Entity Disambiguation with Linkless Knowledge Bases

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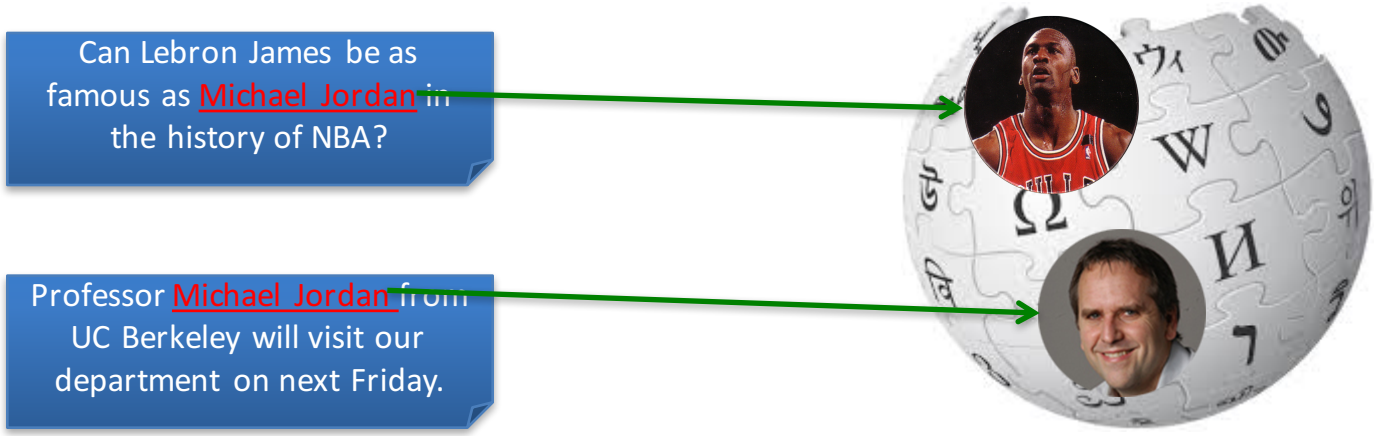
Named Entity Disambiguation (NED)

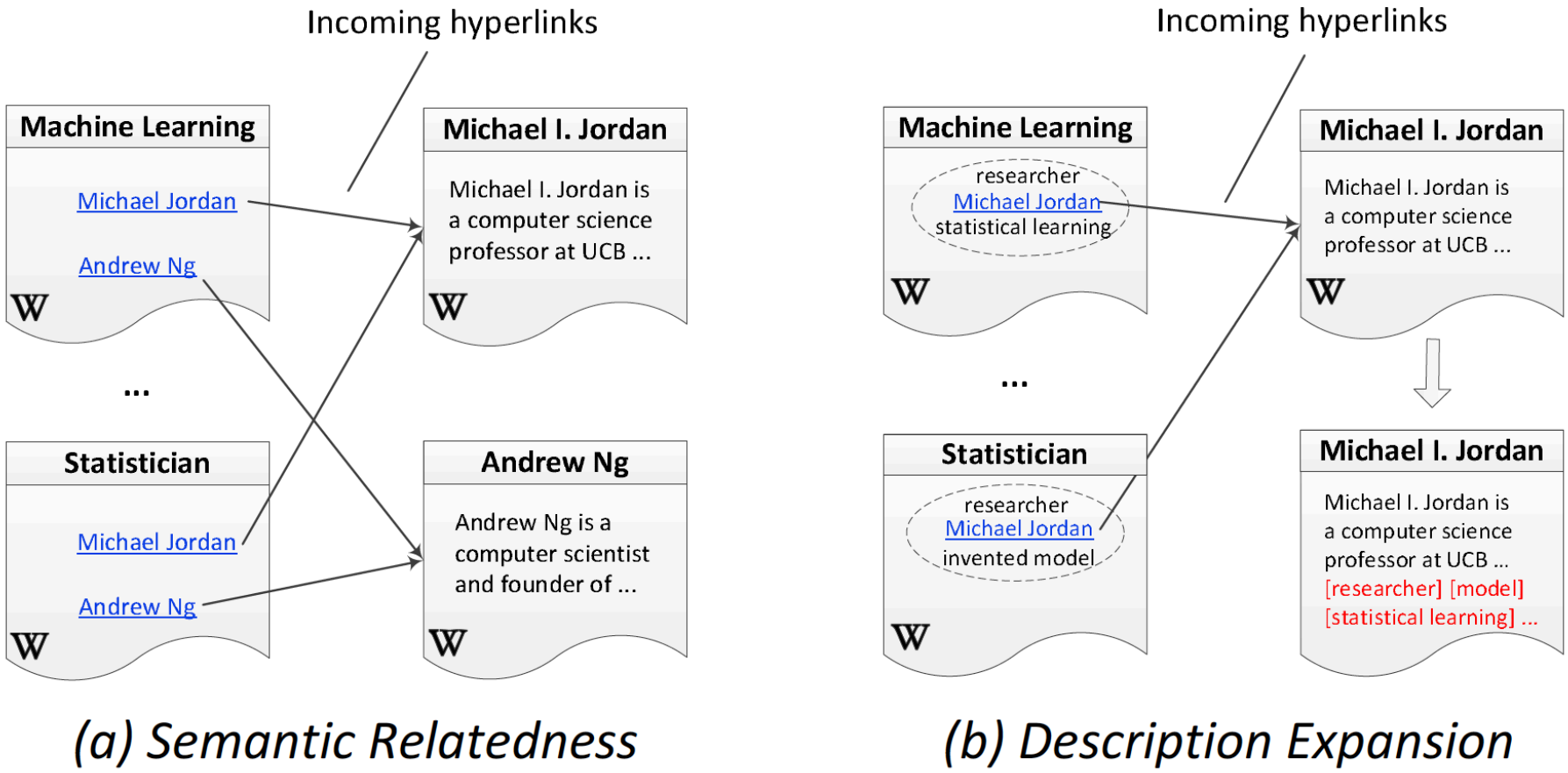
- Goal: map entity mentions in text to their corresponding entities in a reference Knowledge Base (e.g. Wikipedia).



