Data Mining & Analytics

INFO 254 / INFO 154
School of Information / Spring 2019

Prof. Zach Pardos

What will be learned in class?

What will be learned in class?

- Common sense in data mining and machine learning

Zachary A. Pardos
Assistant Professor

Graduate School of Education
School of Information

Research -> zachpardos.com

Areas of study (Big Data in Education)

- Knowledge representation
- Engineering personalized, adaptive affordances

Courses taught

- Digital Learning Environments (EDU Online Fall/Summer)
- Machine Learning in Education (EDU/INFO Fall)
- Data Mining & Analytics (INFO Spring)

Training
PhD in Computer Science (WPI)
Postdoc at MIT CS AI Lab

Research Lab: github.com/CAHLR

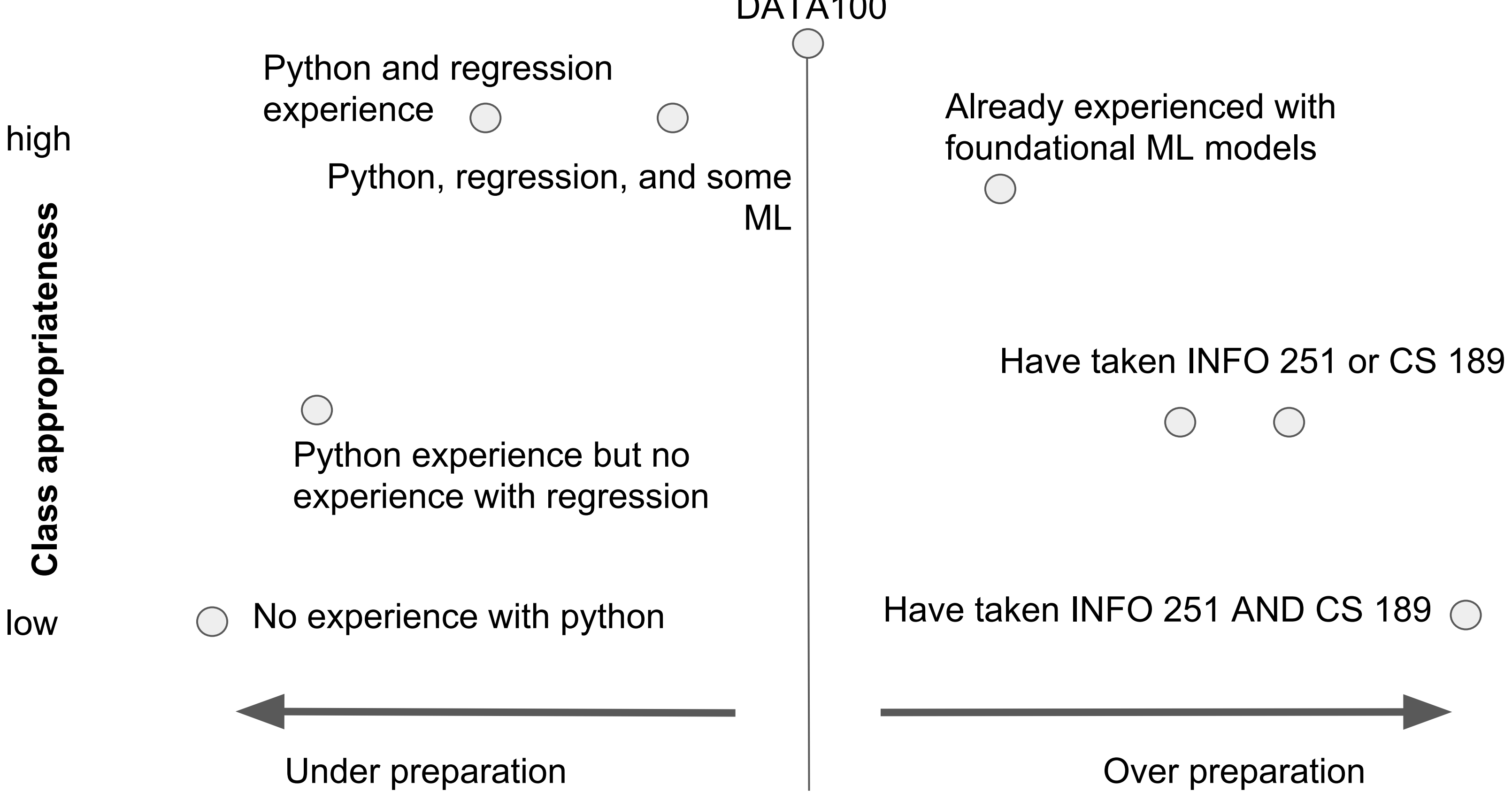
CAHL Computational Approaches to Human Learning (CAHL)

GRADUATE SCHOOL OF EDUCATION UC Berkeley School of Information

Survey results

Bonus question: Piazza or bCourses?

Class Preparation Guidance



Overview of topics covered in class

- First half of the semester
  - Foundational models
  - Culminates in prediction competition & midterm
- Second half of the semester
  - Representation learning approaches (neural networks)
  - Culminates in final project presentation (info 154) and paper (info 254)
- Tools
  - Python/pandas
  - Python/numpy
  - Python/scikit-learn
  - Python/keras

Example Final Projects
from Data Mining and Analytics ‘16 & ‘17

Example Final Project: NBA Player Value

Predicting Basketball Player Salaries

Zubair Marediya, Naya Olmer, Nadar Azari, Boris Lo

Info 290T | Data Mining and Analytics | Spring 2016

Example Final Project: NBA Player Value

Goals

- Predicting **basketball players contract values** using historical contracts and player statistics.
- Comparing predicted contract values with actual contract values to **identify which players are undervalued and overvalued**.

Example Final Project: NBA Player Value

Data

- Player Salaries
- Player Statistics (Minutes, Field Goals, Three Pointers, Rebounds, etc.)

Example Final Project: NBA Player Value

Features

- Games Played
- Team
- Minutes
- Field Goals
- Field Goal Attempts
- Three Pointers
- Three Point Attempts
- Free Throws
- Free Throw Attempts
- Plus/Minus
- Year
- Salary Cap
- Offensive Rebounds
- Defensive Rebounds
- Total Rebounds
- Assists
- Steals
- Blocks
- Turnovers
- Fouls
- Points
- Age
- Salary
- Percentage of Salary Cap

Example Final Project: NBA Player Value

Outcome

Predicted player salaries with an RMSE of only **$2.9 million dollars**.

