Joint Posterior Revision of NLP Entity Annotations via Ontological Knowledge

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Dipartimento di LINGUE E LETTERATURE STRANIERE

Dipartimento di Eccellenza 2023/2027 MIUR

NLP seminar series @ Dublin City University / ADAPT Centre — 13.02.2023

Research Context

- Knowledge graph extraction from text

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)

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- Knowledge graph extraction from text

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dbpedia:Kia_Motors

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NLP Tasks:
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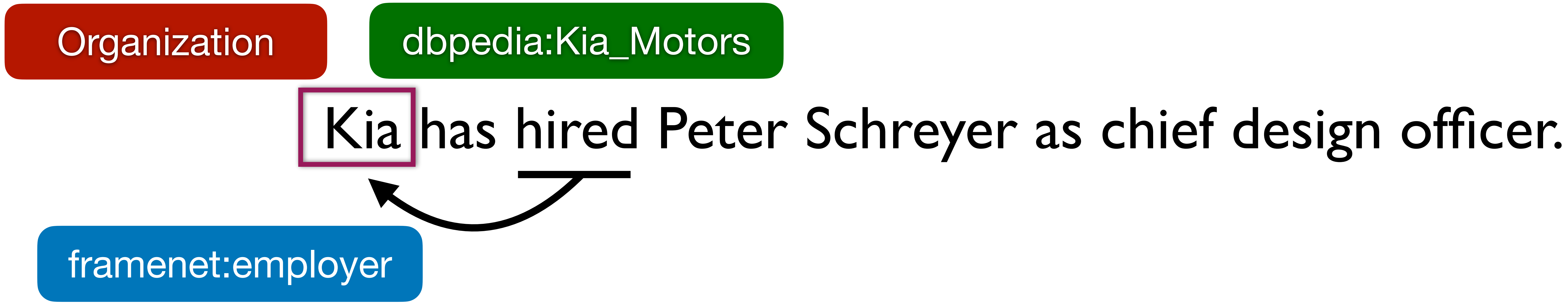
- Entity Linking (EL)

Research Context

- Knowledge graph extraction from text



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

Research Context

- Knowledge graph extraction from text

PIKES

Pikes is a Knowledge Extraction Suite
https://pikes.fbk.eu/

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framenet:employer

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- Entity Linking (EL)
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...

What may happen in practice…

Eric Clapton is one of the greatest guitar players.

Mr. Washington was runner-up at Wimbledon in 1996.

San Jose is one of the strongest hockey teams.

What may happen in practice…

Stanford CoreNLP

DBpedia Spotlight

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What may happen in practice...

Person

Stanford CoreNLP

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DBpedia Spotlight

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Location | Organization | Person | Misc

🤔 San Jose is one of the strongest hockey teams.

dbpedia:San_Jose_Sharks | dbpedia:San_Jose,_California | dbpedia:San_Jose_Earthquakes | dbpedia:SAP_Cent

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

Leveraging Ontological Knowledge!

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

Leveraging Ontological Knowledge!

… $token_1$ $token_2$ $\boxed{token_3\ token_4}$ $token_5$ $token_6$ ….

Leveraging Ontological Knowledge!

$Task_1$ $Task_2$ $Task_n$

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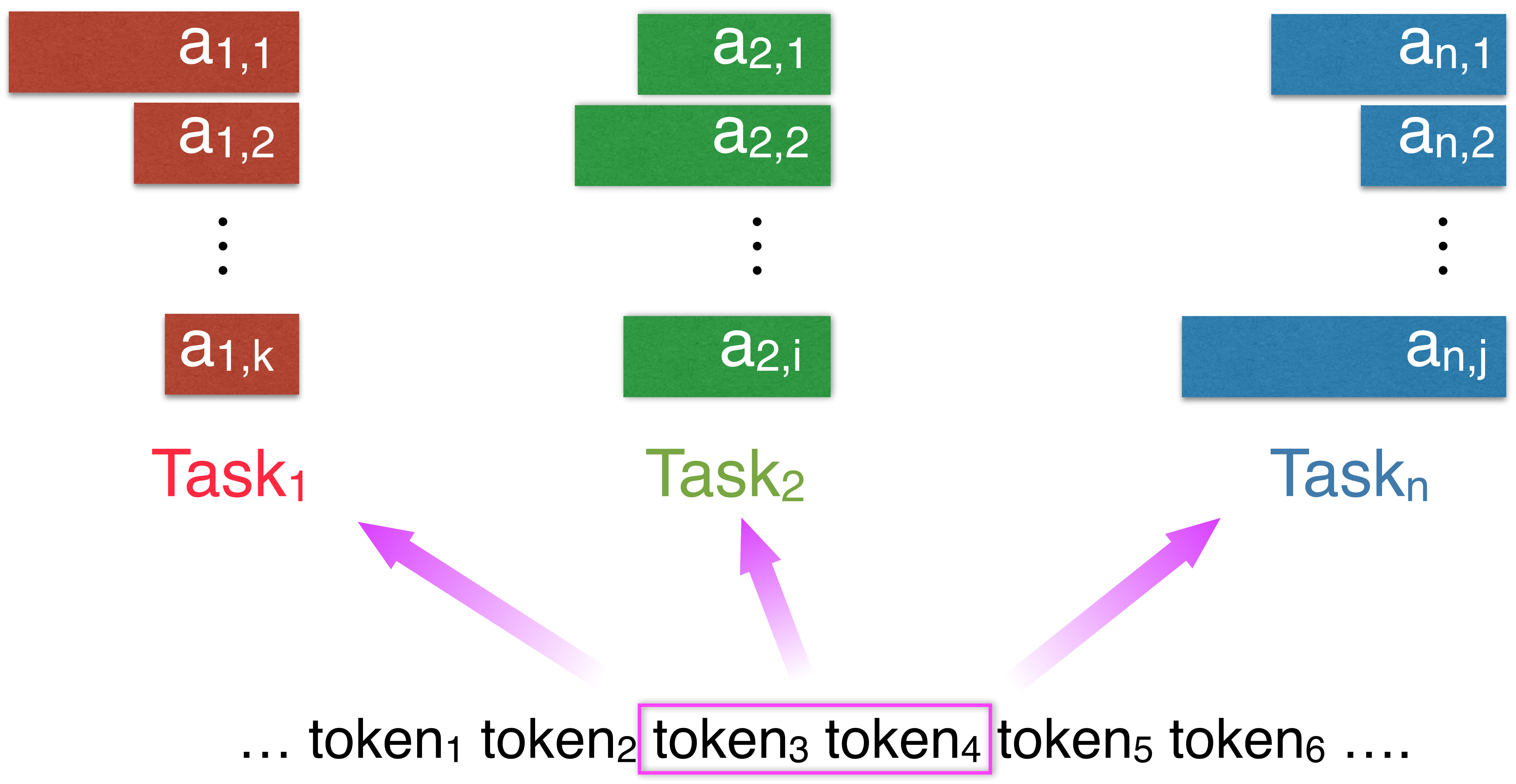

