GATE

CRASH COURSE

DS & AI

Machine learning

Naive Bayes
Lec No. 05

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Topics to be Covered

1. Bayes classifier
2. Naive Bayes.

Classification

In Bayes classifier ⇒

If any new test point is x_i

then we find $\boxed{P(x_i/y_j)P_{y_j}}$

- $P(x_i/y_1)P_{y_1}$ ✓
- $P(x_i/y_2)P_{y_2}$ ✓

⋮

- $P(x_i/y_M)P_{y_m}$ ✓

a No of values/dimension

data

x^1	x^2	x^3	- -	x^D	Y
					M Class
					y_1
					y_2
					⋮
					y_M

$$P_{y_j} = \frac{\text{No of Points of class } y_j}{\text{Total No of Points in dataset.}}$$

So $\underbrace{P(x_i/y_1)}$ P_{y_1} ✓

$\longrightarrow$ this is calculated from dataset

$\Rightarrow \underline{\underline{x_i}} \Rightarrow \underline{\underline{a^D}}$

$$\left.\begin{aligned} P(x_i/y_1) &\longrightarrow a^D \\ P(x_i/y_2) &\longrightarrow a^D \\ P(x_i/y_3) &\longrightarrow a^D \\ &\vdots \\ M\ \text{class.} \end{aligned}\right\}$$ Total No of Parameter $\left((a^D M) + M\right)$

Bayes Classifier

⇒ Work on MAP Rule

⇒ For any point x_i it find $P(x_i c_j)Pc_j$

⇒ For all class we find $P(x_i c_j)Pc_j$

⇒ So, whichever class max $P(x_i c_j)Pc_j$ that class will be assigned to x_i

⇒ $$Pc_j = \frac{\textit{Number} \text{ of points in Class } c_j}{\textit{Total} \text{ number of points in training data}} \Rightarrow M\ probable$$

Topic : Basic of Machine Learning

Bayes Classifier

- $P(x_i c_j)$ = calculated from + training data
- M: Number of classes, D: Number of dimensions, each dimension can take a values,

$$P\left(x_i^1, x_i^2, \ldots x_i^x / c_j\right) \Rightarrow \left(a^D \times M\right)$$

- Total parameters = $(a^D M + M)$ ⇒These parameters are used by the hypothesis to find class of the point.

Bayes Classifier

- @time of testing we get a point (x_j) $\Rightarrow P\left(x_i^1, x_i^2, \ldots x_i^x / c_j^D\right)$ for this we need find $P\left(x_j / c_k\right) P_{ck}$ since x_j will be a combination of D dimensions thus $P(x_j/c_k)$ will be available So, find max $P\left(x_j / c_k\right) P_{c_k} \Rightarrow$ The class with max (px_j/c_k) p_{ck} is assigned.

Bayes Optimum Classifier

- Similar to bayes classifier but here we have more than one hypothesis
- For each hypothesis we need to find $P(x_i / c_k)P_{c_j}$ $\Rightarrow$ $(a^D M + M)$
- For each hypothesis $\rightarrow$ $(a^D M + M)$ parameters
- At time of testing $\sum_{i=1}^{H} P(h_i / D) P(c_j / h_i)$

$\Rightarrow$ H no of hypothesis

$\Rightarrow$ All these parameters are used by each hypothesis to find class for given point i.e $P(c_j/h_i)$

$\Rightarrow$ For any given point this is calculated for each class which ever class has max value that is assigned.

Topic : Basic of Machine Learning

Bayes Classification

$\max[P(x_i/c_j)Pcj]$

- Dimension are ind
- All dimension have equal contribution

$$\max P\left(x_i^1 / c_j\right) P\left(x_i^2 / c_j\right)$$

$$P\left(x_i^D / c_j\right) Pc_j$$

Number of parameters

Naïve Bayes Classifier

Bayes Class	Naive Bayes
$P(x_j/c_j)Pc_j$	$P\left(x_i^1/c_j\right)P\left(x_i^2/c_j\right)\ldots$
Probable for all combined available	$P\left(x_i^D/c_j\right)Pc_j$

Topic : Basic of Machine Learning

Naïve Bayes Classifier

Here also we have to find $P(x_i / y_j) P_{y_j}$

$\Rightarrow P_{y_j} \Rightarrow \dfrac{\# \text{ of Points of class } y_j}{\text{Total No of points}}$

$P(x_i / y_j)$, Since x_i is data Point, this has many dimension

we assume all dimension are Independent

Naïve Bayes Classifier

→ we have D dimension of A values

→ M No of classes.

for each dimension (AM)

for whole data $\boxed{(DAM)}$

Problem in Naïve Bayes Algorithm..

