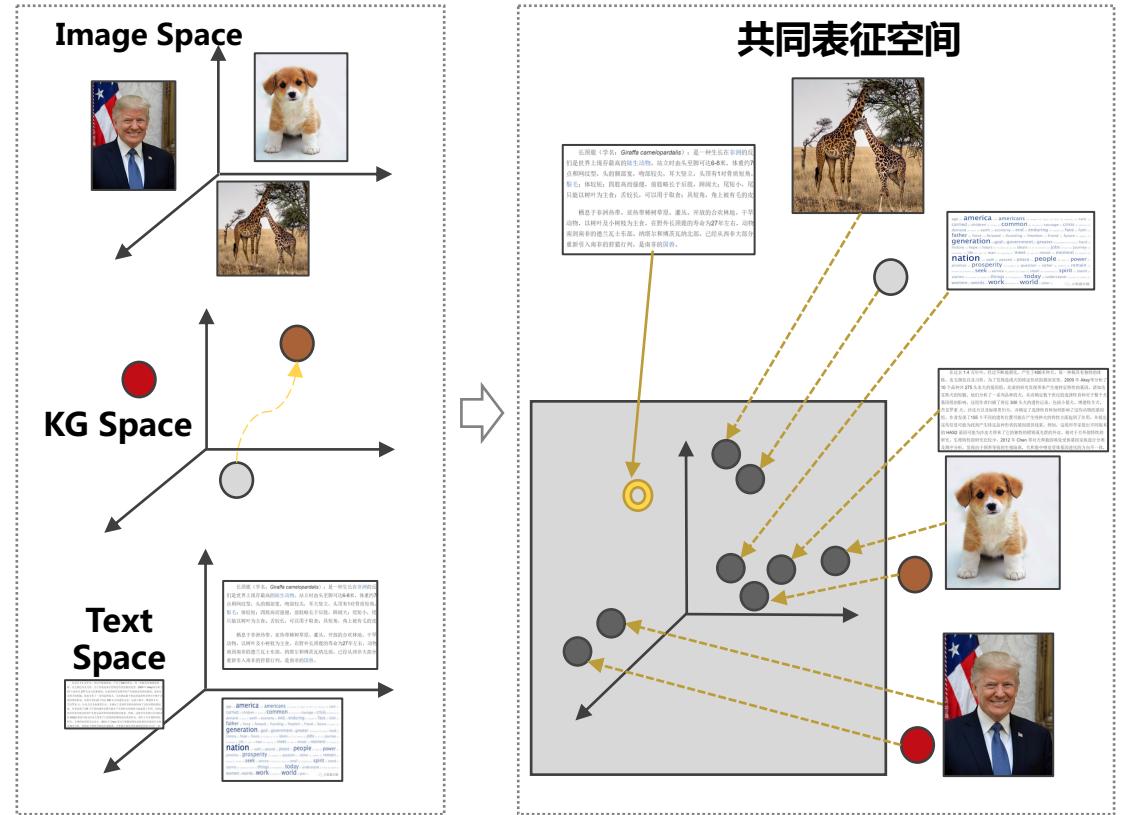
COMM: A core ontology for multimedia annotation, *Handbook on Ontologies*, 2009



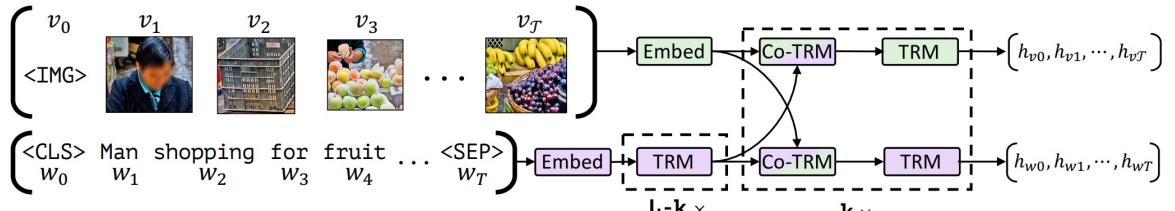
Cross-modal Relations

Data	Types	Cross-modal relations	Domain
DBpedia	Text, Images	✓	Open domain
Wikidata	Text, Images	✓	Open domain
IMGpedia	Text, Images	✓	Open domain
MMKG	Text, Image	✓	Open domain
KgBench	Text, Images	✓	Open domain
Richpedia	Text, Images	✓	Open domain
Knowledge Forest	Text, Images, Video	✓	Education
Baidu KG	Text, Images, Video	✓	Open domain

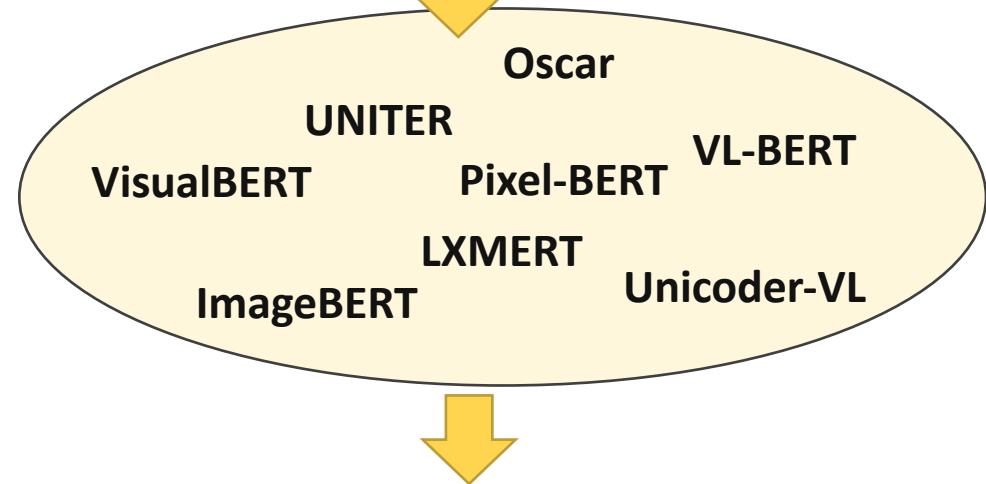
Future “Multi-modal Opportunities”: Representation



Multimodal machine learning: A survey and taxonomy.
IEEE transactions on pattern analysis and machine
intelligence 41.2 (2018): 423-443.



ViLBERT, NeurIPS 2019

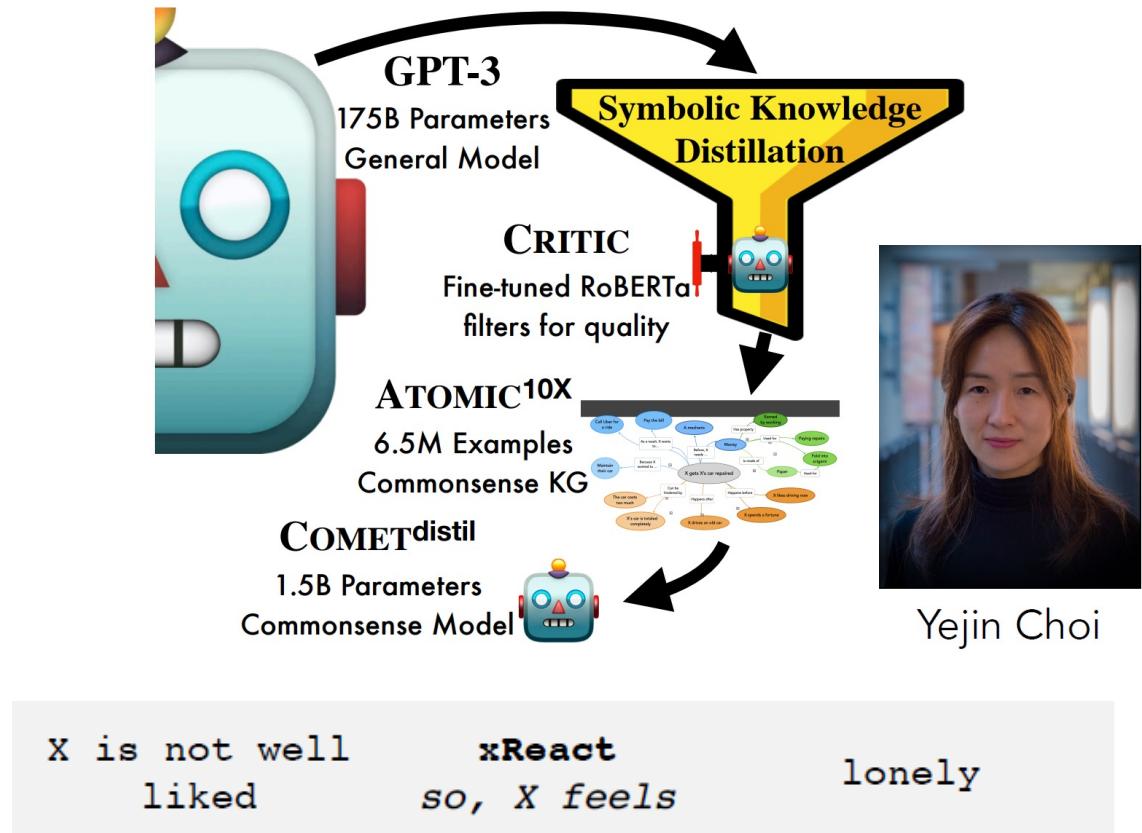


Contrastive Learning

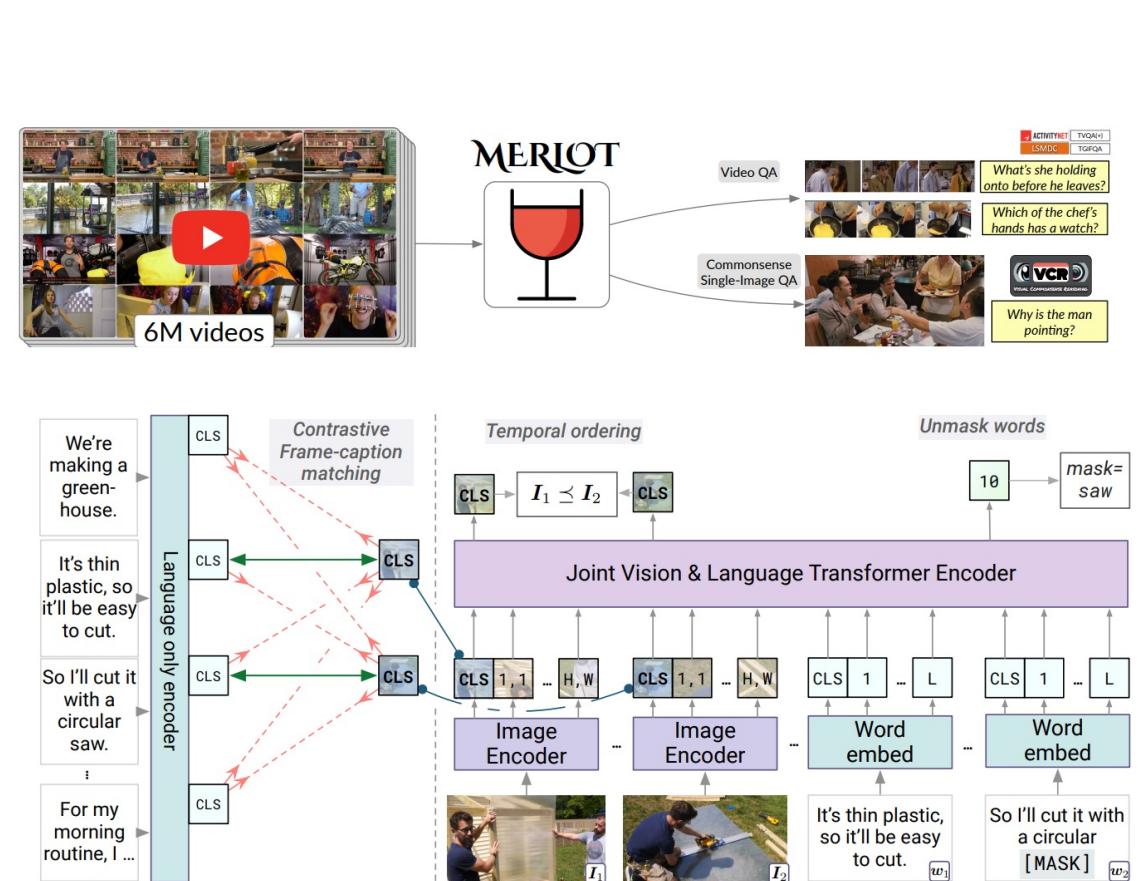
Efficiency Fine-grained Prompt

Few-shot Effect Analysis

Future “Multi-modal Opportunities”: Commonsense Reasoning



Symbolic Knowledge Distillation: from General Language Models to Commonsense Models



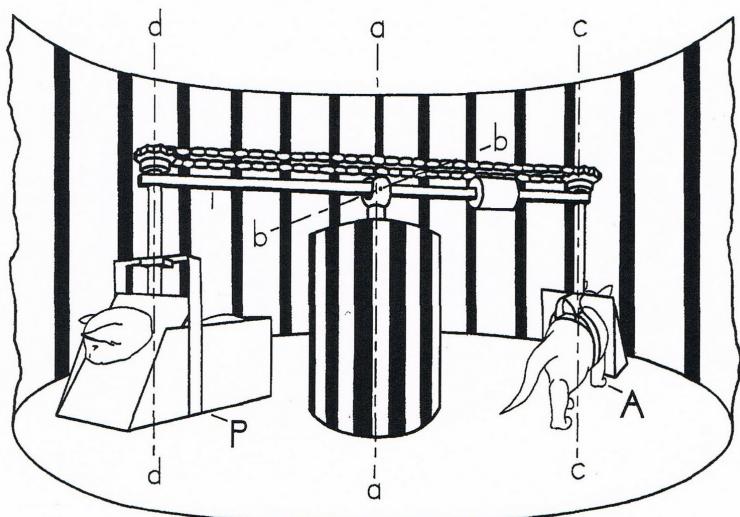
Multimodal **Neural** Script Knowledge Models
NeurIPS 2021

Symbolic+Neural

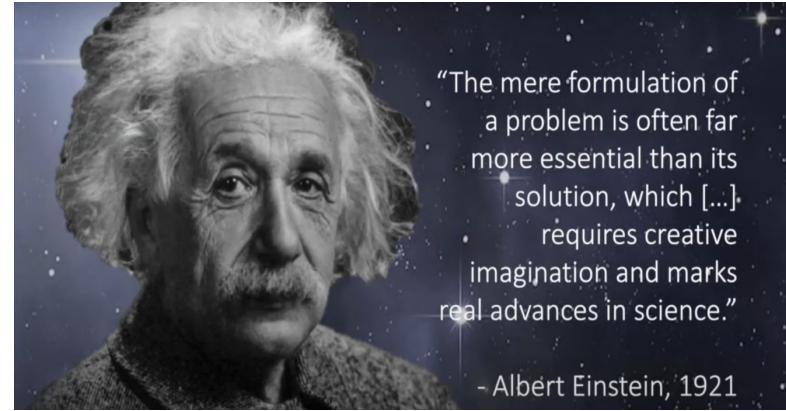
Future “Multi-modal Opportunities”: Embodied



Feifei Li

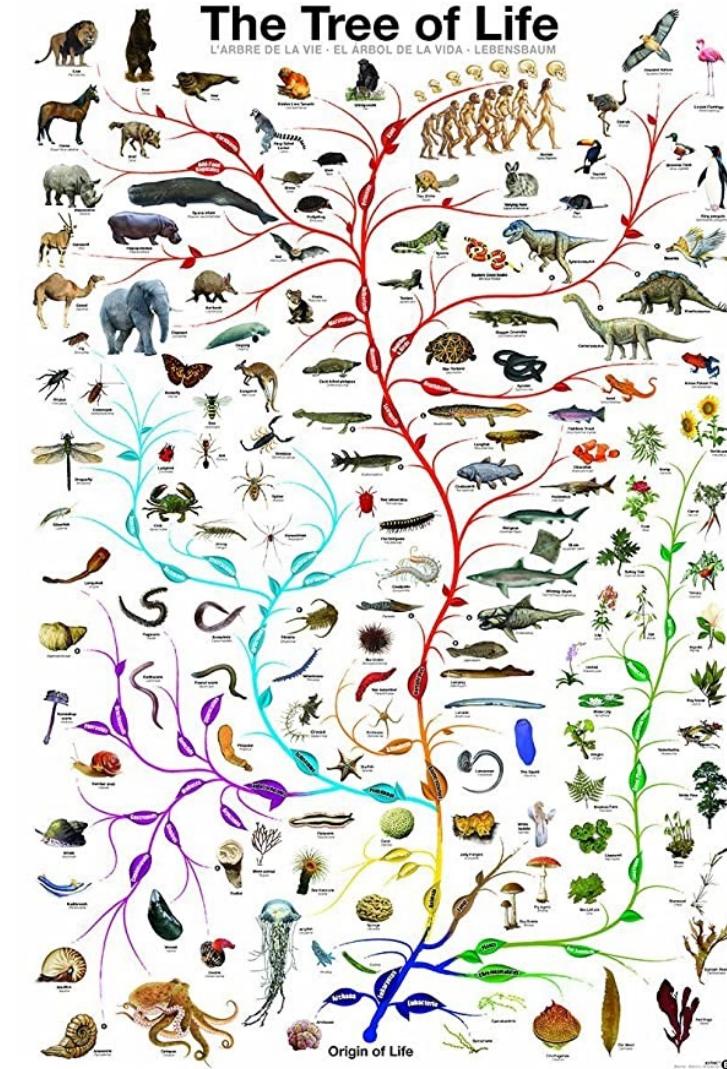


[Held, R. and Hein A. (1963). Movement-produced stimulation in the development of visually guided behavior. Journal of Comparative and Physiological Psychology 56(5): 872-876.]



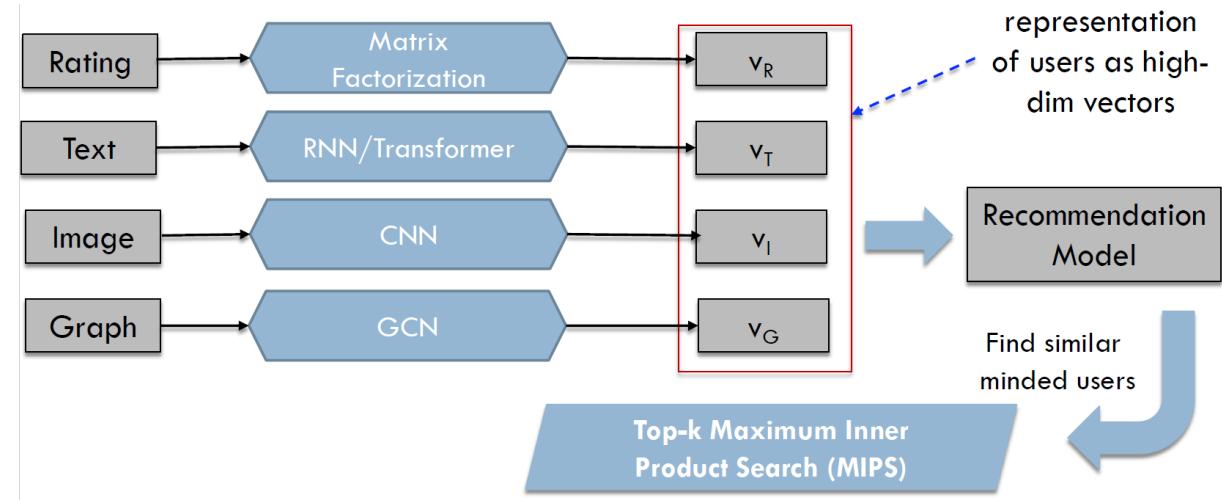
Embodied

- Multi-modal
- Embodied, (inter)active
- Explorative <-> Exploitative
- Multi task, generalizable

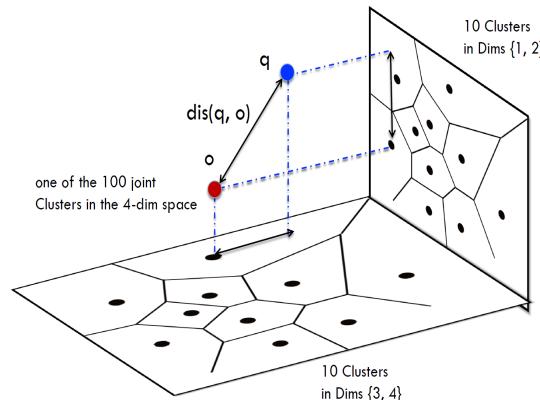


Future “Multi-modal Opportunities”: Database

High-Dimensional Similarity Query Processing

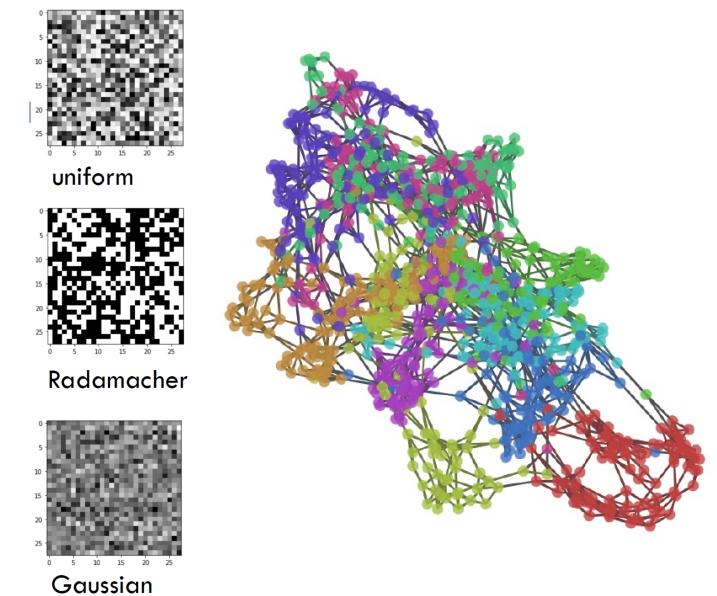


- Nearest Neighbor (of q): o^*
- $\square \text{ dist}(o^*, q) = \min \{\text{dist}(o, q), o \in D\}$
- \square Generalizes to k-NN
- c-Approximate NN: o
- $\square \text{ dist}(o, q) \leq c * \text{dist}(o^*, q)$



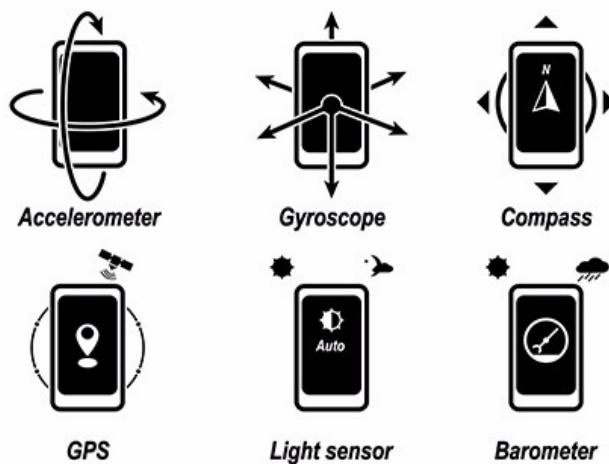
Vectors Querying

The distribution of real multi-modal data in the embedding space

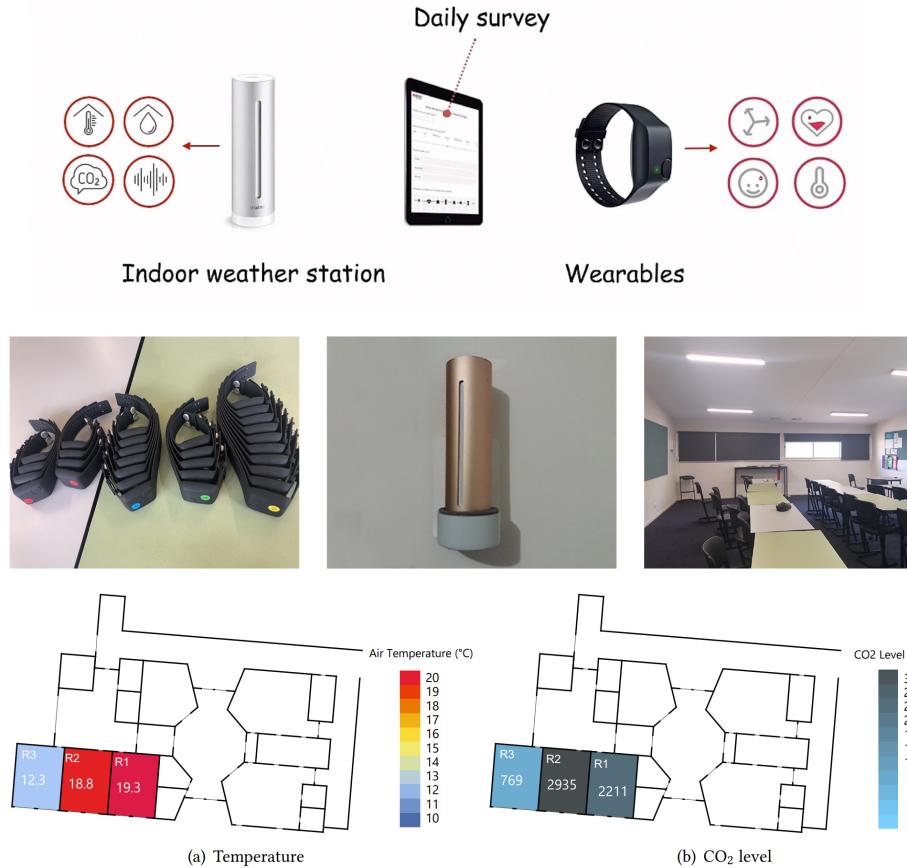


by Wei Wang in PVLDB 2020

Future “Multi-modal Opportunities”: IoT



Non-visual Multi-modal Data



Time-series **segmentation**
Self-supervised learning
Transfer learning with contextual information

