CSE 6363 - Machine Learning Homework-1 Spring 2019

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Q1: MLE and MAP

Criven: per a poisson process probability for the first event to occur is discribed by our exponential distribution

@ MLE for λ of the model given D= gk,...kn}

i) likelihood junction:-
$$L(\lambda: k_1, ..., k_n) = \lambda^n e^{\left(-\lambda \sum_{i=1}^n k_i\right)}$$

Proof:
$$L(\lambda; k_1 - k_n) = \prod_{i=1}^{n} \int_{k_i} k_i (k_i \cdot \lambda)$$

$$= \prod_{i=1}^{n} \lambda e^{(-\lambda k_i)}$$

$$= \lambda^n e^{(-\lambda \sum_{i=1}^{n} k_i)}$$

(ii) log likelihood function:

$$l(\lambda; k_1,...,k_n) = ln(\lambda(\lambda; k_1,...,k_n))$$

$$= ln(\lambda^n \exp(-\lambda \sum_{i=1}^n k_i))$$

$$= ln(\lambda^n) + ln(\exp(-\lambda \sum_{i=1}^n k_i))$$

$$= nln(\lambda) - \lambda \sum_{i=1}^n k_i$$

$$\hat{\lambda} = \underset{\lambda}{\operatorname{arg max}} l(\lambda; k, ..., k_n)$$

$$\Rightarrow \frac{d}{d\lambda} l(\lambda; k, ..., k_n) = 0$$
 — just order condition for a maximum

$$= \frac{d}{d\lambda} \left(\lambda_{i}^{2} k_{i} ... k_{n} \right) = \frac{d}{d\lambda} \left(n \ln(\lambda) - \lambda_{i}^{2} k_{i} \right)$$

$$= \frac{n}{\lambda_{i}^{2}} k_{i}^{2}$$

By setting the value equal to O, we get $\frac{\lambda = \frac{n}{\sum_{i=1}^{n} k_i}}{\sum_{i=1}^{n} k_i}$

$$\lambda = \frac{\gamma}{\sum_{i=1}^{m} k_i}$$

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$$\lambda_{map} = \underset{=}{\operatorname{argymax}} P(D | X) P(X)$$

$$= \lambda^{n} e^{-\lambda \sum x_{i}} \frac{\beta^{\alpha}}{f(\alpha)} \lambda^{\alpha-1} e^{-\beta \lambda}$$

$$= \frac{\beta^{\alpha}}{f(\alpha)} \cdot \lambda^{n+\alpha-1} e^{-\lambda} (\sum x_{i} + \beta)$$

$$= \underset{=}{\operatorname{dama}} (\alpha + n, \sum x_{i} + \beta)$$

$$\log pesterior,$$

$$\log P(\lambda | D) = (n + \alpha + 1) \log \lambda - \lambda (\sum x_{i} + \beta)$$

$$= \underset{=}{\partial} \log (P(\lambda | D)) = \frac{(n + \alpha - 1)}{\lambda} - \sum x_{i} - \beta = 0$$

$$= \lambda = \frac{n + \alpha - 1}{\sum x_{i} + \beta}$$

Given,
$$\alpha = 5$$
, $\beta = 10$, $n = 6$

$$\sum_{i} \chi_{i} = \frac{1.5 + 3 + 2.5 + 2.75 + 2.9 + 3}{6} = \frac{3.60833}{6}$$

$$\lambda = \frac{6 + 5 - 1}{2.60833 + 10} \Rightarrow 0.79312$$

girem
D: { ((170, 57, 32), W), ((192, 95, 28), M), ((170, 65, 29), M), ((175, 78, 35), M), ((185, 90, 32), M), ((185, 48, 31), W), ((185, 48, 31), W), ((182, 80, 30), M), ((182, 80, 30), M), ((182, 80, 28), W), ((180, 80, 27), M), ((160, 50, 31), W), ((175, 72, 30), M),), ((175, 72, 30), M),), ((175, 72, 30), M),), ((175, 72, 30), M),)

