RESLVE: Leveraging User Interest to Improve Entity Disambiguation on Short Text

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A Personalized Approach to Entity Resolution

**Background**
- Task Definitions
- Challenges & Examples
- Attempted Solutions

**Approach**
- Motivations
- Modeling a Knowledge Context
- Implementation: The RESLVE System

**Evaluation**
- Experiments
- Results
- Future Work
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Social Web

10 million pages per day
Social Web

800 million visitors per month
Social Web

7 billion images
(twice 4 years ago)
Task Definition
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Named Entity Recognition (NER)

• Systematically identifying mentions of *entities* (e.g., people, places, concepts, ideas)
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  • Systematically identifying mentions of *entities* (e.g., people, places, concepts, ideas)

Named Entity Disambiguation (NED)
  Resolving the intended meaning of ambiguous entities from multiple *candidate meanings*
Ambigious Entities

aaahh one more day until finn!!! #cantwait

office holiday party

Beetle
Ambiguous Entities

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Beetle
Footage:

office holiday party
Footage:
• Workplace?
Footage:
- Workplace?
- TV Show?
YouTube

office holiday party

Episode 4

Footage:
• Workplace?
• TV Show?
Episode 4

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- US Version?
- UK Version?
Episode 4

office holiday party

Episode 4

office, december 3

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Challenges & Focus
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- Short Length
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Limitations of Extant Research

Tweets severely degrade traditional techniques
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- Stanford NER: $F_1$ drops 90% → 46%
- DBPedia Spotlight & Wikipedia Miner: $P@1 < 40\%$
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Recent strategies
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Recent strategies
  • Crowd-sourcing
    • Limitation: Dependent on reliable human workers
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Recent strategies
• Crowd-sourcing
  • Limitation: Dependent on reliable human workers
• Automated attempts
  • Limitation: Focus on NER not NED
  • Limitation: Generalizability beyond Twitter?
Challenges & Focus

- Short Length
- Sparse Lexical Context
- Noisy
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- Short Length
- Sparse Lexical Context
- Noisy
- Highly personal in nature

- User’s past content on same platform not feasible background corpus
Task Definition

Named Entity Recognition (NER)
- Systematically identifying mentions of entities (e.g., people, places, concepts, ideas)

Named Entity Disambiguation (NED)
Resolving the intended meaning of ambiguous entities from multiple candidate meanings

Our focus: disambiguating any entity detected in users’ text-based utterances on social Web
Exploring a Personalized Solution

- Individual-centric approach to NED
Exploring a Personalized Solution

- Individual-centric approach to NED
- Incorporates external, user-specific semantic data
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- Determine user’s likely intended meaning of ambiguous entity based on similarity between potential meanings and interests
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RESLVE
Resolving Entity Sense by LeVeraging Edits
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• User has core interests
  • User more likely to mention an entity about a topic relevant to personal interests than mention a topic of non-interest
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• Can use a semantic knowledge base to formally represent these topics of interest

  ➢ Bridge user identity between social Web and knowledge base, K
  ➢ Model interests using K’s organizational scheme
  ➢ Rank entity senses according to relevance to interests
Qualitative Analysis: Stable Interests
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User’s topics of contribution similar across Web:
Qualitative Analysis: Stable Interests

User’s topics of contribution similar across Web:

**Same Topics**

Ambiguous YouTube post: *office*, december 3

Same user’s recent Wikipedia edit: <item userid="xxxx" user="xxxx" pageid="31841130" title="The Office (U.S. season 8)"/>
Qualitative Analysis: Stable Interests

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```

**Same categories**

- On average, 52.4% of entities a user mentions in social Web (e.g., “Java”) have at least 1 candidate sense in same parent category of Wikipedia article same user edited (e.g., “Programming language”)
- If extend to just 4 parents up category hierarchy, get all 100%
Theoretical Motivations
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• Online Contribution:
  • Users produce online content about key set of personally-interesting topics because it is fulfilling and seen as having better cost benefit
  • (Harper et al., 2007; Lakhani & von Hippel, 2003; Lerner & Tirole, 2000; Ling et al., 2006; Maslow, 1970)
Theoretical Motivations

