

A-Z Machine Learning using Azure Machine Learning (AzureML)

Hands on AzureML: From Azure Machine Learning Introduction to Advance Machine Learning Algorithms. No Coding Required.

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Created by Jitesh Khurkhuriya Last updated 3/2018 English English

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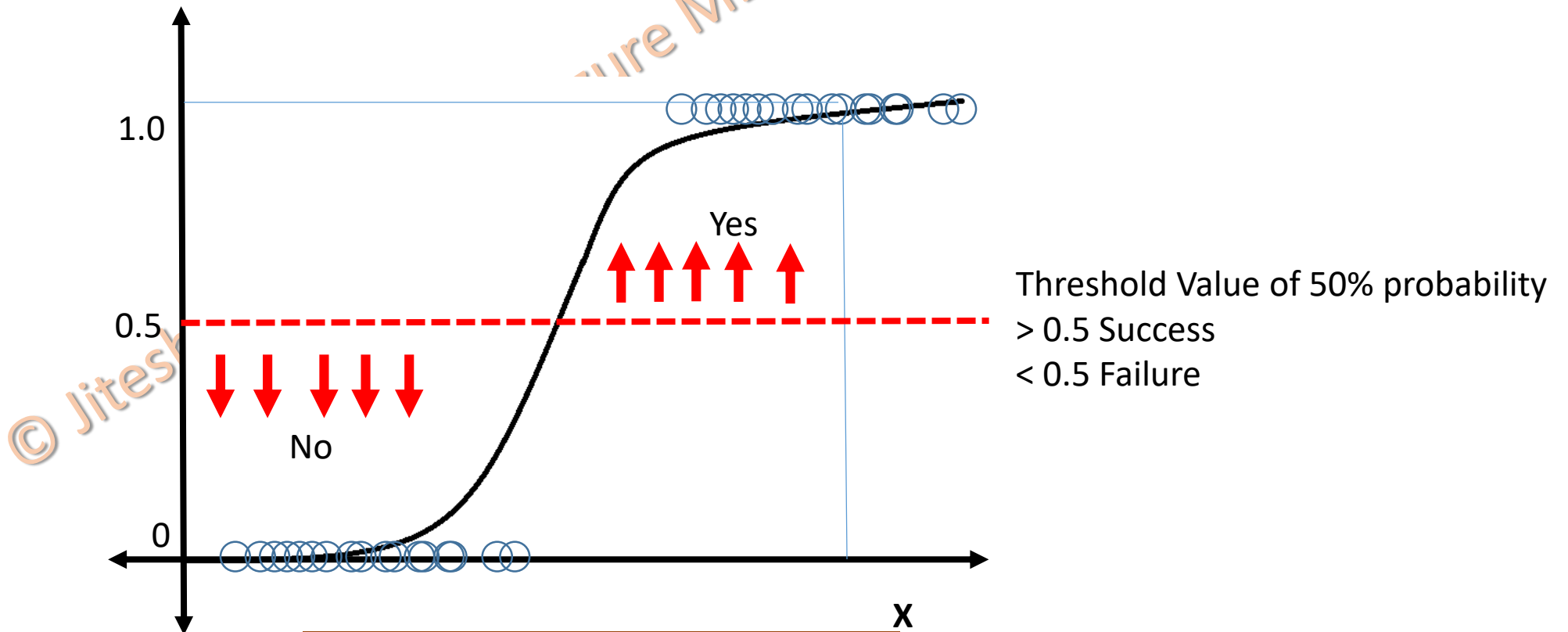
Logistic Regression

What is Logistics Regression?

- Used to predict the probability of an outcome
- Can be binary – Yes/No or Multiple
- Supervised learning method
- Must provide a dataset that already contains the outcomes to train the model.

