New Frontiers of Knowledge Graph Reasoning: Recent Advances and Future Trends

Part IV: Neural Reasoning Beyond Entities and Relations

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KnowComp Group

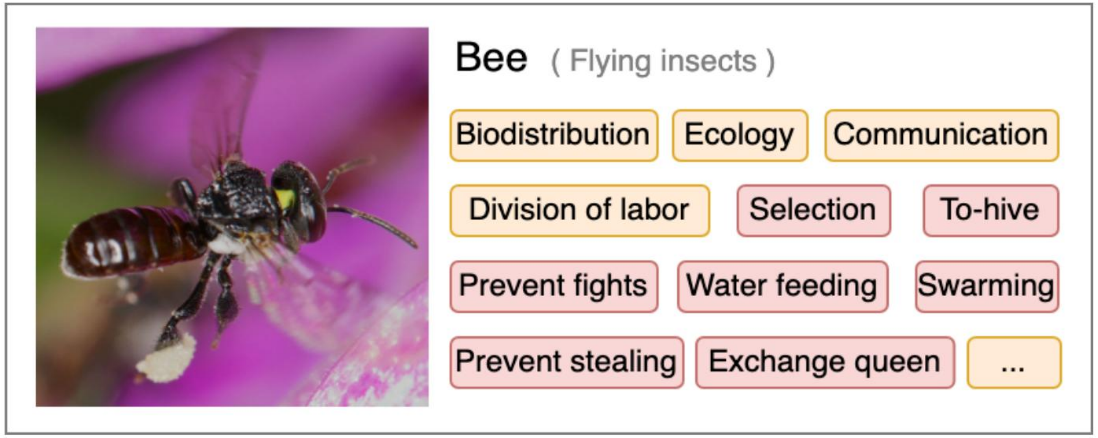
Understanding the World by Computational Knowledge

Roadmap

- **Part I: Knowledge Graph Reasoning: Basic Concepts and Techniques**
- **Part II: Recent Advance #1: Neural Reasoning for Natural Language Queries**
- **Part III: Recent Advance #2: Neural Reasoning for Logical Queries**
- **Part IV: Recent Advance #3: Neural Reasoning Beyond Entities and Relations**
- **Part V: Recent Advance #4: LLM+KGR**
- **Part VI: Open Challenges and Future Directions**

Scope of Knowledge

- Awareness of facts
  - "Knowing that": the truth of propositions
    - E.g., the population of Singapore is 5.92 million (2023)
- A possession of practical skills
  - "Knowing how": understanding how to perform certain actions; procedural knowledge
    - E.g., How to hive bees?
- An experiential acquaintance: familiarity with individuals and situations
  - "Knowing by acquaintance": directly perceiving an object, being familiar with it, or otherwise coming into contact with it.
    - E.g., by eating Durian, one becomes acquainted with the taste of it



The aspects in orange boxes are aspects that convey the knowledge of "know-what" or "know-why", while those in red boxes convey the knowledge of "know-how".

Source: Kuaipedia

https://en.wikipedia.org/wiki/Definitions_of_knowledge#Non-propositional_knowledge

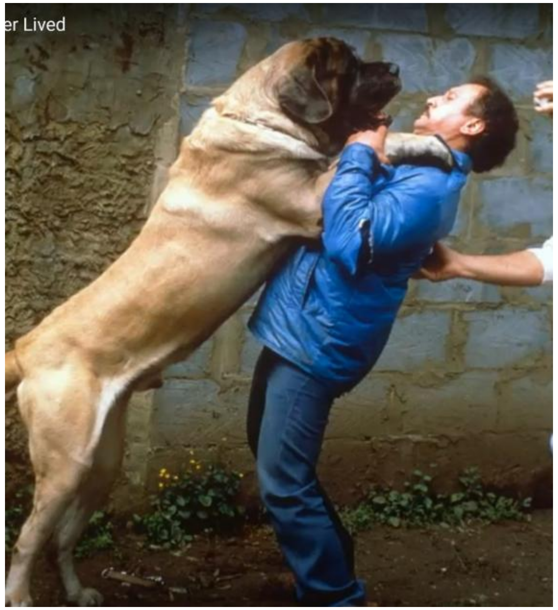
Kuaipedia: a Large-scale Multi-modal Short-video Encyclopedia Haojie Pan, Zepeng Zhai, Yuzhou Zhang, Ruiji Fu, Ming Liu, Yangqiu Song, Zhongyuan Wang, Bing Qin. Arxiv 2022.

Commonsense Knowledge in AI

- "Commonsense knowledge includes the basic facts about events (including actions) and their effects, … how it is obtained, facts about beliefs and desires. It also includes the basic facts about objects and properties. " – John McCarthy

- "While to the average person the term 'commonsense' is regarded as synonymous with 'good judgement', the AI community it is used in a technical sense to refer to the millions of basic facts and understandings possessed by most people." --ConceptNet
  - "Such knowledge is typically omitted from social communications", e.g.,
  - If you forget someone's birthday, they may be unhappy with you.

- Meanwhile, it is not invariably true
  - "a person is larger than a dog"



Source: Zorba - The World's Largest Dog Ever Lived

McCarthy, John. "Artificial intelligence, logic and formalizing common sense." Philosophical logic and artificial intelligence. Springer, Dordrecht, 1989. 161-190.
Hugo Liu and Push Singh, ConceptNet - a practical commonsense reasoning tool-kit, BTTJ, 2004

The Three-dimensional Development of Knowledge Graphs in Computer Science

The deveopment of the Web

In the past years the development of knowledge graph has been largely changed (or revolutionized) by deep learning and NLP

Web 3.0

Web 2.0

Web 1.0

Generations of KGs

G#3: Dual Neural KGs

G#2: Text-Rich KGs

G#1: Entity-Based KGs

Xin Luna Dong. Generations of Knowledge Graphs: The crazy ideas and the business impact. *VLDB*, 2023. Invited paper for **VLDB Women in Database Research Award.** [Paper][Talk]

Entities/Concepts/Properties

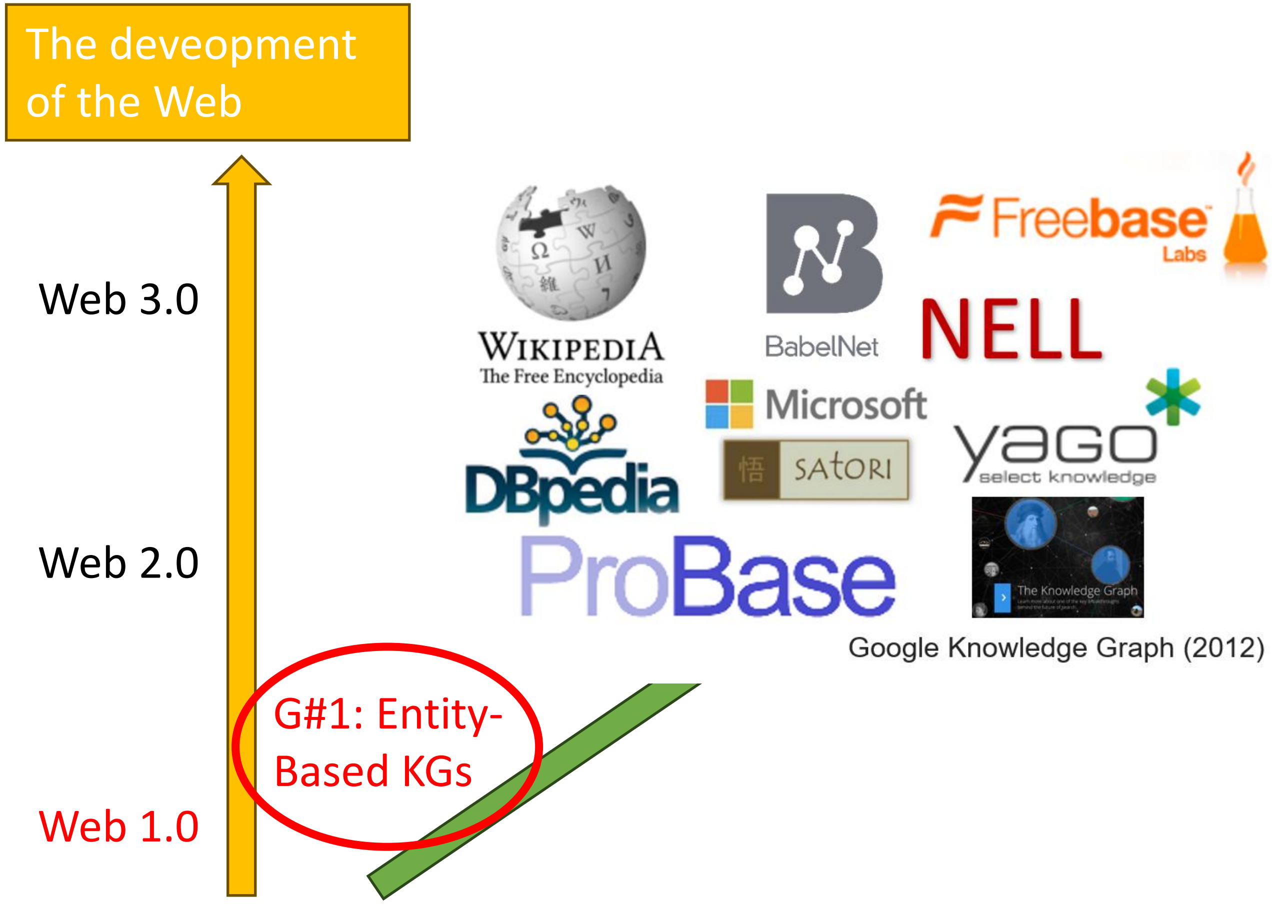
Events/Processes

Intents/Beliefs/Desires

Semantic Units

Generations of KGs: Xin Luna Dong. Generations of Knowledge Graphs: The crazy ideas and the business impact. *VLDB*, 2023. Invited paper for VLDB Women in Database Research Award. [Paper][Talk]

The Three-dimensional Development of Knowledge Graphs in Computer Science



- Many large-scale knowledge graphs about entities and their attributes (property-of) and relations (thousands of different predicates) have been developed
  - Millions of entities and concepts
  - Billions of relationships
- They belong to
  - Generation #1
  - Web 1.0
  - Entity based knowledge

Entities/Concepts/Properties　　Events/Processes　　Intents/Beliefs/Desires

Semantic Units

Generations of KGs: Xin Luna Dong. Generations of Knowledge Graphs: The crazy ideas and the business impact. *VLDB*, 2023. Invited paper for VLDB Women in Database Research Award. [Paper][Talk]

The Three-dimensional Development of Knowledge Graphs in Computer Science

The deveopment of the Web

Web 3.0

Web 2.0

Web 1.0

G#1: Entity-Based KGs

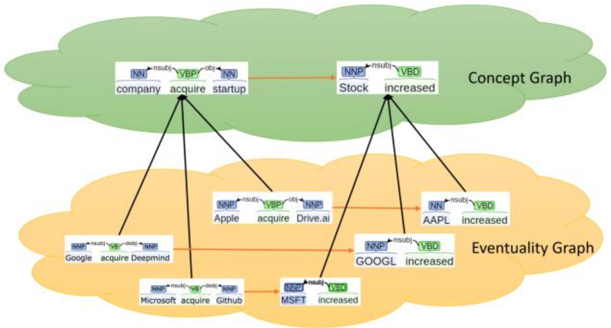
G#2: Text-Rich KGs

G#
Ne

amazon

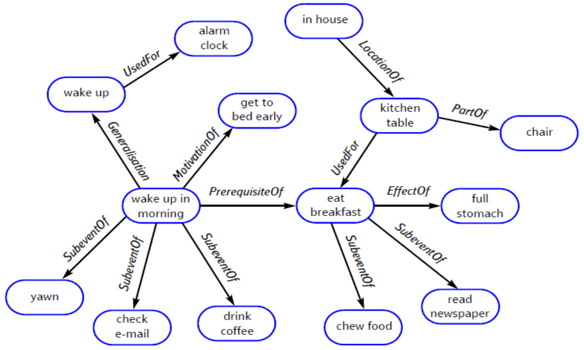
- Product Graph
  - Generation #2
  - Web 1.0
  - Entity (product) based knowledge

ASER



- ASER/Knowlywood
  - Generation #2
  - Web 1.0
  - Event based knowledge

ConceptNet
An open, multilingual knowledge graph



- ConceptNet
  - Generation #2
  - Web 1.0
  - Entity and event based knowledge

Entities/Concepts/Properties Events/Processes Intents/Beliefs/Desires

Semantic Units

Nasser Zalmout, Chenwei Zhang, Xian Li, Yan Liang, Xin Luna Dong. All you need to know to build a product knowledge graph. Tutorial in KDD'2021.
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)
Niket Tandon, Gerard de Melo, Abir De, Gerhard Weikum: Knowlywood: Mining Activity Knowledge From Hollywood Narratives. CIKM 2015: 223-232
Liu, Hugo, and Push Singh. "ConceptNet—a practical commonsense reasoning tool-kit." BT technology journal 22.4 (2004): 211-226.

