Deconstructing Data Science

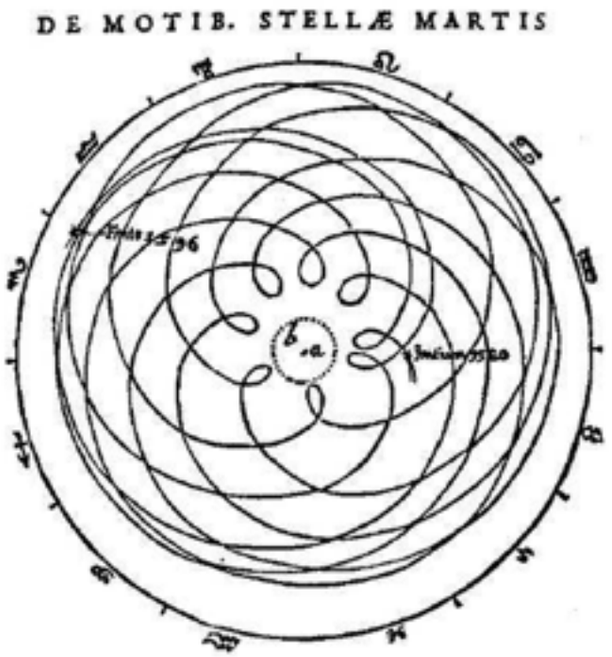
David Bamman, UC Berkeley

Info 290
Lecture 1: Introduction

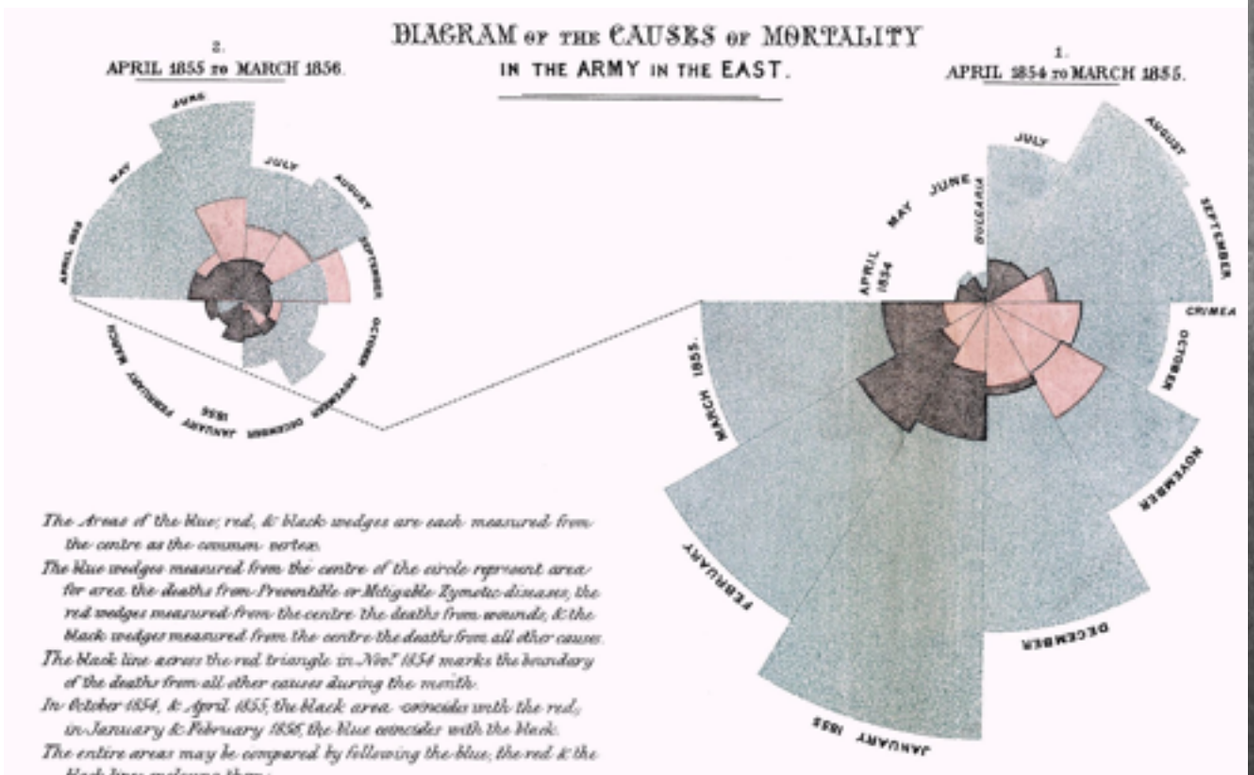
Jan 20, 2016

the “data scientist” trope

johannes kepler,
data scientist



florence nightingale,
data scientist



franz bopp,
data scientist

Software/Libraries

NumPy

SciPy

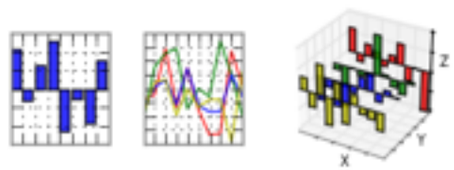
