	Predicted Class			
Actual class		Yes	No	
	Yes	2750	250	3000
	No	150	2850	3000
		2900	3100	6000

Confusion matrix

$$\text{Sensitivity} = \frac{TP}{TP+FN} = \frac{2750}{2750+250}$$

$$\text{Specificity} = \frac{TN}{FP+TN} = \frac{2850}{2850+150}$$

$$\text{Precision} = \frac{TP}{TP+FP} = \frac{2750}{2750+150}$$

$$\text{Recall} = \frac{TP}{TP+FN} = \frac{2850}{2850+150}$$

ROC: Details Part 1

Gentle Reminder:

		Predicted: Yes	Predicted: No
Actual	Yes	**TP**	FN
Actual	No	FP	**TN**

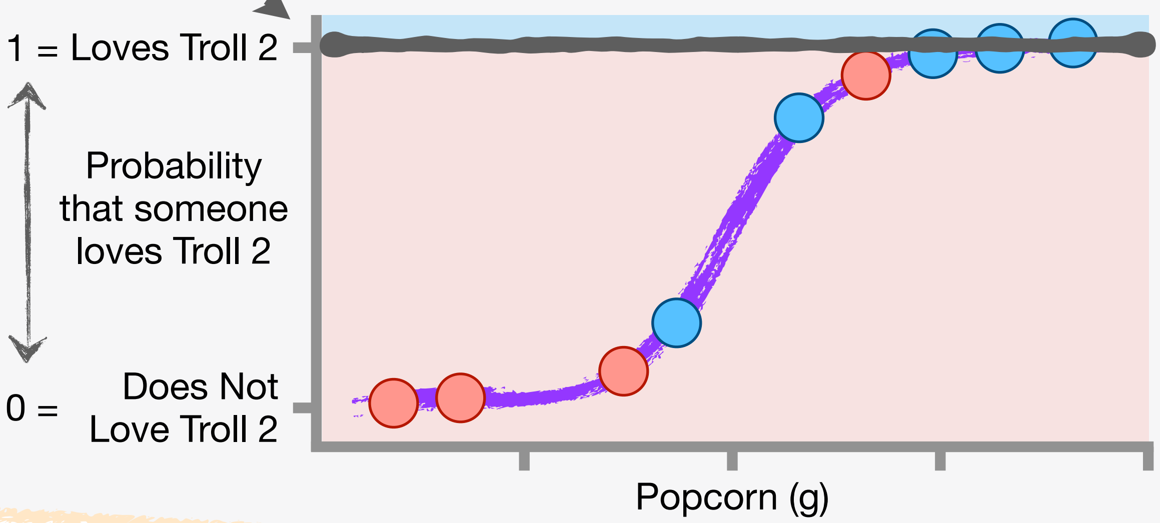
True Positive

False Negative

False Positive

True Negative

1 To get a better sense of how an **ROC** graph works, let's draw one from start to finish. We'll start by using a classification threshold, **1**, that classifies everyone as someone who **Does Not Love Troll 2**...



...and when the classification threshold is set to **1**, we end up with this **Confusion Matrix**.

		Predicted: Yes	Predicted: No
Actual	Yes	0	5
Actual	No	0	4

Threshold = 1

2 Using the values in the **Confusion Matrix**, we can calculate the **True Positive Rate**...

$$\textbf{True Positive Rate} = \frac{\text{True Positives}}{\text{True Positives + False Negatives}}$$

