中国人民大學
RENMIN UNIVERSITY OF CHINA

Knowledge Graph Question Answering

Jing Zhang

Renmin University of China

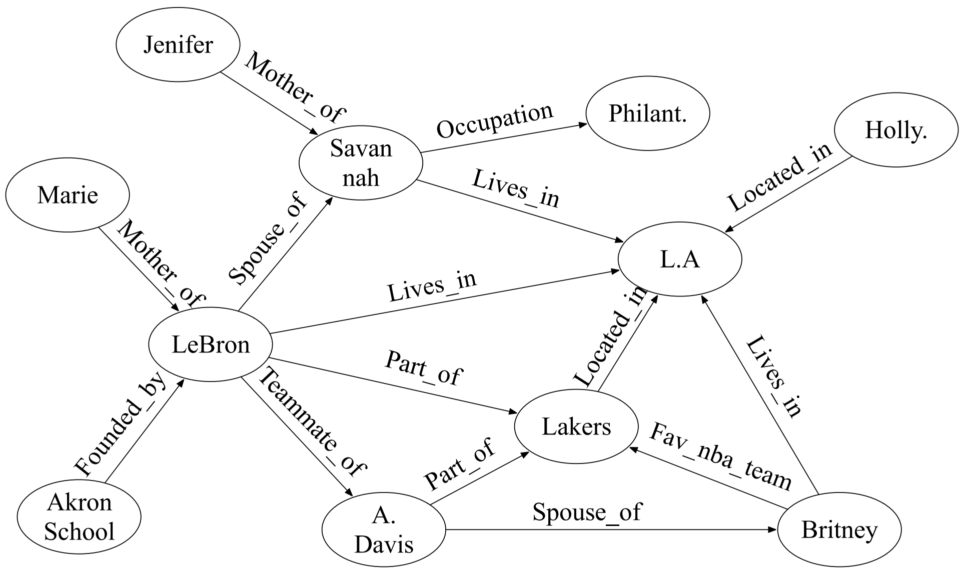
Collaborated with Yu Feng, Xiaokang Zhang, Lingxi Zhang (RUC)

Jifan Yu, Shulin Cao, Jie Tang, Juanzi Li (THU), Jian Tang (Mila)

Background of KGQA

Knowledge Graph Question Answering

- Deduce entities on KGs as the answers to the given query.
- A query is a textural question (knowledge graph question answering, KGQA).



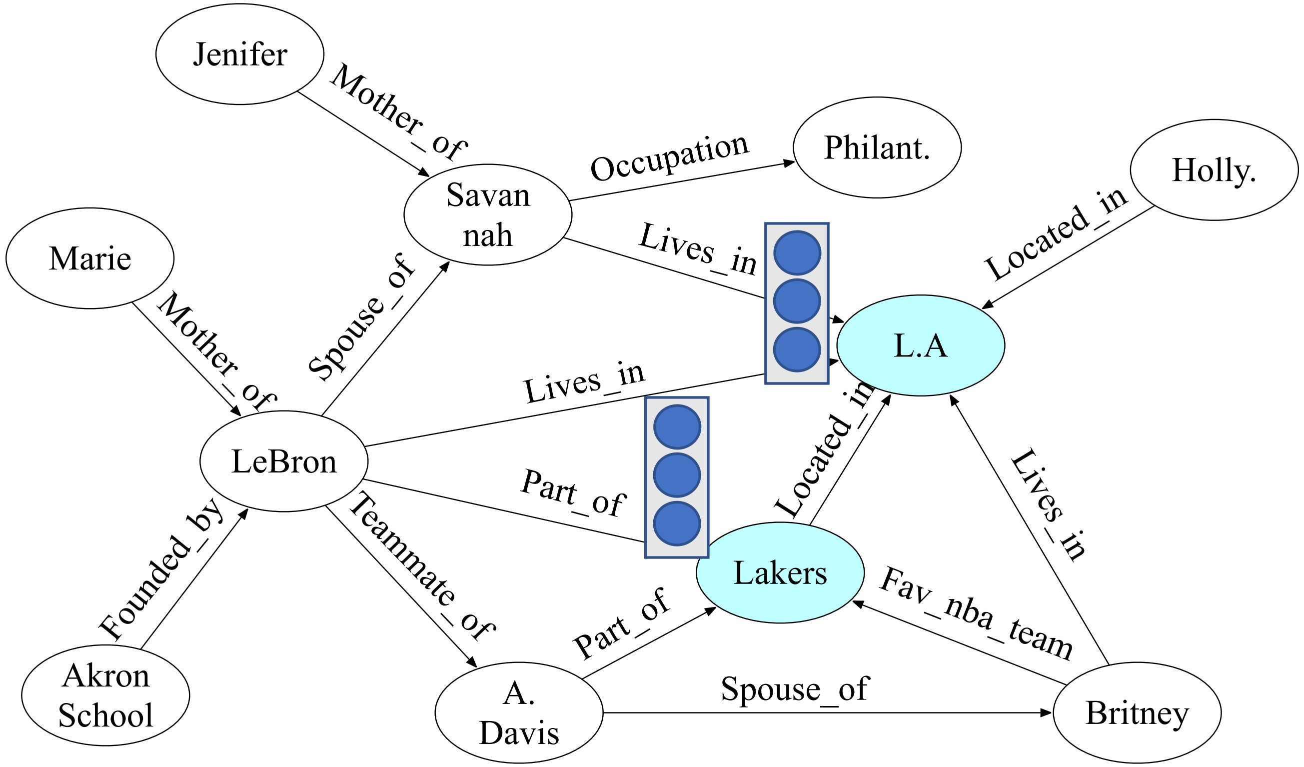
Textual question: Where do the spouses of the team members of Lakers usually live?

