13 – Stylometry

IA161 Advanced Techniques of Natural Language Processing

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1. Stylometry
   - Definition
   - History
   - Author information
   - Field demarcation

2. Stylometry techniques
   - Stylometric-technique categories
   - Examples of stylometric techniques

3. Feature extraction and machine learning
   - Feature extraction
   - Machine learning

Computational stylometry

Definition

Computational stylometry develops techniques that allow us to find out information about the authors of texts on the basis of an automatic linguistic analysis of those texts.

Application

1. basic research on the linguistic properties of text determining style[a]
2. literary research (resolving disputed authorship)
3. forensic applications (disputed authorship of suicide notes, blackmail letters etc.)
4. human resources profiling (describe and explain the causal relations between psychological and sociological properties of authors on the one hand, and their writing style on the other)[Daelemans, 2013]

[a] `http://www.clips.ua.ac.be/~walter/educational/stylometry.html`

History

Mendenhall, T. C. 1887.
The Characteristic Curves of Composition. Science Vol 9: 237–49.

- The first algorithmic analysis
- Calculating and comparing histograms of word lengths
- Authorship verification of Shakespeare's plays

Oxford, Bacon
Derby, Marlowe

Information about author

Stylometry techniques can reveal following information:

1. gender,
2. region of origin,
3. age,
4. personality (extraverted or introverted),
5. education level,
6. indication of the identity of the author:
   - authorship attribution,
   - machine generated text detection:
     - spam detection,
     - automatic translation detection,
7. etc.

Demarcation against other fields

Topic recognition

Topic recognition features	Stylometry features
repeated non-stop-words	(repeated) stop-words
repeated phrases (rare in corpus)	repeated phrases (common in corpus)
usually based on entity detection	mostly without entity detection

Plagiarism detection

Plagiarism detection features	Stylometry features
word n-grams	POS tags n-grams
rare character n-grams	frequent character n-grams
based on word substitution	word choice is important
based on word reordering in sentence	word order is important

Stylometric-technique categories

Categories

1. morphological
2. syntactic
3. lexical
4. other

Assumptions

Author has:

1. unique active vocabulary
2. favourite phrases and word n-grams
3. a certain level of knowledge of grammar (mistakes)
4. personalized handling of typography

Examples: lexical stylometric features

Word length

- use lemmas instead of tokens
- active vocabulary contains long words, preference of longer/shorter words, ...

Vocabulary richness

- Yule, 1944:

$$K = \frac{10^4(\sum i^2 V_i - N)}{N^2} \quad (1)$$

where V_i denotes the number of words with frequency i and N is the number of words in the text.

- Simpson, 1949:

$$D = \sum (V_i \cdot \frac{i}{N} \cdot \frac{i-1}{N-1}) \quad (2)$$

where V_i denotes the number of words with frequency i and N is the number of words in the text.

Examples: morphological stylometric features

N-grams of part-of-speech tags

- $N > 1$ is better in free word order languages
- overcomes topic dependency of token N-grams

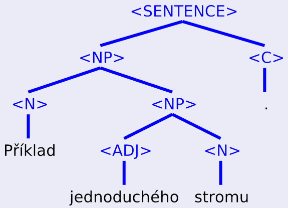
Majka tags n-grams

- Word class bigrams ("myslel bych" $\Rightarrow [k5][kY]$)
- Most frequent reduced tags N-grams
  1. Filter out rare morphological information ($[kYmCp1nS] \Rightarrow [kYp1nS]$)
  2. Find the most common tag sets on test data
  3. Use K the most frequent tag sets as features

Examples: syntactic stylometric features

Requires syntactic analyser

SET (`http://nlp.fi.muni.cz/trac/set`):



N-grams of clause types

1. unigrams: $2 \times [N]$ and $1 \times [ADJ]$
2. bigrams: $1 \times [N][ADJ]$ and $1 \times [ADJ][N]$
3. trigrams: $1 \times [N][ADJ][N]$

Syntactic tree features

1. branching factor
2. depth
3. maximal width

Feature extraction process

Build train corpus

1. consists of texts similar to examined data
2. used to find the most common N-grams, stop words, ...
3. bigger is better

Text normalization (same for train corpus and analysed data)

1. remove automatically generated tags (HTML, XML) and decode encoded entites
2. remove automatic text repetition (e-mails)
3. replace URLs, images, keys, ... by custom tag

Feature extraction process

Text preprocessing

1. annotate document (tokenization, morphological and syntactic analysis, entity and collocation detection, date and time recognition, ...)
2. save documents as object consisting of original text (needed for extending features and debuging) and all analysis outputs

Training: Feature extraction, normalization and selection

- Given F features, generate feature vector $\{f_{f1}, f_{f2}, \ldots, f_{fF}\}$ for each document.
- Normalize each feature fi (linear function S_{fi} with target domain $\langle 0, 1\rangle$ or $\langle -1, 1\rangle$)
- Feature selection $F => F'$.

Feature extraction process

Analysis

- Use F' features, generate feature vector for each document.
- Scale each feature fi using function S_{fi}

Process of document analysis

Pipeline consisting of:

1. Text normalization function: raw text $\Rightarrow$ clean text)
2. Text annotation functions: clean text $\Rightarrow$ support objects containing morphological, syntactic and semantic information about text
3. Feature extraction: support objects $\Rightarrow$ feature vector
4. Feature scaling (normalization): feature vector $\Rightarrow$ scaled feature vector

Machine learning

Machine learning notes

- If using linear models, discretize or divide features (e.g. feature avg. world length convert into short, average and long words relative frequency features)
- Think if you analyse:
  1. seen classes (for authorship attribution, we know all candidates, for gender prediction, there is only fixed number of genres) or
  2. unseen classes (unknown authors, age wasn't present in train data): more difficult, requires tricks using features if data domain
- Think about your target audience:
  1. Is important only result (automatic data classification)? Experiment with feature combinations and all possible features.
  2. Do people want to examine results and evidence (court experties)? Feature need be comprehensible (add explanations of tags, don't use too complicated features). Be prepared to explain why was feature selected (linguistic background).

Thank you

References I

Daelemans, W. (2013).
Explanation in computational stylometry.
In Gelbukh, A., editor, *Computational Linguistics and Intelligent Text Processing*, volume 7817 of *Lecture Notes in Computer Science*, pages 451–462. Springer Berlin Heidelberg.

Kestemont, M. (2014).
Function words in authorship attribution from black magic to theory?
EACL 2014, pages 59–66.

Stamatatos, E. (2009).
A survey of modern authorship attribution methods.
Journal of the American Society for Information Science and Technology, 60(3):538–556.