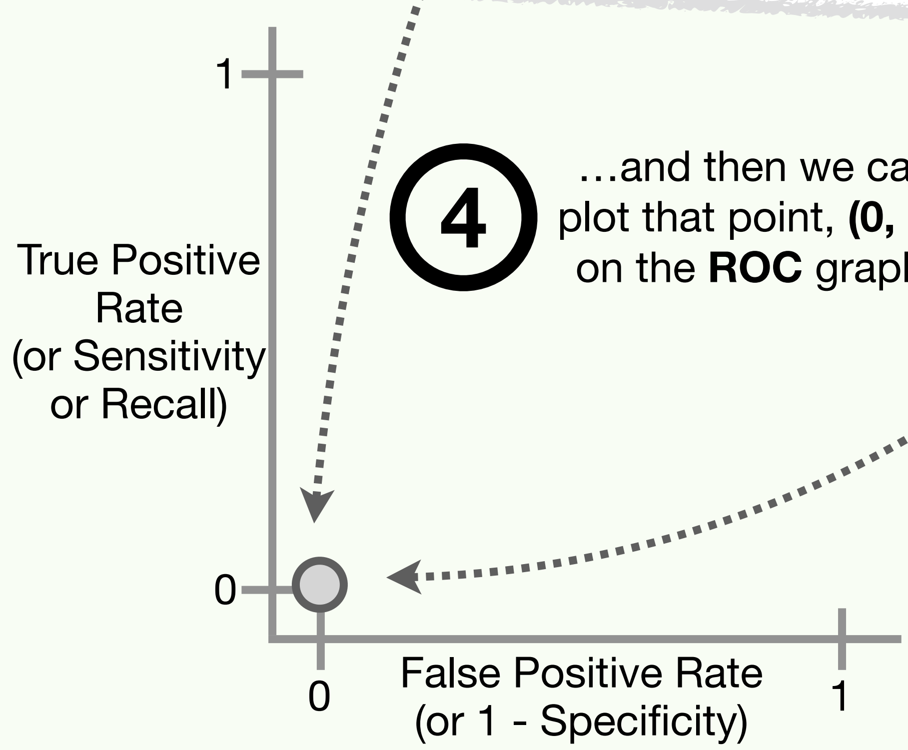
$$= \frac{0}{0 + 5} = 0$$

3 ...and the **False Positive Rate**...

$$\textbf{False Positive Rate} = \frac{\text{False Positives}}{\text{False Positives + True Negatives}}$$

$$= \frac{0}{0 + 4} = 0$$

4 ...and then we can plot that point, **(0, 0)**, on the **ROC** graph.



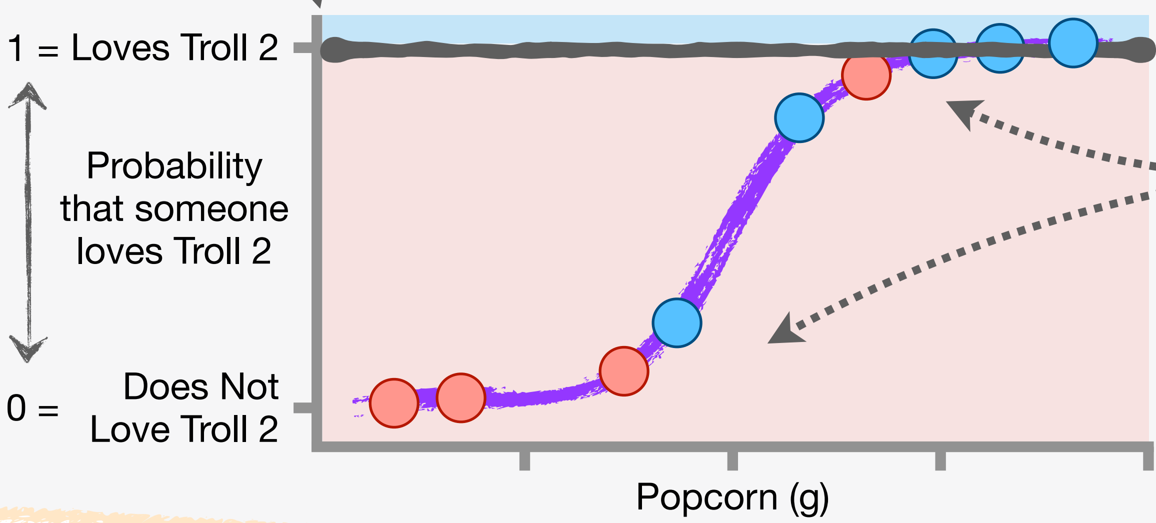
ROC: Details Part 2

Gentle Reminder:

		Predicted	
		Yes	No
Actual	Yes	TP (True Positive)	FN (False Negative)
	No	FP (False Positive)	TN (True Negative)

5 Now let's lower the classification threshold to **0.975**…

…which is just enough to classify one person as someone who **Loves Troll 2**…



…and everyone else is classified as someone who **Does Not Love Troll 2**…

…and that gives us this **Confusion Matrix**.

