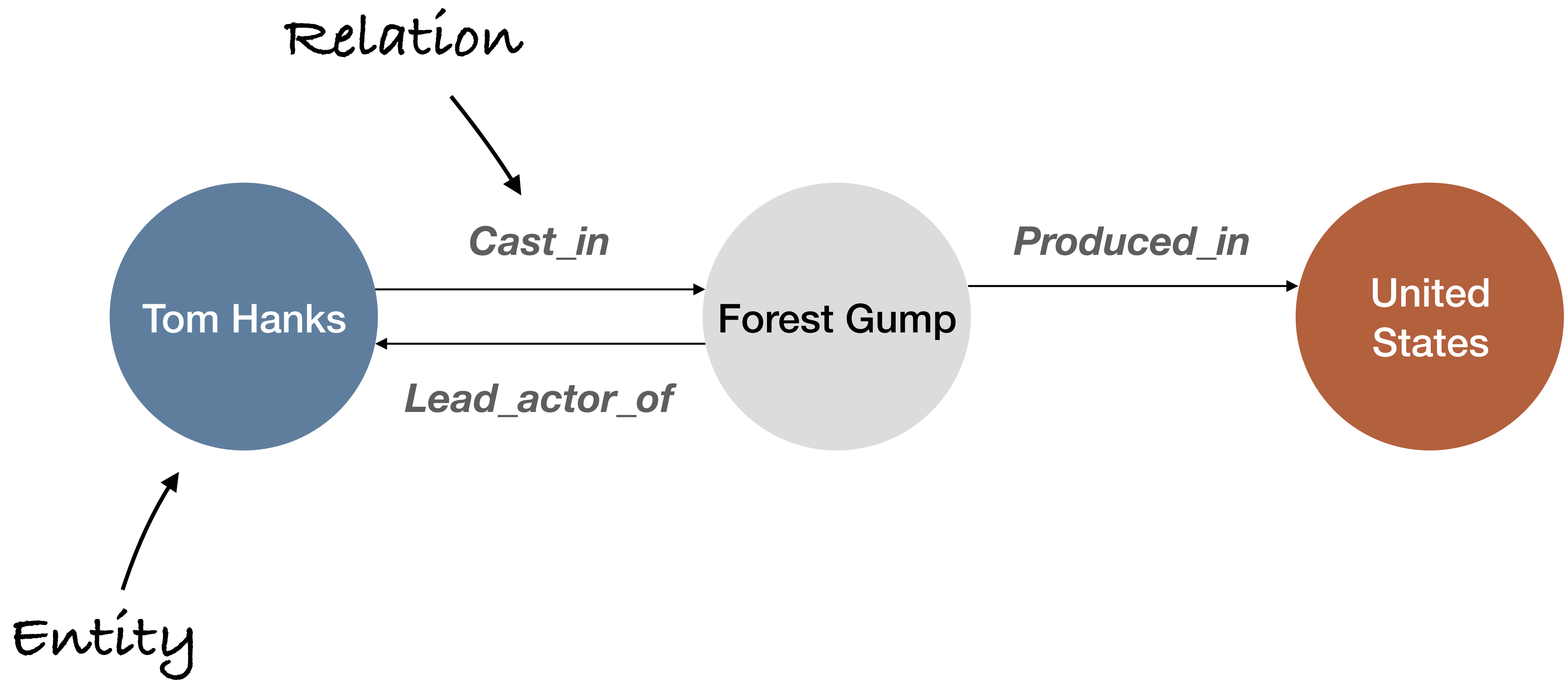
Towards Explainable and Scalable Knowledge Graph Inference

Salesforce Research Lightening Tech Talk ICLR 2019

Presenter: Victoria Lin

When: 10:30am, May 7

Knowledge Graph



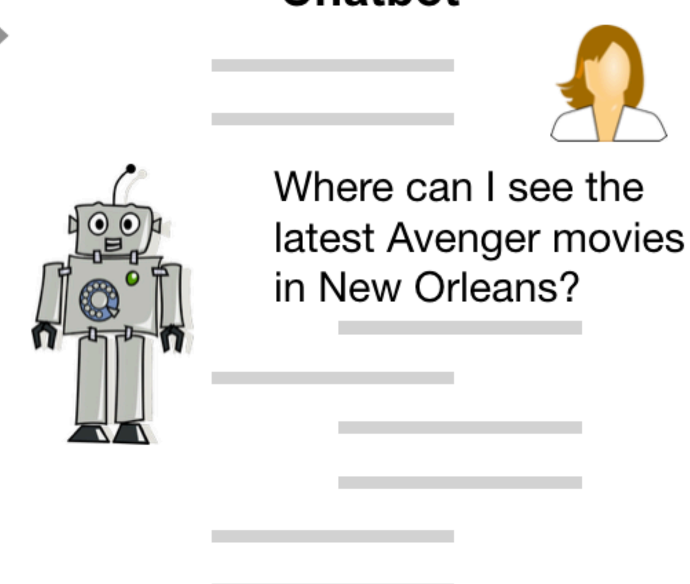
Horsepower of Enterprise AI Applications

Open-domain KGs

Domain-specific KGs

Recommendation System

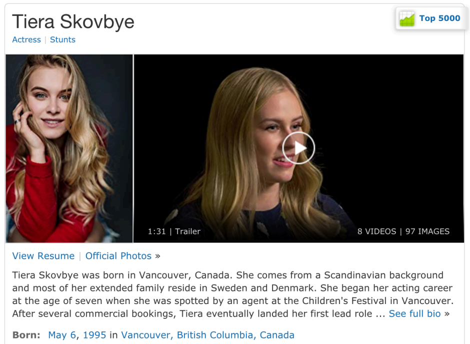
Chatbot

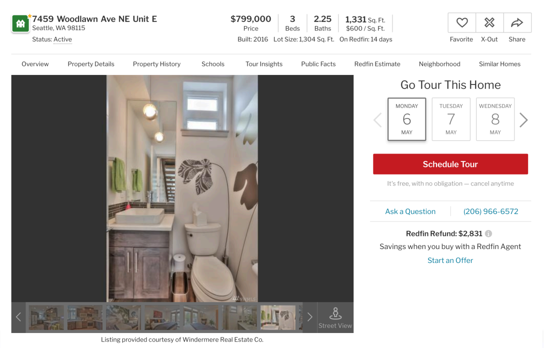


Knowledge Graph Curation

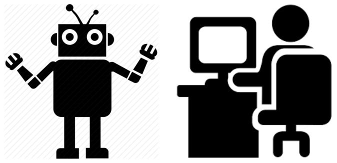
Manual Input / Legacy Ontology

Information Extraction





Verification
Cleaning
Fusion



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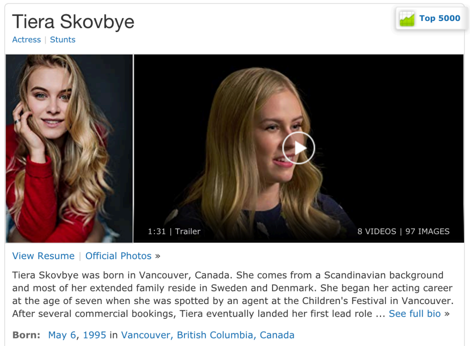

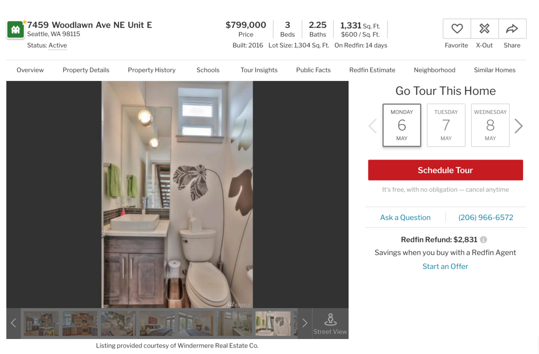

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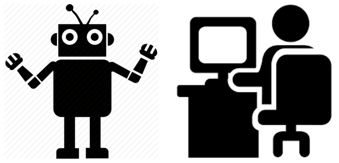

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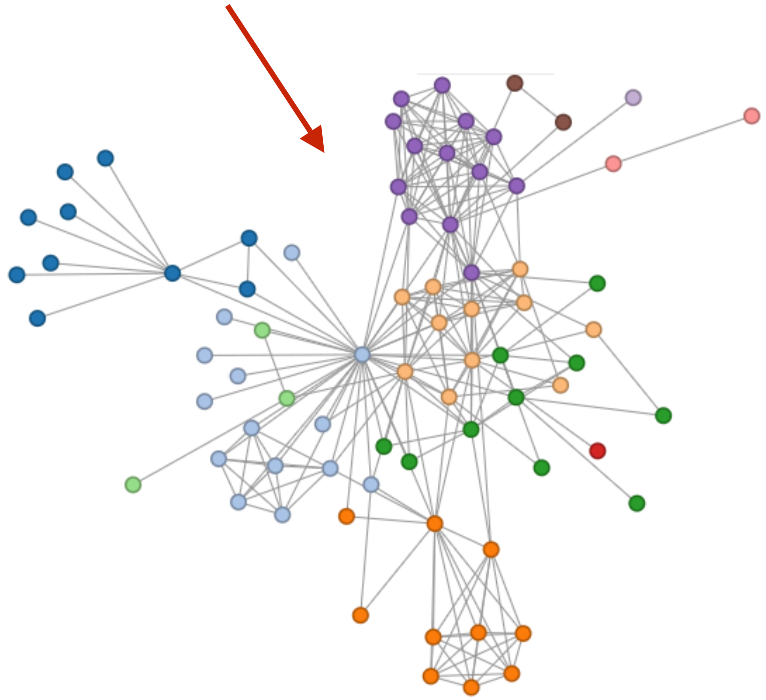

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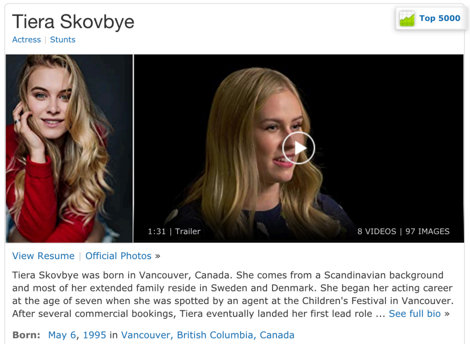

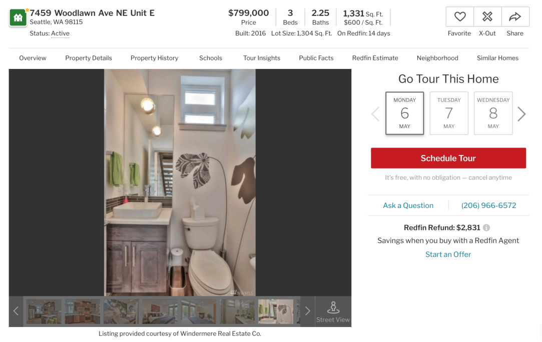

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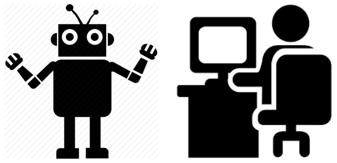

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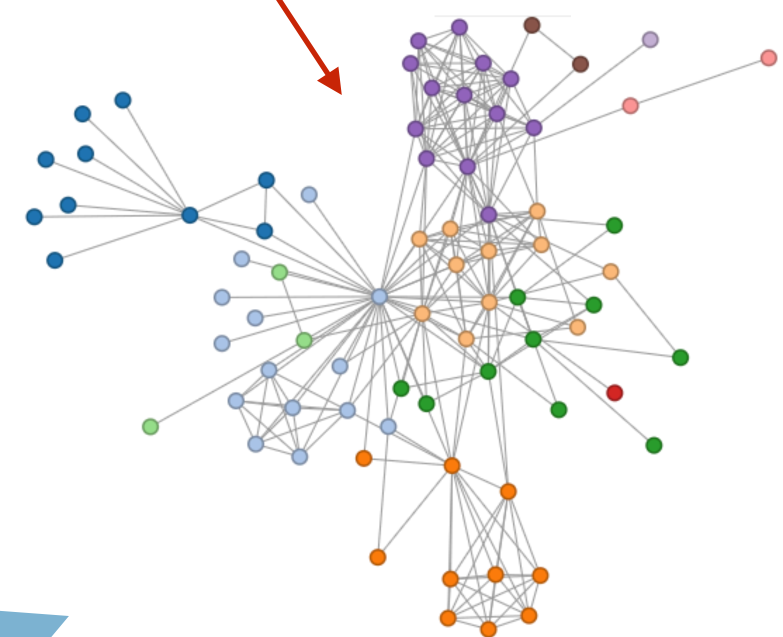
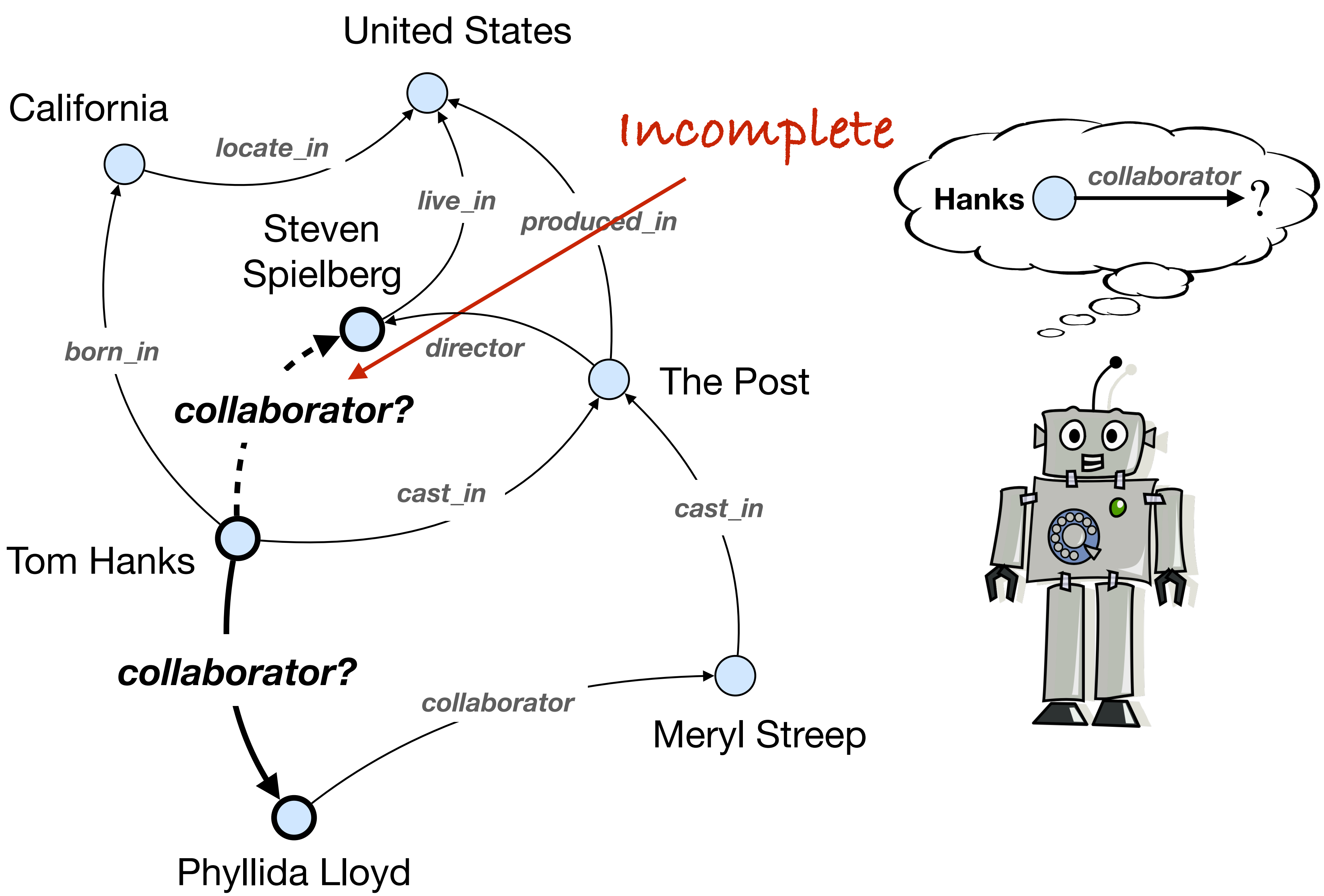
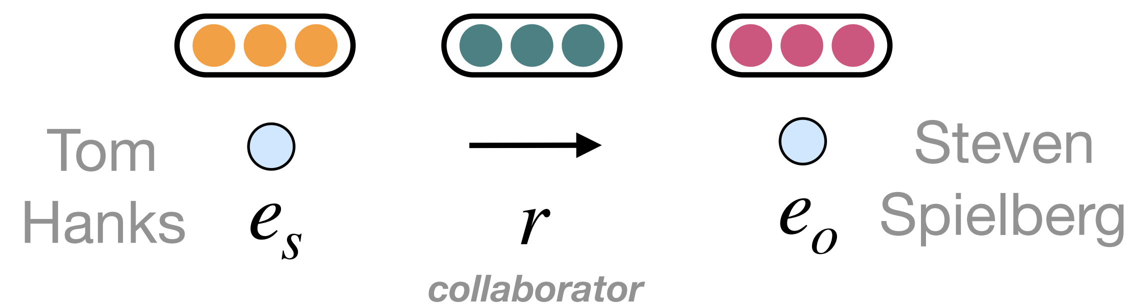