scikit learn

Dato

R

pandas

$y_{it} = \beta' x_{it} + \mu_i + \epsilon_{it}$



TensorFlow

MALLET

machine learning for language toolkit

theano

Data Science

critical thinking

experimental design, validation, representation

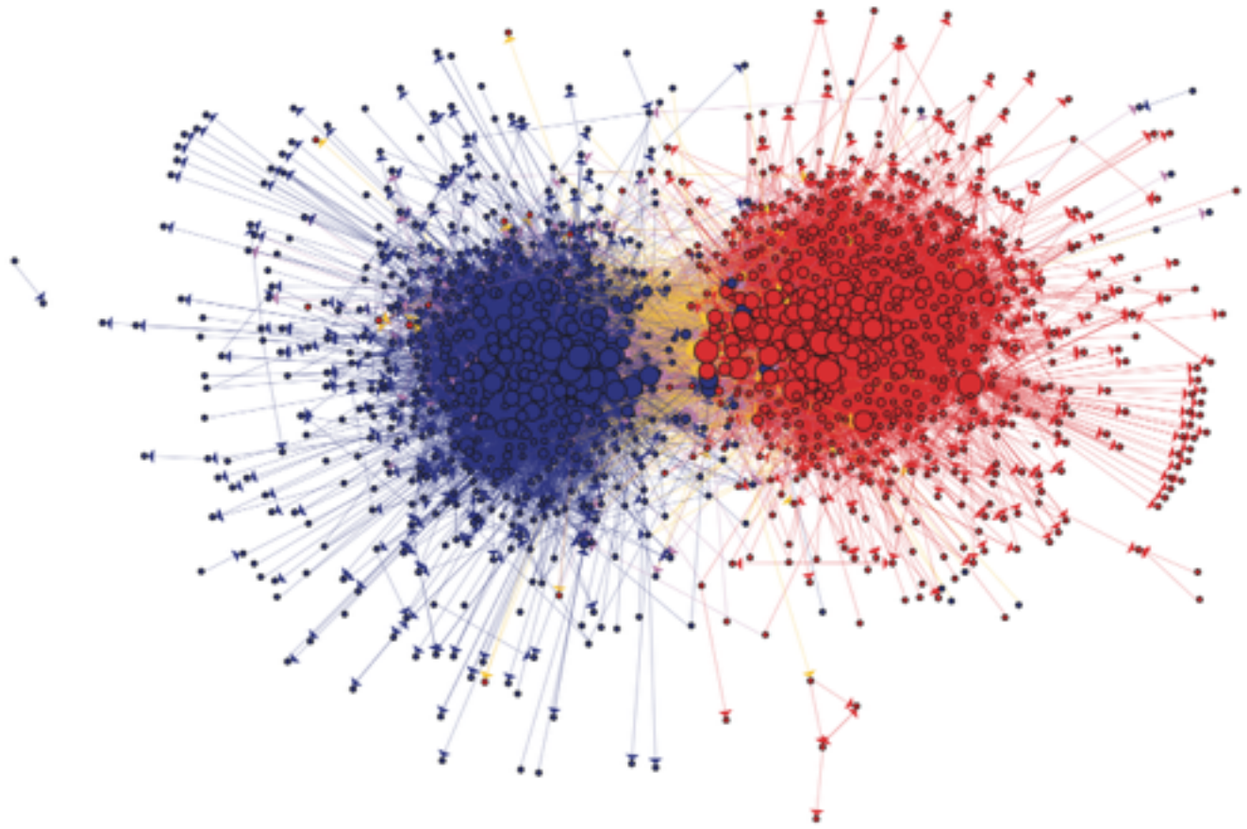
algorithms

classification, regression, clustering, network analysis, prediction, hypothesis testing,

