A Simple Approach to Case-Based Reasoning in Knowledge Bases


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Automated Reasoning

Automated Reasoning

- Ability to infer ***new facts*** from ***observed evidence***.

Automated Reasoning

- Ability to infer ***new facts*** from ***observed evidence***.
- Knowledge Bases (KBs) provide an excellent test bed for automated reasoning

Automated Reasoning

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Article Talk

United States

From Wikipedia, the free encyclopedia

"America", "US", "USA", and "United States of America" redirect here. For the landmass comprising North, Central, South America, and the Caribbean, see Americas. Fo
United States (disambiguation).

This article has multiple issues. Please help **improve it** or discuss these issues on the **talk page**. *(Learn how and when to remove thes*
- This article **may be too long to read and navigate comfortably**. *(February 2020)*
- This article **may contain an excessive amount of intricate detail that may interest only a particular audience**. *(February 2020*

The **United States of America** (**USA**), commonly known as the **United States** (**U.S.** or **US**) or **America**, is a country mostly located in central North America, between Cana
district, five major self-governing territories, and various possessions.[h] At 3.8 million square miles (9.8 million km^2), it is the world's third- or fourth-largest country by total ar
328 million,[7] the U.S. is the third most populous country in the world. The capital is Washington, D.C., and the most populous city is New York City.

Paleo-Indians migrated from Siberia to the North American mainland at least 12,000 years ago,[19] and European colonization began in the 16th century. The United States e
established along the East Coast. Numerous disputes between Great Britain and the colonies led to the American Revolutionary War lasting between 1775 and 1783, leadin

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Amherst, Massachusetts

From Wikipedia, the free encyclopedia

Coordinates: 42.367°N 72.517°W

Amherst (/ˈæmərst/ (listen))[4] is a town in Hampshire County, Massachusetts, United States, in the Connecticut River valley. As of the 2010 census, the population was 37,819,[5] making it the highest populated municipality in Hampshire County (although the county seat is Northampton). The town is home to Amherst College, Hampshire College, and the University of Massachusetts Amherst, three of the Five Colleges. The name of the town is pronounced without the *h* ("AM-erst") by natives and long-time residents,[6] giving rise to the local saying, "only the 'h' is silent", in reference both to the pronunciation and to the town's politically active populace.[7]

Amherst has three census-designated places; Amherst Center, North Amherst, and South Amherst.

Amherst is part of the Springfield, Massachusetts Metropolitan Statistical Area. Lying 22 miles (35 km) north of the city of Springfield, Amherst is considered the northernmost town in the Hartford-Springfield Metropolitan Region, "The Knowledge Corridor".

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1 History
2 Geography and climate
3 Demographics
3.1 Income

Amherst, Massachusetts

Town

Left-right from top: Town Hall, Congregational Church in North Amherst, University of Massachusetts Amherst, Mount Norwottuck, Downtown Amherst

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University of Massachusetts Amherst

From Wikipedia, the free encyclopedia

Coordinates: 42°23′20″N 72°31′40″W

Not to be confused with Amherst College.

The **University of Massachusetts Amherst** (**UMass Amherst**, **UMass**, or **Massachusetts**) is a public research and land-grant university in Amherst, Massachusetts. It is the flagship campus of the University of Massachusetts system. UMass Amherst has an annual enrollment of approximately 1,300 faculty members and more than 30,000 students.[5] The university offers academic degrees in 109 undergraduate, 77 master's and 48 doctoral programs. Programs are coordinated in nine schools and colleges.[5] It is also a member of the Five College Consortium.

The University of Massachusetts Amherst is classified among "R1: Doctoral Universities – Very high research activity".[12] In fiscal year 2014, UMass Amherst had research expenditures exceeding

UMass Amherst sports teams are the Minutemen and Minutewomen, the colors being maroon, black, and white; the school mascot is Sam the Minuteman. All teams participate in NCAA Division I, the Atlantic 10 Conference, while playing ice hockey in Hockey East and football as an FBS Independent.

University of Massachusetts Amherst

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3.2

Rajarshi Das is a Ph.D. student working with Prof. Andrew McCallum and
students!. He completed his Master's from the Language Technologies I
University. There he had a lot of fun working with Prof. Chris Dyer and Pr
Bachelor's in Computer Science from NIT Calicut, India

His research interests are in reasoning on knowledge bases and text, ope
sense reasoning.

He used to co-organize the weekly Machine Learning and Friends Lunch

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University of Massachusetts Amherst
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+1 413 545-1323 (vox)
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Contact
Bio
Vita

Publications
Talks
Projects

Lab
People
Code
Data

Research

The main goal of my research is to dramatically increase our ability to mine actionable knowledge from unstructured text. I am especially interested in information extraction from the We
organizations, expert finding, social network analysis, and mining the scientific literature & community. Toward this end my group develops and employs various methods in statistical ma
and data mining---tending toward probabilistic approaches and graphical models. For more information see our current projects and publications.

News

- We are building an "open reviewing" system for ICLR 2013 and other venues. If you are interested in alternative approaches to peer review, please talk with me!
- FACTORIE is a toolkit for deployable probabilistic modeling, implemented as a software library in Scala. It provides its users with a succinct language for creating relational factor
- I was the General Chair of ICML 2012, with Program Chairs Joelle Pineau and John Langford.
- Generalized Expectation is an accurate way to train models by labeling features.
- We have publicly launched Rexa, a new research paper search engine. It is a sibling to CiteSeer and Google Scholar, except that it provides search and browsing over more "obje

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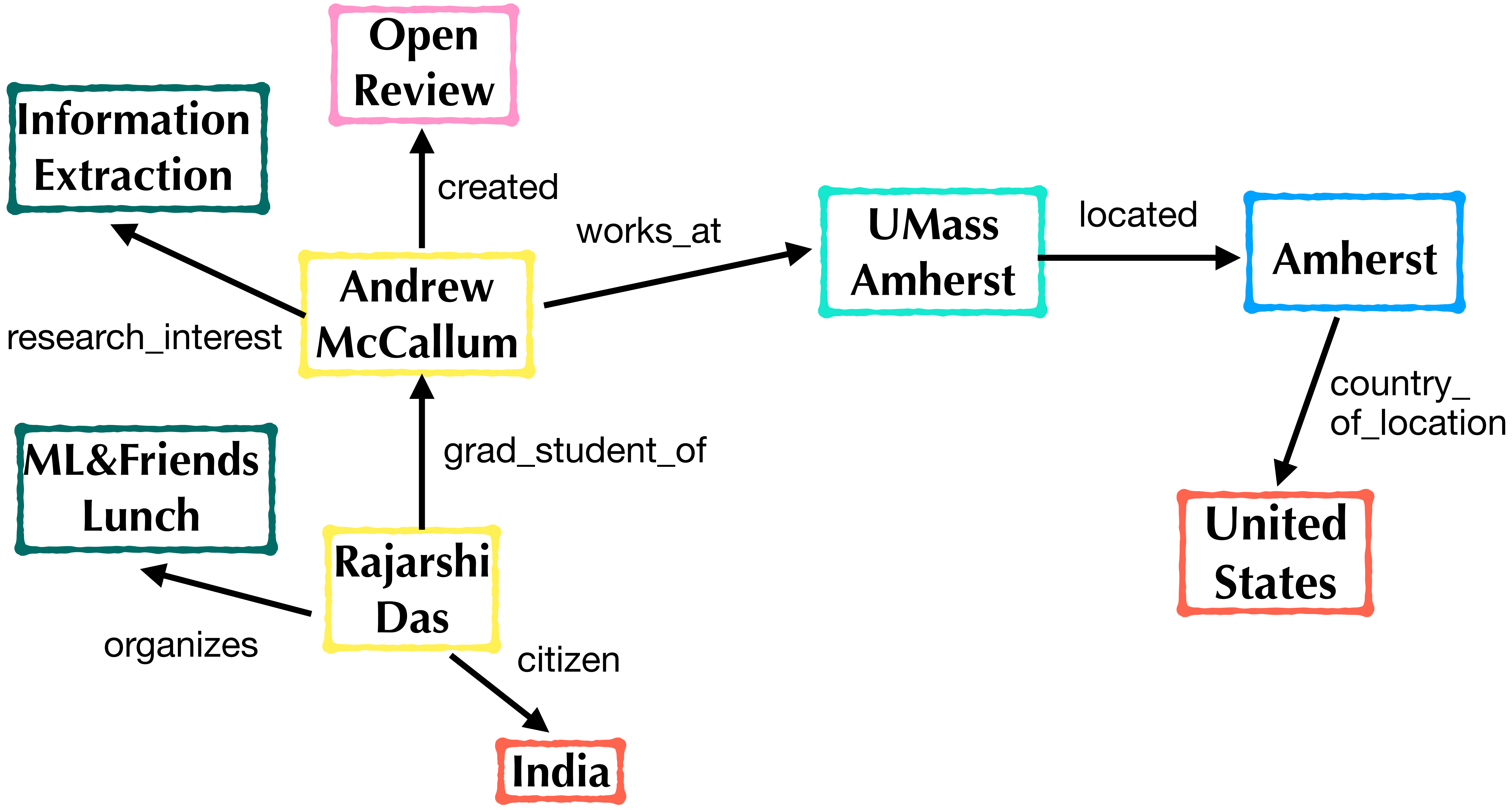

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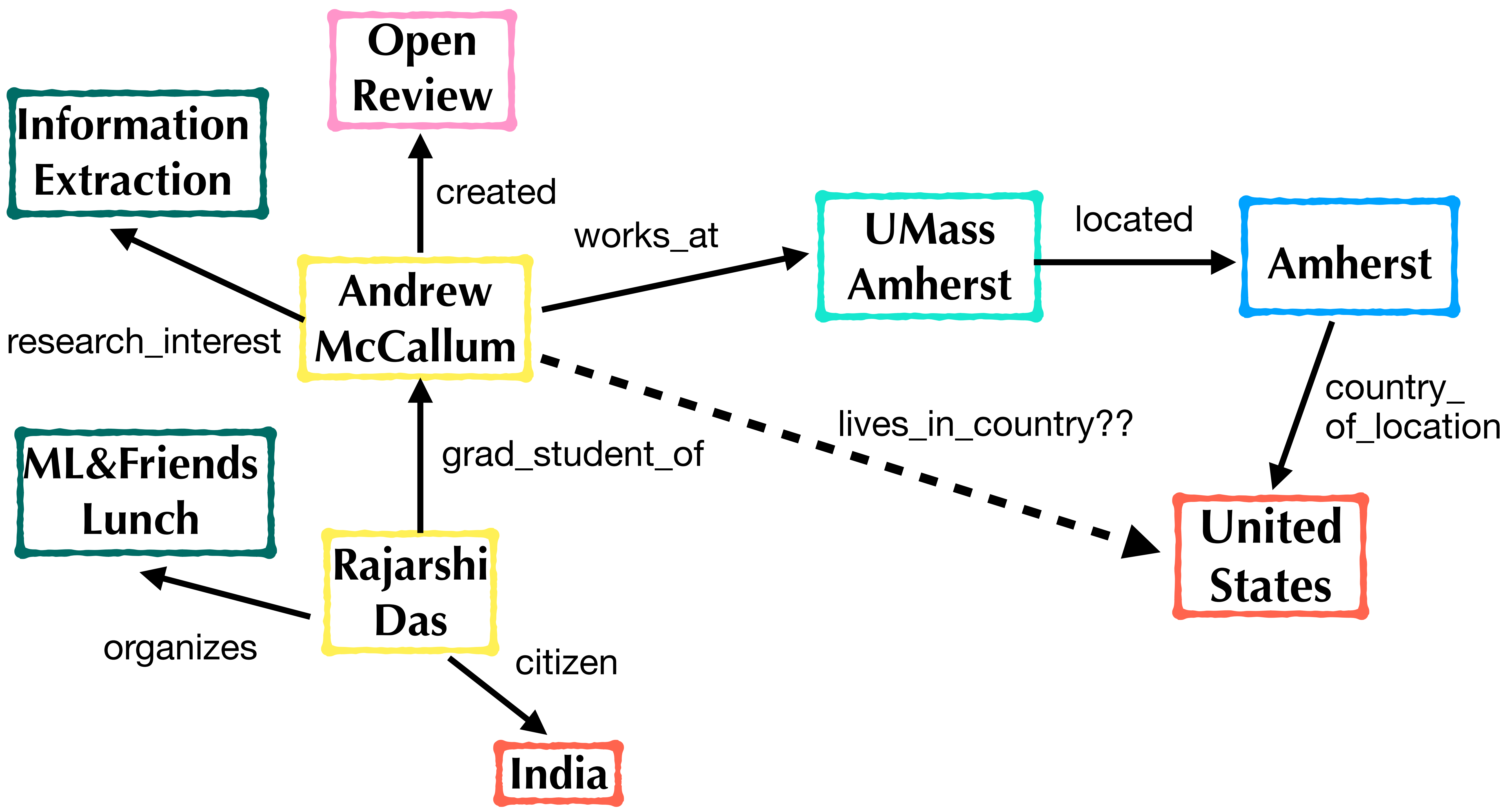

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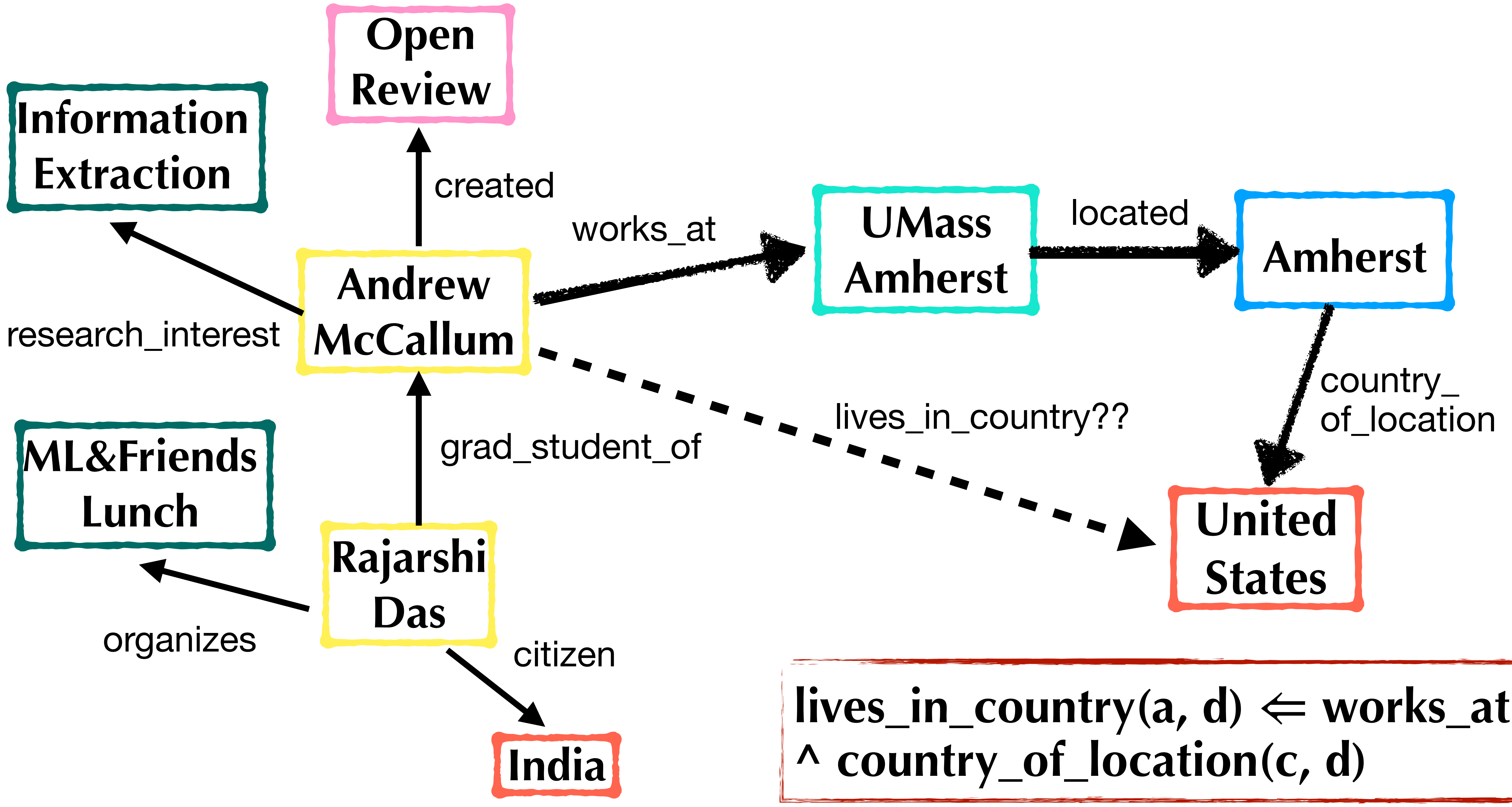
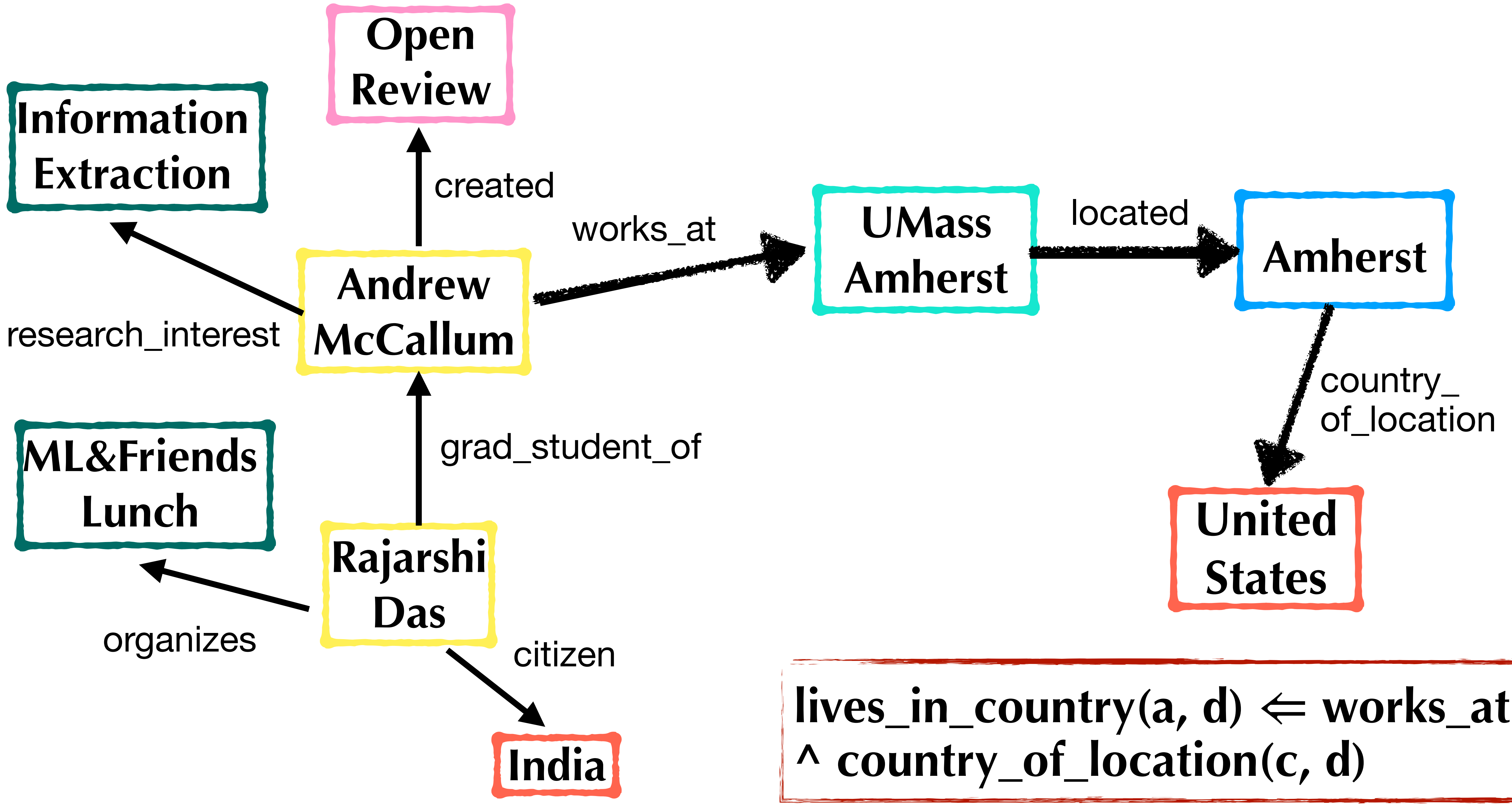


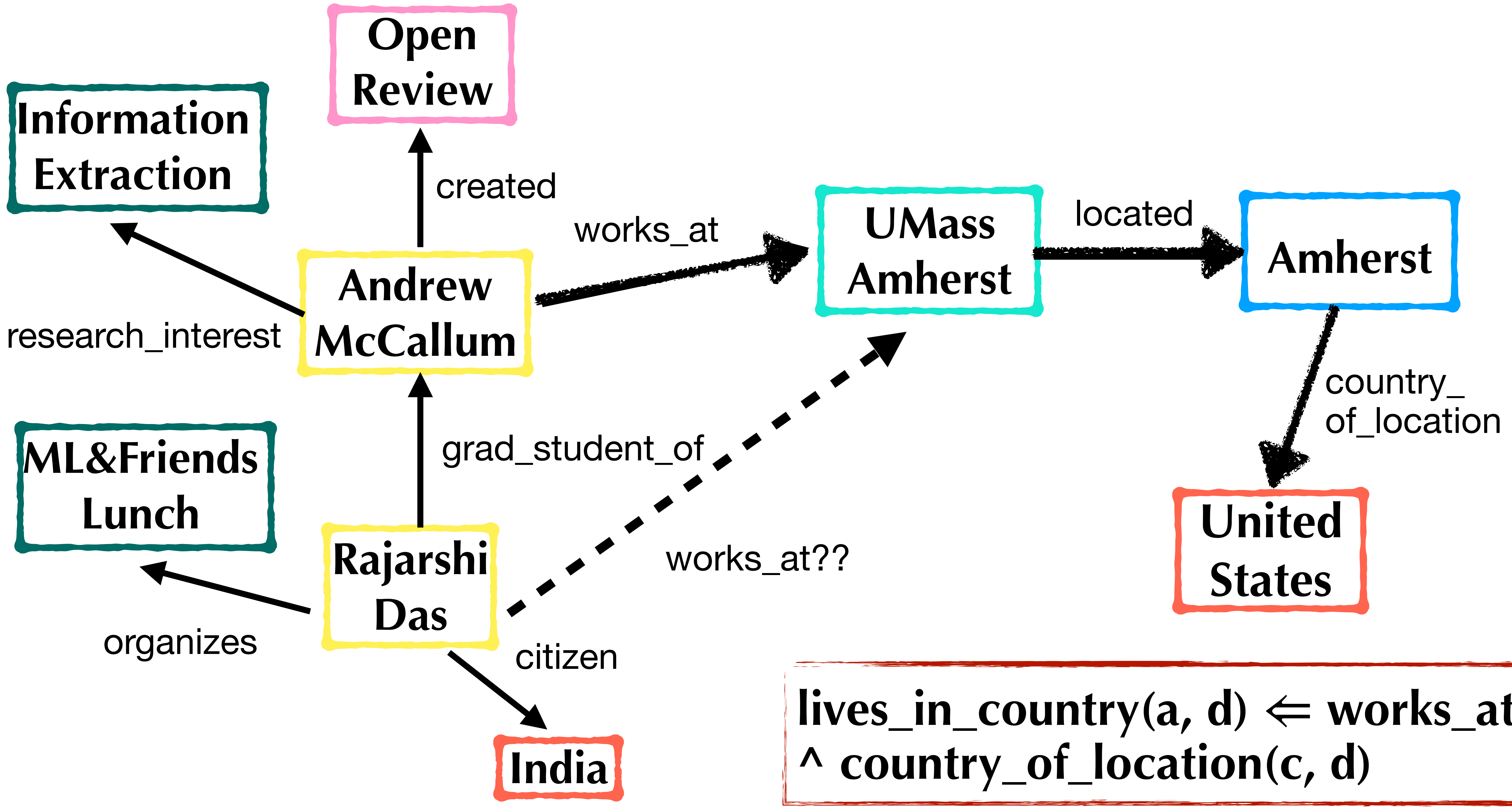
$$\textbf{lives\_in\_country}(a, d) \Leftarrow \textbf{works\_at}(a, b) \wedge \textbf{located}(b, c) \wedge \textbf{country\_of\_location}(c, d)$$