Inference

Knowledge Graph Completion



Knowledge Graph Embeddings



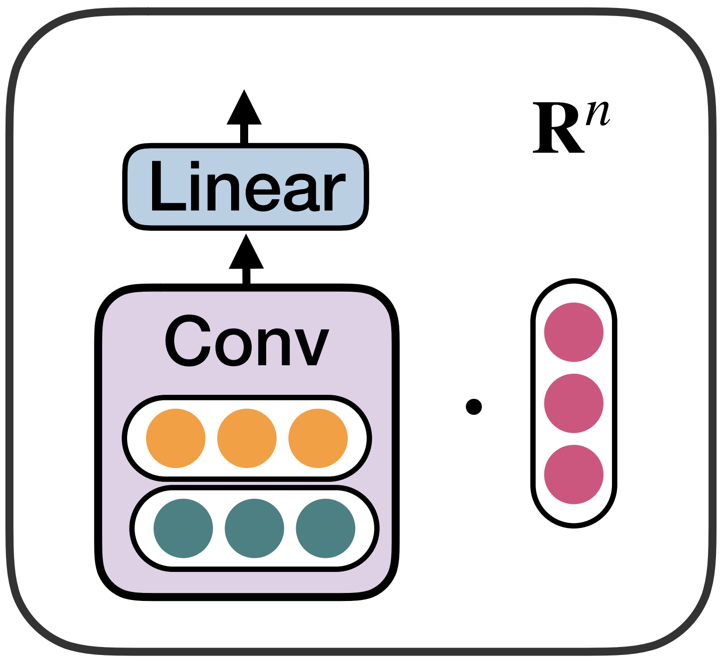
Highly accurate &
Efficient

	MRR
ConvE	0.957 (max = 1)

Tab 1. ConvE query answering performance on the UMLS benchmark dataset (Kok and Domingos 2007)

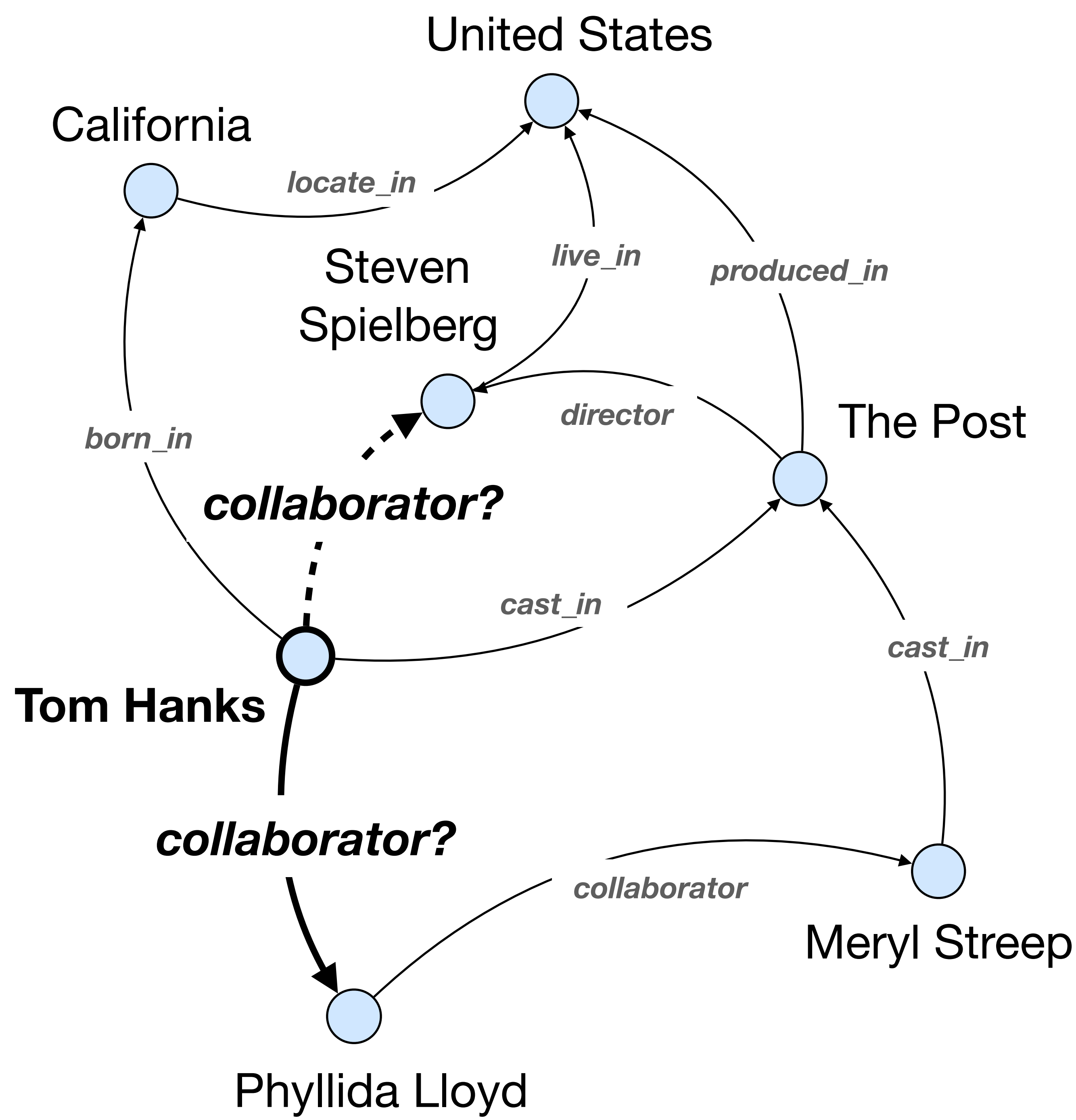
Lack
interpretabilit

Why Spielberg is a collaborator of Hanks?

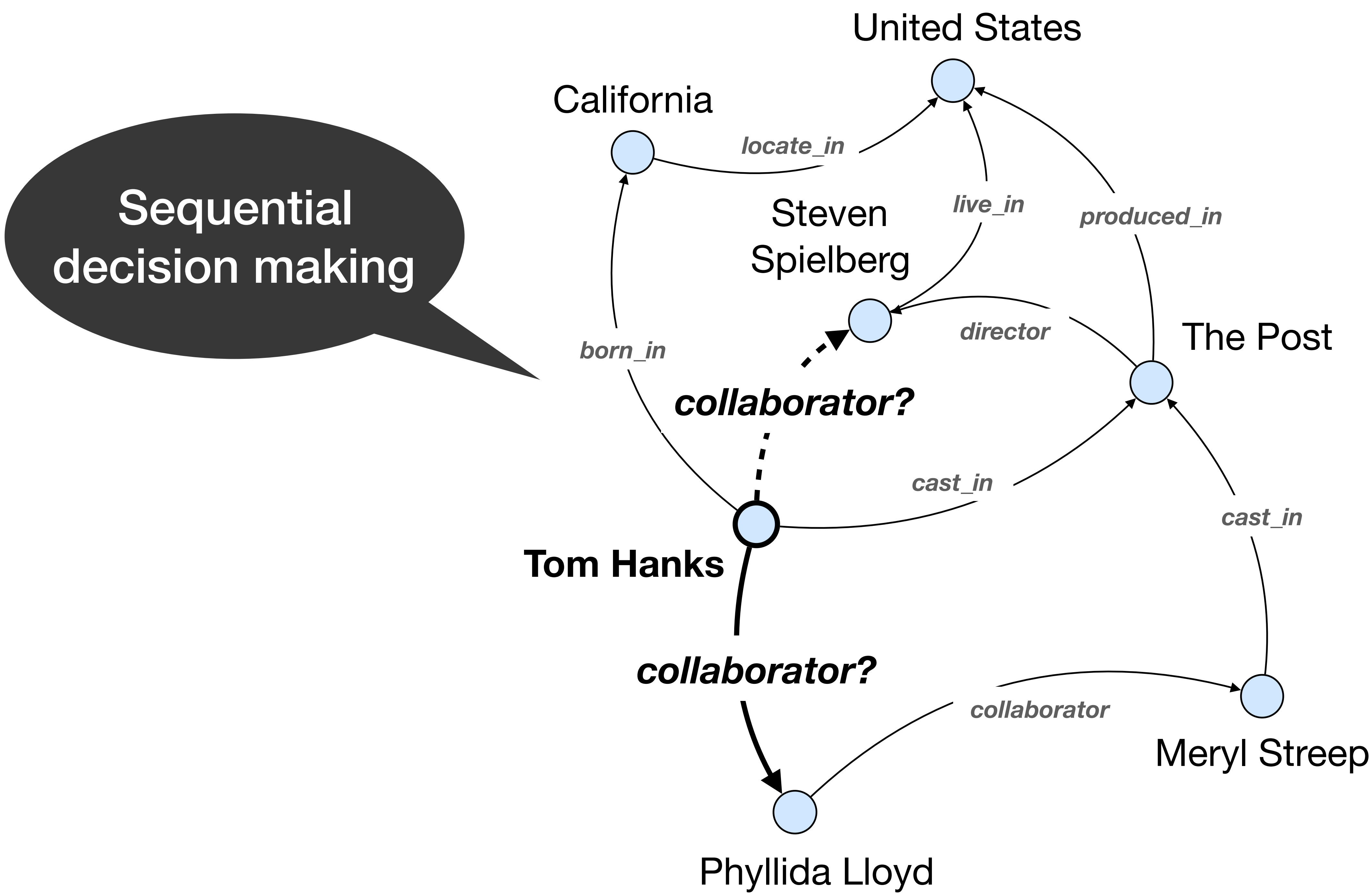


ConvE

Multi-Hop Reasoning Models

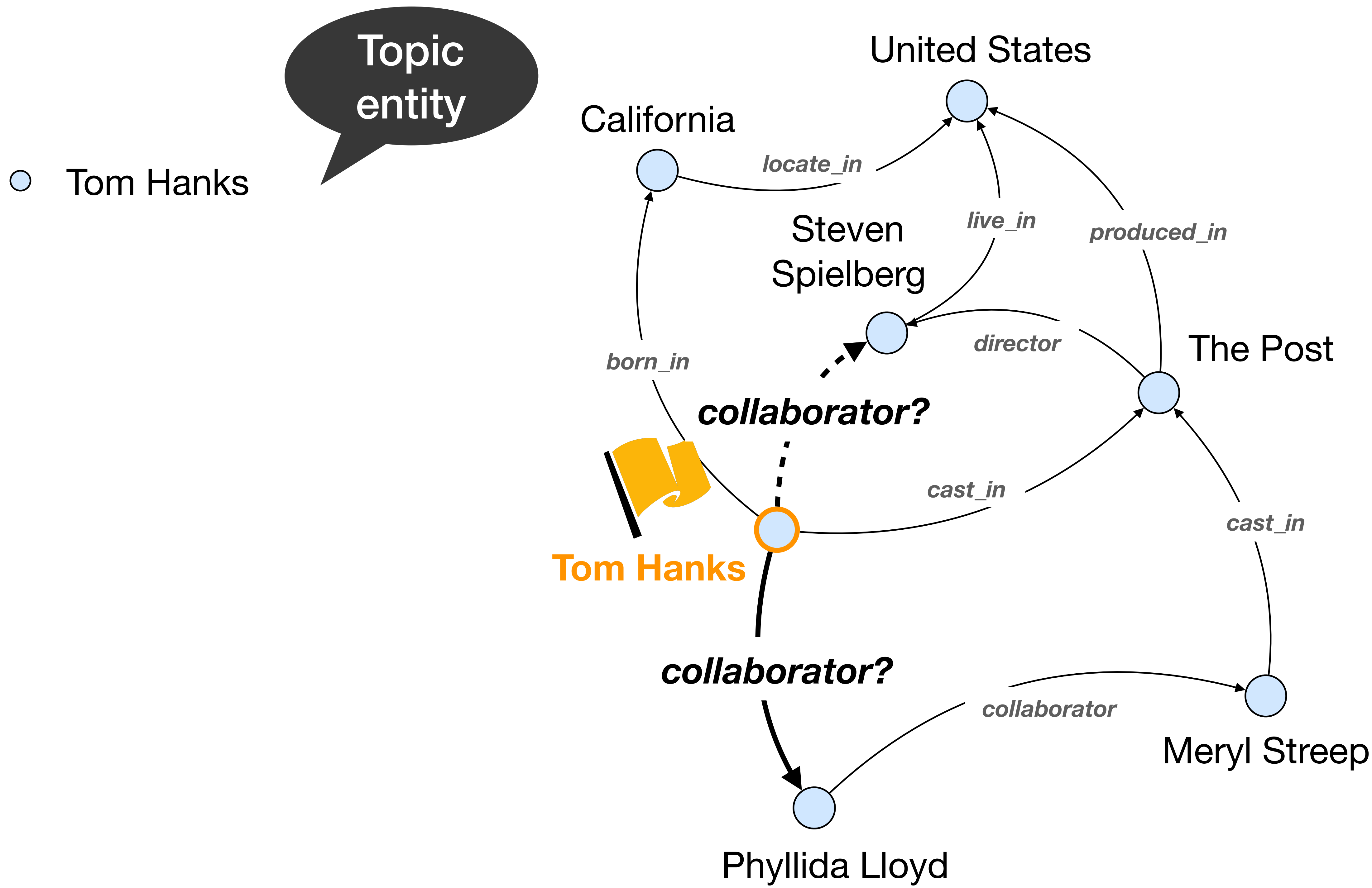


Multi-Hop Reasoning Models



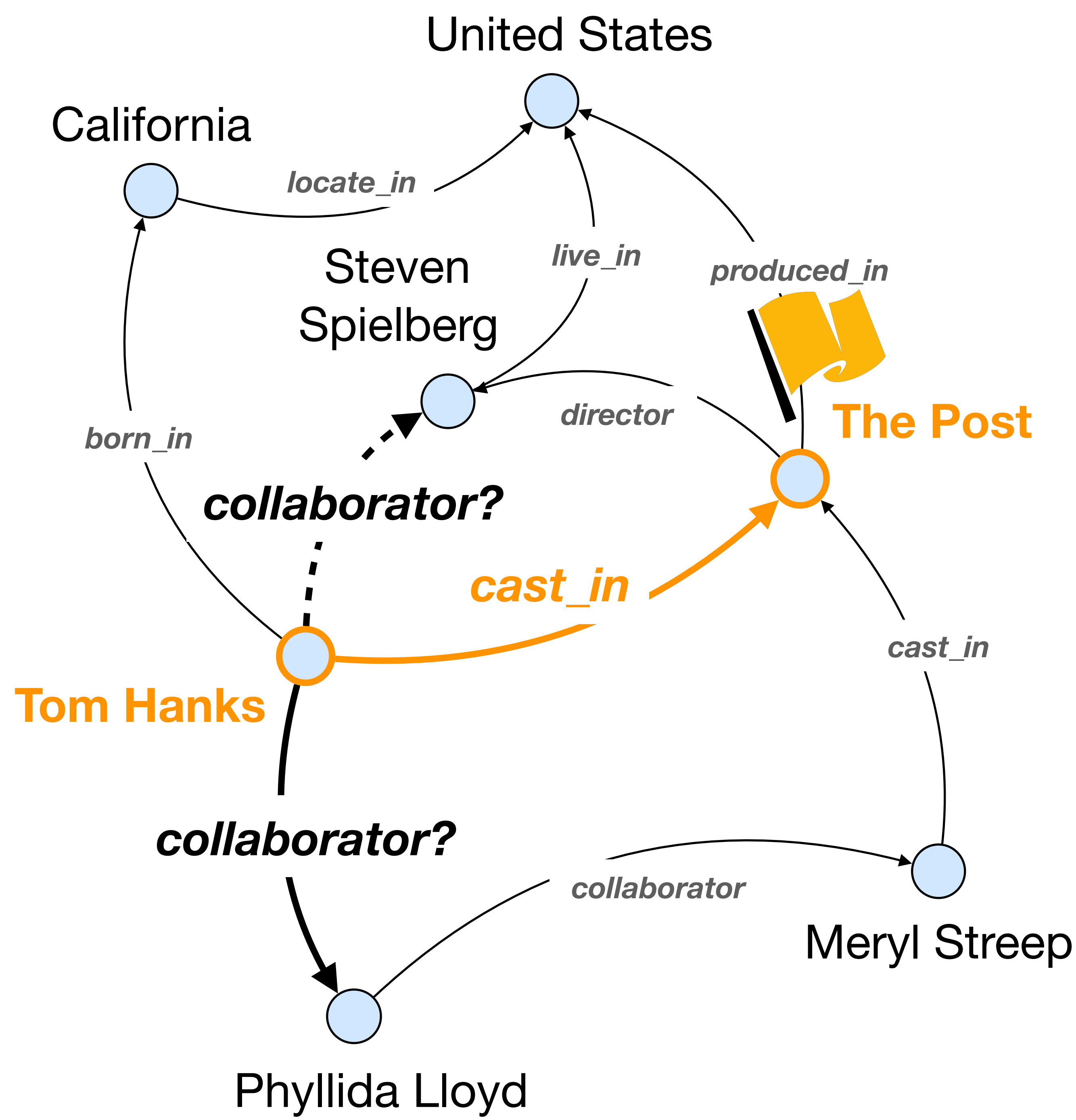
MINERVA (Das et al. 2018)

