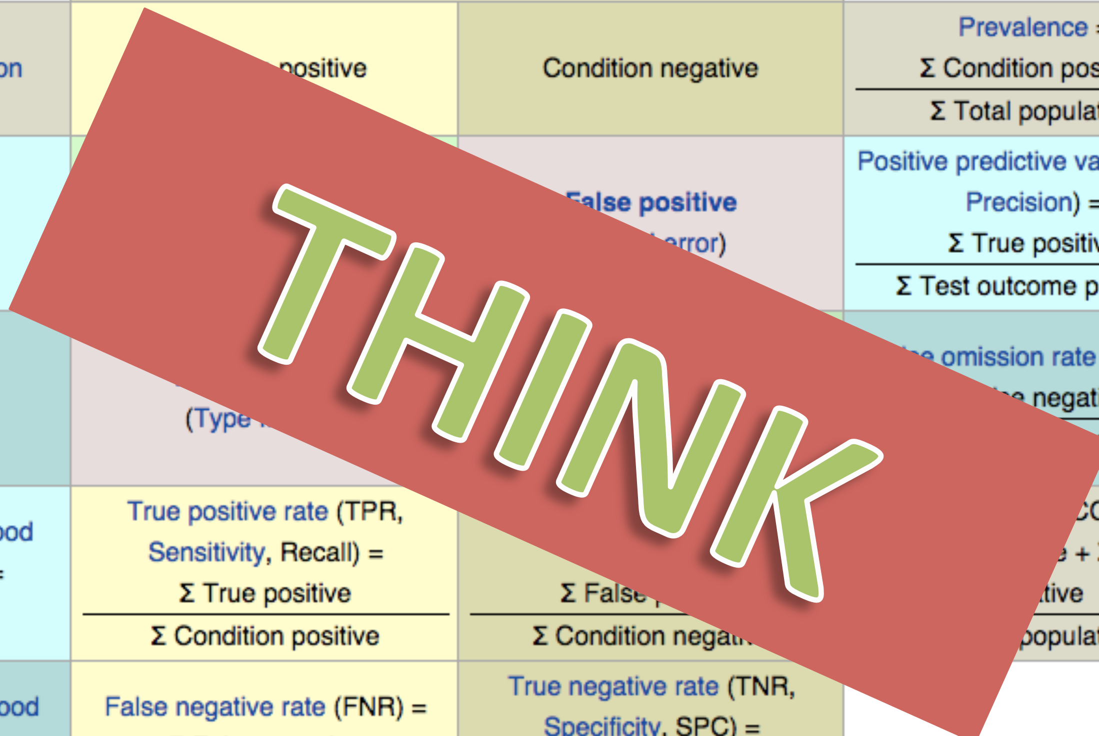
Errors in classification

		Condition (as determined by "Gold standard")			
	Total population	Condition positive	Condition negative	Prevalence = $\frac{\Sigma \text{ Condition positive}}{\Sigma \text{ Total population}}$	
Test outcome	Test outcome positive	**True positive**	**False positive** (Type I error)	Positive predictive value (PPV, Precision) = $\frac{\Sigma \text{ True positive}}{\Sigma \text{ Test outcome positive}}$	False discovery rate (FDR) = $\frac{\Sigma \text{ False positive}}{\Sigma \text{ Test outcome positive}}$
	Test outcome negative	**False negative** (Type II error)	**True negative**	False omission rate (FOR) = $\frac{\Sigma \text{ False negative}}{\Sigma \text{ Test outcome negative}}$	Negative predictive value (NPV) = $\frac{\Sigma \text{ True negative}}{\Sigma \text{ Test outcome negative}}$
	Positive likelihood ratio (**LR+**) = TPR/FPR	True positive rate (TPR, Sensitivity, Recall) = $\frac{\Sigma \text{ True positive}}{\Sigma \text{ Condition positive}}$	False positive rate (FPR, Fall-out) = $\frac{\Sigma \text{ False positive}}{\Sigma \text{ Condition negative}}$	Accuracy (ACC) = $\frac{\Sigma \text{ True positive} + \Sigma \text{ True negative}}{\Sigma \text{ Total population}}$	
	Negative likelihood ratio (**LR–**) = FNR/TNR	False negative rate (FNR) = $\frac{\Sigma \text{ False negative}}{\Sigma \text{ Condition positive}}$	True negative rate (TNR, Specificity, SPC) = $\frac{\Sigma \text{ True negative}}{\Sigma \text{ Condition negative}}$		
	Diagnostic odds ratio (**DOR**) = LR+/LR–				

		Condition (as determined by "Gold standard")			
	Total population	... positive	Condition negative	Prevalence = Σ Condition positive / Σ Total population	
Test outcome	Test outcome positive		False positive (... error)	Positive predictive value (PPV, Precision) = Σ True positive / Σ Test outcome positive	False discovery rate (FDR) = Σ False positive / Σ Test outcome positive
	Test outcome negative	(Type ...		...e omission rate (FOR) = ...e negative / ...gative	Negative predictive value (NPV) = Σ True negative / Σ Test outcome negative
	Positive likelihood ratio (**LR+**) = TPR/FPR	True positive rate (TPR, Sensitivity, Recall) = Σ True positive / Σ Condition positive	Σ False ... / Σ Condition negat...	...CC) = ...e + Σ True ...tive / ...population	
	Negative likelihood ratio (**LR–**) = FNR/TNR	False negative rate (FNR) = Σ False negative / Σ Condition positive	True negative rate (TNR, Specificity, SPC) = Σ True negative / Σ Condition negative		
	Diagnostic odds ratio (**DOR**) = LR+/LR–				



%54 Democrats, %46 republicans

Classify using their votes

%54 Democrats, %46 republicans

Classify using their votes

Model performance:
"How many times did I get it right?"

%54 Democrats, %46 republicans

Classify using their votes

Model performance:
"How many times did I get it right?"

Accuracy: % correct prediction of all predictions

%54 Democrats, %46 republicans

Classify using their votes

Model performance:
“How many times did I get it right?”

Accuracy: % correct prediction of all predictions

95% accuracy: Good job!

%1 have leukemia, %99 are healthy

Classify using health records and tests

%1 have leukemia, %99 are healthy

Classify using health records and tests

"How many times did I get it right?"

Accuracy: % correct prediction of all predictions

%1 have leukemia, %99 are healthy

Classify using health records and tests

“How many times did I get it right?”
Accuracy: % correct prediction of all predictions

Imagine the stupidest predictor:
“Always guess healthy”

%1 have leukemia, %99 are healthy

Classify using health records and tests

“How many times did I get it right?”
Accuracy: % correct prediction of all predictions

Imagine the stupidest predictor:
“Always guess healthy”

What will the accuracy be?

%1 have leukemia, %99 are healthy

Classify using health records and tests

“How many times did I get it right?”
Accuracy: % correct prediction of all predictions

Imagine the stupidest predictor:
“Always guess healthy”

What will the accuracy be?
It will be right 99% of the time!
You won’t catch any sick people. Useless.

