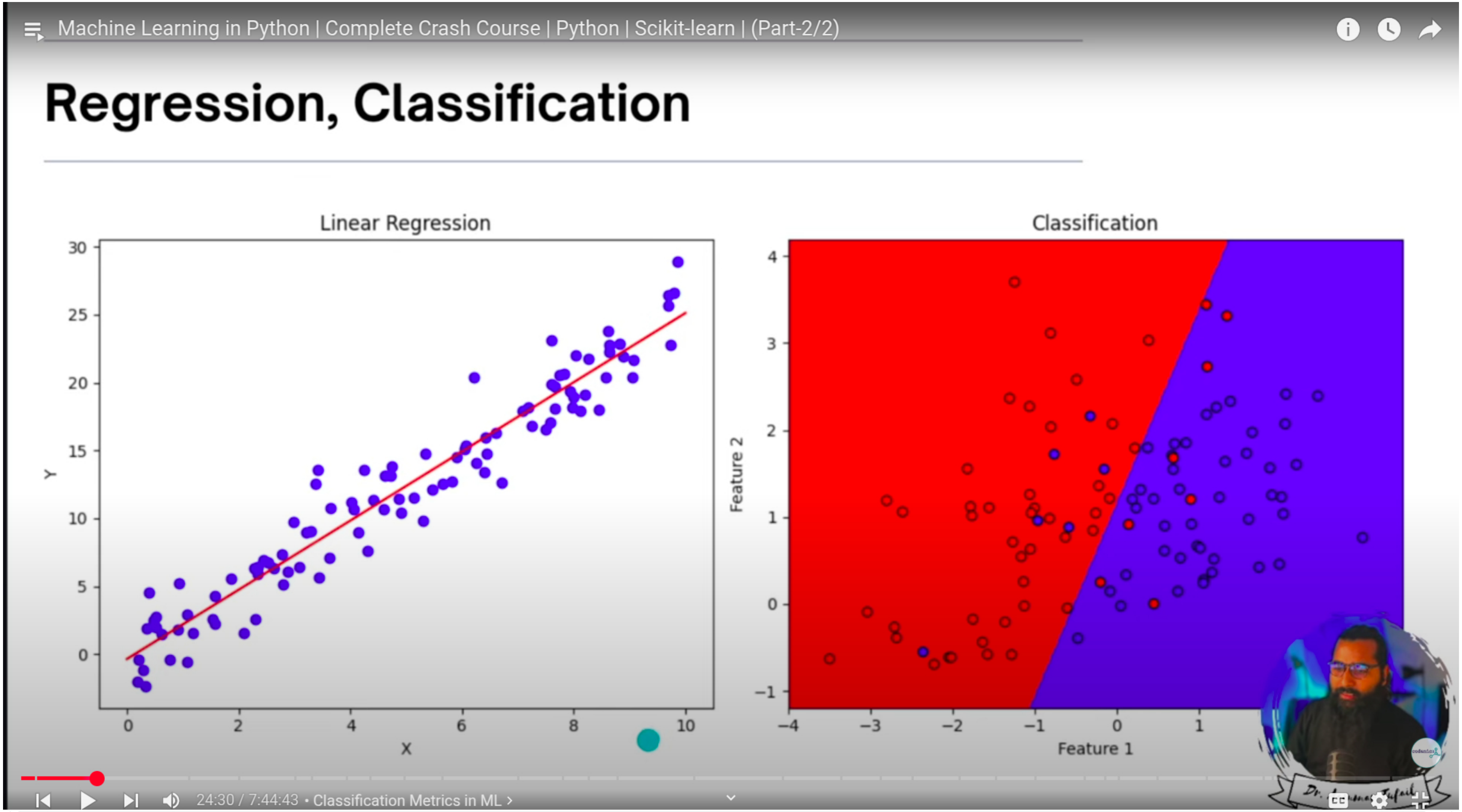