Plotting Logistics Regression

$$\text{Log}\left(\frac{P}{1-P}\right) = b_0 + b_1X$$



Logistic Regression in Azure ML



Two-Class Logistic Regression

1

Properties Project

Two-Class Logistic Regression

Create trainer mode

Single Parameter

Optimization tolerance

1E-07

L1 regularization weight

1

L2 regularization weight

1

Memory size for L-BFGS

20

Random number seed



Allow unknown categorical levels

Parameters to Logistic Regression

Parameters to Logistic Regression

- Create Trainer Mode
 - Single Parameter – Provide specific set of values
 - Parameter Range – specify multiple values and get the optimum set for given configuration
- Optimization Tolerance – Threshold Value to stop the model iterations on trained dataset
- Memory Size for L-BFGS – Amount of memory to use for next steps and direction
- Random Number Seed – Random integer number that is used for reproducing the same results
- Allow Unknown Categorical Levels – Creates an additional “Unknown” level

Properties Project

Two-Class Logistic Regression

Create trainer mode

Single Parameter ▼

Optimization tolerance

1E-07

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☒ Allow unknown categorical levels

Regularization

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Optimization tolerance

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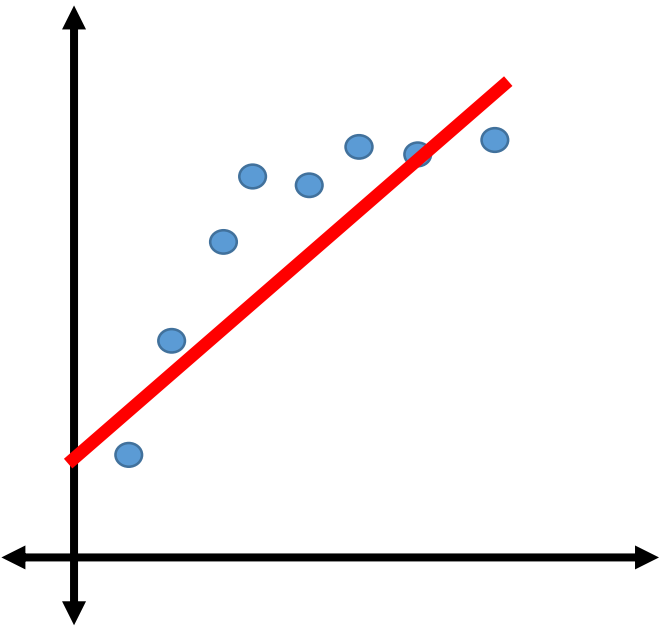
Memory size for L-BFGS