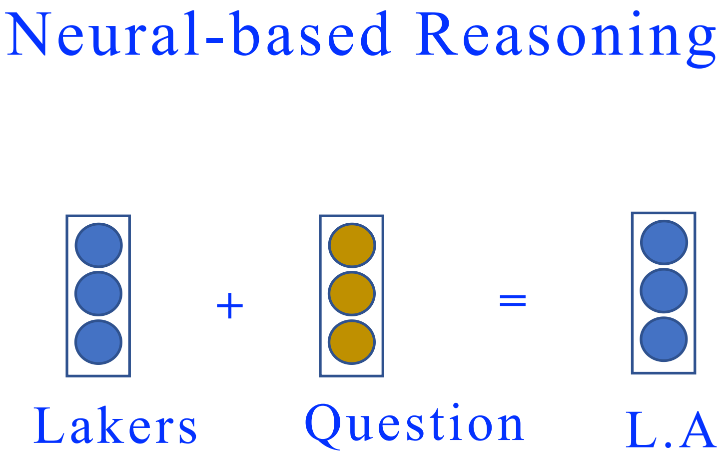
Answer: L.A

Why KGQA

- Structural and semantic data
  - Can provide more precise answer
    - unit, multiple answers, temporal
  - Can support complex logic operators
    - min/max, larger/smaller, equal, and, or, difference
  - Can enable reasoning more easily
    - Spouse_of(z,w) $\wedge$ Lives_in (w,y) $\rightarrow$ Lives_in(z,y)

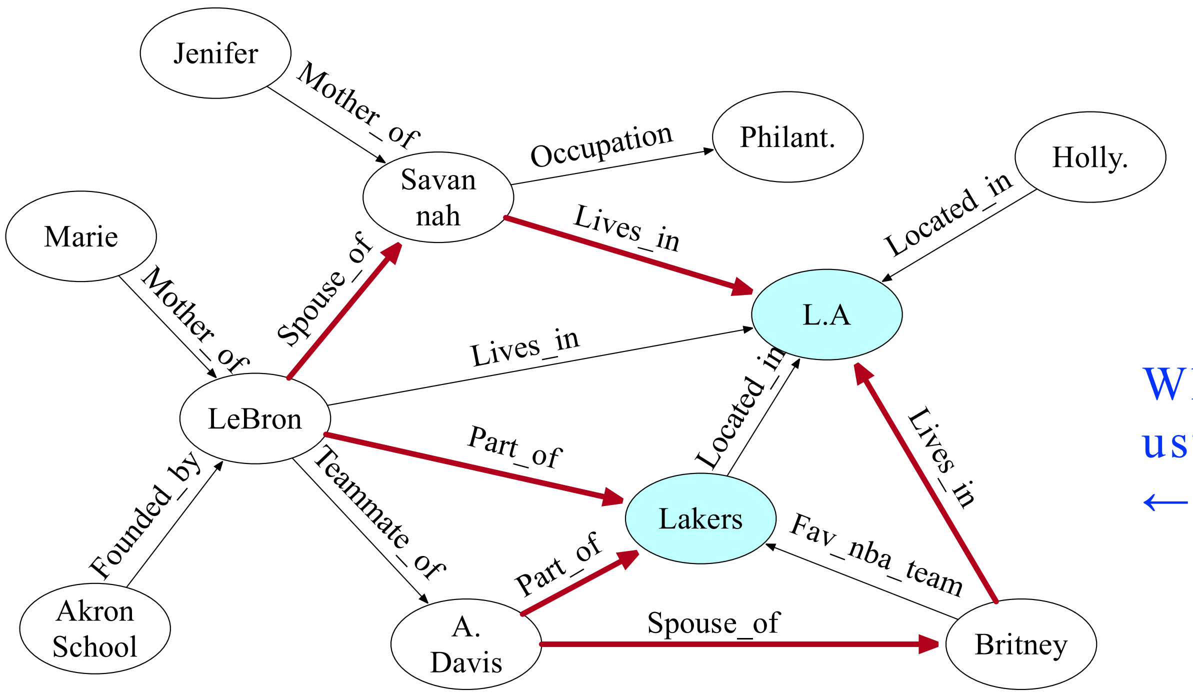
Neural-based KGQA Reasoning





Textual question: Where do the spouses of the team members of Lakers usually live? Reasoning result: L.A

Symbolic-based KGQA Reasoning



Symbolic-based Reasoning

Where do the spouses of the team members of x usually live?
←Part_of(x,z) ∧ Spouse_of(z,w) ∧ Lives_in (w,y)