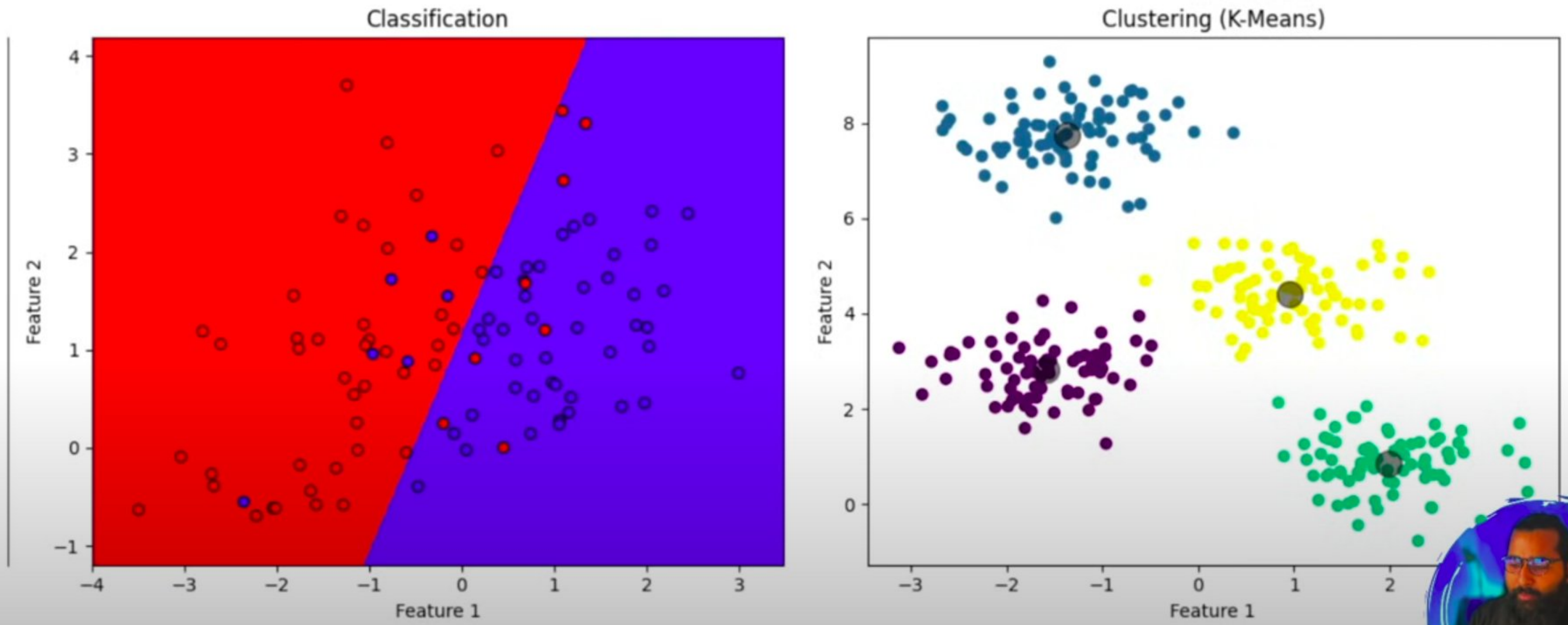