20

Random number seed

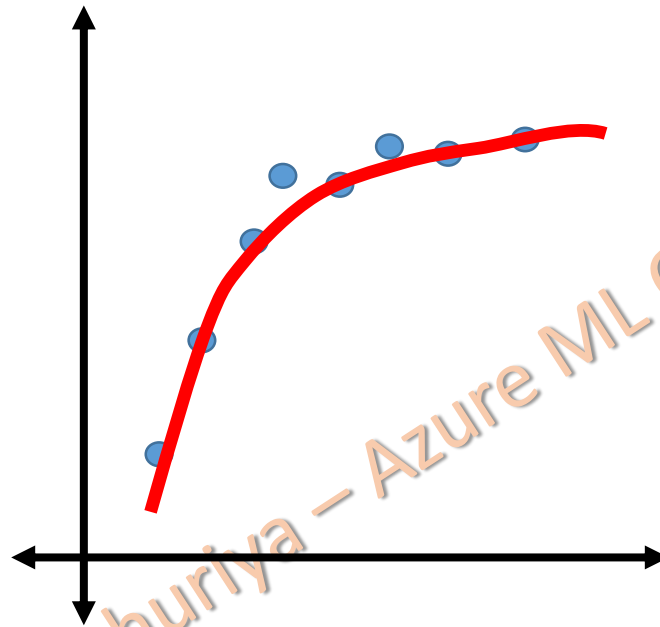
☒ Allow unknown categorical levels

Regularization



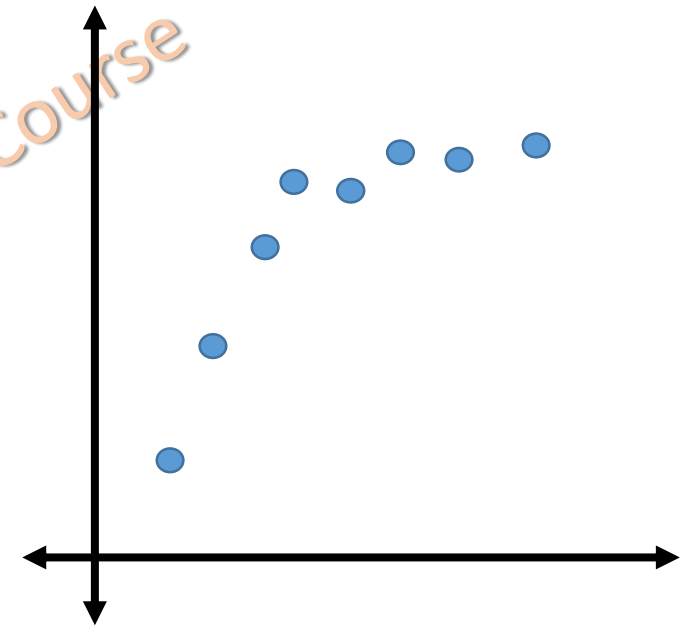
$$b_0 + b_1X$$

Under-fit



$$b_0 + b_1X_1^2$$

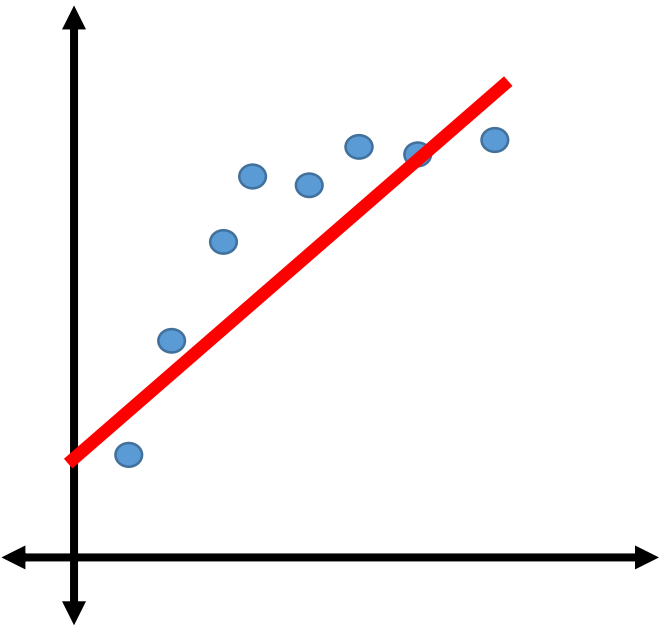
Right



$$b_0 + b_1X_1^2 + b_2X_2^3 \dots$$

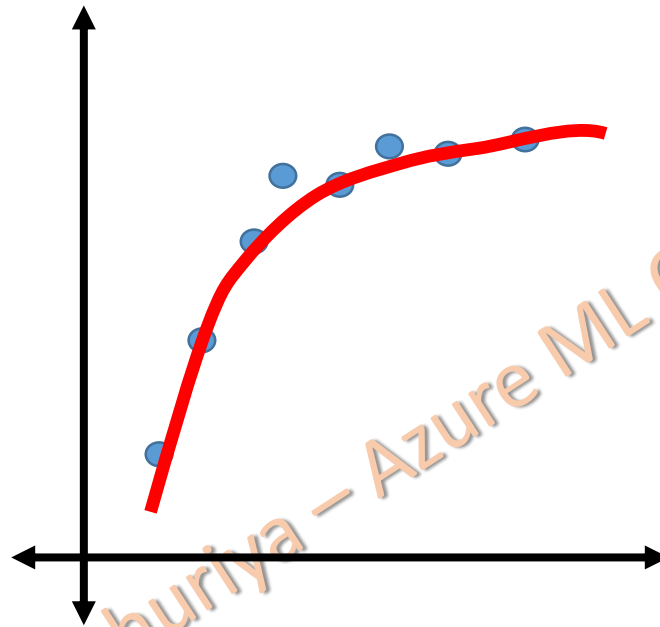
