Machine Learning

4771

Instructor: Tony Jebara

Topic 1

- Introduction
- Machine Learning: What, Why and Applications
- Syllabus, policies, texts, web page
- Historical Perspective
- Machine Learning Tasks and Tools
- Digit Recognition Example
- Machine Learning Approach
- Deterministic or Probabilistic Approach
- Why Probabilistic?

About me

- Tony Jebara, Associate Professor of Computer Science
- Started at Columbia in 2002
- PhD from MIT in Machine Learning
  - Thesis: *Discriminative, Generative and Imitative Learning (2001)*
- Research: Columbia Machine Learning Lab, CEPSR 6LE5
  - www.cs.columbia.edu/learning

Machine Learning: What/Why

Statistical Data-Driven Computational Models

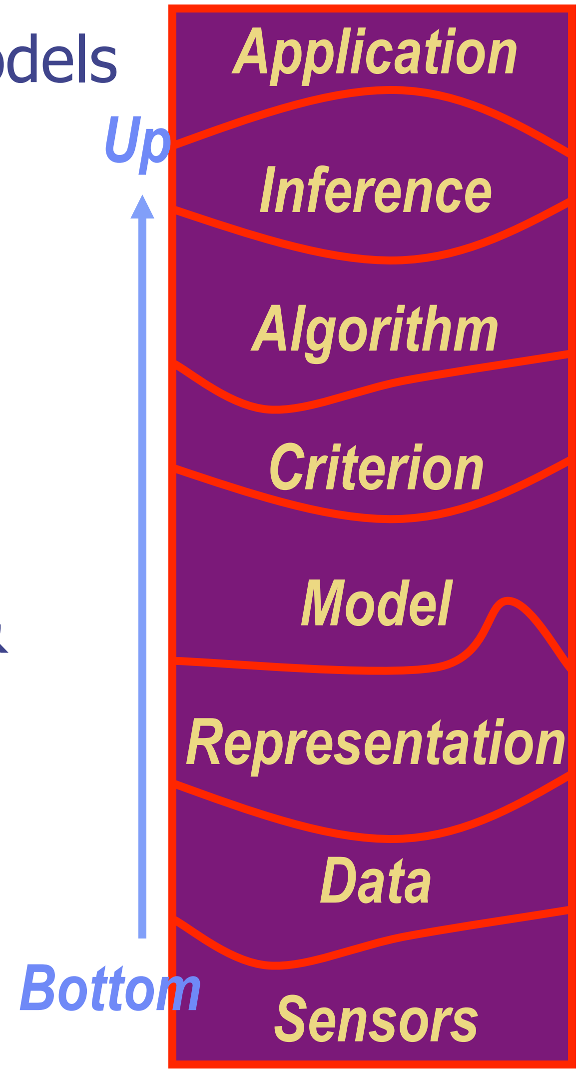
Real domains (vision, speech, behavior):
- no $E=MC^2$
- noisy, complex, nonlinear
- have many variables
- non-deterministic
- incomplete, approximate models

Need: statistical models driven by data & sensors, a.k.a Machine Learning

Bottom-Up: use data to form a model

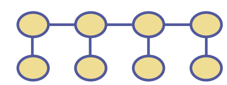
Why? Complex data everywhere, audio, video, internet

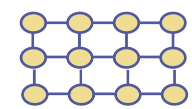
Intelligence = Learning = Prediction

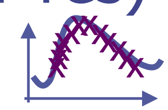


Machine Learning Applications

- ML: Interdisciplinary (CS, Math, Stats, Physics, OR, Psych)
- Data-driven approach to AI
- Many domains are too hard to do manually

Speech Recognition (HMMs, ICA) 

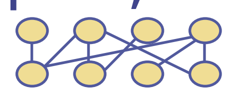
Computer Vision (face rec, digits, MRFs, super-res) 

Time Series Prediction (weather, finance) 

Genomics (micro-arrays, SVMs, splice-sites)

NLP and Parsing (HMMs, CRFs, Google)

Text and InfoRetrieval (docs, google, spam, TSVMs)

Medical (QMR-DT, informatics, ICA) 

Behavior/Games (reinforcement, gammon, gaming)

Course Details & Requirements

- Probability/Stats, Linear Algebra, Calculus, AI
- Mathematical & Data Driven approach to AI
- Lots of Equations!

