Multi-Hop Knowledge Graph Reasoning with Reward Shaping

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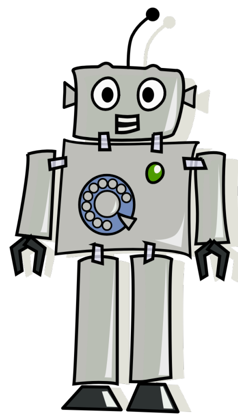
EMNLP 2018

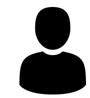
Question Answering System

Text

Images

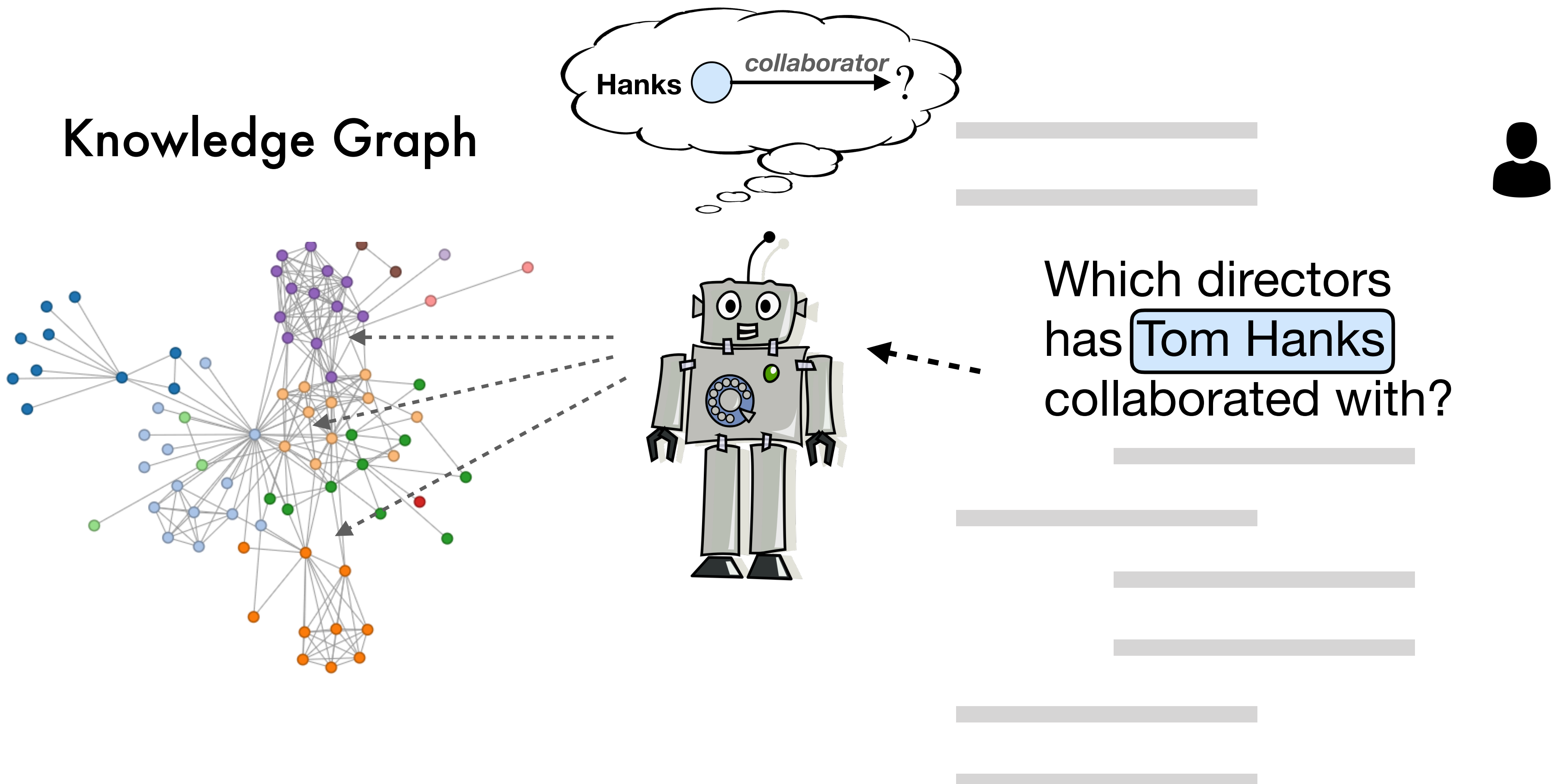
Knowledge Graph



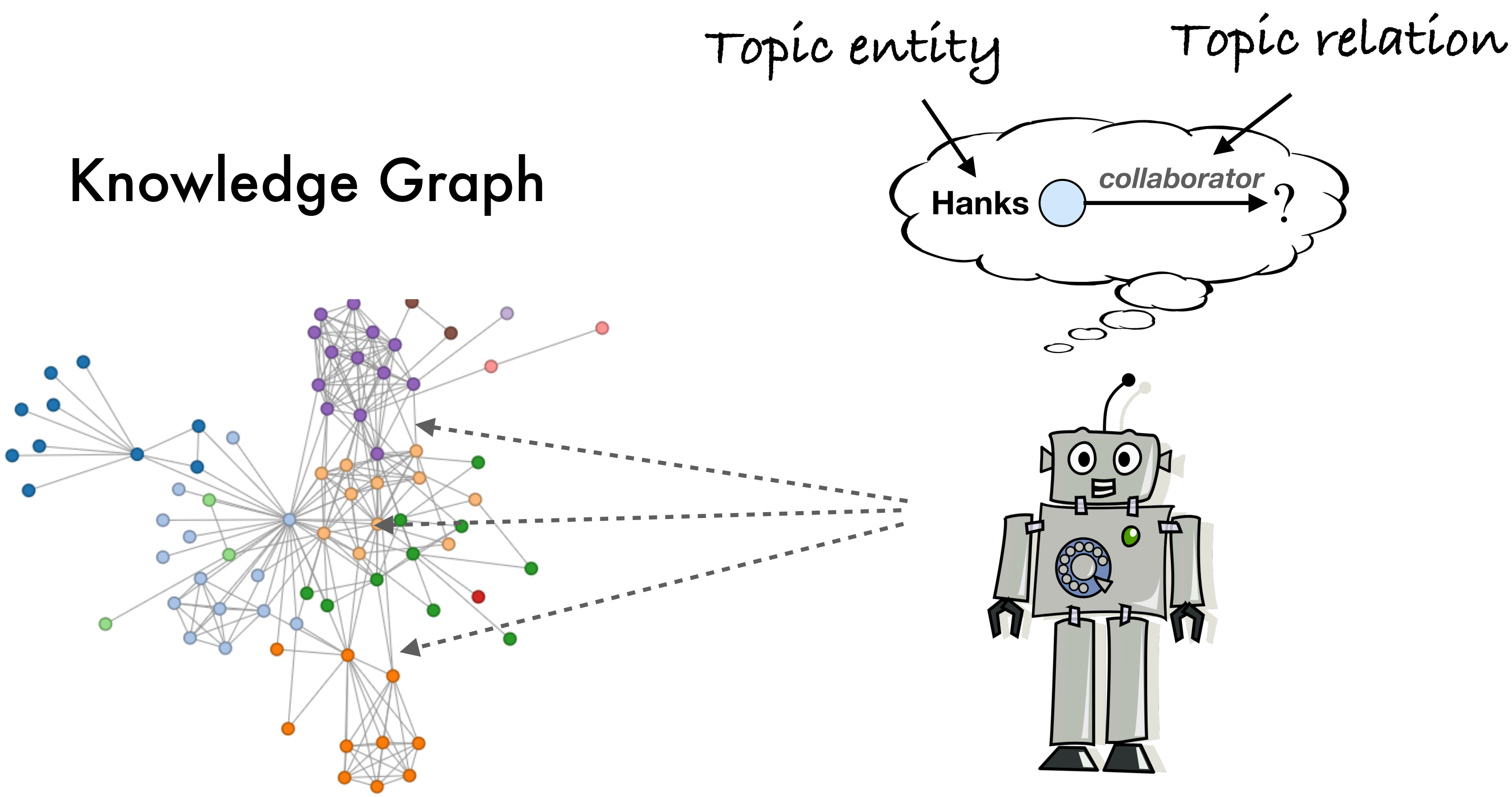


Which directors has Tom Hanks collaborated with?

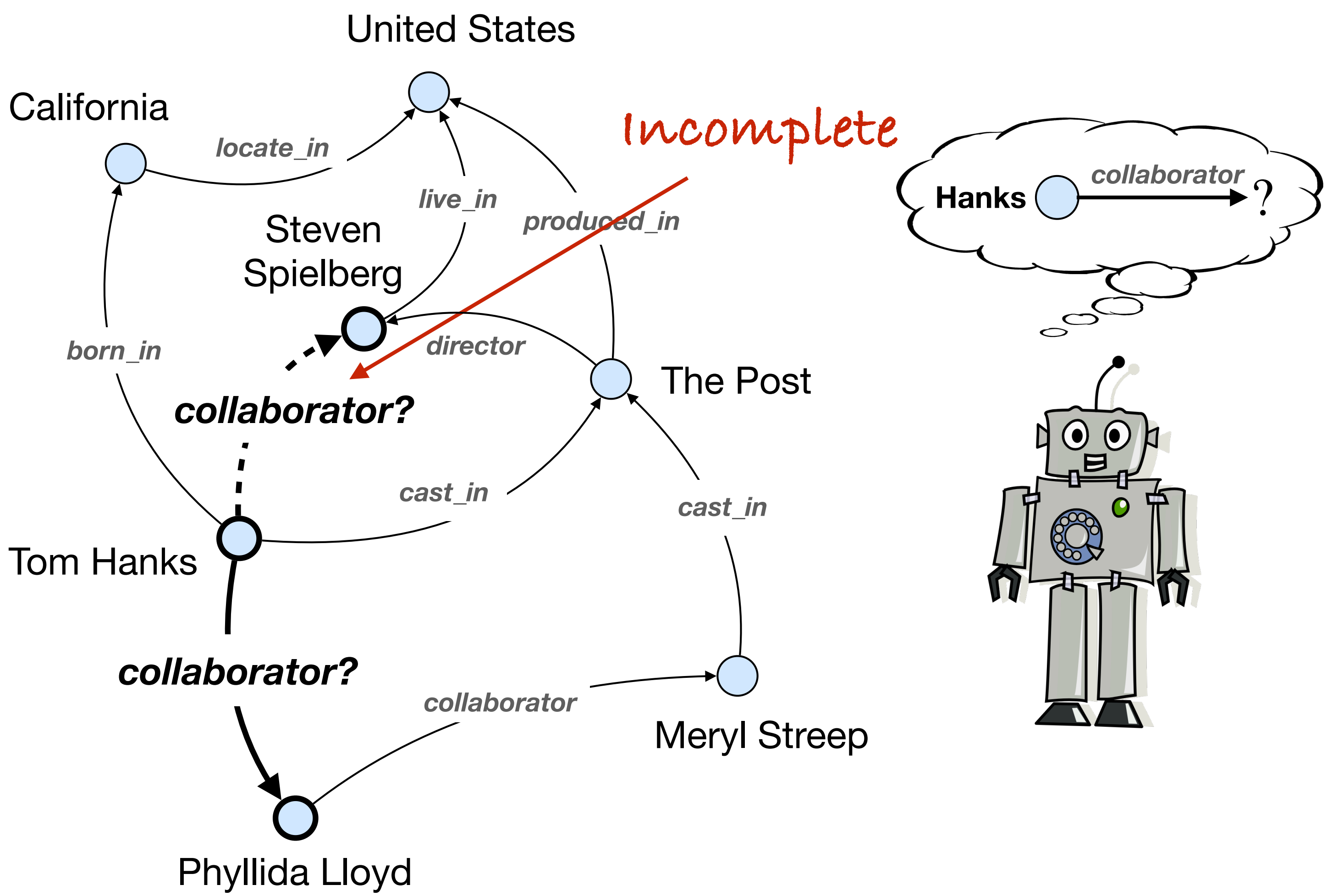
Question Answering System



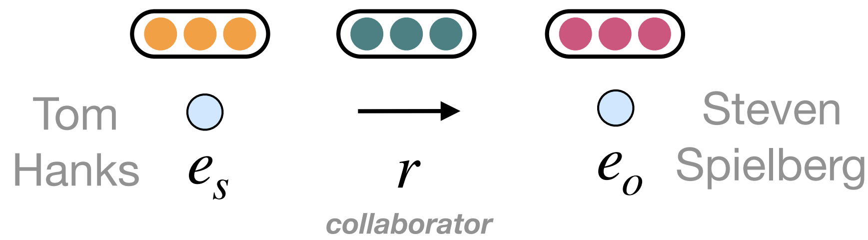
Structured Query Answering



Structured Query Answering



Knowledge Graph Embeddings



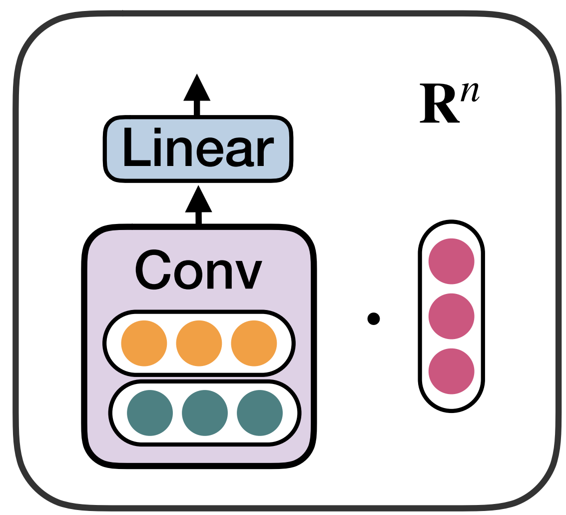
Highly accurate & Efficient

	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?

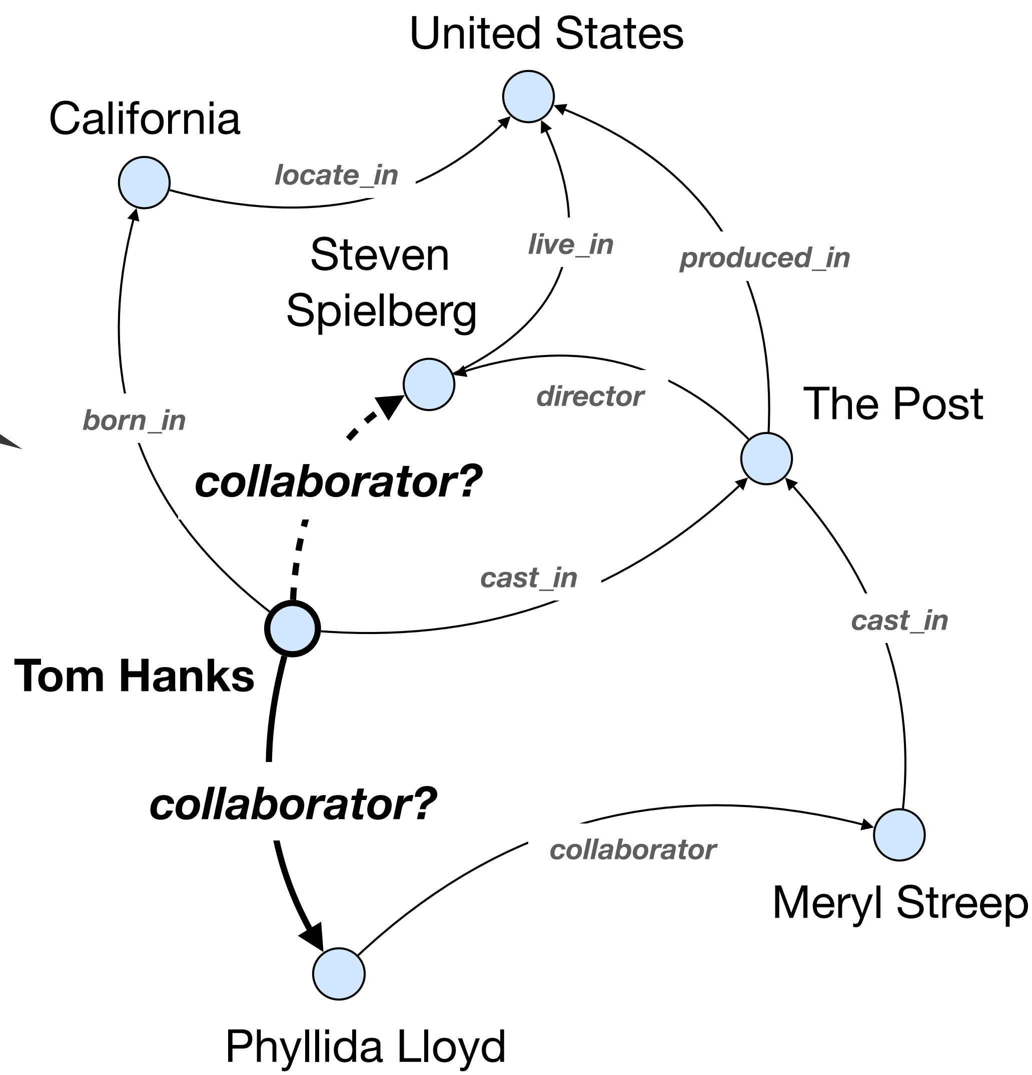


ConvE

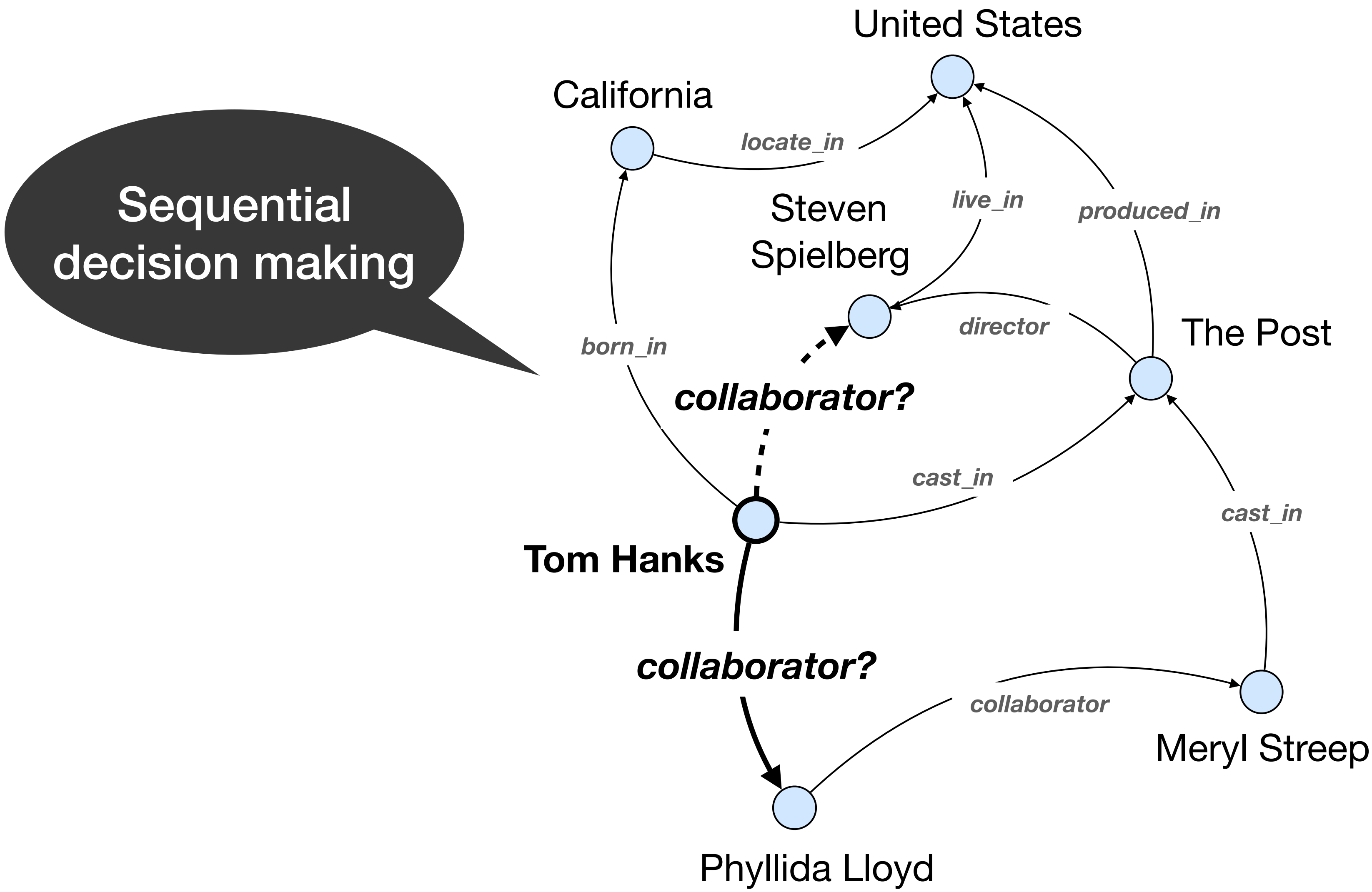
DistMult (Yang et al. 2015), ComplEx (Trouillon et al. 2016), ConvE (Dettmers et al. 2018).

