Workshop: social media and text analysis applied to the study of international courts

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materials: github.com/pablobarbera/icourts-workshop

Overview of text as data methods

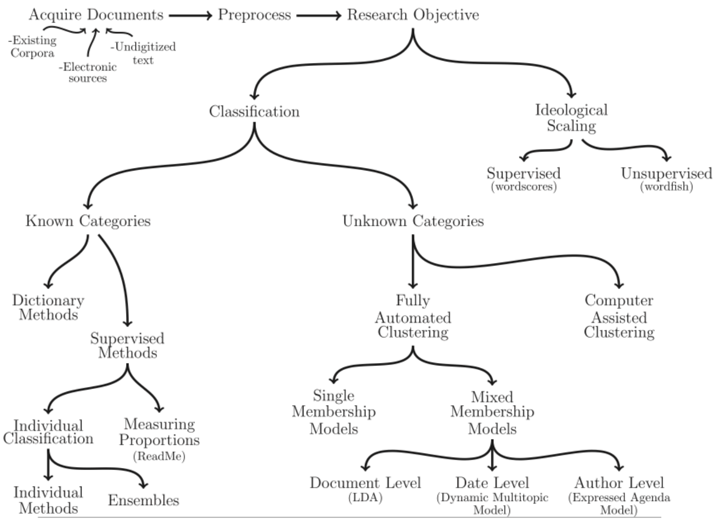

Fig. 1 in Grimmer and Stewart (2013)

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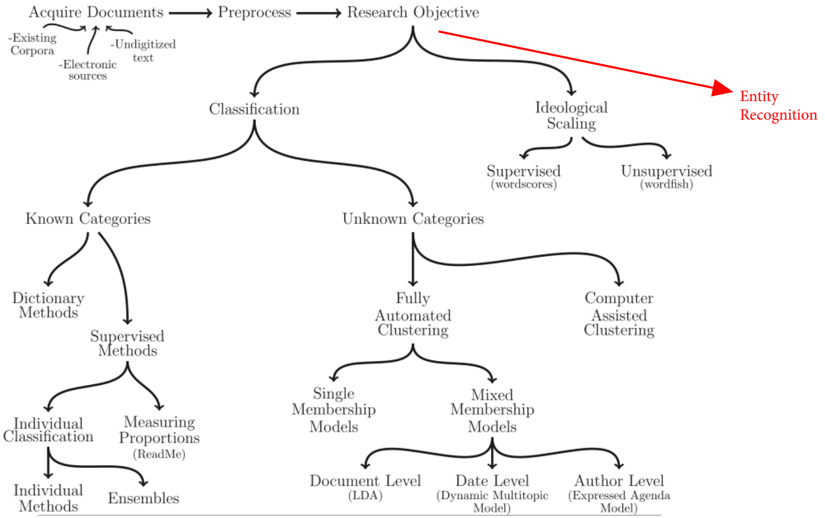

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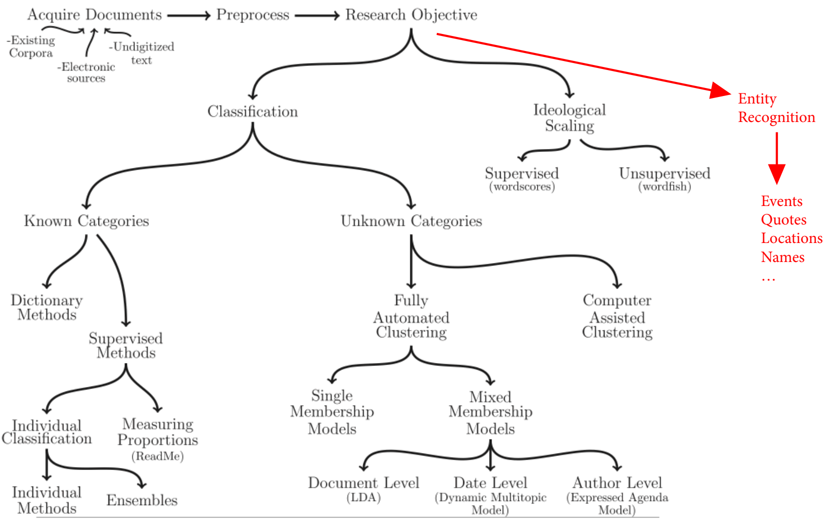

