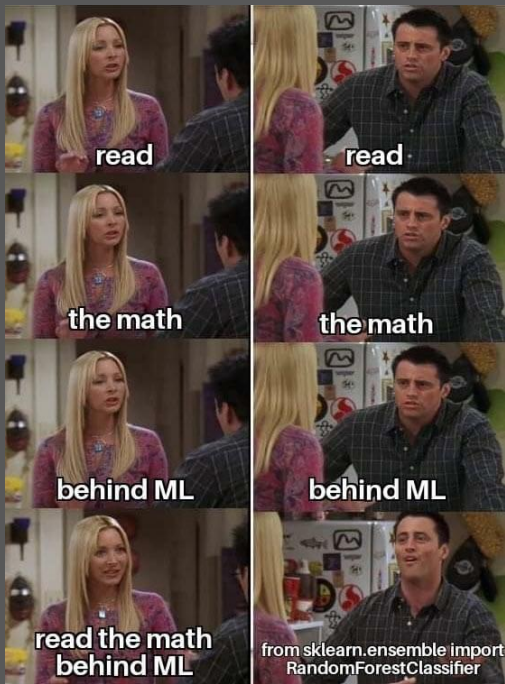




## Discussion ROC



We learned that in logistic regression, our goal is to create a model with maximum likelihood



But we also have an additional way to further evaluate the model

# Introduce: Confusion Matrix

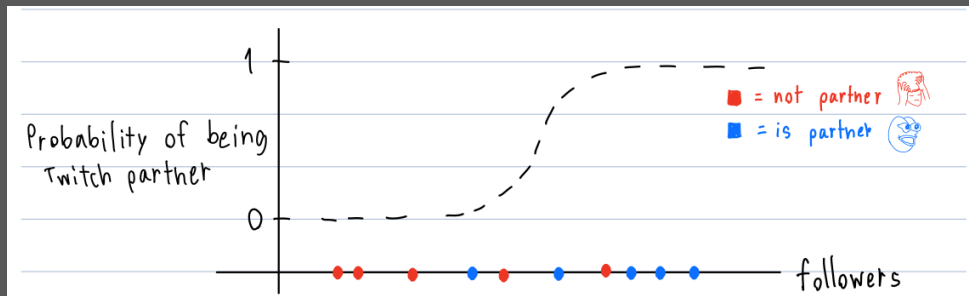


A confusion matrix is a table that is often used to **describe the performance of a classification model**

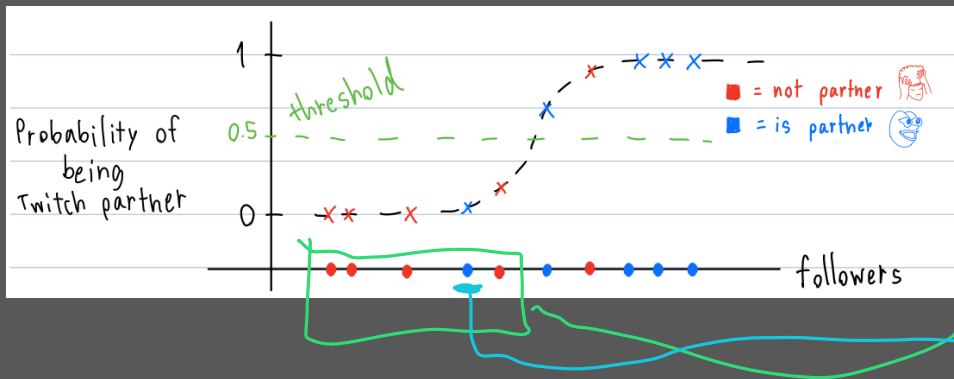
- True positive (TP): predict **positive**, and actually is **positive**
- True negative (TN): predict **negative**, and actually is **negative**
- False positive (FP): predict **positive**, and actually is **negative**
- False negative (FN): predict **negative**, and actually is **positive**

