Andhra Pradesh State Skill Development Corporation(APSSDC)

(Department of Skill Development & Training, Govt. of Andhra Pradesh)

Naive Bayes

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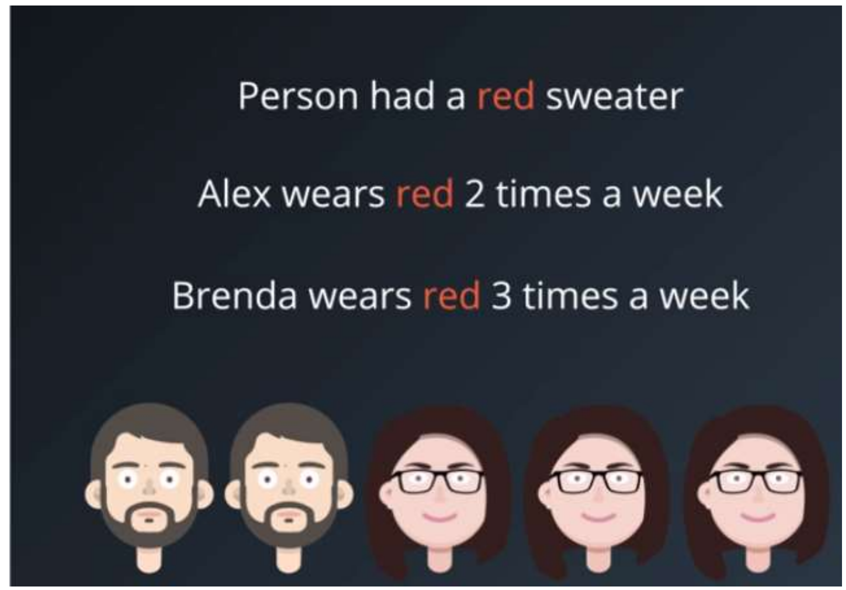
Bayes Theorem

Alex Brenda

$P(\text{Alex}) = 0.5 \quad P(\text{Brenda}) = 0.5$

Prior $P(\text{Alex}) = 0.5 \quad P(\text{Brenda}) = 0.5$

Posterior $P(\text{Alex}) = 0.4 \quad P(\text{Brenda}) = 0.6$



Principle of Naive Bayes Classifier

A Naive Bayes classifier is a probabilistic machine learning model that's used for classification task. The crux of the classifier is based on the Bayes theorem.

Bayes Theorem

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

Using Bayes theorem, we can find the probability of A happening, given that B has occurred. Here, B is the evidence and A is the hypothesis. The assumption made here is that the predictors/features are independent. That is presence of one particular feature does not affect the other. Hence it is called naive.

Types of Naive Bayes Classifier

1. Multinomial Naive Bayes:

This is mostly used for document classification problem, i.e. whether a document belongs to the category of sports, politics, technology etc. The features/predictors used by the classifier are the frequency of the words present in the document.

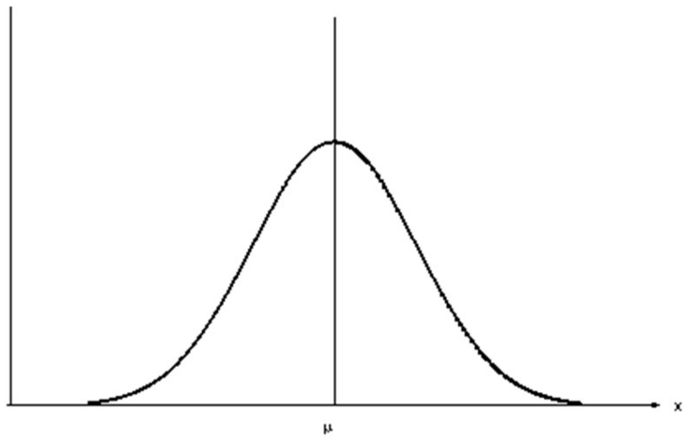
2. Bernoulli Naive Bayes:

This is similar to the multinomial naive bayes but the predictors are Boolean variables. The parameters that we use to predict the class variable take up only values yes or no, for example if a word occurs in the text or not.

3. Gaussian Naive Bayes:

When the predictors take up a continuous value and are not discrete, we assume that these values are sampled from a gaussian distribution.

$$P(x_i|y) = \frac{1}{\sqrt{2\pi\sigma_y^2}} exp\left(-\frac{(x_i-\mu_y)^2}{2\sigma_y^2}\right)$$



Example

	OUTLOOK	TEMPERATURE	HUMIDITY	WINDY	PLAY GOLF
0	Rainy	Hot	High	False	No
1	Rainy	Hot	High	True	No
2	Overcast	Hot	High	False	Yes
3	Sunny	Mild	High	False	Yes
4	Sunny	Cool	Normal	False	Yes
5	Sunny	Cool	Normal	True	No
6	Overcast	Cool	Normal	True	Yes
7	Rainy	Mild	High	False	No
8	Rainy	Cool	Normal	False	Yes
9	Sunny	Mild	Normal	False	Yes
10	Rainy	Mild	Normal	True	Yes
11	Overcast	Mild	High	True	Yes
12	Overcast	Hot	Normal	False	Yes
13	Sunny	Mild	High	True	No

