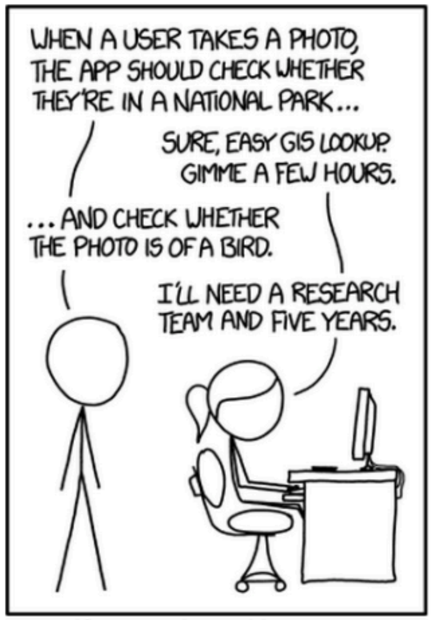
Introduction to Data Science
Math 4100 / COMP 5360

Lecture 29: Final Projects, Recap, Outlook



THE UNIVERSITY OF UTAH

Final Projects

Best Projects 2018

Winners:

Virtual Sommelier: Brian Tillman, Li Jiada,Li, Trevor Olsen

Take Your Shot: a Shot Chart Analysis of the Utah Jazz: Jacob Brown, Kyle Salisbury, Avery Smith

Runner ups:

Tweet, Tweet...Can That Bird Predict Stock Prices??: Jorge Rodriguez and Rebecca Rodriguez

Convective Heat Transfer Coefficient of Solar Panels in Utility-Scale Solar Farms: Adam Vogel, Brooke Stanislawski, Connor DeFriez

Exploratory Analysis of Salt Lake City Police Data: Walter Shearon, Zach St. Clair, Nicholas Bitter

Analysis of Music Trend - Using Spotify API: Puneet Mulay, Vivek Mishal

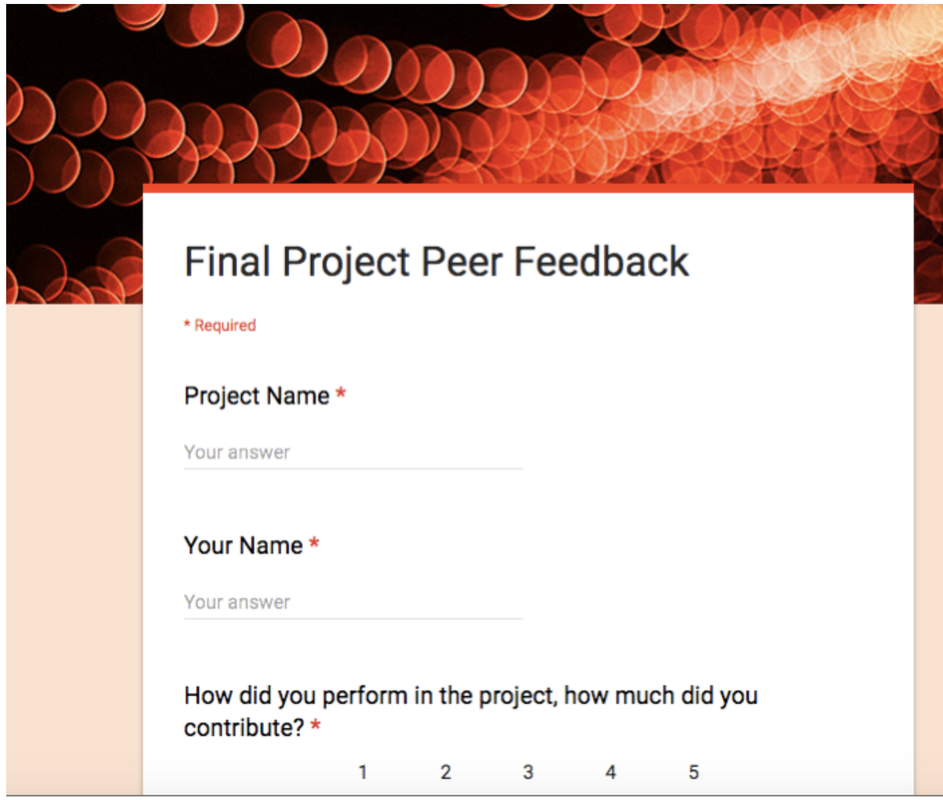
Weather our power consumption will change:James Newman and Aaron Young

Project Peer Assessment

https://goo.gl/forms/S62E2TjXeKIXfRQG2

It is important to provide positive feedback to people who truly worked hard for the good of the team and to also make suggestions to those you perceived not to be working as effectively on team tasks. We ask you to provide an honest assessment of the contributions of the members of your team, including yourself. The feedback you provide should reflect your judgment of each team member's:

- Preparation – were they prepared during team meetings?
- Contribution – did they contribute productively to the team discussion and work?
- Respect for others' ideas – did they encourage others to contribute their ideas?
- Flexibility – were they flexible when disagreements occurred?



Your teammate's assessment of your contributions and the accuracy of your self-assessment will be considered as part of your overall project score.

What did we learn?

Programming! Python!

What is a for loop? What is a function?

Jupyter Notebooks

Python Libraries:

- numpy, scipy, statsmodels, scikit-learn, NLTK, TensorFlow, keras

Data Structures:

- Lists, Dictionaries, Series, Pandas Data Frames

Data Cleanup, Aggregation, Reshaping!

Version Control - Git & GitHub

Masking and Filtering

With pandas we can create boolean arrays that we can use to mask and filt
new array that has "True" for every band formed after 1964:

In [68]:
```
mask = bands_founded > 1964
mask
```

Out[68]:
```
Beatles        False
Zeppelin        True
Pink Floyd      True
Pink Floyd      True
Name: Bands founded, dtype: bool
```

This uses a technique called **broadcasting**. We can use broadcasting with va

In [69]:
```
# Not particularly useful for this dataset..
founding_months = bands_founded * 12
founding_months
```

Out[69]:
```
Beatles        23520
Zeppelin       23616
Pink Floyd     23580
Pink Floyd     24180
Name: Bands founded, dtype: int64
```

We can use a boolean mask to filter a series, as we've seen before:

Getting Data

Web Scraping

- HTML / Inspector
- Retrieving Websites
- Parsing HTML

APIs - REST, JSON

Data Bases - SQL

Scraping with BeautifulSoup

BeautifulSoup is a Python library design for computationally extracting data from html documents. It supports navigating in the DOM and retreiving exactly the data elements you need.

Let's start with a simple example using the lyrics.html file.