- NED is critical for many text analysis/understanding tasks.
  - information network construction
  - tweets tagging
  - advertisements placement

NED - Existing solutions

- Heavily rely on the **cross-document hyperlinks in KB.**



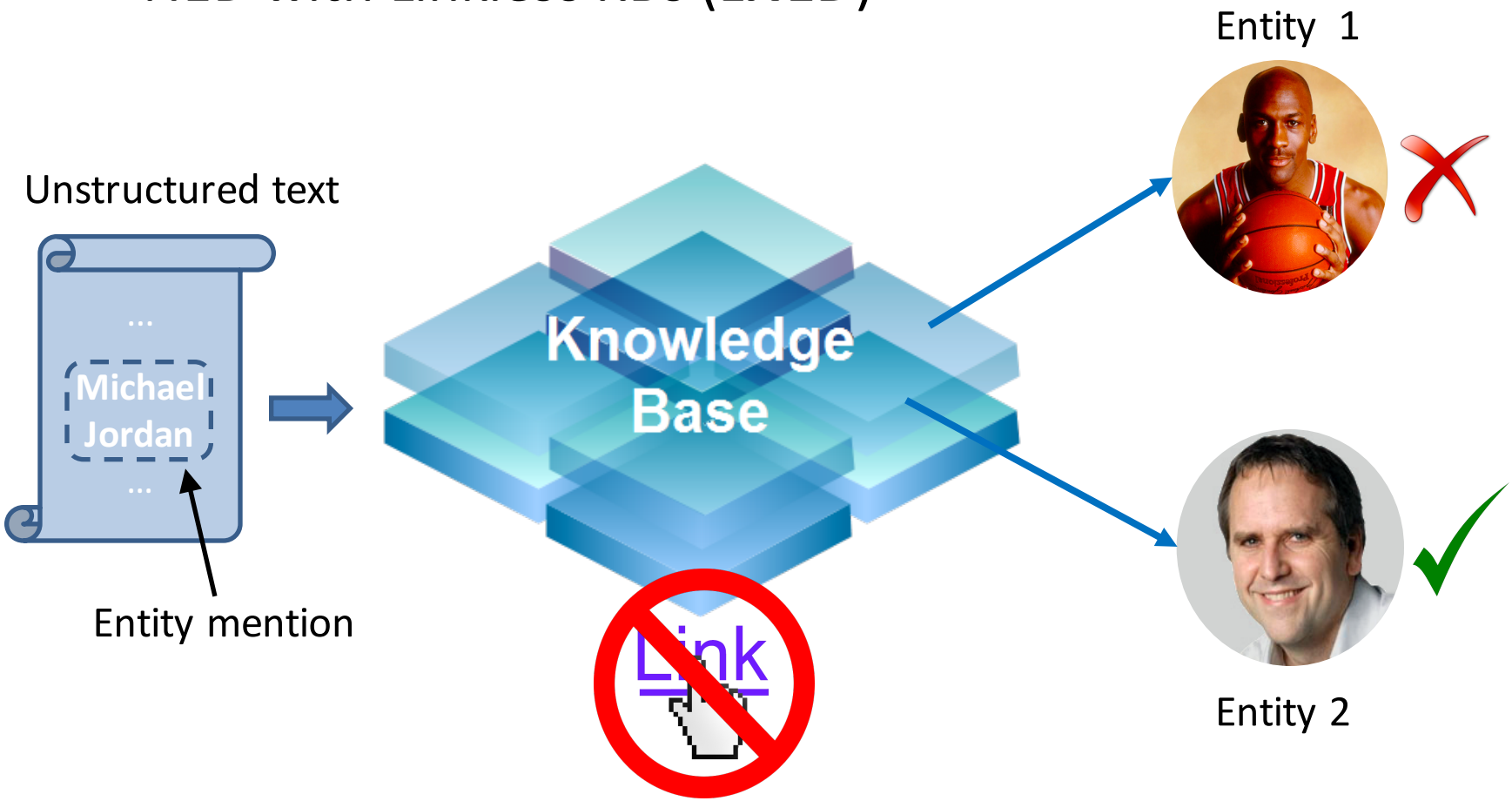
Motivation

- However…
  - Most closed domain KBs contain very few such links
    - Biomedicine
    - Enterprise
  - Manually adding such links into KB is very expensive