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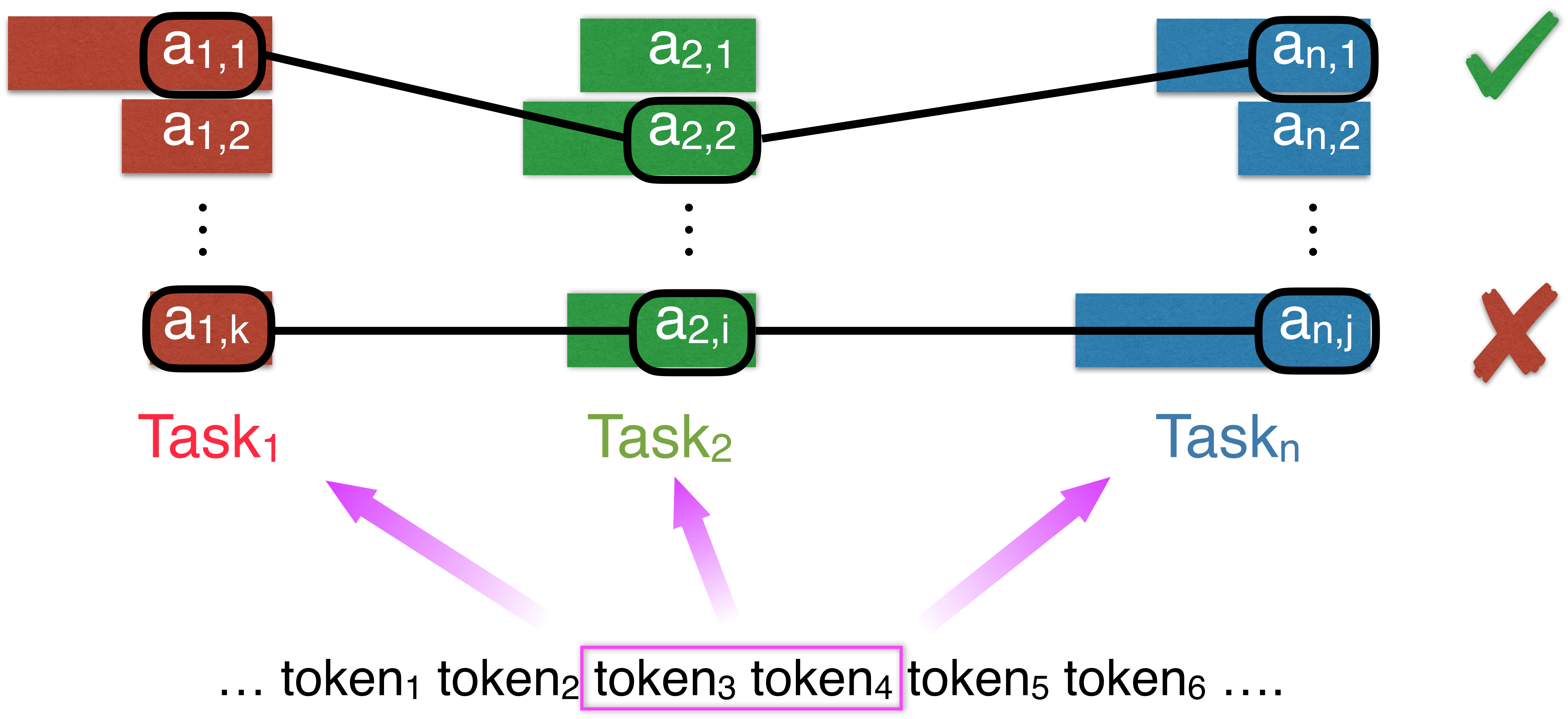

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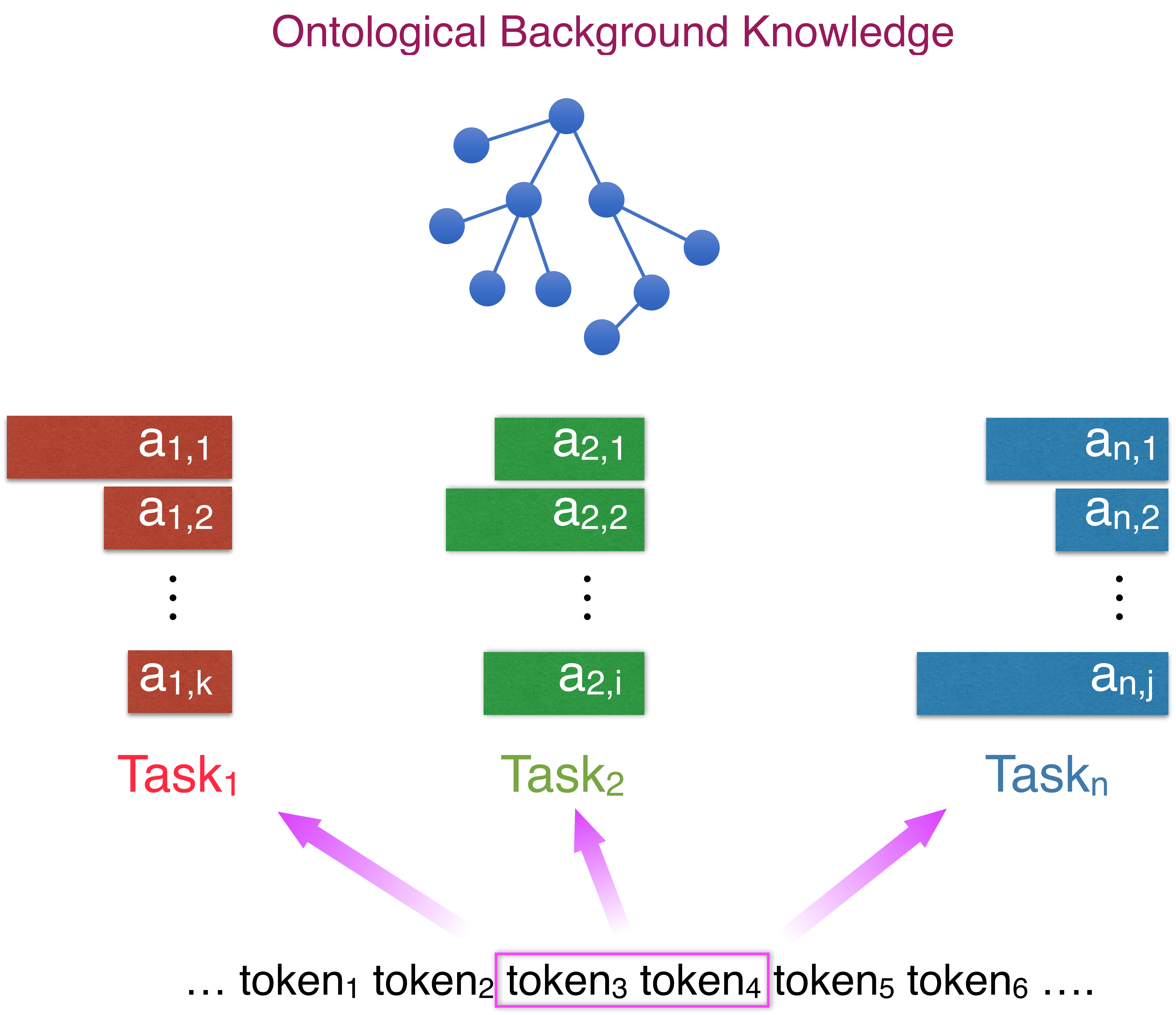