Topic : Bayesian Decision Theory

Test point ⇒ (over cast, mild, normal, weak)

Outlook	Temperature	Humidity	Wind	Play tennis
Sunny	Hot	High	Weak	No
Sunny	Hot	High	Strong	No
Overcast	Hot	High	Weak	Yes
Rain	Mild	High	Weak	Yes
Rain	Cool	Normal	Weak	Yes
Rain	Cool	Normal	Strong	No
Overcast	Cool	Normal	Weak	Yes
Sunny	Mild	High	Weak	No
Sunny	Cool	Normal	Weak	Yes
Rain	Mild	Normal	Strong	Yes
Sunny	Mild	Normal	Strong	Yes
Overcast	Mild	High	Strong	Yes
Overcast	Hot	Normal	Weak	Yes
Rain	Mild	High	Strong	No

we have to find class of this test point

$P_{yes} = \frac{9}{14}$ $P_{No} = \frac{5}{14}$

$\underbrace{P[\text{Test point}/\text{Yes}]}\, P_{Yes}$

and

$P[\text{Test point}/\text{No}]\, P_{No}$

Test point ⇒ (over cast, mild, normal, weak)

In Naive Bayes we assume all dimension are Independent

$P[\text{overcast, mild, normal, weak}/\text{Yes}]$

$$\underbrace{P[\text{overcast}/\text{Yes}]\,P[\text{mild}/\text{Yes}]\,P(\text{normal}|\text{Yes})\,P(\text{weak}|\text{Yes})}_{\text{(from Training data)}}$$

we have to find class of this test point

$P_{Yes} = \frac{9}{14}$ $P_{No} = \frac{5}{14}$

$$\underbrace{P[\text{Test point}/\text{Yes}]}\,P_{Yes}$$

and

$P[\text{Test point}/\text{No}]\,P_{No}$

Topic : Bayesian Decision Theory

Test point ⇒ (over cast, mild, normal, weak)

Outlook	Temperature	Humidity	Wind	Play tennis
Sunny	Hot	High	Weak	No
Sunny	Hot	High	Strong	No
Overcast	Hot	High	Weak	Yes
Rain	Mild	High	Weak	Yes
Rain	Cool	Normal	Weak	Yes
Rain	Cool	Normal	Strong	No
Overcast	Cool	Normal	Weak	Yes
Sunny	Mild	High	Weak	No
Sunny	Cool	Normal	Weak	Yes
Rain	Mild	Normal	Strong	Yes
Sunny	Mild	Normal	Strong	Yes
Overcast	Mild	High	Strong	Yes
Overcast	Hot	Normal	Weak	Yes
Rain	Mild	High	Strong	No

3x2

Outlook	P(P/Yes)	P(O/No)
Sunny	2/9 P(S|Y)	3/5 P(S|No)
Overcast	4/9 P(O|Y)	0 P(O|No)
Rain	3/9 P(R|Y)	2/5 P(R|No)

3x2

Temperature	P(T/Yes)	P(T/No)
Hot	2/9 P(H/Y)	2/5 P(H|No)
Mild	4/9 P(m|Y)	2/5 P(m|No)
Cold	3/9 P(C|Y)	1/5 P(C|No)

2x2

Humidity	P(H/Yes)	P(H/No)
High	3/9	4/5
Normal	6/9	1/5

2x2

Wind	P(W/Yes)	P(W/No)
Weak	6/9	2/5
Strong	3/9	3/5

Topic : Bayesian Decision Theory

Sunny Count → 3 No, 2 Yes } $P(S/Y)=2/9$, $P(S/No)=3/5$

Test point ⇒ (over cast, mild, normal, weak)

Outlook	Temperature	Humidity	Wind	Play tennis
Sunny	Hot	High	Weak	No
Sunny	Hot	High	Strong	No
Overcast	Hot	High	Weak	Yes
Rain	Mild	High	Weak	Yes
Rain	Cool	Normal	Weak	Yes
Rain	Cool	Normal	Strong	No
Overcast	Cool	Normal	Weak	Yes
Sunny	Mild	High	Weak	No
Sunny	Cool	Normal	Weak	Yes
Rain	Mild	Normal	Strong	Yes
Sunny	Mild	Normal	Strong	Yes
Overcast	Mild	High	Strong	Yes
Overcast	Hot	Normal	Weak	Yes
Rain	Mild	High	Strong	No

