

Joint Posterior Revision of NLP Entity Annotations via Ontological Knowledge

Marco Rospocher

(Joint work with Francesco Corcoglioniti @ UniBZ)



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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

Kia has hired Peter Schreyer as chief design officer.

NLP Tasks:

- Named Entity Recognition and Classification (NERC)



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dbpedia:Kia_Motors

Kia has hired Peter Schreyer as chief design officer.

NLP Tasks:

- Named Entity Recognition and Classification (NERC)
- Entity Linking (EL)



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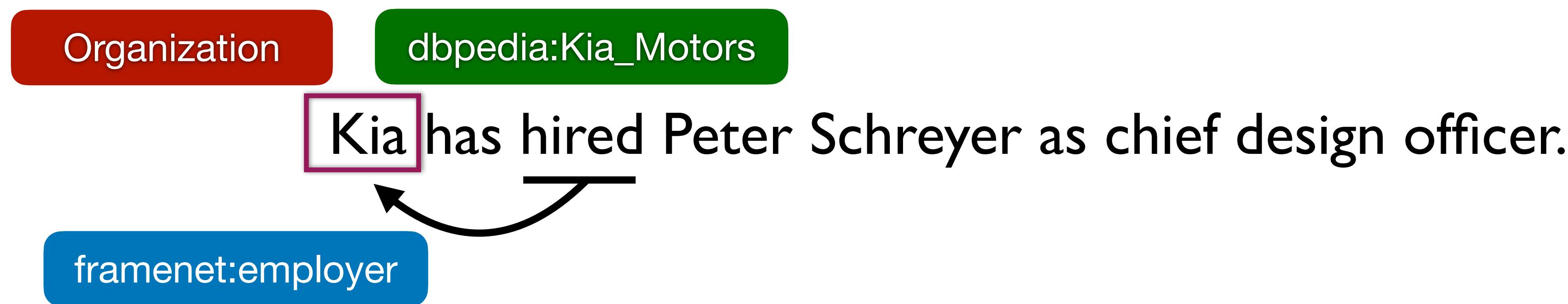
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Research Context

- Knowledge graph extraction from text



NLP Tasks:

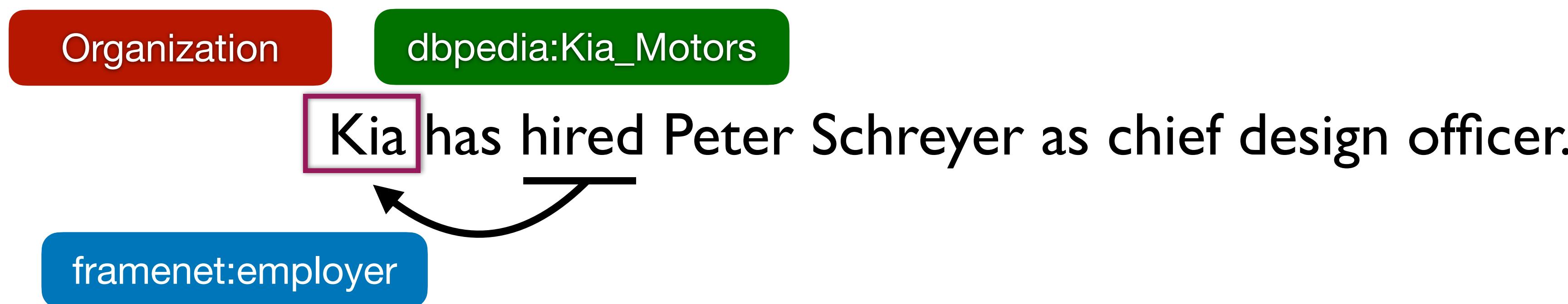
- Named Entity Recognition and Classification (NERC)
- Entity Linking (EL)
- Semantic Role Labeling (SRL)
- ...

Research Context

- Knowledge graph extraction from text



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



NLP Tasks:

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- Entity Linking (EL)
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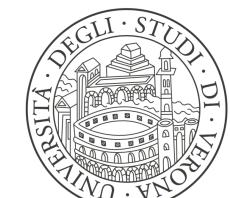
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What may happen in practice...

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

Eric Clapton is one of the greatest guitar players.

DBpedia Spotlight

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dbpedia:Washington_(state)

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Person



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

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Location



San Jose is one of the strongest hockey teams.

dbpedia:San_Jose_Sharks



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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?



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Leveraging Ontological Knowledge!

... token₁ token₂ token₃ token₄ token₅ token₆



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... token₁ token₂ token₃ token₄ token₅ token₆



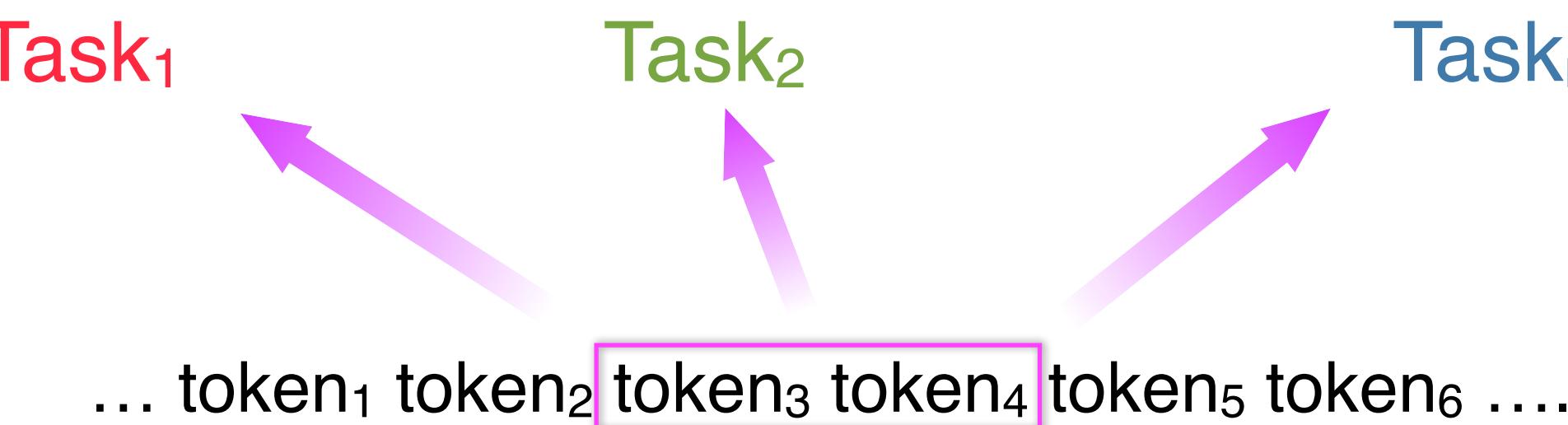
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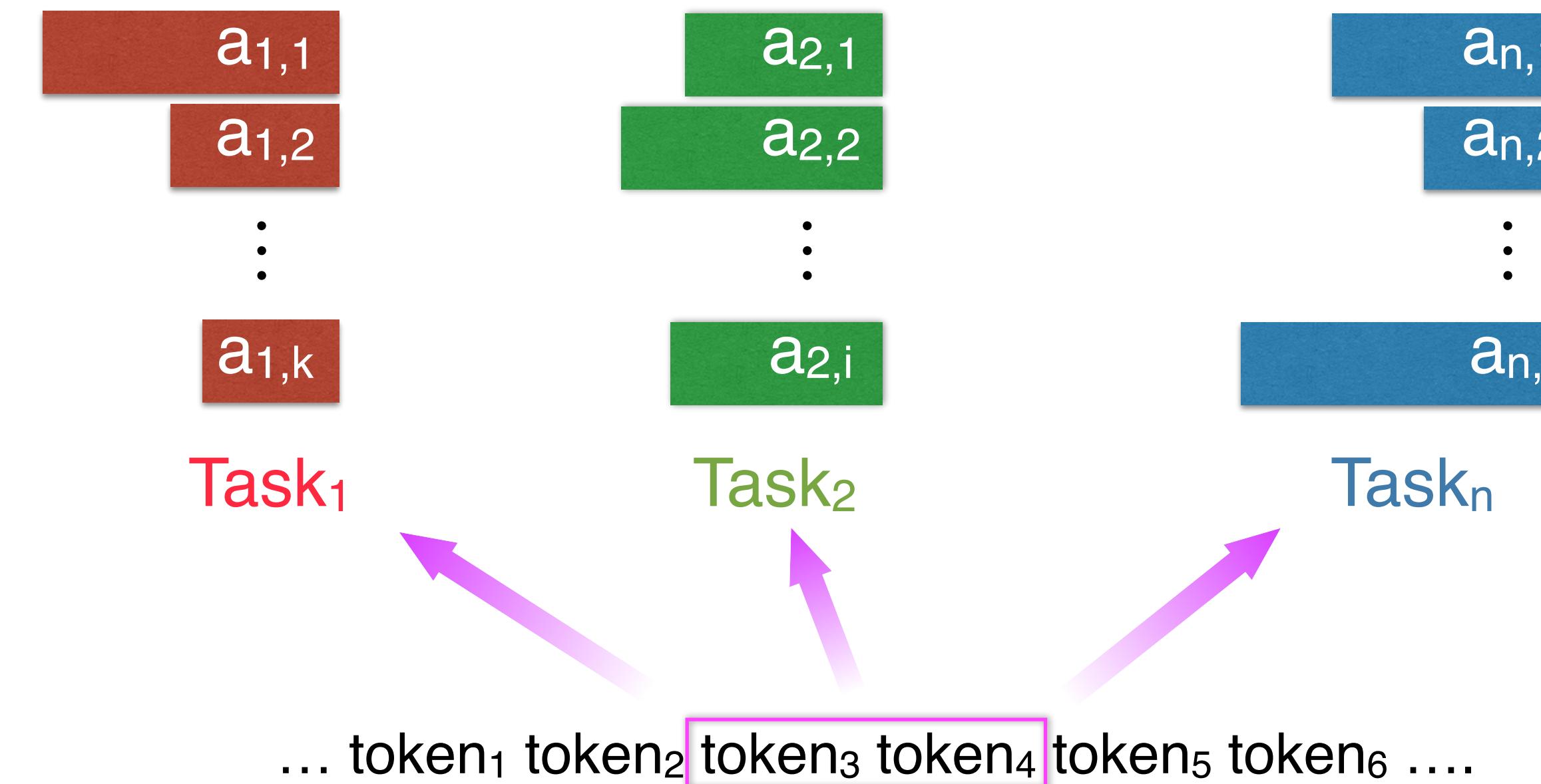


