Statistical Machine Learning for Large and Unstructured Data

Intro to Unstructured Data and Bag-of-Words Model

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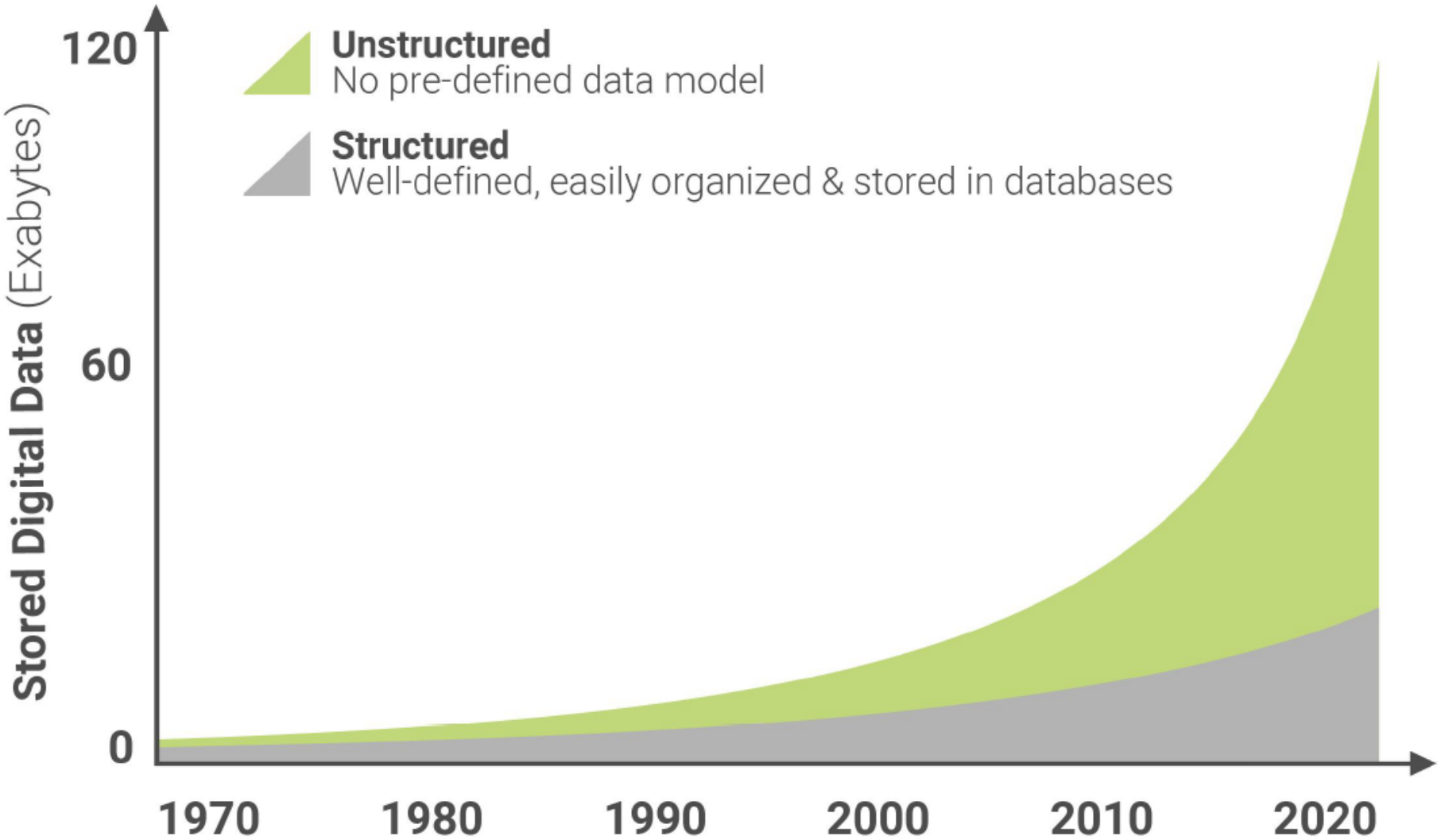
Trends in Data Types



Unstructured Data

Unstructured data does not come organized in a traditional relational database.

Extracting relevant information and separating it from irrelevant information is a primary challenge.

Examples:

1. Text
2. Audio
3. Images
4. Videos

Happenstance Data[1]

Traditional economic data is constructed with a particular measurement in mind, e.g. GDP statistics.

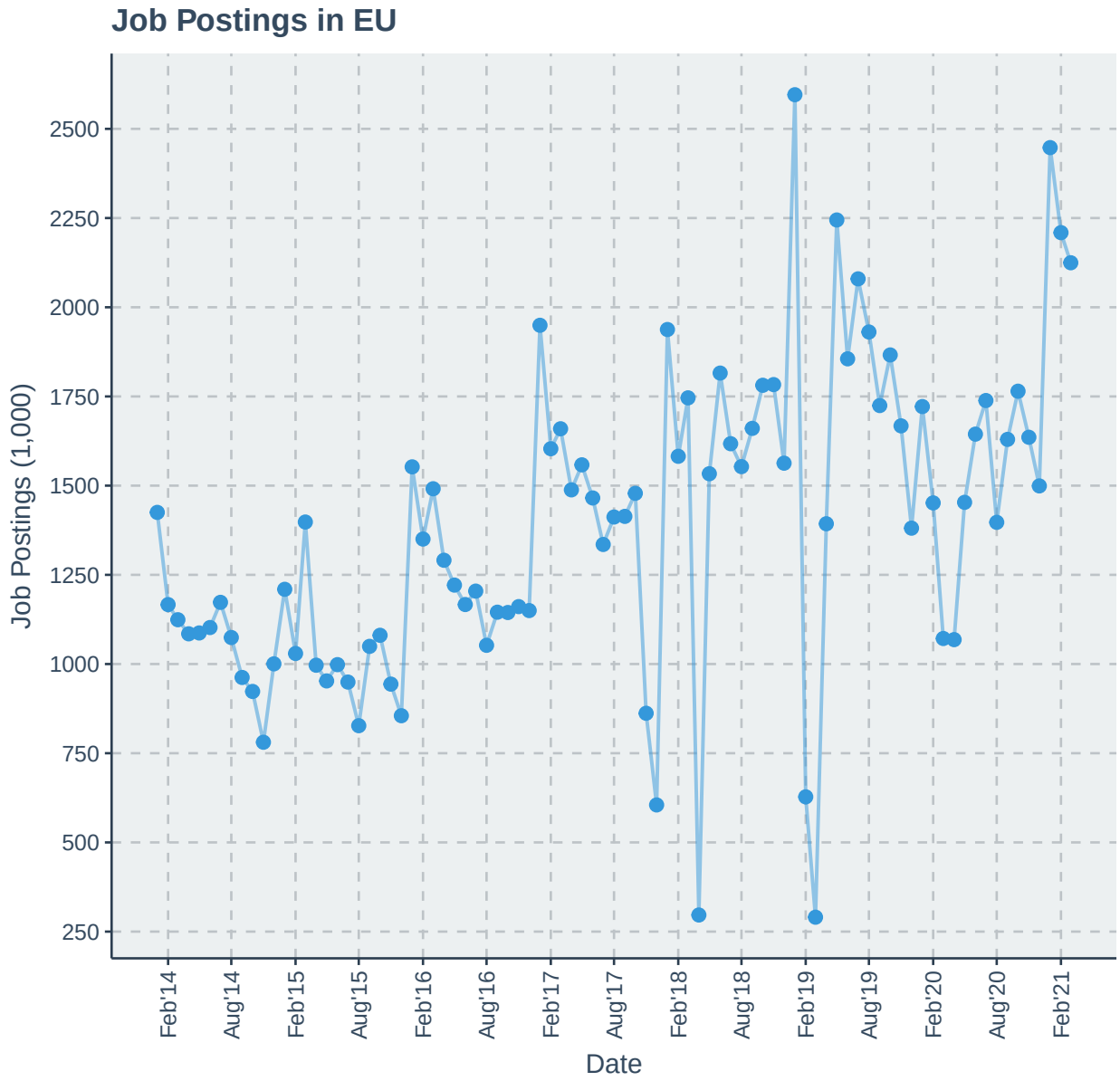
Most data generated in the private sector is happenstance, and arises via the everyday activities of agents ("digital exhaust").

