

Count on it,  
literature is like a spam

Joanna Byszuk & Jeremi Ochab  
DHSI 2024, “DIY Computational Text  
Analysis with R”

# Outline

- Spam: features & filters
- Text classification in literary studies
- Authorship attribution
- Example experiments

How to deal with

**SPAM**



Dear Friend,

It's my pleasure to Brief you with this proposal for a financial and business assistance. I know my message will come to you as a surprise. Don't worry I was totally convinced to write you in reference to the transfer of \$22.5 Million Dollar to your account for onward investment (Hotel industries and Estate building management, Factory and Textile Productions And Extruction of Raw Materials To finished Product For Usage) or any profitable Oriented business in your country.

I Need you to stand as my foreign partner for investment in your country and also next of kin to these fund am about to transfer to you if accepted by you to work with me and receive the fund Amounting to \$22.5m.

Please reply immediately if you are interested, so that I can give you more information. Be Rest Assure that these fund transfer to your custody is risk free and profit oriented to both of us.

To enable me start the process and remittance of the fund into your bank account successfully within 10 banking days, I need the following information from you by e-mail: ...

May Almighty God Bless You!

Regards, Hanson Chife.

Cześć,

Tutaj jest porównywanie:

<https://www.dropbox.com/...>

Normalizację robię Gaussem o parametrach wyestymowanych z połączenia obu.

Są podobieństwa, oraz istotne różnice - ciężko coś powiązać z otwartymi oczami, strasznie to skomplikowane.

Chyba najprościej wziąć jakąś sytuację gdzie ICA działa i spróbować poprawić tym.

Pozdrawiam,  
Zbychu

Ps. Z rozmiarami wykresów sobie poradziłem dodając "Interpolation".

--

Institute of Computer Science and Computer Mathematics, Jagiellonian University, Cracow, Poland



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# Features of spam

- Look at the e-mail address:
  - known/unknown



# Features of spam

- Look at the e-mail address:
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  - `*@uj.edu.pl`

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- Look for attachments





# Features of spam

- Look at the e-mail address:
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- Look for attachments
- Look into content:
  - pragmatic: someone wants you to do something
  - semantic: it's about money
  - register, style, formulaic expressions, etc.



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  - ~~register, style, formulaic expressions, etc.~~
  - word occurrences

# Spam filter

- detecting spam is a ***classification*** problem
- spam filter is a ***classifier***

# Spam filter

- detecting spam is a classification problem
- spam filter is a classifier:
  - collect labelled data  
(spam vs legitimate e-mails)
  - train the model  
(learn for each class)
  - test it  
(compute for a message  
and decide)

# Spam filter

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# Naive **Bayes** spam filter

$$\Pr(S|W) = \frac{\Pr(W|S)\Pr(S)}{\Pr(W|S)\Pr(S) + \Pr(W|H)\Pr(H)}$$

- $\Pr(S|W)$  – probability that the message  $S$  is a spam, given that it contains word  $W$



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 $\Pr(S) = 80\%$ ,  $\Pr(H) = 20\%$



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- we need to train  $\Pr(W|S)$  and  $\Pr(W|H)$  based on known data
- simple threshold criterion, e.g.:  
if  $\Pr(S|W_1, \dots, W_n) > 95\%$  remove that e-mail



# Spam filter summary

- look at features: tokens
- assumption: bag of words („naive” independence)
- correlate with known categories of e-mails
- classify into these (two) categories

How to deal with

**LITERATURE**



# Counting text

- The idea for quantitatively determining authenticity of Pauline epistles by Augustus de Morgan in 1851
- The classics of quantitative text studies is Wincenty Lutosławski's *The origin and growth of Plato's logic: with an account of Plato's style and of the chronology of his writings* from 1897
- The first use of a computing machine (though non-electronic) in stylometry was a study by Thomas C. Mendenhall (1901) A mechanical solution of a literary problem, *Popular Science Monthly* 60
- Father Roberto Busa computationally working on *Index Thomisticus* with IBM starting from 1949

# Classification in literature

**AUTHOR**

# Classification in literature

## AUTHOR

- What's Elena Ferrante's real identity?

*Drawing Elena Ferrante's Profile*. Workshop Proceedings, Padova, Sept 7, 2017.

- How could one tell Galbraith was Rowling?

P Juola (2013). How a Computer Program Helped Show J.K. Rowling write *A Cuckoo's Calling*. *Scientific American*, Aug 20, 2013.

# Classification in literature

## AUTHOR

- Authorial collaborations – who's writing and who's editing?

J Rybicki, M Kestemont, D Hoover (2013). Collaborative authorship: Conrad, Ford and rolling Delta. *Digital Humanities 2013: Conference Abstracts*. Lincoln: University of Nebraska-Lincoln, 368-71

- Are both *Go set a watchman* and *To kill a mockingbird* Harper Lee's?

M Eder, J Rybicki (2015). Go Set A Watchman while we Kill the Mockingbird In Cold Blood  
[https://sites.google.com/site/computationalstylistics/projects/lee\\_vs\\_capote](https://sites.google.com/site/computationalstylistics/projects/lee_vs_capote)

E Gamerman (2015). Data Miners Dig for Answers About Harper Lee, Truman Capote and *Go Set a Watchman*. *Wall Street Journal*, Jul 15, 2015.

# Classification in literature

**AUTHOR**

**TRANSLATOR**





# Classification in literature

## AUTHOR

## TRANSLATOR

- Is the translator invisible? Is the authorial fingerprint retained in translation?

J Rybicki (2013). Stylometryczna niewidzialność tłumacza. *Przekładaniec* 27, 61–87.

J Rybicki (2013). The great mystery of the (almost) invisible translator. In: MP Oakes & M Ji (Eds.) *Quantitative Methods in Corpus-Based Translation Studies*.

- How about the translator's spouse?

J Rybicki (2011). Alma Cardell Curtin and Jeremiah Curtin: the translator's wife's stylistic fingerprint. *Digital Humanities 2011: Conference Abstracts*. Stanford University, Stanford, pp. 308-11.



# Classification in literature

## AUTHOR

## TRANSLATOR

- Or when did a translator die?

J Rybicki and M Heydel (2013). The stylistics and stylometry of collaborative translation: Woolf's 'Night and Day' in Polish. *Literary and Linguistic Computing*, 28(4): 708-17

- How many scribes helped in *Queen Sophia's Bible* translation?

M Eder (2016). Rolling stylometry. *Digital Scholarship in the Humanities*, 31(3): 457-469

# Classification in literature

**AUTHOR**

**TRANSLATOR**

**LANGUAGE**

# Classification in literature

**AUTHOR**

**GENDER**

**TOPIC**

**GENRE**

**NARRATION TYPE**

**LITERATURE PERIOD**

**LITERATURE MOVEMENT**

**TRANSLATOR**

**LANGUAGE**



# Classification in literature

When classes are defined:

- what are the **distinguishing features** (phrases, syntactic structures, themes, emotional cues, plot shapes, mannerisms)?
- do they change in **time**?
- can one interpret what they serve?