Outlook	P(P/Yes)	P(O/No)
Sunny	$\boxed{2/9}$ P(S|Y)	$\boxed{3/5}$
Overcast	4/9 P(O|Y)	0
Rain	3/9 P(R|Y)	2/5

Temperature	P(T/Yes)	P(T/No)
Hot	2/9	2/5
Mild	4/9	2/5
Cold	3/9	1/5

Humidity	P(H/Yes)	P(H/No)
High	3/9	4/5
Normal	6/9	1/5

Wind	P(W/Yes)	P(W/No)
Weak	6/9	2/5
Strong	3/9	3/5

Topic : Bayesian Decision Theory

Overcast : 4 Yes
0 No

$P(O/Y) = \frac{4}{9}$

$P(O/No) = 0/5$

Test point ⇒ (over cast, mild, normal, weak)

Outlook	Temperature	Humidity	Wind	Play tennis
Sunny	Hot	High	Weak	No
Sunny	Hot	High	Strong	No
Overcast	Hot	High	Weak	Yes
Rain	Mild	High	Weak	Yes
Rain	Cool	Normal	Weak	Yes
Rain	Cool	Normal	Strong	No
Overcast	Cool	Normal	Weak	Yes
Sunny	Mild	High	Weak	No
Sunny	Cool	Normal	Weak	Yes
Rain	Mild	Normal	Strong	Yes
Sunny	Mild	Normal	Strong	Yes
Overcast	Mild	High	Strong	Yes
Overcast	Hot	Normal	Weak	Yes
Rain	Mild	High	Strong	No

Outlook	P(P/Yes)	P(O/No)
Sunny	2/9 P(S|Y)	3/5
Overcast	4/9P(O|Y)	0
Rain	3/9 P(R|Y)	2/5

Temperature	P(T/Yes)	P(T/No)
Hot	2/9	2/5
Mild	4/9	2/5
Cold	3/9	1/5

Humidity	P(H/Yes)	P(H/No)
High	3/9	4/5
Normal	6/9	1/5

Wind	P(W/Yes)	P(W/No)
Weak	6/9	2/5
Strong	3/9	3/5

Topic : Bayesian Decision Theory

Rain = 3 Yes, 2 No | P(R/Y) = 3/9, P(R|No) = 2/5

Test point ⇒ (over cast, mild, normal, weak)

Outlook	Temperature	Humidity	Wind	Play tennis
Sunny	Hot	High	Weak	No
Sunny	Hot	High	Strong	No
Overcast	Hot	High	Weak	Yes
Rain	Mild	High	Weak	Yes
Rain	Cool	Normal	Weak	Yes
Rain	Cool	Normal	Strong	No
Overcast	Cool	Normal	Weak	Yes
Sunny	Mild	High	Weak	No
Sunny	Cool	Normal	Weak	Yes
Rain	Mild	Normal	Strong	Yes
Sunny	Mild	Normal	Strong	Yes
Overcast	Mild	High	Strong	Yes
Overcast	Hot	Normal	Weak	Yes
Rain	Mild	High	Strong	No

Outlook	P(P/Yes)	P(O/No)
Sunny	2/9 P(S|Y)	3/5
Overcast	4/9P(O|Y)	0
Rain	3/9 P(R|Y)	2/5

Temperature	P(T/Yes)	P(T/No)
Hot	2/9	2/5
Mild	4/9	2/5
Cold	3/9	1/5

Humidity	P(H/Yes)	P(H/No)
High	3/9	4/5
Normal	6/9	1/5

Wind	P(W/Yes)	P(W/No)
Weak	6/9	2/5
Strong	3/9	3/5

Topic : Bayesian Decision Theory

High $P(H/Y) = 3/9$

$P(H/No) = 4/5$

Normal

$P(N/Y) = 6/9$

$P(N/No) = 1/5$

Test point ⇒ (over cast, mild, normal, weak)