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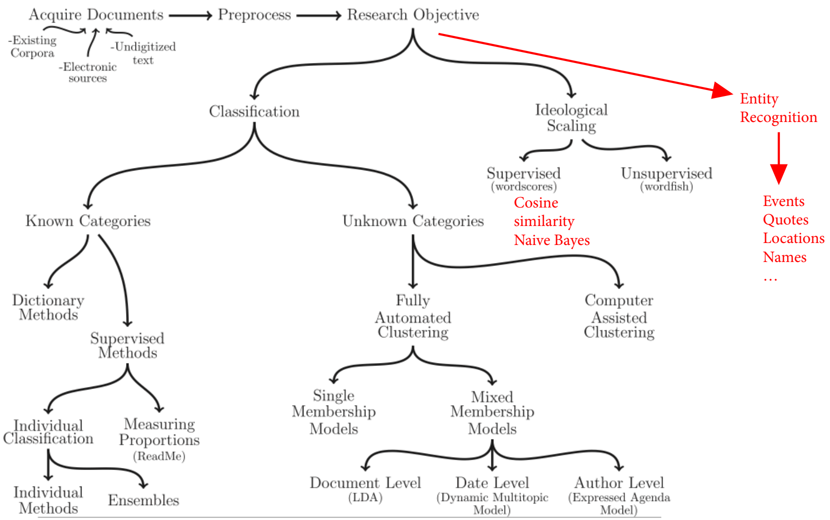

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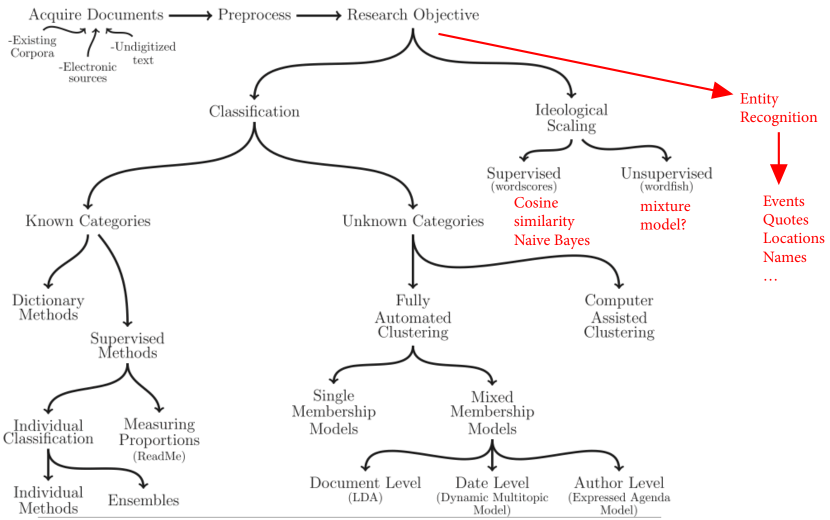