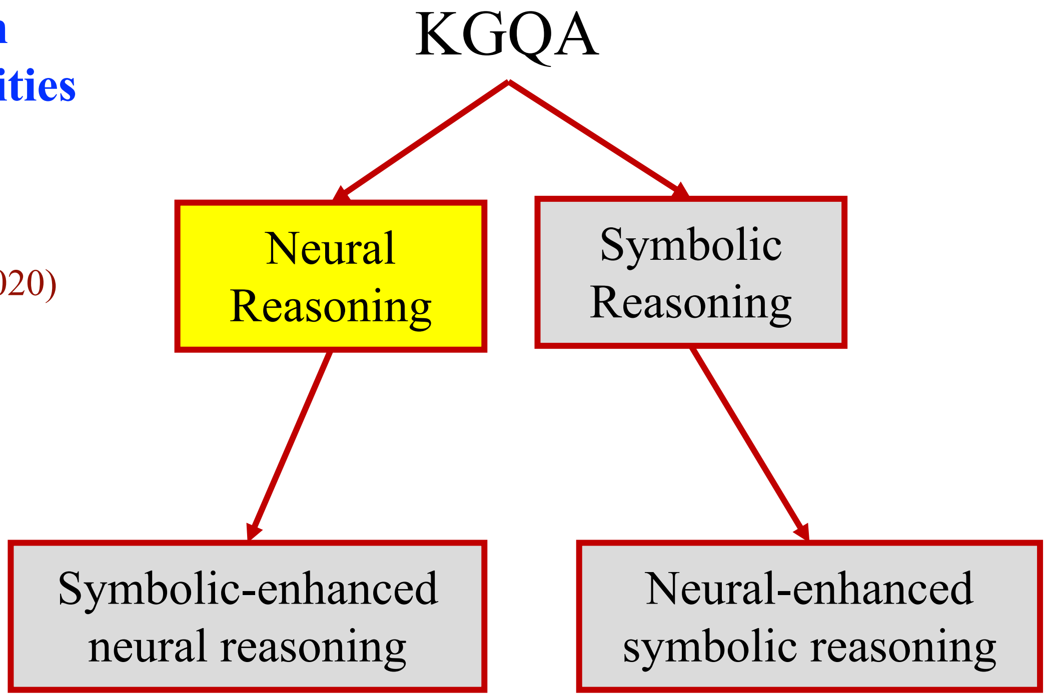
Textual question: Where do the spouses of the team members of Lakers usually live?
Reasoning result: L.A

Neural-Symbolic KGQA

Bridge the gap between question and KB's entities

Multi-hop relation

BAMnet (Chen et al. 2019)
EmbedKGQA (Saxena et al., 2020)
KV-MemNNs (Xu et al., 2021)



Question types

Single-relation	Multi-hop relation	Complex-logic	Constraints

Neural-Symbolic KGQA

Bridge the gap between question and KB's entities

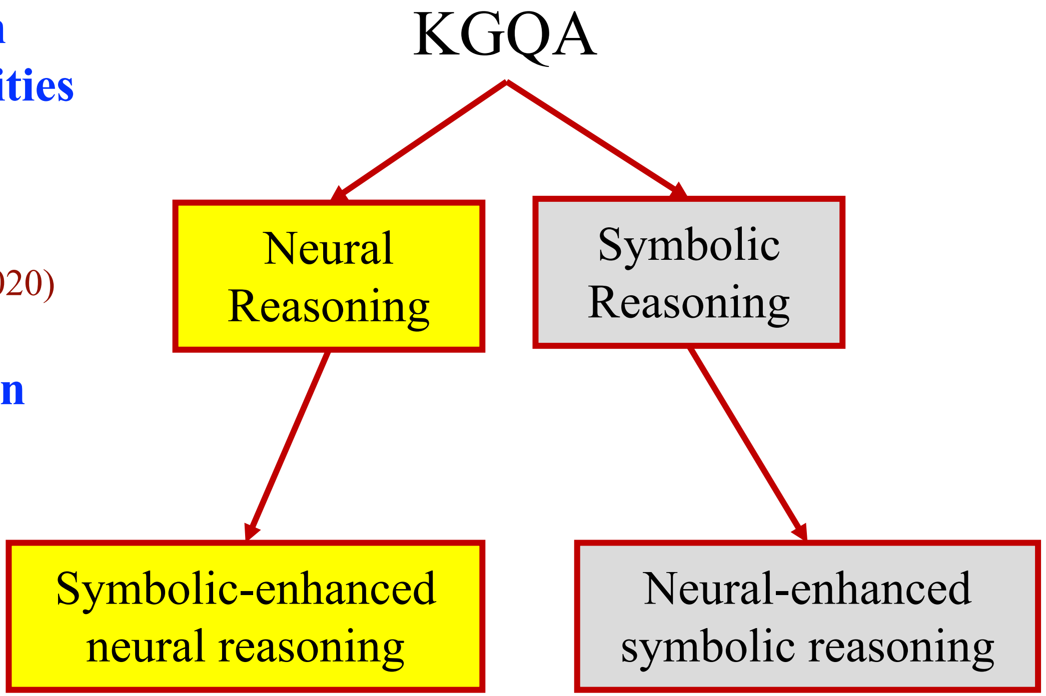
Multi-hop relation

BAMnet (Chen et al. 2019)
EmbedKGQA (Saxena et al., 2020)
KV-MemNNs (Xu et al., 2021)

Define NN for logic operation

Complex logic

GQE (Hamilton et al., 2018) :
Intersection
Query2Box (Ren et al., 2020) :
Intersection, Union
EMQL (Sun et al, 2020):
Intersection, Union
LEGO (Ren et al, 2021),
Parse query tree and embedding update simultaneously



Question types: Single-relation | Multi-hop relation | Complex-logic | Constraints

