Machine Learning Overview

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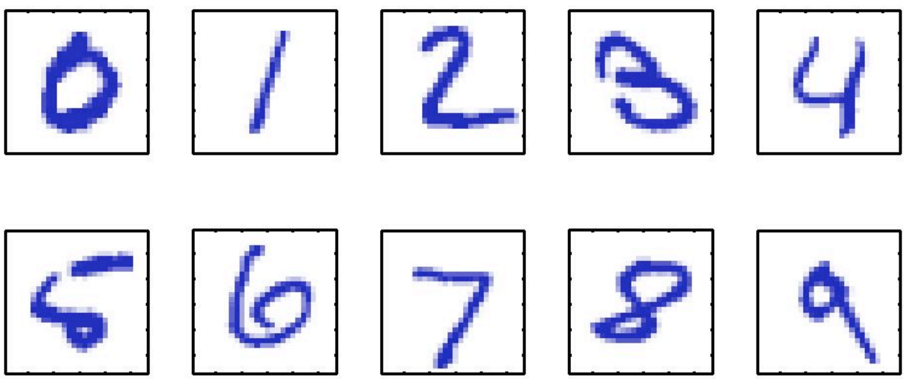
Outline

1. What is Machine Learning (ML)?
2. Types of Information Processing Problems Solved
    1. Regression
    2. Classification
    3. Clustering
    4. Modeling Uncertainty/Inference
3. New Developments
    1. Fully Bayesian Approach
4. Summary

What is Machine Learning?

- Programming computers to:
  - Perform tasks that humans perform well but difficult to specify algorithmically
- Principled way of building high performance information processing systems
  - search engines, information retrieval
  - adaptive user interfaces, personalized assistants (information systems)
  - scientific application (computational science)
  - engineering

Example Problem: Handwritten Digit Recognition



Wide variability of same numeral

- Handcrafted rules will result in large no of rules and exceptions
- Better to have a machine that learns from a large training set

ML History

- ML has origins in Computer Science
- PR has origins in Engineering
- They are different facets of the same field
- Methods around for over 50 years
- Revival of Bayesian methods
  - due to availability of computational methods

Some Successful Applications of Machine Learning

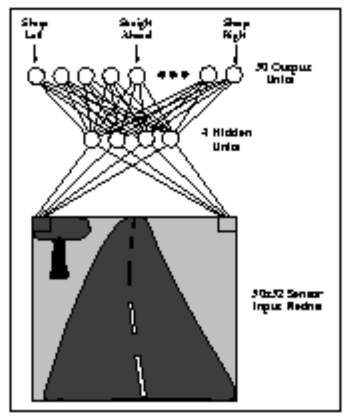
- Learning to recognize spoken words
  - Speaker-specific strategies for recognizing primitive sounds (phonemes) and words from speech signal
  - Neural networks and methods for learning HMMs for customizing to individual speakers, vocabularies and microphone characteristics

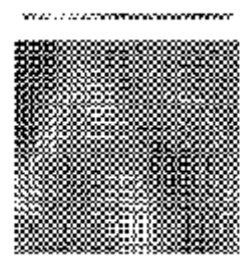
Table 1.1

Some Successful Applications of Machine Learning

- Learning to drive an autonomous vehicle
  - Train computer-controlled vehicles to steer correctly
  - Drive at 70 mph for 90 miles on public highways
  - Associate steering commands with image sequences

