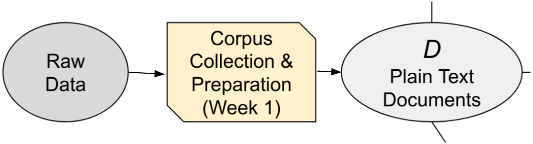
Text Data in Economics

Warwick QAPEC Summer School

2. Corpora, Style Features, and Dictionaries

Corpora



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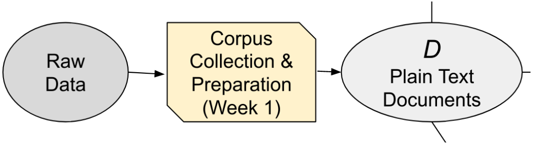

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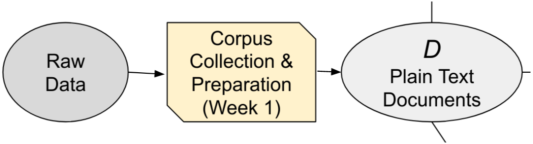

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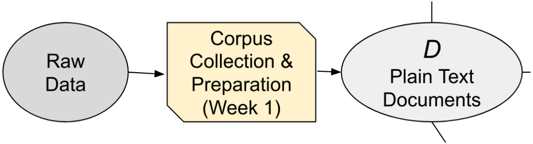

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- All text data approaches will throw away some information:
  - The trick is figuring out how to retain valuable information.
- The tools from Lectures 2 (Tokenization) and 3 (Dimension Reduction) are focused on this step:
  - transforming an unstructured corpus D to a usable matrix X.

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  - we want to relate **text** data to **meta**data.
- e.g., measuring positive-negative sentiment Y in judicial opinions.
  - not that meaningful by itself.
- but how about sentiment Y_{ijt} in opinion i by judge j at time t:
  - how does sentiment vary over time t?
  - does judge from party p_j express more negative sentiment toward defendants from group g_i?

What counts as a document?

The unit of analysis (the “document”) will vary depending on your question.

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What should we use as the document in these contexts? (discuss in pairs)

1. predicting whether a judge is right-wing or left-wing in partisan ideology, from their written opinions.
2. predicting whether parliamentary speeches become more emotive in the run-up to an election
3. measuring whether newspapers use higher or lower sentiment toward different groups.

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  1. query REST API's
  2. run a web scraper in selenium
  3. do pre-processing on corpora, e.g. to remove HTML markup, fix errors associated with OCR.
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- I also recommend everyone to become familiar with hugginface datasets (`https://huggingface.co/docs/datasets/`)
- All of the tools that we discuss in this class are available in many languages, and machine translation is now quite good and automatable (e.g. `huggingface.co/docs/transformers/master/en/model_doc/marian`).

Corpora

Quantity of Text as Data

Dictionary-Based Methods

Sentiment Analysis

Judge Age and Writing Style

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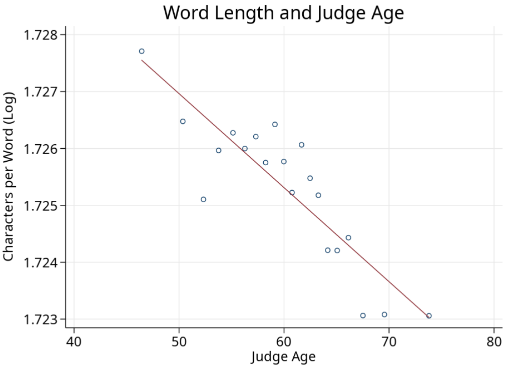

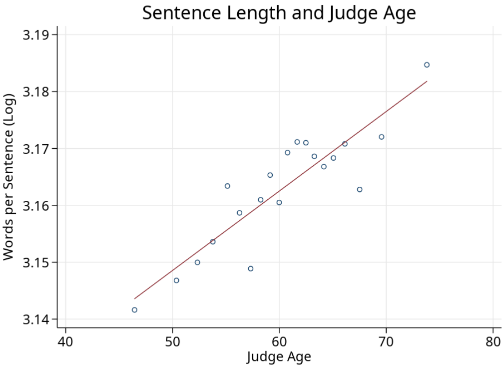

Optimal Legal Complexity (Katz and Bommarito 2014)

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Five largest and smallest titles by token count

