RECSM Summer School: Text Analysis

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Networked Democracy Lab
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Course website:
github.com/pablobarbera/big-data-upf

Text as data

Text as data


Kukuriku
koalicija
Plan
21


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


Et retfærdigt
Danmark


ΕΚΛΟΓΙΚΗ ΔΙΑΚΗΡΥΞΗ
ΣΥΡΙΖΑ
ισχυρός
στη Βουλή
και στους αγώνες
Είναι στο χέρι μας!
ΣΥΡΙΖΑ
ΣΥΝΑΣΠΙΣΜΟΣ ΡΙΖΟΣΠΑΣΤΙΚΗΣ ΑΡΙΣΤΕΡΑΣ


SPÖ
WAHLMANIFEST


GRÜNE NEUE
GESELLSCHAFTS-
VERTRAG
KLIMA • ARBEIT • GERECHTIGKEIT • FREIHEIT


WIR HABEN DIE KRAFT
GEMEINSAM
FÜR UNSER LAND.
REGIERUNGSPROGRAMM 2009 – 2013
CDU CSU

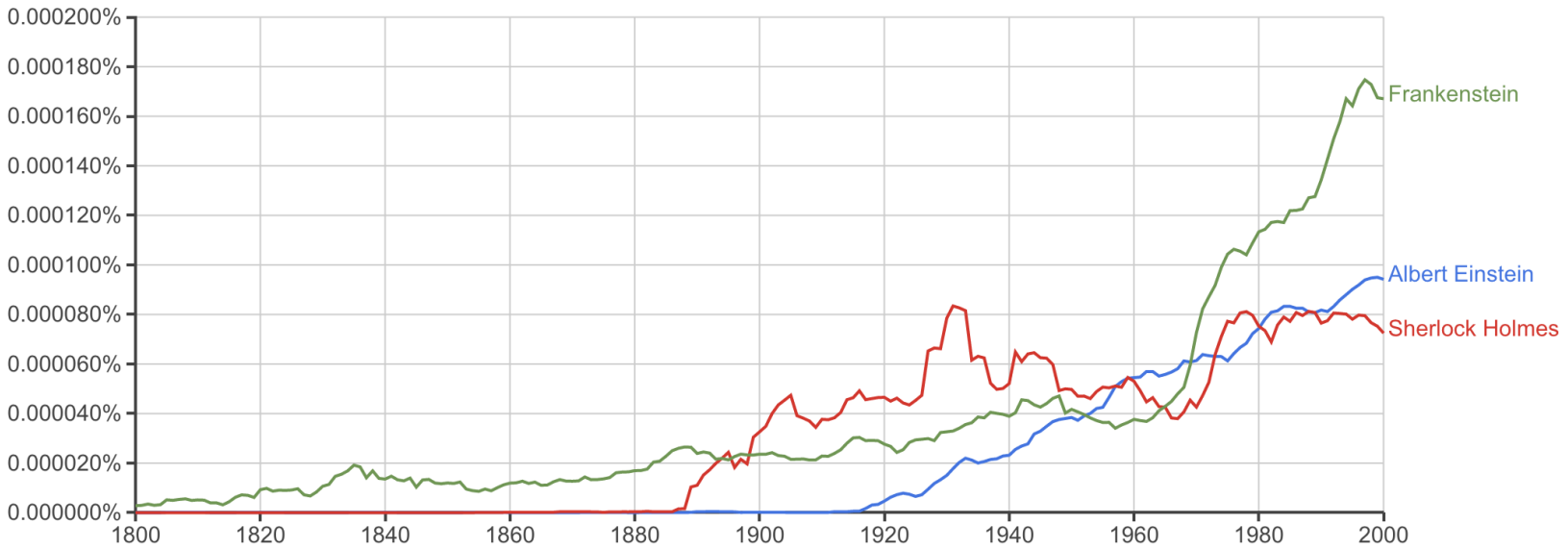

Sozial und
Demokratisch.
Anpacken. Für Deutschland.
Das Regierungsprogramm der SPD
SPD

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



Text as data


facebook
XING
Pinterest
Instagram
Gefällt mir
twitter
LinkedIn
flickr
skype
YouTube