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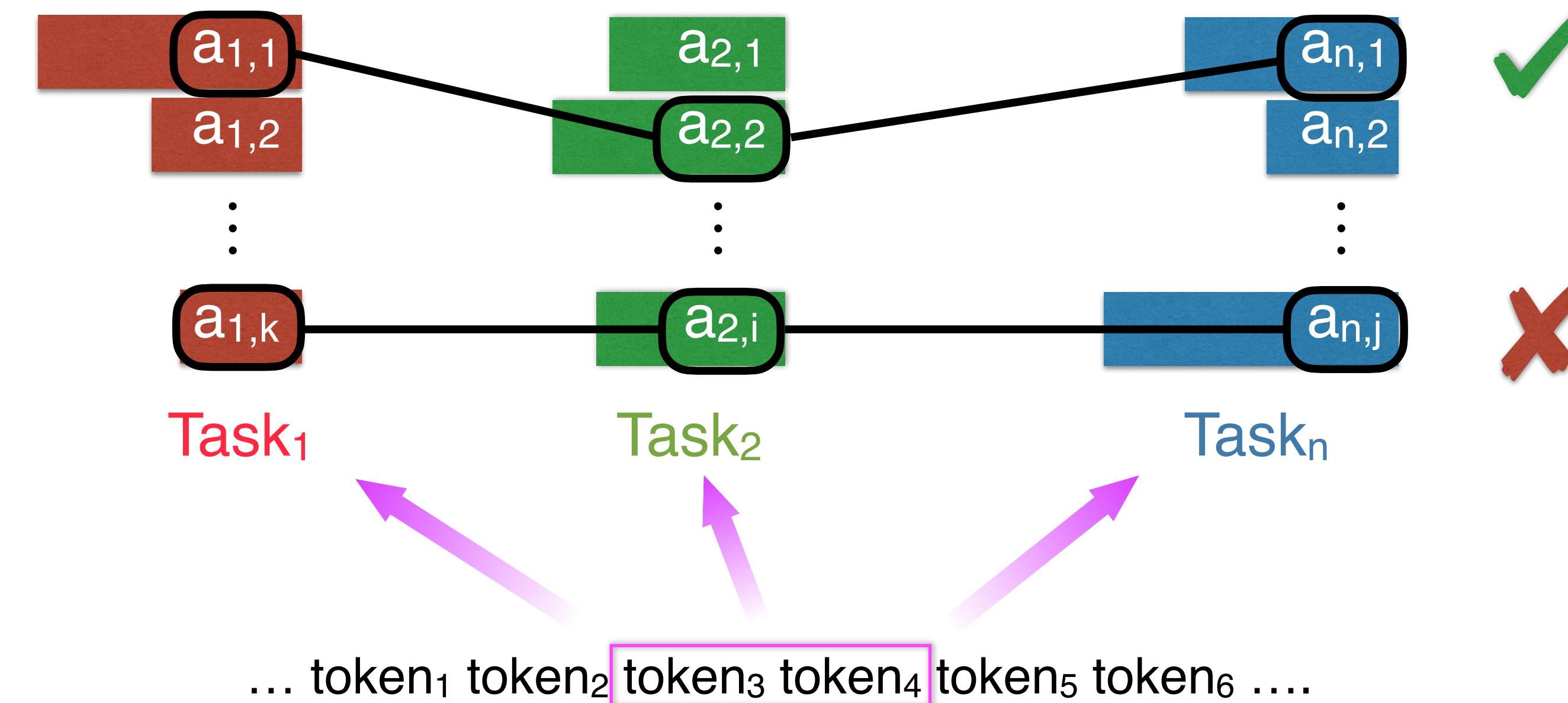
Leveraging Ontological Knowledge!



Leveraging Ontological Knowledge!

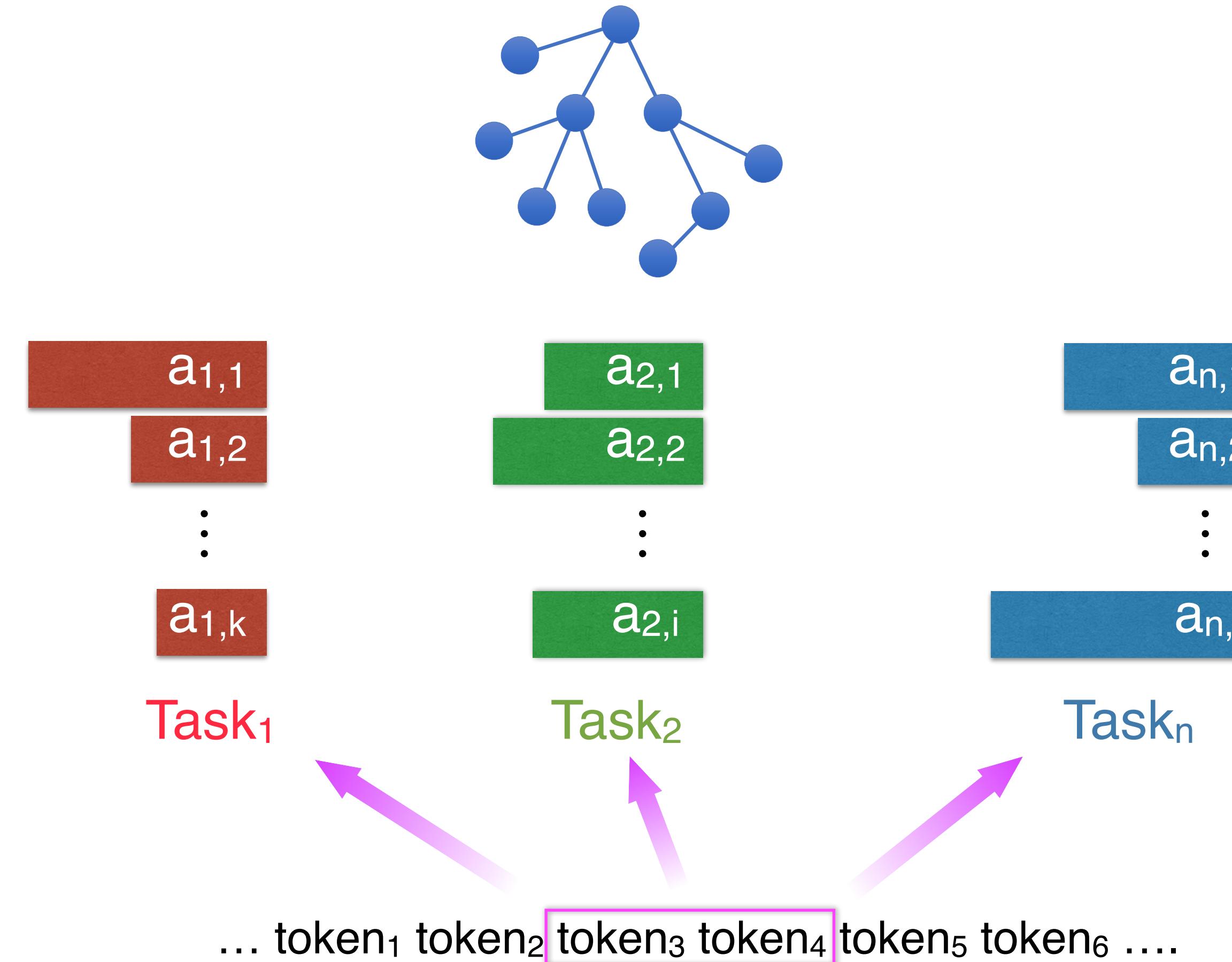


Leveraging Ontological Knowledge!