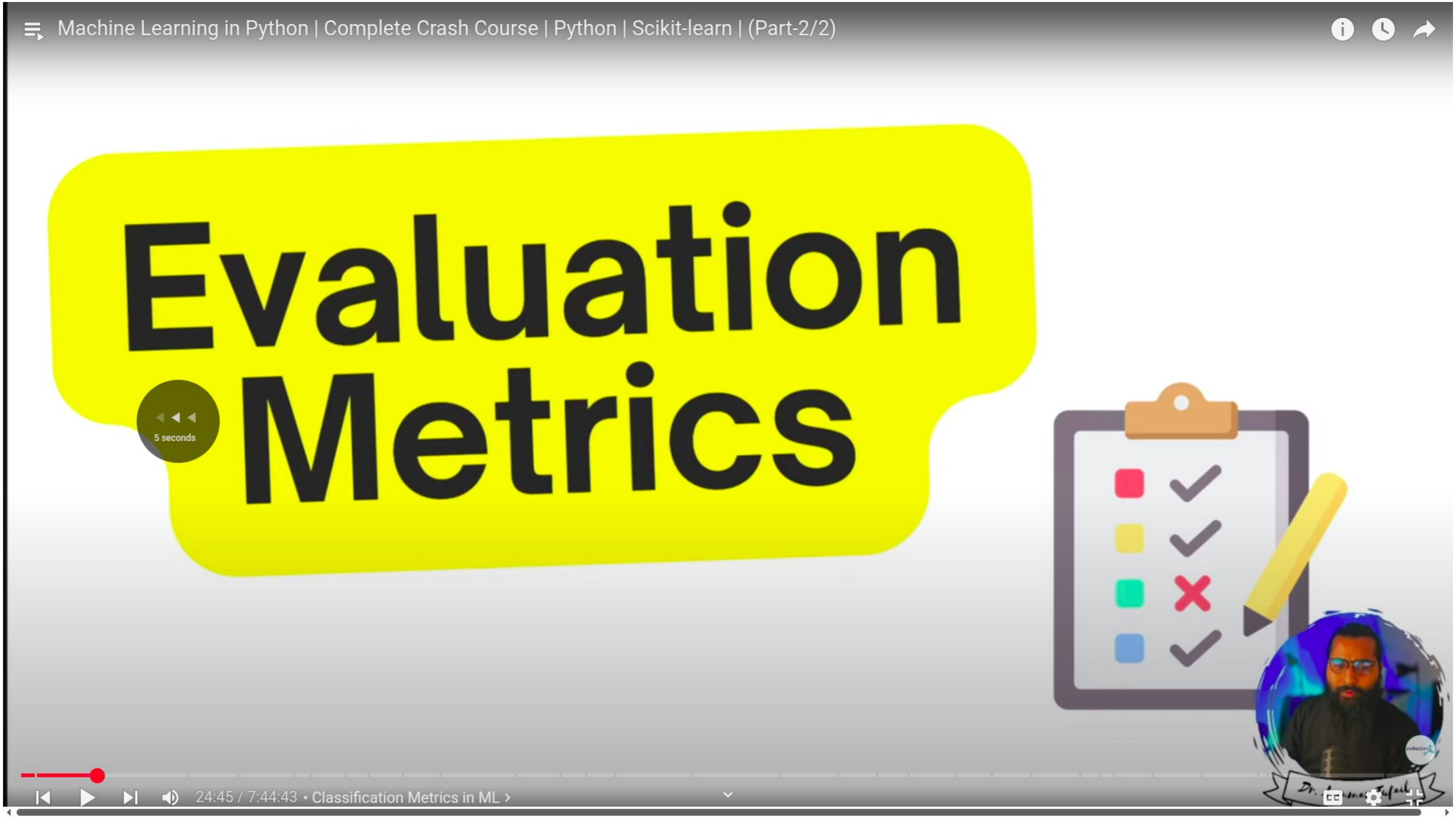