Multi-Hop Reasoning Models



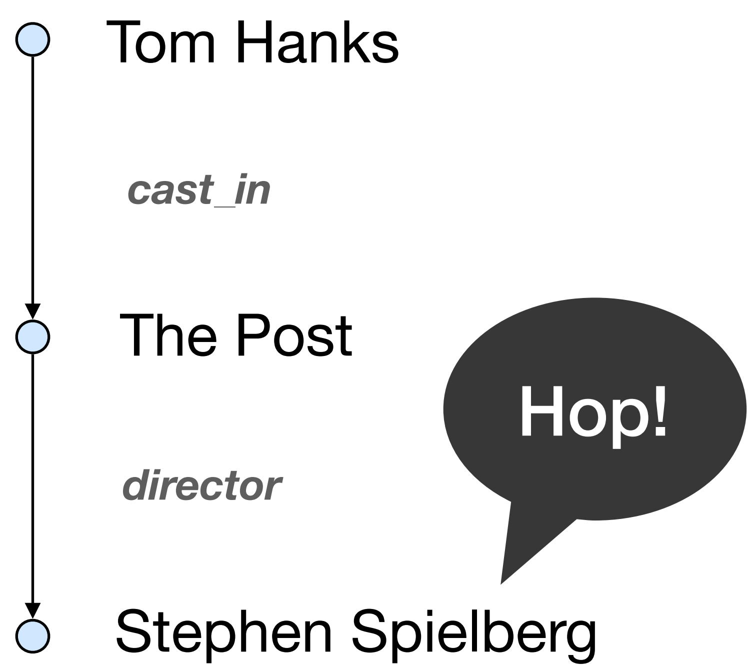
MINERVA (Das et al. 2018)

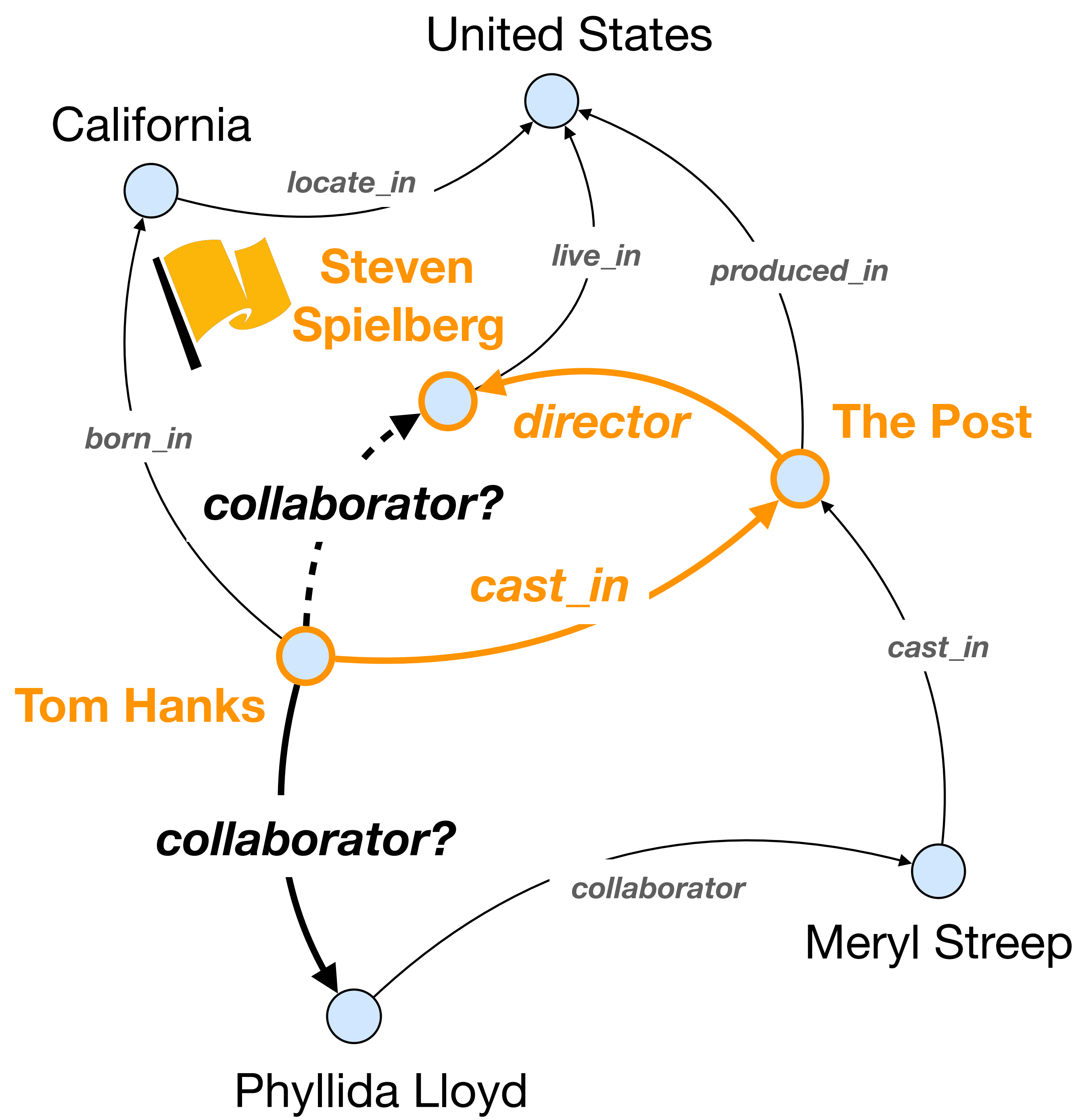
Multi-Hop Reasoning Models



MINERVA (Das et al. 2018)

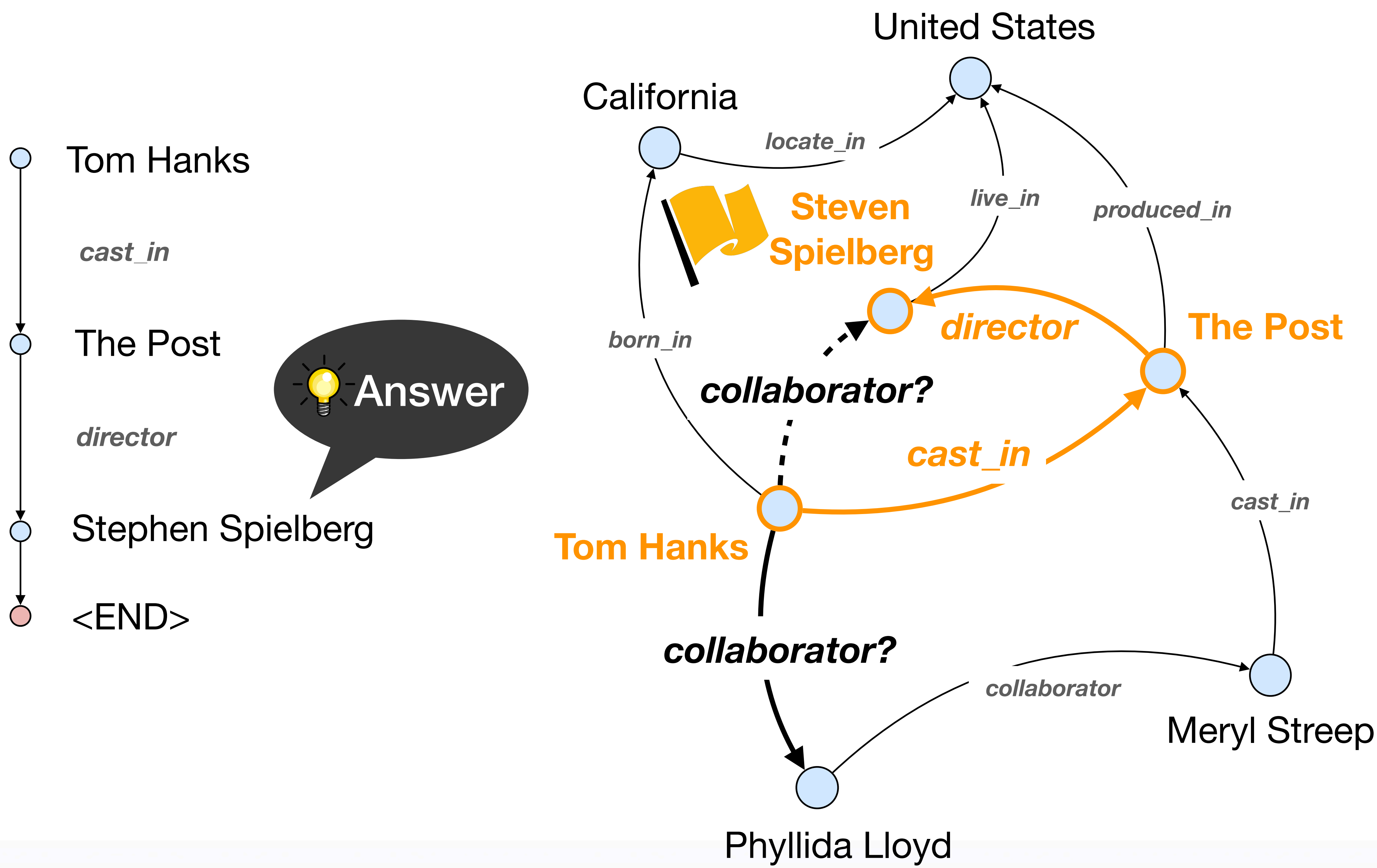
Multi-Hop Reasoning Models





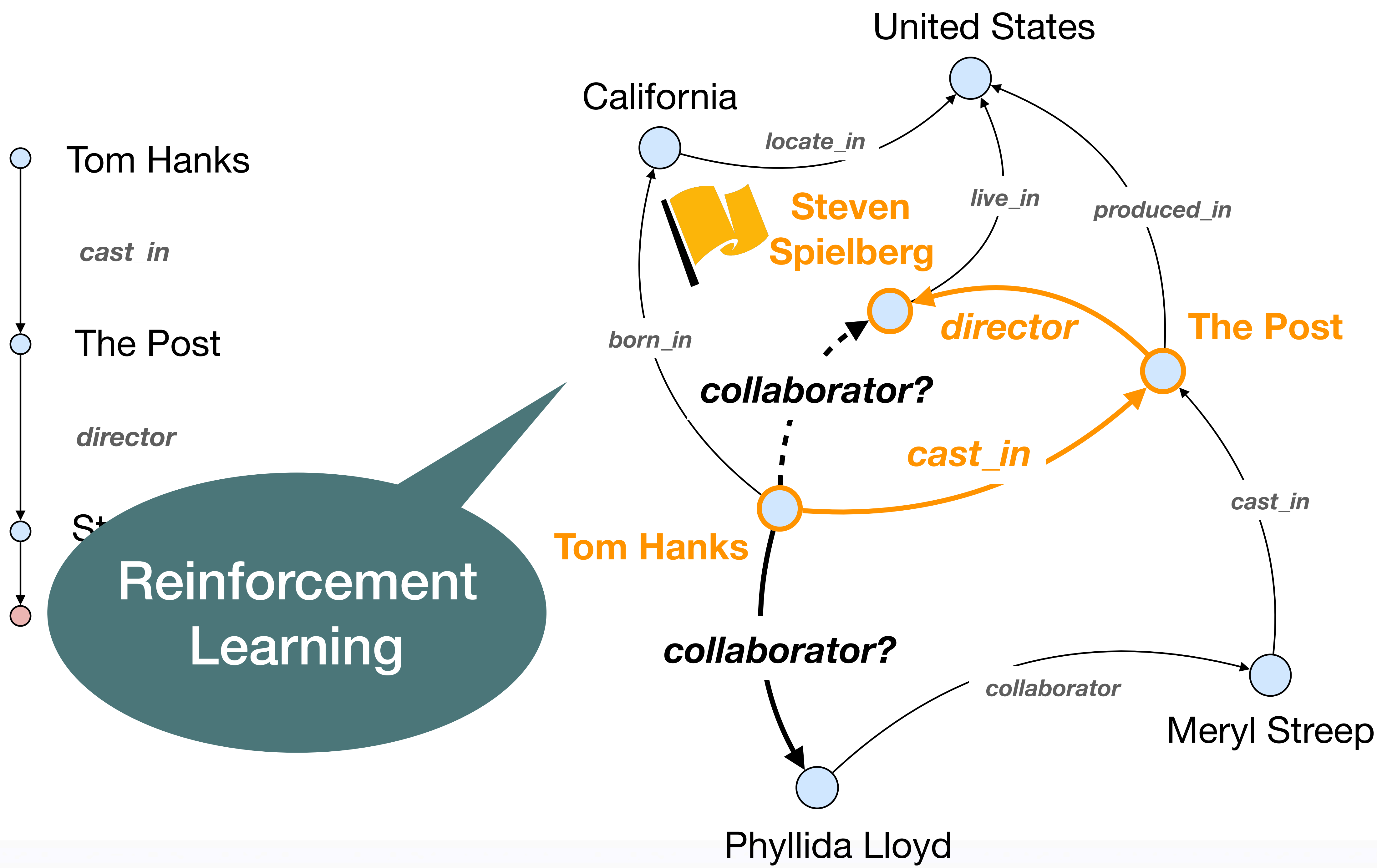
MINERVA (Das et al. 2018)

Multi-Hop Reasoning



MINERVA (Das et al. 2018)

Multi-Hop Reasoning



MINERVA (Das et al. 2018)