The Three-dimensional Development of Knowledge Graphs in Computer Science

The deveopment of the Web

Web 3.0

Web 2.0

Web 1.0

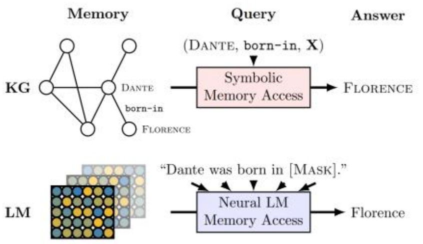
Generations of KGs

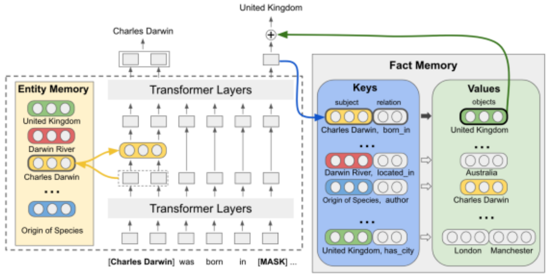
G#3: Dual Neural KGs

G#2: Text-Rich KGs

G#1: Entity-Based KGs

"Language models as knowledge bases"
Neural KGs/Memory Networks/NGDBs





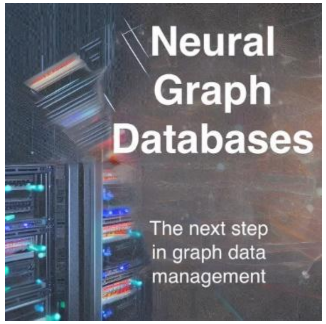


Figure of NGDBs

- Zihao Wang's part
  - Generation #3
  - Web 1.0
  - Entity (product) based knowledge

- Jiaxin Bai's part
  - Generation #3
  - Web 1.0
  - Event and Intention based knowledge

Entities/Concepts/Properties Events/Processes Intents/Beliefs/Desires

Semantic Units

Figure of NGDBs taken from: https://towardsdatascience.com/neural-graph-databases-cc35c9e1d04f

Fabio Petroni, Tim Rocktäschel, Sebastian Riedel, Patrick S. H. Lewis, Anton Bakhtin, Yuxiang Wu, Alexander H. Miller: Language Models as Knowledge Bases? EMNLP/IJCNLP (1) 2019: 2463-2473
Pat Verga, Haitian Sun, Livio Baldini Soares, William W. Cohen: Adaptable and Interpretable Neural Memory Over Symbolic Knowledge. NAACL-HLT 2021: 3678-3691
Maciej Besta, Patrick Iff, Florian Scheidl, Kazuki Osawa, Nikoli Dryden, Michal Podstawski, Tiancheng Chen, Torsten Hoefler: Neural Graph Databases. LoG 2022: 31
Hongyu Ren, Mikhail Galkin, Michael Cochez, Zhaocheng Zhu, Jure Leskovec: Neural Graph Reasoning: Complex Logical Query Answering Meets Graph Databases. CoRR abs/2303.14617 (2023)

The Three-dimensional Development of Knowledge Graphs in Computer Science

The deveopment of the Web

Web 3.0

Web 2.0

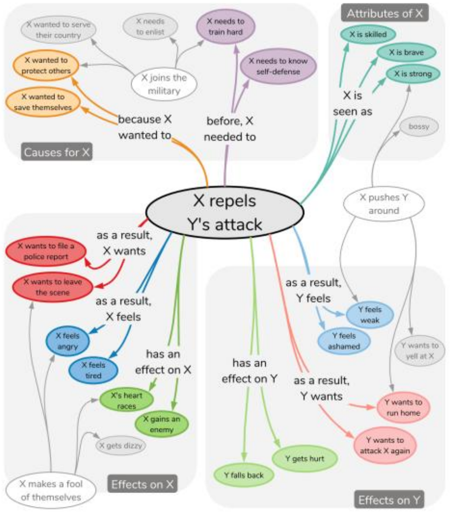
Web 1.0

G#1: Entity-Based KGs

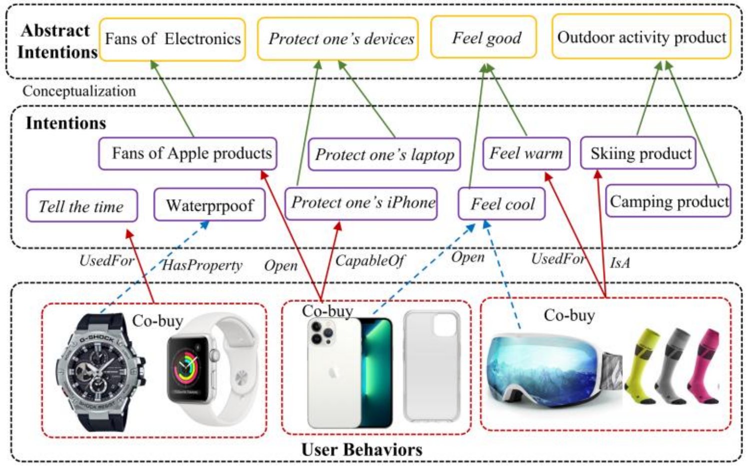
G#2: Text-Rich KGs

G#3: Neu

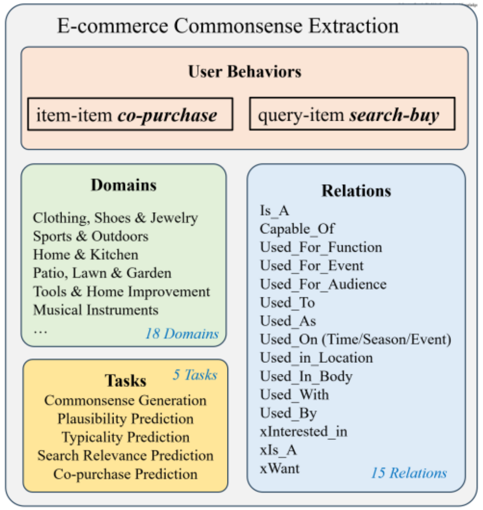
ATOMIC



FolkScope



amazon COSMO



- ATOMIC
  - Generation #2
  - Web 1.0
  - Intention and event (cause-effect) knowledge
- FolkScope
  - Generation #2
  - Web 2.0
  - Intention knowledge
- COSMO
  - Generation #2
  - Web 2.0
  - Intention knowledge

Entities/Concepts/Properties | Events/Processes | Intents/Beliefs/Desires

Semantic Units

Maarten Sap, Ronan LeBras, Emily Allaway, Chandra Bhagavatula, Nicholas Lourie, Hannah Rashkin, Brendan Roof, Noah A. Smith, Yejin Choi: ATOMIC: An Atlas of Machine Commonsense for If-Then Reasoning. AAAI, 2019.

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.

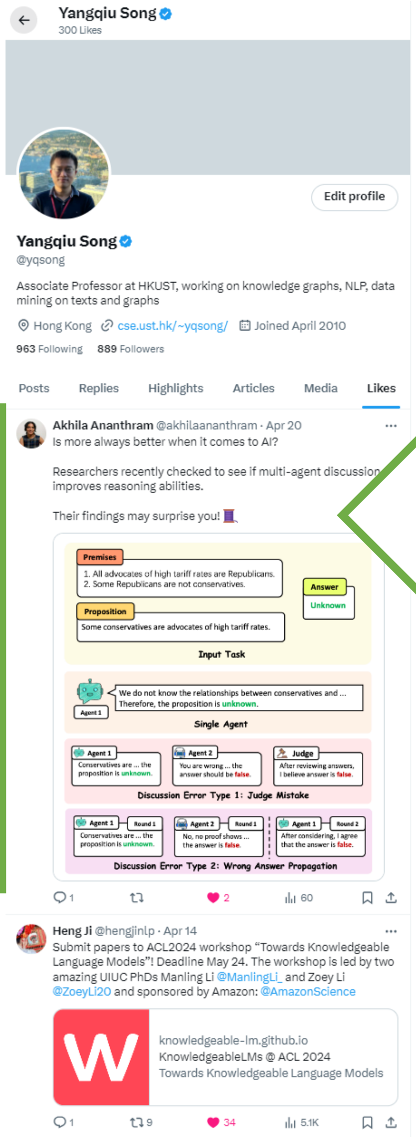
COSMO: A large-scale e-commerce common sense knowledge generation and serving system at Amazon. By Changlong Yu, Xin Liu, Jefferson Maia, Tianyu Cao, Laurence (Yang) Li, Yifan Gao, Yangqiu Song, Rahul Goutam, Haiyang Zhang, Bing Yin, Zheng Li. SIGMOD Industrial Track. 2024.

Why do we want to go beyond entities in Web2.0?

- User centric and user generated content (UGC)
  - Explicit incentives :
    - e.g., user reviews, posting blogs, tweets, photos, videos, etc.
  - Implicit incentives :
    - user behaviors, e.g., following, browsing, clicking, searching, upvoting, etc.

Why do I post this tweet?

Sell my own work, or promote my student?



Why do I like this post? I like the content or promote my own work?

Why do we want to go beyond entities in Web2.0?

"I post this tweet: Sell my own work or promote my student?" Inference involves:

- 1. Theory of Mind
  - i.e., the development of knowledge that others have beliefs, desires, and intentions that are different from one's own
  - Possessing a functional theory of mind is crucial for success in everyday human social interactions
- What makes us take actions?
  - Beliefs and desires are mediated by intentions which in turn controls human's actions (or speech) (Kashima et al., 1998)
  - Intentions are implicit

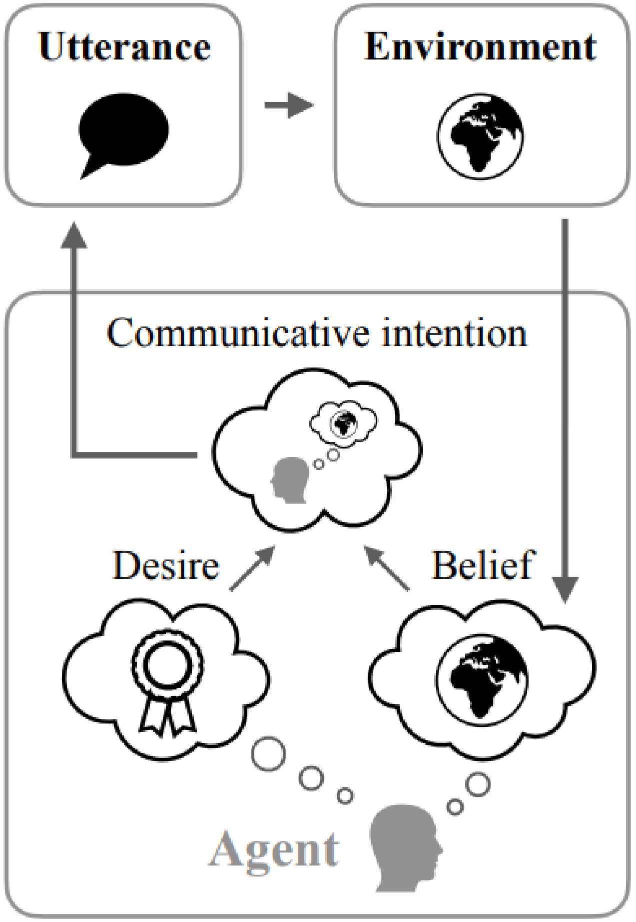


Figure taken from Andreas (2022)

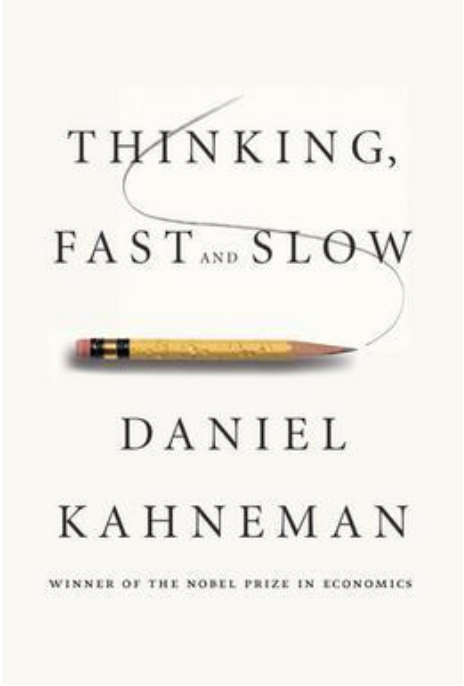
https://en.wikipedia.org/wiki/Intention
https://en.wikipedia.org/wiki/Theory_of_mind

Jacob Andreas: Language Models as Agent Models. EMNLP (Findings) 2022: 5769-5779
Kashima, Yoshihisa, Allison McKintyre, and Paul Clifford. "The Category of the Mind: Folk Psychology of Belief, Desire, and Intention." Asian Journal Of Social Psychology 1, no. 3 (December 1998): 289–313.

Why do we want to go beyond entities in Web2.0?

"I post this tweet: My student gets more visible or not?"
Inference involves:

- 2. System II Processing
  - We need to equip machine learning systems with "slow, logical, sequential, conscious, linguistic, algorithmic, planning, reasoning"

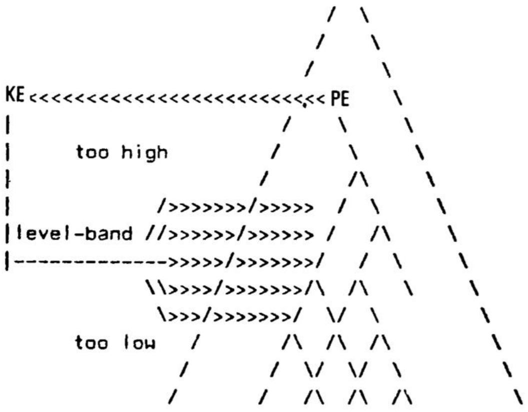


- Particularly, such a system requires the "understanding of how actions interact with changes (of states) in distribution"
  - "Agents face non-stationarities"
  - Conditioned on "different places, times, sensors, actuators, goals, policies, etc"

http://www.iro.umontreal.ca/~bengioy/AAAI-9feb2020.pdf

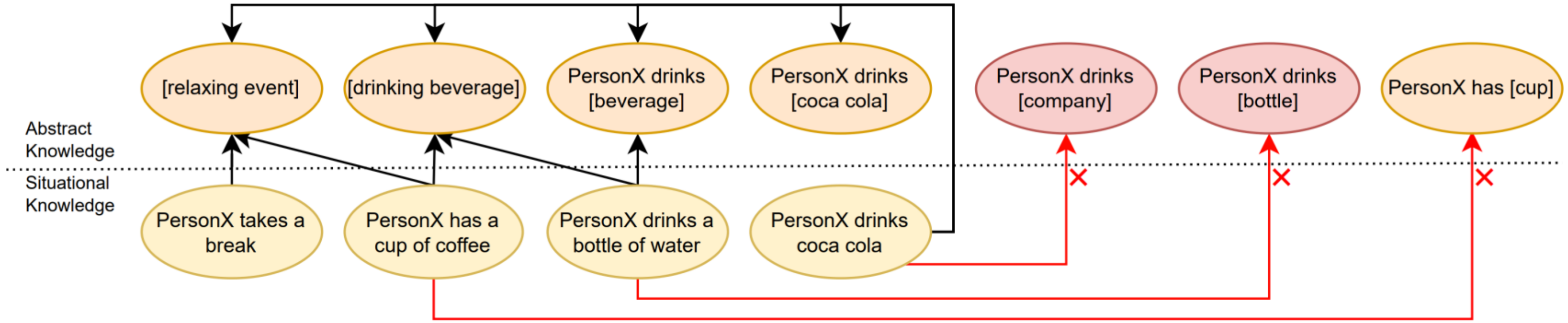
Why Graphs?

