

VR Siddhartha Engineering College Department of Information Technology



20IT6302: MACHINE LEARNING HOME ASSIGNMENT-3 QUESTIONS

User ID	Gender	Age	EstimatedSalary	Purchased	CO2	App
15624510	Male	19	19000	0		
15810944	Male	35	20000	0		
15668575 15603246	Female Female	26 27	43000 57000	0		
15804002	Male	19	76000	0		
15728773	Male	27	58000	0		
15598044	Female	27	84000	0		
15694829	Female	32	150000	1		
15600575	Male	25	33000	0		
15727311	Female	35	65000	0		
15570769	Female	26	80000	0		
15606274	Female	26	52000	0		
15746139	Male	20	86000	0		
15704987	Male	32	18000	0		
15628972	Male	18	82000	0		
15697686	Male Male	29	80000	0		
15733883 15617482	Male	47 45	25000 26000	1		
15704583	Male	46	28000	1		
20.04000					1 1	
15621083	Female	48	29000	1	1 1	
15621083 15649487	Female Male	48 45	29000 22000	1		
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15649487 15736760 heck whetehr to alary=60000 wind the second of the sec	Male Female The customer with	45 47 th features for not.	22000 49000 s Gender=Male; Age	1	CO2	Apj

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3	ID	SPEED	AGILITY	DRAFT		CO2	Apply
	1	2.50	6.00	yes			
	2	3.75	8.00	no			
	3	2.25	5.50	yes			
	4	3.25	8.25	no			
	5	2.75	7.50	no			
	6	4.50	5.00	yes			
	7	3.50	5.25	yes			
	8	3.00	3.25	no			
	9	4.00	4.00	no			
	10	4.25	3.75	yes			
	drafted	d or not is give	•	table. Predict	long with whether rhaey have whether an athelet with t.		
4	ID	SPEED	AGILITY	DRAFT		CO2	Apply
	11	2.00	2.00	no			
	12	5.00	2.50	no			
	13	8.25	8.50	no			
	14	5.75	8.75	yes			
	15	4.75	6.25	yes			
	16	5.50	6.75	no			
	17	5.25	9.50	yes			
	18	7.00	4.25	no			
	19	7.50	8.00	yes			
	20	7.25	5.75	yes			
	drafted	d or not is give	-	table. Predict	long with whether rhaey have whether an athelet with t.		
5	1		g eight points e eans clustering		oresenting locations) into three	CO2	Apply
	A1(2, 1	10), A2(2, 5),	A3(8, 4), A4(5	, 8), A5(7, 5),	A6(6, 4), A7(1, 2), A8(4, 9)		
6			g ten points (weans clustering		esenting locations) into two	CO2	Apply
	1	10), A2 (2,6), 0,12), A10 (7,		4 (6,9), A5 (6,4	I), A6 (1,2), A7 (5,10), A8 (4,9),		
7		,	g eight points eans clustering		presenting locations) into two	CO2	Apply
	A1(2,	10), A2(2, 5)	, A3(8, 4), A4(5, 8), A5(7, 5)	, A6(6, 4), A7(1, 2), A8(4, 9)		
8		,	g ten points (w eans clustering		esenting locations) into three	CO2	Apply
		10), A2 (2,6), 0,12), A10 (7,		4 (6,9), A5 (6,4	I), A6 (1,2), A7 (5,10), A8 (4,9),		

9	- 81	720	22.71	220	88	-	T.						CO2	Apply
		1	2	3	4	5								1 1991
	1	0												
	2	9	0											
	3	3	7	0										
	4	6	5	9	0									
	5	11	10	2	8	0								
			_				_			clusterin	g and find t trix.	he best		
10				a	b			P1	P2	P3	P4	P5	CO2	Apply
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		P1	0.07		0.83			1.04139	C					
		P2	0.85		0.14		P3	0.59304	0.77369	0				
		P3	0.66		0.89		P4	0.46098	0.61612	0.30232	0			
		P4	0.49		0.64		P5	0.81841	0.32388	0.45222	0.35847	0		
	Draw	P5 the de	0.80		0.46 v Per		ning t	he agglo	merativ	e clusterir	ng and find	the hest		
										ance ma		the best		
11	Dis	tance	e a	Ь	С	d	е						CO2	Apply
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	ь		2	0	5	9	8							
	-					100								
	c		6	5	0	4	5							
	d		10	9	4	0	3							
	e		9	8	5	3	0							
			_	-			_			clusterin ance ma	g and find t trix.	he best	~ • •	
12		I	1	< j	p2		p3	I)4	p5	p6		CO2	Apply
	p1	0.0	0000	0.2	2357	(.221	8 0.3	688	0.3421	0.2347			
	p 2	0.2	357	0.0	0000	(.148	33 0.2	042	0.1388	0.2540			
	p 3	0.2	218	0.1	1483	(0.000	0.1	513	0.2843	0.1100]		
	p4	0.3	688	0.2	2042	0	.151	3 0.0	000	0.2932	0.2216			
	p 5	0.3	421	0.1	1388	0	.284	13 0.2	932	0.0000	0.3921]		
	р6	0.2	347	0.2	2540	. (.110	0 0.2	216	0.3921	0.0000	1		
			_	-			_			clusterin	g and find t trix.	he best		

