UMass at English Slot Filling and Cold Start

Unified KB Construction with Universal Schema

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Andrew McCallum

Overview of Relation Extraction

Supervised Classification

Map entity pairs and their mentions to relations

Supervised Classification

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employee(**X**,**Y**)

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Petrie,
UCL

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Petrie, a London native, was a professor at **UCL** from 1892 to 1933.

The **Petrie** Museum at **UCL** preserves an estimated 80,000 objects.

KBP

employee(**X**,**Y**)

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Petrie, UCL	**1**

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Test

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Ferguson is a historian at **Harvard** focusing on British and American Imperialism.

Ferguson is a professor at **Harvard**.

Ferguson, Harvard

Andrew is a professor at **Cambridge**

Andrew teaches history at **Cambridge**

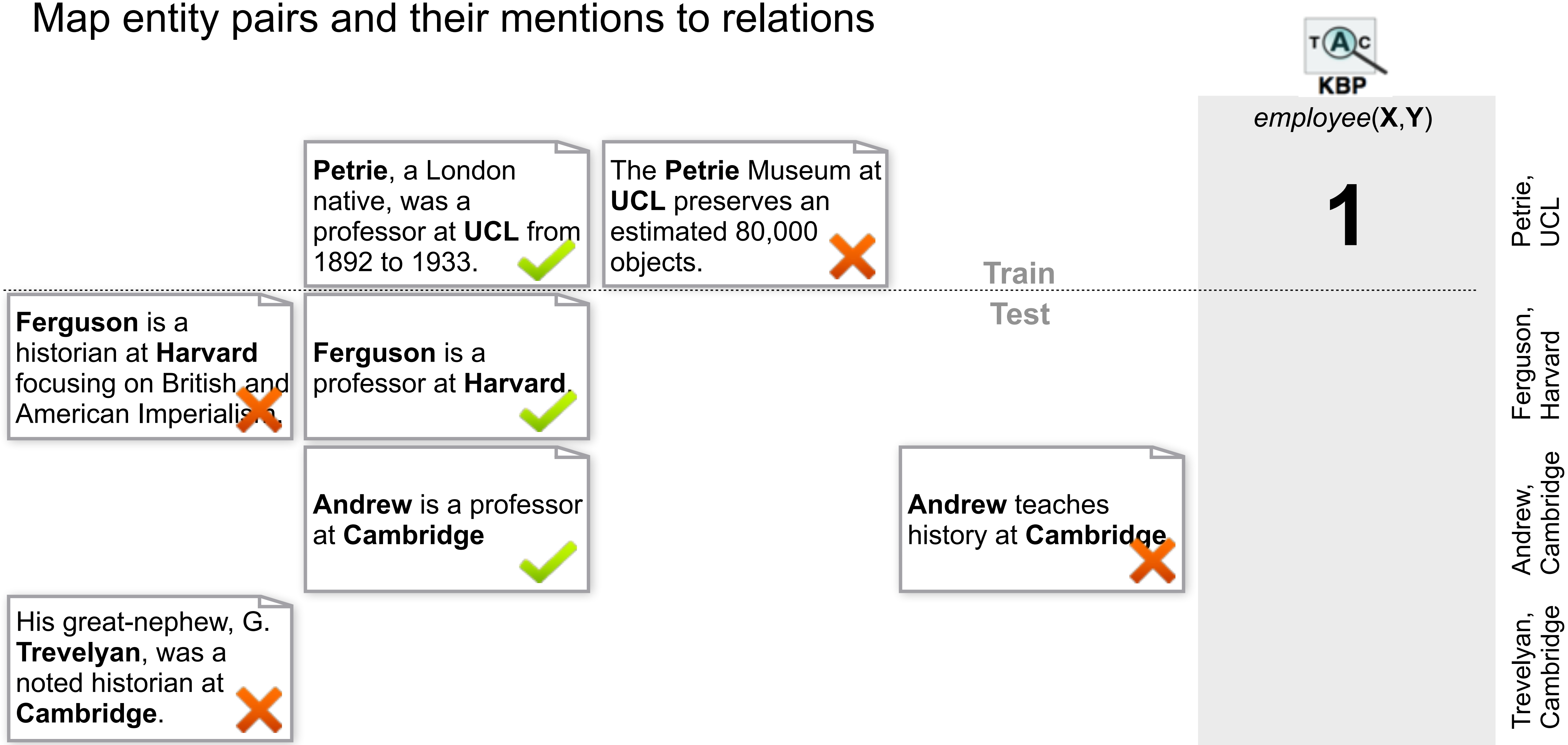
Andrew, Cambridge

His great-nephew, G. **Trevelyan**, was a noted historian at **Cambridge**.

Trevelyan, Cambridge

Supervised Classification

Map entity pairs and their mentions to relations



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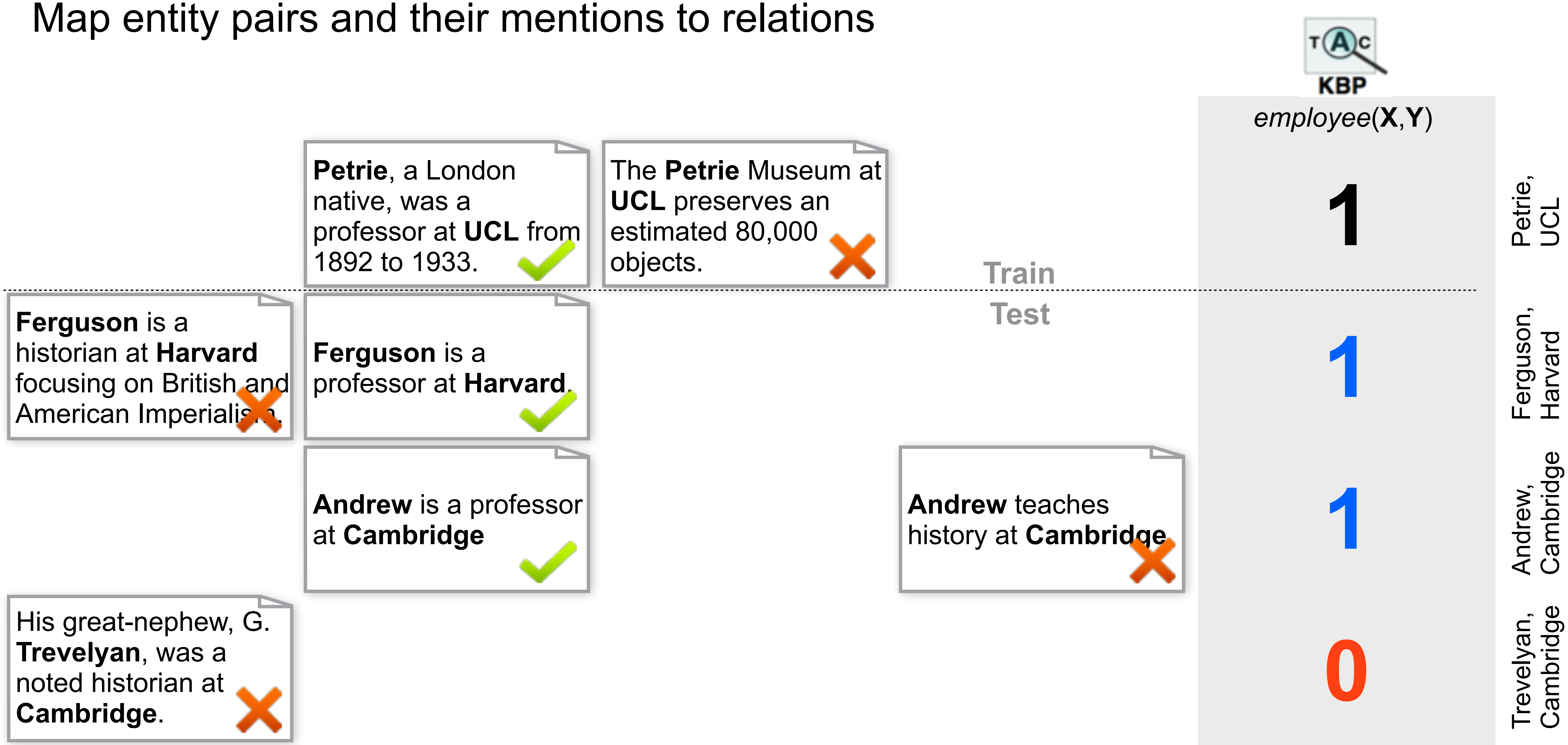

Supervised Classification

Fails for **unseen** patterns

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Matrix Formulation

Convert problem into a **matrix formulation**

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0

Matrix Formulation

Columns correspond to **patterns** between mentions

X-*is-historian-at*-**Y**				*employee*(**X**,**Y**)
	Petrie, a London native, was a professor at **UCL** from 1892 to 1933.	The **Petrie** Museum at **UCL** preserves an estimated 80,000 objects.		1
1	**Ferguson** is a professor at **Harvard**.			1
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1				0

Matrix Formulation

Columns correspond to **patterns** between mentions

X-*is-historian-at*-**Y**	**X**-*is-professor-at*-**Y**
	1
1	1
	1
1	

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employee(**X**,**Y**)
1
1
1
0

Matrix Formulation

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X-*is-historian-at*-**Y**	**X**-*is-professor-at*-**Y**	**X**-*museum-at*-**Y**	**X**-*teaches-history-at*-**Y**	*employee*(**X**,**Y**)
	1	1		1
1	1			1
	1		1	1
1				0

Supervised Classification

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	1	1		1
1	1			?
	1		1	?
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1	1			?
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	1	**1**	Train	**1**
1	**1**		Test	**?**
	1		**1**	**?**
1				**?**

Supervised Classification

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	1	1	Train	1
1	1		Test	?
	1		1	?
1				?

does not generalize, costly to label data

Bootstrapping

X-*is-historian-at*-**Y**	**X**-*is-professor-at*-**Y**	**X**-*museum-at*-**Y**	**X**-*teaches-history-at*-**Y**	*employee*(**X**,**Y**)
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	1	1	Train	1
1	1		Test	?
	1		1	?
1				?

difficult to control generalization, still relies on labeled data

Distant Supervision

X-*is-historian-at*-**Y**	**X**-*is-professor-at*-**Y**	**X**-*museum-at*-**Y**	**X**-*teaches-history-at*-**Y**	*employee*(**X**,**Y**)	/employee
	1			1 Train	1
1	1			Test ?	
	1		1	?	
1				?	

Distant Supervision

TAC KBP | Freebase

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	1			1 Train	1
1	1			Test ?	
	1		1	?	
1				?	

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	1	**1**		**1** Train	**1**
1	**1**			Test **?**	
	1		**1**	**?**	
1				**?**	

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	1	1		1 Train	1
1	1			Test ?	
	1		1	?	
1				?	

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	1	$\boxed{1}$		1 Train	1
1	1			Test ?	
	1		1	?	
1				?	

need alignment to external schema, assumptions may be inaccurate

Other Problems

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  - cityOfHQ(X,Y): many weak co-occurrences of X & Y

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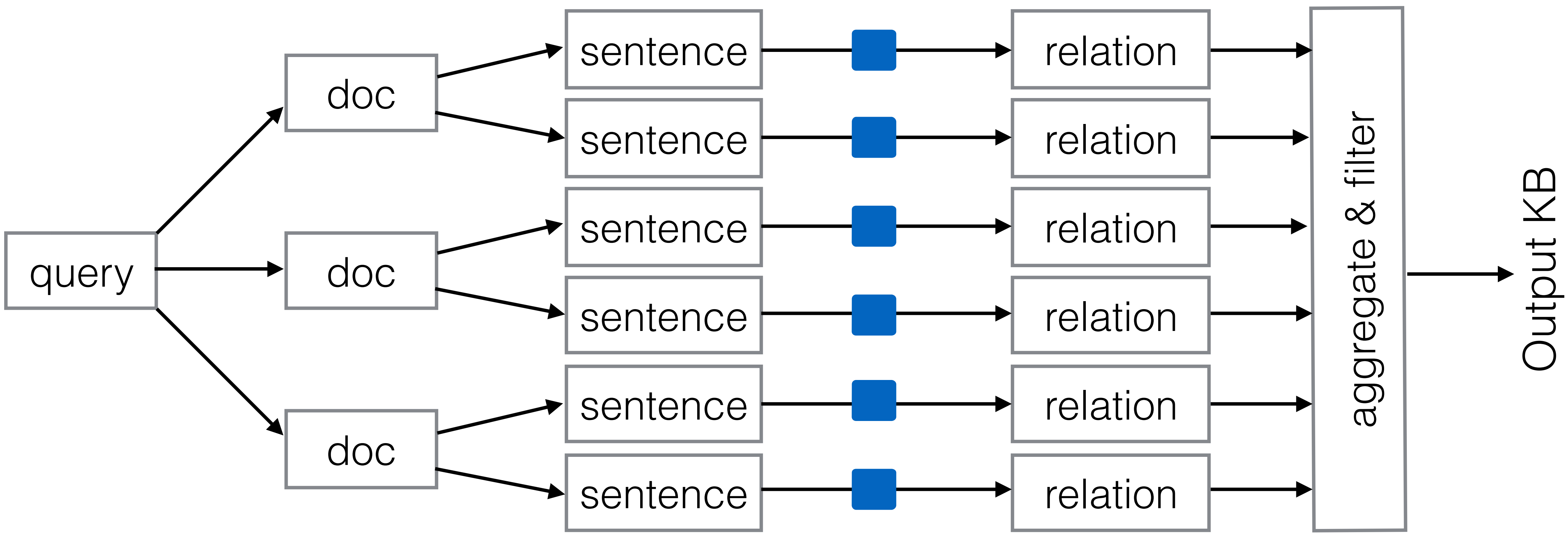
  - cityOfHQ(X,Y): many weak co-occurrences of X & Y
- A relation may be implied by **other predicted relations**
  - topEmployeeOf → employeeOf
  - cityOfResidence → cityOfDeath (probabilistic!)
- A relation may require **context from multiple entities** (that may not be query entities)
  - *X was in Y*: school, company, city, state, country?
  - *X, president of Y*: headOfState, topEmployeeOf

