PA28 Soln LY ANN of or paint of the state of the ML wha god is an antificial numme? others An artificial parone is a mothernotical func ford models billogical numme in an antifi-All. la hural n(w. (ANN). It is a tiny Parat of a computer system that taxes i/p does some calentations, & gives an opp, similar to how a brain cell works. (diagram)-pric 2) Resmibe the multipoint crossours for a ame nt problem. [Done] of differentiate the firety sets for the triangular, & trapitoidal membership functions. the degree of belonging for class within the eram ky afterness of firty sets on the breis on the & forpi mf: load feature 1 m 10. of 4 (9,6,1,2) Panameters 3 (a, b, c) I shape Single PRay Flat-top (thanizoid) (tryon gre) "Complexity Slightly more simplers, fewers Panameters Broders vounge of Application sharp, single-point fun memberskip. focus

4) compane the furtifien & defurtition of a furty inference system.

1) It Converts comsp ilp vals: into fully sets (cm/ 82 hand, faty

ily an FES, it, input intentre for fratitying actionable reque the system's input.

illy It's direction is Comist to futty. in comsp 1/p data 15

given os ilp.

by technique used -MFS ( fm, trace), gruss

vi) It's key franc is enabling heasoning with linguistic vamables.

futtefier Defitition

1) It con vests fings O/P sets into a crisp olp val.

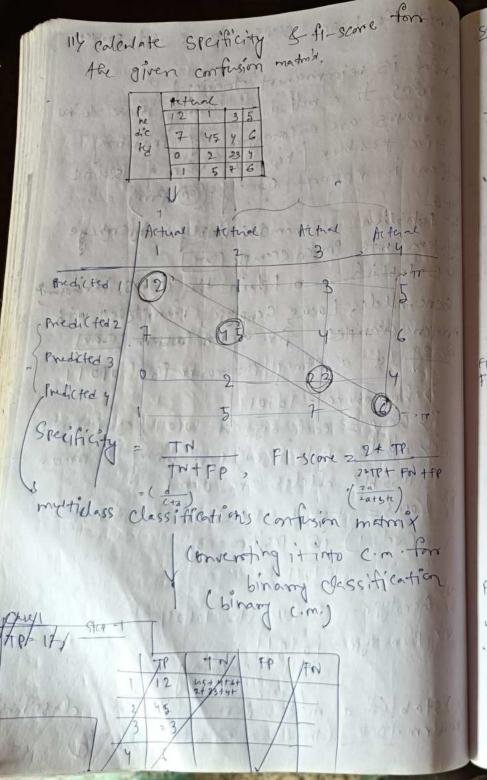
isy out let intenfan In PIS. IN It's & direction is fully to comsp.

is futty op sets from Bry is given 1 03 0/p

De gerhnitue used. Defutification methods (centroid WAV, mean of maxima,

1 It's key func 15 facilitating Prouted decision-making Otrol.

ghroit the basic steps for a ont problem some what is reintmanent, toxing? It refers to a method of learning where desired chariours are encouraged by Providing sitter ted bux henands when a specific tion & lestoned country (00 12m) st Establish a mandari fully interprete sistem with Proper example. [ Pre of Establish a a Explain the terrors, chromosome? cience, Allele, Locus, Genotype, phenotype" with proper examples for a att Problem. [Box] by ef let a string [ chromosom is = 101011 1) chromosome = 101011 in here = each digit of 101011, egz1 on o Tily Allele = (Not of Jene) for brang chromo. possible alleles are on if Locus = tot the locus of the 3rd zero (vd=1) is position= 3 Y henotype = the flue sto 10/011 vi) Pheno type = 10 10 11 encoding Y Establish a mod for a 3-chass classification Problem. Dare (from Data Si, both algo (meg)



Steel the TP of the State of the stindage of
12 2 3+4+5+9+12 7+0+1=8 1+315=9
2 45 12+3+5 + 9 +4++C+ 1+2+5=8 1+4+6=1)
2 23 12+175+ 3+4++ 0+2+4=6
6 12+1+3+ 5+1+4=15 175+7
G
: Specificity of 1 = 1021 (to (2)
2 2 El - to 1
$3 = \frac{9+8}{88+19} = 864$
$F_1$ Sine of $1 = \frac{2+12}{2+12+8+9} = 59\%$
3 2+45+8+11 831.100 P31.100
2+6 2+6 2+6 +15+13 = 0-3 -).