Machine Learning in Python | Complete Crash Course | Python | Scikit-learn | (Part-2/2)
Regression, Classification
Linear Regression
Y
X
0
2
4
6
8
10
0
5
10
15
20
25
30
Classification
Feature 2
Feature 1
−4
−3
−2
−1
0
1
−1
0
1
2
3
4
24:30 / 7:44:43 • Classification Metrics in ML ›

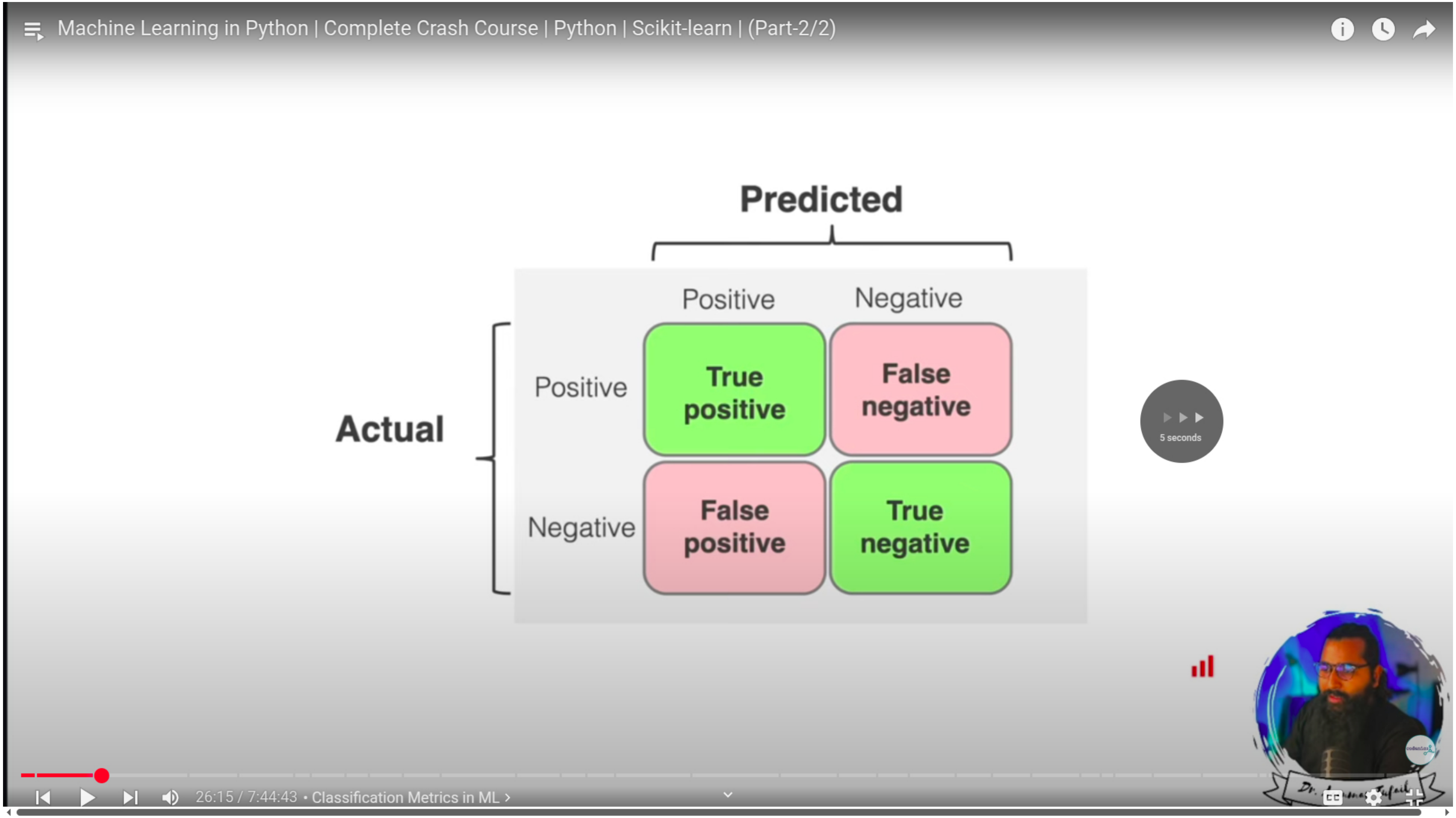
Machine Learning in Python | Complete Crash Course | Python | Scikit-learn | (Part-2/2)