In [6]:
```
from bs4 import BeautifulSoup

# we tell BeautifulSoup and tell it which parser to use
soup = BeautifulSoup(open("lyrics.html"), "html.parser")
# the output corresponds exactly to the html file
soup
```

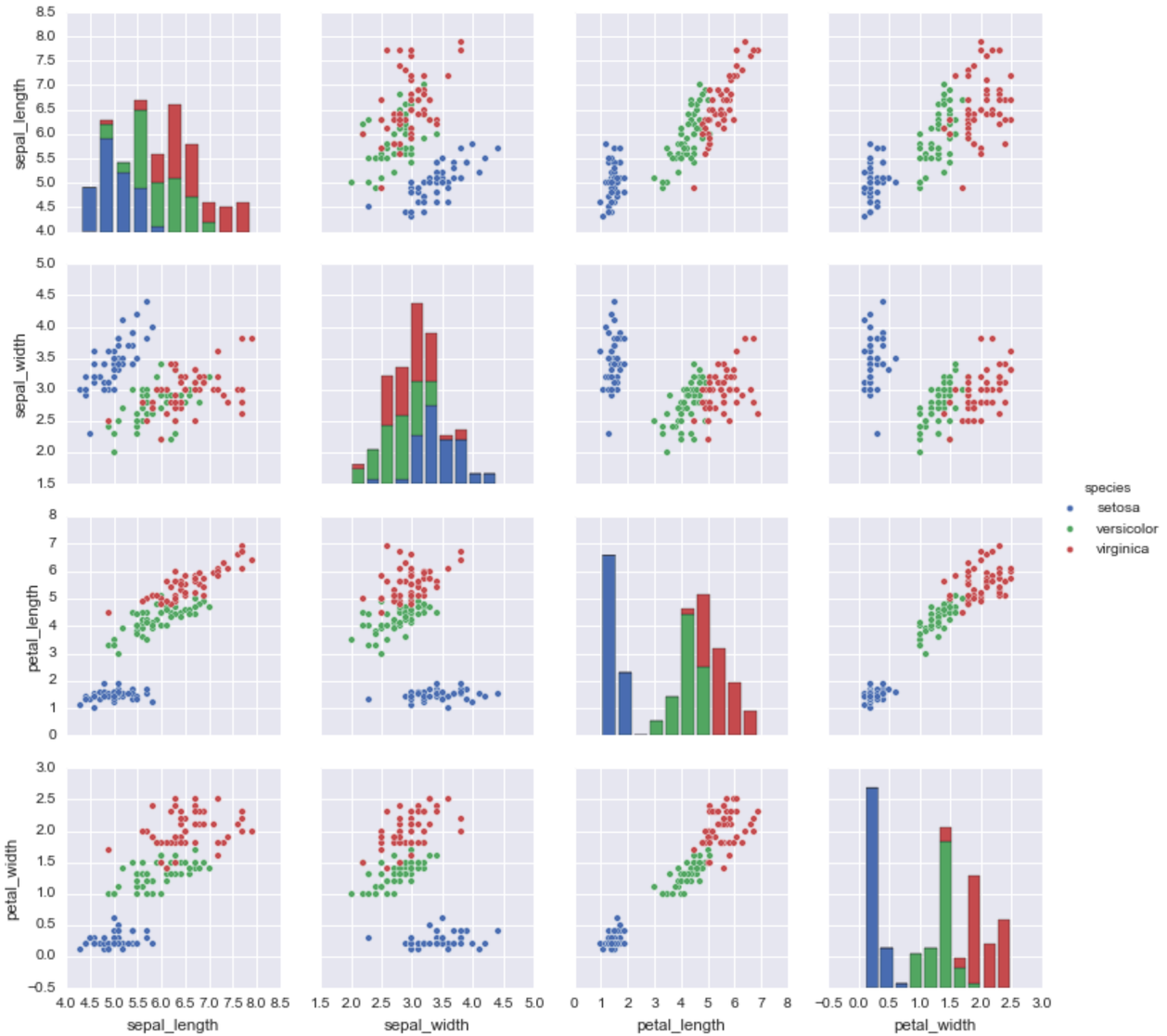
Out[6]:
```
<!DOCTYPE html>

<html lang="en">
<head>
<meta charset="utf-8">
<title>Lyrics</title>
</meta></head>
<body>
<article id="zep">
<span class="date">Published: 2016-08-25</span>
<span class="author">Led Zeppelin</span>
<h1>Ramble On</h1>
<div class="content">
    Leaves are falling all around, It's time I was on my
 way.
```

Visualization

MatPlotLib, seaborn, and GraphX packages

Histograms, Scatterplot Matrices, Decision Trees, Force-Directed Graph Layouts



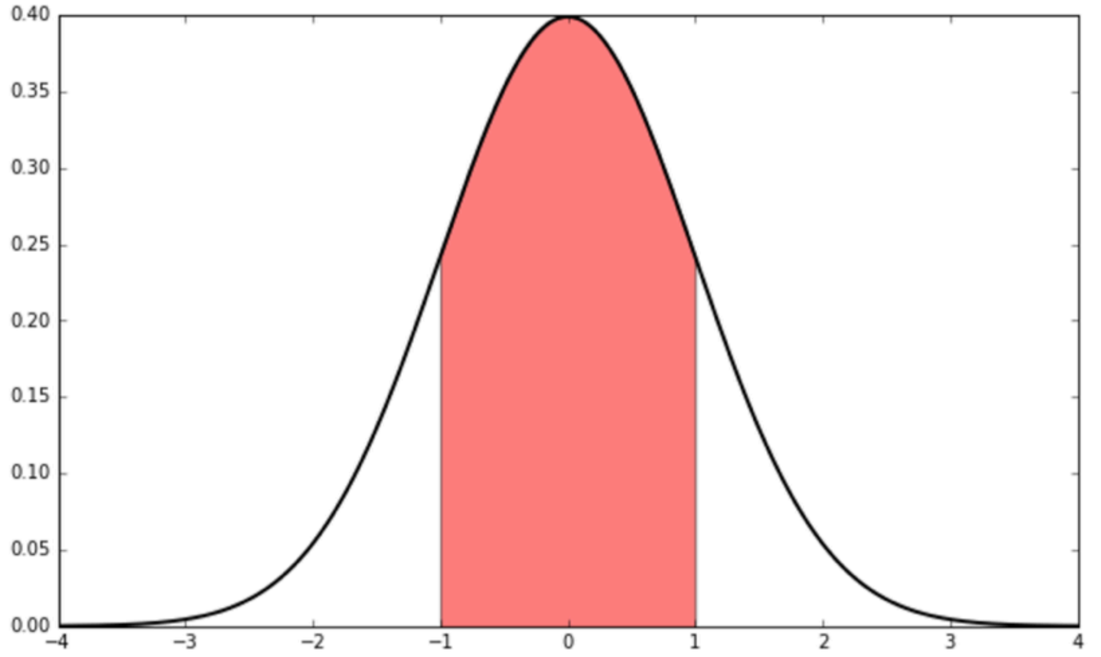
Hypothesis Testing and Statistical Inference

Bernoulli, Binomial, and normal distributions

Hypothesis Significance Testing

A/B Testing

```
plt.plot(x, pdf, linewidth=2, color='k')
x2 = sc.arange(mu-sigma,mu+sigma,0.001)
plt.fill_between(x2, y1= norm.pdf(x2,loc=mu, scale=sigma), facecolor='red'
plt.show()
```



