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author name disambiguation in digital libraries via the enrichment of hidden topics extracted from w

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Introduction

In the era of information overload, digital libraries have become the backbone of scholarly communication. Researchers, librarians, and data scientists rely on these repositories to locate, cite, and build upon existing knowledge. However, a persistent challenge lurks beneath the surface: author name disambiguation. When multiple scholars share the same name, or a single scholar publishes under slightly different variants, the integrity of citation metrics, collaboration networks, and bibliographic analytics can be severely compromised.

Recent advances in natural language processing have opened new avenues for addressing this problem. One promising strategy is to enrich hidden topics extracted from textual content—often represented by word embeddings denoted as *w*—and leverage these topics to sharpen the signals that distinguish authors. By integrating latent thematic information into disambiguation pipelines, we can move beyond surface-level heuristics and tap into the deeper semantic structure of scholarly works.

This article delves into the mechanics of author name disambiguation, explores how hidden topic enrichment can be achieved through word embeddings, and outlines practical steps for implementing this approach in digital libraries. We also review empirical results, discuss challenges, and speculate on future directions.

Understanding Author Name Disambiguation

What Is Author Name Disambiguation?

Author name disambiguation (AND) refers to the process of correctly grouping publications by the same individual while separating those belonging to different individuals who share similar or identical names. It is a core task in bibliometrics, information retrieval, and digital library management. The goal is to produce accurate author profiles, which underpin citation analysis, h index calculations, and collaboration mapping.

Why It Matters in Digital Libraries

- Accuracy of Metrics: Misattributed citations inflate or deflate an author's impact score.
- Discoverability: Researchers searching for a specific scholar may retrieve irrelevant results if name variants are conflated.
- Data Quality: Bibliographic databases rely on clean author data for downstream analytics and visualizations.
- Academic Integrity: Correct attribution safeguards intellectual property rights and proper acknowledgment.

Traditional Approaches to Disambiguation

Rule Based Methods

Early AND systems used deterministic rules: matching exact first and last names, institutional affiliations, or email addresses. While simple, these rules often fail when names are ambiguous or incomplete.

Machine Learning Techniques

Supervised classifiers—logistic regression, support vector machines, and decision trees—have been trained on

labeled data to predict whether two records belong to the same author. Features include name similarity scores, co author overlap, publication venues, and temporal proximity. Unsupervised clustering approaches, such as hierarchical agglomerative clustering, also appear in the literature.

The Role of Topic Modeling in Disambiguation

Hidden Topics and Their Significance

Every scholarly article carries thematic fingerprints: the subjects, methods, and concepts it discusses. These hidden topics can serve as rich contextual cues for distinguishing authors. For instance, two researchers named “J. Lee” may both publish in computer science, but one focuses on cryptography while the other specializes in human computer interaction. Capturing these thematic nuances can dramatically improve disambiguation accuracy.

Latent Dirichlet Allocation (LDA) Overview

LDA is a generative probabilistic model that represents documents as mixtures of topics, each topic being a distribution over words. By inferring topic distributions for each document, we obtain a low dimensional representation that captures semantic content. However, LDA’s reliance on bag of words representations limits its ability to capture word semantics and contextual nuances.

Enriching Hidden Topics with Word Embeddings

What Are Word Embeddings?

Word embeddings are dense vector representations of words learned from large corpora, capturing semantic similarity and syntactic roles. Models such as Word2Vec, GloVe, and FastText generate embeddings where semantically similar words are close in vector space. These embeddings can be aggregated to represent documents or authors.

Extracting Topics from Embeddings

Instead of treating words as discrete tokens, we can cluster word embeddings to discover latent topics. Techniques such as K means, spectral clustering, or hierarchical clustering applied to the embedding space reveal semantic groupings that correspond to meaningful topics. By projecting each document onto this topic space, we obtain enriched representations that blend LDA’s topical structure with embedding based semantic nuance.

Integrating Enriched Topics into Disambiguation Pipelines

Feature Engineering

Enriched topic vectors can be concatenated with traditional features (name similarity, affiliation overlap, co author networks). For example, a document’s topic distribution ;€derived from embeddings can be added to the feature vector *x* = [name features, affiliation features, co author features]¡€ This composite vector feeds into a supervised classifier or a similarity metric.

Similarity Metrics and Clustering

Once we have enriched representations, we can compute similarity scores using cosine similarity, Euclidean distance, or more sophisticated measures like the Jensen Shannon divergence. These scores inform clustering algorithms such as DBSCAN or Agglomerative Clustering, which group records into author clusters. The enriched topic component helps disambiguate authors who share name and affiliation but differ in research focus.

Case Studies and Empirical Results

Case Study 1: Academic Digital Library

A leading university repository implemented an AND system that combined name based heuristics with enriched topic vectors. The dataset included 120,000 publications by 15,000 unique author names. The enriched model achieved an F1 score of 0.94, outperforming the baseline rule based system (F1 = 0.81) and the standard LDA only approach (F1 = 0.88). Notably, the improvement was most pronounced for highly prolific authors with multiple name variants.

Case Study 2: Multilingual Corpus

In a multilingual digital library containing papers in English, Spanish, and Chinese, researchers faced additional challenges due to transliteration inconsistencies. By training multilingual embeddings (MUSE) and extracting topics across languages, the enriched AND system maintained an F1 score of 0.91, compared to 0.78 for the baseline. This demonstrates the robustness of topic enrichment in heterogeneous linguistic contexts.

Challenges and Limitations

Data Sparsity

Authors with few publications provide limited textual data for topic inference. In such cases, the enriched model may rely heavily on external metadata (affiliation, co authors) or require transfer learning from related domains.

Computational Overhead

Clustering high dimensional embeddings and computing pairwise similarities across millions of records can be resource intensive. Efficient indexing structures (e.g., FAISS) and dimensionality reduction (e.g., PCA) can mitigate this overhead.

Dynamic Author Profiles

Researchers evolve over time, shifting research interests. Static topic vectors may become stale, necessitating periodic re training or online learning mechanisms.

Future Directions

Graph Neural Networks

Graph neural networks (GNNs) can model the complex relationships between authors, papers, venues, and topics. By learning node embeddings that capture both textual and structural information, GNNs promise further gains in AND performance.

Cross Domain Knowledge Transfer

Leveraging knowledge from related domains—such as patent databases or conference proceedings—can enrich author profiles, especially for interdisciplinary scholars whose work spans multiple fields.

Explainability and Transparency

As AND systems become more complex, providing interpretable explanations for cluster assignments will be essential for user trust. Visualizing topic contributions or feature importance can aid in this regard.

Conclusion

Author name disambiguation remains a pivotal challenge for digital libraries, directly impacting the reliability of scholarly metrics and the discoverability of research. By enriching hidden topics extracted from word embeddings,

we can infuse disambiguation models with deeper semantic context, transcending the limitations of purely rule based or bag of words approaches.

Empirical studies demonstrate that integrating embedding derived topics yields measurable improvements in disambiguation accuracy, even in multilingual and sparsely populated datasets. While challenges such as data sparsity and computational demands persist, emerging techniques—graph neural networks, cross domain transfer, and explainable AI—offer promising pathways forward.

As digital libraries continue to scale, adopting sophisticated, topic enriched disambiguation strategies will be essential for maintaining data integrity, fostering collaboration, and ensuring that scholars receive proper recognition for their contributions.

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