Recall, Precision, F1, ROC, AUC, and everything

 Data, Data Science, Python, Statistics May 27, 2019May 31, 2019 5 Minutes
Your boss asked you to build a fraud detection classifier, so you've created one.

The output of your fraud detection model is the probability [0.0-1.0] that a transaction is *fraudulent*. If this probability is below **0.5**, you classify the transaction as *non-fraudulent*; otherwise, you classify the transaction as *fraudulent*.

To evaluate the performance of your model, you collect **10,000** manually classified transactions, with **300** *fraudulent* transaction and **9,700** *non-fraudulent* transactions. You run your classifier on every transaction, predict the class label (*fraudulent* or non-*fraudulent*) and summarise the results in the following *confusion matrix*:

		Predicted / Classified		
		- (Negative)	+ (Positive)	
True	- (Negative)	True Negative (TN) 9,000	False Positive (FP) 700	**Overall True Negative: 9,700**
	+ (Positive)	False Negative (FN) 200	True Positive (TP) 100	**Overall True Positive: 300**
		Overall Predicted Negative: 9,100	**Overall Predicted Positive: 900**	

A **True Positive (TP=100)** is an outcome where the model *correctly* predicts the *positive (fraudulent)* class. Similarly, a **True Negative (TN=9,000)** is an outcome where the model *correctly* predicts the *negative (non-fraudulent)* class.

A **False Positive (FP=700)** is an outcome where the model *incorrectly* predicts the *positive (fraudulent)* class. And a **False Negative (FN=200)** is an outcome where the model *incorrectly* predicts the *negative (non-fraudulent)* class.

Asking yourself what percent of your predictions were correct, you calculate the **accuracy**:

$$Accuracy = \frac{True}{True+False} = \frac{TP+TN}{TP+TN+FP+FN} = \frac{100+9{,}000}{100+9{,}000+700+200} = \frac{9{,}100}{10{,}000} = 0.91$$

Wow, 91% accuracy! Just before sharing the great news with your boss, you notice that out of the 300 *fraudulent* transactions, only 100 *fraudulent* transactions are classified correctly. Your classifier missed 200 out of the 300 fraudulent transactions!

Your colleague, hardly hiding her simile, suggests a “better” classifier. Her classifier predicts every transaction as *non-fraudulent* (negative), with a staggering **97%** accuracy!

		Predicted / Classified		
		- (Negative)	+ (Positive)	
True	- (Negative)	True Negative (TN) 9,700	False Positive (FP) 0	**Overall True Negative: 9,700**
	+ (Positive)	False Negative (FN) 300	True Positive (TP) 0	**Overall True Positive: 300**
		Overall Predicted Negative: 9,100	**Overall Predicted Positive: 900**	

$$Accuracy = \frac{True}{True+False} = \frac{TP+TN}{TP+TN+FP+FN} = \frac{0+9{,}700}{100+9{,}000+700+200} = \frac{9{,}700}{10{,}000} = 0.97$$

While *97% accuracy* may seem excellent at first glance, you've soon realized the catch: your boss asked you to build a fraud detection classifier, and with the always-return-*non-fraudulent* classifier you will miss **all** the fraudulent transactions.

> *"Nothing travels faster than the speed of light, with the possible exception of bad news, which obeys its own special laws."*
>
> — *Douglas Adams*

You learned the hard-way that accuracy can be misleading and that for problems like this, additional measures are required to evaluate your classifier.

You start by asking yourself **what percent of the positive *(fraudulent)* cases did you catch**? You go back to the confusion matrix and divide the True Positive (TP – blue oval) by the overall number of **true** fraudulent transactions (red rectangle)

		Predicted / Classified		
		- (Negative)	**+ (Positive)**	
True	**- (Negative)**	True Negative (TN) 9,000	False Positive (FP) 700	**Overall True Negative: 9,700**
	+ (Positive)	False Negative (FN) 200	True Positive (TP) 100	**Overall True Positive: 300**
		Overall Predicted Negative: 9,100	**Overall Predicted Positive: 900**	

$$Recall(TruePositiveRate) = \frac{TP}{TP+FN} = \frac{100}{100+200} \approx 0.333$$

So the classier **caught 33.3%** of the *fraudulent* transactions.