- The K-Line Theory (Minsky, 1980)
  - More than ontology: categories include substances, properties, relations, states of affairs, and events
  - Mental states in our memory are also in a hierarchical structure beyond an ontology; described as a K-pyramid



K-Pyramid: Minsky (1980)

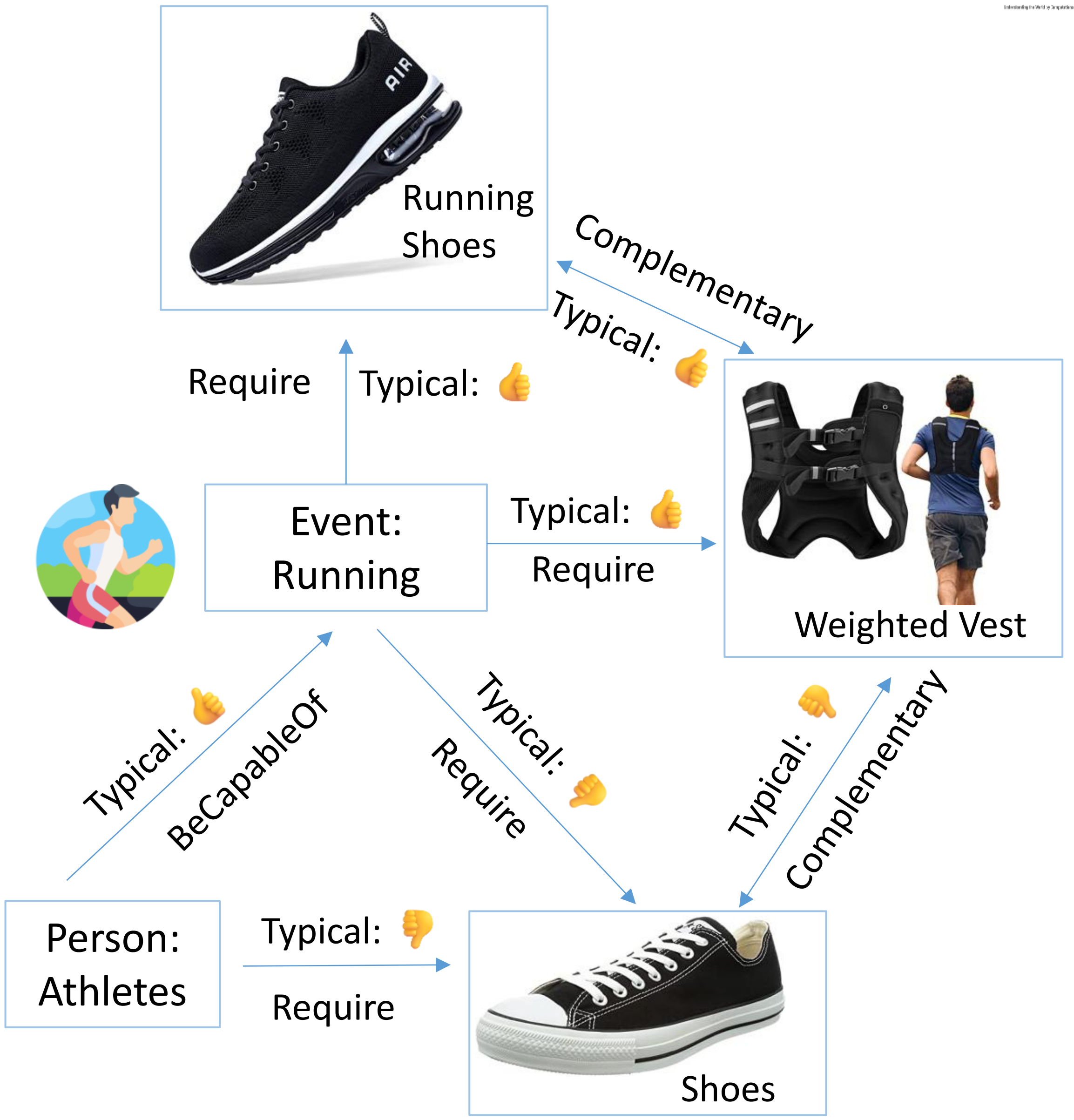
- We need the right level and right perspective of abstraction
  - Different levels of abstractness: “PersonX drinks coca cola” → “[drinking beverage],” “[event]”
  - Different perspectives: “Coca cola” → “[sugary beverage],” “[phosphate containing beverage],” “[iced drink],” not in a strict taxonomy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



M. Minsky, “K-Lines: A theory of Memory," Cognitive Science 4 (1980). 117-133.
Mutian He, Tianqing Fang, Weiqi Wang, and Yangqiu Song. Acquiring and Modelling Abstract Commonsense Knowledge via Conceptualization. Arxiv 2022.

Why Graphs?

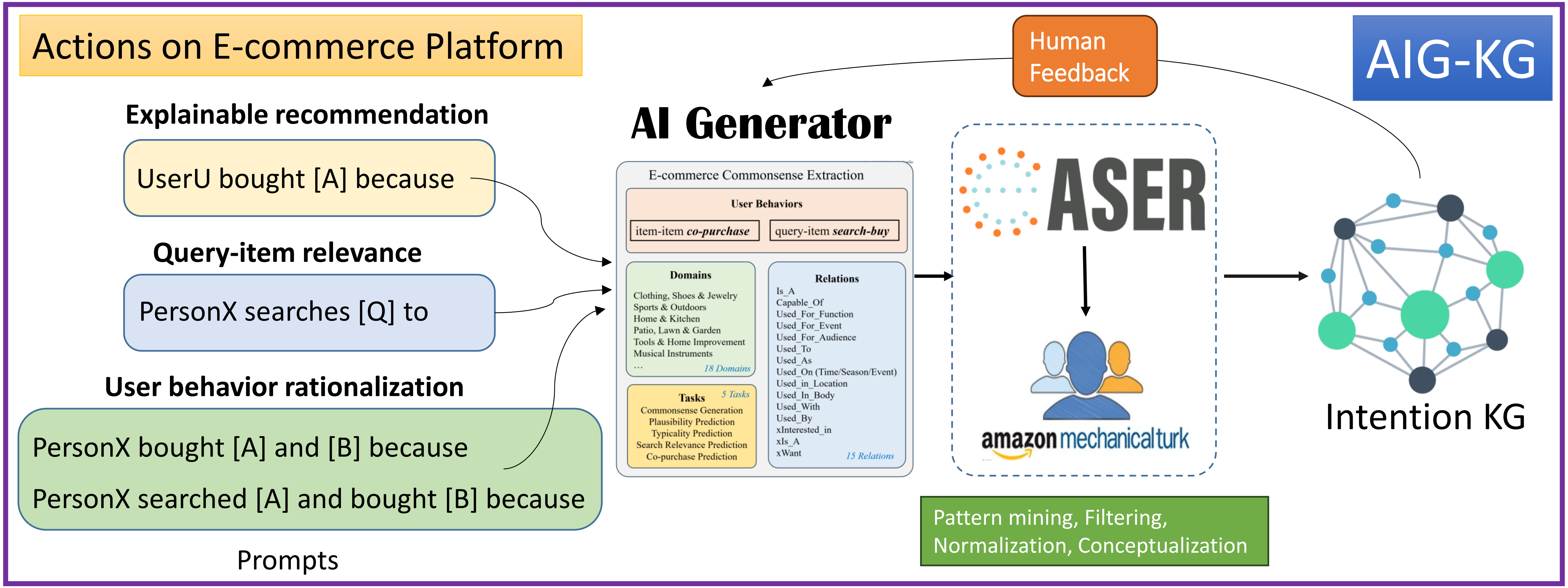
- Sometimes we need concrete, symbolic, and globally referenced knowledge (Edge et al., 2024)
- Ability of commonsense reasoning with high complexity
  - NP-complete problems, e.g., Max-Sat (Chalier et al., 2022) , subgraph matching or counting, subset sum, etc.
- The trade-offs between scalability and computational complexity
  - Intentions can be pre-stored and indexed to be more efficiently accessed online



From Local to Global: A Graph RAG Approach to Query-Focused Summarization. Darren Edge, Ha Trinh, Newman Cheng, Joshua Bradley, Alex Chao, Apurva Mody, Steven Truitt, Jonathan Larson April 2024
Joint Reasoning for Multi-Faceted Commonsense Knowledge. Yohan Chalier, Simon Razniewski, Gerhard Weikum. ACBC. 2022.

FolkScope and COSMO: User-centric Intention KGs

- AI generated knowledge graph construction framework



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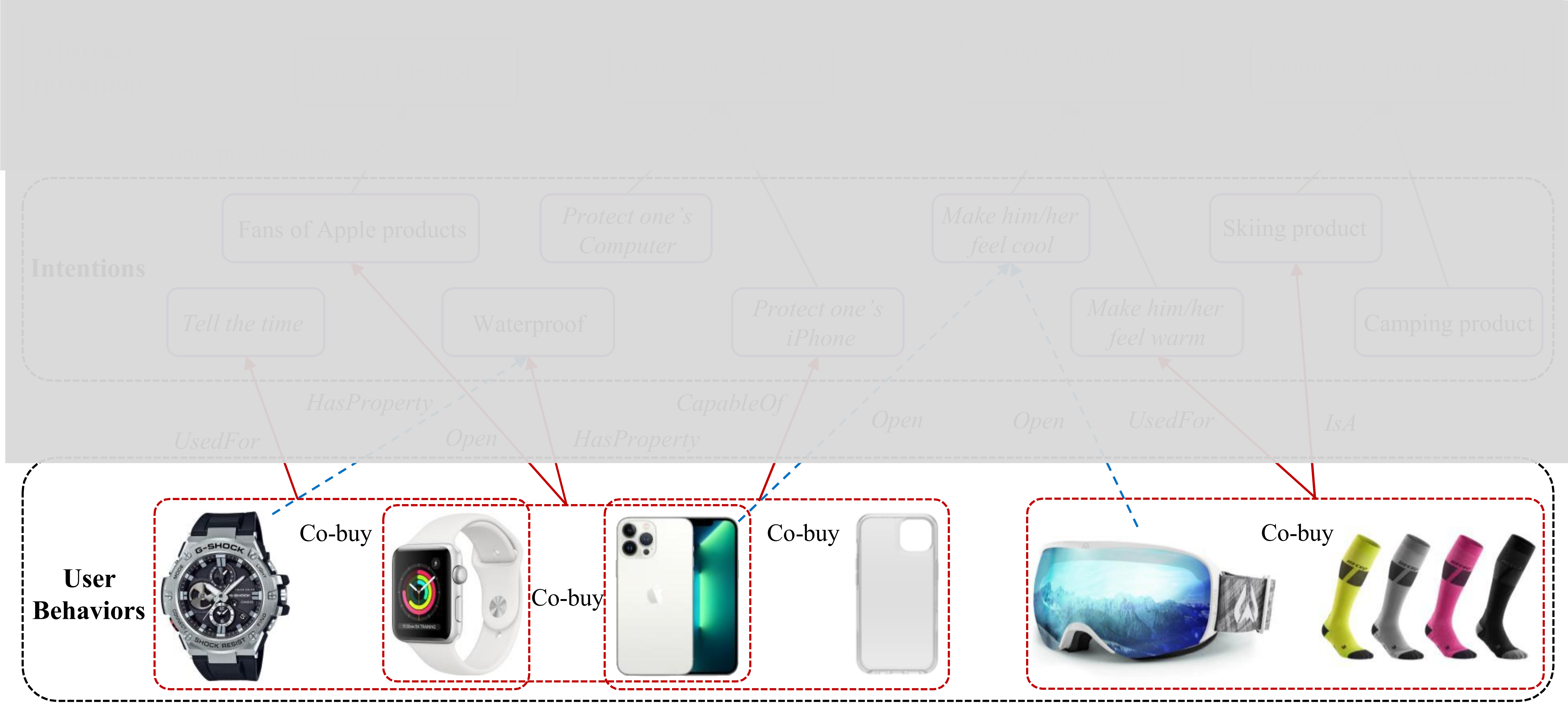
Hongming Zhang*, Xin Liu*, Haojie Pan*, Haowen Ke, Jiefu Ou, Tianqing Fang, and Yangqiu Song. ASER: Towards Large-scale Commonsense Knowledge Acquisition via Higher-order Selectional Preference over Eventualities. Artificial Intelligence, Volume 309, August 2022, 103740.

FolkScope: Collective Intention KG for Co-Purchases

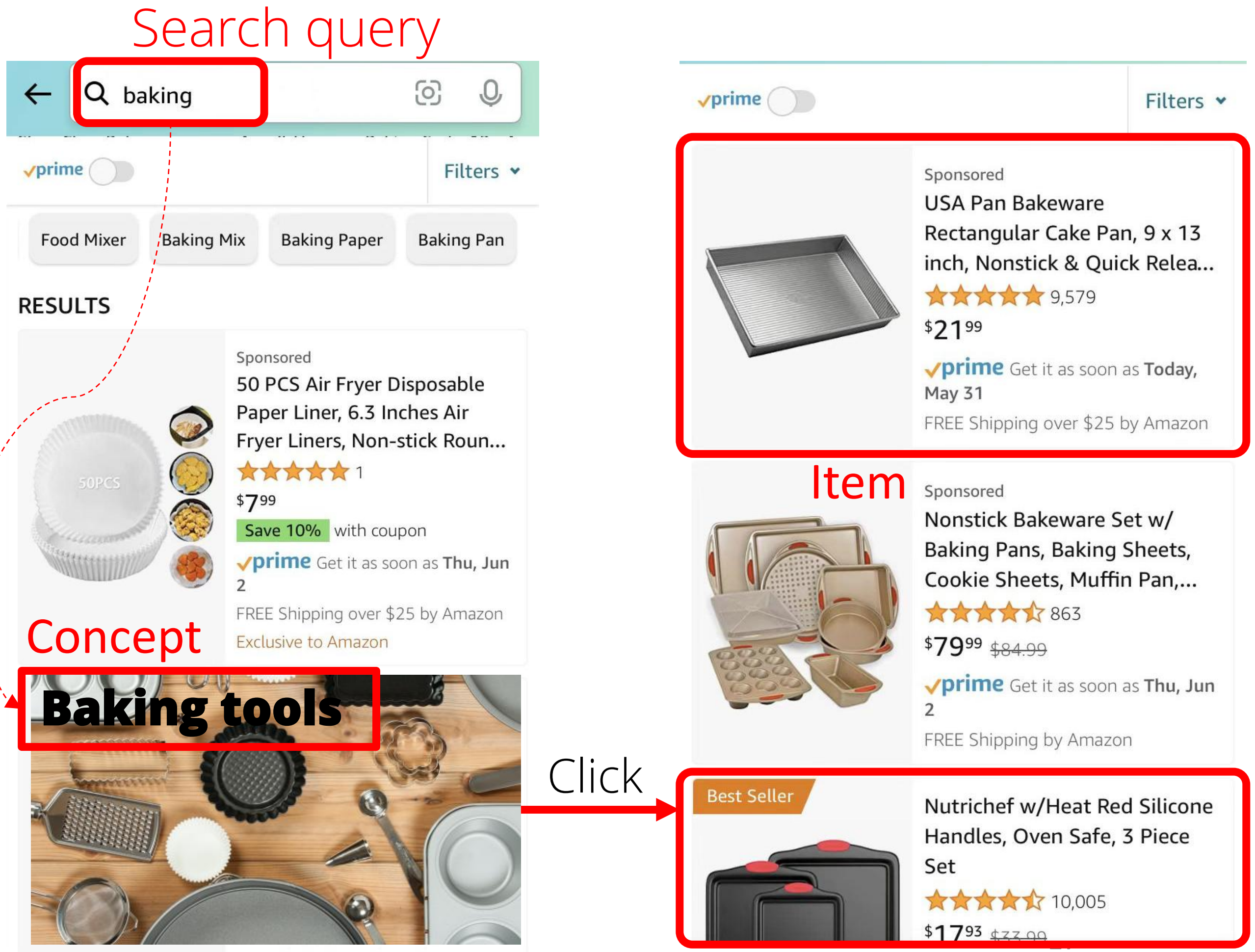


Deployments: COSMO, Intention KG for Search-buy

- Efficient feature store and asynchronous cache store
- Effectively meets Amazon's restricted search latency requirements while maintaining storage costs comparable to real-time serving for the majority of traffic

Search Query Navigation

- A/B tests carried out over several months in total
- approximately 10% of Amazon's U.S. traffic
- a notable 0.7% relative increase in product sales
- translating to hundreds of millions of dollars in annual revenue surge.