Unified KB Construction

Query-time Pipeline



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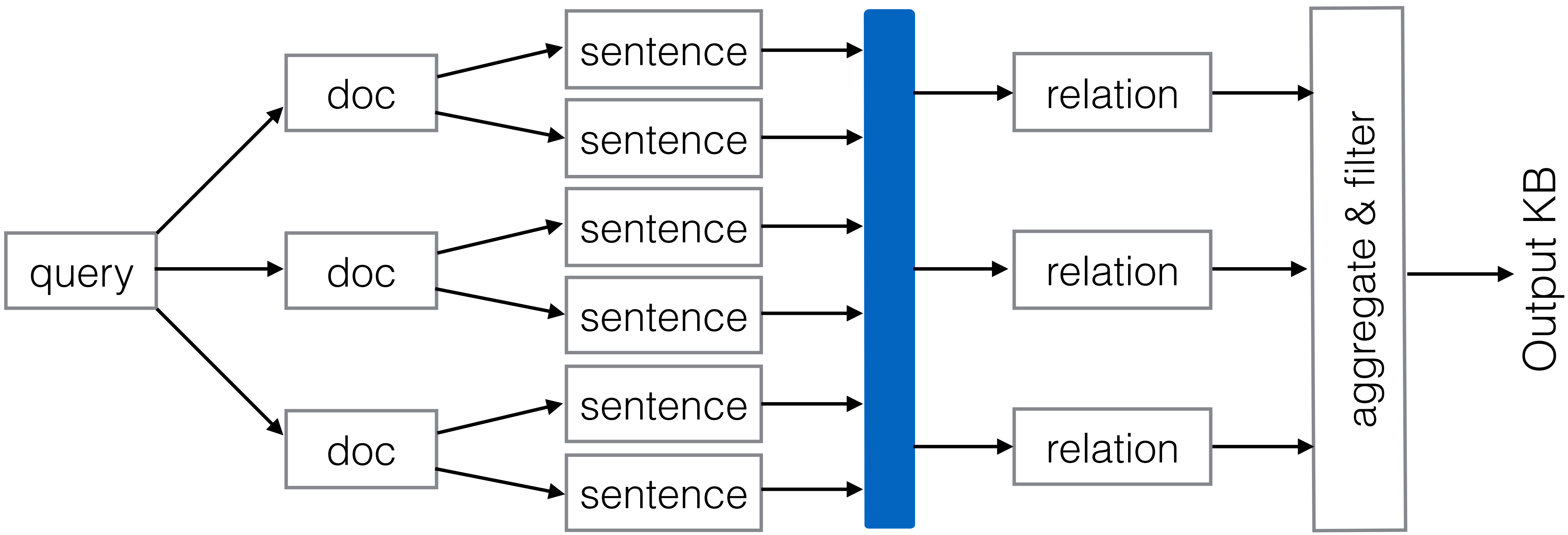
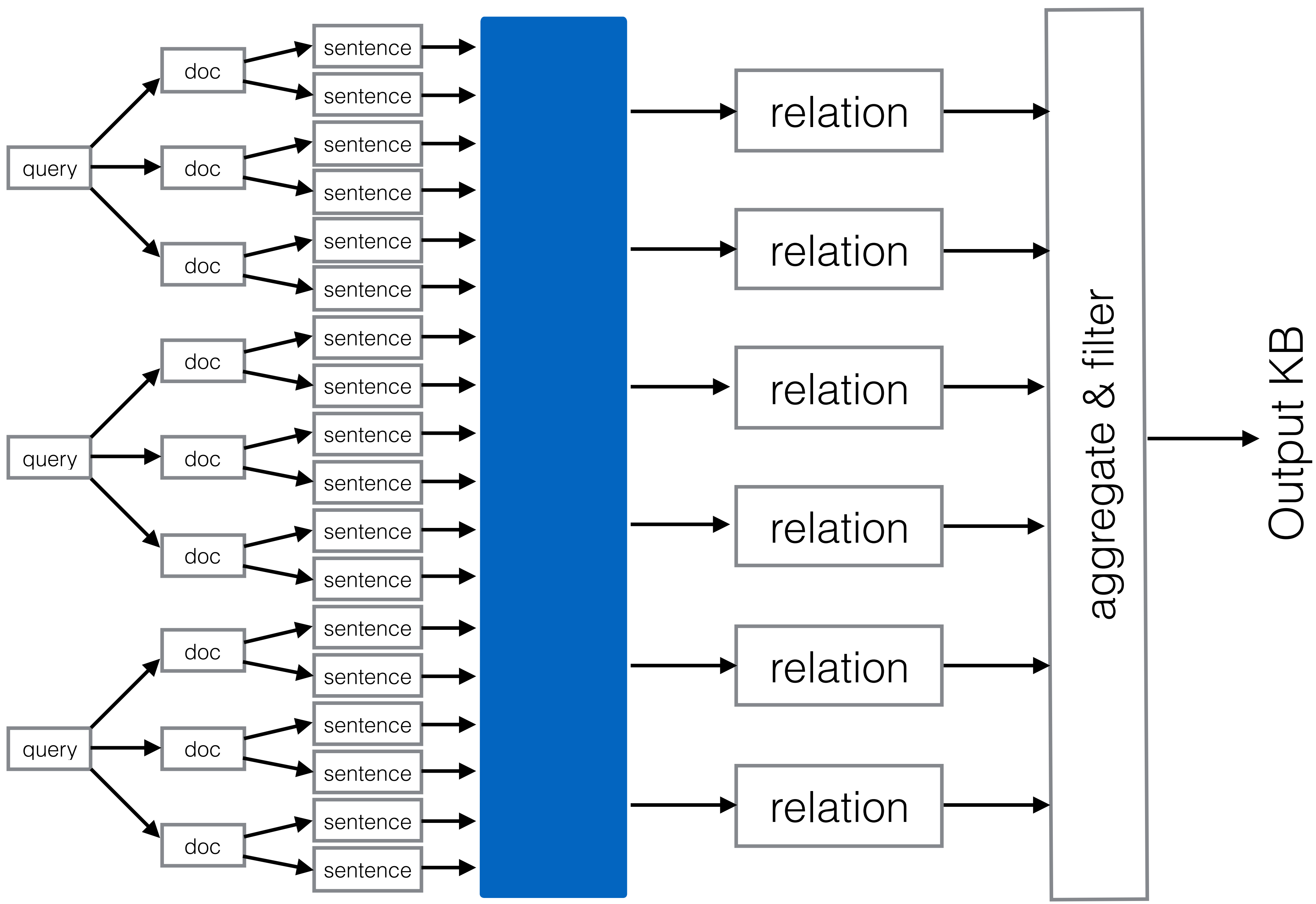
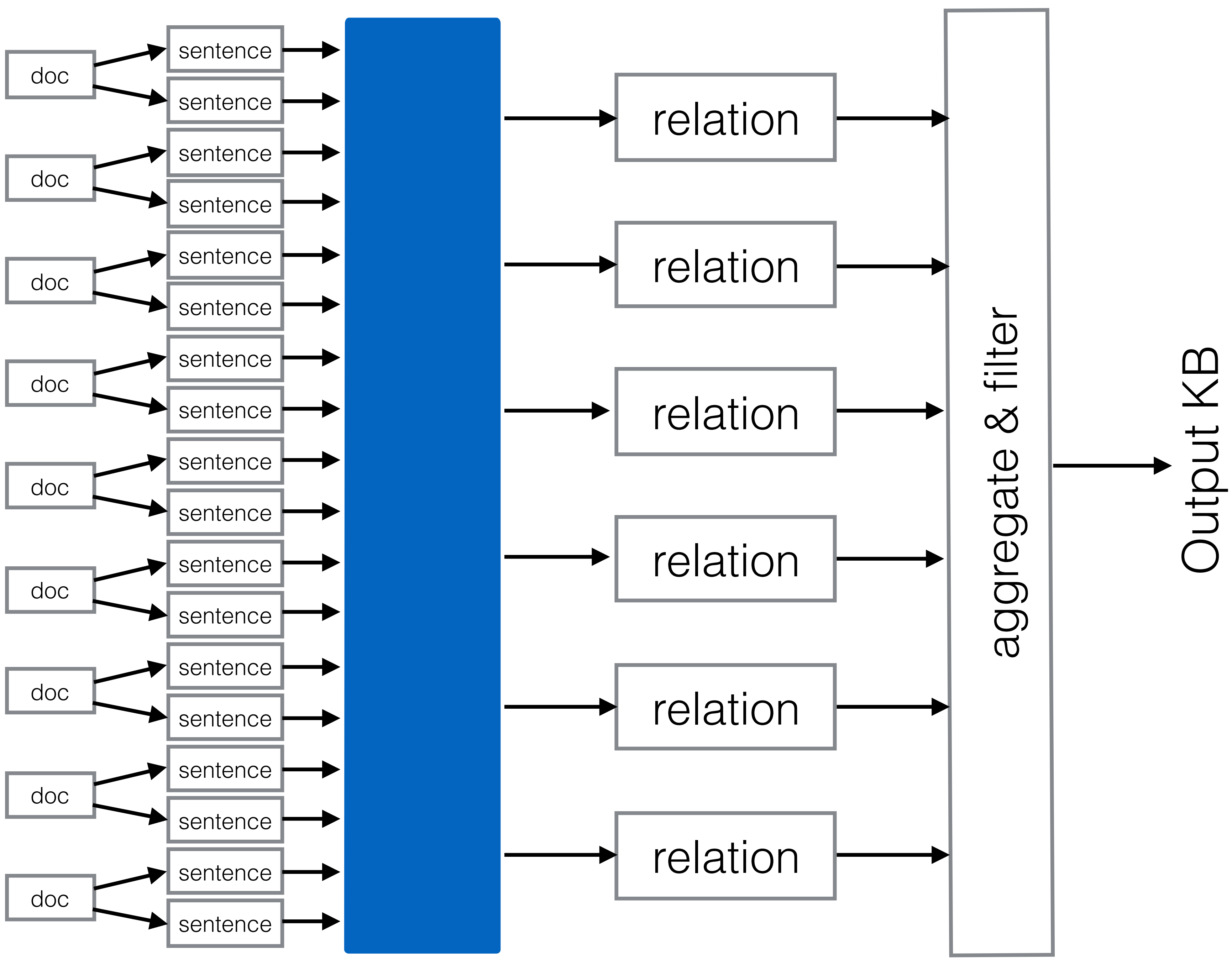


Similar to recent distant supervision systems.

Model all the queries



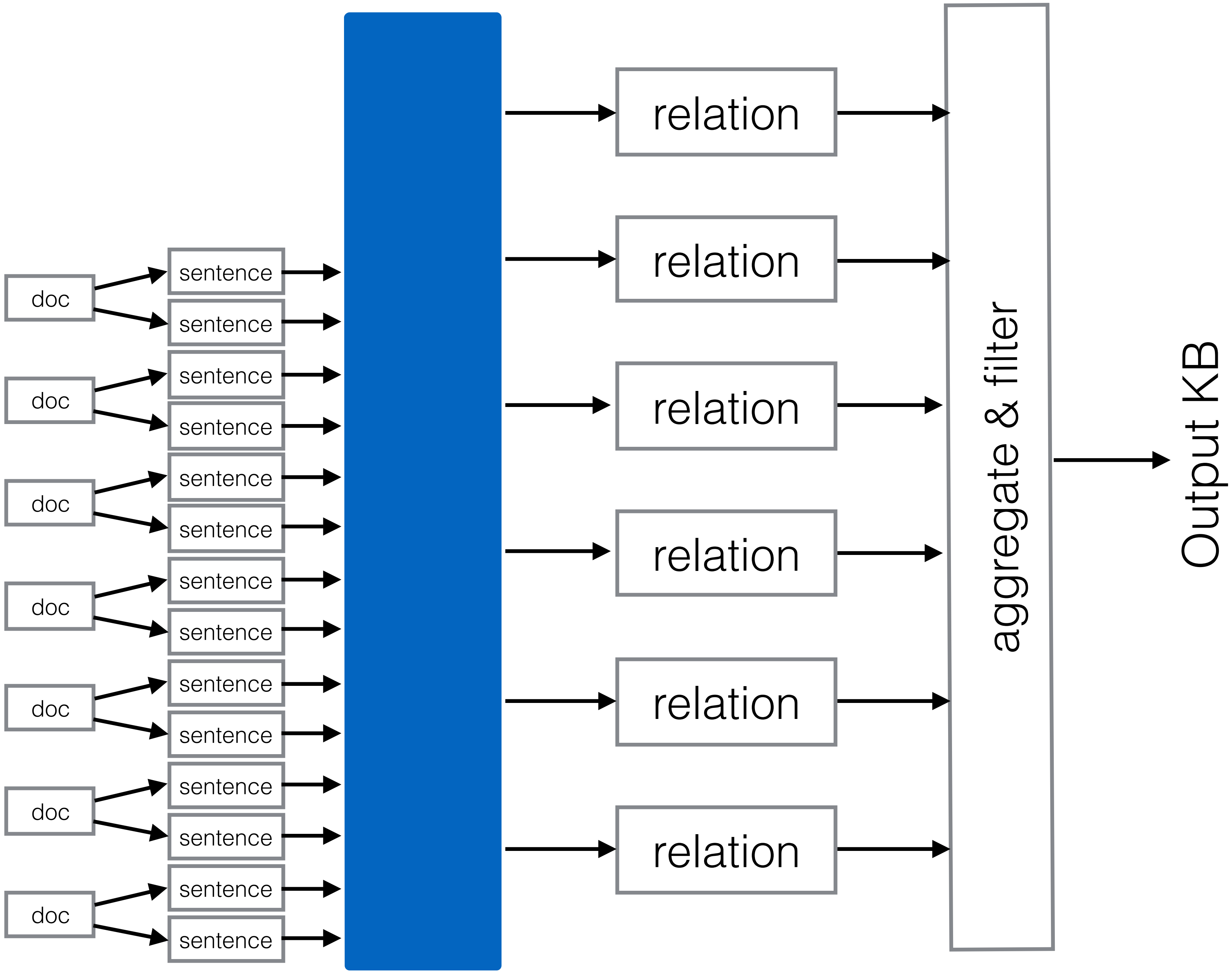
Model all the entities!