Confusion Matrix

	P' (Predicted)	n' (Predicted)
P (Actual)	True Positive	False Negative
n (Actual)	False Positive	True Negative

Confusion Matrix

	Spam (Predicted)	Non-Spam (Predicted)	Accuracy
Spam (Actual)	27	6	81.81
Non-Spam (Actual)	10	57	85.07
Overall Accuracy			83.44

Confusion Matrix

	Spam (Predicted)	Non-Spam (Predicted)	Accuracy	
Spam (Actual)	27	6	81.81	Sensitivity
Non-Spam (Actual)	10	57	85.07	Specificity
Overall Accuracy			83.44	Accuracy

Confusion Matrix

	P' (Predicted)	n' (Predicted)
P (Actual)	True Positive	False Negative
n (Actual)	False Positive	True Negative

Sensitivity = TP / (TP + FN)

Specificity = TN / (TN + FP)

Accuracy = (TP + TN) / (TP + TN + FP + FN)

Confusion Matrix

	P' (Predicted)	n' (Predicted)
P (Actual)	True Positive	False Negative
n (Actual)	False Positive	True Negative

Sensitivity = TP / (TP + FN) TRUE POSITIVE RATE

Specificity = TN / (TN + FP) TRUE NEGATIVE RATE

Accuracy = (TP + TN) / (TP + TN + FP + FN)

Confusion Matrix

	Spam (Predicted)	Non-Spam (Predicted)	Accuracy	
Spam (Actual)	0	10	0.0	Sensitivity
Non-Spam (Actual)	0	990	100.00	Specificity
Overall Accuracy			99	Accuracy

Precision and recall

Precision and recall

Precision: Out of all cases I predicted as positive,
how many times was I right?

Precision and recall

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how many times was I right?
(% times I was right when I told somebody they had leukemia)

Precision and recall

Precision: Out of all cases I predicted as positive,
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Recall: Out of all the (few) positive cases,
how many did I find

Precision and recall

Precision: Out of all cases I predicted as positive,
how many times was I right?
(% times I was right when I told somebody they had leukemia)

Recall: Out of all the (few) positive cases,
how many did I find
(% of actual leukemia patients I could catch with my classifier)

Confusion Matrix

	Spam (Predicted)	Non-Spam (Predicted)	Accuracy	
Spam (Actual)	27	6	81.81	Sensitivity
Non-Spam (Actual)	10	57	85.07	Specificity
Overall Accuracy			83.44	Accuracy

Precision = 27 / 37 = 73.0%

Recall = 27 / 33 = 81.8%

Confusion Matrix

	Spam (Predicted)	Non-Spam (Predicted)	Accuracy	
Spam (Actual)	0	10	0.0	Sensitivity
Non-Spam (Actual)	0	990	100.00	Specificity
Overall Accuracy			99	Accuracy

Precision = 0 / 0 Undefined!

Recall = 0 / 10 = 0%

Confusion Matrix

	P' (Predicted)	n' (Predicted)
P (Actual)	True Positive	False Negative
n (Actual)	False Positive	True Negative

Precision = TP / (TP + FP)

Recall = TP / (TP + FN)

Confusion Matrix

	P’ (Predicted)	n’ (Predicted)
P (Actual)	True Positive	False Negative
n (Actual)	False Positive	True Negative

Focusing on a single class (positive: the one with small prevalence) in skewed cases

Precision = TP / (TP + FP)

Recall = TP / (TP + FN)

Confusion Matrix

	P' (Predicted)	n' (Predicted)
P (Actual)	True Positive	False Negative
n (Actual)	False Positive	True Negative

Focusing on a single class (positive: the one with small prevalence) in skewed cases

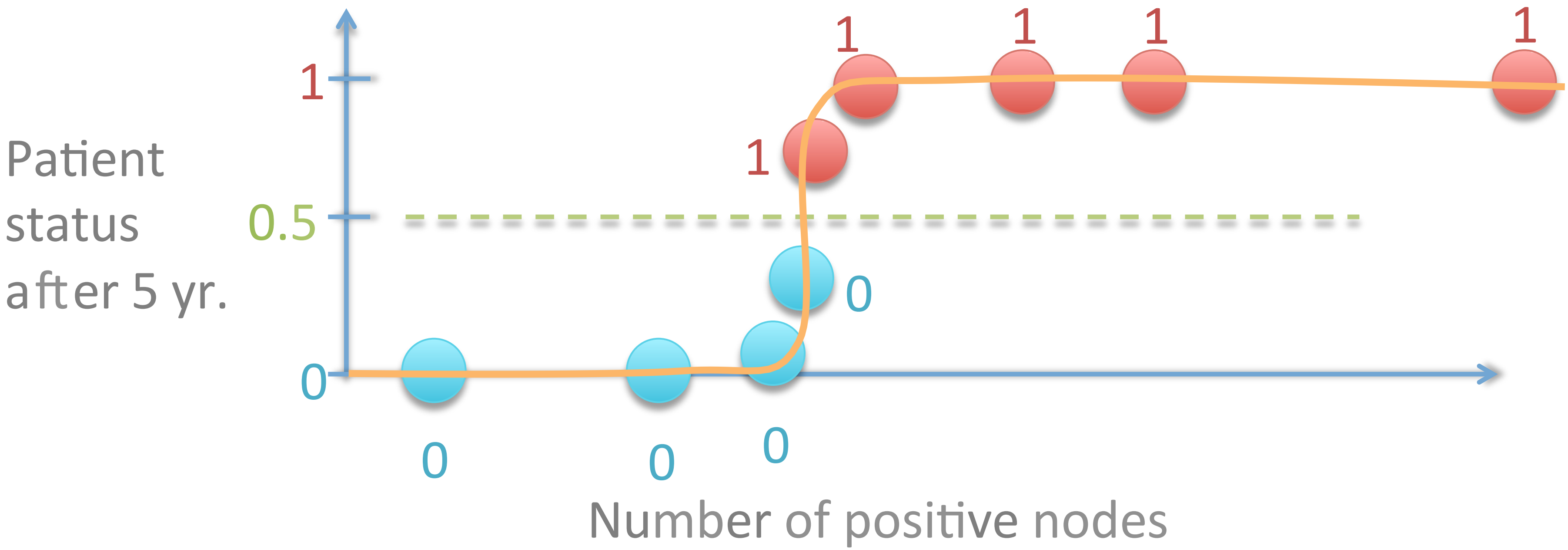
Precision = TP / (TP + FP)

Recall = TP / (TP + FN)