This integral can be computed using the *cumulative distribution function* (CDF)

$$F(x) = \int_{-\infty}^{x} f(x)dx.$$

Regression

Linear Regression

Multilinear Regression

Nonlinear models

Confounders

Exploratory vs. inferential viewpoints

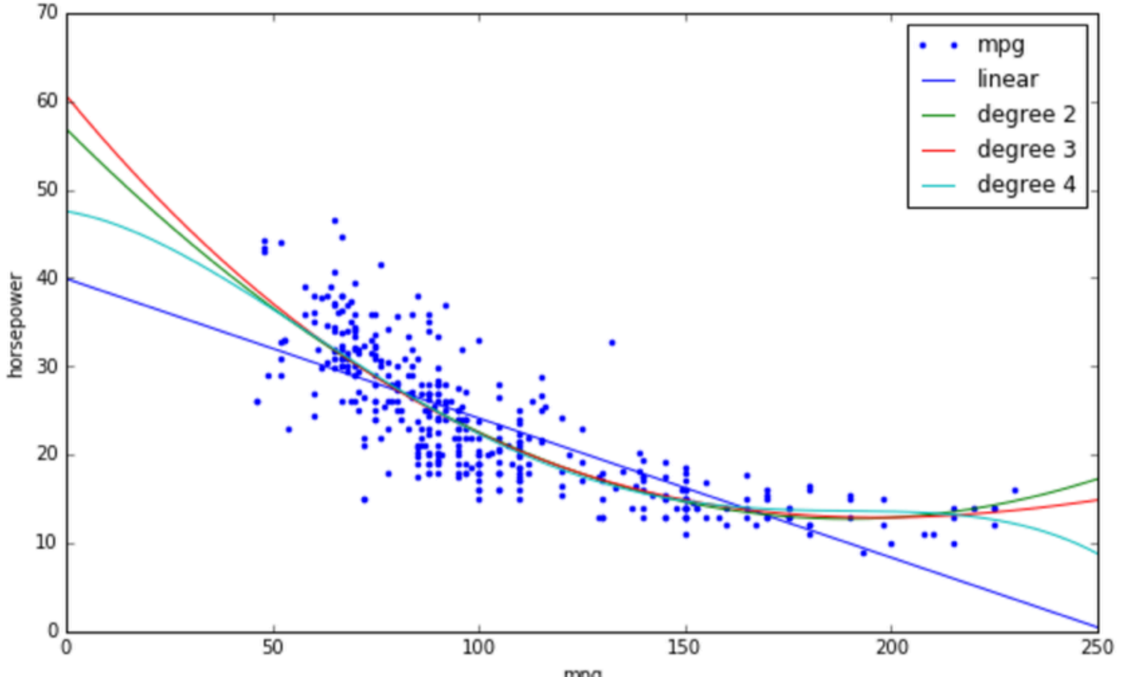
statsmodels, scikit-learn

OLS Regression Results

Dep. Variable:	Rating	R-squared:	0.941
Model:	OLS	Adj. R-squared:	0.940
Method:	Least Squares	F-statistic:	3140.
Date:	Fri, 23 Sep 2016	Prob (F-statistic):	4.70e-244
Time:	15:28:22	Log-Likelihood:	-2019.2
No. Observations:	400	AIC:	4044.
Df Residuals:	397	BIC:	4056.
Df Model:	2		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[95.0% Conf.	Int.]
Intercept	145.3506	3.285	44.249	0.000	138.893	151.808
Income	0.0022	6.06e-05	36.057	0.000	0.002	0.002
Balance	0.2129	0.005	45.810	0.000	0.204	0.222

Omnibus:	63.810	Durbin-Watson:	1.879
Prob(Omnibus):	0.000	Jarque-Bera (JB):	92.125
Skew:	-1.168	Prob(JB):	9.89e-21
Kurtosis:	3.257	Cond. No.	9.95e+04



