Feature Selection in Authorship Attribution: Ordering the Wordlist

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DH Conference 2019 in Utrecht

Research problem

Features in authorship attribution

- Linguistic/stylistic characteristics of texts allowing for authorship identification
- Lexical
  - Word frequencies
- Syntactic
  - Frequencies of grammatical categories
- Prosodic
- … and much more (e.g. char n-grams)

Features in machine learning

- A well-researched topic of feature selection
  - dimension reduction
  - shrinkage
  - penalization
  - …
- We *don't* aim at selecting a subset of features

The aim of the study

- Rearranging the set of lexical features (wordlist)
- Some deeper linguistic understanding of the most distinctive features
- Discover if words efficient in classification share any linguistic properties

What we know

- Grammatical words are strong predictors

  (Mosteller & Wallace, 1964)

- Grammatical words occupy the top of the frequency list

  (Zipf, 1948)

- Therefore: top *N* words are strong predictors

  (common practice, 1980s–)

What we don’t know

- Where is the cut-off point where frequent words don’t discriminate anymore
- (= how many MFWs to take?)
- What is the discrimination power of the features down the list

Most Frequent Words

- MFWs = words ordered according to their frequencies
- = mean TF (term frequencies)
- Prioritizes common grammatical words
- Hapax legomena at the bottom of the list
- Proper nouns (names) somewhere in between

TF-IDF

- Term Frequency / Inverse Document Frequency
- Commonly used in information retrieval
- A way of extracting "keywords"
- It prioritizes words *important* for particular texts
- It prioritizes proper nouns
- Grammatical words usually at the bottom