Over Fit

Regularization Weight



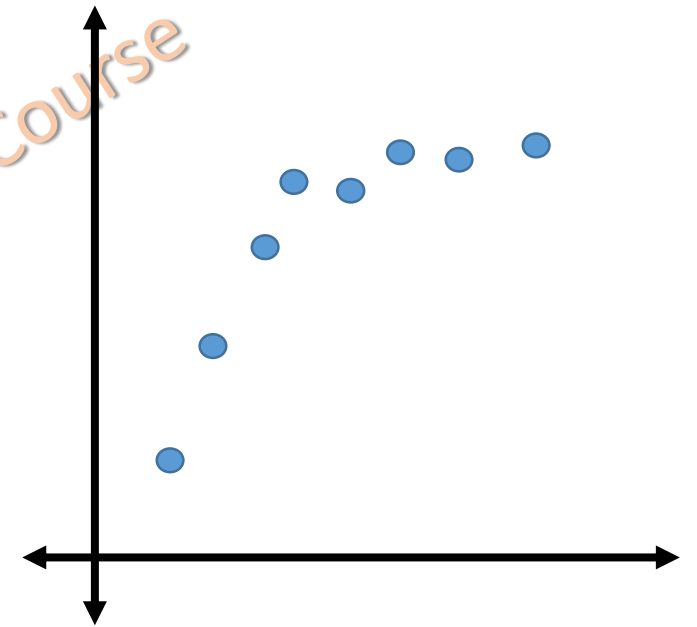
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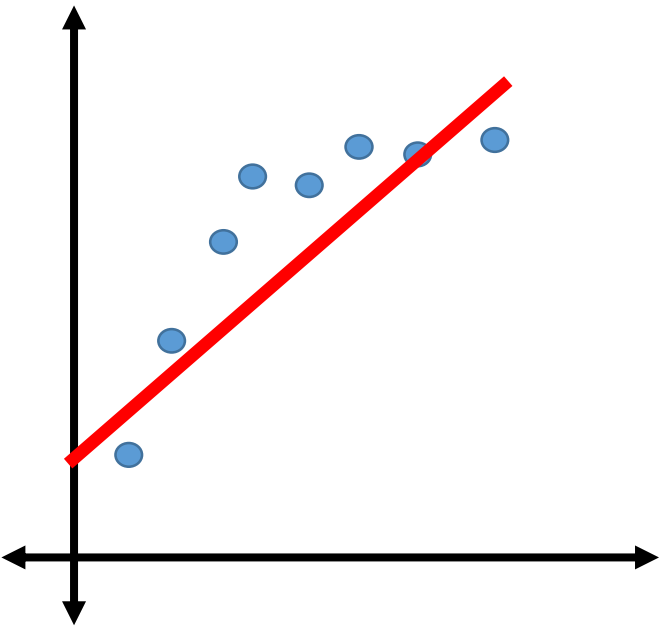


$$b_0 + b_1X_1^2 + b_2X_2^3 \dots$$

Over-fit

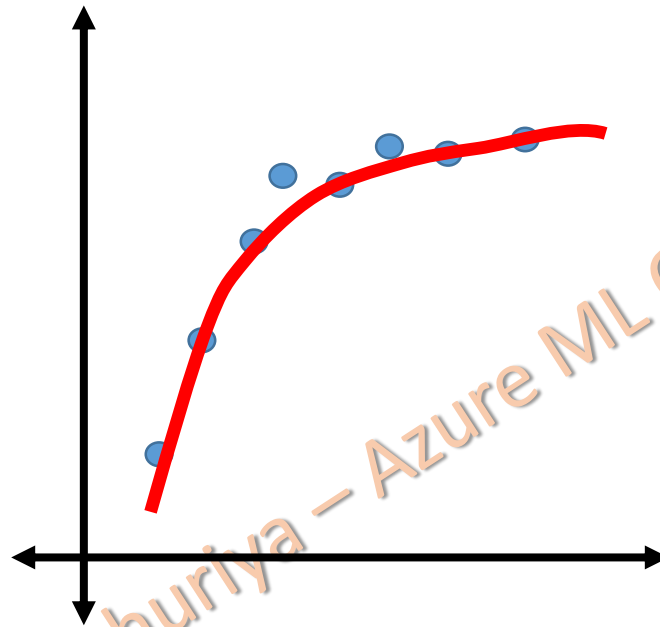
b2 and other such coefficients/weights
are the reasons for the model to over-fit

