An Ontology-Driven Probabilistic Soft Logic Approach to Improve NLP Entity Annotations

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FONDAZIONE BRUNO KESSLER

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Context: Knowledge Extraction

Kia has hired Peter Schreyer as chief design officer.

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Organization

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

Context: Knowledge Extraction

Organization

dbpedia:Kia_Motors

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

Context: Knowledge Extraction

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

...

Motivating Examples

Lincoln is based in Michigan.

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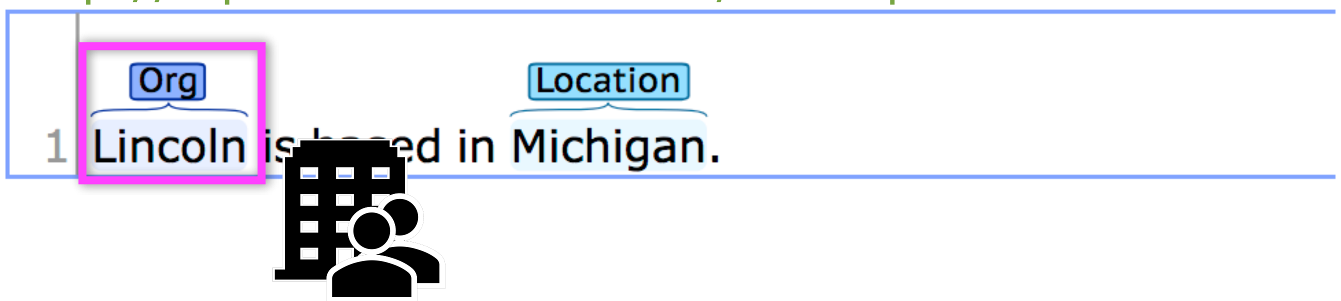
Stanford CoreNLP

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



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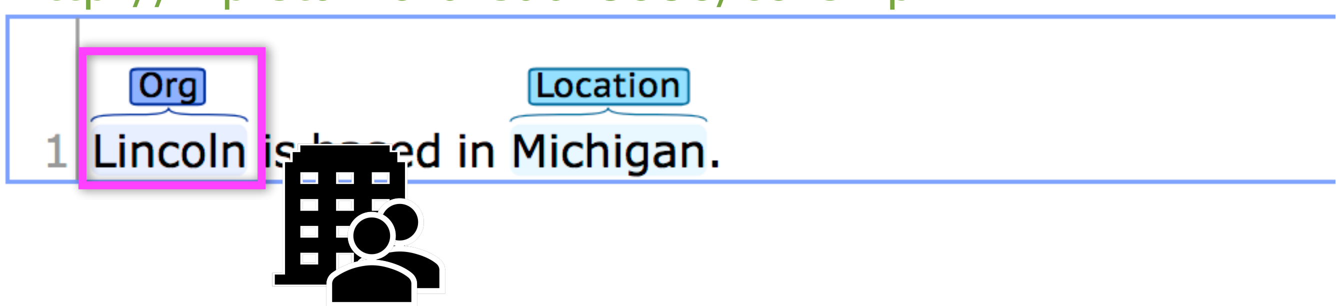
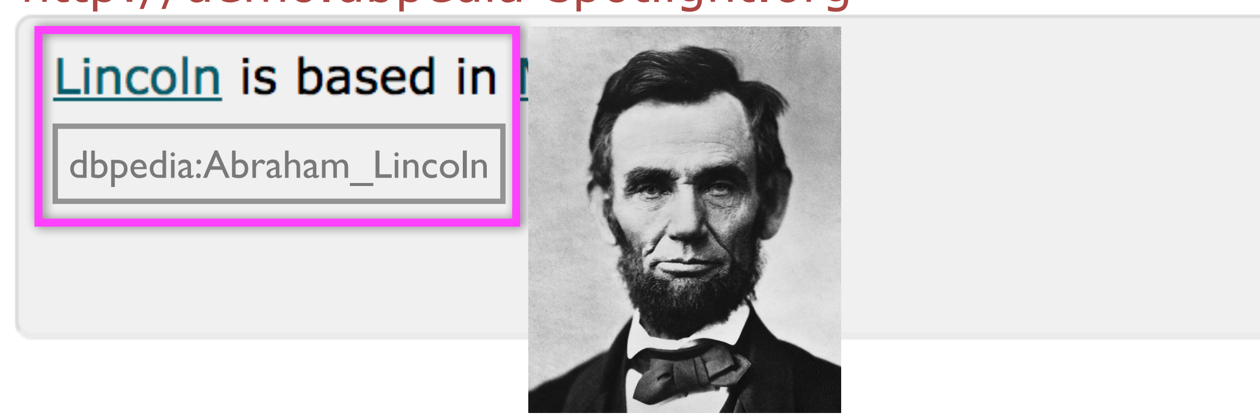


DBpedia Spotlight

http://demo.dbpedia-spotlight.org



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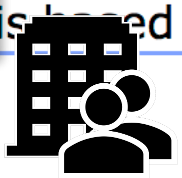

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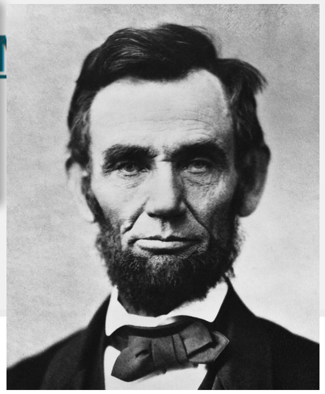
Lincoln is based in

dbpedia:Abraham_Lincoln



San Jose is one of the strongest hockey team.