Name		100	Give Birth		-	Live in Wate			CO3	Apply
human	warm		es	no		no	mammals			
python	cold	n		no	- 1	no	reptiles			
salmon	cold	n		no		yes	fishes			
whale	warm	ye	es	no		yes	mammals			
frog	cold	n	0	no		sometimes	amphibians			
komodo	cold	n		no		no	reptiles			
bat	warm	1000	es	yes		no	mammals			
FF 2000 Contractor		1.53		-		no	birds			
pigeon	warm	n		yes			1 100 11 100 100 100 100 100 100 100 10			
cat	warm	1.55	es	no		no	mammals			
leopard sh	ark cold	l ye	es	no	1	yes	fishes			
turtle	cold	n	0	no	- 1	sometime s	reptiles			
penguin	warm	n	0	no		sometimes				
porcupine	warm	1000	es	no		no	mammals			
eel	cold	n		no		ves	fishes			
		1000		1000000		The second second second second second				
salamande	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	n		no		sometimes				
gila monste	er cold	n	0	no		no	reptiles			
platypus	warm	n	0	no		no	mammals			
owl	warm	n	0	yes	- 1	no	birds			
dolphin	warm	100	es	no		ves	mammals			
eagle	warm	n		ves		no	birds			
	sometimes}	es ii {u	iood typ	JC-C01	iu, give	onth-ye	es, can fly=ye	s, nvc		
	1-Consider the	e following	training da	ataset fo	r a binary	/ classificatio	n problem		CO3	Appl
	Object	Home	Marital		Sex	Income	Defaulted			
	number		status				borrower			
1	paragraphic and other sections.		The second second second			450				
	1	Yes	Married		Female	9 150	No			
	2	Yes	Married		Male	220	Yes			
1		168	Married							
1	3	Yes	Divorced	d	Female	e 75	No			
1										
1	4	No	Single		Female	9 80	Yes			
	5	Yes	Single		Male	110	No			
1										
	6	No	Divorced	d	Male	65	Yes			
1	7							I		
	7	Yes	Single		Female	90	Yes			
	8	No	Married		Female	e 55	No			
	8	No	Married	d	Female	e 55	No			
G. Predict	8 9	No No Yes	Married Divorced Married	d	Female Male Male	e 55 85 95	No No No			
Object	8 9 10 a class for the	No No Yes following	Married Divorced Married	d	Female Male Male	955 85 95 es Classifie	No No No r			
	8 9 10 a class for the	No No Yes following	Married Divorced Married record us	d sing Na	Female Male Male ive Baye	955 85 95 es Classifie	No No No refaulted			
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	Bayesian cla				700		Tl 1 1		
							e. The data have ange of 31 to 35.		
			7			1000	ng the values for		
	department, st	Day of the state o	the state of the s			the state of the			
		departmen	it status	age :	salary	count			
		sales	senior	3135	46K50K	30			
		sales	junior	2630	26K30K	40			
		sales	junior	3135	31K35K	40			
		systems	junior	2125	46K50K	20			
		systems	senior	3135	66K70K	5			
		systems	junior	2630	46K50K	3			
		systems	senior	4145	66K70K	3			
		marketing	senior		46K50K	10			
		marketing	W 50 WELL		41K45K	4			
		secretary			36K40K	4			
		secretary	junior	2630	26K30K	6			
	Let status b	e the class lab	el attribute.						
Ţ	Jse Naïve E	Bayesian cl	assification	n to pred	dict label	of the	8 th tuple.	CO3	Ap
	Example	Colour	Toughness	Fungu	s Appe	arance	Poisonous		
	1	Green	Hard	N	Smo	ooth	N		
	2	Green	Hard	Y	Smo	ooth	N		
	3	Brown	Soft	N	Writ	nkled	N		
	4	Orange	Hard	N	Writ	rkled	Y		
	5	Green	Soft	Y	Smo	ooth	Υ		
	6	Green	Hard	Υ		nkled	Υ		
	7	Orange	Hard	N		rkled	Y		
	8	Green	Soft	Y	Writ	ıkled	?		