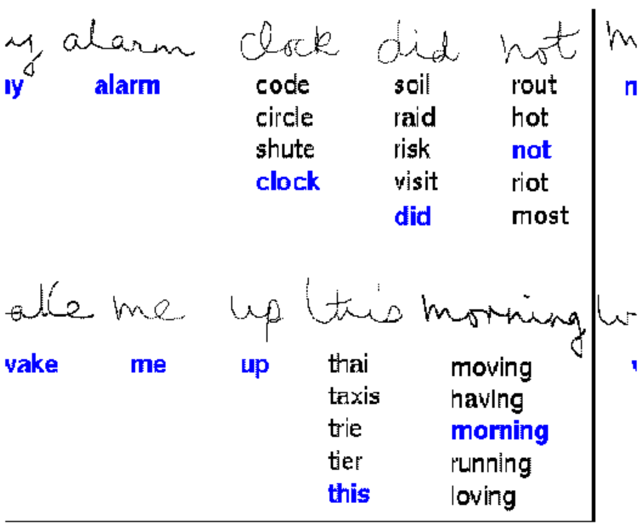
ALVINN [Pomerleau] drives 70 mph on highways





Handwriting Recognition

- **Task *T***
  - recognizing and classifying handwritten words within images
- **Performance measure *P***
  - percent of words correctly classified
- **Training experience *E***
  - a database of handwritten words with given classifications



The ML Approach

- Data Collection
  - Samples
- Model Selection
  - Probability distribution to model process
- Parameter Estimation
  - Values/distributions

- Search
  - Find optimal solution to problem

Generalization

(Training)

Decision

(Inference

OR

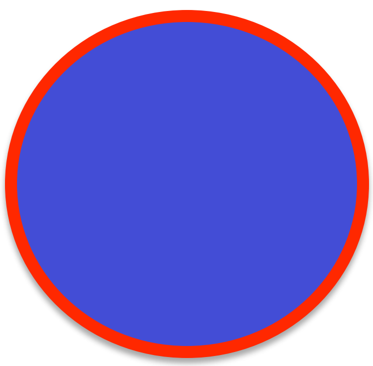
Testing)

Types of Problems machine learning is used for

1. Classification
2. Regression
3. Clustering (Data Mining)
4. Modeling/Inference

Example Classification Problem

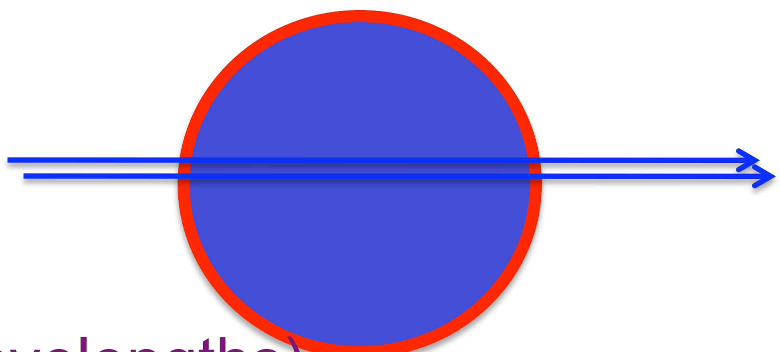
- Off-shore oil transfer pipelines
- Non-invasive measurement of *proportion* of
  - oil,water and gas
- Called Three-phase Oil/Water/Gas Flow



Dual-energy gamma densitometry

- Beam of gamma rays passed through pipe
- Attenuation in intensity provides information on density of material
- Single beam insufficient
  - Two degrees of freedom: fraction of oil, fraction of water

One beam of
Gamma rays
of two energies
(frequencies or wavelengths)