40% of players found over-valued.

60% of players found under-valued.

Example Final Project: NBA Player Value

Example 1: Stephen Curry (2014-2015)

- During the 2014-2015 NBA season, Stephen Curry was named league MVP.

- During this season, Stephen Curry made $10,629,214.

- The ML model predicts that Curry should have earned $12,696,622 for his work in 2014-2015, meaning that Curry far exceeded his team’s projected value.

Example 2: James Harden (2014-2015)

- During the 2014-2015 season, James Harden was the MVP runner up.

- During the season, Harden made $14,728,884.

- The ML model predicts Harden should have made $14,441,376, almost exactly what he actually made. This mean that he met the Rockets’ expectations.

Example Final Project: Mood from Fitbit Data

[Eudae] Sensing Mood From Fitbit Data

Info 290T Final Project, Spring 2016

April Dawn Kester, Audrey Leung, Heidi Huang, Laura Montini, Yiwen Tang

Example Final Project: Mood from Fitbit Data

Goal

Predicting a person’s mood from their Fitbit data using machine learning.

Example Final Project: Mood from Fitbit Data

Data

18 Participants
2 Weeks
4 Mood Surveys per day
Fitbit device continuously tracking

Mood Features
- Arousal Dimension
- Arousal Dimension Slider
- Pleasure Dimension
- Pleasure Dimension Slider

Activity Features
- Steps
- Distance
- Floors
- Minutes Asleep
- Heart Rate

Example Final Project: Mood from Fitbit Data

Outcome

Achieved **80% accuracy** in predicting mood based on Fitbit data.

Best results on aggregate, discrete data

45%	62%	80%	80%
Baseline Accuracy (Majority Class = Neutral)	Random Forest	Neural Network	Logistic Regression

Example Final Project: Maximizing Taxi Tips

NYCe TAXI !

Anand Anubhav Sindhuja

Motivation

Predicting tips for NYC taxi drivers based on the features and characteristics of the taxi rides.

Example Final Project: Maximizing Taxi Tips

PROJECT GOALS

- Maximize tip benefits for taxi drivers
- A generic algorithm that can be extended to any city

Example Final Project: Maximizing Taxi Tips

RELEVANT FIELDS

Unique Fields

- medallion
- hack_license
- vendor_id

Trip Fields

- pickup_datetime
- dropoff_datetime
- trip_time
- trip_distance
- pickup_latitude
- pickup_longitude
- dropoff_latitude
- dropoff_longitude
- passenger_count

Fare Fields

- fare_amount
- **tip_amount**
- tolls_amount
- total_amount
- mta_tax
- payment_type

Outcome

- 98% accuracy on Tip vs. No Tip
- 81% accuracy on Tip Class
- 68% accuracy on Tip Percentage

Example Final Project: Maximizing Taxi Tips

INFERENCES

- Card Payments have higher tip
- Tip varies directly with fare
- Routes with tolls yield less tip
- Tip directly varies with the cost of living index

Example Final Project: Song representation learning

Song2Vec

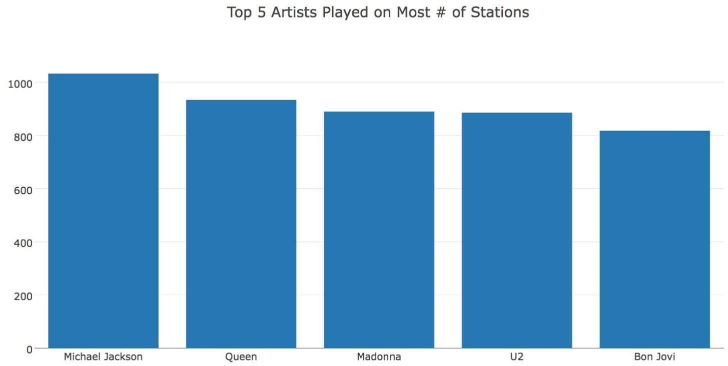
By
Kartik Gupta, Vishnu Murthy, Elias Orellana & Samridh Saluja,

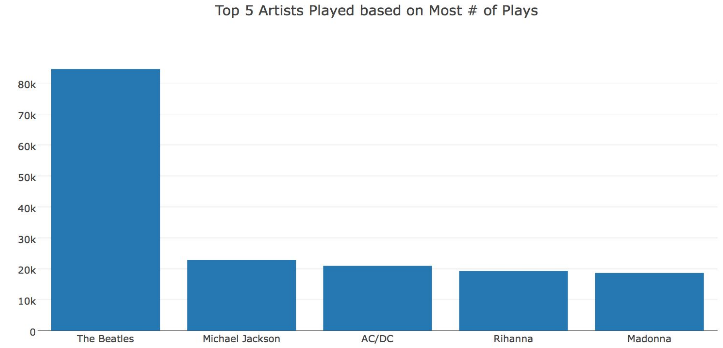
Example Final Project: Song representation learning

Summary Statistics

Total No. of Artists	Total No. of Stations	Total No. of Plays
54,592	3,535	8,477,970

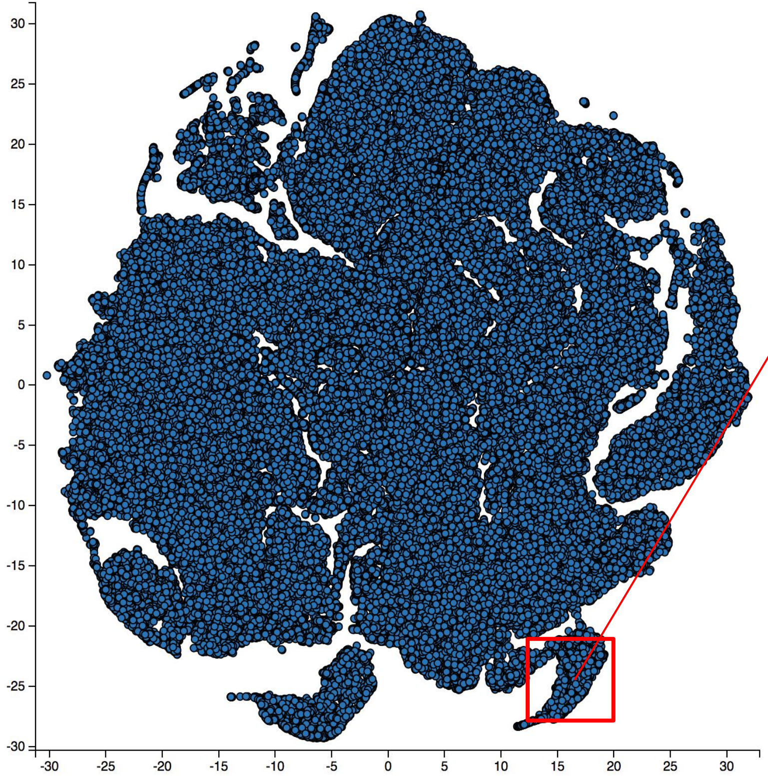
Unique Artist	Mean	Median	Max
No. of Stations	22	9	1033
No. of Plays	156	40	84,587