- So…

Is it possible to perform high-quality NED without using any cross-doc hyperlinks?

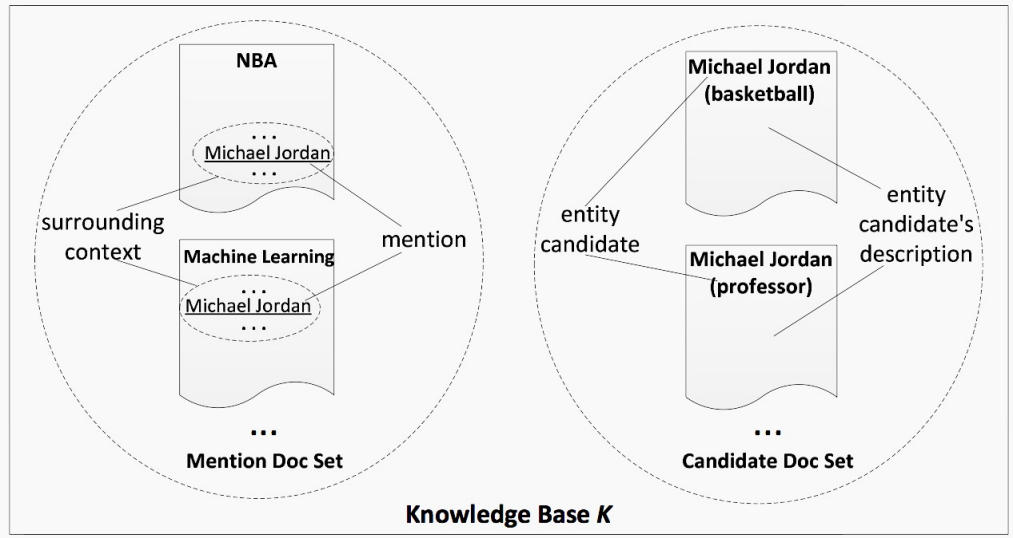
Objectives

- NED with Linkless KBs (**LNED**)



The Evidence Mining Approach

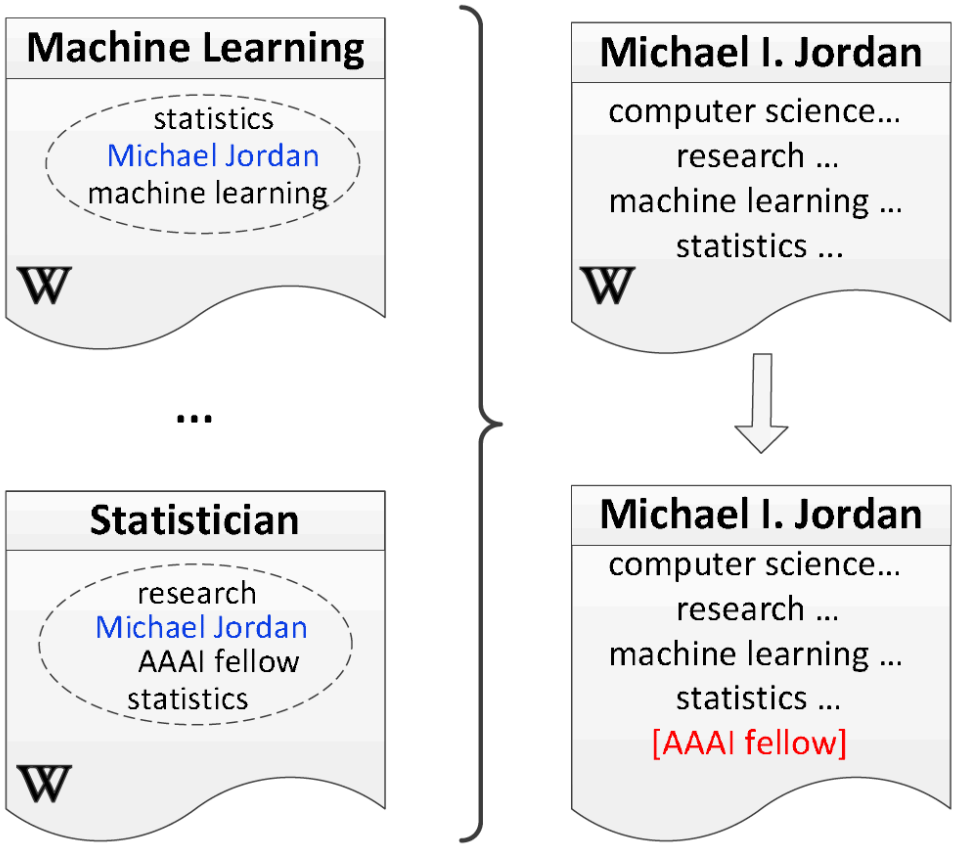
- Goal: bridge the information gap caused by missing links.
  - Input:
    - mention *m* and linkless reference KB *K*
    - *m*'s *candidate documents* and *mention documents*



