Methods workshop: Automated Text Analysis with R

Pablo Barberá
Center for Data Science
New York University

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materials: github.com/pablobarbera/eui-text-workshop

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
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ισχυρός
στη Βουλή
και στους αγώνες
Είναι στο χέρι μας!
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ΣΥΝΑΣΠΙΣΜΟΣ ΡΙΖΟΣΠΑΣΤΙΚΗΣ ΑΡΙΣΤΕΡΑΣ
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GEMEINSAM
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REGIERUNGSPROGRAMM 2009 – 2013
CDU CSU


Sozial und
Demokratisch.
Anpacken. Für Deutschland.
Das Regierungsprogramm der SPD
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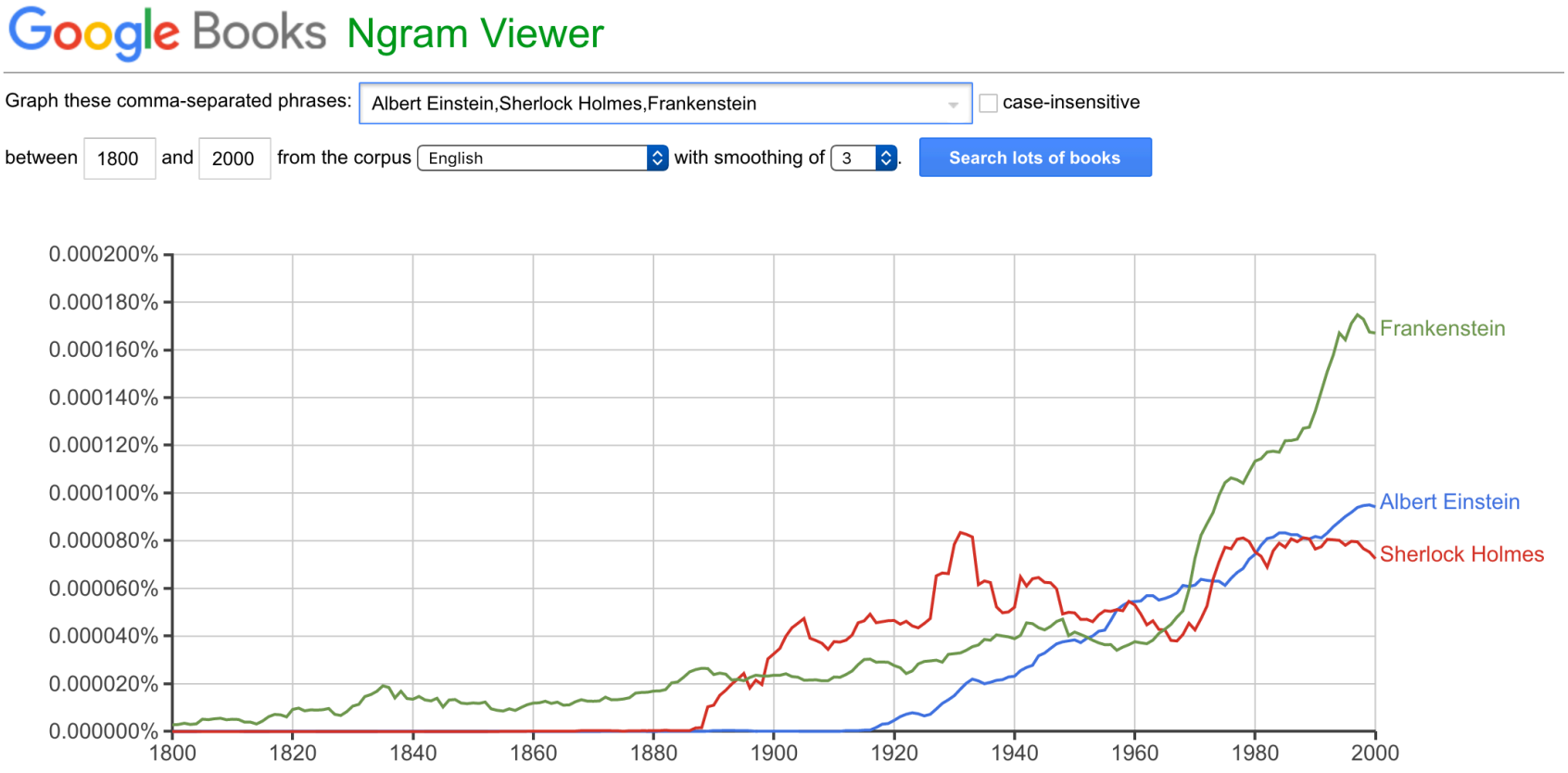
Text as data


Google Books Ngram Viewer
Graph these comma-separated phrases: Albert Einstein,Sherlock Holmes,Frankenstein
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Search lots of books
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Text as data


facebook
XING
Pinterest
Gefällt mir
Instagram
twitter
LinkedIn
flickr
skype
YouTube