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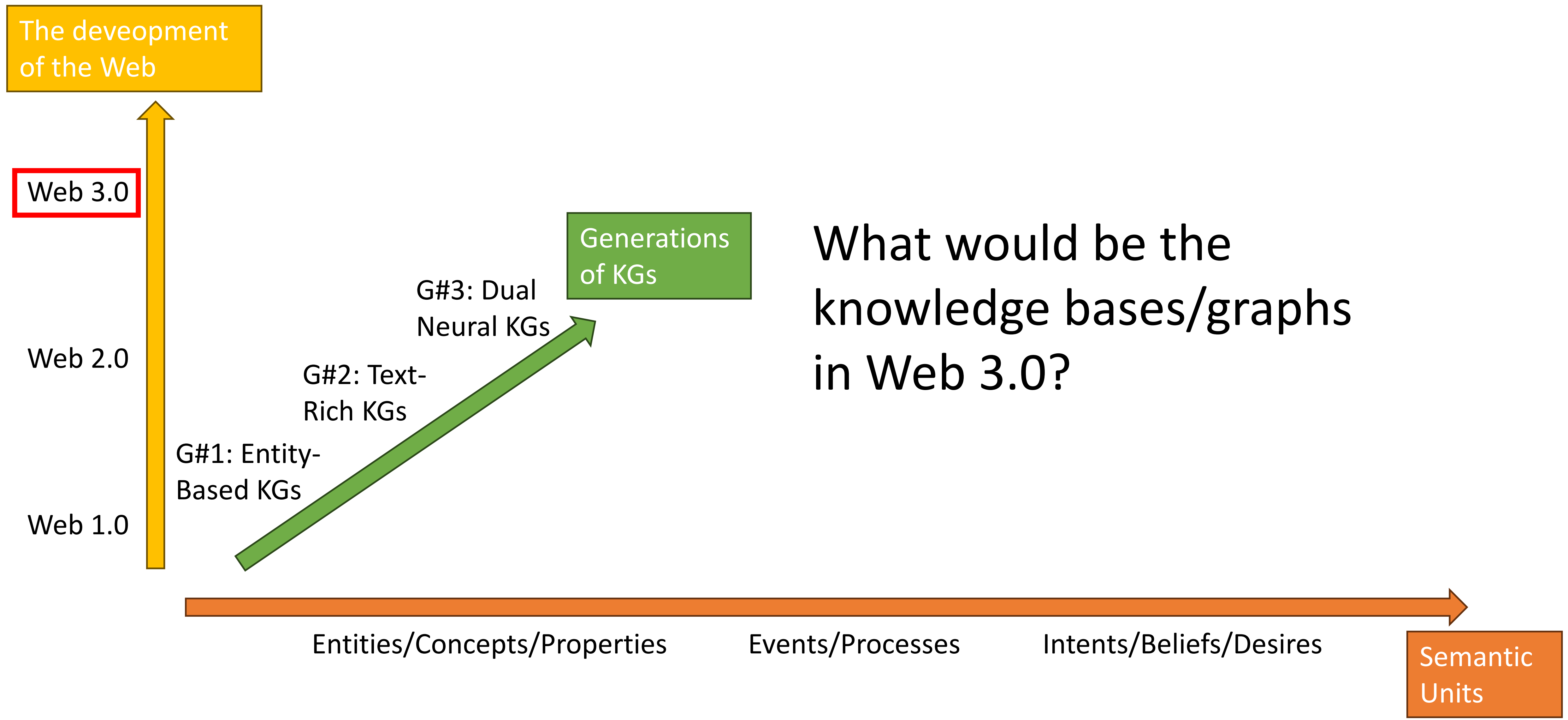
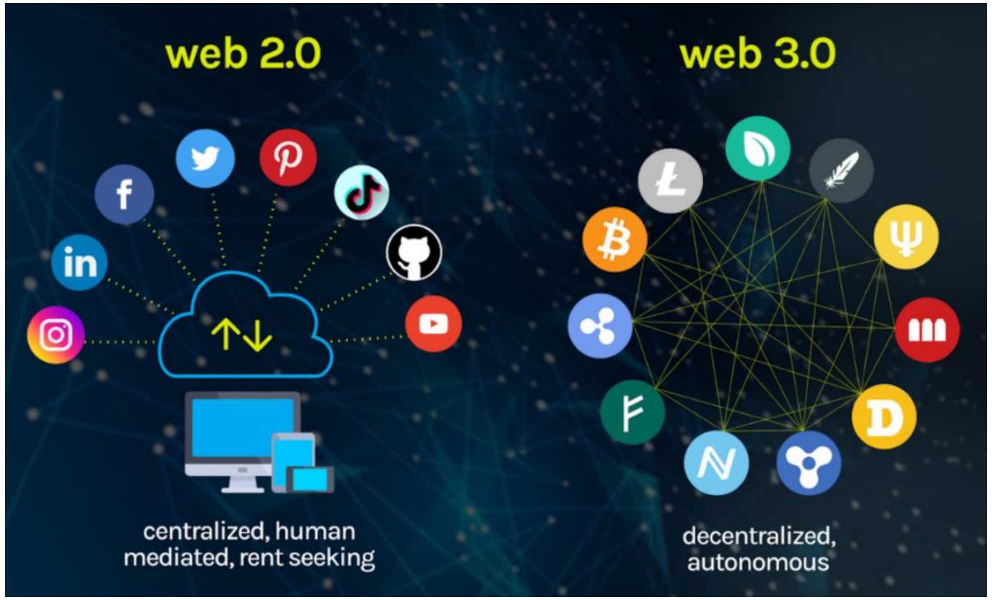
The Three-dimensional Development of Knowledge Graphs in Computer Science



What would be the knowledge bases/graphs in Web 3.0?

An Outlook

- From Web2.0 to Web3.0
  - Decentralized data: users own their (neural) knowledge bases/graphs
    - Monetarize by users' data and time
  - Permissionless, trustless, but accessible to users' owned knowledge or data

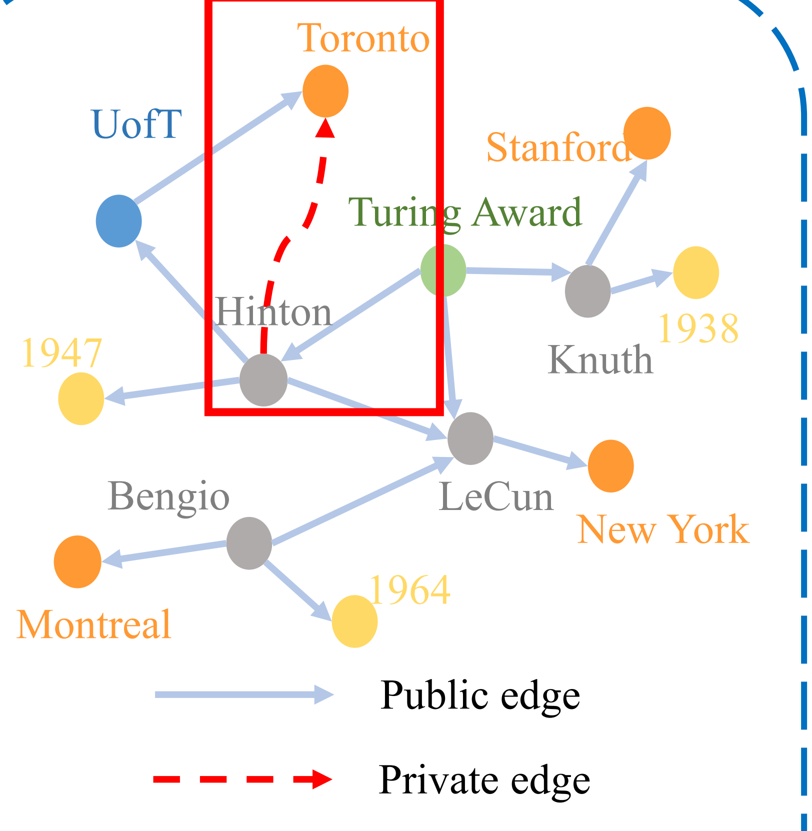


- Security and privacy of data and knowledge is the key!

Figure from: https://vitalflux.com/what-is-web3-0-features-design-skills-nfts/

Privacy-preserved NGDBs

An attacker attempts to infer private information about Hinton's living place in the NGDBs. Attackers can leverage well-designed queries to retrieve desired privacy. The intersection of these queries can make a fair guess.



Neural Graph Databases

Query	$q = V_?.\exists V: Win(V, Turing\ Award) \wedge BornIn(V, 1938) \wedge LiveIn(V, V_?)$
Interpretation	Find where the Turing Award winner who was born in 1938 lived.

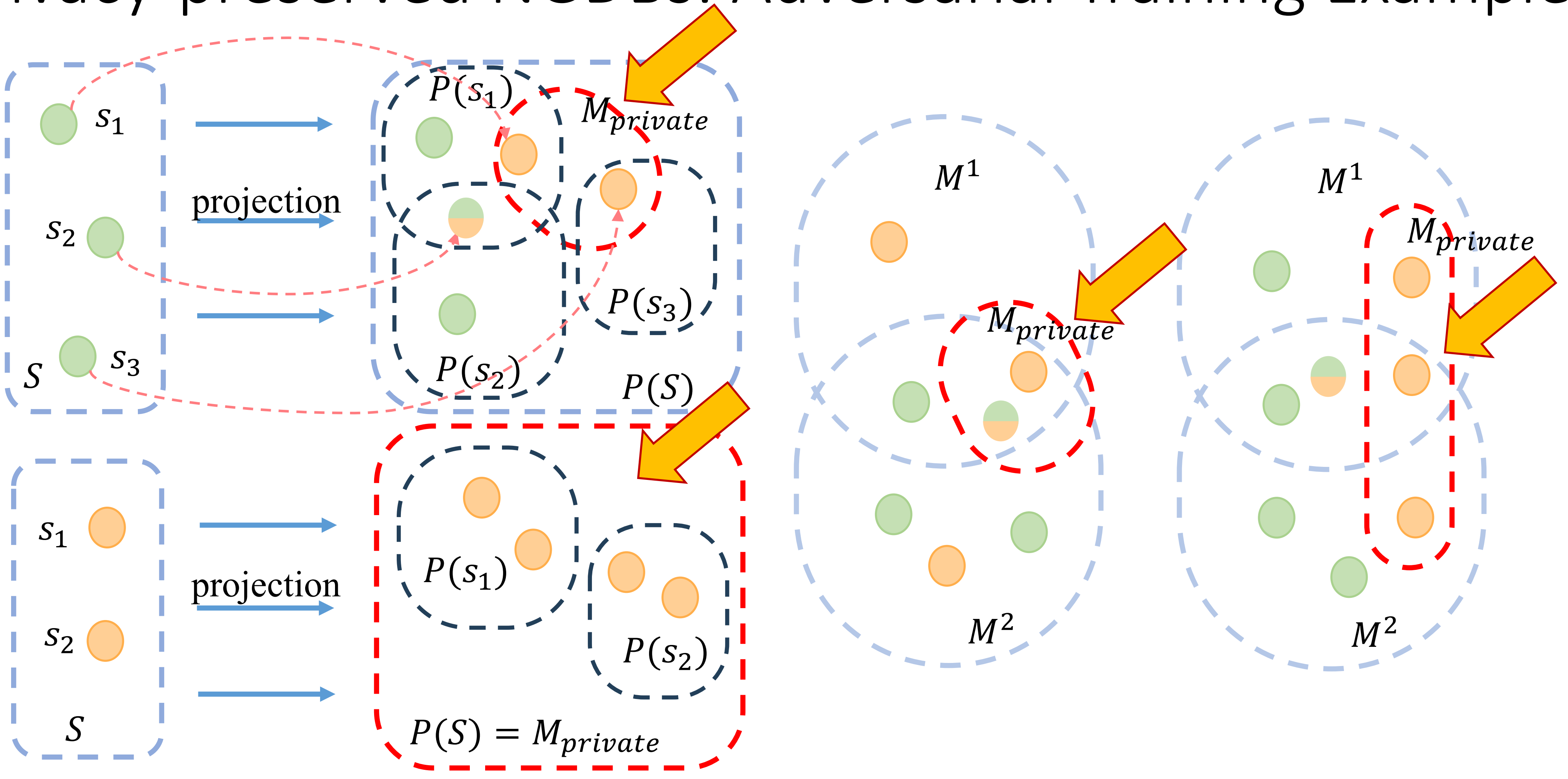
Complex Queries

Query	Answer
$q_1 = V_?.LiveIn(Hinton, V_?)$	Privacy risk query detection
$q_2 = V_?.\exists X_1, X_2: Win(X_1, Turing\ Award) \wedge GreaterThan(X_2, 1940) \wedge BornIn(X_1, X_2) \wedge Livein(X_1, V_?)$	Montreal, Toronto…
$q_3 = V_?.\exists X_1: CollabWith(LeCun, X_1) \wedge LiveIn(X_1, V_?)$	Montreal, Toronto…
$q_4 = V_?.\exists X_1, X_2: Win(X_1, Turing\ Award) \wedge SmallerThan(X_2, 1950) \wedge BornIn(X_1, X_2) \wedge LiveIn(X_1, V_?)$	Toronto, Stanford…

Privacy Risk Queries

Qi Hu, Haoran Li, Jiaxin Bai, Zihao Wang, Yangqiu Song. Privacy-Preserved Neural Graph Databases. Arxiv, 2024.

