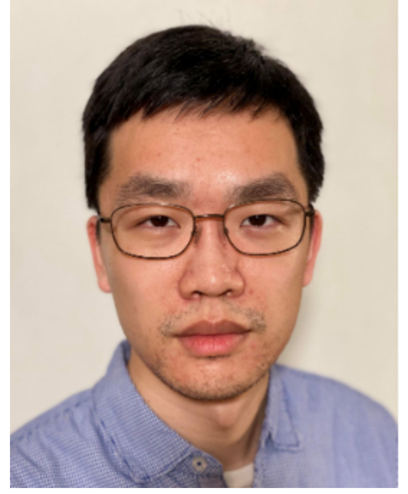
Knowledge Base Question Answering by Case-based Reasoning over Subgraphs

Alternate title: *Semiparametric Subgraph Reasoning for Question Answering over Large Knowledge Bases*





Rajarshi Das | Ameya Godbole | Ankita Naik | Elliot Tower | Manzil Zaheer | Robin Jia | Hannaneh Hajishirzi | Andrew McCallum

UNIVERSITY of WASHINGTON

UMassAmherst College of Information and Computer Sciences

USC Viterbi School of Engineering

Google DeepMind

Amazing Progress of QA systems

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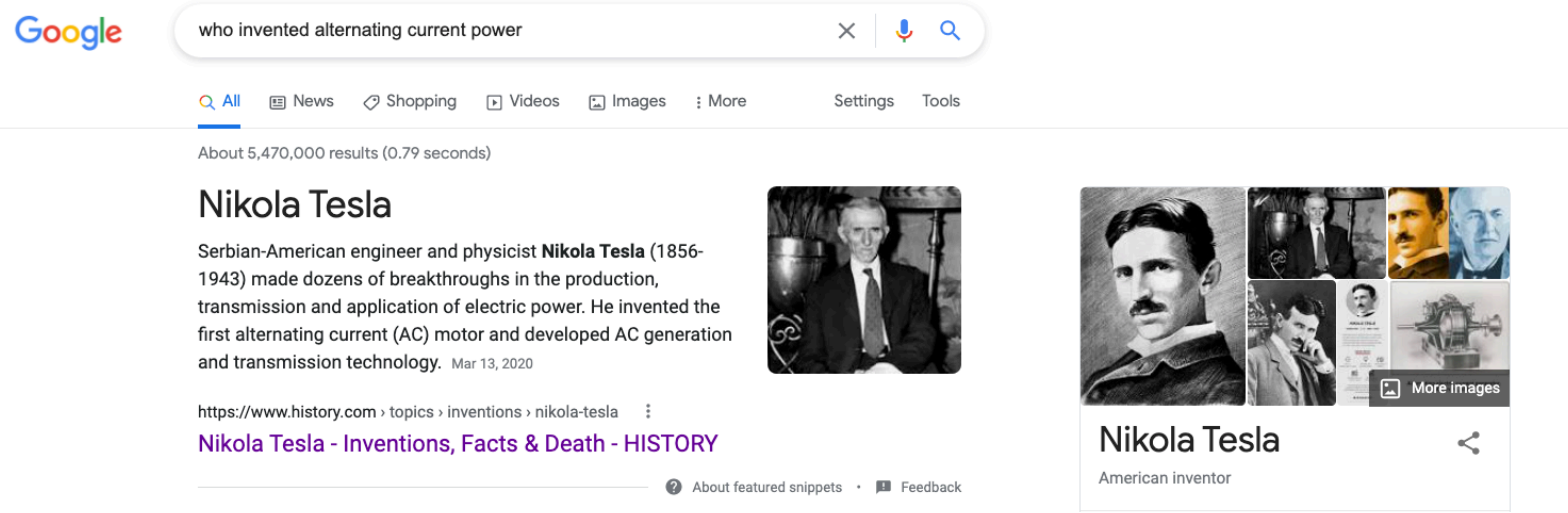

Amazing Progress of QA systems

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Irène Joliot-Curie

French chemist

Irène Joliot-Curie was a French chemist, physicist, and a politician of partly Polish ancestry, the elder daughter of Marie Curie and Pierre Curie, and the wife of Frédéric Joliot-Curie. Wikipedia

Born: September 12, 1897, Paris, France

Died: March 17, 1956, Paris, France

Spouse: Frédéric Joliot-Curie (m. 1926–1956)

Children: Hélène Langevin-Joliot, Pierre Joliot

Parents: Marie Curie, Pierre Curie

Education: Curie Institute, University of Paris, Collège Sévigné

Amazing Progress of QA systems

Structured KGs

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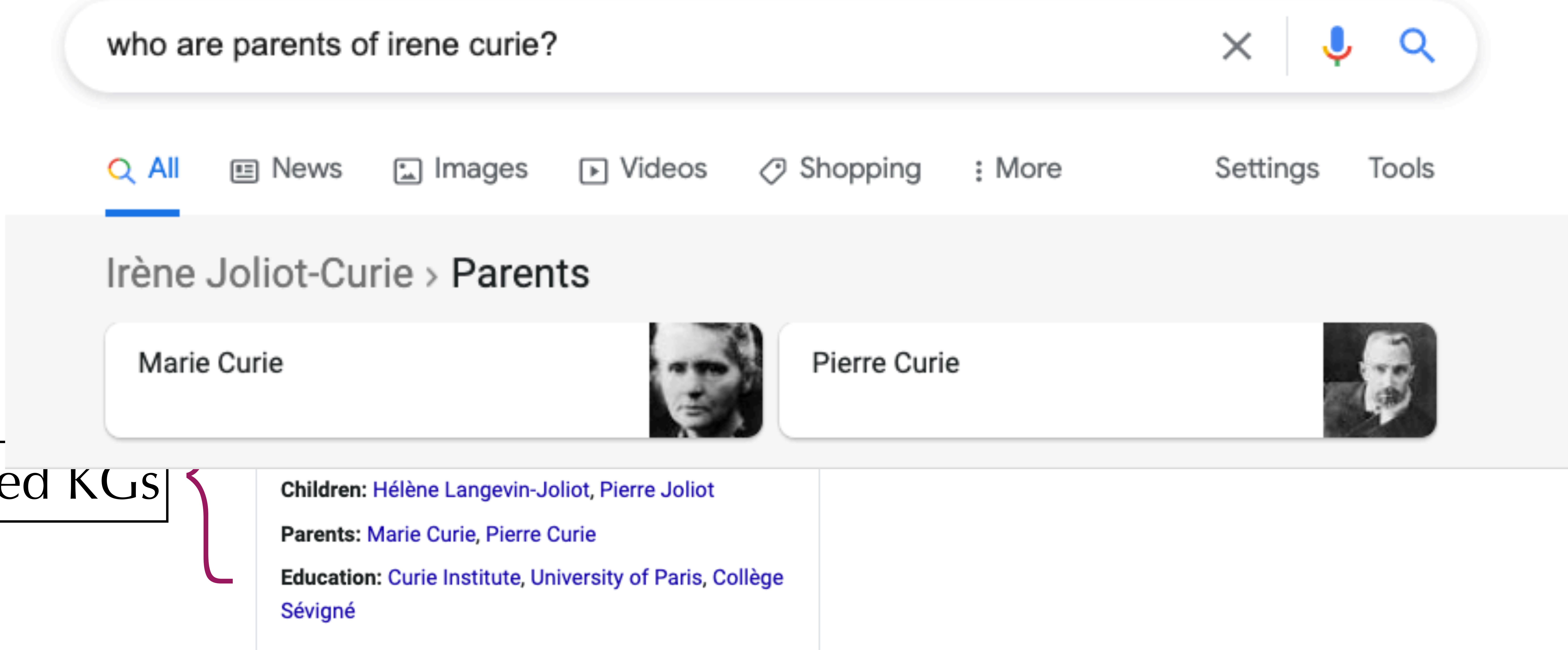

Structured KGs

Question Answering over Knowledge Graphs

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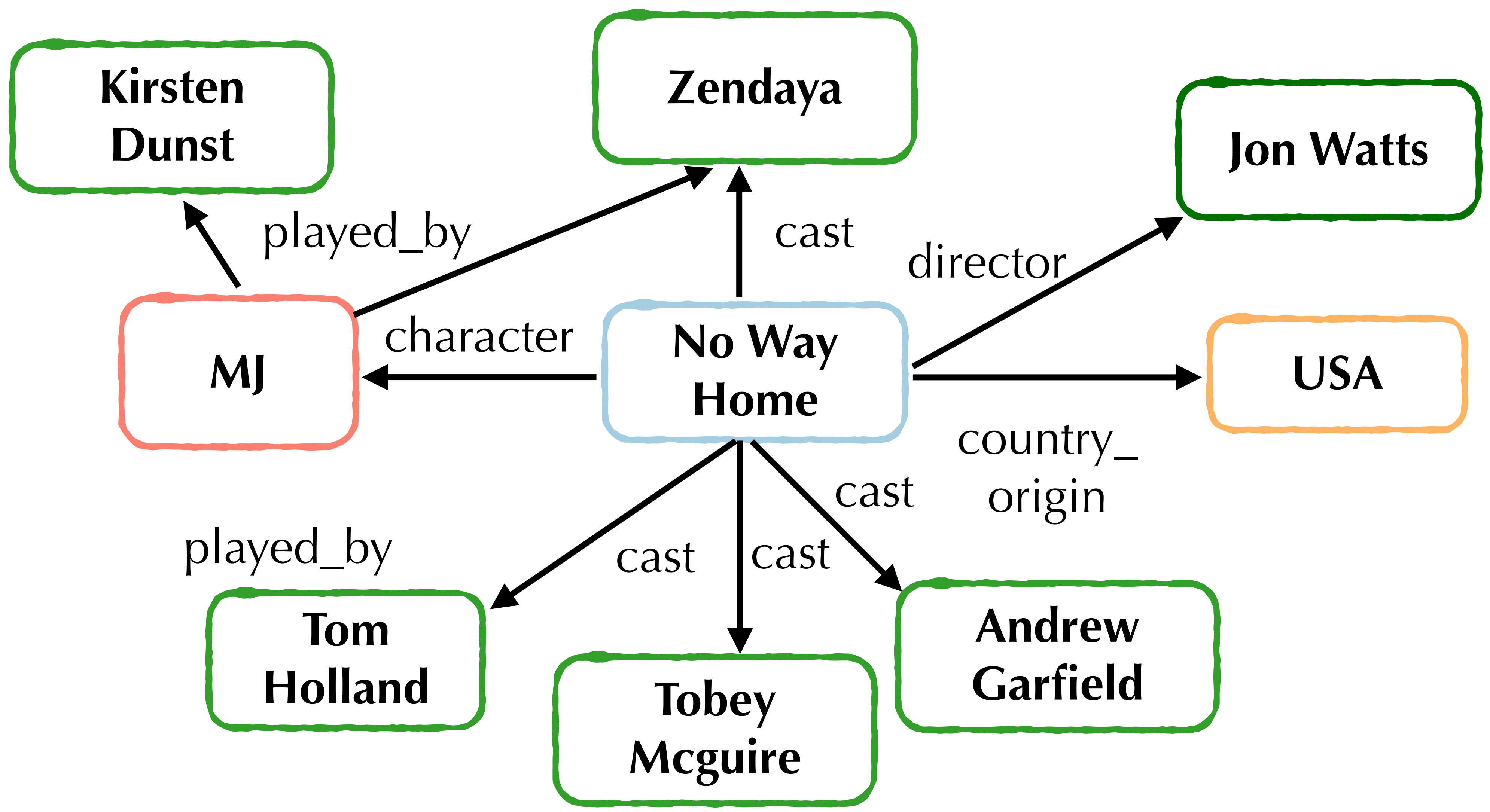
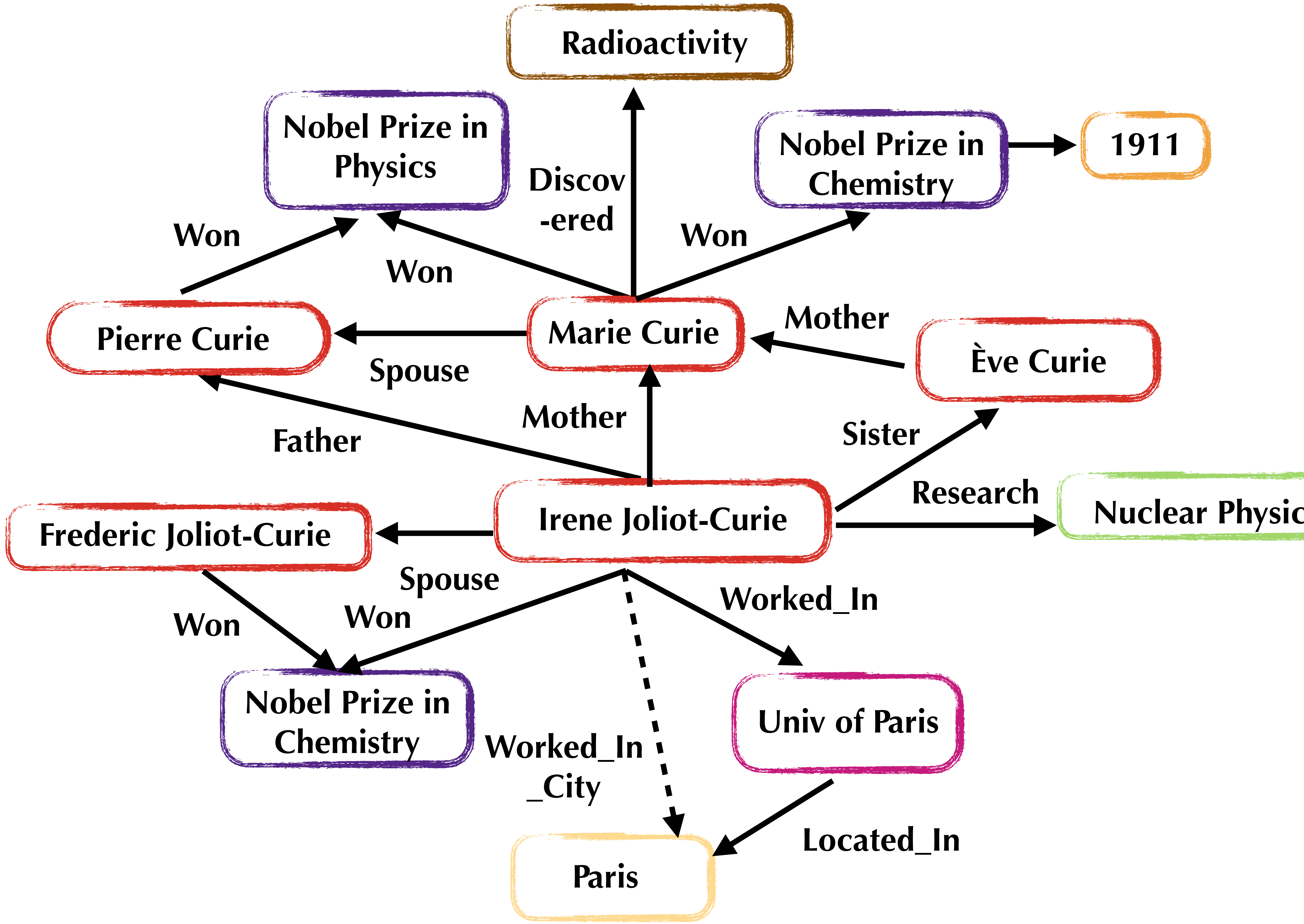
Who plays MJ in Spiderman:No Way Home?



Who all won the Nobel Prize in the Curie Family?



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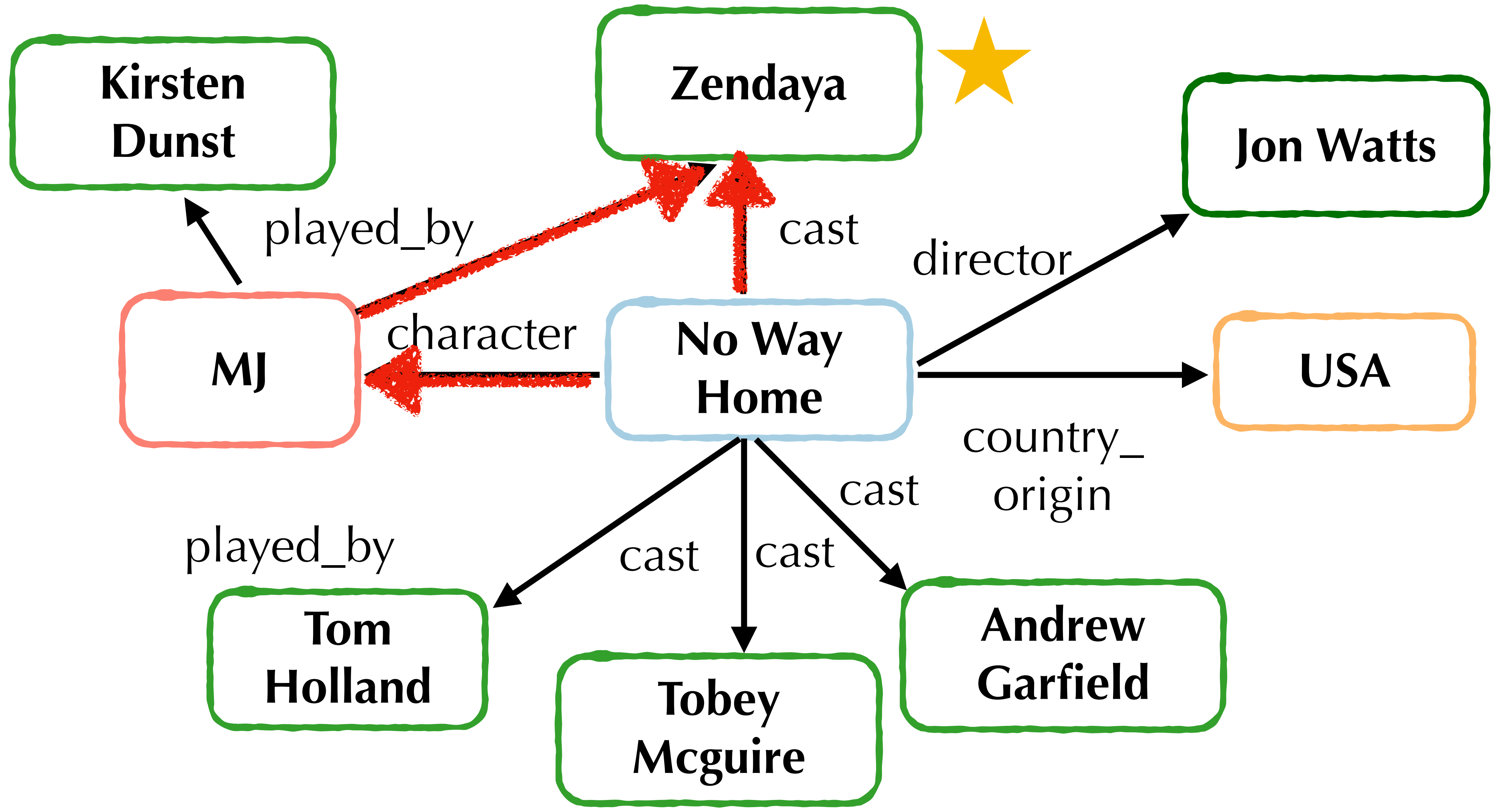

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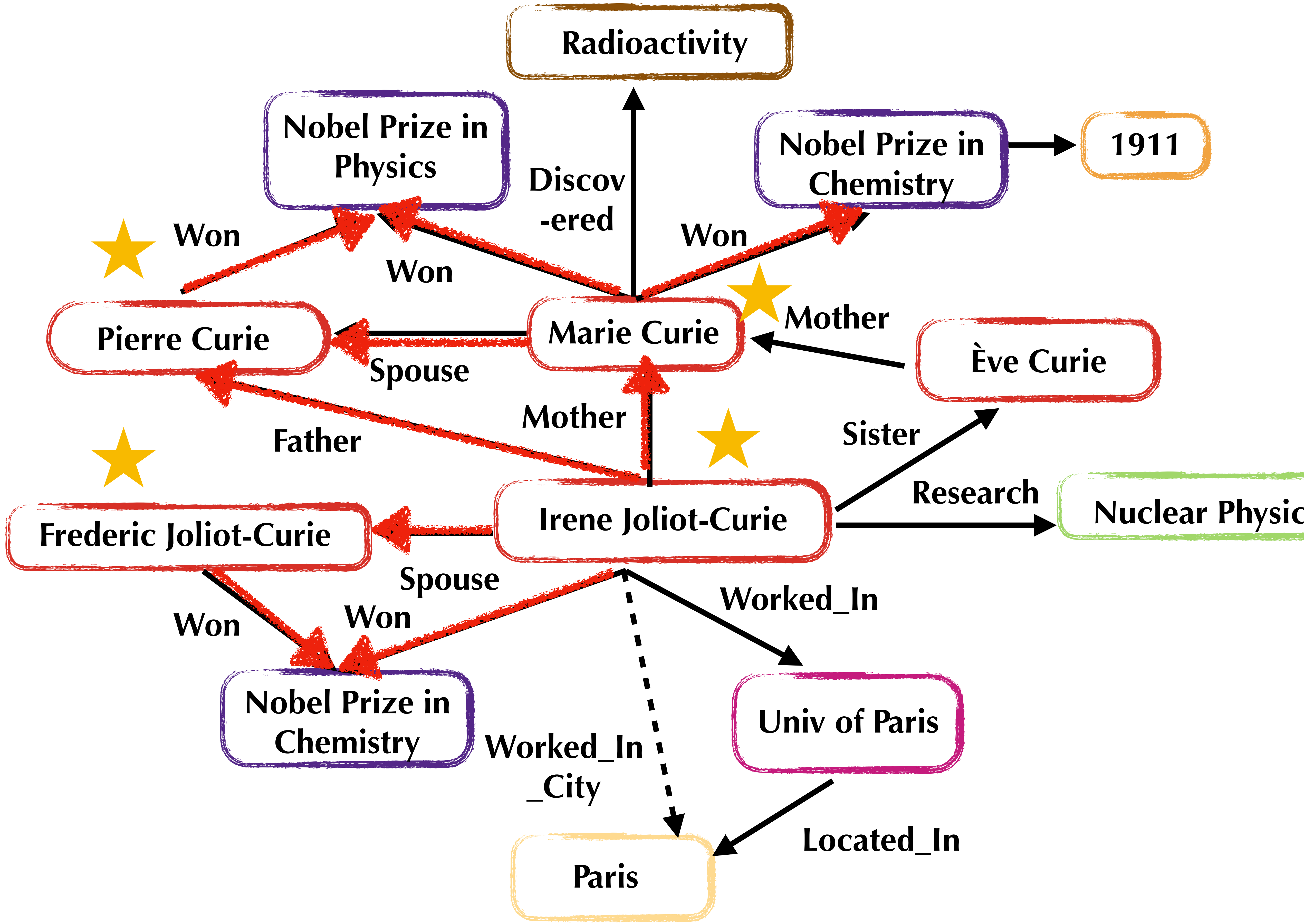

Question Answering over Knowledge Graphs

Who plays MJ in Spiderman:No Way Home?

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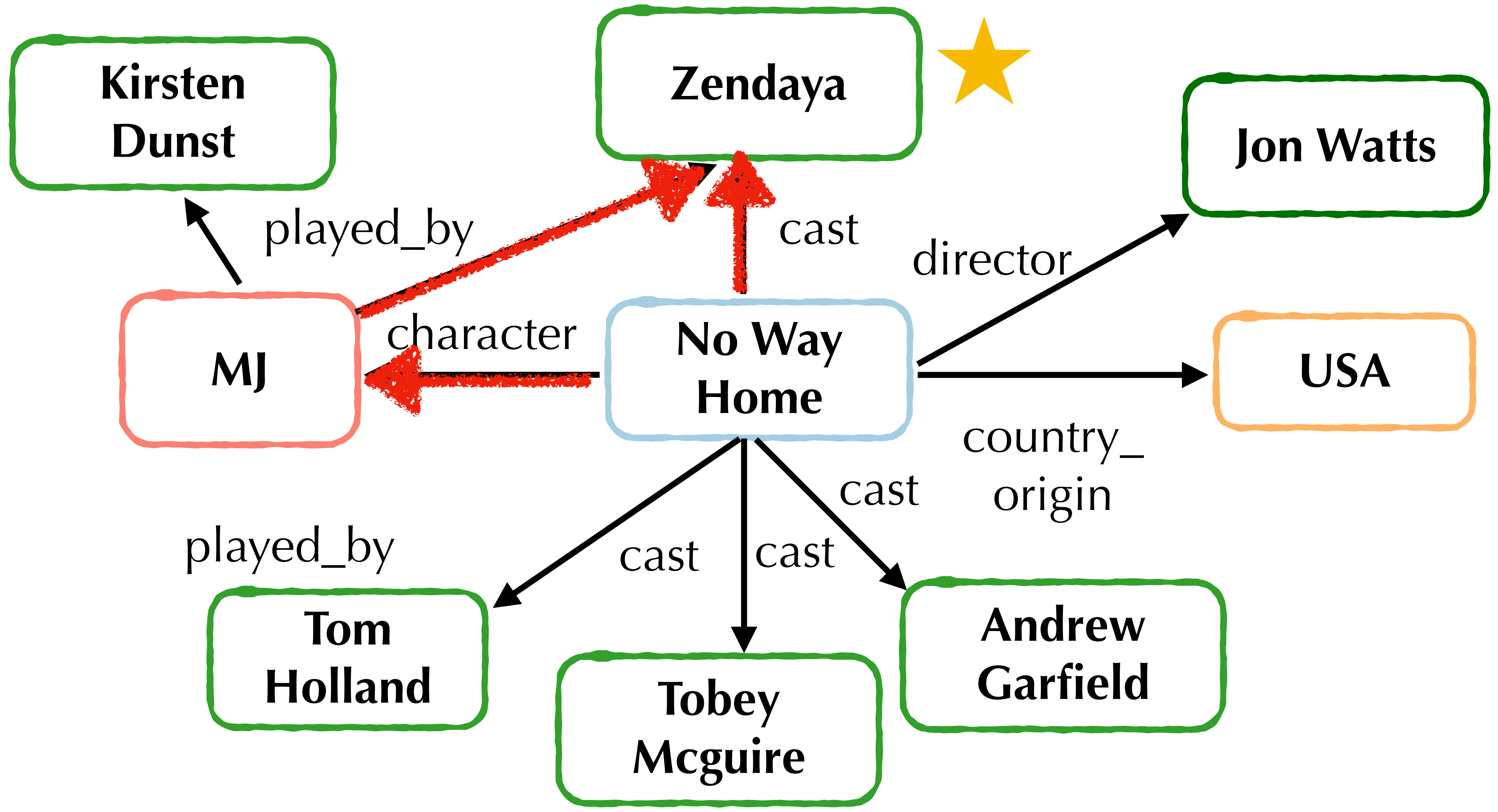
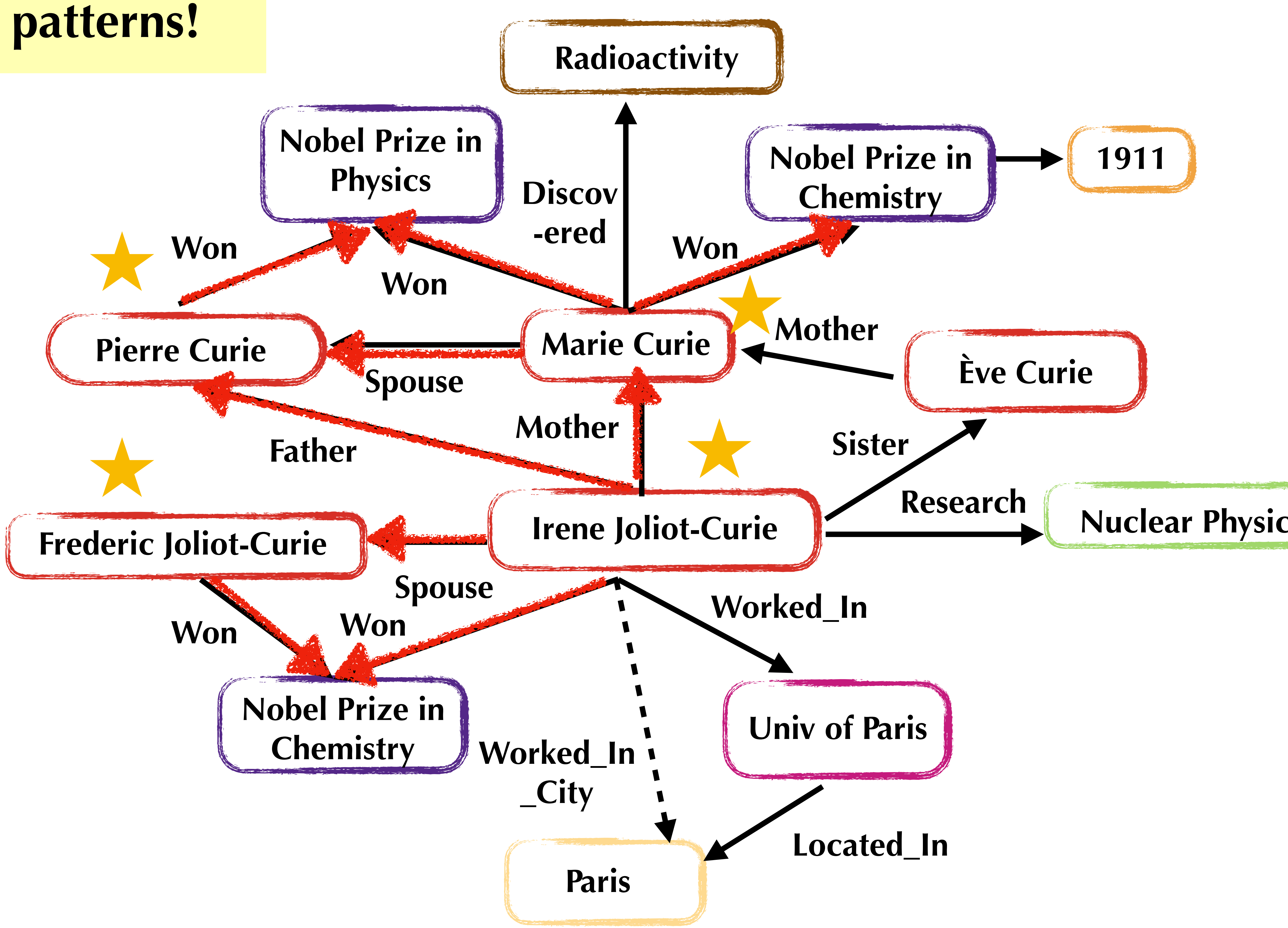
Challenge 1: No annotation of reasoning patterns!





