



# Model Selection Strategies for Author Disambiguation

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# Outline

- Problem Statement
- Disambiguation Workflow
- Clustering & Model Selection
- Data Set & Experiments
- Conclusion

# Problem Statement

## Definition

Given a set of scientific publications/citations, our aim is to **identify distinct authors and their respective publications** within the set

# Problem Statement Examples

Where does ambiguity come from?

- Two distinct authors share the same name
- A single author is referred to by different orthographic variations of her name
- An author has changed her name due to marriage or other causes

3.  Keep   0 Self Citations   1 Authors

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[M Granitzer](#) - Master's Thesis, Graz University of Technology, 2003

... Methods from Machine Learning Michael **Granitzer** Page 2. Hierarchical Text Classification using Methods from Machine ... submitted by Michael **Granitzer** Institute of Theoretical Computer Science (IGI), Graz University of Technology A-8010 Graz, Austria 27th October 2003 ...

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# Application Scenarios

Citation and Impact Analysis

Creating author profiles in social research networks like Mendeley

Recommendation engine for research papers

Facetted Search

**Scholar** Articles and patents anytime include citations Cre

Redo the above query as: Quoted author name Word matching

Advanced Analysis Interface. Go to the Simple interface from [here](#). How to [save](#) my data analysis

**Impact indices**

Normalization	Citations	h-index	g-index	e-index	delta-h	delta-g
none	258	>10	>10	-	-	-
per co-authorship	99.2	7	9	5	3.2	0.8
per age	23.4	3	4	2	0.3	4.5

 **MENDELEY**

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 **Dr. Michael Granitzer**

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**Research field: Computer and Information Science - Information Retrieval**  
Information Retrieval, Machine Learning, Visual Analytics, Knowledge Discovery, Semantic Technologies and Multimedia Semantics

**Publications**

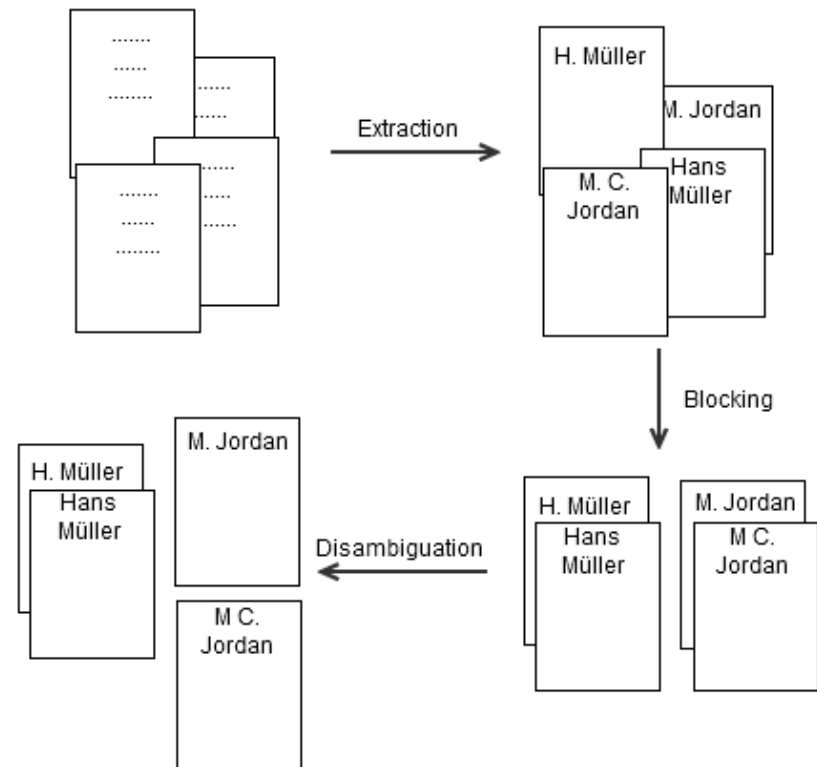
▼ Book (3)

Michael Granitzer (2008) KnowMiner - Konzeption & Entwicklung eines generischen Wissenserschließungsframeworks, 236.  
<http://www.terrashop.de/83647209A/art...>  
Download PDF (4.22 MB)

