MANJARA CHARLTABLE TRUST Page No. rajiv gandhi instit 'UTE OF TECHNOLOGY, MUMBAI ASSIGNMENT - OI types and Subtypes of madeine learning with examples. of machine learning-Superwised dearning: A hairing set of examples with the correct responses (targets) are provided and, based on this training set, the algorithm generalizes to respond correctly to all possible disputs. This is called dearning from examples superun ed Jearninge Huis is a type of problem where response values are predicted. predicting the price of house in a ualue of stock. Clavification: a dupe categorical rain toda today or not.

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| 20 | Usuperuised dearning: Correct responses are not proudded, unstead the algorithm trues to adentify similarities between the apprist that have something |
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| | moulded instead the appointmentines to identify |
| 4 | similarities bothood the inputs that have |
| | something in common are categorized thoughter. |
| | something in common are categorized dogether. Then, statistical approach to unsuperwised dearning is known as density estimation. |
| | in troup on density orthogon |
| | W NDWI) US WEISTY (SITTIMION). |
| AT. | 9) <u>lustering</u> : In this type of problem, similar things are grouped together. |
| T H | trives are excuped together. |
| MA A A | autigs the grouped regards |
| le test | example: aiun pous articles cap be dustered |
| | example: given news articles can be dustered into different types of news. |
| | and allowed and and and and and and and and and an |
| | - duning the same |
| 7/2 | Resnjorcement dearning: Huis is somewhere between |
| 00 | supply and unsineralised dearn con |
| | the algorithm gots told when the answer w |
| | Kern forcement rearring: dus as somewhere between superuised and unsuperuised dearning. The algorithm gets told when the answer is wrong, but does not get told how to correct it. It has to explore and try out different - possibilities until it works out to got the |
| - , | yt has to explore and try out different - |
| | acceptibilities until at works out to got the |
| | possures who ha |
| | answer velghto |
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|------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| 20 | Explain entropy, information gain and gint undex unth their formula. Also define their rule in constructing decision tree. |
| _ <u> </u> | constructing decision tree. |
| lo | Entropy: Entropy is a me commonly used measure in information theory that characterizes the (im)purity of on arbitary collection of examples. |
| | Güren a collection 8, containing positive & negative examples of some target concept, the entropy 8 welative to this dassification ús, |
| | Entropy (8) = $-p_{\oplus}\log_2p_{\oplus} - p_{\ominus}\log_2p_{\ominus}$ $p_{\oplus} \rightarrow p_{\oplus}p_{\oplus}p_{\oplus}p_{\oplus}p_{\oplus}p_{\oplus}p_{\oplus}p_{\oplus}$ |
| 9 | One unterpretation of entropy from information theory is that at specifies the minimum number of tits of information needed to encode classification of an overlay member of 8. |
| | Entropy (s) = & -pilog 2pi, un general. |
| | unse dany Ecahon). |
| Č. | La ather below, and to be worthing on the |
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| 2- | dolarmahan agin: |
|-------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| | <u>dyformation gais</u> : |
| | Information gain is simply the expected vedution in entropy caused by partioning the examples autoraling to this altribute. |
| Alfrance so | The information gain, your (SIA) of an attribute A, we lative to a collection of examples s, is, 46in (SIA) = Entropy (S) - E Sr Entropy (Sv). |
| è | where, solvatues (A) -> solvat all possible ualues for altribute A. su -> subset of 6 for which A has value v. |
| 30 | Gini undex: The um purity (or purity) measure using an build— and dewlind tree. un ta (larrifleation and Rigremium tree (CART) un Gini undex. Gini (p) = 1 - ξ ρι ² i ∈ 91,2, j ρι → fraction of Joms labeled with class i un the set. |
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| 30 | Han logistic regression in a dassification technique? What is the significance of sigmoid function? Logistic regression is one of the basic and p algorithm of some a classification problem. |
|----------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| . F. | what is the standicione of stamoid Junction? |
| | Logistic regression is one of the basic and a algorithm |
| | el soure a classification explore |
| | A problem in sideofficial as dessilication alapsithm when |
| | und energiables are configures un catrie and |
| | A problem in identified as classification algorithm when independent variables are continuous in nature and dependent variable are in catagorical form i.e in |
| | 1000000 (11KO 1000) HVO 0100 00000 (10000) HVO 010000 0100000 0100000000000000000000 |
| <u> </u> | Unlike linear regression unlich outputs unificuous number |
| | values donstic marcosino pransforms ille nutout using |
| | the Logistic signoid tuncker to welter a probable- |
| | Unuke lipoar regression, which outputs confinuous number values, logistic regression transforms its output using the logistic sigmoid function to veturn a probabit - lity udue which can then be mapped to two or |
| | more d'isurle classes. |
| | |
| | |
| | 1 (C × 2) (X 2 1) |
| | Sigmoid function - |
| | |
| | In order to map predicted values to probabilities, we use the sigmond function. The function maps any real value into another value between 0 and 1. |
| | the sigmond function. The function maps any real value |
| | unto another value botween o and ! |
| | $S(z) = \frac{1}{2} \left(\frac{z}{z} \right) = \frac{1}{2} \left(\frac{z}{z} \right)$ |
| | 1+e-Z |
| | It gues the output as a comutional probabilities of |
| | the productions. |
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| _ | ALVERTANCE OF FLE CONTROL OF THE PROPERTY OF |
| | Hilland - N |
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| | = Tree |