  - Output:
    - A word distribution for each entity candidate (i.e., disambiguation evidences), with representative words higher probabilities

Disambiguation Evidences

- Mined evidences can expand the description of an entity.



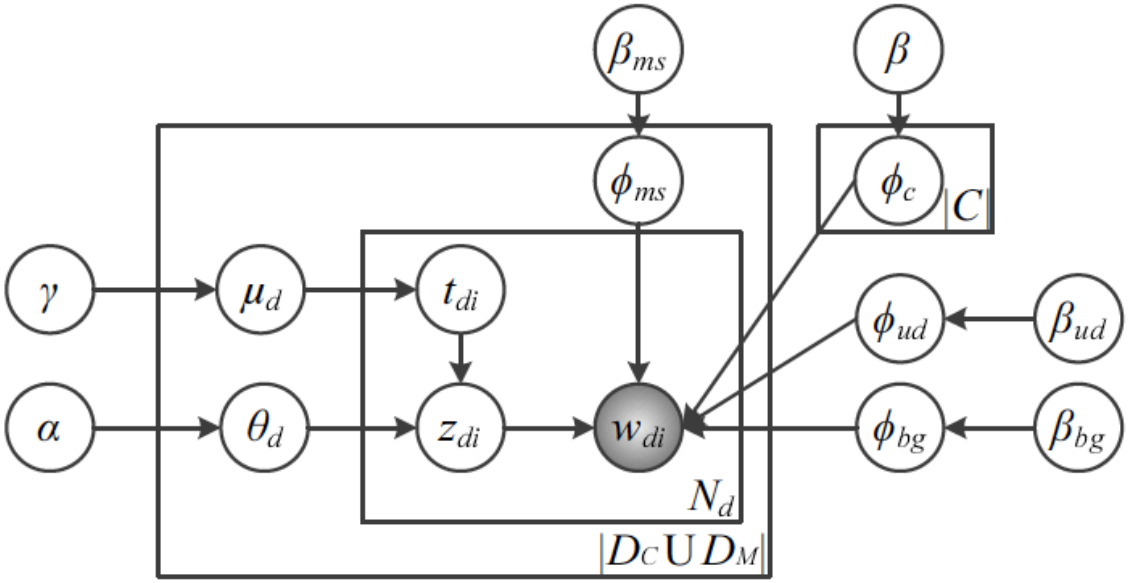
LNED via Evidence Mining

Algorithm 1 LNED via Evidence Mining

Input: Reference knowledge base K (with no links), named entity mention m, query q.

1: Generate candidates list C for mention m
2: Fetch candidate documents set D_C from K
3: Fetch m's mention documents set D_M from K
4: Mine evidences from $D_C \cup D_M$
5: Use mined evidences to rank candidate $c \in C$ for m in q
6: Return top-ranked candidate c_{top} as the genuine entity for m in q