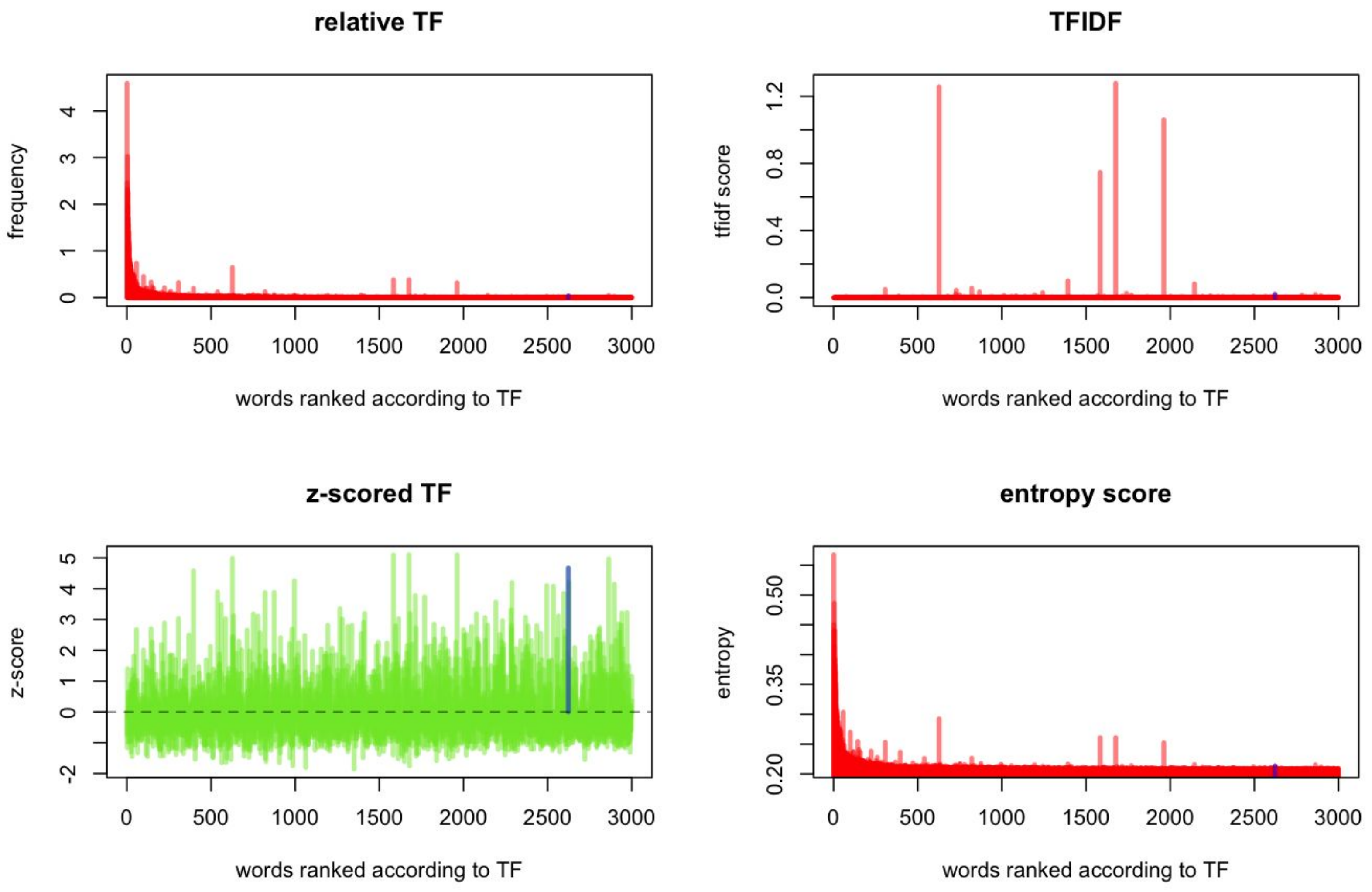
Coefficient of Variation

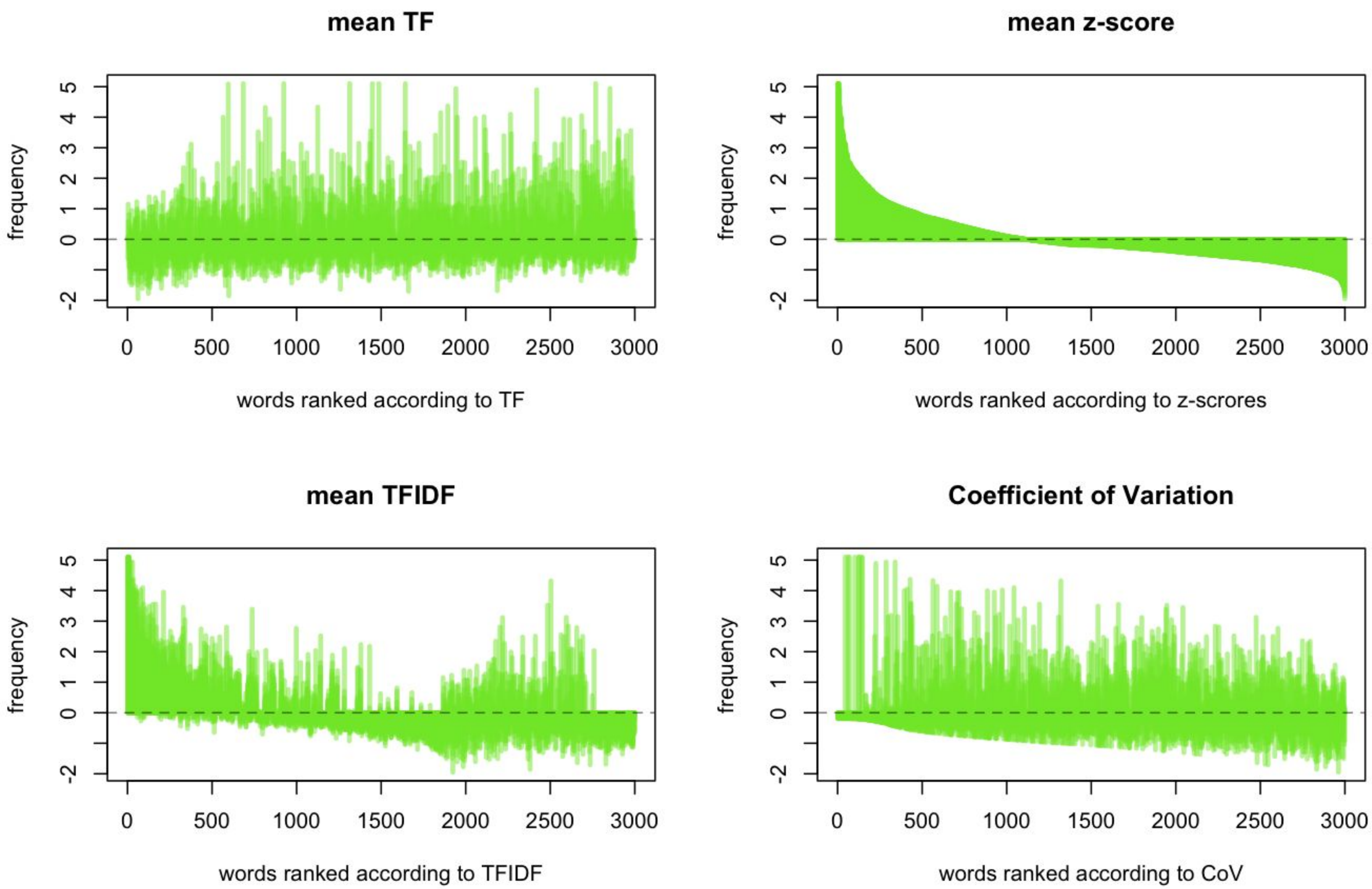
- Variance – the degree to which a given feature (a word) varies in a corpus
- A word of the biggest variance = potential discriminator
- However: variance depends on frequency
- Therefore: coefficient of variation:

$$\mathrm{CoV}_i = \sigma_i / \mu_i$$

Ordering ≠ Weighting

- Features (word frequencies) might be transformed (weighted) differently
  - Term Frequency (= no weighting)
  - Z-scores (cf. Evert et al., 2017, etc.)
  - Term Frequency / Inverse Document Freq.
  - Mutual Information
- This study is *not* about weighting evaluation


relative TF
frequency
0
1
2
3
4
words ranked according to TF
0
500
1000
1500
2000
2500
3000
TFIDF
tfidf score
0.0
0.4
0.8
1.2
words ranked according to TF
z-scored TF
z-score
-2
0
1
2
3
4
5
words ranked according to TF
entropy score
entropy
0.20
0.35
0.50
words ranked according to TF


mean TF
frequency
words ranked according to TF
mean z-score
frequency
words ranked according to z-scrores
mean TFIDF
frequency
words ranked according to TFIDF
Coefficient of Variation
frequency
words ranked according to CoV
0
500
1000
1500
2000
2500
3000
-2
0
1
2
3
4
5

Ordering ≠ Weighting

	TF	z-scores	TF-IDF	z-scored TF-IDF
mean TF (=MFWs)	✗	✓	✗	✗
TF-IDF	✗	✓	✗	✗
variance	✗	✓ (?)	✗	✗
CoV	✗	✓	✗	✗

Data

Dataset

A Small Collection

100 Polish (3 texts per author, one additional)

100 English (3 texts per author, one additional)

– canon literary texts, similar in topic and dates of creation

Preliminary tests also for French and German

Method

Experimental setup

- Supervised classification
- Leave-one-out cross validation
- kNN classifier (k=1), *aka* Delta
  - Also: SVM, NSC
- Cosine Delta distance measure
- A set of 10 subsequent features tested:

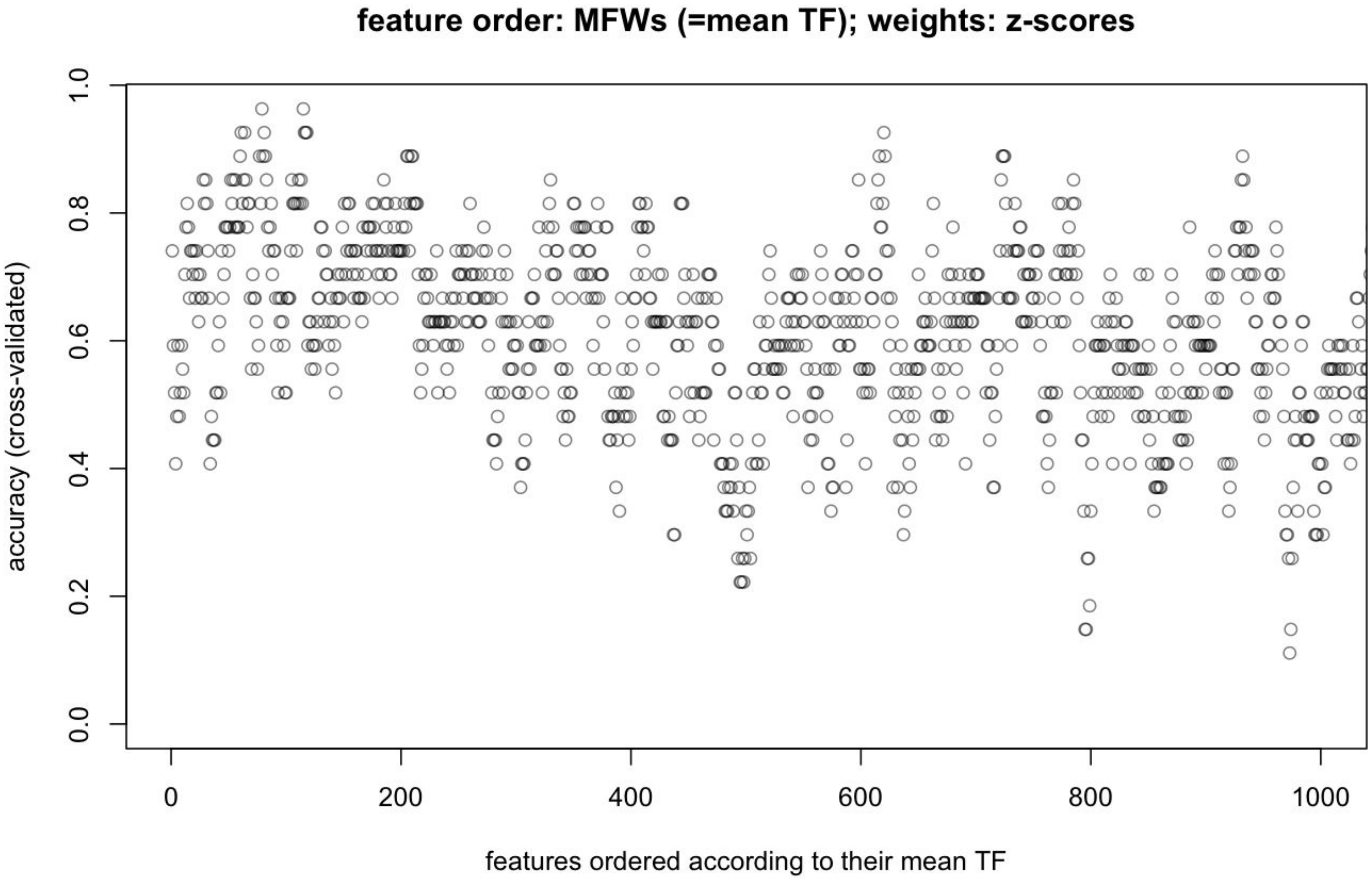
$$F_k = \{w_i, w_{i+1}, \ldots, w_{i+9}\}$$