# Counting text

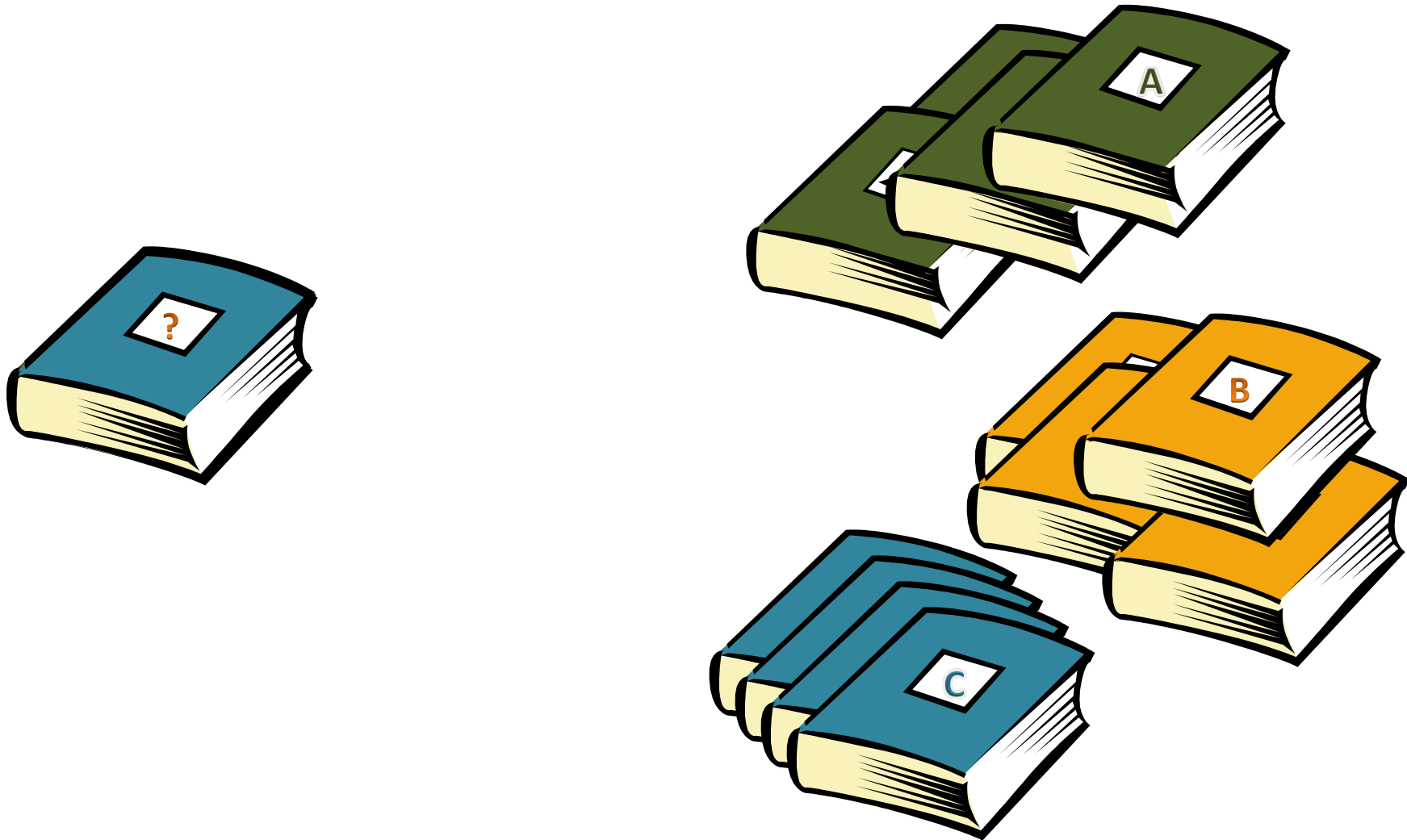
Digitisation age:

- text recognition software (OCR, HTR)
- digital library archives
- new content is digital by origin