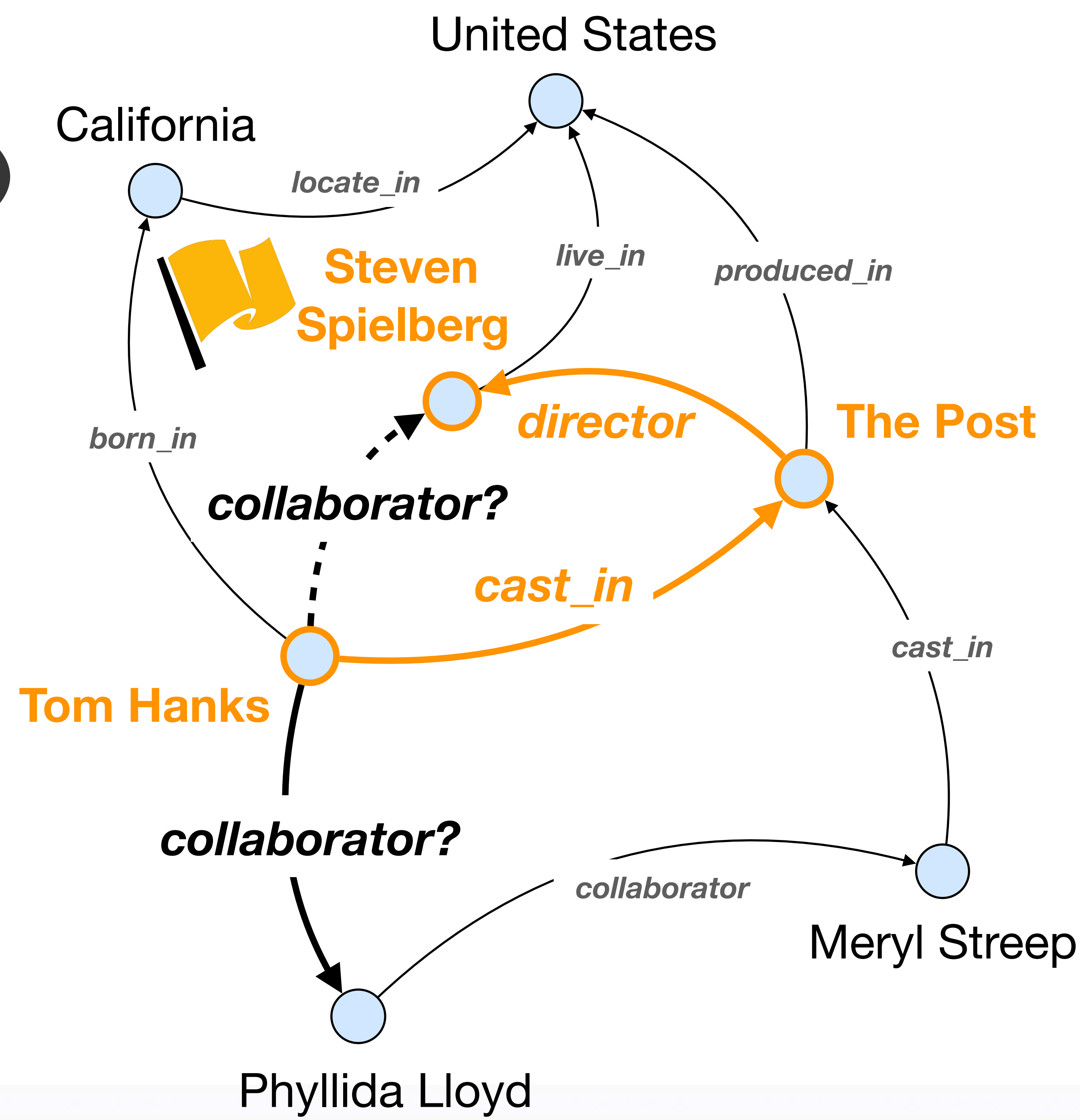
Multi-Hop Reasoning

Interpretable

Harder, hence significant performance gap

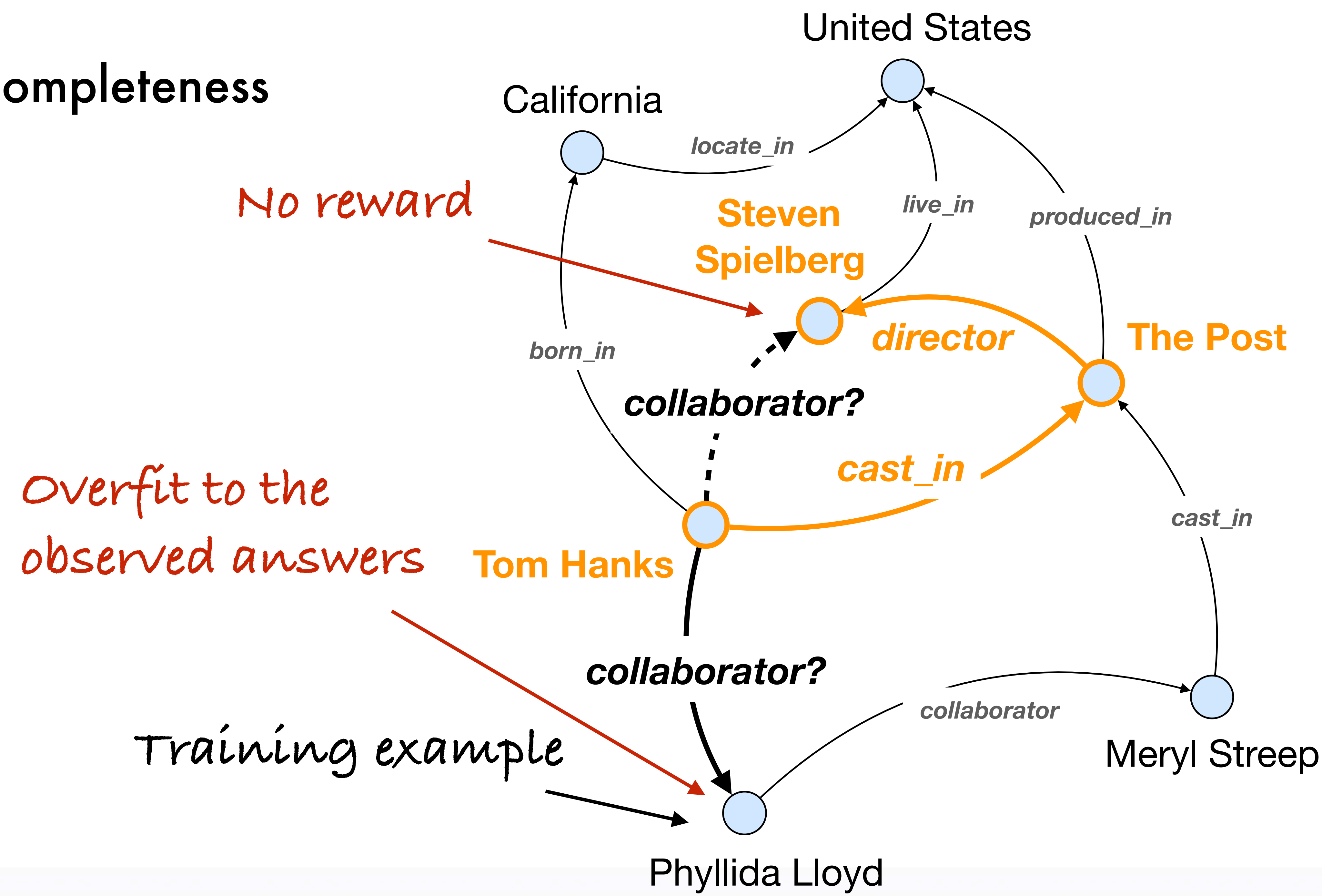
	MRR
ConvE	**0.957**
RL	0.825

Tab 2. ConvE and RL (MINERVA) query answering performance on the UMLS benchmark dataset (Kok and Domingos 2007)

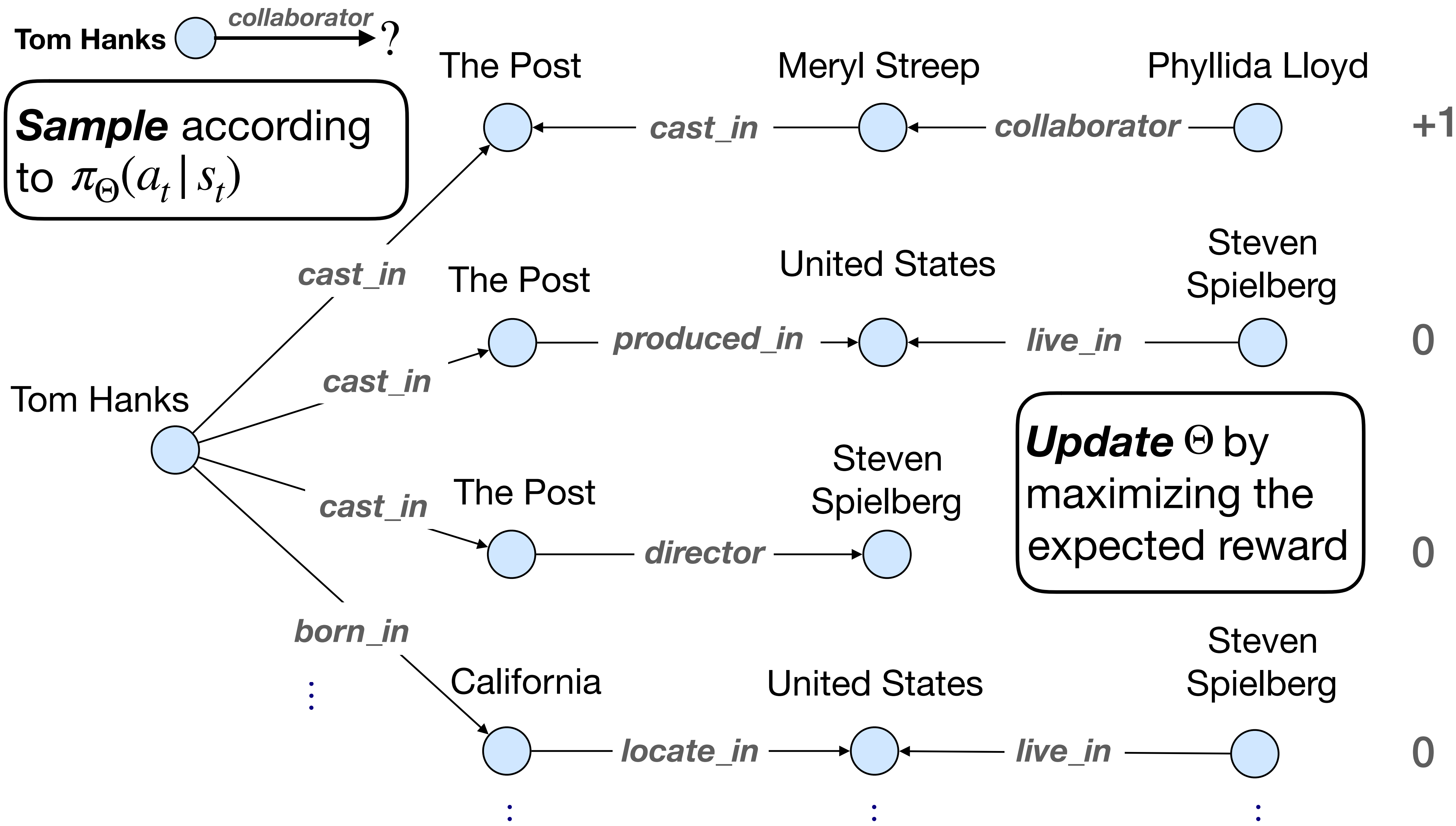


Challenge I

Incompleteness



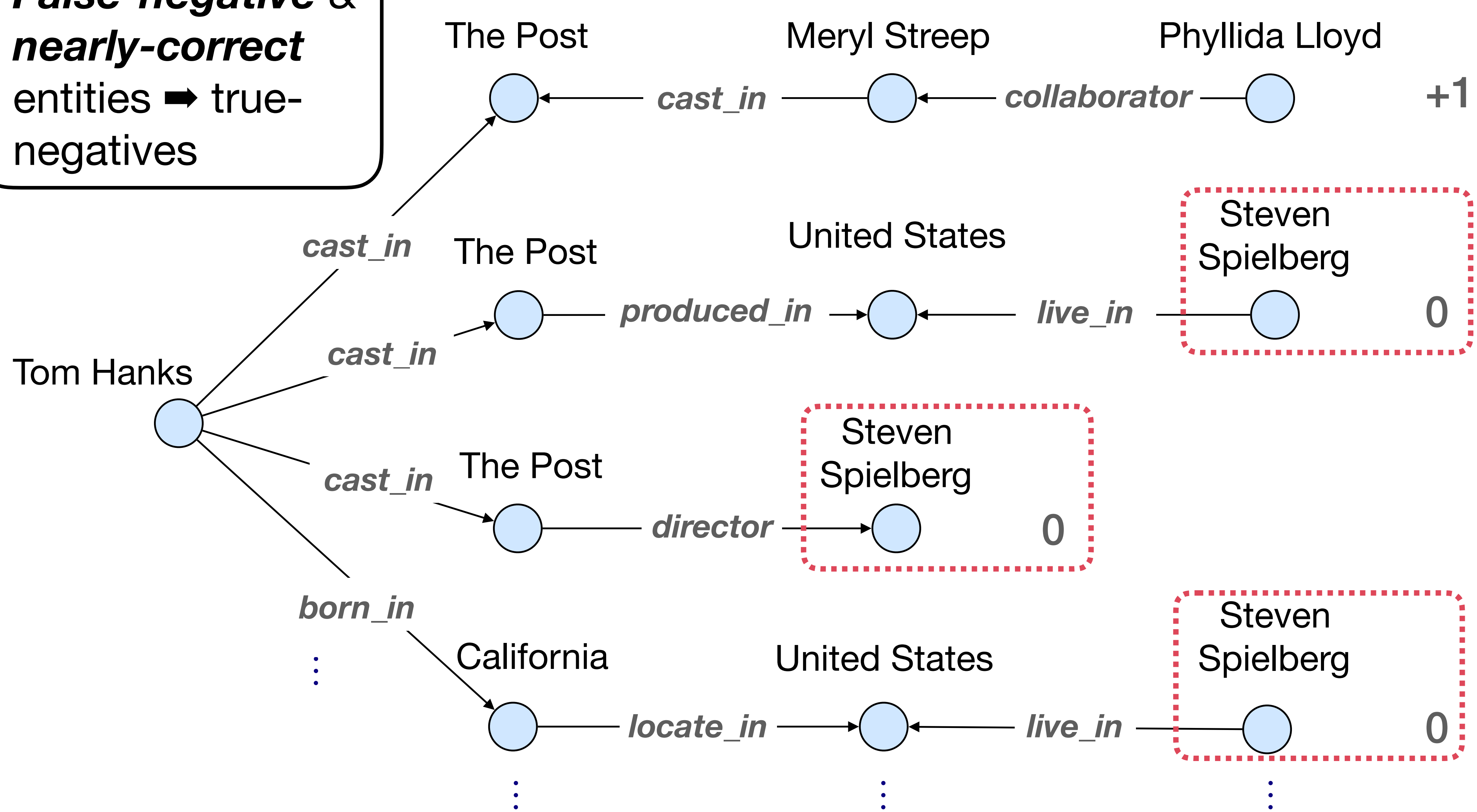
REINFORCE Training



REINFORCE (Williams, 1992)

REINFORCE Training

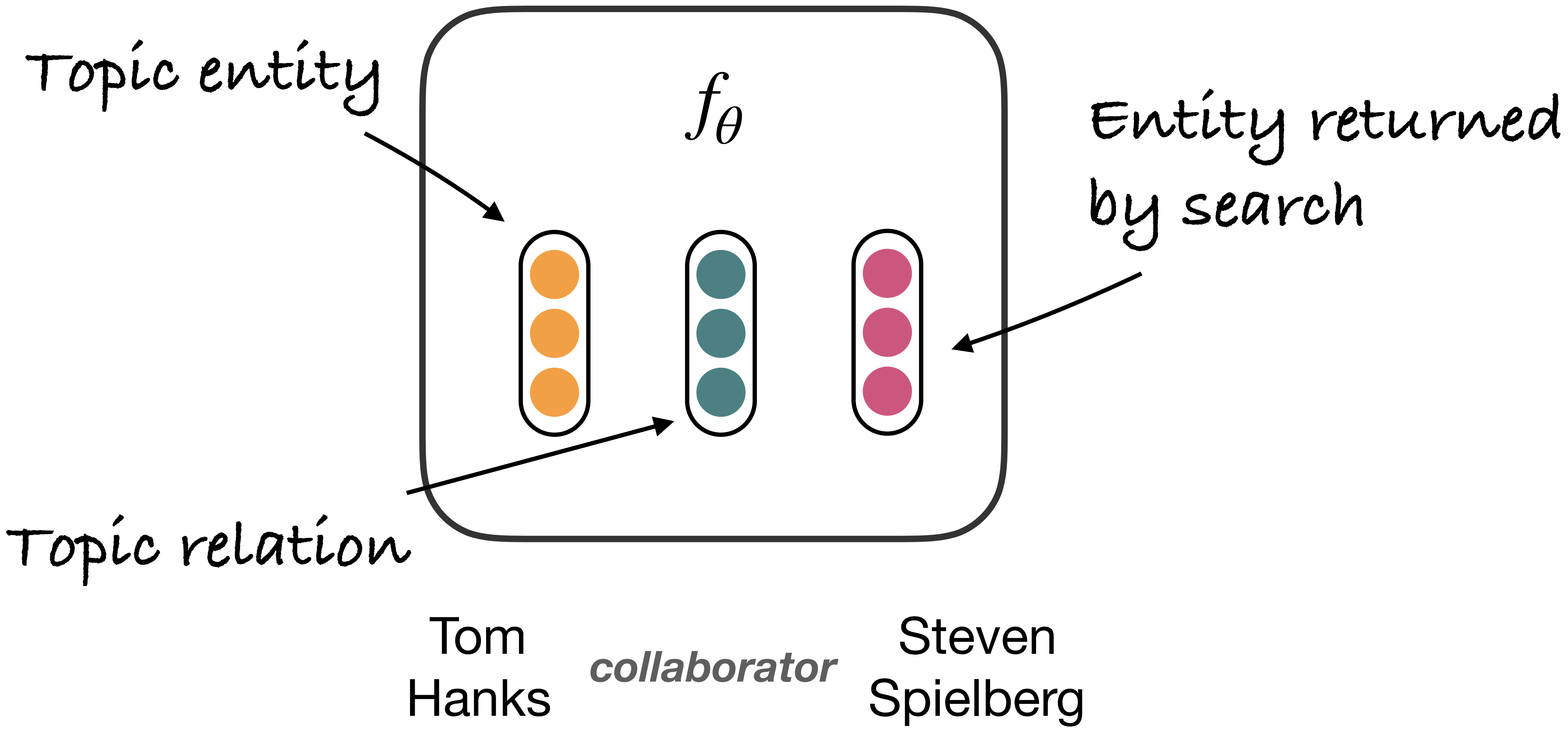
False-negative & ***nearly-correct*** entities ➡ true-negatives



