

Naïve Bayes

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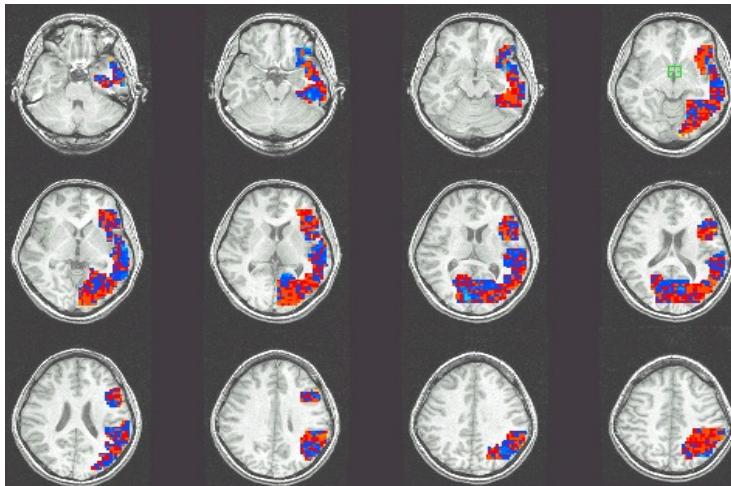
Machine Learning 10-315
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MACHINE LEARNING DEPARTMENT



Multi-class, multi-dimensional classification – Continuous features



Input feature vector, X



High Stress
Moderate Stress
Low Stress

Label, Y

We started with a simple case:

label Y is binary (either “Stress” or “No Stress”)

X is average brain activity in the “Amygdala”

In general: label Y can belong to $K > 2$ classes

X is multi-dimensional $d > 1$ (average activity in all brain regions)

How many parameters do we need to learn (continuous features)?

Class probability:

$$P(Y = y) = p_y \text{ for all } y \text{ in } H, M, L \quad p_H, p_M, p_L \text{ (sum to 1)}$$

K-1 if K labels

Class conditional distribution of features:

$$P(X=x | Y = y) \sim N(\mu_y, \Sigma_y) \text{ for each } y \quad \mu_y - d\text{-dim vector} \\ \Sigma_y - d \times d \text{ matrix}$$

$Kd + Kd(d+1)/2 = O(Kd^2)$ if d features

Quadratic in dimension d! If d = 256x256 pixels, ~ 13 billion parameters!

Multi-class, multi-dimensional classification - Discrete features

0 1 2 3 4 5 6 7
8 9 0 1 2 3 4 5
6 7 8 9 0 1 2 3
4 5 6 7 8 9 0 1
2 3 4 5 6 7 8 9

“0”
“1”
...
“9”

Input feature vector, X

Label, Y



Sports
Science
News

Input feature vector, X

Label, Y

How many parameters do we need to learn (discrete features)?

Class probability:

$$P(Y = y) = p_y \text{ for all } y \text{ in } 0, 1, 2, \dots, 9 \quad p_0, p_1, \dots, p_9 \text{ (sum to 1)}$$

K-1 if K labels

Class conditional distribution of (binary) features:

$P(X=x | Y = y) \sim$ For each label y , maintain probability table with $2^d - 1$ entries

K($2^d - 1$) if d binary features

Exponential in dimension d!

What's wrong with too many parameters?

- How many training data needed to learn one parameter (bias of a coin)?



- Need lots of training data to learn the parameters!
 - Training data > number of (independent) parameters

Naïve Bayes Classifier

- Bayes Classifier with additional “naïve” assumption:

- Features are independent given class:

$$X = \begin{bmatrix} X_1 \\ X_2 \end{bmatrix}$$

$$\begin{aligned} P(X_1, X_2|Y) &= P(X_1|X_2, Y)P(X_2|Y) \\ &= P(X_1|Y)P(X_2|Y) \end{aligned}$$

- More generally:

$$P(X_1 \dots X_d|Y) = \prod_{i=1}^d P(X_i|Y)$$

$$X = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_d \end{bmatrix}$$

- If conditional independence assumption holds, NB is optimal classifier! But worse otherwise.

Conditional Independence

- **X is conditionally independent of Y given Z:**
probability distribution governing X is independent of the value of Y, given the value of Z

$$(\forall x, y, z) P(X = x | Y = y, Z = z) = P(X = x | Z = z)$$

- Equivalent to:
$$P(X, Y | Z) = P(X | Z)P(Y | Z)$$
- e.g., $P(Thunder | Rain, Lightning) = P(Thunder | Lightning)$
Note: does NOT mean Thunder is independent of Rain

Naïve Bayes Classifier

- Bayes Classifier with additional “naïve” assumption:
 - Features are independent given class:

$$P(X_1 \dots X_d | Y) = \prod_{i=1}^d P(X_i | Y)$$

$$\begin{aligned} f_{NB}(\mathbf{x}) &= \arg \max_y P(x_1, \dots, x_d | y) P(y) \\ &= \arg \max_y \prod_{i=1}^d P(x_i | y) P(y) \end{aligned}$$

- How many parameters now?

How many parameters do we need to learn (continuous features)?

➤ Poll

How many parameters do we need to learn (discrete features)?

