On the Feasibility of Author Identification in the Era of Big Data

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Motivation

- Anonymous/pseudonymous contents are everywhere!

Motivation

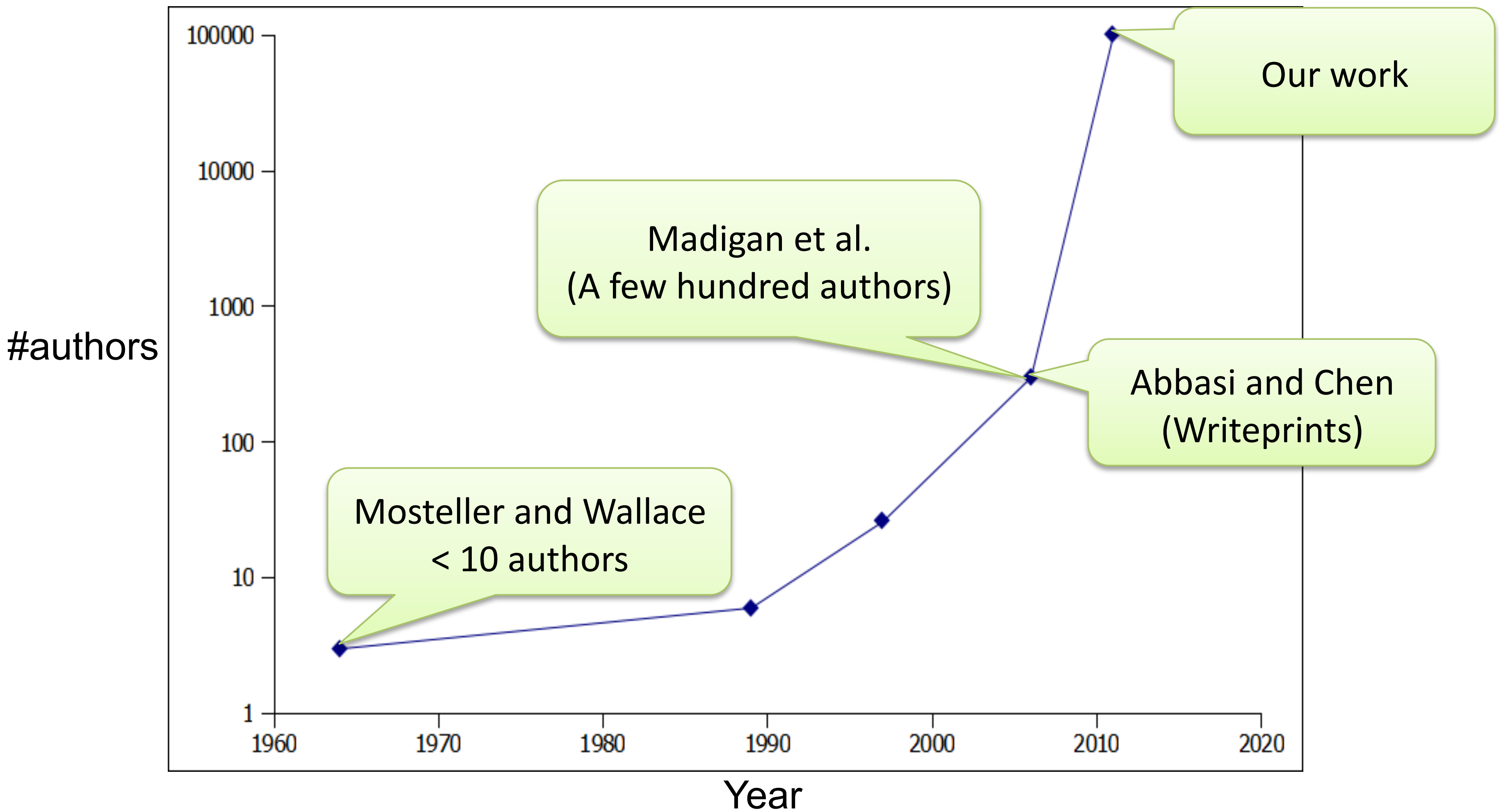
- Anonymous contents:
  - Sensitive political topics
  - Sensitive personal psychological/health issues.
- Identifying authors = huge privacy attack!
- Possible via writing style at Large scale?

Notable Coups for Stylometric Author Identification

Shakespeare-Bacon controversy in 19th century

Disputed Federalist Papers ~50 years ago

Graph of #authors vs. year



Author identification behaves qualitatively different at large scale.

Threat Model

Attacker: oppressive government, etc.