Multi-Hop Reasoning Models

Reasoning over discrete structures



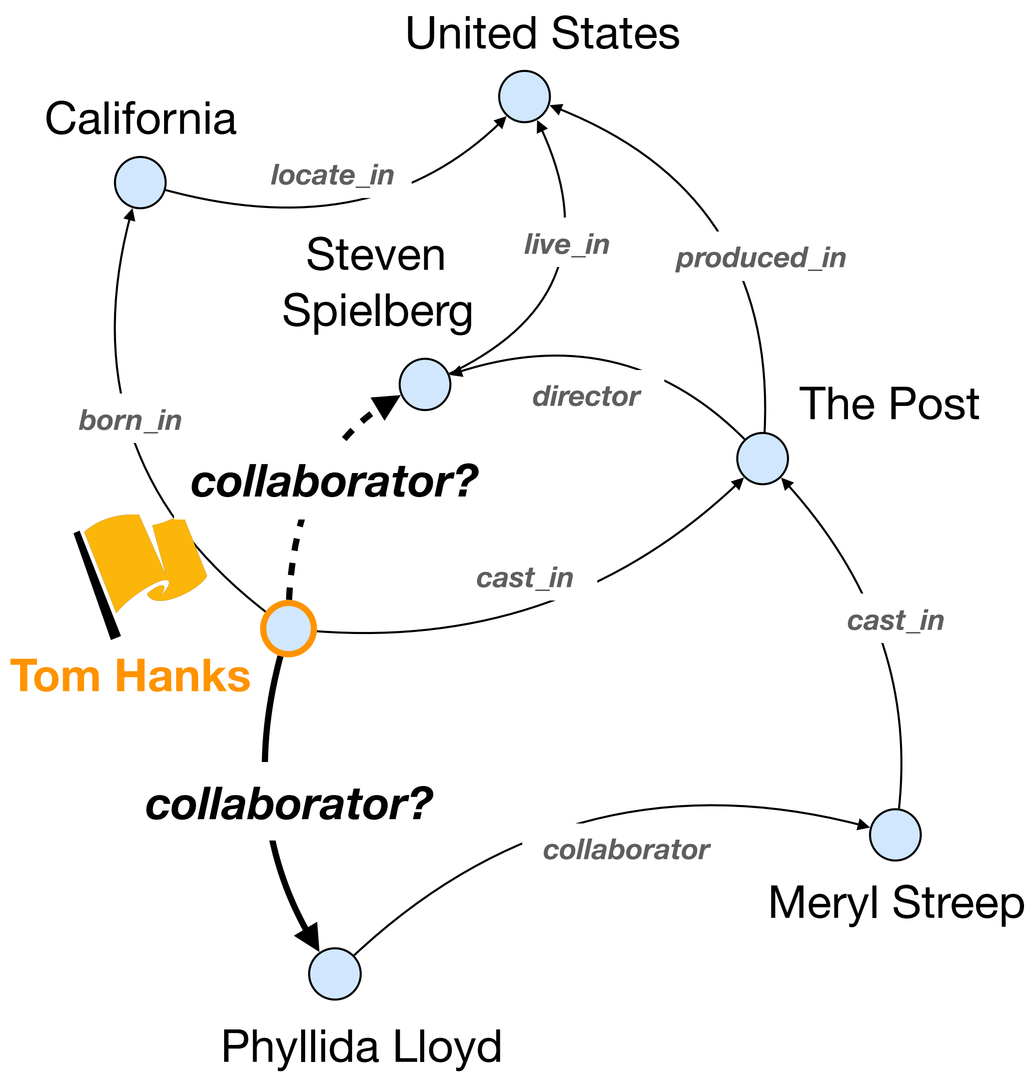
Multi-Hop Reasoning Models



Multi-Hop Reasoning Models

- Tom Hanks

Topic entity



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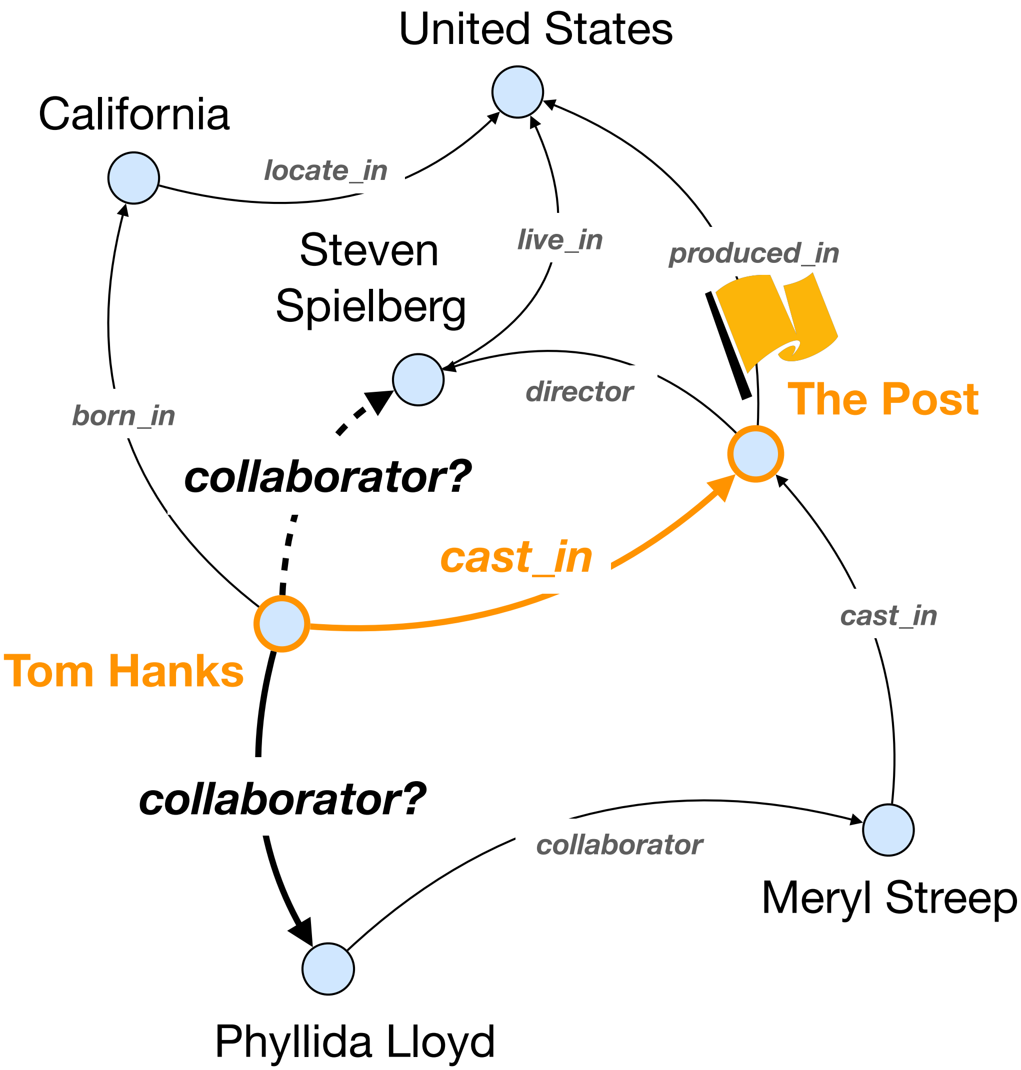

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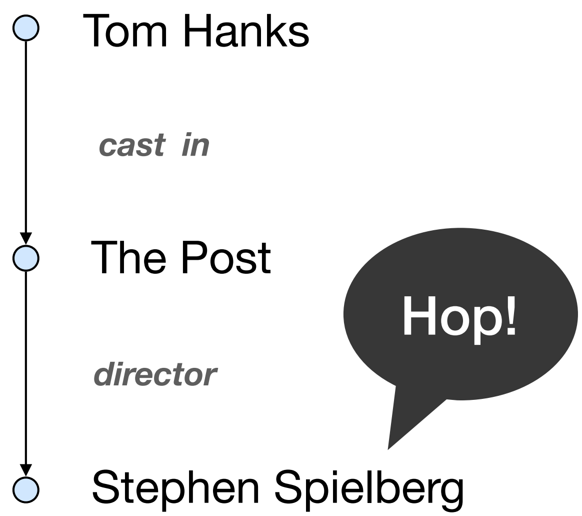
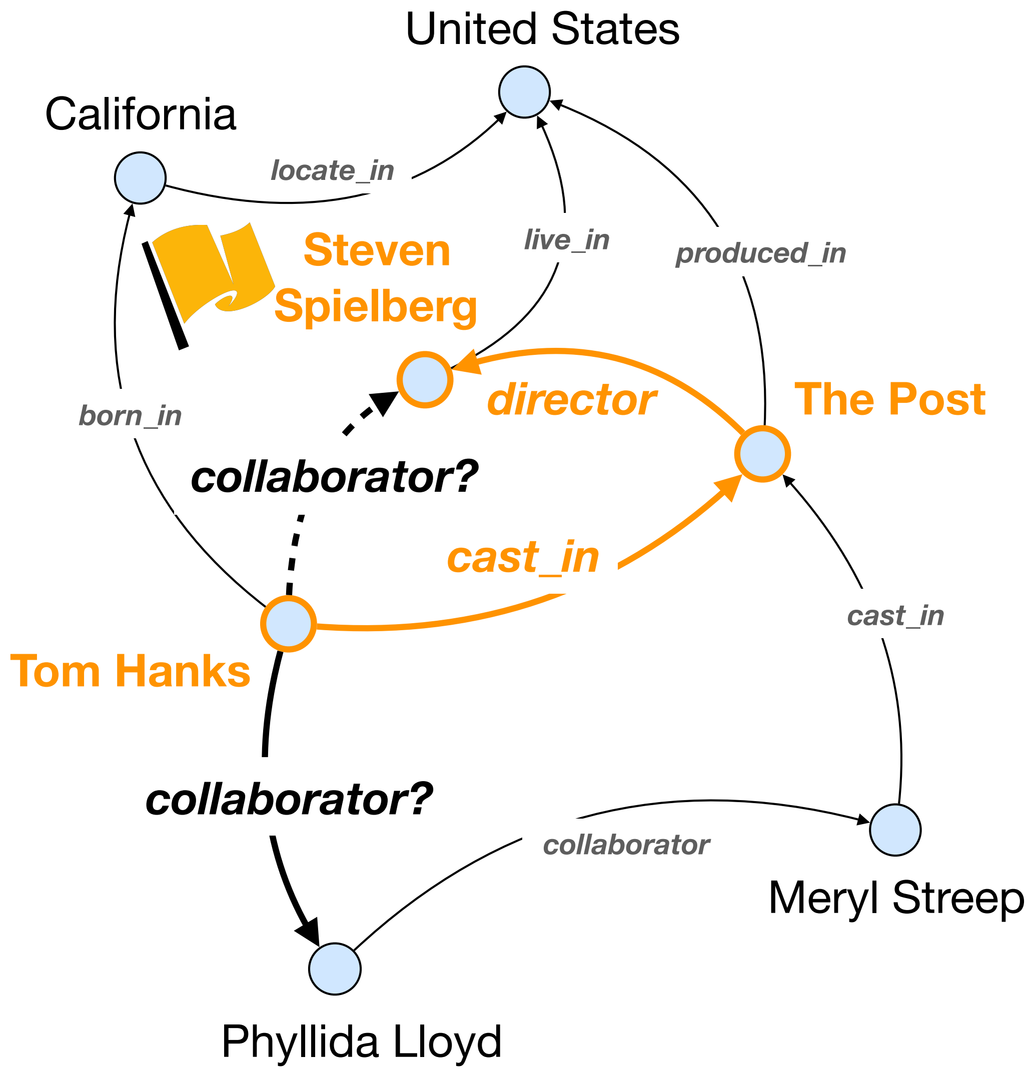
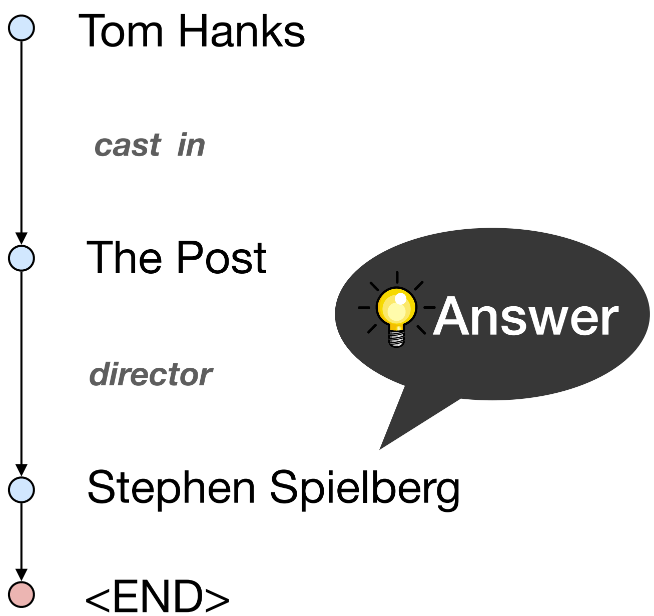
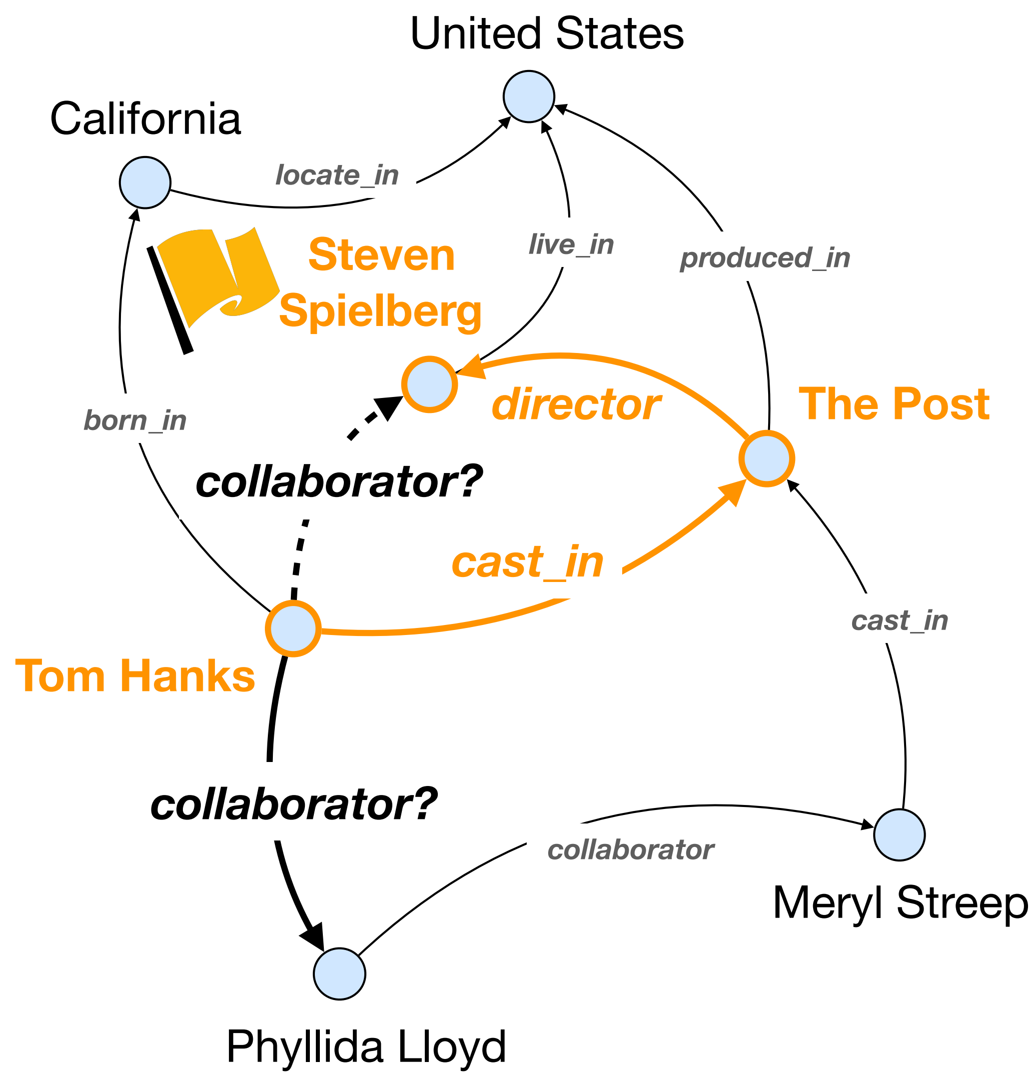




Multi-Hop Reasoning Models





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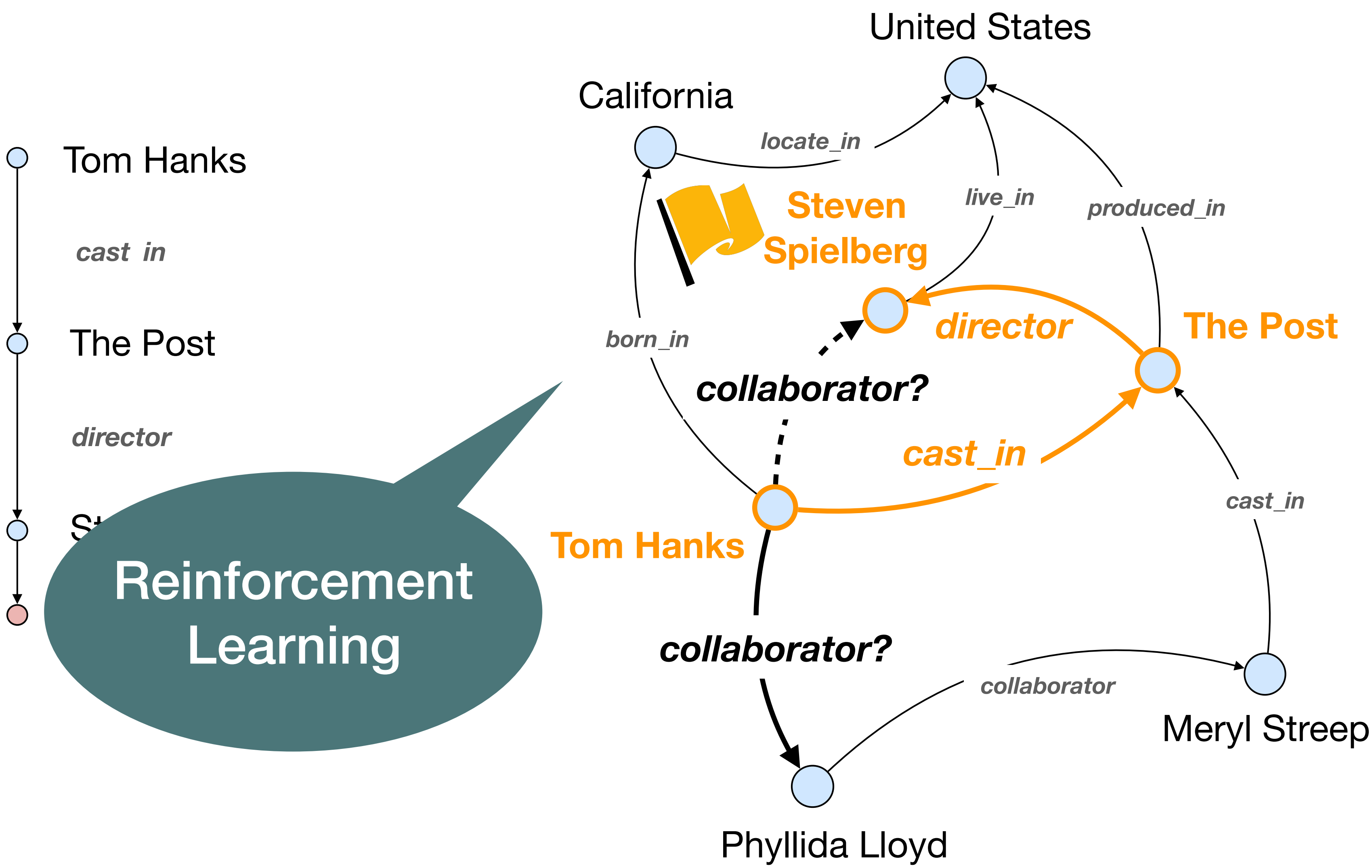


MINERVA (Das et al. 2018)

