

Knowledge Base Population from Text and Graphs

Lucas Sterckx

About Me

- Fourth-year PhD Student
- Research Topics:
 - Relation Extraction
 - Keyphrase Extraction
 - Sequence-to-Sequence Models
- Currently visiting Machine Intelligence Lab under supervision of **prof. Bill Byrne** and **dr. Jason Naradowsky**



NLP @ Ghent University

IDLab
INTERNET & DATA LAB

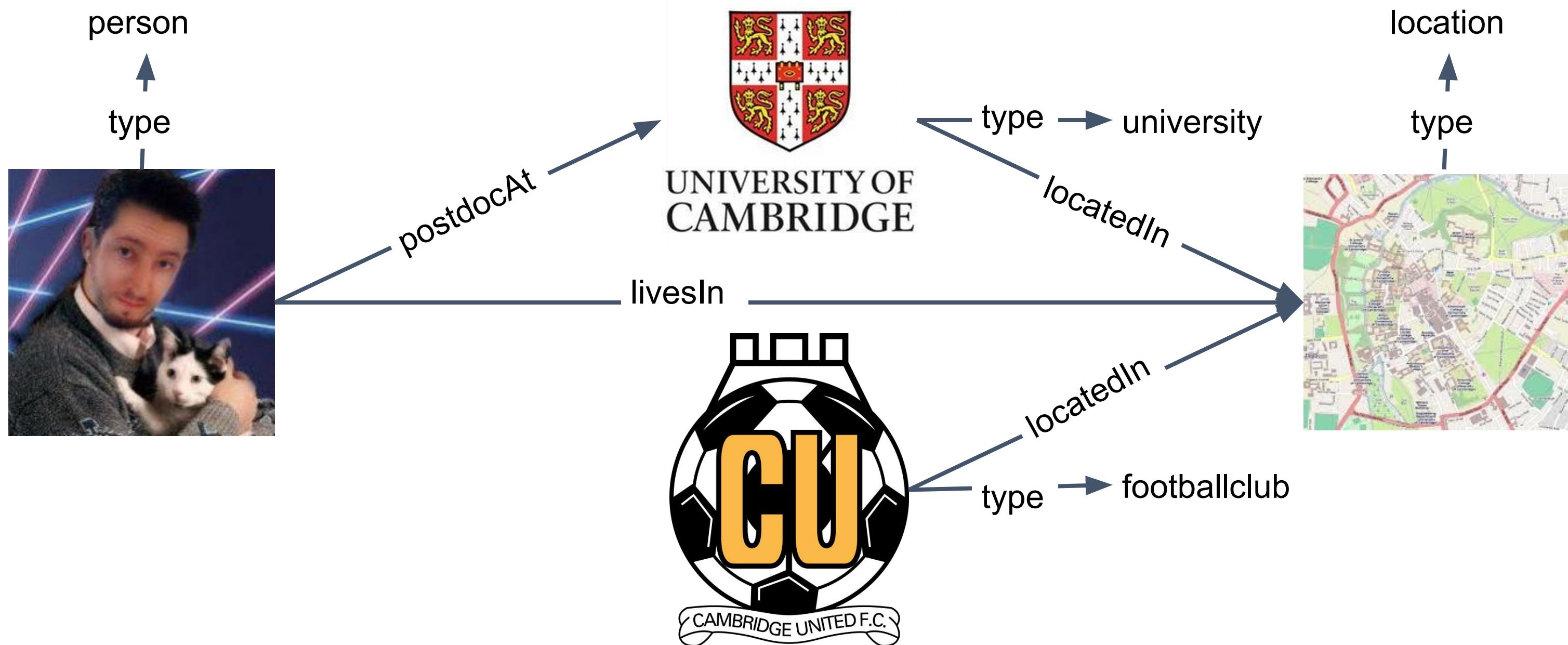
- Part of Internet Technology and Data Science Lab
- Initial focus: Information Retrieval
- NLP and Information Extraction since 2013
- Projects with Flanders' major media providers
 - Named Entity Recognition
 - Named Entity Linking
 - Text Classification
 - Keyphrase extraction



Outline

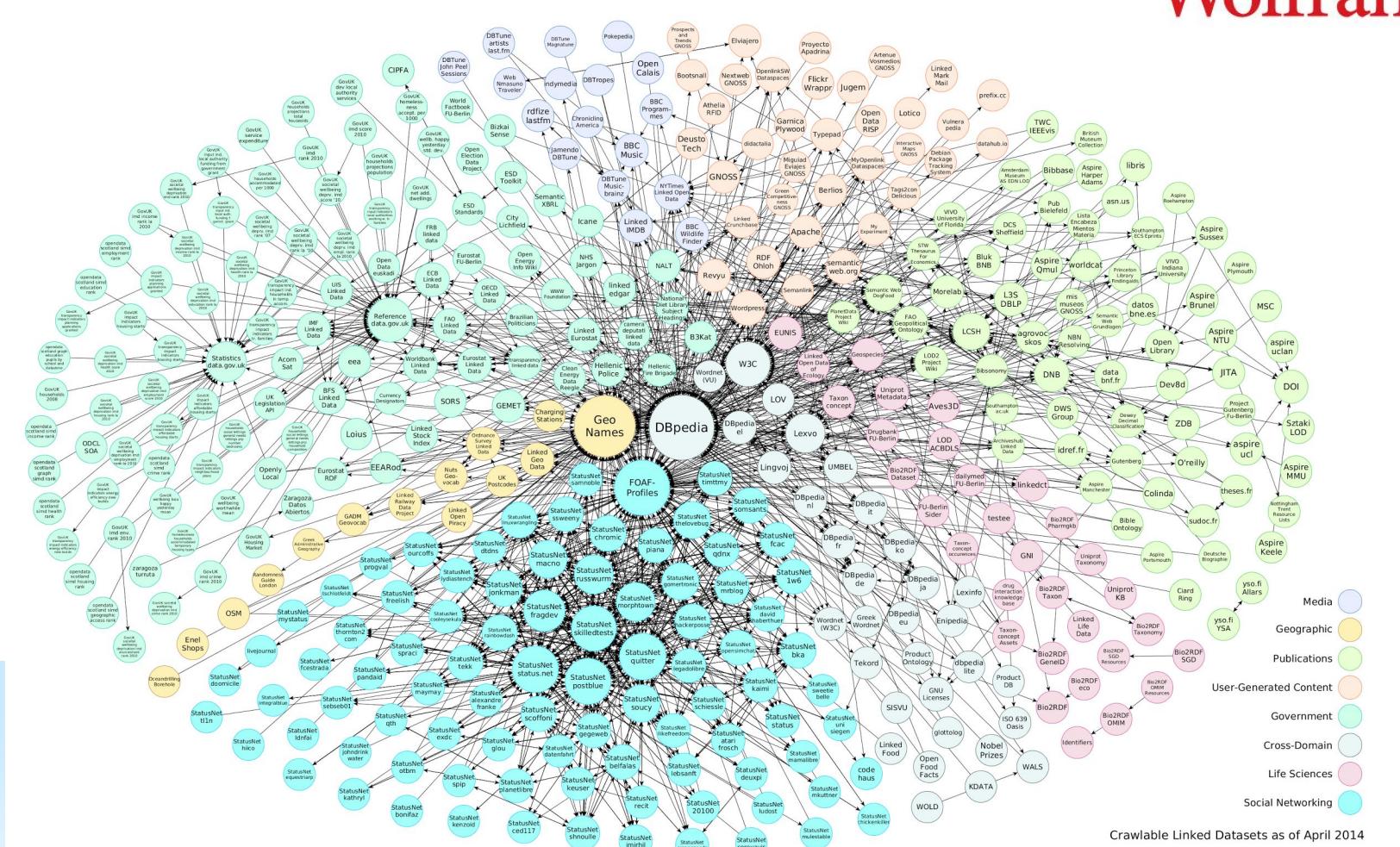
- 1. Knowledge Bases**
2. Knowledge Base Population
 - a. Knowledge Extraction from Text - TAC KBP
 - b. Link Prediction
3. Research Topic at Cambridge

Knowledge Bases as Labeled Graphs



Comprehensive and semantically organized **machine-readable** collection of universally relevant or domain-specific **entities**, **classes**, and **SPO facts** (attributes, relations)

Modern Knowledge Graphs



Applications

cambridge uk

Alle Afbeeldingen Maps Nieuws Video's Meer Instellingen Tools

Ongeveer 298.000.000 resultaten (0,96 seconden)

Cambridge - Wikipedia
<https://en.wikipedia.org/wiki/Cambridge> ▾ Vertaal deze pagina
Cambridge is a university city and the county town of Cambridgeshire, England, on the River Cam about 50 miles (80 km) north of London. At the United ...
University of Cambridge · Cambridgeshire · Cambridge, Massachusetts · St Ives

University of Cambridge
<https://www.cam.ac.uk/> ▾ Vertaal deze pagina
The mission of the University of Cambridge is to contribute to society through the pursuit of education, learning and research at the highest international levels of ...

Cambridge Hotels, Things to Do, Events - Official Cambridge Tourist ...
www.visitcambridge.org/ ▾ Vertaal deze pagina
Official Visitor Information for Cambridge, England. Find things to do, hotels and accommodation, attractions, events, restaurants, shopping maps – everything ...

Cambridge, United Kingdom - TripAdvisor
<https://www.tripadvisor.com/.../England/Cambridgeshire> ▾ Vertaal deze pagina
Cambridge Tourism: TripAdvisor has 128820 reviews of Cambridge Hotels, Attractions, and Restaurants making it your best Cambridge resource.

Cambridge 2017: Best of Cambridge,
<https://www.tripadvisor.co.uk/.../England/Can>
Cambridge Tourism: TripAdvisor has 128820 review Restaurants making it your best Cambridge resourc

Cambridge - Lonely Planet
[https://www.lonelyplanet.com/england/eastern-er](https://www.lonelyplanet.com/england/eastern-england/cambridge) ... and tradition and renowned for its quirky rituals, Cambridge is England's two most venerable university cities

Cambridge City Council
<https://www.cambridge.gov.uk/> ▾ Vertaal deze pagina
Local and community information with sections on er

Cambridge Tourist Information
www.cambridgetouristinformation.co.uk/ ▾ Vertaal deze pagina
Kyan is a Cambridge born musician and he's going to perform at the Kings Chapel Services. Check out his website for more information

Cambridge travel guide - Wikitravel
[wikitravel.org/en/Cambridge_\(England\)](http://wikitravel.org/en/Cambridge_(England)) ▾ Vertaal deze pagina
Cambridge [1] is a university city in Cambridgeshire, England, on the Backs, of green open spaces and cattle grazing

cambridge population

Alle Afbeeldingen Maps Nieuws Shopping Meer Instellingen Tools

Ongeveer 222.000.000 resultaten (0,78 seconden)

Cambridge / Bevolking

123.900
2011

Feedback

bezienswaardigheden cambridge omgeving

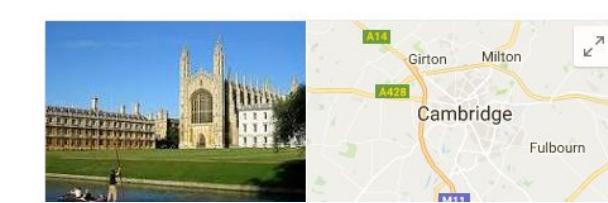
Alle Maps Afbeeldingen Nieuws Shopping Meer Instellingen Tools

Cambridge > Bezienswaardigheden

| | | | | |
|---|--|--|--|---|
| Fitzwilliam Museum Museum en architectuur | Anglesey Abbey Tuin en hortus botanicus | Sedgwick Museum of Earth Scie... Museum en geschiedenis | Kathedraal van Ely Kathedraal, architectuur en geschiedenis | Cambridge Museum of Technolo... Museum |
| Cambridge University Botanic G... Hortus botanicus en tuin | Church of St Mary the Great, Ca... Kerkgebouw | Museum of Archaeology and Ant... Museum en geschiedenis | Whipple Museum of the History ... Museum | Cambridge University Museum o... Museum |
| The Backs Tuin, park en rivier | Heilig Grafkerk Kerkgebouw en architectuur | Museum of Cambridge Museum | Parker's Piece | Museum of Classical Archaeolog... Museum |

Cambridge: attracties en bezienswaardigheden. - Weekendplanner
www.weekendplanner.nl/.../Engeland/Cambridge ▾ Vertaal deze pagina
Cambridge is een mooie stad vlakbij Londen. De attracties en bezienswaardigheden in Cambridge ... Informatie voor een bezoek aan Londen en omgeving ...

Wat te doen in Cambridge: de 10 beste activiteiten - TripAdvisor
<https://www.tripadvisor.nl/.../Verenigd Koninkrijk/Cambridgeshire/Cambridge> ▾ Vertaal deze pagina



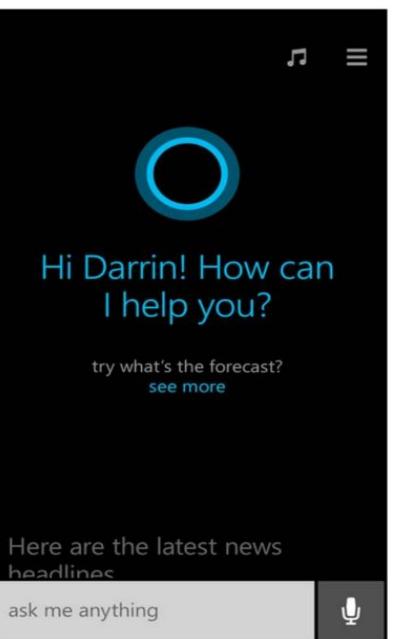
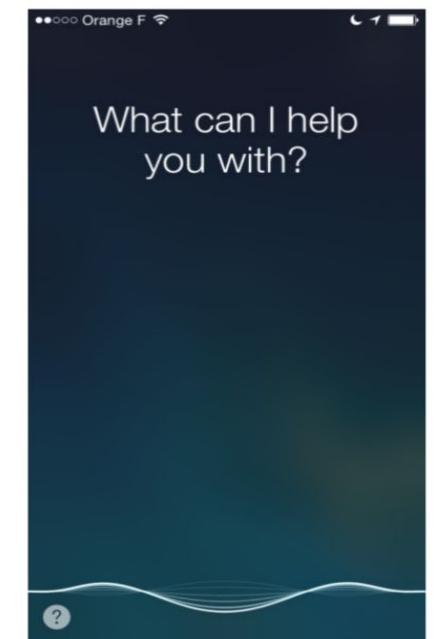
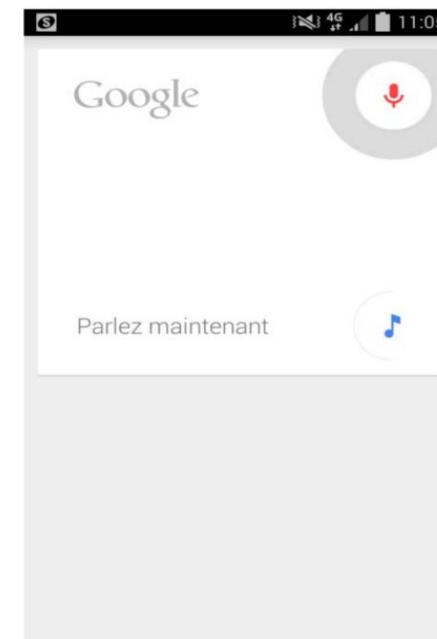
the county town of

St Ives

Applications



The screenshot shows the WolframAlpha search interface. In the search bar at the top, the query "when did the beatles break up" is entered. Below the search bar, there are several small icons: a calculator, a camera, a grid, and a gear. To the right of the search bar are links for "Web Apps", "Examples", and "Random". The main content area is titled "Input interpretation:" and shows the result: "The Beatles (music act) end date". Below this, a large blue button displays the result "Friday, April 10, 1970". At the bottom of the page, there is a photograph of two men standing behind podiums on a stage. The stage has a blue background with various words like "PIENSE", "THINK", "SKEΨΟΥ", "DENKE", and "PENSER" in different languages. The podiums have digital screens showing monetary amounts: "\$24,000", "\$77,147", and "\$21,600". The screens also display questions related to the Beatles.



