Receiver Operator Characteristics (ROC)

and Area Under the Curve (AUC)

Why?

- The Receiver Operator Characteristics let's us evaluate classifiers on biased datasets.
- Example: Cancer prediction. A classifier that always predicts 'no cancer' has 99.9% accuracy because only a small percentage of the population has cancer.

Binary Classification Confusion Matrix

Classifier Output

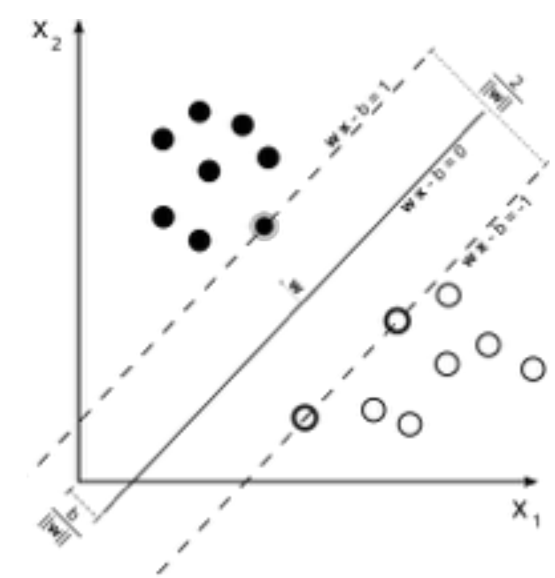
Label

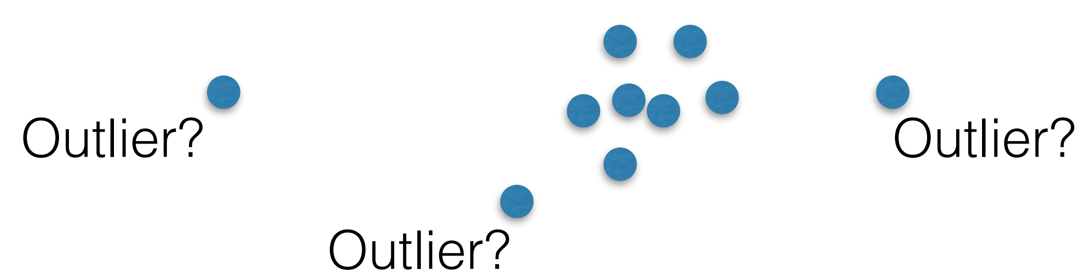
		Predicted condition		
	Total population	Predicted Condition positive	Predicted Condition negative	Prevalence $= \frac{\Sigma \text{ Condition positive}}{\Sigma \text{ Total population}}$
True condition	condition positive	**True positive**	**False Negative** (Type II error)	True positive rate (TPR), Sensitivity, Recall $= \frac{\Sigma \text{ True positive}}{\Sigma \text{ Condition positive}}$
	condition negative	**False Positive** (Type I error)	**True negative**	False positive rate (FPR), Fall-out $= \frac{\Sigma \text{ False positive}}{\Sigma \text{ Condition negative}}$

In binary classification we have some sort of bias parameter

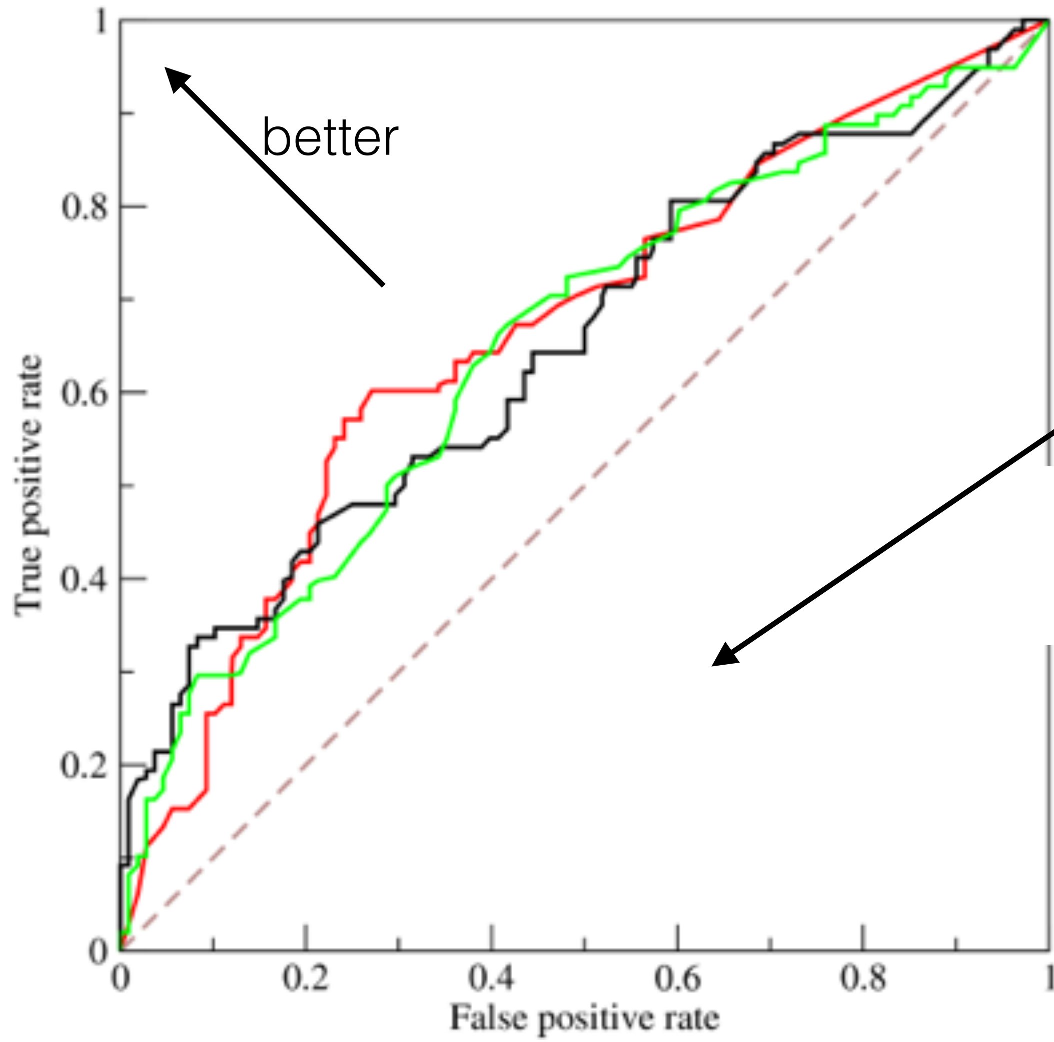
- SVM: Bias parameter that moves our hyperplane orthogonal to it
- Outlier detection: From which distance on should we call a point outlier?

Different bias parameters give different FPR/TPR pairs! We plot these in the Receiver Operator Characteristics (ROC).





Example ROC (Curve)



<u>Area Under the Curve (AUC)</u>

Different ways to measure:
We use trapezoidal rule, i.e. the area that we get from combining (0,0), all (FPR, TPR) points, (1,1), to (0, 0).

This is initially a scatter plot (FPR/TPR points). The points where then linked to create a nicer figure.