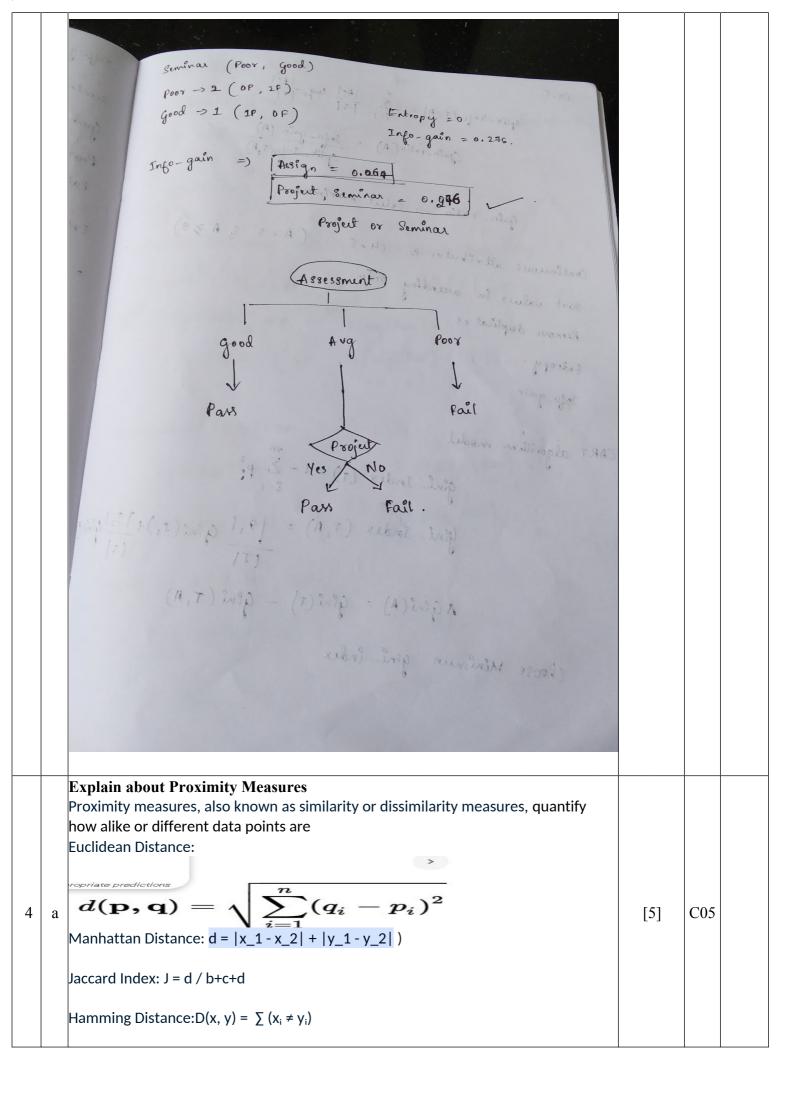
USN					



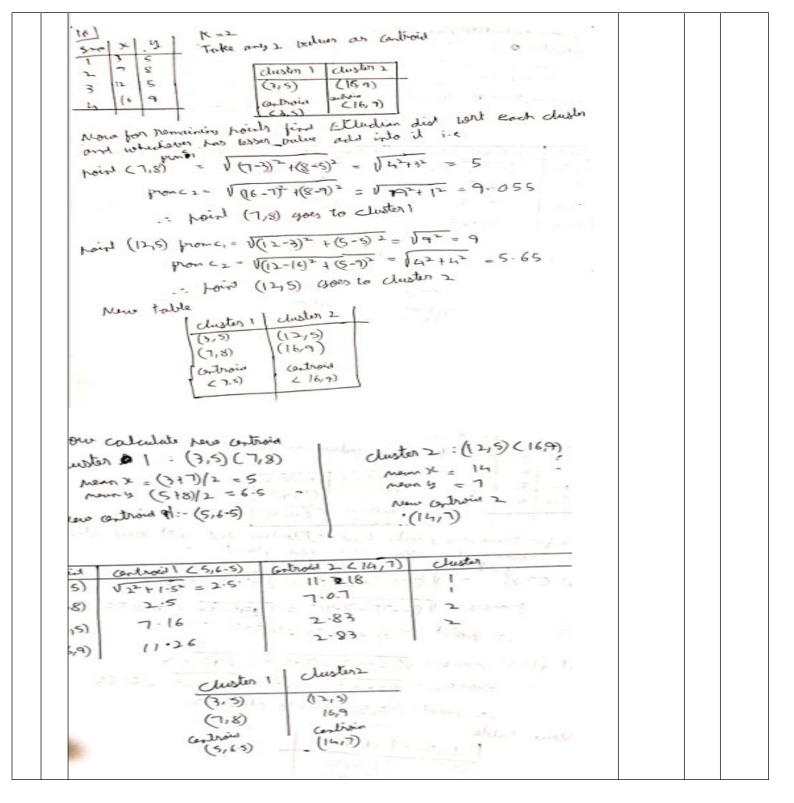
	Machine Learn	ing				Sub Code:	BCS602	Bran	nch:	AInD	S
ate:	Durat	tion: <b>90 mi</b>	nutes	Max Marks:	50	Sem		VI		O	BE
		Answe	er any I	FIVE Question	<u>ns</u>				MARK S	CO	RBT
th va Gi in	k = 3 g1. no  2 2 4 5 6 4 8	Geof individuation is a discretaning Dataset  GPA  9.5  8.0  7.2  6.5  9.5  3.2  6.6  5.4  8.9  7.2  (GPA - 7.8, No. Classifier  (GPA - 1.2  GPA - 1.2  GP	o. of proj	ts based on GPA variable that take  Projects Done 5 4 1 5 4 1 1 1 3 4 ects done - 4), us  projects done  ojects done  A  A  A  A  A  A  A  A  A  A  A  A  A	Yes Yes No Yes No No No No Yes Yes A No Yes Yes A A	training set to continue of $\sqrt{(2.2-3.8)}$ $\sqrt{(3.2-3.8)}$	distance + (c-4) <sup>2</sup> + (4-4) <sup>2</sup> +	et	[7]	C03	

			single depen	dent variabl	e based on one		
independer	nt variable. ( 1	l Mark)					
Polynomial	Regression:	Models non-	linear relatio	nships by ac	lding polynomia	al	
terms to th	e independer	nt variables. (	1 Mark)				
Activations A neural neinput, hidde which dete Marks) Dia  Types inclu output., reclanguage, a pattern recinput data.  