Improving NLP Entity Annotations via Ontological Knowledge

Marco Rospocher

FONDAZIONE BRUNO KESSLER

Context: Knowledge Extraction

Kia has hired Peter Schreyer as chief design officer.

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Context: Knowledge Extraction

Organization

Kia has hired Peter Schreyer as chief design officer.

NLP Tasks:
- Named Entity Recognition and Classification (NERC)

Context: Knowledge Extraction

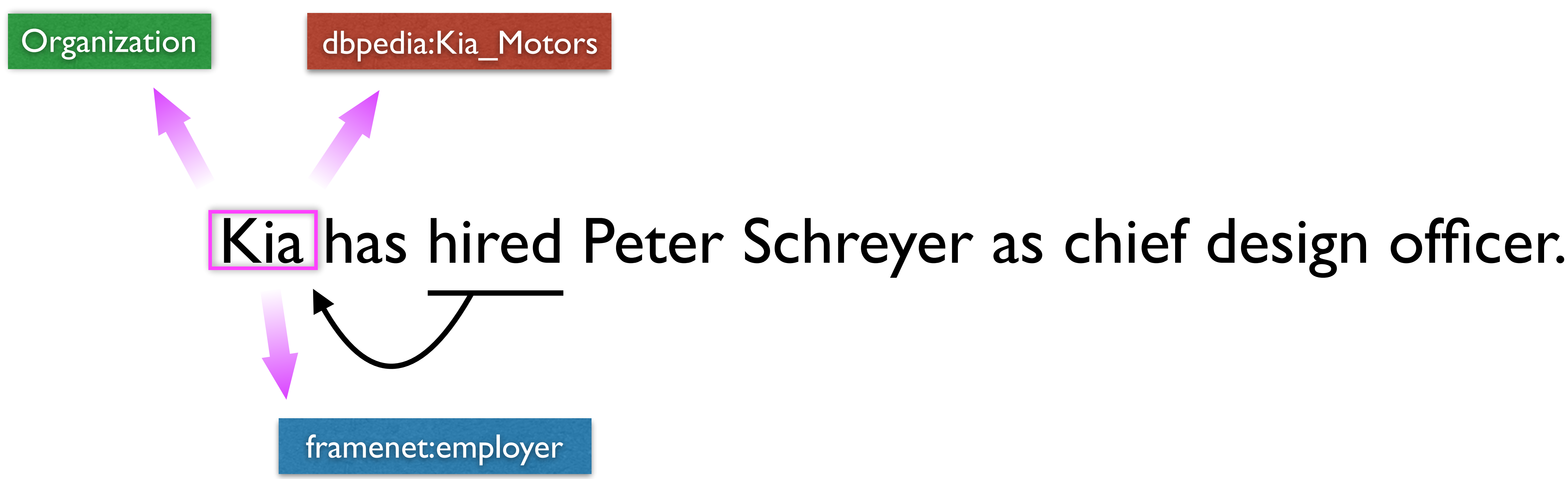
Organization

dbpedia:Kia_Motors

Kia has hired Peter Schreyer as chief design officer.

NLP Tasks:
- Named Entity Recognition and Classification (NERC)
- Entity Linking (EL)

Context: Knowledge Extraction



NLP Tasks:
- Named Entity Recognition and Classification (NERC)
- Entity Linking (EL)
- Semantic Role Labeling (SRL)

...

Motivating Examples

Lincoln is based in Michigan.

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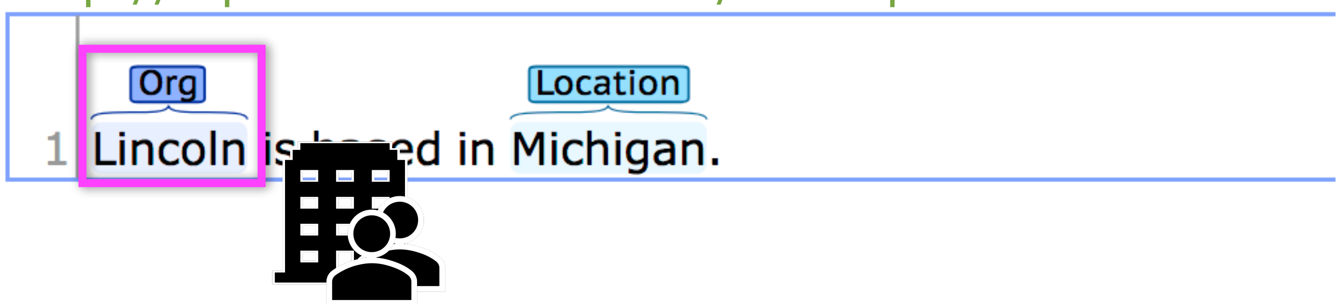
Stanford CoreNLP

http://nlp.stanford.edu:8080/corenlp



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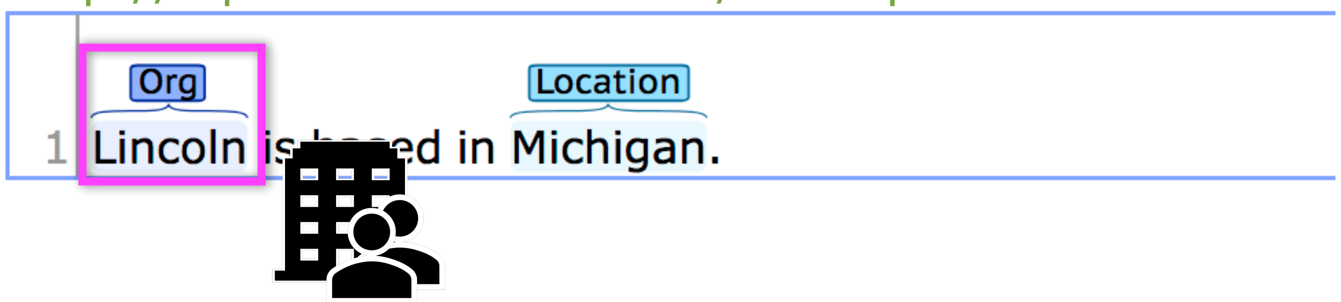
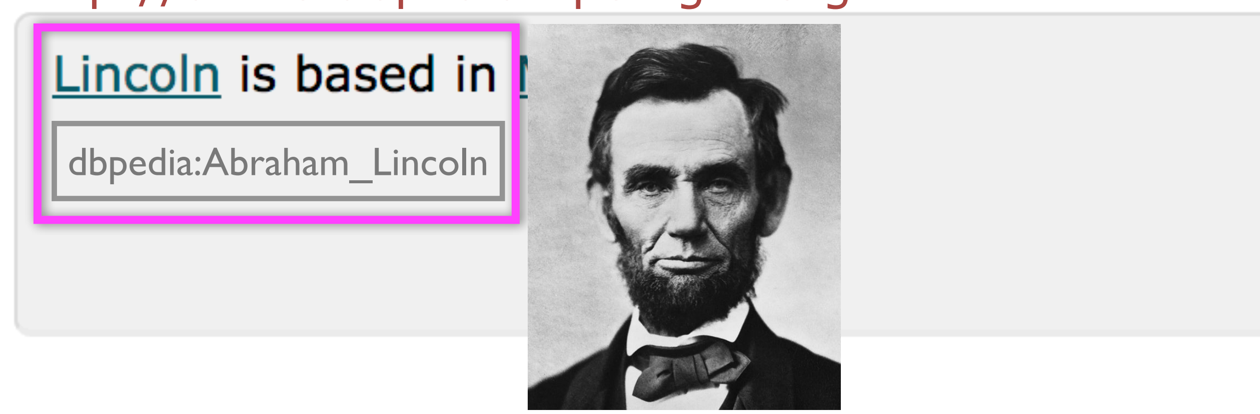


DBpedia Spotlight

http://demo.dbpedia-spotlight.org



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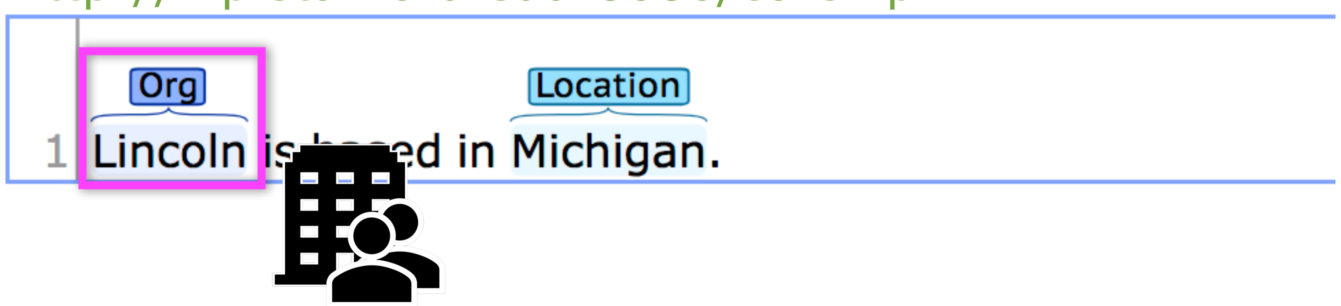

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San Jose is one of the strongest hockey team.