# A Disambiguation Framework Overview

Many systems presented in the literature for author disambiguation share the same workflow

1. Extract author name occurrences from publications/citations
2. Block author names and the publications they occur in
3. Disambiguate authors within each block



# A Disambiguation Framework

## 1. Author Name Extraction

Extraction of author names

- Rule-based** extraction based on known publication layouts
- Machine learning techniques for **sequence tagging** (HMMs, CRFs, SVMs)
- Achievable Performance** (not part of this paper)
  - 0.8-0.9 Precision
  - 0.5-0.8 Recall

→ The result of this stage is **a set of author names for each publication/citation**

# A Disambiguation Framework

## 2. Blocking

- Blocking is the process of **grouping sufficiently similar author names and the publications/citations** associated with them
- Blocking is performed **for performance** and tractability reasons
- Similarity measures** for author names
  - Phonetic hashing via Soundex or Metaphone
  - String hashing methods
- Focus on Recall** – a block must contain all possible unique authors and their publications



# A Disambiguation Framework

## 3. Disambiguation

- Disambiguation is most often achieved via **clustering**
  - For every block
  - Consider all pairs of author names represented as strings and their occurrence in publications
  - Cluster all pairs to groups with unique authors, so that
    - all pairs in a group represent the same unique author
    - All publications of one authors are contained in one group
  
- Core decisions to apply clustering
  - **Features** to represent pairs
  - **Similarity Measures** between pairs
  - **Model Selection** Method, i.e. guessing the number of authors in one block
  - **Clustering algorithm**

# Clustering Properties

## Features & Similarity Measure

### Features

- Noun, adjective and adverbs of publications plain text and information obtained from search engines
- Keywords extracted from a publications plain text (TextRank)
- Tokenized title text
- Tokenized author names

### Cosine as similarity measure



# Clustering Properties

## Model Selection – I

- Guess the number of unique authors in one block
    - Large variance, correct number can range from 1 to 100 (and more)
    - Hard problem, often neglected by related work
  
  - Standard methods exists (e.g. density based, stability based)
    - Preliminary test showed very low accuracy
- ➔ Development of a task specific model selection strategies (main contribution)**

# Clustering Properties

## Model Selection - II

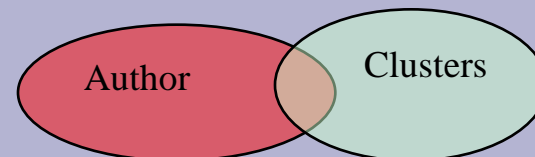
- Approach/Assumption
  - Clustering groups textually similar publications of a block
  - Use different feature kind for model selection: Co-authorship
  - The more co-authors overlapp in a cluster and the less they are spread between cluster, the better
- Use conditional probabilities as measures therefore

$$\bar{P}_{ac} = \frac{1}{|pairs|} \sum_{\forall pairs} 1 - P(author | cluster)$$

$$\bar{P}_{ca} = \frac{1}{|pairs|} \sum_{\forall pairs} 1 - P(cluster | author)$$