Regularization Weight



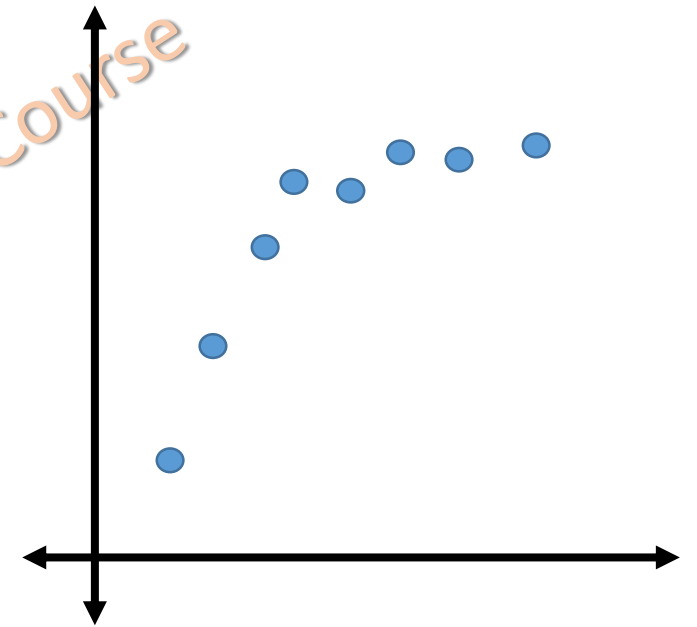
$$b_0 + b_1X$$

Under-fit



$$b_0 + b_1X_1^2$$

Right



$$b_0 + b_1X_1^2 + b_2X_2^3 \dots$$

Over-fit

What if the effect of such weights is reduced significantly
Or reduced to zero

Regularization Weights

- L2 (Ridge) shrinks all the coefficient by the same proportions but eliminates none
- L1 (Lasso) can shrink some coefficients to zero, performing variable selection.

$$b_0 + b_1X_1^2 + b_2X_2^3 + \dots$$

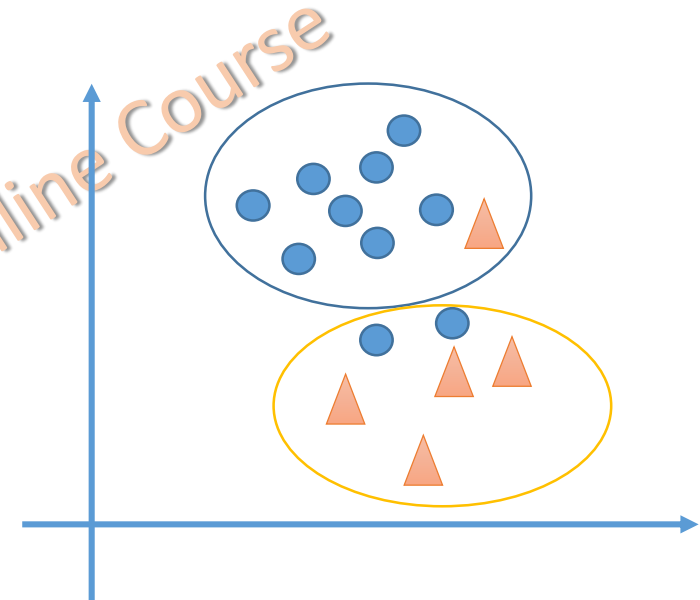
- Both L1 and L2 regularization prevents overfitting by shrinking (imposing a penalty) on the coefficients.
- With L2, you tend to end up with many small weights, while with L1, you tend to end up with larger weights, but more zeros.

Understanding the results

Prediction Outcome

	Predicted Positives	Predicted Negatives
Actual Positives	True Positives	False Negatives
Actual Negative	False Positives	True Negatives

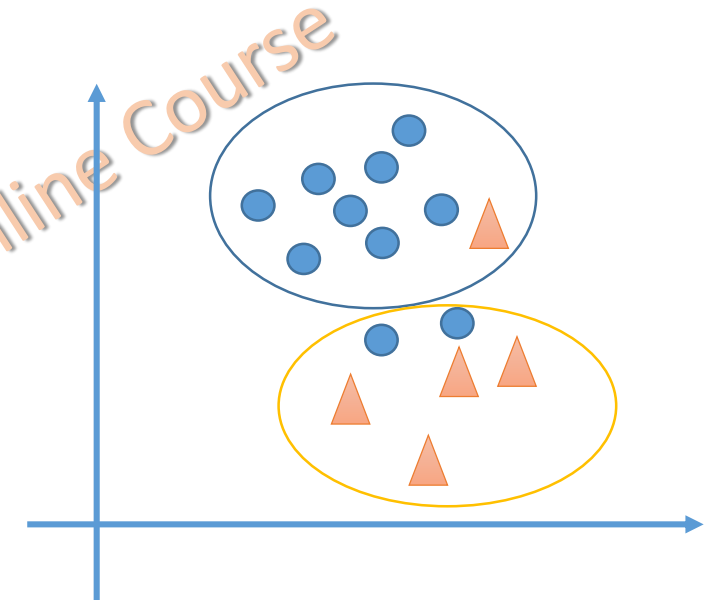
	Predicted Positives	Predicted Negatives	
Actual Positives	8	2	10
Actual Negative	1	4	5
	9	6	