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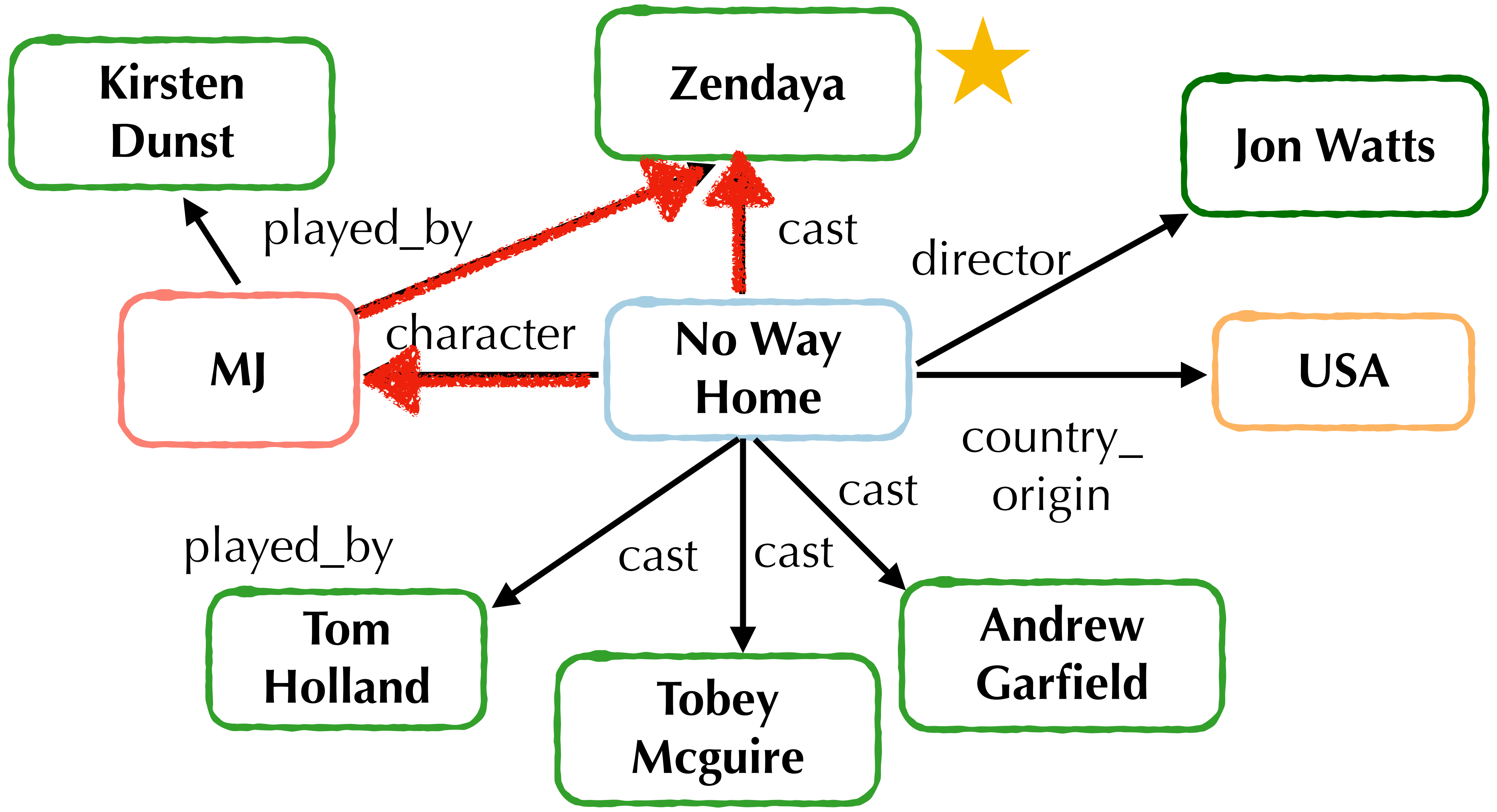

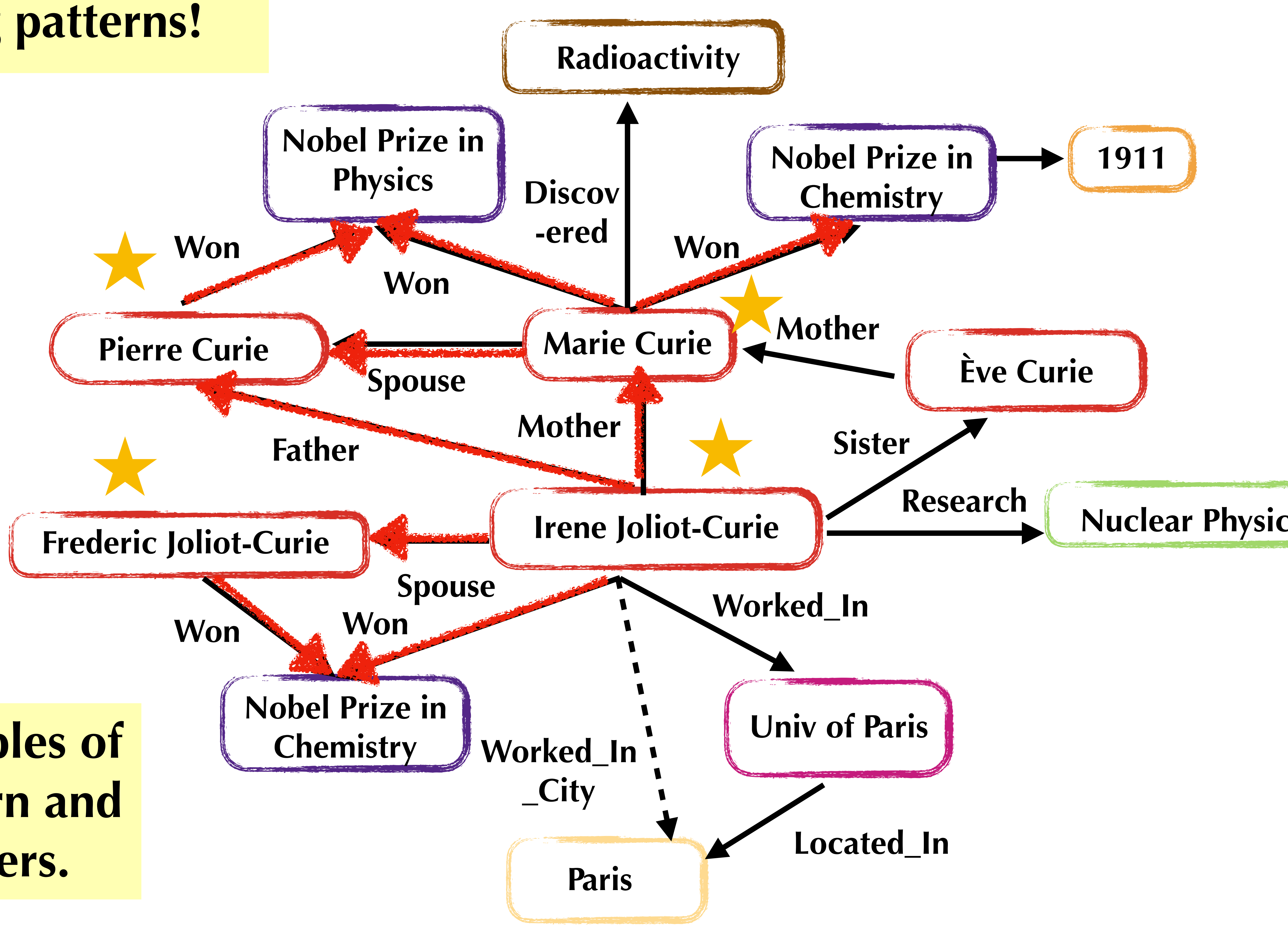

Challenge 2: QA models only encounter few examples of each pattern during training and hence hard to learn and encode the reasoning patterns in model parameters.

Case-based Reasoning (Schank 1982; Kolodner 1983)

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- Solutions to new problems are derived from the ***solutions*** of similar problems.

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1. **Retrieve** 2. **Reuse** 3. **Revise** 4. **Retain**

Case-based Reasoning over Subgraphs

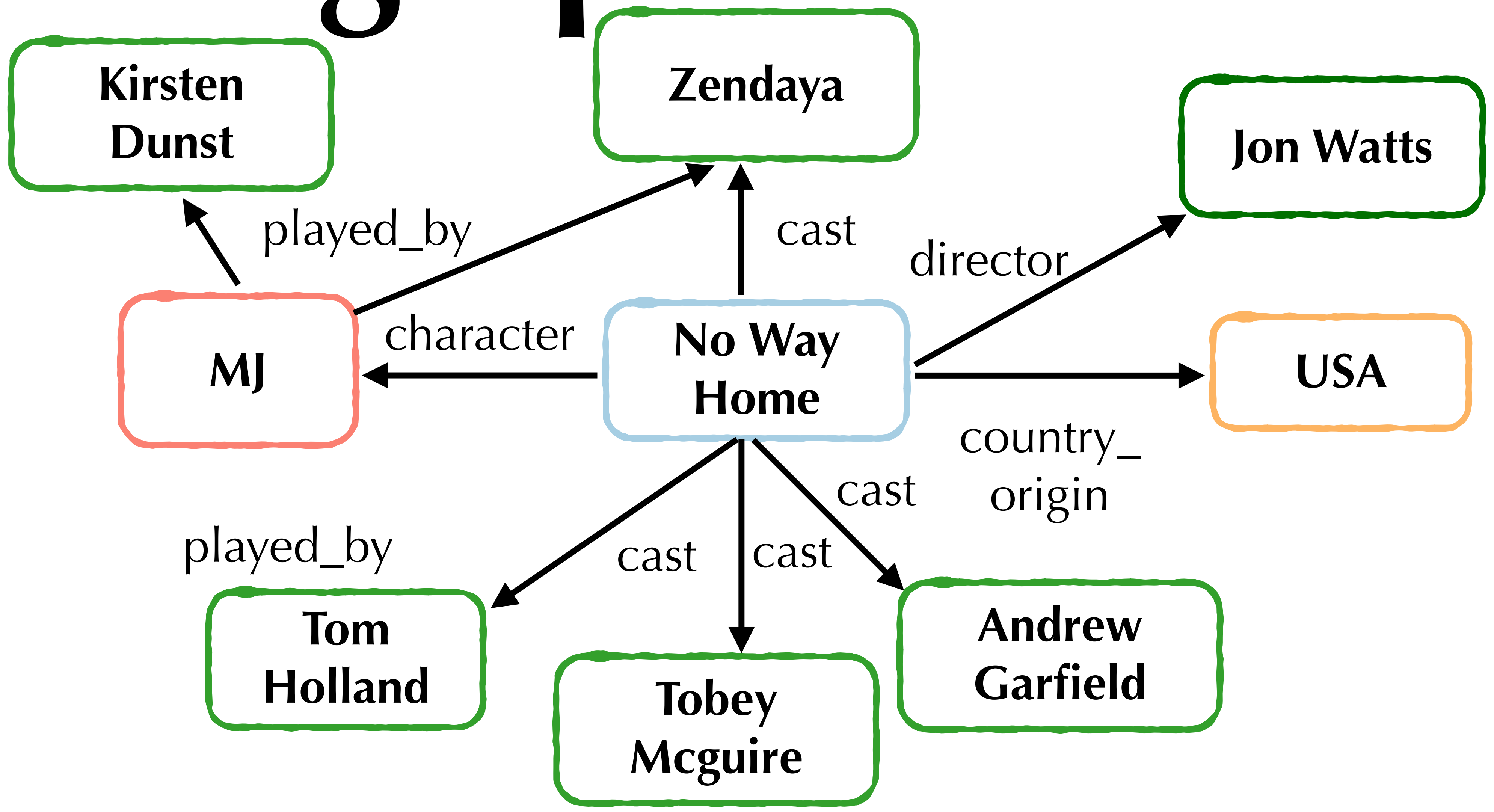
Who plays MJ in Spiderman:No Way Home?

Train set with only (Q,A) pairs
(*no* logical forms)

Case-based Reasoning over Subgraphs

Who plays MJ in Spiderman:No Way Home?

KNN Search



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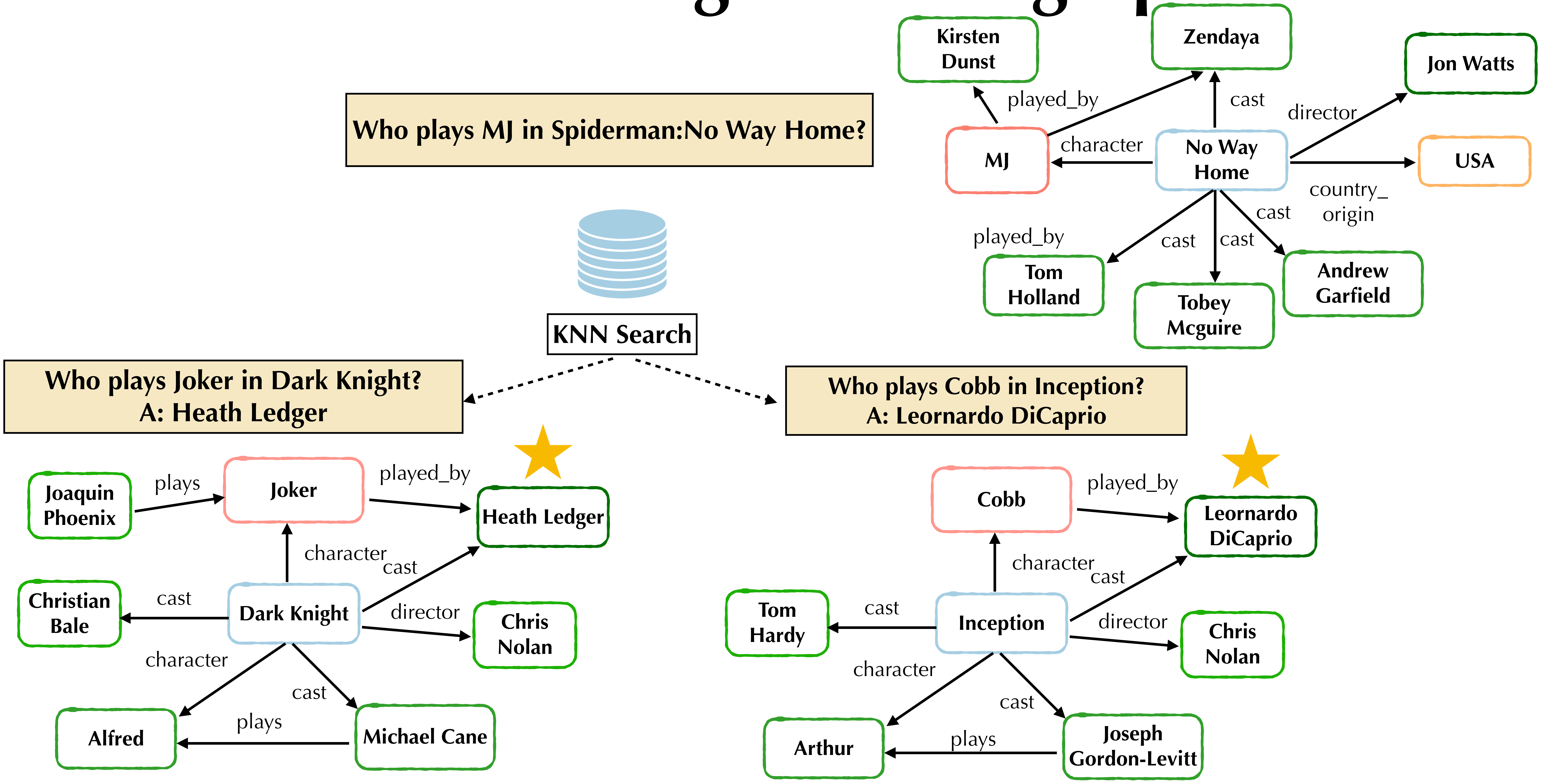

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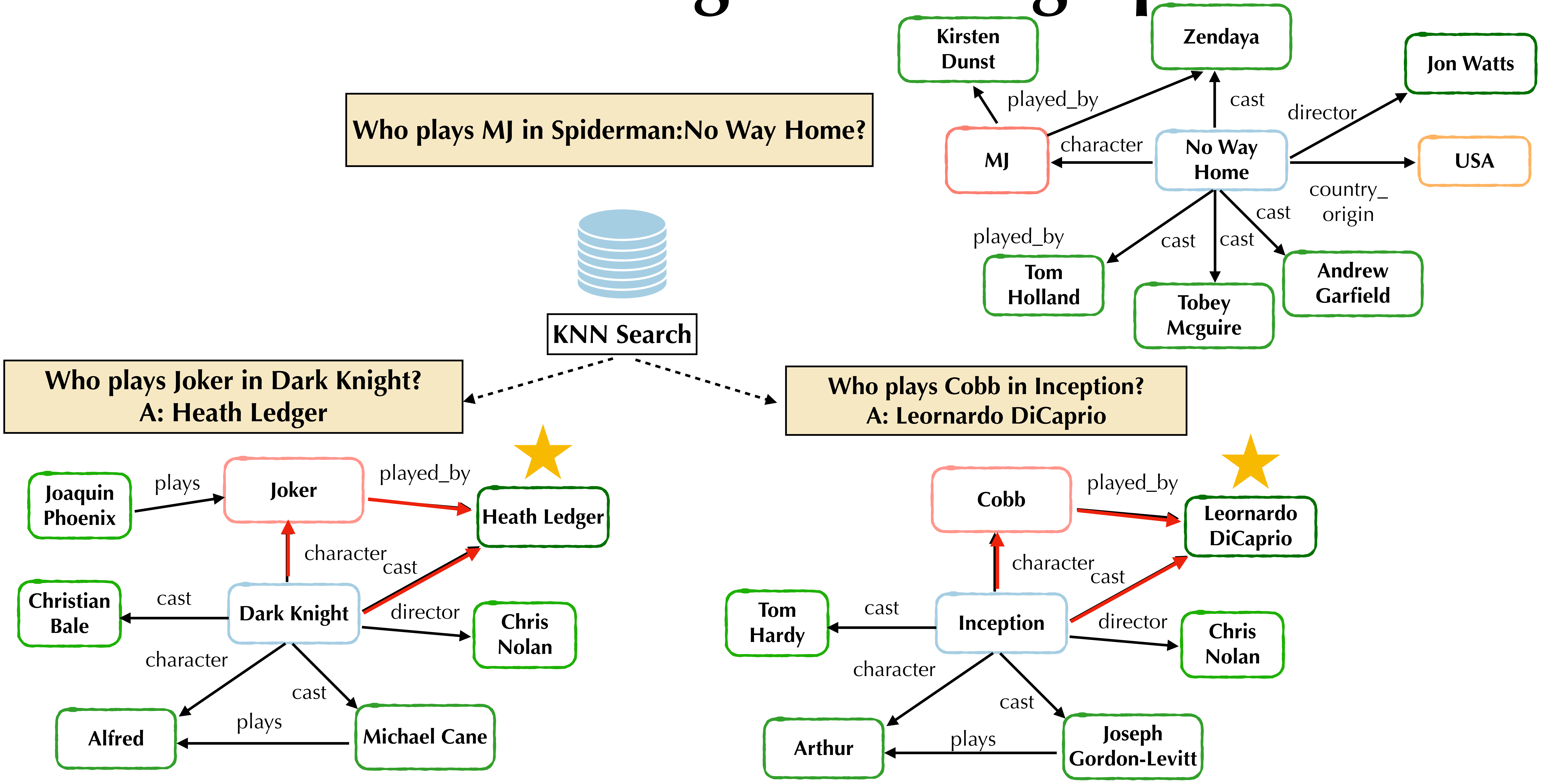

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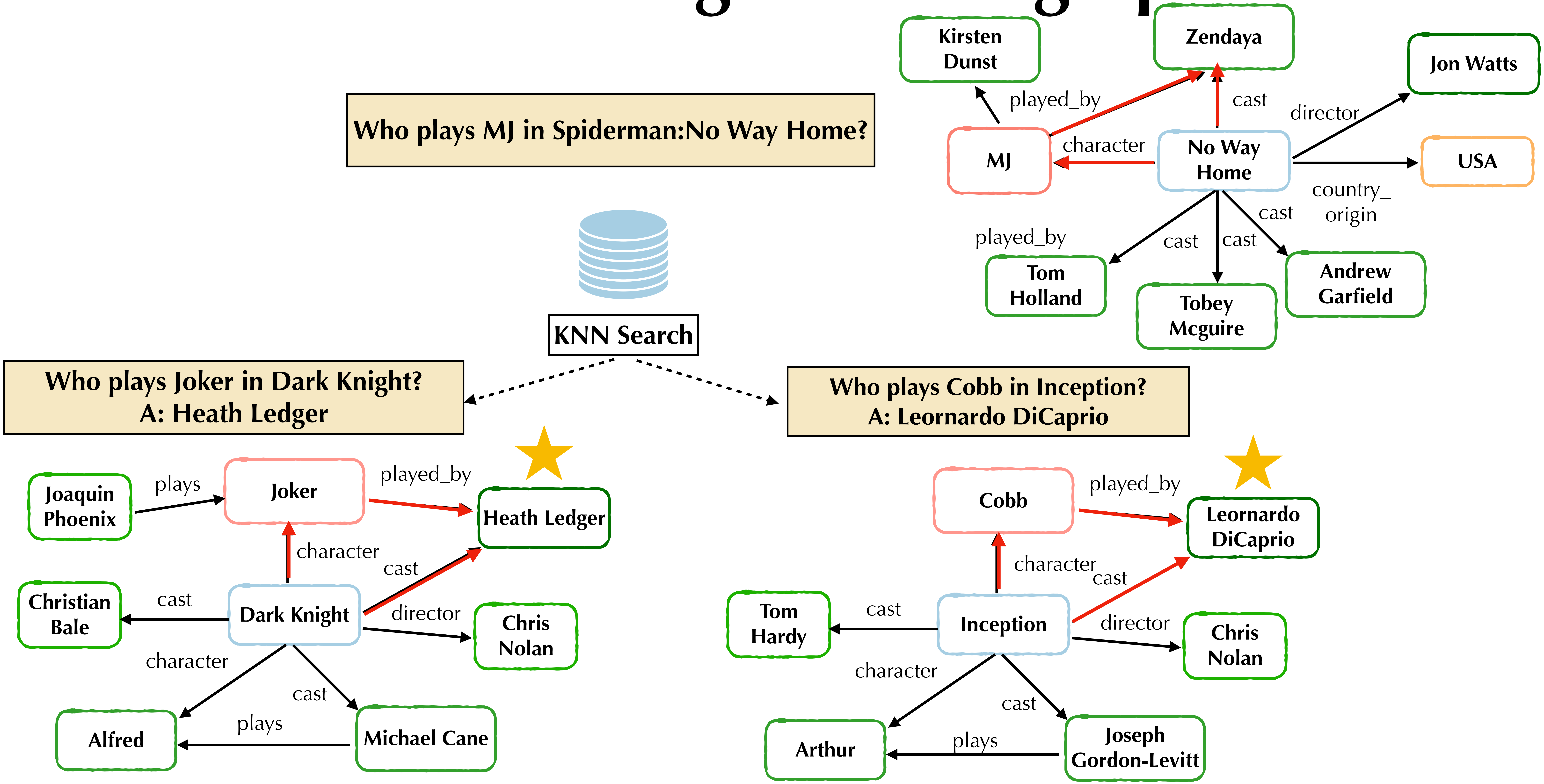

