

Supervised learning

① Naive Bayes

↓ classification

works on completely conditional probability.

① Condition probability

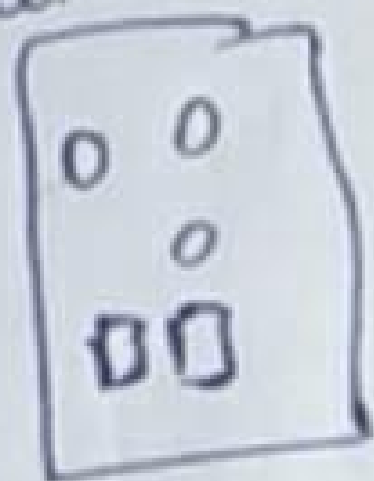
② independent event

③ dependent event

$$(\frac{1}{2} \times \frac{1}{2} = 0.5, 0.5)$$

two 2 wins
independent
each other

Prob keep
in chance &
independent
variables



(event)

In Bag have 5 marbles

Pick one black
Marble

$$\frac{2}{5}$$

Next event (next time
one
black)

$$\frac{1}{4}$$

Condition
prob:

A, B → 2 events

$$P(A|B) = \frac{P(A \cap B)}{P(B)}$$

given

I want find out what probability marbles take
Continuously?

Event (A)
Black
marbles

$\therefore 2/5$ ($P(B)$)

→ already A event performed.

Event (B)

One more
= Black
marbles

$P(B|A)$

$= 1/4$

$P(B) = 2/5$

$P(B|A) = 1/4$

$2/5 \times 1/4 = 2/20 = 1/10$

What is prob
Both event A & B.

How check math or
not?

$$P(B|A) = \frac{P(A \cap B)}{P(A)}$$

$$= \frac{1/10}{2/5}$$

$$= \frac{1/10 \times 5}{2}$$

$$= 1/4$$

dependent.

Try to find out prob of event and
event already performed.
(taken in place)

Bayes theorem:

try to take this condition prob and derive Bayes theorem

$$P(A|B) = \frac{P(A \cap B)}{P(B)}$$

$$P(B|A) = \frac{P(B \cap A)}{P(A)}$$

$$P(A \cap B) = P(B \cap A)$$

① take this denominator put it right side

$$P(A \cap B) = P(A|B) * P(B)$$

$$P(B \cap A) = P(B|A) * P(A)$$

$$P(A|B) * P(B) = P(B|A) * P(A) \rightarrow \text{likelihood}$$

$$P(A|B) = \frac{P(B|A) * P(A)}{P(B)} \rightarrow \text{prior prob.}$$

(Based on Baye Theorem)

(Bayes Theorem)

→ marginal prob

→ posterior prob

Naive Bayes classifier
 Base of classifier is Bayes Theorem

$$P(A|B) = \frac{P(B|A) * P(A)}{P(B)}$$

↳ actually derived by conditional prob.

convert this equation based on our dataset $\rightarrow x = \{x_1, x_2, x_3, \dots, x_n | y\}$

1	2	3	4
5	1	2	3
1	2	3	4
2	3	4	5

1	2	3	4
5	1	2	3
1	2	3	4
2	3	4	5

Convert equation:

$$P(y | x_1, x_2, \dots, x_n) = P(x_1 | y) * P(x_2 | y) * \dots * P(x_n | y) * P(y)$$

$$P(x_1) P(x_2) \dots P(x_n)$$

bind compute

$$P(y) \prod_{i=1}^n P(x_i | y)$$

(It's multiplication prob based on i/p features so)

$$P(x_1) P(x_2) \dots P(x_n)$$

↳ Constant same for every record

$$P(y|x_1, x_2, \dots, x_n) \propto P(y) \prod_{i=1}^n P(x_i|y)$$

we need to ^{take} find argmax what ever computation to bound with respect to $P(y) \times P(\text{all of the features})$

argmax \rightarrow highest prob
 ex: Yes: 0.7 ✓
 No: 0.4

$$y = \text{argmax}_y P(y) \prod_{i=1}^n P(x_i|y)$$

Example: I have some feature Outlook, Temp binary whether play or not.

Outlook

Temperature

	yes	no	prob	prob
Sunny	2	3	2/9	3/5
Overcast	4	0	4/9	0/5
Rainy	3	2	3/9	2/5
total	9	5	100%	100%

	2	2	2/5	2/5
hot	2	2	2/5	2/5
cool	4	2	4/9	2/5
mild	3	1	3/9	1/5
	9	5	100%	100%

play

	Yes	No	total
Yes	9	5	14
No	5	5	10
total	14	10	100%

Problem:

Example

Today is (Sunny, Hot) check whether

today play or not?

