RECSM Summer School: Text Analysis

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Networked Democracy Lab
`www.netdem.org`

Course website:

github.com/pablobarbera/big-data-upf

Text as data

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Kukuriku
koalicija
Plan 21


the TRUE NORTH
STRONG AND FREE
Stephen Harper's plan for Canadians
Conservative


Et retfærdigt
Danmark


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ΣΥΡΙΖΑ
ισχυρός
στη Βουλή
και στους αγώνες
Είναι στο χέρι μας!
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ΣΥΝΑΣΠΙΣΜΟΣ ΡΙΖΟΣΠΑΣΤΙΚΗΣ ΑΡΙΣΤΕΡΑΣ
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GRÜNE NEUE
GESELLSCHAFTS-
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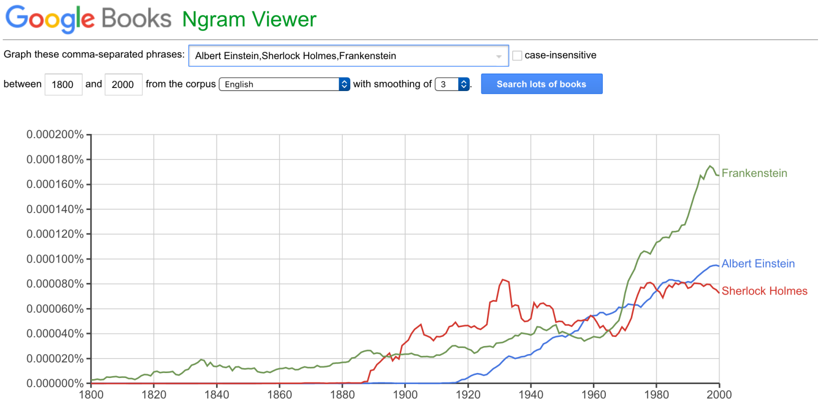
WIR HABEN DIE KRAFT
GEMEINSAM
FÜR UNSER LAND.
REGIERUNGSPROGRAMM 2009 – 2013
CDU CSU


Sozial und
Demokratisch.
Anpacken. Für Deutschland.
Das Regierungsprogramm der SPD
SPD

Text as data



Google Books Ngram Viewer
Graph these comma-separated phrases:
Albert Einstein,Sherlock Holmes,Frankenstein
case-insensitive
between
1800
and
2000
from the corpus
English
with smoothing of
3
Search lots of books
0.000200%
0.000180%
0.000160%
0.000140%
0.000120%
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1800
1820
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1860
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1920
1940
1960
1980
2000
Frankenstein
Albert Einstein
Sherlock Holmes

Text as data


facebook
XING
Gefällt mir
Instagram
twitter
Linked in
Pinterest
skype
flickr
You Tube

Overview of text as data methods

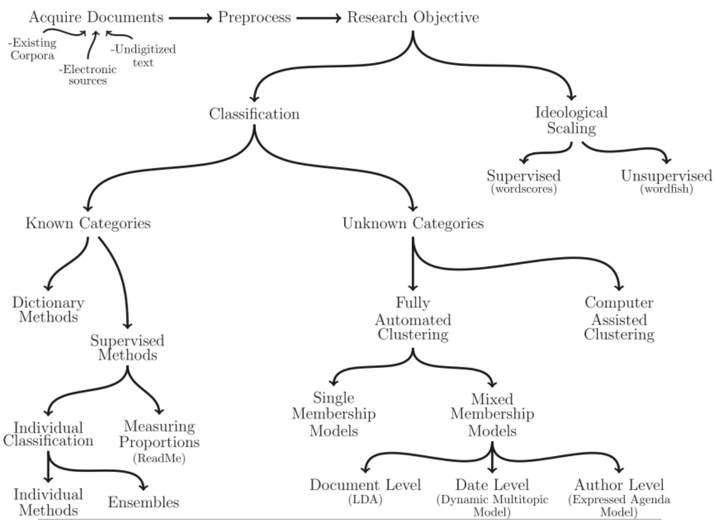

Fig. 1 in Grimmer and Stewart (2013)