If maximite the function, few. 242+94+1, ale 21= 9,11,13, 16 With Colponisone Site out such that is selection operation (Rank selection), ity uniform aussorer, (it) up to 2 Iterations. relection (Rank selection) , civitial) fin String Population | 20 no. 010010 406 0-21 (304) 584 0.3 01011 91101 0.41 1.64 I fry = 1930 (total fitnery) 1. ( = fin) A 12 bound (E.C) 10010 51=011010 52 2011010 54=010010

1	1) Coossores ( Writzam)
7	
	51 = 0 1 1 0 1 9 S3 = 0 1 0 1 1 P
ı	51 =01 1 0 1 9   S31 =01 0 0 1 p
	5,0010101000000000000000000000000000000
4	(ii) Calor the table again for scot and of or.
	Holy Brahmy roll problement & to problem
	oft premin to prof Fill A
	Str. 6-8em N to 10.1 F.C A C
	5. 1 = 1744 0.311.
	521 01000 13 7794 0.31 1.23
	010(10) 11 406 0.16 0.63 1
ı	Sy 010(10) 11 58 (0.16 0.63) 1
ı	7fa) = 25+8
ı	
ı	any ten = 644.5
1	St. D. L. L. C. L.
ı	52/20/00/
ı	$S_{1} = 0[0]$ $S_{1} = 0[0]$ $S_{1} = 0[0]$ $S_{3} = 0[0]$ $S_{3} = 0[0]$
	1 = 0 10 11
	it 2
	off popula Iten PilEil Are Ifon=25tg
	Sil 01101 13 704 0.31 1.23 1 ang tra) = (ny. ]
	Sur (Same esem)
	01001 9 406 0.16 0.63 1

.. the best val. of n after 2 itemtion = 13 (chromose 201101) with fitness val = 104

an-c By considers the fatty set small = of 0/0+ 9/2 1 1/3+ 0/4} & negative - g olit 0-7/2+1/3+ 0.7/4+0/5} & the following fully rule: "Rule 12 If it is small . & y is negative then I is law Find the thing strength of Rule 1 when x = 3 & 7 = 2 where firsty " AdD" Operation 15 the minima m operation. What is ELITISM Small = \$0/0+ 0/2+1/3+0/4}

\$751 regetive= 50/1+0.7/2+1/33+0.7/4+ Rule1: If n is small by is negative 5} then 7 is low

fren, n=3, y=2 & frety AND " oferation is the minimum oferator.

h= 3, compag. I Finding the member ship value of ng y in the respective firsty sets-Smu(3) = 1 > hegative (2) = 0.7 114 Apelying AND orenations =

small (3) AND negative (2) minimum (smalls), regative(2)} minlmam { 1,0.4}

: Flinding Strength is + 0.7

LITISM - In the content of evolutionary agos, elistism is a strategy, where the best individuals from the cument population are generated quaranteed to be included in the hext gene pation. This ensures that the best solutions found so fans, one not lost & can controbute to the search for even betters such in furth future generations. 3) what is arradient - Descent? Drow a very clears 4-3-2 AMN orackitecture with explaining all its components. what is a self-organizing shoodient-Descent - It is an iterative ortini -tation also used to find the minimum of a function. It works by repeatedly adjusting the panameters of a model in the direction of the negative madient, that indicates the direction of the steepert designst 1/p logen

hinz, hy hy = ip feature relitors

1,02 = output class

hy, hiz, hiz = lidden rodes

N = weights

UK = Processing rode

b = bias

P() = Activation func [Q(x)]