Motivating Examples

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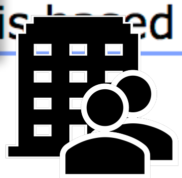
Org Location

1 Lincoln is based in Michigan.



DBpedia Spotlight

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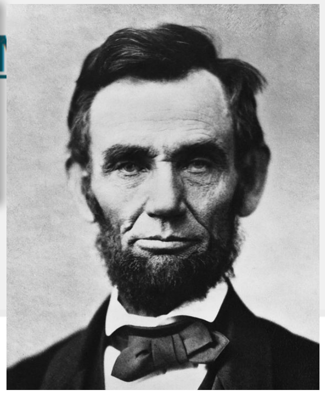
Lincoln is based in

dbpedia:Abraham_Lincoln



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http://demo.dbpedia-spotlight.org

San Jose is one of the strongest hockey team.

dbpedia:San_Jose_Sharks

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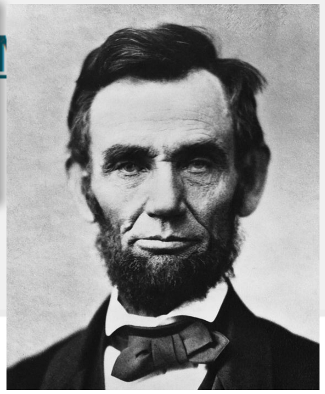

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Location

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Abstracting

… $token_1$ $token_2$ $token_3$ $token_4$ $token_5$ $token_6$ ….

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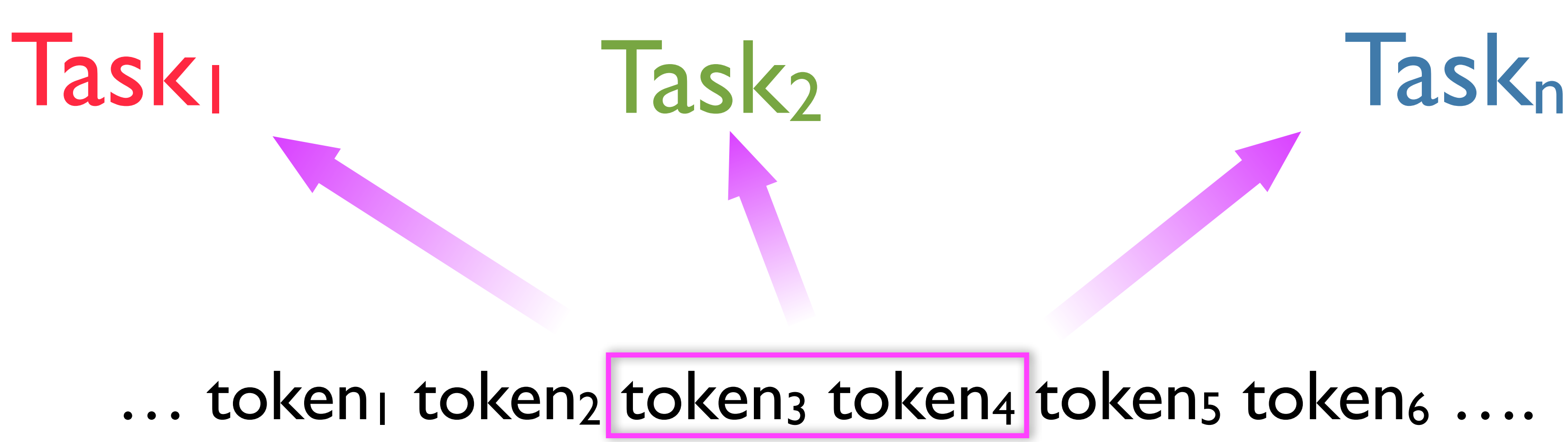

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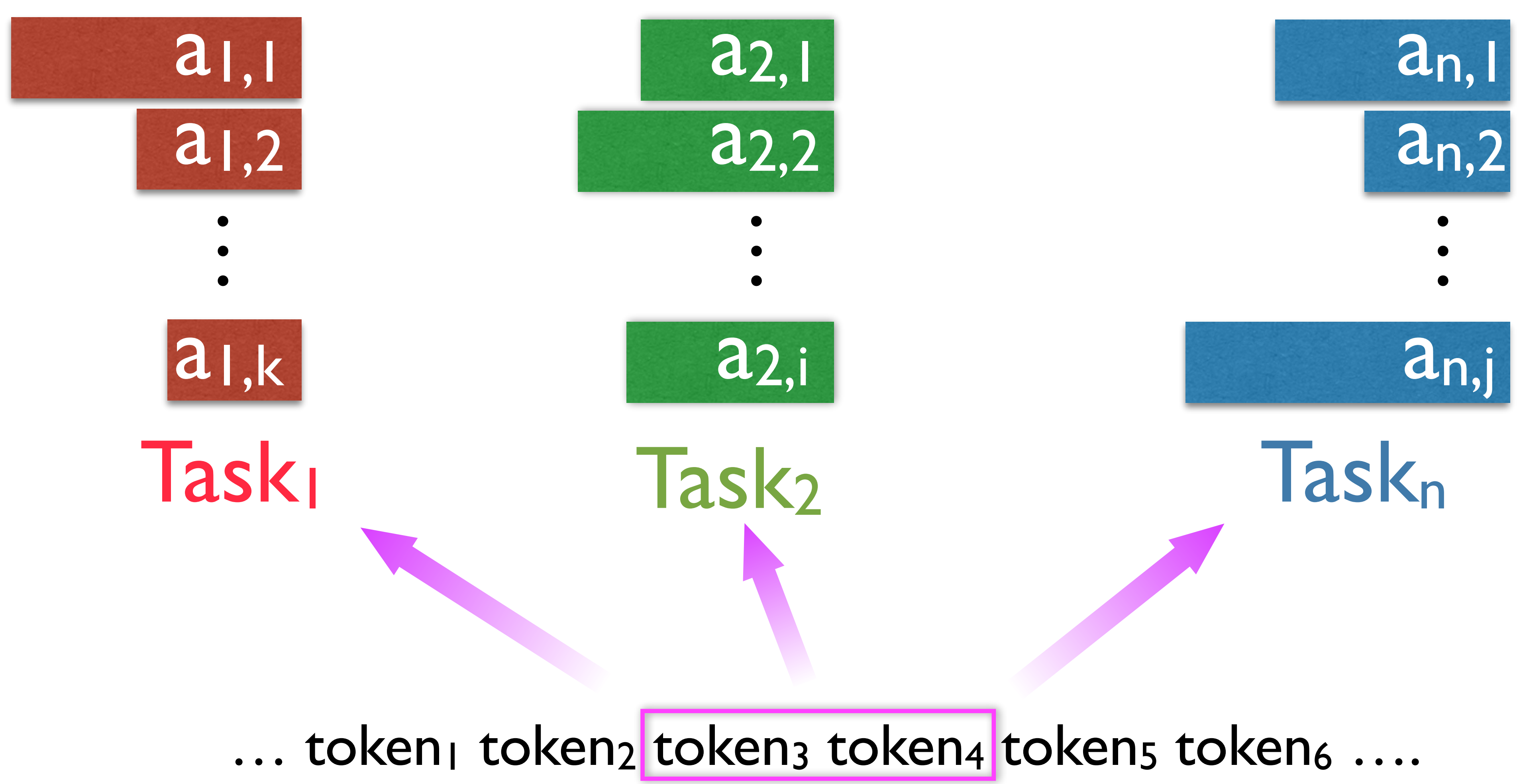