Overview of text as data methods

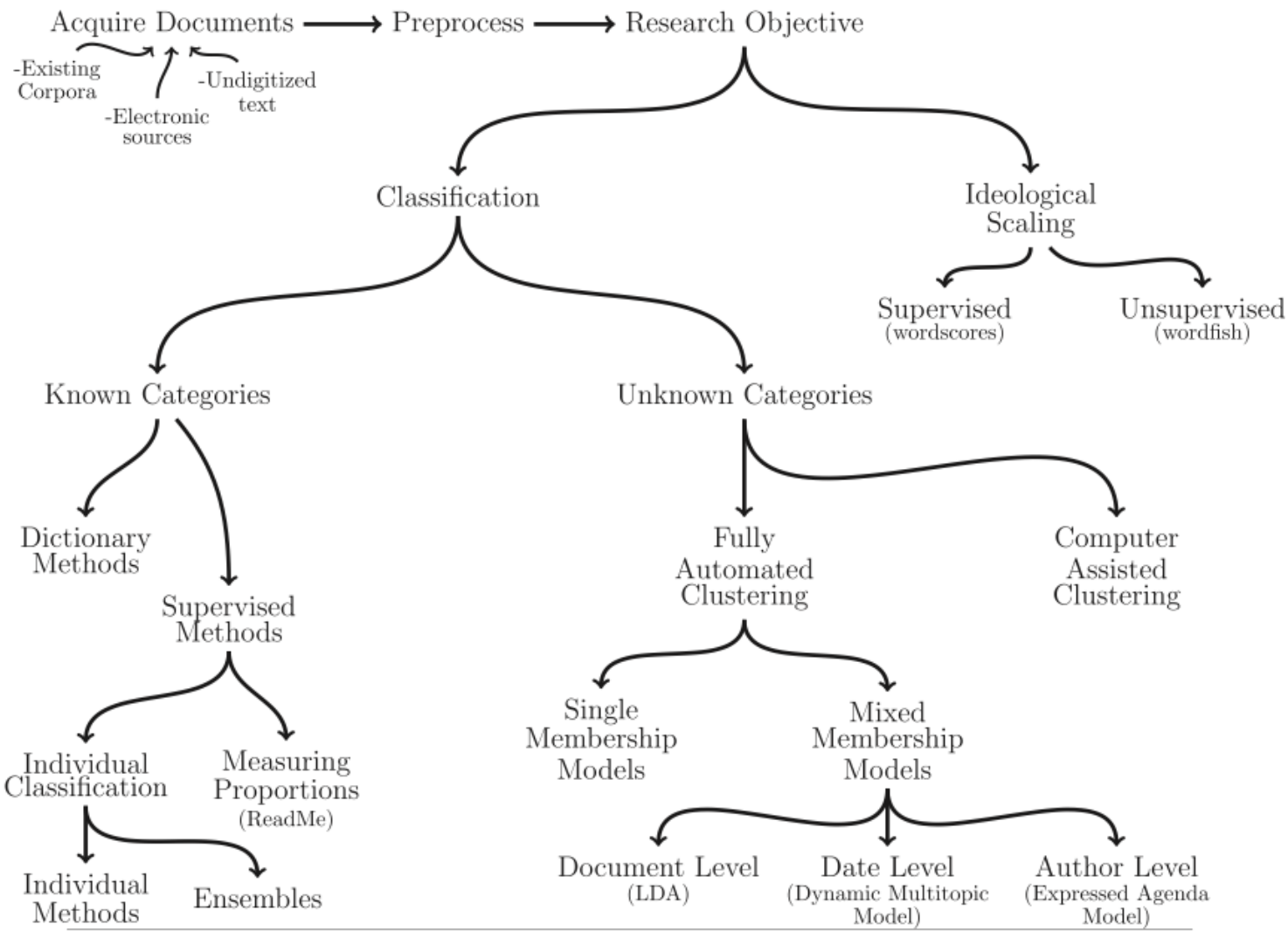
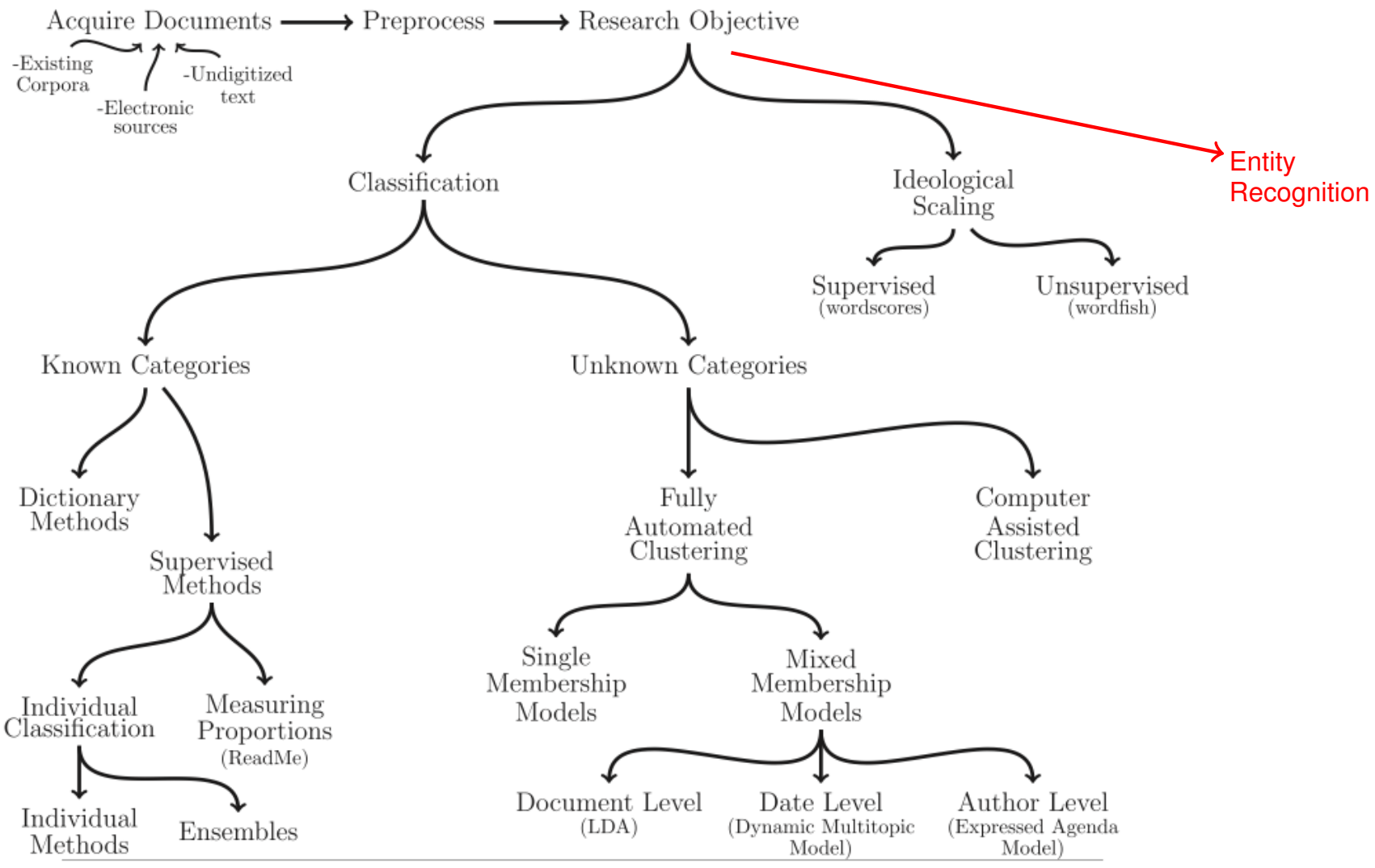