Regression, Classification and Clustering

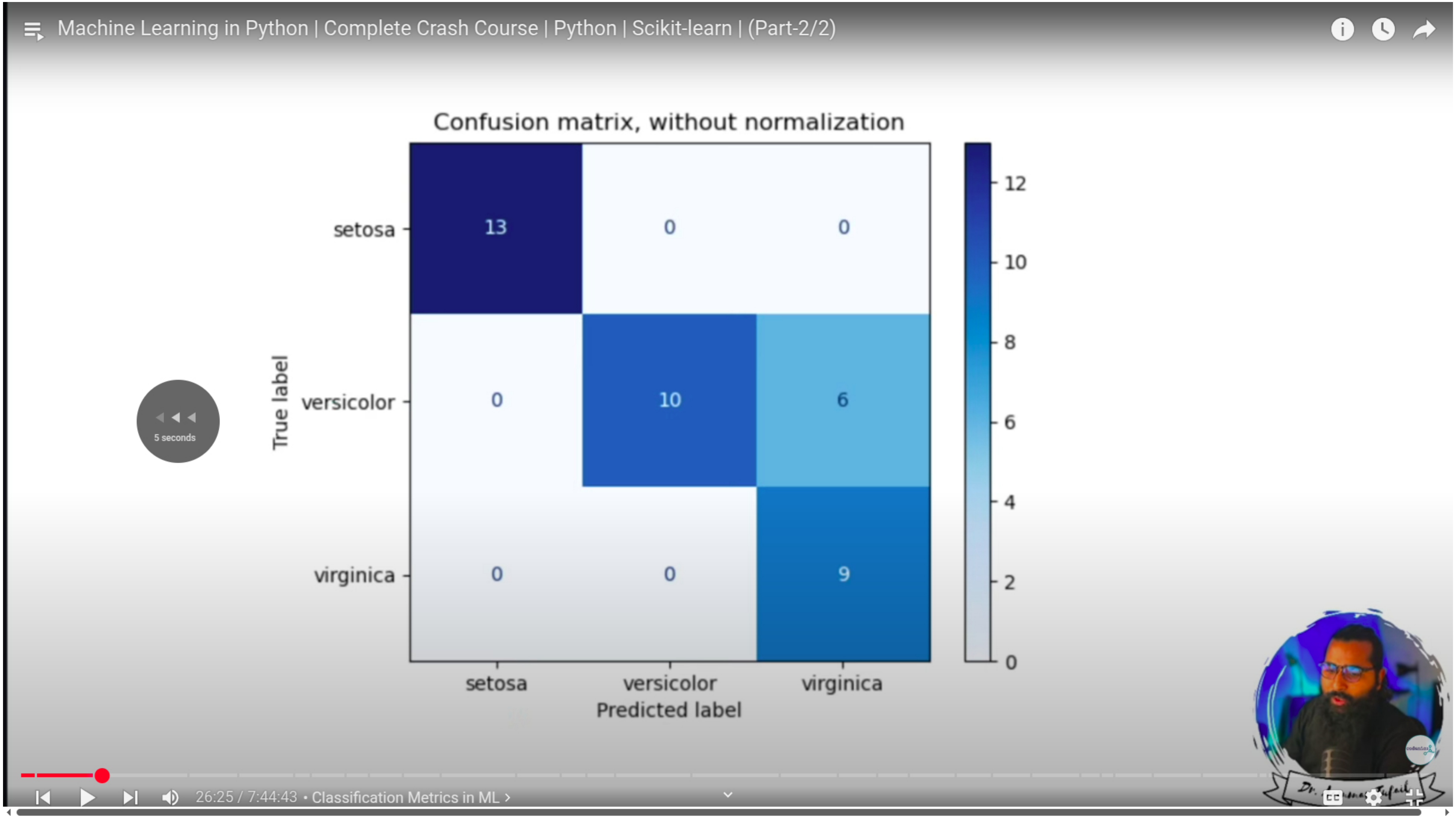