		Predicted	
		Yes	No
Actual	Yes	1	4
	No	0	4

Threshold = 0.975

6 Using the values in the **Confusion Matrix**, we can calculate the **True Positive Rate**…

$$\textbf{True Positive Rate} = \frac{\text{True Positives}}{\text{True Positives + False Negatives}}$$

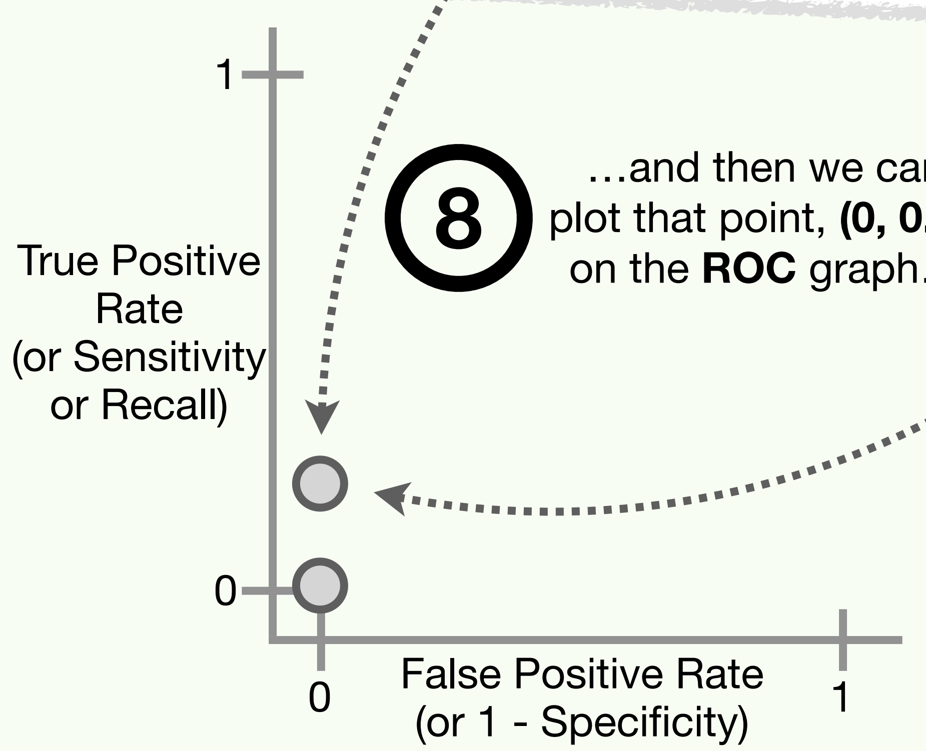
$$= \frac{1}{1 + 4} = 0.2$$

7 …and the **False Positive Rate**…

$$\textbf{False Positive Rate} = \frac{\text{False Positives}}{\text{False Positives + True Negatives}}$$

$$= \frac{0}{0 + 4} = 0$$

8 …and then we can plot that point, **(0, 0.2)**, on the **ROC** graph…



…and the new point is above the first point, showing that the new threshold increases the proportion of *actual* **Positives** that were *correctly* classified. **BAM!!!**

ROC: Details Part 3

Gentle Reminder:

		Predicted: Yes	Predicted: No
Actual	Yes	**TP**	FN
	No	FP	**TN**

True Positive

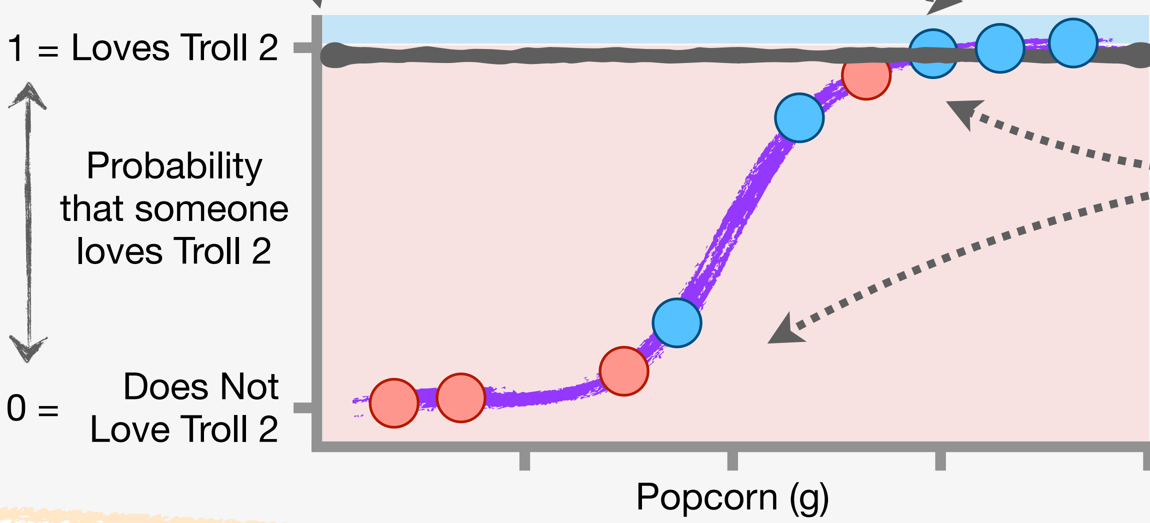
False Negative

False Positive

True Negative

9 Now let's lower the classification threshold to **0.965**…

…which is just enough to classify **2** people as people who **Love Troll 2**…



…and everyone else is classified as someone who **Does Not Love Troll 2**…

…and that gives us this **Confusion Matrix**.

		Predicted: Yes	Predicted: No
Actual	Yes	**2**	3
	No	0	**4**

Threshold = 0.965

10 Using the values in the **Confusion Matrix**, we can calculate the **True Positive Rate**…

$$\textbf{True Positive Rate} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

