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/

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1 Zhejiang University 2 XAI Lab AI Driven X Innovation 3 Southeast University 4 NUS National University of Singapore

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_{th}.

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.

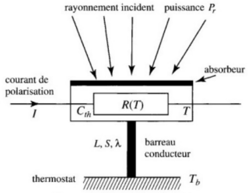


Figure 1 - Schéma d'un bolomètre

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 $T(0) = T0$ and $T(L) = Tb$.

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:
$dT/dx = C_1$

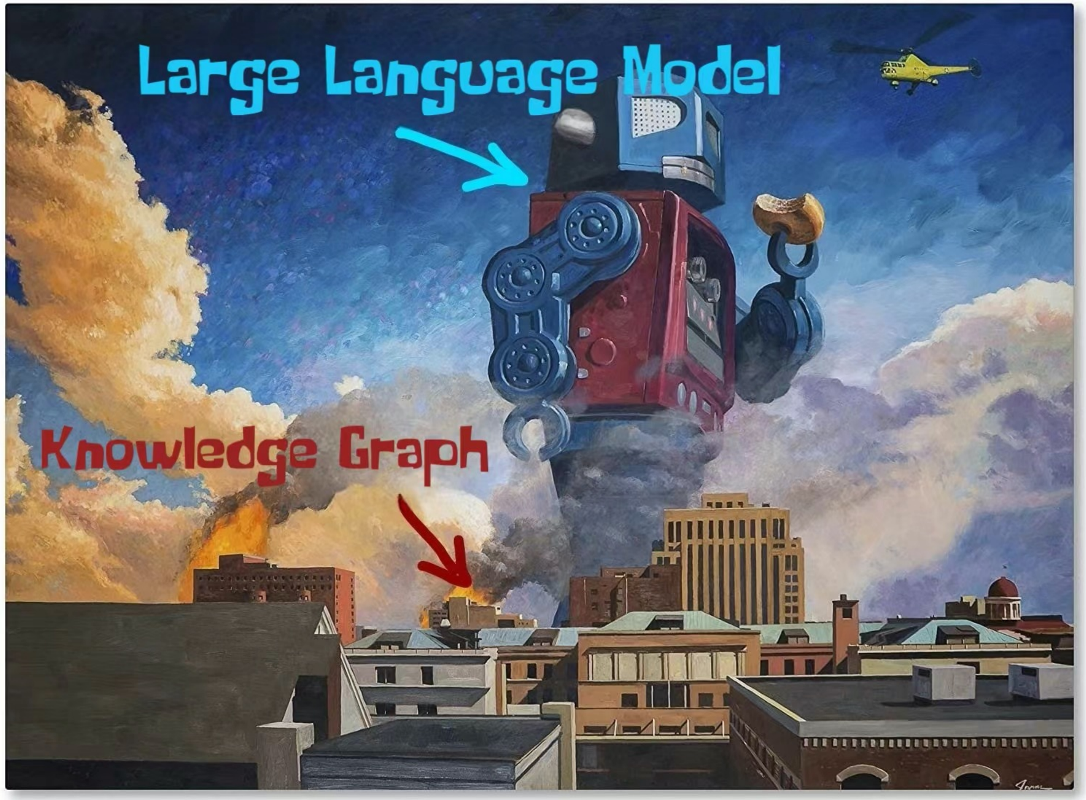
Integrating a second time:
$T(x) = C_1x + C_2$

To determine the constants C_1 and C_2, we use the boundary conditions:
$T(0) = T0$, which gives $C_2 = T0$
$T(L) = Tb$, which gives $C_1 = (Tb - T0)/L$

Finally, the expression for $T(x)$ is:
$T(x) = (Tb - T0) * (x/L) + T0$
This represents a linear temperature profile along the conductive bar, with a slope of $(Tb - T0)/L$.

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.

GPT-4 Technical Report (2023)



The original figure comes from twitter.

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

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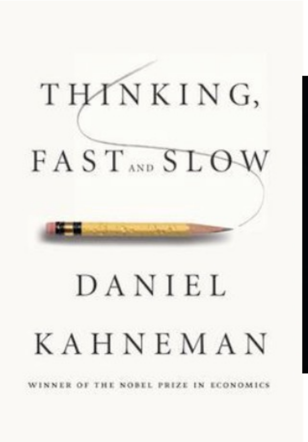
- ❑ Deep Learning for **System II Processing**, as proposed by Yoshua Bengio

- ❑ 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?

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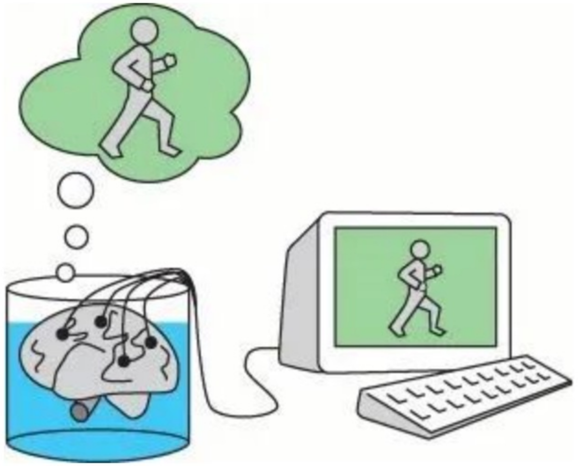
- ❑ Symbol **Grounding**
- ❑ **Common Sense**: The Dark Matter of Language and Intelligence
- ❑ **Objective-Driven** AI



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?

Brain in a Vat: On Missing Pieces Towards Artificial General Intelligence in Large Language Models (2023)

Presenters

Ningyu Zhang | Meng Wang | Tianxing Wu | Shumin Deng

ZHEJIANG UNIVERSITY 1897

XAI Lab AI Driven X Innovation

SOUTHEAST UNIVERSITY 1902

NUS National University of Singapore

Outline

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- ❑ 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

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Introduction to KG Construction and Reasoning

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

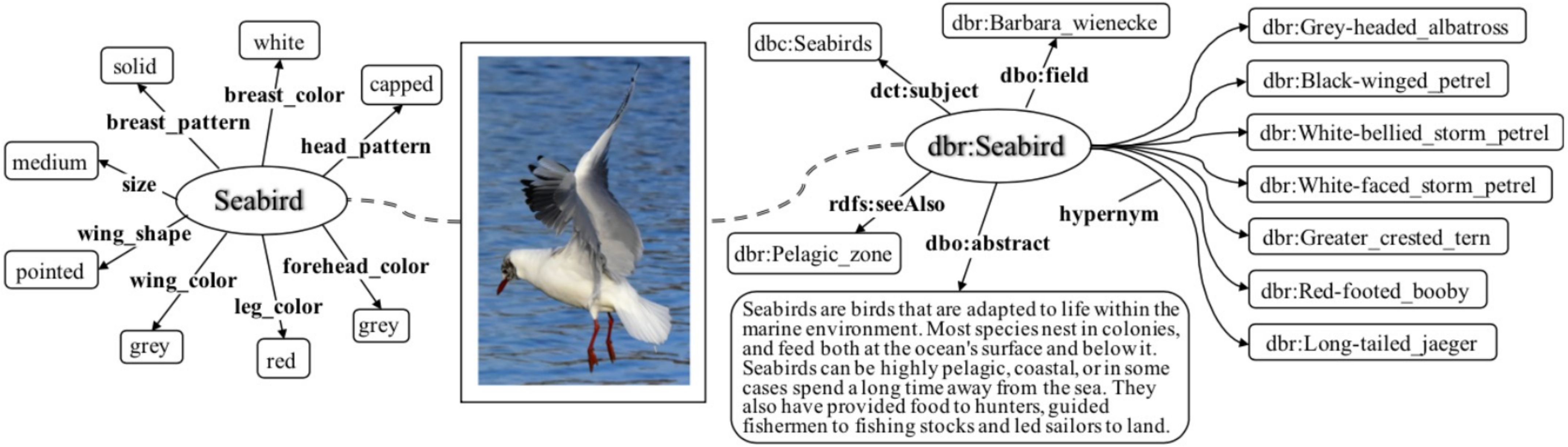
Ningyu Zhang

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



[1] From: What Is a Knowledge Representation?. In AI Magazine (1993)

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"*

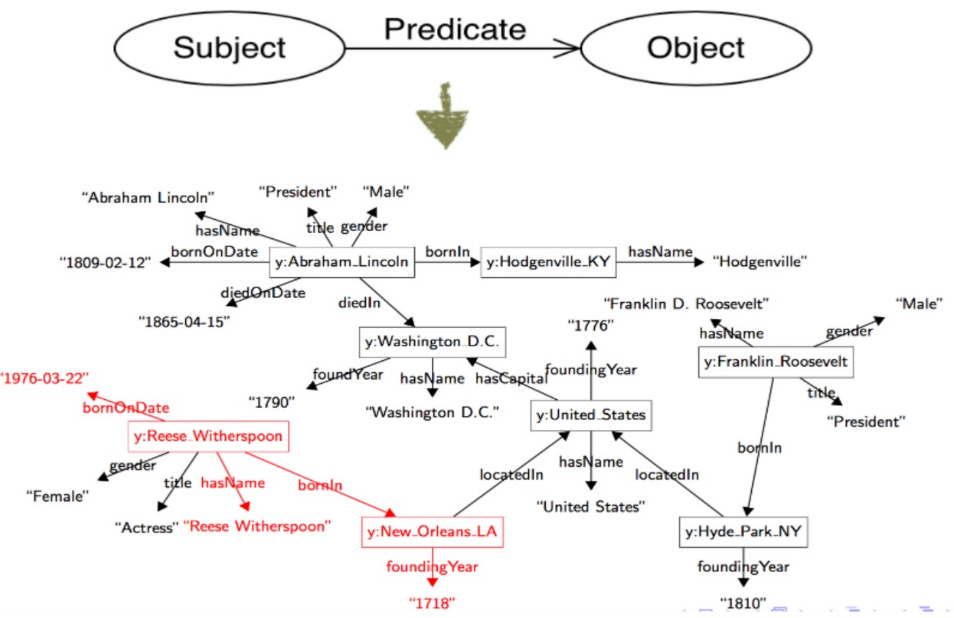
- Large Language Models Are **NOT** Abstract Reasoners

[1] How to Grow a Mind: Statistics, Structure, and Abstraction (Science 2011)
[2] Large Language Models Are Not Abstract Reasoners (2023)

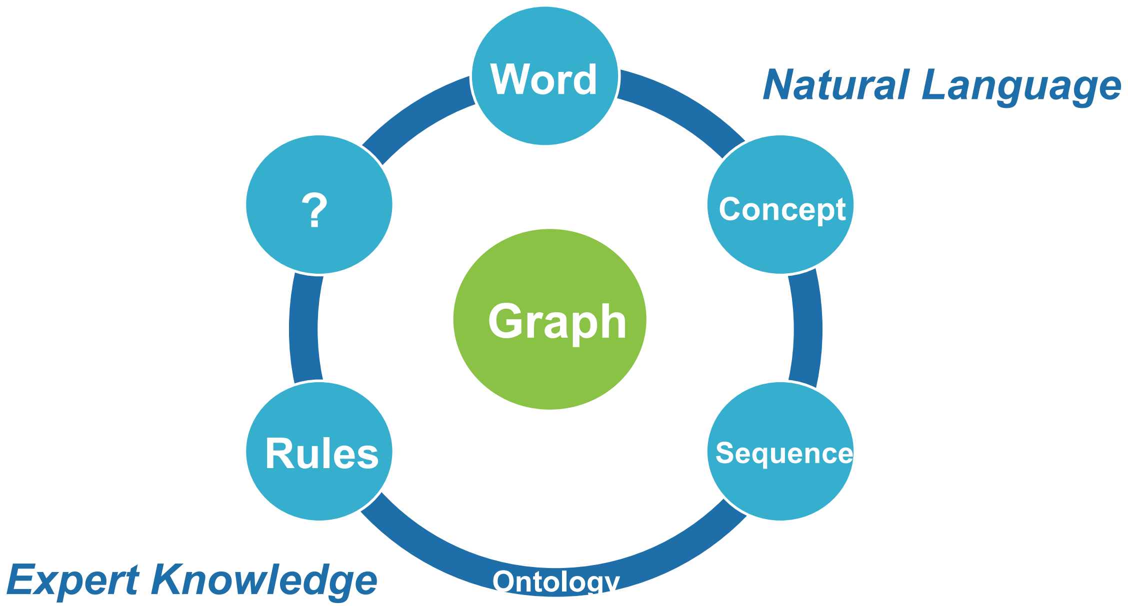
Knowledge Graph

KG = Textual Semantics + Structural Knowledge

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



Human Brain Knowledge?



Natural Language, Knowledge Graph and LLMs

Language $\neq$ Knowledge

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

Knowledge Graph and Applications (General)

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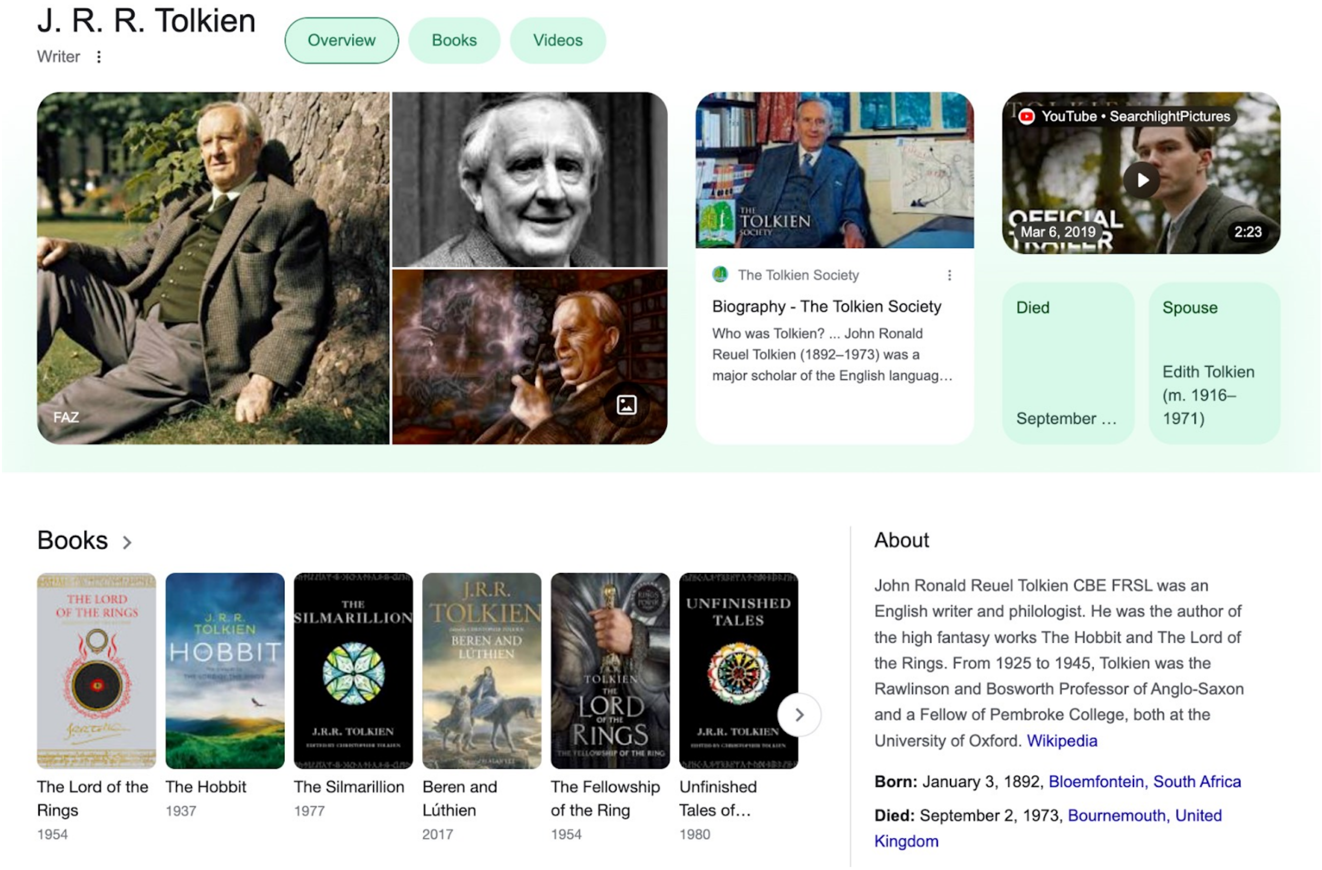
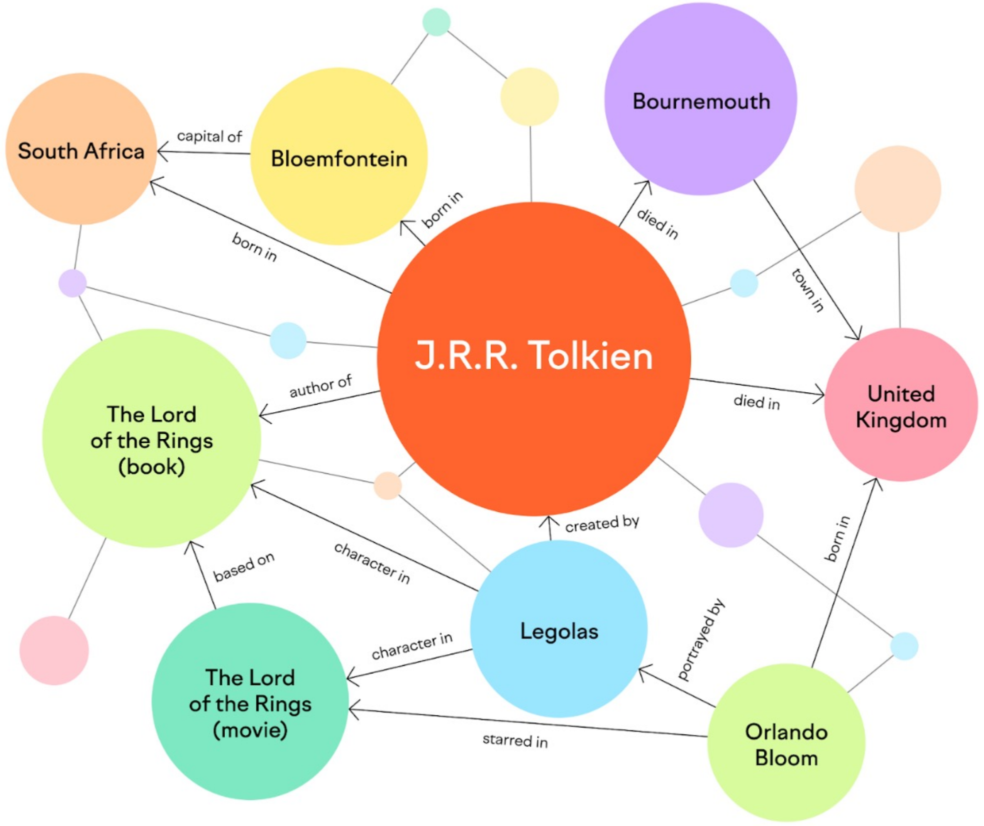
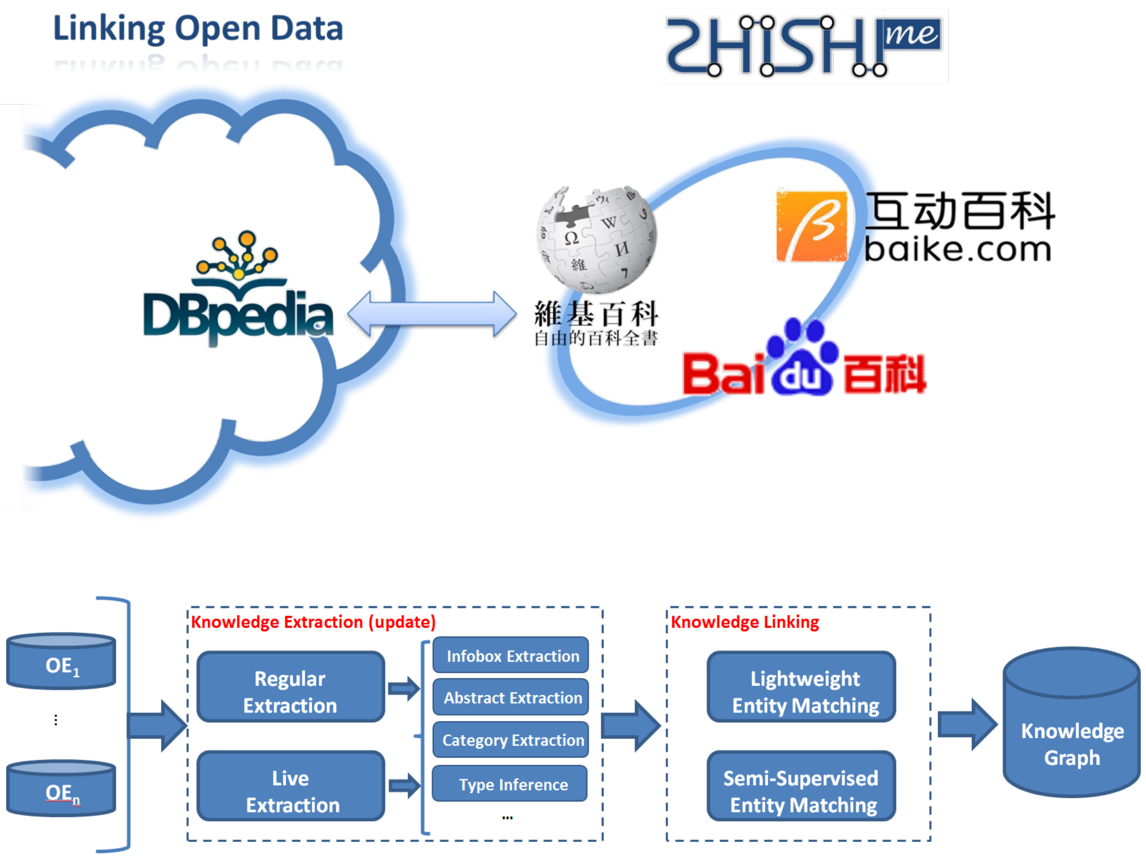
Google's search result for the query "J. R. R. Tolkien"

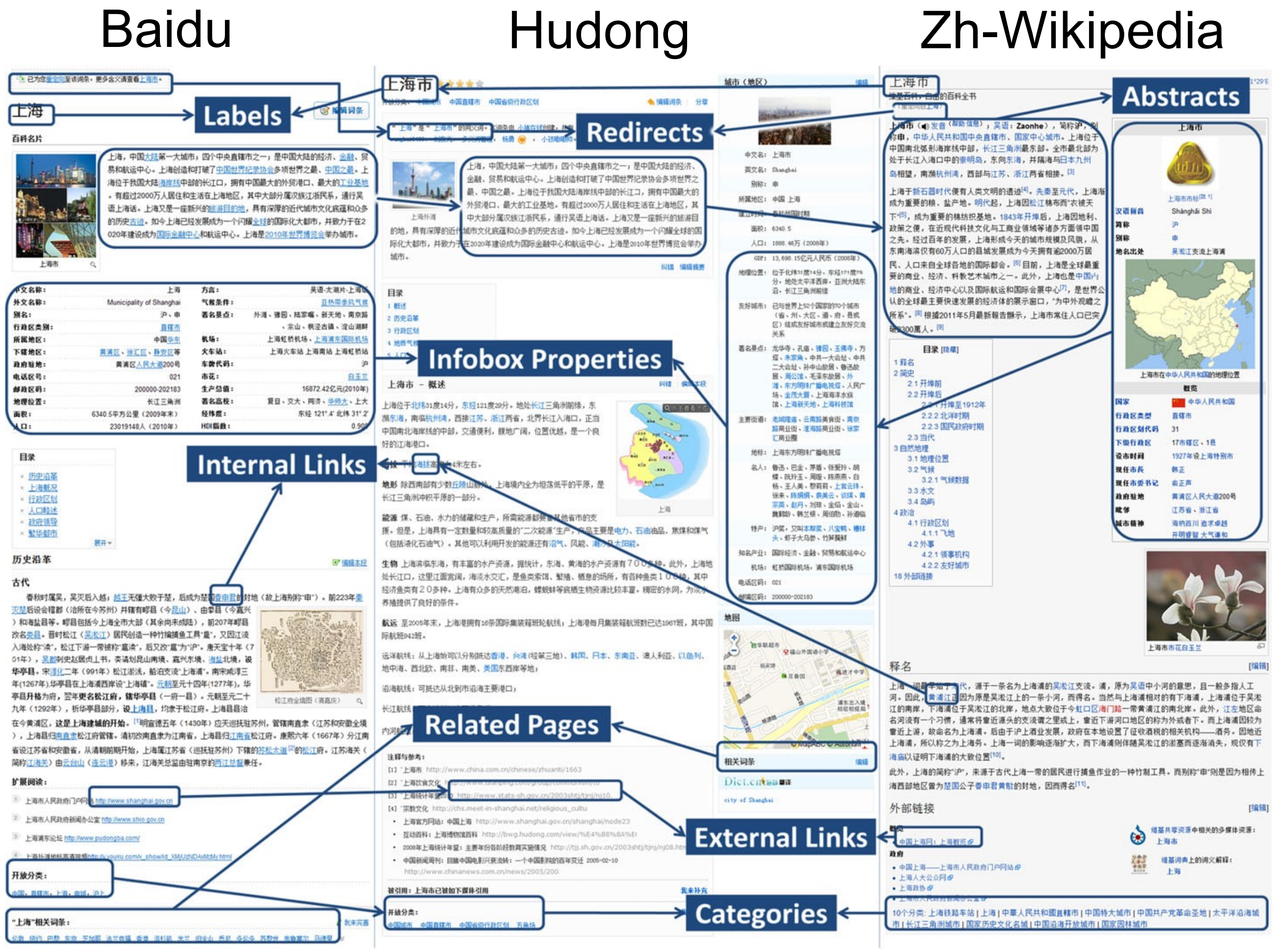




Knowledge Graph and Applications (Chinese)

Zhishi.me

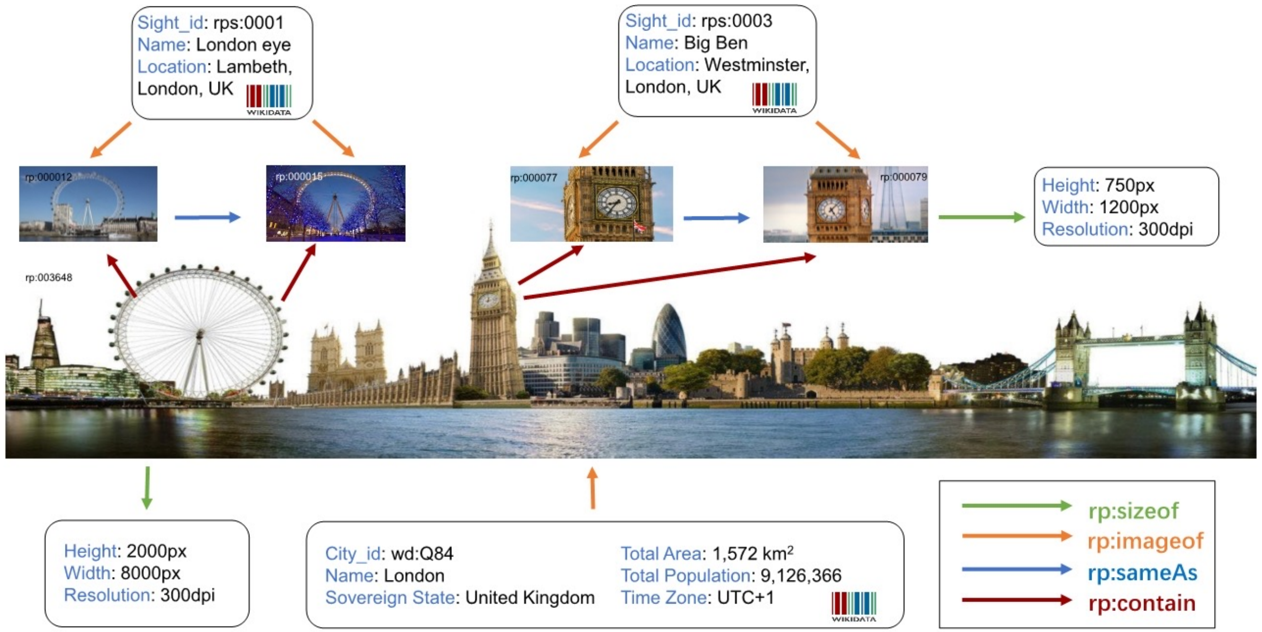


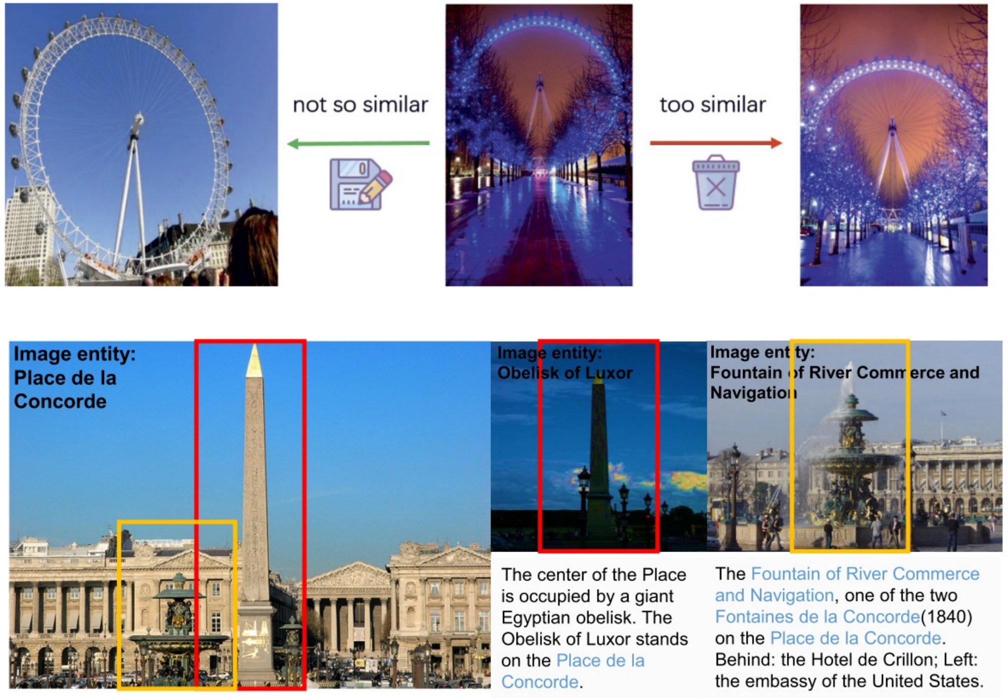


[1] Knowledge graph construction from multiple online encyclopedias. World Wide Web 2020
[2] Zhishi.me - Weaving Chinese Linking Open Data. ISWC 2011

Knowledge Graph and Applications (Chinese)

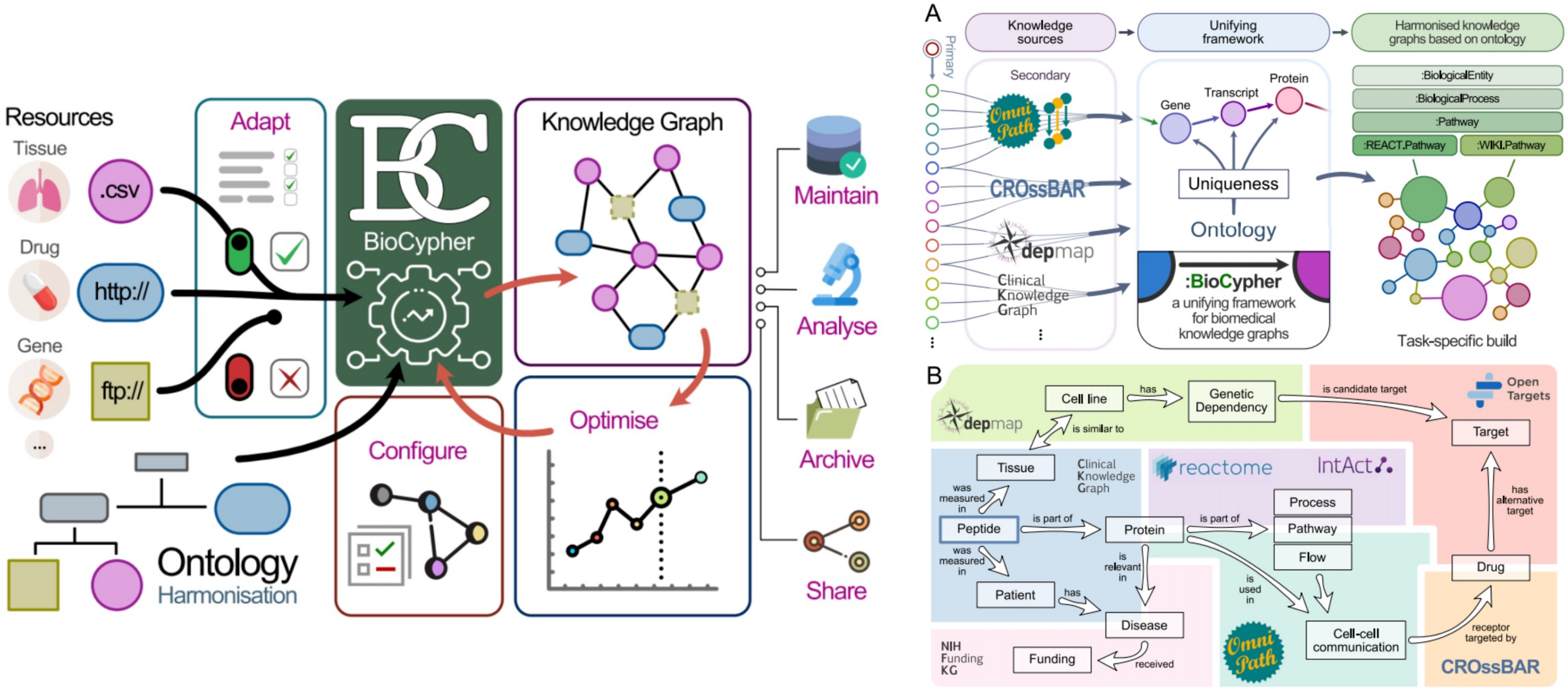
Knowledge Graph and Applications (Multimodal)





[1] Richpedia: A Comprehensive Multi-Modal Knowledge Graph (Bigdata Research 2020)

Knowledge Graph and Applications (Biomedical)



[1] Democratizing knowledge representation with BioCypher (Nature Biotechnology 2023)

Knowledge Graph and Applications (Biomedical)

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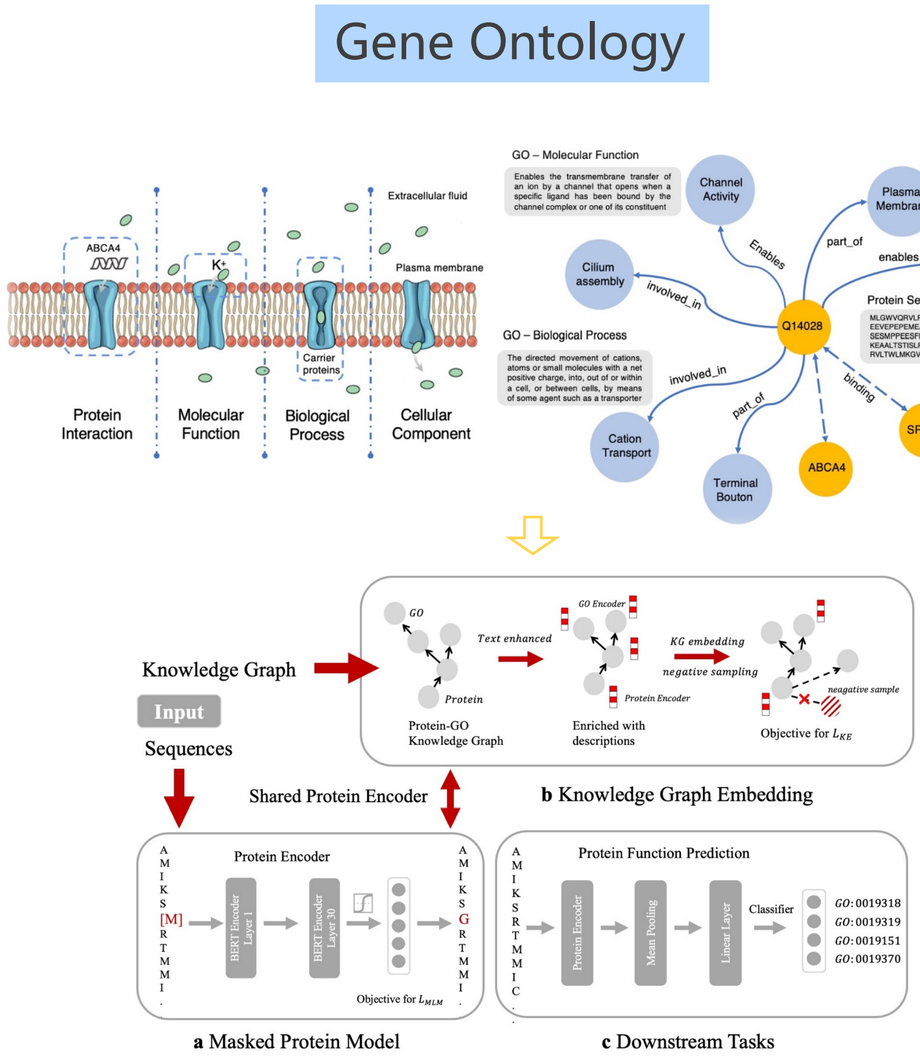

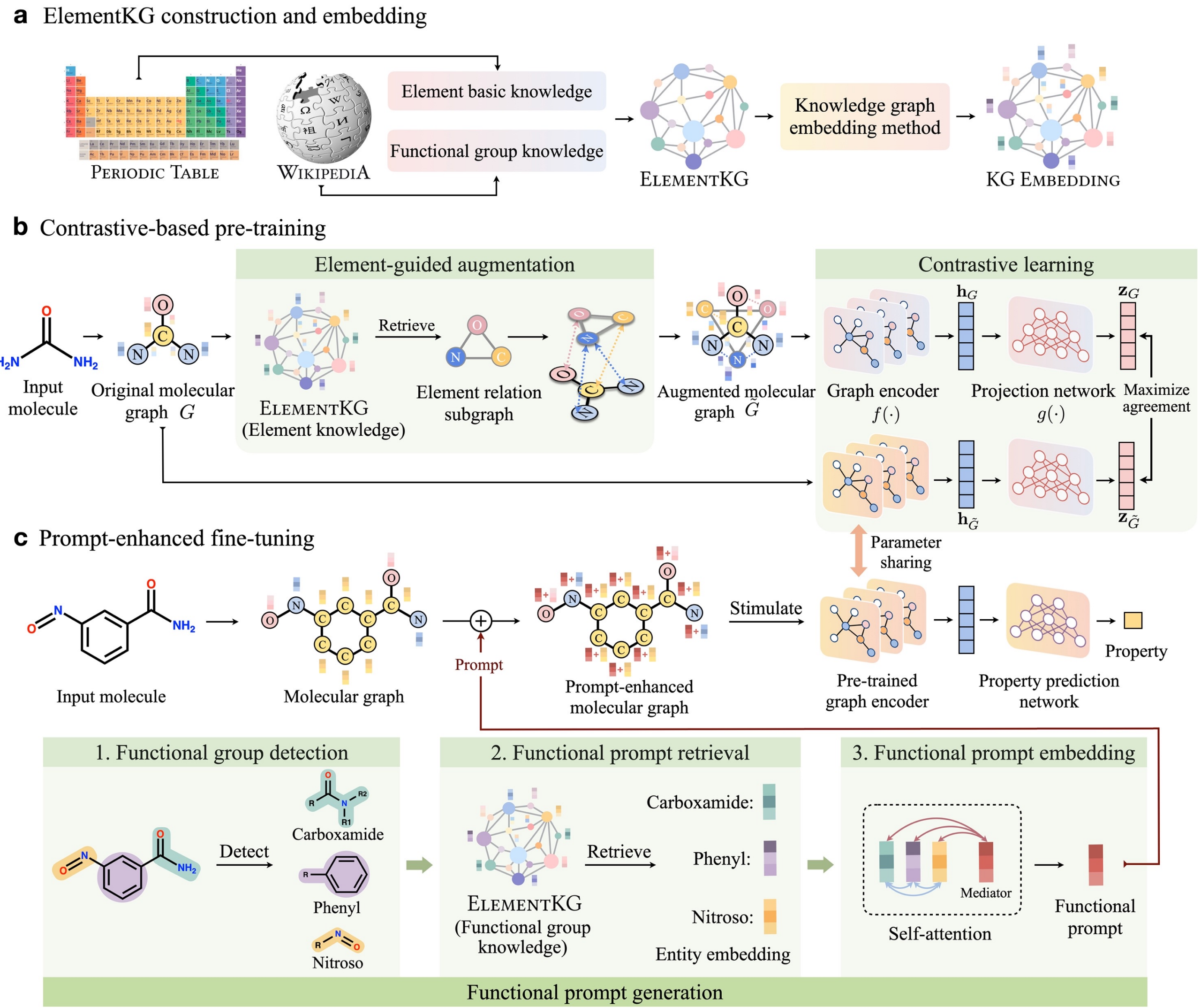

[1] OntoProtein: Protein Pretraining With Gene Ontology Embedding (ICLR 2022)
[2] Knowledge graph-enhanced molecular contrastive learning with functional prompt (Nature Machine Intelligence 2023)

Knowledge Graph and Applications (E-commerce)

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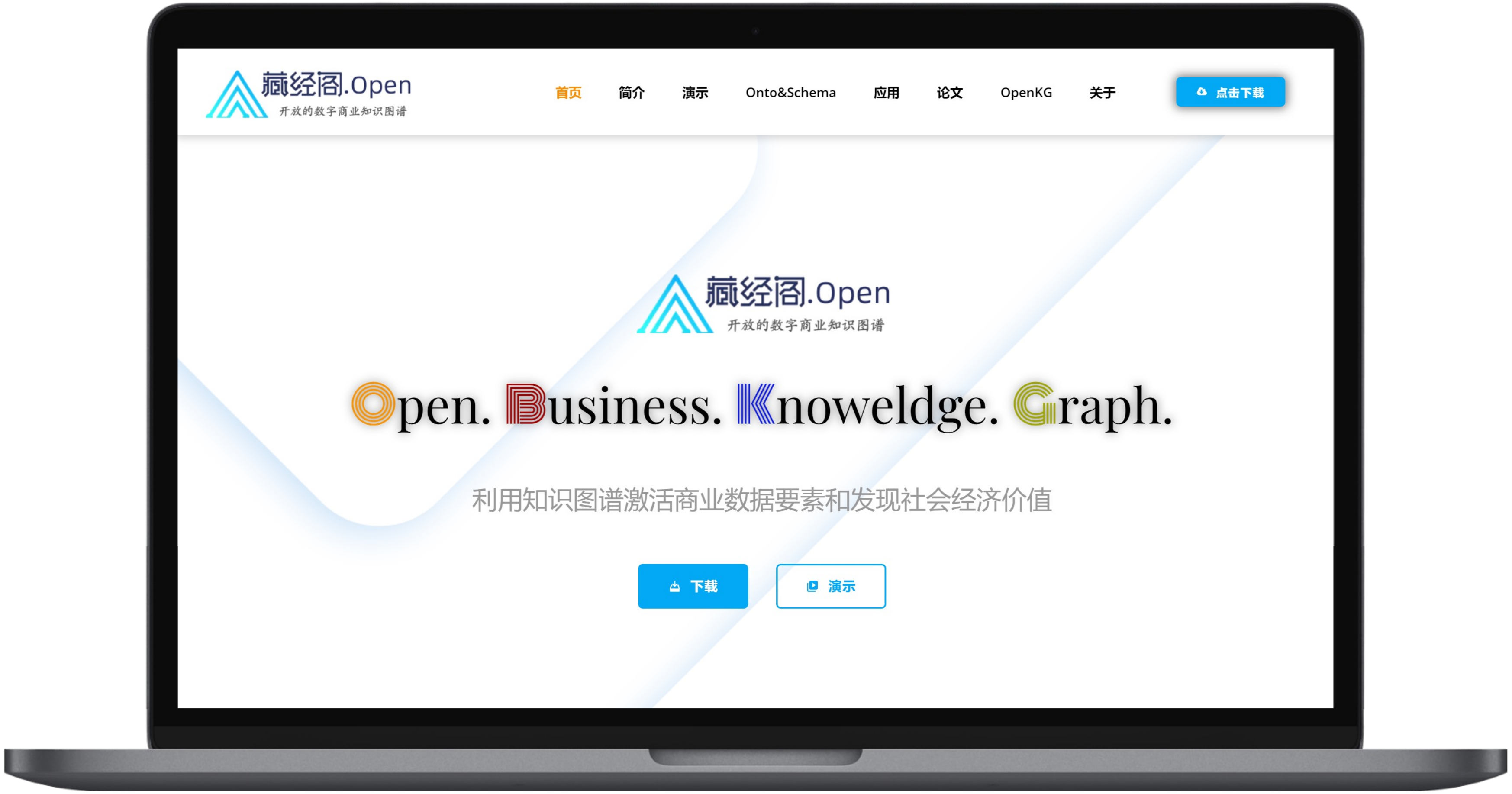


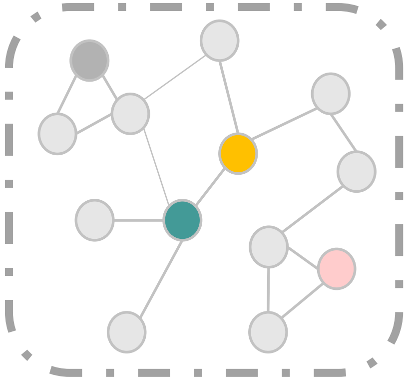
https://kg.alibaba.com/

[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)

Knowledge Graph Construction and Reasoning

KG Construction

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

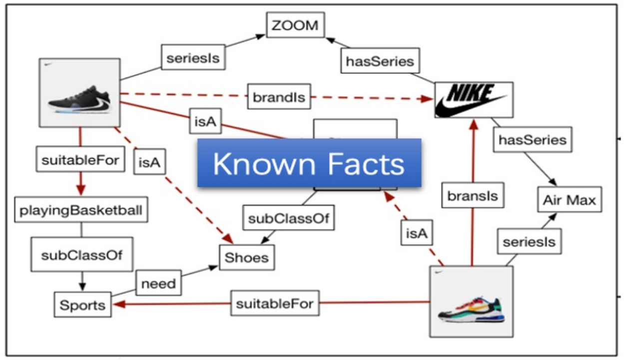


KG

- 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



Infer

New Facts
New Relations
New Axioms
New Rules

Challenges for Open-environment KG Construction and Reasoning

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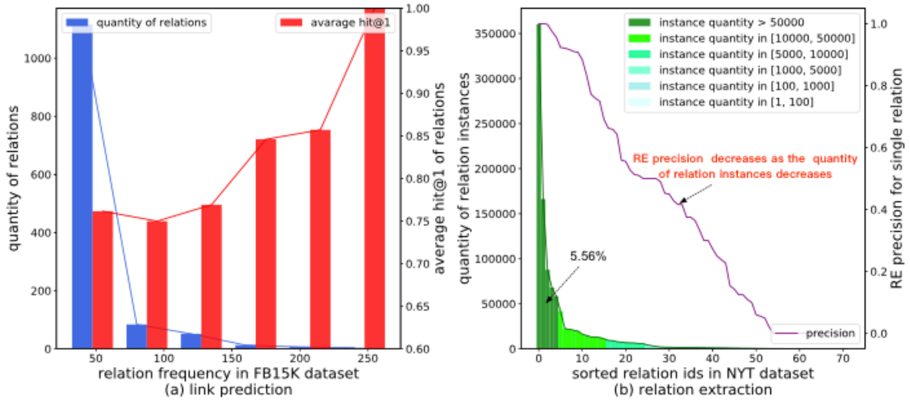
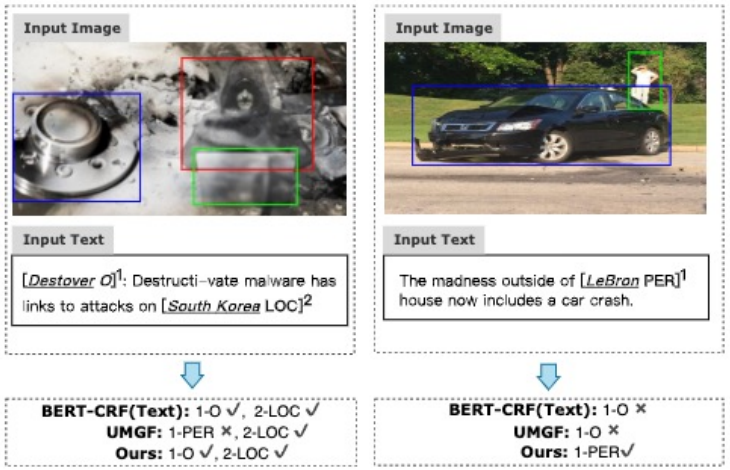
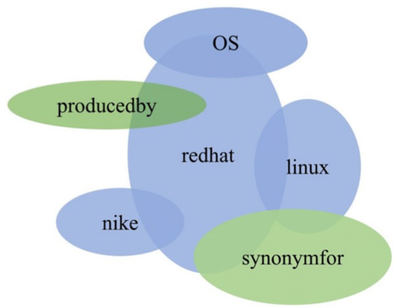
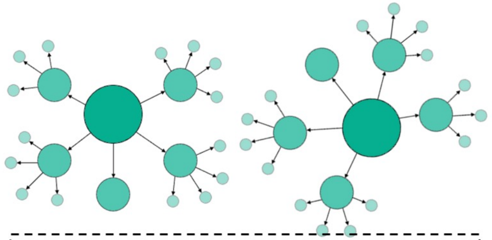
- ❑ **Low-resource**
- ❑ **Multimodal**
- ❑ **Uncertain**
- ❑ More Opportunities







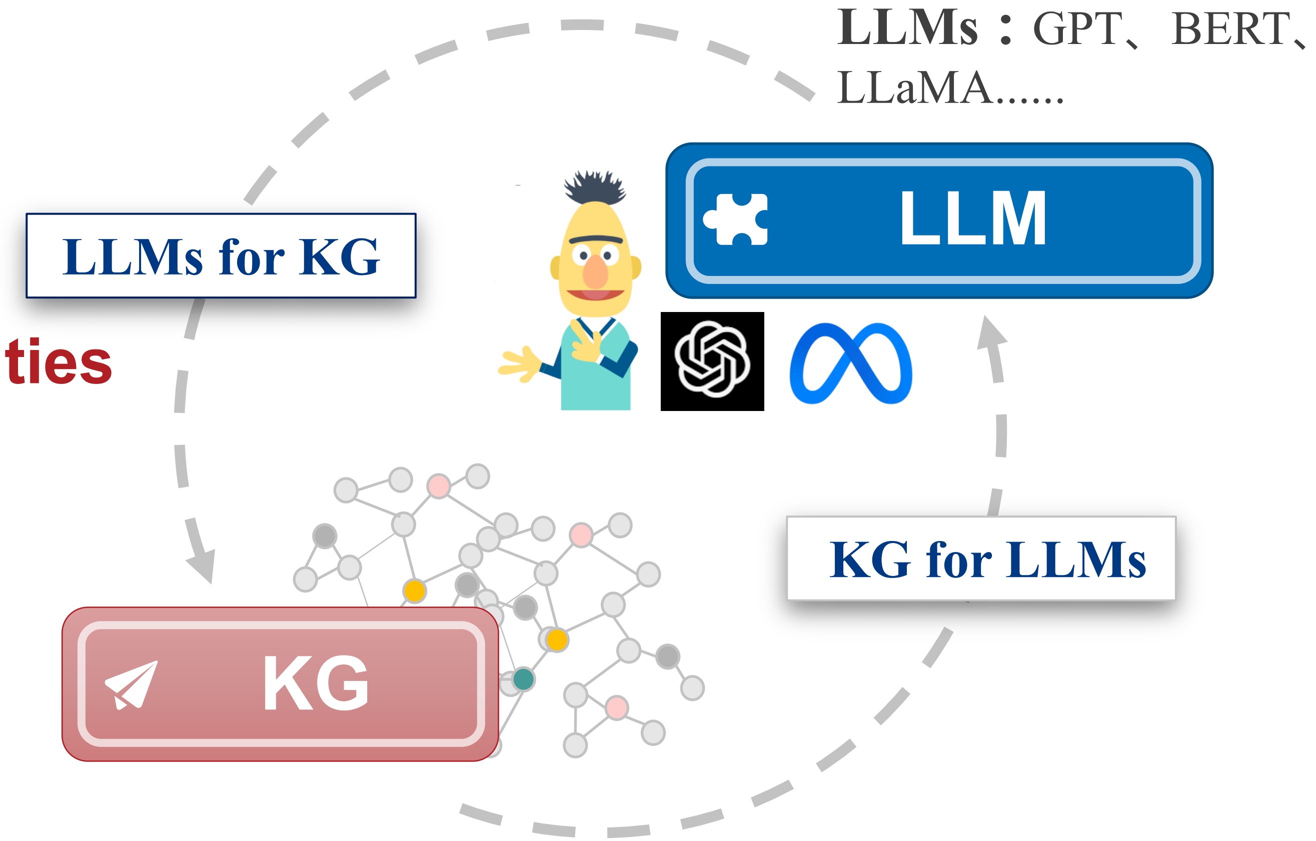
$entity, relation \sim \mathcal{N}(e^{\mu}, e^{\Sigma})$



<AlphaGo, Produced_by, Google>, 0.56
<US, Synonym_for, America>, 0.98

Challenges for Open-environment KG Construction and Reasoning

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



KG：Knowledge **representation**, **acquisition**, **editing**, **reasoning**, **interaction**......