F1 = Their harmonic mean

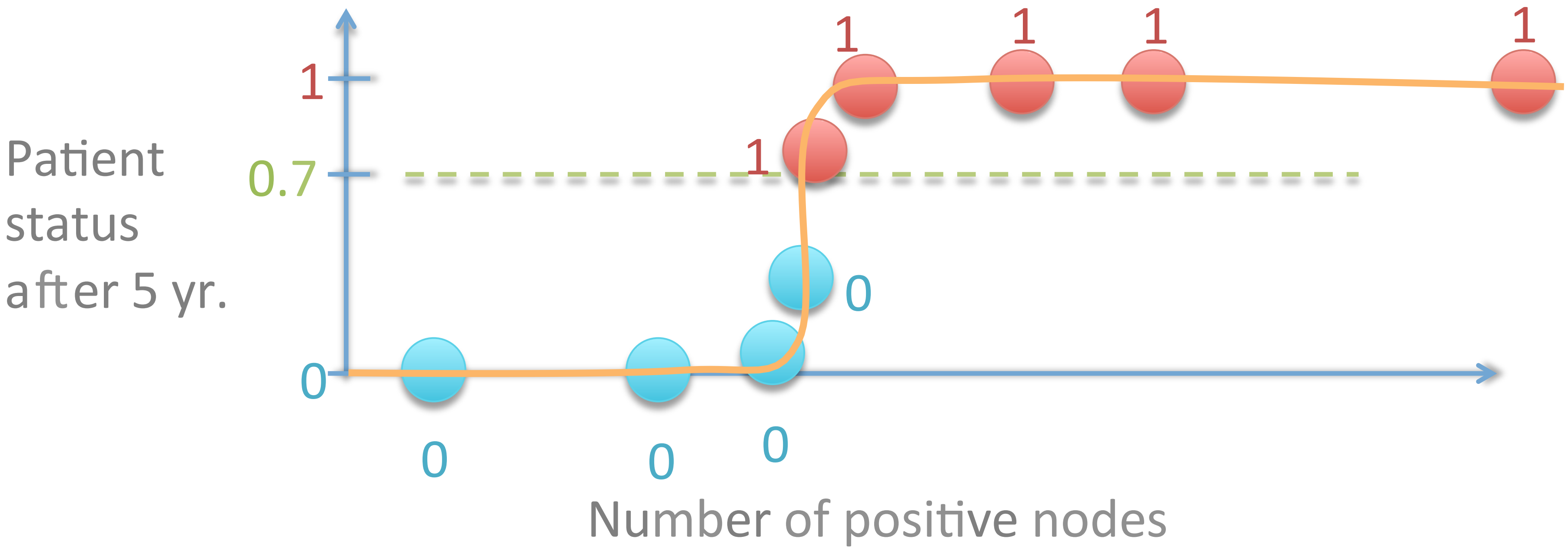
$$F1 = 2 * \frac{\text{precision} * \text{recall}}{\text{precision} + \text{recall}}$$

