FAMTAFOS

Free automated multi-language text anonymization for open science

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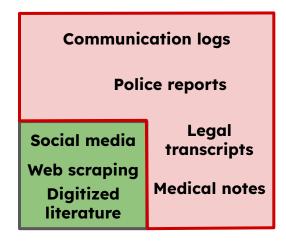
Text anonymization

Problem:

- Sensitive information often prohibit text datasets to be shared publicly (e.g., through GDPR)
 - → Limits progress and collaboration
 - → NLP research biased towards available data

Solution:

- Text anonymization
- Identify and redact potentially sensitive information (PSI) in text



Who is this?

[PRONOUN] is an [LOCATION_1] film actor known for playing [OTHER 1] in the [OTHER_2] series of films. Since [DATE_1], [PRONOUN] has been playing the character but [PRONOUN] confirmed that [OTHER 3] would be [PRONOUN] last [OTHER 1] film. [PRONOUN] was born in [LOCATION 2] on [DATE 2] of [DATE 3] in [DATE_4]. [PRONOUN] moved to [LOCATION_3] when [PRONOUN] parents divorced and lived there until [PRONOUN] was [NUMERIC] years old. [PRONOUN] auditioned and was accepted into the [ORGANIZATION_1] and moved down to [LOCATION_4].

Bond. James Bond.

He is an English film actor known for playing James Bond in the 007 series of films. Since 2005, he has been playing the character but he confirmed that No Time to Die would be his last James Bond film. He was born in Chester on 2nd of March in 1968. He moved to Liverpool when his parents divorced and lived there until he was sixteen years old. He auditioned and was accepted into the National Youth Theatre and moved down to London.

(Automated) text anonymization

- Existing efforts to text anonymization often involve manual work to redact <u>potentially sensitive information</u> (PSI)
 - → Slow and cost-intensive process
- Others resort to hand-crafted rules, without preserving text's semantics (e.g., UK Data Service)

Automated, semantics-preserving text anonymization:

- Use NLP methods to automatically identify and replace PSI in text
- Replace PSI in a meaningful way to preserve semantics

Our approach

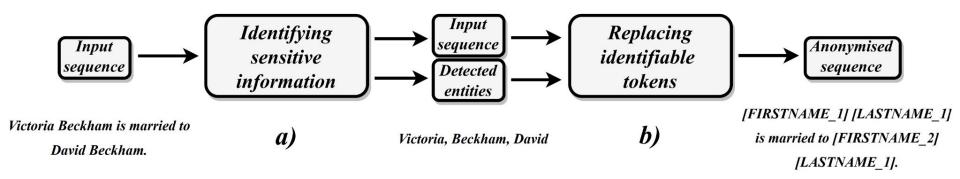
Automated text anonymisation old school vs learning-based

Pillars:

- Fast
- Scalable
- Offline
- Lightweight

- Open science-focused
- Research end user in mind

Anonymization pipeline



Textwash (= current version)

Model:

- Machine learning-based text anonymization
- Model is based on BERT (Devlin et al., 2018)
 - → Fine-tuned with a token classification objective

Data:

 Textwash is built on 3.7k human-annotated documents (British National Corpus, Enron emails, Wikipedia articles)

Textwash: categories

Textwash supports 11 categories

PERSON_FIRSTNAME Jane

PERSON_LASTNAME Smith

OCCUPATION Doctor

LOCATION Netherlands, behind the curtain

TIME 12.59pm, afternoon, midday

ORGANIZATION Microsoft, NWO

DATE 01.01.1970, 3rd of November

ADDRESS 42 London Road

PHONE_NUMBER +44XXXXXXXXX

EMAIL_ADDRESS <u>jane@smith.com</u>

OTHER ?

The importance of evaluation

Example from Mozes and Kleinberg (2021)

Margaret Thatcher, nicknamed the "Iron Lady", served as Prime Minister of the United Kingdom from 1979 to 1990.

FIRSTNAME_1 LASTNAME_1, nicknamed the "Iron Lady", served as OCCUPATION_1 of the LOCATION_1 from DATE_1 to DATE_2.

This anonymization is *almost* perfect (6 out of 7 PSI were anonymized), yet a single entity gives away identity of individual.

Evaluation

Using the **TILD criteria** (Mozes and Kleinberg, 2021)

- How many PSI does it correctly identify?
 - → <u>T</u>echnical evaluation
- 2. How does anonymization affect downstream tasks?
 - → <u>I</u>nformation <u>l</u>oss evaluation
- 3. Can individuals be identified from anonymized texts?
 - → <u>D</u>e-anonymization (motivated intruder testing)

Motivated intruder test

Data protection

Anonymisation: managing data protection risk code of practice

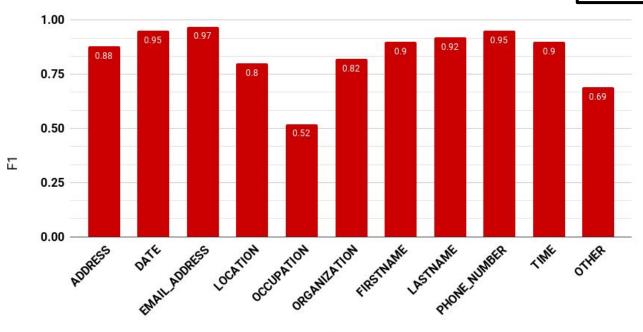
ico.

