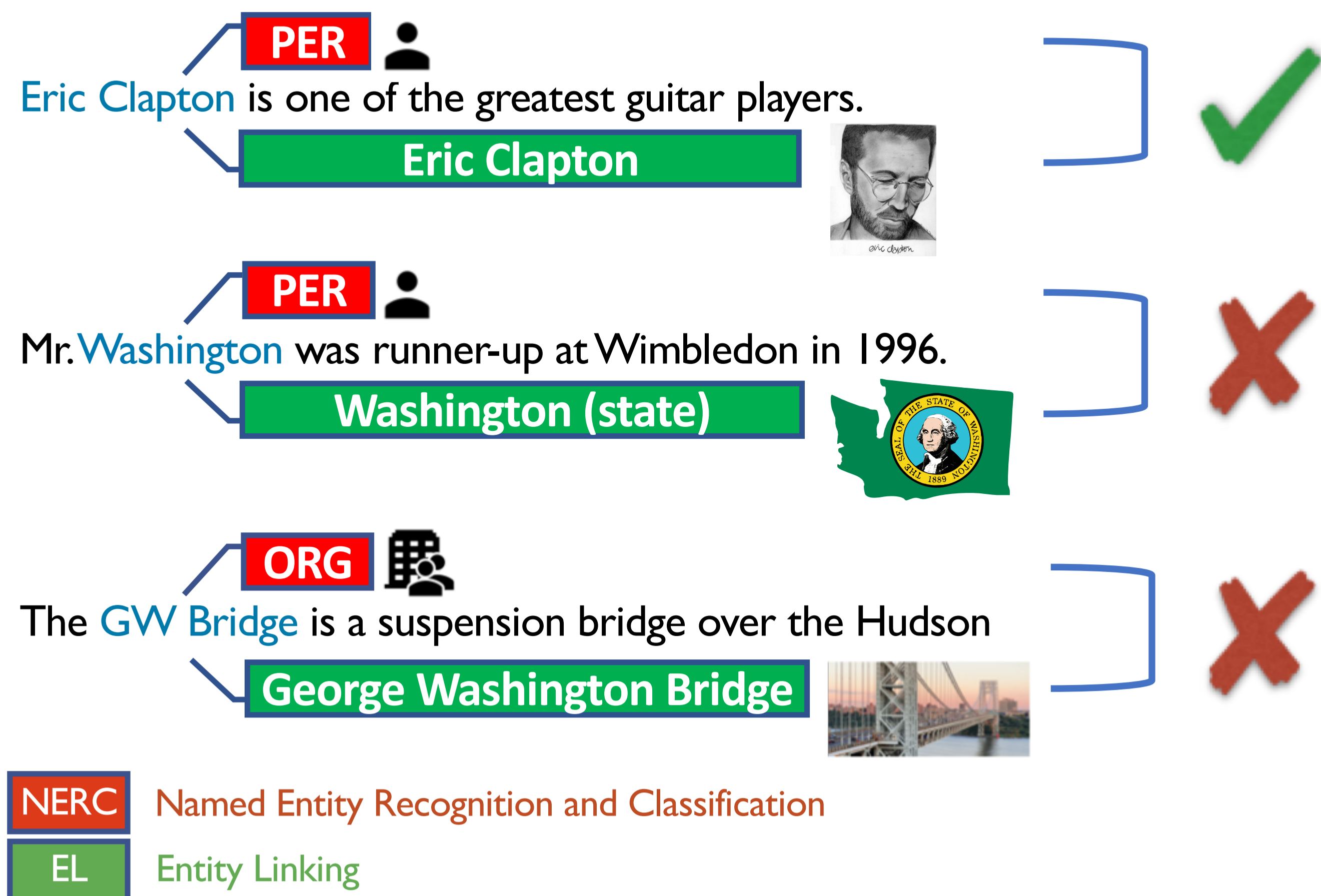


# Joint Posterior Revision of NLP Annotations via Ontological Knowledge

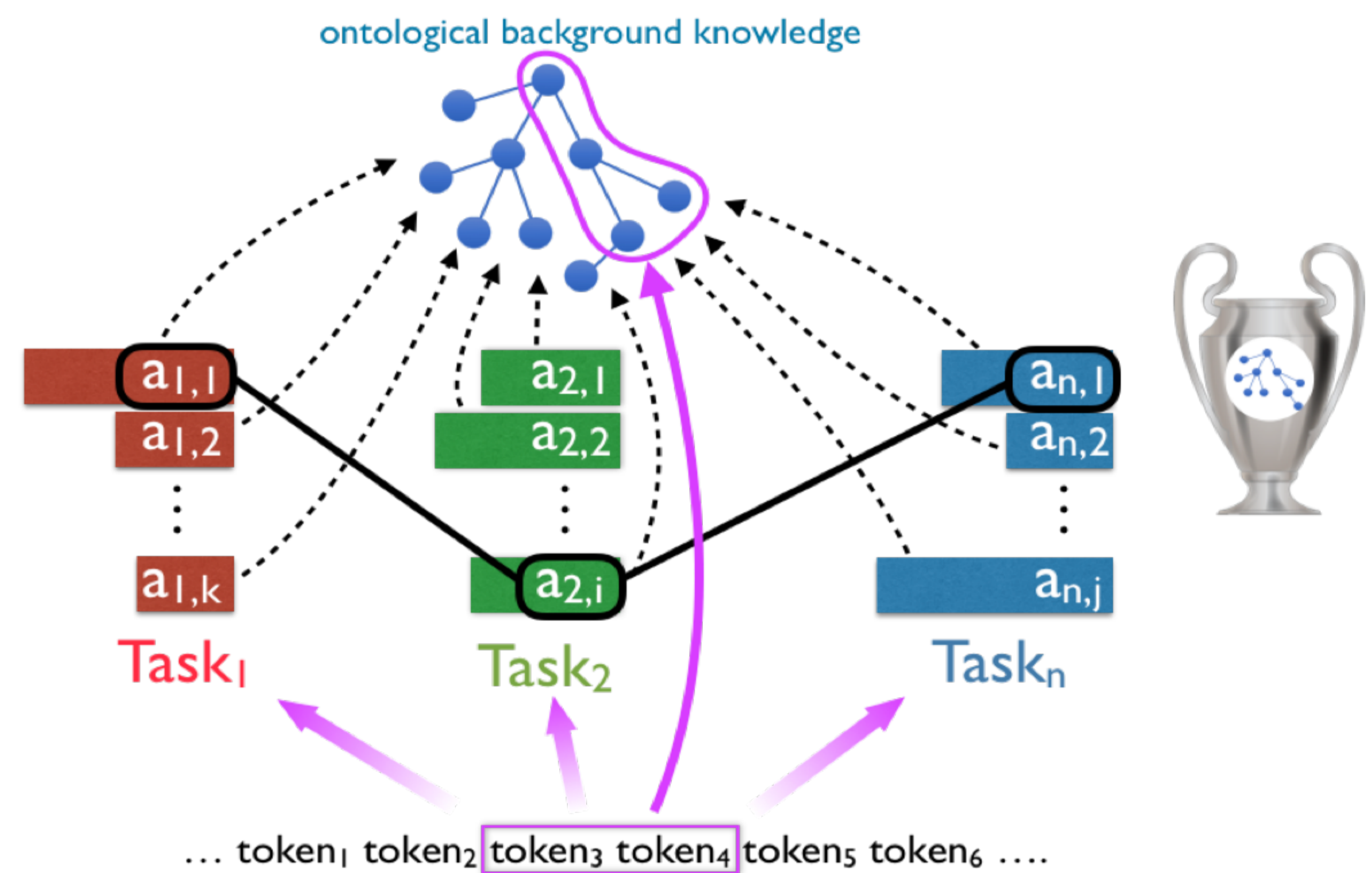


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## 1. Problem: Incoherent Mention-level NLP Annotations



## 2. Solution: Coherence via Ontology



## 3. General Probabilistic Model

**Variables**  
 $m$  entity mention  
 $\mathbf{a} = (a_1 \dots a_n)$  NLP annotations  
 $B$  NLP Background Knowledge  
 $K$  "The" Ontological Knowledge  
 $C$  Entity's ontological class set (from  $K$ )

**Conditional Independence Assumptions**  
 ①  $P(\mathbf{a}|m, B, K, C) = \prod_i P(a_i|m, B, K, C)$   
 ②  $P(a_i|m, B, K) = P(a_i|m, B)$   
 ③  $P(C|a_i, m, B, K) = P(C|a_i, K)$

$$\text{trophy} = \arg \max_{\mathbf{a}} P(\mathbf{a}|m, B, K)$$

$$P(\mathbf{a}|m, B, K) \stackrel{M}{=} \sum_C P(\mathbf{a}, C|m, B, K)$$

$$P(\mathbf{a}, C|m, B, K) \stackrel{CP}{=} P(C|m, B, K) \cdot P(\mathbf{a}|m, B, K, C)$$

