Entity Linking with a Knowledge Base for Heterogeneous Data

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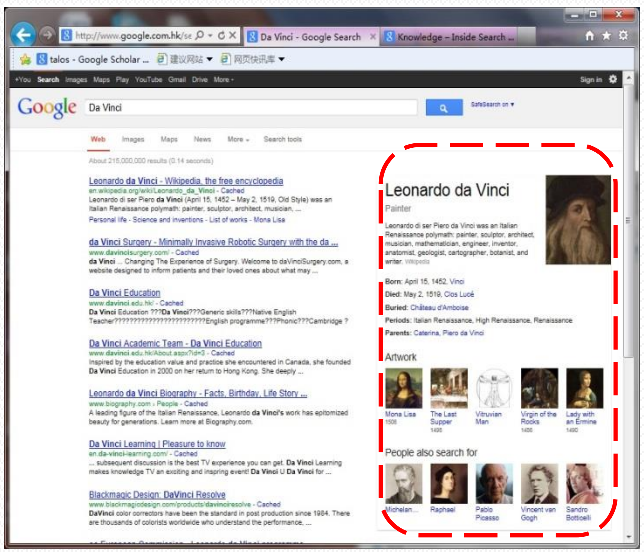
Outline

- Introduction to entity linking with a knowledge base
  - Motivation & definition
- Entity linking for unstructured Web documents
- Entity linking for structured Web lists/tables
- Entity linking for Tweets
- Conclusion

Motivation

- Knowledge base construction from heterogeneous data
  - Better user experience of information search and recommendation is always in great demand
    - Semantic search on the Web, Deep Q/A in NL, …



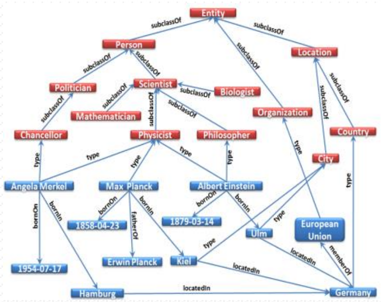
Who was US president when Barack Obama was born?

Motivation

- Knowledge base construction from heterogeneous data
  - Better user experience of information search and recommendation is always in great demand
    - Semantic search on the Web, Deep Q/A in NL, …
  - Structured knowledge discovery from heterogeneous data

Free texts, Tables, Lists, Twitter, Weibo, …

Entities, semantic categories, mutual relations, ...



Freebase
- 68 million entities
- 1 billion facts

Google

Knowledge Graph (as of 2012)
- 570 million entities
- 18 billion facts

DBpedia
- 3.64 million entities

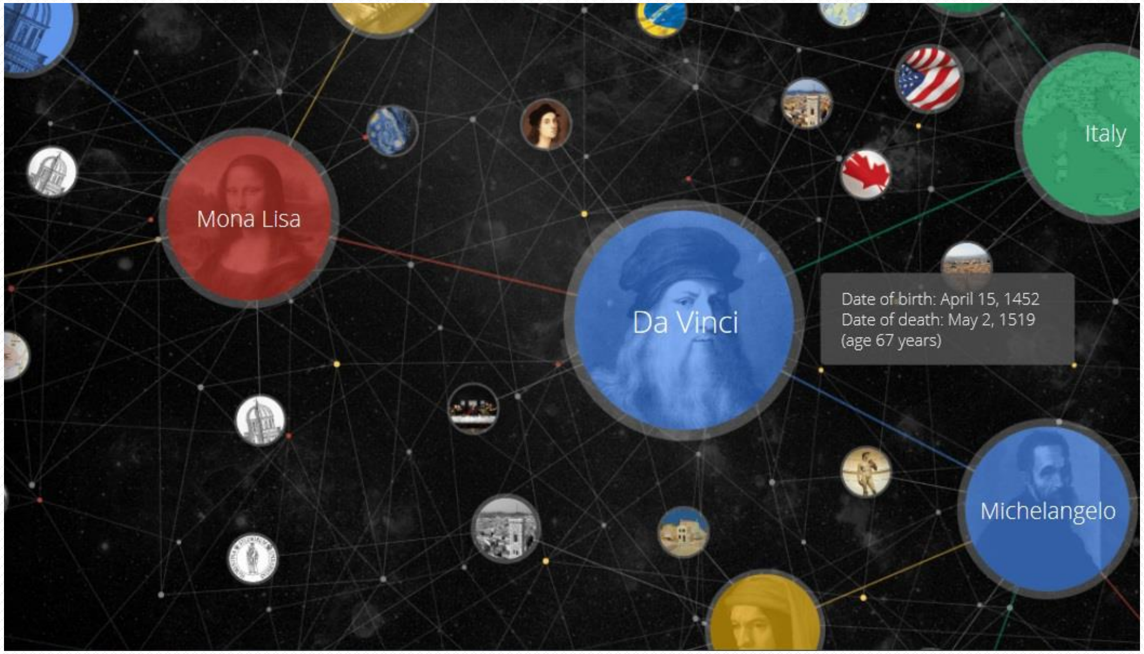
Yago
- Over 10 million entities
- 120 million relations

Motivation

- Existing Knowledge Bases are far from perfect
  - They are large, but their coverage is still low
    - ✓ Popular or well-known person, place or thing
  - E.g., Google's Knowledge graph

As of 2012, its semantic network contained over 570 million objects and more than 18 billion facts about the relationships between these different objects which are used to understand the meaning of the keywords entered for the search

Source: http://en.wikipedia.org/wiki/Google_Knowledge_Graph



Motivation

- Knowledge base population
  - Automatically populating and enriching the existing KB with the newly extracted facts
  - Why?
    - Limited coverage for existing KBs
    - As world evolves
      - New facts come into existence
- Entity linking is inherently considered as an important subtask for knowledge base population

Entity	Relation	Entity
"Michael Jordan"	isPlayerOf	"Bulls"

"Michael Jordan": *Michael J. Jordan (NBA)*; *Michael I. Jordan (Professor)*; *Michael Jordan (footballer)*; ....