Neural-Symbolic KGQA

Bridge the gap between question and KB's entities

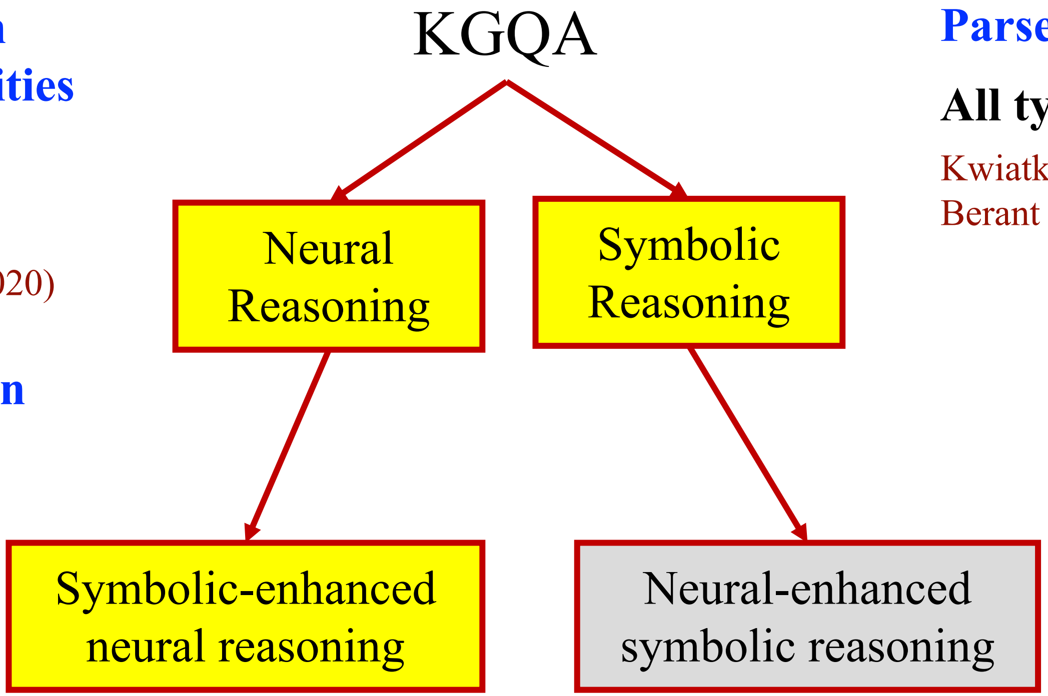
Multi-hop relation

BAMnet (Chen et al. 2019)
EmbedKGQA (Saxena et al., 2020)
KV-MemNNs (Xu et al., 2021)

Define NN for logic operation

Complex logic

GQE (Hamilton et al., 2018) :
Intersection
Query2Box (Ren et al., 2020) :
Intersection, Union
EMQL (Sun et al, 2020):
Intersection, Union
LEGO (Ren et al, 2021),
Parse query tree and embedding update simultaneously



Parse questions into logic expression

All types

Kwiatkowksi et al. 2010
Berant et al., 2014

Question types: Single-relation | Multi-hop relation | Complex-logic | Constraints

Neural-Symbolic KGQA

Bridge the gap between question and KB's entities

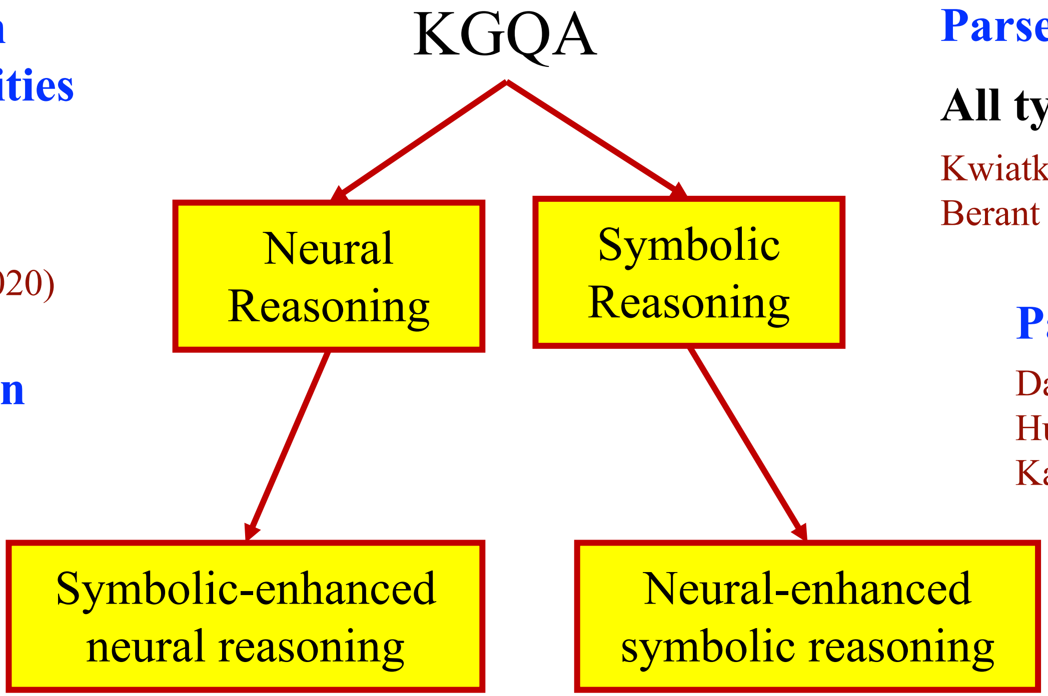
Multi-hop relation

BAMnet (Chen et al. 2019)
EmbedKGQA (Saxena et al., 2020)
KV-MemNNs (Xu et al., 2021)

Define NN for logic operation

Complex logic

GQE (Hamilton et al., 2018) :
Intersection
Query2Box (Ren et al., 2020) :
Intersection, Union
EMQL (Sun et al, 2020):
Intersection, Union
LEGO (Ren et al, 2021),
Parse query tree and embedding update simultaneously



Parse questions into logic expression

All types

Kwiatkowksi et al. 2010
Berant et al., 2014

Parse and execute **All types**

Das et al., 2021 Seq2seq
Huang et al., 2021 Seq2seq
Kapanipathi, 2021 AMR->Query Graph ->SPARQL

Question types: Single-relation | Multi-hop relation | Complex-logic | Constraints

Neural-Symbolic KGQA

KGQA

Neural Reasoning

Symbolic Reasoning

Symbolic-enhanced neural reasoning

Neural-enhanced symbolic reasoning

Bridge the gap between question and KB's entities

Multi-hop relation

BAMnet (Chen et al. 2019)
EmbedKGQA (Saxena et al., 2020)
KV-MemNNs (Xu et al., 2021)