Authors are *not* protecting themselves

Use author ID as first step

Follow up with other methods:

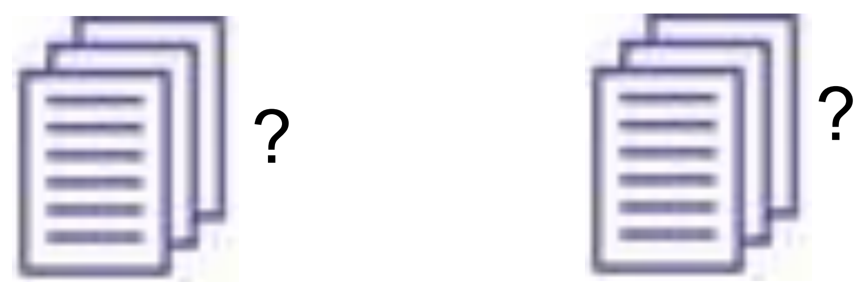
topic, viewpoints, location…

Problem Definition

- Given:
  - N authors

  - A set of labeled documents for each author.

- Target:
  - Identify the author of anonymous documents.



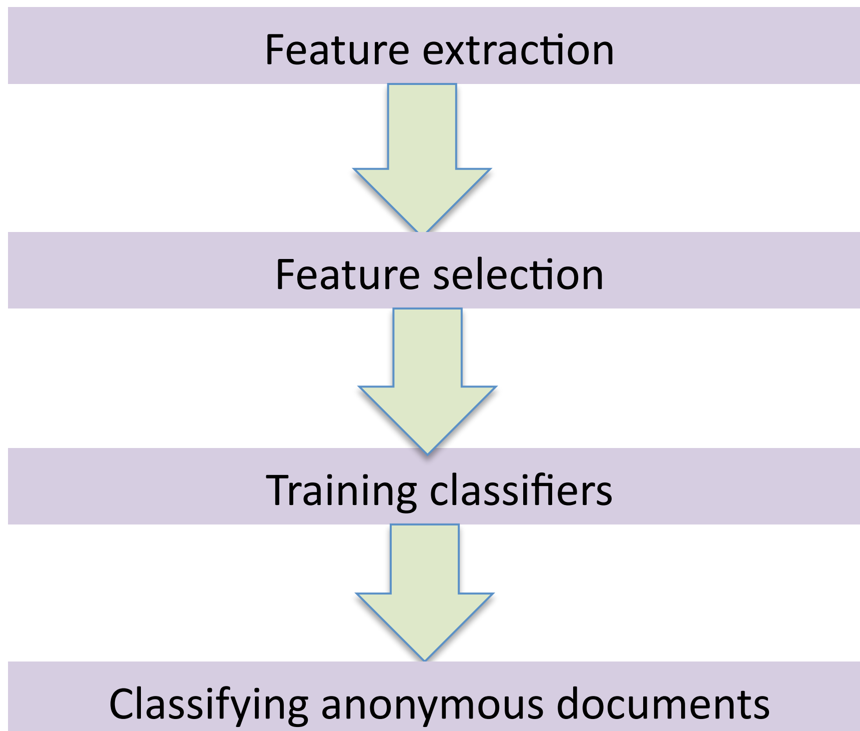
Approach

- Identification is a multi-class classification problem.
  - Classes: authors
  - Training examples: labeled documents
  - Test examples: anonymous documents

Roadmap

- Issues of large scale
- Dataset
- Experimental results
- Conclusion
- Future work

Machine Learning Framework



Scale impacts every part

Feature Extraction

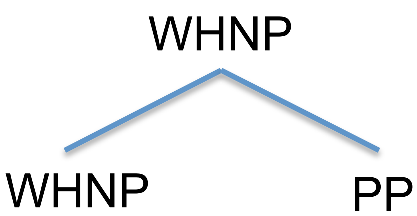
Writeprints features

Category	Description	Count
Length	number of words/characters in post	2
Vocabulary richness	Yule's K^2 and frequency of *hapax legomena*, *dis legomena*, etc.	11
Word shape	frequency of words with all upper-case letters, all lower-case, etc.	5
Word length	frequency of words that have 1–20 characters	20
Letters	frequency of *a* to *z*, ignoring case	26
Digits	frequency of 0 to 9	10
Punctuation	frequency of . ? ! , ; : ( ) " - '	11
Special characters	frequency of other special characters ` ~ @ # $ % ^ & * _ + = [ ] { } \ | / < >	21
Function words	frequency of words like 'the', 'of', and 'then'	293
Syntactic category pairs	frequency of every pair (A, B), where A is the parent of B in the parse tree	789