Overview of text as data methods

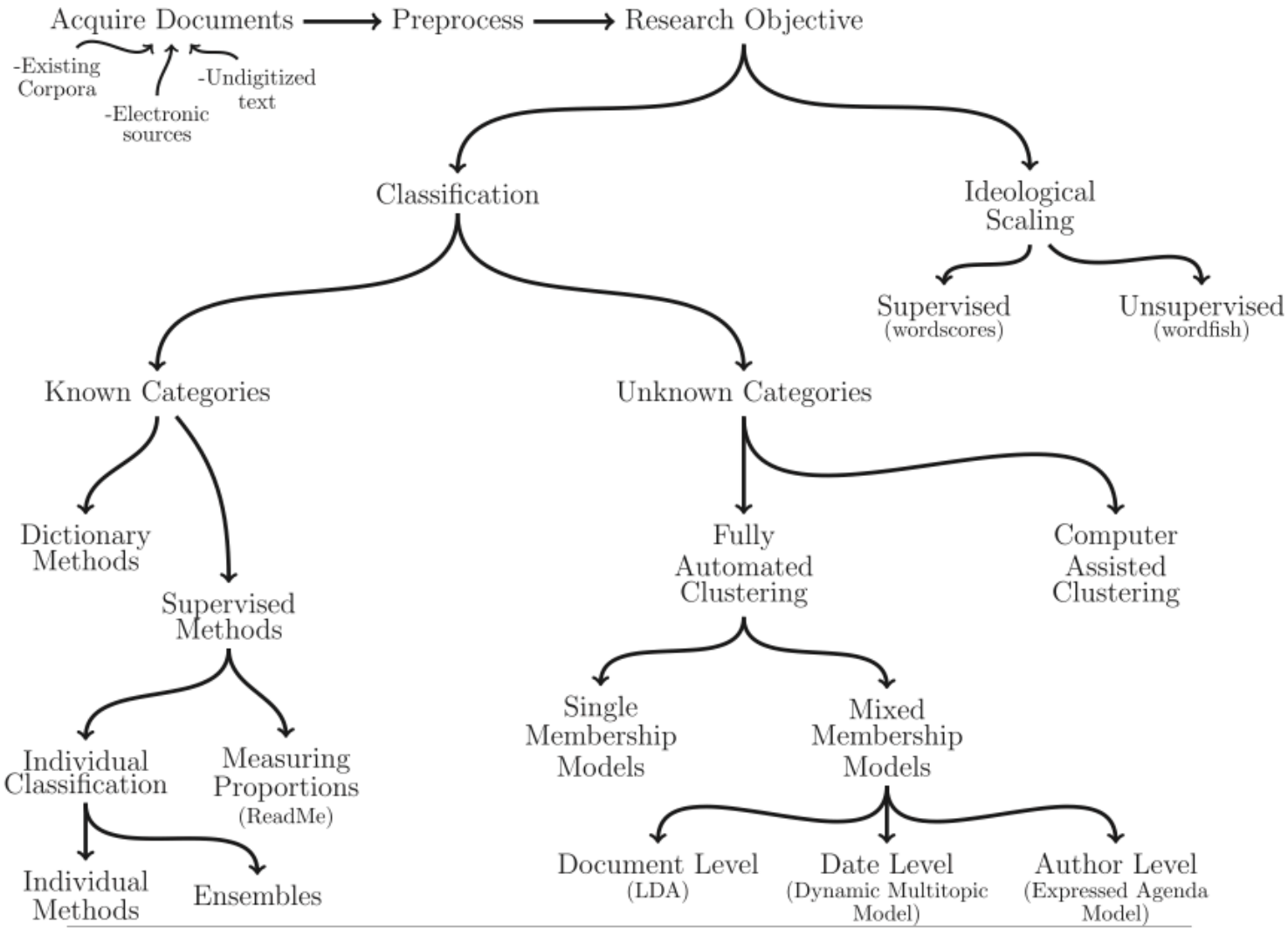
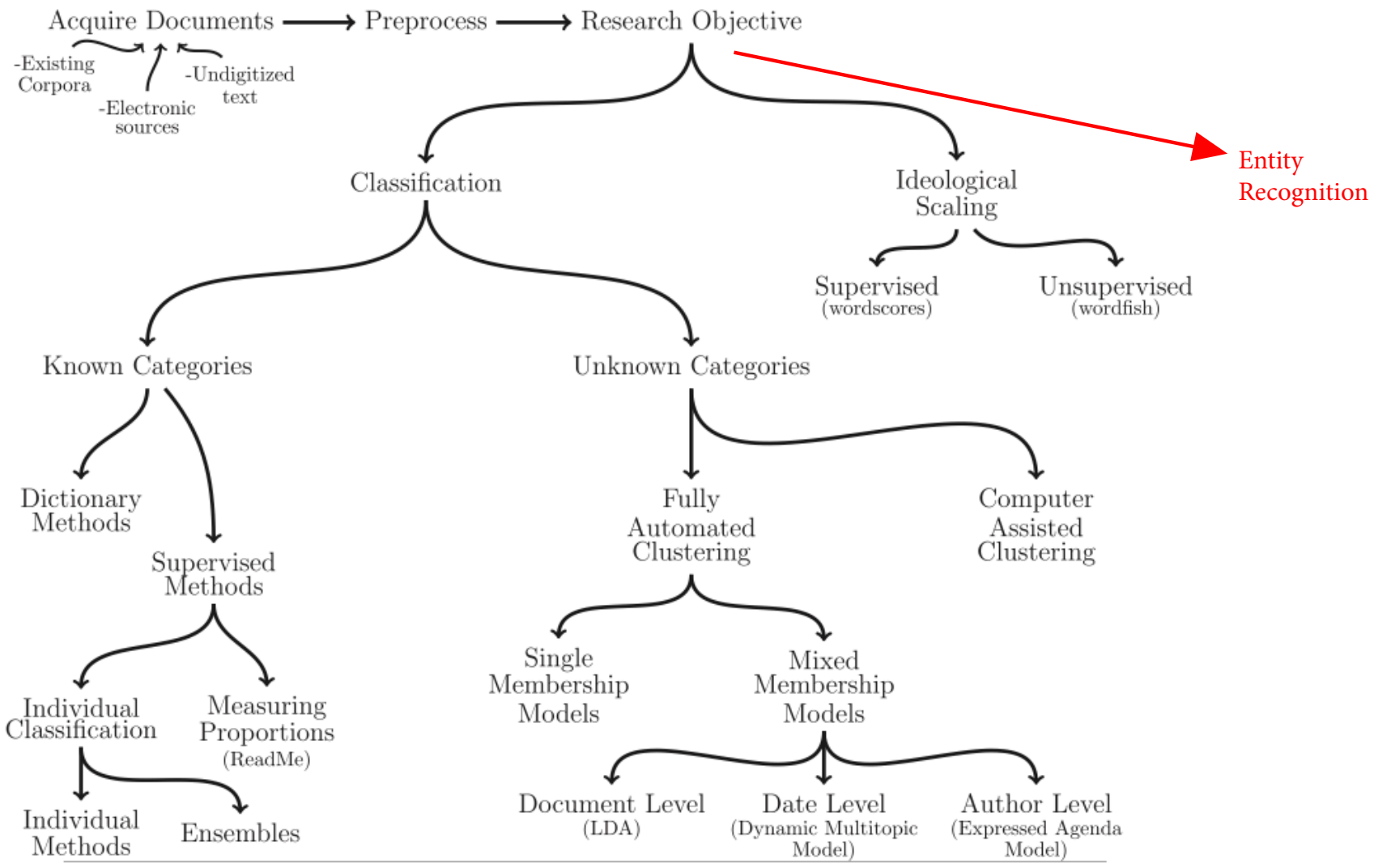


Fig. 1 in Grimmer and Stewart (2013)

Overview of text as data methods



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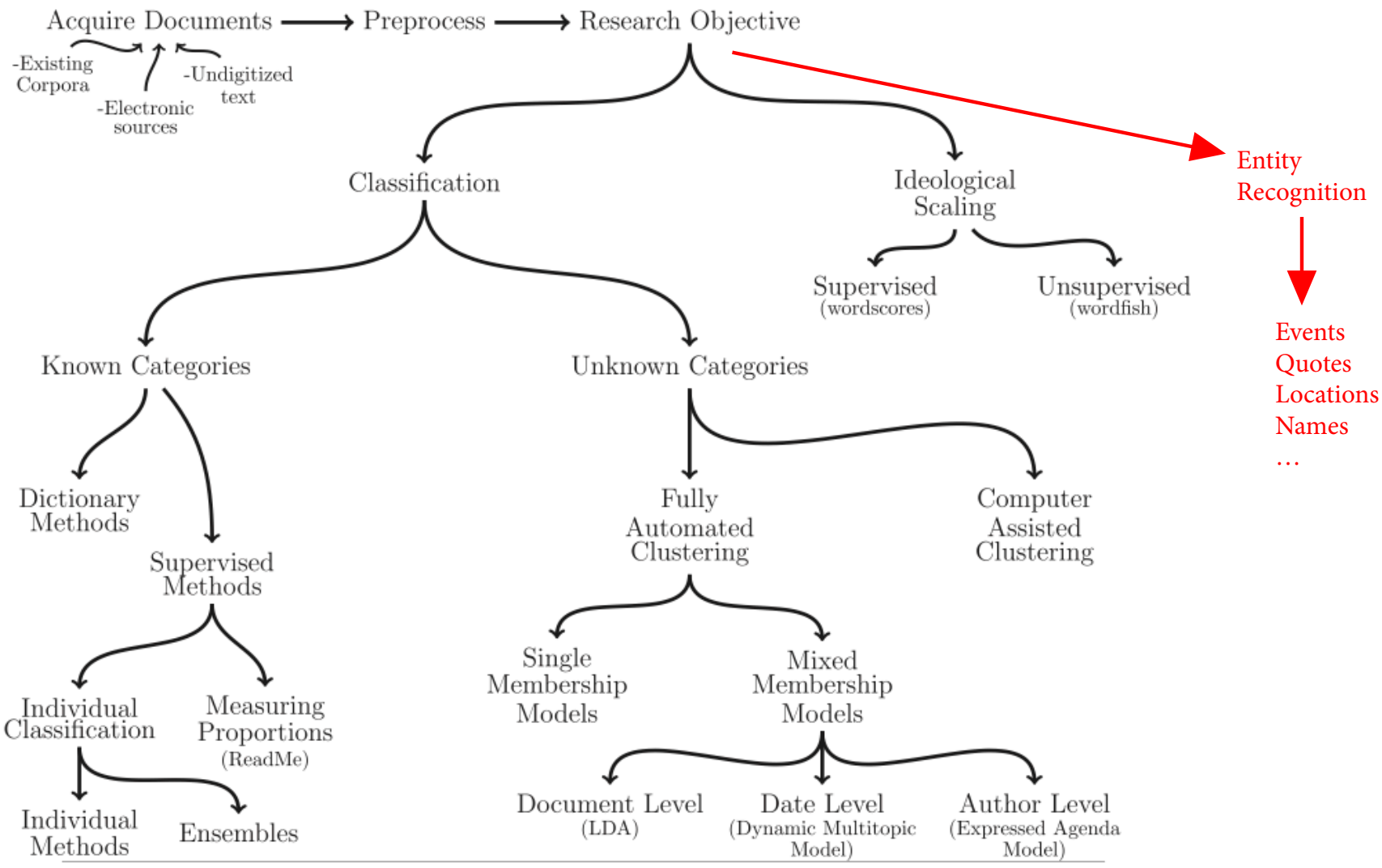