N subsequent features

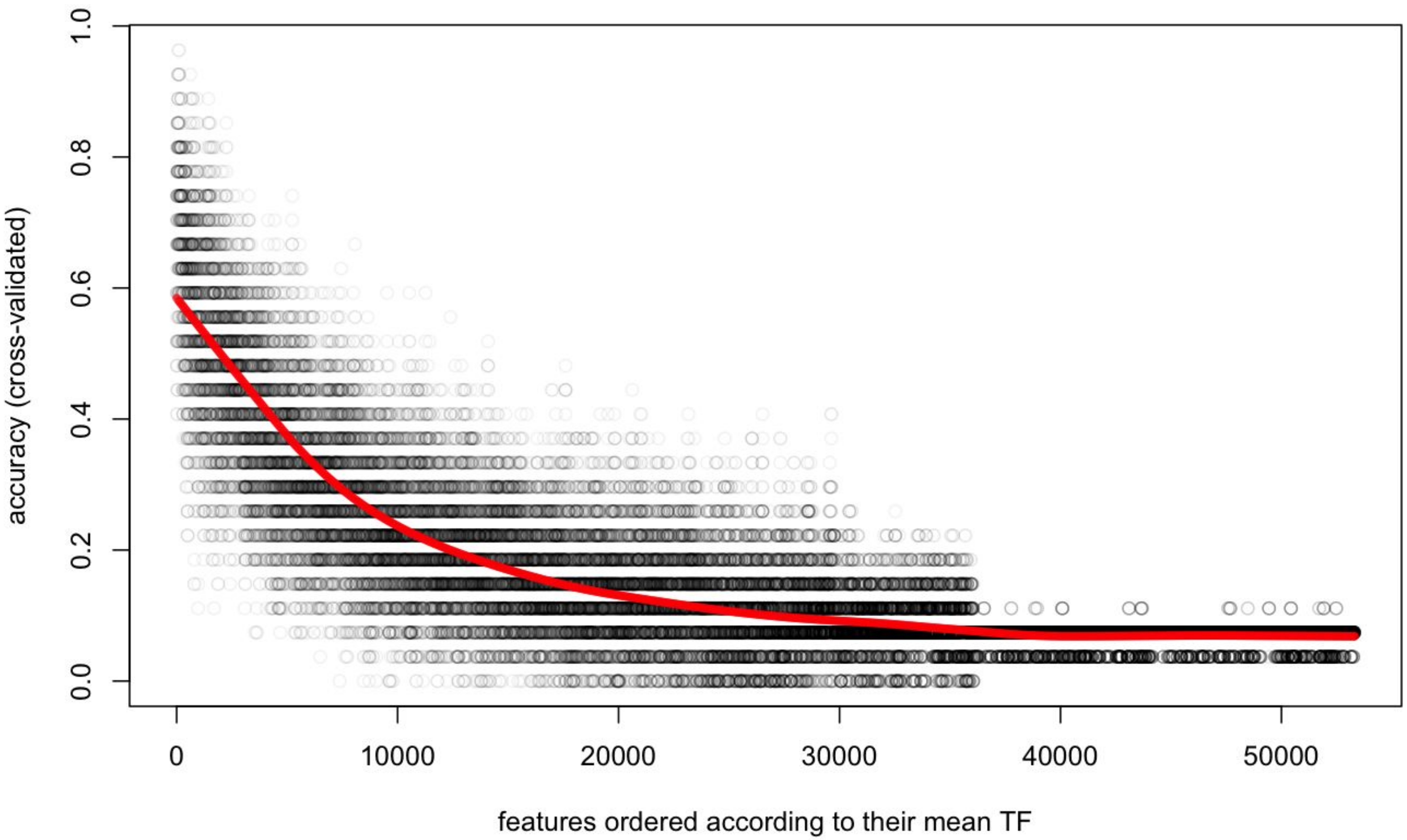
the and to of I a in that he was it you her …