Keynote by *Flora Salim* in KDD 2021

Segmentation

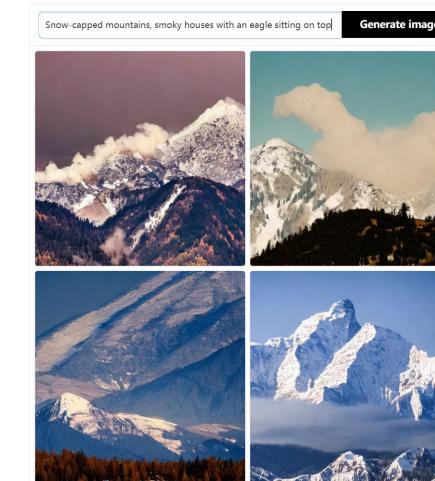
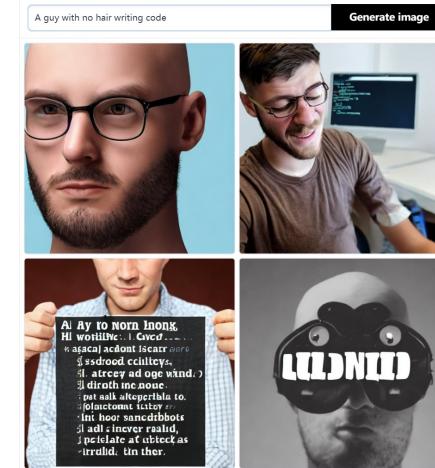
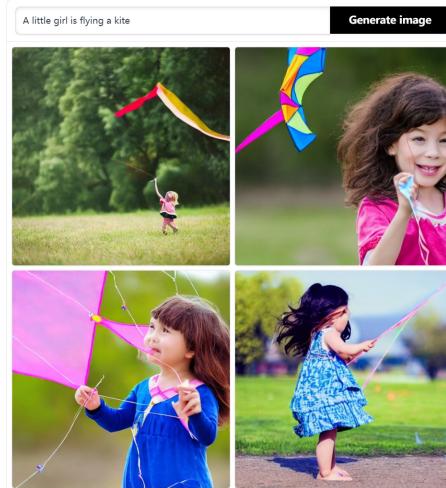
“Segmentation” is critical for multi-modal sensor data

**IMWUT
2020**

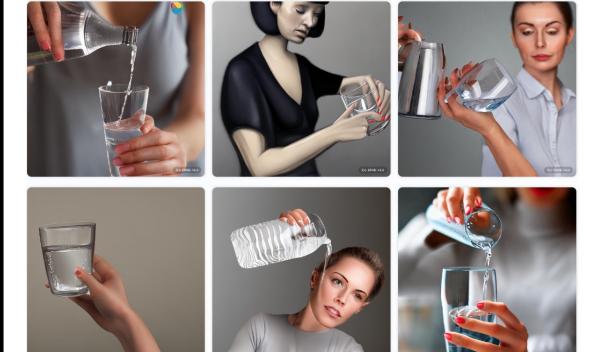
Future “Multi-modal Opportunities”: AIGC

Text to image

- Stable Diffusion:
- Midjourney
- Artflow
- Craiyon
- Disco Diffusion
- Aphantasia
- Text2Art

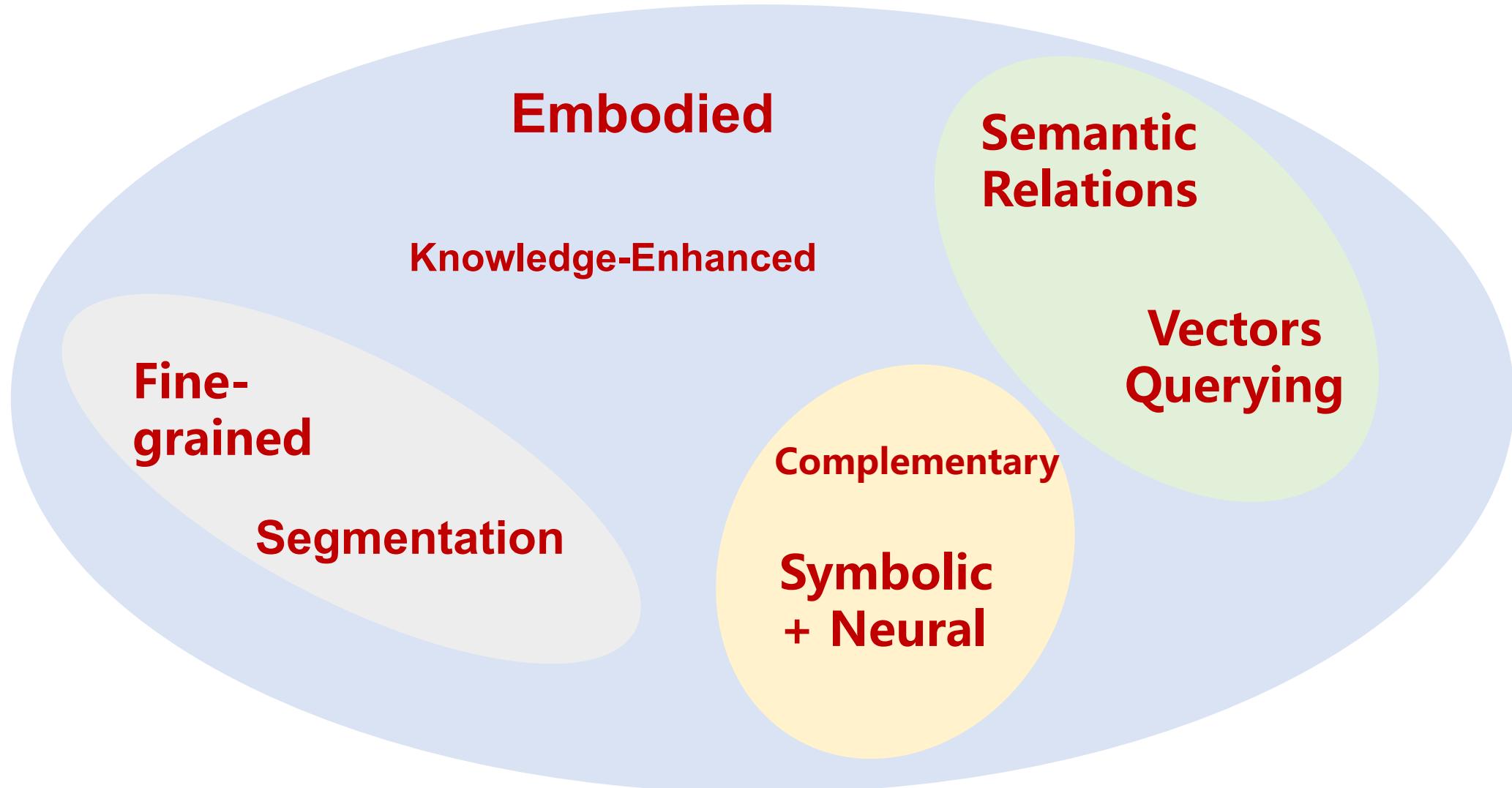


Future “Multi-modal Opportunities”: AIGC

	DAII E	stable diffusion	ERNIE ViLG
A woman is pouring water into her glasses			 <p>Prompt: 一个女人往她的玻璃杯里倒水. 写真风格</p>

Knowledge-Enhanced before Disambiguation

Future “Multi-modal Opportunities”: Keywords





IJCAI/2023 MACAO



IJCAI

International Joint Conferences on
Artificial Intelligence Organization

Thank You



Speaker: Meng Wang



Date: 2023.08.19





IJCAI/2023 MACAO



IJCAI

International Joint Conferences on
Artificial Intelligence Organization

Uncertain KG Construction and Reasoning

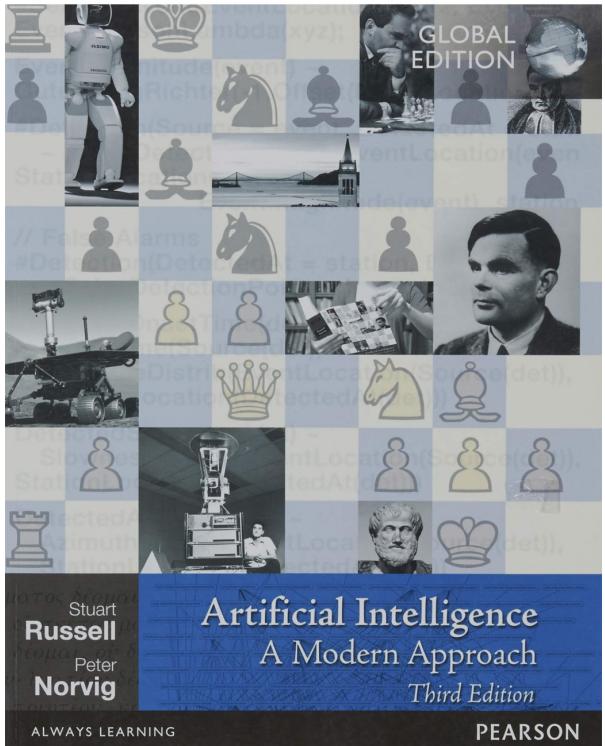
<https://openkg-tutorial.github.io/>

Tianxing Wu

Southeast University

19, Aug, 2023

Uncertainty in Artificial Intelligence



IV Uncertain knowledge and reasoning

- 12 Quantifying Uncertainty ... 385
- 13 Probabilistic Reasoning ... 412
- 14 Probabilistic Reasoning over Time ... 461
- 15 Probabilistic Programming ... 500
- 16 Making Simple Decisions ... 528
- 17 Making Complex Decisions ... 562
- 18 Multiagent Decision Making ... 599

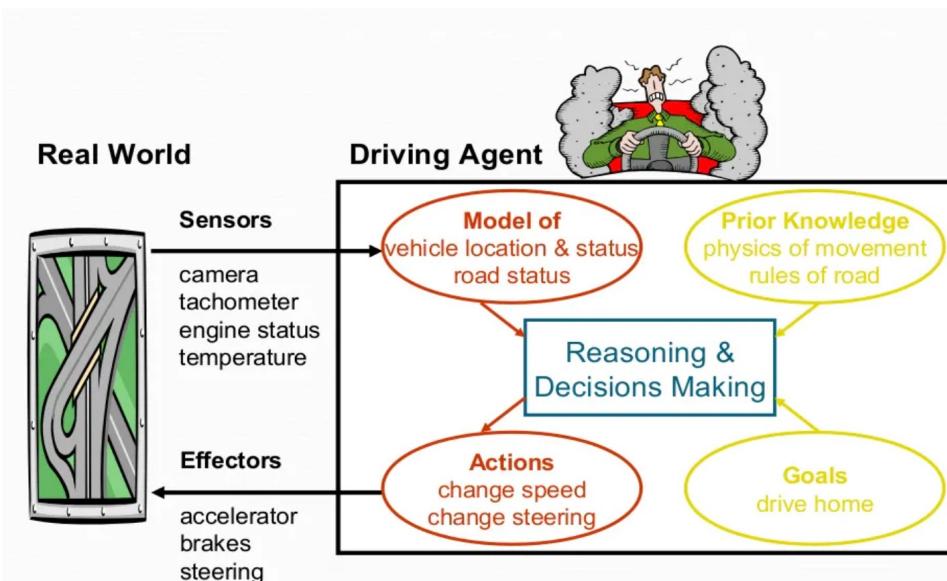
**The Annual Conference on
Uncertainty in Artificial Intelligence**



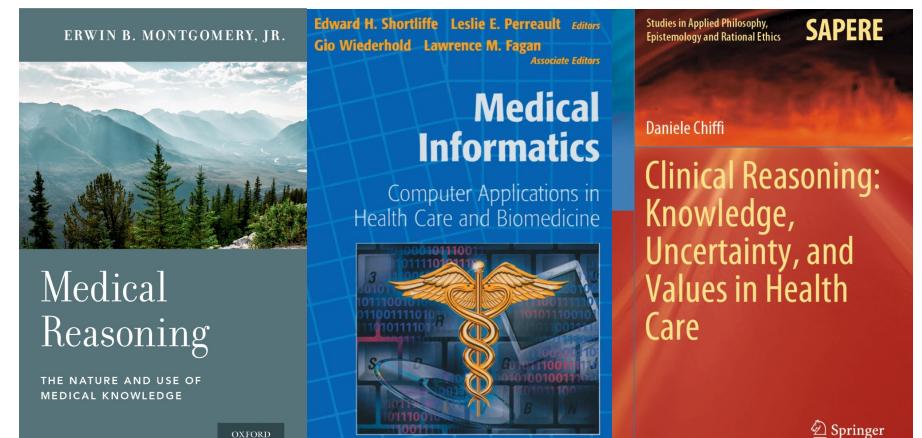
Research Background

Uncertainty in Artificial Intelligence

Autonomous Driving



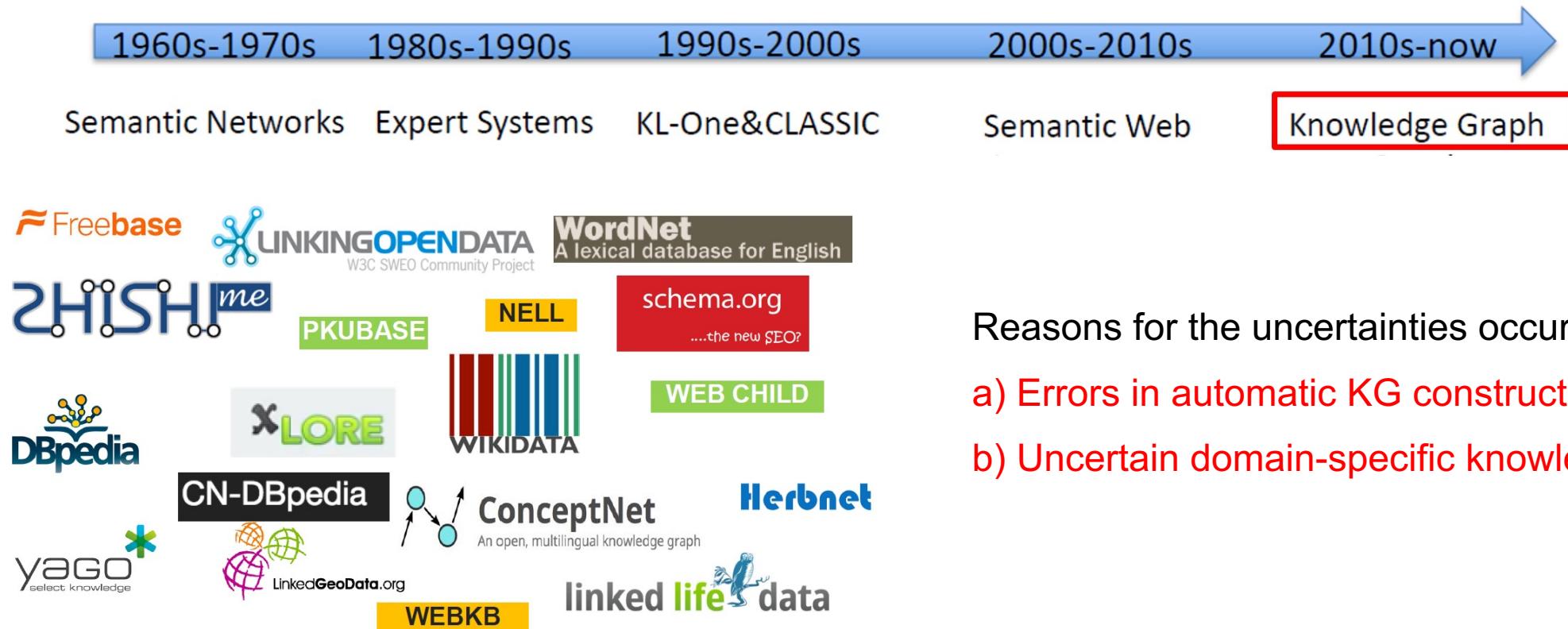
Medical Reasoning



Research Background

Uncertainty in Knowledge Graph (KG)

The Development History of Knowledge Engineering



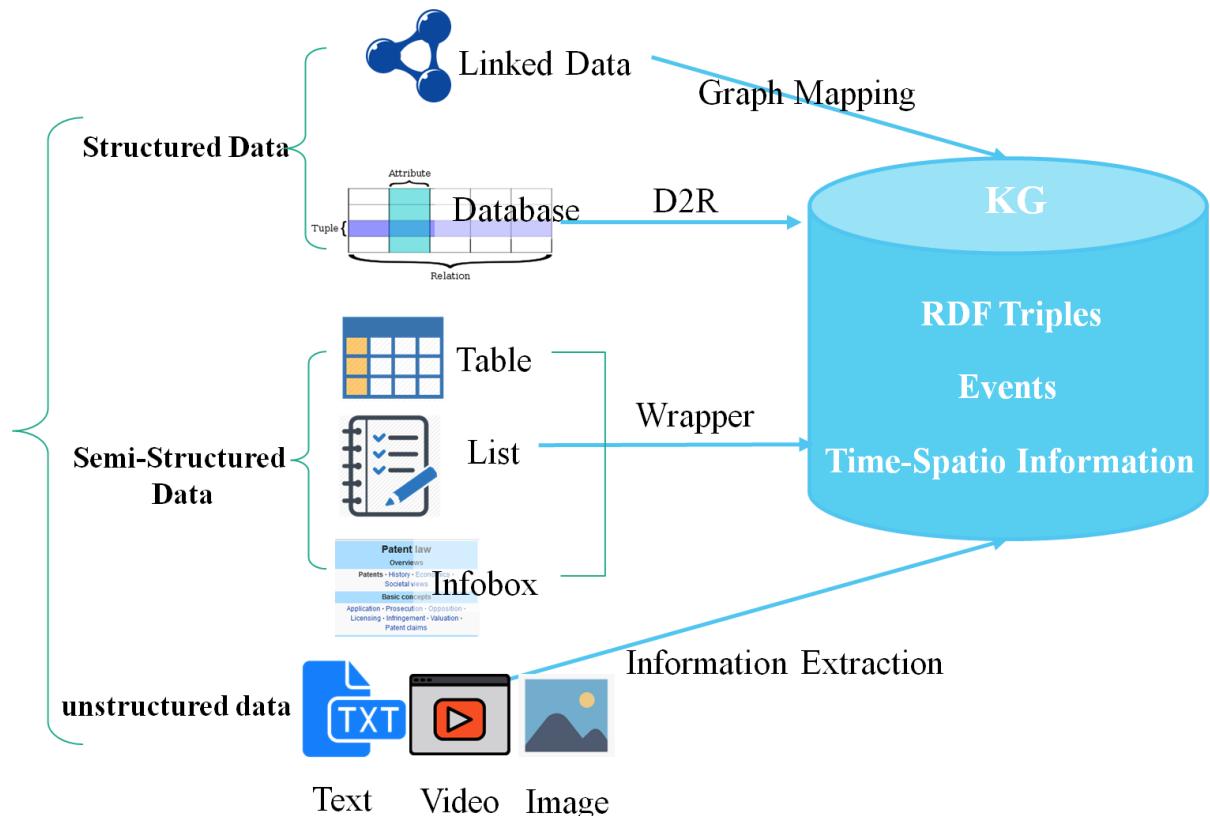
Reasons for the uncertainties occurring:

- a) Errors in automatic KG construction,
- b) Uncertain domain-specific knowledge.

Uncertainty in Knowledge Graph

Reasons for the uncertainties occurring:

- a) Errors in automatic KG construction,
- b) Uncertain domain-specific knowledge.



Uncertainty in Knowledge Graph

Reasons for the uncertainties occurring:

- a) Errors in automatic KG construction,
- b) Uncertain domain-specific knowledge.

KG Triples:

(Honda, competeswith, Toyota), (Honda, competeswith, Chrysler)

Question: Who is the main competitor of Honda?

Answer: Toyota

Uncertainty in Knowledge Graph

Reasons for the uncertainties occurring:

- a) Errors in automatic KG construction,
- b) Uncertain domain-specific knowledge.

KG Triples:

(type 2 diabetes, complication, diabetic nephropathy),
(type 2 diabetes, complication, diabetic foot)

Question: Who is the main complication of type 2 diabetes?

Answer: diabetic nephropathy

Uncertain Knowledge Graph

Deterministic Knowledge Graph

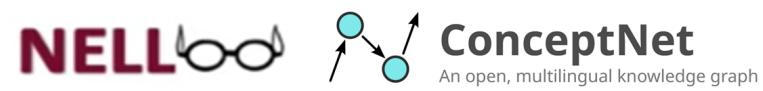


All triple are seen as correct!

<AlphaGo, Produced_by, Google> ✓

<US, Synonym_for, America> ✓

Uncertain Knowledge graph



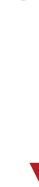
Triples are assigned with confidences to describe uncertainties.