Statistical challenge is that data is not collected with a consistent, representative sample frame.

Organizational challenge is that data access arrangements have yet to be normalized.

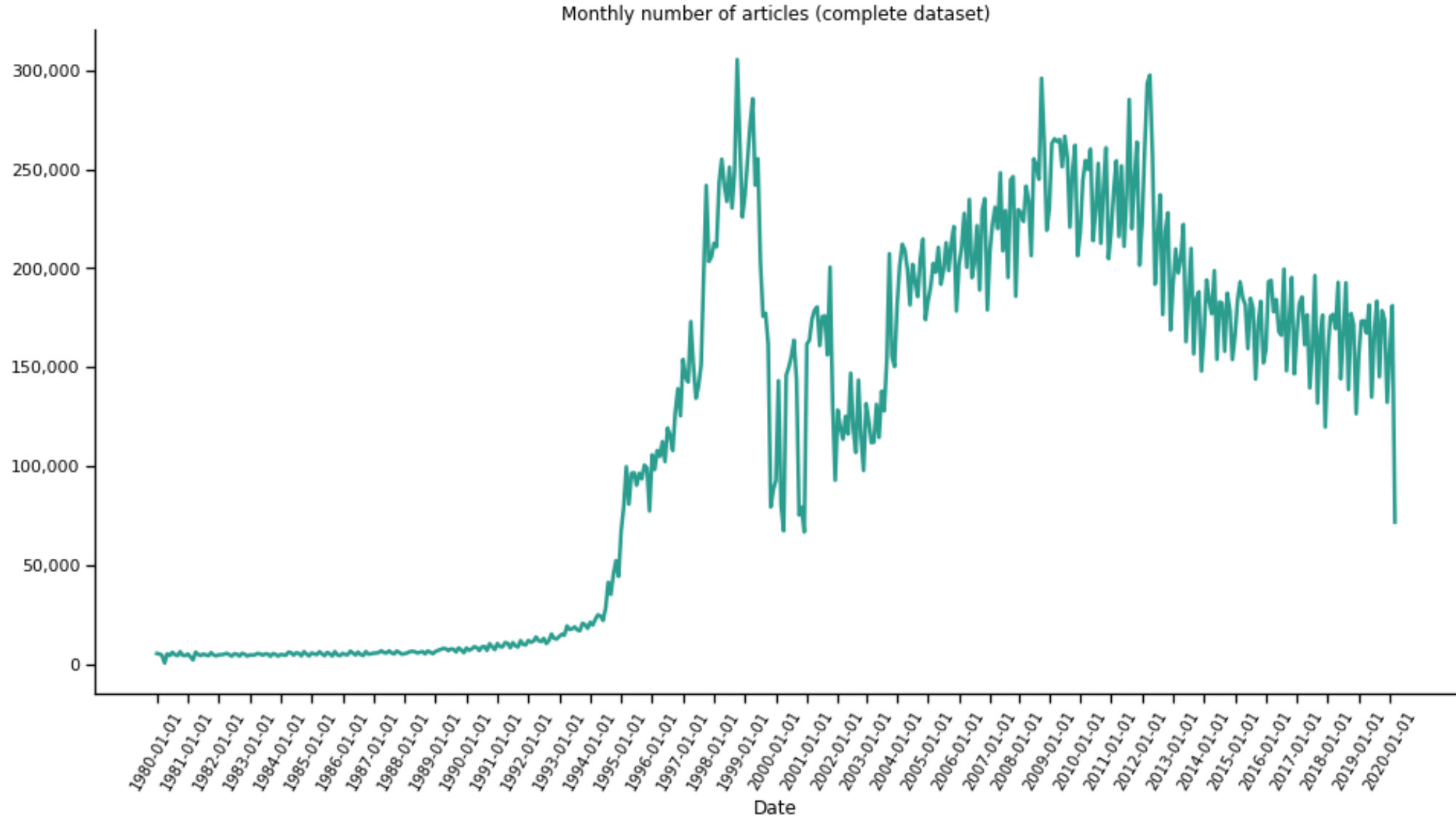
[1] Discussed more fully in `https://rs-delve.github.io/reports/2020/11/24/data-readiness-lessons-from-an-emergency.html`

Monthly Online Job Postings



Source: Web−scraped Job Ads from EU27 Countries, provided by Burning Glass Technologies.

Monthly Newswire Postings



Unstructured vs Happenstance Data

	Administrative	Happenstance
Structured	Traditional Economic Data	Credit Card Transactions Amazon product ratings
Unstructured	10-K Filings FOMC press conferences	Tweets Online Job Postings

What is the Value of Unstructured Data?

The main application of unstructured data in economics and related disciplines has been to measure important phenomena.

Can complement existing measures: e.g. build more granular versions of official data.

Or create entirely new measures: economic policy uncertainty, media slant, central bank communication.

Makes information retrieval methods useful in a wide variety of fields.

This Mini-Course

1. Bag-of-words model
2. Factor models for discrete data (aka topic models)
3. Neural language models (time permitting)

What is Text?

At an abstract level, text is simply a string of characters.

Some of these may be from the Latin alphabet—'a', 'A', 'p' and so on—but there may also be:

1. Decorated Latin letters (e.g. ö)
2. Non-Latin alphabetic characters (e.g. Chinese and Arabic)
3. Punctuation (e.g. '!')
4. White spaces, tabs, newlines
5. Numbers
6. Non-alphanumeric characters (e.g. '@')

Key Question: How can we obtain an informative, quantitative representation of these character strings?

First step is to pre-process strings to convert them into lists of units of meaning, sometimes called tokens.

We delay discussion of pre-processing steps for the first practical class. See also [Denny and Spirling, 2018].

Notation

The corpus is composed of D documents indexed by d.

After pre-processing, each document is a finite, length-N_d list of terms $\mathbf{w}_d = (w_{d,1}, \ldots, w_{d,N_d})$ with generic element $w_{d,n}$.

Let $\mathbf{w} = (\mathbf{w}_1, \ldots, \mathbf{w}_D)$ be a list of all terms in the corpus, and let $N \equiv \sum_d N_d$ be the total number of terms in the corpus.

Suppose there are V **unique** terms in $\mathbf{w}$, where $1 \leq V \leq N$, each indexed by v.

We can then map each term in the corpus into this index, so that $w_{d,n} \in \{1, \ldots, V\}$.

Let $x_{d,v}$ be the count of term v in document d.

Example

Consider three documents:

1. 'stephen is nice'
2. 'john is also nice'
3. 'george is mean'

We can consider the set of unique terms as $\{\text{stephen}, \text{is}, \text{nice}, \text{john}, \text{also}, \text{george}, \text{mean}\}$ so that $V = 7$.

Construct the following index:

stephen	is	nice	john	also	george	mean
1	2	3	4	5	6	7

We then have $\mathbf{w}_1 = (1, 2, 3)$; $\mathbf{w}_2 = (4, 2, 5, 3)$; $\mathbf{w}_3 = (6, 2, 7)$.

Moreover $x_{1,1} = 1$, $x_{2,1} = 0$, $x_{3,1} = 0$, etc.

Bag-of-Words Model

Document-Term Matrix

A popular quantitative representation of text is the *document-term matrix* $\mathbf{X}$, which collects the counts $x_{d,v}$ into a $D \times V$ matrix.

In the previous example, we have

$$\mathbf{X} = \begin{bmatrix} 1 & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 1 & 1 \end{bmatrix}$$

Real-World Example

In "Transparency and Deliberation" we use a corpus of verbatim FOMC transcripts from the era of Alan Greenspan:

- 149 meetings from August 1987 through January 2006.
- A document is a single statement by a speaker in a meeting (46,502).
- Associated metadata: speaker biographical information, macroeconomic conditions, etc.

Executive Time Use Project

Data on each 15-minute block of time for one week of 1,114 CEOs' time classified according to

1. type (e.g. meeting, public event, etc.)
2. duration (15m, 30m, etc.)
3. planning (planned or unplanned)
4. number of participants (one, more than one)
5. functions of participants, divided between employees of the firms or "insiders" (finance, marketing, etc.) and "outsiders" (clients, banks, etc.).

There are 4,253 unique combinations of these five features in the data.