Prediction Outcome

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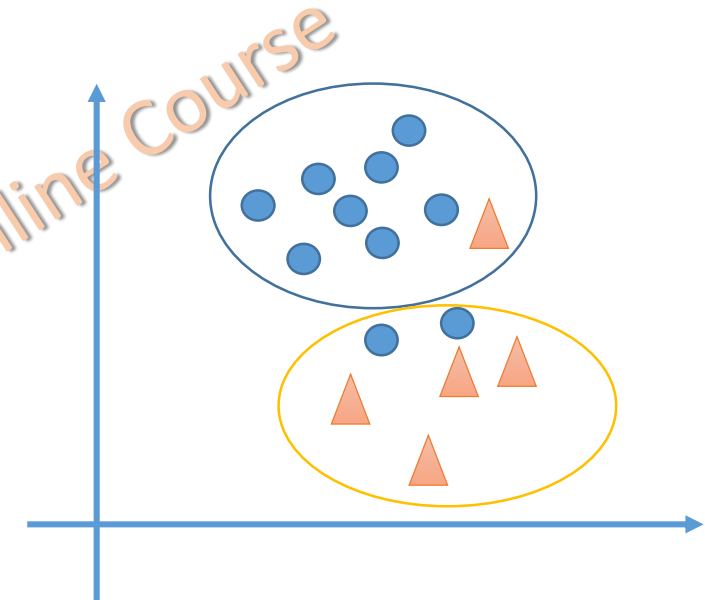
Accuracy – Proportions of total number of correct results

$$\text{Accuracy} = (8 + 4) / 15 = 0.8 \text{ or } 80\%$$

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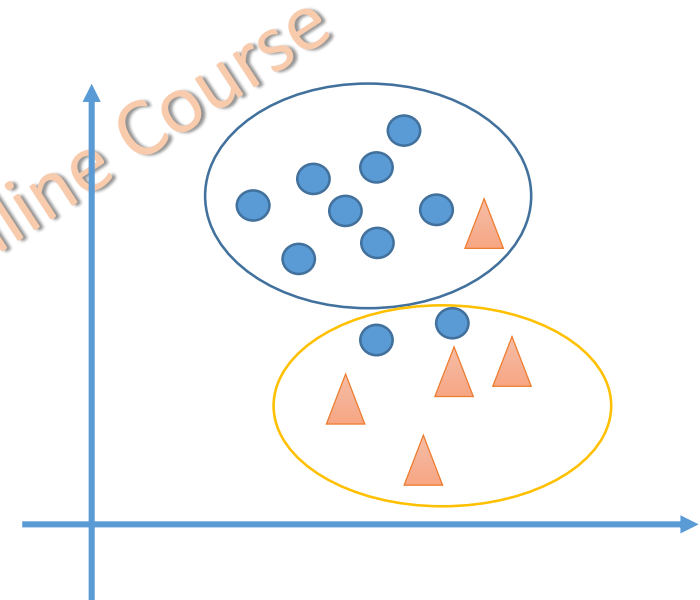
Precision – Proportion of correct positive results out of all predicted positive results

$$\text{Precision} = 8 / 9 = 0.889 \text{ or } 88.9\%$$

Prediction Outcome

	Predicted Positives	Predicted Negatives
Actual Positives	True Positives	False Negatives
Actual Negative	False Positives	True Negatives

	Predicted Positives	Predicted Negatives	
Actual Positives	8	2	10
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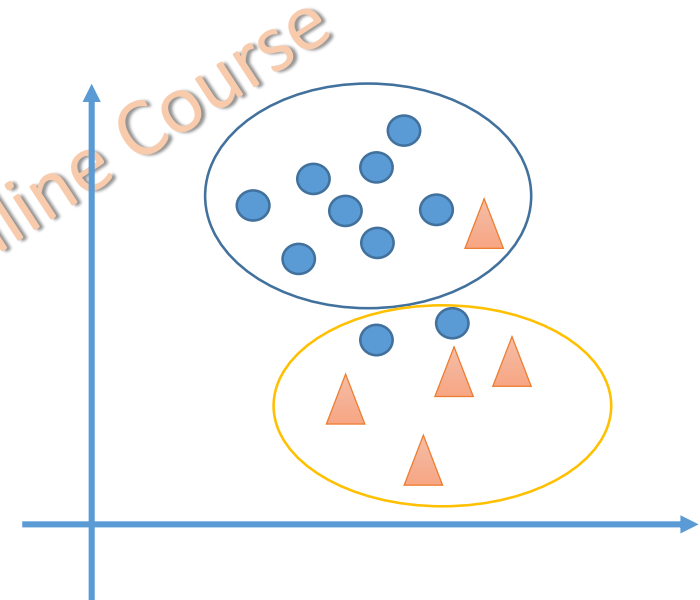
Recall – Proportion of actual positive cases