"Bulls": *Chicago Bulls; Bulls, New Zealand; Bulls (rugby); ... .*

Entity Linking

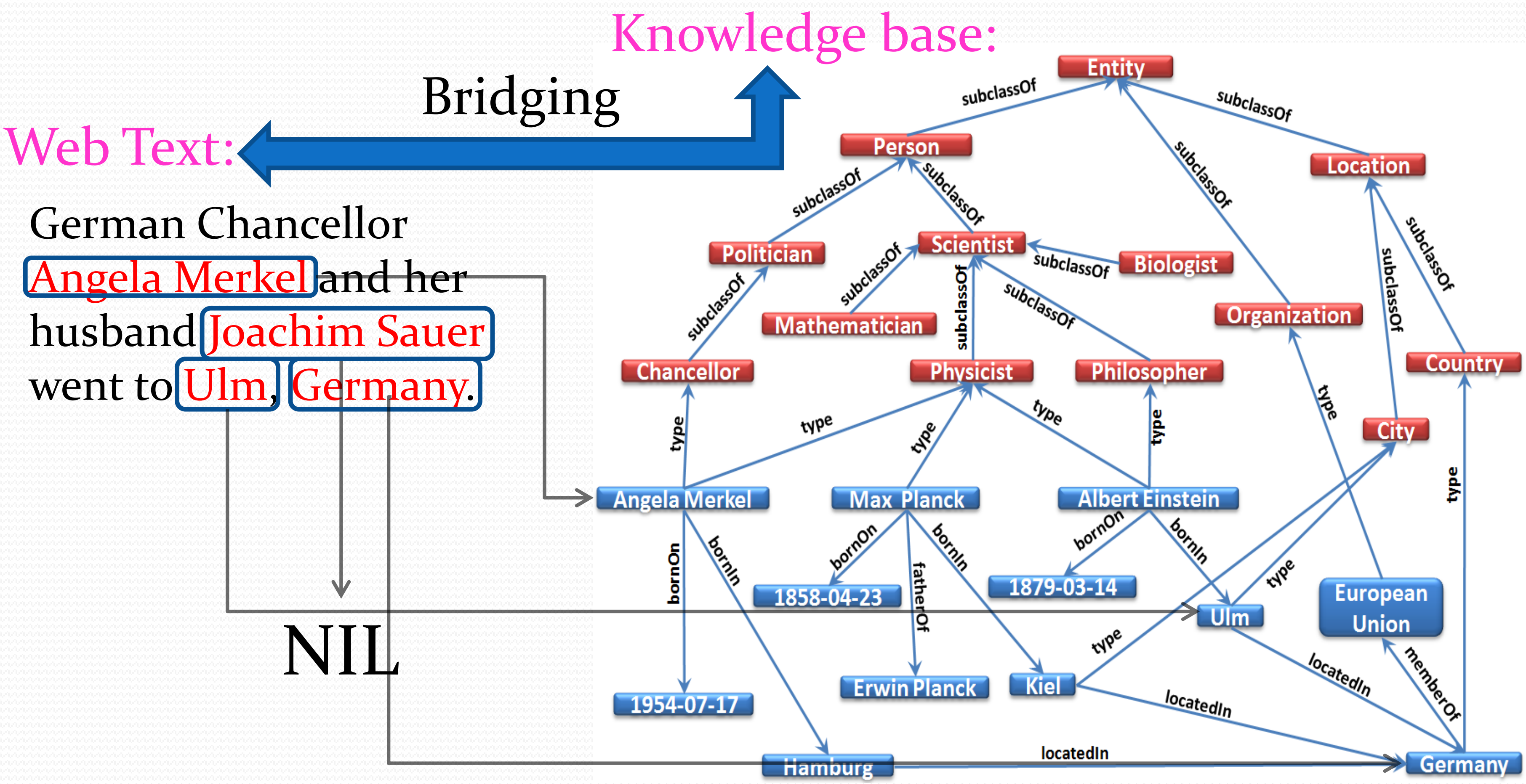


Figure : An example of YAGO

Challenges in Entity Linking

- Entity ambiguity problem
  - Name variations: a named entity may have multiple names
    - *National Basketball Association* → "NBA"
    - *New York City* → "Big Apple"
    - *Osama Bin Laden* → "Abu Abdallah"
  - Entity ambiguity: a name may refer to several different named entities
    - "Michael Jordan"

Michael J. Jordan (NBA player)

Michael I. Jordan (Berkeley professor)

Michael W. Jordan (footballer)

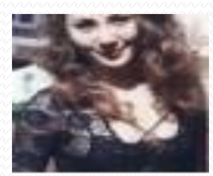
Michael Jordan (mycologist)