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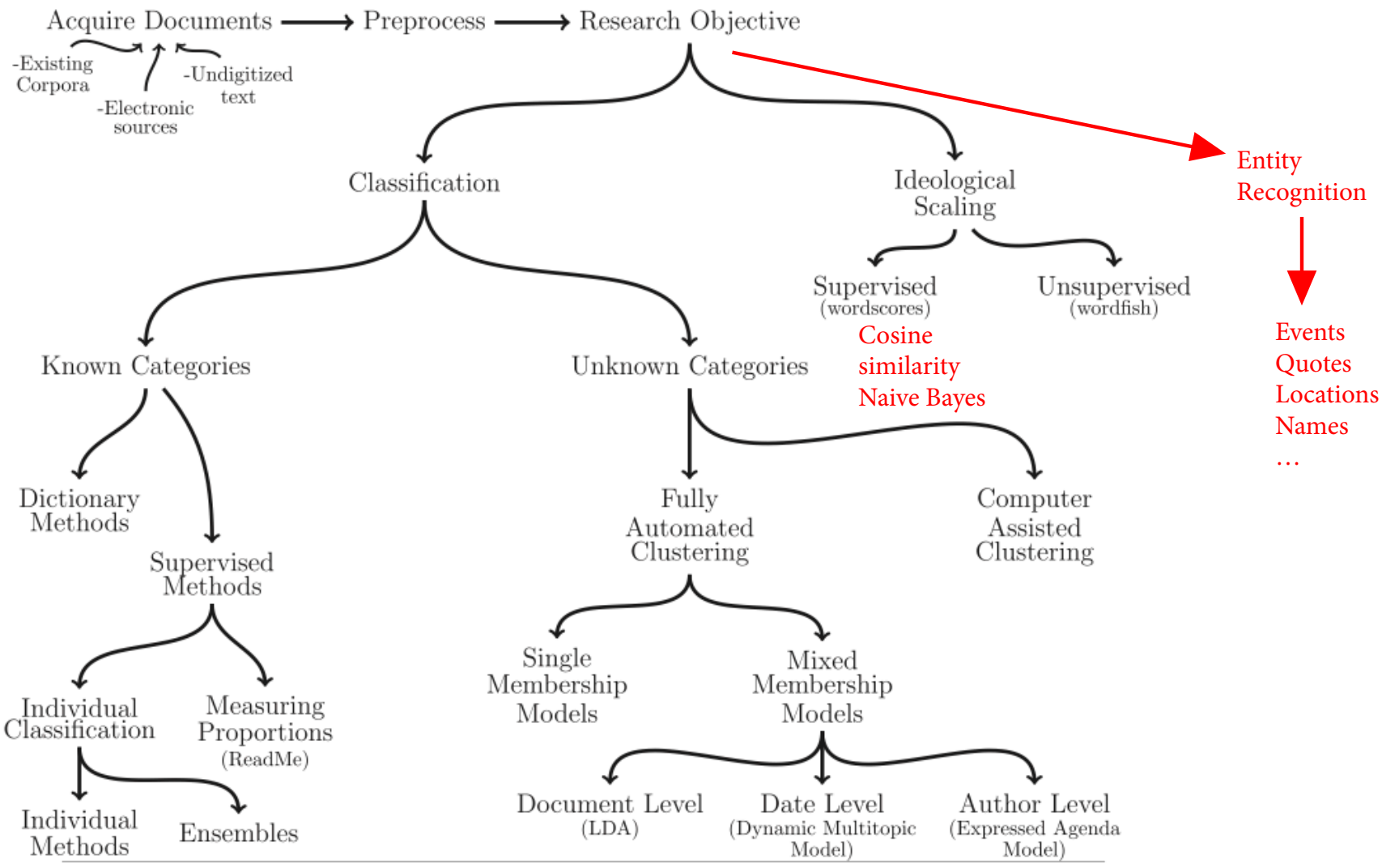

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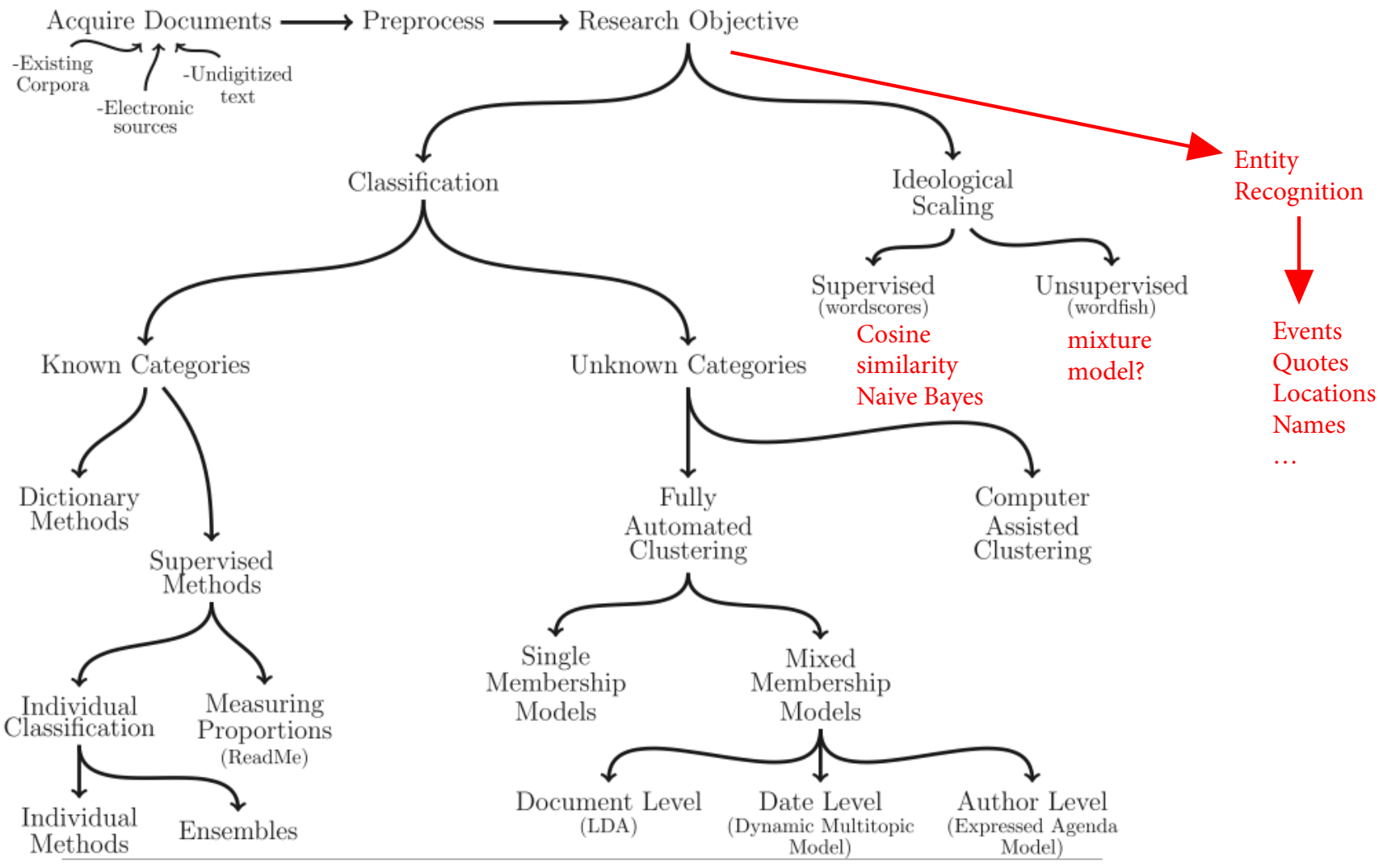

