



Isnad Disambiguation

By Joe Hilleary and Kyle Sayers

Reframing the Problem

- Historians are interested in scholarly transmission
 - Captured by *isnads*
- Name disambiguation problem
 - Manually time consuming
- Can we make suggestions based on limited manual labeling to speed up the process?

حدثنا أبو داود قال: حدثنا هشام، عن قتادة، عن الحسن عن سمرة، أن النبي صلى الله عليه وسلم

Abu Dāwūd transmitted to us, saying, ‘Hishām transmitted to us, from Qatādah, from al-Ḥasan, from Samurah that the Prophet, may the peace and blessing of God be on him¹



Starting Data

- ▶ Partially disambiguated chains
 - ▶ From Ta'rikh Madinat Dimashq by Ibn 'Asakir
 - ▶ All connecting through Muhammed Ibn Sa'd
- ▶ 2,380 chains
- ▶ 14,454 mentions
 - ▶ 13,072 labeled by domain expert
 - ▶ 44 unique individuals

1. Building the Graph

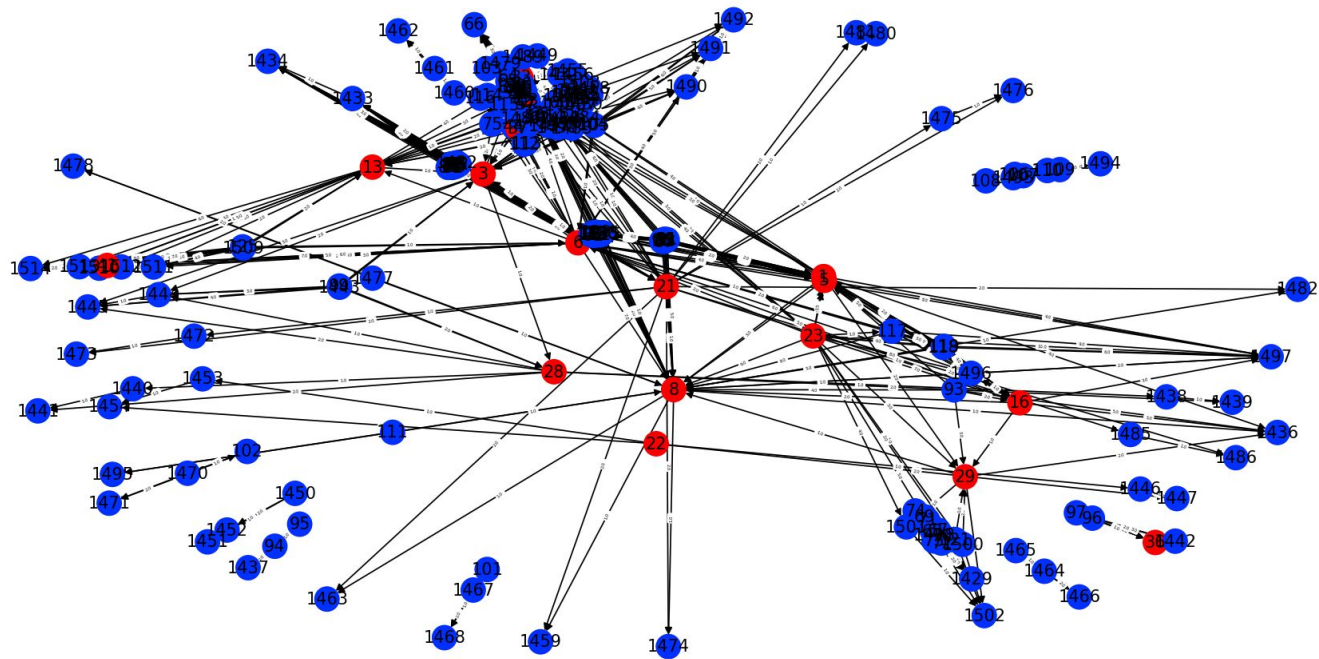




Graph at t_0

- ▶ Read in the data
 - ▶ Select some labels to cover up
 - ▶ Connect nodes based on co-occurrences
 - ▶ Weight directed edges by average position