Define NN for logic operation

Complex logic

GQE (Hamilton et al., 2018) :
Intersection
Query2Box (Ren et al., 2020) :
Intersection, Union
EMQL (Sun et al, 2020):
Intersection, Union
LEGO (Ren et al, 2021),
Parse query tree and embedding update simultaneously

Parse questions into logic expression

All types

Kwiatkowksi et al. 2010
Berant et al., 2014

Parse and execute **All types**

Das et al., 2021 Seq2seq
Huang et al., 2021 Seq2seq
Kapanipathi, 2021 AMR->Query Graph ->SPARQL

End-to-End

Multi-hop

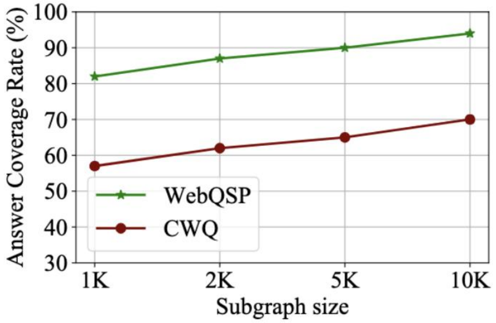
Path-based
IRN (Zhou et al., 2018)
SRN (Qiu et al., 2020)
Graph-based
Graft-net (Sun et al., 2018)
PullNet (Sun et al., 2019)
NSM (He et al., 2021)
Enhance intermediate supervision
Qin et al., 2021
First query relation subgraph, then rank instantiated subgraphs

Question types

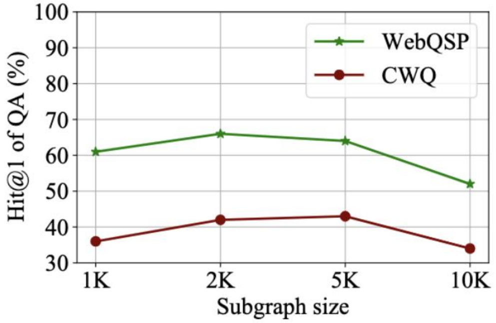
Single-relation	Multi-hop relation	Complex-logic	Constraints

Challenges of End-to-End KGQA

Evidence is inadequate



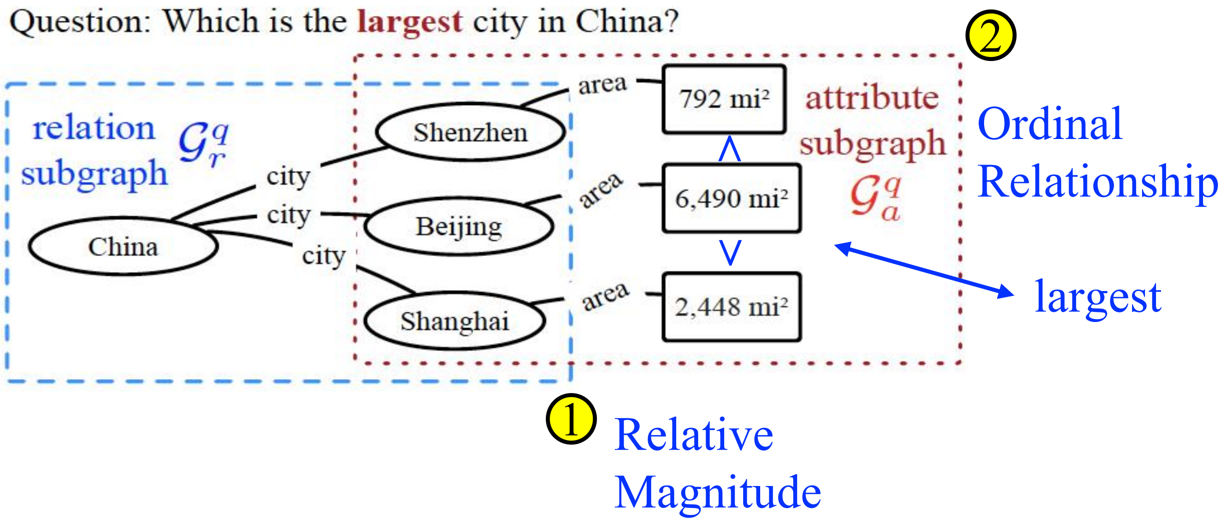
(a) Answer Coverage Rate



(b) Hits@1 of QA

- A small subgraph might exclude the answer.
- A large one might introduce noises.

Complex questions



- Cannot address the ordinal constraints.

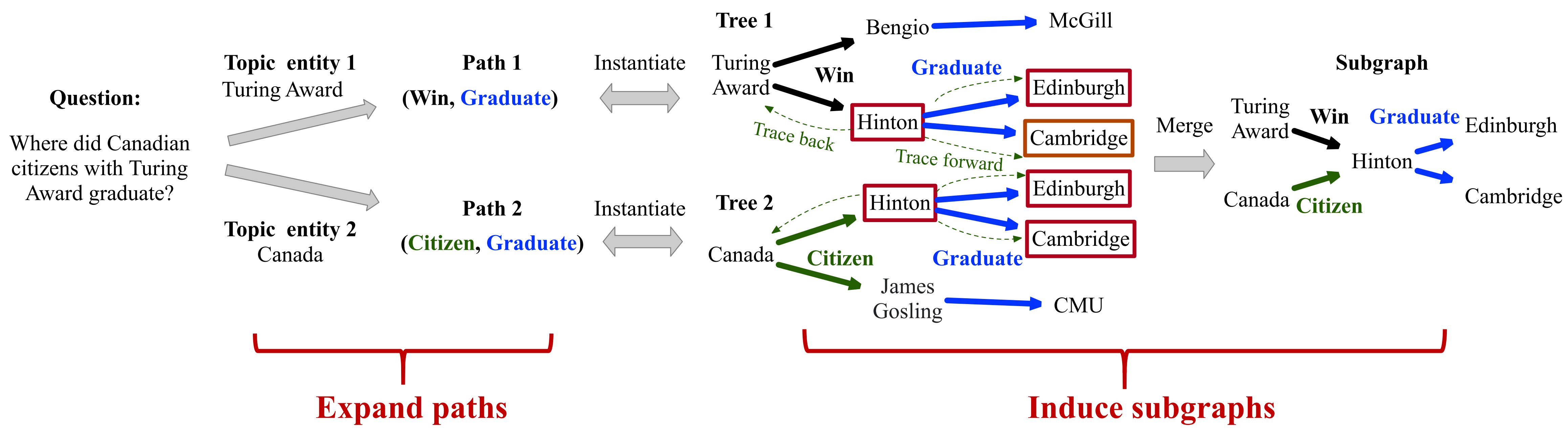
Our Work
- From End-to-End to Retriever-Reasoner