		X Vari	ables		Y Vari <mark>abl</mark> e	CO3	Apply
	Blood Pressure	Fever	Diabetes	Vomit	Suffering from disease 'Z'		
	high	high	yes	no	no		
	high	high	yes	yes	no		
	low	high	yes	no	yes		
	normal	mild	yes	no	yes		
	normal	no fever	no	no	yes		
	normal	no fever	no	yes	no		
	low	no fever	no	yes	yes		
	high	mild	yes	no	no		
	high	no fever	no	no	yes		
	normal	mild	no	no	yes		
	high	mild	no	yes	yes		
	low	mild	yes	yes	yes		
	low	high	no	no	yes		
5	normal	mild	yes	yes	no		
ľ	Low	no fever	yes	yes	?		
l	Use naïve Baye		•	•	label prediction.		
	Example No	. Color	Туре	Origin	Stolen?	CO3	Apply
	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		Imported	No		
	7	Yellow		Imported	Yes		
	8	Yellow	SUV	Domestic	No		
	9	Red	SUV	Imported	No		
	10	Red	Sports	Imported	Yes		
	10	Red					
		sian classit			the class label of the insta		
	Use Naïve Bay	vsian classit pe=SUV, c		nestic}	the class label of the insta	CO3	Apply
	Use Naïve Bay {color=red, Ty	vsian classit pe=SUV, c	origin=dom <i>Tennis</i> : trainin	nestic}	the class label of the insta		Apply
	Use Naïve Bay {color=red, Ty	vsian classif pe=SUV, c	origin=dom Tennis: trainin Temperature Ho Hot	ng examples umidity Wind High Weak	PlayTennis No		Apply
	Use Naïve Bay {color=red, Ty	vsian classif pe=SUV, c Play Day Outlook D1 Sunny D2 Sunny	origin=dom Tennis: trainin Temperature Hu Hot Hot	ng examples umidity Wind High Weak High Strong	PlayTennis No No		Apply
	Use Naïve Bay {color=red, Ty	vsian classif pe=SUV, c Play Oay Outlook D1 Sunny D2 Sunny Overcast	origin=dom Tennis: trainin Temperature Ho Hot Hot Hot	ng examples umidity Wind High Weak High Strong High Weak	PlayTennis No No No Yes		Apply
	Use Naïve Bay {color=red, Ty	vsian classif pe=SUV, c Play Oay Outlook D1 Sunny D2 Sunny Overcast D4 Rain	origin=dom Tennis: trainin Tennis: trainin Temperature Hu Hot Hot Hot Mild	ng examples umidity Wind High Weak High Strong High Weak High Weak	PlayTennis No No Yes Yes		Apply
	Use Naïve Bay {color=red, Ty	rsian classift pe=SUV, c Play Oay Outlook D1 Sunny D2 Sunny D3 Overcast D4 Rain D5 Rain	Tennis: trainin Tennis: trainin Temperature Hu Hot Hot Hot Mild Cool N	ng examples umidity Wind High Weak High Strong High Weak High Weak Normal Weak	PlayTennis No No Yes Yes Yes		Apply
	Use Naïve Bay {color=red, Ty	vsian classif pe=SUV, c Play Day Outlook D1 Sunny D2 Sunny D3 Overcast Rain D5 Rain Rain	Tennis: trainin Tennis: trainin Temperature Hu Hot Hot Hot Cool N Cool N	ng examples umidity Wind High Weak High Strong High Weak High Weak Jormal Weak Jormal Strong	PlayTennis No No Yes Yes Yes No		Apply
	Use Naïve Bay {color=red, Ty	rsian classif pe=SUV, c Play Oay Outlook D1 Sunny D2 Sunny Overcast D4 Rain D5 Rain D6 Rain Overcast	Tennis: trainin Tennis: trainin Temperature Hu Hot Hot Hot Cool N Cool	ng examples umidity Wind High Weak High Strong High Weak High Weak Wormal Weak Wormal Strong Wormal Strong	PlayTennis No No Yes Yes Yes No Yes		Apply
	Use Naïve Bay {color=red, Ty	vsian classif pe=SUV, c Play Day Outlook D1 Sunny D2 Sunny D3 Overcast Rain D5 Rain Rain	Tennis: trainin Temperature Hu Hot Hot Hot Cool N Cool N Mild	ng examples umidity Wind High Weak High Strong High Weak High Weak Jormal Weak Jormal Strong	PlayTennis No No Yes Yes Yes No		Apply
	Use Naïve Bay {color=red, Ty	rsian classification pe=SUV, construction pe=SUV, c	Tennis: trainin Tennis: trainin Tennerature Hu Hot Hot Hot Cool N Cool N Cool N Mild Cool N	ng examples umidity Wind High Weak High Strong High Weak High Weak Jormal Weak Jormal Strong Jormal Strong High Weak	PlayTennis No No No Yes Yes Yes No Yes No		Apply
	Use Naïve Bay {color=red, Ty	rsian classification pe=SUV, construction pe=SUV, c	Tennis: trainin Tennis: trainin Tennerature Hu Hot Hot Hot Cool N Cool N Cool N Cool N Mild Cool N Mild Mild Mild Mild Mild Mild Mild Mild	ng examples umidity Wind High Weak High Strong High Weak High Weak Jormal Weak Jormal Strong Jormal Strong High Weak Jormal Weak Jormal Weak Jormal Weak Jormal Weak	PlayTennis No No No Yes Yes Yes No Yes No Yes		Apply
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- 1	Use Naïve Bay {color=red, Ty	Play Oay Outlook D1 Sunny D2 Sunny D3 Overcast D4 Rain D5 Rain D6 Rain D7 Overcast Sunny D9 Sunny D10 Rain Sunny Sunny D11 Sunny	Tennis: trainin Temperature Ho Hot Hot Hot Cool N Cool N Cool N Mild Cool N Mild Cool N Mild Mild N Mild N Mild N Mild	ng examples umidity Wind High Weak High Strong High Weak High Weak Jormal Strong High Weak Jormal Strong High Weak Jormal Weak Jormal Weak Jormal Weak Jormal Weak Jormal Weak Jormal Strong High Weak Jormal Strong High Weak Jormal Strong	PlayTennis No No No Yes Yes Yes No Yes No Yes No Yes Yes Yes Yes		Apply