Outlook	Temperature	Humidity	Wind	Play tennis
Sunny	Hot	High	Weak	No
Sunny	Hot	High	Strong	No
Overcast	Hot	High	Weak	Yes
Rain	Mild	High	Weak	Yes
Rain	Cool	Normal	Weak	Yes
Rain	Cool	Normal	Strong	No
Overcast	Cool	Normal	Weak	Yes
Sunny	Mild	High	Weak	No
Sunny	Cool	Normal	Weak	Yes
Rain	Mild	Normal	Strong	Yes
Sunny	Mild	Normal	Strong	Yes
Overcast	Mild	High	Strong	Yes
Overcast	Hot	Normal	Weak	Yes
Rain	Mild	High	Strong	No

Outlook	P(P/Yes)	P(O/No)
Sunny	2/9 P(S|Y)	3/5
Overcast	4/9P(O|Y)	0
Rain	3/9 P(R|Y)	2/5

Temperature	P(T/Yes)	P(T/No)
Hot	2/9	2/5
Mild	4/9	2/5
Cold	3/9	1/5

Humidity	P(H/Yes)	P(H/No)
High	3/9	4/5
Normal	6/9	1/5

Wind	P(W/Yes)	P(W/No)
Weak	6/9	2/5
Strong	3/9	3/5

Test = (O, M, N, ω) ⇐ Yes.

$P[O, m, N, \omega / Yes]\, P_{Yes}$

$P(O|Y)\, P(m|Y)\, P(N|Y)\, P(\omega|Y)\, P_Y$

$\left(\frac{4}{9} \times \frac{4}{9} \times \frac{6}{9} \times \frac{6}{9} \times \frac{9}{14}\right)$

$P(O, m, N, \omega / No)\, P_{No}$

$\boxed{P(O|N)}\, P(m|N)\, P(N|No)\, P(\omega / No)\, P_{No}$

0

Topic : Bayesian Decision Theory

Test point ⇒ (over cast, mild, normal, weak)

Outlook	Temperature	Humidity	Wind	Play tennis
Sunny	Hot	High	Weak	No
Sunny	Hot	High	Strong	No
Overcast	Hot	High	Weak	Yes
Rain	Mild	High	Weak	Yes
Rain	Cool	Normal	Weak	Yes
Rain	Cool	Normal	Strong	No
Overcast	Cool	Normal	Weak	Yes
Sunny	Mild	High	Weak	No
Sunny	Cool	Normal	Weak	Yes
Rain	Mild	Normal	Strong	Yes
Sunny	Mild	Normal	Strong	Yes
Overcast	Mild	High	Strong	Yes
Overcast	Hot	Normal	Weak	Yes
Rain	Mild	High	Strong	No

$2+\alpha/9+3\alpha$

Outlook	P(P/Yes)	P(O/No)
Sunny	2/9 P(S|Y)	3/5
Overcast	4/9P(O|Y)	0
Rain	3/9 P(R|Y)	2/5

$4+\alpha/9+3\alpha$

Temperature	P(T/Yes)	P(T/No)
Hot	2/9	2/5
Mild	4/9	2/5
Cold	3/9	1/5

Humidity	P(H/Yes)	P(H/No)
High	3/9 $3+\alpha/9+2\alpha$	4/5
Normal	6/9	1/5

Wind	P(W/Yes)	P(W/No)
Weak	6/9	2/5
Strong	3/9	3/5

Topic : Bayesian Decision Theory

$P(O, M, N, w/yes)\ Pyes \Rightarrow P(O/Y)\ P(M/Y)\ P(N|Y)\ P(W/Y)\ P_Y$

$$\Rightarrow \left(\frac{4}{9} \times \frac{4}{9} \times \frac{6}{9} \times \frac{6}{9} \times \frac{9}{14}\right)$$

$P(O, M, N, w/yes)\ Pyes \Rightarrow P(O/N)\ P(M/N)\ P(N|N)\ P(W/N)\ P_N$

$$\Rightarrow 0 \times \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \Rightarrow 0$$

- Since P(over cost no) = 0
- Thus, in naïve bayes if any test point has 1st dimension = over cost then $P(x_i/No)PN_p - 0$ and test point → Yes class always

Zero Probability problem...

Navive Bayes Algorithm

- This is called zero probable problem
- Reason → Because in whole training data no data point with class no has dimension 1 = over cast

Zero Probability problem...

