Machine Learning
CS 6830

Lecture 06

Razvan C. Bunescu

School of Electrical Engineering and Computer Science

bunescu@ohio.edu

Three Parametric Approaches to Classification

1) Discriminant Functions: construct $f : X \rightarrow T$ that directly assigns a vector **x** to a specific class C_k.
   - Inference and decision combined into a single learning problem.
   - *Linear Discriminant*: the decision surface is a hyperplane in X:
     - Fisher 's Linear Discriminant
     - Perceptron
     - Support Vector Machines

Three Parametric Approaches to Classification

2) Probabilistic Discriminative Models: directly model the posterior class probabilities $p(C_k \mid \mathbf{x})$.
   - Inference and decision are separate.
   - Less data needed to estimate $p(C_k \mid \mathbf{x})$ than $p(\mathbf{x} \mid C_k)$.
   - Can accommodate many overlapping features.
     - Logistic Regression
     - Conditional Random Fields

Three Parametric Approaches to Classification

3) Probabilistic Generative Models:
   - Model class-conditional $p(\mathbf{x} | C_k)$ as well as the priors $p(C_k)$, then use Bayes's theorem to find $p(C_k | \mathbf{x})$.
     - or model $p(\mathbf{x}, C_k)$ directly, then marginalize to obtain the posterior probabilities $p(C_k | \mathbf{x})$.
   - Inference and decision are separate.
   - Can use $p(\mathbf{x})$ for *outlier* or *novelty detection*.
   - Need to model dependencies between features.
     - Naïve Bayes.
     - Hidden Markov Models.

Unbiased Learning of Generative Models

- Let $\mathbf{x} = [x_1, x_2, \ldots, x_M]^T$ be a feature vector with M features.
- Assume Boolean features:

  $\Rightarrow$ distribution $p(\mathbf{x} \mid C_k)$ is completely specified by a table of 2^M probabilities, of which 2^M -1 are independent.

- Assume binary classification:

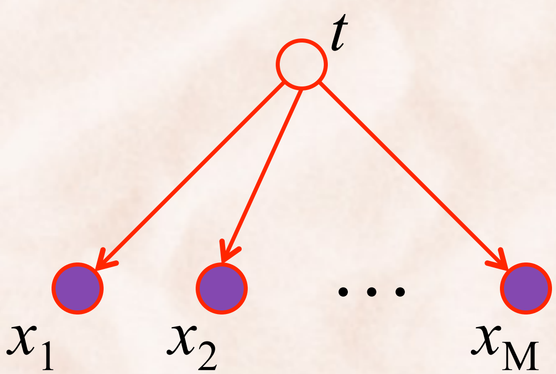
  $\Rightarrow$ need to estimate 2^M -1 parameters for each class

  $\Rightarrow$ total of $2(2^M -1)$ independent parameters to estimate.

  – 30 features $\Rightarrow$ more than 2 billion parameters to estimate!

The Naïve Bayes Model

- Assume features are conditionally independent given the target output:



$$\Rightarrow p(\mathbf{x} \mid C_k) = \prod_{i=1}^{M} p(x_i \mid C_k)$$

- Assume binary classification & features:
  $\Rightarrow$ need to estimate only 2M parameters, a lot less than $2(2^M - 1)$.

The Naïve Bayes Model: Inference

- Posterior distribution:

$$p(C_k \mid \mathbf{x}) = \frac{p(\mathbf{x} \mid C_k)\, p(C_k)}{p(\mathbf{x})}, \text{ where } p(\mathbf{x}) = \sum_j p(\mathbf{x} \mid C_j)\, p(C_j)$$

$$= \frac{p(C_k) \prod_j p(x_j \mid C_k)}{p(\mathbf{x})}$$

- Inference $\equiv$ find C_* to minimize missclassification rate:

$$C_* = \arg\max_{C_k} p(C_k \mid \mathbf{x})$$

$$= \arg\max_{C_k} p(C_k) \prod_j p(x_j \mid C_k)$$

The Naïve Bayes Model: Training

- Training ≡ estimate parameters $p(x_i|C_k)$ and $p(C_k)$.
- Maximum Likelihood (ML) estimation:

$$\hat{p}(x_i = v \mid t = C_k) = \frac{\sum_{(\mathbf{x},t)\in D} \delta_v(x_i)\delta_{C_k}(t)}{\sum_{(\mathbf{x},t)\in D} \delta_{C_k}(t)}$$