Logistic regression

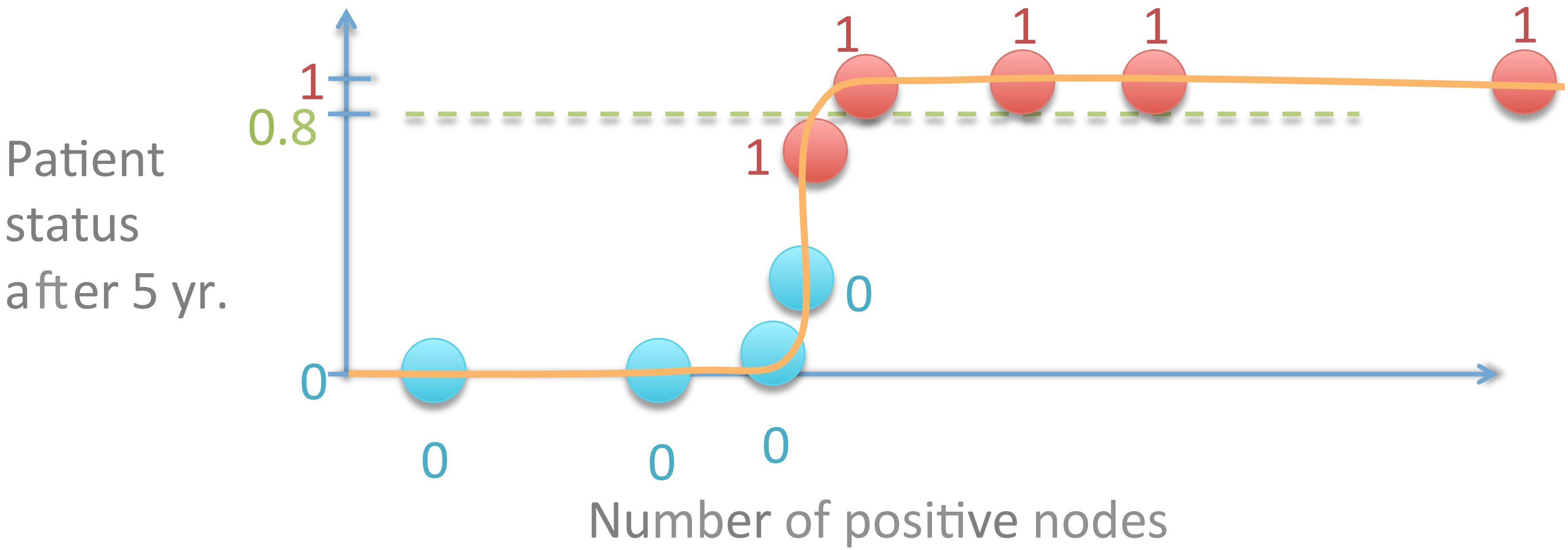


$$y_\beta(x) = \frac{1}{1+e^{-(\beta_0+\beta_1 x+\varepsilon)}}$$

Logistic regression



Logistic regression

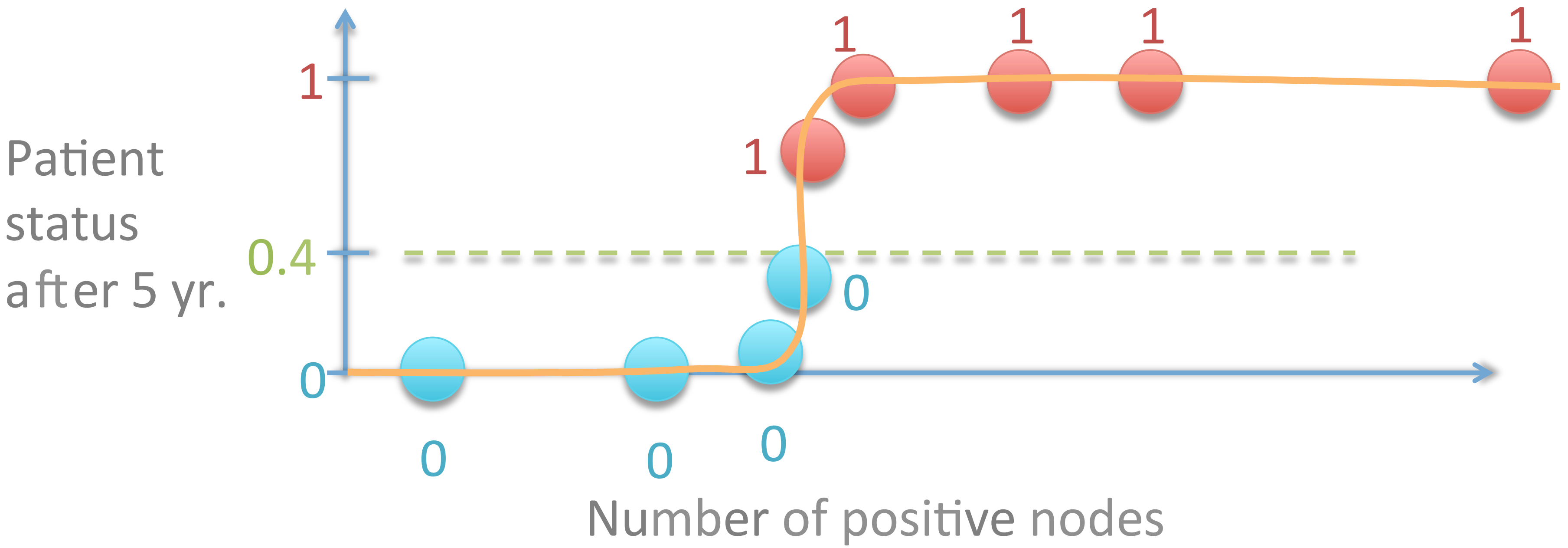


Higher threshold: More sure about positives

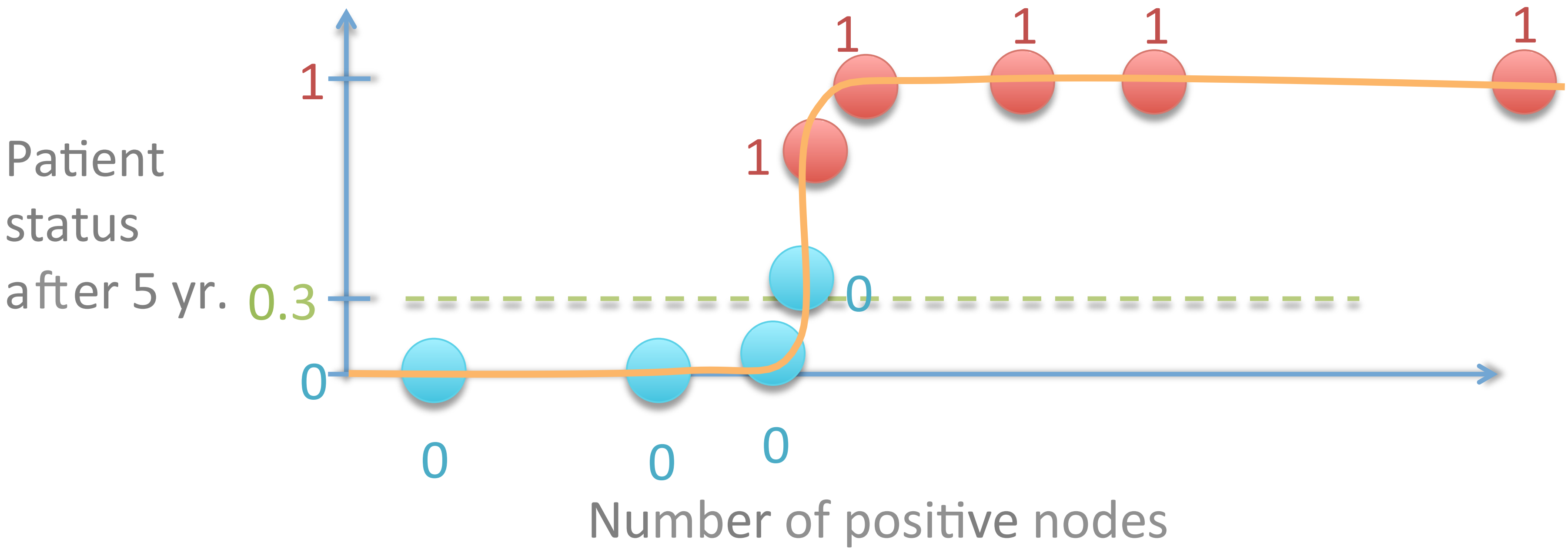
lower recall, higher precision