What are the

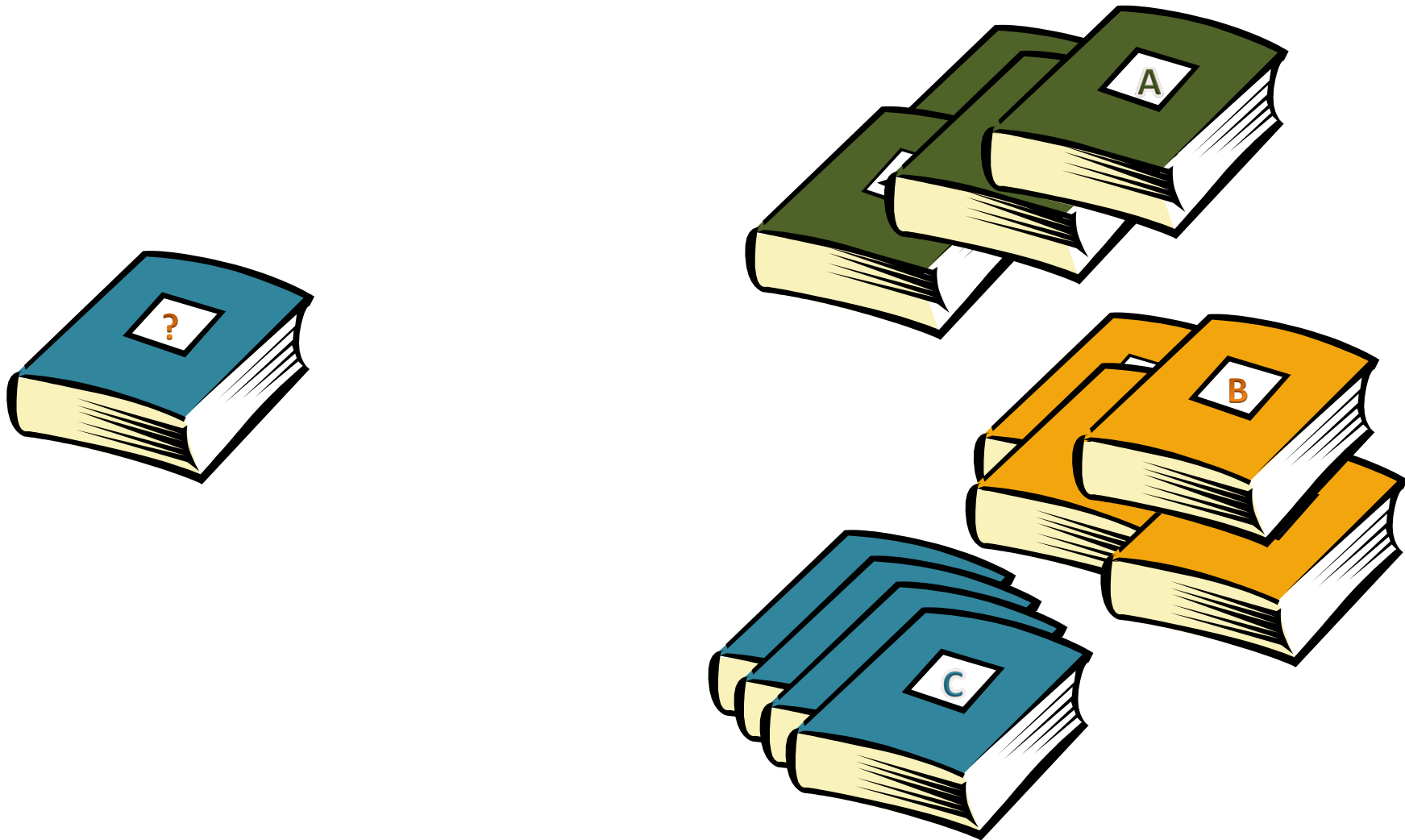
# **PROBLEMS WITH TEXT CLASSIFICATION**

# Example: authorship attribution






# Example: authorship attribution



# Text closeness

Frequencies of:

- characters
  - words
  - sentences?
  - POS-tags
- 
- character N-grams
  - word N-grams
  - POS-tags N-grams

Other:

- Sentence lengths
- Word lengths

# Text closeness

1. Calculate frequencies of words
2. Calculate distances

words	Book A	Book B
a	120	115
the	100	110
of	70	80
...	...	...

	Book A	Book B	...
Book A	0	$d(A,B)$	...
Book B	$d(B,A)$	0	...
...	...	...	...

➡ We get one number  
(distance) for each  
pair





# Text closeness

But:

- Which words/POS should we take?
- How many of them?
- Should we lemmatise them?



# Text closeness

But:

- Which words/POS should we take?
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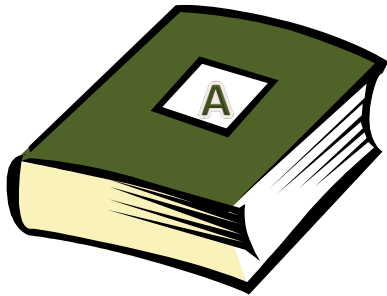
Even before that:

- Which authors should we compare to?
- Which books? How many? How long?

EXPERIMENT 1

**IS GRAMMAR OR  
VOCABULARY AUTHORIAL?**

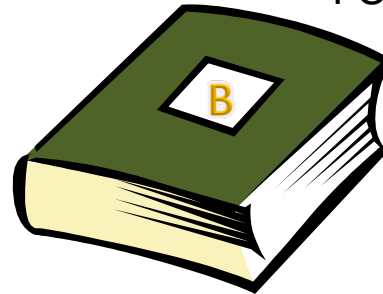
# Fabricate a fake text



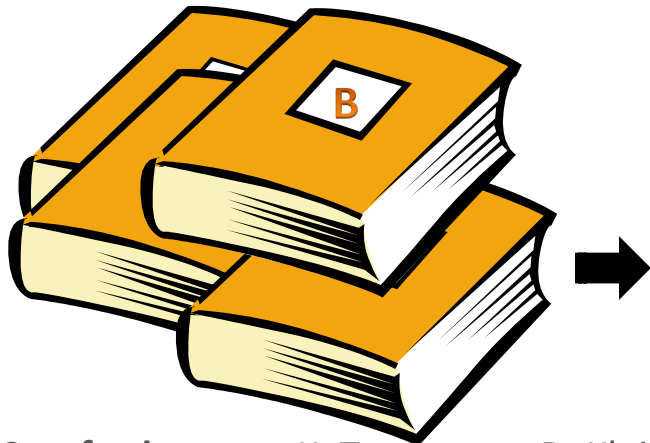
Extract frequencies of POS-tags:  
2 IN, 2 DT, 2 NN, 1 VB...



Put words from **B** in the places of  
POS-tags from **A**.

