

# Announcement

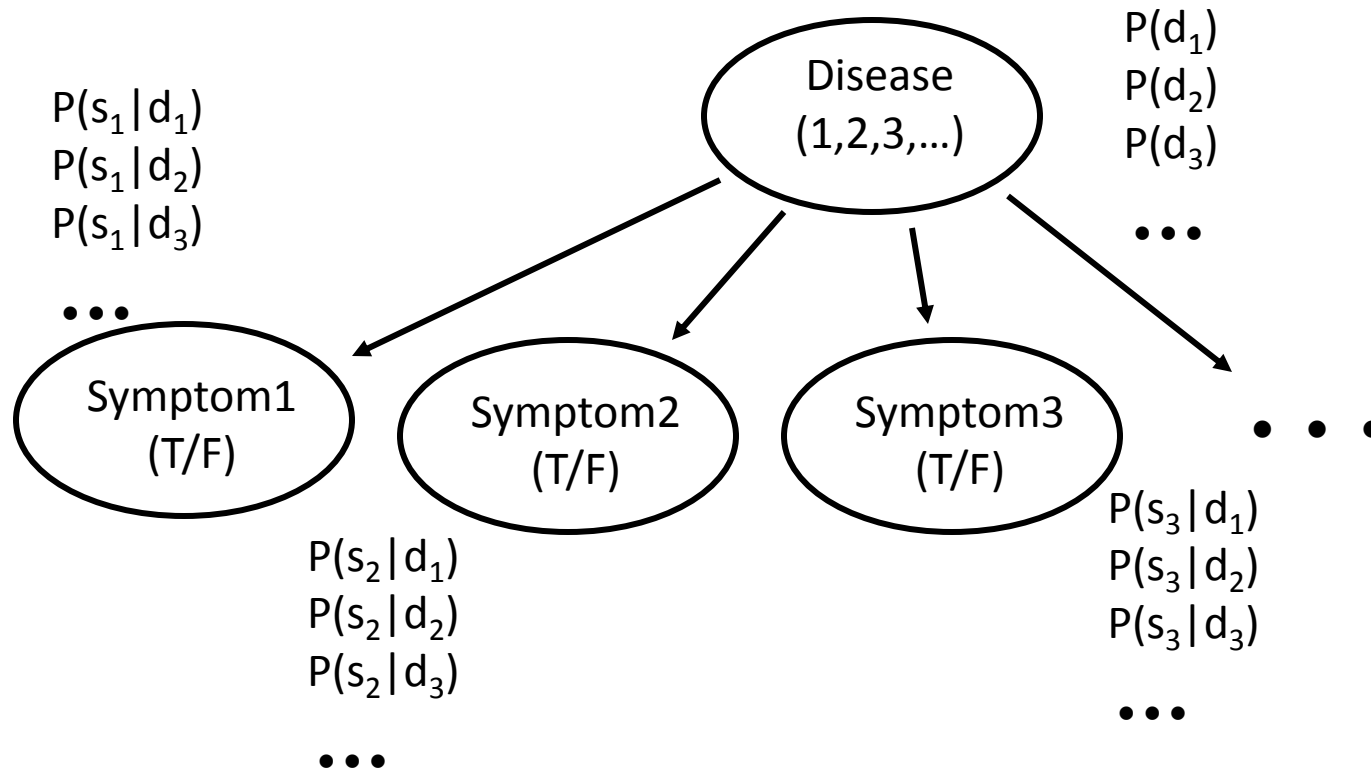
- HW4 on BNs due Tuesday
- Machine Learning Next
- Chapters 18 & 20 in text

# Naïve Bayes

- Symptoms (attributes) are conditionally independent of each other given the Disease (classification)
- Stringent assumptions / Impoverished expressiveness
- Works surprisingly (?) well in practice
- Common first choice

NOTE the use of intentionally impoverished model (for tractability - recall coffee cup)

# Naïve Bayes



Infer likely disease:

$$\arg \max_{d_i} P(d_i | \bar{S})$$

# Naïve Bayes

Diagnose by inference with:

|D| Functions, each assigns probability  
over the Boolean hypercube

Which are / are not probability models?

Fourth is not normalized (why does that work?)

Parameters are adjusted to best fit the world samples

What are the parameters?

A kind of machine learning

We will consider the probability functions

the log probability functions

the decision boundaries

$$\arg \max_{d_i} P(d_i | \bar{S})$$

$$\arg \max_{d_i} \frac{P(d_i) \cdot P(\bar{S} | d_i)}{P(\bar{S})}$$

$$\arg \max_{d_i} \frac{P(d_i) \cdot \prod_j P(s_j | d_i)}{P(\bar{S})}$$

$$\arg \max_{d_i} \left( P(d_i) \prod_j P(s_j | d_i) \right)$$

# Naïve Bayes

$$\arg \max_{d_i} \left( P(d_i) \prod_j P(s_j | d_i) \right)$$

- Suppose we always reason from observed symptoms to diseases
- Characterize the boundaries
- $\text{Log}(x)$  is monotonically increasing,

so:

$$\arg \max_{d_i} \text{Log} \left( P(d_i) \prod_j P(s_j | d_i) \right)$$

- Log of a product is...