Fig. 1 in Grimmer and Stewart (2013)

Overview of text as data methods



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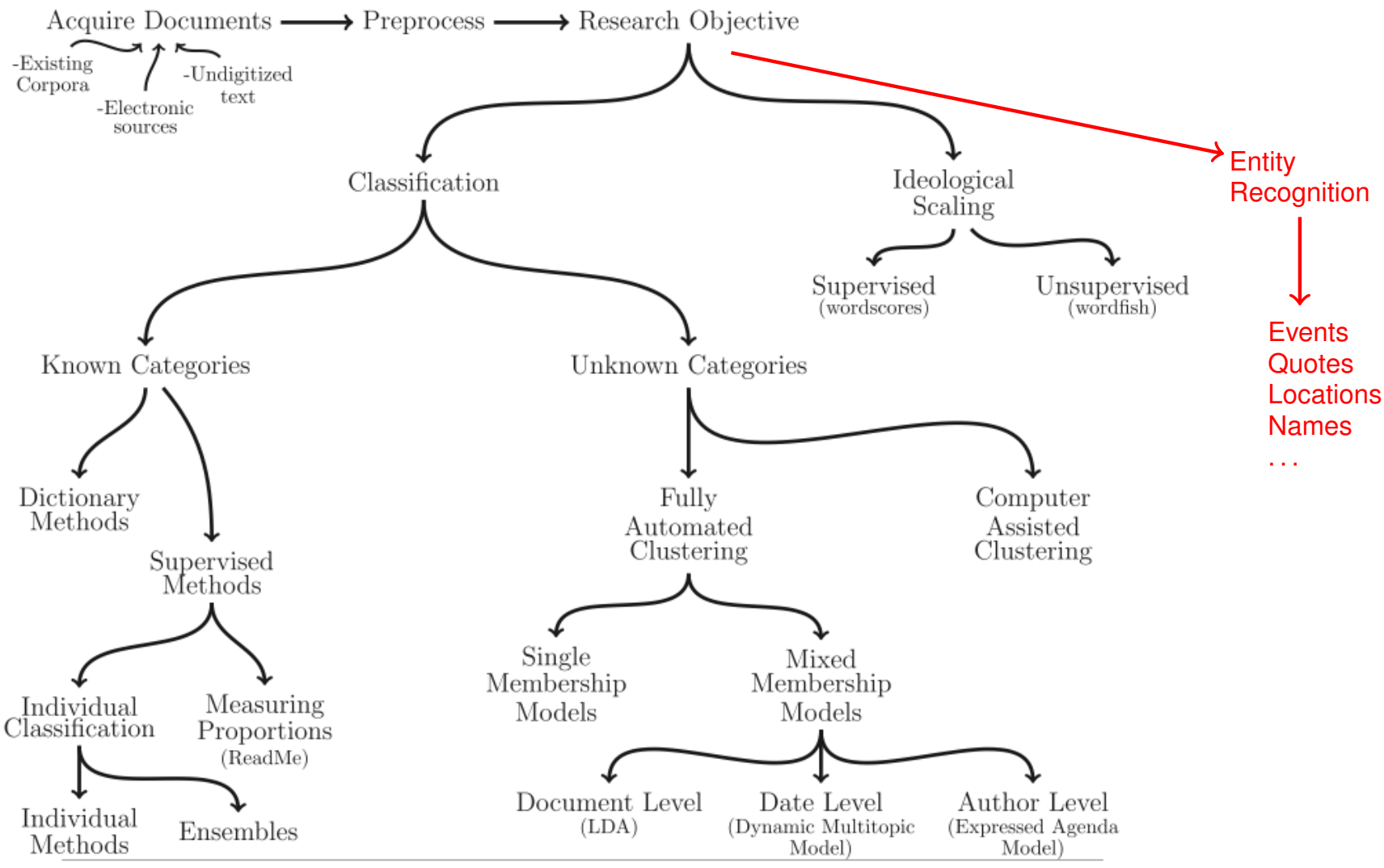