Classification

Logistic Regression

k-Nearest Neighbors

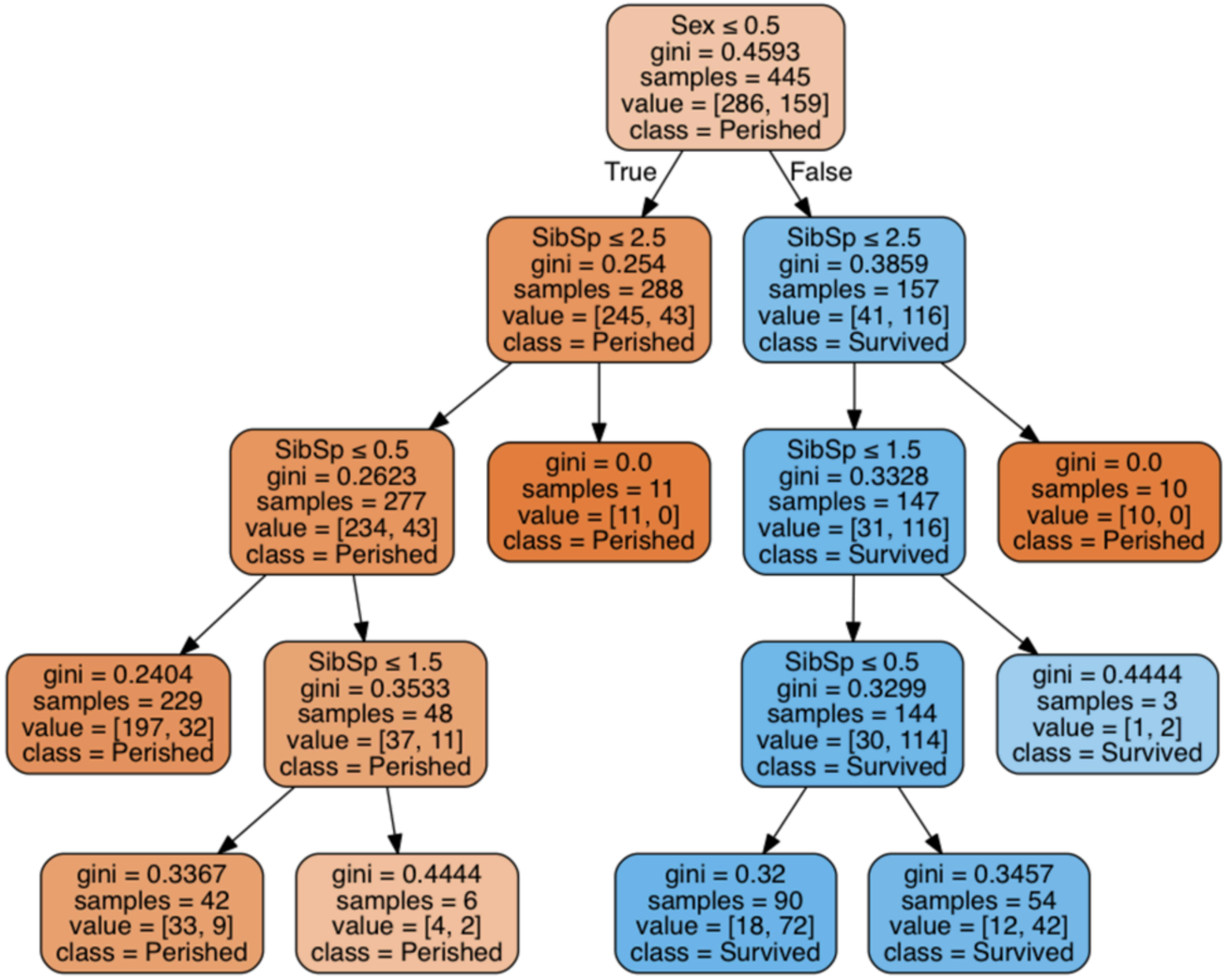
Decision Trees

Support Vector Machines

Neural Networks

generalizability and cross validation

scikit-learn



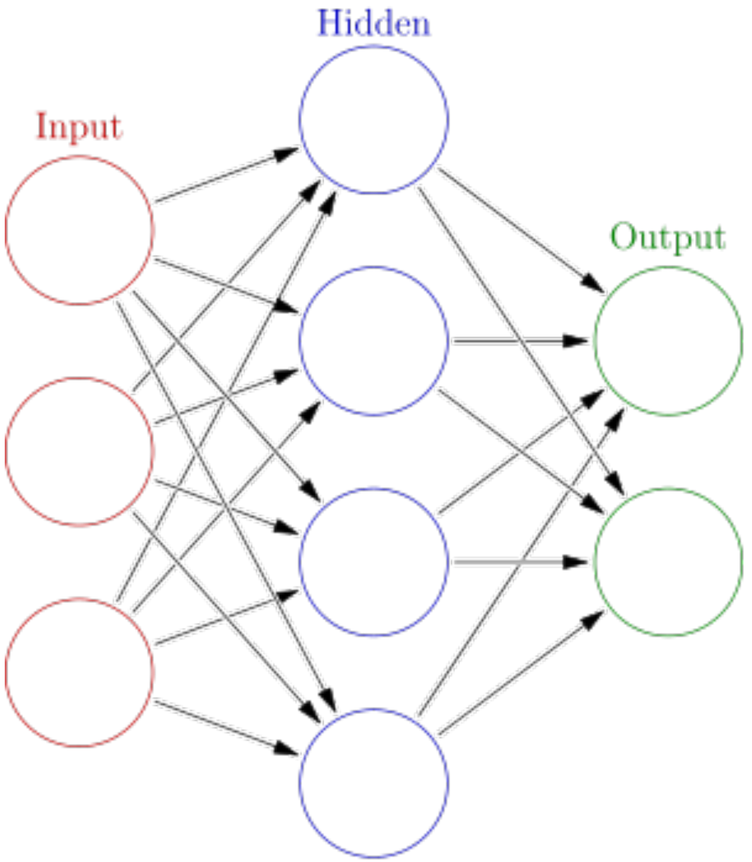
Neural Networks / Deep Learning

Can be used for both classification and regression

Difficult to train

Notoriously difficult to interpret

scikit-learn, TensorFlow, keras



Wikipedia

Clustering

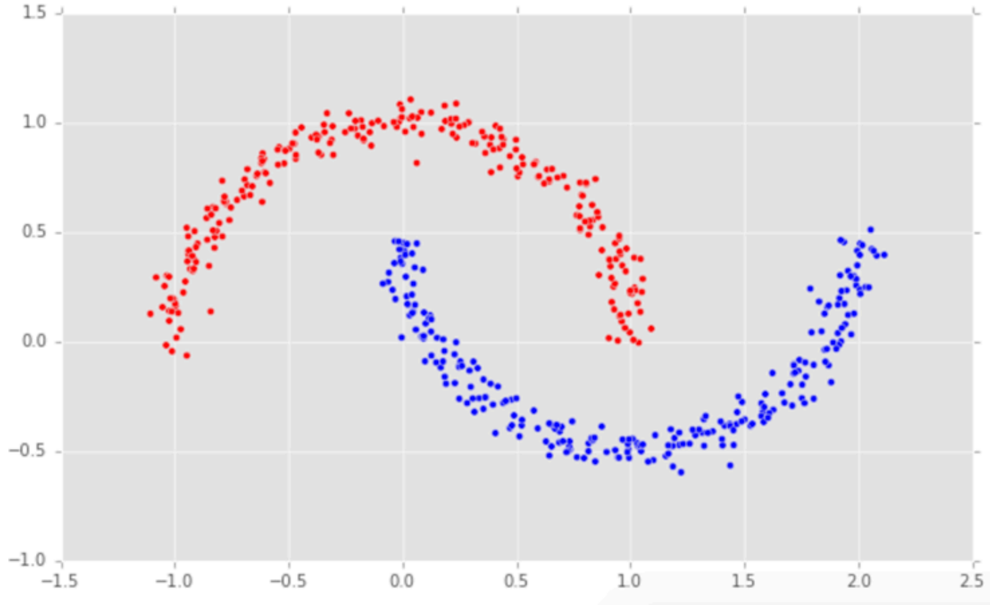
k-Means

Hierarchical Clustering

dendogram plots

scikit-learn

```
X, y = make_blobs(n_samples=n_samples, centers=5, random_sta
y_pred = KMeans(n_clusters=7).fit_predict(X)
plt.scatter(X[:, 0], X[:, 1], c=y_pred,  marker="o", cmap=cm
plt.show()
```

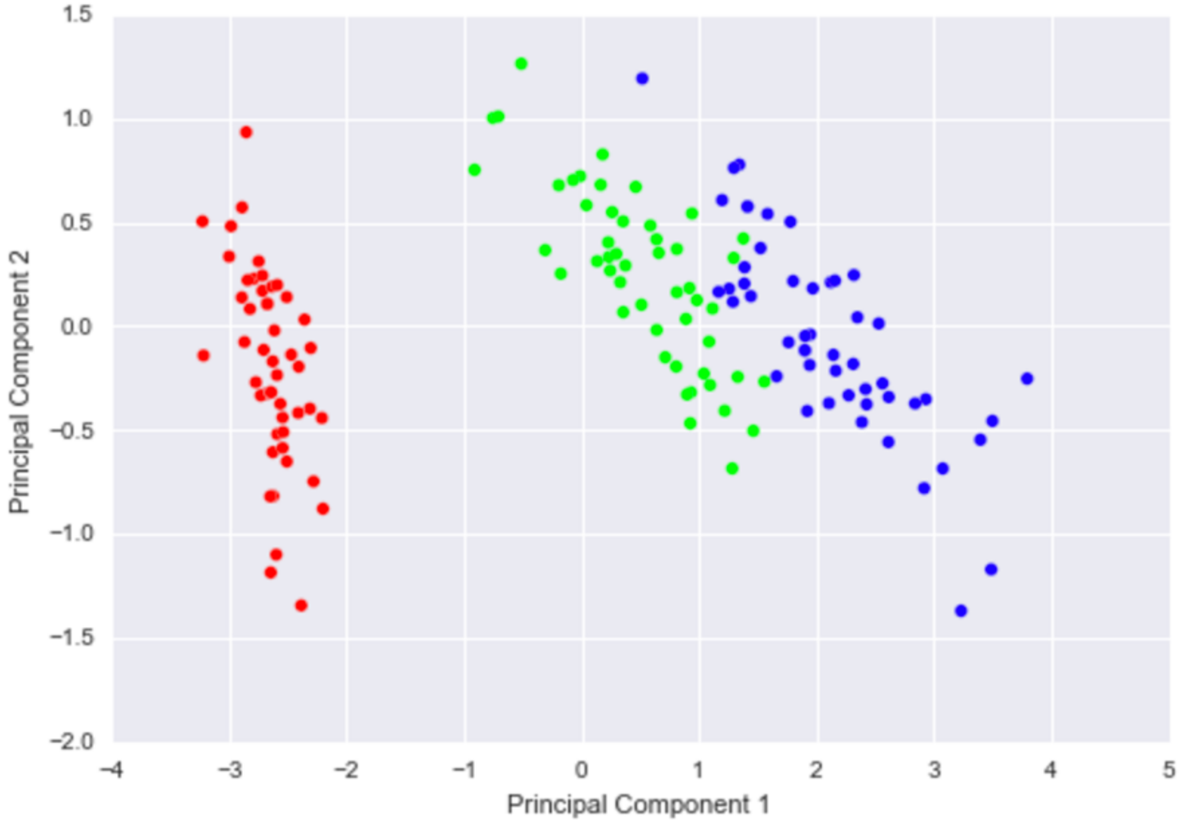


Dimensionality Reduction

Principal Component Analysis (PCA)