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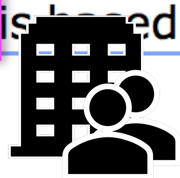

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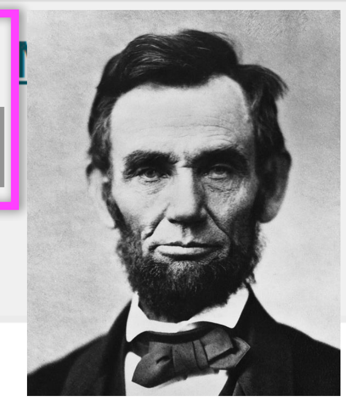

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dbpedia:San_Jose_Sharks

San Jose Sharks

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	Org		Location	
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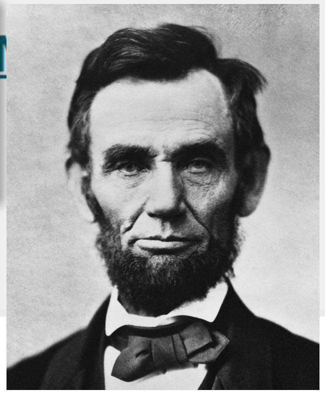

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	Location		Num	
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Abstracting

… token_1 token_2 token_3 token_4 token_5 token_6 ….

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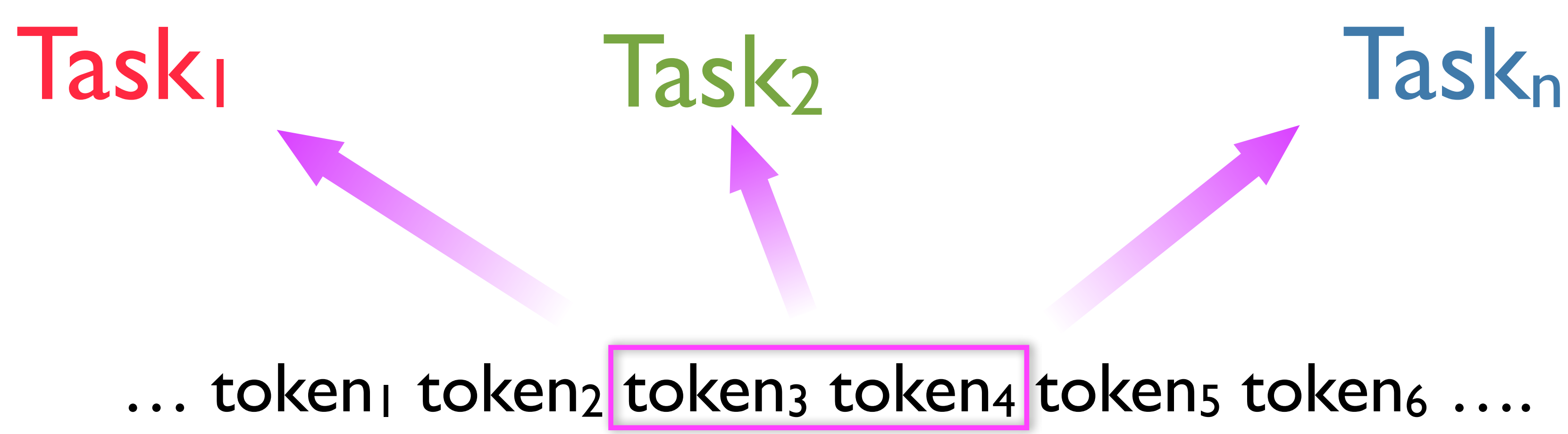
… token_1 token_2 $\boxed{\text{token}_3\ \text{token}_4}$ token_5 token_6 ….