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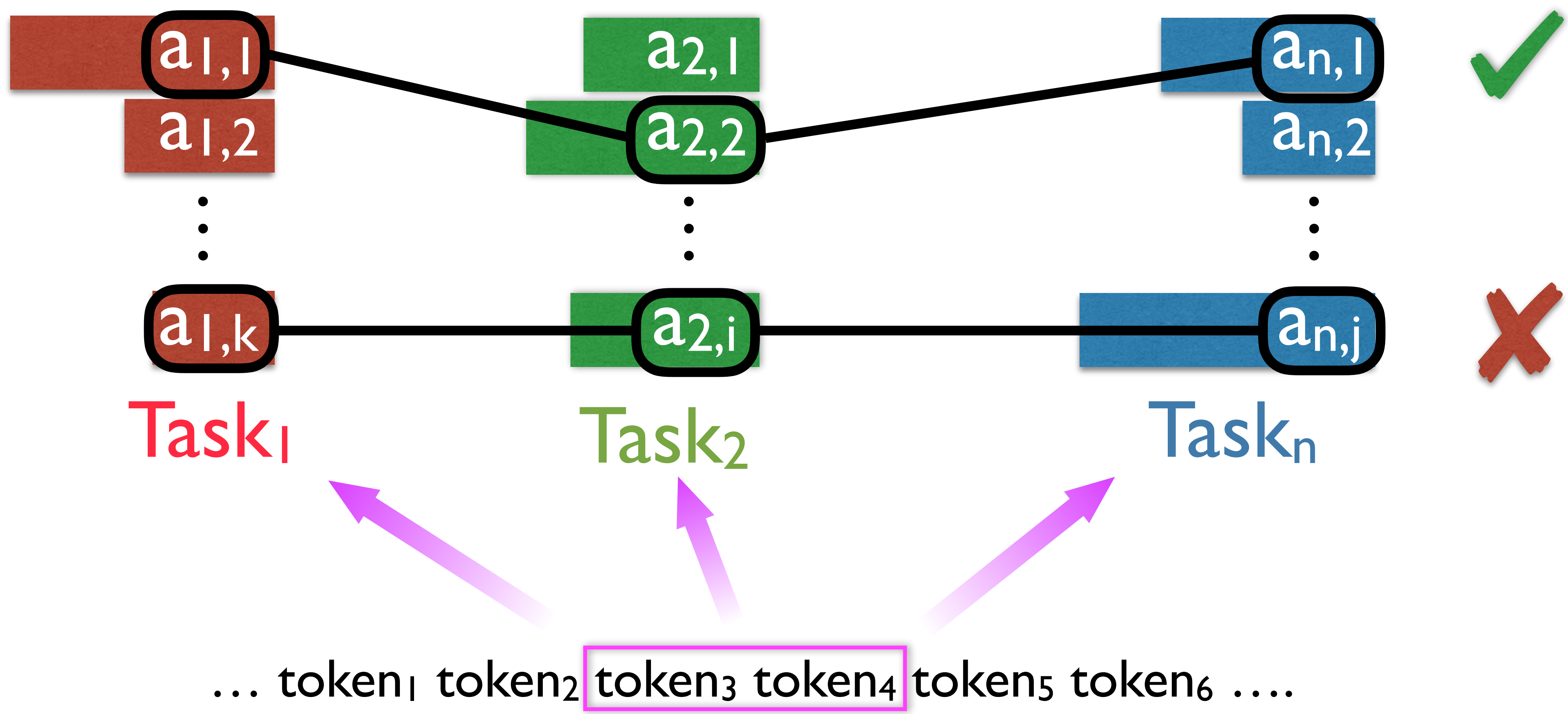

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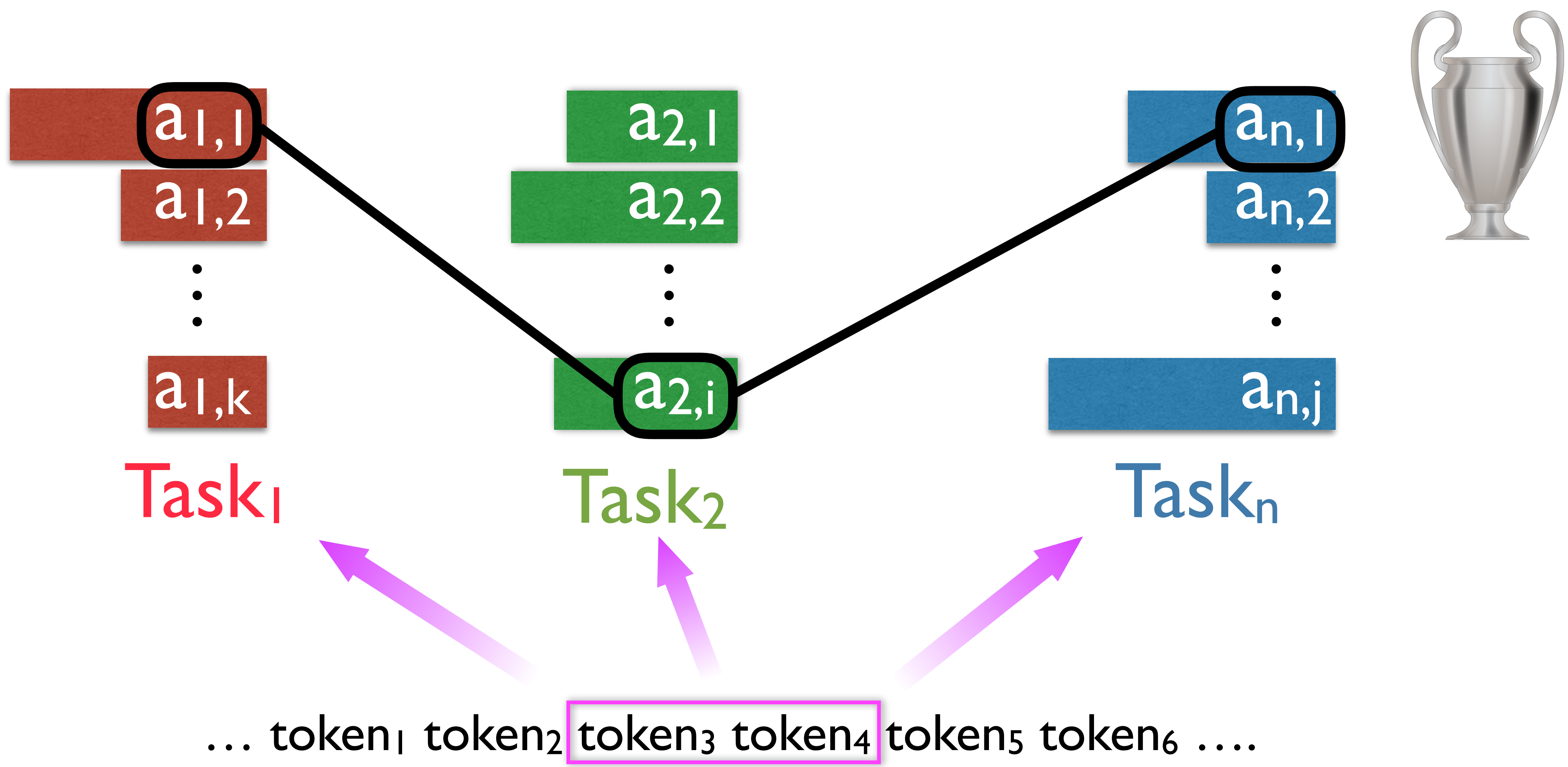
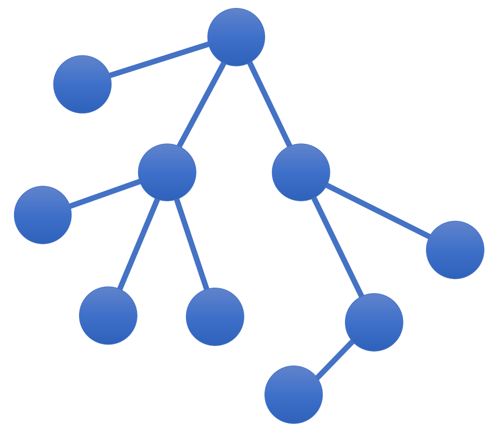