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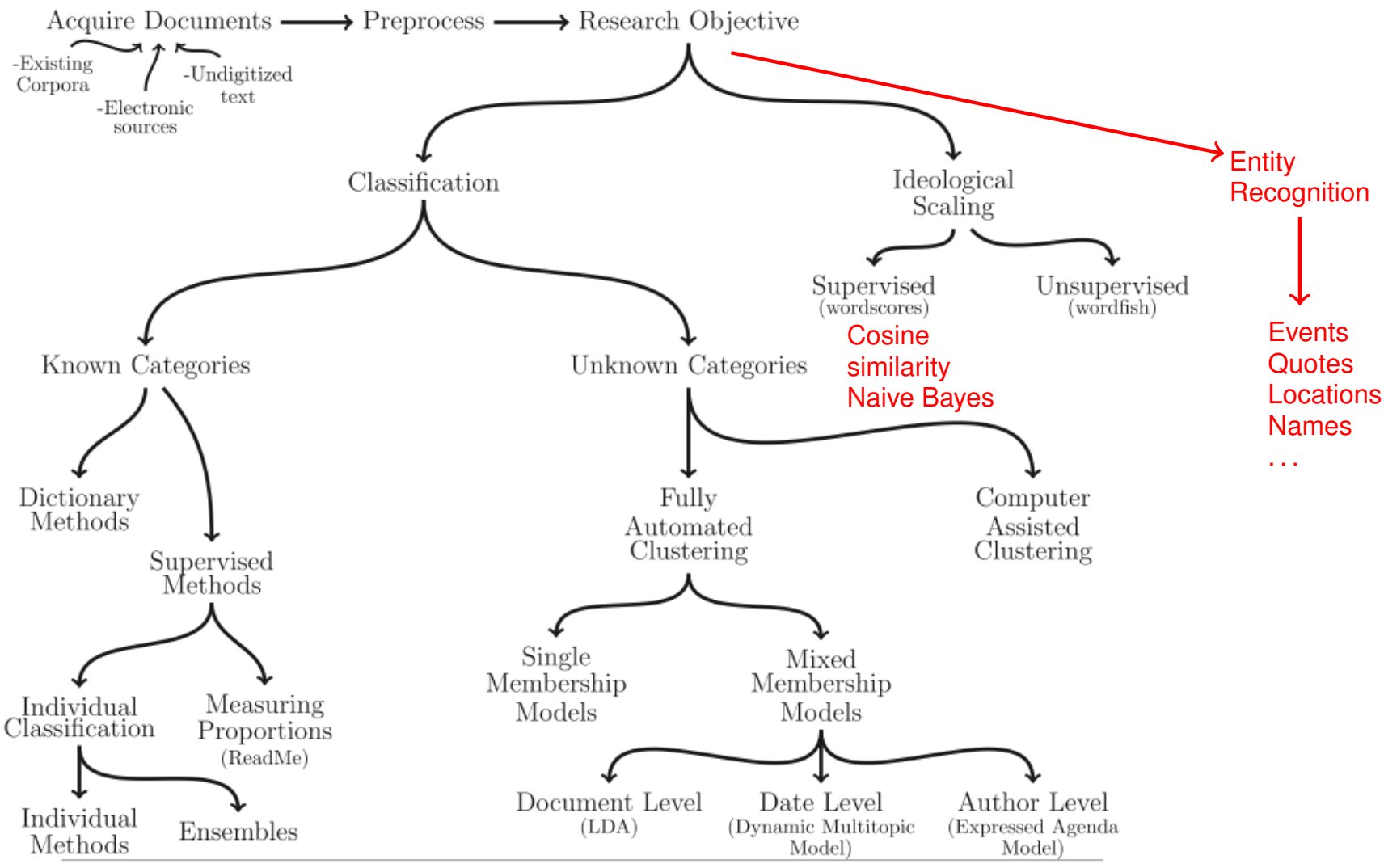

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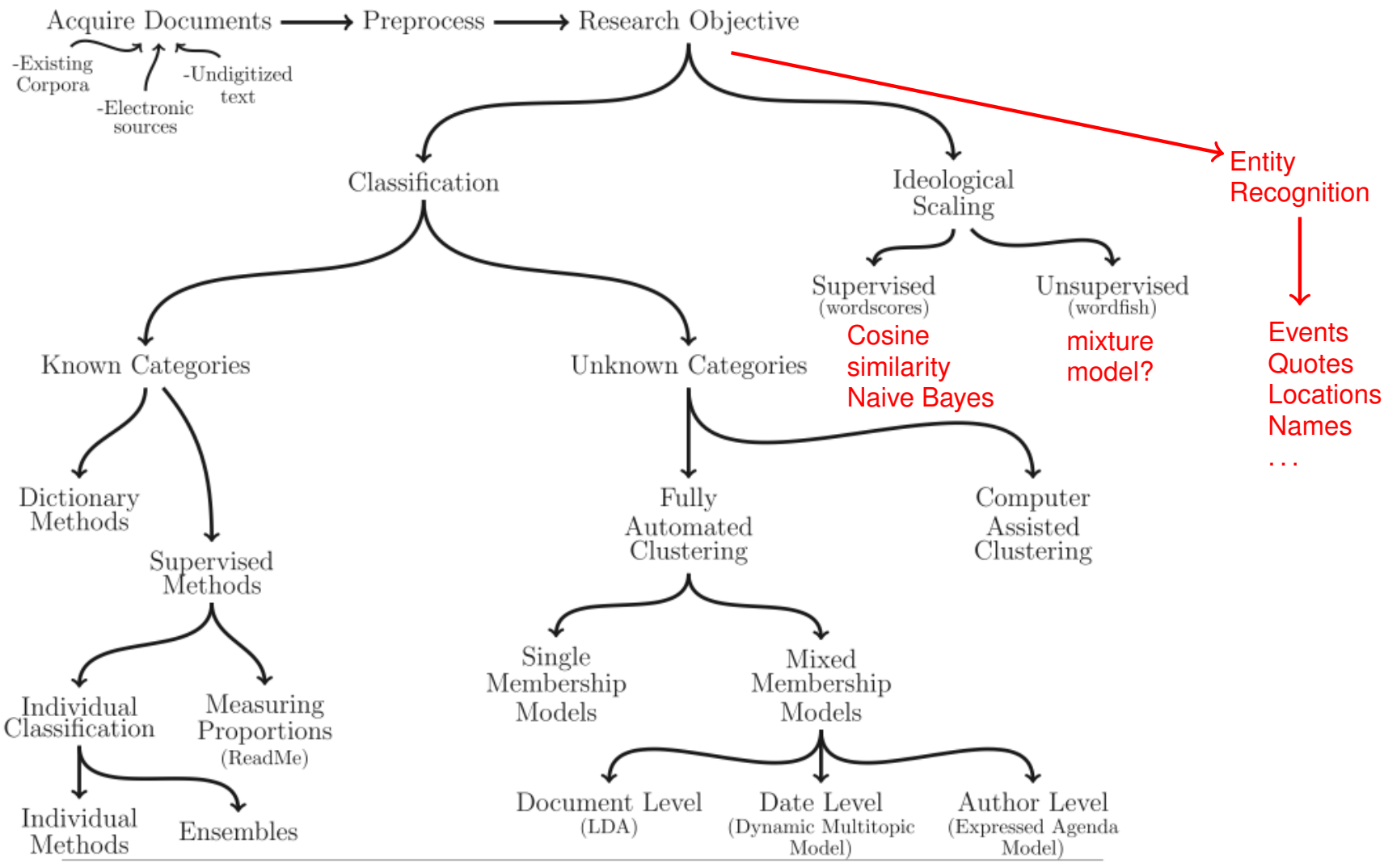

