Activity (or Process), State, and Event-based Knowledge Graphs

Yangqiu Song
Department of CSE, HKUST
Why Do We (Still) Need Knowledge Graphs in the Era of Deep Learning?

• Deep Learning for **System II** Processing, as proposed by Yoshua Bengio
  • We need to equip machine learning systems with “slow, logical, sequential, conscious, linguistic, algorithmic, planning, reasoning”
    • Particularly, such a system requires the “understanding of how actions” (including events and activities/processes) “interact with changes in distribution” which can be reflected by states.
    • Need “new priors to help systematic & OOD generalization”

• Language models need **sensory grounding** for meaning and understanding, as argued by Yann LeCun

• Multi-objective federated learning, proposed by Qiang Yang
  • One of the utility sources to make sure federation follows common sense

• Abductive learning, proposed by Zhihua Zhou
  • KB plays an important role to provide weak labels

https://wp.nyu.edu/consciousness/do-large-language-models-need-sensory-grounding-for-meaning-and-understanding/
Knowledge Graphs

• Many large-scale knowledge graphs about entities and their attributes (property-of) and relations (thousands of different predicates) have been developed since Google released its knowledge graph in 2012
  • Millions of entities and concepts
  • Billions of relationships

Are they enough to characterize our mental world?
Challenge 1: How to Grow a Mind? --Statistics, 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.”

• The ability of performing powerful abstraction is the key

The True Structure of Conceptualization

What you may think of

What it really likes

The nature of conceptual abstraction (aggregation of objects’ attributes) and the (dynamic) compositionality make the number of concepts grow vastly comparable to entities we have in the world.

E.g., mapping Tesla to a company, big company, IT company, AI company, high-tech company, automobile company, when comparing it with Google, Toyota, some small company, needs the right level of comparison.
ProBase (2011 at MSRA)

Probase is a large, universal, probabilistic knowledge base with an extremely large concept space.

Data are available at https://concept.research.microsoft.com/
Challenge 2: Knowledge Graph or More General Mind Graphs to Describe Mental World?

- What is our knowledge?
  - Knowledge is often defined as justified true belief

- What makes us take actions?
  - Beliefs and desires are mediated by intentions which in turn controls human’s actions (Kashima et al., 1998)

- Theory of Mind
  - Needs the reasoning about intents, feelings, mental states, and realities (actions or reactions) (Sap et al., 2022)

https://en.wikipedia.org/wiki/Knowledge
Jacob Andreas: Language Models as Agent Models. EMNLP (Findings) 2022: 5769-5779
Challenge 3: Primitive Semantic Units in Our Mind

- Semantic meaning in our language can be described as ‘a finite set of mental primitives and a finite set of principles of mental combination (Jackendoff, 1990)’.

- The primitive units of semantic meanings include
  - Thing (or Object),
  - Activity (or Process),
  - State,
  - Event,
  - Place,
  - Path,
  - Property,
  - Amount,
  - etc.

Activities and Events can also be Conceptualized

What activities do you find relaxing?

25 Calming Activities to Do in Your House

- Take a hot bath or shower.
- Lay down with your legs elevated and watch your breathing rise and fall.
- Doodle or color.
- Look out a window or let in fresh air.
- Have a warm drink without caffeine or alcohol.
- Engage in a visualization of a place that makes you feel safe.

More items... • 22 Mar 2020

https://www.psychologytoday.com/blog/friendship-20

25 Calming Activities to Do in Your House - Psychology Today

Search for: What activities do you find relaxing?

OutofStress
https://www.outofstress.com/things-stress-relief

86 Fun Activities To Relax and De-Stress

23 May 2022 — 65 deeply relaxing activities that you can do anywhere and anytime. … write about past events that have been on your mind.

Live Bold and Bloom
https://liveboldandbloom.com/self-improvement/re...

29 Relaxing Things To Do To DeStress And Recharge

16 Oct 2022 — 1. Read a book. 2. Take a hike. 3. Practice meditation. 4. Write something. 5. Listen to music. 6. Get a massage from a family member. 7. Play ...