Knowledge Bases: Research Challenges

- **Population:** Knowledge bases are incomplete
 - Knowledge extraction from text
 - Link prediction
- **Validation:** Knowledge bases contain errors
 - Entity resolution
 - Error detection, trustworthiness
- **Interface:** How to easily access knowledge
 - Semantic parsing
 - Question answering
- **General AI:** can AI emerge from Knowledge Graphs?
 - Automatic reasoning and planning
 - Generalization and abstraction

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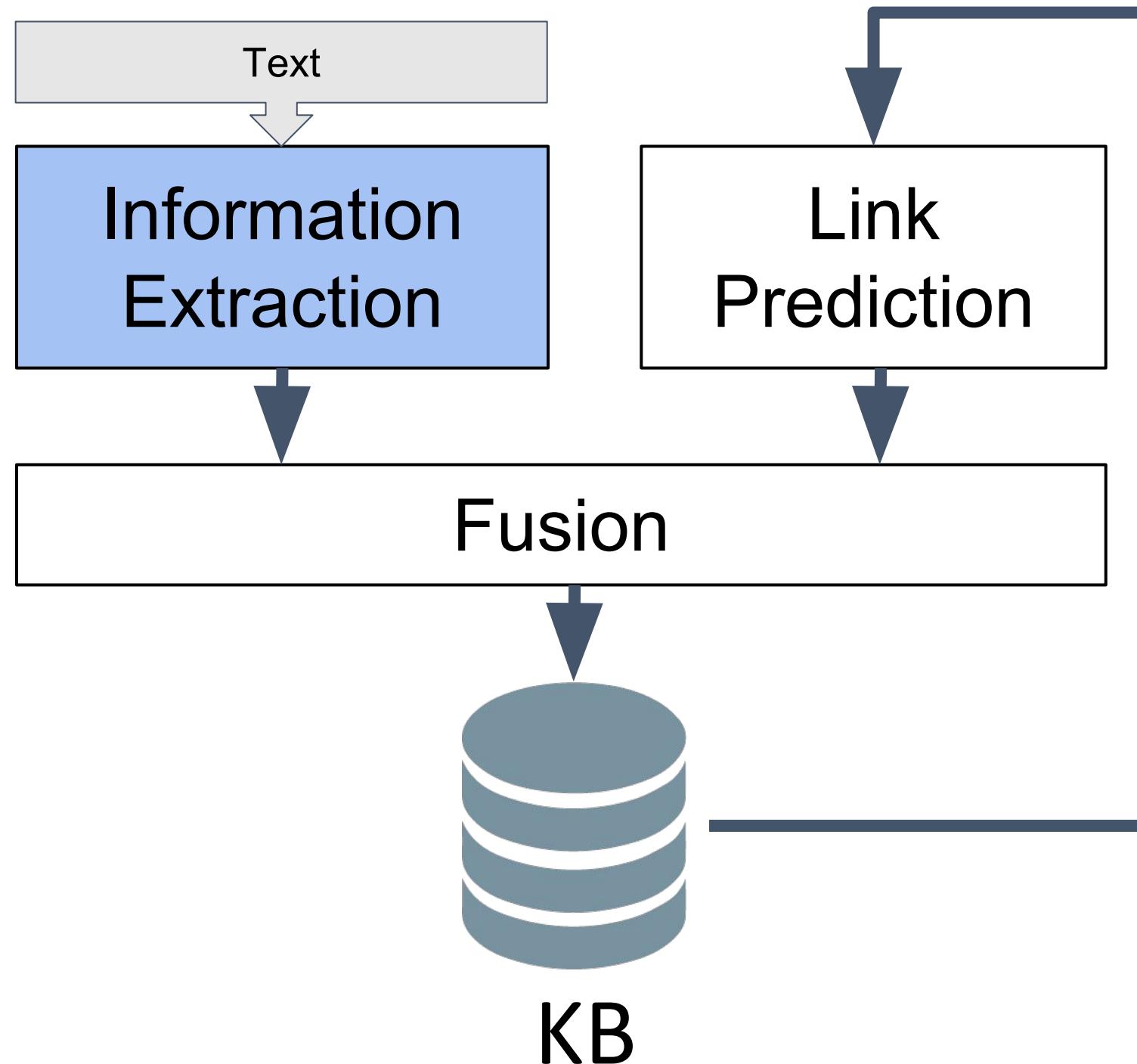
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Text Analysis Conference (TAC)



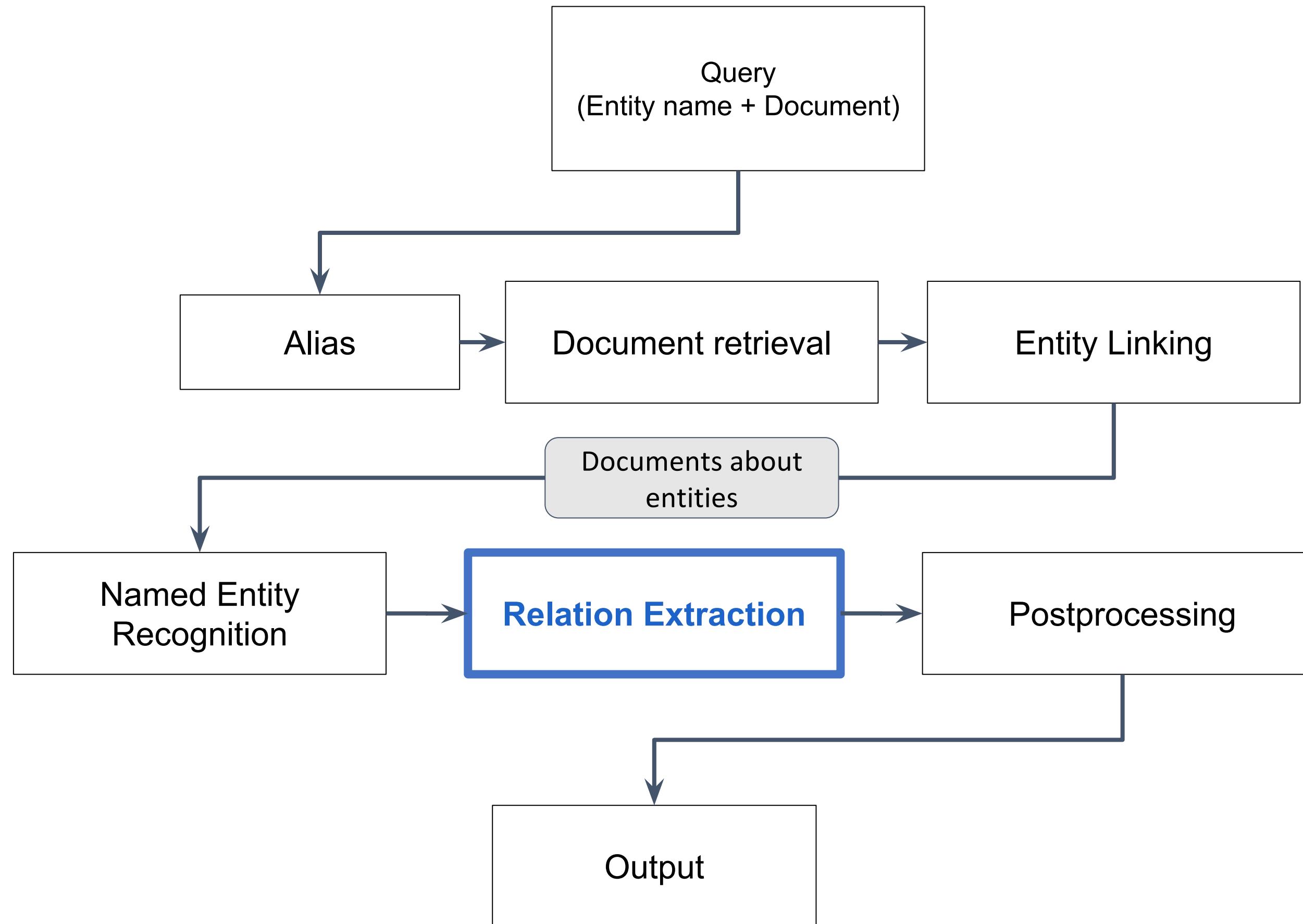
- **Benchmark to promote research** on automated systems that discover information about named entities and incorporate this information in a knowledge source, or database
- Continuation of previous conferences and evaluations, such as MUC and ACE
- Organised by **NIST**, sponsored by US department of Defense
- Extract **41 relations** for **50 persons** and **50 organizations** from **4 million documents**

4

```
<query id="SF_002">
  <name>PhillyInquirer</name>
  <docid>eng-NG-31-141808-9966244</docid>
  <beg>757</beg>
  <end>770</end>
  <enttype>ORG</enttype>
</query>
```

| Person Slots | | | |
|------------------------------|-------|-------|--|
| Name | Type | List? | |
| per:alternate_names | Name | Yes | |
| per:date_of_birth | Value | | |
| per:age | Value | | |
| per:country_of_birth | Name | | |
| per:stateorprovince_of_birth | Name | | |
| per:city_of_birth | Name | | |

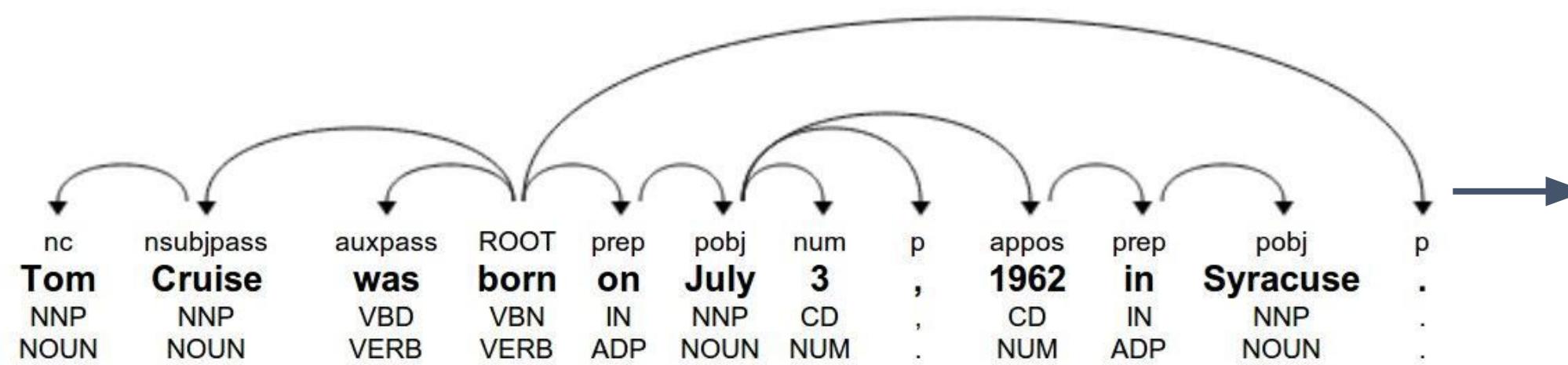
Ghent University at TAC KBP



Supervised Relation Extraction

- Extracting semantic relations between sets of grounded entities
 - Train classifiers from +/- Examples

< person, city_of_birth, location >



X was born on DDDD in Y

- DEP: X \leftarrow nsubjpass \leftarrow on \rightarrow pobj \rightarrow date \rightarrow prep_in \rightarrow Y
 - NER: X=PER, Y=LOC
 - POS: X = NOUN, NNP; Y=NOUN, NNP
 - Context:born, on, in, “born_on”

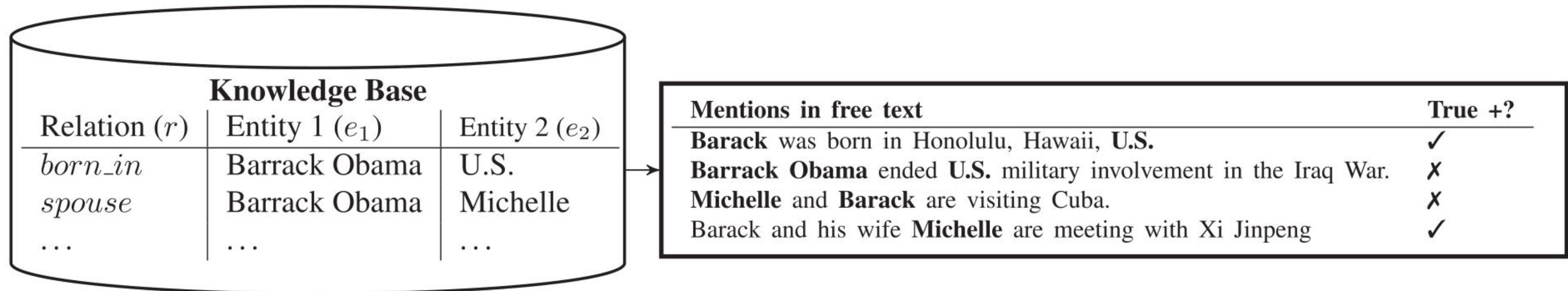
✓ Pro's

- High quality training data
 - Explicit negative examples

- Con's

- Expensive!
 - Can't generalize to other relations and domains

Distant Supervision

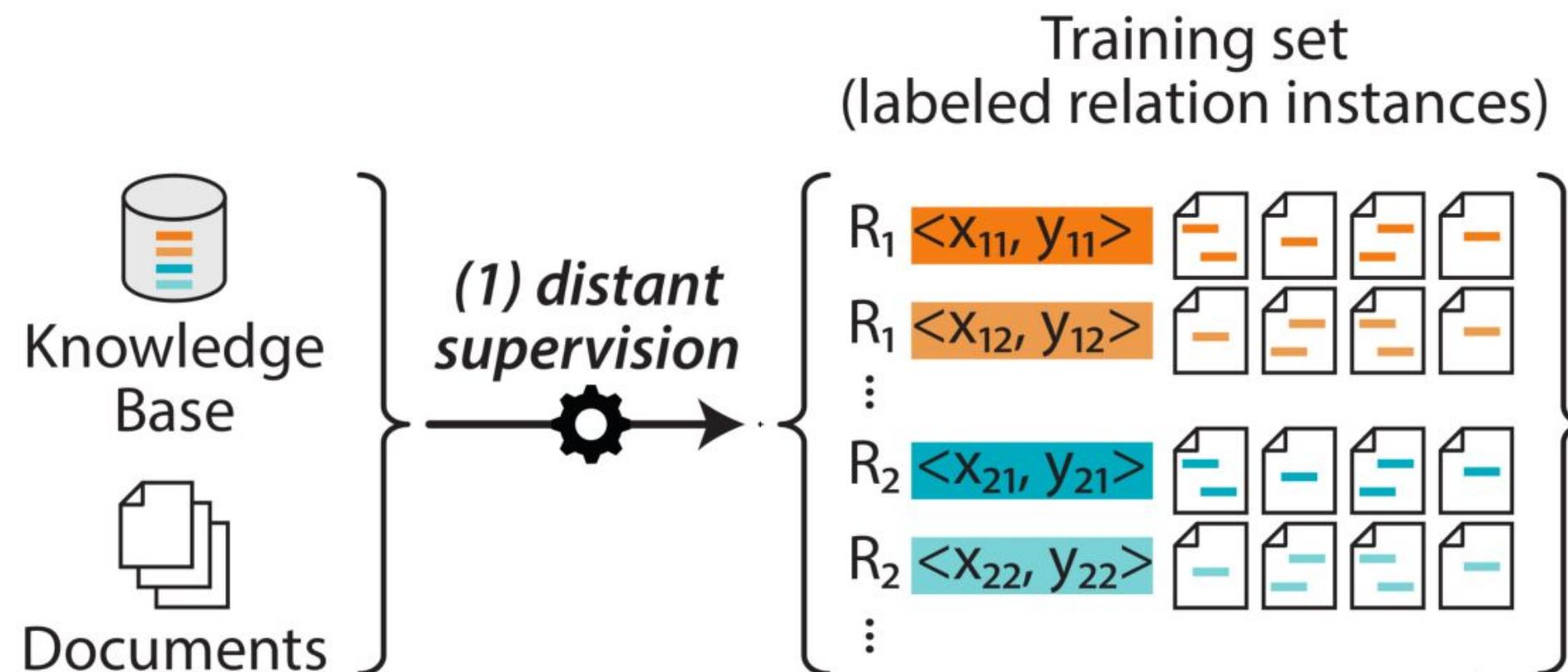


- Existing **Knowledge base + Unlabeled text**

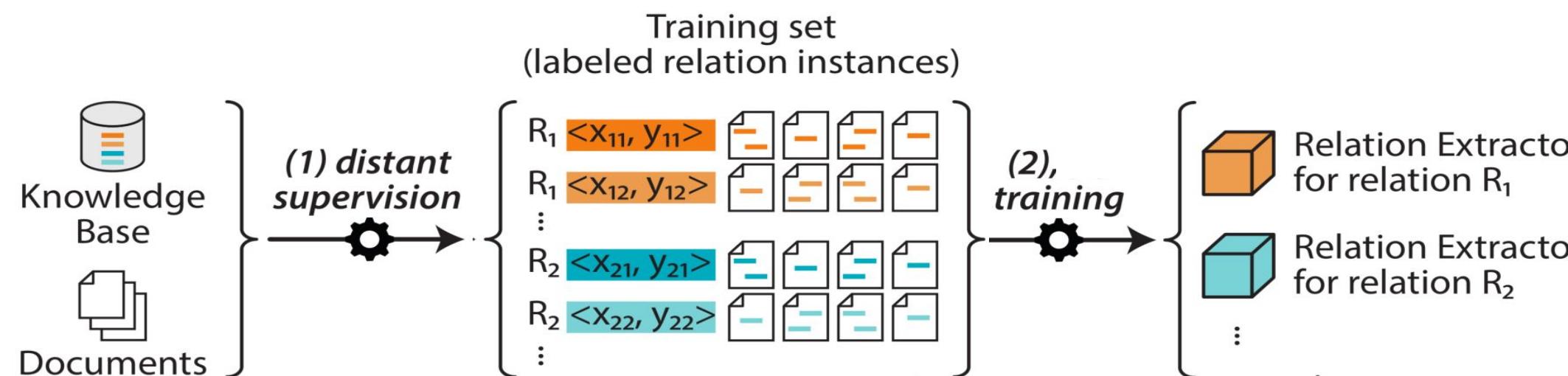
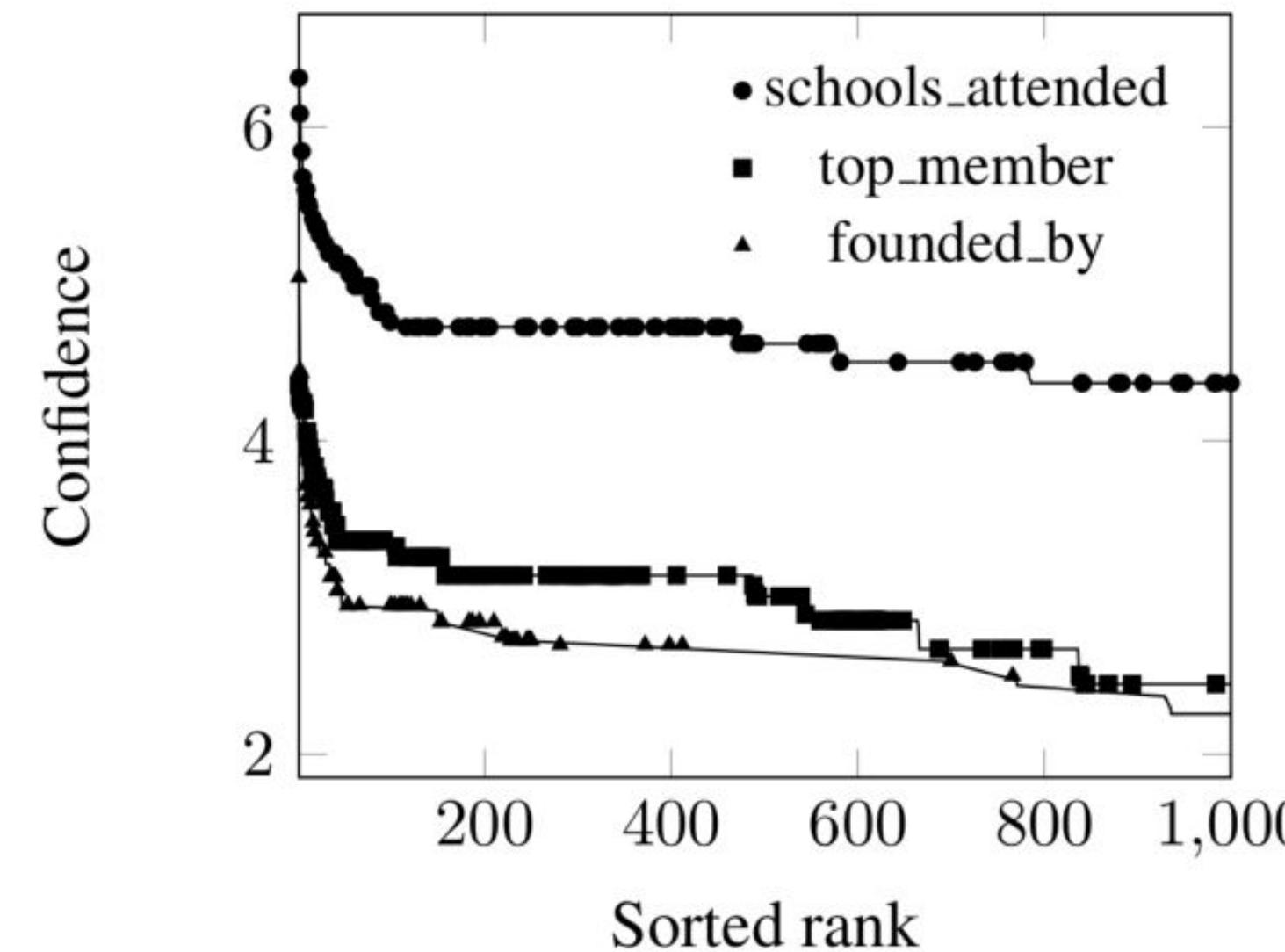
1. Collect many pairs of entities **co-occurring** in sentences from the corpus (Mintz, 2009)
 - Noise