software

Computational Social Science

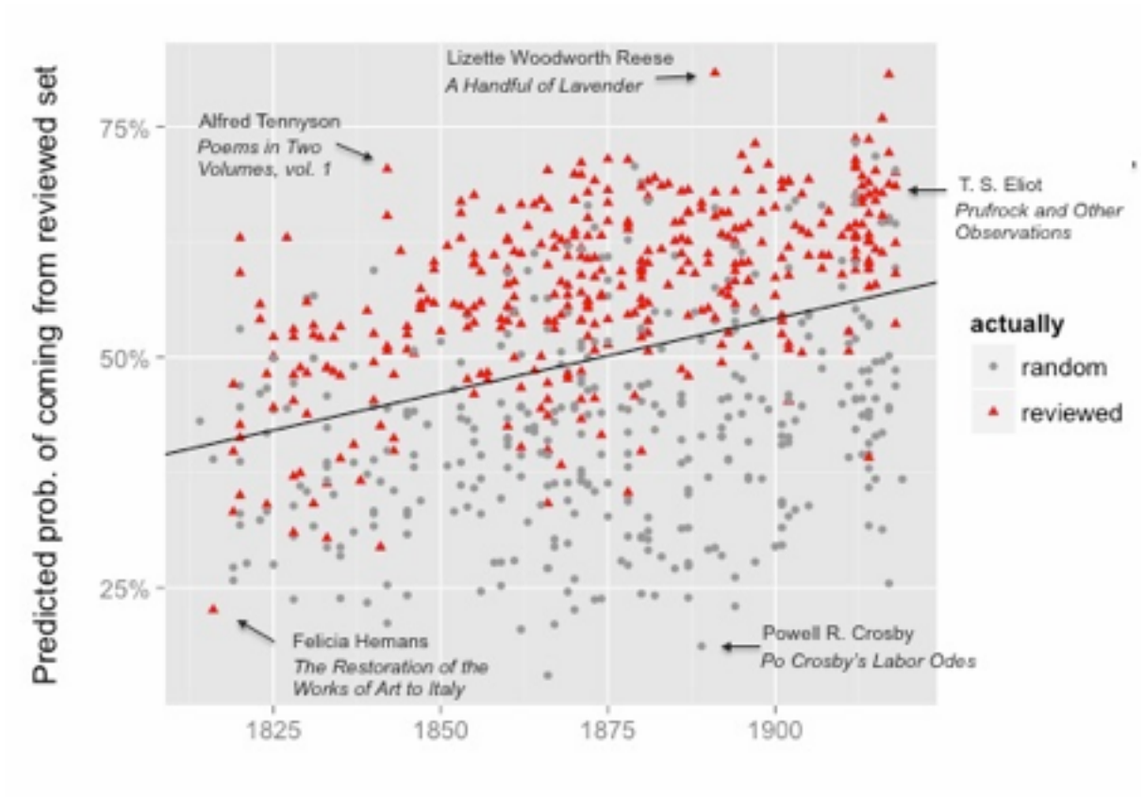
- Inferring ideal points of politicians based on voting behavior, speeches
- Detecting the triggers of censorship in blogs/ social media
- Inferring power differentials in language use