… and all forms of "evidence"

Training Corpus

Test Corpus



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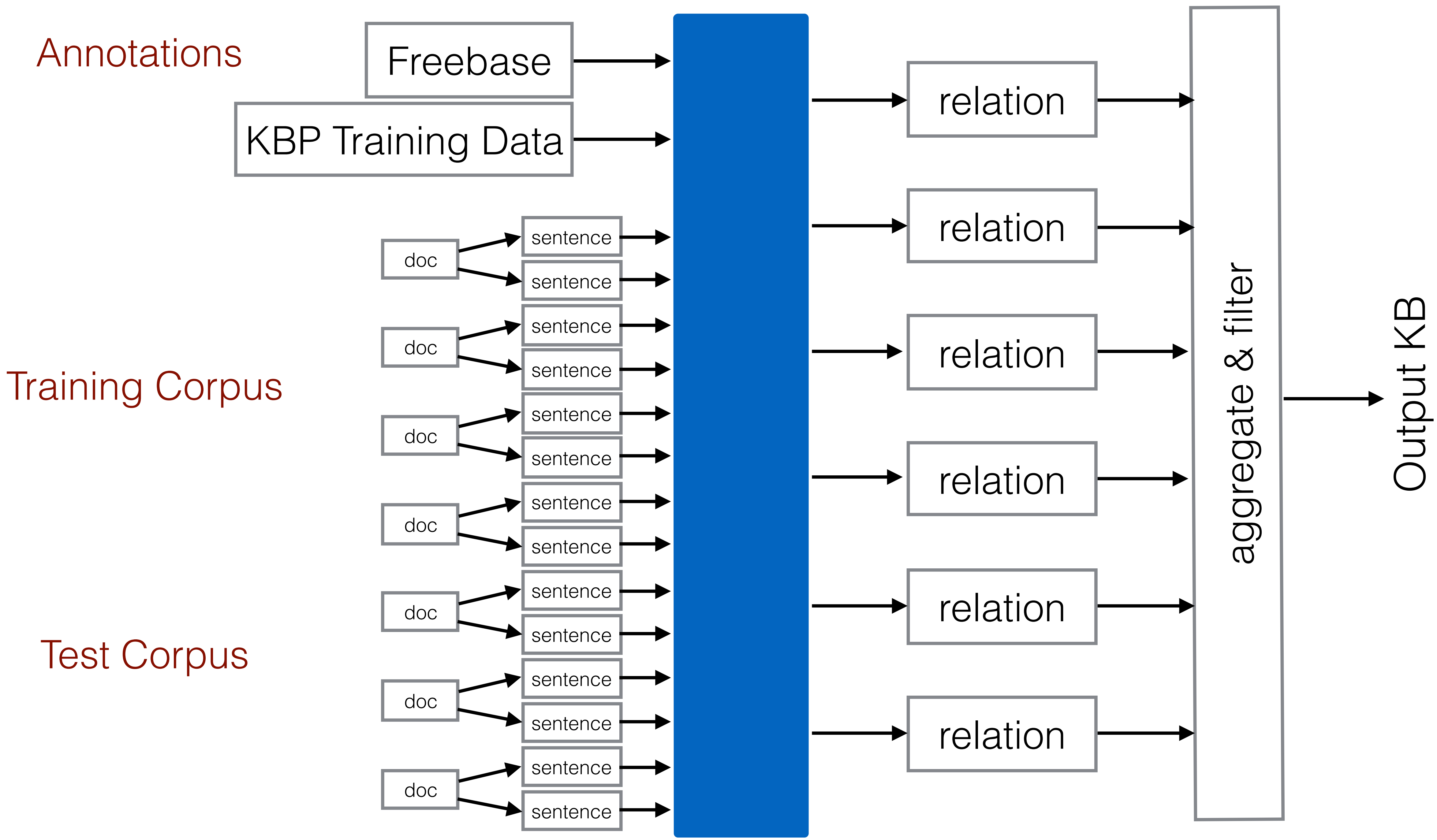

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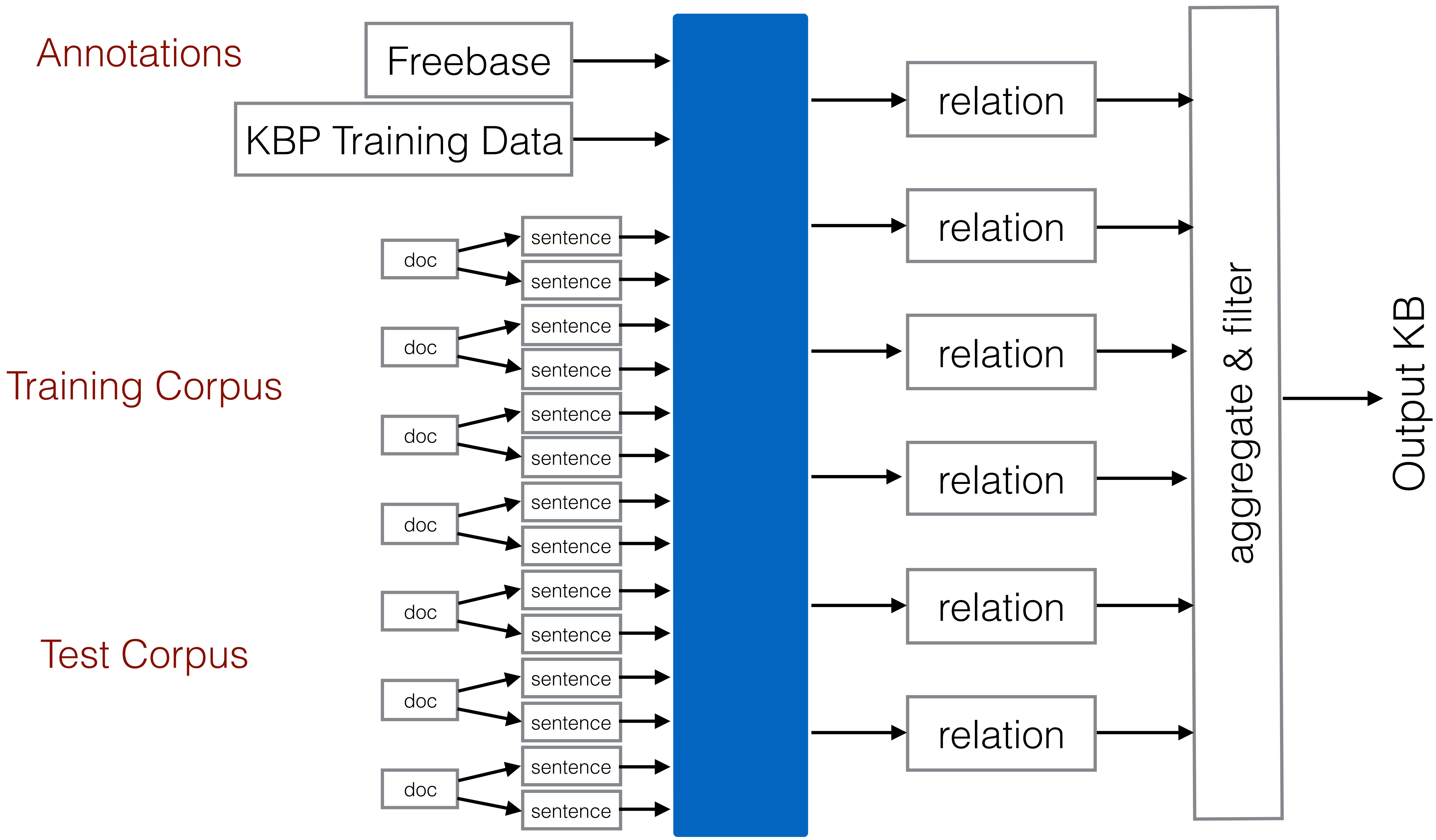

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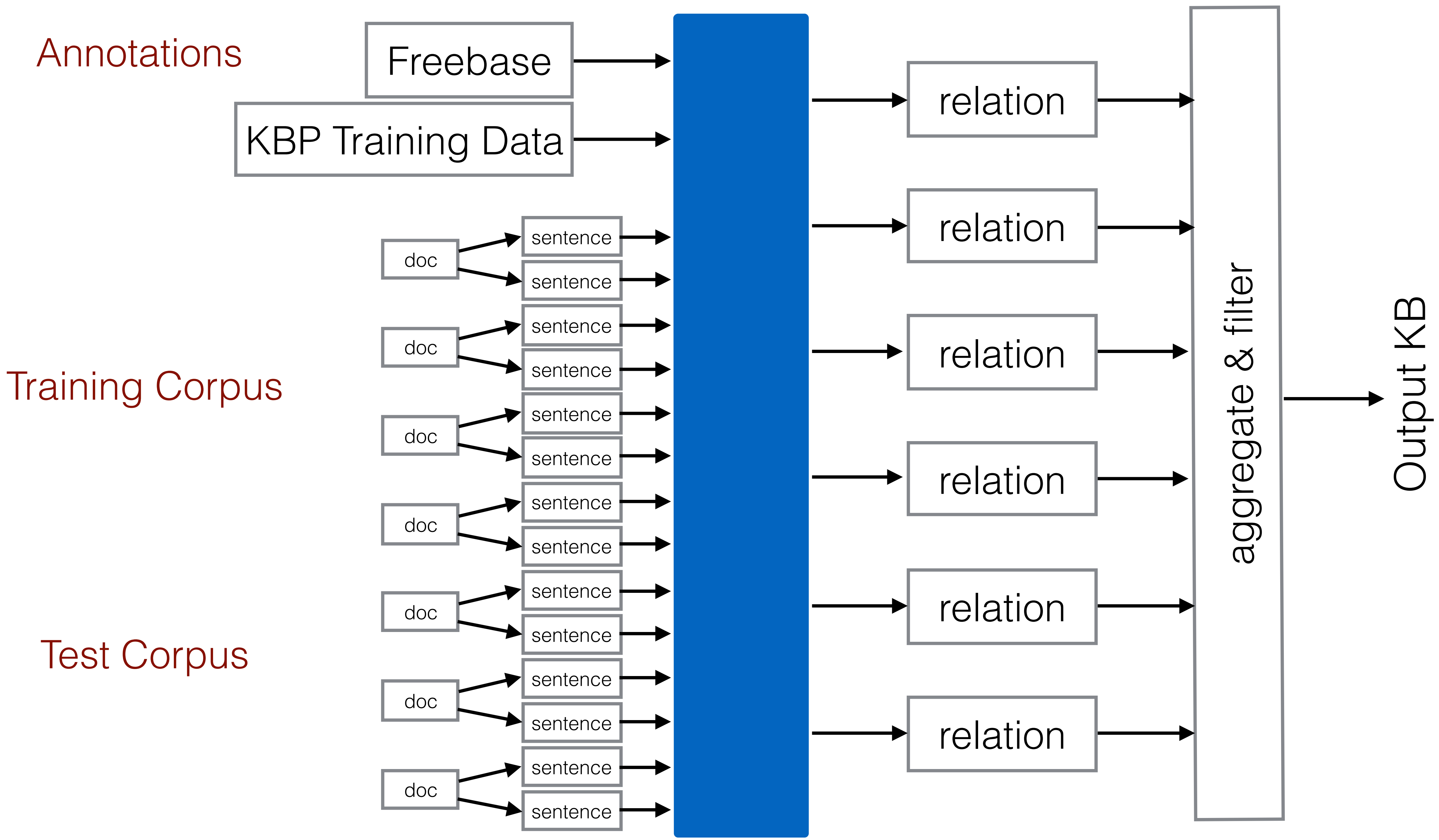