$$F(C) = (\bar{P}_{ac} + \bar{P}_{ca}) / 2$$

All Pairs Venn Diagramm



# Clustering Properties

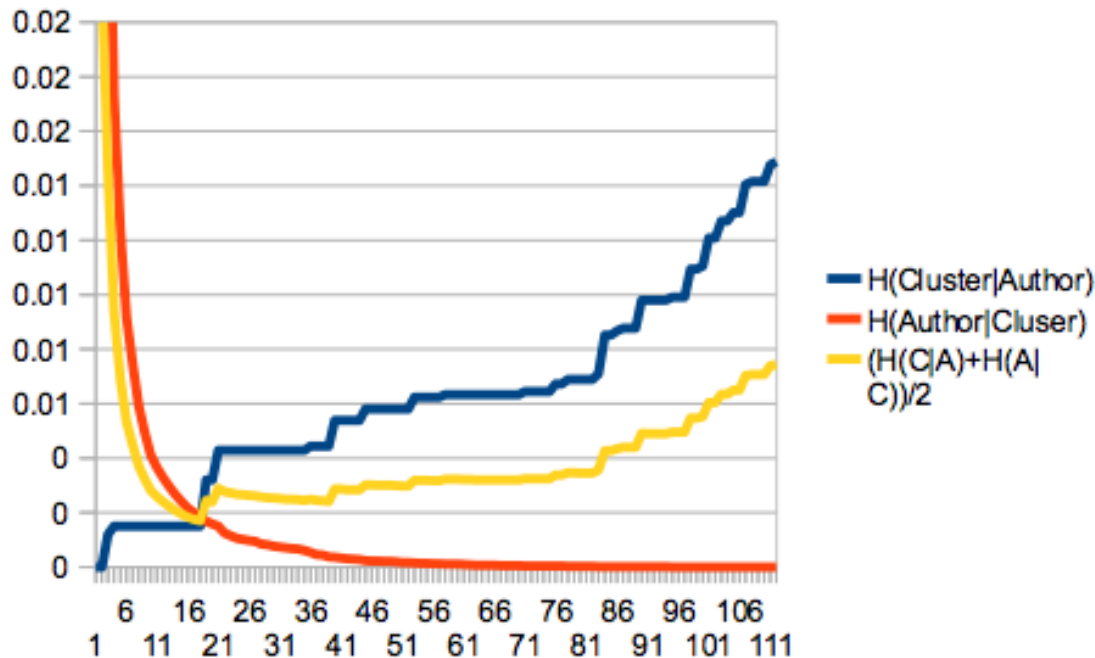
## Model Selection - III

- Similar formulation using point-wise conditional entropy

$$H_{pointwise}(Y|X) \stackrel{\text{def}}{=} - \sum_C p(x, y) \log p(y|x)$$

$$C = \{c | c \in Clusters_{Co-Author}\}$$

- Example



# Experiments Setup

## Two data set

- **Giles** provides a nice dataset of citations with 12 ambiguous author names (<http://bit.ly/aBV8qP>)