$$\text{Recall} = 8 / (8 + 2) = 0.8 \text{ or } 80\%$$

Prediction Outcome

	Predicted Positives	Predicted Negatives
Actual Positives	True Positives	False Negatives
Actual Negative	False Positives	True Negatives

	Predicted Positives	Predicted Negatives	
Actual Positives	8	2	10
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	9	6	



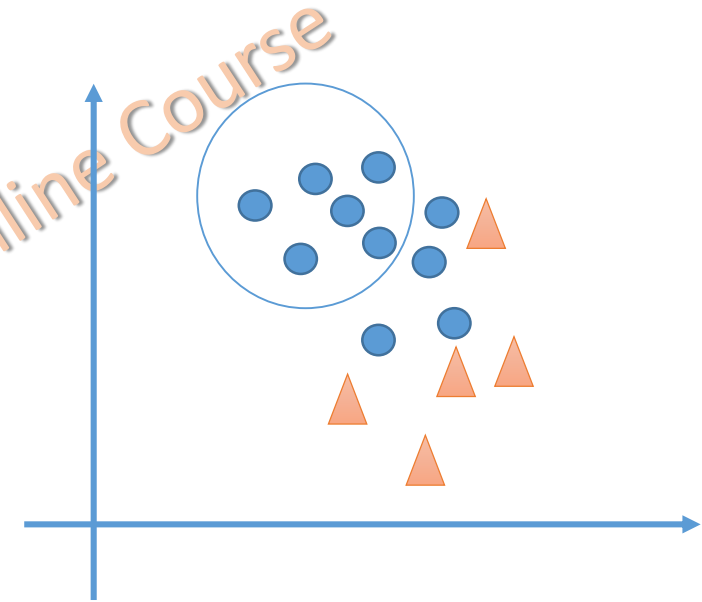
F1-Score – Weighted Average (Harmonic Mean) of Precision and Recall

$$\text{F1Score} = 2 * \text{Precision} * \text{Recall} / (\text{Precision} + \text{Recall}) = 0.84$$

Prediction Outcome

	Predicted Positives	Predicted Negatives
Actual Positives	True Positives	False Negatives
Actual Negative	False Positives	True Negatives

	Predicted Positives	Predicted Negatives	
Actual Positives	6	4	10
Actual Negative	0	5	5
	6	6	



In the Previous example

Precision = 0.889

Recall = 0.8

Average = 0.84

Precision = $6 / 6 = 1$ or 100%

Recall = $6 / (6 + 4) = 0.6$ or 60%

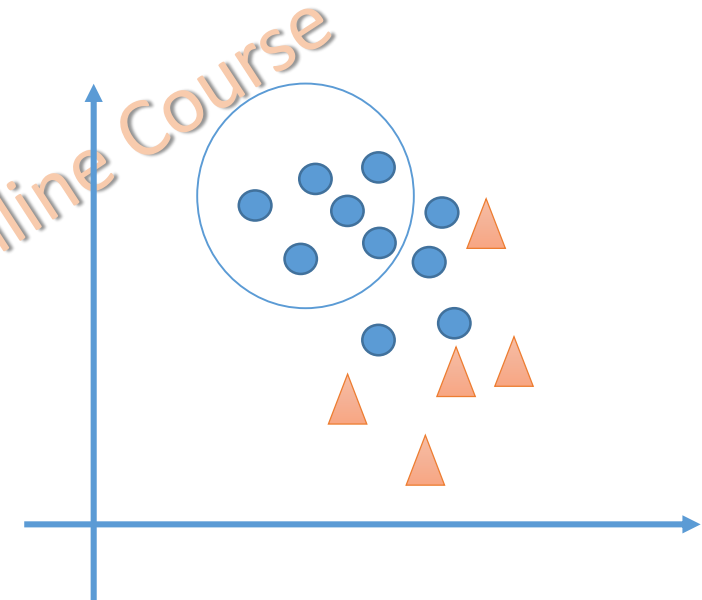
Average = 0.8

May lead to false interpretation

Prediction Outcome

	Predicted Positives	Predicted Negatives
Actual Positives	True Positives	False Negatives
Actual Negative	False Positives	True Negatives