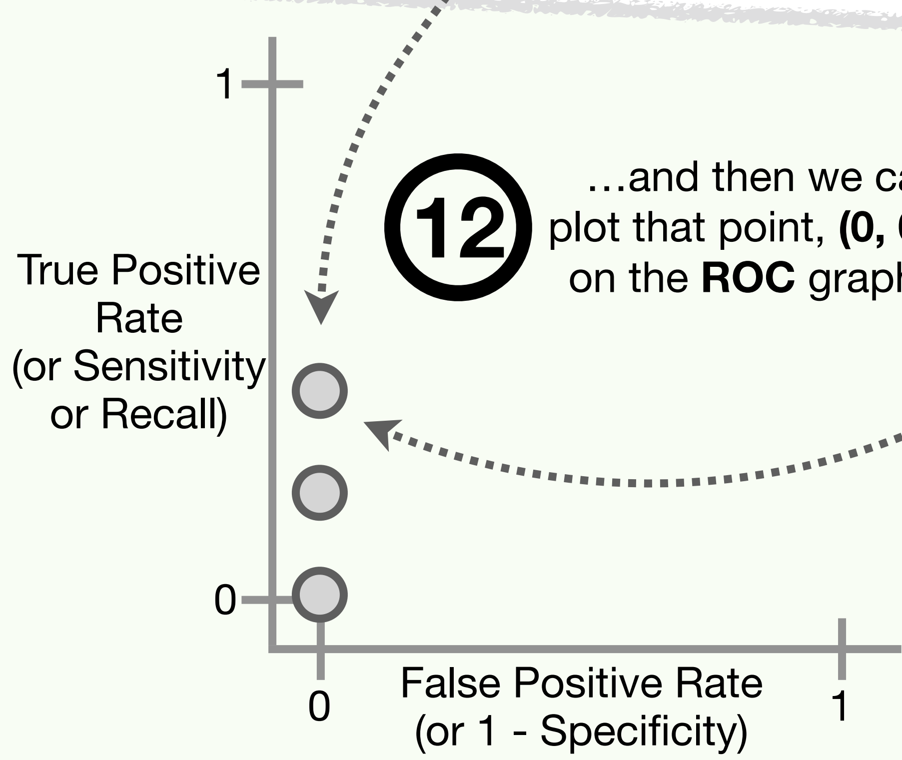
$$= \frac{2}{2 + 3} = 0.4$$

11 …and the **False Positive Rate**…

$$\textbf{False Positive Rate} = \frac{\text{False Positives}}{\text{False Positives} + \text{True Negatives}}$$

$$= \frac{0}{0 + 4} = 0$$

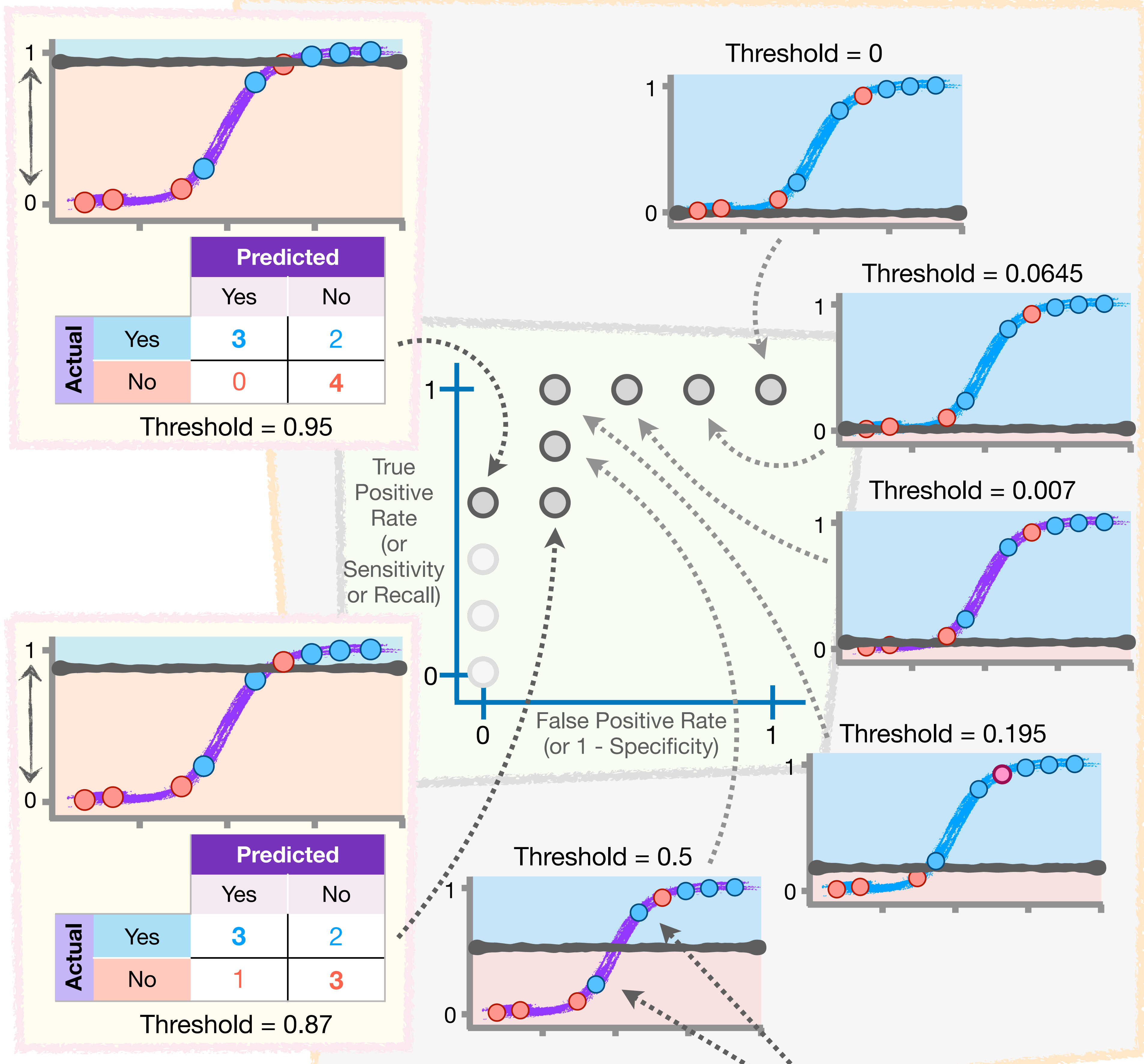
12 …and then we can plot that point, **(0, 0.4)**, on the **ROC** graph…