Numerator: # training examples in which $x_i = v$ and $t = C_k$

Denominator: # training examples in which $t = C_k$

$$\hat{p}(t = C_k) = \frac{\sum_{(\mathbf{x},t)\in D} \delta_{C_k}(t)}{|D|}$$

Numerator: # training examples in which $t = C_k$

The Naïve Bayes Model: Training

- Maximum A-Posteriori (MAP) estimation:
  - assume a Dirichlet prior over the NB parameters, with equal-valued parameters.
  - assume x_i can take V values, label t can take K values.

$$\hat{p}(x_i = v \mid t = C_k) = \frac{\sum_{(\mathbf{x},t)\in D} \delta_v(x_i)\delta_{C_k}(t) + l}{\sum_{(\mathbf{x},t)\in D} \delta_{C_k}(t) + lV}$$

$$\hat{p}(t = C_k) = \frac{\sum_{(\mathbf{x},t)\in D} \delta_{C_k}(t) + l}{|D| + lK}$$

$\Leftrightarrow$ lV "hallucinated" examples spread evenly over all V values of x_i.

$l = 1 \Rightarrow$ *Laplace smoothing*

Text Categorization with Naïve Bayes

- Text categorization problems:
  - Spam filtering.
  - Targeted advertisement in Gmail.
  - Classification in multiple categories on news websites.

- Representation as one feature per word:

  $\Rightarrow$ each document is a very high dimensional feature vector.

- Most words are rare:
  - Zipf's law and heavy tail distribution.

  $\Rightarrow$ feature vectors are sparse.

Text Categorization with Naïve Bayes

- Generative model of documents:
  1) Generate document category by sampling from $p(C_k)$.
  2) Generate a document as a bag of words by repeatedly sampling with replacement from a vocabulary $V = \{w_1, w_2, \ldots, w_{|V|}\}$ based on $p(w_i \mid C_k)$.

- Inference with Naïve Bayes:
  - Input :
    - Document **x** with n words $v_1, v_2, \ldots v_n$.
  - Output:
    - Category $C_* = \arg\max_{C_k} p(C_k) \prod_{j=1}^{n} p(v_j \mid C_k)$

Text Categorization with Naïve Bayes

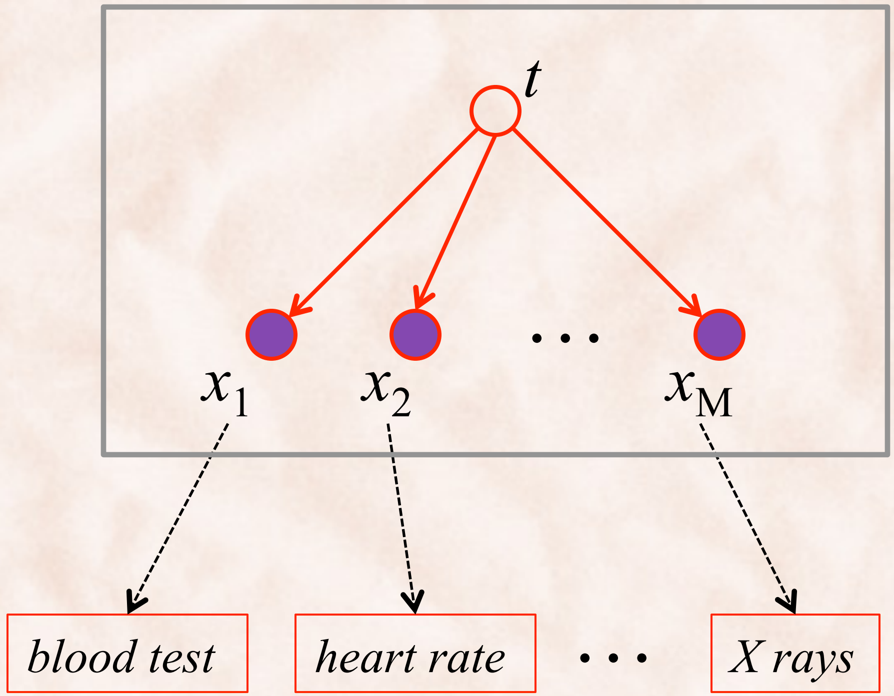
- Training with Naïve Bayes:
  - Input:
    - Dataset of training documents D with vocabulary V.
  - Output:
    - Parameters $p(C_k)$ and $p(w_i \mid C_k)$.