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Low-resource KG Construction and Reasoning

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

Shumin Deng

National University of Singapore

19, Aug, 2023

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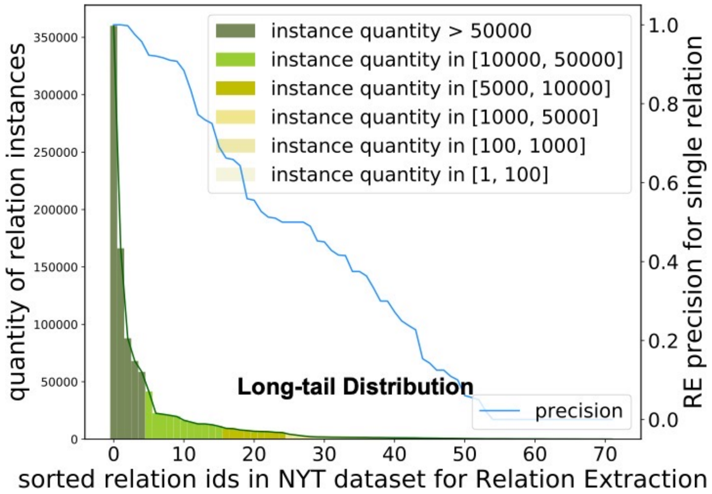
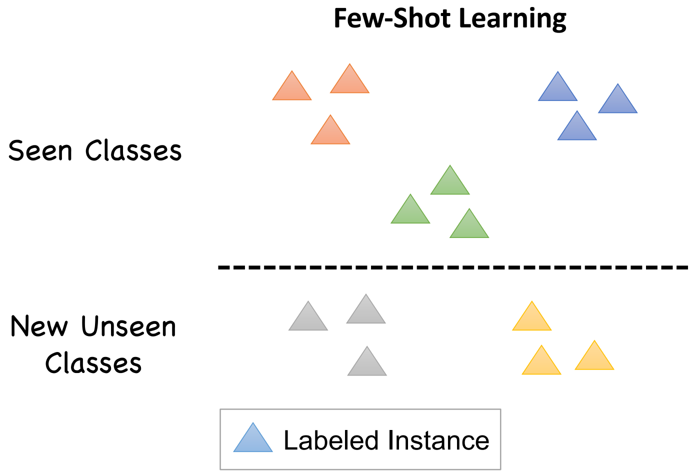
Low-resource Scenarios

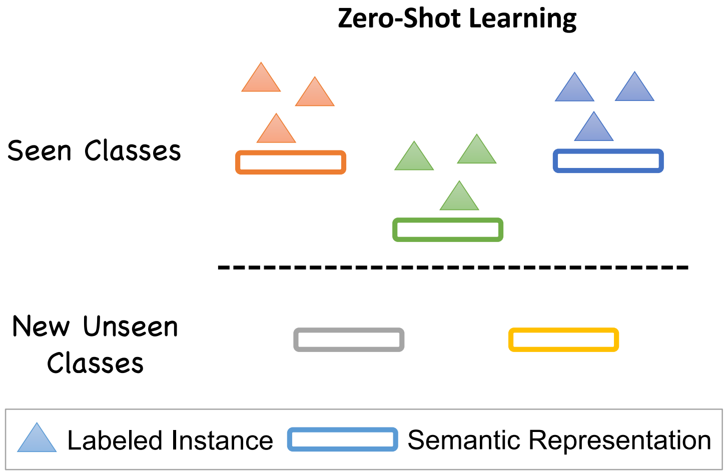
- ❑ In the slides, low-resource refers to low-data-resource
- ❑ Considering maldistribution of samples & new unseen classes, we systematically categorize low-resource scenarios into three aspects



Long-tail Scenario



Few-shot Scenario



Zero-shot Scenario

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

Low-resource Scenarios

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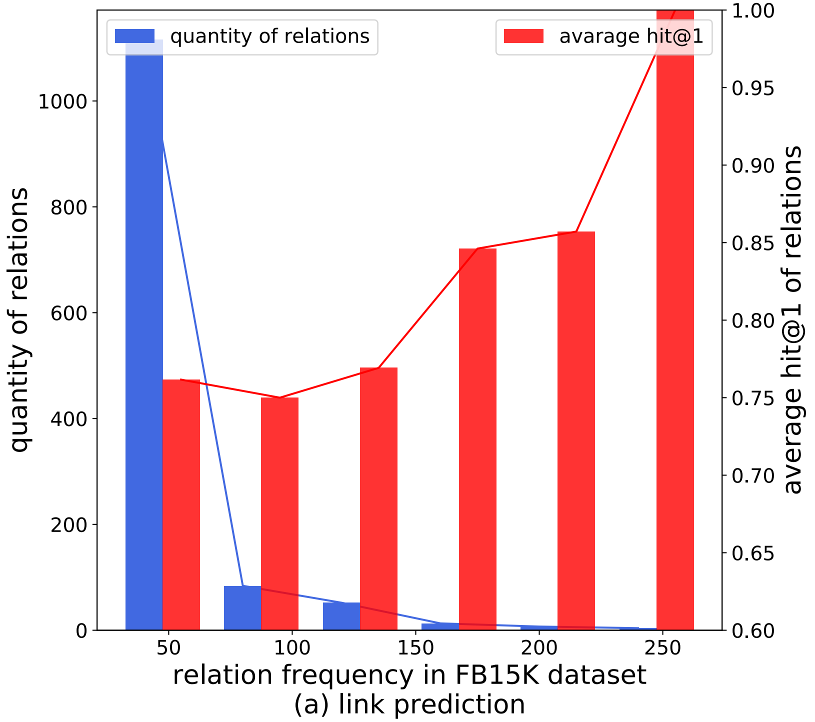
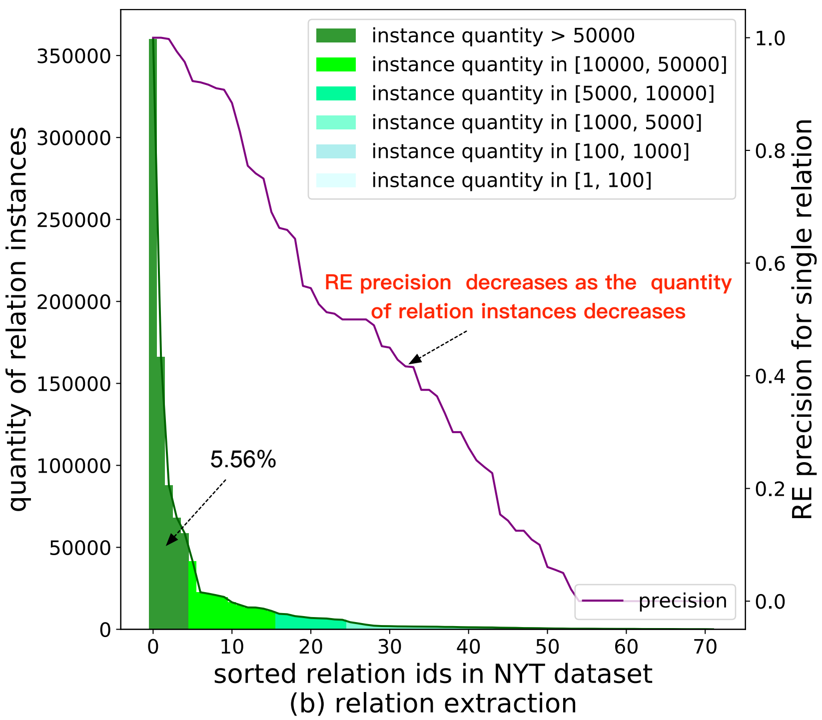
- In the slides, low-resource refers to low-data-resource
- In most cases, the KG construction (KGC) and KG Reasoning (KGR) performance are <u>in positive correlation</u> with quantity of samples



(a) link prediction



(b) relation extraction

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)

Marry

Husband

Wife

Place

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

Trigger

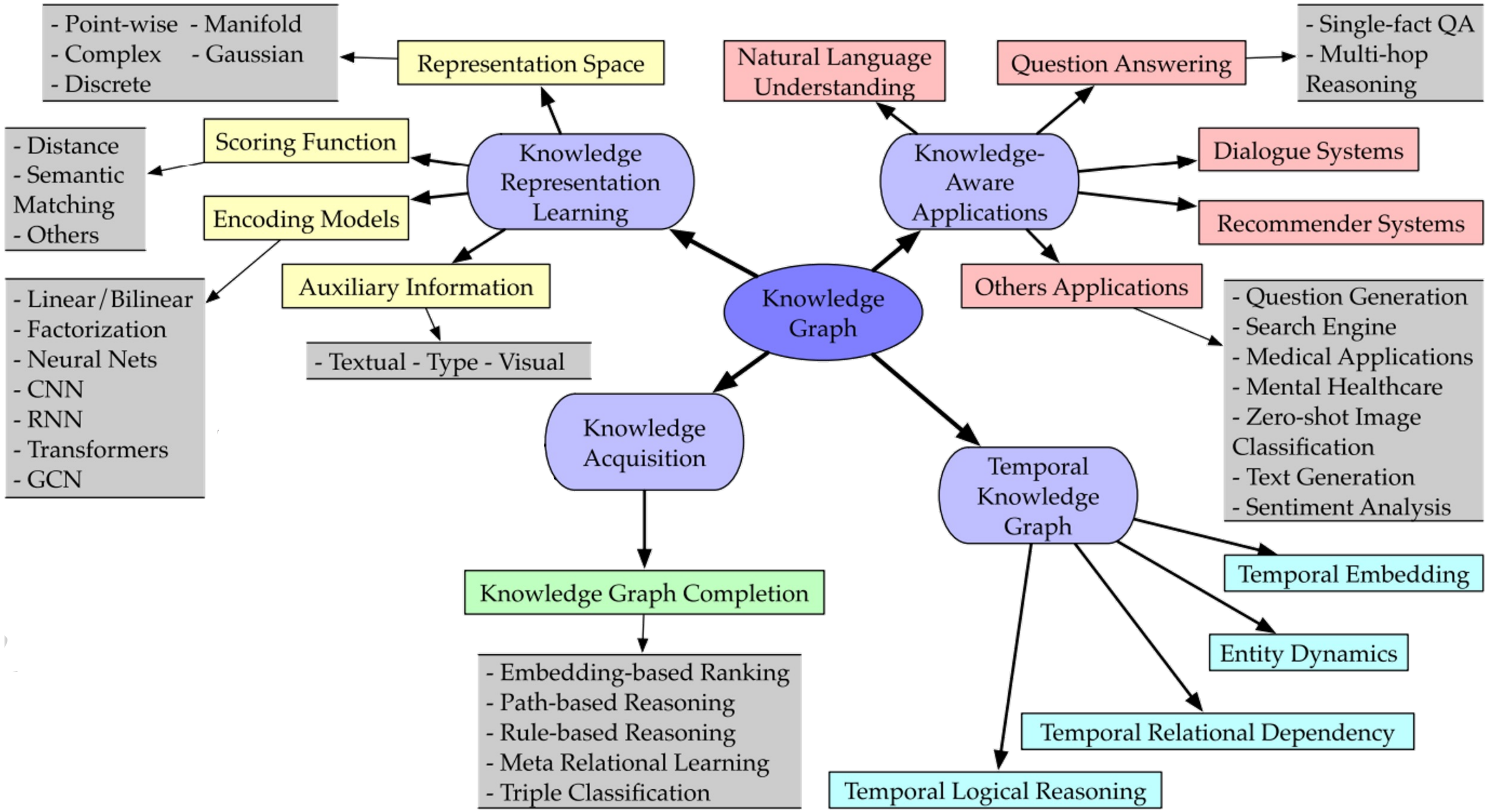
Argument

Role

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)

Taxonomy of Methods

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

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- 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

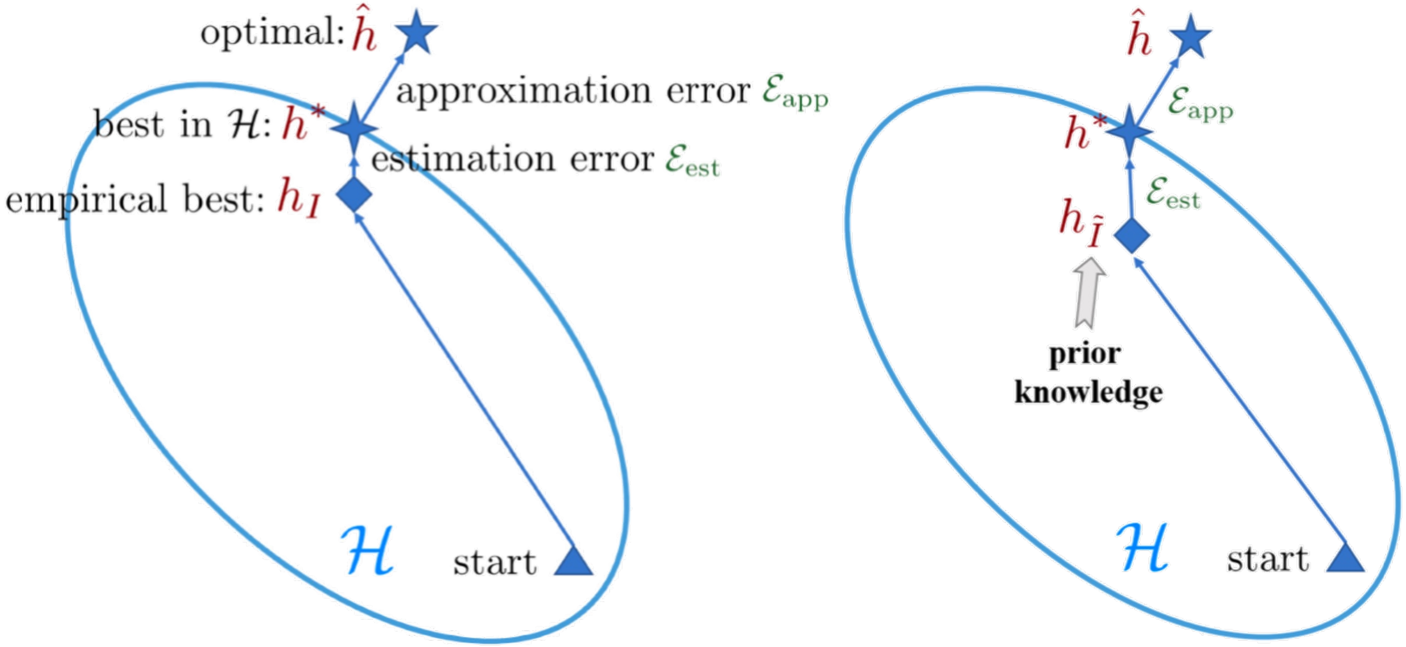
Given a hypothesis h, we want to minimize its expected risk R

$\hat{h} = \arg\min_h R(h)$: 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 Large-Scale Data

With Higher-Resource Data in Low-Resource Scenarios

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

Weakly Supervised Augmentation

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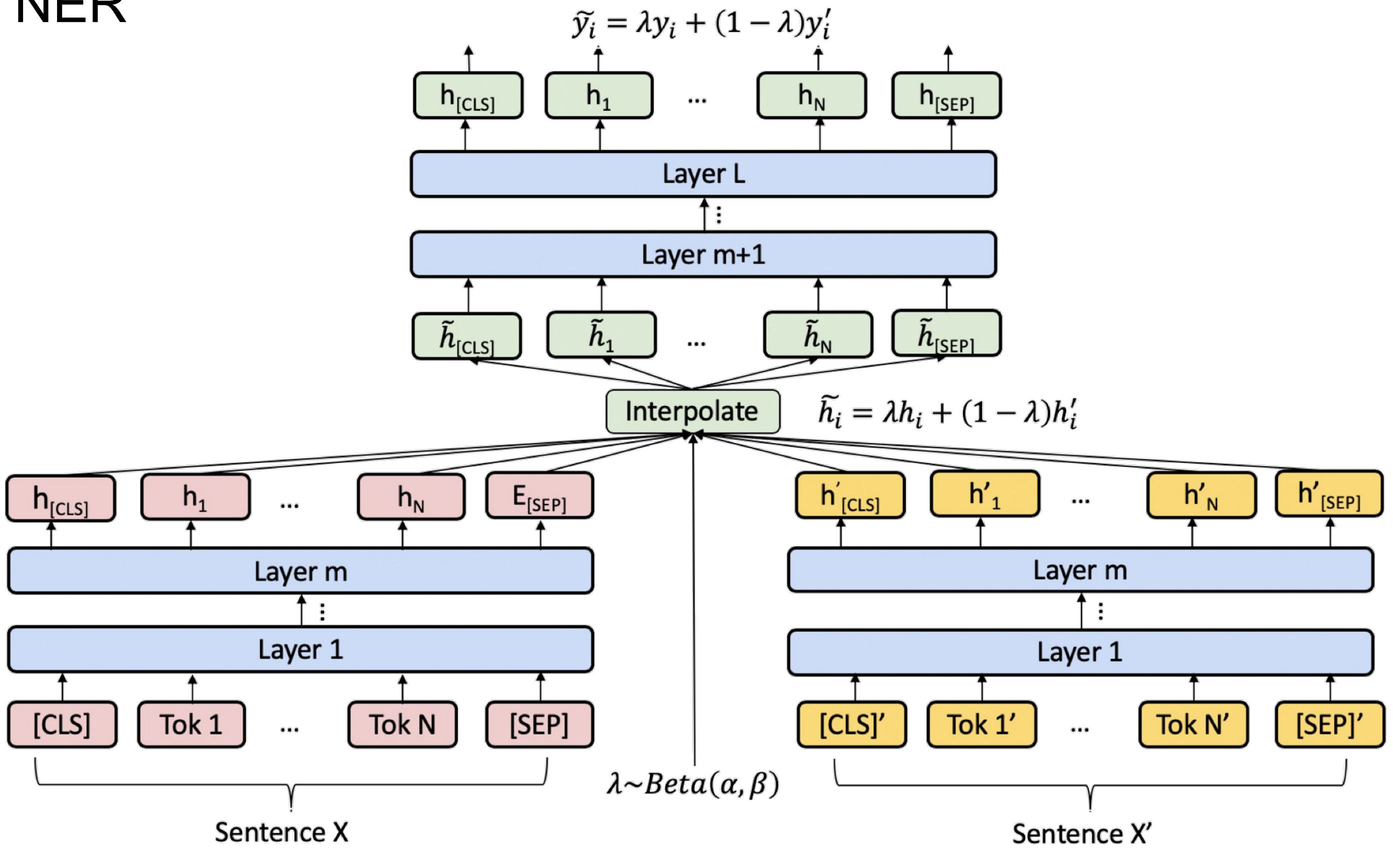
❑ Creating More Samples

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

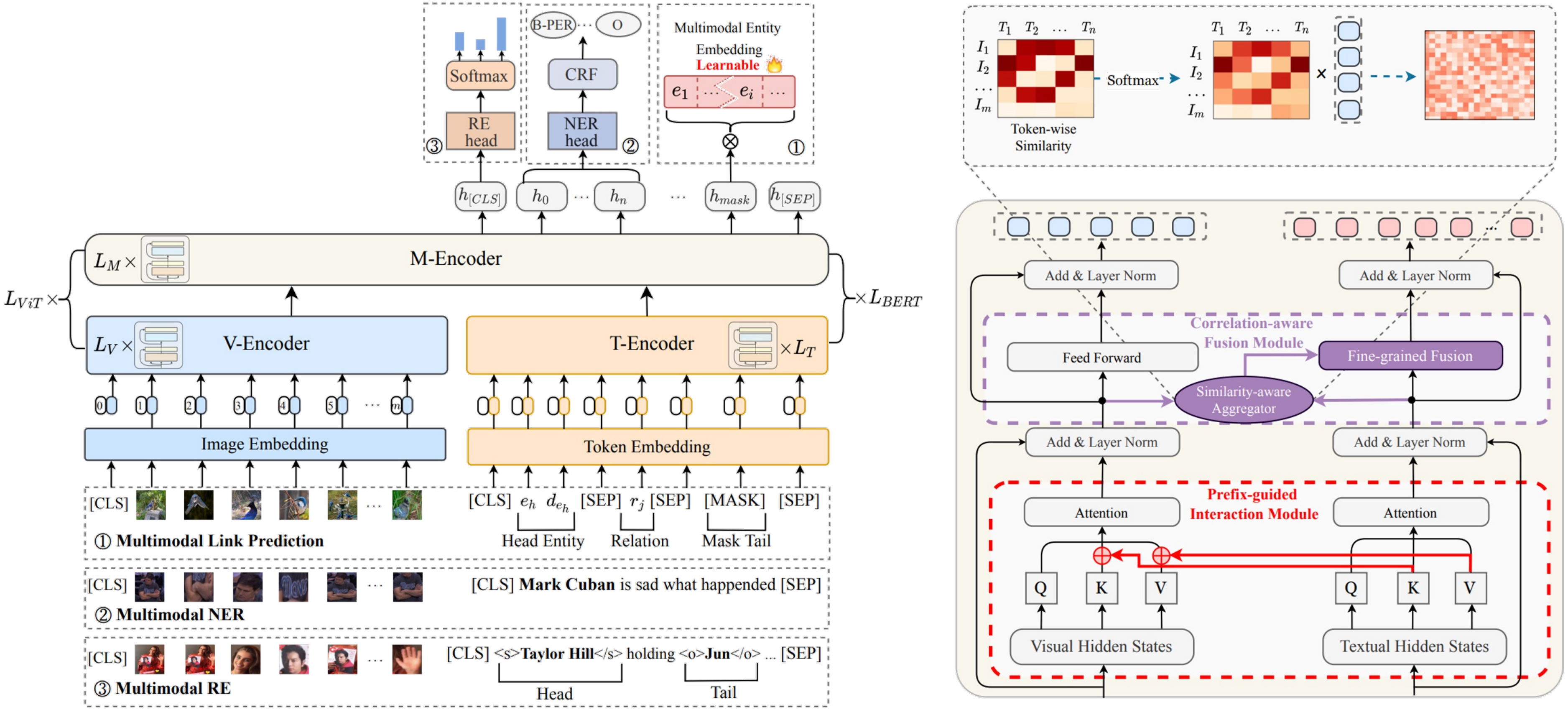


Local Additivity Based Data Augmentation for Semi-supervised NER (EMNLP 2020)

Multi-modal Augmentation

❑ Leveraging Multimodal Knowledge

❑ Multimodal Knowledge Fusion



(a) Unified Multimodal KGC Framework. (b) Detailed M-Encoder.

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

Multi-lingual Augmentation

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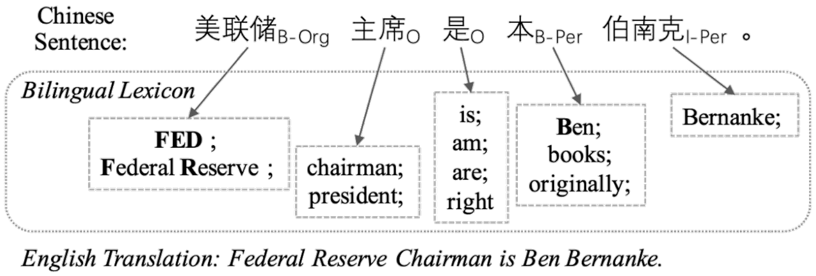
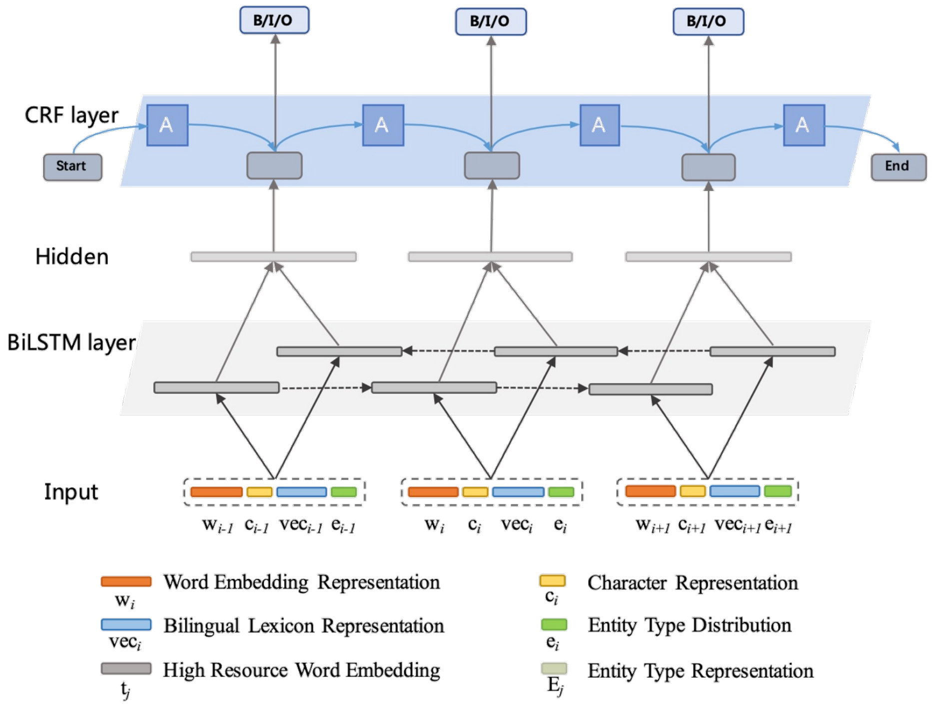
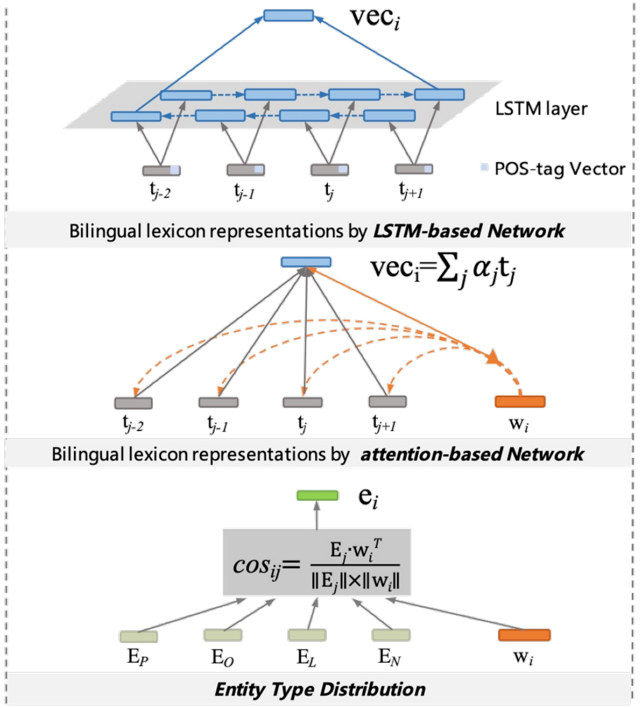
❑ Leveraging Multi-lingual Knowledge

❑ Cross-lingual Knowledge Transfer







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

Auxiliary Knowledge Enhancement

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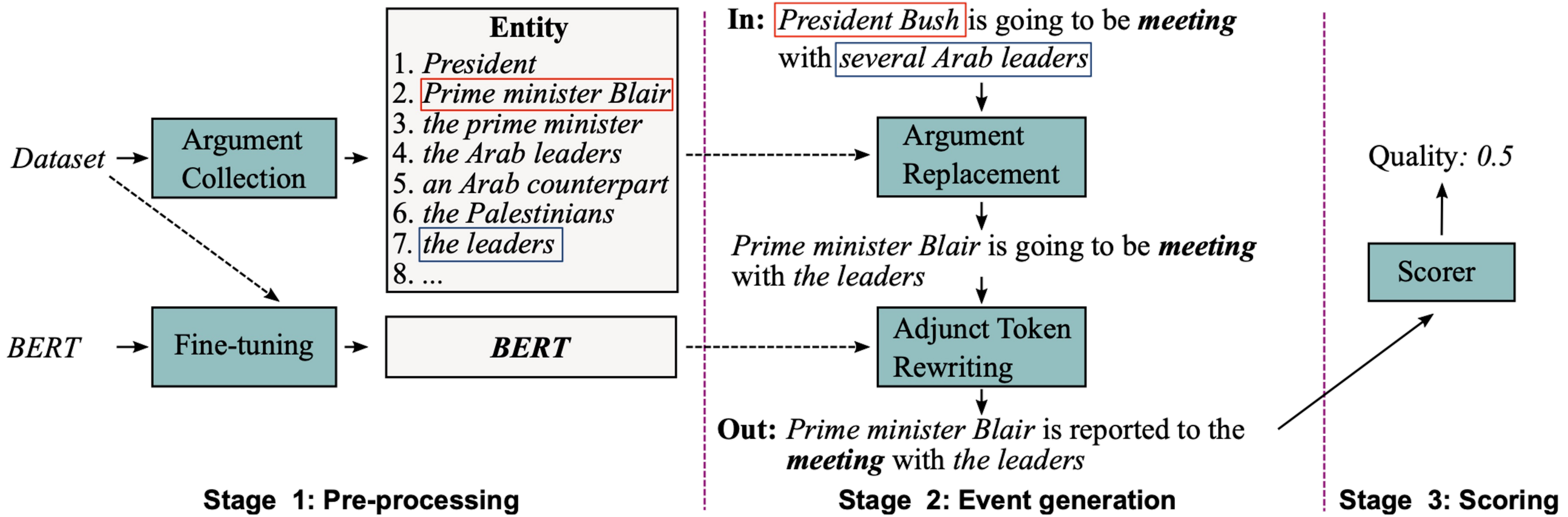
❑ Augmenting More Knowledge with Relevant Text

❑ Sample Augmentation



Generating event samples: Keep the event structure, replace the event arguments

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

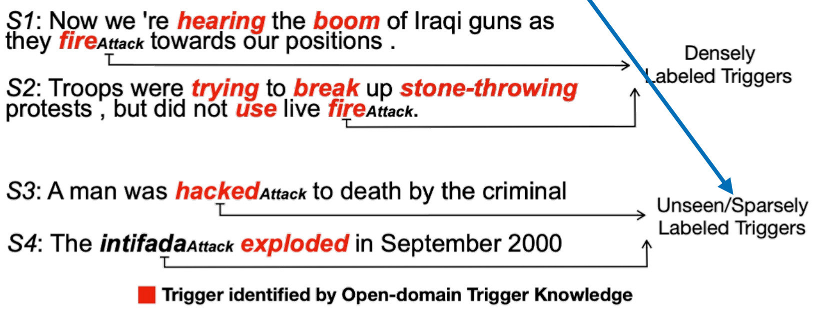
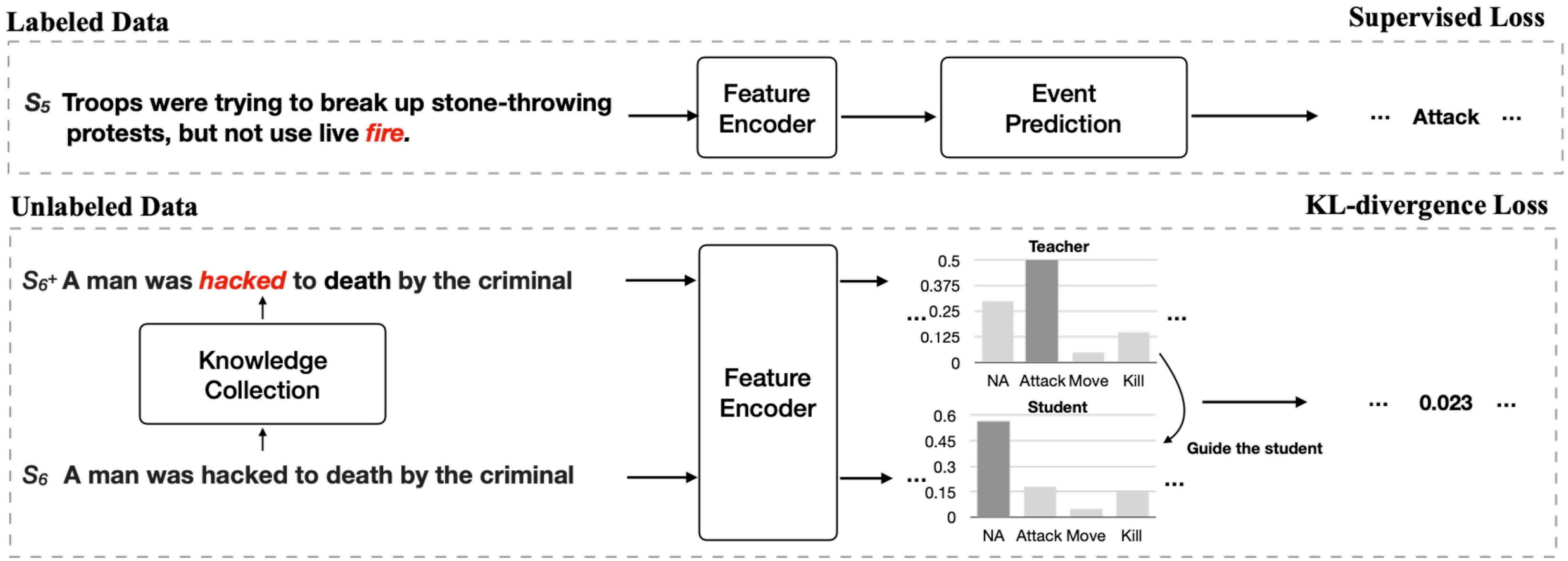


Figure 1: Examples of ED. *fire* is the densely labeled trigger for *Attack* event in ACE2005. *Hacked* and *intifada* are the unseen/sparsely labeled triggers in the training corpus. The red ones illustrate the triggers identified by open-domain trigger knowledge.



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

Improving Event Detection via Open-domain Trigger Knowledge (ACL 2020)

Auxiliary Knowledge Enhancement

❑ Augmenting More Knowledge with KG

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

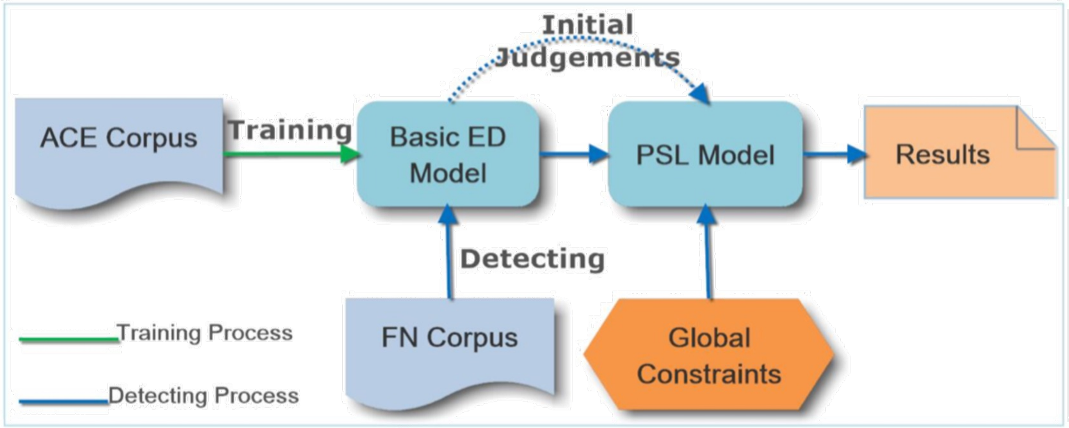


Figure 1: Our framework for detecting events in FN (including training and detecting processes).

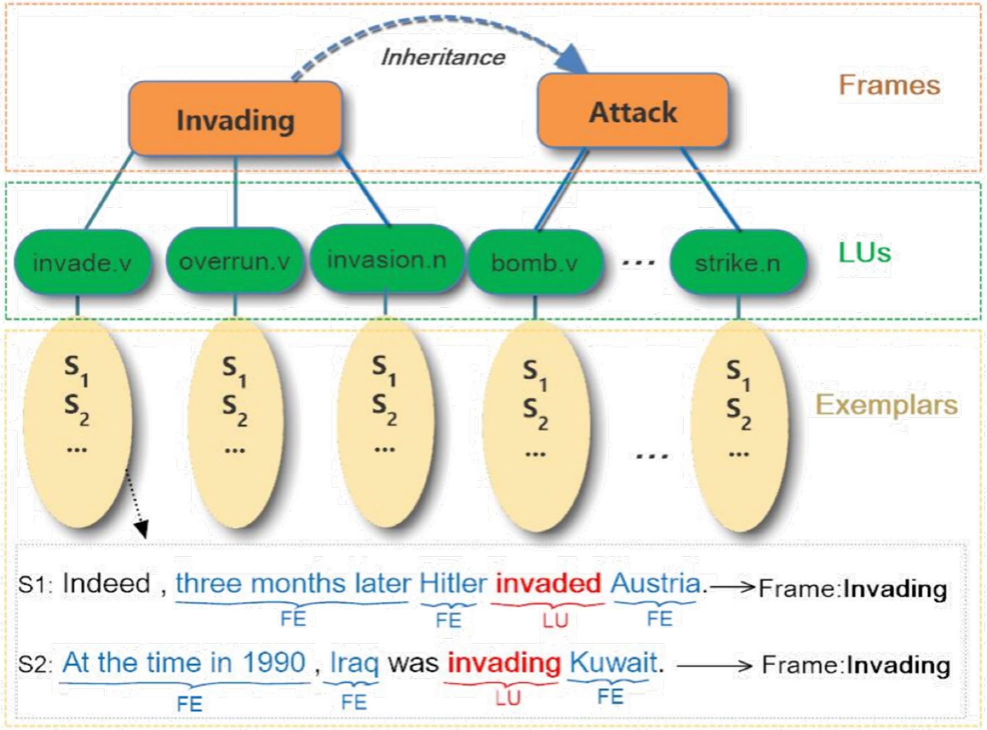


Figure 2: The hierarchy of FN corpus, where each S_k under a LU is a exemplar annotated for that LU. *Inheritance* is a semantic relation between the frames `Invading` and `Attack`.

Leveraging FrameNet to Improve Automatic Event Detection (ACL 2016)

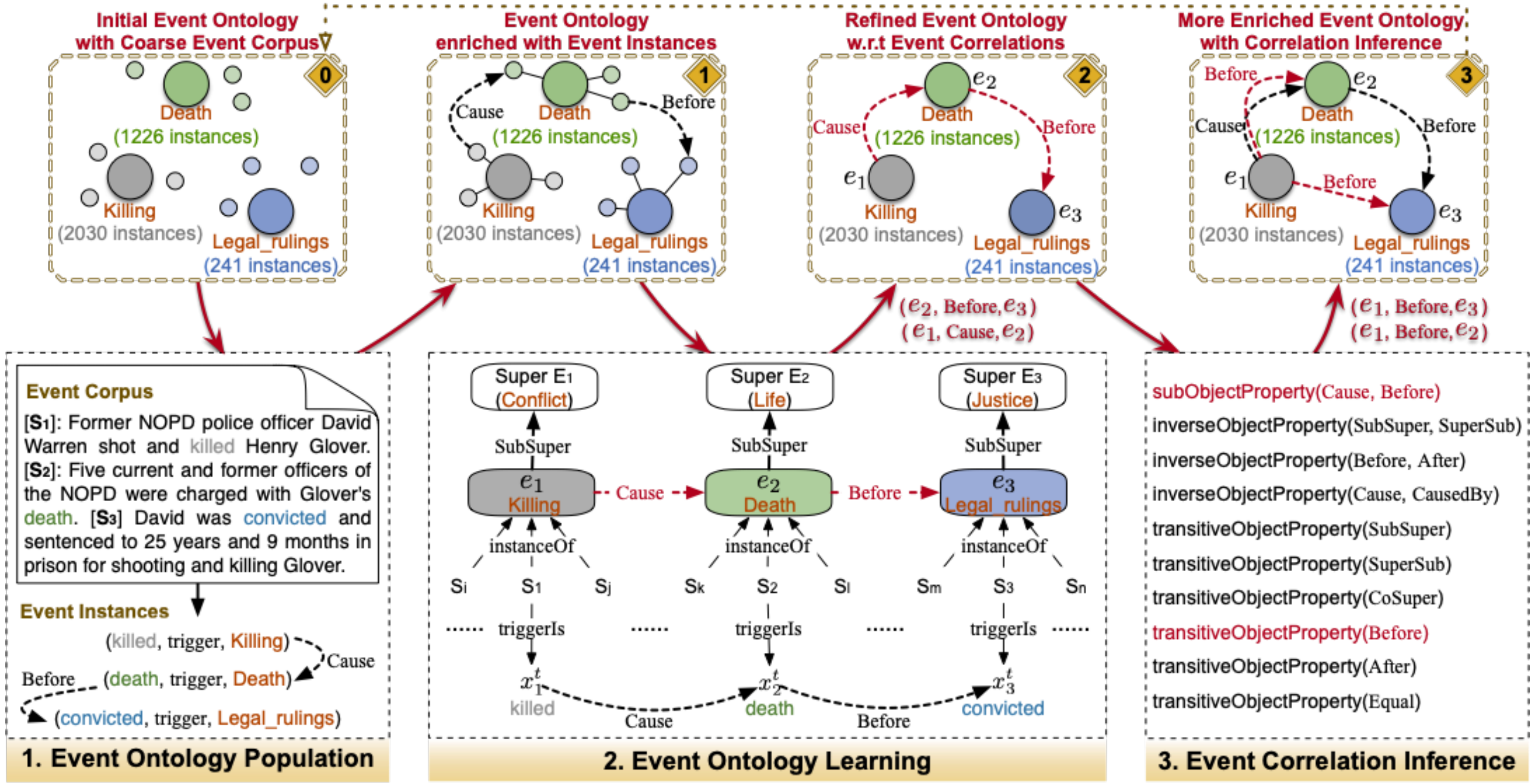
Auxiliary Knowledge Enhancement

IJCAI/2023 MACAO

❑ Augmenting More Knowledge with Ontology & Logical Rules

$(e_1, \text{Cause}, e_2) \rightarrow (e_1, \text{Before}, e_2)$

$(e_1, \text{Before}, e_2) \wedge (e_2, \text{Before}, e_3) \rightarrow (e_1, \text{Before}, e_3)$



- ❑ Establishing correlation among samples
- ❑ Populating more data

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

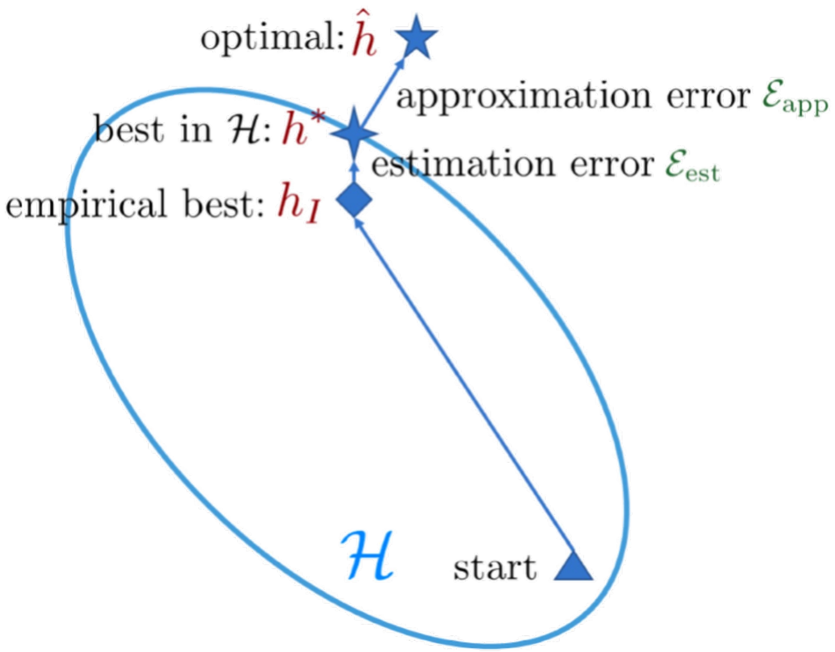
Given a hypothesis h, we want to minimize its expected risk R

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

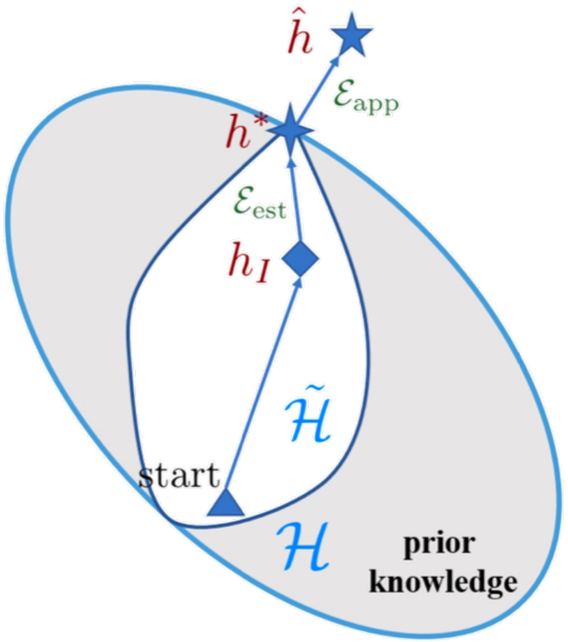
$h^* = \arg\min_{h\in\mathcal{H}} R(h)$: the function in $\mathcal{H}$ that minimizes the expected risk

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

$\mathcal{H}$: hypothesis space



With Large-Scale Data

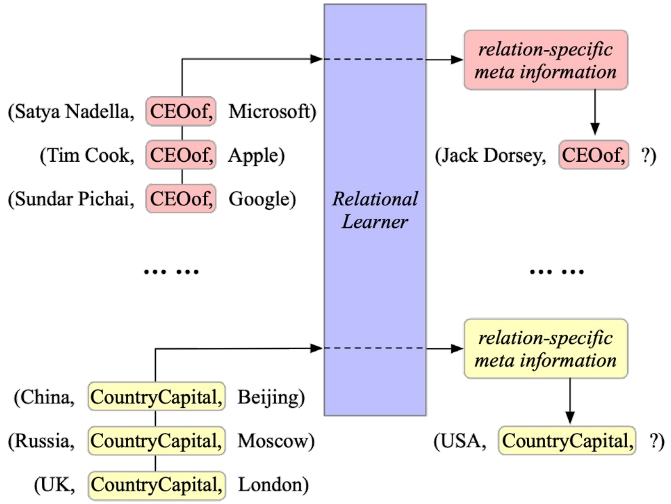


With Stronger Models in Low-Resource Scenarios

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

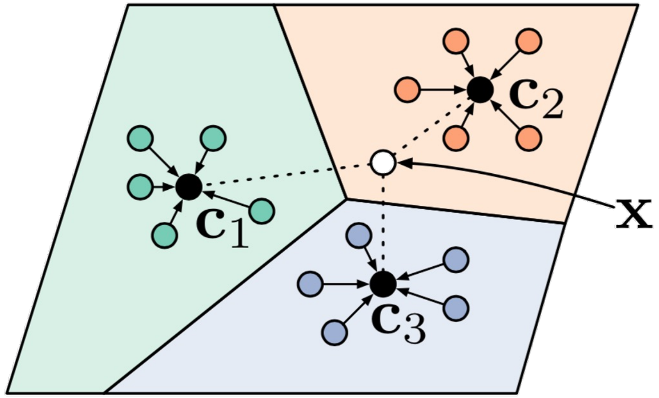
Meta Learning

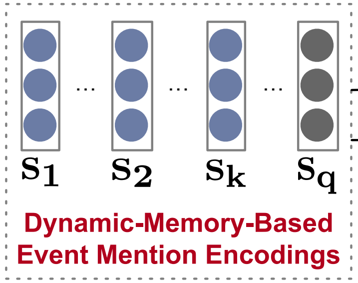
❑ Meta Knowledge Learner



Few-shot KGC

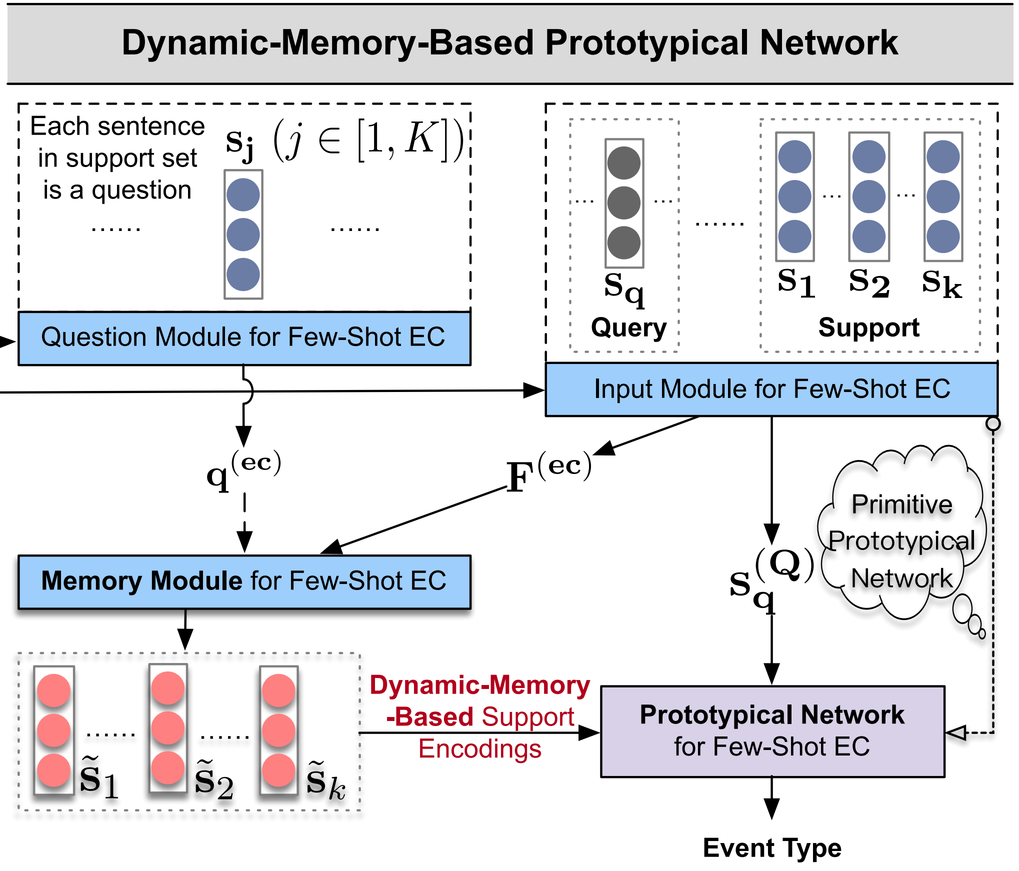
Class-specific meta knowledge
- ❑ Distinguish
- ❑ E.g., CEO_Of & Capital_Of





How does this event mention contribute to event prototype learning?