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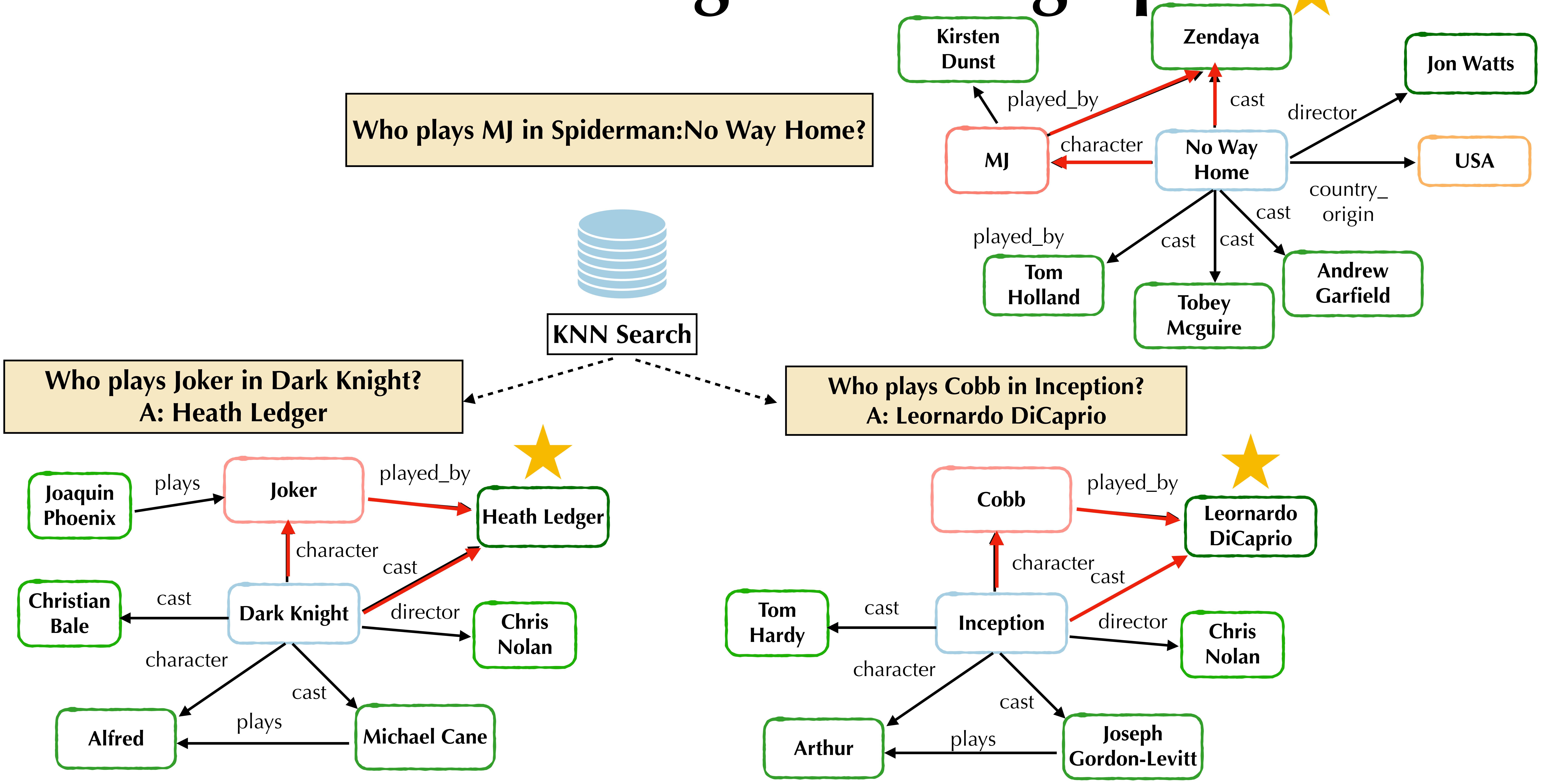
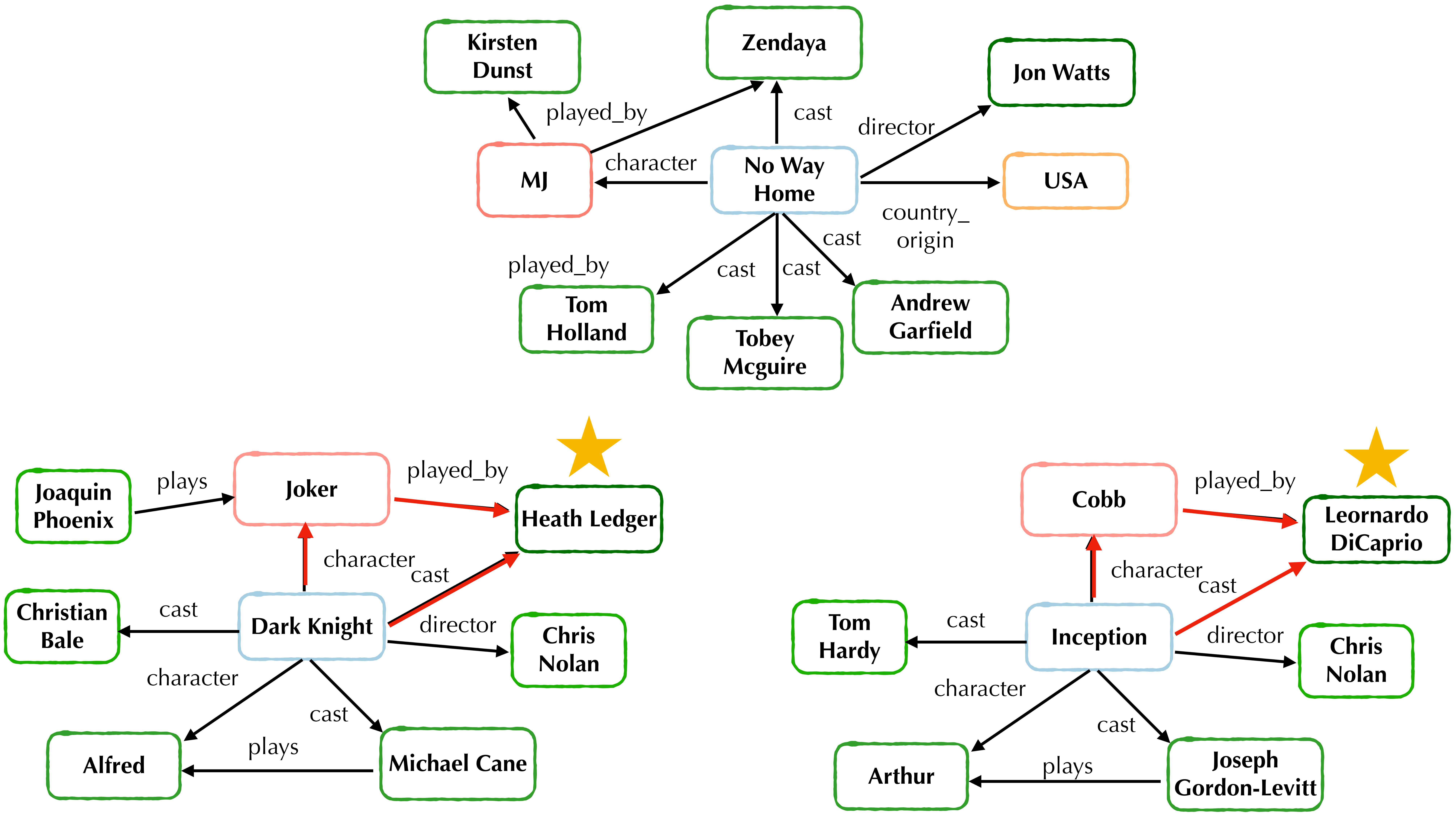


Graph Neural Networks and Contrastive Learning



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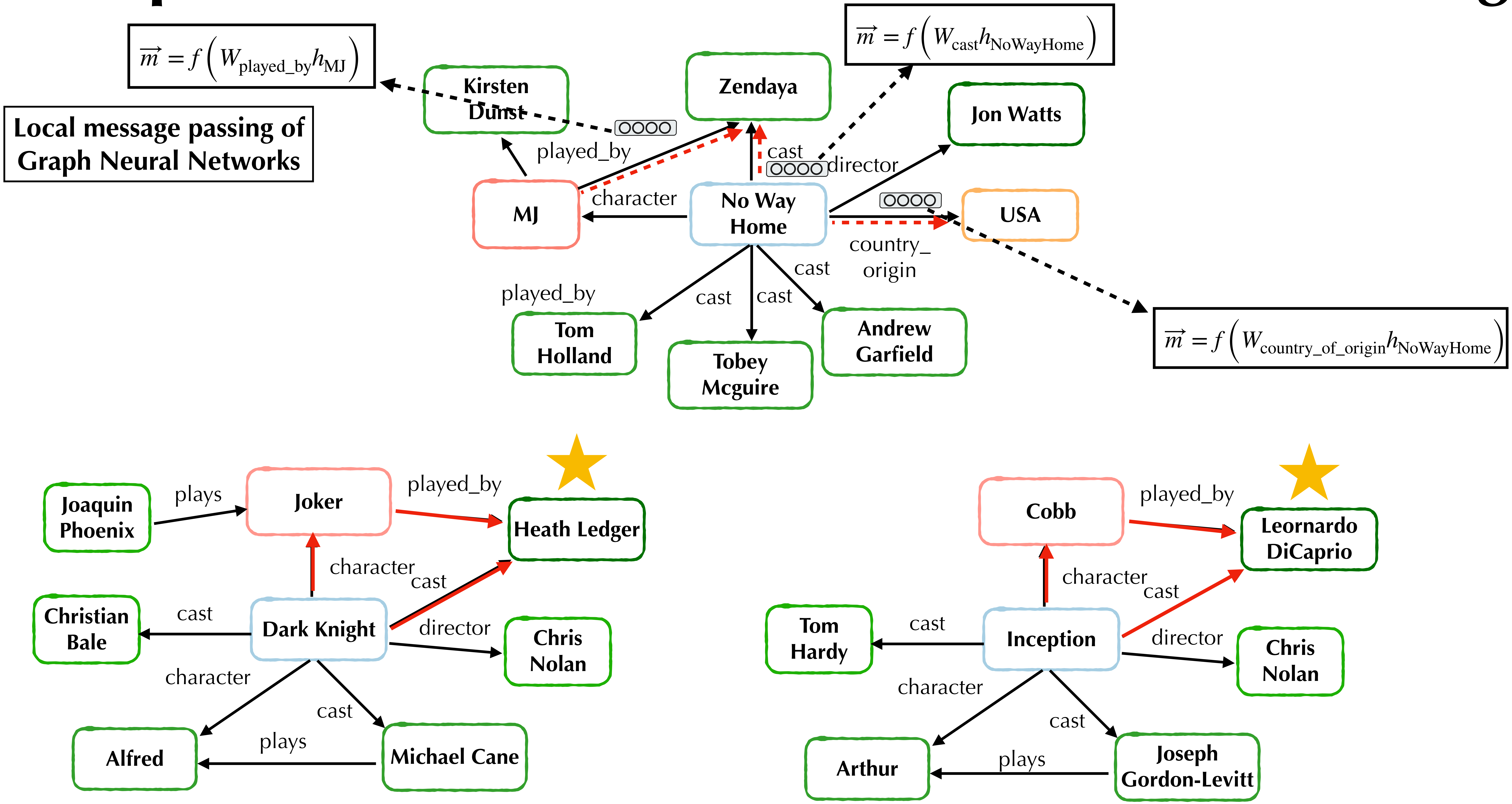
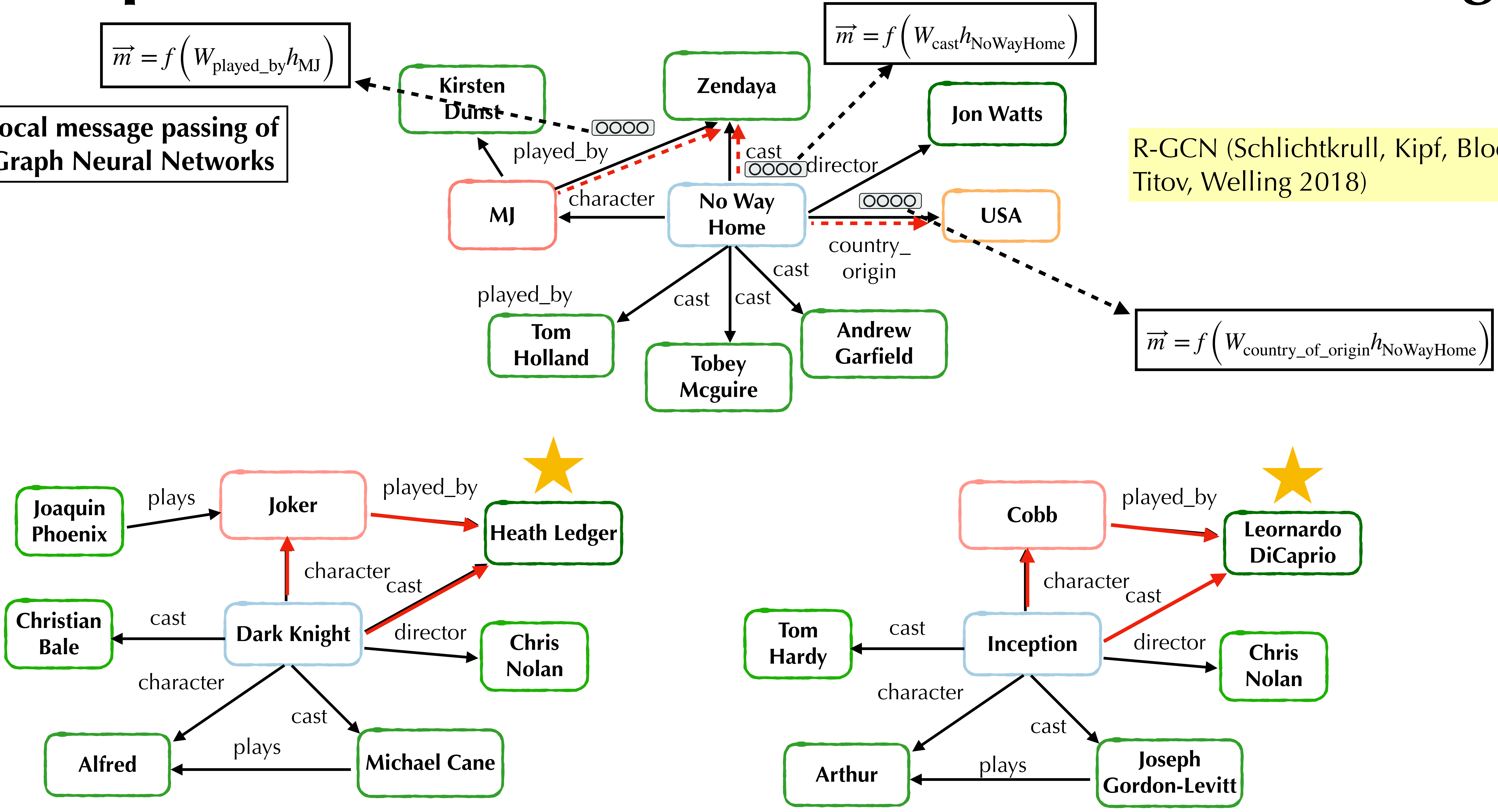


Graph Neural Networks and Contrastive Learning

Local message passing of Graph Neural Networks

R-GCN (Schlichtkrull, Kipf, Bloem, Berg, Titov, Welling 2018)



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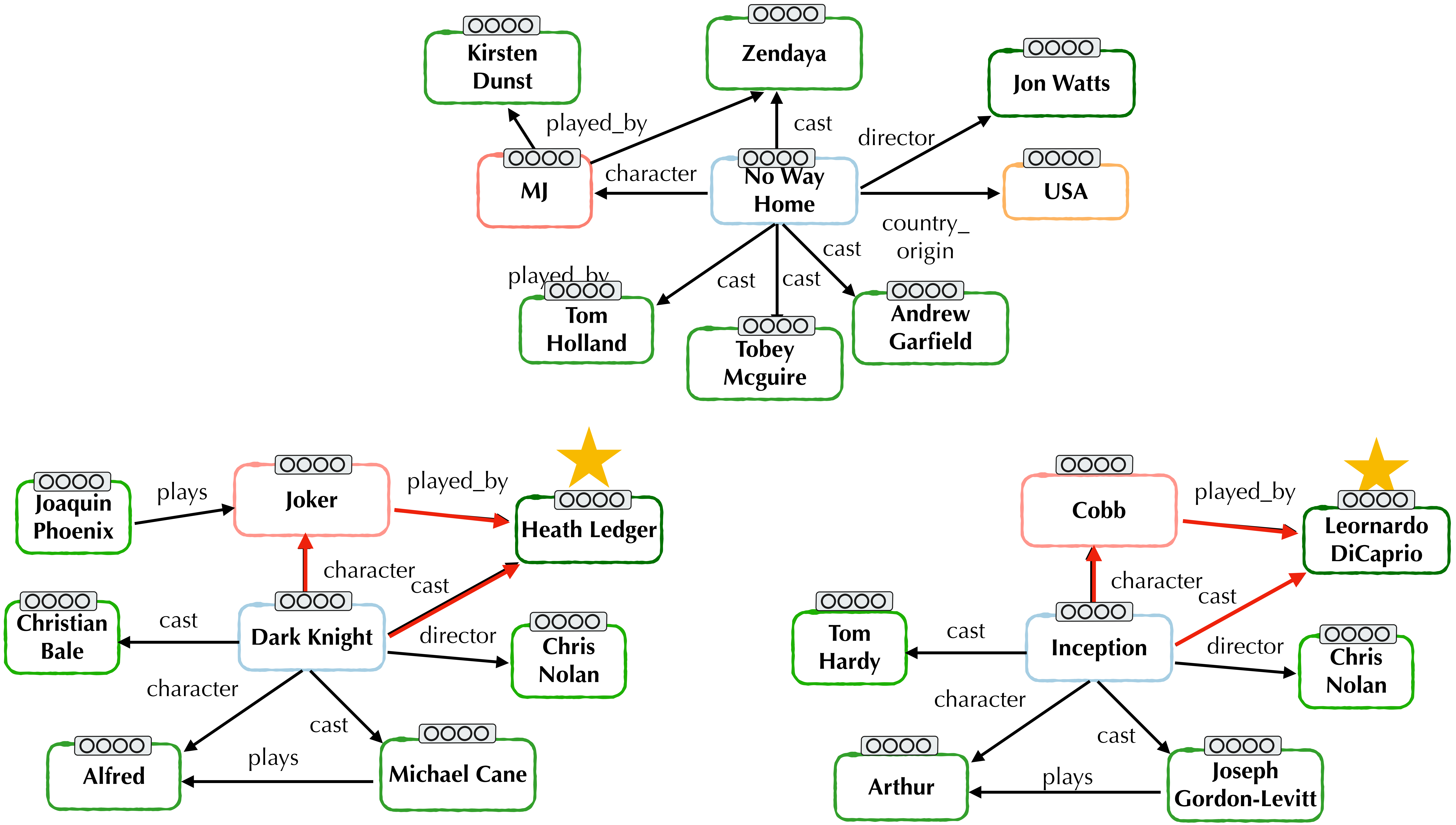

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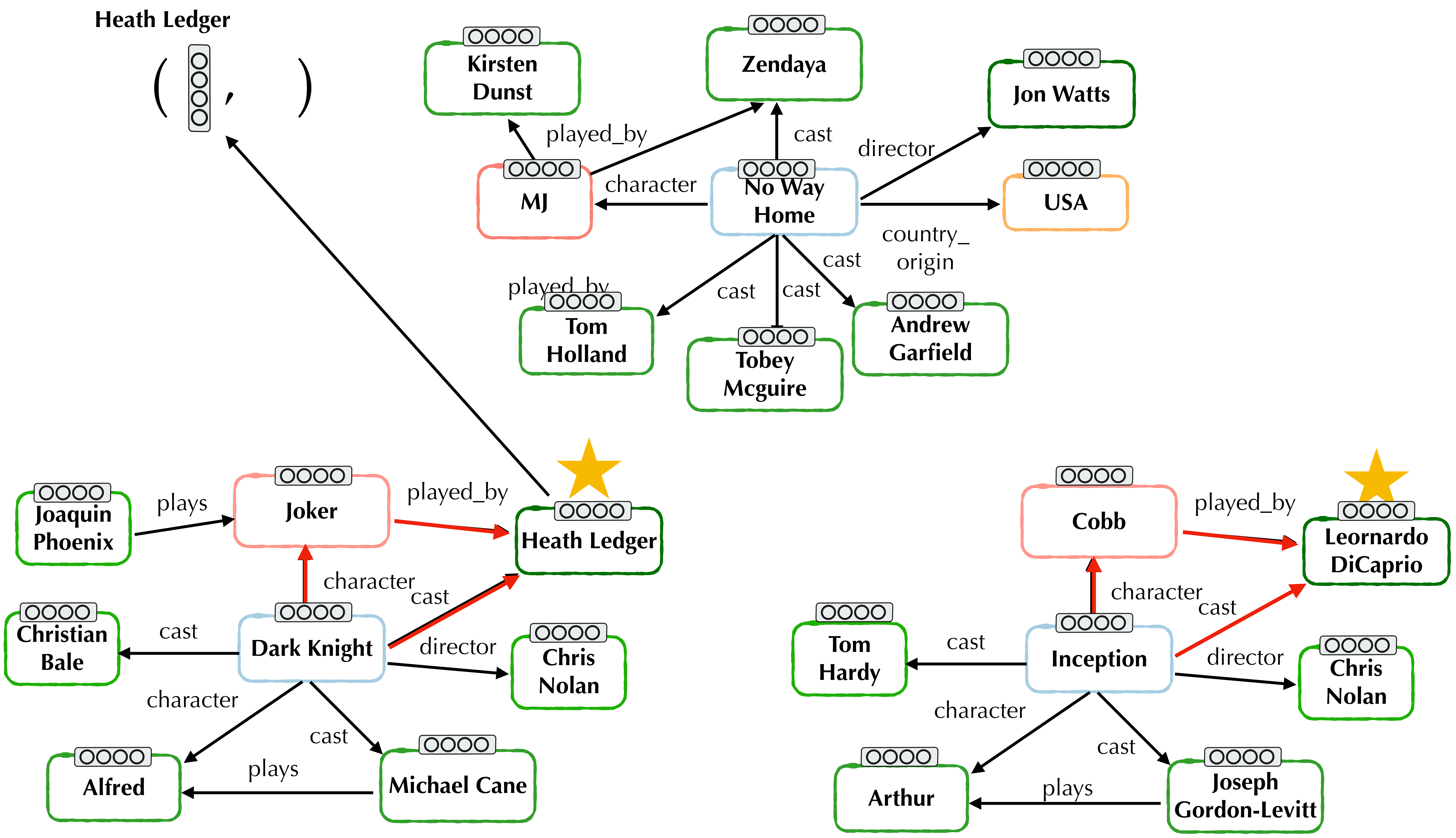

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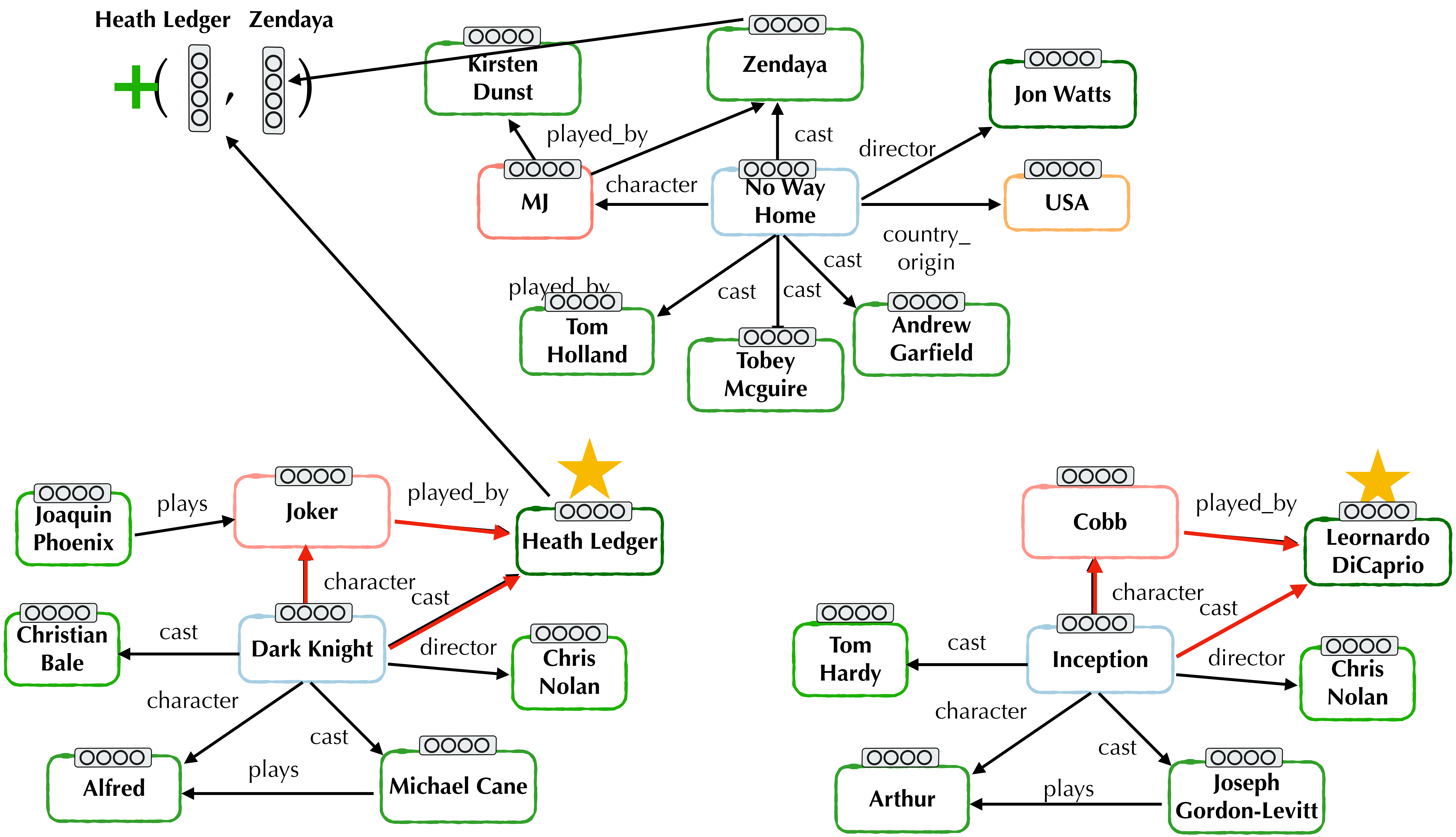

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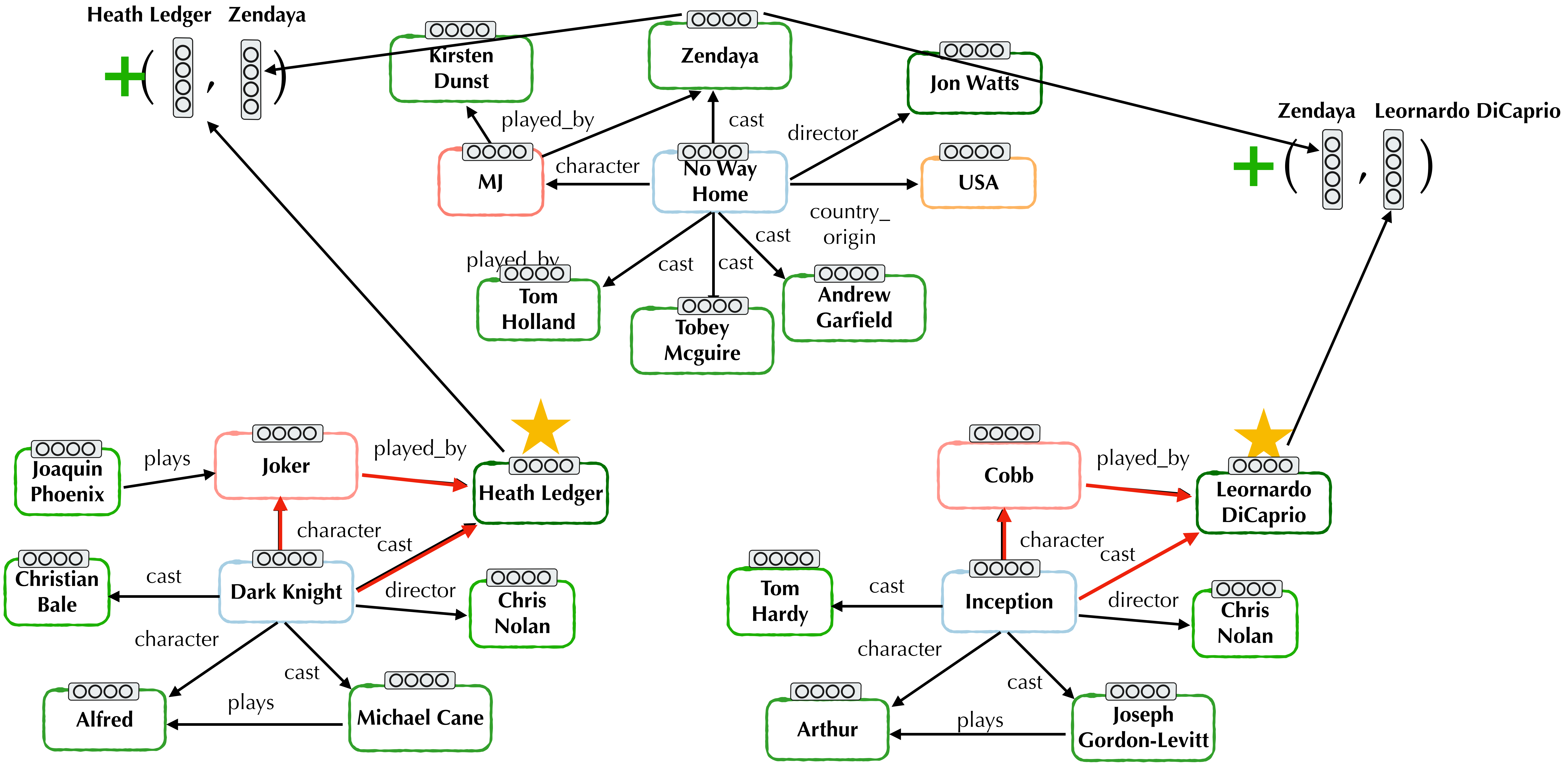