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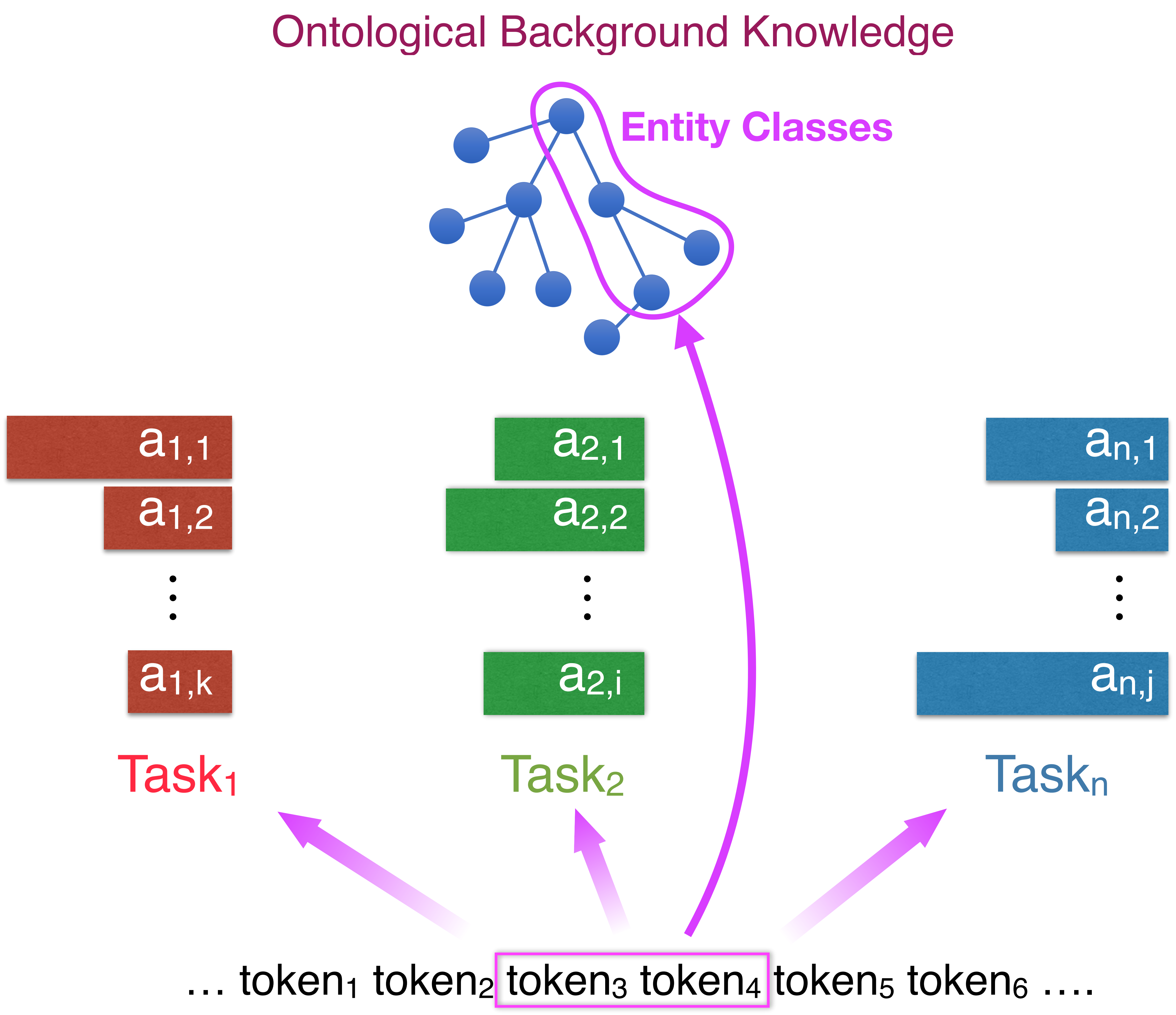

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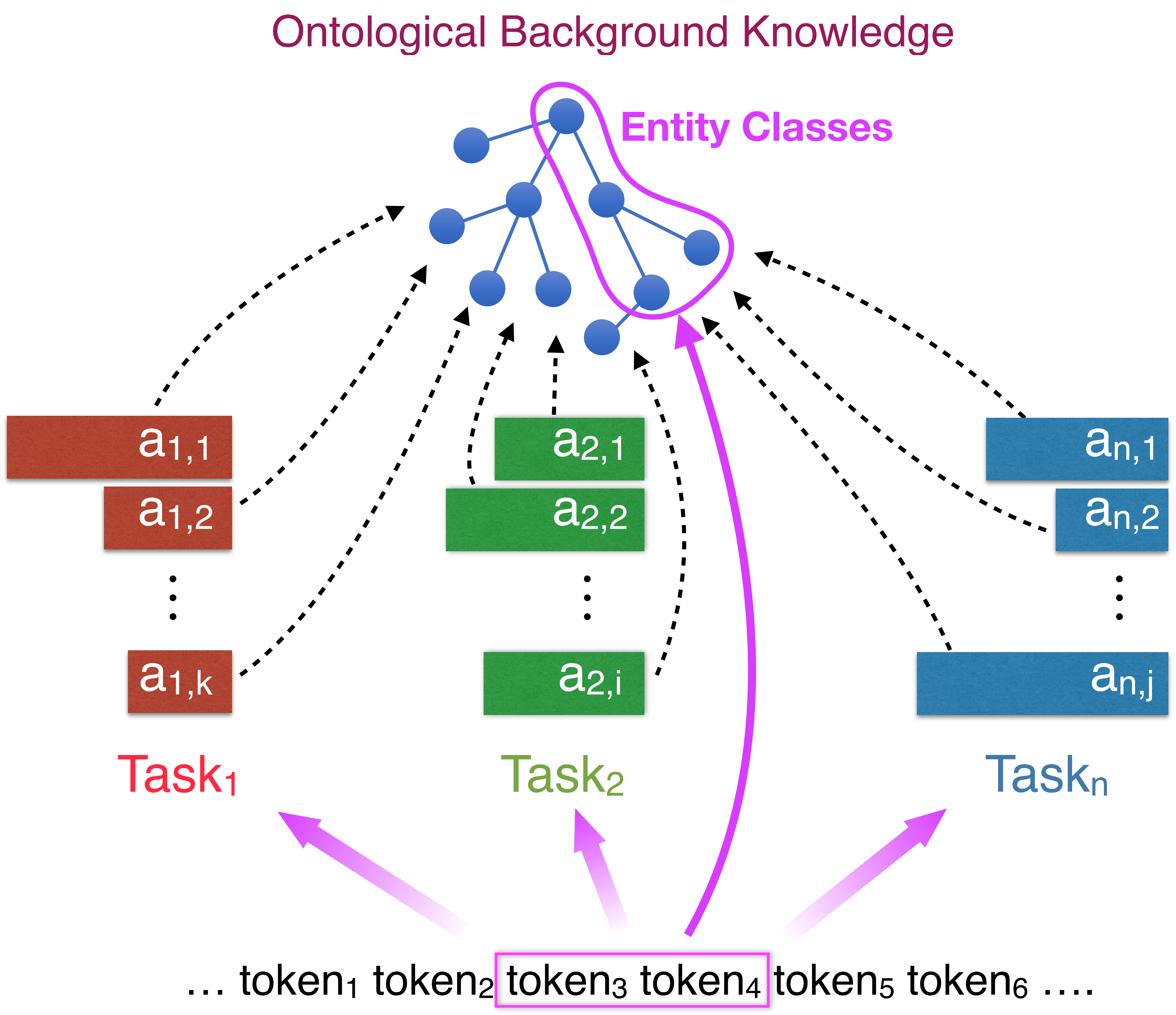