Automated Reasoning



lives_in_country(a, d) ⇐ works_at(a, b) ^ located(b, c) ^ country_of_location(c, d)

Automated Reasoning



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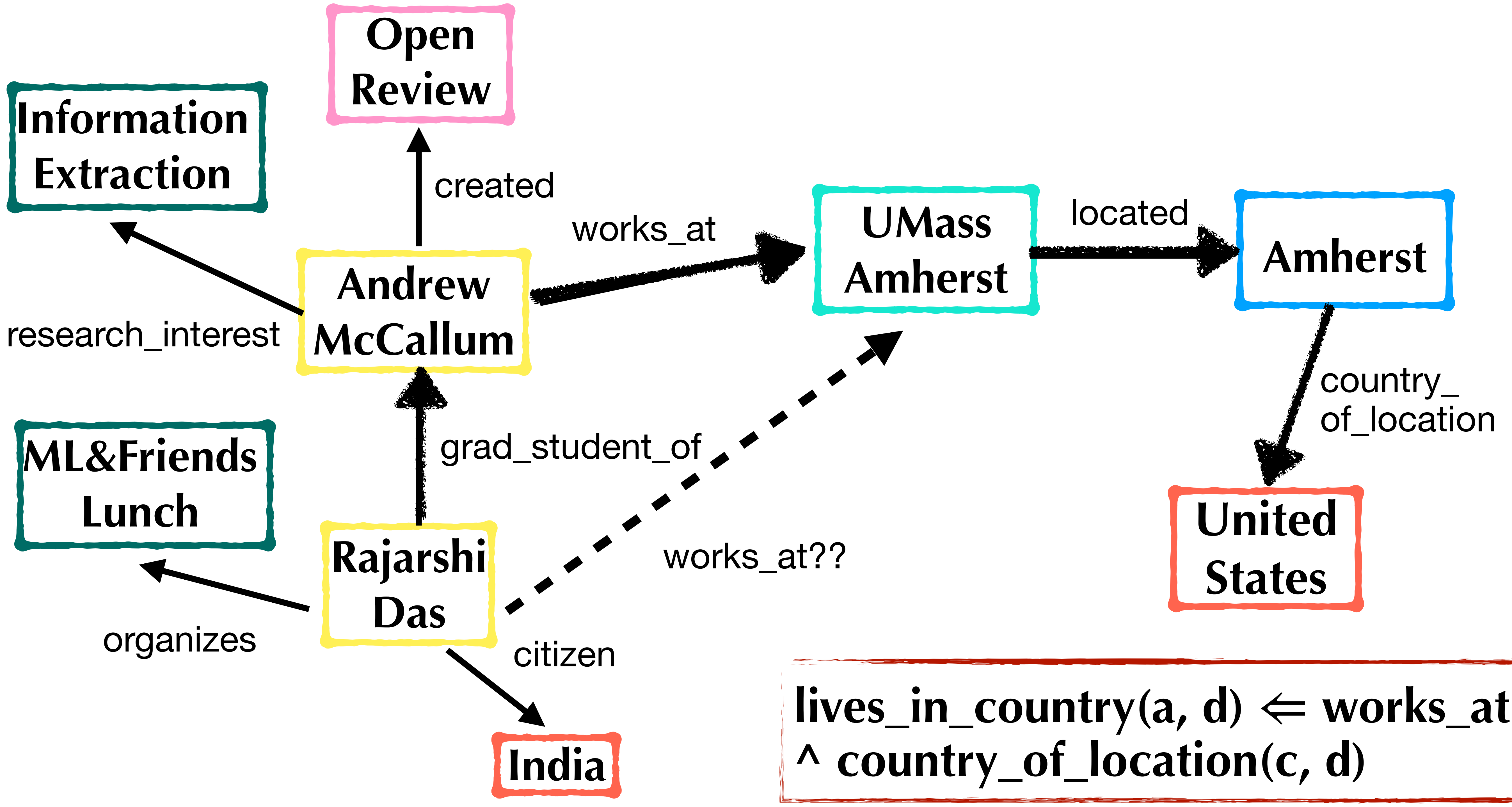
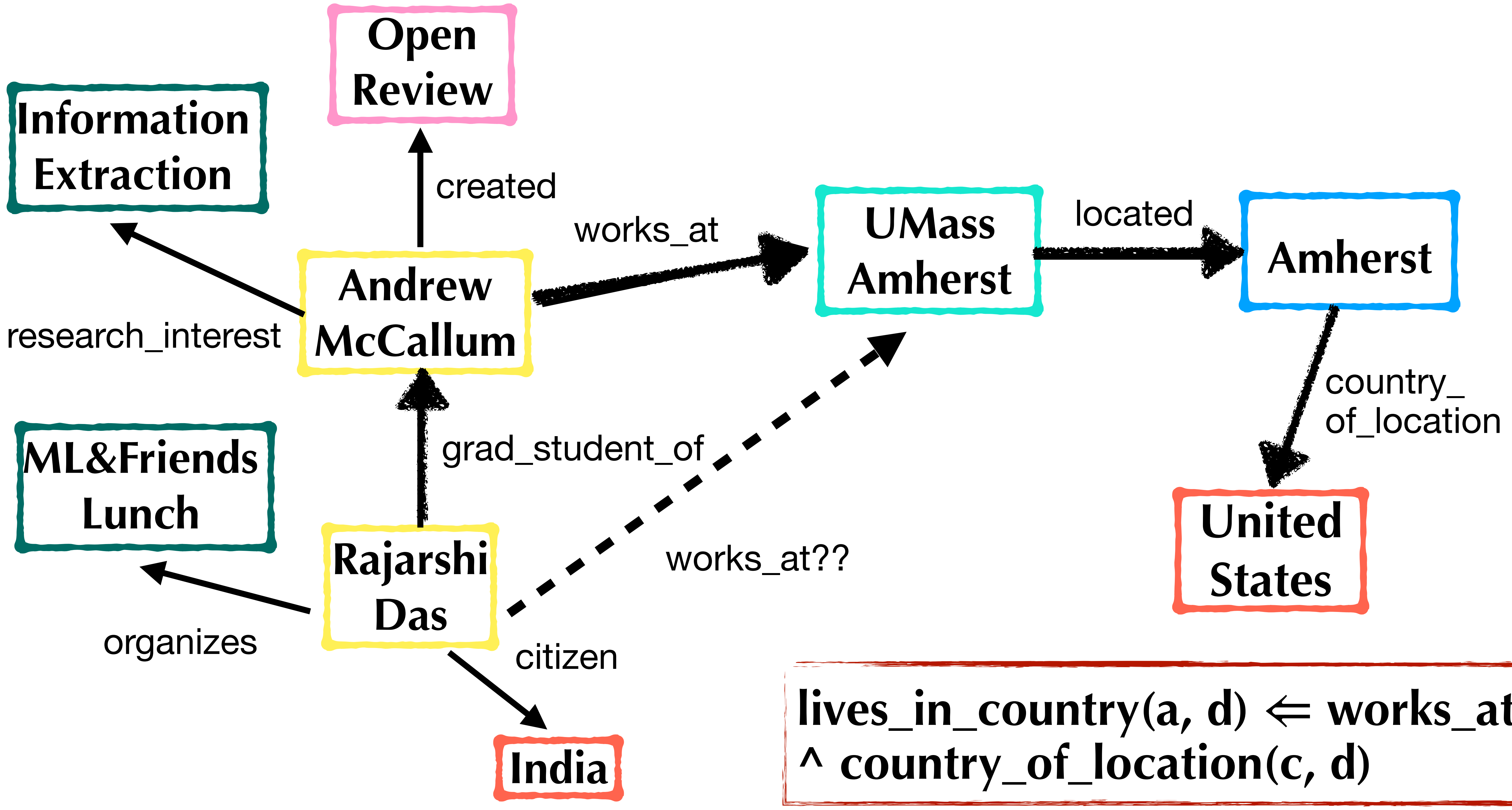


lives_in_country(a, d) ⇐ works_at(a, b) ^ located(b, c) ^ country_of_location(c, d)

works_at(x, z) ⇐ grad_student_of(x, y) ^ works_at(y, z)

Automated Reasoning



Store rules for logical inference in the model parameters.

- (Lao, Mitchell, Cohen EMNLP 2011)
- (Neelakantan, Roth, McCallum ACL 2015)
- (Das, Neelakantan, Belanger, McCallum EACL 2017)
- (Rocktäschel and Riedel Neurips 2017)
- (Xiong, Hoang, Wang EMNLP 2017)
- (Das, Dhuliawala, Zaheer, Vilnis, et al. ICLR 2018)
- (Lin, Socher, Xiong EMNLP 2018)
- (Minervini, Bošnjak, Rocktäschel, Riedel, Grefenstette AAAI 2020)

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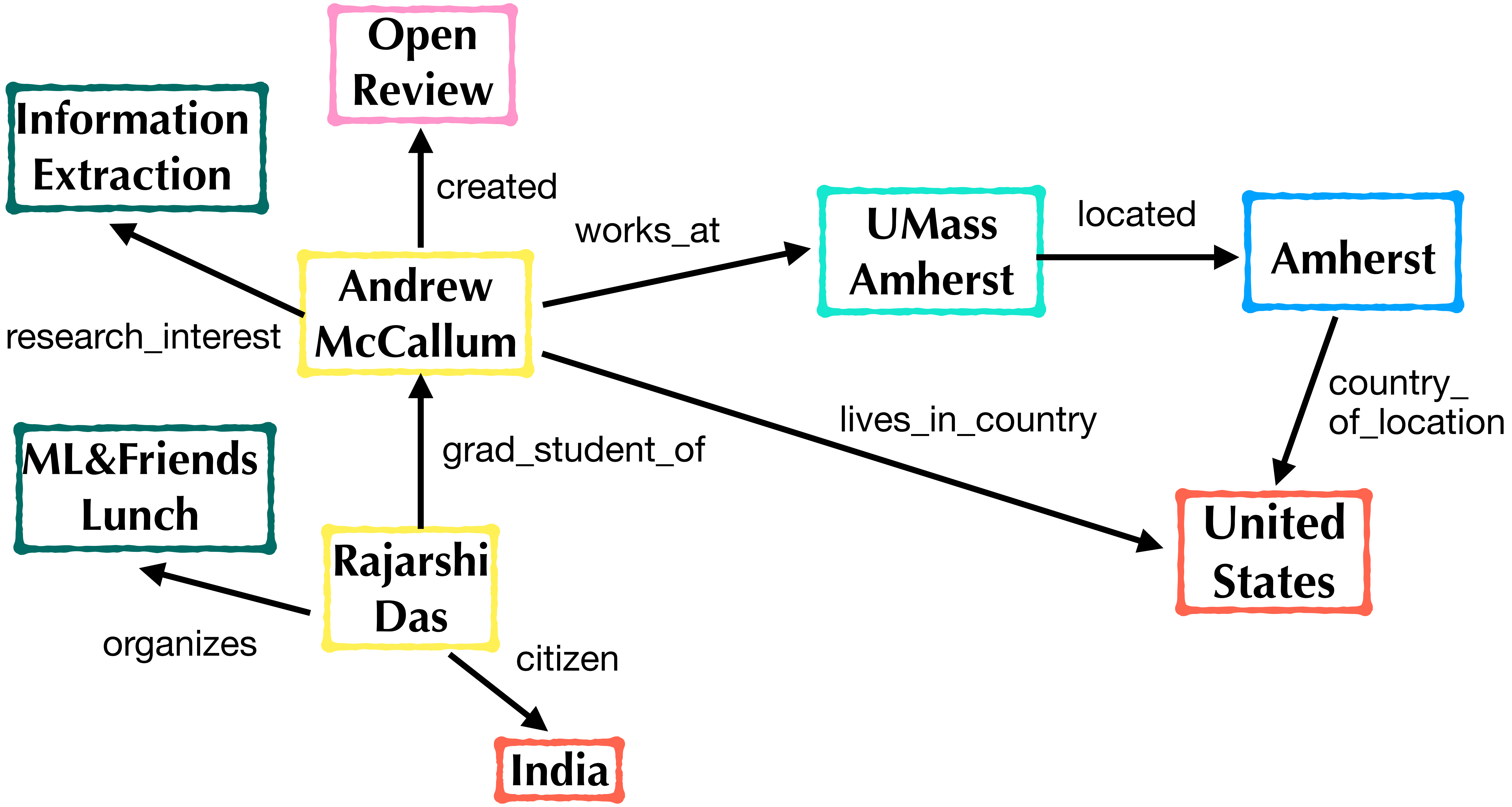
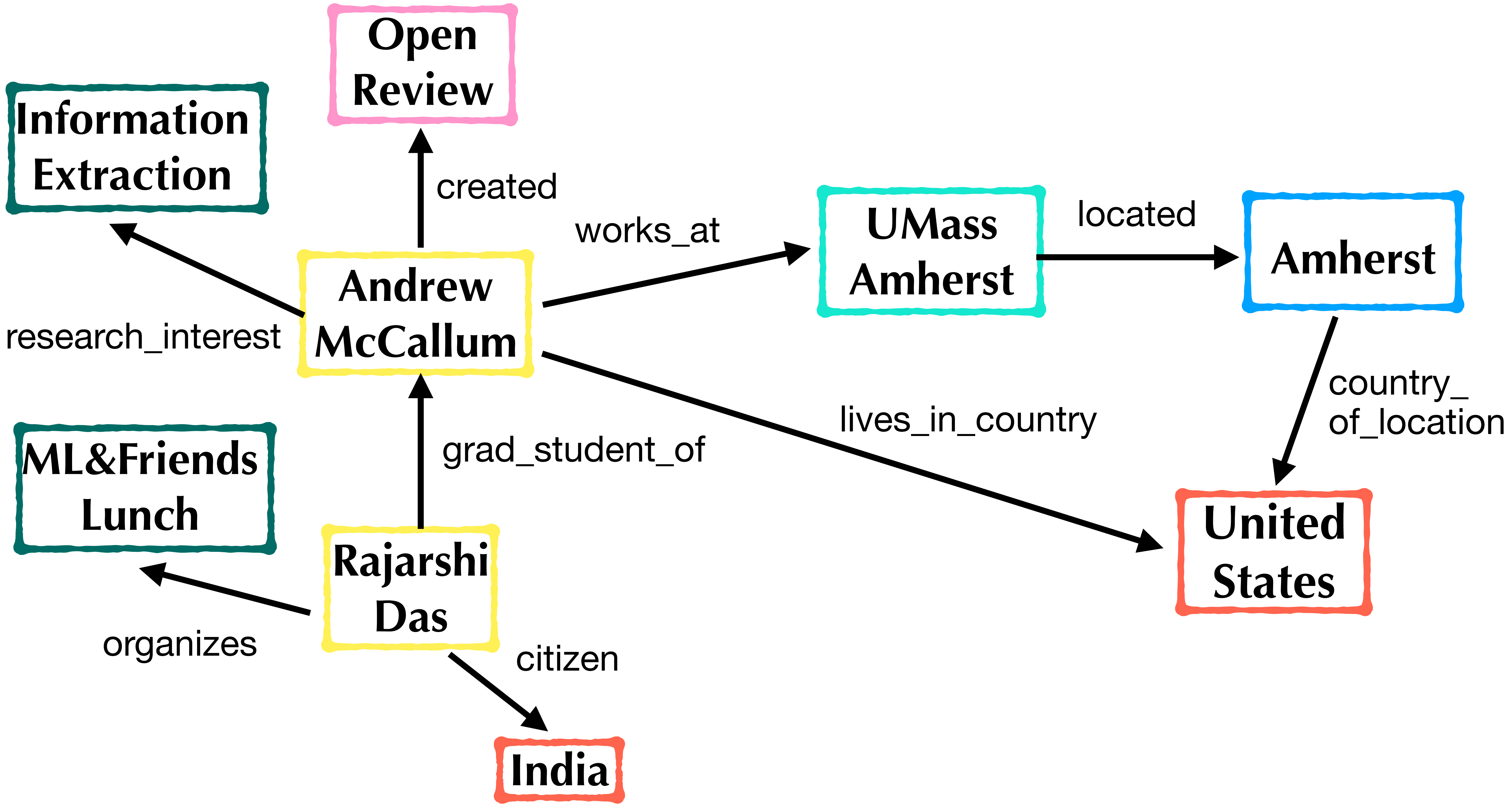
Contextual Reasoning



Contextual Reasoning

Do I need visa for traveling to AKBC 2021??



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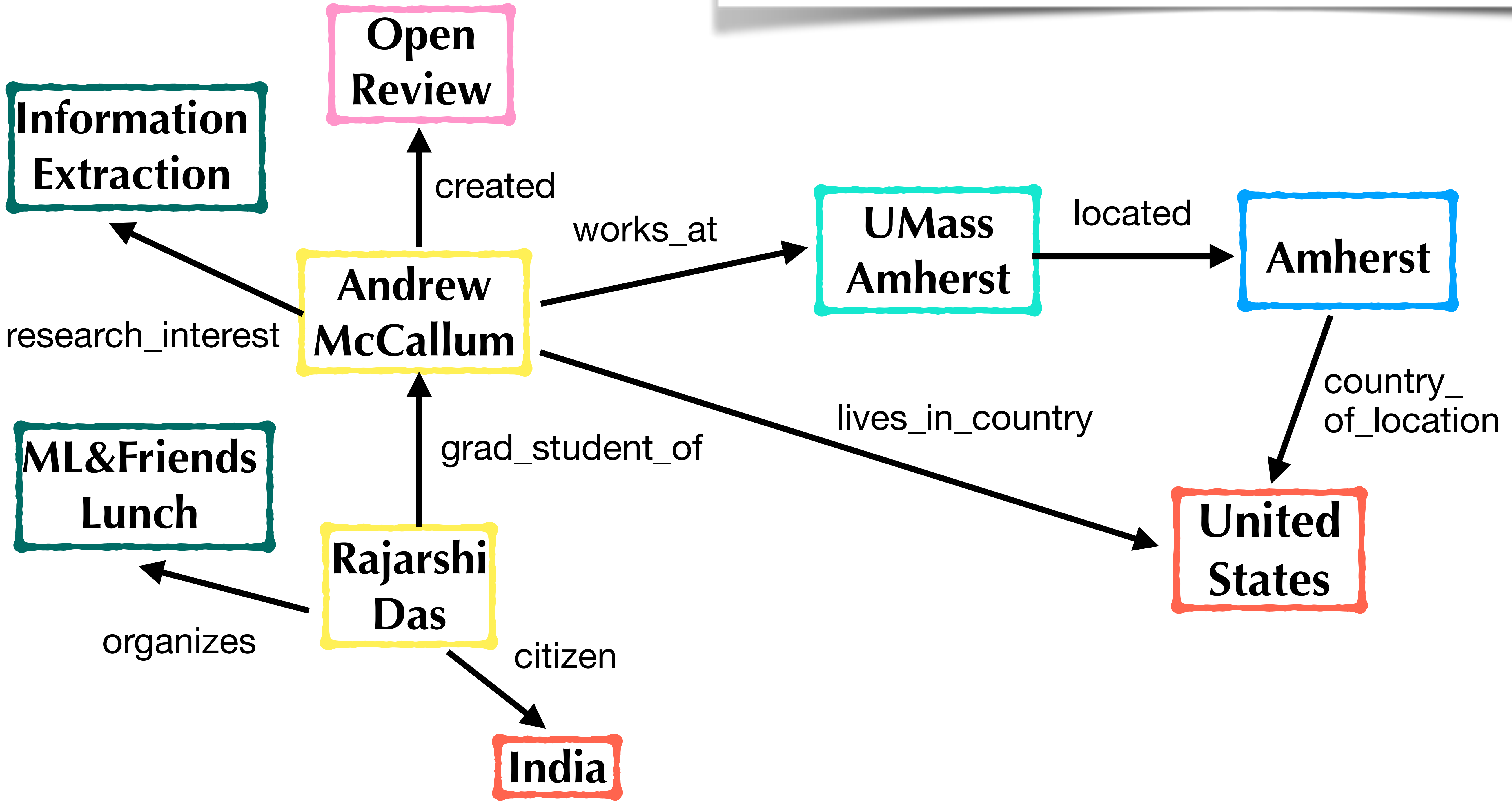

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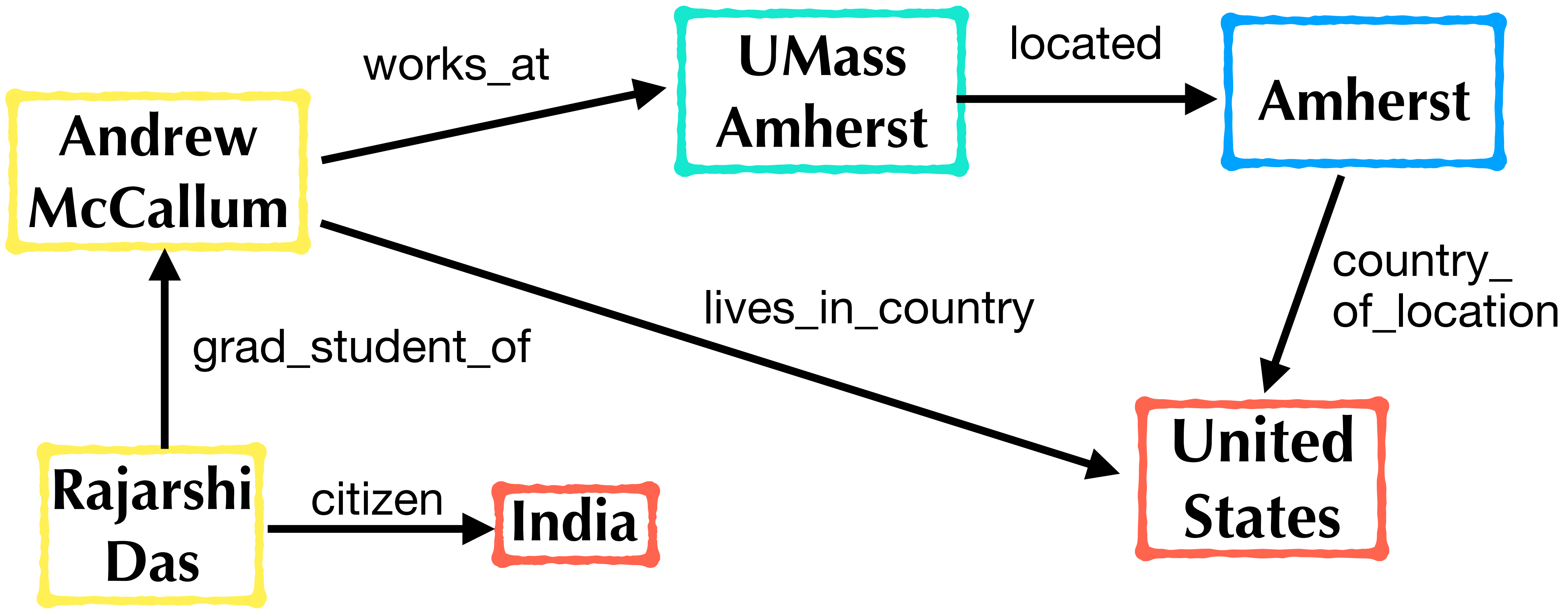