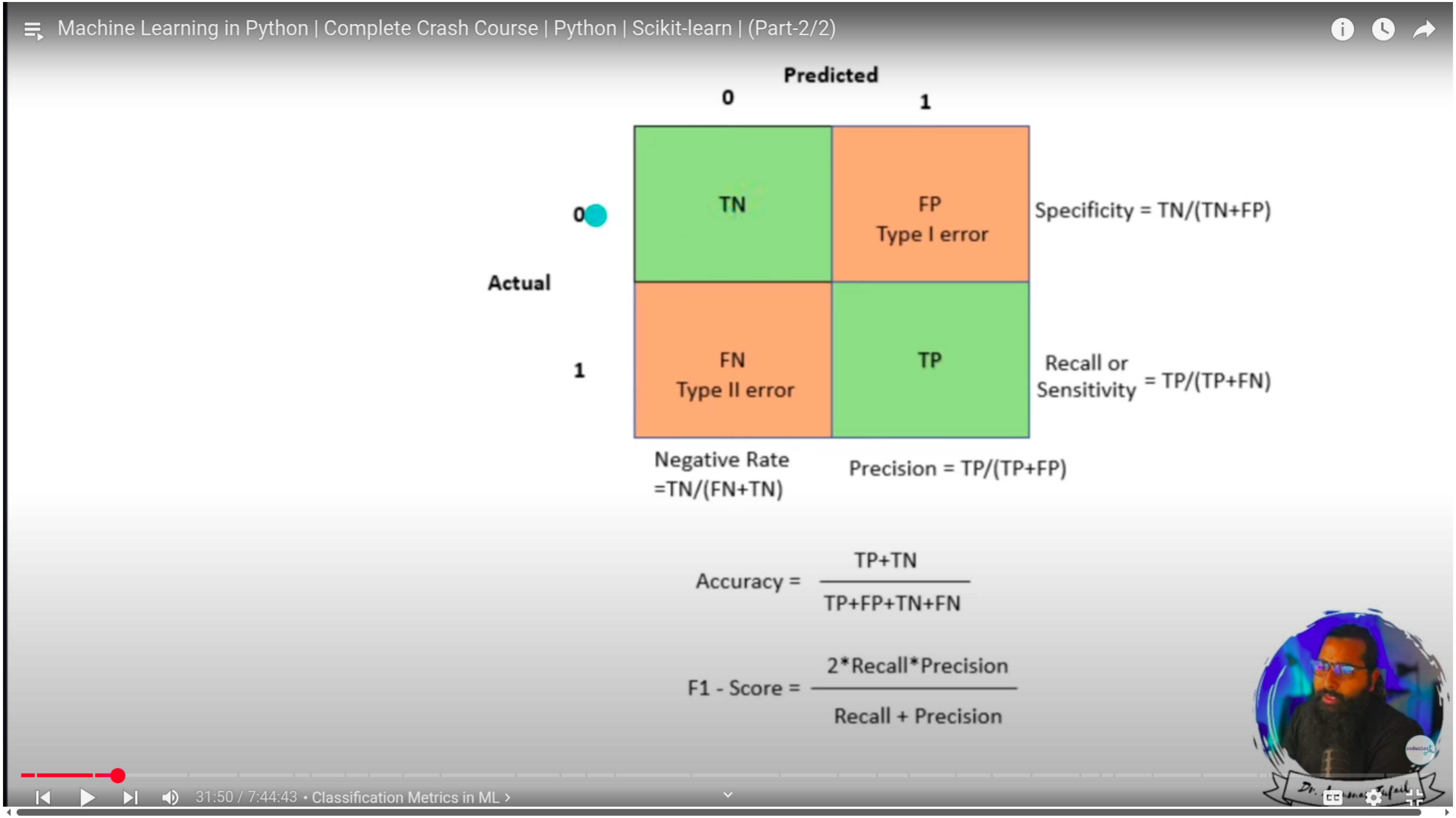
24:35 / 7:44:43 • Classification Metrics in ML ›

