Summer Institute in Computational Social Science

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4. Text as Data

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- Text data is **unstructured**:
  - the information we want is mixed together with (lots of) information we don't.
- All text data approaches will throw away some information:
  - The trick is figuring out how to retain valuable information.

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   - Analyze values, attitudes, and ideology
6. **Syntactic / semantic parsing to identify agents, actions, and attributes**
   - "who" does "what" to "whom"

Outline

Outline

[4]:
```
from sklearn.datasets import fetch_20newsgroups
data = fetch_20newsgroups() # object is a dictionary
data.keys()
```

[4]:
```
dict_keys(['data', 'filenames', 'target_names', 'target', 'DESCR'])
```

Data Set Characteristics:

[5]:
```
print(data['DESCR'])
```

```
.. _20newsgroups_dataset:

The 20 newsgroups text dataset
------------------------------

The 20 newsgroups dataset comprises around 18000 newsgroups posts on
20 topics split in two subsets: one for training (or development)
and the other one for testing (or for performance evaluation). The split
between the train and test set is based upon a messages posted before
and after a specific date.
```

[6]:
```
W, y = data.data, data.target
n_samples = y.shape[0]
n_samples
```

[6]:
```
11314
```

[7]:
```
y[:10] # news story categories
```

[7]:
```
array([ 7,  4,  4,  1, 14, 16, 13,  3,  2,  4])
```

[8]:
```
doc = W[0]
doc
```

[8]:
```
"From: lerxst@wam.umd.edu (where's my thing)\nSubject: WHAT car is this!?\nNntp
-Posting-Host: rac3.wam.umd.edu\nOrganization: University of Maryland, College
Park\nLines: 15\n\n I was wondering if anyone out there could enlighten me on t
his car I saw\nthe other day. It was a 2-door sports car, looked to be from the
late 60s/\nearly 70s. It was called a Bricklin. The doors were really small. In
addition,\nthe front bumper was separate from the rest of the body. This is \na
ll I know. If anyone can tellme a model name, engine specs, years\nof productio
n, where this car is made, history, or whatever info you\nhave on this funky lo
oking car, please e-mail.\n\nThanks,\n- IL\n   ---- brought to you by your neig
hborhood Lerxst ----\n\n\n\n\n"
```

```
df = pd.DataFrame(W,columns=['text'])
df['topic'] = y
df.head()
```

	text	topic
0	From: lerxst@wam.umd.edu (where's my thing)\nS...	7
1	From: guykuo@carson.u.washington.edu (Guy Kuo)...	4
2	From: twillis@ec.ecn.purdue.edu (Thomas E Will...	4
3	From: jgreen@amber (Joe Green)\nSubject: Re: W...	1
4	From: jcm@head-cfa.harvard.edu (Jonathan McDow...	14

Corpus cleaning

- Pre-Processing Steps:
  - Remove HTML markup, extra white space, and unicode
  - page numbers
  - hyphenations at line breaks
  - table of contents, indexes, etc.

Corpus cleaning

- Pre-Processing Steps:
  - Remove HTML markup, extra white space, and unicode
  - page numbers
  - hyphenations at line breaks
  - table of contents, indexes, etc.
- OCR (Optical Character Recognition)
  - Your data might be in PDF's or images. Needs to be converted to text.
  - I have had good success with abbby finereader (expensive)
  - there is a new package called layoutparser that is supposed to be very good

Languages

- All of the tools that we discuss in this class are available in many languages.
  - See, e.g., `https://spacy.io/usage/models`.
- Machine learning models are language-independent.
- Now many multilingual document encoders available (see e..g. SentenceTransformers, sbert.net)
- Can also translate (e.g., huggingface NMT model).

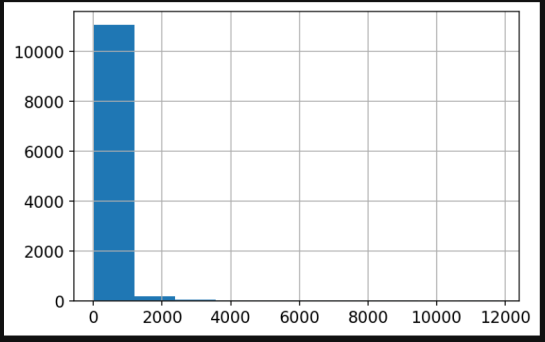
Outline

Count words per document.

[13]:
```
def get_words_per_doc(txt):
    # split text into words and count them.
    return len(txt.split())

# apply to our data
df['num_words'] = df['text'].apply(get_words_per_doc)
df['num_words'].hist()
```

[13]: <AxesSubplot:>



Judge Age and Writing Style

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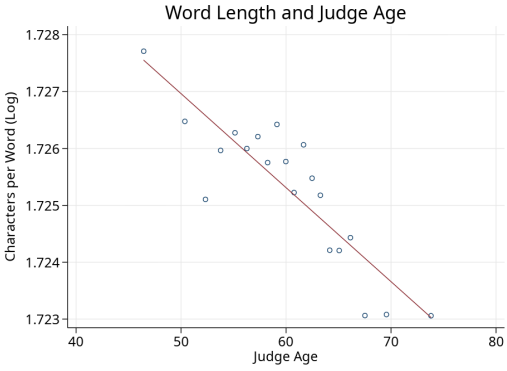

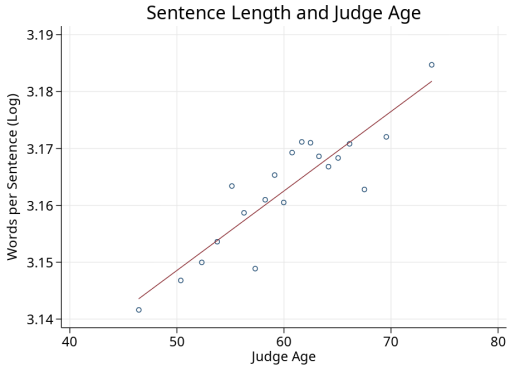

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Overview of Dictionary-Based Methods

- Dictionary-based text methods use a pre-selected list of words or phrases to analyze a corpus.
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  - (e.g., number of times a judge says “justice” vs “efficiency”)

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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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Normalize resulting article counts by total newspaper articles that month.

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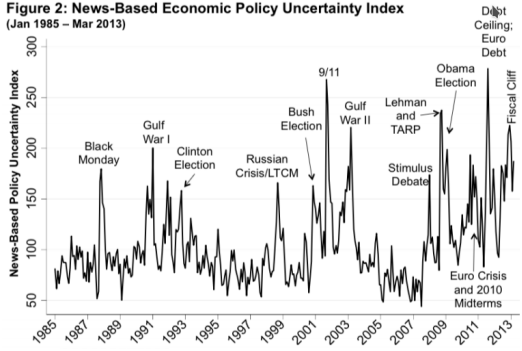

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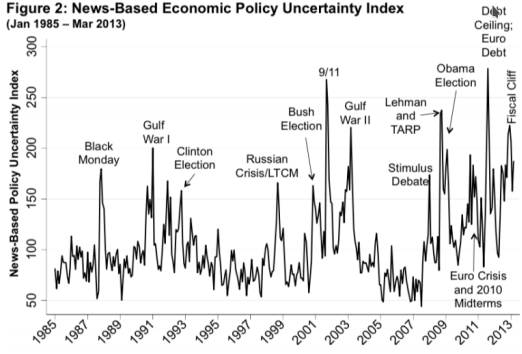

- but see Keith et al (2020), showing some big problems with this measure (`https://arxiv.org/abs/2010.04706`).

Sentiment Analysis: Extract a "tone" dimension – positive, negative, neutral

- standard approach is lexicon-based (eg NLTK Vader), but they fail easily: e.g., "good" versus "not good" versus "not very good"

Sentiment Analysis

[16]:
```
# Dictionary-Based Sentiment Analysis

from nltk.sentiment.vader import SentimentIntensityAnalyzer
sid = SentimentIntensityAnalyzer()
polarity = sid.polarity_scores(doc)
print(polarity)
```

```
{'neg': 0.012, 'neu': 0.916, 'pos': 0.072, 'compound': 0.807}
```

- huggingface sentiment analyzer uses a modern transformer-based method.

```
from transformers import pipeline
sentiment_analysis = pipeline("sentiment-analysis")

pos_text = "I enjoy studying computational algorithms."
neg_text = "I dislike sleeping late everyday."

pos_sent = sentiment_analysis(pos_text)[0]
print(pos_sent['label'],0 pos_sent['score'])

neg_sent = sentiment_analysis(neg_text)[0]
print(neg_sent['label'], neg_sent['score'])
```

Pre-Fab Dictionaries

- WordNet: English word database: 118K nouns, 12K verbs, 22K adjectives, 5K adverbs. Synonym sets (synsets) are a group of near-synonyms, plus a gloss (definition).
  - also contains information on antonyms (opposites), holonyms/meronyms (part-whole).

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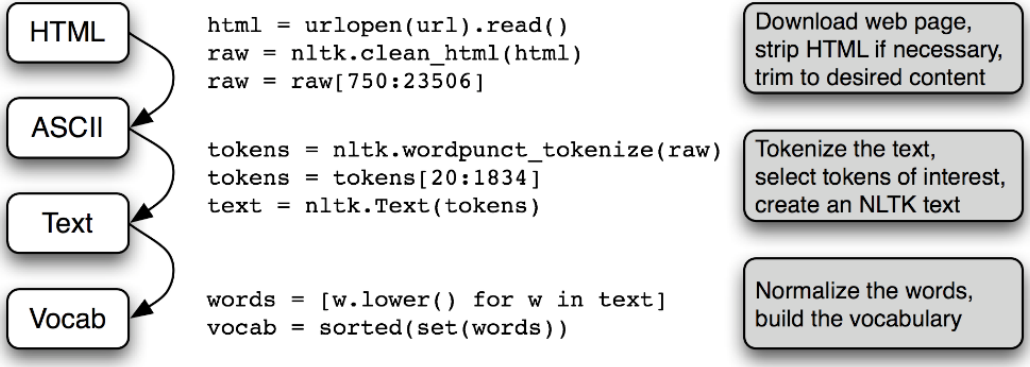
- Mohammad and Turney (2011):
  - code 10,000 words along four emotional dimensions: joy–sadness, anger-fear, trust-disgust, anticipation-surprise

Outline

Goals of Featurization

- The goal: produce features that are
  - **predictive** in the learning task
  - **interpretable** by human investigators
  - **tractable** enough to be easy to work with



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  - some features are more interpretable
- Standard pre-processing steps:
  - drop capitalization, punctuation, numbers, stopwords (e.g. "the", "such")
  - remove word stems (e.g., "taxes" and "taxed" become "tax")

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More generally:

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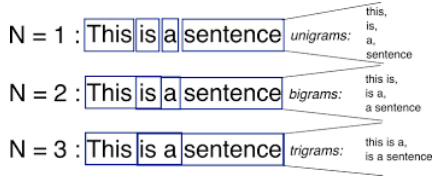
Building a vocabulary:

- Compute document frequencies for all words
- Inspect low-frequency words and determine a minimum document threshold.
  - e.g., 10 documents, or .25% of documents.

N-grams

- N-grams are phrases, sequences of words up to length N.
  - bigrams, trigrams, quadgrams, etc.



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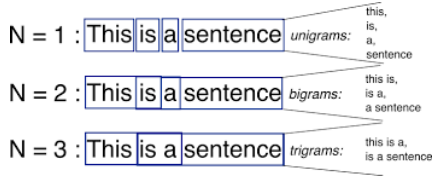

- capture information and familiarity from local word order.
  - e.g. “estate tax” vs “death tax”
- will blow up feature space – drop rare n-grams, or filter out n-grams that are not predictive in your task.