Abstracting



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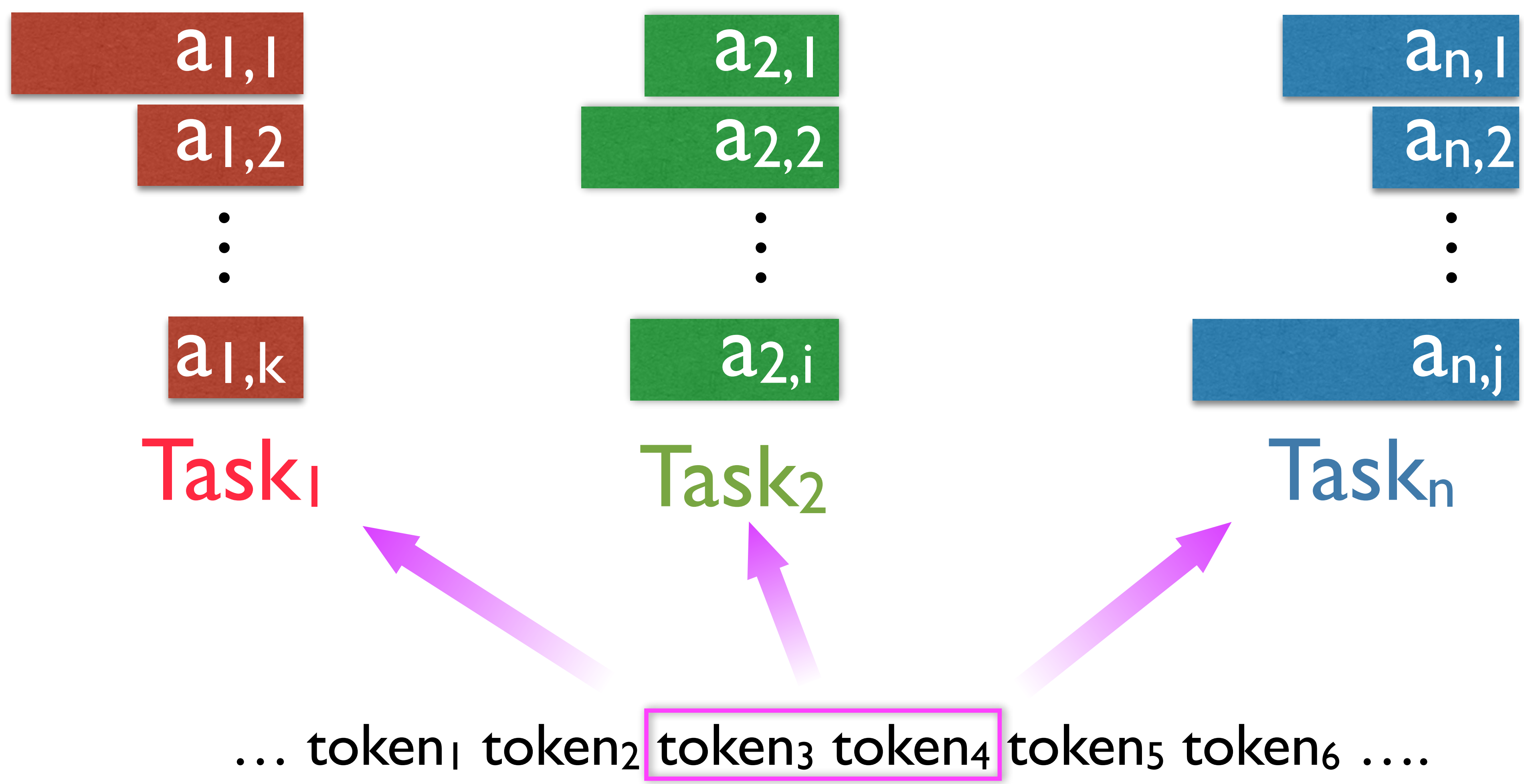

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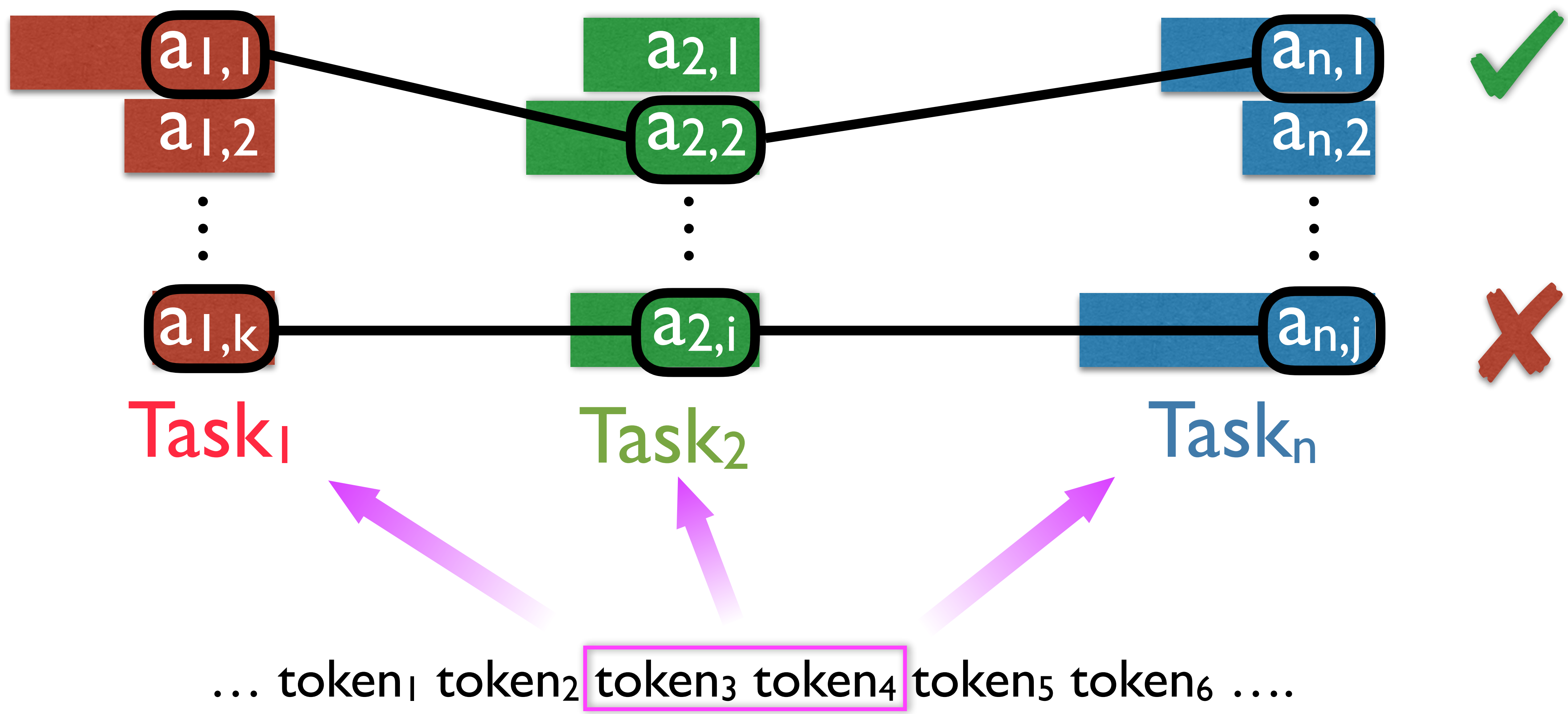