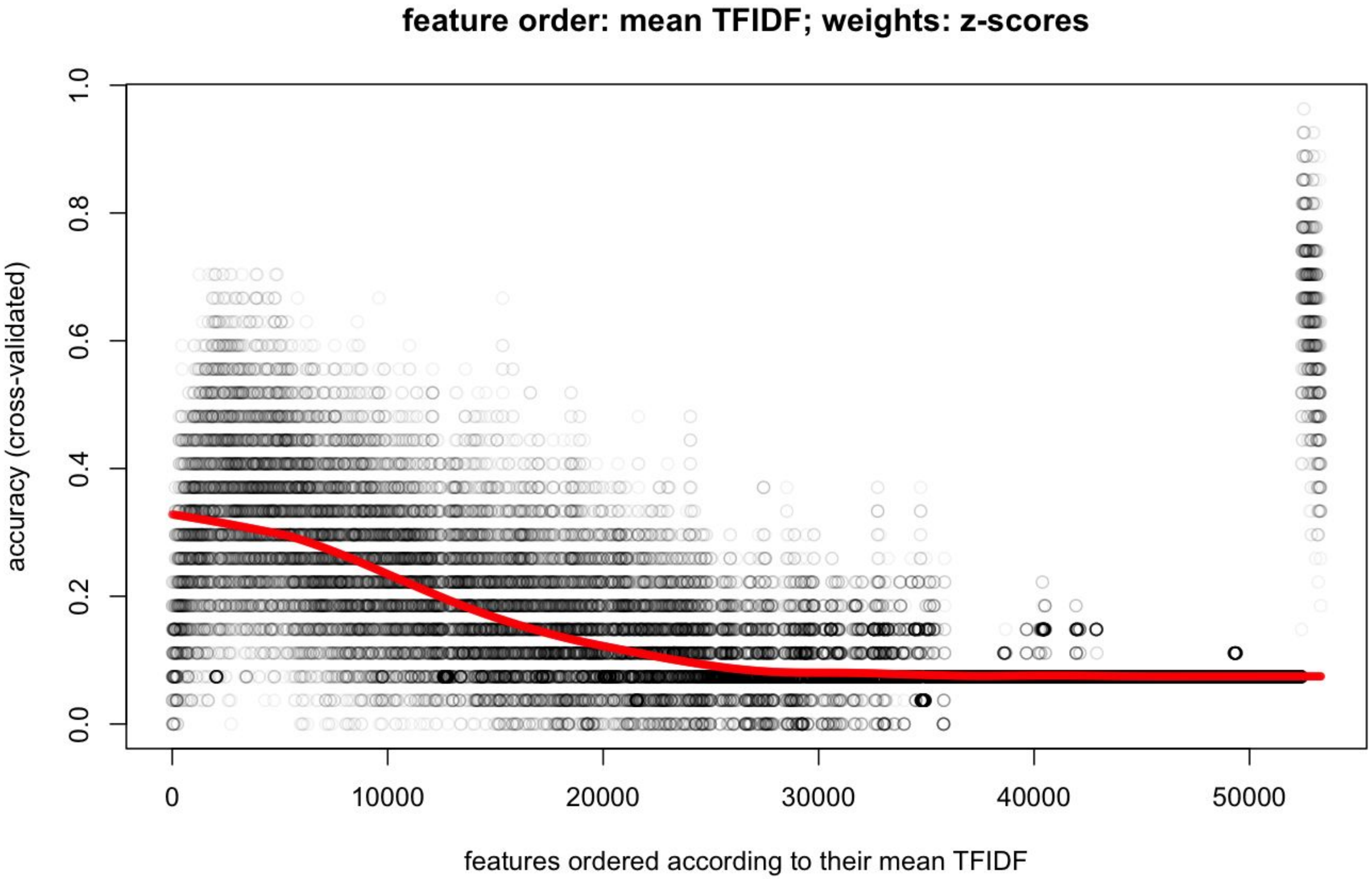
1. the and to of I [# 1]
2. and to of I a [# 2]
3. to of I a in […]
4. of I a in that […]
5. … … … … … [# *n*]

