Introduction
In this course we will build models that help us to understand data in order to gain insights and make predictions.
Examples – Recommender Systems

**Prediction:** what (star-) rating will a person give to a product? e.g. rating(julian, Pitch Black) = ?

**Application:** build a system to recommend products that people are interested in

![Review](https://via.placeholder.com/150)

103 of 115 people found the following review helpful

🌟🌟🌟🌟🌟 Excellent Sci-Fi
Pitch Black was arguably one of the most overlooked films of the early year. Although the setting of the film could seem routine to a casual viewer (space travelers stranded and bickering on a hostile planet infested with alien nasties), director David Twohy's wonderful use of color and stylistic flourishes more than makes up for any trivial complaints.

For...

[Read the full review >](https://www.example.com)

Published on September 12, 2000 by Eric J. Pray

**Insights:** how are opinions influenced by factors like time, gender, age, and location?
Examples – Social Networks

**Prediction:** whether two users of a social network are likely to be friends

**Application:** “people you may know” and friend recommendation systems

**Insights:** what are the features around which friendships form?
**Examples** – **Advertising**

**Prediction:** will I click on an advertisement?

**Application:** recommend relevant (or likely to be clicked on) ads to maximize revenue

**Insights:** what products tend to be purchased together, and what do people purchase at different times of year?
Examples – Medical Informatics

**Prediction:** what symptom will a person exhibit on their next visit to the doctor?

**Application:** recommend preventative treatment

**Insights:** how do diseases progress, and how do different people progress through those stages?
What we need to do data mining

1. Are the data associated with meaningful outcomes?
   • Are the data **labeled**?
   • Are the instances (relatively) independent?

- e.g. who likes this movie?
  Yes! “Labeled” with a rating

- e.g. which reviews are sarcastic?
  No! Not possible to objectively identify sarcastic reviews
What we need to do data mining

2. Is there a clear objective to be optimized?
   • How will we know if we’ve modeled the data well?
   • Can actions be taken based on our findings?

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For...
Read the full review →
Published on September 12, 2000 by Eric J. Pray

e.g. who likes this movie?

How wrong were our predictions on average?

\[
\frac{1}{N} \sum_{ratings}^{N} (r_{u,i} - \text{prediction}(u, i))^2
\]
What we need to do data mining

3. Is there enough data?
   • Are our results statistically significant?
   • Can features be collected?
   • Are the features useful/relevant/predictive?
What is CSE 158?

This course aims to teach

- How to **model** data in order to make **predictions** like those above
- How to **test and validate** those predictions to ensure that they are meaningful
- How to **reason about** the findings of our models

(i.e., “data mining”)
What is CSE 158?

But, with a focus on applications from recommender systems and the web

- **Web** datasets

- Predictive tasks concerned with human activities, behavior, and opinions (i.e., recommender systems)
Basic data processing

- Text manipulation: count instances of a word in a string, remove punctuation, etc.
- Graph analysis: represent a graph as an adjacency matrix, edge list, node-adjacency list etc.
- Process formatted data, e.g. JSON, html, CSV files etc.
Expected knowledge

**Basic** mathematics

- Some linear algebra
  \[ Ax = y \rightarrow x = (A^T A)^{-1} A^T y \]
- Some optimization
  \[ \frac{d}{dx} (Ax - y)^2 \]
- Some statistics (standard errors, p-values, normal/binomial distributions)
Expected knowledge

All coding exercises will be done in **Python** with the help of some libraries (numpy, scipy, NLTK etc.)
The two most related classes are
• CSE 150 (“Introduction to Artificial Intelligence: Search and Reasoning”)
• CSE 151 (“Introduction to Artificial Intelligence: Statistical Approaches”)

None of these courses are prerequisites for each other!
• CSE 158 is more “hands-on” – the focus here is on applying techniques from ML to real data and predictive tasks, whereas 150/151 are focused on developing a more rigorous understanding of the underlying mathematical concepts
CSE 258 is the **graduate** version of this class. It is roughly the same, though there are some differences:

• CSE 258 will have more on graphical models (we’ll cover it a little bit in 158, but not much)
• CSE 258 will have a little bit more on optimization (e.g. gradient based methods). We’ll cover these too, but not really with complex derivations – in this class some of the more complex linear algebra / calculus will be treated in more of a “black box” way
• CSE 258 will cover more academic papers