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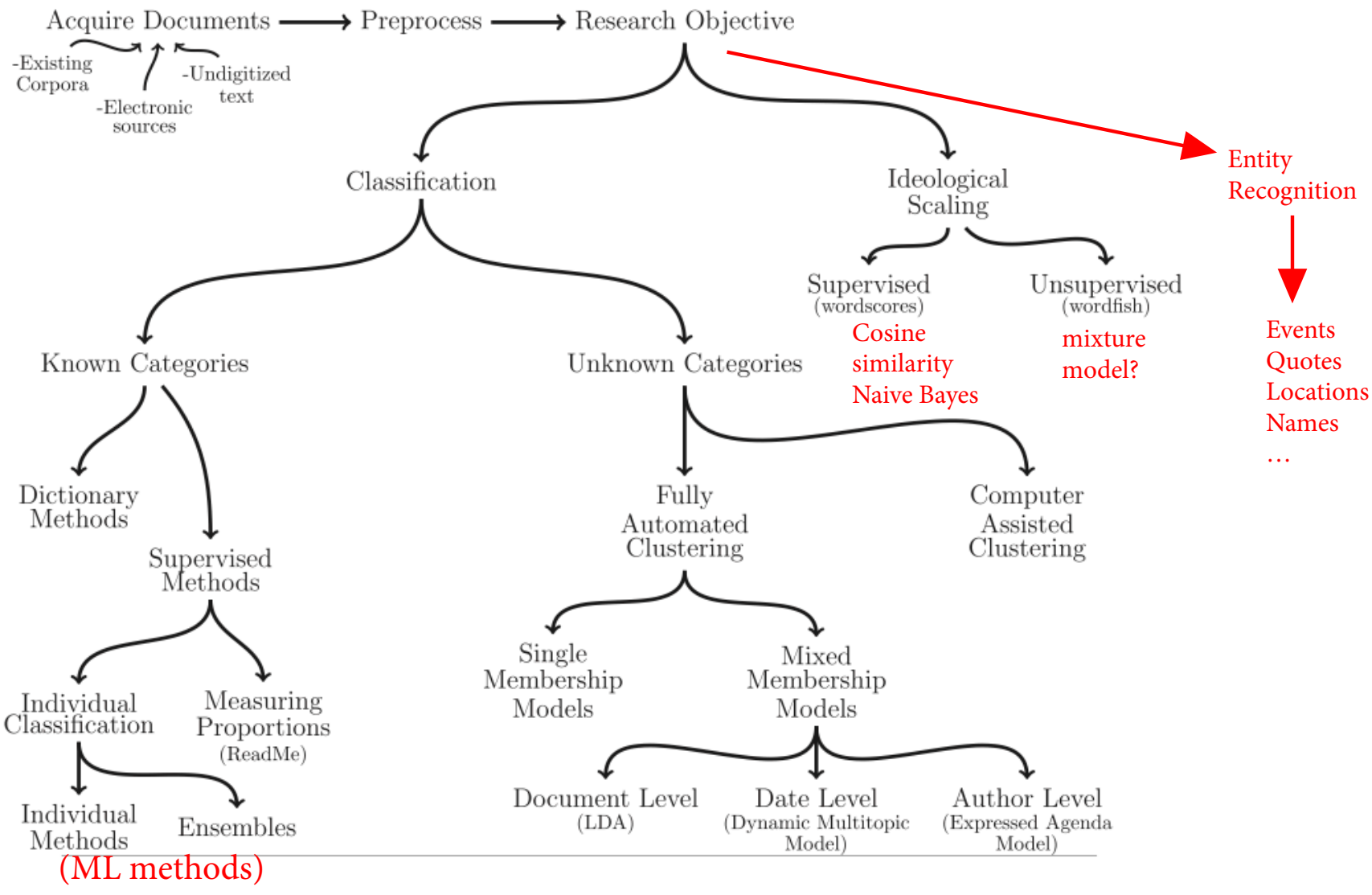

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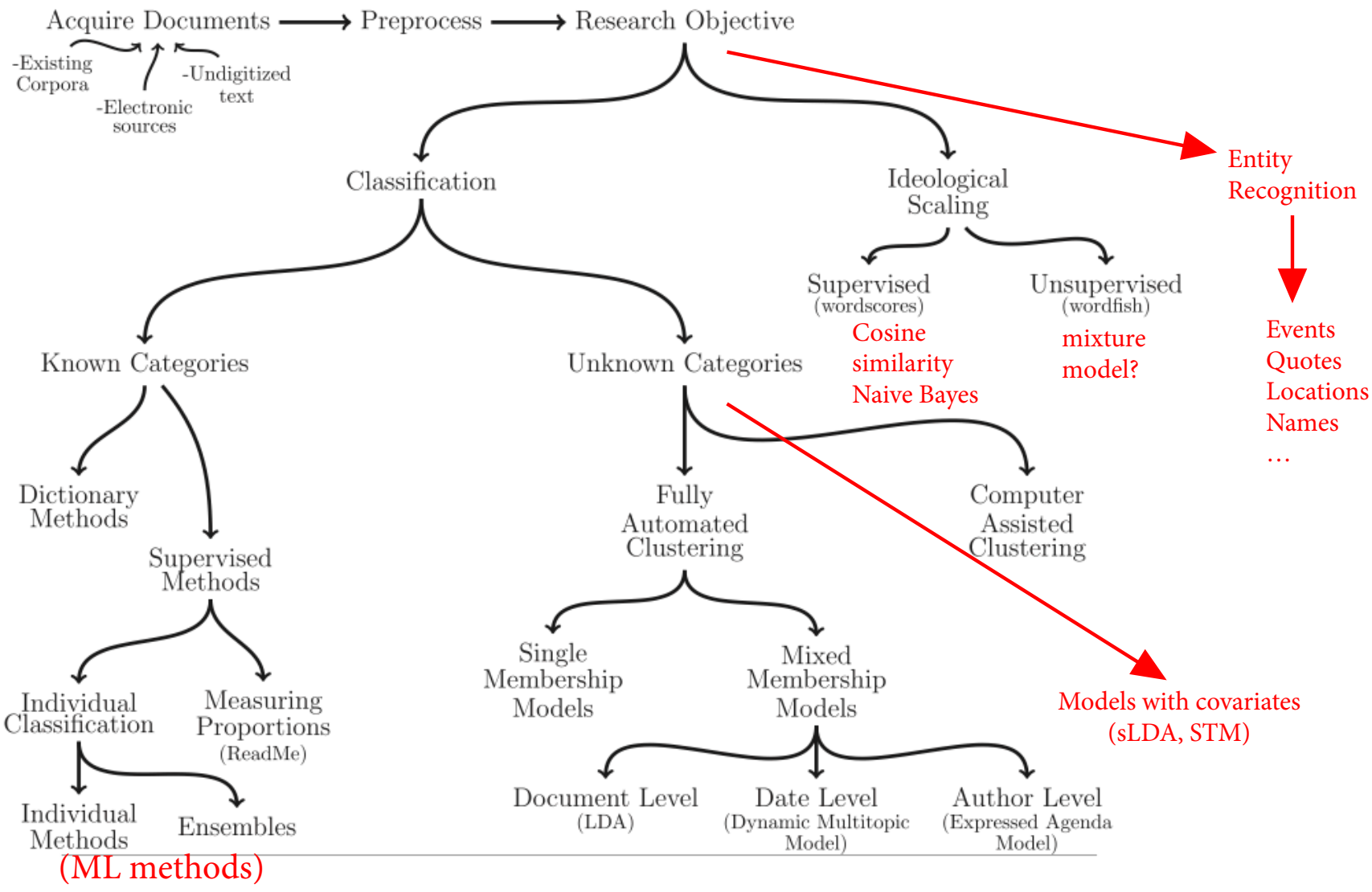

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From words to numbers

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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	@	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 n	0	1	1	0	0	0	…	

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**:

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

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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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

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- Why? Avoids overfitting.

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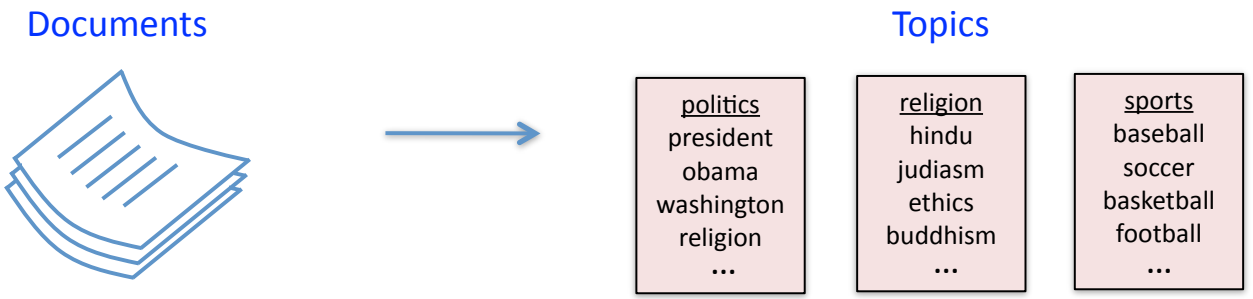
  - $S^*_{vd} = (S_{vd} - \overline{S_{vd}}) \left(\frac{SD_{rd}}{SD_{vd}} \right) + \overline{S_{vd}} \rightarrow$ Rescaled scores.