20 ways to switch off the stress
8 Sept 2016

1. Sydney Float Centre 2. Hang upside down 3. Walk the Royal Na... 4. Get your shit toget... 5. Connect to counfr… 6. Take a bath at ...

Eventbrite
https://www.eventbrite.co.uk/blog/10-unusual-...}

Pre-Event Chill: 10 Best Ways to Relax When Traditional ...

pro-activ.com
https://www.pro-activ.com/.../Active Lifestyle

How to relieve stress: 10 fun & relaxing activities - Pro-Activ
10 ways to relieve stress: · Breathe deep: If your breathing is quick and shallow, rest a hand on your chest and watch it rise and fall. · Try a massage · Doodle ...

Apartment Therapy
https://www.apartmenttherapy.com/rest-relaxation-id...

83 Ways to Rest and Recharge, Whether You Have 5 ...
18 May 2021 — 1. Go on a walk. · 2. Do a body scan meditation. · 3. Focus on a hobby. · 4. Curate a book list. · 5. Start a dance party. · 6. Stand outside or near ...

Declutter The Mind
https://declutterthemind.com/Blog

11 Relaxing Activities Before Bed to Fall Asleep Fast

1. Listen to ASMR · 2. Practice meditation · 3. Listen to sleep hypnosis audio recordings · 4. ...
That’s Why ConceptNet was Designed in Such a Way

• Knowledge in ConceptNet
  • Things, Spatial, Location, Events, Causal, Affective, Functional, Agents

Figure taken from: [https://ocw.mit.edu/courses/media-arts-and-sciences/mas-961-ambient-intelligence-spring-2005/lecture-notes/week4_push_singh.pdf](https://ocw.mit.edu/courses/media-arts-and-sciences/mas-961-ambient-intelligence-spring-2005/lecture-notes/week4_push_singh.pdf)
A More Fundamental Layer is Called K-Line

• Encode memories in “abstract” form.

• Search all memory for the “nearest match.”

• Use prototypes with detachable defaults.


Figure taken from: https://ocw.mit.edu/courses/media-arts-and-sciences/mas-961-ambient-intelligence-spring-2005/lecture-notes/week4_push_singh.pdf
The Implementation of K-Line Theory

• We need the right level and right perspective of conceptualization of events
  • Different levels of abstractness
    • “PersonX drinks coca cola” → “[drinking coca cola],” “[drinking beverage],” “[event]”
  • Different perspectives
    • “Coca cola” → “[sugary beverage],” “[phosphate containing beverage],” “[iced drink],” not in a strict hierarchical taxonomy
      • PersonX drinks [iced drink], xReact, refreshed
      • PersonX drinks [sugary beverage], xEffect, gain weight

Mutian He, Tianqing Fang, Weiqi Wang, and Yangqiu Song. Acquiring and Modelling Abstract Commonsense Knowledge via Conceptualization. 2022.

Figure taken from:
M. Minsky (1980)
Mourelatos’ taxonomy (1978)

- **State**: A state is usually described by a stative verb and cannot be qualified as actions.
  - “The coffee machine is ready for brewing coffee.”
- **Activity (or process)**: Both activity and event are occurrences (actions) described by active verbs.
  - “The coffee machine is brewing coffee with following steps: …”
- **Event**: An event is defined as an occurrence that is inherently countable.
  - “The coffee machine brews a cup of coffee once more” is an event because it admits a countable noun “a cup” and cardinal count adverbials “once”

Bach’s taxonomy (1986)

- **EVENTUALITY TYPES**
  - **STATE**
  - **PROCESS**
  - **EVENT**
- **non-state**
  - dynamic
  - static
- **protracted**
  - momentaneous
  - happenings
  - culminations

**Principle 1:** Comparing semantic meanings by fixing grammar (Katz and Fodor, 1963)

**Principle 2:** The need of language inference based on ‘partial information’ (Wilks, 1975)
Scales of Verb Related Knowledge Graphs

- FrameNet (Baker et al., 1998)
- ACE (Aguilera et al., 2014)
- PropBank (Palmer et al., 2005)
- TimeBank (Pustejovsky et al., 2009)
- OMCS in ConceptNet (Liu & Singh, 2004)
- Event2Mind (Smith et al., 2018)
- ProPora (Dalvi et al., 2018)
- ATOMIC (Sap et al., 2018)
- Knowlywood (Tandon et al., 2015)
- ASER (core)
- ASER (full)