One can summarize the data with a 1114×4253 matrix where the (i, j)th element is the number of 15-minute time blocks that CEO i spends in activities with a particular combination of features j.

Other Examples

Network data can be represented by an adjacency matrix which is typically high dimensional, sparse, and discrete.

Bag-of-visual words model in image processing.

Overview

We now proceed to analyze the document-term matrix in three ways:

1. Distance between documents.
2. Basic statistical model of documents with no covariate dependence.
3. Statistical model of documents with covariate dependence.

Document Similarity

Documents as Vectors

We can view the documents that make up the rows of $\mathbf{X}$ as vectors.

Let each vocabulary term v have its own vector $\mathbf{e}_v \in \mathbb{R}^V$ where

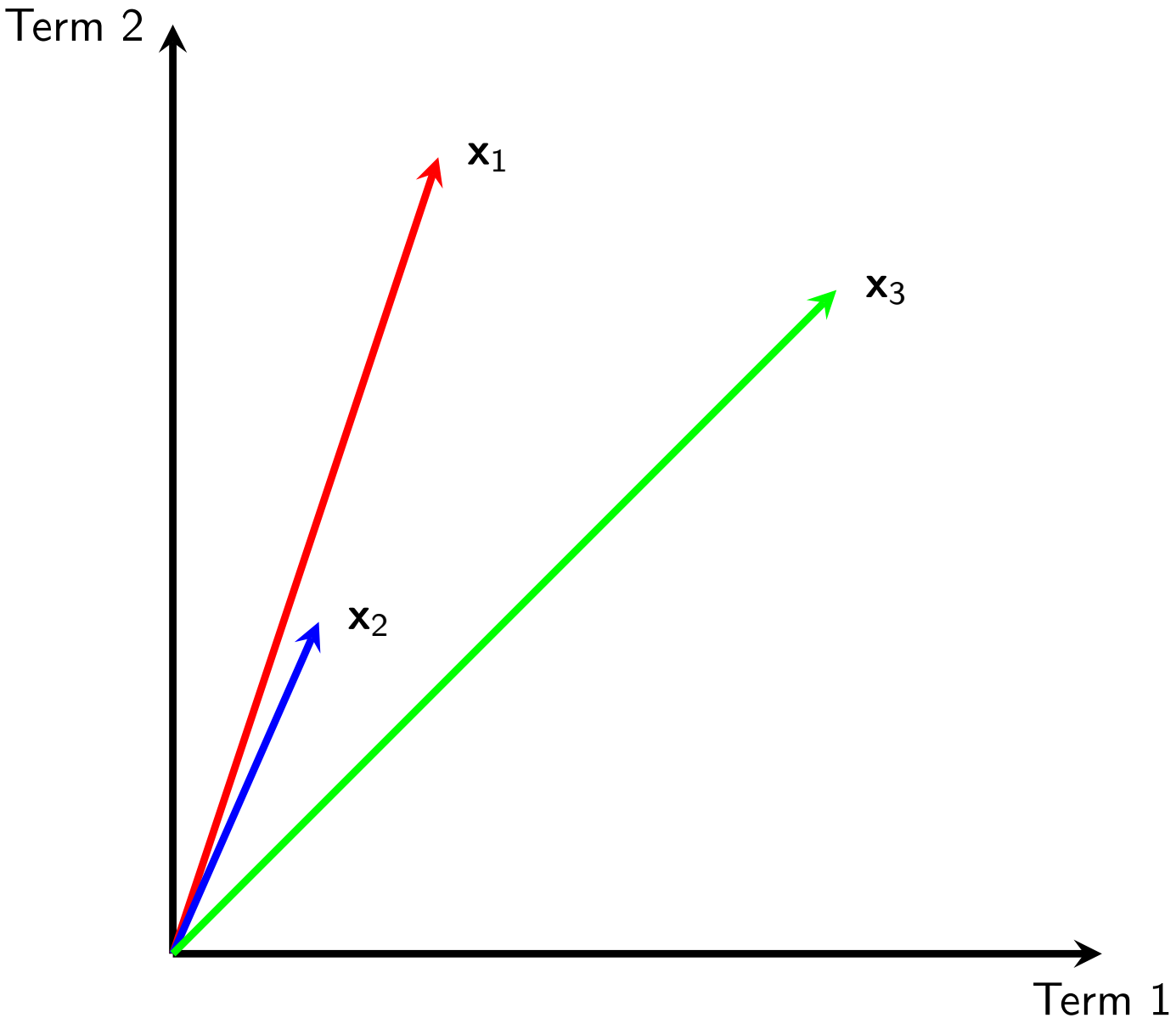
$$e_{v,v'} = \begin{cases} 1 & \text{if } v = v' \\ 0 & \text{otherwise} \end{cases}$$

Note that each term's vector is orthogonal to every other term's vector.

We can express document d as

$$\mathbf{x}_d = x_{d,1}\mathbf{e}_1 + x_{d,2}\mathbf{e}_2 + \ldots + x_{d,V}\mathbf{e}_V$$

Three Documents



Distance in the Vector Space

An initial question of interest is how similar are any two documents in the vector space.

Initial instinct might be to use Euclidean distance $\sqrt{\sum_v (x_{i,v} - x_{j,v})^2}$.

What is the problem with Euclidean distance? How can we correct this?

Cosine Similarity

Define the cosine similarity between documents i and j as

$$CS(i,j) = \frac{\mathbf{x}_i \cdot \mathbf{x}_j}{\|\mathbf{x}_i\| \, \|\mathbf{x}_j\|}$$

1. Since document vectors have no negative elements $CS(i,j) \in [0,1]$.
2. $\mathbf{x}_i / \|\mathbf{x}_i\|$ is unit-length, correction for different distances.

Application

An important theoretical concept in industrial organization is location on a product space.

Industry classification measures are quite crude proxies of this.

[Hoberg and Phillips, 2010] and [Hoberg and Phillips, 2016] take product descriptions from 49,408 10-K filings and use the vector space model to compute similarity between firms.

Data available from `http://alex2.umd.edu/industrydata/`.

Application

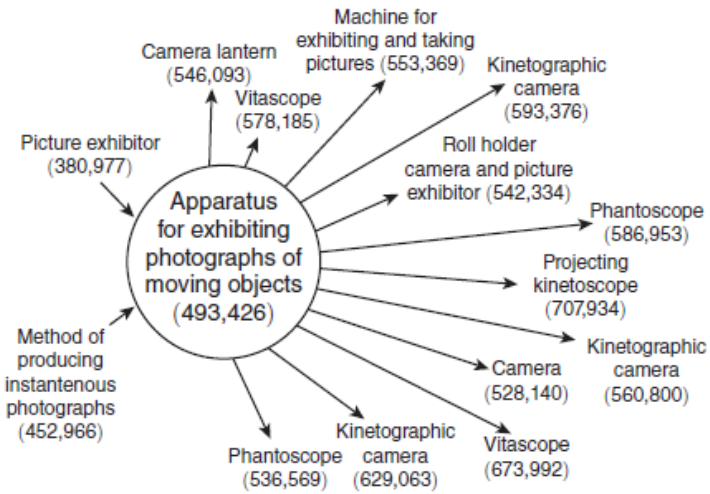
[Kelly et al., 2021] uses the text of US patents to identify radical innovation.

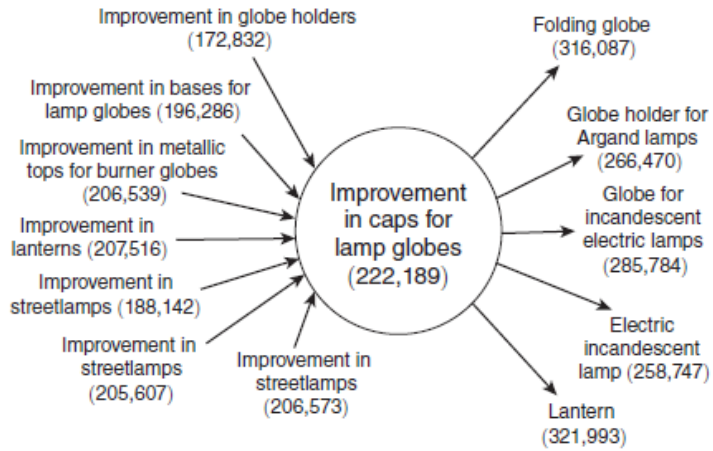
An individual patent is said to be influential when its backward similarity is low and its forward similarity is high.