# Naïve Bayes

$$\arg \max_{d_i} \text{Log} \left( P(d_i) \prod_j P(s_j | d_i) \right)$$

- We represent the symptoms  $S$  (evidence) is a Boolean vector:

$$\begin{aligned} s_k &= 1 \text{ if } k\text{'th symptom is present} \\ &= 0 \text{ if absent} \end{aligned}$$

- Becomes  $\arg \max_i F_i(S)$   
where  $S$  is the Boolean vector of evidence
- $F_i(S) = \text{Log } P(d_i) + \sum \text{Log } P(s_k | d_i)$
- Form is  $F_i(S) = a_i + B_i \cdot S$   $B_i$  is a vector of weights (one for each...?)  
$$\begin{aligned} a_i &= \text{Log } P(d_i) + \sum \text{Log } P(s_k=0 | d_i) \\ b_{ik} &= \text{Log } P(s_k=1 | d_i) - \text{Log } P(s_k=0 | d_i) \end{aligned}$$
- The Log Prob fcns are hyperplanes over the Boolean hypercube

# Naïve Bayes

$$\arg \max_{d_i} \text{Log} \left( P(d_i) \prod_j P(s_j | d_i) \right)$$

- Form  $F_i(S) = a_i + B_i \cdot S$   
Each is a linear polynomial in  $S$
- Diagnose using the highest valued function at a point  $S$
- What are the Naïve Bayes decision boundaries?
- (How do hyperplanes interact?)
- How do we determine  $a$ 's and  $B$ 's?
- These are *generative models* for the diseases