Title	Tokens	Tokens per section
Public Health and Welfare (Title 42)	2,732,251	369.22
Internal Revenue Code (Title 26)	1,016,995	487.07
Conservation (Title 16)	947,467	200.48
Commerce and Trade (Title 15)	773,819	336.88
Agriculture (Title 7)	751,579	274.00
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Intoxicating Liquors (Title 27)	6,515	144.78
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Public Health and Welfare (Title 42)	10.79
Conservation (Title 16)	10.75
Navigation and Navigable Waters (Title 33)	10.67
Foreign Relations and Intercourse (Title 22)	10.67
Intoxicating Liquors (Title 27)	9.01
President (Title 3)	8.89
National Guard (Title 32)	8.50
General Provisions (Title 1)	8.49
Arbitration (Title 9)	8.24

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- Corpus-specific: counting sets of words or phrases across documents
  - (e.g., number of times a judge says "justice" vs "efficiency")
- General dictionaries: WordNet, LIWC, MFD, etc.

Measuring uncertainty in macroeconomy

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For each newspaper on each day since 1985, submit the following query:

1. Article contains "uncertain" OR "uncertainty", AND
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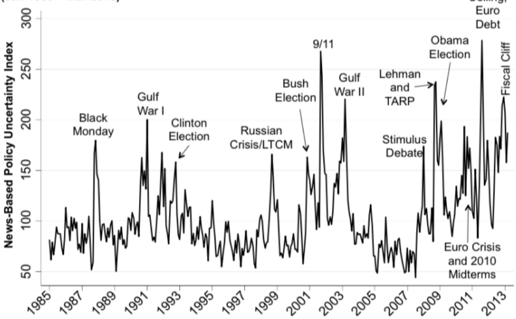
Figure 2: News-Based Economic Policy Uncertainty Index
(Jan 1985 – Mar 2013)



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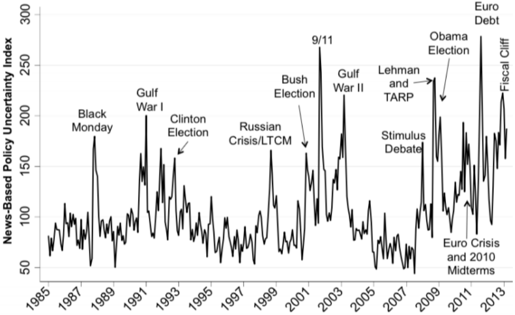

- but see Keith et al (2020), showing some problems with this measure (`https://arxiv.org/abs/2010.04706`).

WordNet

- English word database: 118K nouns, 12K verbs, 22K adjectives, 5K adverbs

The noun "bass" has 8 senses in WordNet.
1. bass^1 - (the lowest part of the musical range)
2. bass^2, bass part^1 - (the lowest part in polyphonic music)
3. bass^3, basso^1 - (an adult male singer with the lowest voice)
4. sea bass^1, bass^4 - (the lean flesh of a saltwater fish of the family Serranidae)
5. freshwater bass^1, bass^5 - (any of various North American freshwater fish with lean flesh (especially of the genus Micropterus))
6. bass^6, bass voice^1, basso^2 - (the lowest adult male singing voice)
7. bass^7 - (the member with the lowest range of a family of musical instruments)
8. bass^8 - (nontechnical name for any of numerous edible marine and freshwater spiny-finned fishes)

Figure 19.1 A portion of the WordNet 3.0 entry for the noun *bass*.

- Synonym sets (synsets) are a group of near-synonyms, plus a gloss (definition).
  - also contains information on antonyms (opposites), holonyms/meronyms (part-whole).
- Nouns are organized in categorical hierarchy (hence "WordNet")
  - "hypernym" – the higher category that a word is a member of.
  - "hyponyms" – members of the category identified by a word.

WordNet Supersenses (Word Categories)

Category	Example	Category	Example	Category	Example
ACT	*service*	GROUP	*place*	PLANT	*tree*
ANIMAL	*dog*	LOCATION	*area*	POSSESSION	*price*
ARTIFACT	*car*	MOTIVE	*reason*	PROCESS	*process*
ATTRIBUTE	*quality*	NATURAL EVENT	*experience*	QUANTITY	*amount*
BODY	*hair*	NATURAL OBJECT	*flower*	RELATION	*portion*
COGNITION	*way*	OTHER	*stuff*	SHAPE	*square*
COMMUNICATION	*review*	PERSON	*people*	STATE	*pain*
FEELING	*discomfort*	PHENOMENON	*result*	SUBSTANCE	*oil*
FOOD	*food*			TIME	*day*

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Supersense	Verbs denoting ...
body	grooming, dressing and bodily care
change	size, temperature change, intensifying
cognition	thinking, judging, analyzing, doubting
communica-tion	telling, asking, ordering, singing
competition	fighting, athletic activities
consumption	eating and drinking
contact	touching, hitting, tying, digging
creation	sewing, baking, painting, performing
emotion	feeling
motion	walking, flying, swimming
perception	seeing, hearing, feeling
possession	buying, selling, owning
social	political and social activities and events
stative	being, having, spatial relations
weather	raining, snowing, thawing, thundering

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- Mohammad and Turney (2011):
  - code 10,000 words along four emotional dimensions: joy–sadness, anger-fear, trust-disgust, anticipation-surprise
- Warriner et al (2013):
  - code 14,000 words along three emotional dimensions: valence, arousal, dominance.