…and the new point is above the first two points, showing that the new threshold increases the proportion of *actual* **Positives** that were *correctly* classified.

ROC: Details Part 4

13 Likewise, for each threshold that increases the number of **Positive** classifications (in this example, that means classifying a person as someone who **Loves Troll 2**), we calculate the **True Positive Rate** and **False Positive Rate** until everyone is classified as **Positive**.



		Predicted Yes	Predicted No
Actual	Yes	3	2
	No	0	4

Threshold = 0.95

		Predicted Yes	Predicted No
Actual	Yes	3	2
	No	1	3

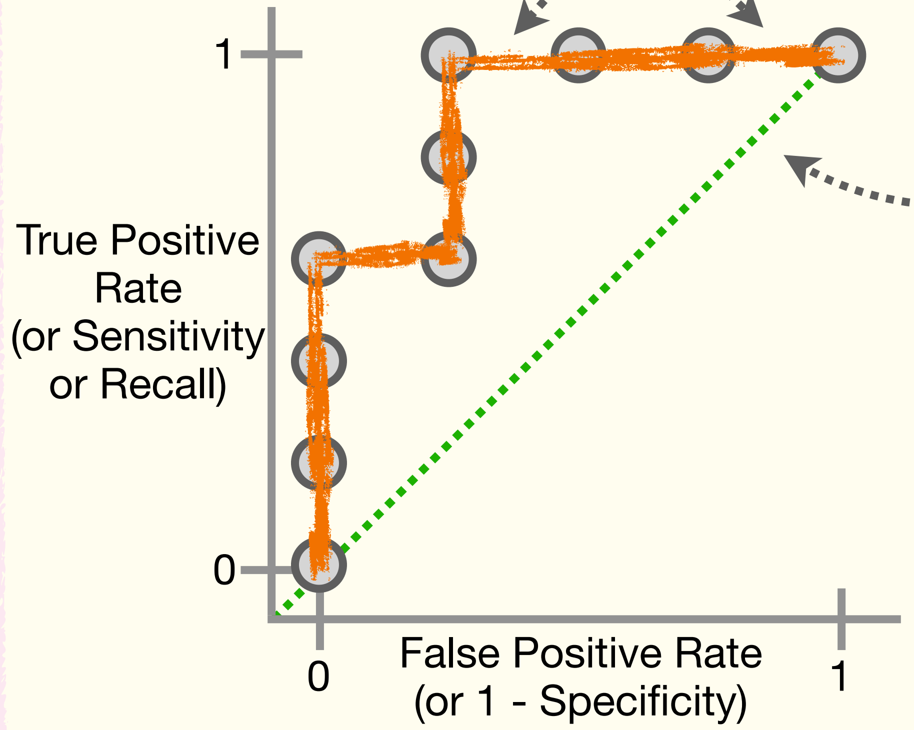
Threshold = 0.87

NOTE: Although there are a lot of potential thresholds between these two points, they all result in the same **True Positive Rate** and the same **False Positive Rate**, so it doesn't matter which one we pick, we just have to pick one of them.