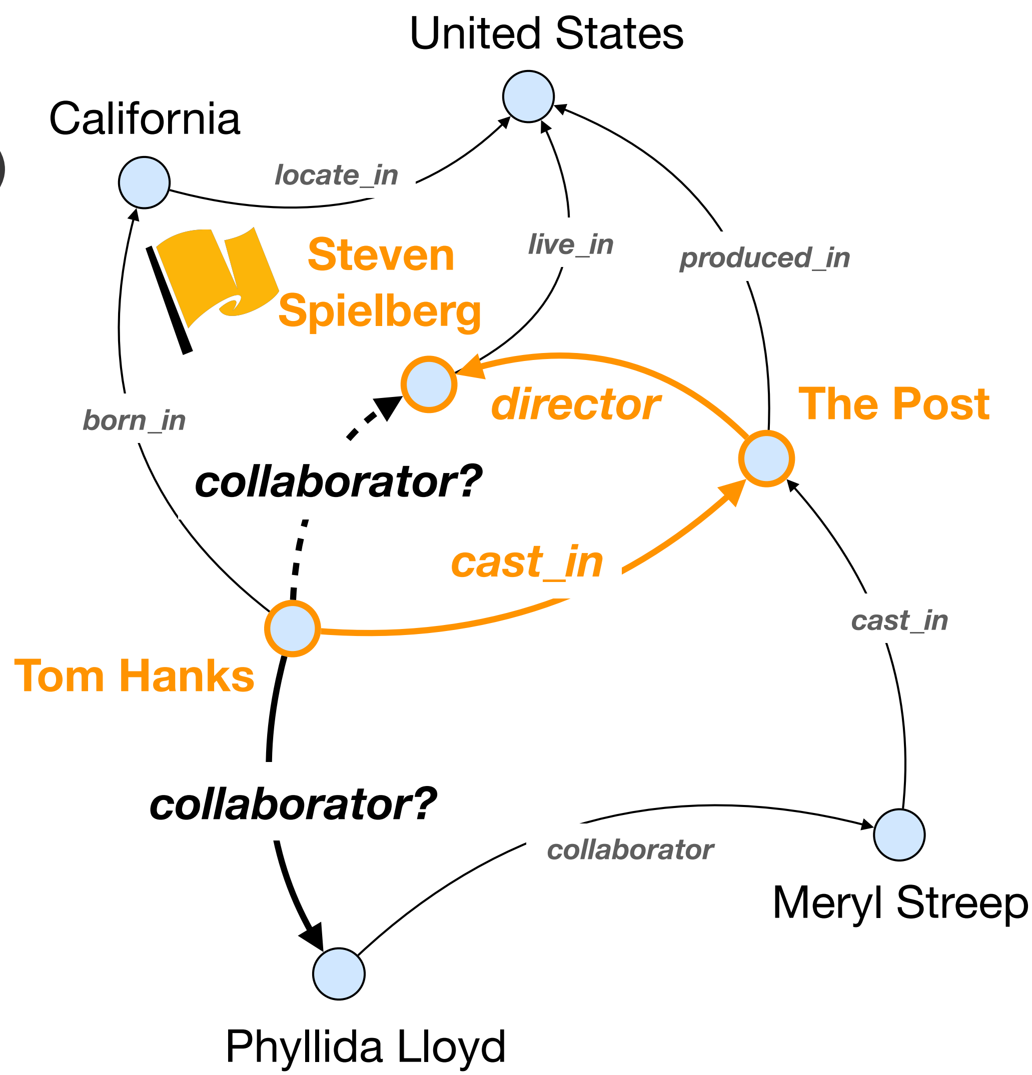
Multi-Hop Reasoning Models

Interpretable

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)



Multi-Hop Reasoning Models: Ideal Case

Interpretable

Significant performance gap

	MRR
ConvE	0.957
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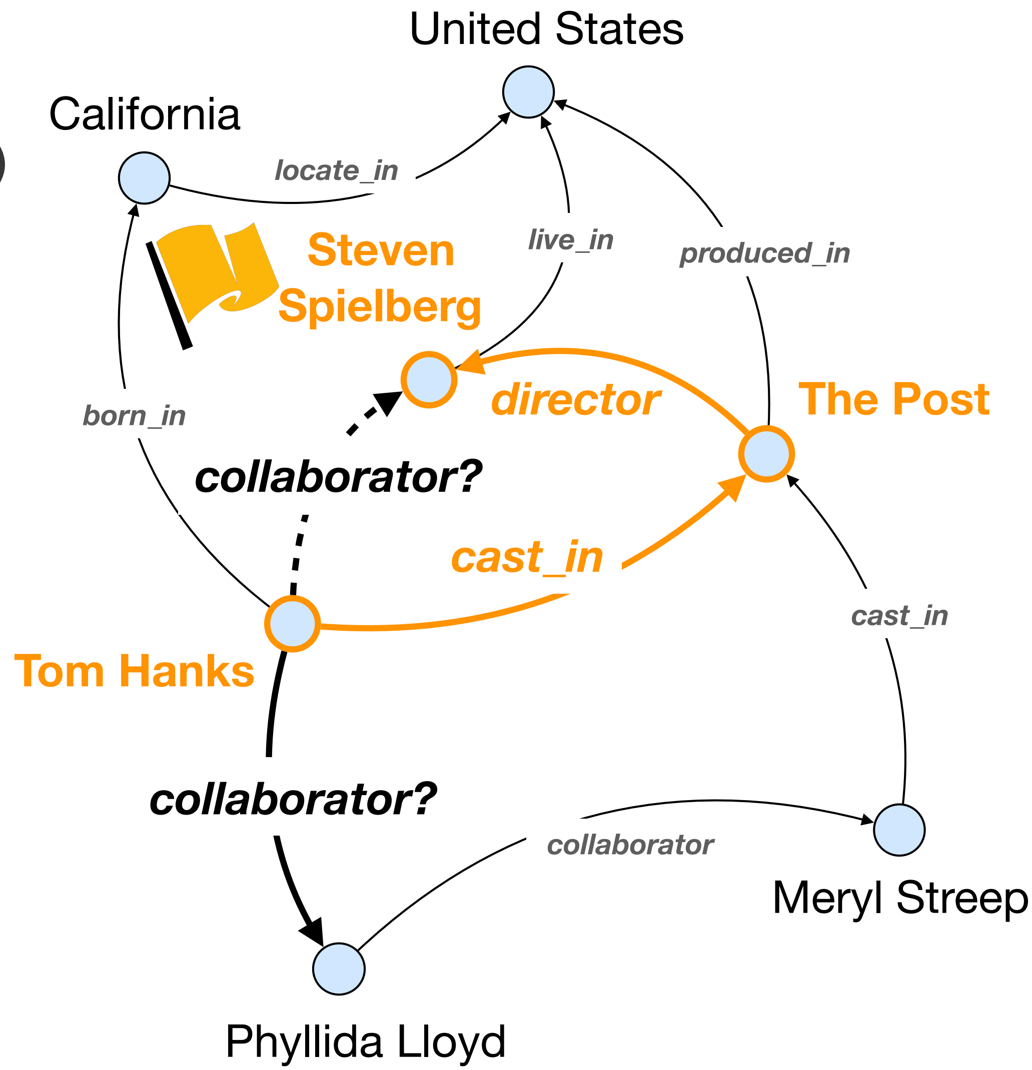
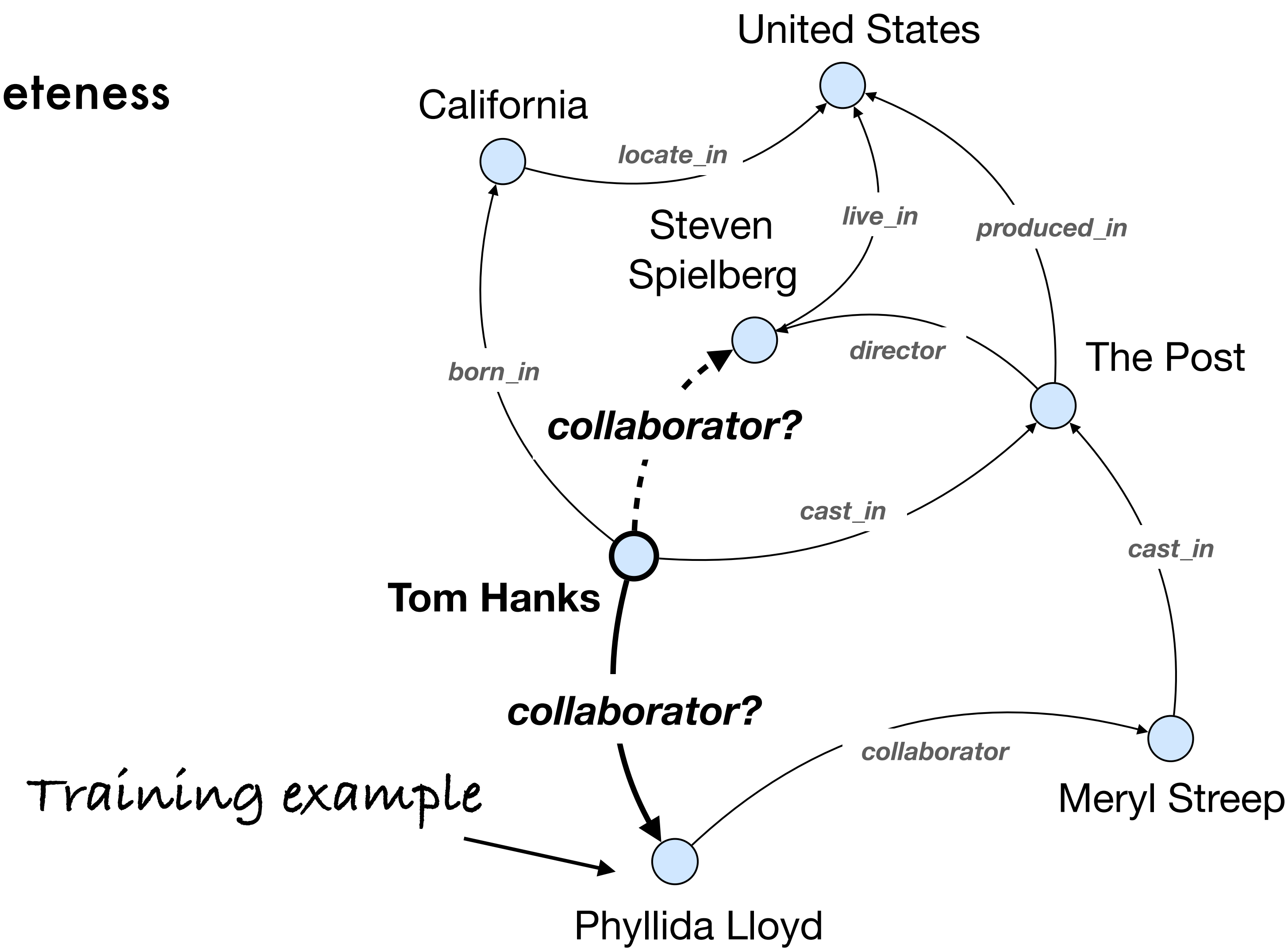


Challenges

Incompleteness



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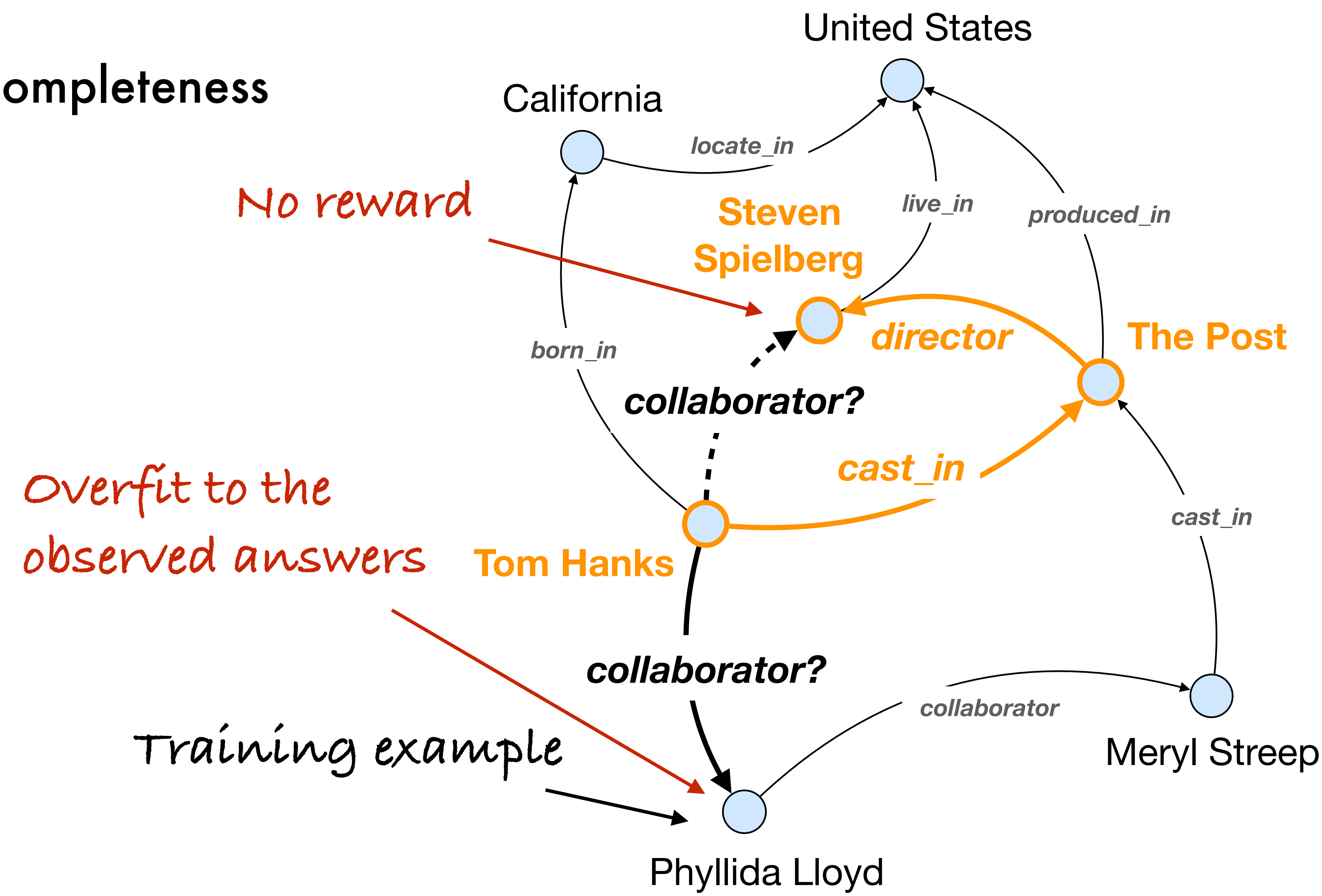
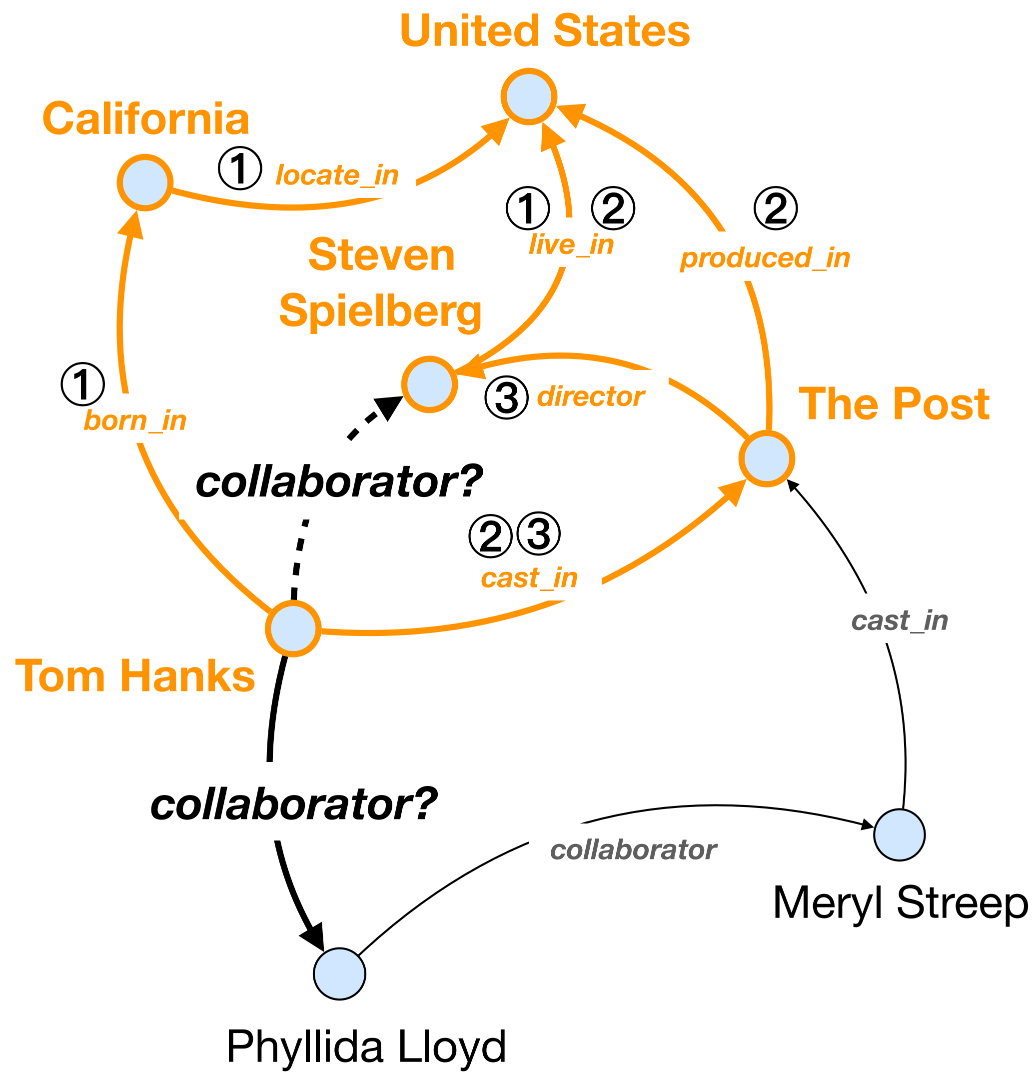


Challenges

Path Diversity

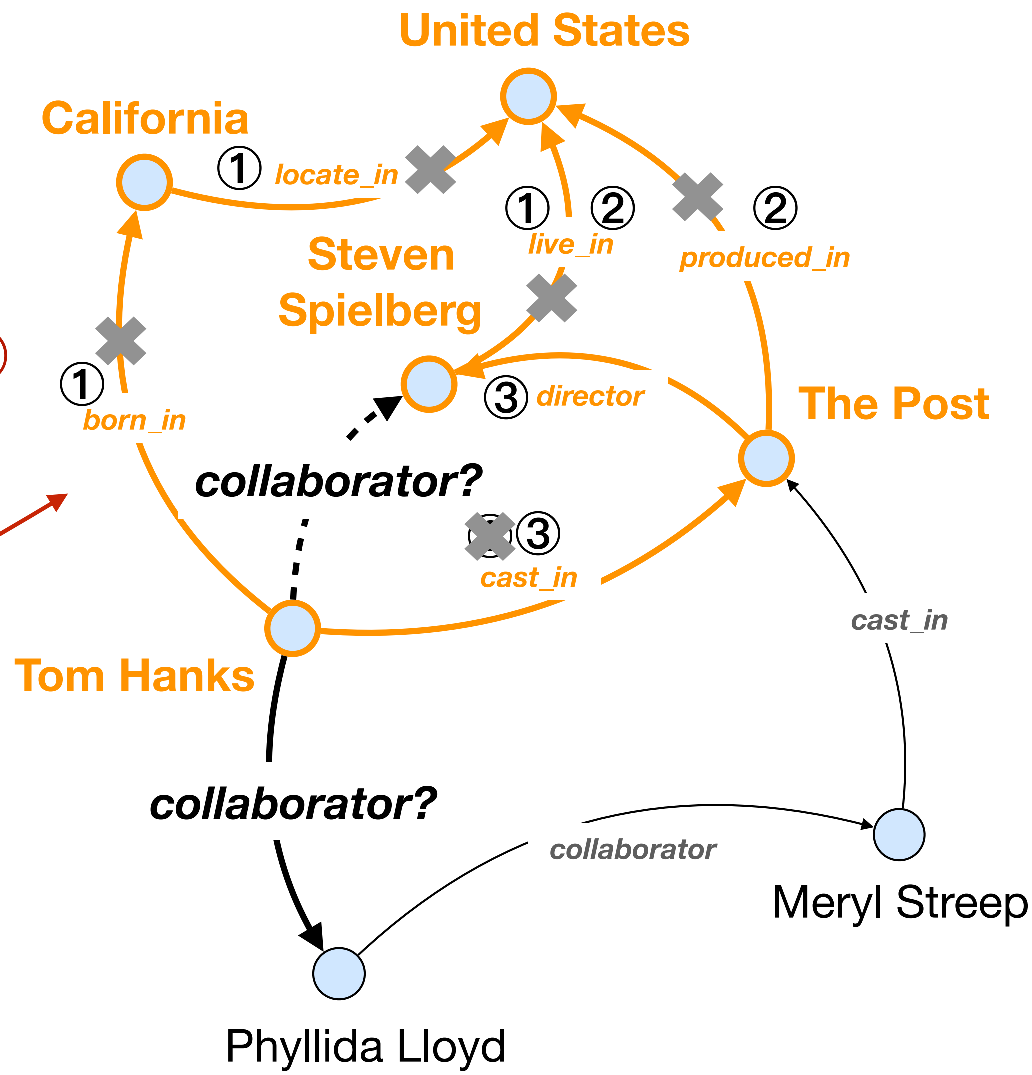


Challenges

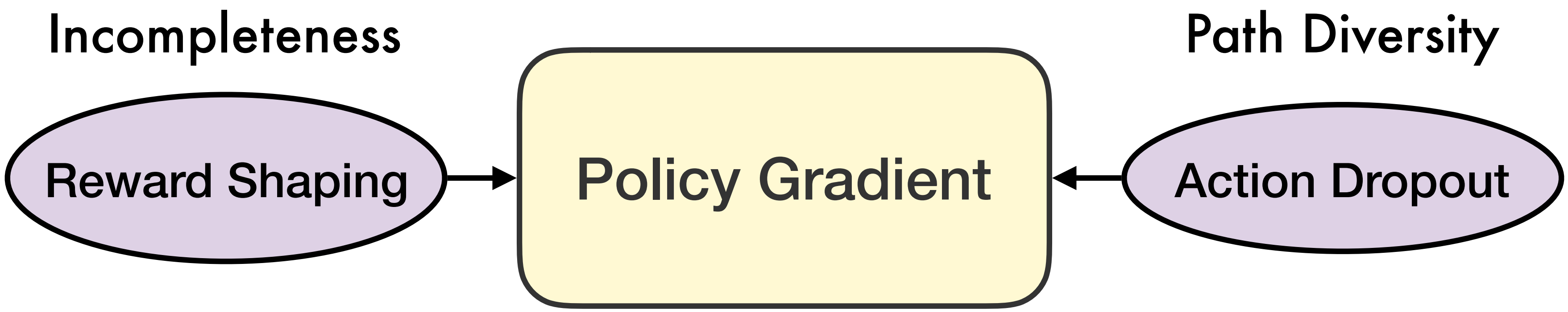
Path Diversity

False positive (spurious) paths ① ②

Overfit to the spurious paths

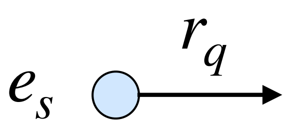


Proposed Solutions



Reinforcement Learning Framework

Environment | State | Action | Transition | Reward



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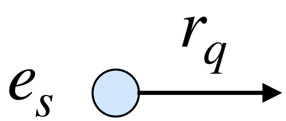