Example Final Project: Song representation learning

Visualization of the Data - Unique Songs

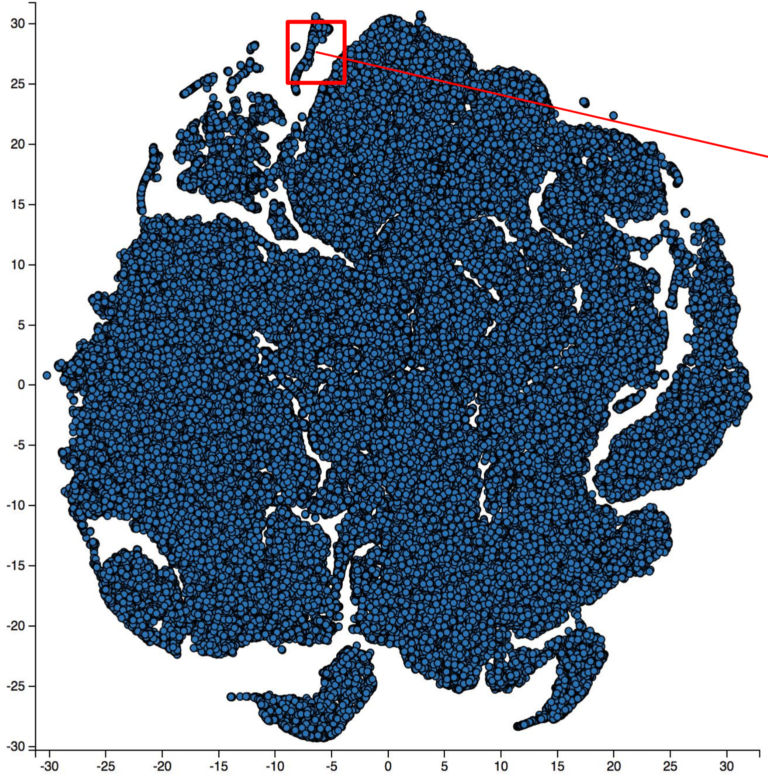


Genre-based clusters

Rap/contemporary

1) Jay-Z - Run This Town feat. Rihanna & Kanye West
2) 2Pac - Hit 'Em Up
3) Dr. Dre - Xxplosive
4) Young Money - Bedrock (Ft Lloyd)
5) Chris Brown - No Bull

Visualization of the Data - Unique Songs



Genre-based clusters

Classic Rock

1) The Beatles - Mr. Moonlight
2) Paul Mccartney - Ever Present Past
3) John Lennon - Real Love
4) Johnny Cash - In My Life
5) George Harrison - Here Comes The Sun

Sanity Check

Same genre

Same sound

Record label

```
model.most_similar(positive=['Drake'])
```

```
[('Lil Wayne', 0.9860175848007202),
 ('T-Pain', 0.968503236770629 9),
 ('DJ Khaled', 0.9681740999221802),
 ('Fabolous', 0.959853827953338 6),
 ('Big Sean', 0.957724034786224 4),
 ('Cee-Lo', 0.956097722053527 8),
 ('diddy dirty money', 0.9537268877029419),
 ('Nicki Minaj', 0.9485852718353271),
 ('J Cole', 0.946276307106018 1),
 ('Mindless Behavior', 0.9460246562957764)]
```

Findings

Artist Specific

−

=

Daddy Yankee
Reggaeton

Drake
Hip Hop

Reily (Reyli)
Latin Pop
0.80

DMA ‘17 Class Final Project Titles (1 of 2)

Exploring Online Political Climates

Using Machine Learning to Predict Asthma Risk

Anomaly Detection in time-series data (Water Usage)

Predicting Reasons for Medical Non-adherence

Representation Learning and ML on Materials Data Set

Boston Airbnb Neighborhood Price Analytics

The Effects of Climate Change on East Coast Hurricanes

Sequence to Sequence Approach to Finding Relevant answers in MOOC forums

DMA ‘17 Class Final Project Titles (2 of 2)

Indoor Localization

Asmi, Artificial Social Media Intern

song2vec

Generating Semantic Descriptions for Images

Computer Vision Classification of Cervix Types

How Does Temperature Affect Carbon Dioxide Release

Sentiment Analysis : Emotion in Text

Ipredict

Fake News

Structure of the class

Tuesdays: Concepts introduced, quiz answers reviewed

Thursdays: Quiz (10m), software tutorial, lab begins

Grading:

- Homeworks/Labs - 30%
- Midterm - 25%
- Quizzes - 10%
- Final Project - 35%

Local optimization vs. Strategic goals

- Local optimization
  - Increasing accuracy (hyper parameter tuning, feature selection, ensembling)
- Strategic goals
  - Who does the predictive analysis benefit and why is it needed instead of descriptive stats?