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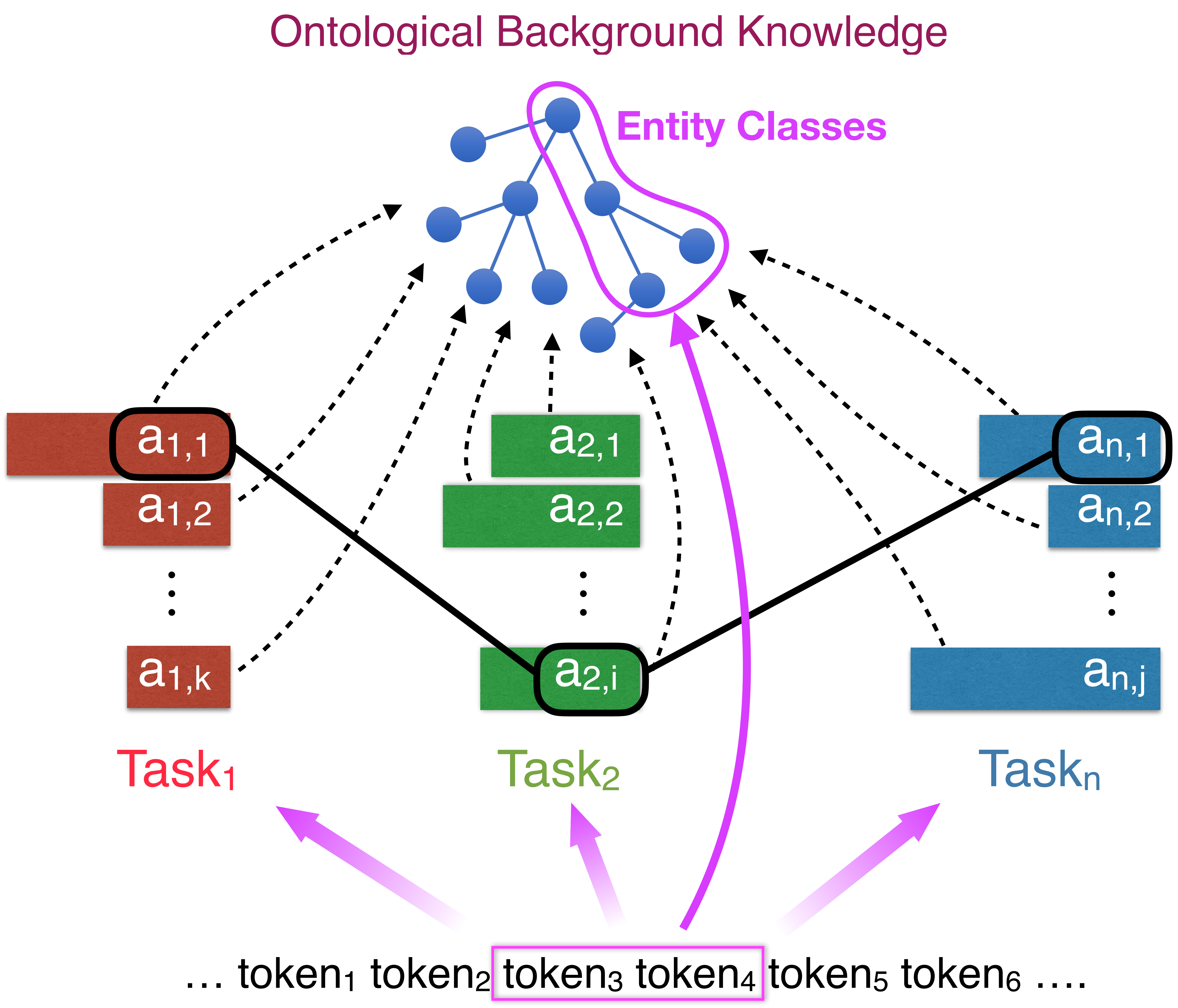
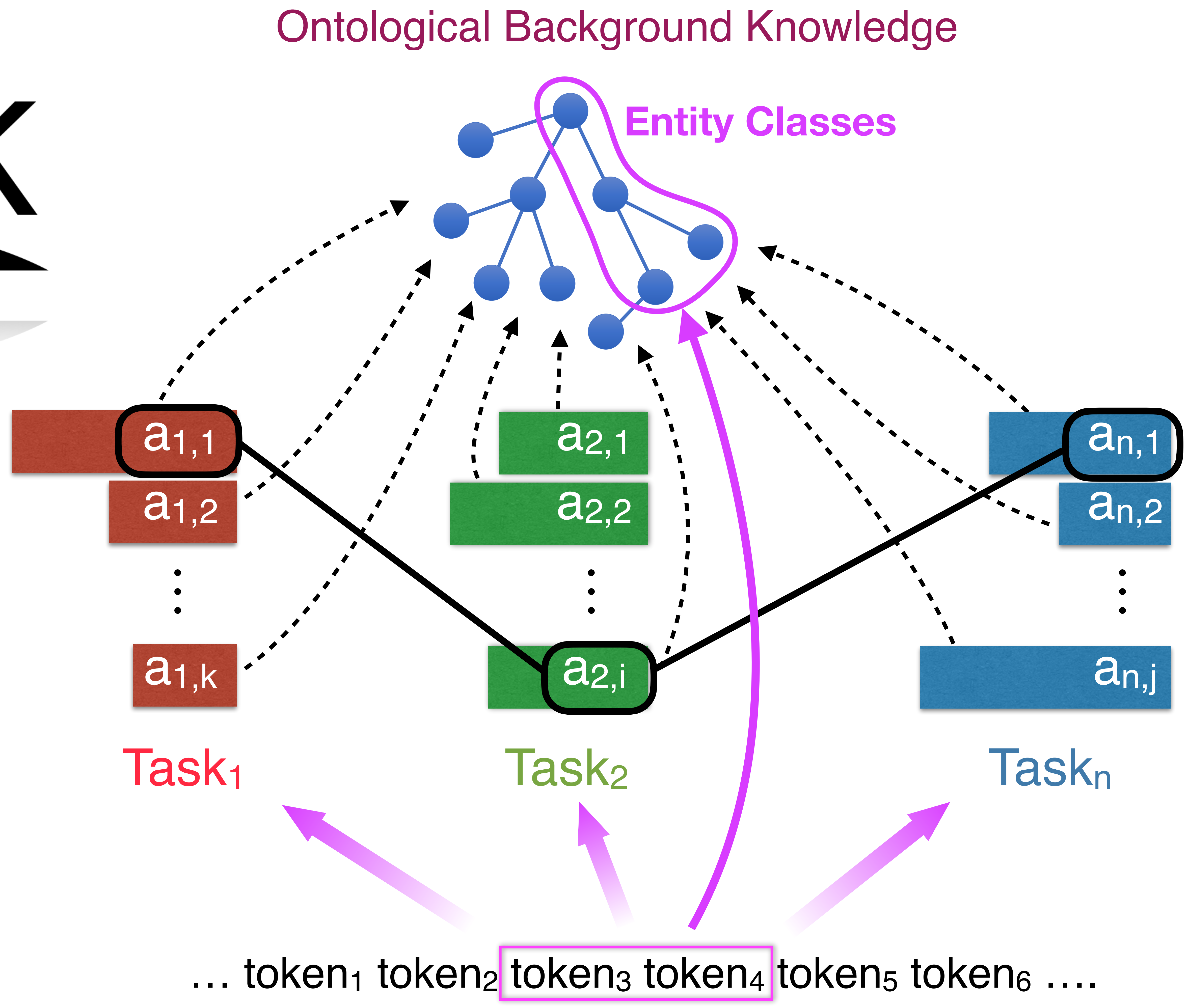


Leveraging Ontological Knowledge!

JPARK



How does JPARK work?

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

How does JPARK work?