2. Calculating Features

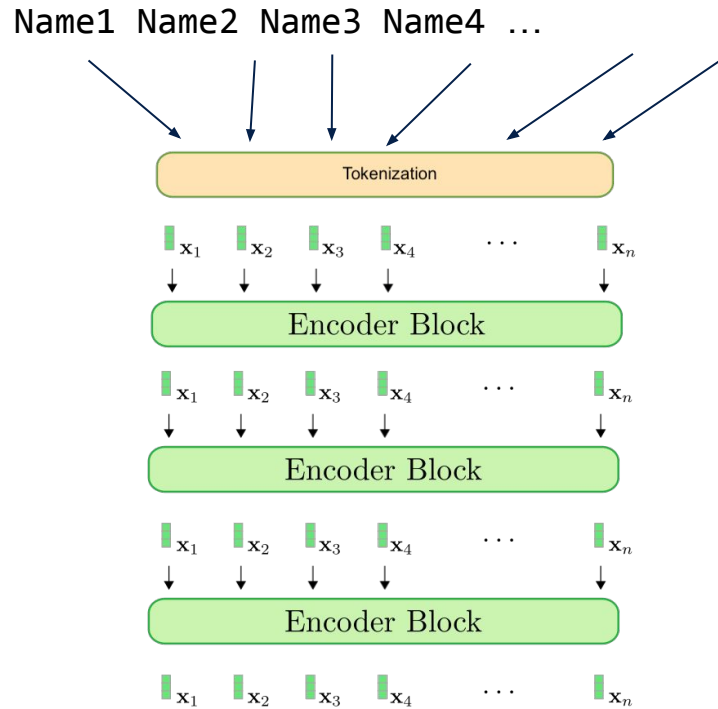




Social Hashing

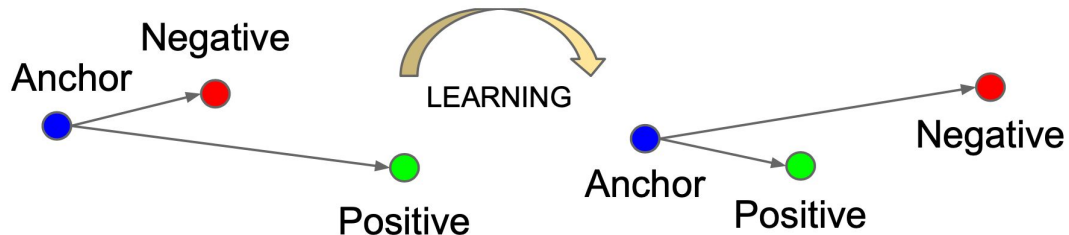
- ▶ 2 social feature vectors
 - ▶ # co-occurrences
 - ▶ average relative position in co-occurrences
- ▶ Length equal to the number of nodes in the graph

Context Embedded Tokens



Contrastive Name Embeddings

- ▶ Supervised learning of name representations
- ▶ Initially used the same test set for contrastive learning and graph prediction, but found it was unnecessary