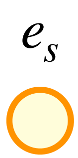

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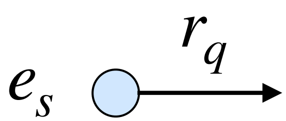
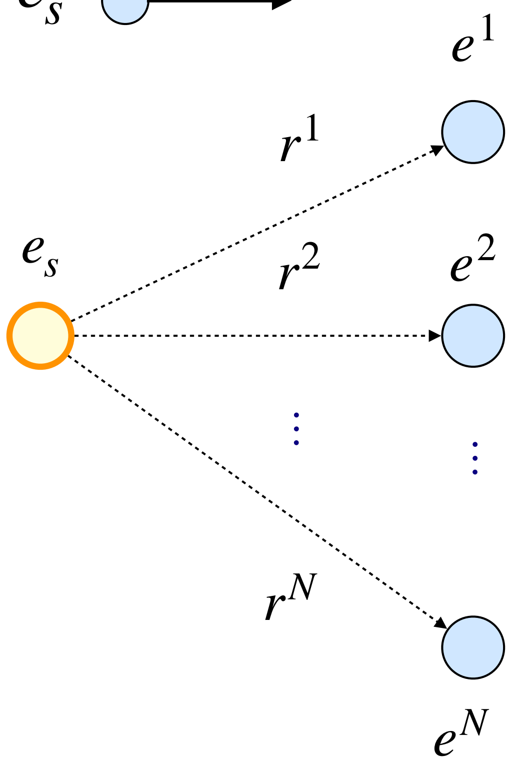


A_t



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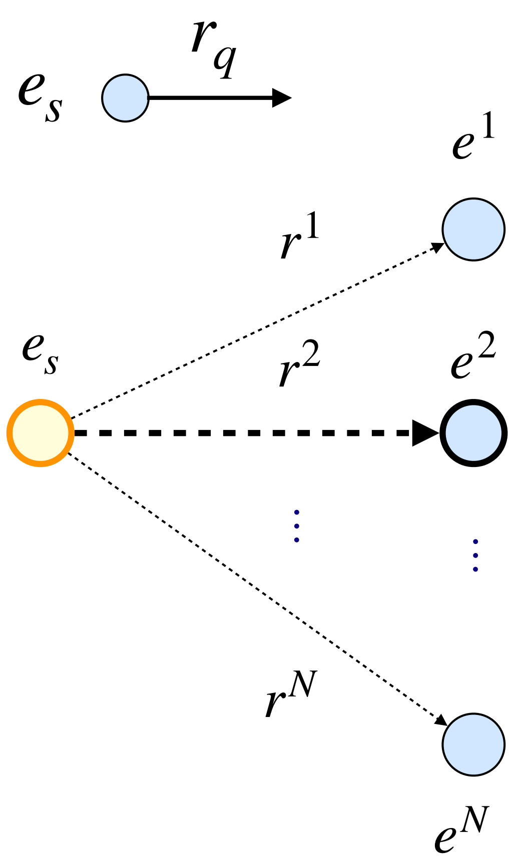

A_t

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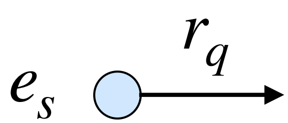

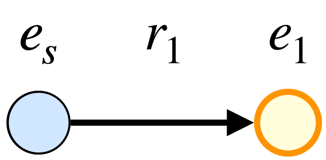

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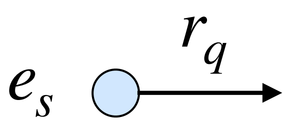

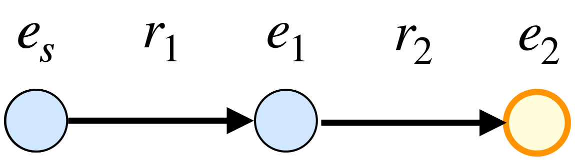

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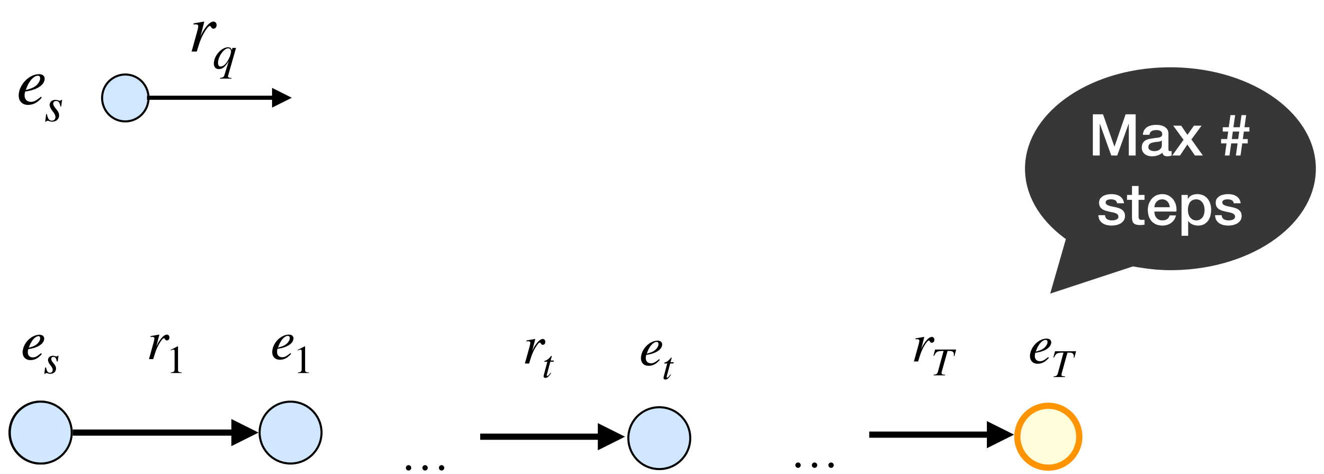

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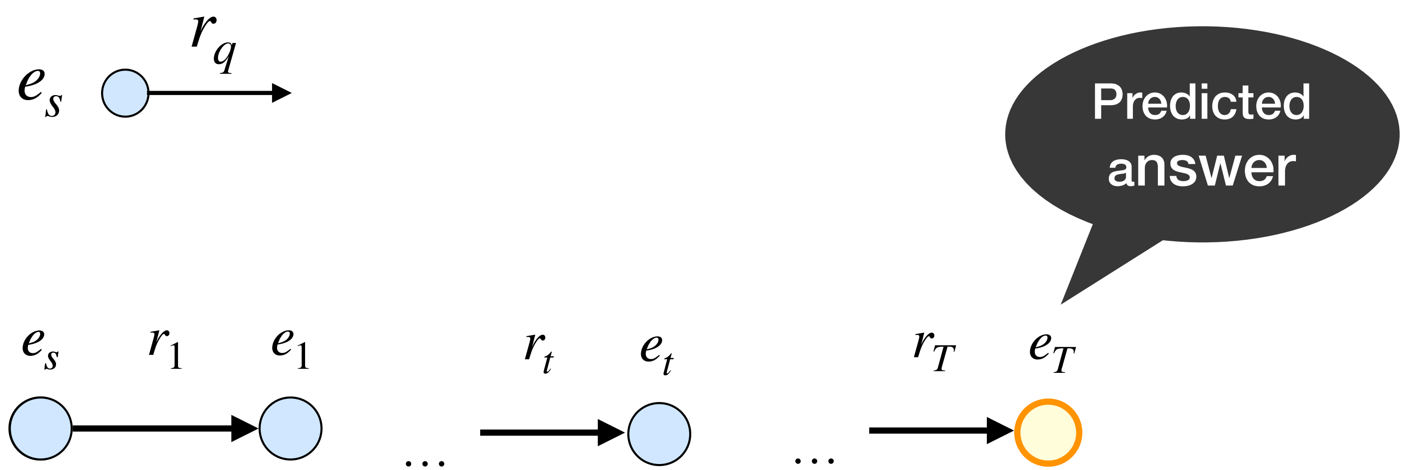

Reinforcement Learning Framework

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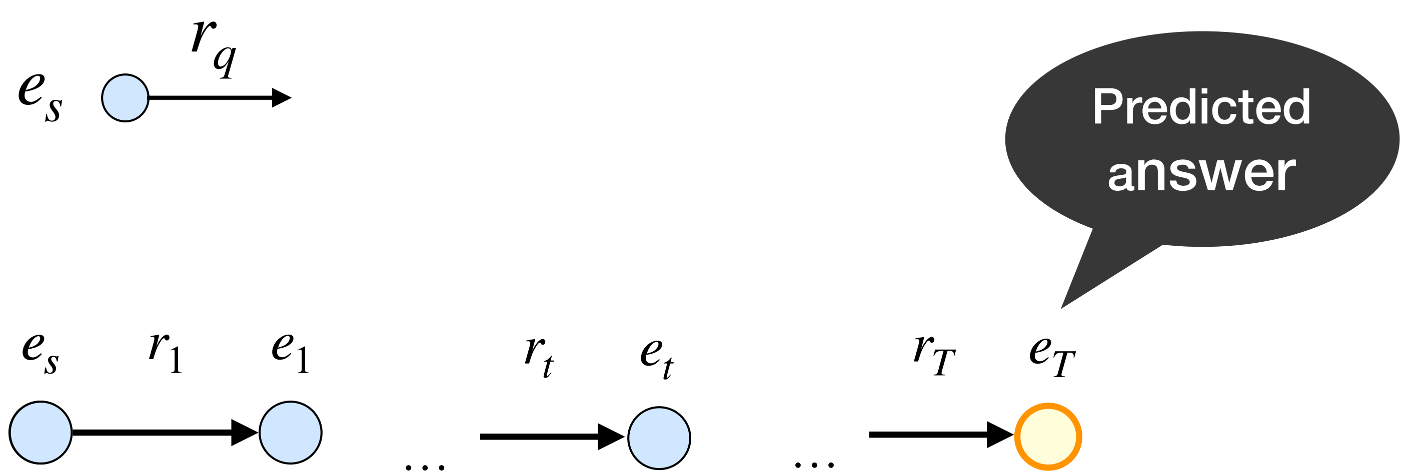
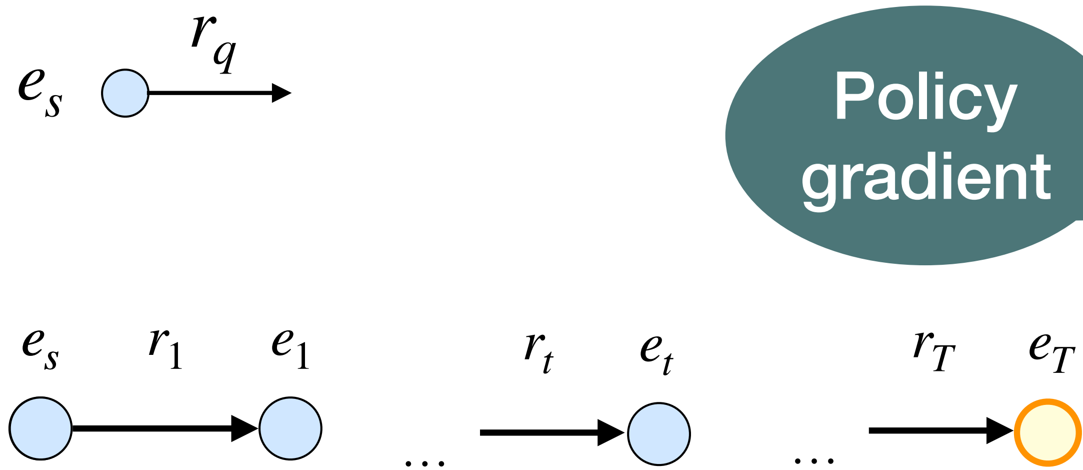


$$\boxed{R_b(s_T) = \mathbf{1}\{(e_s, r_q, e_T) \in G\}}$$

Reinforcement Learning Framework

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



Policy gradient

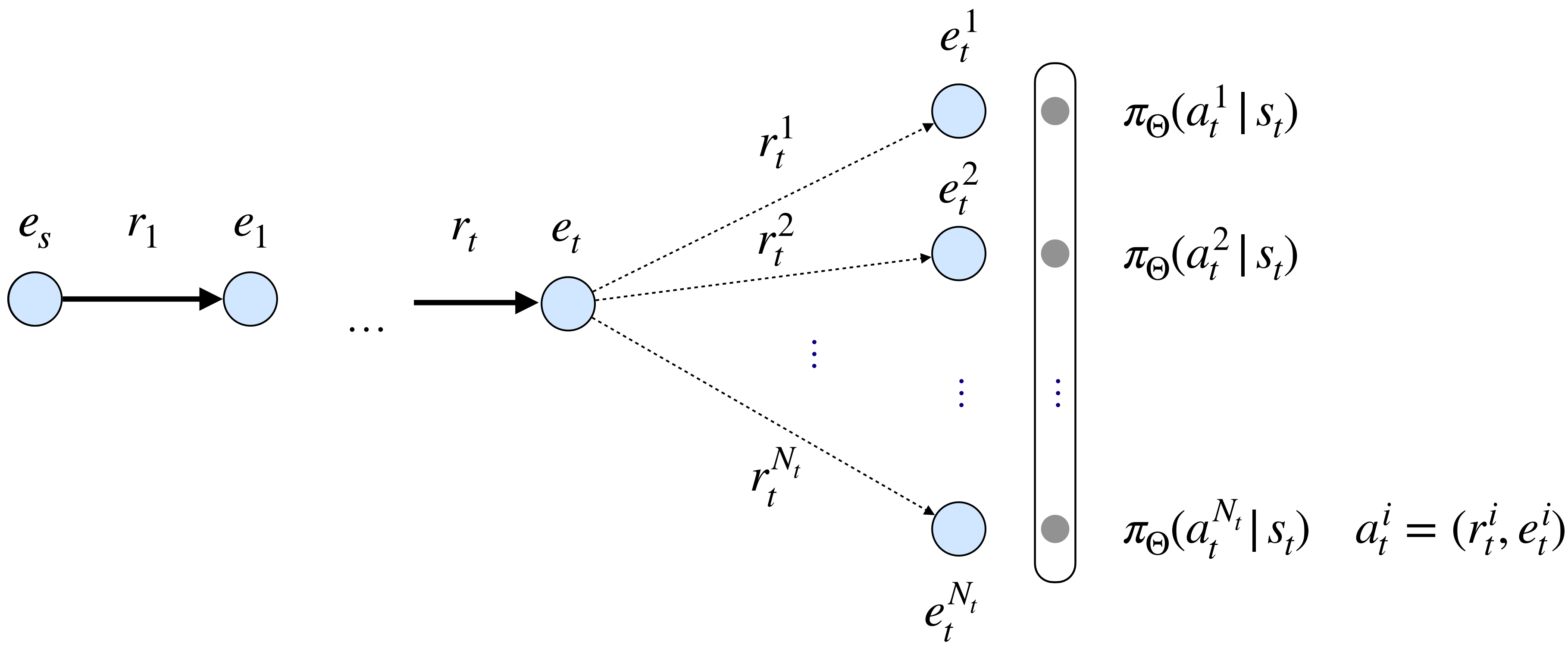
Learn ***which action to choose*** given a state

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

Policy Gradient

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

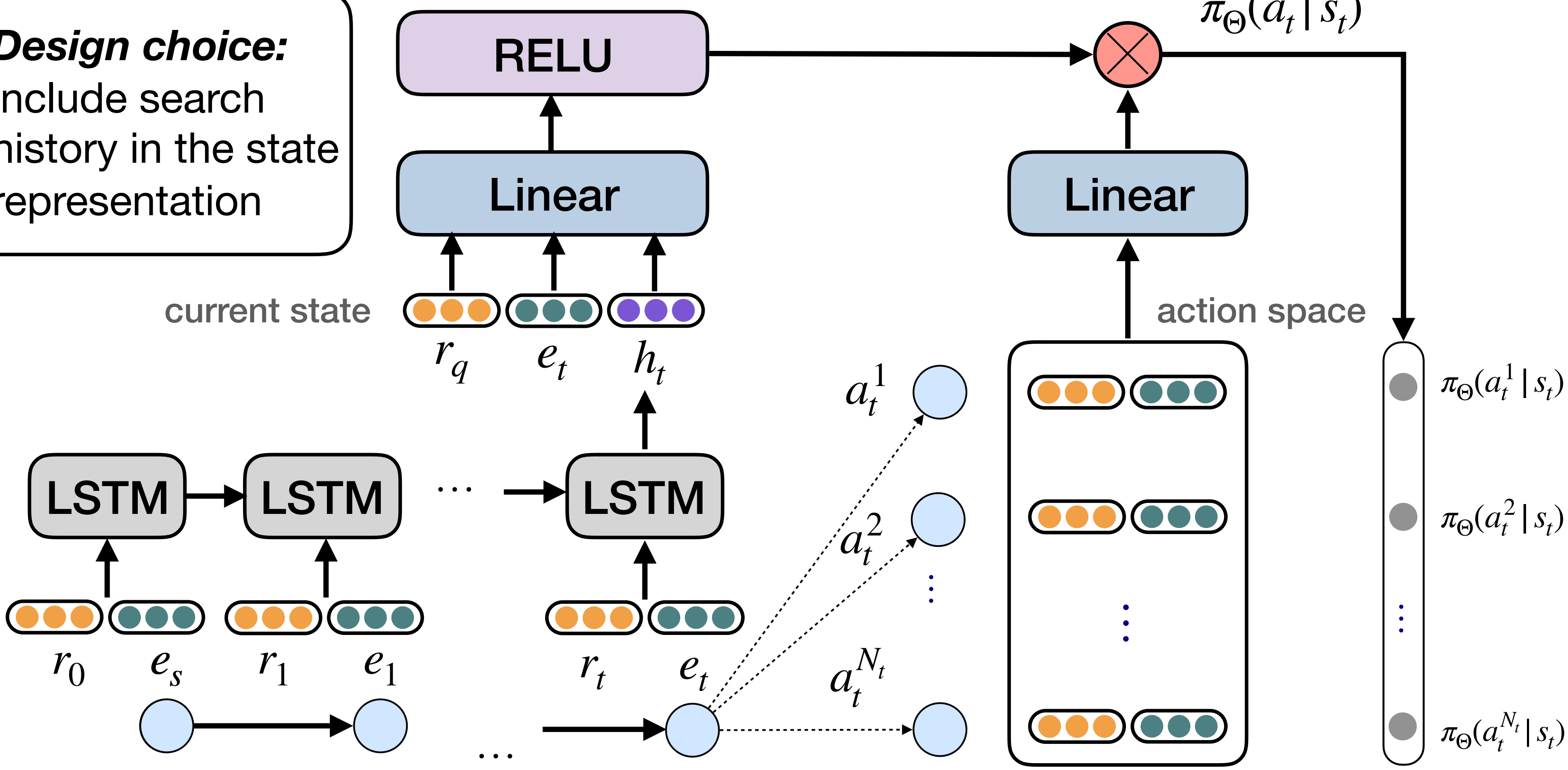
Probability of choosing an action given the current state