lower True Positive Rate, lower False Positive Rate

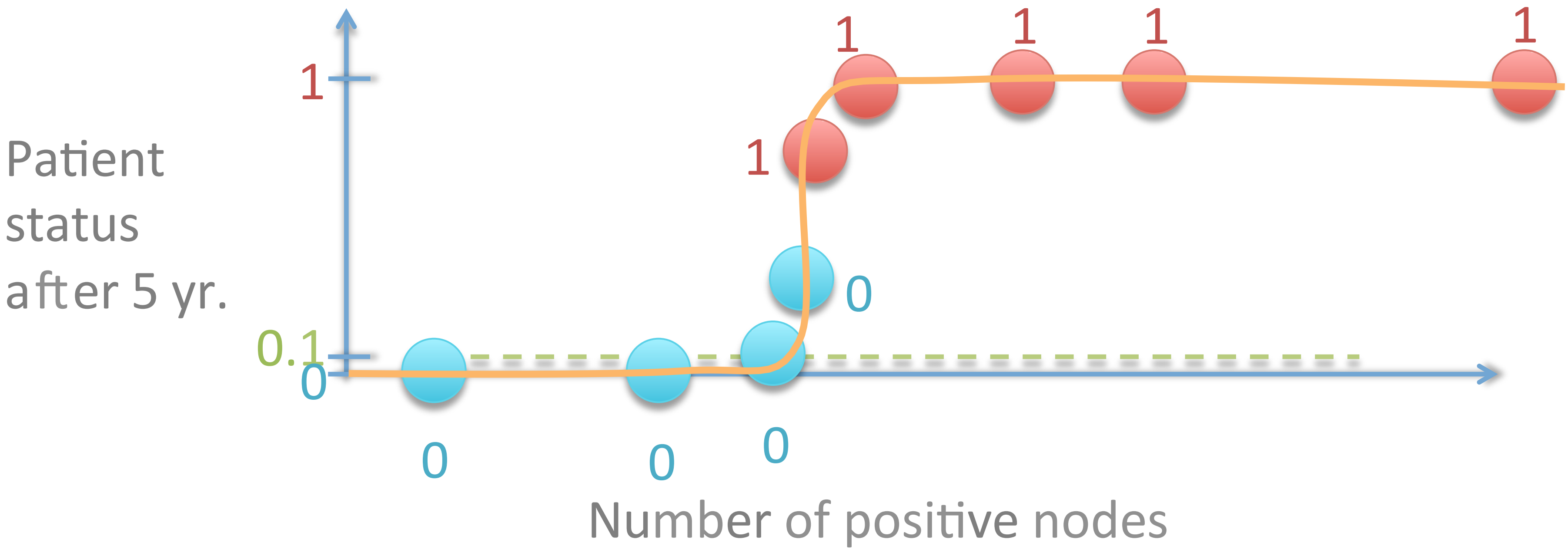
Logistic regression



Logistic regression



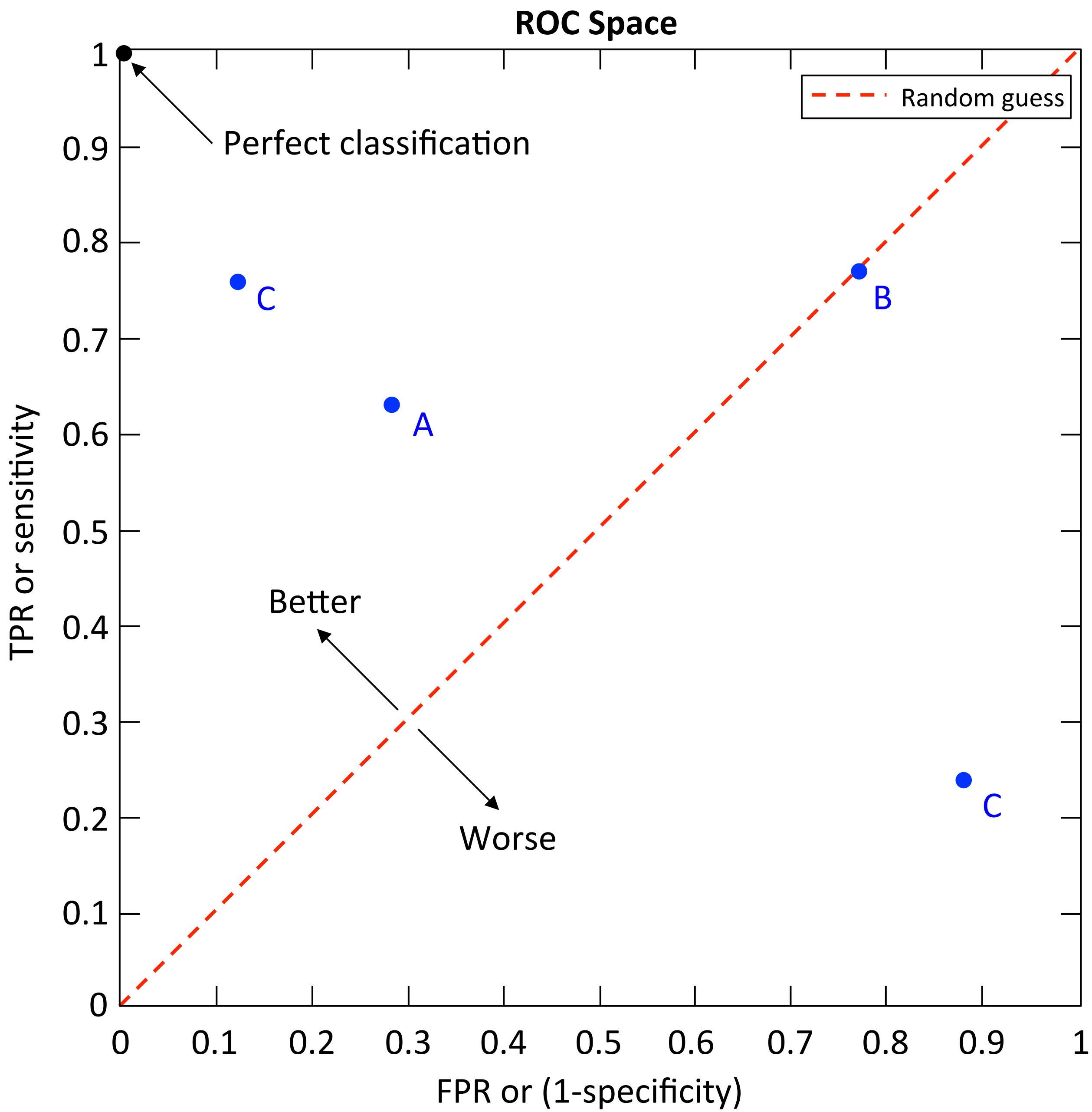
Logistic regression

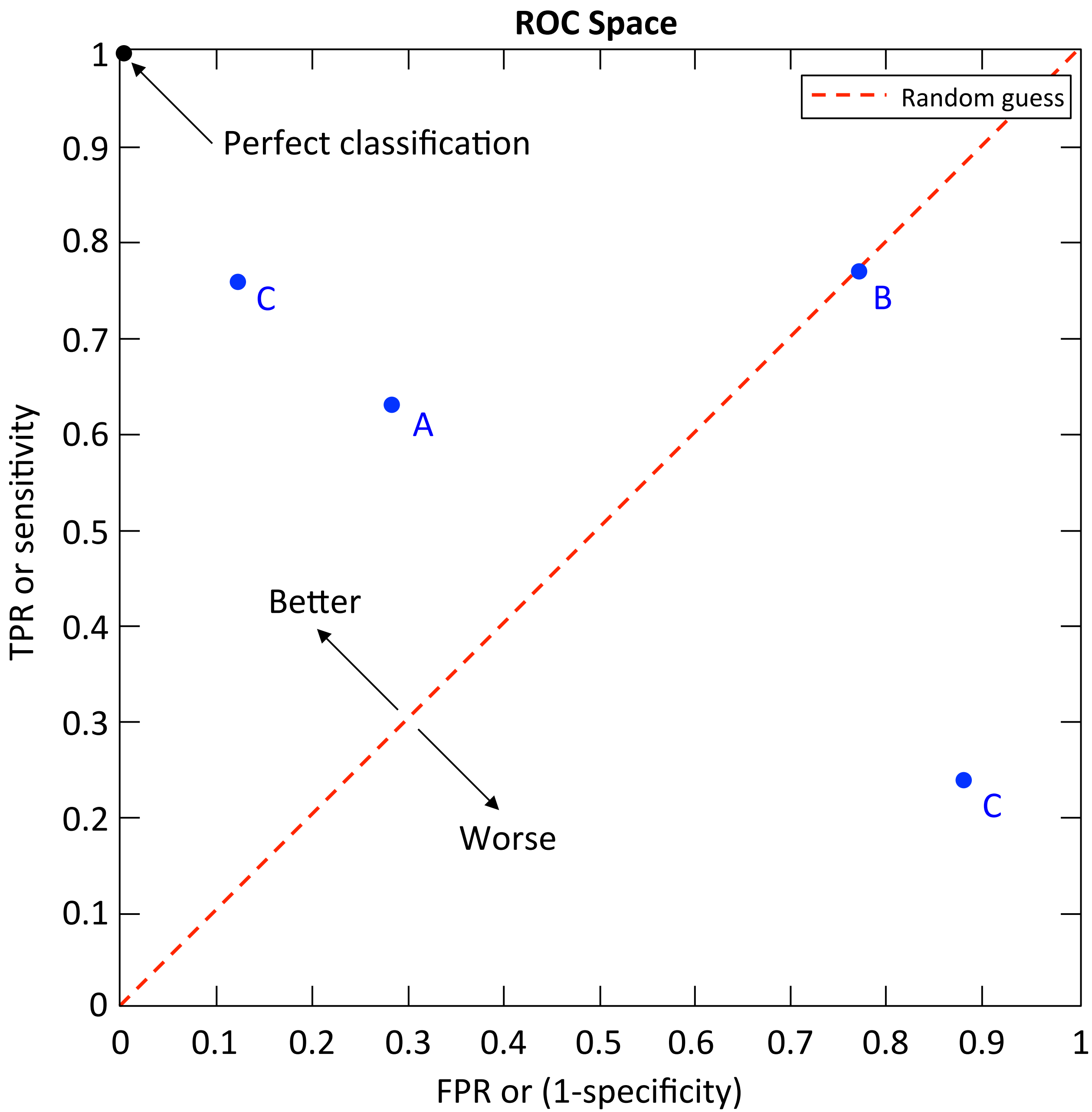


Lower threshold: Better at catching positives
higher recall, less precision