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

Entity mention

NLP Background Knowledge

$\mathrm{P}\left(\boldsymbol{a} \,\middle|\, m, B, K\right)$ "The" Ontological Knowledge

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set of classes from K

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

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confidence score (tool)

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

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learned from data

$\boxed{\mathrm{P}\left(C \mid a_i, K\right)}$

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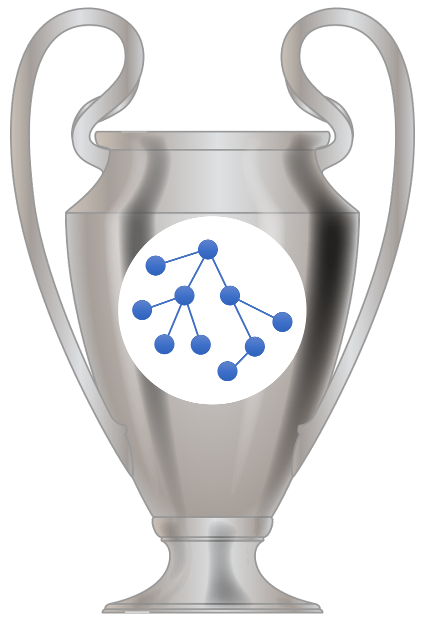

$$= \arg\max_{\boldsymbol{a}} \mathrm{P}\left(\boldsymbol{a} \,|\, m, B, K\right)$$

"The" Ontological Knowledge

set of classes from K

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$$\boxed{\mathrm{P}\left(C \,|\, a_i, K\right)}$$

Building a JPARK model for NERC and Entity Linking

Handling NERC Annotations

- a_{NERC} is a NERC type such as PER, ORG, LOC, MISC, …
- We have to estimate

$$\mathrm{P}\left(C \middle| a_{\mathrm{NERC}}, K\right) =$$

- We rely on a Gold Standard G containing entity mentions that
  - are annotated with ground truth NERC types a_{NERC}
  - can be related directly or indirectly to class sets C in K

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occurrences

$$\mathrm{P}\left(C \mid a_{\text{NERC}}, K\right) = \frac{n_G\left(C, a_{\text{NERC}}\right)}{\sum_{C^*} n_G\left(C^*, a_{\text{NERC}}\right)}$$

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$$P\left(C \mid a_{\mathrm{NERC}}, K\right) = (1-\alpha) \cdot \frac{n_G\left(C, a_{\mathrm{NERC}}\right)}{\sum_{C^*} n_G\left(C^*, a_{\mathrm{NERC}}\right)} + \alpha \cdot \boxed{\frac{n_K(C)}{\sum_{C^*} n_K\left(C^*\right)}}$$

Prior for unseen class sets
(e.g., class set popularity in K)

- We rely on a Gold Standard G containing entity mentions that
  - are annotated with ground truth NERC types a_{NERC}
  - can be related directly or indirectly to class sets C in K

Handling EL Annotations

- a_{EL} is an entity in the Linking knowledge base L
- The L linking knowledge base and the K ontological background knowledge are not necessary the same
  - However, in general, we can deterministically align entities/classes between the two, and so we can obtain a corresponding class set C_K for a_{EL}

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$$\mathrm{P}\left(C \,|\, a_{\mathrm{EL}}, K\right) = \begin{cases} 1 & C = C_K\left(a_{\mathrm{EL}}\right) \\ 0 & \text{otherwise} \end{cases}$$

Handling EL Annotations: NIL

- What about NIL (i.e., an entity lacking a corresponding referent in the linking knowledge base)? Can we estimate $\mathrm{P}\left(C \mid \mathrm{NIL}, K\right)$?

$$\mathrm{P}\left(C \mid \mathrm{NIL}, K\right) = \sum_{a_{\mathrm{NERC}}} \mathrm{P}\left(C \mid a_{\mathrm{NERC}}, K\right) \cdot \mathrm{P}\left(a_{\mathrm{NERC}} \mid \mathrm{NIL}, K\right)$$

Handling EL Annotations: NIL

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Already computed for handling NERC

$$\mathrm{P}\left(C \middle| \mathrm{NIL}, K\right) = \sum_{a_{\mathrm{NERC}}} \boxed{\mathrm{P}\left(C \middle| a_{\mathrm{NERC}}, K\right)} \cdot \boxed{\mathrm{P}\left(a_{\mathrm{NERC}} \middle| \mathrm{NIL}, K\right)}$$

Also computable from corpus G

Choice of Ontological Classes

- Practically, we may restrict to consider a limited number of popular classes from the ontological background knowledge K
  - most of the classes in K never or rarely occur in the corpus G
  - leaf classes deep in K class taxonomy may be affected by incomplete knowledge
  - a large number of class sets slows down the use of JPARK
- Intuition: we keep only the classes in K that occur a substantial number n^* of times in G
  - By construction, this strategy ends up keeping only the top level, informative classes of K class taxonomy

Evaluation

Datasets

- Three datasets, annotated with NERC (4-type CoNLL2003) and EL (DBpedia)
  - AIDA CoNLL-YAGO [Hoffart et al., 2011] - news wire articles from Reuters
    - its train part used as corpus G
  - MEANTIME [Minard et al., 2016] - news articles from Wikinews
  - TAC-KBP [Ji et al., 2011] - news wire articles, posts from blogs, newsgroups, and fora

Dataset	Docs	Mentions					NILs					Avg. Mentions
		Total	PER	ORG	LOC	MISC	frac.	PER	ORG	LOC	MISC	per Entity
AIDA eng.train	946	23,411	.28	.27	.30	.15	.20	.44	.37	.09	.10	4.54
AIDA eng.testb	231	5,624	.29	.29	.30	.12	.20	.52	.27	.08	.14	2.91
MEANTIME	120	793	.09	.59	.32	-	.08	.15	.46	.39	-	4.42
TAC	2,231	4,969	.43	.30	.26	-	.46	.50	.32	.18	-	3.82
MERGED	2,582	11,386	.34	.32	.28	.06	.31	.50	.31	.15	.05	3.28

Background Ontological Knowledge

YAGO

Version 3

# entities:	6,016,695
# classes:	568,255
# class sets:	2,126,074

DBpedia

Version 2016-04

# entities:	5,109,890
# classes:	754
# class sets:	413

Wikidata

Dump 2018.08

# entities:	5,854,808
# classes:	21,864
# class sets:	32,648

Background Ontological Knowledge

WIKIPEDIA
The Free Encyclopedia

yago
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owl:sameAs links

EL Knowledge Base

1:1

DBpedia

owl:sameAs links

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711

owl:sameAs links

EL Knowledge Base

1:1

DBpedia

owl:sameAs links

Tools

Experiment A:

popular, frequently used tools

CoreNLP
[Manning et al, 2014]

CONLL2003 (PER, ORG, LOC, MISC)

DBpedia Spotlight
[Mendes et al, 2011]

DBpedia, NIL

Experiment B:

high-performance neural approaches

flair
[Akbik et al, 2018]

CONLL2003 (PER, ORG, LOC, MISC)

End-to-End Neural EL
[Kolitsas et al, 2018]

Wikipedia/DBpedia, NO NIL

Does the JPARK a posteriori joint revision of annotations by NERC and EL tools, performed leveraging ontological knowledge, improve NERC and EL performance?