Apply tf-idf weighting.

Measure validated with historically important patents, forward citations, market value.

Similarity Networks





Basic Statistical Model

Simple Probability Model

Consider the list of terms $\mathbf{x} = (w_1, \ldots, w_N)$ where $w_n \in \{1, \ldots, V\}$.

Suppose that each term is iid, and that $\Pr[\, w_n = v \,] = \beta_v \in [0, 1]$.

Let $\mathbf{x}$ be vector of term counts associated with $\mathbf{x}$, where x_v is count of term v.

Given the above data generating process, we obtain

$$\mathbf{x} \sim \text{Multinomial}(\boldsymbol{\beta}, N)$$

where $\boldsymbol{\beta} = (\beta_1, \ldots, \beta_V) \in \Delta^{V-1}$ is a vector of multinomial probabilities.

Maximum Likelihood Inference

We focus on the problem of inferring $\boldsymbol{\beta}$ from the observed data $\mathbf{x}$. The likelihood function is

$$\Pr[\mathbf{x} \mid \boldsymbol{\beta}] = \prod_v \beta_v^{x_v}$$

The Lagrangian for the MLE problem is

$$\mathfrak{L}(\boldsymbol{\beta}, \lambda) = \underbrace{\sum_v x_v \log(\beta_v)}_{\text{log-likelihood}} + \lambda \underbrace{\left(1 - \sum_v \beta_v\right)}_{\text{Constraint on } \boldsymbol{\beta}}.$$

First order condition is $\frac{x_v}{\beta_v} - \lambda = 0 \Rightarrow \beta_v = \frac{x_v}{\lambda}$.

Constraint gives $\frac{\sum_v x_v}{\lambda} = 1 \Rightarrow \lambda = \sum_v x_v = N$.

So MLE estimate is $\widehat{\beta}_v = \frac{x_v}{N}$, the empirical frequency of term v.

Implications of MLE

Suppose you do not speak Portuguese, but someone lists for you 10,000 possible words the spoken language might contain.

You are then shown a single snippet of text 'eles bebem'. The parameters that best explain this data put $1/2$ probability each on 'eles' and on 'bebem' and 0 on every other possible word.

Is this a reasonable model? We 'know' that working languages contain hundreds of regularly spoken words; we 'know' that the distribution of word frequencies is highly skewed; we 'know' that the language is similar to Spanish, and should inherit a similar frequency distribution; and so on.

The MLE estimates relies solely on the data we observe.

Bayes' Rule

Bayesian inference is operationalized via the application of Bayes' rule:

$$p(\boldsymbol{\beta} \mid \mathbf{x}) = \frac{p(\mathbf{x} \mid \boldsymbol{\beta})\, p(\boldsymbol{\beta})}{p(\mathbf{x})}$$

where:

- $p(\boldsymbol{\beta} \mid \mathbf{x})$ is the *posterior distribution*.
- $p(\mathbf{x} \mid \boldsymbol{\beta})$ is the *likelihood function*.
- $p(\boldsymbol{\beta})$ is the *prior distribution* on the parameter vector.
- $p(\mathbf{x})$ is a normalizing constant sometimes called the *evidence*.

The prior is often parametrized by *hyperparameters*.

What is a Bayesian Estimate?

There are several ways of reporting the Bayesian estimate of $\boldsymbol{\beta}$:

1. MAP estimate is the value at which the posterior distribution is highest, i.e. its mode.
2. Expected value of $\boldsymbol{\beta}$ under the posterior.
3. Compute credible interval $\Pr[\boldsymbol{\beta} \in A \mid \mathbf{x}]$ for some set A.

All of these depend fundamentally on the posterior distribution.

If we can compute the posterior, we can do Bayesian inference.

Dirichlet Distribution

The Dirichlet distribution is parametrized by $\boldsymbol{\eta} = (\eta_1, \ldots, \eta_V)$; is defined on the $V-1$ simplex; and has probability density function

$$\text{Dir}(\boldsymbol{\beta} \mid \boldsymbol{\eta}) \propto \prod_v \beta_v^{\eta_v - 1}.$$

The normalization constant is $B(\boldsymbol{\eta}) \equiv \prod_{v=1}^{V} \Gamma(\eta_v) / \Gamma\left(\sum_{v=1}^{V} \eta_v\right)$.

Marginal distribution is

$$\beta_v \sim \text{Beta}(\eta_v, \sum_v \eta_v - \eta_v)$$

Mean and variance are

$$\mathbb{E}[\,\beta_v\,] = \frac{\eta_v}{\sum_v \eta_v} \text{ and } V[\,\beta_v\,] = \frac{\eta_v(\sum_v \eta_v - \eta_v)}{(\sum_v \eta_v)^2(\sum_v \eta_v + 1)}.$$

Interpreting the Dirichlet

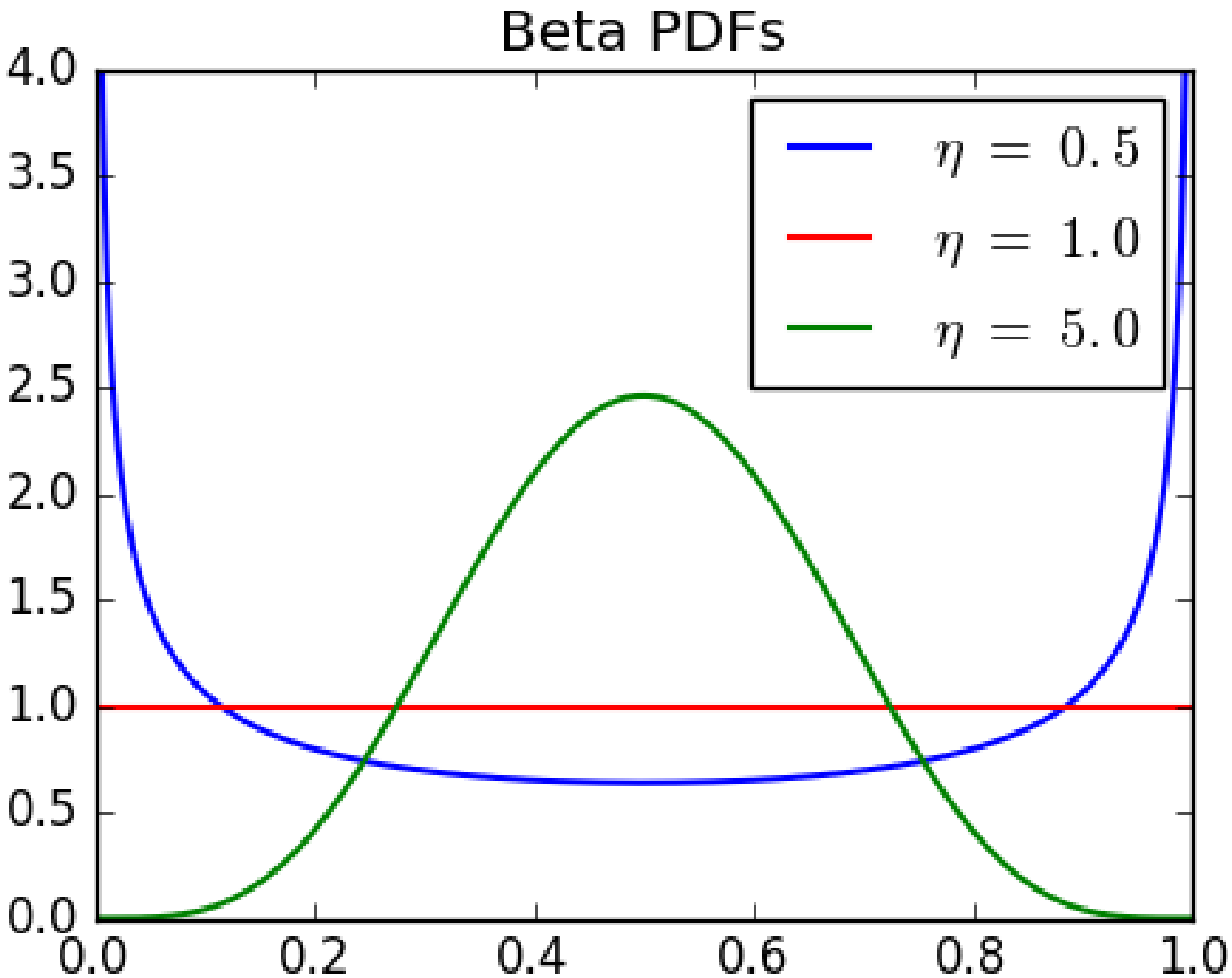
Consider a symmetric Dirichlet in which $\eta_v = \eta$ for all v. Agnostic about favoring one component over another.