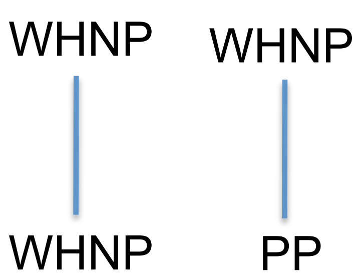
Our new feature

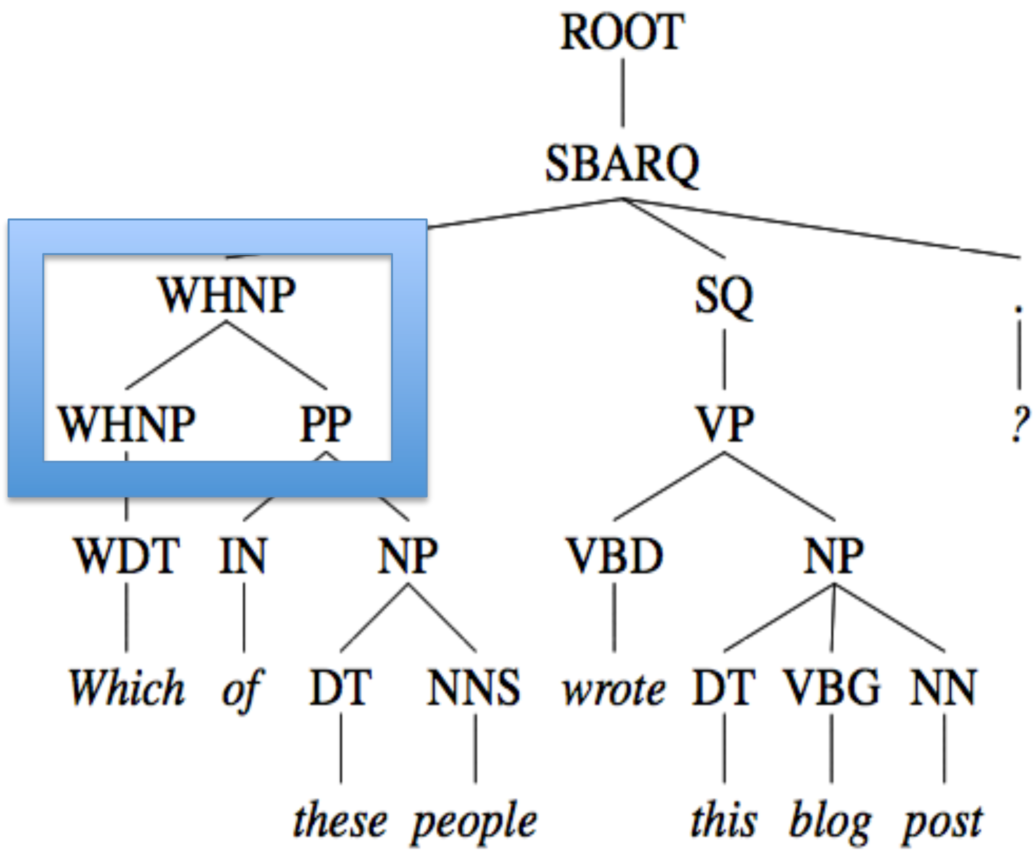
Syntactic Features

Previous feature:



Our feature:

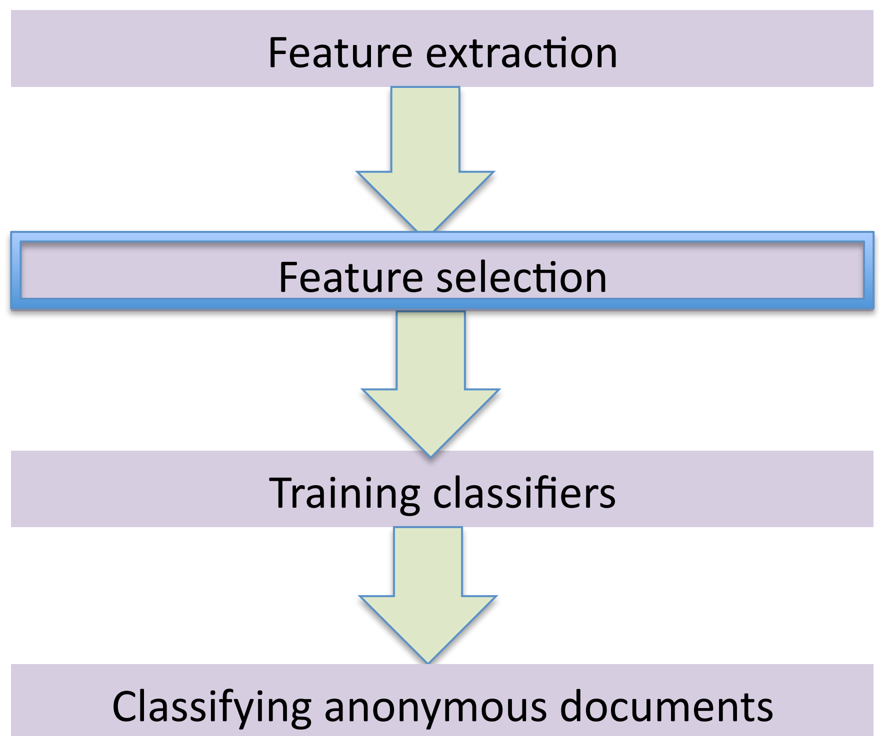




A sample parse tree produced by the Stanford Parser.

~1200 features!

Machine Learning Framework

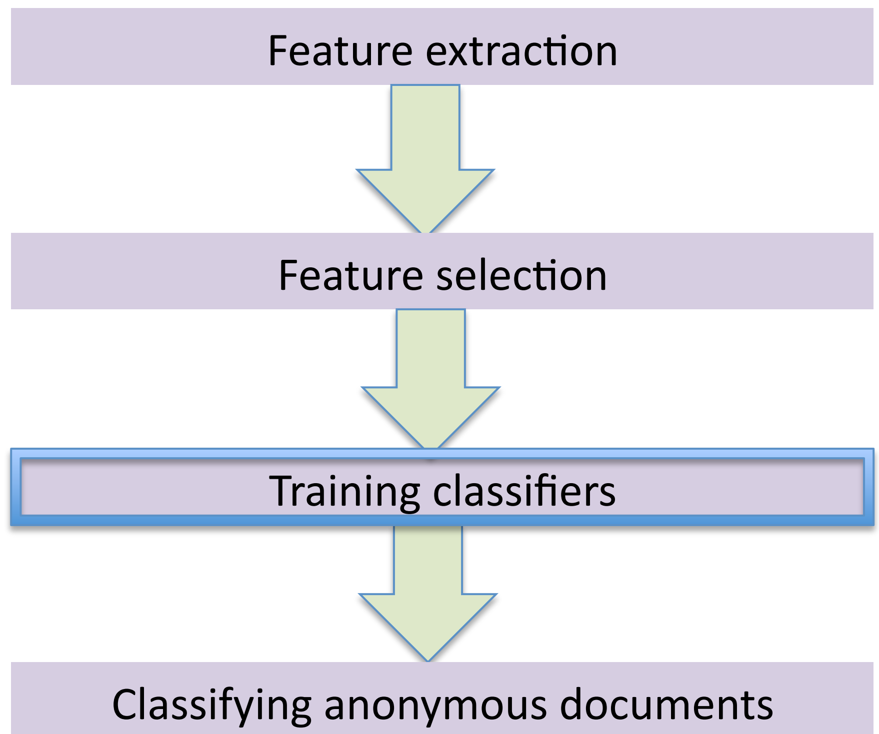


Feature Selection

- Information gain
- Document frequency

- Helpful for small scale
- Not helpful for large scale

Machine Learning Framework



Classifiers

- Nearest neighbor (NN)
- Naïve Bayes (NB)
- Support vector machines (SVM)
- Regularized least square classifier (RLSC)
- Ensemble classifier
  - NN + RLSC

Regularized Least Square Classifier (RLSC)

- Comparable accuracy to SVM
- Much more scalable than SVM
- One-vs-all
  - Training binary classifier for each author
- Class imbalance
  - Subsampling a small number of negative examples
  - Cost sensitive learning. ✔
    - Penalizing more for misclassifying positive examples