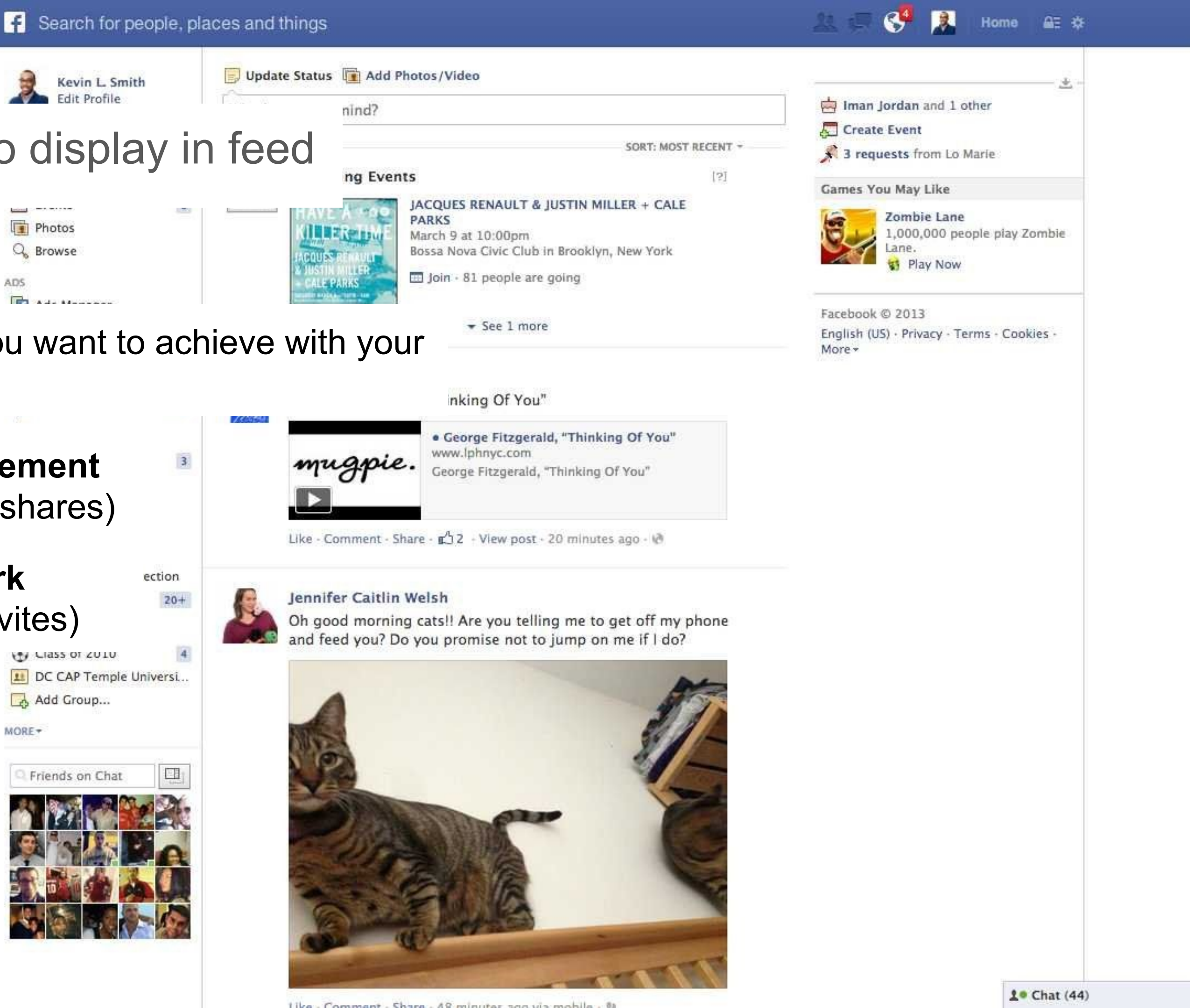
Strategy comes first!

Example 1

Selecting stories to display in feed

What outcome might you want to achieve with your selection criteria?

- Maximize **engagement** (likes/comments/shares)
- Maximize **network growth** (friend invites)



General ML approach to classification:

1. Create features of the post (p_n)
2. Create features of the reader/user (u_n)
3. Choose outcome to optimize (Y)
4. Learn historical relationship between features and outcome

features of post		features of user		outcome
p_1	p_n	u_1	u_n	Y

$$f(p_1,..p_n,u_1,..u_n) = Y$$

Example 2

ucberkeleyofficial
Sproul Plaza
16h

4,492 likes

ucberkeleyofficial Happy #MLKDay, everyone! 🌟 #FiatLux
Dr. King spoke on Sproul Plaza on May 17, 1967, to a crowd of 7,000.
Photo copyright Ron Riesterer/Photoshelter)
#ucberkeley #martinlutherking #sproulplaza #crowd

view all 14 comments

Comment highlighting

das_the_shef incredible

catstanton i love this school (,:

General ML approach to sentiment classification

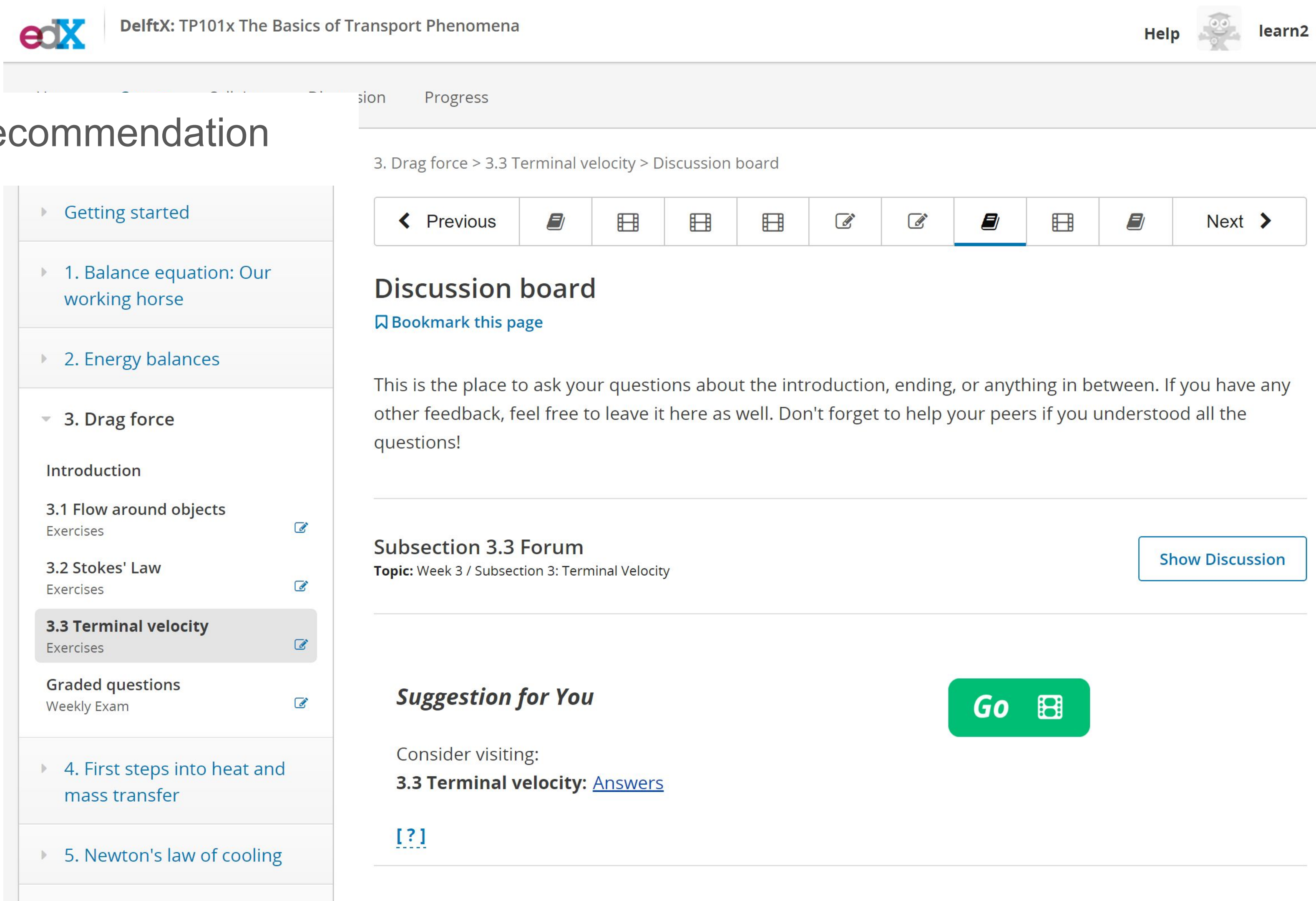
1. Create word frequency featureset
2. Hand code sentiment of a sample of comments
3. Learn the influence (weights) of each word wrt the code