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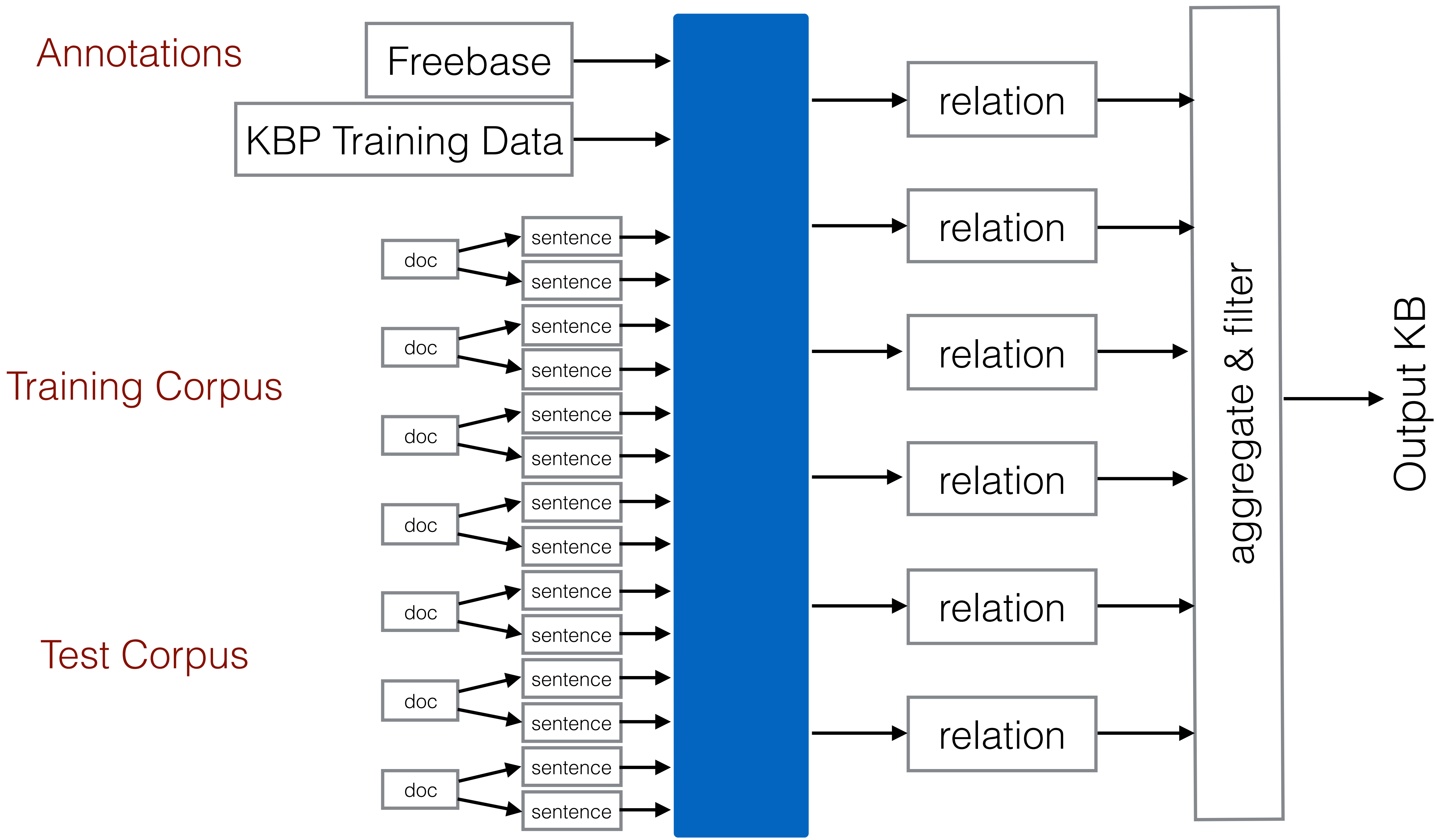

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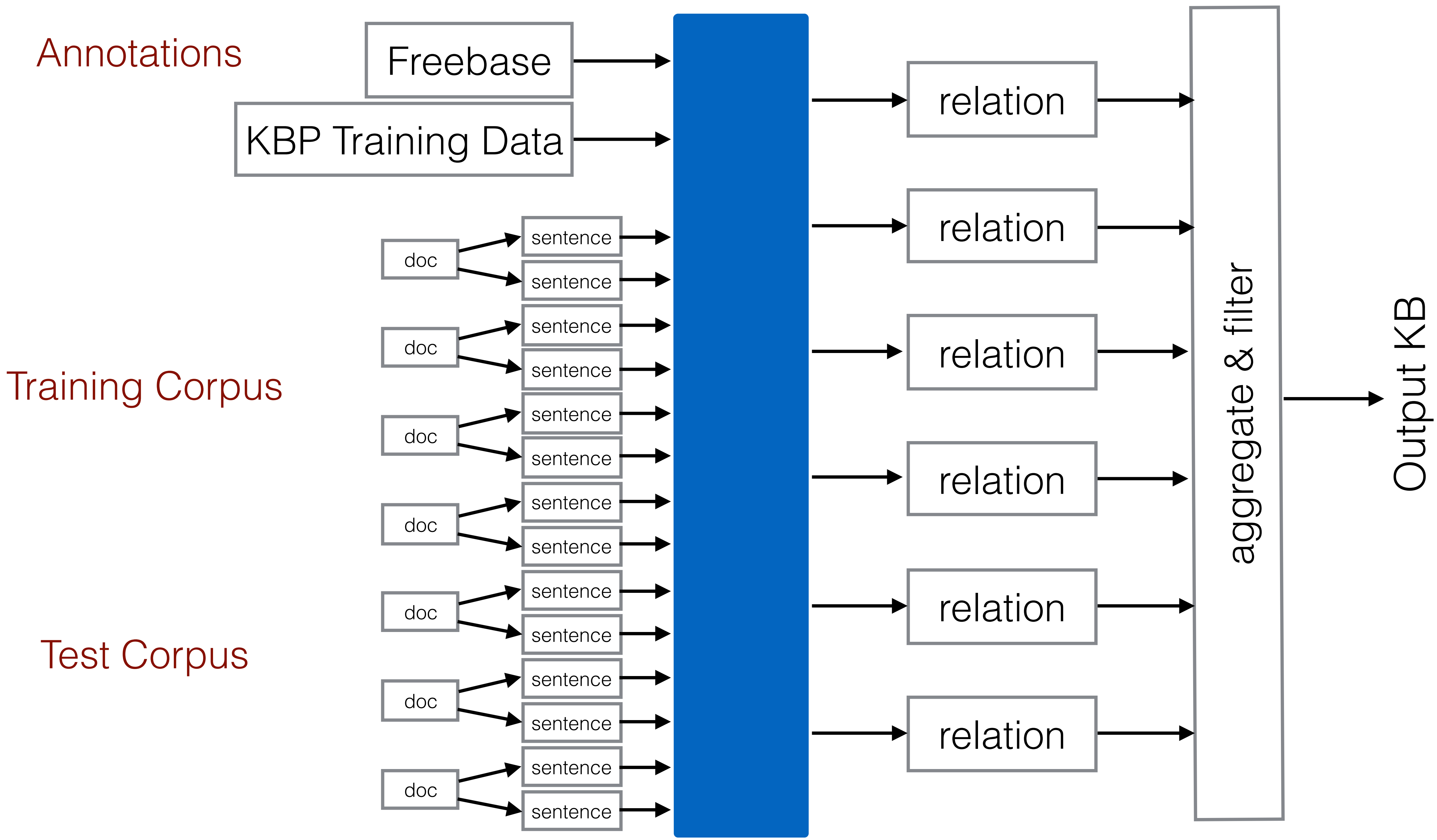

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  - KBP and Freebase relations
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  - entity context and relations

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- Needs to accurately learn all **correlations** amongst:
  - KBP and Freebase relations
  - patterns and relations
  - entity context and relations
- Needs to be **scalable**, since we will run it over:
  - all documents in the corpus
  - all entities that appear in them
  - all facts from the external KB and TAC RefKB

Universal Schema

Universal Schema

Text documents: relations from dependency parses

	president of	*prime minister of*	*chancellor of*	*chief executive*	*leader of*	*head of state*	headOf	Top Member
Obama, U.S.								
Merkel, Germany								
S Harper Canada								
V Putin Russia								
Larry Page Google								
V. Rometty IBM								
Tim Cook Apple								
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330k columns

3 million rows

[Yao, Riedel, McCallum, AKBC 2012]

Universal Schema

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Freebase

TAC KBP

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Combination of structured and OpenIE

[Yao, Riedel, McCallum, AKBC 2012]

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Model & fill in matrix with *Low-Rank Matrix Factorization* (ala NetFlix)

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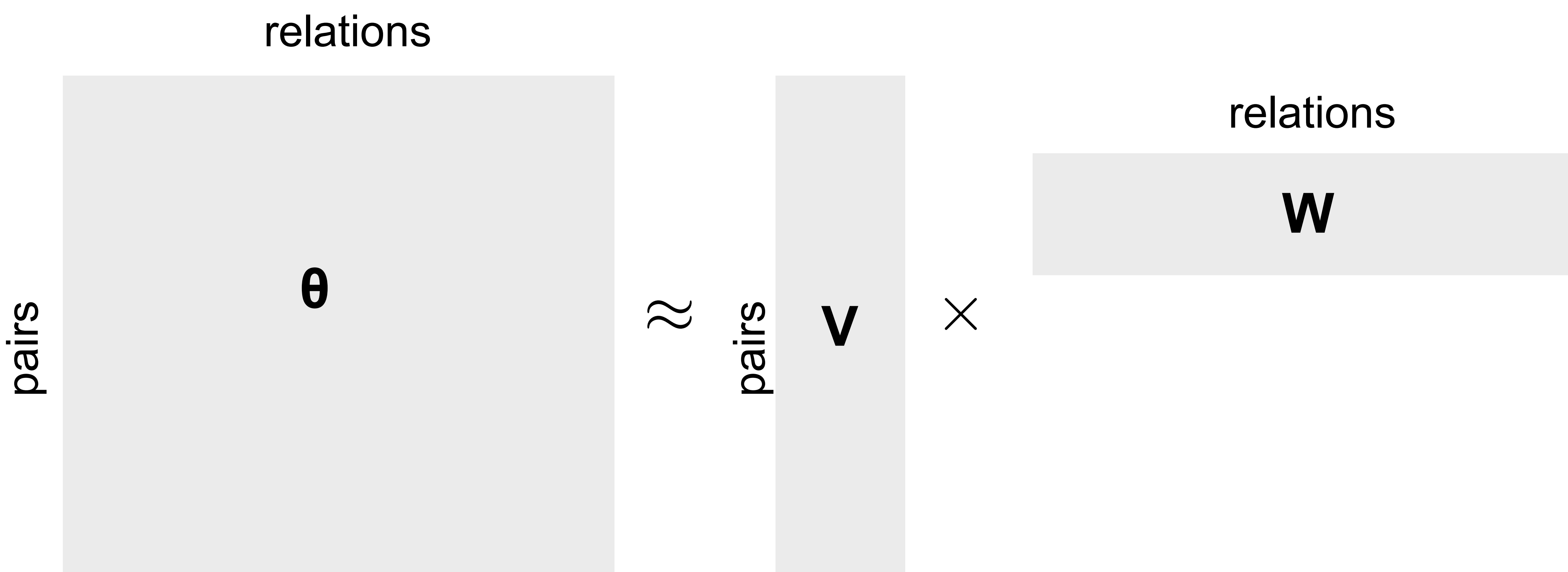
Model



$$\theta^{x,y}_{\text{emp}} =< \mathbf{v}^{x,y}, \mathbf{w}_{\text{emp}} > \qquad p(y^{x,y}_{\text{emp}} = 1 | \ldots) \propto \exp \theta^{x,y}_{\text{emp}}$$

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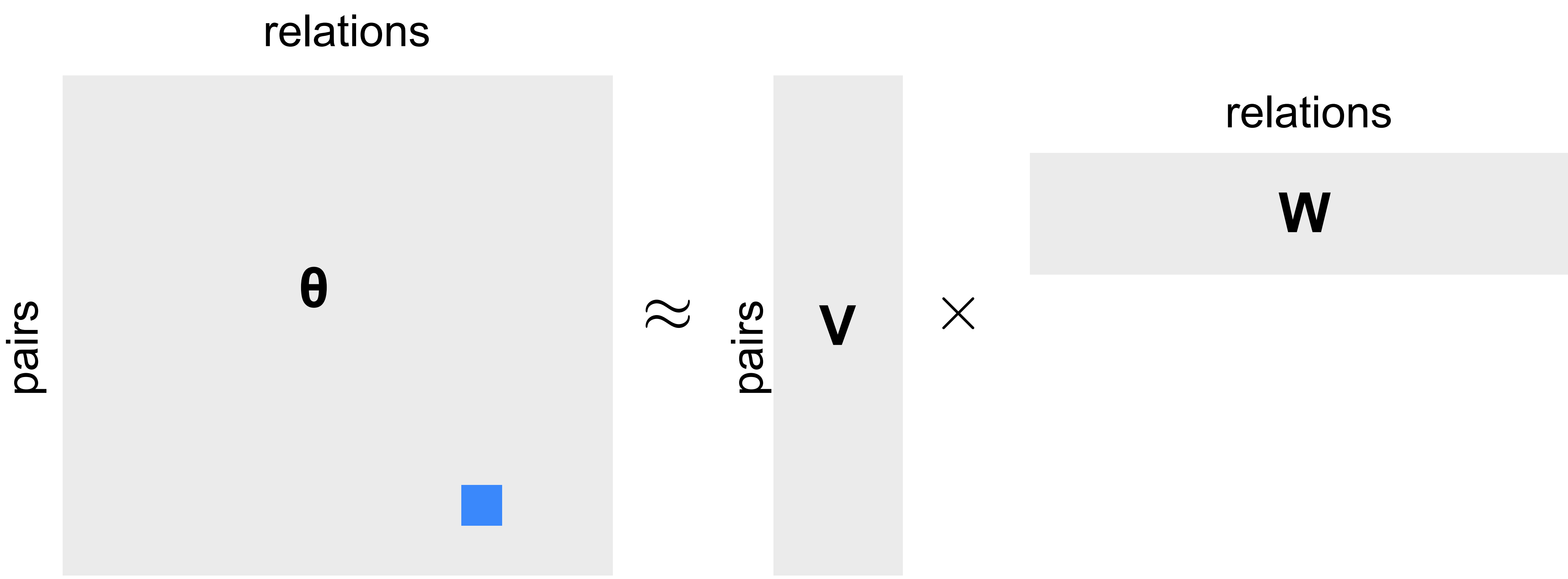

