Logistic Regression

To solve classification → Binary → Dependent → 2 categories
→ Multiclass classification → More than 2 categories.

Dataset

UPSC Exam

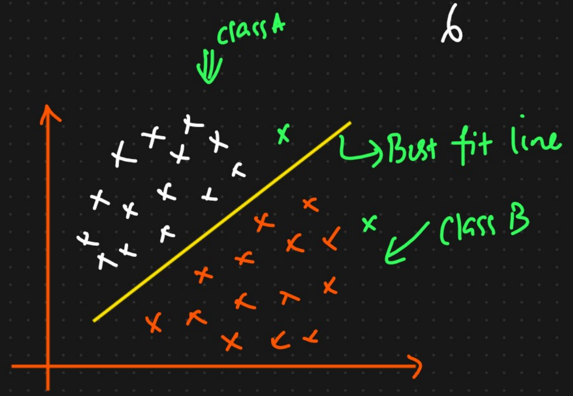
No.of study hours	O/p Pass/Fail
0	0
1	0
2	0
3	0
2	1
4	1
5	1
6	1

TRAIN ↓

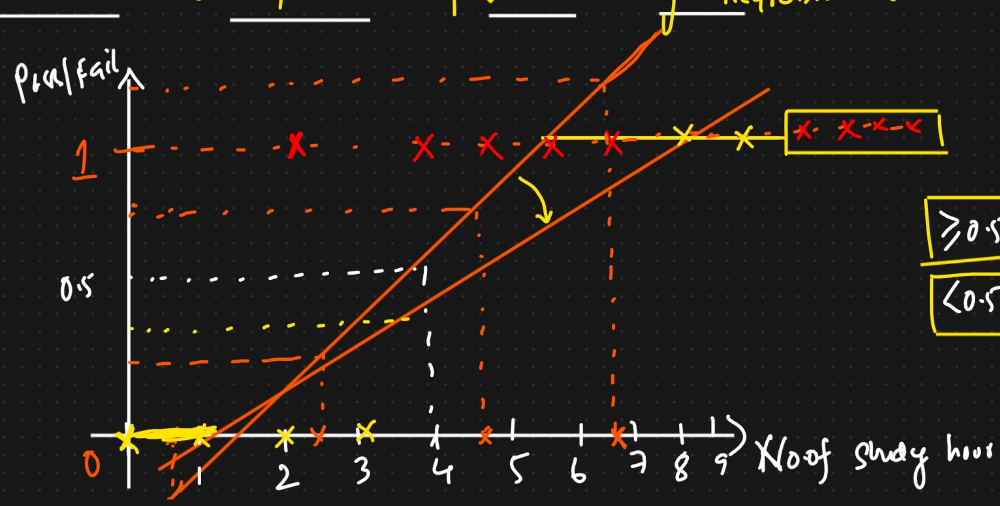
New test data → Model → Pass/Fail

↓

Acc ↑↑



Can we solve this classification problem using Regression?



① Outliers
② >1 and <0

$\boxed{\geq 0.5} \Rightarrow 1$

$\boxed{< 0.5} \Rightarrow 0$

$\boxed{0 \text{ or } 1}$ $\qquad > 1$ & < 0

$\Downarrow$

Best fit line $\quad h_\theta(x) = \theta_0 + \theta_1 x_1 \Rightarrow z$

$\Downarrow$

Squash the best fit line $\Rightarrow$ Sigmoid fn $\Rightarrow$ 0 to 1 $\Rightarrow \dfrac{1}{1+e^{-z}}$