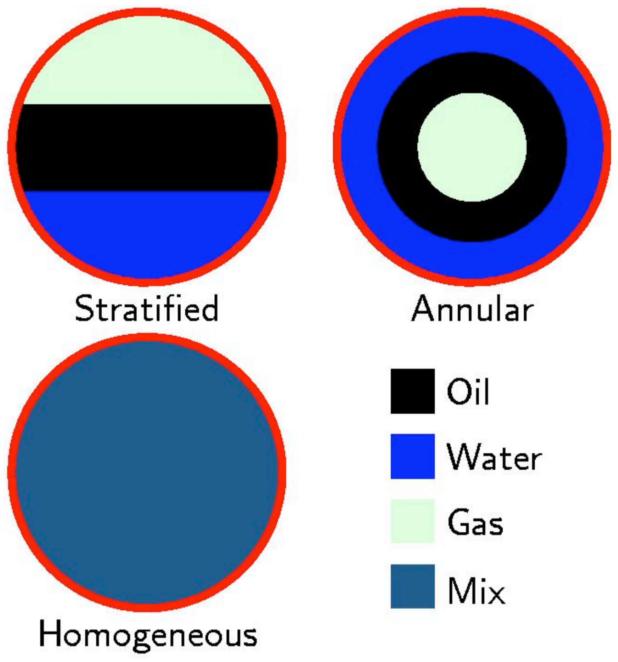


Detector

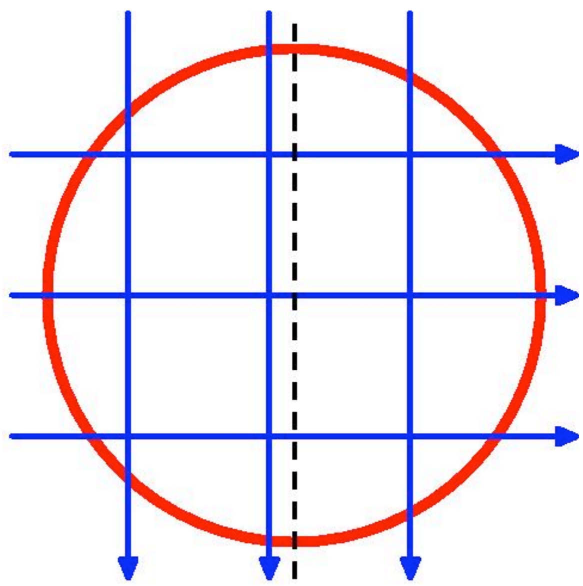
Complication due to Flow Velocity

1. Low Velocity: Stratified configuration
   – Oil floats on top of water, gas above oil
2. Medium Velocity: Annular configuration
   – Concentric cylinders of Water, oil, gas
3. High-Turbulence: Homogeneous
   – Intimately mixed

- Single beam is insufficient
  – Horizontal beam thru stratified indicates only oil



Multiple dual energy gamma densitometers

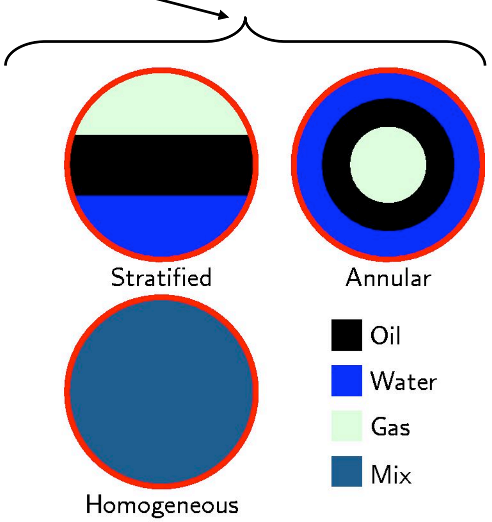


- Six Beams
- 12 measurements
  - attenuation

Prediction Problems

1. Predict Volume Fractions of oil/ water/gas
2. Predict geometric configuration of three phases

- Twelve Features
  - Fractions of oil and water along the paths
- Learn to classify from data