		True Class	
		Positive	Negative
Predicted Class	Positive	TP	FP
	Negative	FN	TN

## Example



Set threshold at 0.5



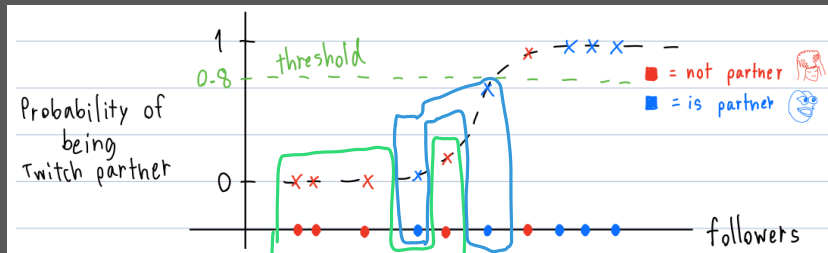
Predicted



Actual

	Is partner	Is not partner
Is partner	4	1
Is not partner	1	4

Now change threshold to 0.8



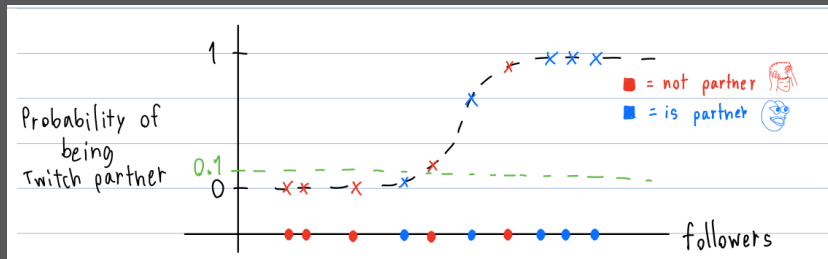
Predicted



Actual

	Is partner	Is not partner
Is partner	3	1
Is not partner	2	4

Now change threshold to 0.1



Predicted



Actual

	Is partner	Is not partner
Is partner	4	2
Is not partner	1	3

Actual

threshold at 0.5

Predicted

	Is partner	Is not partner
Is partner	4	1
Is not partner	1	4

Actual

threshold at 0.8

Predicted

	Is partner	Is not partner
Is partner	3	1
Is not partner	2	4

Actual

threshold at 0.1

Predicted

	Is partner	Is not partner
Is partner	4	2
Is not partner	1	3

**From these tables, what can we infer?**

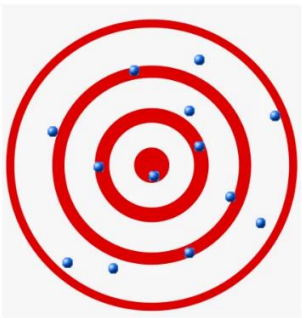
- **Accuracy:** Overall, how often is the classifier correct?
- **Precision:** When it predicts yes, how often is it correct? (It tells us how much you should trust the model when it says it found something)
- **F Score:** This is a weighted average of the true positive rate (recall) and precision
- **Recall:** (aka sensitivity, true positive rate) It tells us how much the model can find the thing you're looking for



A: accurate and precise



B: precise, but not accurate



C: neither accurate nor precise



D: accurate, but not precise



By looking at the matrices, it is difficult to visualize, so let's make a graph!

Predicted.

threshold at 0.8

Actual

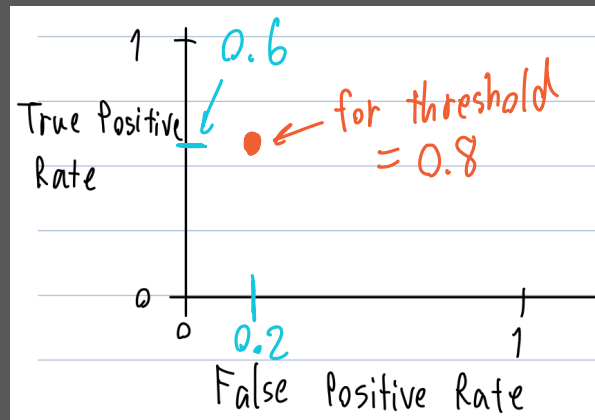
	Is partner	Is not partner
Is partner	3	1
Is not partner	2	4