Guiding Bootstrapped Relation Extractors

Knowledge Base Population using Semantic Label Propagation
(Knowledge Based Systems, Sterckx, 2016)

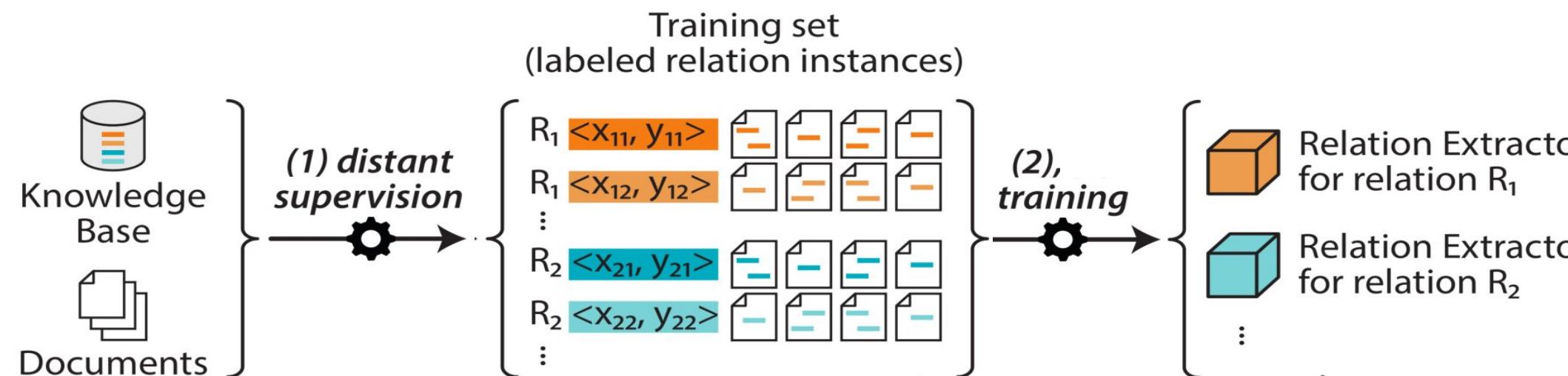


Guiding Bootstrapped Relation Extractors



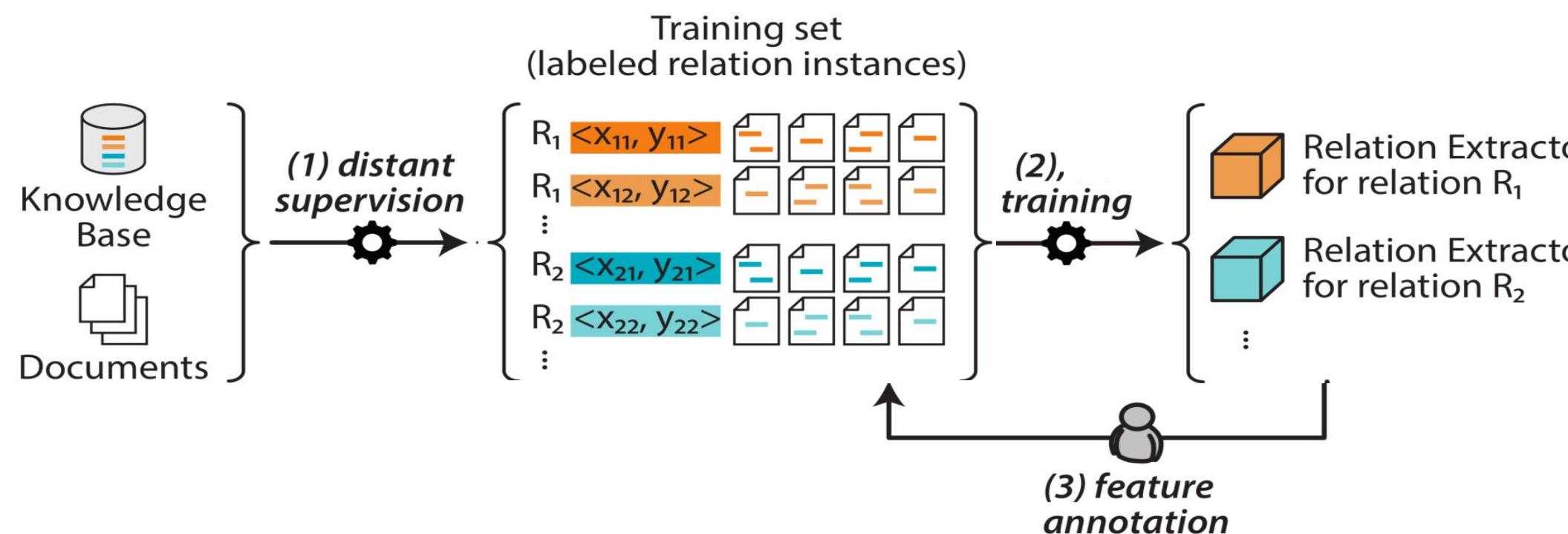
Guiding Bootstrapped Relation Extractors

| Relation | Top SDP |
|-----------------------|---|
| top_members_employees | $\text{PER} \xleftarrow{\text{appos}} \text{executive} \xrightarrow{\text{prep_of}} \text{ORG}$ $\text{PER} \xleftarrow{\text{appos}} \text{chairman} \xrightarrow{\text{appos}} \text{ORG}$ $\text{ORG} \xleftarrow{\text{nn}} \text{founder} \xrightarrow{\text{prep_of}} \text{PER}$ |
| children | $\text{PER-2} \xleftarrow{\text{appos}} \text{son} \xrightarrow{\text{prep_of}} \text{PER-1}$ $\text{PER-1} \xleftarrow{\text{appos}} \text{father} \xrightarrow{\text{prep_of}} \text{PER-2}$ $\text{PER-2} \xleftarrow{\text{nn}} \text{grandson} \xrightarrow{\text{prep_of}} \text{PER-1}$ |
| city_of_birth | $\text{PER} \xleftarrow{\text{rcmod}} \text{born} \xrightarrow{\text{prep_in}} \text{LOC}$ $\text{PER} \xleftarrow{\text{nsubj}} \text{mayor} \xrightarrow{\text{prep_of}} \text{LOC}$ $\text{PER} \xleftarrow{\text{appos}} \text{historian} \xrightarrow{\text{prep_from}} \text{LOC}$ |



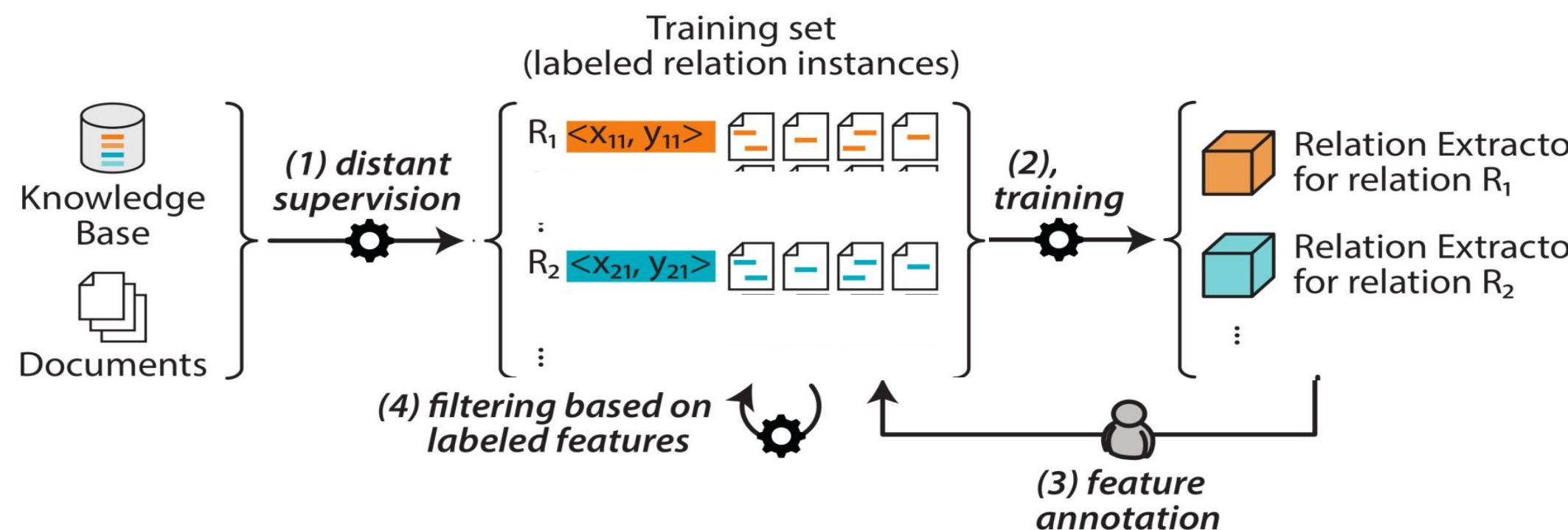
Guiding Bootstrapped Relation Extractors

| Relation | Top SDP | Assessment |
|-----------------------|---|-------------|
| top_members_employees | $\text{PER} \xleftarrow{\text{appos}} \text{executive} \xrightarrow{\text{prep_of}} \text{ORG}$ $\text{PER} \xleftarrow{\text{appos}} \text{chairman} \xrightarrow{\text{appos}} \text{ORG}$ $\text{ORG} \xleftarrow{\text{nn}} \text{founder} \xrightarrow{\text{prep_of}} \text{PER}$ | ✓ ✓ ✗ |
| children | $\text{PER-2} \xleftarrow{\text{appos}} \text{son} \xrightarrow{\text{prep_of}} \text{PER-1}$ $\text{PER-1} \xleftarrow{\text{appos}} \text{father} \xrightarrow{\text{prep_of}} \text{PER-2}$ $\text{PER-2} \xleftarrow{\text{nn}} \text{grandson} \xrightarrow{\text{prep_of}} \text{PER-1}$ | ✓ ✓ ✗ |
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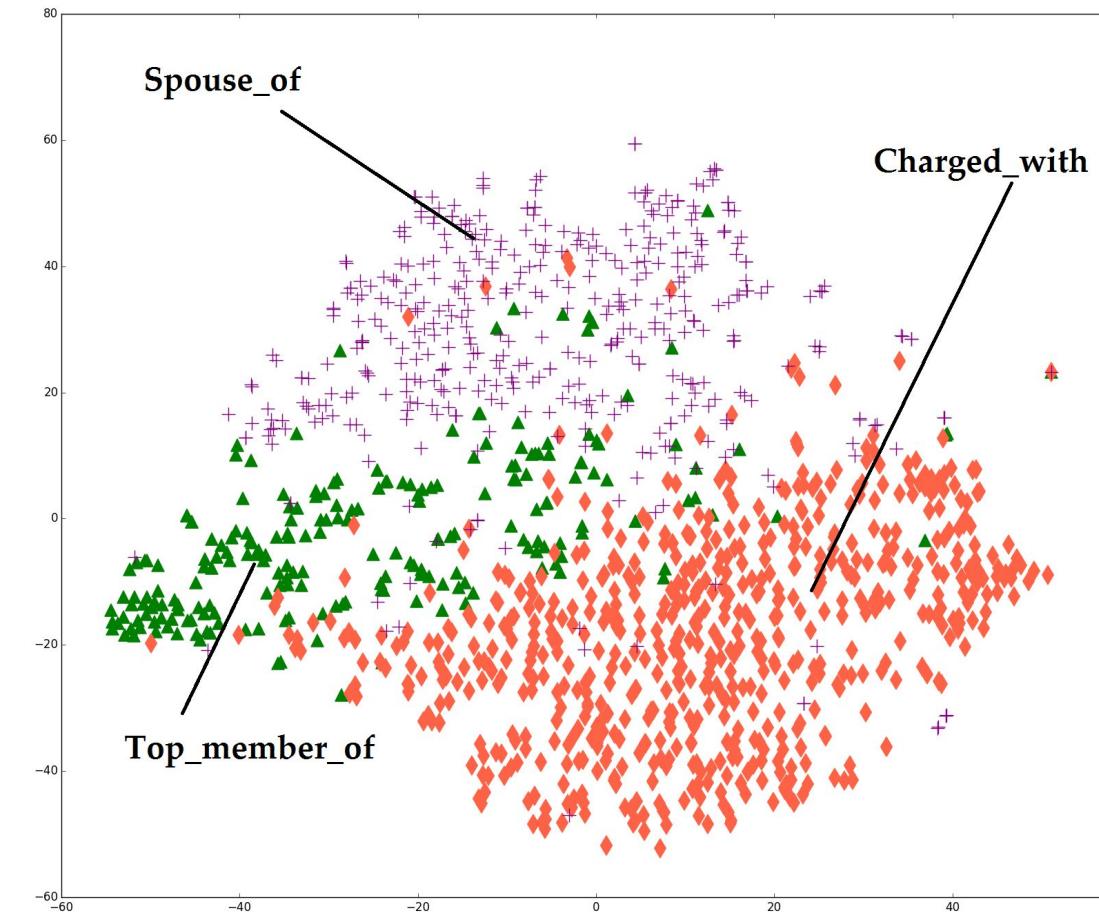


Guiding Bootstrapped Relation Extractors

- Filter non-labeled patterns
 - Include weaker features in log-linear classifiers
 - Regularize
- Recall ↓↓