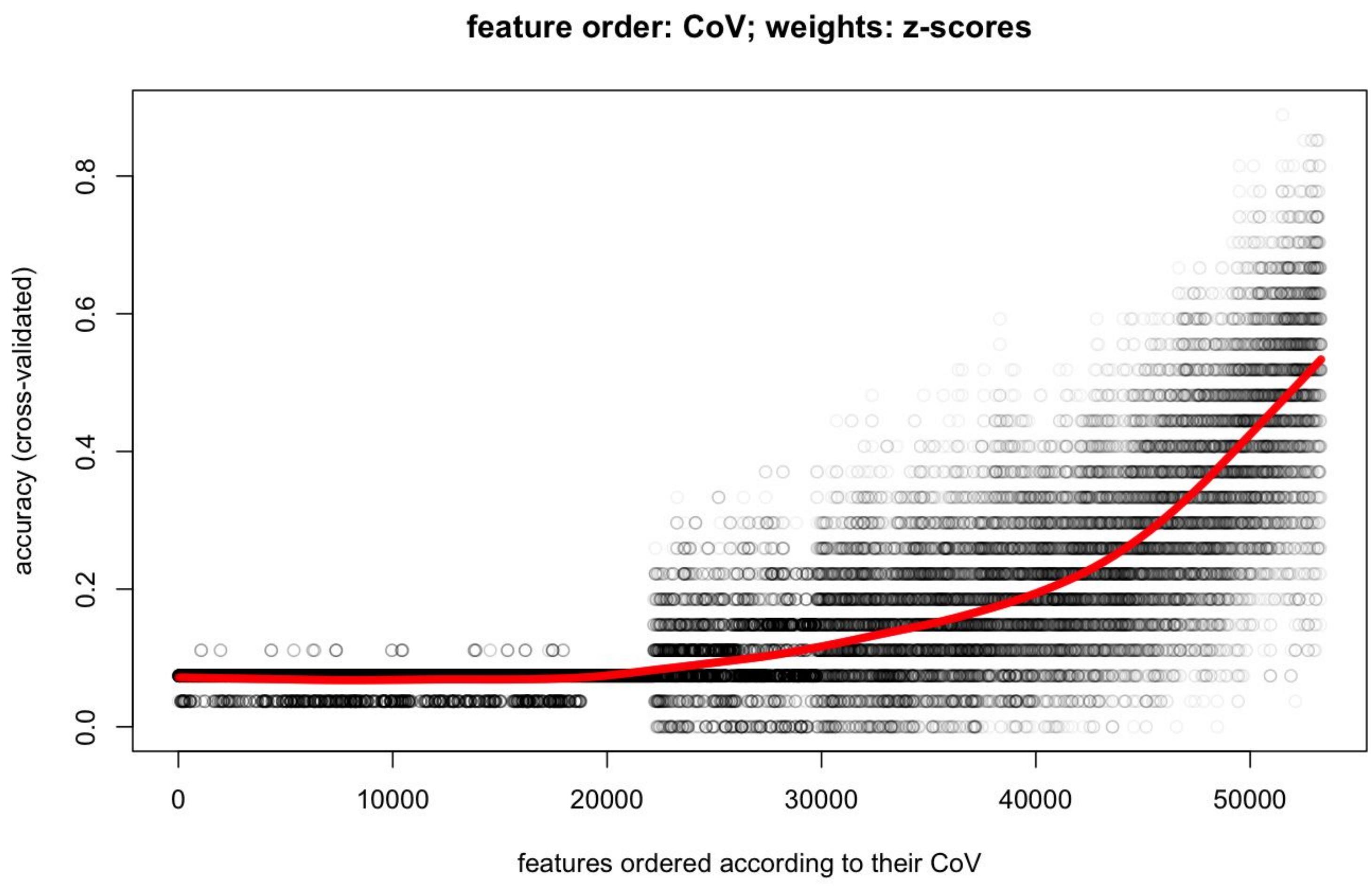
Results


feature order: MFWs (=mean TF); weights: z-scores
accuracy (cross-validated)
0.0
0.2
0.4
0.6
0.8
1.0
0
200
400
600
800
1000
features ordered according to their mean TF