…

李娜
(LI Na)

Tennis player

diver



actress

singer

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    - The LINDEN framework (WWW'12)
- Entity linking for structured Web lists/tables
  - Entities detected from structured Web lists/tables
    - The LIEGE framework (KDD'12)
- Entity linking for Tweets
  - Entities detected from short and noisy Tweets
    - The KAURI framework (KDD'13)
- Conclusion

Entity linking for unstructured Data
—Problem Definition

- Entity linking task
  - Input:
    - A textual named entity mention *m*, already recognized in the unstructured Web document
  - Output:
    - The corresponding real world entity *e* in the knowledge base
  - If the matching entity *e* for entity mention *m* does not exist in the knowledge base, we should return a NIL for *m*

Entity Linking for Unstructured Data
—Previous Methods

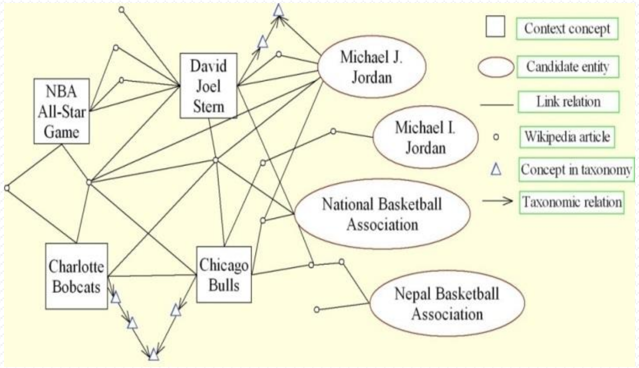
- Essential step of entity linking
  - Define a similarity measure between the text around the entity mention and the document associated with the entity
- Bag of words model
  - Represent the context as a term vector
  - Measure the co-occurrence statistics of terms
  - Cannot capture the semantic knowledge
- Example:
  - Text: Michael Jordan wins NBA champion.

- Entity name: Michael J. Jordan
  Description text: American basketball player
- Entity name: Michael I. Jordan
  Description text: Berkeley professor in AI

The bag of words model cannot work well!

Entity Linking for Unstructured Data
—Our solution: The LINDEN Framework

- **Define four features**
  - **Feature 1: *Prior probability***
    - *Based on the count information*
  - Semantic network based features
    - **Feature 2: *Semantic associativity***
      - Based on the Wikipedia hyperlink structure
    - **Feature 3: *Semantic similarity***
      - Derived from the taxonomy of YAGO
    - **Feature 4: *Global coherence***
      - Global document-level topical coherence among entities



Entity mentions: Michael Jordan, NBA

- To rank the candidates, we compute a score by a linear combination of the four features
  - $Score_m(e) = \overrightarrow{w} \cdot F_m(e)$, where $F_m(e) =< LP(e|m), SA(e), SS(e), GC(e) >$
  - Use a max-margin technique to automatically learn the weights

$$\overrightarrow{w} \cdot F_m(e^*) - \overrightarrow{w} \cdot F_m(e) \geq 1 - \xi_m \qquad (12)$$

  - Minimize over $\xi_m \geq 0$ and the objective $||\overrightarrow{w}||_2^2 + \alpha \Sigma_m \xi_m$

Entity Linking for Unstructured Data
—Our solution: Experimental Study

Table 3: Experimental results over the CZ data set

	# of total mentions	LINDEN		Cucerzan	
		#	Accu.	#	Accu.
All	614	**581**	**0.9463**	549	0.8941
Linkable	522	**493**	**0.9444**	466	0.8927
Unlinkable	92	**88**	**0.9565**	83	0.9022