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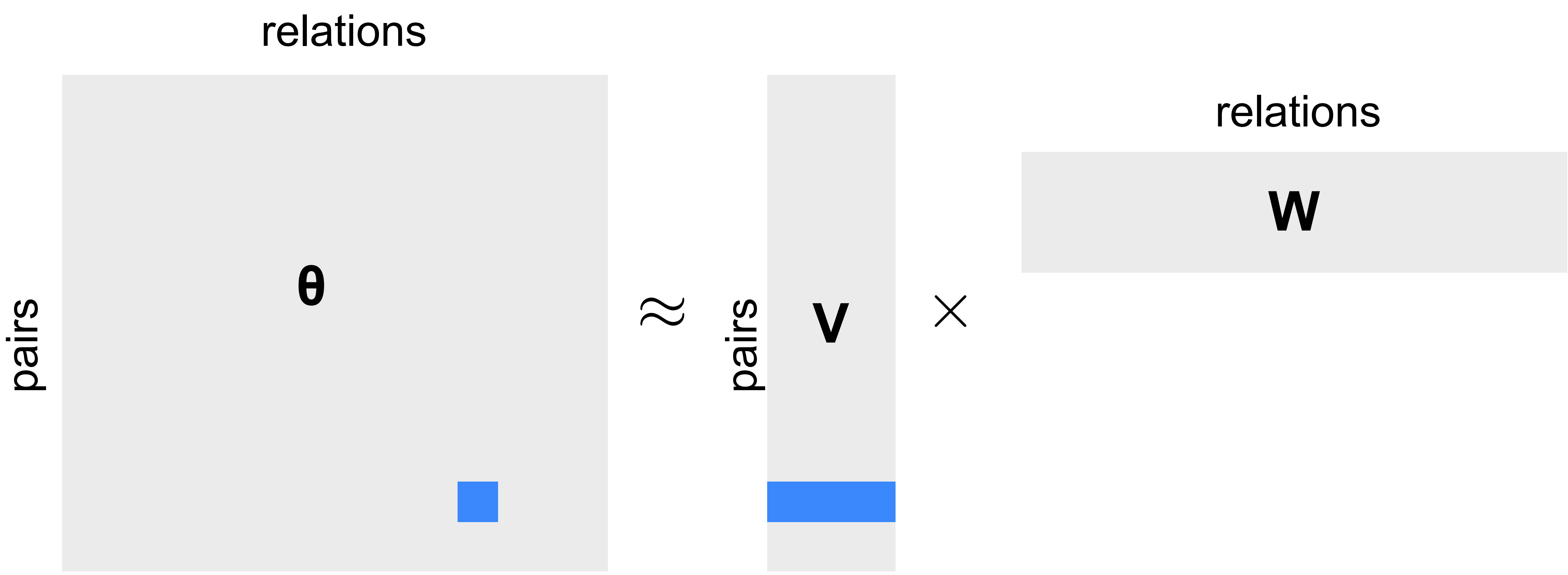

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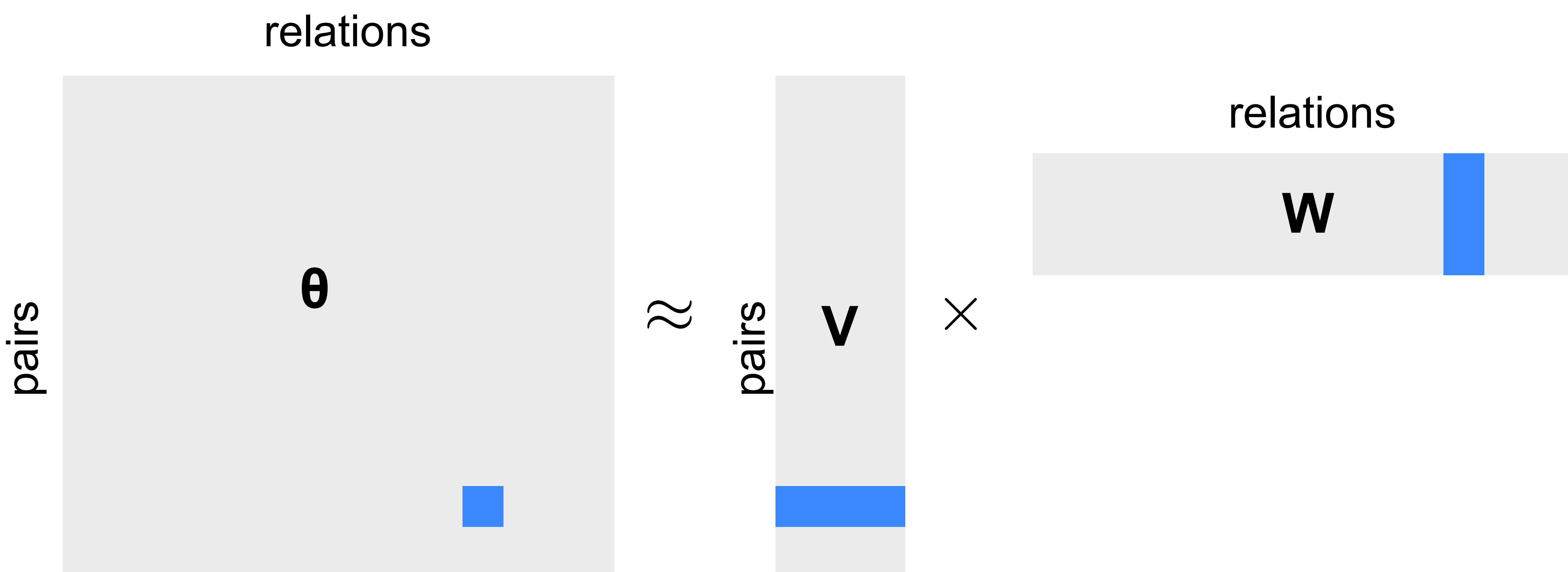

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Training

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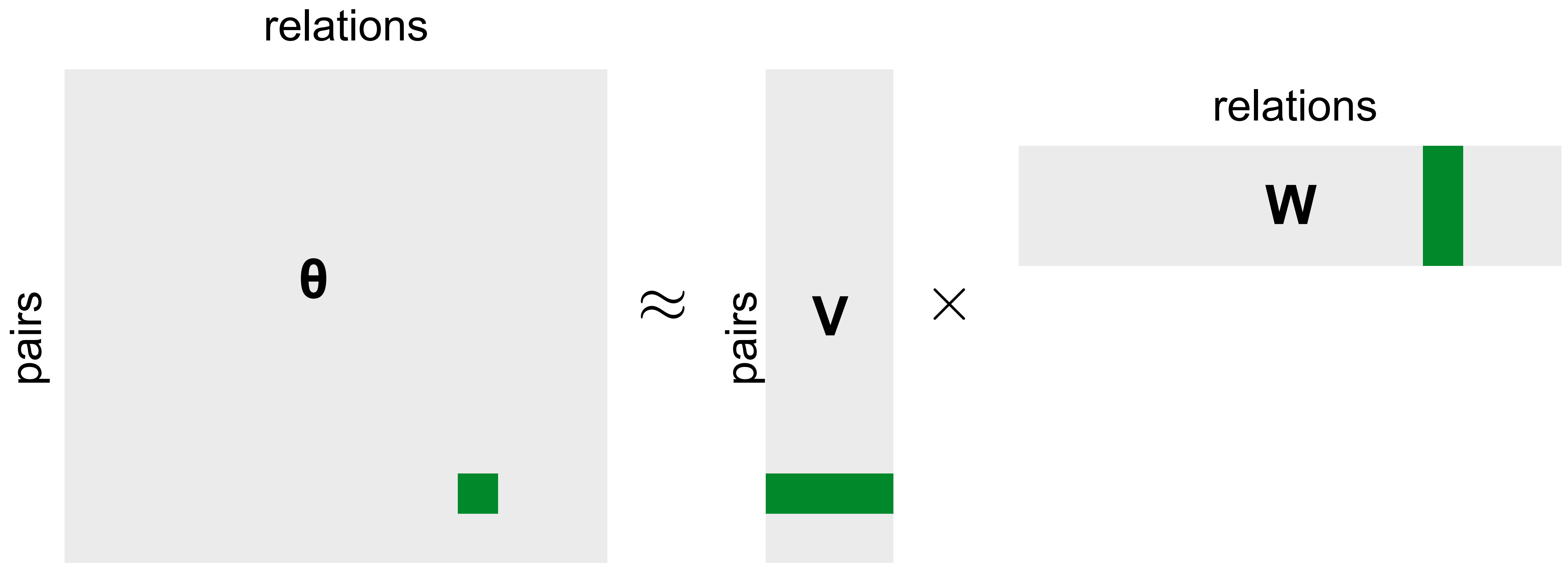

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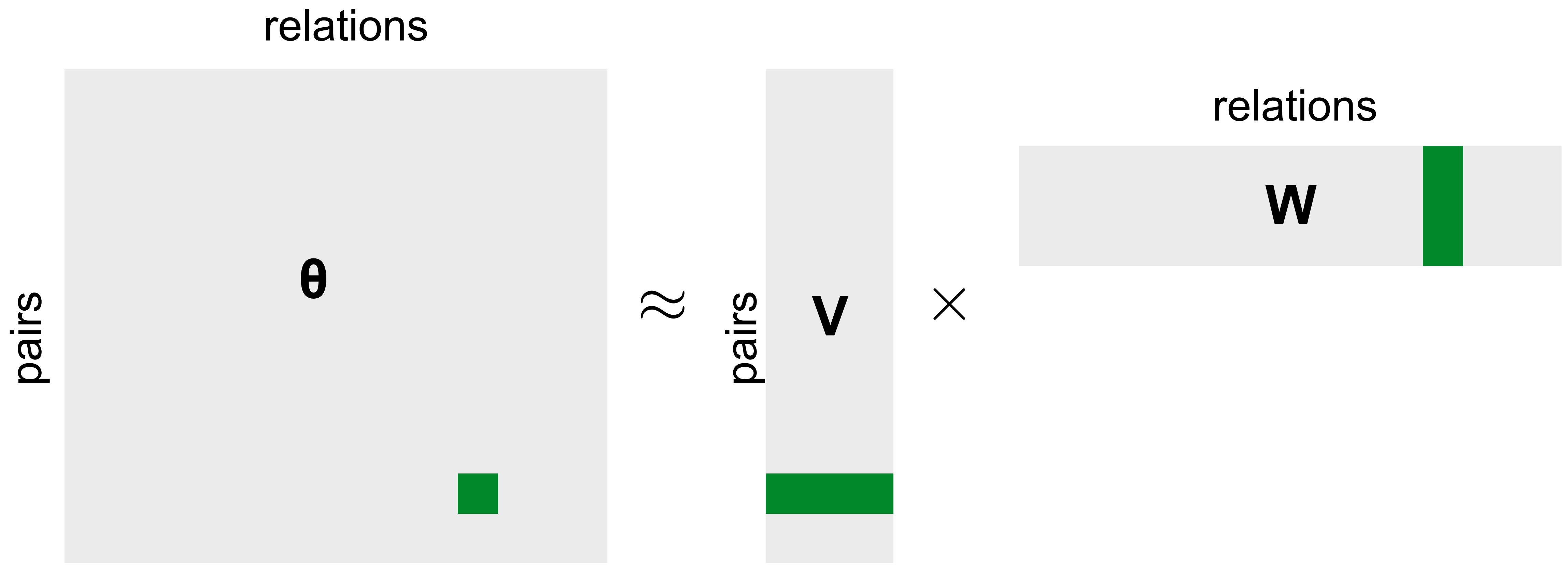