Evaluation Measures

- Three measures, typically adopted in NERC and EL evaluation campaigns:
  - type: a correct mention has the same span and NERC type as a gold annotation
  - link: a correct mention has the same span and EL entity as a gold annotation
  - type+link: a correct mention has the same span, NERC type, and EL entity as a gold annotation
- Metrics: precision (P), recall (R), and F_1
  - computed via TAC-KBP official scorer
- We don't specifically address the capability to detect entity mentions
  - our approach fully relies on the mentions detected by the NLP tools

Evaluation Procedure

- We create a JPARK model for each background knowledge resource (DBpedia, Yago, Wikidata)
  - AIDA eng.train (corpus G), AIDA eng.testa (hyper-parameters)
  - evaluation on: AIDA eng.testb, MEANTIME, and TAC-KBP (and MERGED)

- Experiment A (CoreNLP + DBpedia Spotlight)

baseline vs. JPARK vs. JPARK +NIL

- Experiment B (Flair + E2E Neural EL)

baseline vs. JPARK

Experiment A

CoreNLP + DBpedia Spotlight

dataset	setting	back. know.	type (F_1)	link (F_1)	type+link (F_1)
AIDA	baseline		.908	.656	.630
	JPARK	YAGO	**.006**	**.006**	**.016**
		DBpedia	**.004**	**.008**	**.014**
		Wikidata	**.008**	.005	**.015**
	m.a.i.		.053	.102	.127
MEANTIME	baseline		.777	.621	.561
	JPARK	YAGO	**.028**	.001	**.031**
		DBpedia	**.030**	-.002	**.027**
		Wikidata	**.028**	.000	**.029**
	m.a.i.		.096	.106	.162
TAC KBP	baseline		.760	.412	.376
	JPARK	YAGO	**.012**	**.007**	**.019**
		DBpedia	**.019**	**.019**	**.035**
		Wikidata	**.016**	**.017**	**.034**
	m.a.i.		.073	.172	.208
MERGED	baseline		.838	.568	.535
	JPARK	YAGO	**.011**	**.006**	**.019**
		DBpedia	**.012**	**.011**	**.024**
		Wikidata	**.013**	**.009**	**.024**
	m.a.i.		.065	.133	.165

stat. sign. results in bold

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stat. sign. results in bold

- Improvement (mostly stat. sign.) almost everywhere

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- Particularly effective in selecting the correct annotation couple

Experiment A

CoreNLP + DBpedia Spotlight

dataset	setting	back. know.	type (F_1)	+NIL	link (F_1)	+NIL	type+link (F_1)	+NIL
AIDA	baseline		.908		.656		.630	
	JPARK	YAGO	**.006**	**.005**	**.006**	**.023**	**.016**	**.035**
		DBpedia	**.004**	**.004**	**.008**	**.013**	**.014**	**.024**
		Wikidata	**.008**	**.005**	.005	**.013**	**.015**	**.027**
	m.a.i.		.053		.102		.127	
MEANTIME	baseline		.777		.621		.561	
	JPARK	YAGO	**.028**	**.021**	.001	-.005	**.031**	**.025**
		DBpedia	**.030**	**.026**	-.002	.000	**.027**	**.030**
		Wikidata	**.028**	**.024**	.000	.008	**.029**	**.042**
	m.a.i.		.096		.106		.162	
TAC KBP	baseline		.760		.412		.376	
	JPARK	YAGO	**.012**	**.013**	**.007**	**.027**	**.019**	**.049**
		DBpedia	**.019**	**.015**	**.019**	**.031**	**.035**	**.054**
		Wikidata	**.016**	**.014**	**.017**	**.026**	**.034**	**.051**
	m.a.i.		.073		.172		.208	
MERGED	baseline		.838		.568		.535	
	JPARK	YAGO	**.011**	**.009**	**.006**	**.024**	**.019**	**.041**
		DBpedia	**.012**	**.010**	**.011**	**.020**	**.024**	**.037**
		Wikidata	**.013**	**.010**	**.009**	**.019**	**.024**	**.039**
	m.a.i.		.065		.133		.165	

stat. sign. results in bold

- Improvement (mostly stat. sign.) almost everywhere
- Particularly effective in selecting the correct annotation couple
- NIL strategy almost on par with NO-NIL on type, but better on link and type+link

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CoreNLP + DBpedia Spotlight

			=		<		<	
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	JPARK	YAGO	**.006**	**.005**	**.006**	**.023**	**.016**	**.035**
		DBpedia	**.004**	**.004**	**.008**	**.013**	**.014**	**.024**
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		DBpedia	**.019**	**.015**	**.019**	**.031**	**.035**	**.054**
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CoreNLP + DBpedia Spotlight

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AIDA	baseline		.908		.656		.630	
	JPARK	YAGO	**.006**	.005	**.006**	.023	**.016**	.035
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		DBpedia	**.019**	.015	**.019**	.031	**.035**	.054
		Wikidata	**.016**	.014	**.017**	.026	**.034**	.051
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		DBpedia	**.012**	.010	**.011**	.020	**.024**	.037
		Wikidata	**.013**	.010	**.009**	.019	**.024**	.039
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AIDA	baseline		.908		.656		.630	
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		Wikidata	**.008**	.005	.005	.013	**.015**	.027
	m.a.i.		.053		.102		.127	
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	m.a.i.		.073		.172		.208	
MERGED	baseline		.838		.568		.535	
	JPARK	YAGO	**.011**	.009	**.006**	.024	**.019**	.041
		DBpedia	**.012**	.010	**.011**	.020	**.024**	.037
		Wikidata	**.013**	.010	**.009**	.019	**.024**	.039
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stat. sign. results in bold

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- Particularly effective in selecting the correct annotation couple
- NIL strategy almost on par with NO-NIL on type, but better on link and type+link
- Improvement consistent with all background knowledge resources
- Improvement ~10-20% of the maximum achievable one

Experiment B

flair + End-to-End Neural EL

dataset	setting	back. know.	type (F_1)	link (F_1)	type+link (F_1)
AIDA	baseline		.949	.798	.786
	JPARK	YAGO	.001	**.004**	**.005**
		DBpedia	.001	**.002**	**.003**
		Wikidata	.000	**.004**	**.004**
	m.a.i.		.033	.079	.091
MEANTIME	baseline		.845	.705	.669
	JPARK	YAGO	.006	.001	.007
		DBpedia	**.008**	.001	**.010**
		Wikidata	**.008**	.001	**.010**
	m.a.i.		.069	.024	.060
TAC KBP	baseline		.843	.458	.448
	JPARK	YAGO	**.003**	.001	**.004**
		DBpedia	**.004**	.003	**.007**
		Wikidata	**.004**	**.013**	**.017**
	m.a.i.		.033	.062	.072
MERGED	baseline		.898	.686	.672
	JPARK	YAGO	**.002**	**.003**	**.005**
		DBpedia	**.002**	**.003**	**.005**
		Wikidata	**.003**	**.006**	**.009**
	m.a.i.		.036	.069	.083

stat. sign. results in bold

Experiment B

flair + **End-to-End Neural EL**

dataset	setting	back. know.	type (F_1)	link (F_1)	type+link (F_1)
AIDA	baseline		.949	.798	.786
	JPARK	YAGO	.001	**.004**	**.005**
		DBpedia	.001	**.002**	**.003**
		Wikidata	.000	**.004**	**.004**
	m.a.i.		.033	.079	.091
MEANTIME	baseline		.845	.705	.669
	JPARK	YAGO	.006	.001	.007
		DBpedia	**.008**	.001	**.010**
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	m.a.i.		.069	.024	.060
TAC KBP	baseline		.843	.458	.448
	JPARK	YAGO	**.003**	.001	**.004**
		DBpedia	**.004**	.003	**.007**
		Wikidata	**.004**	**.013**	**.017**
	m.a.i.		.033	.062	.072
MERGED	baseline		.898	.686	.672
	JPARK	YAGO	**.002**	**.003**	**.005**
		DBpedia	**.002**	**.003**	**.005**
		Wikidata	**.003**	**.006**	**.009**
	m.a.i.		.036	.069	.083

stat. sign. results in bold

- Improvement (mostly stat. sign.) in all cases except one

Experiment B

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dataset	setting	back. know.	type (F_1)	link (F_1)	type+link (F_1)
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MERGED	baseline		.898	.686	.672
	JPARK	YAGO	**.002**	**.003**	**.005**
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	JPARK	YAGO	**.002**	**.003**	**.005**
		DBpedia	**.002**	**.003**	**.005**
		Wikidata	**.003**	**.006**	**.009**
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	JPARK	YAGO	**.003**	.001	**.004**
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Overall Outcome