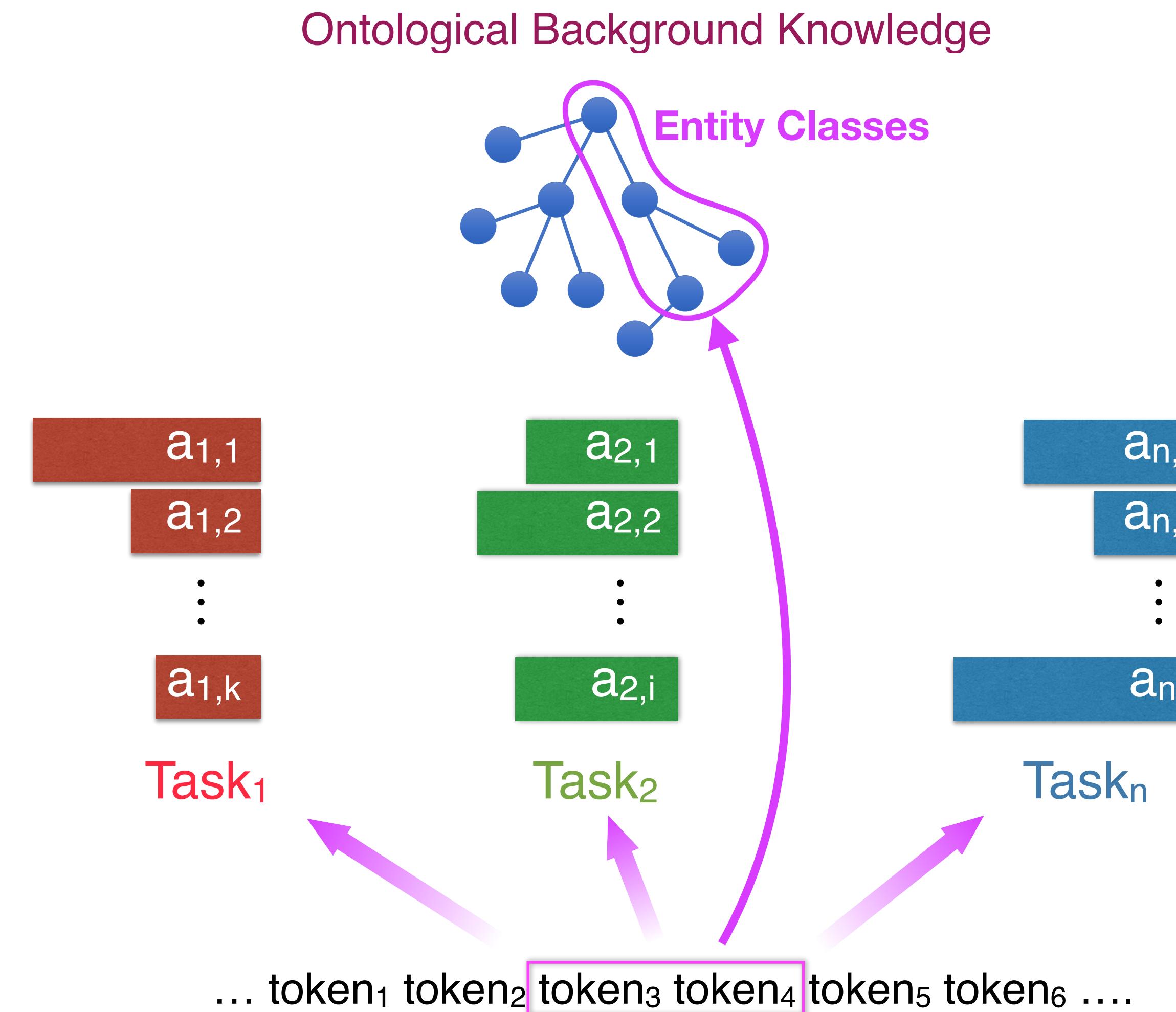


Leveraging Ontological Knowledge!

