

## Naive Bayes Classifier

Car Theft example Attributes are color type original & the subject, stolen be either yes or no.

Data set:

Car No	Color	type	original	stolen
1	Red	sports	Domestic	Yes
2	Red	sports	Domestic	No
3	Red	sports	Domestic	Yes
4	Yellow	sports	Domestic	No
5	Yellow	sports	Imported	Yes
6	Yellow	SUV	Imported	No
7	Yellow	SUV	Imported	Yes
8	Yellow	SUV	Domestic	No
9	Red	SUV	Imported	No
10	Red	sports	Imported	Yes

We want to classify a Red, domestic, SUV unseen sample. Note there is no example of a Red Domestic SUV, SUVs is our data set.

$$P(\text{yes}) = 5/10$$

$$P(\text{no}) = 5/10$$



Color:

$$P(\text{Red} / \text{Yes}) = 3/5$$

$$P(\text{Yellow} / \text{Yes}) = 2/5$$

$$P(\text{Red} / \text{No}) = 2/5$$

$$P(\text{Yellow} / \text{No}) = 3/5$$

Type:

$$P(\text{SUV} / \text{Yes}) = 1/5$$

$$P(\text{Sports} / \text{Yes}) = 4/5$$

$$P(\text{SUV} / \text{No}) = 3/5$$

$$P(\text{Sports} / \text{No}) = 2/5$$

Origin:

$$P(\text{Domestic} / \text{Yes}) = 2/5$$

$$P(\text{Imported} / \text{Yes}) = 3/5$$

$$P(\text{Domestic} / \text{No}) = 3/5$$

$$P(\text{Imported} / \text{No}) = 2/5$$

An unseen sample  $x = \langle \text{Red}, \text{Domestic}, \text{SUV} \rangle$

$$P(x / \text{Yes}) \cdot P(\text{Yes})$$

$$= P(\text{Red} / \text{Yes}) \cdot P(\text{Domestic} / \text{Yes}) \cdot P(\text{SUV} / \text{Yes}) \cdot P(\text{Yes})$$

$$= \frac{3}{5} \times \frac{2}{5} \times \frac{1}{5} \times \frac{5}{10}$$

$$= 0.024$$

$$P(x / \text{No}) \cdot P(\text{No})$$

$$= P(\text{Red} / \text{No}) \cdot P(\text{Domestic} / \text{No}) \cdot P(\text{SUV} / \text{No}) \cdot P(\text{No})$$

$$= \frac{2}{5} \times \frac{3}{5} \times \frac{3}{5} \times \frac{5}{10}$$

$$= 0.072$$

Since  $0.072 > 0.024$ , our example gets classified as 'No'.



Apriori example :

<u>T/O</u>	<u>Items</u>
T1	11 12 15
T2	12 14
T3	12 13
T4	11 12 14
T5	11 13
T6	12 13
T7	11 13
T8	11 12 13 15
T9	11 12 13
T10	

minimum confidence = 50 %

minimum support count = is 2

i)  $k=1$

I1	6
I2	7
I3	8
I4	2
I5	2



ii)	Itenset	sup-count
	$I_1, I_2$	4
	$I_1, I_3$	4
	$I_1, I_4$	1
	$I_1, I_5$	2
	$I_2, I_3$	4
	$I_2, I_4$	2
	$I_2, I_5$	2
	$I_3, I_4$	0
	$I_3, I_5$	1
	$I_4, I_5$	0

remove

$I_3, I_4$	$0 < 2$
$I_3, I_5$	$1 < 2$
$I_4, I_5$	$0 < 2$

iii)	$I_1, I_2, I_3$	2
	$I_1, I_2, I_3$	2

Now,

$$\text{confidence } (A \rightarrow B) = \frac{\text{support count } (A \cup B)}{\text{support count } (A)}$$

$(I_1, I_2) \rightarrow I_3$	2/4	50%
$(I_1, I_3) \rightarrow I_2$	2/4	50%
$(I_2, I_3) \rightarrow I_1$	2/4	50%
$I_1 \rightarrow (I_2, I_3)$	2/6	33%
$I_2 \rightarrow (I_1, I_3)$	2/7	28%
$I_3 \rightarrow (I_1, I_2)$	2/6	33%

$\therefore$  min confidence is 50%.

$\therefore$  first three

$(I_1, I_2) \rightarrow I_3$
$(I_1, I_3) \rightarrow I_2$
$(I_2, I_3) \rightarrow I_1$

can be consider as strong association rules.



9). Perform Agglomerative Algorithm on the following data & plot a dendrogram using single link approach. The given data indicates the distance b/w elements.

Item	E	A	C	B	D
E	0	1	2	2	3
A	①	0	2	5	3
C	2	2	0	1	6
B	2	5	1	0	3
D	3	3	6	3	0

Pair E, A.

	(E, A)	C	B	D
(E, A)	0			
C	2	0		
B	2	①	0	
D	3	6	3	0

Pair (B, C).

	(E, A)	(B, C)	D
(E, A)	0		
(B, C)	②	0	
D	3	3	0

Pair (E, A) & (B, C) .

	(E, A), (B, C)	D
(E, A), (B, C)	0	0
D	2	0

Pair (E, A), (B, C), D

	(E, A, B, C, D)
(E, A, B, C, D)	0