Guiding Bootstrapped Relation Extractors



**Labeled
Shortest Dependency
Path**

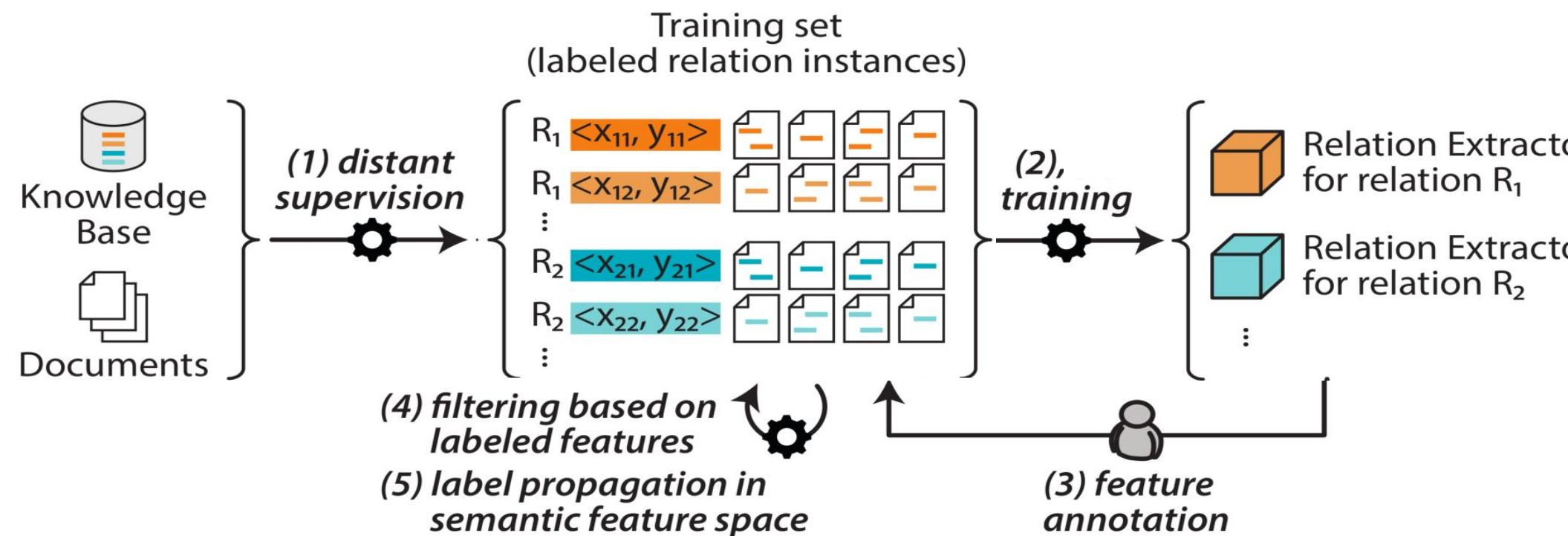
Embedding

Cosine Similarity

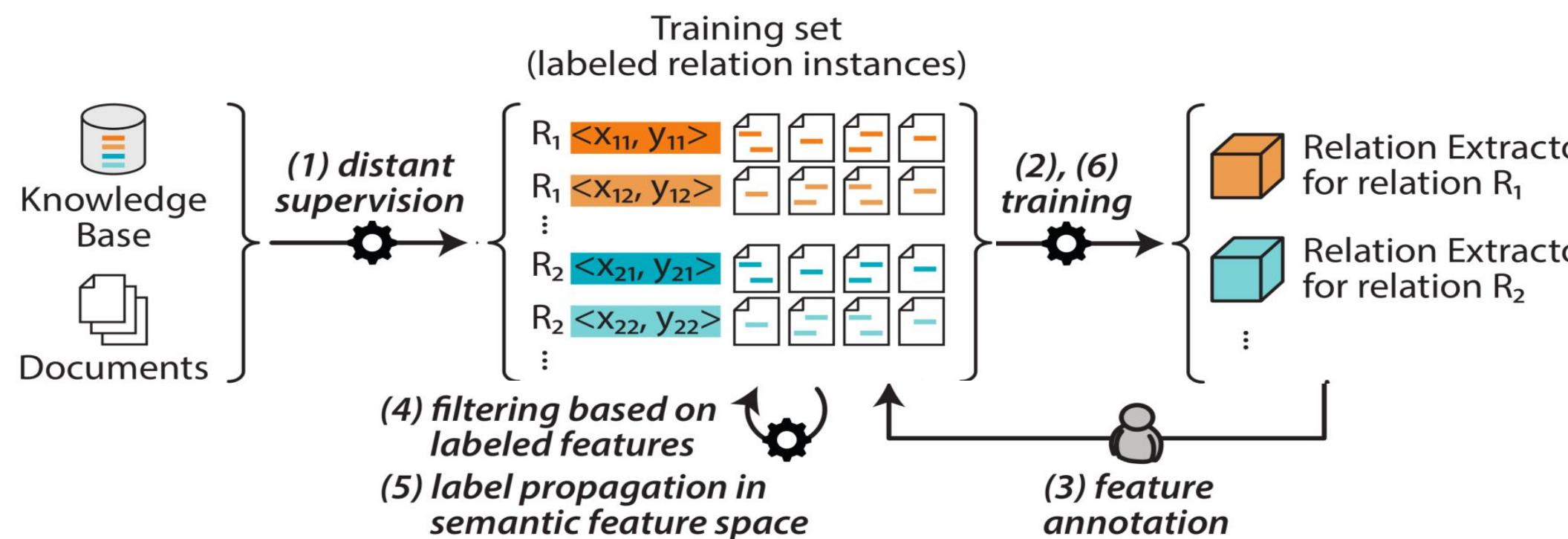
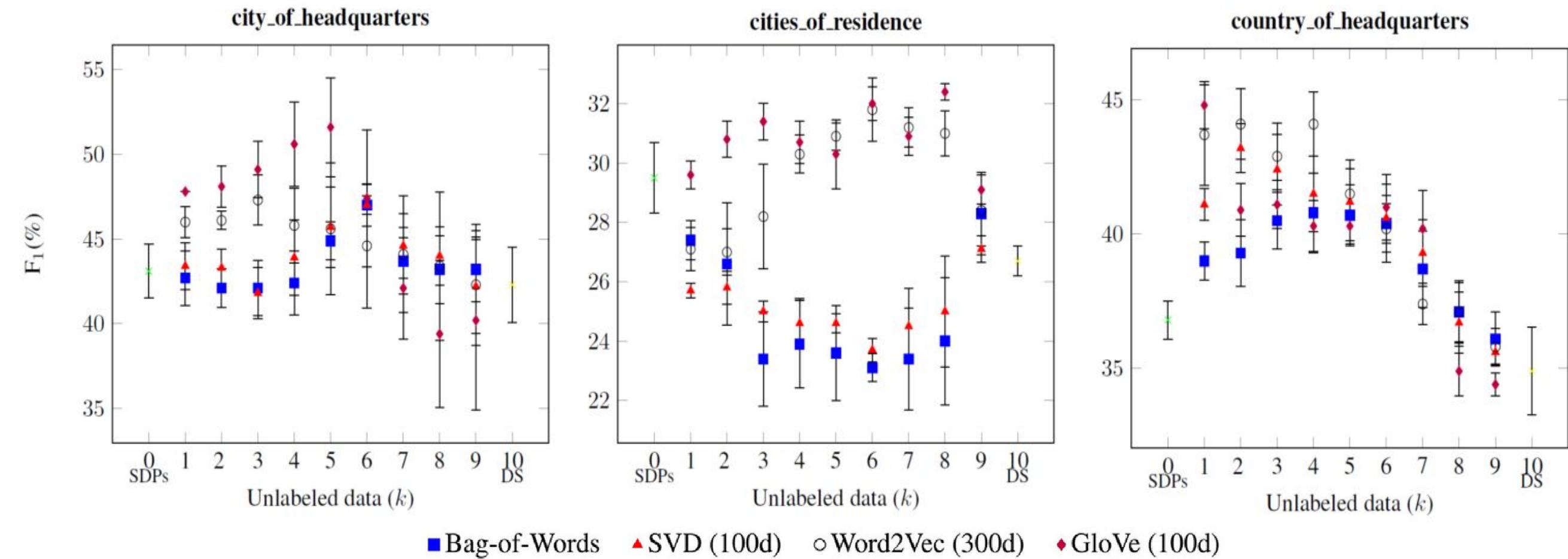
PER $\xleftarrow{\text{appos}}$ executive $\xrightarrow{\text{prep-of}}$ ORG

$$\vec{C} = \text{CBOW}(\text{executive}, \text{of})$$

$$\text{Sim}(\vec{C}_t, \vec{C}_{DS}) = \frac{\vec{C}_t \cdot \vec{C}_{DS}}{|\vec{C}_t| \cdot |\vec{C}_{DS}|}$$

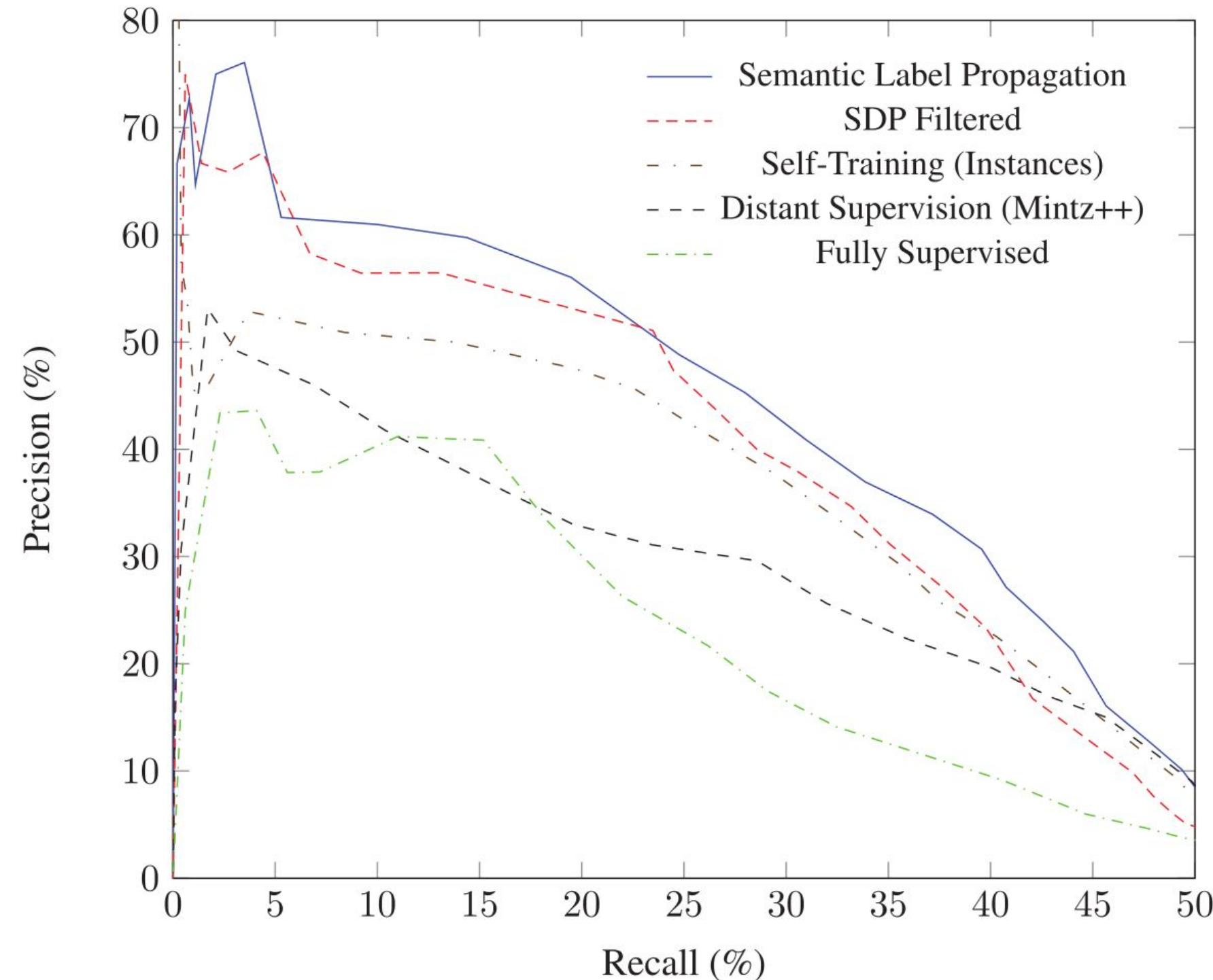


Guiding Bootstrapped Relation Extractors

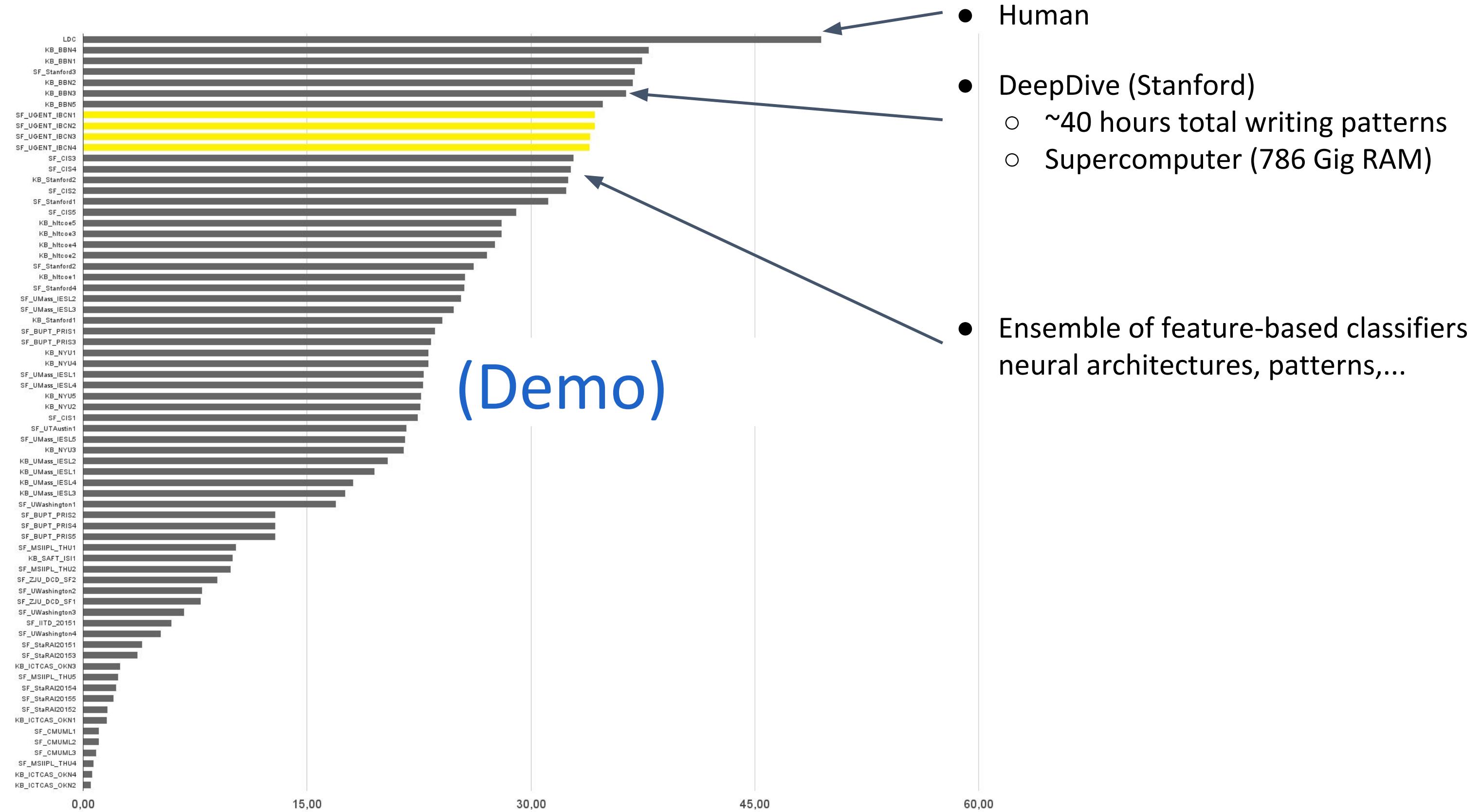


Ghent University at TAC KBP

- Recall ↑↑
- Minimal supervision (5 min. per relation, 2u30 for TAC-KBP)



Ghent University at TAC KBP



Outline

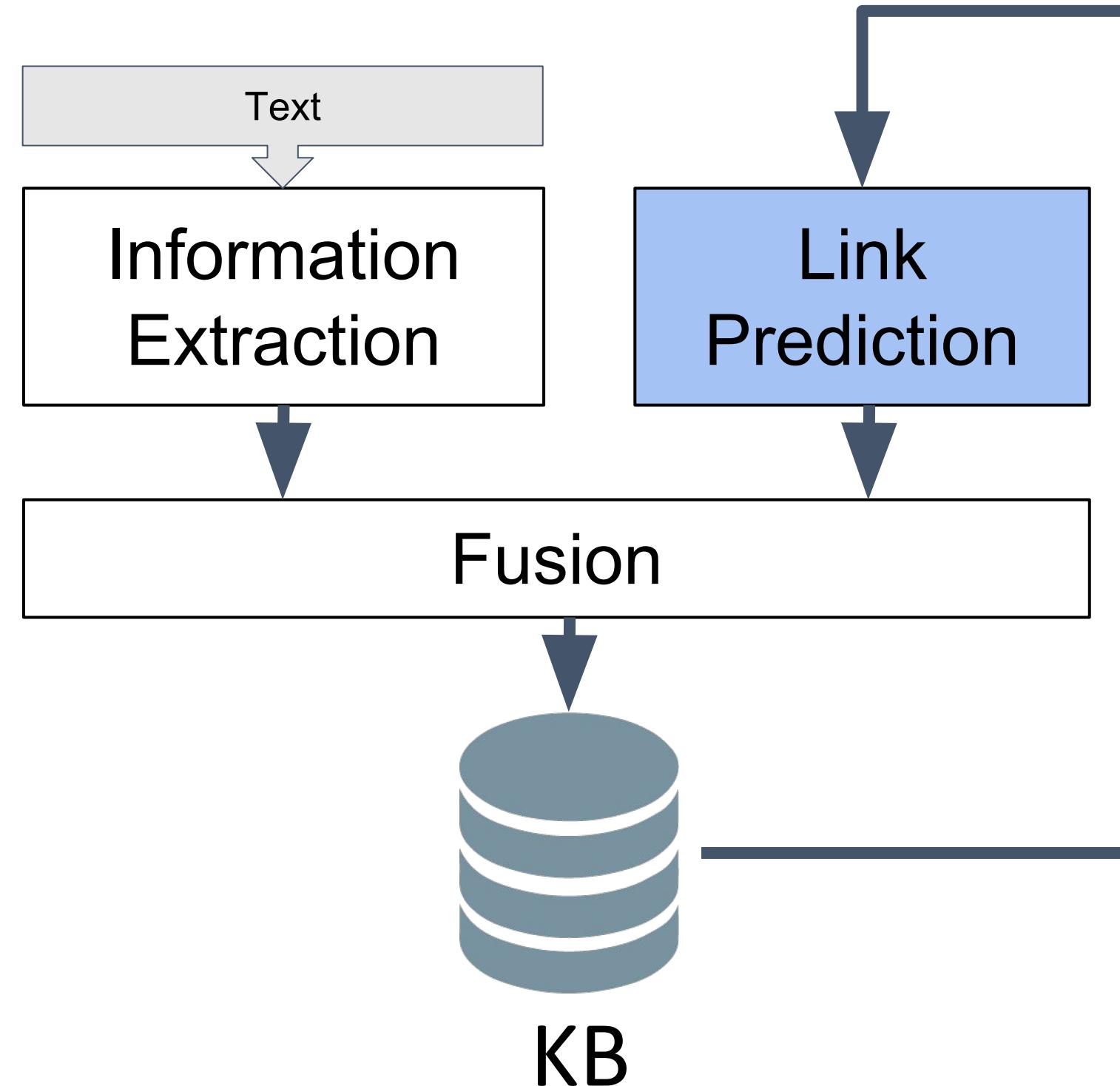
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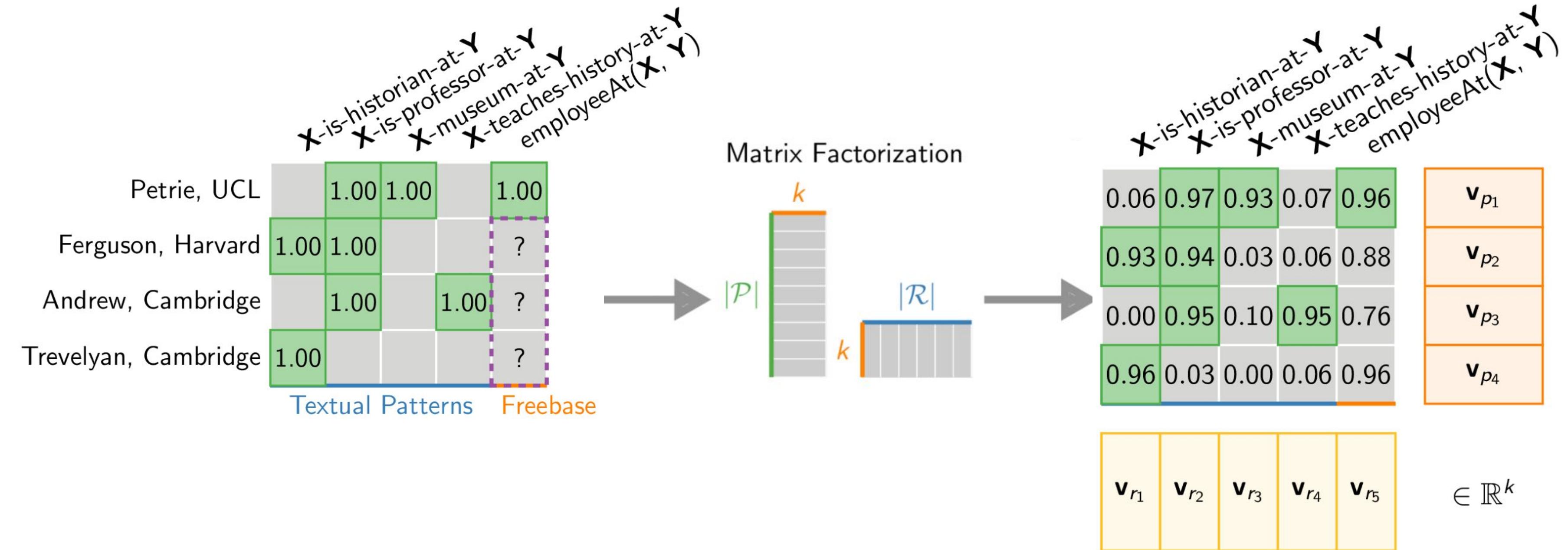
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Relation Extraction by Matrix Factorization (Riedel, 2013)



$$p(\text{fact}) = p(x_{ij}=1 \mid Graph)$$

[neural] vector representations,

- + Similarity, approximate inference
- Fails for little alignment, hard to fix mistakes