Next, you ask yourself **what percent of positive *(fraudulent)* predictions were correct?** You go back to the *confusion matrix* and divide the True Positive (TP – blue oval) by the overall number of **predicted** fraudulent transactions (red rectangle)

		Predicted / Classified		
		- (Negative)	**+ (Positive)**	
True	**- (Negative)**	True Negative (TN) 9,000	False Positive (FP) 700	**Overall True Negative: 9,700**
	+ (Positive)	False Negative (FN) 200	True Positive (TP) 100	**Overall True Positive: 300**
		Overall Predicted Negative: 9,100	**Overall Predicted Positive: 900**	

$$Precision = \frac{TP}{TP+FP} = \frac{100}{100+700} = 0.125$$

So now you know that when your classifier predicts that a transaction is *fraudulent*, **only 12.5% of the time your classifier is correct**.

F1 Score combines Recall and Precision to one performance metric. F1 Score is the weighted average of Precision and Recall. Therefore, this score takes both false positives and false negatives into account. F1 is usually more useful than Accuracy, especially if you have an uneven class distribution.

$$F1 = 2 * \frac{Recall*Precision}{Recall+Precision} = 2 * \frac{0.333*0.125}{0.333+0.125} \approx 0.182$$

Finally, you ask yourself what percent of **negative *(non-fraudulent)* predictions were incorrect?** You go back to the *confusion matrix* and divide the False Positive (FP – blue oval) by the overall number of **true** *non-fraudulent* transactions (red rectangle)

		Predicted / Classified		
		- (Negative)	**+ (Positive)**	
True	**- (Negative)**	True Negative (TN) 9,000	False Positive (FP) 700	**Overall True Negative: 9,700**
	+ (Positive)	False Negative (FN) 200	True Positive (TP) 100	**Overall True Positive: 300**
		Overall Predicted Negative: 9,100	**Overall Predicted Positive: 900**	

$$FalsePositiveRate = \frac{FP}{FP+TN} = \frac{700}{700+9{,}000} \approx 0.072$$

7.2% of the non-fraudulent transactions were **classified incorrectly** as **fraudulent** transactions.

ROC (**Receiver Operating Characteristics**)

You soon learn that you must examine **both** Precision and Recall. Unfortunately, Precision and Recall are often in tension. That is, improving Precision typically reduces Recall and vice versa.

The overall performance of a classifier, summarized over all possible thresholds, is given by the Receiver Operating Characteristics (ROC) curve. The name "ROC" is historical and comes from communications theory. ROC Curves are used to see how well your classifier can separate positive and negative examples and to identify the best threshold for separating them.

To be able to use the ROC curve, your classifier should be able to rank examples such that the ones with higher rank are more likely to be positive (*fraudulent*). As an example, Logistic Regression outputs *probabilities*, which is a score that you can use for ranking.

You train a new model and you use it to predict the outcome of 10 new test transactions, summarizing the result in the following table: the values of the middle column (True Label) are either zero (0) for *non-fraudulent* transactions or one (1) for *fraudulent* transactions, and the last column (Fraudulent Prob) is the probability that the transaction is *fraudulent*:

Transaction ID	True Label	Fraudulent Prob
0	0	0.01
1	0	0.1
2	1	0.2
3	0	0.3
4	1	0.4
5	0	0.5
6	0	0.6
7	1	0.7
8	1	0.8
9	1	0.9

Remember the **0.5** threshold? If you are concerned about missing the two *fraudulent* transactions (red circles), then you may consider lowering this threshold.

Transaction ID	True Label	Fraudulent Prob
0	0	0.01
1	0	0.1
2	1	0.2
3	0	0.3
4	1	0.4
5	0	Threshold 0.5
6	0	0.6
7	1	0.7
8	1	0.8
9	1	0.9

For instance, you might lower the threshold and label any transaction with a probability below 0.1 to the *non-fraudulent* class, catching the two *fraudulent* transactions that you previously missed.

