Deconstructing Data Science

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Info 290
Lecture 2: Survey of Methods

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Announcements

- Python and Jupyter workshop (sign up through bCourses)


Linear regression
Deep learning
Decision trees
Ordinal regression
Probabilistic graphical models
Random forests
Logistic regression
Networks
Support vector machines
Topic models
Survival models
K-means clustering
Neural networks
Hierarchical clustering
Perceptron

Classification

A mapping h from input data x (drawn from instance space $\mathcal{X}$) to a label (or labels) y from some enumerable output space $\mathcal{Y}$

$\mathcal{X}$ = set of all skyscrapers
$\mathcal{Y}$ = {art deco, neo-gothic, modern}

x = the empire state building
y = art deco

Classification

h(x) = y
h(empire state building) = art deco

Classification

Let h(x) be the “true” mapping. We never know it. How do we find the best $\hat{h}(x)$ to approximate it?

One option: rule based

if x has “sunburst motif”:
  $\hat{h}(x)$ = art deco

Classification

Supervised learning

Given training data in the form of <x, y> pairs, learn $\hat{h}(x)$

task	$\mathcal{X}$	$\mathcal{Y}$
spam classification	email	{spam, not spam}
authorship attribution	text	{jk rowling, james joyce, …}
genre classification	song	{hip-hop, classical, pop, …}
image tagging	image	{fun, B&W, color, ocean, …}

Methods differ in form of $\hat{h}(x)$ learned

Model differences

- Binary classification: $|\mathcal{Y}| = 2$
  [one out of 2 labels applies to a given x]
- Multiclass classification: $|\mathcal{Y}| > 2$
  [one out of N labels applies to a given x]
- Multilabel classification: $|y| > 1$
  [multiple labels apply to a given x]

Regression

A mapping from input data x (drawn from instance space $\mathcal{X}$) to a point y in $\mathbb{R}$

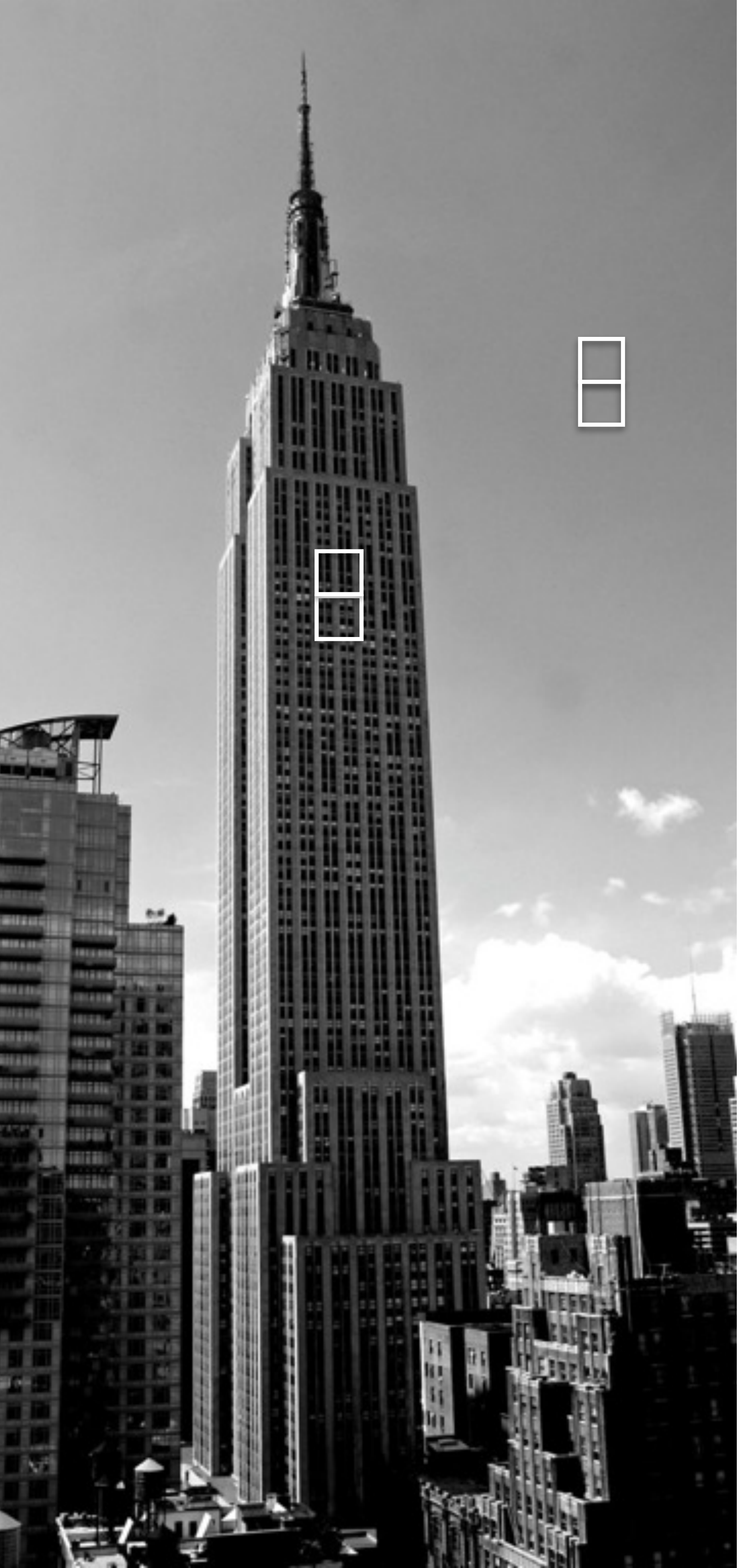
($\mathbb{R}$ = the set of real numbers)

