

## Conditional Probability Revision.

[Prob. 1]

$$P(A/B) = \frac{P(A \cap B)}{P(B)} \quad \therefore P(A \cap B) = P(A/B) \cdot P(B)$$

### Conditional Independence

$$\begin{aligned} P(A, B/C) &= P(A \cap B \cap C) / P(C) \\ &= P(A/B, C) P(B \cap C) / P(C) \end{aligned}$$

Now if A, B are conditionally independent.

$$P(A, B/C) = P(A/C) \cdot P(B/C)$$

Thus for 'n' values we have.

$$P(A_1, A_2, \dots, A_n / C) = P(A_1/C) P(A_2/C) \dots P(A_n/C)$$

### [Baye's Theorem Revisited.]

Consider the given scenario:

'h'  $\rightarrow$  customer will buy computer

'D'  $\rightarrow$  35 yr old cust, income = \$50,000 PA

$P(h/D)$  = customer will buy computer, given age, income.

$P(h)$  = Any customer will buy computer regardless of age, income.

$P(D)$   $\rightarrow$  Person is 35 yr old, earns = \$50 k PA

$$P(h/D) = \frac{P(D/h) P(h)}{P(D)}$$

# Data table

| Sl Nos | Age | Income | Buys computer |
|--------|-----|--------|---------------|
| 1      | 35  | Med    | Yes           |
| 2      | 30  | High   | No            |
| 3      | 40  | Low    | No            |
| 4      | 35  | Med    | Yes           |
| 5      | 45  | Low    | Yes           |
| 6      | 35  | high   | Yes           |
| 7      | 35  | Med    | No            |
| 8      | 25  | Low    | No            |
| 9      | 28  | high   | No            |
| 10     | 35  | Med.   | Yes           |

Assume

Med inc = \$50k

From the data we have.

$$P(\text{buys computer}) = 5/10 = 0.5$$

$$P(\text{Age} = 35, \text{Earnings} = \text{Med}) = 4/10 = 0.4$$

Now given that: Buys a computer = Yes.

$$P(\underbrace{35\text{yrs} + \text{Med}}_3 / \underbrace{\text{buys} = \text{Yes}}_{5 \text{ Nos}}) = 3/5 = 0.6 \quad \frac{5/10}{5/10}$$

$$P(h_1/E) = \frac{P(E/h_1) P(h_1)}{P(E)} = \frac{0.6 \times 0.5}{0.4} = 0.75$$

$h_1$  = Cust buys a computer

$E$  = Earnings Med Aged 35.



# Naive Bayes classifier

NB-1]  
-x-

Usage] classify docs as spam / Legit etc.

[Assumption] - Each feature is independent of the value of the other.

Naive Bayes] Considers each feature to contribute independently irrespective of correlation between the features

The model]

Baye's Theorem:  $P(H)$  Probability of the hypothesis.

$P(H/E)$  Probability of the hypothesis after getting the evidence.

$$P(H/E) = \frac{P(E/H) P(H)}{P(E)}$$

Typical Applications:

- .] Spam vs no spam
- .] Doc subject classification
- .] Movie Reviews.

Text classification.

Input a document 'd'

Fixed set of classes:  $C = (C_1, C_2, \dots, C_j)$

output : Predicted class

## Supervised m/c learning.

[NB-2]  
-x-

input:

a doc 'd'

Fixed set of classes  $C = \{C_1, C_2, C_3 \dots C_d\}$

Training set of 'm' hand labelled docs.

$(d_1, c_1) \rightarrow (d_m, c_m)$

output

a learned classifier  $\gamma: d \rightarrow c$ .

Applying Bayes' Theorem to doc class for doc 'd' and class 'c'

$$P(c/d) = \frac{P(d/c) P(c)}{P(d)}$$

Now we have.

$C_{Map}$  = 'Maximum a posteriori' most likely class.

$$C_{Map} = \operatorname{argmax} P(c/d)$$

=  $\operatorname{argmax} P(d/c) P(c)$  dropping denominator.

$$= \operatorname{argmax} P(x_1, x_2, \dots, x_n / c) P(c)$$

↓  
doc represented as features.