- \rightarrow Proposed by ICO
- → Human re-identification
- \rightarrow Can use any resources
- \rightarrow No prior knowledge
- \rightarrow No specialist skills

Technical evaluation

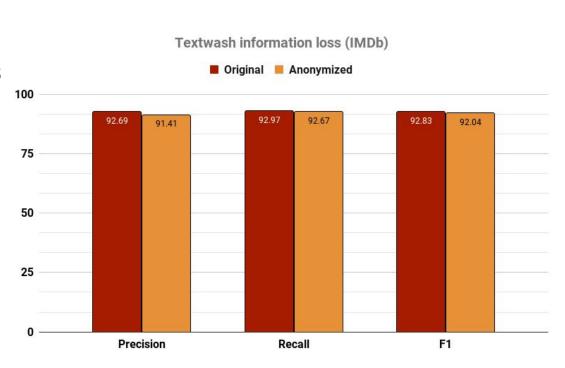






Information loss

- RoBERTa (Liu et al., 2019) fine-tuned on IMDb (Maas et al., 2011)
 - \rightarrow Original dataset
 - → Anonymized dataset
- Performance differences are small
 - → Preserves utility



Motivated intruder testing

Human participants are asked to identify individuals on three levels

- Famous individuals (e.g., Emma Watson, Daniel Craig)
- Semi-famous individuals (e.g., Kenny Kramm)
- Fictitious individuals

Collecting descriptions

- Each category consisted of 10 items
- n=401 participants wrote 3 descriptions each (total of 1202 descriptions)

Intruder testing

• *n*=366 participants, each judged 10 items in a single group

De-anonymization rates

	Famous	Semi-famous	Fictitious
% identified	18.25	1.01	2.01

Rates are highest for famous individuals (expected)

Replication study

- Repeated intruder testing for 20 famous individuals
- Collection: n=200 participants wrote five descriptions each
- Testing: *n*=222 individuals, 10 texts each
- Results: de-anonymization rate of 26.39% (very famous celebrities)

Using Textwash

- Currently available on GitHub
- Supports txt files, runs smoothly on CPU

```
$ python3 anon.py --input_dir examples --output_dir anonymized_examples
```

Docs and guidelines on GitHub.

Textwash becomes FAMTAFOS

- Extension to the Dutch language
- High quality annotations of Wikipedia corpora (Dutch and English)
- Completed with 2.5k documents → 783k annotated entities (21% in PSI categories)
- Addition of new categories:
 - TITLE (of a song, prize, book, etc.)
 - CULTURAL IDENTITY (e.g., religion, sexual orientation, ethnicity)

Next phase: scaled-up crowdsourced annotation

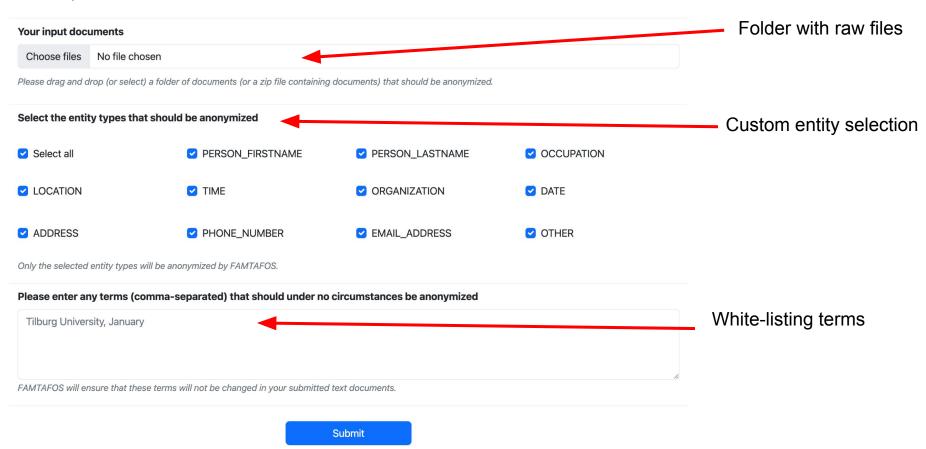
- 8k documents with ~ 2.5m annotated entities (~ 500k PSI entities)
- Training the Dutch model
- Updating the English model

Textwash becomes FAMTAFOS

- 1. Extension to the Dutch language
- 2. Graphical user interface (GUI) for non-programmers

FAMTAFOS User Interface

This is a simple UI demo for FAMTAFOS.

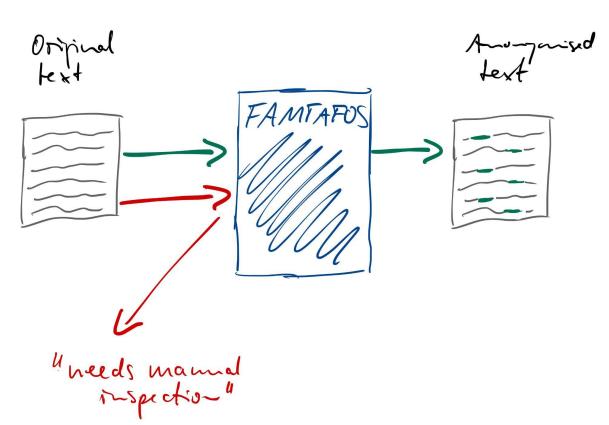


Textwash becomes FAMTAFOS

- 1. Extension to the Dutch language
- 2. Graphical user interface (GUI) for non-programmers
- 3. Custom white-listing
- 4. Custom black-listing
- Risk score model

Textwash becomes FAMTAFOS

- Extension to the Dutch language
- 2. Graphical user interface (GUI) for non-programmers
- 3. Custom white-listing
- 4. Custom black-listing
- 5. Risk score model



Where are we?

- Netanos software → 2016-2018
- Textwash software → 2019-2020
- Textwash validation studies → 2021
- FAMTAFOS development

<u>Famtafos will be available from March 2023 onward.</u>

Thank you

Paper: https://arxiv.org/abs/2208.13081

GitHub: <u>https://github.com/maximilianmozes/textwash</u>

References

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