[X = input]

his = 9(mi) = tanh(mi) [ say A F= tanh(x)]

= tanh(mi) [ say A F= tanh(x)]

= tan(Min Mit Wig + N2 t - - Min + My)

= out one]

Teg, 019, 112 ux + b (pt box)

= 21 \* hut wage hiz + was \* his to

01 = (1 (71") = tanh (71")

= tanh (wai \* his)

= outrome 7

The legen - the 1st layers of Ann, consisting 24 numers ( nodes - Forth nodes are fortune. It layers necessary data.

Hidden lyen - the and layer, consists 3 nodes | numbers. It proceeds i/p data from i/p layer.

the final layers, consists of 2 nows.

It knowled the final output of
the final output of
the final of is actual ofp
not predicted ofp)

reights - It is the connections by nodes in diff. layers. the values of we draws lie by walls. are adjusted during training.

Activation fune-they introduce run lineamity into the n-n, allowing it to learn complene parterms.

Bigs - A.F. contains some comment to Stop it a Smooth val. is added to the processed hyp (he), that is called bias.

of Sofm no self-onsaniting feature map It is also known as Rohonen map. It is a type of hu neural n/ w that learns to represent the 1/p data in a lovep dimentional space, while Preserviba the topological relationships bla the data Points. 14/ what is clustering? what are the main Panameters for a good Consterning taknique what are conventional & fully get theories? Define uniform chossover single point Chossoven in GA. [Done], [due] main Papameters for god Constanting 1) No. of clusters ( too few clusters = overgenera - Martin, too many 2 tragmentation) i) Distance metroic (enchidean, man hattan ety (1) clustoming algo (choosing the mosh clustering algo is very ( parends on data & desired attorne) & convention of set theory - there, an dement eithers belongs to a set on it doesn't. This is binary classification.

FAZZY Set theory - It allows for Pantial membership, where an element can liding to a set to a centain digner this is more flexible & can handle uncentainty & ambiguity better. 15) what is FCA & Why is it important? Describe each step of RA by considering a propen example give some Real time APRICA tem of neural potunes. s red time applications of NA ily Health cane natural language Processing ill speech reagnistion in Facial necognition VI computers Vision & DIP( Disited Frage) vii) See social media Processing VX) Deep learning x) Frank defection Hat thy is naine Bayes so naine 1961 you Came to know that your model is suffering from low bias & high variance. which algo should you use to tackle it? why? (c) what do for understand about Type I & Type II enoms ? (d) what is non linear physitication Supervised learning? Fxplain with on

Obone 9 19 andles 111 a) Naire Bayes is called 'naire' as it makes a strong assumption took all features are conditionally independent Tiren the class label. this means if assumes that the presence on absence of a particulars feature doesn't influ -ence the presence on absence of in hed-world Scenamos. by TO tackie low bias & high vaniance one s we should use (a regularition method on ensemble method like RF or Random forest on Gradient Brosting AS these methods help to hadence overfitting, that is the cause of high variance, while still maintaining low

variance, while still maintaining low bias.

dy Nm. linear classification is a type of supervised learning where the decision boundary bin classes is not a strained straight line. For eg, a SVM with a non-linear remel such as FBF (Pardial basis fune), tout an Cheate Complex decision boundaries to