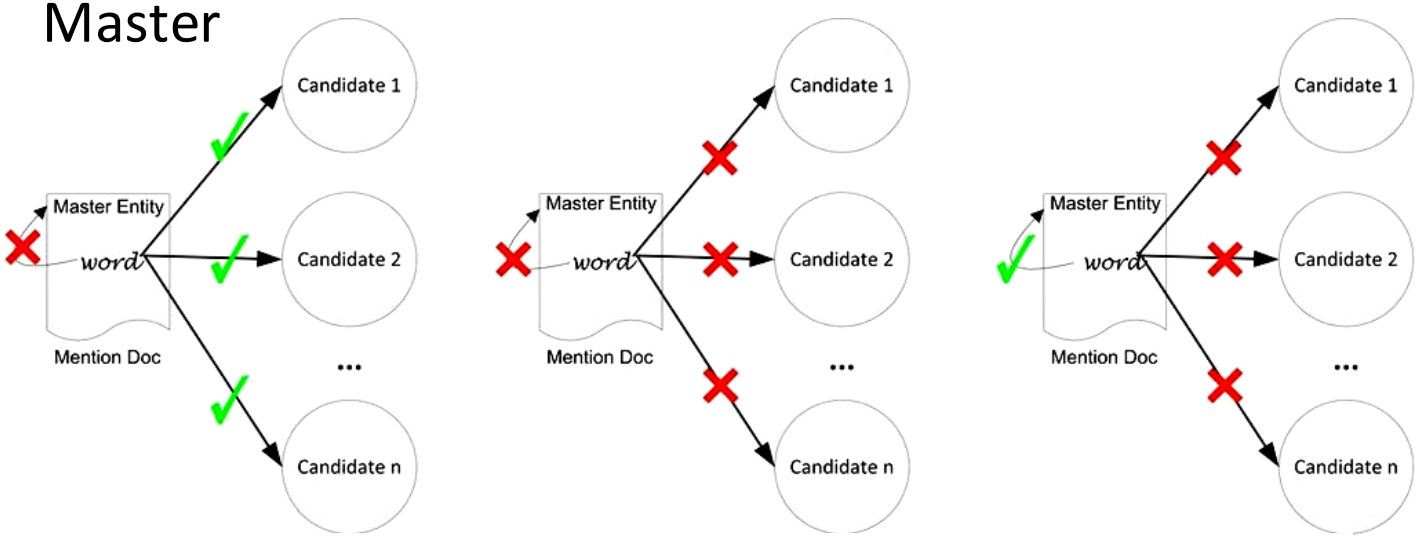
Evidence Mining Model



- A Generative Model
  - Given a target mention, D_C (candidate doc set), D_M (mention doc set)
    - model each of its entity candidates as a topic/label
    - introduce some special topics/labels to capture noisy/useless words
    - Generate the words in D_C & D_M based on such topics

Evidence Mining Model

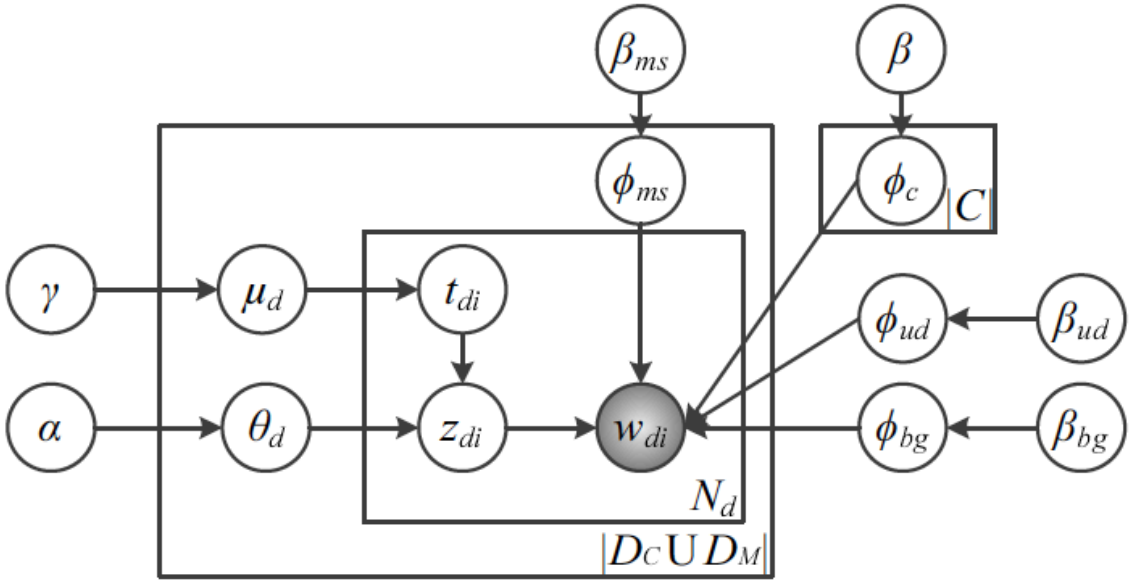
- Three special types of topics/labels:
  - Background
  - Undefined
  - Master



(a) Background (b) Undefined (c) Master

- For a mention with K referent entity candidates, the total number of topics/labels is K+2+| master entity set | or K+2+| mention document set|

Evidence Mining Model



$for\ w_{di} \in D_C$	$for\ w_{di} \in D_M$
z_{di} is either the corresponding candidate label, or "background"	For words surrounding mention (width-*W* window): z_{di} is either drawn from the referent entity candidates' labels plus "undefined", or "background", or "master" For other words: z_{di} is "master"

Model Inference

- Approximate Inference via Gibbs Sampling:
  - Blocked Gibbs Sampling
  - Sample $\{z_{di}, t_{di}\}$ together given all other variables