Privacy-preserved NGDBs: Adversarial Training Examples



(A) Projection (B) Intersection (C) Union

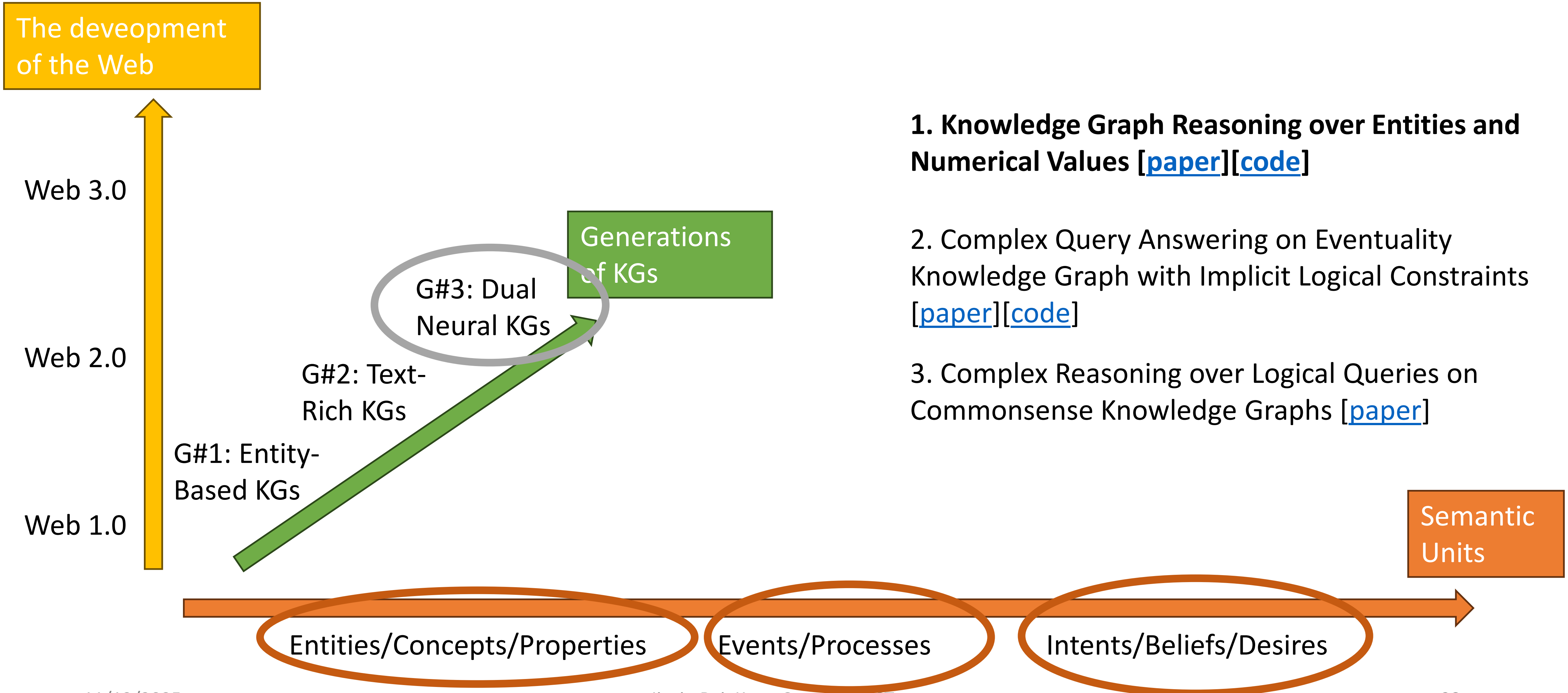
Green nodes denote non-private answers, orange nodes denote privacy-threatening answers, and orange-green nodes denote different privacy risks in subsets. Red dashed arrows denote privacy projection. The answers circled in red dashed line are at risk to leak privacy.

Conclusions for Part 4-1

- We have reviewed the frontier of recent development of knowledge graphs in terms of three dimensions
  - Three generations: entity, text, and neural
  - Semantic units: entity/attributes, events/processes, intent/desire/belief
  - **Web 1.0/2.0/3.0**

- More methods will be introduced in Part 4-2 by Jiaxin Bai
  - In terms of different types of semantic units

The Three-dimensional Development of Knowledge Graphs in Computer Science



1. Knowledge Graph Reasoning over Entities and Numerical Values [paper][code]

2. Complex Query Answering on Eventuality Knowledge Graph with Implicit Logical Constraints [paper][code]

3. Complex Reasoning over Logical Queries on Commonsense Knowledge Graphs [paper]

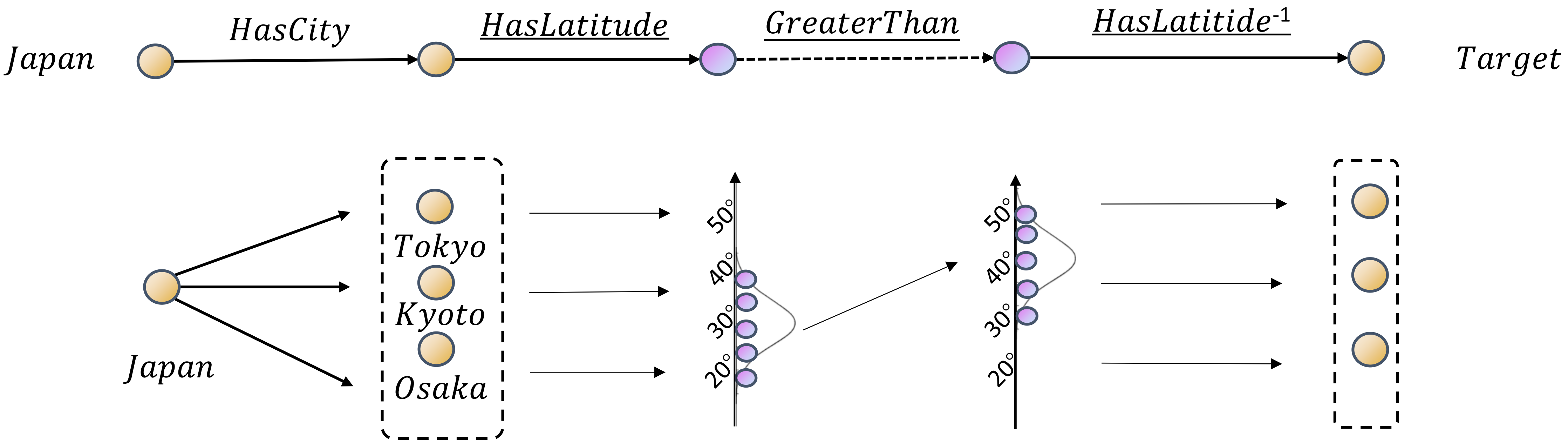
Numerical Complex Query Answering

Category	Complex Queries	Interpretations
Numerical CQA	$q_2 = V_? \,.\, \exists X_1, X_2 \colon Win(V_?, TuringAward) \wedge \underline{GreaterThan}(1927, X_2) \wedge \underline{BornIn}\,(V_?, X_2)$	Find the Turing award winners that <u>is born before</u> the year of 1927.
Numerical CQA	$q_3 = V_? \,.\, \exists X_1, X_2 \colon LocatedIn(V_?, UnitedStates) \wedge \underline{HasLatitude}(V_?, X_1) \wedge \underline{GreaterThan}(X_1, X_2) \wedge \underline{HasLatitude}(Beijing, X_2)$	Find the states in US that have <u>a higher latitudes</u> than Beijing.
Numerical CQA	$q_4 = V_? \,.\, \exists X_1, X_2, X_3 \colon LocatedIn(V_?, UnitedStates) \wedge \underline{HasPopulation}(V_?, X_1) \wedge \underline{SmallerThan}(X_1, X_2) \wedge \underline{TimesByTwo}(X_2, X_3) \wedge \underline{HasPopulation}(California, X_3)$	Find the states in US that have a <u>twice smaller population</u> than California?

Number Reasoning Network

Find the cities that have a higher latitudes than Japanese cities.

$q = V_? \,.\, \exists V_1, X_1, X_2 : \underline{HasLatitude}(V_?, X_2) \wedge \underline{GreaterThan}(X_2, X_1) \wedge \underline{HasLatitude}(V_1, X_1) \wedge LocatedIn(V_1, Japan)$



(1) Relational Projection

(2) Attribute Projection

(3) Numerical Projection

(4) Reverse Attribute Projection

Jiaxin Bai, Chen Luo, Zheng Li, Qingyu Yin, Bing Yin, Yangqiu Song: Knowledge Graph Reasoning over Entities and Numerical Values. KDD 2023: 57-68

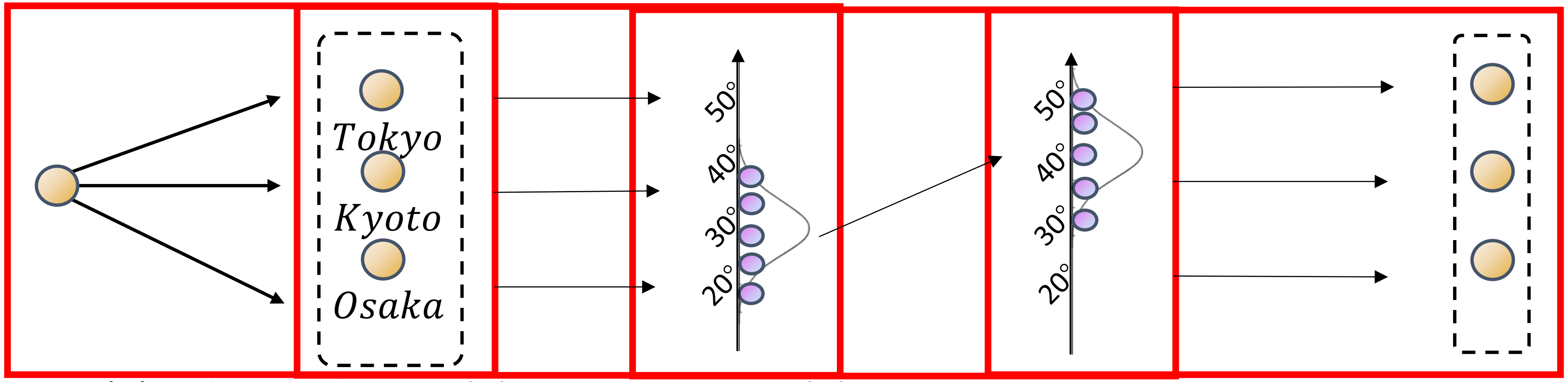
Number Reasoning Network

(1) Relational Projection (rp):
Query Embedding → Entity Set

(2) Attribute Projection (ap):
Query Embedding → Value Distribution

(3) Numerical Projection (np):
Value Distribution → Value Distribution

(4) Reverse Attribute Projection (rap):
Value Distribution → Query Embedding



(1) Relational Projection

(2) Attribute Projection

(3) Numerical Projection

(4) Reverse Attribute Projection

Number Reasoning Network

(1) Relational Projection:
Adopted from the backbones:
GQE, Query2Box, Query2Particles.

(2) (3) (4) Other Projections: Gated Transitions

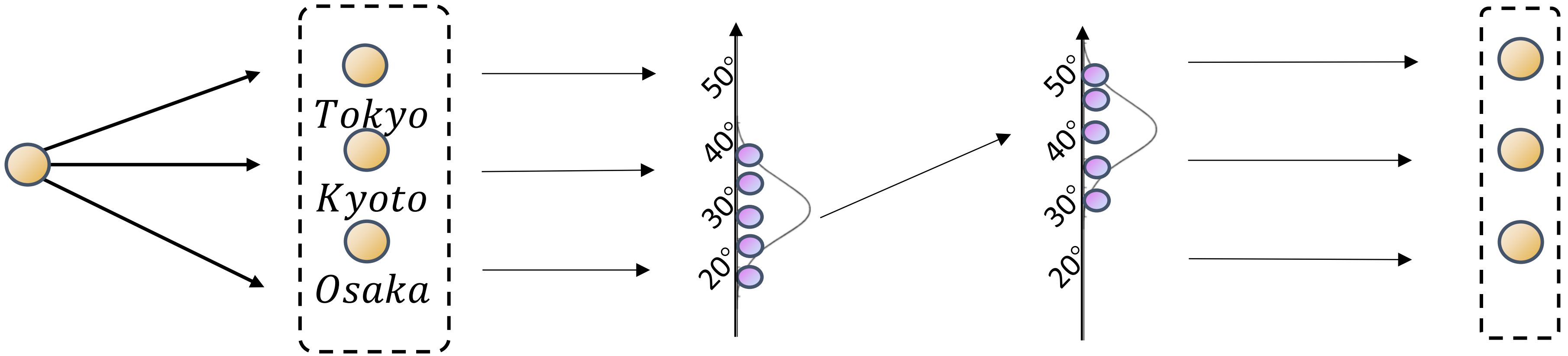
$$p_i = W_p^p q^i + b_p^p$$ Linear projection

$$z_i = \sigma\,(W_z^p e_a + U_z^p p_i + b_z^p)$$

$$r_i = \sigma\,(W_r^p e_a + U_r^p p_i + b_r^p)$$

$$t_i = \varphi\,(W_h^p e_a + U_h^p (r_i \odot p_i) + b_h^p)$$ MLP

$$\theta_{i+1} = (1 - z_i) \odot p_i + z_i \odot t_i$$ Gate selection



(1) Relational Projection

(2) Attribute Projection

(3) Numerical Projection

(4) Reverse Attribute Projection

Number Reasoning Network

Entity embeddings:
Adopted from the backbones:
GQE, Query2Box, Query2Particles.