- JPARK enables to consistently improve NERC and EL performances
  - with different combinations of NERC and EL tools
  - with different background knowledge resources
  - on three different datasets

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- JPARK enables to consistently improve NERC and EL performances
  - with different combinations of NERC and EL tools
  - with different background knowledge resources
  - on three different datasets

Does the JPARK a posteriori joint revision of annotations by NERC and EL tools, performed leveraging ontological knowledge, improve NERC and EL performance?

Observations

- Very same instantiation of the model (trained on AIDA) works well on different data and with different tools
- Improvement over the baselines also on AIDA, where most of the considered tools (CoreNLP, Flair, and E2E Neural EL) were trained and developed
- Applicability to other NERC and EL tools: JPARK works on NERC and EL candidate annotations, and not on tools
  - same NERC types and linking KB: the evaluation model can be applied as-is
  - other NERC types and linking KB: reconstruct the model on an appropriate corpus G
- Implemented as a Java module of PIKES (https://pikes.fbk.eu/)
  - performance of the approach clearly depends on the size of the model
  - computation and required memory are basically negligible compared to the annotation tools

Conclusions

JPARK

- A knowledge-driven general probabilistic model for assessing and improving the coherence of NLP annotations
- Concrete implementation of the model for NERC and Entity Linking
- Comprehensive evaluation with various datasets, tools, and background knowledge resources empirically confirmed the benefits of the approach

Future Work

- NERC + EL scenario
  - Application and evaluation with other EL reference knowledge bases and NERC types (e.g., with fine-grained NERC tools)

- Application and validation of the approach to other NLP entity analyses
  - Semantic Role Labeling:

    - role annotations may imply some ontological classes (c.f., “employer” role)
  - Relation Extraction:
    - the type of the relation has implications on the subject and object entities (c.f., “born in” relation)

References

JPARK

Full results and evaluation material:
https://pikes.fbk.eu/jpark.html

Joint Posterior Revision of NLP Annotations via Ontological Knowledge
Marco Rospocher and Francesco Corcoglioniti
27th Int. Joint Conference on Artificial Intelligence, IJCAI 2018
July 13-19, 2018, Stockholm, Sweden
DOI: 10.24963/ijcai.2018/600

Knowledge-driven joint posterior revision of named entity classification and linking
Marco Rospocher and Francesco Corcoglioniti
Journal of Web Semantics vol. 65:100617 (2020)
DOI: 10.1016/j.websem.2020.100617

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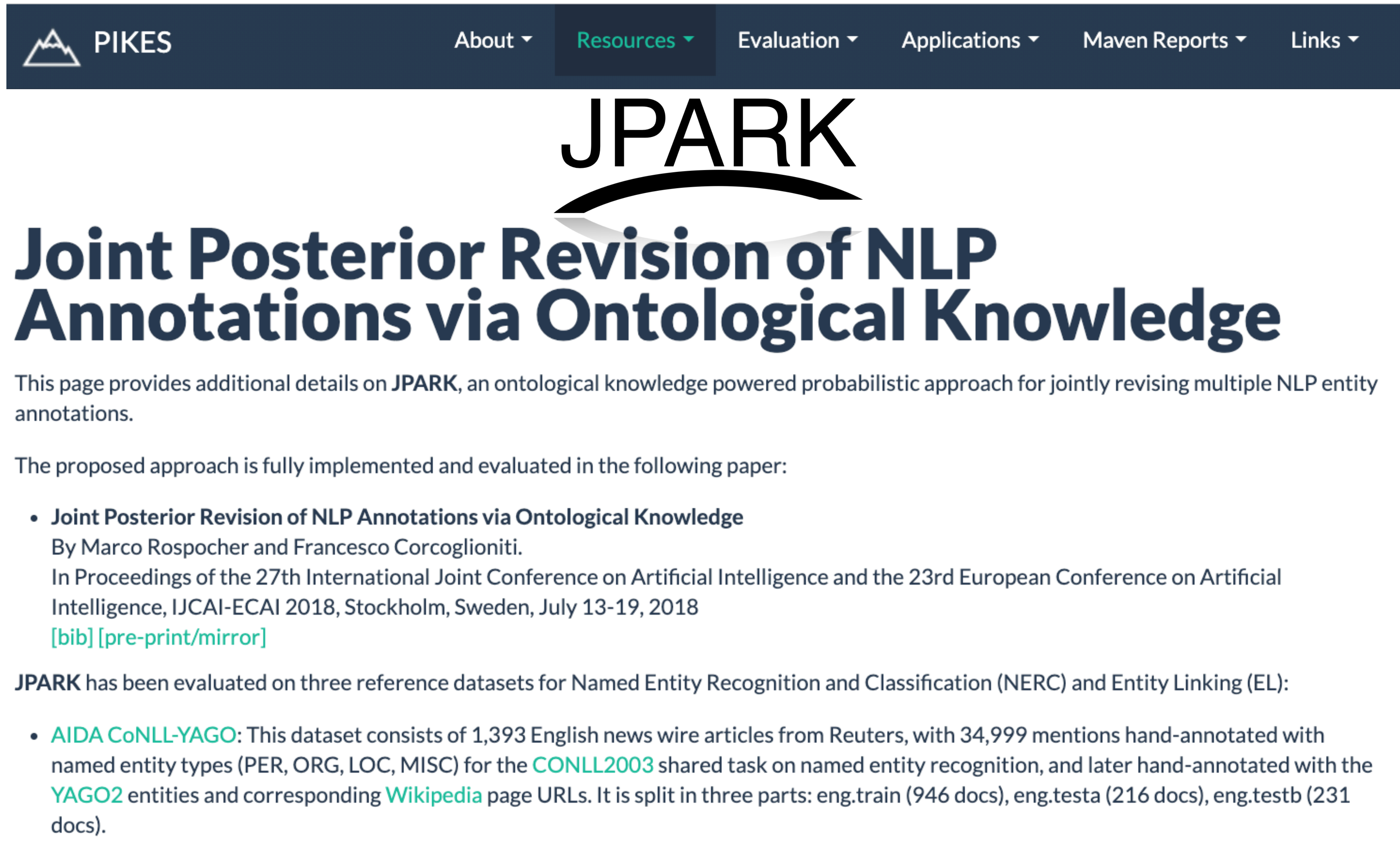
PIKES About Resources Evaluation Applications Maven Reports Links

JPARK

Joint Posterior Revision of NLP Annotations via Ontological Knowledge

This page provides additional details on **JPARK**, an ontological knowledge powered probabilistic approach for jointly revising multiple NLP entity annotations.