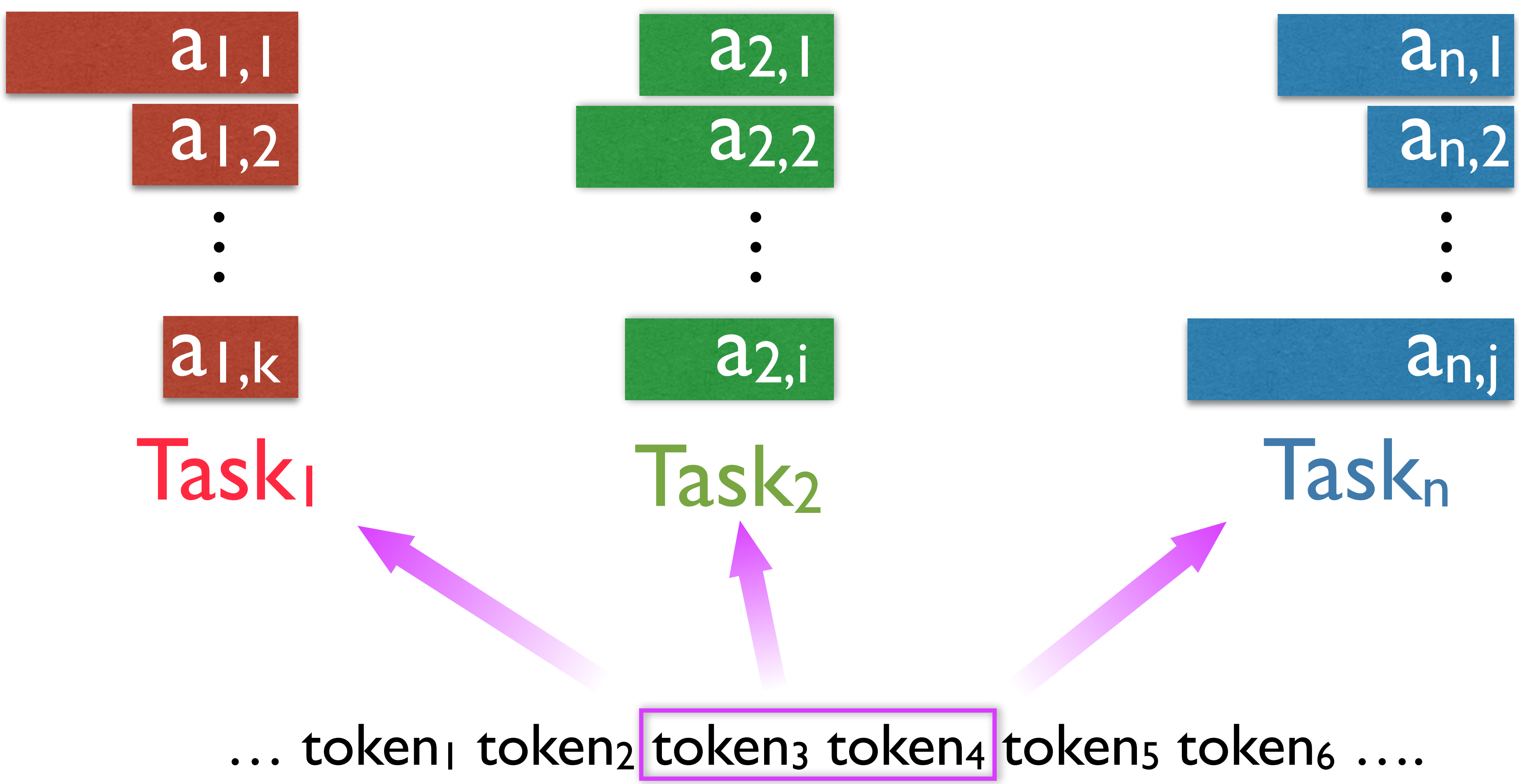
RESEARCH PROBLEM

How can we assess and improve the coherence of the various NLP annotations on an entity mention?

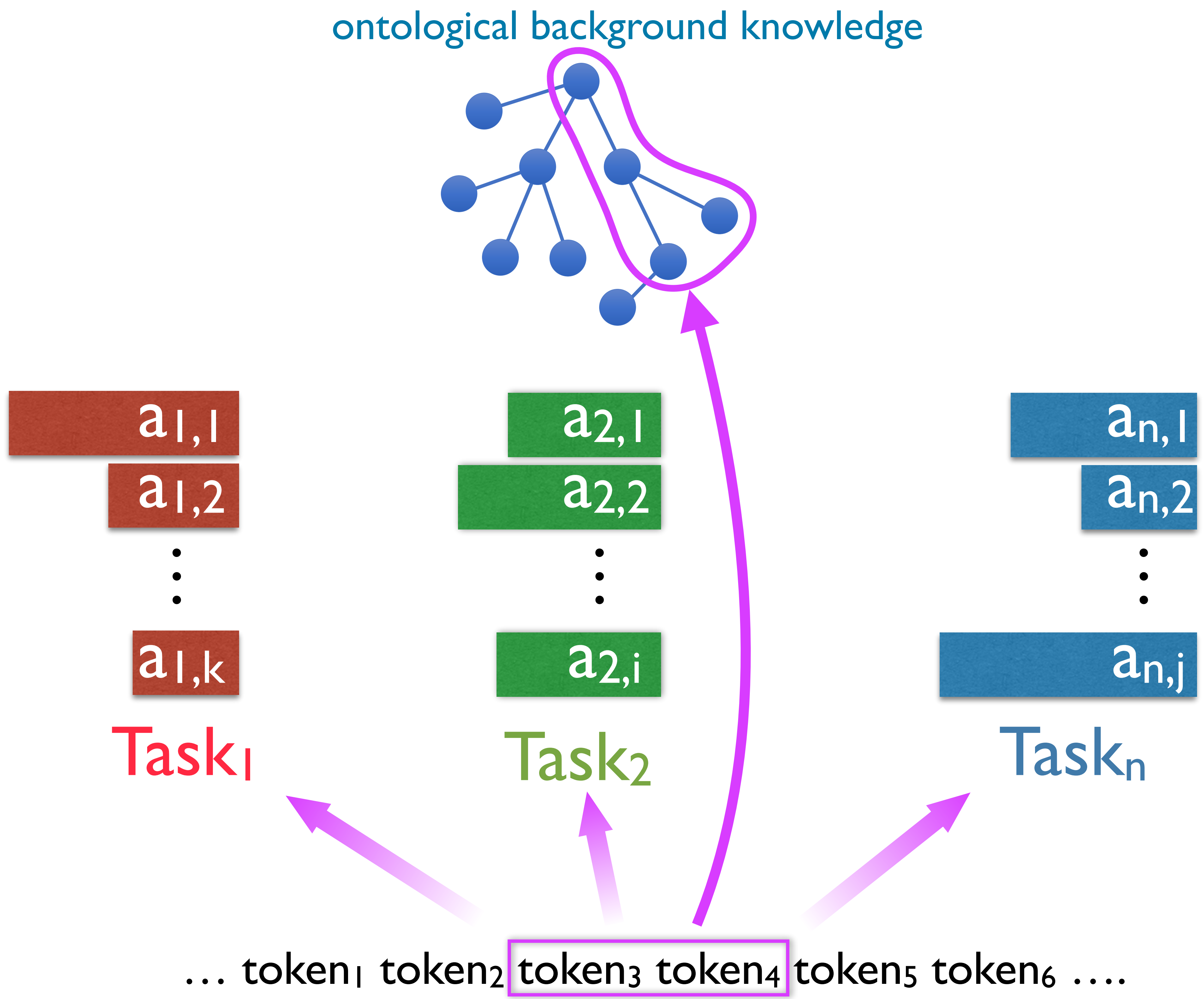
In a nutshell

ontological background knowledge





In a nutshell



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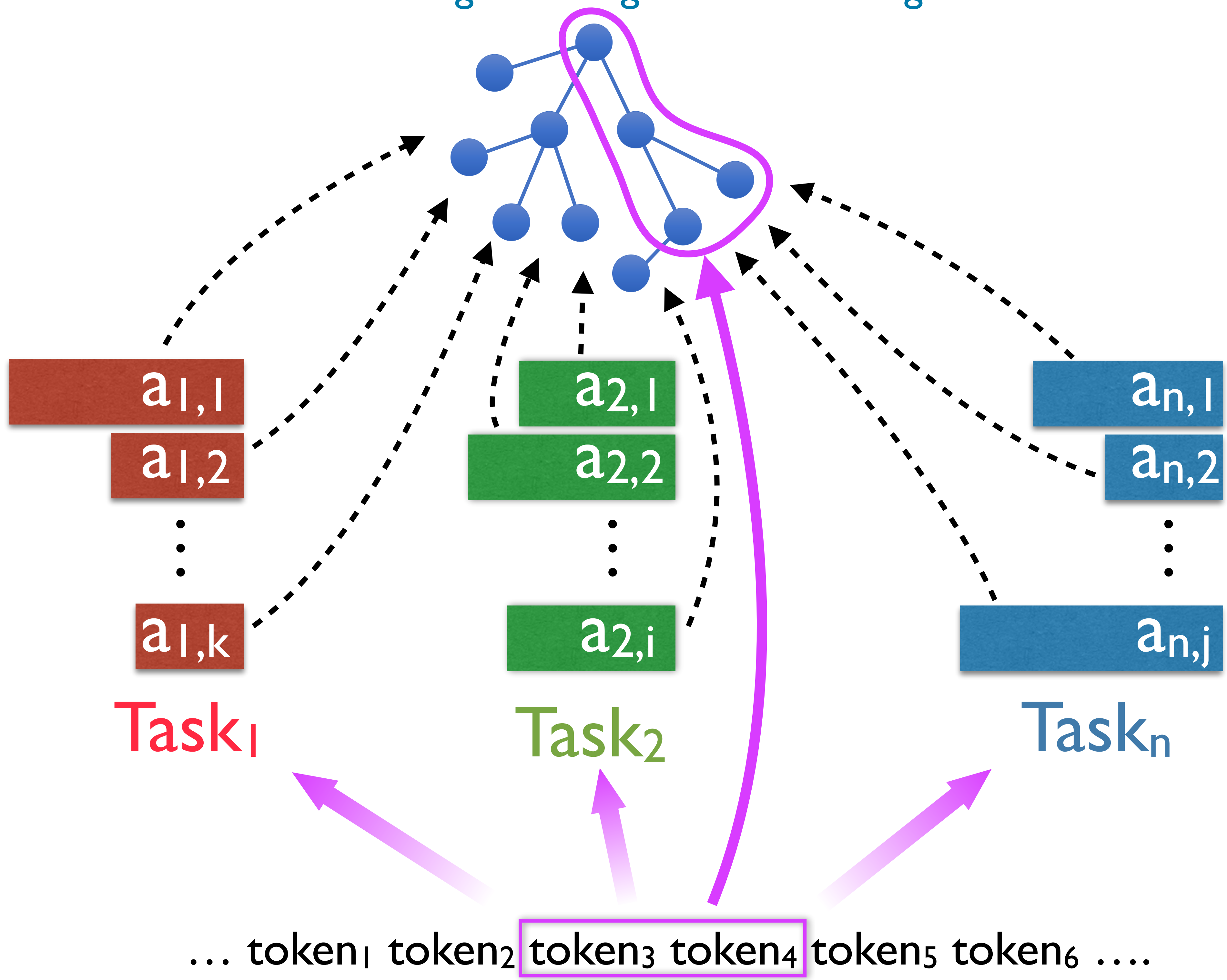