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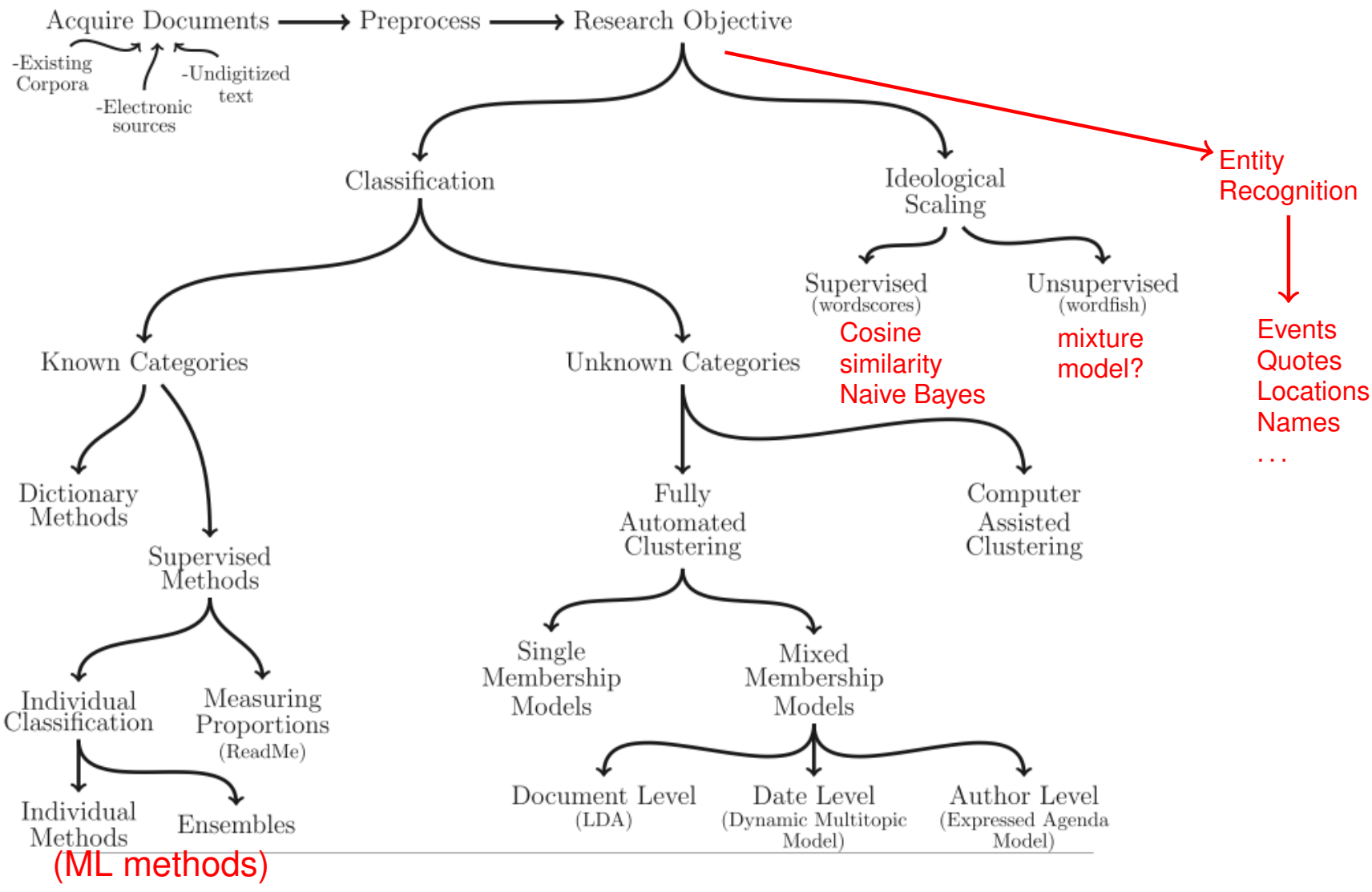