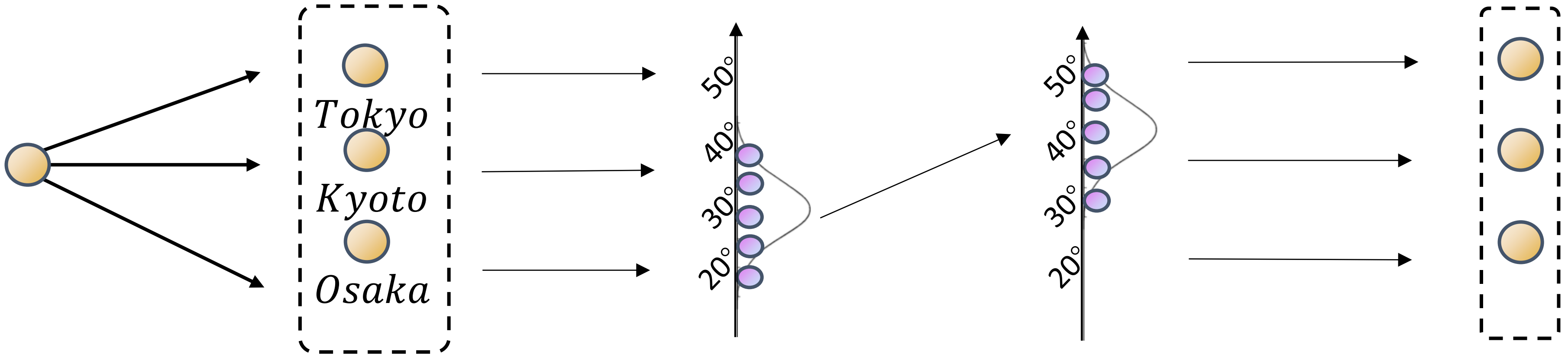
Input number embeddings

- DICE

$$\psi(v)_d = \begin{cases} \sin^{d-1}(\alpha)\cos(\alpha) \\ \sin^{D}(\alpha) \end{cases}$$

- Sinusoidal

$$\psi(v)_d = \begin{cases} \sin\frac{v}{v^{d/D}}, & d \equiv 0\ (mod\ 2) \\ \cos\frac{v}{v^{(d-1)/D}}, & d \equiv 1\ (mod\ 2) \end{cases}$$



(1) Relational Projection

(2) Attribute Projection

(3) Numerical Projection

(4) Reverse Attribute Projection

Dhanasekar Sundararaman, Shijing Si, Vivek Subramanian, Guoyin Wang, Devamanyu Hazarika, and Lawrence Carin. 2020. Methods for Numeracy-Preserving Word Embeddings. In EMNLP. 4742–4753
Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention is All you Need. NeurIPS 2017

Number Embeddings and Learning Objective

End-to-end training by Joint optimization of two losses:

$$L_A = \frac{1}{M}\sum_{j=1}^{M}\left(-\log \boxed{p_{\theta_I^{(j)}}\left(\psi\left(v^{(j)}\right)\right)} - \log \boxed{\phi_{t^{(j)}}\left(\theta_I^{(j)}\right)}\right)$$

The likelihood of the value $v^{(j)}$ sampled from distribution of $\theta_I^{(j)}$

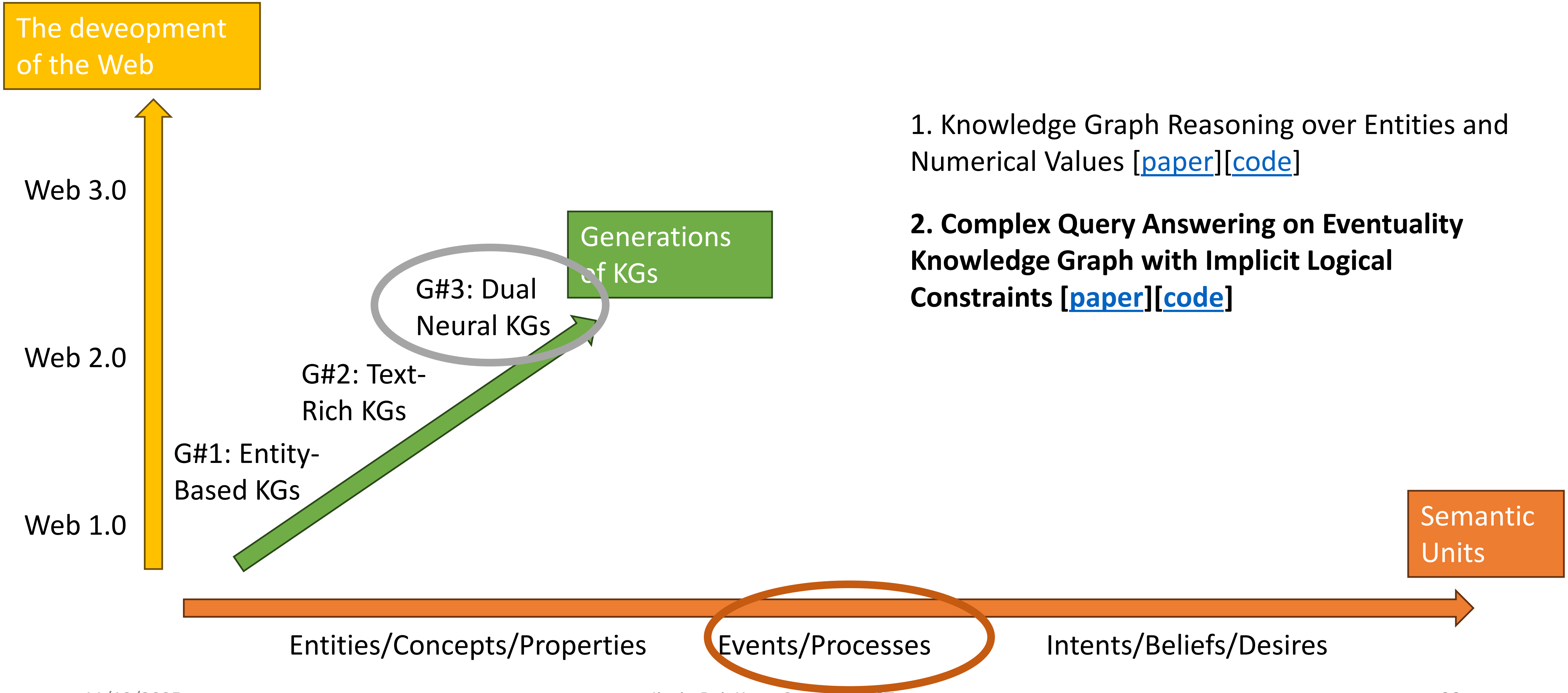
The likelihood of the distribution parameter $\theta_I^{(j)}$ is of type $t^{(j)}$

$$L_E = -\frac{1}{N}\sum_{j=1}^{N}\log \boxed{p\left(q_I^{(j)}, v^{(j)}\right)}$$

The likelihood of the entity $v^{(j)}$ is the answer of the query encoding $q_I^{(j)}$.

j is means the j-th sample, and I means the last step of distribution parameter encoding.

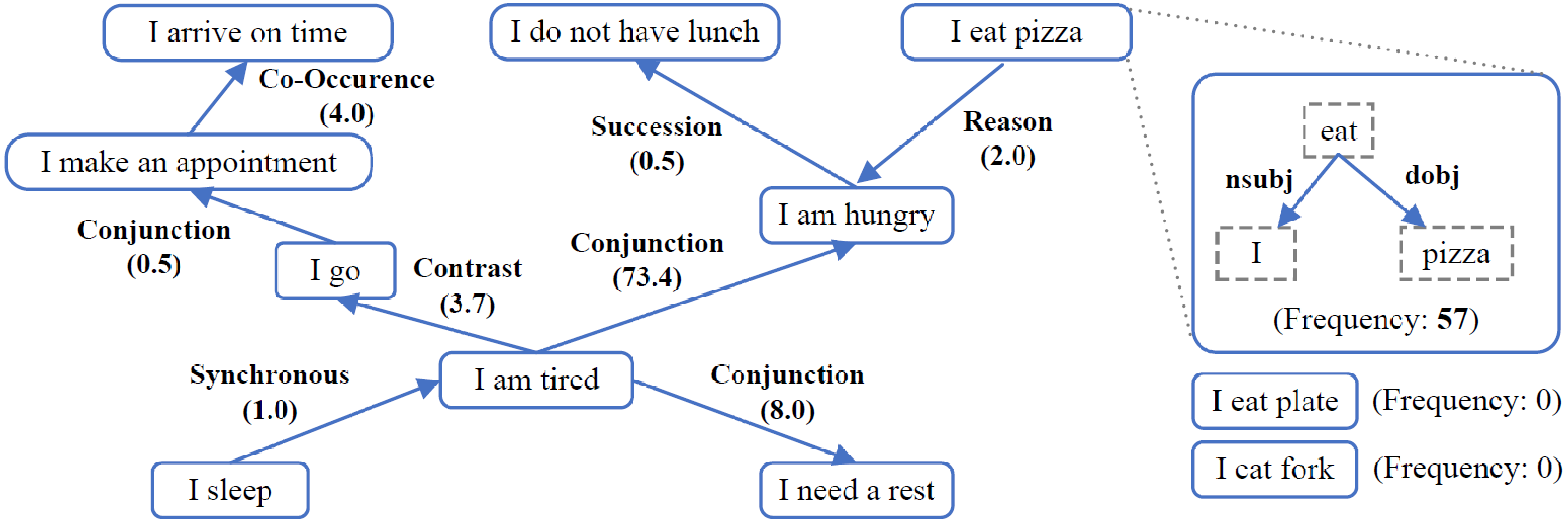
The Three-dimensional Development of Knowledge Graphs in Computer Science



1. Knowledge Graph Reasoning over Entities and Numerical Values [paper][code]

2. Complex Query Answering on Eventuality Knowledge Graph with Implicit Logical Constraints [paper][code]

ASER(Activities, States, Events, and their Relations)



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)

https://github.com/HKUST-KnowComp/ASER
Hongming Zhang, Xin Liu, Haojie Pan, Yangqiu Song, Cane Wing-Ki Leung: ASER: A Large-scale Eventuality Knowledge Graph. WWW 2020: 201-211
Katz, J. J., & Fodor, J. A. (1963). The structure of a semantic theory. Language, 39(2), 170–210.
Yorick Wilks. 1975. An intelligent analyzer and understander of English. Communications of the ACM, 18(5):264–274.

CQA on Eventuality Knowledge Graph

Complex query on eventuality graphs are **different** from the entity-relation graph

Whether and **when** the eventualities occur are important

Queries	Type	Interpretations
$q_1 = V_?.\exists V: \text{Interact}(V_?, V) \wedge \text{Assoc}(V, \mathit{Alzheimer}) \wedge \text{Assoc}(V, \mathit{MadCow})$	Entity	Find the substances that interact with the proteins associated with Alzheimer's and Mad cow disease.
$q_2 = V_?.\text{Precedence}(\mathit{Food\ is\ bad}, \mathit{PersonX\ add\ soy\ sauce}) \wedge \text{Reason}(\mathit{Food\ is\ bad}, V_?)$	Eventuality	Food is bad before PersonX add soy sauce. What is the reason for food being bad?
$q_3 = V_?.\text{Precedence}(V_?, \mathit{PersonX\ go\ home}) \wedge \text{ChosenAlternative}(\mathit{PersonX\ go\ home}, \mathit{PersonX\ buy\ an\ umbrella})$	Eventuality	Instead of buying an umbrella, PersonX go home. What happened before PersonX go home?

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

Discourse Relations and Implicit Constraints

- PersonX did not eat anything because PersonX was full

Reason(*PersonX did not eat anything, PersonX was full*)

Occurrence Constraint

$$\eta(\textit{PersonX did not eat anything}) \wedge \eta(\textit{PersonX was full})$$
$$\wedge\, \eta(\textit{PersonX did not eat anything}) \leftarrow \eta(\textit{PersonX was full})$$

Temporal Constraints

$$\tau(\textit{PersonX did not eat anything}) \succ \tau(\textit{PersonX was full})$$

$\eta(A)$ = 1 if and only if it occurs
$\tau(A) \succ \tau(\mathrm{B})$: A happens after B

Discourse Relations and Implicit Constraints

- Food is bad before PersonX add soy sauce

Precedence(*Food is bad, PersonX adds soy sauce*)

Occurrence Constraint

$\eta(\textit{Food is bad}) \wedge \eta(\textit{PersonX adds soy sauce})$

Temporal Constraints

$\tau(\textit{Food is bad}) \prec \tau(\textit{PersonX adds soy sauce})$

$\tau(A) \prec \tau(\mathrm{B})$: A happens before B
$\eta(A)$ = 1 if and only if it occurs

Discourse Relations and Implicit Constraints

- Instead of buying an umbrella, PersonX go home

ChosenAlternative(buying an umbrella, $PersonX$ go home)

Occurrence Constraint

$\eta(PersonX \textit{ go home}) \wedge \neg\, \eta(PersonX \textit{ buy an umbrella})$

$\eta(A)$ = 1 if and only if it occurs

Logical Constraints behind Discourse Relations

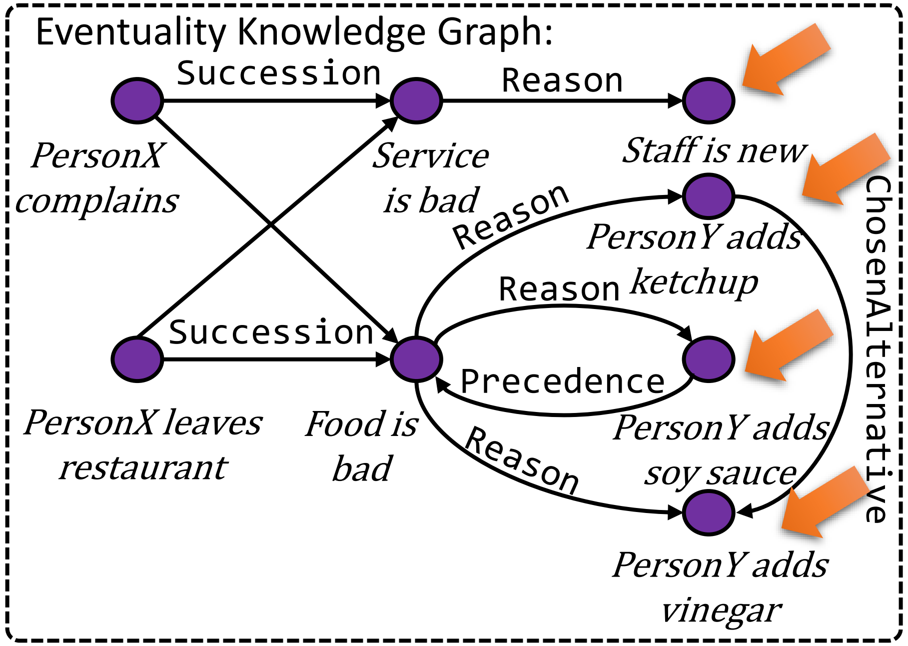
Discourse Relations	Semantics	Implicit Constraints	
		Occurrence Constraints	Temporal Constraints
Precedence(A, B)	A occurs before B.	η(A) $\wedge$ η(B)	τ(A) $\prec$ τ(B)
Succession(A, B)	A occurs after B happens.	η(A) $\wedge$ η(B)	τ(A) $\succ$ τ(B)
Synchronous(A, B)	A occurs at the same time as B.	η(A) $\wedge$ η(B)	τ(A) = τ(B)
Reason(A, B)	A occurs because B.	η(A) $\wedge$ η(B) $\wedge$ (η(A) $\leftarrow$ η(B))	τ (A) $\succ$ τ (B)
Result(A, B)	A occurs as a result B.	η(A) $\wedge$ η(B) $\wedge$ (η(A) $\rightarrow$ η(B))	τ (A) $\prec$ τ (B)
Condition(A, B)	If B occurs, A.	η(A) $\rightarrow$ η(B)	τ (A) $\succ$ τ (B)
Concession(A, B)	B occurs, although A.	η(A) $\wedge$ η(B)	-
Constrast(A, B)	B occurs, but A.	η(A) $\wedge$ η(B)	-
Conjunction(A, B)	A and B both occur.	η(A) $\wedge$ η(B)	-
Instantiation(A, B)	B is a more detailed description of A.	η(A) $\wedge$ η(B)	-
Restatement(A, B)	A restates the semantics of B.	η(A) $\leftrightarrow$ η(B)	-
Alternative(A, B)	A and B are alternative situations.	η(A) $\vee$ η(B)	-
ChosenAlternative(A, B)	Instead of B occurs, A.	η(A) $\wedge$ $\neg$ η(B)	-
Exception(A, B)	A, except B.	$\neg$ η(A) $\wedge$ η(B) $\wedge$ ($\neg$ η(B) $\rightarrow$ η(A))	-