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| 100 4° | Peyform linear regression using wast square | | | | | | | |
| | method on the following too data. If x=16, find Y. | | | | | | | |
| First Hills | in butter it is a first to the first the state of the sta | | | | | | | |
| | X(Input) Y(output) x2 xy | | | | | | | |
| 75 W TE | 3 9 925 | | | | | | | |
| | 6 - 33 - 36 - 198 | | | | | | | |
| i a | 8 m 37 64 296 n=7 | | | | | | | |
| | 12 45 144 540 | | | | | | | |
| er im a | 15 53 225 795 | | | | | | | |
| Mills 1 | 20 57 400 1140 | | | | | | | |
| I A H | 22 67 484 1474 | | | | | | | |
| 1 | 86 317 1362 5368 | | | | | | | |
| | | | | | | | | |
| 1 | By loost square method, $b_1 = \underbrace{\Sigma XY - (\Sigma X \Sigma Y)/N}_{\Sigma X^2 - (\Sigma X)^2/N}$ | | | | | | | |
| | | | | | | | | |
| | | | | | | | | |
| | | | | | | | | |
| 5 5 7 1 1 1 | b1= 5368 - (86×817)/7 | | | | | | | |
| -to the | 1362 - (86)2/7 | | | | | | | |
| | 61= 4.824. | | | | | | | |
| | 60= EY - 61 EX = 317 - 4,824×86 | | | | | | | |
| | n a | | | | | | | |
| - | bo = -13.98 | | | | | | | |
| | | | | | | | | |
| | $y = -13.98 + 4.824 \times$ | | | | | | | |
| · . | when n = 16, y = -13.98 + 4.824x16 | | | | | | | |
| | y = 63.14. | | | | | | | |
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| 5. | Apply logistic regression algorithm to classify Jollouning data. Also find a curracy. |
| | $\begin{array}{cccccccccccccccccccccccccccccccccccc$ |
| | 7.2 2.7 1 6.5 1.8 1 7.6 3.5 1 |
| 2) | For $x_1 = 1.64$, $x_2 = 2.63$ y = 1 $1 + e^{-(bo + b1x1 + b2x2)}$ |
| | $y = 0.1212$) For $x_1 = 3.4$, $x_2 = 4.1$ |
| <u> </u> | y = 0.10 $y = 0.10$ |
| Û | y = 0.916 |
| (კე | For $x_1 = 6.5$, $x_2 = 1.8$ y = 0.944 |
| u)_ | For $x.1 = 7.6$ $x2 = 3.5$ $y = 0.861$ |