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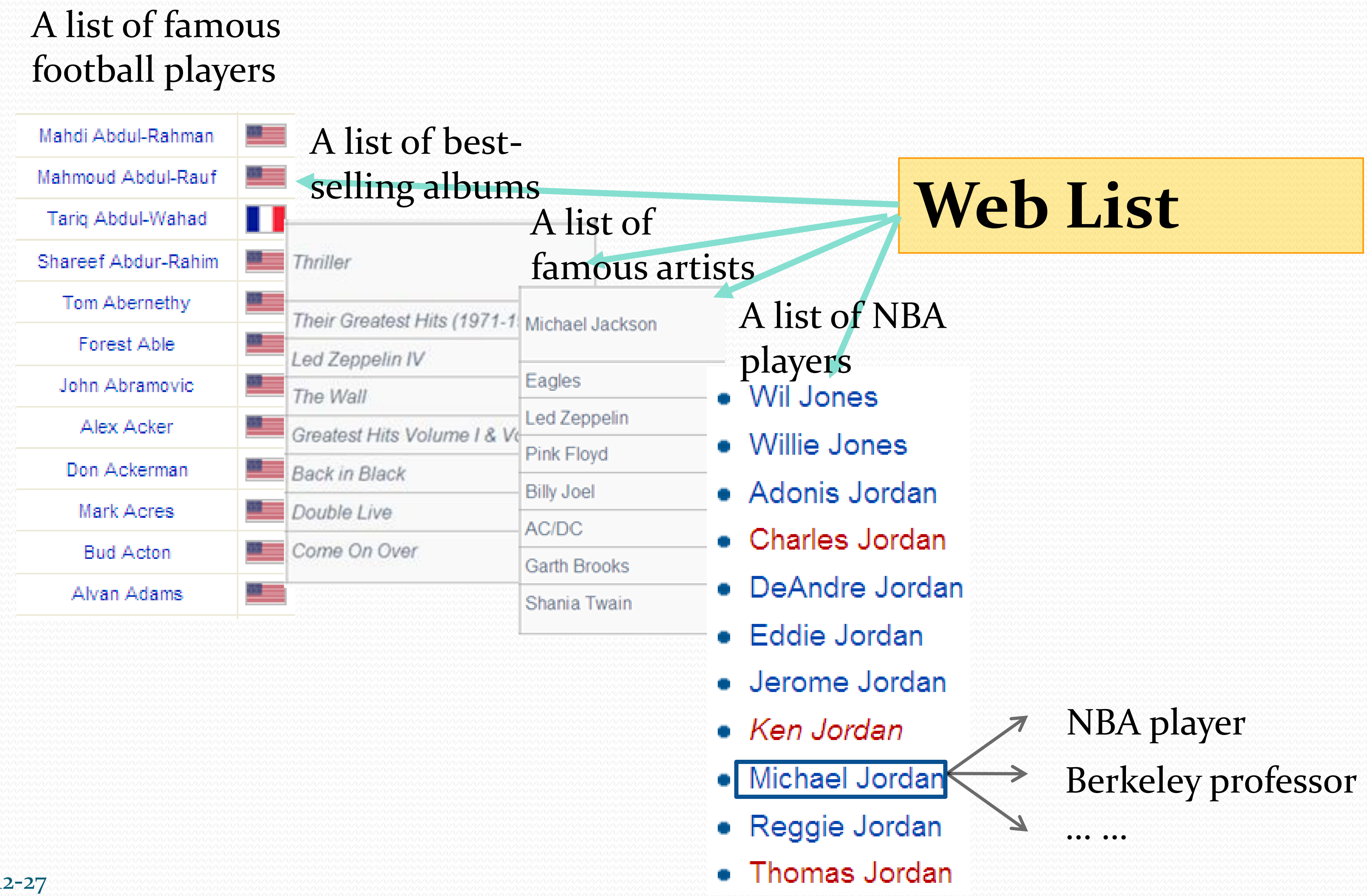
Entity Linking for Structured Data —Motivation



Entity Linking for Structured Data
—Problem Definition

- List linking task
  - Link the entity mentions that appear in the Web lists with the corresponding real world entities in the knowledge base

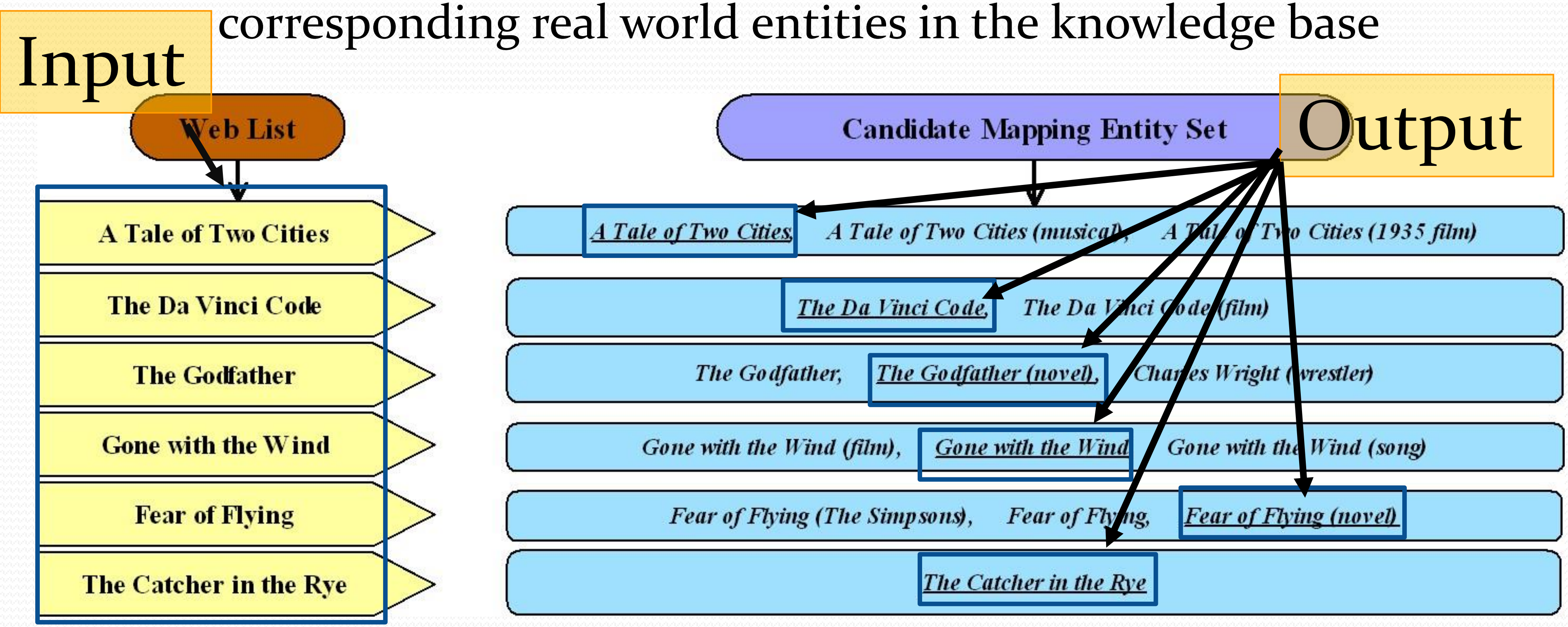


Figure: An illustration of the list linking task. The Web list enumerates some best-selling single volume books. Candidate mapping entities from knowledge base for each list item are shown on the right of the figure; true mapping entity for each list item is underlined.