- Estimating Document-Label Association:

$$\theta_d^{(c)} = \frac{|w \in d, t_w = 1, z_w = c| + \alpha_c}{|w \in d, t_w = 1| + |C| \cdot \alpha + \alpha_{ud}}$$

- Estimating Label-Word Association:

$$\phi_c^{(v)} = \frac{|w = v, t_w = 1, z_w = c| + \beta}{|t_w = 1, z_w = c| + V \cdot \beta}$$

Ranking Referent Candidates

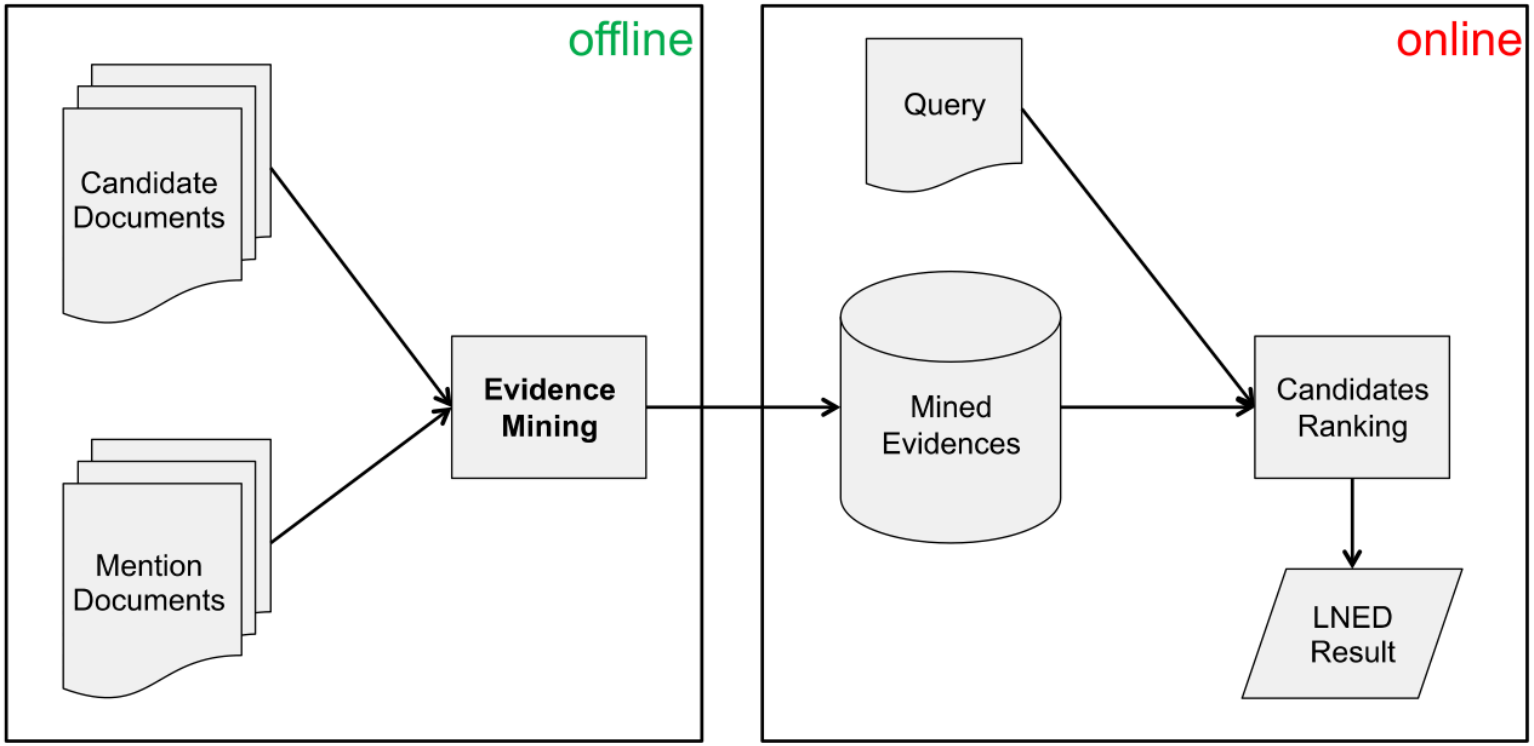
- Utilize the knowledge learned from the evidence mining model to rank referent entity candidates, and choose the top-ranked candidate as disambiguation result.