① How does Logistic Regression solve Classification

$$h_\theta(x) \Rightarrow \boxed{\frac{1}{1+e^{-(\theta_0+\theta_1 x_1)}}}$$

$\Downarrow$

Logistic Regression

Logistic Regression

$$\boxed{h_\theta(x) = \frac{1}{1+e^{-(\theta_0+\theta_1 x_1)}}}$$

$h_\theta(x)$

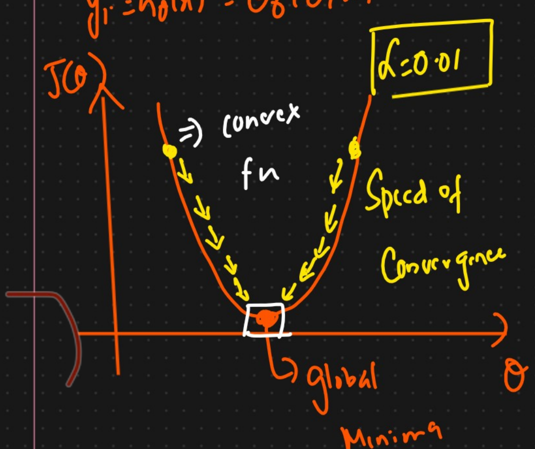
$\Uparrow$

$\hat{y}_1 = \theta_0 + \theta_1 x_1$

Linear Regression Cost fn

$$J(\theta_0,\theta_1) = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

$\hat{y}_i = h_\theta(x) = \theta_0 + \theta_1 x_1$



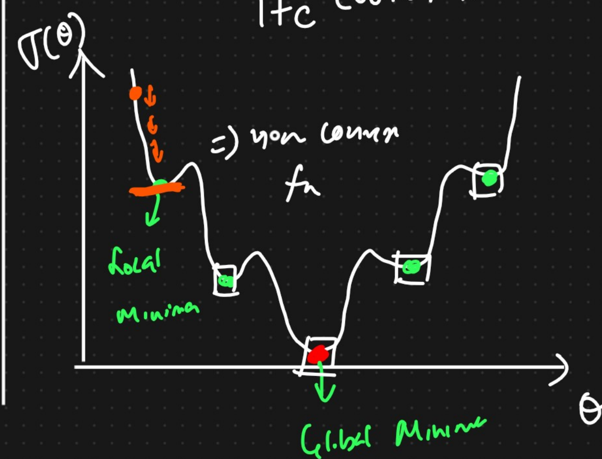
Convex function

To overcome from local minima so we r using loss function instead of cost function

Logistic Regression Cost fn

$$J(\theta_0,\theta_1) = \frac{1}{n}\sum_{i=1}^{n}(y_i - h_\theta(x)_i)^2$$

$$h_\theta(x) = \frac{1}{1+e^{-(\theta_0+\theta_1 x_1)}} \Rightarrow 0 \text{ to } 1$$



When it convergence it will stuck at local minima so loss function is used

Log Loss Cost fn

$\hat{y}_i$ Predicted

$$J(\theta_0,\theta_1) = -y_i \log\left(h_\theta(x)_i\right) - (1-y_i)\log\left(1-h_\theta(x)_i\right)$$ ⇒ Gradient Descent Curve.

$$\boxed{h_\theta(x) = \frac{1}{1+e^{-(\theta_0+\theta_1 x_1)}}}$$ ⇒ $\hat{y}$ ⇒ predicted

$$J(\theta_0,\theta_1) = \begin{cases} -\log(h_\theta(x_i)) & \text{if } y=1 \\ -\log(1-h_\theta(x)_i) & \text{if } y=0 \end{cases}$$

Final Aim : Minimize Cost fn $J(\theta_0,\theta_1)$ by changing θ_0, θ_1

Convergence

Repeat until Convergence

$\{$

$$\theta_j := \theta_j - \alpha \frac{\partial}{\partial \theta} J(\theta_0,\theta_1$$

$\}$

Logistics Regression With Reguralization Parameters

Cost fn

$$J(\theta_0,\theta_1) = -y\log(h_\theta(x)) - (1-y)\log(1-h_\theta(x))$$

$$J(\theta_0,\theta_1) = \begin{cases} -\log(h_\theta(x)) & \text{if } y=1 \\ -\log(1-h_\theta(x)) & \text{if } y=0 \end{cases}$$

[Reduce Overfitting]

$$J(\theta_0,\theta_1) = -y\log(h_\theta(x)) - (1-y)\log(1-h_\theta(x)) + L_2 \text{ Reguralization}$$

$$J(\theta_0,\theta_1) = -y\log(h_\theta(x)) - (1-y)\log(1-h_\theta(x)) + L_1 \text{ Reg}$$ [Feature Selection].

$$J(\theta_0,\theta_1) = -y\log(h_\theta(x)) - (1-y)\log(1-h_\theta(x)) + L_2 \text{ Reg} + L_1 \text{Reg}.$$

L2 Regularization ⇒ Reduce Overfitting ⇒ Ridge Regression.

$$J(\theta_0,\theta_1) = -y\log(h_\theta(x)) - (1-y)\log(1-h_\theta(x)) + \lambda \sum_{i=1}^{n} (\text{slope})^2$$

L1 Regularization ⇒ feature selection ⇒ Lasso

$$J(\theta_0,\theta_1) = -y\log(h_\theta(x)) - (1-y)\log(1-h_\theta(x)) + \lambda \sum_{i=1}^{n} |\text{slope}|$$

Elastic Net

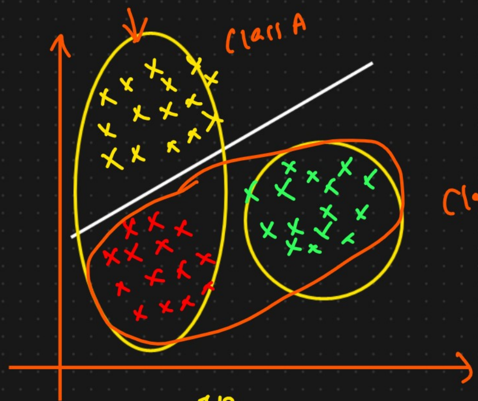
$$J(\theta_0,\theta_1) = -y\log(h_\theta(x)) - (1-y)\log(1-h_\theta(x)) + \lambda_1 \sum_{i=1}^{n} (\text{slope})^2 + \lambda_2 \sum_{i=1}^{n} |\text{slope}|.$$

$$\boxed{C \propto \frac{1}{\lambda}}$$

$\Downarrow$

$\boxed{C}$ → Sklearn hyper para

Multiclass Logistic Regression



I/P

f1	f2	f3

final result will be

Multinomial ⟹ Index of o/p

OVR {One Versus Rest} ⟹ Probabilities of all categories.

