

LOGIC BEHIND TYPES OF NB

① Multinoulli / Categorical NB

→ used when all input features are categorical or ^{con seq} follow multinoulli distribution

Eg Data →

gender	Pclass	Survived
M	P1	1
F	P2	0
F	P3	0
F	P1	1

• even though gender is bernoulli but as we are applying Categorical NB, we are assuming it to be categorical / multinoulli distribution

• Acc to Naive Bayes:

new query = { M, F3 } → Predict → 0, 1

$$P(1 | M, P3)$$

$$= P(1) \times P(M|1) \times P(P3|1)$$

$$\Rightarrow P(1) = \frac{392}{891}$$

$$\Rightarrow P(M|1) = \frac{2}{3}$$

$$\Rightarrow P(P3|1) = \frac{1}{5}$$

$$\frac{392}{891} \times \frac{2}{3} \times \frac{1}{5} = 0.6$$

$$P(0 | M, P3)$$

$$= P(0) \times P(M|0) \times P(P3|0)$$

$$\Rightarrow P(0) = \frac{496}{891}$$

$$\Rightarrow P(M|0) = \frac{4}{15}$$

$$\Rightarrow P(P3|0) = \frac{5}{8}$$

$$\Rightarrow \frac{496}{891} \times \frac{4}{15} \times \frac{5}{8} = 0.9$$

- Since $P(0|m, P_3)$ is highest, 0 will be predicted
 i.e. person will not survive
- That's how categorical / multinomial works
- and LAS will be applied as same
- ⇒ i.e. $\frac{1 + \alpha}{1 + n\alpha}$, generally $\alpha=1$, n is
 no. of categories in column.

(2) Bernoulli Naive Bayes

- works well on data where each feature follows Bernoulli distribution i.e. binary features (2 categories)

f_1	f_2
1	0
0	0
0	1
1	0

- Where can we find this type of data?
- Using BOW (Binary)
- In this, it only tells whether the word is there or not, instead of count

Ex →

Binary BOW

Ex	Chinese	Beijing	Shanghai	Moscow	Tokyo	Japan
d1	1	1	0	0	0	0
d2	1	0	1	0	0	0
d3	1	0	0	1	0	0
d4	1	0	0	0	1	1
d5	1	0	0	0	1	1

- All features follows Bernoulli distribution
- hence, we will apply Bernoulli NB
- New Query $\rightarrow d5 \rightarrow$ prediction Y or No?

$$P(Y | \text{Chinese}=1, \text{bei}=0, \text{shan}=0, \text{mos}=0, \text{tok}=1, \text{jap}=1)$$

$$= P(Y) \times P(\text{Chinese}=1|Y) \times P(\text{bei}=0|Y) \times P(\text{shan}=0|Y) \times P(\text{mos}=0|Y) \times P(\text{tok}=1|Y) \times P(\text{jap}=1|Y)$$

$$\Rightarrow P(\text{Chinese}=1|Y) = \frac{3}{3} = 1$$

$$\Rightarrow P(\text{bei}=0|Y) = \frac{2}{3}$$

$$\Rightarrow P(\text{shan}=0|Y) = \frac{2}{3}$$

$$\Rightarrow P(\text{mos}=0|Y) = \frac{2}{3}$$

$$\Rightarrow P(\text{tok}=1|Y) = P(\text{jap}=1|Y) = \frac{0}{3} = 0$$

$$\Rightarrow P(Y) = \frac{3}{4}$$

$$P(N | \text{Chinese}=1, \text{bei}=0, \text{shan}=0, \text{mos}=0, \text{tok}=1, \text{jap}=1)$$

$$\Rightarrow P(N) = \frac{1}{4}$$

$$P(\text{Chinese}=1|N) = \frac{1}{1} = 1$$

$$P(\text{bei}=0|N) = \frac{1}{1} = 1$$

$$P(\text{shan}=0|N) = \frac{1}{1} = 1$$

$$P(\text{tok}=1|N) = \frac{1}{1} = 1$$

$$P(\text{jap}=1|N) = \frac{1}{1} = 1$$

- Behind you are using Bernoulli dist
- $P(X=k) = p^k + (1-p)(1-k)$
- where p is probability of success

Ex. k value = $\{0, 1\}$

$$\text{Ex } P(\text{Chinese}=1|Y) \Rightarrow$$

$$P(X=1) = p^1 \times (1-p)^{(1-1)} = p^1 \times 1$$

$$P(\text{Chinese}=1|Y) = \frac{3}{3} = 1$$

$$1 \times \frac{2}{3} \times \frac{2}{3} \times \frac{2}{3} \times \frac{1}{3} \times \frac{1}{3}$$

• That's how Bernoulli is used

① How Bernoulli is different from categorical?