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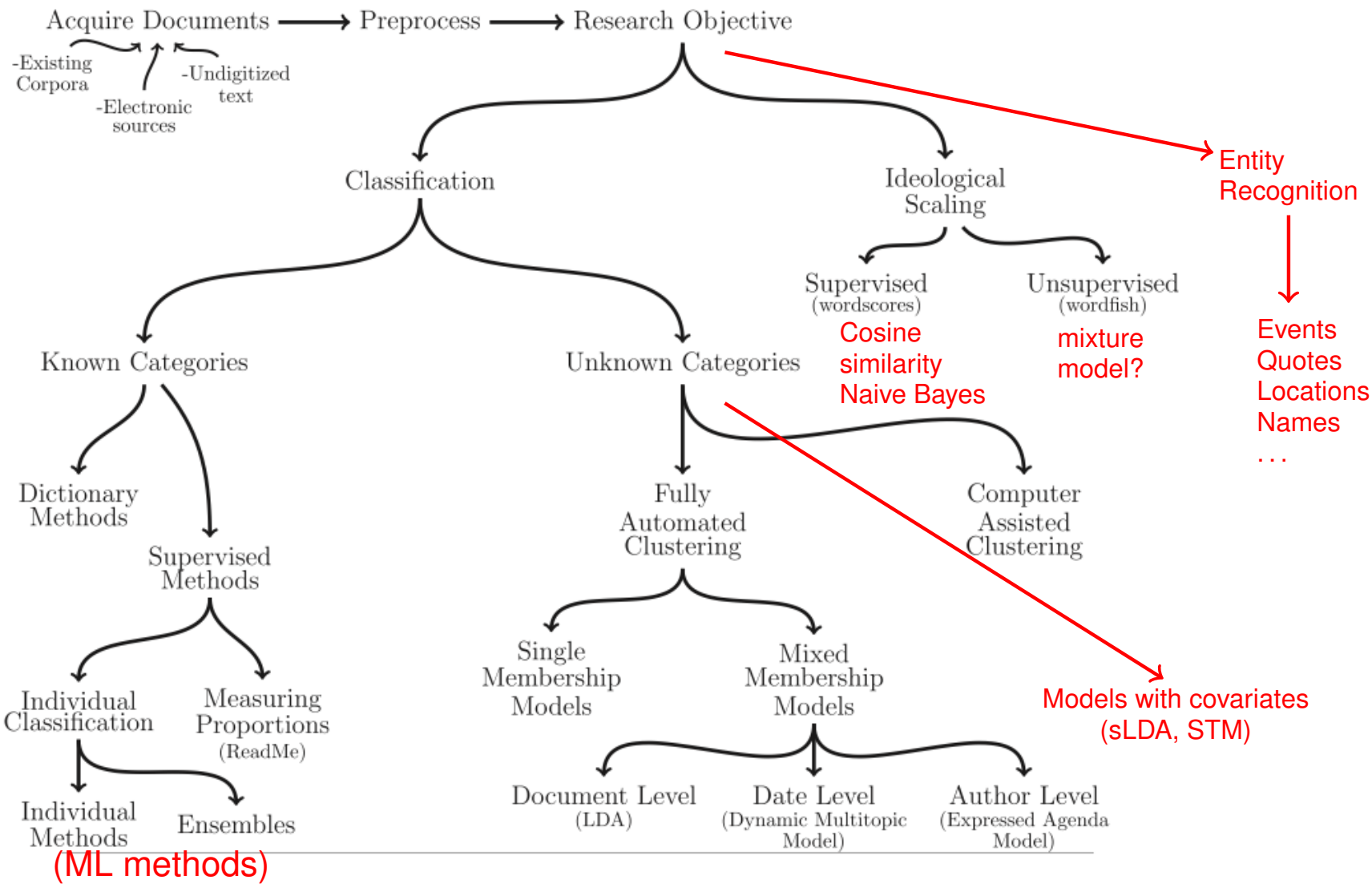

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From words to numbers

1. Bag-of-words assumption

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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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From words to numbers

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1. Preprocess text: lowercase, remove stopwords and punctuation, stem,

   “@ thank congratul~~ations~~, you’r~~e~~ best #ep2014”

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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	...	

Dictionary methods

Classifying documents when categories are known using dictionaries:

- Lists of words that correspond to each category:
  - Positive or negative, for sentiment
  - Sad, happy, angry, anxious... for emotions
  - Insight, causation, discrepancy, tentative... for cognitive processes
  - Sexism, homophobia, xenophobia, racism... for hate speech

    many others: see LIWC, VADER, SentiStrength, LexiCoder...
- Count number of times they appear in each document
- Normalize by document length (optional)
- Validate, validate, validate.
  - 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

Supervised machine learning

Goal: classify documents into pre existing categories.
e.g. authors of documents, sentiment of tweets, ideological position of parties based on manifestos, tone of movie reviews...
What we need:

- Hand-coded dataset (labeled), to be split into:

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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

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

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

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

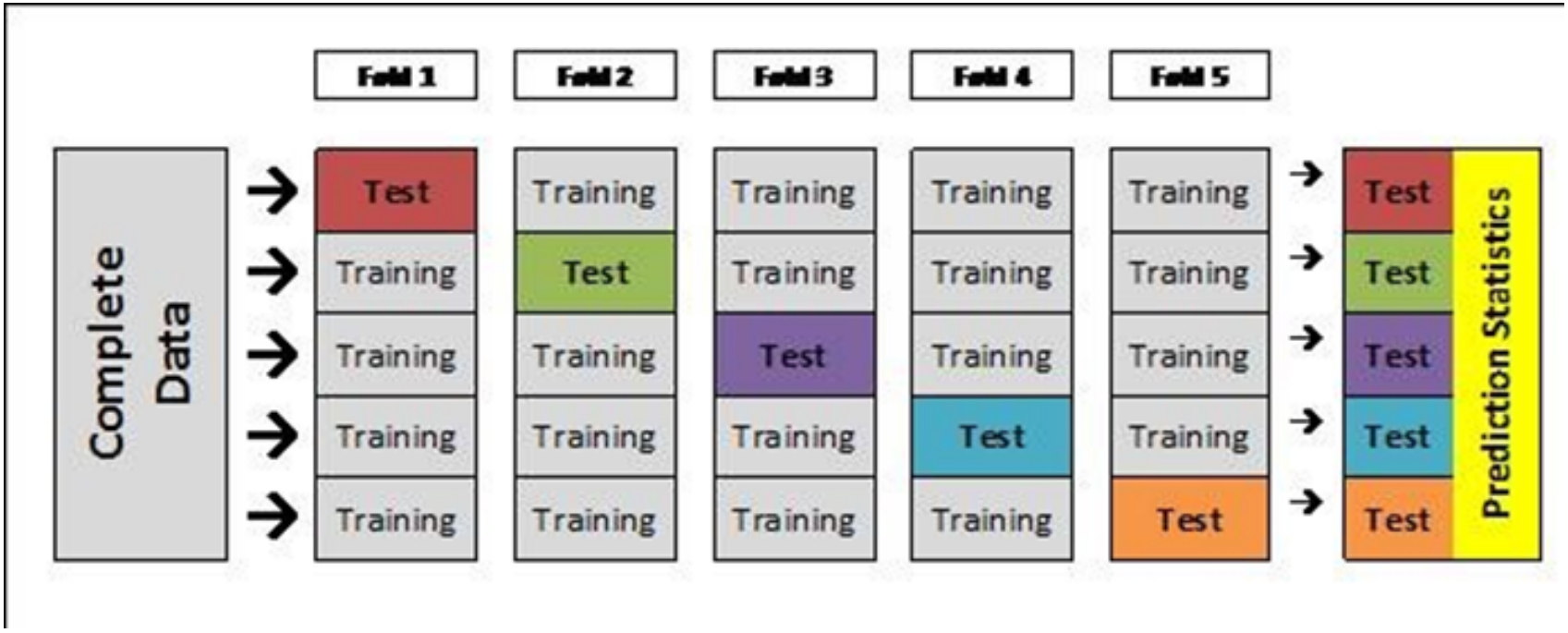
$$F_{\text{Liberal}} = \frac{2\text{Precision}_{\text{Liberal}}\text{Recall}_{\text{Liberal}}}{\text{Precision}_{\text{Liberal}} + \text{Recall}_{\text{Liberal}}}$$