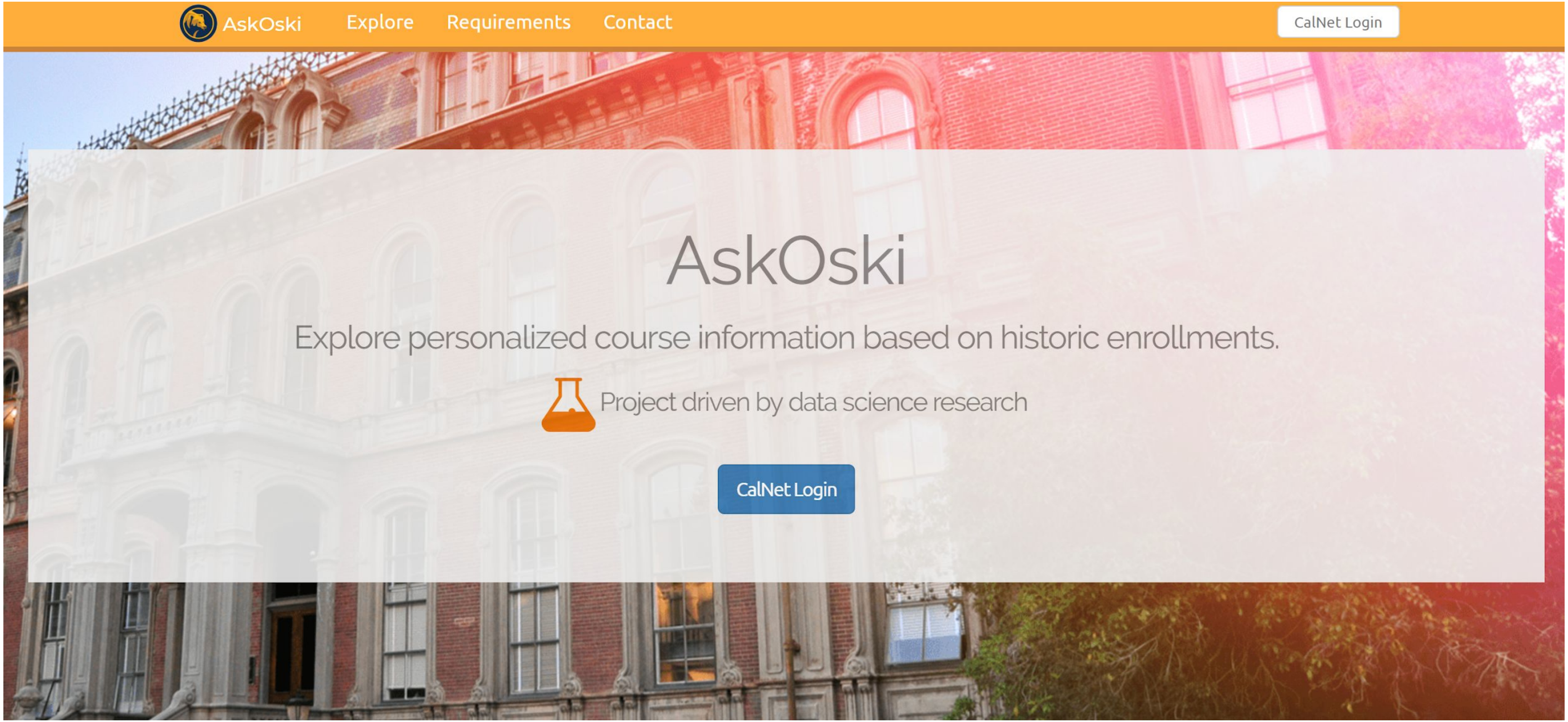
frequency of each words in the comment				outcome
w_1	w_2	...	w_n	Y

$$f(w_1, w_{2,} .. w_n) = Y$$

Example 3

Personalized recommendation





AskOski.berkeley.edu

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- Tools
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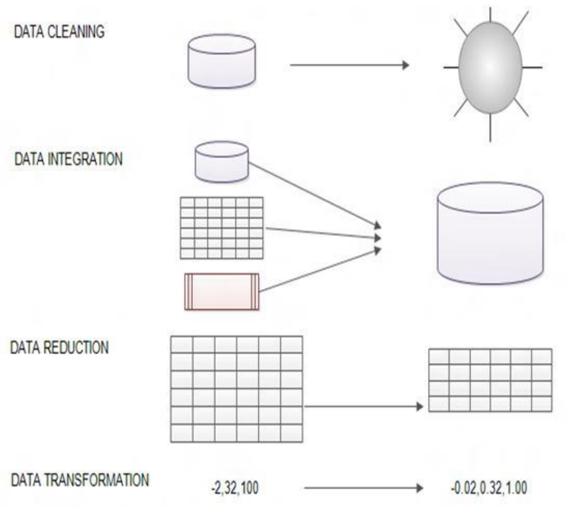
  - Python/keras