Latent Dirichlet allocation (LDA)

- **Topic models** are powerful tools for exploring large data sets and for making inferences about the content of documents



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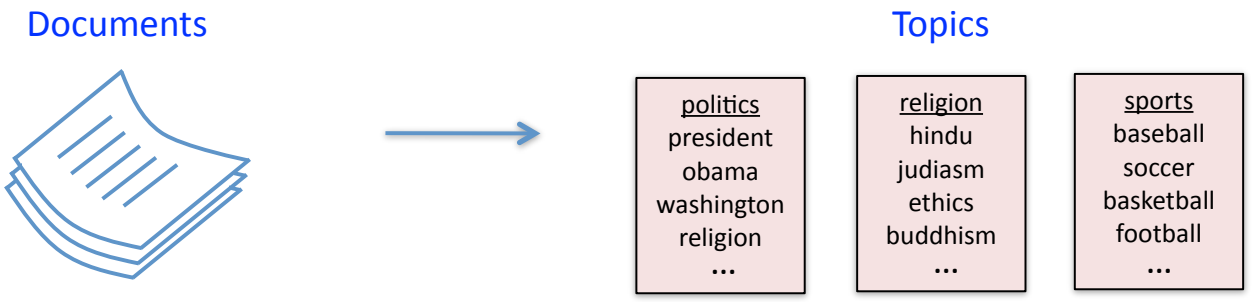
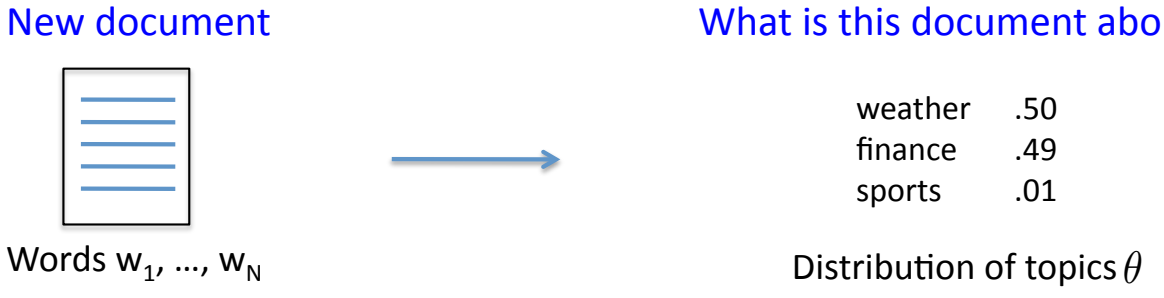


- Many applications in information retrieval, document summarization, and classification



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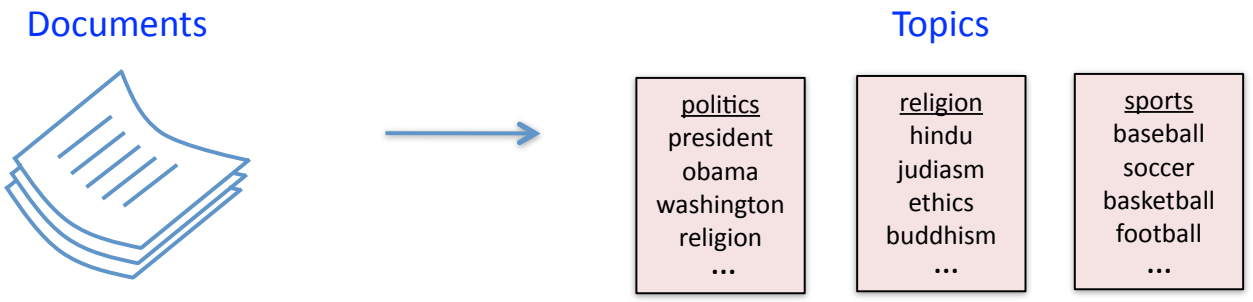

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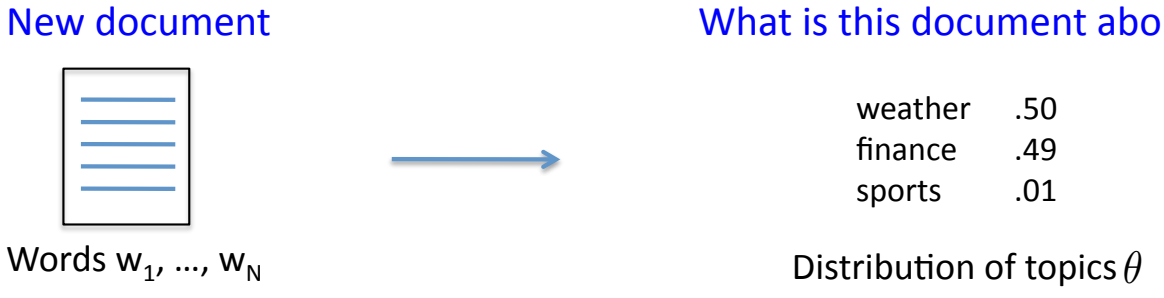

- LDA is one of the simplest and most widely used topic models

Latent Dirichlet Allocation

- Document = random mixture over latent topics
- Topic = distribution over n-grams

Probabilistic model with 3 steps:

1. Choose $\theta_i \sim \text{Dirichlet}(\alpha)$
2. Choose $\beta_k \sim \text{Dirichlet}(\delta)$
3. For each word in document i:
   - Choose a topic $z_m \sim \text{Multinomial}(\theta_i)$
   - Choose a word $w_{im} \sim \text{Multinomial}(\beta_{i,k=z_m})$

where:
α=parameter of Dirichlet prior on distribution of topics over docs.
θ_i=topic distribution for document i
δ=parameter of Dirichlet prior on distribution of words over topics
β_k=word distribution for topic k

Plate notation

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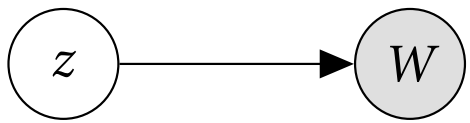

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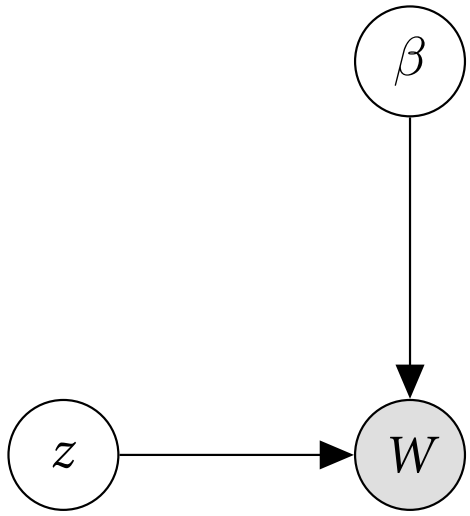

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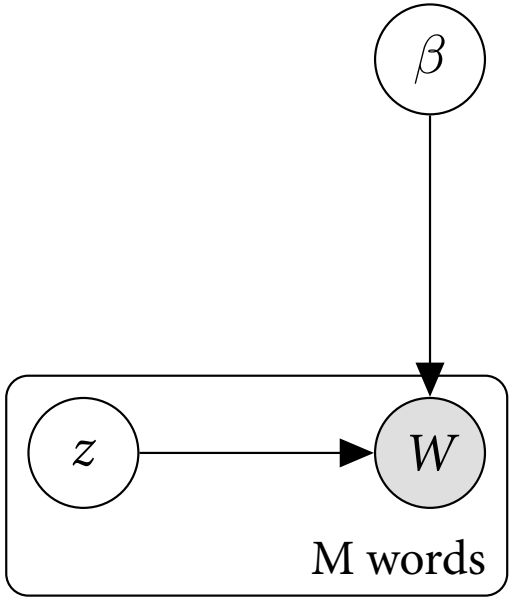