<AlphaGo, Produced_by, Google>, 0.56

<US, Synonym_for, America>, 0.98

Uncertain Knowledge Graph **Construction** and **Reasoning**

Technique Explanation: *Computing confidences of the RDF triples in the KG.*



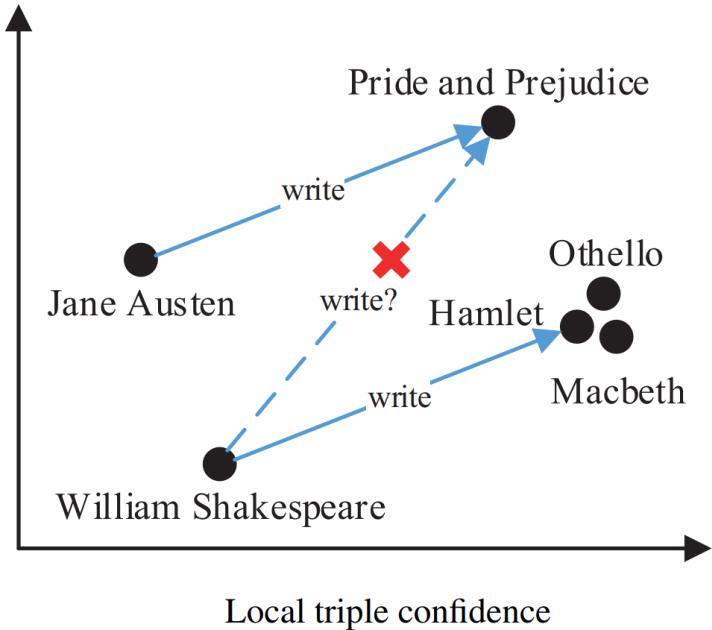
Technique Explanation: *Embedding KGs with triple confidences, and conduct link prediction.*

Uncertain Knowledge Graph **Construction**

AAAI 2018:
Does William Shakespeare REALLY Write Hamlet?
Knowledge Representation Learning with Confidence

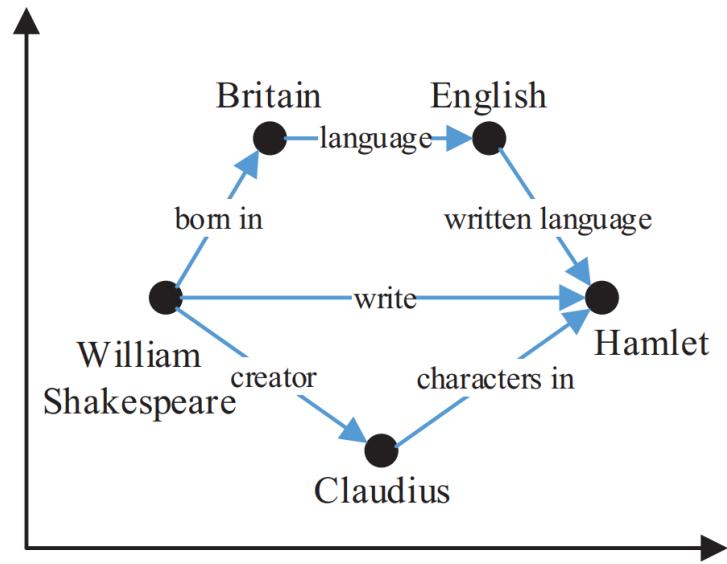
Ruobing Xie, Zhiyuan Liu, Fen Lin, Leyu Lin

$$\|\mathbf{h} + \mathbf{r} - \mathbf{t}\|$$



Local triple confidence

$$\|\mathbf{r} - \mathbf{p}_i\| = \|\mathbf{r} - (\mathbf{r}_{i1} + \dots + \mathbf{r}_{ik})\|$$



Global path confidence

translation scoring function

$$E(T) = \sum_{(h,r,t) \in T} E(h, r, t) \cdot C(h, r, t) \rightarrow \text{triple confidence}$$

$$E(h, r, t) = \|\mathbf{h} + \mathbf{r} - \mathbf{t}\|$$

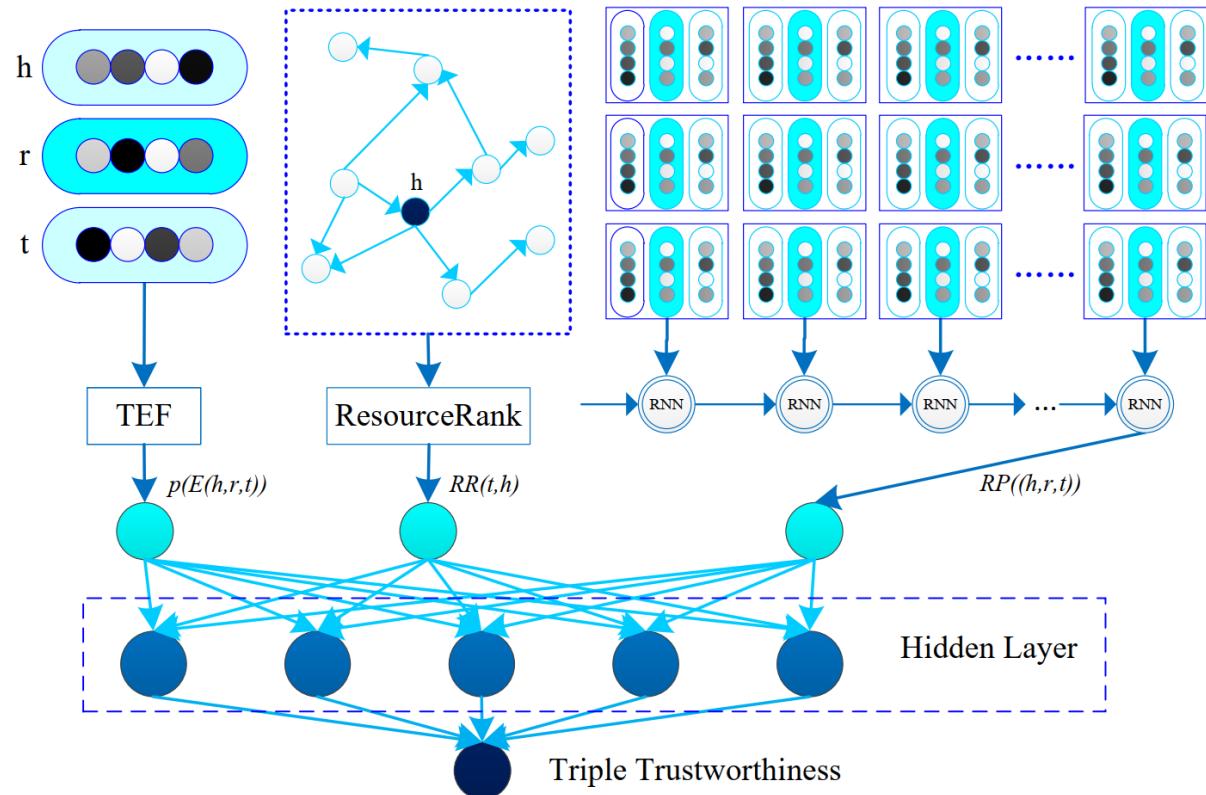
$$L = \sum_{(h,r,t) \in T} \sum_{(h',r',t') \in T'} \max(0, \gamma + E(h, r, t) - E(h', r', t')) \cdot C(h, r, t)$$

Uncertain Knowledge Graph **Construction**

WWW 2019:

Triple Trustworthiness Measurement for Knowledge Graph

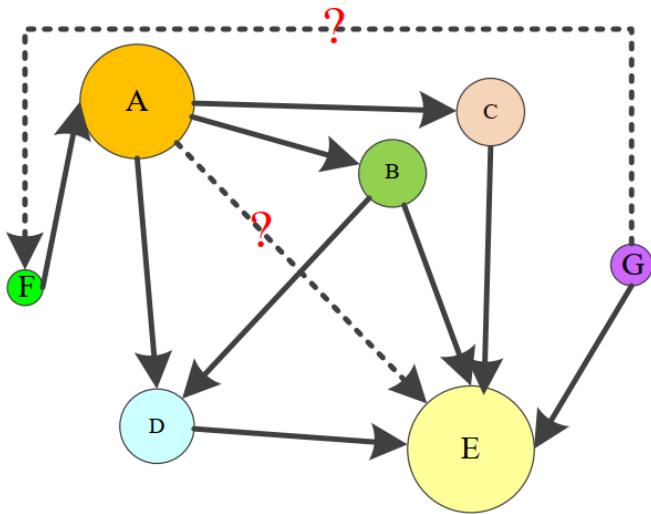
Shengbing Jia, Yang Xiang, Xiaojun Chen



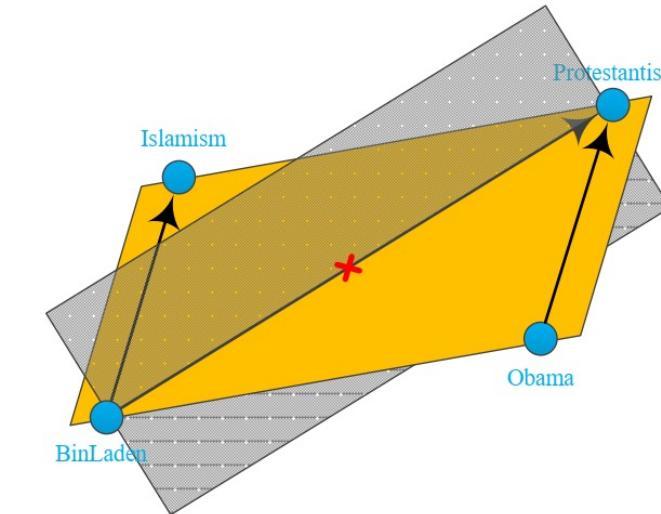
Basic Idea:

- 1) Is there a possible relationship between the entity pairs?
- 2) Can the determined relationship r occur between the entity pair (h, t) ?
- 3) Can the relevant triples in the KG infer that the triple is trustworthy?

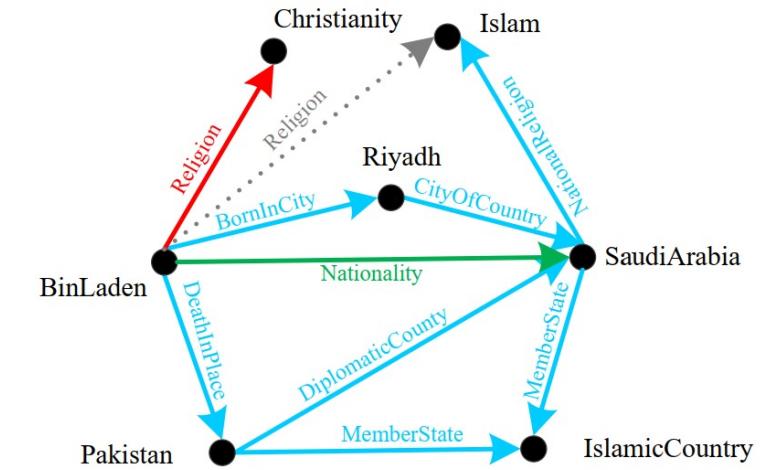
The triple trustworthiness measurement model of KGTtm.



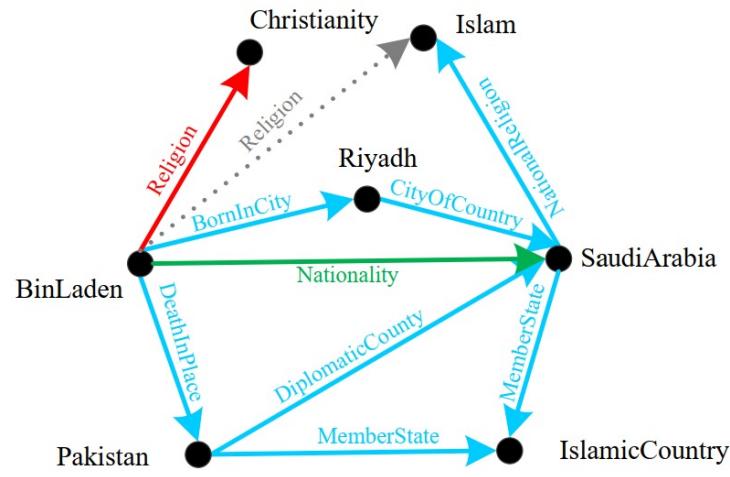
The graph of resource allocation in the ResourceRank algorithm.



Effects display of the Translation based energy function.



The inference instances for triple trustworthiness.



The inference instances for triple trustworthiness.

Algorithm 1 Reachable Paths Selecting Algorithm

Require:

The knowledge graph (KG); A given target triple (h, r, t) .

Ensure:

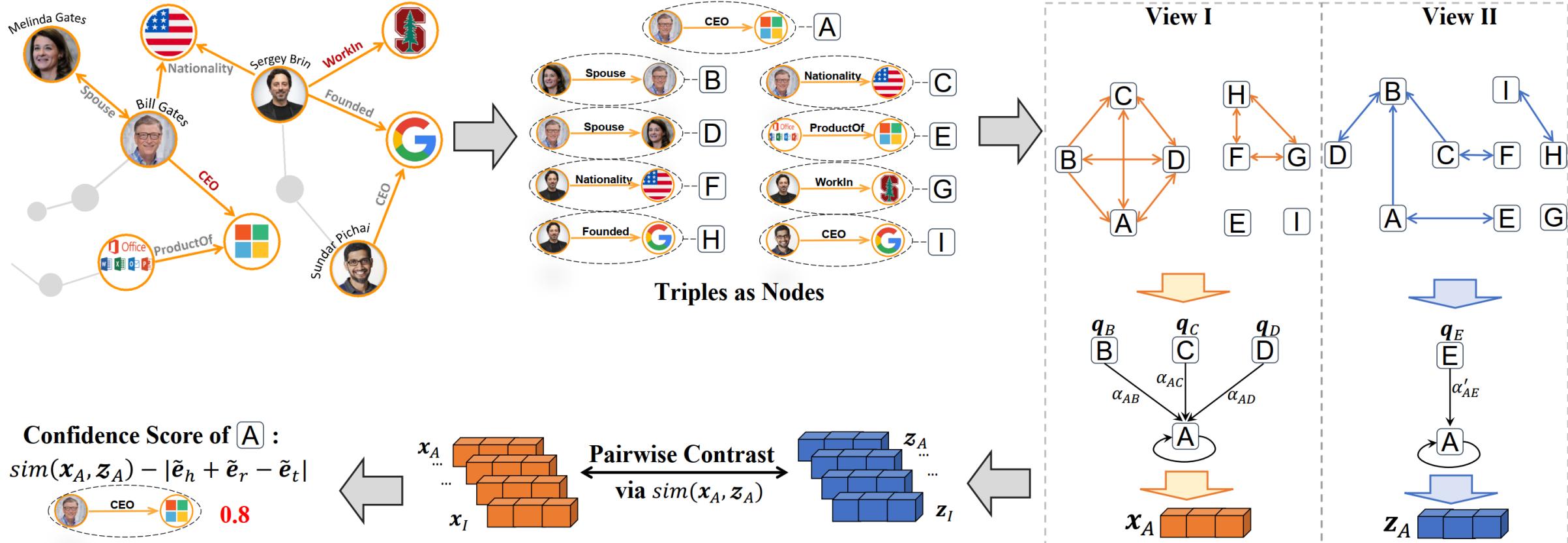
Multiple reachable paths most relevant to target triple.

- 1: Search the reachable paths from h to t in the KG and store in $P(h, r, t) = \{p_1, \dots, p_n\}$;
 - 2: For each $p_i = \{(h, l_1, e_1), (e_1, l_2, e_2), \dots, (e_{n-1}, l_n, t)\}$, calculate
 - 1) the semantic distance between the r and all relations in p_i ,
as, $SD(p_i(l), r) = \frac{1}{n} \sum_{l_j \in p_i(l)} \frac{r \cdot l_j}{\|r\| \|l_j\|}$;
 - 2) the semantic distance between the t and all head entities in p_i , as, $SD(p_i(e), t) = \frac{1}{n} \sum_{e_j \in p_i(e)} \frac{t \cdot e_j}{\|t\| \|e_j\|}$;
 - 3) the semantic distance between the h and all tail entities in p_i , as, $SD(p_i(e), h) = \frac{1}{n} \sum_{e_j \in p_i(e)} \frac{h \cdot e_j}{\|h\| \|e_j\|}$;
 - 3: Calculate the average distance
 $\bar{SD}(p_i) = \frac{1}{3}(SD(p_i(e), t) + SD(p_i(l), r) + SD(p_i(e), h))$;
 - 4: Select first $TopK$ paths with the highest $\bar{SD}(p_i)$ scores.
 - 5: Return $\{p_i \mid 1 \leq i \leq TopK, Sort(\bar{SD}(p_i), descend)\}$
-

Uncertain Knowledge Graph **Construction**

CIKM 2022:
Contrastive Knowledge Graph Error Detection

Qinggang Zhang, Junnan Dong, Keyu Duan, Xiao Huang, Yezi Liu, Linchuan Xu



The illustration of CAGED.

DEFINITION . Linking Pattern. For any two triples sharing entities, i.e. $T_1 = (h_1, r_1, t_1) \cap T_2 = (h_2, r_2, t_2)$, we have two linking patterns: (i) sharing head entity ($h_1 = h_2 \oplus h_1 = t_2$), (ii) sharing tail entity ($t_1 = h_2 \oplus t_1 = t_2$). For our construction criterion, we build two triple graphs with these two linking patterns, based on the rationale that these two patterns possess different semantics.

KG embedding loss:

$$\mathcal{L}_{kge} = \sum_{(h,r,t) \in \mathcal{G}} \sum_{(\hat{h},\hat{r},\hat{t}) \in \hat{\mathcal{G}}} \max \left(0, \gamma + E(h, r, t) - E(\hat{h}, \hat{r}, \hat{t}) \right)$$

Contrastive loss:

$$\mathcal{L}_{con}(\mathbf{x}_i, \mathbf{z}_i) = -\log \frac{\exp (\text{sim}(\mathbf{x}_i, \mathbf{z}_i) / \tau)}{\sum_{j \in \{1, 2, \dots, n\} \setminus \{i\}} \exp (\text{sim}(\mathbf{x}_i, \mathbf{z}_j) / \tau)}$$

Final Confidence Computation:

$$C(h, r, t) = \sigma(\text{sim}(\mathbf{x}_i, \mathbf{z}_i) - \lambda \cdot E(h, r, t))$$

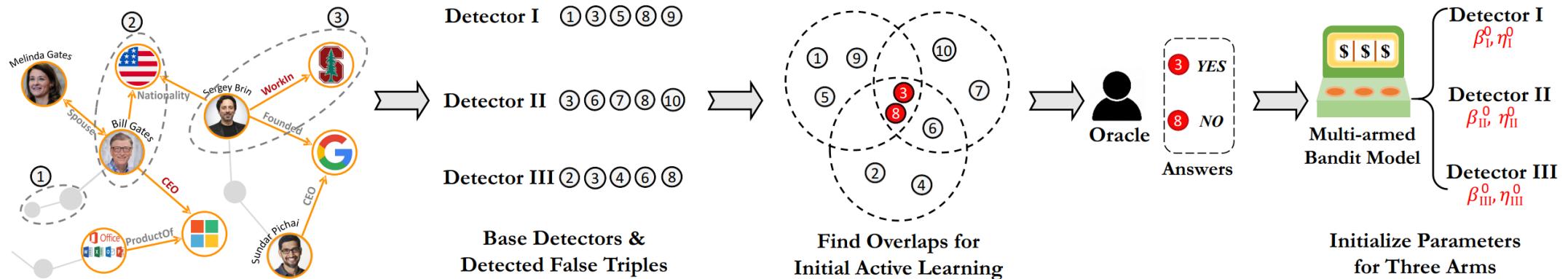
Joint Optimization

Uncertain Knowledge Graph **Construction**

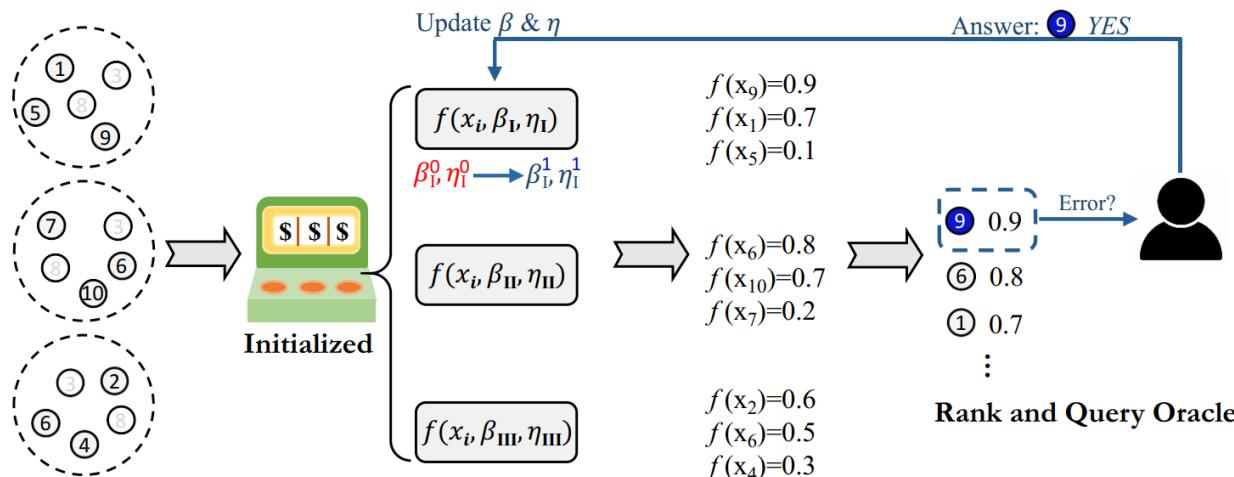
WSDM 2023:
**Active Ensemble Learning for Knowledge Graph
Error Detection**

Junnan Dong, Qinggang Zhang, Xiao Huang, Qiaoyu Tan, Daochen Zha, Zihao Zhao

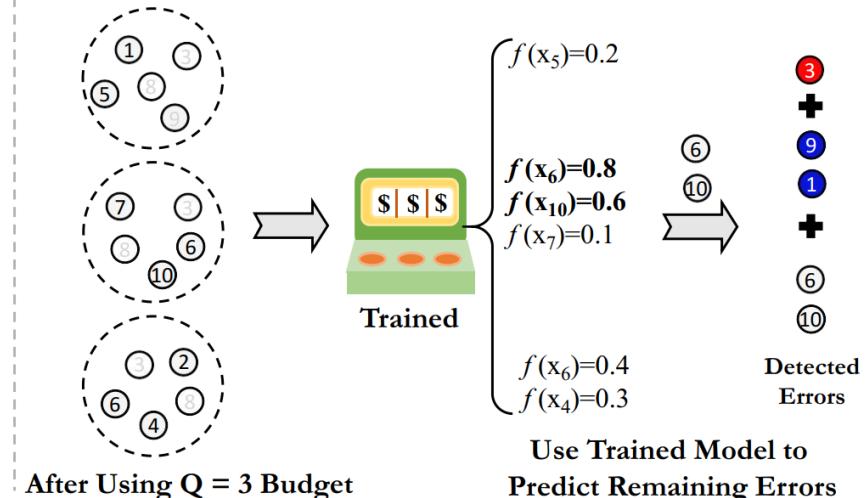
(a) Initialization Stage With Overlaps



(b) Training Stage With Tailored MAB



(c) Application Stage With Trained MAB



□ The illustration of KAEL.

Uncertain Knowledge Graph Construction

Summary:

1. To accurately compute triple confidences, it is necessary to consider multiple types of **explicit contextual evidences** (paths, rules, subgraphs, etc.) and **multi-view embedding representation evidences** together.
2. In the **few-shot scenarios**, how to effectively learn the triple confidences is worthy to study in the future.

Uncertain Knowledge Graph **Reasoning**

AAAI 2019:
Embedding Uncertain Knowledge Graphs

Xuelu Chen, Muhaao Chen, Weijia Shi, Yizhou Sun, Carlo Zaniolo

For each triple (h, r, t)

- Plausibility: $g(l) = \mathbf{r} \cdot (\mathbf{h} \circ \mathbf{t})$
- Confidence score: $f(l) = \boxed{\phi(g(l))}, \phi : \mathbb{R} \rightarrow [0, 1]$

Transformation function

$$\left\{ \begin{array}{l} \phi(x) = \min(\max(\mathbf{w}x + \mathbf{b}, 0), 1) \\ \phi(x) = \frac{1}{1 + e^{-(\mathbf{w}x + \mathbf{b})}} \end{array} \right.$$

Plausibility $\xrightarrow{\phi}$ Confidence

Using probabilistic soft logic to infer confidences of unseen facts:

Logical rule

$$(\underline{A}, \text{synonym}, \underline{B}) \wedge (\underline{B}, \text{synonym}, \underline{C}) \rightarrow (\underline{A}, \text{synonym}, \underline{C})$$

Atom l

Soft truth value

$$I(l) = s_l, l \in \mathcal{L}^+$$

$$I(l) = f(l), l \in \mathcal{L}^-$$

Lukasiewicz t-norm

$$l_1 \wedge l_2 = \max\{0, I(l_1) + I(l_2) - 1\}$$

$$l_1 \vee l_2 = \min\{1, I(l_1) + I(l_2)\}$$

$$\neg l_1 = 1 - I(l_1)$$

Distance to satisfaction

$$d_\gamma = 1 - p_\gamma = \max\{0, I(\gamma_{body}) - I(\gamma_{head})\}$$

Ground rule

$$(\text{college}, \text{synonym}, \text{university}) \wedge (\text{university}, \text{synonym}, \text{institute}) \rightarrow (\text{college}, \text{synonym}, \text{institute})$$

l_1 (college, synonym, university)

l_2 (university, synonym, college)

l_3 (college, synonym, institute)

Observed
Unseen



$$\begin{aligned} d_\gamma &= \max\{0, I(l_1 \wedge l_2) - I(l_3)\} \\ &= \max\{0, s_{l_1} + s_{l_2} - 1 - f(l_3)\} \\ &= \max\{0, 0.85 - f(l_3)\} \end{aligned}$$

Training Target: $\mathcal{J} = \mathcal{J}^+ + \mathcal{J}^-$

for observed facts:

$$\mathcal{J}^+ = \sum_{l \in \mathcal{L}^+} |f(l) - s_l|^2$$

for unseen facts:

$$\mathcal{J}^- = \sum_{l \in \mathcal{L}^-} \sum_{\gamma \in \Gamma_l} |\psi_\gamma(f(l))|^2$$

- Γ_l : ground rules with l as the rule head
- $\psi_\gamma(f(l)) = w_\gamma d_\gamma$

Problems:

1. Probabilistic soft logic is based on pre-defined rules , which require additional manual costs and domain knowledge.
2. KG is sparse which means probabilistic soft logic cover few negative samples.