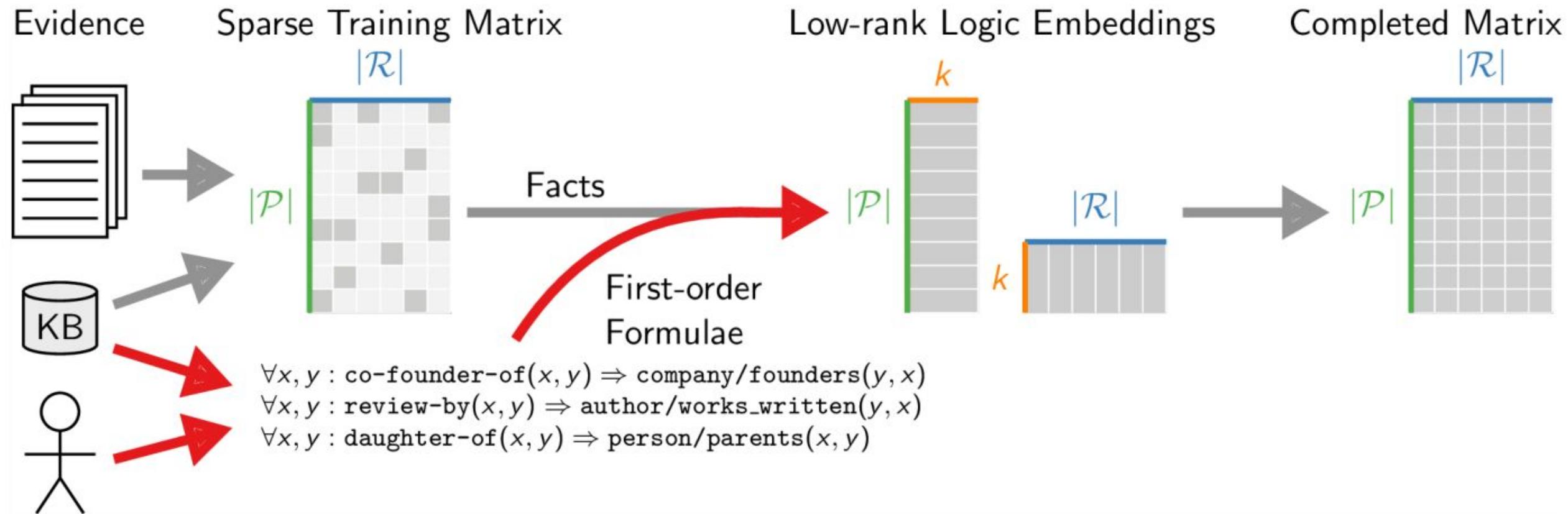
[symbolic] efficient (“lifted”) injection of prior knowledge “prof_at \Rightarrow works_for”

- + Easy to modify
- Brittle, no generalization

combine **neural** and **symbolic** representations

to leverage advantages of both

Injecting Logical Formulae (Rocktäschel, 2015)



- Inject general 1st order formulae
 - expressed in terms of probabilities of all training facts
 - e.g. model for $r_p \Rightarrow r_q$: by grounding over entities

$$p((r_p, e) \Rightarrow (r_q, e)) \approx 1 - p(r_p, e)(1 - p(r_q, e))$$

- Lessons learned:
 - + joint training of facts and rules works best
 - due to grounding, only practical for few rules

Lifted implication rules (Demeester, 2016)

When is rule “`prof_at` \Rightarrow `works_for`” satisfied?

$$\forall e \in \mathcal{E} : p(\text{prof_at}(e)) \leq p(\text{works_for}(e))$$

$$\sigma(\mathbf{v}_{\text{prof_at}} \cdot \mathbf{v}_e) \leq \sigma(\mathbf{v}_{\text{works_for}} \cdot \mathbf{v}_e)$$

$$\mathbf{v}_{\text{prof_at}} \cdot \mathbf{v}_e \leq \mathbf{v}_{\text{works_for}} \cdot \mathbf{v}_e$$

“compatibility”

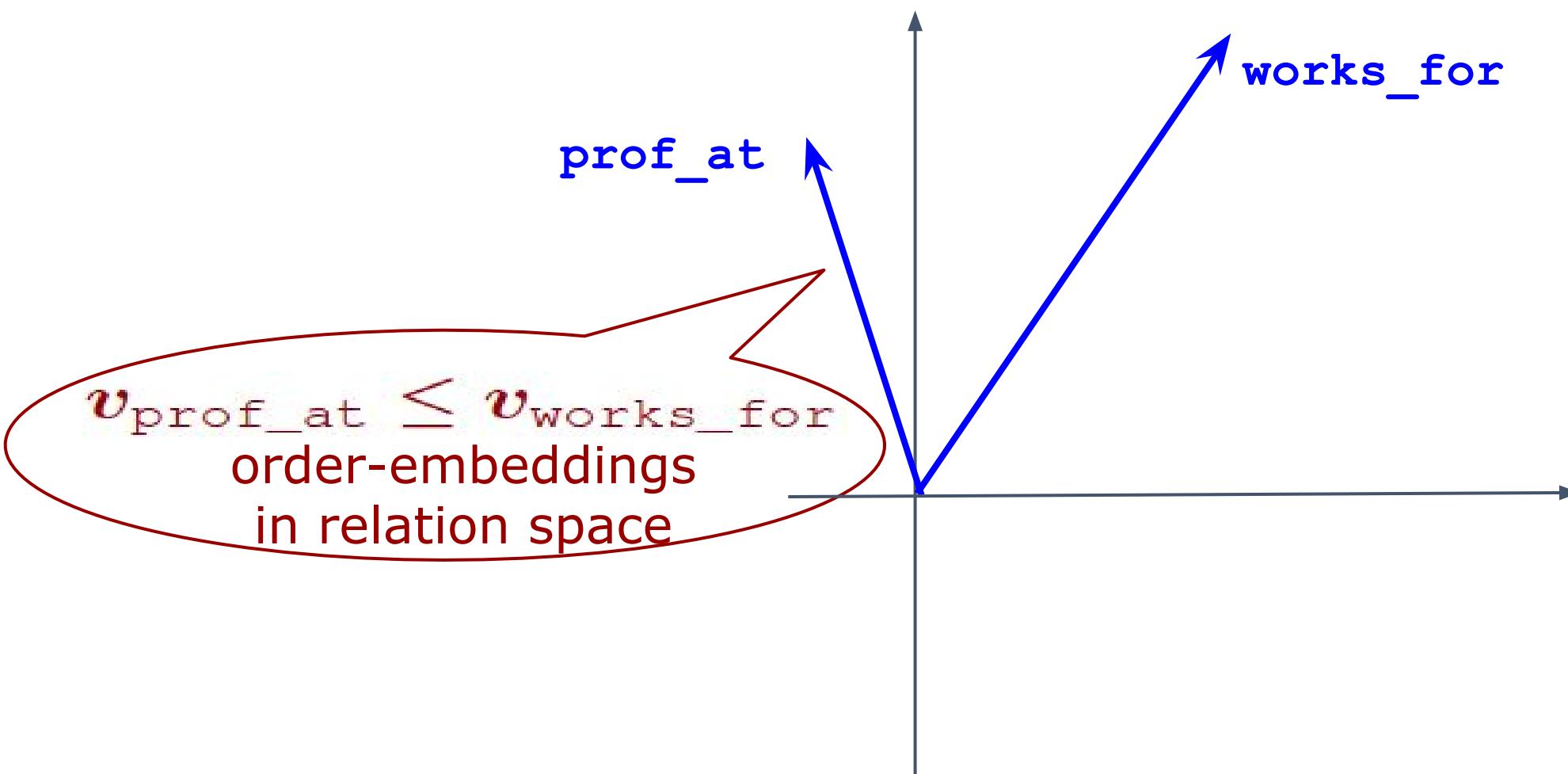
Sufficient (even stricter) condition:

$$\begin{cases} \mathbf{v}_{\text{prof_at}} \leq \mathbf{v}_{\text{works_for}} & \text{ordered relation embeddings} \\ \forall e \in \mathcal{E} : \mathbf{v}_e \in \mathbb{R}^{k,+} & \text{non-negative tuple embeddings} \end{cases}$$

Lifted implication rules - illustration

rule $\text{prof_at} \Rightarrow \text{works_for}$

becomes: $\forall v_e : v_{\text{prof_at}} \cdot v_e \leq v_{\text{works_for}} \cdot v_e$



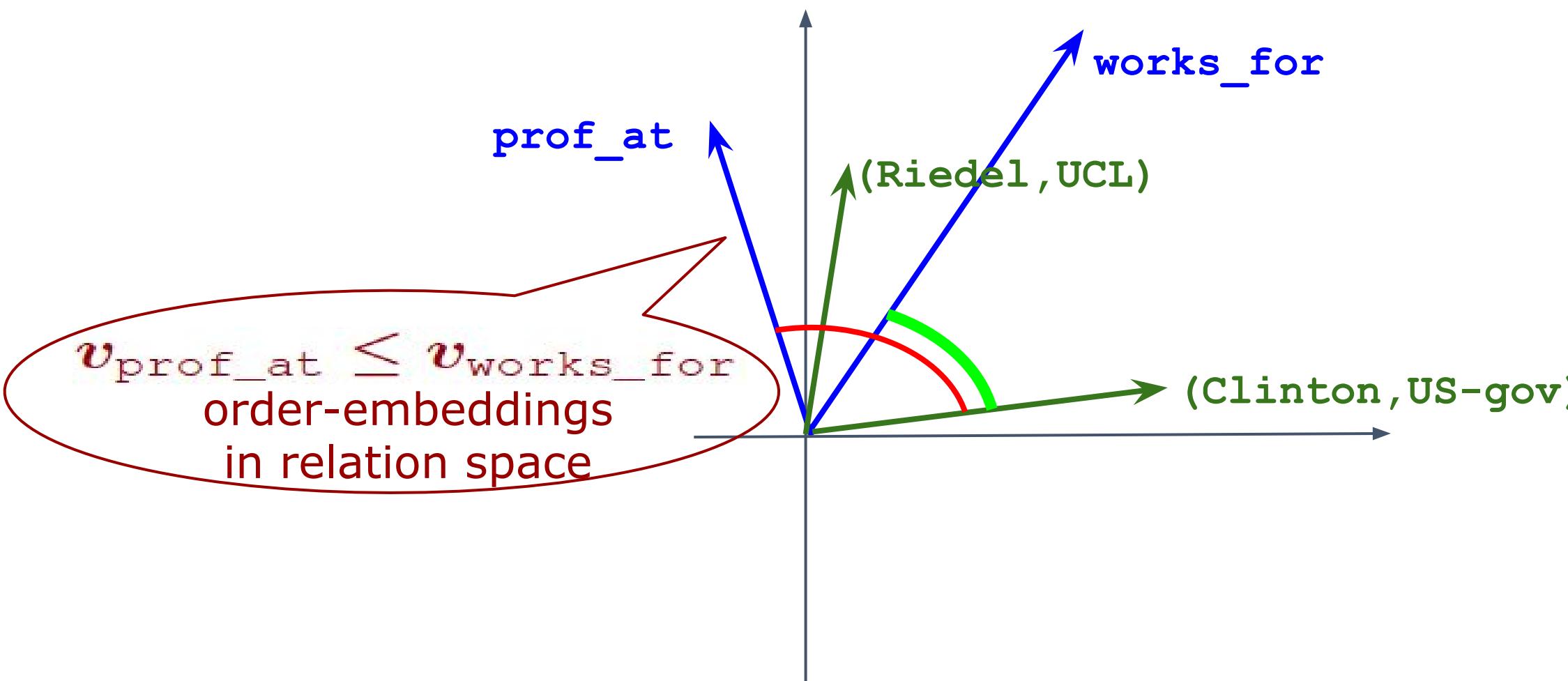
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Given: training facts

$\text{works_for}(\text{Clinton}, \text{US-Gov})$
 $\text{prof_at}(\text{Riedel}, \text{UCL})$



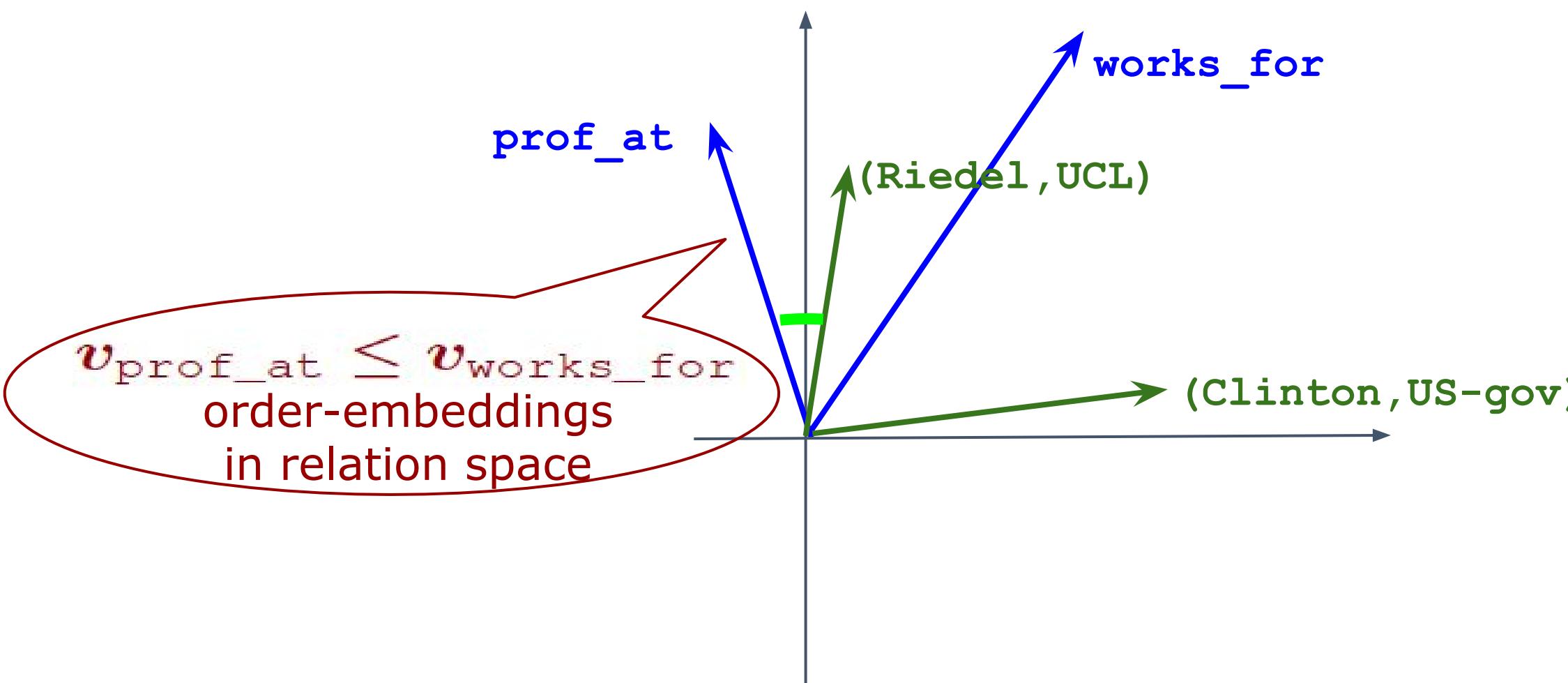
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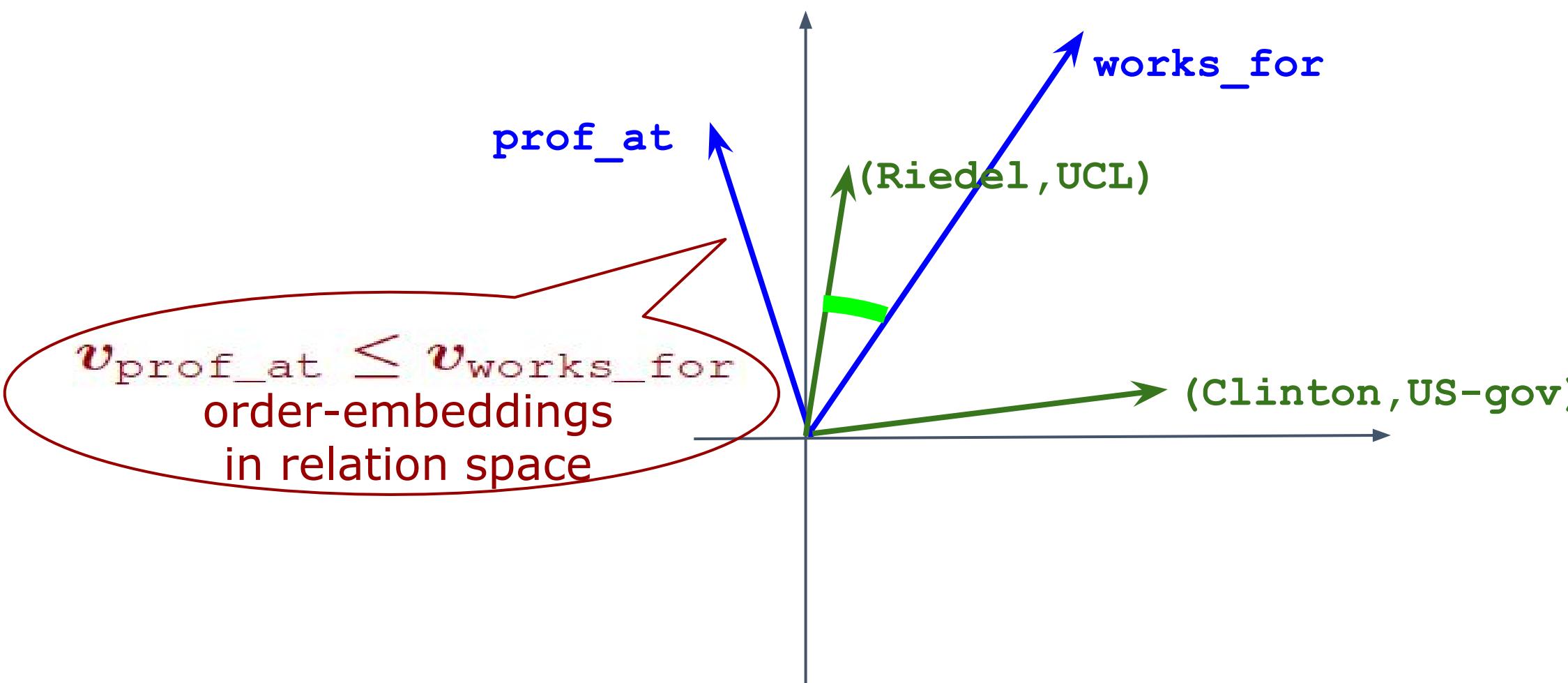
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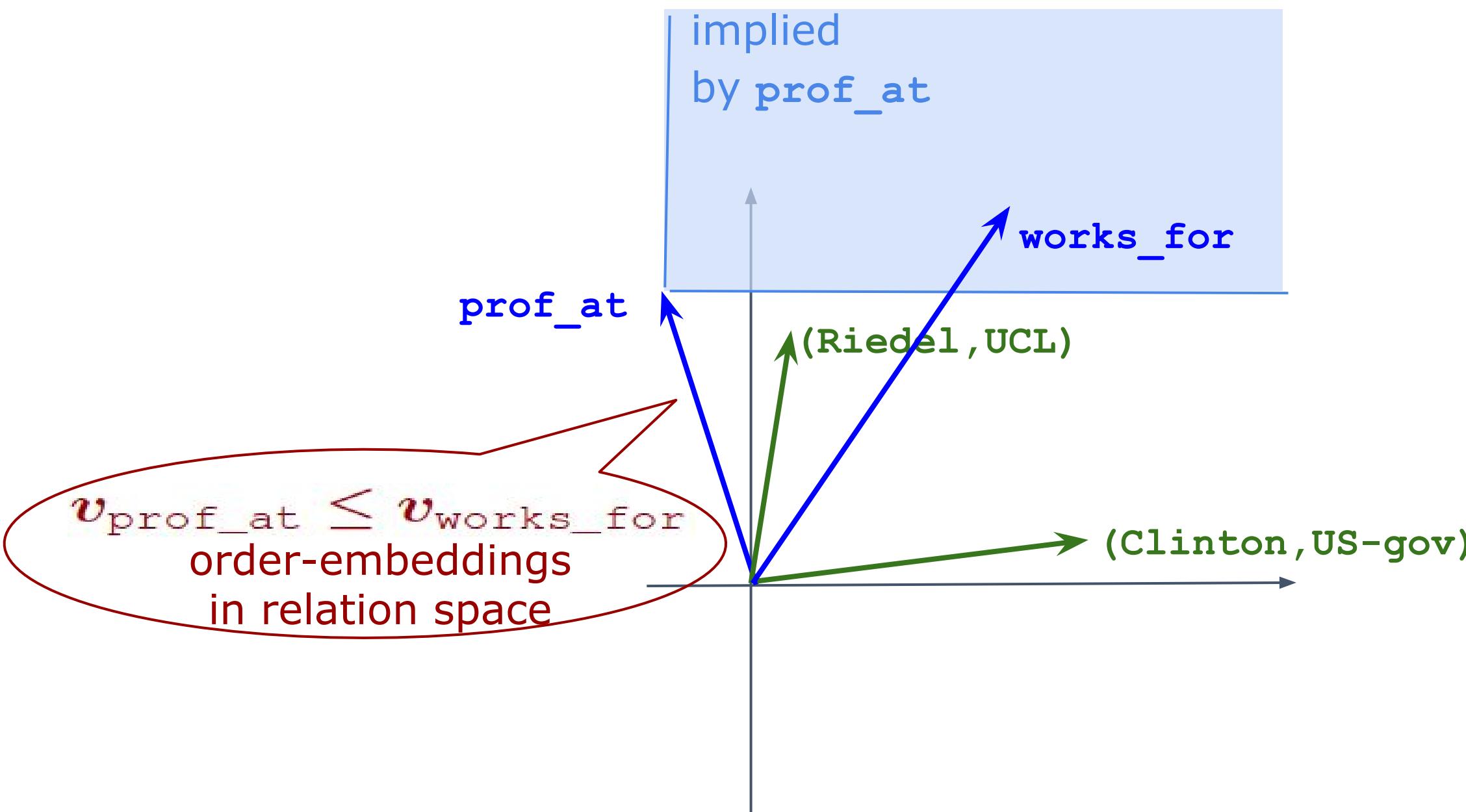
$\text{works_for}(\text{Clinton}, \text{US-Gov})$
 $\text{prof_at}(\text{Riedel}, \text{UCL})$