• As long as you do the CSE 158 assessments, you’re welcome to attend either class (but not this week!)
CSE 158 vs. CSE 258

Both classes will be podcast in case you want to check out the more advanced material:

(last year’s links)

CSE158:  
http://podcasts.ucsd.edu/podcasts/default.aspx?PodcastId=3004&v=1

CSE258:  
http://podcasts.ucsd.edu/podcasts/default.aspx?PodcastId=3003&v=1
In Lectures I try to cover:

- The basic material (obviously)
- Motivation for the models
- Derivations of the models

- Code examples
- Difficult homework problems / exam prep etc.
- Anything else you want to discuss
The course webpage is available here: http://cseweb.ucsd.edu/classes/wi17/cse158-a/

This page will include data, code, slides, homework and assignments
(last year’s course webpage is here): http://cseweb.ucsd.edu/classes/fa15/cse190-a/

This quarter’s content will be (roughly) similar (though the weighting of assignments/midterms etc. is different)
Course outline

This course is in two parts:

1. **Methods** (weeks 1-4):
   - Regression
   - Classification
   - Unsupervised learning and dimensionality reduction

2. **Applications** (weeks 4-):
   - Recommender systems
   - Text mining
   - Social network analysis
   - Mining temporal and sequence data
   - Something else... visualization/crawling/online advertising etc.
Week 1: Regression

- Linear regression and least-squares
  - (a little bit of) feature design
- Overfitting and regularization
  - Gradient descent
- Training, validation, and testing
  - Model selection
Week 1: Regression

How can we use features such as product properties and user demographics to make predictions about real-valued outcomes (e.g. star ratings)?

How can we prevent our models from overfitting by favouring simpler models over more complex ones?

How can we assess our decision to optimize a particular error measure, like the MSE?
Week 2/3: Classification

- Logistic regression
- Support Vector Machines
- Multiclass and multilabel classification
- How to evaluate classifiers, especially in “non-standard” settings
Week 2/3: Classification

Next we adapted these ideas to **binary** or **multiclass** outputs.

- What animal is in this image?
- Will I **purchase** this product?
- Will I **click on** this ad?

- Combining features using naïve Bayes models
- Logistic regression
- Support vector machines
Week 3/4: Dimensionality Reduction

• Dimensionality reduction
• Principal component analysis
  • Matrix factorization
  • K-means
• Graph clustering and community detection
Week 3/4: Dimensionality Reduction

Principal component analysis

Community detection
Week 4/5: Recommender Systems

- Latent factor models and matrix factorization (e.g. to predict star-ratings)
- Collaborative filtering (e.g. predicting and ranking likely purchases)
Week 4/5: Recommender Systems

Rating distributions and the missing-not-at-random assumption

Latent-factor models
Week 5/6: Text Mining

- Sentiment analysis
- Bag-of-words representations
  - TF-IDF
- Stopwords, stemming, and (maybe) topic models
Week 5/6: Text Mining

Yeast and minimal red body thick light a flavor sugar strong quad. grape over is molasses lace the low and caramel fruit Minimal start and toffee. dark plum, dark brown Actually, alcohol Dark oak, nice vanilla, has brown of a with presence. light carbonation. bready from retention. with finish. with and this and plum and head, fruit, low a Excellent raisin aroma Medium tan

Bags-of-Words

What we would like:

67% of 52 people found the following review helpful.

(review of "The Chronicles of Riddick")

Topic models

Sentiment analysis
Week 6: Midterm (Feb 15)!

(More about grading etc. later)
Week 8: Social & Information Networks

• Power-laws & small-worlds
  • Random graph models
  • Triads and “weak ties”
• Measuring importance and influence of nodes (e.g. pagerank)
Week 8: Social & Information Networks

- Hubs & authorities
- Power laws
- Small-world phenomena
- Strong & weak ties
Week 9: Something else (advertising?)