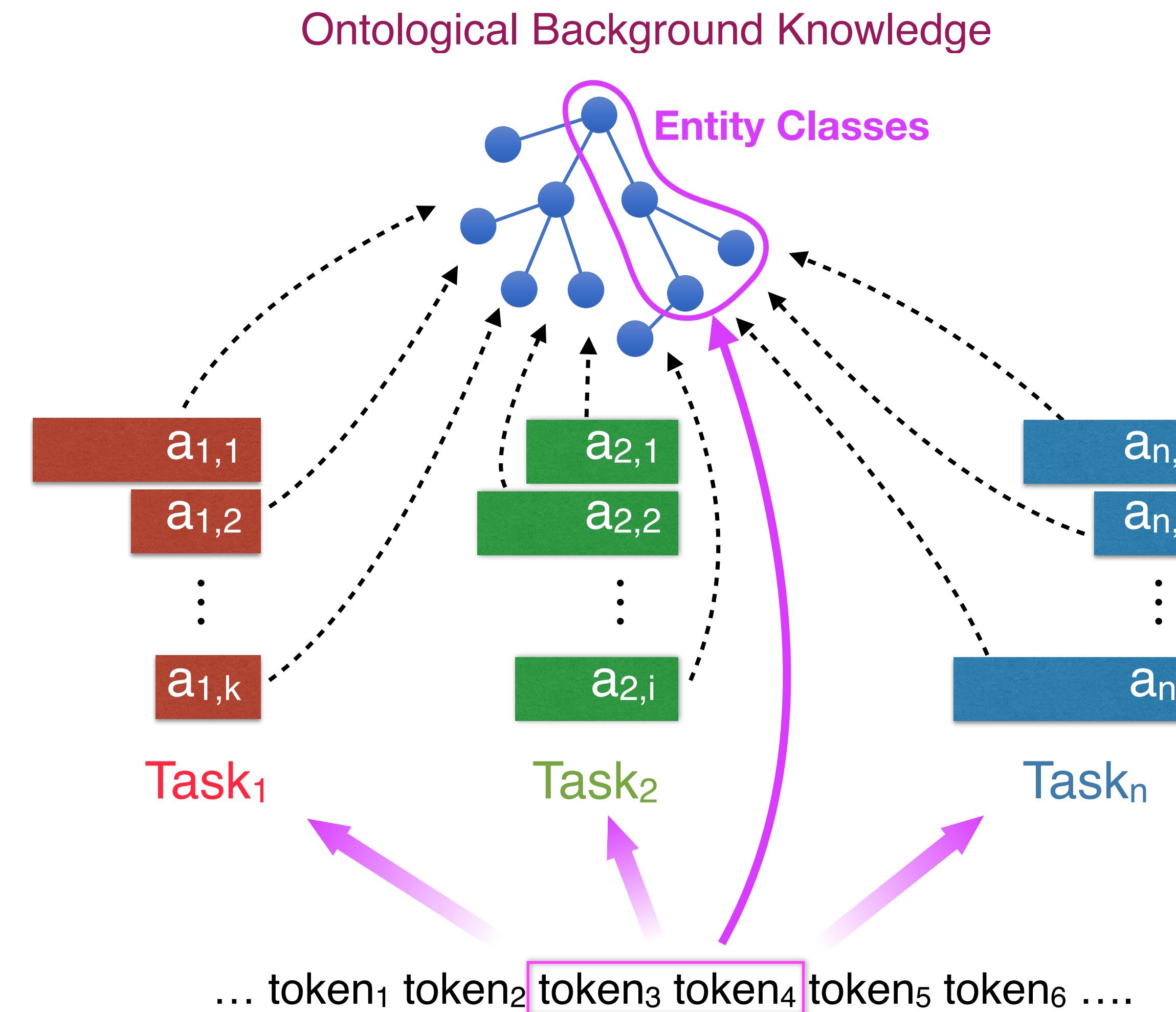
Ontological Background Knowledge



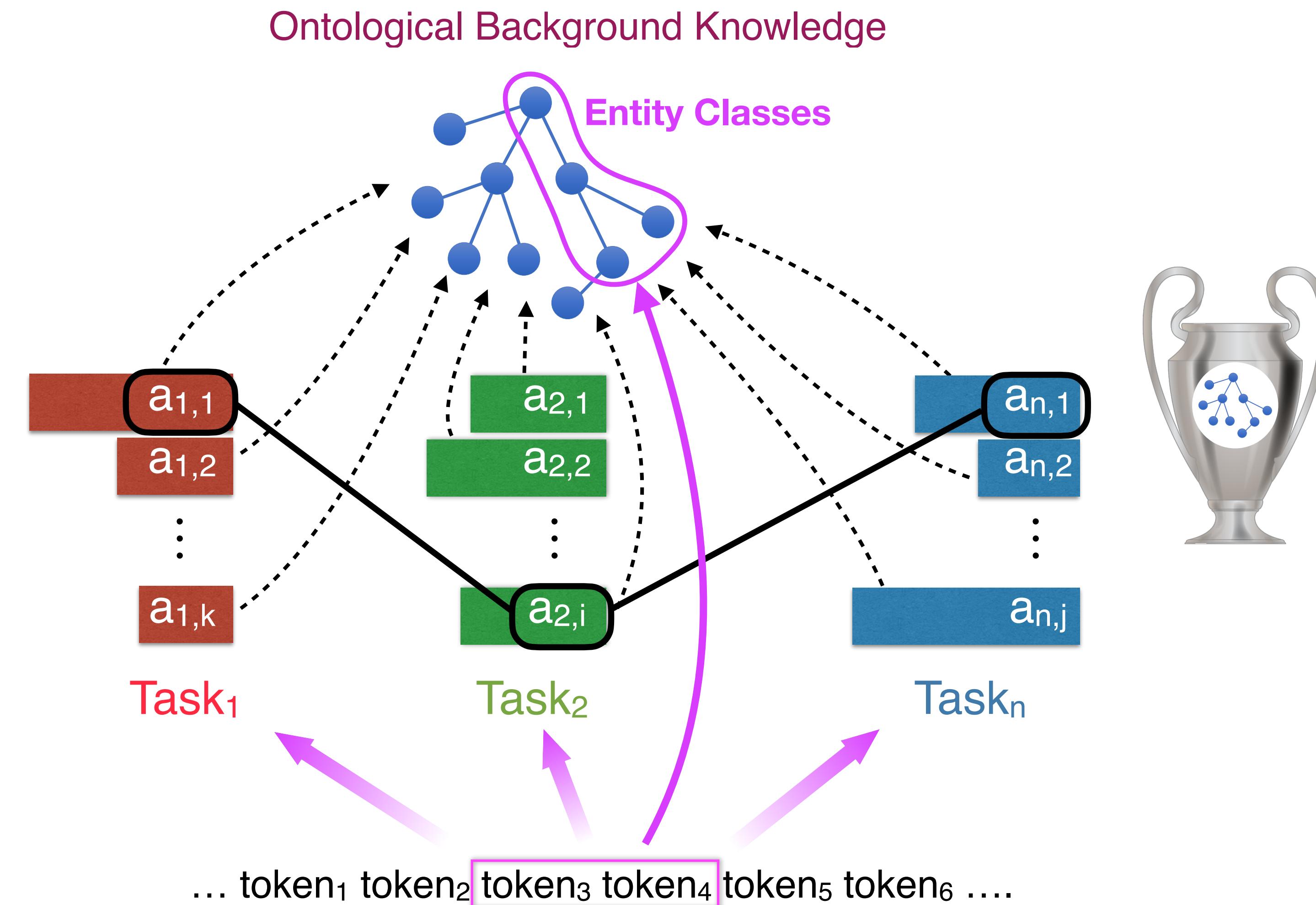
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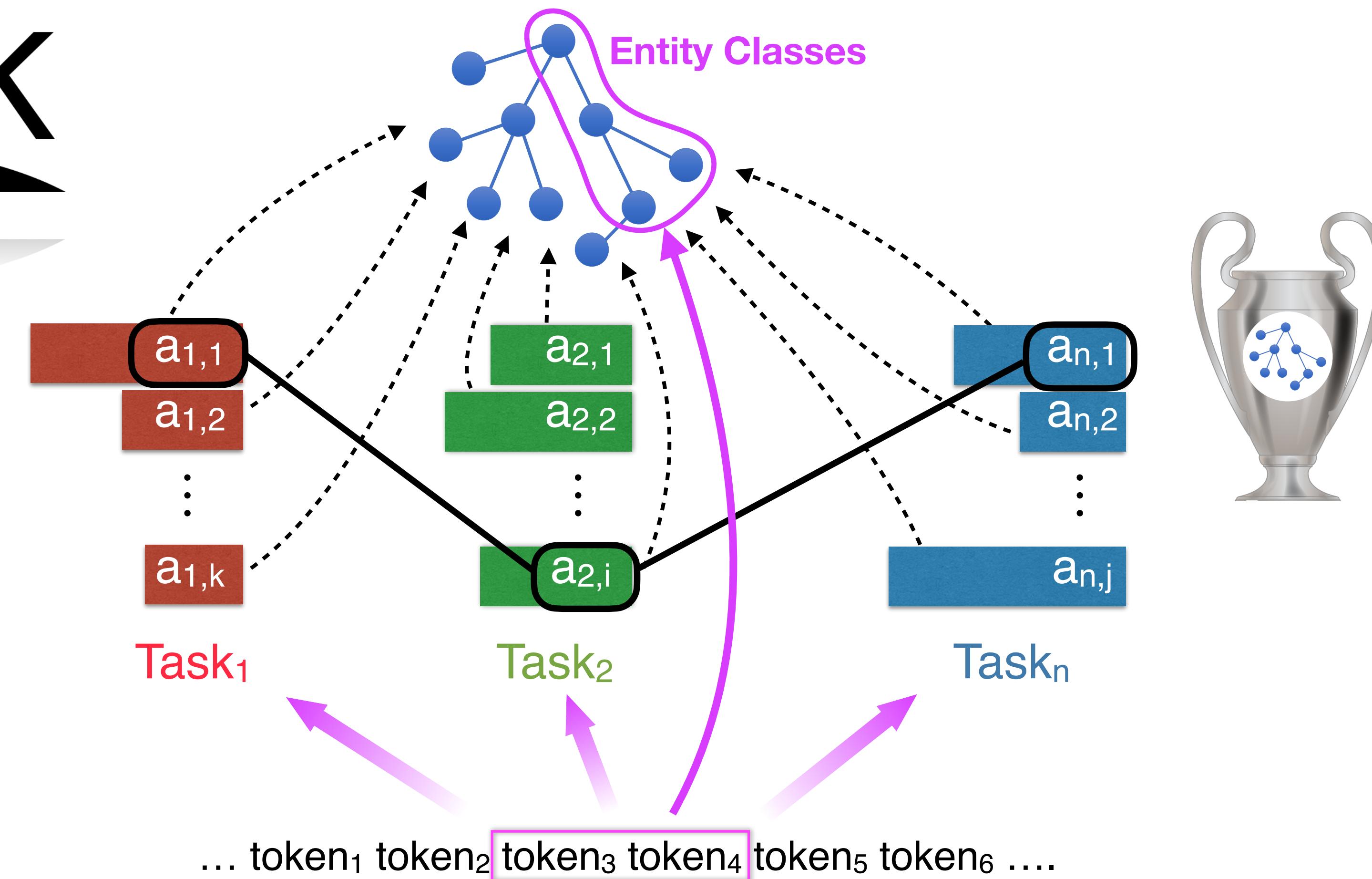
Leveraging Ontological Knowledge!



Leveraging Ontological Knowledge!



Ontological Background Knowledge



How does JPARK work?



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



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How does JPARK work?



