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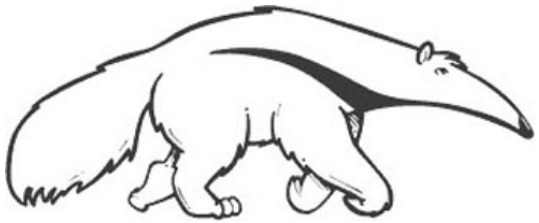
CS178: Machine Learning and Data Mining

Introduction

Prof. Erik Sudderth



Some materials courtesy Alex Ihler & Sameer Singh

Artificial Intelligence (AI)

- Building “intelligent systems”
- Lots of parts to intelligent behavior

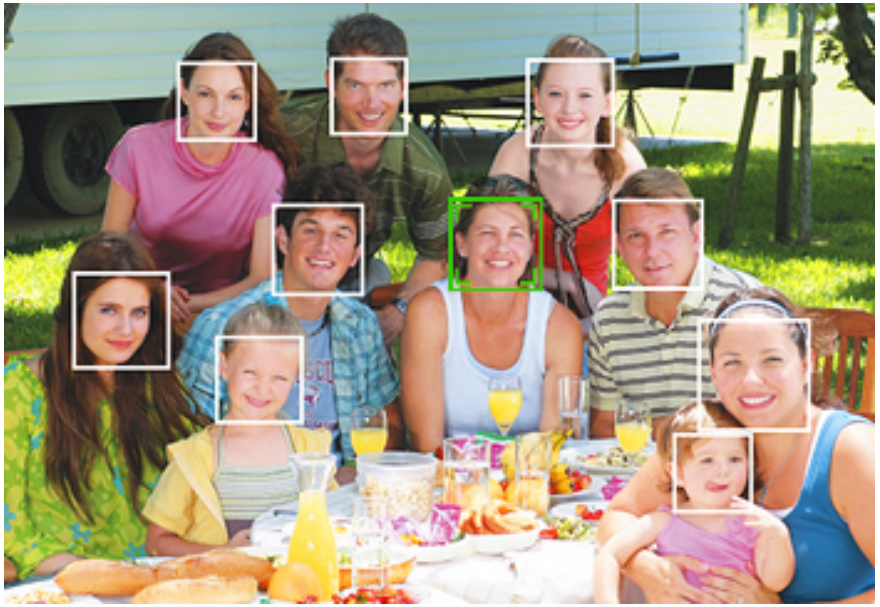
Darpa GC (Stanley)

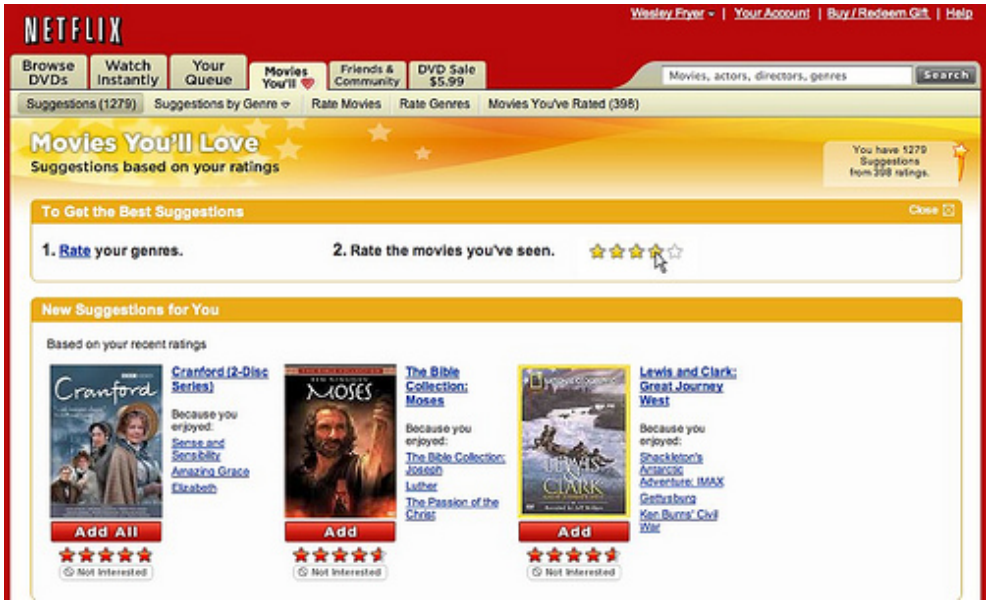
RoboCup

Chess (Deep Blue v. Kasparov)

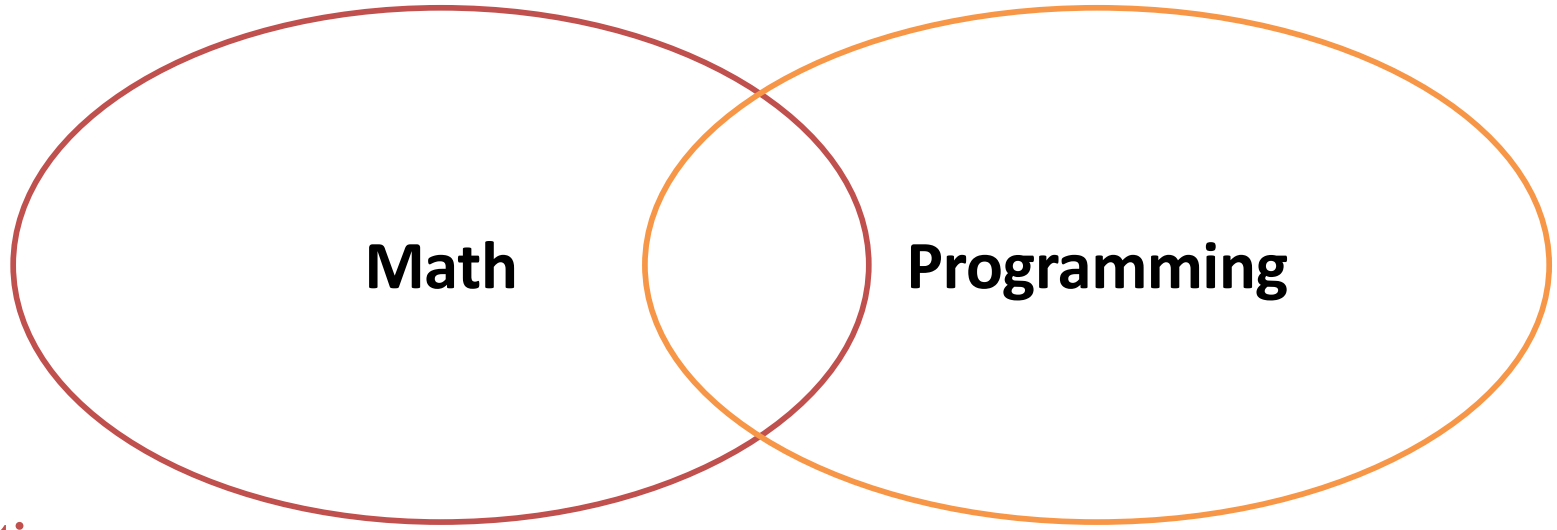
Machine learning (ML)

- One (important) part of AI
- Making predictions (or decisions)
- Getting better with experience (data)
- Problems whose solutions are “hard to describe”





CS178: Machine Learning & Data Mining

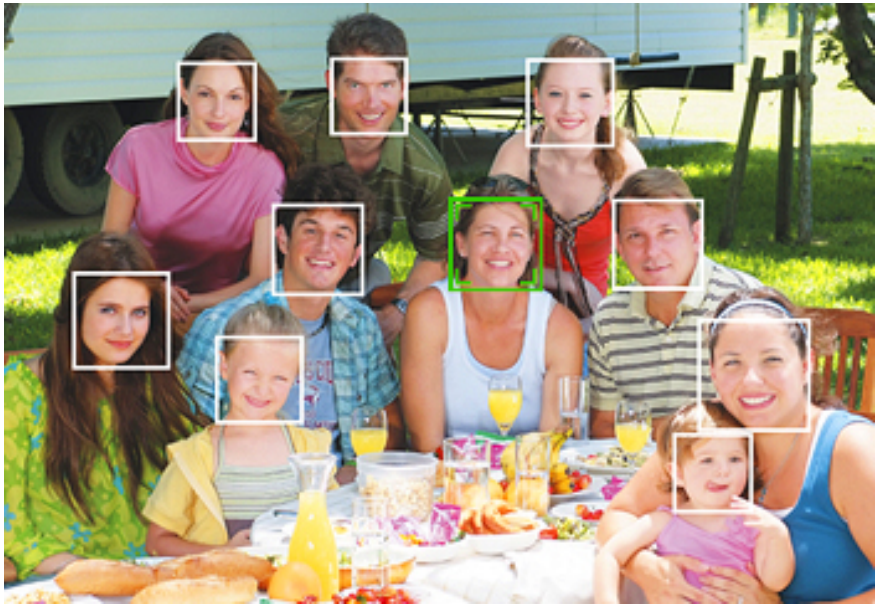


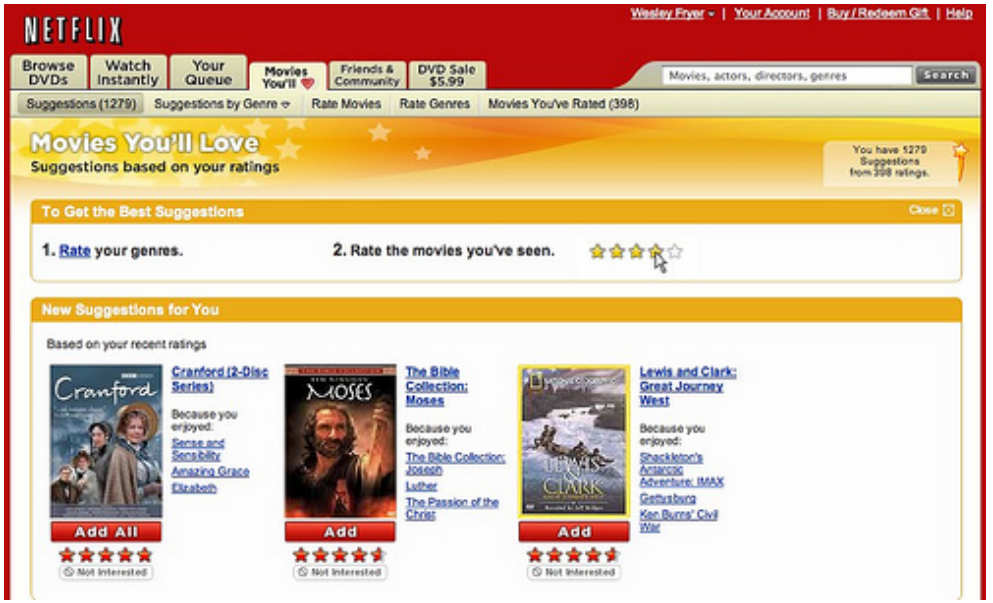
Statistics,
Probability,
Linear Algebra,
Optimization