- Required Text: Introduction to Graphical Models
  by M. Jordan & C. Bishop (Online)
  Pattern Recognition & Machine Learning
  by C. Bishop (Spring 2006 Edition)
- Reference Text: Pattern Classification (3rd Edition)
  by Duda, Hart and Stork

- Homework: Every 2-3 weeks
- Grading: homework, midterm, 2 quizzes & final examination

- Software Requirements: Matlab software & Acis account

Course Web Page

http://www.cs.columbia.edu/~jebara/4771

Slides will be available on handouts web page

Each week, check NEWS link for readings, homework deadlines, announcements, etc.

Syllabus

www.cs.columbia.edu/~jebara/4771/MLInfo.htm

- **Intro to Machine Learning**
- **Least Squares Estimation**
- **Logistic Regression**
- **Perceptrons**
- **Neural Networks**
- **Support Vector Machines**
- **Kernels**
- **Probability Models**
- **Maximum Likelihood**
- **Multinomial Models**
- **Bernoulli Models**
- **Gaussian Models**
- **Principal Components Analysis**
- **Bayesian Inference**
- **Exponential Family Models**
- **Mixture Models**
- **K-means**
- **Expectation Maximization**
- **Graphical Models**
- **Bayesian Networks**
- **Junction Tree Algorithm**
- **Hidden Markov Models**

Historical Perspective (Bio/AI)

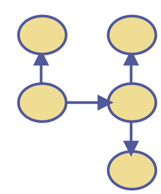
- 1917: Karel Capek (Robot)
- 1943: McCullogh & Pitts (Bio, Neuron)
- 1947: Norbert Weiner (Cybernetics, Multi-Disciplinary)
- 1949: Claude Shannon (Information Theory)
- 1950: Minsky, Newell, Simon, McCarthy (Symbolic AI, Logic)
- 1957: Rosenblatt (Perceptron)
- 1959: Arthur Samuel
  Coined Machine Learning
  Learning Checkers

- 1969: Minsky & Papert (Perceptron Linearity, no XOR)
- 1974: Werbos (BackProp, Nonlinearity)
- 1986: Rumelhart & McLelland (MLP, Verb-Conjugation)
- 1980's: NeuralNets, Genetic Algos, Fuzzy Logic, Black Boxes

Historical Perspective (Stats)

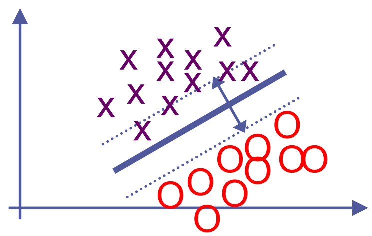
- 1763: Bayes (Prior, Likelihood, Posterior)
- 1920's: Fisher (Maximum Likelihood)
- 1937: Pitman (Exponential Family)
- 1969: Jaynes (Maximum Entropy)
- 1970: Baum (Hidden Markov Models)
- 1978: Dempster (Expectation Maximization)
- 1980's: Vapnik (VC-Dimension)
- 1990's: Lauritzen, Pearl (Graphical Models)

- 2000's: Bayesian & Statistical & Structure & Priors
  Graphical Models: Expectation Maximization,
  Kalman Filtering, Hidden Markov Models,
  Sigmoid Belief Nets, Markov Random Fields
  SVMs, Learning Theory, Boosting, Kernels

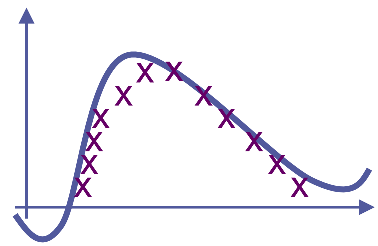


Machine Learning Tasks

Classification y=sign(f(x))

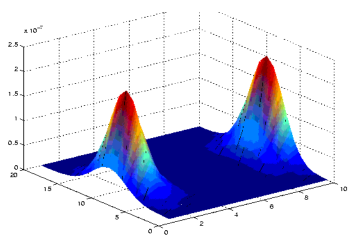


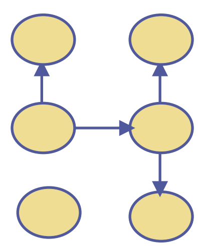
Regression y=f(x)



