

Joint Tech Internship Community Program

Assignment 1

SUBMITTED BY:

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CANDIDATE ID: 2024060193

THE GIVEN TABLE:

Make Year	Brand	Variant	Mileage	Fuel	Transmission	Resale
						Price
						(INR)
2015	BMW	520D	80000	Diesel	Automatic	2500000
2016	Audi	A6	92000	Petrol	Automatic	1900000
2018	Mercedes	E200	61000	Petrol	Automatic	3400000
	Benz					
2014	Skoda	Superb	95000	Petrol	Automatic	600000
2020	Benz	E200	35000	Petrol	Automatic	12000000

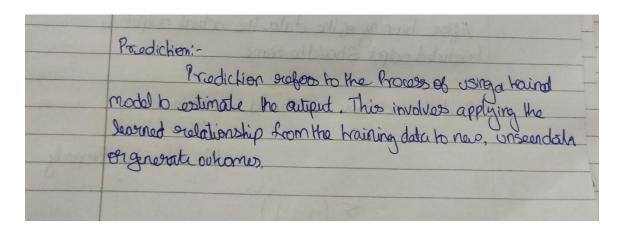
Feature:

From the given table the inputs are Make Year, Brand, Variant, Mileage, Fuel, Transmission. these input determines the price of the car. And price depends on the inputs.

LABEL:

From the given table the Label is the Resale price which is predicted with the help of its feature.

Prediction:



Outlier:

From the given table since there exist of one value which is different from the majority values it is univariate outlier

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						(INR)
2015	BMW	520D	80000	Diesel	Automatic	2500000
2016	Audi	A6	92000	Petrol	Automatic	1900000
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Dictation can be done by the Z-Score if it is \pm 3.29 or beyond

$$\text{Z-Score} = \frac{x_i - \overline{x}}{s}$$

 $\overline{x} \rightarrow mean \rightarrow 4,080,000$ $x_i \rightarrow outlier\ value \rightarrow 12000000$ $s \rightarrow standard\ deviation \rightarrow 4,063,200.71$

Z-Score =
$$\frac{12000000 - 4,080,000}{4,063,200.71}$$
 = 1.95

it is not considered an outlier based on the Z-score analysis.

	The state of the s
	1) Domain knowledge 3) Math Statushia 2) Visualization Two standard // deviction
	2) Visualigation Two standard // Dulliers: Outliers: Outliers are coast that have data values that are very different from the data values for the majority of cases in the data sate.
pand?	-> An outlier is an Observation that is substantially different from the other observation
all redist	egench acuta esperior data analysis
notices skids	Typos of outliers
2011.0217.0	univoriate
-	univariate outlier are asso that have on unusual value bra Single Variable.
Introget -	Universate con be Producted with it
all say in	Z-Score = (i-mean)/standard deissen $Zi = \frac{x_i - x_i}{s}$

multivasiate -> multivociate outliers are cosos that have an unusual combination of values by a number obvariables > It can be detected by the Matalanders Distance (D2) Probability is loss than 0.001 Mahalandois distanci: Dm= V(2-4) TE 1(2-4) Whose Hismon > is covarione man Cronocalination of Z-Scoros to multi-dimensional stace. > Roplace univariate man with multivarite mean -> Replace Standard devotion of the covorience Mahal fun Z-Score $Zi = 2i - 2i - 2i \longrightarrow \sqrt{(x-\mu)}^{\dagger} Z'(x-\mu)$

Training Data:

From the given table assuming that 80 percent of the data is training data.