- Poll

Naïve Bayes Classifier

- Bayes Classifier with additional “naïve” assumption:
 - Features are independent given class:

$$P(X_1 \dots X_d | Y) = \prod_{i=1}^d P(X_i | Y)$$

$$\begin{aligned} f_{NB}(\mathbf{x}) &= \arg \max_y P(x_1, \dots, x_d | y) P(y) \\ &= \arg \max_y \prod_{i=1}^d P(x_i | y) P(y) \end{aligned}$$

- Has fewer parameters, and hence requires fewer training data, even though assumption may be violated in practice

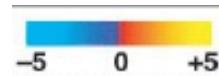
Learned Gaussian Naïve Bayes Model

Means for $P(\text{BrainActivity} \mid \text{WordCategory})$

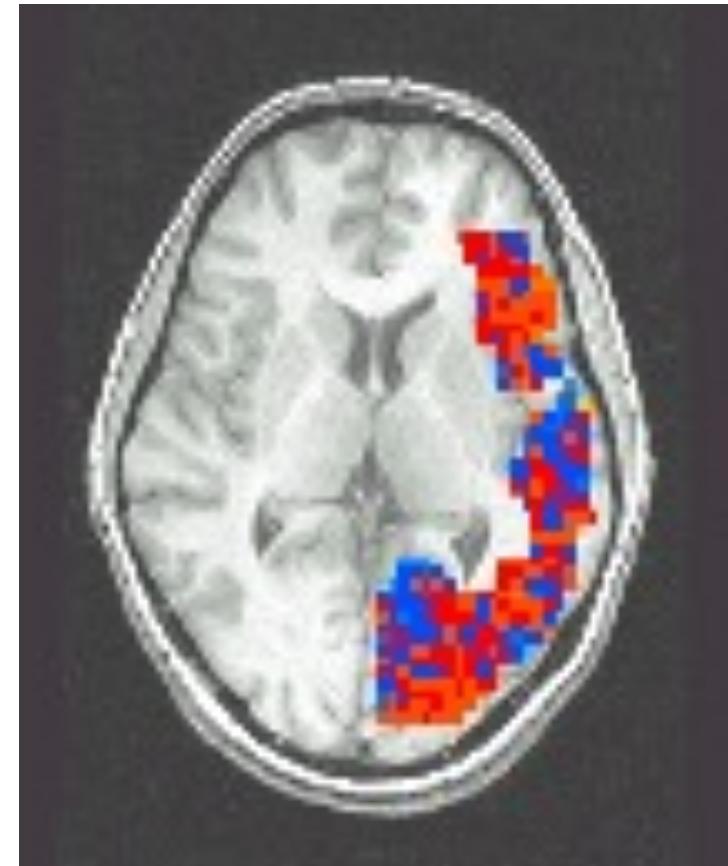
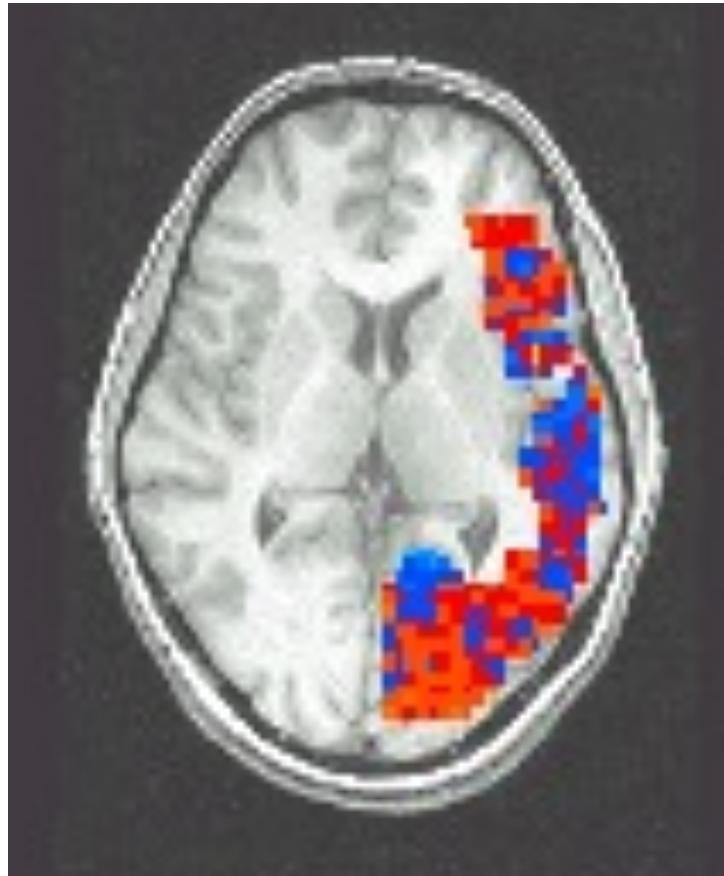
Pairwise classification accuracy: 85%

[Mitchell et al.03]

People words



Animal words



Text classification

Raw input → Features → Model for input features



word1	5	$P(X=x Y=y)$
word2	2	$= P(\text{word1} = 5, \text{word2} = 2,$
word3	10	$\text{word3} = 10, \dots Y=y)$
word4	20	
word5	12	
word6	5	
word7	8	
word8	4	
.	.	
.	.	
.	.	

HW1!
Bag of words + Naïve Bayes