Transaction ID	True Label	Fraudulent Prob
0	0	0.01
1	0	Threshold 0.1
2	1	0.2
3	0	0.3
4	1	0.4
5	0	0.5
6	0	0.6
7	1	0.7
8	1	0.8
9	1	0.9

To derive the ROC curve, you calculate the **True Positive Rate (TPR)** and the **False Positive Rate (FPR)**, starting by setting the threshold to **1.0**, where every transaction with a Fraudulent Prob of less than **1.0** is classified as *non-fraudulent (0)*. The column "T=1.0" shows the predicted class labels when the threshold is 1.0:

Transaction ID	True Label	Fraudulent Prob	T=1.0
0	0	0	0
1	0	0.1	0
2	1	0.2	0
3	0	0.3	0
4	1	0.4	0
5	0	0.5	0
6	0	0.6	0
7	1	0.7	0
8	1	0.8	0
9	1	0.9	0

Threshold

The confusion matrix for the Threshold=1.0 case:

		Predicted / Classified		
		- (Negative)	+ (Positive)	
True	- (Negative)	True Negative (TN) 5	False Positive (FP) 0	Overall True Negative: 5
	+ (Positive)	False Negative (FN) 5	True Positive (TP) 0	Overall True Positive: 5
		Overall Predicted Negative: 10	Overall Predicted Positive: 0	

The **ROC** curve is created by plotting the **True Positive Pate (TPR)** against the **False Positive Rate (FPR)** at various **threshold** settings, so you calculate both:

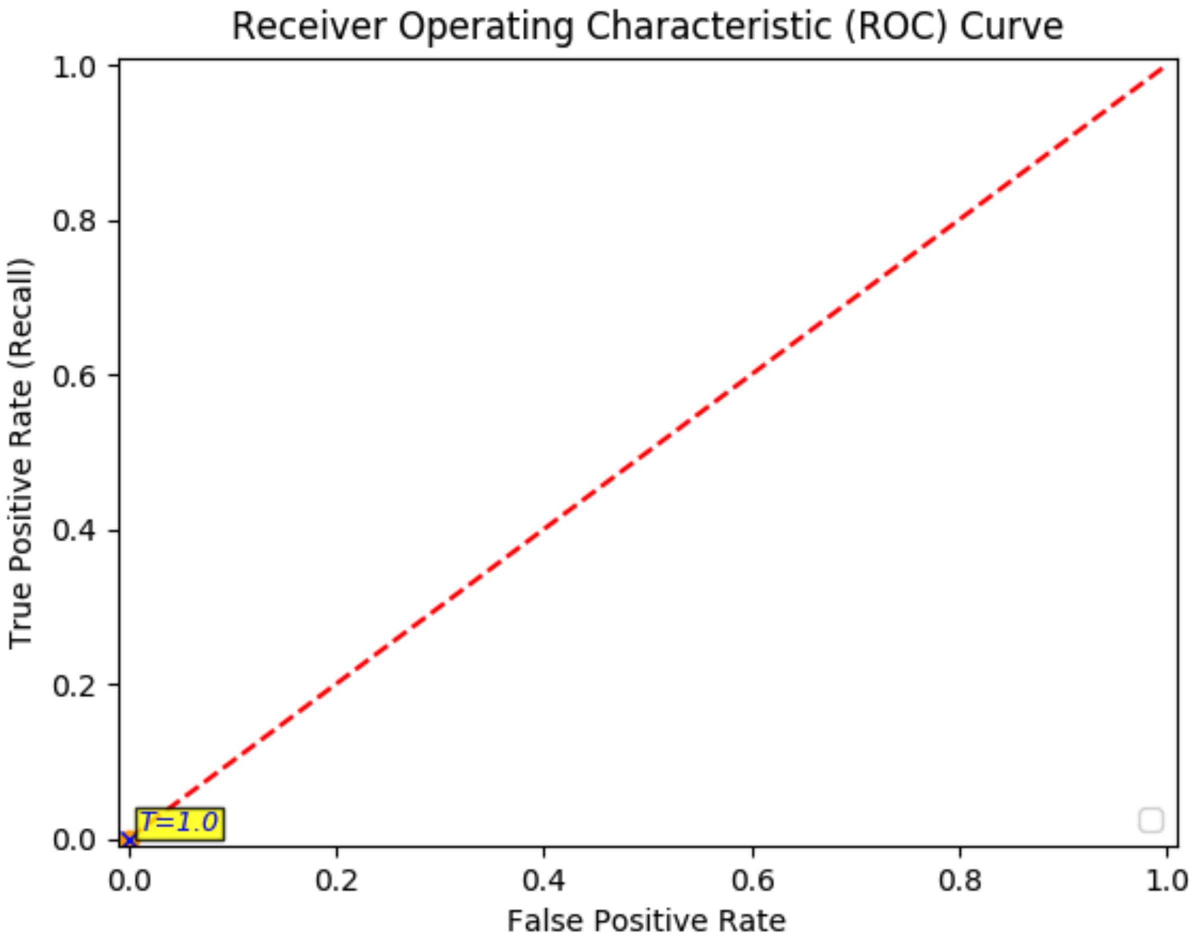
$$TruePositiveRate(Recall) = \frac{TP}{TP+FN} = \frac{0}{0+5} = 0$$

$$FalsePositiveRate = \frac{FP}{FP+TN} = \frac{0}{0+5} = 0$$

You summarize it in the following table:

Threshold	False Positive Rate	True Positive Rate	F1
1.0	0	0	0

Now you can finally plot the first point on your ROC graph! A random guess would give a point along the dotted diagonal line (the so-called *line of no-discrimination*) from the left bottom to the top right corners



You now lower the threshold to 0.9, and recalculate the FPR and the TPR:

Transaction ID	True Label	Fraudulent Prob	T=1.0	T=0.9
0	0	0	0	0
1	0	0.1	0	0
2	1	0.2	0	0
3	0	0.3	0	0
4	1	0.4	0	0
5	0	0.5	0	0
6	0	0.6	0	0
7	1	0.7	0	0
8	1	0.8	0	0
9	1	0.9	0	1

Threshold

The confusion matrix for Threshold=0.9:

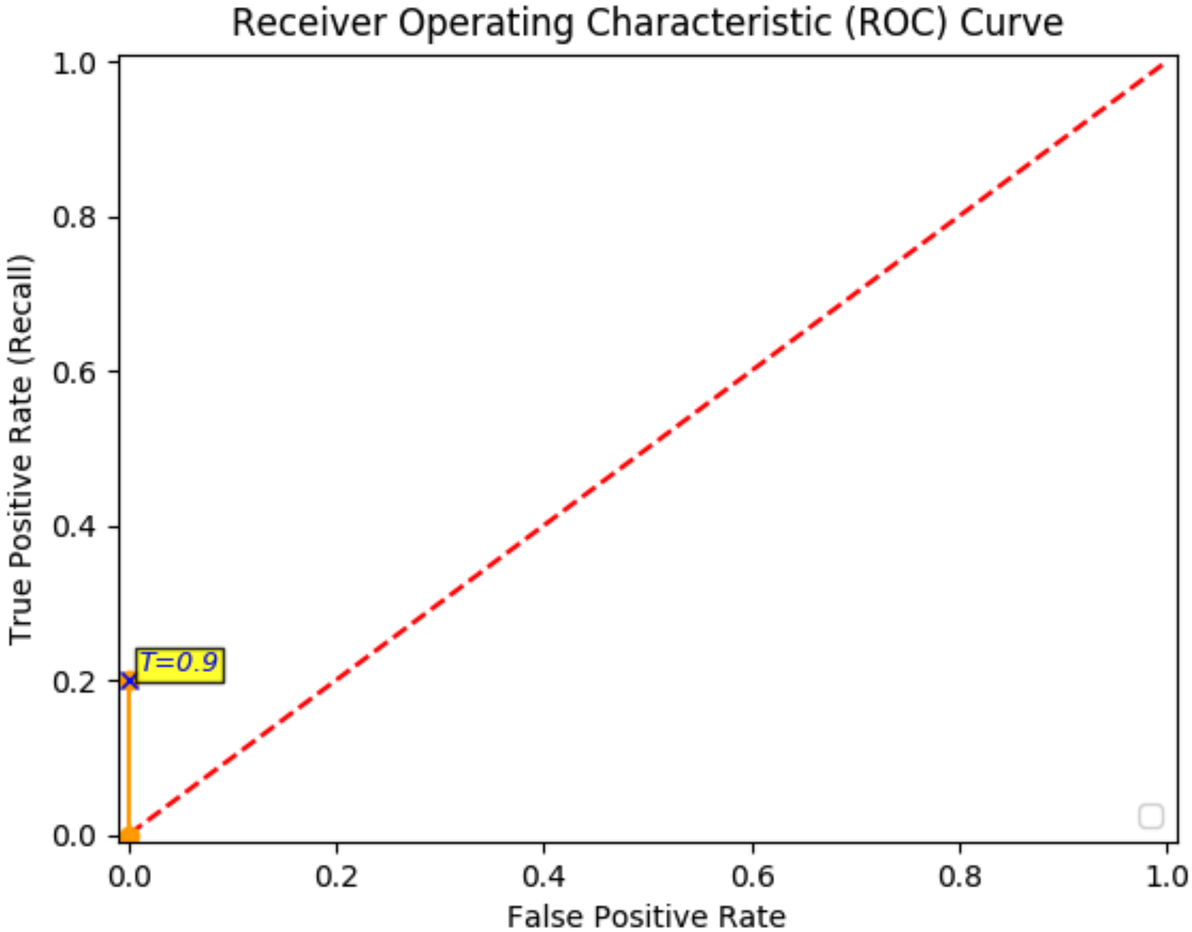
		Predicted / Classified		
		- (Negative)	+ (Positive)	
True	- (Negative)	True Negative (TN) 5	False Positive (FP) 0	Overall True Negative: 5
	+ (Positive)	False Negative (FN) 4	True Positive (TP) 1	Overall True Positive: 5
		Overall Predicted Negative: 9	Overall Predicted Positive: 1	