Feature selection using univariate comparisions

- χ^2 (chi2) is a fast feature selection routine for classification tasks
  - features must be non-negative
  - works on sparse matrices
  - works on multi-class problems

```
#%% Univariate feature selection using chi2
from sklearn.feature_selection import SelectKBest, chi2,
select = SelectKBest(chi2, k=10)
Y = df['topic']==1
X_new = select.fit_transform(X, Y)
```

- With negative predictors:
  - use `f_classif`
- For regression tasks:
  - use `f_regression`

TF-IDF Weighting

- TF/IDF: "Term-Frequency / Inverse-Document-Frequency."
- The formula for word w in document k:

$$\underbrace{\frac{\text{Count of } w \text{ in } k}{\text{Total word count of } k}}_{\text{Term Frequency}} \times \underbrace{\log\left(\frac{\text{Number of documents in } D}{\text{Count of documents containing } w}\right)}_{\text{Inverse Document Frequency}}$$

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- The formula up-weights relatively rare words that do not appear in all documents.
  - These words are probably more distinctive of topics or differences between documents.
- Note that this is a normalizer, so it matters for vector distances, but not for features in a regression.

scikit-learn's TfidfVectorizer

https://scikit-learn.org/stable/modules/feature_extraction.html#text-feature-extraction

https://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.text.TfidfVectorizer.html

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```
>>> from sklearn.feature_extraction.text import TfidfVectorizer
>>> vectorizer = TfidfVectorizer()
>>> vectorizer.fit_transform(corpus)
<4x9 sparse matrix of type '<... 'numpy.float64'>'
    with 19 stored elements in Compressed Sparse ... format>
```

- `corpus` is a sequence of strings, e.g. pandas data-frame columns.
- pre-processing options: strip accents, lowercase, drop stopwords,
- n-grams: can produce phrases up to length n (words or characters).
- vocab options: min/max frequency, vocab size
- post-processing: binary, l2 norm, (smoothed) idf weighting, etc

Application: What Drives Media Slant?

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  - congressional text is 2005 Congressional Record.
- Pre-process text, stripping away prepositions, conjunctions, pronouns, and common words
  - get bigrams and trigrams
- Identify polarizing phrases using χ^2 metric.

TABLE I

MOST PARTISAN PHRASES FROM THE 2005 *CONGRESSIONAL RECORD*[a]

Panel A: Phrases Used More Often by Democrats		
Two-Word Phrases		
private accounts	Rosa Parks	workers rights
trade agreement	President budget	poor people
American people	Republican party	Republican leader
tax breaks	change the rules	Arctic refuge
trade deficit	minimum wage	cut funding
oil companies	budget deficit	American workers
credit card	Republican senators	living in poverty
nuclear option	privatization plan	Senate Republicans
war in Iraq	wildlife refuge	fuel efficiency
middle class	card companies	national wildlife
Three-Word Phrases		
veterans health care	corporation for public broadcasting	cut health care
congressional black caucus		civil rights movement
VA health care	additional tax cuts	cuts to child support
billion in tax cuts	pay for tax cuts	drilling in the Arctic National
credit card companies	tax cuts for people	victims of gun violence
security trust fund	oil and gas companies	solvency of social security
social security trust	prescription drug bill	Voting Rights Act
privatize social security	caliber sniper rifles	war in Iraq and Afghanistan
American free trade	increase in the minimum wage	civil rights protections
central American free	system of checks and balances	credit card debt
	middle class families	

TABLE I—*Continued*

Panel B: Phrases Used More Often by Republicans		
Two-Word Phrases		
stem cell	personal accounts	retirement accounts
natural gas	Saddam Hussein	government spending
death tax	pass the bill	national forest
illegal aliens	private property	minority leader
class action	border security	urge support
war on terror	President announces	cell lines
embryonic stem	human life	cord blood
tax relief	Chief Justice	action lawsuits
illegal immigration	human embryos	economic growth
date the time	increase taxes	food program
Three-Word Phrases		
embryonic stem cell	Circuit Court of Appeals	Tongass national forest
hate crimes legislation	death tax repeal	pluripotent stem cells
adult stem cells	housing and urban affairs	Supreme Court of Texas
oil for food program	million jobs created	Justice Priscilla Owen
personal retirement accounts	national flood insurance	Justice Janice Rogers
energy and natural resources	oil for food scandal	American Bar Association
global war on terror	private property rights	growth and job creation
hate crimes law	temporary worker program	natural gas natural
change hearts and minds	class action reform	Grand Ole Opry
global war on terrorism	Chief Justice Rehnquist	reform social security

[a]The top 60 Democratic and Republican phrases, respectively, are shown ranked by χ^2_{pt}. The phrases are classified as two or three word after dropping common "stopwords" such as "for" and "the." See Section 3 for details and see Appendix B (online) for a more extensive phrase list.

Consumers drive media slant (GS 2010)

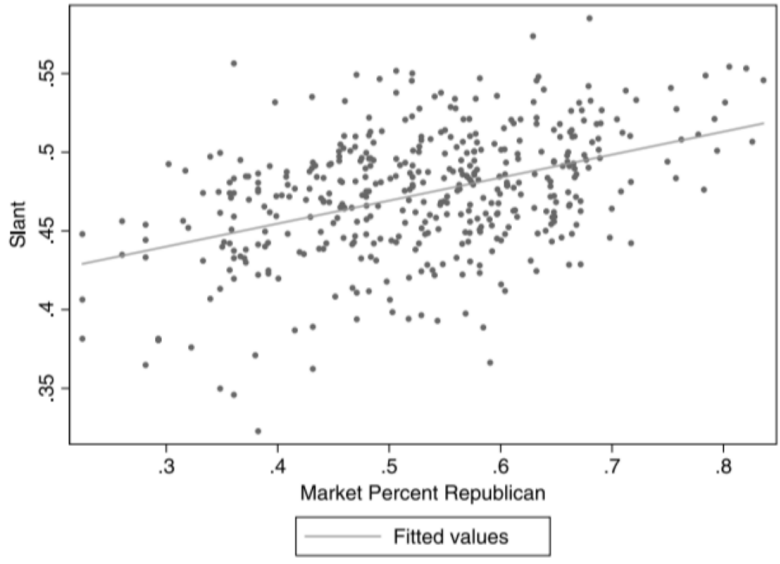

FIGURE 4.—Newspaper slant and consumer ideology. The newspaper slant index against Bush's share of the two-party vote in 2004 in the newspaper's market is shown.

Outline

Text Re-Use

- Text Re-Use algorithms (like "Smith-Waterman") measure similarity by finding and counting shared sequences in two texts above some minimum length, e.g. 10 words.
  - useful for plagiarism detection, for example.
- precise but slow

Cosine Similarity

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  - that is, documents are rays, and similar documents have similar vectors.
- Can measure similarity between documents i and j by the cosine of the angle between x_i and x_j :
  - With perfectly collinear documents (that is, $x_i = \alpha x_j$, $\alpha > 0$), $\cos(0) = 1$
  - For orthogonal documents (no words in common), $\cos(\pi/2)=0$

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  - that is, documents are rays, and similar documents have similar vectors.
- Can measure similarity between documents i and j by the cosine of the angle between x_i and x_j :
  - With perfectly collinear documents (that is, $x_i = \alpha x_j$, $\alpha > 0$), $\cos(0) = 1$
  - For orthogonal documents (no words in common), $\cos(\pi/2)$=0

Cosine similarity is computable as the normalized dot product between the vectors:

$$\text{cos\_sim}(x_1, x_2) = \frac{x_1 \cdot x_2}{||x_1||||x_2||}$$

```
from sklearn.metrics.pairwise import
cosine_similarity
# between two vectors:
sim = cosine_similarity(x, y)[0,0]
# between all rows of a matrix:
sims = cosine_similarity(X)
```

Text analysis of patent innovation

Kelly, Papanikolau, Seru, and Taddy (AERI 2020)

"Measuring technological innovation over the very long run"

- Data:
  - 9 million patents since 1840, from U.S. Patent Office and Google Scholar Patents.
  - date, inventor, backward citations
  - text (abstract, claims, and description)

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  - date, inventor, backward citations
  - text (abstract, claims, and description)
- Text pre-processing:
  - drop HTML markup, punctuation, numbers, capitalization, and stopwords.
  - remove terms that appear in less than 20 patents.
  - 1.6 million words in vocabulary.

Measuring Patent Similarity

- Each patent $i = x_i =$ TF-IDF word features (vector with 1.6m entries)
- Compute (roughly) TF-IDF cosine similarity ρ_{ij} between patents i and j.
  - 9m$\times$9m similarity matrix = 30TB of data.
  - enforce sparsity by setting similarity $< .05$ to zero (93.4% of pairs).

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  - enforce sparsity by setting similarity $< .05$ to zero (93.4% of pairs).
- Validation:
  - For pairs with higher ρ_{ij}, patent j more likely to cite patent i.
  - Within technology class (assigned by patent office), similarity is higher than across class.

- "Novelty" is defined by dissimilarity (negative similarity) to previous patents:

$$\text{Novelty}_j = -\sum_{i \in B(j)} \rho_{ij}$$

where $B(j)$ is the set of previous patents (in, e.g., last 20 years).

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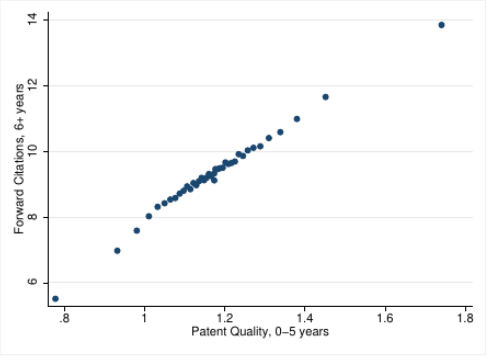
- A patent has high **quality** if it is **novel** and **impactful**:

$$\log \text{Quality}_k = \log \text{Impact}_k + \log \text{Novelty}_k$$

- Higher quality patents get more cites:



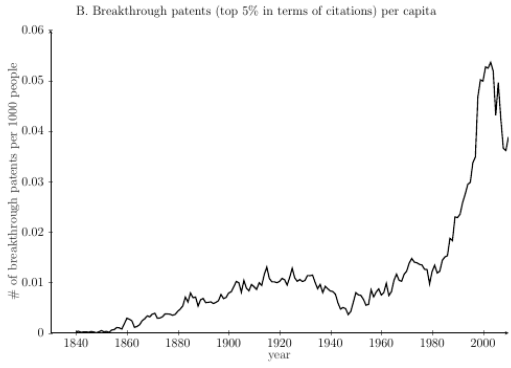
Most Innovative Firms

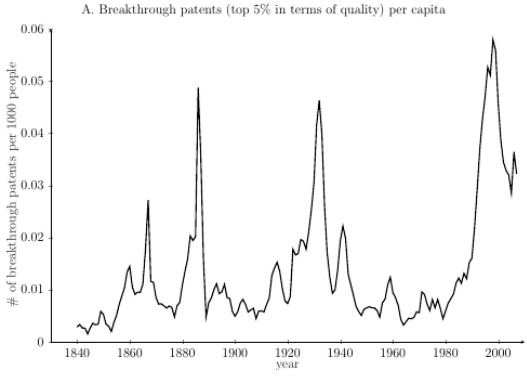
Kelly, Papanikolau, Seru, and Taddy (2018)

Assignee	First Year	# Breakthroughs
General Electric	1872	3,457
Westinghouse Electric Co.	1889	1,762
Eastman Kodak Co.	1890	2,244
Western Electric Co.	1899	1,222
AT&T (includes Bell Labs)	1899	5,645
Standard Oil Co.	1900	1,212
Dow Chemical Co.	1902	1,235
Du Pont	1905	3,353
International Business Machines	1908	14,913
American Cyanamid Co.	1909	690
Universal Oil Products Co.	1919	590
RCA	1920	3,222
Monsanto Company (inc. Monsanto Chemicals)	1921	902
Honeywell International, inc.	1928	872
General Aniline & Film Corp.	1929	1,181
Massachusetts Institute of Technology	1935	504
Philips	1939	1145
Texas Instruments	1960	2,088
Xerox	1961	2,198
Applied Materials	1971	510
Digital Equipment	1971	1,101
Hewlett-Packard Co.	1971	2,661
Intel	1971	2,629
Motorola, inc.	1971	4,129
Regents of the University of California	1971	823
United States Navy	1945	791
NCR	1973	737
Advanced Micro Devices	1974	1,195
Apple Computer	1978	864

Breakthrough patents: citations vs quality

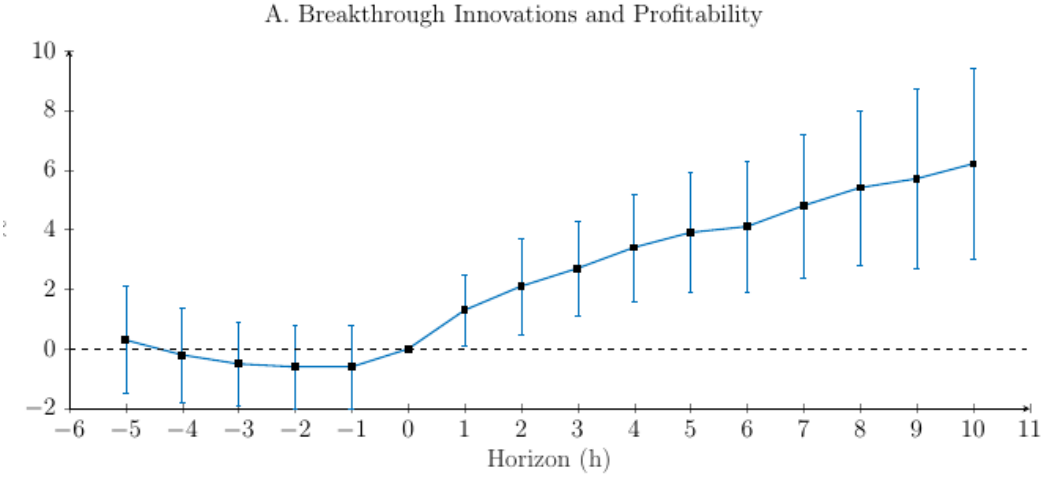
Kelly, Papanikolau, Seru, and Taddy (2018)





Breakthrough patents and firm profits

Kelly, Papanikolau, Seru, and Taddy (2018)



Outline

Machine Learning with Text Data

- We have a corpus (or dataset) D of $n_D \geq 1$ documents (or data points), whose features can be represented as a matrix of vectors $\boldsymbol{x}$ with $n_x \geq 1$ features.

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- Each document has an associated outcome or label $\boldsymbol{y}$ with dimensions $n_y \geq 1$
- Some documents are unlabeled $\rightarrow$ we would like to train a model to machine-classify them.

XGBoost

- Feurer et al (2018) find that XGBoost beats a sophisticated AutoML procedure with grid search over 15 classifiers and 18 data preprocessors.
- A good starting point for any machine learning task.

- easy to use
- actively developed
- efficient / parallelizable
- provides model explanations
- takes sparse matrices as input

