Name Disambiguation in AMiner:

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An Example in AMiner



Three Scenarios



Full ND

Name disambiguation
when the system is
built from scratch

Candidate p_2 p_3 p- C_1 ? (p_4) (p_5) ? (p_{10}) Candidate $p_6)$ p C_2 Target paper Candidate (p_8) (p_9) C_3

Continuous ND

Name disambiguation when persons' profilesare continuously updated



Error

ences

 Error detection upon existing persons' profiles

1st Scenario: Full ND

• Stage One: Constructing candidate sets of potential matchings.



Stage Two: Similarity Matching

• Constructing similarity matrix for each candidate set.



Stage Three: Clustering

• Partitioning each candidate set based on similarity.



Feature-based Matching

TABLE 1 Attributes of Each Publication p_i

Attribute	Description	
pi.title	title of p_i	
p _i .pubvenue	published conference/journal of p_i	
p _i .year	published year of p_i	
p _i .abstract	abstract of p_i	
p _i .authors	authors name set of $p_i \{a_i^{(0)}, a_i^{(1)}, \dots, a_i^{(u)}\}$	
p _i .references	references of p_i	

Local features

Similarity between a paper and its cluster centroid according to papers' attributes

TABLE 2 Relationships between Papers

R	W	Relation Name	Description
r_1	w_1	CoPubVenue	p_{i} .pubvenue = p_{j} .pubvenue
r_2	w ₂	CoAuthor	$\exists r, s > 0, a_i^{(r)} = a_j^{(s)}$
r_3	<i>w</i> ₃	Citation	p_i cites p_j or p_j cites p_i
<i>r</i> ₄	<i>w</i> ₄	Constraint	feedback supplied by users
r_5	<i>w</i> ₅	τ-CoAuthor	τ -extension co-authorship (τ >1)

Correlation features

• Similarities between two papers according to their relationships.

Embedding-based Matching

- Calculating similarities between embeddings.
 - **Global embeddings**



- Map every paper to a **unified**
- representation space.
- Share supervision across different candidate sets.

• For each candidate set: build a graph by linking each two similar papers.

 g_1

Encoder

Local Embedding

 $\mathbf{Z} \in \mathbb{R}^{N imes d_g}$

Reconstruction Error

Decoder

 $\tilde{\mathbf{A}} \in \mathbb{R}^{N \times N}$

• Train a graph auto-encoder to learn separate representation space.

Local embeddings

 $\mathbf{Y} \in \mathbb{R}^{N imes d_f}$

 $\mathbf{A} \in \mathbb{R}^{N \times N}$

 $\mathcal{G} = (\mathcal{D}, \mathcal{E})$

2nd Scenario: Continuous ND

- Papers come in a streaming fashion (500,000/month).
- Assigning new papers to right persons continuously.
- Stage One: Constructing candidates related to the author of the target paper.



Stage Two: Similarity Matching

- Matching the target paper and each candidate.
- Assigning the paper to the candidate with the largest matching score.



Interaction-based matching

- Calculating the similarities between the embeddings of each pairs of tokens in *p* and *c*.
- Capturing both the exact and the soft matches.



3rd Scenario: Error Detection

- The accuracy of ND algorithms cannot be 100%.
- An additional error detection function is needed.
- Stage One: Extract patterns that can distinguish the right (normal) and wrong (abnormal) assigned papers.



Image Reference: Xin Luna Dong and Divesh Srivastava. Big data integration. Tutorial in ICDE'13, VLDB'13

Pattern Extraction

- Construct a multi-relation egonet for each candidate c.
 - Co-author, co-venue, citation relationships
- For each relation, extract:
 - Number of neighbors of ego c
 - Number of edges in c's egonet
 - Total weight of c's egonet
 - Principal eigenvalue of the weighted adjacency matrix of c's egonet



Image Reference: Xin Luna Dong, Christos Faloutsos, et al. Fact Checking: Theory and Practice. Tutorial in KDD'18

User Feedbacks

Merge Function: Merge person profiles



Add function:

Assign new papers to persons



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Dataset: https://www.aminer.cn/na-data **AMiner**: https://www.aminer.cn/