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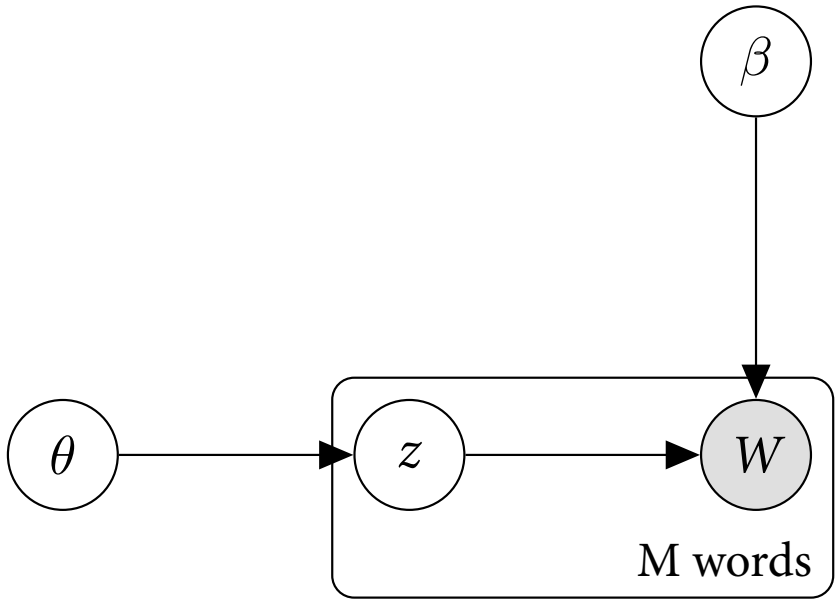

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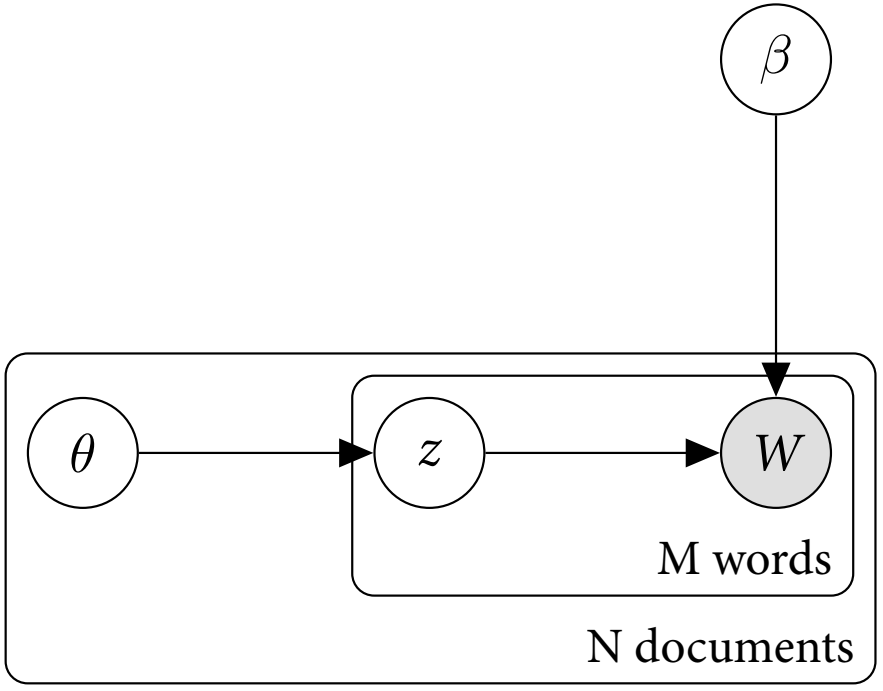

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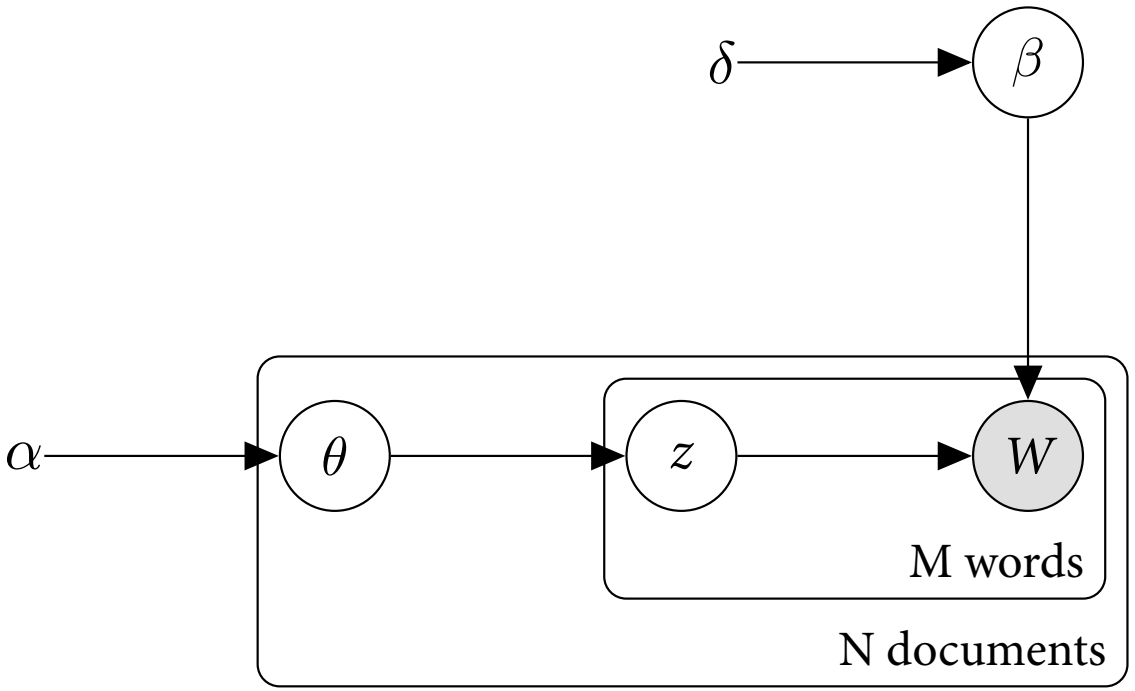

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4. Hypothesis validity
   - Can topic variation be used effectively to test substantive hypotheses?

Eexample: topics in US legislators' tweets

- Data: 651,116 tweets sent by US legislators from January 2013 to December 2014, collected by the SMaPP lab.
- 2,920 documents = 730 days $\times$ 2 chambers $\times$ 2 parties
- Why aggregating? Applications that aggregate by author or day outperform tweet-level analyses (Hong and Davidson, 2010)
- $K = 100$ topics (more on this later)
- Validation: http://j.mp/lda-congress-demo

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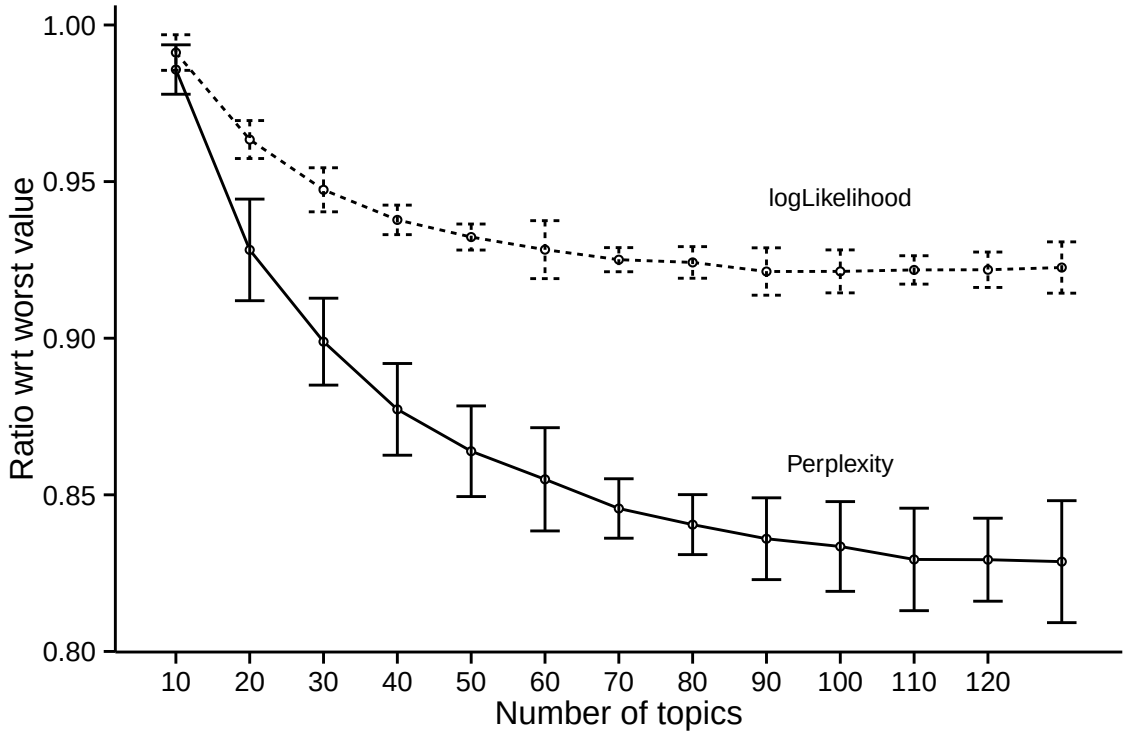