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- **Modeling Interests:**
  - Effective to model these topic interests from lexical features of these text-based contributions
  - (Chen et al., 2010; Cosley et al., 2007; Pennacchiotti & Popescu, 2011)
Modeling a Knowledge Context

- Knowledge base, $K$
- $K=(N,E)$
- 2 node types:
  - Categories
  - Topics
The Knowledge Graph
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- **Category** nodes: $N_{\text{Category}} \subset N$
The Knowledge Graph

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- **Topic** nodes: $N_{\text{Topic}} \subset N$
  - Unique identifier
  - Belongs to one or more categories
  - Associated with text-based description
User Interest Model
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- Editing a description signals interest in associated topic
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User Interest Model

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\[
\begin{array}{c|cccc}
  & c1 & c2 & c3 & c4 \\
\hline
t1 & \frac{1}{2} & 1 & \frac{1}{3} & 0 \\
t2 & \frac{1}{2} & 1 & \frac{1}{2} & 1 \\
t3 & 0 & 0 & \frac{1}{2} & 1 \\
\end{array}
\]
User Interest Model

• Editing a description signals interest in associated topic
• Topic nodes: all topics user edited description of
• Category nodes: categories reachable in knowledge graph from those topics
• Edge weight = inverse of shortest path length

- Same representation for candidates

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<td>t1</td>
<td>(\frac{1}{2})</td>
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Instantiating the Model

- Wikipedia
- DBPedia
- Freebase
Instantiating the Model

• Wikipedia
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Instantiating on Wikipedia

- Articles, categories effectively represent topics (Syed, 2008)
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• Compatible with NER toolkits
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- Article editing behavior effective for modeling interests (Cosley, 2007; Lieberman & Lin, 2009; Wattenberg et al., 2007)
### Article editing signals topic interest

**Editing behaviors indicative of user interest:**

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# Article editing signals topic interest

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## Less Meaningful Edits

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<th>Ignore Irrelevant Edits</th>
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<td>Articles with less than 100 non-stopwords</td>
<td>Stem, tokenize, lowercase; remove stopwords, punctuation, non-printable characters.</td>
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<td>Trivial edits, i.e., typo correction, vandalism reversion.</td>
<td>Parse Wiki Markup to remove article maintenance information</td>
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<td>List pages merely containing widely diverse sets of topics that are all not necessarily indicative of the piece personally relevant to the user</td>
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Implementation: The RESLVE System

RESLVE (Resolving Entity Sense by Leveraging Edits) addresses NED by:

1. **BRIDGING USER IDENTITY**
   - User utterances
   - Username
   - Unstructured short texts

2. **MODELING USER INTEREST**
   - User contributed structured documents
   - Detected entities & candidate meanings ("m")

3. **RANKING CANDIDATES BY PERSONAL RELEVANCE**
   - DBPedia Spotlight
   - Top ranked personally-relevant candidates
   - User interest model
   - Detected entities & candidate meanings ("m")
Implementation: The RESLVE System

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1. Connecting social Web + Wikipedia editor identity
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Phase 1: Bridging Web Identities

- Connect identity of social media user with Wikipedia editor
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- Simple string matching
  - Iofciu, 2011; Perito, 2011
Phase 2: Representing Users and Entities

- Models user’s topics of interest using bridged Wiki account’s editing-history
- Compares similarity of those topics to topic associated with candidate sense
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- Content-based & knowledge-graph based similarity
- Weighted vectors used to represent user and candidate sense
Content-based similarity

• Bag-Of-Words
  • Titles of articles user edited
  • Candidate’s article title
  • Words from those articles’ pages & category titles

• TF-IDF weighted
Content-based similarity

• Bag-Of-Words
  • Titles of articles user edited
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  • Words from those articles’ pages & category titles
• TF-IDF weighted