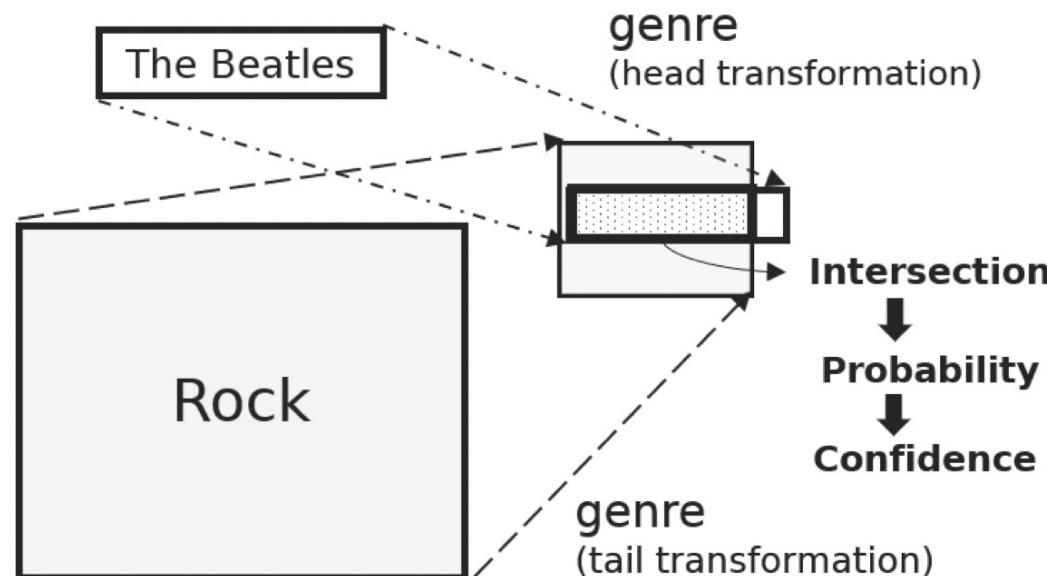
Uncertain Knowledge Graph **Reasoning**

NAACL 2021:
**Probabilistic Box Embeddings for Uncertain
Knowledge Graph Reasoning**

Xuelu Chen, Michael Boratko, Muhao Chen, Shib Sankar Dasgupta, Xiang Lorraine Li, Andrew McCallum

In the embedding space,
entities are modeled as Gumbel boxes (axis-aligned hyperrectangles),
relations are modeled as head/tail affine transforms, and
confidences are modeled as intersections between boxes.

(The Beatles, genre, Rock): confidence?



- Gumbel boxes

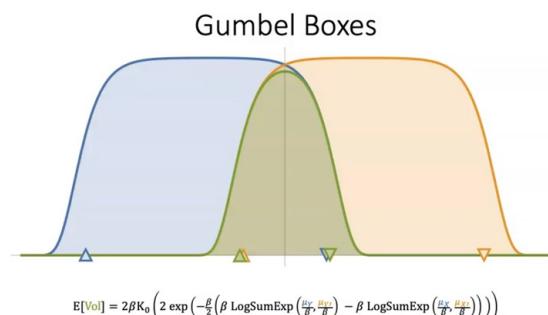
$$\text{Box}(X) = \prod_{i=1}^d [x_i^m, x_i^M] \quad \text{where}$$

$$\begin{aligned} x_i^m &\sim \text{GumbelMax}(\mu_i^m, \beta), \\ x_i^M &\sim \text{GumbelMin}(\mu_i^M, \beta). \end{aligned}$$

- Expected volume of a Gumbel box

$$\mathbb{E} [\text{Vol}(\text{Box}(X))] \approx$$

$$\prod_{i=1}^d \beta \log \left(1 + \exp \left(\frac{\mu_i^M - \mu_i^m}{\beta} - 2\gamma \right) \right)$$



- For entities, location parameters are *cen* and *off*:

$$\mu_i^m = \text{cen}(\text{Box}(X)) - \text{off}(\text{Box}(X)).$$

$$\mu_i^M = \text{cen}(\text{Box}(X)) + \text{off}(\text{Box}(X)).$$

- For relations, transformations are parametrized by a translation vector τ and a scaling vector Δ :

$$\text{cen}(f(\text{Box}(X); \tau, \Delta)) = \text{cen}(\text{Box}(X)) + \tau,$$

$$\text{off}(f(\text{Box}(X); \tau, \Delta)) = \text{off}(\text{Box}(X)) \circ \Delta,$$

- The conditional probability is used to model confidences:

$$\phi(h, r, t) = \frac{\mathbb{E}[\text{Vol}(f_r(\text{Box}(h)) \cap g_r(\text{Box}(t)))]}{\mathbb{E}[\text{Vol}(g_r(\text{Box}(t)))]}$$

- f_r : head affine transform; g_r : tail affine transform
- If (h, r, t) holds, then $g_r(\text{Box}(t)) \subseteq f_r(\text{Box}(h))$.

- Incorporating logical constraints:

Transitivity Constraint

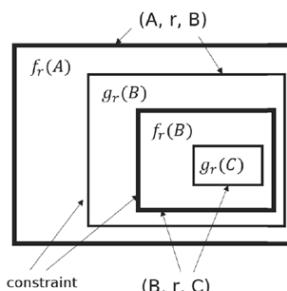
$$(A, r, B) \wedge (B, r, C) \implies (A, r, C)$$

$$g_r(\text{Box}(B)) \subseteq f_r(\text{Box}(B))$$



Loss

$$L_{\text{tr}}(r) = \frac{1}{|\Phi|} \sum_{u \in \Phi} \|P_{\text{Box}}(g_r(u) \mid f_r(u)) - 1\|^2$$



Composition Constraint

$$(A, r_1, B) \wedge (B, r_2, C) \implies (A, r_3, C)$$

$$f_{r_3} = f_{r_2}(f_{r_1}(u)), \quad g_{r_3} = g_{r_2}(g_{r_1}(u))$$



Loss

$$\begin{aligned} L_c(r_1, r_2, r_3) = & \frac{1}{|\Phi|} \sum_{u \in \Phi} f_{r_3}(u) \oplus f_{r_2}(f_{r_1}(u)) \\ & + g_{r_3}(u) \oplus g_{r_2}(g_{r_1}(u)) \end{aligned}$$

Final Loss

$$\mathcal{J}_1 = \sum_{l \in \mathcal{L}^+} |\phi(l)| - s_l|^2 + \alpha \sum_{l \in \mathcal{L}^-} |\phi(l)|^2$$



$$\mathcal{J}_2 = w_{\text{tr}} \sum_{r \in \mathcal{R}_{\text{tr}}} L_{\text{tr}}(r) + w_c \sum_{(r_1, r_2, r_3) \in \mathcal{R}_c} L_c(r_1, r_2, r_3)$$

Uncertain Knowledge Graph **Reasoning**

AAAI 2021:

PASSLEAF: A Pool-bAsed Semi-Supervised LEArning Framework for Uncertain Knowledge Graph Embedding

Zhu-Mu Chen, Mi-Yen Yeh, Tei-Wei Kuo

Confidence Computation:

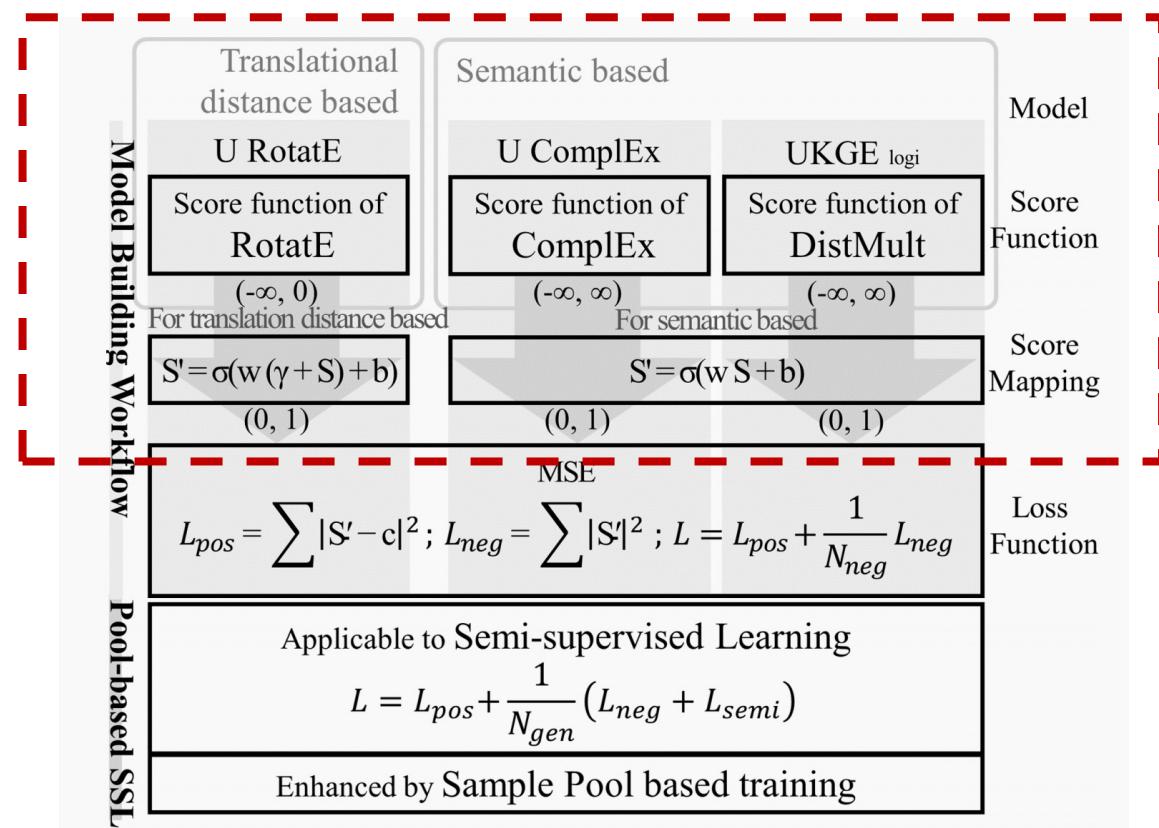
- For different types of scoring functions, it sets different mapping functions:

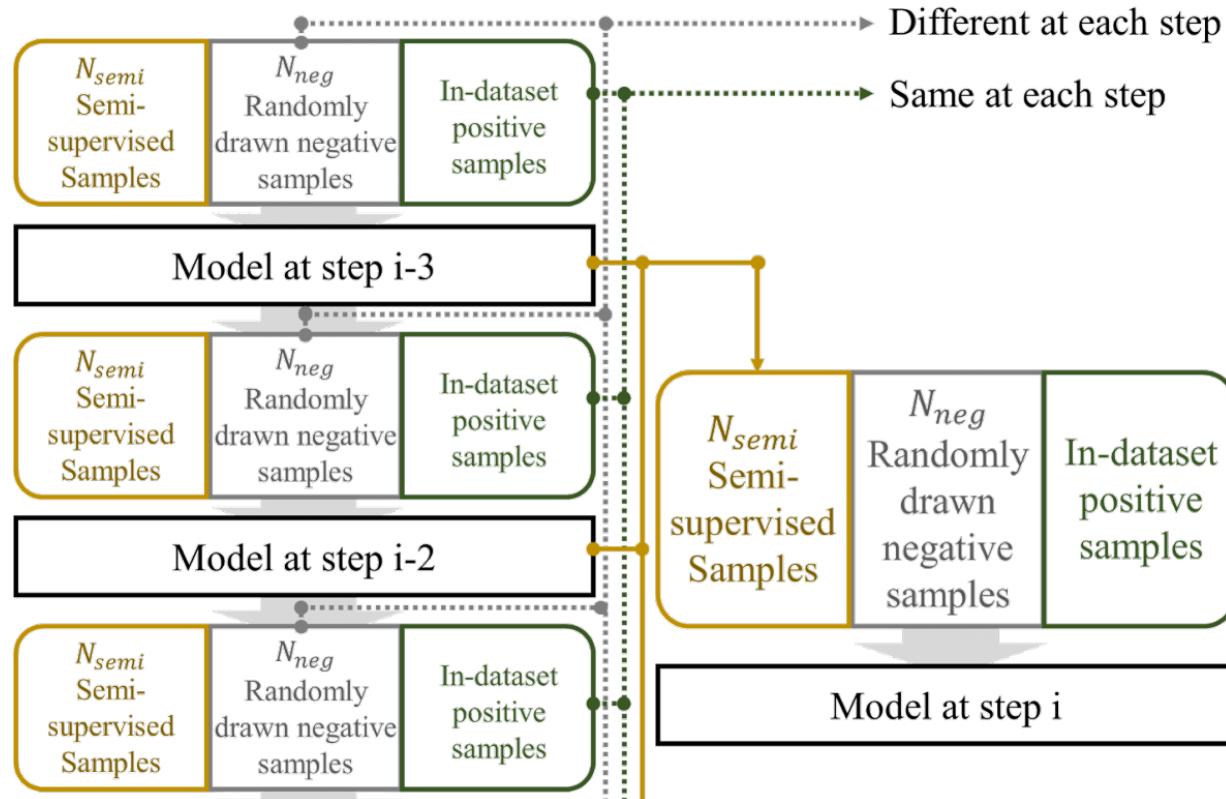
for translational distance models:

$$S'(\bar{h}, \bar{r}, \bar{t}) = \frac{1}{1 + e^{-(b+w(\gamma+S(\bar{h}, \bar{r}, \bar{t})))}}$$

for semantic matching models:

$$S'(\bar{h}, \bar{r}, \bar{t}) = \frac{1}{1 + e^{-(b+wS(\bar{h}, \bar{r}, \bar{t}))}}$$





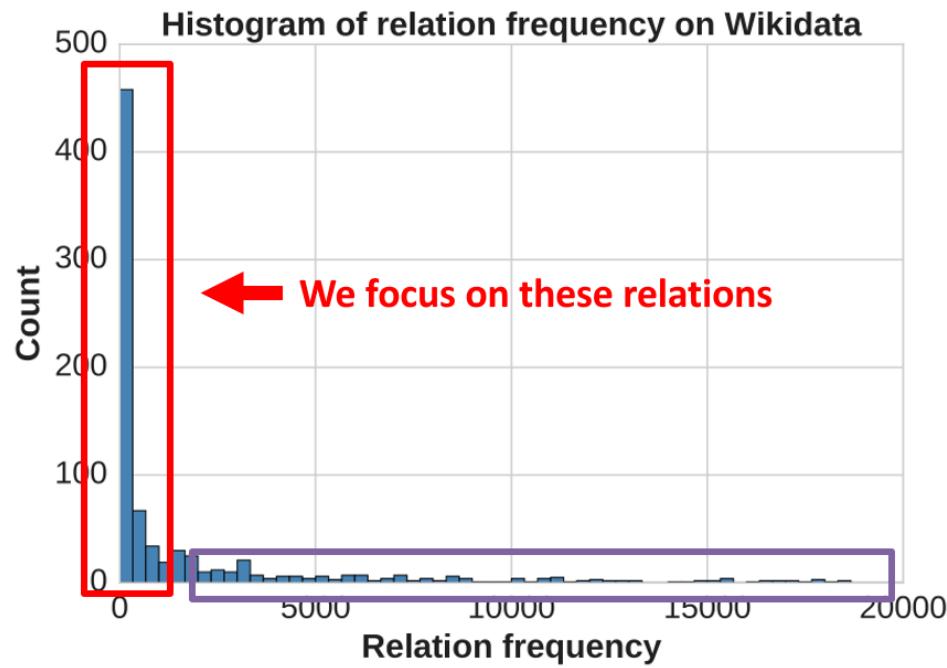
- 1) **Semi-supervised samples** are picked in the same way as randomly drawn negative samples, by corrupting either the head or tail entity of an in-training-set triplet.
- 2) **The difference** is that the confidence score of each semi-supervised sample will be **estimated and specified by the current model** instead of zeroing them.

Uncertain Knowledge Graph **Reasoning**

DASFAA 2021:
Gaussian Metric Learning for Few-Shot Uncertain
Knowledge Graph Completion

Jiatao Zhang, Tianxing Wu, Guilin Qi

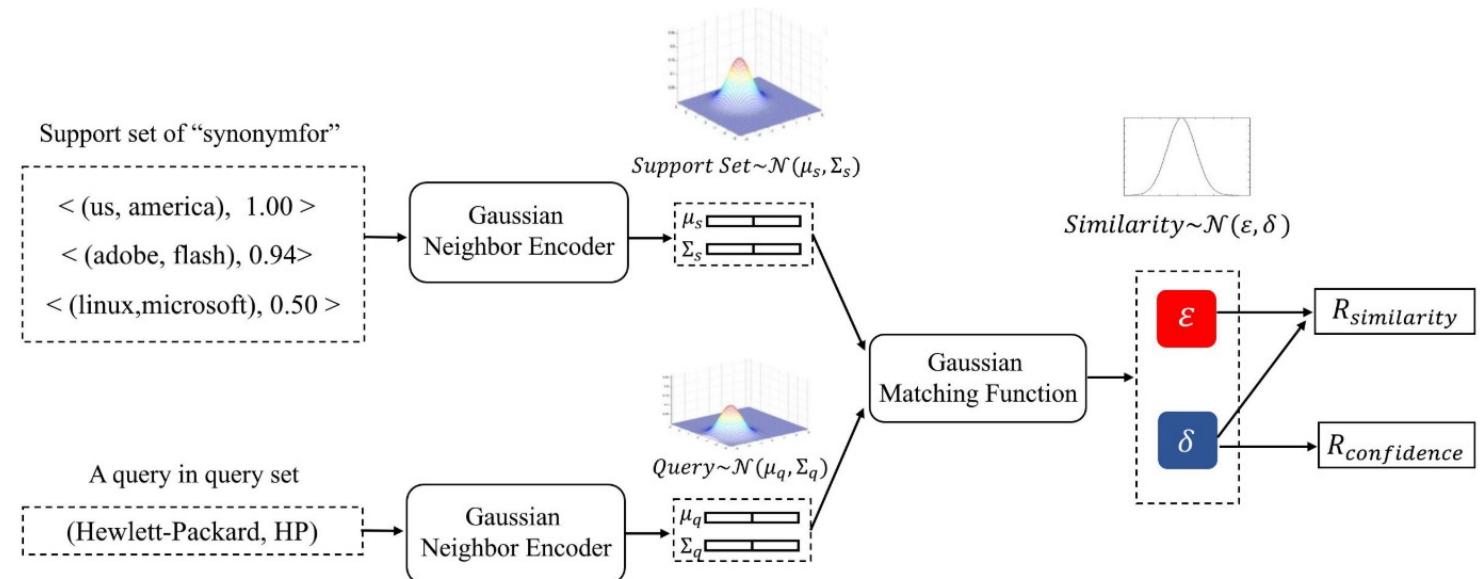
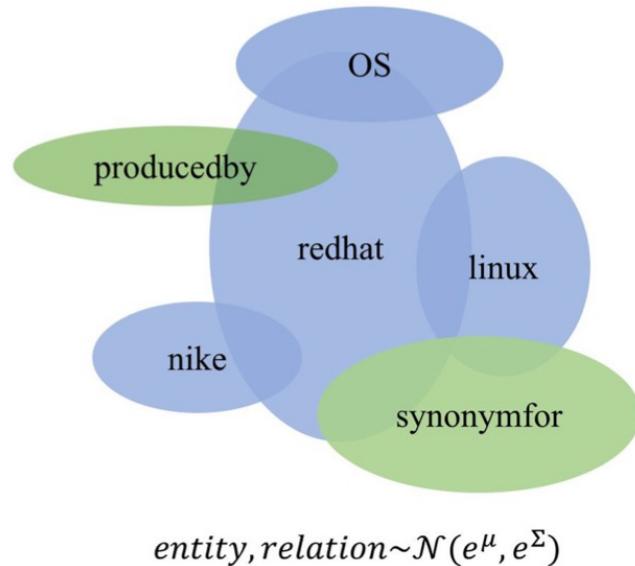
Existing approaches assume that training data are sufficient, and the long-tail problem is neglected.



- Most relations are described by few triples.
- Few training data affects the quality of KG embedding.

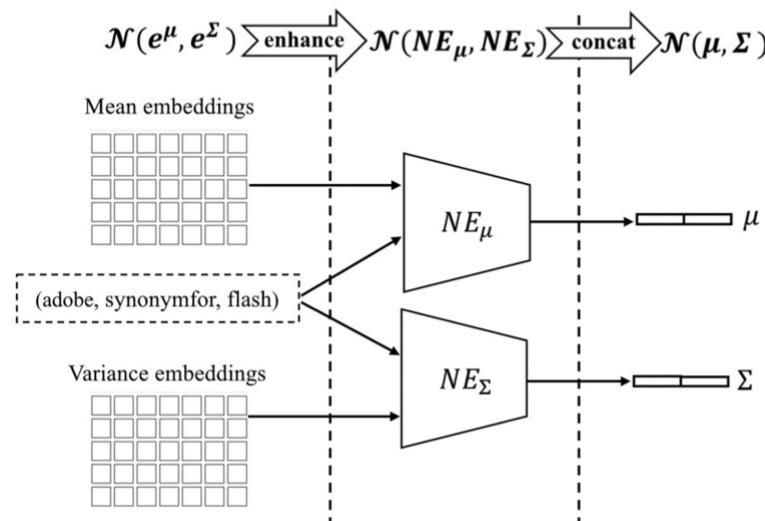
GMUC applies **multi-dimensional Gaussian distribution** to entities and relations, which takes the **uncertainties** of entities and relations into consideration.

A **few-shot metric learning framework** is used to KG completion.

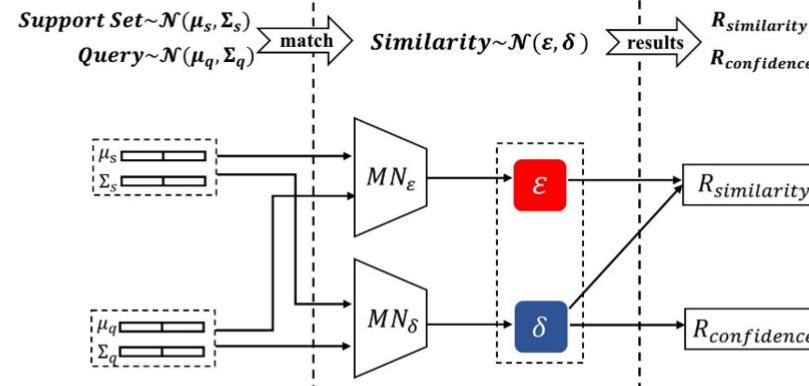


Model

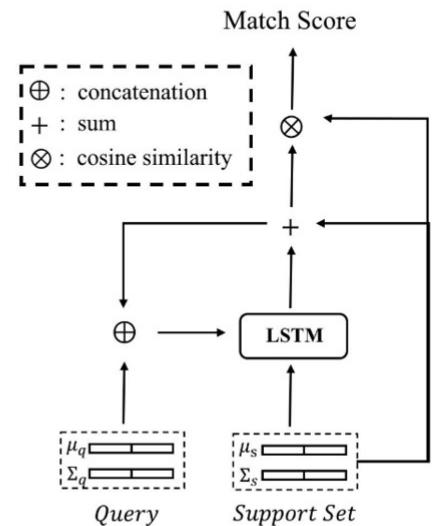
Gaussian Neighbor Encoder



Gaussian Matching Function



(a) Gaussian Matching Function



(b) Matching Network

Training Target:

- Ranking loss: $\mathcal{L}_{rank} = \sum_{<(h,t),s>\in\mathcal{Q}_r^{thr}} \sum_{(h,t')\in\mathcal{Q}_r^{thr-}} s \cdot [\gamma + \varepsilon_{(h,t)} - \varepsilon_{(h,t')}]_+$
- MSE loss:

$$\mathcal{L}_{mse} = \sum_{<(h,t),s>\in\mathcal{Q}_r} |R_{confidence} - s|^2$$

Algorithm 1: GMUC Training Procedure

Input:

- Meta-training task (relation) set \mathcal{T}_{train} ;
- Embeddings of entities and relations φ ;
- Initial parameters θ of the metric model

```

1 for epoch:=0 to MAXepoch do
2   for  $T_r$  in  $\mathcal{T}_{train}$  do
3     Sample few entity pairs as support set  $\mathcal{S}_r$ 
4     Sample a batch of positive queries  $\mathcal{Q}_r$  and filtered queries  $\mathcal{Q}_r^{thr}$ 
5     Pollute the tail entity of queries to get  $\mathcal{Q}_r^{thr-}$ 
6     Calculate the loss by Eq. (14)
7     Update parameters  $\theta$  and  $\varphi$ 
8 return Optimal model parameters  $\theta$  and  $\varphi$ 

```

Dataset : NL27K-N0/1/2/3 is of the noise proportion 0%/ 10%/ 20%/ 40%.