Reward Shaping

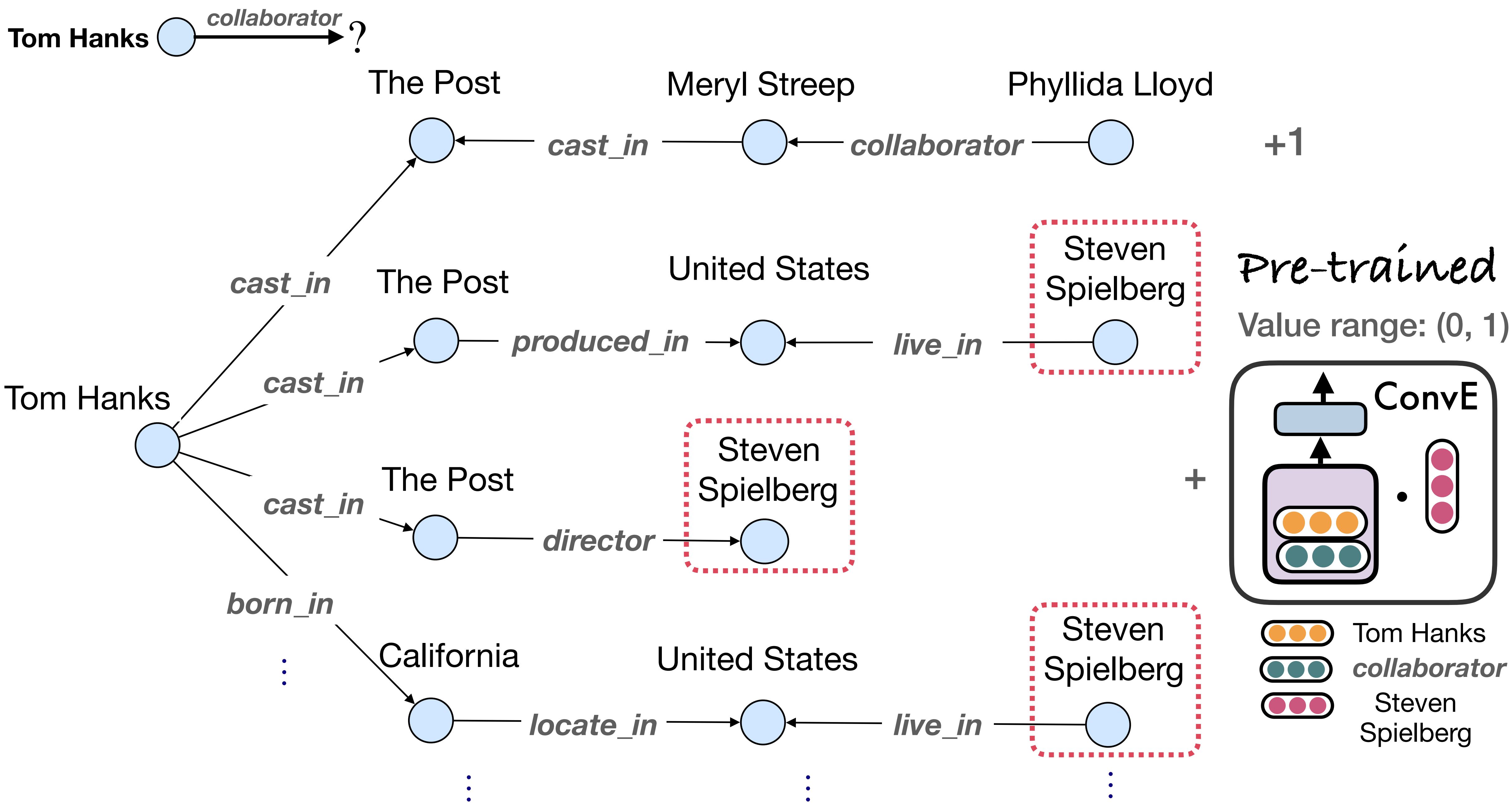
Unobserved facts

Soft correctness



(Lin, Socher, Xiong. EMNLP 2018)

Reward Shaping



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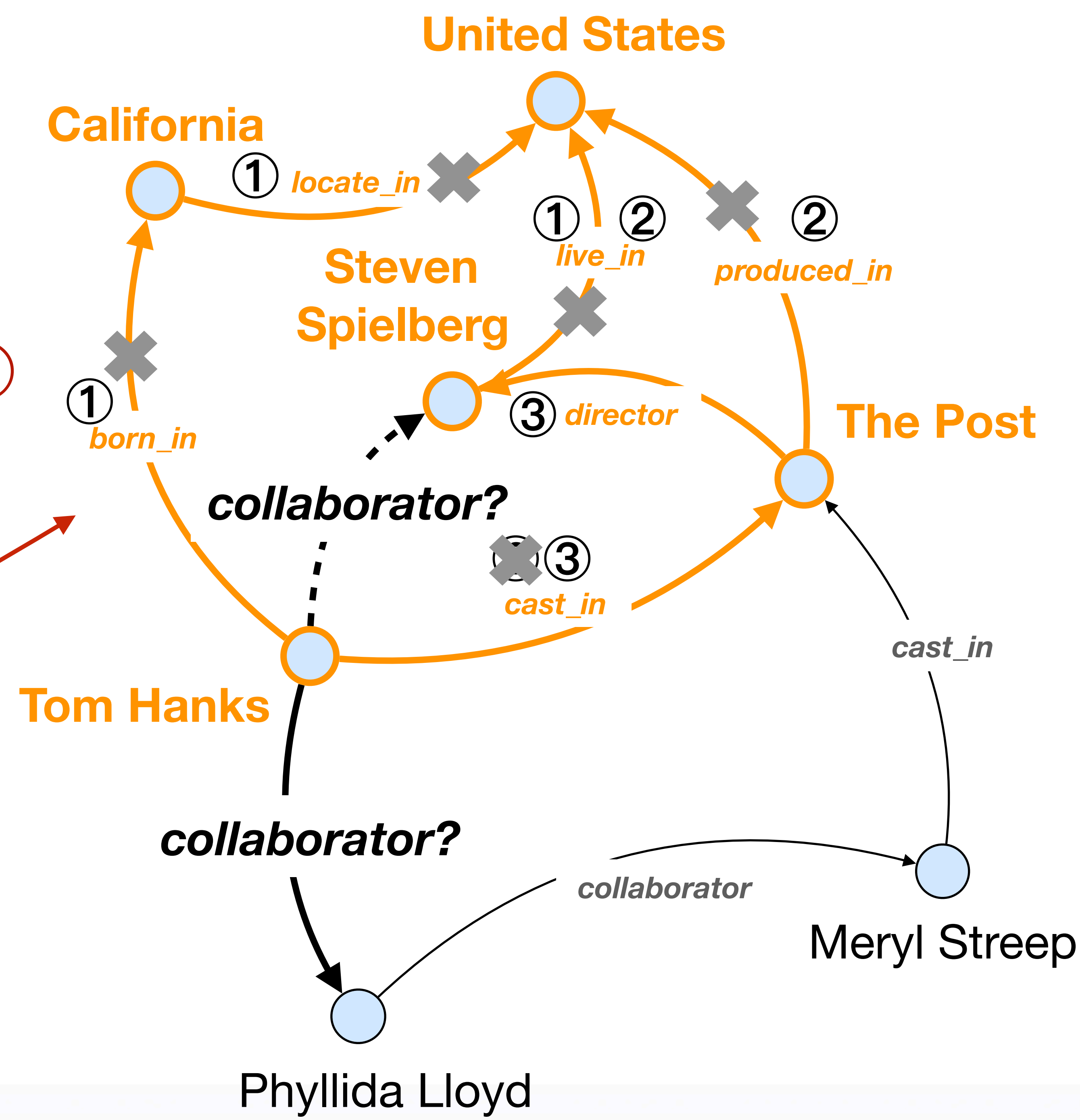
Challenge II

Path Diversity

False positive (spurious) paths ① ②

Overfit to the spurious paths



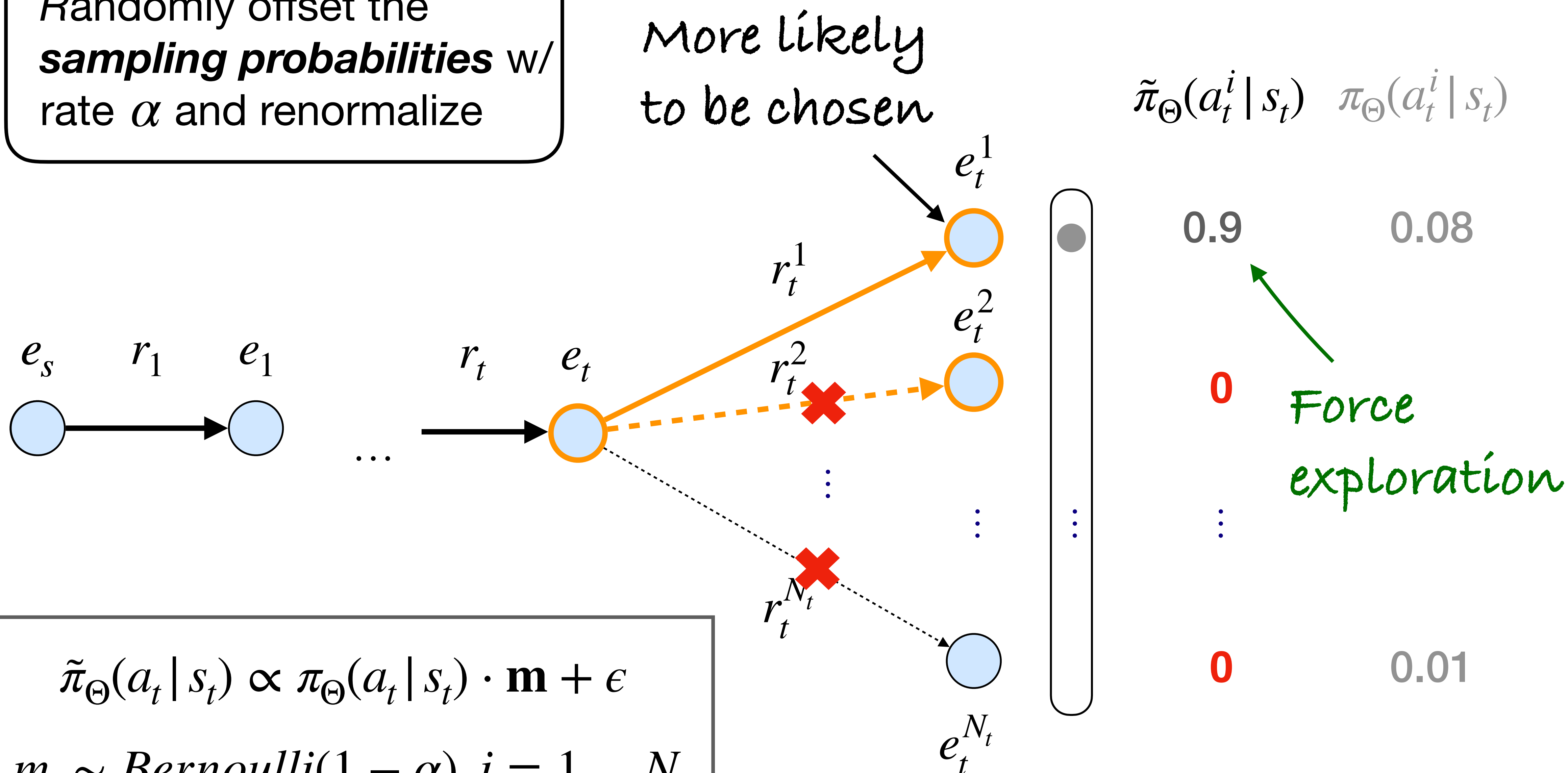
Action Dropout

Intuition: ***prevent the agent from being stuck*** with past actions that ***had received rewards***

(Lin, Socher, Xiong. EMNLP 2018)

Action Dropout

Randomly offset the ***sampling probabilities*** w/ rate α and renormalize



$$\tilde{\pi}_\Theta(a_t \mid s_t) \propto \pi_\Theta(a_t \mid s_t) \cdot \mathbf{m} + \epsilon$$

$$m_i \sim Bernoulli(1 - \alpha), i = 1, \ldots N$$

(Lin, Socher, Xiong. EMNLP 2018)

Main Results

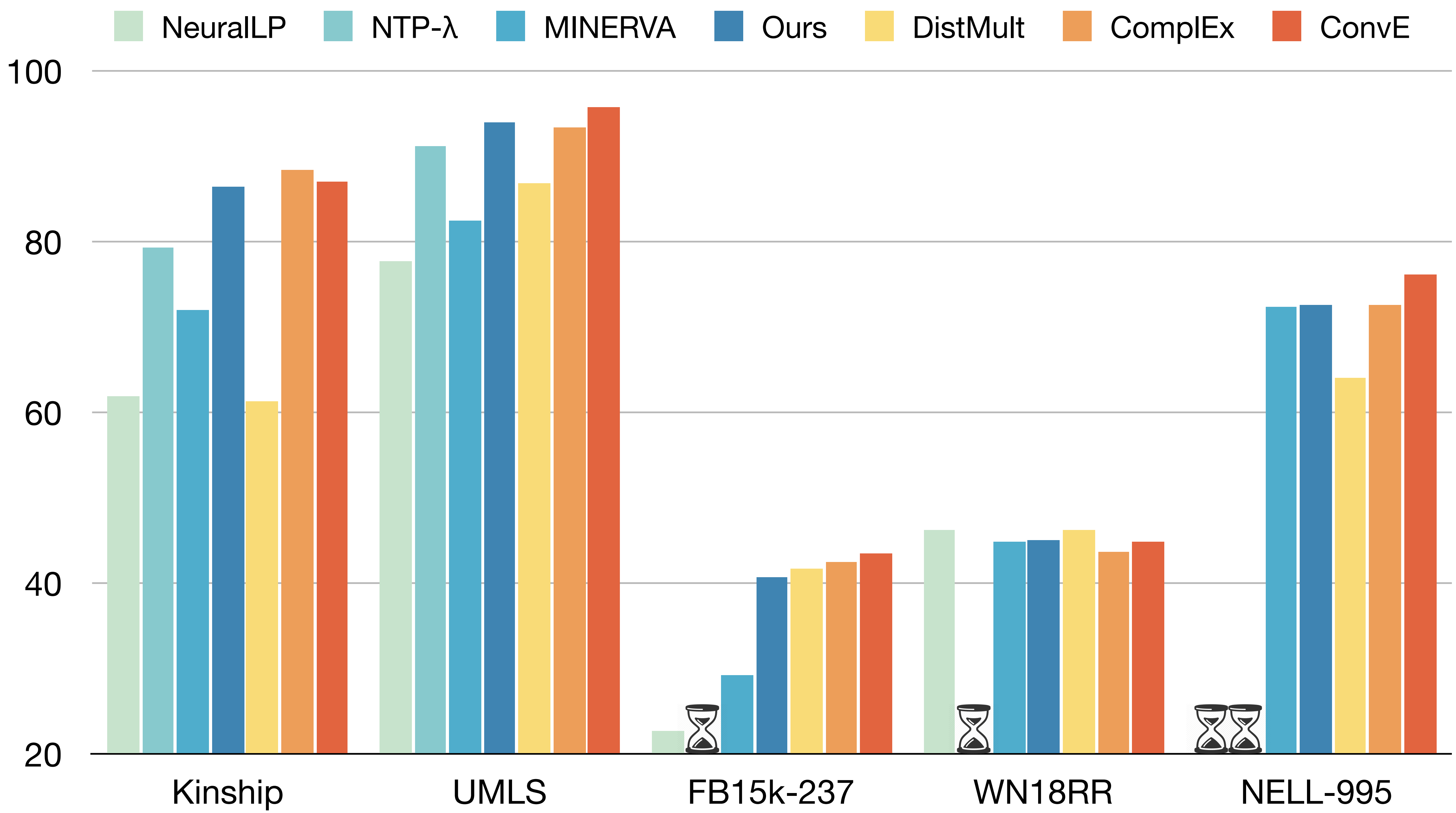


Fig 3. Test set MRR (x100) compared to SOTA multi-hop reasoning and embedding-based approaches