Subgraph Retriever → Subgraph Reasoner

Enhance evidence

Enhance numerical reasoning

Trainable Subgraph Retrieval



Dual encoder: $s(q,r) = f(q)^\top h(r)$

Merge the same entities in different subgraph.

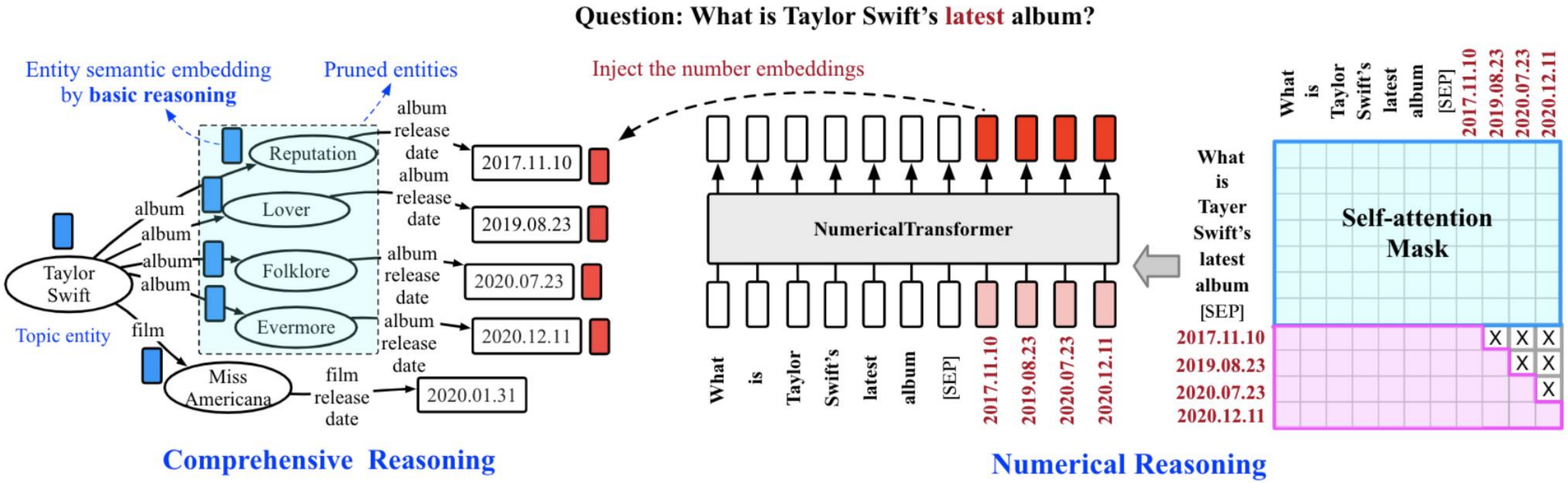
Question update: $f(q^{(t)}) = \text{RoBERTa}([q; r_1; \cdots; r_t])$

Path end: $p(r|q^{(t)}) = \dfrac{1}{1 + \exp\left(s(q^{(t)}, r) - s(q^{(t)}, \text{END})\right)}$

Zhang et al. Subgraph Retrieval Enhanced Model for Multi-hop Knowledge Base Question Answering. ACL 2022

Enhance Numerical Reasoning

- Preserve the relative magnitude of numbers 1≺2≺3
- Learn the ordinal properties of numbers to make the embedding of 1 in 1≺2≺3 closer to ``smallest'' than 2 and 3



Feng et at. A Pretraining Numerical Reasoning Model for Ordinal Constrained Question Answering on Knowledge Base. EMNLP Findings 2021
Feng et al. Injecting Numerical Reasoning Skills into Knowledge Base Question Answering Models. TKDE second round

Challenges of Parse-and-Execute KGQA

Training Data

Question: locate politicians whose weight is less than 83.0?
Logical expression: (AND government.politician (lt people.person.weight_kg 83.0))
Question: heavyweight boxing classifies which boxers?
Logical expression: (AND sports.boxer (JOIN sports.boxer.weight_division m.02t3ww))

Compositional Test Set

Question: which boxer weighs the most?
Logical expression: (ARGMAX sports.boxer people.person.weight_kg)

- **Compositional Generalization**: knowledge is covered in the training set but the compositions of knowledge are unseen

Zero-shot Test Set

Question: the terminuses of antonito belong to what railway?
Logical expression: (AND rail.railway (JOIN rail.railway.terminuses m.01zsrrk))