feature order: MFWs (=mean TF); weights: z-scores



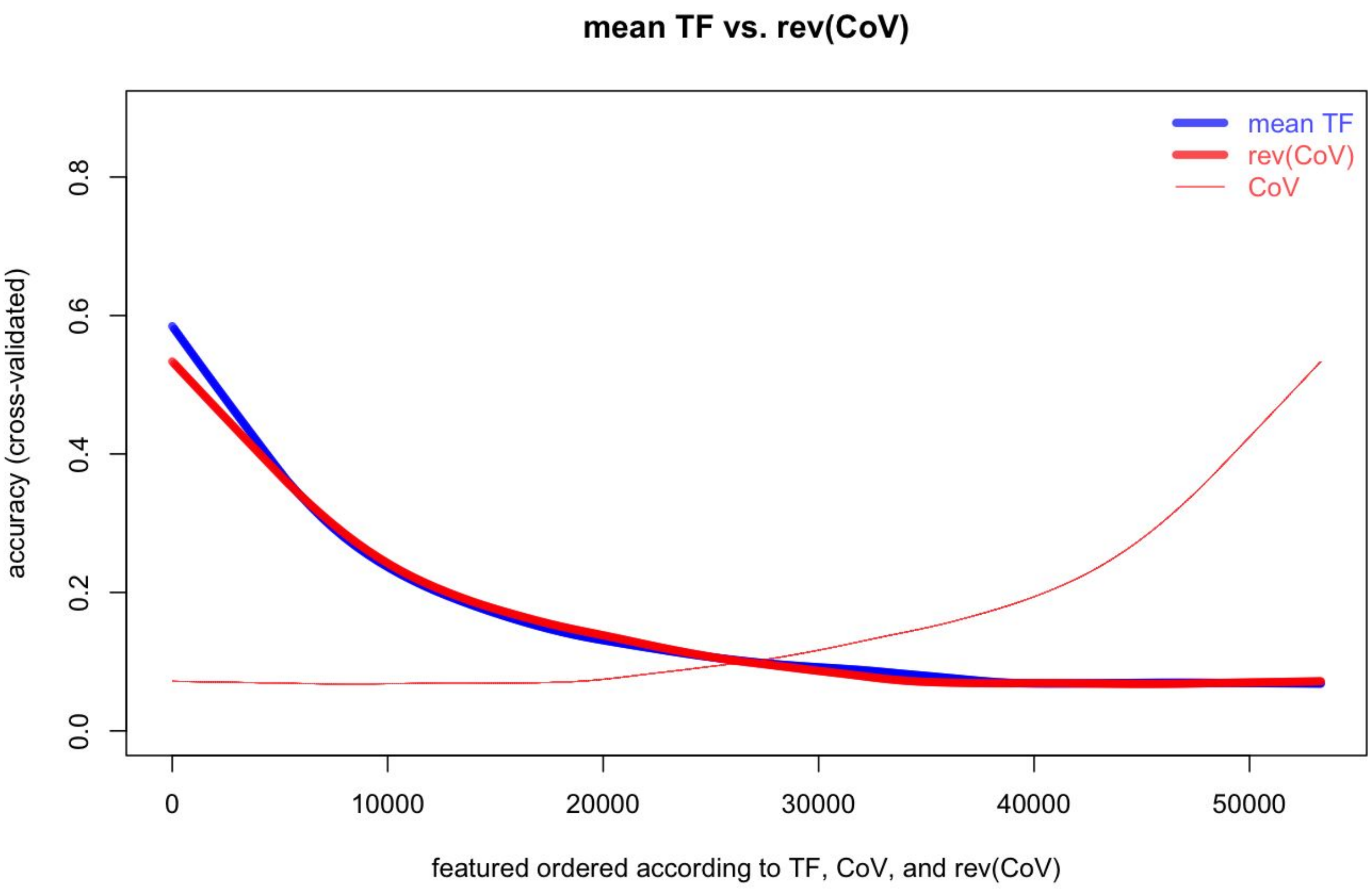

feature order: mean TFIDF; weights: z-scores
accuracy (cross-validated)
0.0
0.2
0.4
0.6
0.8
1.0
0
10000
20000
30000
40000
50000
features ordered according to their mean TFIDF


feature order: CoV; weights: z-scores
accuracy (cross-validated)
0.0
0.2
0.4
0.6
0.8
0
10000
20000
30000
40000
50000
features ordered according to their CoV

First observations

- MFW – working great (phew, we knew!)
- CoV – unexpectedly well, in fact…
- CoV aggregating good features even better than MFW!