x = the empire state building
y = 17444.5625”


Linear regression
Deep learning
Decision trees
Ordinal regression
Probabilistic graphical models
Random forests
Networks
Support vector machines (regression)
Survival models
Neural networks
Perceptron

Big differences

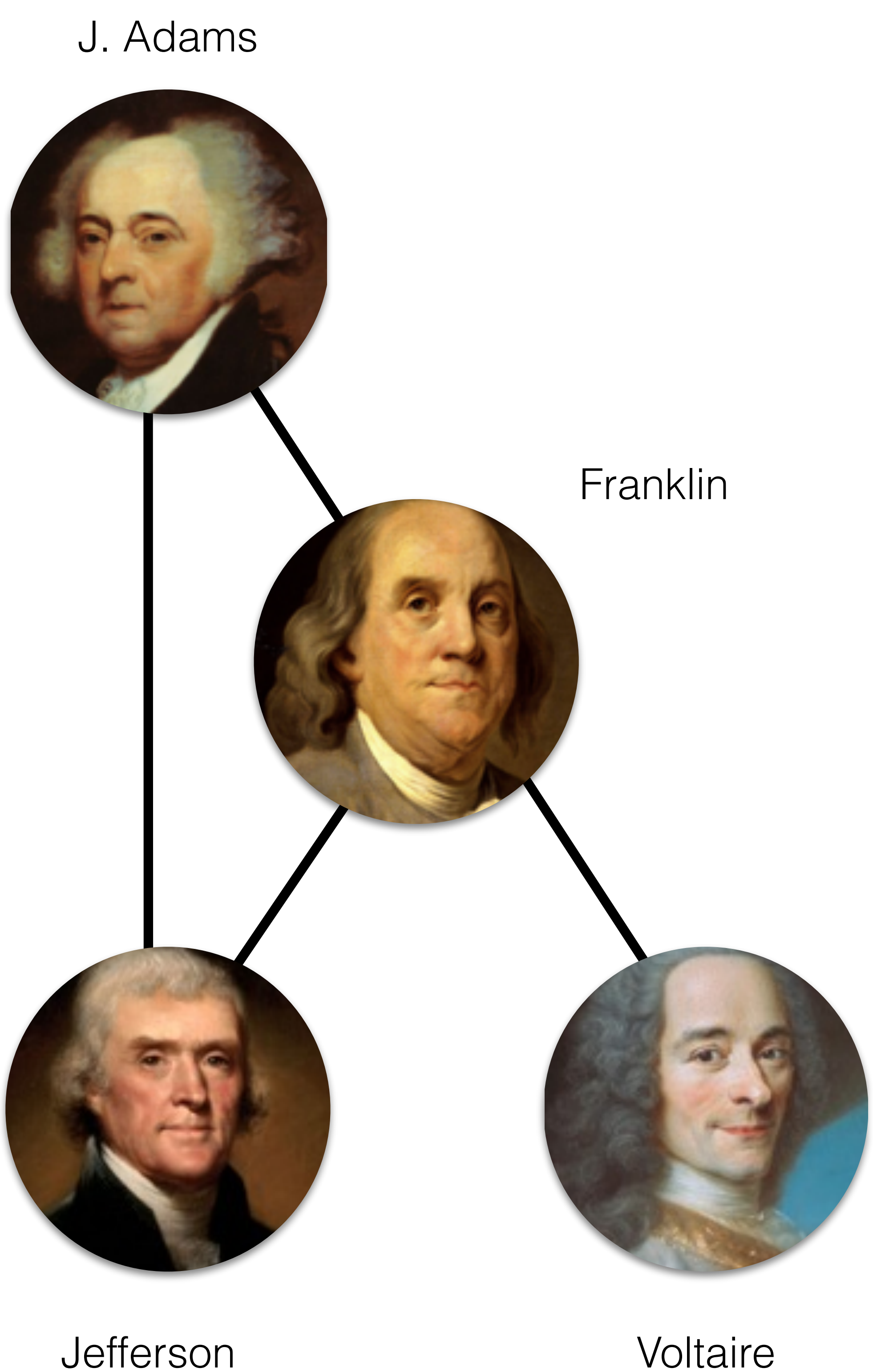
- Are the labels y_j and y_k for two different data points x_j and x_k independent? During learning and prediction, would your guess for y_j help you predict y_k?



Label dependence

- Object recognition in images
- Neighboring pixels tend to have similar values (building, sky)

Label dependence



- Homophily in social networks
- Friends to have similar attribute values

Big differences

- Are the labels y_j and y_k for two different data points x_j and x_k independent? During learning and prediction, would your guess for y_j help you predict y_k?

- [Part of speech tagging, network homophily, object recognition in images]

- Sequence models (HMMs, CRFS, LSTMs) and general graphical models (MRFs) but come at a high computational cost

Big differences

- How do the features in x interact with each other?
  - Independent? [Naive Bayes]
  - Potentially correlated but non-interacting? [Logistic regression, linear regression, perceptron, linear SVM]
  - Complex interactions? [Non-linear SVM, neural networks, decision trees, random forests]

Feature interactions

training data

I like the movie	1
I hate the movie	-1
I do not like the movie	-1
I do not hate the movie	1

how predictive is:

- like
- hate
- not
- not like
- not hate

What do you need?

1. Data (emails, texts)

2. Labels for each data point (spam/not spam, which author it was written by)

3. A way of “featurizing" the data that’s conducive to discriminating the classes

4. To know that it works.

What do you need?

Two steps to building and using a supervised classification model.

1. Train a model with data where you know the answers.

2. Use that model to predict data where you don't.

Recognizing a Classification Problem

- Can you formulate your question as a *choice* among some universe of possible classes?

- Can you create (or find) labeled data that marks that choice for a bunch of examples? Can *you* make that choice?

- Can you create features that might help in distinguishing those classes?