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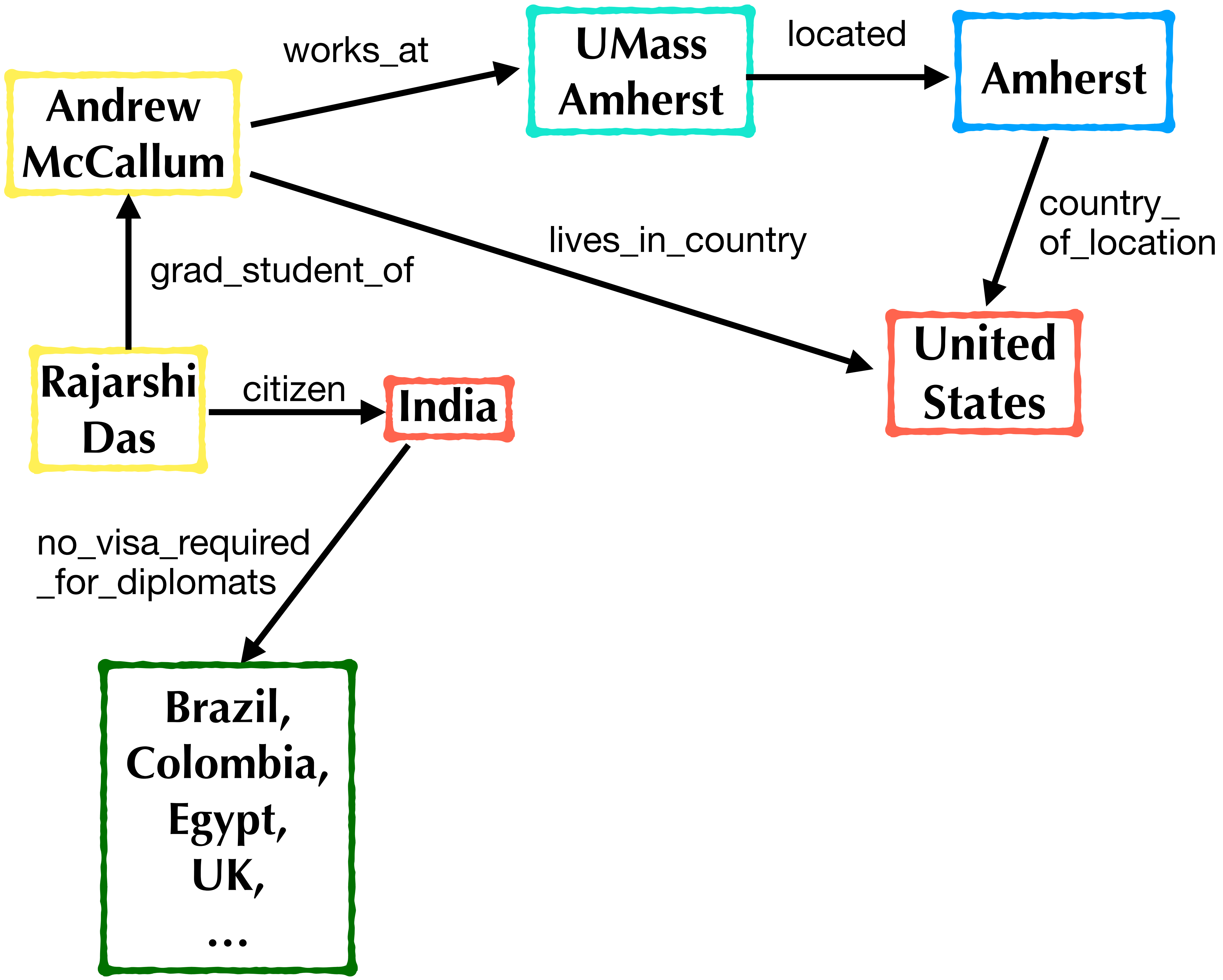

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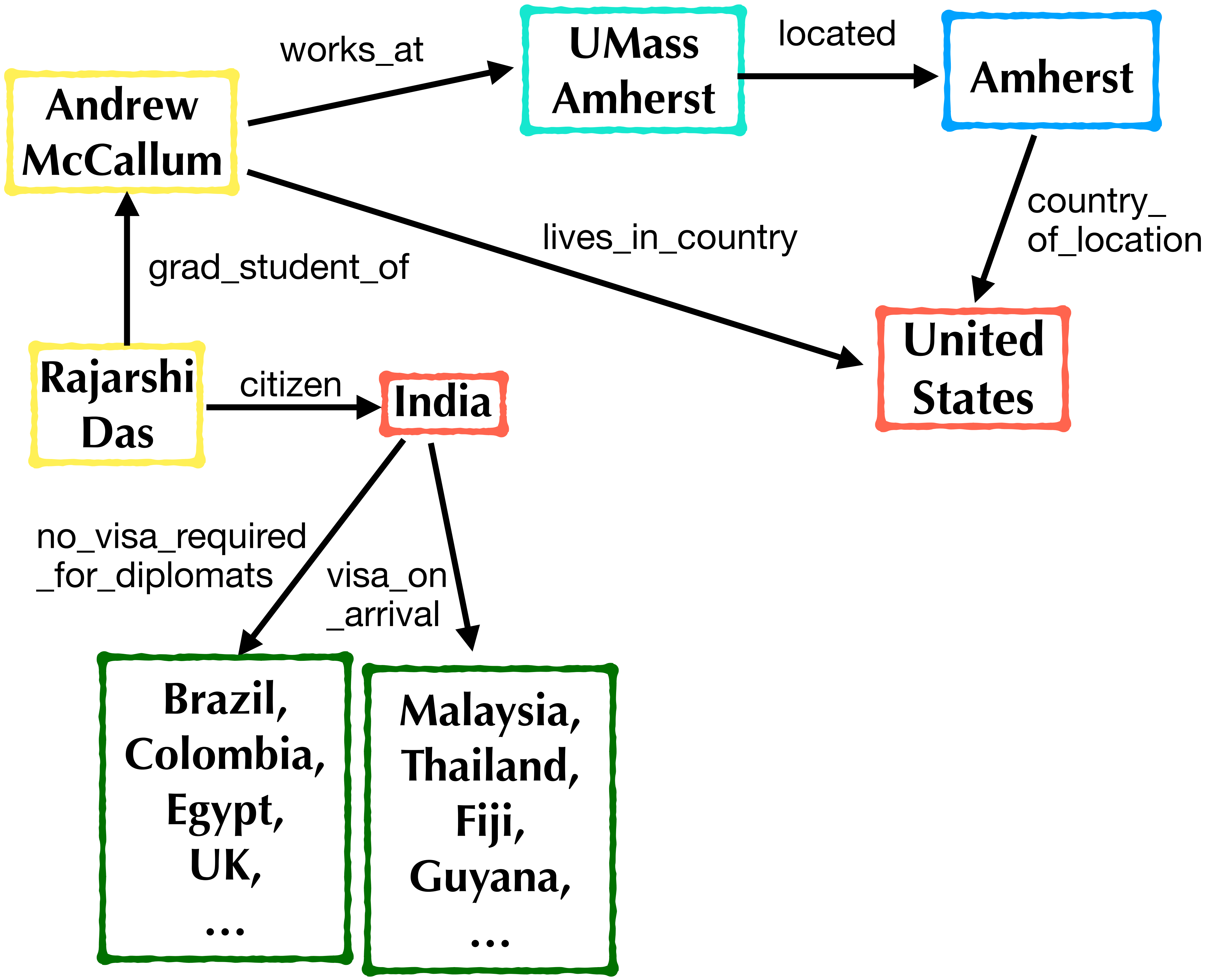

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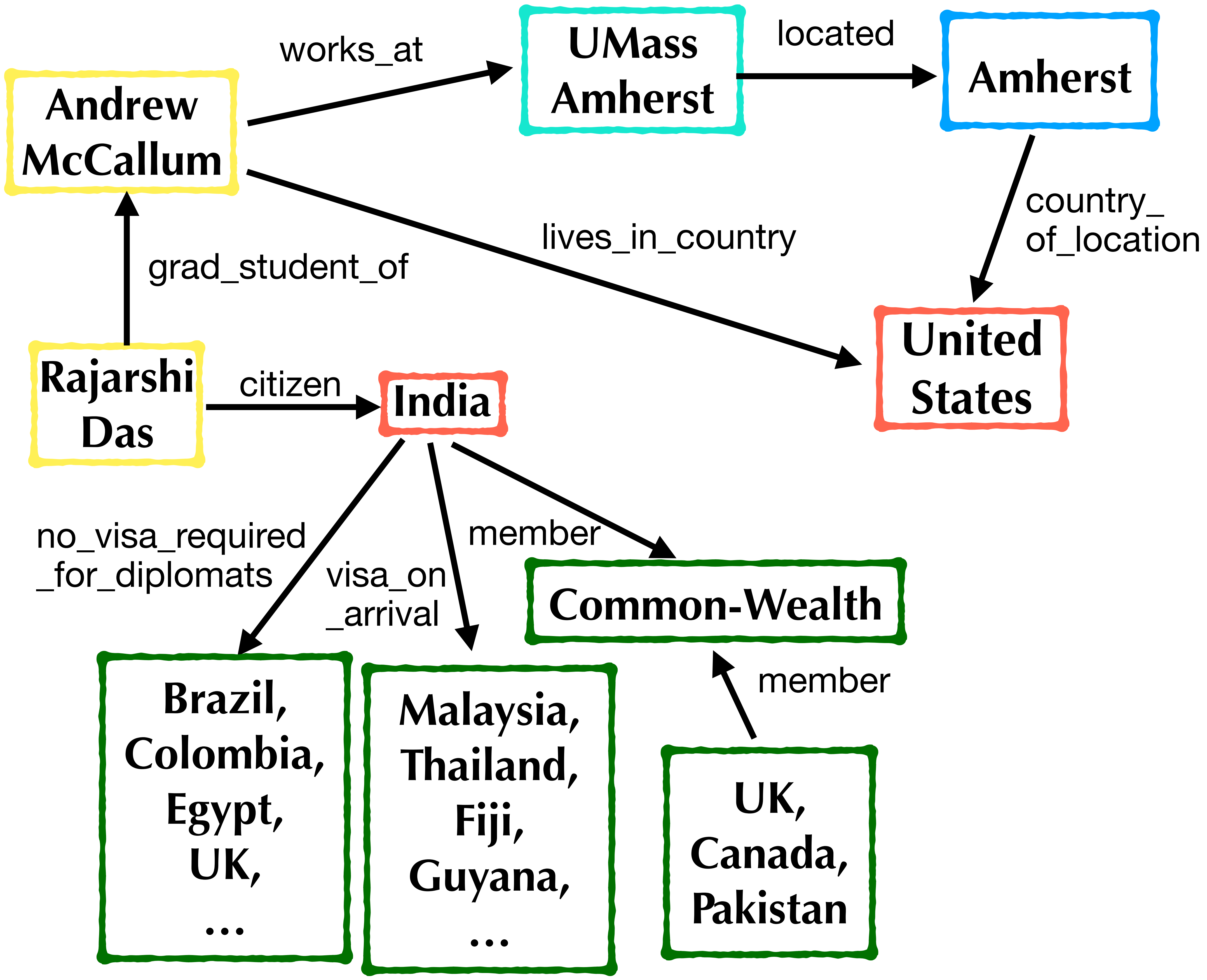
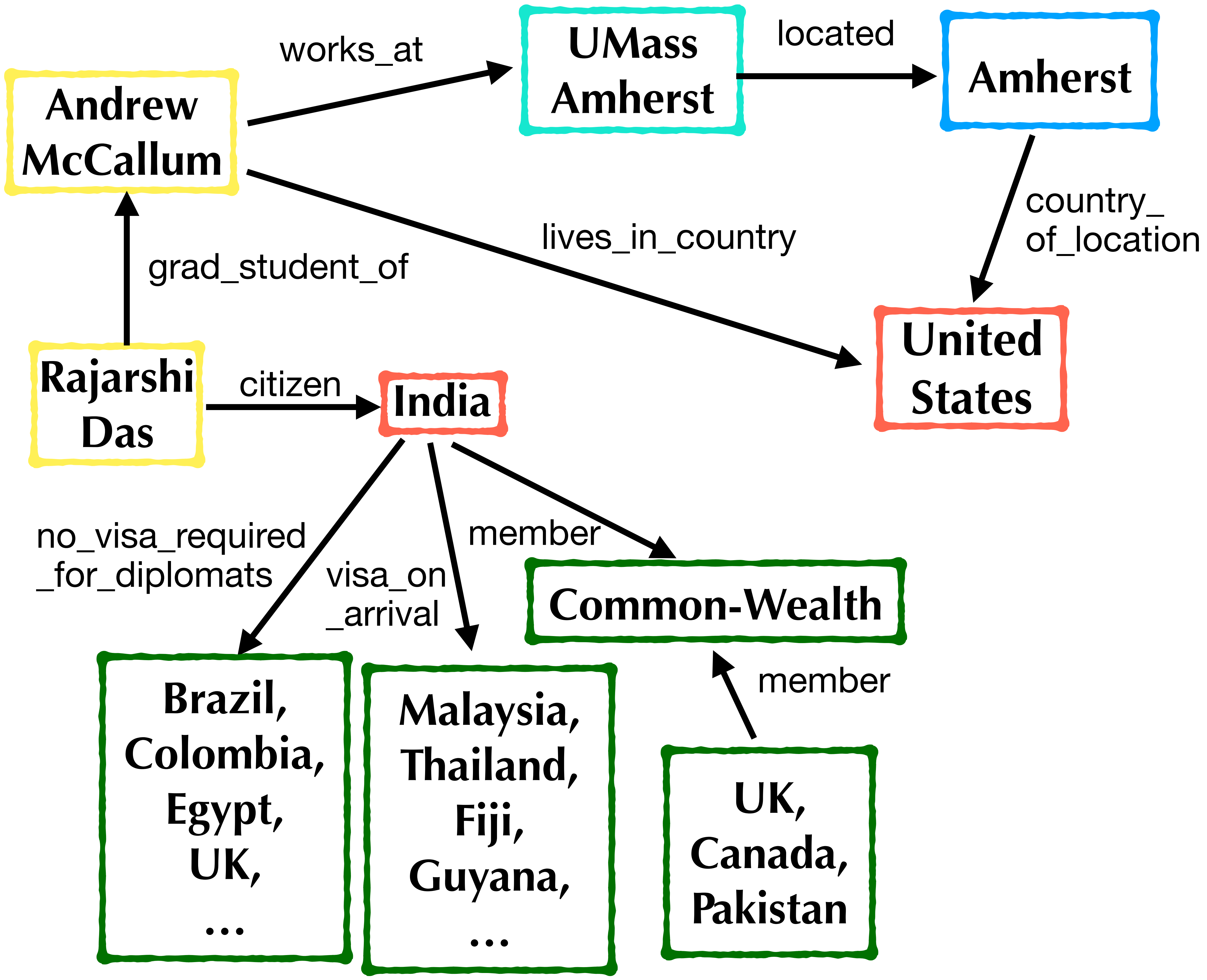


Contextual Reasoning

(Andrew, needs_visa_for_countries, ?)



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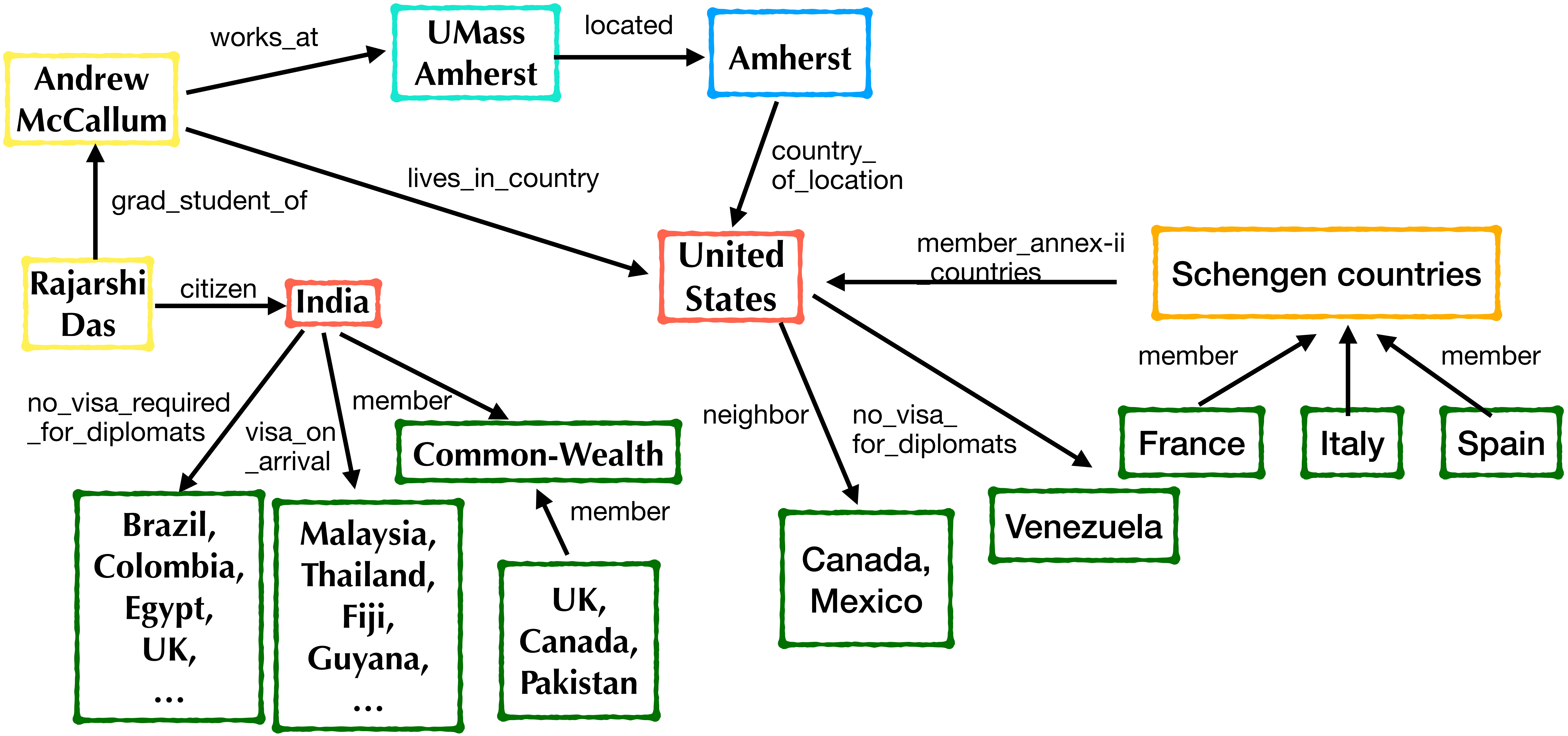

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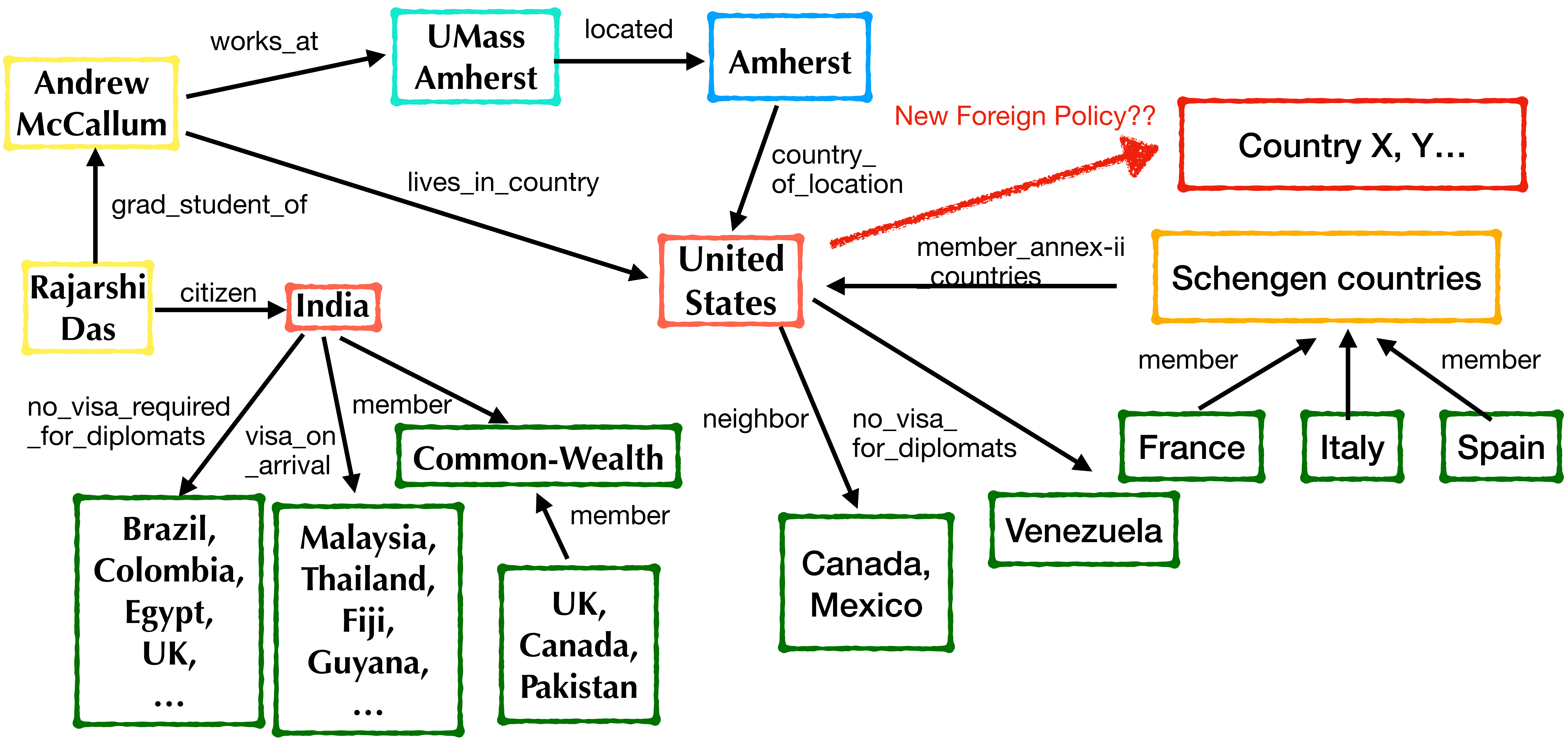

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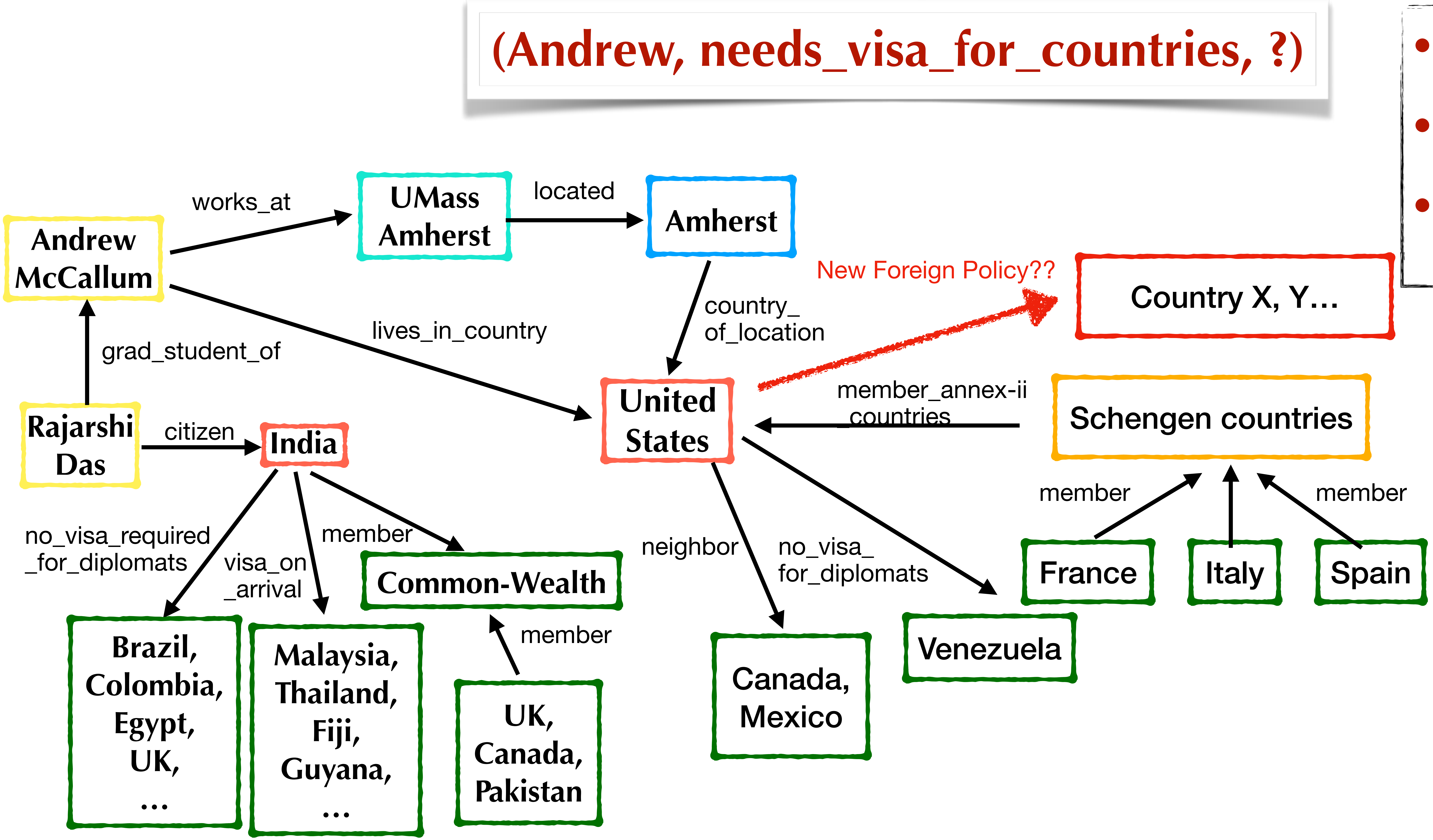

- Different fine-grained rule for each entity
- Hard to store all of them in parameters
- Unclear how parameters will adapt with changing data

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This Work

- Learn fine-grained rules tailored for each entity
- Derive logical rules dynamically from *"contextual entities"* rather than storing in parameters
- In fact, other than entity embeddings we have *"no parameters!"*
- Since rules are derived at inference, can handle updates seamlessly.