```
from xgboost import XGBClassifier
model = XGBClassifier()

model.fit(X_train, y_train,
          early_stopping_rounds=10,
          eval_metric="logloss",
          eval_set=[(X_eval, y_eval)]
          )

y_pred = model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
```

Interpreting Tree Ensembles

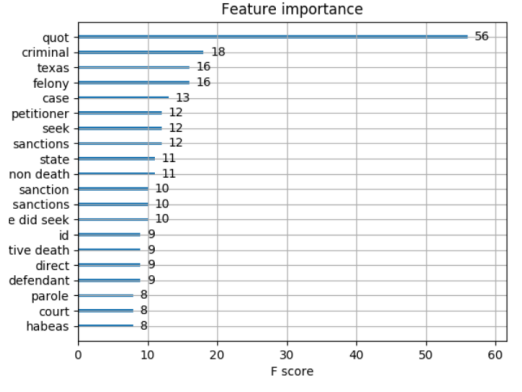
XGBoost's Feature Importance Metric:

- At each decision node, compute **information gain** for feature j **(change in predicted probability)**.
- Average across all nodes for each j.

Ranks predictors by their relative contributions.

```
from xgboost import plot_importance
plot_importance(xgb_reg, max_num_features=20)
```

```
<IPython.core.display.Javascript object>
```



Application: Predicting Political Party from Text

Andrew Peterson and Arthur Spirling, "Classification accuracy as a substantive quantity of interest: Measuring polarization in Westminster systems," *Political Analysis* (2018).

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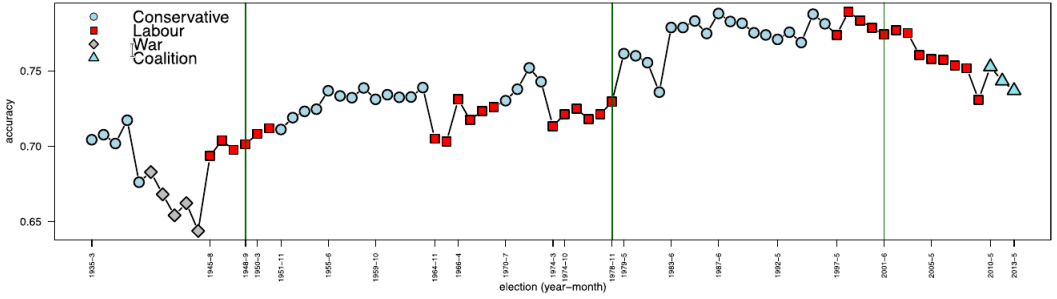
In years that classifier is more accurate, speech is more polarized:



Outline

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  - Each topic is a distribution over words.
  - Each document is a distribution over topics.

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- Input: $N \times M$ document-term count matrix X
- Assume: there are K topics (tunable hyperparameter, use coherence).
- Like PCA or NMF, LDA works by factorizing X into:
  - an $N \times K$ **document-topic matrix**
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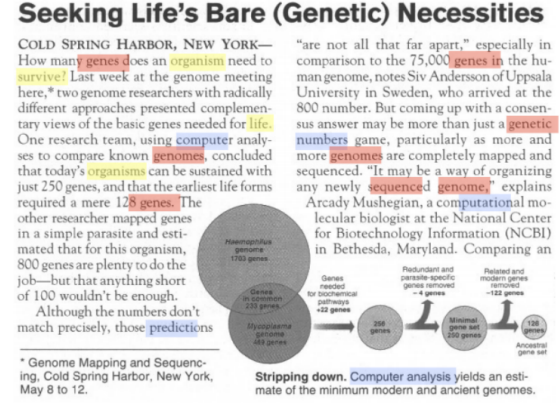

Seeking Life's Bare (Genetic) Necessities

COLD SPRING HARBOR, NEW YORK— How many genes does an organism need to survive? Last week at the genome meeting here,* two genome researchers with radically different approaches presented complementary views of the basic genes needed for life. One research team, using computer analyses to compare known genomes, concluded that today's organisms can be sustained with just 250 genes, and that the earliest life forms required a mere 128 genes. The other researcher mapped genes in a simple parasite and estimated that for this organism, 800 genes are plenty to do the job—but that anything short of 100 wouldn't be enough.

Although the numbers don't match precisely, those predictions "are not all that far apart," especially in comparison to the 75,000 genes in the human genome, notes Siv Andersson of Uppsala University in Sweden, who arrived at the 800 number. But coming up with a consensus answer may be more than just a genetic numbers game, particularly as more and more genomes are completely mapped and sequenced. "It may be a way of organizing any newly sequenced genomes," explains Arcady Mushegian, a computational molecular biologist at the National Center for Biotechnology Information (NCBI) in Bethesda, Maryland. Comparing an

* Genome Mapping and Sequencing, Cold Spring Harbor, New York, May 8 to 12.

Stripping down. Computer analysis yields an estimate of the minimum modern and ancient genomes.

Image from Hanna Wallach

```
# creating the term dictionary
from gensim import corpora
dictionary = corpora.Dictionary(doc_clean)
```

Converting list of documents (corpus) into Document Term Matrix using dictionary prepared above.

```
doc_term_matrix = [dictionary.doc2bow(doc) for doc in doc_clean]
```

```
# train LDA with 10 topics and print
from gensim.models.ldamodel import LdaModel