Main Results

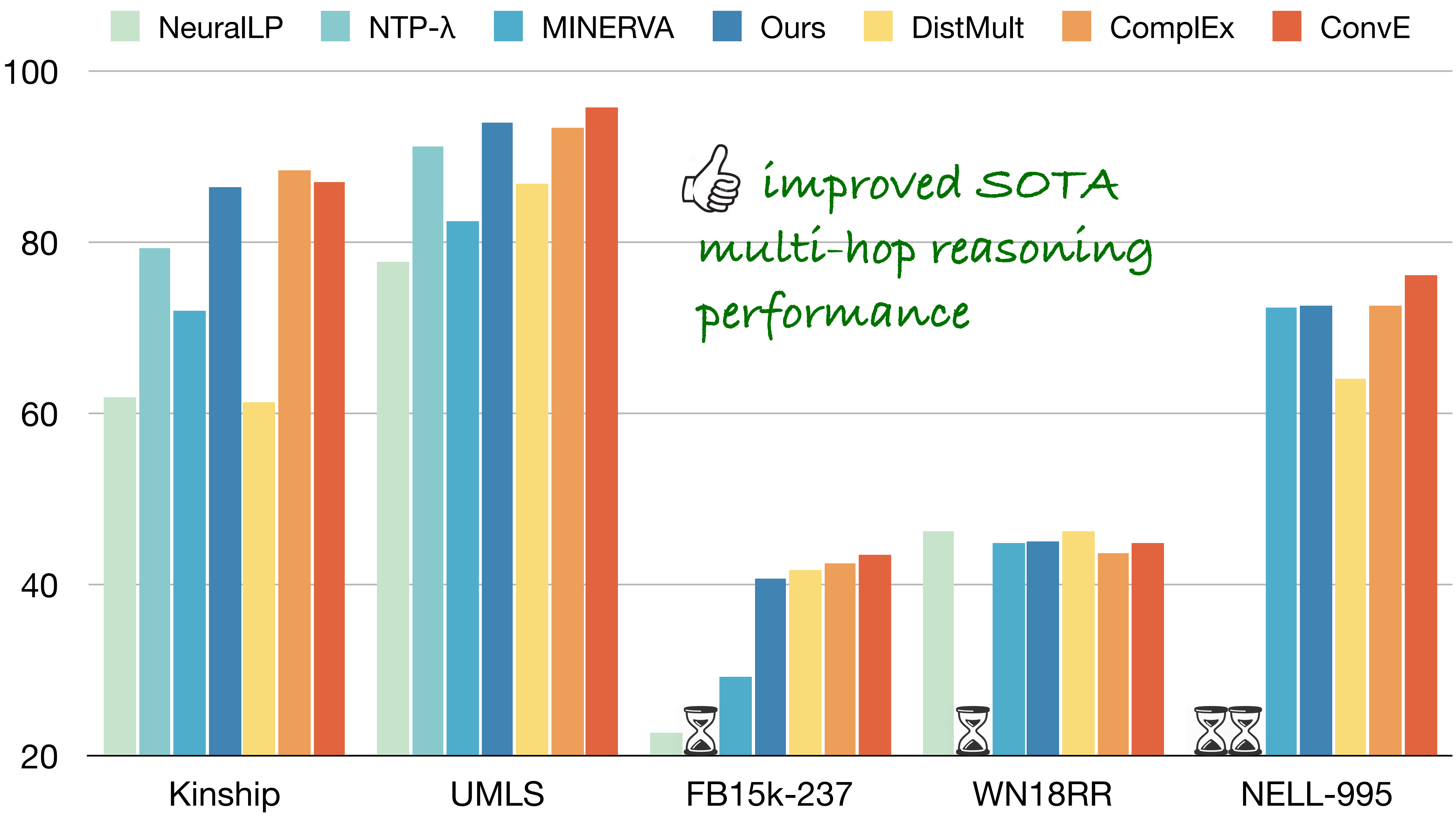


Fig 3. Test set MRR (x100) compared to SOTA multi-hop reasoning and embedding-based approaches

Main Results

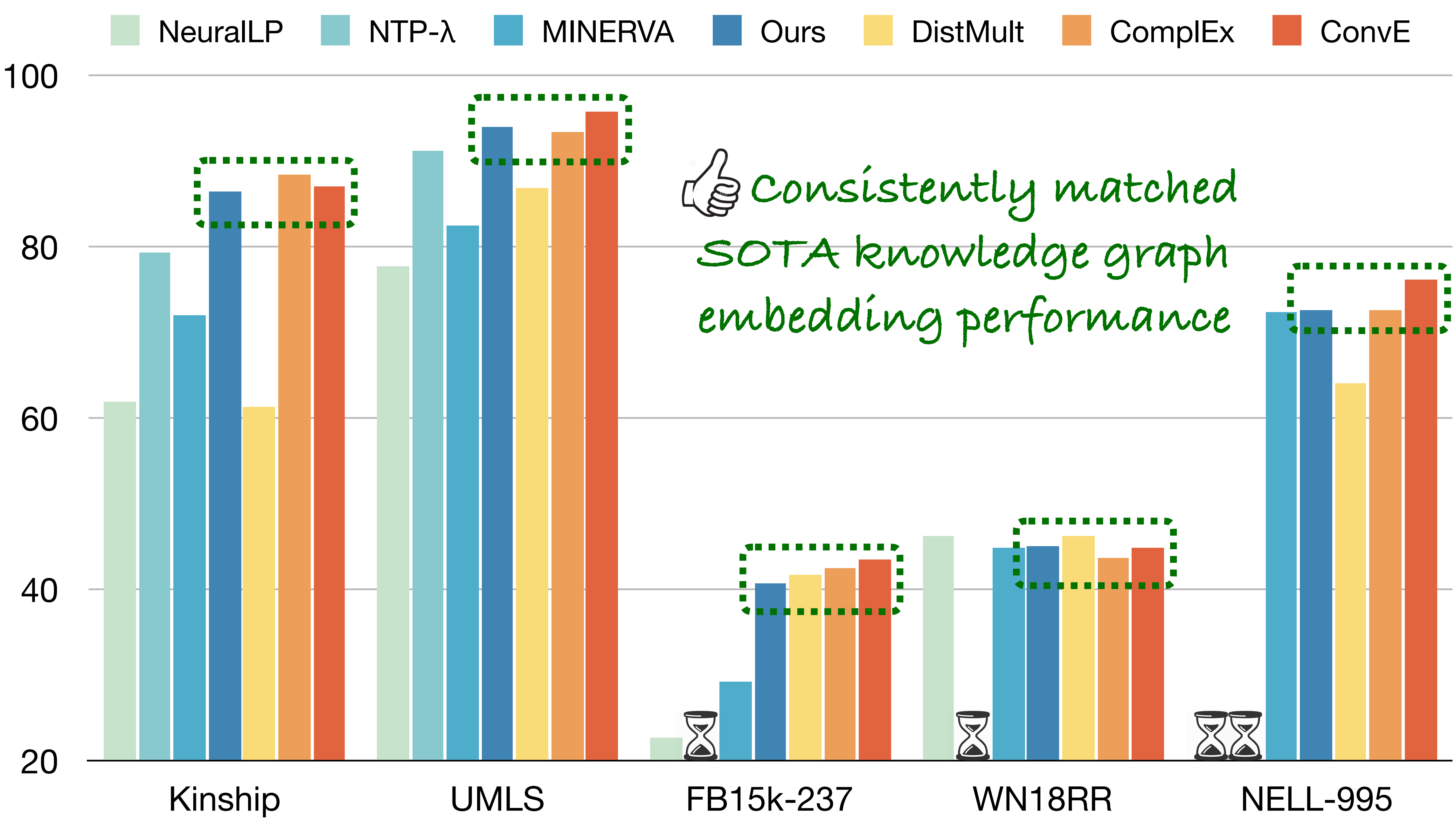
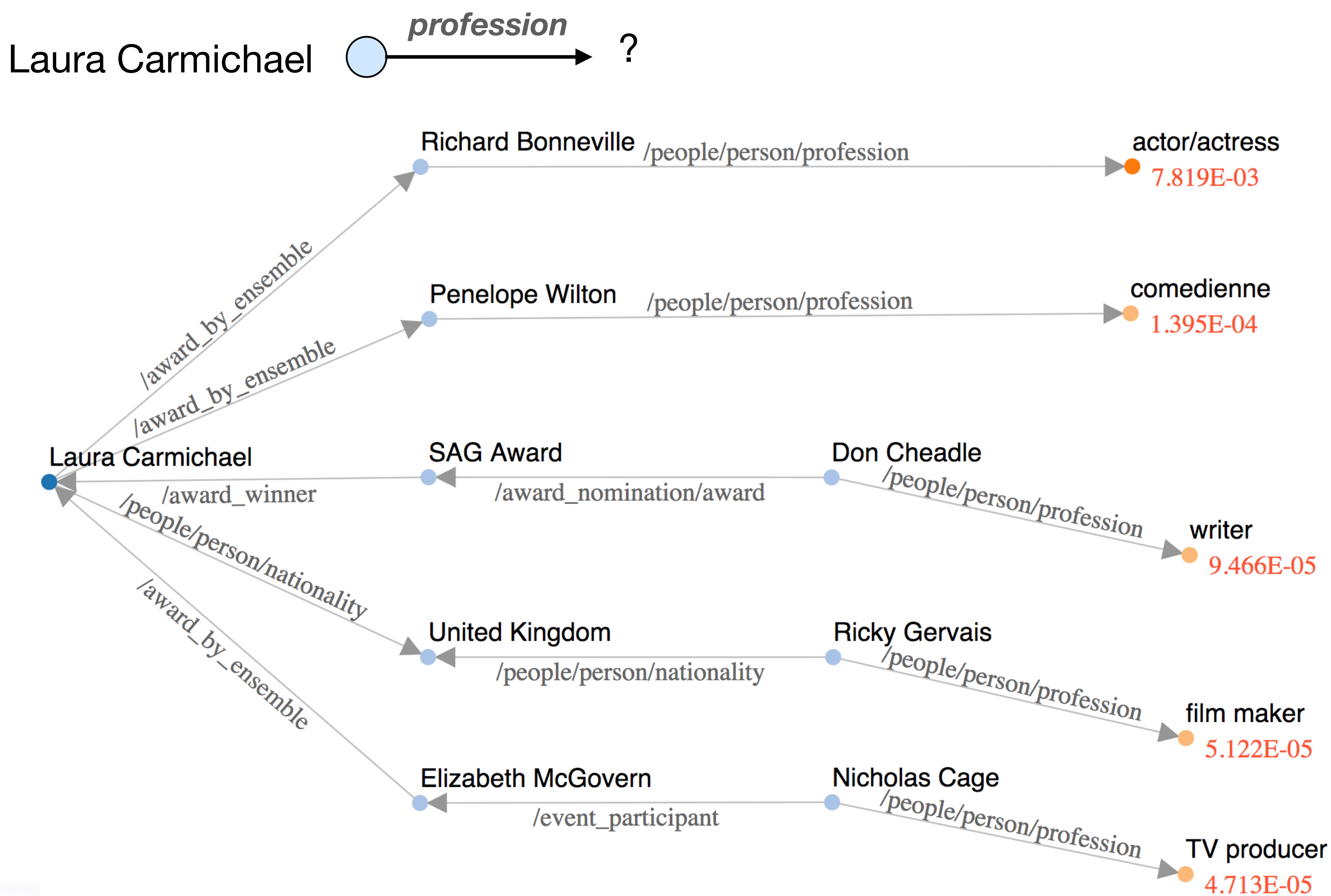


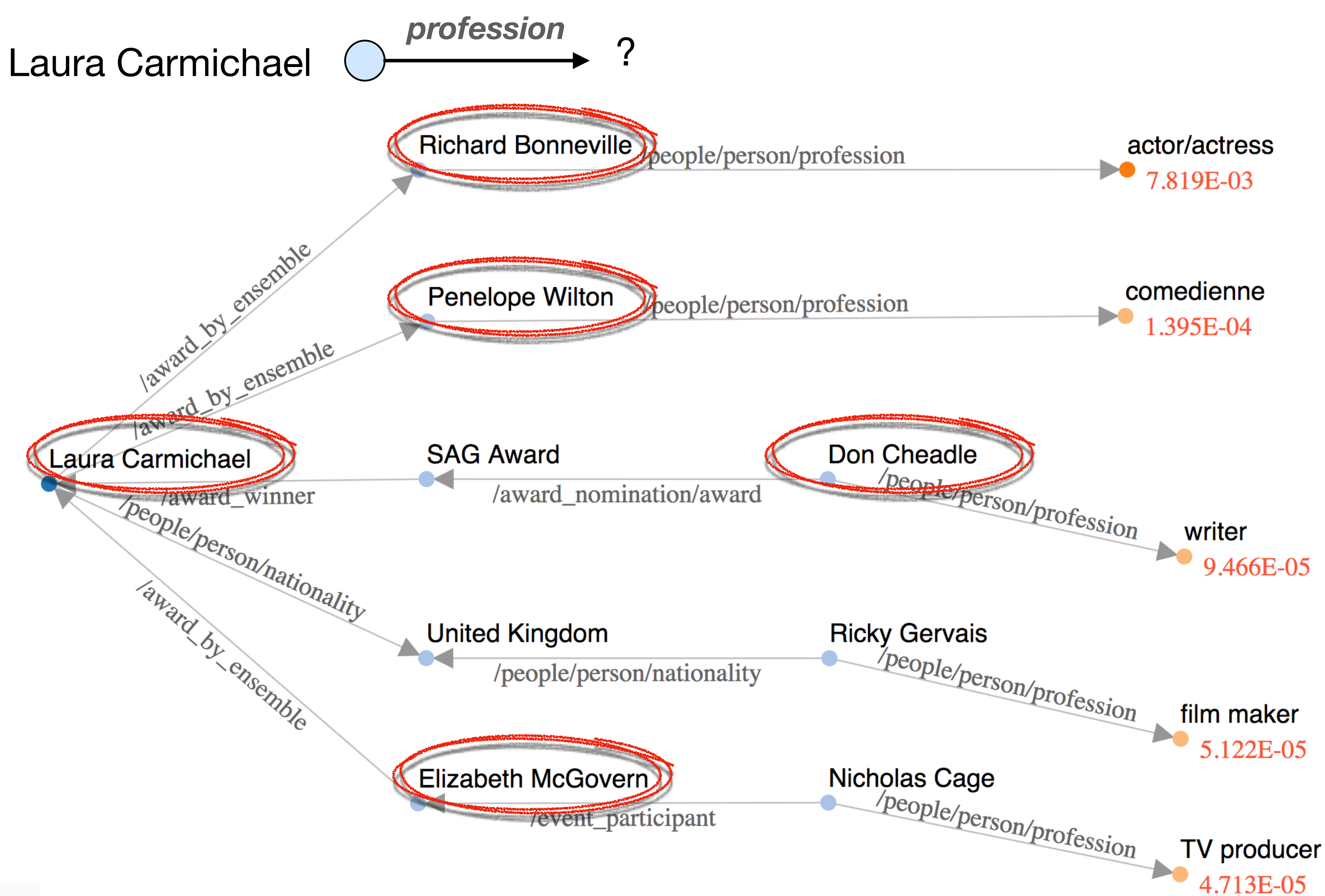
Fig 3. Test set MRR (x100) compared to SOTA multi-hop reasoning and embedding-based approaches

Interpretable Results



(Lin, Socher, Xiong. EMNLP 2018)

Interpretable Results



(Lin, Socher, Xiong. EMNLP 2018)

Related Work

- Go for a Walk and Arrive at the Answer: Reasoning Over Paths in Knowledge Bases using Reinforcement Learning. Das et. al. ICLR 2018.
- M-Walk: Learning to Walk over Graphs using Monte Carlo Tree Search. Shen et. al. NeurIPS 2018.
- Memory augmented policy optimization for program synthesis and semantic parsing. Liang et. al. 2018
- Path Reasoning over Knowledge Graph: A Multi-Agent and Reinforcement Learning Based Method. Li et. al. ICDMW 2018.
- Neural Logic Machines. Dong et. al. ICLR 2019.