3. Match and Merge

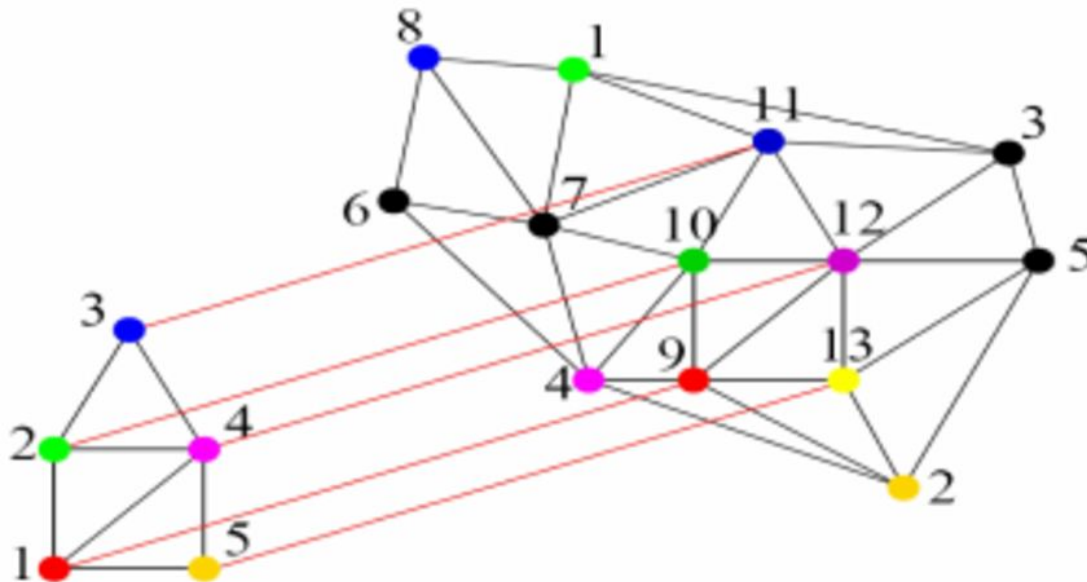




Calculate Similarity Matrix

- ▶ Cosine similarity between all nodes
- ▶ Dynamic computation
- ▶ Memoization of results
- ▶ Multithreaded computation (limited)

Subgraph Matching





Merge Until Stable

- ▶ Each unlabeled node matched to label
 - ▶ Uniquely assigned
 - ▶ Assigned to an existing label
- ▶ Recompute features each iteration
 - ▶ Using features from composite nodes
- ▶ Stop when all ambiguous nodes have been assigned a label

4. Concessions for Performance





Computational Limits

- ▶ Size of the similarity matrix
- ▶ Networkx limits multithreading (graph tool)
- ▶ Recomputation after every merge
- ▶ More efficient hash recomputation
- ▶ Locality sensitive hashing



Processing

- ▶ Batches of top 50 nodes at each stage of recalculation
- ▶ Can't match unlabeled node to unlabeled node
 - ▶ If nodes begin to resemble each other later on, matches are already fixed
- ▶ Only check labeled neighbors

5. Results





Evaluating

- ▶ CoNLL
 - ▶ Composite measure of cluster similarity
 - ▶ MUC , B^3 , $CEAF_e$
- ▶ Did we re-cluster nodes known to share a label?

Comparison with Muther & Smith

	kNN100_leiden	Surface Form	Our Method (33%)
B^3	.756	.868	.603
CEAF _e	.444	.523	.664
CoNLL	.727	.790	.753

Our Method

	Muthur & Smith Embeddings (33%)	Contrastive Embeddings (33%)	No Social Features (33%)
B^3	.603	.742	.979
CEAF _e	.664	.530	.826
CoNLL	.753	.755	.934



Conclusion

- ▶ NLP embeddings seem to be a better way to tackle this problem than social features
- ▶ Contrastive embeddings appear more effective



5. What's Next?





This Project

- ▶ Parameter tuning
- ▶ Ambiguous to ambiguous matching
 - ▶ No known starting labels
- ▶ Shifting weights
 - ▶ Move from NLP to social as more is known



Future Work

- ▶ Locality sensitive hashing
 - ▶ Similarity \rightarrow collisions
- ▶ Deep features
 - ▶ *Neural Subgraph Matching (Rex Ying, Andrew Wang)*
- ▶ Jaccard Index for subgraph matching
- ▶ Other distance metrics for social features

Citations

Goebel, Peter & Vincze, Markus. (2007). Implicit Modeling of Object Topology with Guidance from Temporal View Attention.

R. Muther and D. Smith, 'The Fellowship of the Authors: Disambiguating Names from Social Network Context'. arXiv, 2022.

R. Muther, D. Smith, and S. Savant, 'From Networks to Named Entities and Back Again Exploring Classical Arabic Isnad Networks'. *Journal of Historical Network Research* 5, 2023.

Rex *et al.*, 'Neural Subgraph Matching'. arXiv, 2020.