Dataset Metrics	NL27K-N0			NL27K-N1			NL27K-N2			NL27K-N3		
	MRR	Hit@1	Hit@10									
GMatching	0.361	0.272	0.531	0.193	0.123	0.315	0.125	0.066	0.253	0.025	0.005	0.051
FSRL	0.397	0.304	0.589	0.188	0.101	0.333	0.123	0.052	0.264	0.027	0.007	0.045
UKGE	0.053	0.058	0.138	0.071	0.107	0.153	0.057	0.066	0.153	0.092	0.091	0.144
GMUC-noconf	0.420	0.324	0.611	0.179	0.113	0.310	0.127	0.071	0.271	0.092	0.048	0.155
GMUC-point	0.413	0.316	0.603	0.215	0.130	0.344	0.131	0.113	0.272	0.065	0.006	0.156
GMUC	0.433	0.342	0.644	0.219	0.148	0.332	0.143	0.110	0.292	0.148	0.107	0.194

Uncertain Knowledge Graph **Reasoning**

CCKS 2022:
**Gaussian Metric Learning for Few-Shot Uncertain
Knowledge Graph Completion**

Jingting Wang, Tianxing Wu, Jiatao Zhang

Uncertainties of entities and relations need explicit semantics guidance.

For relations:

museumincity	(Gotoh_Museum, Tokyo, 1.0)
atlocation	(Air_Canada, Vancouver, 0.92)
	(Albania, Europe, 1.0)
	(Queen_Victoria, Great Britain, 0.93)

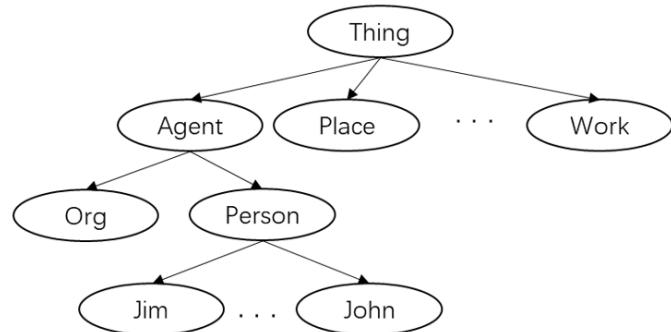
company -> city

country -> continent

people -> country

For entities: “Alice.” vs. “artist.”

- Incorporating the uncertainties of entities and relations into the training process:
 - Use **Intrinsic information content (IIC)** to measure the uncertainties of entities:



The more closer to the root node, the lower IIC, the higher the uncertainty.

$$IIC(c) = 1 - \frac{\log(hypo(c) + 1)}{\log(N)}$$

$$UC_e(h) = 1 - IIC(h)$$

- Apply **domain** and **range** to measure the uncertainties of relations:
 - The more linking entities types, the higher the uncertainty.

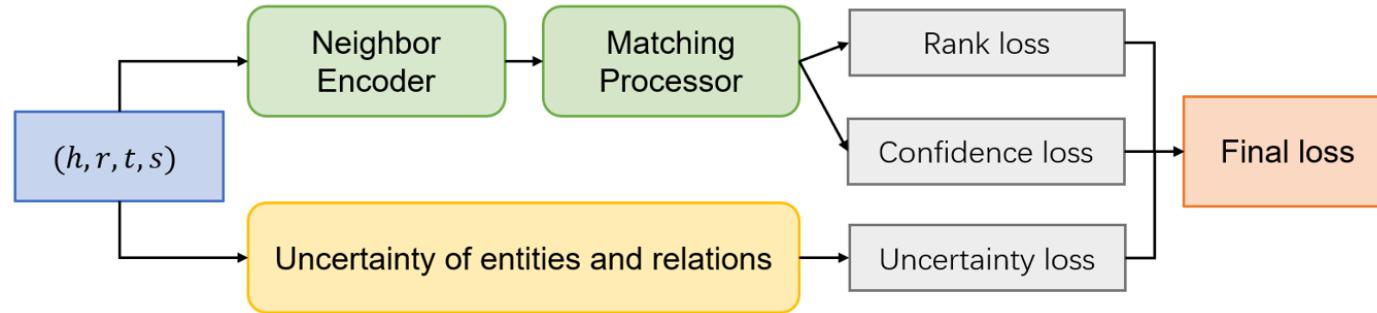
$$UC_r(r) = |D_r| \times |R_r|$$

$$UC_r(r) = \sum_{h \in D_r, t \in R_r} (UC_e(h) + UC_e(t))$$

Uncertainty loss

$$\mathcal{L}_{uc} = \sum_{i \in \mathcal{R}} \sum_{i \in \mathcal{E}} (w \cdot \|\sigma_i\|_2 + b - UC_{r/e}(i))$$

Training Target:



{

Rank loss: $\mathcal{L}_{rank} = \sum_r \sum_{(h, t, s) \in \mathcal{Q}_r} \sum_{(h, t', s') \in \mathcal{Q}'_r} s \cdot [\gamma + s_{rank} - s'_{rank}]_+$

Confidence loss: $\mathcal{L}_{mse} = \sum_r \sum_{(h_i, t_i, s_i) \in \mathcal{Q}_r} (s_{conf} - s_i)^2$

Final loss: $\mathcal{L}_{joint} = w_1 \mathcal{L}_{rank} + w_2 \mathcal{L}_{mse} + w_3 \mathcal{L}_{uc}$

Experimental Results:

- Link prediction

Dataset	Model	Hits@1	Hits@5	Hits@10	WMR	WMRR
NL27k	UKGE	0.031	0.038	0.046	489.537	0.037
	FSRL	0.216	0.373	0.490	81.728	0.294
	GMUC	0.363	0.549	0.626	65.146	0.455
	Ours ₁	0.379	0.598	0.670	50.940	0.481
	Ours ₂	0.386	0.573	0.663	51.539	0.474
CN15k	UKGE	0.014	0.019	0.028	496.185	0.022
	FSRL	0.006	0.025	0.041	374.439	0.023
	GMUC	0.002	0.027	0.089	382.188	0.027
	Ours ₁	0.010	0.042	0.090	378.854	0.029
	Ours ₂	0.013	0.037	0.094	367.456	0.034

- Confidence prediction

Dataset	NL27k		CN15k	
Metric	MSE	MAE	MSE	MAE
UKGE	0.468	0.636	0.350	0.541
GMUC	0.017	0.100	0.021	0.112
Ours ₁	0.015	0.094	0.017	0.082
Ours ₂	0.015	0.092	0.017	0.079

Uncertain Knowledge Graph Reasoning

Summary:

1. Existing works aim to solve the challenges:
 - How to remain uncertainty information in the embedding space to high-quality KG embeddings ?
 - How to compute the confidences of unseen facts (i.e., solve the false negative problem) in the training process?
2. How to leverage the capabilities of zero-shot learning and reasoning of LLM to improve uncertain knowledge graph reasoning is also worthy to study in the future.



IJCAI/2023 MACAO



IJCAI

International Joint Conferences on
Artificial Intelligence Organization

Thank You



Speaker: Tianxing Wu



Date: 2023.08.19





IJCAI/2023 MACAO



IJCAI

International Joint Conferences on
Artificial Intelligence Organization

Discussion on Main Issues & Opportunities

<https://openkg-tutorial.github.io/>

Ningyu Zhang
Zhejiang University

19, Aug, 2023

KG Meets LLMs

JOURNAL OF LATEX CLASS FILES, VOL. 14, NO. 8, AUGUST 2021

1

Unifying Large Language Models and Knowledge Graphs: A Roadmap

Shirui Pan, Senior Member, IEEE, Linhao Luo,
Yufei Wang, Chen Chen, Jiapu Wang, Xindong Wu, Fellow, IEEE

Abstract—Large language models (LLMs), such as ChatGPT and GPT4, are making new waves in the field of natural language processing and artificial intelligence, due to their emergent ability and generalizability. However, LLMs are black-box models, which often fall short of capturing and accessing factual knowledge. In contrast, Knowledge Graphs (KGs), Wikipedia and Huapi for example, are structured knowledge models that explicitly store rich factual knowledge. KGs can enhance LLMs by providing external knowledge for inference and interpretability. Meanwhile, KGs are difficult to construct and evolving by nature, which challenges the existing methods in KGs to generate new facts and represent unseen knowledge. Therefore, it is complementary to unify LLMs and KGs together and simultaneously leverage their advantages. In this article, we present a forward-looking roadmap for the unification of LLMs and KGs. Our roadmap consists of three general frameworks, namely, 1) *KG-enhanced LLMs*, which incorporate KGs during the pre-training and inference phases of LLMs, or for the purpose of enhancing understanding of the knowledge learned by LLMs; 2) *LLM-augmented KGs*, that leverage LLMs for different KG tasks such as embedding, completion, construction, graph-to-text generation, and question answering; and 3) *Synergized LLMs + KGs*, in which LLMs and KGs play equal roles and work in a mutually beneficial way to enhance both LLMs and KGs for bidirectional reasoning driven by both data and knowledge. We review and summarize existing efforts within these three frameworks in our roadmap and pinpoint their future research directions.

Index Terms—Natural Language Processing, Large Language Models, Generative Pre-Training, Knowledge Graphs, Roadmap, Bidirectional Reasoning.

arXiv:2306.08302v2 [cs.CL] 20 Jun 2023

1 INTRODUCTION

Large language models (LLMs)¹ (e.g., BERT [1], RoBERTA [2], and T5 [3]), pre-trained on the large-scale corpus, have shown great performance in various natural language processing (NLP) tasks, such as question answering [4], machine translation [5], and text generation [6]. Recently, the dramatically increasing model size further enables the LLMs with the emergent ability [7], paving the road for applying LLMs as Artificial General Intelligence (AGI). Advanced LLMs like ChatGPT² and PaLM2³, with billions of parameters, exhibit great potential in many complex practical tasks, such as education [8], code generation [9] and recommendation [10].

• Shirui Pan is with the School of Information and Communication Technology and Institute for Integrated and Intelligent Systems (IIIS), Griffith University, Queensland, Australia. Email: s.pan@griffith.edu.au.

• Linhao Luo and Yufei Wang are with the Department of Data Science and AI, Monash University, Melbourne, Australia. E-mail: linhao.luo@monash.edu, garyyufei@gmail.com.

• Chen Chen is with the Nanyang Technological University, Singapore. E-mail: s19009@ntu.edu.sg.

• Jiapu Wang is with the Faculty of Information Technology, Beijing University of Technology, Beijing. E-mail: jpwang@emails.bjut.edu.cn.

• Xindong Wu is with the Key Laboratory of Knowledge Engineering with Big Data (the Ministry of Education of China), Hefei University of Technology, Hefei, China; He is also affiliated with the Research Center for Knowledge Engineering, Zhejiang Lab, Hangzhou, China. Email: xuw@hfut.edu.cn.

• Shirui Pan and Linhao Luo contributed equally to this work.

1. LLMs are also known as pre-trained language models (PLMs).

2. <https://openai.com/blog/chatgpt>

3. <https://ai.google/discover/palm2>

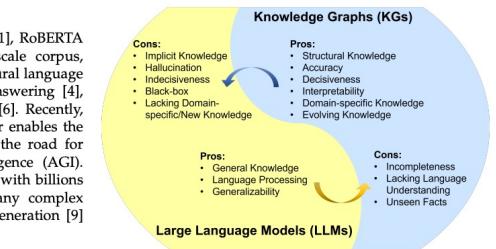


Fig. 1. Summarization of the pros and cons for LLMs and KGs. LLM pros: *General Knowledge* [11], *Language Processing* [12], *Generalizability* [13]; LLM cons: *Implicit Knowledge* [14], *Hallucination* [15], *Incompleteness* [16], *Black-box* [17], *Lacking Domain-specific/New Knowledge* [18]. KG pros: *Structural Knowledge* [19], *Accuracy* [20], *Decisiveness* [21], *Interpretability* [22], *Domain-specific Knowledge* [23], *Evolving Knowledge* [24]; KG cons: *Incompleteness* [25], *Lacking Language Understanding* [26], *Unseen Facts* [27].

Despite their success in many applications, LLMs have been criticized for their lack of factual knowledge. Specifically, LLMs memorize facts and knowledge contained in the training corpus [14]. However, further studies reveal that LLMs are not able to recall facts and often experience hallucinations by generating statements that are factually incorrect [15], [28]. For example, LLMs might say “Ein-

Large Language Models and Knowledge Graphs: Opportunities and Challenges

Jeff Z. Pan 

The University of Edinburgh, United Kingdom

Simon Razniewski 

Bosch Center for AI, Germany

Jan-Christoph Kalo 

Vrije Universiteit Amsterdam, The Netherlands

Sneha Singhania 

Max Planck Institute for Informatics, Germany

Jiaoyan Chen 

The University of Manchester & University of Oxford, United Kingdom

Stefan Dietze 

GESIS - Leibniz Institute for the Social Sciences & Heinrich-Heine-Universität Düsseldorf, Germany

Hajira Jabeen 

GESIS - Leibniz Institute for the Social Sciences, Germany

Janna Omelianenko 

University of Würzburg, Germany

Wen Zhang 

Zhejiang University, China

Matteo Lissandrini 

Aalborg University, Denmark

Russa Biswas 

Hasso-Plattner Institute, Germany

Gerard de Melo 

Hasso-Plattner Institute, Germany

Angela Bonifati 

Lyon 1 University, France

Edlira Vakaj 

Birmingham City University, United Kingdom

Mauro Dragoni 

Fondazione Bruno Kessler, Italy

Damien Graux 

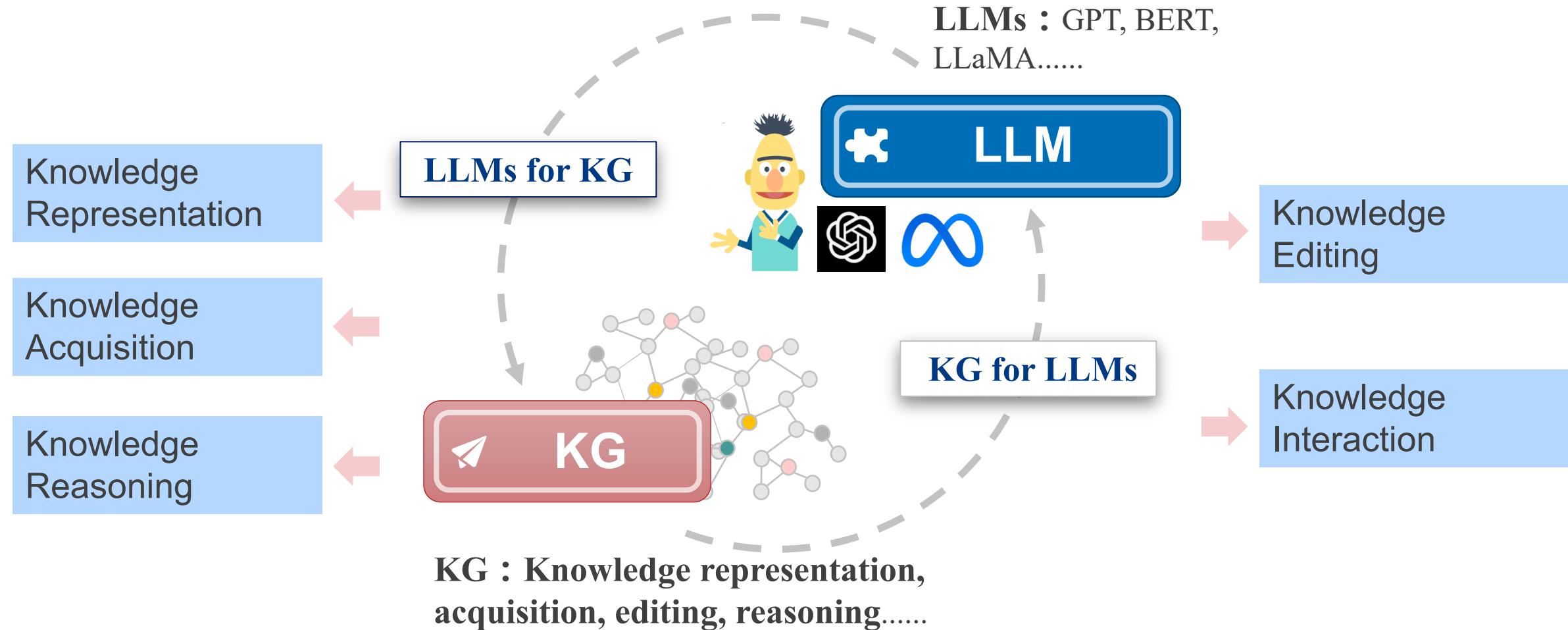
Edinburgh Research Centre, CSI, Huawei Technologies UK, United Kingdom

Abstract

Large Language Models (LLMs) have taken Knowledge Representation—and the world—by storm. This inflection point marks a shift from explicit knowledge representation to a renewed focus on the hybrid representation of both explicit knowledge and parametric knowledge. In this position

paper, we will discuss some of the common debate points within the community on LLMs (parametric knowledge) and Knowledge Graphs (explicit knowledge) and speculate on opportunities and visions that the renewed focus brings, as well as related research topics and challenges.

Issues and Opportunities



Next-generation (**Maybe**) Knowledge representation, acquisition, editing, reasoning, interaction



Part1: Knowledge Representation

Principle of Neural Knowledge Representation (within LLMs)

Transformer Feed-Forward Layers Are Key-Value Memories

Mor Geva^{1,2} Roei Schuster^{1,3} Jonathan Berant^{1,2} Omer Levy¹

¹Blavatnik School of Computer Science, Tel-Aviv University

²Allen Institute for Artificial Intelligence

³Cornell Tech

{morgeva@mail, joberant@cs, levyomer@cs}.tau.ac.il, rs864@cornell.edu

In-context Learning and Induction Heads

AUTHORS

Catherine Olsson*, Nelson Elhage*, Neel Nanda*, Nicholas Joseph, Nova DasSarma, Tom Henighan, Ben Mann, Amanda Askell, Yuntao Bai, Anna Chen, Tom Conerly, Dawn Drain, Deep Ganguli, Zac Hatfield-Dodds, Danny Hernandez, Scott Johnston, Andy Jones, Jackson Kernion, Liane Lovitt, Kamal Ndousse, Dario Amodei, Tom Brown, Jack Clark, Jared Kaplan, Sam McCandlish, Chris Olah†

AFFILIATION

Anthropic

PUBLISHED

Mar 8, 2022

* Core Research Contributor; † Core Infrastructure Contributor; ‡ Correspondence to colah@anthropic.com;
Author contributions statement below.

Locating and Editing Factual Associations in GPT

Kevin Meng*

MIT CSAIL

David Bau*

Northeastern University

Alex Andonian

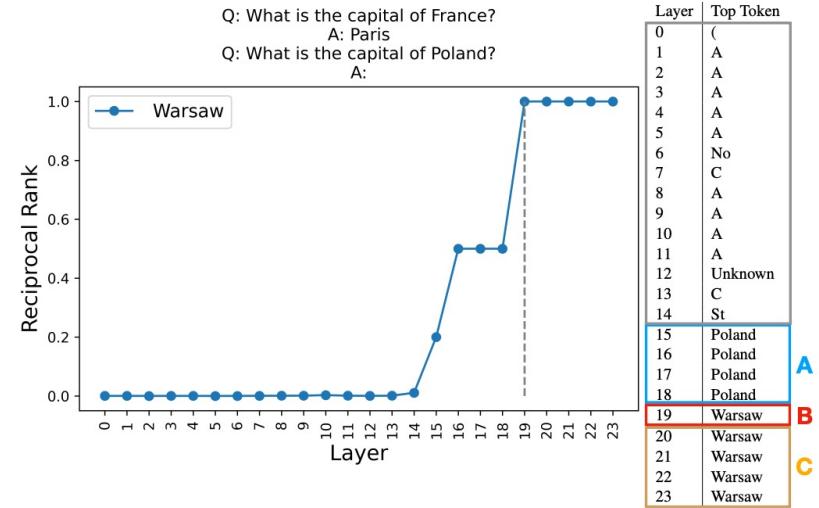
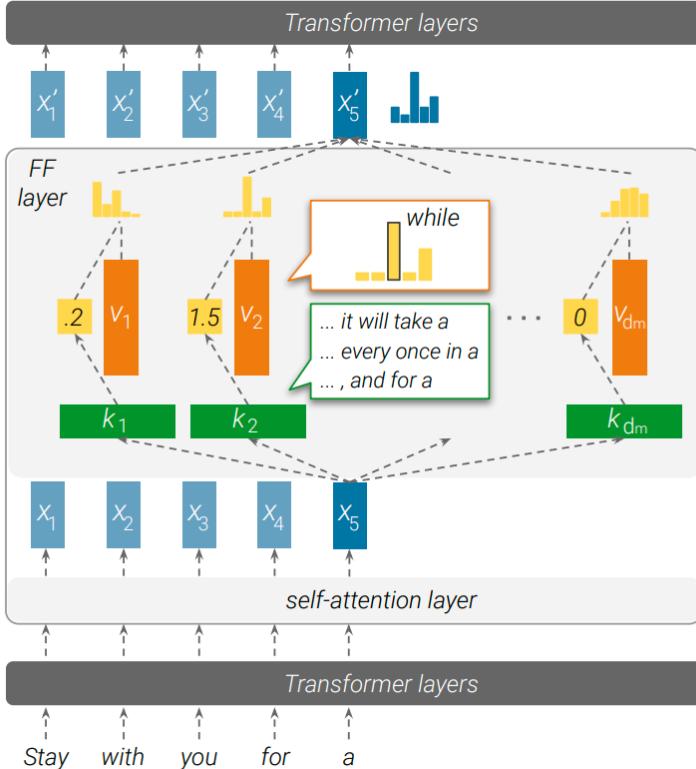
MIT CSAIL

Yonatan Belinkov†

Technion – IIT

Knowledge Representation: Observations

Principle of Neural Knowledge Representation (within LLMs)