Here the η parameter measures the concentration of distribution on the center of the simplex, where the mass on each term is more evenly spread:

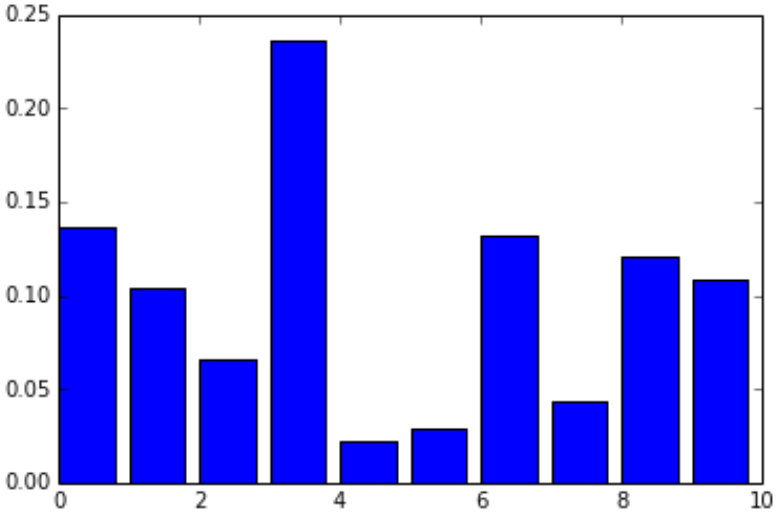
1. $\eta = 1$ is a uniform distribution.
2. $\eta > 1$ puts relatively more weight in center of simplex.
3. $\eta < 1$ puts relatively more weight on corners of simplex.

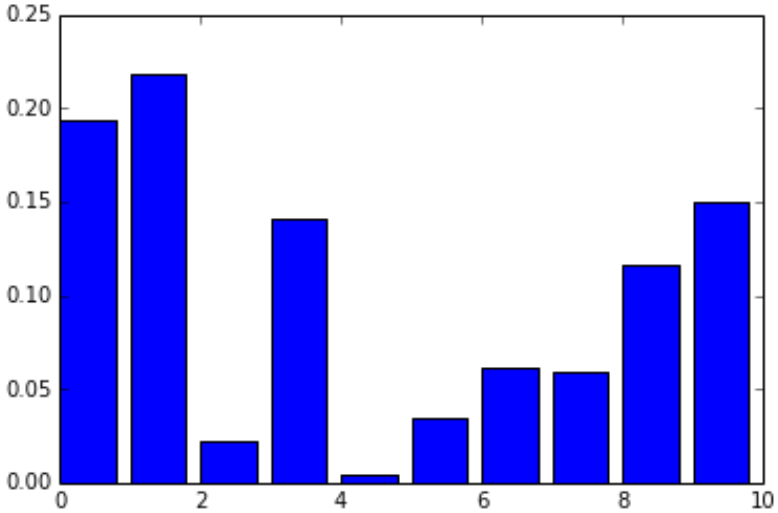
When $V = 2$, the Dirichlet becomes the beta distribution.