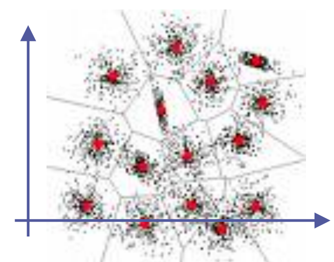
Supervised

Modeling p(x)

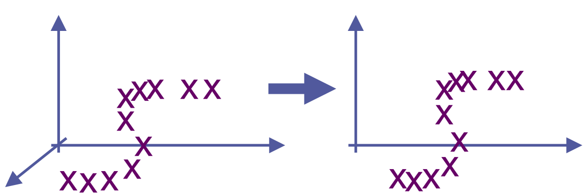




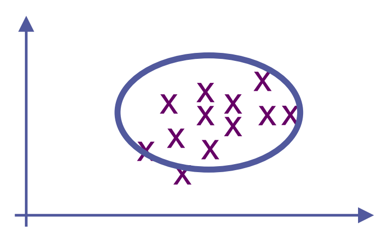
Clustering



Feature Selection

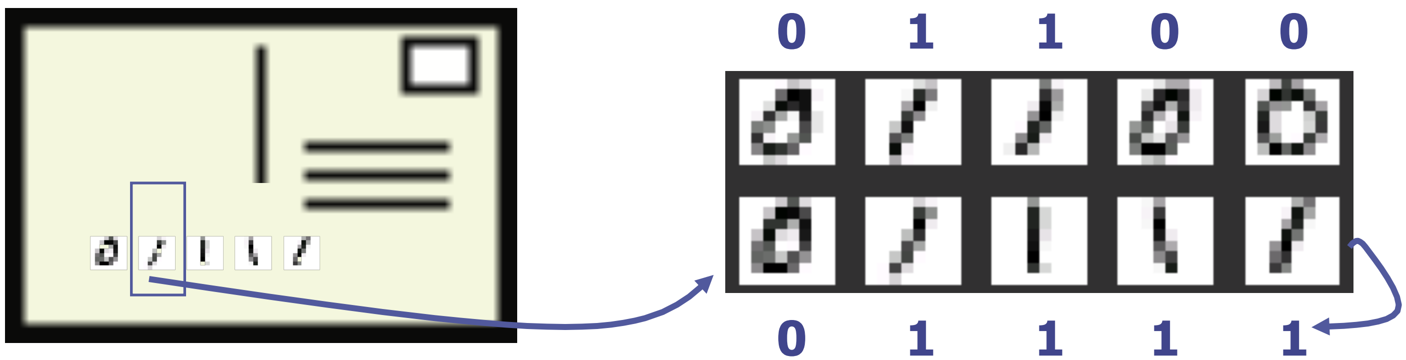


Detection p(x)<t

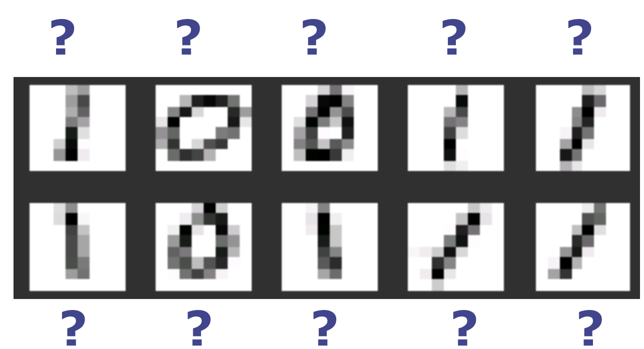


Unsupervised

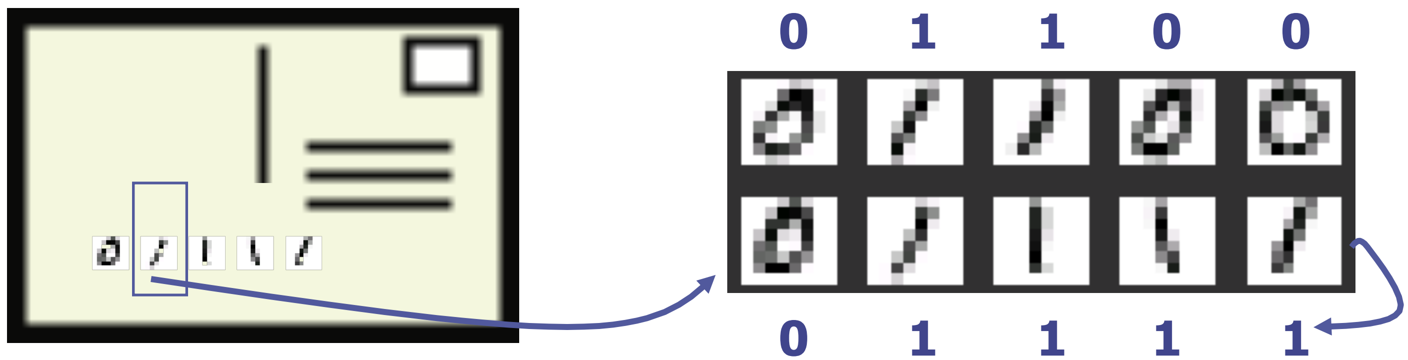
ML Example: Digit Recognition



- Want to automate zipcode reading in post office
- Look at an image and say if it is a '1' or '0'
- 8x8 pixels of gray-level (0.0=dark, 0.5=gray, 1.0=white)
- Learn from above labeled training images
- Predict labels on testing images