- **Zero-shot Generalization**: knowledge is unseen in the training set

Our Work
- From Parser-and-Executor to Retriever-Parser-Executor

Retriever → **Parser** → **Executor**

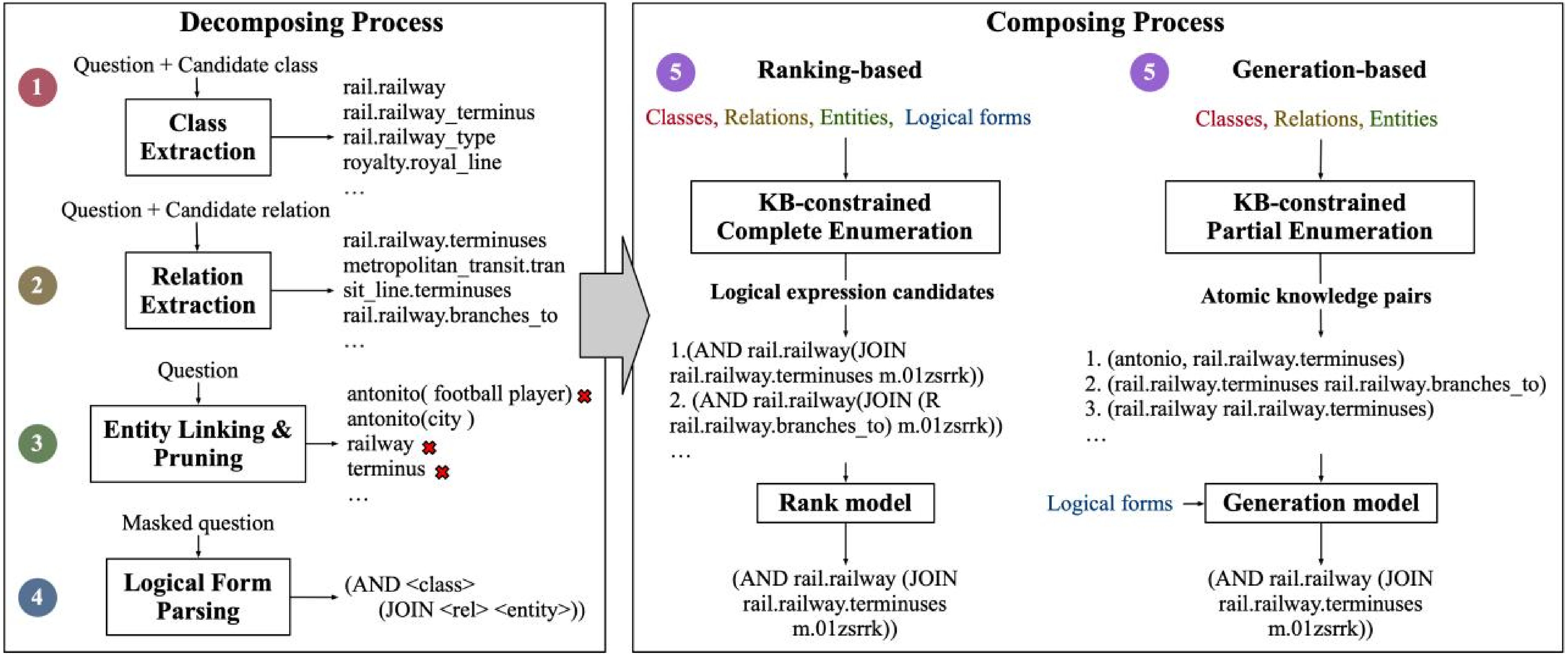
Decouple knowledge and logic form

Pairwise knowledge augmented parser

Model-oriented executor

DeCompose and Compose KGQA Framework

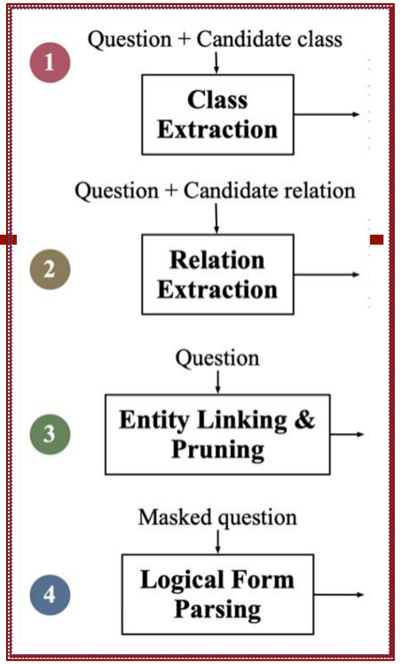
Question: The terminuses of Antonio belongs to what railway? **Target logical expression**: (AND rail.railway (JOIN rail.railway.terminuses m.01zsrrk))

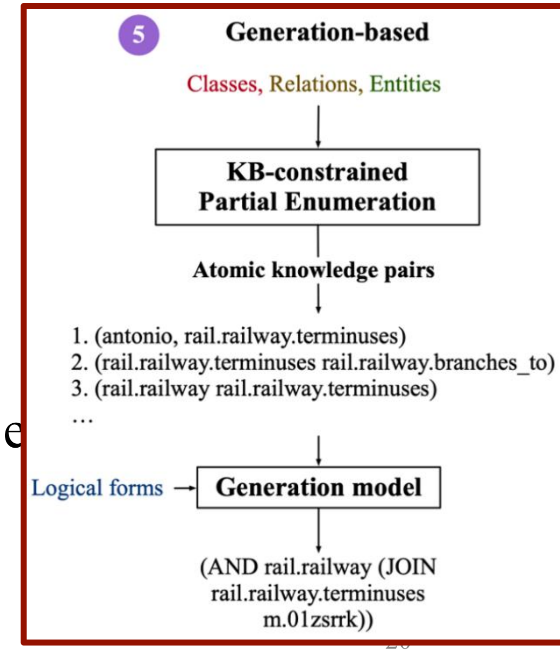


Zhang et al. DeCC : A Decompose-and-compose Framework for Knowledge Base Question Answering. Under review