- **Mendeley** provided us with a much larger dataset retrieved from user profiles (<3 Mendeley)
- For every publication/citation we also **gathered web search results** for additional data from Google, Bing, ACM (until we got blocked), e.g. plain text

## Workflow Setup

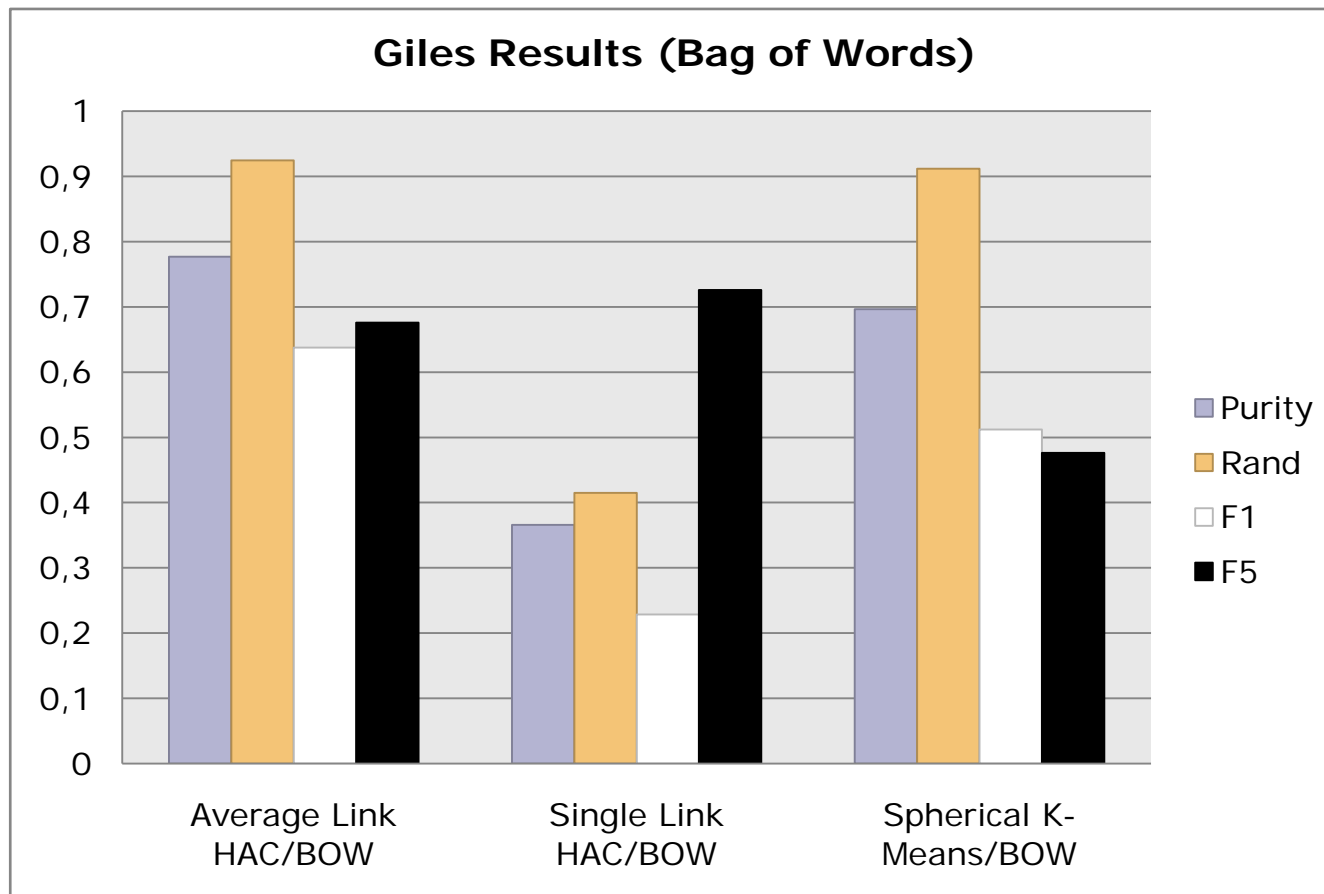
- Identification (Step 1) was not necessary
- Blocking – used Ground-Truth to create forename subsets: Lee, Martin, Gupta, Kumar, Chen, Johnson