method of dimensionality reduction for, e.g., visualization

scikit-learn



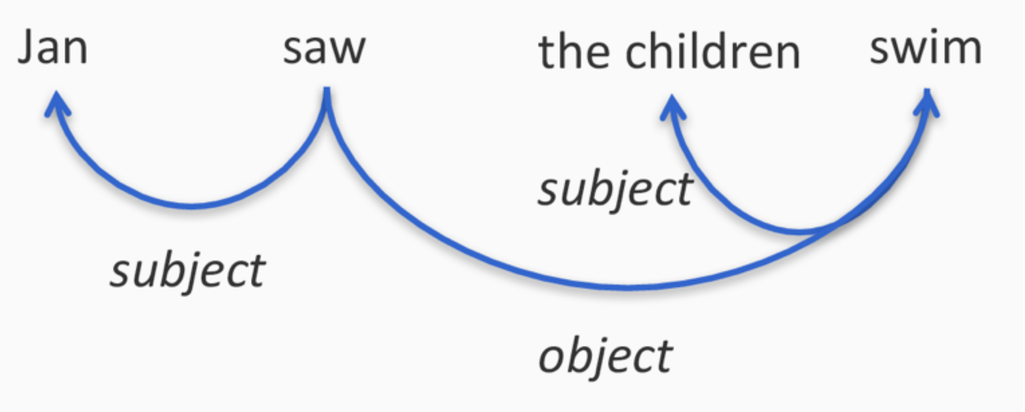
Natural Language Processing

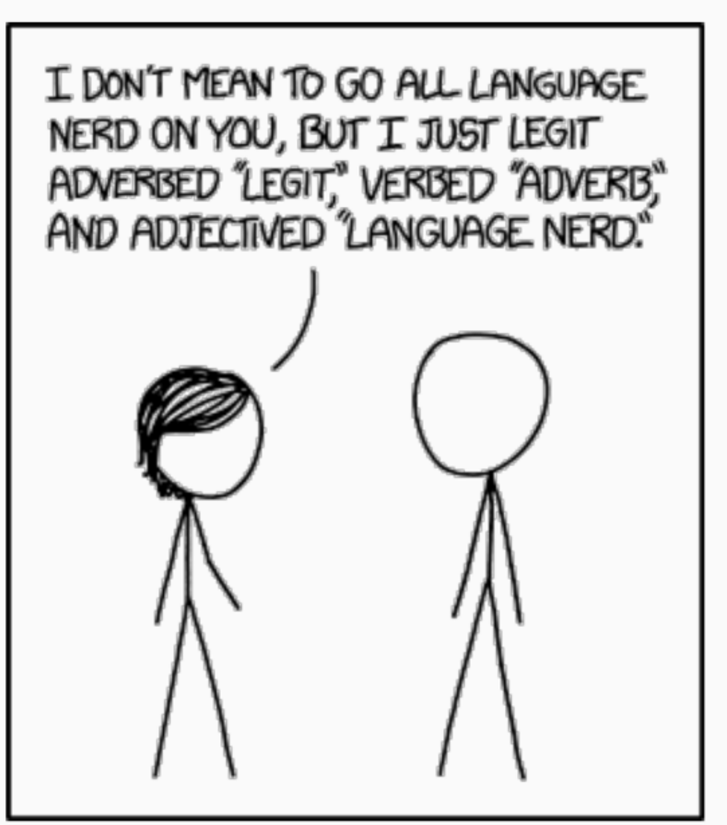
Guest lecture: Vivek Srikumar

Semantic analysis

Regular expressions

Natural Language Toolkit (NLTK)





https://xkcd.com/1443/

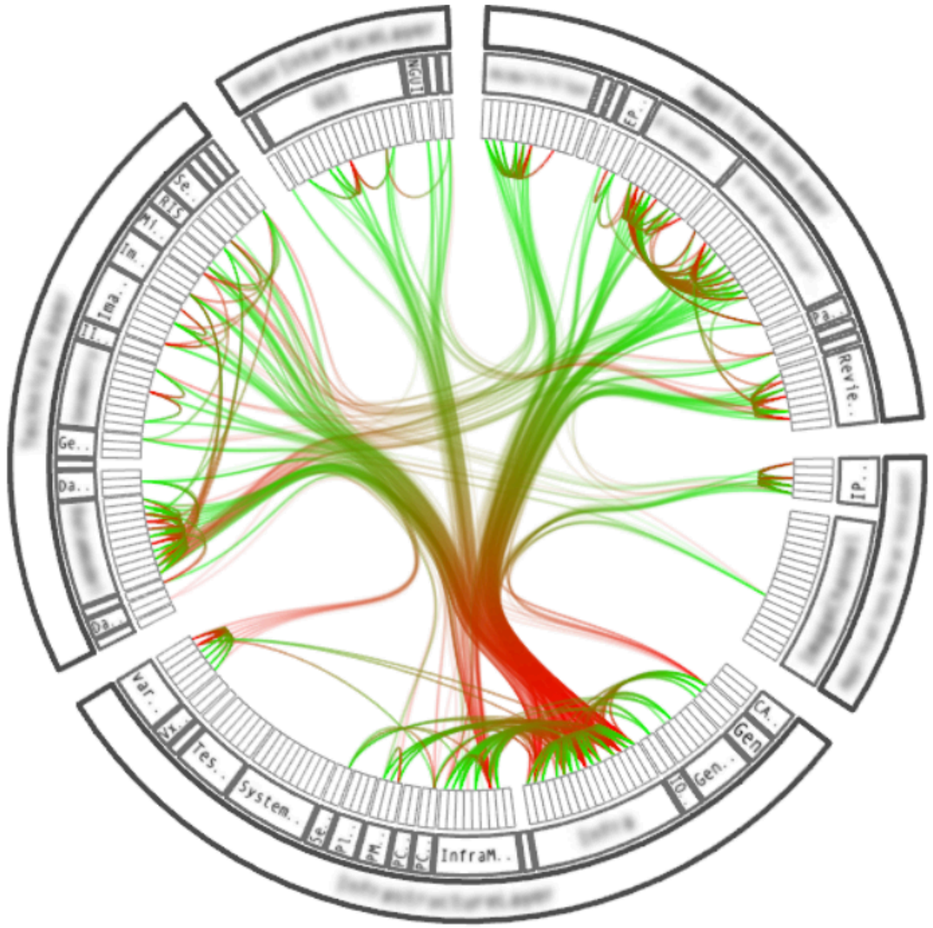
Graphs

Centrality Measures

PageRank

Path Finding

Graph Visualization



Time Series

Guest Lecture: Curtis Miller

Getting and Visualizing Stock Data

Moving averages

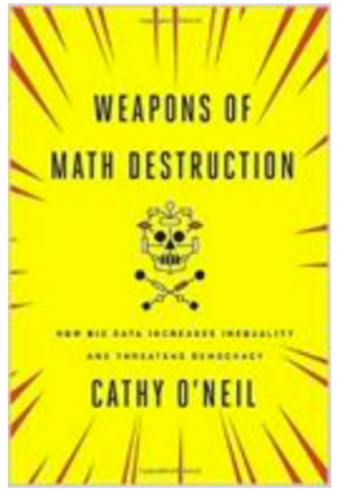
Trading Strategies

Pandas, Yahoo! Finance API

```
In [26]: apple["50d"] = np.round(apple["Close"].rolling(window = 50, center = False).mean(), 2)
         apple["200d"] = np.round(apple["Close"].rolling(window = 200, center = False).mean(), 2)

         pandas_candlestick_ohlc(apple.loc['2016-01-04':'2016-08-07',:], otherseries = ["20d", "50d", "200
         d"])
```

Ethics in Data Analysis



Guest lecture: Katie Shelef

The age of automated decision making

Where does bias come from?