Case-Based Reasoning (Schank 1982; Kolodner 1983)

- Process of solving new problems based on solution to similar past problems.

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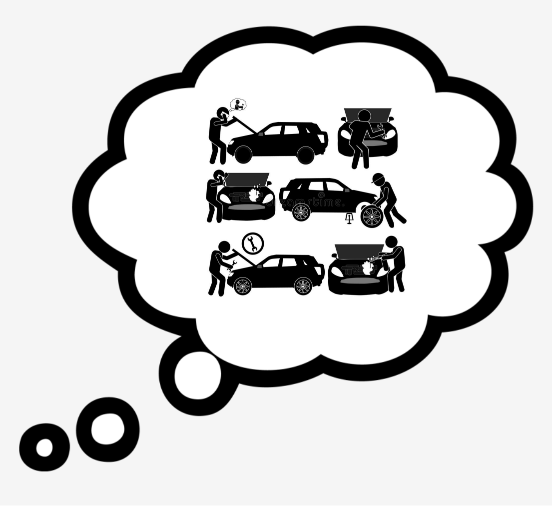

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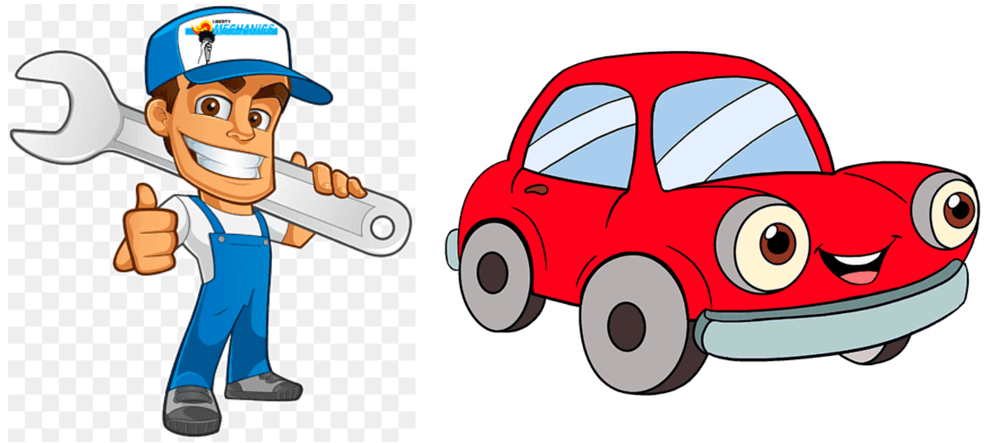

A case is an abstract representation of a (past) problem and its solution.

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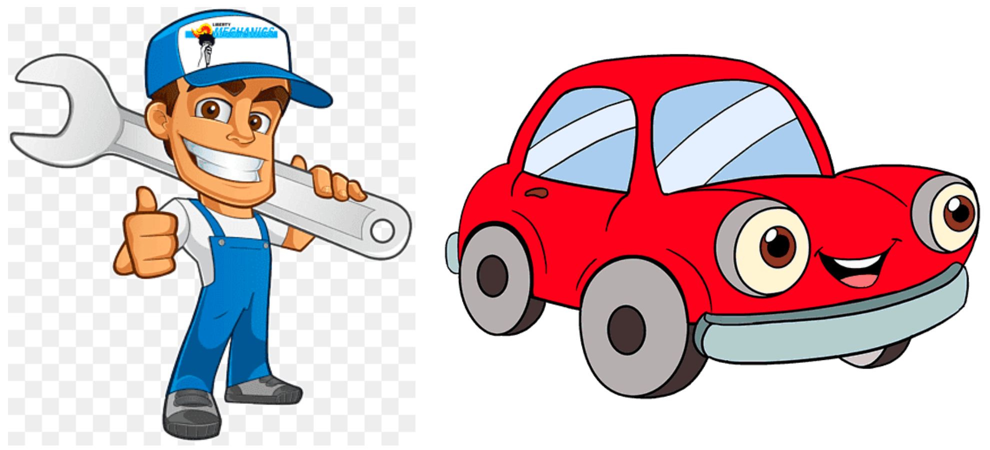

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4 step process:

Case-Based Reasoning (Schank 1982; Kolodner 1983)

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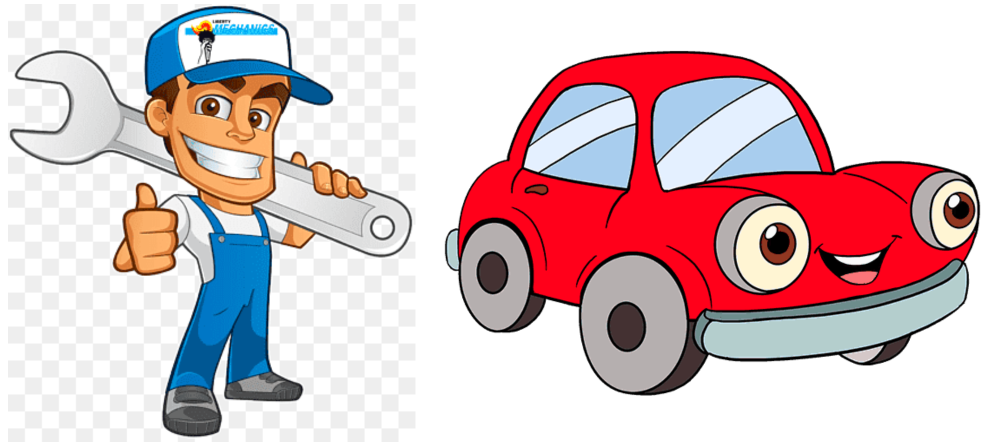

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4 step process:

i) Retrieve: Given a new problem, retrieve the relevant cases from memory.

Case-Based Reasoning (Schank 1982; Kolodner 1983)

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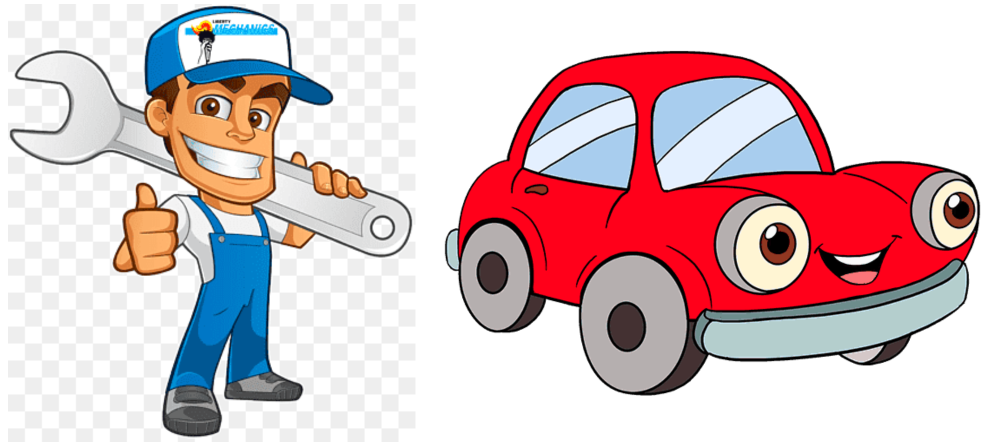


A case is an abstract representation of a (past) problem and its solution.

4 step process:

i) Retrieve: Given a new problem, retrieve the relevant cases from memory.

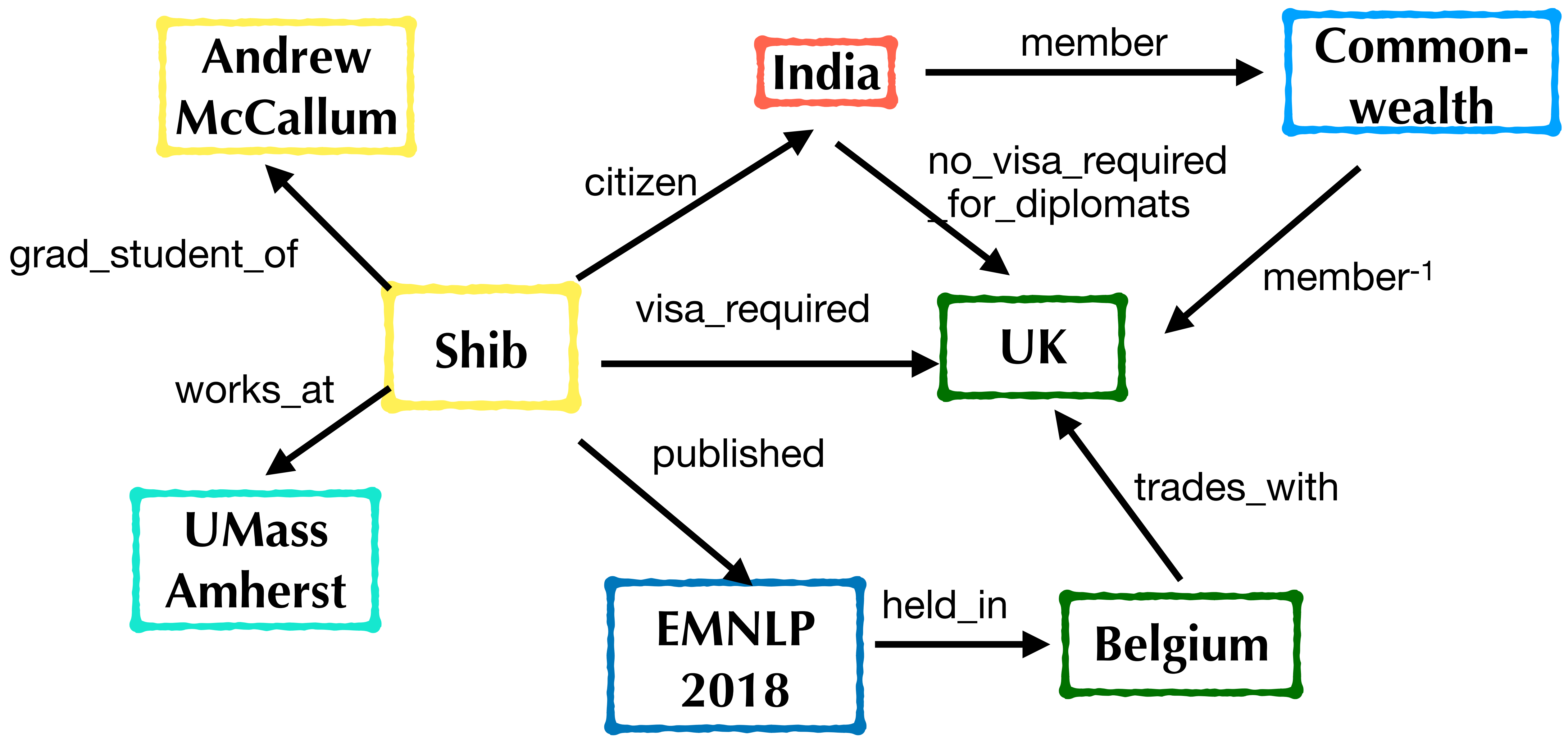
ii) Reuse: the solutions to the previous case, if possible.

iii) Revise: the solutions, if necessary

iv) Retain: If the solution is successful, retain it in the memory.

Case-Based Reasoning in Knowledge Bases

How do we represent a case?



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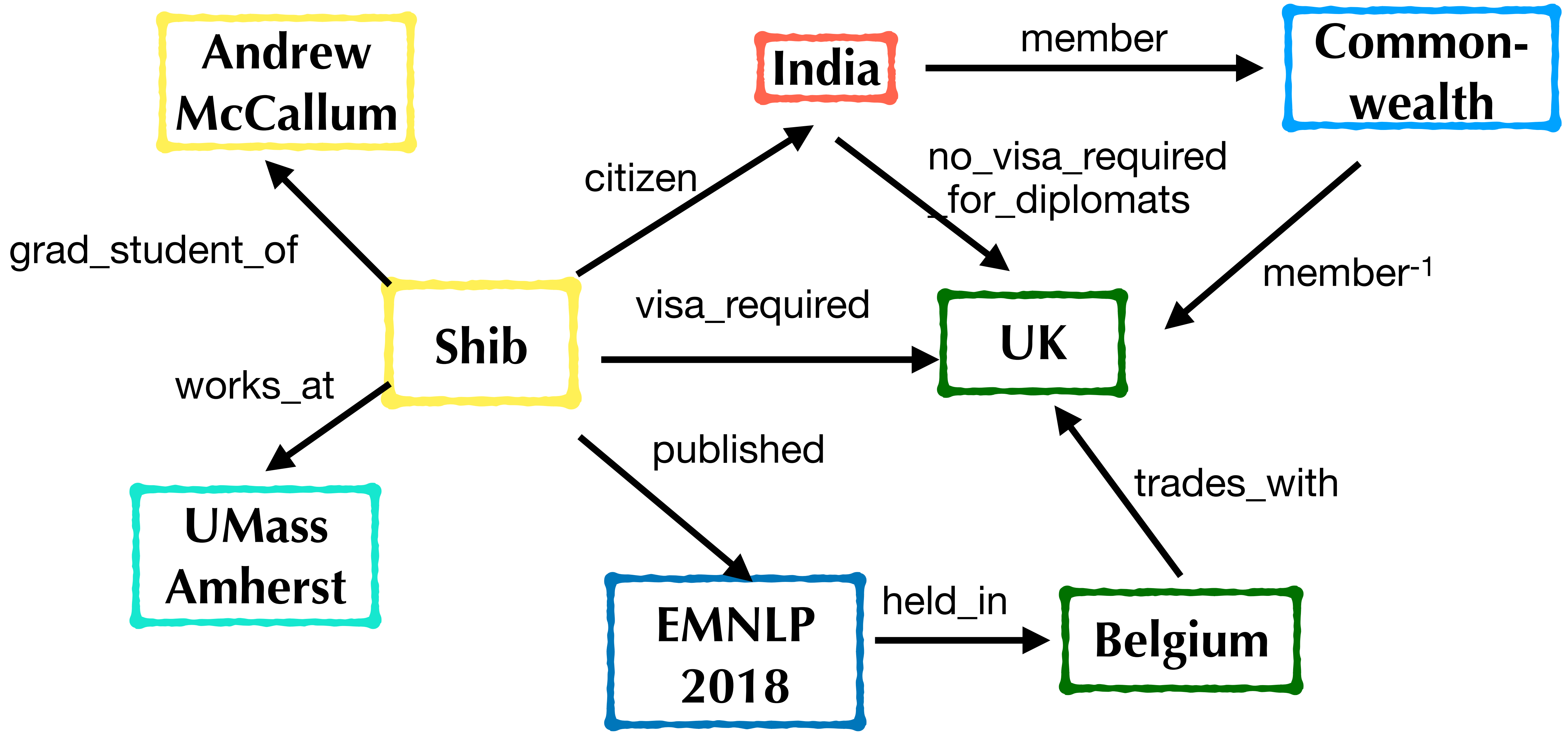

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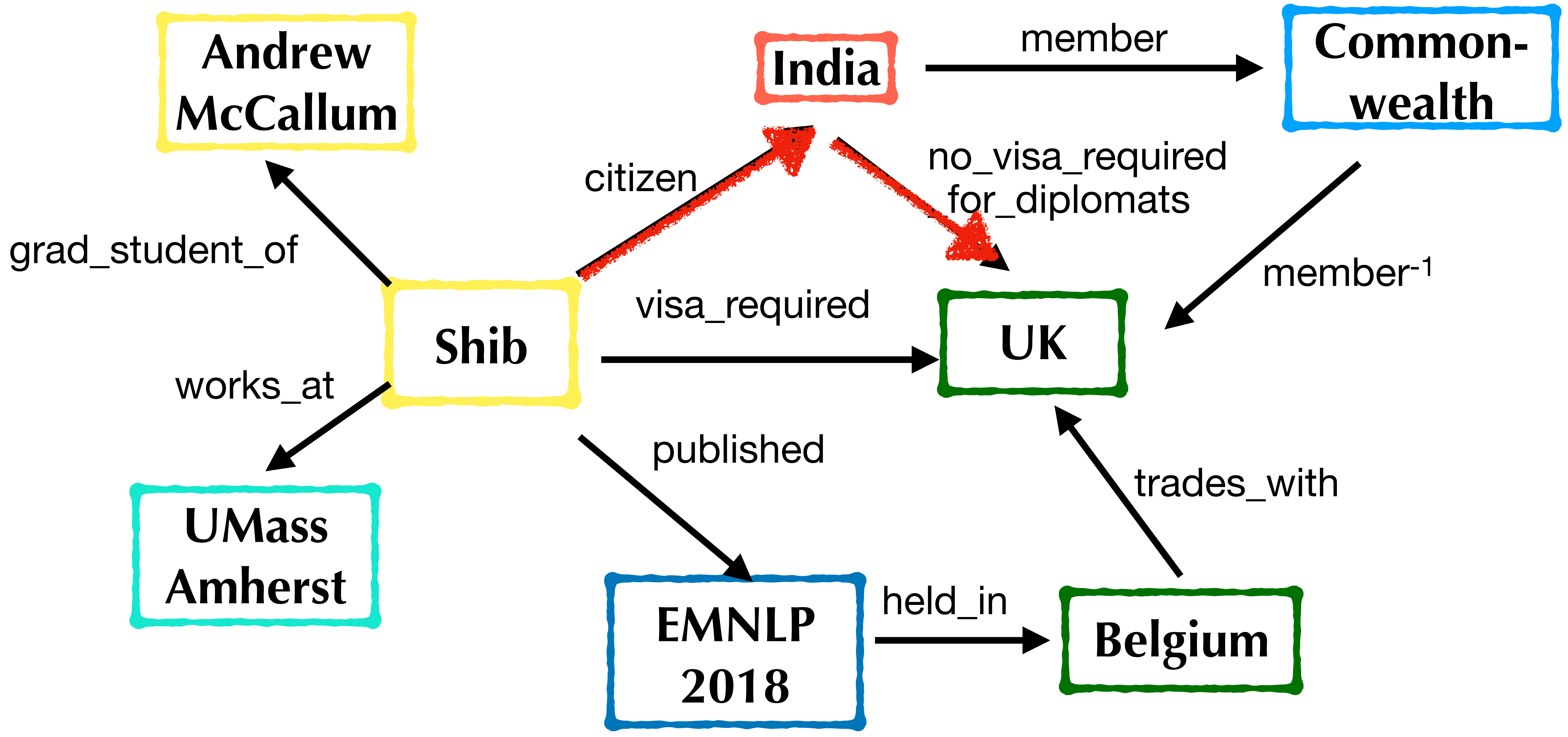

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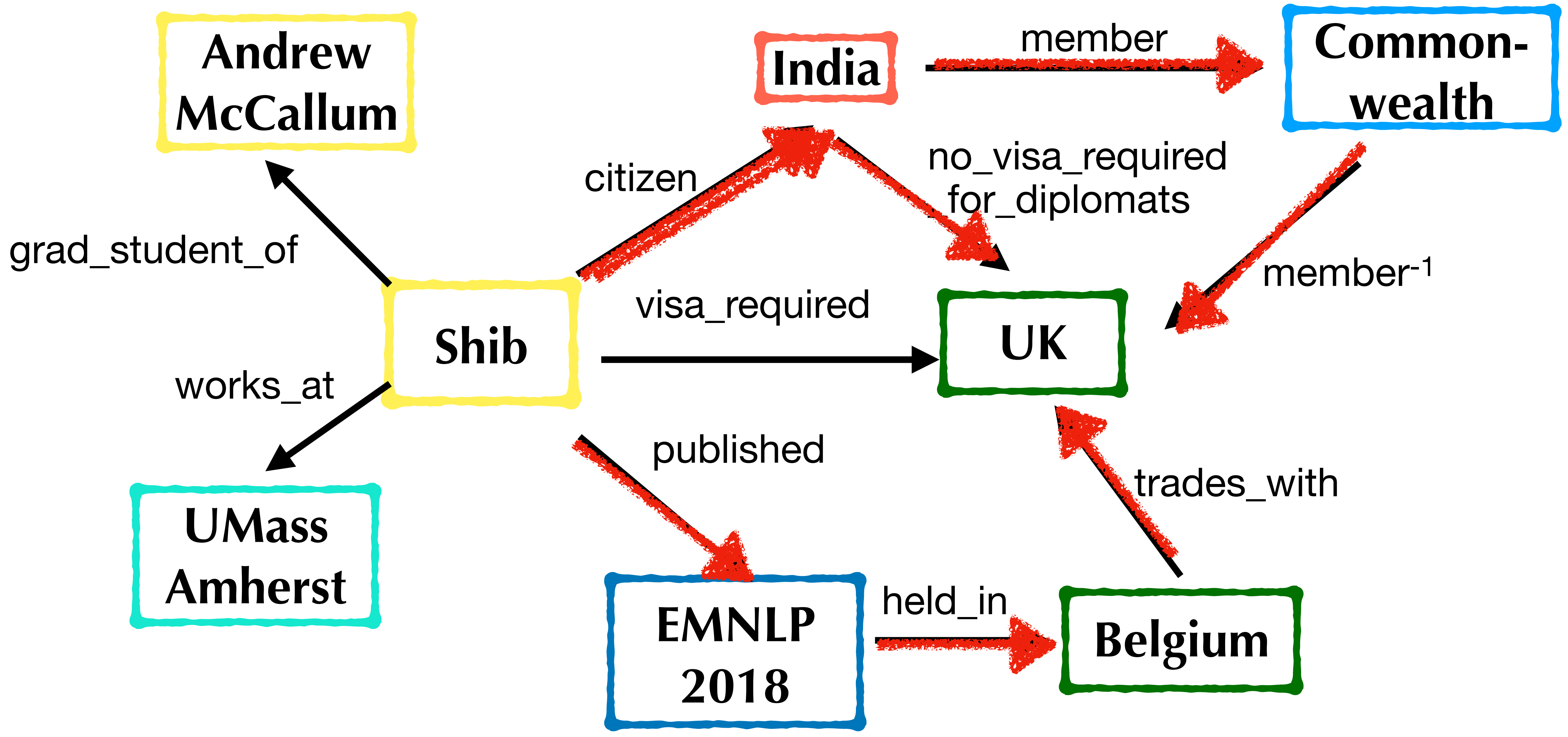
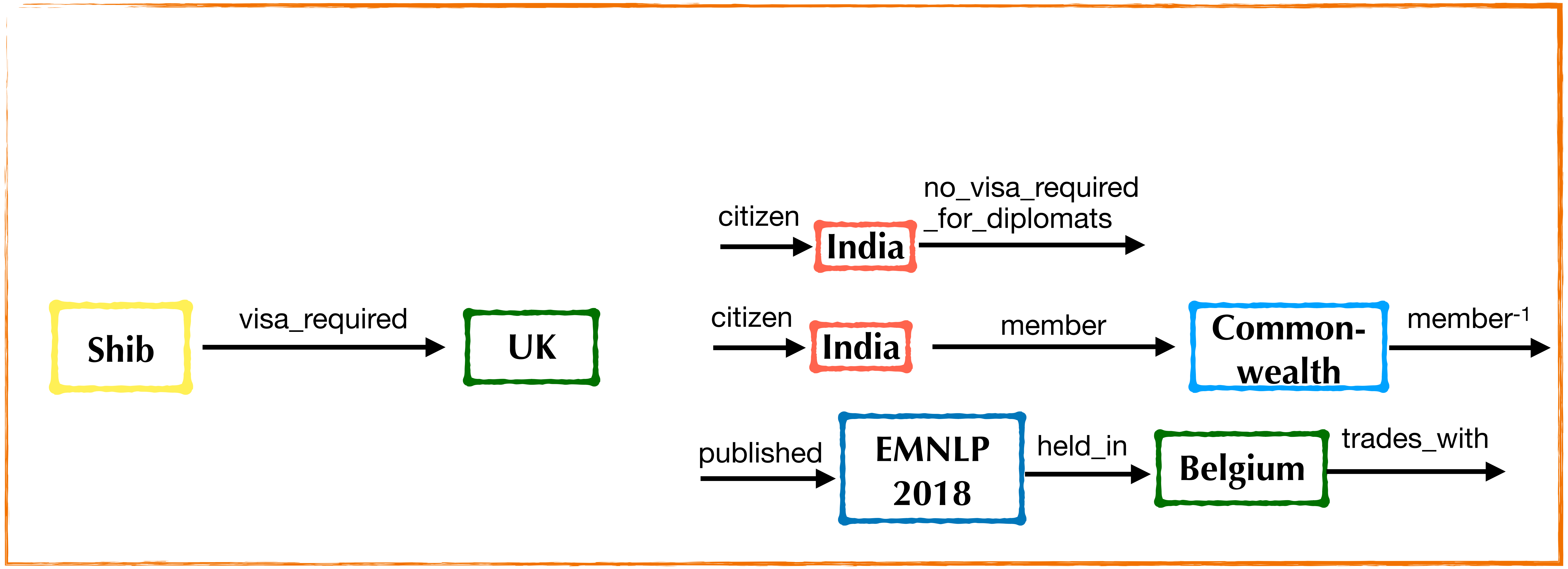