Class-general meta knowledge
- ❑ Induce
- ❑ E.g., Marry & Divorce

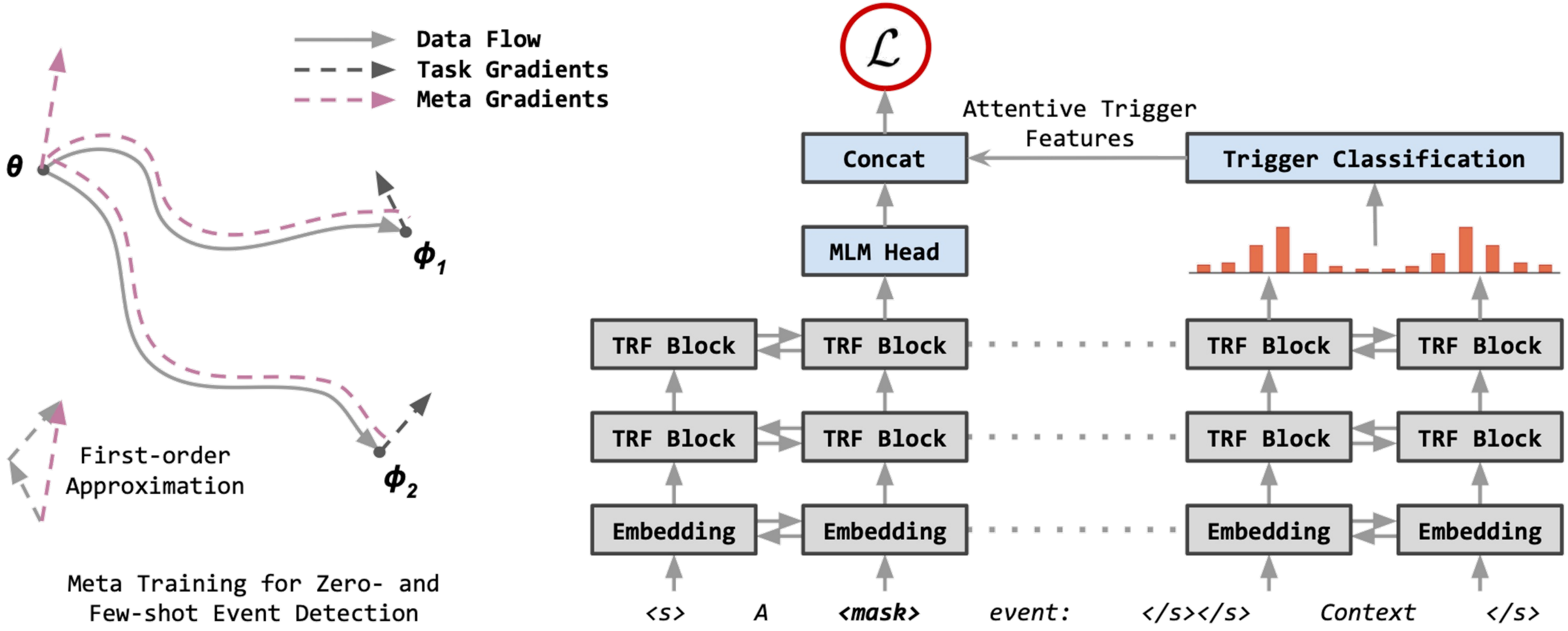


Few-Shot Event Classification

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



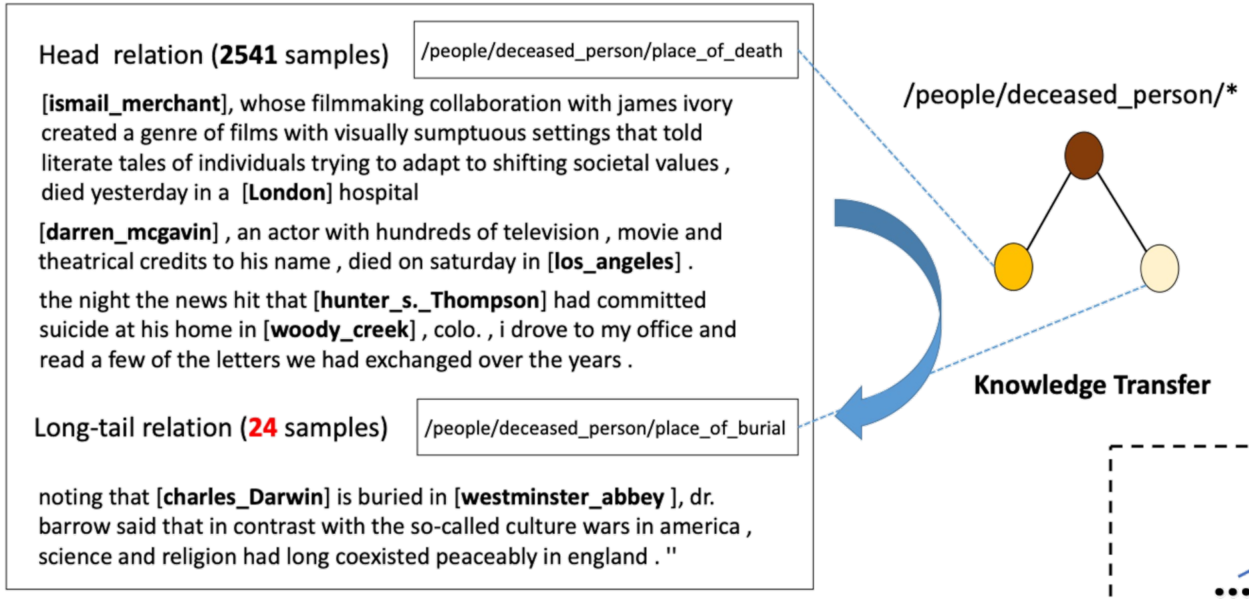
cloze-based prompt + a trigger-aware soft verbalizer

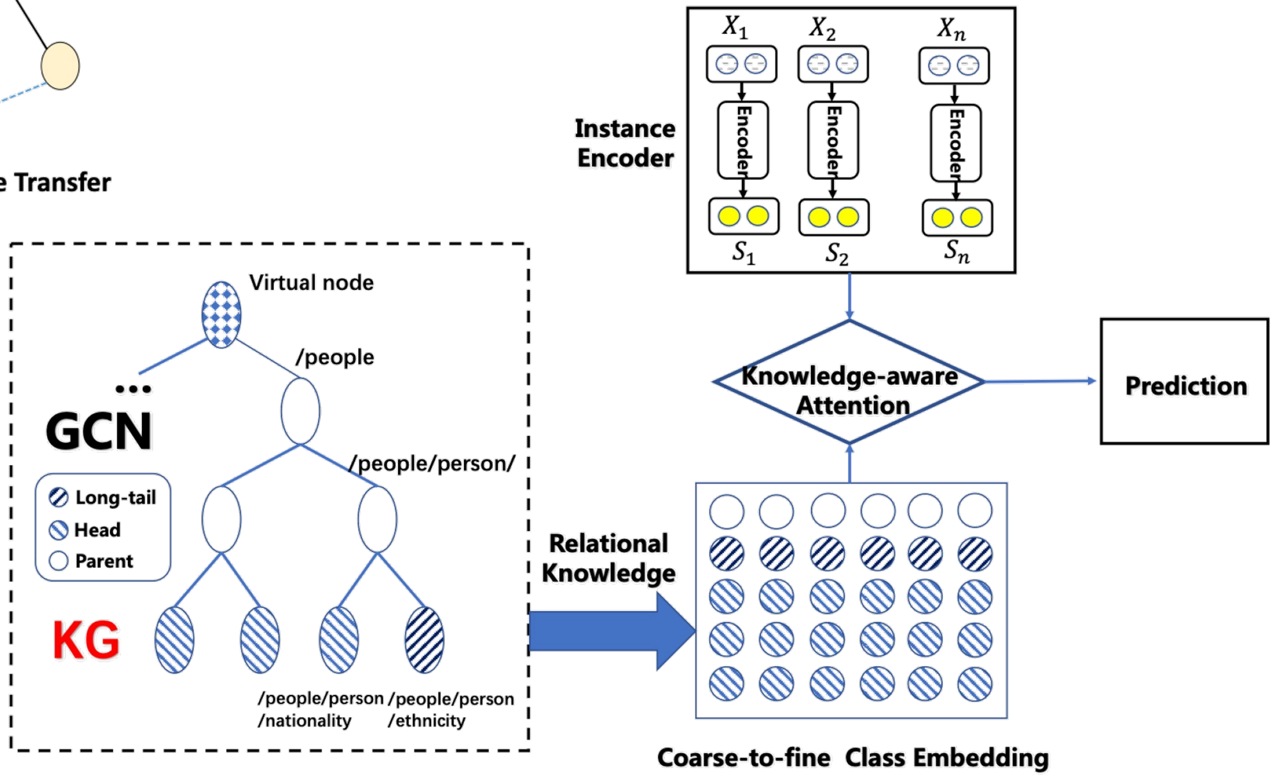
Figure 2: The proposed MetaEvent. The left subfigure illustrates the optimization process w.r.t. the initial parameter set θ with meta learning, and the right subfigure describes the proposed event detection model in MetaEvent.

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

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❑ Transferring Pre-trained Language Representations

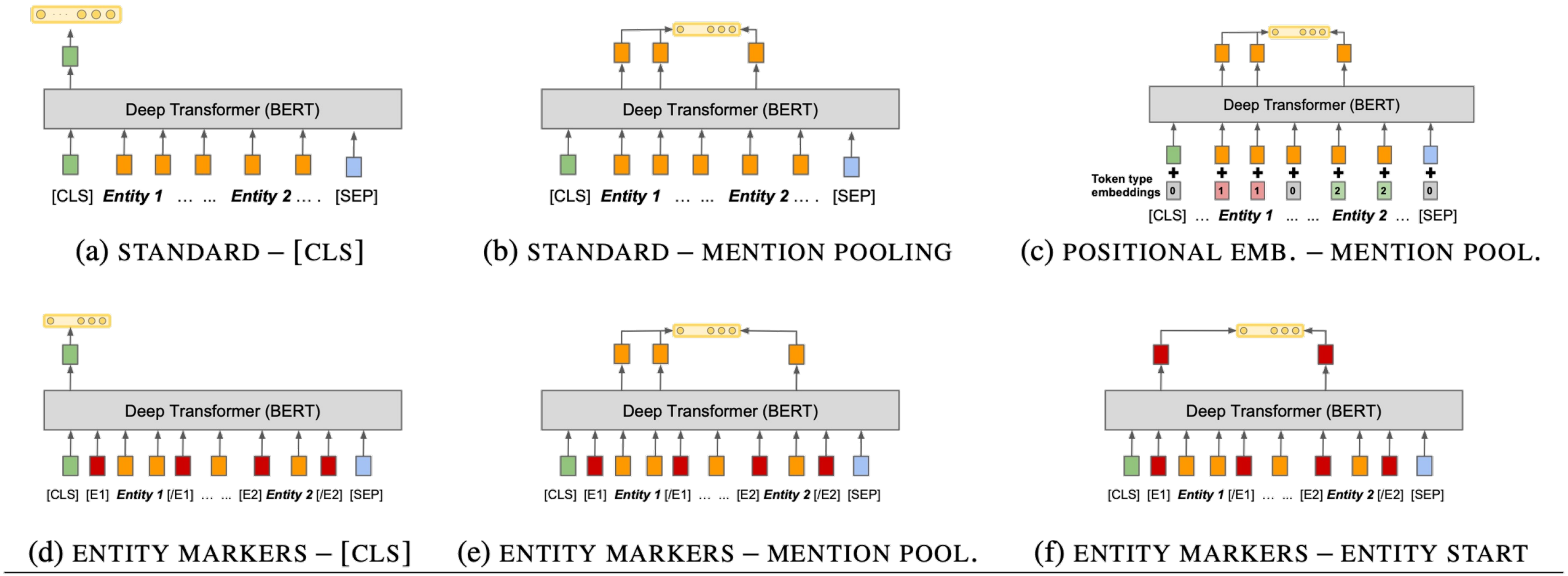


Figure 3: Variants of architectures for extracting relation representations from deep Transformers network. Figure (a) depicts a model with STANDARD input and [CLS] output, Figure (b) depicts a model with STANDARD input and MENTION POOLING output and Figure (c) depicts a model with POSITIONAL EMBEDDINGS 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

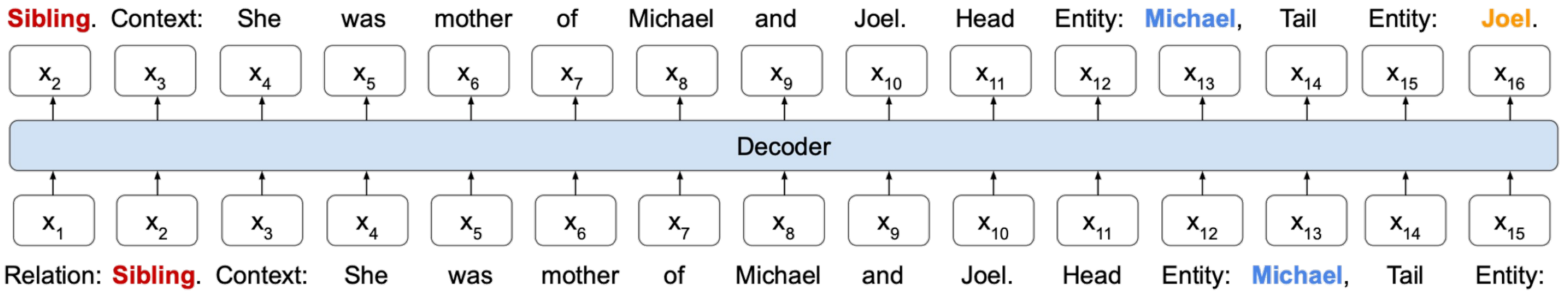
❑ Vanilla Prompt Learning

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

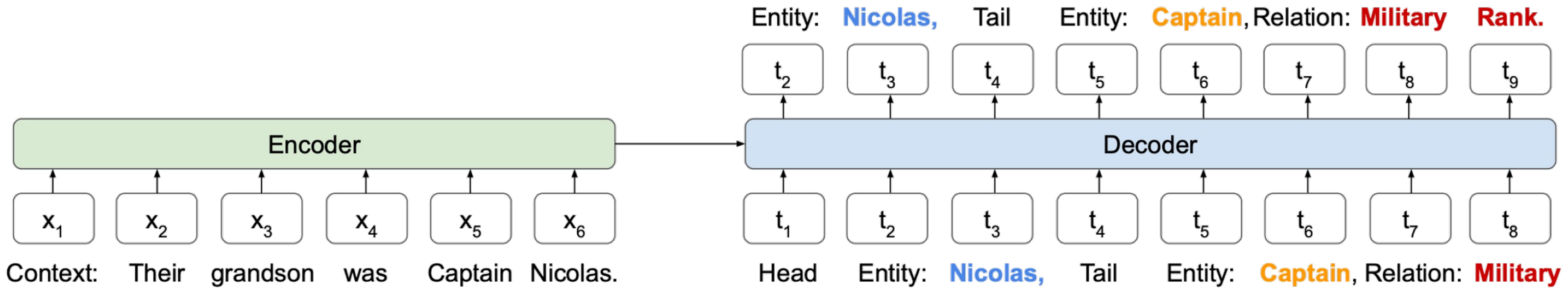
(a) Structured template for relation generator.

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

(b) Structured template for relation extractor.



(a) Training process for relation generator.



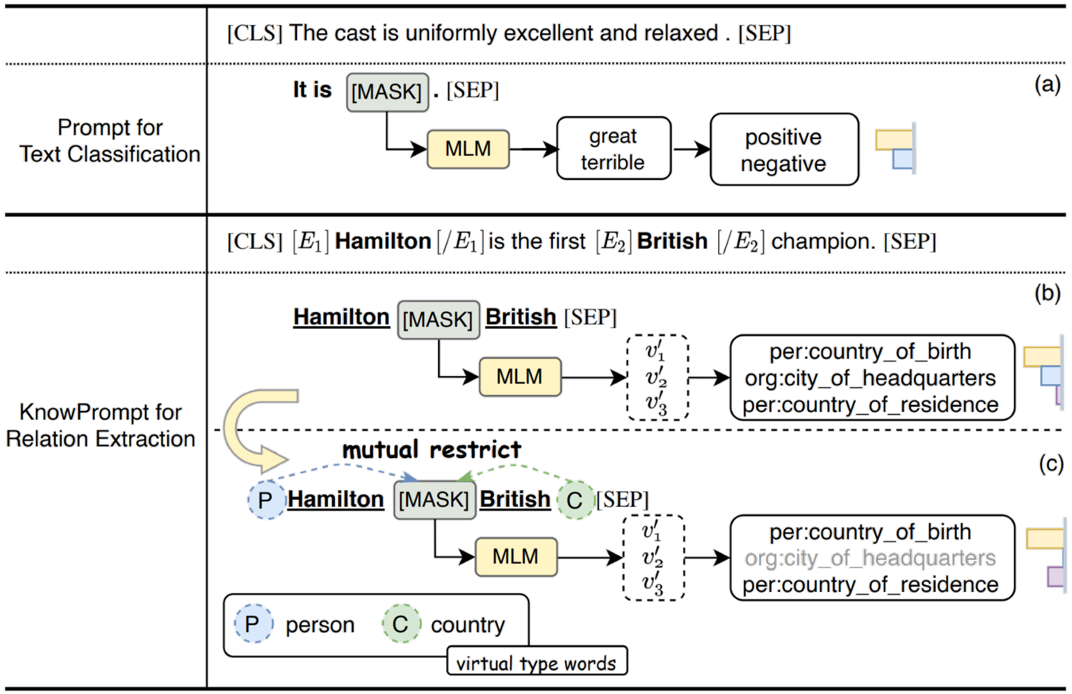
(b) Training process for relation extractor.

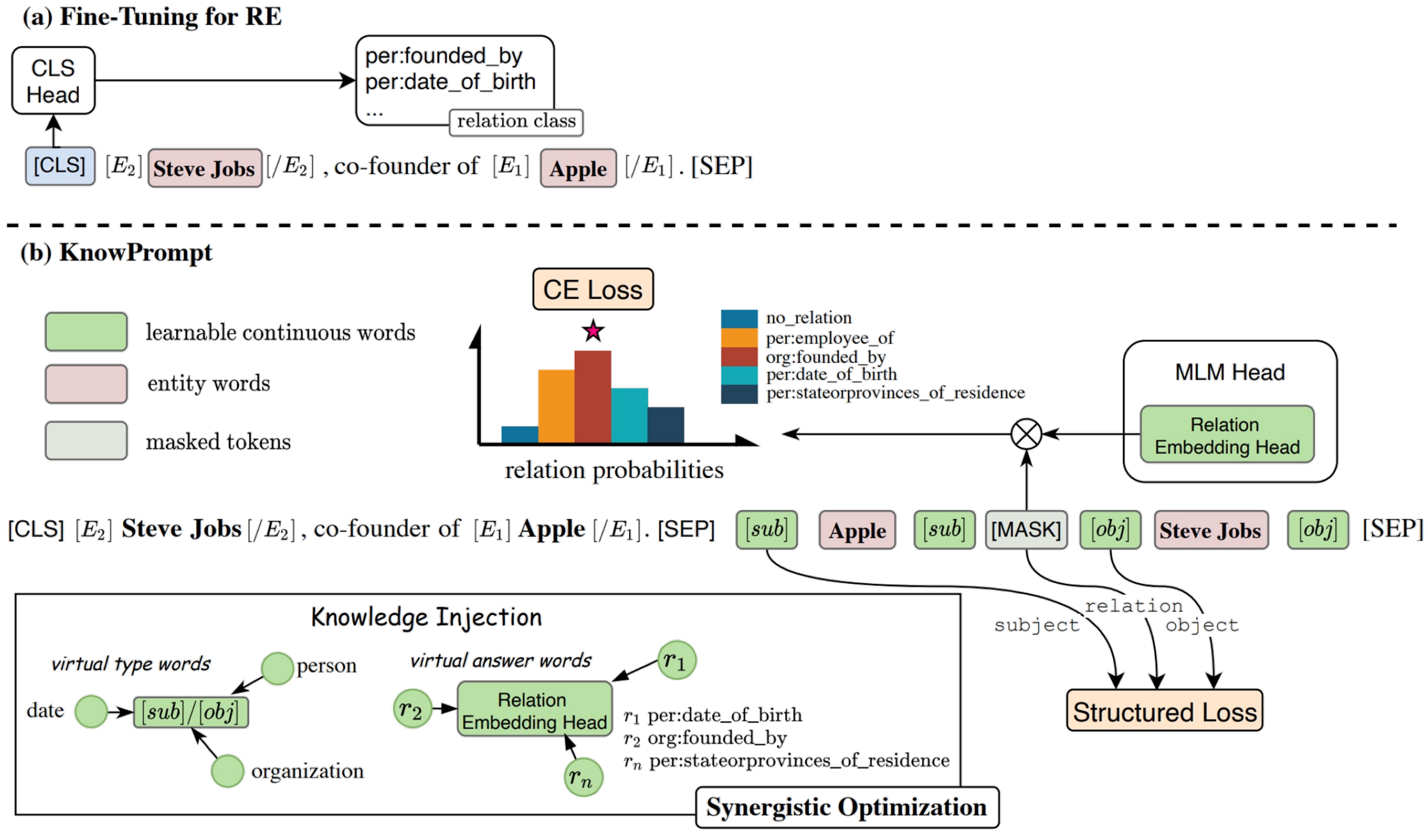
RelationPrompt: Leveraging Prompts to Generate Synthetic Data for Zero-Shot Relation Triplet Extraction (ACL 2022, Findings)

Prompt Learning

❑ Augmented Prompt Learning

❑ Schema Knowledge (virtual)





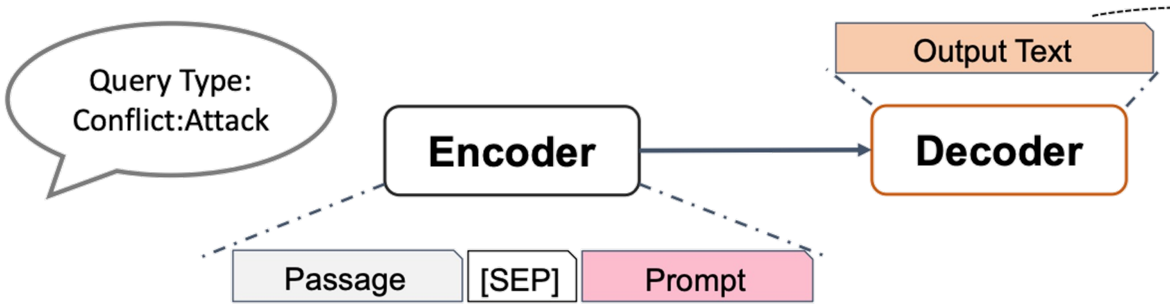
Knowledge-aware Prompt-tuning

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

Prompt Learning

❑ Augmented Prompt Learning

❑ Schema Knowledge (manually design, textual)



Event Trigger	*detonated*
Attacker	*Palestinian*
Target	*jeep, soldiers*
Instrument	*bomb*
Place	*Gaza Strip*

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

Task-Specific Prompt

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

Prompt Learning

❑ Augmented Prompt Learning

❑ Instances & Schema Knowledge (automatically, pluggable)

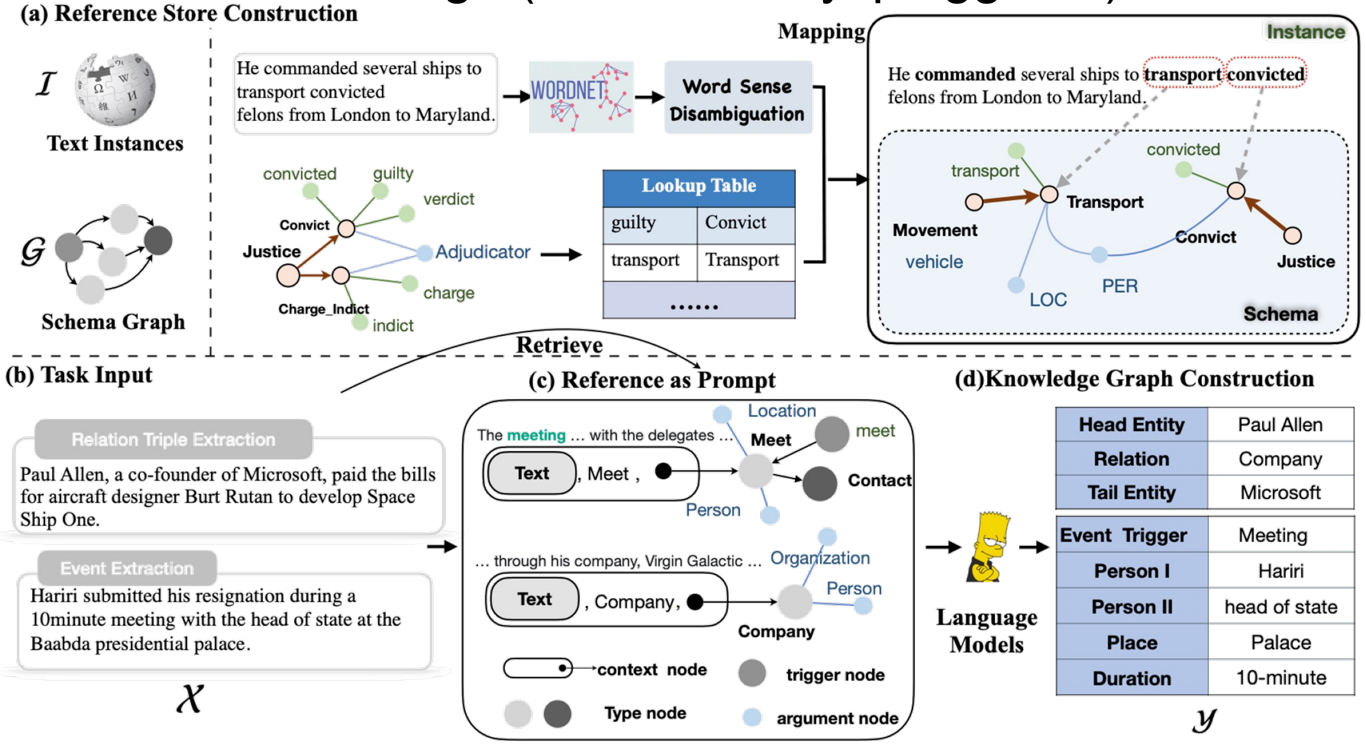


Figure 2: The architecture of schema-aware Reference As Prompt (RAP), which is model-agnostic and is readily pluggable into many existing KGC approaches TEXT2EVENT [34], DEGREE [18], PRGC [57], RelationPrompt [12] and so on.

Schema-aware Reference as Prompt

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

Developing *Stronger* Data-Efficient Models

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

CONTENTS

SEEKING TRUTH
PURSUING INNOVATION

Optimizing Data & Models *Together*

IJCAI/2023 MACAO

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

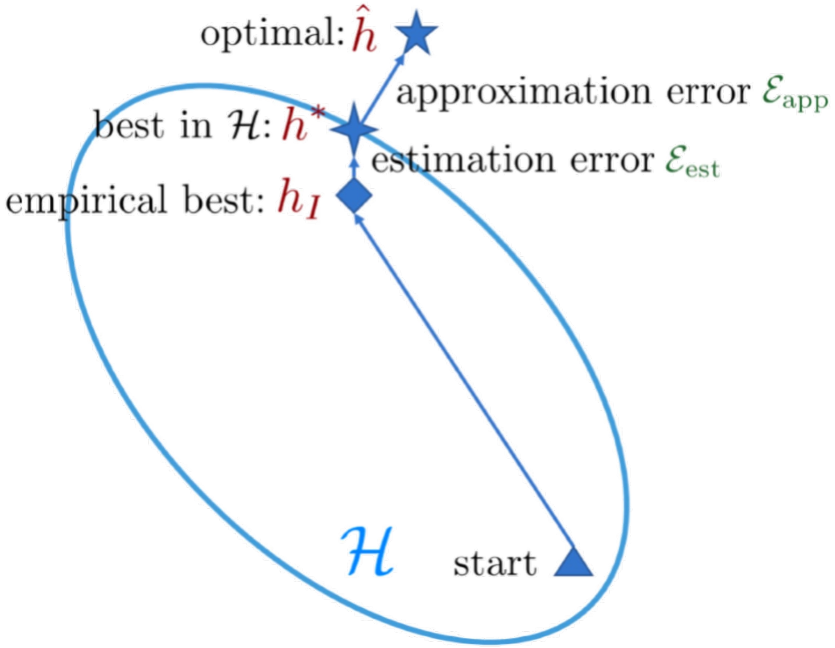
Given a hypothesis h, we want to minimize its expected risk R

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

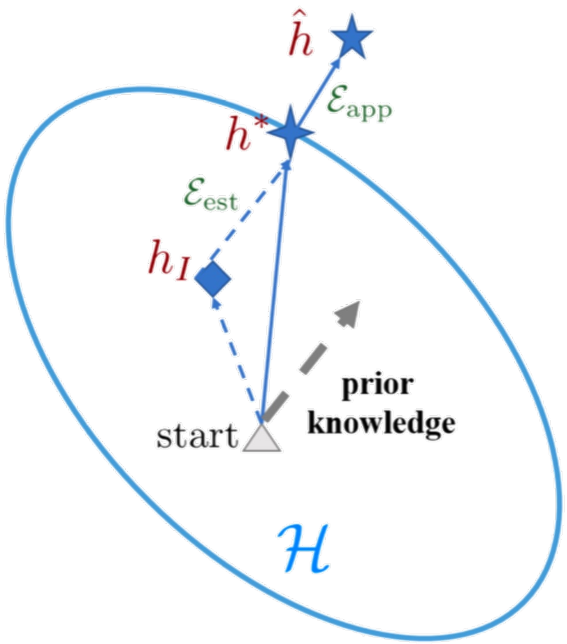
$h^* = \arg\min_{h\in\mathcal{H}} R(h)$: the function in $\mathcal{H}$ that minimizes the expected risk

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

$\mathcal{H}$: hypothesis space



With Large-Scale Data



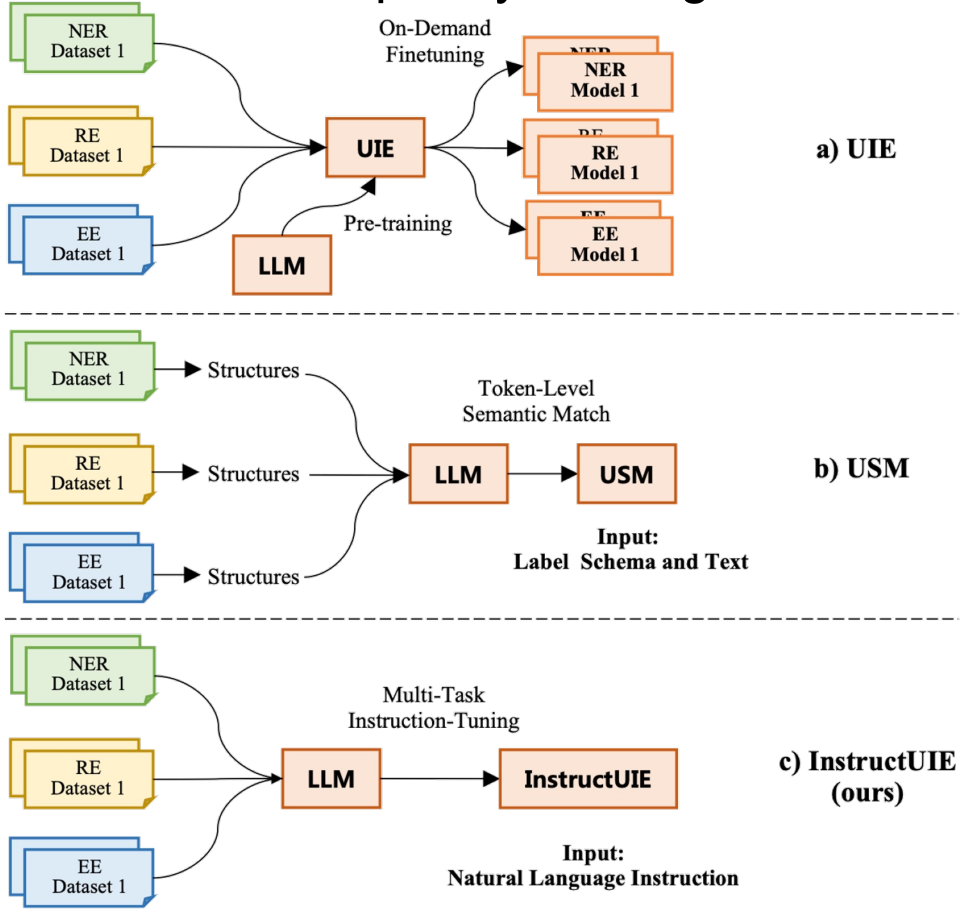
With Optimizing Data & Models Together in Low-Resource Scenarios

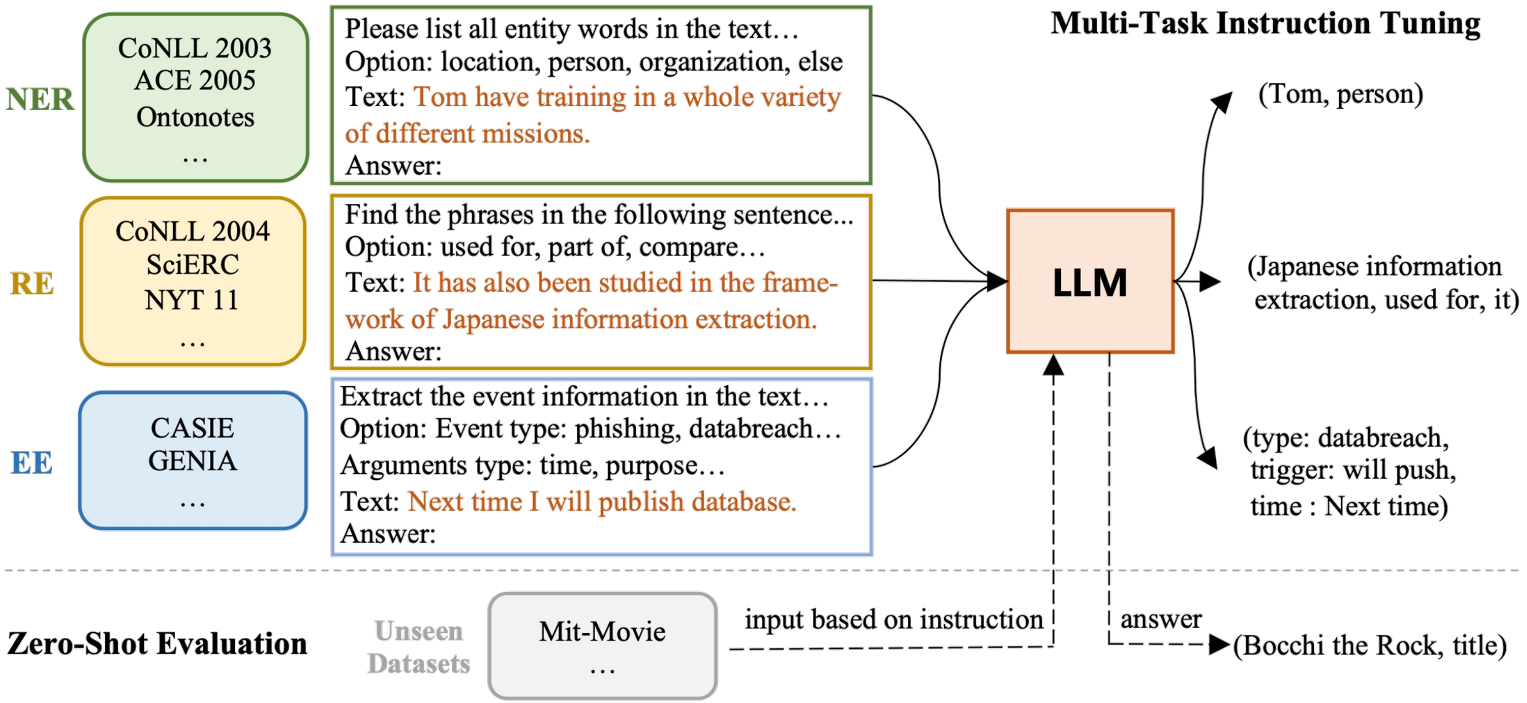
Generalizing from a Few Examples: A Survey on Few-shot Learning (ACM Computing Surveys, 2020)

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

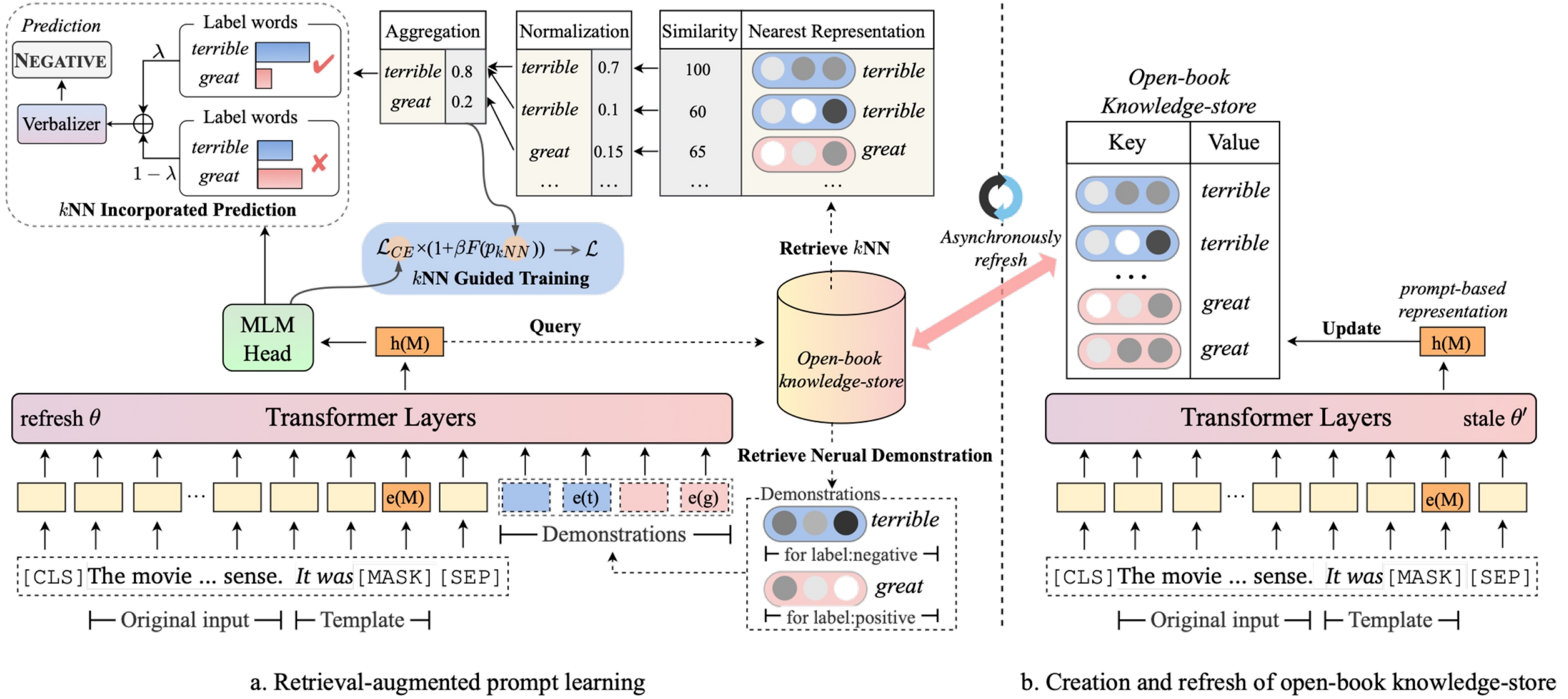
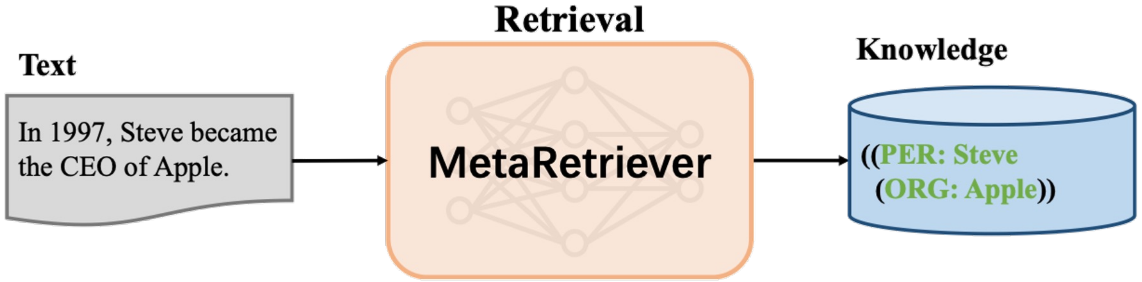


Figure 2: Overview of RETROPROMPT. Note that $e(\cdot)$ denotes word embedding function in the PLM $\mathcal{M}$, while "M","t" and "g" in $e(\cdot)$ specifically refers to "[MASK]", "terrible" and "great".

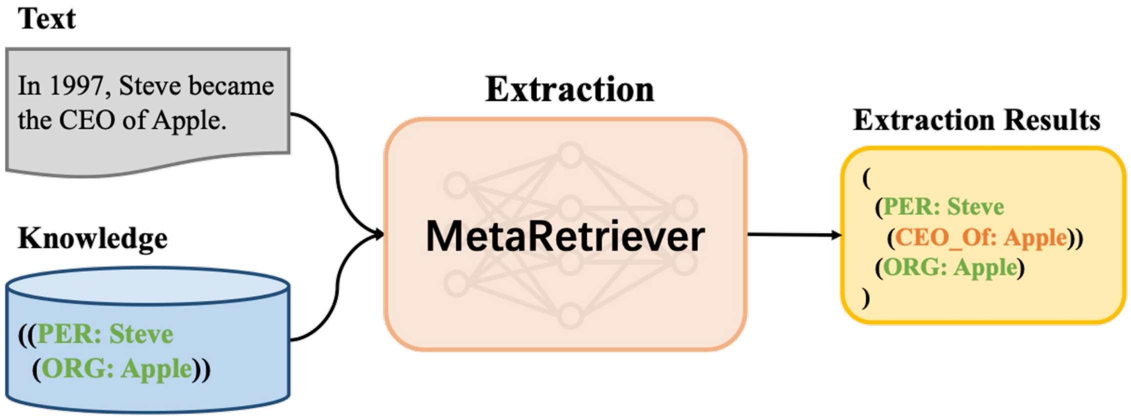
Decoupling Knowledge from Memorization: Retrieval-Augmented Prompt Learning (NeurIPS 2022)

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

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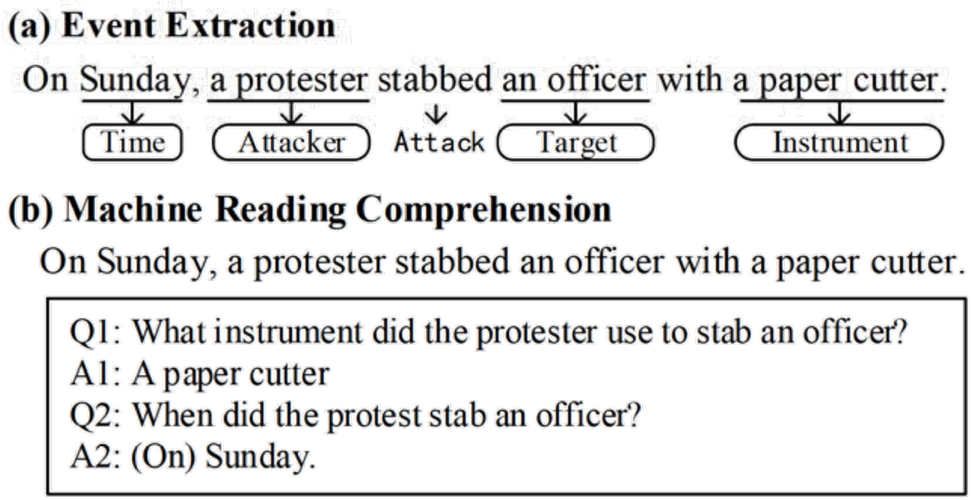
❑ KGC → QA/MRC



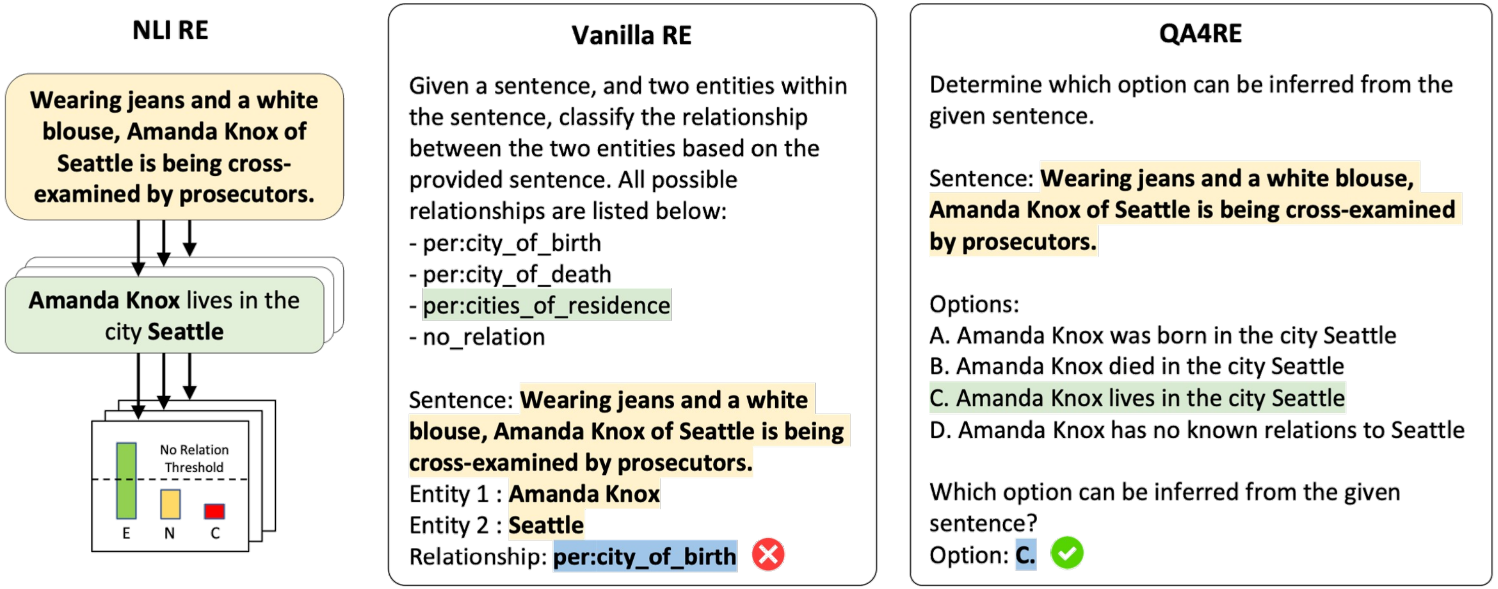


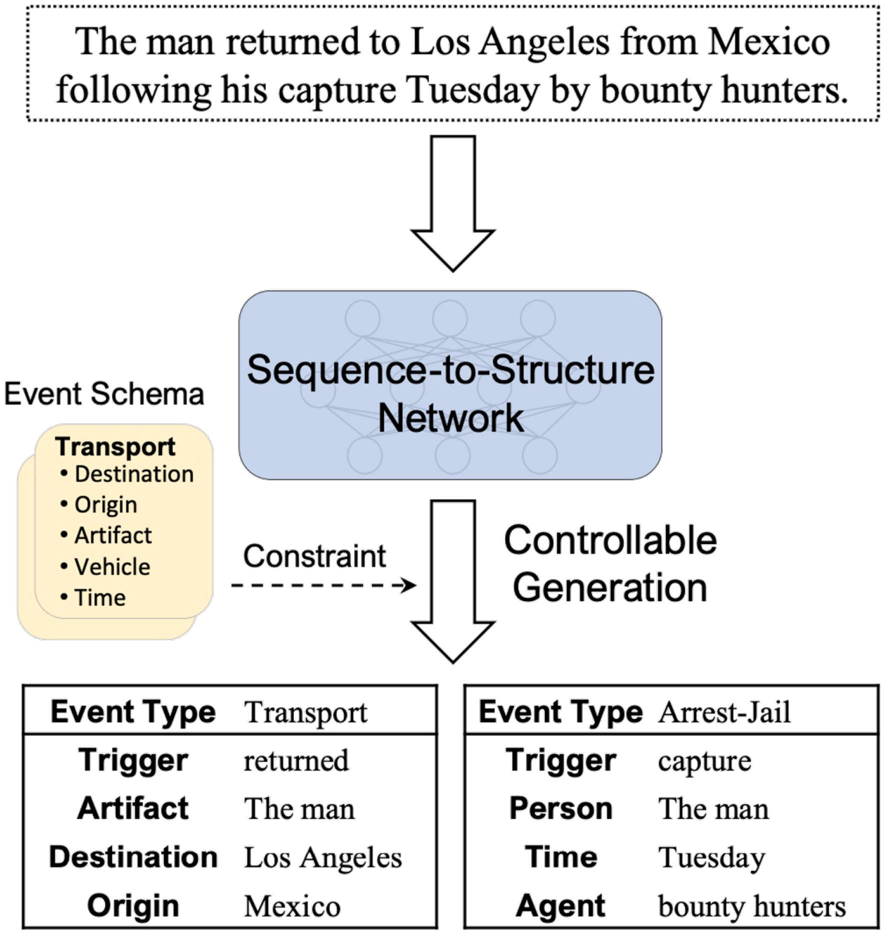
Figure 2: This figure shows a schematic of the SoTA NLI zero-shot framework in which each sentence must be compared with each relation template (left), the vanilla formulation for prompting GPT-3 for RE as done in Jimenez Gutierrez et al. (2022) (center) and our multiple-choice QA setting, in which each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

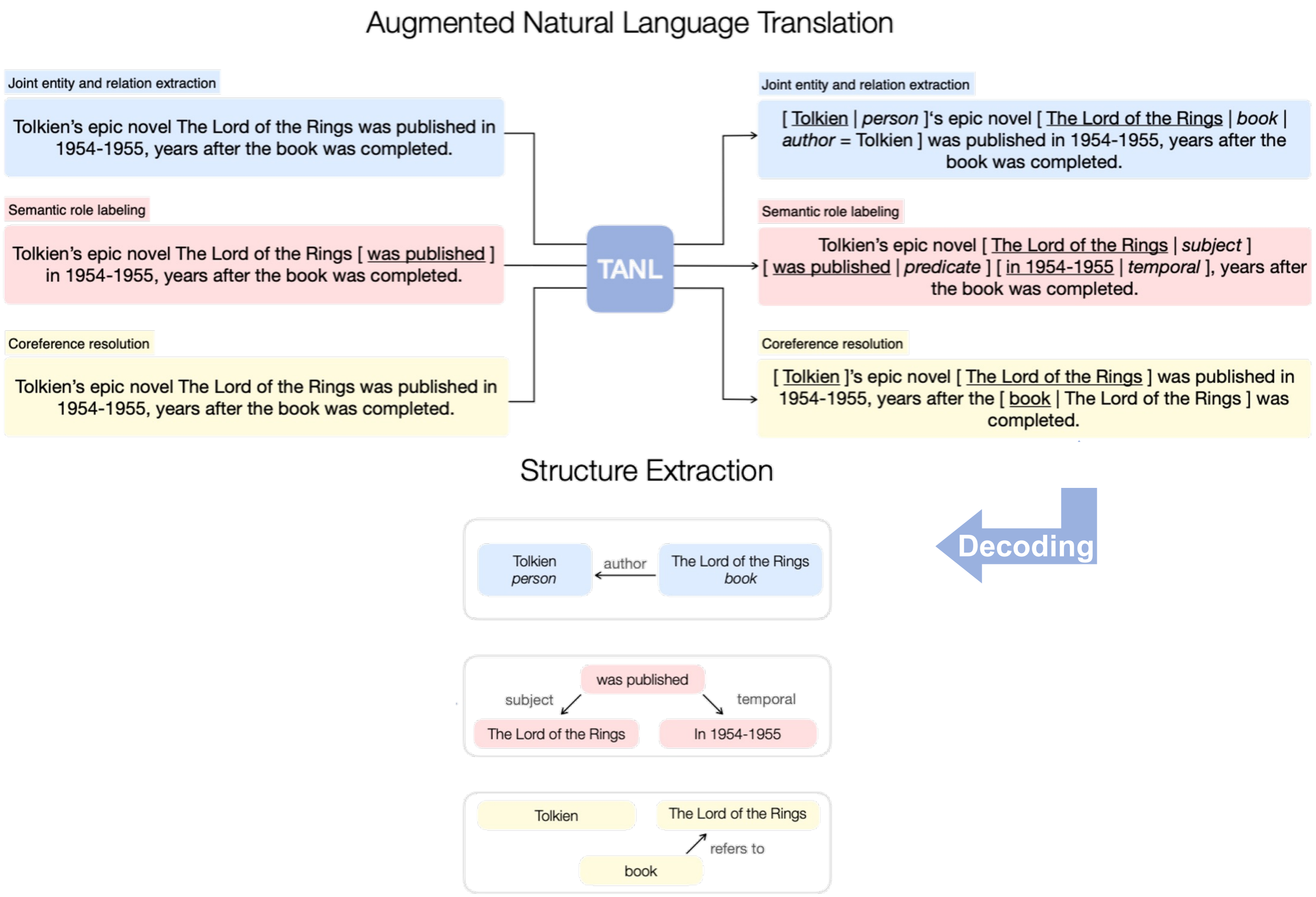
Event Extraction as Machine Reading Comprehension (EMNLP 2020)
Aligning Instruction Tasks Unlocks Large Language Models as Zero-Shot Relation Extractors (ACL 2023, Findings)

Task Reformulation

IJCAI/2023 MACAO

❑ KGC → Text-to-Structure Generation



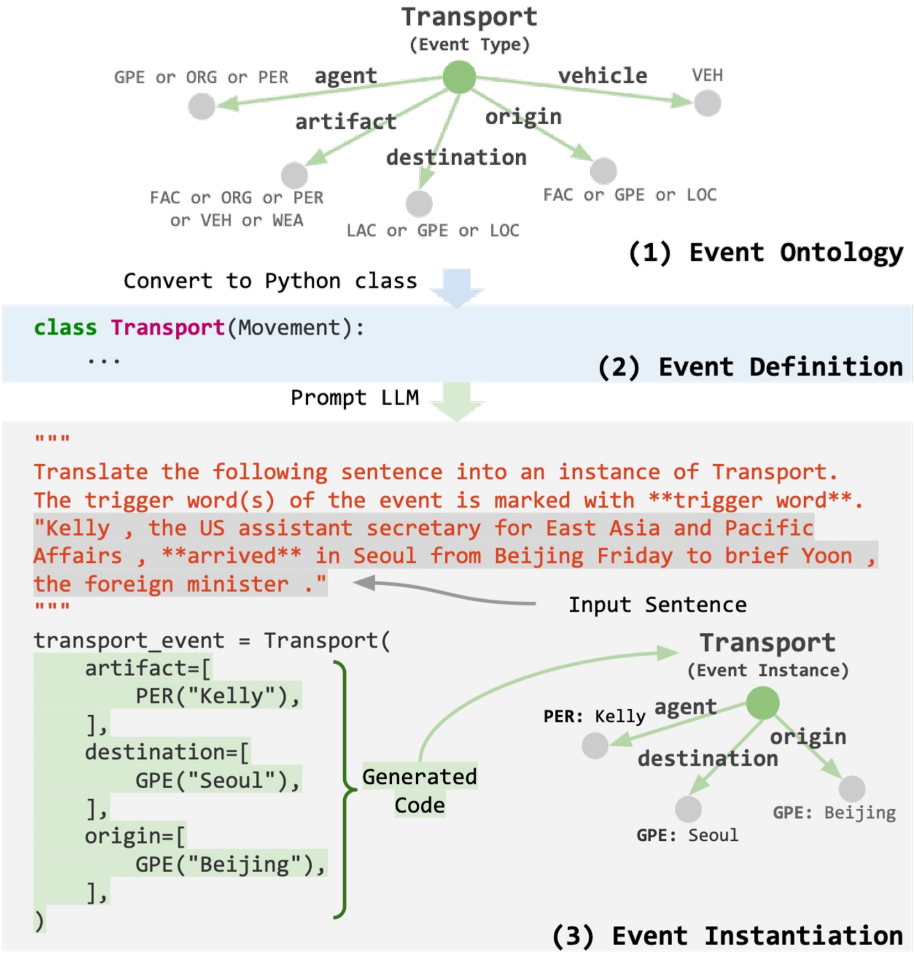


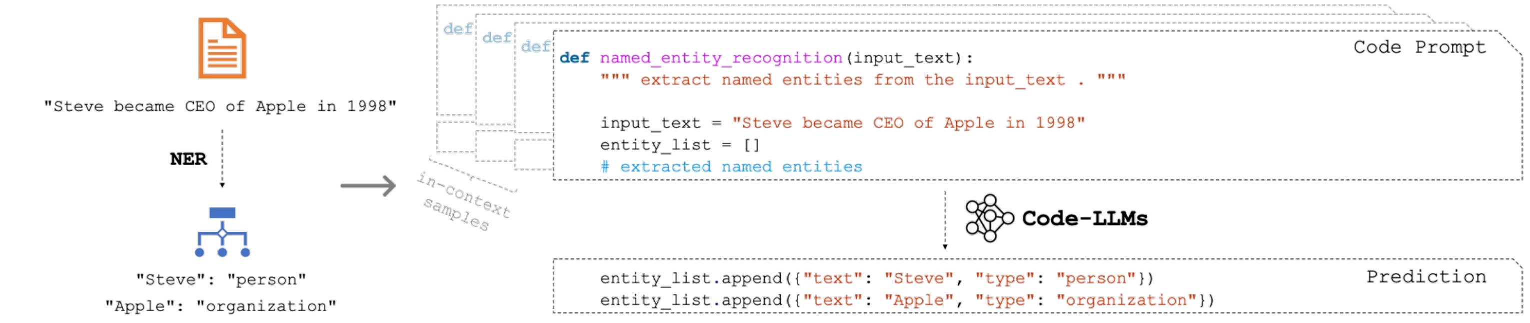
Text2Event: Controllable Sequence-to-Structure Generation for End-to-end Event Extraction (ACL 2021)
Structured Prediction as Translation between Augmented Natural Languages (ICLR 2021)