• User, $u$: $V_{content, u}$
• Candidate meaning, $m$: $V_{content, m}$

$$sim_{content}(u, m) = cossim(V_{content, u}, V_{content, m})$$
Knowledge-context based similarity

- Vectors of articles’ category IDs
- Weight is distance between the article (topic) and category in knowledge graph
- E.g., “American Television Series” > “Broadcasting”
Knowledge-context based similarity

- Vectors of articles’ category IDs
- Weight is distance between the article (topic) and category in knowledge graph
- E.g., “American Television Series” > “Broadcasting”

- User, $u : V_{\text{category}, u}$
- Candidate meaning, $m: V_{\text{category}, m}$

$$sim_{\text{category}}(u, m) = \text{cossim}(V_{\text{category}, u}, V_{\text{category}, m})$$
Phase 3: Ranking by Personal Relevance

Output highest scoring candidate as intended meaning by measuring:

\[ \text{sim}(u,m) = \alpha \times \text{sim}_{\text{content}}(u,m) + (1-\alpha) \times \text{sim}_{\text{category}}(u,m) \]
Pre-processing & preparation modules
Pre-processing & preparation modules

**Tweets:**
- Normalize @name to MENTION
- Remove RT (retweet) tag
- Remove leading “#” but keep hash tag’s target concept if English word

**YouTube, Flickr:**
- Bypass auto-generated file names like IMG_336.jpg or MOV_02.AVI
- Remove file type suffix, e.g., “.png”, but leave file name if an English word
- Ignore auto-generated tags, e.g., “hidden:filter=Boost” machine-tag on Flickr

**All utterances:**
- Remove URLs
- Remove non-English
Pre-processing & preparation modules

**Pre-processor**

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**Language based:**
- Non-English
- Single characters and parse errors

**Entity based:**
- Non-entities, i.e., detected terms that are not a Noun class (NN, NNS, NNP, NP) or Named Entity class (e.g., location, person, organization) according to named entity corpora IEER, ACE, or CoNLL
- Non-ambiguous entities (0 or 1 meaning)
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Experiment

Data Sample
- Twitter: tweets
- YouTube: video titles, descriptions
- Flickr: photo tags, titles, descriptions
Experiment

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- String-matched usernames of posters to Wikipedia accounts
- Mechanical Turk used to confirm accounts were same person
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For confirmed matches:

- Collected 100 most recent utterances
- ID, title, page content, categories of edited articles
Experiment

Labeling correct entity meaning

• 1545 valid ambiguous entities
• Mechanical Turk Categorization Masters
• Averaged observed agreement across all coders and items = 0.866
• Average Fleiss Kappa = 0.803
• 918 unanimously labeled ambiguous entities
Dataset Characteristics
Text Length

Longest utterances still shorter than even shortest texts from NER task corpora like Reuters-21578, Brown-Corpus
High Ambiguity

- NER services have low confidence
High Ambiguity

- NER services have low confidence

- Many potential candidates (2 to 163, avg. 5-6, median 4)
High Ambiguity

- 91% of utterances contain at least 1 ambiguous entity
- 2/3 of entities detected are ambiguous
- Almost no entities without at least 2 senses to disambiguate

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<td><strong>(a)</strong></td>
<td>Tweet</td>
<td>Title</td>
<td>Desc</td>
</tr>
<tr>
<td>93%</td>
<td>88%</td>
<td>98%</td>
<td></td>
</tr>
<tr>
<td><strong>(b)</strong></td>
<td>64%</td>
<td>55%</td>
<td>46%</td>
</tr>
<tr>
<td></td>
<td>Title</td>
<td>Desc</td>
<td>Tag</td>
</tr>
<tr>
<td>92%</td>
<td>97%</td>
<td>77%</td>
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</tr>
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<td></td>
<td>66%</td>
<td>44%</td>
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Performance