Case-Based Reasoning in Knowledge Bases

A case in a KB is represented by:



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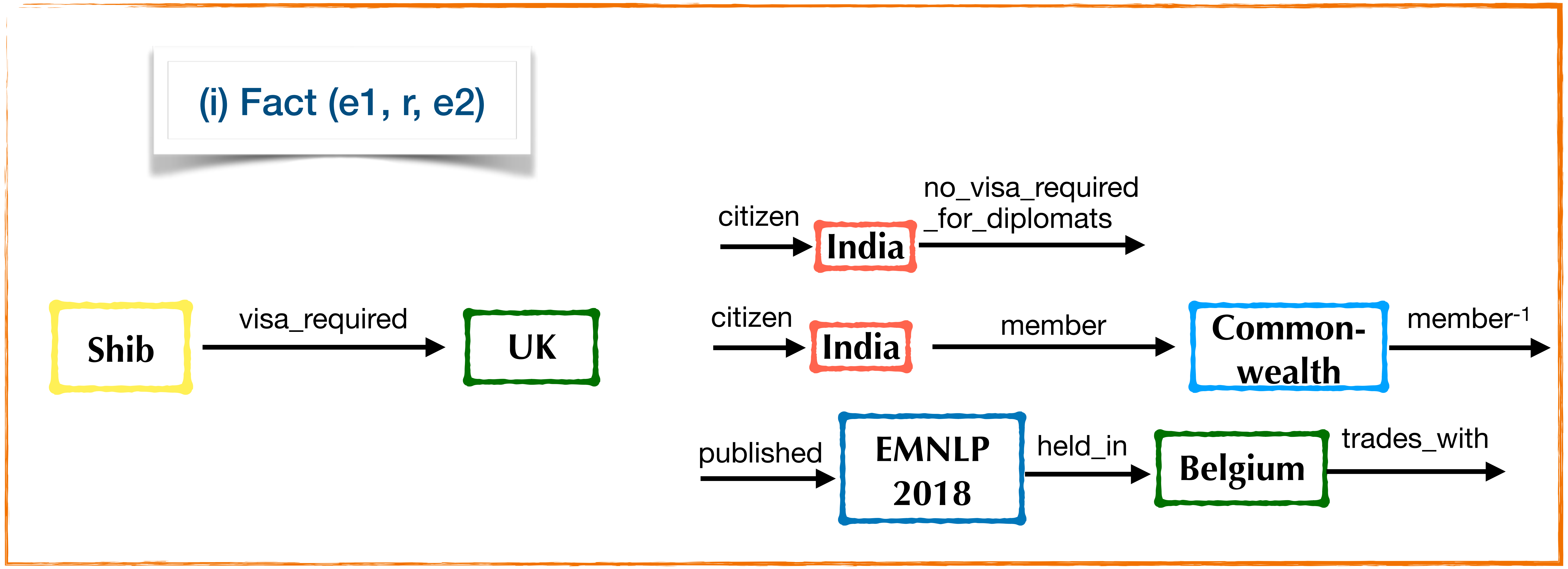

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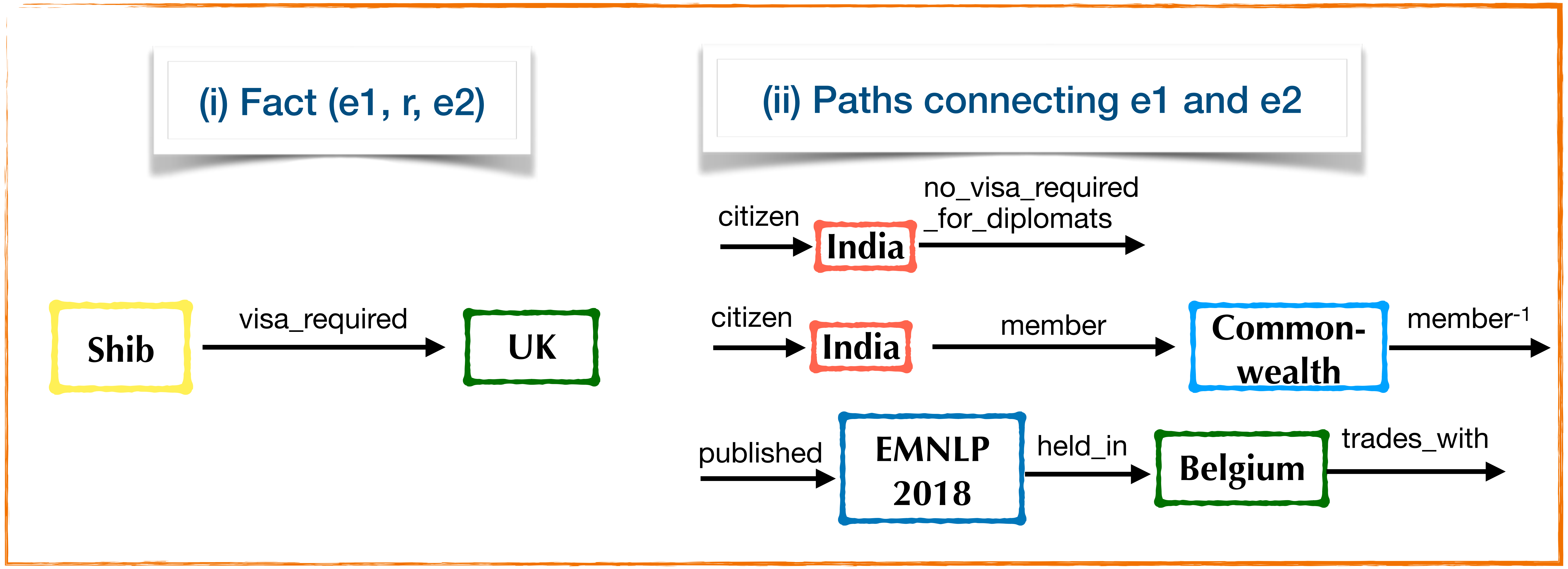

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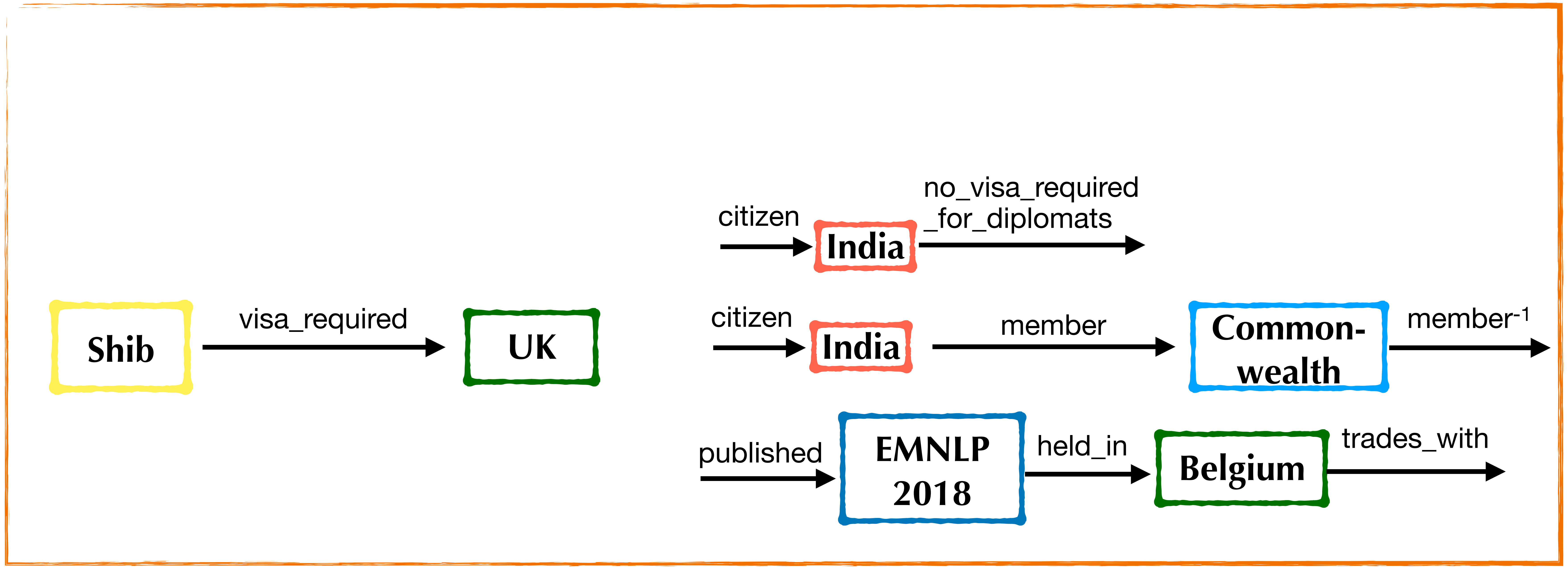

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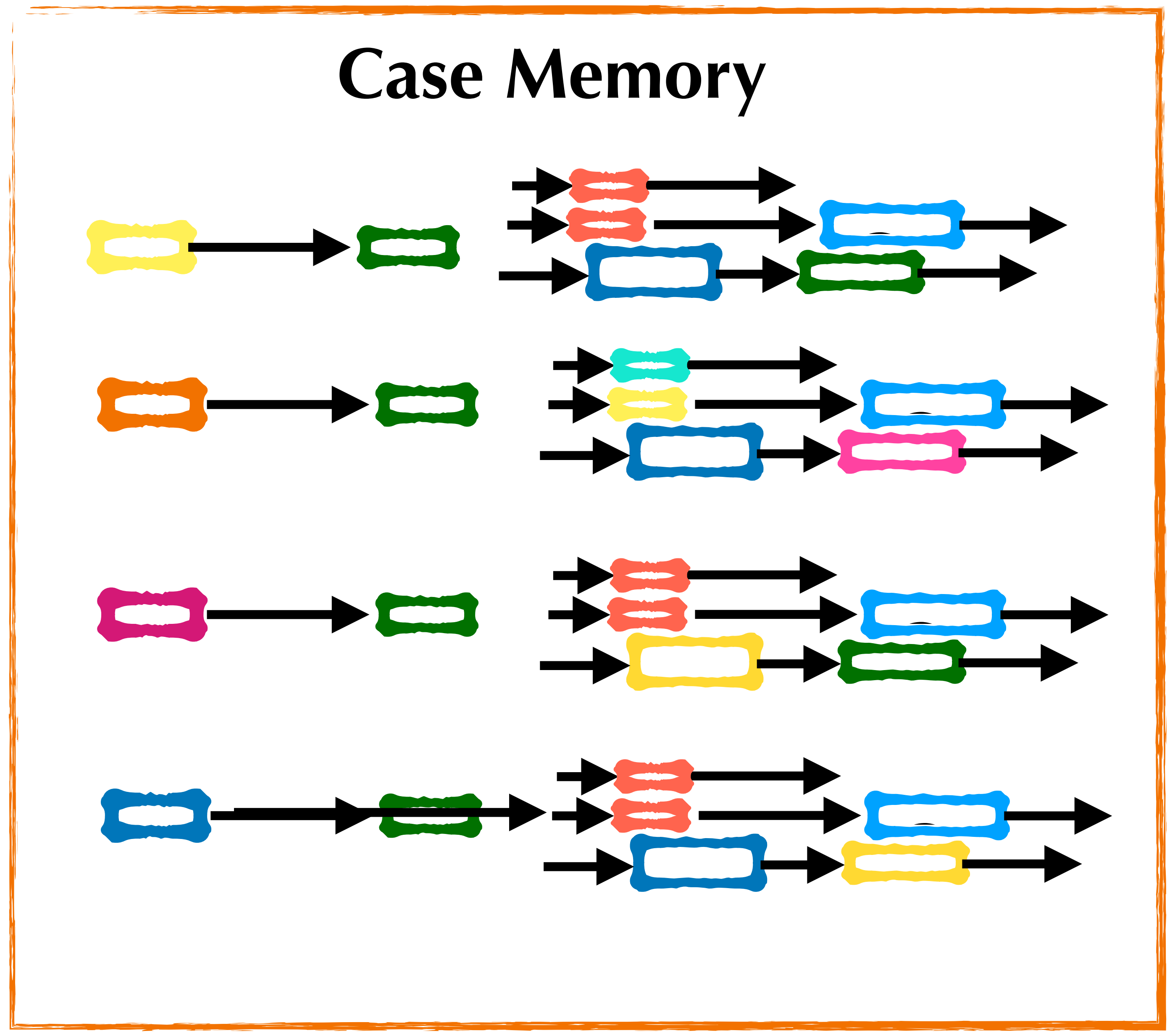
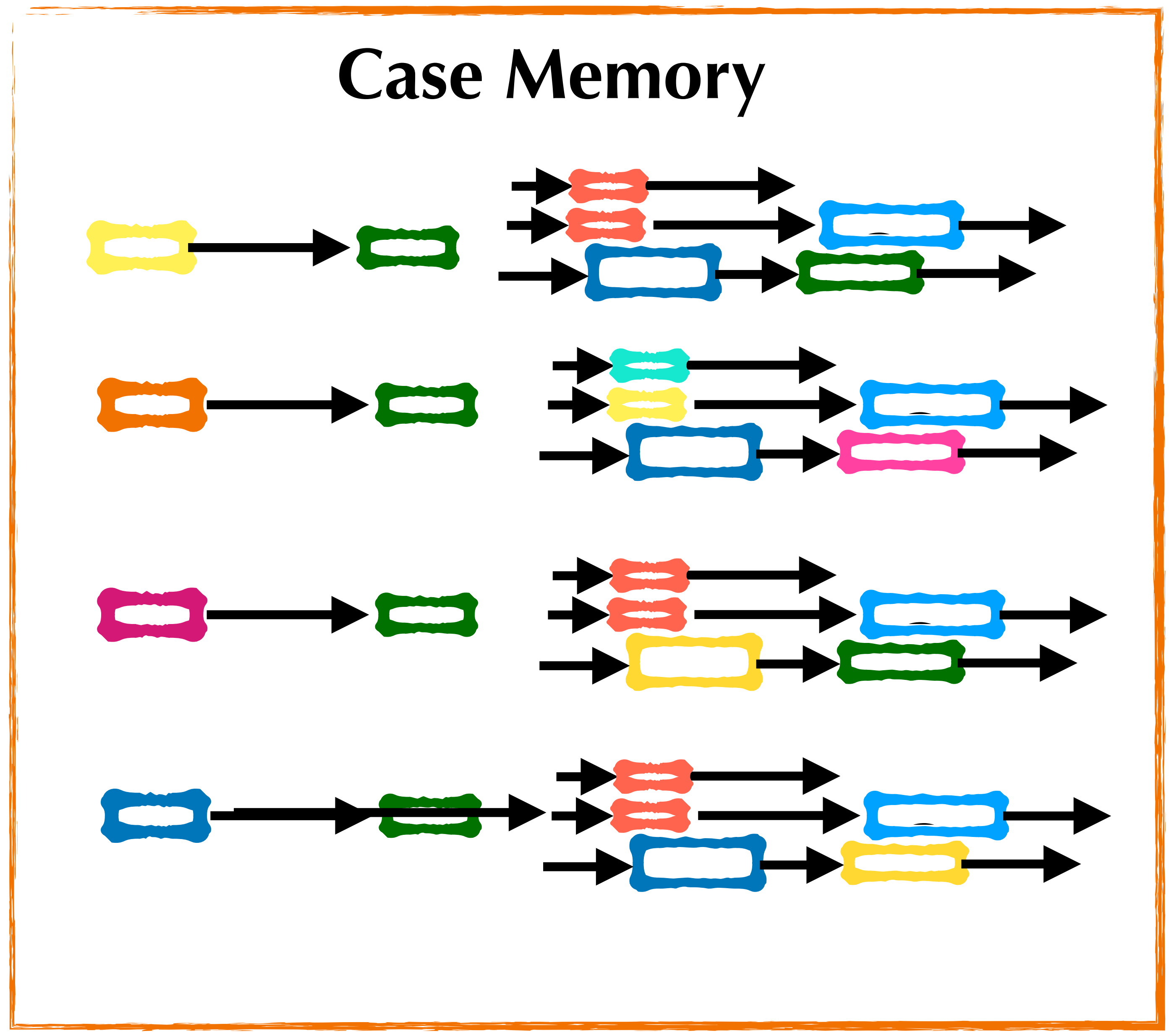


Case-Based Reasoning in Knowledge Bases

(Raj, needs_visa_for, ?)



Case-Based Reasoning in Knowledge Bases

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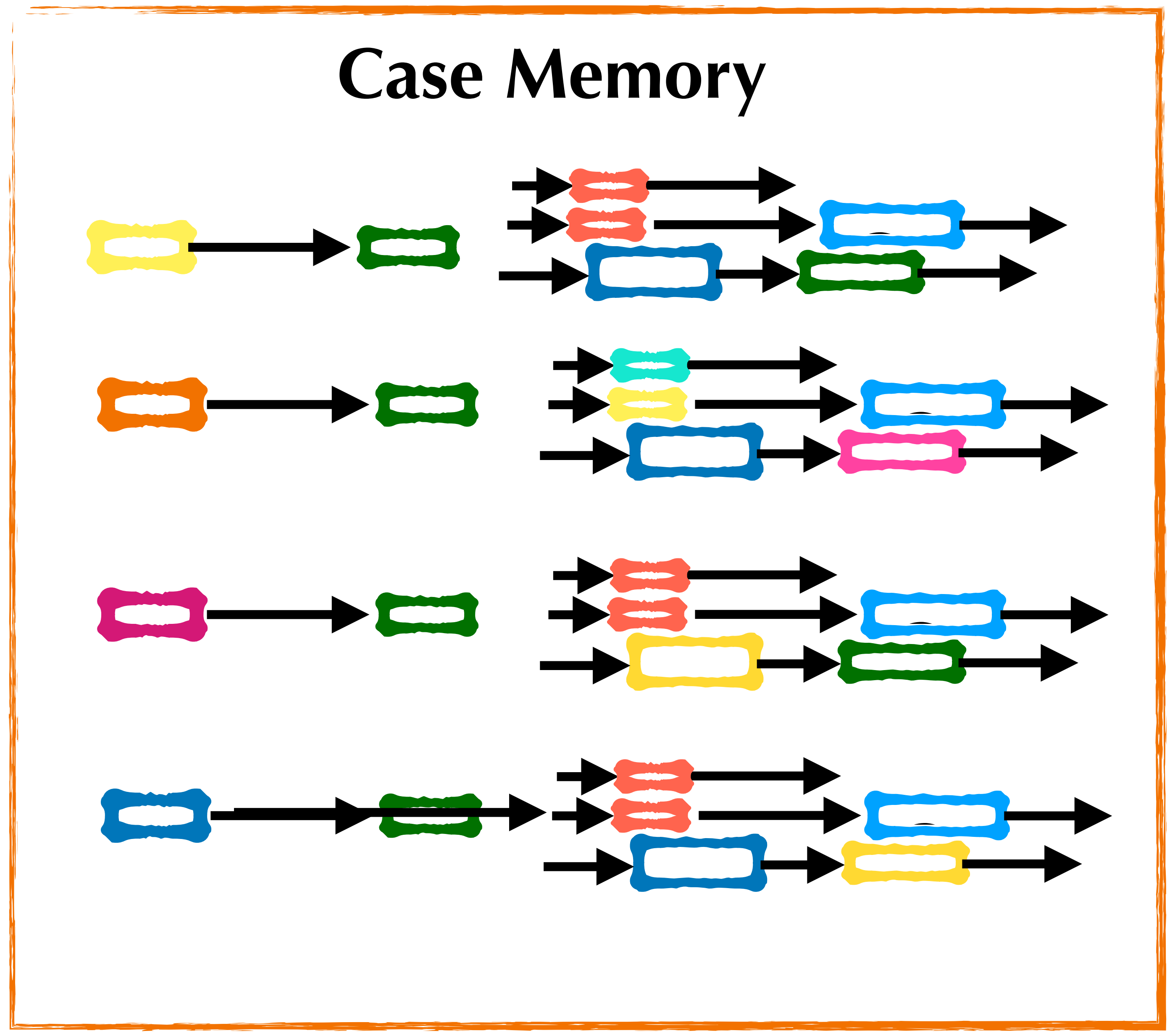
1. Retrieve 'K' relevant cases from memory:



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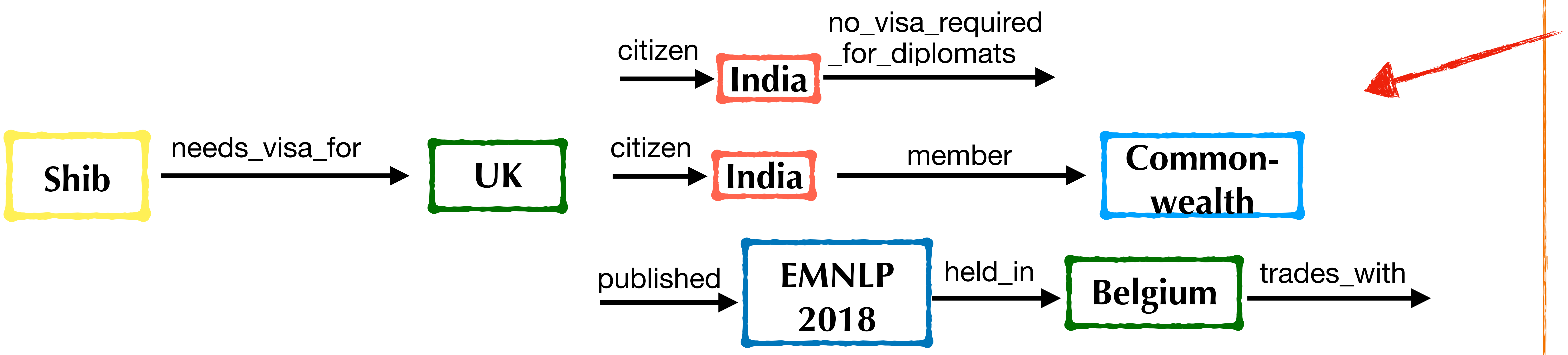