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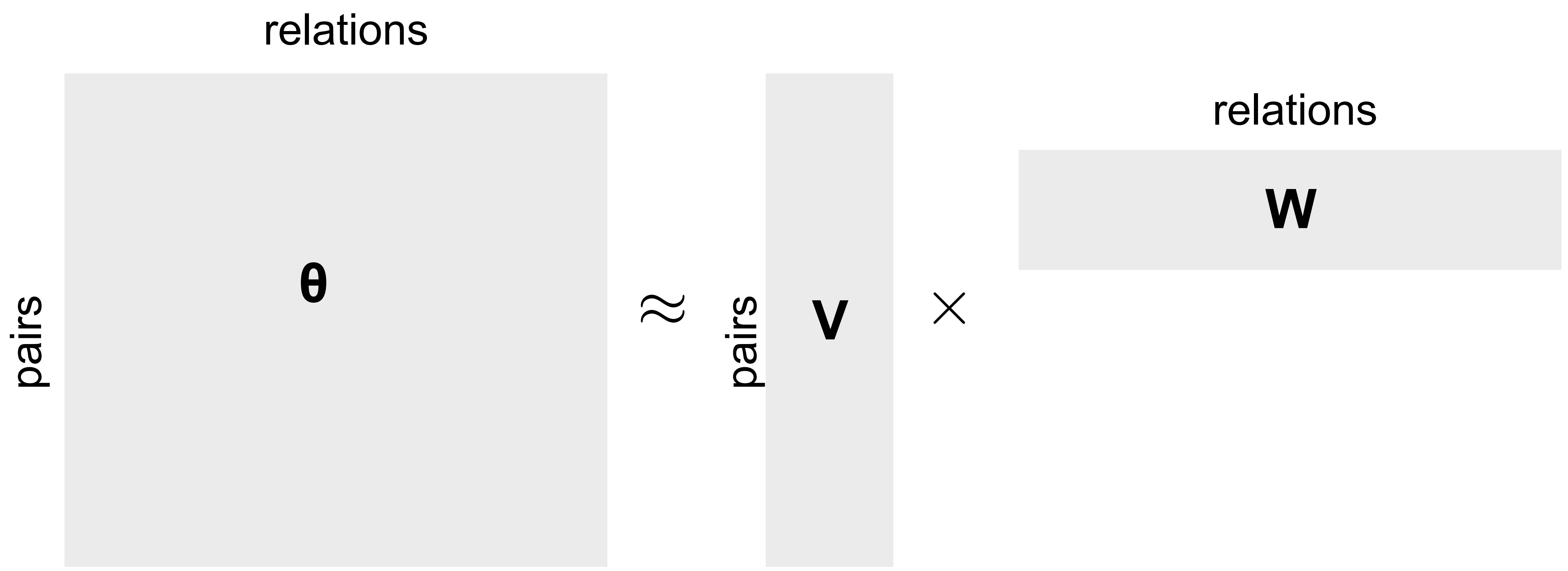

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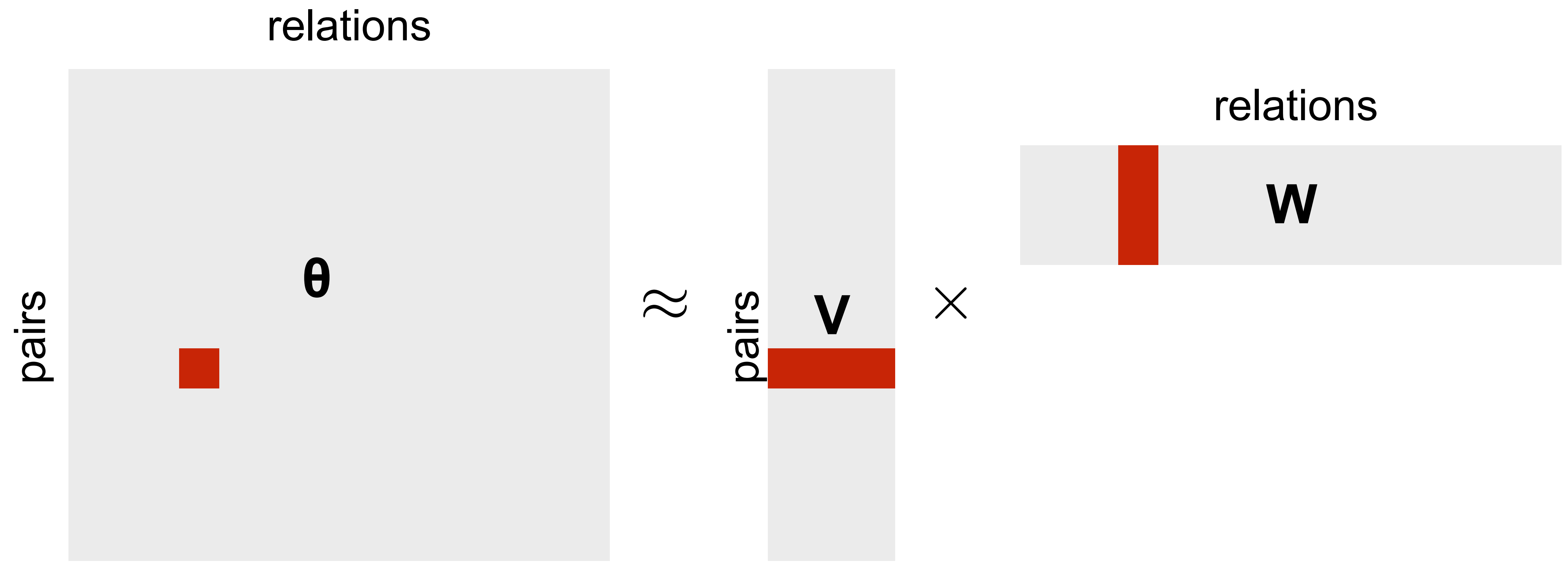

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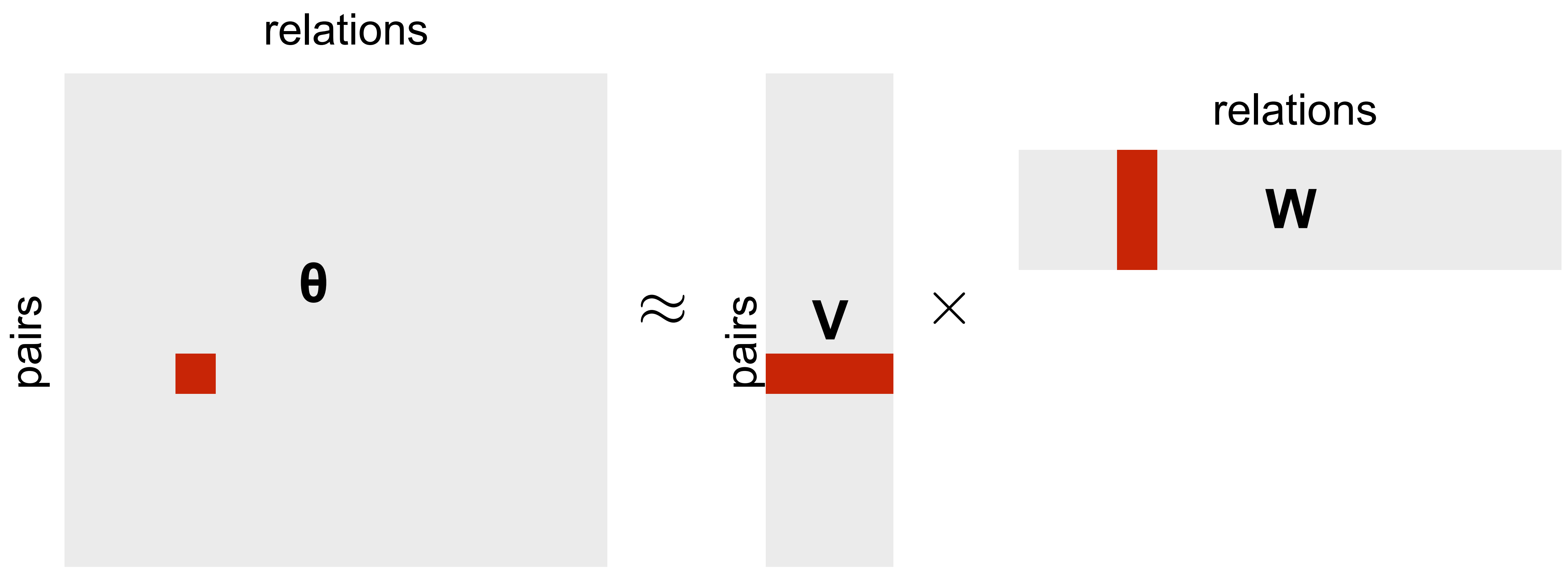

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- Entity Pair embeddings, **v**

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- Relation embeddings, **w**
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    - independent foundedBy and employeeOf relations

Similar Embeddings

similar underlying embedding

similar embedding

	X **own percentage of** Y	X **buy stake in** Y
Time, Inc Amer. Tel. and Comm.	**1**	**1**
Volvo Scania A.B.		**1**
Campeau Federated Dept Stores		
Apple HP		

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Successfully predicts
"Volvo owns percentage of Scania A.B."
from "Volvo bought a stake in Scania A.B."

Implications

X historian at Y → X professor at Y

(Freeman,Harvard)
→
(Boyle,OhioState)

	X **professor at** Y	X **historian at** Y
Kevin Boyle Ohio State		**1**
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Learns asymmetric entailment:

PER historian at UNIV → PER professor at UNIV

but PER professor at UNIV ↛ PER historian at UNIV

Experiments

20 years NYTimes

extract entity mentions, perform entity resolution

350k entity pairs, 23k unique relation surface forms

Freebase

6k entity pairs resolved with NYTimes pairs

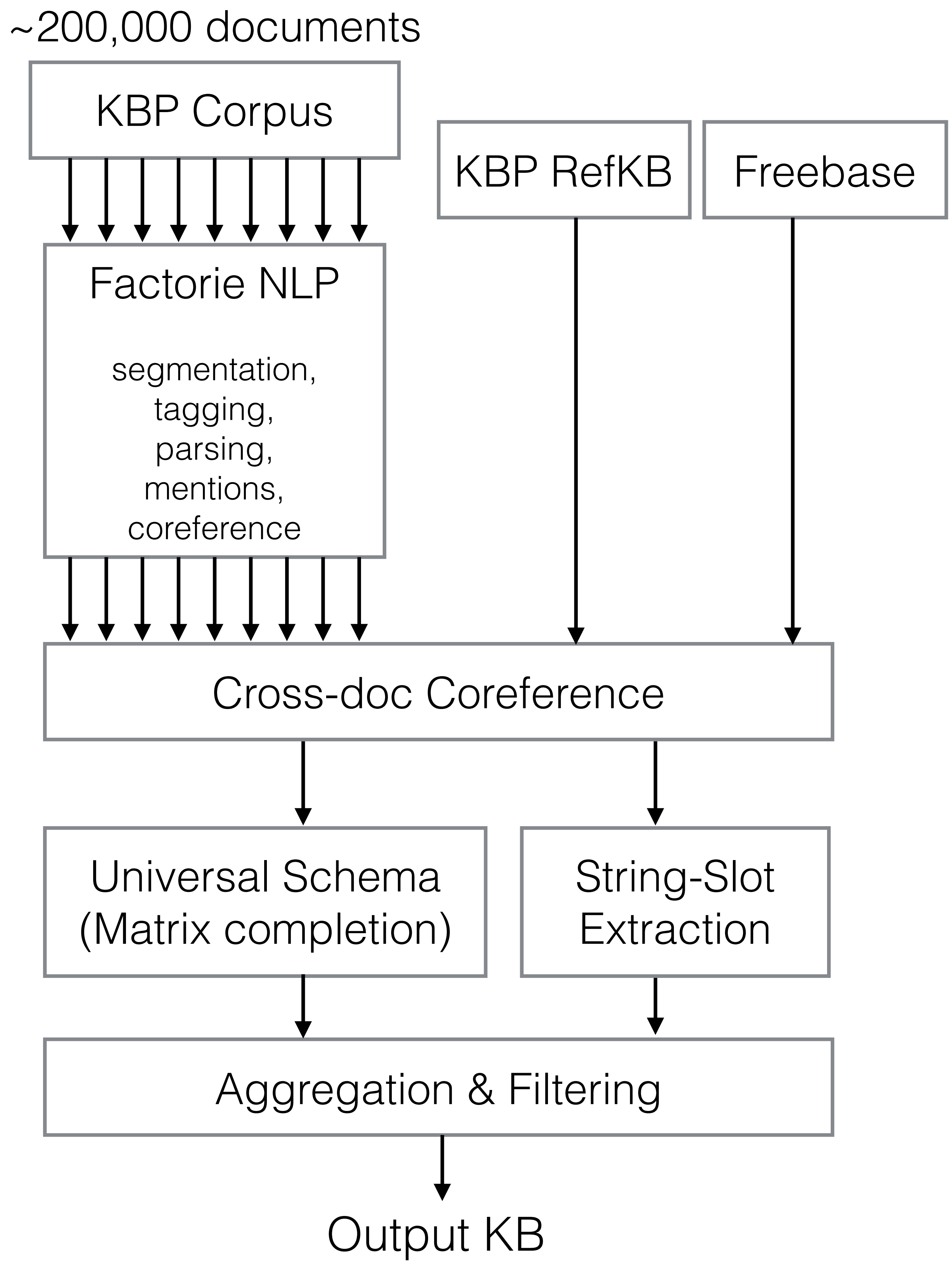
116 relations

[Riedel, Yao, McCallum, Marlin, NAACL 2013]

Relation	Distant Supervision [UMass 2011]	Unsup Clustering [UMass 2012]	MIML > Mintz, Hoffmann [Stanford 2012]	Univ Schema [UMass 2013]
place lived	0.18	0.28	0.1	**0.59**
work for	0.67	0.64	0.7	**0.75**
contained by	0.48	0.51	0.54	**0.68**
author/work	0.5	0.51	0.52	**0.61**
nationality	0.14	**0.4**	0.13	0.19
parent comp	0.14	0.25	0.62	**0.76**
death	0.79	0.79	**0.86**	0.83
birth	0.78	0.75	0.82	**0.83**
person parent	0.24	0.27	**0.58**	0.53
Weighted Average (on even more types)	0.48	0.52	0.57	**0.69**