Data Structures,
Algorithms,
Computational Complexity,
Data Management

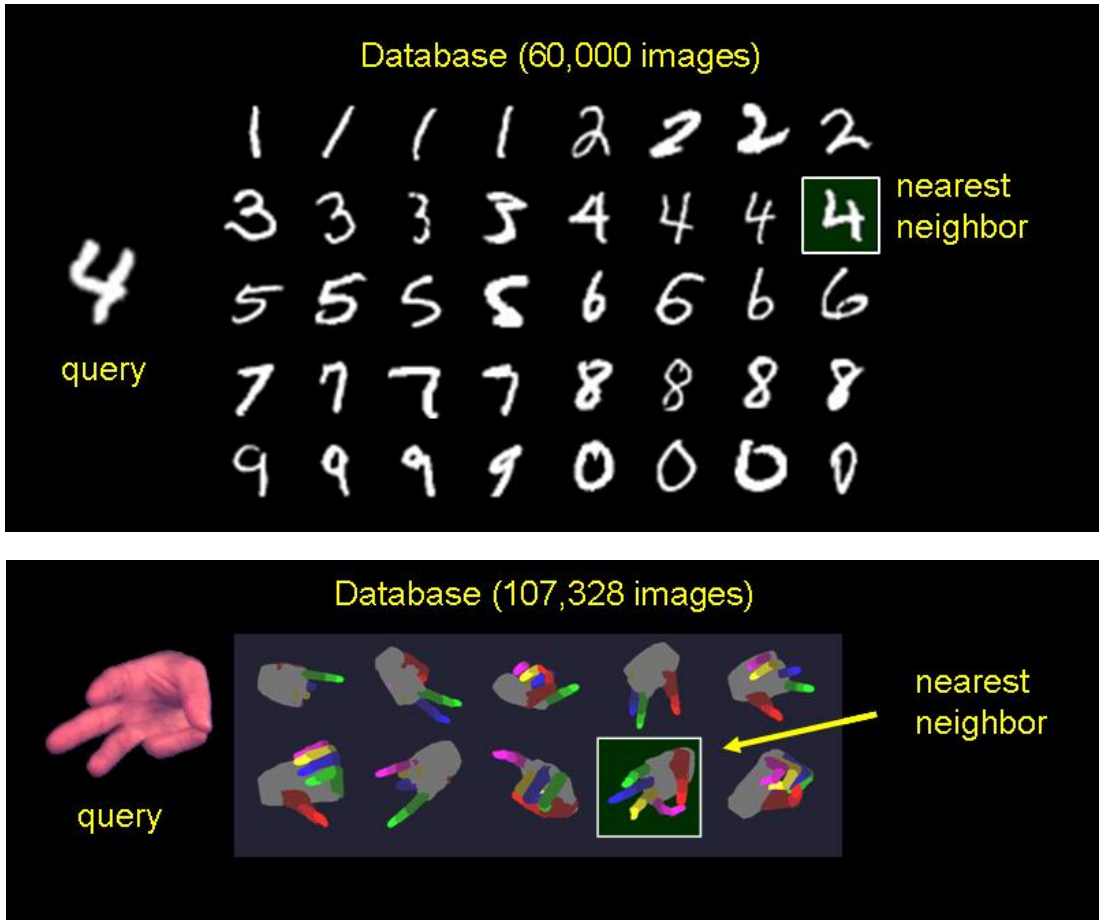
Types of prediction problems

- Supervised learning
  - "Labeled" training data
  - Every example has a desired target value (a "best answer")
  - Reward prediction being close to target
  - **Classification:** a discrete-valued prediction (often: action / decision)
  - **Regression:** a continuous-valued prediction





Digit & Hand Gesture Recognition

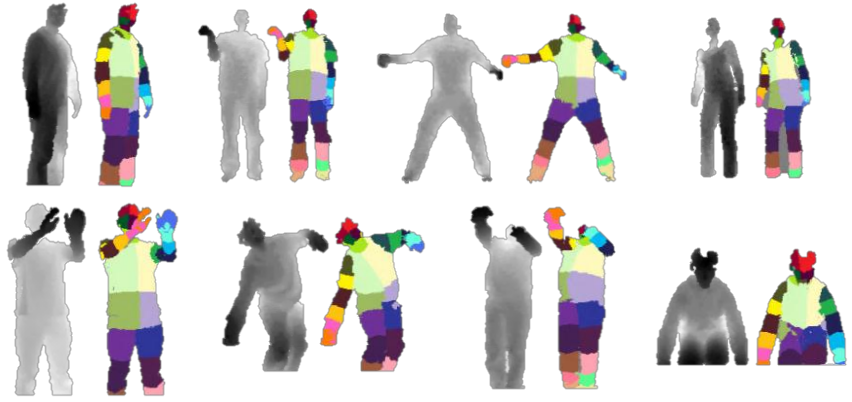


Athitsos et al., CVPR 2004 & PAMI 2008

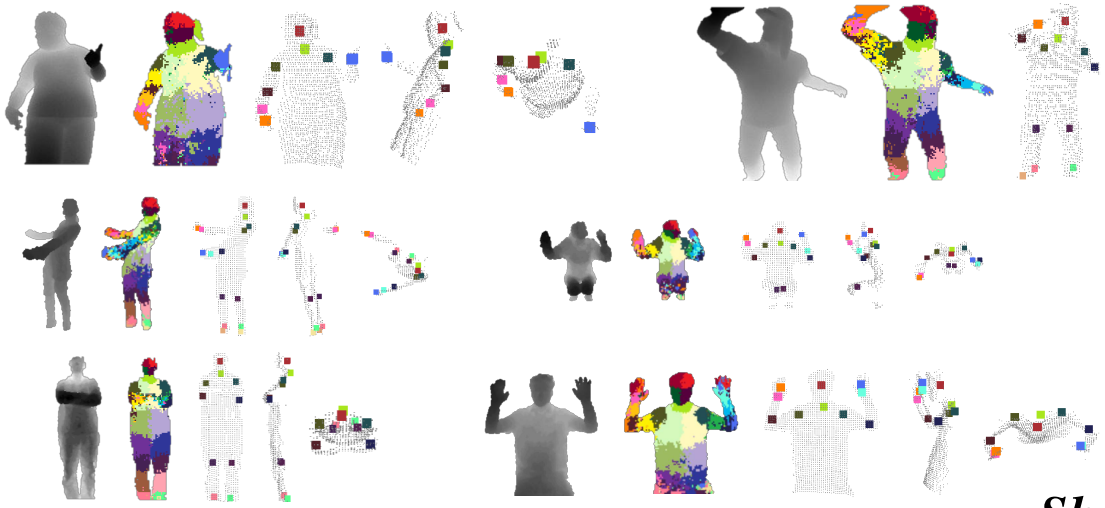
Microsoft Kinect Pose Estimation

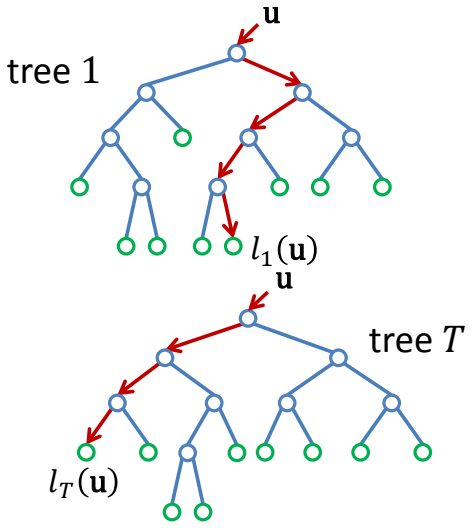
synthetic (train & test)

real (test)



body part classification



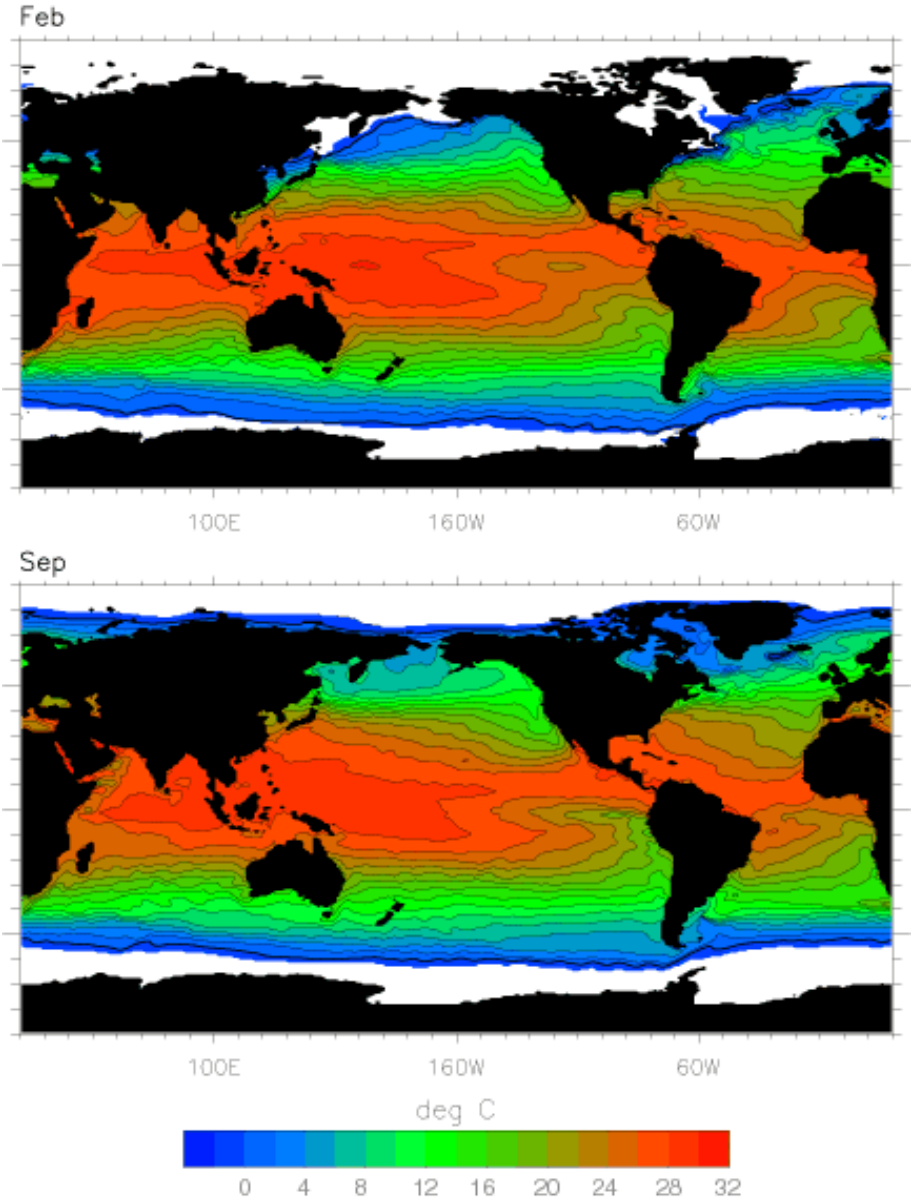


Shotton et al., PAMI 2012

Climate Modeling

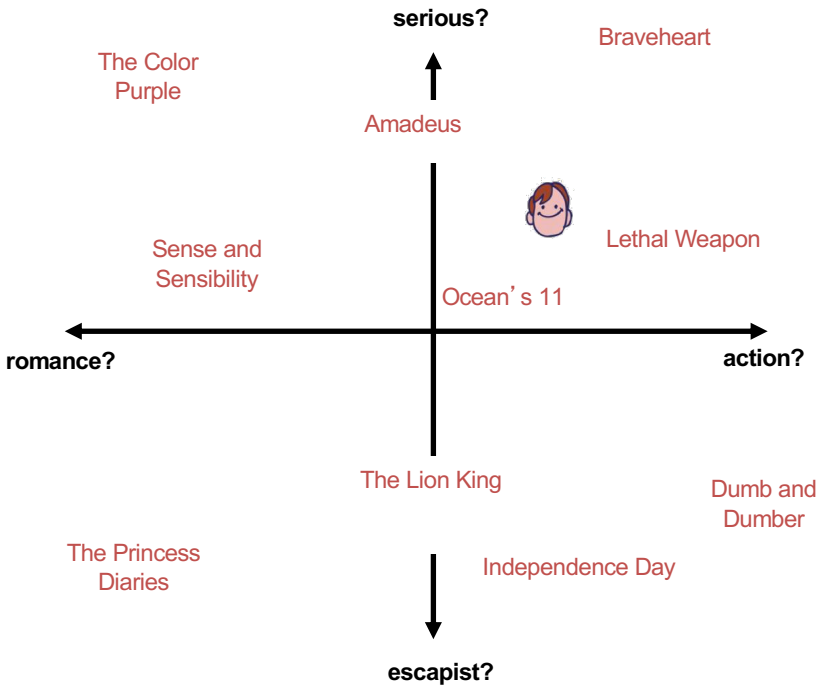
- **Satellites measure sea-surface temperature at sparse locations**
  - **Noisy (atmosphere & sensors)**
  - **Partial coverage of ocean surface (satellite tracks)**
  - **Sometimes hidden by clouds**
- **Would like to infer a dense temperature field, and track its temporal evolution**