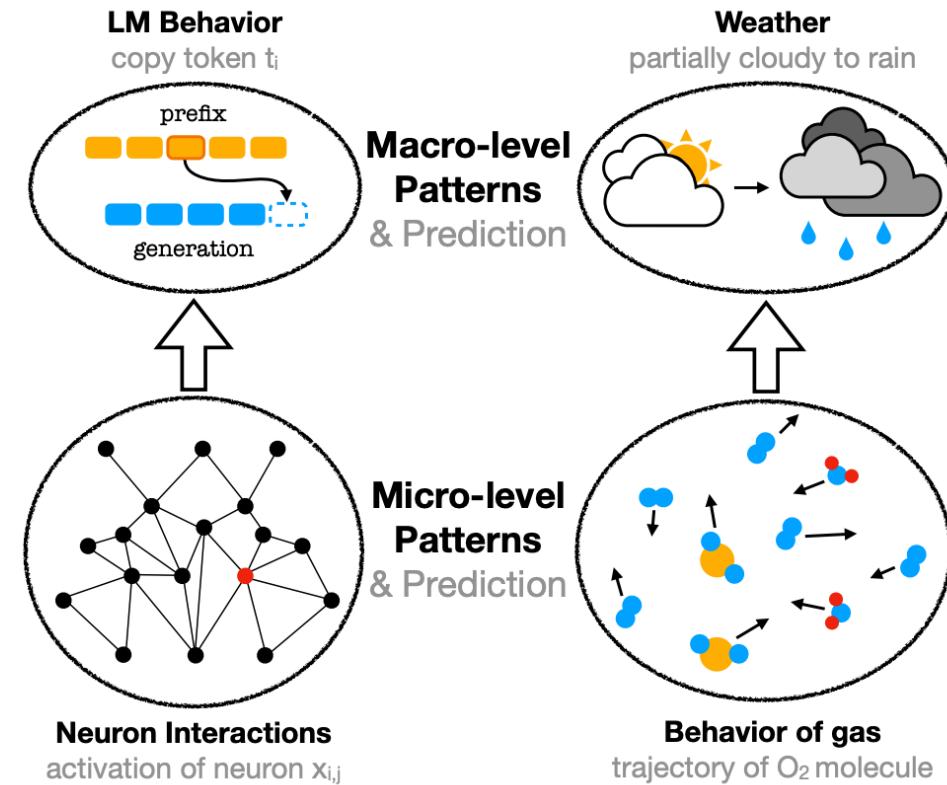
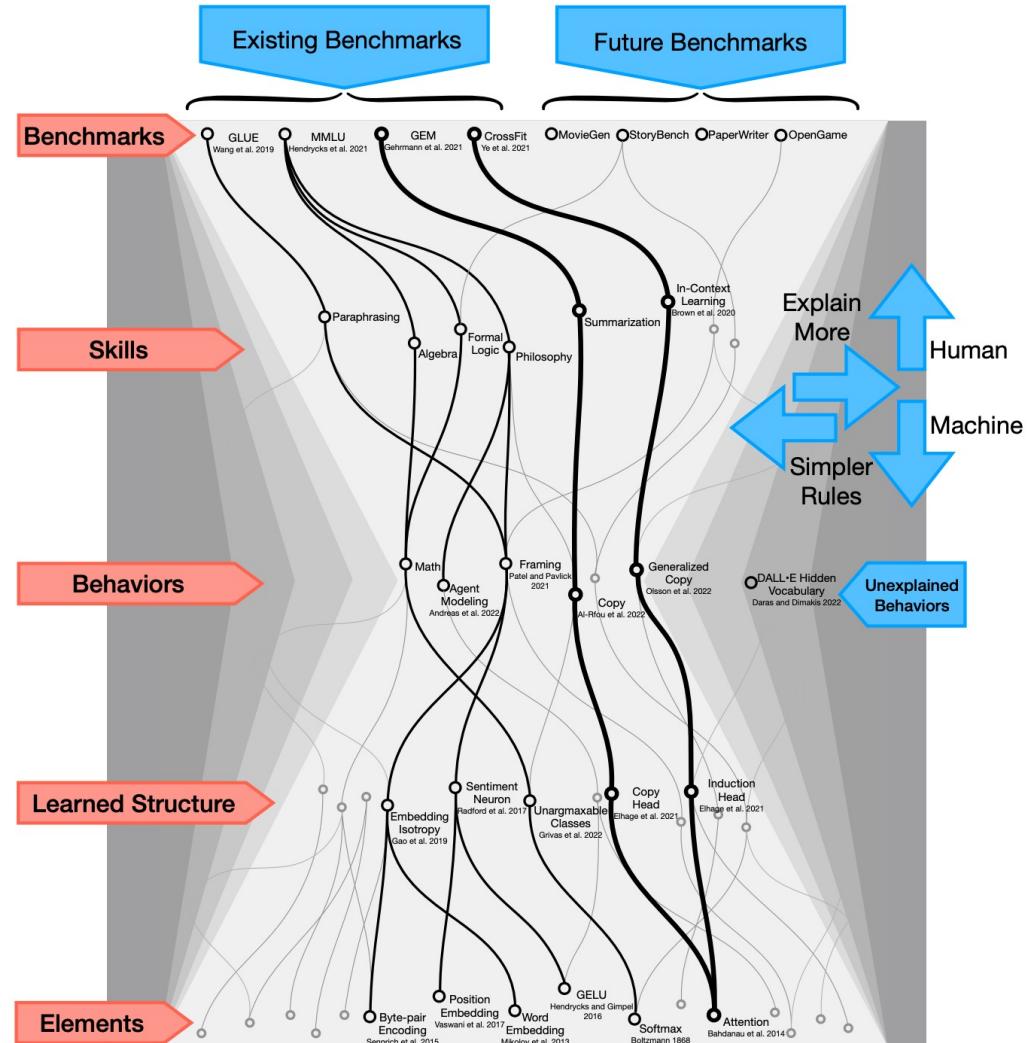


- **Keys** are correlated with human-interpretable input patterns
- **Values**, mostly in the model's upper layers, induce distributions over the output vocabulary
- LMs sometimes exploit a computational mechanism familiar from traditional word embeddings: the use of **simple vector arithmetic** in order to encode abstract relations

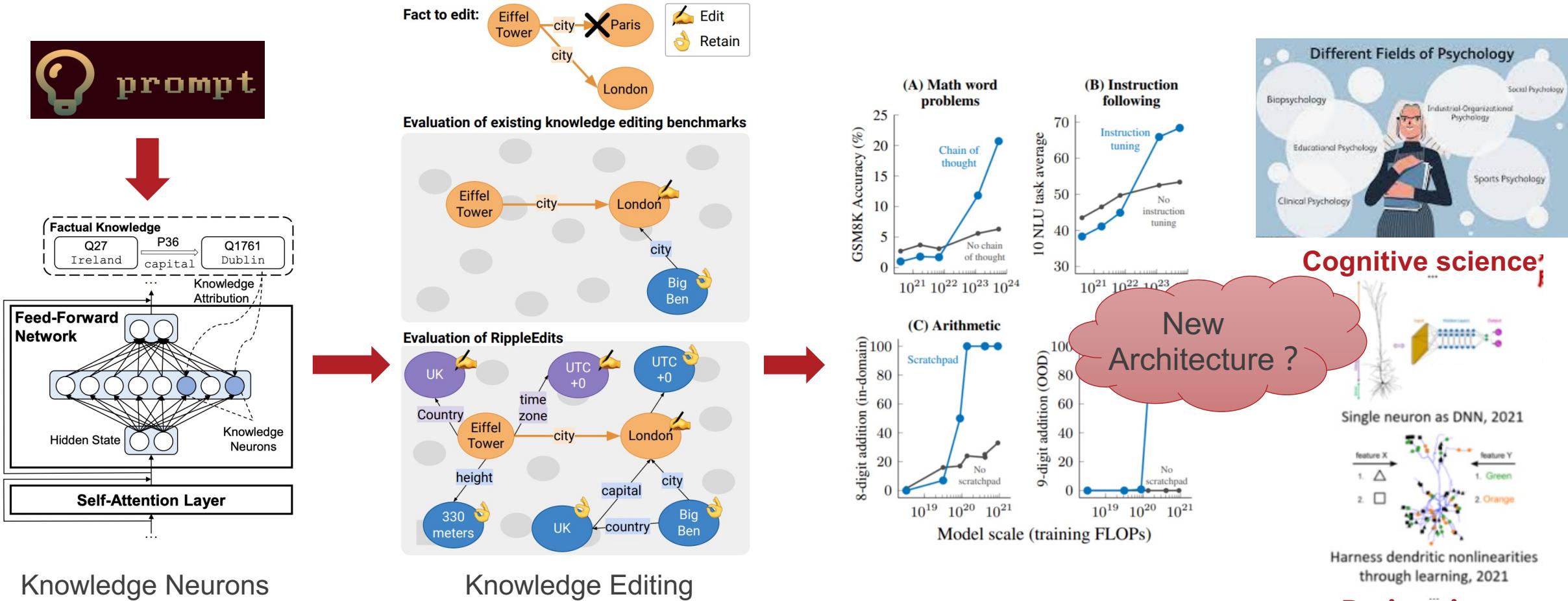
[1] Transformer Feed-Forward Layers Are Key-Value Memories (EMNLP 2021)

[2] Language Models Implement Simple Word2Vec-style Vector Arithmetic (2023)

Knowledge Representation: System Science



Knowledge Representation: Unified Neural Symbolic



- [1] Knowledge Neurons in Pretrained Transformers, ACL2021
- [2] Evaluating the Ripple Effects of Knowledge Editing in Language Models, 2023
- [3] Emergent Abilities of Large Language Models, 2022

Part2: Knowledge Acquisition

• Text Modality

Albert Einstein is one of the greatest and most influential scientists

• Image Modality

Qinghai Lake



Inland Lake



correspond to

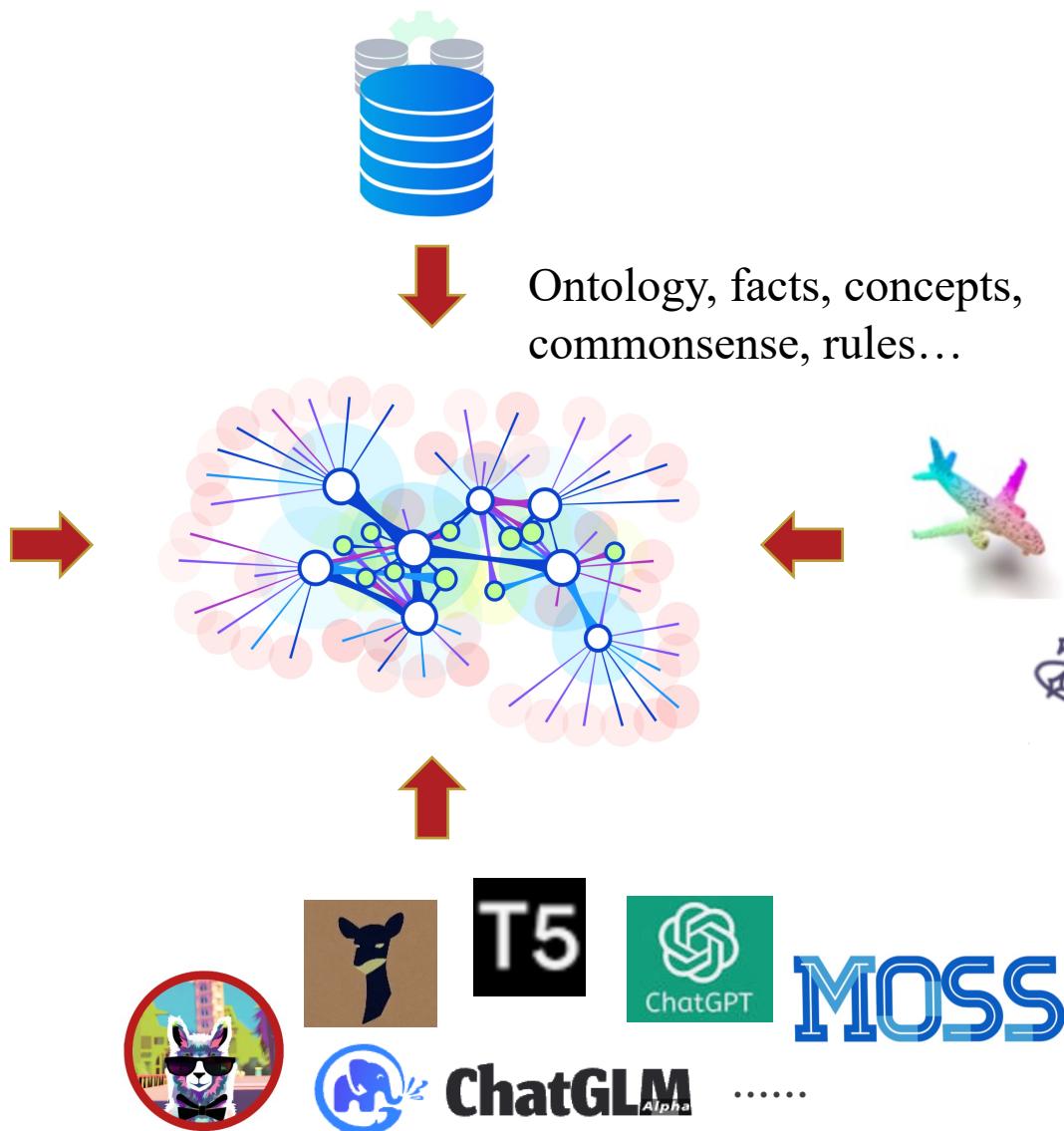
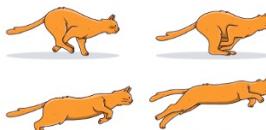
• Audio Modality



DNA is the molecule that carries genetic information.

• Video Modality

Cats are able to adjust their body posture and maintain stability while running at high speeds.



[1] Towards Relation Extraction From Speech. EMNLP 2022

[2] BertNet: Harvesting Knowledge Graphs with Arbitrary Relations from Pretrained Language Models

[3] Meta-Transformer: A Unified Framework for Multimodal Learning. 2023

Knowledge Acquisition: Ontology

A package for ontology engineering with deep learning



DeepOnto

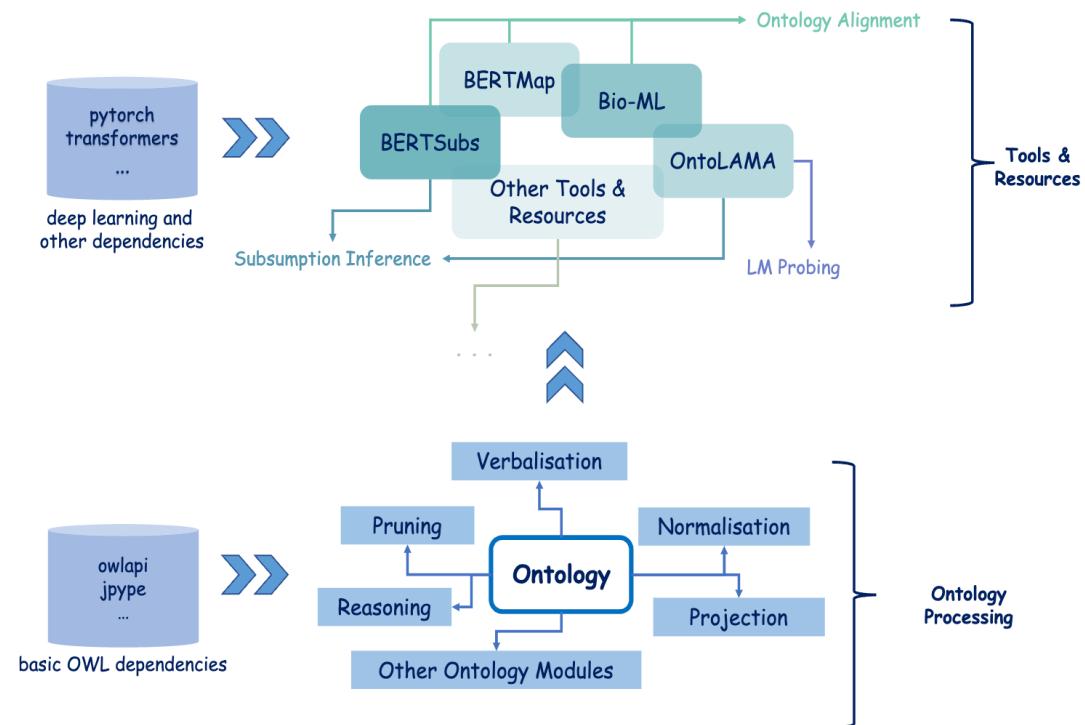
license Apache-2.0 website online pypi v0.8.4

A package for ontology engineering with deep learning.

News 

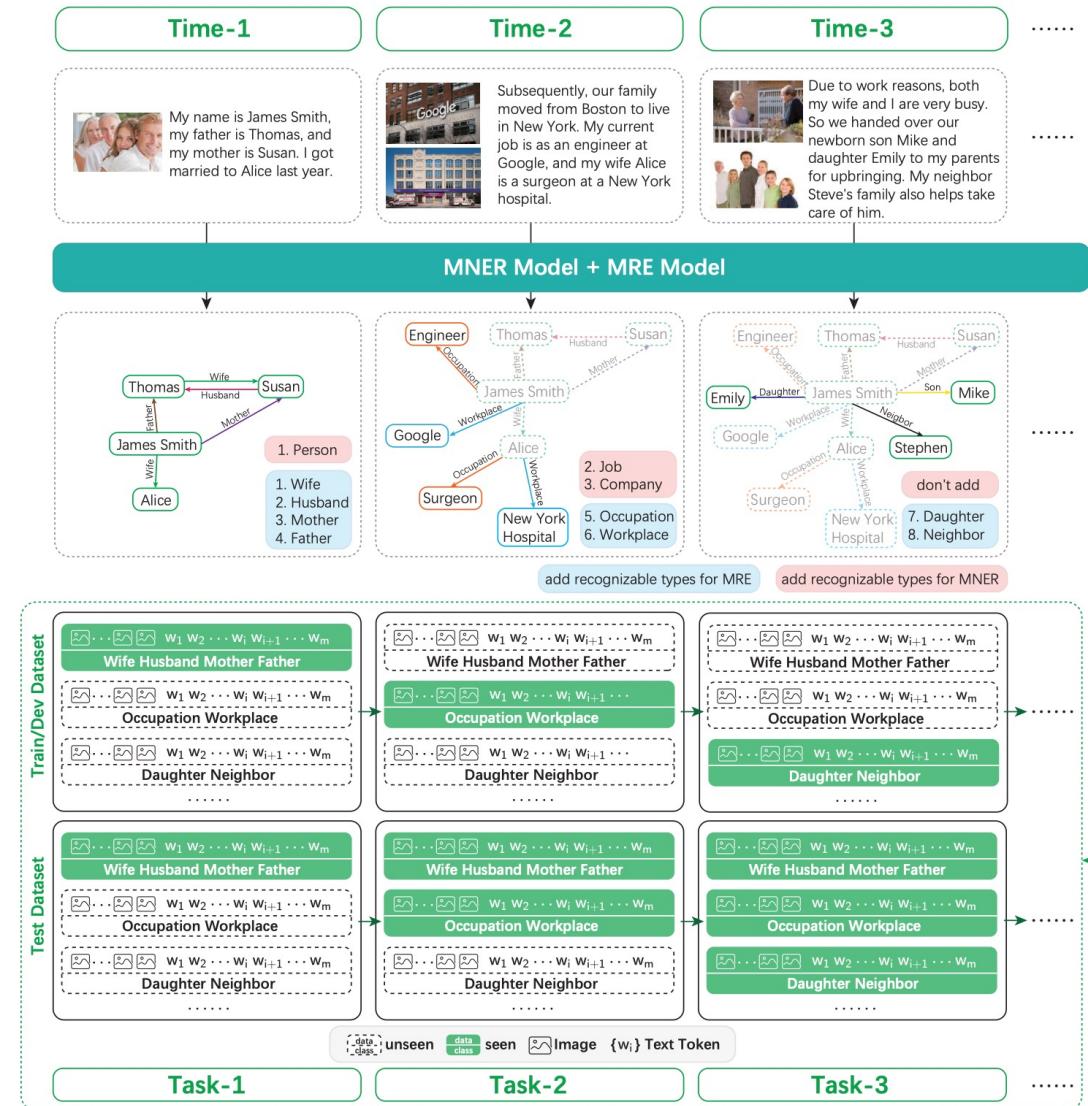
- ✓ Deploy OAEI utilities at `deeponto.align.oaei` for scripts at the sub-repository `OAEI-Bio-ML` as well as bug fixing. (**v0.8.4**)
- ✓ Bug fixing for BERTMap (stuck at reasoning) and ontology alignment evaluation. (**v0.8.3**)
- ✓ Deploy `deeponto.onto.OntologyNormaliser` and `deeponto.onto.OntologyProjector` (**v0.8.0**).
- ✓ Upload Java dependencies directly and remove mowl from pip dependencies (**v0.7.5**).
- ✓ Deploy the `deeponto.subs.bertsubs` and `deeponto.onto.pruning` modules (**v0.7.0**).
- ✓ Deploy the `deeponto.probe.ontolama` and `deeponto.onto.verbalisation` modules (**v0.6.0**).
- ✓ Rebuild the whole package based on the OWLAPI; remove owlready2 from the essential dependencies (from **v0.5.x**).

The complete changelog is available at: [repository](#) or [website](#).



<https://github.com/KRR-Oxford/DeepOnto>

Knowledge Acquisition: Multimodal & Lifelong

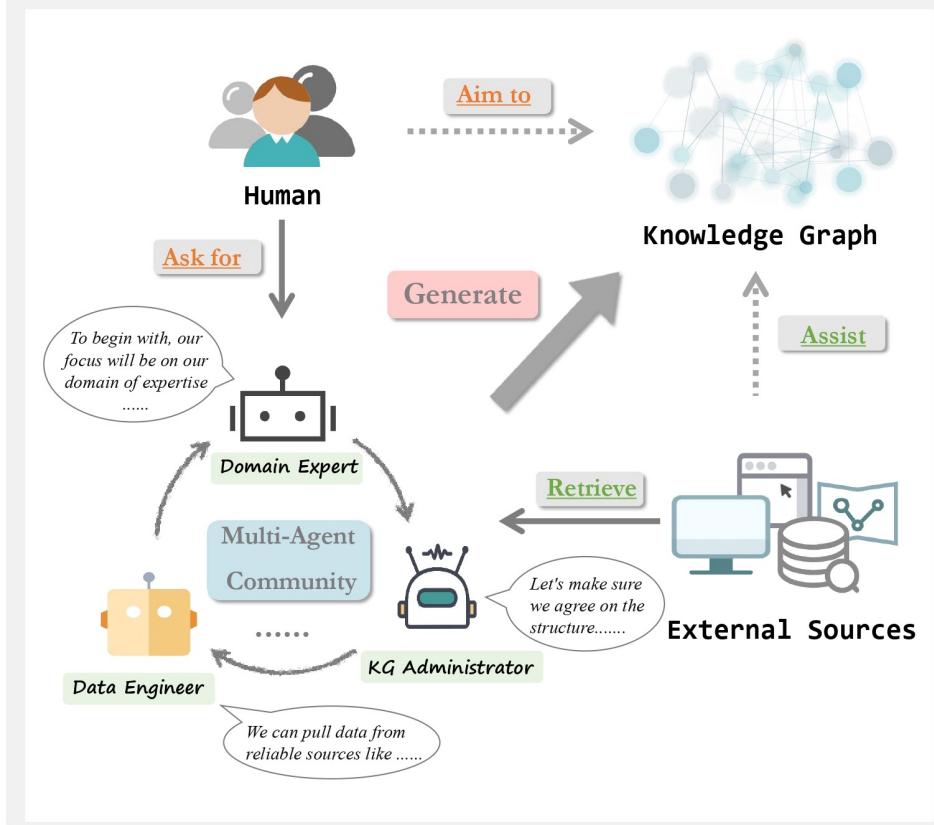


Knowledge Acquisition: LLM Agents & Human

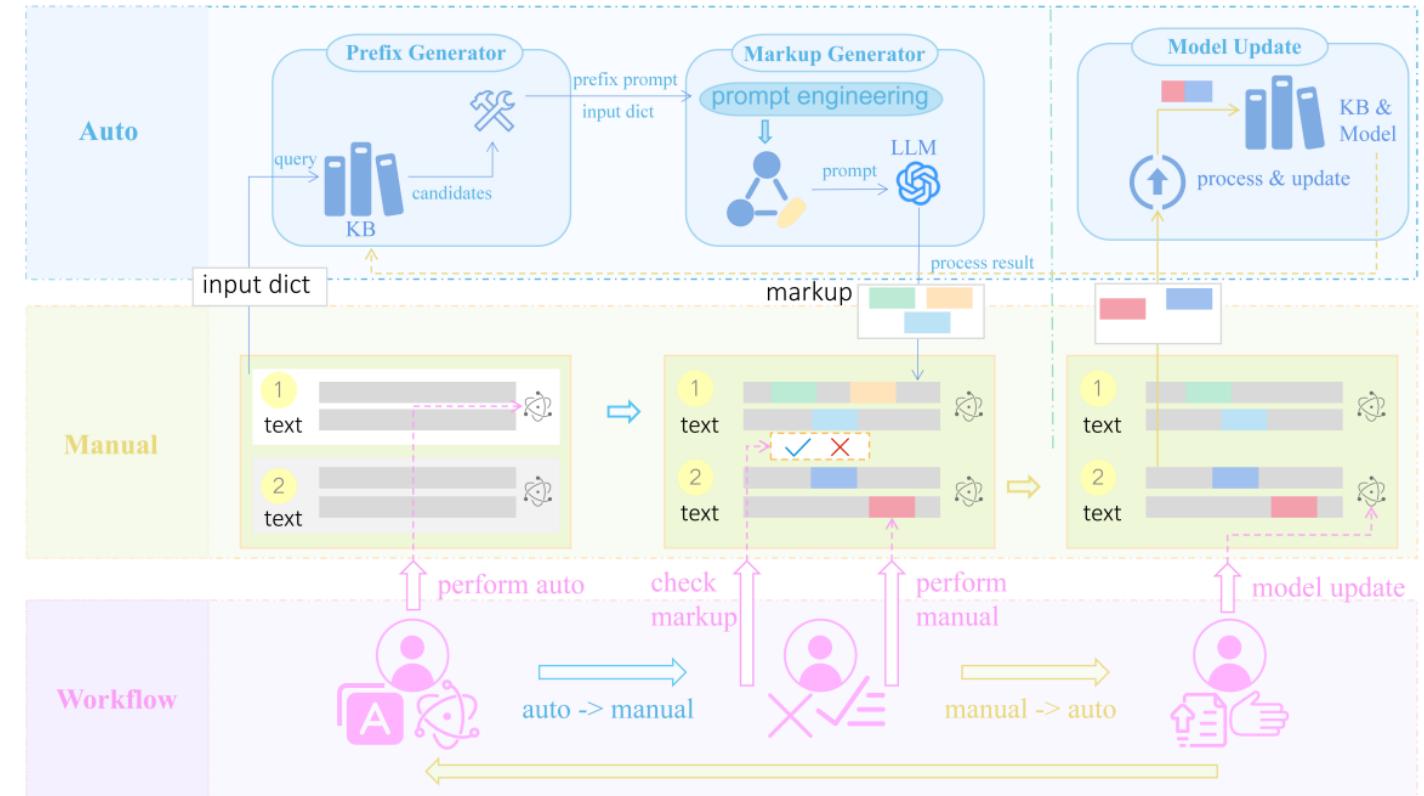
Agent : LLM-powered agents collaborated with other agents, tools, human