- End-to-End Differentiable Proving. Rocktäschel and Riedel. NeurIPS 2017.
- Logical Rule Induction and Theory Learning Using Neural Theorem Proving. Campero et. al. ArXiv 2018.
- Towards Neural Theorem Proving at Scale. Minervini et. al. ArXiv 2018.
- DeepProbLog: Neural Probabilistic Logic Programming. Manhaeve et. al. NeurIPS 2018.
- Differentiable Learning of Logical Rules for Knowledge Base Reasoning. Yang et. al. NeurIPS 2017.

Future Directions

- The method proposed in our EMNLP paper behaves differently across graphs. Which graph properties matter most? How to improve the RL algorithm to be more robust against these properties?
- Design more systematic reward functions for queries with multiple correct answers
- Joint inference over knowledge graph and other data modal (text, web-pages and images)
- Automatically detect initial search state for questions that does not explicitly mention topic entity and topic relation
- Answer complex questions (e.g. questions that contain multiple topic entities — “Where can I watch Avengers: Endgame in New Orleans?”) and offer explanation (semantic parsing 🙂)


THANK YOU

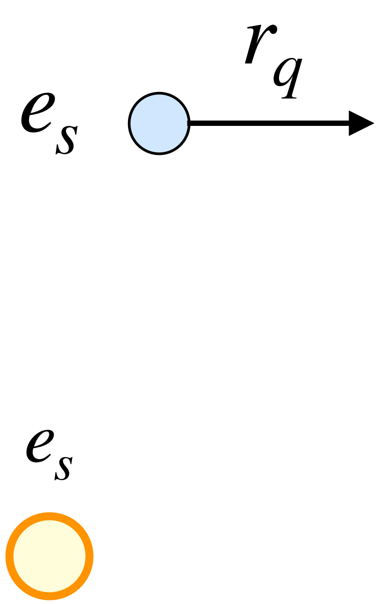
Reinforcement Learning Framework

Environment | State | Action | Transition | Reward

$e_s \xrightarrow{r_q}$

Reinforcement Learning Framework

Environment | **State** | Action | Transition | Reward



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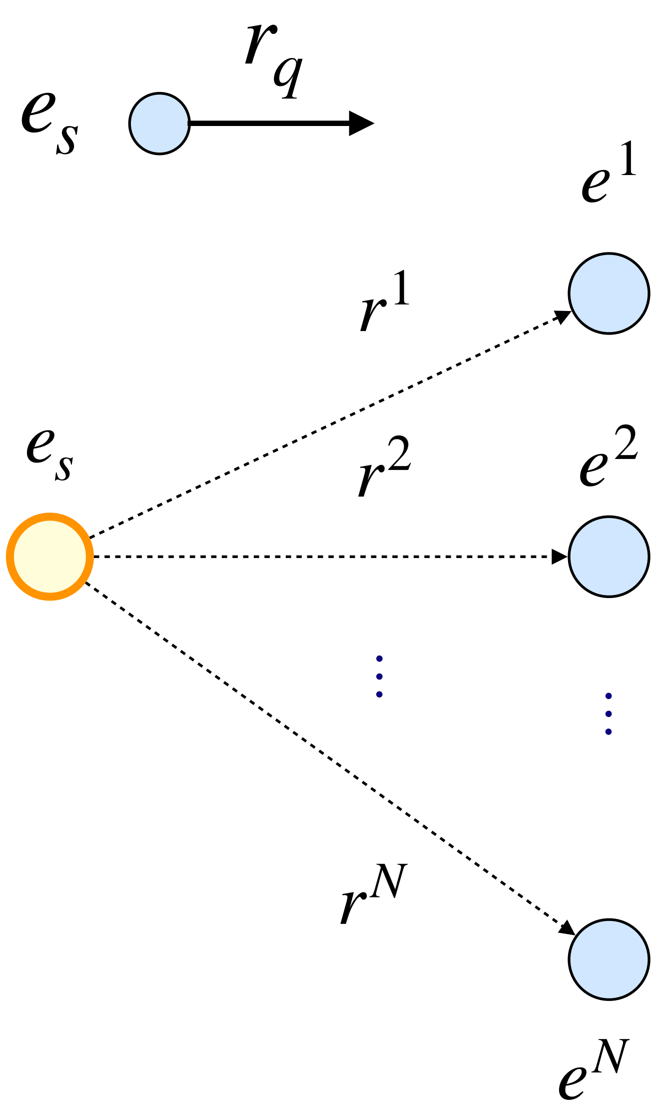

A_t

Reinforcement Learning Framework

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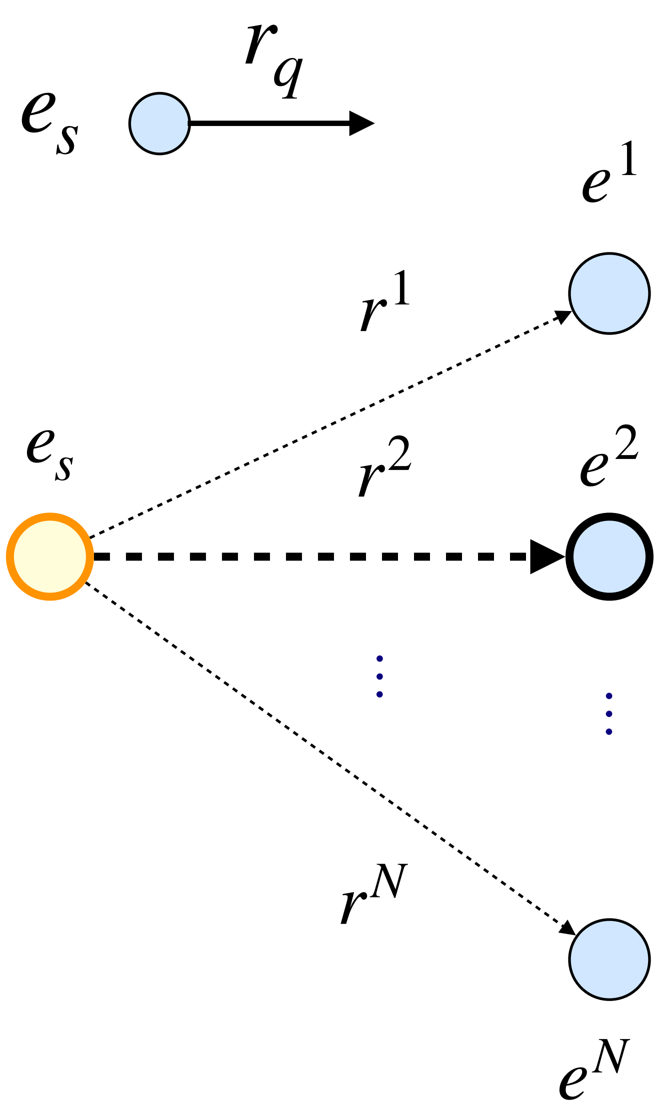

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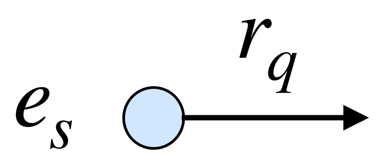

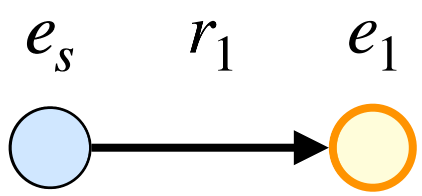

Reinforcement Learning Framework

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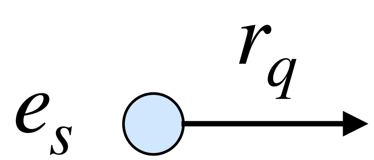
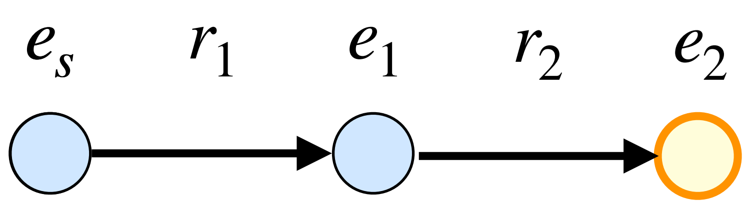
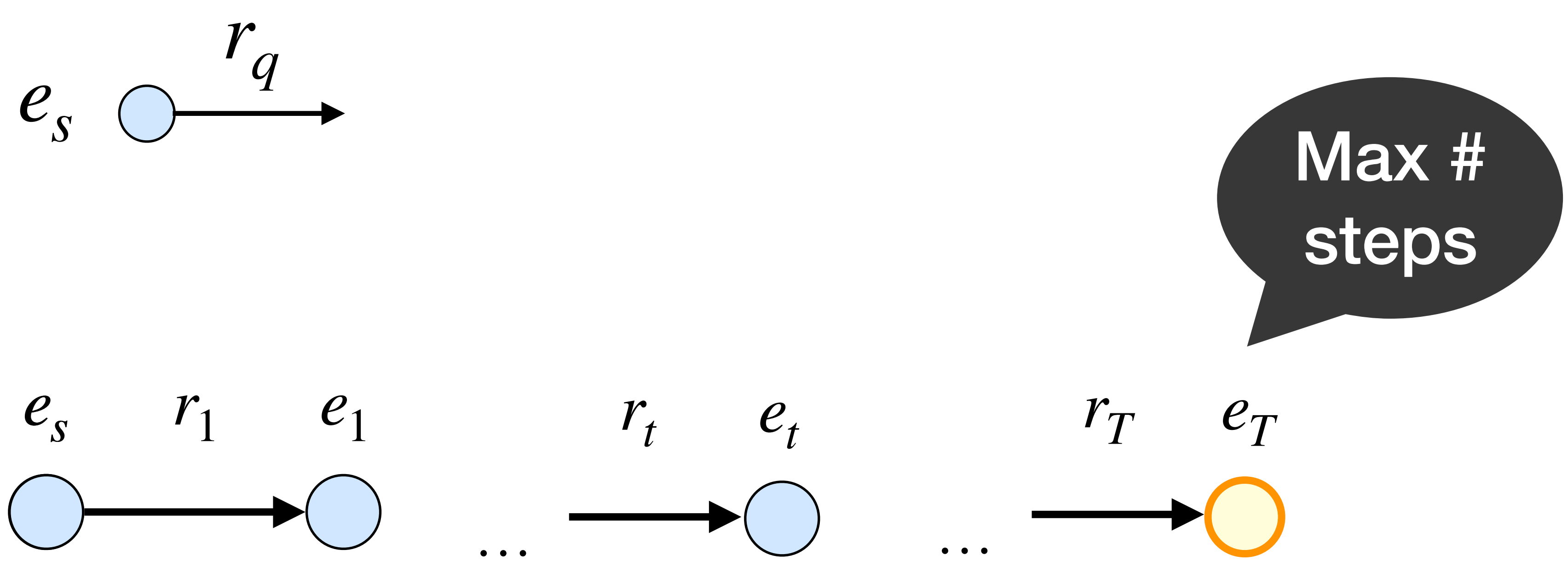




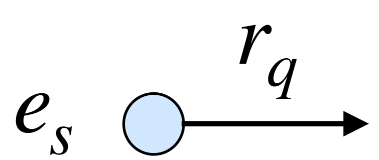
Reinforcement Learning Framework

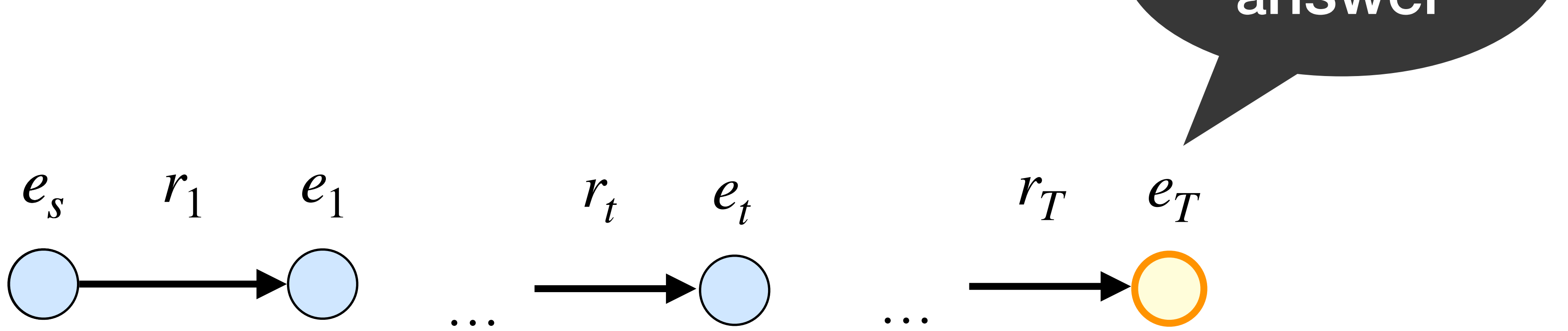
Environment | State | Action | **Transition** | Reward



Reinforcement Learning Framework

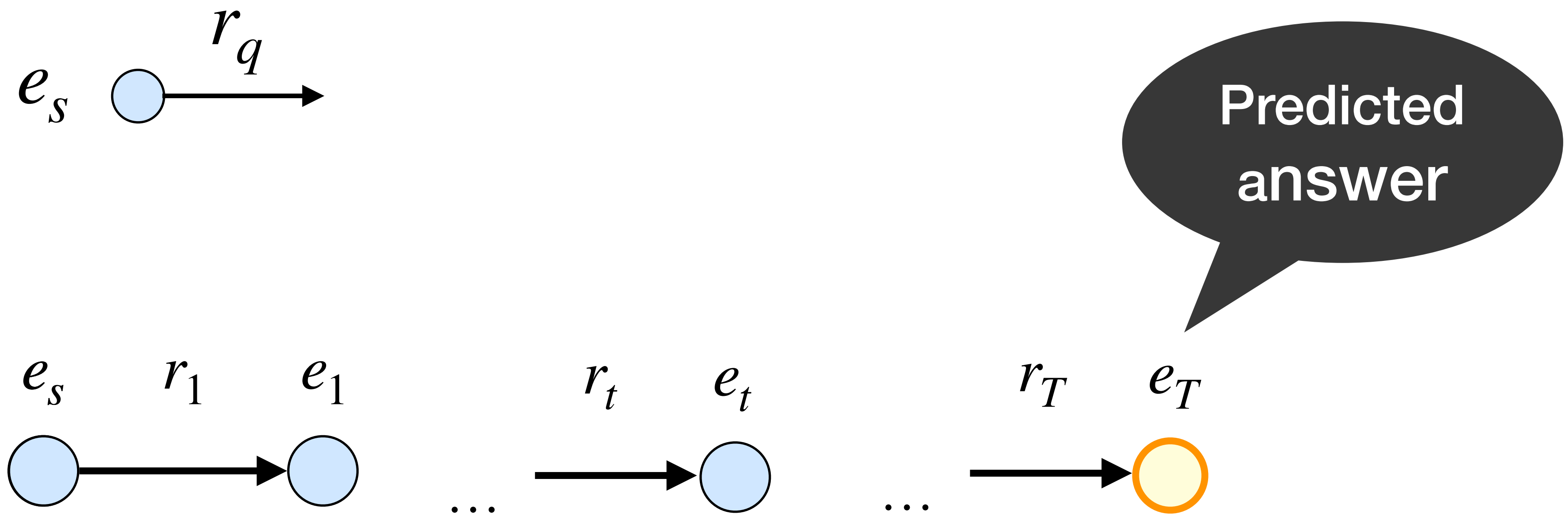
Environment | State | Action | **Transition** | Reward