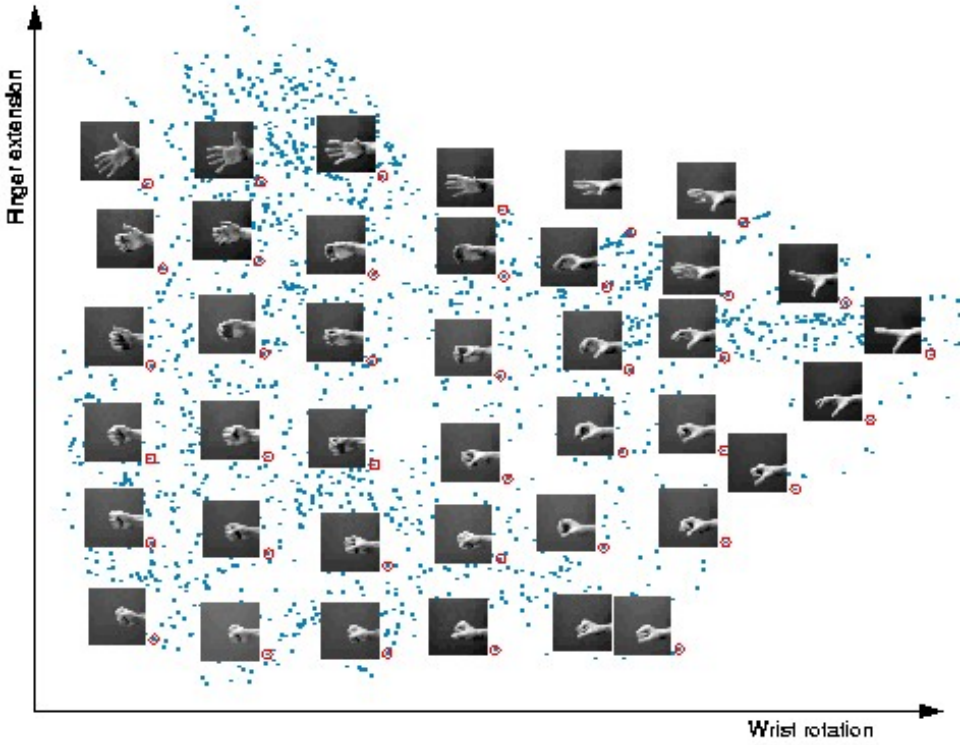
NASA Seasonal to Interannual Prediction Project
http://ct.gsfc.nasa.gov/annual.reports/ess98/nsipp.html



Types of prediction problems

- Supervised learning
- Unsupervised learning
  - No known target values
  - No targets = nothing to predict?
  - Reward “patterns” or “explaining features”
  - Often, data mining

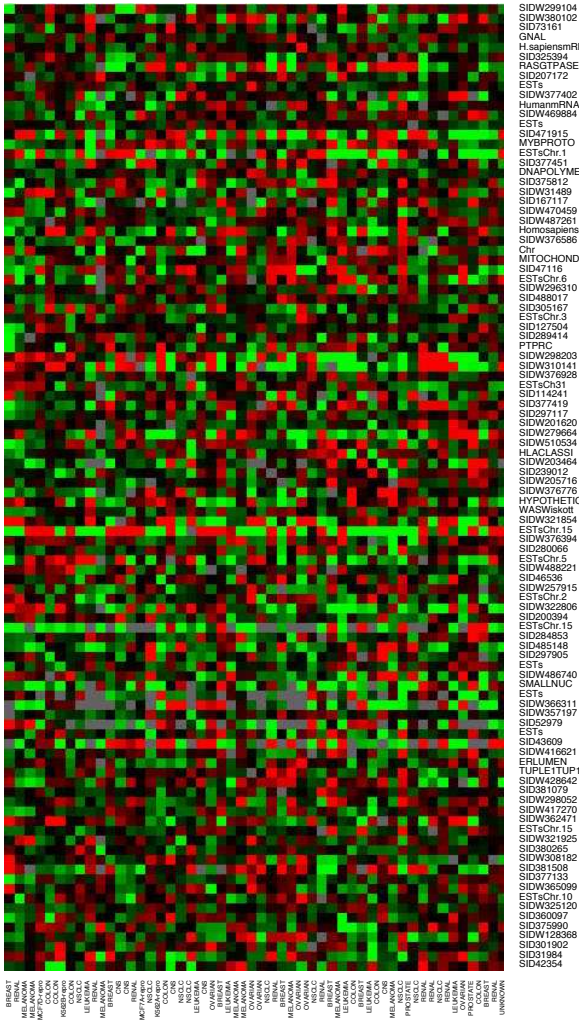




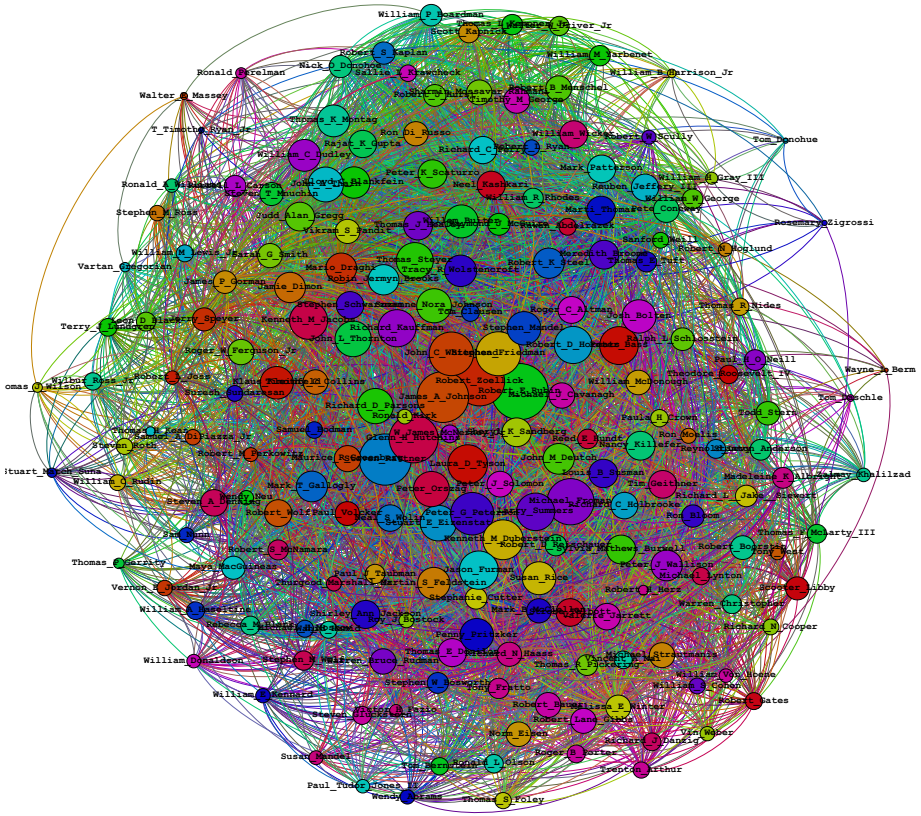
Human Tumor Microarray Data

- **6830x64 matrix of real numbers**
- **Rows correspond to genes, columns to tissue samples**
- **Cluster rows (genes) to deduce function of unknown genes from experimentally known genes with similar profiles**
- **Cluster columns (samples) to hypothesize disease profiles**

Hastie, Tibshirani, & Friedman 2009



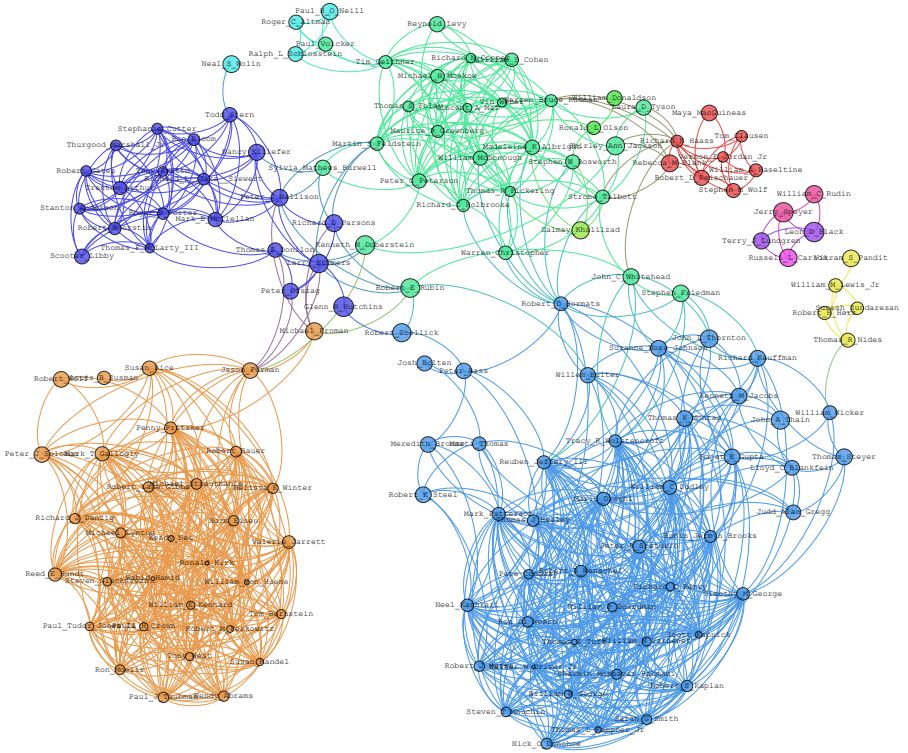
Social Networks & Relationships



Kim et al., NIPS 2013

LittleSis* is a free database of who-knows-who at the heights of business and government.