Task Reformulation

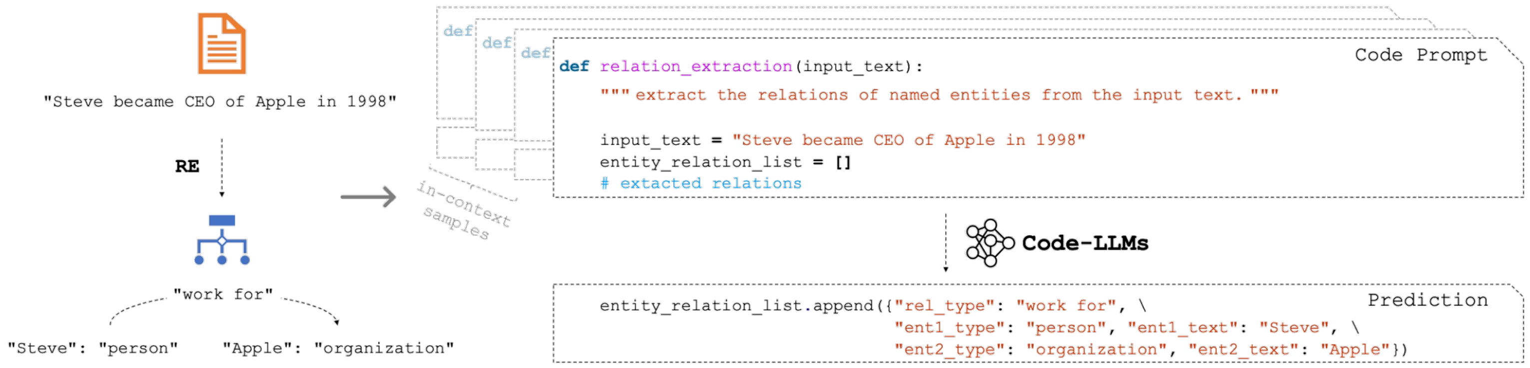
IJCAI/2023 MACAO

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





(a) Converting NER into code generation task



(b) Converting RE into code generation task

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

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🤗 **We are in the era of LLMs!**

CONTENTS

Knowledge & LM

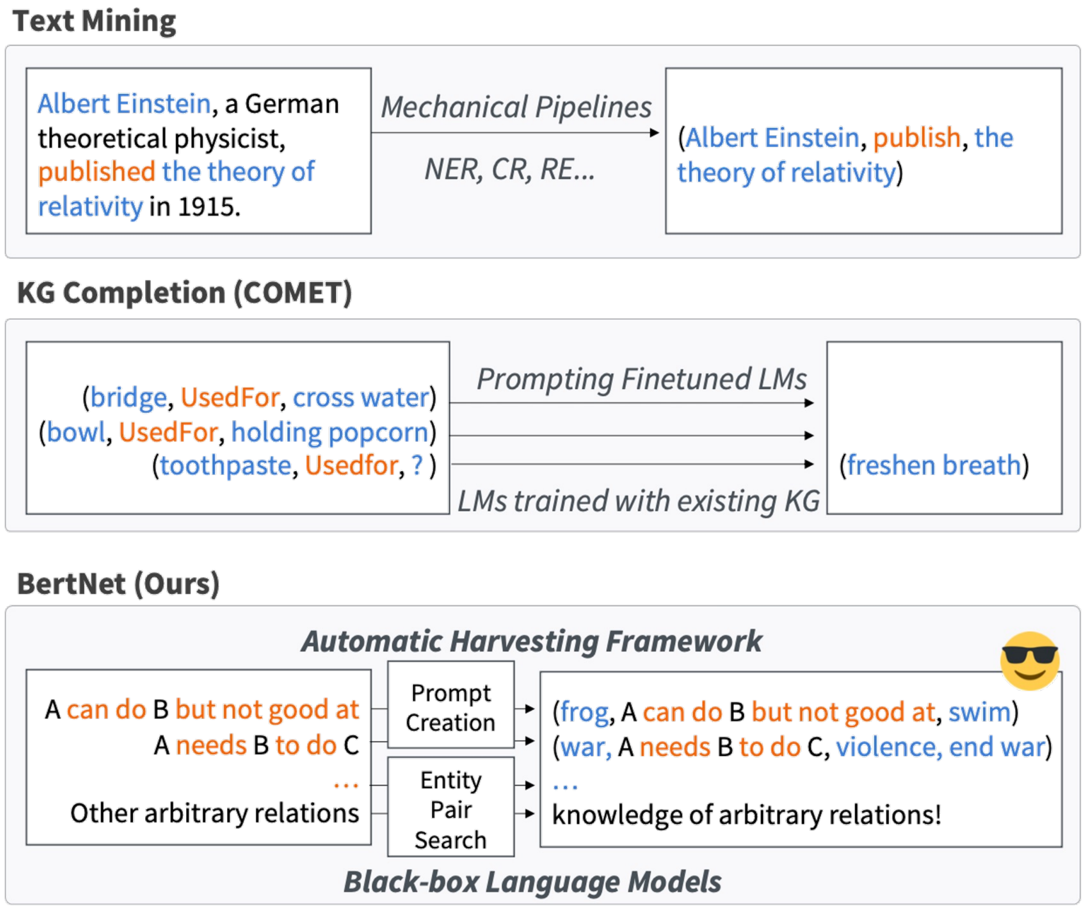
IJCAI/2023 MACAO

Extracting Knowledge from Texts → Probing Knowledge from LMs

Factual knowledge extraction from Texts

Factual knowledge query from KB

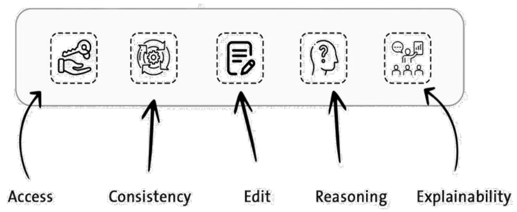
Factual knowledge probing from LM



Require enough annotated samples

Require schema engineering

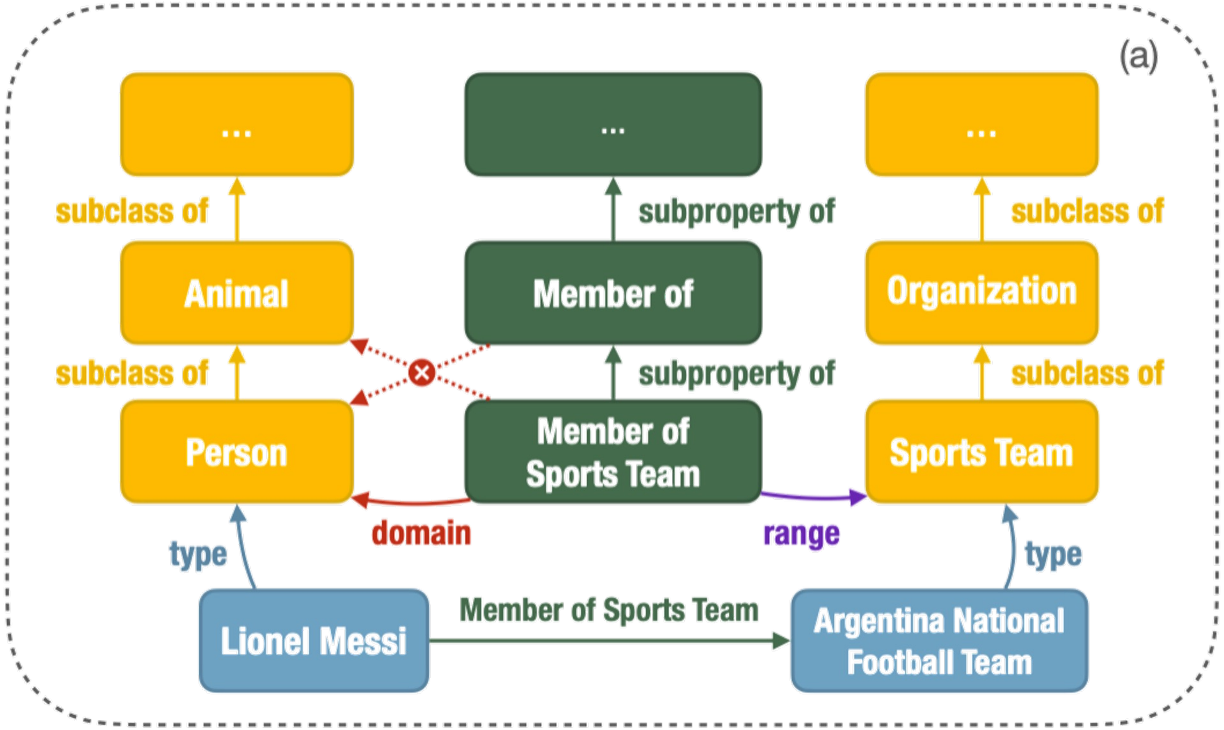
LMs-as-KBs



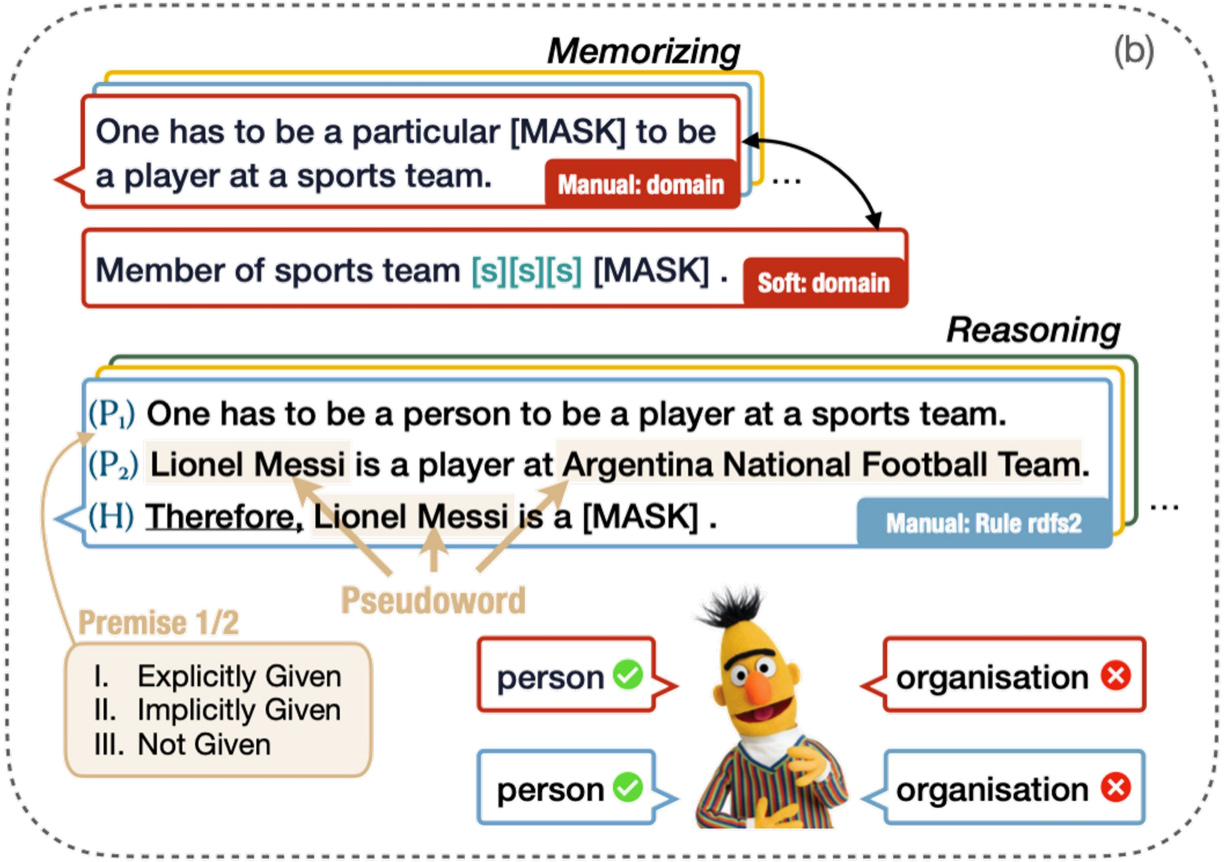
Support for open domain queries

Language Models as Knowledge Bases? (EMNLP 2019)
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)

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

Do PLMs Know and Understand Ontological Knowledge? (ACL 2023)

LLMs for KG Construction and Reasoning

IJCAI/2023 MACAO

❑ 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)

LLMs for KG Construction and Reasoning

IJCAI/2023 MACAO

❑ 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 5-shot	FewNERD 10-shot	FewNERD 20-shot	TACREV 20-shot	TACREV 50-shot	TACREV 100-shot	ACE 5-shot	ACE 10-shot	ACE 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)
LLM	InstructGPT	53.6 (–)	54.6 (–)	57.2 (–)	60.1 (–)	58.3 (–)	62.7 (–)	52.9 (–)	52.1 (–)	49.3 (–)
SLM	FSLS / KnowPrompt	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)
SLM	+ Ensemble	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)
S+L	+ Ensemble + LLM Rerank	**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)

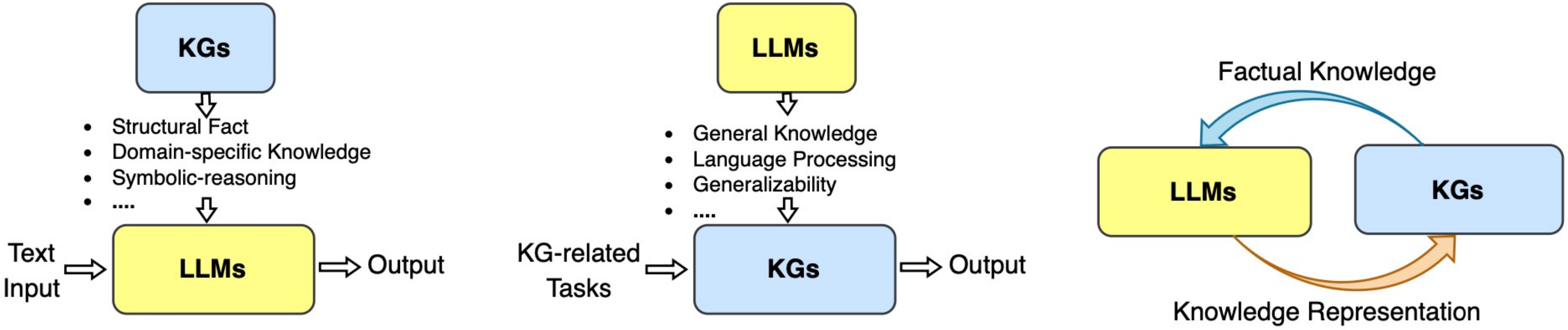
Model	Knowledge Graph Construction DuIE2.0	Re-TACRED	MAVEN	SciERC
Fine-Tuned SOTA	69.42	91.4	68.8	53.2
Zero-shot				
text-davinci-003	11.43	9.8	30.0	4.0
ChatGPT	10.26	15.2	26.5	4.4
GPT-4	31.03	15.5	34.2	7.2
One-shot				
text-davinci-003	30.63	12.8	25.0	4.8
ChatGPT	25.86	14.2	34.1	5.3
GPT-4	41.91	22.5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

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❑ 📊 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 Text2KGBench

❑ 🛠 Toolkits

- ❑ Traditional
  - ❑ DeepKE, OpenUE, Zshot, OpenNRE, OmniEvent, OpenKE, NeuralKG, NeuralKG-ind, DeepOnto, PromptKG, …
- ❑ LLM-based
  - ❑ KnowLM, AutoKG, GPT4IE, ChatIE, …

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IJCAI
International Joint Conferences on Artificial Intelligence Organization

Thank You

Speaker: Shumin Deng

Date: 2023.08.19

Paper list on low-resource KGC

Website

LLM-based toolkit for KGC

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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

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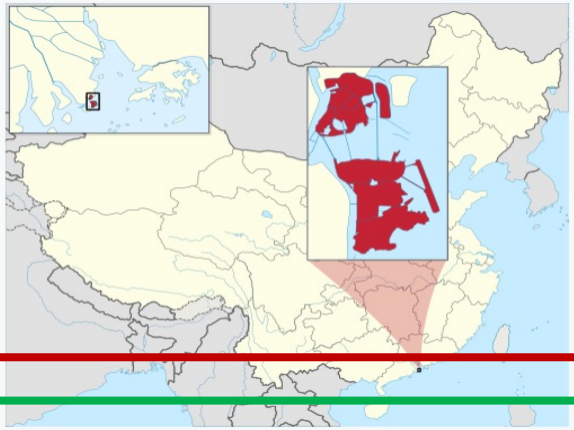
Casinos on the Macanese skyline

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

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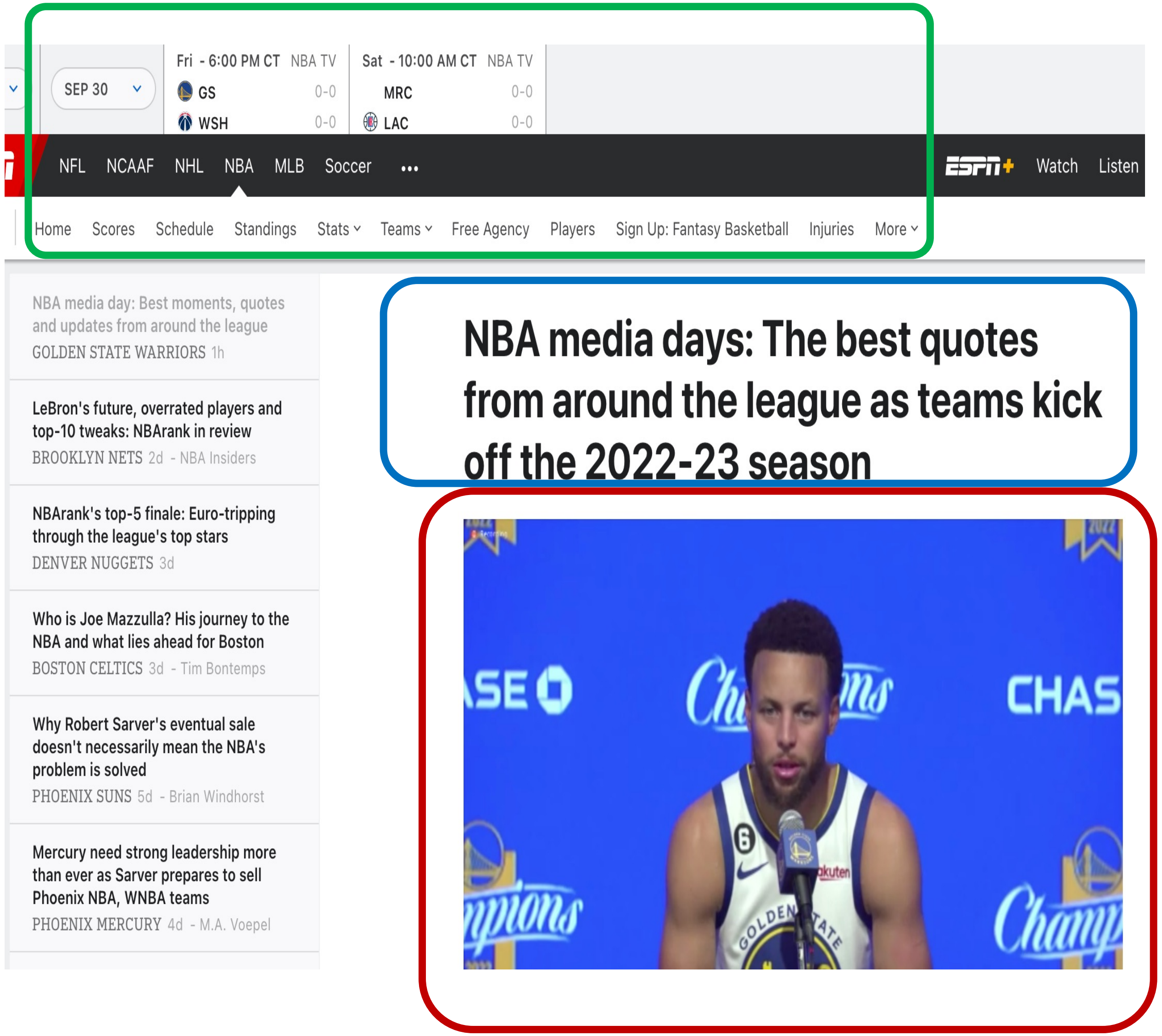

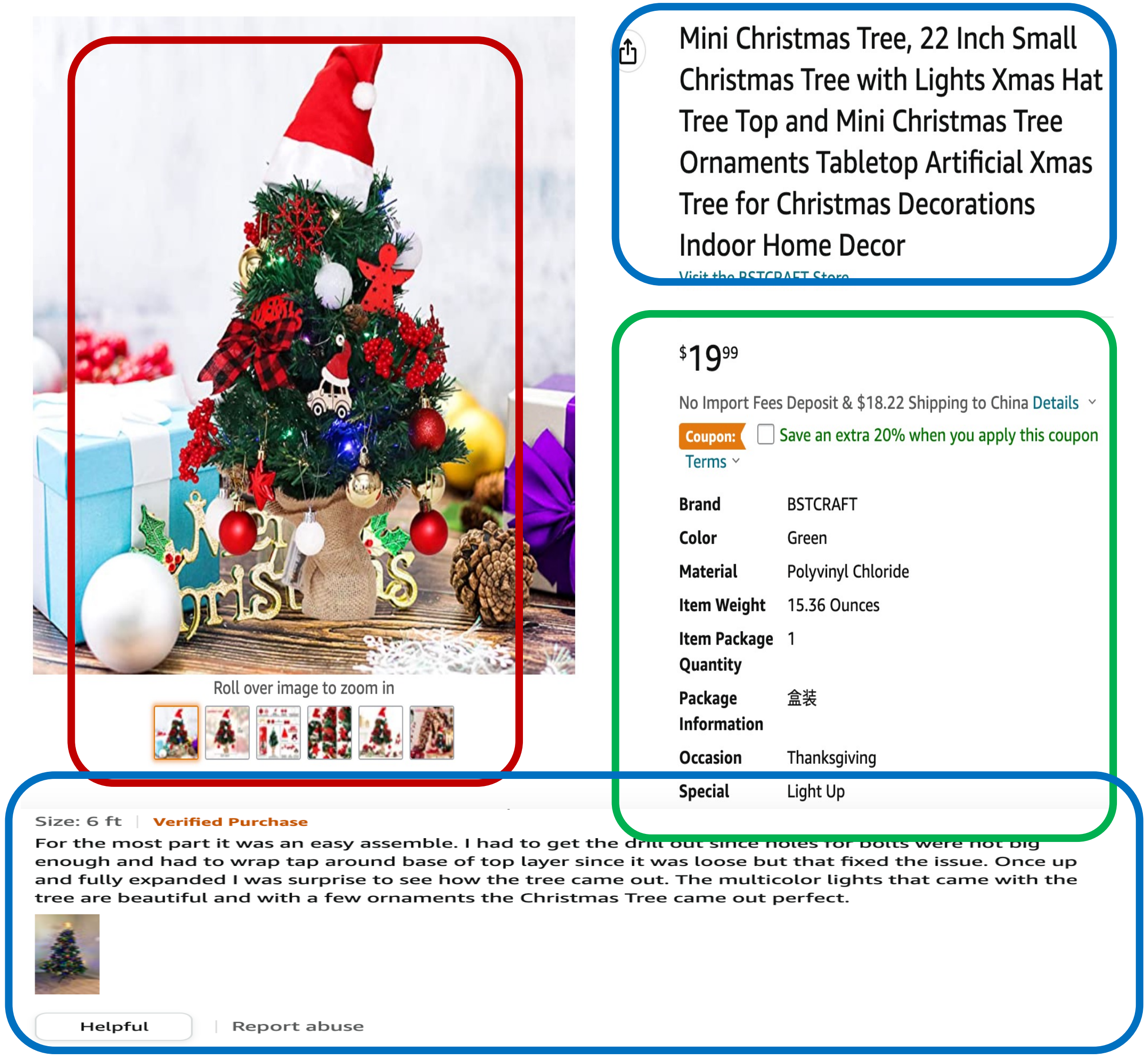

Multimodal Knowledge

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

Why we need multimodality and reasoning?

Multimodal Knowledge

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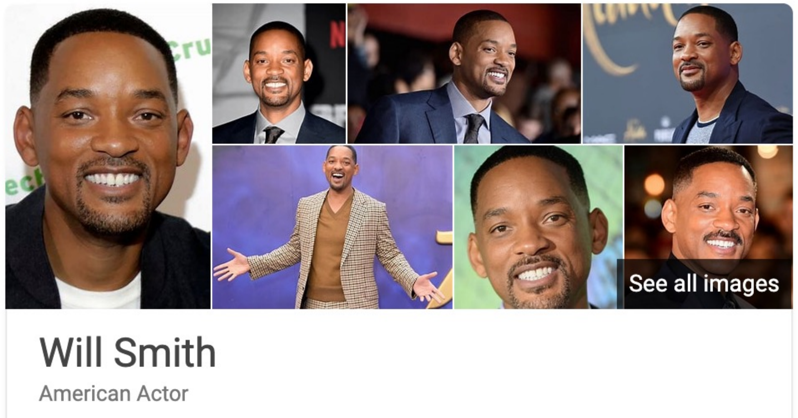
Result：
Yao Ming (100)
Will Smith (39)
…



Visual Entity Disambiguation

Multimodal Knowledge

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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

基本信息

中文名	刘欢	毕业院校	国际关系学院法国文学专业
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
国　籍	中国		的问、这一拜、好汉歌、从头再来、凤凰于飞
民　族	汉族	主要成就	CCTV MTV音乐盛典最受欢迎男歌手
星　座	处女座		《音乐风云榜》终身成就奖
血　型	O型		北艺协会电视剧优秀音乐创作奖
身　高	173cm		第十届华语歌曲"榜中榜"之"评委会特别奖"
出生地	天津		第四届中国金唱片"最佳流行专辑"
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

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

Textual Entity Disambiguation

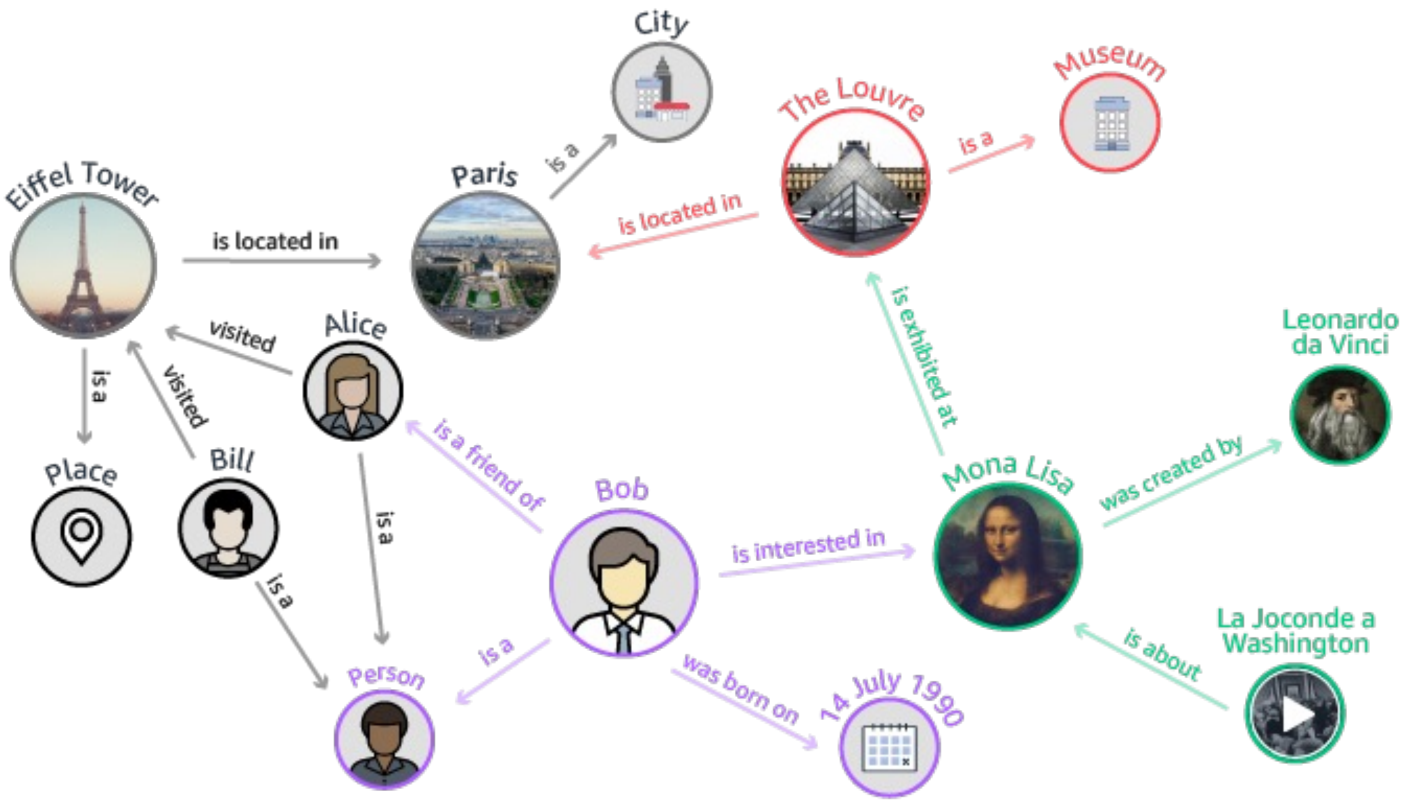
Multimodal Knowledge Graph

Node:

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

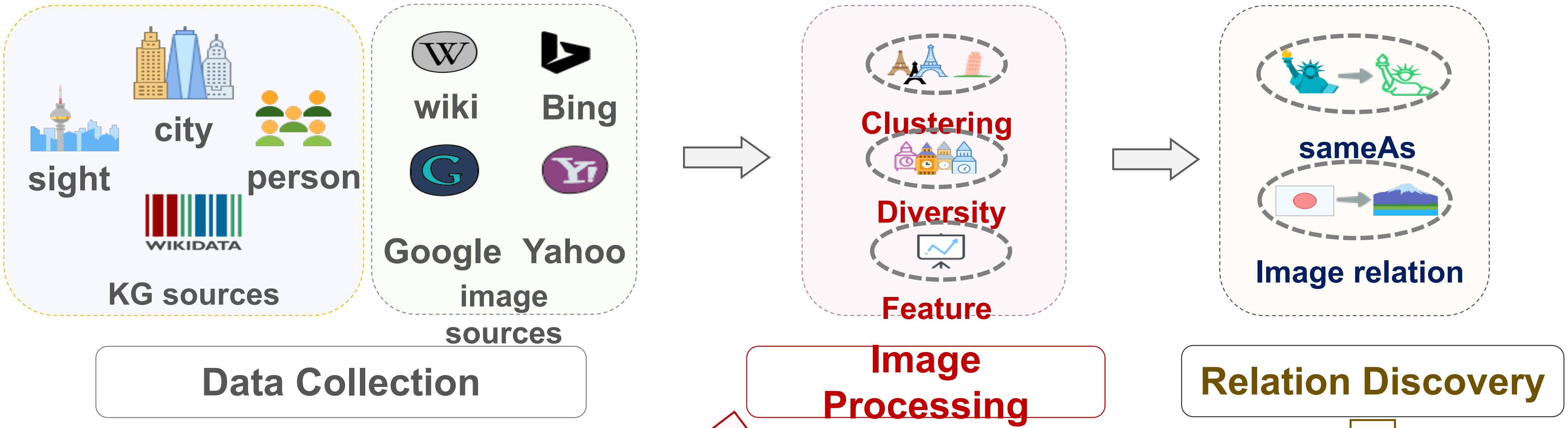
Relation:

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

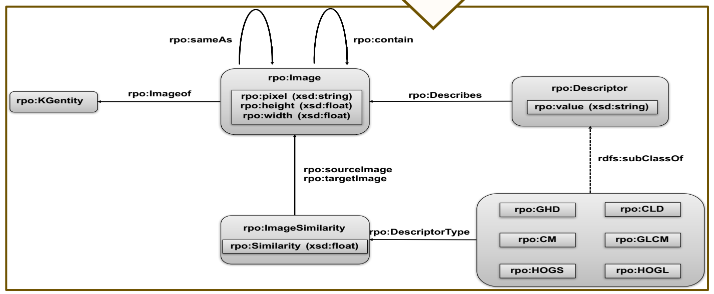


Dihong Gong , Daisy Zhe Wang
Towards Building Large-Scale Multimodal Knowledge Bases

Multimodal Knowledge Graph



Diversity detection



Visual relation ontology

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

Multimodal Knowledge Graph

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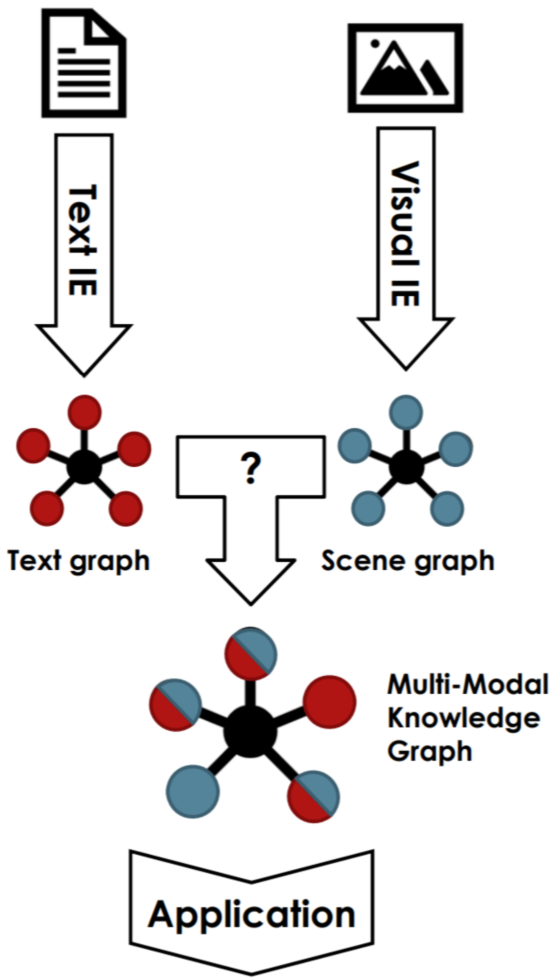
- Challenges:
  - Parsing text to structured semantic graph
  - Parsing images/videos to structures
  - Grounding event/entities across modalities
  - Multimodal argument role
- Applications
  - Story Generation and Summarization
  - Question Answering
  - Commonsense Discovery



Shih-Fu Chang, Alireza Zareian, Hassan Akbari, Brian Chen, Heng Ji, Spencer Whitehead, Manling Li
Multimodal Knowledge Graphs: Automatic Extraction & Applications

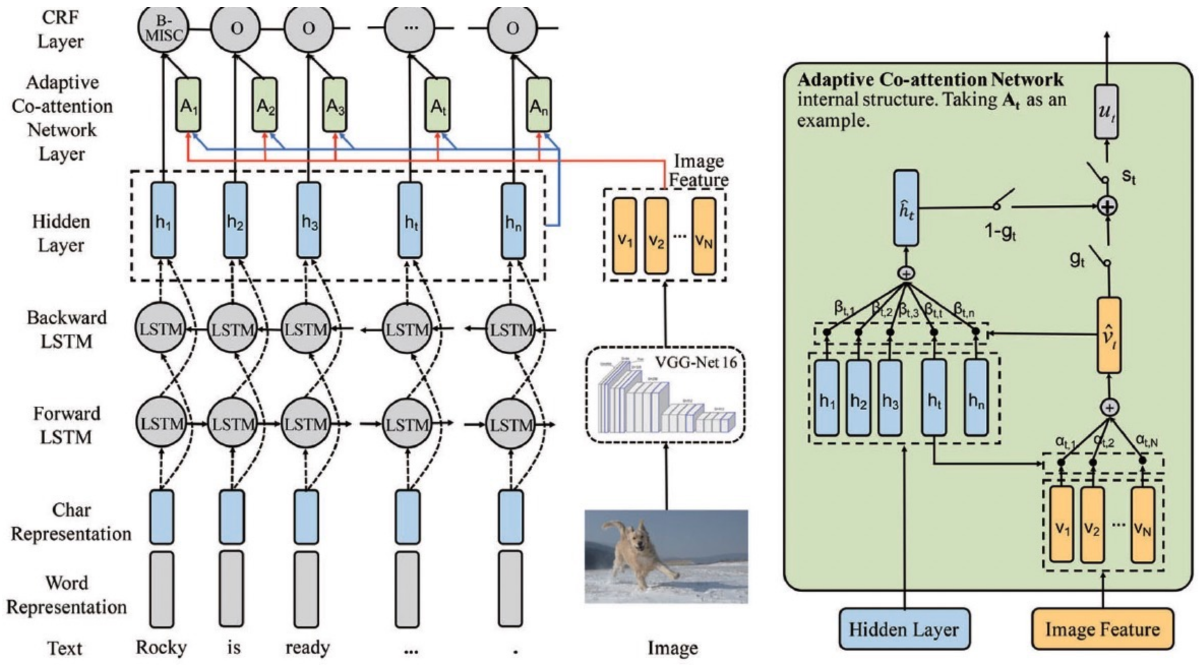
Multimodal KG Construction Tasks

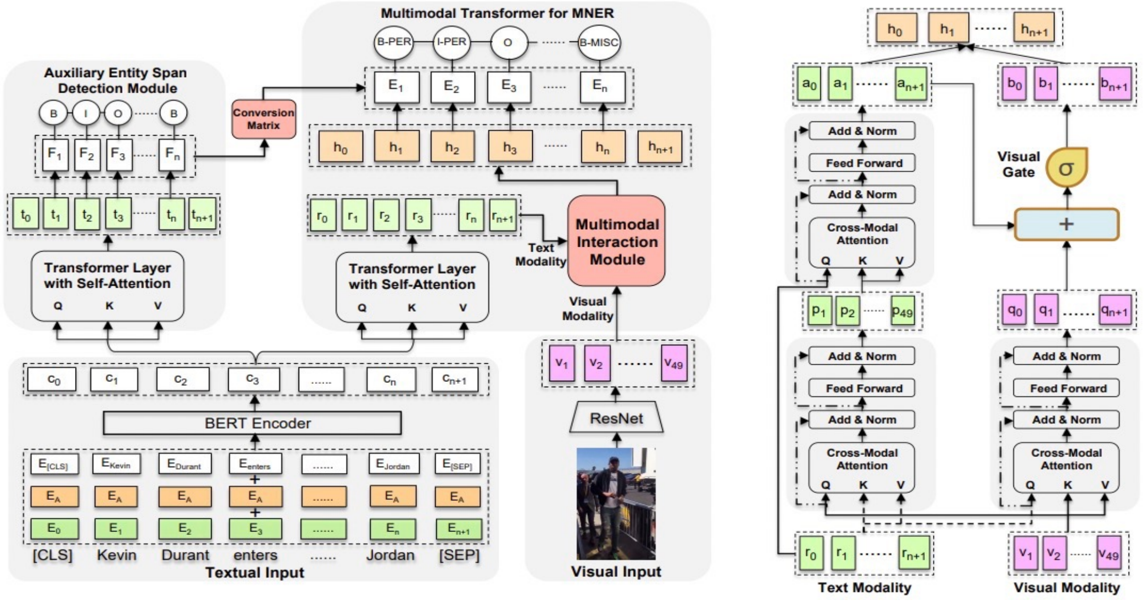
- Multimodal Named Entity Recognition
- Multimodal Relation Extraction
- Multimodal Entity Alignment

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





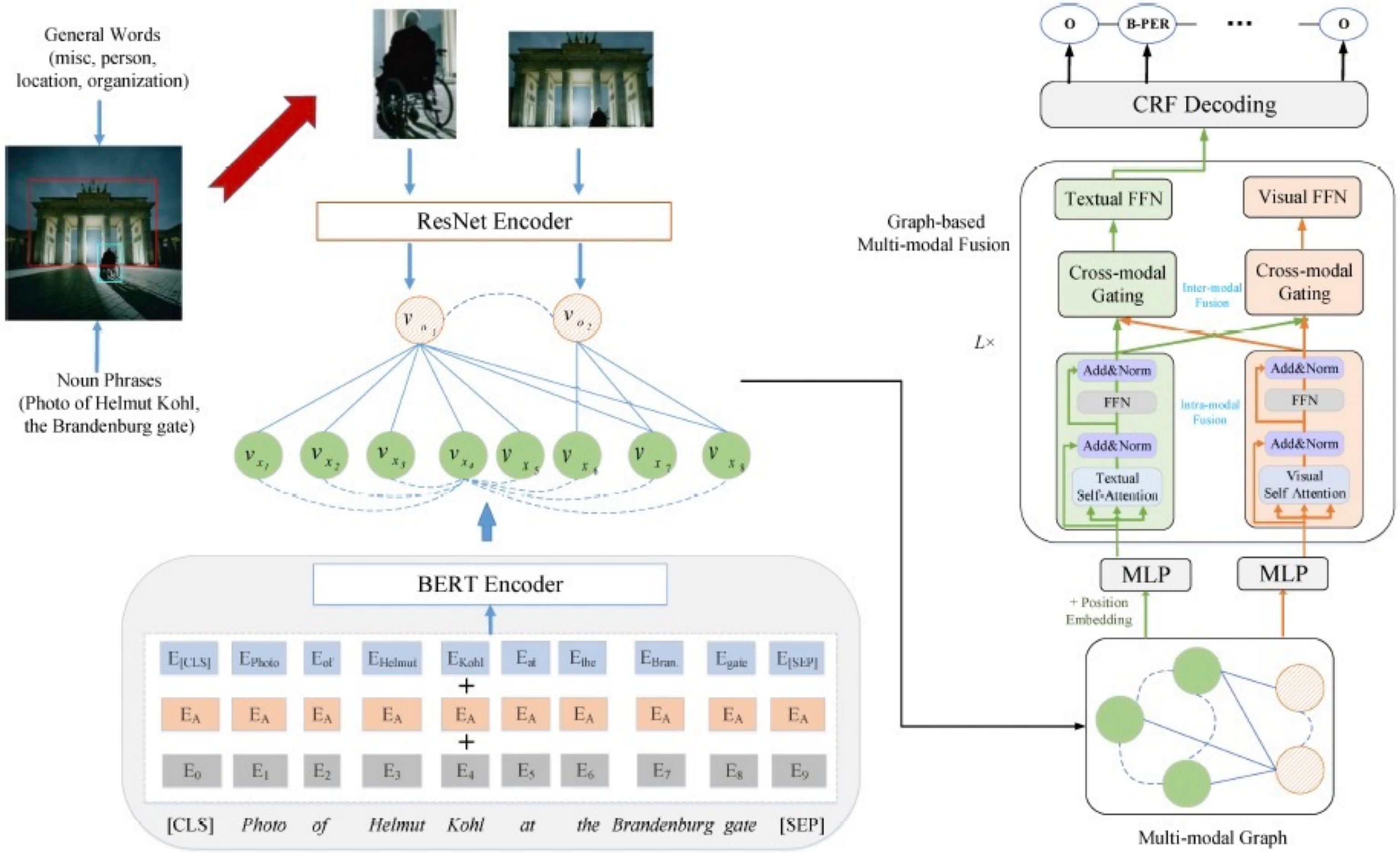
Adaptive Co-Attention Network for Named Entity Recognition in Tweets (AAAI 2018)

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

Multimodal KG Construction: MNER

IJCAI/2023 MACAO

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

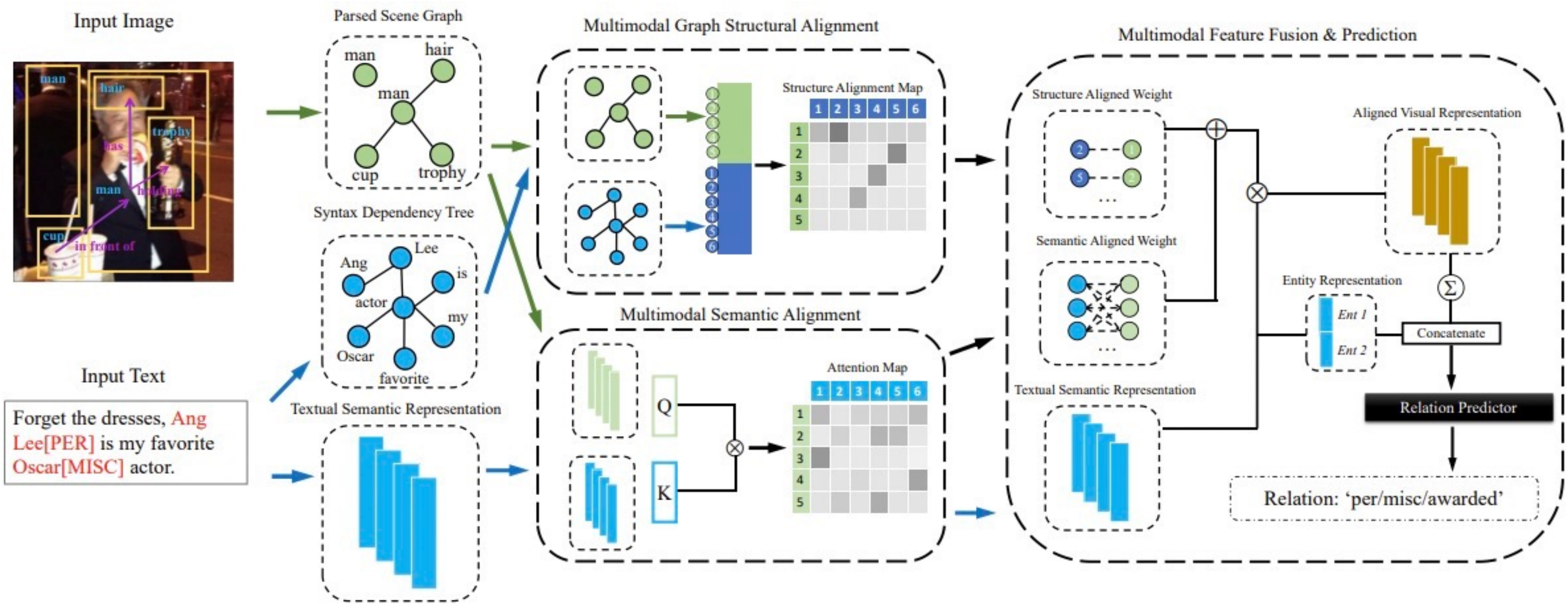


Multi-modal Graph Fusion for Named Entity Recognition with Targeted Visual Guidance (AAAI 2021)

Multimodal KG Construction: MRE

IJCAI/2023 MACAO

Dual graph alignment method to capture this correlation for better performance

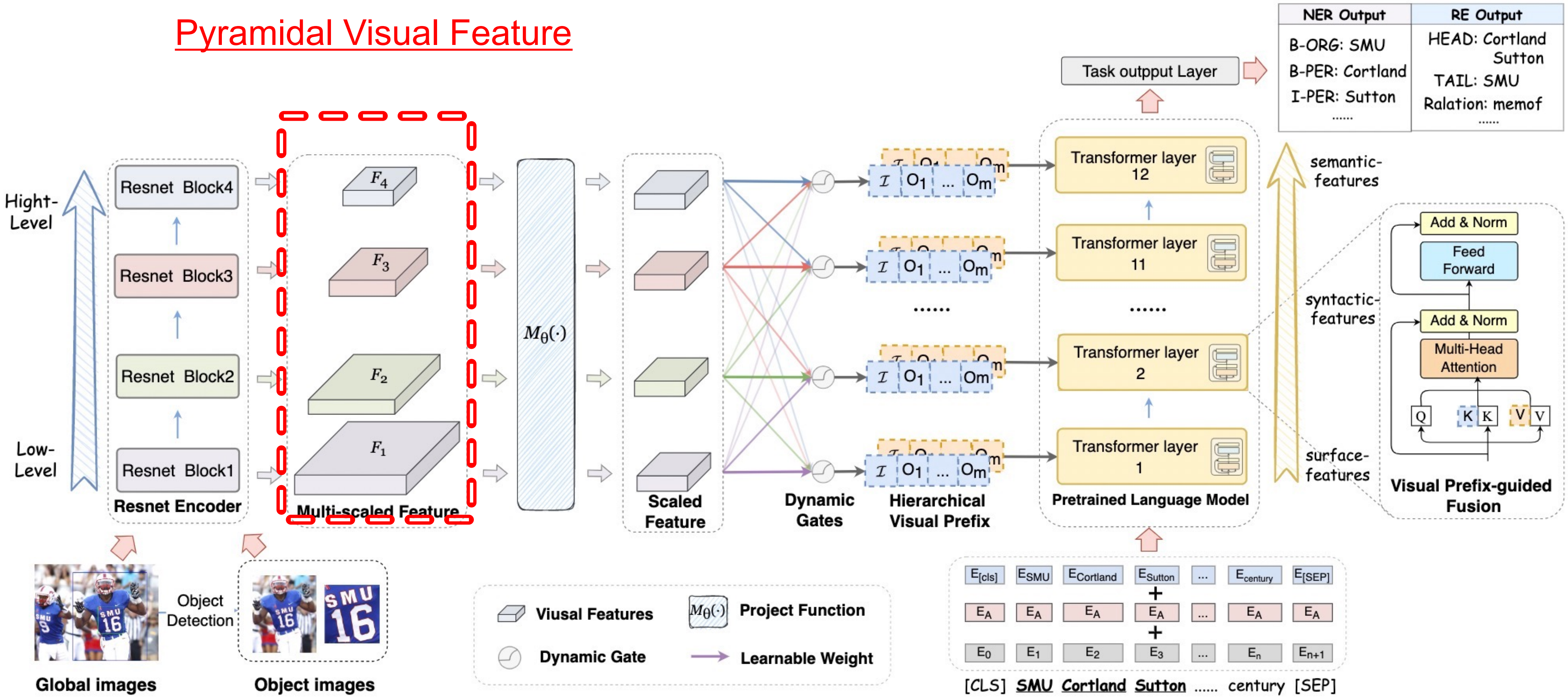


Multimodal Relation Extraction with Efficient Graph Alignment (ACM MM 2021)