Okay, first look dataset

When the 0.1 Sunny has 2 time yes 3 time No

So the Prob yes $\left(\frac{2}{5}\right)$ total no of yes values

Prob No $\left(\frac{3}{5}\right)$ total no of No values

Next Hot in temp has 2 times Yes

2 times No

Apply Naive Bayes:

$$P(Y/\text{Today}) = \frac{P(\text{sunny}|\text{yes}) * P(\text{Hot}|\text{yes}) * P(\text{Yes})}{P(\text{Today})}$$

$$= \frac{2}{5} * \frac{2}{5} * \frac{2}{7}$$

$$= \boxed{0.031}$$

Similarly No

$$P(N/\text{Today}) = \frac{P(\text{sunny}|\text{No}) * P(\text{Hot}|\text{No}) * P(\text{No})}{P(\text{Today})}$$

$$p(\text{no} | \text{today}) = \frac{3}{5} \times \frac{2}{5} \times \frac{5}{4}$$

$$= 0.0857$$

How did determine whether y or n?

You can take values if I want to calculate $p(y)$ with respect to condition I have to output that, but output

normalized

$$\frac{0.031}{0.031 + 0.857}$$

$p(y)$

$$\approx 0.27$$

likely

$p(n) \times 2$ have subtract $1 - p(y)$

$$1 - 0.27$$

$$= 0.73$$

argmax

So

today not play.

Summary:

We have dataset Outlook, Temp,
i/p features and one dependent feature (target)
is today play or not based on outlook,
temp features. Records actually say
Yes - or No.

Based on the Particular Prob
Calculated.

But we show today is Sunny,
not apply naive bayes based on
bayes theorem. Calculating finally
normalize which is maximum that
is our Output. Here No is maximum.

No is higher argument than Yes.

$$P(\text{No} | \text{Sunny}) = 0.19 > P(\text{Yes} | \text{Sunny}) = 0.09$$

$$P(\text{No} | \text{Sunny}) = 0.19 > P(\text{Yes} | \text{Sunny}) = 0.09$$

$$P(\text{No} | \text{Sunny})$$

$$P(\text{No} | \text{Sunny})$$

Conclusion: The forecast is No.

Forecast is No.

Forecast is No.

③ Apply naive Bayes classifier

on text data.

How does it actually work on

data

I taken Restaurant Review

text $\begin{cases} \rightarrow \text{good} \\ \rightarrow \text{bad} \end{cases}$

\rightarrow bins nlp concepts \rightarrow remove some (preprocessing)

good - 1
bad - 0

After preprocessing we get vector like

this is

$x_1 \quad x_2 \quad x_3 \quad x_4 \quad \dots \quad x_n$
The food delicious bad

$$P(y = \text{yes} | \text{sent}) = P(y = \text{yes} | (x_1, x_2, \dots, x_n))$$

$$\propto P(y) * \prod_{i=1}^n P(x_i | y = \text{yes}) * P(x_2 | y = \text{yes}) \dots P(x_n | y = \text{yes})$$

Sent1: The food is delicious

Sent2: The food is bad.

Sent Food is Bad

t_1	t_2	t_3	t_4	o/p
The	good	delicious	bad	
1	1	1	0	1
1	1	0	1	0
0	1	0	1	0
0	1	1	1	1
0	0	0	1	0

$$p(y = \text{yes}) * p(x_1 | y = \text{yes}) * p(x_2 | y = \text{yes}) * \dots * p(x_n | y = \text{yes})$$

$$= \frac{2}{5} * \frac{1}{2} * \frac{2}{4} * \frac{2}{2} * \frac{0}{3}$$

$$= \frac{2}{5} * \frac{1}{2} * \frac{1}{2}$$

$$= \frac{1}{5} * \frac{1}{2} = \frac{1}{10} = 0.1$$

Similarly compute No.

$$p(y=No) * p(x_1|y=No) * \dots * p(x_n|y=No)$$

$$= 3/5 * 1/2 * 2/4 * 1/2 * 2/3$$

$$= 0.03 * 3/5 * 1/2 = 3/200 = 0.015$$

Normalized

$$= \frac{0.01}{0.01 + 0.15}$$

$$p(yes) = \frac{0.01}{0.25} = 0.04 = 4\%$$

$$p(No) = 1 - 0.4 = 0.6 = 60\%$$

$$\max_y p(y) = 60\%$$

so No