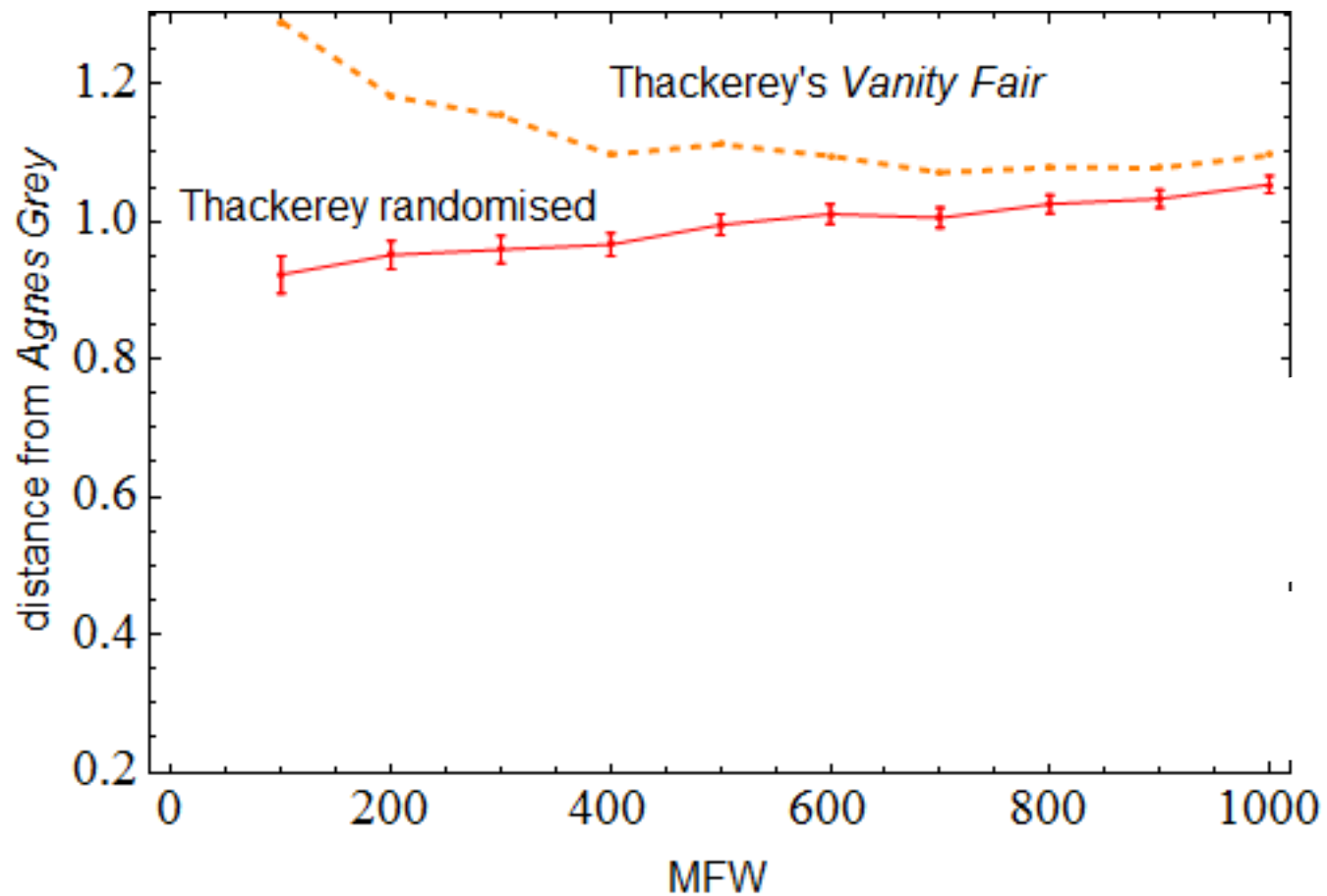


of a sate the estate with his  
time and perpetually , she  
swim gloomily cultivated to  
birthday .



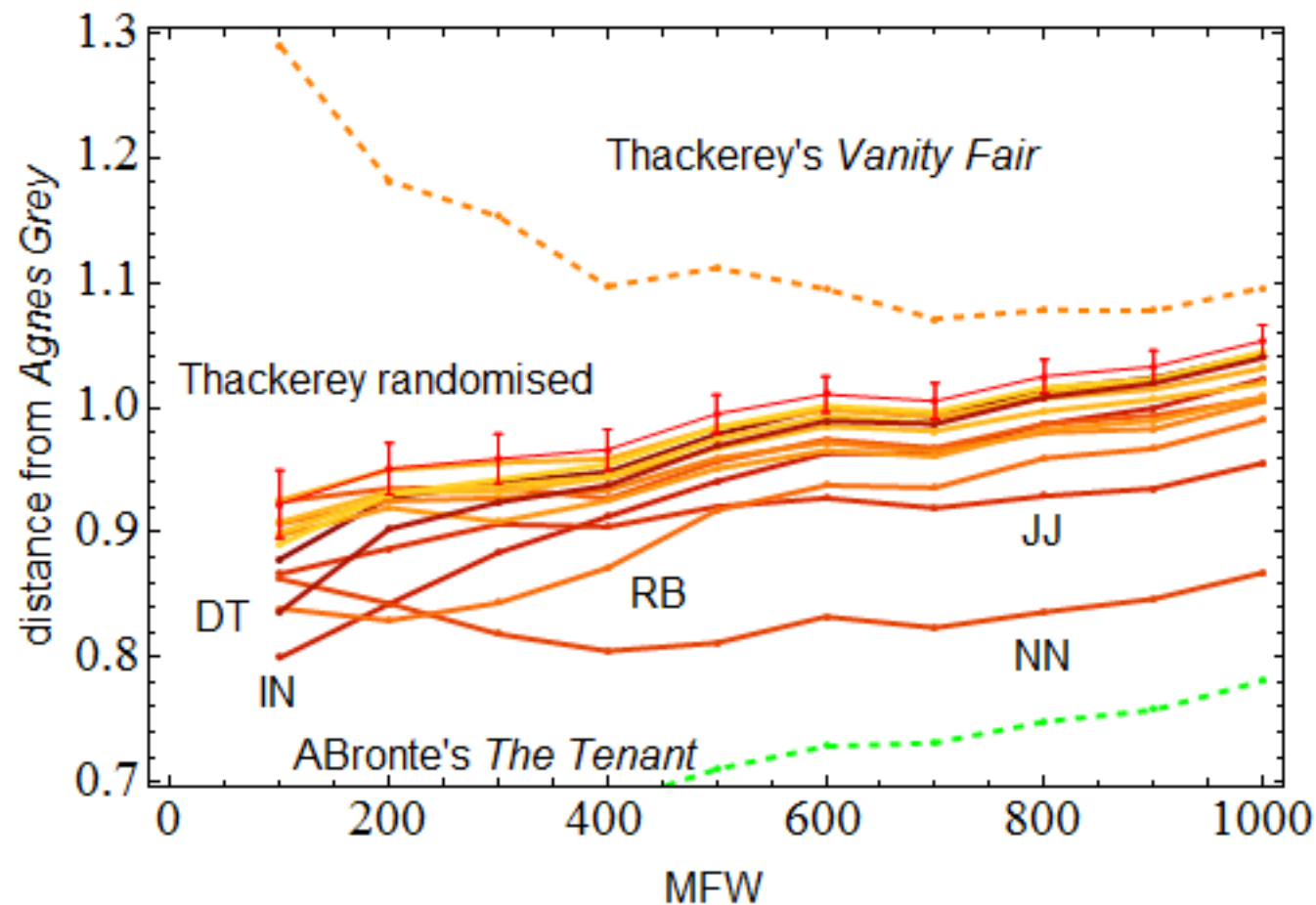
Extract words with given POS-tags:  
IN → whether, with, ...  
DT → this, the, ...  
...

# Fabricate a fake text





# Fabricate a fake text



Take-home message:

- stylometric distance depends on both **vocabulary** and (implicitly) **syntax**