Data Preprocessing

- “Garbage in, garbage out”
- Majority of data miners spend 60% or more of their time on data cleaning and preparation) *
  http://www.kdnuggets.com/polls/2003/data preparation.htm

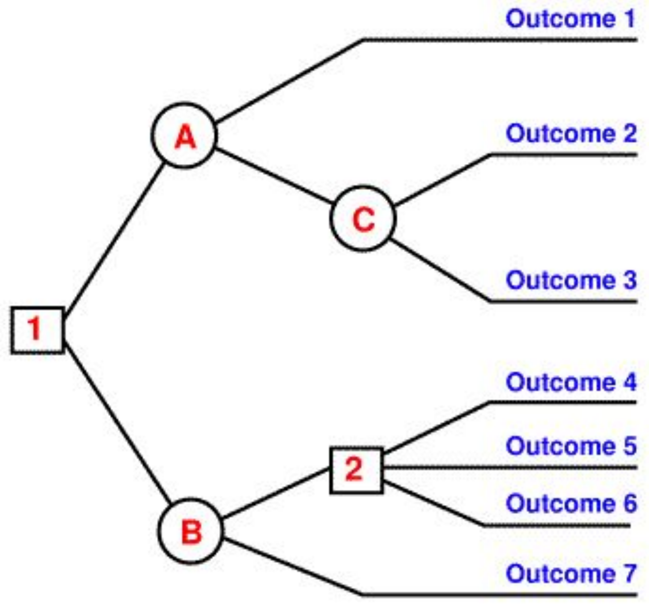
Topics

- Data Cleaning (missing values, noisy data)
- Data Reduction (PCA, Regression and Binning)
- Data Transformation (Aggregation, Smoothing)



Decision Trees

- Decision Trees (DTs) are a non-parametric supervised learning method used for classification. The goal is to create a model that predicts the value of a target variable by learning simple decision rules inferred from features.

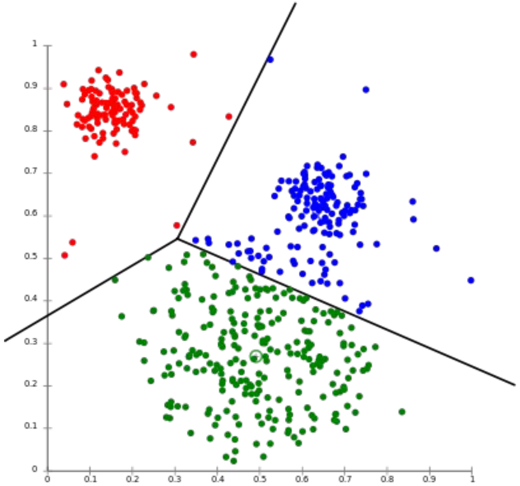


Topics

- Decision Tree Induction
- Attribute Selection Measures - Information Gain, Gain Ratio, Gini Index
- Tree Pruning

Clustering

- Cluster analysis or clustering is the task of grouping a set of objects in such a way that objects in the same group (called a cluster) are more similar (by some measure) to each other than to those in other groups. This is a popular form of unsupervised learning.



Topics

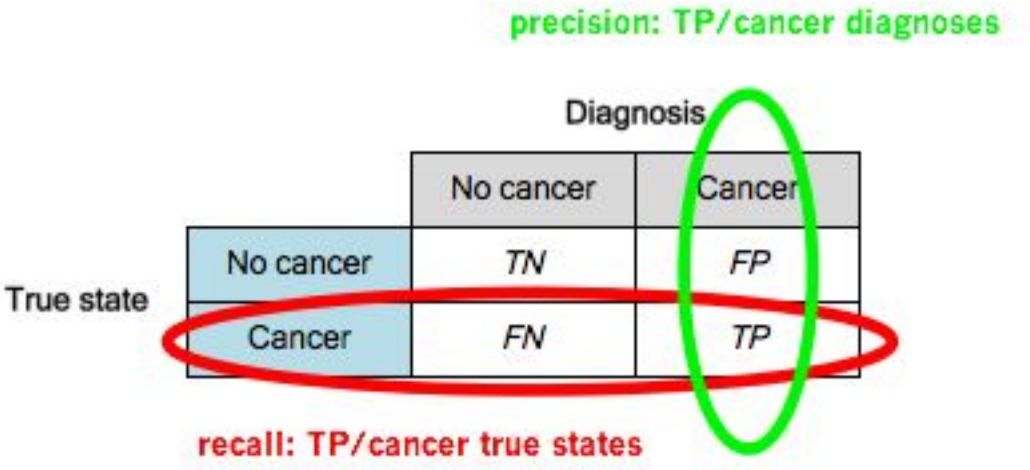
- K-means Clustering
- Spectral Clustering
- Cluster Quality (Elbow method,Silhouette Coefficient)

Error Metrics

- Metrics for evaluating classifier performance

Topics

- Confusion matrix
- Accuracy
- AUC
- Specificity
- Precision and Recall

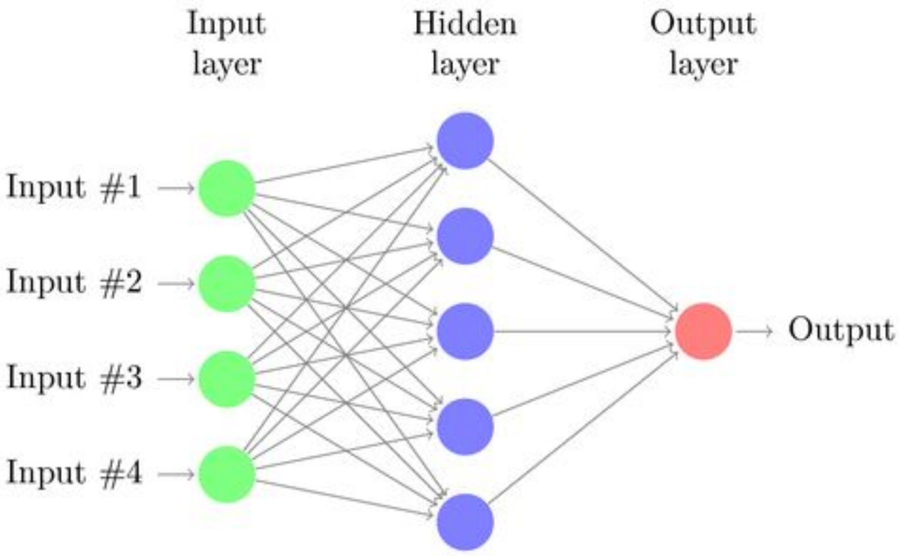


Neural Networks

- Artificial neural networks are a series of nodes (w/activations) and edges (w/weights) that can learn arbitrary functions and were loosely inspired by the neural structure of the brain.