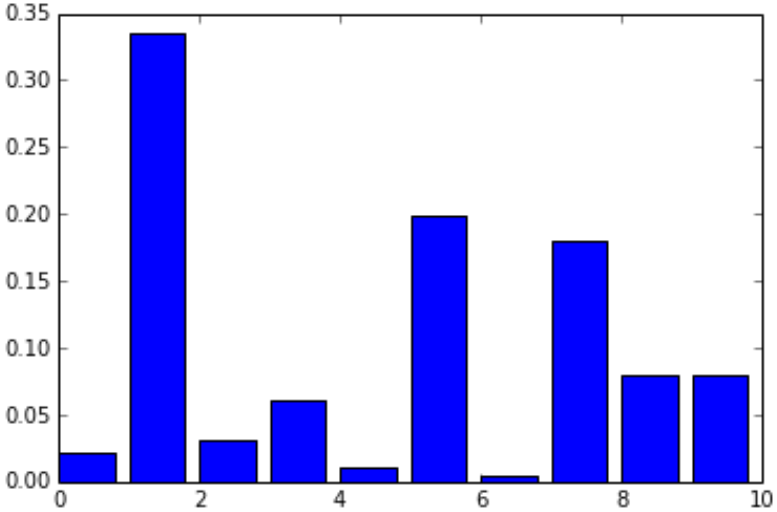
Beta with Different Parameters

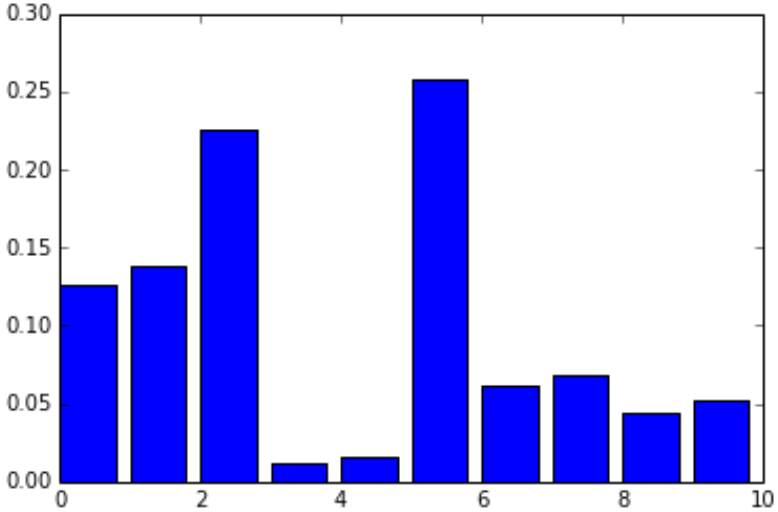


Draws from Dirichlet with $\eta = 1$

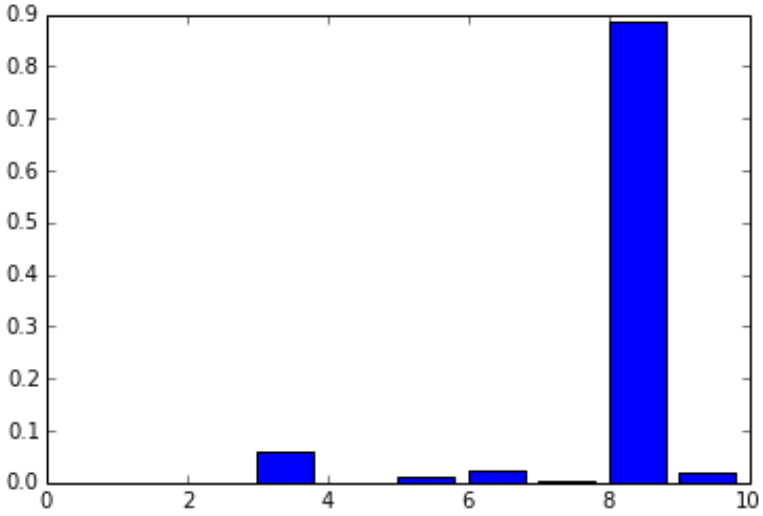


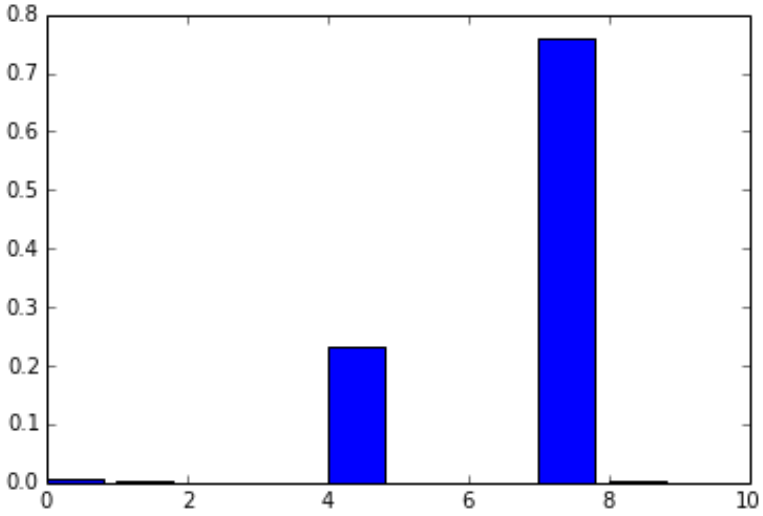


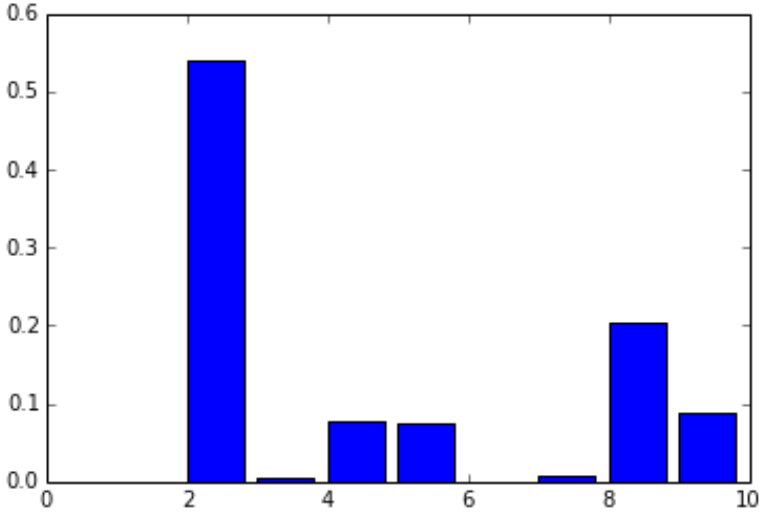


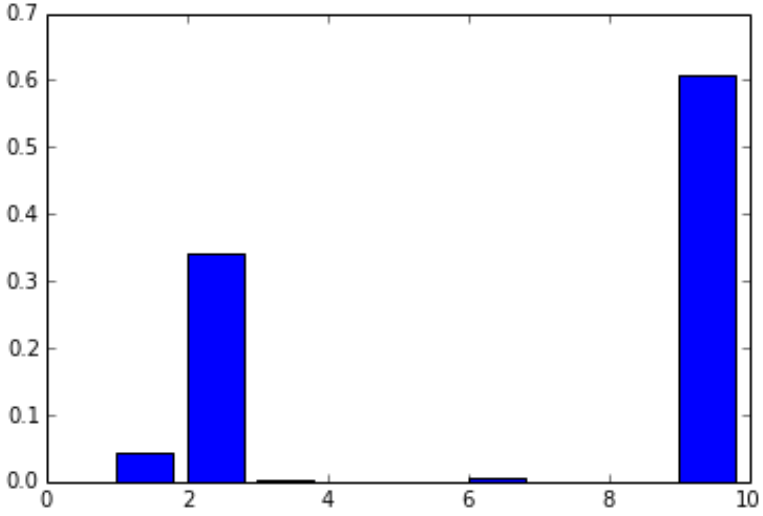


Draws from Dirichlet with $\eta = 0.1$

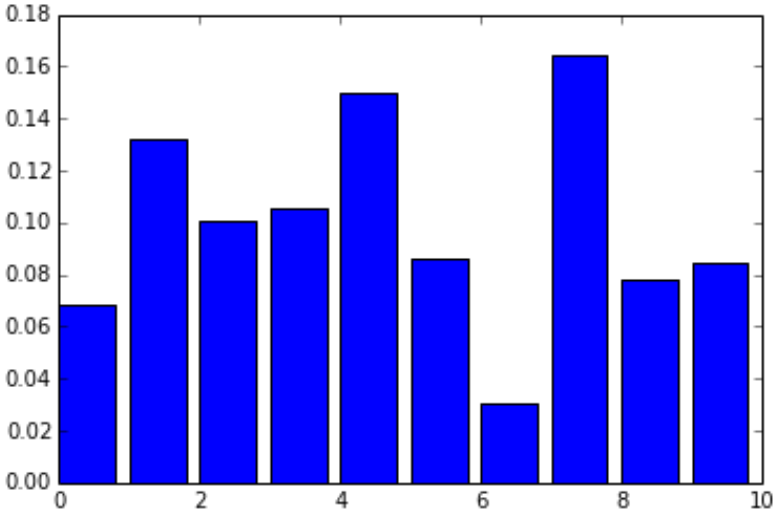


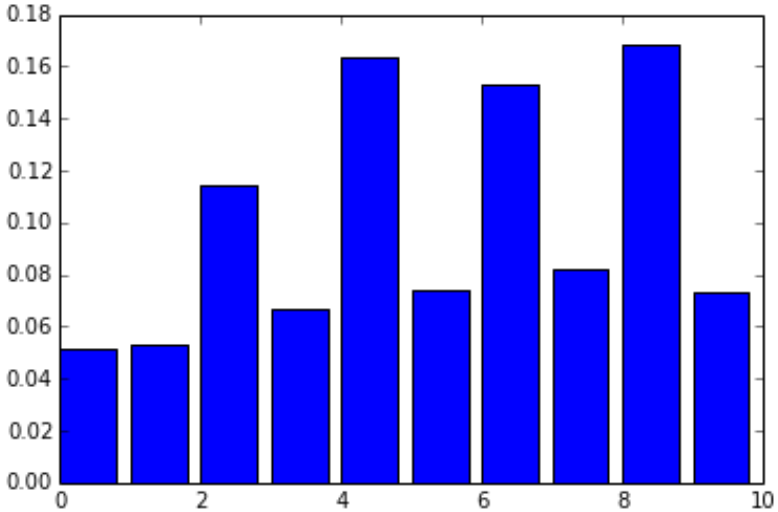


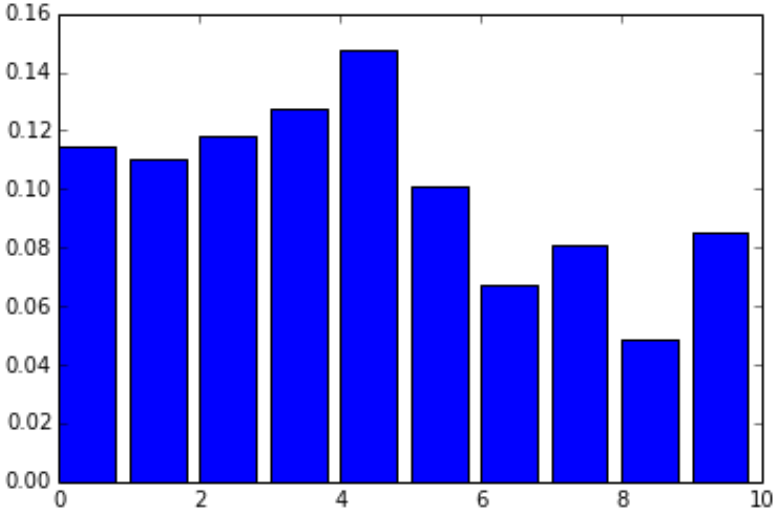


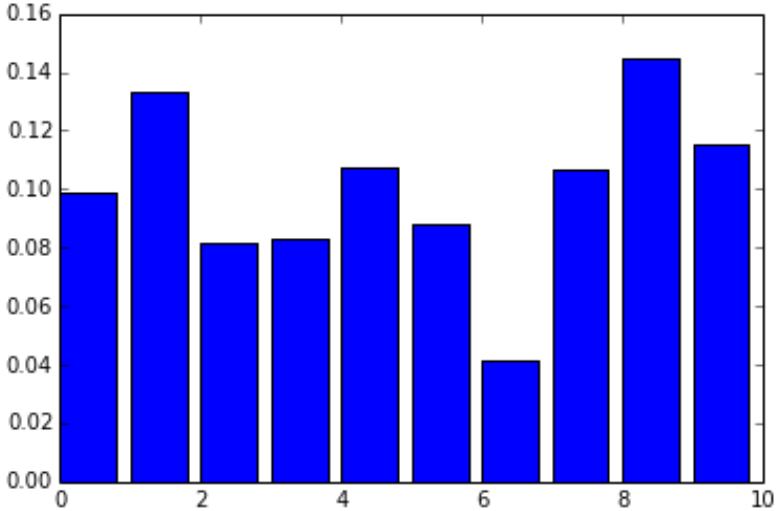


Draws from Dirichlet with $\eta = 10$









Posterior Distribution

$$\Pr[\boldsymbol{\beta} \mid \mathbf{x}] \propto \Pr[\mathbf{x} \mid \boldsymbol{\beta}] \Pr[\boldsymbol{\beta}] \propto \prod_{v=1}^{V} \beta_v^{x_v} \prod_{v=1}^{V} \beta_v^{\eta_v - 1} = \prod_{v=1}^{V} \beta_v^{x_v + \eta_v - 1}.$$

Posterior is a Dirichlet with parameters $(\eta'_1, \ldots, \eta'_V)$ where $\eta'_v \equiv \eta_v + x_v$.