Policy Gradient

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

Design choice: include search history in the state representation



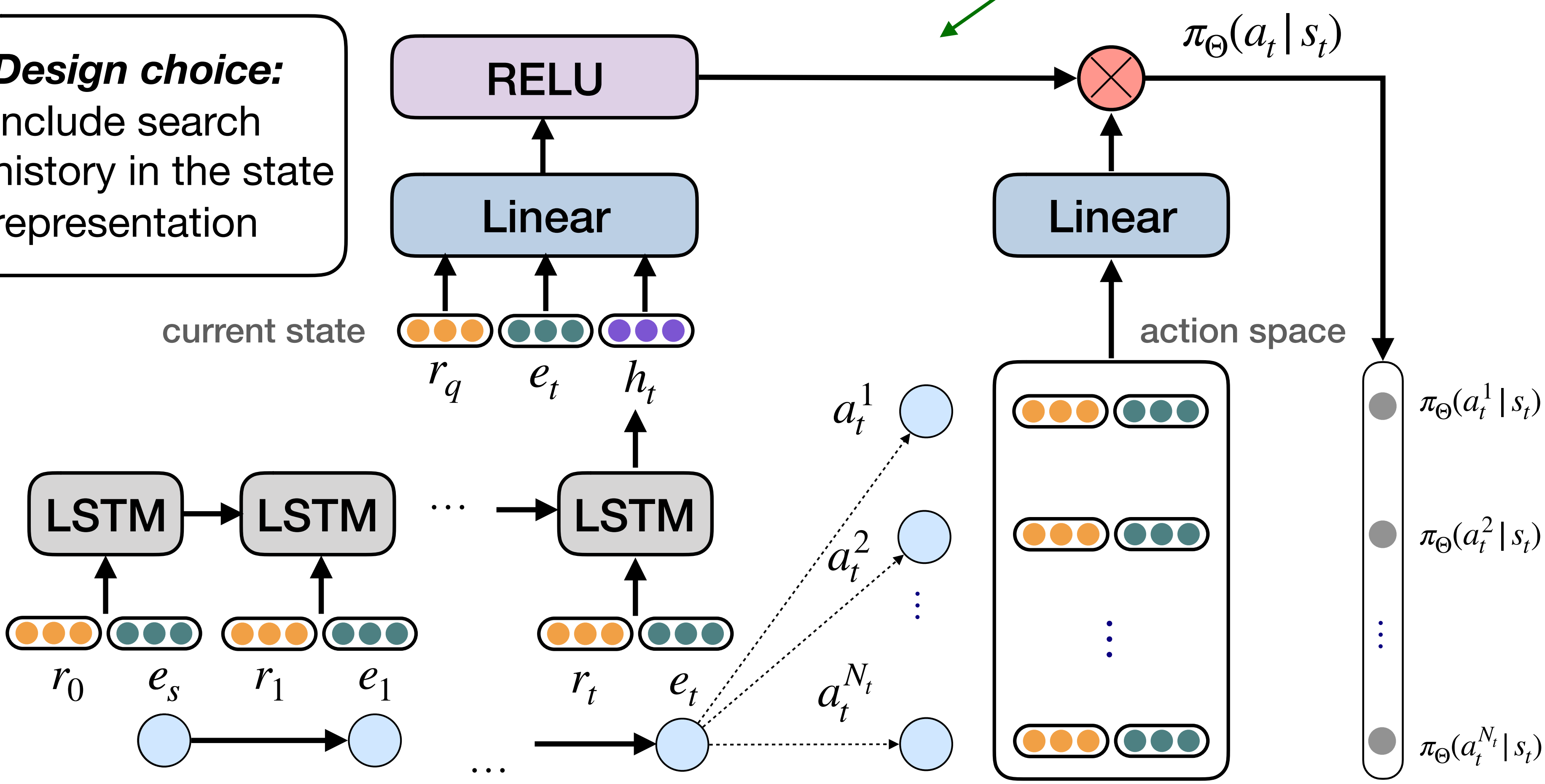
MINERVA (Das et al. 2018)

Policy Gradient

Our model extensions are applicable to any parameterization of π_Θ

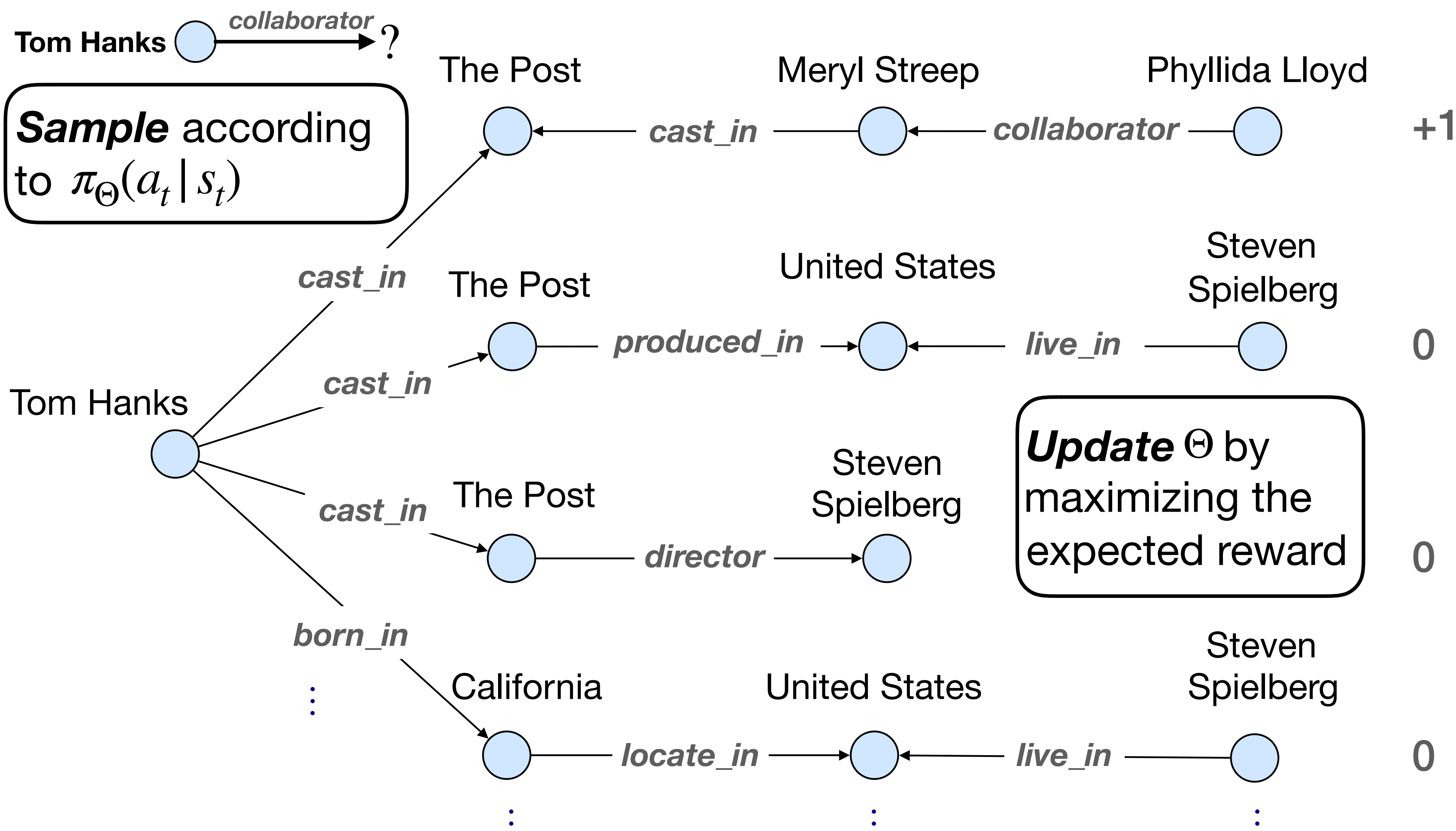
Policy function $\pi_\Theta(a_t | s_t)$

Design choice: include search history in the state representation



MINERVA (Das et al. 2018)

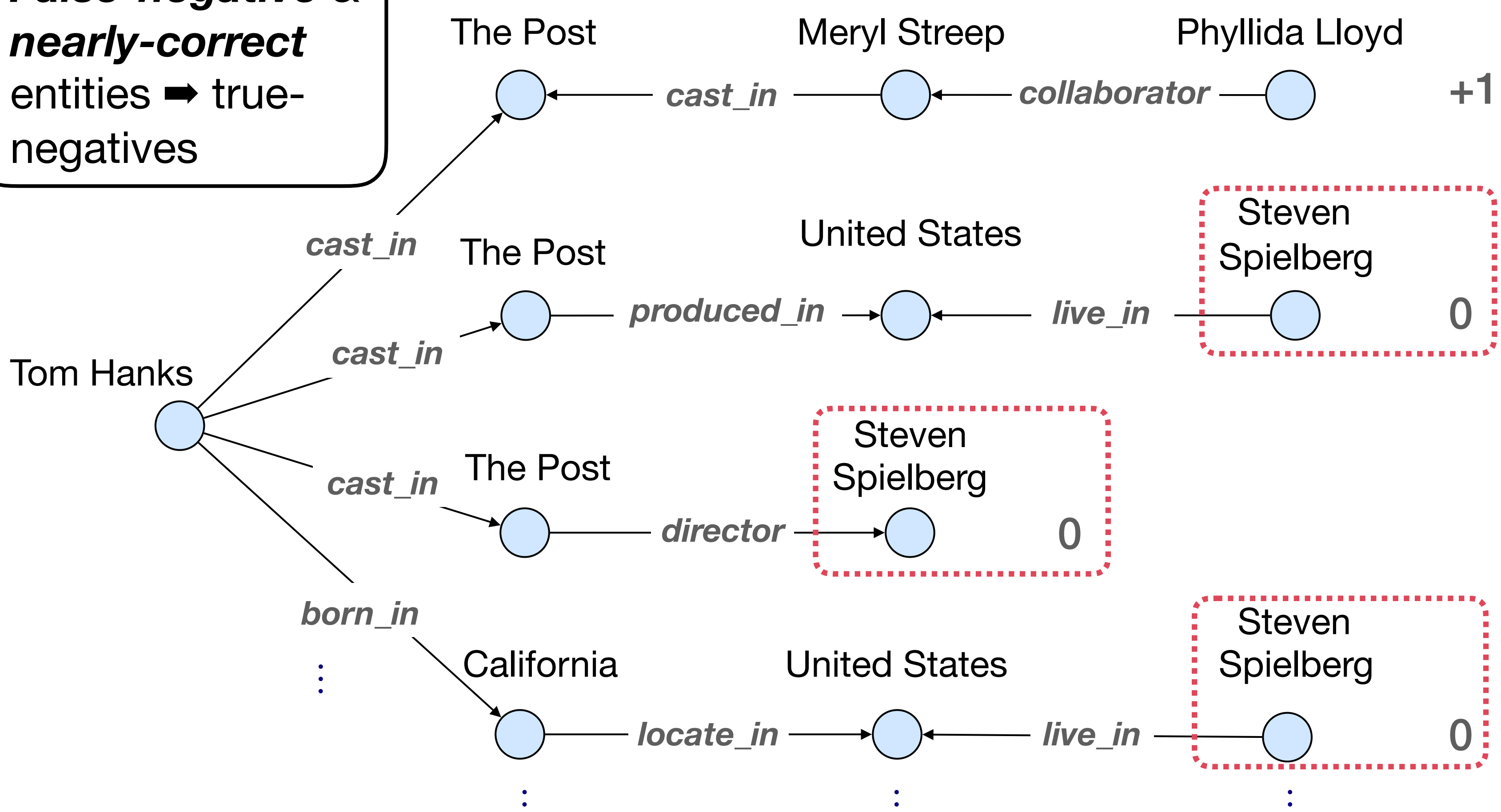
REINFORCE Training



REINFORCE (Williams, 1992)

REINFORCE Training

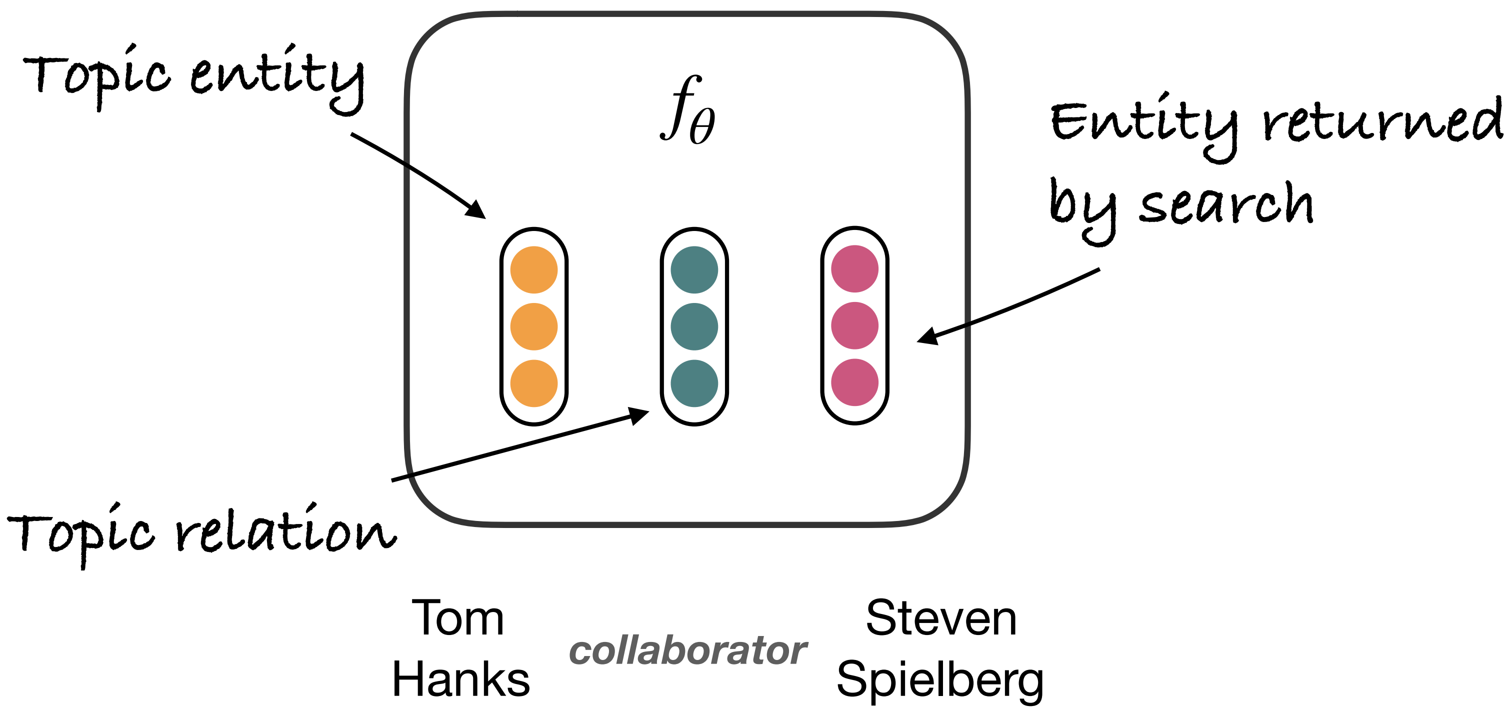
False-negative & ***nearly-correct*** entities ➡ true-negatives



Reward Shaping

Unobserved facts

Soft **correctness**



Reward Shaping

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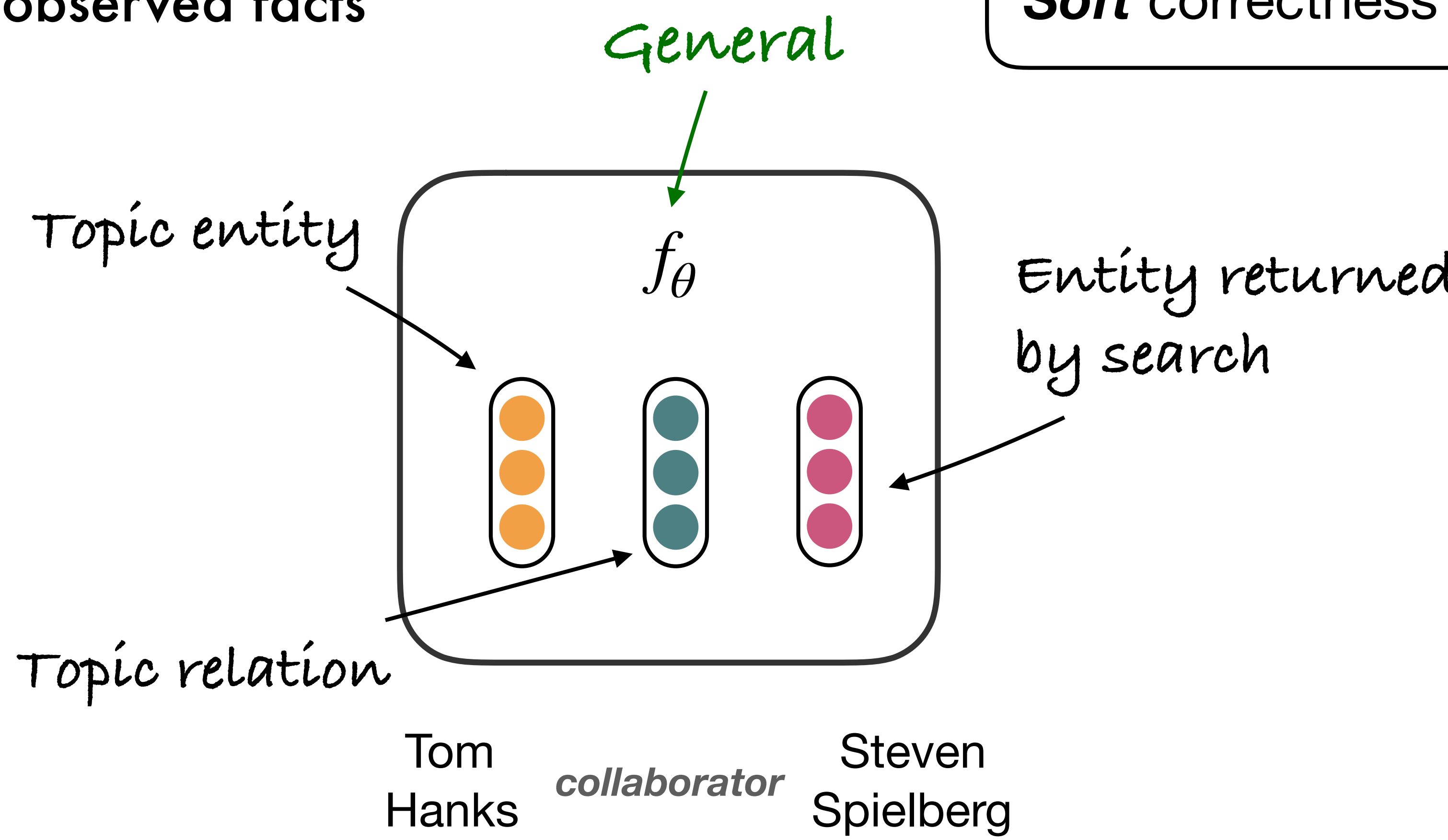
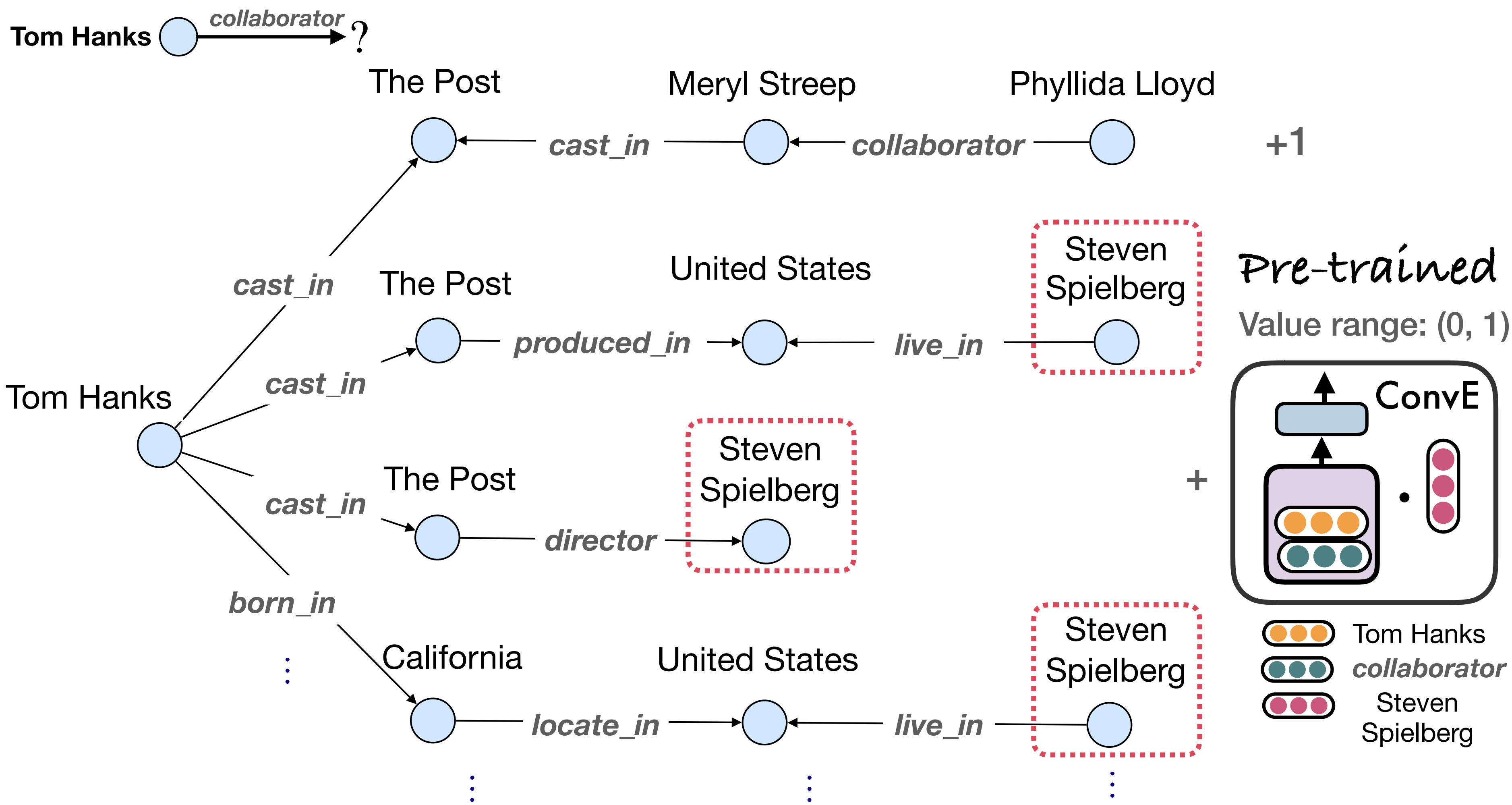


