# Towards a More Fine Grained Analysis of Scientific Authorship

Predicting the Number of Authors Using Stylometric Features

Andi Rexha, Stefan Klampfl, Mark Kröll, Roman Kern

Know-Center - Research Center for Data-Driven Business and Big Data Analytics

**BIR 2016** 

# Introduction

# Setting of our Work

## Intrinsic Plagiarism Detection

Detect a change in writing style within a document

- A change in the style can be seen as indicator for a change in authorship
- For single author documents this might indicate some form of "lifted" text

## **Authorship Attribution**

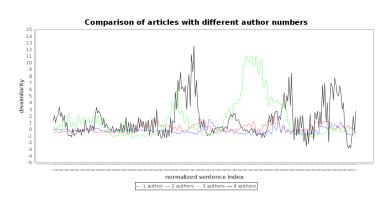
Attribute certain writing styles to different authors

- Usually documents are assumed to be authored by a single person
- The authors and reference documents are known beforehand

## **Past Work**

#### In previous work we:

- We applied techniques from intrinsic plagiarism detection on multi-author papers
- More changes in writing style for papers with more authors



## Motivation

#### **Main Research Question**

To which extend is it possible to predict for a given paper the correct **number of authors**?

#### Goal

- More fine grained analysis of the individual author contribution & roles
- Improved researchers' profiles
- Tune parameters for authorship profiling & intrinsic plagiarism detection

#### Limitations

#### There are a number of limitations/caveats with this approach:

- Writing papers is a highly dynamic, individual and complex process
  - Instead of a rigid mapping of sections to single authors
  - Native vs non-native speakers
  - E.g. even single sentences might be written by multiple authors
- Many authors may contribute little to the written part
  - E.g. mentors, engineers, co-workers, ...
  - Would not show up
- Highly sensitive issue (plagiarism, varying degree of contributions, ...)
- Hard task even for humans

# Method

# Approach & Setting

## Algorithmic Approach

- Supervised machine learning
  - Requires labelled training data-set
- Classification algorithms
  - Comparison of various algorithms
- Features extracted from the papers
- Papers are directly taken as PDF documents

# **Pre-Processing Pipeline**

#### **PDF Extraction**

- PDF is the most common file format for scientific articles
  - ... but it does not contain any structural information
  - Therefore the PDF needs to be parsed and analysed
- Result of PDF Extraction
  - Main text of the article as plain text

#### Limitation of PDF Extraction

- PDF extraction is an complex task with many steps
  - Each step may introduce noise and errors

# PDF Extraction Pipeline

- PDF as starting point, parsing with Apache PDFBox
  - Characters -> Words -> Lines -> Blocks
- Oetection of:
  - Decoration (e.g. page numbers)
  - Captions, tables & images
  - Headings & main text
  - Reference section
- Reverse engineer the structure
  - Sort by reading-order
  - Automatic table of contents from the headings
  - Analyse tables
- Classification
  - Meta-data: title, journal name, authors, ...
  - References & citations (within the text, reference section)
- Post-processing
  - De-hyphenation
  - Merging & splitting of paragraphs

#### **Features**

- Focus on stylometric features
  - Instead of content related features, e.g. unigrams
- Applied on various granularity levels
  - Sentence, paragraph, document
- Aggregated for a single set of features for each article
  - Min, max, mean and variance for each feature
  - Each instance (paper) consists of 60 numeric features

# Type of Features

Table 1: Overview of the stylometric features used, grouped by their type

Type of Feature	Examples
Character-based statistics Vocabulary usage	Ratio of upper/lower case characters Relation size of vocabulary to number of words
Averages	Hapax legomena Average length of words Average length of sentence

# **Classification Algorithms**

#### Focus on two well-know classification algorithms

- Logistic regression
  - Commonly used for textual classification tasks
- Random forests
  - Popular in many different domains (e.g. image analysis)

## **Dataset**

## **Dataset Overview**

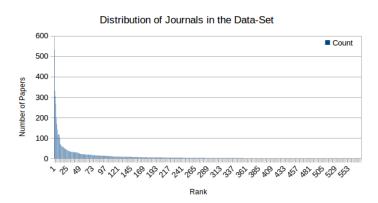
- Papers with a varying degree of authors
  - Ranging from 1 to 5 authors
- Based on PubMed
  - Mostly papers from the bio-medical domain
- Selected 6144 papers on random
  - Only labelled as research\_article
  - Yielded 563 different journals

# Top Journals

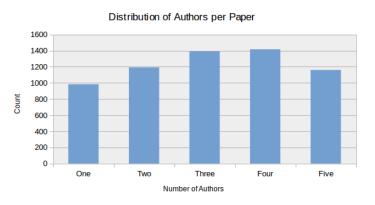
Table 2: Top 5 journals in the data-set

Name	Count
Environmental Health Perspectives	531
Nucleic Acids Research	331
PLoS ONE	304
The Yale Journal of Biology and Medicine	267
BMC Bioinformatics	199

## Distribution of Journals



## **Distribution of Authors**



# Results

## **Baselines**

#### **Point of reference**

- Random guessing
  - 20% chance for correct decision
- Most frequent
  - Always pick 4 authors
  - $-F_1$  of 0.09

# **Logistic Regression**

Table 3: Results for logistic regression for 10-fold cross-validation

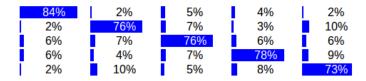
Metric	Value
Precision	0.365
Recall	0.376
$F_1$	0.362

## Random Forest

Table 4: Results for the random forest algorithm for 10-fold cross-validation

Metric	Value
Precision	0.759
Recall	0.755
$F_1$	0.755

## **Confusion Matrix**



Confusion matrix for the random forest algorithm

- Best performance for single author
- Worst performance for 5 authors

## Discussion

- Surprisingly good results
  - The features are able to discriminate between the classes
    - ★ I.e. papers are different (regardless of true number of writers)
    - ★ But no linear relationships
  - The pre-processing pipeline keeps the main features intact
- 1 author papers appear different to others
  - I.e. easier to discriminate against multi-author papers

# Thank You!