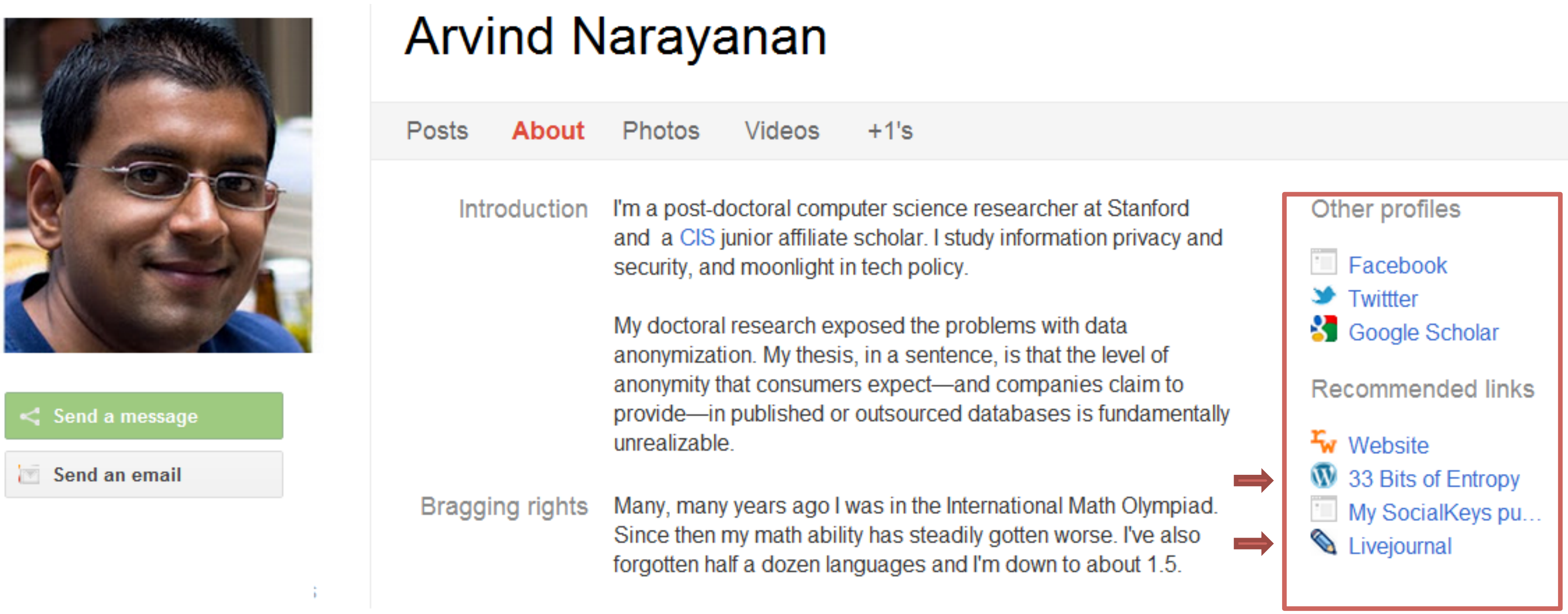
Dataset

spinn3r

ICWSM 2009 Dataset: ~94k blogs

Minimum 7,500 characters per blog
(roughly 8 paragraphs)