Topics

- Multi-perceptron FFNN
- Back propagation
- Recurrent Neural Networks

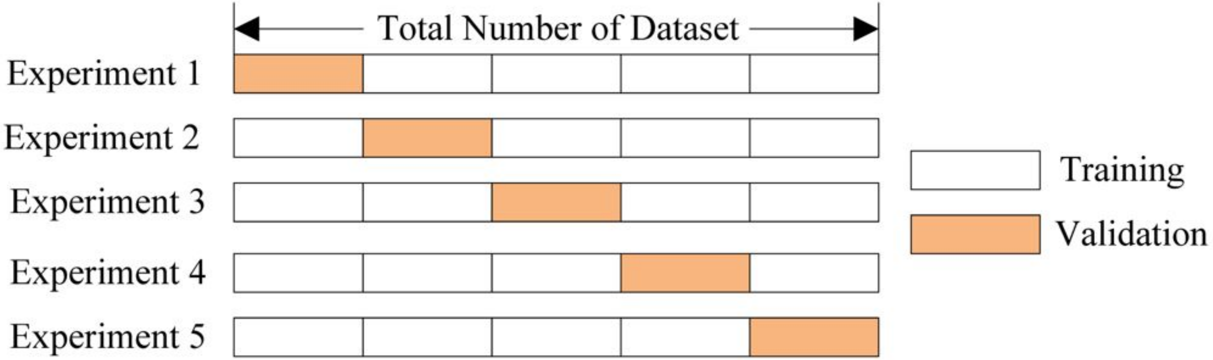


Cross-validation and Classifier Enhancement

- An evaluation to improve reliability of performance

Topics

- Hold out strategies
- Generalization
- Statistical significance

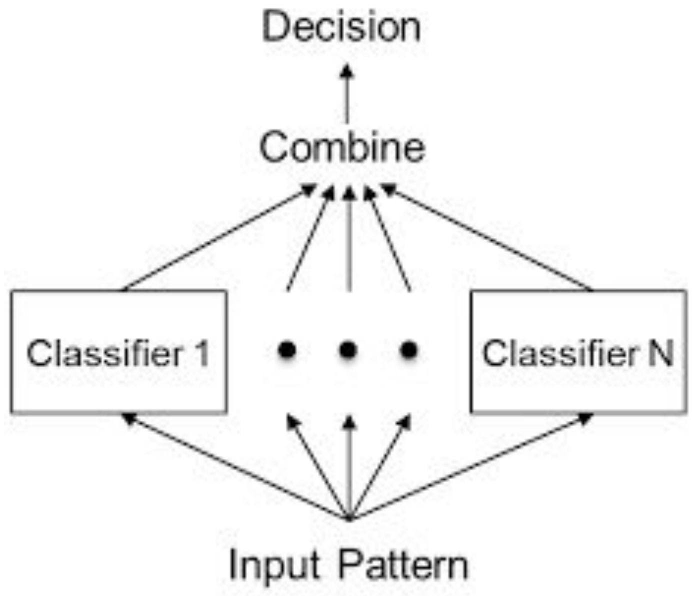


Ensemble Learning

- Ensemble learning is the combination of predictors that often results in better performance than the individual predictors could achieve alone

Topics

- Bagging
- Boosting (Adaboost)
- Random forests



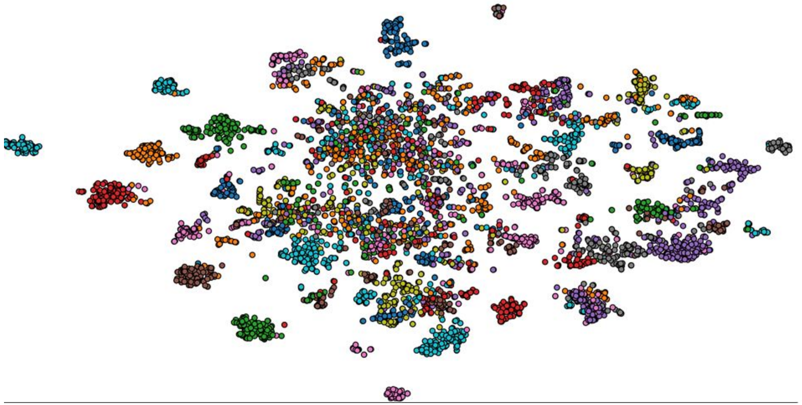
Second half of semester

Representation Learning

- New approach to ML: Instead of hand engineering features, learn them from the raw data

Topics

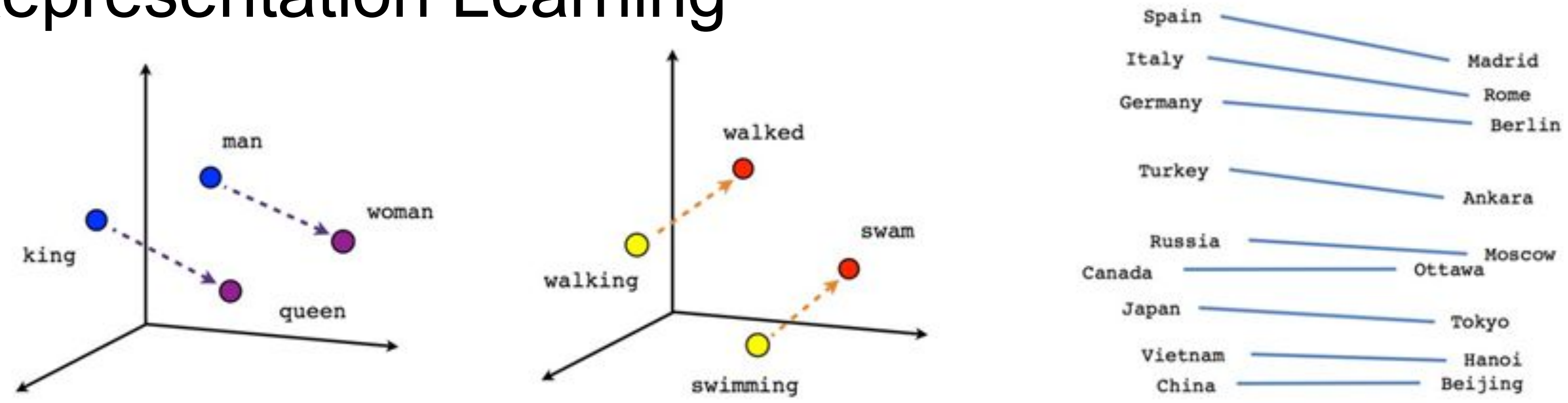
- Skip-grams
- RNNs (“deep” learning)
- Dimensionality reduction
- Visualization (cluster analysis)