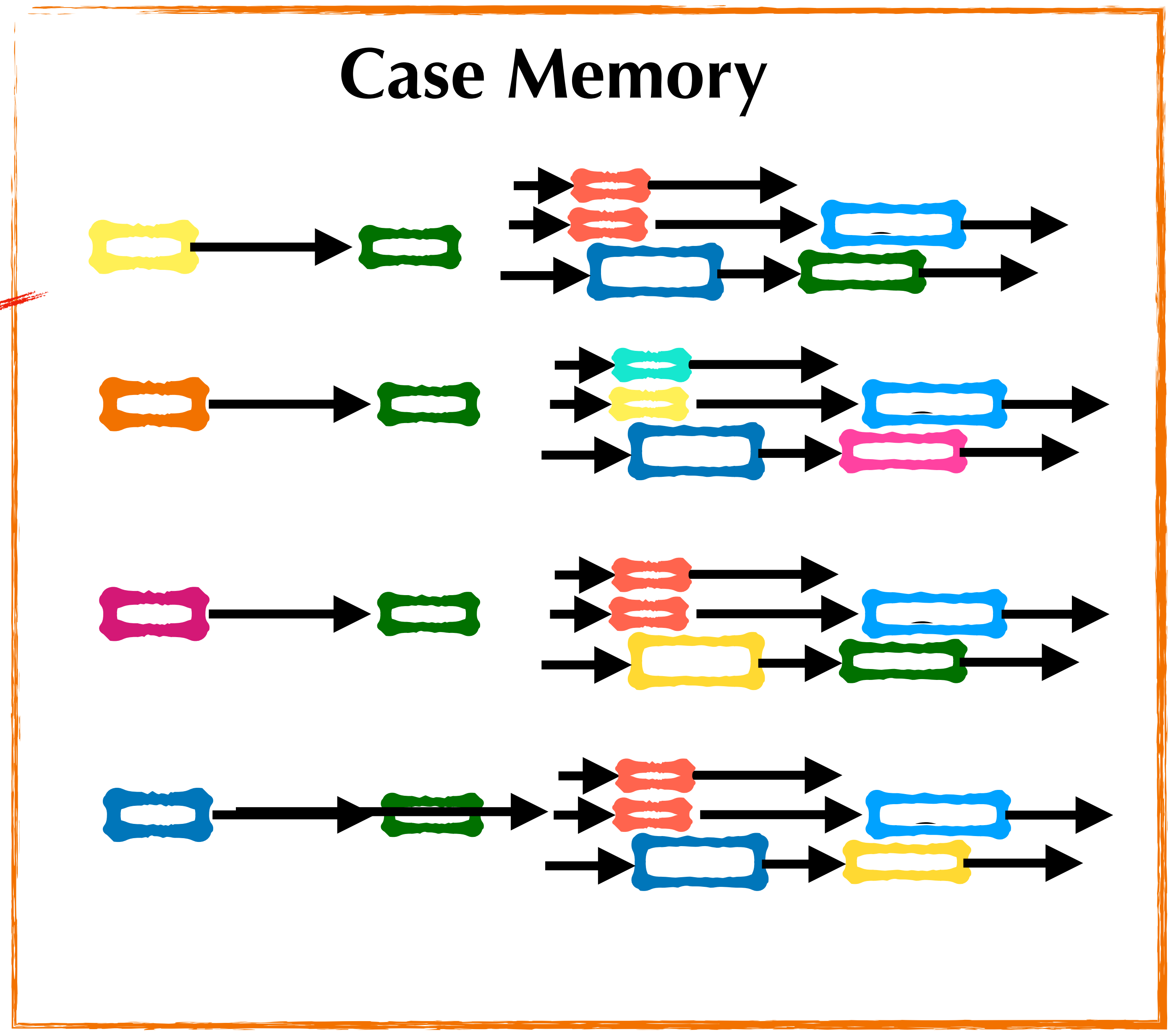

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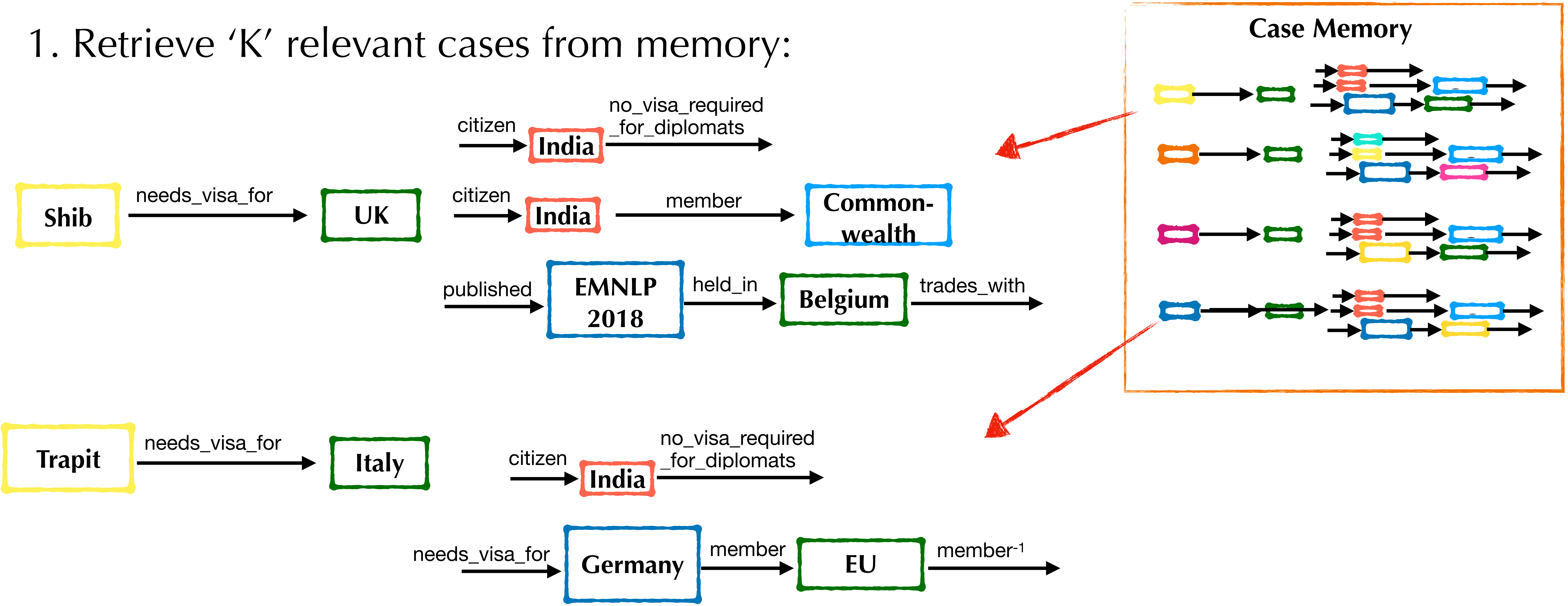

Case-Based Reasoning in Knowledge Bases

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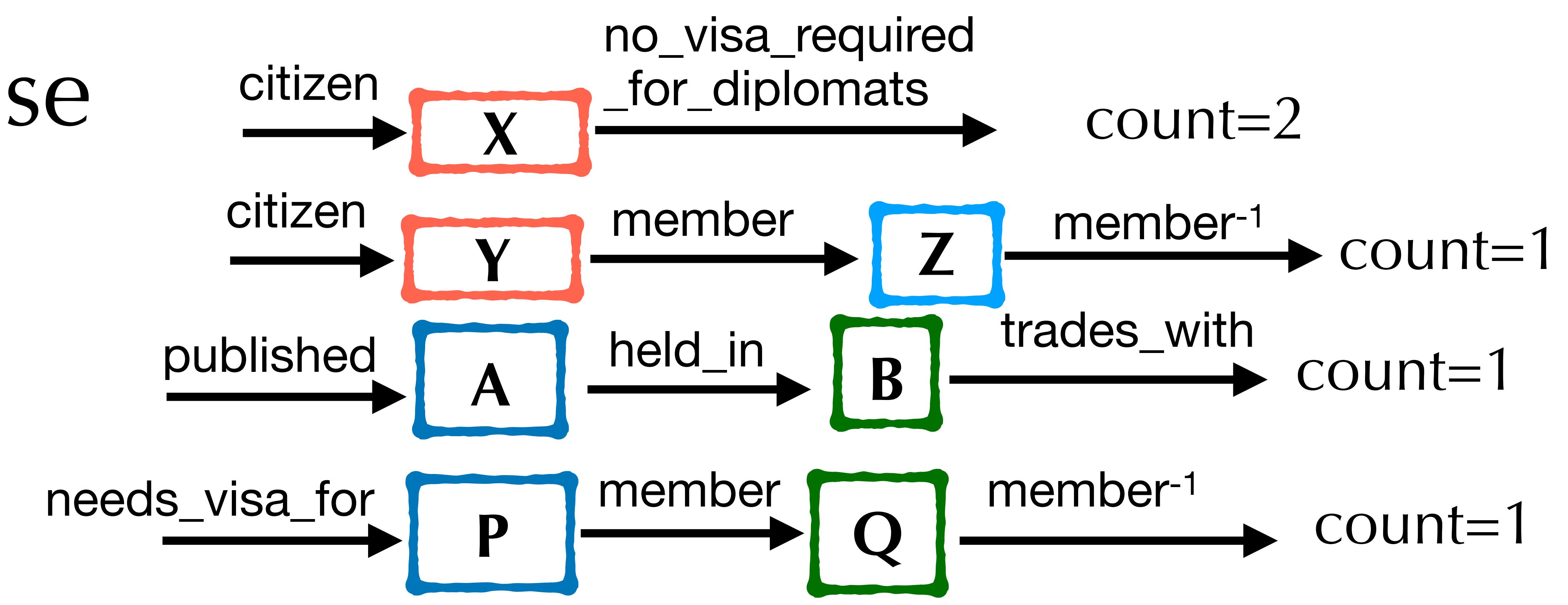
Revise



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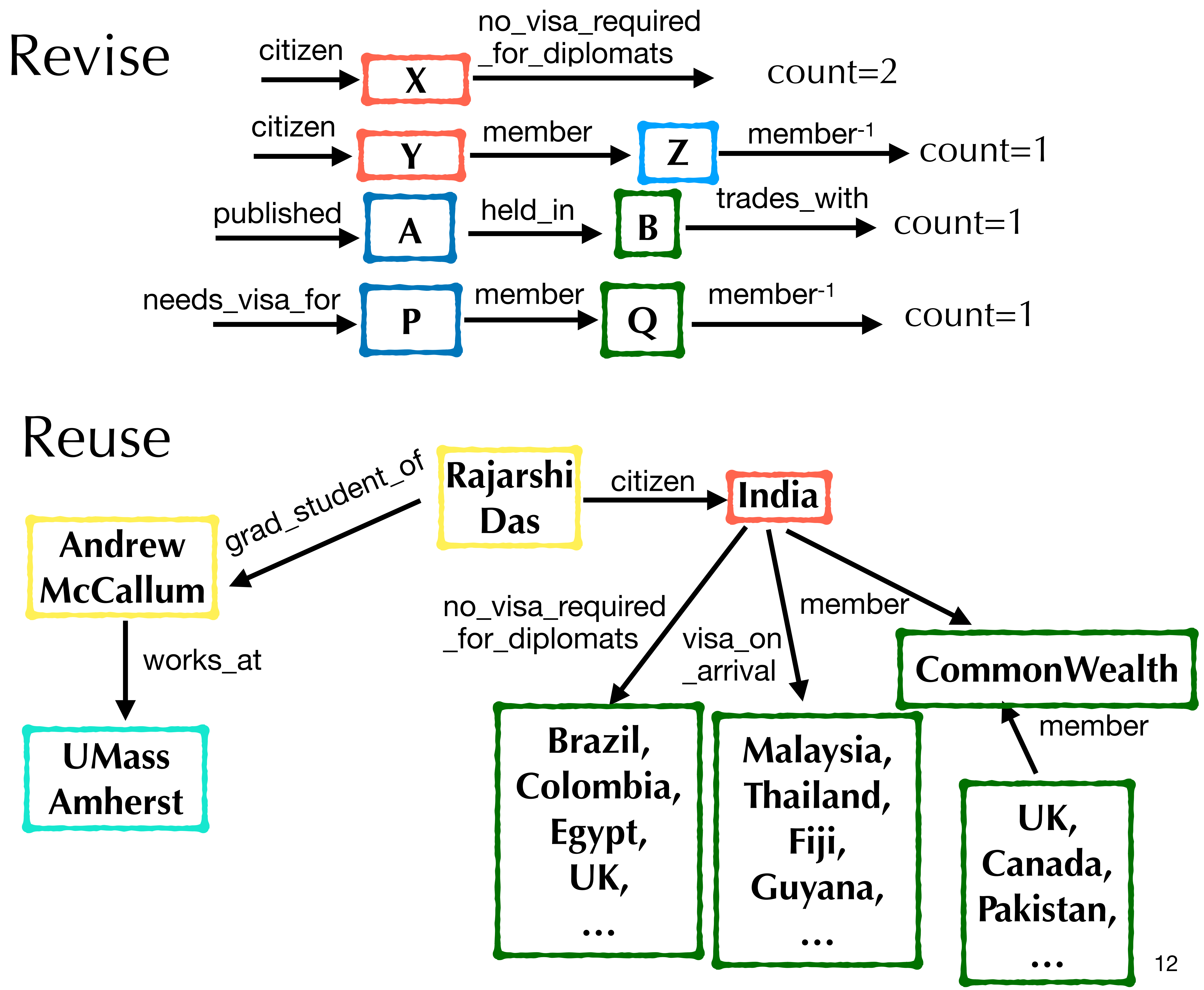

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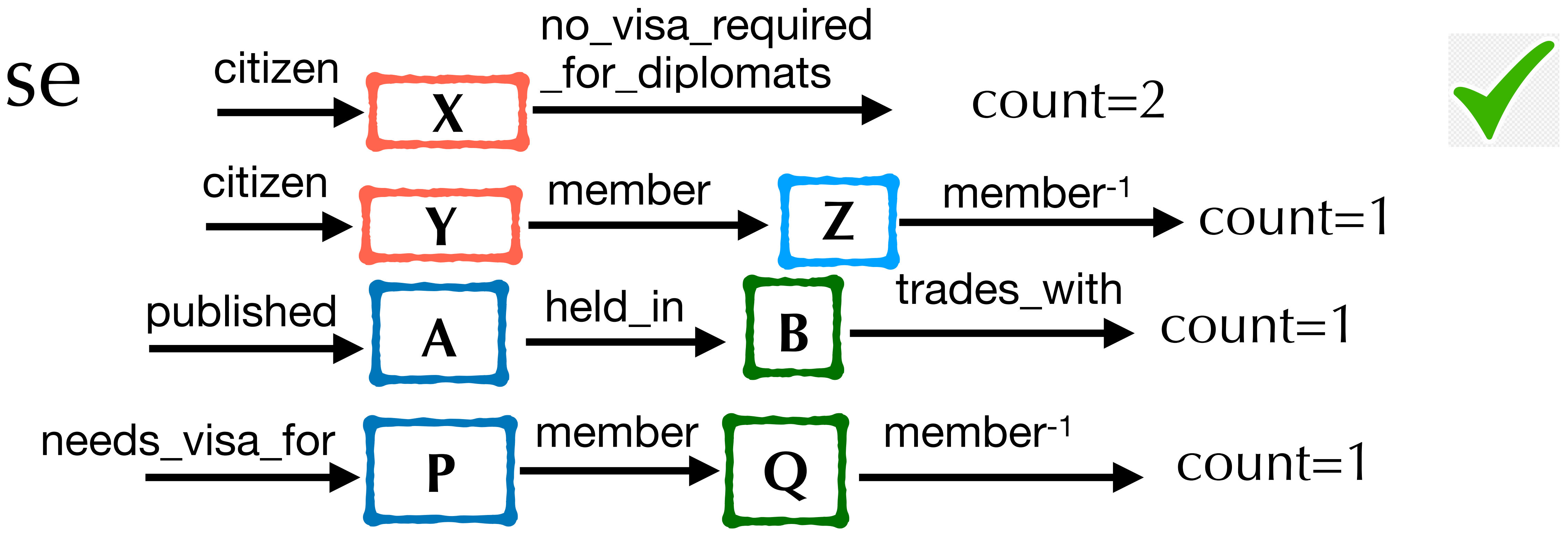

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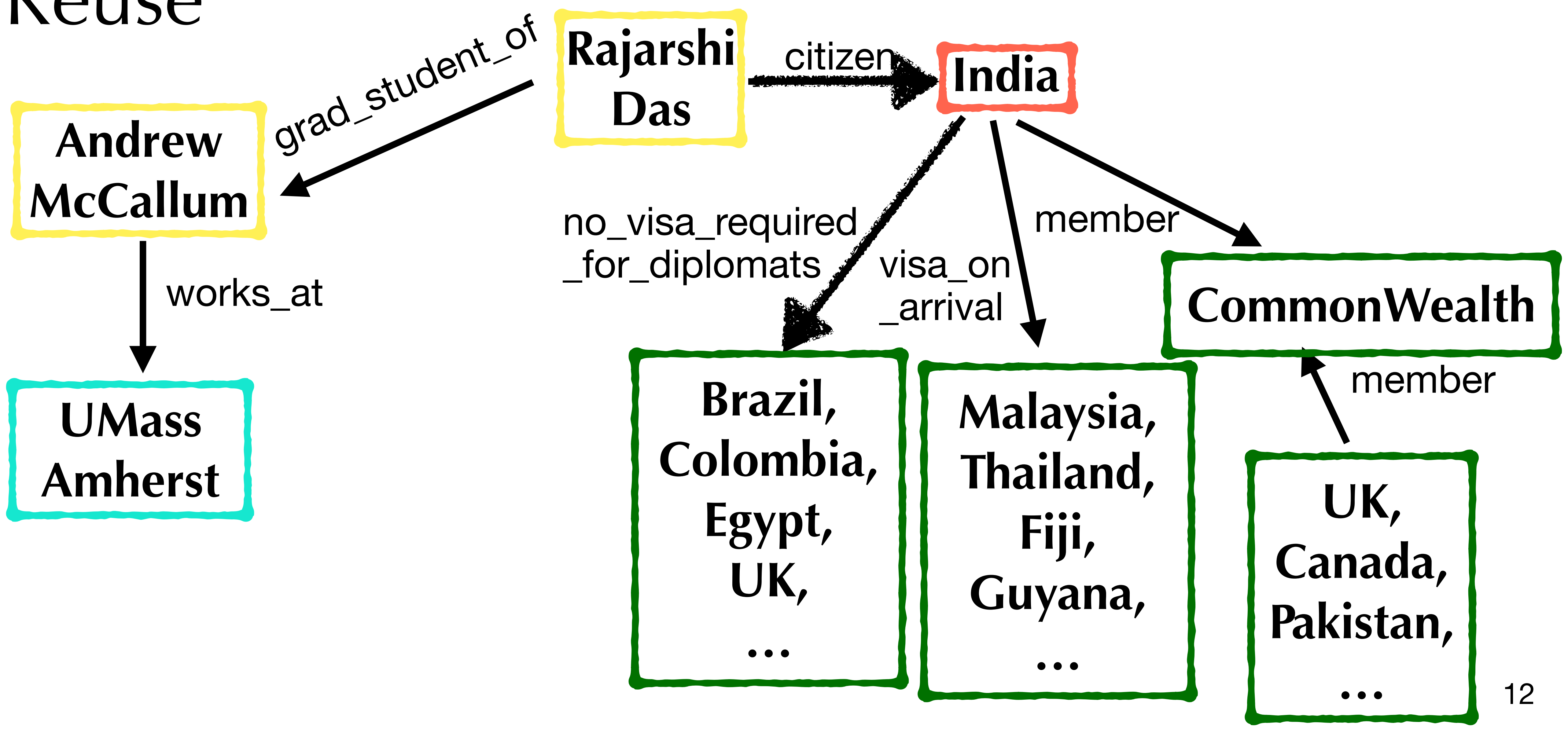

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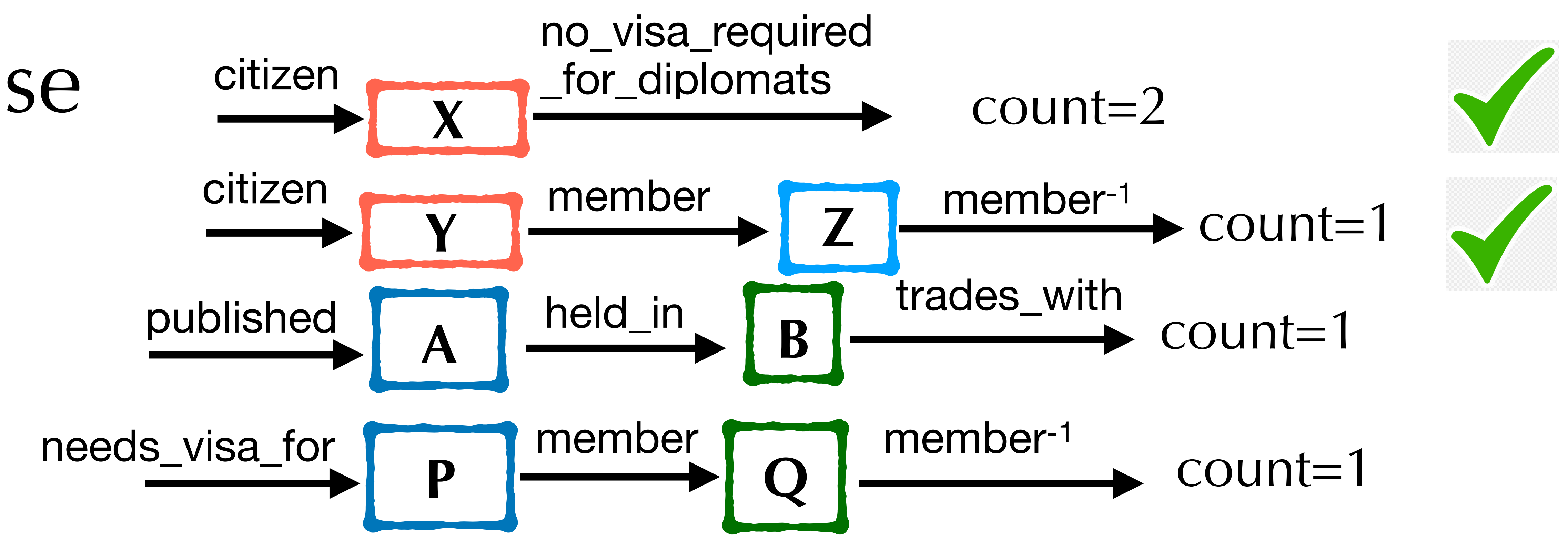
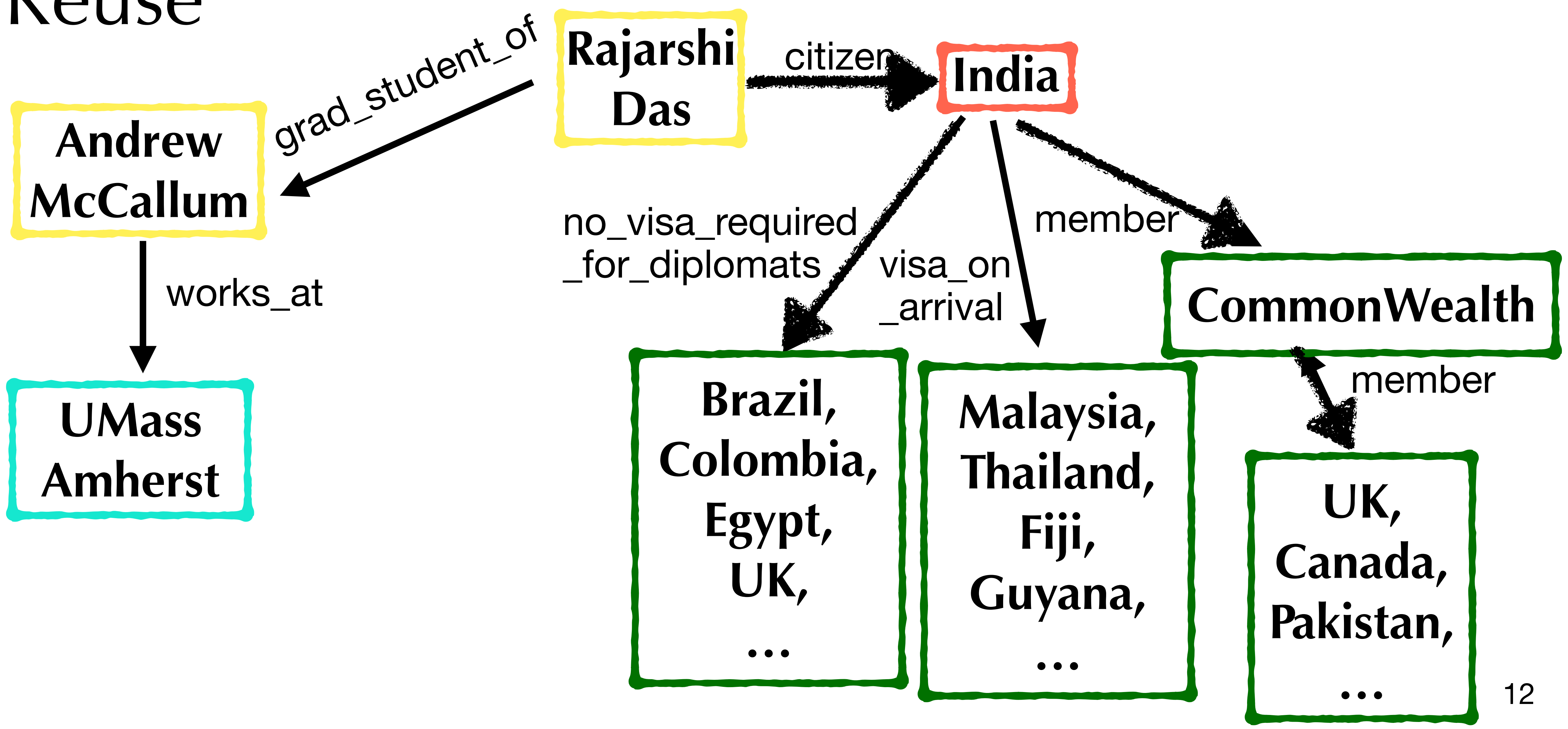