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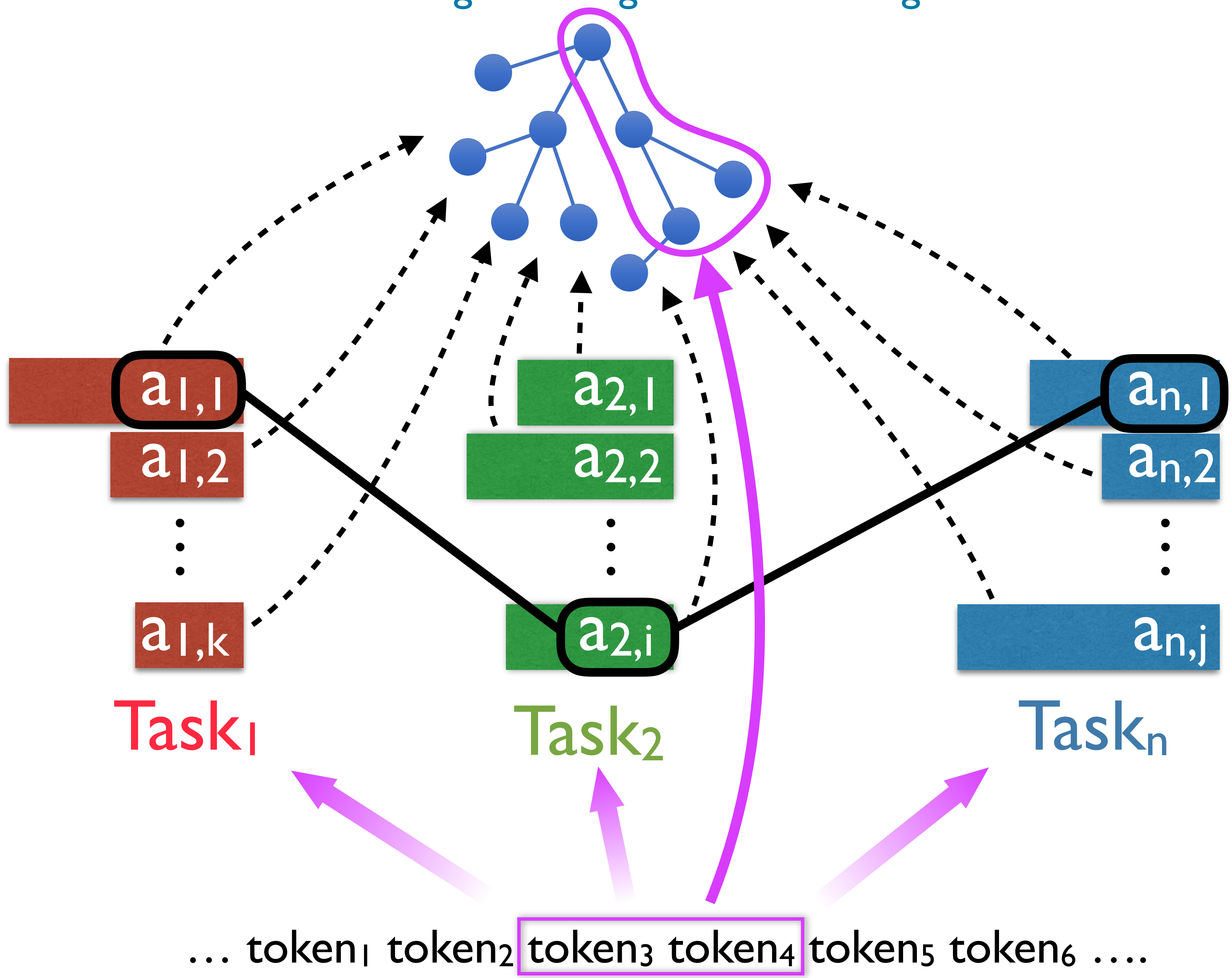

Contributions

JPARK

Marco Rospocher, Francesco Corcoglioniti
Joint Posterior Revision of NLP Annotations via Ontological Knowledge
IJCAI-18

PSL4EA

Marco Rospocher
An Ontology-Driven Probabilistic Soft Logic Approach to Improve NLP Entity Annotations
ISWC-18

Contributions

- A concrete instantiation of the models for NERC and EL (using YAGO as ontological knowledge)
- Application of the NERC and EL models to revise the annotations of Stanford NER and DBpedia Spotlight

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JPARK

The JPARK Model

$$\mathrm{P}(\boldsymbol{a}|m, B, K)$$

The JPARK Model

entity mention

NLP Background Knowledge

$(a_i, \ldots, a_n)$ NLP Annotations

"The" Ontological Knowledge

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The JPARK Model

entity mention

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$$\mathrm{P}(\boldsymbol{a}|m, B, K)$$

set of classes from K || (M)

$$\sum_C \mathrm{P}(\boldsymbol{a}, C|m, B, K)$$

The JPARK Model

entity mention NLP Background Knowledge

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$$\sum_C \mathrm{P}(\boldsymbol{a}, C|m, B, K)$$

|| (CP)

$$\mathrm{P}(C|m,B,K) \cdot \mathrm{P}(\boldsymbol{a}|m,B,K,C)$$

The JPARK Model

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$$\mathrm{P}(C|m,B,K) \cdot \mathrm{P}(\boldsymbol{a}|m,B,K,C)$$

|| (CIA-1)

$$\prod_i \mathrm{P}(a_i|m, B, K, C)$$

The JPARK Model

$(a_i, \ldots, a_n)$ NLP Annotations

entity mention

NLP Background Knowledge

"The" Ontological Knowledge

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|| (CIA-1)

$$\prod_i \mathrm{P}(a_i|m, B, K, C)$$

|| (CP)

$$\frac{\prod_i \mathrm{P}(a_i, C|m, B, K)}{\mathrm{P}(C|m, B, K)^n}$$

The JPARK Model

entity mention
NLP Background Knowledge
$(a_i, \dots, a_n)$ NLP Annotations
"The" Ontological Knowledge

$$\mathrm{P}(\boldsymbol{a}|m, B, K)$$

$\boxed{\text{set of classes}}$ from K || (M)

$$\sum_C \mathrm{P}(\boldsymbol{a}, C|m, B, K)$$

||

$$\frac{\prod_i \mathrm{P}(a_i, C|m, B, K)}{\mathrm{P}(C|m, B, K)^{n-1}}$$

The JPARK Model

$$\mathrm{P}(C|m, B, K)$$

$$\mathrm{P}(a_i, C|m, B, K)$$

The JPARK Model

$$\mathrm{P}(C|m,B,K) \overset{(M^*)}{=} \left(\prod_i \sum_{a_i} \mathrm{P}(a_i,C|m,B,K)\right)^{\frac{1}{n}}$$

$$\mathrm{P}(a_i,C|m,B,K)$$

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(CIA-2) ||

$$\mathrm{P}(a_i|m,B)$$

The JPARK Model

$$\mathrm{P}(C|m,B,K) \overset{(M^*)}{=} \left(\prod_i \sum_{a_i} \mathrm{P}(a_i,C|m,B,K)\right)^{\frac{1}{n}}$$

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(CIA-2) || || (CIA-3)

$$\mathrm{P}(a_i|m,B) \qquad \mathrm{P}(C|a_i,K)$$

The JPARK Model

$$\mathrm{P}(C|m,B,K) \overset{(M^*)}{=} \left(\prod_i \sum_{a_i} \mathrm{P}(a_i, C|m,B,K)\right)^{\frac{1}{n}}$$

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(CIA-2) || || (CIA-3)

$$\boxed{\mathrm{P}(a_i|m,B)} \qquad \mathrm{P}(C|a_i,K)$$

confidence score

The JPARK Model

$$\mathrm{P}(C|m,B,K) \overset{(M^*)}{=} \left(\prod_i \sum_{a_i} \mathrm{P}(a_i,C|m,B,K)\right)^{\frac{1}{n}}$$

$$\mathrm{P}(a_i,C|m,B,K) \overset{(CP)}{=} \mathrm{P}(a_i|m,B,K) \cdot \mathrm{P}(C|a_i,m,B,K)$$

(CIA-2) || || (CIA-3)

$\boxed{\mathrm{P}(a_i|m,B)}$ $\boxed{\mathrm{P}(C|a_i,K)}$

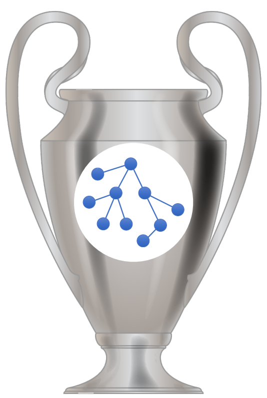
confidence score   learned from data

The JPARK Model

$$\mathrm{P}(\boldsymbol{a}|m, B, K)$$

$$\mathrm{P}(a_i|m, B) \qquad \mathrm{P}(C|a_i, K)$$

The JPARK Model



$$= \arg\max_{\boldsymbol{a}} \mathrm{P}(\boldsymbol{a}|m, B, K)$$

$$\mathrm{P}(a_i|m, B) \qquad \mathrm{P}(C|a_i, K)$$

NERC and EL Model

Ontological Background Knowledge

6,016,695 entities

Taxonomy of 568,255 classes

[Suchanek et al., 2007]