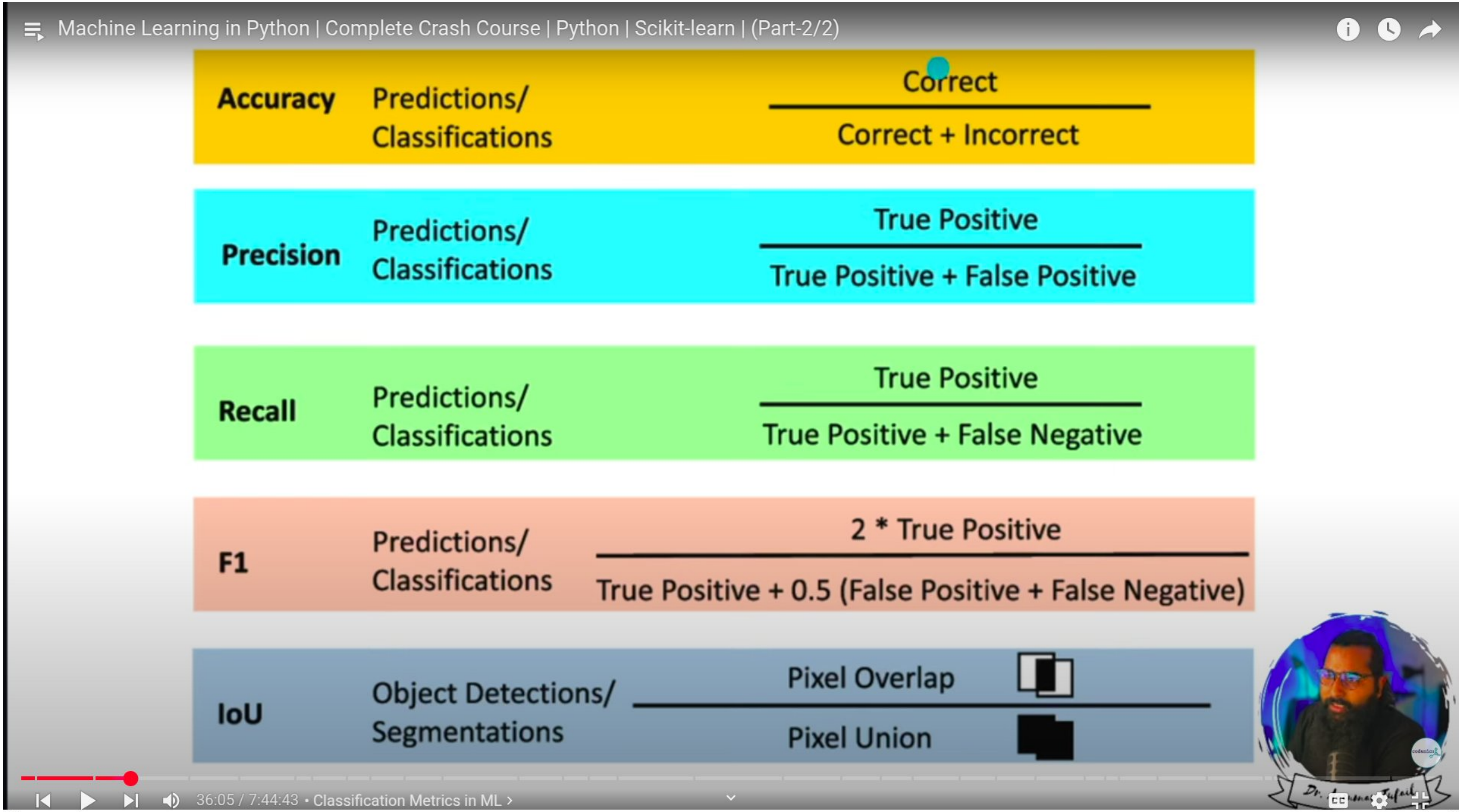

Machine Learning in Python | Complete Crash Course | Python | Scikit-learn | (Part-2/2)
Evaluation Metrics
5 seconds
24:45 / 7:44:43 • Classification Metrics in ML ›



Machine Learning in Python | Complete Crash Course | Python | Scikit-learn | (Part-2/2)
Predicted
Positive
Negative
Actual
Positive
True positive
False negative
Negative
False positive
True negative
5 seconds
26:15 / 7:44:43 • Classification Metrics in ML ›