higher True Positive Rate, higher False Positive Rate

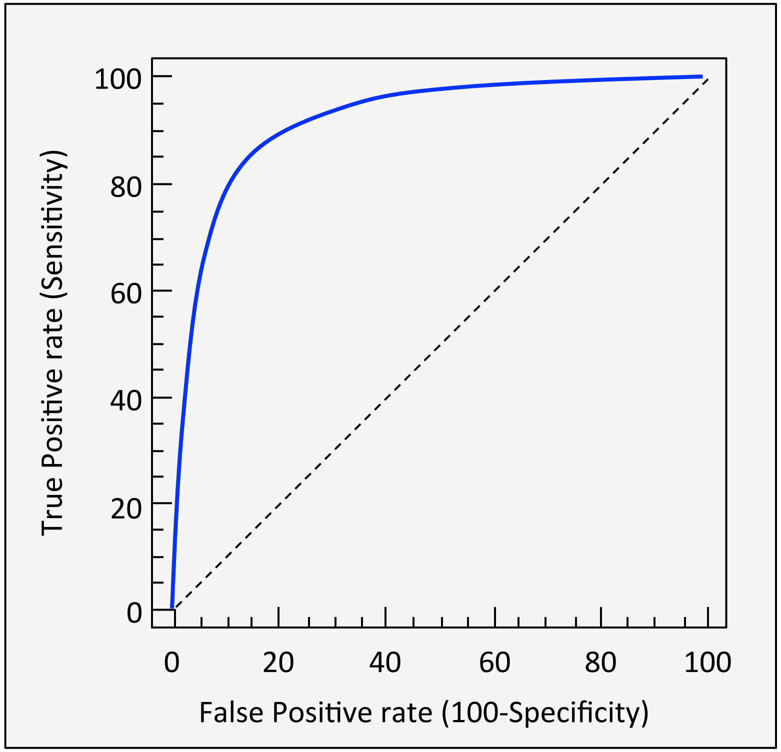
Each threshold is a different model

Plot their True Positive Rate & False Positive Rate


ROC Space
Random guess
Perfect classification
Better
Worse
A
B
C
C
TPR or sensitivity
FPR or (1-specificity)
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1