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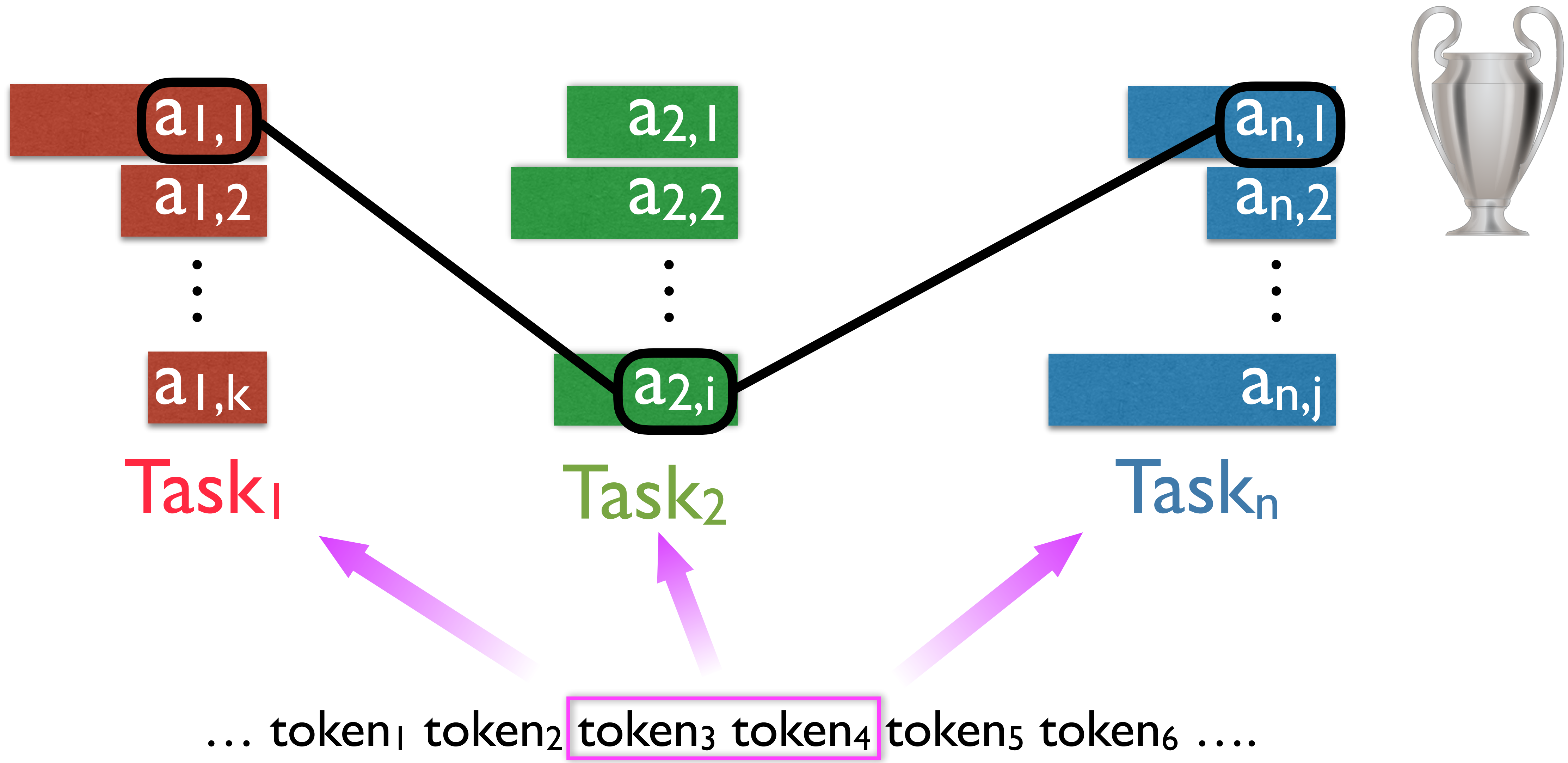
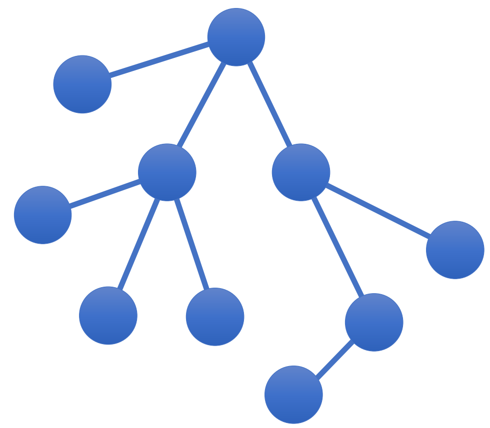