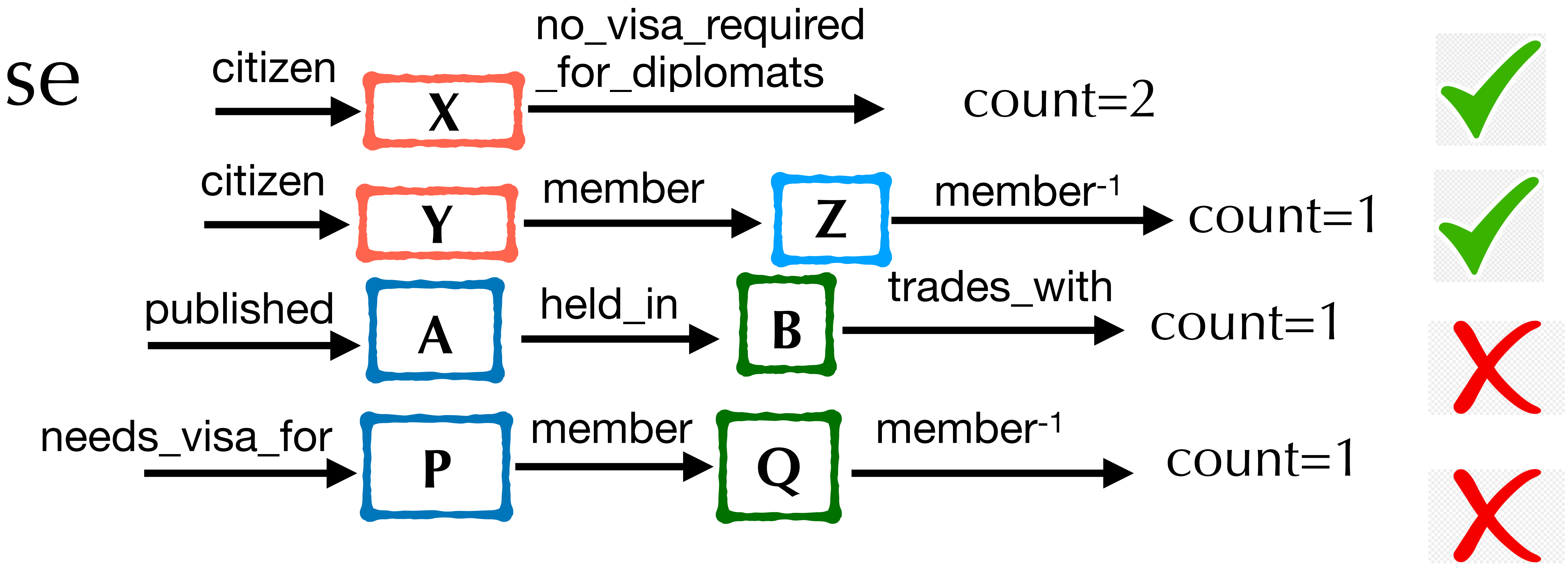
Reuse



Case-Based Reasoning in Knowledge Bases

(Raj, needs_visa_for, ?)

Revise



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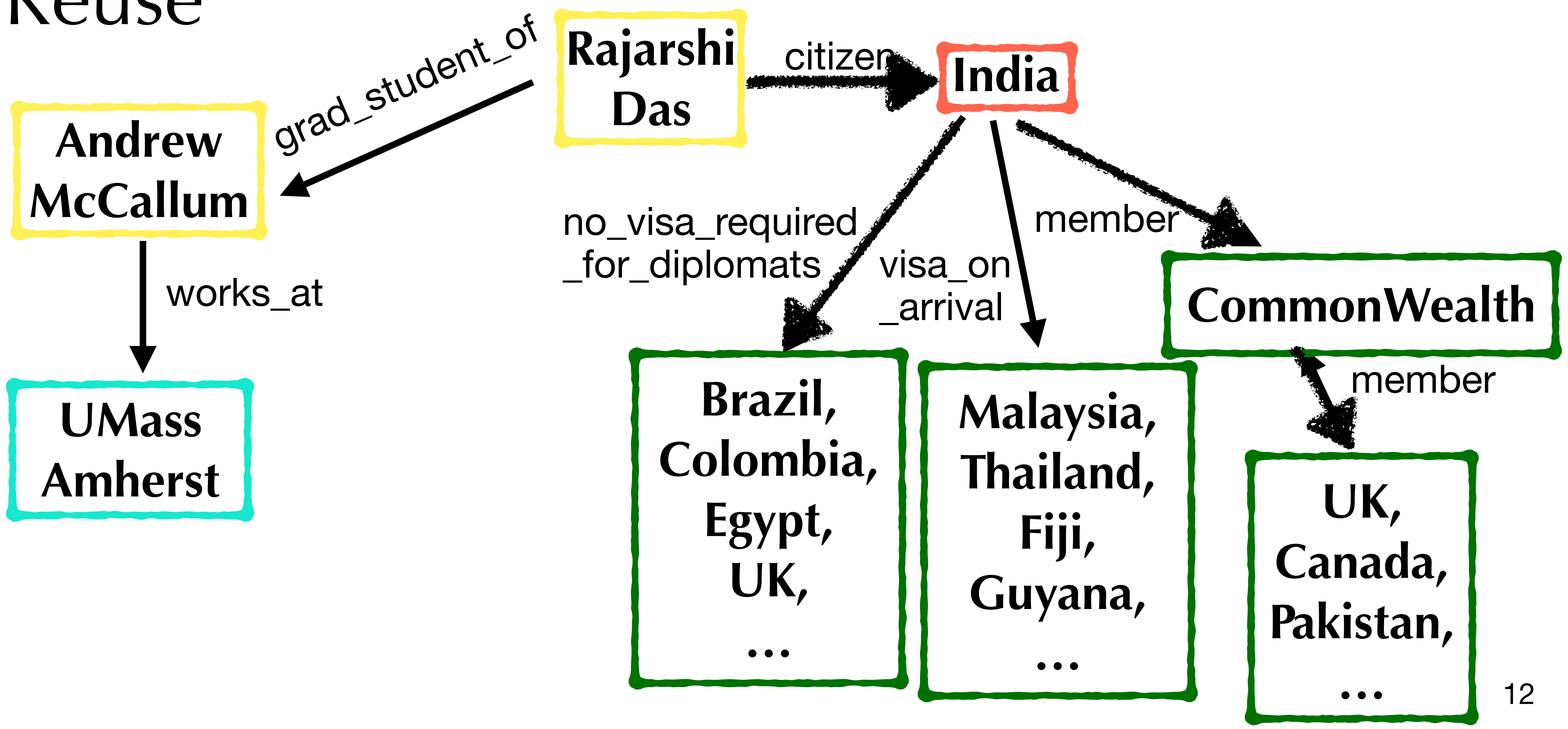

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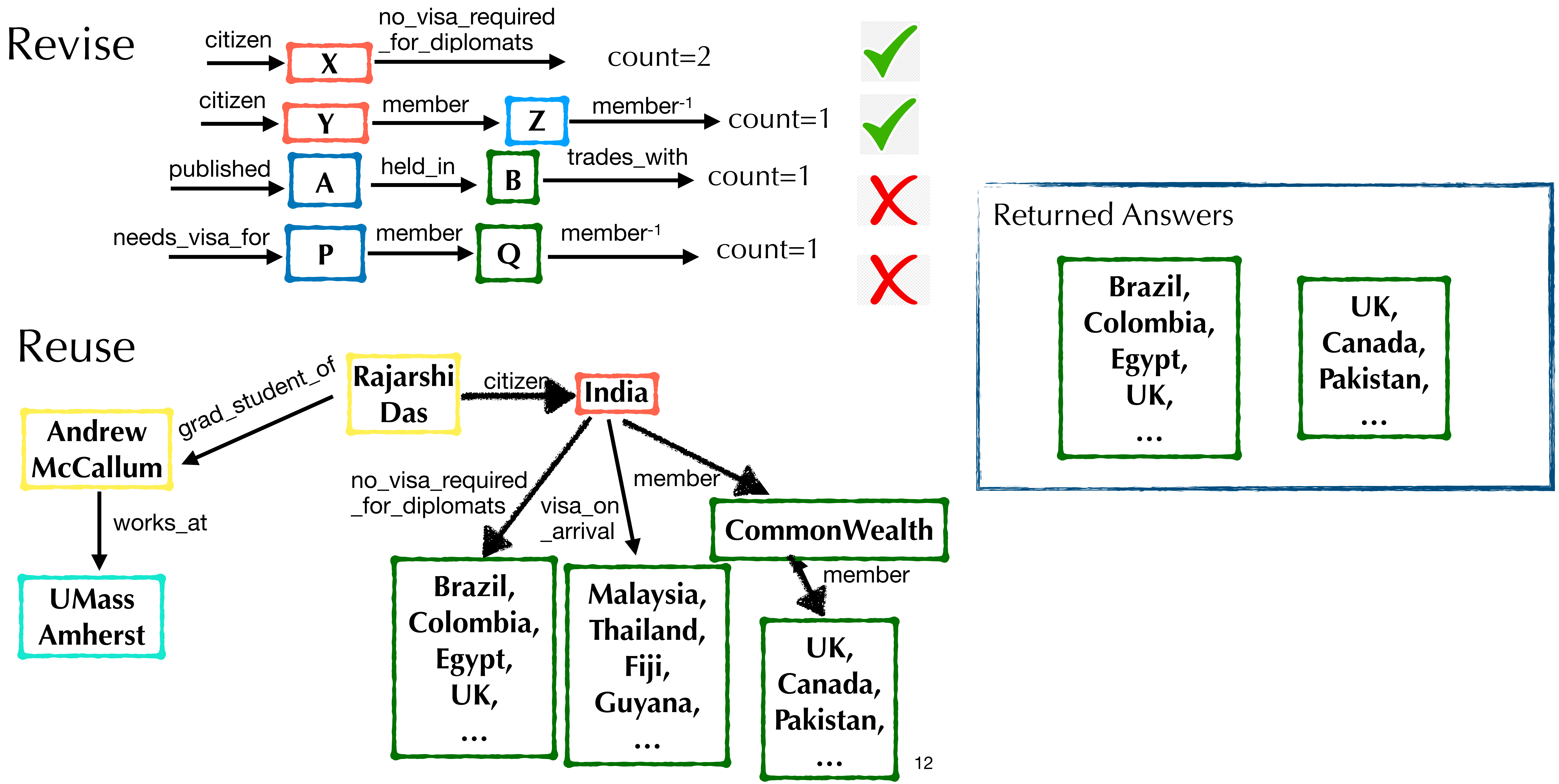
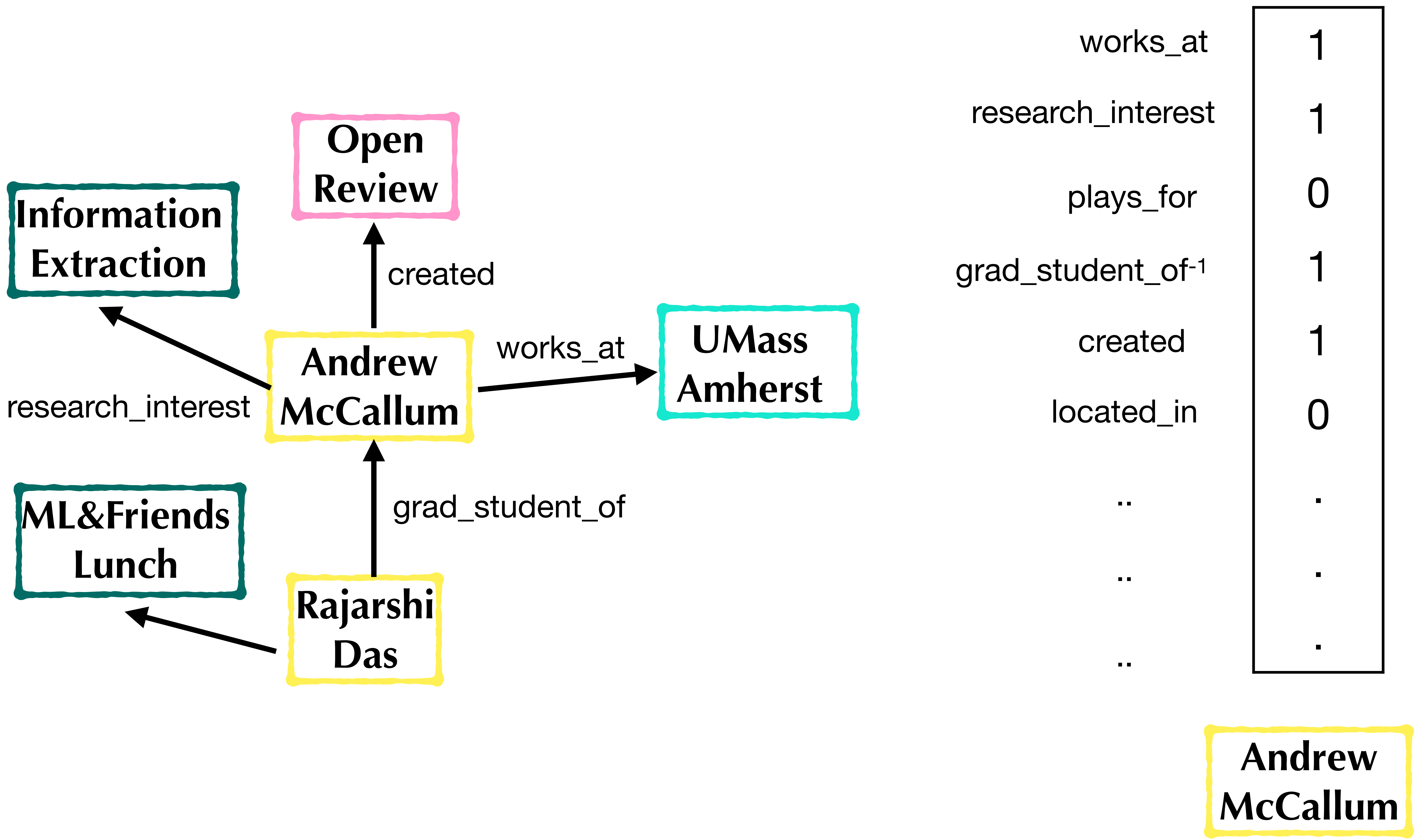


Representing Entities

- Entities are represented as (sparse) vectors of neighboring relations.



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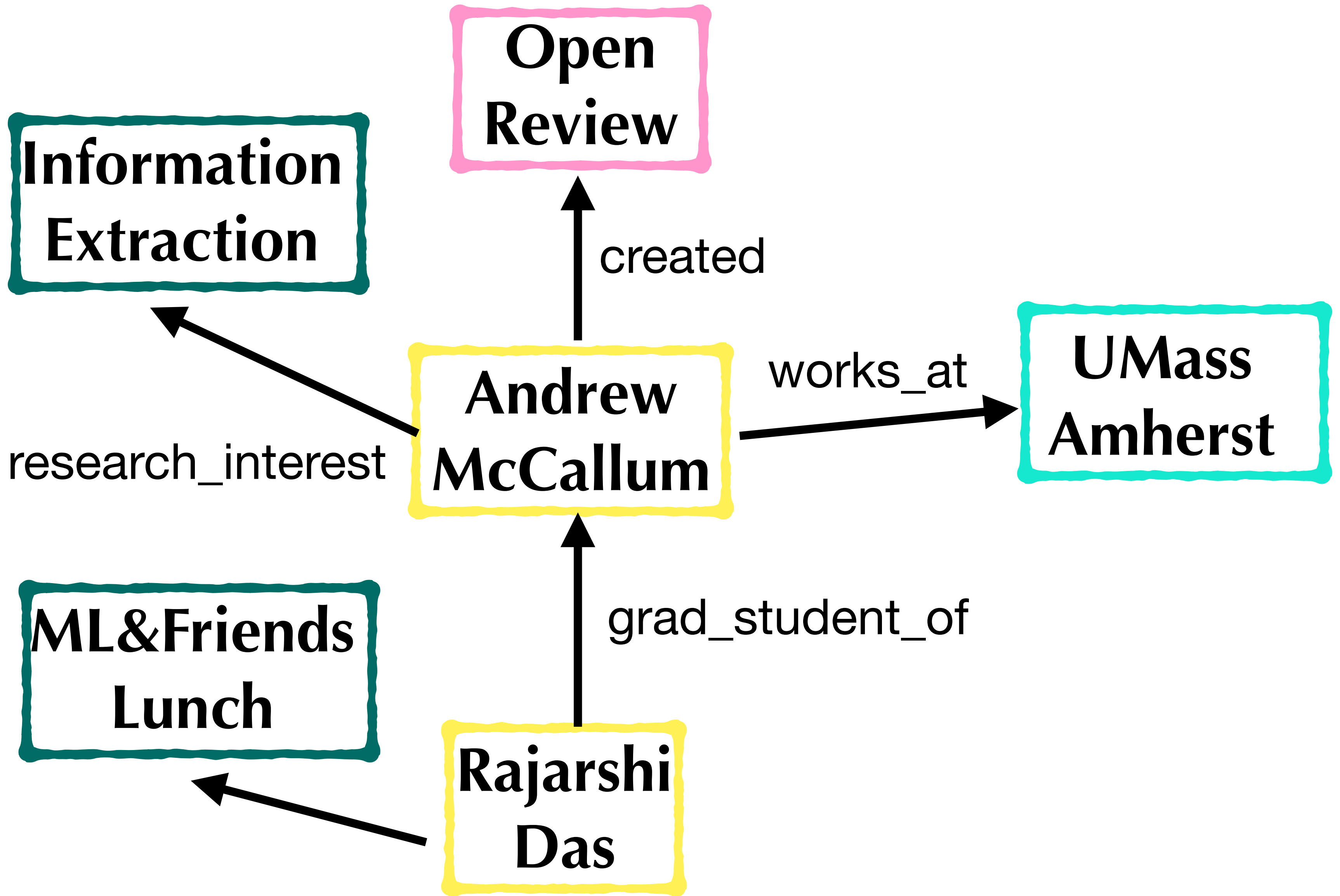

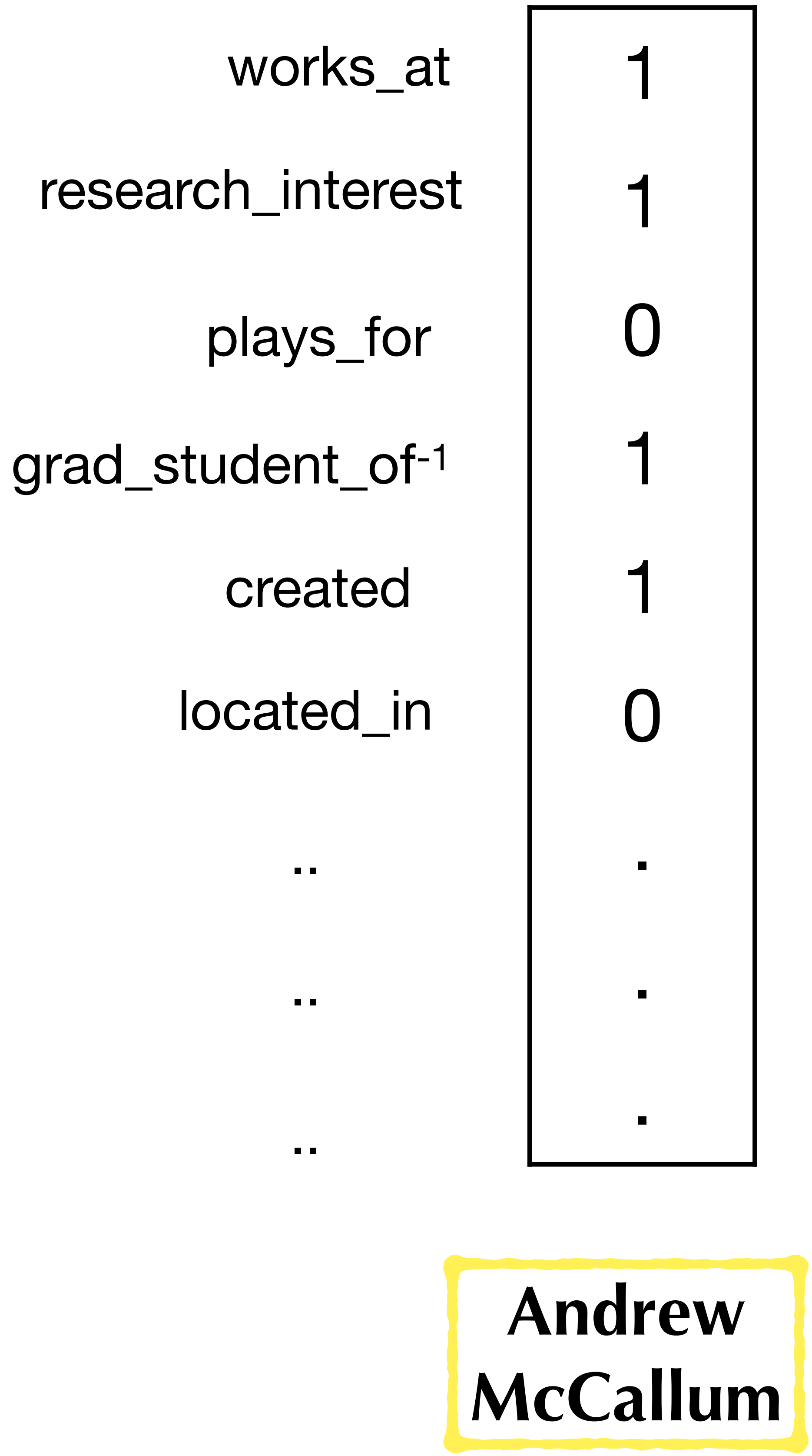

No other parameters!!
No training!!