Lifted implication rules - illustration

rule $\text{prof_at} \Rightarrow \text{works_for}$

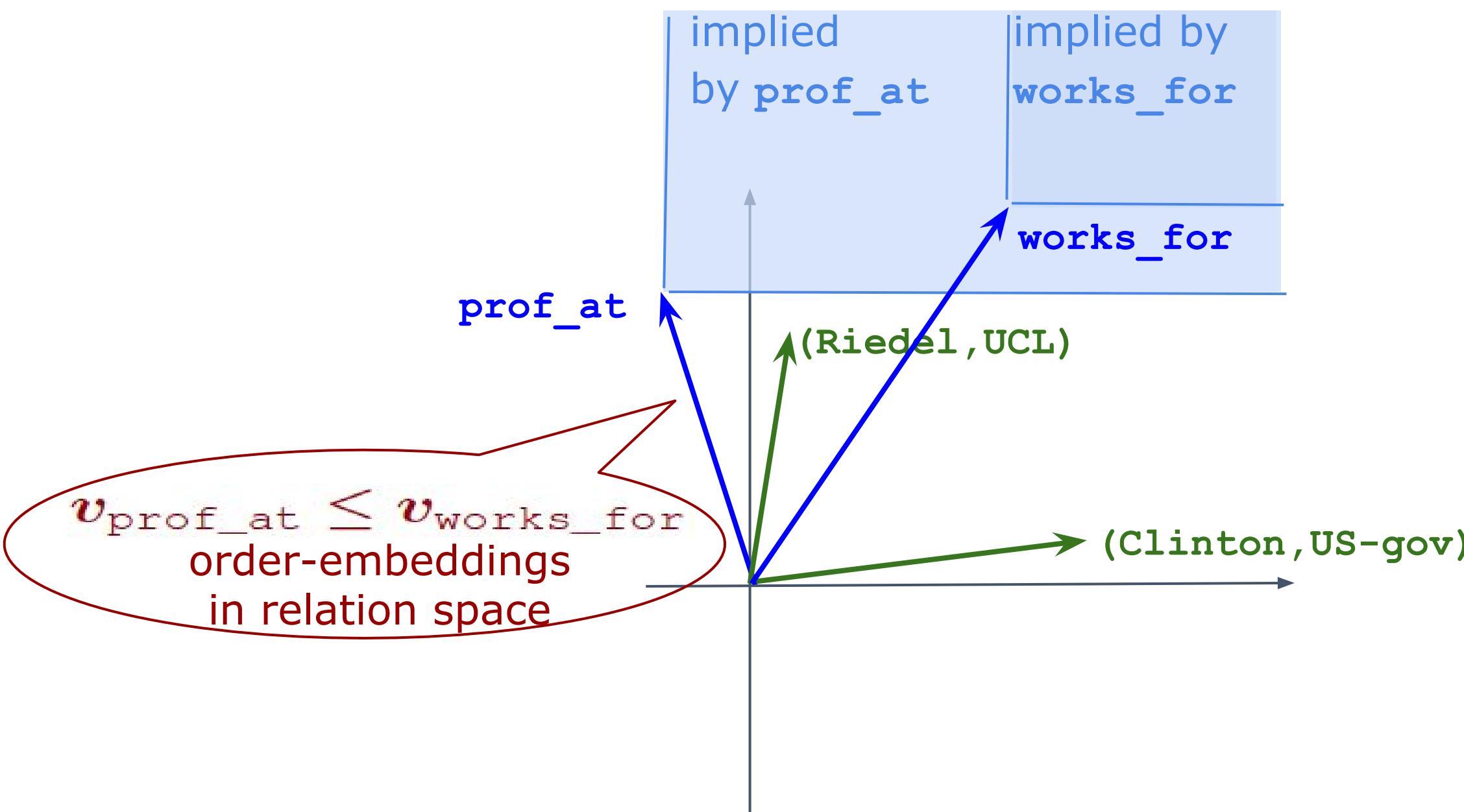
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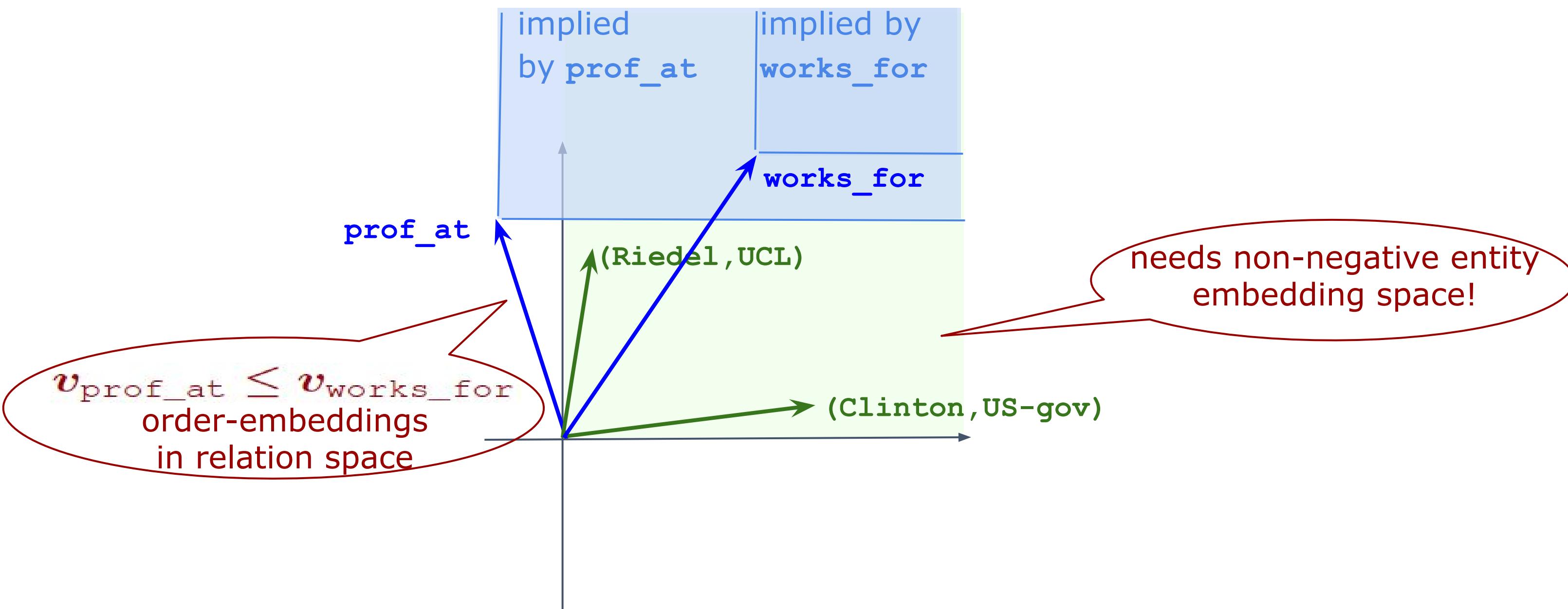
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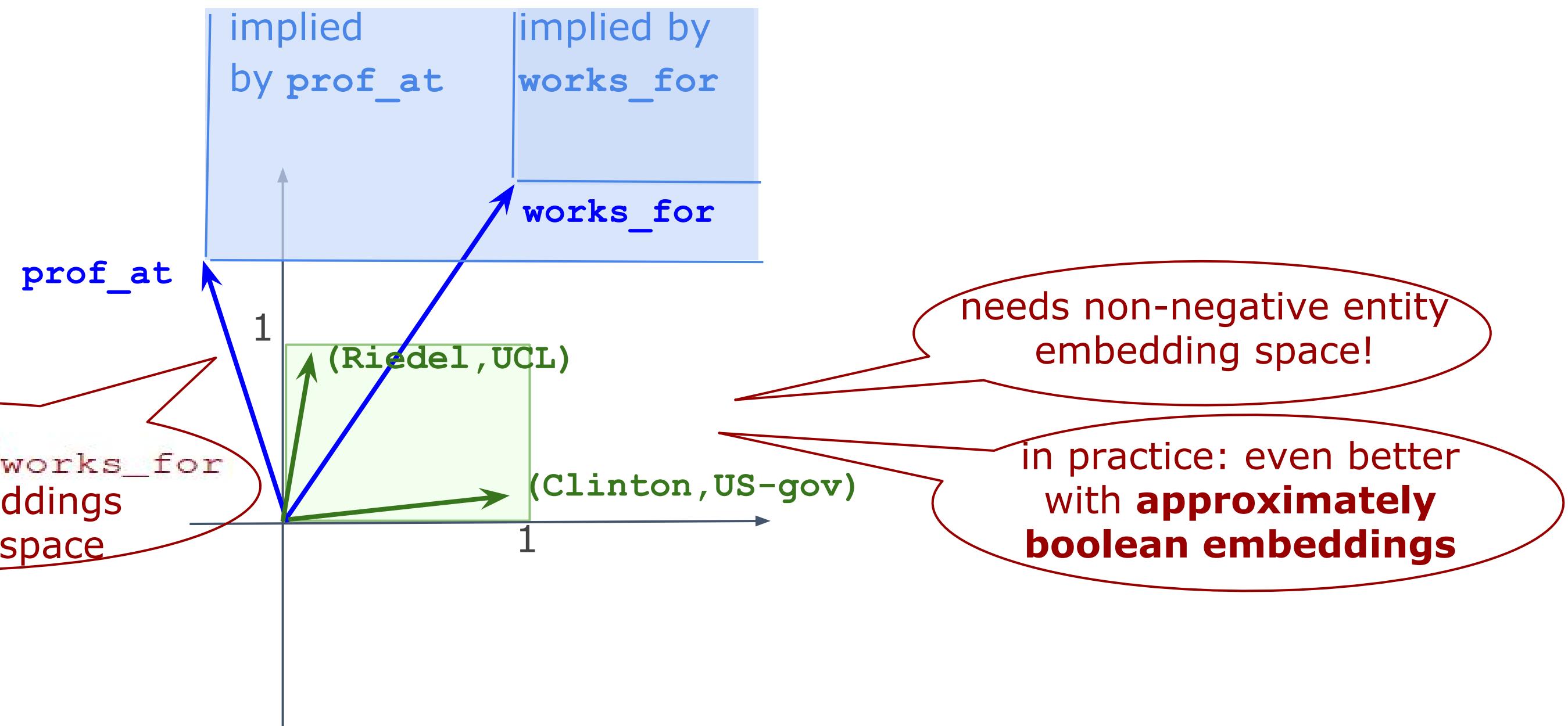
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Lifted implication rules - illustration

rule $\text{prof_at} \Rightarrow \text{works_for}$

becomes: $\forall v_e : v_{\text{prof_at}} \cdot v_e \leq v_{\text{works_for}} \cdot v_e$



Lifted implication rules - in practice

Non-negative entity embeddings?

Differentiable mapping of $e \in \mathbb{R}^k$ to $\tilde{e} \in \mathbb{R}^{k,+}$

Options:

$$\tilde{e} := \exp(e) \in \mathbb{R}^{k,+}$$

$$\tilde{e} := \text{ReLU}(e) \in \mathbb{R}^{k,+}$$

$$\tilde{e} := \sigma(e) \in (0, 1)^k$$

strongest restriction, but works best!
“Approximately Boolean embeddings”

Ordered relation embeddings?

1 additional “lifted” loss term per implication rule:

$$\text{minimize } \mathcal{L}_{\text{rule}} = \sum_i \max(0, [v_{\text{prof_at}} - v_{\text{prof_at}}]_i)$$

upper bound to
“grounded” loss

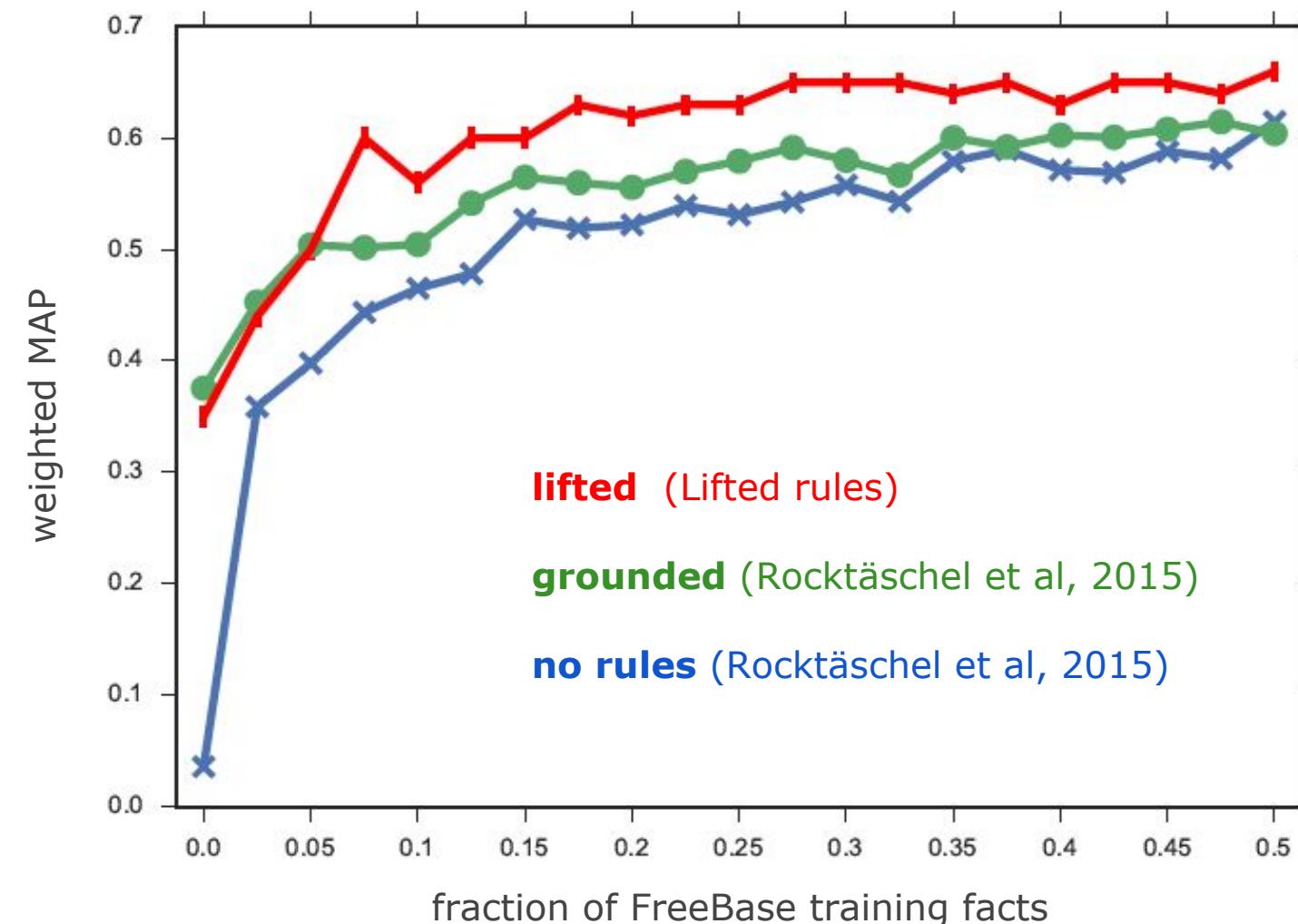
Experiments: Grounded versus Lifted?

More efficient:

| 1 epoch (single CPU) | 0 rules | 36 rules | 427 rules |
|----------------------|---------|----------|-----------|
| | 6.33s | 6.76 | 6.97s |

only
10% overhead
due to rules

Higher precision:



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At Cambridge: Learning to Annotate

Learn to explain hard-to-interpret text

- Genius.com
- 950.000 lyrics-annotation pairs
- English-to-English text generation
 - (Summarizing, Simplification, Paraphrasing,...)
- Statistical and Neural Machine Translation?
- Translation vs. Retrieval based?
- Evaluation ?
- Paraphrasing vs. External Knowledge ?