lda = LdaModel(doc_term_matrix, num_topics=10,
               id2word = dictionary, passes=3)
lda.show_topics(formatted=False)
```

orbit titan launch orbiter probe space earth mission jupiter cassini saturn gravity surface atmosphere satellite system lunar solar mars high imaging isas missions ray data stars assist shuttle informix global asteroid possible launched flyby phone observer venus study years project posting subject com key cd rocket nasda would energy registered first advanced resolution observing transit fire toshiba
genocide armenian one turks com jews russian armenians people war subject windows lines army turkish turkey organization article latvia see nazi population world post software muslim source state documents religion ottoman reply writes could would like soviet still many list things kurds help think armenia western university east van pp leaders new day cities
power flights module lines organization ssf option capability subject shuttle station redesign external space mfc system host posting com things think would writes nasa ms hp reference gov nntp using two orbiter used one font window dos jsc mode options human acne bc acrv actrix
lines organization subject reserve university board naval th would nntp thanks scsi writes article information csiro posting conference cameras please reply list host marine final dicta people email buffalo washington blakey cs clock cc game close question

Using an LDA Model

Once trained, can easily get topic proportions for a corpus.

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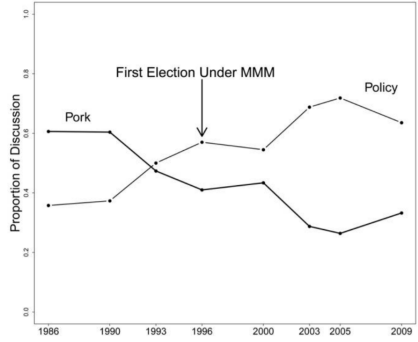
Can then use the topic proportions as variables in a social science analysis.

- e.g., Catalinac (2016) shows that after a Japanese political reform that reduced intraparty competition, candidate platforms reduced local pork and increased national policy.



Topic modeling Federal Reserve Bank transcripts

Hansen, McMahon, and Prat (QJE 2017)

- Analyze speech transcripts from FOMC (Federal Open Market Committee).
  - private discussions among committee members at Federal Reserve (U.S. Central Bank)
  - 150 meetings, 20 years, 26,000 speeches, 24,000 unique words.

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- Pre-processing:
  - drop stopwords, stems; vocab = 10,000 words
- LDA:
  - $K = 40$ topics selected for interpretability / topic coherence.

													Pro-cyclicality
Topic0[1]	product	increas	wage	price	cost	labor	rise	acceler	inflat	pressur	trend	compens	0.024
Topic1[1,2]	growth	slow	economi	continu	expans	strong	trend	inflat	will	recent	slowdown	moder	0.023
Topic2[2]	inflat	expect	core	measur	higher	path	slack	gradual	continu	remain	view	suggest	0.017
Topic3[1]	percent	year	quarter	growth	month	rate	last	next	state	averag	california	employ	0.007
Topic4	number	data	look	chang	measur	use	point	show	revis	estim	gdp	actual	0.007
Topic5[1,2]	polici	inflat	monetarpol	need	time	can	monetari	move	tighten	view	action	believ	0.005
Topic6[2]	rate	term	expect	real	lower	increas	rise	level	declin	short	nomin	year	0.005
Topic7	statement	word	chang	meet	languag	discuss	issu	want	read	sentenc	view	use	0.005
Topic8[2]	chairman	support	mr	direct	recommend	agre	asymmetr	prefer	symmetr	move	toward	favor	0.004
Topic9[1]	employ	continu	growth	job	nation	region	seem	state	manufactur	greenbook	busi	bit	0.004
Topic10	dollar	unitedstates	export	countri	import	foreign	japan	growth	abroad	trade	develop	currenc	0.003
Topic11	model	use	simul	shock	effect	scenario	nairu	differ	rule	chang	baselin	altern	0.003
Topic12[2]	risk	may	balanc	seem	side	uncertainti	possibl	economi	probabl	reason	upsid	much	0.003
Topic13	forecast	greenbook	staff	project	differ	assumpt	littl	assum	somewhat	lower	end	period	0.002
Topic14	period	committe	consist	econom	run	maintain	futur	read	slightli	stabil	expect	develop	0.002
Topic15	invest	incom	spend	capit	household	consum	busi	hous	consumpt	sector	stock	stockmarket	0.002
Topic16[1]	month	report	increas	survey	expect	indic	remain	continu	last	recent	data	activ	0.002
Topic17[1]	project	forecast	year	quarter	expect	will	percent	revis	anticip	growth	next	recent	0.002
Topic18	question	ask	issu	let	want	answer	rais	discuss	don	start	without	okay	0.001
Topic19	peopl	talk	lot	much	comment	around	differ	number	realli	look	thing	hear	0.001
Topic20	presid	ye	governor	parri	stern	vice	hoenig	minehan	kelley	jordan	moskow	mcteer	0.001
Topic21	move	can	evid	signific	stage	inde	will	issu	economi	may	quit	clearli	0.001
Topic22[2]	chairman	thank	mr	time	meet	laughter	comment	let	will	point	call	may	0.0
Topic23[1]	year	panel	line	shown	right	chart	expect	project	percent	middl	left	next	0.0
Topic24	district	nation	area	continu	sector	construct	manufactur	report	activ	region	economi	remain	0.0
Topic25	know	someth	happen	right	thing	want	look	sure	can	realli	anyth	els	0.0
Topic26[1,2]	polici	might	committe	market	may	tighten	eas	risk	action	staff	possibl	potenti	-0.001
Topic27	year	continu	product	price	level	industri	will	sale	increas	auto	last	district	-0.001
Topic28[1]	inventori	product	sale	level	order	will	sector	come	good	quarter	much	adjust	-0.001
Topic29	price	oil	increas	energi	effect	import	suppli	product	demand	will	market	oilprices	-0.002
Topic30	term	might	point	can	sens	run	short	probabl	time	longer	tri	someth	-0.002
Topic31	seem	may	time	certainli	bit	littl	quit	much	far	perhap	better	might	-0.003
Topic32	money	aggreg	borrow	seem	rang	reserv	rate	target	time	altern	suggest	million	-0.003
Topic33[2]	move	market	point	will	fundsrate	rate	basispoints	need	fed	today	basi	time	-0.004
Topic34[1]	report	busi	compani	year	contact	firm	sale	worker	expect	plan	director	industri	-0.004
Topic35	will	fiscal	ta	budget	cut	govern	effect	billion	state	spend	deficit	year	-0.005
Topic36	will	economi	world	rather	problem	believ	can	situat	much	seem	view	good	-0.008
Topic37	realli	look	side	thing	lot	problem	concern	littl	pretti	situat	kind	much	-0.012
Topic38	bank	credit	market	loan	financi	debt	lend	fund	concern	financ	problem	spread	-0.018
Topic39[1,2]	economi	weak	recoveri	recess	confid	eas	neg	econom	will	turn	declin	period	-0.059

Pro-Cyclical Topics

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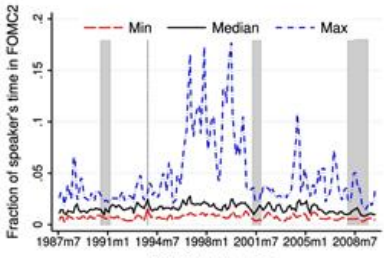
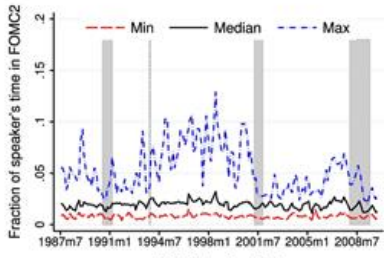


(A) Topic 0 'Productivity'



(B) Topic 1 'Growth'

Counter-Cyclical Topics

Hansen, McMahon, and Prat (QJE 2017)

(A) Topic 38 'Financial sector'

(B) Topic 39 'Economic weakness'

Effect of Transparency

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Effect of Transparency

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- In 1993, there was an unexpected transparency shock where transcripts became public.
- Increasing transparency results in:
  - higher discipline / technocratic language (probably beneficial)
  - higher conformity (probably costly)
- Highlights tradeoffs from transparency in bureaucratic organizations.

Structural Topic Model = LDA + Metadata

Roberts, Stewart, and Tingley

STM provides two ways to include contextual information:

- Topic prevalence can vary by metadata
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- Structural topic model is not a prediction model:
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- The main implementation is in R. Python gensim has a light-weight version called "author topic model".

Outline

Word2Vec & GloVe

- "Word embeddings" often refer to Word2Vec or GloVe – these are particular (popular) models for producing word embeddings.
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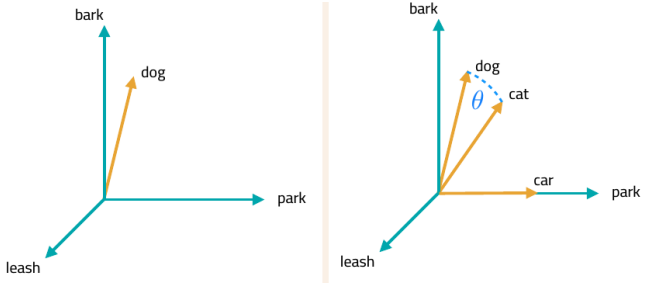
  - rather than predicting some metadata (such as classifying topic labels) they predict the co-occurence of neighboring words.
- "You shall know a word by the company it keeps":
  - "He filled the **wampimuk**, passed it around and we all drunk some."
  - "We found a little, hairy **wampimuk** sleeping behind the tree."

Word Similarity

- Once words are represented as vectors, we can use linear algebra to understand the relationships between words:
  - Words that are geometrically close to each other are similar: e.g. "dog" and "cat":

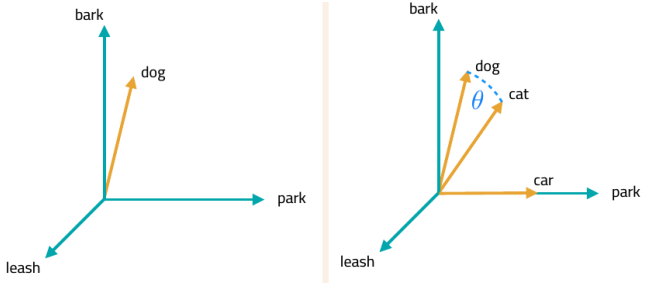


- The standard metric for comparing vectors is cosine similarity:

$$\cos\theta = \frac{v_1 \cdot v_2}{||v_1||||v_2||}$$

Word Similarity

- Once words are represented as vectors, we can use linear algebra to understand the relationships between words:
  - Words that are geometrically close to each other are similar: e.g. "dog" and "cat":



- The standard metric for comparing vectors is cosine similarity:

$$\cos\theta = \frac{v_1 \cdot v_2}{||v_1||||v_2||}$$

- Thanks to linearity, can compute similarities between groups of words by averaging the groups.

```
# train the model
from gensim.models import Word2Vec
w2v = Word2Vec(sentences,  # list of tokenized sentences
               workers = 8, # Number of threads to run in parallel
               size=300,  # Word vector dimensionality
               min_count =  25, # Minimum word count
               window = 5, # Context window size
               sample = 1e-3, # Downsample setting for frequent words
               )

# done training, so delete context vectors
w2v.init_sims(replace=True)

w2v.save('w2v-vectors.pkl')
```

```
w2v.wv.most_similar('man') # most similar words
```

```
[('christ', 0.7512136697769165),
 ('woman', 0.7265682220458984),
 ('jesus', 0.7187944650650024),
 ('satan', 0.6972118616104126),
 ('lord', 0.6948500275611877),
 ('god', 0.6891006231307983),
```

Word2Vec/GloVe Encode Linguistic Relations

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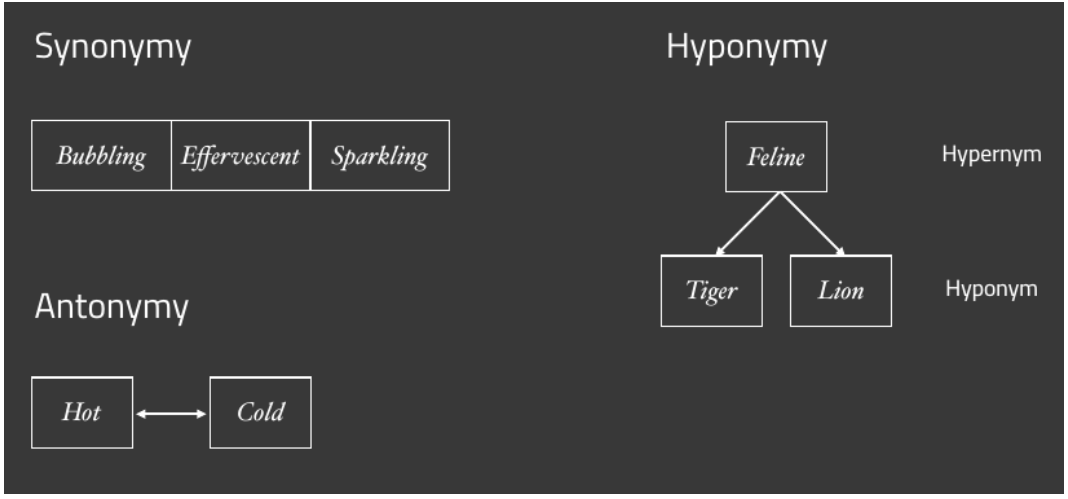

Similarity vs. Relatedness (Budansky and Hirst, 2006)

- Semantic **similarity**: words sharing salient attributes / features
  - synonymy (car / automobile)
  - hypernymy (car / vehicle)
  - co-hyponymy (car / van / truck)

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  - function (car / drive)
  - meronymy (car / tire)
  - location (car / road)
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- Semantic **relatedness**: words semantically associated without necessarily being similar
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  - location (car / road)
  - attribute (car / fast)
- Word embeddings will recover one or both of these relations, depending on how contexts are constructed.

Most similar words to "dog", depending on context window size

- Small windows pick up substitutable words; large windows pick up topics.

The black sheep problem

- The trivial or obvious features of a word are not mentioned in standard corpora.

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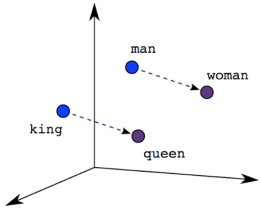
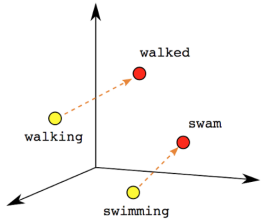
- This is really important when we will use embeddings to anayze beliefs/attitudes.
- Relatedly, antonyms are often rated similarly, have to be careful with that.

Vector Directions ↔ Meaning

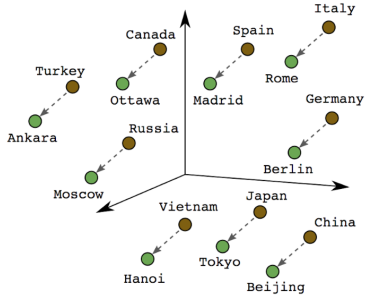
- Intriguingly, word2vec algebra can depict conceptual, analogical relationships between words:



Male-Female



Verb Tense



Country-Capital

Pre-trained word embeddings

- In many settings (e.g. a small corpus), better to use pre-trained embeddings.