RESEARCH PROBLEM

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

In a nutshell

ontological background knowledge



$a_{1,1}$ $a_{1,2}$ $\vdots$ $a_{1,k}$ — Task_1

$a_{2,1}$ $a_{2,2}$ $\vdots$ $a_{2,i}$ — Task_2

$a_{n,1}$ $a_{n,2}$ $\vdots$ $a_{n,j}$ — Task_n

… token_1 token_2 $\boxed{\text{token}_3\ \text{token}_4}$ token_5 token_6 ….

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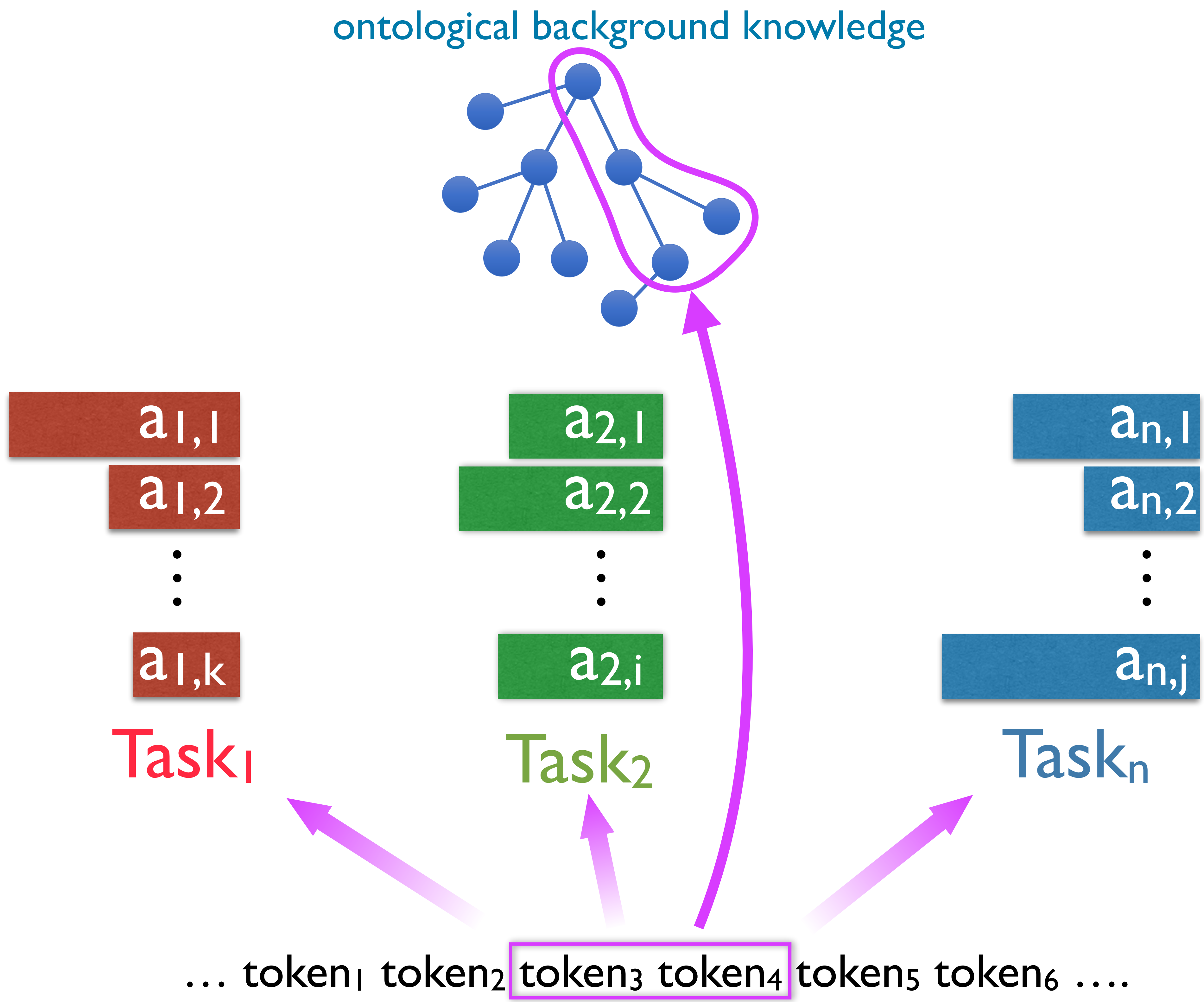