	Predicted Positives	Predicted Negatives	
Actual Positives	6	4	10
Actual Negative	0	5	5
	6	6	



In the first example

Precision = $6 / 6 = 1$ or 100%

Recall = $6 / (8 + 2) = 0.6$ or 60%

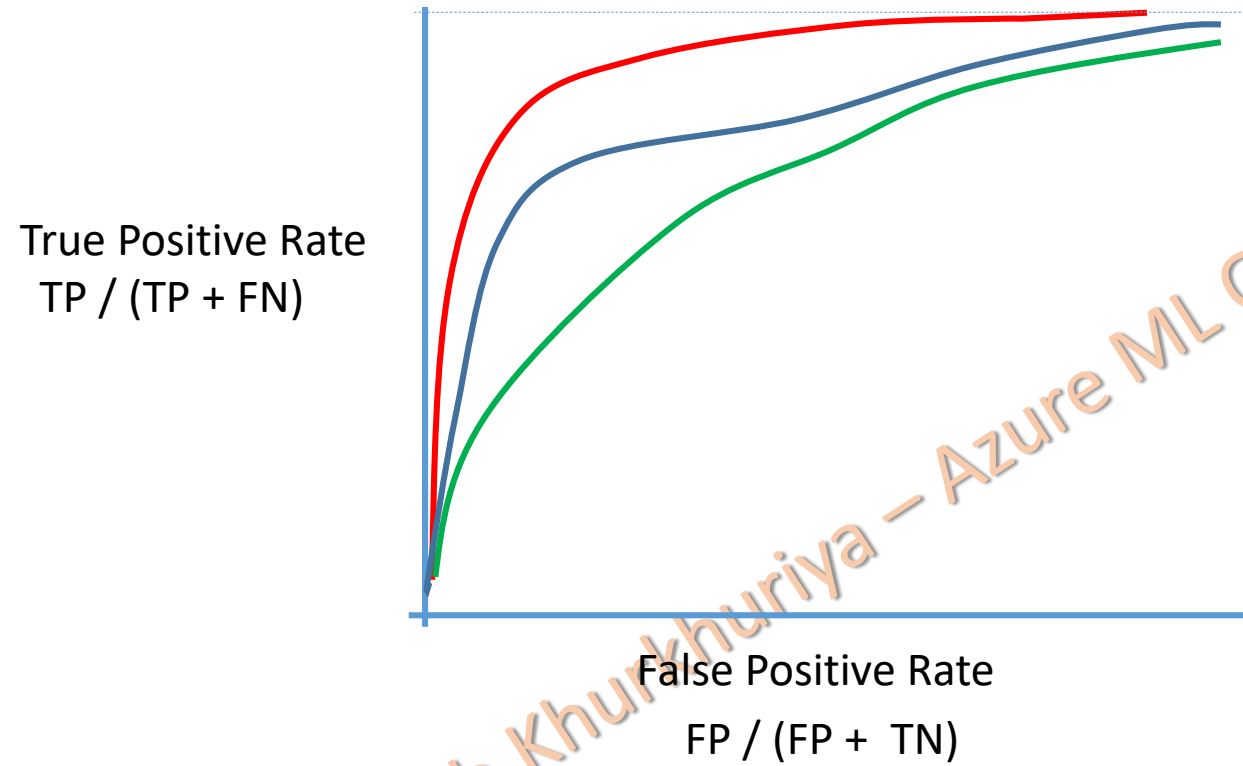
F1Score = 0.75

Precision = 0.889

Recall = 0.8

F1Score = 0.84

AUC ROC



AUC – Area Under the Curve

ROC – Receiver Operating Characteristics

First used during World War II for the analysis of radar signals

Following the attack on Pearl Harbor in 1941, the United States army began new research to increase the prediction of correctly detected Japanese aircraft from their radar signals.

For this purposes they measured the ability of radar receiver operators to make these important distinctions, which was called the Receiver Operating Characteristics

Provides a single number that lets you compare models of different types.

Thank You and Have a Great Time !