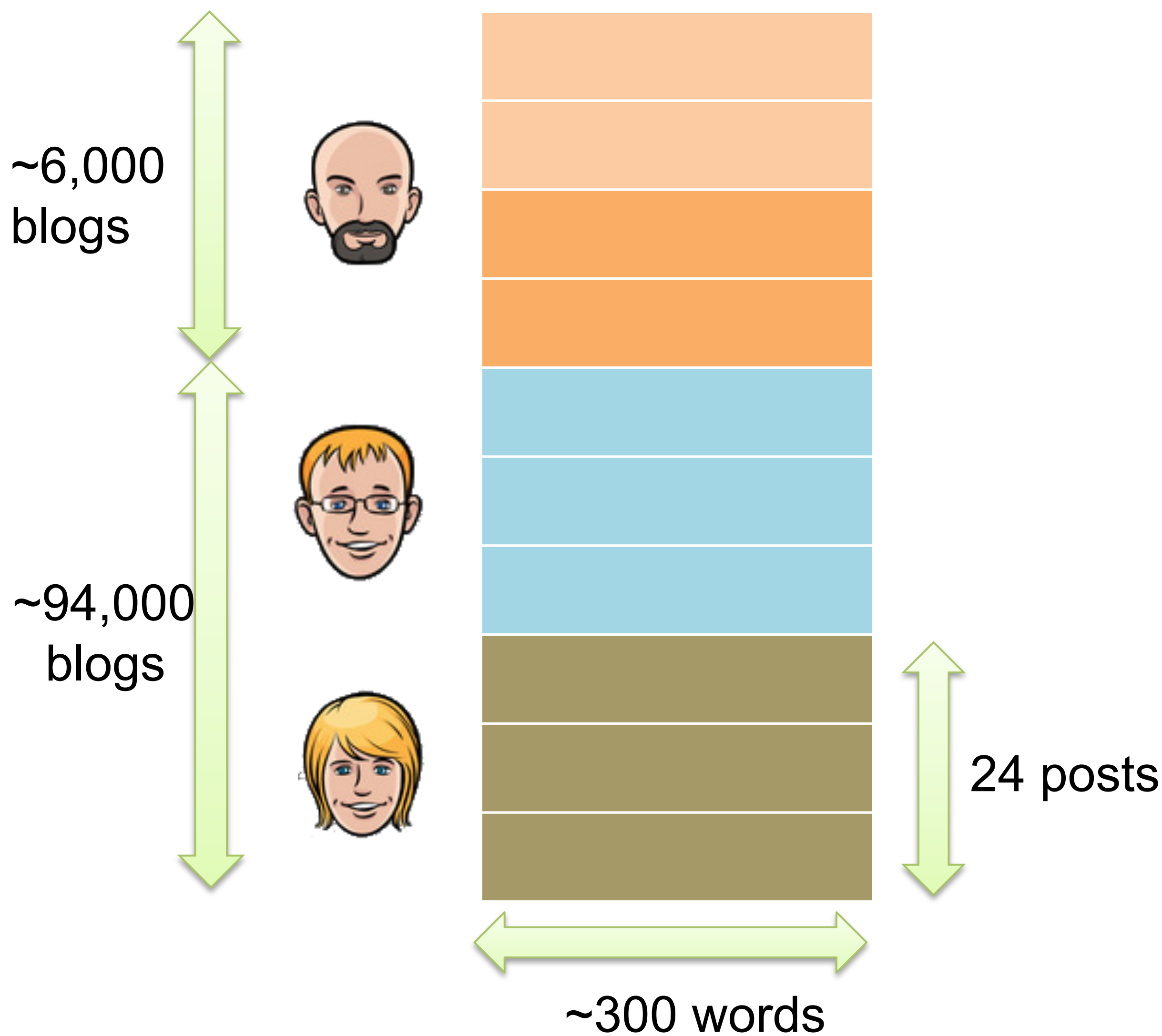
Dataset : Google Profiles



~6,000 blogs

~3,600 authors

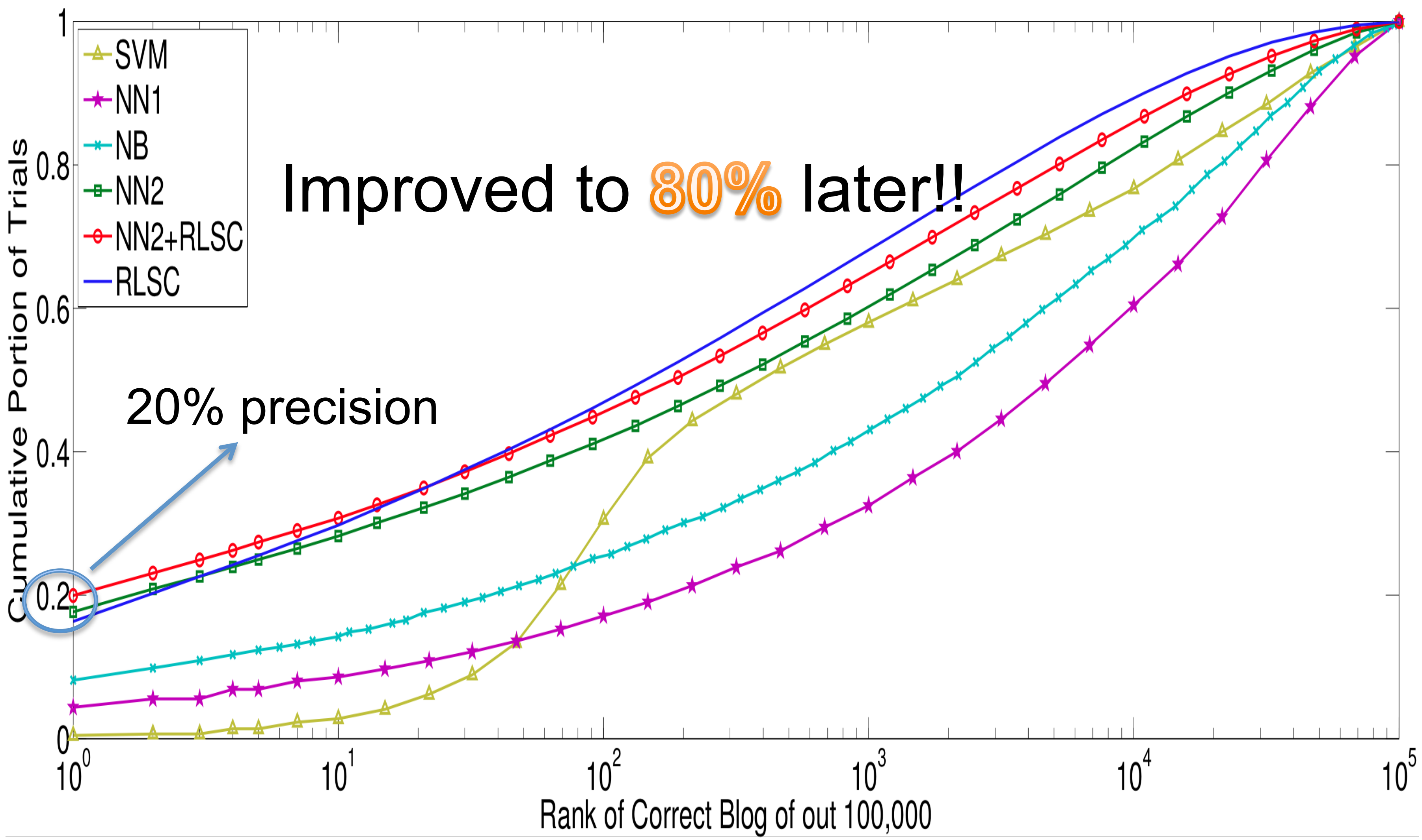
Data Size



Experimental Design

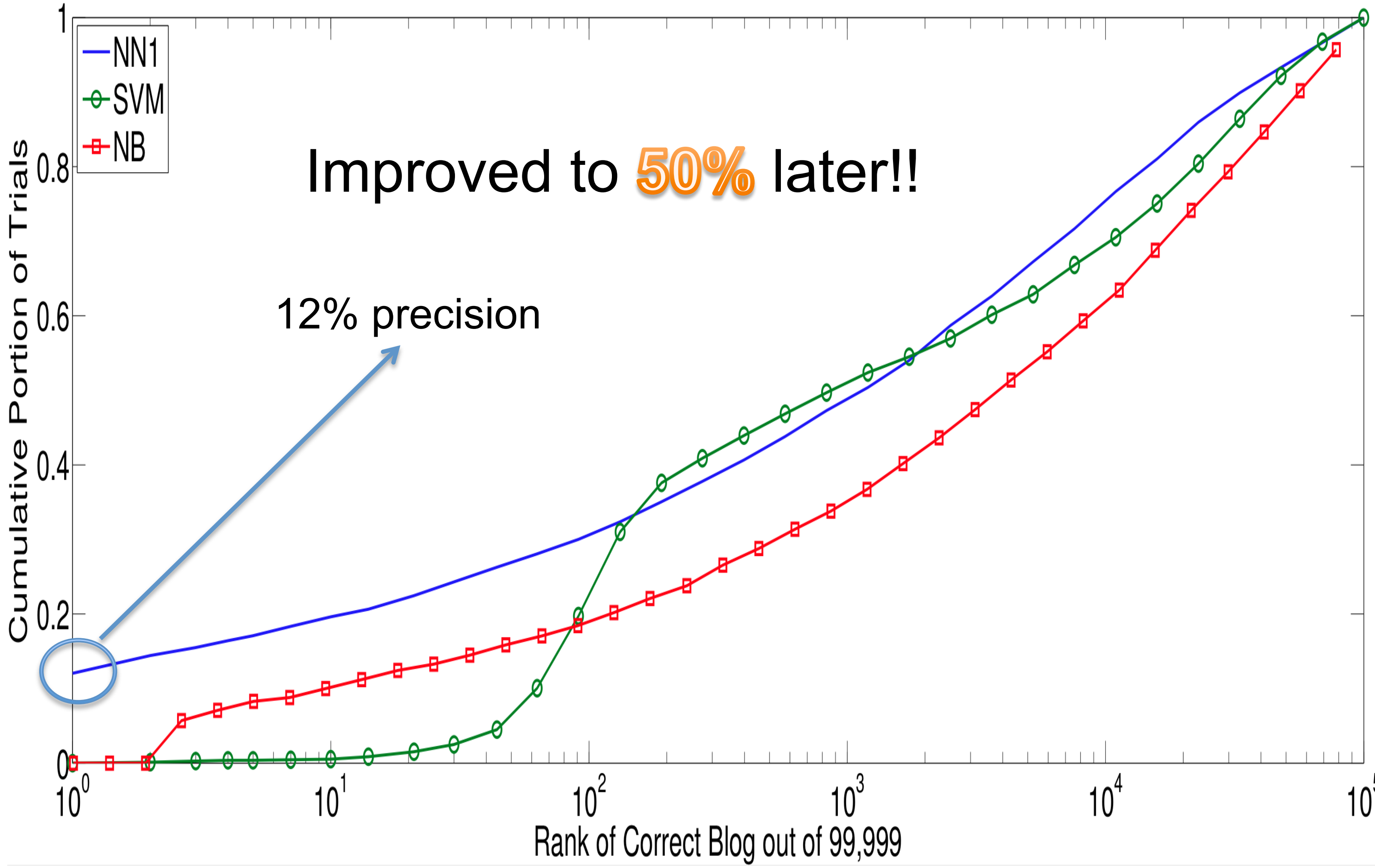
- <u>Post-to-blog experiment</u>
  - Identifying a single or a few anonymous posts.
  - Test posts: random sample a few (e.g., 3) posts from each blog
- <u>Blog-to-blog experiment</u>
  - Identifying an entire blog
  - Test blogs: blogs crawled from URLs specified in Google profiles belong to the same author.