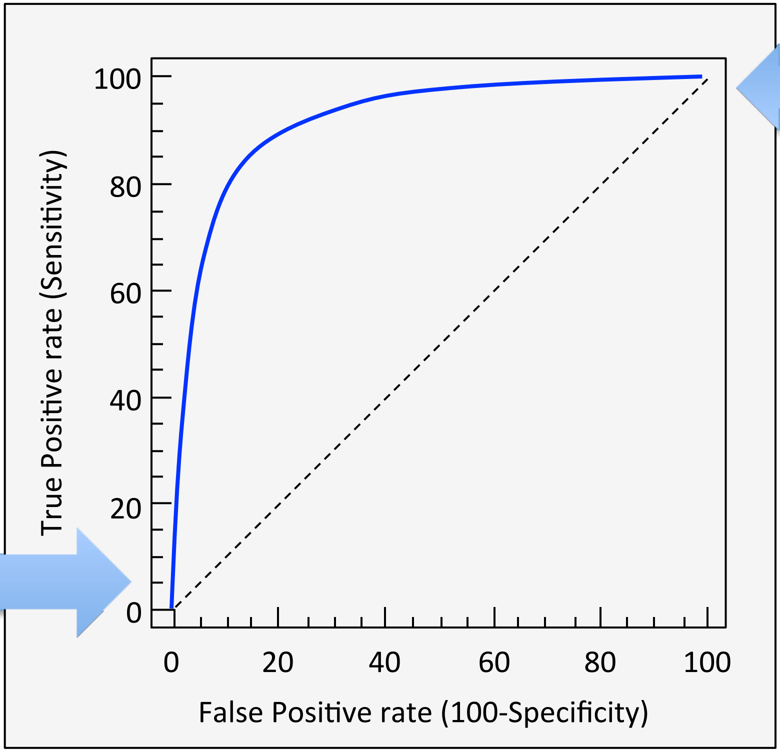


Receiver Operating Characteristic

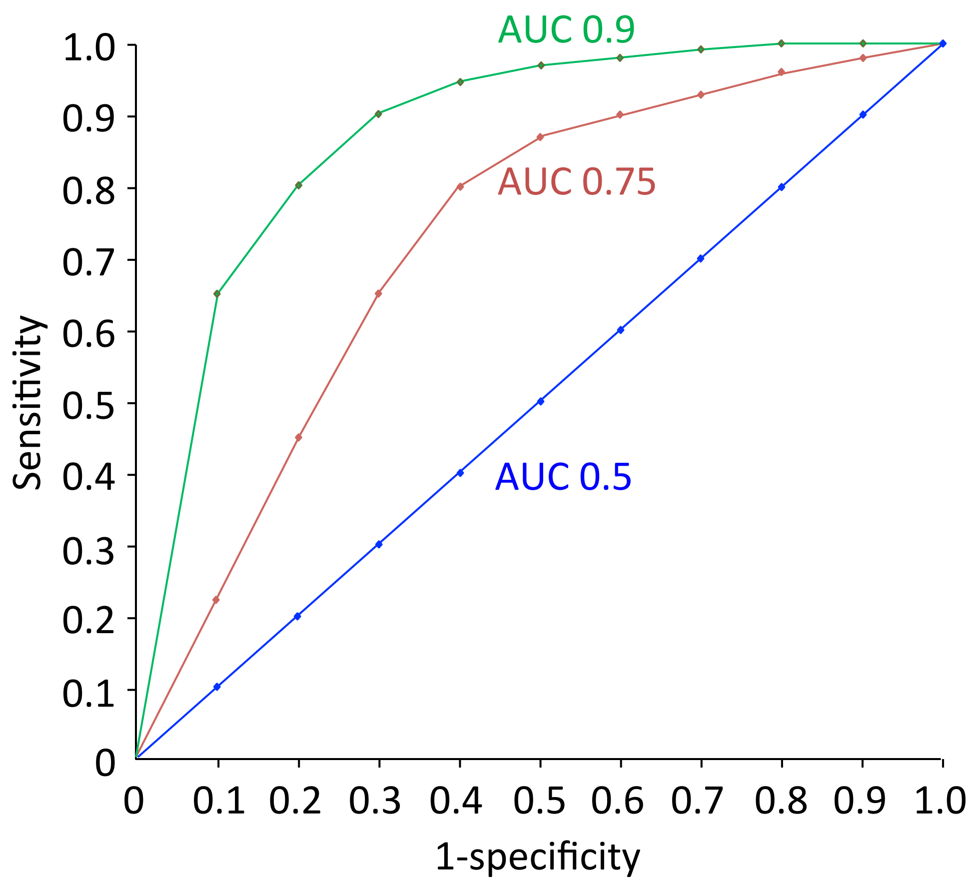


100
80
60
40
20
0
0
20
40
60
80
100
True Positive rate (Sensitivity)
False Positive rate (100-Specificity)

Lower threshold: Better at catching positives
higher recall, less precision
higher True Positive Rate, higher False Positive Rate



Higher threshold: More sure about positives
lower recall, higher precision
lower True Positive Rate, lower False Positive Rate

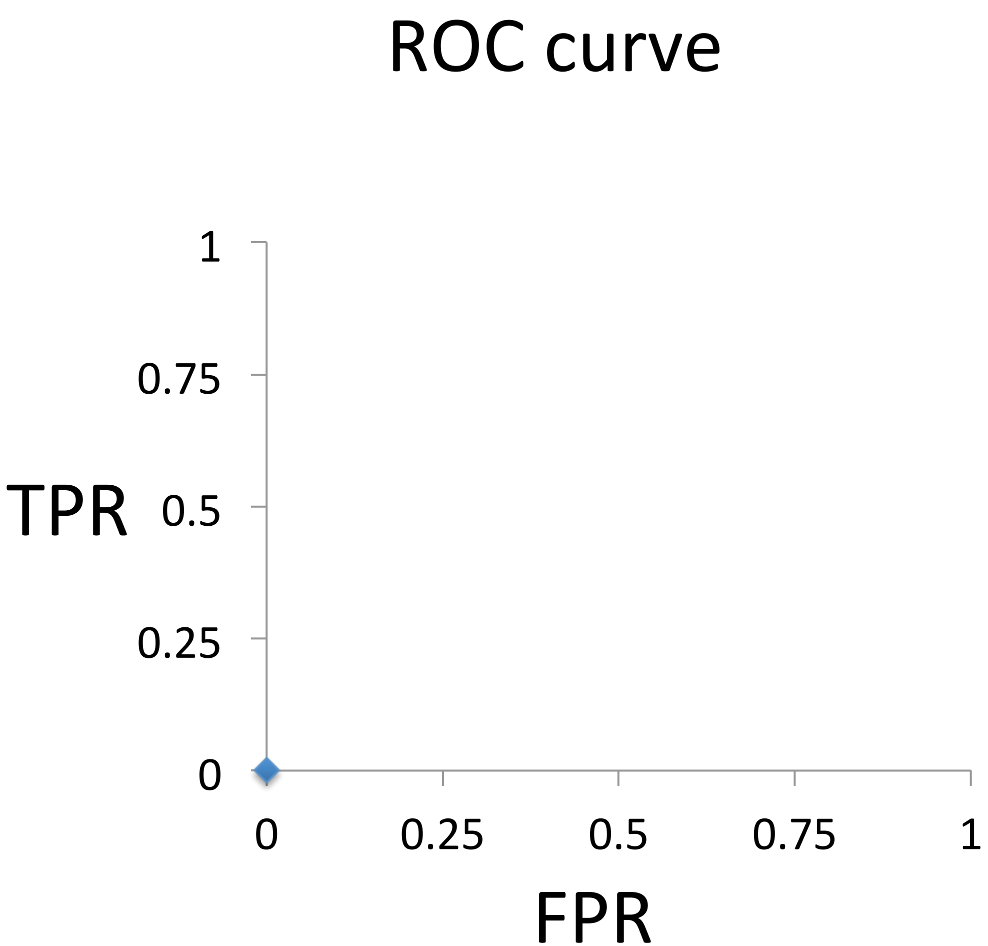


Area under curve (AUC)

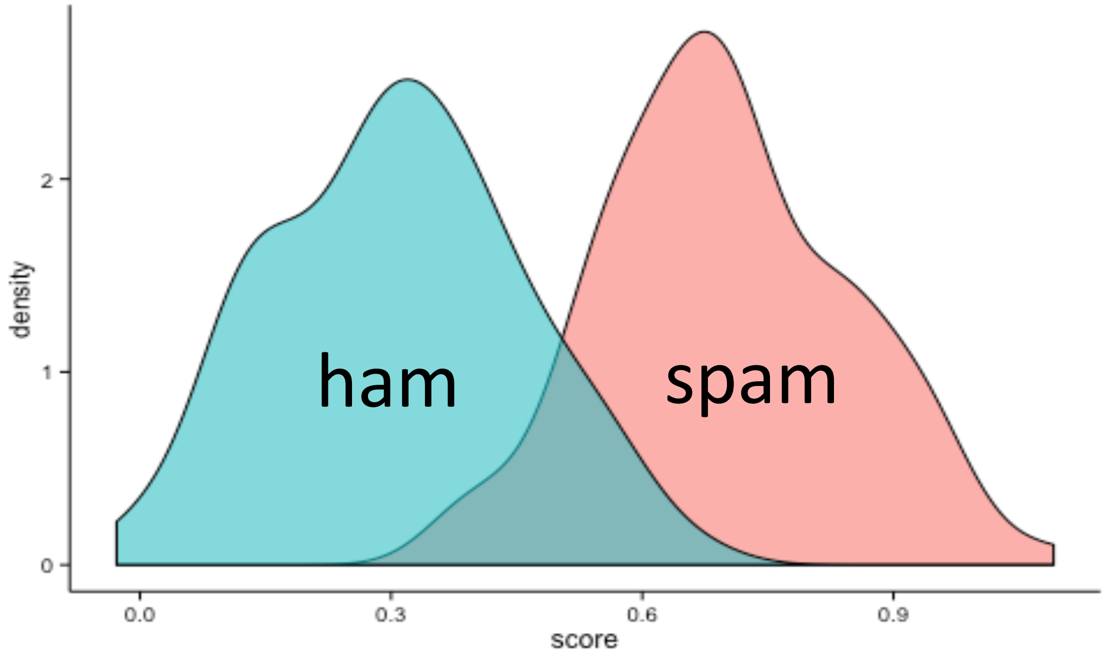
An evaluation of a classification algorithm