- Binary Classification [0,1]
- What to do?



Ex: Setting up the Problem



Problem or Task

Representation

Data & Labels

Prior Parameters

Prior Structure

Model

Objective or Cost Function

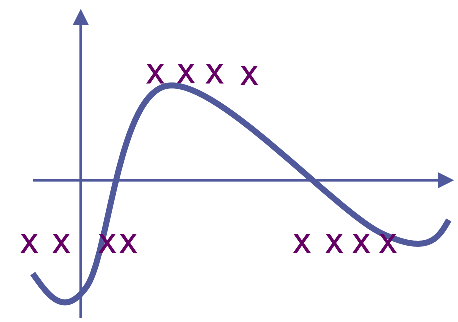
Algorithm

Evaluate & Repeat

Ex: Two Approaches

In ML, we will consider two complementary approaches:

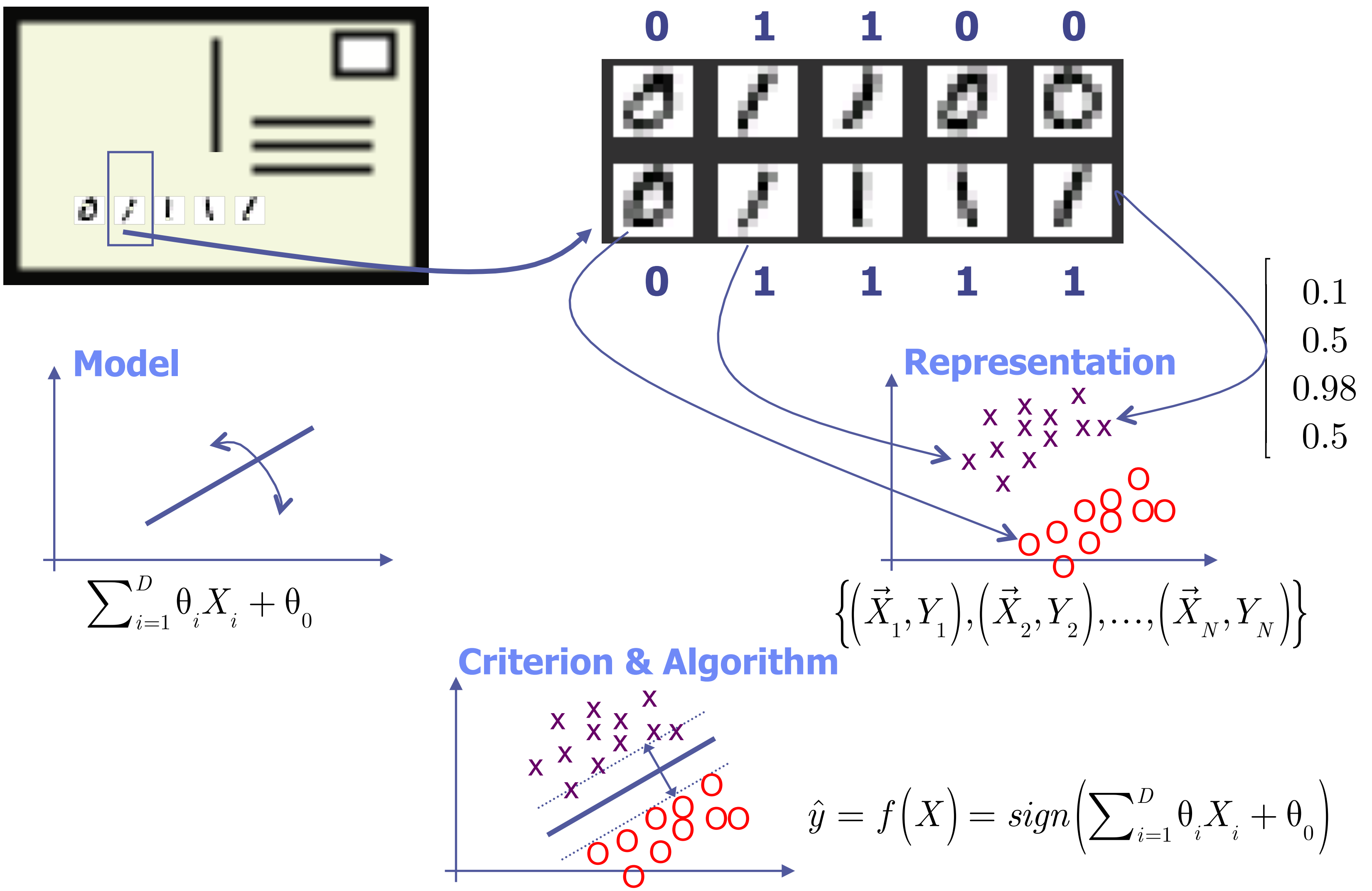
1) Deterministic:
   All variables/observables are treated as certain/exact
   Find/fit a function f(X) on an image X
   Output 0 or 1 depending on input
   Class label given by y=sign(f(X))/2 + 1/2