Entity Linking for Structured Data
—List Linking

- The list linking task is practically important
  - Knowledge base population and table annotation
- Challenge
  - No textual context
  - Different from the task of linking entities in free text
- Assumption
  - Entities mentioned in a Web list can be any collection of entities that have the same conceptual type

Entity Linking for Structured Data
—Our solution: Linking Quality Metric

- **Prior probability**
  - Define the popularity of an entity based on the link count information from Wikipedia
- **Coherence**
  - The type of the candidate mapping entity should be coherent with the types of the other mapping entities in the same Web list
  - **Type hierarchy based similarity**
  - **Distributional context similarity**

Entity Linking for Structured Data
—Our solution: Linking Quality

Linking quality for candidate entity $r_{i,j}$

Prior probability

Coherence

Type hierarchy based similarity

$$LQ(r_{i,j}) = \alpha * P_{pr}(r_{i,j}) + \beta * \frac{1}{|L|-1}\sum_{u=1,u\neq i}^{|L|} Sim_{hr}(r_{i,j}, m_u)$$

$$+\gamma * \frac{1}{|L|-1}\sum_{u=1,u\neq i}^{|L|} Sim_{ds}(r_{i,j}, m_u)$$

Distributional context similarity

$\overrightarrow{w} = \langle \alpha, \beta, \gamma \rangle$ Weight vector $\alpha + \beta + \gamma = 1$

- We utilize the **max-margin** technique to automatically learn the weight vector which gives proper weights for different features (Details in paper)

Entity Linking for Structured Data
—Our solution: Iterative Substitution Algorithm

Algorithm 1 *Iterative Substitution Algorithm*

Input: Web list L, candidate mapping entity sets R.
Output: mapping entity list M.

for each $l_i \in L$ **do**
    $m_i^{(0)} = \arg\max_{r_{i,j}} P_{pr}(r_{i,j}),\ r_{i,j} \in R_i$
end for
$M^{(0)} = \{m_i^{(0)} | l_i \in L\}$
$iter = 1$
while true **do**
    for each $l_i \in L$ **do**
        for each $r_{i,j} \neq m_i^{(iter-1)} \in R_i$ **do**
            $M_{r_{i,j}}^{(iter)} = (M^{(iter-1)} - \{m_i^{(iter-1)}\}) \bigcup \{r_{i,j}\}$
            $IncreLQ_{r_{i,j}} = LQ(M_{r_{i,j}}^{(iter)}) - LQ(M^{(iter-1)})$
        end for
    end for
    $r_{i,j}^{max} = \arg\max_{r_{i,j}} IncreLQ_{r_{i,j}},\quad r_{i,j} \in R_i, R_i \in R$
    if $IncreLQ_{r_{i,j}^{max}} > 0$ **then**
        $M^{(iter)} = (M^{(iter-1)} - \{m_i^{(iter-1)}\}) \bigcup \{r_{i,j}^{max}\}$
        $iter{+}{+}$
    else
        break
    end if
end while
$M = M^{(iter-1)}$

Initialization:

• Pick the candidate entity that has the maximum *prior probability* as the initial estimate of the mapping entity for the list item

Iterative substitution:

• Iteratively refine the mapping entity list to improve its *linking quality*

- When the maximum improvement is smaller than zero, we stop the iteration.
- We prove that this algorithm is guaranteed to **converge.**

Entity Linking for Structured Data

—Our solution: Experimental Study

Table 3: Experimental results over Wiki_Manual

Approach	# correctly linked	Accuracy
TableAnno	1419	0.8392
$\text{LIEGE}_{\beta=0,\gamma=0}$	1461	0.8640
$\text{LIEGE}_{\beta=0}$	1519	0.8983
$\text{LIEGE}_{\gamma=0}$	1498	0.8859
LIEGE_{full}	**1536**	**0.9083**

$$LQ(r_{i,j}) = \alpha * P_{pr}(r_{i,j}) + \beta * \frac{1}{|L|-1} \sum_{u=1,u\neq i}^{|L|} Sim_{hr}(r_{i,j}, m_u)$$
$$+\gamma * \frac{1}{|L|-1} \sum_{u=1,u\neq i}^{|L|} Sim_{ds}(r_{i,j}, m_u)$$