Multimodal KG Construction: MNER and MRE

Hierarchical visual prefix fusion network

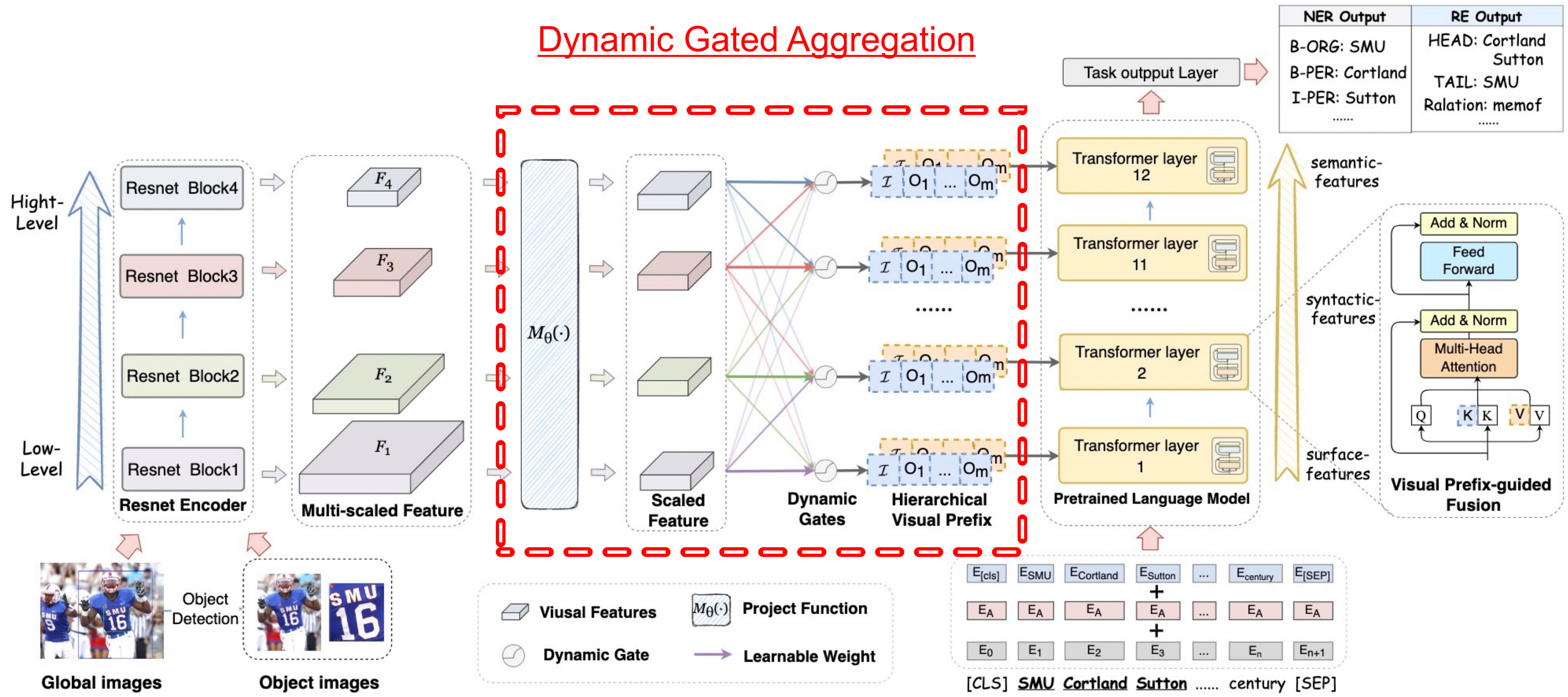
Pyramidal Visual Feature



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

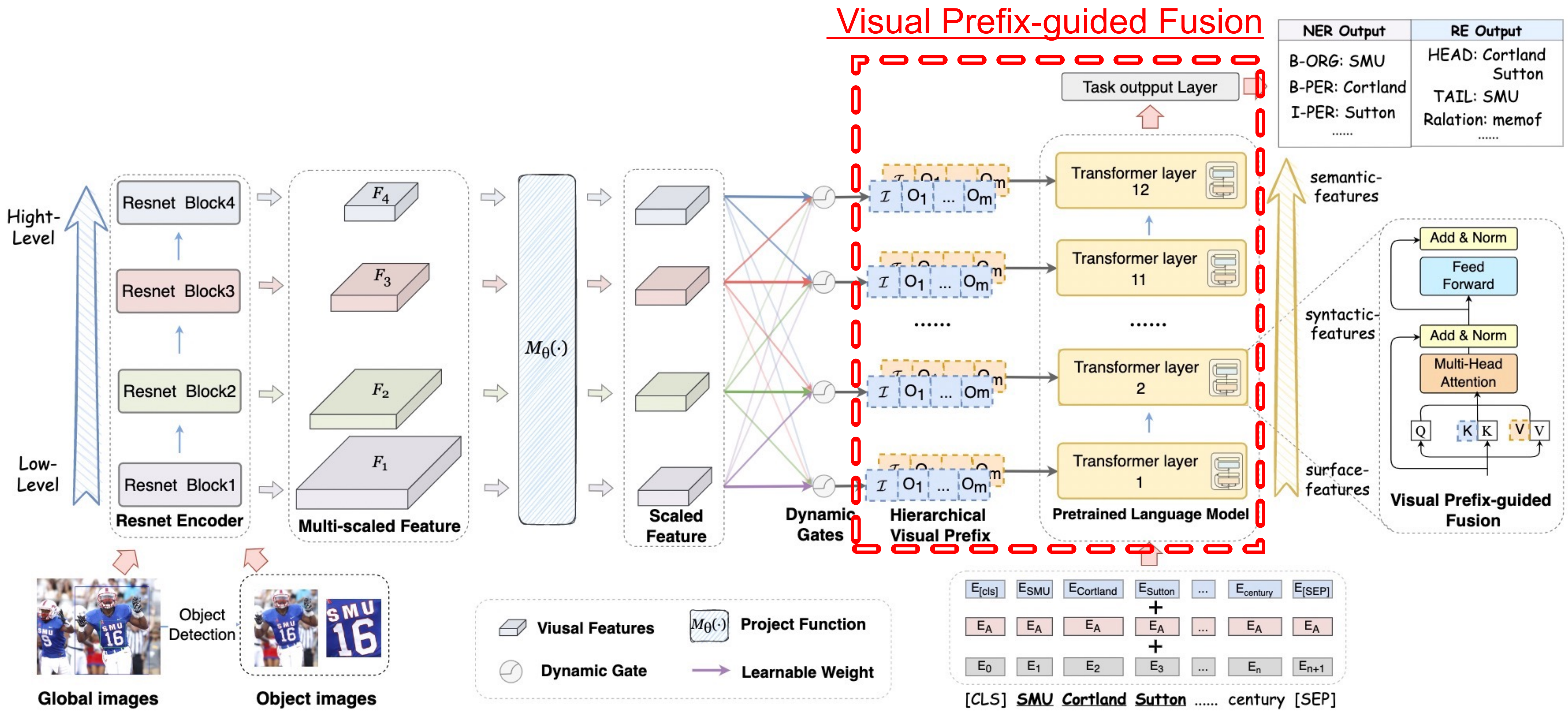
Hierarchical visual prefix fusion network



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

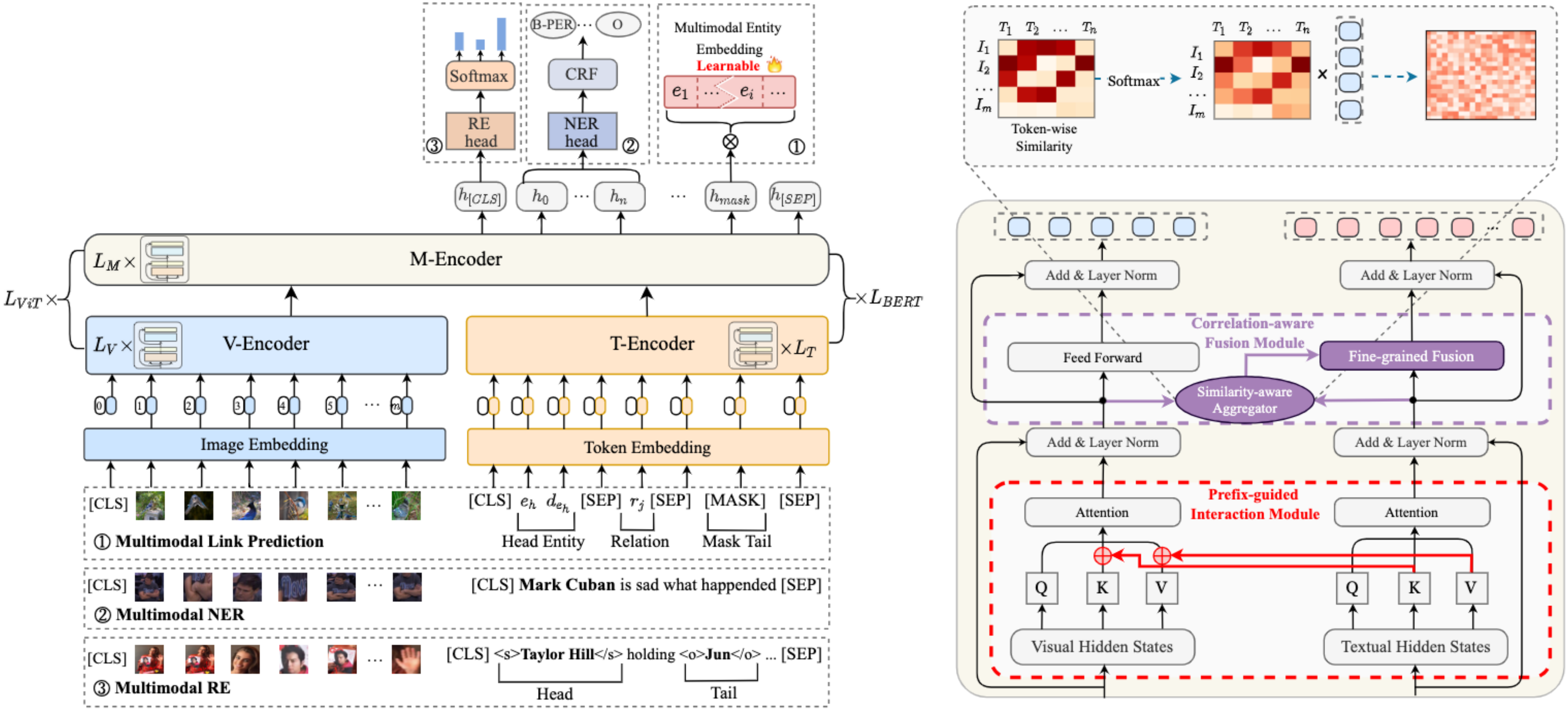


Good Visual Guidance Makes A Better Extractor:
Hierarchical Visual Prefix for Multimodal Entity and Relation Extraction (NAACL 2022 Findings)

Multimodal KG Construction: MNER and MRE

IJCAI/2023 MACAO

MKGformer, a hybrid transformer for unified multimodal knowledge discovery



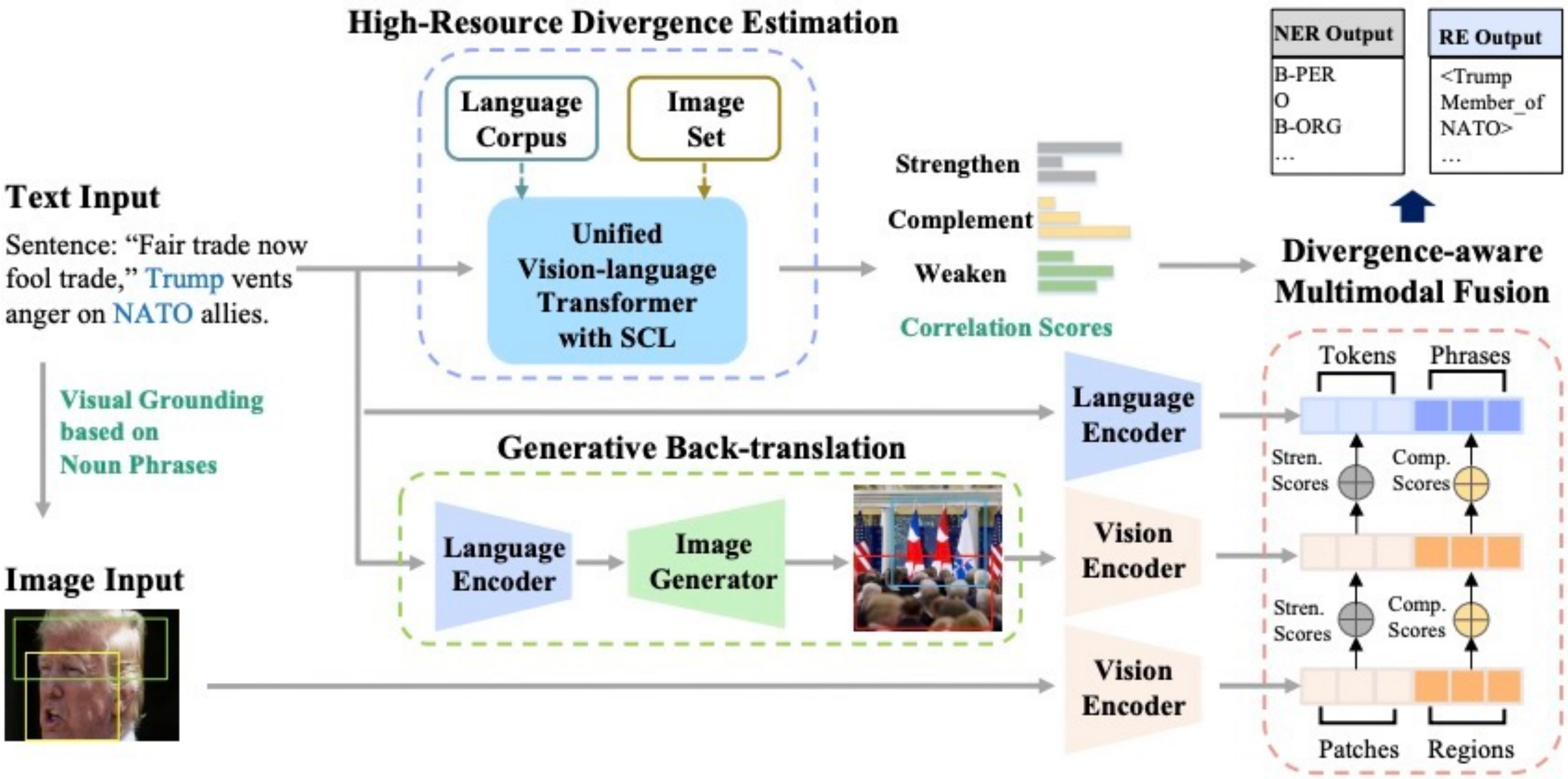
(a) Unified Multimodal KGC Framework.

(b) Detailed M-Encoder.

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

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

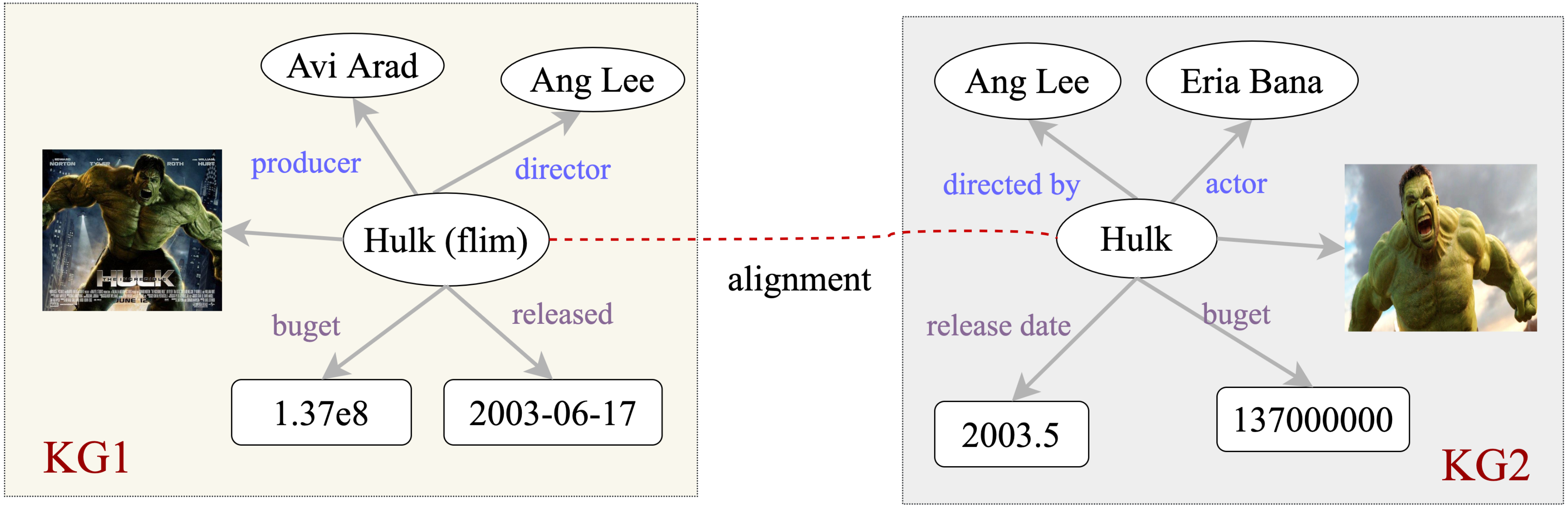


Rethinking Multimodal Entity and Relation Extraction from a Translation Point of View (ACL 2023)

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

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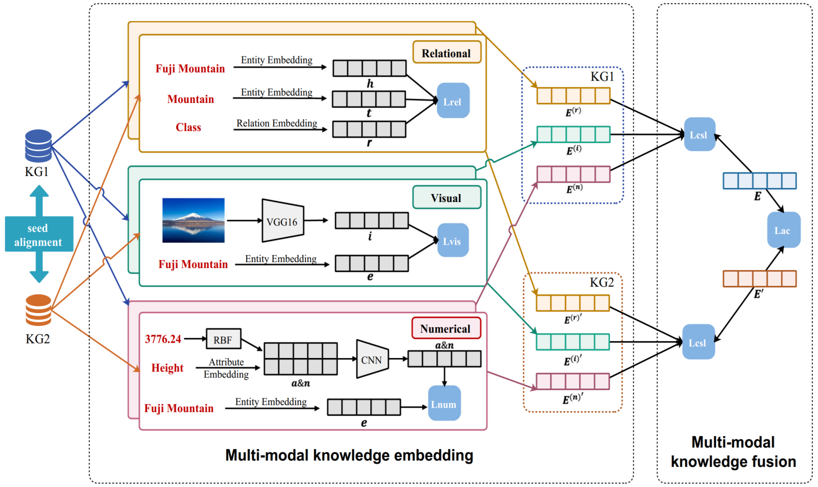
Existing Models:

- **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

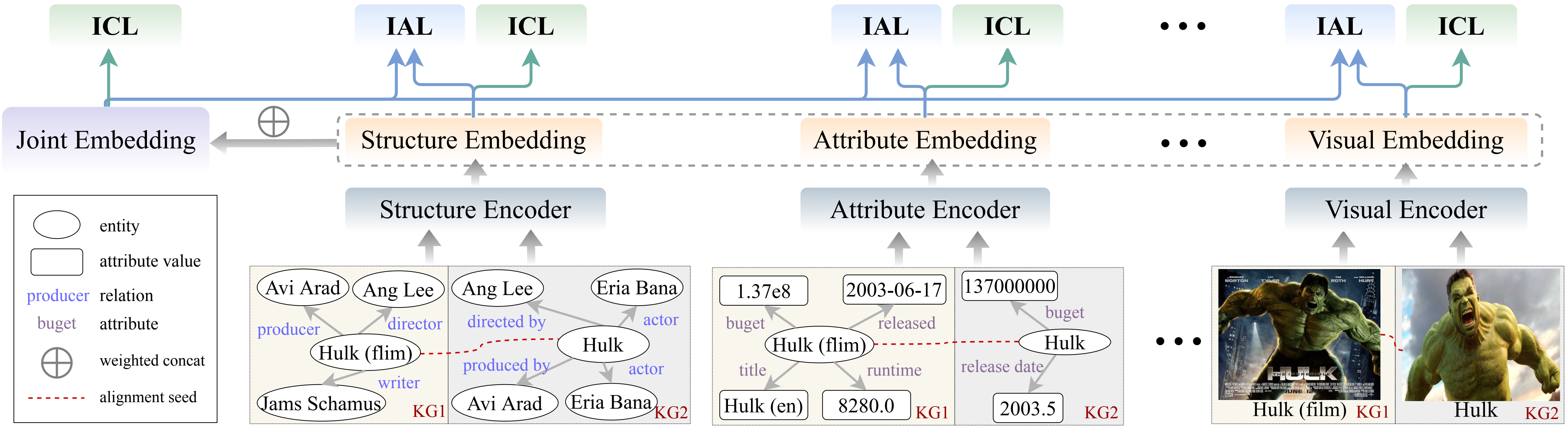
- These methods focus on how to utilize and encode information from different modalities (views), **while it is not trivial to leverage multi-modal knowledge in entity alignment because of the modality heterogeneity**.
- These methods mainly utilize multi-modal representations to enhance the contextual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

Multimodal KG Construction: MMEA

MCLEA, a **M**ulti-modal **C**ontrastive **L**earning based **E**ntity **A**lignment 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

IJCAI/2023 MACAO

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	.265	.541	.357	.234	.480	.317
	EVA∗	.134	.338	.201	.098	.276	.158
	MCLEA (Ours)	**.445**	**.705**	**.534**	**.388**	**.641**	**.474**
	Improv. best %	67.9	30.3	49.6	65.8	33.5	49.5
50%	PoE	.464	.658	.533	.347	.536	.414
	HMEA	.262	.581	–	.265	.581	–
	MMEA	.417	.703	.512	.403	.645	.486
	EVA∗	.223	.471	.307	.240	.477	.321
	MCLEA (Ours)	**.573**	**.800**	**.652**	**.543**	**.759**	**.616**
	Improv. best %	23.5	13.8	22.3	34.7	17.7	26.7
80%	PoE	.666	.820	.721	.573	.746	.635
	HMEA	.417	.786	–	.433	.801	–
	MMEA	.590	.869	.685	.598	**.839**	.682
	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

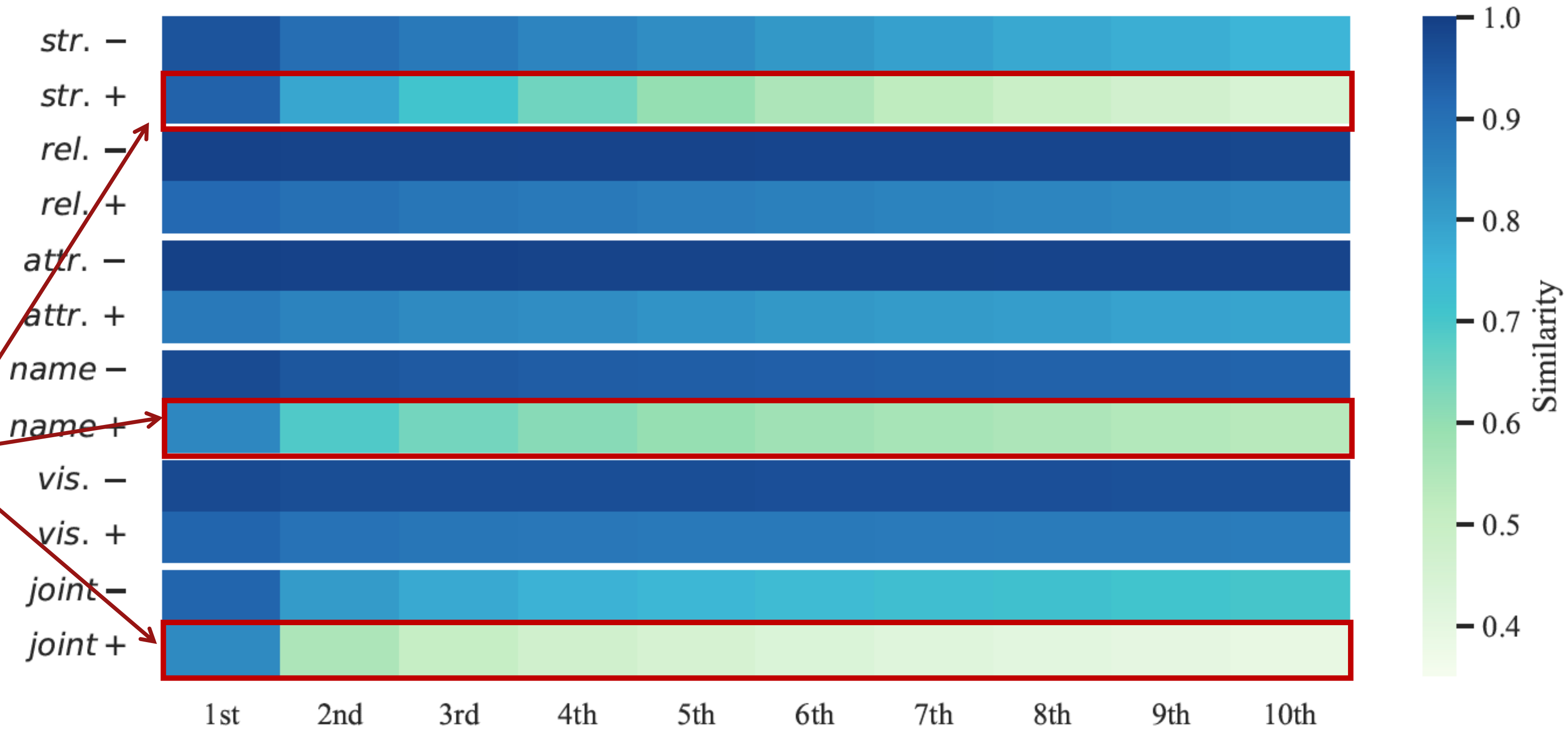
IJCAI/2023 MACAO

Similarity Distribution of Representations

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

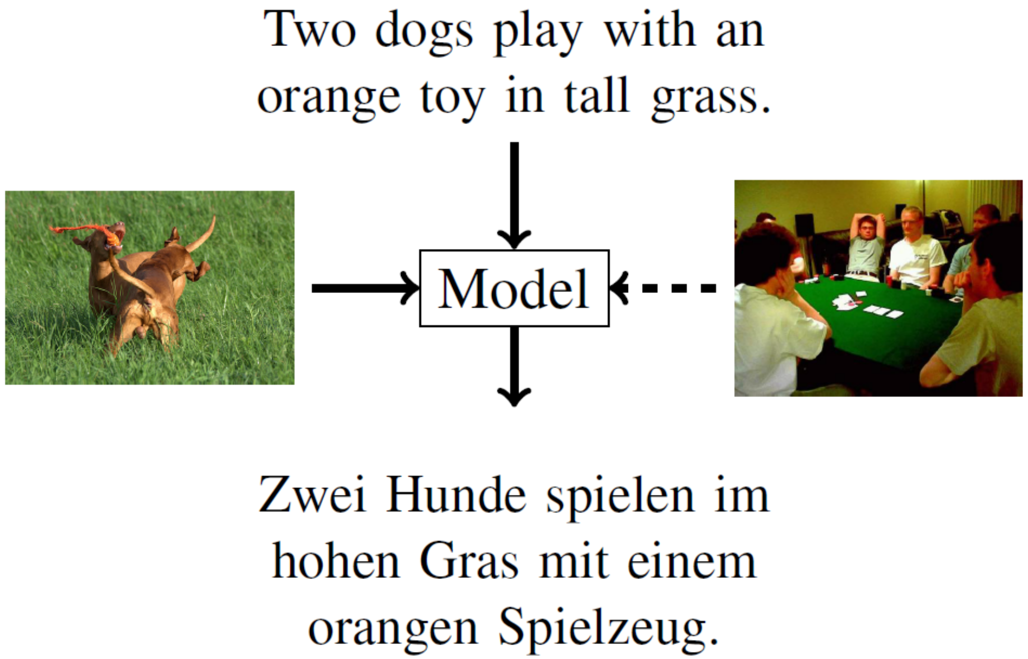
+: with ICL/IAL
-: without ICL/IAL

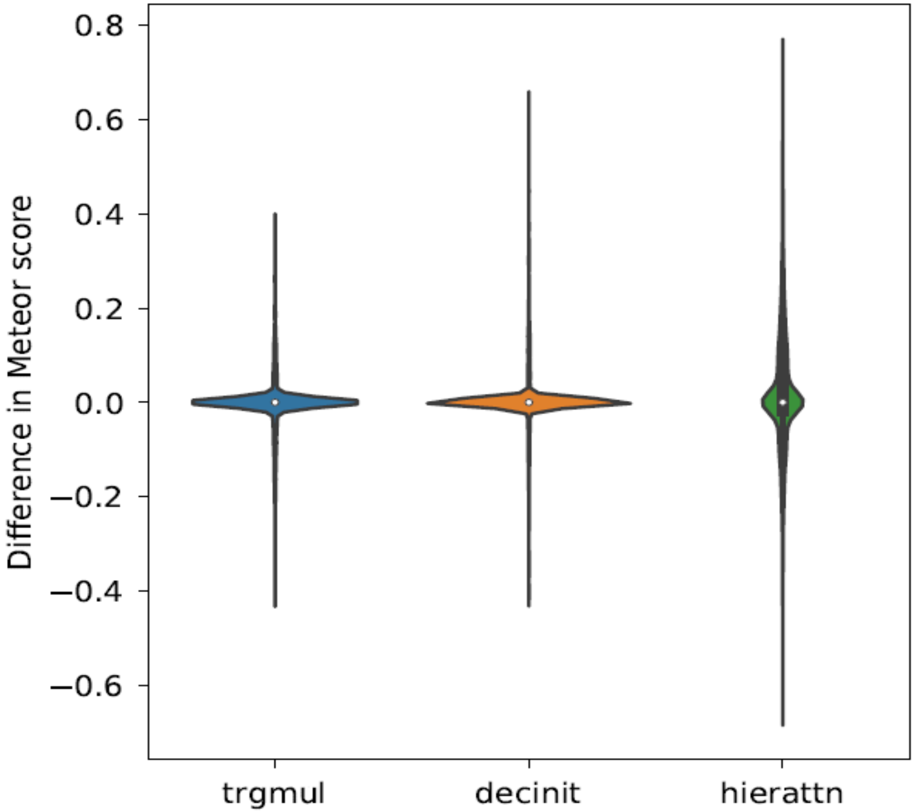
high top-1 similarity and a large similarity variance



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

Is the multi-modal really helpful?





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

Adversarial Evaluation of Multimodal Machine Translation. EMNLP 2018

Is the multi-modal really helpful?

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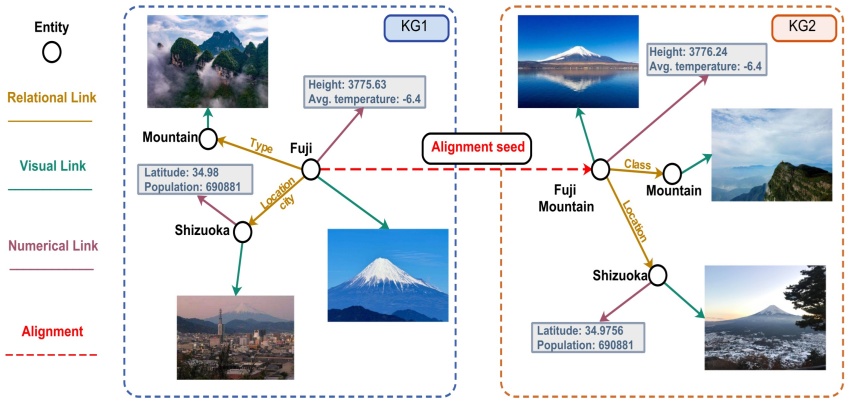
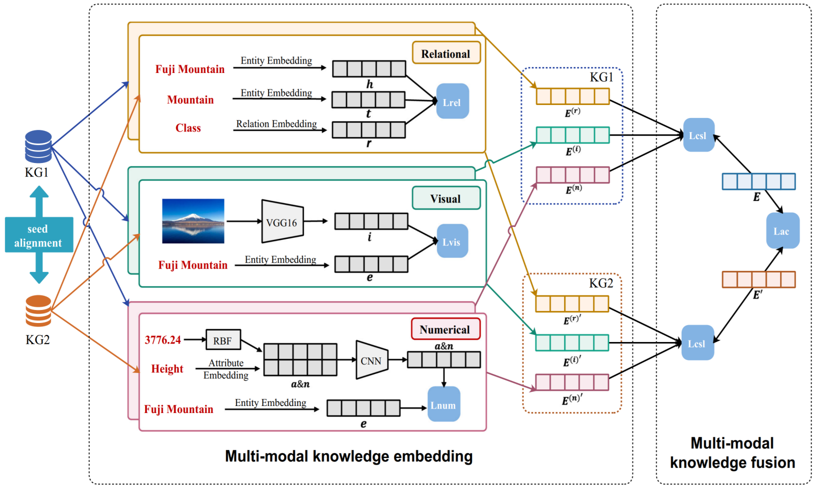
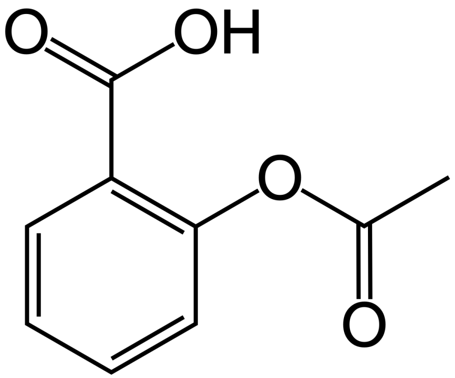




Datasets:
MMKG FB15K-DB15K and FB15K-YAGO15K

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



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

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

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)*

From French DBpedia

Skyline of *Oakland,_California*

From English DBpedia

Logo of *Little_Mix*

From French DBpedia

Little_Mix at a music festival

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?

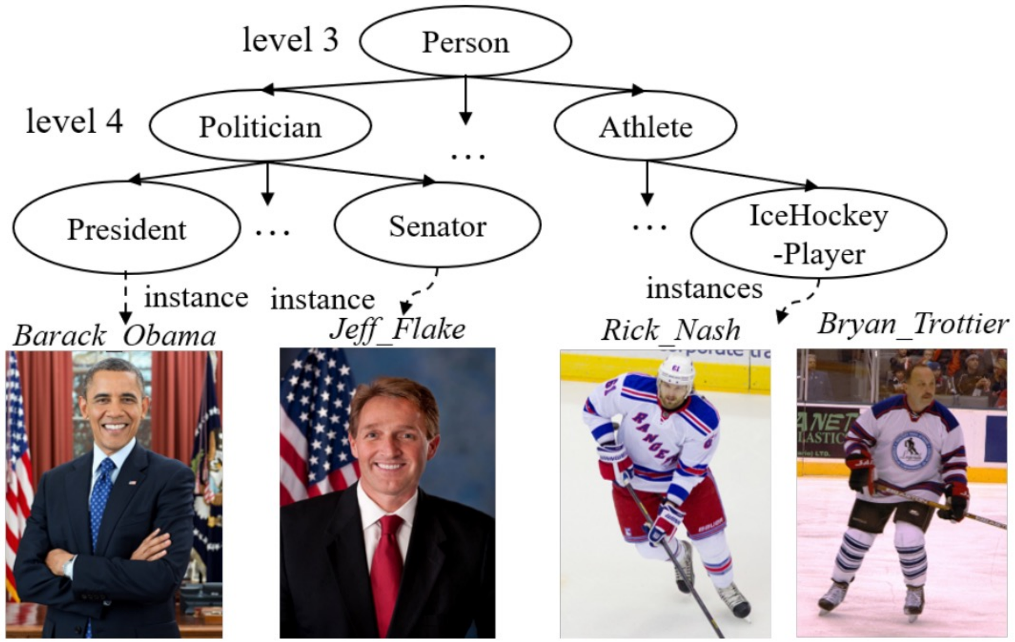
Probing the Impacts of Visual Context in Multimodal Entity Alignment[J]. Data Science and Engineering, 2023, 8(2): 124-134.

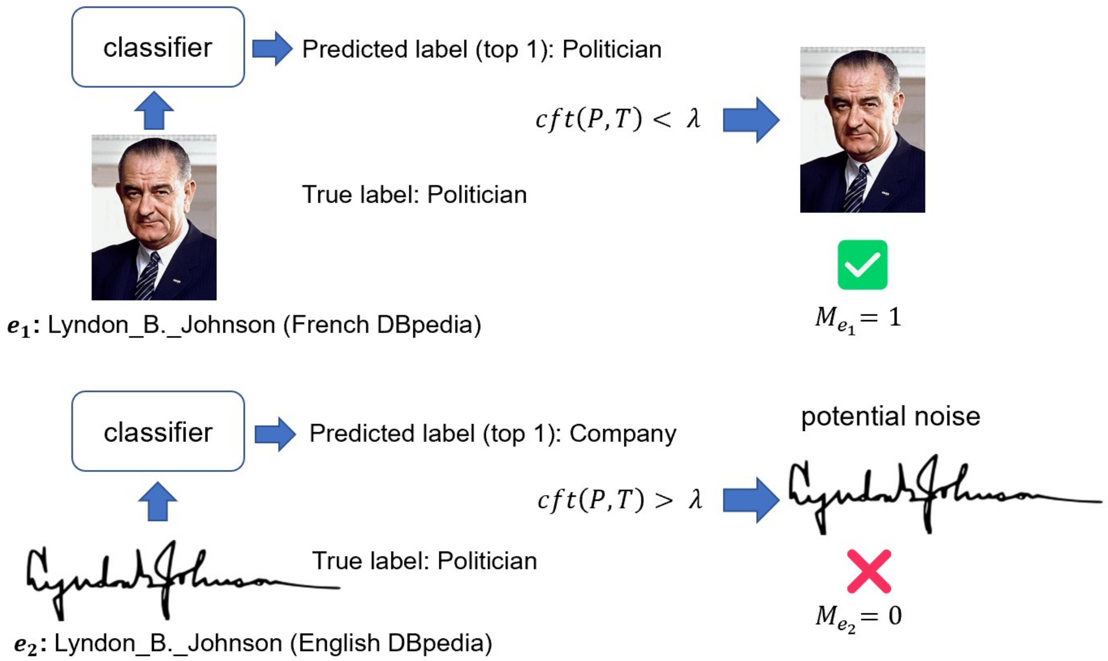
Is the multi-modal really helpful?

IJCAI/2023 MACAO

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.





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?

IJCAI/2023 MACAO

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]	0.700 ±.005	0.891 ±.005	0.768 ±.004	0.622 ±.004	0.846 ±.008	0.701 ±.005	0.596 ±.007	0.816 ±.008	0.674 ±.007
SimpleEA	0.504 ±.005	0.826 ±.004	0.616 ±.005	0.505 ±.005	0.797 ±.006	0.608 ±.005	0.479 ±.005	0.772 ±.007	0.582 ±.006
Masked-MMEA (λ_0)	0.661 ±.007	0.889 ±.004	0.742 ±.006	0.602 ±.004	0.852 ±.006	0.692 ±.004	0.582 ±.006	0.827 ±.008	0.670 ±.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

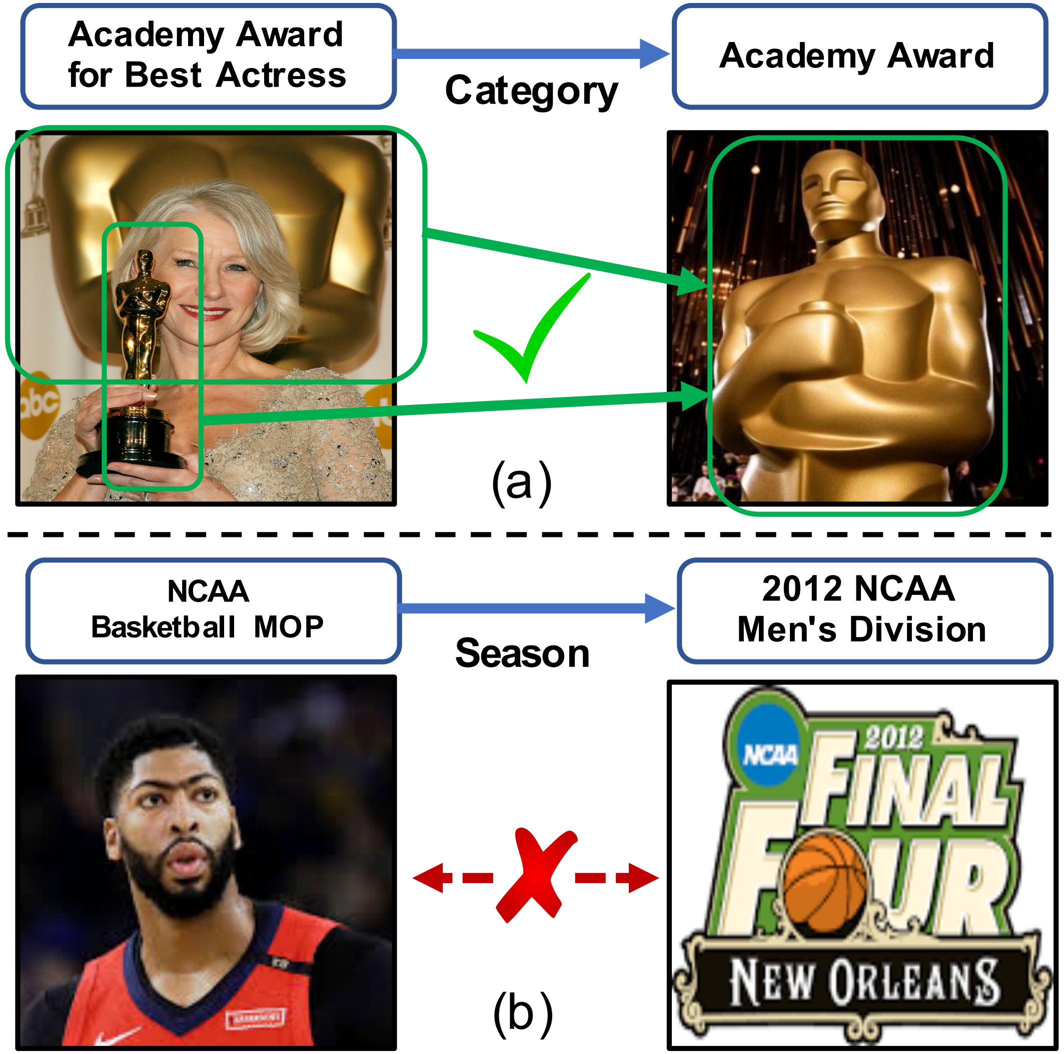
SimpleEA:
using only structural information

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?



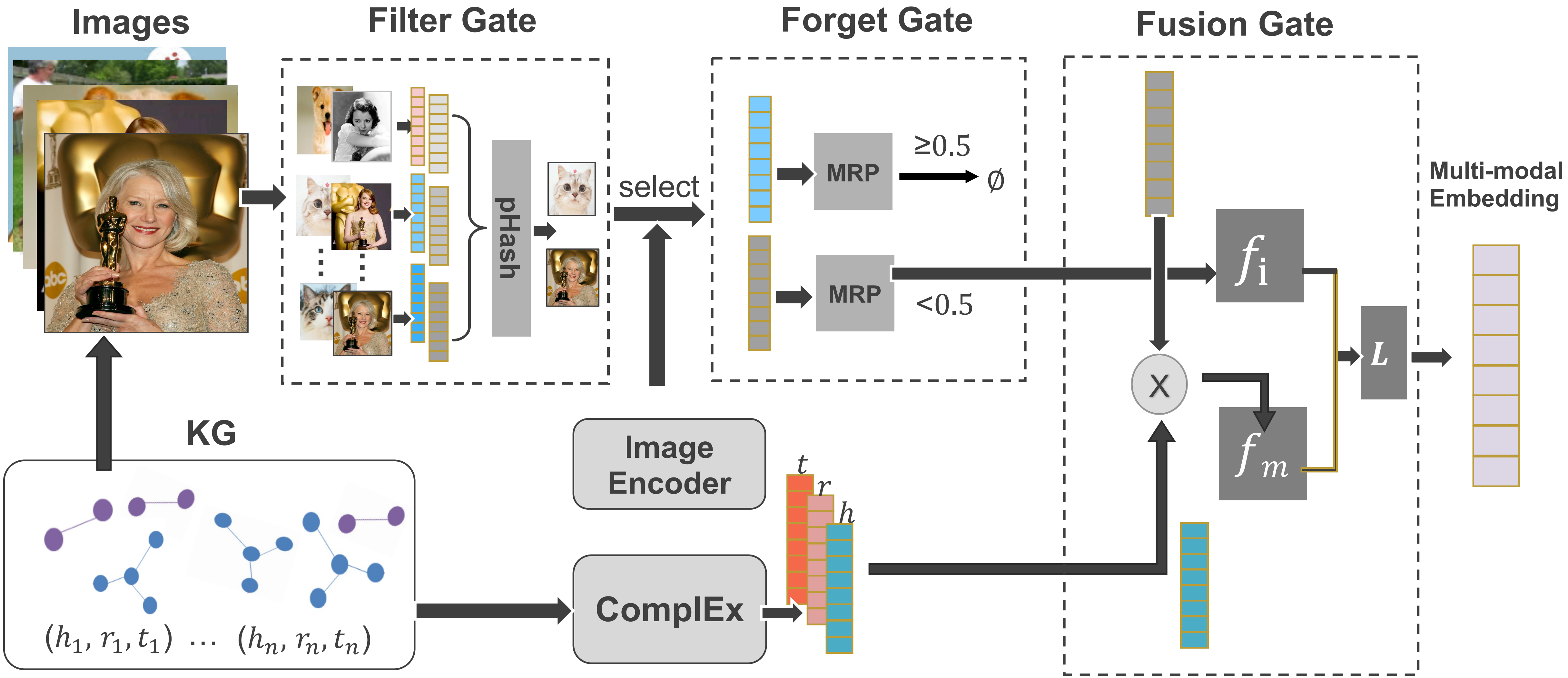
- What extent the visual context can improve the quality of knowledge graph tasks over unimodal models?

  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?

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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_moieties	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

Meng Wang, Guilin Qi et al. *Is Visual Context Really Helpful for Knowledge Graph?* **ACM MM 2021**

Is the multi-modal really helpful?

Results on real-world dataset

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.

Model	Hits@1 ↑	Hits@3 ↑	Hits@10 ↑	MR ↓	MRR ↑
Unimodal approach					
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
Multimodal approach					
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.

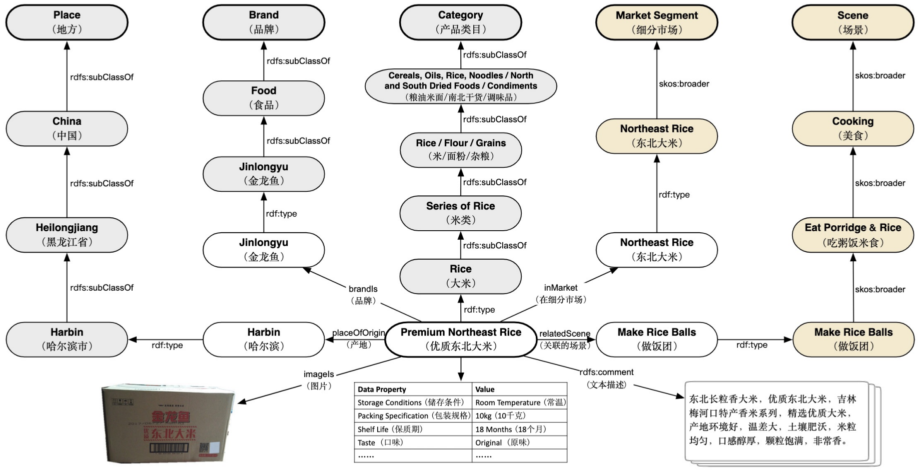

Figure 4: A snapshot of OpenBG.