- #Eventualities
- #Relations

- 6000x larger
- 300x larger
You, will have, a duckling

I, have, my own horse

He, have, a little dog

You, will have, a duckling

P( ResultIn | (person, have, animal) , (positive-emotion, come) ) = 0.281 \times 3 \times 0.087 + 0.333 \times 2 \times 0.125 = 0.157
Conceptualization Examples

Conceptualized ASER

- **PersonX gives PersonY Red-Meat**
  - Conjunction (0.05)
- **PersonX order Meat**
  - Result (0.077)
- **PersonX be hungry**
- **PersonX be thirsty**
  - Synchronous (7.5)
- **PersonX eat dish**
  - Succession (0.042)
  - Conjunction (1.0)
  - Precedence (0.057)
- **PersonX be full**

Eventualities:
- He orders meat (Pr = 0.1)
- He orders beef (Pr = 0.2)
- He orders chicken (Pr = 0.1)

- **AIJ’22**

 Riyu Zhang, Xin Liu, Haojie Pan, Haowen Ke, Jiefu Ou, Tianqing Fang, Yangqiu Song: ASER: Towards large-scale commonsense knowledge acquisition via higher-order selectional preference over eventualities. Artif. Intell. 309: 103740 (2022)
Apply the Same Tech to ATOMIC: AbstractATOMIC

3x Larger (about 2.95M triplets) than ATOMIC

Mutian He, Tianqing Fang, Weiqi Wang, and Yangqiu Song. Acquiring and Modelling Abstract Commonsense Knowledge via Conceptualization. 2022.
<table>
<thead>
<tr>
<th>Model</th>
<th>CSKB</th>
<th>a-NLI</th>
<th>CSQA</th>
<th>PIQA</th>
<th>SIQA</th>
<th>WG</th>
<th>Avg.</th>
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<td>71.1</td>
<td>64.4</td>
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**Backbone: RoBERTa-Large 340M**

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<th>CSKB</th>
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<th>SIQA</th>
<th>WG</th>
<th>Avg.</th>
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<td>RoBERTa-L (MR) (Ma et al., 2021)</td>
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<td>ATOMIC</td>
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<td>73.2_{↑1.1}</td>
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<td>ATM^{C}</td>
<td>72.7_{↑1.9}</td>
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**Backbone: DeBERTa-v3-Large 435M**

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<th>Model</th>
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<th>a-NLI</th>
<th>CSQA</th>
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<th>SIQA</th>
<th>WG</th>
<th>Avg.</th>
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<td>DeBERTa-v3-L (MR) (Ma et al., 2021)</td>
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<td>76.0</td>
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<td>62.1</td>
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<td>CAR-DeBERTa-v3-L (Ours)</td>
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<td>78.2_{↑2.2}</td>
<td>73.9_{↑2.1}</td>
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**Large Language Models**

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<th>Model</th>
<th>CSKB</th>
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<th>SIQA</th>
<th>WG</th>
<th>Avg.</th>
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**Supervised Learning & Human Performance**

<table>
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<th>Model</th>
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<th>CSQA</th>
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<td>Human Performance</td>
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<td>94.9</td>
<td>86.9</td>
<td>94.1</td>
<td>91.2</td>
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</tbody>
</table>

Language models finetuned by AbstractATOMIC can significantly improve their zero-shot ability on downstream commonsense QA tasks.
ASER Statistics

1.0 (in 2019): Rule based extraction (14 Eventuality Patterns)
   - 272 millions eventualities and 206 millions relations

2.0 (in 2021): Discourse Parser (18 Eventuality Patterns + Wang and Lan 2015)
   - 439 millions eventualities and 649 millions relations