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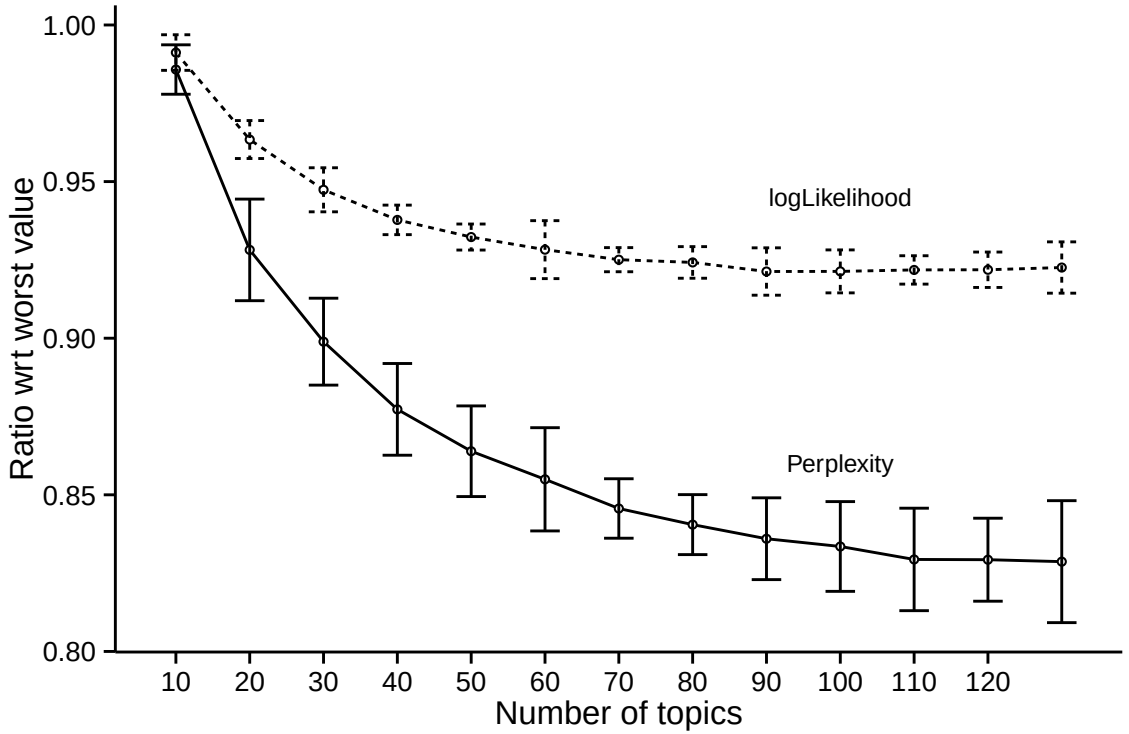

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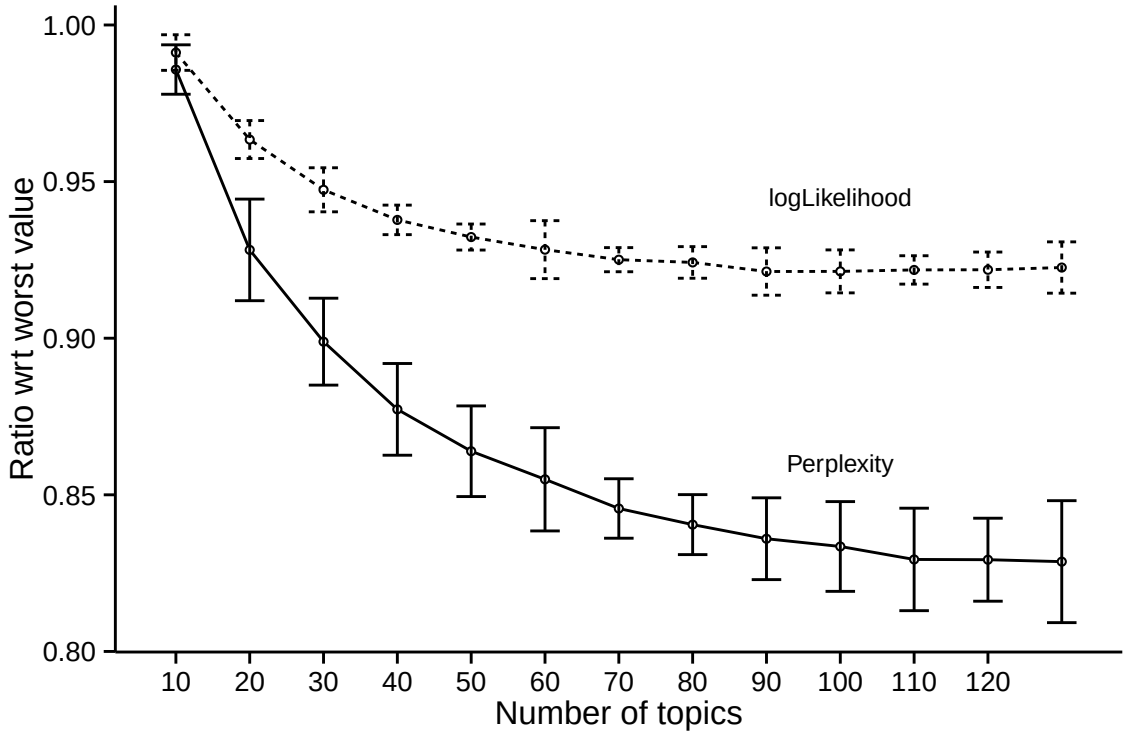


- **BUT**: "there is often a negative relationship between the best-fitting model and the substantive information provided".
- GS propose to choose K based on "substantive fit."

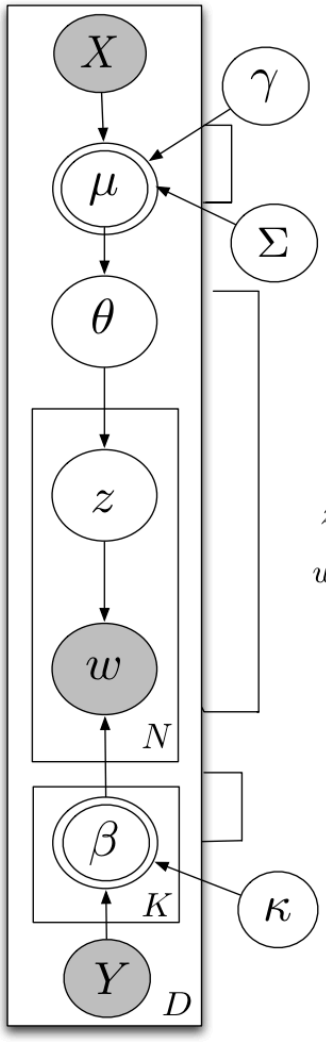
Extensions of LDA

1. Structural topic model (Roberts et al, 2014, AJPS)
2. Dynamic topic model (Blei and Lafferty, 2006, ICML; Quinn et al, 2010, AJPS)
3. Hierarchical topic model (Griffiths and Tenembaun, 2004, NIPS; Grimmer, 2010, PA)

Why?

- Substantive reasons: incorporate specific elements of DGP into estimation
- Statistical reasons: structure can lead to better topics.