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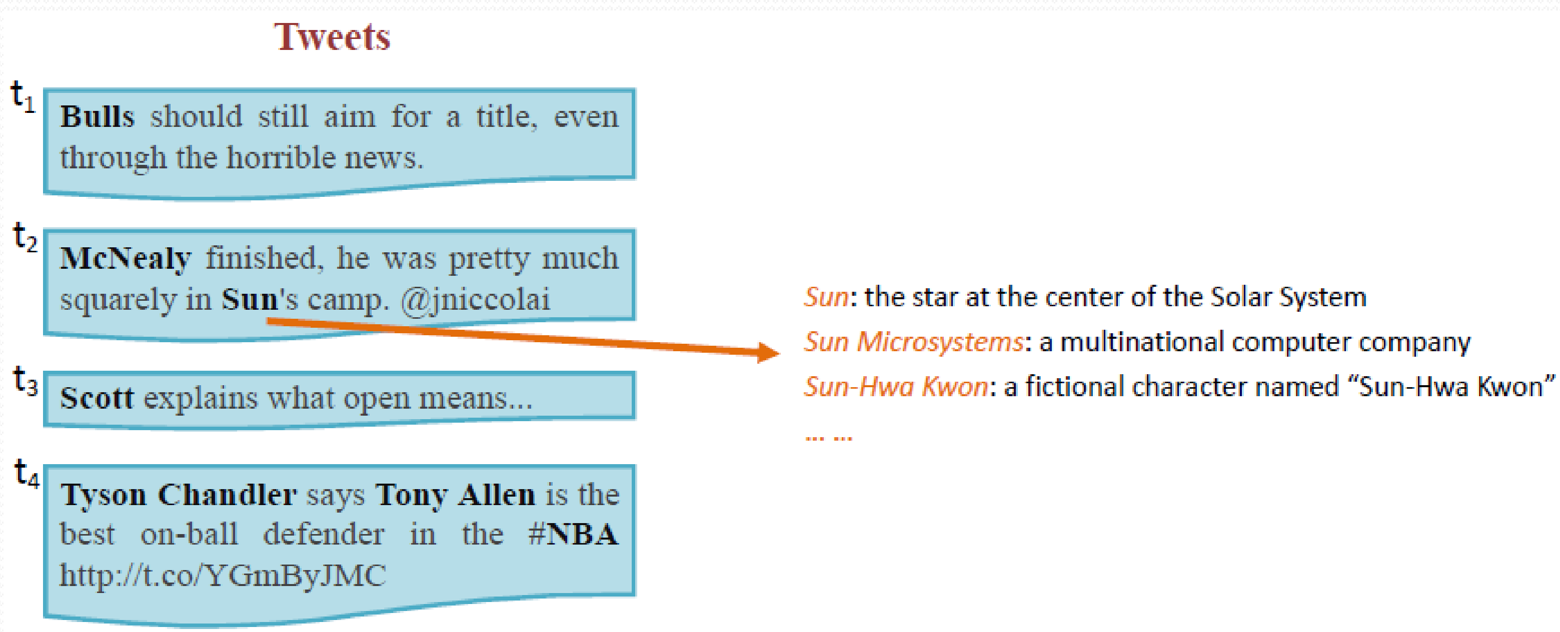
Entity Linking for Tweets
—Motivation

- Twitter: important information source
- Beneficial for exploiting and understanding this huge corpus of valuable text data on the Web, and also helps populate and enrich the existing knowledge bases.



Entity Linking for Tweets
—Problem Definition

- Tweet entity linking
  - link the textual named entity mentions detected from tweets with their mapping entities existing in a knowledge base