Navive Bayes Algorithm

Solution to zero probable problem ⇒

2 solutions

1. inc the data
2. add the arbitrary points → smoothening process ✓

Topic : Bayesian Decision Theory

Navive Bayes Algorithm

Solving the zero probability problem..

- Smoothing techniques, adding virtual entries..
- Additional data...

Smoothening by α

1^{st} dimension

Yes

S
S
O
O
O
O
R
R
R

$P(S/Y) = 2/9$

$P(O/Y) = 4/9$

$P(R/Y) = 3/9$

No

S
S
S
R
R

$P(S/N) = \frac{3}{5}$

$P(R/N) = 2/5$

$P(O/N) = 0$

Smoothening by α

1^{st} dimension

Yes

S
S
O
O
O
O
R
R
R

$\leftarrow$ α times S, R, O

$P(S/Y) = \frac{2+\alpha}{9+3\alpha}$

$P(O/Y) = \frac{4+\alpha}{9+3\alpha}$

$P(R/Y) = \frac{2+\alpha}{9+3\alpha}$

No

S
S
S
R
R

α times S
α times R
α times O

$P(S/N) = \frac{3+\alpha}{5+3\alpha}$

$P(R/N) = \frac{2+\alpha}{5+3\alpha}$

$P(O/N) = \alpha/5+3\alpha$

If smoothening is done in any dimension

$P(S/Y) = \frac{2}{9} \longrightarrow \frac{2+\alpha}{9+3\alpha}$

3: bcoz dimension has 3 values.

$P(S/No) = 3/5 \longrightarrow \frac{3+\alpha}{5+3\alpha}$

Topic : Bayesian Decision Theory

After smoothing new probable $\Rightarrow \dfrac{\textit{Old}\text{ value }\alpha}{\textit{Old}\text{ value k}\alpha}$

K = number of values a dimension can take

3rd dimension

H
H
H
N
N
N
N
N
N
. . .
. . .
. . .

$P(H|Y) = \dfrac{3+\alpha}{9+2\alpha}$

$P(N|Y) = \dfrac{6+\alpha}{9+2\alpha}$

Topic : Bayesian Decision Theory

Test point $\Rightarrow$ (over cast, mild, normal, weak)