Remember when I used to eat sardines for dinner
Peace to Ron G, Brucey B, Kid Capri
Funkmaster Flex, Lovebug Starski (wassup?)
I'm blowing up like you thought I would
Call the crib, same number, same hood (that's right)
It's all good (it's all good)
And if you don't know, now you know, nigga

[Hook: Total]
You know very well who you are
Don't let 'em hold you down, reach for the stars
You had a goal, but not that many
Cause you're the only one
I'll give you good and plenty

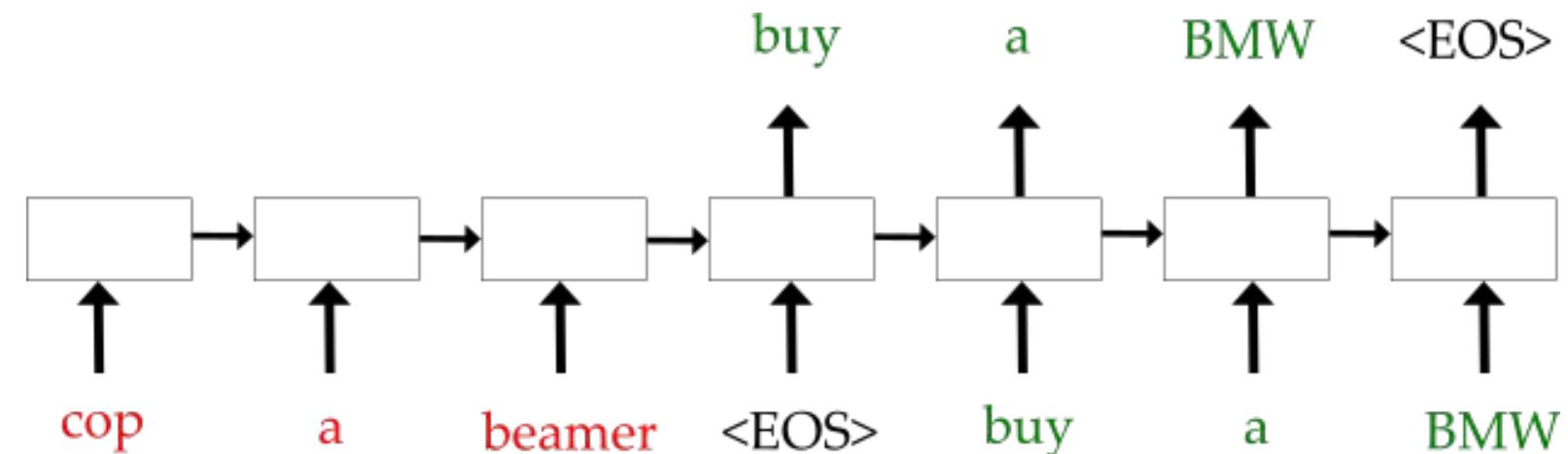
[Verse 2: The Notorious B.I.G.]
I made the change from a common thief
To up close and personal with Robin Leach
And I'm far from cheap, I smoke skunk with my peeps all day
Spread love, it's the Brooklyn way

Genius Annotation 1 contributor

This iconic hook, sung by girl-group [Total](#), is a flip on the chorus of [Mtume's "Juicy Fruit"](#), which is sampled for the beat. The lyrics of the original are as follows:

“ You know very well what you are
You're my sugar thing, my chocolate star
I've had a few, but not that many
But you're the only love, that gives me good
and plenty

Biggie's version flips the meaning, addressing his aspiration to fame rather than romantic love, but keeps the reference to [Good & Plenty candy](#), which B.I.G. presumably ate by the handful.



Learning to Annotate

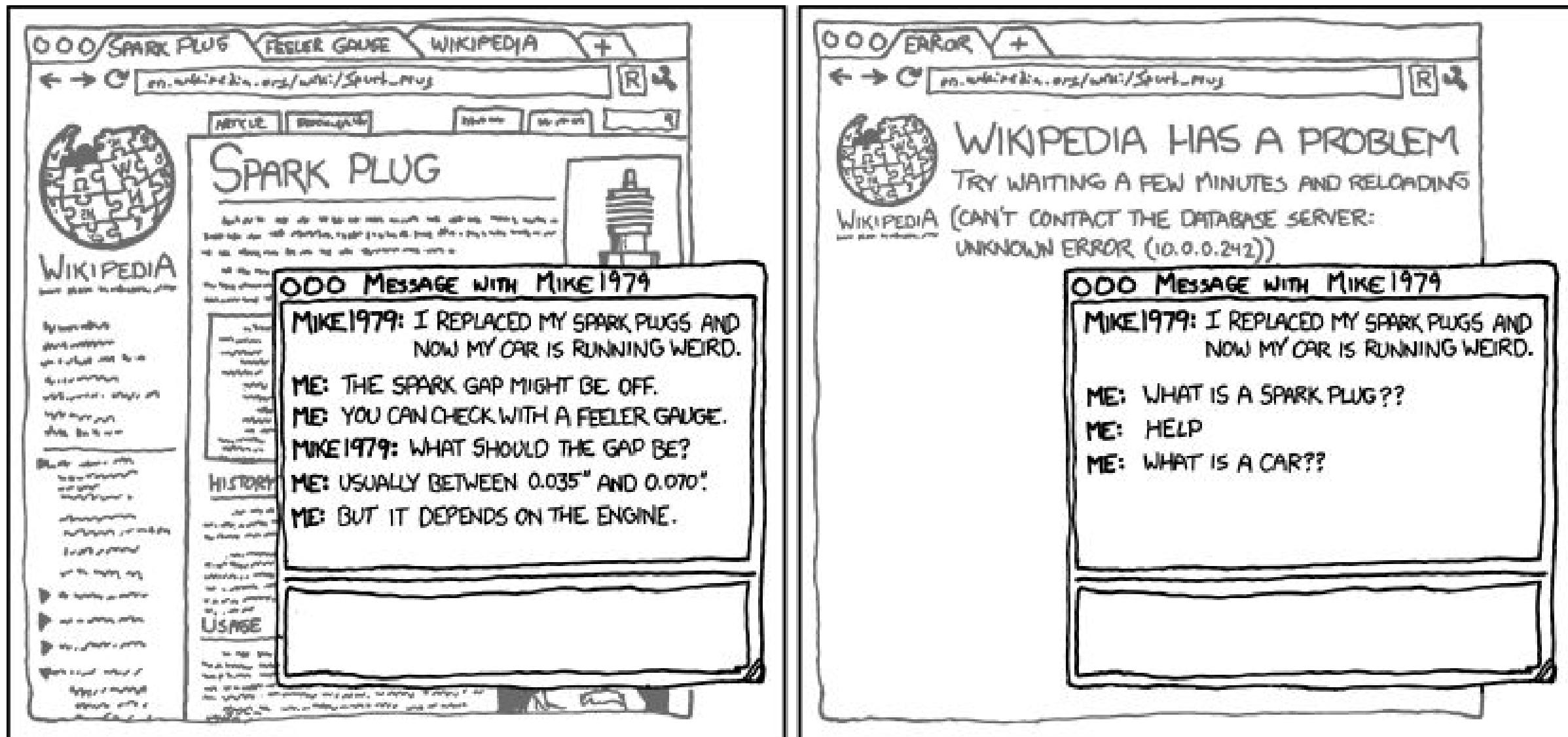
Lyrics: roll on my arm
True: he's always rocking a rolex
Retr.: (5) he wears a rolex, rolex manufactures expensive wristwatches.
LSTM: (4) he wears his rolex

Lyrics: i blast ya cabbage
True: think "head of cabbage". he's gonna shoot you in the head.
Retr.: (3) brains, post-headshot
LSTM: (4) he's gonna shoot you .

Lyrics: i used to have to pack a mack in back of the ac
True skits called "packin a mac in the back of the ac" appeared on pun's first two albums
Retr.: (5) he's "packin a mac [pakinamac] in the back of the ac [meaning acura]
vinnie is saying that he'll put you in the back of an accura right next to big pun's mac.
LSTM: (4) he used to have a gun in the back of the car

Lyrics: behold the flyest; bentley drivers louis vuitton buyers, jet fuel abusers
driving bentleys,
True: buying louis vuitton swag, and burning fuel in private jets are ways to show the cash that biggie and jay-z have to spend.
(they are the flyest)
Retr.: (2) for rich people/ballers only, prestigious (expensive as hell) name brand.
LSTM: (4) he's got a lot of money and expensive cars , and he's got a lot of expensive brands .

Thank you ! Questions, Comments?



WHEN WIKIPEDIA HAS A SERVER OUTAGE, MY APPARENT IQ DROPS BY ABOUT 30 POINTS.

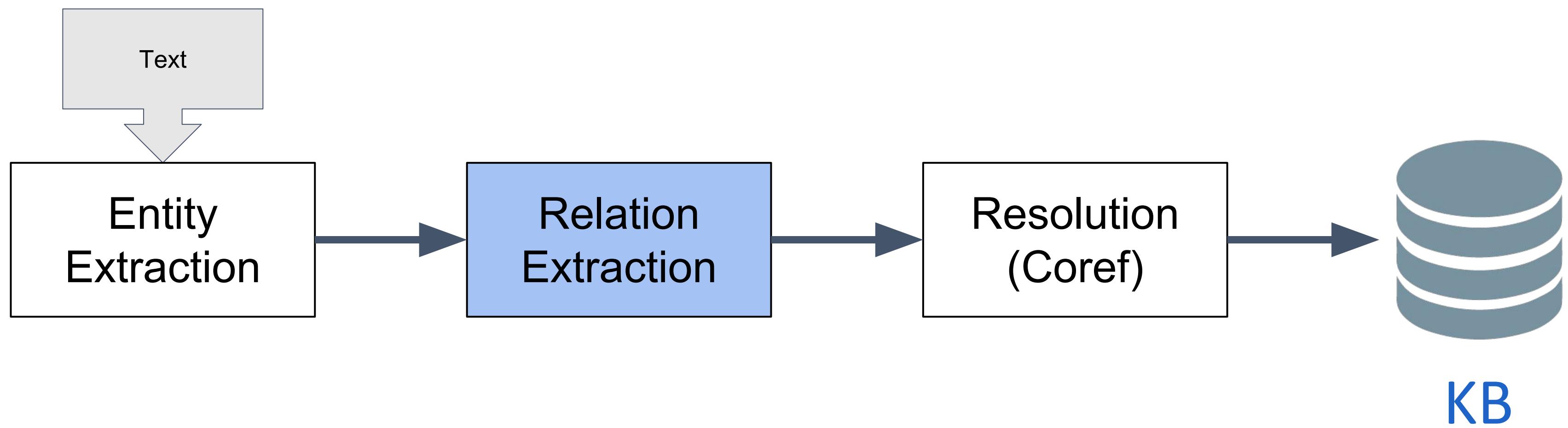
Xkcd extended miind

Lucas Sterckx

lusterck.github.io

@lusterck

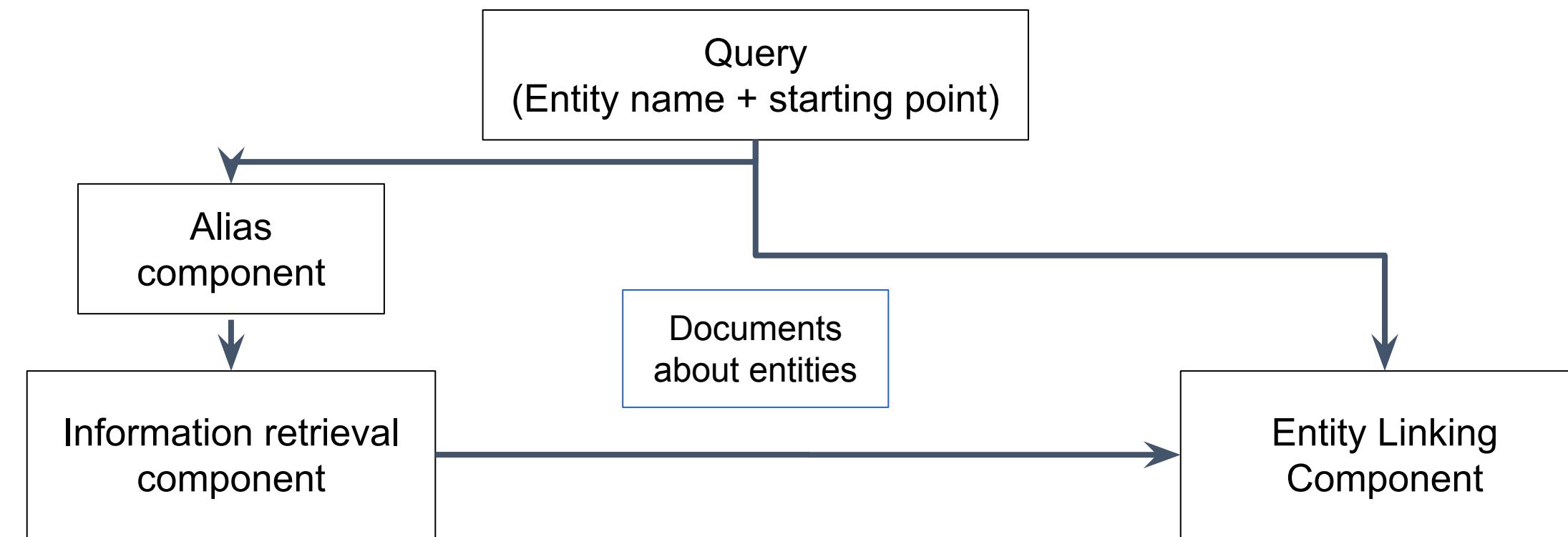
Information Extraction



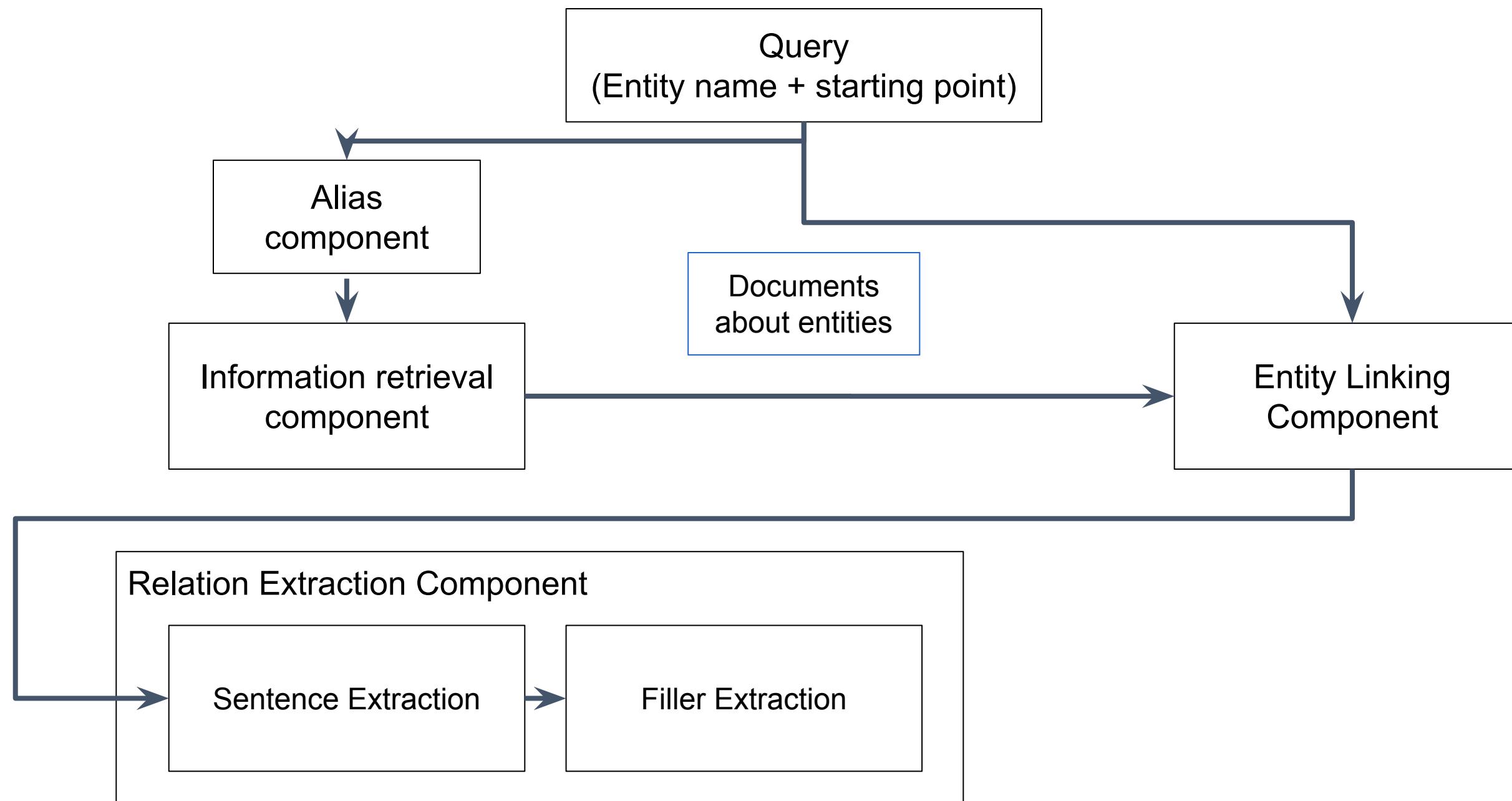
Ghent University at TAC KBP

Query
(Entity name + starting point)