seperate date points belonging to siff course. 16) Describe spe generative & distriminative m. l. technitues. suppose a genetic algorithm uses chromosomes of the from 2 = about of the with a fixed tength of eight genes. Jack Jene can be any day to the of s. Let the fitness of individual 20 be contented as: fin = coto) \* (ctd) + cetf) - (g+h). ed the hitfal formlation consist of 4 & individuals with the following Chromo some S: xy= 7 24135 32 372 = 97 12 16 al; x3 = 53 22 1285; Ny = 71 85 24 34. Use the tallowing (i) Franke the fitness of each individual, it cross the fitnes fitest 2 individuals using one-point inussovers, at the middle paid, (ii) Bralhate the Attness of the newsprulation with the best "4 thromosomes (2 old & 2 new) (i) person (i) & to 11) upto 3 iterations. Generative ml techniques of fours on learning the understying patterns of data to create new data instances that resemble the original data set . It often uses the unsuper brised learning for training. Discrominative ml. technitury It alms to distinguish bin diff categories of data & Promardly used for classification toos tike + It often uses supervised leaving for the training

fin) = (a+ b) \* c(+d) + (c+4) - cg+ h) f(m) = (1+2) \*(h+1) + (3+5) - (3+2)= 48 t(n2)= (3+7) @(1+2) + (1+6) - (0+1) = 54. fix3)= (5+3) \*(2+2)+(1+2) - (8+5)-22 firm= (7+1) \*(8+5)+ (2+4) + (9+4) = 97 185 2494 72:3712 1601 1: 71851601 n2: 9712 2494 1:7185 1601 12: 9+12 24 741 53771285 72413532 532212851 f(x,1)= (++1) \* (8 +5) + (1+6) - (0+1)= 110 f(121) = (9+7) 2 (1+2) + (2+1) - (9+4)= 41 fing') = (7-12) = (4+1) + (3+5) - (3+2) 2 48 fch(1) = (5+3) + (2+2) + (1+2) - (9+5) 2 22

V/ 5+ = 1 + 10 1 + ( 2+1 ) + ( 2+2 ) ( 1+1 NULL B ( 3 & B) - (00 H) + (03) 4 9 1:71851601 h,": 7(85 3532 (new) -(h/1)= (++1)\* (8+5) + (3+5) - (3+2) = 107 (m2h) = (7+2) x (h+1) + (1+6) - (0+1) = 51 f(h3b) = (9+7) + (1+2) + (2+4) - (9+4) = 41 (Chus) = (5+3) x (2+2) +(1+2) - (8+5) = 22 hus = (114) - (111) (11) (11) (11) 2, 4: 71853532 m2h: 7241 1601 21, 111; 71851601 (old)

fry") = (7+1) (8+5) + (1+6) - (0+1) = 10 f(1)") = (++2)\*(4+1)+ (3+5)-(3+2)2 48 f(h341)=15+7) x(172)+(2+4)-(5+4)=41 fchy") = (5+3) \*(2+2) + (1+2) - (8+5) = 22

n.111: 7185 1601

21"; 7185 35 3 2 (new) huis: 53221285 new: 7241 \$601 (new) hu": 53221285 f(h,1")= (7+1) + (8+5) + (3+5) - (3+2) = 107 fhillz (7+2) \* (+1)+(1+6) - (0+1)= 51 f(131)= (3+7) + (1+2) + (2+4) - (3+4)= 41 t(41)= (5+3) \* (2+2) + (1+2) - (8+5)= 22

new house it when to the same. if it. I s when there when be a TOP continion sly to try to find out the neumeric

Data Rithoressing if Permone holsy data (outliers)

row data into a crean [e] heigh 6.11, funget to give is, so

suppose then the height-611th

this is outlierd potte Data imputation (missing value this is outsien)