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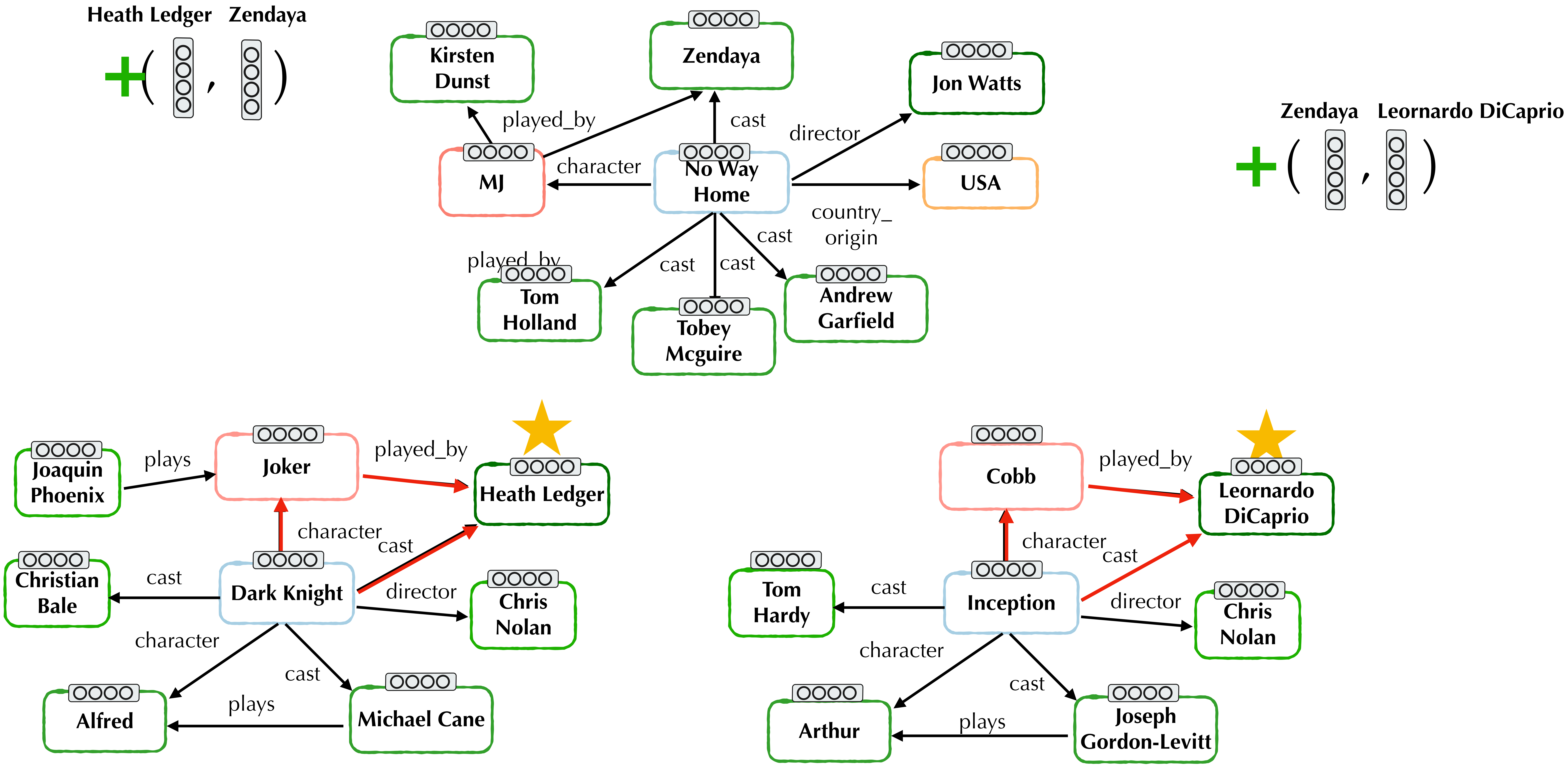

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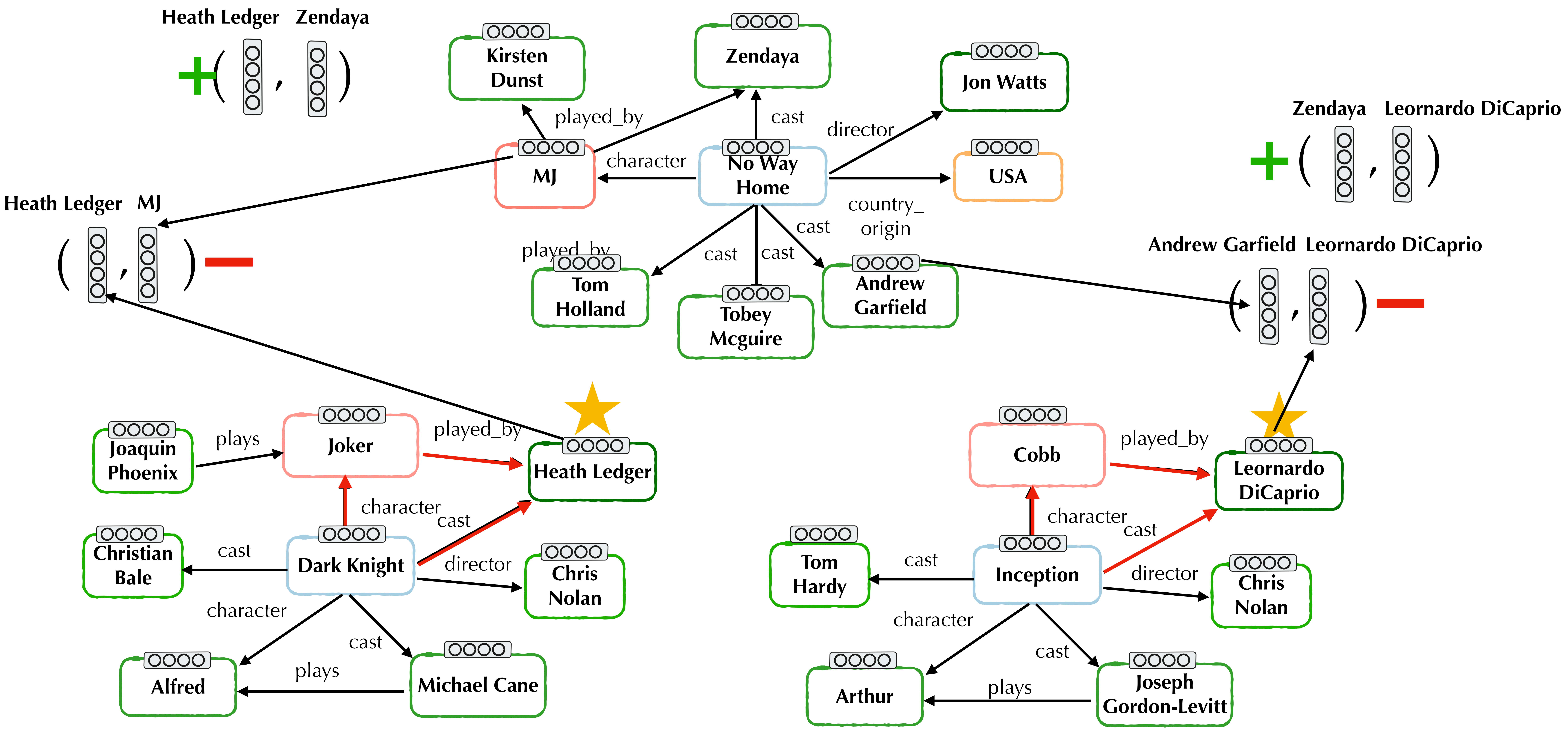

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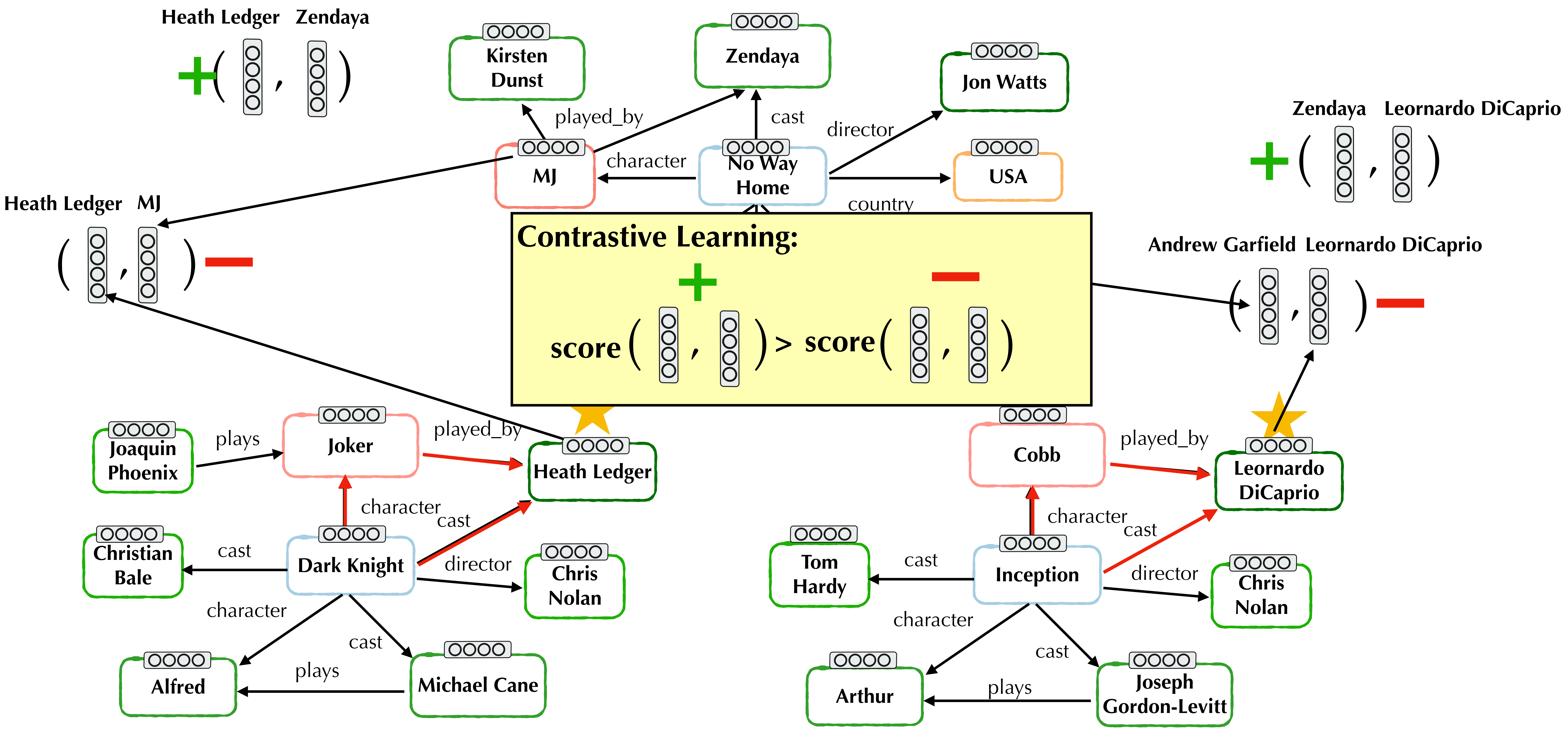
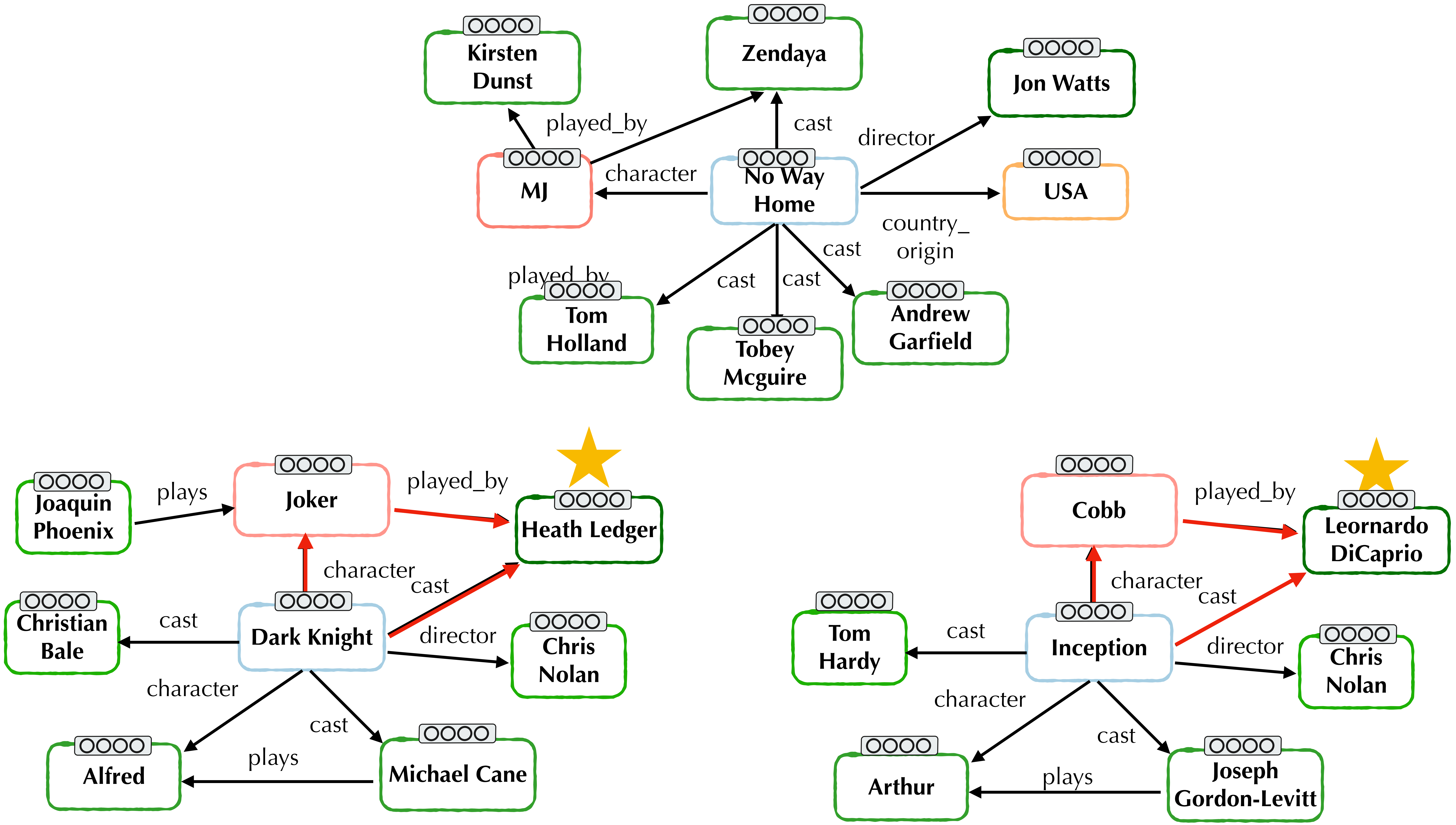
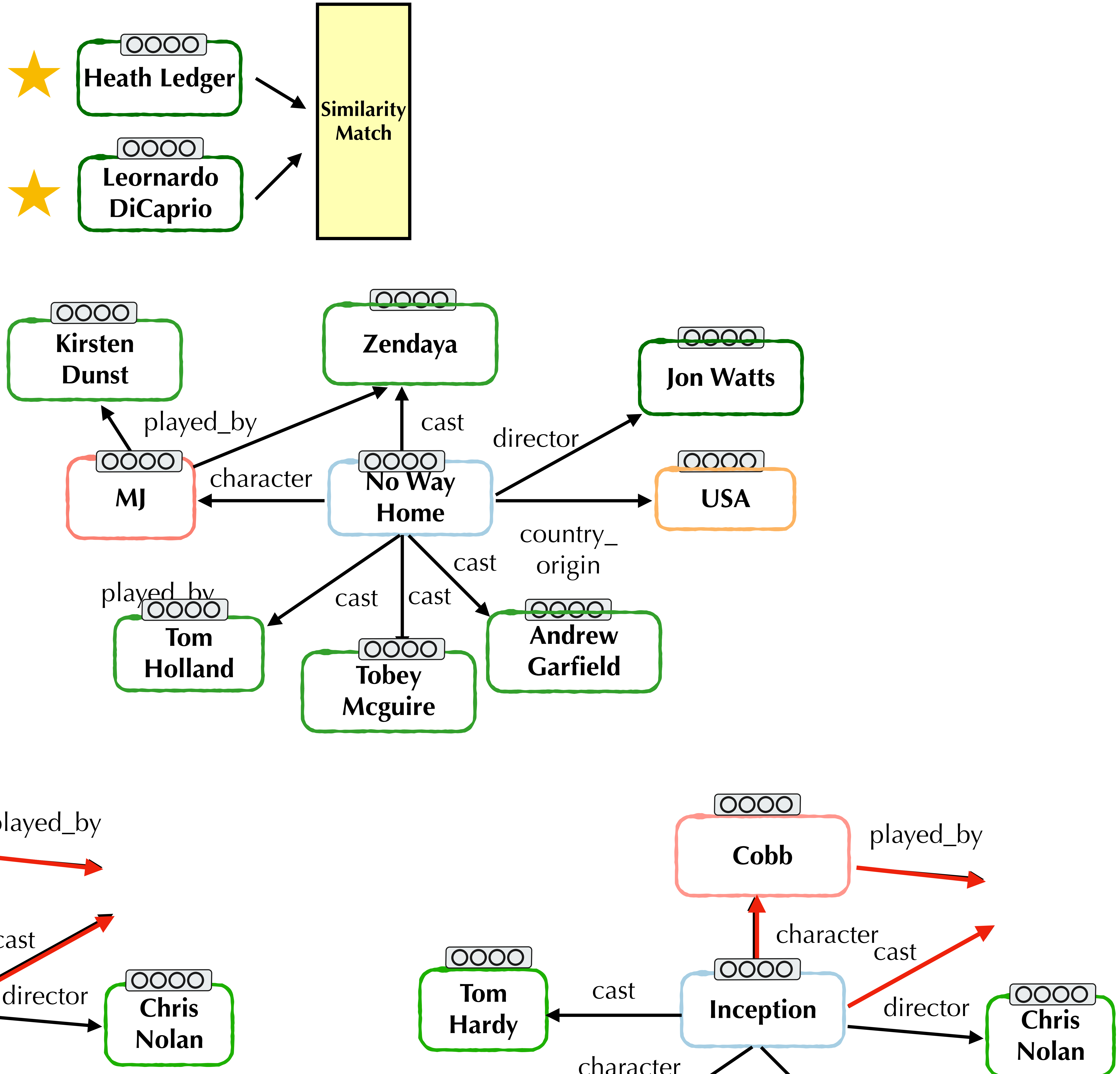


Inference


Kirsten Dunst
Zendaya
Jon Watts
played_by
cast
director
MJ
character
No Way Home
USA
country_origin
cast
played_by
cast
cast
Tom Holland
Tobey Mcguire
Andrew Garfield
Joaquin Phoenix
plays
Joker
played_by
Heath Ledger
character
cast
Christian Bale
cast
Dark Knight
director
Chris Nolan
character
cast
Alfred
plays
Michael Cane
Cobb
played_by
Leornardo DiCaprio
character
cast
Tom Hardy
cast
Inception
director
Chris Nolan
character
cast
Arthur
plays
Joseph Gordon-Levitt

Inference


Heath Ledger
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Similarity Match
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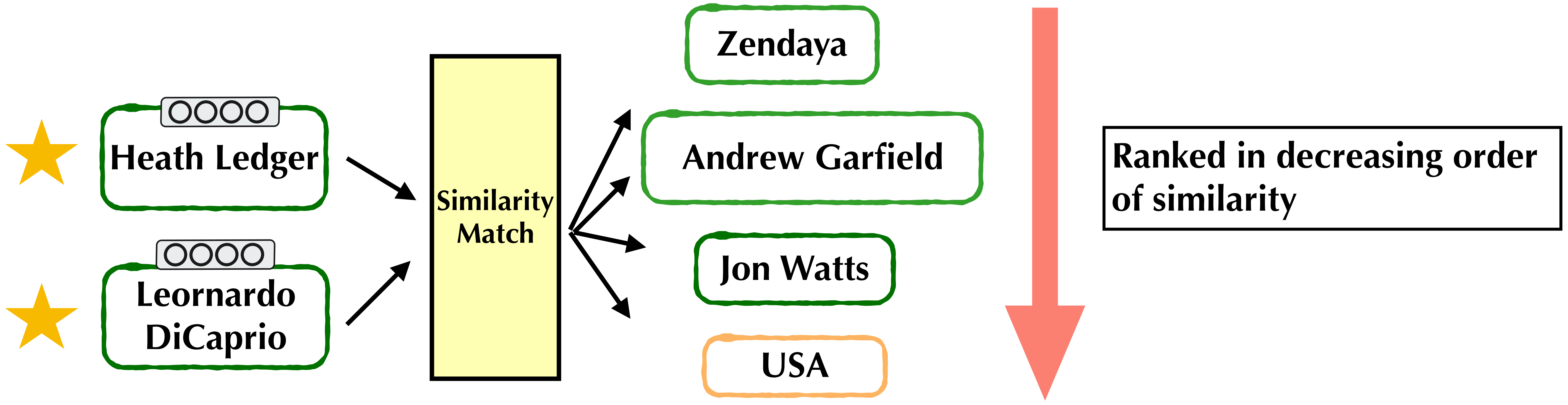
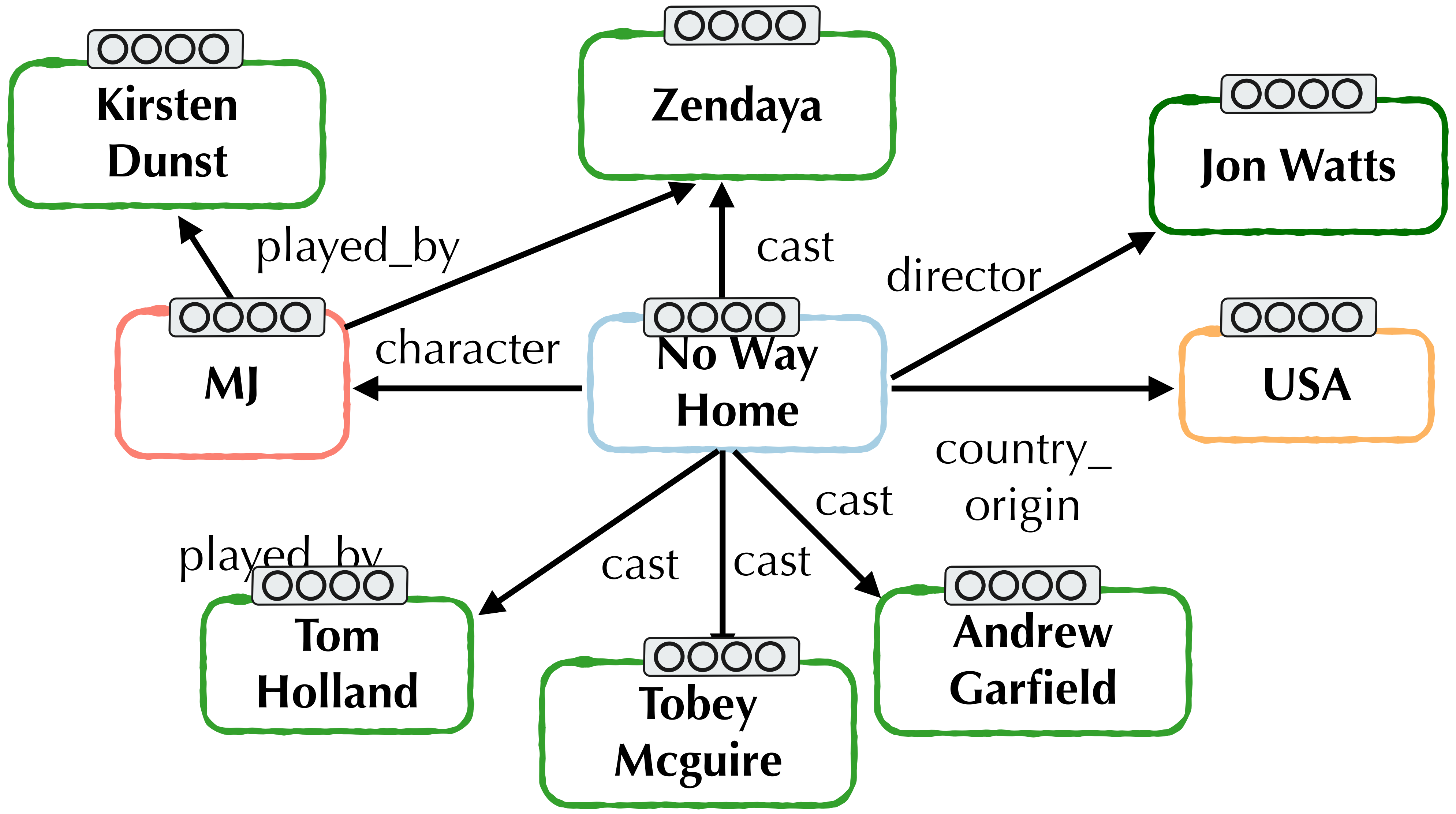
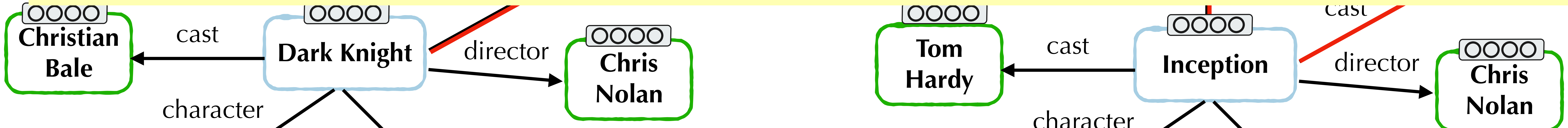
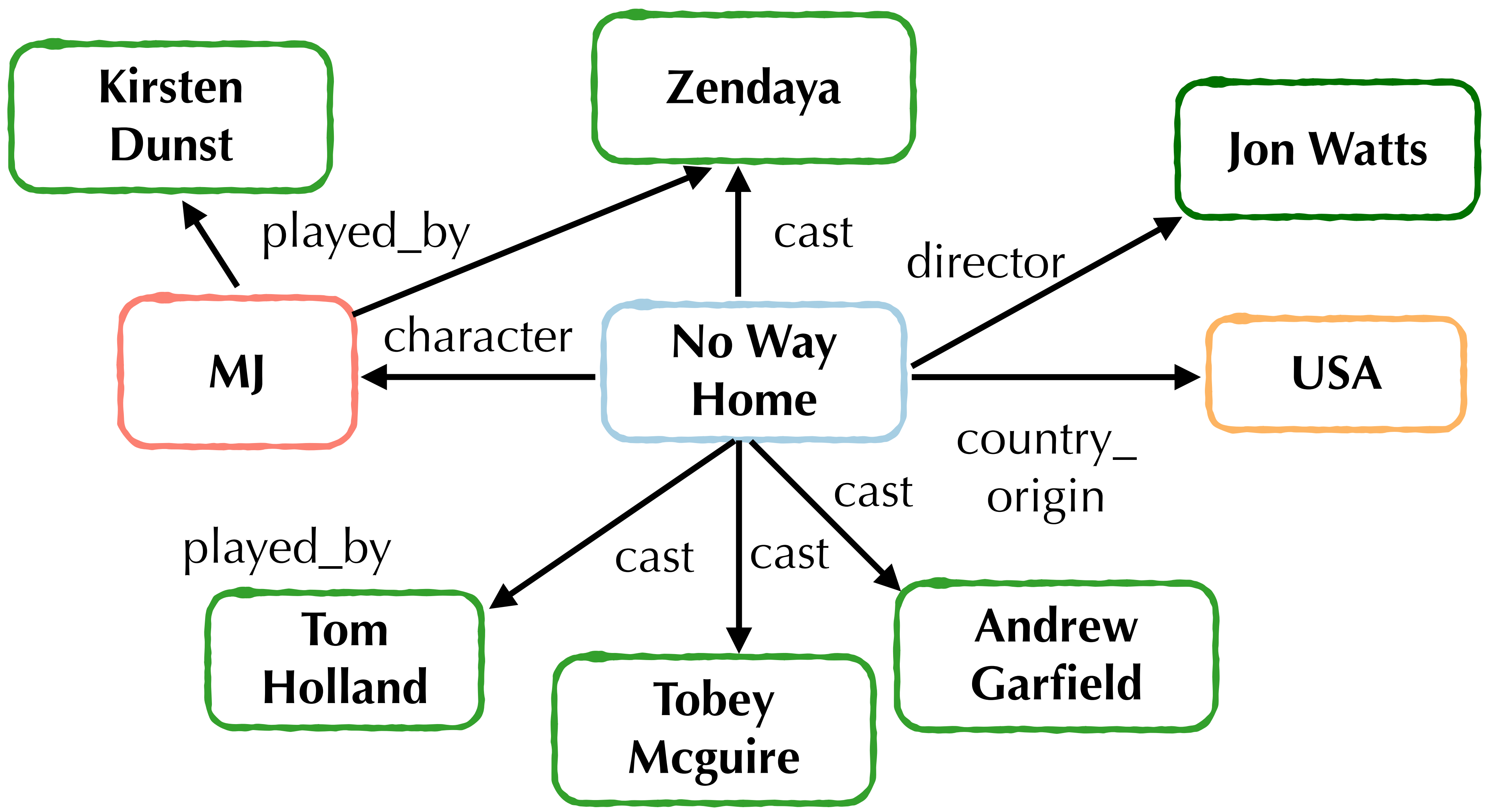




Inference: Search for most similar node in query subgraph wrt KNN answer nodes.