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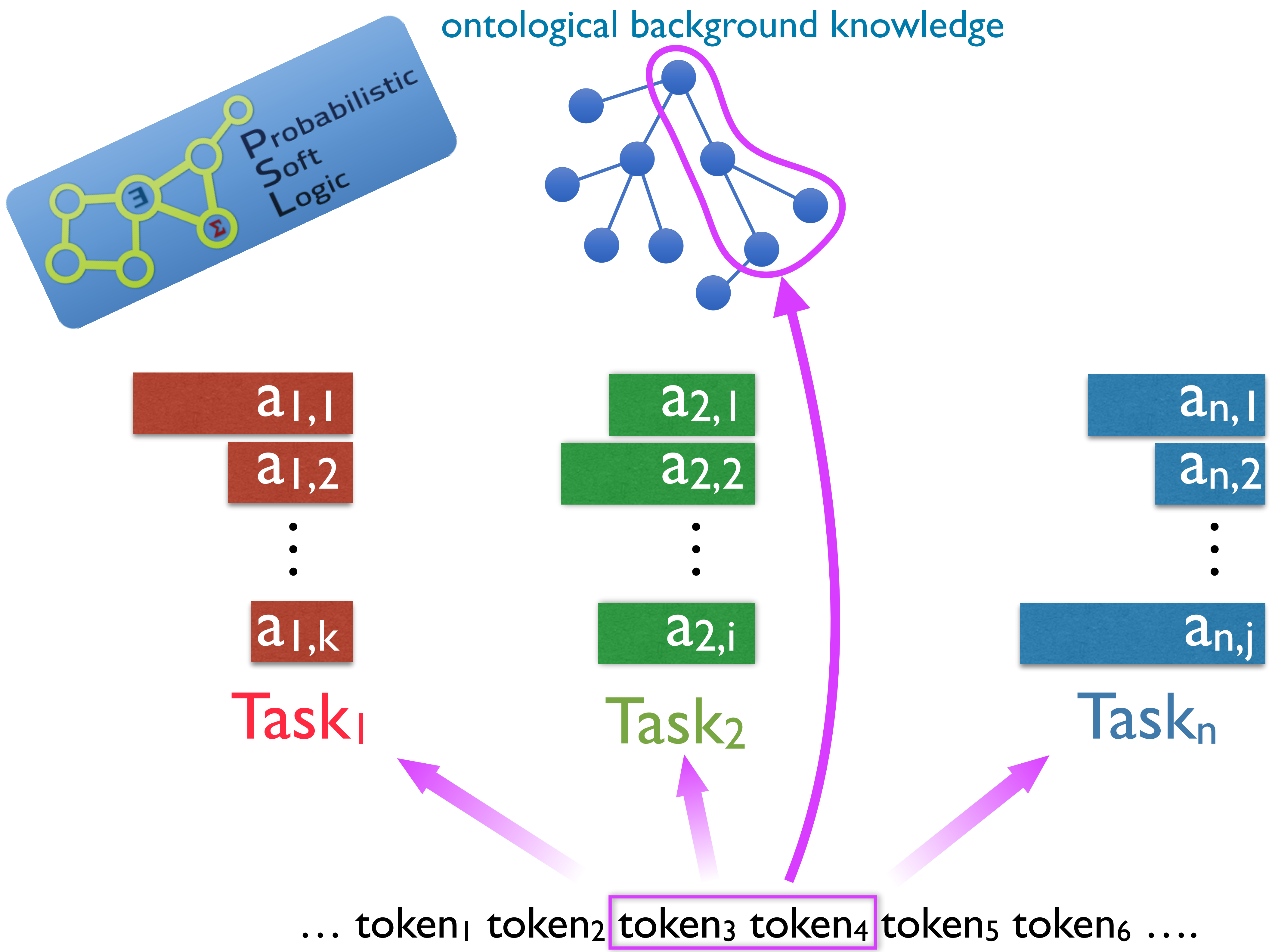