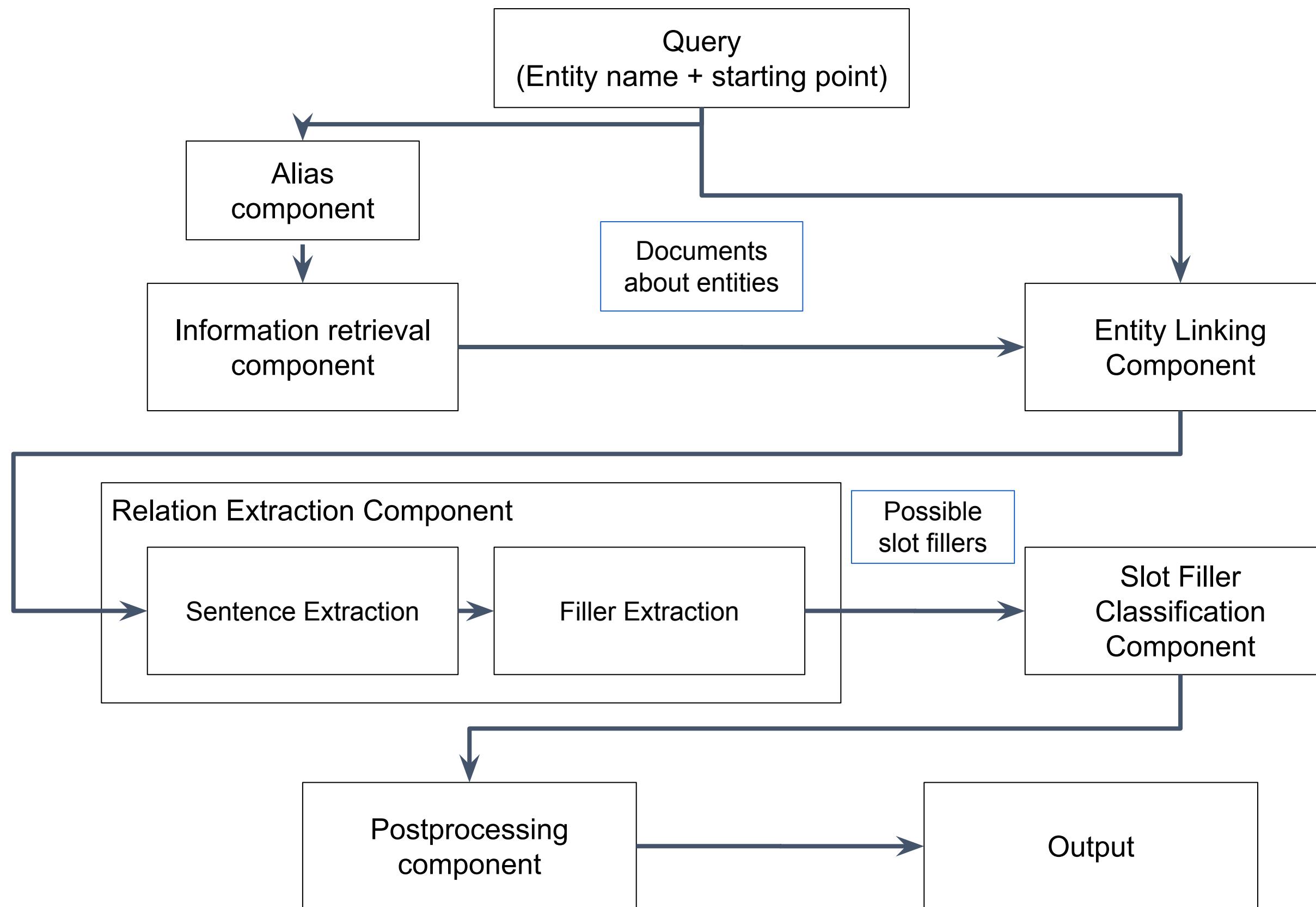
Ghent University at TAC KBP



Ghent University at TAC KBP

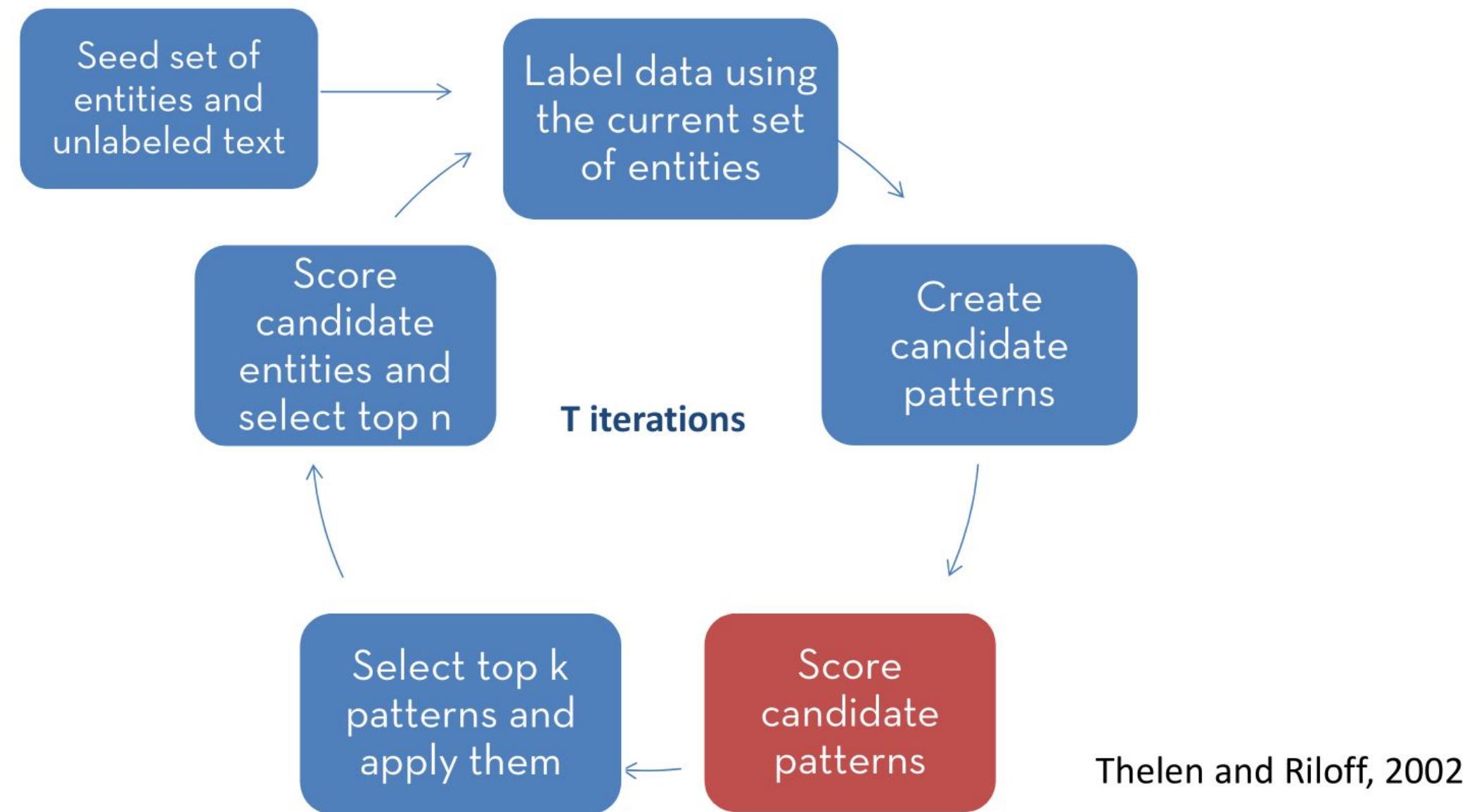


Ghent University at TAC KBP



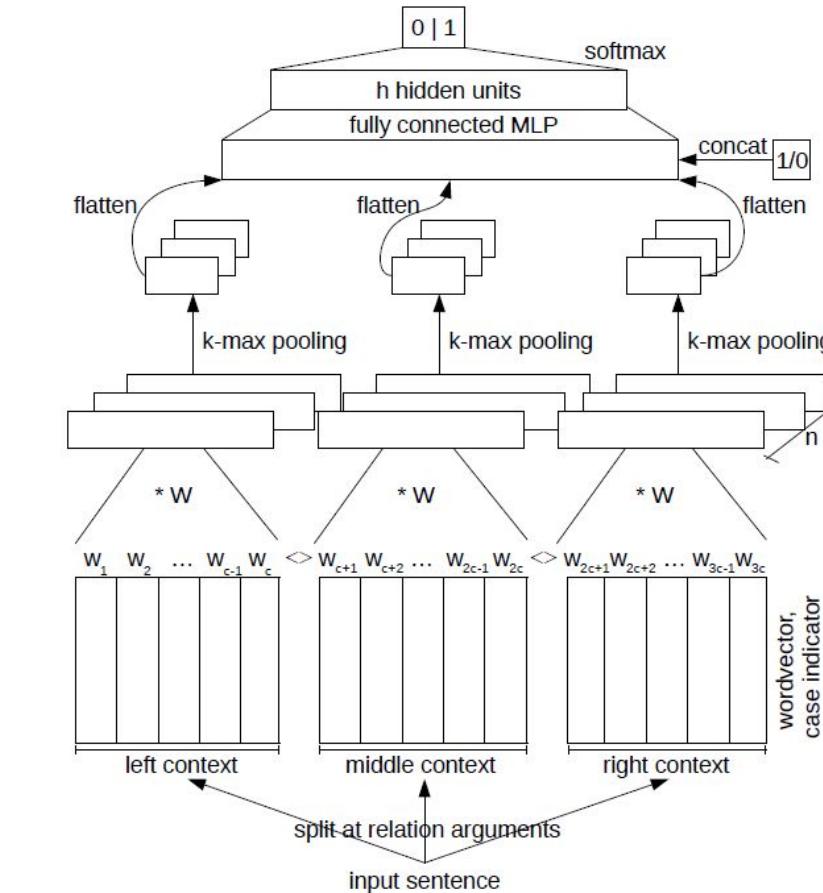
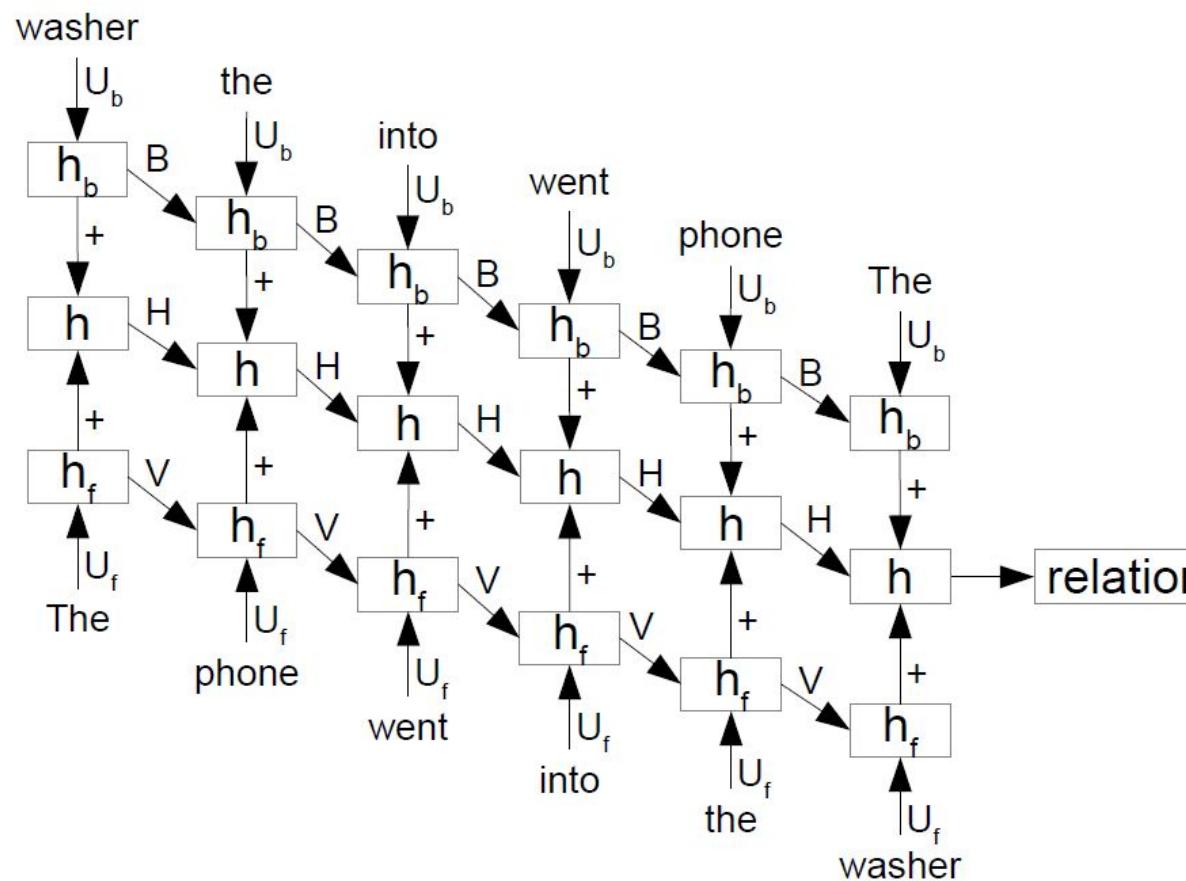
Semi-Supervised Relation Extraction

→ **Bootstrapping** (Hearst, DIPRE, Snowball, BRED)



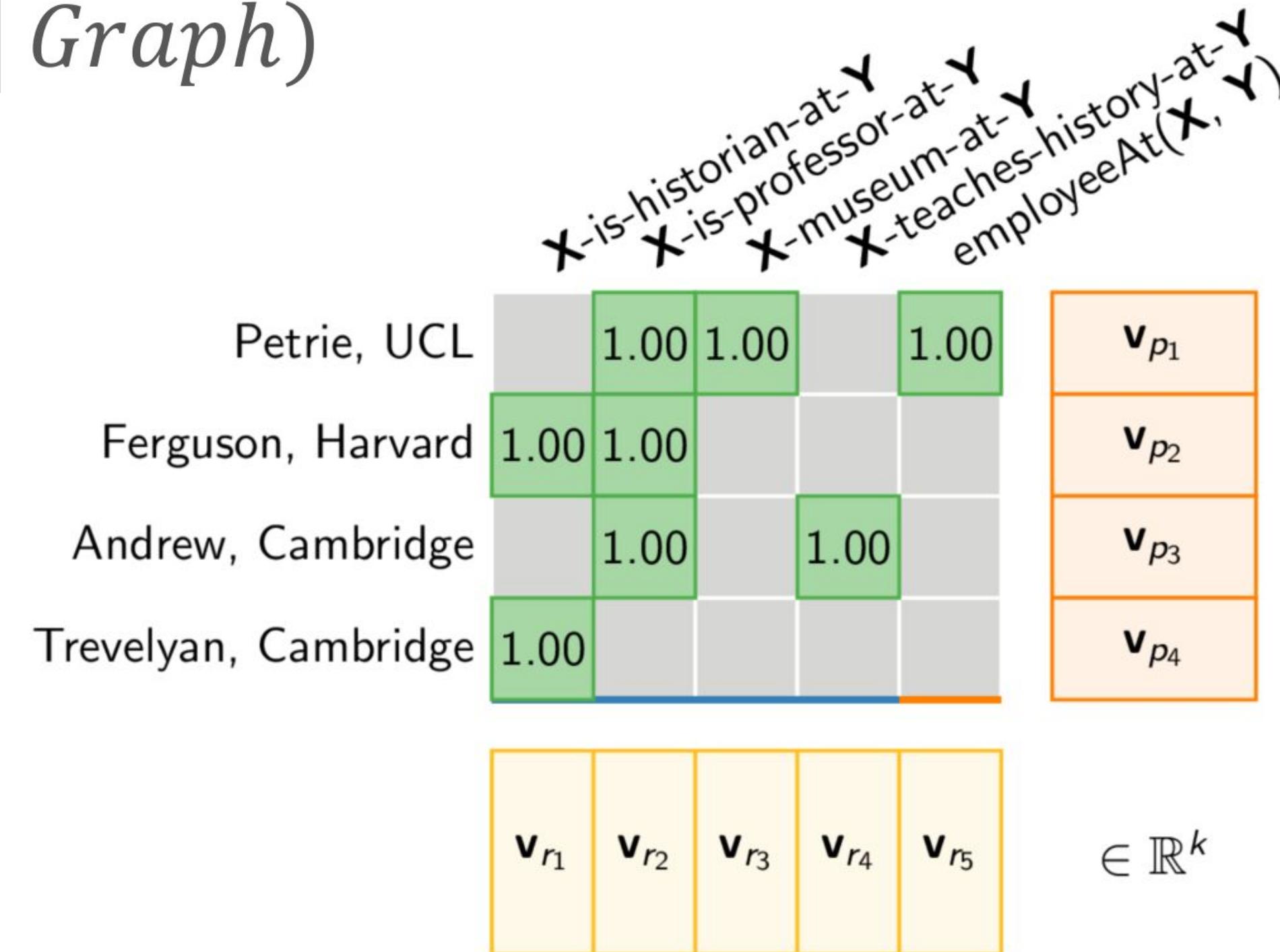
Supervised Relation Extraction

- **LSTM or CNN-based** sentence classifiers



Link Prediction in Knowledge Graphs

$$\Pr(x_{ijk} = 1 \mid Graph)$$



Knowledge Bases enable AI

- “**Knowledge is Power**”
 - “If a program is to perform a complex task well, it must know a great deal about the world in which it operates.”
- **Graphs** can be processed **efficiently** and offer a convenient abstraction
- **Enabling technology** for:
 - Machine reasoning
 - Disambiguation in written and spoken data
 - Semantic search in terms of entities & relations (not keywords & pages)

Knowledge representations



Whisky



Tarzan



Snoopy

| | is_cat | is_dog | is_animal |
|--------|--------|--------|-----------|
| Whisky | 1 | 0 | 1 |
| Tarzan | 1 | 0 | 1 |
| Snoopy | 0 | 1 | 1 |

Knowledge representations

neural

symbolic



Whisky



Tarzan



Snoopy

low-dimensional representations

- can capture similarity / hierarchy
- can be trained from raw facts
- Difficult to incorporate prior knowledge!

“all cats are animals”

grounded in
all entities!

$$\mathbf{v}_{\text{Whisky}}, \mathbf{v}_{\text{is_cat}}, \mathbf{v}_{\text{is_animal}} \in \mathbb{R}^k$$

$$\mathbf{v}_{\text{Whisky}} \approx \mathbf{v}_{\text{Tarzan}}$$

$$p(\text{fact}) := \sigma(\mathbf{v}_{\text{predicate}} \cdot \mathbf{v}_{\text{entity}})$$

$$\sigma(\mathbf{v}_{\text{is_cat}} \cdot \mathbf{v}_{\text{Tarzan}}) \approx 1$$

$$\sigma(\mathbf{v}_{\text{is_cat}} \cdot \mathbf{v}_{\text{Whisky}}) \approx 1$$

$$\sigma(\mathbf{v}_{\text{is_animal}} \cdot \mathbf{v}_{\text{Tarzan}}) \approx 1$$

$$\sigma(\mathbf{v}_{\text{is_animal}} \cdot \mathbf{v}_{\text{Whisky}}) \approx 1$$

Knowledge representations

neural

symbolic



Whisky



Tarzan



Snoopy

symbols as representations (e.g. entities, predicates)

easy to integrate domain knowledge: add rules

- powerful logic reasoning tools (prolog)

**“lifted”
formulation**

```
is_cat(Tarzan) .
```

% Tarzan is a cat

```
is_animal(X) :- is_cat(X)
```

% rule: all cats are animals

```
?- is_animal(Tarzan)
```

% is Tarzan an animal?

```
yes
```

- No notion of similarity (Whisky ≠ Tarzan)

```
?- is_animal(Whisky)
```

no idea : (

not suited for approximate inference

Guiding Bootstrapped Relation Extractors