Advantage: ability to le handle nois to new info  DisAdvanta computation data (1 Marks)  Activations  Activations Sign Rel	Used in ANN. Etwork is structen, and output rmine the streagram (1 Mark de feedforwat current: Design and convolution ognition. Use (3 Marks)  s: Artificial New arn complex re sy or incomplex formation, and onal costs, pot ornal costs, pot orna	etured as intent layers. The ength and infok)  rd: where in gned for sequence for sequence for sequence for sequence for sequence for sequence for the ential for over the entire for ential for over the entire for ential for over the entire for ent	erconnected se layers are fluence of conformation fluential data, etworks: Speal layers to learn interpretable erfitting, and ivation. Eivation. 2 Marks)	layers of articonnected innections between times and as times ecialized for arn hierarch nerous advarocess infortomatically a data. (1 Mility (the "blathe need for a the n	ack box" nature or large amount	biases, s. (2  input to ral ing and om ing their lel, and s, adapt [8+2]	C04
1.	Good	Yes	Yes	Good	Pass		
2.	Average	Yes	No	Poor	Fail		
3.	Good	No	Yes	Good	Pass		
4.	Poor	No	No	Poor	Fail		
5.	Good	Yes	Yes	Good	Pass		
6.	Average	No	Yes	Good	Pass	[10]	C03
7.	Good	No	No	Fair	Pass	[-3]	
8.	Poor	Yes	Yes	Good	Fail		
9.	Average	No	No	Poor	Fail		
10.	Good	Yes	Yes	Fair	Pass		
1						1	1 1



