

Intro to Machine Learning (CS436/CS580L)

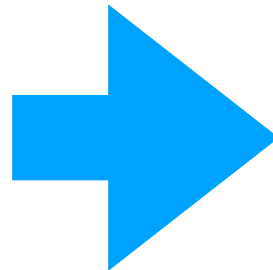
Course Overview

Xi Peng, Fall 2018

Thanks to Tom Mitchell, Andrew Ng, Ben Taskar, Carlos Guestrin, Eric Xing, Hal Daume III, David Sontag, Jerry Zhu, and Tina Eliassi-Rad for some slides & teaching material.


Instructor

- Xi Peng
- Office hours: Tuesday 3:00 pm - 4:00 pm
- Place: N16 (may change in a few weeks)
- TA (TBD)



My Research

- Deep Learning
- Machine Learning
- Computer Vision

A medium shot of actress Anne Hathaway on a television news set. She is seated, facing slightly to the left of the frame. She has short, dark, curly hair and is wearing a dark, patterned top. She has multiple piercings: a nose ring, a lip ring, and a small ring in her lower lip. The background is a blurred studio set with blue and purple lighting. A yellow and blue graphic overlay is at the bottom of the screen.

LIVE IN TIMES SQUARE

ANNE HATHAWAY

"RIO 2"

SECOND INTERNATIONAL WORKSHOP ON STATISTICAL AND COMPUTATIONAL THEORIES OF
VISION – MODELING, LEARNING, COMPUTING, AND SAMPLING

VANCOUVER, CANADA, JULY 13, 2001.

Robust Real-time Object Detection

Paul Viola

viola@merl.com

Mitsubishi Electric Research Labs

201 Broadway, 8th FL

Cambridge, MA 02139

Michael Jones

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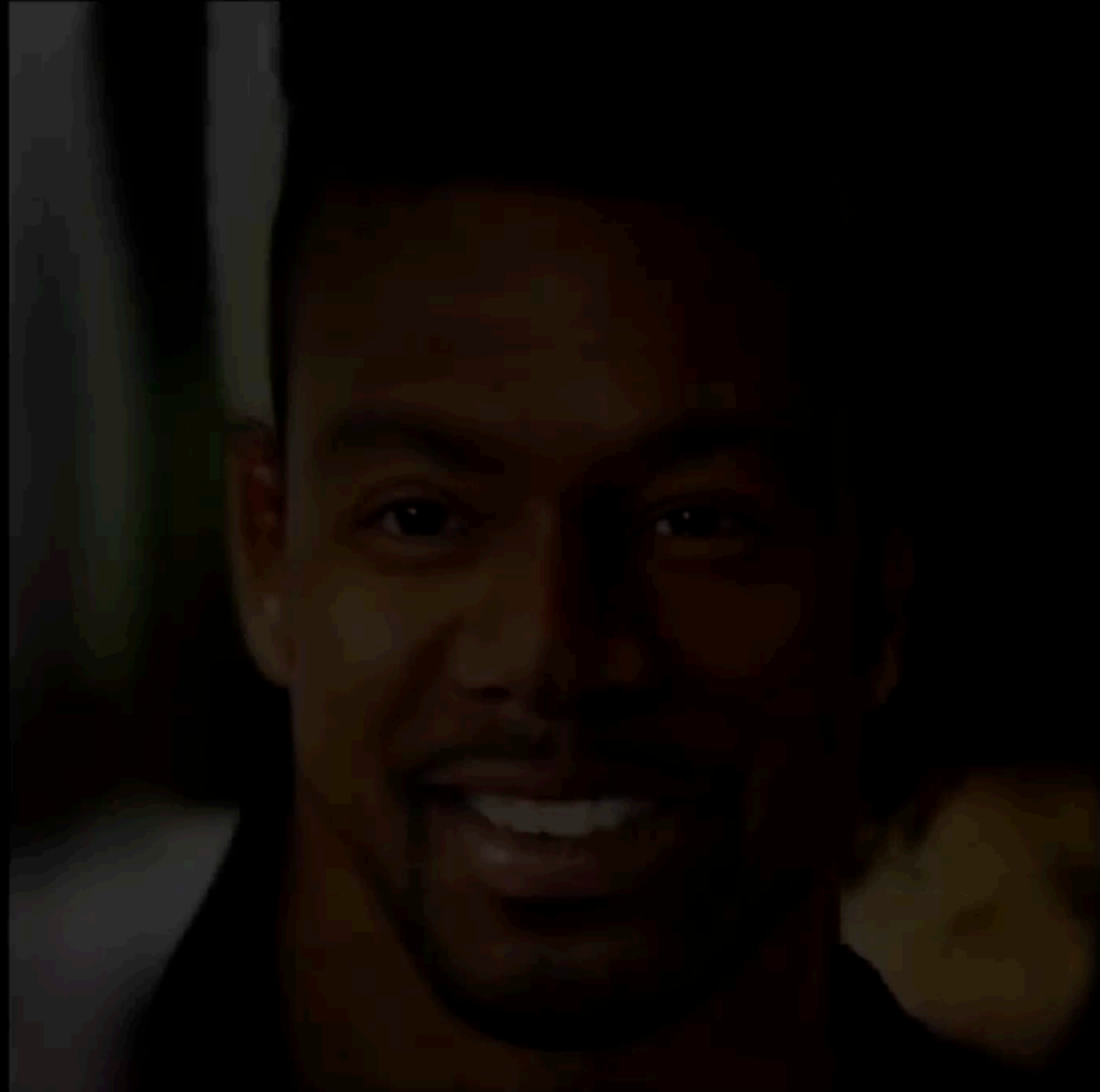
Compaq CRL