```
import spacy
en = spacy.load('en_core_web_lg') # higher-quality vectors (but 800MB)
apple = en('apple')
apple.vector[:10] # vector for 'apple'
```

```
[158]: array([-0.36391 ,  0.43771 , -0.20447 , -0.22889 , -0.14227 ,  0.27396 ,
       -0.011435, -0.18578 ,  0.37361 ,  0.75339 ], dtype=float32)
```

```
[159]: apple.similarity(apple)
```

```
[159]: 1.0
```

```
[166]: orange = en('orange')
       apple.similarity(orange)
```

```
[166]: 0.5618917538704213
```

- e,g, spaCy's GloVe embeddings:
  - one million vocabulary entries, 300-dimensional vectors, trained on the Common Crawl corpus
- Can initialize models with pre-trained embeddings, can fine-tune as needed.

Caliskan, Bryson, and Narayanan (2017)

"We replicated a spectrum of known biases, as measured by the Implicit Association Test, using a widely used, purely statistical machine-learning model trained on a standard corpus of text from the World Wide Web. . . "

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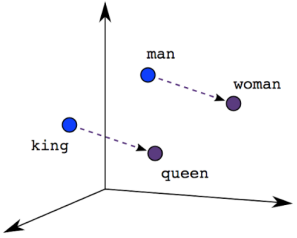

Analogies

- king : queen :: man : woman
- walked : walking :: swam : swimming

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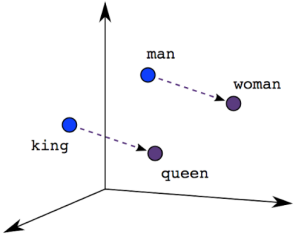
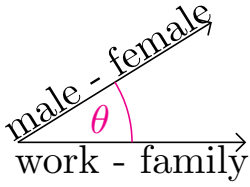


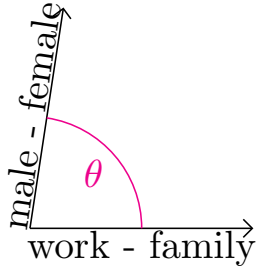
Analogies

- king : queen :: man : woman
- walked : walking :: swam : swimming
- **man : programmer :: woman : homemaker**
- **he : physician :: she : nurse**

Measuring Gender Stereotypes using Cosine Similarity



(a)



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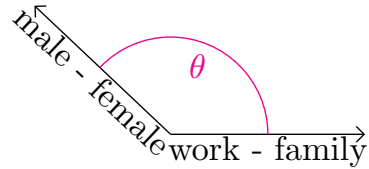

(c)

Example Stimuli (Caliskan et al 2017)

- Targets:
  - **Flowers**: aster, clover, hyacinth, marigold, poppy, azalea, crocus, iris, orchid, rose, bluebell, daffodil, lilac, pansy, tulip, buttercup, daisy, lily, peony, violet, carnation, gladiola, magnolia, petunia, zinnia.
  - **Insects**: ant, caterpillar, flea, locust, spider, bedbug, centipede, fly, maggot, tarantula, bee, cockroach, gnat, mosquito, termite, beetle, cricket, hornet, moth, wasp, blackfly, dragonfly, horsefly, roach, weevil.

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- Attributes:
  - **Pleasant**: caress, freedom, health, love, peace, cheer, friend, heaven, loyal, pleasure, diamond, gentle, honest, lucky, rainbow, diploma, gift, honor, miracle, sunrise, family, happy, laughter, paradise, vacation.
  - **Unpleasant**: abuse, crash, filth, murder, sickness, accident, death, grief, poison, stink, assault, disaster, hatred, pollute, tragedy, divorce, jail, poverty, ugly, cancer, kill, rotten, vomit, agony, prison.

Results (Caliskan et al 2017)

- Pleasant vs. Unpleasant?
  - Flowers vs. Insects
  - Musical instruments vs. weapons.

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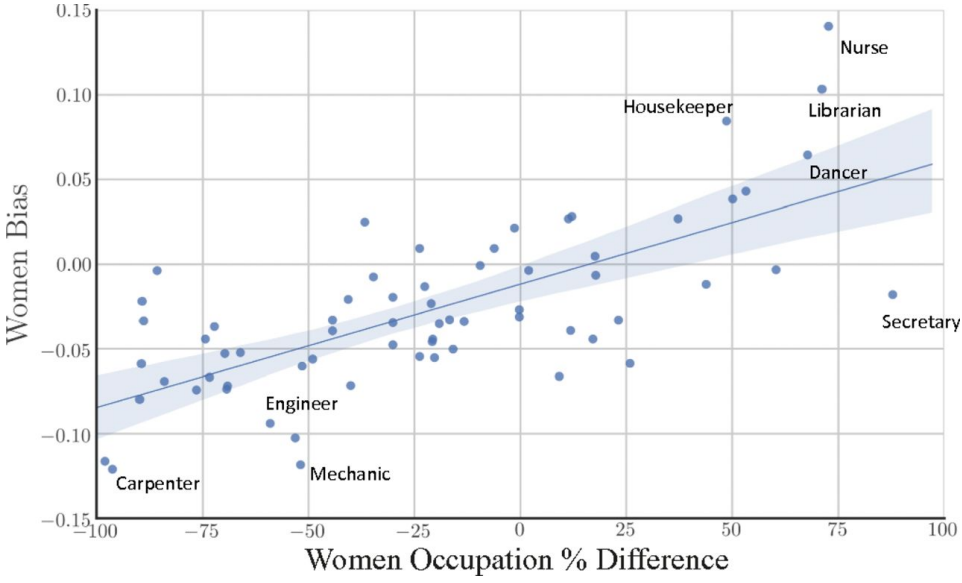
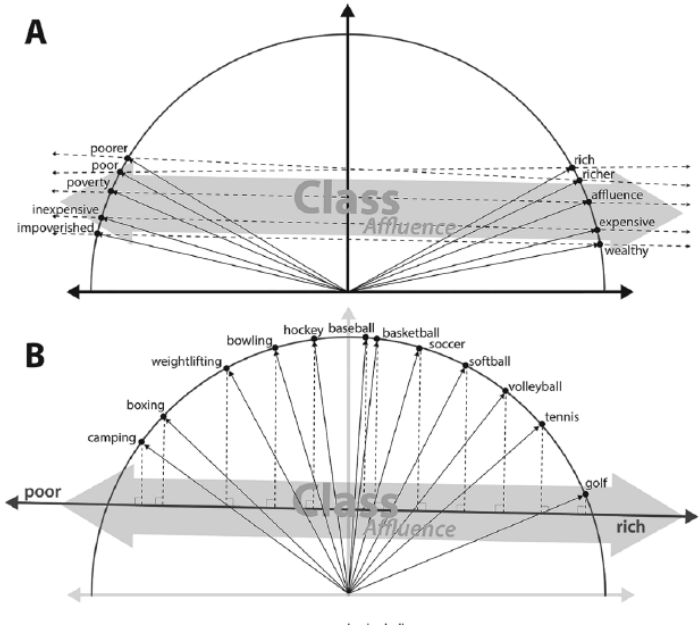
  - European-American names vs. African-American names
- Male names vs. Female names:
  - Career words (e.g. professional, corporation, ...) vs. family words (e.g. home, children, ...)
  - Math/science words vs arts words

Garg, Schiebinger, Jurafsky, and Zou (PNAS 2018)



Women's occupation relative percentage vs. embedding bias in Google News vectors.

Kozlowski, Evans, and Taddy (ASR 2019)



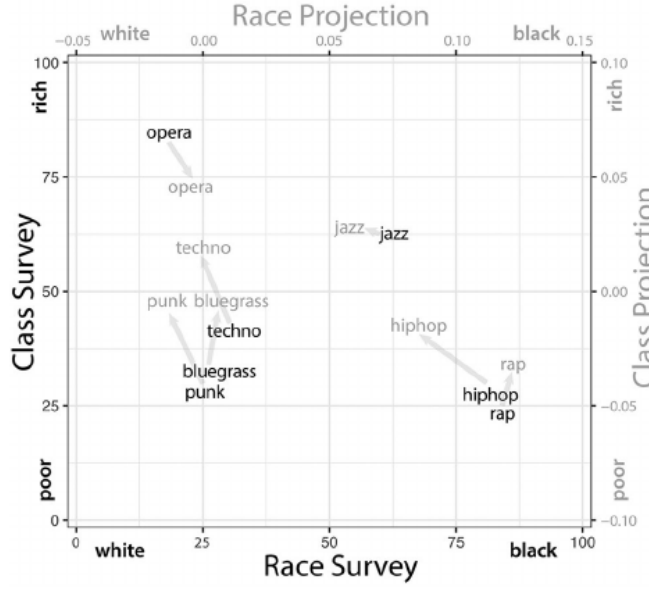


Figure 3. Projection of Music Genres onto Race and Class Dimensions of the Google News Word Embedding (Gray) and Average Survey Ratings for Race and Class Associations (Black)

Time Series Analysis of Affluence

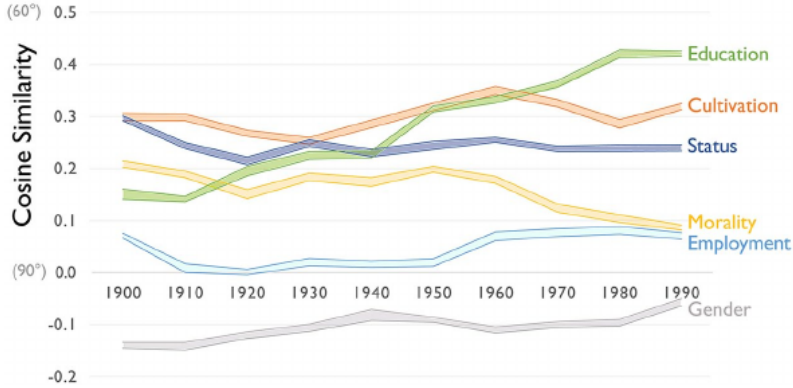


Figure 5. Cosine Similarity between the Affluence Dimension and Six Other Cultural Dimensions of Class by Decade; 1900 to 1999 Google Ngrams Corpus
Note: Bands represent 90 percent bootstrapped confidence intervals produced by subsampling.

"Among the 10 nouns most highly projecting on the affluence dimension in the first decade of the twentieth century are "fragrance," "perfume," "jewels," and "gems," ..."

Measuring stereotypical beliefs in the judiciary (Ash, Chen, and Ornaghi 2021)

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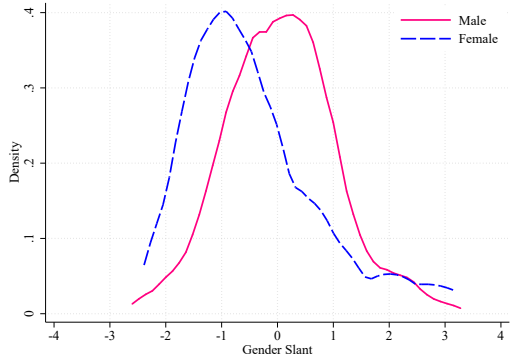
Adjectives associated with

Male and **Female**

in **judicial opinion text**.

Gender Slant, by Judge Gender



Distribution of the slant measure (cosine similarity between the gender and career-family dimensions), by judge gender. (p=0.012)

Does Gender Stereotyping Matter? (Ash, Chen, and Ornaghi 2021)

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1. It matters for **decisions**: More stereotyped judges tend to vote against expanding women's rights.

2. It matters for **treatment of colleagues**: More stereotyped judges more likely to reverse female judges and less likely to cite them.

3. It reshapes the **language of the law**, which could influence culture and society.

Outline

Vectorizing Documents

- Quantitative analysis of language requires that documents be transformed to numbers – that is, vectors.
- We started with the baseline approach: documents become sparse vectors of token counts/frequencies.
  - high-dimensionality can cause issues
  - doesnt directly capture similar meanings for related words

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- Baseline:

$$\vec{D} = \sum_{w \in D} a_w \vec{w}$$

- The "continuous bag of words" representation for document D is the sum, or the average (potentially weighted by a_w), of the vectors $\vec{w}$ for each word w in the document.
  - word vectors $\vec{w}$ constructed using Word2Vec or GloVe (pre-trained or trained on the corpus).
  - "Document" could be sentence, paragraph, section, etc.
  - set a_w to weight words by inverse term frequency or inverse document frequency (that is, up-weight rare/informative words)

Doc2Vec (Le and Mikolov)

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```
from gensim.models.doc2vec import Doc2Vec, TaggedDocument
doc_iterator = [TaggedDocument(doc, [i]) for i, doc in enumerate(docs)]
d2v = Doc2Vec(doc_iterator,
              min_count=10, # minimum word count
              window=10,    # window size
              vector_size=200, # size of document vector
              sample=1e-4,
              negative=5,
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              #dbow_words = 1 # uncomment to get word vectors too
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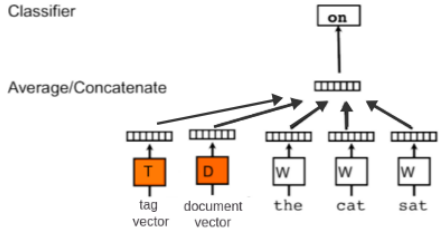
- Just as directions in word space encode semantic information about the words, directions in document space encode topical information about the documents.
- In topic models, each dimension has a topical interpretation; in document embeddings, a direction (might) have a topical interpretation.

Tagged Documents for Classifier Features

- Can add additional non-unique document "tags"; these will be embedded separately from the unique doc ID:




```
In [168]: tagged_docs[3]

Out[168]: TaggedDocument(words=['aftershere', 'project', 'finishing', 'stages', 'home', 'decor', 'kitchen', 'design', 'beforeher
          e', 'project', 'finishing', 'stages', 'home', 'decor', 'kitchen', 'design', 'afterhere', 'project', 'finishing', 'stag
          es', 'home', 'decor', 'kitchen', 'design', 'beforehere', 'project', 'finishing', 'stages', 'home', 'decor', 'kitchen',
           'design'], tags=['Remodeling & Renovating', 'SENT_3'])
```

- will improve performance if using the embeddings to classify the tag.

Doc2Vec on Wikipedia

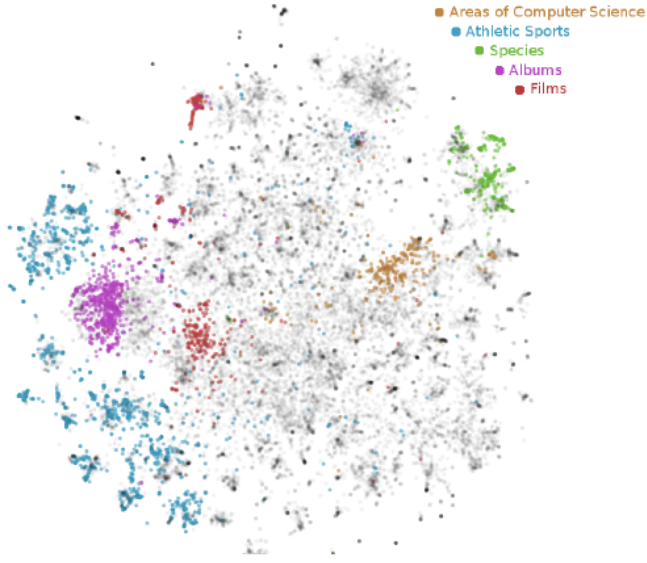


Figure 3: Visualization of Wikipedia paragraph vectors using t-SNE.

Table 5: arXiv nearest neighbours to "Distributed Representations of Sentences and Documents" using Paragraph Vectors.

Title	Cosine Similarity
Evaluating Neural Word Representations in Tensor-Based Compositional Settings	0.771
Polyglot: Distributed Word Representations for Multilingual NLP	0.764
Lexicon Infused Phrase Embeddings for Named Entity Resolution	0.757
A Convolutional Neural Network for Modelling Sentences	0.747
Distributed Representations of Words and Phrases and their Compositionality	0.740
Convolutional Neural Networks for Sentence Classification	0.735
SimLex-999: Evaluating Semantic Models With (Genuine) Similarity Estimation	0.735
Exploiting Similarities among Languages for Machine Translation	0.731
Efficient Estimation of Word Representations in Vector Space	0.727
Multilingual Distributed Representations without Word Alignment	0.721

Table 2: Wikipedia nearest neighbours

(a) Wikipedia nearest neighbours to "Lady Gaga" using Paragraph Vectors. All articles are relevant.

Article	Cosine Similarity
Christina Aguilera	0.674
Beyonce	0.645
Madonna (entertainer)	0.643
Artpop	0.640
Britney Spears	0.640
Cyndi Lauper	0.632
Rihanna	0.631
Pink (singer)	0.628
Born This Way	0.627
The Monster Ball Tour	0.620

(b) Wikipedia nearest neighbours to "Lady Gaga" - "American" + "Japanese" using Paragraph Vectors. Note that Ayumi Hamasaki is one of the most famous singers, and one of the best selling artists in Japan. She also has an album called "Poker Face" in 1998.

Article	Cosine Similarity
Ayumi Hamasaki	0.539
Shoko Nakagawa	0.531
Izumi Sakai	0.512
Urbangarde	0.505
Ringo Sheena	0.503
Toshiaki Kasuga	0.492
Chihiro Onitsuka	0.487
Namie Amuro	0.485
Yakuza (video game)	0.485
Nozomi Sasaki (model)	0.485

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- Corpus: floor speeches in U.S. Congress (House and Senate), 1858-2014
- Tokenization: stemmed nouns, adjectives, and verbs.

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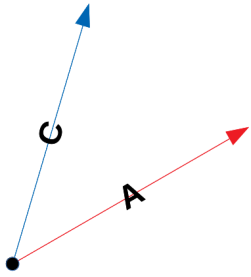
$\vec{A}$ = affective, $\vec{C}$ = cognitive centroid



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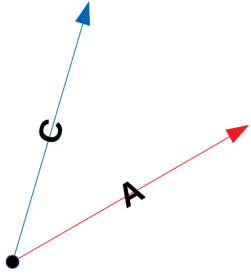
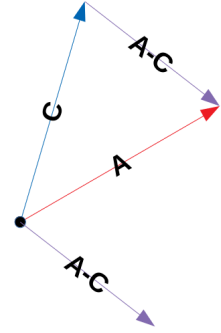
$\vec{A} - \vec{C}$ = emotion-cognition dimension





Emotionality Metric

- Construct document vector for speech i as the average of the word vectors in the speech (Arora, Liang, and Ma 2016)

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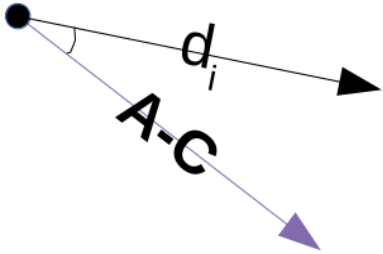

- Relative emotionality of i is **cosine similarity** to the emotion-cognition dimension:

$$Y_i = \frac{\vec{d}_i \cdot (\vec{A} - \vec{C})}{\left\|\vec{d}_i\right\| \left\|\vec{A} - \vec{C}\right\|}$$

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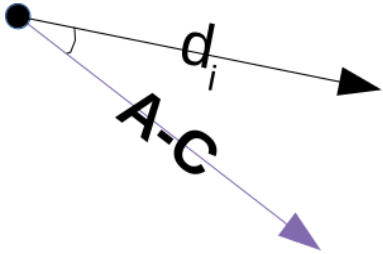

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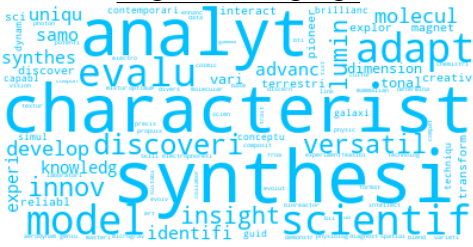
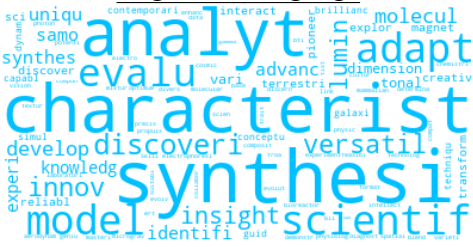
Increase in $Y_i \leftrightarrow$ shift towards emotion pole and away from cognition pole.

Cognition Language



- "In my judgment, neither is true in the case of this amendment."
- "Is that correct?"
- "R. 15 contains a provision that is similar but, in fact, broader in scope."

Cognition Language



- "In my judgment, neither is true in the case of this amendment."
- "Is that correct?"
- "R. 15 contains a provision that is similar but, in fact, broader in scope."

Emotion Language

- “With joy in his heart and a smile on his face he graced practically every social occasion with a song.”
- “We Democrats may disagree, but we love our fellow men and we never hate them.”

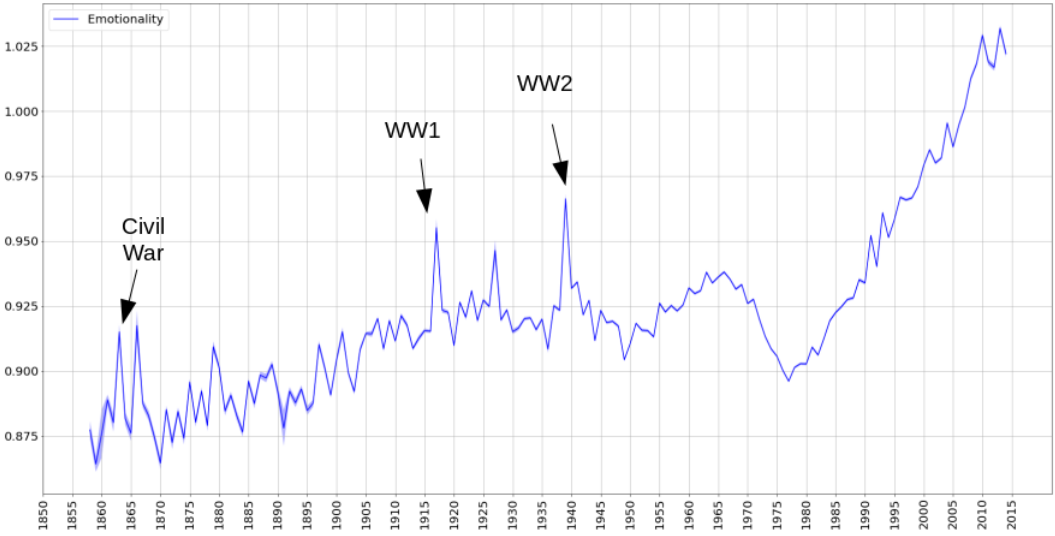
Human Validation

Table 3: HUMAN VALIDATION

	Full Sample			Restricted Sample English Comprehension			Restricted Sample Consistent Coding		
	(1) Accuracy	(2) Blank	(3) Sample	(4) Accuracy	(5) Blank	(6) Sample	(7) Accuracy	(8) Blank	(9) Sample
Panel A: Main Analysis									
Overall	**0.874**	**0.035**	**1714**	**0.923**	**0.029**	**1158**	**0.927**	**0.013**	**1388**

- the embedding measure matches human judgment much more often than a dictionary based measure.

Emotion Language in Congress, 1958-2014

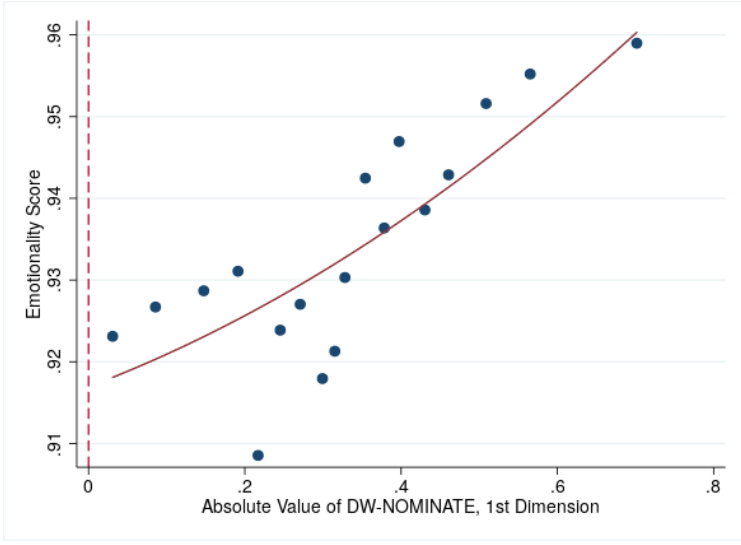


Relation to Congressman Characteristics

	(1)	(2)	(3)	(4)	(5)
	Estimated Effect on Emotionality Score				
Female	0.0516**		0.0475**	0.0489**	0.0301**
	(0.00651)		(0.00752)	(0.00645)	(0.00285)
Democrat		0.00638*	0.00502*	0.00315	0.00409**
		(0.00254)	(0.00252)	(0.00250)	(0.00136)
Female × Democrat			0.00405		
			(0.0110)		
Black				0.0282*	0.0208**
				(0.0117)	(0.00645)
Hispanic				0.0149	0.0133*
				(0.0113)	(0.00613)
Catholic				0.00953*	0.00567*
				(0.00442)	(0.00235)
Jewish				0.0109	0.00272
				(0.00780)	(0.00356)
Chamber-Year FE	X	X	X	X	X
Topic FE					X
N	5869780	5869780	5869780	5869780	5839095
adj. R^2	0.062	0.060	0.062	0.063	0.479

Std err. in parens, clustered by speaker. + p < .1, * p < .05, ** p<0.01.

Ideologically Extreme Politicians are More Emotive



Outline

Beyond Word Order

- The models we have seen so far have counted words and phrases, or embedded sequences
  - the only language structure used is the ordering of words.

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- How to identify whether the defendant was negligent?
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  - "The defendant, a driver, was negligent"
- Syntactic and semantic parsing will do this.

Dependency Grammar

- The basic idea:
  - **Syntactic structure** consists of **words**, linked by binary symmetric relations called **dependencies**.
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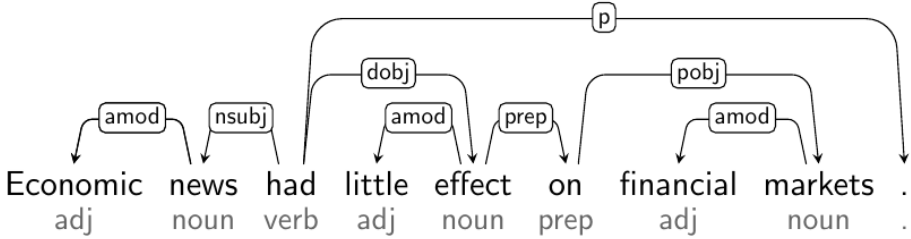

- Dependency structures represent grammatical relations between words in a sentence

dependencies in spaCy