EXPERIMENT 2: noise

**DOES DIGITISATION  
SPOIL ATTRIBUTION?**

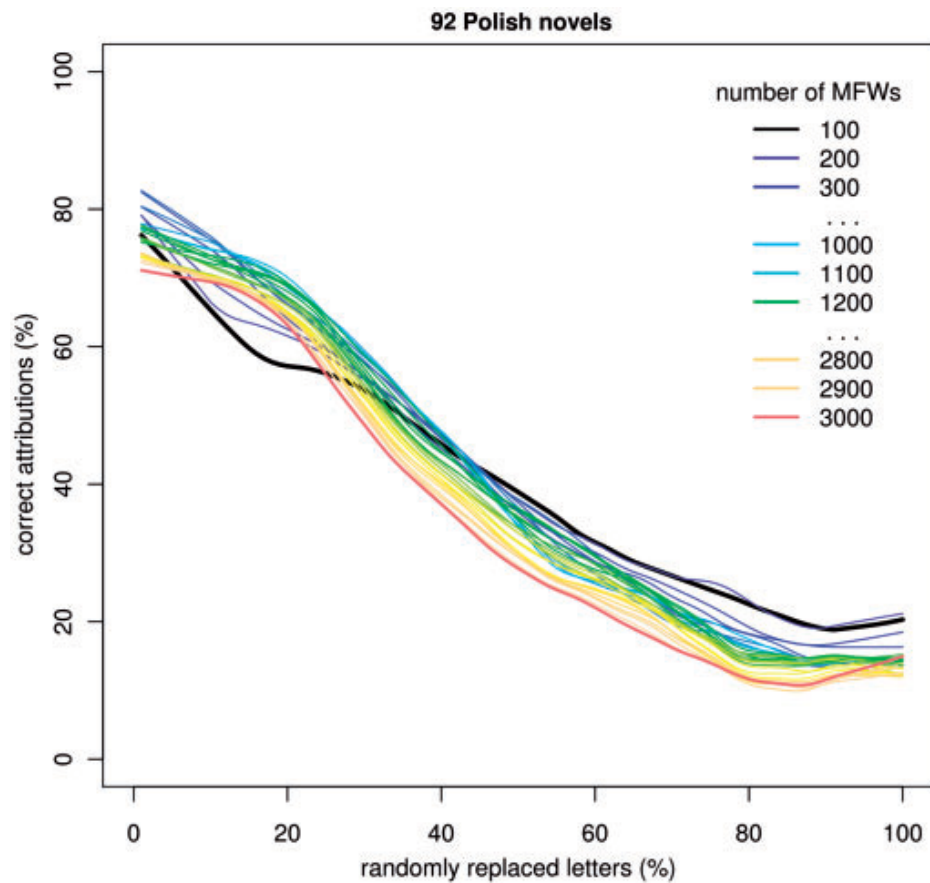
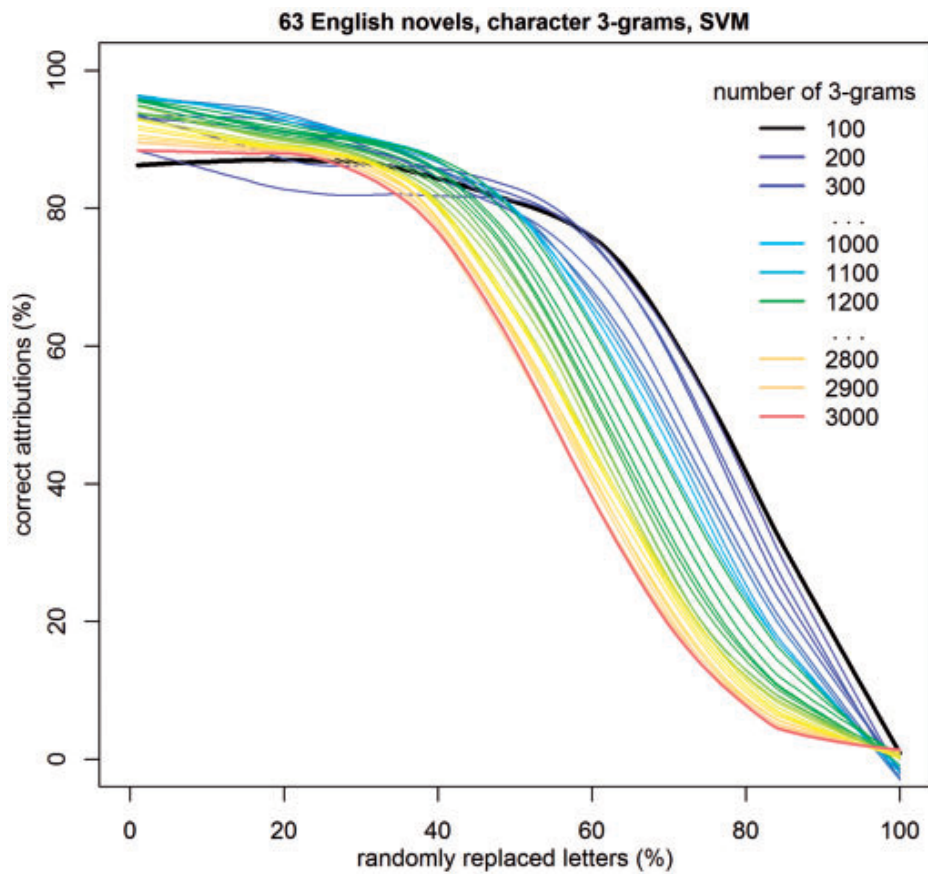


## Digitisation:

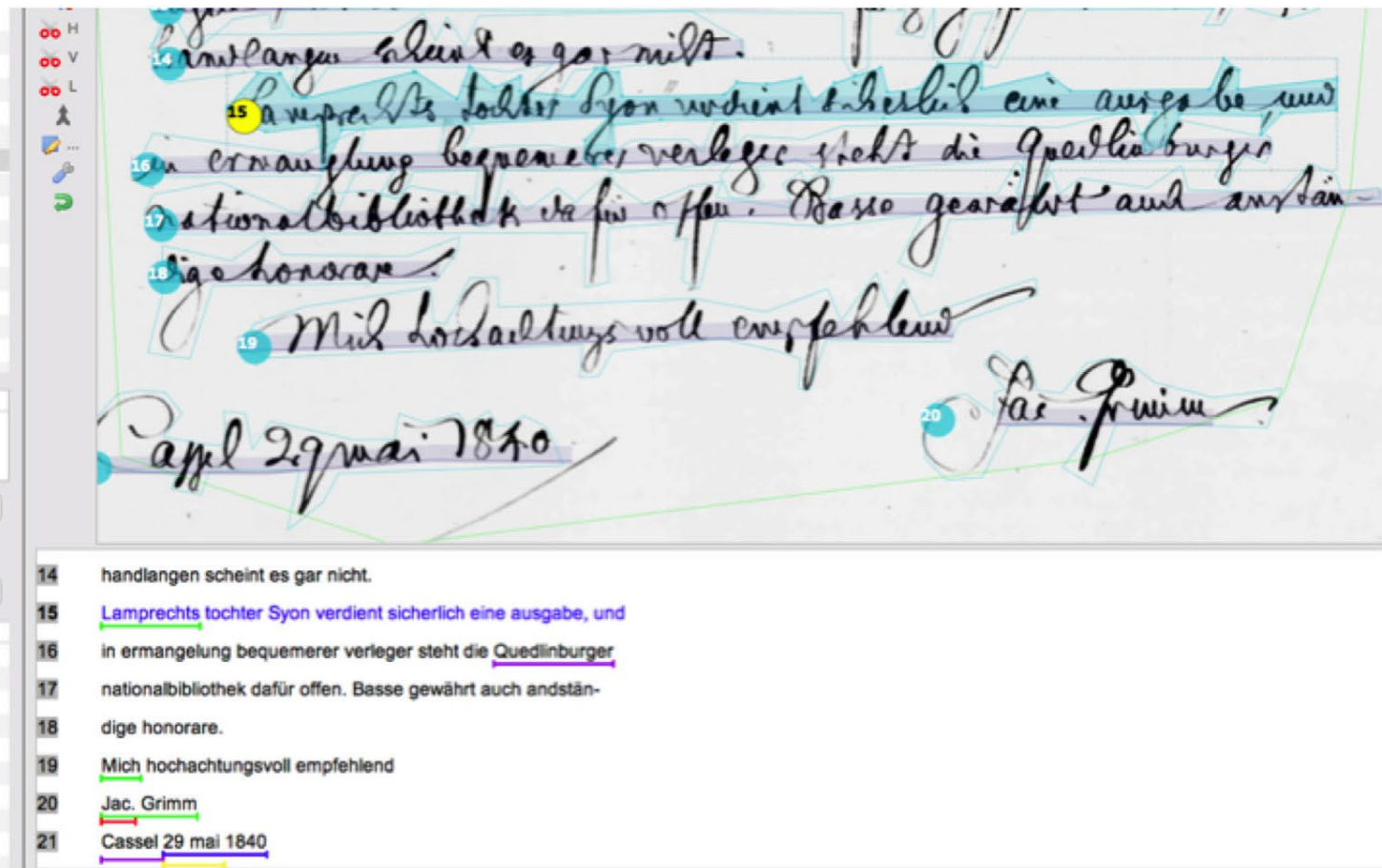
- Optical Character Recognition (OCR)
- Handwritten Text Recognition (HTR)
- Gold standard: human expert transcription