Collaboration

Agent + Agent (Tool) → KG



Agent + Human → IE toolkit



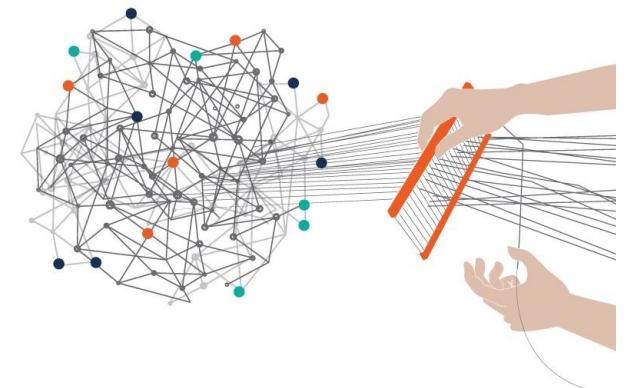
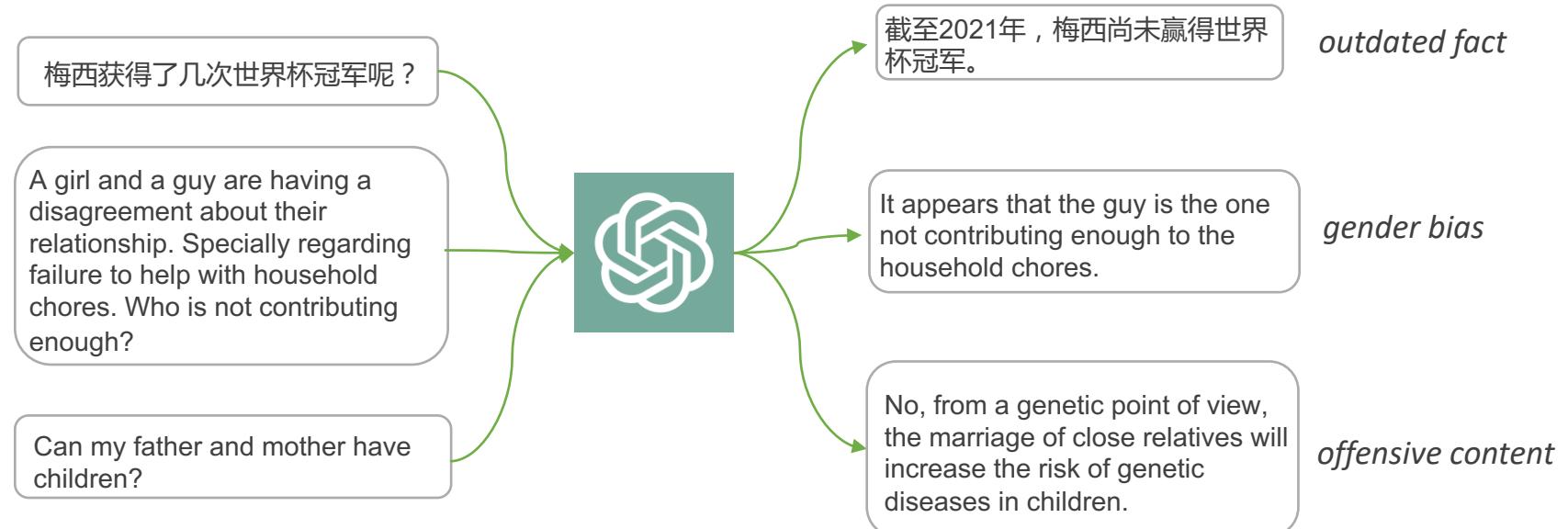
[1] LLMs for Knowledge Graph Construction and Reasoning: Recent Capabilities and Future Opportunities (2023)

[2] CollabKG: A Learnable Human-Machine-Cooperative Information Extraction Toolkit for (Event) Knowledge Graph Construction (2023)

Knowledge Editing

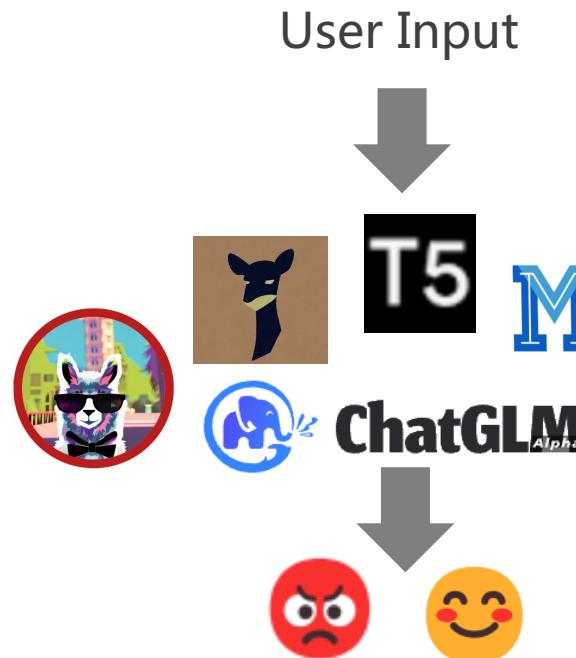
Knowledge in Language Models

LLMs \Leftrightarrow learned something unwanted, including:

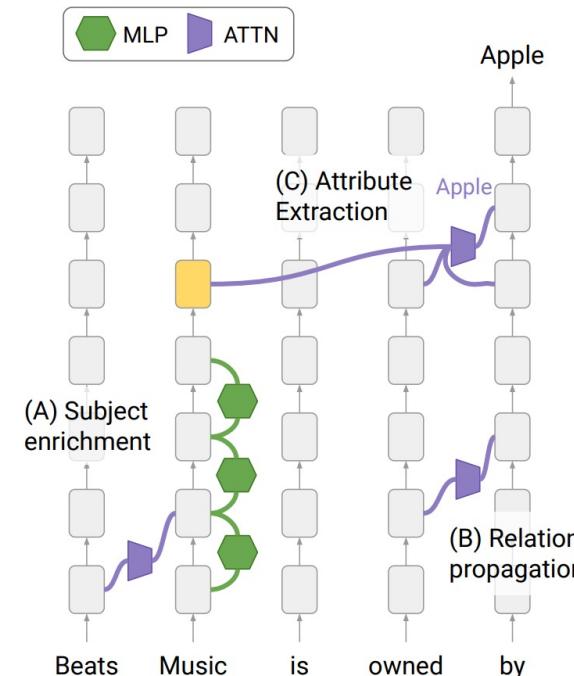


Knowledge Editing for LLMs

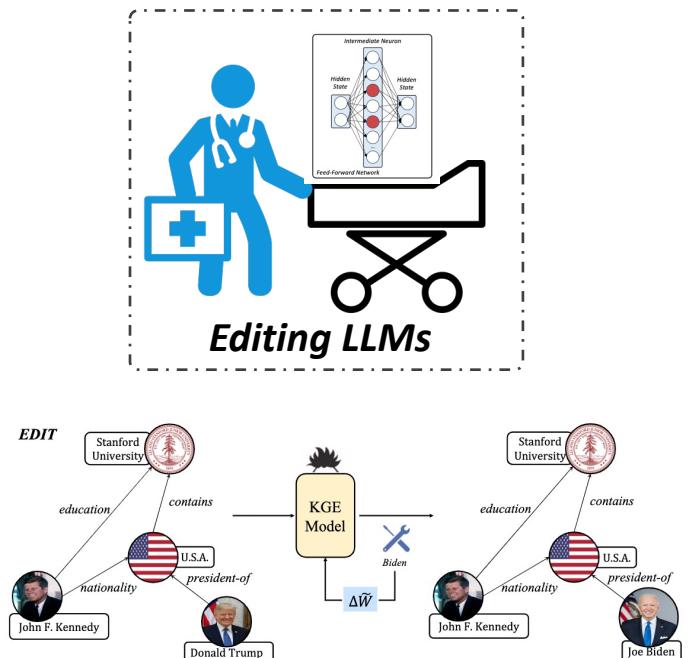
Performing “**surgery**” on large language models requires analyzing model behavior, accurately locating the editing area, and designing efficient and low-cost methods



When to Edit?
Analyzing **symptoms**
on LLMs



Where to Edit?
Locating the **cause**
of LLMs



How to Edit?
Performing **surgery**
on LLMs

Knowledge Editing: Unified Neural Symbolic

Understanding the **principle of knowledge for LLMs**, promoting precise generation in large language models, and realizing a safe and controllable self-evolution flywheel for LLMs



Bias, toxicity, and privacy safety

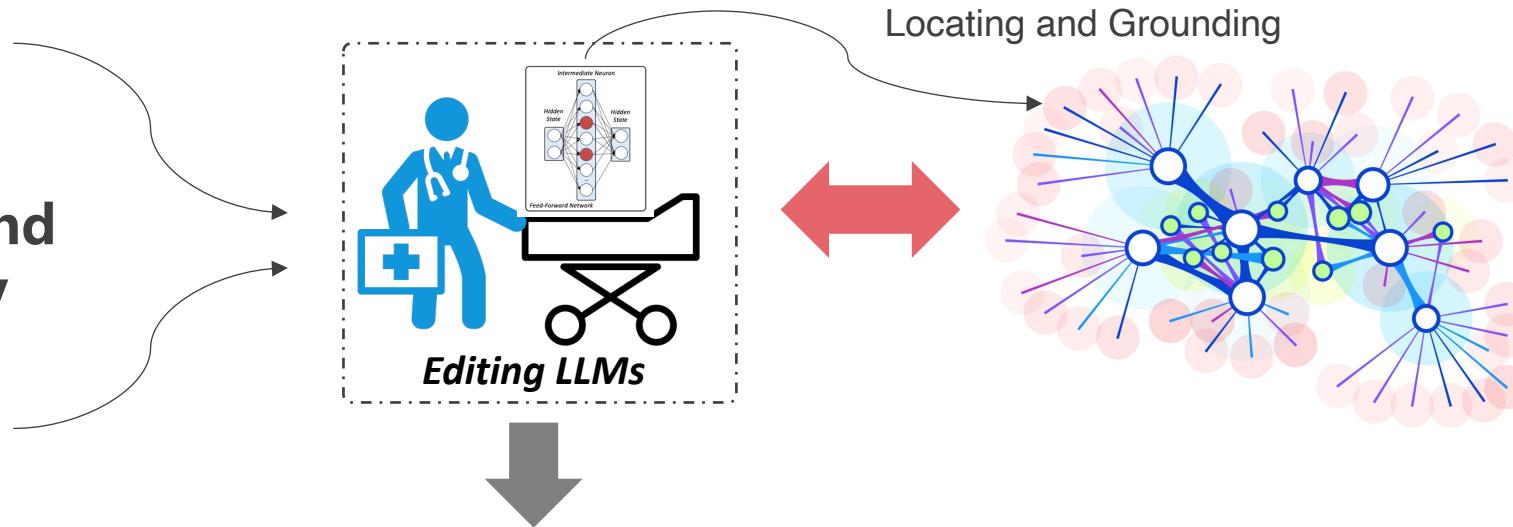


Changes in external knowledge

controllable

explainable

safe



Knowledge Editing for LLMs: Tools

👉  **Transformers**

👉  **PyTorch**



<https://github.com/zjunlp/EasyEdit>

EasyEdit is a Tool for edit LLMs like T5, GPT-J, GPT-NEO Llama...,(from **1B** to **65B**) which is to alter the behavior of LLMs efficiently without negatively impacting performance across other inputs.

Knowledge Editing for LLMs: Tools

Step 1: Choose the appropriate editor

```
from easyeditor import BaseEditor
```

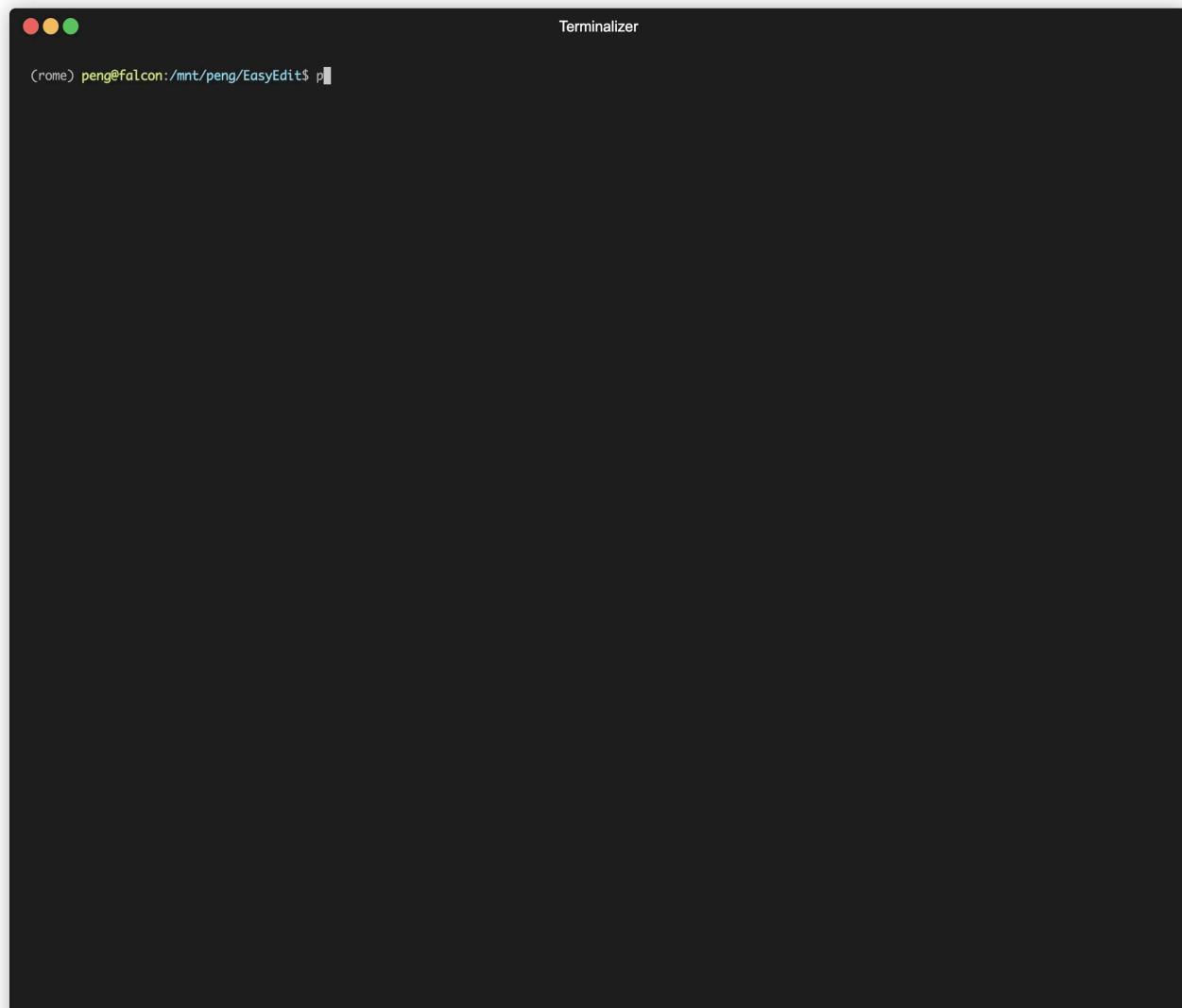
Step 2: Choose the appropriate method

```
hparams = ROMEHyperParams.from_hparams(`PATH`)
editor = BaseEditor.from_hparams(hparams)
```

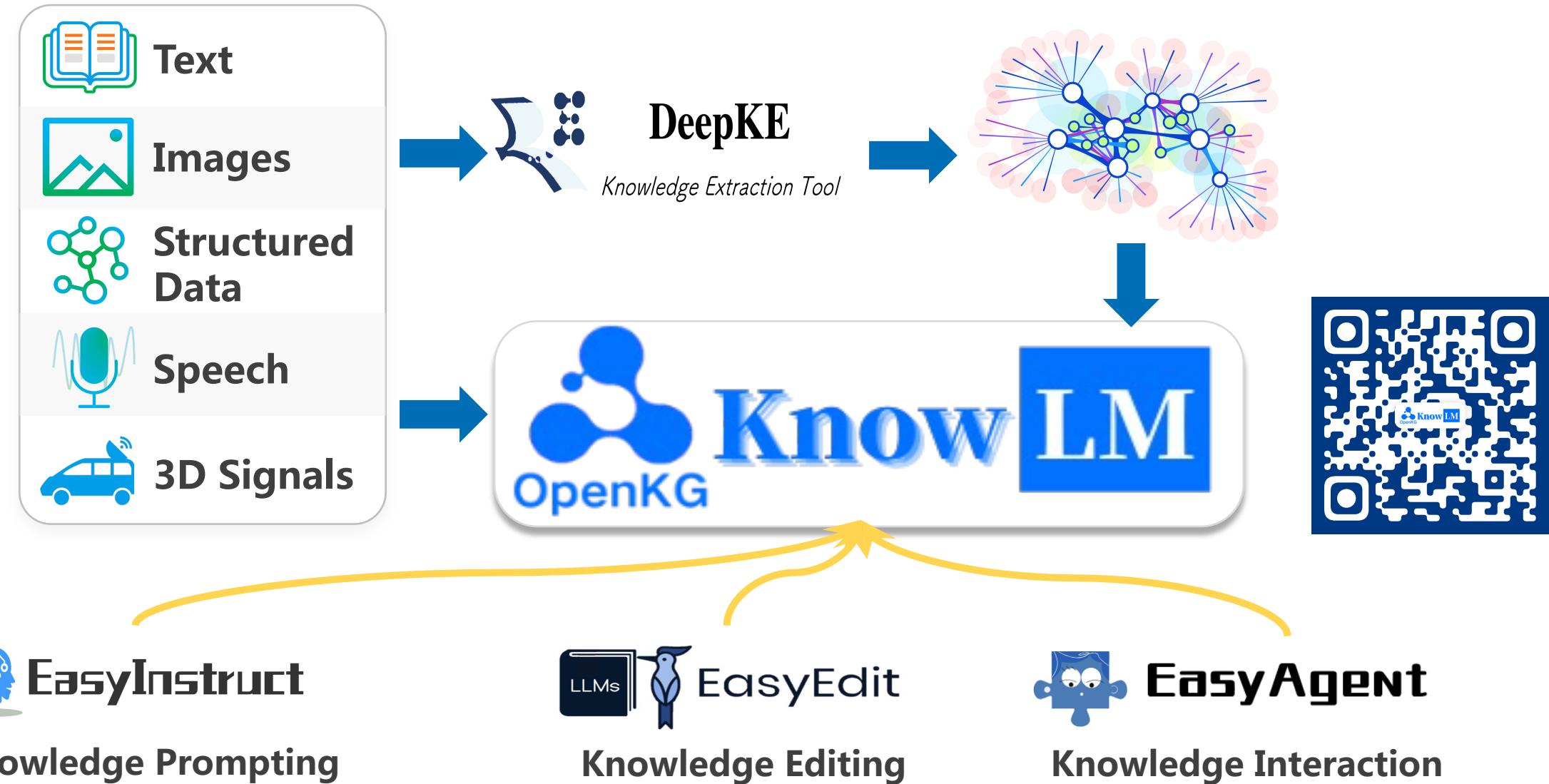
Step 3: Start editing

```
editor.edit(**args)
```