Ontological Background Knowledge

6,016,695 entities

Taxonomy of 568,255 classes

yago select knowledge

[Suchanek et al., 2007]

+

Wikipedia

The Free Encyclopedia

(only ingoing links)

Estimating $\mathrm{P}(C | a_{\mathrm{NERC}}, K)$

Leverage a gold standard corpus G annotated with NERC types and ontological classes (or EL annotations)

Estimating $\mathrm{P}(C|a_{\mathrm{NERC}}, K)$

Leverage a gold standard corpus G annotated with NERC types and ontological classes (or EL annotations)

\# co-occurences

$$\simeq \frac{\boxed{n_G(C, a_{\mathrm{NERC}})}}{\sum_{C'} n_G(C', a_{\mathrm{NERC}})}$$

Estimating $\mathrm{P}(C|a_{\mathrm{NERC}}, K)$

$$\frac{n_G(C, a_{\mathrm{NERC}})}{\sum_{C'} n_G(C', a_{\mathrm{NERC}})}$$

Estimating $\mathrm{P}(C|a_{\mathrm{NERC}}, K)$

$$\alpha \cdot \mathrm{P}(C|K) + (1-\alpha) \cdot \mathrm{P}(C|a_{\mathrm{NERC}}, G)$$

$$\parallel$$

$$\frac{n_G(C, a_{\mathrm{NERC}})}{\sum_{C'} n_G(C', a_{\mathrm{NERC}})}$$

Estimating $\mathrm{P}(C|a_{\mathrm{NERC}}, K)$

$$\alpha \cdot \mathrm{P}(C|K) + (1-\alpha) \cdot \mathrm{P}(C|a_{\mathrm{NERC}}, G)$$

$$\mathrm{P}(C|K) = \frac{n_K(C)}{\sum_{C'} n_K(C')} \qquad \mathrm{P}(C|a_{\mathrm{NERC}}, G) = \frac{n_G(C, a_{\mathrm{NERC}})}{\sum_{C'} n_G(C', a_{\mathrm{NERC}})}$$

Prior (popularity based on entity ingoing links)

Estimating $\mathrm{P}(C|a_{\mathrm{NERC}}, K)$

$$\alpha \cdot \mathrm{P}(C|K) + (1-\alpha) \cdot \mathrm{P}(C|a_{\mathrm{NERC}}, G)$$

$$\mathrm{P}(C|K) = \frac{n_K(C)}{\sum_{C'} n_K(C')} \qquad \mathrm{P}(C|a_{\mathrm{NERC}}, G) = \frac{n_G(C, a_{\mathrm{NERC}})}{\sum_{C'} n_G(C', a_{\mathrm{NERC}})}$$

Prior (popularity based on entity ingoing links)

Consider only class sets restricted to popular classes

Estimating $\mathrm{P}(C|a_{\mathrm{EL}}, K)$

Leverage alignments between EL Knowledge Base and yago select knowledge

Estimating $\mathrm{P}(C|a_{\mathrm{EL}}, K)$

Leverage alignments between EL Knowledge Base and yago

$$\mathbf{1}_{\{C_K(a_{\mathrm{EL}})\}}(C) \begin{cases} 1 & \text{entity } a_{\mathrm{EL}} \text{ is “instance” of } C \\ 0 & \text{otherwise} \end{cases}$$

yago classes of the entity from linking

JPARK

Application and Evaluation

Tools

- NERC: **Stanford CoreNLP** [Finkel et al., 2005]
- EL: DBpedia Spotlight [Daiber et al., 2013]

NERC+EL Datasets

- AIDA CoNLL-YAGO [Hoffart et al., 2011]
- MEANTIME [Minard et al., 2016]
- TAC-KBP [Ji et al., 2011]

NERC+EL Datasets

- AIDA CoNLL-YAGO [Hoffart et al., 2011]

  $\mathrm{P}(C|a_{\mathrm{NERC}}, K)$ learned from AIDA CoNLL-YAGO (**train**)

- MEANTIME [Minard et al., 2016]

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Research Question

Does the JPARK posteriori joint revision of the annotations from Stanford NER and DBpedia Spotlight, via YAGO, improve their NERC and EL performances?

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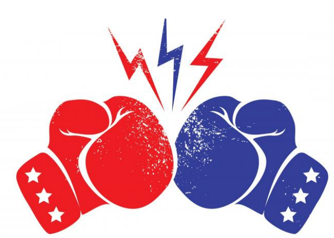

JPARK
Stanford CoreNLP
DBpediaSpotlight

Results

		type			link			type+link		
		P	R	F_1	P	R	F_1	P	R	F_1
AIDA (5616)	*standard*	.943	.875	.908	.662	.652	.656	.634	.625	.630
	with JPARK	.950	.881	.914	.671	.654	.662	.655	.637	.646
	Δ	**.007**	**.006**	**.006**	**.009**	**.002**	**.006**	**.021**	**.012**	**.016**
MEANTIME (792)	*standard*	.882	.695	.777	.703	.556	.621	.635	.502	.561
	with JPARK	.914	.720	.805	.705	.557	.622	.670	.530	.592
	Δ	**.032**	**.025**	**.028**	.002	.001	.001	**.035**	**.028**	**.031**
TAC-KBP (4969)	*standard*	.911	.652	.760	.401	.423	.412	.367	.386	.376
	with JPARK	.926	.663	.772	.412	.426	.419	.389	.402	.395
	Δ	**.015**	**.011**	**.012**	**.011**	.003	**.007**	**.022**	**.016**	**.019**

Bold = statistical significant (approx. rand. test)

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Probabilistic
Soft
Logic

Probabilistic Soft Logic

Don't miss: 21 Nov 2018
Lise Getoor Keynote!

Probabilistic Soft Logic in a nutshell (1/3)

$$1.2: \ \mathsf{WorksFor}(b,c) \ \wedge \ \mathsf{BossOf}(b,e) \rightarrow \mathsf{WorksFor}(e,c)$$

Probabilistic Soft Logic in a nutshell (1/3)

$$\underbrace{1.2}_{\text{weight}} : \ \mathsf{WorksFor}(b, c) \ \wedge \ \mathsf{BossOf}(b, e) \rightarrow \mathsf{WorksFor}(e, c)$$

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$$\underbrace{1.2}_{\text{weight}} : \ \mathsf{WorksFor}(\underbrace{b}_{\text{variable}}, c) \wedge \mathsf{BossOf}(b, e) \rightarrow \mathsf{WorksFor}(e, c)$$

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Probabilistic Soft Logic in a nutshell (1/3)

$$\underbrace{1.2}_{\text{weight}} : \overbrace{\mathsf{WorksFor}(\underbrace{b}_{\text{variable}}, c) \wedge \underbrace{\mathsf{BossOf}}_{\text{predicate}}(b, e)}^{\text{body}} \rightarrow \underbrace{\mathsf{WorksFor}(e, c)}_{\text{atom}}$$

Probabilistic Soft Logic in a nutshell (1/3)

$$\underbrace{1.2}_{\text{weight}} : \overbrace{\mathsf{WorksFor}(\underbrace{b}_{\text{variable}}, c) \wedge \underbrace{\mathsf{BossOf}}_{\text{predicate}}(b, e)}^{\text{body}} \rightarrow \overbrace{\underbrace{\mathsf{WorksFor}(e, c)}_{\text{atom}}}^{\text{head}}$$

Probabilistic Soft Logic in a nutshell (1/3)

$$1.2: \ \mathsf{WorksFor}(b,c) \ \wedge \ \mathsf{BossOf}(b,e) \rightarrow \mathsf{WorksFor}(e,c)$$

grounding

$$\mathsf{WorksFor}(John, FBK)$$

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soft-truth value $\in [0,1]$

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soft-truth value ∈ [0,1]

Interpretation $I : \{\text{ground atoms}\} \rightarrow [0,1]^n$

Probabilistic Soft Logic in a nutshell (2/3)

Lukasiewicz
t-norm/co-norm

$$
\begin{aligned}
I(a_1) \wedge I(a_2) &= max\{I(a_1) + I(a_2) - 1, 0\} \\
I(a_1) \vee I(a_2) &= min\{I(a_1) + I(a_2), 1\} \\
\neg I(a_1) &= 1 - I(a_1)
\end{aligned}
$$

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0.6 0.6 0.5

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0.6	0.6	0.5	✓
WorksFor$(John, FBK)$ $\wedge$	BossOf$(John, Jack)$ $\rightarrow$	WorksFor$(Jack, FBK)$	
0.8	0.9	0.3	✗

Probabilistic Soft Logic in a nutshell (2/3)