Link structure in political blogs
Adamic and Glance 2005

Digital Humanities

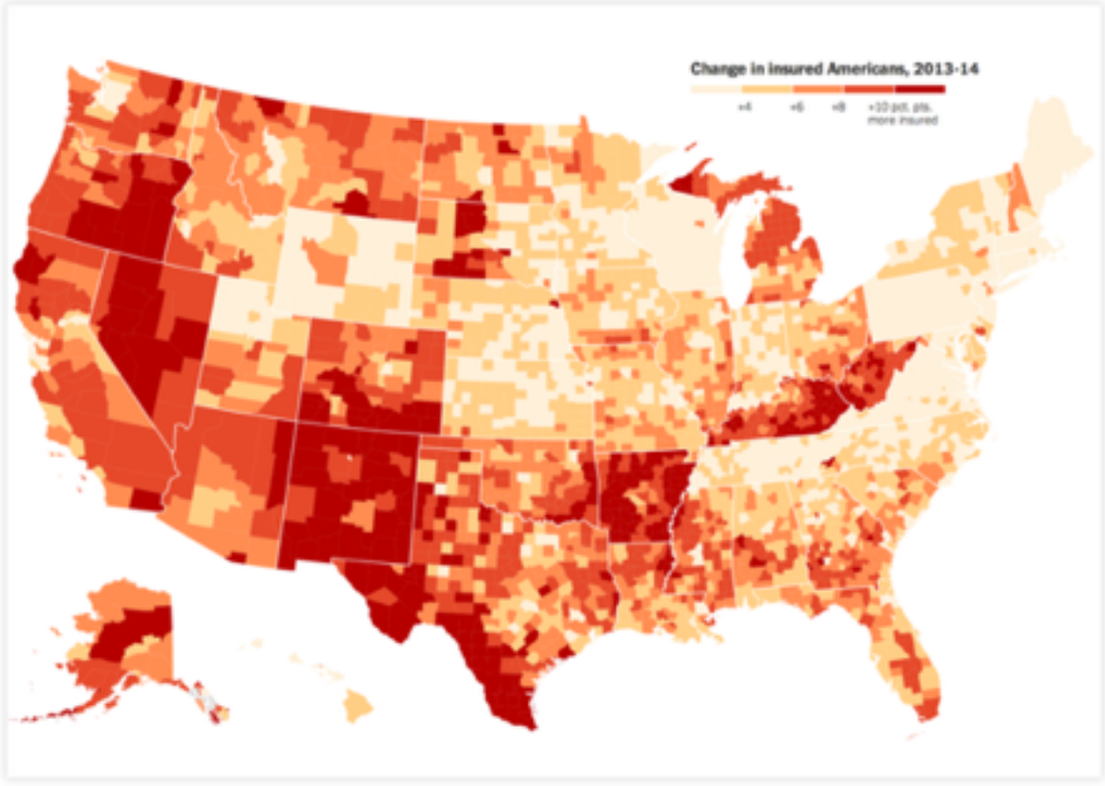
- Authorship attribution (literary texts, paintings, music)
- Genre classification (literary genre, music genre)
- Inferring plot, character types



Predicting reviewed texts
Underwood and Sellers (2015)

Computational Journalism

- Exploratory data analysis for lead generation
- Information extraction from unstructured text
- Data-driven stories



Change in insured Americans under the ACA, NY Times (Oct 29, 2014)

What to expect

- Each class: learn about a technical method (e.g., random forests), and an discuss application area that makes use of it.

- As the course goes on, we'll compare methods with those we've already learned to critically assess the assumptions that they make and understand what methods are appropriate for different contexts.

- We will learn by example: Lots of reading.