Construction and Applications of Open Business Knowledge Graph 2022

Future "Multi-modal Opportunities"

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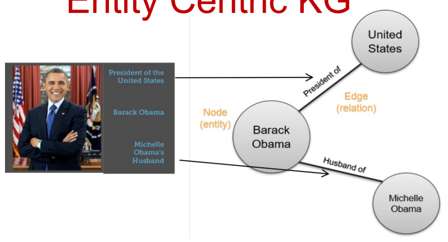
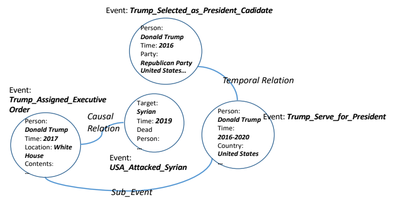
Entity Centric KG



(Barack Obama, Spouse, Michelle Obama)

Triples in form of (s, p, o)

Event Centric KG

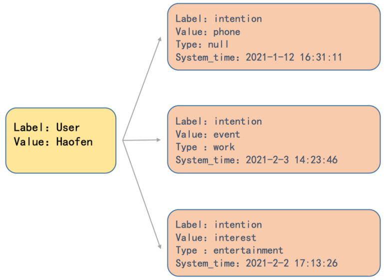


Event Frames

Birth	Marriage	EndPosition
birth date birth place name	date location male female	time company position

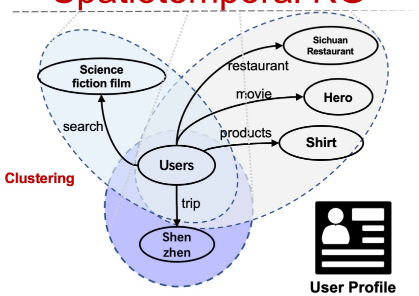
Event Relations: Causal relation, Temporal relation, Co-reference relation, Sub-class relation…

Personal KG



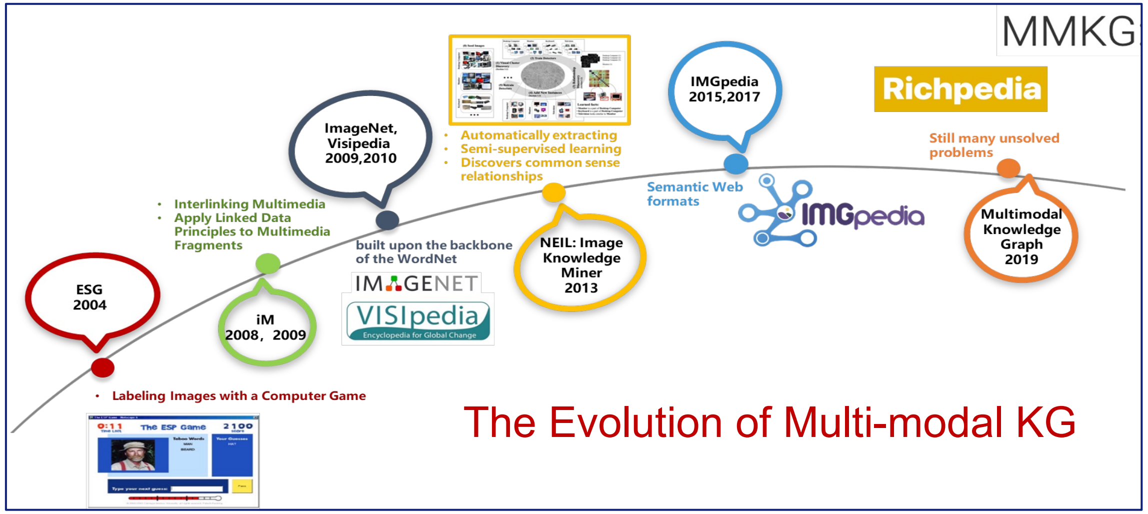
Graph composing events, interests, behaviors of an individual under the protection of privacy and security

Spatiotemporal KG

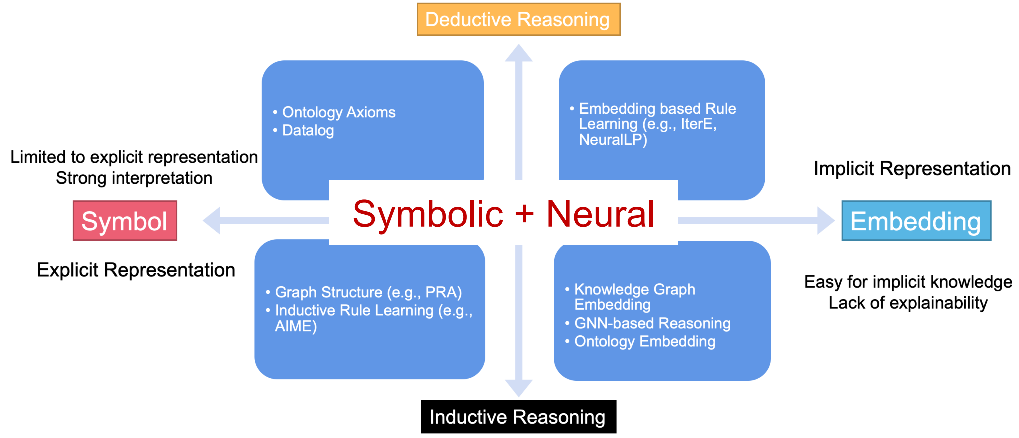


Expand knowledge representation level in time series and space dimensions

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



The Evolution of Multi-modal KG



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"

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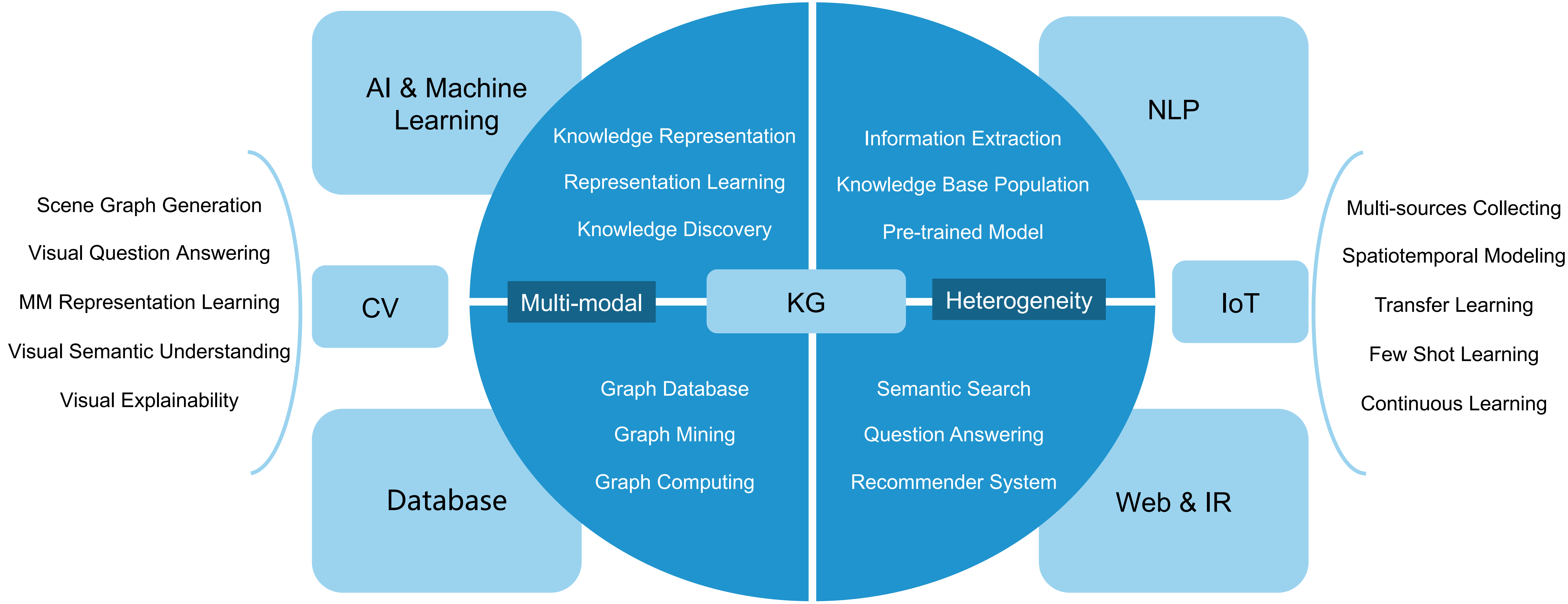

The life cycle of KG construction: more types/sources, advanced techs, rapid updates, and widely used applications

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

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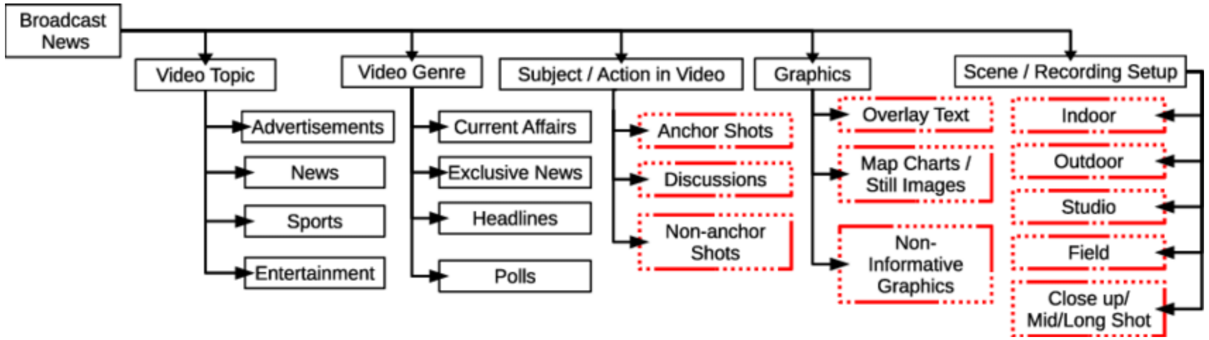
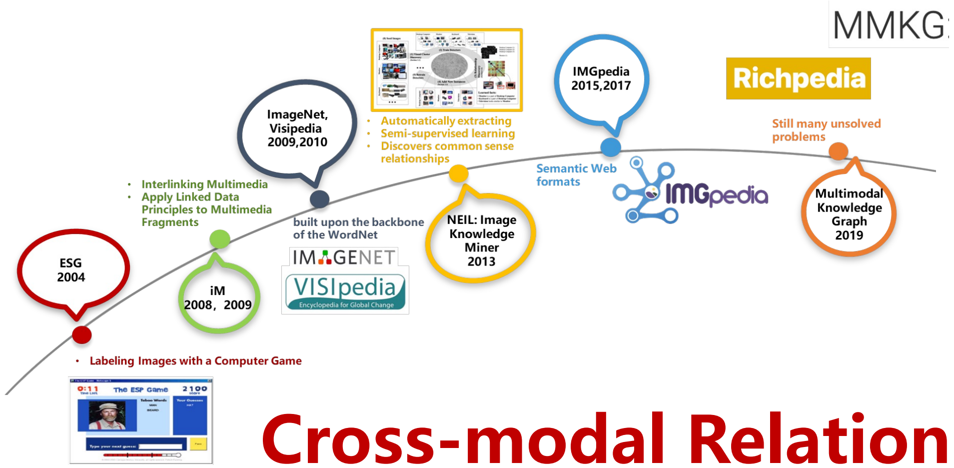
LSCOM



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

COMM

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

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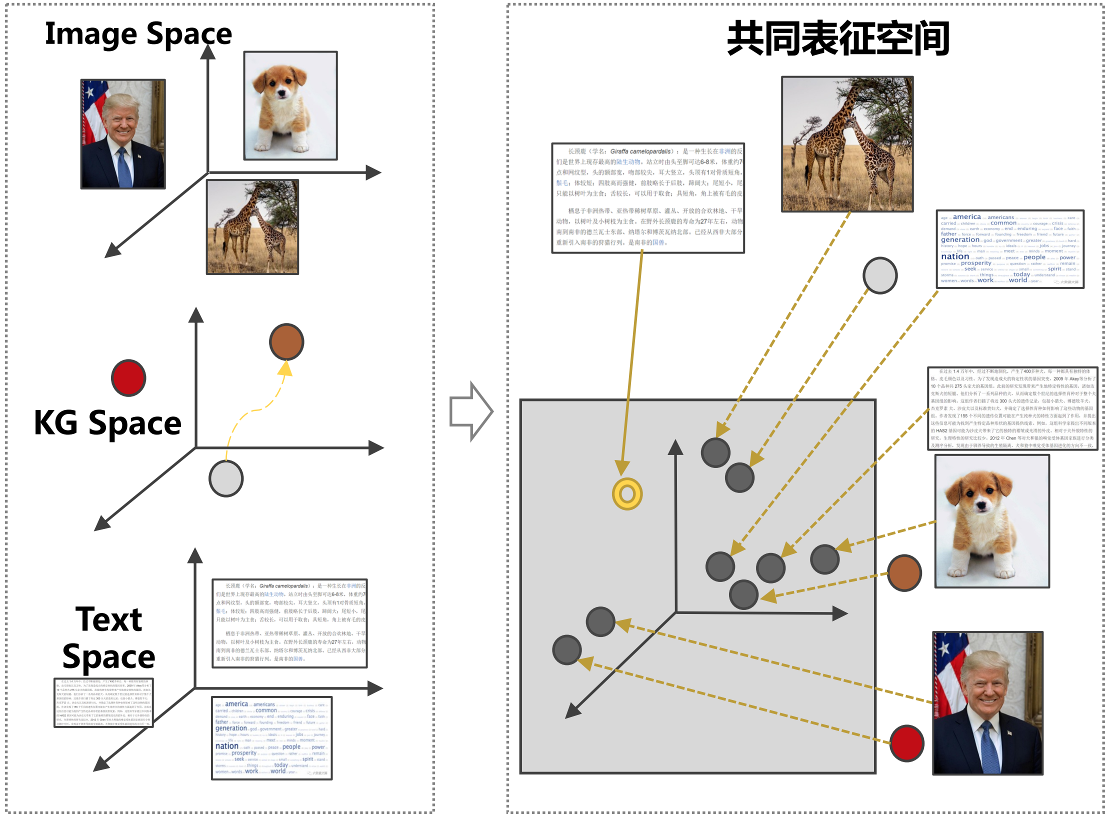
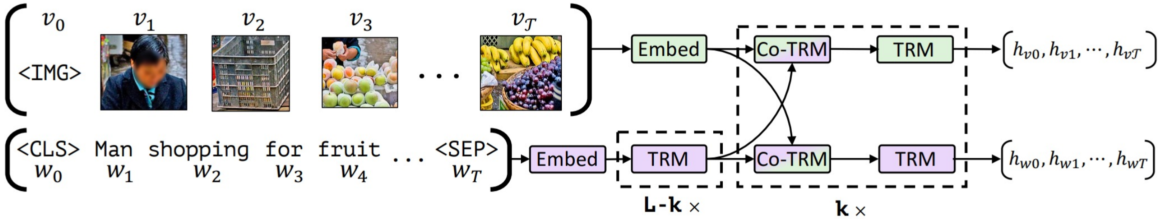


Multimodal machine learning: A survey and taxonomy. IEEE transactions on pattern analysis and machine intelligence 41.2 (2018): 423-443.



ViLBERT, NeurIPS 2019

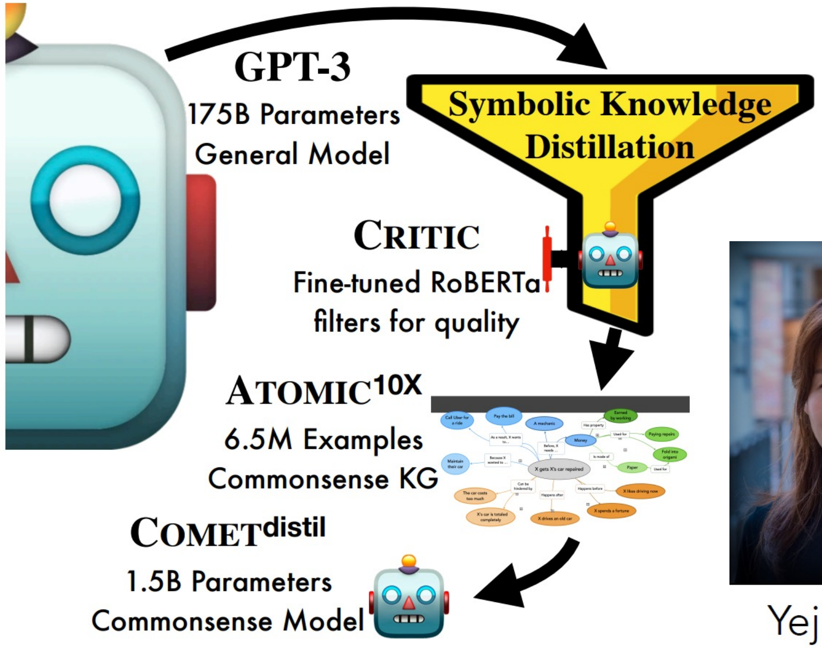
Oscar
UNITER
VL-BERT
VisualBERT
Pixel-BERT
LXMERT
ImageBERT
Unicoder-VL

Contrastive Learning

Efficiency **Fine-grained** **Prompt**

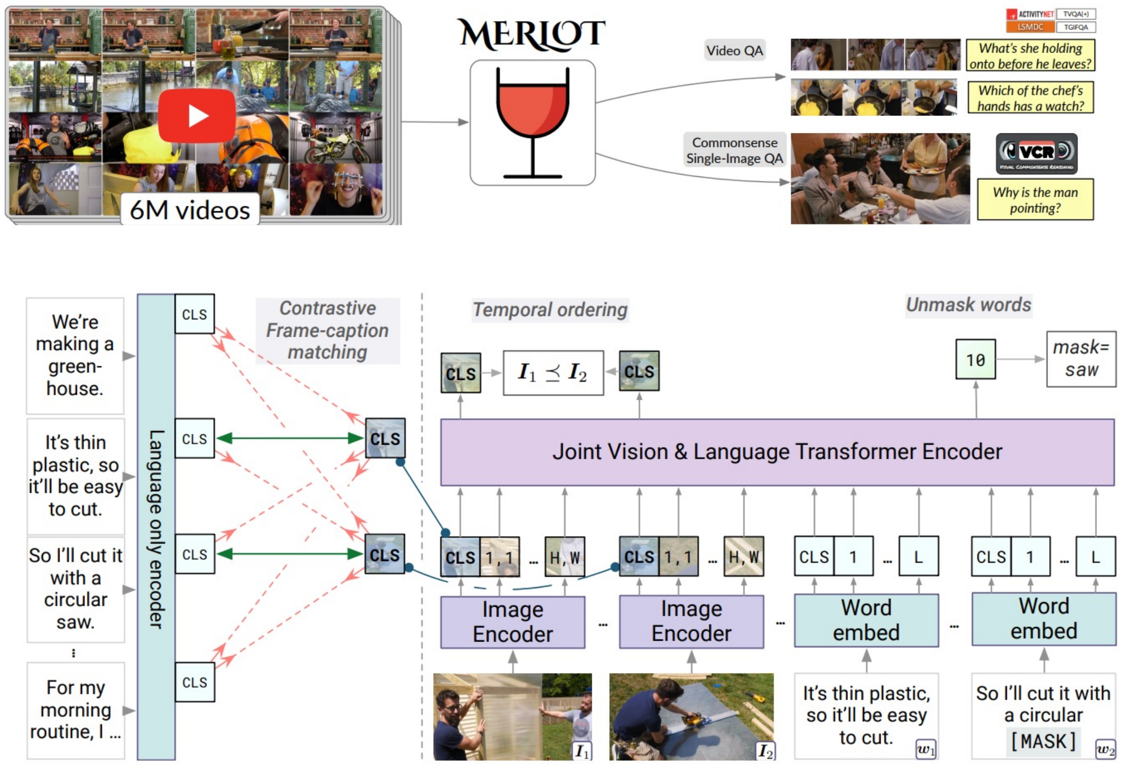
Few-shot **Effect Analysis**

Future "Multi-modal Opportunities": Commonsense Reasoning



Yejin Choi

X is not well liked	**xReact** *so, X feels*	lonely



Symbolic Knowledge Distillation: from General Language Models to Commonsense Models

Multimodal **Neural** Script Knowledge Models
NeurIPS 2021

Symbolic+Neural

Future "Multi-modal Opportunities": Embodied

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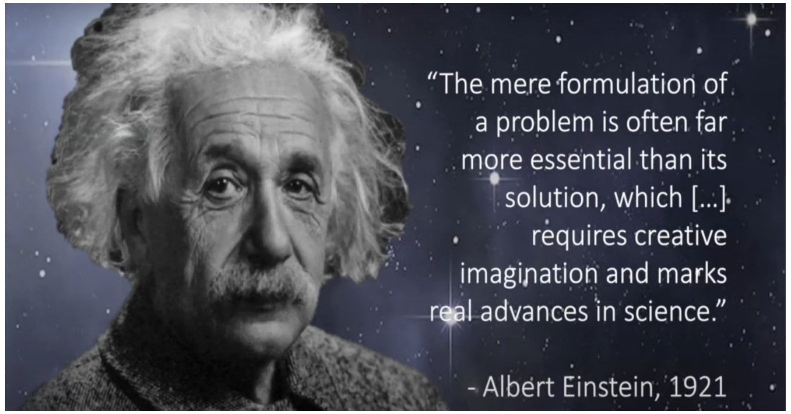
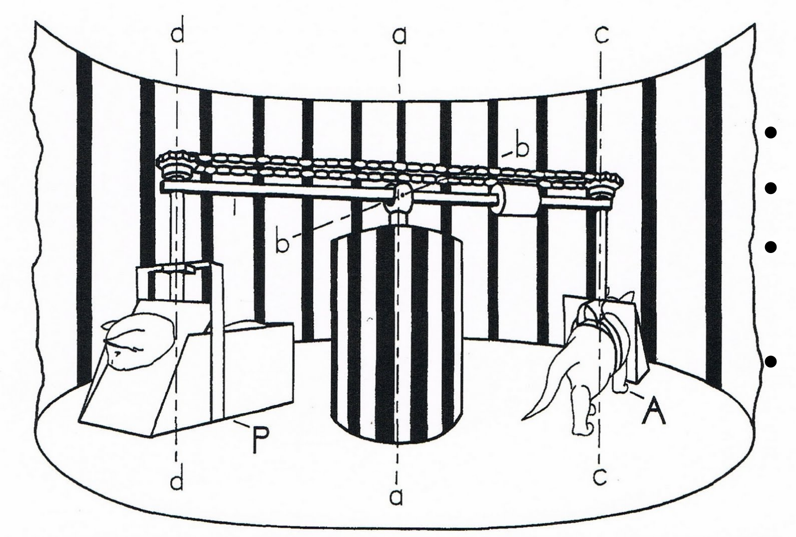
Feifei Li

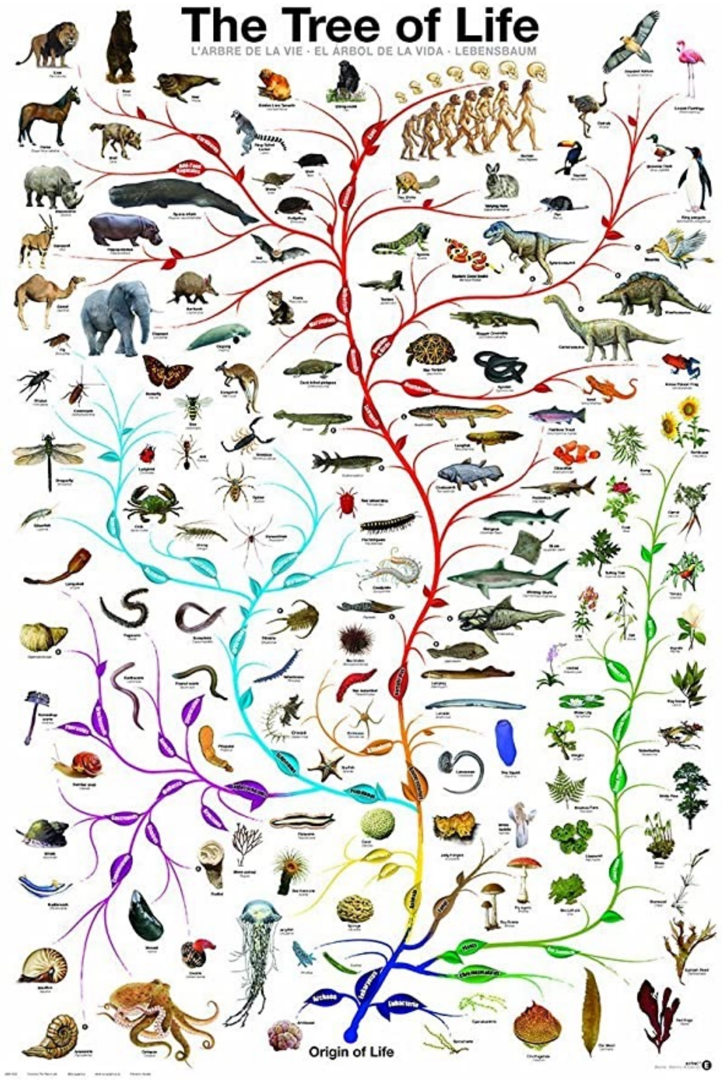




[Held, R. and Hein A. (1963). Movement-produced stimulation in the development of visually guided behavior. Jouranal of Comparative and Physiological Psychology 56(5): 872-876.]

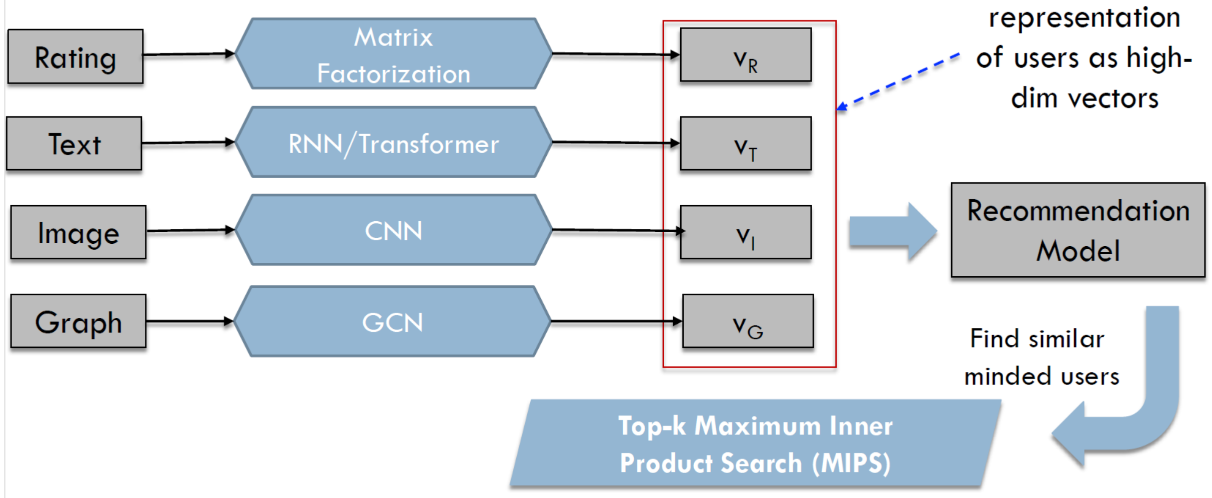
Embodied

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



Future "Multi-modal Opportunities": Database

High-Dimensional Similarity Query Processing

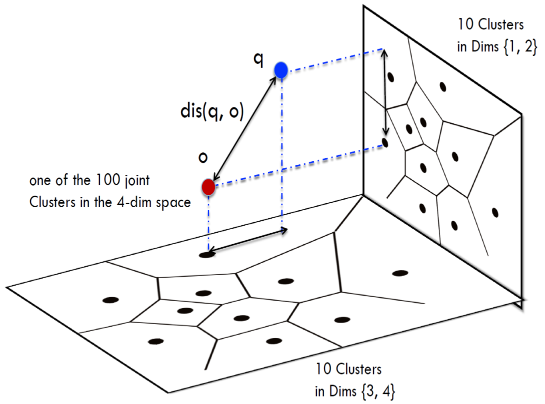


Nearest Neighbor (of q): o*

- dist(o*, q) = min {dist(o, q), o ∈ D}
- Generalizes to k-NN

c-Approximate NN: o

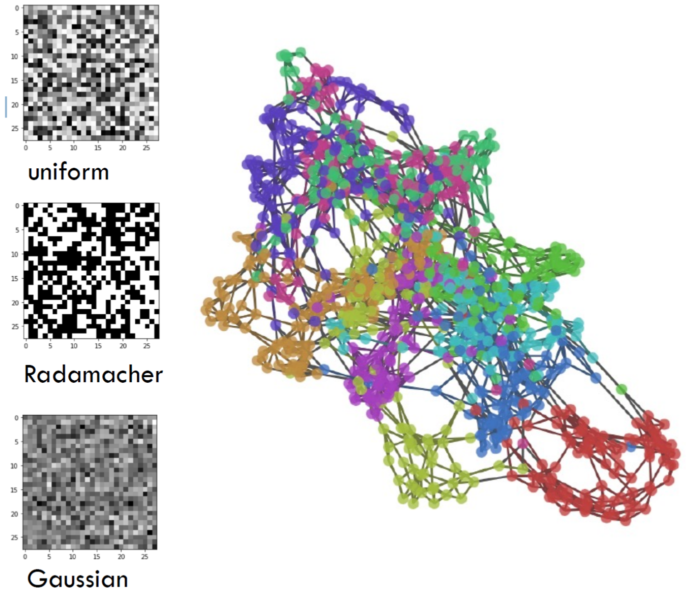
- dist(o, q) ≤ c * dist(o*, q)



by *Wei Wang* in PVLDB 2020

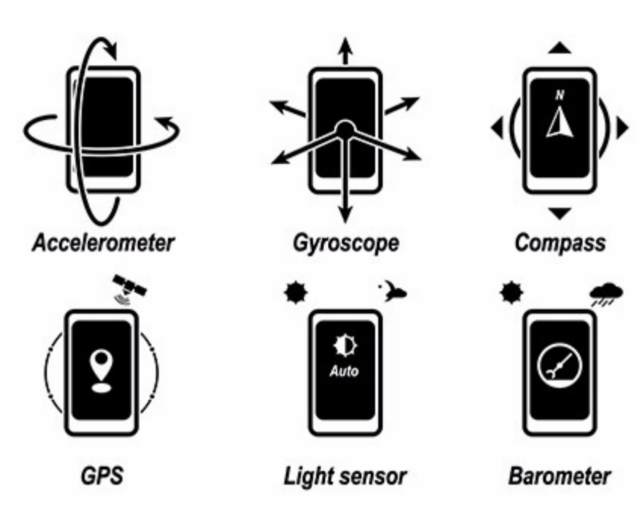
Vectors Querying

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

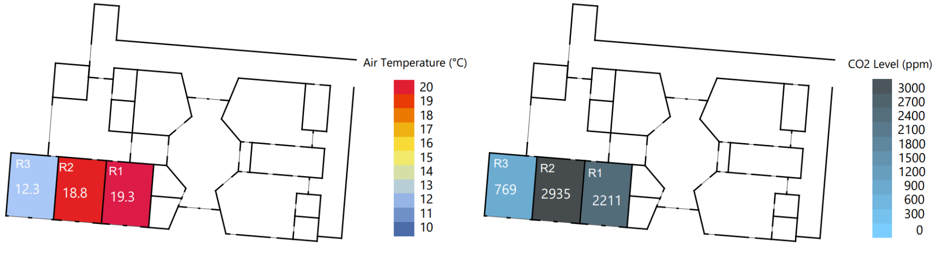


Future "Multi-modal Opportunities": IoT

IJCAI/2023 MACAO



Non-visual Multi-modal Data



(a) Temperature (b) CO_2 level

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

Keynote by *Flora Salim* in KDD 2021

Segmentation

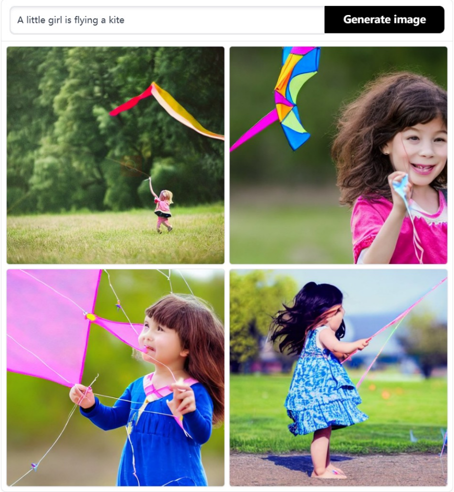
"Segmentation" is critical for multi-modal sensor data

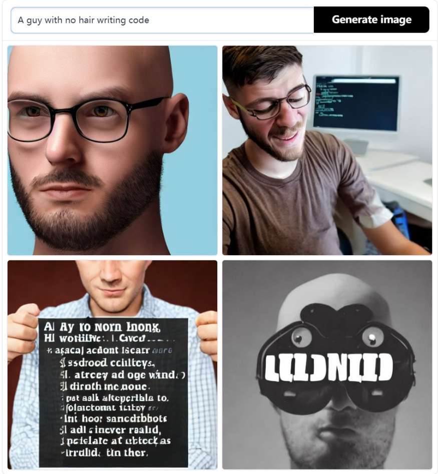
IMWUT 2020

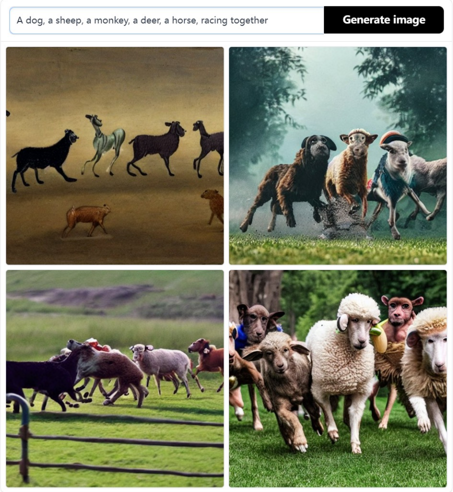
Future "Multi-modal Opportunities": AIGC

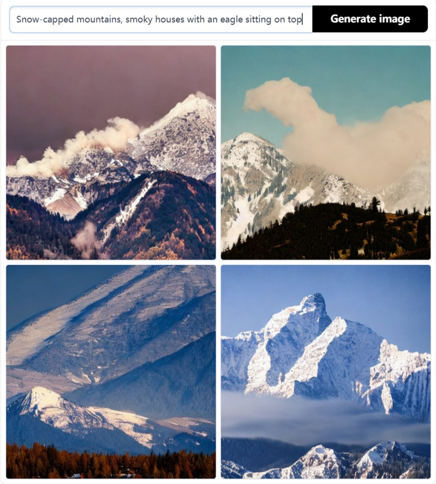
Text to image

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









Future “Multi-modal Opportunities”: AIGC

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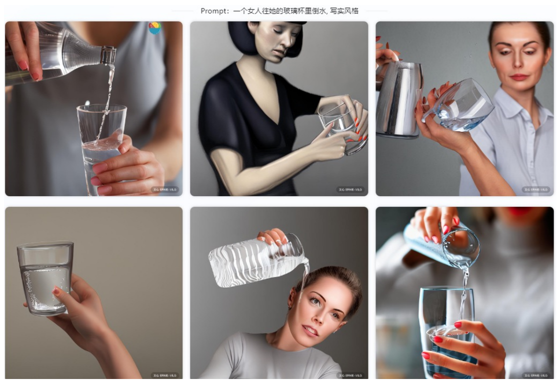
	DAll E	stable diffusion	ERNIE VilG
A woman is pouring water into her glasses			

Knowledge-Enhanced before Disambiguation

Future "Multi-modal Opportunities": Keywords

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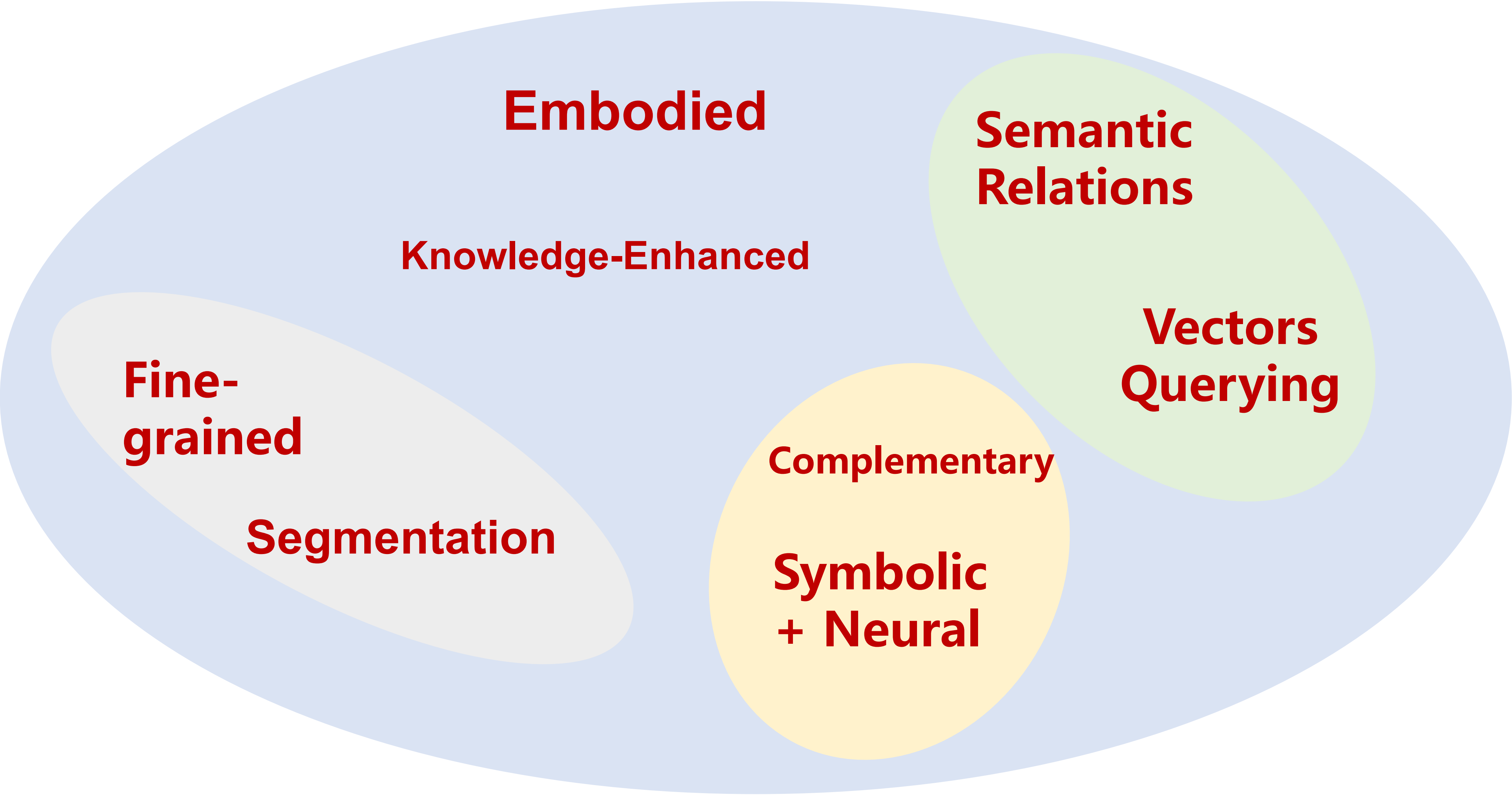


IJCAI/2023 MACAO

IJCAI
International Joint Conferences on
Artificial Intelligence Organization

Thank You

Speaker: Meng Wang

Date: 2023.08.19

Website

IJCAI/2023 MACAO

IJCAI
International Joint Conferences on Artificial Intelligence Organization

Uncertain KG Construction and Reasoning

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

Tianxing Wu

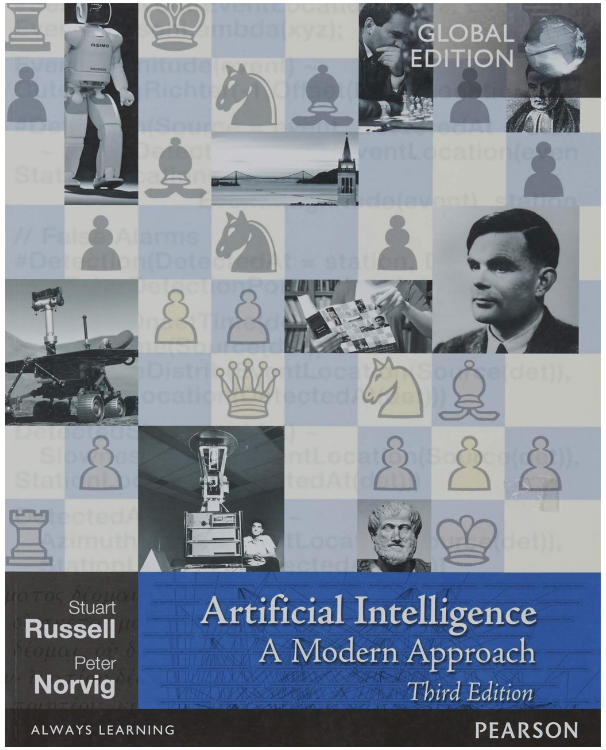
Southeast University

19, Aug, 2023

Research Background

IJCAI/2023 MACAO

Uncertainty in Artificial Intelligence



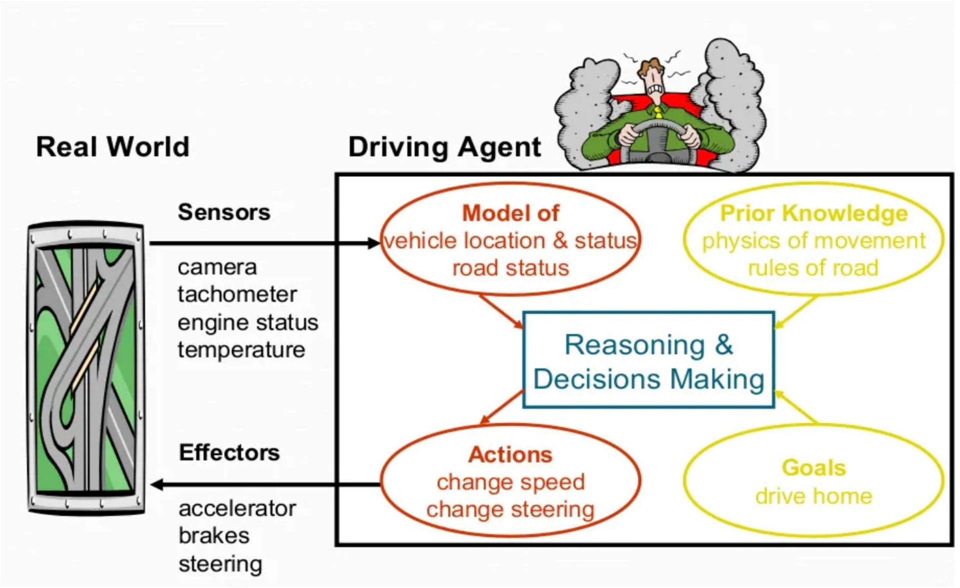
The Annual Conference on Uncertainty in Artificial Intelligence

uai

Research Background

Uncertainty in Artificial Intelligence

Autonomous Driving



Medical Reasoning

Research Background

Uncertainty in Knowledge Graph (KG)

The Development History of Knowledge Engineering

1960s-1970s	1980s-1990s	1990s-2000s	2000s-2010s	2010s-now
Semantic Networks	Expert Systems	KL-One&CLASSIC	Semantic Web	Knowledge Graph

Reasons for the uncertainties occurring:

a) Errors in automatic KG construction,

b) Uncertain domain-specific knowledge.

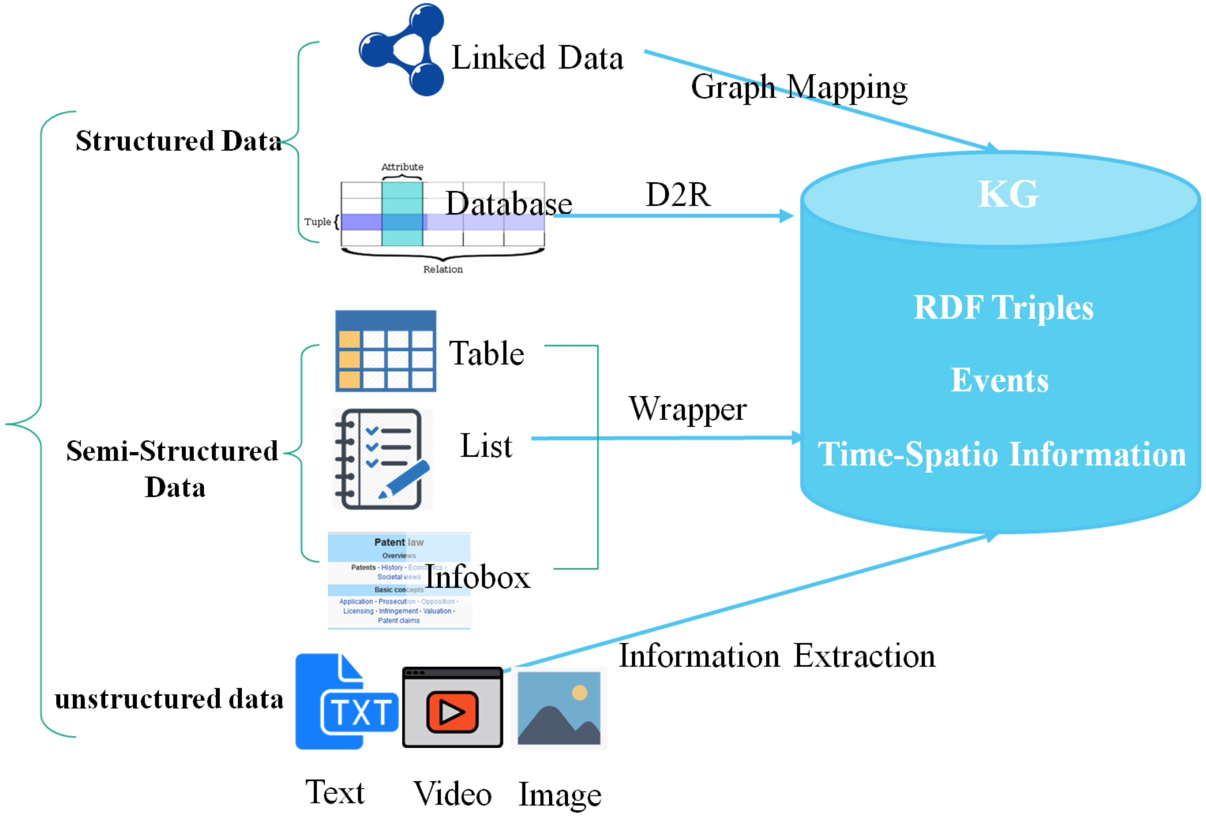
Research Background

Uncertainty in Knowledge Graph

Reasons for the uncertainties occurring:

a) Errors in automatic KG construction,

b) Uncertain domain-specific knowledge.



Research Background

IJCAI/2023 MACAO

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

Research Background

IJCAI/2023 MACAO

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

Research Background

Uncertain Knowledge Graph

Deterministic Knowledge Graph

DBpedia yago select knowledge

All triple are seen as correct!

<AlphaGo, Produced_by, Google> ✓
<US, Synonym_for, America> ✓

Uncertain Knowledge graph

NELL ConceptNet An open, multilingual knowledge graph

Triples are assigned with confidences to describe uncertainties.

<AlphaGo, Produced_by, Google>, 0.56
<US, Synonym_for, America>, 0.98

Research Background

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.***

Representative Works

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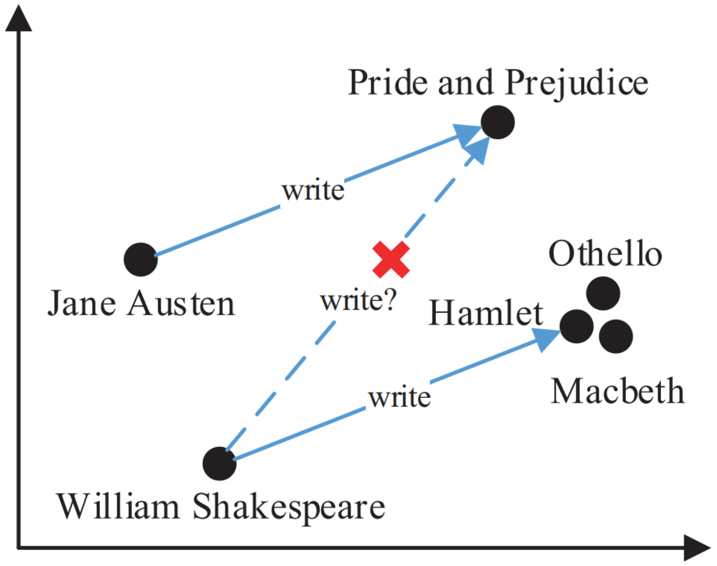
Uncertain Knowledge Graph Construction

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

Ruobing Xie, Zhiyuan Liu, Fen Lin, Leyu Lin

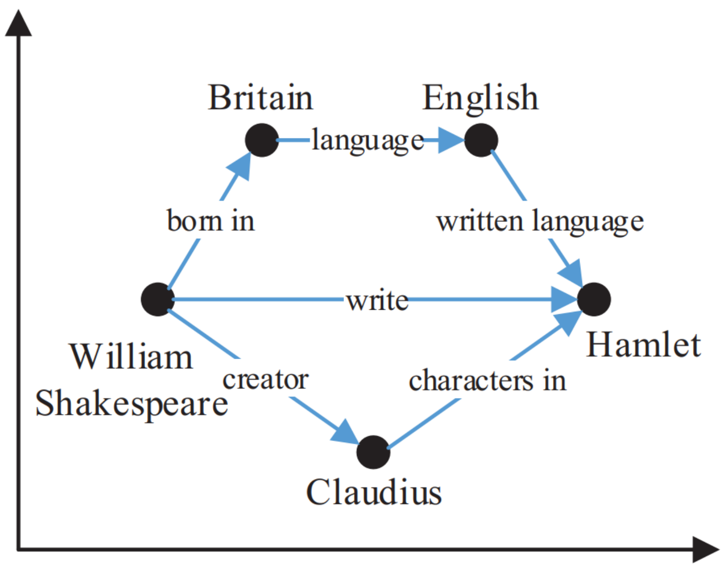
CKRL

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



Local triple confidence

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



Global path confidence

translation scoring function

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

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

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

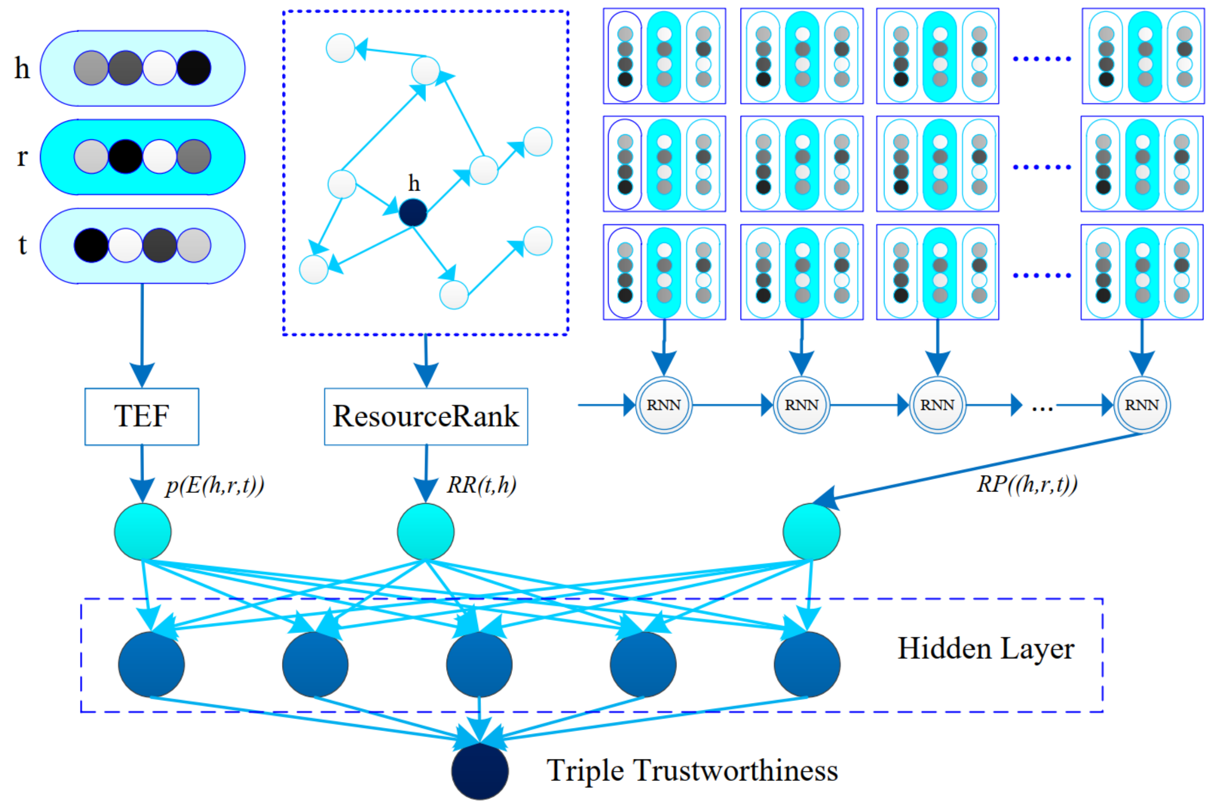
Representative Works

Uncertain Knowledge Graph Construction

WWW 2019:
Triple Trustworthiness Measurement for Knowledge Graph

Shengbing Jia, Yang Xiang, Xiaojun Chen

KGTtm

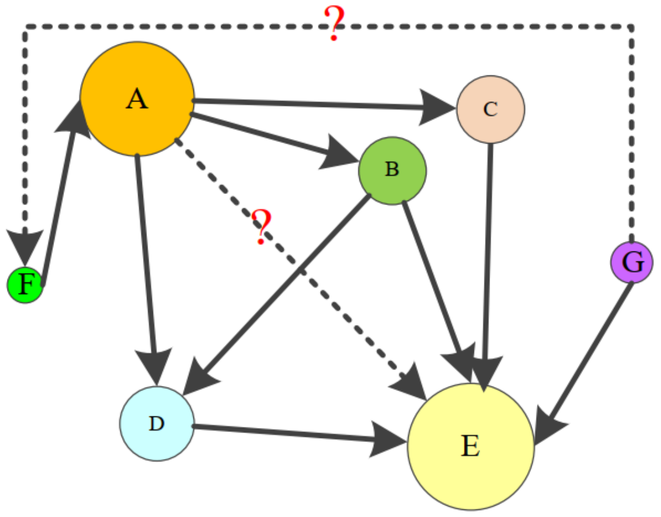


The triple trustworthiness measurement model of KGTtm.

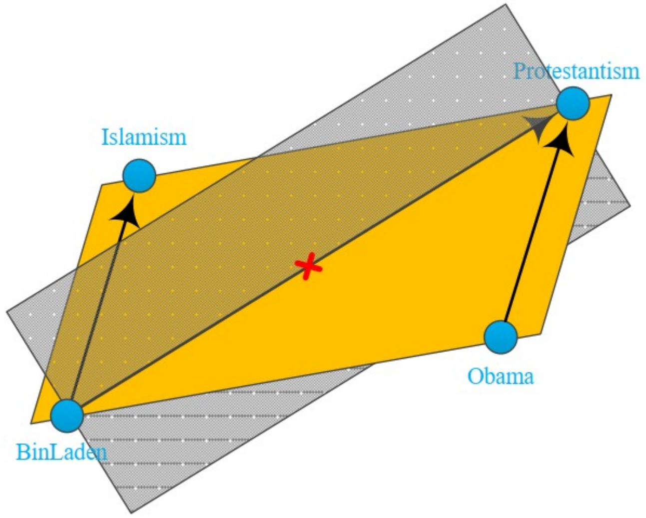
Basic Idea:

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?**

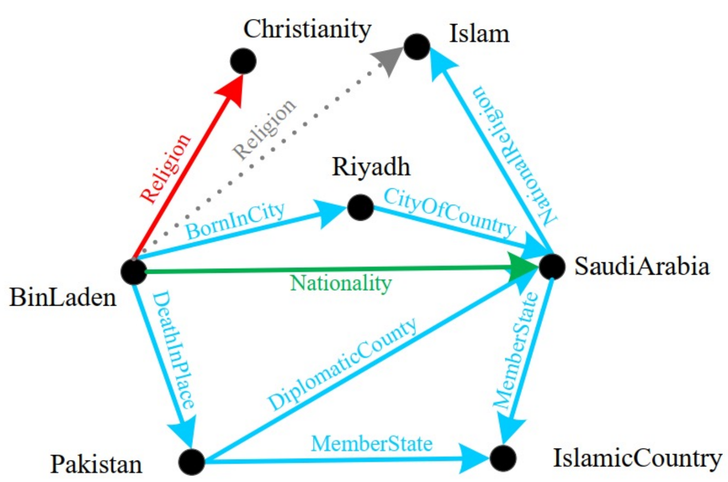
KGTtm



The graph of resource allocation in the ResourceRank algorithm.

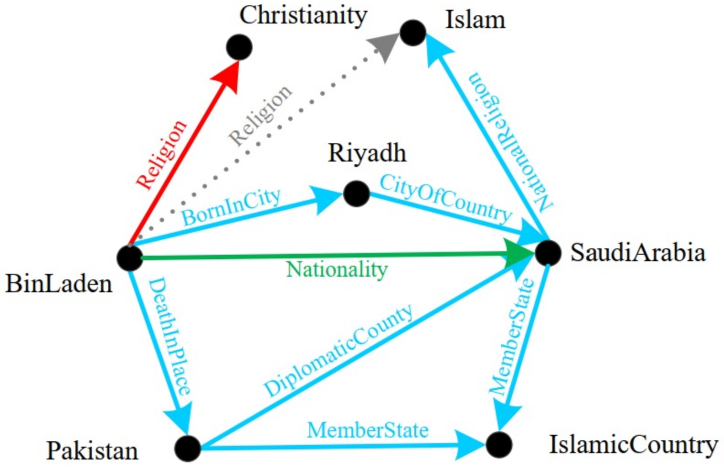


Effects display of the Translation based energy function.



The inference instances for triple trustworthiness.

KGTtm



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.

Search the reachable paths from h to t in the KG and store in $P_{(h,r,t)} = \{p_1, \ldots, p_n\}$;

For each $p_i = \{(h, l_1, e_1), (e_1, l_2, e_2), \ldots, (e_{n-1}, l_n, t)\}$, 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, $SD(p_i(e), h) = \frac{1}{n} \sum_{e_j \in p_i(e)} \frac{h \cdot e_j}{\|h\| \|e_j\|}$;

Calculate the average distance
$\bar{SD}(p_i) = \frac{1}{3}(SD(p_i(e), t) + SD(p_i(l), r) + SD(p_i(e), h))$;

Select first $TopK$ paths with the highest $\bar{SD}(p_i)$ scores.

Return $\{p_i \mid 1 \leqslant i \leqslant TopK, Sort(\bar{SD}(p_i), descend)\}$

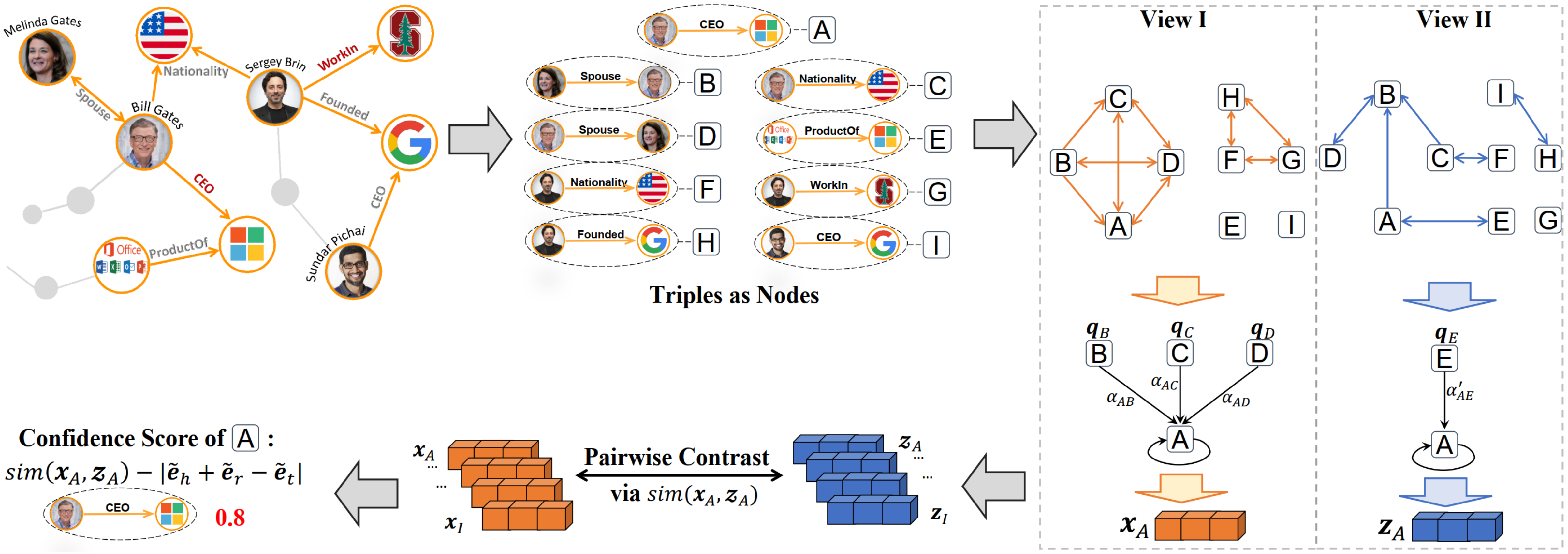
Representative Works

Uncertain Knowledge Graph Construction

CIKM 2022:
Contrastive Knowledge Graph Error Detection

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

CAGED



The illustration of CAGED.