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$\mathrm{WorksFor}(John, FBK)$	$\wedge$	$\mathrm{BossOf}(John, Jack)$	$\rightarrow$	$\mathrm{WorksFor}(Jack, FBK)$	
0.6		0.6		0.5	✔
0.8		0.9		0.3	✘

$d(r) = 0.4$

Probabilistic Soft Logic in a nutshell (3/3)

$$f(I) = \frac{1}{Z} \exp\left[- \sum_{r \in R} w_r d(r)^p \right]$$

Probabilistic Soft Logic in a nutshell (3/3)

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constant

all rules

Probabilistic Soft Logic in a nutshell (3/3)

weight

$$f(I) = \frac{1}{Z} \exp\left[-\sum_{r \in R} w_r d(r)^p\right]$$

constant

all rules

Probabilistic Soft Logic in a nutshell (3/3)

weight distance to satisfaction

$$f(I) = \frac{1}{Z} \exp\left[- \sum_{r \in R} w_r d(r)^p \right]$$

constant all rules

Probabilistic Soft Logic in a nutshell (3/3)

weight distance to satisfaction

$$f(I) = \frac{1}{Z} \exp\left[- \sum_{r \in R} w_r d(r)^p \right]$$

{1,2}

constant

all rules

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weight distance to satisfaction

{1,2}

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Most Probable Explanation (MPE): overall interpretation with the maximum probability

PSI4EA

NLP annotations → Classes

Classes → Annotation coherence

NLP annotations → Classes

M mention

A_i^T candidate annotation for task T on M

c ontological class from background knowledge K

NLP annotations $\Rightarrow$ Classes

M mention

A_i^T candidate annotation for task T on M

c ontological class from background knowledge K

$$w(M, A_i^T) : \mathsf{Ann}_T(M, A_i^T) \wedge \mathsf{ImpCl}_T(A_i^T, c) \rightarrow \mathsf{ClAnn}_T(M, A_i^T, c)$$

NLP annotations ⟶ Classes

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NLP annotation

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$$\underbrace{w(M, A_i^T)}_{\text{confidence score}} : \overbrace{\mathsf{Ann}_T(M, A_i^T)}^{\text{NLP annotation}} \wedge \mathsf{ImpCl}_T(A_i^T, c) \rightarrow \mathsf{ClAnn}_T(M, A_i^T, c)$$

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NLP annotations → Classes

- M mention
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NLP annotations → Classes

$$\mathsf{ImpCl}_{NERC}(t,c)$$

NLP annotations ⇨ Classes

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Leverage a gold standard corpus G annotated with NERC types and ontological classes (or EL annotations)

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$$1.0 : \mathsf{Gold}_{NERC}(m,t) \wedge \mathsf{ImpCl}_{NERC}(t,c) \rightarrow \mathsf{Gold}_{C}(m,c)$$
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$$\mathsf{ImpCl}_{EL}(e,c)$$

Leverage alignments between EL Knowledge Base and Background Knowledge K

NLP annotations ➡ Classes

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$$\mathsf{ImpCl}_{EL}(e,c) \begin{cases} 1 & \text{entity } e \text{ is instance of } c \\ 0 & \text{otherwise} \end{cases}$$

Leverage alignments between EL Knowledge Base and Background Knowledge K

Classes ➡ Annotation coherence

$$w_1 : \mathsf{ClAnn}_{NERC}(m,t,c) \wedge \mathsf{ClAnn}_{EL}(m,e,c) \rightarrow \mathsf{Ann}_{PSL}(m,t,e)$$

$$w_2 : \mathsf{ClAnn}_{NERC}(m,t,c) \wedge \neg\mathsf{ClAnn}_{EL}(m,e,c) \rightarrow \neg\mathsf{Ann}_{PSL}(m,t,e)$$

$$w_3 : \neg\mathsf{ClAnn}_{NERC}(m,t,c) \wedge \mathsf{ClAnn}_{EL}(m,e,c) \rightarrow \neg\mathsf{Ann}_{PSL}(m,t,e)$$

Classes ⇨ Annotation coherence

coherence estimation

$$w_1 : \mathsf{ClAnn}_{NERC}(m,t,c) \wedge \mathsf{ClAnn}_{EL}(m,e,c) \rightarrow \overline{\mathsf{Ann}_{PSL}(m,t,e)}$$

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Classes → Annotation coherence

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$$\boxed{w_3} : \neg\mathsf{ClAnn}_{NERC}(m,t,c) \wedge \mathsf{ClAnn}_{EL}(m,e,c) \rightarrow \neg\mathsf{Ann}_{PSL}(m,t,e)$$

hyperparameters

MPE Inference

- Determine soft-truth value of Ann_{PSL} for all combination of annotations for a given mention

- Best combination: highest soft-truth value of Ann_{PSL}

- Trust model prediction only if above a given threshold

Example

Lincoln is based in Michigan.

Example

Lincoln is based in Michigan.

$$0.9 : \mathsf{Ann}_{NERC}(\mathrm{L}, \mathrm{ORG}) \wedge \mathsf{ImpCl}_{NERC}(\mathrm{ORG}, c) \rightarrow \mathsf{ClAnn}_{NERC}(\mathrm{L}, \mathrm{ORG}, c)$$

$$0.1 : \mathsf{Ann}_{NERC}(\mathrm{L}, \mathrm{PER}) \wedge \mathsf{ImpCl}_{NERC}(\mathrm{PER}, c) \rightarrow \mathsf{ClAnn}_{NERC}(\mathrm{L}, \mathrm{PER}, c)$$

Example

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$$0.5 : \mathsf{Ann}_{EL}(\mathrm{L}, \mathrm{A.\ Lincoln}) \wedge \mathsf{ImpCl}_{EL}(\mathrm{A.\ Lincoln}, c) \rightarrow \mathsf{ClAnn}_{EL}(\mathrm{L}, \mathrm{A.\ Lincoln}, c)$$
$$0.3 : \mathsf{Ann}_{EL}(\mathrm{L}, \mathrm{Lincoln\ MC}) \wedge \mathsf{ImpCl}_{EL}(\mathrm{Lincoln\ MC}, c) \rightarrow \mathsf{ClAnn}_{EL}(\mathrm{L}, \mathrm{Lincoln\ MC}, c)$$
$$0.2 : \mathsf{Ann}_{EL}(\mathrm{L}, \mathrm{Lincoln\ UK}) \wedge \mathsf{ImpCl}_{EL}(\mathrm{Lincoln\ UK}, c) \rightarrow \mathsf{ClAnn}_{EL}(\mathrm{L}, \mathrm{Lincoln\ UK}, c)$$

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$$0.5 : \mathsf{Ann}_{EL}(\mathrm{L}, \mathrm{A.\ Lincoln}) \ \wedge \ \mathsf{ImpCl}_{EL}(\mathrm{A.\ Lincoln}, c) \rightarrow \mathsf{ClAnn}_{EL}(\mathrm{L}, \mathrm{A.\ Lincoln}, c)$$

$$0.3 : \mathsf{Ann}_{EL}(\mathrm{L}, \mathrm{Lincoln\ MC}) \ \wedge \ \mathsf{ImpCl}_{EL}(\mathrm{Lincoln\ MC}, c) \rightarrow \mathsf{ClAnn}_{EL}(\mathrm{L}, \mathrm{Lincoln\ MC}, c)$$

$$0.2 : \mathsf{Ann}_{EL}(\mathrm{L}, \mathrm{Lincoln\ UK}) \ \wedge \ \mathsf{ImpCl}_{EL}(\mathrm{Lincoln\ UK}, c) \rightarrow \mathsf{ClAnn}_{EL}(\mathrm{L}, \mathrm{Lincoln\ UK}, c)$$

$$10 : \mathsf{ClAnn}_{NERC}(m, t, c) \ \wedge \ \mathsf{ClAnn}_{EL}(m, e, c) \rightarrow \mathsf{Ann}_{PSL}(m, t, e)$$

$$10 : \mathsf{ClAnn}_{NERC}(m, t, c) \ \wedge \ \neg\mathsf{ClAnn}_{EL}(m, e, c) \rightarrow \neg\mathsf{Ann}_{PSL}(m, t, e)$$

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Application and Evaluation

Background Knowledge

6,016,695 entities

Taxonomy of 568,255 classes

yago
select knowledge

[Suchanek et al., 2007]

Tools

- NERC: **Stanford CoreNLP** [Finkel et al., 2005]
- EL: DBpedia Spotlight [Daiber et al., 2013]

NERC+EL Datasets

- AIDA CoNLL-YAGO [Hoffart et al., 2011]
- MEANTIME [Minard et al., 2016]
- TAC-KBP [Ji et al., 2011]

NERC+EL Datasets

- AIDA CoNLL-YAGO [Hoffart et al., 2011]

  ImpCl_{NERC} learned from AIDA CoNLL-YAGO (**train**)

- MEANTIME [Minard et al., 2016]

- TAC-KBP [Ji et al., 2011]