Data scientists are responsible for their algorithms

Algorithms should be interpretable and transparent

(Physical and digital) data is people

Rating/Ranking/Elections

Least squares method for rating/ranking

Arrow’s Impossibility Theorem

2016-17 SEASON

NORTH DIVISION	CONFERENCE	OVERALL
4 Washington	8-1	11-1
Washington State	7-2	8-4
18 Stanford	6-3	9-3
California	3-6	5-7
Oregon State	3-6	4-8
Oregon	2-7	4-8
SOUTH DIVISION	**CONFERENCE**	**OVERALL**
8 Colorado	8-1	10-2
11 USC	7-2	9-3
20 Utah	5-4	8-4
Arizona State	2-7	5-7
UCLA	2-7	4-8
Arizona	1-8	3-9

What is Missing?

Reinforcement learning

The third pillar of machine learning beyond unsupervised and supervised learning

Related to optimal control

This statistical model can evolve over time

	from input ***x***, output:
unsupervised	summary ***z***
supervised	prediction ***y***
reinforcement	action ***a*** to maximize reward ***r***

source

Recommender Systems

Example: In 2009, Netflix offered a $1M prize to the winner of a competition to develop an algorithm that improves the accuracy of predictions about how much someone is going to enjoy a movie based on their movie preferences.

Collaborative filtering: build a model from a user's past behavior (e.g. items previously purchased) and similar decisions made by other users.

One approach: matrix completion

	Item 1	Item 2	Item 3	Item 4	Item 5
User 1	0	3	0	3	0
User 2	4	0	0	2	0
User 3	0	0	3	0	0
User 4	3	0	4	0	3
User 5	4	3	0	4	0

A matrix of user/item ratings

Ensemble Methods

Idea: use multiple learning algorithms on the same problem to get better performance

“Use alternative hypothesis”

Ensemble Method: Bootstrapping / Bagging

Used in classification and regression to avoid overfitting and improve performance

Sample the data (with replacement) and train several models, then average the output (regression) or vote (classification).

When this idea is used for decision trees, the result is called a random forest model.

Ensemble Method: Boosting

Can a set of weak learners create a single strong learner?

Idea: A sequence of classifiers are developed where each one is tweaked to more heavily weigh the data that were misclassified by previous classifiers.

Probabilistic / Bayesian Methods

- data, $\mathbf{X}$
- parameters in a probabilistic model, θ
- The *prior distribution* is the distribution of the parameters before any data is observed, $p(\theta)$.
- The *sampling distribution* or *likelihood function* is the distribution of the observed data conditional on its parameters, $p(\mathbf{X} \mid \theta)$.
- The *marginal likelihood* is the distribution of the observed data over the parameter(s),

$$p(\mathbf{X}) = \int_{\theta} p(\mathbf{X} \mid \theta) p(\theta) d\theta.$$

- The *posterior distribution* is the distribution of the parameter(s) after taking into account the observed data. This is computed using *Bayes' rule*,

$$p(\theta \mid \mathbf{X}) = \frac{p(\mathbf{X} \mid \theta) p(\theta)}{p(\mathbf{X})} \propto p(\mathbf{X} \mid \theta) p(\theta).$$

Research Reproducibility

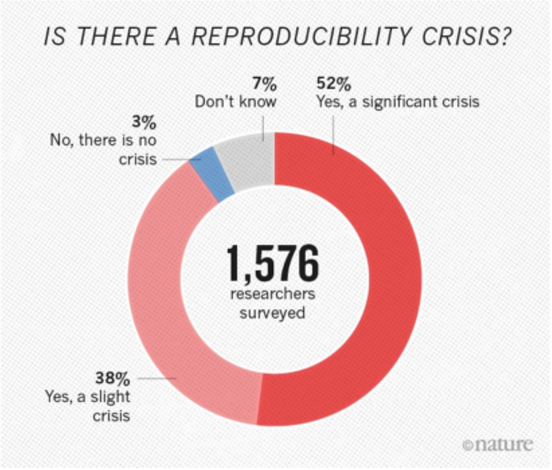
There is a “Replication Crisis”, particularly in psychology and medicine.

Reasons: Publication bias, cherrypicking, small N, irreproducible experiments, ….

Reproducibility is critical, but not everything can be described in paper

One step: provide raw data and scripts (Jupyter Notebooks!) for analysis methods

- Assumptions can be checked
- Data can be analyzed with different assumptions/methods
- Methods can be applied to different data



http://www.nature.com/news/1-500-scientists-lift-the-lid-on-reproducibility-1.19970

Where can you learn more?

Further courses of interest

Mathematics / Statistics

Math 1070: Introduction to Statistical Inference

Math 3070: Applied Statistics

Math 5080/6824: Statistical Inference I

Math 5090/6828: Statistical Inference II

Math 5010/6805: Introduction to Probability

Math 6010: Linear Regression Analysis

Math 6020: Multilinear Models

Math 6070: Mathematical Statistics

Math 5770/6640: Introduction to Optimization

Computer Science

CS 2420: Introduction to Algorithms & Data Structures

CS 4964: Math for Data (Foundations of Data Analysis)

CS 5130/6130: Computational Statistics

CS 5140/6140: Data Mining

CS 5340/6340: Natural Language Processing

CS 5350/6350: Machine Learning

CS 5630/6630: Visualization

MSTAT degree

Master of Statistics Program:

Data Science Option

http://mstat.utah.edu/

Masters in Statistics: MATHEMATICS

The Masters in Statistics (Mathematics) requires a thesis project. The degree consists of 36 credit hours of graduate level classes, 3 of which should be thesis hours.

AFFILIATED FACULTY

Tom Alberts, Tom Fletcher (School of Computing), Lajos Horvath, Davar Khoshevisan, Braxton Osting, Jeff Phillips (School of Computing), Firas Rassoul-Agha, Suresh Venkatasubramanian (School of Computing).

DATA SCIENCE OPTION

Prerequisites

Math: Calculus I-III (Math 1210, 1220, 2210), Linear Algebra (Math 2270), Probability (Math 5010), or equivalent coursework.
CS: Introduction to Algorithms and Data Structures (CS 2420), Algorithms (CS 4150), or equivalent coursework.