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.*

Final Confidence Computation:

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

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:

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

Joint Optimization

Representative Works

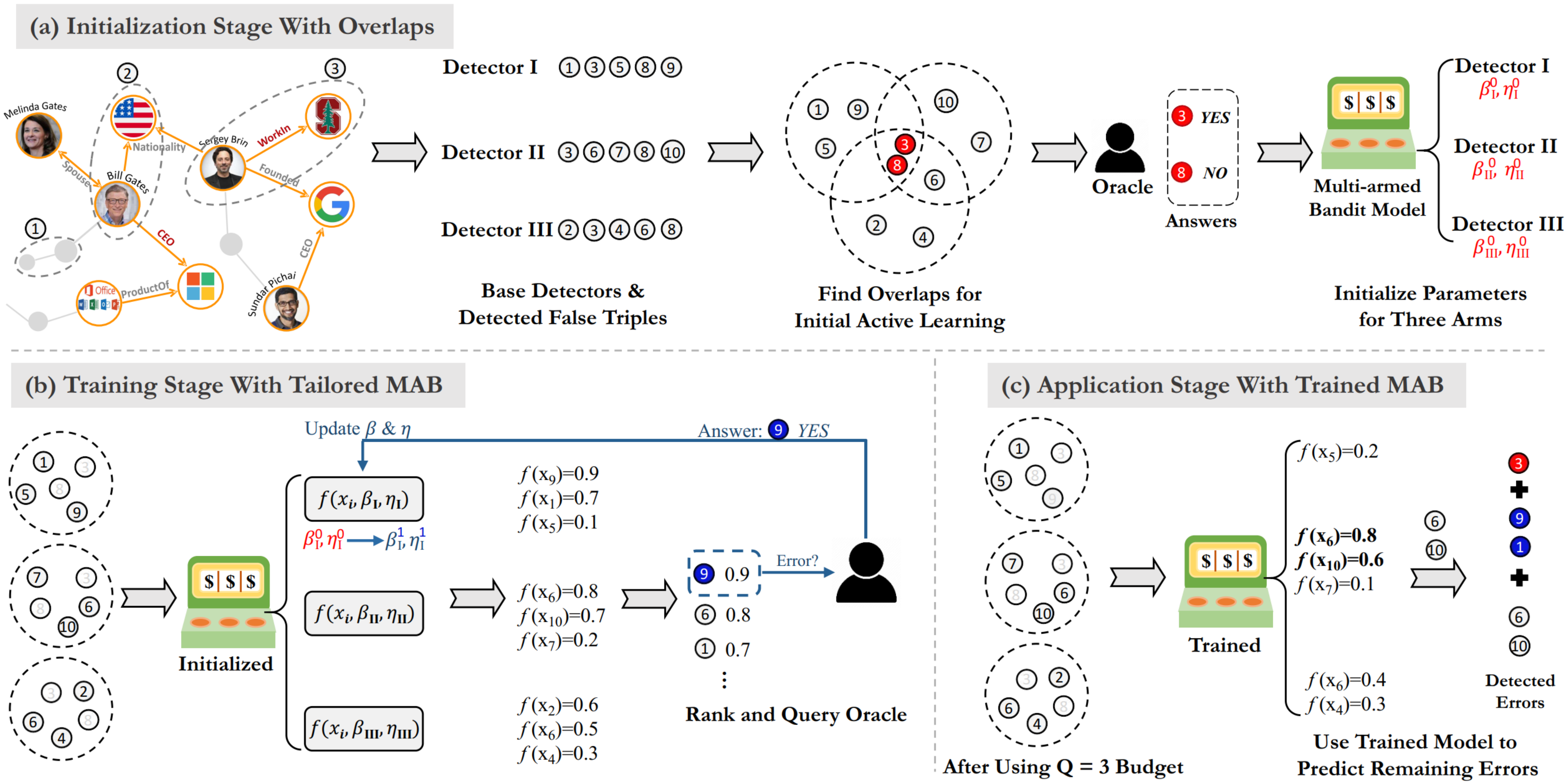
Uncertain Knowledge Graph Construction

WSDM 2023:
Active Ensemble Learning for Knowledge Graph Error Detection

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

KAEL

IJCAI/2023 MACAO



The illustration of KAEL.

Representative Works

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.

Representative Works

Uncertain Knowledge Graph Reasoning

AAAI 2019:
Embedding Uncertain Knowledge Graphs

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

UKGE

For each triple (*h*, *r*, *t*)

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

Transformation function
$$\begin{cases} \phi(x) = \min(\max(\mathbf{w}x + \mathbf{b}, 0), 1) \\ \phi(x) = \dfrac{1}{1 + e^{-(\mathbf{w}x+\mathbf{b})}} \end{cases}$$

$$\text{Plausibility} \xrightarrow{\phi} \text{Confidence}$$

UKGE

Using probabilistic soft logic to infer confidences of unseen facts:

Logical rule

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

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

(college, synonym, university) $\wedge$ (university, synonym, institute) $\rightarrow$ (college, synonym, institute)

l_1 (college, synonym, university)
l_2 (university, synonym, college)
l_3 (college, synonym, institute)

$\left.\begin{array}{l} l_1 \\ l_2 \end{array}\right\}$ Observed

l_3 Unseen

$\Downarrow$

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

UKGE

IJCAI/2023 MACAO

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.

Representative Works

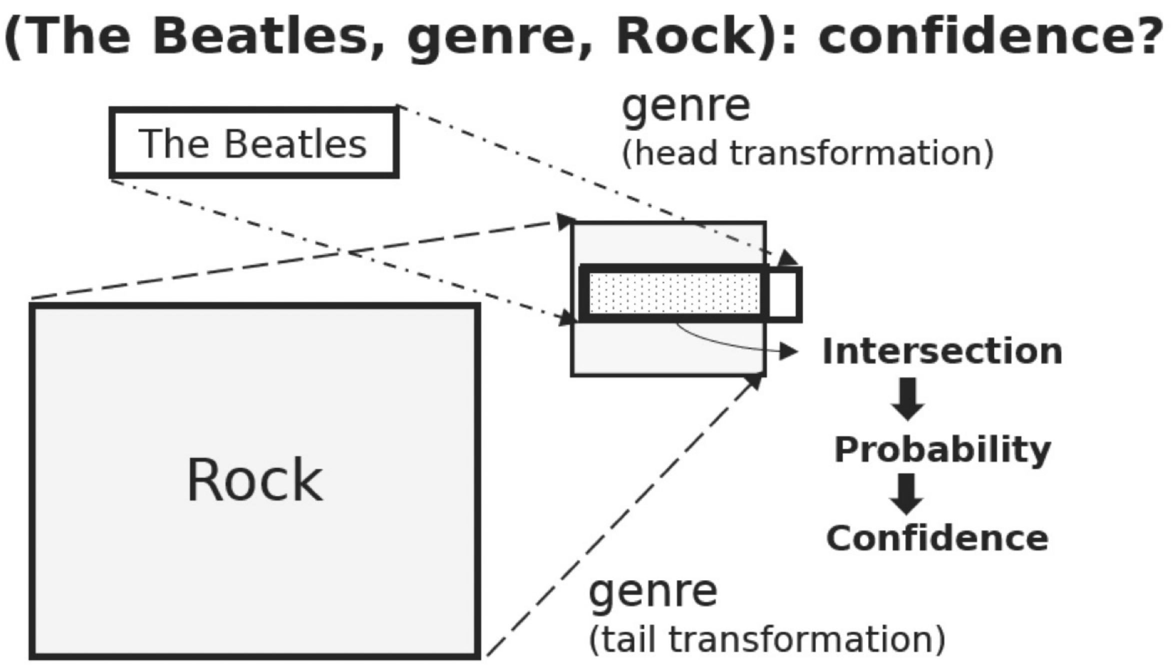
Uncertain Knowledge Graph Reasoning

NAACL 2021:
Probabilistic Box Embeddings for Uncertain Knowledge Graph Reasoning

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

BEUrRE

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.



BEUrRE

- Gumbel boxes

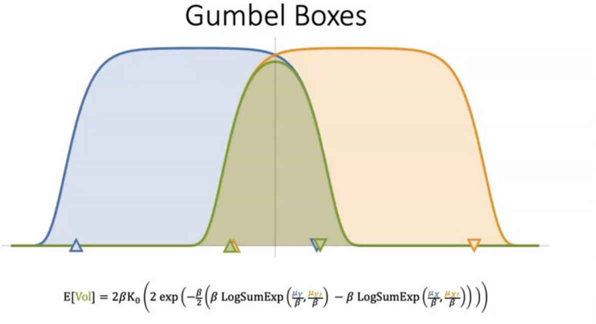
$$\mathrm{Box}(X) = \prod_{i=1}^{d} [x_i^{\mathrm{m}}, x_i^{\mathrm{M}}] \quad \text{where}$$

$$x_i^{\mathrm{m}} \sim \mathrm{GumbelMax}(\mu_i^{\mathrm{m}}, \beta),$$

$$x_i^{\mathrm{M}} \sim \mathrm{GumbelMin}(\mu_i^{\mathrm{M}}, \beta).$$

- Expected volume of a Gumbel box

$$\mathbb{E}\left[\mathrm{Vol}(\mathrm{Box}(X))\right] \approx \prod_{i=1}^{d} \beta \log\left(1 + \exp\left(\frac{\mu_i^{\mathrm{M}} - \mu_i^{\mathrm{m}}}{\beta} - 2\gamma\right)\right)$$



- For entities, location parameters are cen and off:

$$\mu_i^{\mathrm{m}} = \mathrm{cen}(\mathrm{Box}(X)) - \mathrm{off}(\mathrm{Box}(X)),$$

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

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

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

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

- The conditional probability is used to model confidences:

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

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

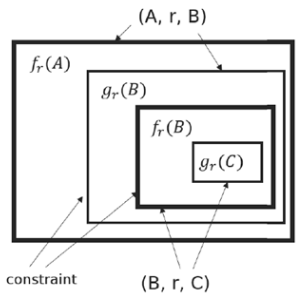
BEUrRE

- Incorporating logical constraints:

Transitivity Constraint

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

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



$\Downarrow$

Loss

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

Composition Constraint

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

$$f_{r_3} = f_{r_2}(f_{r1}(u)), \quad g_{r_3} = g_{r_2}(g_{r_1}(u))$$

$\Downarrow$

Loss

$$L_{\mathrm{c}}(r_1, r_2, r_3) = \frac{1}{|\Phi|} \sum_{u \in \Phi} f_{r_3}(u) \oplus f_{r_2}(f_{r_1}(u)) + g_{r_3}(u) \oplus g_{r_2}(g_{r_1}(u))$$

Final Loss $\mathcal{J}_1 = \sum_{l \in \mathcal{L}^+} |\phi(l)| - s_l|^2 + \alpha \sum_{l \in \mathcal{L}^-} |\phi(l)|^2$ **+** $\mathcal{J}_2 = w_{\mathrm{tr}} \sum_{r \in \mathcal{R}_{\mathrm{tr}}} L_{\mathrm{tr}}(r) + w_{\mathrm{c}} \sum_{(r_1, r_2, r_3) \in \mathcal{R}_{\mathrm{c}}} L_{\mathrm{c}}(r_1, r_2, r_3)$

Representative Works

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

PASSLEAF

Confidence Computation:

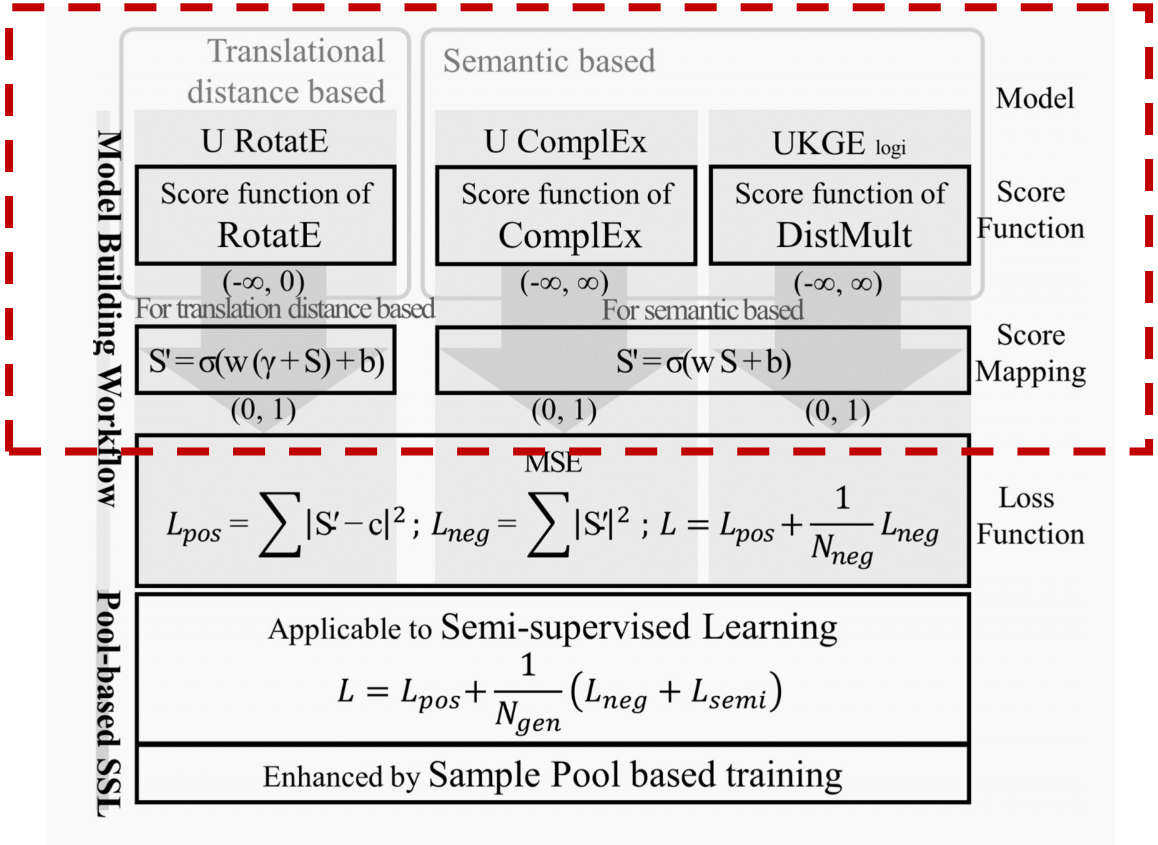
- For different types of scoring functions, it sets different mapping functions:

  for translational distance models:

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

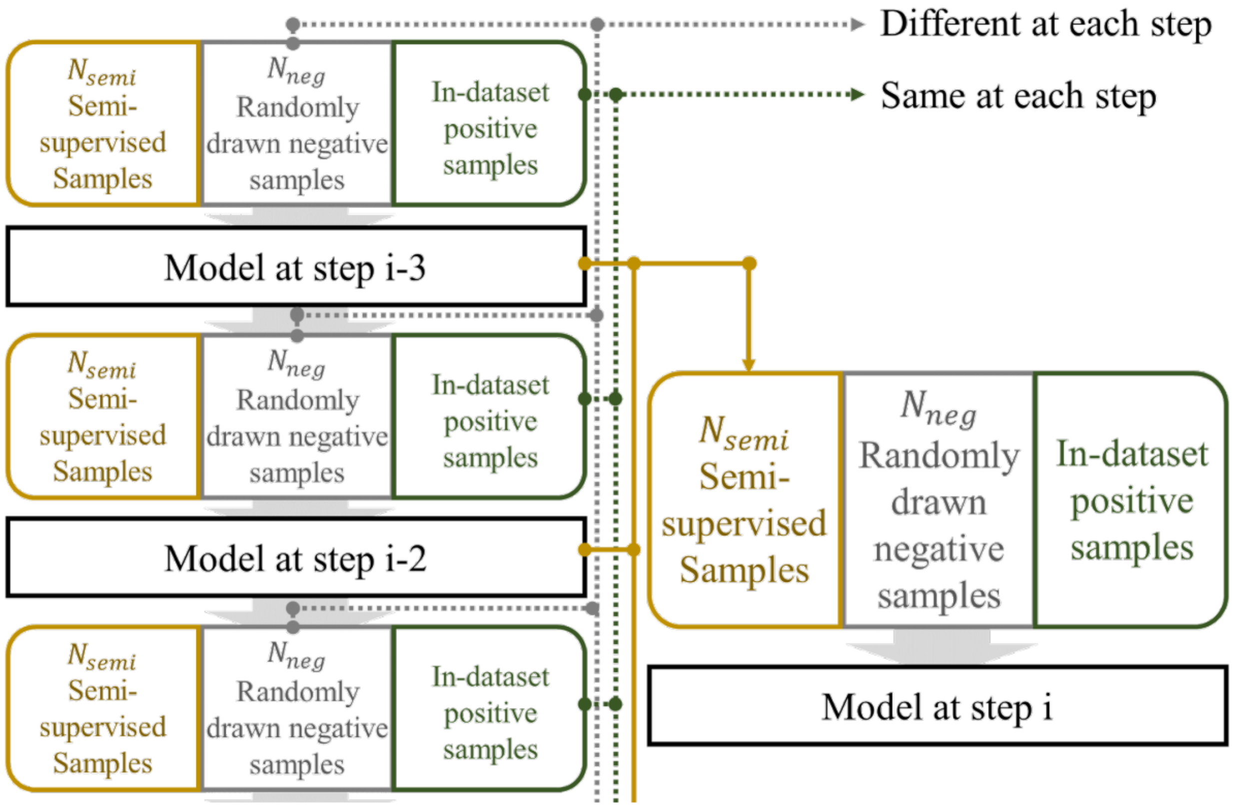
  for semantic matching models:

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



PASSLEAF

IJCAI/2023 MACAO



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.

Representative Works

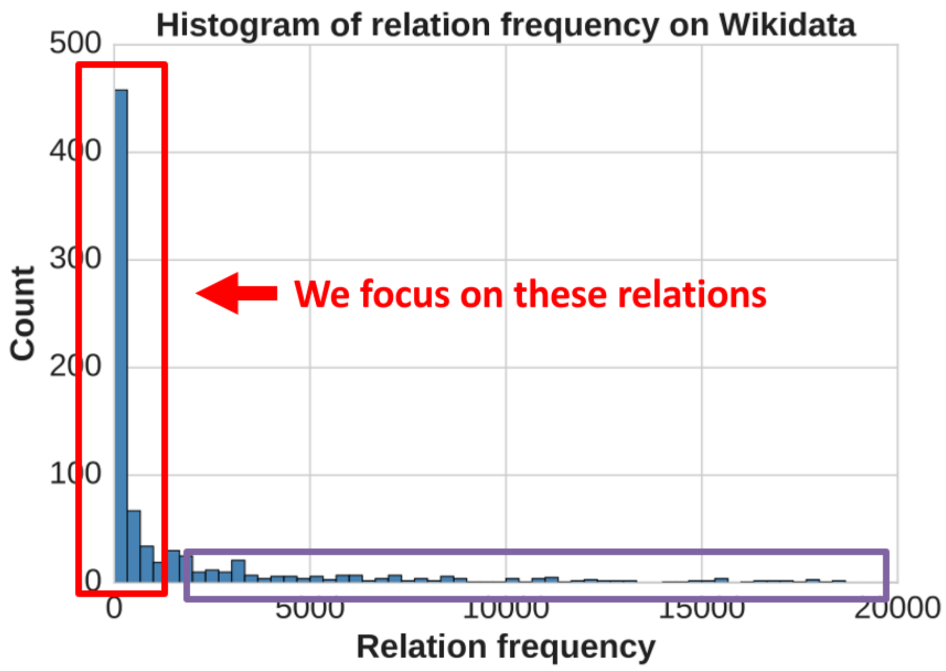
Uncertain Knowledge Graph Reasoning

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

Jiatao Zhang, Tianxing Wu, Guilin Qi

GMUC

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

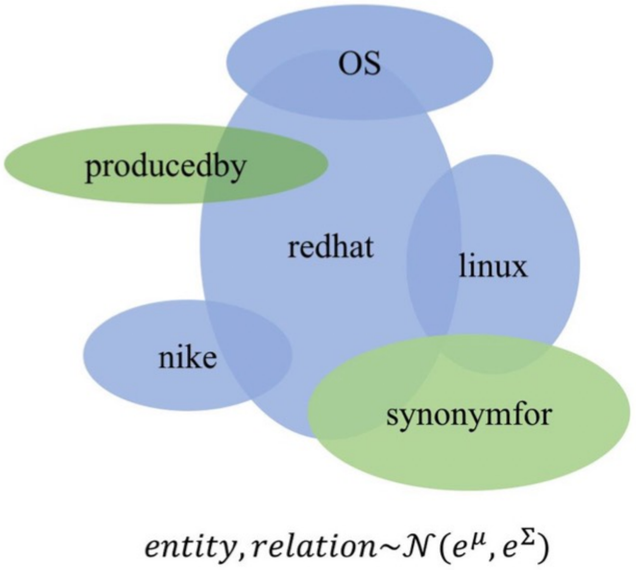


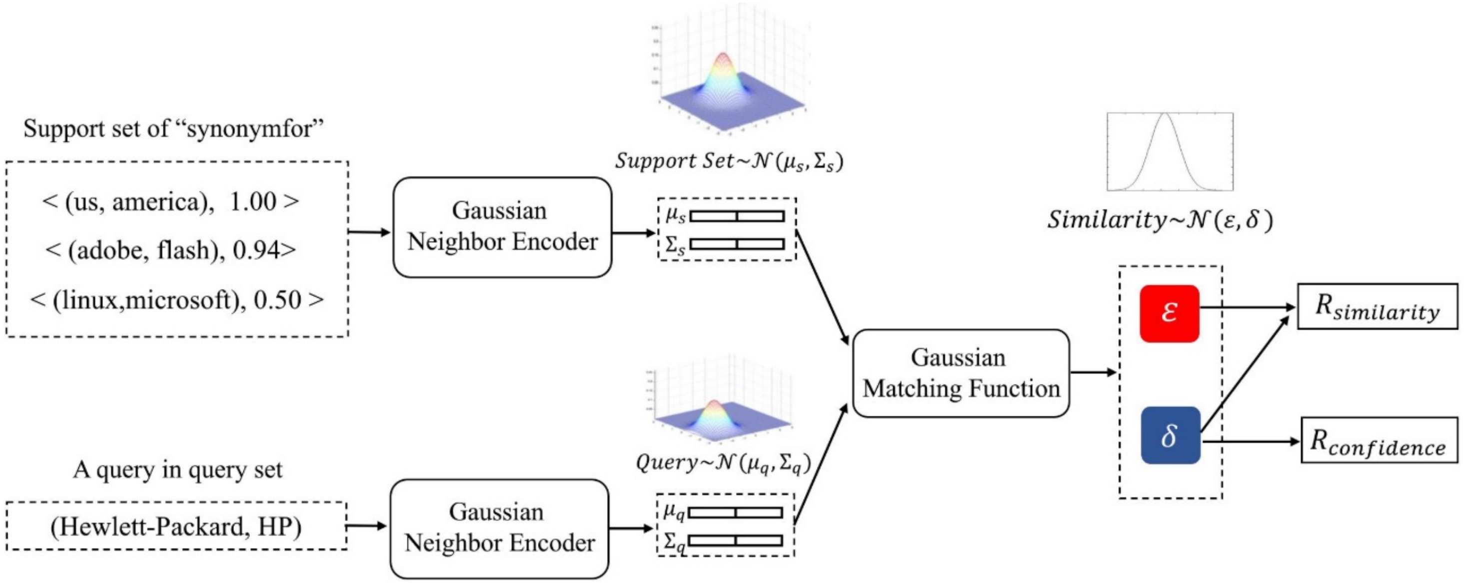
- Most relations are described by few triples.
- Few training data affects the quality of KG embedding.

GMUC

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.

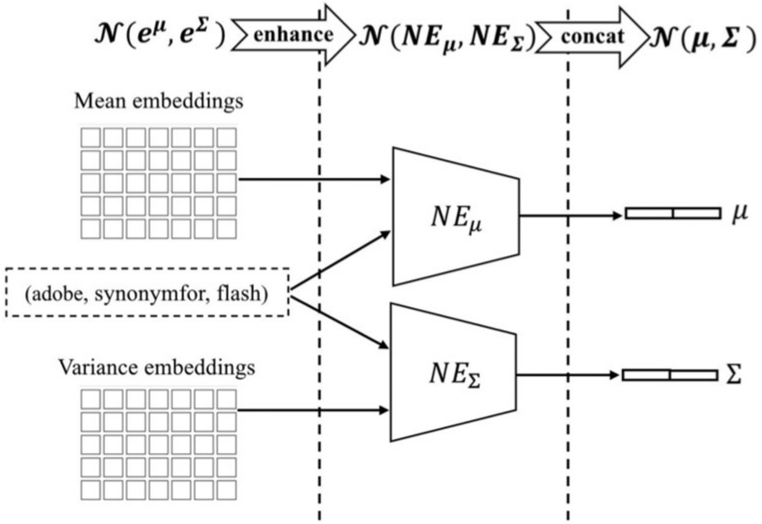




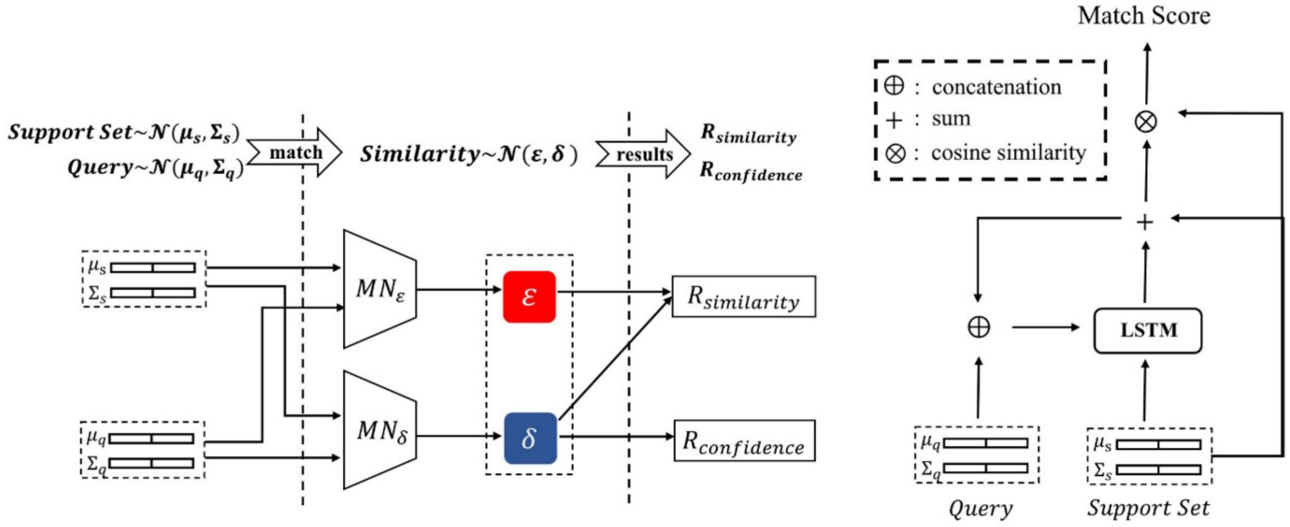
GMUC

Model

Gaussian Neighbor Encoder



Gaussian Matching Function



(a) Gaussian Matching Function

(b) Matching Network

GMUC

IJCAI/2023 MACAO

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

```
for epoch:=0 to MAX_epoch do
    for T_r in T_train do
        Sample few entity pairs as support set S_r
        Sample a batch of positive queries Q_r and filtered queries Q_r^thr
        Pollute the tail entity of queries to get Q_r^thr-
        Calculate the loss by Eq. (14)
        Update parameters θ and φ
return Optimal model parameters θ and φ
```

GMUC

IJCAI/2023 MACAO

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

Dataset	NL27K-N0			NL27K-N1			NL27K-N2			NL27K-N3		
Metrics	MRR	Hit@1	Hit@10	MRR	Hit@1	Hit@10	MRR	Hit@1	Hit@10	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**

Representative Works

Uncertain Knowledge Graph Reasoning

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

Jingting Wang, Tianxing Wu, Jiatao Zhang

GMUC+

IJCAI/2023 MACAO

Uncertainties of entities and relations need explicit semantics guidance.

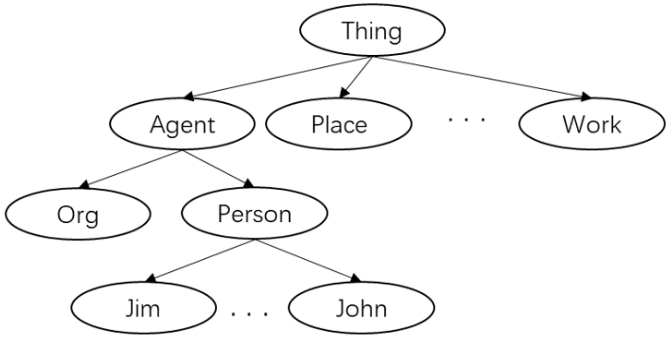
For relations:

museumincity	(Gotoh_Museum, Tokyo, 1.0)	
atlocation	(Air_Canada, Vancouver, 0.92)	company -> city
	(Albania, Europe, 1.0)	country -> continent
	(Queen_Victoria, Great Britain, 0.93)	people -> country

For entities: **“Alice.” vs. “artist.”**

GMUC+

- 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.

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

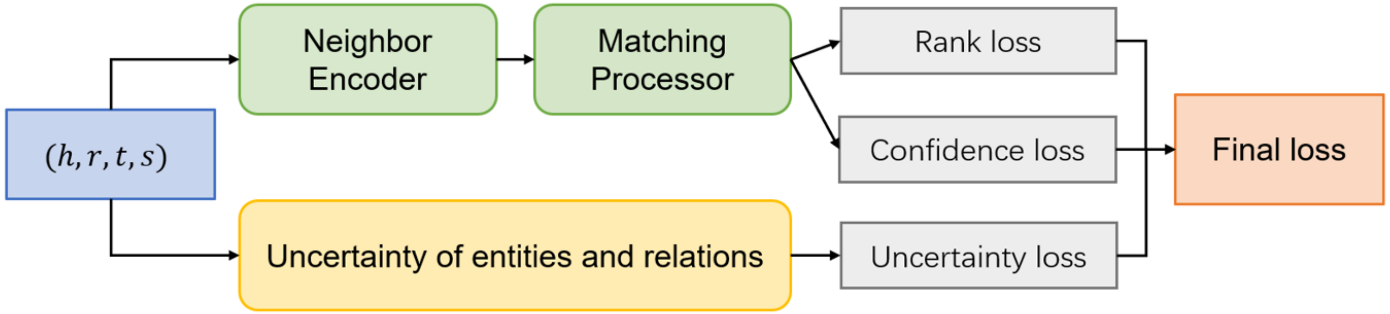
$$UC_r(r) = \sum_{h \in D_r, t \in R_r} (UC_e(h) + UC_e(t))$$

Uncertainty loss

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

GMUC+

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

GMUC+

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**

Representative Works

IJCAI/2023 MACAO

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

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International Joint Conferences on Artificial Intelligence Organization

Thank You

Speaker: Tianxing Wu

Date: 2023.08.19

Website

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Discussion on Main Issues & Opportunities

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

Ningyu Zhang

Zhejiang University

19, Aug, 2023

KG Meets LLMs

IJCAI/2023 MACAO

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 Huapu 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.

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 ChatGPT[2] and PaLM2[3], with billions of parameters, exhibit great potential in many complex practical tasks, such as education [8], code generation [9] and recommendation [10].

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- *Shirui Pan and Linhao Luo contributed equally to this work.*
- *Corresponding Author: Xindong Wu.*

1. LLMs are also known as pre-trained language models (PLMs).
2. https://openai.com/blog/chatgpt
3. https://ai.google/discover/palm2

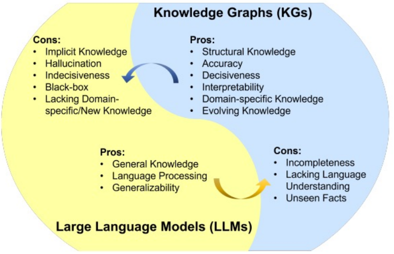

Fig. 1. Summarization of the pros and cons for LLMs and KGs. LLM pros: *General Knowledge* [11], *Language Processing* [12], *Generalizability* [13]; LLM cons: *Implicit Knowledge* [14], Hallucination [15], Indecisiveness [16], Black-box [17], Lacking Domain-specific/New Knowledge [18]. KG pros: *Structural 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

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Simon Razniewski
Bosch Center for AI, Germany
Jan-Christoph Kalo
Vrije Universiteit Amsterdam, The Netherlands
Sneha Singhania
Max Planck Institute for Informatics, Germany
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Hajira Jabeen
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Wen Zhang
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Matteo Lissandrini
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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.

..., Vol. 000, Issue 111, Article No. 42, pp. 42:1–42:30
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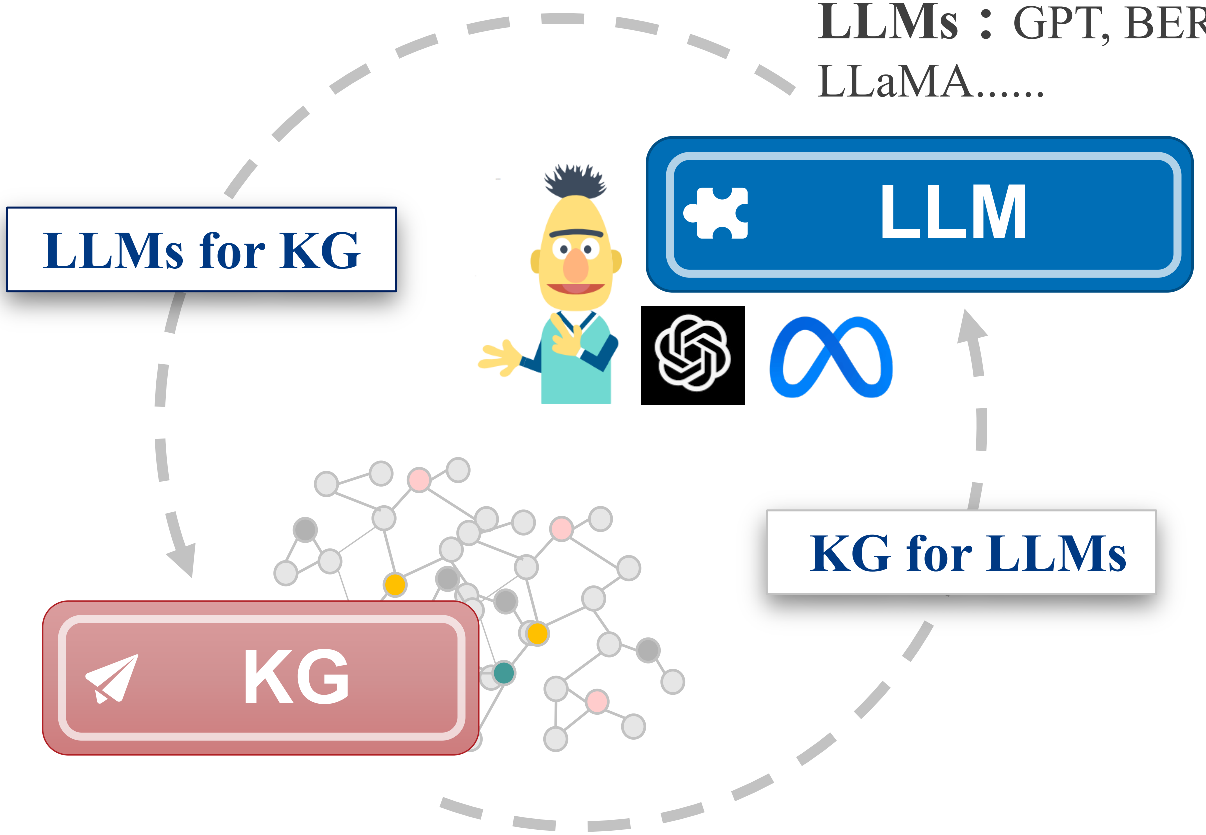
Issues and Opportunities

LLMs： GPT, BERT, LLaMA……

Knowledge Representation

Knowledge Acquisition

Knowledge Reasoning



Knowledge Editing

Knowledge Interaction

KG：Knowledge representation, acquisition, editing, reasoning……

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

Part1: Knowledge Representation

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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 Levy**[1]

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[2]Allen Institute for Artificial Intelligence

[3]Cornell Tech

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In-context Learning and Induction Heads

AUTHORS

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AFFILIATION

Anthropic

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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

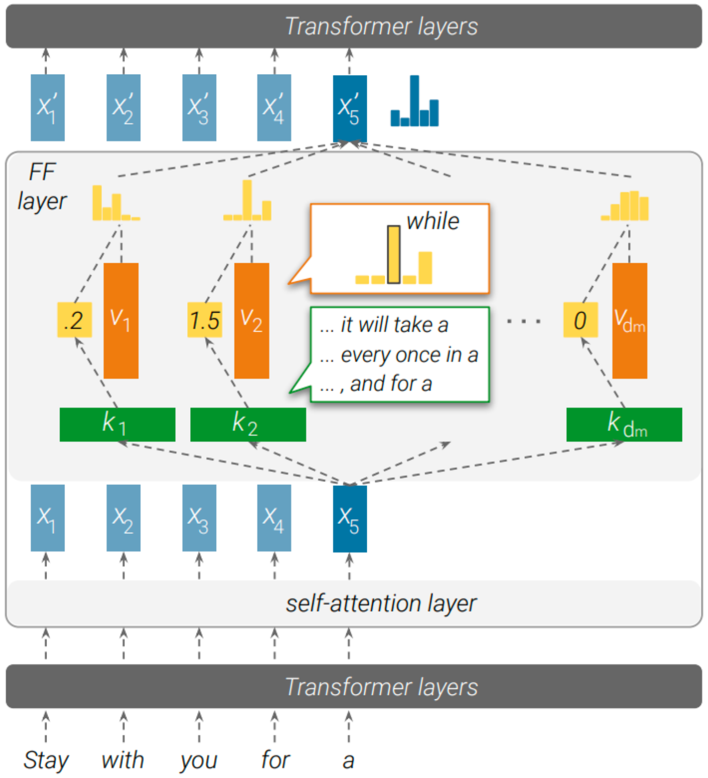
David Bau* Northeastern University

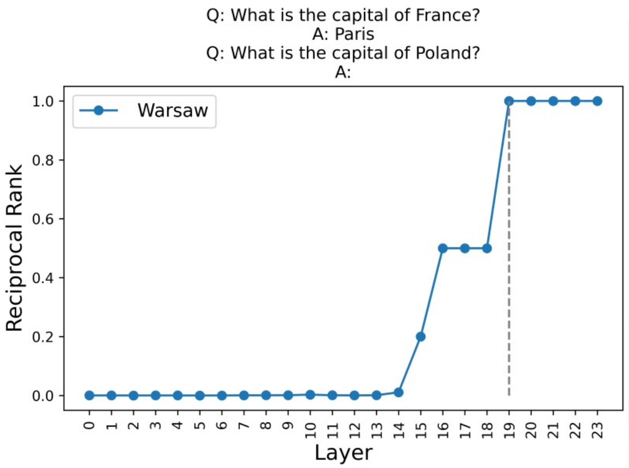
Alex Andonian MIT CSAIL

Yonatan Belinkov† Technion – IIT

Knowledge Representation: Observations

Principle of Neural Knowledge Representation (within LLMs)



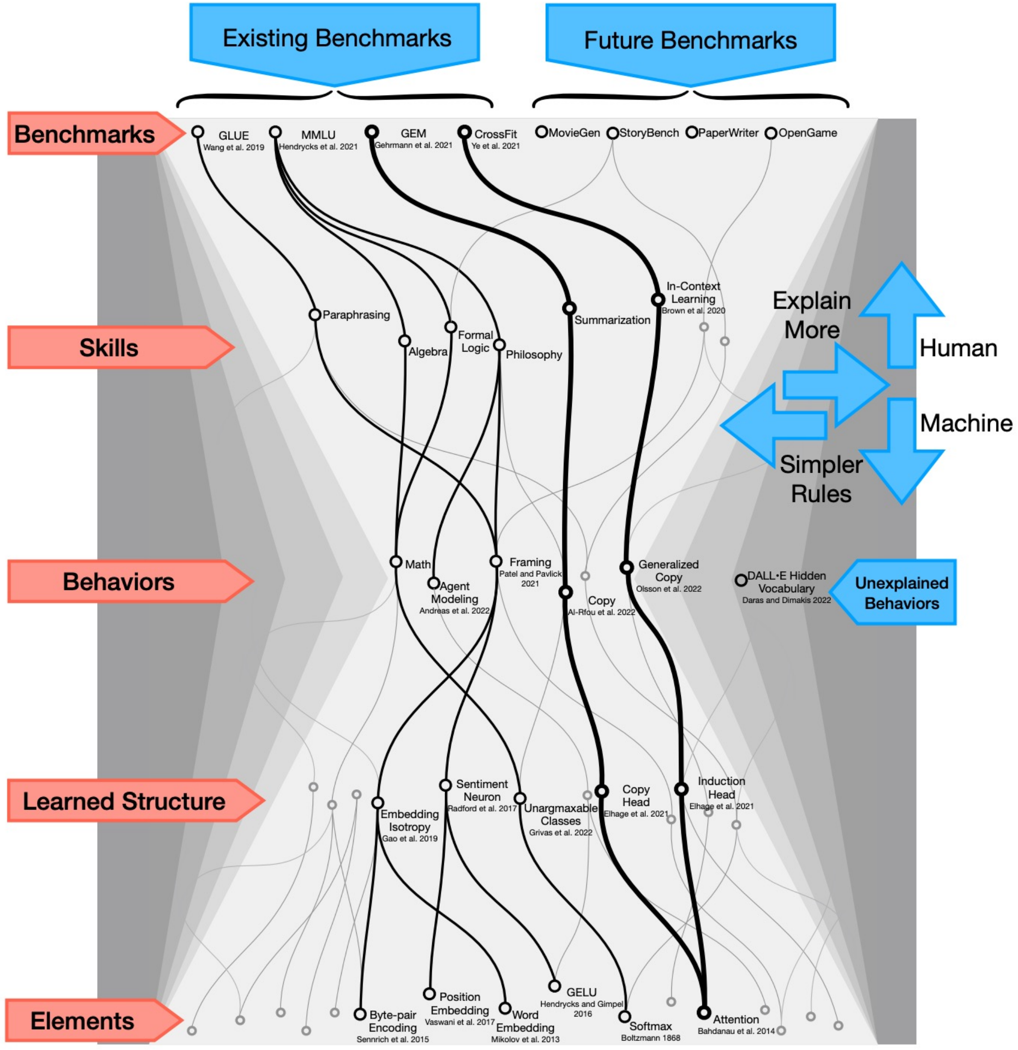


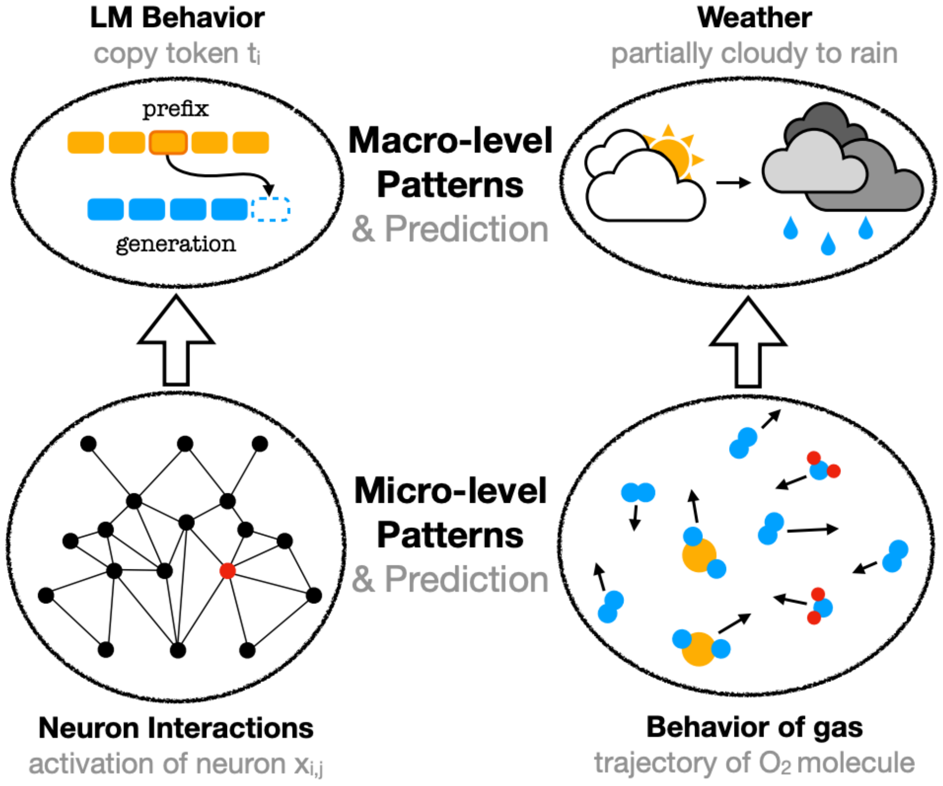
Layer	Top Token	
0	(	
1	A	
2	A	
3	A	
4	A	
5	A	
6	No	
7	C	
8	A	
9	A	
10	A	
11	A	
12	Unknown	
13	C	
14	St	
15	Poland	A
16	Poland	A
17	Poland	A
18	Poland	A
19	Warsaw	B
20	Warsaw	C
21	Warsaw	C
22	Warsaw	C
23	Warsaw	C

- **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)

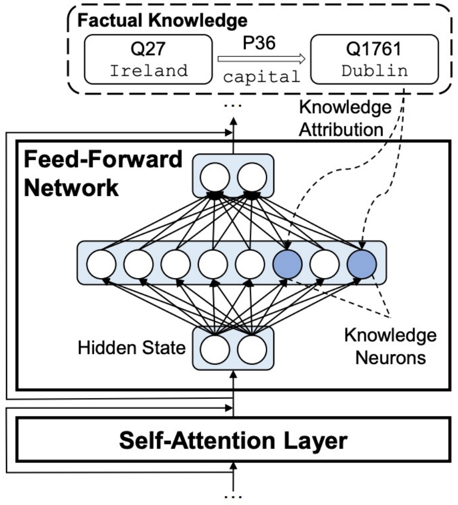
Knowledge Representation: System Science



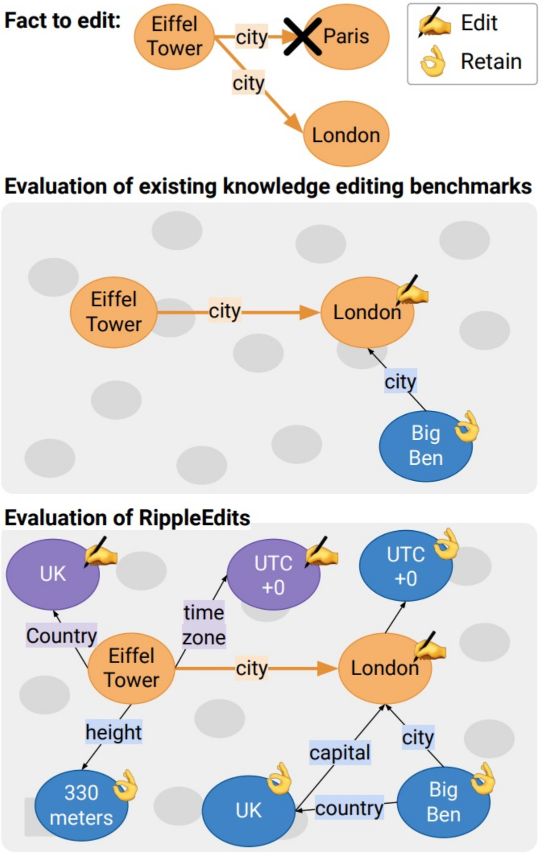


[1] Generative Models as a Complex Systems Science: How can we make sense of large language model behavior? (2023)

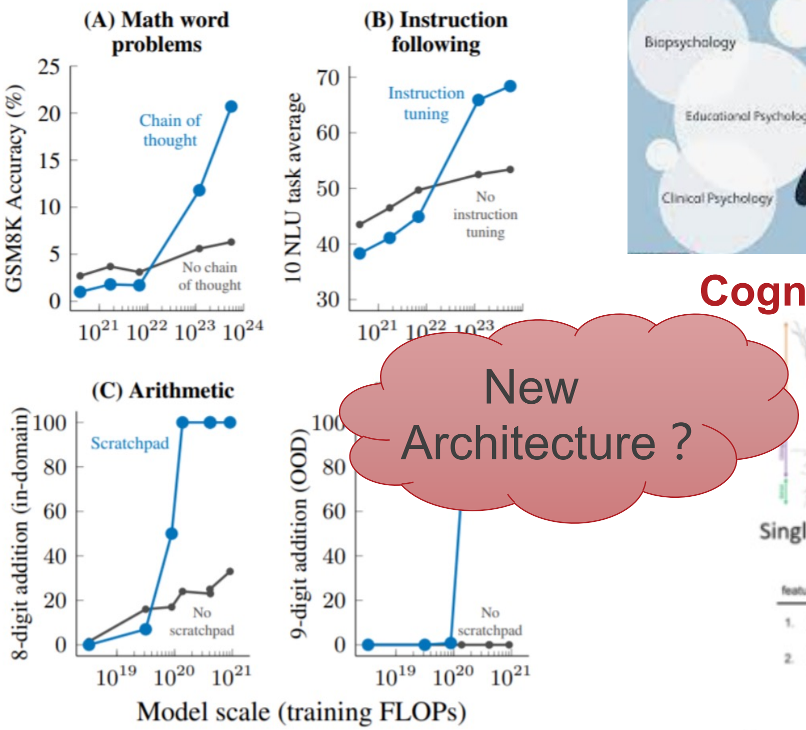
Knowledge Representation: Unified Neural Symbolic



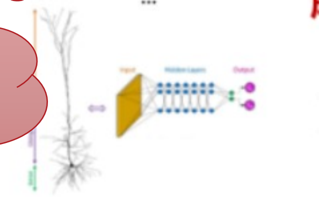
Knowledge Neurons



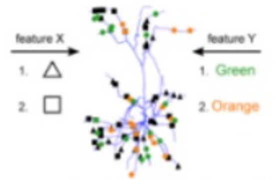
Knowledge Editing



Cognitive science



Single neuron as DNN, 2021



Harness dendritic nonlinearities through learning, 2021

Brain science

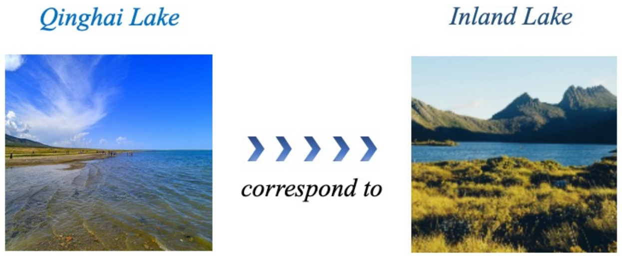
[1] Knowledge Neurons in Pretrained Transformers, ACL2021
[2] Evaluating the Ripple Effects of Knowledge Editing in Language Models, 2023
[3] Emergent Abilities of Large Language Models, 2022

Part2: Knowledge Acquisition

- **Text Modality**

Albert Einstein is one of the greatest and most influential scientists

- **Image Modality**

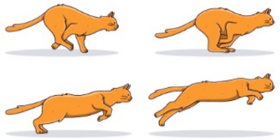


- **Audio Modality**

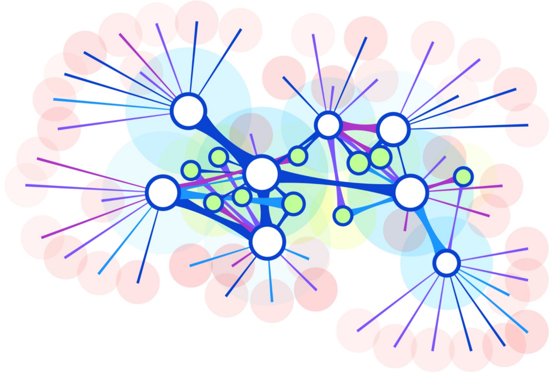
DNA is the molecule that carries genetic information.