Structural topic model



Topic Prevalence:

$$\mu_{d,k} = X_d\gamma_k$$
$$\gamma_k \sim \mathcal{N}(0, \sigma_k^2)$$
$$\sigma_k^2 \sim \text{Gamma}(s^\gamma, r^\gamma)$$

Language Model:

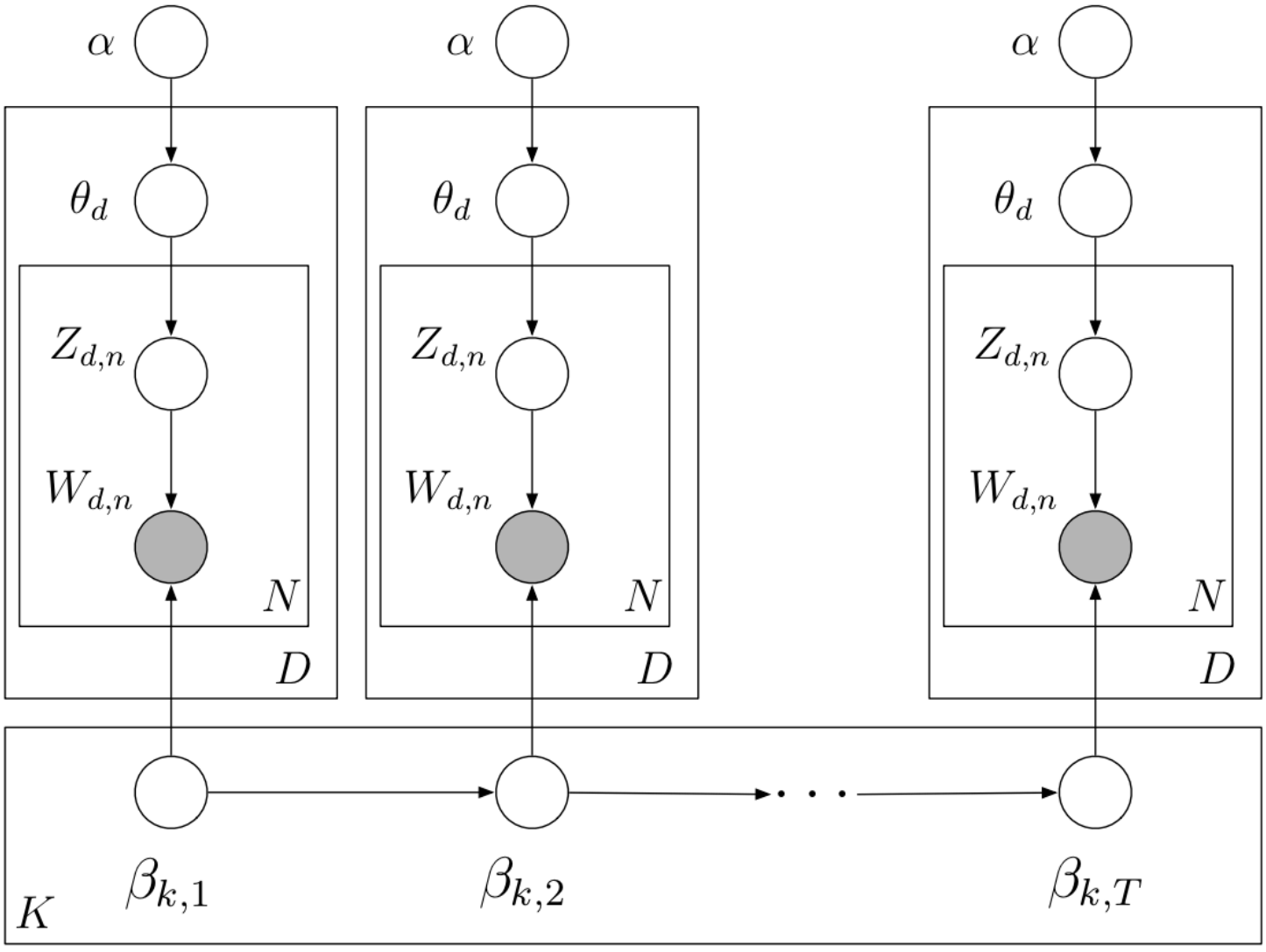
$$\theta_d \sim \text{LogisticNormal}(\mu_d, \Sigma)$$
$$z_{d,n} \sim \text{Mult}(\theta_d)$$
$$w_{d,n} \sim \text{Mult}(\beta_d^{k=z_{d,n}})$$

Topical Content:

$$\beta_{d,v}^k \propto \exp(m_v + \kappa_v^{\cdot,k} + \kappa_v^{y,\cdot} + \kappa_v^{y,k})$$
$$\kappa_v^{y,k} \sim \text{Laplace}(0, \tau_v^{y,k})$$
$$\tau_v^{y,k} \sim \text{Gamma}(s^\kappa, r^\kappa)$$

- **Prevalence**: Prior on the mixture over topics is now document-specific, and can be a function of covariates (documents with similar covariates will tend to be about the same topics)
- **Content**: distribution over words is now document-specific and can be a function of covariates (documents with similar covariates will tend to use similar words to refer to the same topic)

Dynamic topic model



Source: Blei, "Modeling Science"

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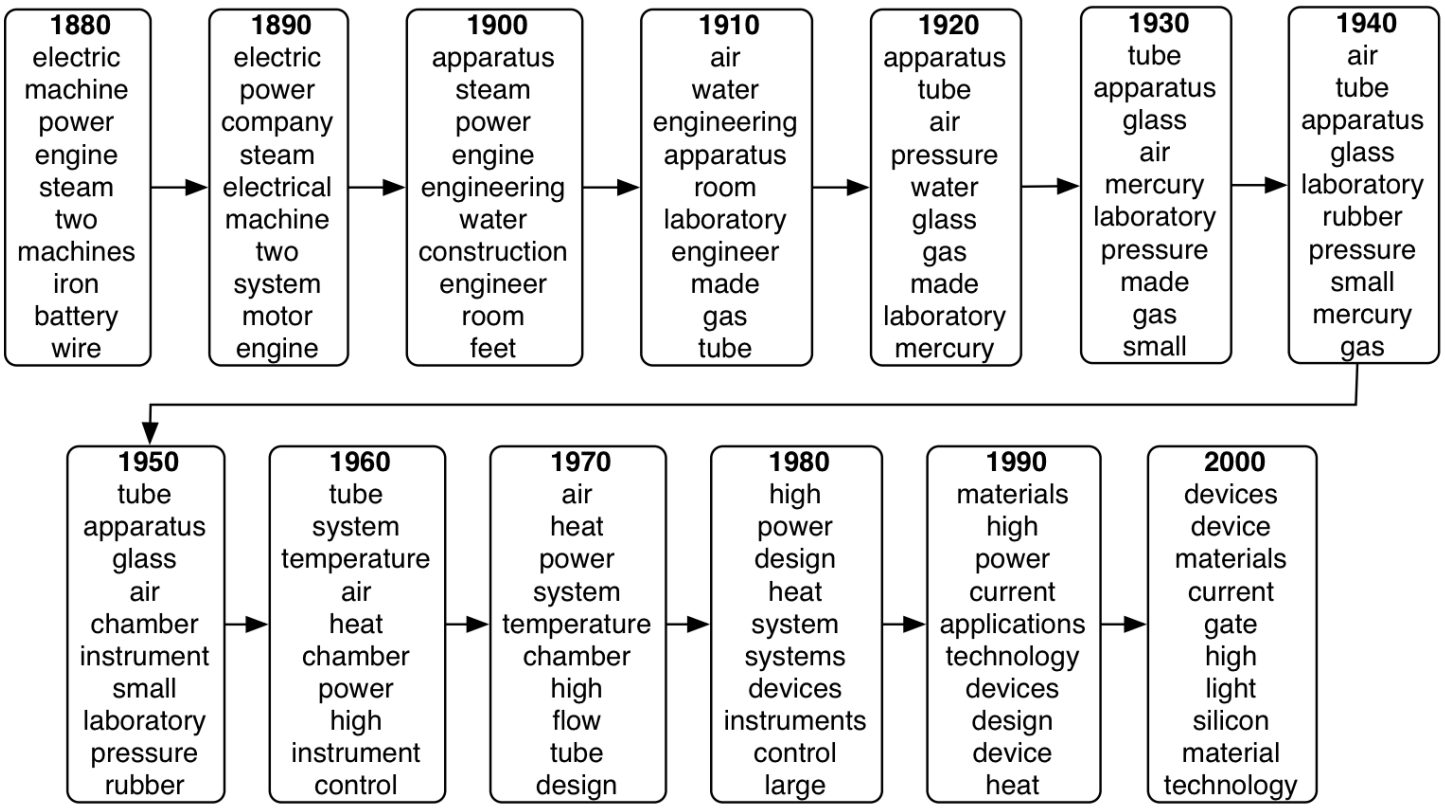

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