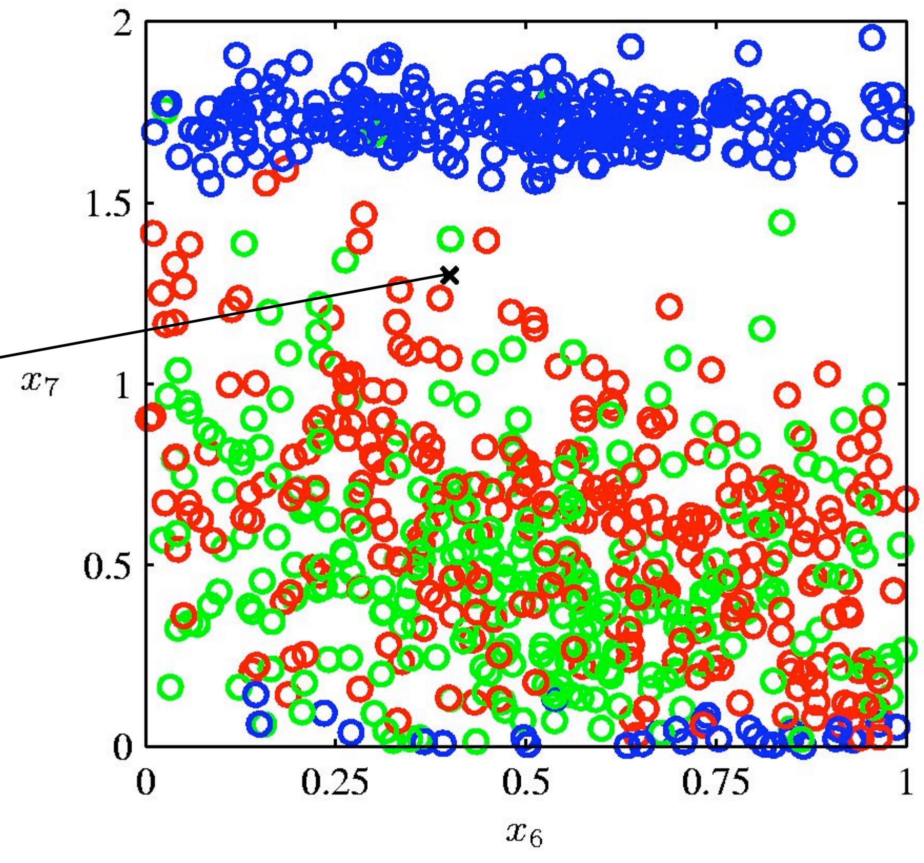


Feature Space

- Three classes (Stratified,Annular,Homogeneos)