Uses of classification

Two major uses of supervised classification/regression

Prediction

Train a model on a sample of data <x, y> to predict values for some new data x'

Interpretation

Train a model on a sample of data <x, y> to understand the relationship between x and y

Clustering

- Clustering (and unsupervised learning more generally) finds *structure* in data, using just X

X = a set of skyscrapers

What is structure?

- Unsupervised learning finds *structure* in data.
  - clustering data into groups
  - discovering “factors”

Methods differ in the kind of structure learned

Structure

- Partitioning *X* into N disjoint sets [K-means clustering, PGMs]
- Assigning *X* to hierarchical structure [Hiearchical clustering]
- Assigning *X* to partial membership in N different sets [EM clustering, PGMs, PCA]
- Learning a representation of x in *X* that puts similar data points close to each other [Deep learning]

Uses of clustering

Exploratory data analysis

- Discovering interesting or unexpected structure can useful for hypothesis generation

→ Input to supervised models

- Unsupervised learning generates alternate representations of each x as it relates to the larger X.

→ Input to supervised models

Brown clusters trained from Twitter data: every word is mapped to a single (hierarchical) cluster

^001010110 (29)	never neva nvr gladly nevr #never neverr nver neverrr nevaa nevah nva neverrrr letchu letcha ne'er -never neveer glady #inever bever nevaaa neever nerver enver neeever nevet neeeever nevva
^001010111 (23)	ever eva evar evr everrr everr everrrr evah everrrrr everrrrrr evaa evaaa everrrrrrr nevar eveer evaaaa eveeer everrrrrrrr everrrrrrrrr evea eveeeer evaaaaa evur
^00101100 (16)	only onli onlyy ony onlii 0nly -only olny onlyyy onlt onlly onyl onlu onlee onle inly

http://www.cs.cmu.edu/~ark/TweetNLP/cluster_viewer.html

Recognizing a Classification/Regression/Clustering Problem

- I want to predict a star value {1, 2, 3, 4, 5} for a product review

- I want to find all of the texts that have allusions to *Paradise Lost*.

- Optical character recognition

- I want to associate photographs of cats with animals in a taxonomic hierarchy

- I want to reconstruct an evolutionary tree for languages

boyd and Crawford

- danah boyd and Kate Crawford (2012), "Critical Questions for Big Data," Information, Communication and Society
- Specifically about "big data" but we can read it as a commentary on much quantitative practice using social data

1. “big data” changes the definition of knowledge

- How do computational methods/quantitative analysis pragmatically affect epistemology?
- Restricted to what data is available (twitter, data that’s digitized, google books, etc.). How do we counter this in experimental designs?
- Establishes alternative norms for what “research” looks like

2. claims to objectivity and accuracy are misleading

- What is still subjective in data/empirical methods? What are the interpretive choices still to be made?
- Interpretation introduces dependence on individuals. Is this ever avoidable?
- What does an experiment (or results) “mean”?

2. claims to objectivity and accuracy are misleading

- Data collection, selection process is subjective, reflecting belief in what matters.

- Model design is likewise subjective

    - model choice (classification vs. clustering etc.)
    - representation of data
    - feature selection

- Claims need to match the sampling bias of the data.

3. bigger data is not always better data

- Uncertainty about its source or selection mechanism [Twitter, Google books]

- Appropriateness for question under examination

- How did the data you have get there? Are there other ways to solicit the data you need?

- Remember the value of small data: individual examples and case studies

4. taken out of context, big data loses it meaning

- A representation (through features) is a necessary approximation; what are the consequences of that approximation?
- Example: quantitative measures of “tie strength” and its interpretation

5. just because it is accessible does not make it ethical

- Anonymization practices for sensitive data (even if born public)
- Accountability both to research practice and to subjects of analysis

6. limited access to “big data” creates new digital divides

- Inequalities in access to data and the production of knowledge

- Privileging of skills required to produce knowledge

Wednesday 1/27

- Bring examples of hard problems that would fall under the domain of classification, and how you could approach training data collection