➔ **Error Analysis focuses solely on clustering properties**

# Experiments

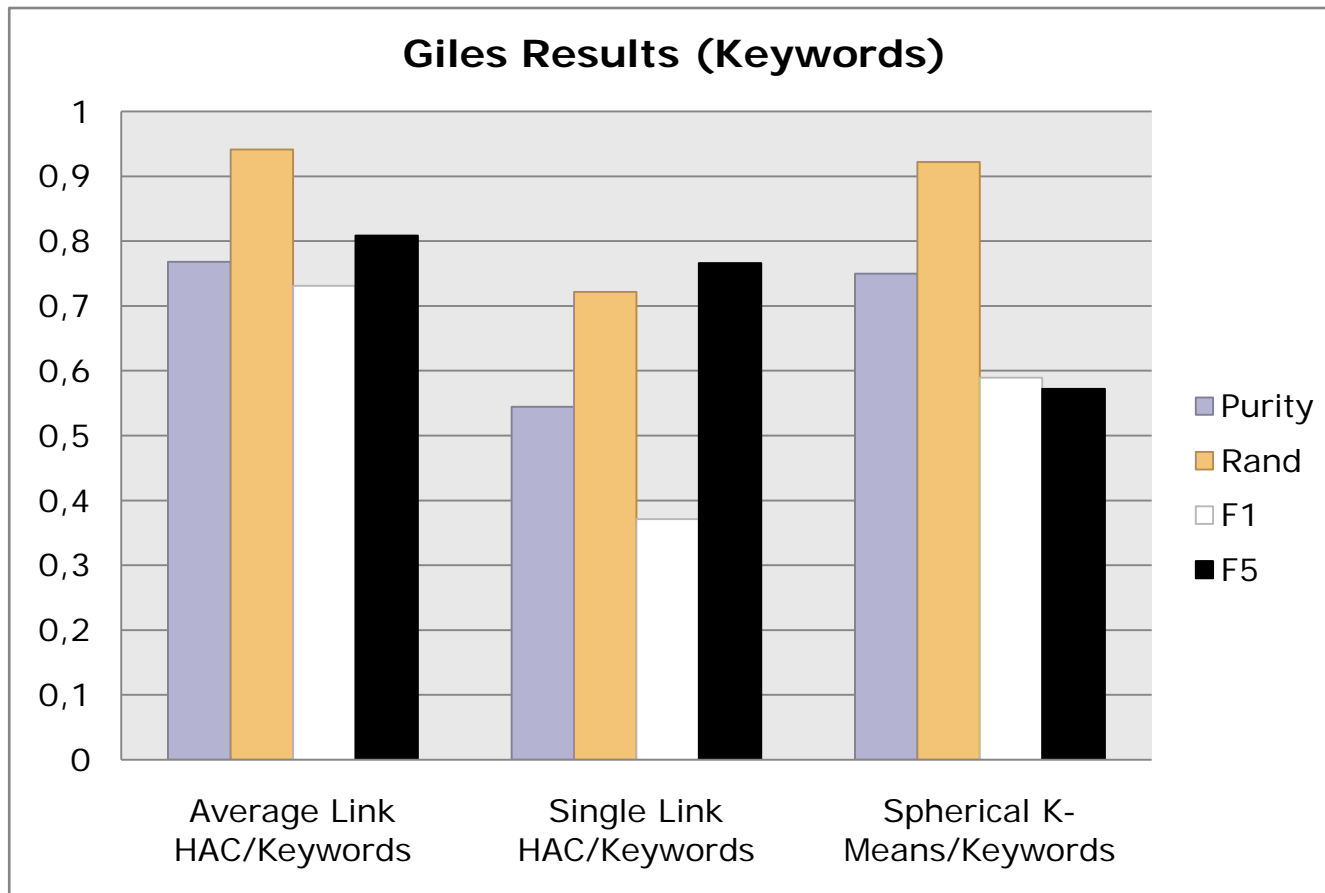
## Results Clustering Algorithms

Fix number of clusters to the true number of unique authors



# Experiments

## Results Clustering Algorithms



HAC with average linking seems is best clustering approach



# Experiments

## Results Features

- Again, assume number of unique authors known

Author	Title	Keyword	Stem	Normalize	Purity	F1
✓	✓	✓		✓	0.92	0.9
✓	✓	✓	✓	✓	0.91	0.89
		✓		✓	0.87	0.84
		✓			0.87	0.84
✓		✓	✓	✓	0.88	0.83

Table I

BEST 5 RESULTS USING HAC CLUSTERING ON THE GILES-MARTIN SUBSET. SORTED BY F1. 16 DISTINCT AUTHORS, 112 PUBLICATIONS.

Author	Title	Keyword	Stem	Normalize	Purity	F1
✓	✓	✓	✓	✓	0.72	0.50
✓	✓	✓		✓	0.70	0.48
✓	✓	✓	✓		0.70	0.46
	✓	✓	✓	✓	0.61	0.42
✓	✓	✓			0.66	0.39

Table II

BEST 5 RESULTS ON HAC CLUSTERING ON THE GILES LEE SUBSET. SORTED BY F1. 100 DISTINCT AUTHORS, 1419 PUBLICATIONS.

- Results on the Martin subset are encouraging. Reason: full-text features contain less noise

# Experiments

## Results Model Selection

- What is the difference if we have to guess the author number?

	Dataset	$K_{real}$	$F1_{best}$	$K_{guess}$	$F1_{guess}$	$F1_{real}$
→	Mendely-lee	49	61%	44	28%	27%
→	Giles-martin	16	90%	16	84%	84%
→	Giles-gupta	26	65%	14	43%	65%
→	Giles-kumar	14	70%	14	44%	44%
→	Giles-chen	61	46%	12	10%	37%
→	Giles-johnson	15	78%	11	60%	75%
→	Giles-lee	100	50%	21	5%	38%

Table IV

MODEL SELECTION RESULTS USING POINT-WISE CONDITIONAL  
ENTROPY ON KEYWORDS ONLY

- Performance varies, but gives good results when clustering comes close to the real groups (i.e. Martin Subset)
- Underestimate correct number of clusters



# Conclusion

- HAC as empirical best algorithm for disambiguation
- New Model Selection Strategies work good given good clustering results
- Automatic Author Disambiguation still unsolved for practical scenarios
- Identification and Blocking as additional error sources
- Future Work
  - reduce the effect of blocking errors and model selection through outlier detection
  - Improved feature selection and cleaning

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