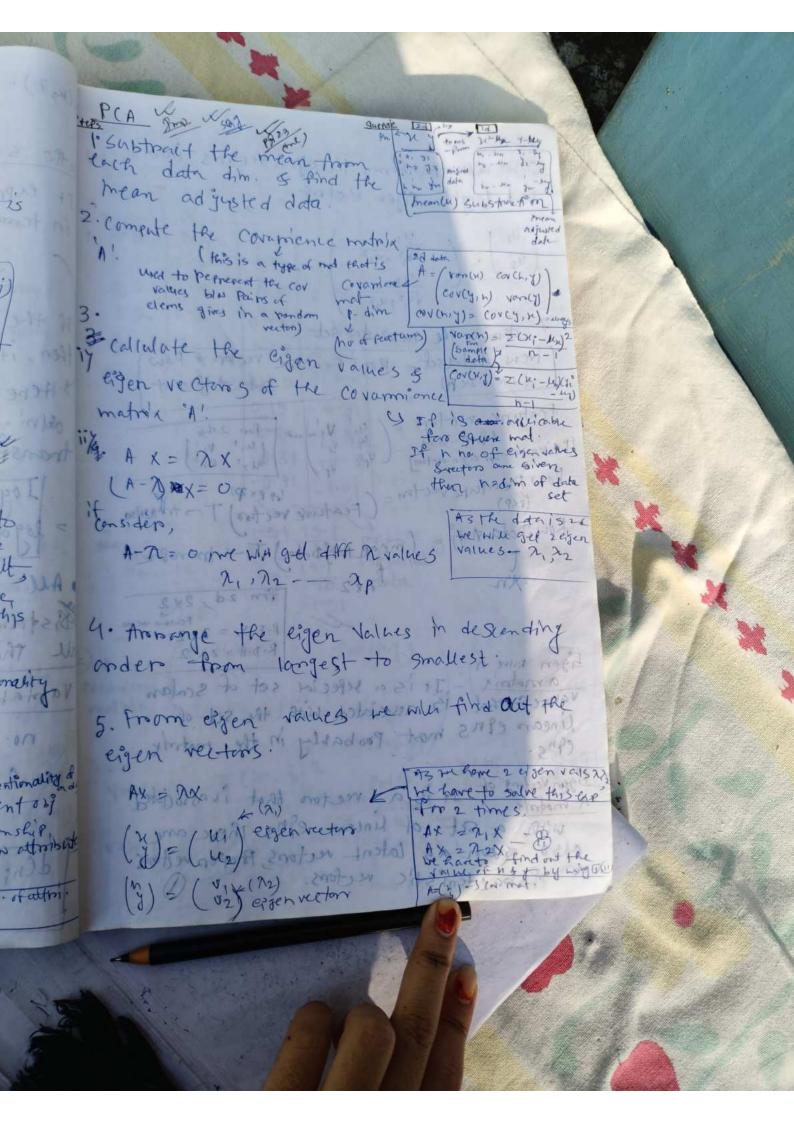
[we to pestimate the values of the missing taples , we can apply in various statistical computation] in simentionality reduction (Faature extraction) (attrobutes)