(a_i, \dots, a_n) NLP Annotations

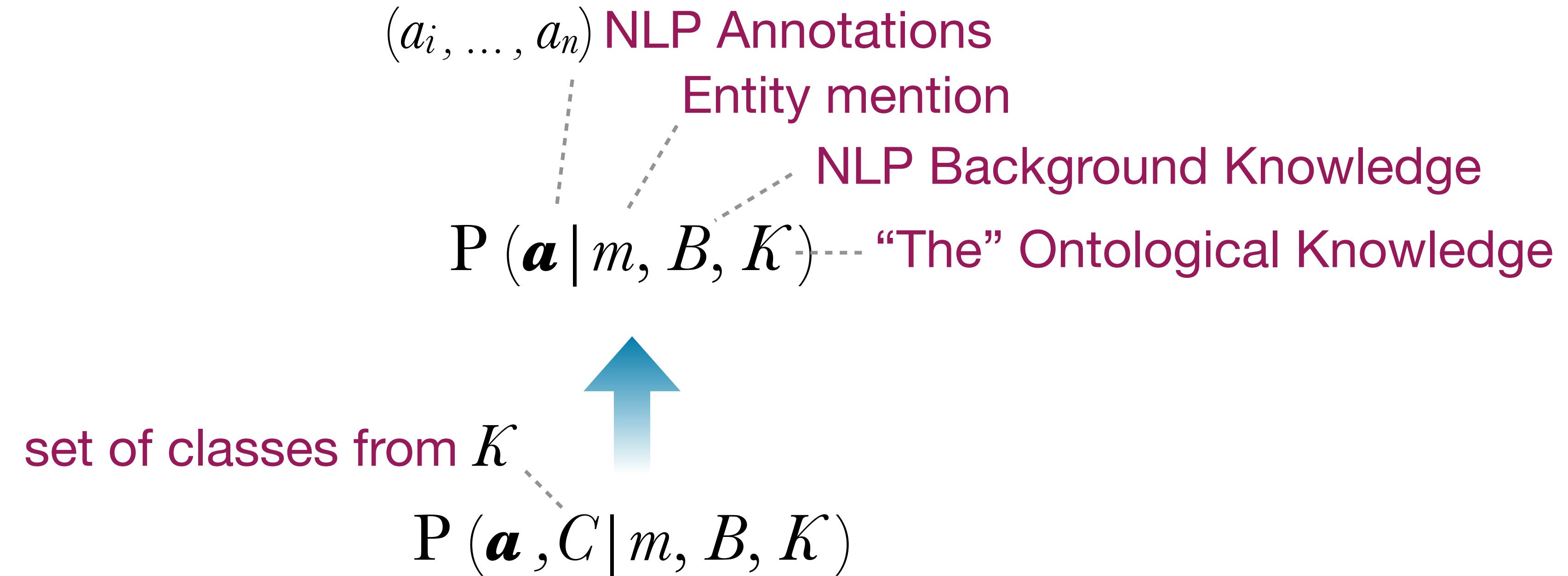
Entity mention

NLP Background Knowledge

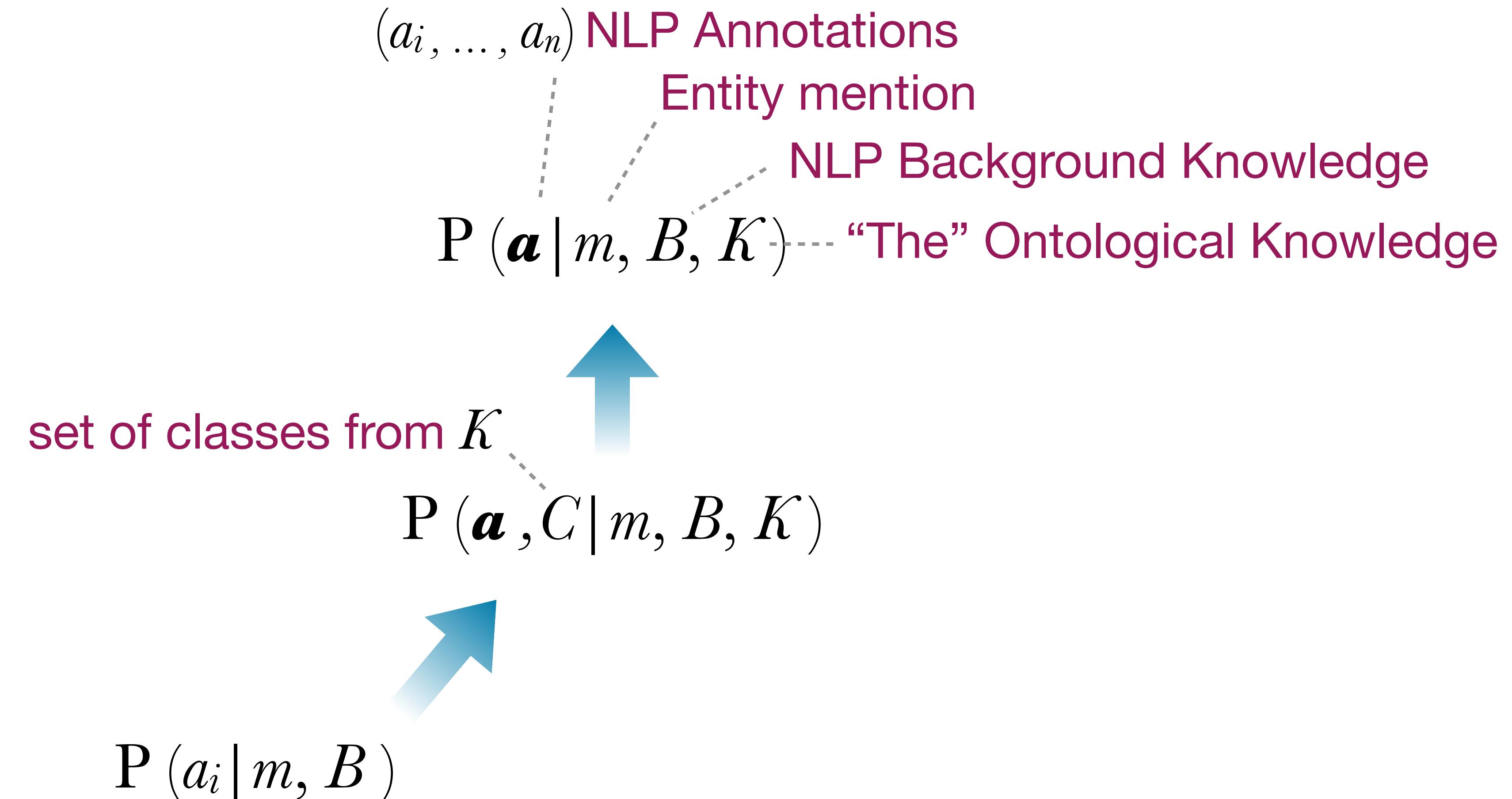
$P(a | m, B, K)$ “The” Ontological Knowledge



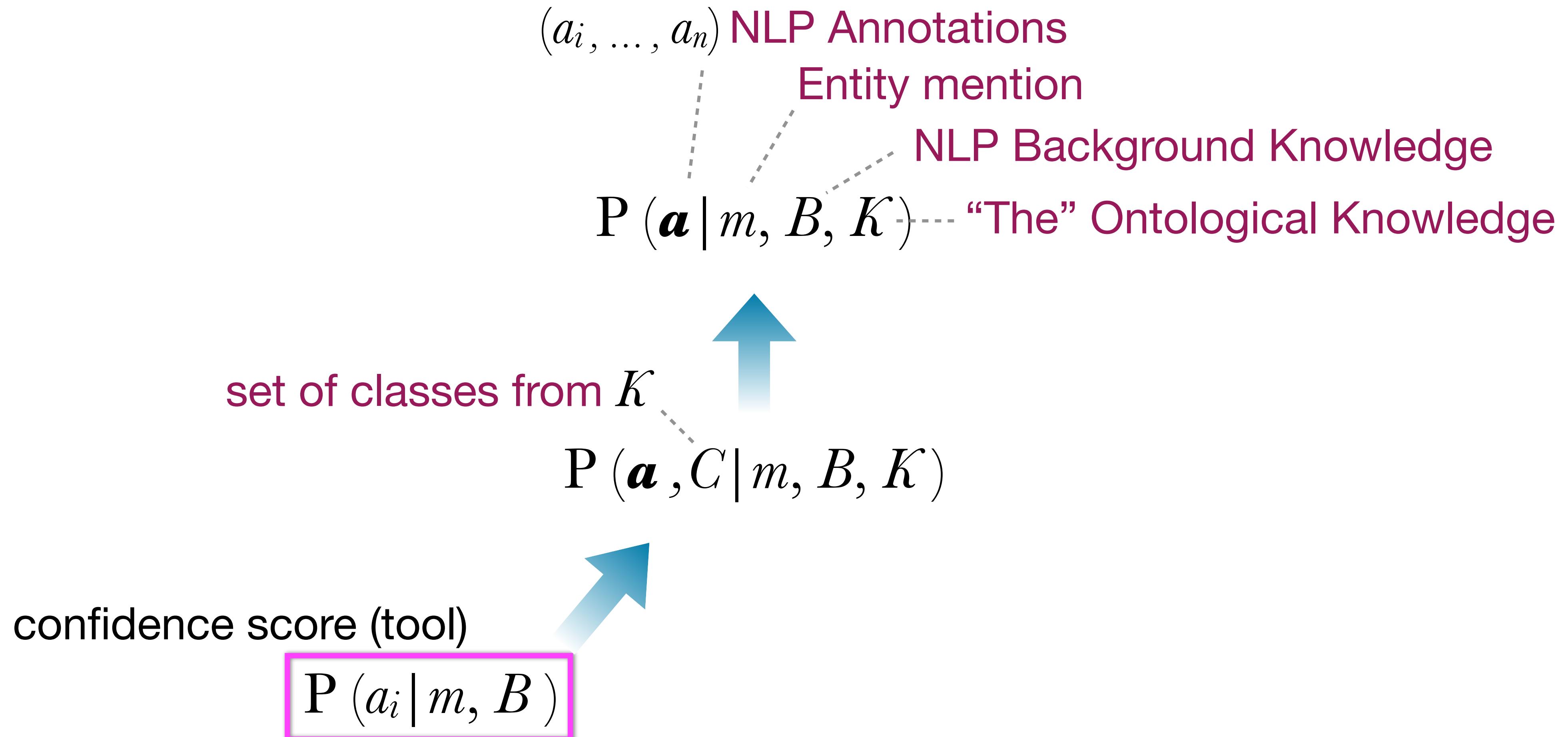
How does JPARK work?