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- Off-the-shelf scores may be trained on biased corpora, eg online writing – may not work for legal text, for example.
  - Hamilton et al (2016) and Zorn and Rice (2019) show how to make domain-specific sentiment lexicons using word embeddings (more on this later).

Problems with Sentiment Analyzers: NLP System Bias

```
text_to_sentiment("Let's go get Italian food")
2.0429166109
text_to_sentiment("Let's go get Chinese food")
1.4094033658
text_to_sentiment("Let's go get Mexican food")
0.3880198556
```

```
text_to_sentiment("My name is Emily")
2.2286179365
text_to_sentiment("My name is Heather")
1.3976291151
text_to_sentiment("My name is Yvette")
0.9846380213
text_to_sentiment("My name is Shaniqua")
-0.4704813178
```

Is this sentiment model racist?

Source: Kareem Carr slides.

NLP “Bias” is statistical bias

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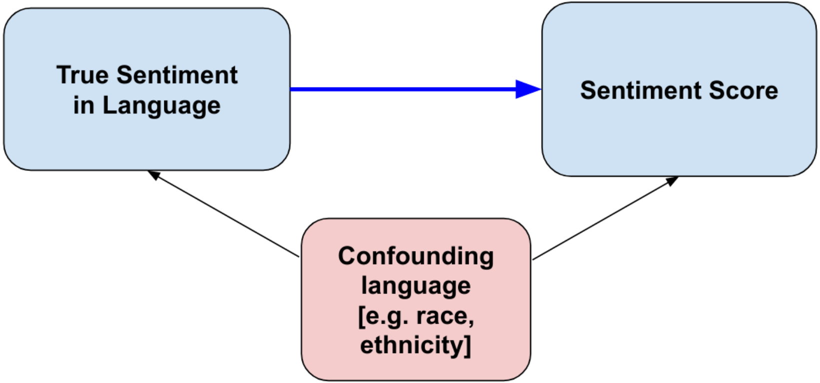
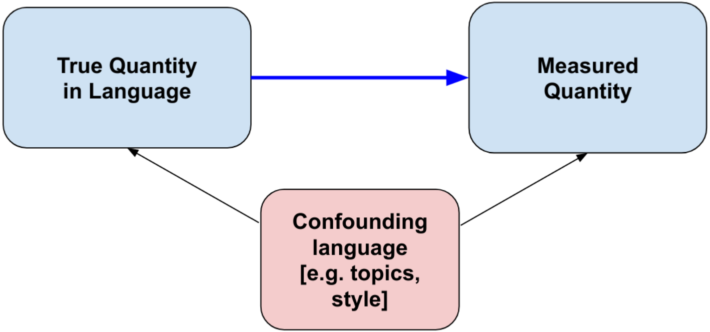


- Supervised sentiment models are confounded by correlated language factors.
  - e.g., in the training set maybe people complain about Mexican food more often than Italian food because Italian restaurants tend to be more upscale.

This is a universal problem



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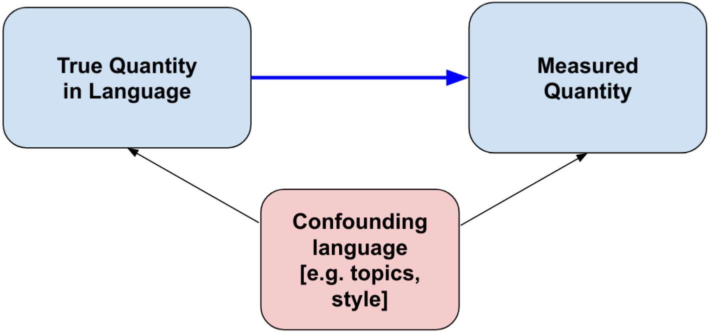

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- unsupervised models (topic models, word embeddings) learn correlations between topics / contexts.
- **dictionary methods**, while having other limitations, mitigate this problem
  - the researcher intentionally "regularizes" out spurious confounders with the targeted language dimension.
  - helps explain why economists often still use dictionary methods.