6. Naive Bayes

Naive Bayes is best suited for ML applications. Wherein the feature vectors of are discrete.

Example: ML-based e-mail SPAM filter.

Comider a feation vector 2 of size N, where N is the number of words in the English Language dictionary. The labels y = 0, 1 indicate genuine, span emails respectively.

xj=1, if the email contains the jth word of.

dj=0, else

Prior Probabilities

The quantities p (x; = v; | y = u) are the prior probabilities.

How to calculate there? consider the availability of M training paint (FL(i), y(i)). The various Prior probabilities can now be calculated as follows.

Probability of jth word in SPAM e-mail

No. of SPAM emails with jth word

No. of SPAM emails

$$p(\pi_{i}=1|y=1) = \frac{\sum_{i=1}^{m} 1(\pi_{i}(i)=1, y(i)=1)}{\sum_{i=1}^{m} 1(y(i)=1)}$$

The various often probabilities can now be calculated as follows.

$$p(x_{i}=1|y=0) = \frac{\sum_{i=1}^{M} 1(x_{i}(i)=1, y(i)=0)}{\sum_{i=1}^{M} 1(y(i)=0)}$$

$$p(\hat{y}=\hat{y}) = \sum_{i=1}^{M} \underline{1(y(i)=i)}$$

Problem 1: Words und in SPAM smails.

Comidu ou take below.

5,9		25 10
0	20	1 × 1
40	80	

Evaluate tu following:

(i) Probability of x_1 does not occur in genuine email $p(x_1=0)y=0=\frac{60}{60+20}=\frac{3}{4}$

(ii)
$$p(x_1=1|y=1) = \frac{80}{80+40} = \frac{2}{3}$$

(iii)
$$p(y=0) = \frac{60+20}{60+20+40+80} = \frac{80}{200} = \frac{2}{5}$$

(iv)
$$P(y=1) = \frac{40+80}{60+20+40+80} = \frac{3}{5}$$

$$(6x)$$
 $1-\frac{2}{5}=\frac{3}{5}$

Also note,

$$p(x_j = 0 | y = 1) = 1 - p(x_j = 1 | y = 1)$$

 $p(x_j = 0 | y = 0) = 1 - p(x_j = 1 | y = 0)$

Naive Bayer an umption.

The different words are conditionally independent, given the label y.

$$p(\pi = \forall | y = \omega) = p(\pi_1 = \forall i, ..., \pi_N = \forall i, | y = \omega)$$

$$= p(\pi_1 = \forall i, | y = \omega) \times \times p(\pi_N = \forall i, | y = \omega)$$

$$= \prod_{j=1}^{N} p(\pi_j = \forall j, | y = \omega)$$

Posterior Probabilities

The posterior probabilities are calculated as follows. $p(y=1|\pi=\overline{v}) = \frac{p(\pi=\overline{v}|y=1) \times p(y=1)}{p(\pi=\overline{v})} \times p(y=1).$ $p(y=0|\pi=\overline{v}) = p(\pi=\overline{v}|y=0) \times p(y=0)$ $p(\pi=\overline{v})$

Span classification.

Email is classified as spam if p(y=1|x=v) > p(y=0|x=v) $\Rightarrow p(\bar{x}=v|y=v) \times p(y=v) > p(\bar{x}=v|y=v) \times p(y=v)$ $\Rightarrow p(\bar{x}=v|y=v) \times p(y=v) > p(\bar{x}=v|y=v) \times p(y=v)$ $\Rightarrow p(\bar{x}=v|y=v) \times p(y=v) > p(\bar{x}=v|y=v) \times p(y=v)$

pin implier, choose C, spam if $\frac{1}{11} p(x_{j} = v_{j} | y = i) \times p(y = i) > \frac{1}{11} p(x_{j} = v_{j} | y = o) \times p(y = o)$ -> SPAM amail Q1 L Q0 -> Grammine email Laplace Smoothing - Naive Bouges has a problem. - Lets say a new word "IITK" appears in your smail, which is not present in any training emails. - Consider the Index of "IITK" in the dictionary is j. The prior probabilities are $\sum_{i=1}^{M} 1(x_i(i)=1, y(i)=1) = 0$ p(ny=1)y=1) = $\sum_{i=1}^{m} 1(y(i)=i)$ p(xj=1/y=0) = \(\frac{\(\frac{1}{2}\)}{2} \) \(\frac{1}{2}\) \(\frac{1}\) \(\frac{1}{2}\) \(\frac{1}{2}\) \(\frac{1}{2}\) \(\frac{1}{2}\) \(\f $\sum_{i=1}^{M} \underline{1}(y(i)=0)$ Then cause problems in computation of the Posterior probabilities Therefore, we use the following prior probabilities instead.

p(x;=1|y=1) = 1+ \(\int_{i=1} \) 1(x;(i)=1, y(i)=1). p(aj=1/y=1)= $2 + \sum_{i=1}^{M} 1(y(i) = 1)$ p (n;=1 |y=0) = 1+ Zim 1 (n;(i)=1, y(i)=0) 2+ = 1 (y(i)=0)

- This is termed as Laplace Smoothing.

Problem 2: Given

	12,=0	N=1
y=0	. 60	20
· \ \ \ \ \ \ = 1	4-0	80

Evaluate p(x,=0/y=0), p(x,=1/y=1) with Laplice smoothing.

(i)
$$p(x_1=0|y=0) = \frac{1+60}{1+82} = \frac{61}{82}$$

(ii)
$$p(x_1=1|y=1) = \frac{1+80}{2+40+80} = \frac{81}{122}$$