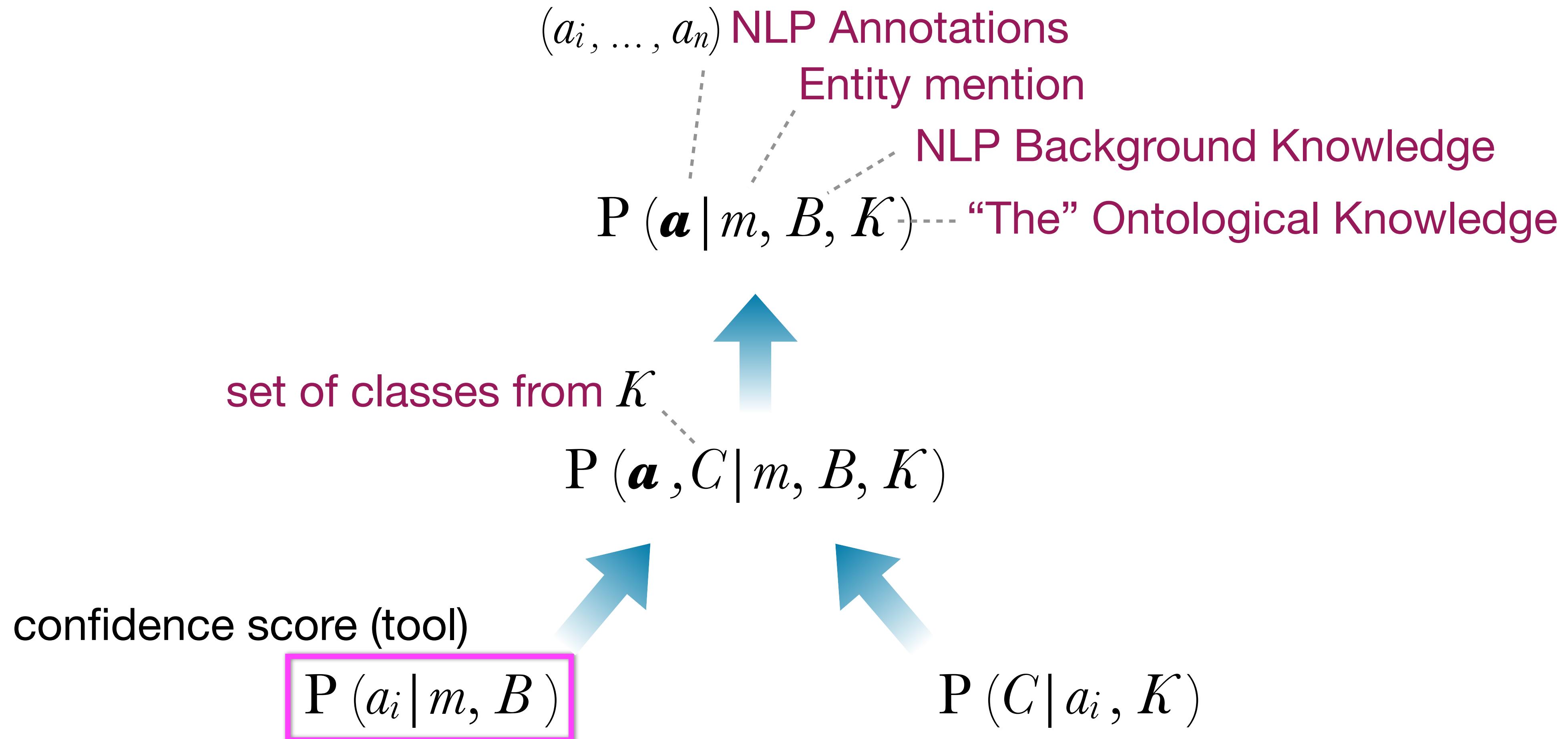
How does JPARK work?



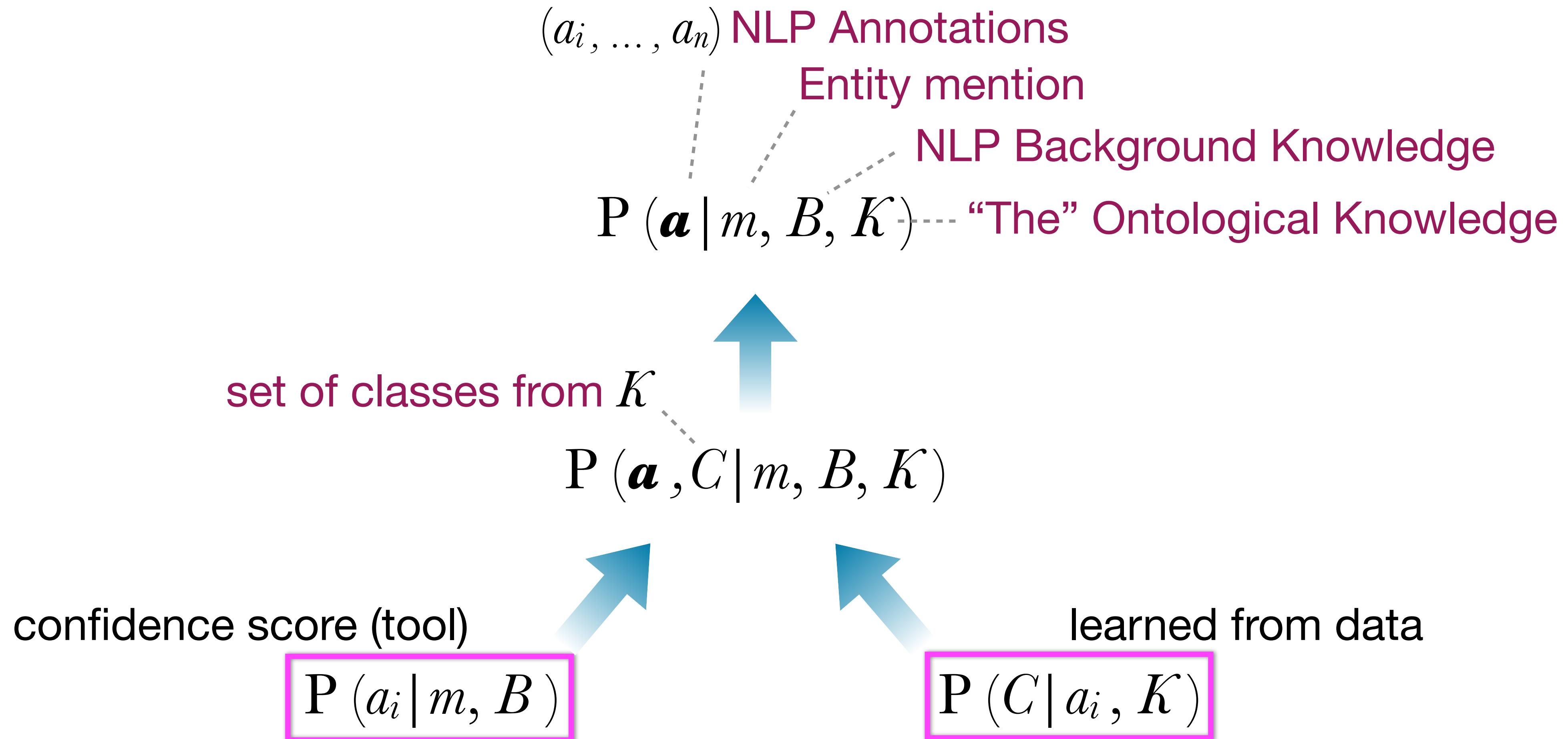
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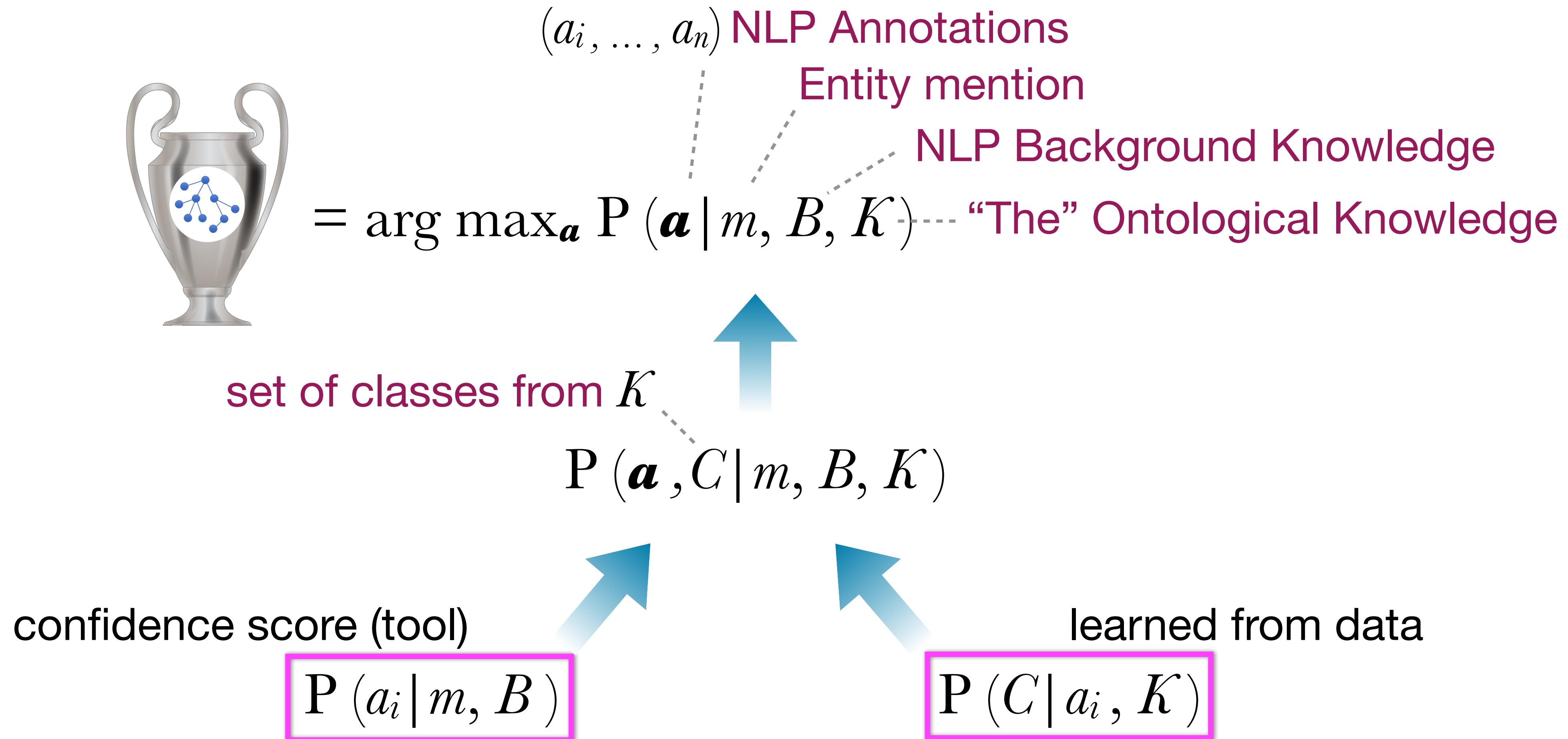
How does JPARK work?