Post-to-blog



Three test posts (roughly 900 words) for each blog.

Blog-to-blog

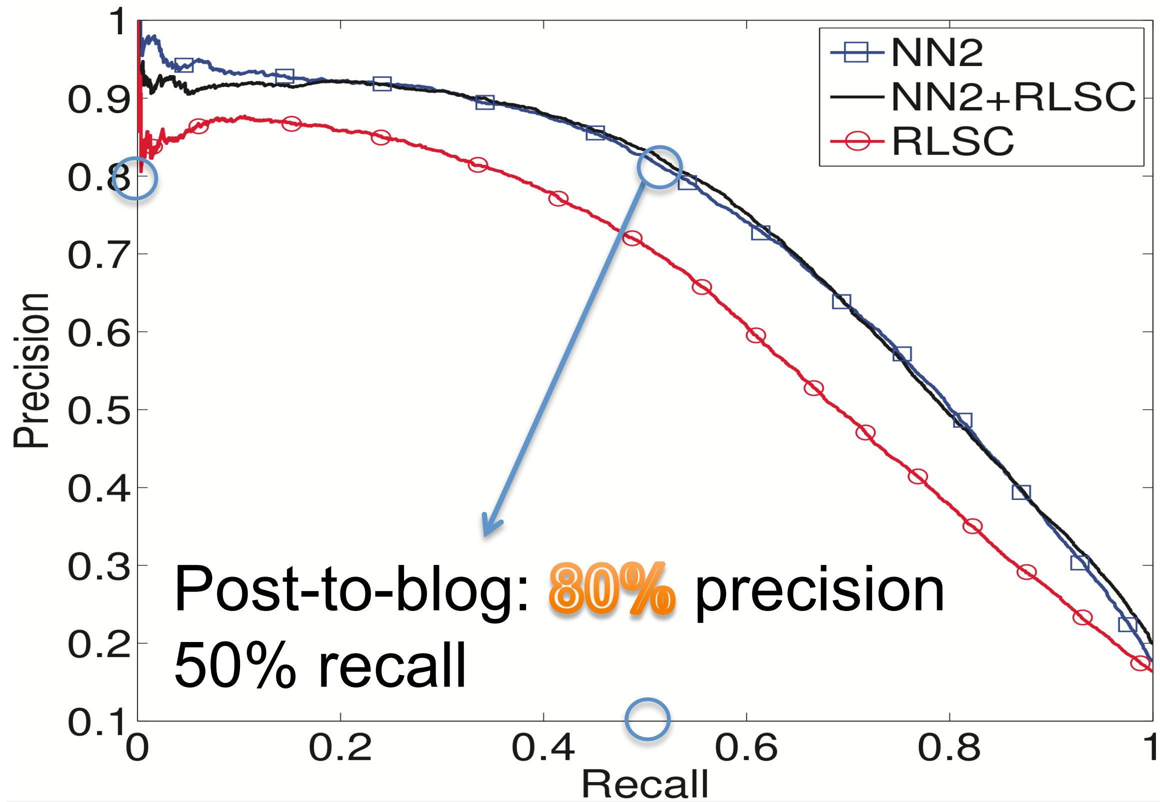


Improved to 50% later!!
12% precision
NN1
SVM
NB
Cumulative Portion of Trials
Rank of Correct Blog out of 99,999
0
0.2
0.4
0.6
0.8
1
10^0
10^1
10^2
10^3
10^4
10^5

Confidence estimation

- Mapping input/output pair of classifier to real values
- Gap Statistics
  - Similarity or distance difference between the best and second best match
- Output the prediction when 'gap' is bigger than some threshold

Confidence estimation



Blog-to-blog: 50% precision. 50% recall

Experiments Summary

- Post-to-blog
  - Best classifier: NN + RLSC.
  - Three test posts, exact match: 20% precision
  - More training/test data, exact match: 40-50%
  - Confidence estimation: 80% precision. 50% recall
- Blog-to-blog
  - Exact match: 12%
  - Confidence estimation: 50% precision. 50% recall

Conclusion

- We identified issues introduced by large scale author identification
- We introduced/discussed strategies to address them
- Large-scale author identification is possible!

- People should be informed
- Be careful when you post sensitive content

Future work

- Better understand what makes authors more/ less fingerprintable
- Design better classifiers
- Automatically transform writing style while preserving document semantics

Thanks!