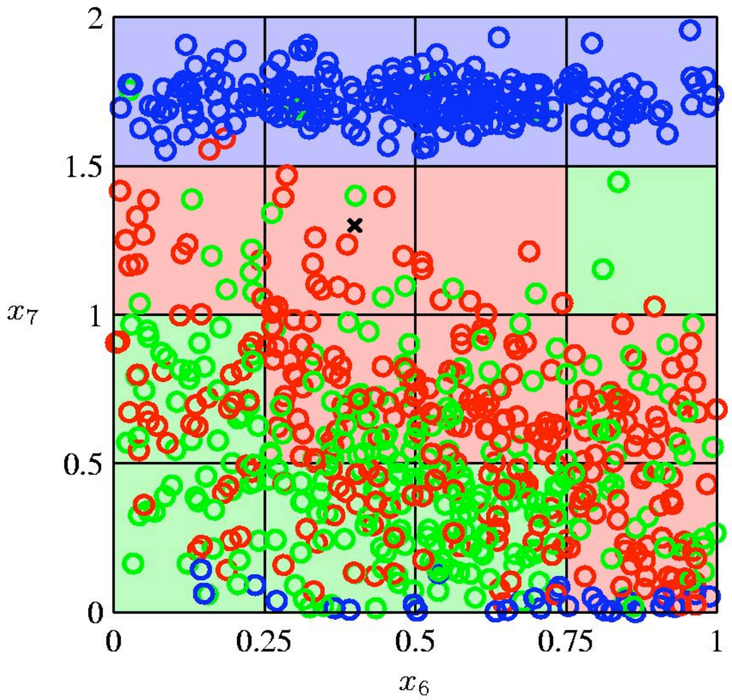
- Two variables shown
- 100 points

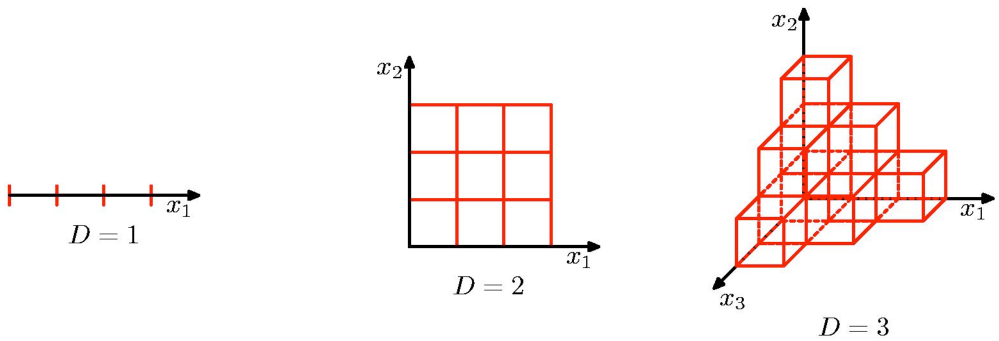
Which class should x belong to?



Cell-based Classification

- Naïve approach of cell based voting will fail
  - exponential growth of cells with dimensionality
  - 12 dimensions discretized into 6 gives 3 million cells
- Hardly any points in each cell





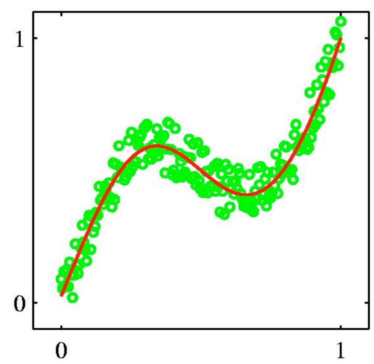
Popular Statistical Models

- Generative
  - Naïve Bayes
  - Mixtures of multinomials
  - Mixtures of Gaussians
  - Hidden Markov Models (HMM)
  - Bayesian networks
  - Markov random fields

- Discriminative
  - Logistic regression
  - SVMs
  - Traditional neural networks
  - Nearest neighbor
  - Conditional Random Fields (CRF)

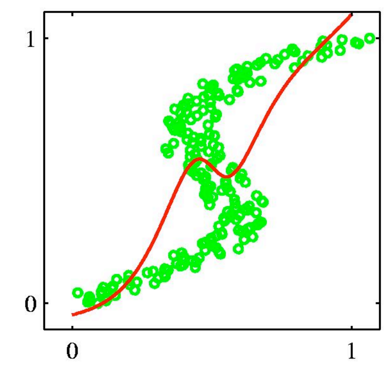
Regression Problems

Forward problem
data set



Red curve is result of
fitting a two-layer
neural network
by minimizing
sum-of-squared
error

Corresponding inverse
problem by reversing
x and t

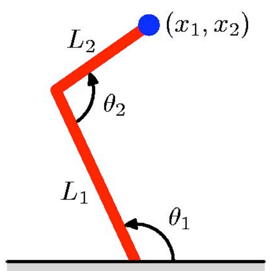


Very poor fit
to data:
GMMs used here

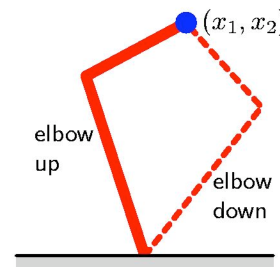
Forward and Inverse Problems

- Kinematics of a robot arm

Forward problem:
Find end effector position given joint angles
Has a unique solution



Inverse kinematics: two solutions:
Elbow-up and elbow-down



- Forward problems correspond to causality in a physical system
  have a unique solution
  e.g., symptoms caused by disease
- If forward problem is a many-to-one mapping, inverse has multiple solutions