Add term counts to the prior distribution's parameters to form posterior distribution. The Dirichlet hyperparameters can be viewed as *pseudo-counts*, i.e. observations made before observing $\mathbf{x}$.

Therefore we obtain

$$\mathbb{E}[\beta_v \mid \mathbf{x}] = \frac{\eta_v + x_v}{\sum_v \eta_v + N},$$

which is a smoothed version of the MLE estimate.

Bayesian estimation provides statistically well founded regularization.

Data Overwhelming the Prior

Recall the MLE estimates for $\widehat{\beta}_v$ satisfies $N\widehat{\beta}_v = x_v$. We then have

$$\mathbb{E}[\,\beta_v\,] = \frac{\eta_v + N\widehat{\beta}_v}{\eta + N} \text{ and } V[\,\beta_v\,] = \frac{(\eta_v + N\widehat{\beta}_v)(\eta + N - \eta_v - N\widehat{\beta}_v)}{(\eta + N)^2(\eta + N + 1)}.$$

If we take the limit as $N \to \infty$, we obtain a degenerate posterior distribution concentrated fully on the MLE parameter estimates.

Intuition: the more data we see, the less our priors should influence our beliefs.

More general result: Bernstein-von Mises theorem.

Relating Text to Metadata

Text Regression

Suppose that the text has associated metadata $\mathbf{y}_d$, which might contain speaker ID, timestamp, or any other numeric covariate.

Associating text with metadata involves associating $\mathbf{x}_d$ and $\mathbf{y}_d$.

Most straightforward approach would regress $y_{d,j}$ on $\mathbf{x}_d$ and $\mathbf{y}_{d,-j}$.

Due to strong dependence structure in $\mathbf{x}_d$, strong case for use of non-linear models.

Generative vs Discriminative Models

A generative model estimates the full joint distribution $p(y_d, \mathbf{x}_d)$ whereas typical regression estimates discriminative model $p(y_d \mid \mathbf{x}_d)$.

[Efron, 1975] shows that discriminative classifiers obtain a lower asymptotic error than generative ones.

Two motivations for nevertheless studying generative models:

1. [Ng and Jordan, 2001] show that generative classifiers can approach their (higher) asymptotic error faster.
2. They can reveal interesting structure, e.g. $p(\mathbf{x}_d \mid y_d)$.

A generative model requires a probability model for $\mathbf{x}_d$.

One example is a Naive Bayes Classifier.

Inverse Regression

Inverse regression models specify a model for $p(\mathbf{x_d} \mid y_d)$.

Well-known example is [Gentzkow and Shapiro, 2010].

Drawing on this paper as motivation, [Taddy, 2013] and [Taddy, 2015] propose fully generative models for inverse regression.

[Gentzkow et al., 2019] uses these models to study political polarization.

Multinomial Inverse Regression

Model takes the form

$$\mathbf{x}_d \sim \mathrm{MN}(\mathbf{q}_d, N_d) \text{ where } q_{d,v} = \frac{\exp(a_v + \mathbf{y}_d^T \mathbf{b}_v)}{\sum_v \exp(a_v + \mathbf{y}_d^T \mathbf{b}_v)}.$$

Generalized linear model with a (multinomial) logistic link function.

MLE estimates of multinomial regression coefficients can be approximated by estimating V separate Poisson regression models of $x_{d,v}$ on $\mathbf{y}_d$.

LASSO prior used to regularize regression parameters.

Application to Congressional Speech

[Gentzkow et al., 2019] use MNIR to model speech data from the *US Congressional Record* from 1873-2016.

Select speeches by Democrats/Republicans (7,732 speakers). Total 36,161 unique speaker-session.

Count two-word phrases (bigrams): 508,351 phrases with count ≥ 10 in at least one session.

$\mathbf{y}_d$ includes party, state, chamber, gender.

Democratic Phrases

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	additional tax cuts	civil rights movement
VA health care	pay for tax cuts	cuts to child support
billion in tax cuts	tax cuts for people	drilling in the Arctic National
credit card companies	oil and gas companies	victims of gun violence
security trust fund	prescription drug bill	solvency of social security
social security trust	caliber sniper rifles	Voting Rights Act
privatize social security	increase in the minimum wage	war in Iraq and Afghanistan
American free trade	system of checks and balances	civil rights protections
central American free	middle class families	credit card debt

Republican Phrases

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

Polarization

Let $q^D_{t,v}(\mathbf{y}')$ be the probability that a Democrat at time t with observables $\mathbf{y}'$ speaks phrase v. Similarly define $q^R_{t,v}(\mathbf{y}')$.

Given phrase v, posterior probability of the speaker being a Democrat is (assuming uniform prior)

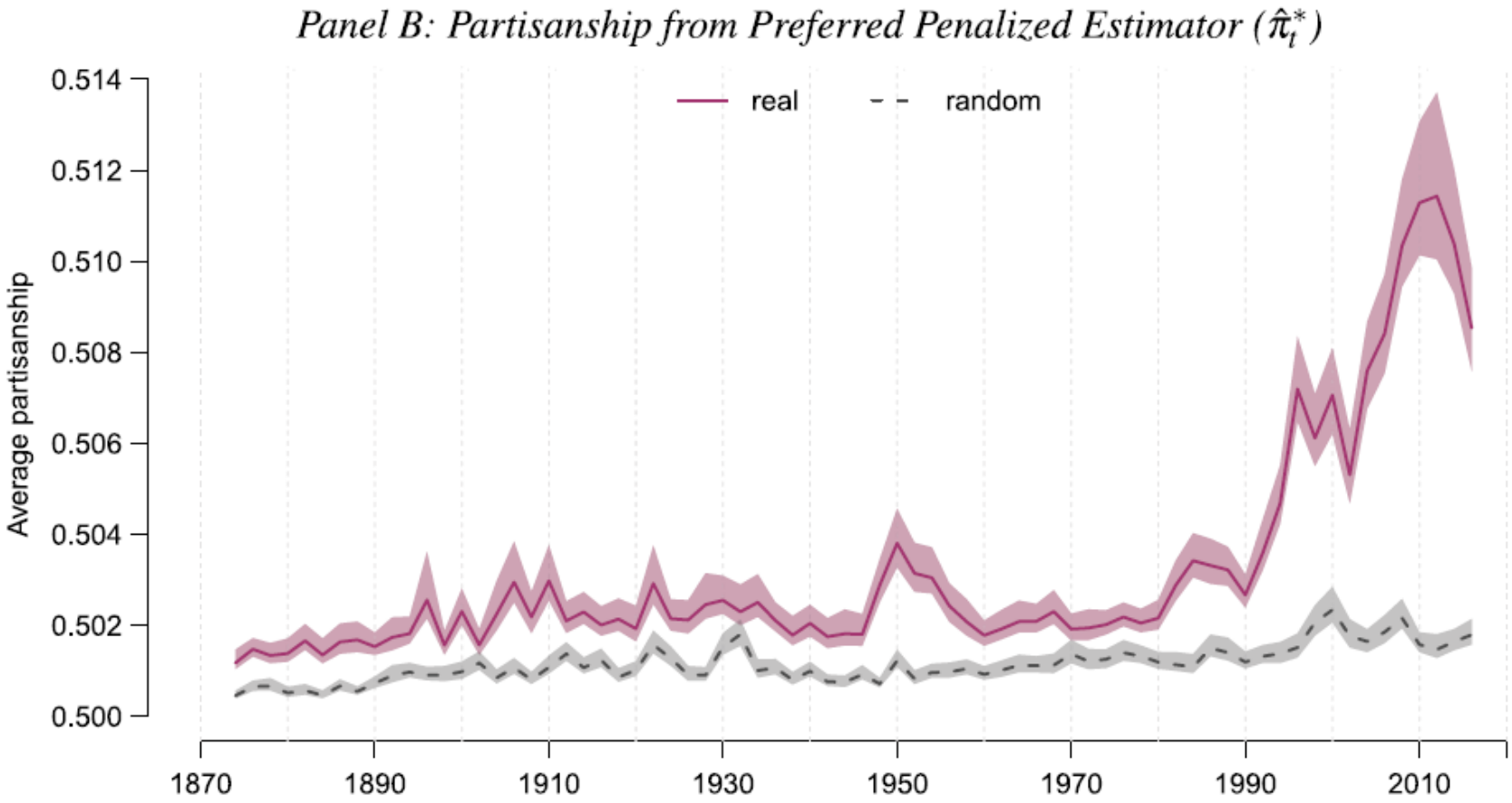
$$\rho_{t,v}(\mathbf{y}') = \frac{q^D_{t,v}(\mathbf{y}')}{q^D_{t,v}(\mathbf{y}') + q^R_{t,v}(\mathbf{y}')}$$