```
for sent in doc.sents:
    print(sent)
    print(sent.root)
    print([(w, w.dep_) for w in sent.root.children])
    print()
```

```
Science cannot solve the ultimate mystery of nature.
solve
[(Science, 'nsubj'), (can, 'aux'), (not, 'neg'), (mystery, 'dobj'), (., 'punct')]

And that is because, in the last analysis, we ourselves are a part of the mystery
that we are trying to solve.
is
[(And, 'cc'), (that, 'nsubj'), (are, 'advcl'), (., 'punct')]
```

- For production, use spaCy processing pipelines (`https://spacy.io/usage/processing-pipelines`)
  - customizable and parallelizable

Unsupervised Discovery of Gendered Language (Hoyle et al 2019)

- This paper builds on the "gender bias" NLP papers by adding in syntactic information:

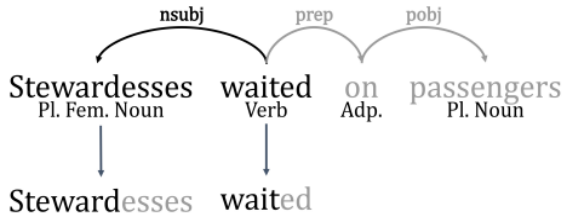

Figure 2: An example sentence with its labeled dependency parse (top) and lemmatized words (bottom).

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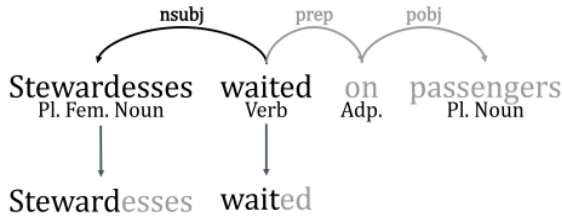

Figure 2: An example sentence with its labeled dependency parse (top) and lemmatized words (bottom).

- Corpus: dependency parse of 3.5 million books from Goldberg and Orwant (2013).
  - 37 million noun-adjective pairs
  - 41-million subject-verb pairs
  - 14 million verb-object pairs

Extracting gendered language

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Extracting gendered language

- Hoyle et al (2019) extract the set of adjectives and verbs attached to nouns that are predictive of the gender of the noun.
- Interpreting the dimensions:
  - categorize adjectives/verbs by sentiment (positive, negative, neutral)
  - categorize adjectives/verbs as related to the body and emotions.

Gendered Adjectives

$\tau_{\text{MASC-POS}}$		$\tau_{\text{MASC-NEG}}$		$\tau_{\text{MASC-NEU}}$		$\tau_{\text{FEM-POS}}$		$\tau_{\text{FEM-NEG}}$		$\tau_{\text{FEM-NEU}}$	
Adj.	Value	Adj.	Value	Adj.	Value	Adj.	Value	Adj.	Value	Adj.	Value
faithful	2.3	unjust	2.4	german	1.9	pretty	3.3	horrible	1.8	virgin	2.8
responsible	2.2	dumb	2.3	teutonic	0.8	fair	3.3	destructive	0.8	alleged	2.0
adventurous	1.9	violent	1.8	financial	2.6	beautiful	3.4	notorious	2.6	maiden	2.8
grand	2.6	weak	2.0	feudal	2.2	lovely	3.4	dreary	0.8	russian	1.9
worthy	2.2	evil	1.9	later	1.6	charming	3.1	ugly	3.2	fair	2.6
brave	2.1	stupid	1.6	austrian	1.2	sweet	2.7	weird	3.0	widowed	2.4
good	2.3	petty	2.4	feudatory	1.8	grand	2.6	harried	2.4	grand	2.1
normal	1.9	brutal	2.4	maternal	1.6	stately	3.8	diabetic	1.2	byzantine	2.6
ambitious	1.6	wicked	2.1	bavarian	1.5	attractive	3.3	discontented	0.5	fashionable	2.5
gallant	2.8	rebellious	2.1	negro	1.5	chaste	3.3	infected	2.8	aged	1.8
mighty	2.4	bad	1.9	paternal	1.4	virtuous	2.7	unmarried	2.8	topless	3.9
loyal	2.1	worthless	1.6	frankish	1.8	fertile	3.2	unequal	2.4	withered	2.9
valiant	2.8	hostile	1.9	welsh	1.7	delightful	2.9	widowed	2.4	colonial	2.8
courteous	2.6	careless	1.6	ecclesiastical	1.6	gentle	2.6	unhappy	2.4	diabetic	0.7
powerful	2.3	unsung	2.4	rural	1.4	privileged	1.4	horrid	2.2	burlesque	2.9
rational	2.1	abusive	1.5	persian	1.4	romantic	3.1	pitiful	0.8	blonde	2.9
supreme	1.9	financial	3.6	belted	1.4	enchanted	3.0	frightful	0.5	parisian	2.7
meritorious	1.5	feudal	2.5	swiss	1.3	kindly	3.2	artificial	3.2	clad	2.5
serene	1.4	false	2.3	finnish	1.1	elegant	2.8	sullen	3.1	female	2.3
godlike	2.3	feeble	1.9	national	2.2	dear	2.2	hysterical	2.8	oriental	2.2
noble	2.3	impotent	1.7	priestly	1.8	devoted	2.0	awful	2.6	ancient	1.7
rightful	1.9	dishonest	1.6	merovingian	1.6	beauteous	3.9	haughty	2.6	feminist	2.9
eager	1.9	ungrateful	1.5	capetian	1.4	sprightly	3.2	terrible	2.4	matronly	2.6
financial	3.3	unfaithful	2.6	prussian	1.4	beloved	2.5	damned	2.4	pretty	2.5
chivalrous	2.6	incompetent	1.7	racial	0.9	pleasant	1.8	topless	3.5	asiatic	2.0

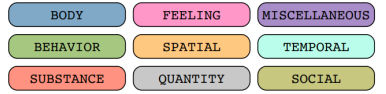
Gendered Verbs (as agent)

$\tau_{\text{MASC-POS}}$		$\tau_{\text{MASC-NEG}}$		$\tau_{\text{MASC-NEU}}$		$\tau_{\text{FEM-POS}}$		$\tau_{\text{FEM-NEG}}$		$\tau_{\text{FEM-NEU}}$	
Verb	Value	Verb	Value	Verb	Value	Verb	Value	Verb	Value	Verb	Value
succeed	1.6	fight	1.2	extend	0.7	celebrate	2.4	persecute	2.1	faint	0.7
protect	1.4	fail	1.0	found	0.8	fascinate	0.8	faint	1.0	be	1.1
favor	1.3	fear	1.0	strike	1.3	facilitate	0.7	fly	1.0	go	0.4
flourish	1.3	murder	1.5	own	1.1	marry	1.8	weep	2.3	find	0.1
prosper	1.7	shock	1.6	collect	1.1	smile	1.8	harm	2.2	fly	0.4
support	1.5	blind	1.6	set	0.8	fan	0.8	wear	2.0	fall	0.1
promise	1.5	forbid	1.5	wag	1.0	kiss	1.8	mourn	1.7	wear	0.9
welcome	1.5	kill	1.3	present	0.9	champion	2.2	gasp	1.1	leave	0.7
favour	1.2	protest	1.3	pretend	1.1	adore	2.0	fatigue	0.7	fell	0.1
clear	1.9	cheat	1.3	prostrate	1.1	dance	1.7	scold	1.8	vanish	1.3
reward	1.8	fake	0.8	want	0.9	laugh	1.6	scream	2.1	come	0.7
appeal	1.6	deprive	1.5	create	0.9	have	1.4	confess	1.7	fertilize	0.6
encourage	1.5	threaten	1.3	pay	1.1	play	1.0	get	0.5	flush	0.5
allow	1.5	frustrate	0.9	prompt	1.0	give	0.8	gossip	2.0	spin	1.6
respect	1.5	fright	0.9	brazen	1.0	like	1.8	worry	1.8	dress	1.4
comfort	1.4	temper	1.4	tarry	0.7	giggle	1.4	be	1.3	fill	0.2
treat	1.3	horrify	1.4	front	0.5	extol	0.6	fail	0.4	fee	0.2
brave	1.7	neglect	1.4	flush	0.3	compassionate	1.9	fight	0.4	extend	0.1
rescue	1.5	argue	1.3	reach	0.9	live	1.4	fake	0.3	sniff	1.6
win	1.5	denounce	1.3	escape	0.8	free	0.9	overrun	2.4	celebrate	1.1
warm	1.5	concern	1.2	gi	0.7	felicitate	0.6	hurt	1.8	clap	1.1
praise	1.4	expel	1.7	rush	0.6	mature	2.2	complain	1.7	appear	0.9
fit	1.4	dispute	1.5	duplicate	0.5	exalt	1.7	lament	1.5	gi	0.8
wish	1.4	obscure	1.4	incarnate	0.5	surpass	1.7	fertilize	0.5	have	0.5
grant	1.3	damn	1.4	freeze	0.5	meet	1.1	feign	0.5	front	0.5

Gendered Verbs (as patient)

$\tau_{\text{MASC-POS}}$		$\tau_{\text{MASC-NEG}}$		$\tau_{\text{MASC-NEU}}$		$\tau_{\text{FEM-POS}}$		$\tau_{\text{FEM-NEG}}$		$\tau_{\text{FEM-NEU}}$	
Verb	Value	Verb	Value	Verb	Value	Verb	Value	Verb	Value	Verb	Value
praise	1.7	fight	1.8	set	1.5	marry	2.3	forbid	1.3	have	1.0
thank	1.7	expel	1.8	pay	1.2	assure	3.4	shame	2.5	expose	0.8
succeed	1.7	fear	1.6	escape	0.4	escort	1.2	escort	1.3	escort	1.4
exalt	1.2	defeat	2.4	use	2.1	exclaim	1.0	exploit	0.9	pour	2.1
reward	1.8	fail	1.3	expel	0.9	play	2.7	drag	2.1	marry	1.3
commend	1.7	bribe	1.8	summon	1.7	pour	2.6	suffer	2.2	take	1.1
fit	1.4	kill	1.6	speak	1.3	create	2.0	shock	2.1	assure	1.6
glorify	2.0	deny	1.5	shop	2.6	have	1.8	fright	2.4	fertilize	1.6
honor	1.6	murder	1.7	excommunicate	1.3	fertilize	1.8	steal	2.0	ask	1.0
welcome	1.9	depose	2.3	direct	1.1	eye	0.9	insult	1.8	exclaim	0.6
gentle	1.8	summon	2.0	await	0.9	woo	3.3	fertilize	1.6	strut	2.3
inspire	1.7	order	1.9	equal	0.4	strut	3.1	violate	2.4	burn	1.7
enrich	1.7	denounce	1.7	appoint	1.7	kiss	2.6	tease	2.3	rear	1.5
uphold	1.5	deprive	1.6	animate	1.1	protect	2.1	terrify	2.1	feature	0.9
appease	1.5	mock	1.6	follow	0.7	win	2.0	persecute	2.1	visit	1.3
join	1.4	destroy	1.5	depose	1.8	excel	1.6	cry	1.8	saw	1.3
congratulate	1.3	deceive	1.7	want	1.1	treat	2.3	expose	1.3	exchange	0.8
extol	1.1	bore	1.6	reach	0.9	like	2.2	burn	2.6	shame	1.6
respect	1.7	bully	1.5	found	0.8	entertain	2.0	scare	2.0	fade	1.2
brave	1.7	enrage	1.4	exempt	0.4	espouse	1.4	frighten	1.8	signal	1.2
greet	1.6	shop	2.7	tip	1.8	feature	1.2	distract	2.3	see	1.2
restore	1.5	elect	2.2	elect	1.7	meet	2.2	weep	2.3	present	1.0
clear	1.5	compel	2.1	unmake	1.5	wish	1.9	scream	2.3	leave	0.8
excite	1.2	offend	1.5	fight	1.2	fondle	1.9	drown	2.1	espouse	1.3
flatter	0.9	scold	1.4	prevent	1.1	saw	1.8	rape	2.0	want	1.1

Female		Male	
Positive	Negative	Positive	Negative
beautiful	battered	just	unsuitable
lovely	untreated	sound	unreliable
chaste	barren	righteous	lawless
gorgeous	shrewish	rational	inseparable
fertile	sheltered	peaceable	brutish
beauteous	heartbroken	prodigious	idle
sexy	unmarried	brave	unarmed
classy	undernourished	paramount	wounded
exquisite	underweight	reliable	bigoted
vivacious	uncomplaining	sinless	unjust
vibrant	nagging	honorable	brutal

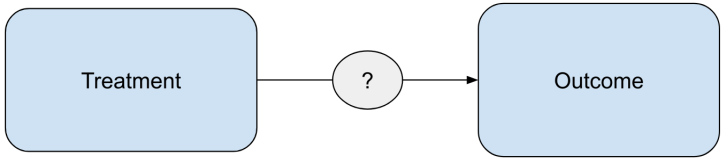


- Female nouns were correlated with adjectives/verbs related to the body and to emotions.

Outline

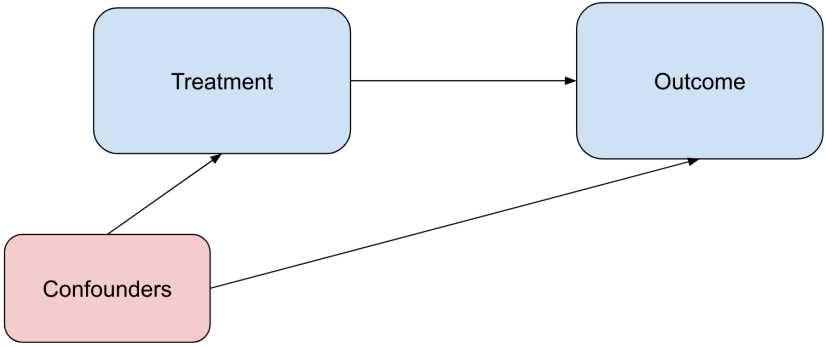
Outline

Causal Graphs



- In social science, we are interested in estimating a causal effect (if any) of a "treatment" on an "outcome".

- ***Unobserved Confounders*** are variables that affect both the treatment and the outcome, which we don't have in our dataset:



- **Observed confounders** are not a problem, because we can adjust (control) for them in causal inference analysis (that is, including them in a regression).

- **Reverse (or joint) causation**: "the outcome" affects "the "treatment".

- e.g., effect of tax collections on economic growth.
- Resulting estimates are biased (not causal), and cannot be fixed by adjusting for observed confounders.

With joint causality, or with unobserved confounders, it is often impossible to produce statistical estimates with a causal interpretation.

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- The gold standard: randomized control trials.
  - often not available – e.g., randomly assigning a politician to be Democrat or Republican on a given day.

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- The gold standard: randomized control trials.
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- Second best: natural experiments.
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  - instrumental variables: use a third variable ("instrument") that randomly shifts the probability of treatment.

Fong and Grimmer (2016): Causal effect of political messaging

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- What biographical characteristics of politicians influence voter evaluations?
- Could run a survey experiment:
  - `Document 1: He earned his Juris Doctor in 1997 from Yale Law School, where he operated free legal clinics for low-income residents of New Haven, Connecticut...`
  - `Document 2: He served in South Vietnam from 1970 to 1971 during the Vietnam War in the Army Rangers' 75th Ranger Regiment, attached to the 173rd Airborne Brigade. He participated in 24 helicopter assaults...`
- But hard to generalize what features drive differences without running a huge survey where each feature is permuted.

Fong and Grimmer (2016): Approach

- Lab experiment: 1,886 participants, 5,303 responses

1. Randomly assign texts, X_i , to respondents i
   - Sees up to 3 texts from the corpus of $>$ 2200 Wikipedia biographies
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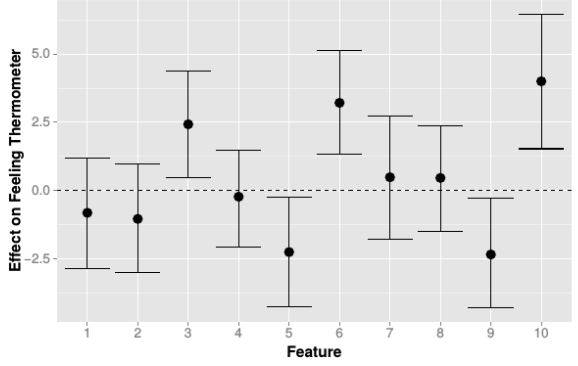
4. Measure causal effects of these treatments on Y_i

Fong and Grimmer (2016): Results

Treatment	Keywords
3	director, university, received, president, phd, policy
5	elected, house, democratic, seat
6	united_states, military, combat, rank
9	law, school_law, law_school, juris_doctor, student
10	war, enlisted, united_states, assigned, army



Outline

Bias in NLP Systems

Sentiment Analysis