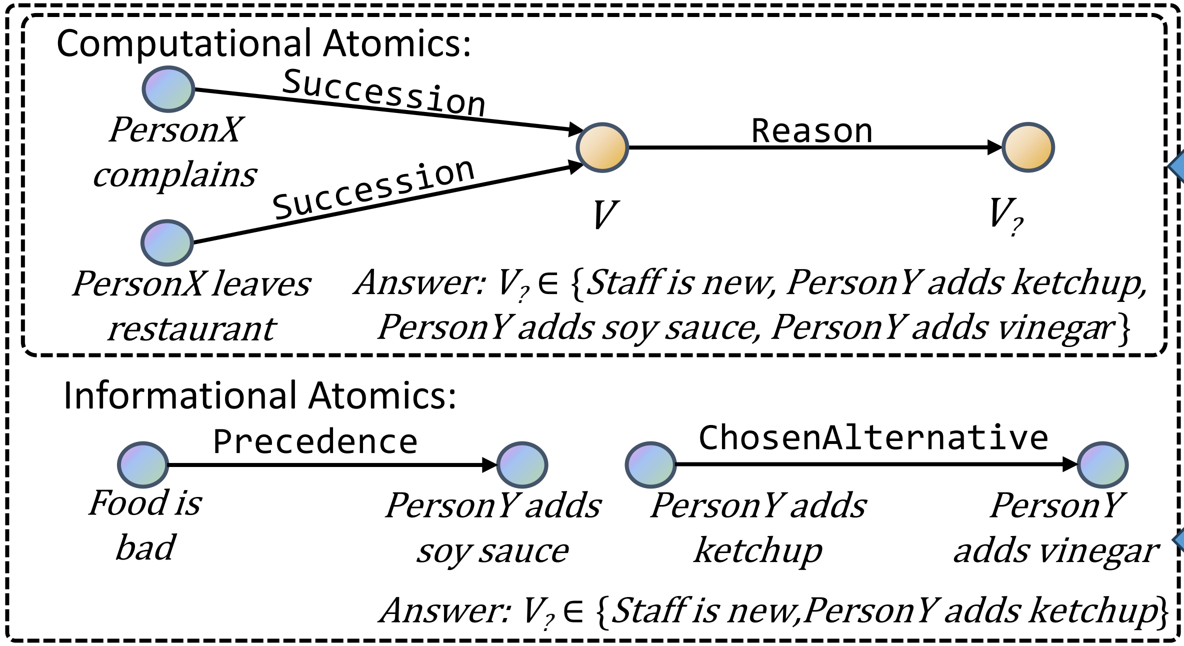
$\tau(A) \prec \tau(\mathrm{B})$: A happens before B, $\eta(A)$ = 1 if and only if it occurs

Logical Query with Implicit Constraints

Question: Food is bad before PersonY adds soy sauce. Instead of adding vinegar, PersonY adds ketchup. PersonX complains after V. PersonX leaves the restaurant after V. The reason V is V'?. What is V'?

Query on Graph: $q = V_?\,.\ \exists V$: Succession(*PersonX complains, V*) ∧ Succession(*PersonX leaves restaurant, V*) ∧ Reason(V, $V_?$) ∧ Precedence(*Food is bad, PersonY adds soy sauce*) ∧ ChosenAlternative(*PersonY adds ketchup, PersonY adds vinegar*)

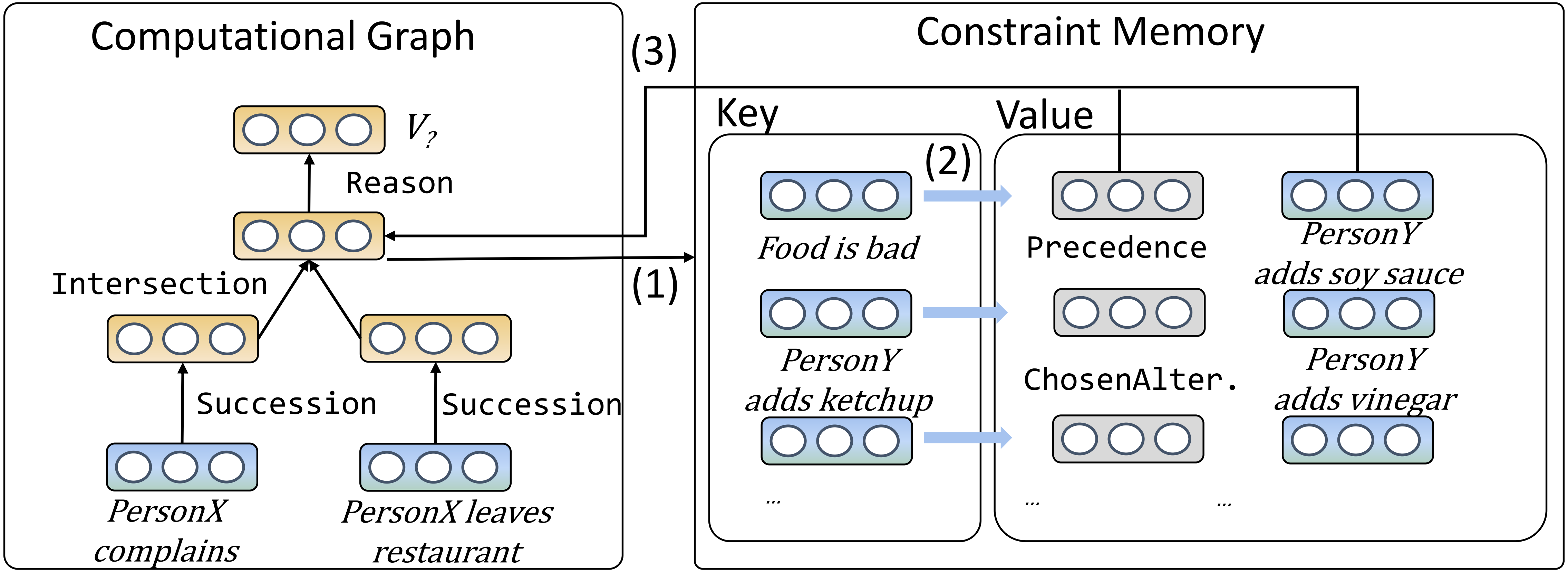




Without context and its constraints: 4 answers

With Implicit Constraints: Only 2 answers

Query Encoding with Constraint Memory



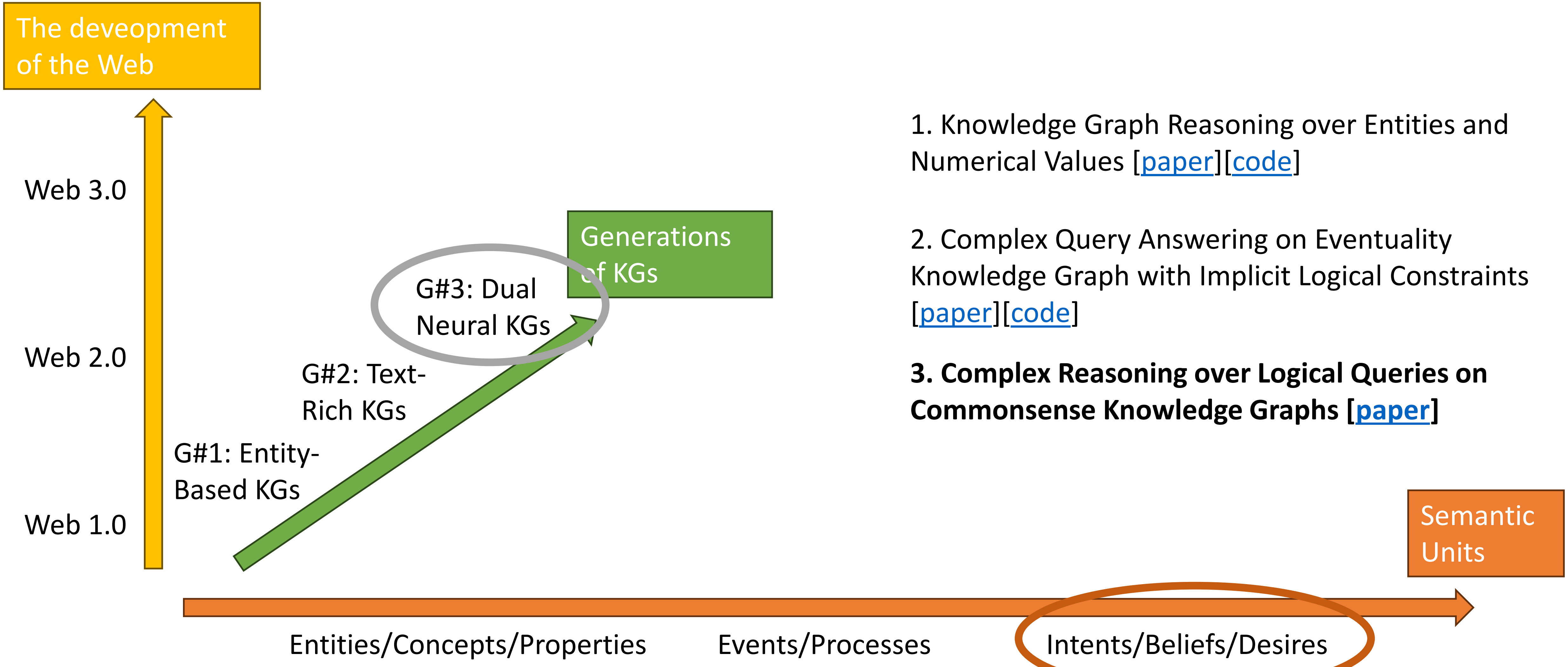
(1) $s_{i,m} = < q_i,\ c_h^{(m)} >$
Computes the relevance of query embedding to the head of the memory key at position m.

(2) $v_i = \sum_{m=1}^{M} s_{i,m} \left(c_r^{(m)} + c_t^{(m)}\right)$
Computes the aggregated memory values across M memory cells with the importance weighted by relevance scores.

(3) $q_i = q_i + MLP(v_i)$
Computes the query embedding with memory values with the help of a MLP layer.

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

The Three-dimensional Development of Knowledge Graphs in Computer Science



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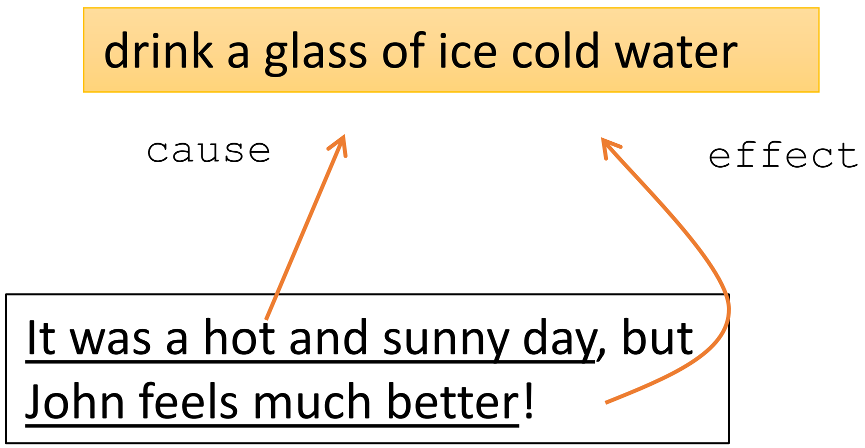
2. Complex Query Answering on Eventuality Knowledge Graph with Implicit Logical Constraints [paper][code]

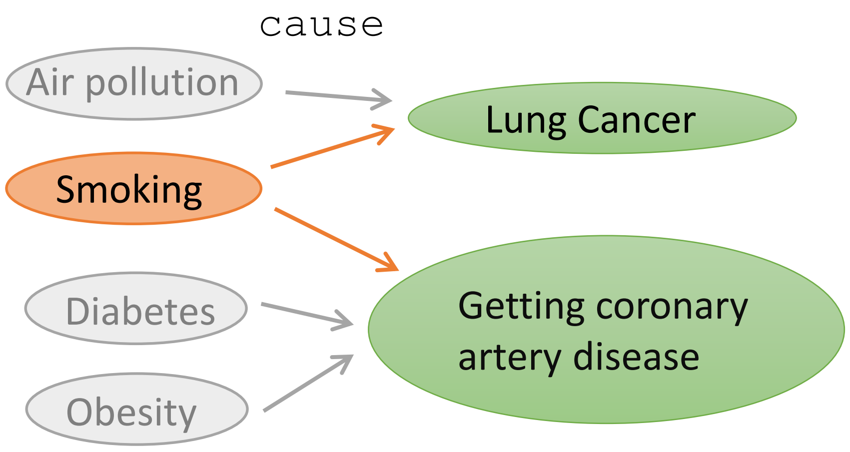
3. Complex Reasoning over Logical Queries on Commonsense Knowledge Graphs [paper]

Moving towards intention based commonsense complex question answering

- Reasoning on real-world text and narratives requires complex reasoning over **multiple events,** and **inferring implicit context**.



Abduction



Common cause

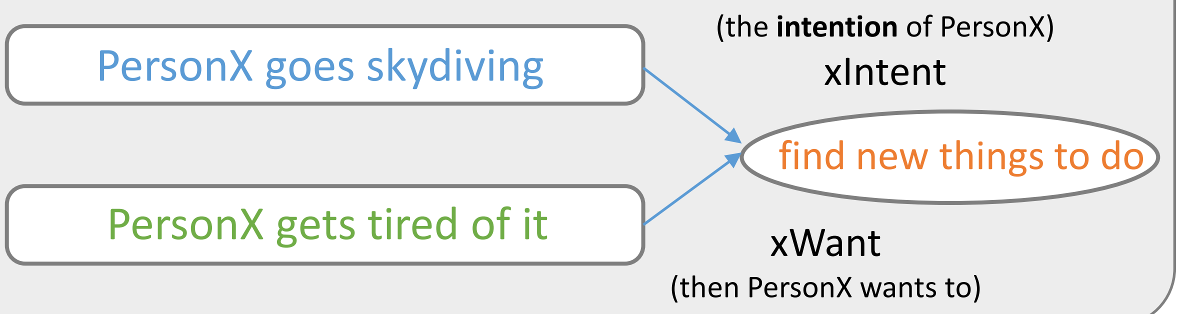
multi-hop effects

Tianqing Fang, Zeming Chen, Yangqiu Song, Antoine Bosselut. Complex Reasoning over Logical Queries on Commonsense Knowledge Graphs. Arxiv 2024.