2) Probabilistic/Bayesian/Stochastic:
   Variables/observables are random (R.V.) and uncertain
   Probability image is a '0' digit: p(y=0|X) = 0.43
   Probability image is a '1' digit: p(y=1|X) = 0.57
   Output label with larger p(y=0|image) or p(y=1|image)

These are interconnected! Deterministic approaches can be generated from (more general) probabilistic approaches

Ex: 1) Deterministic Approach



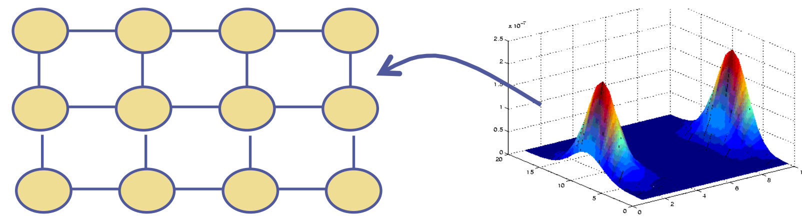
$$\sum_{i=1}^{D} \theta_i X_i + \theta_0$$

$$\left\{ \left(\vec{X}_1, Y_1\right), \left(\vec{X}_2, Y_2\right), \ldots, \left(\vec{X}_N, Y_N\right) \right\}$$

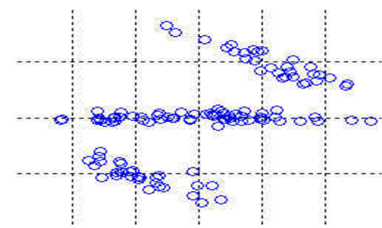
$$\hat{y} = f\left(X\right) = sign\left(\sum_{i=1}^{D} \theta_i X_i + \theta_0\right)$$

Ex: 2) Probabilistic Approach

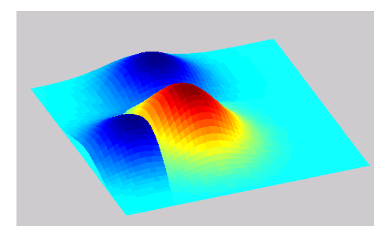
a) Provide Prior Model
  Parameters & Structure
  e.g. nearby pixels are
    co-dependent



b) Obtain Data and Labels $\left\{\left(X_1,Y_1\right),\ldots,\left(X_T,Y_T\right)\right\}$