Reward Shaping



Action Dropout

Intuition: ***avoid sticking to*** past actions that ***had received rewards***

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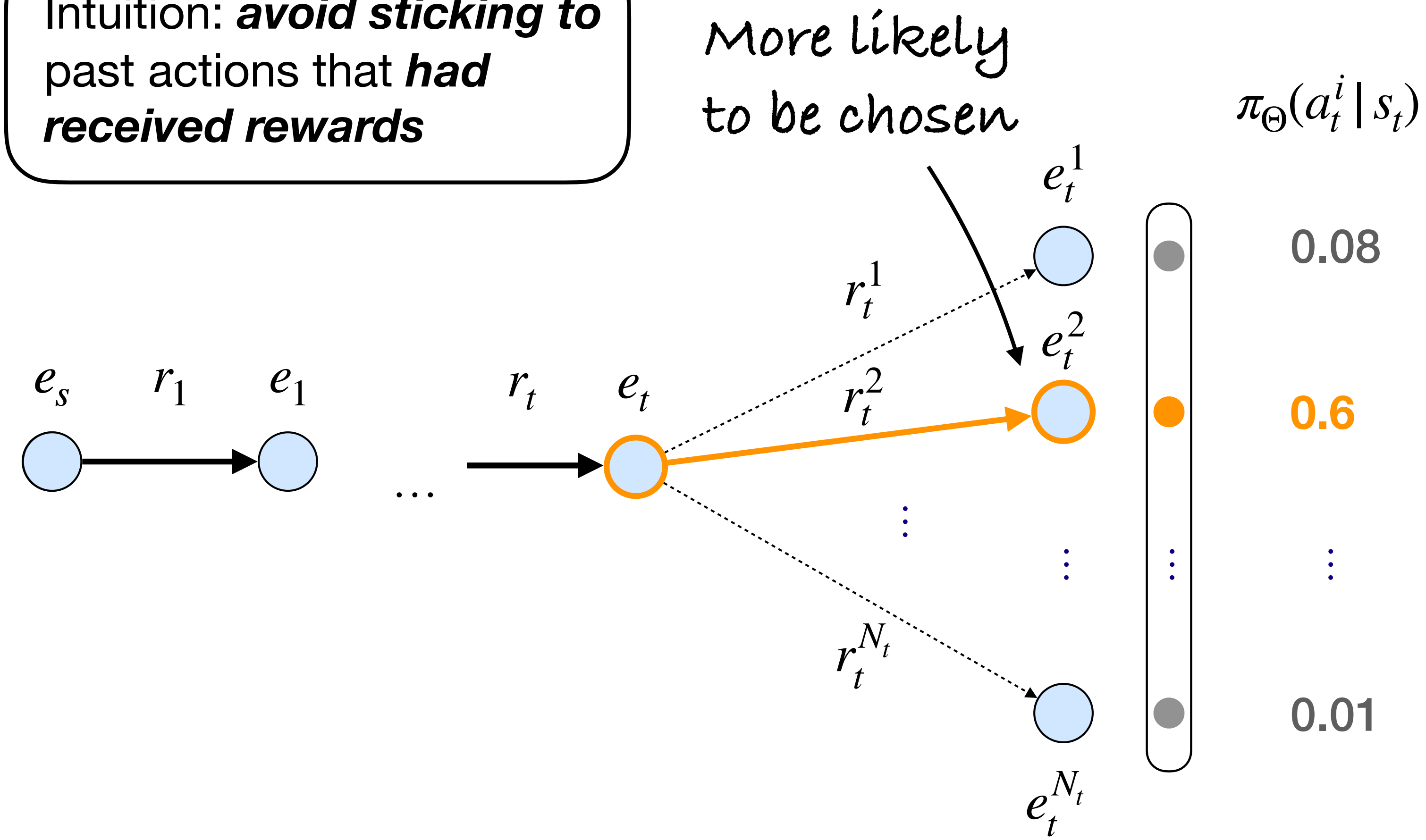
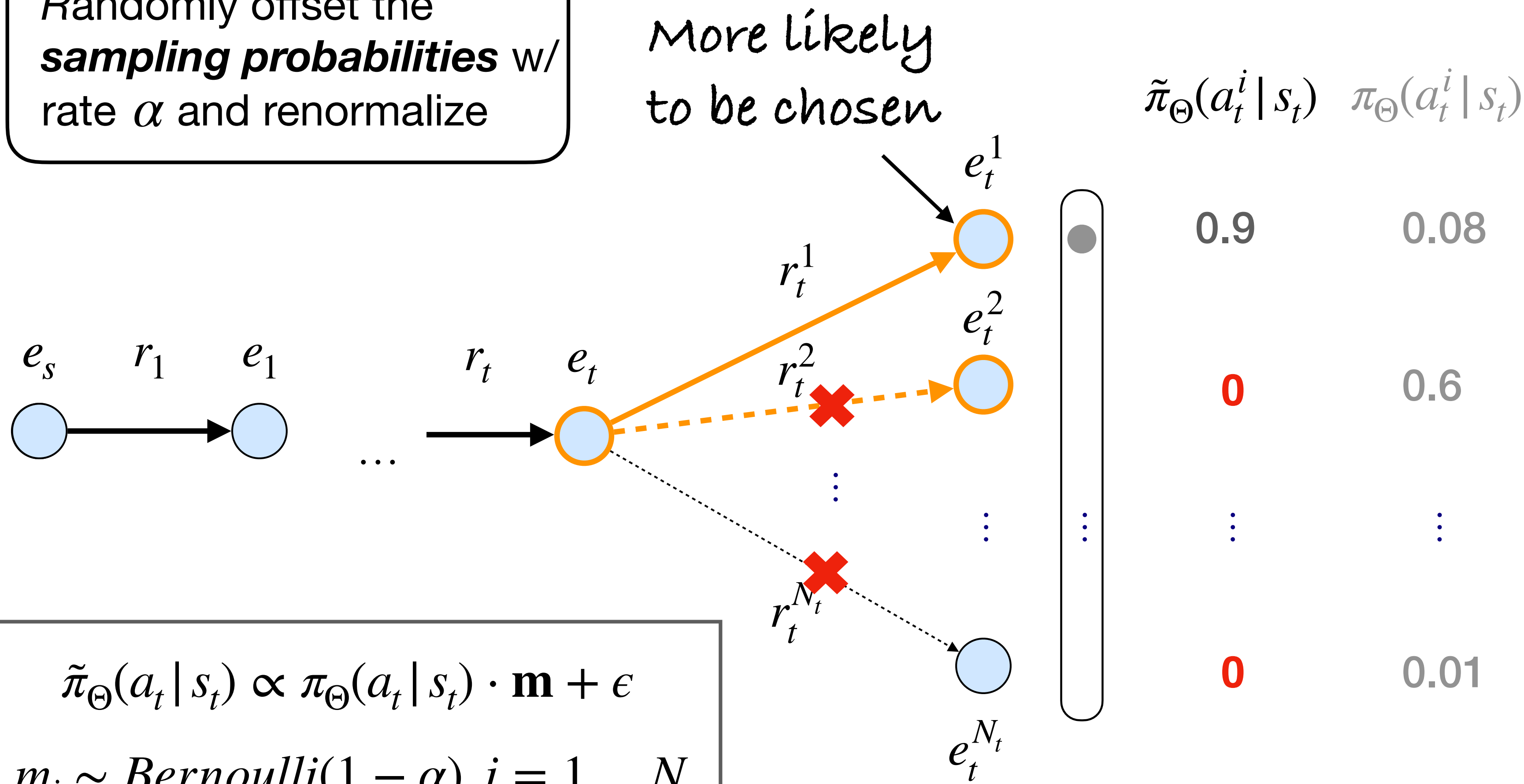


Action Dropout

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



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

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

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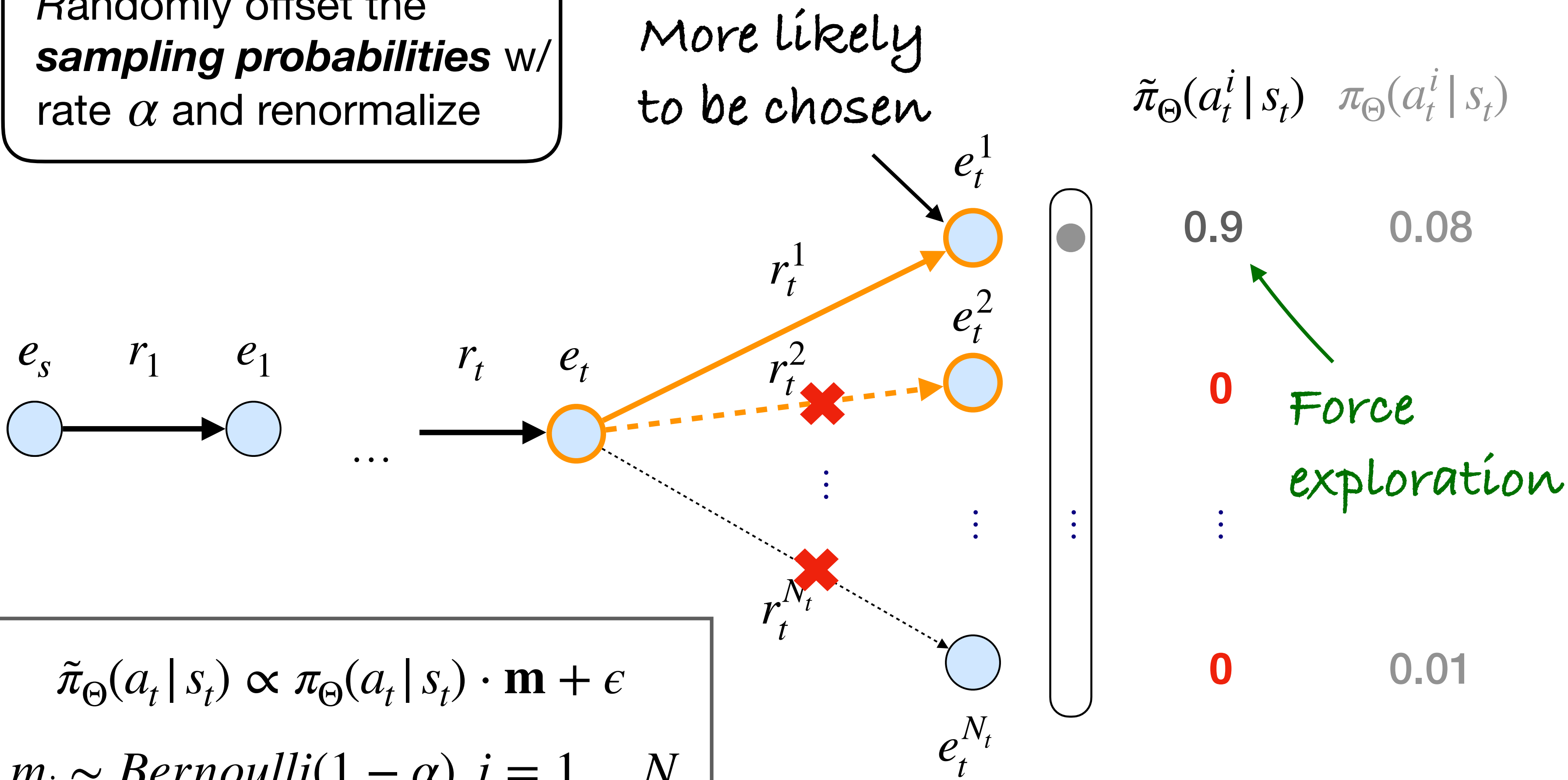
Randomly offset the ***sampling probabilities*** w/ rate α and renormalize



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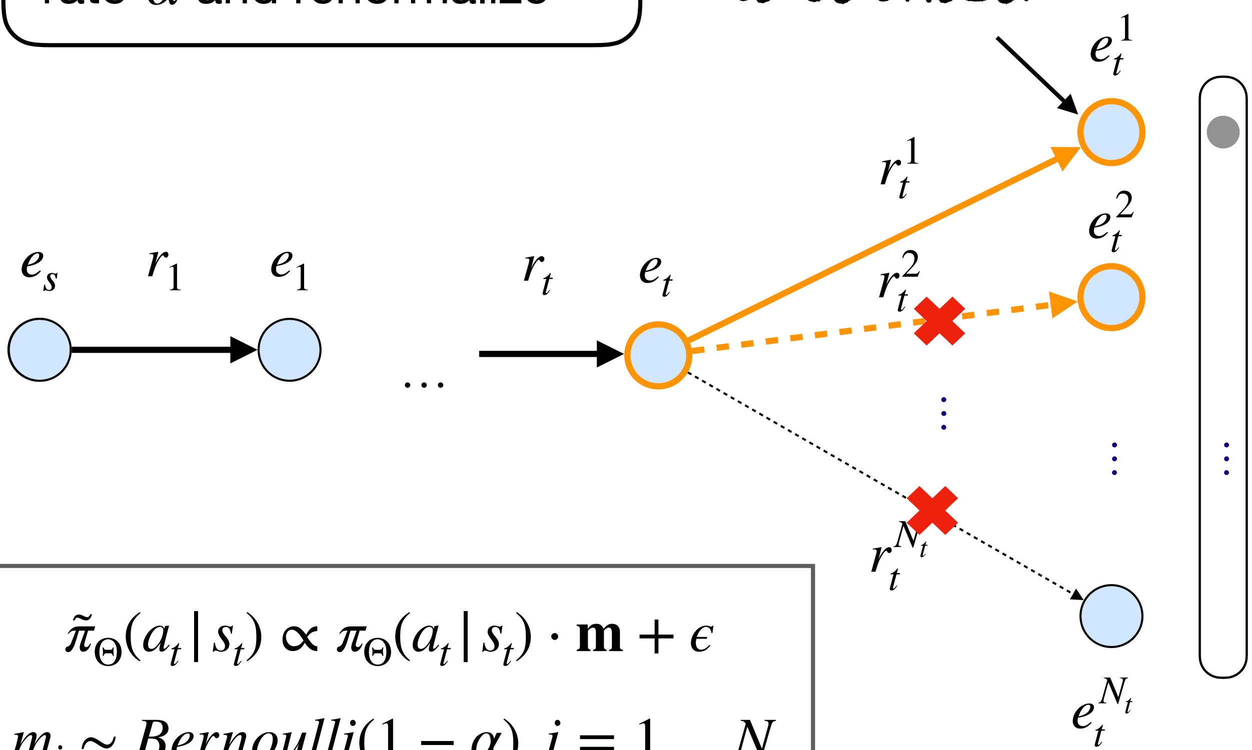
Action Dropout

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

More likely to be chosen

Up to ×**8** # path traversed



$\tilde{\pi}_\Theta(a_t^i \mid s_t)$	$\pi_\Theta(a_t^i \mid s_t)$
0.9	0.08
0	
⋮	
0	0.01

Force exploration

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

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

Experiment Setup

KG Benchmarks

Name	# Ent.	# Rel.	# Fact	# Degree Avg	# Degree Median
Kinship	104	25	8,544	85.15	82
UMLS	135	46	5,216	38.63	28
FB15k-237	14,505	237	272,115	19.74	14
WN18RR	40,945	11	86,835	2.19	2
NELL-995	75,492	200	154,213	4.07	1

Decreasing connectivity

Evaluation Protocol: MRR (Mean Reciprocal Rank)

Ablation Studies

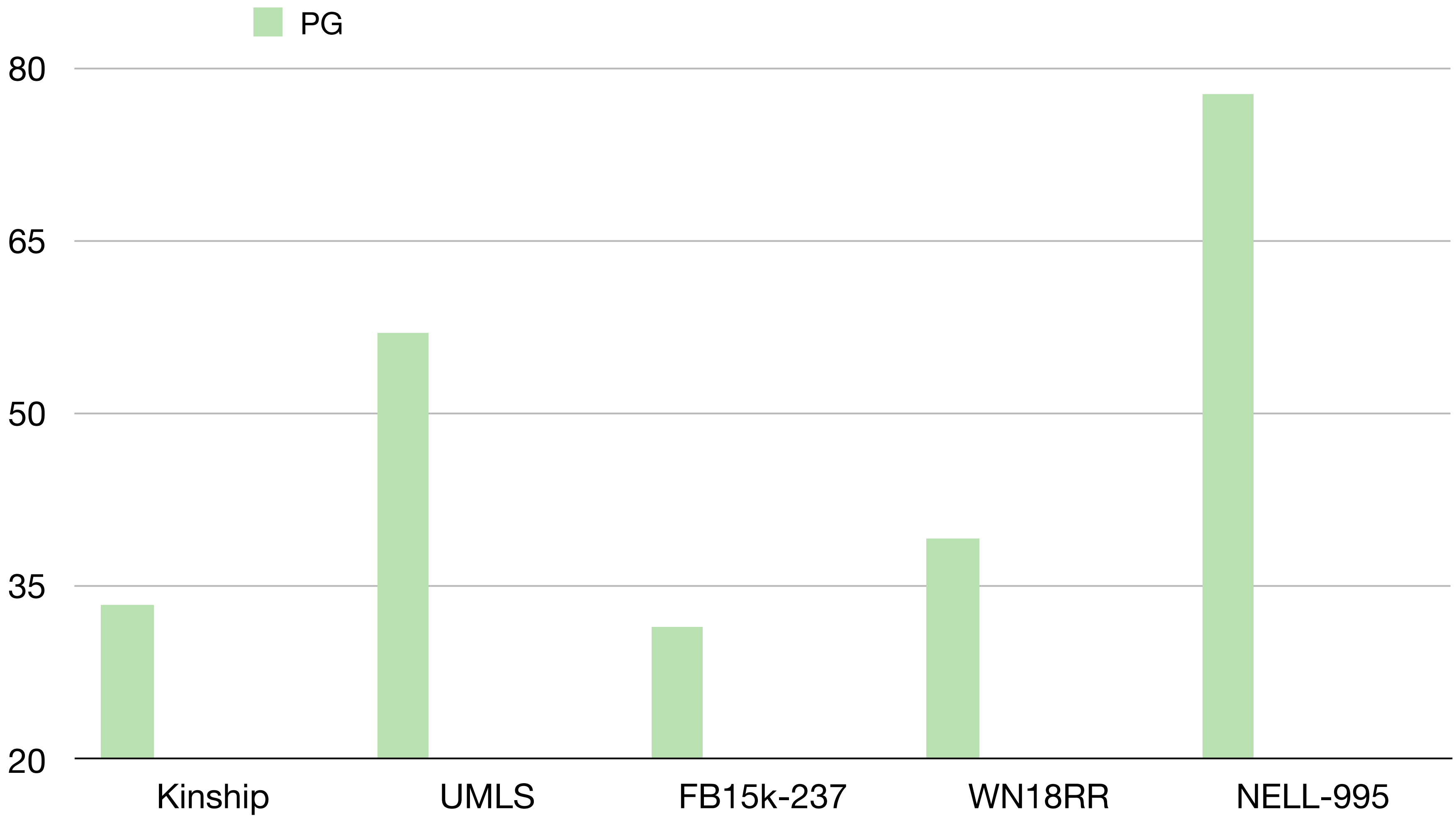
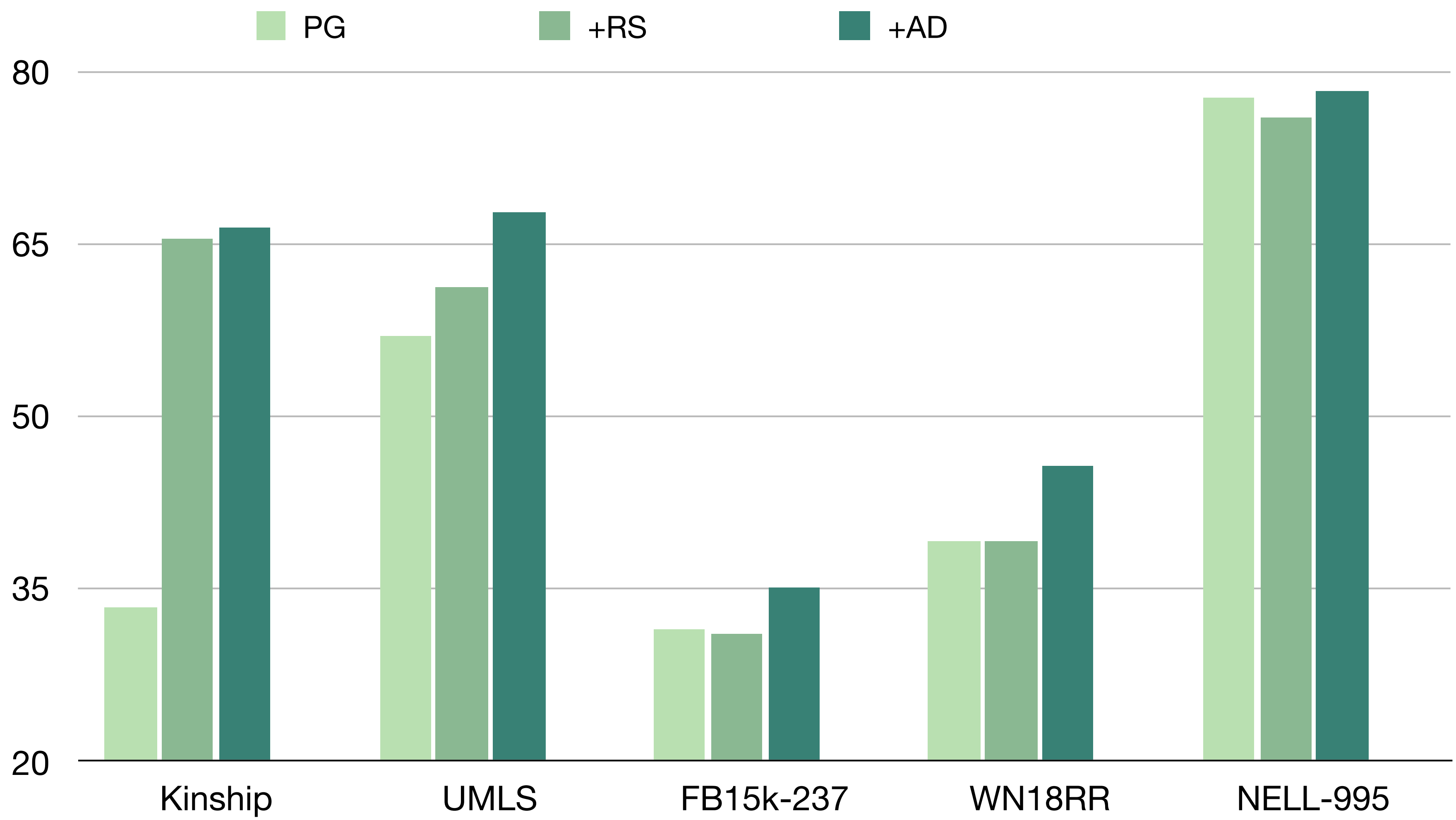