$$\stackrel{①}{=} P(C|m, B, K) \cdot \prod_i P(a_i|m, B, K, C)$$

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

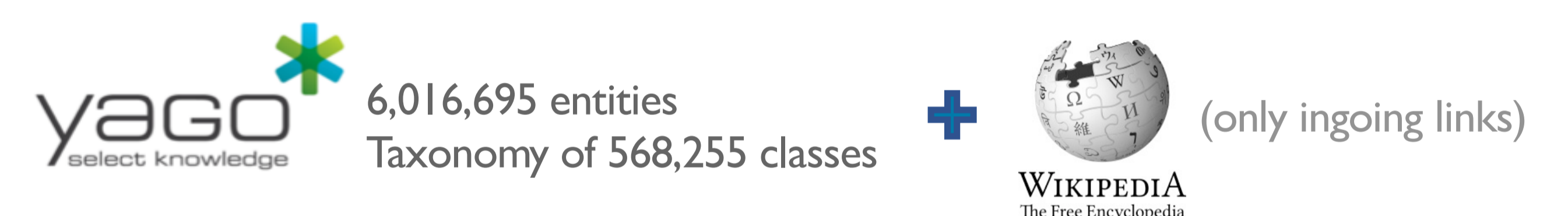
$$P(C|m, B, K) \stackrel{M^*}{=} \left( \prod_i \sum_{a_i} P(a_i, C|m, B, K) \right)^{\frac{1}{n}}$$

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

$$\stackrel{②③}{=} \underbrace{P(a_i|m, B)}_{\text{confidence score}} \cdot \underbrace{P(C|a_i, K)}_{\text{learned from data}}$$

## 4. Model Instantiated on NERC + EL

**Ontological Background Knowledge**



**Estimating NERC**

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

$$\frac{n_K(C)}{\sum_{C'} n_K(C')}$$

Prior (popularity based on entity ingoing links)

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

Computed from gold corpus (NERC + class annotations)

⚠ Consider only class sets restricted to popular classes (seen at least  $n^*$  times in the gold corpus)

**Estimating EL**

$$P(C|a_{\text{EL}}, K) = \mathbf{1}_{\{C_K(a_{\text{EL}})\}}(C)$$

Deterministically computable from the classes of the entity (possibly leveraging alignments between EL Knowledge Base and YAGO)

## 5. Evaluation

Tools: **Stanford CoreNLP** **DBpedia Spotlight**

Gold Corpus (NERC): AIDA CoNLL-YAGO (train)

Datasets: ① AIDA CoNLL-YAGO (test-b)  
 ② MEANTIME ③ TAC-KBP

Research question: Does the JPARK posterior joint revision of the annotations from Stanford CoreNLP (NERC) and DBpedia Spotlight (EL), via YAGO, improve their performances?

Measures: NERC / EL / NERC+EL

	NERC			EL			NERC+EL		
	P	R	F <sub>1</sub>	P	R	F <sub>1</sub>	P	R	F <sub>1</sub>
AIDA standard	94.30%	87.50%	90.80%	66.20%	65.20%	65.60%	63.40%	62.50%	63.00%
with JPARK	95.00%	88.10%	91.40%	67.10%	65.40%	66.20%	65.50%	63.70%	64.60%
Δ	<b>0.70%</b>	<b>0.60%</b>	<b>0.60%</b>	<b>0.90%</b>	<b>0.20%</b>	<b>0.60%</b>	<b>2.10%</b>	<b>1.20%</b>	<b>1.60%</b>
MEANTIME standard	88.20%	69.50%	77.70%	70.30%	55.60%	62.10%	63.50%	50.20%	56.10%
with JPARK	91.40%	72.00%	80.50%	70.50%	55.70%	62.20%	67.00%	53.00%	59.20%
Δ	<b>3.20%</b>	<b>2.50%</b>	<b>2.80%</b>	0.20%	0.10%	0.10%	<b>3.50%</b>	<b>2.80%</b>	<b>3.10%</b>
TAC-KBP standard	91.10%	65.20%	76.00%	40.10%	42.30%	41.20%	36.70%	38.60%	37.60%
with JPARK	92.60%	66.30%	77.20%	41.20%	42.60%	41.90%	38.90%	40.20%	39.50%
Δ	<b>1.50%</b>	<b>1.10%</b>	<b>1.20%</b>	<b>1.10%</b>	0.30%	<b>0.70%</b>	<b>2.20%</b>	<b>1.60%</b>	<b>1.90%</b>

Restricted to gold mentions. Similar improvements also considering all mentions, and macro-averaging by document or by NERC type.



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