Berkeley Course Representation

Word2Vec

Representation Learning



Male-Female

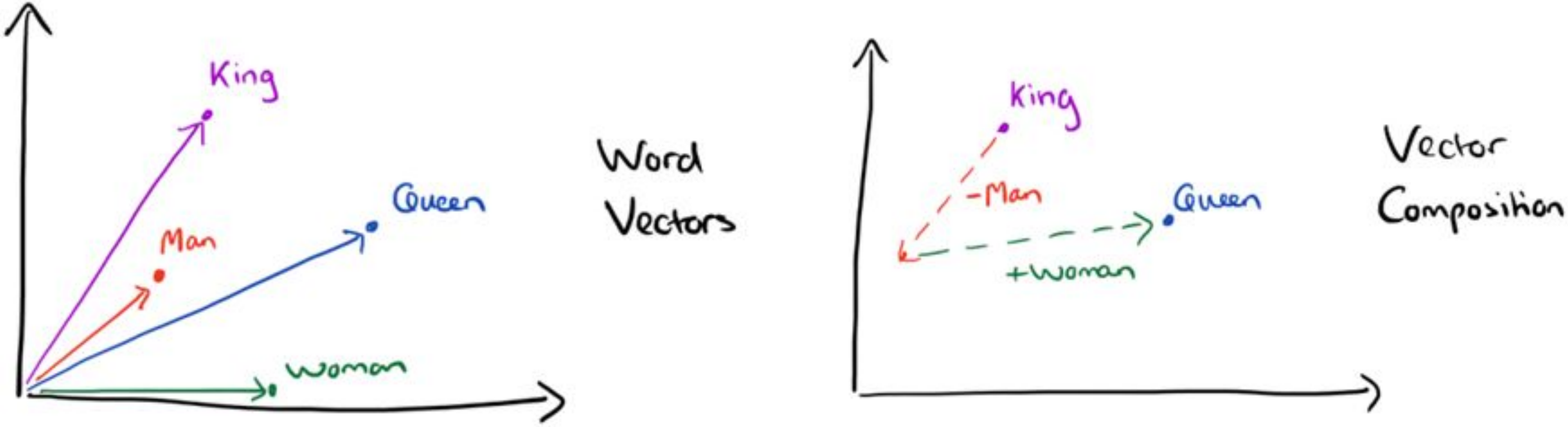
Verb tense

Country-Capital

Mikolov, T., & Dean, J. (2013)

Word2Vec

Representation Learning



(Adrian Colyer, 2016)

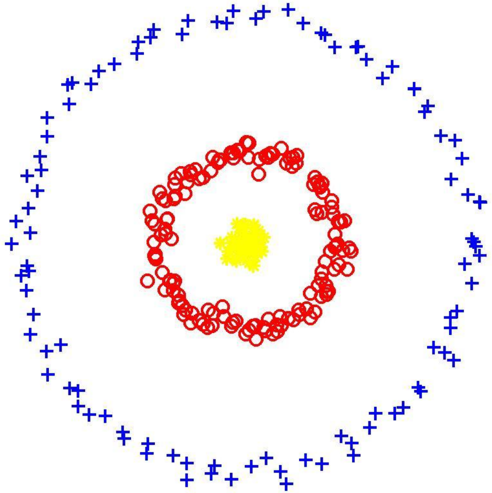
KING[vec] – MAN[vec] + WOMAN[vec] ≈ QUEEN[vec]

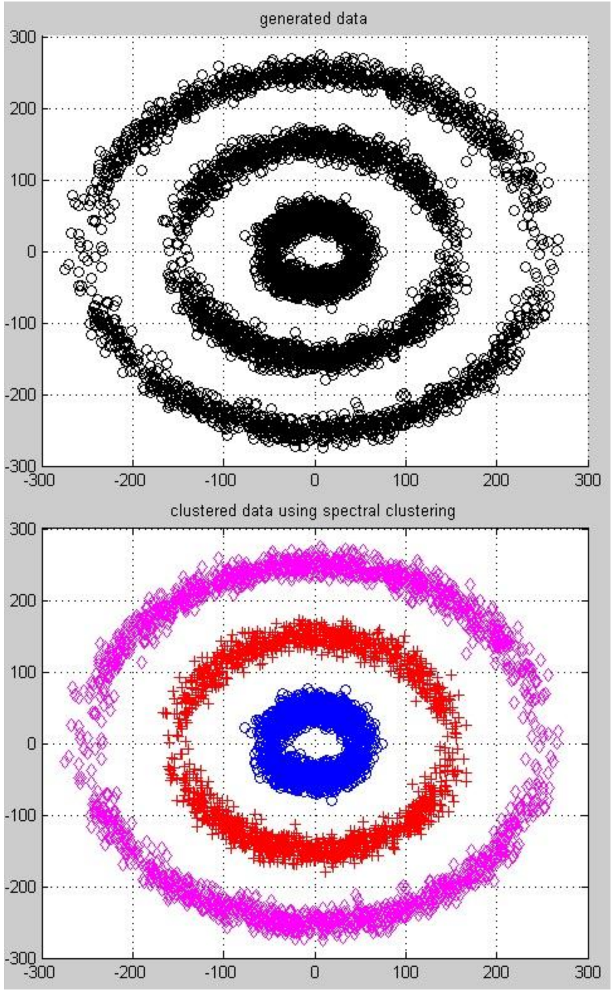
Finding implicit bias in language

Bolukbasi (2016); Caliskan (2017)

Advanced Clustering

- Graph theoretic form of clustering
- Can capture geometric patterns instead of only spherical gaussians (*k-means*)





[see you Tuesday]

Questions?

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