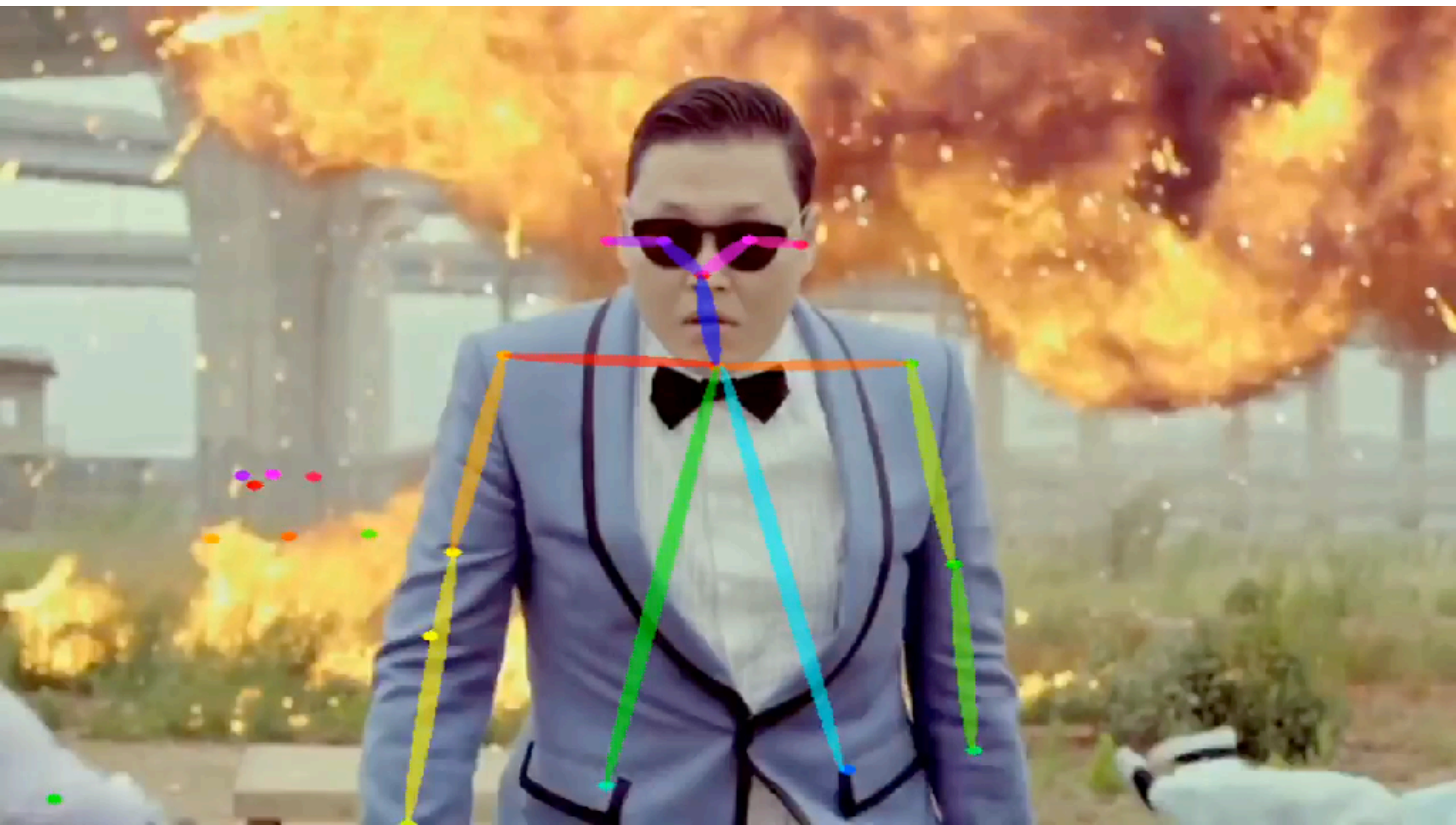
One Cambridge Center

Cambridge, MA 02142

Abstract









Course Overview

This graduate-level course introduces the preliminary theory, models, and applications of machine learning.

Topics covered include regression, classification, kernel methods, neural networks, unsupervised learning, dimensionality reduction, and practical applications.

This is a HARD course:

- a lots of reading
- a lots of math
- the project would take a lot of time.

Course Overview

- What is machine learning?
- Supervised learning:
 - linear regression;
 - logistic regression (classification);
 - decision trees;
 - SVM;
 - (deep) neural network;
- Unsupervised learning:
 - clustering;
 - KNN;
 - PCA;
- Reinforcement learning;

Prerequisite

1. Math: Calculus (required), Linear Algebra (required), Statistics (recommended).
2. CS: Data Structure & Algorithms (required), Numerical Analysis (recommended).
3. Coding: Matlab (required), Python (recommended).

Prerequisite

Write down answers (anonymous or not)

1. What is your program?

- Senior, Master, PhD (what is your research area)

2. Any machine learning experience? Project or research?

3. What is your math background? Write down what you know:

- Integral, derivative
- Vectors, matrices, multiplication
- Inverse of a matrix, rank, eigenvalues

4. What is your background in programming
Matlab? Python? C++/Java?

5. What are the problems you have worked on or are interested in that could use machine learning?

Textbook

1. “Pattern Recognition and Machine Learning”, Christopher Bishop (2006). (required)
2. “Machine Learning, A Probabilistic Perspective”, Kevin Murphy (2012).

Policies

1. Watson School Student Academic Honesty Code.
2. Homework must be done individually.
3. One A4 cheating sheet can be used for the exam.