ImpCl_{NERC}

PER (4522)	ORG (4564)
PhysicalEntity100001930 (.991)	YagoPermanentlyLocatedEntity (.945)
CausalAgent100007347 (.988)	Abstraction100002137 (.945)
Object100002684 (.963)	YagoLegalActorGeo (.938)
YagoLegalActorGeo (.963)	YagoLegalActor (.925)
Whole100003553 (.962)	Group100031264 (.924)
YagoLegalActor (.961)	SocialGroup107950920 (.923)
LivingThing100004258 (.960)	Organization108008335 (.914)
Organism100004475 (.960)	Association108049401 (.642)
Person100007846 (.960)	Club108227214 (.637)
WikicatLivingPeople (.850)	Unit108189659 (.340)

LOC (6689)	MISC (2764)
YagoPermanentlyLocatedEntity (.986)	YagoPermanentlyLocatedEntity (.843)
YagoLegalActorGeo (.967)	YagoLegalActorGeo (.679)
PhysicalEntity100001930 (.909)	PhysicalEntity100001930 (.614)
Object100002684 (.907)	Object100002684 (.609)
YagoGeoEntity (.905)	YagoGeoEntity (.591)
Location100027167 (.889)	Location100027167 (.572)
Region108630985 (.883)	Region108630985 (.571)
District108552138 (.866)	AdministrativeDistrict108491826 (.568)
AdministrativeDistrict108491826 (.865)	District108552138 (.568)
Country108544813 (.524)	Country108544813 (.549)

Research Question

Does the ontology-driven **PSL4EA** a posteriori joint revision of the annotations from Stanford NER and DBpedia Spotlight, improve their NERC and EL performances?

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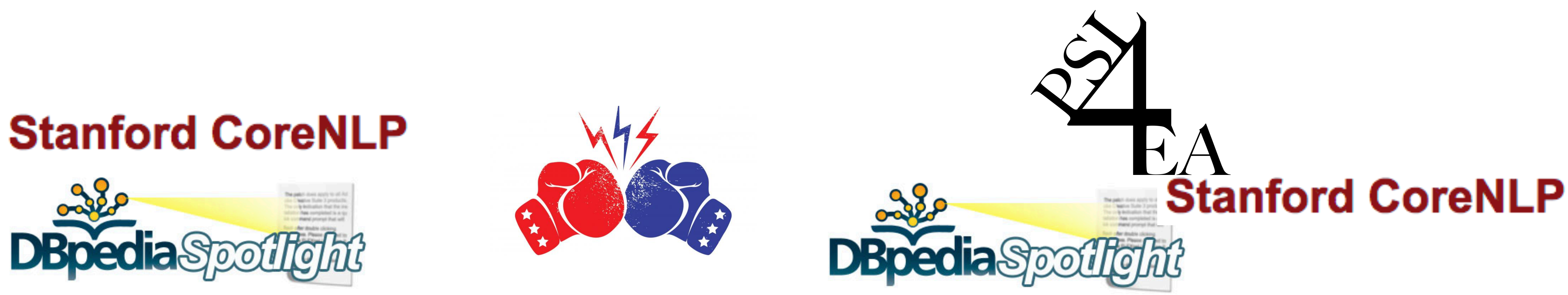

Results

		type			link			type+link		
		P	R	F_1	P	R	F_1	P	R	F_1
AIDA (5616)	*standard*	.943	.875	.908	.662	.652	.656	.634	.625	.630
	*with **PSL4EA***	.947	.879	.912	.670	.659	.665	.646	.635	.640
	Δ	**.004**	**.004**	**.004**	**.008**	**.007**	**.009**	**.012**	**.010**	**.010**
MEANTIME (792)	*standard*	.882	.695	.777	.703	.556	.621	.635	.502	.561
	*with **PSL4EA***	.902	.711	.795	.714	.564	.630	.667	.527	.589
	Δ	**.020**	**.016**	**.018**	.011	.008	.009	**.032**	**.025**	**.028**
TAC-KBP (4969)	*standard*	.911	.652	.760	.401	.423	.412	.367	.386	.376
	*with **PSL4EA***	.925	.662	.772	.408	.430	.419	.384	.404	.394
	Δ	**.014**	**.010**	**.012**	**.007**	**.007**	**.007**	**.017**	**.018**	**.018**

bold = statistical significant (approx. rand. test)

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bold = statistical significant (approx. rand. test)

Research Question

Does the ontology-driven **PSL4EA** a posteriori joint revision of the annotations from Stanford NER and DBpedia Spotlight, improve their NERC and EL performances?

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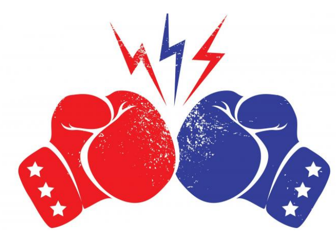
JPARK

PSI4EA

		type			link			type+link		
		P	R	F_1	P	R	F_1	P	R	F_1
AIDA (5616)	*with JPARK*	**.007**	**.006**	**.006**	**.009**	.002	.006	**.021**	**.012**	**.016**
	with PSL4EA	.004	.004	.004	.008	**.007**	**.009**	.012	.010	.010
MEANTIME (792)	*with JPARK*	**.032**	**.025**	**.028**	.002	.001	.001	**.035**	**.028**	**.031**
	with PSL4EA	.020	.016	.018	**.011**	**.008**	**.009**	.032	.025	.028
TAC-KBP (4969)	*with JPARK*	**.015**	**.011**	**.012**	**.011**	.003	**.007**	**.022**	.016	**.019**
	with PSL4EA	.014	.010	**.012**	.007	**.007**	**.007**	.017	**.018**	.018

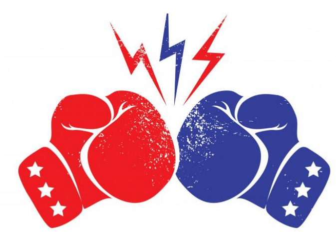
JPARK



PSL4EA

		type			link			type+link		
		P	R	F_1	P	R	F_1	P	R	F_1
AIDA (5616)	*with JPARK*	**.007**	**.006**	**.006**	**.009**	.002	.006	**.021**	**.012**	**.016**
	with PSL4EA	.004	.004	.004	.008	**.007**	**.009**	.012	.010	.010
MEANTIME (792)	*with JPARK*	**.032**	**.025**	**.028**	.002	.001	.001	**.035**	**.028**	**.031**
	with PSL4EA	.020	.016	.018	**.011**	**.008**	**.009**	.032	.025	.028
TAC-KBP (4969)	*with JPARK*	**.015**	**.011**	**.012**	**.011**	.003	**.007**	**.022**	.016	**.019**
	with PSL4EA	.014	.010	**.012**	.007	**.007**	**.007**	.017	**.018**	.018

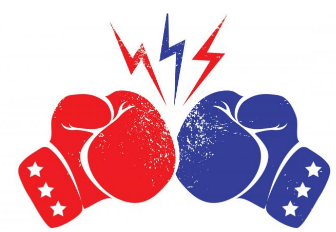
JPARK



PSL4EA

- ✓ very fast
- ✓ simple model construction

		type			link			type+link		
		P	R	F_1	P	R	F_1	P	R	F_1
AIDA (5616)	*with JPARK*	**.007**	**.006**	**.006**	**.009**	.002	.006	**.021**	**.012**	**.016**
	with PSL4EA	.004	.004	.004	.008	**.007**	**.009**	.012	.010	.010
MEANTIME (792)	*with JPARK*	**.032**	**.025**	**.028**	.002	.001	.001	**.035**	**.028**	**.031**
	with PSL4EA	.020	.016	.018	**.011**	**.008**	**.009**	.032	.025	.028
TAC-KBP (4969)	*with JPARK*	**.015**	**.011**	**.012**	**.011**	.003	**.007**	**.022**	.016	**.019**
	with PSL4EA	.014	.010	**.012**	.007	**.007**	**.007**	.017	**.018**	.018



- ✓ very fast
- ✓ simple model construction

- ✓ intuitive formulation
- ✓ extensible to cross-mention information

Conclusions

- Ontological knowledge does really help improving NLP entity annotations
- Two approaches: JPARK PSI4EA
- Instantiation of the models for the NERC and EL tasks

Conclusions

- Empirical confirmation (3 datasets) of the capability of the models to improve the quality of the annotations

- Applicable to "any" NERC and EL tools

- Future Work:
  - application to other tasks (e.g., SRL)
  - application to fine-grained NERC
  - Testing different background knowledge (e.g., DBpedia, Wikidata)
  - cross-mention coherence

JPARK
pikes.fbk.eu/jpark

KE4IR
pikes.fbk.eu/ke4ir

KnowledgeStore
knowledgestore.fbk.eu

RDFpro
rdfpro.fbk.eu

PIKES
pikes.fbk.eu

PSL4EA
pikes.fbk.eu/psl4ea

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BPMN Ontology
dkm.fbk.eu/bpmn-ontology

PESCaDO
bit.ly/pescado-onto

NewsReader
POST HOC ERGO PROPTER HOC
Event & Situation Ontology
github.com/newsreader/eso

PREMON
premon.fbk.eu

MoKi
the Modelling WiKi ---
moki.fbk.eu

TEX-OWL
github.com/dkmfbk/TexOwl