Machine Learning in Python | Complete Crash Course | Python | Scikit-learn | (Part-2/2)
Confusion matrix, without normalization
setosa
versicolor
virginica
True label
13
0
0
0
10
6
0
0
9
setosa
versicolor
virginica
Predicted label
12
10
8
6
4
2
0
5 seconds
26:25 / 7:44:43 • Classification Metrics in ML ›


Machine Learning in Python | Complete Crash Course | Python | Scikit-learn | (Part-2/2)
Predicted
0
1
Actual
0
1
TN
FP
Type I error
FN
Type II error
TP
Specificity = TN/(TN+FP)
Recall or
Sensitivity = TP/(TP+FN)
Negative Rate
=TN/(FN+TN)
Precision = TP/(TP+FP)
Accuracy = TP+TN / TP+FP+TN+FN
F1 - Score = 2*Recall*Precision / Recall + Precision
31:50 / 7:44:43 • Classification Metrics in ML ›


Machine Learning in Python | Complete Crash Course | Python | Scikit-learn | (Part-2/2)
Accuracy
Predictions/ Classifications
Correct / Correct + Incorrect
Precision
Predictions/ Classifications
True Positive / True Positive + False Positive
Recall
Predictions/ Classifications
True Positive / True Positive + False Negative
F1
Predictions/ Classifications
2 * True Positive / True Positive + 0.5 (False Positive + False Negative)
IoU
Object Detections/ Segmentations
Pixel Overlap / Pixel Union
36:05 / 7:44:43 • Classification Metrics in ML ›

Machine Learning in Python | Complete Crash Course | Python | Scikit-learn | (Part-2/2)

		Actual class (ground truth)		
Total (n)=100		Dog (Positive)	Not a Dog (Negative)	
Predicted class	Dog (Positive)	15 (TP)	20 (FP, Type I Error)	**Precision** =TP/(TP+FP) =0.42
	Not a Dog (Negative)	5 (FN, Type II Error)	60 (TN)	
	Accuracy =(TP+TN)/Total =0.75	**Sensitivity,Recall, TPR** =TP/(TP+FN) = 0.75	**FPR** = FP/(FP+TN) =0.25	**F1 Score** =2*(Precision*Recall) / (Precision+Recall) =0.53
	Error Rate =(FP+FN)/Total =0.25	**Miss Rate, FNR** =FN/(TP+FN) =0.25	**Specificity, TNR** = TN/(FP+TN) =0.75	

40:40 / 7:44:43 • Classification Metrics in ML ›

Machine Learning in Python | Complete Crash Course | Python | Scikit-learn | (Part-2/2)

Metric	Description	Pros	Cons	Example
Accuracy	Proportion of correctly predicted observations to the total observations.	Simple and intuitive.	Can be misleading in imbalanced datasets.	For 100 predictions with 90 correct predictions, accuracy is 90%.
Precision	Proportion of correctly predicted positive observations to the total predicted positive observations.	Focuses on the relevancy of results.	Doesn't consider true negative results.	For 30 true positive predictions out of 40 total positive predictions, precision is 75%.
Recall (Sensitivity)	Proportion of correctly predicted positive observations to all observations in actual class.	Useful in cases where False Negatives are costly.	Can lead to ignoring the true negatives.	For 30 true positive predictions out of 40 actual positive instances, recall is 75%.
F1 Score	Harmonic mean of Precision and Recall.	Balances Precision and Recall.	May not be a good measure when an unbalanced importance between Precision and Recall.	With Precision = 75% and Recall = 75%, F1 Score is 2*(0.75*0.75)/(0.75+0.75) = 75%.
Area Under the ROC Curve (AUC-ROC)	Measures the ability of a classifier to distinguish between classes.	Effective for binary classification problems.	Less informative for multi-class problems.	If the AUC is 0.90, there's a 90% chance that the model will be able to ...ish between positive and neg...
Confusion Matrix	A table showing actual vs. predicted values.	Provides a detailed breakdown of correct and incorrect classifications.	More complex to interpret.	A matrix showing Tru... Positives, True Negati... Negatives.

50:45 / 7:44:43 • Classification Metrics in ML ›