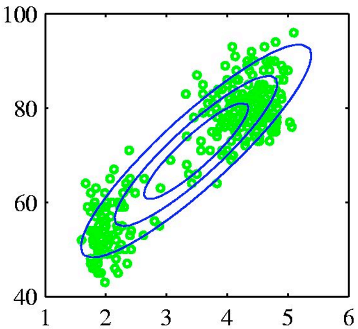
Clustering

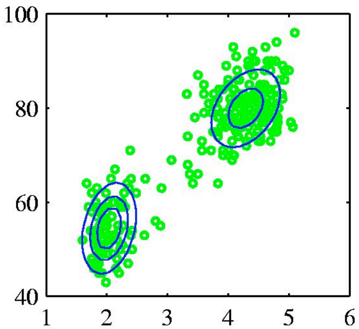
- Old Faithful (Hydrothermal Geyser in Yellowstone)
  - 272 observations
  - Duration (mins, horiz axis) *vs* Time to next eruption (vertical axis)
  - Simple Gaussian unable to capture structure
  - Linear superposition of two Gaussians is better
- Gaussian has limitations in modeling real data sets
- Gaussian Mixture Models give very complex densities

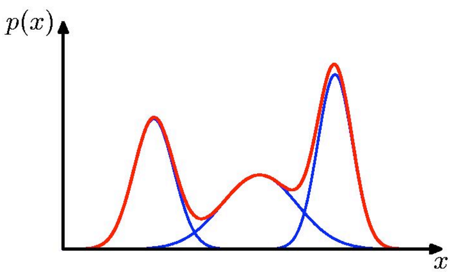
$$p(\mathrm{x}) = \sum_{k=1}^{K} \pi_k N(x \mid \mu_k, \Sigma_k)$$

π_k are mixing coefficients that sum to one

- One –dimension
  - Three Gaussians in blue
  - Sum in red







Estimation for Gaussian Mixtures

- Log likelihood function is

$$\ln p(X \mid \pi, \mu, \Sigma) = \sum_{n=1}^{N} \ln \left\{ \sum_{k=1}^{K} \pi_k N\left(\mathrm{x}_n \mid \mu_k, \Sigma_k\right) \right\}$$

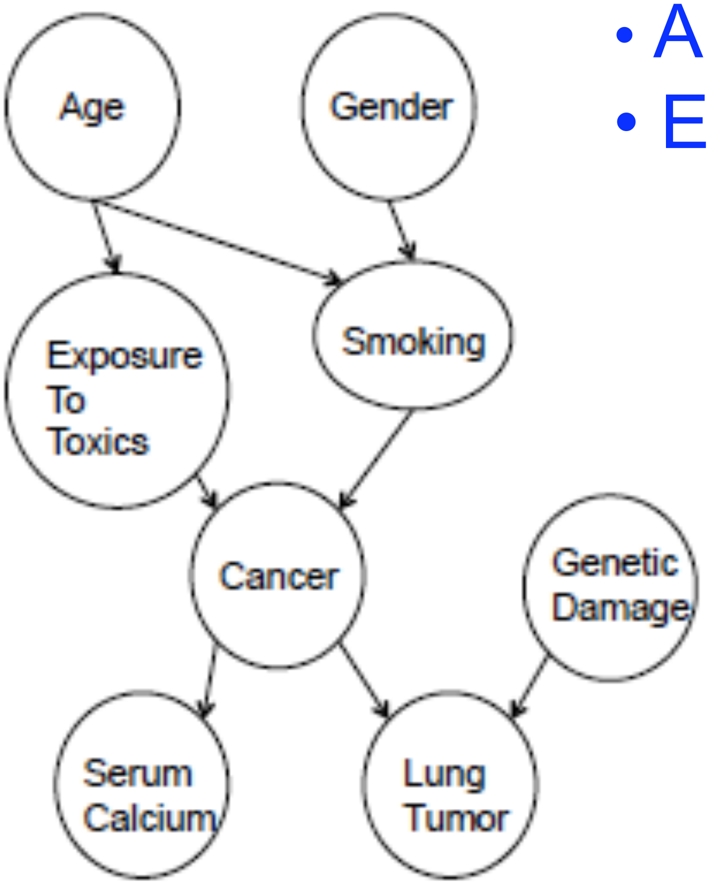
- No closed form solution
- Use either iterative numerical optimization techniques or *Expectation Maximization*