Input Entity Representation



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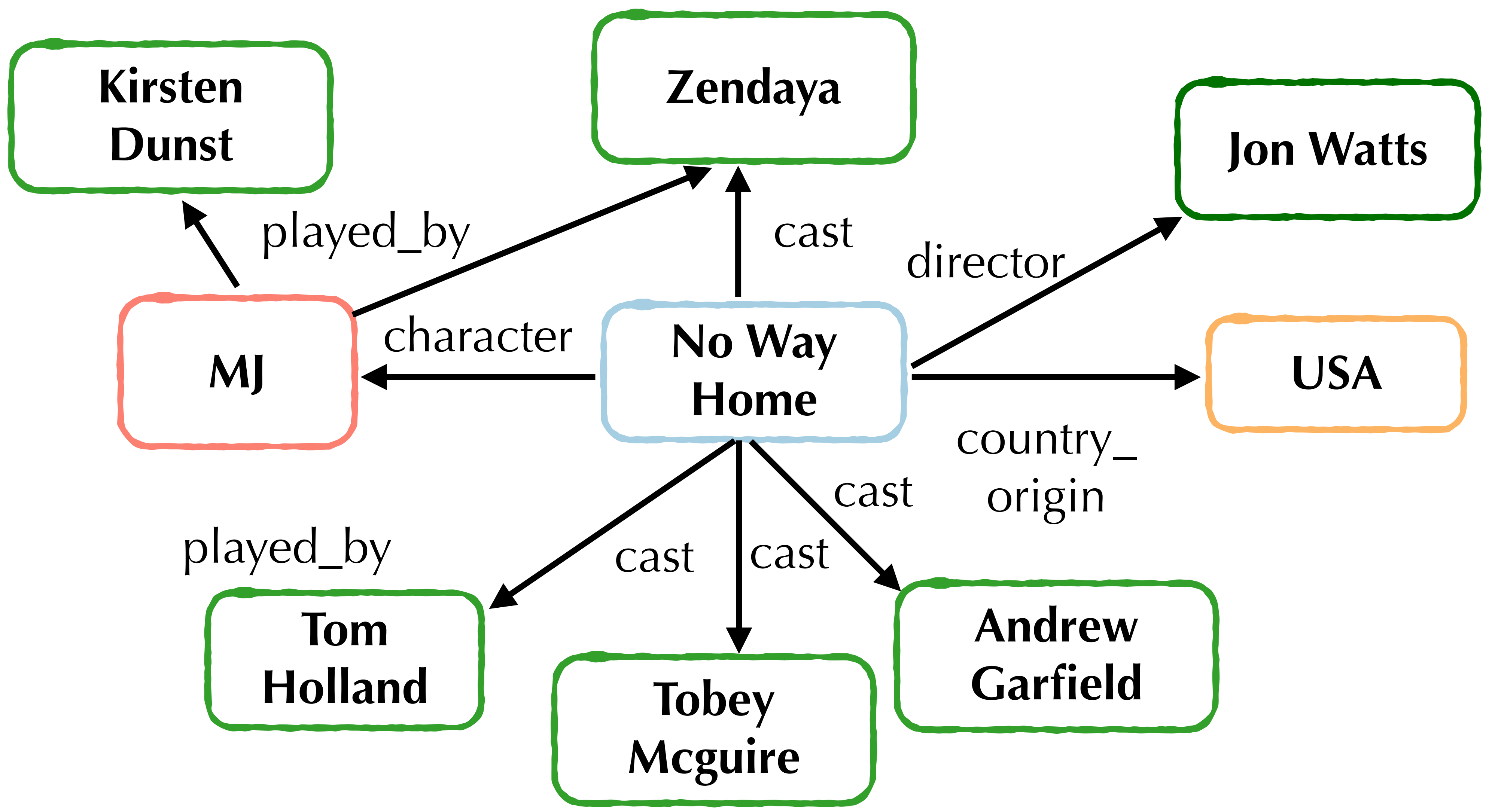

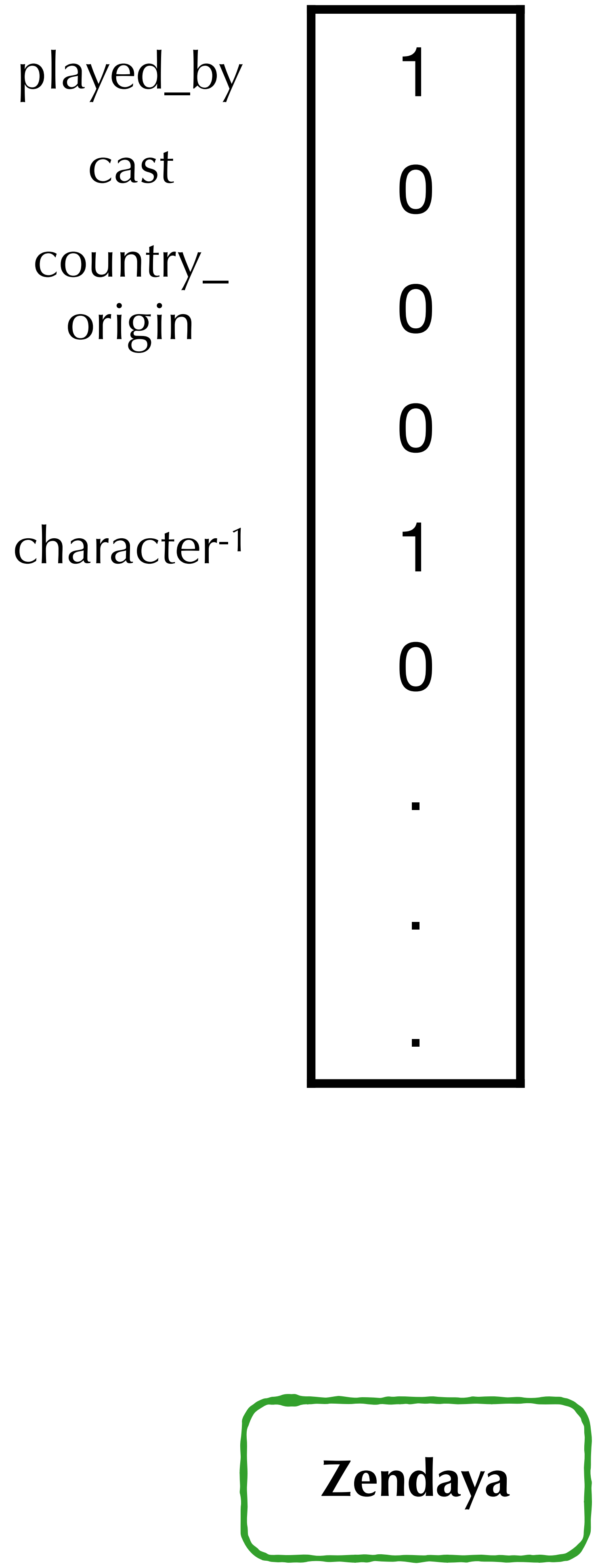

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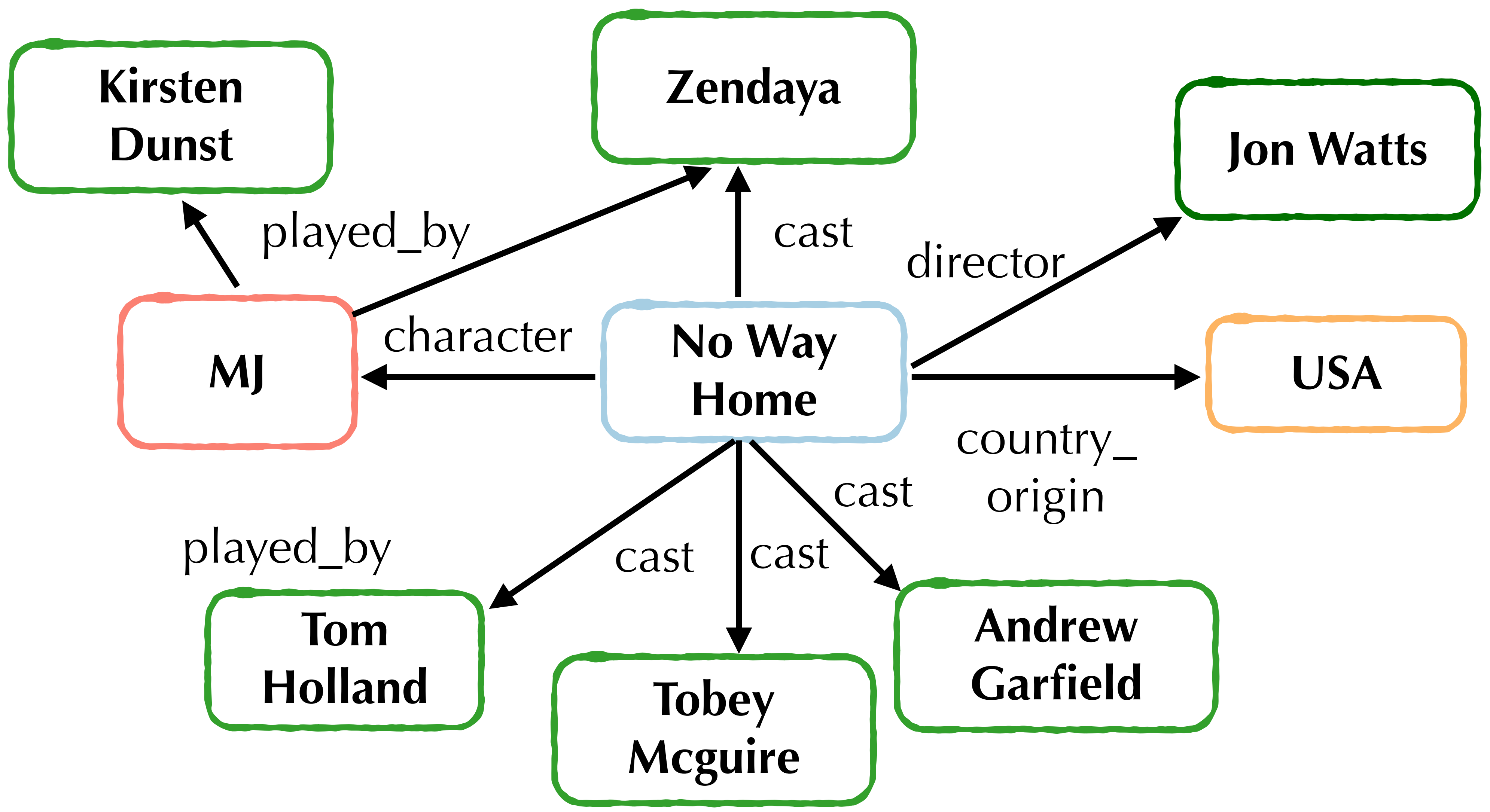
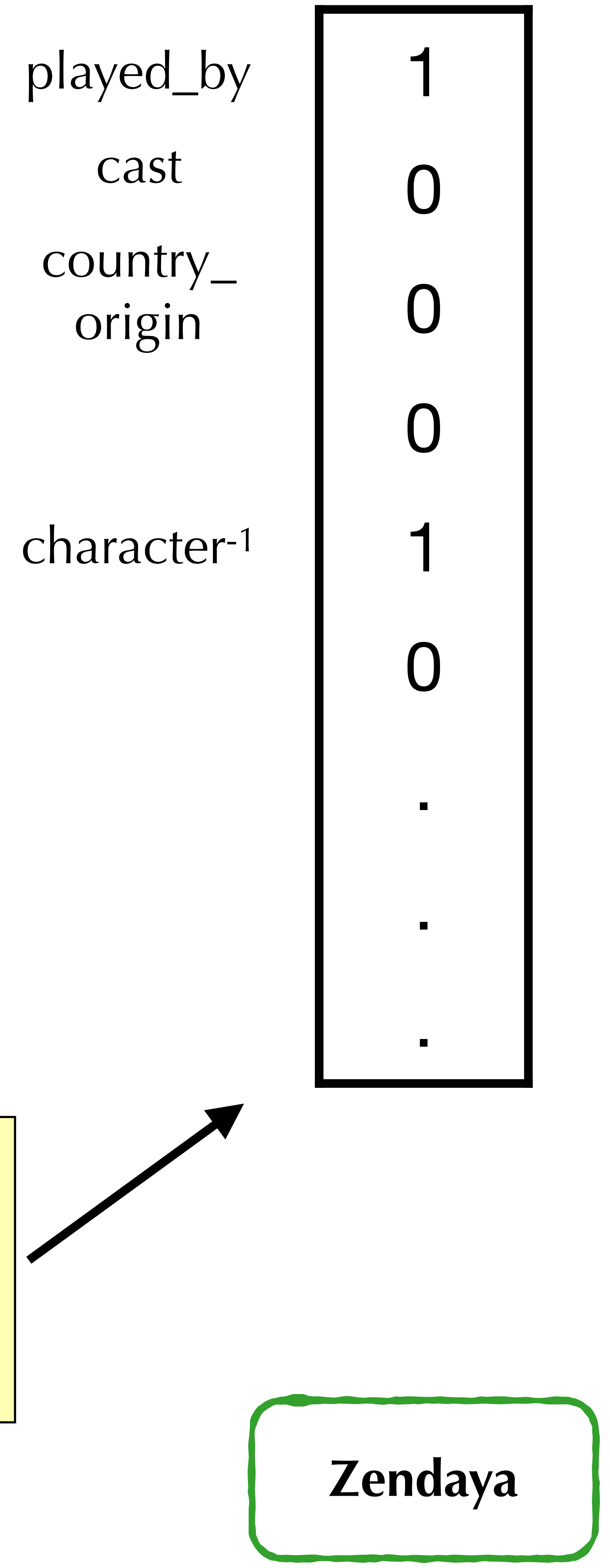
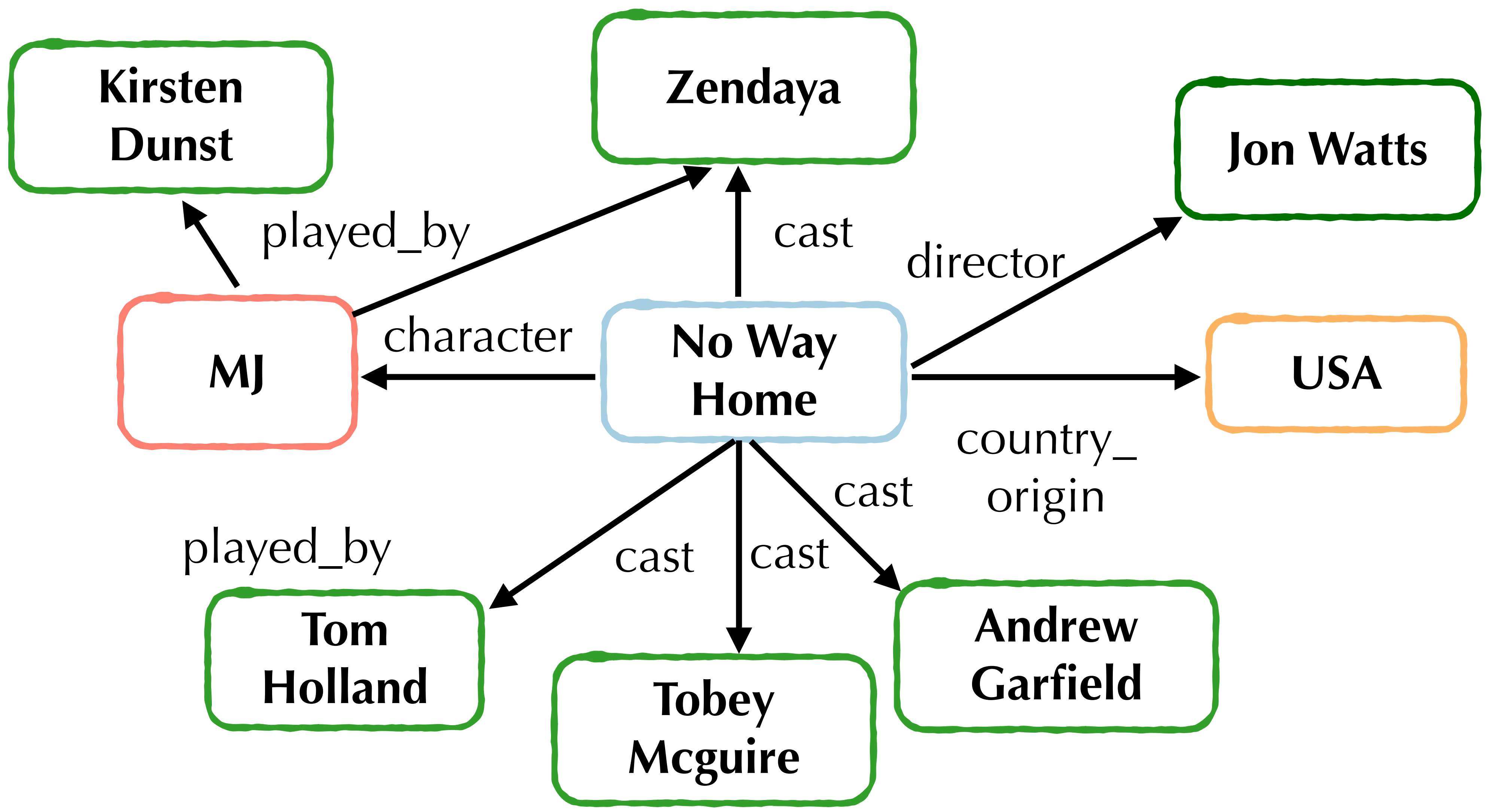
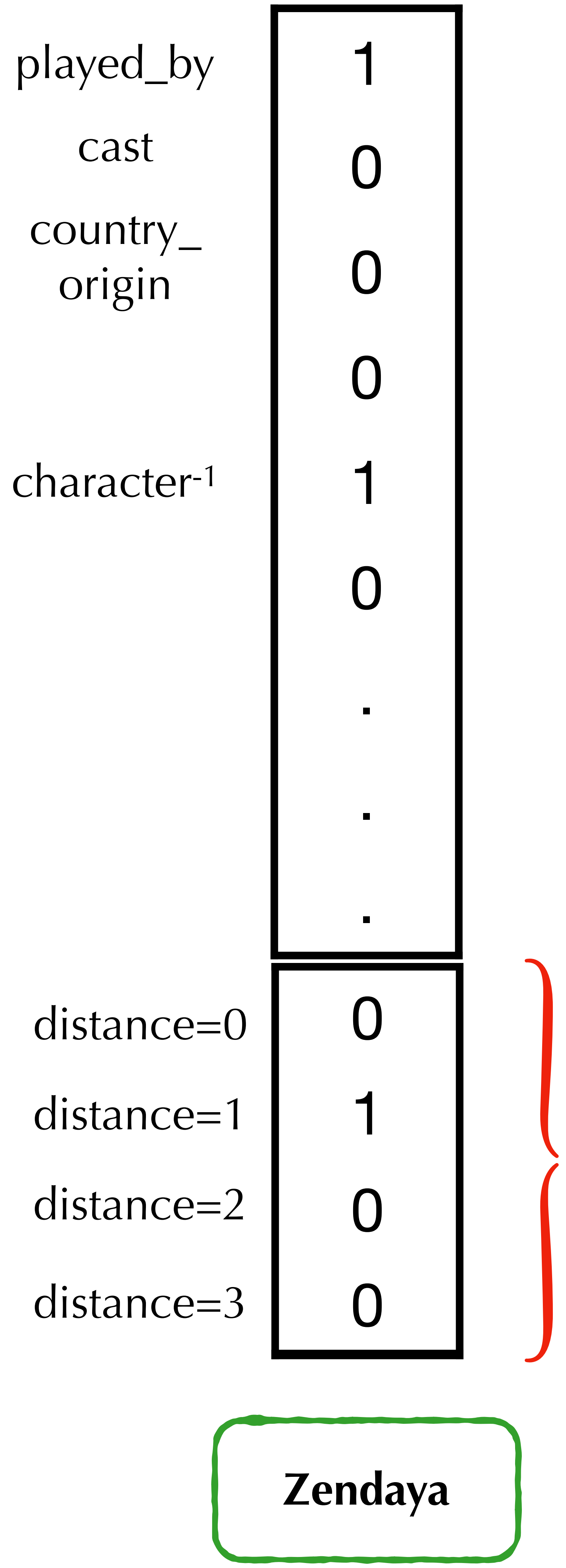




Trivial to represent new entities and update representation of existing entities

Input Entity Representation

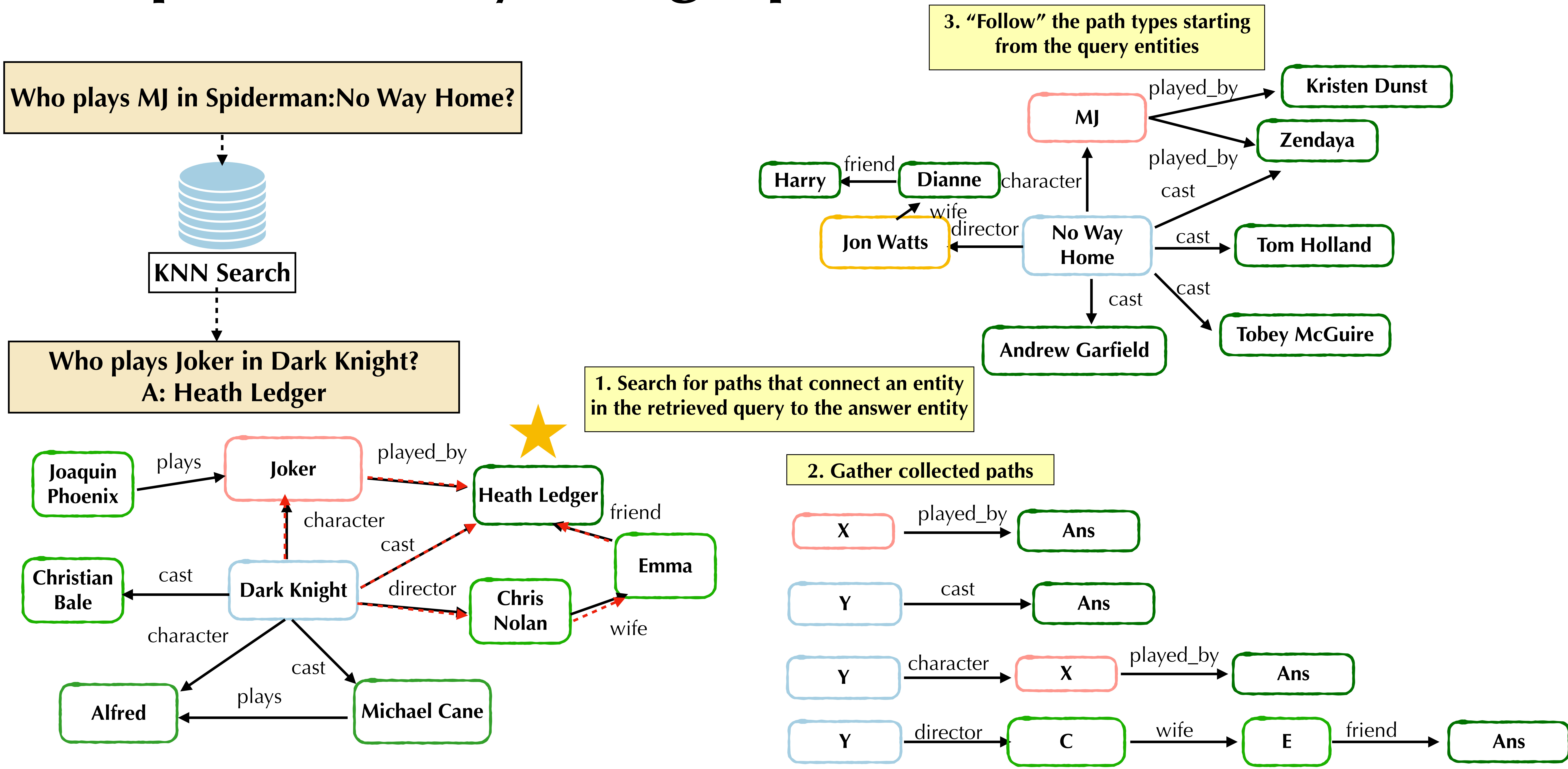




Trivial to represent new entities and update representation of existing entities

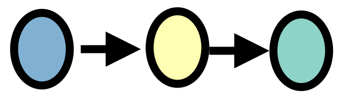
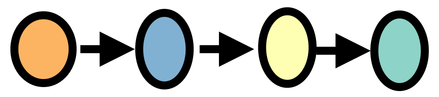
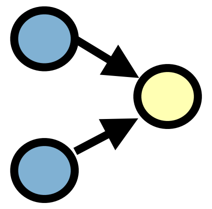
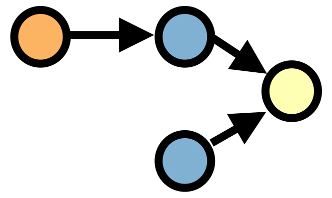
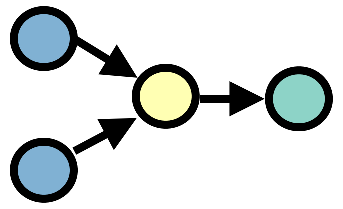
Distance from query entities

Adaptive Query-Subgraph Collection



Results (Subgraph Reasoning Patterns)

Evaluation Metric: Accuracy(%)

Model						Avg.
Random	0.83	0.83	0.83	0.83	0.83	0.83
Our Model (No training)	68.56	84.35	23.00	34.85	35.35	47.28
GNN + TransE	80.03	74.49	80.00	52.67	81.53	72.69
Our Model	**96.64**	**88.43**	**90.46**	**70.02**	**86.81**	**85.68**