Source: Grimmer, 2014, "Text as Data" course week 14

Cross-validation

Intuition:

- Create K training and test sets (“folds”) within training set.



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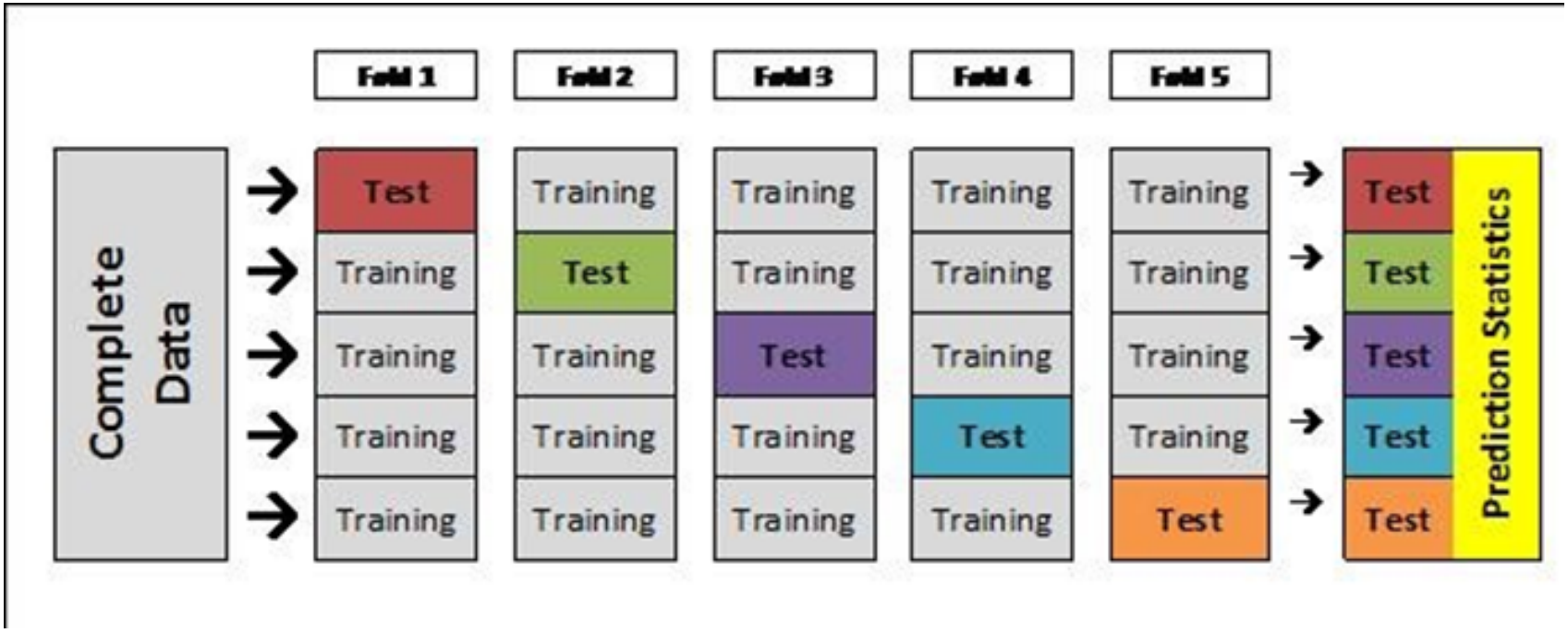