4. Late submission will be charged 20% penalty each late day and 3 days maximum.
5. Class project can be done either individually or in groups of two.
6. Only Matlab/Python can be used for homework.
7. Any programming language can be used for class project.
8. Zero-tolerance for cheating or plagiarism.

Coding

1. Make sure test your codes on CSD environment before the submission.
 - Lose 50% credits if your codes can't run.
 - CS Classroom: EB-222, EB-G7.
 - Remote.cs systems.
 - Use CS LDAP not PODS to access.
 - Use sysadmin website (referenced in the email) to change your password to something easier to remember.

Grading

1. Three theory/coding homework (30%).
2. Mid-tem exam (30%).
3. Class project:
 - Proposal (10%): 2 pages + 5 min pitch.
 - Report (15%): 8 pages.
 - In-class presentation (15%): 15 min.

1. Five theory/coding homework (30%).
2. Mid-tem exam (30%).
3. Final exam (40%).

A

or

B

Senior, Master, PhD

Grading

Class Project:

- Proposal (10%): 2 pages plus 5 min pitch. Should answer the following questions:
 1. What is the problem? Why is it interesting and important?
 2. What are the existing solutions? What are the limitations?
 3. Which ML model you will use to solve the problem? And why?
 4. What data sets and metrics will be used to validate your method?
- Report (15%): 8 pages maximum follow publication template. Adding details of your solution and experimental results:
 1. What is the overview of your approach/solution?
 2. What are the detailed designs/specifics of the major components of your approach/solution?
 3. How does your approach/solution performs? How about comparing with other methods?
- In-class presentation (15%): 15 min maximum.

To Do

- Read “Bishop”: Ch1 & Ch 2.
- Read “Statistics” and “Linear Algebra” resources as required.
- Start to think about your class project.