	b	Minkowski Distance: $D(x, y) = (\sum  xi - yi ^{2})^{n}/(1/p)$ Consider the following dataset in Table 5.11 where the week and number of working hours her week spent by a research scholar in a library are tabulated. Based on the dataset, predict the number of hours that will be spent by the research scholar in the $7^{m}$ and $9^{m}$ week. Apply linear egression model.  Table 5.11: Sample Data  (Week)  1 2 3 4 5  (Hours Spent)  12 18 22 28 35  (Hours Spent)  13 4 5  (Hours Spent)  14 3 4 5  (Week)  (Hours Spent)  15 4 3 4 5  (Week)  (Hours Spent)  16 12 18 22 28 35  27 4 66  4 29 16 112  3 4 66  4 29 16 112  3 4 66  4 29 16 112  3 4 66  4 29 16 112  3 4 66  4 29 16 112  3 4 66  4 29 16 112  3 5 3 3 4 5  4 6 6 112  3 5 3 3 5 145  4 6 6 112  3 5 3 3 5 145  4 6 6 112  3 6 6 6 112  3 7 7 8 15 8 16 17 8 18 18 18 18 18 18 18 18 18 18 18 18 1	[5]	C03	
5		Take a real-time example of predicting the result of a student using Naïve Bayes algorithm. The raining dataset T consists of 8 data instances with attributes such as 'Assessment', 'Assignment', Project' and 'Seminar' as shown in Table 8.17. The target variable is Result which is classified as Pass or Fail for a candidate student. Given a test data to be (Assessment = Average, Assignment = Yes, Project = No and Seminar = Good), predict the result of the student. Apply Laplace Correction if Zero probability problem occurs.	[10]	C04	

S.No.	Assessment	Assignment	Project	Semi	nar	Result	
1.	Good	Yes	Yes	Good		Pass	
2.	Average	Yes	No	Poor		Fail	
3.	Good	No	Yes	Good		Pass	
4.	Average	No		Poor		Fail	
5.	Average	No	No	Good		Pass	
6.	Good	No	Yes	Poor		Pass	
7.	Average		No	_			
8.	Good	Yes Yes	Yes	Good		Fail Pass	
Sus (2)	1 Good 2 Avg 3 Good 4 Avg 5 Avg 6 Good 7 Avg 8	9 No 9 No 9 No 9 Yes	o o o o o o o o o o o o o o o o o o o	Yes No Yes No Yes No Yes No	Good Poox Good Poox Good	pars fail  pars pars fail	
A A A A A A A A A A A A A A A A A A A	M Jelikel	4/5   Prob 1/5   1	(Jui) 7/3 3/3 Jag Mat	Assign Pass Yes 2 No 3	Jail 2	2/5 2/3 3/5 1/3	
program Gro A Proj Proj award.	M dikel  Tow fail Par  Jan  M Jakel  Tow fail Par  Jan  Jan  Jan  Jan  Jan  Jan  Jan  J	1/5   Prob- 1/5   Prob- 1/5   Gent   Gent	(Jusi)  7/3  3/3  Joseph Mat  minus Pars Je  shood 3  poor/ 2  2	Assign Pass Yes 2 No 3  Vitalih Vil Pass 1 3/5 2 2/5	1 2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	2/5 2/3 3/5 1/3	
program Gro A Proj Proj award.	M dikel  Tow fail Par  A 1 3/5  2 2 2/6  The following data show	1/5   Prob- 1/5   Prob- 1/5   Gent   Gent	(Jus)  7/3  3/3  Joseph Mat  minus Pars Je  shood 3  poor 2  k-means algorithm	Assign Pass Yes 2 No 3  Vitalih Vil Pass 1 3/5 2 2/5	1 2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	2/5 2/3 3/5 1/3	



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