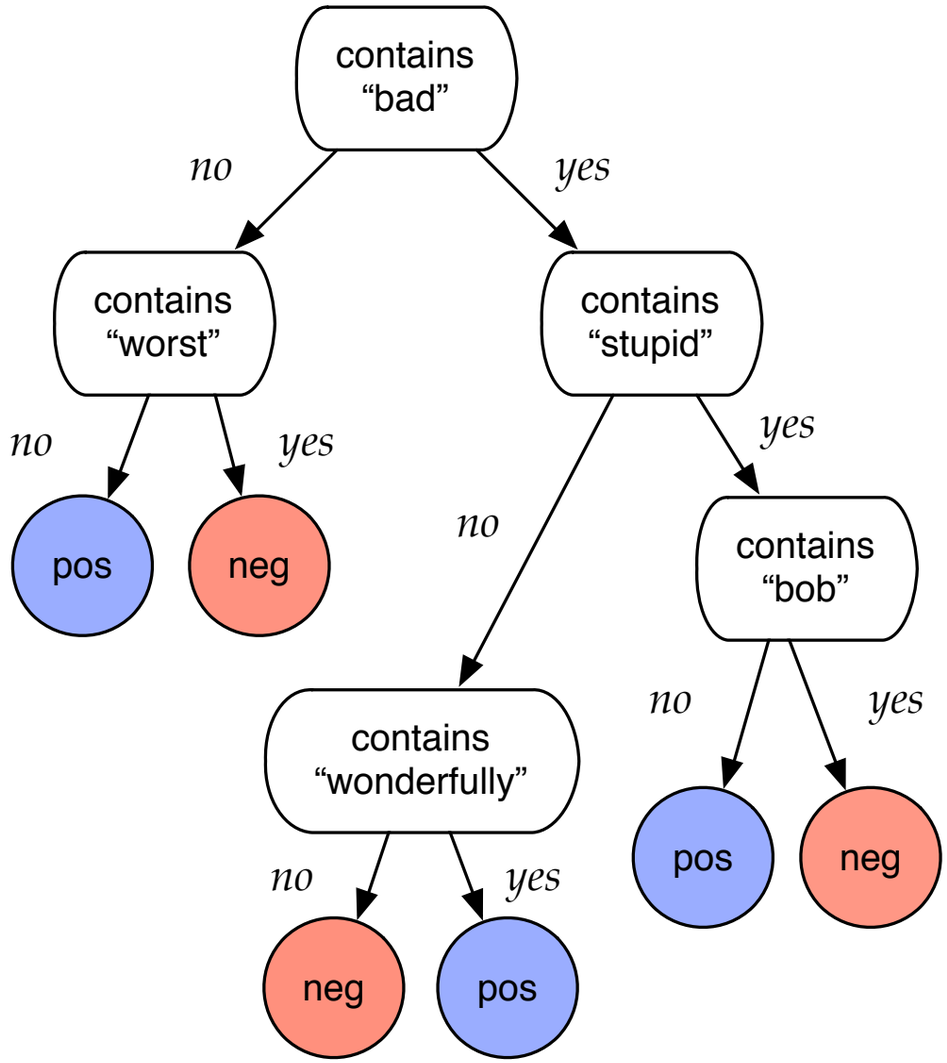
Themes

1. Validity

How do we assess that a model is valid?

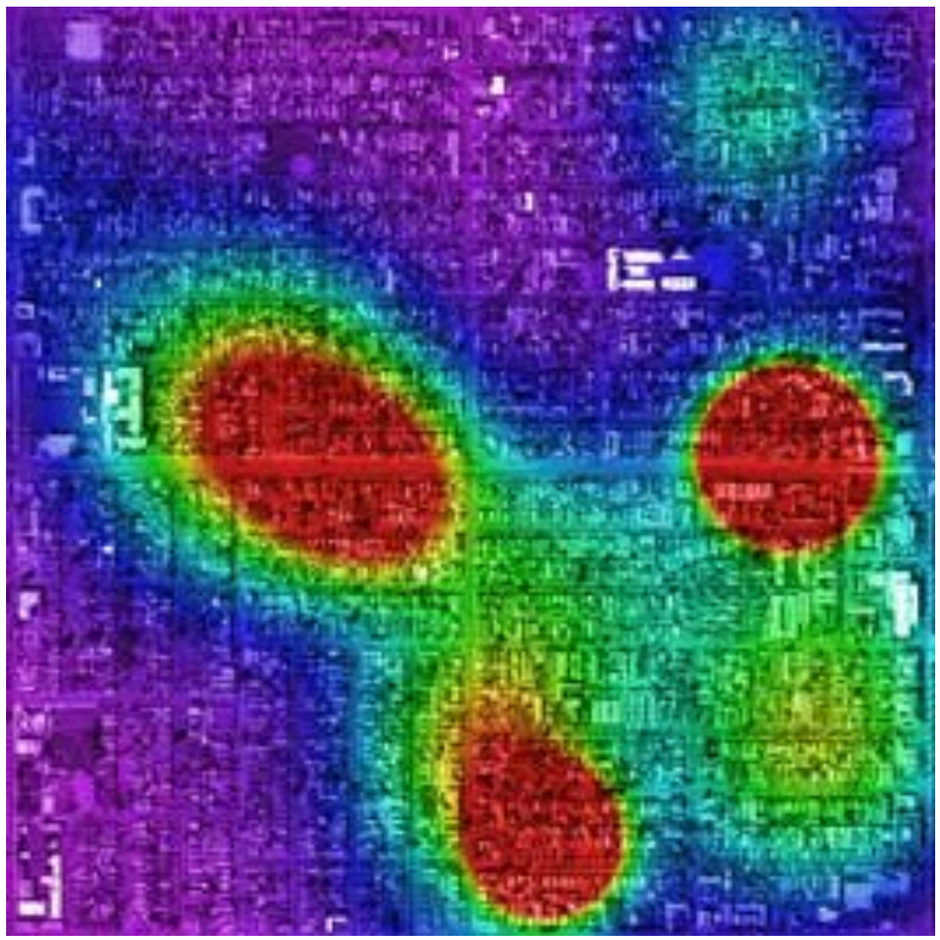
2. Transparency

How do we understand what a model is learning?



3. Fairness

To what degree does a problem translate biases in the input data into biases in its the output?