The proposed approach is fully implemented and evaluated in the following paper:

- **Joint Posterior Revision of NLP Annotations via Ontological Knowledge**
  By Marco Rospocher and Francesco Corcoglioniti.
  In Proceedings of the 27th International Joint Conference on Artificial Intelligence and the 23rd European Conference on Artificial Intelligence, IJCAI-ECAI 2018, Stockholm, Sweden, July 13-19, 2018
  [bib] [pre-print/mirror]

JPARK has been evaluated on three reference datasets for Named Entity Recognition and Classification (NERC) and Entity Linking (EL):

- AIDA CoNLL-YAGO: This dataset consists of 1,393 English news wire articles from Reuters, with 34,999 mentions hand-annotated with named entity types (PER, ORG, LOC, MISC) for the CONLL2003 shared task on named entity recognition, and later hand-annotated with the YAGO2 entities and corresponding Wikipedia page URLs. It is split in three parts: eng.train (946 docs), eng.testa (216 docs), eng.testb (231 docs).

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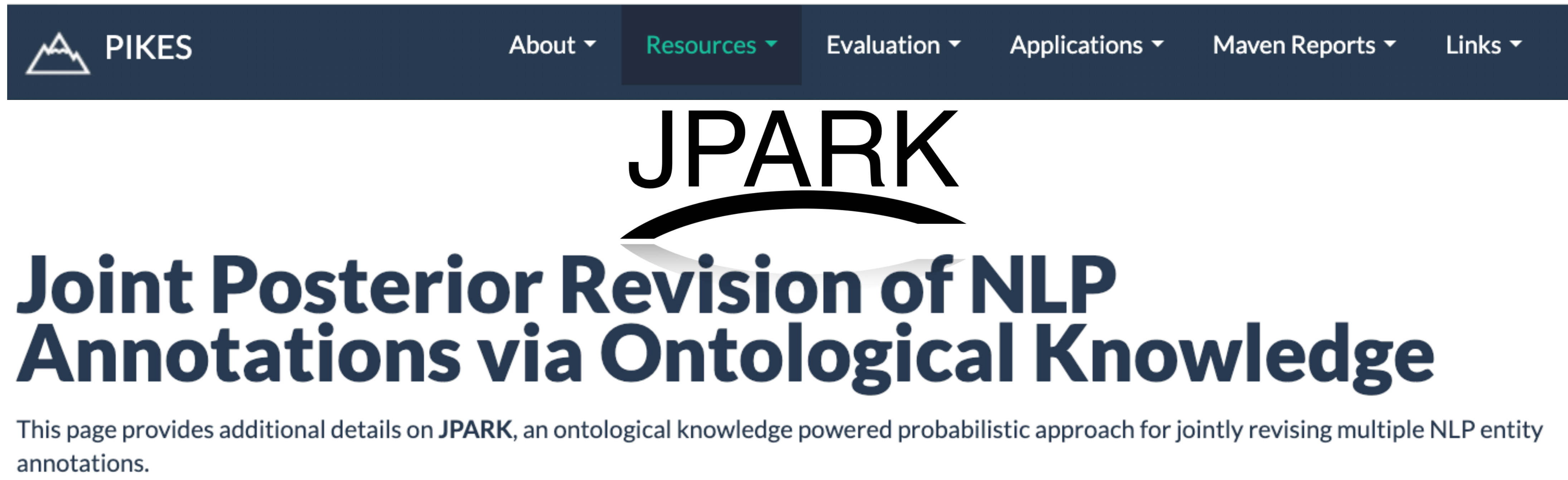

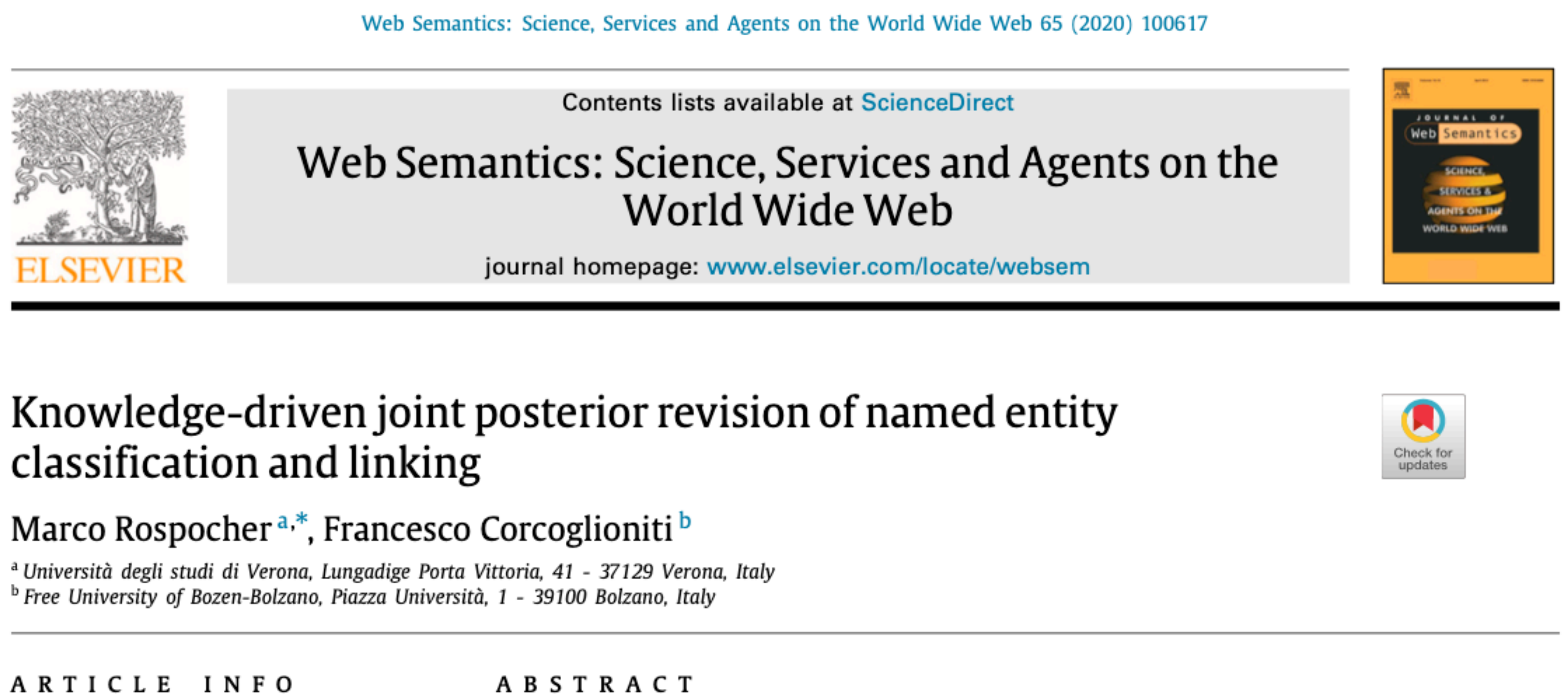

pikes.fbk.eu/jpark

pikes.fbk.eu/ke4ir

BPMN Ontology

dkm.fbk.eu/bpmn-ontology

premon.fbk.eu

bit.ly/pescado-onto

Event & Situation Ontology

github.com/newsreader/eso

pikes.fbk.eu

pikes.fbk.eu/psl4ea

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UNIVERSITÀ di VERONA

Dipartimento di LINGUE E LETTERATURE STRANIERE

Dipartimento di Eccellenza 2018/2022 MIUR

Slides

github.com/rospocher/explicit-lyrics-detection/

rdfpro.fbk.eu

KnowledgeStore

knowledgestore.fbk.eu

the Modelling WiKi ---

moki.fbk.eu

github.com/dkmfbk/TexOwl