---

for each category C_k:
    let D_k be the subset of documents in category C_k
    set $p(C_k) = |D_k| / |D|$
    let n_k be the total number of words in D_k
    for each word $w_i \in \mathrm{V}$:
        let n_{ki} be the number of occurrences of w_i in D_k
        set $p(w_i \mid C_k) = (n_{ki}+1) / (n_k + |V|)$

Medical Diagnosis with Naïve Bayes

- Diagnose a disease T={*Yes*, *No*}, using information from various medical tests.



$$p(\mathbf{x} \mid C_k) = \prod_{i=1}^{M} p(x_i \mid C_k)$$

Medical tests may result in continuous values
⇒ need Naïve Bayes to work with *continuous features*.

Naïve Bayes with Continuous Features

- Assume $p(x_i \mid C_k)$ are Gaussian distributions $N(\mu_{ik}, \sigma_{ik})$.
- Training: use ML or MAP criteria to estimate μ_{ik}, σ_{ik}:

$$\hat{\mu}_{ik} = \frac{\sum_{(\mathbf{x},t)\in D} x_i \delta_{C_k}(t)}{\sum_{(\mathbf{x},t)\in D} \delta_{C_k}(t)} \qquad \hat{\sigma}_{ik}^2 = \frac{\sum_{(\mathbf{x},t)\in D} (x_i - \hat{\mu}_{ik})^2 \delta_{C_k}(t)}{\sum_{(\mathbf{x},t)\in D} \delta_{C_k}(t)}$$

- Inference:

$$C_* = \arg\max_{C_k} p(C_k \mid \mathbf{x}) = \arg\max_{C_k} p(C_k) \prod_i p(x_i \mid C_k)$$

Numerical Issues

- Multiplying lots of probabilities may results in underflow:
  - especially when many attributes (e.g. text categorization).

- Compute everything in *log space*:

$$p(\mathbf{x} \mid C_k) = \prod_{i=1}^{M} p(x_i \mid C_k) \Leftrightarrow \boxed{\ln p(\mathbf{x} \mid C_k) = \sum_{i=1}^{M} \ln p(x_i \mid C_k)}$$

$$C_* = \arg\max_{C_k} p(C_k \mid \mathbf{x}) \Leftrightarrow \boxed{C_* = \arg\max_{C_k} \ln p(C_k \mid \mathbf{x})}$$

$$= \arg\max_{C_k} \left\{ \ln p(C_k) + \ln p(\mathbf{x} \mid C_k) \right\}$$

Naïve Bayes

- Often has good performance, despite strong independenc assumptions:
  - quite competitive with other classification methods on UCI datasets.
- It does not produce accurate probability estimates when independence assumptions are violated:
  - the estimates are still useful for finding max-probability class.
- Does not focus on completely fitting the data $\Rightarrow$ resilient to noise.

Probabilistic Generative Models: Binary Classification (K = 2)

- Model class-conditional $p(\mathbf{x} \mid C_1)$, $p(\mathbf{x} \mid C_2)$ as well as the priors $p(C_1)$, $p(C_2)$, then use Bayes's theorem to find $p(C_1 \mid \mathbf{x})$, $p(C_2 \mid \mathbf{x})$:

$$p(C_1 \mid \mathbf{x}) = \frac{p(\mathbf{x} \mid C_1)p(C_1)}{p(\mathbf{x} \mid C_1)p(C_1) + p(\mathbf{x} \mid C_2)p(C_2)}$$