Why Can DeCC Work

- ➢Question-related logical expressions contain
  - ➢KB-relevant atomic knowledge
  - ➢KB-irrelevant logical form.
- ➢DeCC retrieves atomic knowledge and logical form separately
  - ➢To keep the generalization ability
- ➢DeCC composes the pairwise knowledge
  - ➢To reduce the composition difficulty
  - ➢(entity, relation) e.g. (antonio, rail.railway.terminuses)
  - ➢(relation, relation) e.g. (rail.railway.terminuses, rail.railway.branche
  - ➢(class, relation) e.g. (rail.railway rail.railway.terminuses)





Experiment

	Overall		I.I.D.		Compositional		Zero-Shot	
	EM	F1	EM	F1	EM	F1	EM	F1
T5-base	22.7	23.4	61.8	64.1	28.3	29.0	0.3	0.3
RNG-KBQA	71.4	76.8	86.5	88.9	61.6	68.8	69.0	74.8
DeCC-Enumerate	71.7	74.3	78.7	80.3	62.0	65.4	72.7	75.3
DeCC-Rank	**77.5**	**83.1**	**88.3**	**91.1**	**67.8**	**76.3**	**76.8**	**82.5**
DeCC-Generate	75.2	80.5	87.9	90.6	63.5	71.9	74.6	79.8
–Knowledge	23.1	24.0	62.1	64.2	29.5	31.0	0.3	0.3
–Knowledge Pairs	53.6	55.6	70.2	72.3	44.0	46.0	50.3	52.2
–Logical Form	73.3	78.7	83.1	86.7	62.1	69.8	74.0	79.2

Both DeCC-Rank and DeCC -Generate achieve better performance than RNG-KBQA

Summary and Future Challenges

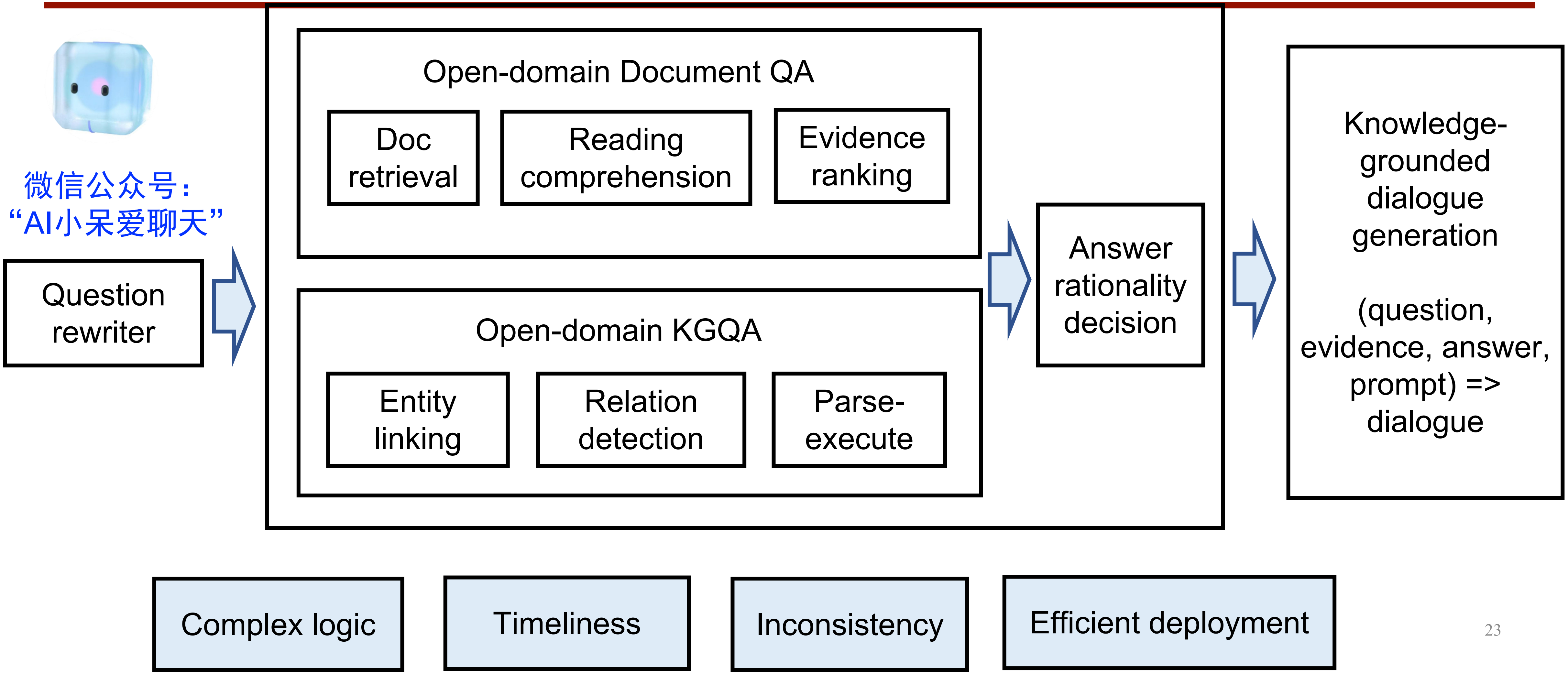
- Parse-and-Execute sounds more flexible to handle various questions

- Compositional generalization is still challenging
    - Logic form compositional generalization may also need to consider

- Zero-shot generalization is most challenging
    - Gap between token representation of natural language question and knowledge
    - Gap between structure representation of natural language question and knowledge

- KG is always incomplete, thus executor might not only rely on KG

Xiaodai: Knowledge-ground Dialogue System



Yu et al. XDAI: A Tuning-free Framework for Exploiting Pre-trained Language Models in Knowledge Grounded Dialogue Generation. KDD 2022

Thank You