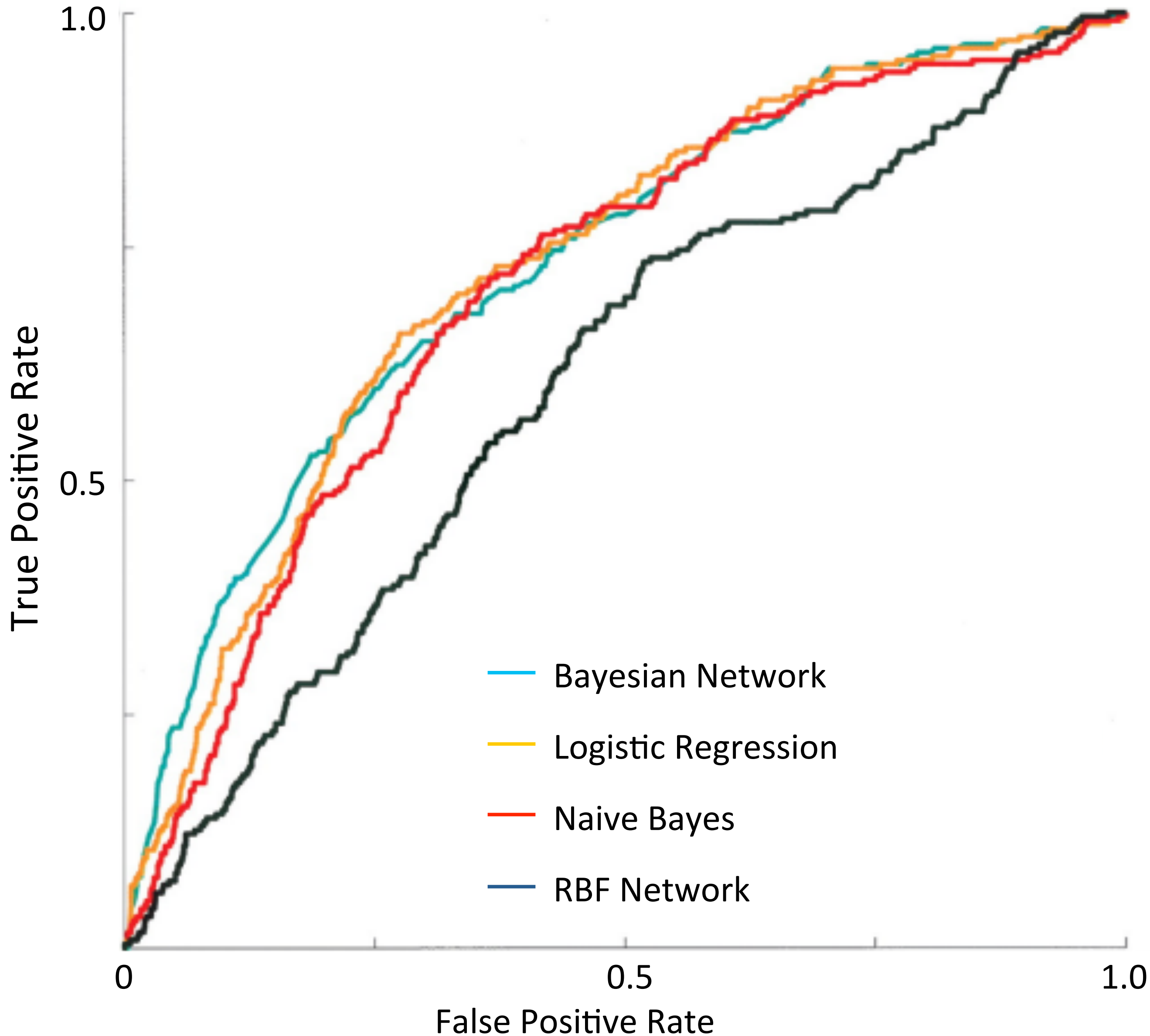
(including all possible thresholds)

Score	True Label
0.93	Spam
0.91	Spam
0.84	Spam
0.6	Ham
0.54	Spam
0.22	Ham
0.10	Ham
0.02	Ham



Another interpretation of AUC (cf. common language effect size)





1.0
0.5
True Positive Rate
0
0.5
1.0
False Positive Rate
Bayesian Network
Logistic Regression
Naive Bayes
RBF Network

from sklearn.metrics import ......

Classification metrics

See the *Classification metrics* section of the user guide for further details.

metrics.accuracy_score(y_true, y_pred[, ...])	Accuracy classification score.
metrics.auc(x, y[, reorder])	Compute Area Under the Curve (AUC) using the trapezoidal rule
metrics.average_precision_score(y_true, y_score)	Compute average precision (AP) from prediction scores
metrics.classification_report(y_true, y_pred)	Build a text report showing the main classification metrics
metrics.confusion_matrix(y_true, y_pred[, ...])	Compute confusion matrix to evaluate the accuracy of a classification
metrics.fl_score(y_true, y_pred[, labels, ...])	Compute the F1 score, also known as balanced F-score or F-measure
metrics.fbeta_score(y_true, y_pred, beta[, ...])	Compute the F-beta score
metrics.hamming_loss(y_true, y_pred[, classes])	Compute the average Hamming loss.
metrics.hinge_loss(y_true, pred_decision[, ...])	Average hinge loss (non-regularized)
metrics.jaccard_similarity_score(y_true, y_pred)	Jaccard similarity coefficient score
metrics.log_loss(y_true, y_pred[, eps, ...])	Log loss, aka logistic loss or cross-entropy loss.
metrics .matthews_corrcoef(y_true, y_pred)	Compute the Matthews correlation coefficient (MCC) for binary classes
metrics .precision_recall_curve(y_true, ...)	Compute precision-recall pairs for different probability thresholds
metrics.precision_recall_fscore_support(...)	Compute precision, recall, F-measure and support for each class
metrics.precision_score(y_true, y_pred[, ...])	Compute the precision
metrics.recall_score(y_true, y_pred[, ...])	Compute the recall
metrics.roc_auc_score(y_true, y_score[, ...])	Compute Area Under the Curve (AUC) from prediction scores
metrics.roc_curve(y_true, y_score[, ...])	Compute Receiver operating characteristic (ROC)
metrics.zero_one_ioss(y_true, y_pred[, ...])	Zero-one classification loss.

Always remember,

Fit the model to a training set,

Calculate performance
(accuracy, precision, recall, f1, AUC, etc.)
on a test set
or (better) on a k-fold cross validation scheme