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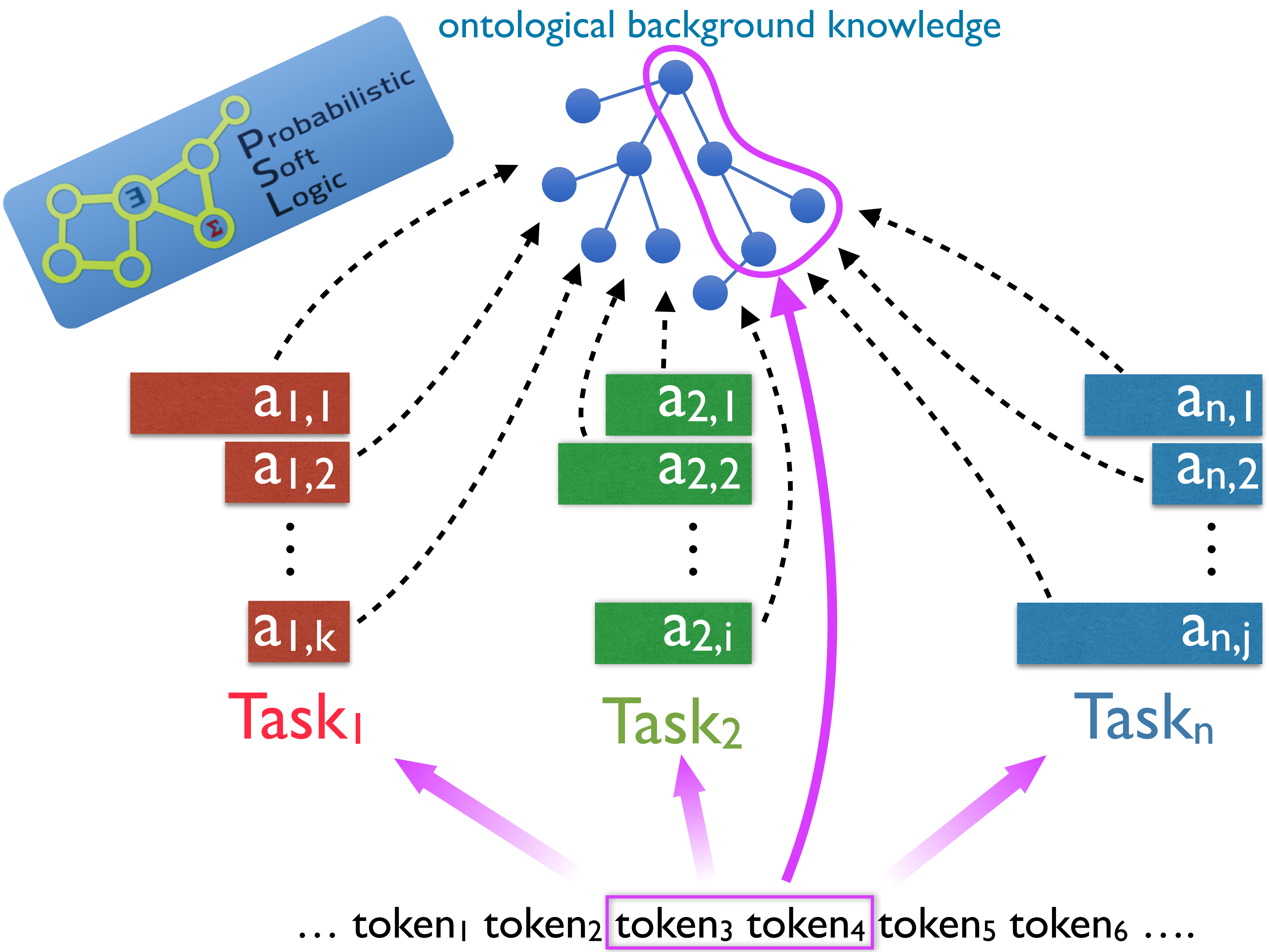

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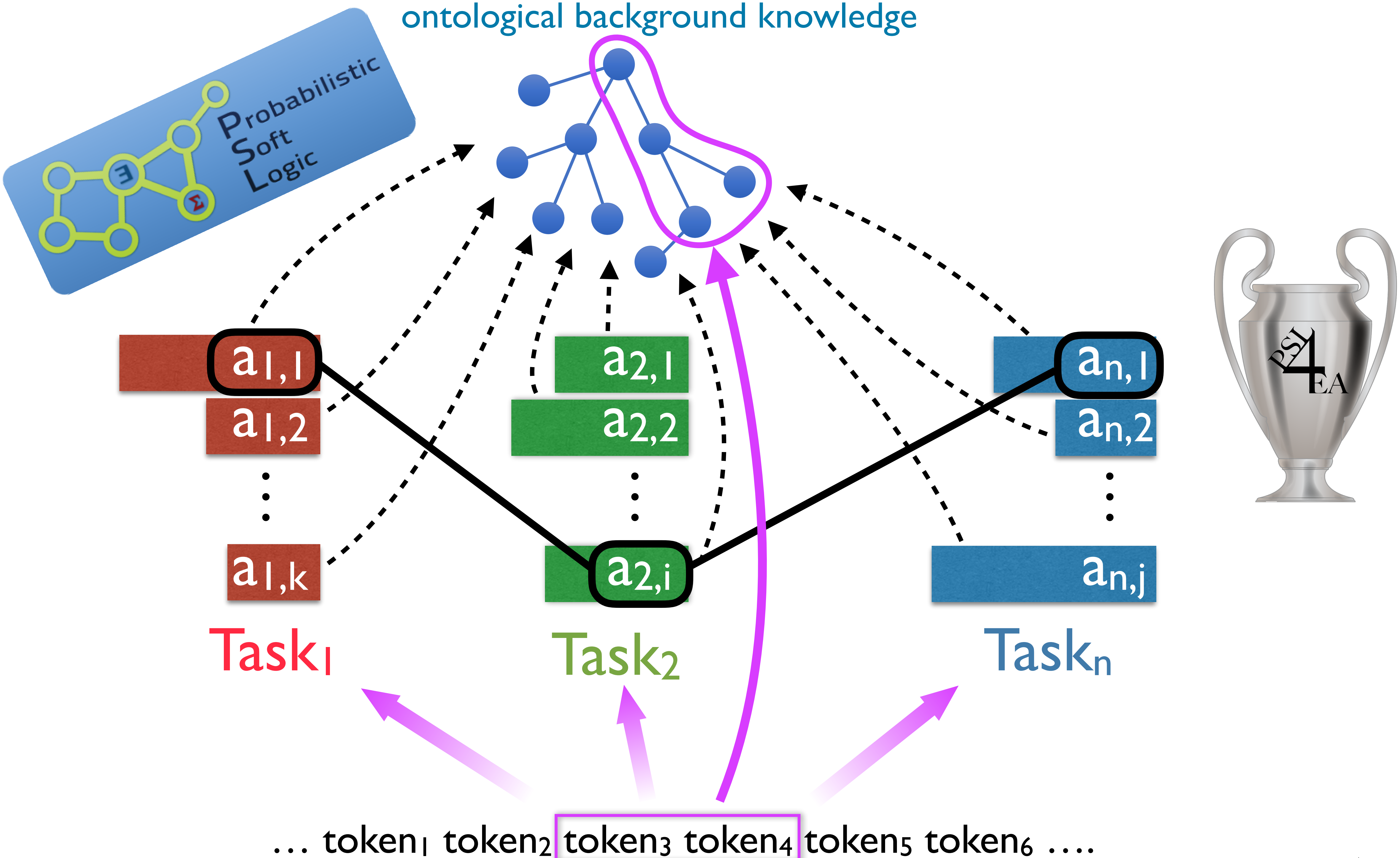