H. Benzerroug, S. Khennouf (2017). Author identification of corrupted OCR-based texts. *HDSKD journal* 3 (2) pp. 91-99

M. Eder (2013). Mind your corpus: systematic errors in authorship attribution. *Literary and Linguistic Computing*, 28(4), 603-614.



M. Eder (2013). Mind your corpus: systematic errors in authorship attribution. *Literary and Linguistic Computing*, 28(4), 603-614.



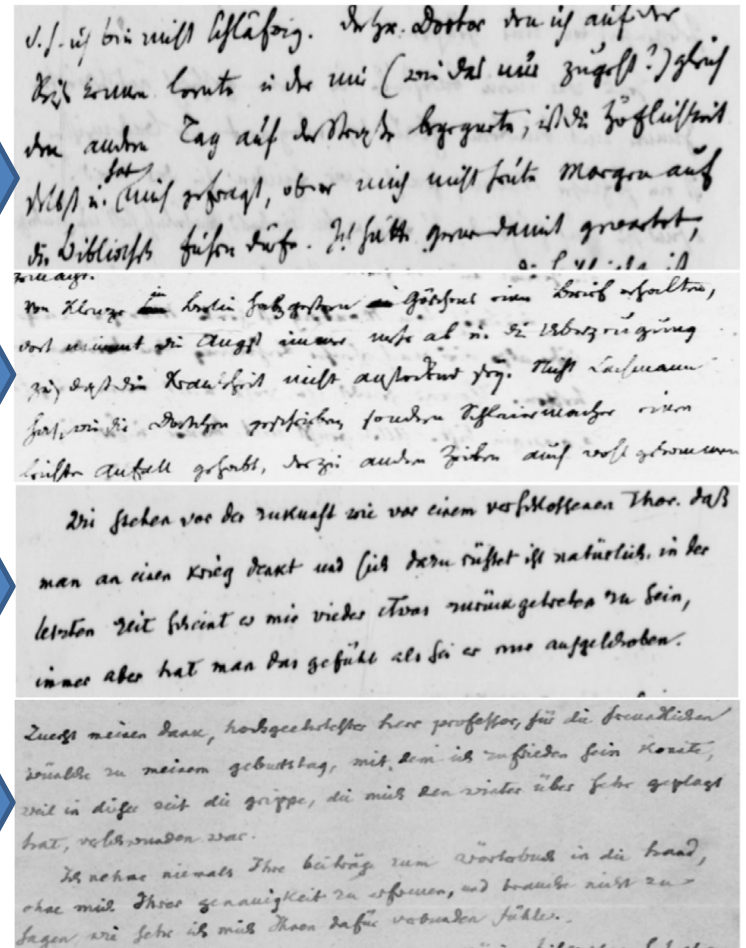
Jander, M. (2016). *Handwritten Text Recognition – Transkribus: A User Report*. Göttingen, Germany:

eTRAP Research Group, University of Göttingen.

# Legibility and cleanliness

## Wilhelm Grimm's letters:

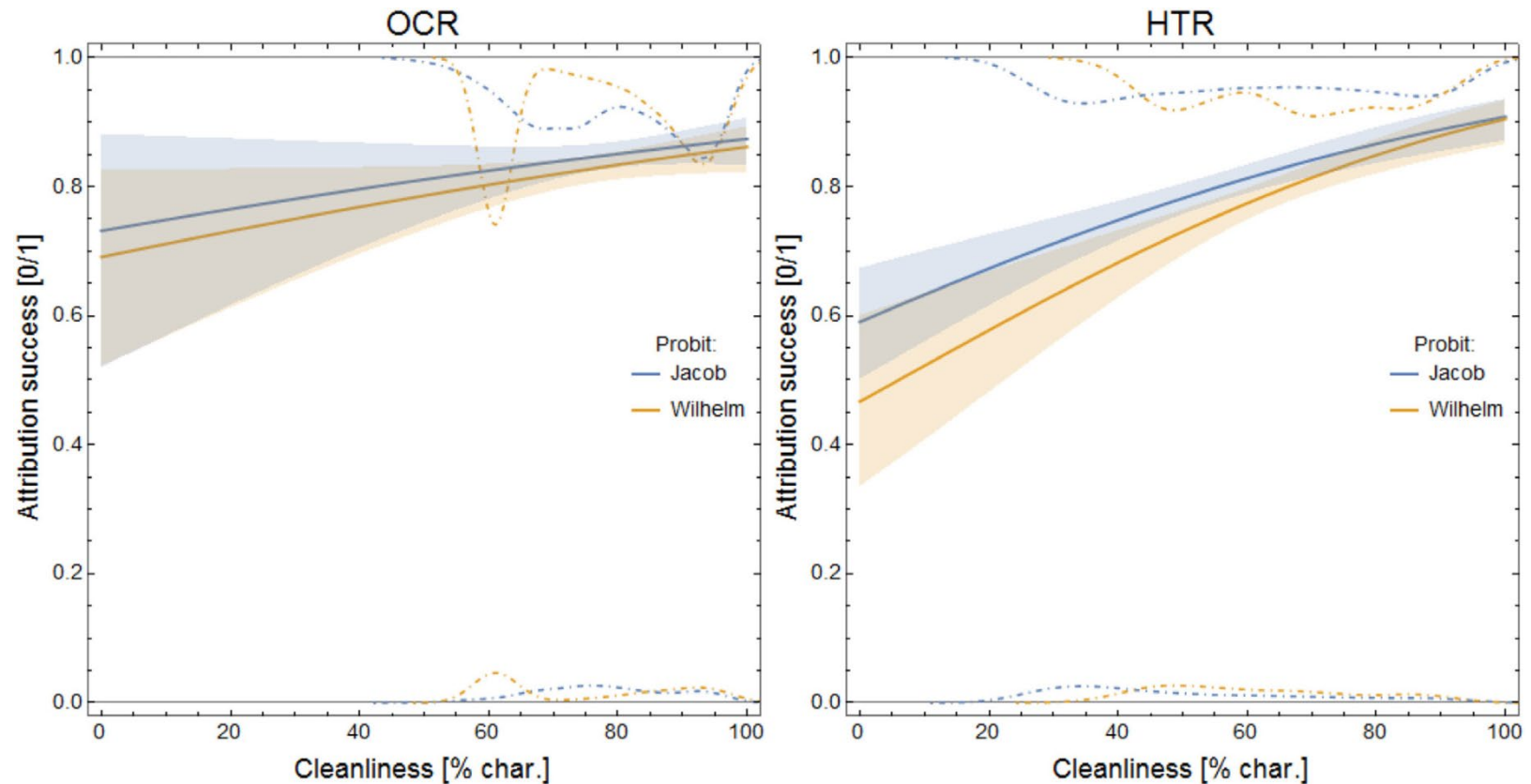
- **very low** legibility  
(Br 5993, 7 years old)
- **low** legibility  
(Br 2680, 45 years old)
- **medium** legibility  
(Br 2743, 73 years old)
- **high** legibility  
(Br 2736, 69 years old)