* opposite of Big Brother



Types of prediction problems

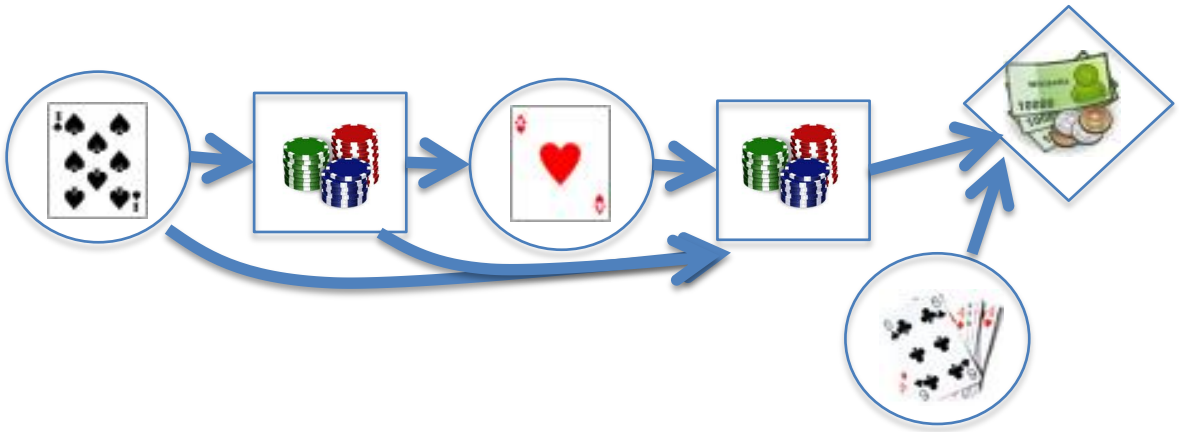
- Supervised learning
- Unsupervised learning
- Semi-supervised learning
  - Similar to supervised
  - some data have unknown target values

- Ex: medical data
  - Lots of patient data, few known outcomes
- Ex: image tagging
  - Lots of images on Flikr, but only some of them tagged

Types of prediction problems

- Supervised learning
- Unsupervised learning
- Semi-supervised learning
- Reinforcement learning

- "Indirect" feedback on quality
  - No answers, just "better" or "worse"
  - Feedback may be delayed



Issues to Understand

- **Given two candidate models, which is better?**
  - Accuracy at predicting training data?
  - Complexity of classification or regression function?
  - Are all mistakes equally bad?
- **Given a family of classifiers with free parameters, which member of that family is best?**
  - Are there general design principles?
  - What happens as I get more data?
  - Can I test all possible classifiers?
  - What if there are lots of parameters?

Probability & Statistics

Algorithms & Linear Algebra

Machine Learning

Introduction to Machine Learning

Course Logistics

Data and Visualization

Supervised Learning

CS178 Course Staff

- **Instructor:** **Prof. Erik Sudderth**
  Research Interests: Statistical machine learning, computer vision, AI, …
- **Teaching Assistants and Readers:** Twaha Ibrahim, Daokun Jiang, Zhenhan Li, Debora Sujono, Tamanna Hossain, Haoyu Ma

Course Information

Canvas page: **https://canvas.eee.uci.edu/courses/24330**
Course information, lecture slides, homework handouts.

Gradescope page: **https://www.gradescope.com/courses/109546**
Homework submission and grading.

Piazza page: **http://piazza.com/uci/spring2020/cs178**
For all questions and discussion of course material!

No required textbook:

- All necessary information covered in lectures.
- Recommended references on Canvas.

Video Lectures

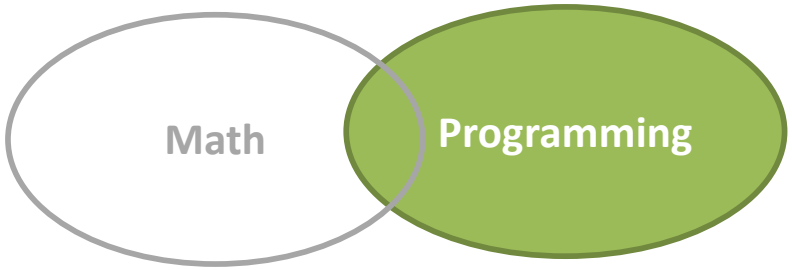
Official Lecture Time: *Tuesdays and Thursdays at 12:30pm Pacific*

- **Before Lecture:** Watch linked YouTube videos reviewing new technical concepts and methods.
- **During Lecture:** Prof. Sudderth will highlight key points, discuss examples, and take questions.
- **Viewing Live Lectures:** Use a UCI zoom account (and login with your UCInetID) to connect to the CS178 webinar: https://uci.zoom.us/j/297577761
- **After Lecture:** Video recordings will be posted to the CS178 Yuja channel (linked from Canvas)

Discussions

Python Notebooks

- **Present demos**
- **Questions about coding**
- **Hints for homeworks**
- **Led by TAs on Mondays starting April 6**
- **Video streaming and recording information will be announced via Canvas**



Homework Assignments

Homework 1 due April 16, released early next week.

5 Programming Assignments

- **We will drop lowest grade**

Objective

- **Learn to apply ML techniques**
- **Submission is a "report"**

Source Code (Python)

- **Submit relevant code snippets**
  - **We will not run it, but will read it**
- **Statement of collaboration, if any**
  - **Only limited discussions allowed**

Exams

Dates: April 21, May 5, May 19, June 2

4 Short Online Exams

- **Taken online, mixture of multiple choice and free response**
- **Short length (30-45 minutes), but you will have a longer (several hour) time window to start exam**
- **We will drop lowest grade, average other 3 equally**
- **More details about format and timing to be announced later**

Content

- **Test concepts covered in lecture**
- **Will also require computations related to homework assignments and examples from lecture**

Project

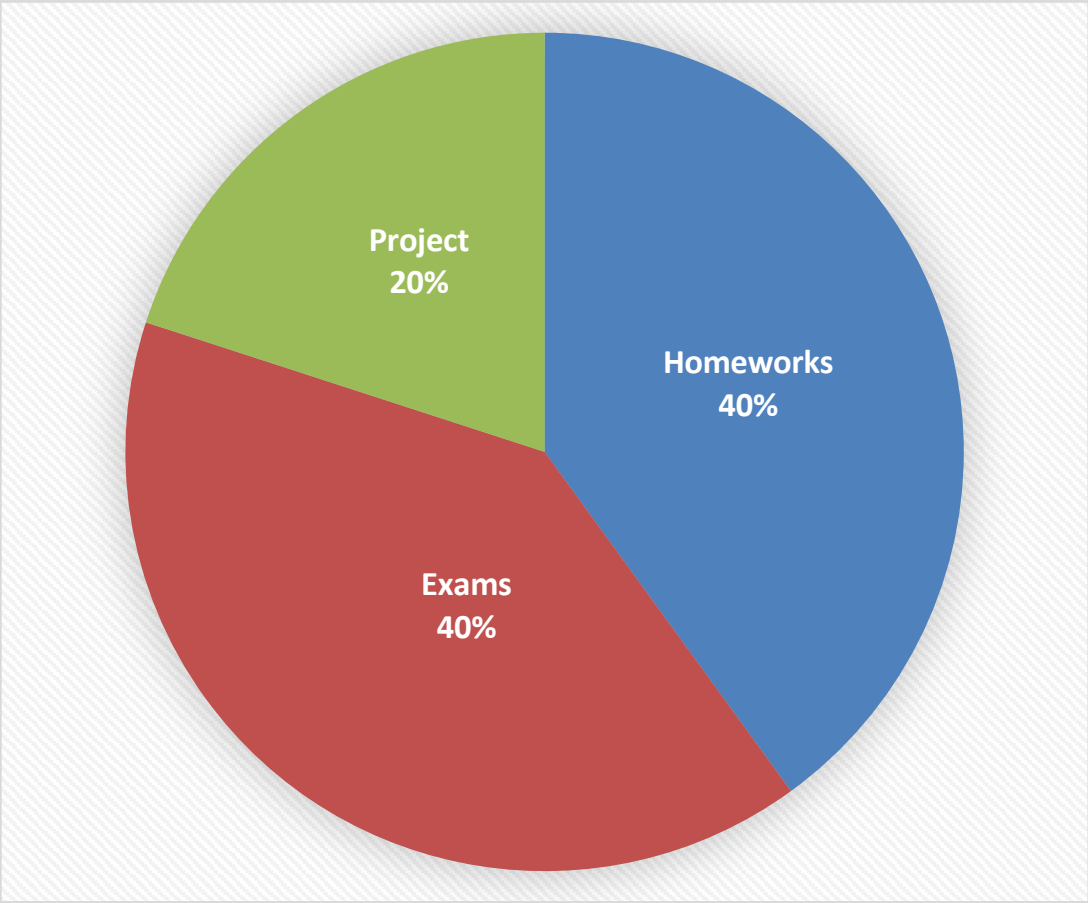
Kaggle InClass competitions make machine learning fun.

Use our free, self-service platform to create classroom competitions that engage and inspire your students.

Groups for the Project

- **Team size should be 3**
  - **Larger teams not allowed**
  - **Smaller in special cases, with instructor permission**
- **More details coming later (most work in second half of quarter)**
- **Report (two pages) due during finals week (June 10)**

Grading



- **Homeworks:** **Best 4 scores out of 5 homeworks.**
- **Exams:** **Best 3 scores out of 4 online exams.** ***Must take on announced dates:***
  April 21, May 5, May 19, June 2
- **Project:** **Enter a Kaggle ML competition in groups of 3, report due during finals week.**
- **No midterm or final exam!**

Machine Learning

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Data exploration

- Machine learning is a data science
  - Look at the data; get a “feel” for what might work
- What types of data do we have?
  - Binary values? (spam; gender; …)
  - Categories? (home state; labels; …)
  - Integer values? (1..5 stars; age brackets; …)
  - (nearly) real values? (pixel intensity; prices; …)
- Are there missing data?
- “Shape” of the data? Outliers?

Scientific software

- **Python**
  - **Numpy, MatPlotLib, SciPy…**
- Matlab
  - Octave (free)
- R
  - Used mainly in statistics
- C++
  - For performance, not prototyping
- And other, more specialized languages for modeling…

Representing data

- Example: Fisher's "Iris" data

  http://en.wikipedia.org/wiki/Iris_flower_data_set

- Three different types of iris
  - "Class", y
- Four "features", $x_1,\ldots,x_4$
  - Length & width of sepals & petals
- 150 examples (data points)

Representing the data in Python

- Have m observations (data points)

$$\left\{x^{(1)} \ldots, x^{(m)}\right\}$$

- Each observation is a vector consisting of n features

$$x^{(j)} = [x_1^{(j)} x_2^{(j)} \ldots x_n^{(j)}]$$

- Often, represent this as a "data matrix"

$$\underline{X} = \begin{bmatrix} x_1^{(1)} & \ldots & x_n^{(1)} \\ \vdots & \ddots & \vdots \\ x_1^{(m)} & \ldots & x_n^{(m)} \end{bmatrix}$$

```
import numpy as np    # import numpy
iris = np.genfromtxt("data/iris.txt",delimiter=None)
X = iris[:,0:4]       # load data and split into features, targets
Y = iris[:,4]
print X.shape         # 150 data points; 4 features each
   (150, 4)
```