$$\text{True positive rate} = \frac{TP}{(TP + FN)} = \frac{3}{(3 + 2)} = 0.6$$

$$\text{False positive rate} = \frac{FP}{(FP + TN)} = \frac{1}{(1 + 4)} = 0.2$$

Positive  $\longleftrightarrow$  is partner

Negative  $\longleftrightarrow$  not partner



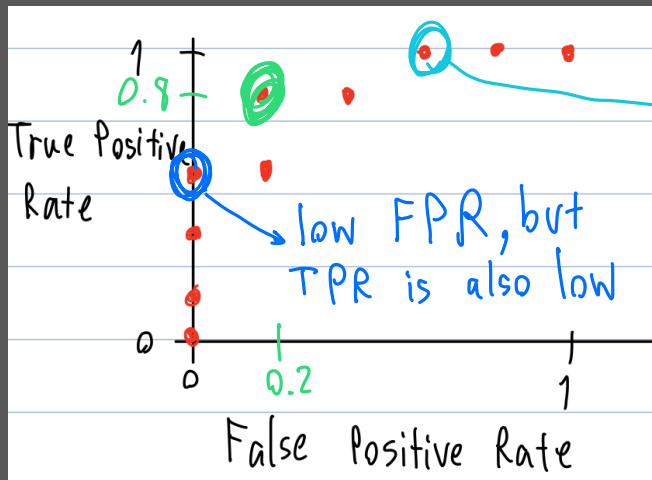
Keep plotting with different threshold, and we will have the following ROC curve graph for this model:



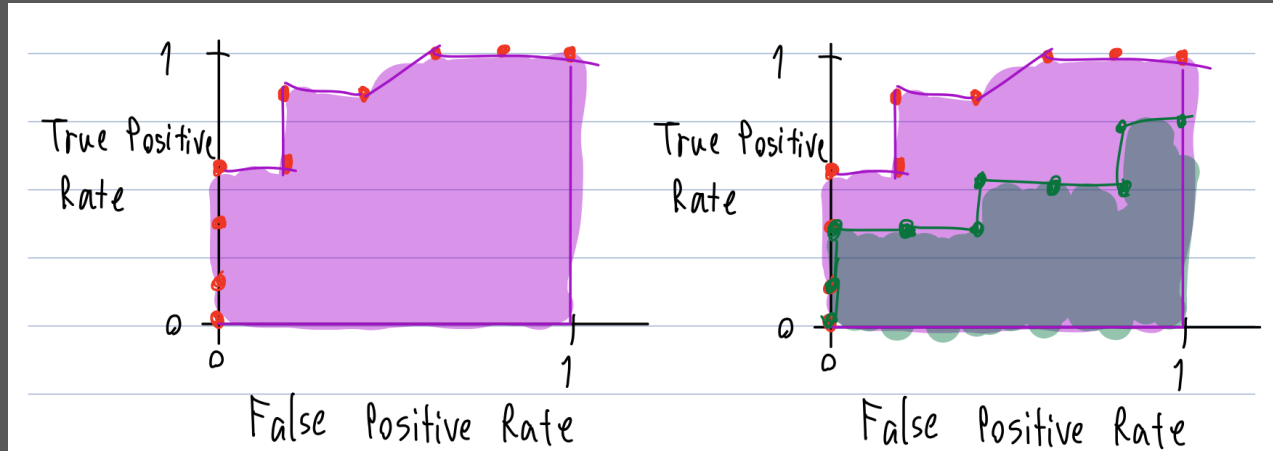
There are 2 things we can consider from ROC curve:

1. We can choose which threshold is good for our goal. For example, we want least false positive rate, we will choose the very left one

Note: always consider TP, FP.  
For example, incorrectly classify that a person has a disease [FP]



2. When we create multiple classification model, each model has its own ROC curve. In general, the best performance model has higher area under the curve (AUC)



Ex

Pink  $\rightarrow$  logistic regression , Green  $\rightarrow$  Decision Tree

## But you know, I learned something today

class 1: 0.2  
class 2: 0.6  
class 3: 0.1  
class 4: 0.1



Note: Multiclass

↓  
Generally, classify as class  $n$ , if it returns highest probability.

- We use confusion matrix to get TP, FP, TN, FN
- We can evaluate our model's performance from confusion matrix
- On our model, we have to weigh whether to include FP/FN at a cost of accuracy

Break until 2:05