ROC: Details Part 5

14 After we finish plotting the points from each possible **Confusion Matrix**, we usually **connect the dots**…

…and add a **diagonal line** that tells us when the **True Positive Rate = False Positive Rate.**

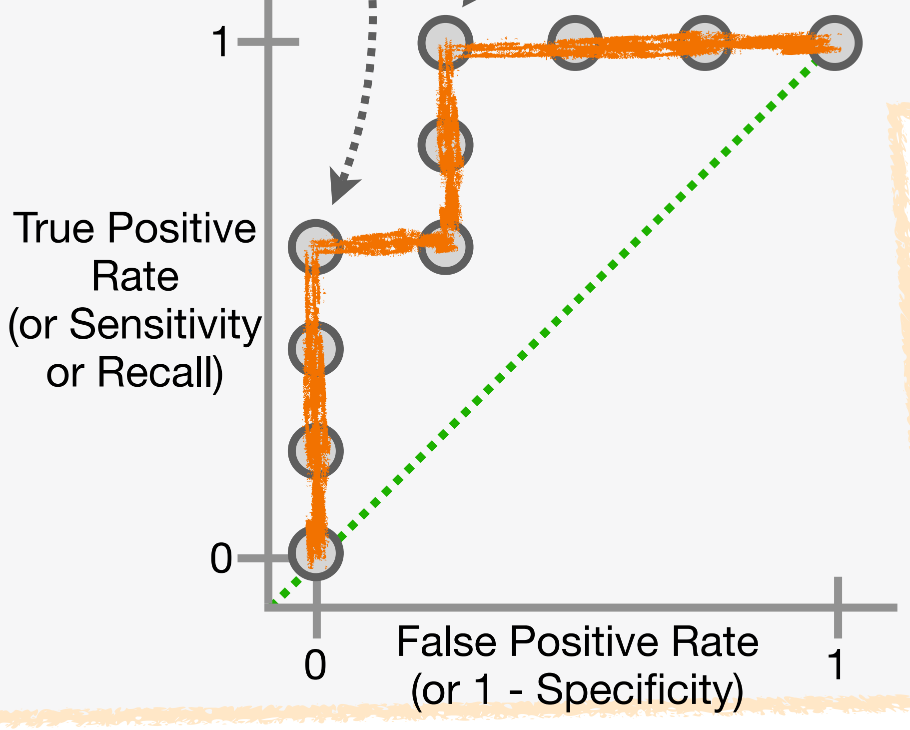


15 Now, without having to sort through a huge pile of **Confusion Matrices**, we can use the **ROC** graph to pick a classification threshold.

If we want to avoid all **False Positives**, but want to maximize the number of actual **Positives** correctly classified, we would pick this threshold…

…but if we can tolerate a few **False Positives**, we would pick this threshold because it *correctly* classifies all of the actual **Positives**.

BAM!!!



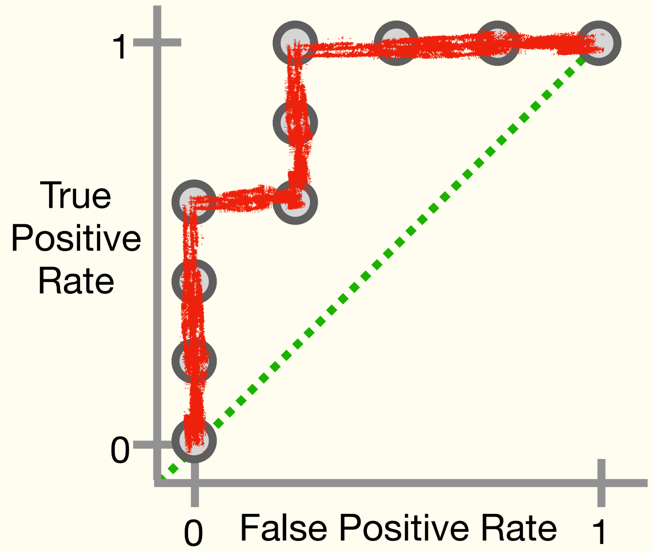
16 **ROC** graphs are great for selecting an optimal classification threshold for a model. But what if we want to compare how one model performs vs. another? This is where the **AUC**, which stands for **Area Under the Curve**, comes in handy. So read on!!!