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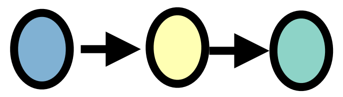
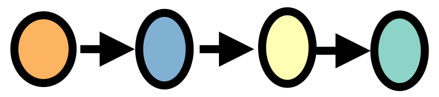
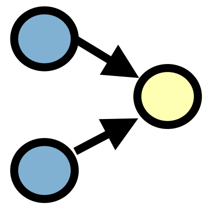
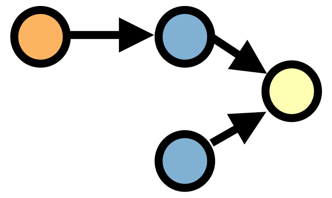
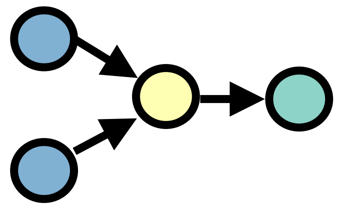
Model						Avg.
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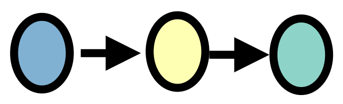
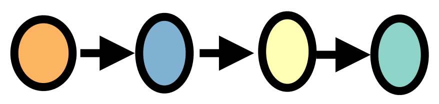
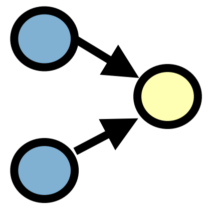
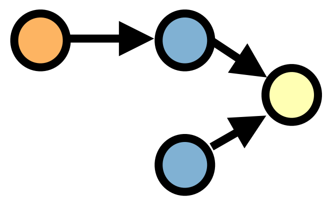
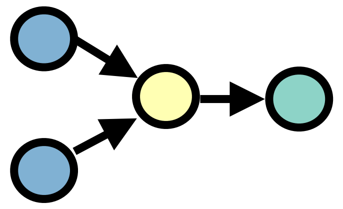
Model						Avg.
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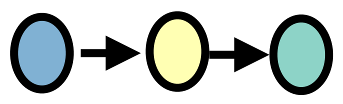
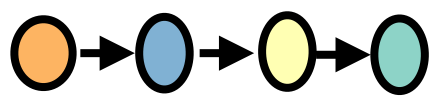
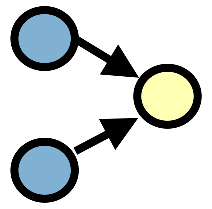
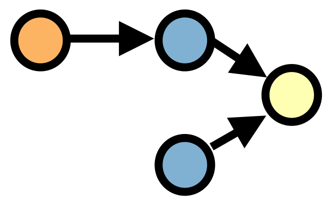
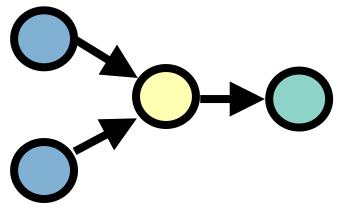
Comparison to parametric models

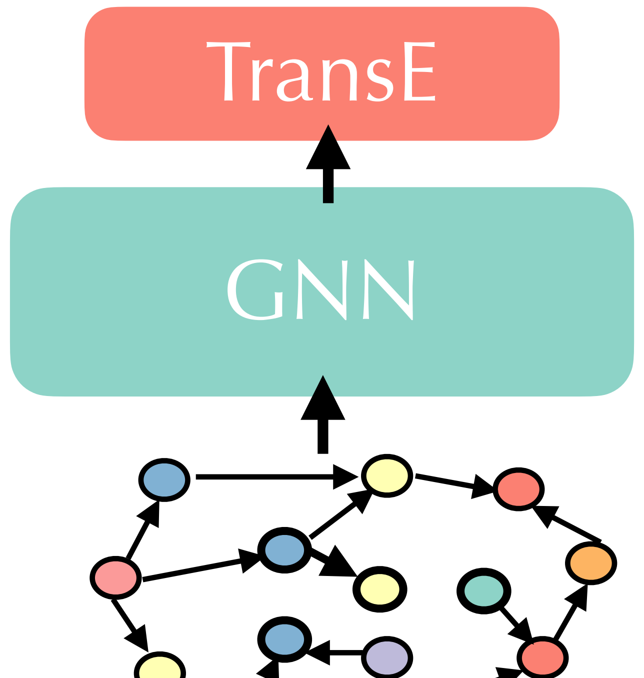
Results (Subgraph Reasoning Patterns)

Evaluation Metric: Accuracy(%)

Model						Avg.
Random	0.83	0.83	0.83	0.83	0.83	0.83
Our Model (No training)	68.56	84.35	23.00	34.85	35.35	47.28
GNN + TransE	80.03	74.49	80.00	52.67	81.53	72.69
Our Model	**96.64**	**88.43**	**90.46**	**70.02**	**86.81**	**85.68**

Our model has the right inductive bias

Comparison to parametric models



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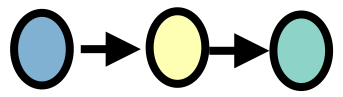
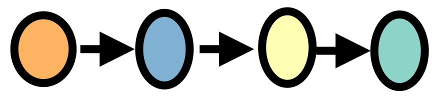
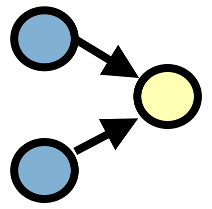
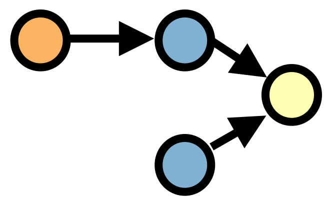
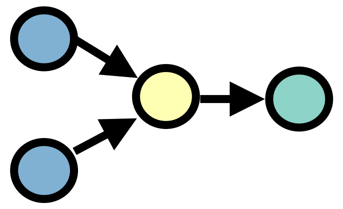
Model						Avg.
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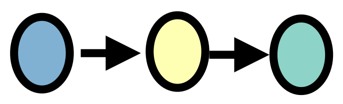
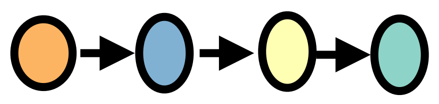
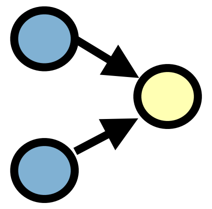
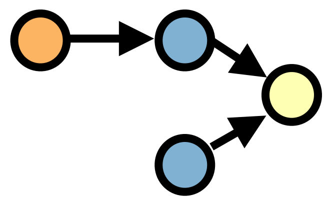
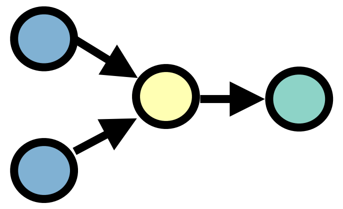
Model						Avg.
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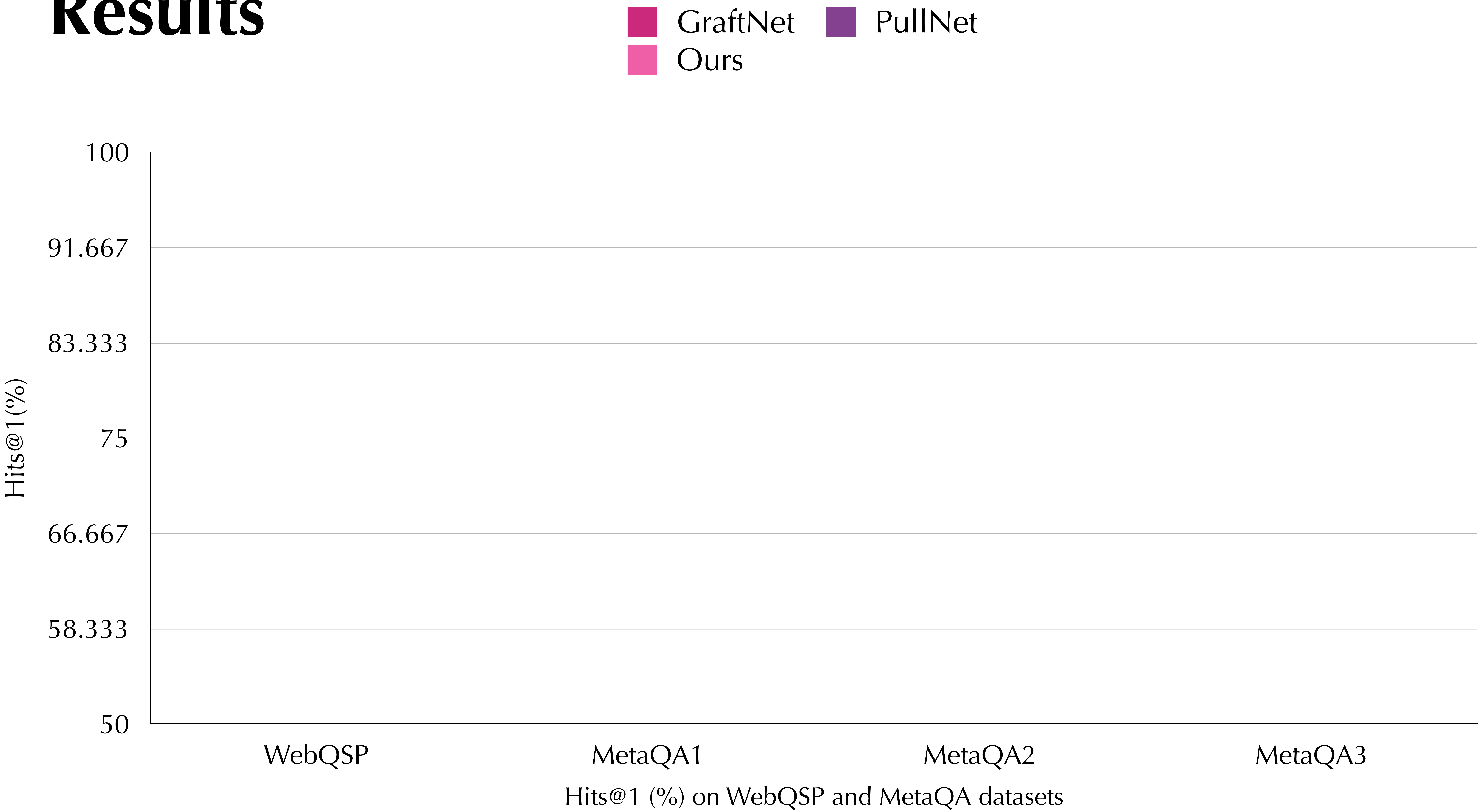
Comparison to parametric models

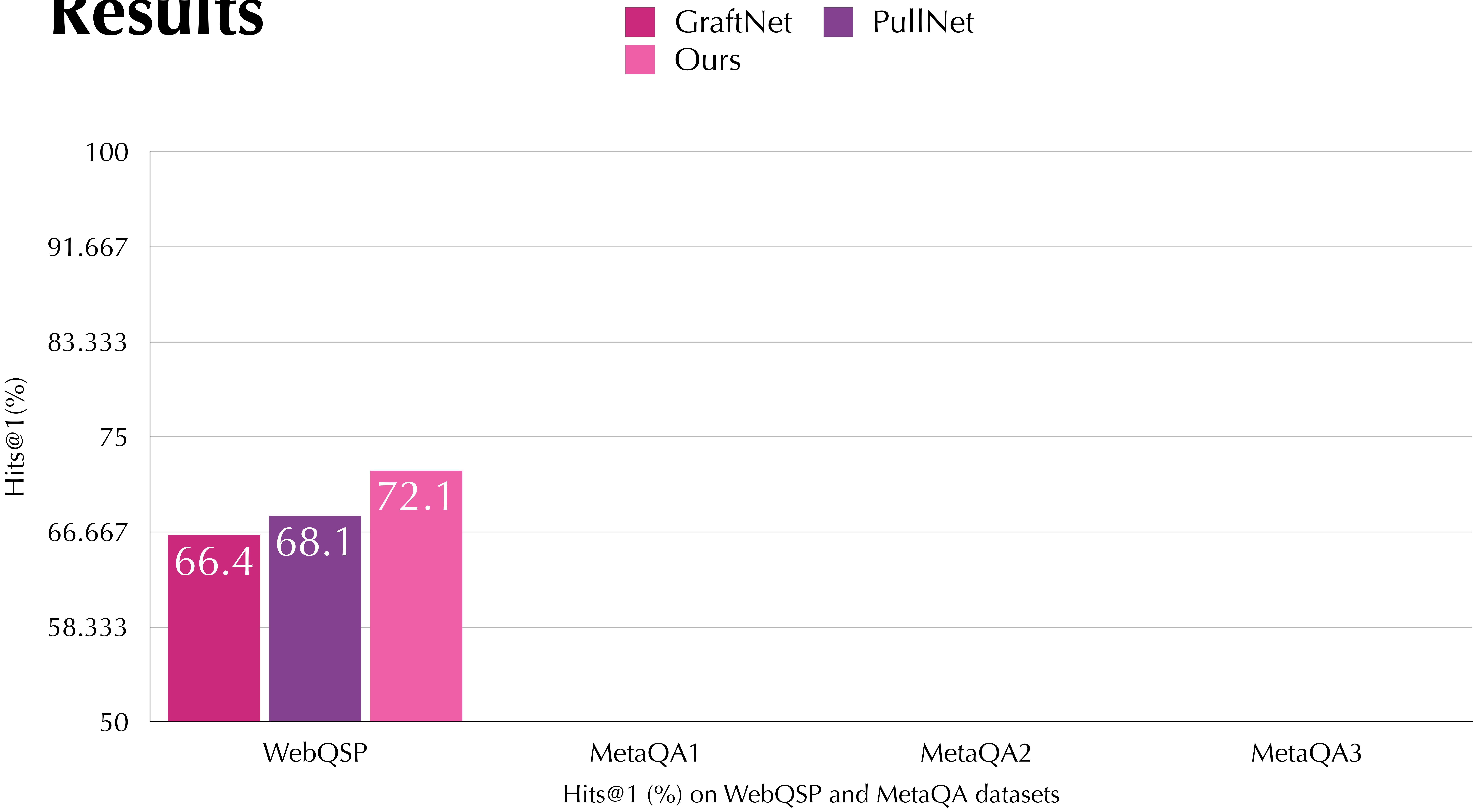
+13%

Results

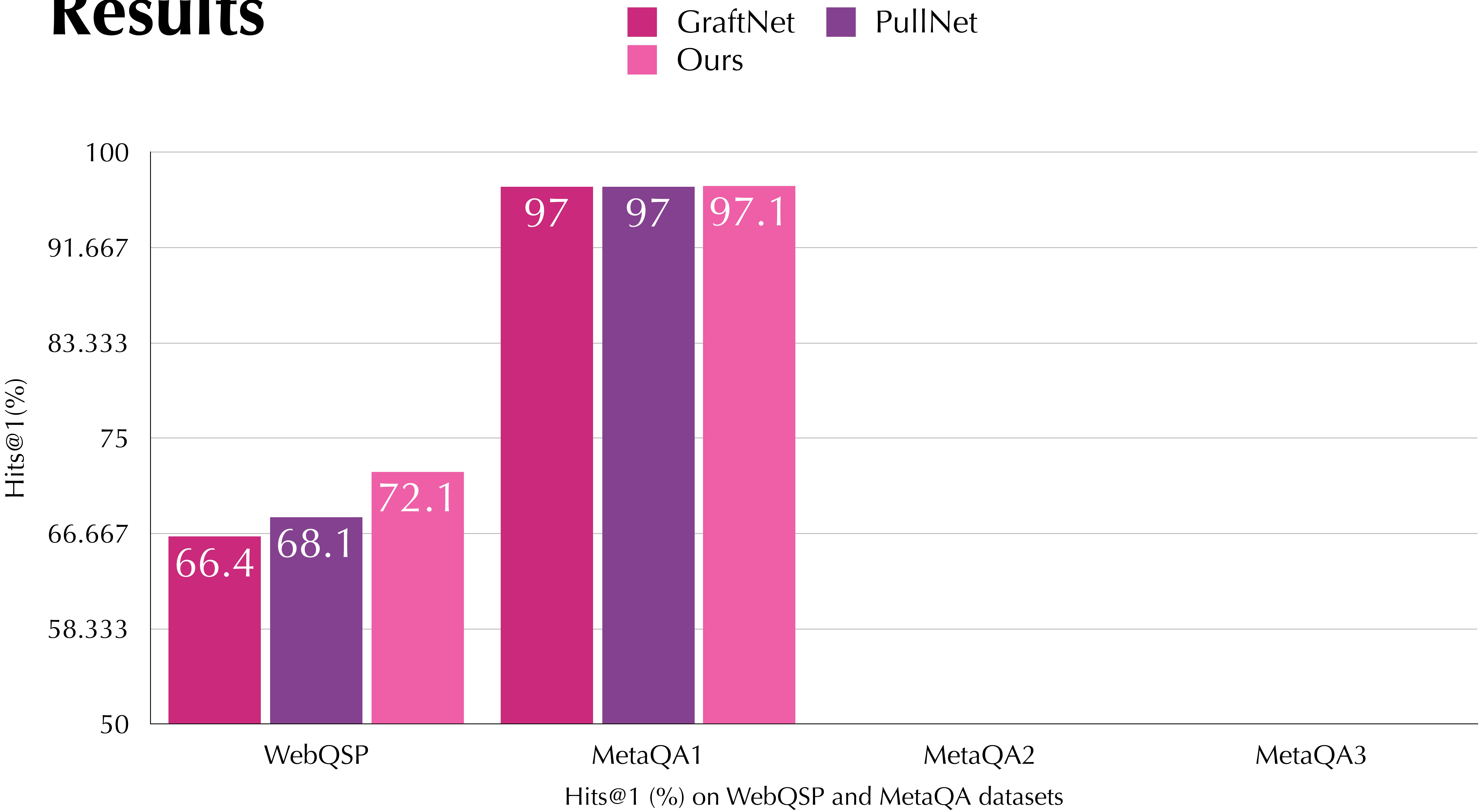
Results


GraftNet
PullNet
Ours
100
91.667
83.333
75
66.667
58.333
50
Hits@1(%)
WebQSP
MetaQA1
MetaQA2
MetaQA3
Hits@1 (%) on WebQSP and MetaQA datasets

Results


GraftNet
PullNet
Ours
100
91.667
83.333
75
66.667
58.333
50
Hits@1(%)
66.4
68.1
72.1
WebQSP
MetaQA1
MetaQA2
MetaQA3
Hits@1 (%) on WebQSP and MetaQA datasets

Results


GraftNet
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100
91.667
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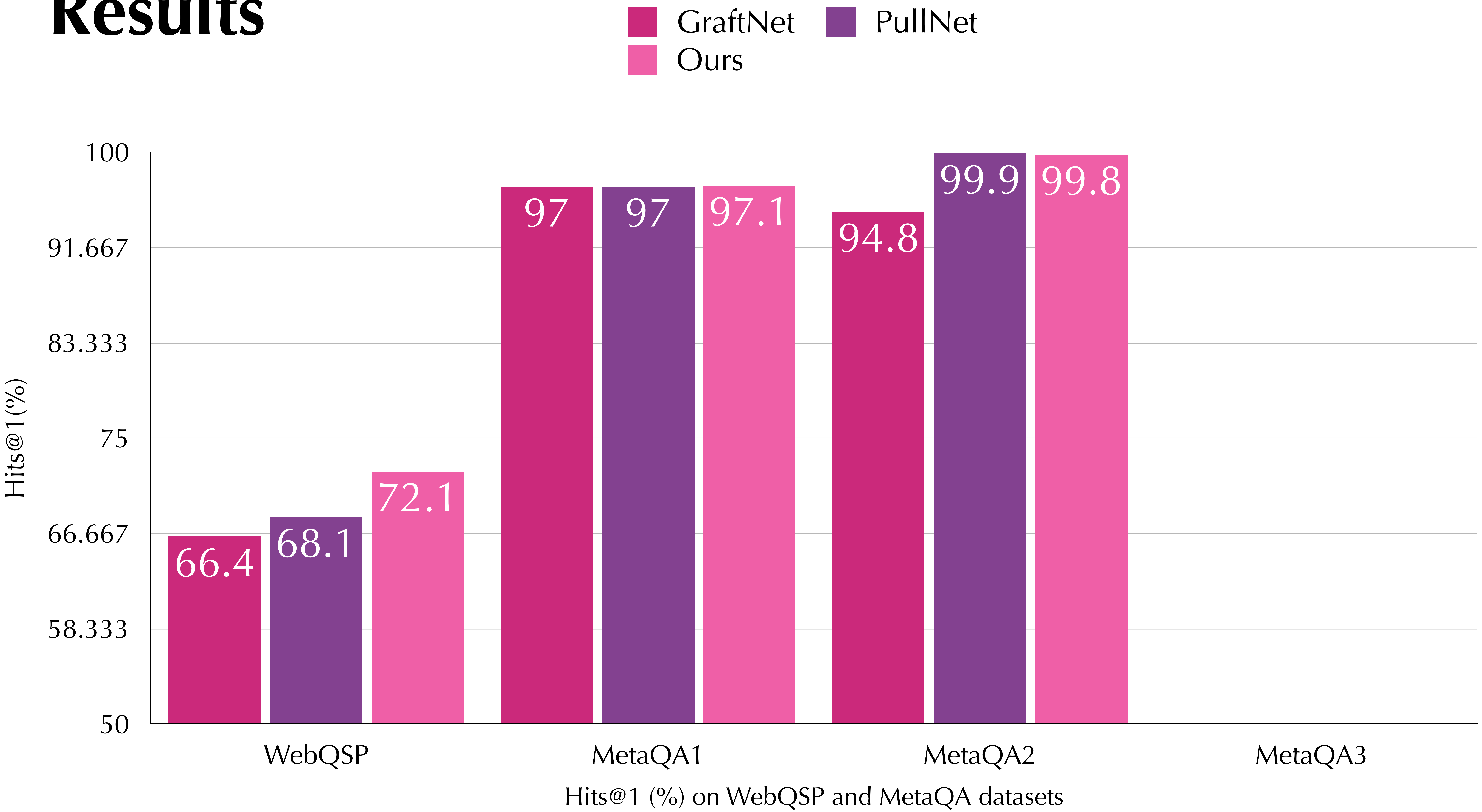
Hits@1(%)
66.4
68.1
72.1
97
97
97.1
WebQSP
MetaQA1
MetaQA2
MetaQA3
Hits@1 (%) on WebQSP and MetaQA datasets

Results



GraftNet
PullNet
Ours
100
91.667
83.333
75
66.667
58.333
50
Hits@1(%)
66.4
68.1
72.1
97
97
97.1
94.8
99.9
99.8
WebQSP
MetaQA1
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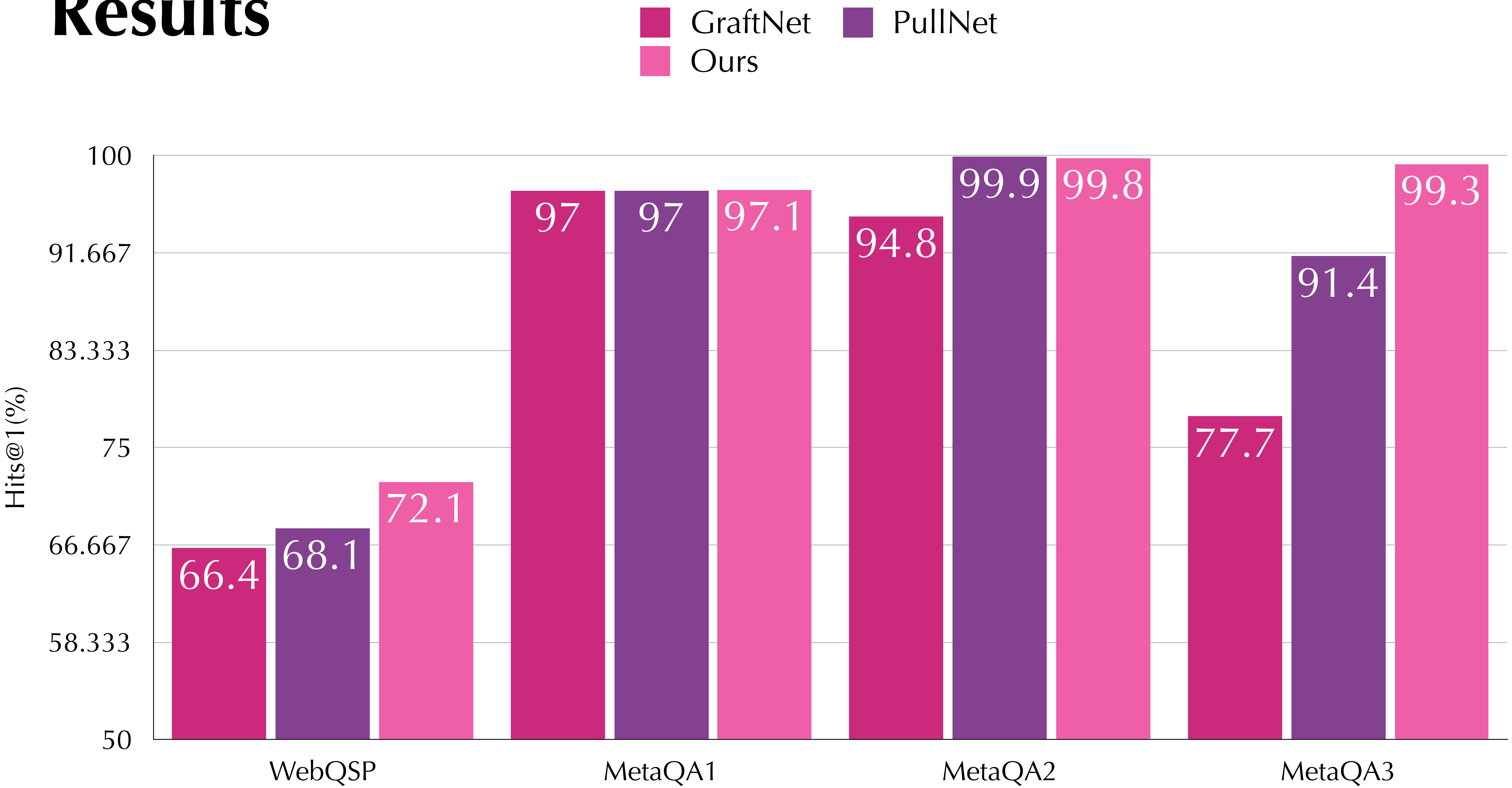
MetaQA3
Hits@1 (%) on WebQSP and MetaQA datasets

Results



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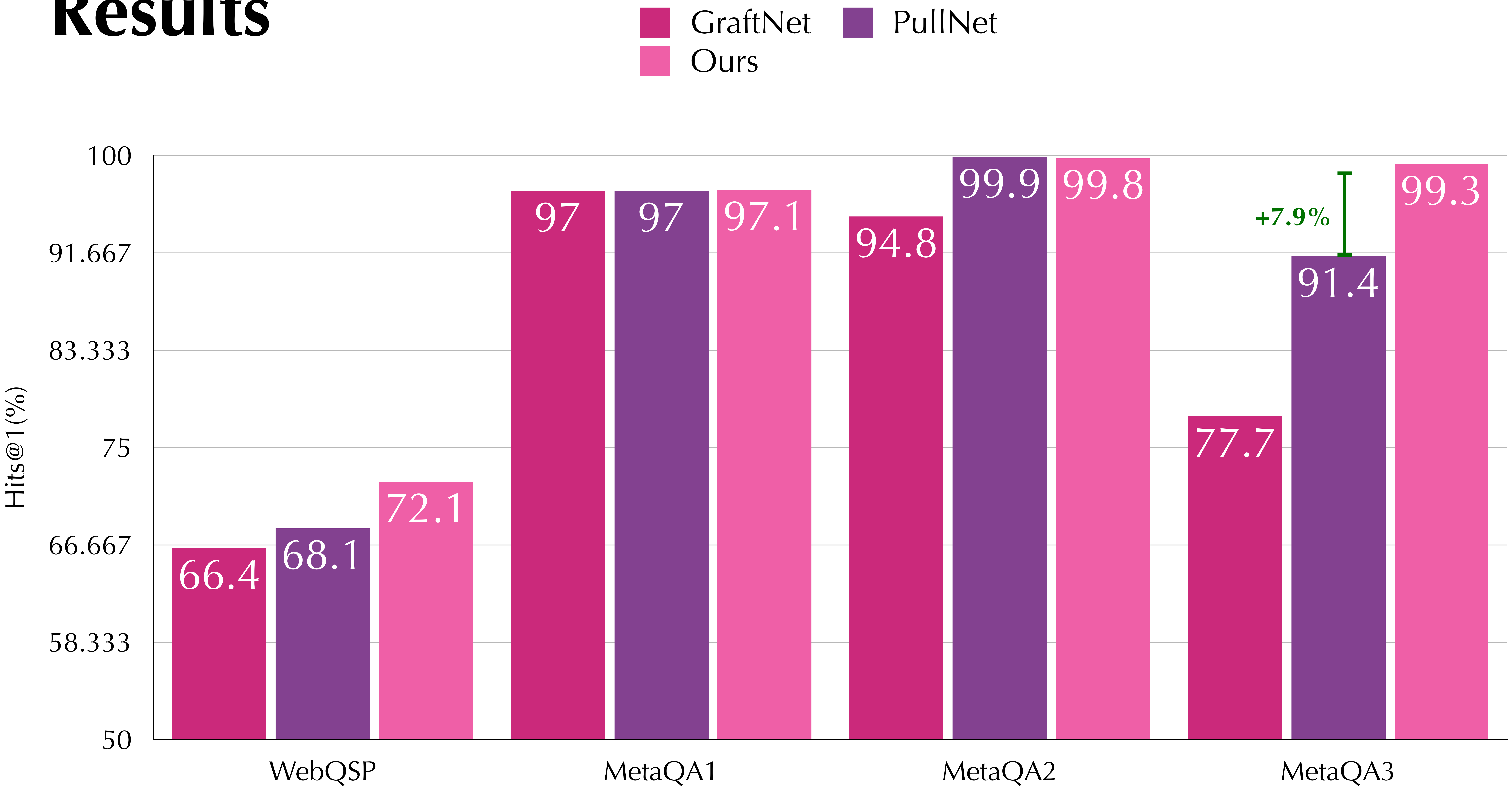
Results