$$TruePositiveRate(Recall) = \frac{TP}{TP+FN} = \frac{1}{1+4} = 0.2$$

$$FalsePositiveRate = \frac{FP}{FP+TN} = \frac{0}{0+5} = 0$$

Adding a new row to your summary table:

Threshold	False Positive Rate	True Positive Rate	F1
1.0	0	0	0
0.9	0	0.2	0.333

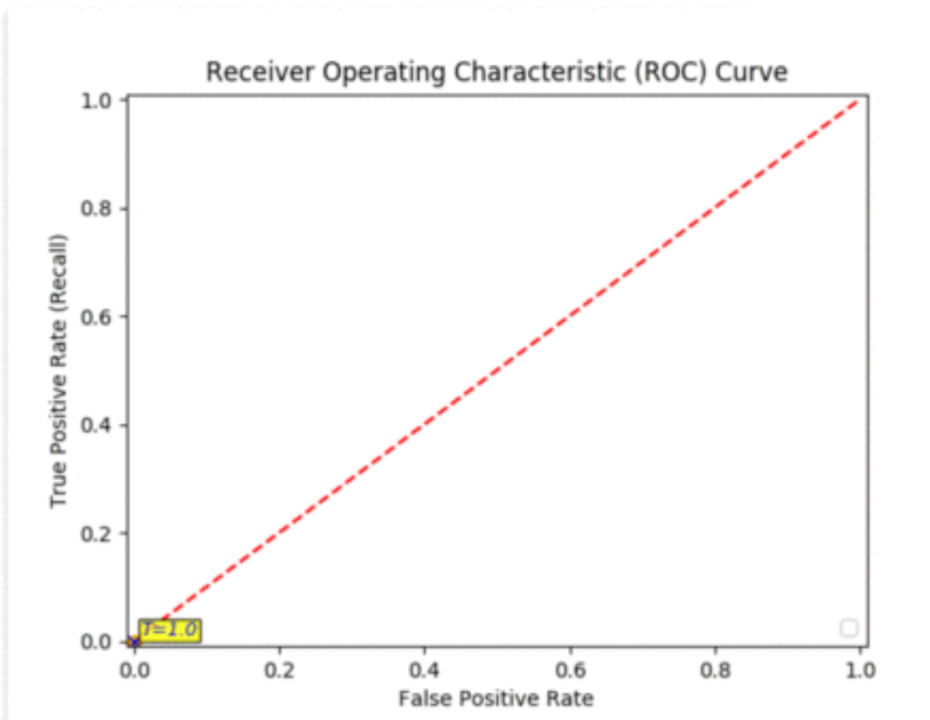


You continue and plot the **True Positive Pate (TPR)** against the **False Positive Rate (FPR)** at various **threshold** settings:

Threshold = 1.0

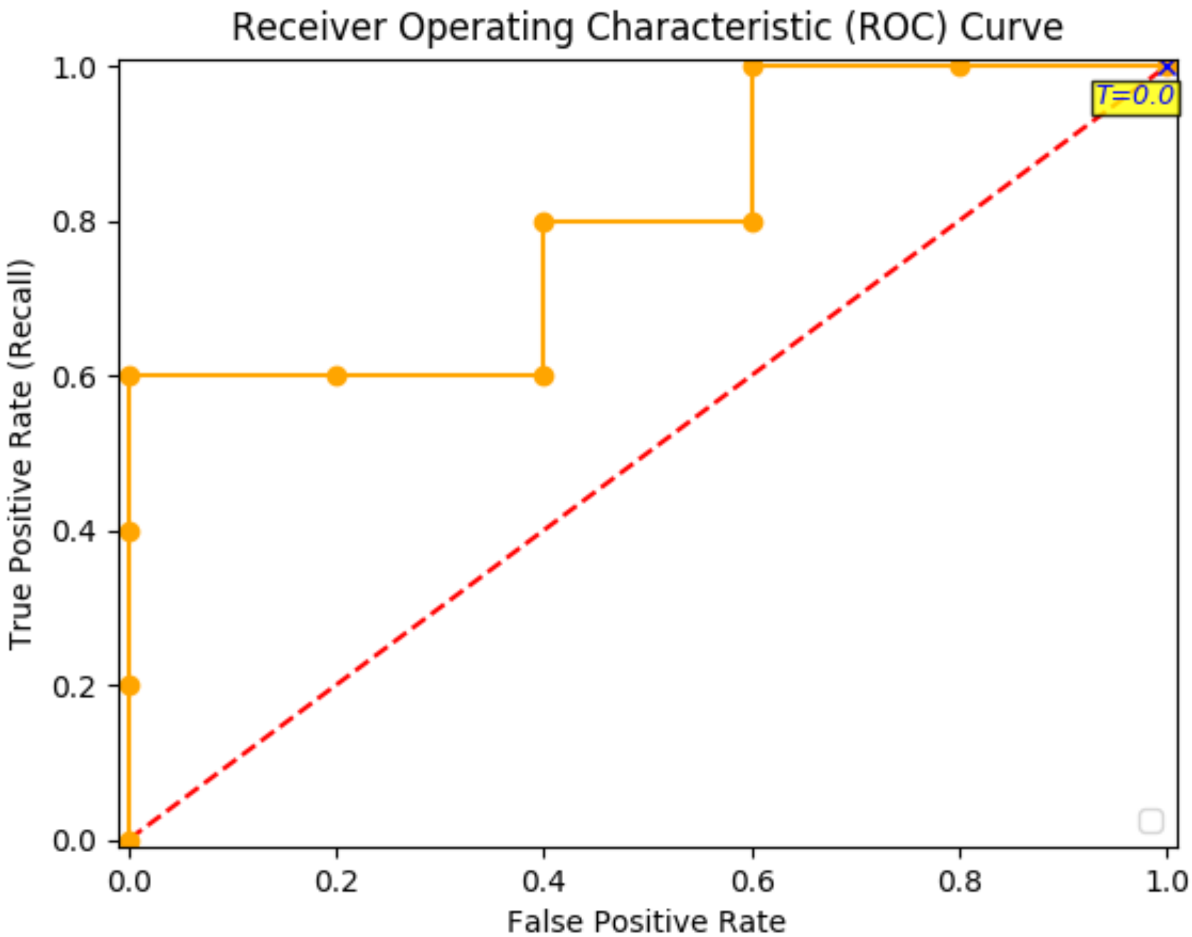
Transaction ID	True Label	Fraudulent Prob	T=1.0
0	0	0	0
1	0	0.1	0
2	1	0.2	0
3	0	0.3	0
4	1	0.4	0
5	0	0.5	0
6	0	0.6	0
7	1	0.7	0
8	1	0.8	0
9	1	0.9	0