Fig 2. Dev set MRR (x100) comparison

Ablation Studies



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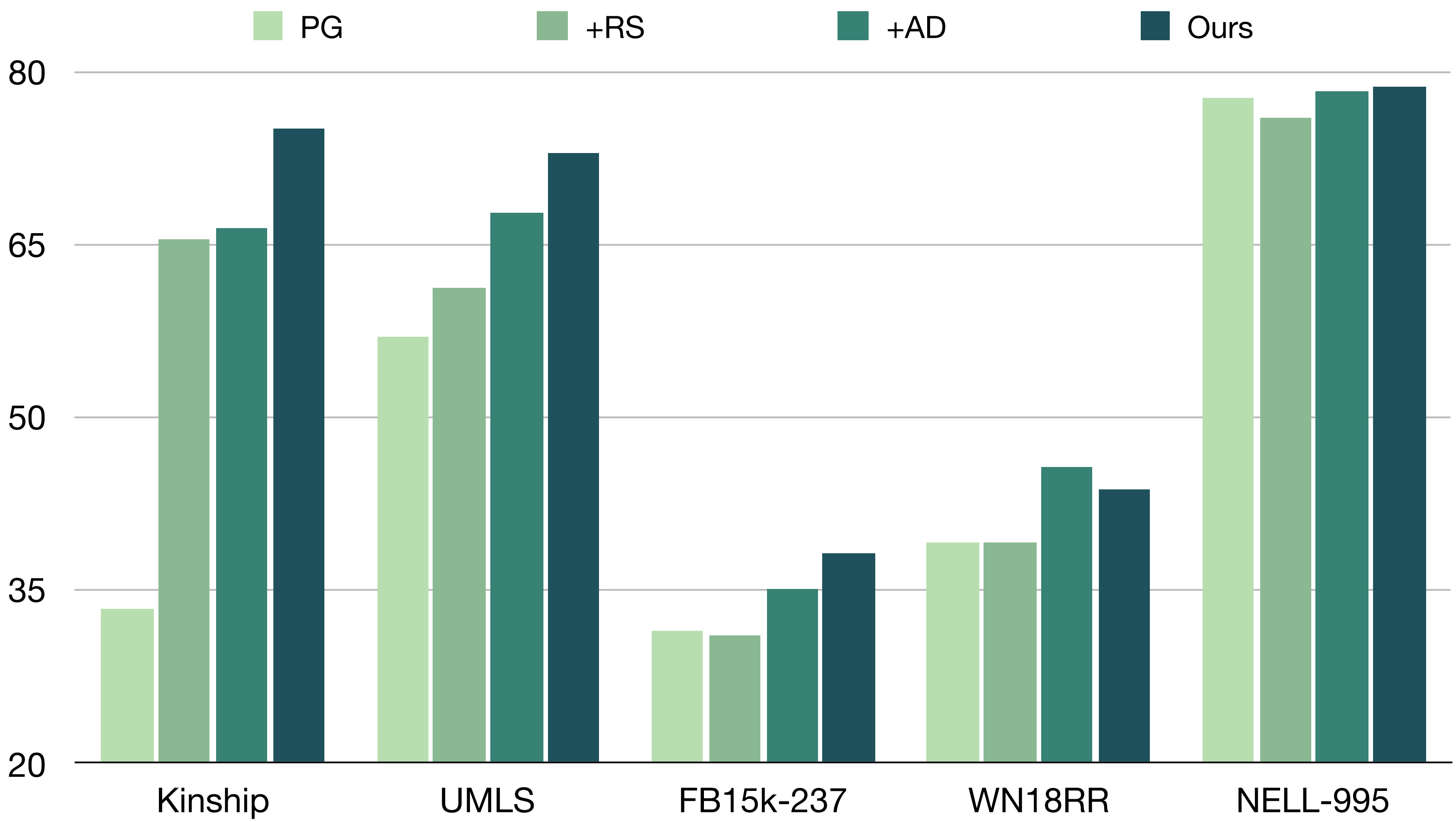

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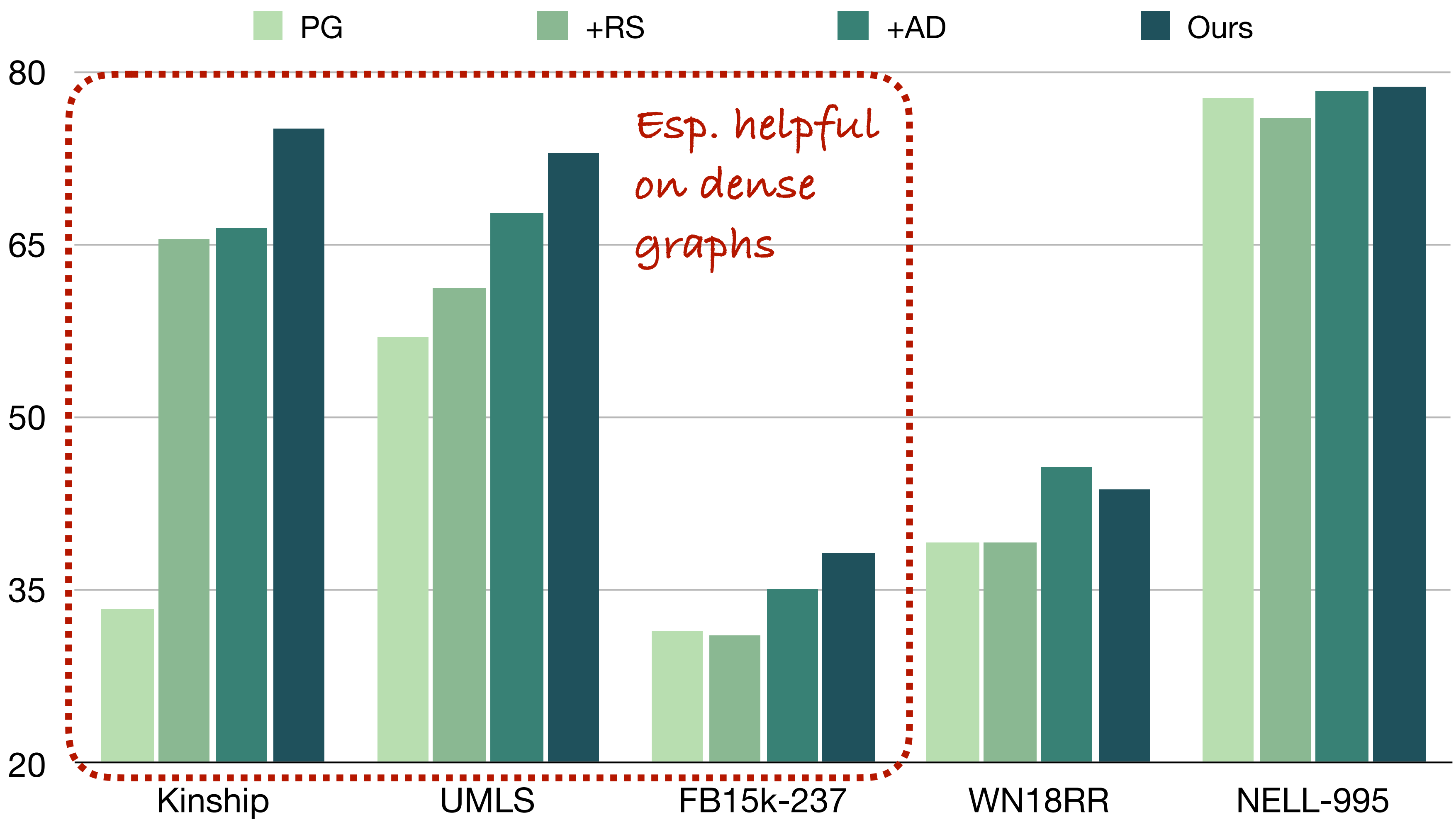

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Main Results

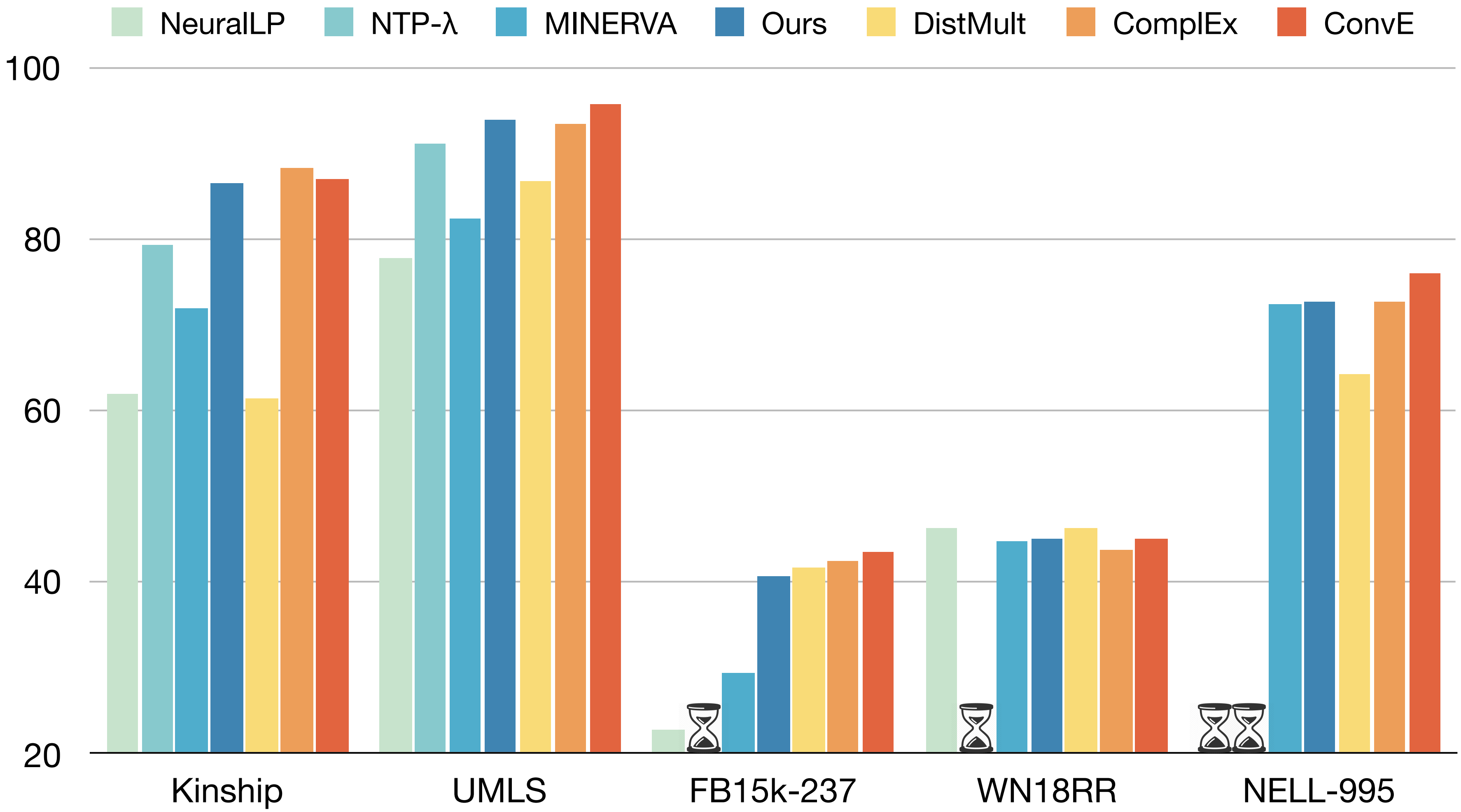
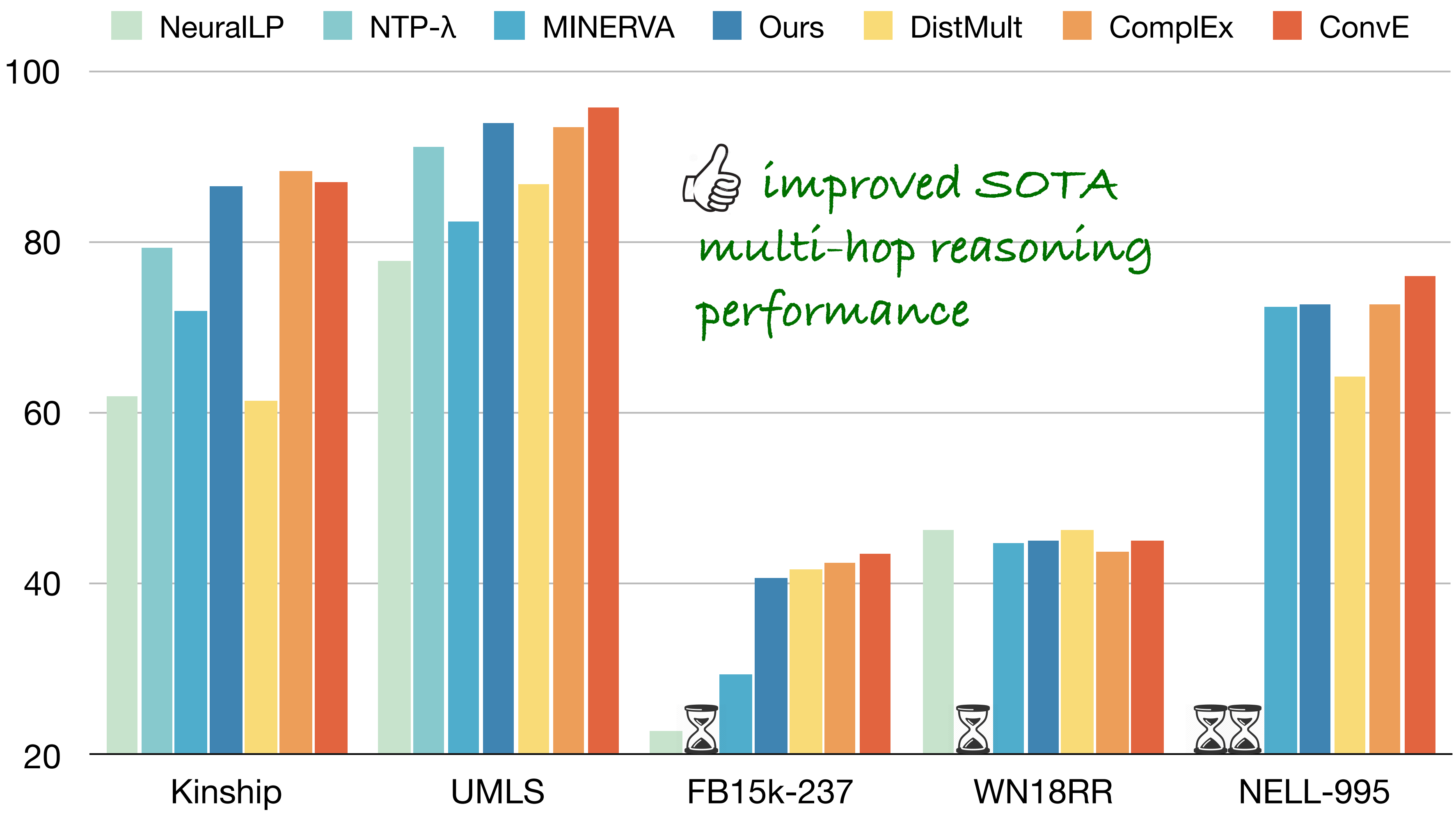


Fig 3. Test set MRR (x100) compared to SOTA multi-hop reasoning and embedding-based approaches

Main Results



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Main Results

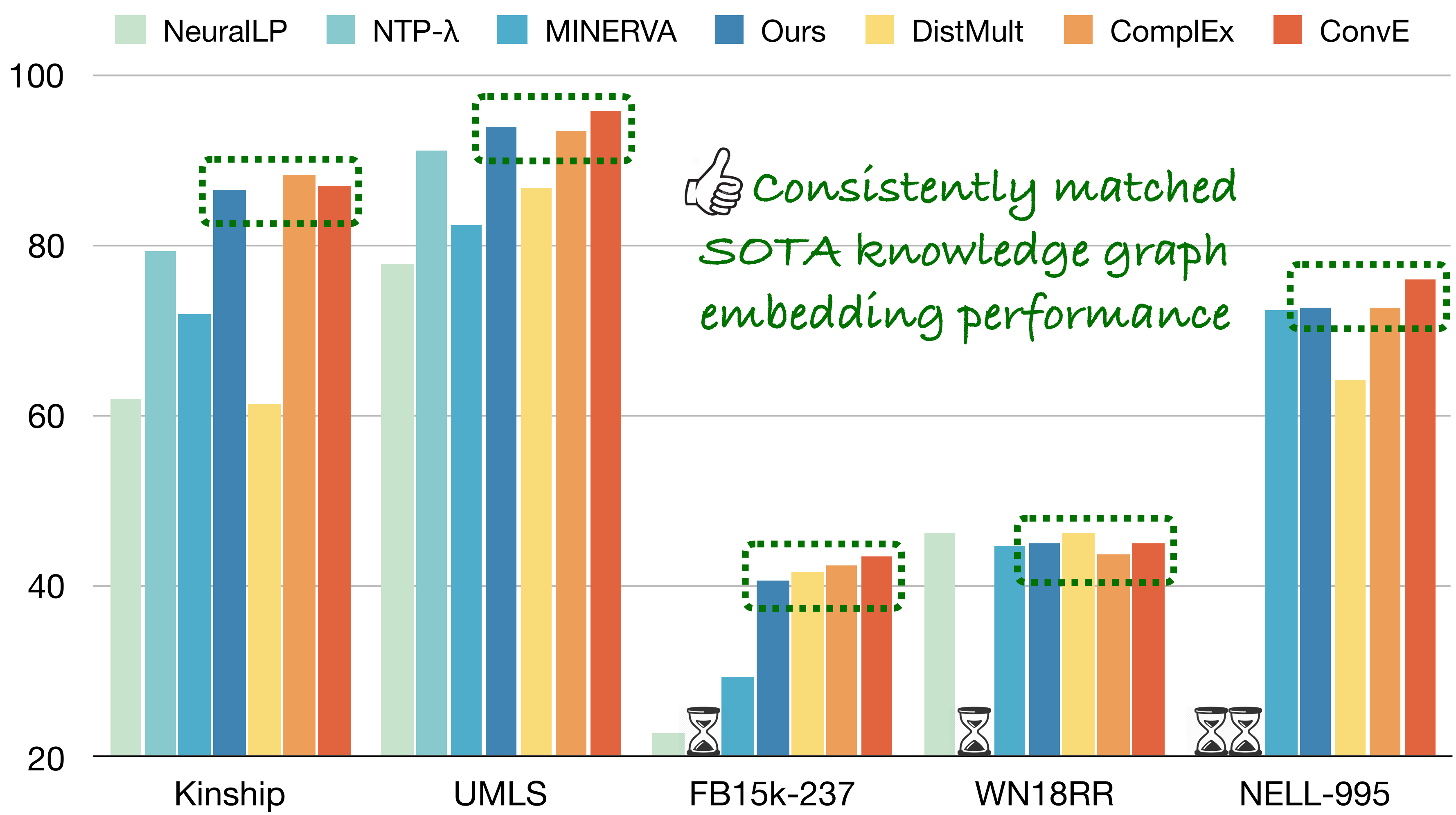
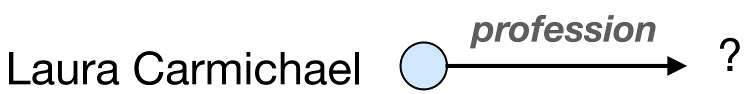
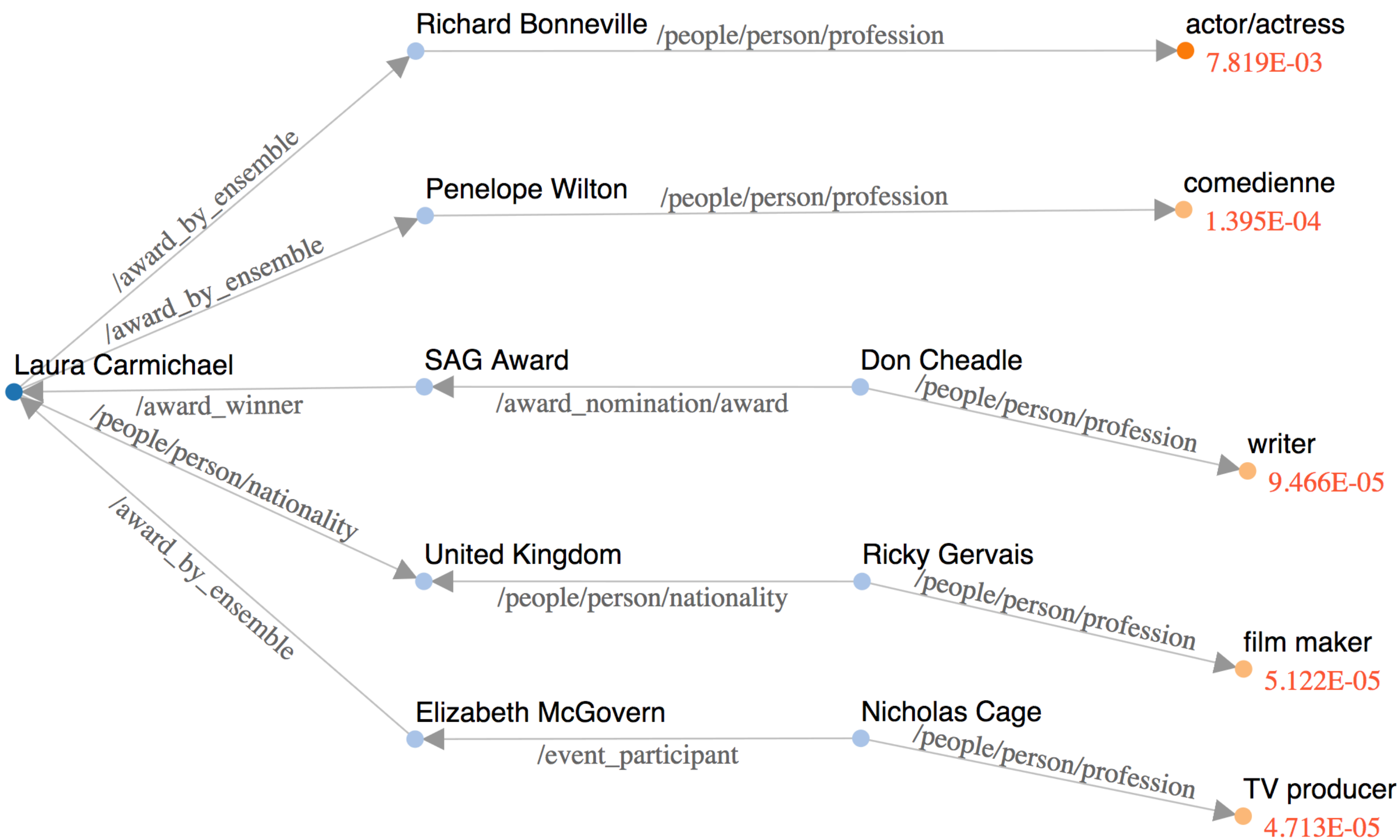