Predictive policing; heat map indicating increased risk of certain crimes
http://magazine.ucla.edu/depts/quicktakes/a-weapon-to-fight-crime-try-math/

Topics

- Overview of methods (classification, regression, clustering)
- Classification: decision trees, random forests, probabilistic models (naive bayes, logistic regression), SVM, neural networks
- Clustering: latent variable models (topic models), PCA, factor analysis, K-means, hierarchical clustering
- Linear regression
- Networks (structural properties, diffusion)
- Temporal data: time series forecasting and survival analysis

Applications

- Authorship attribution
- Latent attribute prediction
- Predicting movie revenue
- Recommender systems
- Music genre classification
- Visual style classification
- Text reuse
- Genre clustering
- Predicting elections/stock market
- Predicting high school dropout rates

… *in medias res*

- Task: predict political preference of Twitter users.

- Assume access to training data <x, y> where:

  x = set of Twitter users
  y = {Democrat, Republican}

Representation

- How can you best represent a data point to enable learning?

TWEETS 508 | FOLLOWING 400 | FOLLOWERS 799 | LIKES 133 | LISTS 2

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Joined October 2009

10 Photos and videos

Tweets | Tweets & replies | Photos & videos

David Bamman Retweeted

Ted Underwood @Ted_Underwood · 6h

How have the differences between descriptions of men and women in fiction changed over the last 200 yrs? (ICYMI) tedunderwood.com/2016/01/09/the…

8 13 View summary

David Bamman @dbamman · Jan 6

"Figure Eights" (Max Roach/Buddy Rich, 1959) is just dazzling. Probably no video of them anywhere? open.spotify.com/track/23EssvWY…

View summary

David Bamman Retweeted

Anders Søgaard @soegaarducph · Jan 6

@stanfordnlp @brendan642 @jacobeisenstein Here goes: twitter-research.ccs.neu.edu/language/

x = feature vector

Feature	Value
follow clinton	0
follow trump	0
“benghazi”	0
negative sentiment + “benghazi”	0
“illegal immigrants”	0
“republican” in profile	0
“democrat” in profile	0
self-reported location = Berkeley	1

$$\sum_{i=1}^{F} x_i \beta_i = x_1 \beta_1 + x_2 \beta_2 + \ldots + x_F \beta_F$$

$$= x^\top \beta \qquad \text{(dot product, inner product)}$$

$$\hat{y}_i = \begin{cases} 1 & \text{if } \sum_i^F x_i \beta_i \geq 0 \\ -1 & \text{otherwise} \end{cases}$$

x = feature vector

Feature	Value
follow clinton	0
follow trump	0
“benghazi”	0
negative sentiment + “benghazi”	0
“illegal immigrants”	0
“republican” in profile	0
“democrat” in profile	0
self-reported location = Berkeley	1

β = coefficients

Feature	β
follow clinton	-3.1
follow trump	6.8
“benghazi”	1.4
negative sentiment + “benghazi”	3.2
“illegal immigrants”	8.7
“republican” in profile	7.9
“democrat” in profile	-3.0
self-reported location = Berkeley	-1.7

	“benghazi”	follows trump	follows clinton	∑	prediction
β	1.4	6.8	-3.1		
x	1	1	0	8.2	1
x	0	0	1	-3.1	-1
x	1	0	1	-1.7	-1

$$(1 \times 1.4) + (1 \times 6.8) + (0 \times -3.1) = 8.2$$

Learning

How do get good values for β?

Feature	β
follow clinton	-3.1
follow trump	6.8
“benghazi”	1.4
negative sentiment + “benghazi”	3.2
“illegal immigrants”	8.7
“republican” in profile	7.9
“democrat” in profile	-3.0
self-reported location = Berkeley	-1.7

Online learning

- Go through the training data <x, y> one data point at a time.

- Make a prediction $\hat{y}$ with current estimate of β; if it's right ($y = \hat{y}$), do nothing.