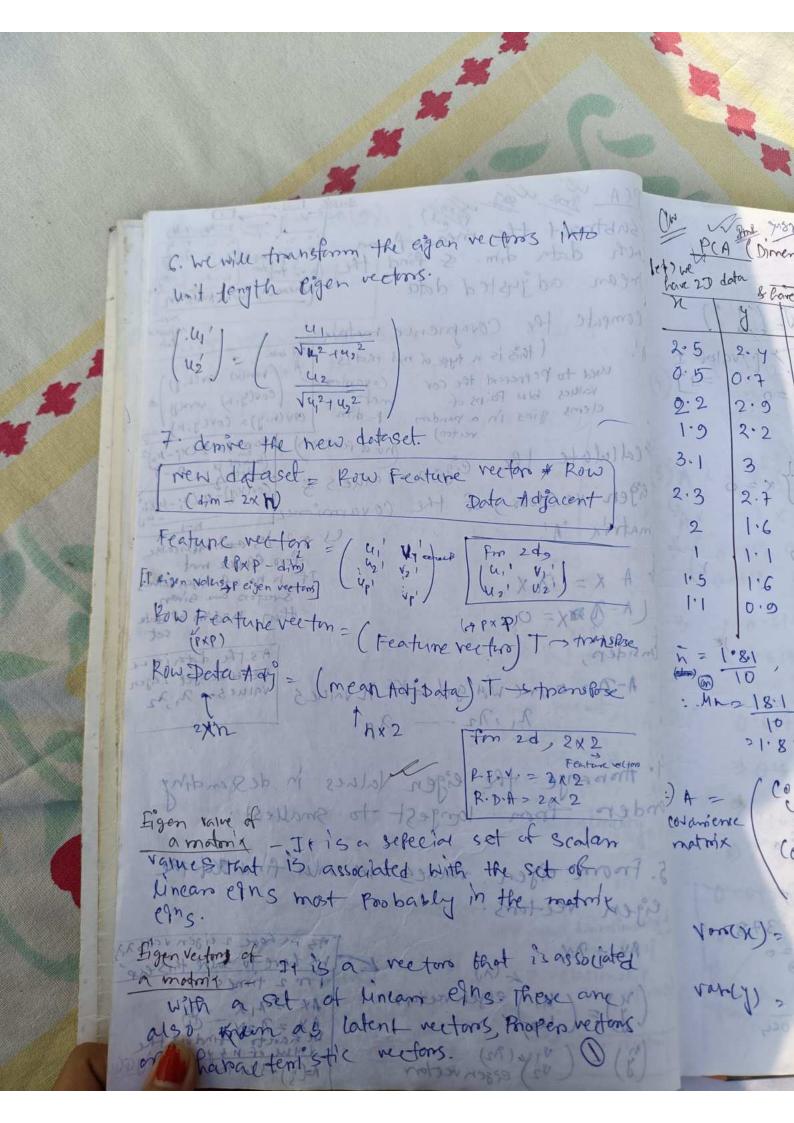
then Pyyys them! model fails to other us the desired he sult. this problem is N= auddinar rate x1 = updated value called curse of dimentimality. This x; = x; - X min can be salved by dimensionality reduction ore F. For F.S. I've will remove the very less imp attribute / feature ] that wie not give any impact to the terriget citybuter 11/ Standalod Scale We will try to find out the less imp feature Franka for normalization & with homore it this is called feature Schaffen (F. 5). There are many algos for this.

We'll try to approximately the minima entermo attrabutes

Into ho of attrabutes to get desired

attrab result [9,10,000 ~ 100], this called feature in we have to pen to the other se execution (F.E). There is an also for it Entrypes of la that is called principal. Component analysis hers I have it will do the same is it. (A)) iv) Data transfer mation ( pata remaditation) rumeric Ceites In ds, diff attributes have diff boarges! If on this we apply the Process it when Continuous Disc give us the desired nesult. So we have to take them are in same range. I + has 2 types - i min -max to ham who will Faternal Patio Scale Scale 1) my 1 11 A ( 11) Standard Scaler (7- score) Continuous - A Try to thanstorm the date in 51 N (0,1) + pange Waty too sout sof ? postupoin by in 6150) was I'm the values Techtebe Stendary Dixnete values in





date But disclos

Compare

Com (prov)

K= The no. of reighbours into that we we to

build ours classification model.

Semied learning -ance-based approach to classify I predict

the grouping of a deter point III

ON Alge 1) stone a (Clacks) 24 For Co 3) seanch let V= 5 input obj 1 N. D. O. P. 7 (versicur) reasest dist cencidean . of flower (versition) [ (= (1,12,13) [(120] 44 Foro ( flower (m1) for each AS the NDOF towards Uzis the most, so of obj 5 We'll considers that unknown obj falls into -org to ( Hord ) Etrabate 000) & 5) The - Cal. the dis blu the U.f. & au other flowing of see, the shortest that blu luf. & K no. of hin charest heighbours), here 5 n.n.