Bayesian Representation of Uncertainty

- Not just frequency of random, repeatable event
- It is a quantification of uncertainty
- Example: Whether Arctic ice cap will disappear by end of century
  - We have some idea of how quickly polar ice is melting
  - Revise it on the basis of fresh evidence (satellite observations)
  - Assessment will affect actions we take (to reduce greenhouse gases)
- Handled by general Bayesian interpretation

- Use of probability to represent uncertainty is not an ad-hoc choice
- If numerical values represent degrees of belief,
  - then simple axioms for manipulating degrees of belief leads to sum and product rules of probability

Modeling Uncertainty



- A Causal Bayesian Network
- Example of Inference:

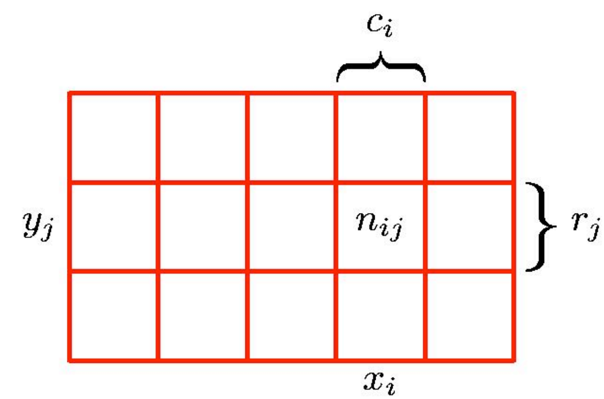
  Cancer is independent of Age and Gender given exposure to Toxics and Smoking

The Fully Bayesian Approach

- Bayes Rule
- Bayesian Probabilities
- Concept of Conjugacy
- Monte Carlo Sampling

Rules of Probability

- Given random variables X and Y
- Sum Rule gives Marginal Probability



$$p(X = x_i) = \sum_{j=1}^{L} p(X = x_i, Y = y_j) = \frac{c_i}{N}$$

- Product Rule: joint probability in terms of conditional and marginal

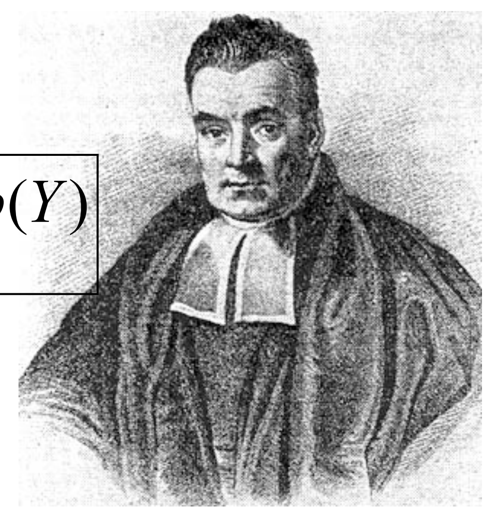
$$p(X,Y) = \frac{n_{ij}}{N} = p(Y \mid X)p(X) = \frac{n_{ij}}{c_i} \times \frac{c_i}{N}$$