```
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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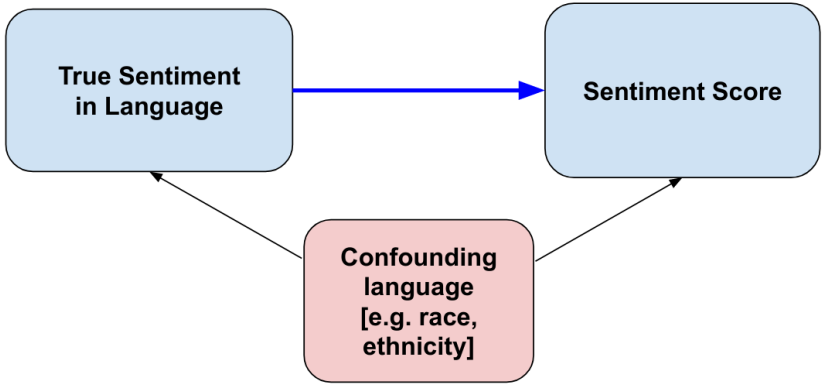
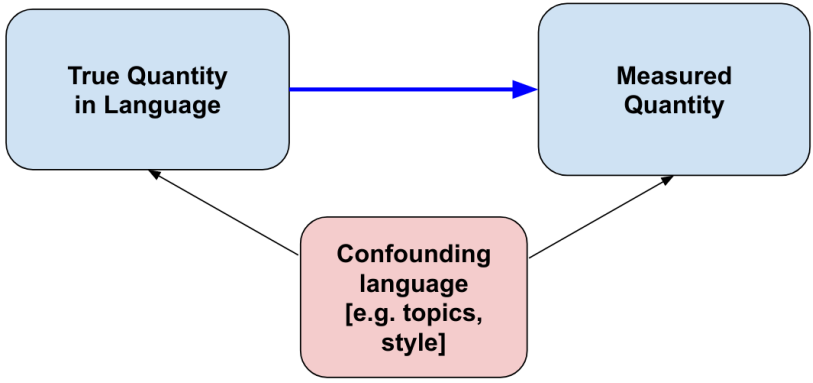


- Supervised sentiment models are confounded by correlated language factors.
  - e.g., in the training set maybe people complain about Mexican food more often than Italian food.

This is a universal problem



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- unsupervised models (topic models, word embeddings) learn correlations between topics / contexts.

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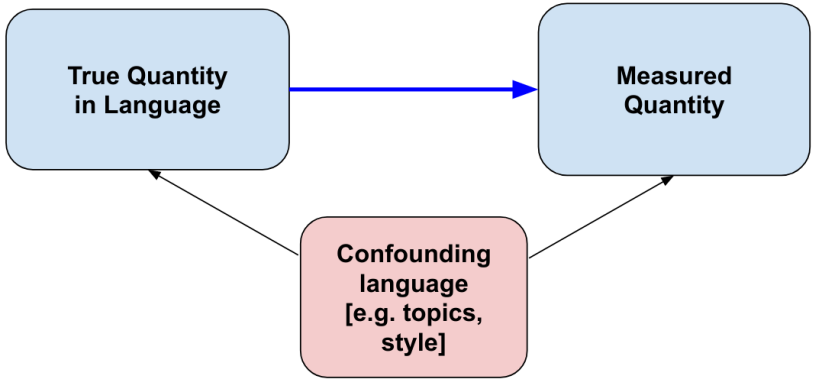

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- unsupervised models (topic models, word embeddings) learn correlations between topics / contexts.
- Note: dictionary methods are less prone to this (perhaps explaining why they are often used by economists), but they have other serious limitations.

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- Policy priorities → predicted probability of speeches/laws being about a particular policy topic.

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When is measurement confounding important?

- By itself, producing measurements that are biased by confounders might not be a problem.
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  - but would matter a lot for summary statistics in a new domain [e.g., Congress vs Fox News]
- even in domain, will matter for assessing the causal effect of a treatment, e.g. the electoral cycle:
  - elections might cause politicians to focus on social issues rather than economic issues,
  - if social/economic issues are confounded with partisanship, the resulting estimates are biased.

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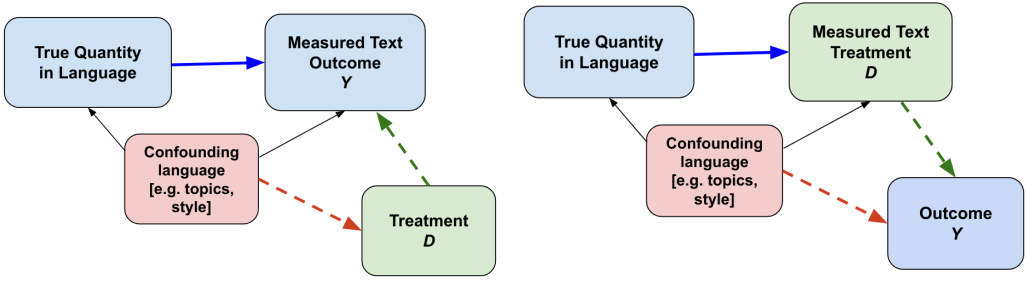

- When text is outcome, the confounders cannot be correlated with the treatment.
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  - e.g.: estimating the effect of politician speech sentiment on his/her reelection chances.