Ans Because in Bernoulli, you find prob of ~~its~~ also Bernoulli

• Because in ~~prob~~ Bernoulli, you not only find the prob of word present but also prob of word not present

• In Bernoulli $\rightarrow P(Y|X)$ indicates word is present
 $\Rightarrow P(N|X)$ " " is not "

Categorical

• In categorical, you only account of for prob of word present

Ex Classification \rightarrow Dog, Cat, horse

- No of prob will be $P(\text{Dog}|X)$, $P(\text{Cat}|X)$, $P(\text{horse}|X)$
- It is not accounting for probability of not a dog, prob of not cat, or horse

LAS

- In this, you can also apply LAS in same way

③ Multinomial Naive Bayes

Applied when all features are discrete

Ex	chinese	Beijing	Shanghai	Macao	Toky	Jap	
d1	2	1	0	0	0	0	✓
d2	2	0	1	0	0	0	✓
d3	1	0	0	1	0	0	✓
d4	1	0	0	0	1	1	✓
Query { d5	3	0	0	0	1	1	?

• Predict for d5

• Two prob will be calculated

$$i) P(Y | \text{chinese}=3 | \text{tok}=0 | \text{sha}=0 | \text{Jap}=0 | \text{mac}=0 | \text{tok}=1, \text{Jap}=1)$$

= ~~0~~

• Note

- In other types, ex Bernoulli NB, we considered all features to follow Bernoulli distribution

Imp

Q. So, similarly in multinomial, what is the thing that follows multinomial distribution?

Ans You will treat each column as a multinomial distribution and each row as multinomial distribution
understanding by example

Eg:

• Treat every new sentence as bag which contain words $\Rightarrow [0000]$

• and whenever new query comes, effectively you are asking tell what is the probability of 3 chinese words, 1 Tokyo word, 1 Japan word

• similar to Q4

• where we are asking P of 3 students get placed 1 student opt out and 6 not placed.

• similarly: we are asking prob of 3 Chinese words, 1 Tokyo and 1 Japan out of the 5 words taken out of bag.

Can be rewritten as:

• chinese chinese chinese Tokyo Japan

$$P(\text{chinese} | Y) \times P(\text{chinese} | Y) \times P(\text{chinese} | Y) \times P(\text{Tokyo} | Y) \times P(\text{Japan} | Y)$$

Q1 What is this $P(\text{chinese} | Y)$?

Ans Out of total Yes words, how many are chinese

$$= \frac{5}{8} = P(\text{chinese} | Y)$$

Q2

=) What is $P(\text{Tokyo} | Y)$?

$$= \frac{0}{8}, \quad P(\text{Jap} | Y) \text{ is also same}$$

In short $P(Y | X) =$

$$= \left(\frac{5}{8}\right)^3 \left(\frac{0}{8}\right)^1 \left(\frac{0}{8}\right)^1 \times P(Y) = P(Y | X)$$

• There are also prob of Beijing and shang but they are not present in test data \therefore their raised to power is 0

$\Rightarrow P(\text{bei} | Y)^0 = 1$. Hence no need to mention

• Refer to Q4, you will understand

Q2 In multinomial, we are also multiplying it with permutation but in this we are not why?

Ans

Why we are not multiplying it with:-

$5!$ \rightarrow no of total words in query
 $3! \cdot 1! \cdot 1!$ \rightarrow 3 categories \Rightarrow chinese = 3, ~~tokyo~~ = 1, ~~japan~~ = 1

Ans: Because, we are only asking for that best combination chin ce.:-
 chinese w_1 chinese w_3 chinese w_3 Tokyo w_4 Japan w_4

Note:

- Since, rows represent multinomial that's why in laplace additive smoothing it $+ \frac{1}{n}$
- $+ \frac{1}{n}$
 \rightarrow n is no of features not no of categories in features

④ Out of core Naive Bayes

- can apply partial fit
- useful when dataset is large
- Divide large data into chunks
- Because text data is usually large
- Training will continue from at that chunk part
- Other algos also provide this method