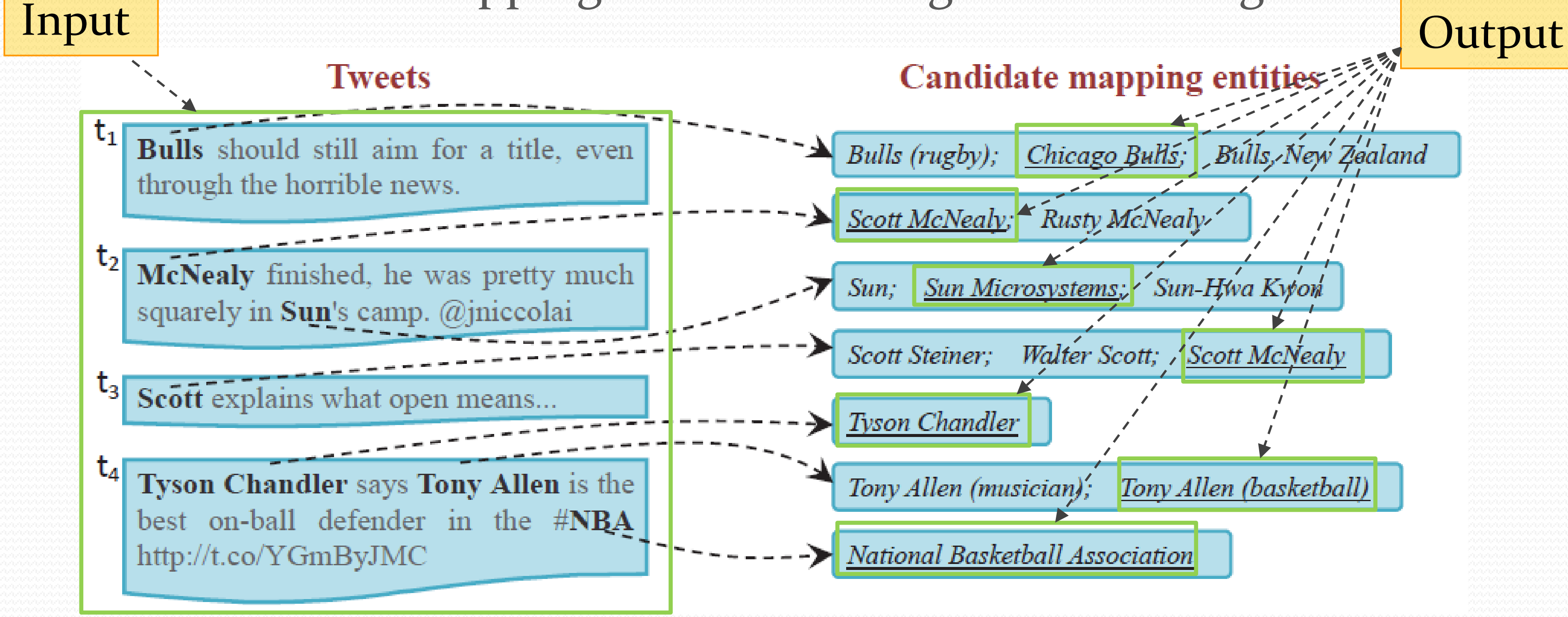
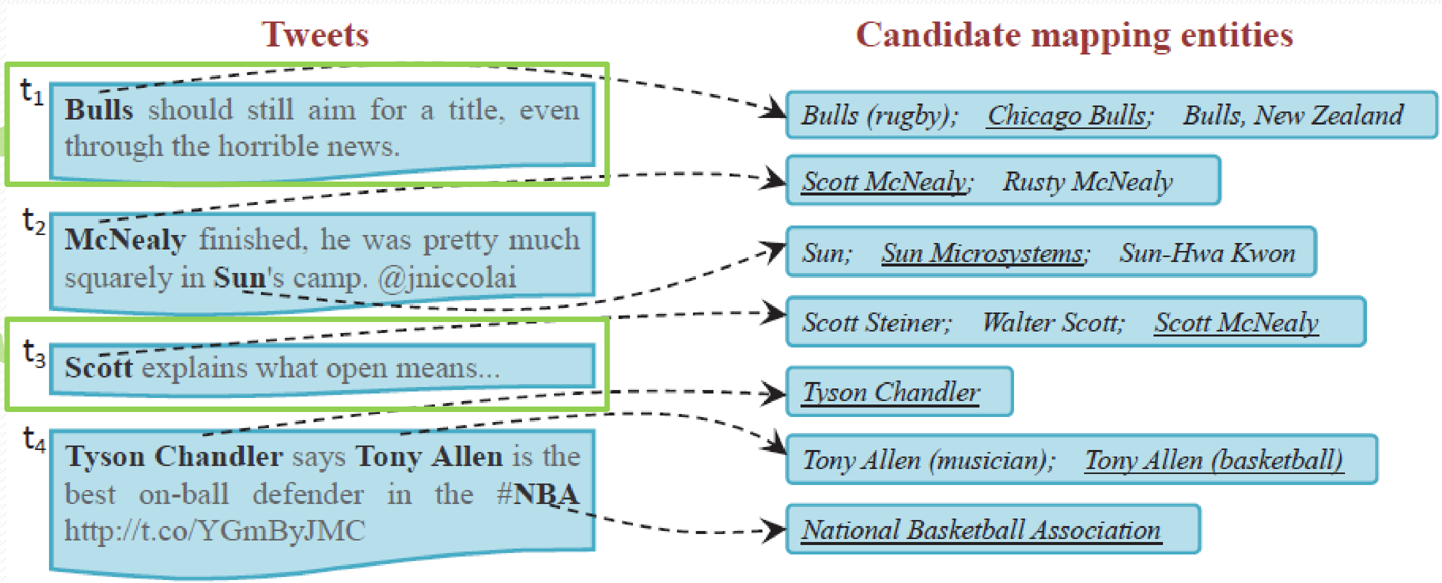


Figure: An illustration of the tweet entity linking task. Named entity mentions detected in tweets are in bold; candidate mapping entities for each entity mention are generated by a dictionary-based method and ranked by their prior probabilities in decreasing order; true mapping entities are underlined.