So what if…

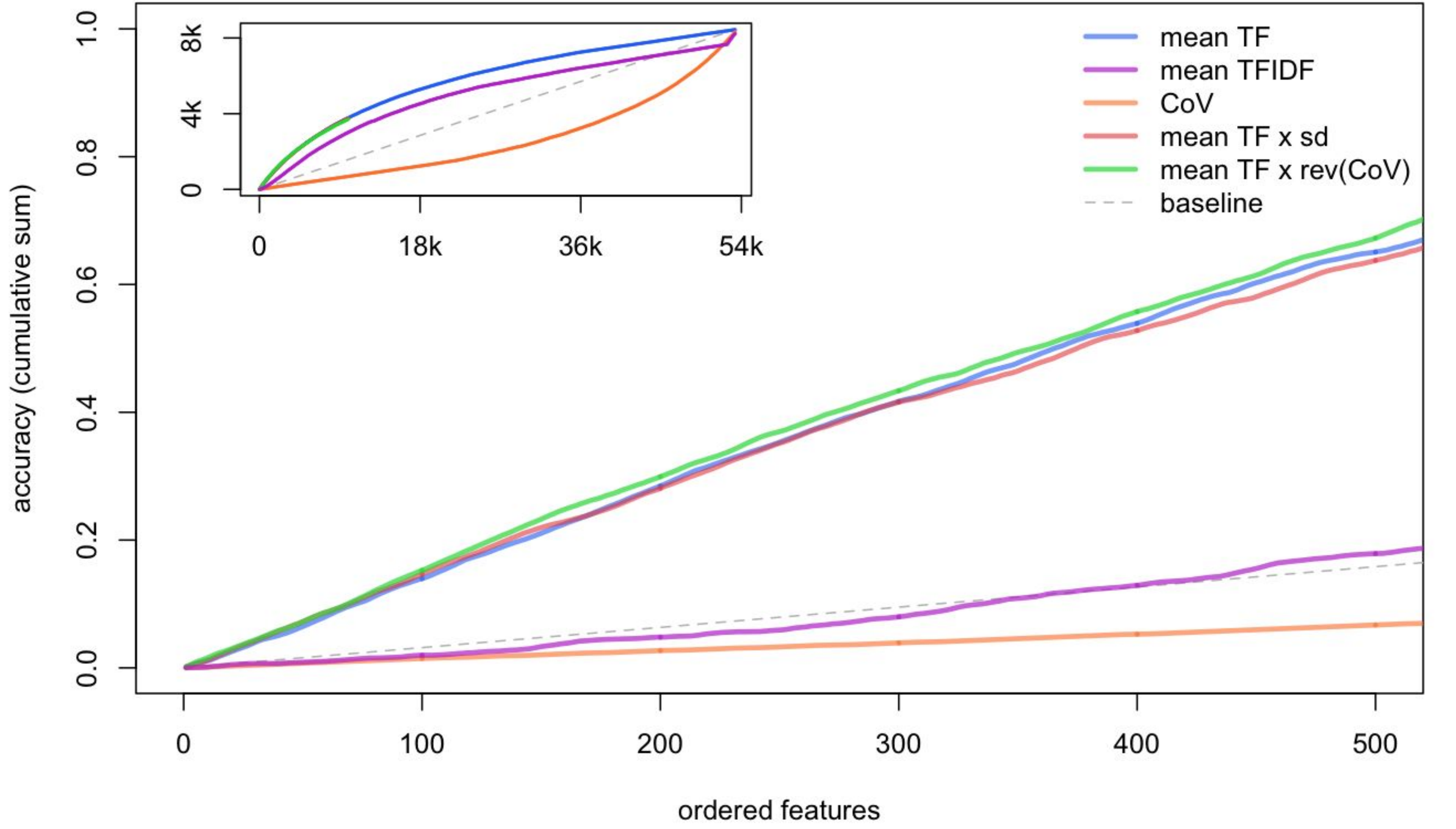

mean TF vs. rev(CoV)
mean TF
rev(CoV)
CoV
accuracy (cross-validated)
0.0
0.2
0.4
0.6
0.8
0
10000
20000
30000
40000
50000
featured ordered according to TF, CoV, and rev(CoV)

Combining TF and rev(CoV)?

$$\omega_i = TF_i \times rev(CoV)_i$$

Which can be represented as:

$$\omega_i = \mu_i \times rev(\sigma_i / \mu_i)$$



mean TF
mean TFIDF
CoV
mean TF x sd
mean TF x rev(CoV)
baseline
accuracy (cumulative sum)
ordered features
0.0
0.2
0.4
0.6
0.8
1.0
0
100
200
300
400
500
0
4k
8k
18k
36k
54k

Conclusions

- TF aka MFW – confirmed as a generally good way of ordering of features
- TF-IDF – useful for detection of what to cull
- TFxCOV – a promising update of traditional approach

Acknowledgements

We are grateful for the financial support we received:

JB was partially funded for the research by Poland's National Science Centre (grant number 2017/26/HS2/01019).

ME was partially funded by Poland’s National Science Centre (grant number 2014/12/W/ST5/00592).

National Science Centre Poland

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Thank you!

Presentation (and future place for code):
https://github.com/JoannaBy/Feature-Selection-in-Authorship-Attribution

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What words in TFxCoV?

- largely overlaps with word frequencies (so basically - term frequencies),
- with some of the words taking primary position over personal pronouns:
    - e.g. the discriminative power of prepositions, such as "to", "as", "with", "for", "at", "from", "before.