$x_1, x_2 \dots x_n$

Multinomial Naive Bayes Independence Assumptions

Consider  $P(d/c) = P(x_1, x_2, \dots, x_n / c)$

Considering independence of features, we get.

$$P(x_1, \dots, x_n / c) = P(x_1 / c) \cdot P(x_2 / c) \dots P(x_n / c)$$



Thus

$$c_{NB} = \operatorname{argmax}_c P(c) \prod_{x \in X} P(x/c)$$

Naive Bayes's Learning

First iteration: Use frequencies in the data.

$$\hat{P}(c_j) = \frac{\text{doc. count } c=c_j}{\text{Tot Nos of docs.}}$$

$$\hat{P}(w_i/c_j) = \frac{\text{Count}(w_i, c_j)}{\sum \text{Count}(w_i, c_j)}$$

Example . . Which class does document '5' belong to?

| Set    | Doc | Words                  | class. |
|--------|-----|------------------------|--------|
| Train. | 1   | china Beijing<br>china | c      |
|        | 2   | china china Shanghai   | c      |
|        | 3   | china Macao            | c      |
|        | 4   | Delhi India china      | i      |
| Test   | 5   | China china Delhi      | ?      |

ProblemFind  $P(c/d_5)$   
and  $P(i/d_5)$ 

Soln.

$$P(c/d_5) = \frac{P(d_5/c) P(c)}{P(d_5)}$$

Step 1]

Priors:

$$P(c) = \frac{\text{doc count}(c)}{\text{Tot Docs.}} = \frac{3}{4}$$

Similarly  $P(i) = 1/4$ .

[STEP 1] We have the Prior Probabilities.

$$P(c) = 3/4 \quad P(i) = 1/4$$

[Step 2] - Compute likelihood.

[NB-0]  
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likelihood: Conditional probability of a word occurring in a document given that document belongs to a particular category.

$$P(\text{word/category}) = \frac{(\text{Nos of occurrence of the word in all docs from a category} + 1)}{(\text{All words in all docs from the category} + \text{Total unique word count})}$$

Thus  $P(\text{word/category}) = \frac{\text{Count}(w, c) + 1}{\text{Count } C + M}$

Now we have the following

List of unique words:]

China  
Beijing  
Shanghai  
Macao  
Delhi  
India

Thus  $M = 6$

For class 'c'

Count  $C = 8$

For class 'i'

Count  $i = 3$

Thus we have the following. For class 'c'

$$P(\text{China}/c) = (5+1)/(8+6) = 3/7$$

$$P(\text{Beijing}/c) = (1+1)/(8+6) = 1/7$$

$$P(\text{Shanghai}/c) = (1+1)/(8+6) = 1/7$$

$$P(\text{Macao}/c) = (1+1)/(8+6) = 1/7$$

$$P(\text{Delhi}/c) = (0+1)/(8+6) = 1/14$$

$$P(\text{India}/c) = (0+1)/(8+6) = 1/14$$



Thus for class 'i' we get the following

[NB-5]

$$P(\text{china}/i) = (2+1)/(3+6) = 2/9$$

$$P(\text{Beijing}/i) = (0+1)/(3+6) = 1/9$$

$$P(\text{Shanghai}/i) = (0+1)/(3+6) = 1/9$$

$$P(\text{Macao}/i) = (0+1)/(3+6) = 1/9$$

$$P(\text{Delhi}/i) = (1+1)/(3+6) = 2/9$$

$$P(\text{India}/i) = (1+1)/(3+6) = 2/9$$

Thus Now we can find

$$P(c/ds) = P(c) * \prod P(\text{word in } ds/c)$$

Thus

$$P(c/ds) = \frac{3}{4} \times \left[ \left( \frac{3}{7} \right)^2 \times \frac{1}{14} \right] = \frac{3}{4} \times \frac{9}{49} \times \frac{1}{14} = \frac{27}{2744} = 0.0098$$

$$P(i/ds) = \frac{1}{4} \times \left[ \left( \frac{2}{9} \right)^2 \times \frac{2}{9} \right] = \frac{1}{4} \times \frac{4}{81} \times \frac{2}{9} = \frac{8}{2916} = 0.0027$$

Thus document 5 [china, china, Delhi]

↳ classified as class 'c'