## Assignment 4

9.1	- Explain the intuition behind Logistic Regression
,	in detail. Is the decision boundary Linear or
اجرب	inon-linear in the case of a itogistic Regrescion
1	i model ? Also explain the impact of autiers
	along logistic regressionstand mistors
$\Rightarrow$	Fermine apoce.
مال <sub>ت</sub>	Intuition behind bogistical Regression?
1	decicion boundary ou bo expressed or
	Logistic regression is supervised learning algorithm
	used primarily fort binary destification problems.
	Despite its name, logistic agression is actually
	- a classifications algorithmen not a medicession one
	The invegression the term lighted abecause the
	model estimater probabilities pandiprobabilities
( )	are continuous volves between 0 and 2.
	The code video behind logistic regression is
11	ath atticare want for model the probability
	that a given input belonge to a particular
	states single one linguistic or provides
antoni	This probability is modeled as signoid (logistic)
	function applied to a linear combination of
	sinput a features. 10 million de trogat.
•	o Is the Declaign Bounday Linear of Montlinear
20	To the Declarate Bounday Linear of Non-Linear
	notob site
	To linear begrescion logistic regression the
~o!	and colsion is boundary unis! The arrive to activities
-	This is because the model is fundamentally



TSEC ENGINEERING COLLEGE based jon abrilinder recombination of lingut 1. 2. The signoid Functions transformes the Minear combination into inprobabilities labort the decision bounding of remains linear in the Feature space.
- For iseggy Fort two Feature Misaind Me, the decicion boundary can be expressed as a line! 1- Lagionic regression is appenyised learning agostly molden not without wented to be plinoming boss - Despite its name, logistie negression is actually month you twon to Nondin ear to decision bandaries, and agourson bextend abogisticoi regression Thy adilidading polynomiata features or other types - Cofin Feature to the matter with no i time that tagge to the decision boundary can id become honelinear intelline original feature However, the core logistic regression = model itiend birispiralways belinear in dermisirof the input feature Finedian applied to a linear combination of · Impact of outliers on Logistic Regression! significantly different from the majority of significant impact bécause logisticines ession l'observois di parametric modeled si sitti



Q.2 What are the assumptions made in logistic regression! can we solve the multiclass desci-They est than bowed and it is a local to a local to the second of the se This evalencion is done sight outling · Assumption Made in Logistic Regreration! (our) and one-verone (our) entending The observations are independent O. D. Logistich regression ladsumes that withe abservations in the datacet are independent of each nother that is nother observations sishould not come? From repeated measurements of the signification dividual son obe related to each - The entired hinetickership extraposition of the 1900 of the lobel of 2) Thereats no multicollinearity among explanatory variables. Multicollinearity occurs when two or more On explanatory variables over highly correlated to each other, such that they do not provide sounique or independent information in regression model. (D) zoolo svingen entres 11111 3 The sample size - is sufficiently dange To logistic regression assumes that the sample 100 platzer of the dataset if storge enough to draw valid conclusions from the Fitted logistic regression model.



Solving Multiclars, valacilitation problem! . The logistic regression can be extended to solve multiclass alassification problems. This extension is done using multinominal logistic regression or by wing of one with read (OVR) and one-vs-one (ovo) stratergies. Multinominal logistic megressions is the direct extension of logistics regression for multidas classification problems where the outcomes vosiable dan have threet or more ortegosies. Interior uces asoftmax? function hotor generalize logistic regression for multiple relasses. The softmax functions computes probabilities for each class label, and the label with predicted class. soldiers. Fit one binary-logistic regression classifier per clave. For each classin we treat that class was the positive class(12) and all the other classes as the negative class (0). This results in multiple binary classifier. - When predicting, are computer the probability that the sample belongs to leach ches and choose the das with the highest Their or probigibility. some amisularen bilor sonal lebon, whis mote



In the one-vs-one approach, we build a binary dagsifier for every pair of clames. - For each pair of classes, we train a de classifier to distinguish detiren those tuo a dassestably no ment all to bugbus For say problem toolthat tollogogist we create K(K-1) olacellier. . anitopalisanto all of 23 salar "not and isoalo" mest and -Offerton predictioning we apply reach classifier and choose the class that sind the most pairwise ef comparisonal one on parisonal de \$13 Why to is: Logistico regression etermed as I Rogression to estimate probabilities and charifican - 1 - Logistic regression tois alled "regression" even though it is austedictionicallass ificationit because of Tits sorigins and nature to fathe model. In The linear regression wer predict to continous outcome using a linear combination of the a Hinputos Feature lado Po amostuo anto is continuous, which is then mapped to bloomer y = what it we me at -to - sight whom the logistic regression also acomputes all linear combination of input features is but it applies the logistic Function to transform the output into a probability between 0 and 2.