Make Year	Brand	Variant	Mileage	Fuel	Transmission	Resale
						Price
						(INR)
2015	BMW	520D	80000	Diesel	Automatic	2500000
2016	Audi	A6	92000	Petrol	Automatic	1900000
2018	Mercedes	E200	61000	Petrol	Automatic	3400000
	Benz					
2014	Skoda	Superb	95000	Petrol	Automatic	600000

Test Data:

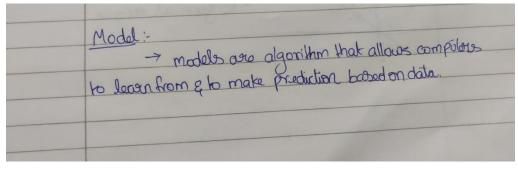
From the given table assuming that 80 percent of the data is training data and remaining 20 percent is Test data.

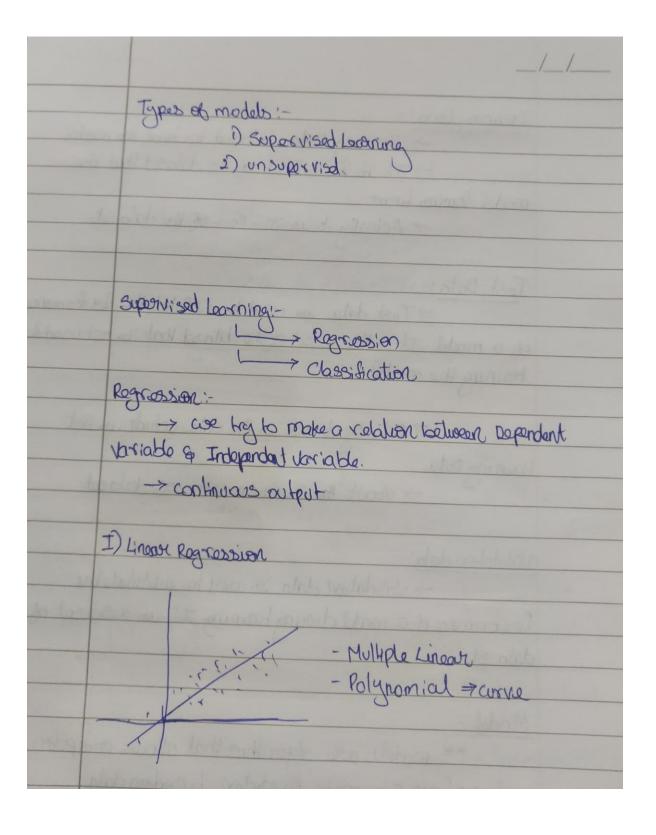
Make Year	Brand	Variant	Mileage	Fuel	Transmission	Resale
						Price
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2020	Benz	E200	35000	Petrol	Automatic	12000000

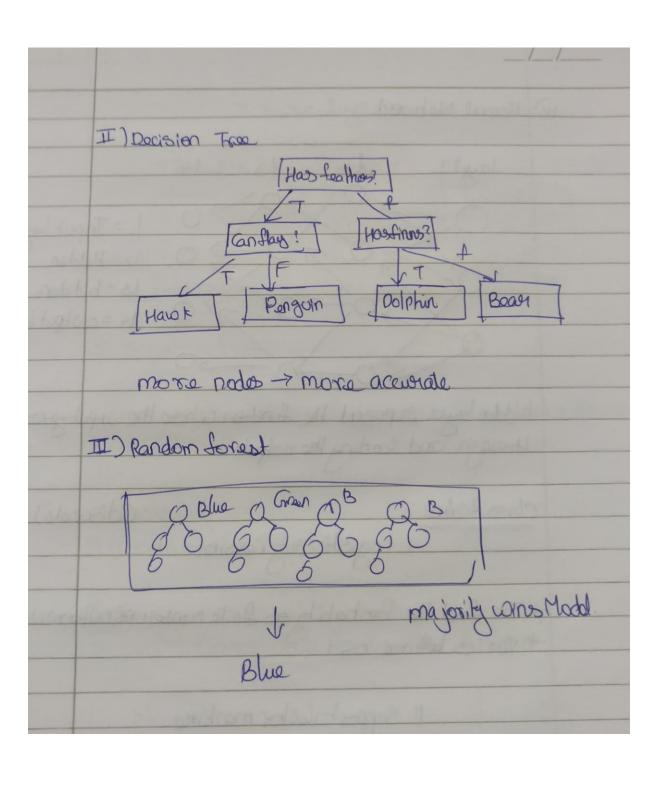
Validation Data:

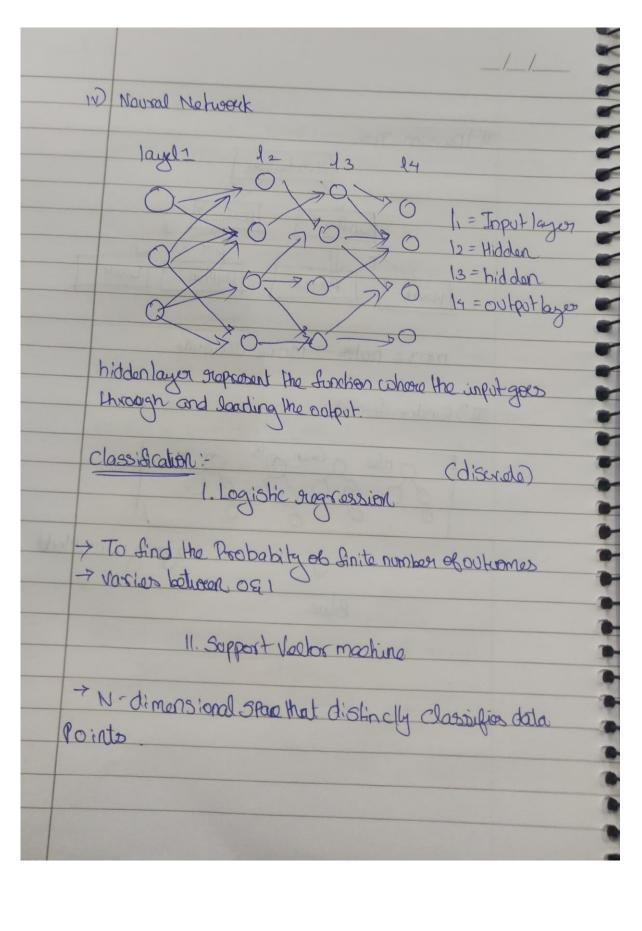
Validation data!
= Validation data as used to sublisher
Performance of a model during training It is a subset of
data sote:

Models:





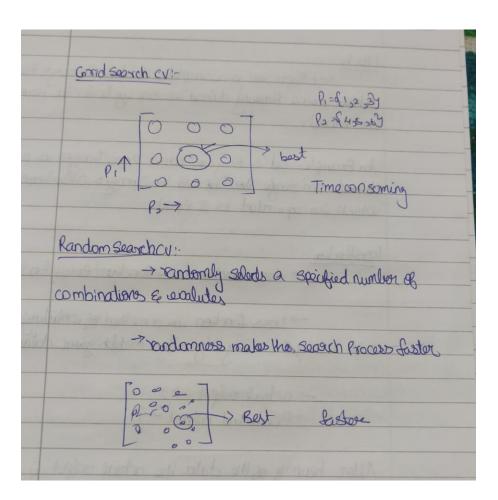




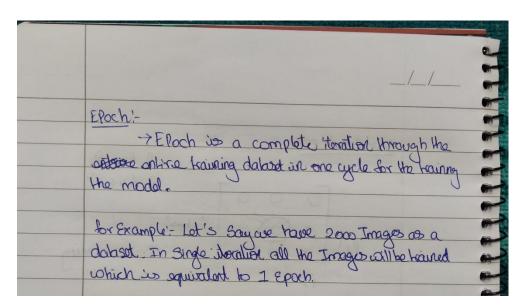
	//_
III. Naivos B	negos
P(BIA) = Postarior Probability	P(A) P(B) P(A) Predictor
to labolled outcomes	com input dataco i bout responso
1) Clustoring 2) Dimensionality Reduction	Compression Comments
Clustering:- Carroup data Pa	pints into clusters
> K-means > Hisorochical > Mean Shift > Density-based	*** =
	of supera to the Pa