- If the prediction is wrong ($y \neq \hat{y}$), change β to make it slightly less wrong.

$$\hat{y}_i = \begin{cases} 1 & \text{if } \sum_i^F x_i \beta_i \geq 0 \\ -1 & \text{otherwise} \end{cases}$$

“benghazi”	follows trump	follows clinton	y
1	1	0	1
0	0	1	-1
1	0	1	-1

training data

$$\hat{y}_i = \begin{cases} 1 & \text{if } \sum_i^F x_i \beta_i \geq 0 \\ -1 & \text{otherwise} \end{cases}$$

“benghazi”	follows trump	follows clinton	y	ŷ
1	1	0	1	1
0	0	1	-1	-1
1	1	1	1	-1

true $y = -1$

predicted $\hat{y} = 1$

$$\sum_{i}^{F} x_i \beta_i$$

We want this value (function of β) to be small

$$\frac{\partial}{\partial \beta_i} \sum_{i}^{F} x_i \beta_i = x_i$$

The derivative tells us the direction to go to make it bigger or smaller

$$\beta_{t+1} = \beta_t - x$$

Update rule

true $y = 1$

predicted $\hat{y} = -1$

$$\sum_{i}^{F} x_i \beta_i$$

We want this value (function of β) to be big

$$\frac{\partial}{\partial \beta_i} \sum_{i}^{F} x_i \beta_i = x_i$$

The derivative tells us the direction to go to make it bigger or smaller

$$\beta_{t+1} = \beta_t + x$$

Update rule

if $\hat{y} = 1$ and $y = -1$

$$\beta_{t+1} = \beta_t - x$$

	β	x	β
	3.6	0	3.6
	3.4	1	2.4
	1.2	1	0.2
	0.7	0	0.7
$\sum x_i \beta_i$	4.6		2.6
$\hat{y}$	1		1

if $\hat{y} = -1$ and $y = 1$

$$\beta_{t+1} = \beta_t + x$$

	β	x	β
	3.6	0	3.6
	-3.4	1	-2.4
	1.2	1	2.2
	0.7	0	0.7
$\sum x_i \beta_i$	-2.2		-0.2
$\hat{y}$	-1		-1

if $\hat{y} = 1$ and $y = -1$

$$\beta_{t+1} = \beta_t - x$$

if $\hat{y} = -1$ and $y = 1$

$$\beta_{t+1} = \beta_t + x$$

$$\beta_{t+1} = \beta_t + yx$$

Why $\beta_{t+1} = \beta_t + yx$?

[Approximation of stochastic gradient
in binary logistic regression (lecture 9)]

Perceptron

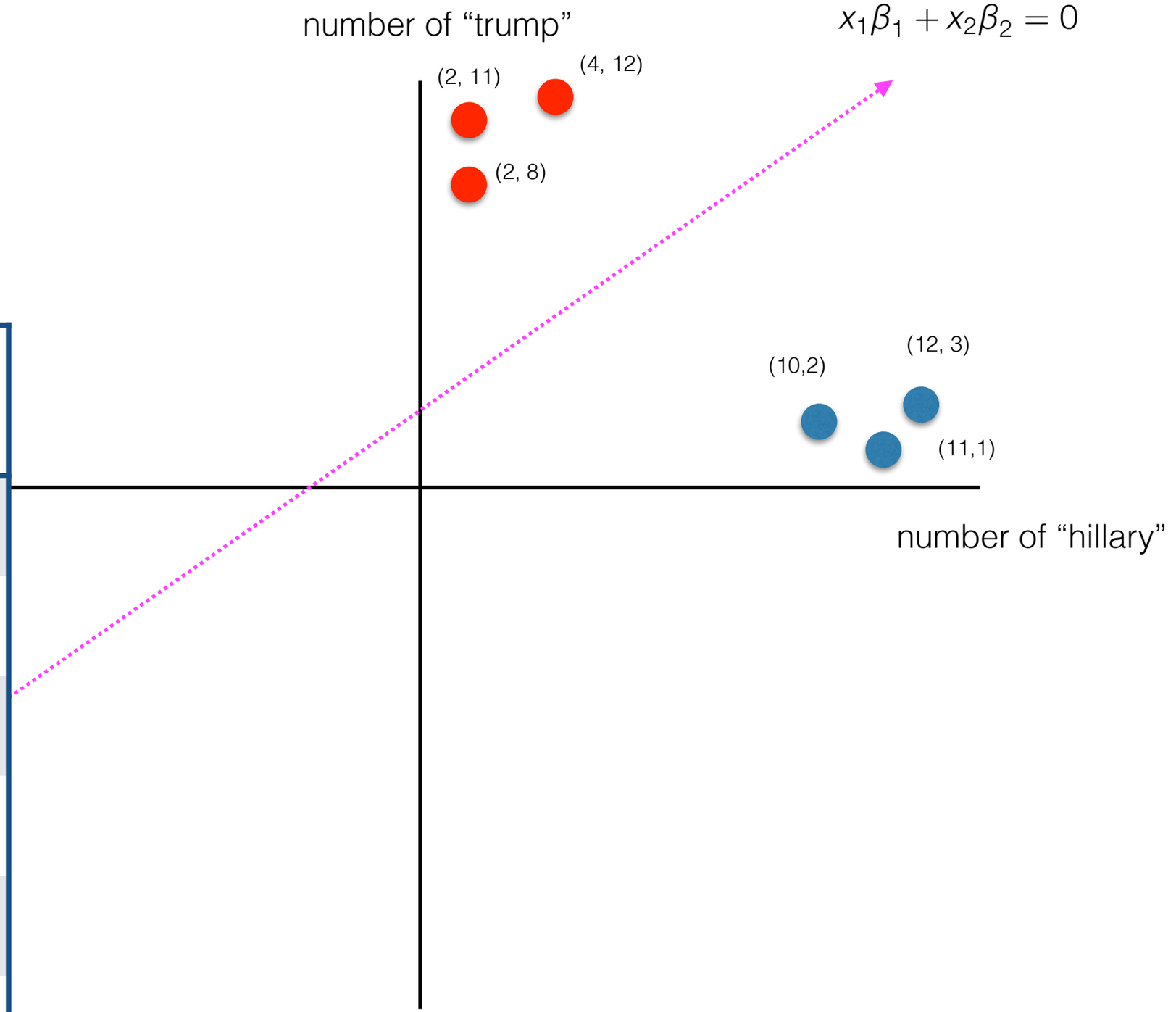
Data: training data $x \in R^F$, $y \in \{-1, +1\}$, i = 1 ... N;
initialize $\beta_0 = 0^F$;
k=0;
while *not converged* **do**
  k = k + 1;
  i = k mod N;
  if $\hat{y}_i \neq y_i$ **then**
    $\beta_{t+1} = \beta_t + y_i x_i$
  else
    do nothing;
  end
end