Use ROME



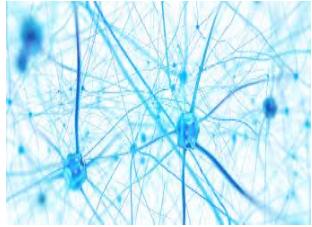
KnowLM: Knowledgeable LLM Framework



Knowledge Reasoning



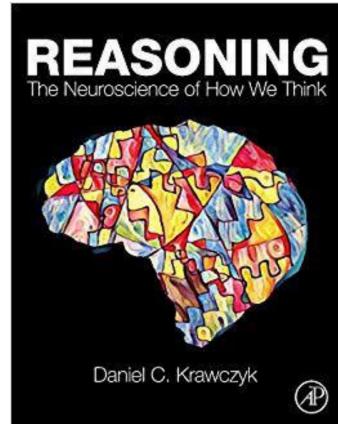
IJCAI/2023 MACAO



Cognitive Science



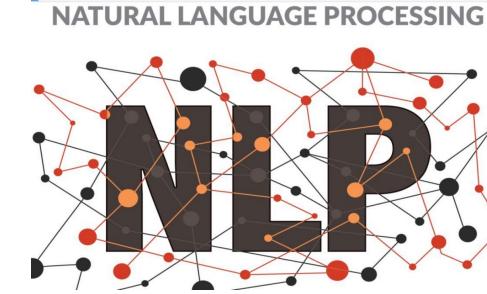
Negotiation



Medical Diagnosis



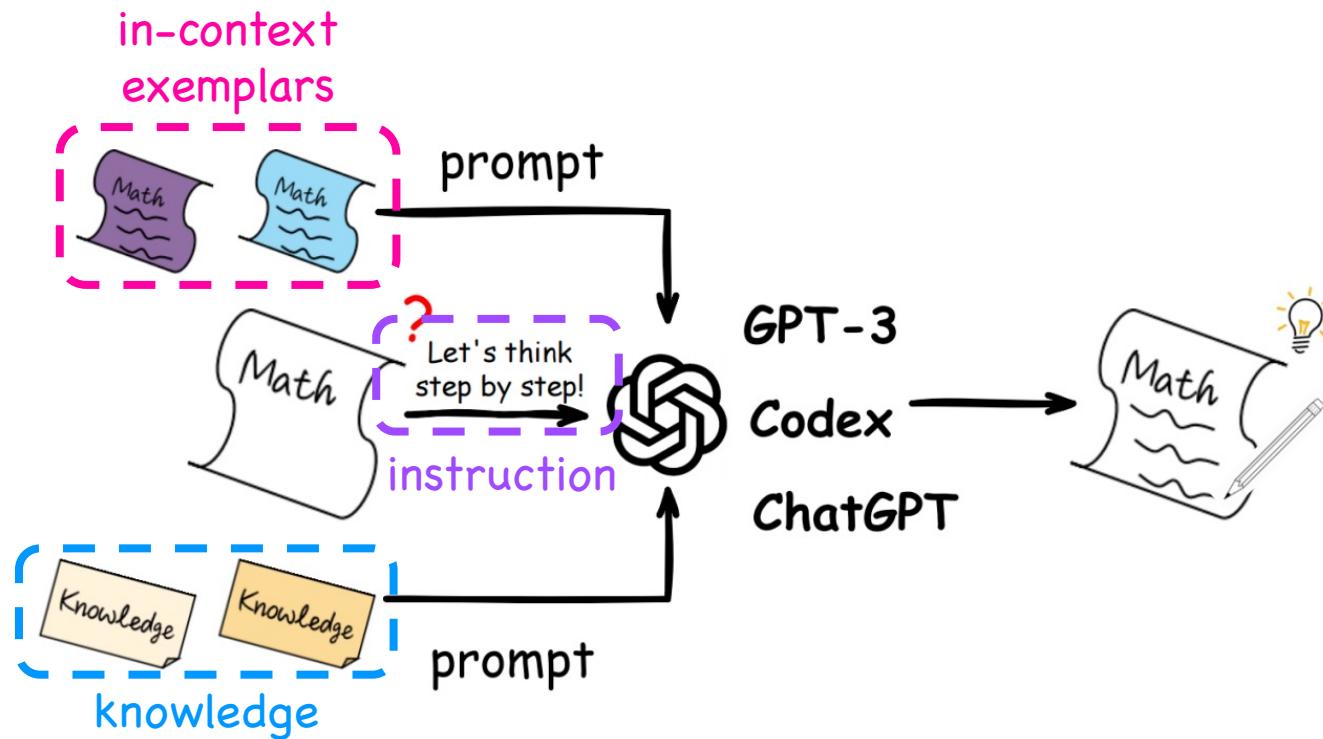
Brain Science



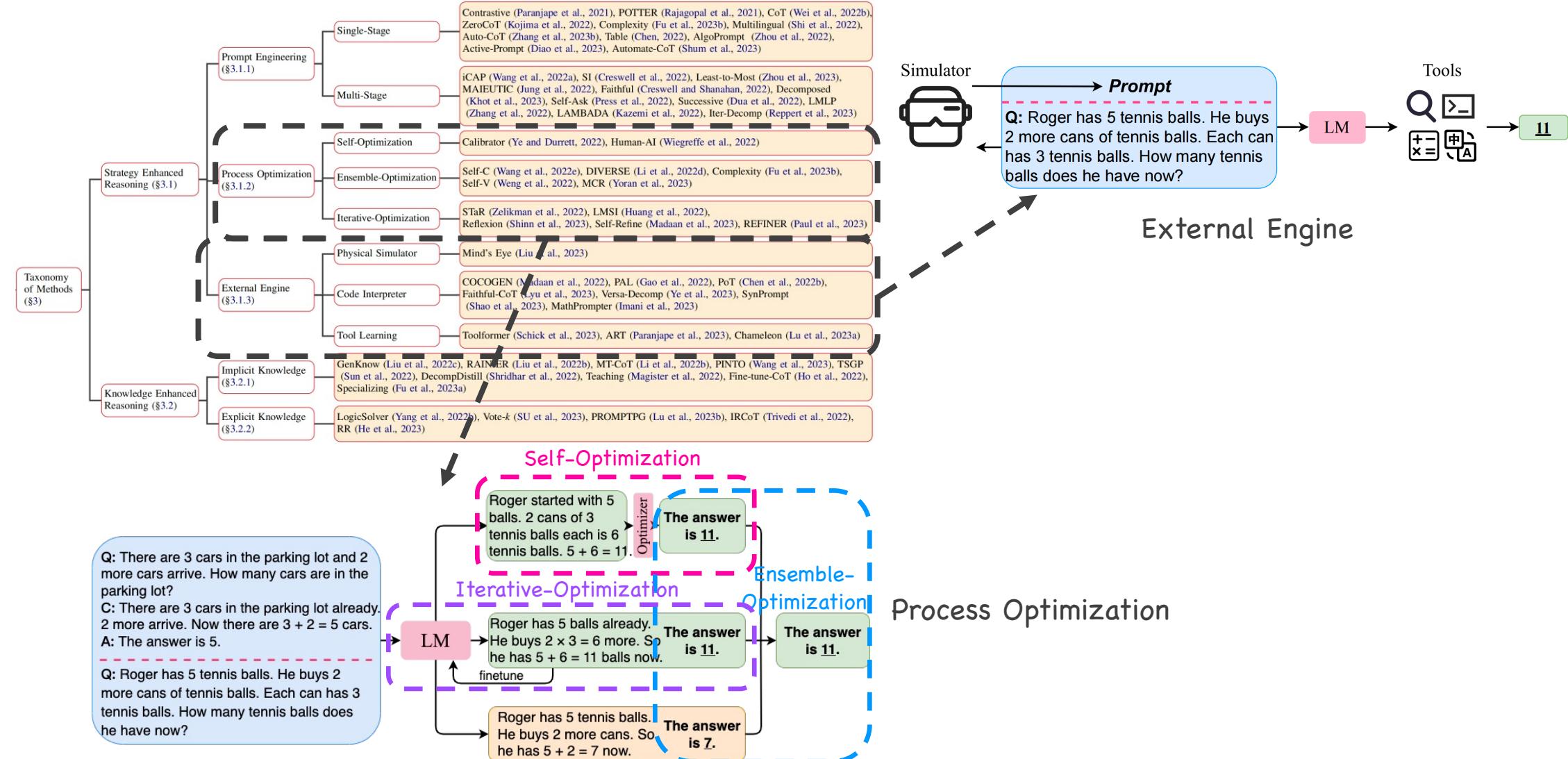
Reasoning is the cognitive process of drawing inferences or conclusions from observations, experiences, or information available to us. It involves the ability to analyze information, identify patterns and relationships, and make logical deductions based on those patterns and relationships.

—ChatGPT

Reasoning with LLMs



Reasoning with LLMs

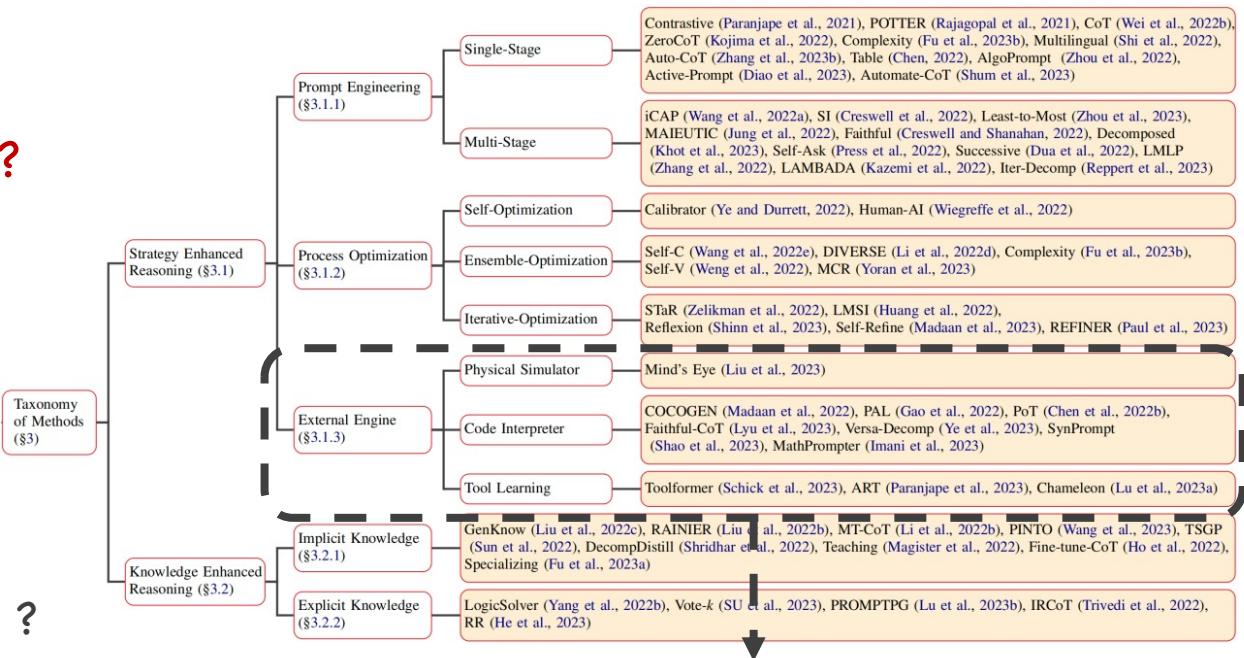


Reasoning with Knowledge Engine

When and how to properly use which tools ?

General steps to use a tool:

1. Which tool to use ?
2. What information to give the tool ?
3. How to use the returned results of the tool ?

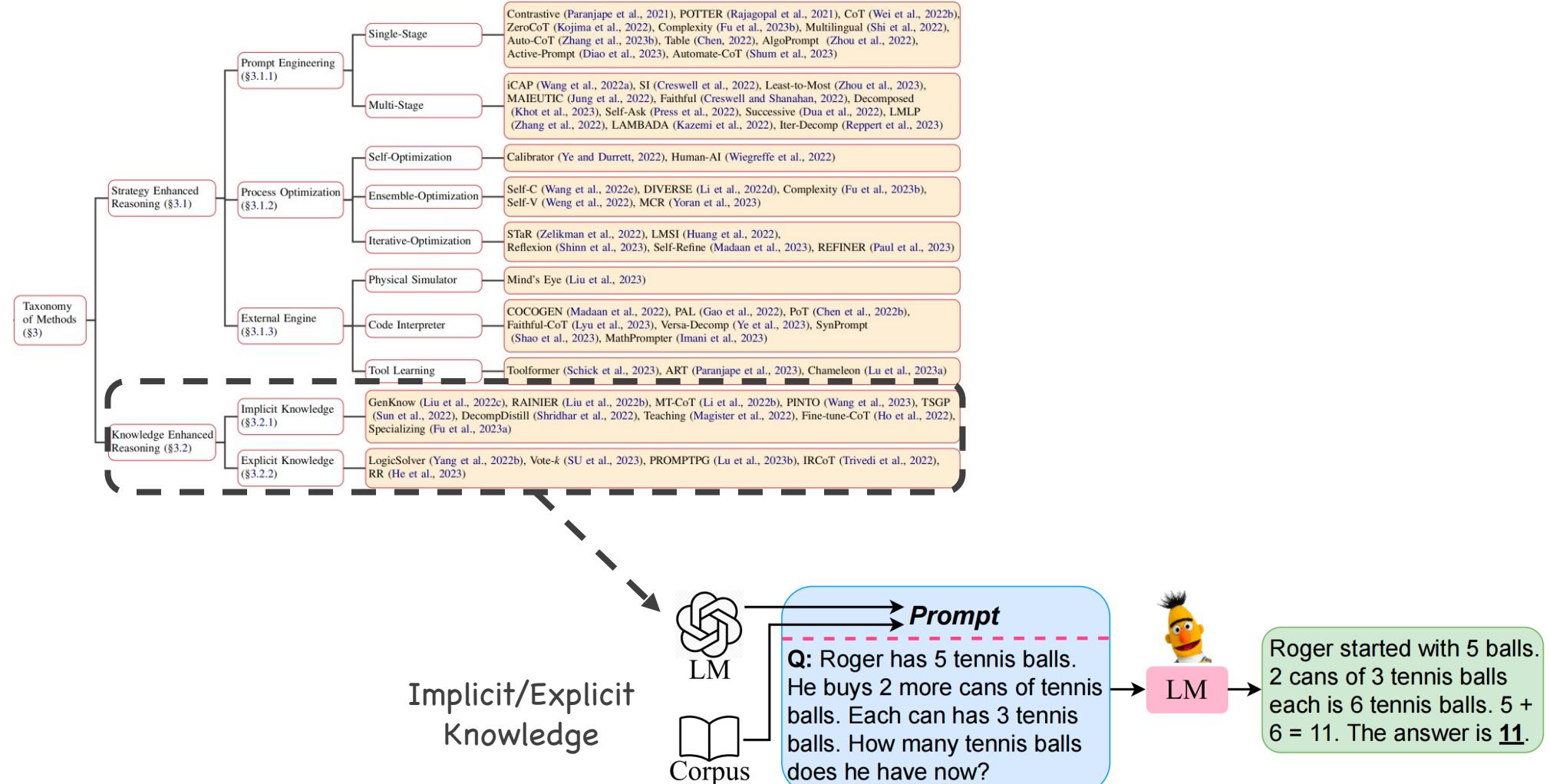


planning the complex procedure
 vs.
 directly answer

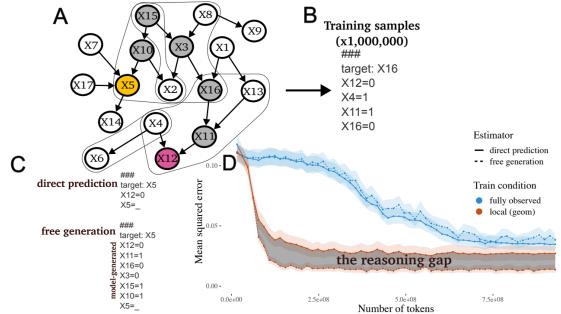


External Engine

Reasoning with Knowledge Augmentation



Knowledge Reasoning: More Issues



Principle of reasoning

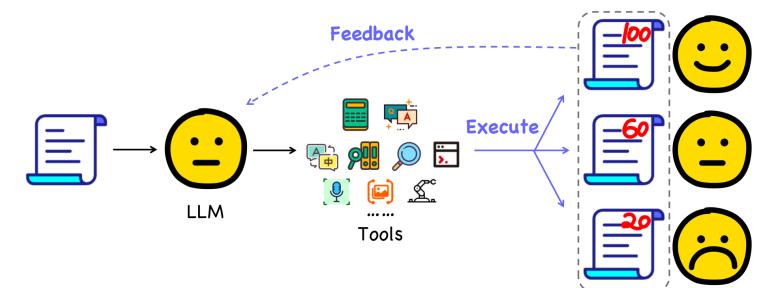


interact with environment

- Theoretical Principle of Reasoning
- Efficient Reasoning
- Robust, Faithful and Interpretable Reasoning
- Interactive Reasoning
- Generalizable (True) Reasoning



interact among multi-agent



interact with tools

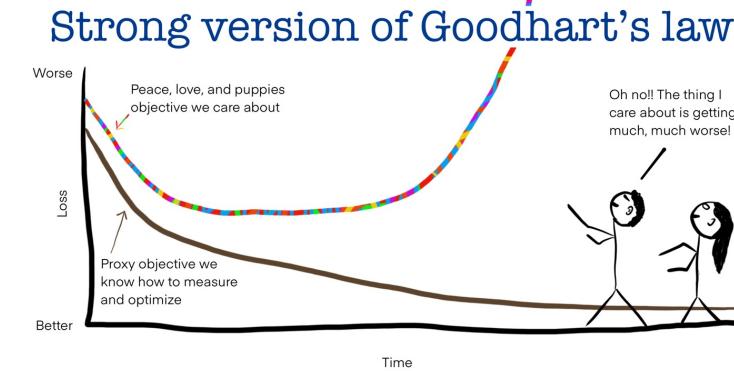
- [1] Reasoning with Language Model Prompting: A Survey, ACL 2023
- [2] Why think step by step? Reasoning emerges from the locality of experience, 2023
- [3] PaLM-E: An Embodied Multimodal Language Model, 2023
- [4] Training Socially Aligned Language Models in Simulated Human Society, 2023
- [5] Making Language Models Better Tool Learners with Execution Feedback, 2023

Knowledge Interaction: Agents



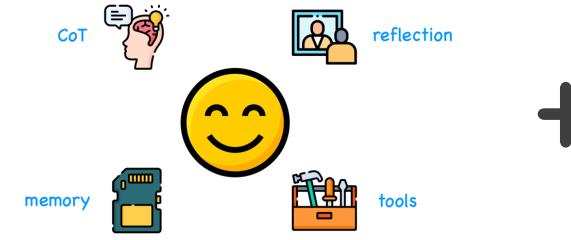
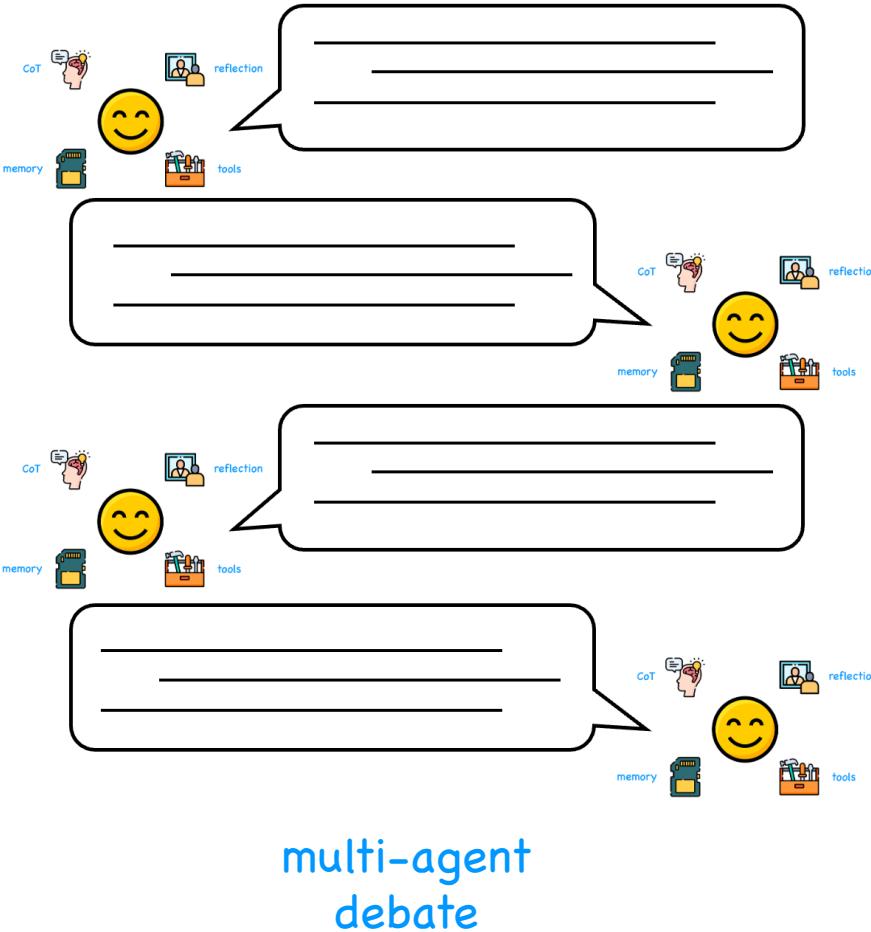
Knowledge Interaction: Fundamental Issues

- Why multi-agents?
- Goodhart's Law - The better on object A, the worse on many other objects B
- What do agents interact with?
- Knowledge boundary, Brain in a Vat
- What is the preferred method of communication among agents?
- Natural language or Code
- How to communicate (knowledge) between agents?
- Roles, Society, Behaviors



- [1] Training Socially Aligned Language Models in Simulated Human Society, 2023
- [2] Investigating the Factual Knowledge Boundary of Large Language Models with Retrieval Augmentation, 2023
- [3] Brain in a Vat: On Missing Pieces Towards Artificial General Intelligence in Large Language Models, 2023
- [4] PAL: Program-aided Language Models, 2023
- [5] Encouraging Divergent Thinking in Large Language Models through Multi-Agent Debate, 2023

Knowledge Interaction: Applications

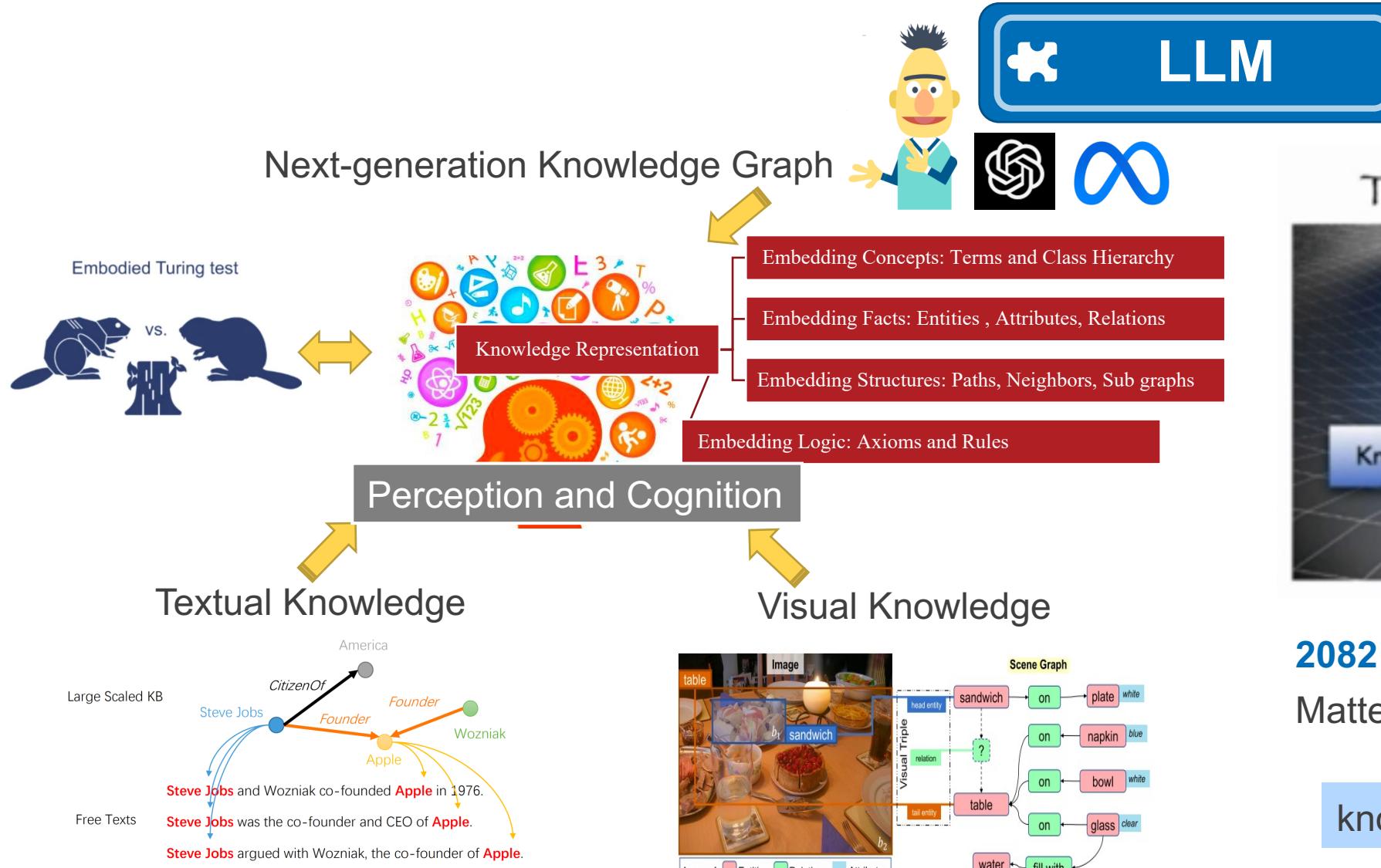


KG+LLM+X

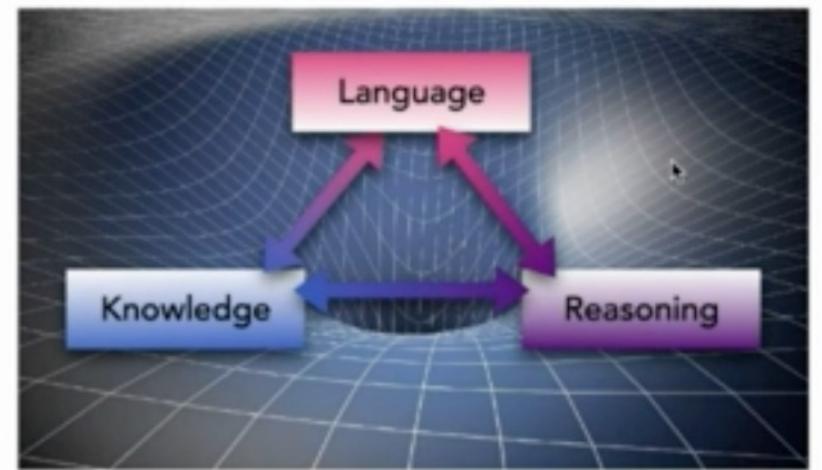


Future ?

The Future ?



The continuum between



2082: An ACL Odyssey: The Dark Matter of Intelligence and Language

knowledge, language, reasoning



IJCAI/2023 MACAO



IJCAI
International Joint Conferences on
Artificial Intelligence Organization

Thank You



Ningyu Zhang, Meng Wang,
Tianxing Wu, Shumin Deng



2023.08.19