If the option chosen is ovr then a binary problem is fit for each label

Label ⟹

O/P	M1 (o/p)	M2	M3
	A	B	C
A	1	0	0
B	0	1	0
C	0	0	1
C	0	0	1
B	0	1	0

OVR

M1, M2, M3

→ [0.20, 0.30, 0.50]

3 diff model Created

C

o/p

sklearn.linear_model.LogisticRegression

class sklearn.linear_model.LogisticRegression(penalty='l2', *, dual=False, tol=0.0001, C=1.0, fit_intercept=True, intercept_scaling=1, class_weight=None, random_state=None, solver='lbfgs', max_iter=100, multi_class='auto', verbose=0, warm_start=False, n_jobs=None, l1_ratio=None) [source]

For imbalanced data

Logistic Regression (aka logit, MaxEnt) classifier.

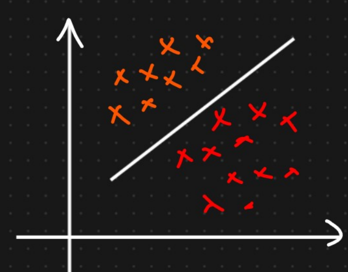
In the multiclass case, the training algorithm uses the one-vs-rest (OvR) scheme if the 'multi_class' option is set to 'ovr', and uses the cross-entropy loss if the 'multi_class' option is set to 'multinomial'. (Currently the 'multinomial' option is supported only by the 'lbfgs', 'sag', 'saga' and newton-cg solvers.)

A → 900 } Imbalance dataset

B → 100 ⟹ 1000

{B : 10}

Performance Metrics, Accuracy, Precision, Recall, F-Beta.



① Confusion Matrix

Predicted \ Actual	1	0
1	2	2
0	1	1

x_1	x_2	y	$\hat{y}$	
-	-	0	1	→ wrong
		1	1	→ correct
		0	0	
		1	1	
		1	1	
		0	1	
		1	0	

Predicted \ Actual	1	0
Positive ← 1	TP	FP
Negative ← 0	FN	TN

FP & FN Are Errors

$$Acc = \frac{TP + TN}{FP + TP + FN + TN} = \frac{4}{7} = 57.1\%$$

3+2+1+1

DATASET : Imbalance Dataset

1000 datapoints → 900 1's ; → 100 0's } ⇗ Imbalanced ⇓ $\boxed{Acc = 90\%}$

→ Dumb Model → $\hat{y} \rightarrow 1$

For any data it will give 1as output so that 90% accuracy

Predicted \ Actual	1	0
1	TP	FP
	FN	TN

③ Precision : $\dfrac{TP}{TP+FP}$

} Out of all the actual values how many are correctly prediction

⇑ FP is Important ⇓⇓ FP

	1	0
1	TP	FP
0	FN	TN

④ Recall : $\dfrac{TP}{\boxed{TP+FN}}$

} Out of all the predicted value how many are correctly predicted with actual values.

⇓

$\boxed{FN ⇓⇓⇓}$ ⇒ Reduce FN

FN is imp to reduce FN

Usecase 1 : Spam classification.

	1	0 (Actual)
1	TP	FP⇓⇓⇓
0	FN	TN

Text ⇒ Model ⇒ Spam/ Not Spam.

$\boxed{FN⇓⇓⇓}$ Wrong Scenario {
- Text → Spam ⇗ FN
- Model → Not a Spam

Text ⇒ Spam
Model ⇒ Spam } Accurate. ⇒ good scenario.

Blunder : { →FP
- Text → Not a Spam
- Model ⇒ Spam

Text ⇒ Not a Spam
Model ⇒ Not a Spam } ⇒ Accuracy

Usecase : FN is Important

To predict whether a person has diabetes or Not

Actual → Diabetes
Model → Diabetes } Correct ⇒ TP

Actual ⇒ No Diabetes
Model ⇒ Diabetes } FP Wrong Prediction.

Actual → No Diabetes
Model → No Diabetes } Correct ⇒ TN

Actual ⇒ Diabetes
Model ⇒ No Diabetes } FN Blunder

I was Joking

Gulab Jamoon

Assignment : $\boxed{\text{Tomorrow the Stock Market will crash or Not}}$

Reduce FP or FN

1. Protection of people
2. Protection of Companies.

F-Beta Score