CORE CLASSES (to be completed in the first year of study)	
Math 5080	Intro to Statistical Inference I
Math 5090	Intro to Statistical Inference II
CS 6140	Data Mining
CS 6350	Machine Learning

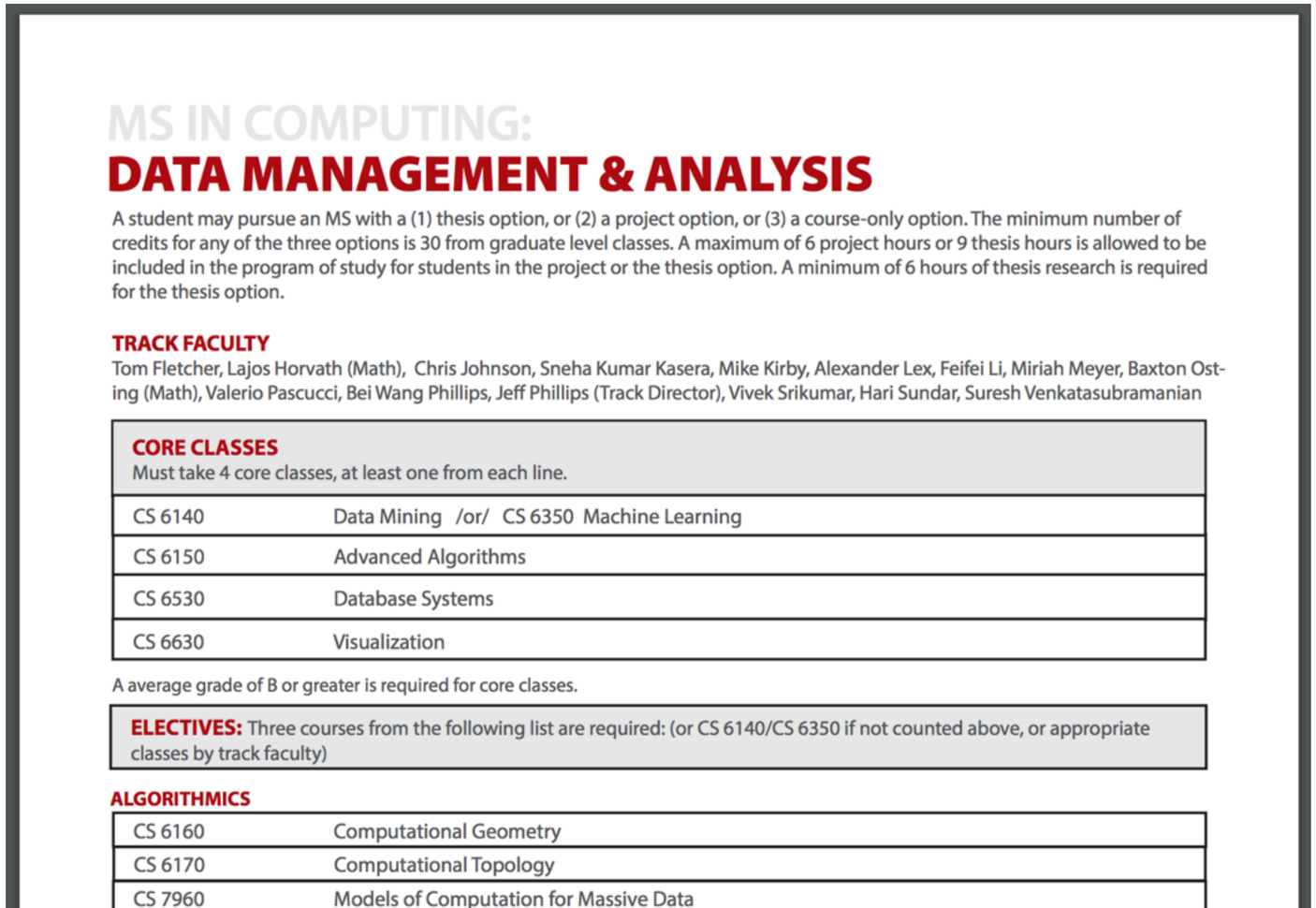
Electives: A total of 9 elective courses are required. Two must be taken from the Math elective list, and two must be taken from the CS elective list. The remaining electives may be taken from these lists, or from other departments on campus (subject to the approval of a student's advisor).

MATH ELECTIVES	
Math 5030	Actuarial Mathematics
Math 5040-50	Stochastic Processes & Simulation I-II
Math 5600	Survey of Numerical Analysis
Math 5610-20	Introduction to Numerical Analysis I-II
Math 5650	Topics in Numerical Analysis
Math 5660	Parallel Numerical Methods
Math 5740	Mathematical Modeling
Math 5075	Time Series
Math 5770	Introduction to Optimization
Math 6010	Linear Models
Math 6030	Multivariate Models
Math 6040	Probability
Math 6070	Mathematical Statistics
CS ELECTIVES	
CS 5530	Database System
CS 6150	Advanced Algorithms
CS 6190	Probabilistic Learning
CS 6300	Artificial Intelligence
CS 6340	Natural Language Processing
CS 6630	Visualization
CS 6961	Structured Prediction

MS in Computing Track: Data Management and Analysis

Designed for full-time students

http://www.cs.utah.edu/docs/Graduate/handbook16-17/datamang-2016-17.pdf



MS IN COMPUTING:

DATA MANAGEMENT & ANALYSIS

A student may pursue an MS with a (1) thesis option, or (2) a project option, or (3) a course-only option. The minimum number of credits for any of the three options is 30 from graduate level classes. A maximum of 6 project hours or 9 thesis hours is allowed to be included in the program of study for students in the project or the thesis option. A minimum of 6 hours of thesis research is required for the thesis option.

TRACK FACULTY

Tom Fletcher, Lajos Horvath (Math), Chris Johnson, Sneha Kumar Kasera, Mike Kirby, Alexander Lex, Feifei Li, Miriah Meyer, Baxton Osting (Math), Valerio Pascucci, Bei Wang Phillips, Jeff Phillips (Track Director), Vivek Srikumar, Hari Sundar, Suresh Venkatasubramanian

CORE CLASSES
Must take 4 core classes, at least one from each line.

CS 6140	Data Mining /or/ CS 6350 Machine Learning
CS 6150	Advanced Algorithms
CS 6530	Database Systems
CS 6630	Visualization

A average grade of B or greater is required for core classes.

ELECTIVES: Three courses from the following list are required: (or CS 6140/CS 6350 if not counted above, or appropriate classes by track faculty)

ALGORITHMICS

CS 6160	Computational Geometry
CS 6170	Computational Topology
CS 7960	Models of Computation for Massive Data