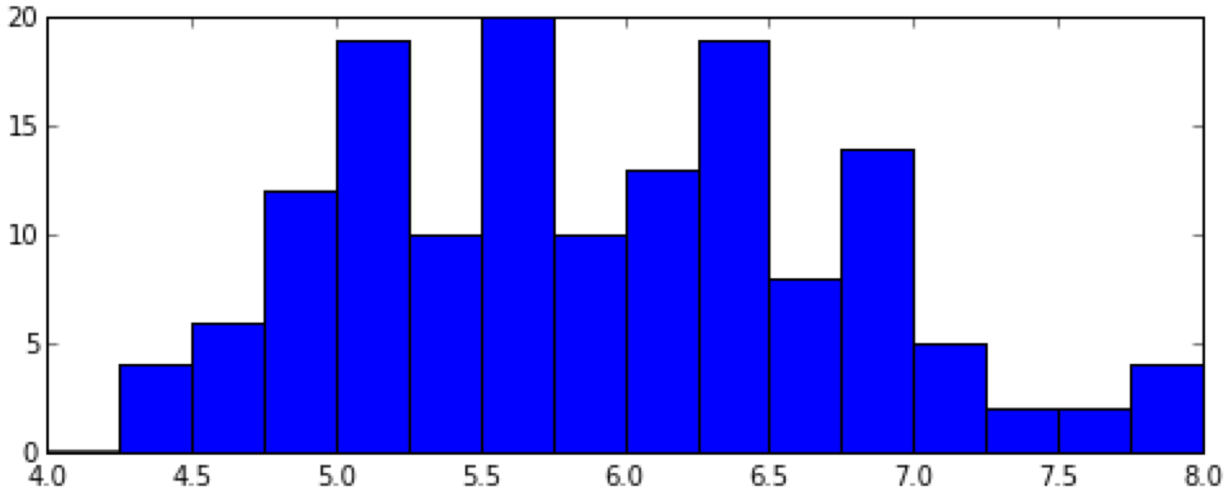
Basic statistics

- Look at basic information about features
  - Average value? (mean, median, etc.)
  - "Spread"? (standard deviation, etc.)
  - Maximum / Minimum values?

```
print np.mean(X, axis=0)          # compute mean of each feature
 [ 5.8433   3.0573   3.7580   1.1993 ]
print np.std(X, axis=0)           #compute standard deviation of each feature
 [ 0.8281   0.4359   1.7653   0.7622 ]
print np.max(X, axis=0)           # largest value per feature
 [  7.9411   4.3632   6.8606   2.5236 ]
print np.min(X, axis=0)           # smallest value per feature
 [  4.2985   1.9708   1.0331   0.0536  ]
```

Histograms

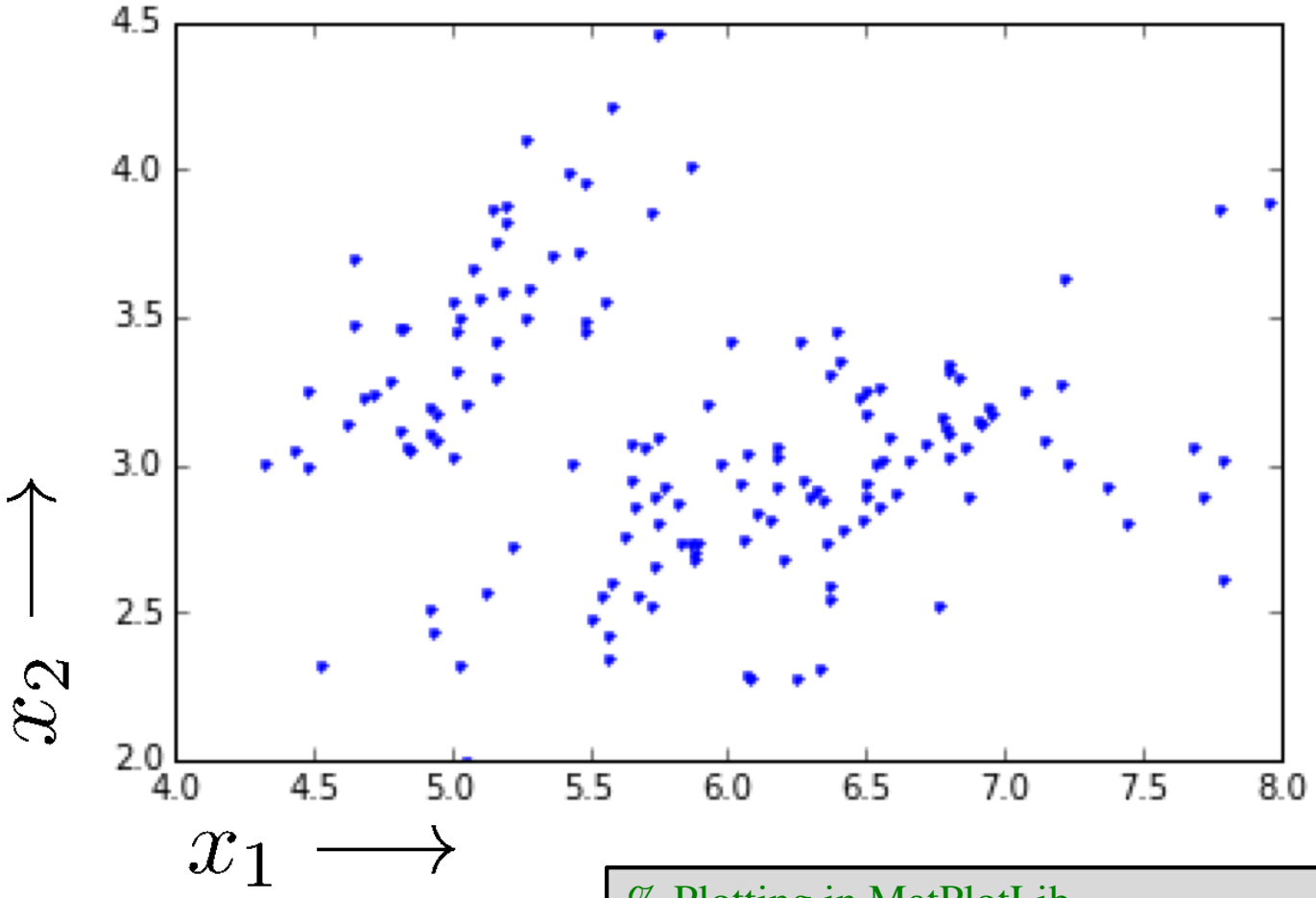
- Count the data falling in each of K bins
  - "Summarize" data as a length-K vector of counts (& plot)
  - Value of K determines "summarization"; depends on # of data
    - K too big: every data point falls in its own bin; just "memorizes"
    - K too small: all data in one or two bins; oversimplifies




```
% Histograms in MatPlotLib
import matplotlib.pyplot as plt
X1 = X[:,0]                    # extract first feature
Bins = np.linspace(4,8,17)     # use explicit bin locations
plt.hist( X1, bins=Bins )      # generate the plot
```

Scatterplots

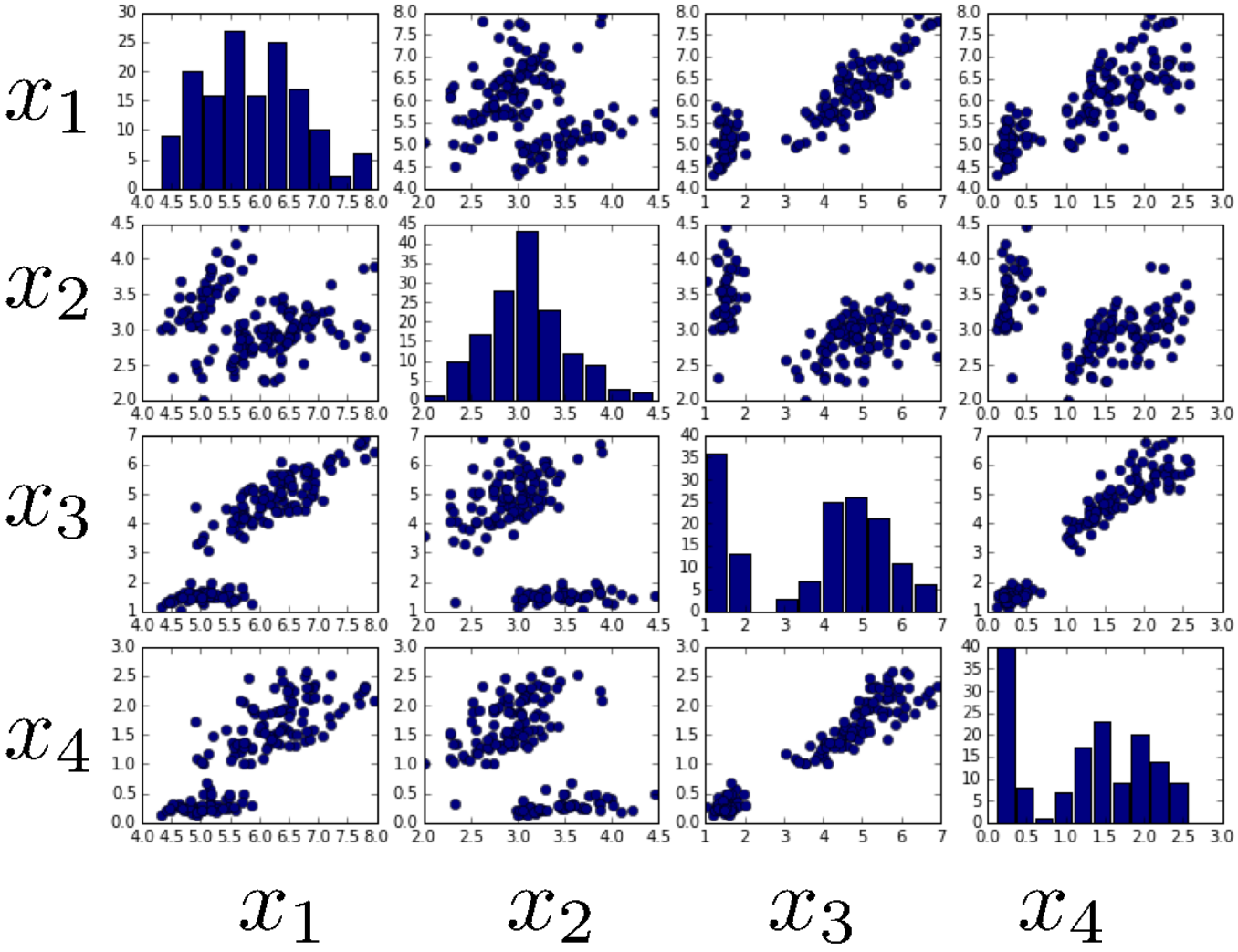
- Illustrate the relationship between two features




```
% Plotting in MatPlotLib
plt.plot(X[:,0], X[:,1], 'b.');   % plot data points as blue dots
```

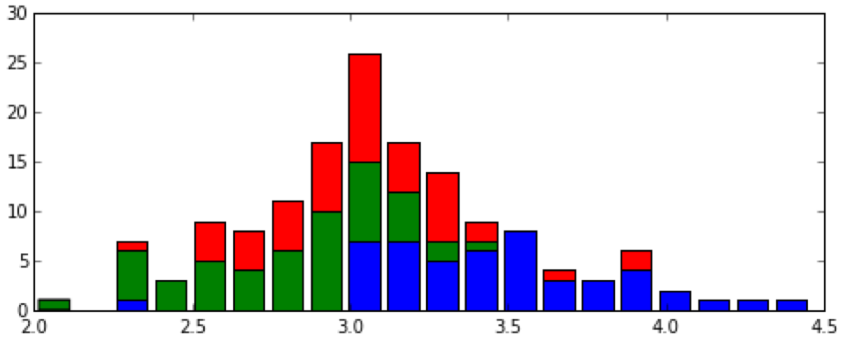
Scatterplots

- For more than two features we can use a pair plot:

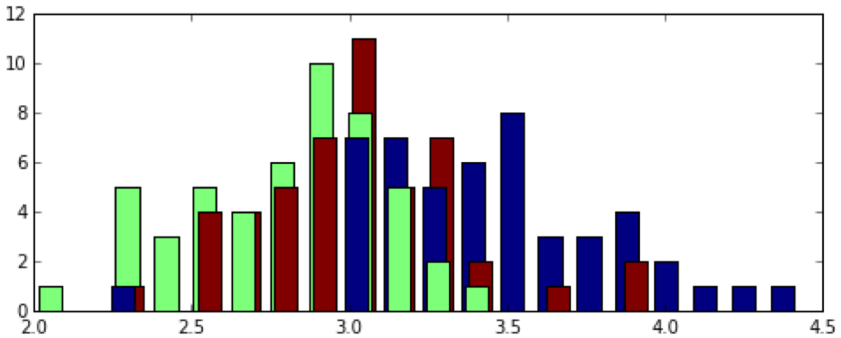


Supervised learning and targets

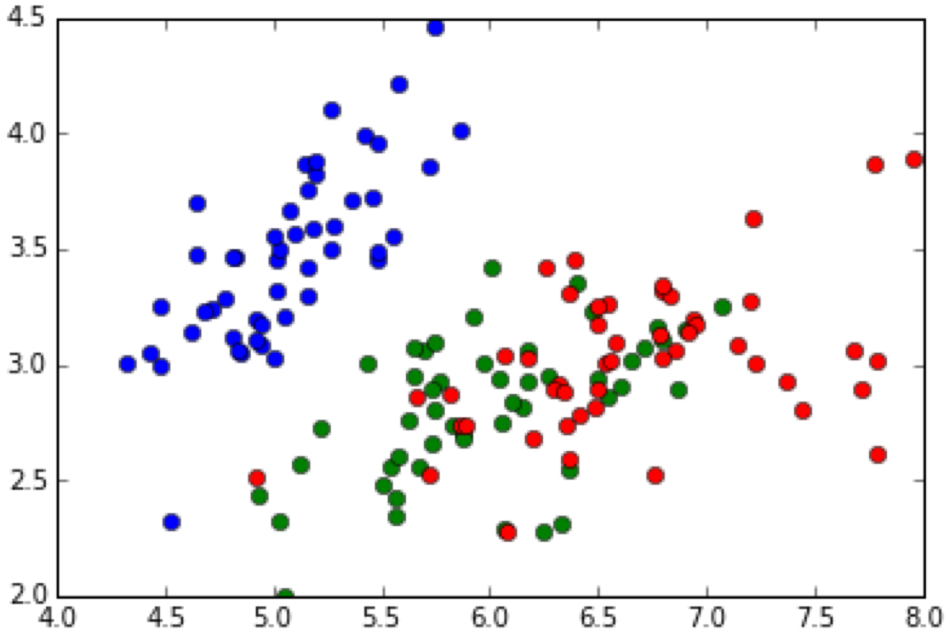
- Supervised learning: predict target values
- For discrete targets, often visualize with color




```
plt.hist( [X[Y==c,1] for c in np.unique(Y)] ,
          bins=20, histtype='barstacked')
```




```
ml.histy(X[:,1], Y, bins=20)
```




```
colors = ['b','g','r']
for c in np.unique(Y):
    plt.plot( X[Y==c,0], X[Y==c,1], 'o',
              color=colors[int(c)] )
```

Machine Learning

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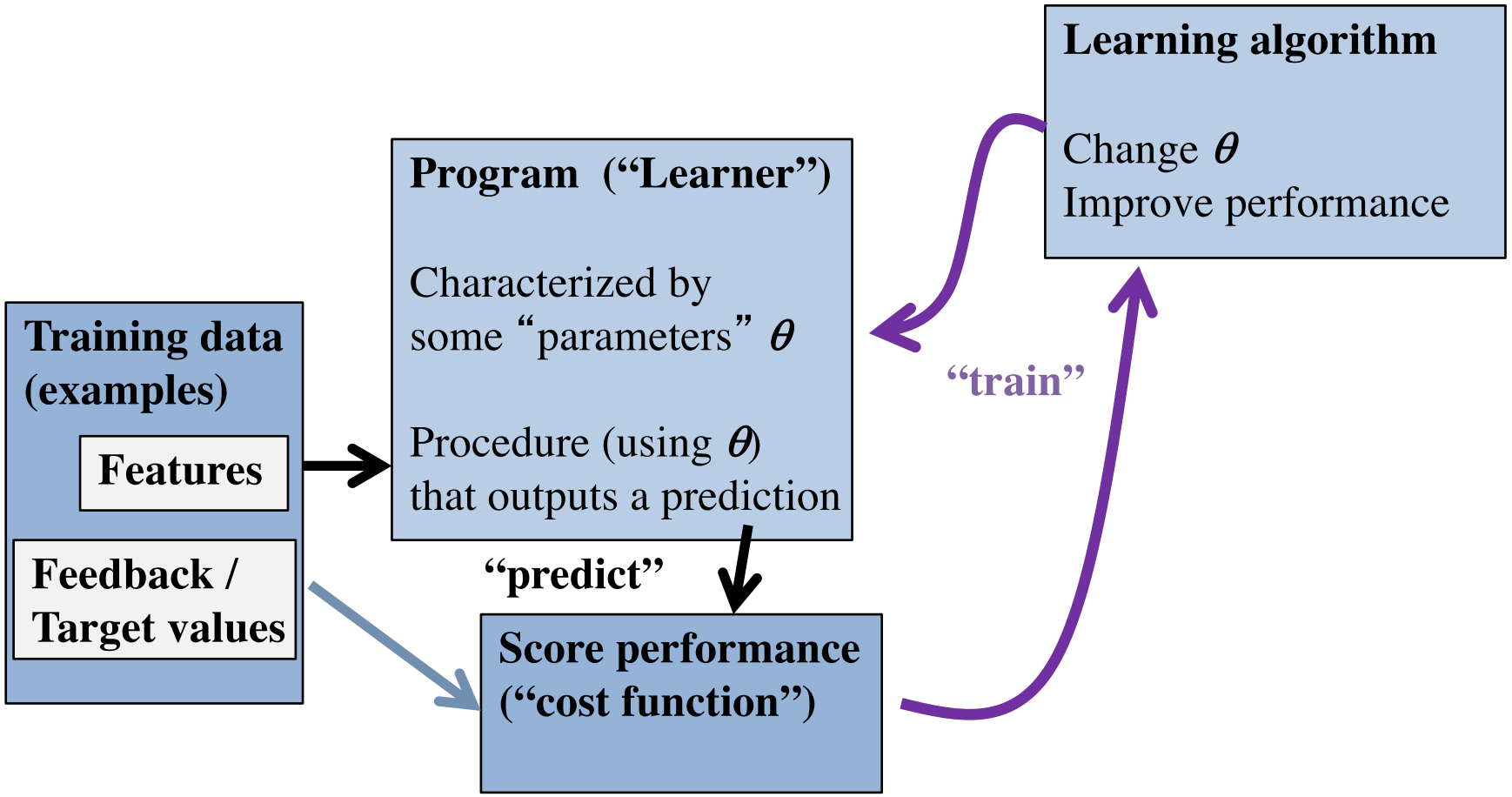
Supervised Learning

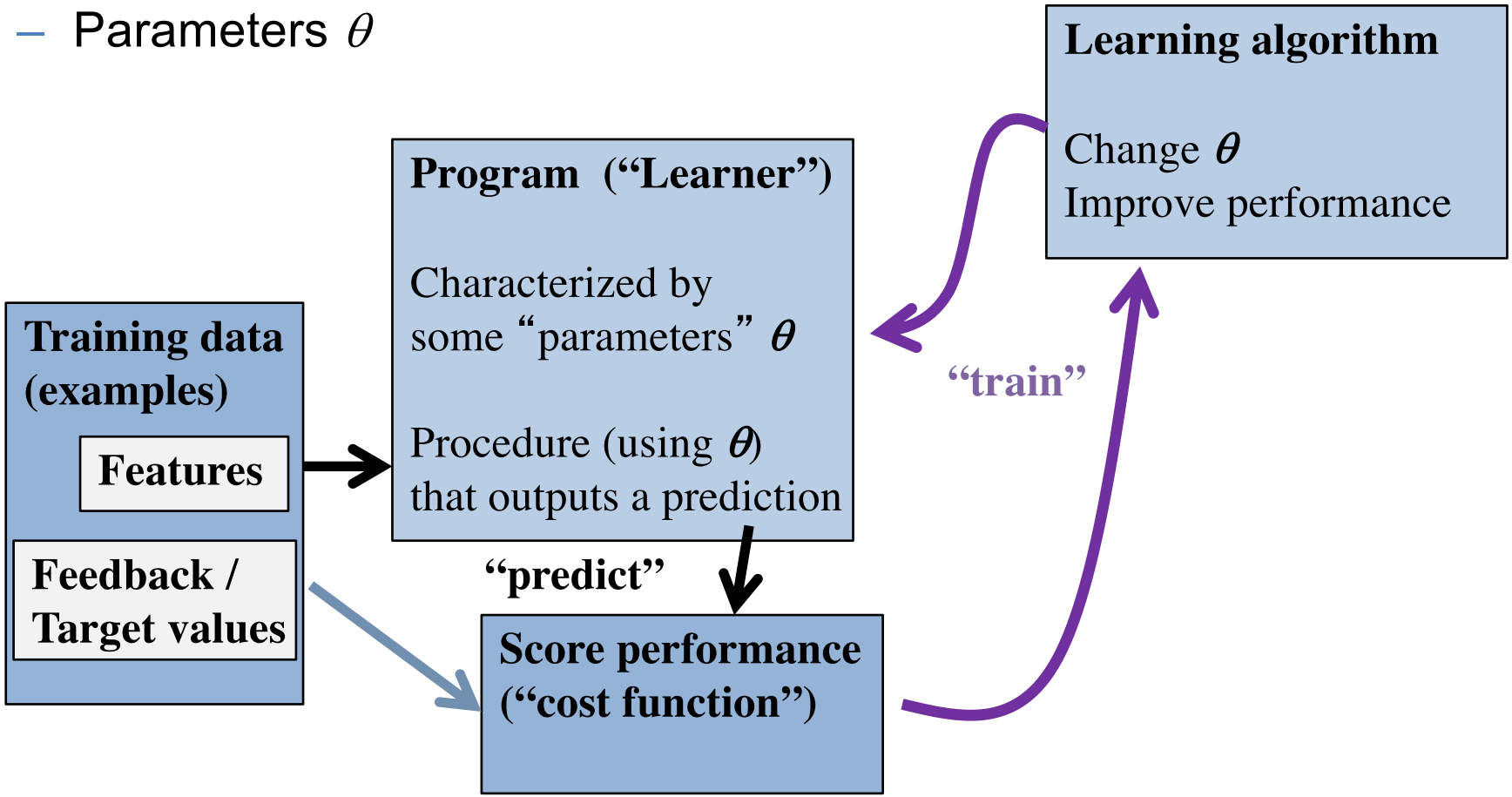
How does machine learning work?