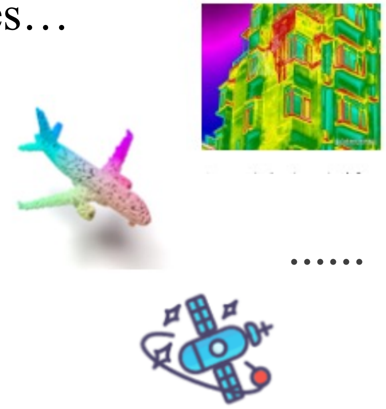
- **Video Modality**

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



Ontology, facts, concepts, commonsense, rules…





T5 ChatGPT MOSS ChatGLM ……

[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

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A package for ontology engineering with deep learning

DeepOnto

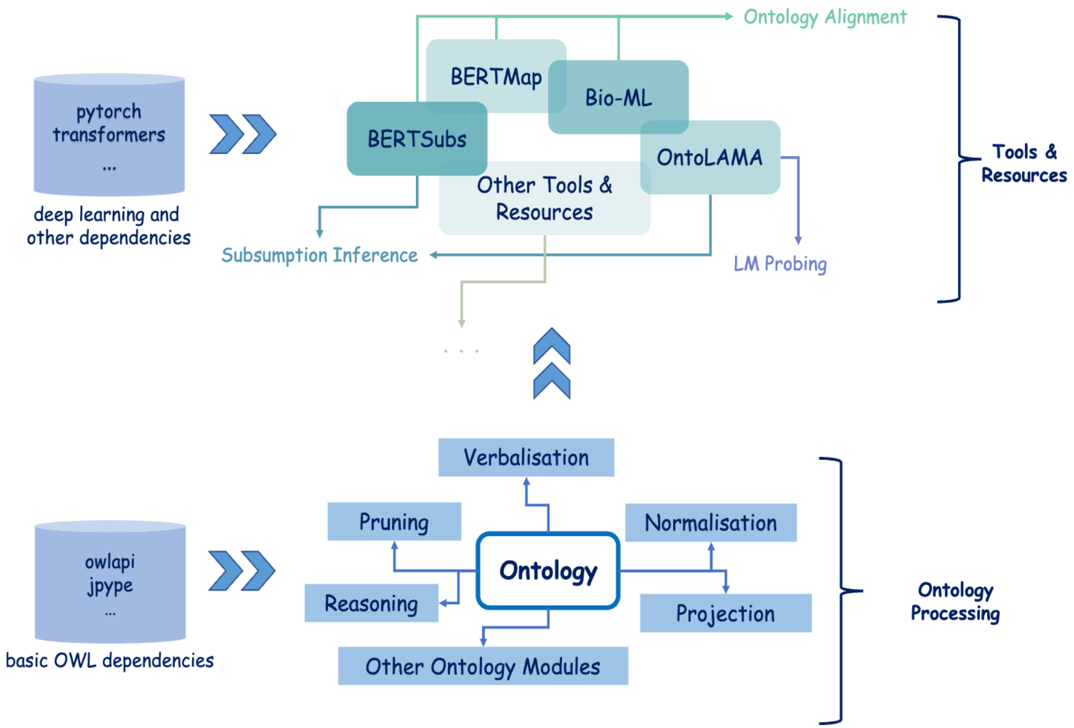
license Apache-2.0 website online pypi v0.8.4

A package for ontology engineering with deep learning.

News

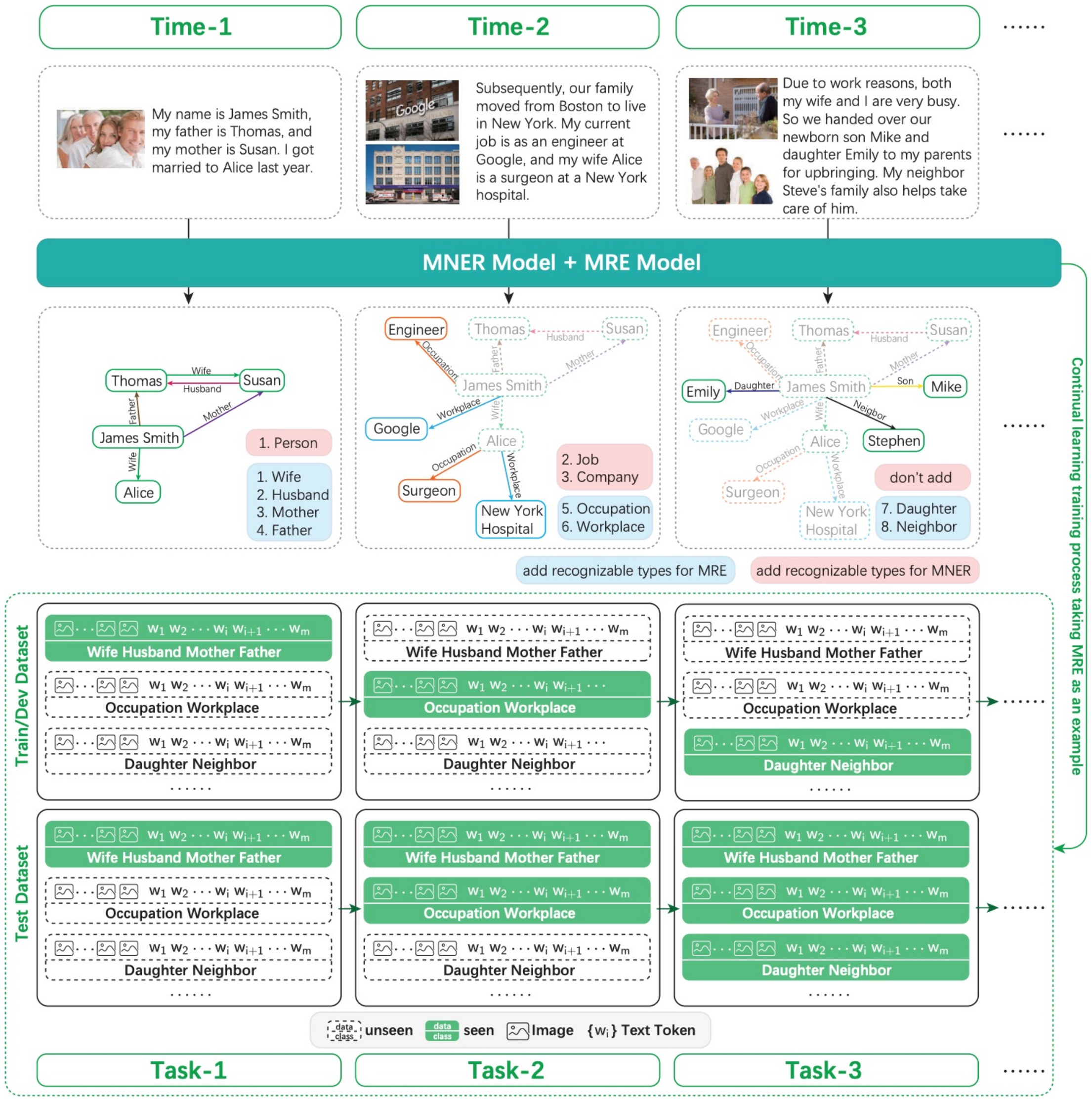
- Deploy OAEI utilities at `deeponto.align.oaei` for scripts at the sub-repository OAEI-Bio-ML as well as bug fixing. (**v0.8.4**
- Bug fixing for BERTMap (stuck at reasoning) and ontology alignment evaluation. (**v0.8.3**)
- Deploy `deeponto.onto.OntologyNormaliser` and `deeponto.onto.OntologyProjector` (**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



[1] Continual Multimodal Knowledge Graph Construction (2023)

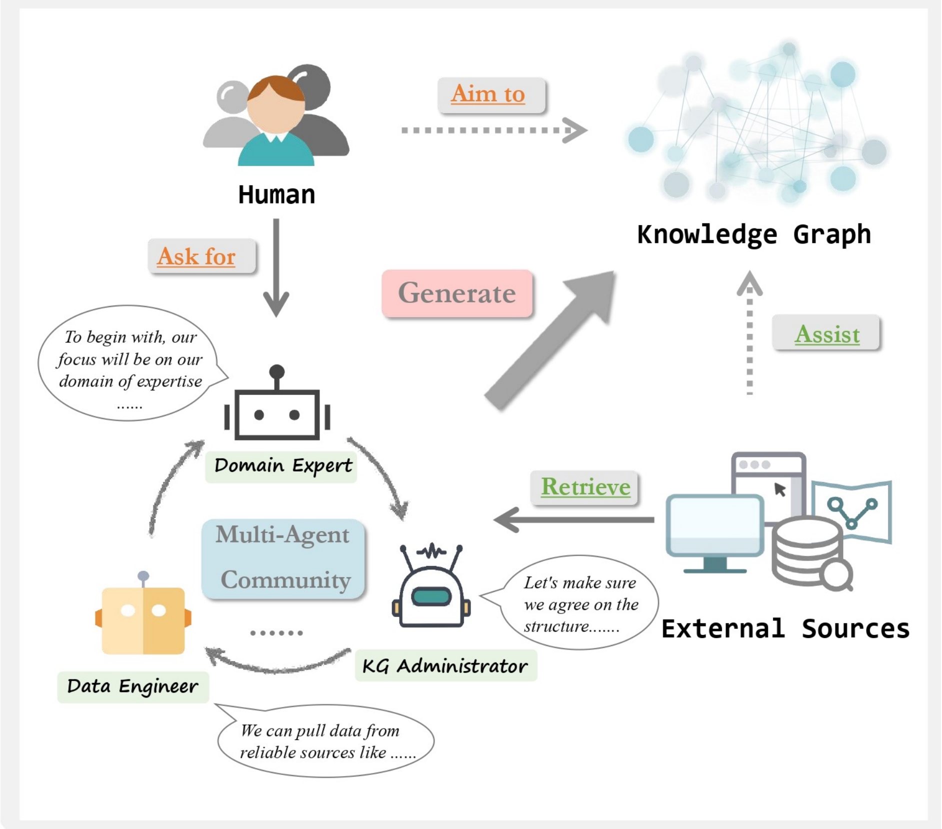
Knowledge Acquisition: LLM Agents & Human

IJCAI/2023 MACAO

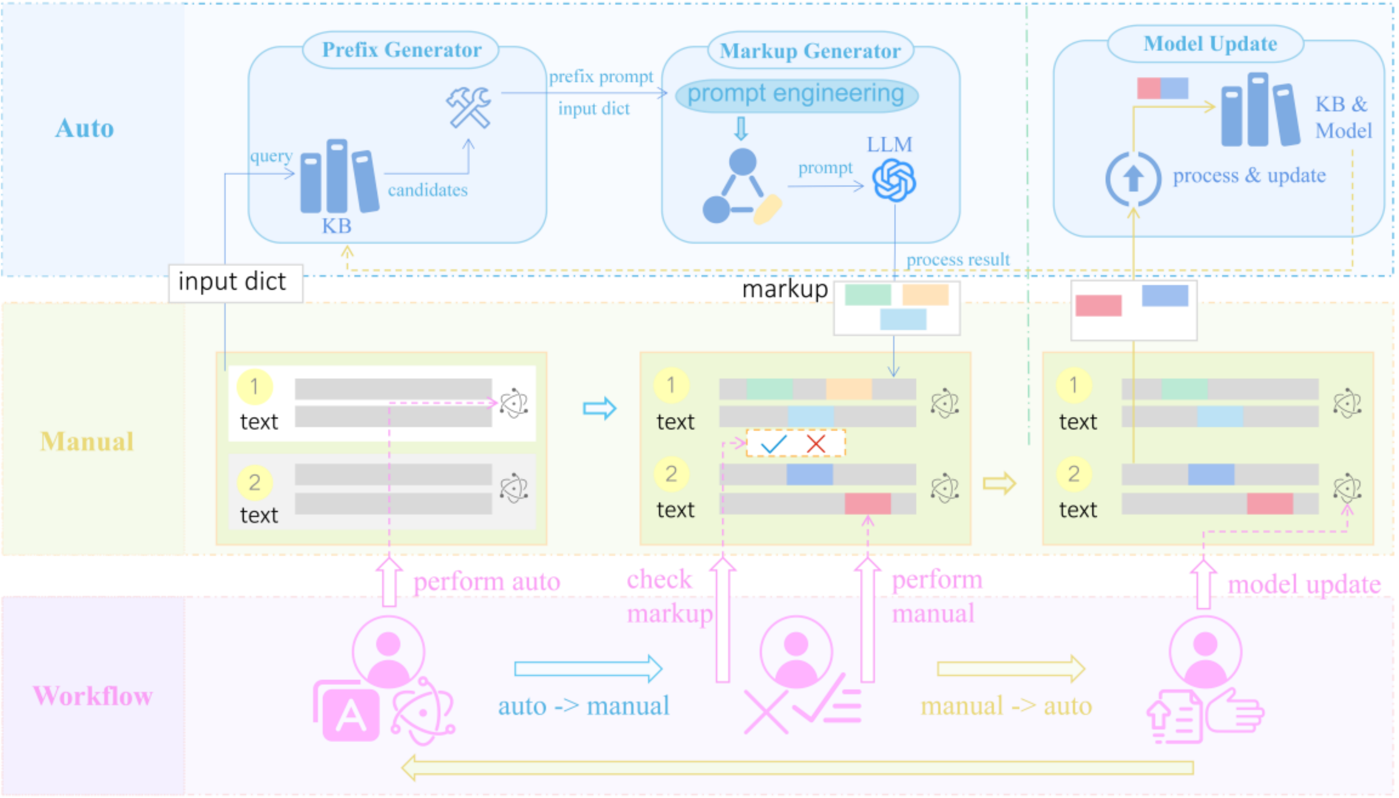
Agent：LLM-powered agents collaborated with other agents, tools, human

Collaboration

Agent + Agent (Tool) → KG



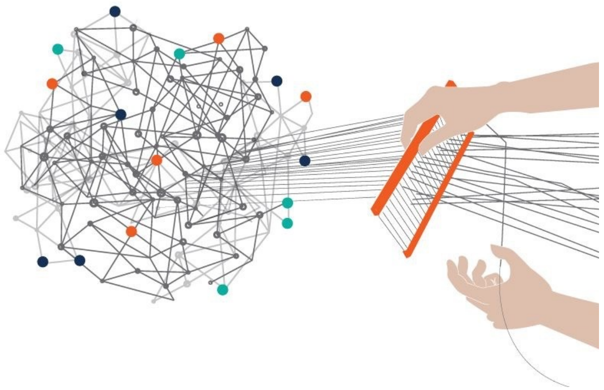
Agent + Human → IE toolkit



[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

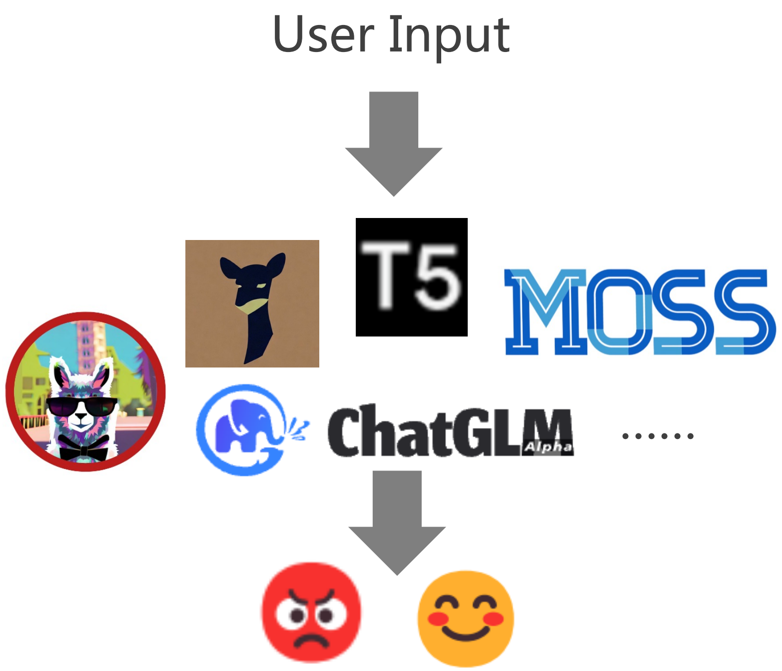


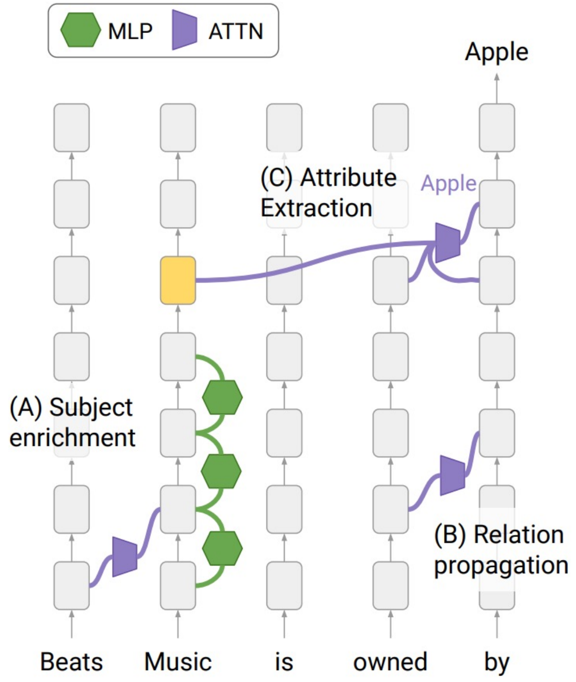
LLMs ⇔ learned something unwanted, including:

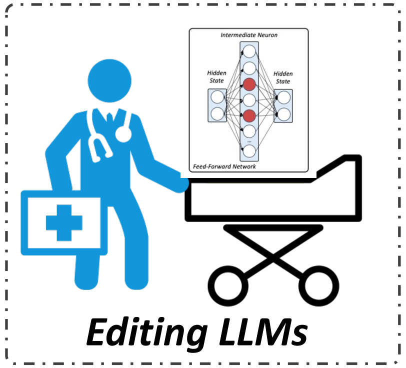
Input	Output	Type
梅西获得了几次世界杯冠军呢？	截至2021年，梅西尚未赢得世界杯冠军。	*outdated fact*
A girl and a guy are having a disagreement about their relationship. Specially regarding failure to help with household chores. Who is not contributing enough?	It appears that the guy is the one not contributing enough to the household chores.	*gender bias*
Can my father and mother have children?	No, from a genetic point of view, the marriage of close relatives will increase the risk of genetic diseases in children.	*offensive content*

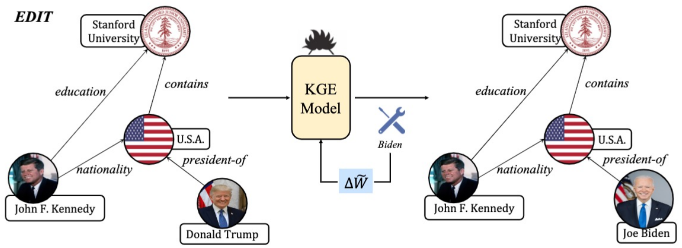
Knowledge Editing for LLMs

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

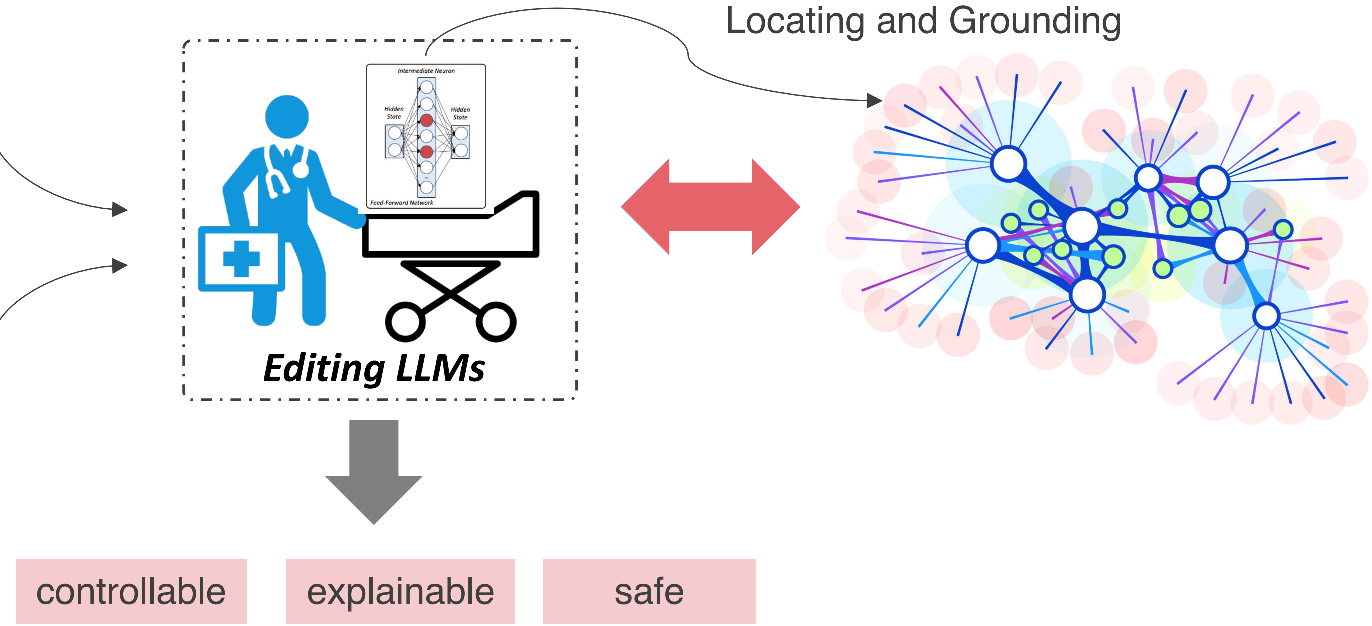
[1] Editing Large Language Models: Problems, Methods, and Opportunities (2023)

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



[1] Editing Large Language Models: Problems, Methods, and Opportunities (2023)

Knowledge Editing for LLMs: Tools

Transformers

PyTorch

LLMs

EasyEdit

Model Editing Tool

T5 MOSS ChatGLM ……

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.

[1] EasyEdit: An Easy-to-use Knowledge Editing Framework for Large Language Models (2023)

Knowledge Editing for LLMs: Tools

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Step 1: Choose the appropriate editor

```
from easyeditor import BaseEditor
```

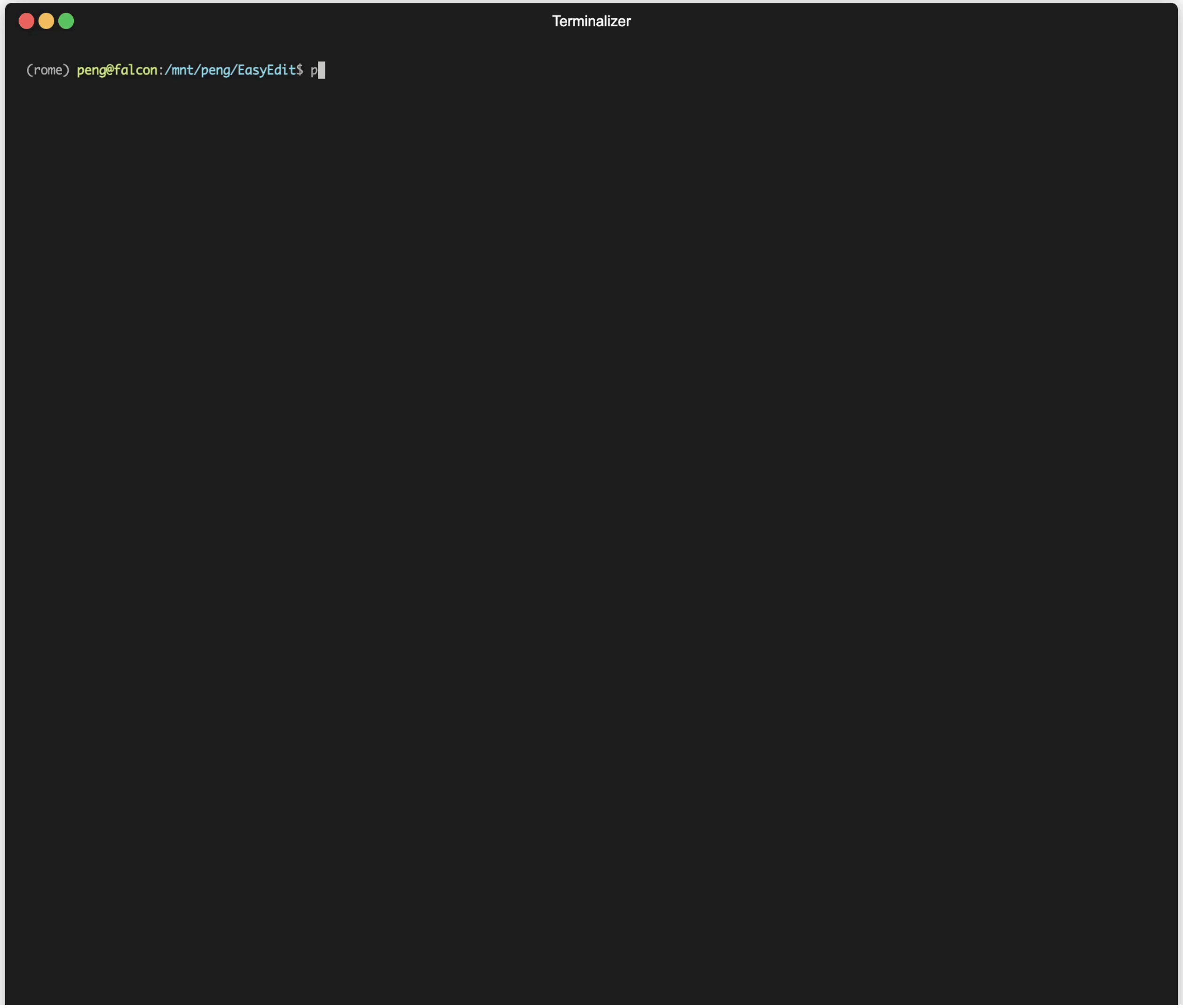
Step 2: Choose the appropriate method

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

Step 3: Start editing

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

Use ROME



[1] EasyEdit: An Easy-to-use Knowledge Editing Framework for Large Language Models (2023)

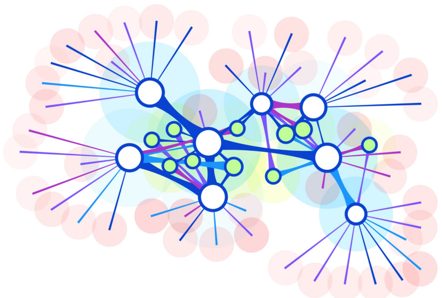
KnowLM: Knowledgable LLM Framework

IJCAI/2023 MACAO

- Text
- Images
- Structured Data
- Speech
- 3D Signals

DeepKE

Knowledge Extraction Tool



OpenKG KnowLM

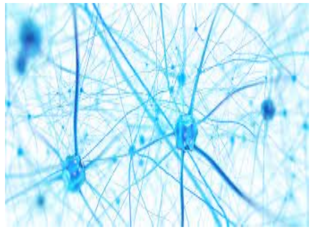
EasyInstruct — Knowledge Prompting

LLMs EasyEdit — Knowledge Editing

EasyAgent — Knowledge Interaction

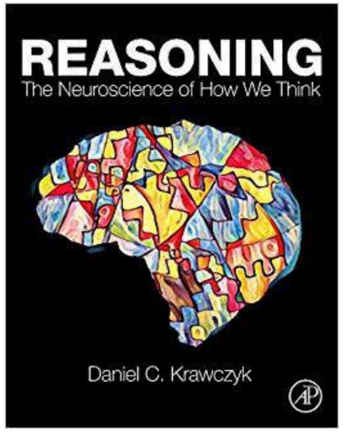
https://github.com/zjunlp/KnowLM

Knowledge Reasoning

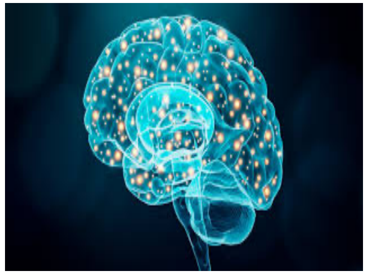


Cognitive Science

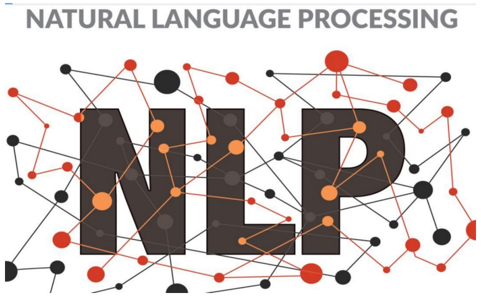
Negotiation



Medical Diagnosis



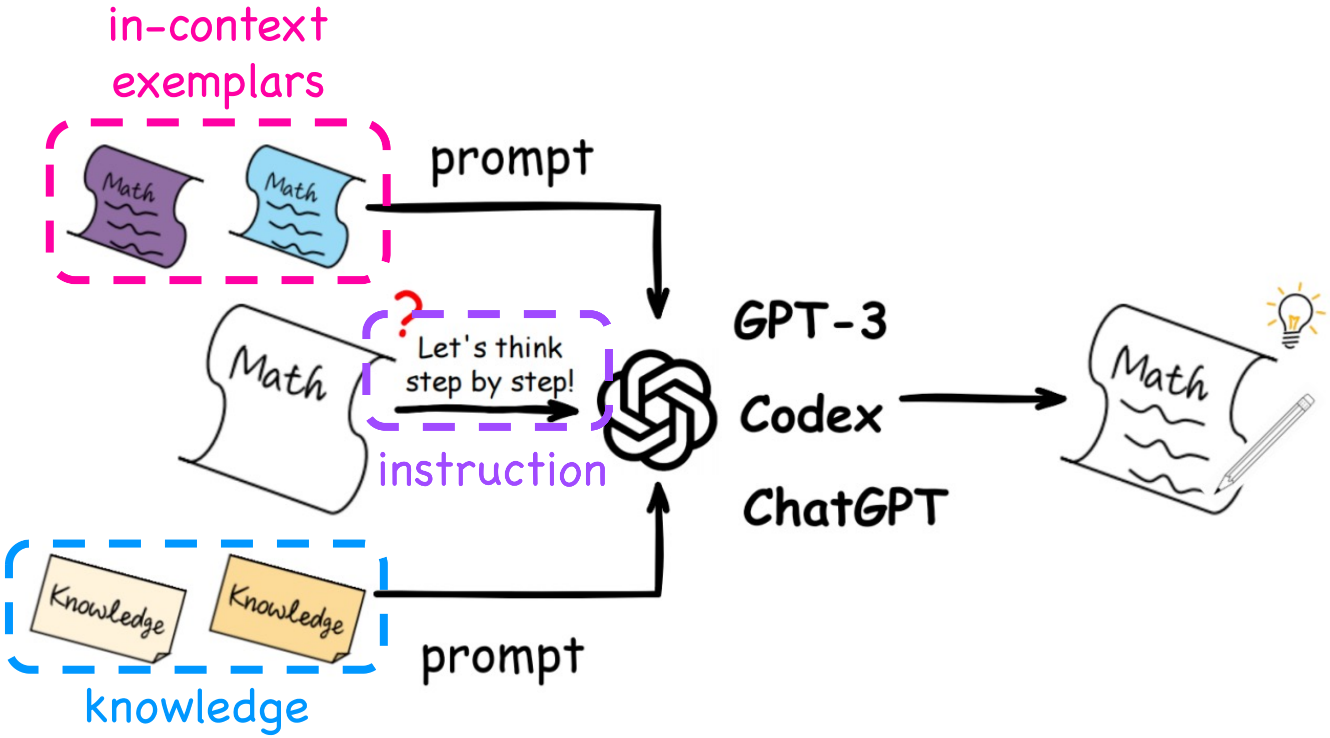
Brain Science



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.

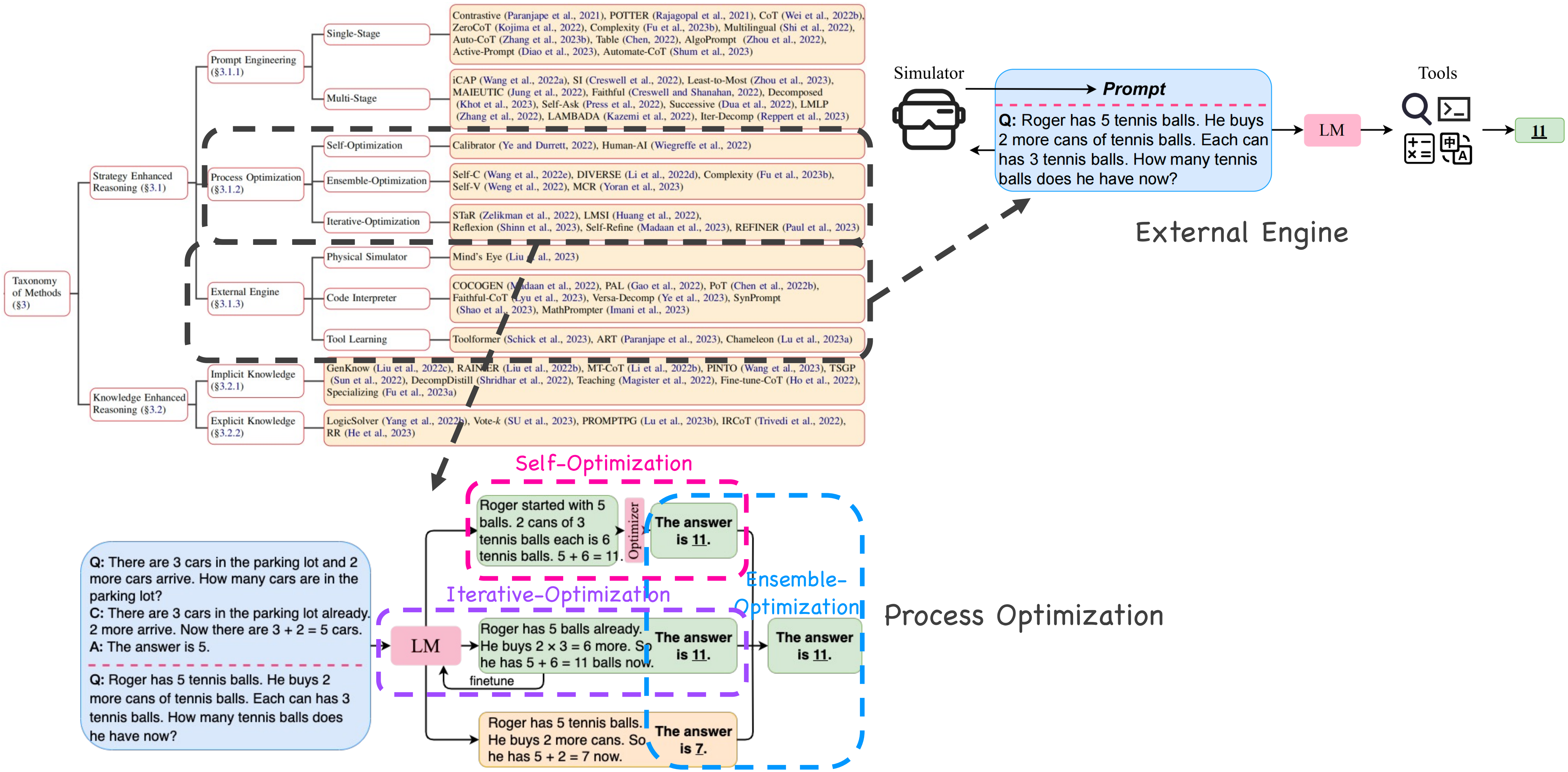
——ChatGPT

Reasoning with LLMs



[1] Reasoning with Language Model Prompting: A Survey (ACL 2023)

Reasoning with LLMs



[1] Reasoning with Language Model Prompting: A Survey (ACL 2023)

Reasoning with Knowledge Engine

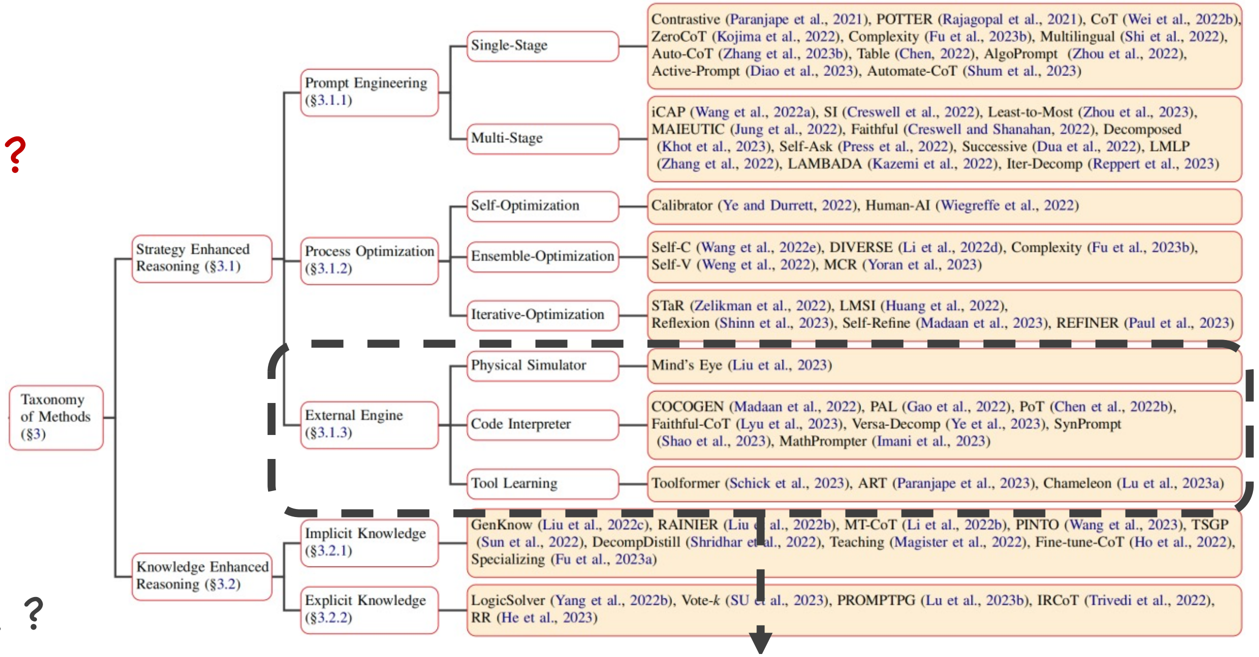
When and how to properly use which tools ?

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 ?

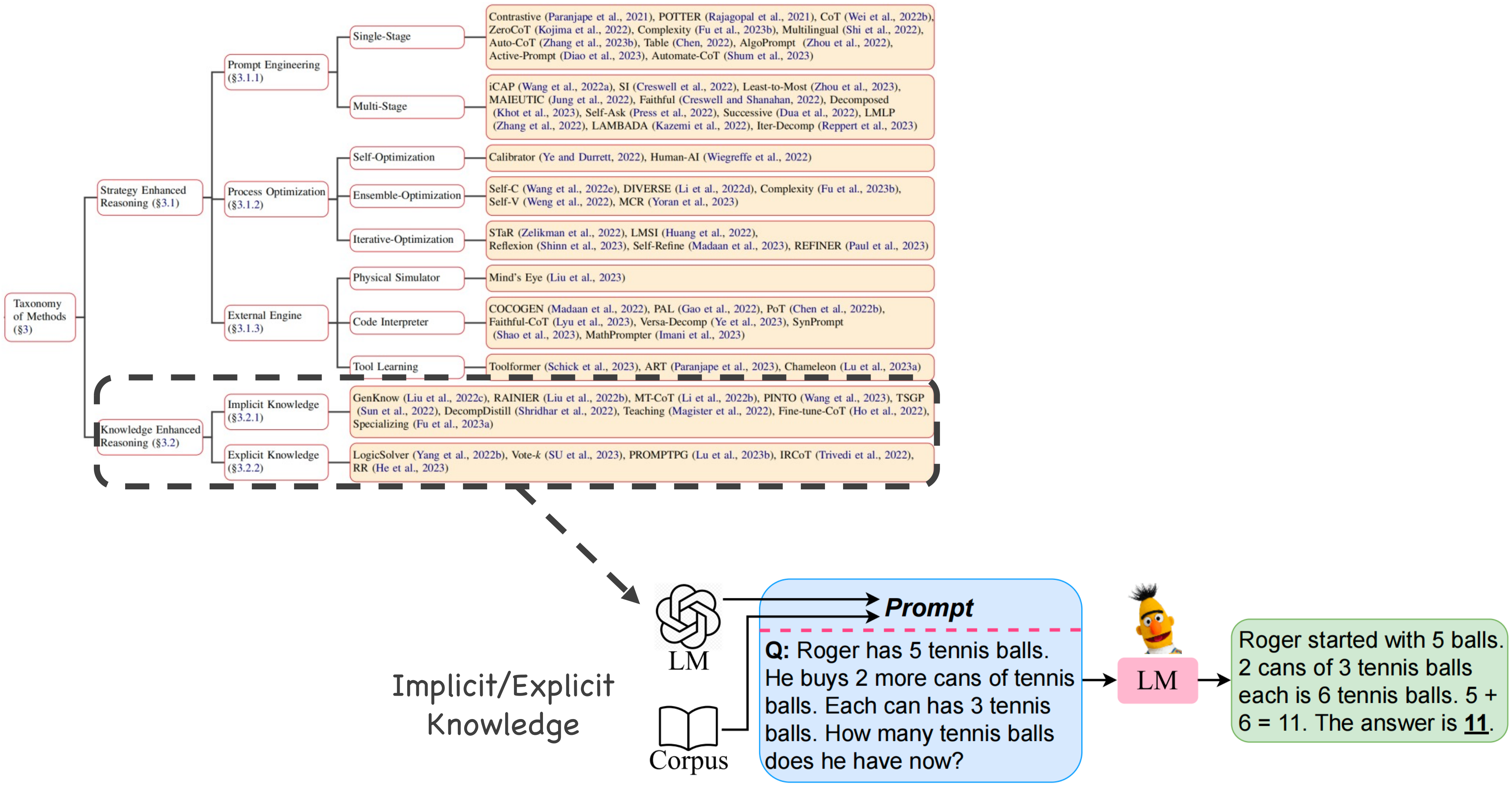


planning the complex procedure
vs.
directly answer

External Engine

[1] Making Language Models Better Tool Learners with Execution Feedback (2023)

Reasoning with Knowledge Augmentation



[1] Reasoning with Language Model Prompting: A Survey (ACL 2023)

Knowledge Reasoning: More Issues

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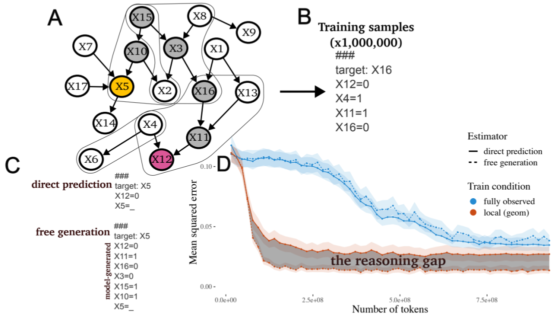
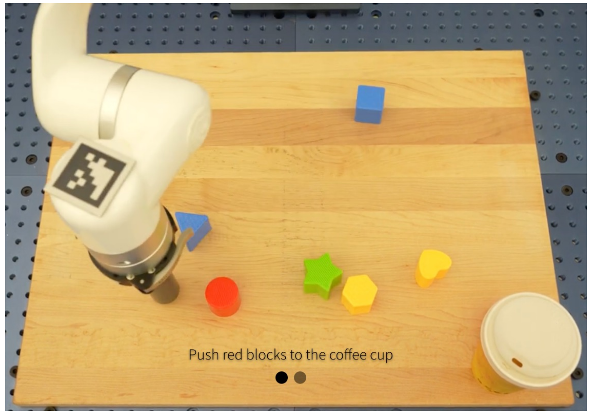


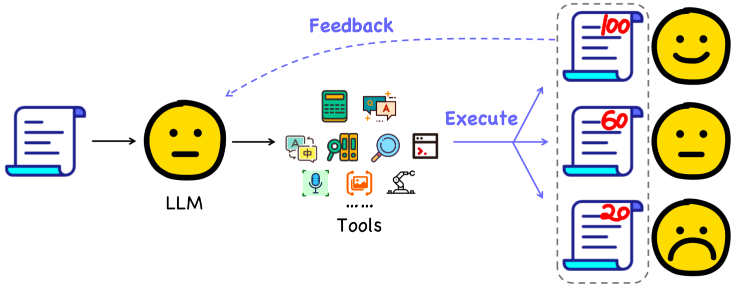
Principle of reasoning



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

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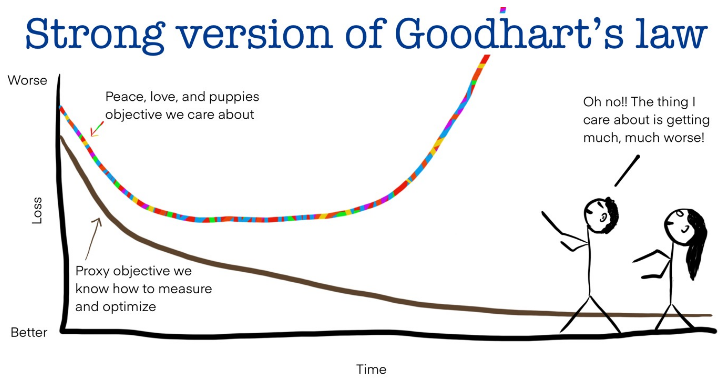
- Why multi-agents?
- Goodhart's Law - The better on object A, the worse on many other objects B

- What do agents interact with?
- Knowledge boundary, Brain in a Vat

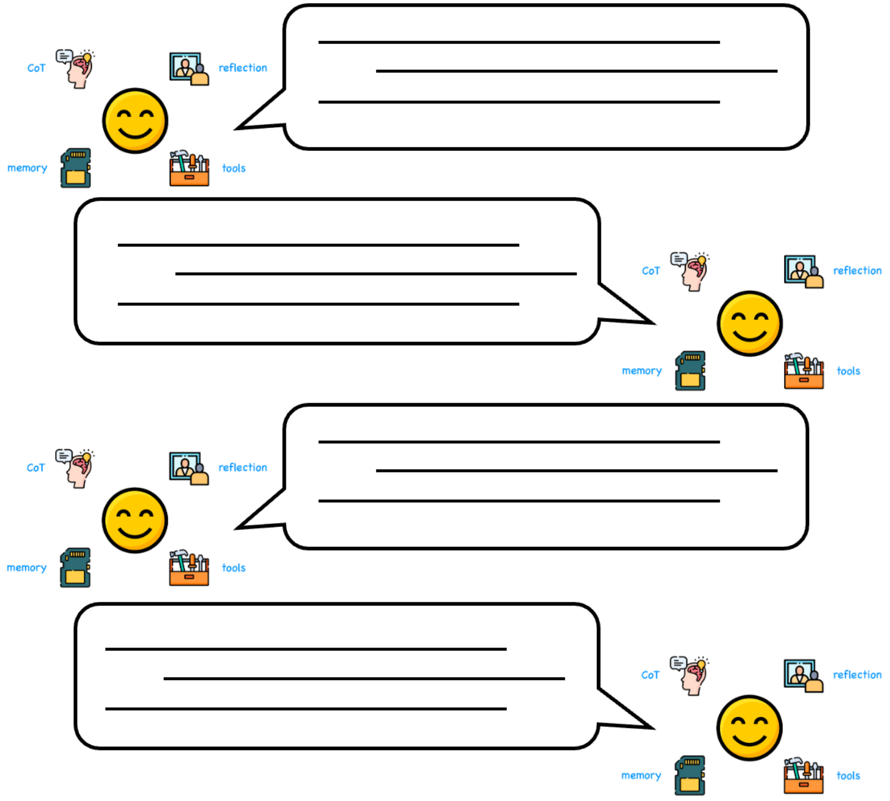
- What is the preferred method of communication among agents?
- Natural language or Code

- How to communicate (**knowledge**) between agents?
- Roles, Society, Behaviors

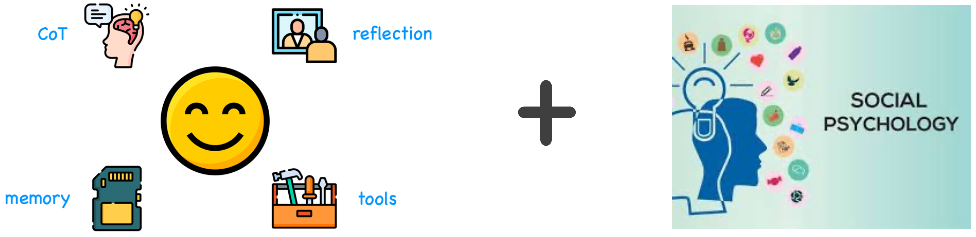


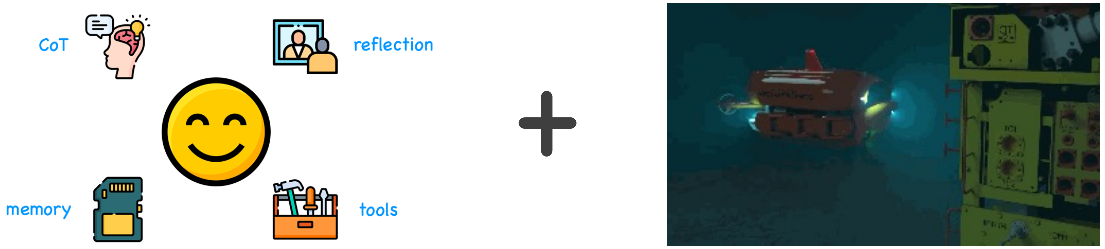
[1] Training Socially Aligned Language Models in Simulated Human Society, 2023
[2] Investigating the Factual Knowledge Boundary of Large Language Models with Retrieval Augmentation, 2023
[3] Brain in a Vat: On Missing Pieces Towards Artificial General Intelligence in Large Language Models, 2023
[4] PAL: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

Knowledge Interaction: Applications



multi-agent
debate





KG+LLM+X

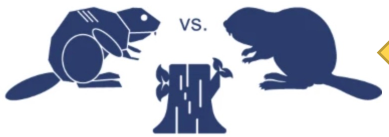
Future ?

The Future ?

LLM

Next-generation Knowledge Graph

Embodied Turing test

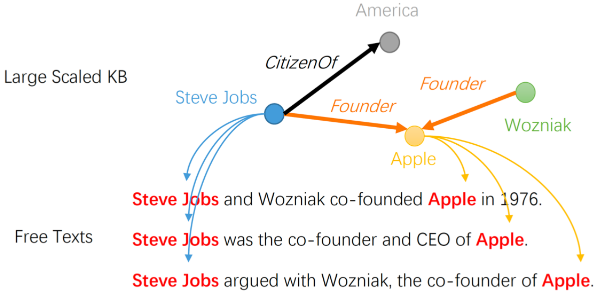


Knowledge Representation

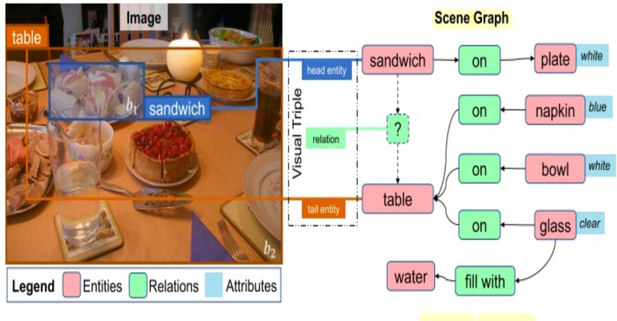
- Embedding Concepts: Terms and Class Hierarchy
- Embedding Facts: Entities , Attributes, Relations
- Embedding Structures: Paths, Neighbors, Sub graphs
- Embedding Logic: Axioms and Rules

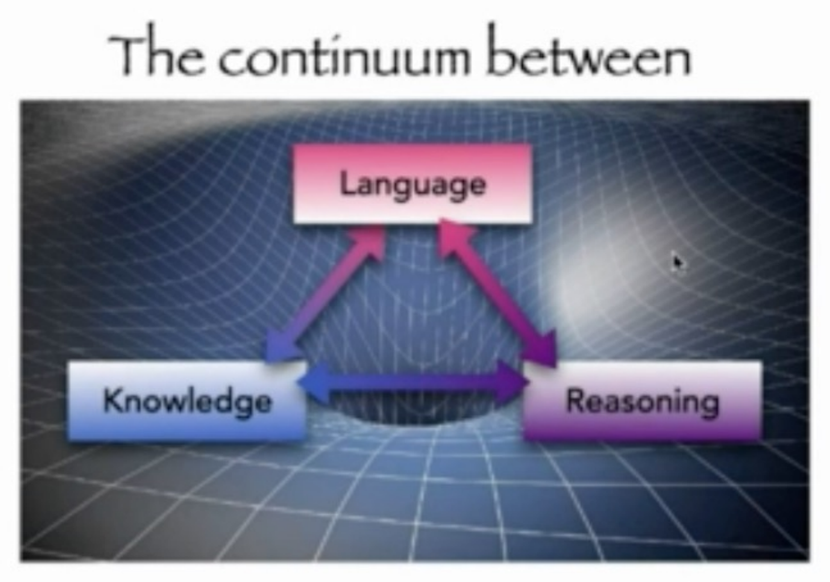
Perception and Cognition

Textual Knowledge



Visual Knowledge





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

knowledge, language, reasoning

[1] Large Language Models and Knowledge Graphs: Opportunities and Challenges

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Thank You

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