AUC: Main Ideas

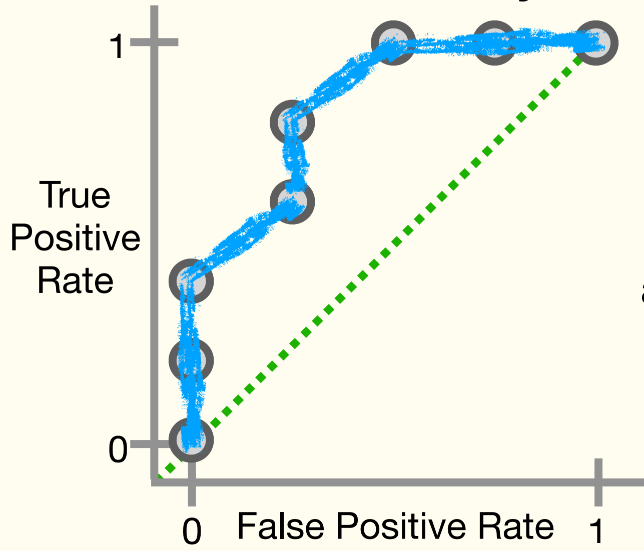
1 Now, imagine we created **Logistic Regression** and **Naive Bayes** models and tested them with the same data, and we wanted to know which model performed better.

In theory, we could compare the individual **ROC** graphs, and when we only have two models to compare, this is a pretty good option.

ROC for Logistic Regression



ROC for Naive Bayes



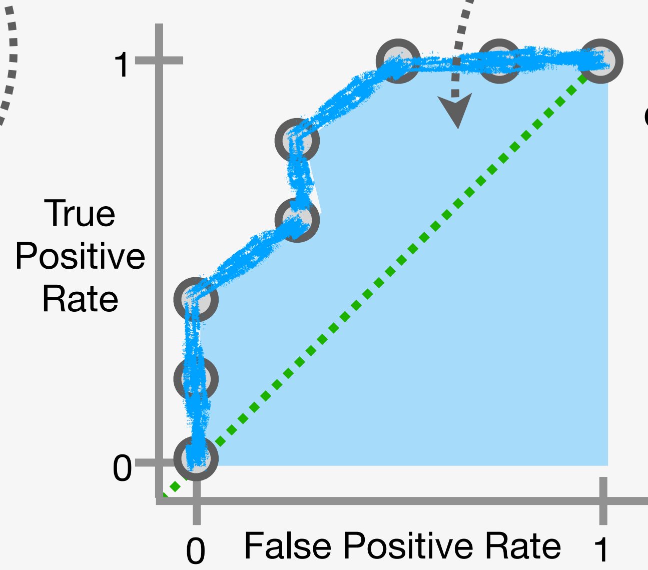
However, if we wanted to compare a bunch of models, this would be just as tedious as comparing a bunch of **Confusion Matrices**.

UGH!!!

2 So, instead of comparing a bunch of **ROC** graphs, one simple way to summarize them is to calculate and compare the **AUC:** the **Area Under** each **Curve**.

In this case, the **AUC** for **Logistic Regression** is **0.9**…

…and the **AUC** for **Naive Bayes** is **0.85**…



…and because **Logistic Regression** has a larger **AUC**, we can tell that, overall, **Logistic Regression** performs better than **Naive Bayes** with these data.

BAM!!!