Conceptualization Core (Using top 5 concepts for each detected instance):
   - Concepts: 15 millions (based on 14 millions eventualities, 1.X times)
   - Concept Relations: 224 millions (based on 53 millions eventuality relations, 4.X times)

https://github.com/HKUST-KnowComp/ASER
Hongming Zhang, Xin Liu, Haojie Pan, Haowen Ke, Jiefu Ou, Tianqing Fang, Yangqiu Song: ASER: Towards large-scale commonsense knowledge acquisition via higher-order selectional preference over eventualities. Artif. Intell. 309: 103740 (2022)
TransOMCS: Transform ASER to ConceptNet

Knowledge Base Population (KBP)

Relation: AtLocation
Pattern: (H)\langle nsubj\rangle\langle (T)\rangle\langle obl\rangle\langle (at)\rangle
Knowledge: (Student, AtLocation, School)

Relation: Causes
Pattern: (H)\langle dobj\rangle\langle ()\rangle\langle Result\rangle\langle (T)\rangle
Knowledge: (Good grades, Causes, Graduate)

100x Larger (about 18M triplets) than OMCS in ConceptNet
Transform ASER to ATOMIC

Knowledge Base Population (KBP)


Tianqing Fang, Hongming Zhang, Weiqi Wang, Yangqiu Song, and Bin He. DISCOS: Bridging the Gap between Discourse Knowledge and Commonsense Knowledge. WWW, 2021.

3x Larger (about 3.4M triplets) than ATOMIC
Incorporating More Types: **Process Induction**

**Buy + House**

- Observed process graph set $G$
  - Rent + House
  - Sell + House
  - Repair + House

**Observed Sub-event Sequences**

1. (Search car) $\rightarrow$ (Apply loan) $\rightarrow$ ...
2. (Select apple) $\rightarrow$ (Pay)
3. (Go to bakery) $\rightarrow$ (Pick cake) $\rightarrow$ (Pay)
4. (Contact dealer) $\rightarrow$...
5. (Check house)
6. (Set price) $\rightarrow$ (Contact dealer) $\rightarrow$ ...
7. (Identify problem) $\rightarrow$ (Hire worker) $\rightarrow$ ...

**Abstractive representations**

1. (Search product, 0.53) $\rightarrow$ ...
2. (Pay, 0.95)
3. (Search house) $\rightarrow$ (Contact dealer) $\rightarrow$ ...
4. (Pay)

**Step 1: Semantic Decomposition**

**Step 2: Semantic Abstraction with Event Conceptualization**

**Step 3: Sub-event Sequence Prediction with Event Instantiation**

Incorporating More Types: **Process Generation**

Coherence controller: a candidate is coherent with the process and prior generated sub-events

- **Local coherence**: randomly copy a sub-event in the current process and place it at a random location.
- **Global coherence**: randomly choose a sub-event from other processes with a different theme and insert it at a random location.

Zhaowei Wang, Hongming Zhang, Tianqing Fang, Yangqiu Song, Ginny Y. Wong, and Simon See. SubeventWriter: Iterative Sub-event Sequence Generation with Coherence Controller. EMNLP, 2022
Beyond Belief/Knowledge Graph: **FolkScope**

- **Intention Knowledge Graph** for E-commerce Commonsense Discovery

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**Explainable recommendation**
- UserU bought [A] because

**Query-item relevance**
- PersonX searches [Q] to

**User behavior rationalization**
- PersonX bought [A] and [B] because
- PersonX searched [A] and bought [B] because

**AI Generator**

**ASER**

**Pattern mining, Filtering, Normalization, Conceptualization**

**Intention KG**

---

**ACL’23**

**AIG-KG**

---

Changlong Yu, Weiqi Wang, Xin Liu, Jiaxin Bai, Yangqiu Song, Zheng Li, Yifan Gao, Tianyu Cao, and Bing Yin. FolkScope: Intention Knowledge Graph Construction for E-commerce Commonsense Discovery. Findings of ACL. 2023.
Beyond Belief/Knowledge Graph: FolkScope
How to help LLMs?