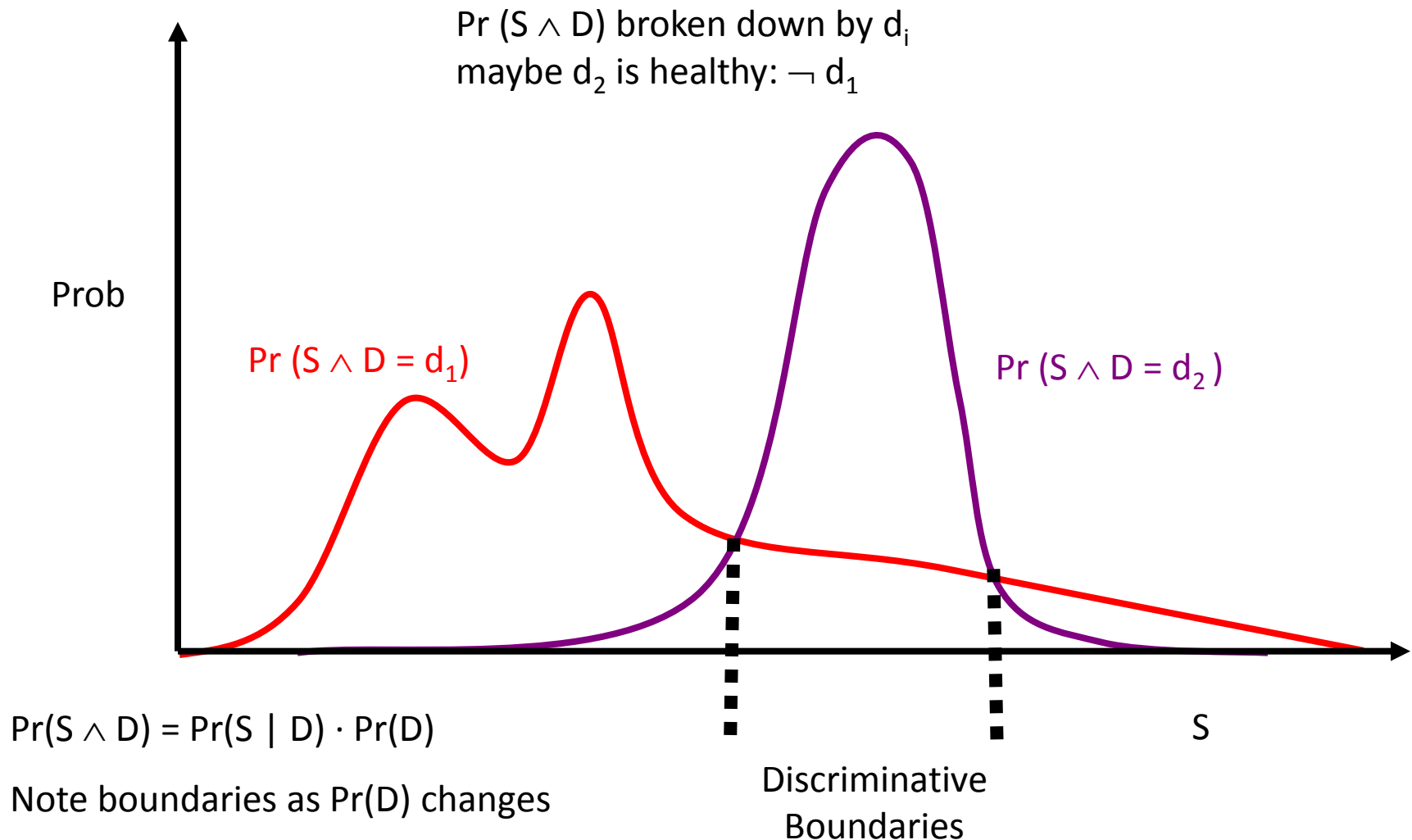
# Generative vs. Discriminative Models

- Generative
  - Model “generation” of data (if perfect, don’t need the world to sample)
  - Represent joint probability approximately\* in some form
    - $\Pr(D=d_i, S=s_k)$  or  $\text{Log } \Pr(D=d_i, S=s_k)$  or ...
    - Usually a compact representation (e.g., Bayes net)
  - Infer  $d_i$  query probabilities from the generative model
    - From observed evidence  $S$
    - Compute  $\Pr(D=d_i \mid S=s_k)$  for each  $i$ ,
    - Choose highest
    - Note: Can infer other things, like  $\Pr(S=s_k)$
- Discriminative
  - Model the boundaries between  $d_i$  values of  $D$
  - Represent the query probabilities directly
    - Perhaps model  $\Pr(D=d_i \mid S=s_k)$
    - Or more directly  $F: S \rightarrow D$
    - Note: Can no longer infer  $\Pr(S=s_k)$

\* sometimes VERY approximately



# Generative vs. Discriminative Models



# Generative vs. Discriminative Models

Encountered before in  
Reinforcement Learning  
Which is which?

# Machine Learning

## using fitted generative model

- Adopt a parametric model
- LEARNING: Train model on data / observations
  - A little training for a simple model
  - A LOT of training for a complex model
- Estimate parameter values from data
- INFERENCE: Apply the model
  - Compute probabilities conditioned on evidence
  - Answer queries
  - Classify new data inputs

# Markov Random Fields

- Undirected graphical models
- No ordering of nodes for construction
- Denote “direct” causes
- Markov blanket = neighboring nodes only
- Simple conditional independence given evidence
- BN  $\rightarrow$  MRF, moralize the graph  
(connect unconnected parents)
- Potential functions (unnormalized) over maximal cliques
- $Z$  = sum over assignments of product of potentials is the partition function (from statistical physics)
- Boltzmann Gibbs distribution
- Learning and inference are generally harder (iterative)

# Simple Word Probability Models for English

- Train from some text corpus NYT, Shakespeare, alt.politics.paranoid,...
- $\Pr(w_i)$  (1<sup>st</sup> order Markov)

REPRESENTING AND SPEEDILY IS AN GOOD APT OR COME CAN DIFFERENT  
NATURAL HERE HE THE A IN CAME THE TO OF TO EXPERT GRAY COME TO  
FURNISHES THE LINE MESSAGE HAD BE THESE

- $\Pr(w_{i+1} | w_i)$  (2<sup>nd</sup> order Markov)

THE HEAD AND IN FRONTAL ATTACK ON AN ENGLISH WRITER THAT  
THE CHARACTER OF THIS POINT IS THEREFORE ANOTHER METHOD FOR THE  
LETTERS THAT THE TIME OF WHOEVER TOLD THE PROBLEM FOR AN UNEXPECTED

# Train Three Model Instances

- alt.politics.paranoid
- alt.politics.republican
- alt.politics.democrat
  
- Get new texts
  - newsgroup postings
  - Speeches
  - NYT articles
- Compute fit  
(probability of each model given the text)

# The Infamous Dr. Bayes

(or is logical inference really so bad?)

- Dr. Bayes has a statistics degree (*not* an MD)
- He makes diagnoses using his rule and other notions from statistics
- A plague has descended; there are two treatments: A and B
- He has tried them both and seen the results on his own patients
- He does not see patients but holds phone consultations with other (real) doctors

Find a data sample that justifies the following  
interchange with Dr. Bayes

Is the patient male or female?

Male

then administer treatment A

Is the patient male or female?

Female

then administer treatment A

Is the patient male or female?

Unknown

then administer treatment B



# Is this POSSIBLE?

- How to tell a statistician from a normal individual

# How to proceed?

- Build an empirical model (well, hybrid – in fact mostly analytic)
- Dr. Bayes interactions are constraints on model parameters
- Then, either
  - Choose parameters to satisfy constraints  
and  
make up data to yield these parameters
  - OR Convince ourselves of their inconsistency