(a) (i) input > (155, 40,35)

Height 170 192 150 170 175 185 170 155	Weight 57 95 45 65 78 90 65 48 55	Age 32 28 30 29 35 32 28 31 30	383888333	Distance 22.869 66.655 8.660 29.765 42.941 58.386 29.983 8.944 16.583	2 4
160		30	W	16.583	

	And the Control of th		1			
	185	80	30	M	48.518	T
	175	69	28	W	35.916	
-	180	80	27	M	47.843	
-	160	50	31	W	11.274	3
THE OWNER OF THE OWNER OWNER OF THE OWNER OWNE	175	72	30	m	38.065	

If
$$K=1$$

distance = $\sqrt{(x_1-x_2)^2+(y_1-y_2)^2+(z_1-z_2)^2}$
wher x_2 height, y_2 weight and z_3 age
distance = 8.660 Gender = Woman

If
$$k=3$$

distance = $\sqrt{(21-2)^2+(y_1-y_2)^2+(z_1-z_2)^2}$
distance 1 = 8.660 Genote = woman ?
 $2 = 8.944$ Genote = woman ?
 $3 = 11.874$ Grender = woman

If
$$K = 5$$

distance $1 = 8.660$ (render = woman
 $2 = 8.944$ (gender = woman
 $3 = 11.874$ (gender = woman
 $4 = 16.583$ Gender = woman
 $5 = 22.869$ (gender = woman

(i) Input = (170,70,32)

Height	weight	Age		Distance	
170	57	32	W	13	
192	95	28	M	33.541	
150	45	30	W	32.078	
170	65	29	\sim	5.830	2
175	78	35	M	9.899	5
185	90	32	m	25	
170	65	28	W	6.403	3
155	48	31	W	26.645	
160	55	30	W	18.138	
182	80	30	m	15.748	
175	69	28	W	6.480	4
180	80	27	\sim	15	
160	50	31	W	22.383	
175	12	30	M	5.744	1

```
J K=1, distance = 5.744, Gender = Man

2, 5.830, Gender = Man

3, 6.403, Gender = Man

2, 5.830, Gender = Man

2, 5.830, Gender = Man

3, 6.403, Gender = Woman

4, 6.480, Gender = Woman

5, 9.899, Gender = Man

5, 9.899, Gender = Man
```

(iii) Input = (175,70,35)

	Height	Weight	Age		Diteonce	7
	170	57	32	W	14.247	
	192	95	28	M	31.032	
	150	45	30	W	35.707	
	170	65	29	M	9. 273	4
	175	78	35	M	8	3
	185	90	32	M	22.561	
	170	65	28	W	9.949	5
	155	48	31	W	30	
	160	55	30	W	21.794	
	182	80	30	M	13.190	
	175	69	28	W	7.071	2
	180	80	27	m	13.747	
	160	50	31	W	25.317	
	175	72	30	m	5.385	1
-						

y K=1,	distance = 5.385, Gender = Male	
y K:3,	distance 1 = 5.385 Gendy = Male 2 = 7.071 Gendy = woman man 3:8 Gendy = male = male	
J K=5	distance 1 = 5.385 Gender : Man 2 : 7.071 Gender : Woman 3 = 8 Gender : Man 4 = 9.273 Gender : Man 5 : 9.949 Gender : Woman	ν

(iv) Juput: (180,90,20)

	1		-	+	
Height	Weight	Age		Distance	1
170	57	32	W	36.510	
192	95	28	M	15.264	4
150	45	30	W	55	
170	65	29	M	28. 3 90	
175	78	35	M	19.849	5
185	90	32	M	13	2
170	65	28	W	28.089	
155	48	31	W	50.099	
160	55	30	W	41. 533	
182	80	30	m	14.282	3
175	69	28	W	23,021	
180	%	27	m	12.206	1
160	50	31	W	46.054	
175	72	B 0	M	21.1897	

```
J K=3, distance = 12.206, Gendu = Man

2 = 13, Gendu = Man

3 = 14.282, Gendu = Man

2 = 13, Gendu = Man

3 = 14.282, Gendu = Man

2 = 13, Gendu = Man

3 = 14.282, Gendu = Man

4 = 15.264, Gendu = Man

5 = 19.849, Gendu = Man

Gendu = Man
```