- Amony the N DOF, He can see > £3,3,333 Mg. (demonstration) class Eg-0 200 Datase (n.n.) ic the majournity of the nearest floren Sil B belowly to Us, so that u.f blongs to 3nd Catagory 1 cl3. \( \center{2} = \frac{1}{5} = 0.2, \frac{1}{5} = \frac{1}{5} = 0.2 \) 2 If we have a by ticampte no of hin or 8-5/N the closes we can inchean the 3 value of K & see the same ( May 1) - \$ 3, 2, 3, 2, 13 d, d2 d3 dy dq water det de Gompane de tos if (dited) of (detda), then dat u. K (dred3) y (d2 rdy) 2 then cl2 4 4K

1) stone ale the input deta in the toainingert. 2) For each object in the test set seanch for K nearest reighbours wto the input 05/15 / Pattern using any 4/3 tance material list-(unidean et etc) en 44 Foro Classification with compute the confidence いまし for each classes as Colk where Co is the no. 1,50 of objs among the K-neurost neighbours below sinto 5) The classification fron the 1/P obj is the or flowing class with the heighest confidence (g of binary plassification) Eg-1 2000 51875 Class label Dataset of ettin bute Assim SI proj m pout CAPA ngs Pass 2.2 8.5 Donhin 1935 8.0 2 8 (8.14) 8.5 (avail9) 5 Fail 5-0 5 6.5 PASS -87.2 Fail of 8 PTV 3.8 2-0 et 5.8 1995 9.1 8.9

uy model desiming catagony of muchine learning model similar Unsupervised learing 1885 clusters Sc (usterring 1) suproped learning Possible my Reinforming coment learning - Barons - Brows · ims data - Selosa, vepsicolon, virginica, Potal length, sepal length & width (total Unsupervised Learning we don't know which obj falls into which calagony. eg In above eg dada there will be clusters of 3 types of flowers but we con't disting the that which cluster is of which Acuen. Superised learning Here we basically Town own model, & it there is a animoun obj in the model it the con it talks into. Reinforcement learly Simisufernised learning. Here Step by Step we try to imfrare our me model to get accurate result. If the model is n't string accounte he sult then

Penalize it otherwise give it reward (Save Fg- self driving I'm's data. The ihis data are a data frame of 150 measurements of ims Polol of sepal length of width, with 50 measurements for each species of setosa, 'vensialor's virginia'. Unsupervised learning - It is a type of me that learns from data Nithout human sufer -vision. Unlike apenvised learning, unsitemize m. I models are given unlabeled data & allowed to discovers Patterns & insights Without any expercit quidance l'instruction. supervised learning - It is a category of m. I that uses labeled datasets to train algorithms to predict outcomes & necognite Pattern S. Unlike unsupermised L., S. 1. algos are given labeled training to learn the relationship 51 m the 1/p & 0/15. gold and Reinforcement learning - It is a m.l. training method based on newarding desined behaviours & punishing undesined ones In general, a prinforcement learning the entity being trained is able to represent learn through trial & environment, take retions &





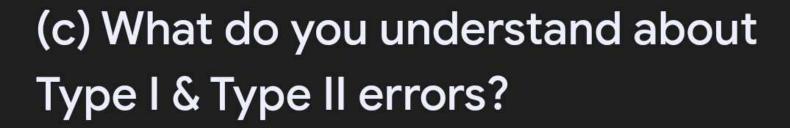


## solution



## 2. Draw a very clear 4-3-2 ANN architecture with explaining all its components.

Component	Explanation
Input Layer	The first layer of the ANN, consisting of 4 neurons. It receives the input data.
Hidden Layer 1	The second layer, consisting of 3 neurons. It processes the input data from the input layer.
Hidden Layer 2	The third layer, consisting of 2 neurons. It further processes the data from the previous layer.
Output Layer	The final layer, consisting of 2 neurons. It produces the final output of the ANN.
Weights	The connections between neurons in different layers. They represent the strength
Are these re	esults Yes No ×



## Type I error (False Positive):

This occurs when you reject a true null hypothesis. In other words, you predict something to be true when it's actually false.

## Type II error (False Negative):

This occurs when you fail to reject a false null hypothesis. In other words, you predict something to be false when it's actually true.