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.**

(a) Semantic Relatedness

(b) Description Expansion
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 $D_C \cup D_M$ based on such topics
Evidence Mining Model

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

- For a mention with $K$ referent entity candidates, the total number of topics/labels is $K+2+|\text{master entity set}|$ or $K+2+|\text{mention document set}|$
**Evidence Mining Model**

\[
\begin{align*}
\text{for } w_{di} \in D_C & \quad \text{for } w_{di} \in D_M \\
\begin{array}{l}
z_{di} \text{ is either the } \\
\text{corresponding} \\
\text{candidate label,} \\
\text{or “background”}
\end{array} & \begin{array}{l}
\text{For words surrounding mention (width-}W\text{ window):} \\
z_{di} \text{ is either drawn from the referent entity candidates’} \\
\text{labels plus “undefined”, or “background”, or “master”} \\
\text{For other words: } z_{di} \text{ is “master”}
\end{array}
\end{align*}
\]
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

\[ L_{ED}(d) = \text{argmax}_c \theta_d^{(c)} \]
LNED via Evidence Mining

**Offline**
- Candidate Documents
- Mention Documents
- Evidence Mining

**Online**
- Query
- Mined Evidences
- Candidates Ranking
- LNED Result
Experiments Setup

• Datasets

<table>
<thead>
<tr>
<th></th>
<th>TAC-KBP2009</th>
<th>Twitter</th>
</tr>
</thead>
<tbody>
<tr>
<td># of Queries</td>
<td>424</td>
<td>340</td>
</tr>
<tr>
<td>Avg Length of Queries (words)</td>
<td>53.15</td>
<td>16.46</td>
</tr>
<tr>
<td>Avg # of Candidates</td>
<td>~24</td>
<td>~19</td>
</tr>
</tbody>
</table>

• 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 Linking Evidences in Not well linked Sources (LENS).
Effectiveness of Evidence Mining

![Bar chart showing NED accuracy for TAC-KBP2009 and Twitter datasets. The chart compares Labeled-LDA, MENED, and LENS methods.](chart.png)
End-to-end NED Accuracy

![Bar chart showing NED accuracy for TAC-KBP2009 and Twitter datasets. The chart compares the accuracy of Wikifier (w/o link), AIDA (w/o link), LENS (w/o link), Wikifier (w/ link), and AIDA (w/ link).]
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


[2] Y. Li et. al, “Mining evidences for named entity disambiguation”