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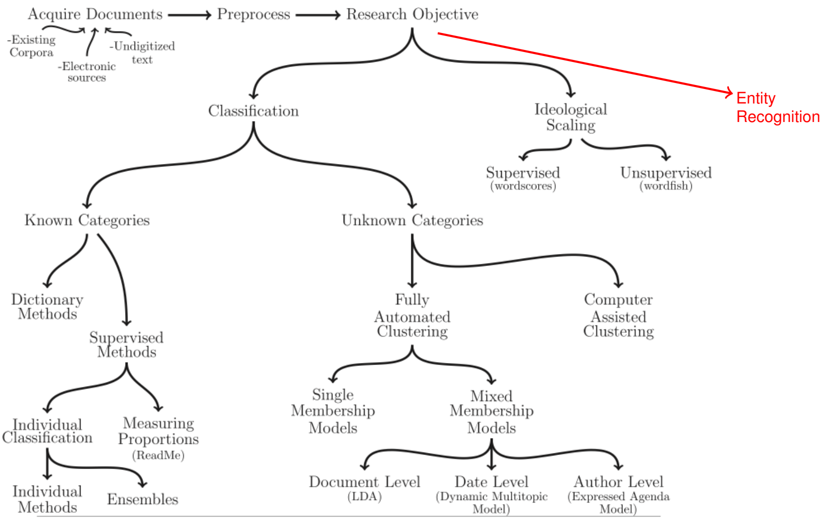

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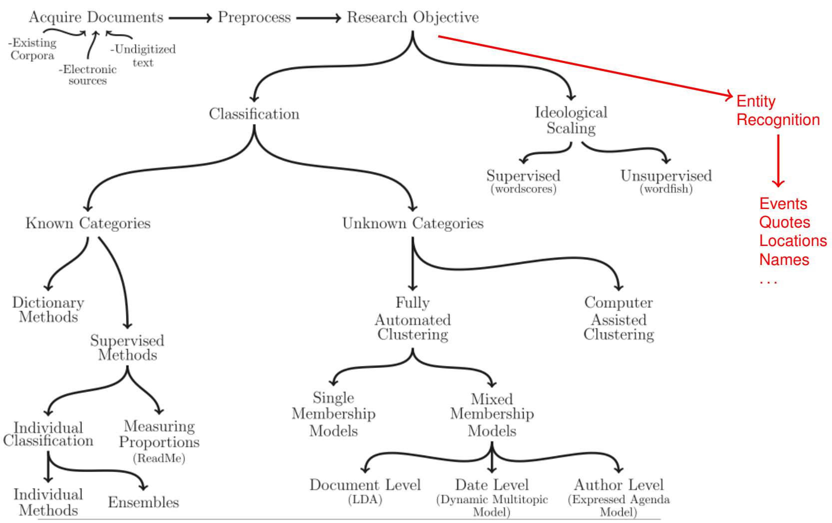

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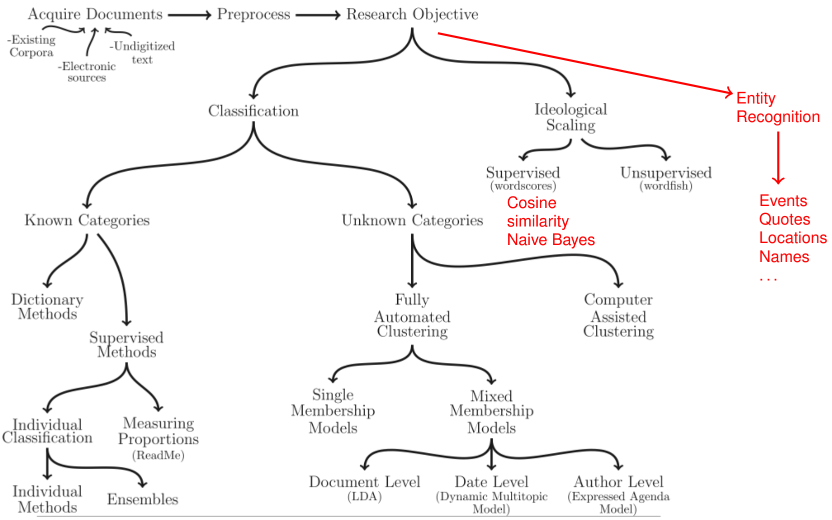

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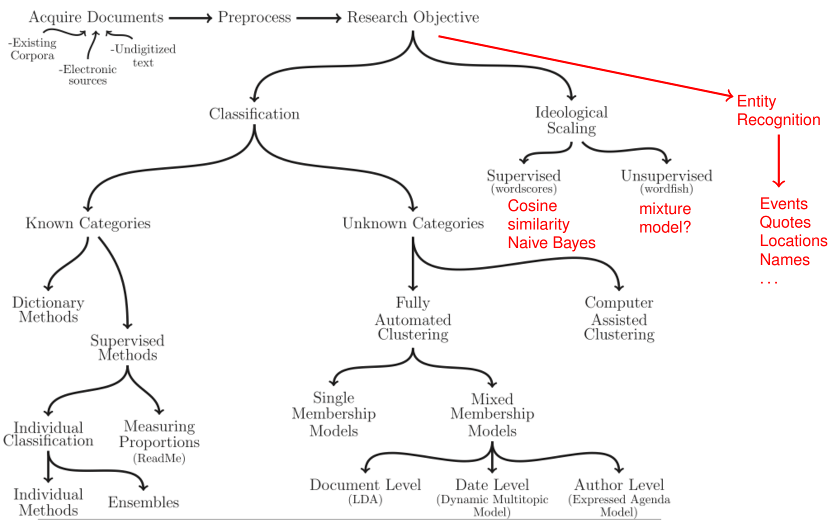