20 Repeat KNN prediction removing age data.

Crisen:

(i) Input = (155, 40)

-				
Hught	weight		Distance	
170	57	W	22-671	5
192	95	m	66.287	F
150	45	W	7.071	1
170	65	m	29.154	-
175	78	m	42.941	3
185	90	M	58.309	sil
170	65	W	29.154	
155	48	W	8	2
160	55	W	15.811	4
182	80	M	48.259	10
175	69	N	35. 227	ý
180	80	M	47.169	-
160	50	W	11.180	3
175	72	M	37.735	

```
J K=1, distance = 7.071, Gender = Woman

J (x:3, distance > 1) 7.071, Gender = Woman

2) 8, Gender = Woman

3) 11.180, Gender = Woman

2) 8, Gender = Woman

2) 8, Gender = Woman

3) 11.180, Gender = Woman

4) 15.811, Gender = Woman

5) 22.671, Gender = Woman
```

(ii) Input: (170,70)

,					
	Height	Height		Distance	
	170	57	W	13	5
	192	95	M	33.301	
	150	45	W	32.015	1
-	170	65	M	5	1
	175	78	M	9.433	4
	185	90	M	25	h 23
	170	65	N	5	21
	155	48	W	26.627	1
	160	<i>55</i>	W	18.027	
	182	80	M	15.620	
	175	69	N	5.099	2
	180	80	M	14.142	
	160	50	N	22.360	
	175	72	M	5.385	3

(11) Input > (175,70)

Meight	kleight		Distance	
170	57	W	13.928	1
192	95	M	30.232	
150	45	W	35.355	
170	65	M	7.071	3
175	78	M	8	5
185	90	M	22.360	
170	65	W	7.071	4
155	48	W	29.732	
160	55	W	21.213	
182	80	М	12.206	
175	69	N	1	1
180	80	M	11.180	8 8
160	50	W	25	
175	72	M	2	2

(iv) Input > (180,90)

				-
Might	pleight		Distance	
170	57	W	34.481	1
192	95	14	13	5
150	45	W	54.083	
170	65	M	26.925	
175	78	M	13	4
185	90	M	5	1
170	65	W	26.925	
155	48	W	48.877	
160	55	W	40.311	
182	80	M	10.198	3
175	69	N	21.587	
180	80	M	10	2
160	50	W	44.721	
175	72	M	18.681	
			100	

quistion a

Conclusion:

Form the calculations and predictions seen in 20 and 20 we can clearly see that 20 provides a better prediction. With the eage data present the prediction is more accurate.

If we remove the age data we can see that there are redundant predictions made which can either result in Man or Woman.

à Gireni data from 92

Probabilistic dassifier

posterior: prior x likelihood evidence

 $P(C_k, \alpha_1, \dots, \alpha_n)$

P(xi) xi+1...., xn, Ck) = P(xi/Ck)

= P(CK) The P(Xi /CK)

). ŷ = argmax p(Ck) TT p(2:1Ck)
KE(1,...K)

Gaussian Naire Bayes:

$$P(x=y)(k) = \frac{1}{\sqrt{2\pi\sigma^2}}e^{\left(-\frac{(k-\mu)^2}{2\sigma^2}\right)}$$

Determine:

posterior (male) = P(male) p(height/male) p (weight/male) p (age/male)
evidence

posterior (woman) = P(woman) p(height/woman) p(weight/woman) Rage/woman)
enidence

p(woman) = 0.5

Man:

woman:

19(1999) =

$$P(\text{height} | \text{male}) = \frac{1}{\sqrt{2\pi r^2}} exp(-\frac{(155-179.865)^2}{2\sigma^2}) = 0.00017$$

$$P(\text{weight | male}) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(40-80)^2}{2\sigma^2}\right) = 1.664 \times 10^{-5}$$

$$P(\text{age}|\text{male}) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(35-30.142)^2}{2\sigma^2}\right) = 0.02863$$

$$P(\text{heighd}|\text{woman}) = \frac{1}{\sqrt{2\pi\sigma^2}} exp(-(155-162.857)^2) = 0.03023$$

$$P(\text{weight/woman}) = \frac{1}{\sqrt{2\pi\sigma^2}} = \exp\left(-\frac{(40 - 55.57)^2}{2\sigma^2}\right) = 0.00962$$

$$P(age)woman) = \frac{1}{\sqrt{2\pi\sigma^2}} exp(-\frac{(35-30)^2}{2\sigma^2}) = 0.00123$$

posterios(man) = P(M) P(Hight|m) P(weight|m) P(Age|M)

considering only the numerator

=) (0.5) (0.0017)(1.664 x 10⁻⁵) (0.02863)

=> 4.1602 \times 10⁻¹¹

Posterior (W) = P(W) P(reight | W) P(weight | W) P(Age | W)
(considering the numerator:

=> (0.5)(0.0302)(0.0096)(0.00123)

=) 1.7914×10⁻⁷

As the posterior (w) is greater thom posterior (M) the prediction for (155, 40, 35) => woman.

(ii) input:
$$(170,70,32)$$
 $\Rightarrow P(\text{height}|M) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(170-179.86)^2}{2\sigma^2}\right) = 0.02205$
 $\Rightarrow P(\text{height}|M) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(70-80)^2}{2\sigma^2}\right) = 0.0241$
 $\Rightarrow P(\text{agr}|M) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(32-30.14)^2}{2\sigma^2}\right) = 0.11725$
 $\Rightarrow P(\text{height}|W) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(170-162.857)^2}{2\sigma^2}\right) = 0.03227$
 $\Rightarrow P(\text{weight}|W) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(70-55.57)^2}{2\sigma^2}\right) = 0.01197$
 $\Rightarrow P(\text{agr}|W) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(32-30)^2}{2\sigma^2}\right) = 0.11083$

Posterior (max) = $(0.5)(0.02205)(0.0241)(0.11725)$

since posterior(M) is greater than posterior(W)
given input (170,70,32) -> Man

(ii) Exput > (175,70,35)
-> P(huight | m) =
$$\frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(175-179.86)^2}{2\sigma^2}\right) = 0.04368$$

-> P(weight | m) = $\frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(70-80)^2}{2\sigma^2}\right) = 0.0241$
-> P(age | m) = $\frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(35-30.14)^2}{2\sigma^2}\right) = 0.02863$

->
$$P(\text{huight}|w) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(175-162.857)^2}{2\sigma^2}\right) = 0.0179$$

-> $P(\text{weight}|w) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(70-55.57)^2}{2\sigma^2}\right) = 0.0197$

$$\rightarrow P(age|w) = \frac{1}{\sqrt{2\pi\sigma^2}} exp\left(-\frac{(35-30)^2}{2\sigma^2}\right) = 0.00123$$

$$=> 1.512 \times 10^{-5} => 0.00001512$$
Posterior (W) = 0.5 (0.0179) (0.0119) (0.00123)

Since posterior (w) < posterior (m)

$$(175,70,35) \longrightarrow man$$

(iv) input > (180, 90, 20)
>P(night|m)=
$$\frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(180-179.86)^2}{2\sigma^2}\right) = 0.0543$$