Rosenblatt 1957

Code

decision boundary in 2 dimensions

# of "hillary"	# of "trump"	y
2	8	1
2	11	1
4	12	1
10	2	-1
11	1	-1
12	3	-1



Trends

- Counts later points more than earlier points (voted perceptron, averaged perceptron)
- Only linear decision boundaries
- Prone to overfitting
- Extraordinarily simple and accurate classifier

Problem assumptions

- Is this the right task (classification vs. clustering vs. regression, time series forecasting etc.)

- Is the data appropriate for the problem?

Administrivia

- David Bamman
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  Office hours: Thursdays 10am-noon, 314 SH
  — or by appointment

- Noura Howell, TA

  Office hours: Friday 2:30-4:30, 110 South Hall

Grading

- Class participation (10%)
- Homeworks (4 x 10%)
- Project (50%)

All deliverables (homeworks, project components) have deadlines; late work not accepted

Homeworks, broadly

A

- Implement a quantitative method and evaluate it on a dataset

B

- Write an analysis/ critique of an algorithm and published work that has used it

Homework Example

Binary perceptron classifies into two classes. For inferring political preference, this corresponds to a simple {Democrat, Republican} distinction. Assume rather that the training data you have is hierarchical. Design a perceptron-style algorithm that can exploit this hierarchical structure during learning.

y1	Republican > Tea Party Republican
y2	Republican > Social Conservatives
y3	Republican > Neoconservative
y4	Republican > Social Conservative
y5	Democrat > Centrist Democrat
y6	Democrat > Progressive

A

Code and evaluate on test data

B

What are the comparative advantages and disadvantages of binary vs. multiclass vs. hierarchical categories? Under what circumstances should either be used? (2 pages, single-spaced)

Project

- Use methods learned in class to draw inferences about the world and critically assess the quality of the results.

- Collaborative (2-3 students). Choose wisely! Everyone in group will receive the same grade; you will be evaluated both on the empirical methodology and the domain questions you're asking

Project

- Milestones:
  - Proposal and literature review (5%). 2 pages, 5 sources.
  - Midterm report (10%). 4 pages, 10 sources.
  - Final report (20%). 10 pages.
  - Presentation (5%). 15-20 min. conference-style talk in front of peers.

- Evaluated according to standards for conference publication—clarity, originality, soundness, substance, evaluation, meaningful comparison, impact.