Reinforcement Learning Framework

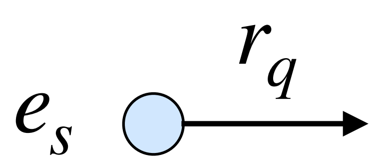
Environment | State | Action | Transition | **Reward**



$$R_b(s_T) = \mathbf{1}\{(e_s, r_q, e_T) \in G\}$$

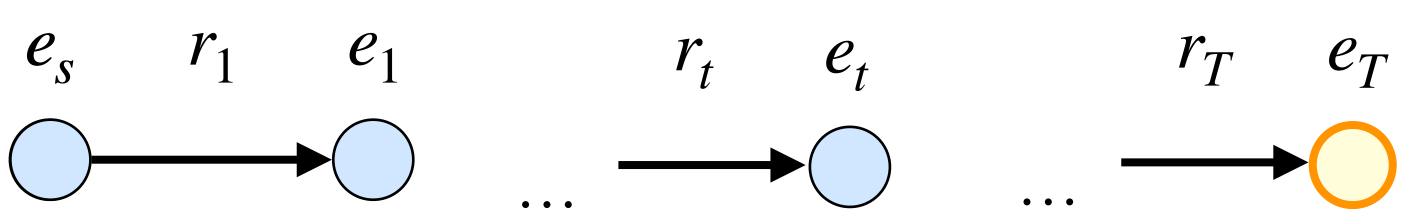
Reinforcement Learning Framework

Environment | State | Action | Transition | **Reward**



Policy gradient

Learn a policy function that models ***which edge to choose*** at a given state



$$\boxed{R_b(s_T) = \mathbf{1}\{(e_s, r_q, e_T) \in G\}}$$

BKI - Error Analysis

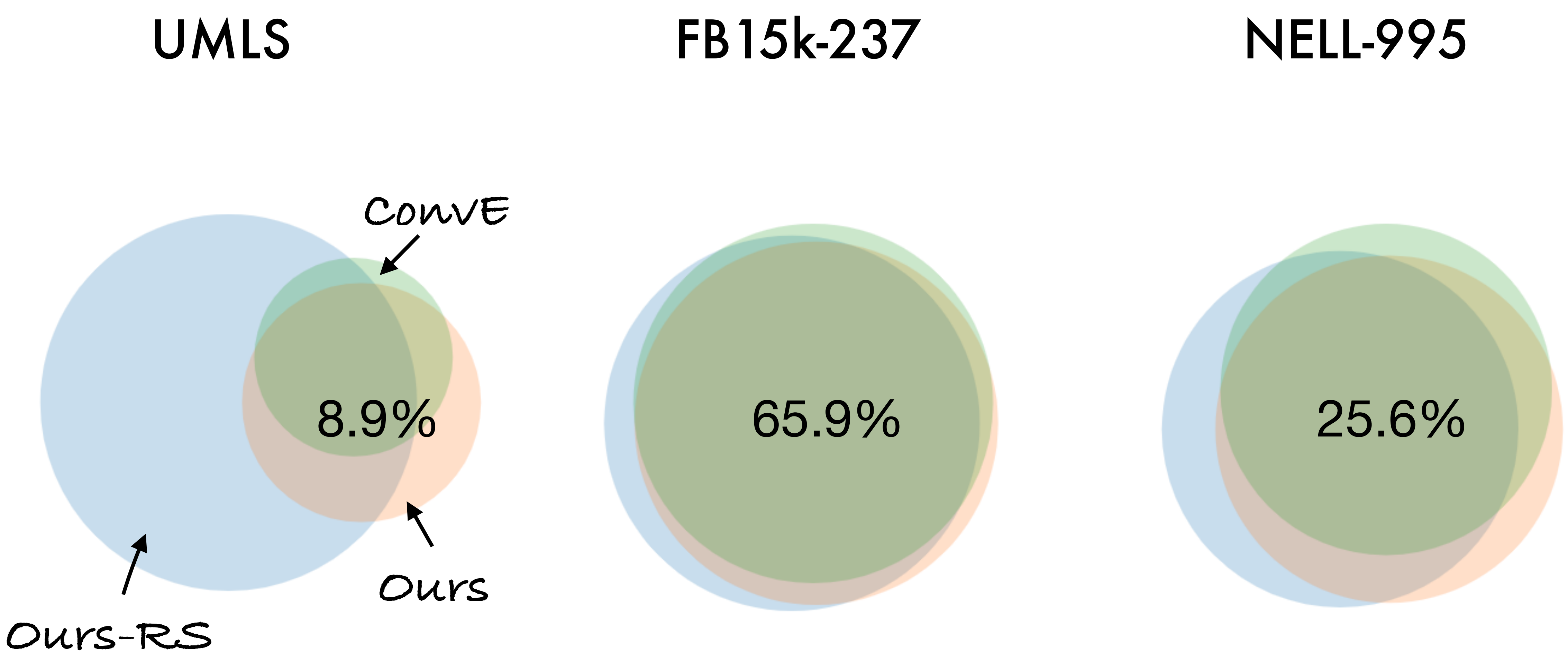


Fig 4. Dev set top-1 prediction error overlap of ConvE, Ours and Ours-RS. The absolute error rate of Ours is shown.

BK II - Challenges

Incompleteness

≈ 30% false negative feedback

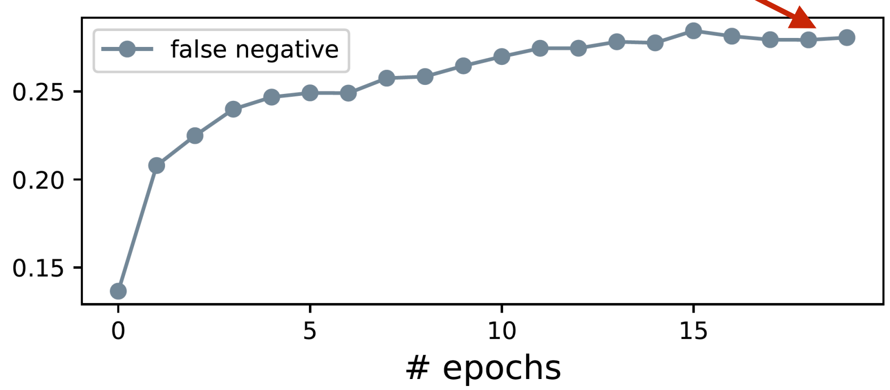
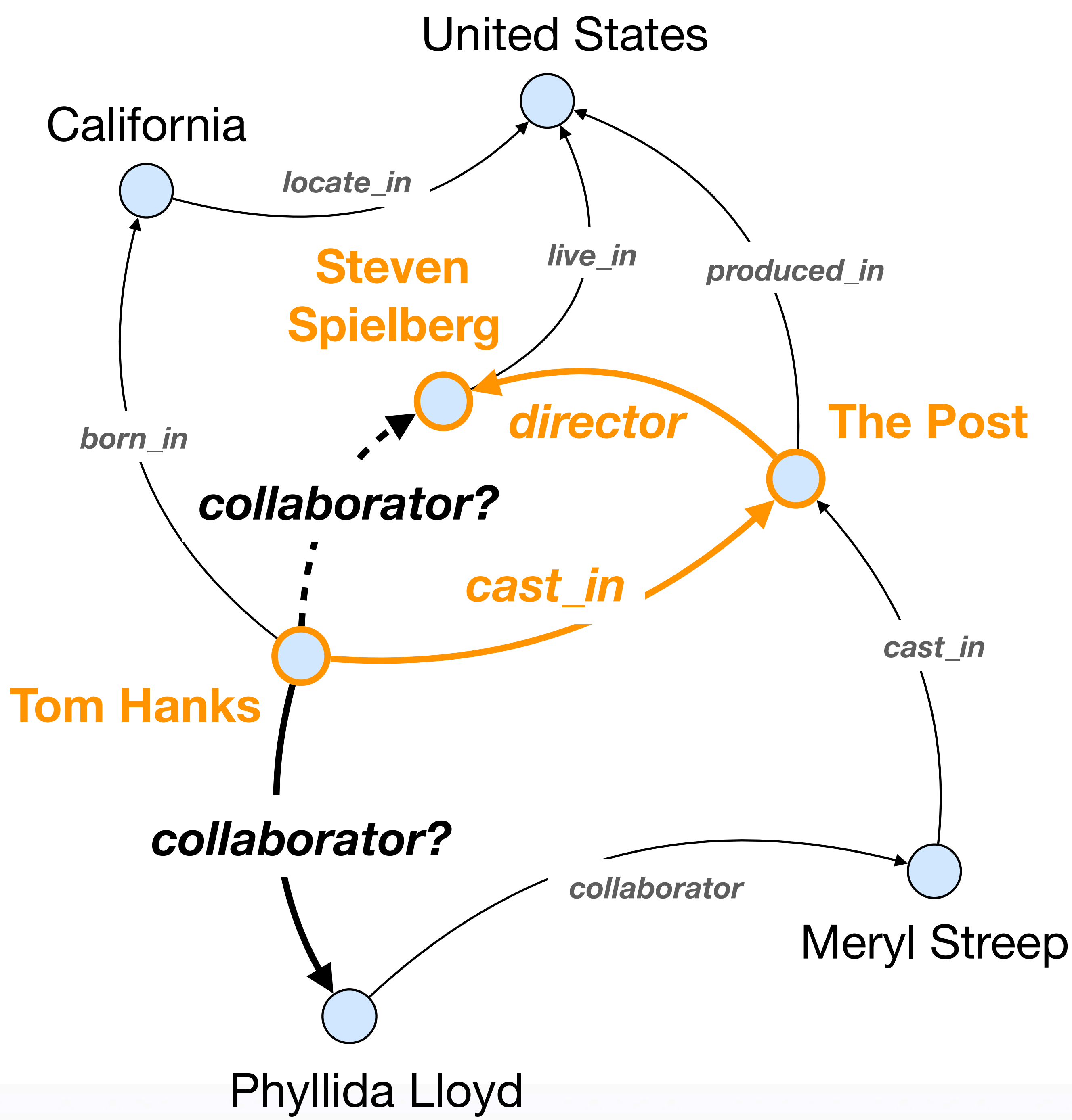
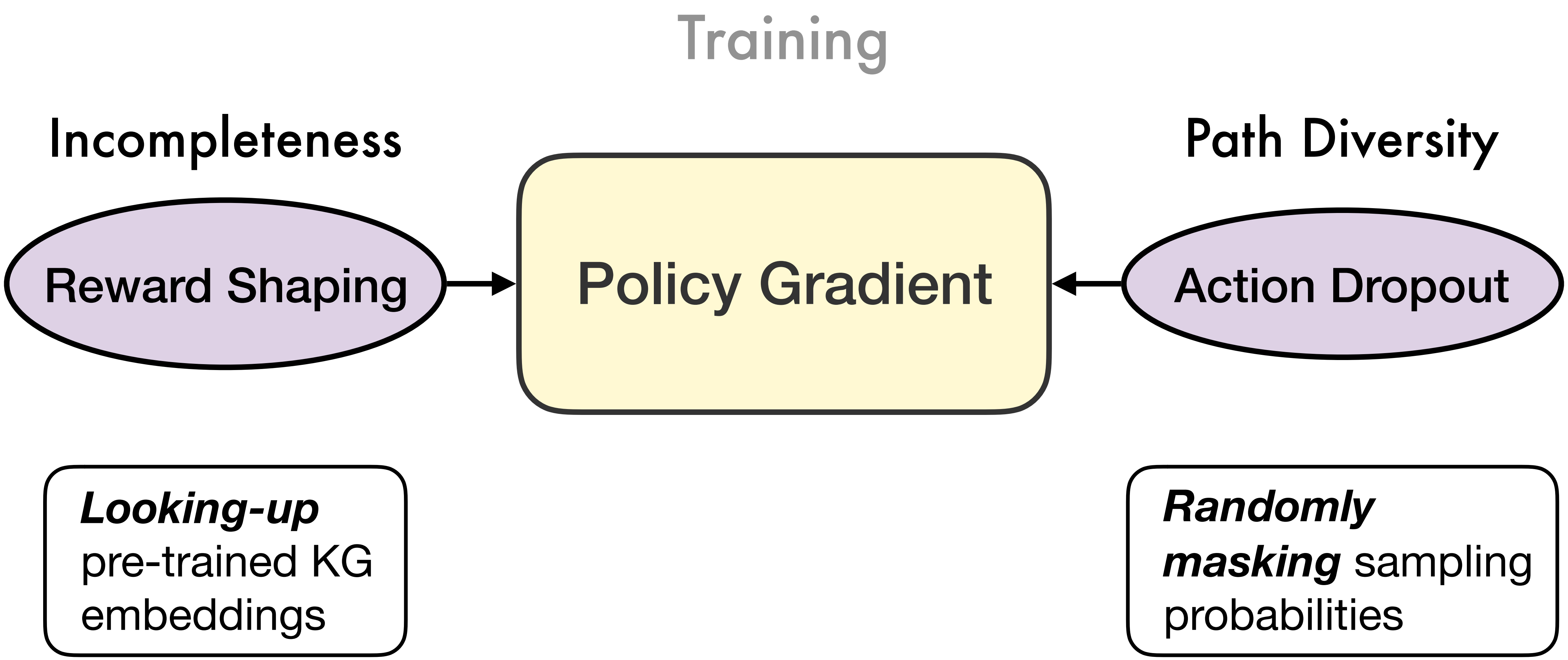


Fig 1. % of false negative hit in the first 20 epochs of RL training on the UMLS KG benchmark (Kok and Domingos 2007)



BKIII - Efficient Training & Inference

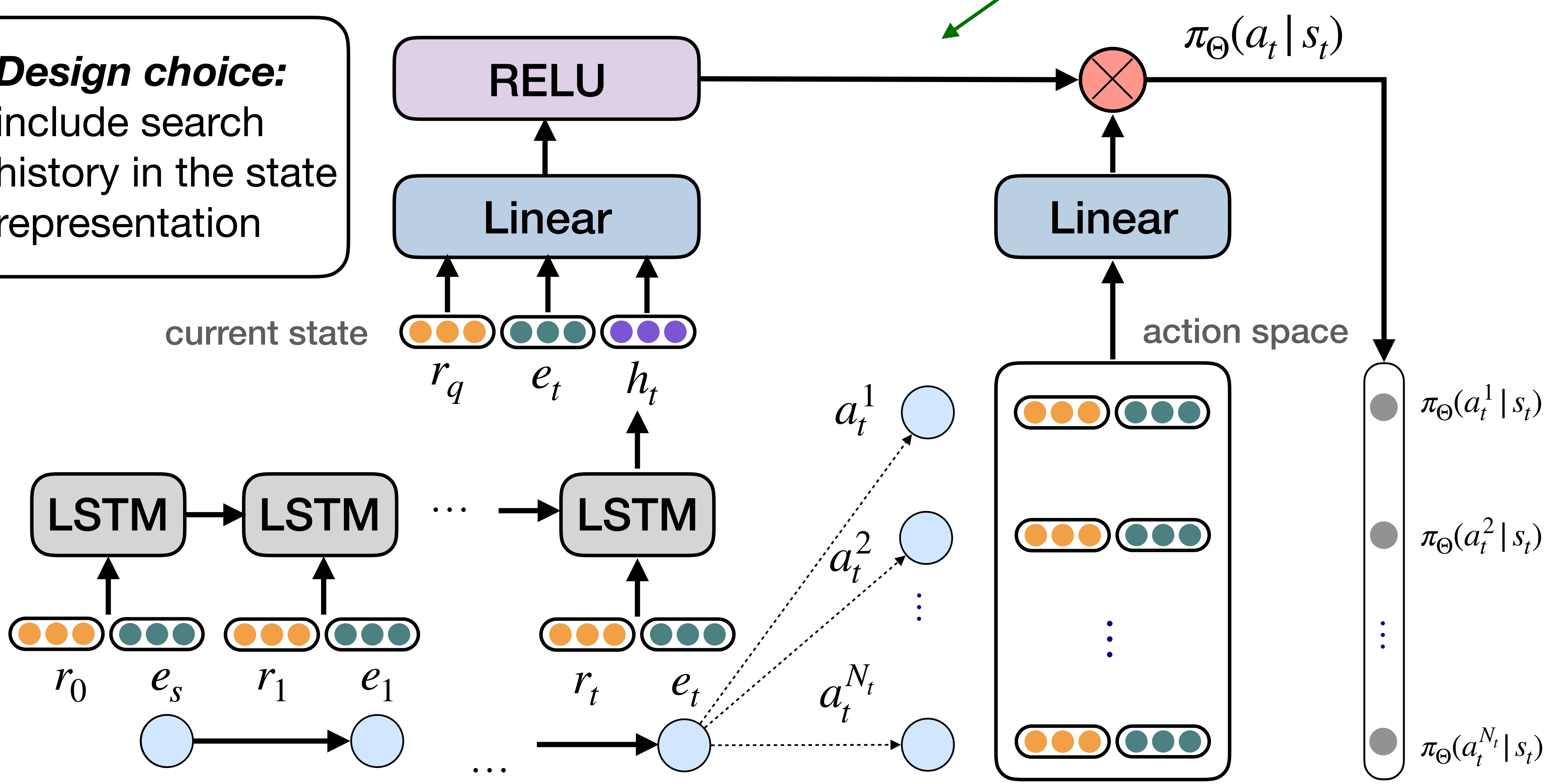


BK IV - Policy Gradient

Our model extensions are applicable to any parameterization of π_Θ

Policy function $\pi_\Theta(a_t | s_t)$

Design choice: include search history in the state representation



MINERVA (Das et al. 2018)