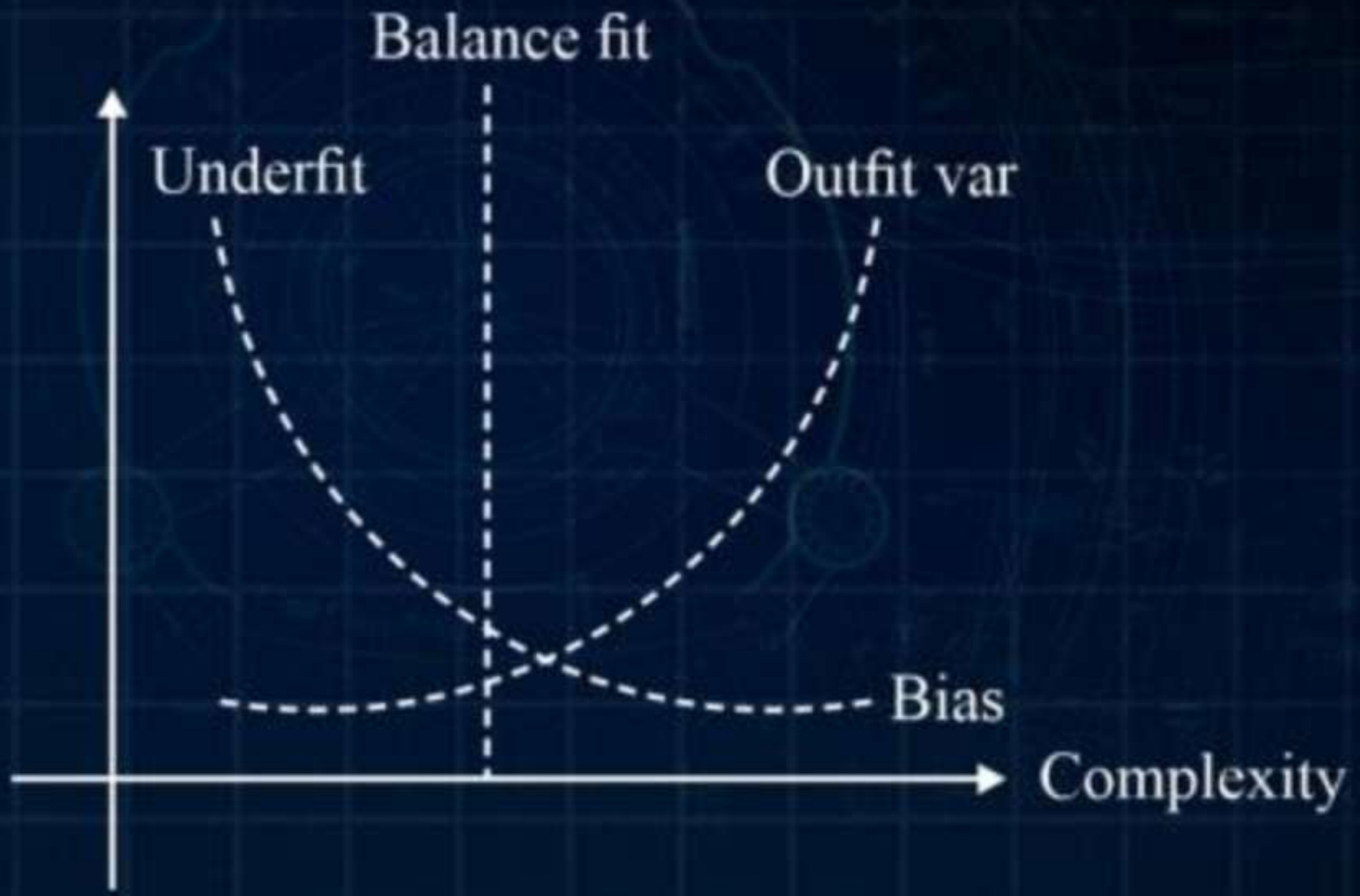
Outlook	Temperature	Humidity	Wind	Play tennis
Sunny	Hot	High	Weak	No
Sunny	Hot	High	Strong	No
Overcast	Hot	High	Weak	Yes
Rain	Mild	High	Weak	Yes
Rain	Cool	Normal	Weak	Yes
Rain	Cool	Normal	Strong	No
Overcast	Cool	Normal	Weak	Yes
Sunny	Mild	High	Weak	No
Sunny	Cool	Normal	Weak	Yes
Rain	Mild	Normal	Strong	Yes
Sunny	Mild	Normal	Strong	Yes
Overcast	Mild	High	Strong	Yes
Overcast	Hot	Normal	Weak	Yes
Rain	Mild	High	Strong	No

Outlook	P(O/Yes)	P(O/No)
Sunny	$2/9 \Rightarrow 2+\alpha/9+3\alpha$	$3/5 \Rightarrow 3+\alpha/5+3\alpha$
Overcast	$4/9 \Rightarrow 4+\alpha/9+3\alpha$	$0 \Rightarrow 0+\alpha/5+3\alpha$
Rain	$3/9 \Rightarrow 3+\alpha/9+3\alpha$	$2/5 \Rightarrow 2+\alpha/5+3\alpha$

Temperature	P(T/Yes)	P(T/No)
Hot	$2/9 = \frac{2+\alpha}{9+3\alpha}$	$2/5 \quad \frac{2+\alpha}{5+3\alpha}$
Mild	4/9	2/5
Cold	3/9	1/5

Humidity	P(H/Yes)	P(H/No)
High	$3/9 \Rightarrow \frac{3+\alpha}{9+2\alpha}$	$4/5 \Rightarrow \frac{4+\alpha}{5+2\alpha}$
Normal	$6/9 \Rightarrow \frac{6+\alpha}{9+2\alpha}$	$1/5 \Rightarrow \frac{1+\alpha}{5+2\alpha}$

Laplace Smoothing $\Rightarrow$ Mean $\alpha = 1$



$\alpha = 0$ ✓	$\alpha=0$	$\alpha \Rightarrow$ Very large	
Fitting $\Rightarrow$	Overfit ✓	Balance fit	Underfitting ✓
Bias $\Rightarrow$	Low ✓	Low	High
Variance $\Rightarrow$	High ✓	Low	Low