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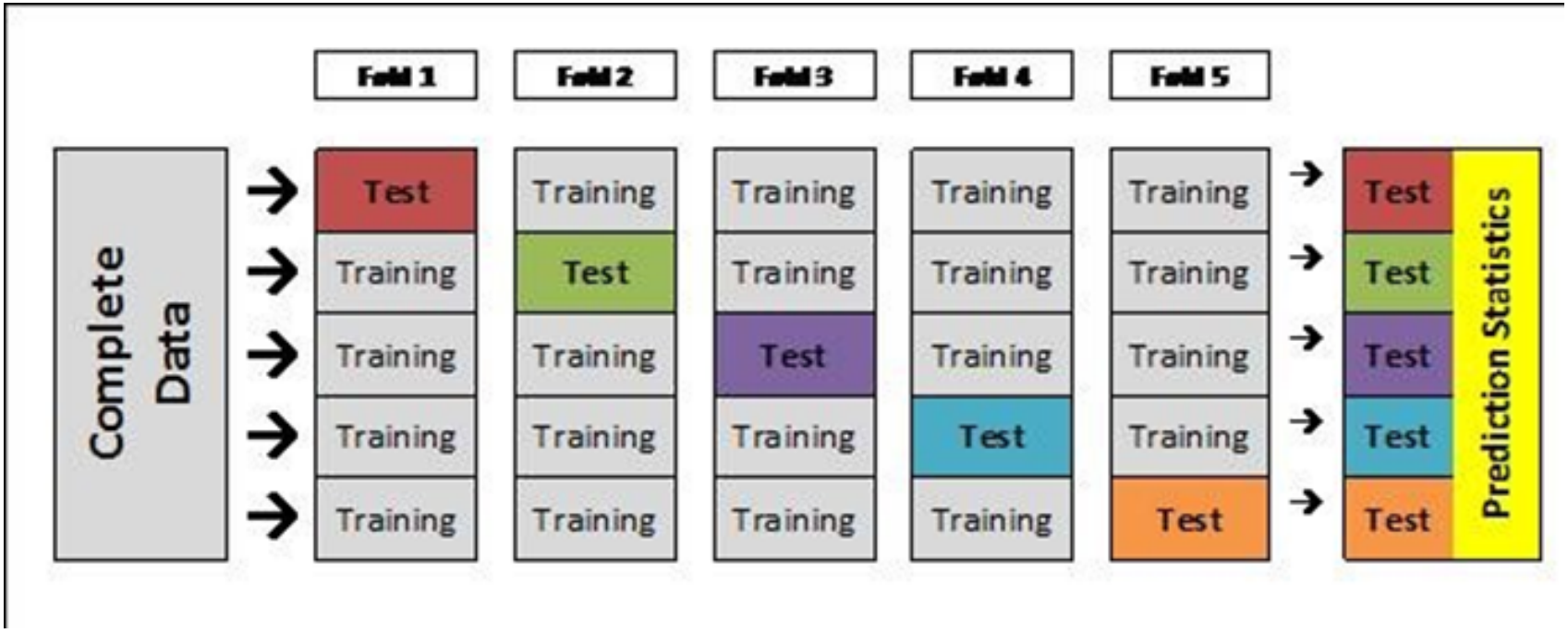
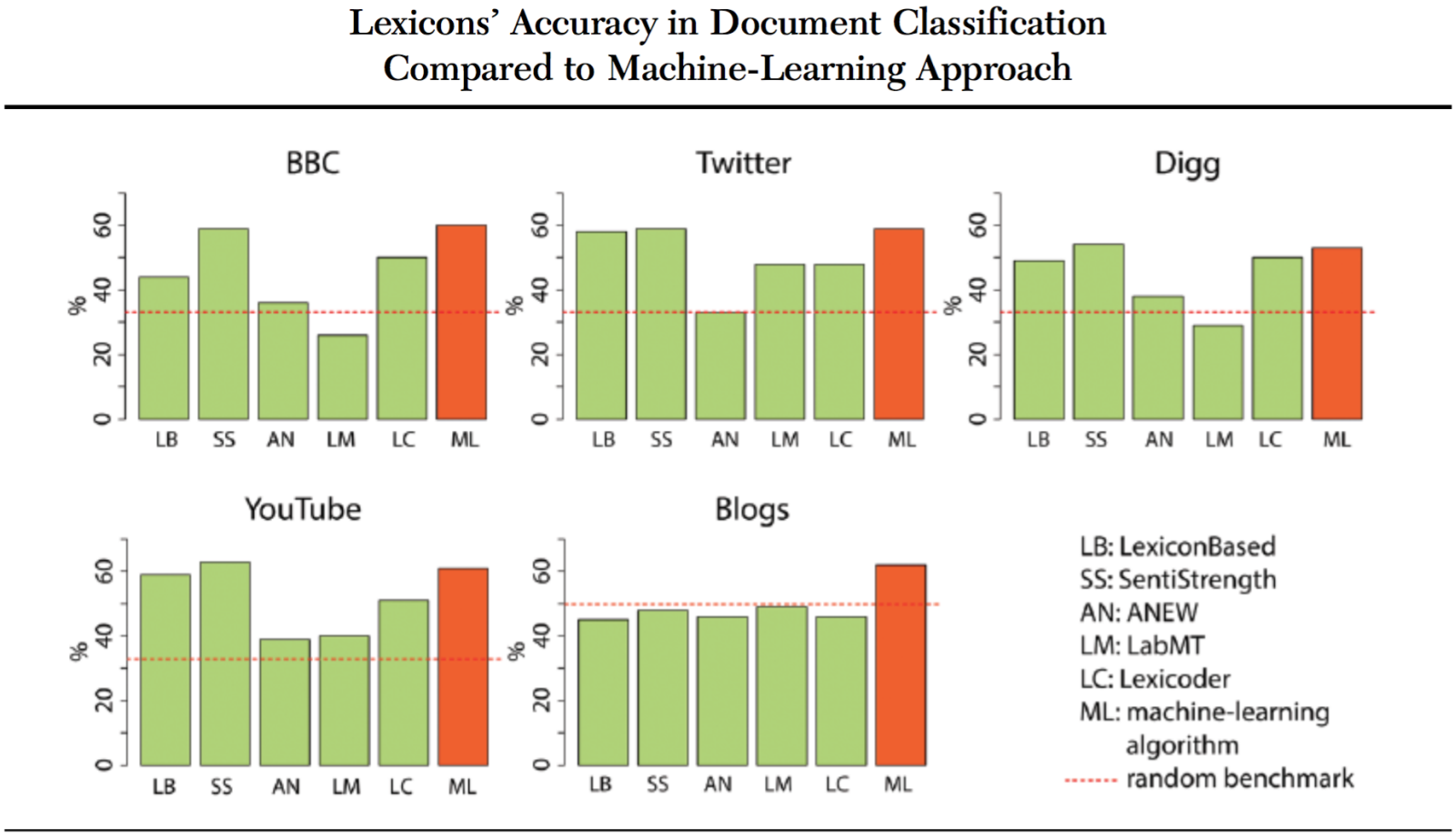
- For each k in K, run classifier and estimate performance in test set within fold.
- Why? Find best classifier and avoid overfitting



Dictionaries vs supervised learning



Source: González-Bailón and Paltoglou (2015)

Regularized regression

Suppose we have N documents, with each document i having label $y_i \in \{-1, 1\} \rightsquigarrow \{\text{liberal, conservative}\}$
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

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

where:

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

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Wordscores (Laver, Benoit, Garry, 2003, APSR)

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