12110	1 10 P (y = 2 10x) 4 = 2 10 - 2 - 13 10 2 4 10 2 4 400 Math
	1 : P (y = 1/x) == 2 (win, +w2 n2 + + wn myb)
	The each poly of classes, we form
الموري	The logistic function convents the continuous
	output of the linear combination into a
	probability is allowing that to ober used for
	classification.
-	The term "classification" refers to the
	Things Hask yoff assigning blabels (0 and 2)
with wind	but ologisticio regnessionio deserribe the mother
^	of calculating the probability of those
	models.
	Logistic regression doesn't directly volosify;
-	instead, it regresses on the features
	to estimate probabilities , and classifiction
aven	missather" steps thigh moceous basterdonen the
	nestimated soprobabilities is in devot
	. Although Hogistic regression is aced for
2 month no	odásisification, ito fite a continous decisión
	Boundaynidance coord a prizer emotion
	The outcome of the linear combination
	is continuous, which is then mapped to a
dham	roange of to to a rueling the sigmoid
	Function.
6090	This continues noutput is a hallmark lot
291199	p tiegressions modelugai de noitanidados
	the legistic function to desperon the
	no o agrecial includadada a atal tuatus





9,4 Can we suce Mean square From às la cost function of formlogistic regression as trustify your ordinamento a de lo acordo ente mossessos Ston smood nakeda APM mand bavingb TNO, Mean & quared Error (MSE) is not appropriate il as a cost function for logistic regression. different for appinisation algorithms lit 1) MSE assumes a linear relationship msE is poimorily used in linear regression, Where the relationship between the dependent and independent variables is assumed to doing beneficience som to storingh sate - 1-It works well in this adontext processe is another predicted include and true trialnes are him siboth continuous praid MSE measures the squared différence between them. With 100-1026 the gradient of the cost finet 2) Non-linearity 1 of the Sigmoid Function > Mysistic regorderson uses the sigmoid function to map the linear combination of the input Features to a probability value. P(y = 1 | x) = 1 1+e-(wTx+b) The sigmoid function is non-linear and bounded between 0 and 2, where MSB assumes the output can take on any real volue.



4200	B) MRE teads to Non- Convex cost Function
YUUU I	=) : When using a the seighmoid function in logistic
	regression, the chape of the cost Function
	derived from MSE often become non-
	coconvex. (32M) cored boroup 2 100/4 , DM .
	Anon-convex costinhunction can apple e it
	difficult For aphimization algorithms like
	gradient descent to Fraductie 3 glabal
	minimismos efficiently or as as as ( )
	where the relationship between the dep
oh	4) In appropriate a Gradient a colith MSR
	=> The derivate of MSE resolideard which.
9200	may inot be sistifable sufor applicating The
9,70	sweights with hate dogistics segression wince the
9	Houtputs are said homeomodite to the dignoid
	transformation, ed energy dib becoupe
	- With log-loss, the gradient of the cost function
	nisonbetter palignold with logistred function,
nort only	recylling in more reffective inight
Lugar	supplientes during optimization com of
\	reculting the more perfective to displife of updates divings optimization and of
	(d+1200)-9 11 = (N12 = 4)9
	(d+16mm)-9 1.1
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DOM	acades, a puro o assurant popular
- Va	us Jetot non fugina afte samusan
+	sed volve.





9.5	Compare Naive Bayesian with Logistic regression plassifier.	
	regression olassifier.	
=)		
	Naive Bayes	logistic Regression
	i) model type is	i) model type is
	generative.	discriminative.
		2) No assumption about
	independent of each	Independence.
	other.	
	3) Model complexity is	3) More complex, allowing
	relatively simple,	For modeling intricate
	computationally efficient	
	4) well-suited for	4) Versatile, can handle
	categorical data, effective	
	For discrete features	categorical Features.
1	and dext classification.	
	and text classification.  5) Highly interpretable	5) Good interpretability
	due to simplicity and	through coefficients,
	the assumption of	indicating the stoengths
	Feature independence.	and direction of feature
		relationships.
	6) Performs well with	6) May require a larger
	small dataset.	dataset to avoid
		overfitting.
	7) Suitable For text	7) suitable for customer
	classification, spam	churn prediction,
	Altering, etc.	coedit scoring.
	/\lambda	
	120	