Metric

- Precision at rank 1 \((P@1)\)
Performance

Metric
• Precision at rank 1 (P@1)

Methods of comparison
• Human annotated gold standard
• RC: Randomly sorted candidates
• PF: Prior frequency
• RU: RESLVE given a random Wikipedia user's interest model
• DS: DBPedia Spotlight
• WM: Wikipedia Miner
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<td>WM</td>
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<td>DS</td>
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Discussion

- Best performance on YouTube texts (longest) due to content-based sim
Discussion

- Best performance on YouTube texts (longest) due to content-based sim
  ![YouTube logo]

- Outperforms on more personal text (e.g., tweets)
  ![Twitter logo]

- Random user model less effective
Discussion

- Best performance on YouTube texts (longest) due to content-based sim
- Outperforms on more personal text (e.g., tweets)
- Random user model less effective

- Less effective on impersonal text (e.g., photo geo-tags)
  - High prior frequency so standard methods suffice
  - Personally-unfamiliar topics so not likely to make Wiki edits about them
  - Stable interests assumption breaks down here
Error Cases

- Automated messages
  - “I uploaded a video on @youtube” → 1945 European Films
Error Cases

• Automated messages
  • “I uploaded a video on @youtube” → 1945 European Films

• Entities not in knowledge base
  • “Peter on the dock”
Error Cases

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• Entities not in knowledge base
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• Less prolific contributors
Future Work
Future Work

- Computability
  - Wikipedia has 5M articles, 700K categories → Vector pruning
Future Work

• Computability
  • Wikipedia has 5M articles, 700K categories ➔ Vector pruning

• User identity & modeling interests
## Bridging User Accounts

<table>
<thead>
<tr>
<th>Platform</th>
<th># Usernames</th>
<th>Exist on Wikipedia</th>
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<tr>
<td>Twitter</td>
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<td>46.1%</td>
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<td>YouTube</td>
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<td>19.6%</td>
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<tr>
<td>Flickr</td>
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<td>21.7%</td>
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## Bridging User Accounts

<table>
<thead>
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Bridging User Accounts
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a. True negative (no identity in knowledge base)
Bridging User Accounts

a. True negative (no identity in knowledge base)

b. False negative (same person, different usernames)
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c. False positives (string match, but different people)
Bridging User Accounts

a. True negative (no identity in knowledge base)
   - Collaborative filtering techniques to approximate user's own interests with contributions of social connections

b. False negative (same person, different usernames)

c. False positives (string match, but different people)
Bridging User Accounts

a. True negative (no identity in knowledge base)
   ✓ Collaborative filtering techniques to approximate user's own interests with contributions of social connections

b. False negative (same person, different usernames)
   ✓ Consider more profile attributes than username

c. False positives (string match, but different people)
Bridging User Accounts

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   ✔ Collaborative filtering techniques to approximate user's own interests with contributions of social connections

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Bridging User Accounts

a. True negative (no identity in knowledge base)
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b. False negative (same person, different usernames)
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  ![Green Checkmark]

c. False positives (string match, but different people)

   - Use other knowledge base besides Wikipedia
Bridging User Accounts

a. True negative (no identity in knowledge base)
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  ![Green check mark]

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• Use other knowledge base besides Wikipedia
• Model user interest from additional kinds of participation (e.g., page visits, bookmarking favoriting)
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c. False positives (string match, but different people)
   - Use other knowledge base besides Wikipedia
   - Model user interest from additional kinds of participation (e.g., page visits, bookmarking favoriting)
   - Interest drift & time-frame of postings
Summary & Conclusion

• Social Web texts: *short & highly personal*

• User posts about same topics across communities (but not always)

• Models *user interest as personal context* with respect to a knowledge base’s categorical organization scheme

• Ranking technique compares entity’s potential meanings to user’s interests to determine *intended meaning*
  • Language and context independent

• Promising performance *gains*

• Going forward: such a strategy becomes increasingly necessary, feasible, and effective
Thank You!

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• Questions?