- Via Incremental Gibbs Sampling:
  - only sample the words in the query document
  - converge very fast

- Predict with Maximal Marginal Probability

$$LNED(d) = argmax_c \theta_d^{(c)}$$

LNED via Evidence Mining



Experiments Setup

- Datasets

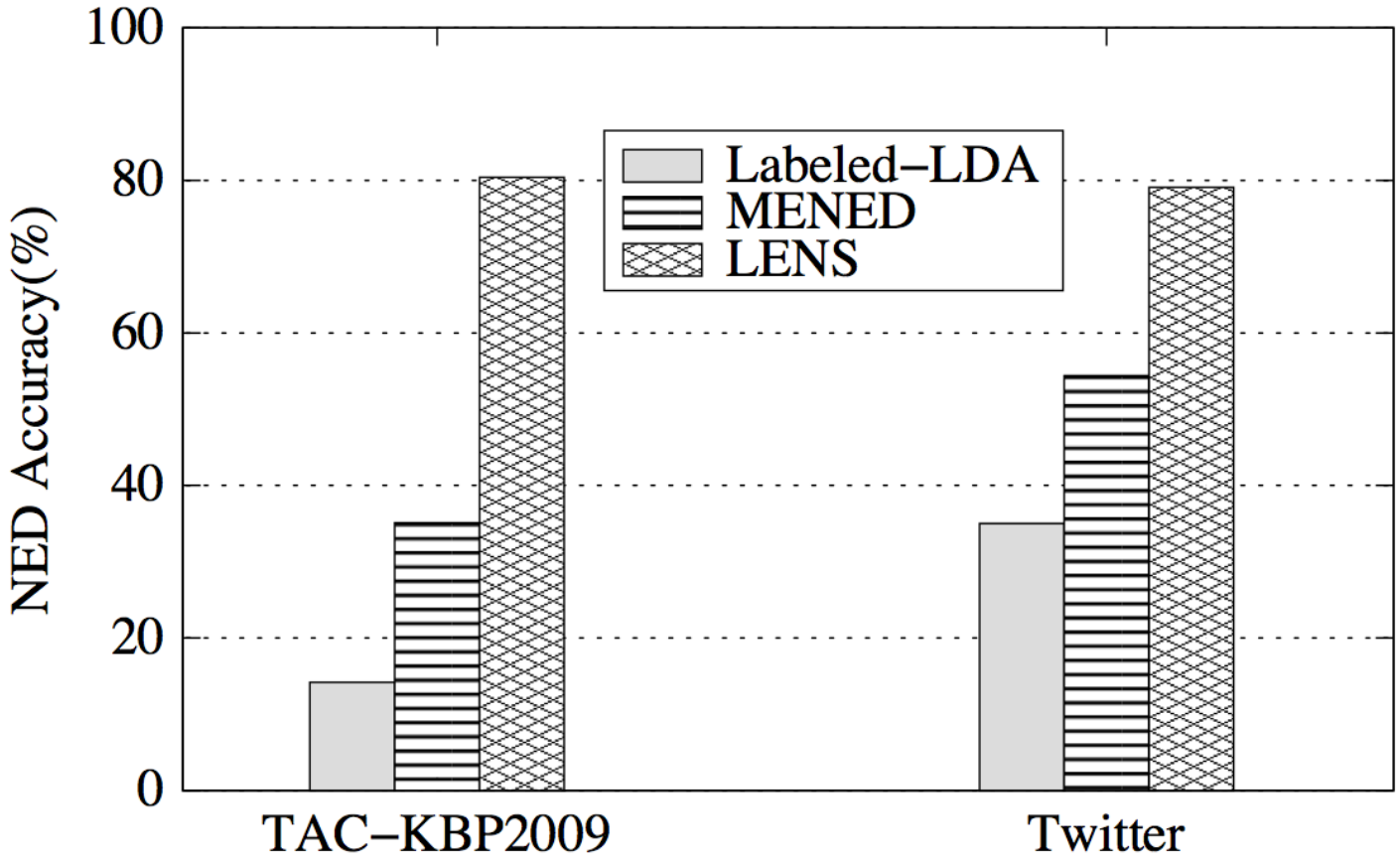
	TAC-KBP2009	Twitter
# of Queries	424	340
Avg Length of Queries (words)	53.15	16.46
Avg # of Candidates	~24	~19

- Reference Knowledge Base
  - Wikipedia (with all hyperlinks removed)
- Parameter Setting
  - tuned on a small test dataset
  - $\alpha = 0.01, \alpha_{df} = 0.1, \beta = 0.01, \beta_{df} = 0.1, \beta_{bg} = 0.1, \beta_{ms} = 0.01$
  - $\gamma_1 = 0.01, \gamma_2 = 1, \gamma_3 = 2$

