Methods for automatic dating of documents

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Section 1

Introduction

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- Once relevant info is now outdated.
- There's a need for ways of distinguishing between relevant, once relevant and irrelevant.

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- ... and even then they can be in all kinds of different formats.
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We need automatic tools for dating documents.

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- Need to use text itself to determine a more accurate timestamp.

Section 2

Methods of automatic dating

Two groups of methods

1. Language Model based methods

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- 2. Time Expression based methods

- chronon
- tf-idf

nllr

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- tf-idf Text frequency, inverse document frequency.
 - An algorithm for determining most "relevant" words from a document.
- *nllr* Non-linear logarithmic likelihood ratio.
 - "How much is this thing like this other thing"

Subsection 2

Language Model based methods

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- Compare a document with unknown date to the chronons using NLLR.
- Pick the chronon with highest NLLR result.
- Reportedly 20 24% accuracy with three month chronons and newspaper articles.

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- Non-NLP improvements:
 - Better interpolation.
 - Temporal Entropy.



Kumar et al. (2011, 2012), Dalli & Wilks (2006)

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- Comparison of effectiveness not possible due to different corpuses used.

Subsection 3

Time Expression based methods

Chambers (2012)

• Look for time expressions.

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 - since 2005
 - until February 2000

Chambers (2012)

- · Look for time expressions.
 - since 2005
 - until February 2000
- Use those to determine likely dates.

Section 3

Weaknesses of LM based dating methods

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- Newspapers user homogenous language, perhaps LM-methods don't generalize?
- Newspapers also have high overlap within chronons if multiple papers are used in the same corpus: Same event in all the sources.

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- A perfect reference corpus would comprise of all the texts from a chronon.
- But then we would already know when all the texts were dated...
- Therefore, the reference corpus is incomplete and contains an amount of error.

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- Need to interpolate non-zero values where zero values would be.
- Interpolation causes fuzziness and introduces error.
- Sources of error are not additive but multiplicative.

Section 4

Stemming as a preprocessing step

The logic behind stemming

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- From a dating perspective, *tsunami* and *tsunamis* are the same thing.
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- Differentiation is detrimential from an NLLR perspective.

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- In the stemmed sentences, all the difference is lost:
 - 1. Presidentti Niinistö lähteä tänään Mäntyniemi Sotši
 - 2. Presidentti Niinistö lähteä tänään Sotši Mäntyniemi

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- For stemming to be useful, the benefit must outweight the negative effect from an accuracy perspective.
- Seems fair enough for English:
 - Little inflection.
 - Information such as shown above would already be lost since word order is lost.
- · Less clear for Finnish:
 - Highly agglunative.
 - Stemming removes information that would otherwise be present.

Section 5

A case study

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 - Snowball (Porter2) stemmer.
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 - Snowball (Porter2) stemmer.
 - English and Finnish rules selectable.
- Can analyze both single texts (from manual input) or corpuses (from files).
- Keeps track of correct and incorrect answers for corpus analysis, provided that the analyzed corpus contains real dates for the texts.



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- Articles from Reuters, spanning a few months in 1987.
- Used a python script to convert the original SGML to CSV, then manual labour to remove some badly formatted lines.
- *n* = 14899 with a 2-12 split:
 - Smaller set of n = 2768
 - Larger set of n = 12131

Results for 12-2 split

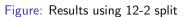
 Bigger set as training data (reference corpus), smaller set as test data.

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Results for 12-2 split

- Bigger set as training data (reference corpus), smaller set as test data.
- Run for all four chronons, both with and without stemming.
- Difference between stemmed and non-stemmed runs is weird.



Window length

Try a new run, this time with 2-12 split, to confirm the results.

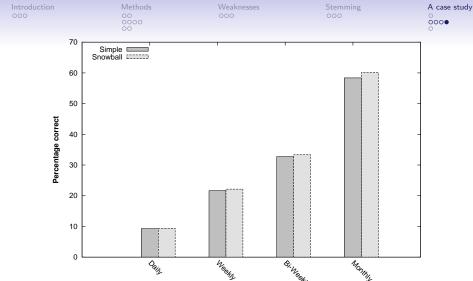


Figure: Results using 2-12 split

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- This time, something of a trend in favor of Snowball.
- Still less improvement than expected.
- What does this mean for the concerns about stemming presented earlier?

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- Stemming doesn't seem to do much even with English.
- If the benefit from stemming is so small with English, can the benefit compensate for the larger loss of information when dealing with Finnish.
- Trying to get hold of a sufficiently large Finnish corpus with known dates for the texts.