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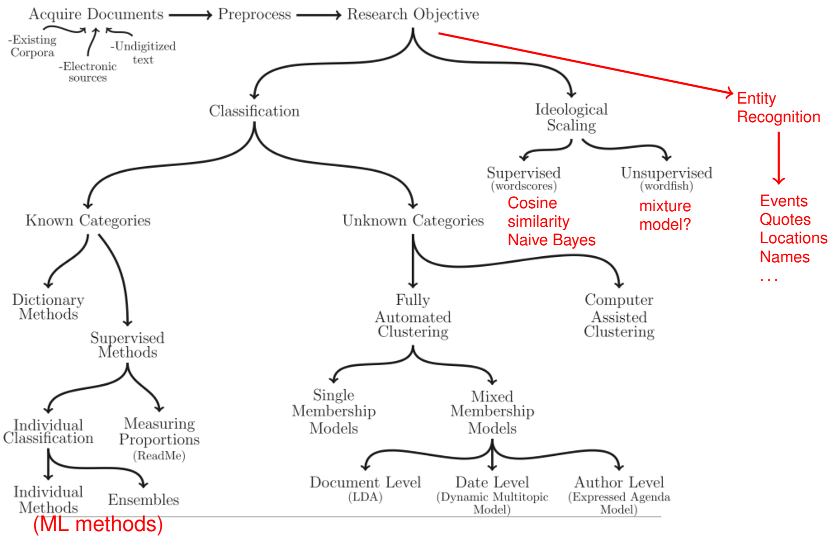

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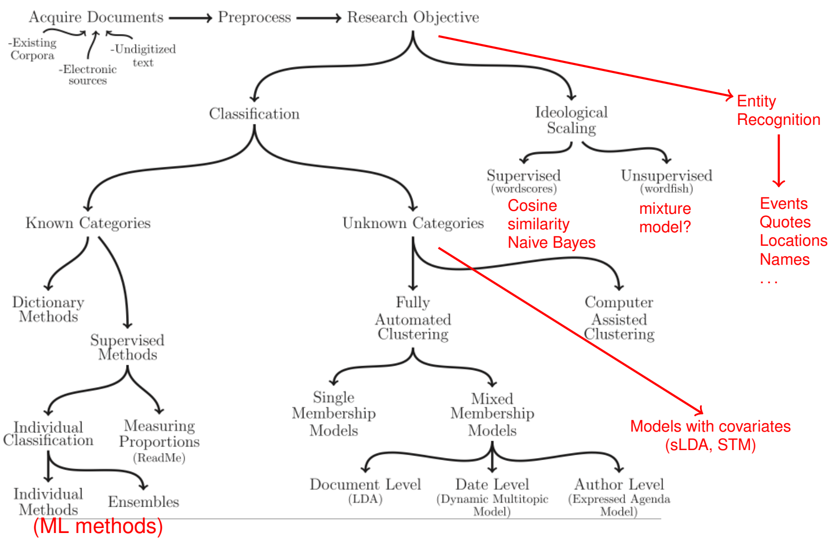

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   - Usually large matrix, but sparse (so it fits in memory)

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1. Preprocess text:

“@MEPcandidate thank you and congratulations, you’re the best #EP2014”

“@MEPcandidate You’re an idiot, I would never vote for you”

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1. Preprocess text: lowercase, remove stopwords and punctuation, stem, tokenize into unigrams and bigrams (bag-of-words assumption)

   [@, thank, congratul, you’r, best, #ep2014, @ thank, thank congratul, congratul you’r, you’r best, best, best #ep2014]

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2. Document-term matrix:
   - **W**: matrix of N documents by M unique n-grams
   - w_{im}= number of times m-th n-gram appears in i-th document.

	@	thank	congratul	you'r	#ep2014	@ thank	...	M words
Document 1	1	1	1	1	1	1	...	
Document 2	1	0	0	1	0	0	...	
...								
Document n	0	1	1	0	0	0	...	

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  - Check sensitivity of results to exclusion of specific words
  - Code a few documents manually and see if dictionary prediction aligns with human coding of document

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- Performance metric to choose best classifier and avoid overfitting: confusion matrix, AUC, accuracy, precision, recall...