Complex Commonsense Reasoning

- Sampling conjunctive logical queries over existing CSKG

$$q[V_?] = V_?\text{: xIntent(X goes sky diving}, V_?) \wedge \text{xWant (X gets tired of it}, V_?)$$



- Sampling synthetic query at scale
- Perform verbalization to make the query in natural language
- Define reasoning (question) based on the relations.

Base CSKG: ATOMIC2020

Verbalization

LLM-added context *PersonX is living a boring life.*

Rule-based discourse After getting tired of it PersonX goes skydiving

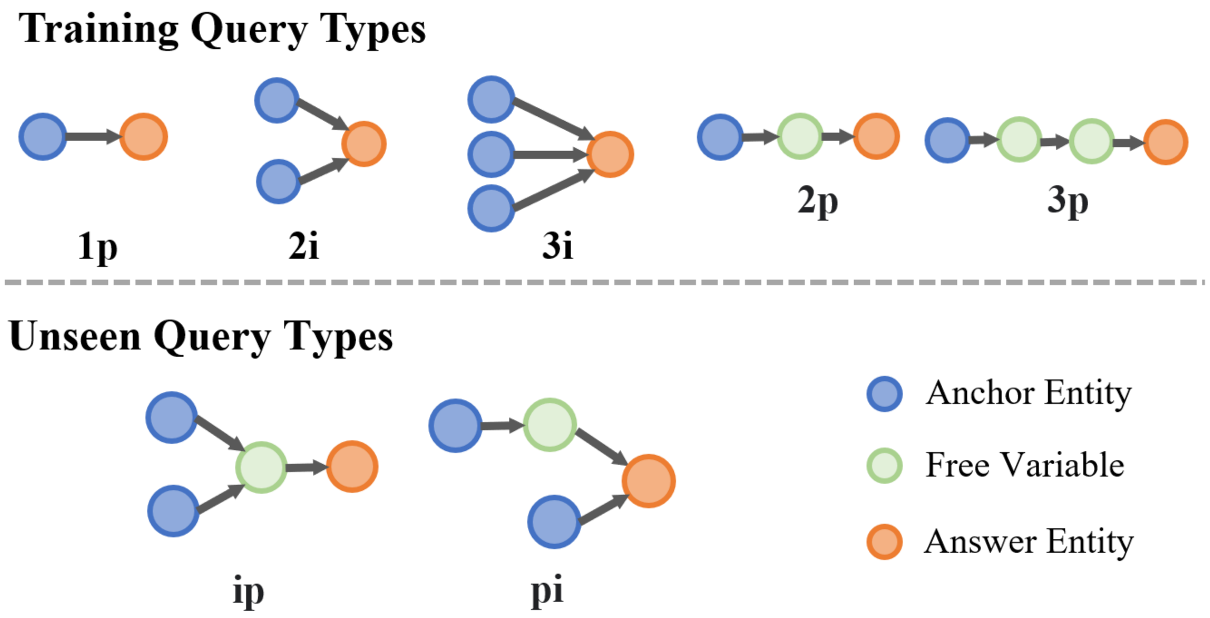
Question: What's both the intention of PersonX going skydiving and what X wants to do after PersonX getting tired of it?

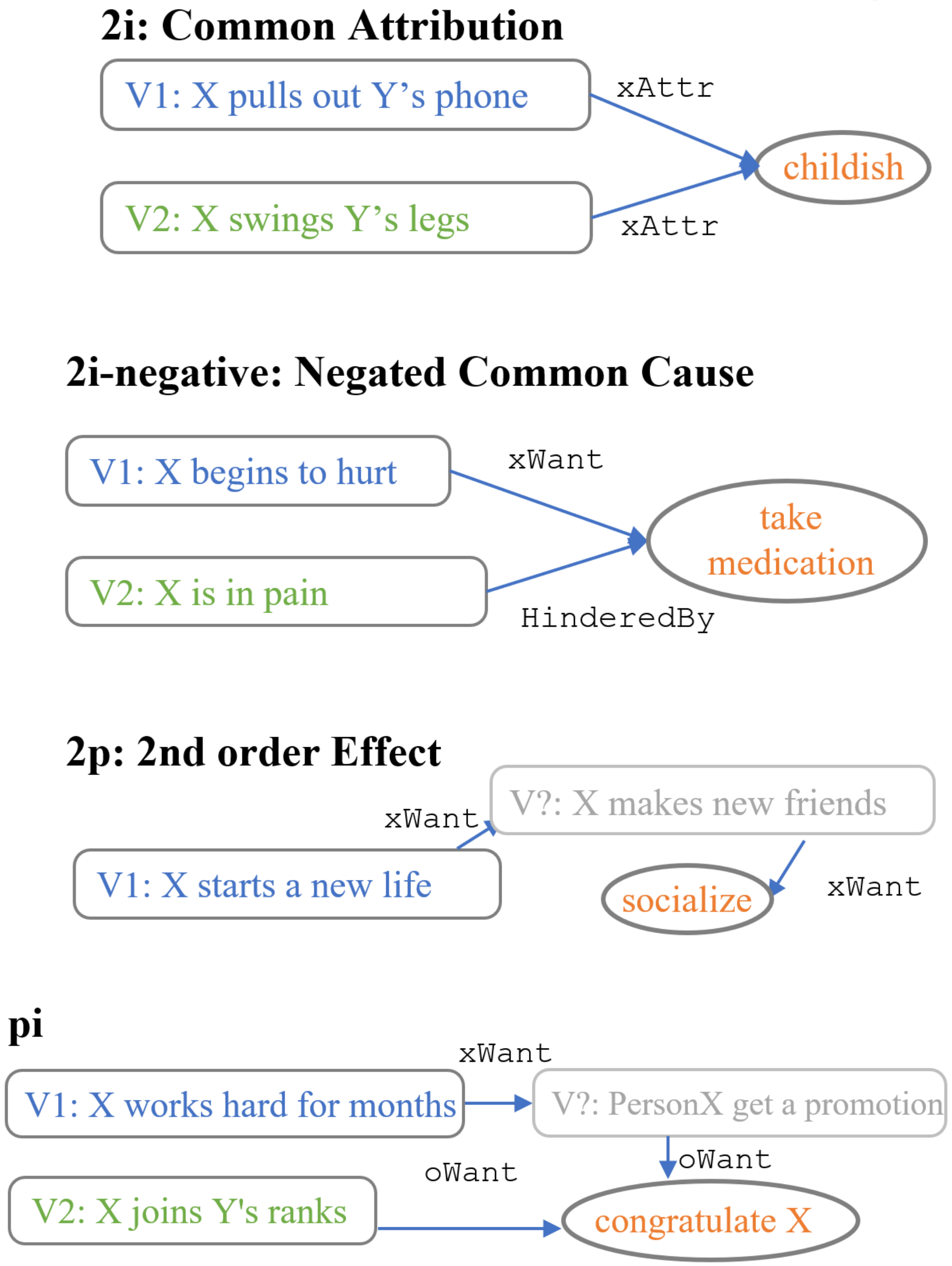
Answer: find new things to do

Tianqing Fang, Zeming Chen, Yangqiu Song, Antoine Bosselut. Complex Reasoning over Logical Queries on Commonsense Knowledge Graphs. Arxiv 2024.

Conjunctive Logical Queries

- Similar to CQA problems





Tianqing Fang, Zeming Chen, Yangqiu Song, Antoine Bosselut. Complex Reasoning over Logical Queries on Commonsense Knowledge Graphs. Arxiv 2024.

Benchmarking

- Multiple-Choice QA:
  - Negative sampling: 2 are randomly sampled across CSKB, 2 are randomly sampled across one-hop answers (hard negative).
  - An additional "No answers are correct option"
- Generative complex commonsense reasoning
  - 53 annotators
  - Fleiss Kappa: 0.445; IAA: 78%
  - All disagreements are fixed by experts

#Train	790k
#Eval (annotated)	1,317
%wrong verbalization	4.5%
%sampled answers that are plausible	52.1%
%sampled negatives that are plausible	23.5%

Tianqing Fang, Zeming Chen, Yangqiu Song, Antoine Bosselut. Complex Reasoning over Logical Queries on Commonsense Knowledge Graphs. Arxiv 2024.

LLMs Still Fall Short on This Task

Method	2i	2i-neg	3i	2p	ip	pi	All
API-based LLMs							
`gpt-3.5-turbo-0613`	33.56	43.12	42.01	38.66	38.05	28.40	37.74
- 1-shot	43.31	35.31	58.45	57.73	51.33	62.96	48.22
- 1-shot w/ CoT	45.80	36.43	54.34	57.73	50.44	66.67	48.75
- 8-shot (2i, 2p)	48.52	41.26	57.08	67.53	53.10	74.07	53.22
- 8-shot (2i, 2p) w/ CoT	52.61	46.10	60.27	59.79	52.21	65.43	54.37
`gpt-4-1106-preview`	44.67	46.47	52.05	32.47	40.71	53.08	44.64
- 1-shot	47.85	42.01	50.68	38.66	44.25	50.62	45.63
- 1-shot w/ CoT	48.97	46.46	52.96	49.48	52.21	58.02	50.04
- 8-shot (2i, 2p)	54.87	46.47	58.90	45.88	52.21	66.67	53.00
- 8-shot (2i, 2p) w/ CoT	57.82	49.07	62.56	61.34	52.21	66.67	57.40
Open-source (QA) Language Models							
HyKAS (Ma et al., 2021, zero-shot)	34.92	39.41	27.85	41.75	37.17	33.33	35.76
CAR (Wang et al., 2023a, zero-shot)	37.41	30.48	37.44	57.73	32.74	53.09	39.56
Llama2 (7B) (Touvron et al., 2023)	35.15	21.93	39.27	35.57	28.32	51.85	33.64
Vera (5B) (Liu et al., 2023)	47.62	27.51	40.18	66.49	52.21	58.02	46.09
UnifiedQA-v2 (Khashabi et al., 2022)	56.23	39.41	62.56	58.76	51.33	62.96	54.21
Flan-T5 (11B) (Chung et al., 2022)	58.28	47.21	65.30	**76.29**	56.64	79.01	60.97
Fine-tuned on COM^2							
DeBERTa-v3-Large (+COM^2)	60.09	**58.36**	69.41	61.86	**59.29**	81.48	62.79
CAR-DeBERTa-v3-Large (+COM^2)	**61.22**	56.13	**69.86**	68.56	56.64	**85.19**	**63.78**

Table 1: Model performance (%) on the multiple-choice question answering evaluation set of COM^2.

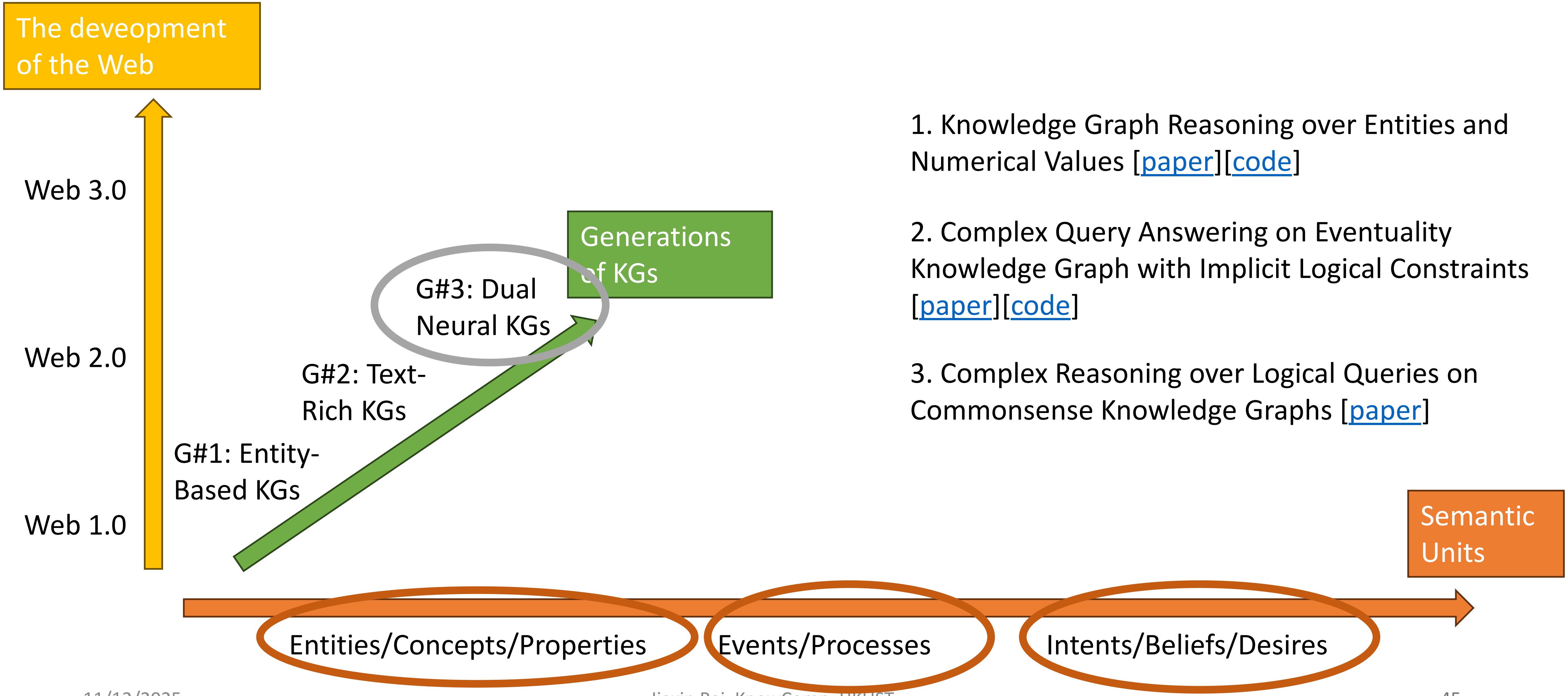
GPT:
37.74%~57.40%

Open LLMs:
33.64%~60.97%

Finetuned:
62.79%~63.78%

Tianqing Fang, Zeming Chen, Yangqiu Song, Antoine Bosselut. Complex Reasoning over Logical Queries on Commonsense Knowledge Graphs. Arxiv 2024.

The Three-dimensional Development of Knowledge Graphs in Computer Science



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Conclusions for Part 4-2

- We have reviewed the frontier of recent development of knowledge graphs in terms methods of different demantic units:
  - Entity/attributes
  - Events/processes
  - Intent/desire/belief
- More recent advances in KG reasoning combined with LLMs will be introduced in Part 5 by Lihui Liu