[Riedel, Yao, McCallum, Marlin, NAACL 2013]

KBP Pipeline


~200,000 documents
KBP Corpus
KBP RefKB
Freebase
Factorie NLP
segmentation,
tagging,
parsing,
mentions,
coreference
Cross-doc Coreference
Universal Schema
(Matrix completion)
String-Slot
Extraction
Aggregation & Filtering
Output KB

String-Slot Extraction

String-Slot Extraction

- Lexicons created from Freebase
  - Religion: /religion
  - Cause of Death: /people/cause_of_death
  - Charges: /base/fight/crime_type
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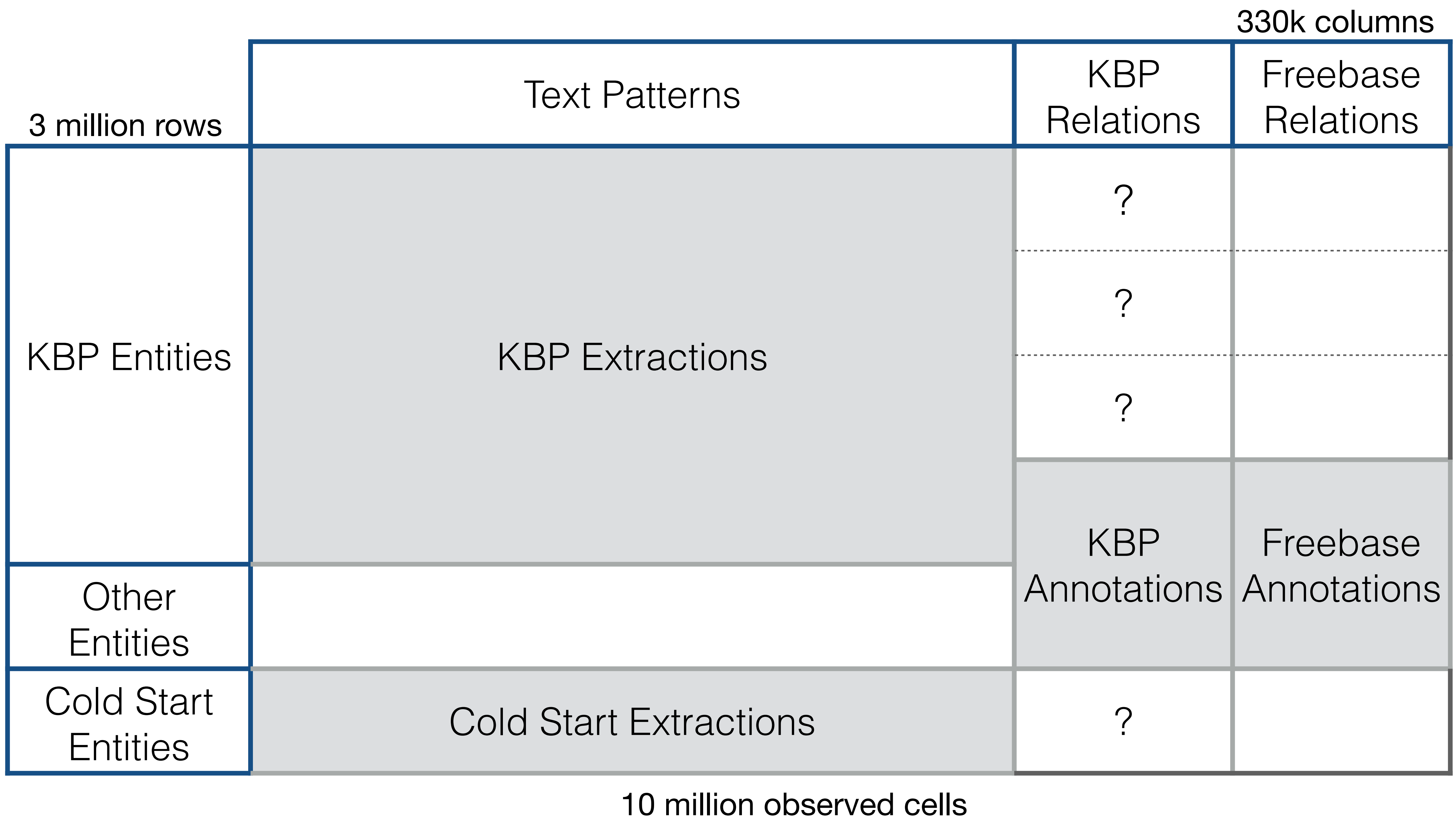
- Use Natty library to extract relative and absolute dates

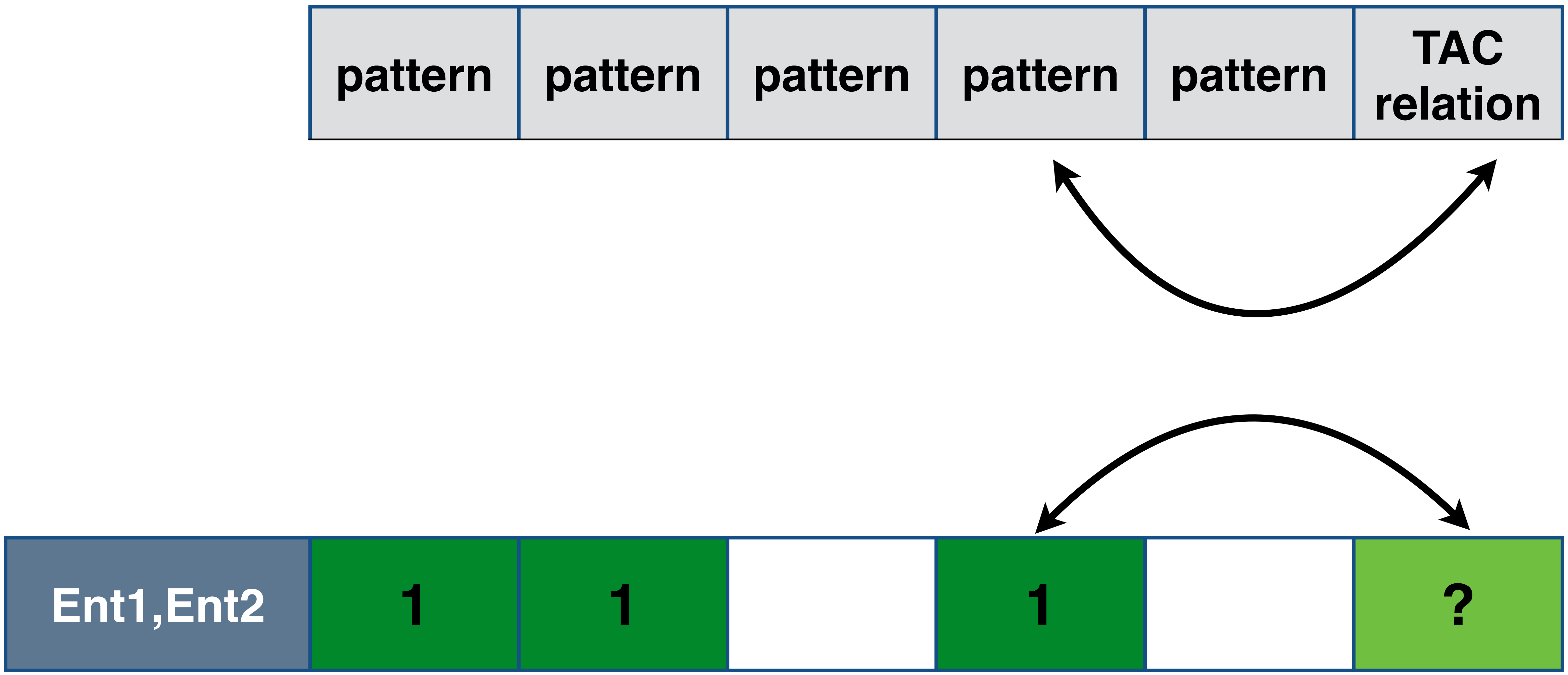
Matrix for KBP



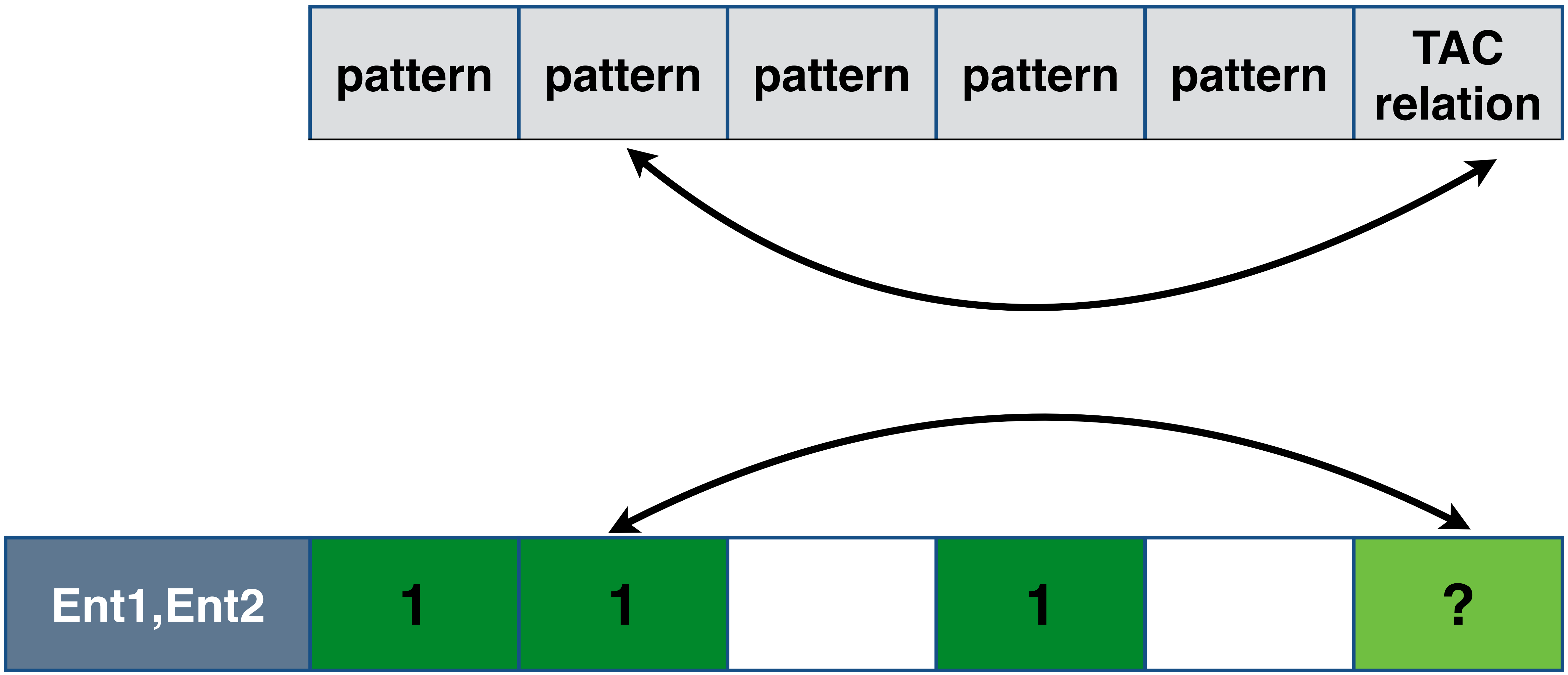
Provenance

	pattern	pattern	pattern	pattern	pattern	TAC relation
Ent1,Ent2	1	1		1		?

Provenance


pattern
pattern
pattern
pattern
pattern
TAC relation
Ent1,Ent2
1
1
1
?