Hits@1 (%) on WebQSP and MetaQA datasets

Results

Performance on FreebaseQA

Model	Accuracy (%)
KBQA-Adapter (Wu et al 2019)	28.78
FoFE (Jiang et al 2019)	37.00
BuboQA (Mohammed et al 2018)	38.25
Ours	**52.07**

Results

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KB-only models

+13%

Results

Performance on FreebaseQA

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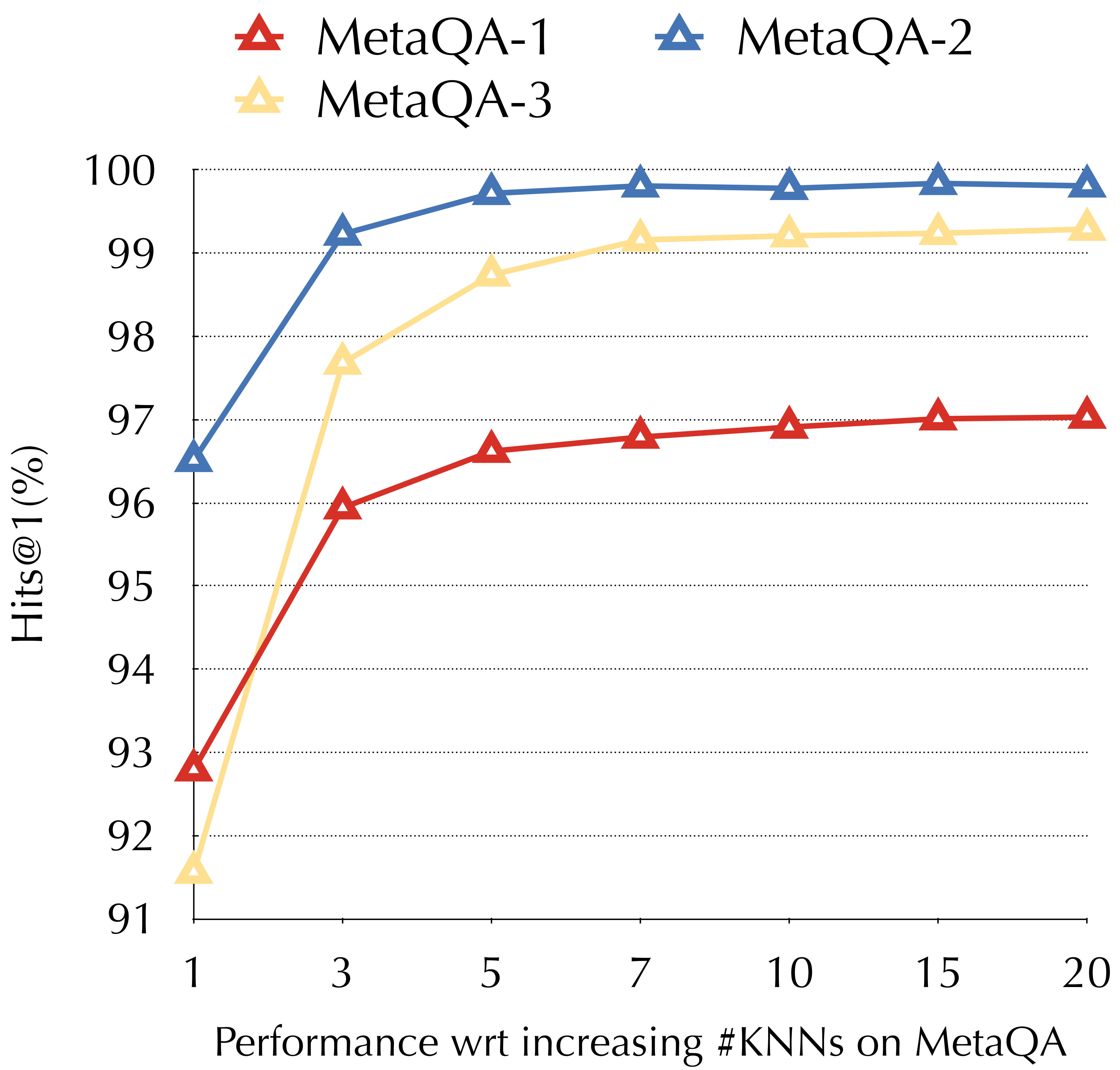
KB-only models	KBQA-Adapter (Wu et al 2019)	28.78
	FoFE (Jiang et al 2019)	37.00
	BuboQA (Mohammed et al 2018)	38.25
	Ours	**52.07**
Large LM + pre-training + KB	Entity-as-Experts (Fevry et al 2020)	53.4
	Facts-as-Experts (Verga et al 2021)	**63.3**

+13%

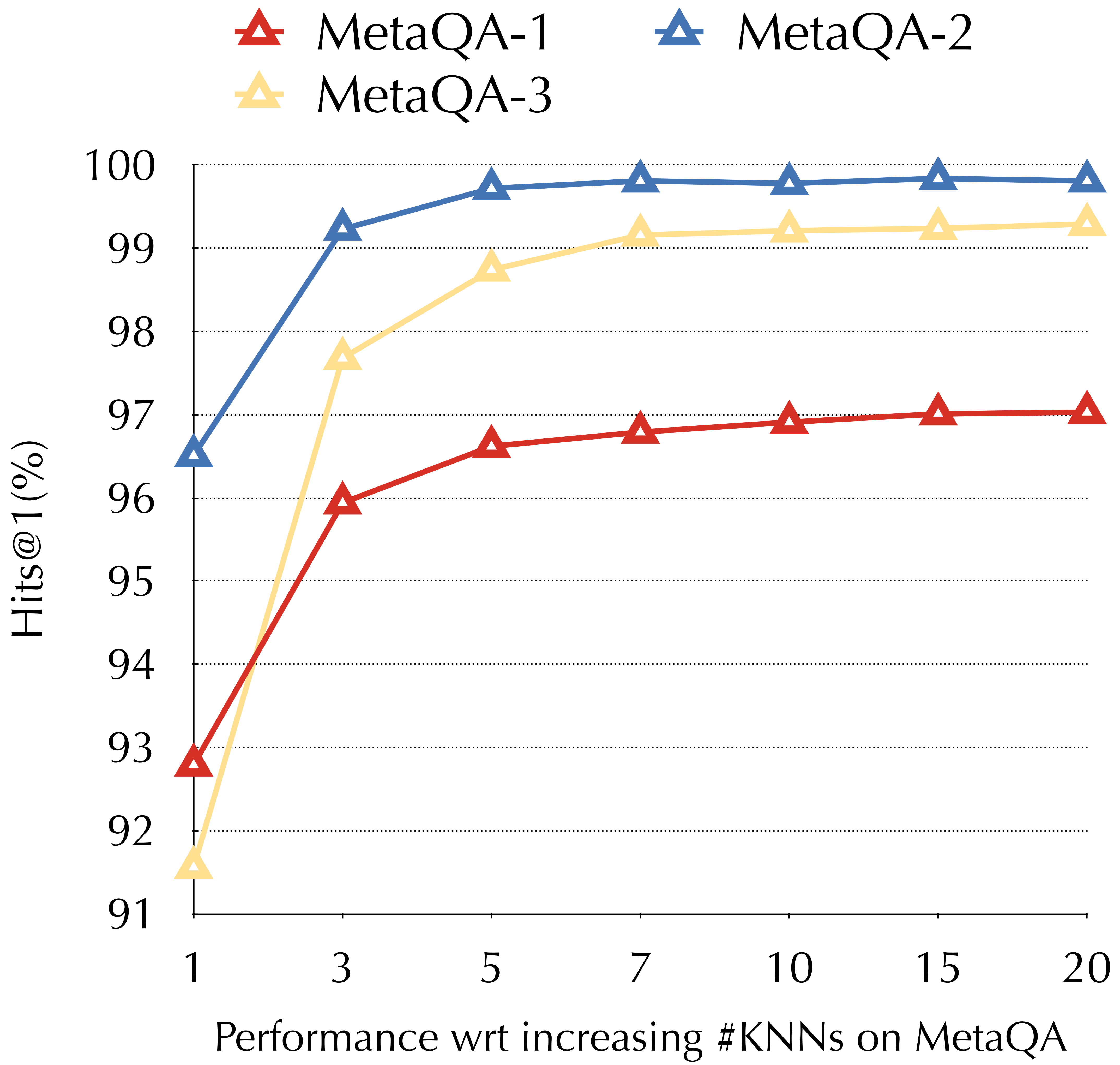
Analysis

Analysis



MetaQA-1
MetaQA-2
MetaQA-3
100
99
98
97
96
95
94
93
92
91
Hits@1(%)
1
3
5
7
10
15
20
Performance wrt increasing #KNNs on MetaQA

Analysis



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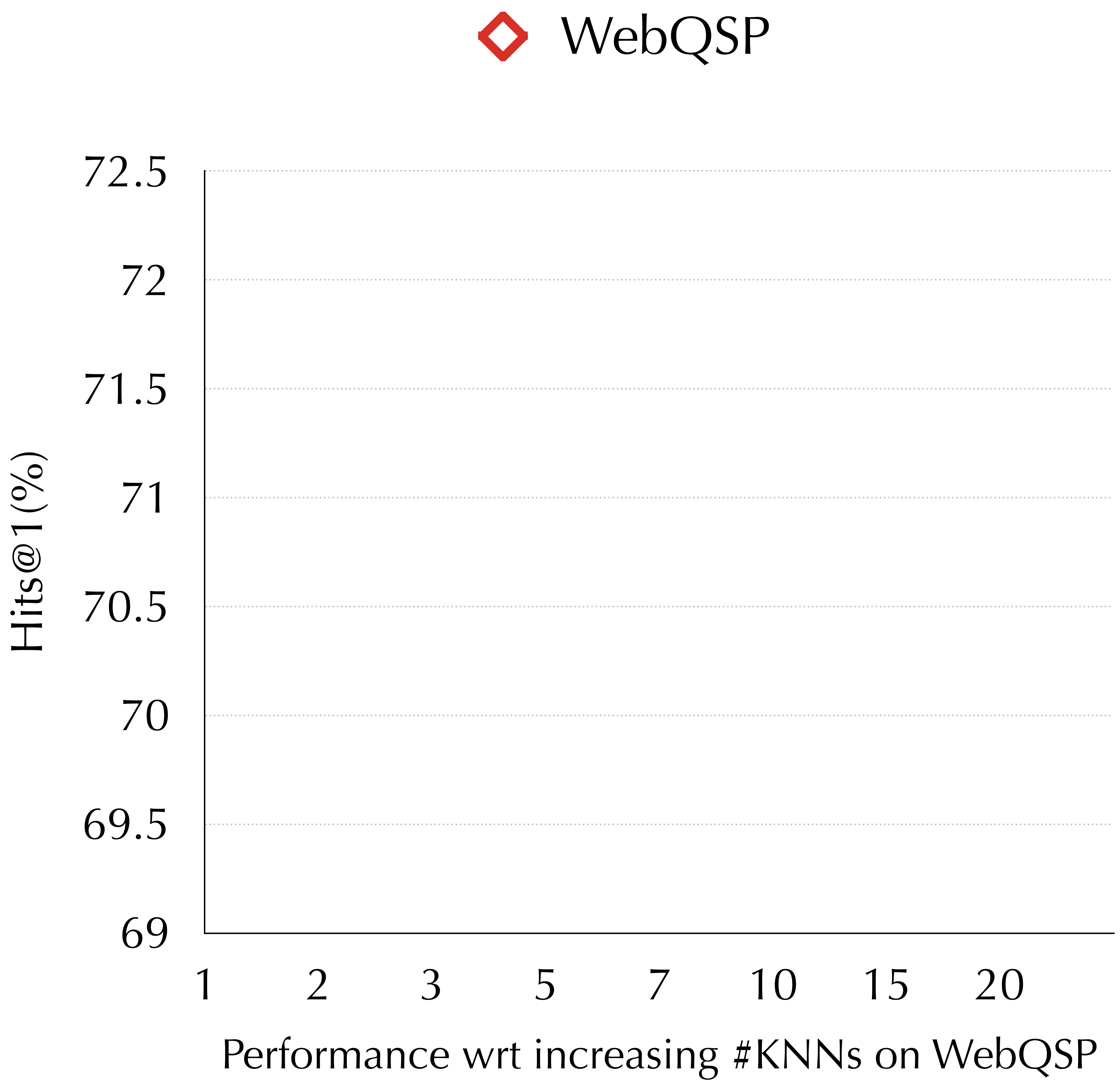
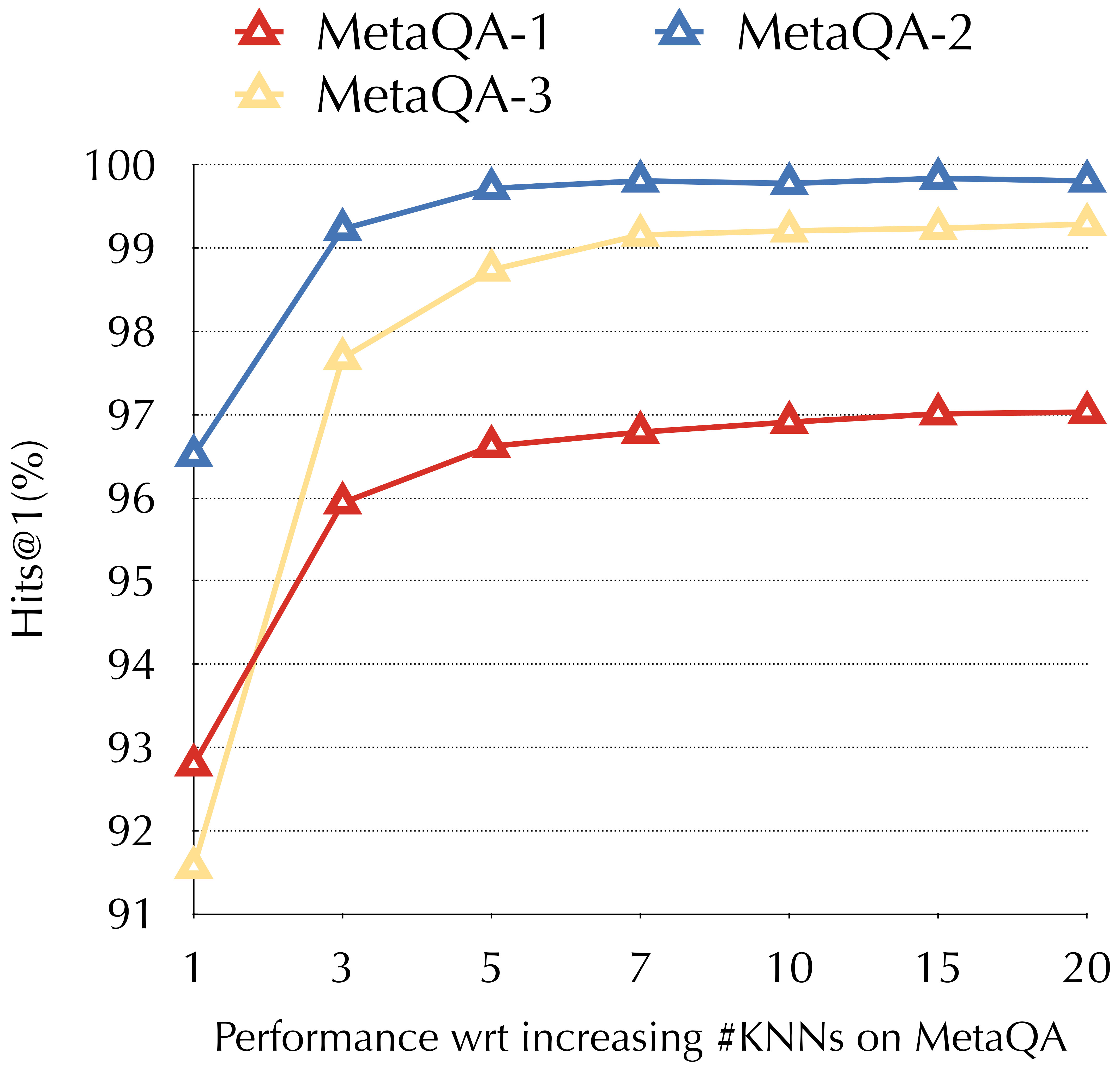


WebQSP
72.5
72
71.5
71
70.5
70
69.5
69
Hits@1(%)
1
2
3
5
7
10
15
20
Performance wrt increasing #KNNs on WebQSP

Analysis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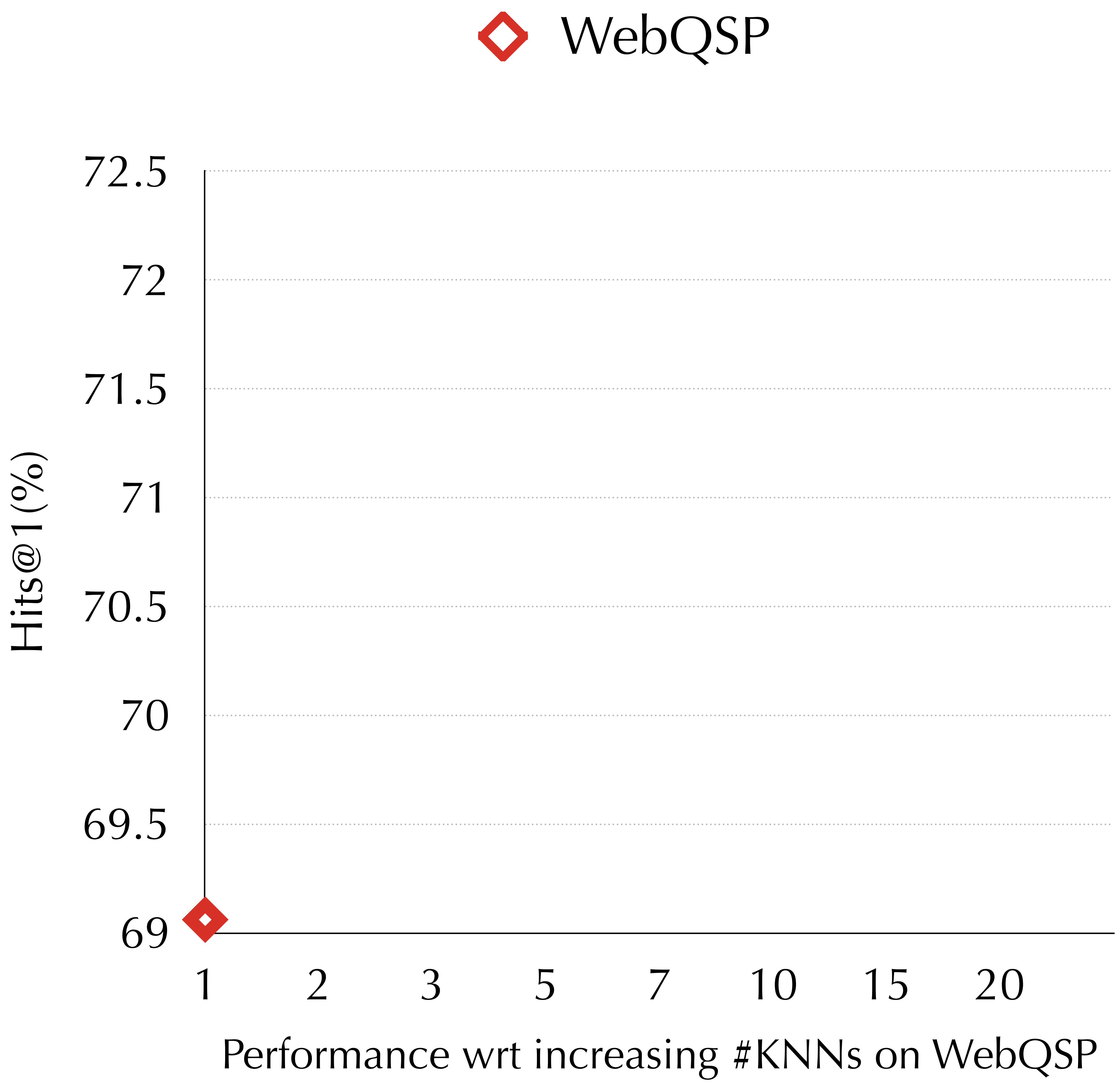
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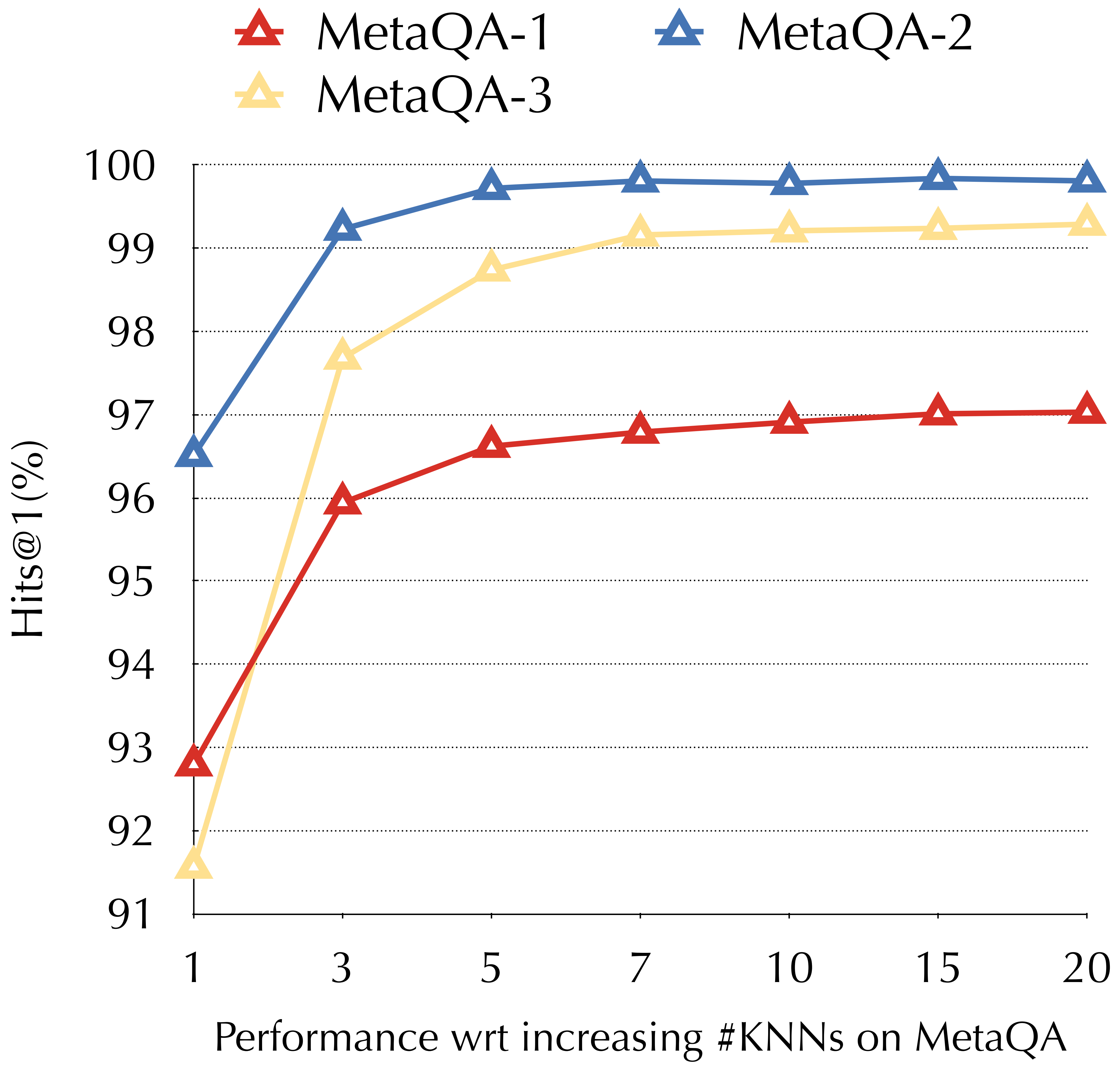
Performance wrt increasing #KNNs on WebQSP

Analysis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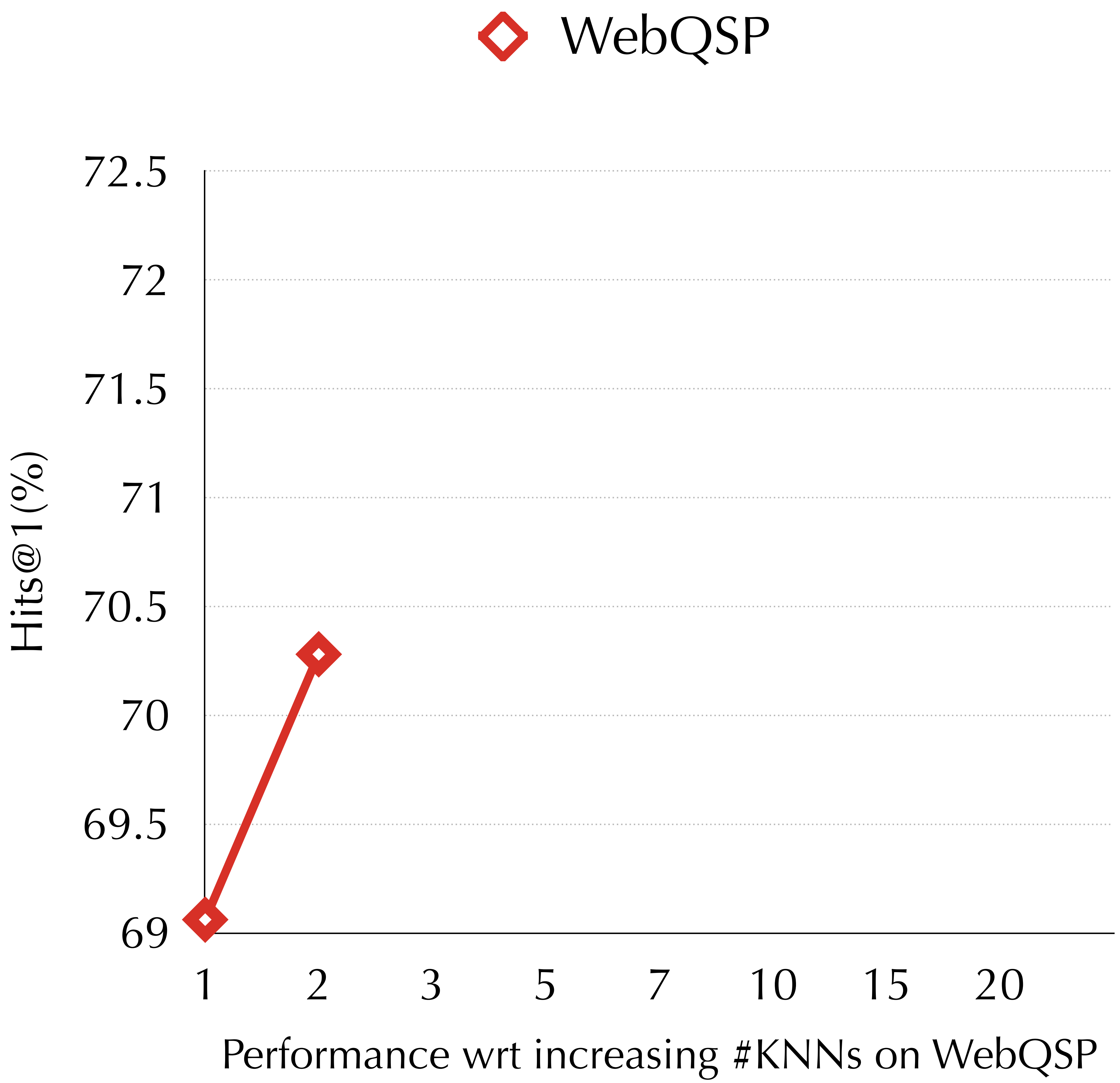
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Performance wrt increasing #KNNs on WebQSP