->P(weight|M) = $\frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(90-80)^2}{2\sigma^2}\right) = 0.02419$
->P(age|M) = $\frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(80-3014)^2}{2\sigma^2}\right) = 0.00011$
->P(height|W) = $\frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(180-162.857)^2}{2\sigma^2}\right) = 0.00736$
->P(weight|W) = $\frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(90-355.57)^2}{2\sigma^2}\right) = 2.39 \times 10^{-5}$
->P(age|W) = $\frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(30-30)^2}{2\sigma^2}\right) = 1.3310^{-10}$
Posteuor(man) = $0.5(0.0543)(0.0241)(0.00011)$
=> $\frac{7.319 \times 10^{-6}}{2000}$
Posteuor(W) = $\frac{0.5(0.00736)(2.39\times10^{-5})(1.3\times10^{-10})}{2000}$

(180,90,20) -> Man

Scanned by CamScanner

(c) Removing the age parameter.

(i) Input -> (155, 40)

P(height | m) =
$$\frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(155 - 179.86)^2}{3\sigma^2}\right) = 0.00017$$

P(weight | m) = $\frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(40 - 80)^2}{3\sigma^2}\right) = 1.664 \times 10^5$

P(hught | w) = $\frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(155 - 162.857)^2}{3\sigma^2}\right) = 0.03023$

P(weight | w) = $\frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(40 - 55.57)^2}{3\sigma^2}\right) = 0.00962$

P(height | M) =
$$\frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(170 - 179.86)^2}{2\sigma^2}\right) = 0.02205$$

P(height | M) = $\frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(70 - 80)^2}{2\sigma^2}\right) = 0.02419$
P(height | W) = $\frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(170 - 162.857)^2}{2\sigma^2}\right) = 0.03227$
P(weight | W) = $\frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(70 - 55.57)^2}{2\sigma^2}\right) = 0.01197$
Posterior (M) = $0.5(0.02205)(0.02419)$

Posterior
$$(M) = 0.5(0.02205)(0.02419)$$

$$=> 0.0002667$$

Posterior (W) = 0.5 (0.03227) (0.01197)

Phight mon) =
$$\frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(175-179.86)^2}{2\sigma^2}\right) = 0.04368$$

Phight mon) = $\frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(70-80)^2}{2\sigma^2}\right) = 0.02419$

Pheight | w) = $\frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(175-162.857)^2}{2\sigma^2}\right) = 0.01794$

Pheight | w) = $\frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(70-55.57)^2}{2\sigma^2}\right) = 0.01197$

Pesterior | m) = 0.5 (0.04368) (0.02419)

=> 5.2×10⁻⁴

=> 0.000528

Putwor | w) = 0.5 (0.0179) (0.01197)

>> 1.07×10⁻⁴

Since
$$posterior(m) > posterior(w)$$

 $(175,70) \rightarrow Man$

=) 0.000101

(iv) Input > (180,90)

P(huight | m) =
$$\frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(180-179.86)^2}{3\sigma^2}\right) = 0.05437$$

P(weight | m) = $\frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(90-80)^2}{3\sigma^2}\right) = 0.02419$

P(huight | w) = $\frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(180-162.857)^2}{3\sigma^2}\right) = 0.00736$

P(weight | w) = $\frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(90-55.57)^2}{3\sigma^2}\right) = 2.39 \times 10^5$

Posterior (m) = 0.5 (0.05437) (0.02419)

=> 6.5 × 10

=> 0.000657

Posterior (W) = 0.5 (0.00736) (2.39 × 10⁵)

$$\Rightarrow$$
 8.809 x 10⁻⁸
Since posterior (m) > posterior (w)
(180,90) -> Man

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Conclusions:

Based on the 2 classifier test performed in 2b,C and 3b,C we can see that there are both pro's an cong in both the classifiers. in KNN the age parameter removed make redundant predictions which are not justifiable. Similarly in Naire Bayes classifiers removing the eige parameter causes changes in the probabilistic values and will result in inconclusive predictions.

Kron classifiers assign category based on selected

neaust neighbours.

The Naire Bayes classifier chooses the probability based on the prior knowledge of the value & its probability.

Hence Naive Bayes are comparitively better than

KNN vensidning large data sets.