

Logistic Regression with Regularization

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→ Cost Function

$$J(\theta_0, \theta_1) = -4 \log(h_0(x)) - (1-4) \log(1-h_0(x)) + L_2$$

We Add L_2 Regularization

↳ Reduce Overfitting

We can Add L_1 Regularization

↳ Feature selection

We can Add Both $L_1 + L_2$ Regularization

For L_2 we Add $\lambda \sum_{i=1}^n (\text{slope})^2$

For L_1 we Add $\lambda \sum_{i=1}^n |\text{slope}|$

$\lambda = \text{Hyperparameter}$

$$C = \frac{1}{\lambda}$$

C & lambda (λ) Relationship

$$C = \frac{1}{\lambda}$$

* Performance metrics, Accuracy, Precision, Recall and F-Beta

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1) confusion matrix

	1	0	Actual value	α_1	α_2	y	\hat{y}
1	3	2	(4)	-	-	0	1
0	1	1		-	-	1	1
Predicted value				-	-	0	1
				-	-	1	0

(\hat{y})

	1	0	Actual value
1	TP	FP	(4)
0	FN	TN	
Predicted value			

value

(\hat{y})

$$\text{Model Accuracy} = \frac{TP + TN}{TP + FP + FN + TN}$$

$$= \frac{3+1}{3+2+1+1} = \frac{4}{7} = 0.57$$

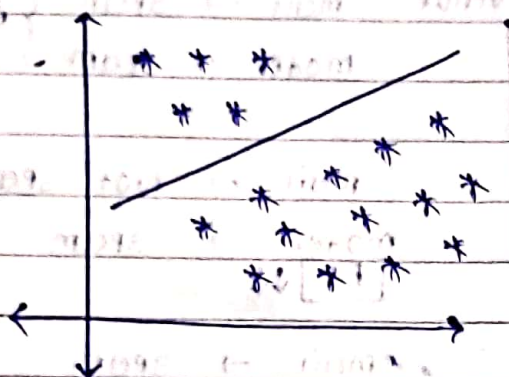
$$= \frac{4}{7} = 0.57$$

Model Accuracy = 57%

Accuracy

1) confusion matrix

2) Accuracy of model



* dataset \rightarrow Imbalance dataset

100.0
datapoint \rightarrow $\begin{cases} 900 \rightarrow 1 \\ 100 \rightarrow 0 \end{cases}$

Dumb model \rightarrow O/P \rightarrow 1

Accuracy \rightarrow 90%

out of 900 datapoints

\rightarrow In the case of Imbalance dataset, we can't use Accuracy performance.

\rightarrow Here we use Precision or Recall.

$$\text{Precision} = \frac{TP}{TP + FP}$$

1	TP	TN
0	FN	FP

Here, TP \rightarrow out of all the actual values how many are correctly predicted.

FP is Important

Here FP \downarrow [Reduce False Positive]

Recall = $\frac{TP}{TP + FN}$ \rightarrow out of all the predicted values how many are correctly predicted with actual values.

\rightarrow Use case \rightarrow 1

Spam classification

mail

$\begin{cases} \rightarrow \text{Spam} \\ \rightarrow \text{Not-Spam} \end{cases}$

		Actual value		
		1	0	
Predicted value	1	TP	FP	mail → spam } good model → spam
	0	FN	TN	mail → Not spam } Blunder model → spam [FP] ↓↓
				mail → spam } fine model → Not a spam [FN]

For These scenarios we use precision metrics.

→ use case - 2

To predict whether person has diabetes or not

		1	0	Actual value
		1	0	
Actual	→ 1	TP	FP	good
Model Predict	→ 1			
Actual	→ 0	FN	TN	
Model Predict	→ 0			
Actual	→ 1			Blunder Predicted
Model Predict	→ 0			

we can Reduce FN if Recall is use.

→ Health disease use Recall is use.

Assignment 1) Tomorrow stock market will crash or not.

	TEST		0	1	ACTUAL
ACTUAL → crash	}	good	TP	FP	}
Predict → crash		Blunder	FN	TN	
			Predicted		

Actual → Not crash
Predict → crash

* F-Beta score :-
$$(1 + \beta^2) \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

If FP & FN are both important $\beta = 1$

F1 score =
$$\frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$
 } Harmonic score

If FP is more imp than FN //

$\beta = 0.5$

F 0.5 score =
$$(1 + 0.25) \frac{P * R}{P + R}$$

If FN >> FP $\beta = 2$

F2 score =
$$(1 + 4) \frac{P * R}{P + R}$$