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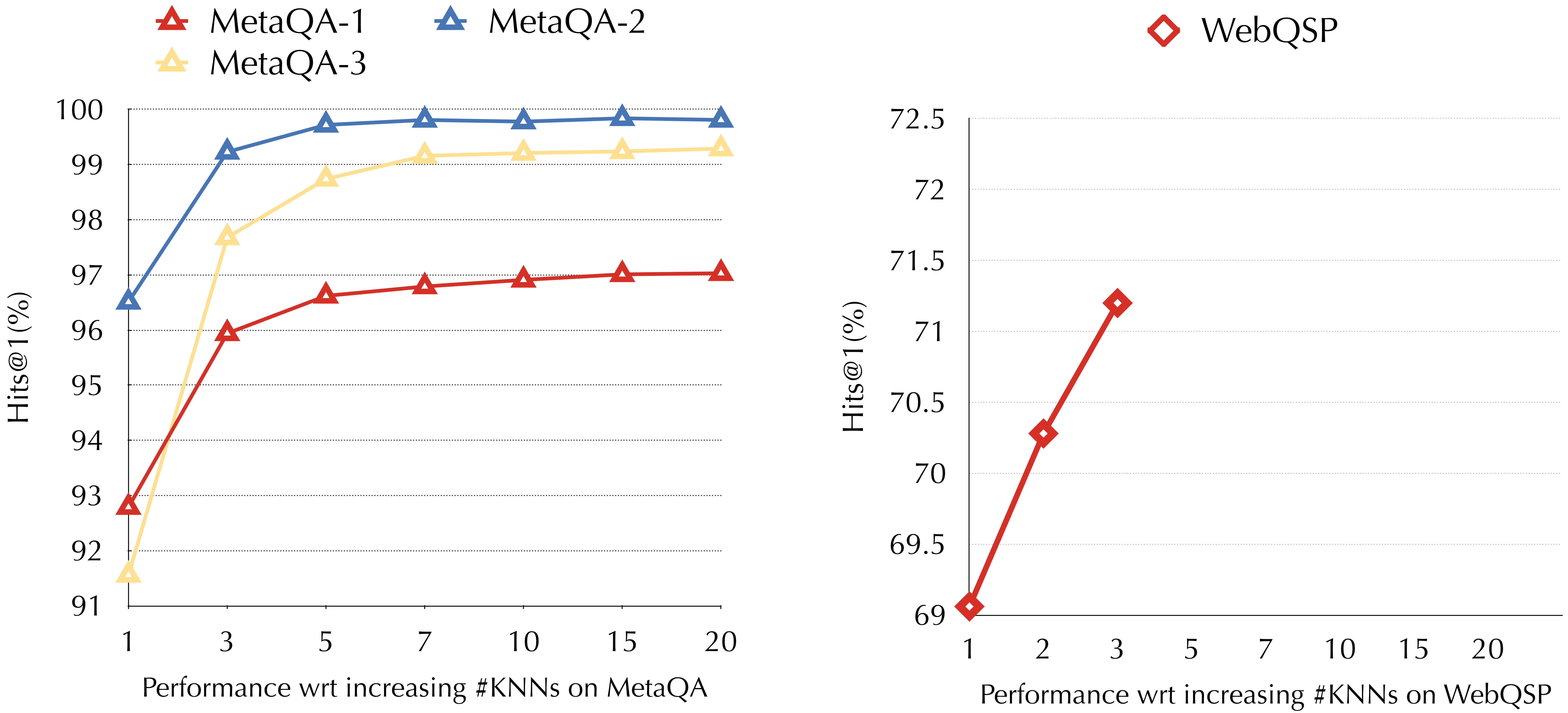

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Performance wrt increasing #KNNs on MetaQA
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Performance wrt increasing #KNNs on WebQSP

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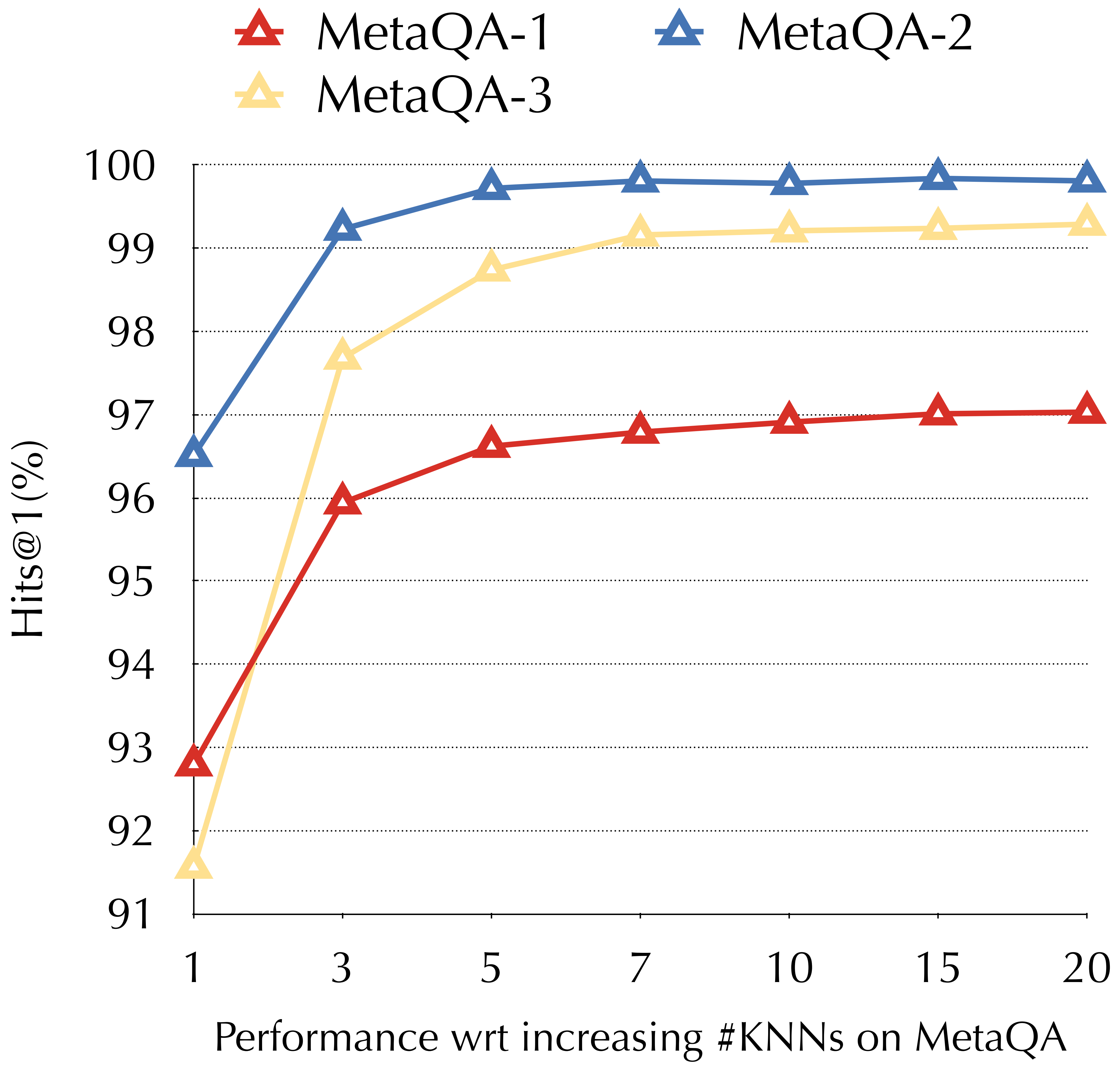
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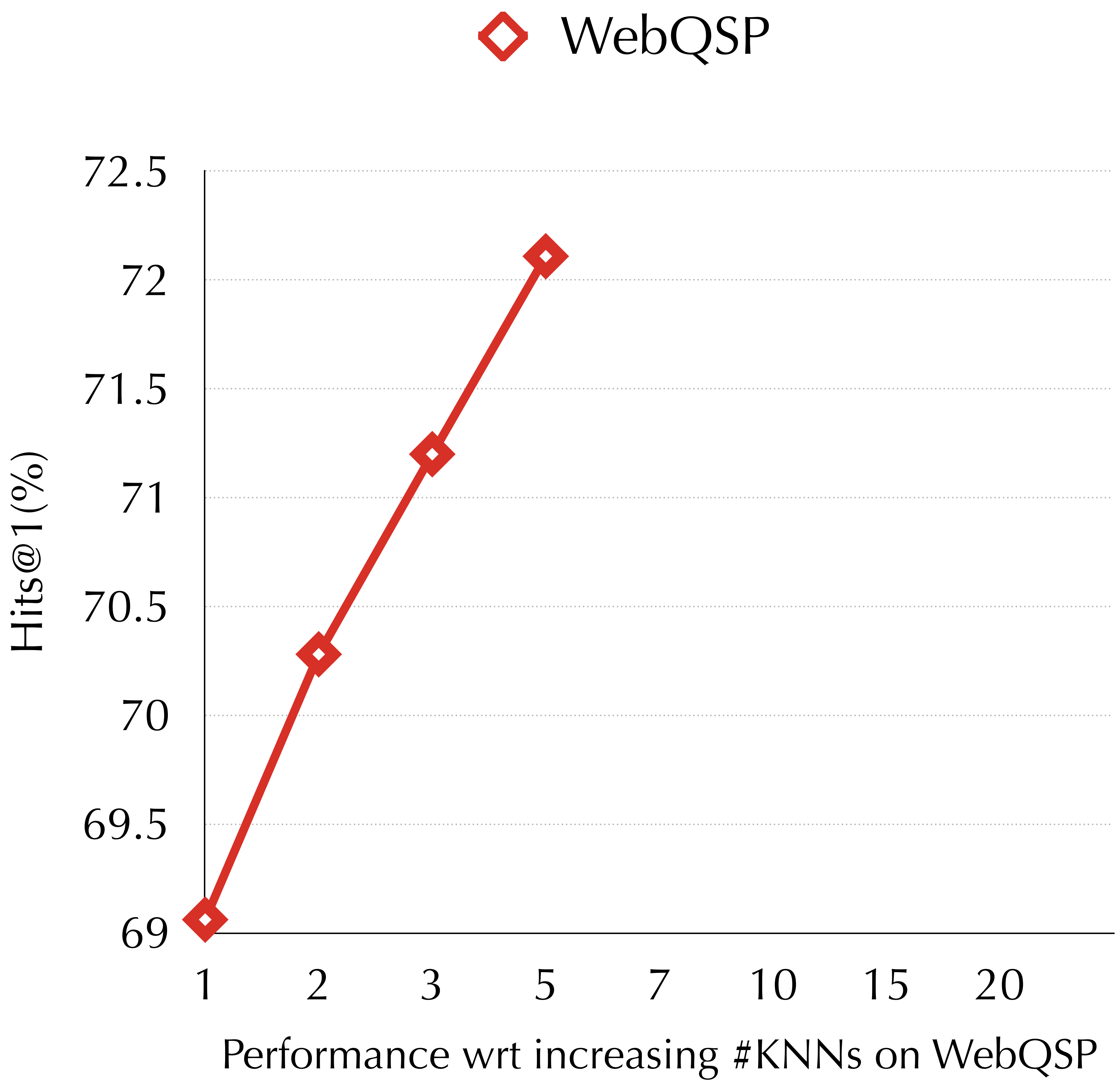
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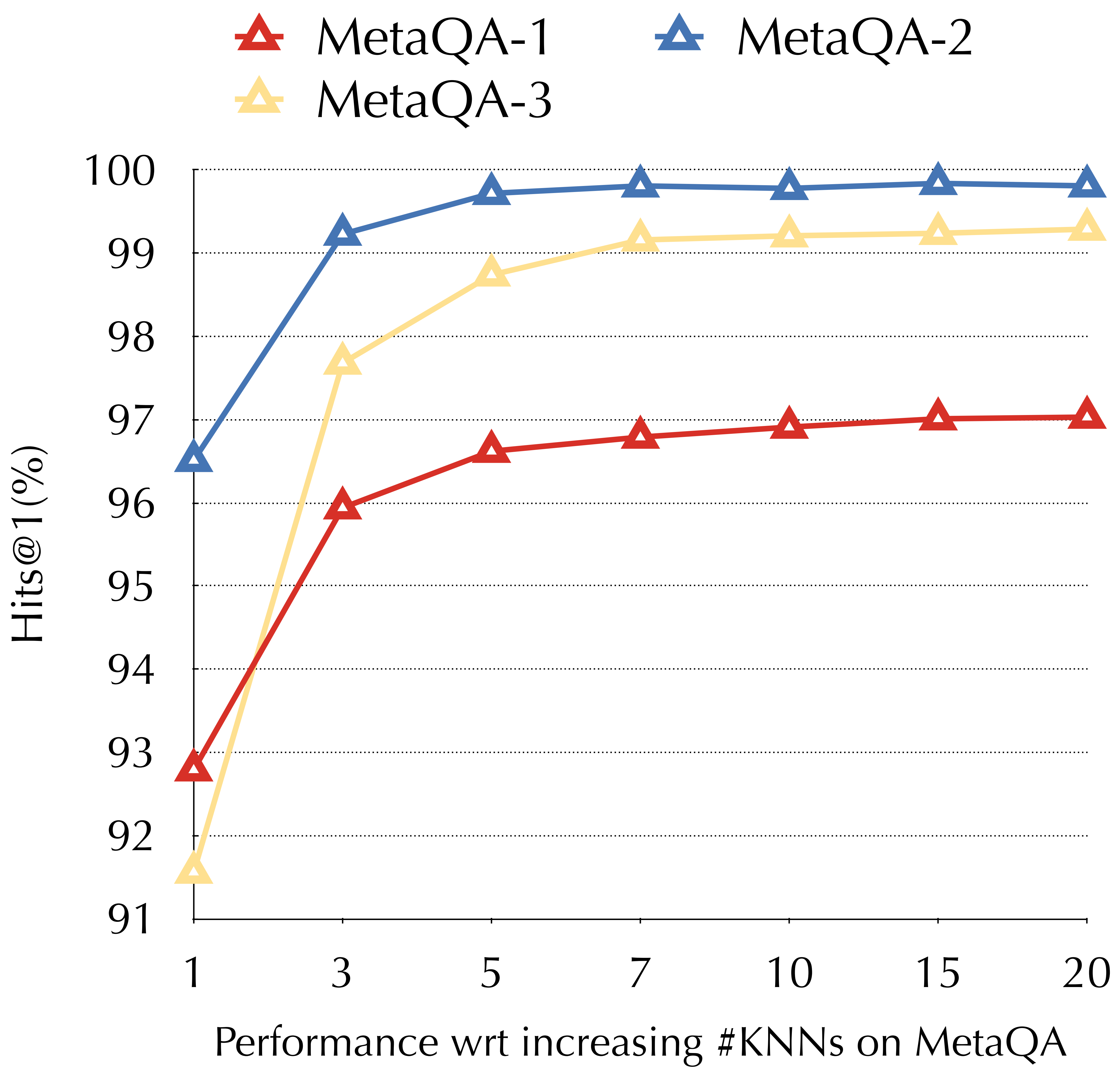
Performance wrt increasing #KNNs on WebQSP

Analysis



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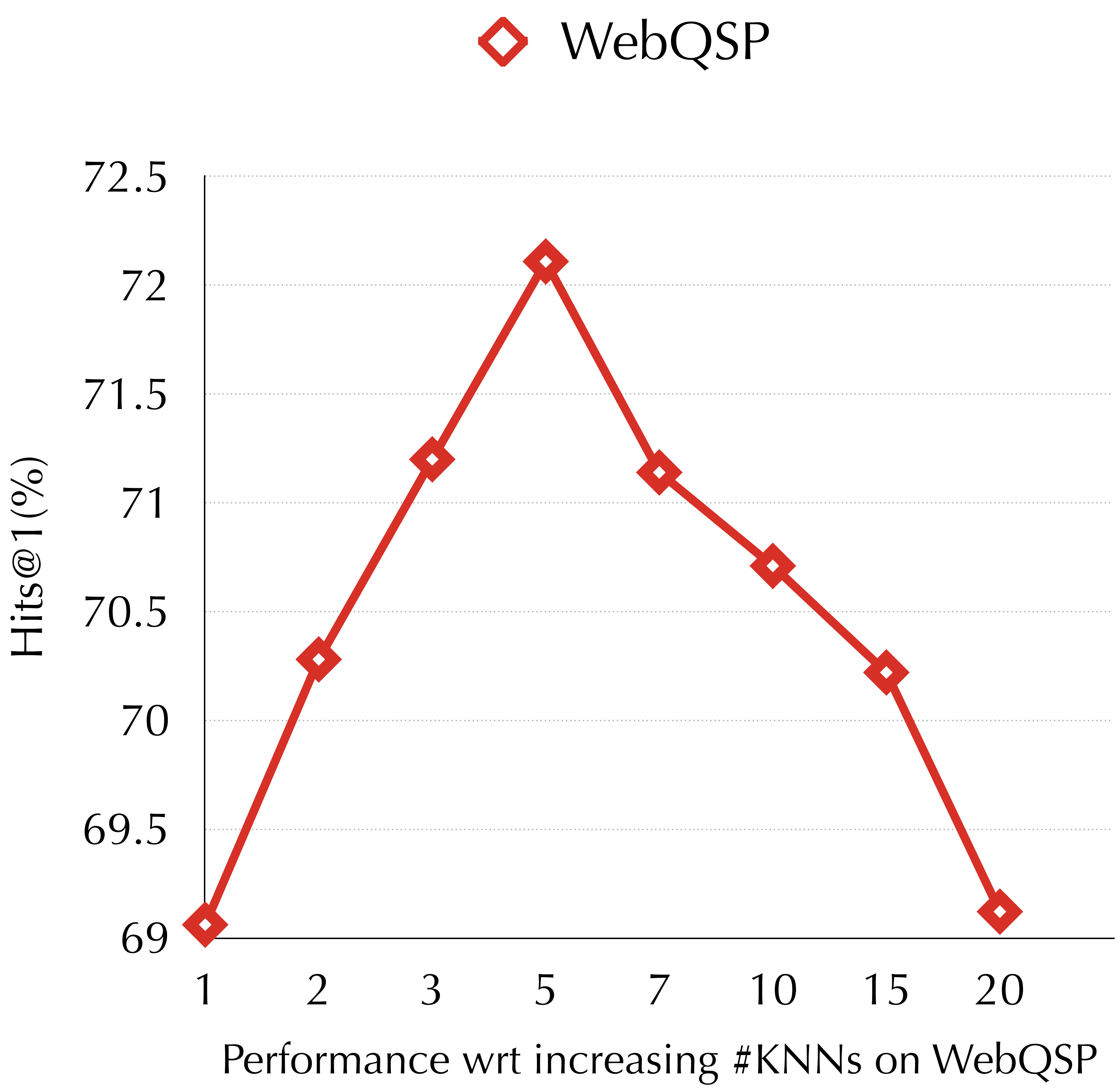

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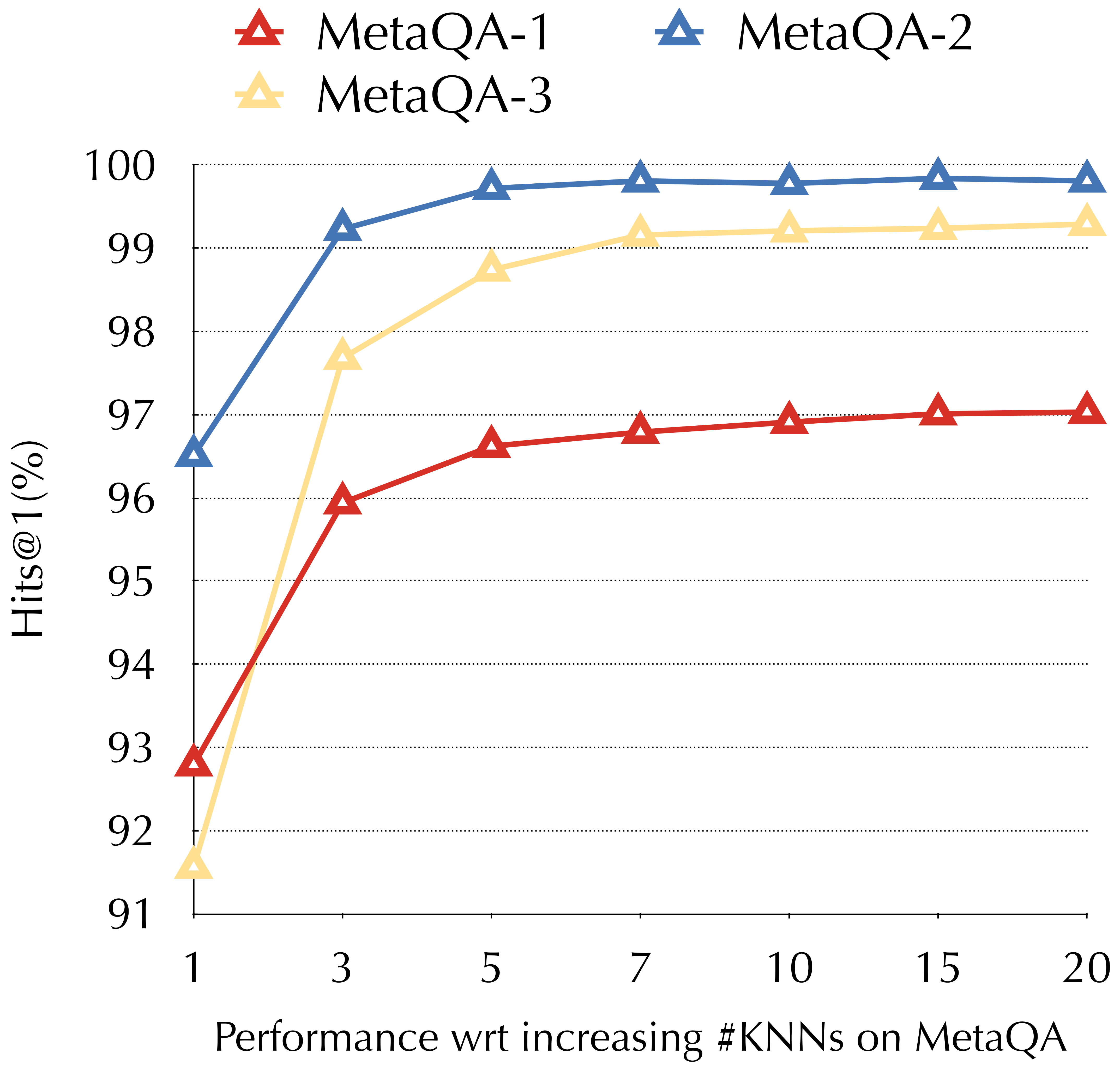
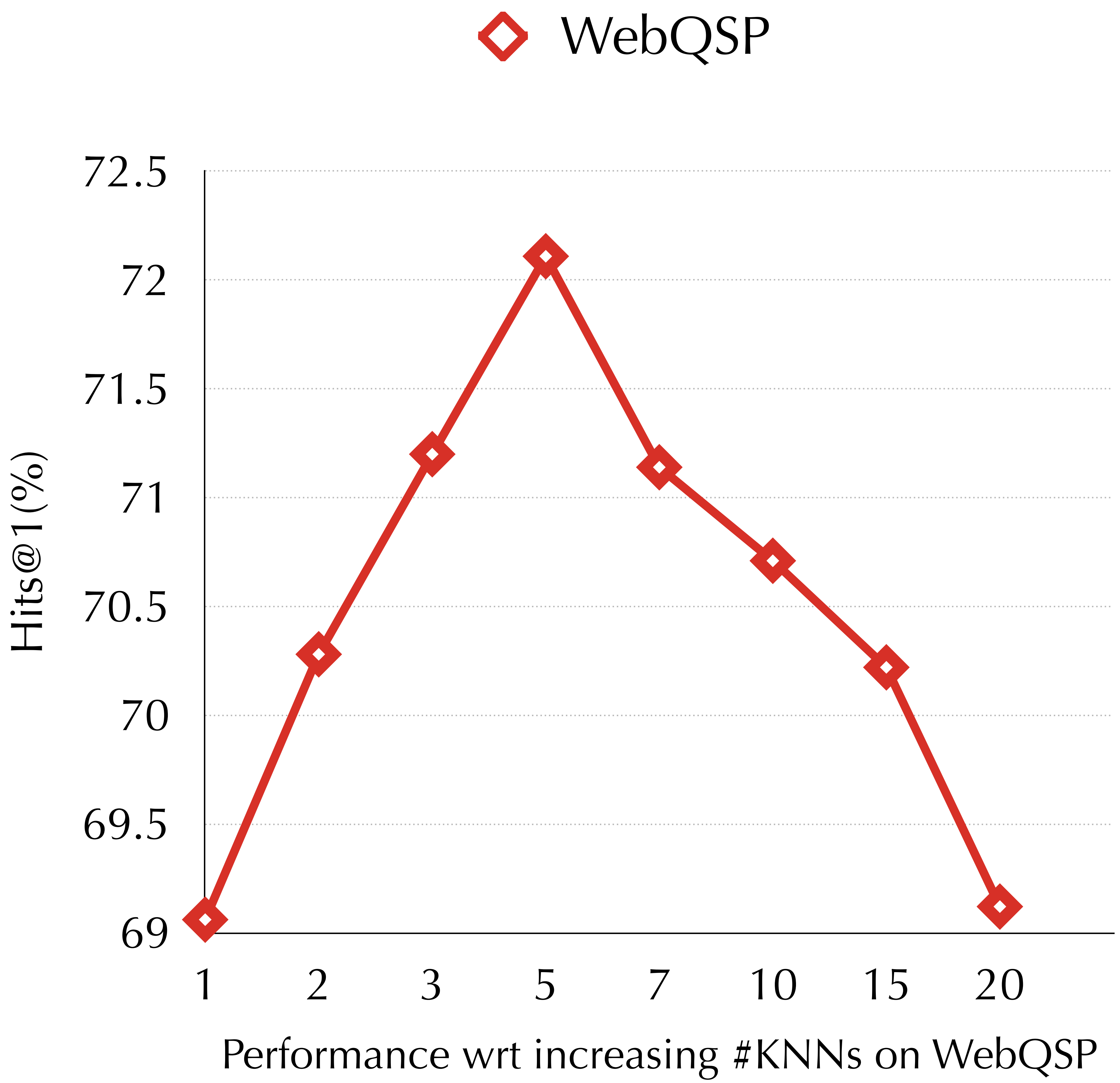
Performance wrt increasing #KNNs on WebQSP

Analysis

WebQSP has a small train set, hence adding more #KNNs ends up adding more noise





Analysis

Subgraph	#edges	#relations	#entities	coverage(%)
WebQSP				
Graft-net	4306.00	294.69	1447.68	89.93%
CBR-SUBG	2234.35	40.38	1627.37	94.30%
% diff	-48.11%	-86.5%	+12.4%	+4.85%
MetaQA-3				
Graft-net	1153.0	18.00	497.00	99%
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Table 5. Our adaptive subgraph collection strategy produces a compact subgraph for a query while increasing recall.

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Subgraph	WebQSP	MetaQA-3
GraftNet	65.61%	96.90%
Adaptive	71.92%	99.30%

Table 4. Performance of CBR-SUBG with adaptive subgraph and GraftNet subgraph

Summary

- This paper introduces a nonparametric approach for reasoning over subgraphs of similar questions to answer a given question
- Motivated by Case-based Reasoning
- Also proposed a novel adaptive subgraph collection strategy to produce query-specific subgraphs.
- Trained with contrastive learning objective and inference as KNN search.
- SoTA results on multiple KBQA benchmarks.

Summary

Contact:
Rajarshi Das
rajarshi@cs.washington.edu

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Poster: Session 1
Tuesday July 19

Code, Models, Data at