How does JPARK work?



How does JPARK work?



Building a JPARK model for NERC and Entity Linking



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Handling NERC Annotations

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

$$P(C | a_{\text{NERC}}, K) =$$

- 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



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Handling NERC Annotations

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

$$\text{P} (C | a_{\text{NERC}}, K) = \frac{\text{\# occurrences}}{\sum_{C^*} n_G (C^*, a_{\text{NERC}})}$$

$n_G (C, a_{\text{NERC}})$

- We rely on a Gold Standard G containing entity mentions that
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Handling NERC Annotations

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

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

occurrences
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 necessarily 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}

$$P(C | a_{\text{EL}}, K) =$$



Handling EL Annotations

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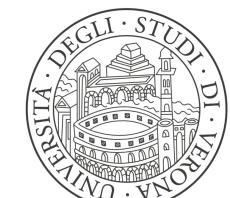
$$P(C | a_{\text{EL}}, K) = \begin{cases} 1 & C = C_K(a_{\text{EL}}) \\ 0 & \text{otherwise} \end{cases}$$



Handling EL Annotations: NIL

- What about **NIL** (i.e., an entity lacking a corresponding referent in the linking knowledge base)? Can we estimate $P(C|NIL, K)$?

$$P(C|NIL, K) = \sum_{a_{\text{NERC}}} P(C|a_{\text{NERC}}, K) \cdot P(a_{\text{NERC}}|NIL, K)$$



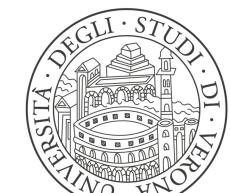
Handling EL Annotations: NIL

- What about NIL (i.e., an entity lacking a corresponding referent in the linking knowledge base)? Can we estimate $P(C|NIL, K)$?

Already computed for handling NERC

$$P(C|NIL, K) = \sum_{a_{\text{NERC}}} P(C|a_{\text{NERC}}, K) \cdot P(a_{\text{NERC}}|NIL, K)$$

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 **JPAR \overline{K}**
- **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



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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 per Entity
		Total	PER	ORG	LOC	MISC	frac.	PER	ORG	LOC	MISC	
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



Version 3
entities: 6,016,695
classes: 568,255
class sets: 2,126,074



Version 2016-04
entities: 5,109,890
classes: 754
class sets: 413



Dump 2018.08
entities: 5,854,808
classes: 21,864
class sets: 32,648



Background Ontological Knowledge



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owl:sameAs links

EL Knowledge Base

1:1



owl:sameAs links



WIKIPEDIA
The Free Encyclopedia



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2,041

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35

Dump 2018.08
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class sets: ~~32,648~~
711

owl:sameAs links

EL Knowledge Base



1:1

owl:sameAs links

Tools

Experiment A:

popular, frequently used tools



CONLL2003 (PER, ORG, LOC, MISC)



DBpedia, NIL

Experiment B:

high-performance neural approaches



CONLL2003 (PER, ORG, LOC, MISC)

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

Wikipedia/DBpedia, NO NIL

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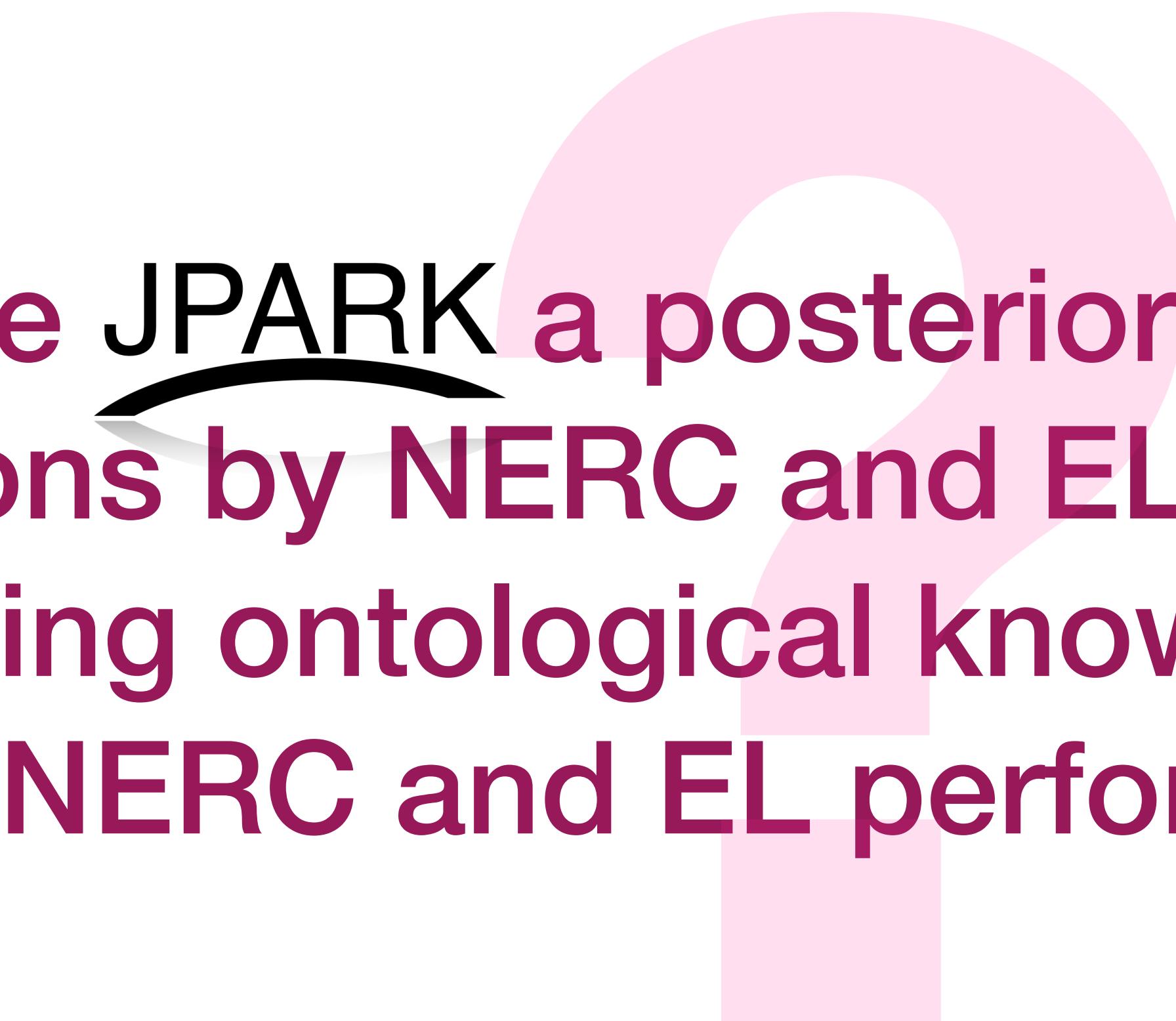


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Joint Posterior Revision of NLP Entity Annotations via Ontological Knowledge



**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.

The logo for JPARK + NIL. It features the word "JPARK" in large, bold, black capital letters at the top. Below it is a thick, black, curved swoosh graphic that dips down towards the right. To the right of the swoosh, the word "NIL" is written in large, bold, magenta capital letters, with a plus sign ("+" in magenta) positioned to its left.

- Experiment B (Flair + E2E Neural EL)

baseline

vs.