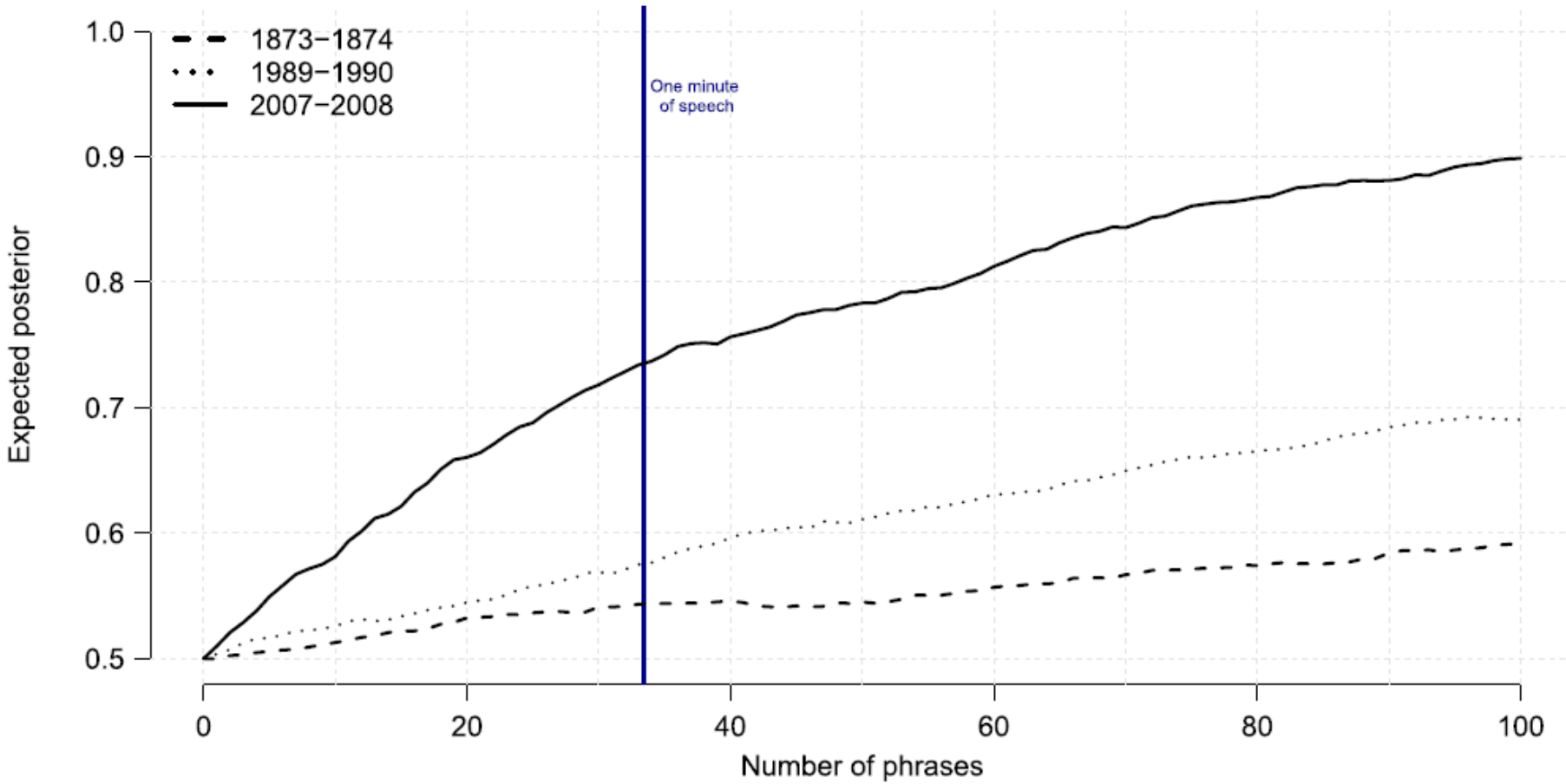
Partisanship is the expected posterior after hearing a single phrase by a speaker with characteristics $\mathbf{y}'$:

$$\pi_t(\mathbf{y}') = \frac{1}{2}\mathbf{q}^D_t(\mathbf{y}') \cdot \boldsymbol{\rho}_t(\mathbf{y}') + \frac{1}{2}\mathbf{q}^R_t(\mathbf{y}') \cdot (1 - \boldsymbol{\rho}_t(\mathbf{y}'))$$

Let s_t be total speakers in session t. Average partisanship is

$$\overline{\pi}_t = \frac{1}{s_t}\sum_{i=1}^{s_t} \pi_{it}(\mathbf{y}'_{it})$$


Panel B: Partisanship from Preferred Penalized Estimator ($\hat{\pi}_t^*$)
real
random
Average partisanship
0.514
0.512
0.510
0.508
0.506
0.504
0.502
0.500
1870
1890
1910
1930
1950
1970
1990
2010


1873−1874
1989−1990
2007−2008
One minute
of speech
Expected posterior
1.0
0.9
0.8
0.7
0.6
0.5
0
20
40
60
80
100
Number of phrases

Sufficient Reduction Projection

There remains the issues of how to use the estimated model for classification.

Let $z_{d,j} = \mathbf{f}_d^T \hat{\mathbf{b}}_j$ be the *sufficient reduction projection* for the jth covariate for document d, where $\mathbf{f}_d = \mathbf{x}_d / N_d$ is a vector of term frequencies.

$z_{d,j}$ is sufficient for predicting $y_{d,j}$ in the sense that

$$y_{d,j} \perp \mathbf{x}_d, N_d \mid z_{d,j}, \mathbf{y}_{d,-j}.$$

All the information contained in the high-dimensional frequency counts relevant for predicting $y_{d,j}$ can be summarized in the SR projection.

Dimensionality reduction targeted at specific covariate.

Classification

For classification, use the SR projections to build a forward regression that models $y_{d,j}$ as some function of $z_{d,j}, \mathbf{y}_{d,-j}$: OLS; logistic; with or without non-linear terms in $z_{d,j}$, etc.

To predict $y_{d',j}$ for an out-of-sample document d':

1. Form $z_{d',j}$ given the estimated $\hat{\mathbf{b}}_j$ coefficients in the training data.
2. Use the estimated forward regression to generate a predicted value for $y_{d',j}$.

Conclusion

The document-term matrix can be used to address important measurement problems relevant for text-as-data in economics and finance.

Term-count analysis has been, and will continue to be, very influential.

Strength is that matrix-structured data is relatively familiar to economists, and analysis is relatively straightforward.

Nevertheless, all sequential information is ignored and much of natural language's meaning depends on context.

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