CS Big Data Certificate

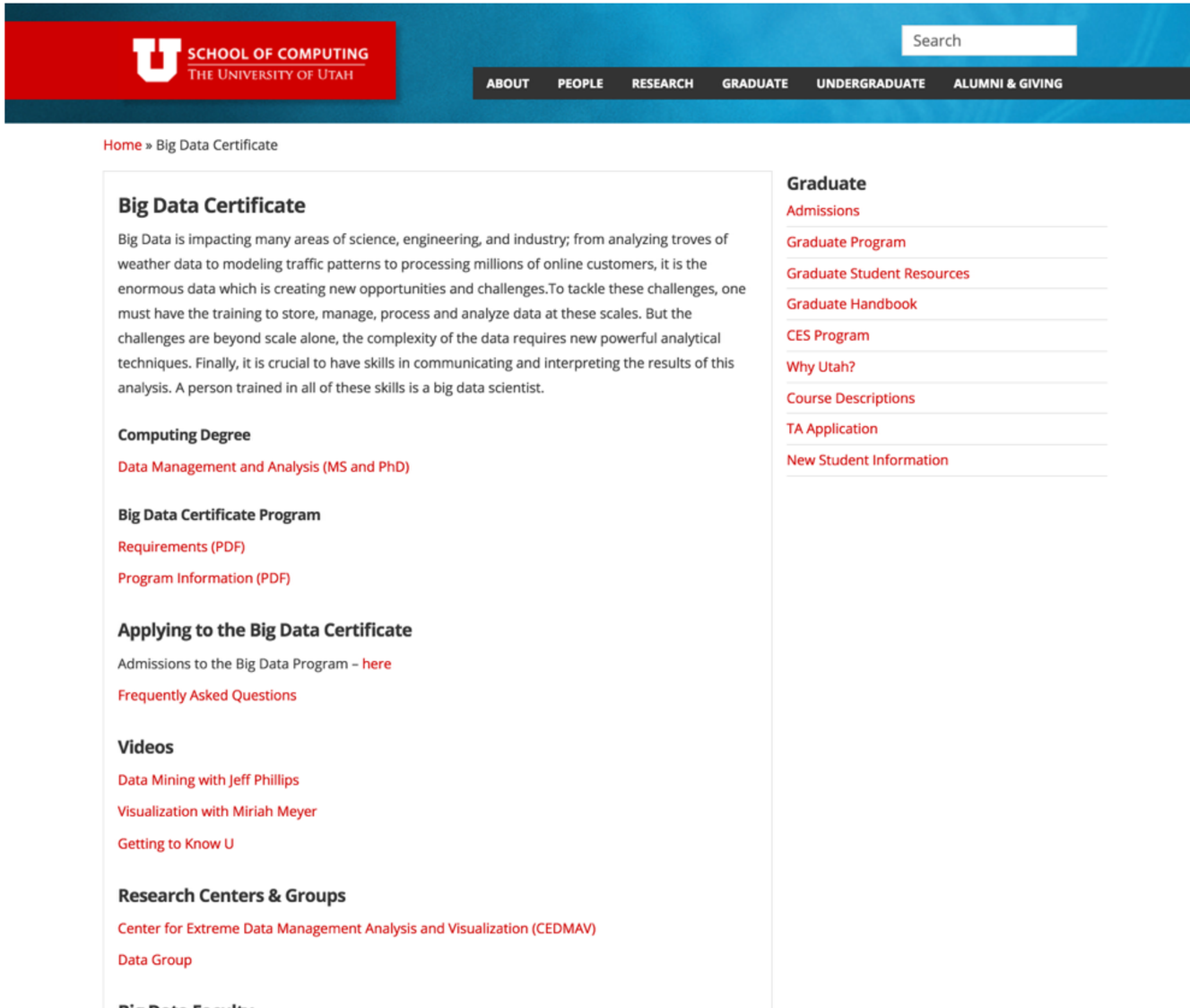
www.cs.utah.edu/bigdata/

Designed for professionals working full-time

Goes through many higher level CS data courses

Undergrad required

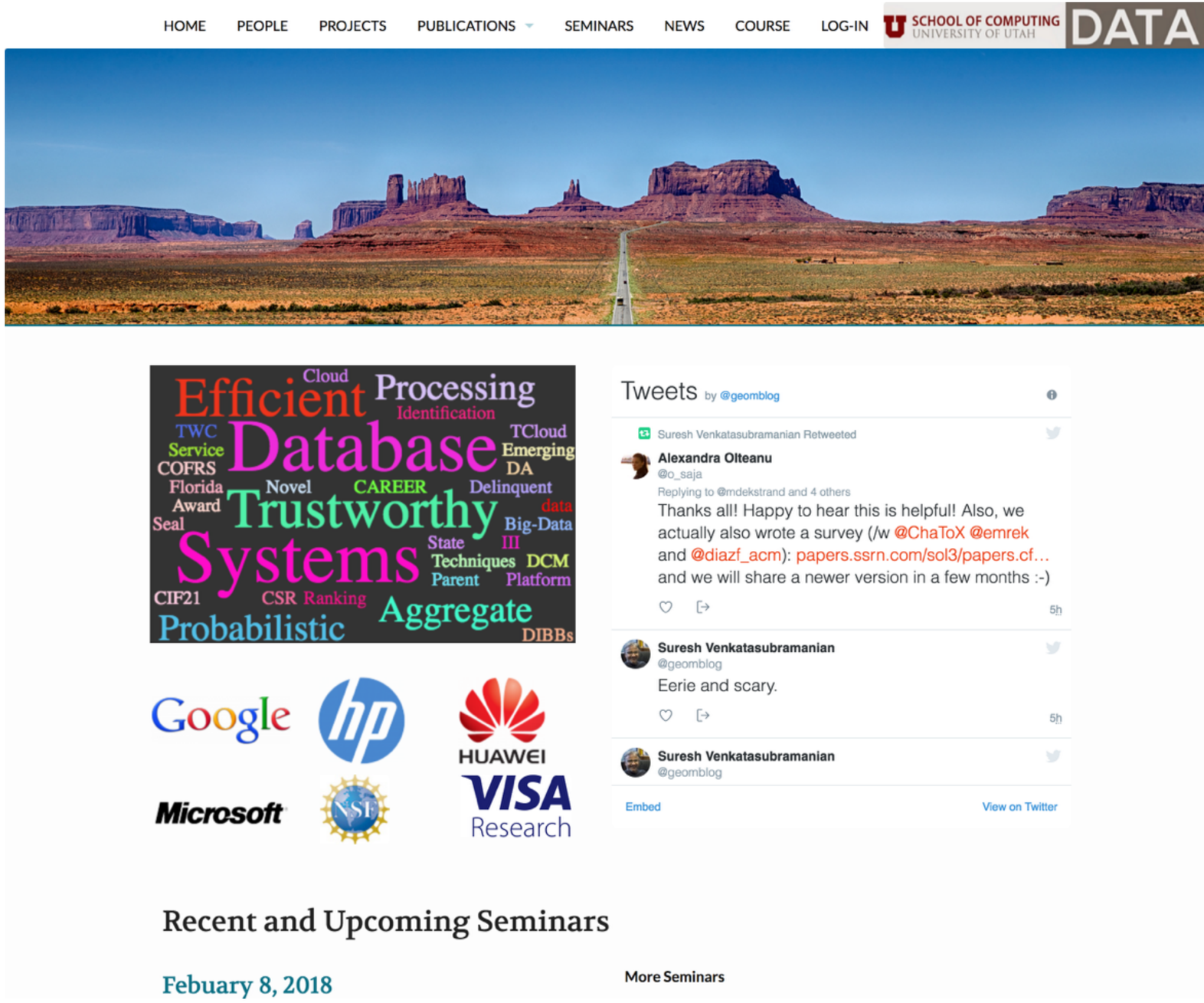
Not a MS degree!



Data Group

Meets weekly to discuss methods and applications in data analysis

Data Group Website



Data Science Day @ Utah

Friday. Jan 13, 2017

Data Science Day welcomes all students, staff, and faculty at the University of Utah to present a poster or demo at the Utah Data Science Day 2017.

Consider presenting your class projects!

http://datascience.utah.edu/dataday/

Data Science Job Fair

Welcome: Data Science at Utah

Panel: Data Science in Industry

Posters and Demos

Data Science + X Talks

Keynote

Poster Awards !!

How did it Go?

Feedback Please!

Were your expectations met?

What else would you have liked to learn about?

Was the order good?

Did you feel prepared? Are the prerequisites appropriate?

Was it too much work? Was it too easy?

Too little math? Too much math?

Too little programming? Too much programming?

Did you like Python / Jupyter / GitHub?

Did you enjoy the project?

Should we have had exams?

Course Evaluation

https://goo.gl/lbhkEr

Please Take 5 Min now to evaluate this course!

Evaluations are important for us to improve the course and our teaching!

Thanks!

To you for participating and coming to lectures!

To our guest lecturers: Curtis Miller, Katie Shelef, and Vivek Srikumar!

To our TAs Kiran Gadhave, Shuvrajit Mukherjee, and RK Yoon!