Entity Linking for Tweets
—Challenge

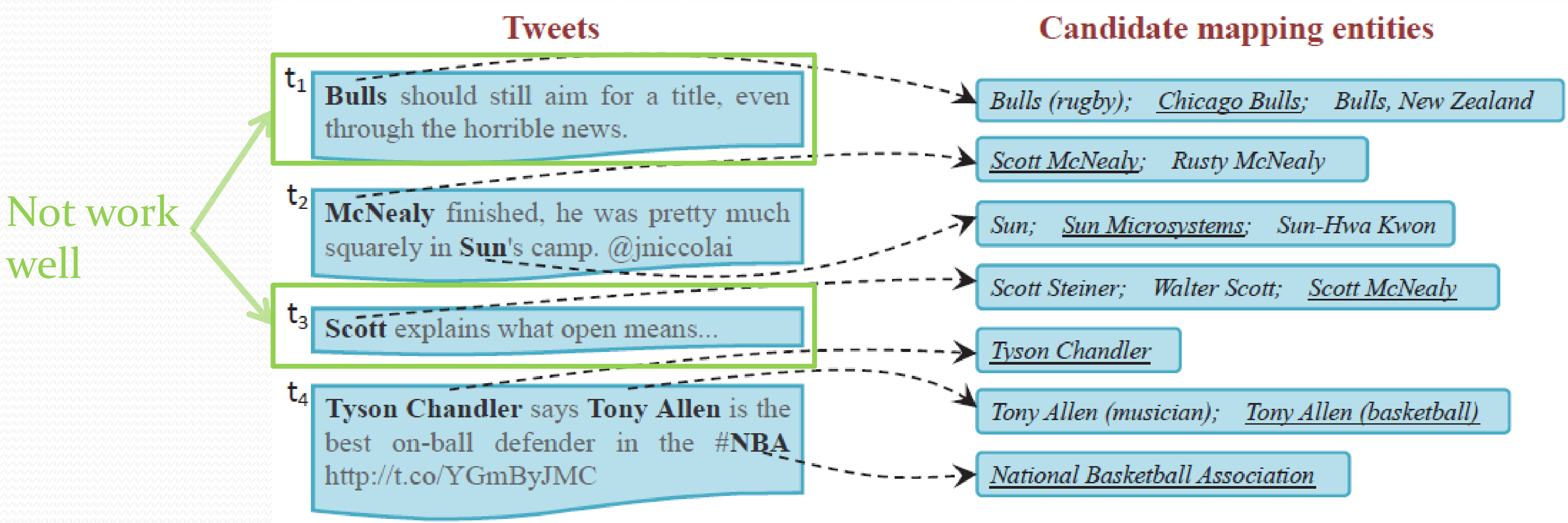
- Challenge
  - noisy, short, and informal nature of tweets
- Previous entity linking methods (EACL'06, EMNLP'07, KDD'09, SIGIR'11, EMNLP'11, and WWW'12)
  - focus on linking entities in Web documents
  - Context Similarity
  - Topical Coherence

Not work well



Entity Linking for Tweets
—Our Solution: The KAURI Framework

- We can increase the linking accuracy, if we
  - combine intra-tweet local information
  - with inter-tweet user interest information



Entity Linking for Tweets
—Our Solution: Intra-tweet Local Information

The initial interest score

Context similarity

bag of words cosine similarity

$$p^i_{j,q} = \alpha * Pp(r^i_{j,q}) + \beta * Sim(r^i_{j,q}) + \gamma * Coh(r^i_{j,q})$$

Prior probability

Topical coherence in tweet

entity frequency in the Wikipedia article corpus

estimated using the *iterative substitution algorithm* proposed in our LIEGE model.

$$\vec{w} = \langle \alpha, \beta, \gamma \rangle$$

Weight vector

$$\alpha + \beta + \gamma = 1$$

- We utilize the **max-margin** technique to automatically learn the weight vector which gives proper weights for those three intra-tweet local features.

W. Shen, J. Wang, P. Luo, and M. Wang. Liege: Link entities in web lists with knowledge base. In *SIGKDD'12*.

Entity Linking for Tweets
—Our Solution: User interest propagation alg'

The final interest score vector

The interest propagation strength matrix

column-normalized

$$\overrightarrow{\mathbf{s}} = \boxed{\lambda}\overrightarrow{\mathbf{p}} + (1-\lambda)B\overrightarrow{\mathbf{s}}$$

The initial interest score vector

Normalized $p_{j,q}^{i}$

- Initialization: $\overrightarrow{\mathbf{s}} = \overrightarrow{\mathbf{p}}$
- Then apply this formula iteratively until $\overrightarrow{\mathbf{s}}$ stabilizes within some threshold

Entity Linking for Tweets
—Our Solution: Experimental Study

Method	Linkable		Unlinkable		All	
	#	Accu.	#	Accu.	#	Accu.
LINDEN	1852	0.827	353	0.808	2205	0.824
$\text{LOCAL}_{\beta=0,\gamma=0}$	1784	0.796	355	0.812	2139	0.799
$\text{LOCAL}_{\gamma=0}$	1795	0.801	355	0.812	2150	0.803
$\text{LOCAL}_{\beta=0}$	1862	0.831	355	0.812	2217	0.828
LOCAL_{full}	1863	0.832	355	0.812	2218	0.829
$\text{KAURI}_{\beta=0,\gamma=0}$	1882	0.840	356	0.815	2238	0.836
$\text{KAURI}_{\gamma=0}$	1894	0.846	357	0.817	2251	0.841
$\text{KAURI}_{\beta=0}$	1913	0.854	371	0.849	2284	0.853
KAURI_{full}	**1923**	**0.858**	**373**	**0.854**	**2296**	**0.858**

Table: Experimental results over the data set

$$p_{j,q}^{i} = \alpha * Pp(r_{j,q}^{i}) + \beta * Sim(r_{j,q}^{i}) + \gamma * Coh(r_{j,q}^{i})$$

LINDEN is our model proposed to address the task of linking entities in Web documents.

W. Shen, J. Wang, P. Luo, and M. Wang. Linden: linking named entities with knowledge base via semantic knowledge. In *WWW'12*.

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Conclusion

- Entity linking is an interesting and challenging task
- Entity linking is very important for knowledge base population
- Recent progress
  - Entity linking for Web documents (many existing work)
    - Popularity + semantic knowledge
  - Entity linking for Web lists (LIEGE is the first one)
    - Coherence + iterative refining
  - Entity linking for Tweets (a few papers)
    - Global user interest propagation
- Future directions
  - Efficient, large-scale entity linking
  - Entity linking with domain-specific knowledge bases
    - E.g., in the domains of computer science, biomedicine, entertainment, products, finance, tourism, etc.
  - Crowdsourcing-based entity linking

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Thanks for your attention!