Fig 3. Test set MRR (x100) compared to SOTA multi-hop reasoning and embedding-based approaches

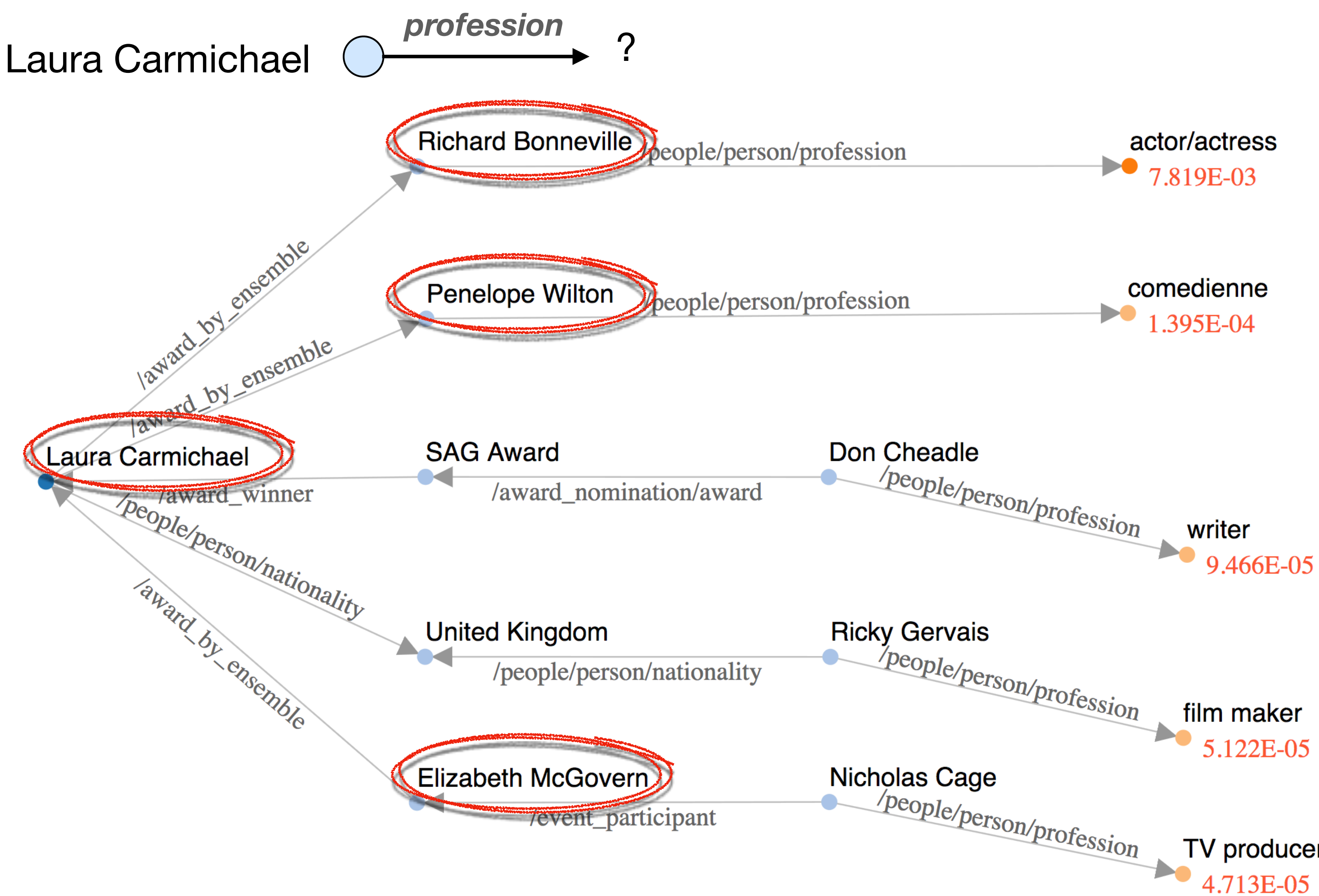
Interpretable Results





FB15k-237 (Toutanova and Chen 2016)

Interpretable Results



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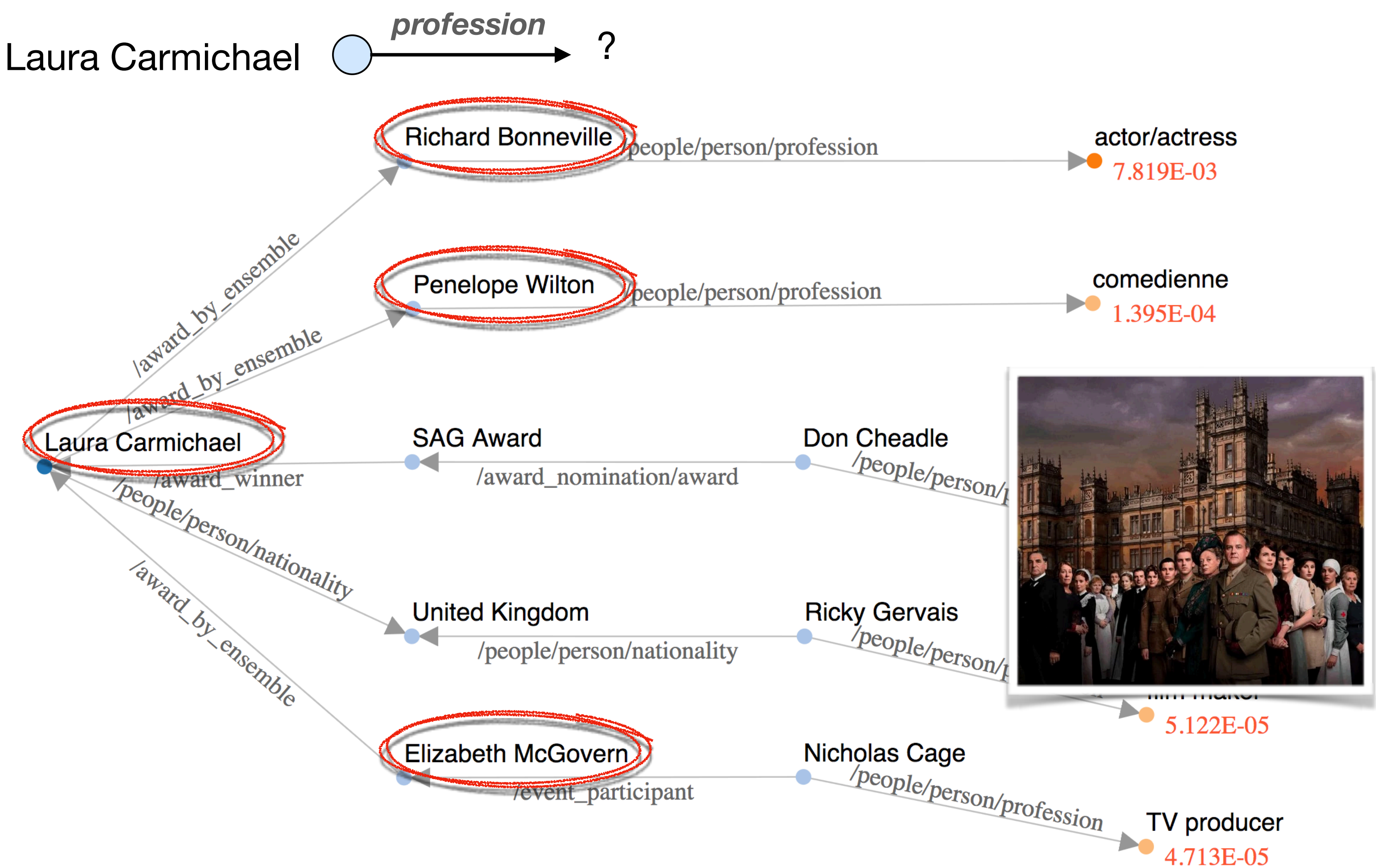
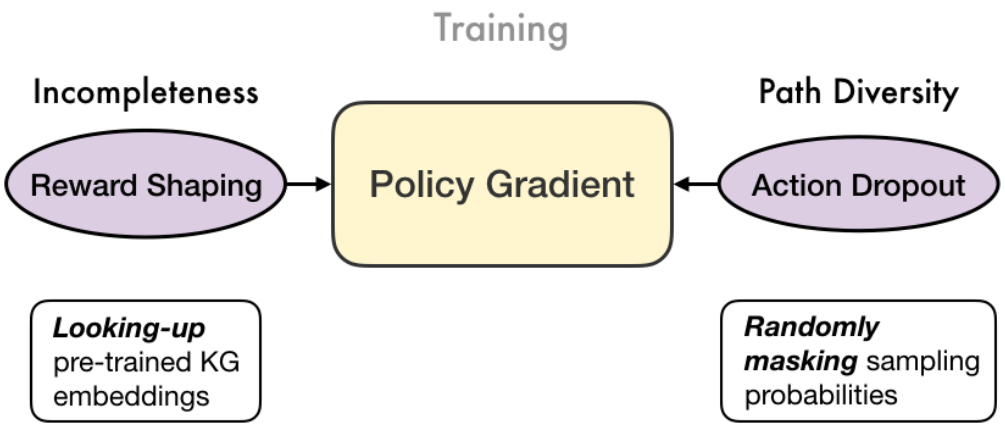
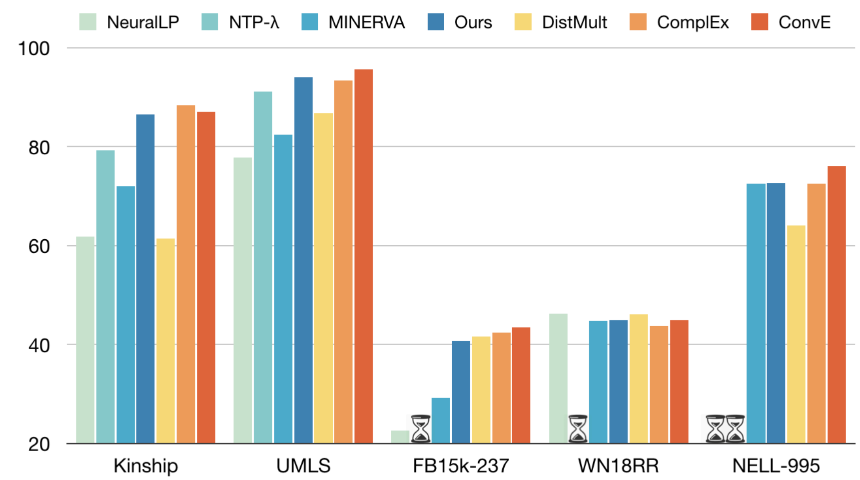


FB15k-237 (Toutanova and Chen 2016)

Code: https://github.com/salesforce/MultiHopKG





Future directions

- Learn better reward shaping functions
- Investigate similar techniques for other RL paradigms (e.g. Q-learning)
- Extend to more complicated structured queries (e.g. more than one topic entities)
- Extend to natural language QA

BKI - Error Analysis

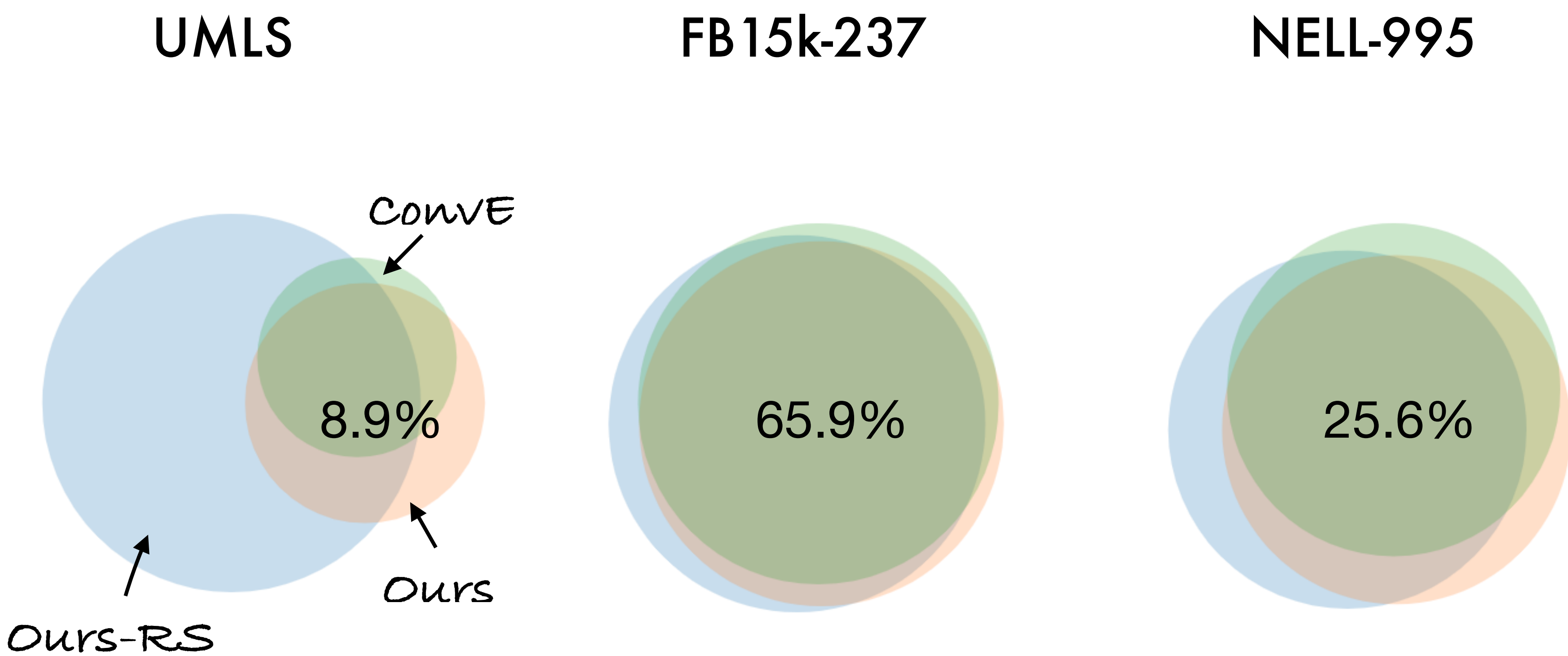


Fig 4. Dev set top-1 prediction error overlap of ConvE, Ours and Ours-RS. The absolute error rate of Ours is shown.

BK II - Challenges

Incompleteness

≈ 30% false negative feedback

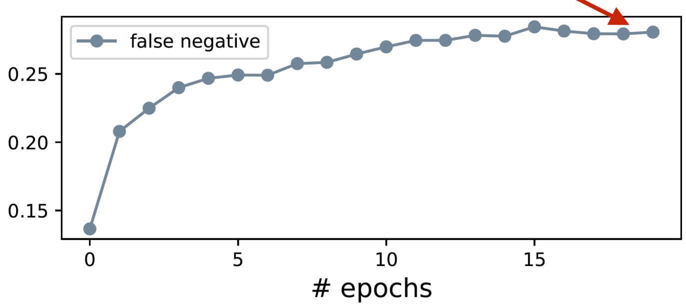
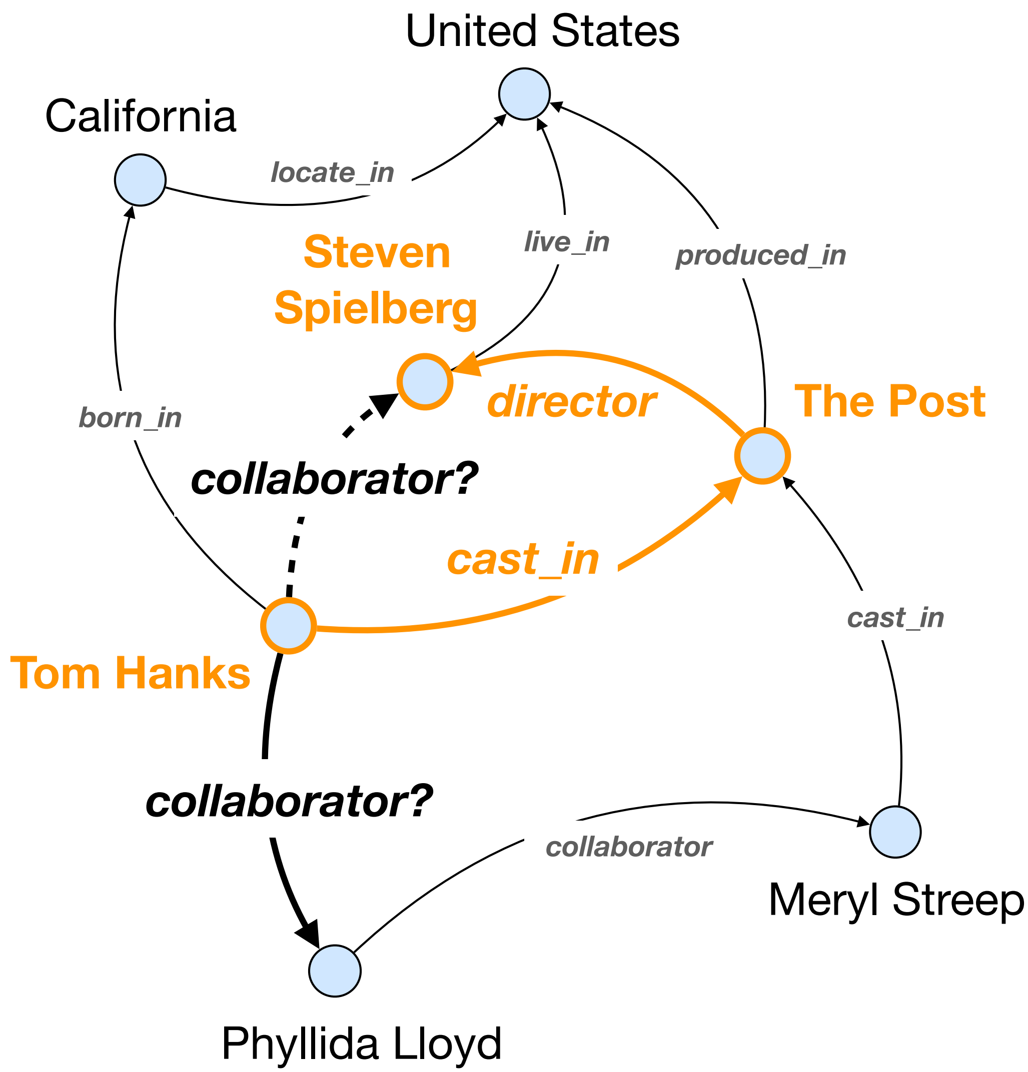


Fig 1. % of false negative hit in the first 20 epochs of RL training on the UMLS KG benchmark (Kok and Domingos 2007)



BKIII - Efficient Training & Inference