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| | | 0.121 | | 0 | | | |
| | | 0.10 | | 0 | | | .) |
| | | 0.91 | 6 | 1 V | 14 17 | 3 | |
| | | 094 | | | -0.1 | 1 | |
| | | 08 | | 1 3 | 1 | | |
| | | 0.6 | | | | | |
| , | | Acum | au = (10) | rect predicti | on/no el r | oredictions) | *100 |
| | | 11001 | = (5) | 5)*100 | 4 | 1,2 | 3 |
| | | | = 100 | | | | |
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| 6. | Ca | onsider | Inllowir | ng data. algorith | find room | ot element | of the |
| <u> </u> | h | 00 11 | sing ID3 | algorit | m · | | <u> </u> |
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$$E(s) = Grue) = -2 lg_2 2 - 2 lg_2 2$$

$$E(s = hrangle) = -1 lg_21$$

$$\frac{I(form) = 4x}{6} + \frac{2x}{6}$$

For attribute colour,

$$yellow(3): +: 0, -: 3$$

 $E(idour= red) = -2 log_2 - 1 log_2 1$
 $3 y^2 8 8 y^2 8$

Elwour=yellow) =
$$-3 \log_2 \frac{3}{3}$$

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| | $\frac{I(\omega our) = 3x + 3x}{6}$ |
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| | (aîn (colour) = |
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| | for attribute size, |
| | Small (3): +:1, -:2 |
| | big (3) : +:1 ,-:2 |
| | U |
| | $E(8 \le ize = small) = -1 \times log_2 \frac{1}{3} - 2 log_2 \frac{2}{3}$ |
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|-------|---------------------------------------------------------------|------------|------------|------|------------|----------|--|
| 70 | Consider Jollowing data, using CART algorithm Jund | | | | | | |
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| | C 1761 | s = target | F/dass) | | | | |
| | No. | Sewrity | sodary | Debt | reputation | risk | |
| | 1. | none | \$0 to 30k | high | bad | high | |
| | 2. | none | 30 to 60k | high | unknown | high | |
| | 3. | none | 30 to 60K | low | unknown | moderate | |
| | 4. | hone | 0 to 30k | low | un known | high | |
| | 8. | none | over 60k | 100 | unknown | low | |
| | G. | adequate | over 60 K | low | unknown | low | |
| | ٦. | none | 0 1030K | low | bad | lugh | |
| | 8. | adequate | over 60K | 1000 | bad | moderate | |
| | 9. | none | Over 60K | low | good | low | |
| | 10. | adequate | OVER 60K | high | good | low | |
| | 11. | none | 0 to 30K | high | godel | lugh | |
| | 12. | none | 30 to 60K | high | 8009 | moderate | |
| | 18. | hone | over 60K | high | 9000 | low | |
| | 14. | none | 30 to 60K | high | bad | lugh | |
| | | | | U | | | |
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| 8. | Define Support voutor Machine, luper plane, margin and support voutors with switable diagram. |
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| | and support notice with suitable digarame |
| 20- | Communication of the communica |
| | Support Veutor Machines: In madine Jearning, syms are suppervised Jearning models with associated Jearning algorithms that analyze data used for classification and regression analysis. |
| | support verd logration module with associated legition |
| | algorithms that analyza data used for classification and |
| | xooxosioo analisis |
| | |
| 1 | Given a sot of training examples, each marked as helonging to one or the other of two categories, an sym training algorithm builds a model (that assigns new examples to one category or the other, making it a non-probabilistic binary clanification. |
| | holossias to one or the other of the categories as |
| | sum beginns apprishen huilds a model that assigns |
| | para examples to one interpril or the other, making it |
| | a poo explosification himani alamilicatione |
| | a none probabasine sale ag a angus |
| _ | A SVM model in a representation of the examples as points in space, mapped so that the examples of the capavale calegories are divided by a clear |
| | as mints up some manned so that the examples |
| | of the apparely caleapties are divided by a clear |
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| Margin: - A margin in a soparation of the to | | JUHU VERSOVA LINK ROAD, VERSOVA, ANDHERI (WEST), MUMBAI - 53. |
|----------------------------------------------------------------------------------------------------------------------------------------|-----------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Margin: - A margin in a soparation of line its the classest class points | At 1 | Hyperplane 8 |
| - A margin in a soparation of time its | in r sv | The optimum hyperplane un the dinear classifier with the maximum margin for a given finite set of learning patterns |
| - A margin in a soparation of line uto | bar. Aris | Margin: |
| Support voctors: | | A margin in a sommhon of time its ithe closest class points. A good margin in one where itsere is ithing he had allows the points to be in their respective classes without crossing to other class. |
| - The vertices that define the hyperphine are the support vertices - The extreme points in the data sots that define the lupperplane. | | - The extreme points up the data sots that define the |