symp	toms and	revious pat diagnosis		0 30011	COGION	are trieff		CO3	Αp
	Ch	lls runny n	ose he	adache	fever	flu?			
		' N		Mild	Y	N			
	1	Y Y		No	N	Y			
	3	' N	5	Strong	TY	Y			
	1			Mild	Y	Y			
	1			No	N	N			
	1			Strong	Y	Y			
	1			Strong	N	N			
Dolb	_		the fallow	20110-5					
DOIDE	meve mar a	patient with	tue ioliow	nng symp	MOTHS TH				
	ch		ose he	adache	fever	flu?			
		N N		Mild	Y	?			
	Vaïve Baye	s classifier fo	r the follo	wing Pie	dataset	in order to de	termine the	CO3	Aı
			y, filling	-size=thin	, filling	shade=white,	shape=square]		
			Pie D	ataset			-		
×12	8	Crust	1	Fillin	g	Shape	3		
Example	Size	Shade	Size	7-5325000 Ac	hade		Class		
Ex1	Thick	Gray	Thic	98	Dark	circle	positive		
Ex2	Thick	White	Thic		Dark	circle	positive		
Ex3	Thick	Dark	Thic	34	iray	triangle	positive		
Ex4	Thin	White	Thin		Dark	circle	positive		
Ex5	Thick	Dark	Thin		Vhite	square	positive		
Ex6	Thick	White	Thin		Dark	circle			
Ex7	Thick	Gray	Thic		Vhite	circle	positive		
Ex8	Thick	White	Thic				negative		
Ex9	Thin	Gray	Thin	100	Bray Dark	square triangle	negative		
Ex10	Thick	Dark	Thic		Vhite	circle	negative		
Ex10	Thick	White	Thic) Dark	- 16			
-	-3	SA CHENNEL TO			10.5	square	negative		
Ex12	Thick	White	Thic	k C	этау	triangle	negative		
							e for a binary	CO3	A
							icting whether a is/her loan.		_
	Tid Ho	ome M	arital	Annu		Defaulted			
			atus	Incon	Elizari.	Borrower			
-	11111		ingle	125k		No			
1			arried ingle	100k		No			
-		Mariana tarina	arried	120		No			
1	.1	7.0	orced	95K		Yes			
1	1838		arried	60K		No			
			orced	220h		No		[[
-	1,116.6		ingle	85K		Yes			
	9		arried	75K		No			
		No S	ingle	90K		Yes			
Using the	10		e discus	sed in th	ne class	, predict th	ne class label for		
	10 NB appr	oach that w					ne class label for erried, Income =		