Entities/Facts as Memories

Neural Graph Databases

Figure taken from: Pat Verga, Haitian Sun, Livio Baldini Soares, William W. Cohen: Adaptable and Interpretable Neural Memory Over Symbolic Knowledge. NAACL-HLT 2021: 3678-3691

Figure taken from: https://towardsdatascience.com/neural-graph-databases-cc35c9e1d04f
Logical Queries over Knowledge Graphs

Benchmarking EFO-1 (Existential First-Order Queries with Single Free Variable)

EFO-1 queries with cycles

EFO-K more than one variables

Data

_models

Particle filtering of logical sequential queries

Learning in the inference step as a GNN (one-hop logical inference based MPNN)

Number and attribute queries

Hang Yin, Zihao Wang, and Yangqiu Song. EFO_k-CQA: Towards Knowledge Graph Complex Query Answering beyond Set Operation. Arxiv 2023

Jiaxin Bai, Chen Luo, Zheng Li, Qingyu Yin, Bing Yin, Yangqiu Song. Knowledge Graph Reasoning over Entities and Numerical Values. KDD 2023

Hang Yin, Zihao Wang, and Yangqiu Song. Rethinking Existential First Order Queries and their Inference on Knowledge Graphs. Arxiv 2023

Zihao Wang, Yangqiu Song, Ginny Y. Wong, and Simon See. Logical Message Passing Networks with One-hop Inference on Atomic Formulas. In The Eleventh International Conference on Learning Representations, ICLR 2023

Jiaxin Bai, Zihao Wang, Hongming Zhang, and Yangqiu Song. Query2Particles: Knowledge Graph Reasoning with Particle Embeddings. In Findings of the Association for Computational Linguistics: NAACL-HLT 2022, 2022

Zihao Wang, Hang Yin, and Yangqiu Song. Benchmarking the Combinatorial Generalizability of Complex Query Answering on Knowledge Graphs. In NeurIPS Datasets and Benchmarks Track, 2021

NeurIPS’21

Arxiv’23

NAACL’22

ICLR’23

KDD’23
Logical Queries on ASER with Logical Constraints

Logical Query: \[ q = V, \exists V: Succession(PersonX complains, V) \land Succession(PersonX leaves restaurant, V) \land Reason(V, V') \land Precedence(Food is bad, PersonY adds soy sauce) \land ChosenAlternative(PersonY adds ketchup, PersonY adds vinegar) \]

Implicit Constraints:
\[ \tau(V) < \tau(PersonX complains) \land \eta(V) \land \eta(PersonX complains) \land \tau(V) < \tau(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta(PersonX leaves restaurant) \land \eta(V) \land \eta Persona

Query Types: \((p, i, (p, (e)), (p, (e)))\)

Computational Graph:

Eventuality Knowledge Graph:

- Succession
- Reason
- Staff is new
- PersonX leaves restaurant
- Food is bad
- PersonX adds ketchup
- PersonX adds soy sauce
- PersonY adds ketchup
- PersonY adds soy sauce

Constraints:
- Precedence(V1, V2)
  - V1 occurs before V2
- ChosenAlternative(V1, V2)
  - Instead of V2 occurs, V1 occurs

Jiaxin Bai, Xin Liu, Weiqi Wang, Chen Luo, Yangqiu Song. Complex Query Answering on Eventuality Knowledge Graph with Implicit Logical Constraints. Arxiv 2023
Knowledge Logical Counting or Subgraph Counting

• Such KG query needs global memory and inference
• Subgraph counting is NP-Complete; Very Difficult for LLMs (Transformer) to conduct


Xin Liu and Yangqiu Song. Graph Convolutional Networks with Dual Message Passing for Subgraph Isomorphism Counting and Matching. In the AAAI Conference on Artificial Intelligence (AAAI), 2022.

Xin Liu, Haojie Pan, Mutian He, Yangqiu Song, Xin Jiang, and Lifeng Shang. Neural Subgraph Isomorphism Counting. In ACM SIGKDD Conference on Knowledge Discovery and Data Mining (KDD), 2020.
To Conclude

• We build new types of graphs
  • Related to activity (or process), state, and event
  • Beyond knowledge and believes

• We develop data sources and packages to support
  • Knowledge grounding
  • Complex knowledge queries
  • Logical reasoning
  • Improved zero-shot learning or indirect supervision for LLMs
  • Trustworthy LLMs
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Thank you for your attention! 😊