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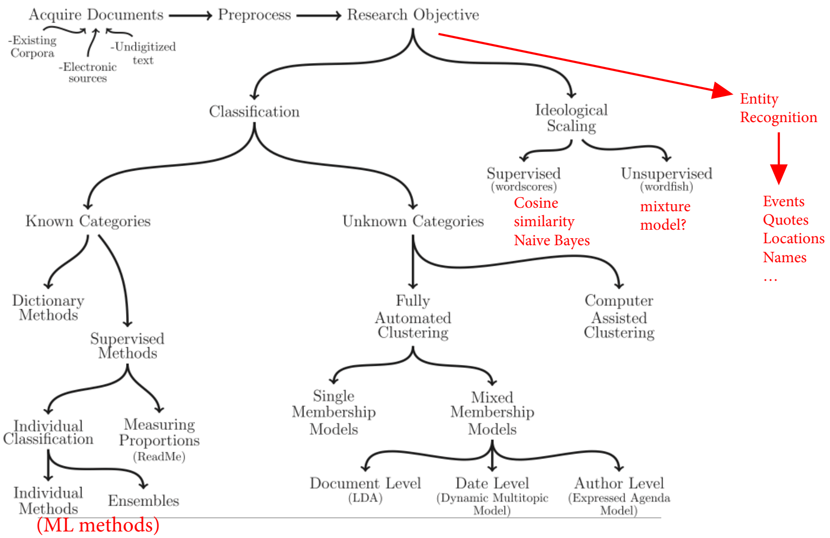

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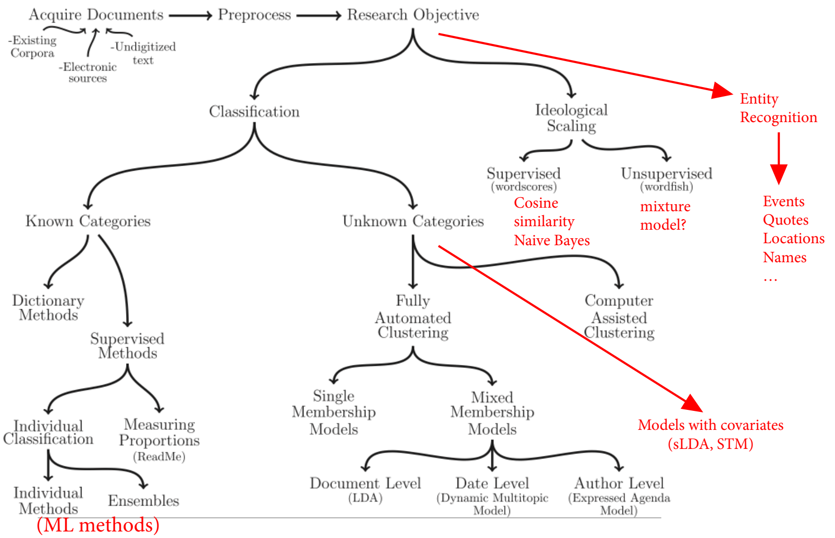

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Text preprocessing

From words to numbers

1. Preprocess text:

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

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

Text preprocessing

From words to numbers

1. Preprocess text: lowercase,

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Text preprocessing

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

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Text preprocessing

From words to numbers

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

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

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Text preprocessing

From words to numbers

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 words
   - W_{im}= number of times m-th words 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 n	0	1	1	0	0	0	…	

Sentiment analysis

Sentiment, tone, valence, affective score... = % positive messages about a subject

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Two main approaches:

1. Dictionary methods

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2. Machine learning

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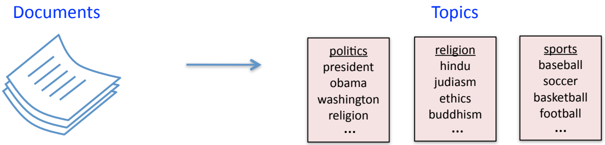
Challenges: sarcasm, intensity, subject identification.
In practice, accuracy over 80% is impossible (and that's ok)

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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Documents

Topics

politics	religion	sports
president	hindu	baseball
obama	judiasm	soccer
washington	ethics	basketball
religion	buddhism	football
...	...	...

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

New document

Words $w_1, \ldots, w_N$

What is this document about?

weather	.50
finance	.49
sports	.01

Distribution of topics θ

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Distribution of topics θ

- 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