Provenance


pattern
pattern
pattern
pattern
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1
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1
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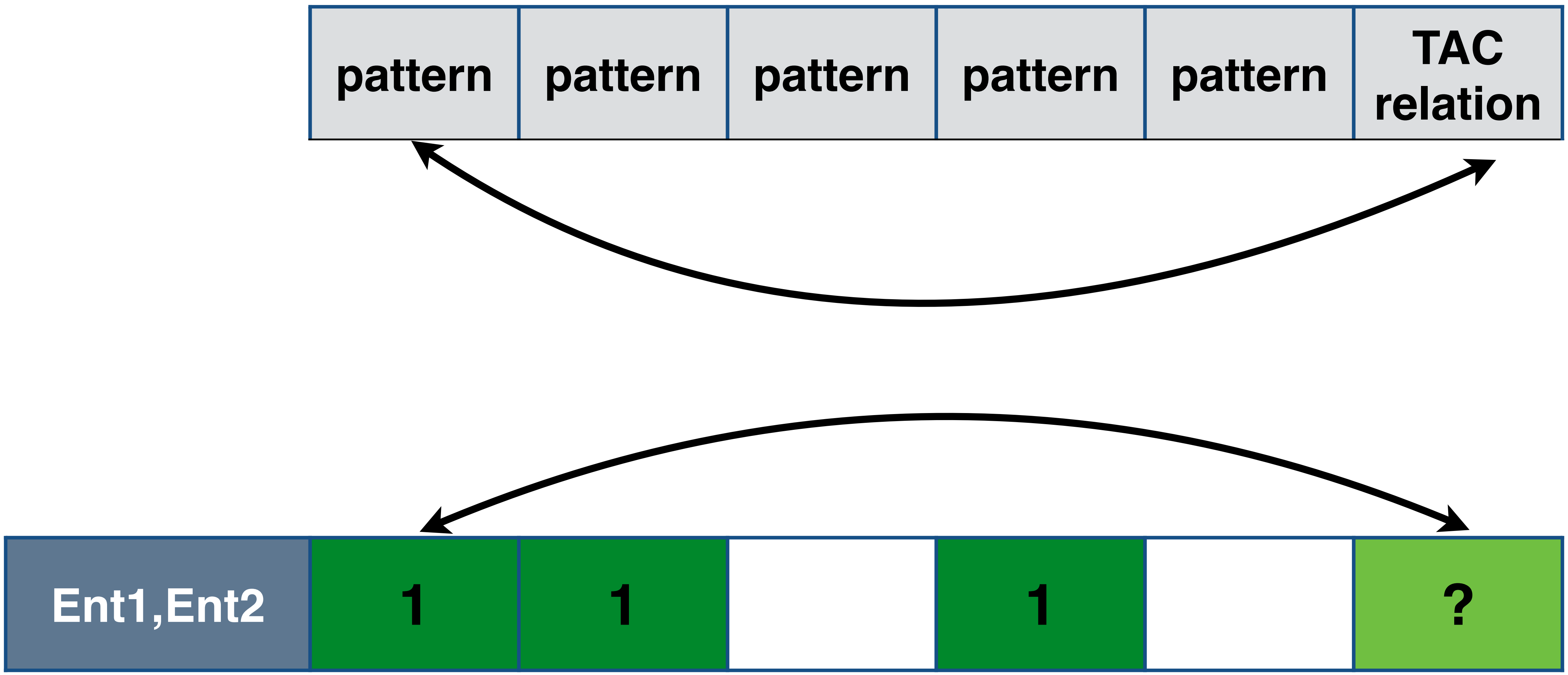

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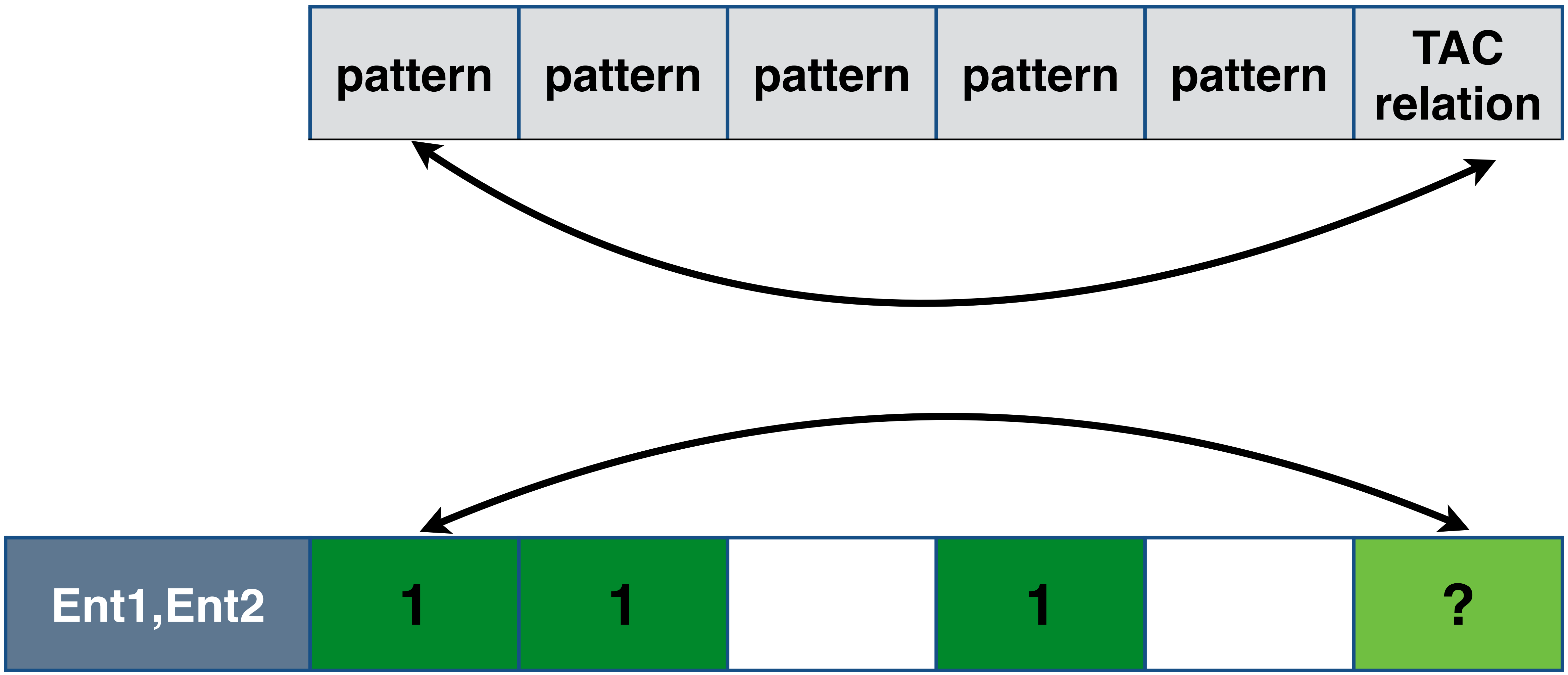
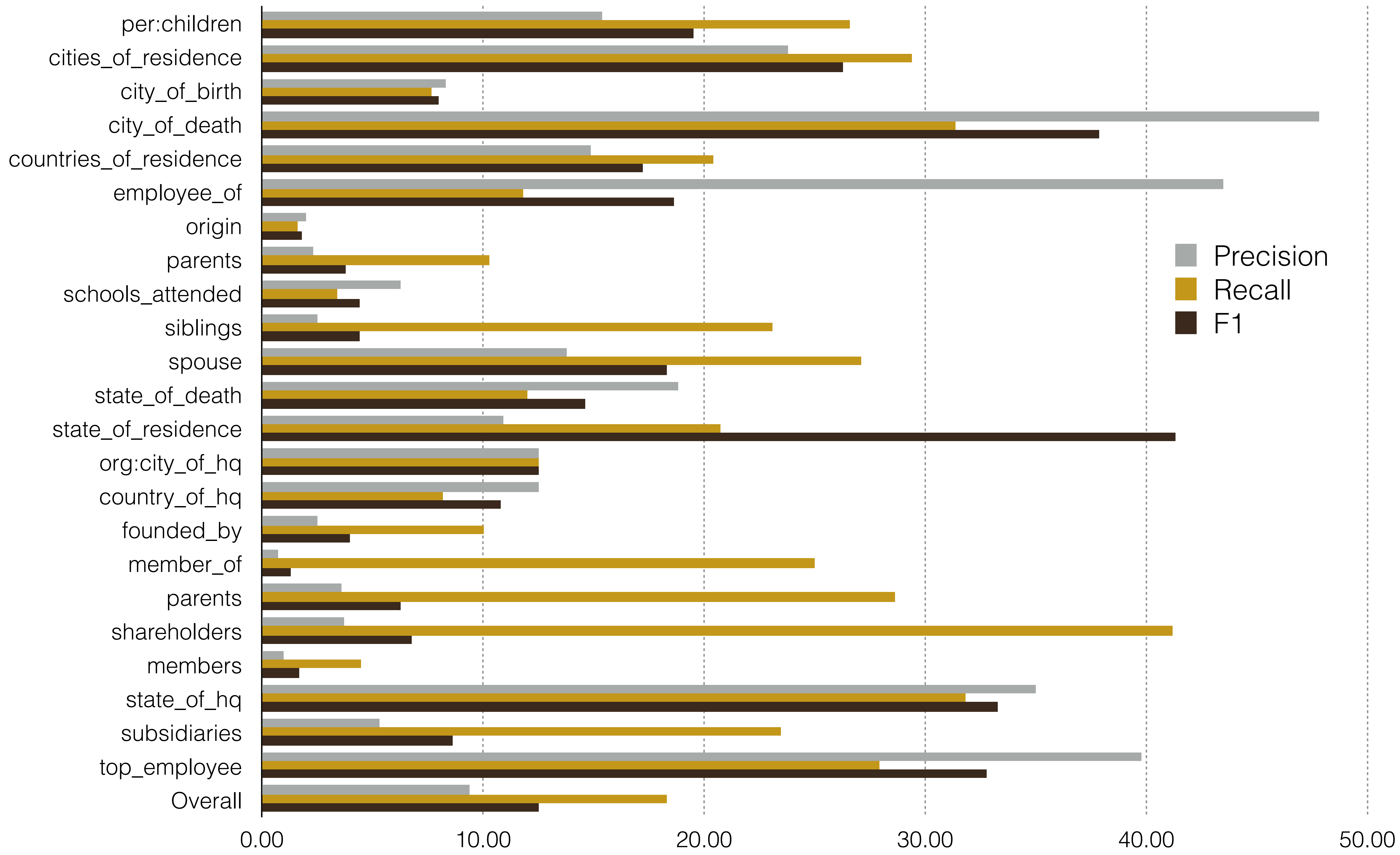


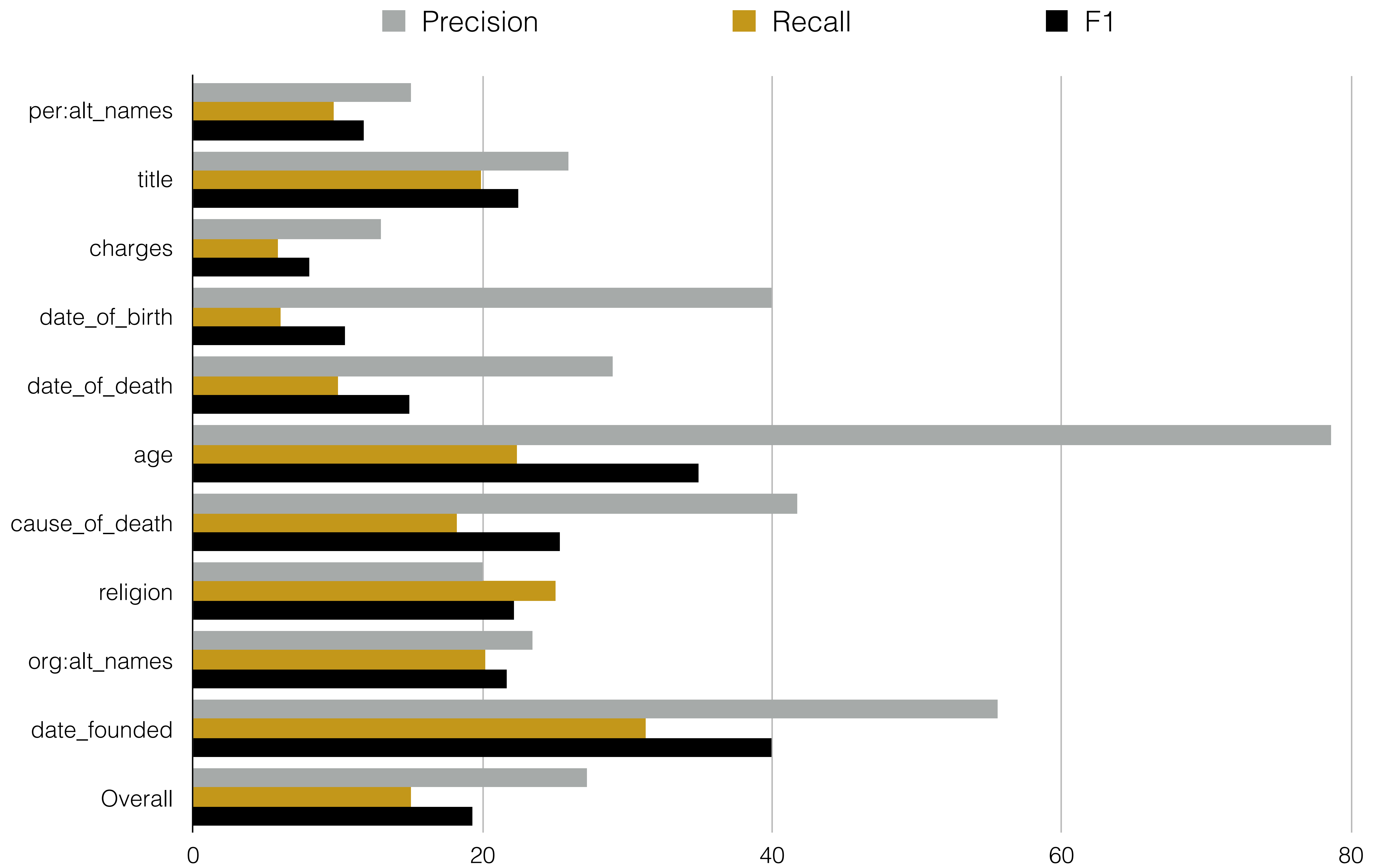
Pick Provenance

KBP 2013 Results

Entity-Based Slots



String-Based Slots



Overall Results

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English Slot Filling Task

Type of Slots	Precision	Recall	F1

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cityOfResidence

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schoolsAttended

- from his/her days in college at -
- hockey player for -
- be graduate of -
- be junior at -
- have resign in protest from -
- lawyer be hire by -
employee_or_member_of
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Conclusions

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  - can be used for predicting new relations

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- Participate in **TAC KBP 2014**!

Thank you!