Performance metrics

Confusion matrix:

	Actual Label	
Classification (algorithm)	Liberal	Conservative
Liberal	True Liberal	False Liberal
Conservative	False Conservative	True Conservative

$$\text{Accuracy} = \frac{\text{TrueLib} + \text{TrueCons}}{\text{TrueLib} + \text{TrueCons} + \text{FalseLib} + \text{FalseCons}}$$

$$\text{Precision}_{\text{Liberal}} = \frac{\text{True Liberal}}{\text{True Liberal} + \text{False Liberal}}$$

$$\text{Recall}_{\text{Liberal}} = \frac{\text{True Liberal}}{\text{True Liberal} + \text{False Conservative}}$$

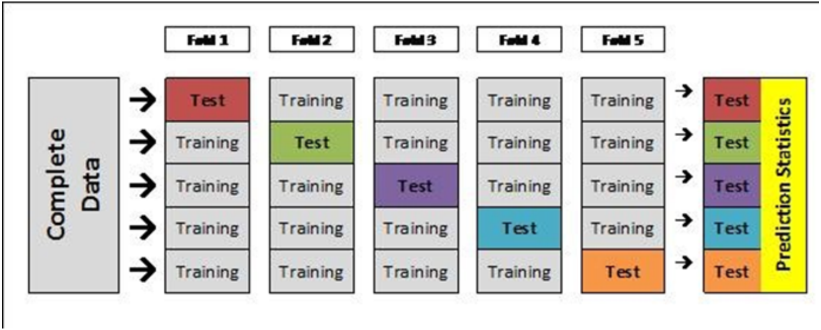
$$F_{\text{Liberal}} = \frac{2\text{Precision}_{\text{Liberal}}\text{Recall}_{\text{Liberal}}}{\text{Precision}_{\text{Liberal}} + \text{Recall}_{\text{Liberal}}}$$

Source: Grimmer, 2014, “Text as Data” course week 14

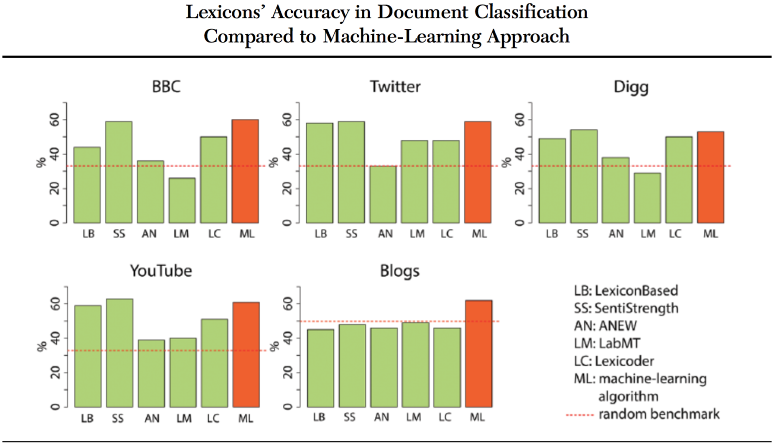
Cross-validation

Intuition:

- Create K training and test sets (“folds”) within training set.
- For each k in K, run classifier and estimate performance in test set within fold.
- Why? Find best classifier and avoid overfitting



Dictionaries vs supervised learning



Source: González-Bailón and Paltoglou (2015)

Regularized regression

Suppose we have N documents, with each document i having label $y_i \in \{-1, 1\} \rightsquigarrow$ {liberal, conservative}
We represent each document i is $\boldsymbol{x}_i = (x_{i1}, x_{i2}, \ldots, x_{iJ})$.

$$
\begin{aligned}
f(\beta, \boldsymbol{X}, \boldsymbol{Y}) &= \sum_{i=1}^{N} \left(y_i - \beta' \boldsymbol{x}_i\right)^2 \\
\widehat{\beta} &= \arg\min_{\beta} \left\{ \sum_{i=1}^{N} \left(y_i - \beta' \boldsymbol{x}_i\right)^2 \right\} \\
&= \left(\boldsymbol{X}' \boldsymbol{X}\right)^{-1} \boldsymbol{X}' \boldsymbol{Y}
\end{aligned}
$$

Problem:

- J will likely be large (perhaps $J > N$)
- There many correlated variables

Source: Grimmer, 2014, “Text as Data” course week 15

Regularized regression

Penalty for model complexity

$$f(\beta, \boldsymbol{X}, \boldsymbol{Y}) \;=\; \sum_{i=1}^{N}\left(y_i - \;\beta_0 + \sum_{j=1}^{J}\beta_j x_{ij}\right)^2 + \underbrace{\lambda\sum_{j=1}^{J}\beta_j^2}_{\text{Penalty}}$$

where:

- $\beta_0 \leadsto$ intercept
- $\lambda \leadsto$ penalty parameter

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  - $S^*_{vd} = (S_{vd} - \overline{S_{vd}}) \left(\frac{SD_{rd}}{SD_{vd}} \right) + \overline{S_{vd}} \rightarrow$ Rescaled scores.