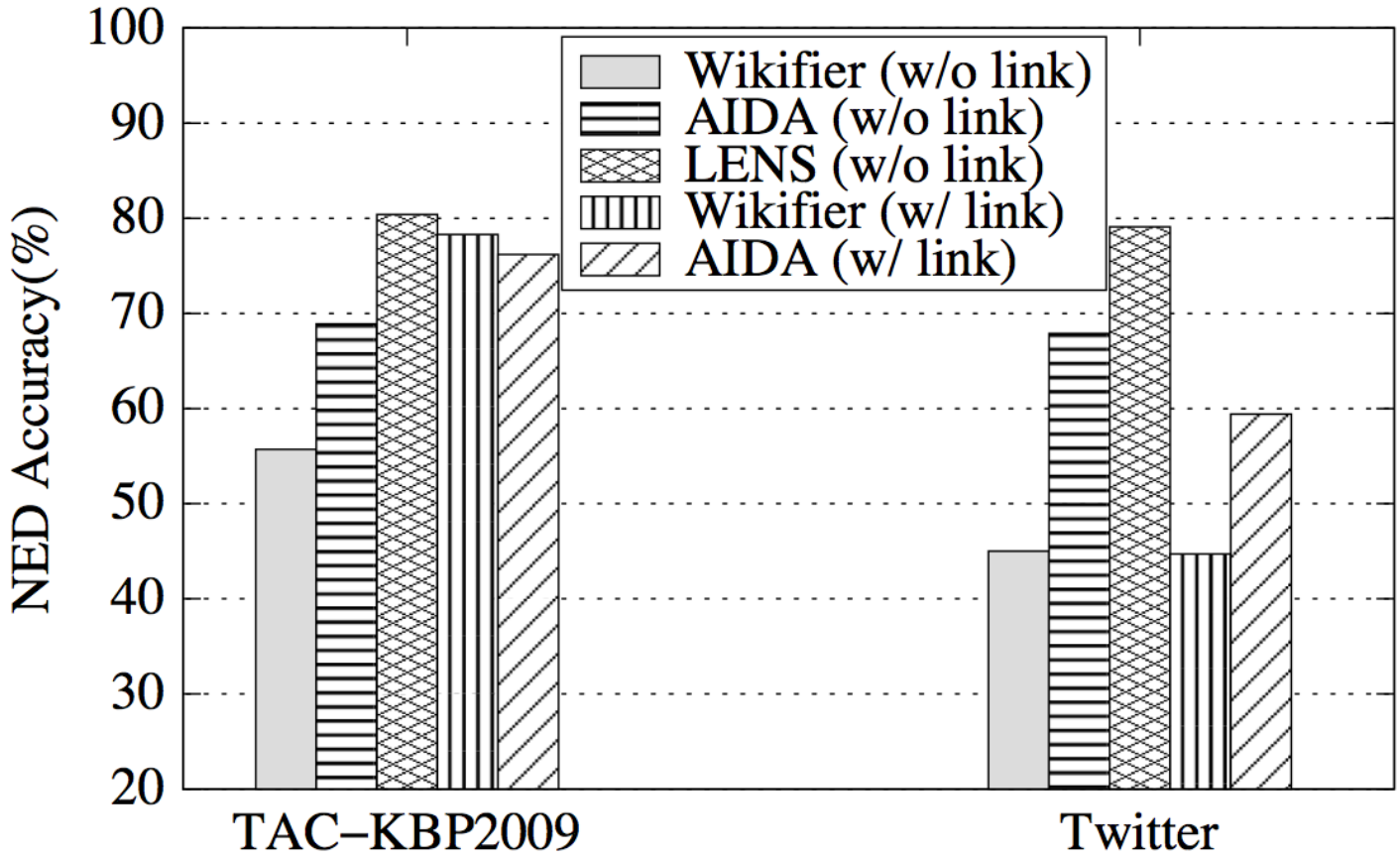
Experiments Setup

- Compared methods:
  - ***Labeled-LDA***: a model which learns label-word association from labeled documents and infers labels for unlabeled documents. [1]
  - ***MENED***: a model designed to mine additional evidences from external corpus to help NED. [2]
  - ***Wikifier***: a widely-used NED system using a machine learning based hybrid strategy to combine various kinds of features. [3]
  - ***AIDA***: a robust NED system making use of weighted mention-entity graph to find the best joint mention-entity mapping. [4]
  - ***LENS***: our method, we name it as **L**inking **E**vidences in **N**ot well linked **S**ources (LENS).

Effectiveness of Evidence Mining



End-to-end NED Accuracy



Conclusions

- Named Entity Disambiguation with Linkless Knowledge Bases (LNED)
  - LNED is a critical and challenging task, especially in domains of biomedicine, enterprise, etc.
  - Our evidence mining approach provides an effective way to tackle the LNED problem.

- Future work
  - Investigating possibility to test in closed domains
  - Automatically generating entity candidates without relying on any mention-entity mapping dictionaries.

References

[1] D. Ramage *et. al*, "Labeled lda: A supervised topic model for credit attribution in multi-labeled corpora"

[2] Y. Li *et. al*, "Mining evidences for named entity disambiguation"

[3] L. Ratinov *et. al*, "Local and global algorithms for disambiguation to Wikipedia"

[4] J. Hoffart *et. al, "*Robust disambiguation of named entities in text"