Hyperparameter:

	Hyporparamotor:	1
	-> Hy per brameter are Parameters whome	1
Nilo Ni	Values are set before the lecouning fracess begins	
	-> used to control the leaving Process	4
	common Hyporparameter:	1
	Dearning Rate	0
	2) Epochs	1
	3) Batch singe	7
	0	1
	Hyporparameter Tuning!	
	Darid Search	1
	2) Rando m Sooh	
	heard whereast s	
	HT reforms to the Process of choosing the optimum set	
(of hyperparameters for a machineleaving model	2.56



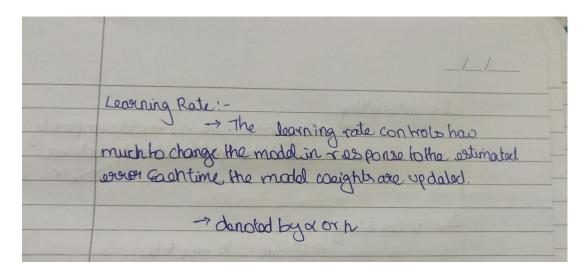
Epoch:



Loss Function:

	loss function:
30.1	-> loss function cost function error function
rote A	coall machine loaning algorithm models given dotores.
	-> actual outpot => y -> Producted outpot >> y
	These function I cost function I arrow donction These function is a method of sublitinghouse coall machine leavining algorithm models given dotroids. The actual output => y Producted output => y After training of the data the actual output & Producted output Should be some.
	if it is not some it should be minimum. If
	model is trained Proportly
	= Z (y-g)

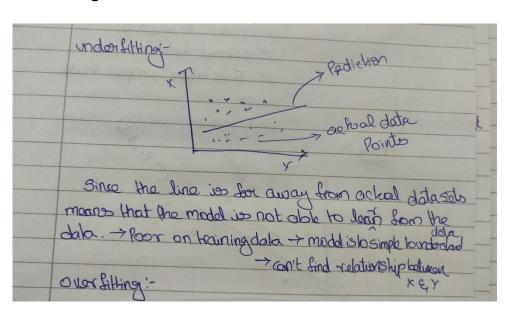
Learning Rate:



Overfitting:

5	Ovar filting:	Con't find relationship bothwan x E, Y
sultred old	ten surrent a	
	This is the on training dail	to but at time of testing the model is not

Underfitting:



fix undoclitting:

By Increasing the model complemely

Should be good relationship between

Fix o ver fitting:

Train with more data

Train aloss complex model

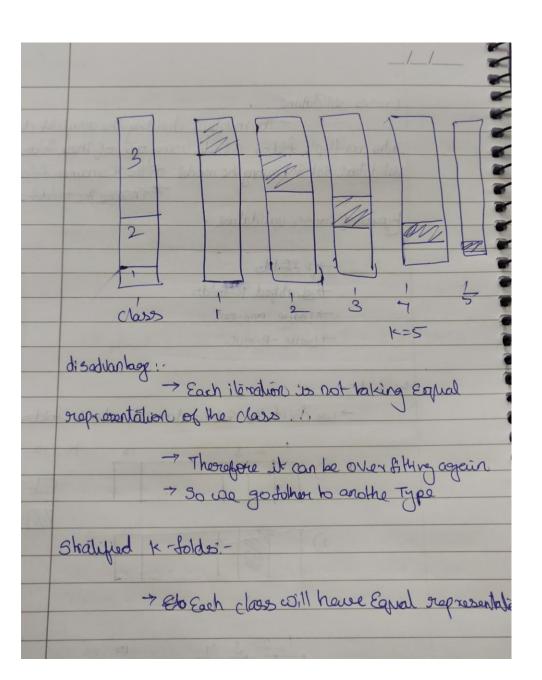
Regularization:

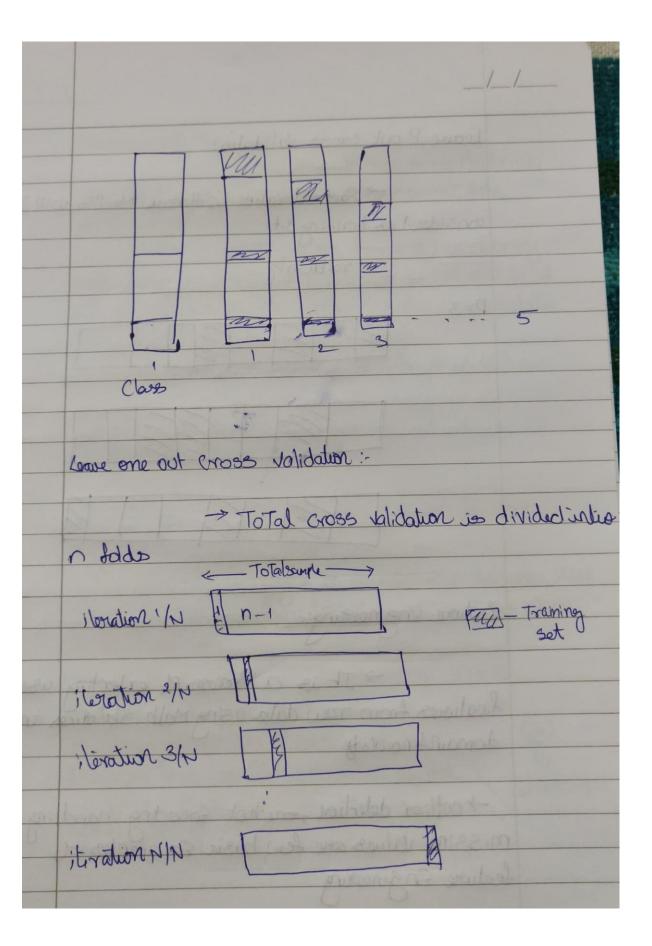
Regularination: Regularination avoids overfilting by adding a parally to the model loss fonction: Regularination = Lossfonction + Panally
Regularingthon avoids over filling by adding a penalty to the model loss fonction: Regularingthon = Loss fonction + Panalty
Regularination avoids over filling by adding a penalty to the model loss fonetion: Regularination = Lossfonction + Panalty
Regulari mation = Loss-fonction + Panalty
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3 tochniques
→ L2 regularingation
-7 L ₁
→ Elastic Not
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Ridge Regrossion Coel Linckon = Loss Lonchon+1/2 /
where wish the slope of the line
Notice was the slope of the line. A control to stranget of suggistingation.
if the exploder the strongth
resplanination will be eliminated

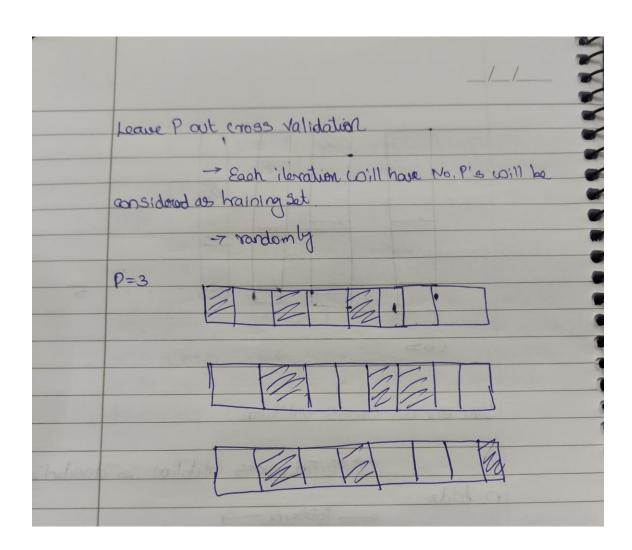
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	+	λ	16:01
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Elastic No. Regul	- uses both	L18L2	
	Complete St. 5		11
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Cross-Validation:

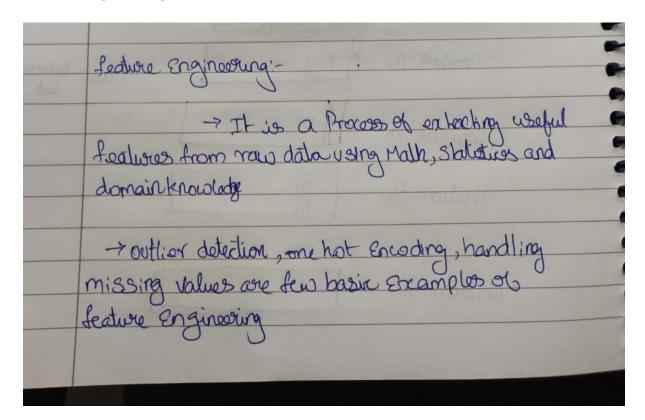
4	
1	(ross validation:
	into multiple bld or 30bsols, using one of those foldows a
	Validation set & training the model on the Tensinny folds.
	types of cross validation:
	> K-folds
	→ Leave-one-out
	→ Leave - P-out
403	k-fold:- → use divide the Entire dataset into k-folds
	1 2 3 10 1 = 10
4	Training Training
	2)
1000	Land Second March And St.
	16)
1	







Feature Engineering:



Dimensionality Reduction:

	//_
0.00	Dimonsionally Raducken:- -> ml methodshave some difficulty when dealing with such high-dimonsional data
	high-dimensional data into a lawor dimensional datal. That Still Prosocues the essence of the original data
lot of	-> wad to reduce the no. of features
10000	Types:- 1) Feature Selection 2) Seature Selection
1 sypio	7 Feature Bolochion 7 Finding k of the total of n features that give us the most information & we discord the other
	(n-k) dimensions $n=10$
	2) feature Enchrackion -> Linding a new set of k
	Soutures that are the combination of the discarder orginial n features

feature extration -> Principal component Analysis (PCA) -> Linear Discriminant Analysis (LDA) PCA:--> Introduced to Karl Rearson -> It workes on the condition that while the data in a higher dimensional space is mapped to data in alason dimension space, The varance of the data in the Lourse dimensional slave should be minimum steps: -> constrits covariance matrix of the data - find the Eigenvectors are used to succonstruct a large straction fraction of Variance of the original data.

Bias:

Train along	s complete model
Bias:-	A Gradien
To the state of th	A Cra
	I tott agara
	= remail 2 cours
The inability for a merhin	2 logenia mother
(like linear grangerssian) to cay use called Bios.	phose the true relationship

	Parties the difference botuseon the expected
E	Prediction of our model & the true value.
	orepeted values and the free dicted values are known as
11/000	di Ledispanom paperari di alla paparari de la
2 Junipage	ow Bias: - The model will closely maken the training dataset
A CANADA	gh Bias: The model will not make the training dataset
h	ighbias -rundonfitting.

Variance:

	Variance:
alor odukari	model when using differt footions of the hairing or last
401	how much it is sometime to another 30bsot of the
an al	Lawing datasat

LOW variance: - 1 Low variance means that the model is less sometime to changes in the training data > case of under fitting High variance: High variance meanesthat the model is vory sensitive to charges in the traing data & con result in significant Change in the estimate of the larget fuction when trained on different solosals -> Case of over fitting high Bias, Low briance => under filling high vor, Low Bias > ONOx Sitting high vor, high Blas => inconsistent & inaccurate Prodictions Low Bias, Low Variance -> consistent & accurate Predictions. Bias ubriance brade off: -> An model or Algorithm and to more complex & less complex at the same time