Contributions

1. PSL4EA: a PSL model capable to estimate a posteriori the overall confidence of NLP annotations

2. A concrete instantiation of the model for NERC and EL (using YAGO as ontological knowledge)

3. Application of the NERC and EL model to revise the annotations of Stanford NER and DBpedia Spotlight

Probabilistic Soft Logic

Probabilistic Soft Logic in a nutshell (1/3)

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

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weight

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grounding

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

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

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

Probabilistic Soft Logic in a nutshell (2/3)

Lukasiewicz
t-norm/co-norm

$$I(a_1) \land I(a_2) = max\{I(a_1) + I(a_2) - 1, 0\}$$
$$I(a_1) \lor I(a_2) = min\{I(a_1) + I(a_2), 1\}$$
$$\neg I(a_1) = 1 - I(a_1)$$

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$$\overset{0.6}{\text{WorksFor}(John, FBK)} \wedge \overset{0.6}{\text{BossOf}(John, Jack)} \rightarrow \overset{0.5}{\text{WorksFor}(Jack, FBK)} \quad ✓$$

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

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$d(r) = 0.4$

Probabilistic Soft Logic in a nutshell (3/3)

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

constant

all rules

Probabilistic Soft Logic in a nutshell (3/3)

weight

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

PSI4EA

1. Classes implied by NLP annotations

M mention

A_i^T candidate annotation for task T on M

c ontological class from background knowledge K

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

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NLP annotation

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confidence score

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

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Leverage alignments between EL Knowledge Base and Background Knowledge K

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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

2. Annotation Coherence via Classes

$$w_1 : \mathsf{ClAnn}_{NERC}(m,t,c) \ \wedge \ \mathsf{ClAnn}_{EL}(m,e,c) \rightarrow \mathsf{Ann}_{PSL}(m,t,e)$$
$$w_2 : \mathsf{ClAnn}_{NERC}(m,t,c) \ \wedge \ \neg\mathsf{ClAnn}_{EL}(m,e,c) \rightarrow \neg\mathsf{Ann}_{PSL}(m,t,e)$$
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2. Annotation Coherence via Classes

coherence estimation

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

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

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

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

Application and Evaluation

Background Knowledge

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

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

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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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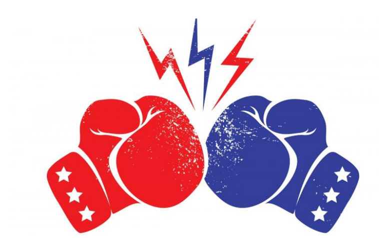
Stanford CoreNLP
DBpedia Spotlight



PSL4EA
Stanford CoreNLP
DBpedia Spotlight

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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Conclusions

- PSL model, leveraging ontological knowledge, for improving NLP entity annotations
- Instantiation of the model for the NERC and EL tasks
- Empirical confirmation (3 datasets) of the capability of the model to improve the quality of the annotations
- Applicable to other NERC and EL tools

- Future Work: application to other tasks (e.g., SRL)

PSI4EA
pikes.fbk.eu/psl4ea

JPARK
pikes.fbk.eu/jpark

KE4IR
pikes.fbk.eu/ke4ir

PIKES
pikes.fbk.eu

KnowledgeStore
knowledgestore.fbk.eu

RDFpro
rdfpro.fbk.eu

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BPMN Ontology
dkm.fbk.eu/bpmn-ontology

PESCaDO
bit.ly/pescado-onto

PREMON
premon.fbk.eu

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

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

TEX-OWL
github.com/dkmfbk/TexOwl