	MAN	OCR	HTR
Accuracy	91.66	91.66	88.88
F1 score	88.46	88.46	84.61



Franzini G, et al. (2018) Attributing Authorship in the Noisy Digitized Correspondence of Jacob and Wilhelm Grimm. *Front. Digit. Humanit.* 5:4



Take-home message:

- significant relation between auth. attr. **performance** and **cleanliness** for **HTR**
- auth. attr. **performs** as **well** on **OCR** as on human transcription

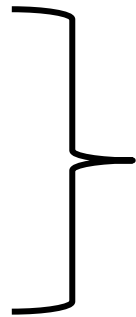
EXPERIMENT 3: the temporal

**ONE STEP BEYOND  
BAG OF WORDS**



Until now only:

- character
- word
- POS-tags



and their N-grams



Until now only:

- character
  - word
  - POS-tags
- } and their N-grams

But text is comprised of symbolic **sequences**.



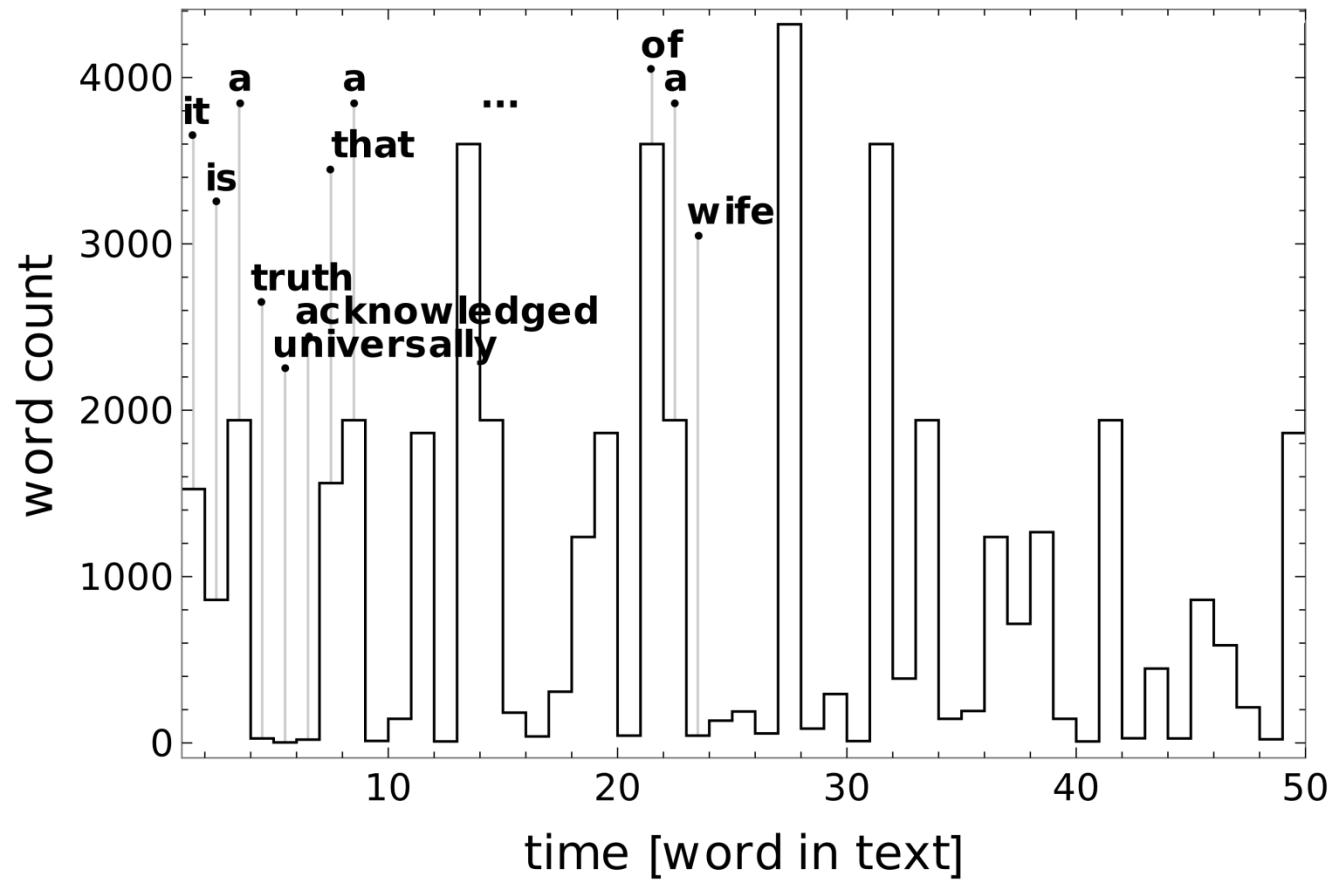
Until now only:

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But text is comprised of symbolic **sequences**.

Imagine DNA or heart rate time series.