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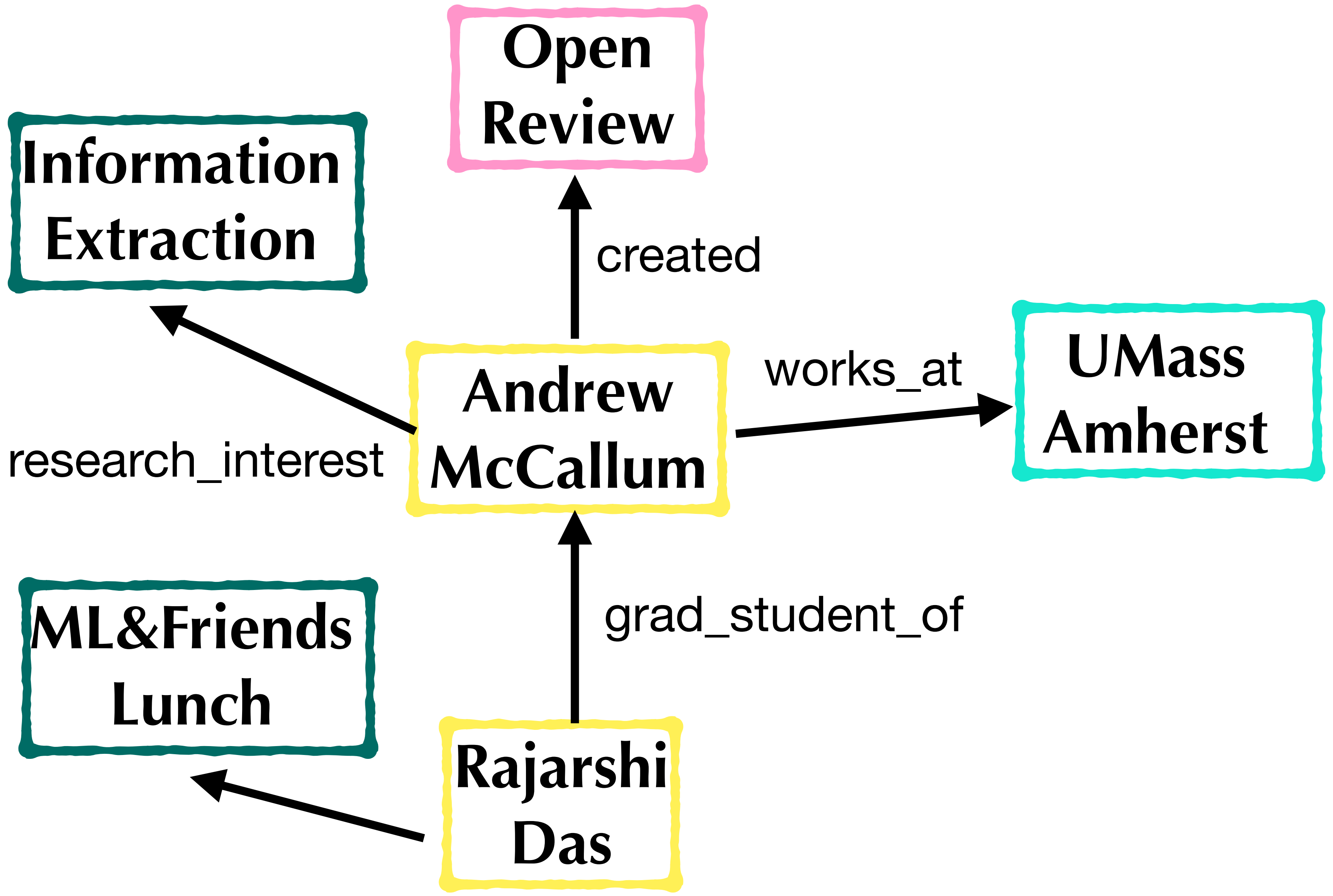
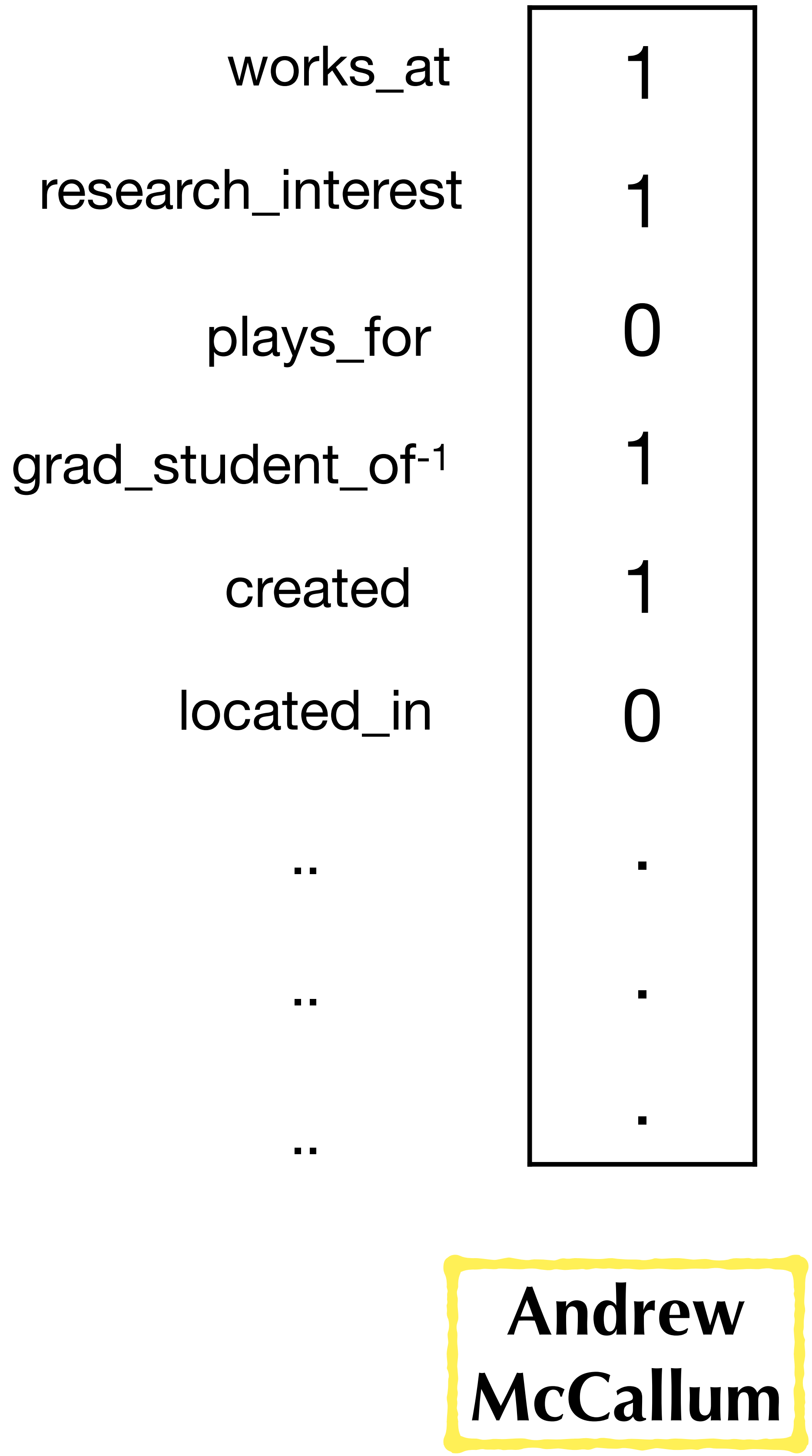




No other parameters!!
No training!!

- Cosine similarity between entities
- We consider only those entities for which we observe the query relation.

Experiments

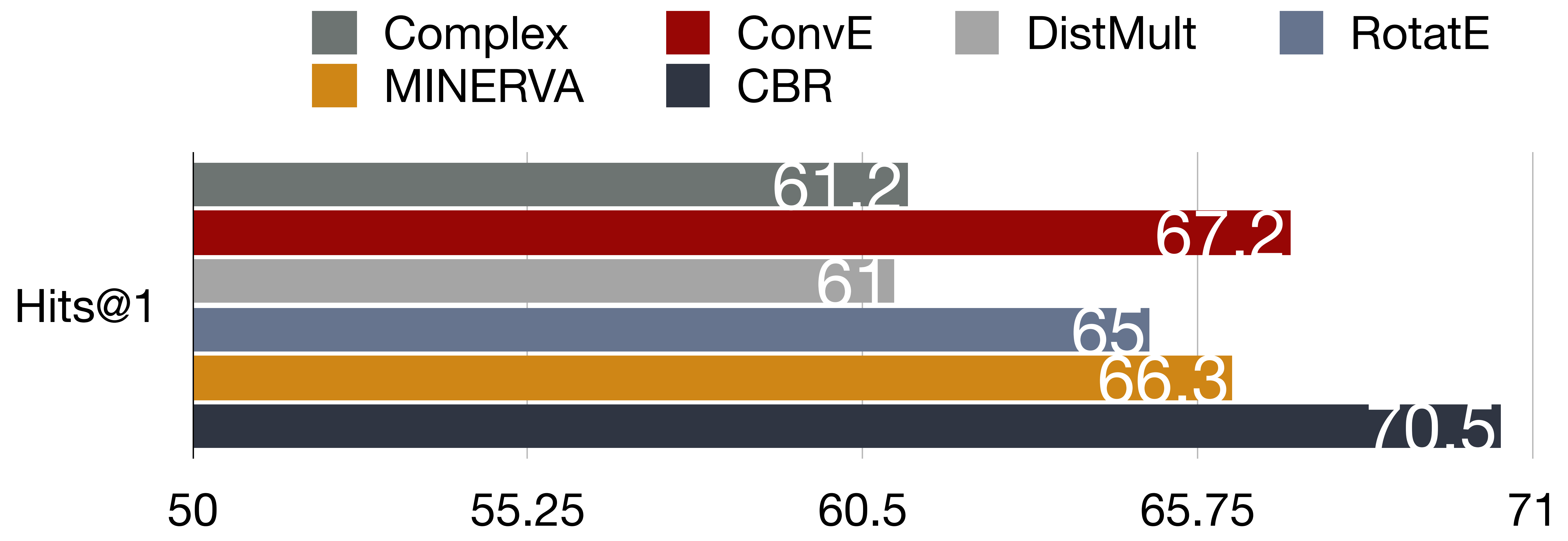
- Task: Knowledge Base Completion (e1, r, ?) or (?, r^{-1}, e2)
- Data:

	$\|\mathscr{V}\|$	$\|\mathscr{R}\|$	$\|\mathscr{E}\|$
NELL-995	75,492	200	154,213
FB122	9,738	122	112,476
WN18RR	40,943	11	93,003

- Baselines:
  - Parametric Rule Learning methods
    - MINERVA (Das, Dhuliawala, Zaheer, Vilnis, Krishnamurthy, Smola, McCallum ICLR 2018)
    - GNTPs (Minervini, Bošnjak, Rocktäschel, Riedel, Grefenstette AAAI 2020)
  - Embedding based methods:
    - RotatE (Sun, Deng, Nie, Tang ICLR 2019)
    - ConvE (Dettmers, Minervini, Stenetorp, Riedel AAAI 2018)
    - Complex (Trouillon, Welbl, Riedel, Gaussier, Bouchard ICML 2017)
    - DistMul (Yang, Yih, He, Gao, Deng ICLR 2015)
    - TransE (Bordes, Usunier, Garcia-Duran, Weston, Yakhnenko Neurips 2013)

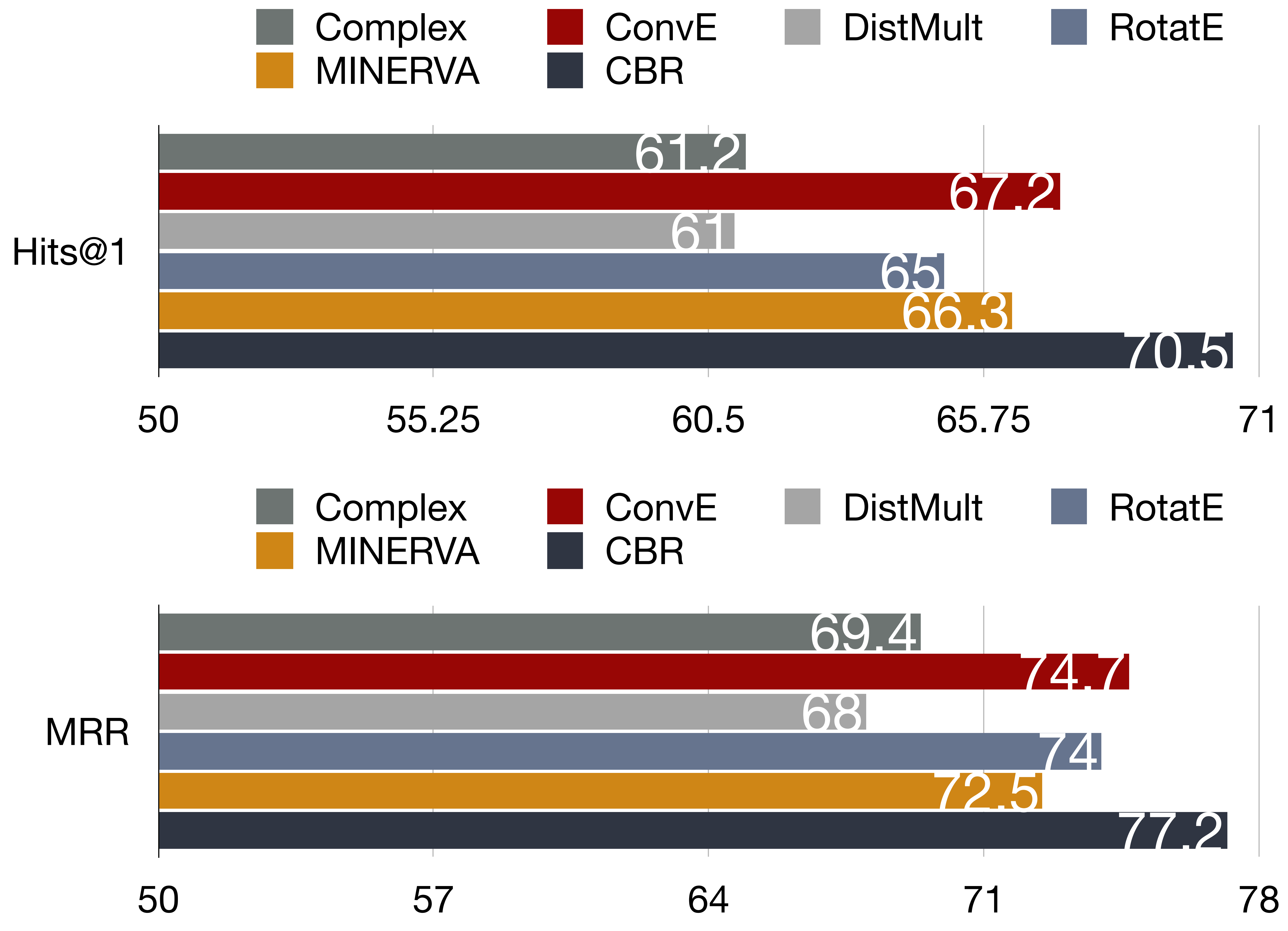
NELL-995

NELL-995



Complex
ConvE
DistMult
RotatE
MINERVA
CBR
61.2
67.2
61
65
66.3
70.5
Hits@1
50
55.25
60.5
65.75
71

NELL-995



Complex
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Hits@1
61.2
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65.75
71
Complex
ConvE
DistMult
RotatE
MINERVA
CBR
MRR
69.4
74.7
68
74
72.5
77.2
50
57
64
71
78

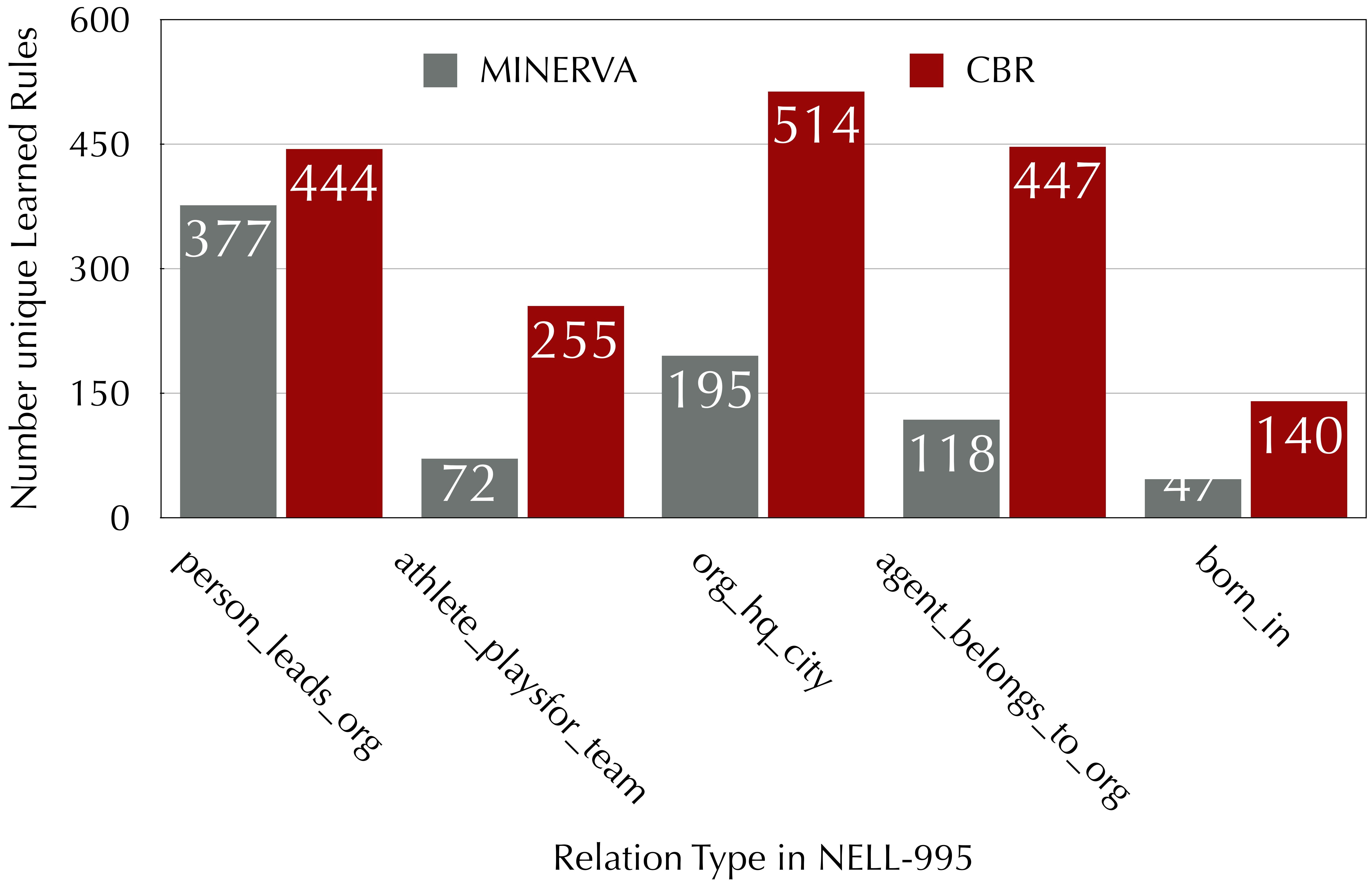
WN18RR

	TransE	DistMult	ComplEx	ConvE	RotatE	GNTPs	CBR
Hits@1	-	0.39	0.41	0.40	**0.43**	0.41	0.38
Hits@3	-	0.44	0.46	0.44	**0.49**	0.44	0.46
Hits@10	0.50	0.49	0.51	0.52	**0.57**	0.48	0.51
MRR	0.23	0.43	0.44	0.43	**0.48**	0.43	0.43

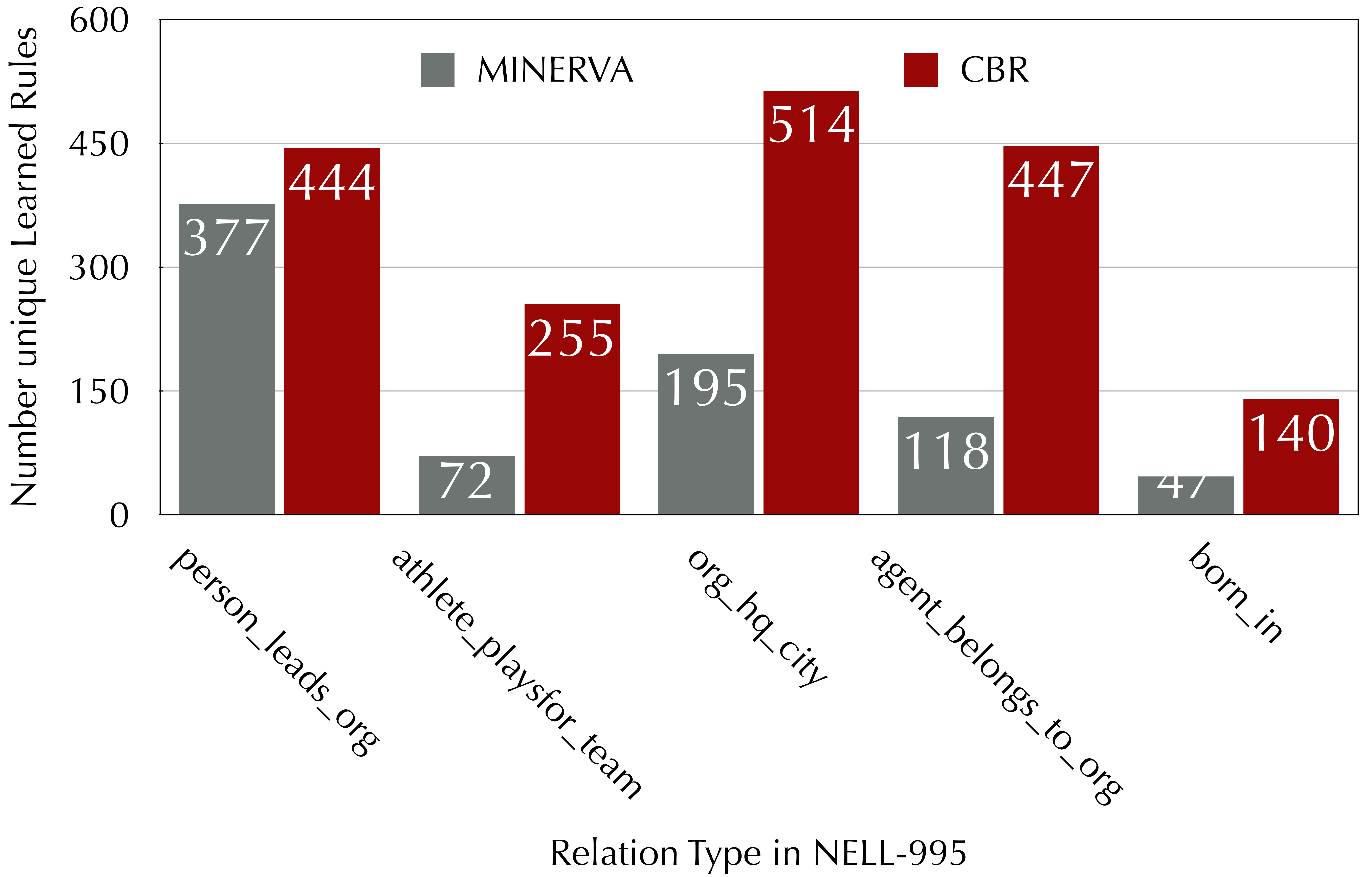
FB122

	Model	Hits@3	Hits@5	Hits@10	MRR
With Rules	KALE-Pre	35.8	41.9	49.8	29.1
	KALE-Joint	38.4	44.7	52.2	32.5
	ASR-DistMult	36.3	40.3	44.9	33.0
	ASR-ComplEx	37.3	41.0	45.9	33.8
Without Rules	TransE	36.0	41.5	48.1	29.6
	DistMult	36.0	40.3	45.3	31.3
	ComplEx	37.0	41.3	46.2	32.9
	GNTPs	33.7	36.9	41.2	31.3
	CBR	**40.0**	44.5	48.8	**35.9**

Learned Rules



Learned Rules



More number of fine-grained rules

Future Work

- We introduce a general framework of CBR for KB reasoning.
- Future steps:
    - Richer entity representation and similarity metric
    - Better matching of paths using path embeddings
    - Better Ranking of paths
    - Considering subgraphs instead of paths as solution to cases.

Conclusion

- We introduce a new approach
  - that derives reasoning rules dynamically for each entity instead of storing them in model parameters
  - Requires no training
  - Outperform existing rule-induction methods and are comparable to existing embedding based approaches.
  - Lot of exciting future directions.

Conclusion

- We introduce a new approach
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Thank you!