JPARK



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Experiment A



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

stat. sign. results in bold



Experiment A

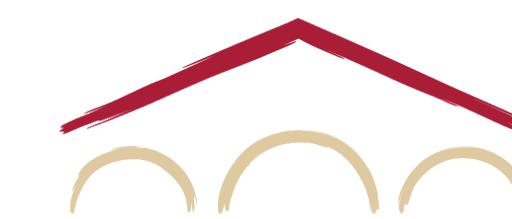


dataset	setting	back. know.	type (F_1)	+NIL	link (F_1)	+NIL	type+link (F_1)	+NIL
AIDA	JPARK	baseline	.908		.656		.630	
		YAGO	.006	.005	.006	.023	.016	.035
		DBpedia	.004	.004	.008	.013	.014	.024
	m.a.i.	Wikidata	.008	.005	.005	.013	.015	.027
			.053		.102		.127	
MEANTIME	JPARK	baseline	.777		.621		.561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

stat. sign. results in bold



Experiment A



dataset	setting	back. know.	type (F_1)	+NIL	link (F_1)	+NIL	type+link (F_1)	+NIL
AIDA	JPARK	baseline	.908		.656		.630	
		YAGO	.006	.005	.006	.023	.016	.035
		DBpedia	.004	.004	.008	.013	.014	.024
	m.a.i.	Wikidata	.008	.005	.005	.013	.015	.027
		baseline	.053		.102		.127	
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MEANTIME	JPARK	DBpedia	.028	.021	.001	-.005	.031	.025
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TAC KBP	JPARK	Wikidata	.019	.015	.019	.031	.035	.054
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		DBpedia	.011	.009	.006	.024	.019	.041
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MERGED	m.a.i.	baseline	.065		.133		.165	
		YAGO	.013	.010	.009	.019	.024	.039

stat. sign. results in bold

- Improvement (mostly stat. sign.) almost everywhere

Experiment A



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

stat. sign. results in bold

- Improvement (mostly stat. sign.) almost everywhere
- Particularly effective in selecting the correct annotation couple

Experiment A



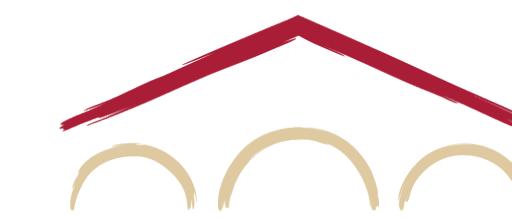
=

dataset	setting	back. know.	type (F_1)	+NIL	link (F_1)	+NIL	type+link (F_1)	+NIL
AIDA	JPARK	baseline	.908		.656		.630	
		YAGO	.006	.005	.006	.023	.016	.035
		DBpedia	.004	.004	.008	.013	.014	.024
	m.a.i.	Wikidata	.008	.005	.005	.013	.015	.027
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MEANTIME	JPARK	DBpedia	.028	.021	.001	-.005	.031	.025
		Wikidata	.030	.026	-.002	.000	.027	.030
		m.a.i.	.028	.024	.000	.008	.029	.042
	m.a.i.	baseline	.096		.106		.162	
		YAGO	.760		.412		.376	
		DBpedia	.012	.013	.007	.027	.019	.049
TAC KBP	JPARK	Wikidata	.019	.015	.019	.031	.035	.054
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		Wikidata	.012	.010	.011	.020	.024	.037
	m.a.i.	baseline	.013	.010	.009	.019	.024	.039
		YAGO	.065		.133		.165	

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Experiment A



=

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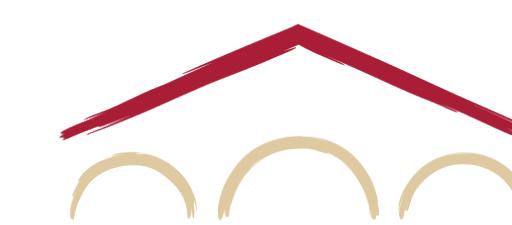
<

dataset	setting	back. know.	type (F_1)	+NIL	link (F_1)	+NIL	type+link (F_1)	+NIL
AIDA	JPARK	baseline		.908		.656		.630
		YAGO		.006		.005		.016
		DBpedia		.004		.004		.014
	m.a.i.	Wikidata		.008		.005		.015
		baseline		.053		.102		.127
		YAGO		.028		.021		.031
MEANTIME	JPARK	DBpedia		.030		.026		.027
		Wikidata		.028		.024		.029
		m.a.i.		.096		.106		.162
	JPARK	baseline		.760		.412		.376
		YAGO		.012		.013		.019
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	m.a.i.	Wikidata		.013		.010		.024
MERGED	JPARK	baseline		.065		.133		.165
		YAGO						
		DBpedia						
	m.a.i.	Wikidata						

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Experiment A



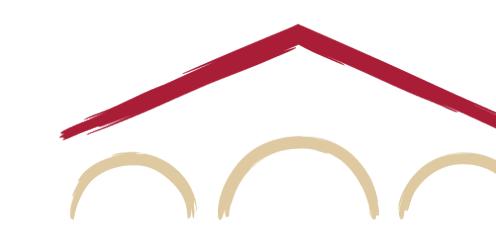
dataset	setting	back. know.	type (F_1)	+NIL	link (F_1)	+NIL	type+link (F_1)	+NIL
AIDA	JPARK	baseline	.908		.656		.630	
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		baseline	.065		.133		.165	

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- NIL strategy almost on par with NO-NIL on type, but better on link and type+link
- Improvement consistent with all background knowledge resources



Experiment A



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

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
- 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	JPARK	baseline	.949	.798	.786
		YAGO	.001	.004	.005
		DBpedia	.001	.002	.003
		Wikidata	.000	.004	.004
	m.a.i.		.033	.079	.091
MEANTIME	JPARK	baseline	.845	.705	.669
		YAGO	.006	.001	.007
		DBpedia	.008	.001	.010
		Wikidata	.008	.001	.010
	m.a.i.		.069	.024	.060
TAC KBP	JPARK	baseline	.843	.458	.448
		YAGO	.003	.001	.004
		DBpedia	.004	.003	.007
		Wikidata	.004	.013	.017
	m.a.i.		.033	.062	.072
MERGED	JPARK	baseline	.898	.686	.672
		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



End-to-End
Neural EL

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

stat. sign. results in bold



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Experiment B

flair +

End-to-End
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		YAGO	.001	.004	.005
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End-to-End
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		YAGO	.001	.004	.005
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MERGED	JPARK	Wikidata	.003	.006	.009
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Experiment B



End-to-End
Neural EL

dataset	setting	back. know.	type (F_1)	link (F_1)	type+link (F_1)
AIDA	JPARK	baseline	.949	.798	.786
		YAGO	.001	.004	.005
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		m.a.i.	.036	.069	.083
			stat. sign. results in bold		

- Improvement (mostly stat. sign.) in all cases except one
- Particularly effective in selecting the correct annotation couple
- Improvement consistent with all background knowledge resources
- Improvement ~10-20% of the maximum achievable one



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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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

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



- 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



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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



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](https://doi.org/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](https://doi.org/10.1016/j.websem.2020.100617)



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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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JPARK Joint Posterior Revision of NLP Annotations via Ontological Knowledge

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Joint Posterior Revision of NLP Annotations via Ontological Knowledge

Marco Rospocher, Francesco Corcoglioniti

Proceedings of the Twenty-Seventh International Joint Conference on Artificial Intelligence
Main track. Pages 4316-4322. <https://doi.org/10.24963/ijcai.2018/600>



[PDF](#) [BibTeX](#)

Different well-established NLP tasks contribute to elicit the semantics of entities mentioned in natural language text, such as Named Entity Recognition and Classification (NERC) and Entity Linking (EL). However, combining the outcomes of these tasks may result in NLP annotations -- such as a NERC organization linked by EL to a person -- that are unlikely or contradictory when interpreted in the light of common world knowledge about the entities these annotations refer to. We thus propose a general probabilistic model that explicitly captures the relations between multiple NLP annotations for an entity mention, the ontological entity classes implied by those annotations, and the background ontological knowledge those classes may be consistent with. We use the model to estimate the posterior probability of NLP annotations given their confidences (prior probabilities) and the ontological knowledge, and consequently revise the best annotation choice performed by the NLP tools. In a concrete scenario with two state-of-the-art tools for NERC and EL, we experimentally show on three reference datasets that for these tasks, the joint annotation revision performed by the model consistently improves on the original results of the tools.

Keywords:

Natural Language Processing: NLP Applications and Tools
Natural Language Processing: Knowledge Extraction
Natural Language Processing: Named Entities

References



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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 screenshot shows the IJCAI 2018 conference website. At the top, there's a navigation bar with links for HOME, CONFERENCES, PROCEEDINGS, AWARDS, TRUSTEES/OFFICERS, AI JOURNAL, and ABOUT. The main content area displays the paper "Joint Posterior Revision of NLP Annotations via Ontological Knowledge" by Marco Rospocher and Francesco Corcoglioniti. Below the title, it says "Proceedings of the Twenty-Seventh International Joint Conference on Artificial Intelligence Main track. Pages 4316-4322. <https://doi.org/10.24963/ijcai.2018/600>". To the right, there's a small logo for "IJCAI ECAI 2018". At the bottom right, there are PDF and BibTeX download links.

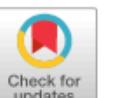
Web Semantics: Science, Services and Agents on the World Wide Web 65 (2020) 100617



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World Wide Web

journal homepage: www.elsevier.com/locate/websem



Knowledge-driven joint posterior revision of named entity classification and linking

Marco Rospocher ^{a,*}, Francesco Corcoglioniti ^b

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^b Free University of Bozen-Bolzano, Piazza Università, 1 - 39100 Bolzano, Italy

ARTICLE INFO

ABSTRACT



BPMN Ontology

dkm.fbk.eu/bpmn-ontology



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

KnowledgeStore
knowledgestore.fbk.eu



Slides



github.com/dkmfbk/TexOwl

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