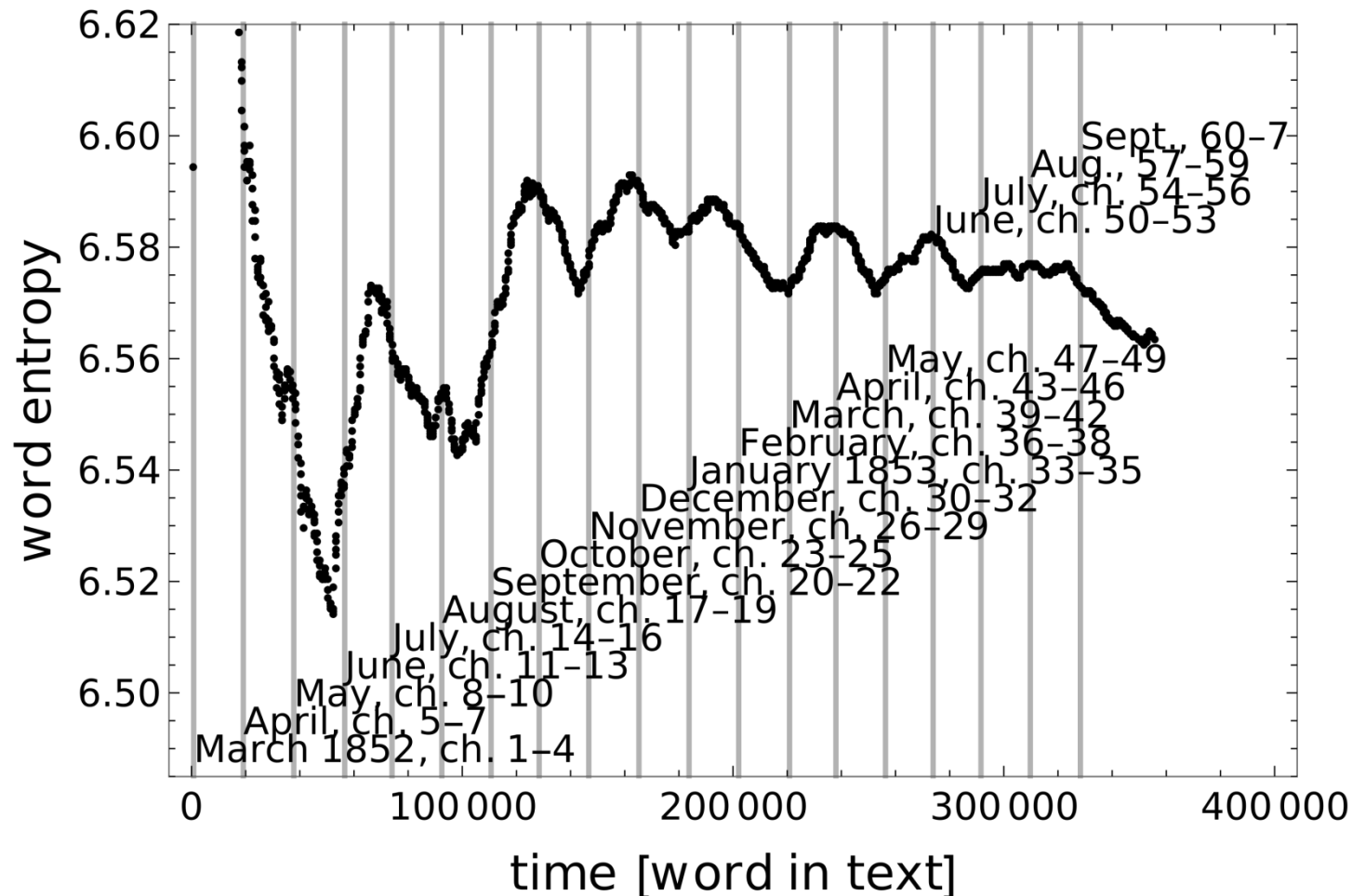
# Sequence of ranks



M. A. Montemurro and P. A. Pury, *Fractals* 10, 451 (2002).

M. Ausloos, *Phys. Rev. E* 86, 031108 (2012).

# Development of vocabulary



Ochab JK (2016). Time Series Analysis Enhances Authorship Attribution. *Digital Humanities* conference abstracts, July 11-16, 2016, Kraków.



## Take-home message:

- „Temporal” features can be used to characterise and classify texts, too.

A. Pawłowski, in Travaux de linguistique quantitative, Vol. 62 (Honoré Champion, Paris, Geneve: Champion-Slatkine, 1998).

A. Pawłowski, Journal of Quantitative Linguistics 6, 70 (2011).





# Conclusions

- Texts can be quantified in a number of ways
- Technological breakthrough not only for tech companies but for research in humanities

Based on:

Ochab JK, Byszuk J, Pielström S, Eder M (2019)

Identifying Similarities in Text Analysis: Hierarchical Clustering (Linkage) versus Network Clustering (Community Detection).

*Digital Humanities* conference abstracts, July 9-12, 2019, Utrecht.

Škvrňák J, Škvrňák M, Ochab JK (2019)

How To Detect Coup d'État 800 Years Later.

*Digital Humanities* conference abstracts, July 9-12, 2019, Utrecht.

Ochab JK, Essler H (2019)

Stylometry of literary papyri.

*3rd International Conference on Digital Access to Textual Cultural Heritage (DATeCH2019)*, May 8-10, 2019, Brussels, Belgium.

Franzini G, et al. (2018)

Attributing Authorship in the Noisy Digitized Correspondence of Jacob and Wilhelm Grimm.

*Front. Digit. Humanit.* 5:4

Ochab JK (2017)

Stylometric networks and fake authorships.

*Leonardo* 50

Ochab JK (2017)

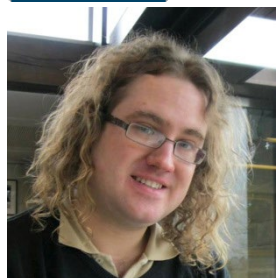
Randall Munroe's Thing Explainer: The Tasks in Translation of a Book Which Explains the World With Images.

*Przekładaniec* 34-35

Ochab JK (2016)

Time Series Analysis Enhances Authorship Attribution.

*Digital Humanities* conference abstracts, July 11-16, 2016, Kraków.



M Kestemont



M Büchler  
G Franzini  
G Rotari  
M Jander  
E Franzini



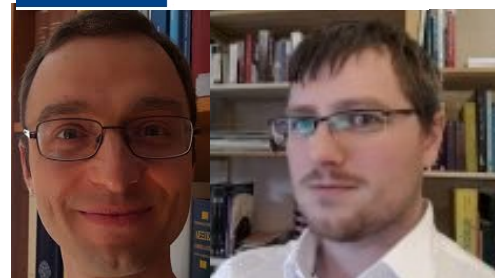
M Eder  
J Byszuk



Institute of English Studies  
Jagiellonian University



J Rybicki



H Essler  
S Pielström



10 Computational 01  
01 Stylistics 0101000  
11 Group 011010110

[computationalstylistics.github.io](https://computationalstylistics.github.io)  
[github.com/computationalstylistics/](https://github.com/computationalstylistics/)

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[facebook.com/dhkrakow/](https://facebook.com/dhkrakow/)



**Digital Humanities Lab**

Flagship Project at Jagiellonian University

<https://dhlabs.id.uj.edu.pl/>