Matching problems

AdWords

Bandit algorithms
• Sliding windows & autoregression
  • Hidden Markov Models
  • Temporal dynamics in recommender systems
• Temporal dynamics in text & social networks
Week 10: Temporal & Sequence Data

Topics over time

Social networks over time

Memes over time
There is no textbook for this class

- I will give chapter references from *Bishop: Pattern Recognition and Machine Learning*

- I will also give references from Charles Elkan’s notes ([http://cseweb.ucsd.edu/classes/wi17/cse158-a/files/elkan_dm.pdf](http://cseweb.ucsd.edu/classes/wi17/cse158-a/files/elkan_dm.pdf))
Evaluation

- There will be four homework assignments worth 8% each. Your lowest grade will be dropped, so that 4 homework assignments = 24%
- There will be a midterm in week 6, worth 26%
- One assignment on recommender systems (after week 5), worth 25%
- A short open-ended assignment, worth 25%
Evaluation

HW = 24%
Midterm = 26%
Assignment 1 = 25%
Assignment 2 = 25%

Actual goals:
• Understand the basics and get comfortable working with data and tools (HW)
• Comprehend the foundational material and the motivation behind different techniques (Midterm)
• Build something that actually works (Assignment 1)
• Apply your knowledge creatively (Assignment 2)
Evaluation

• Homework should be delivered by the beginning of the **Monday** lecture in the week that it’s due
• All submissions will be made **electronically** (instructions will be in the homework spec, on the class webpage)
Schedule (subject to change but hopefully not):

Week 1: Hw 1 out
Week 3: Hw 1 **due**, Hw2 out
Week 5: Hw 2 **due**, Hw3 out, Assign. 1 out
Week 6: **midterm**
Week 7: Hw 3 **due**, Hw4 out, Assign. 2 out
Week 8: Assignment 1 **due**
Week 9: Hw4 **due**
Week 10: Assignment 2 **due**
Previous assignments...
Assignment 1

- Prediction tasks on Amazon electronics data, run as a competition on Kaggle

  - Rating prediction
  - Purchase prediction
  - Helpfulness prediction
We’ll definitely do this again, but with different data and possibly different tasks.
Assignment 2

Raw rating data    binned regression    dual regression

"inflection" point

Andrew Prudhomme – “Finding the Optimal Age of Wine”
Assignment 2

ratings vs. time

ratings vs. review length

Ruogu Liu – “Wine Recommendation for CellarTracker”
Assignment 2

**cellartracker:**
- positive words in wine reviews
- negative words in wine reviews

**RateBeer:**
- positive words in beer reviews
- negative words in wine reviews

Ben Braun & Robert Timpe – “Text-based rating predictions from been and wine reviews”
User age

- Rating vs. age
- Aroma vs. age
- Day of week vs. age
- Year vs. age
- Hour of day vs. age
- Category vs. age

Joseph Luttrell, Spenser Cornett
Assignment 2

Figure 3: Restaurant Ratings

Figure 6: Average rating per location

ratings per location

k-means of ratings per location

3.52

4.00
Assignment 2

\[ \hat{r}_{ui} = \mu + b_u + b_i + (q_i + \frac{1}{|M(i)|} \sum_{n \in M(i)} |s_n|) p_u \]

set of geographic neighbours
impact of neighbours

Long Jin & Xinchi Gu – “Rating Prediction for Google Local Data”
Mohit Kothari & Sandy Wiraatmadja – “Reviews and Neighbors Influence on Performance of Business”

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Assignment 2

Wikispeededia navigation traces:

Figure 5: Graph of a complete path

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<th>Average Time</th>
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<td>Finished Path Back</td>
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<td>Unfinished Path Back</td>
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<td>836.00</td>
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Assignment 2

Images from Chictopia

Power laws!

Wei-Tang Liao & Jong-Chyi Su – “Image Popularity Prediction on Social Networks”
Crime (Chicago)

Goal: to predict the number of incidents of crime on a given day

Over 15 years

Over 7 years

Hour of the day

Joshua Wheeler, Nathan Moreno, Anjali Kanak
Predicting Taxi Tip-Rates in NYC

(data from archive.org)

(pickup and dropoff)

Distance, time taken, speed, and time of day (also on geo)

Sahil Jain, Alvin See, Anish Shandilya
• Piyush Anil Nahar
• Apurva Pathak
• Rishikesh Ghewari

TAs will do most of the grading, and run office hours (in addition to my own)
Office hours

- I will hold office hours on Tuesday mornings (9:00am-1:00pm, CSE 4102)
- TA office hours will be held on Mondays and Fridays from 10:00am-12:00pm in B260A
Questions?

Most announcements will be posted to Piazza

https://piazza.com/ucsd/winter2017/cse158/home

please participate!