- Combining we get Bayes Rule

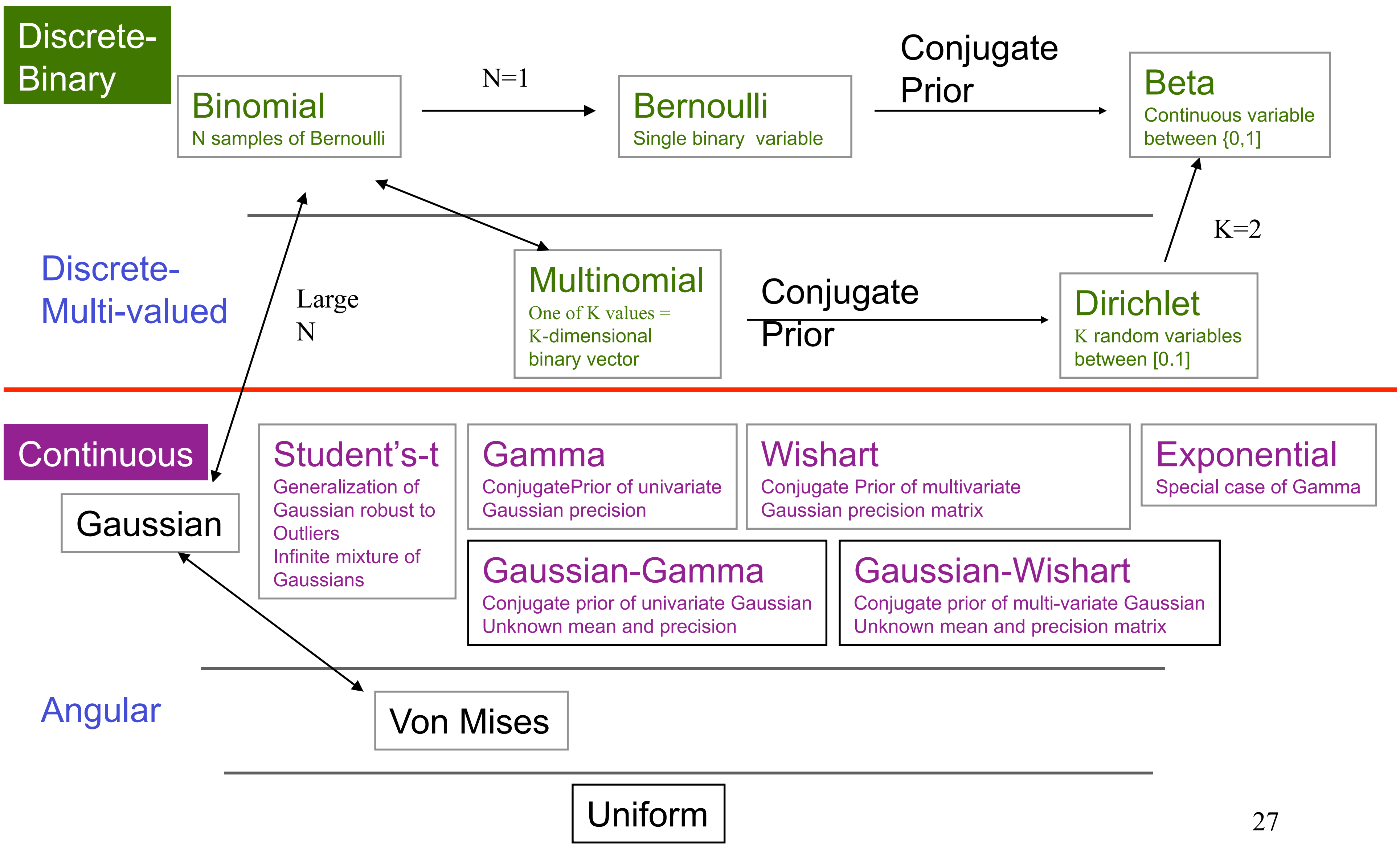
$$p(Y \mid X) = \frac{p(X \mid Y)p(Y)}{p(X)}$$ where $$p(X) = \sum_{Y} p(X \mid Y)p(Y)$$

Viewed as

Posterior α likelihood x prior



Probability Distributions: Relationships



Fully Bayesian Approach

- Feasible with increased computational power
- Intractable posterior distribution handled using either
  - variational Bayes or
  - stochastic sampling
    - e.g., Markov Chain Monte Carlo, Gibbs

Summary

- ML is a systematic approach instead of ad-hockery in designing information processing systems
- Useful for solving problems of classification, regression, clustering and modeling
- The fully Bayesian approach together with Monte Carlo sampling is leading to high performing systems
- Great practical value in many applications
  - Computer science
    - search engines
    - text processing
    - document recognition
  - Engineering