- "Meta-programming"
  - Predict – apply rules to examples
  - Score – get feedback on performance
  - Learn – change predictor to do better

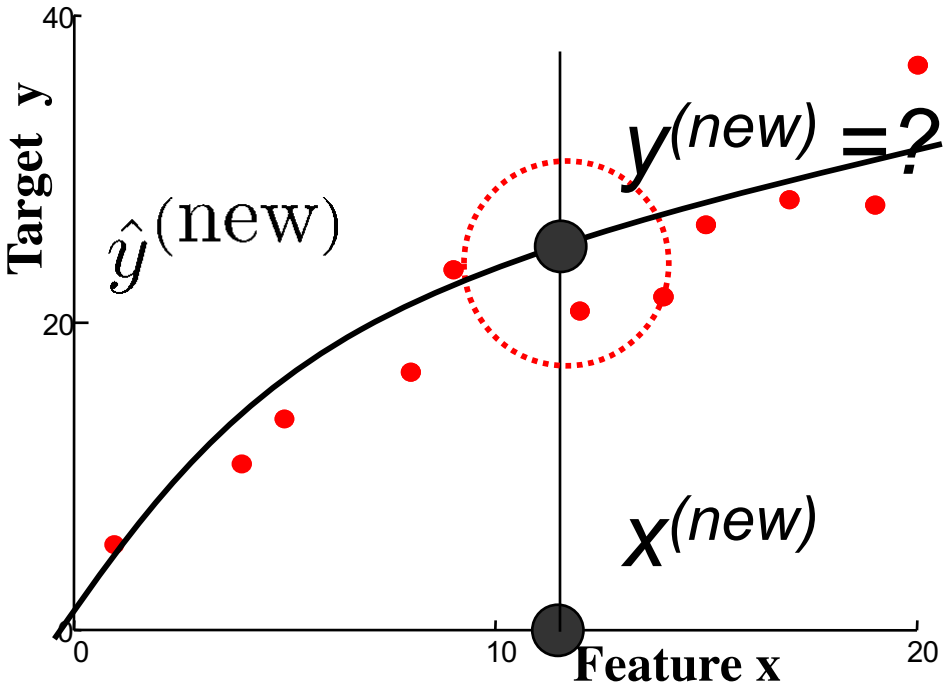


Supervised learning

- Notation
  - Features x
  - Targets y
  - Predictions $\hat{y} = f(x\ ;\ \theta)$
  - Parameters θ

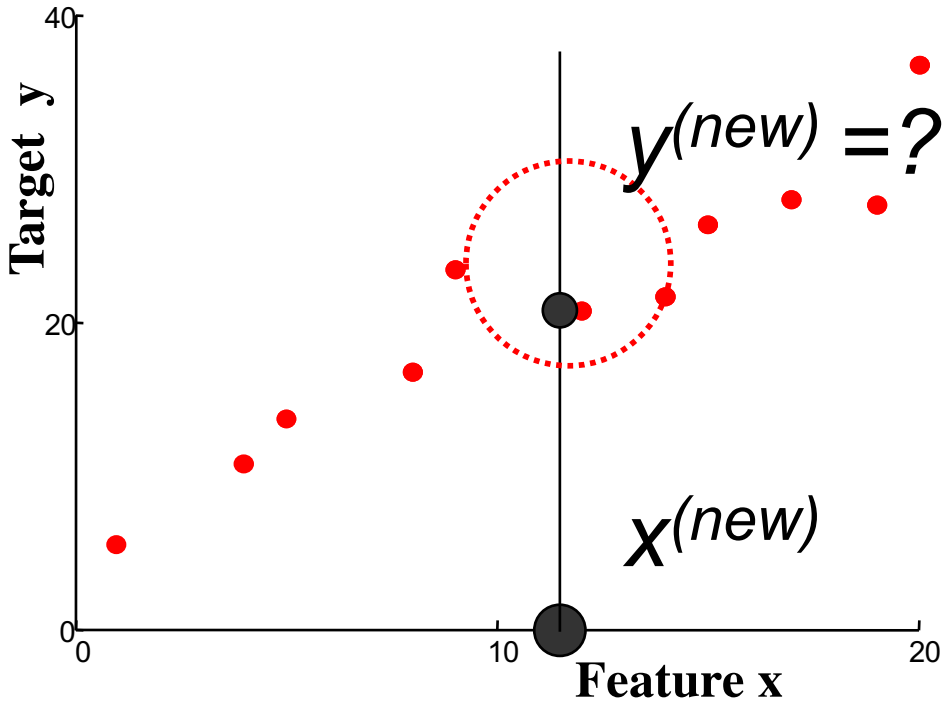


Regression; Scatter plots



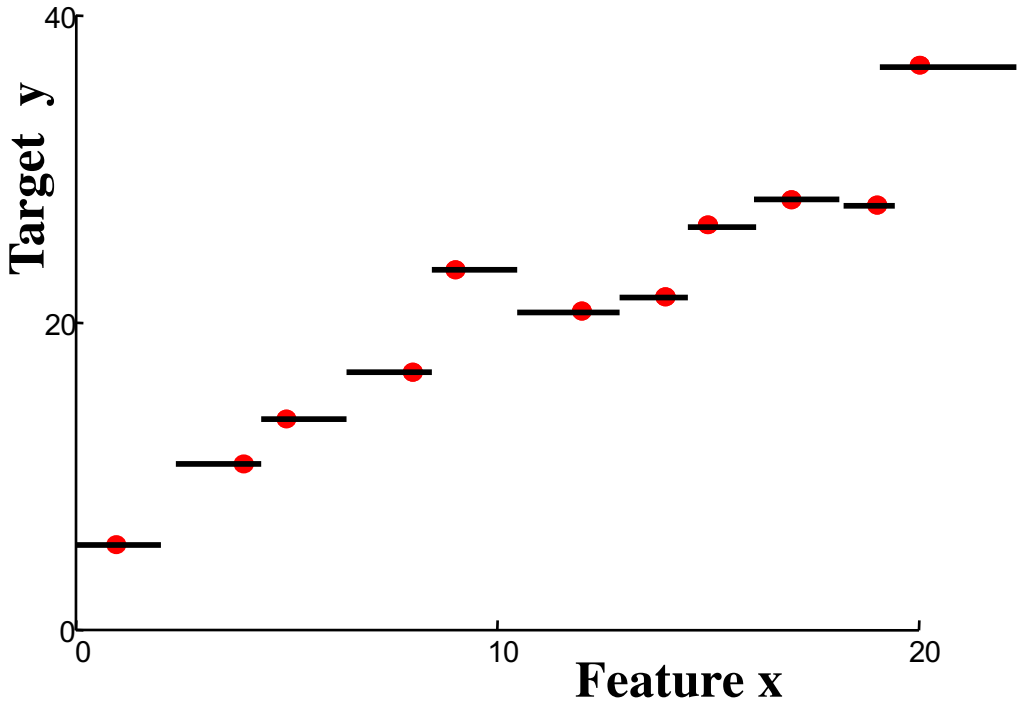
- Suggests a relationship between x and y
- *Prediction*: new x, what is y?

Nearest neighbor regression



- Find training datum $x^{(i)}$ closest to $x^{(new)}$
  Predict $y^{(i)}$

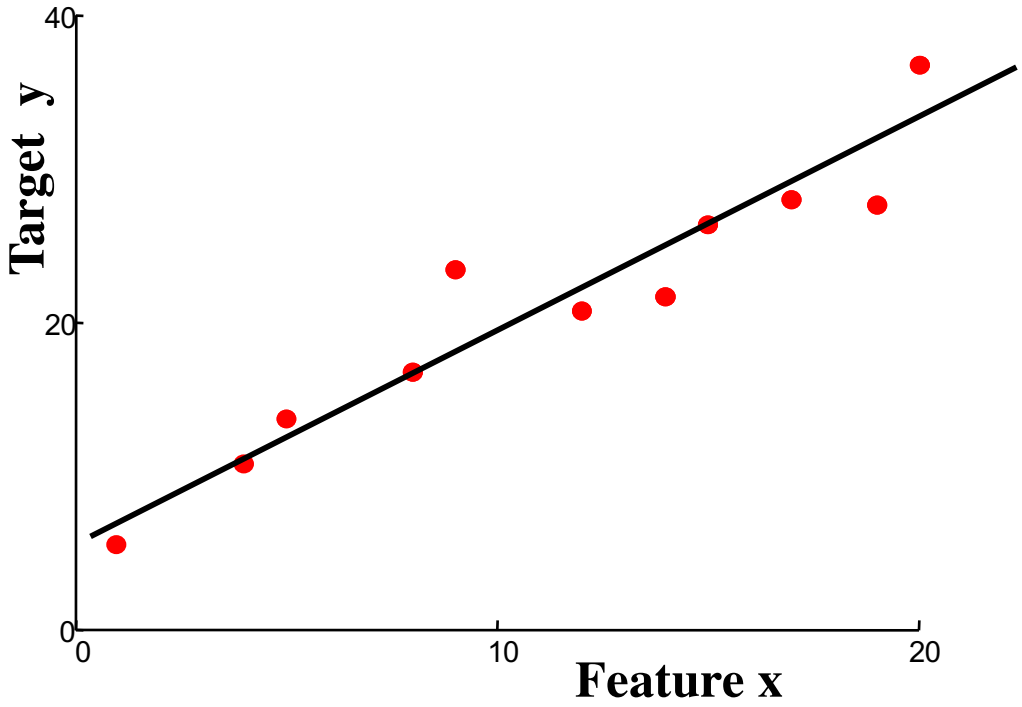
Nearest neighbor regression



"Predictor":
Given new features:
Find nearest example
Return its value

- Defines a function f(x) implicitly
- "Form" is piecewise constant

Linear regression



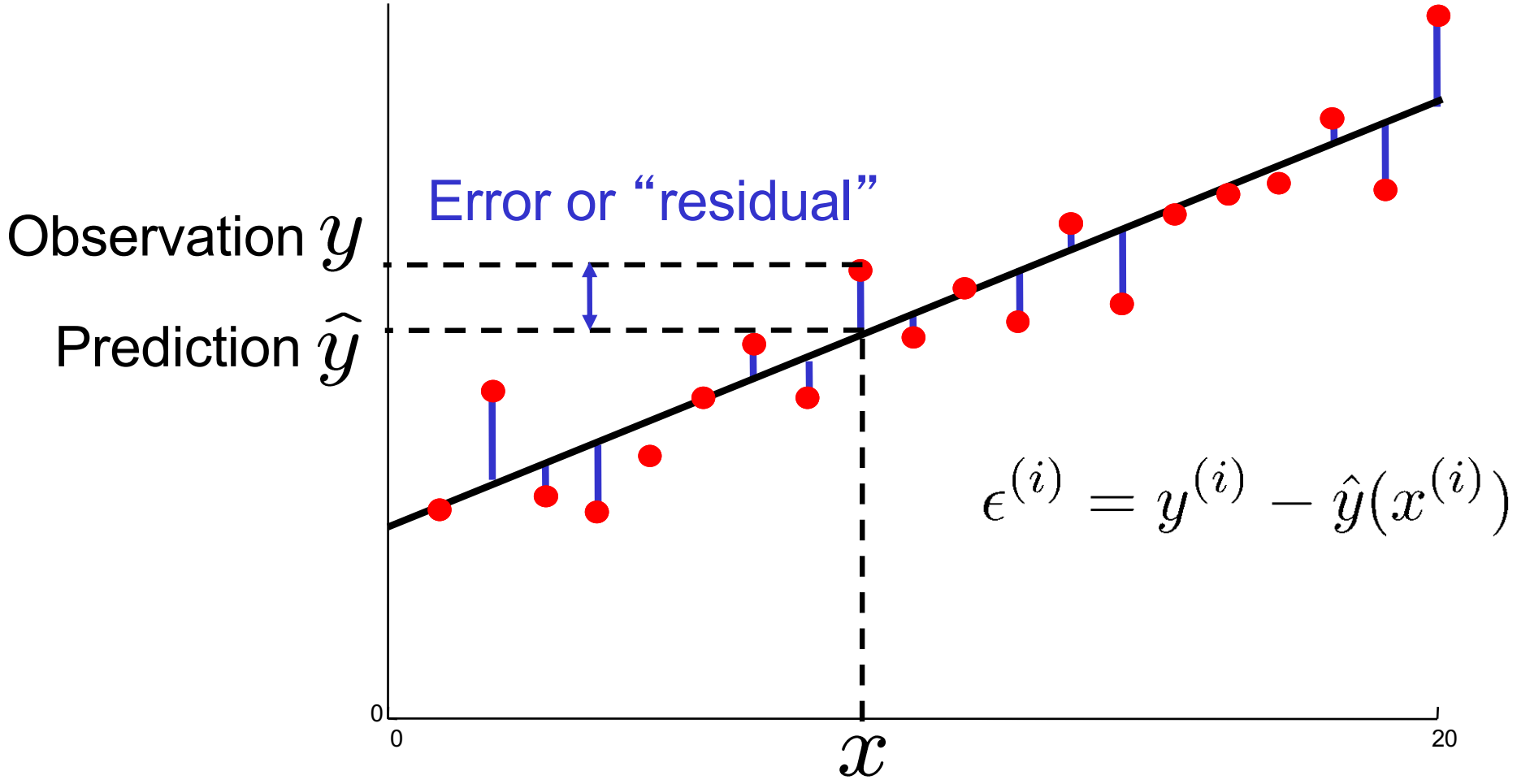
"Predictor":
Evaluate line:

$$r = \theta_0 + \theta_1 x_1$$

return r

- Define form of function f(x) explicitly
- Find a good f(x) within that family

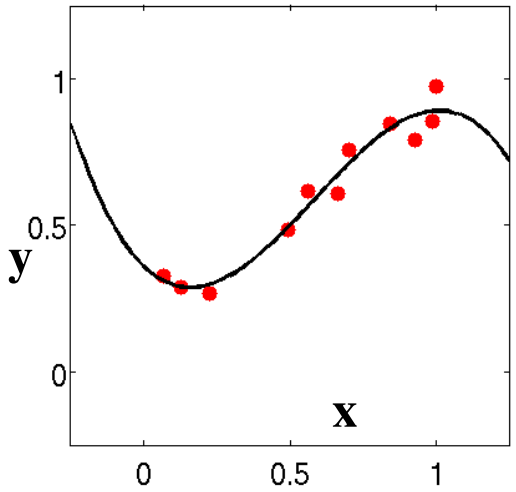
Measuring error



$$\text{MSE} = \frac{1}{m} \sum_i \left(y^{(i)} - \hat{y}(x^{(i)}) \right)^2$$

Regression vs. Classification

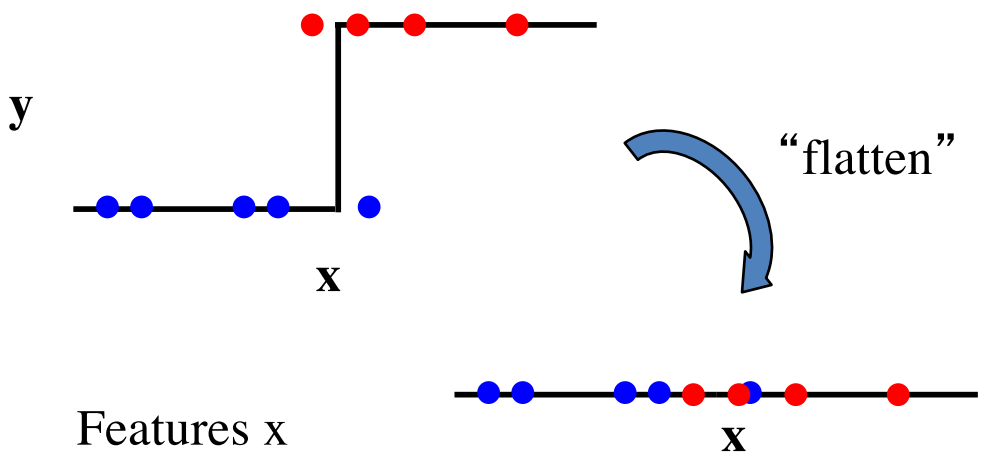
Regression



Features x
Real-valued target y

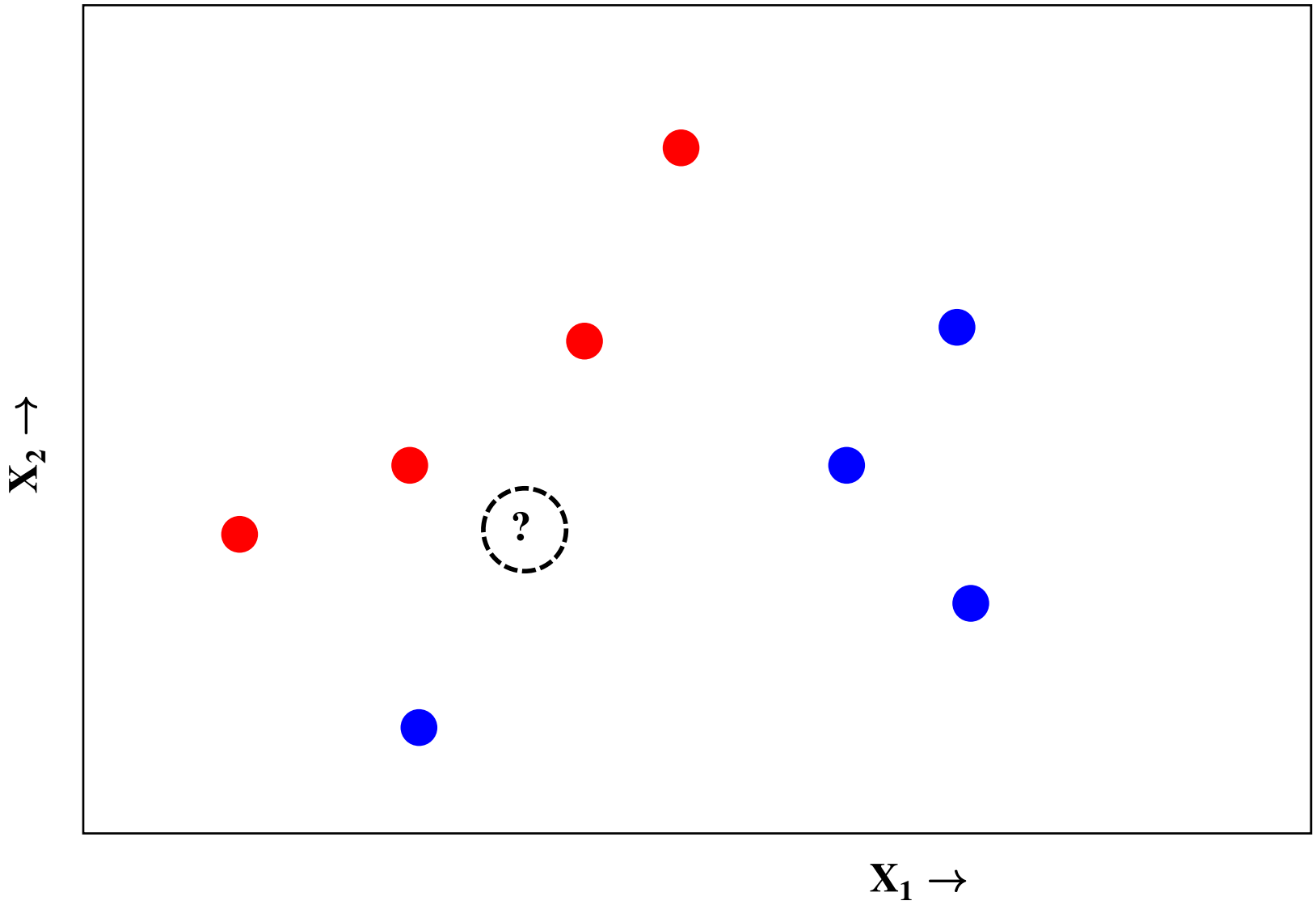
Predict continuous function $\hat{y}(x)$

Classification



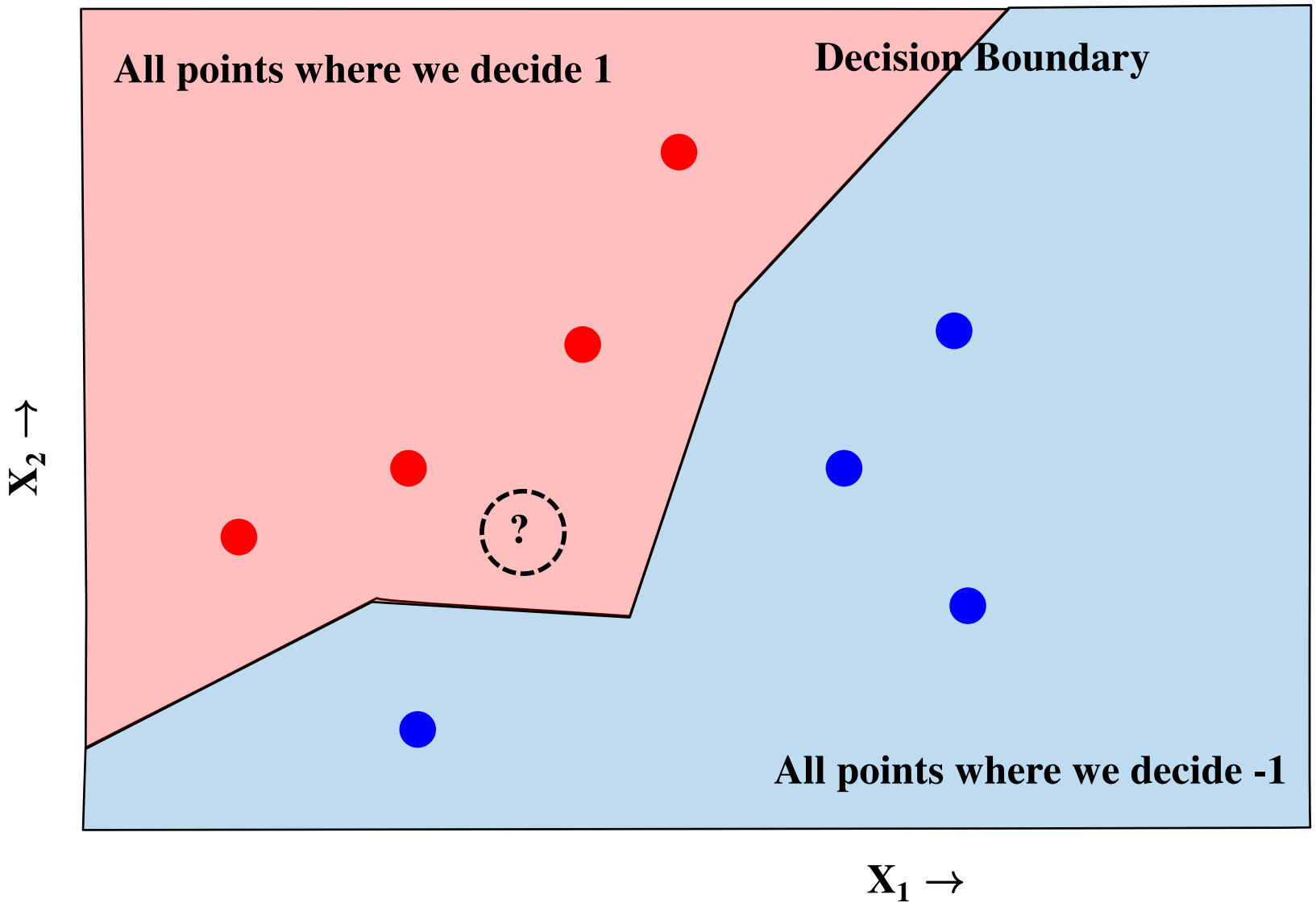
Features x
Discrete class c
(usually 0/1 or +1/-1)
Predict discrete function $\hat{y}(x)$

Classification



Classification

$$\text{ERR} = \frac{1}{m} \sum_{i} \left[y^{(i)} \neq \hat{y}(x^{(i)}) \right]$$



Summary

- What is machine learning?
  - Types of machine learning
  - How machine learning works
- Supervised learning
  - Training data: features x, targets y
- Regression
  - (x,y) scatterplots; predictor outputs f(x)
- Classification
  - (x,x) scatterplots
  - Decision boundaries, colors & symbols