Summarizing the Dataset

	outlook	temp.	humidity	windy	play
D1	sunny	hot	high	false	no
D2	sunny	hot	high	true	no
D3	overcast	hot	high	false	yes
D4	rainy	mild	high	false	yes
D5	rainy	cool	normal	false	yes
D6	rainy	cool	normal	true	no
D7	overcast	cool	normal	true	yes
D8	sunny	mild	high	false	no
D9	sunny	cool	normal	false	yes
D10	rainy	mild	normal	false	yes
D11	sunny	mild	normal	true	yes
D12	overcast	mild	high	true	yes
D13	overcast	hot	normal	false	yes
D14	rainy	mild	high	true	no

Should I play Today?

- **Total Sample:** 14
- **No. of Attributes:** 4
- **No. of Class:** 1

Total Yes: **9** ***P(Yes):*** **9/14**

Total No: **5** ***P(No):*** **5/14**

Frequency of Each Attribute

	outlook	temp.	humidity	windy	play
D1	sunny	hot	high	false	no
D2	sunny	hot	high	true	no
D3	overcast	hot	high	false	yes
D4	rainy	mild	high	false	yes
D5	rainy	cool	normal	false	yes
D6	rainy	cool	normal	true	no
D7	overcast	cool	normal	true	yes
D8	sunny	mild	high	false	no
D9	sunny	cool	normal	false	yes
D10	rainy	mild	normal	false	yes
D11	sunny	mild	normal	true	yes
D12	overcast	mild	high	true	yes
D13	overcast	hot	normal	false	yes
D14	rainy	mild	high	true	no

Outlook		
	Yes	No
Sunny	2	3
Overcast	4	0
Rainy	3	2

Temperature		
	Yes	No
Hot	2	2
Mild	4	2
Cool	3	1

Humidity		
	Yes	No
High	3	4
Normal	6	1

Windy		
	Yes	No
False	6	2
True	3	3

Probability of Each Attribute P(A)

	outlook	temp.	humidity	windy	play
D1	sunny	hot	high	false	no
D2	sunny	hot	high	true	no
D3	overcast	hot	high	false	yes
D4	rainy	mild	high	false	yes
D5	rainy	cool	normal	false	yes
D6	rainy	cool	normal	true	no
D7	overcast	cool	normal	true	yes
D8	sunny	mild	high	false	no
D9	sunny	cool	normal	false	yes
D10	rainy	mild	normal	false	yes
D11	sunny	mild	normal	true	yes
D12	overcast	mild	high	true	yes
D13	overcast	hot	normal	false	yes
D14	rainy	mild	high	true	no

Outlook			
	Yes	No	P(attrib)
Sunny	2	3	5/14
Overcast	4	0	4/14
Rainy	3	2	5/14
Total			100%

Temperature			
	Yes	No	P(attrib)
Hot	2	2	4/14
Mild	4	2	6/14
Cool	3	1	4/14
Total			100%

Humidity			
	Yes	No	P(attrib)
High	3	4	7/14
Normal	6	1	7/14
Total			100%

Windy			
	Yes	No	P(attrib)
False	6	2	8/14
True	3	3	6/14
Total			100%

Probability of Each Attribute P(B)

	outlook	temp.	humidity	windy	play
D1	sunny	hot	high	false	no
D2	sunny	hot	high	true	no
D3	overcast	hot	high	false	yes
D4	rainy	mild	high	false	yes
D5	rainy	cool	normal	false	yes
D6	rainy	cool	normal	true	no
D7	overcast	cool	normal	true	yes
D8	sunny	mild	high	false	no
D9	sunny	cool	normal	false	yes
D10	rainy	mild	normal	false	yes
D11	sunny	mild	normal	true	yes
D12	overcast	mild	high	true	yes
D13	overcast	hot	normal	false	yes
D14	rainy	mild	high	true	no

Play		Probability
Yes	9	9/14
No	5	5/14
Total	14	100%

Probability of Each Attribute P(A|B)

Outlook				
	Yes	No	P(Yes)	P(No)
Sunny	2	3	2/9	3/5
Overcast	4	0	4/9	0/5
Rainy	3	2	3/9	2/5
Total			100%	100%

Temperature				
	Yes	No	P(Yes)	P(No)
Hot	2	2	2/9	2/5
Mild	4	2	4/9	2/5
Cool	3	1	3/9	1/5
Total			100%	100%

Humidity				
	Yes	No	P(Yes)	P(No)
High	3	4	3/9	4/5
Normal	6	1	6/9	1/5
Total			100%	100%

Windy				
	Yes	No	P(Yes)	P(No)
False	6	2	6/9	2/5
True	3	3	3/9	3/5
Total			100%	100%

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