Threshold	False Positive Rate	True Positive Rate
1.0	0	0



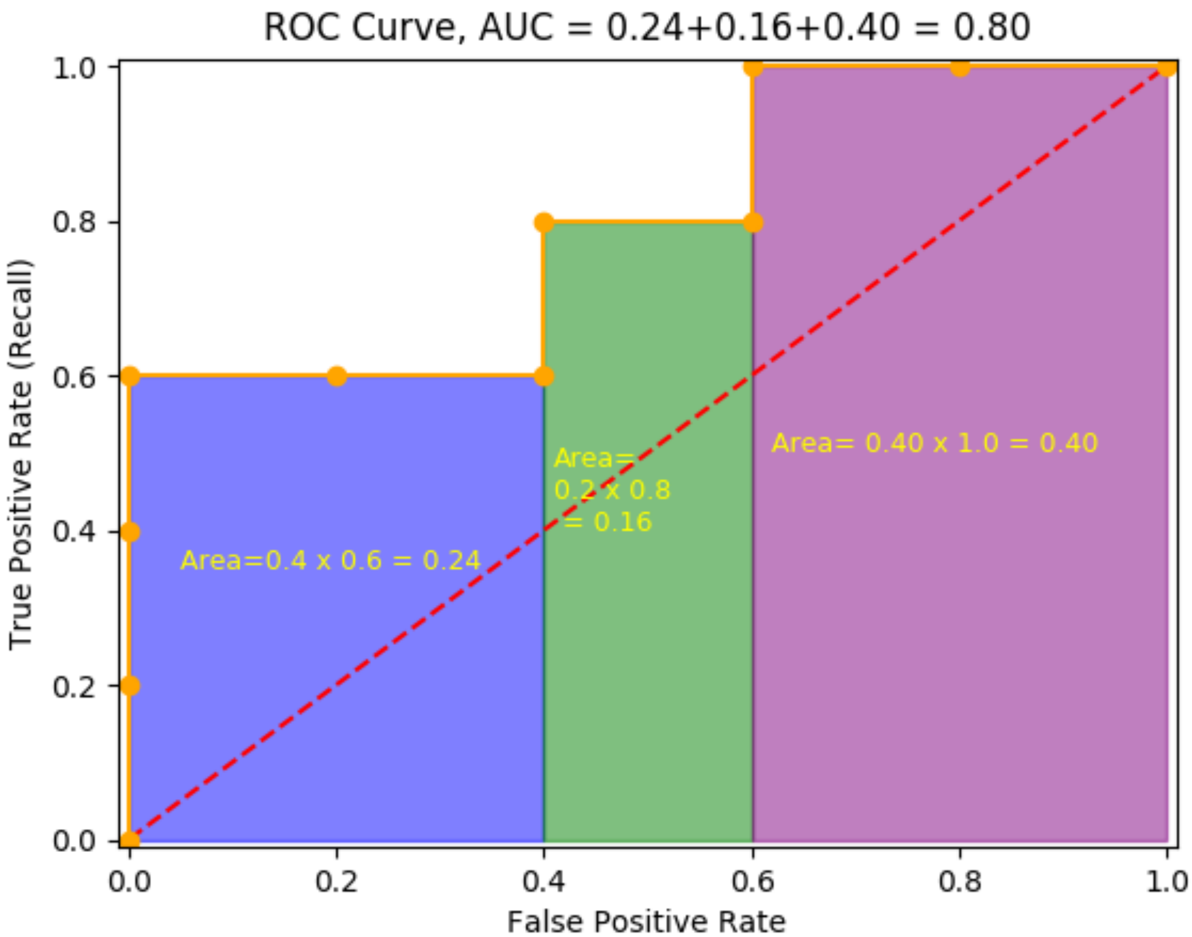
Receiver Operating Characteristics (ROC) curve

And voila, here is your ROC curve!



AUC (**Area Under the Curve)**

The model performance is determined by looking at the area under the ROC curve (or AUC). An excellent model has AUC near to the 1.0, which means it has a good measure of separability. For your model, the AUC is the combined are of the blue, green and purple rectangles, so the AUC = 0.4 x 0.6 + 0.2 x 0.8 + 0.4 x 1.0 = 0.80.



You can validate this result by calling roc_auc_score, and the result is indeed 0.80.

```
auc = roc_auc_score(dfSortedByProbability['True Label'], dfSortedByProbability['Fraudulent Prob'])
print('AUC: {:.2f}'.format(auc))
# AUC: 0.80
```

Conclusion

- Accuracy will not always be the metric.
- Precision and recall are often in tension. That is, improving precision typically reduces recall and vice versa.
- AUC-ROC curve is one of the most commonly used metrics to evaluate the performance of machine learning algorithms.
- ROC Curves summarize the trade-off between the true positive rate and false positive rate for a predictive model using different probability thresholds.
- The ROC curve can be used to choose the best operating point.

Thanks for Reading! You can reach me at LinkedIn (https://www.linkedin.com/in/ofirshalev) and Twitter (https://twitter.com/ofirdi).

References:

[1] An Introduction to Statistical Learning [James, Witten, Hastie, and Tibshirani]

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