Topic : Bayesian Decision Theory

- How to solve for continuous dimension in naive bayes.
  In this case $P(x_i c_j) Pc_j$

  $$\left(P\left(x_i^1 / C_j\right)...P_{C_j}\right)$$

  What if the dimension are continuous in nature

  $P(S|Y) = 2/9$
  $P(O|Y) = 4/9$
  $P(R|Y) = 3/9$
  $P(S|N) = 3/5$
  $P(O|Y) = 0$
  $P(R|N) = 2/5$

Topic : Bayesian Decision Theory

Naïve Bayes Algorithm

What if the dimension are continuous in nature

mean ⇒ 70.8
var ⇒ 41.36

$\mu =$ 74.6
$\sigma^2 = 49.84$

The numeric weather data with summary statistics

Outlook			Temperature		[redacted]	Windly			Play	
	Yes	No	Yes	No			Yes	No	Yes	No
Sunny	2	3	83	85		False	6	2	9	5
Overcast	4	0	70	80		True	3	3		
Rainy	3	2	68	65						
			64	72						
			69	71						

$P_Y = 9/14$
$P_N = 5/14$

$P(S/Y) = 2/9$
$P(S/N) = 3/5$
$P(O/Y) = 4/9$
$P(O/N) = 0$

$P(R/Y) = 3/9$
$P(R/N) = 2/5$

$P(T/Y) = N(70.8, 41.36)$
$P(T/N) = N(74.6, 49.84)$

$P(F/Y) = \frac{6}{9}$
$P(F/N) = 2/5$
$P(T/Y) = 3/9$
$P(T/N) = 3/5$

- Find class of (Sunny, 78, ~~85~~, true)

$P[S, 78, T/Yes]\, P_{Yes}$

$P(S/Y)\, P(78/Y)\, P(T/Y)\, P_Y$

$\frac{2}{9} \times \frac{1}{\sqrt{2\pi\sigma^2}} e^{-(x-\mu)^2/2\sigma^2} \times \frac{3}{9} \times \frac{9}{14}$

$x = 78$, $\mu = 70.8$, $\sigma^2 \to 41.36$

$= .03314$

$P[S, 78, T/No]\, P_{No}$

$P(S|N)\, P(78|N)\, P(T|N)\, P_{No}$

$\frac{3}{5} \times \frac{1}{\sqrt{2\pi\sigma^2}} e^{-(x-\mu)^2/2\sigma^2} \times \frac{3}{5} \times \frac{5}{14}$

$x = 78$, $\mu = 74.6$, $\sigma^2 \to 49.8$

$.0503$ ✓

5 5 14

Topic : Bayesian Decision Theory

Naïve Bayes Algorithm

The numeric weather data with summary statistics

Outlook			Temperature		Humidity		Windly			Play	
	Yes	No	Yes	No	Yes	No		Yes	No	Yes	No
Sunny	2	3	83	85	86	85	False	6	2	9	5
Overcast	4	0	70	80	96	90	True	3	3		
Rainy	3	2	68	65	80	70					
			64	72	65	95	$\rightarrow \Sigma = 86.2$				
			69	71	70	91	$\sigma^2 = 75.76$				
			75	↓	80						
			75	$\Sigma=74.6$	70						
			72	$\sigma^2 = 49.84$	90	$\rightarrow$ mean = 79.11					
			81		75	$\rightarrow \sigma^2 = 72.76$					

Topic : Bayesian Decision Theory

- PDF of temp and Humidity $\Rightarrow$

$$P(T/Y) \Rightarrow \frac{1}{\sqrt{2\pi \times 34.66}} e^{\frac{-(x73)^2}{2\times 34.66}}$$

$$P(T/N) \Rightarrow \frac{1}{\sqrt{2\pi \times 49.84}} e^{\frac{-(x-74.6)^2}{2\times 49.84}}$$

$$P(h/Y) \Rightarrow \frac{1}{\sqrt{2\pi \times 92.76}} e^{\frac{-(x-79.11)^2}{2\times 92.76}}$$

$$P(h/N) \Rightarrow \frac{1}{\sqrt{2\pi \times 75.76}} e^{\frac{-(x-86.2)^2}{2\times 75.76}}$$

The numeric weather data with summary statistics											
Outlook			Temperature		Humidity		Windly			Play	
	Yes	No	Yes	No	Yes	No		Yes	No	Yes	No
Sunny	2	3	83	85	86	85	False	6	2	9	5
Overcast	4	0	70	80	96	90	True	3	3		
Rainy	3	2	68	65	80	70					
			64	72	65	95					
			69	71	70	91					
			75		80						
			75		70						
			72		90						
			81		75						

Thank

THANK

Keep Hustling!