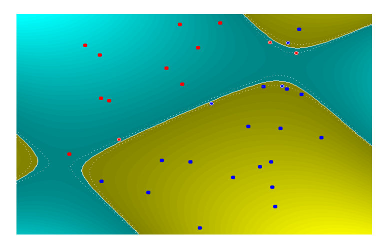


c) Learn a probability model with data
  p(all system variables) $p\left(X,Y\right)$



d) Use model for inference (classify/predict)

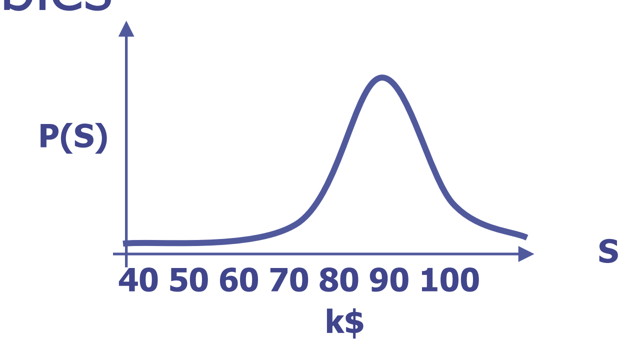
Probability image is '0': p(y=0|X)
Probability image is '1': p(y=1|X)
Output: arg max$_i$ p(y=i|X) $p\left(Y \mid X\right)$



Why Probabilistic Approach?

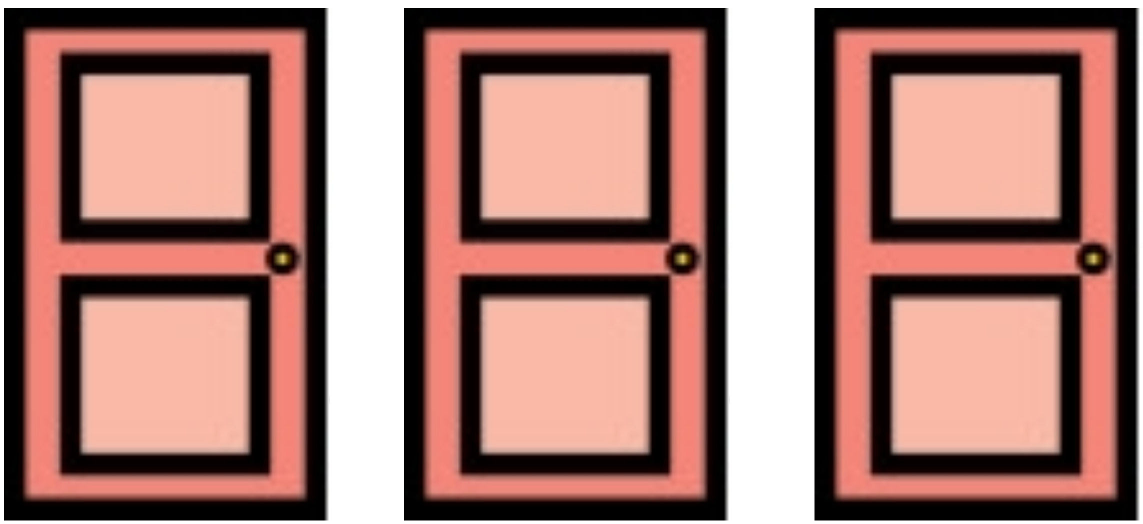
- Decision making often involves uncertainty
- Hidden variables, complexity, randomness in system
- Input data is noisy and uncertain
- Estimated model is noisy and uncertain
- Output data is uncertain (no single correct answer)

- Example: Predict your salary in the future
- Inputs: Field, Degree, University, City, IQ
- Output: $Amount
- There is uncertainty and hidden variables
- No one answer (I.e. $84K) is correct
- Answer = a distribution over salaries



Why Probabilistic? Monty Hall

- Behind one door is a prize (car? 1$?)
- Pick a door



Door A Door B Door C

Monty Hall Solution

Probabilistic Graphical Model Bayesian Network

Probabilistic Interpretation is Best

Bayesian Solution: Change your mind!

Assume we always start by picking A.

If prize behind A: Opens B/C → Change A to C/B → Lose

If prize behind B: Opens C → Change A to B → Win

If prize behind C: Opens B → Change A to C → Win

Probability of winning if change your mind = 66%
Probability of winning if stick to your guns = 33%