$$= \sigma(a(\mathbf{x}))$$

logistic sigmoid

$$\text{where } \sigma(a) = \frac{1}{1 + \exp(-a)}$$

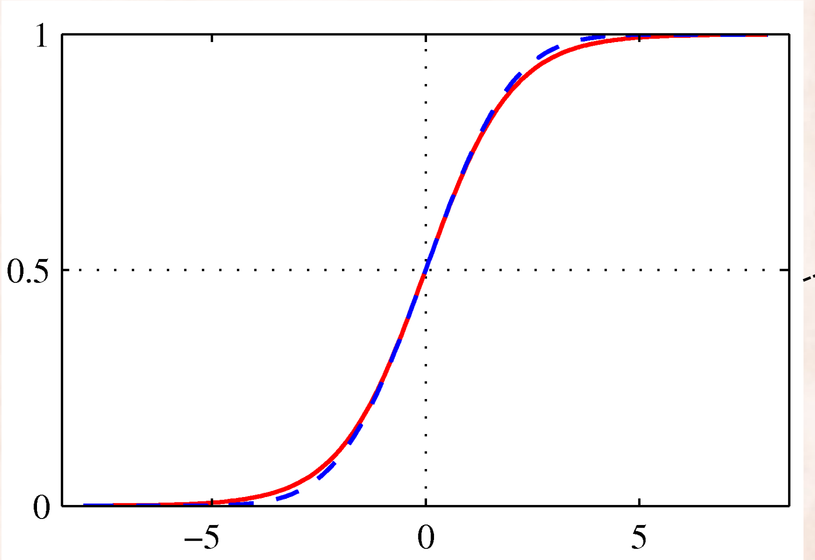
log odds

$$a(\mathbf{x}) = \ln \frac{p(\mathbf{x} \mid C_1)p(C_1)}{p(\mathbf{x} \mid C_2)p(C_2)} = \ln \frac{p(C_1 \mid \mathbf{x})}{p(C_2 \mid \mathbf{x})}$$

Probabilistic Generative Models: Binary Classification (K = 2)

- If $a(\mathbf{x})$ is a linear function of x $\Rightarrow p(C_1 \mid \mathbf{x})$ is a *generalized linear model*:

$$p(C_1 \mid \mathbf{x}) = \frac{1}{1+\exp(-a(\mathbf{x}))} = \sigma(a(\mathbf{x})) = \sigma(\boldsymbol{\lambda}^T \mathbf{x})$$



$\sigma(a)$ is a *squashing function*

The Naïve Bayes Model

- Assume binary features $x_i \in \{0,1\}$:

$$\Rightarrow p(\mathbf{x} \mid C_k) = \prod_{i=1}^{M} p(x_i \mid C_k)$$

$$= \prod_{i=1}^{M} \mu_{ki}^{x_i} (1-\mu_{ki})^{1-x_i} \text{ , where } \mu_{ki} = p(x_i = 1 \mid C_k)$$

$$\Rightarrow p(C_k \mid \mathbf{x}) = \frac{\exp(a_k(\mathbf{x}))}{\sum_j \exp(a_j(\mathbf{x}))}$$

$$\text{, where } a_k(\mathbf{x}) = \sum_{i=1}^{M} \left\{ x_i \ln \mu_{ki} + (1-x_i) \ln(1-\mu_{ki}) \right\} + \ln p(C_k)$$

$$= \boldsymbol{\lambda}_k^T \mathbf{x}$$ $\Rightarrow$ NB is a *generalized linear model.*

Probabilistic Generative Models: Multiple Classes (K ≥ 2)

- Model class-conditional $p(\mathbf{x} | C_k)$ as well as the priors $p(C_k)$, then use Bayes's theorem to find $p(C_k | \mathbf{x})$:

$$p(C_k | \mathbf{x}) = \frac{p(\mathbf{x} | C_k) p(C_k)}{\sum_j p(\mathbf{x} | C_j) p(C_j)}$$

$$= \frac{\exp(a_k(\mathbf{x}))}{\sum_j \exp(a_j(\mathbf{x}))}$$

normalized exponential
i.e. softmax function

where $a_k(\mathbf{x}) = \ln p(\mathbf{x} | C_k) p(C_k)$

- If $a_k(\mathbf{x}) = \boldsymbol{\lambda}_k^T \mathbf{x} \Rightarrow p(C_k | \mathbf{x})$ is a *generalized linear model.*