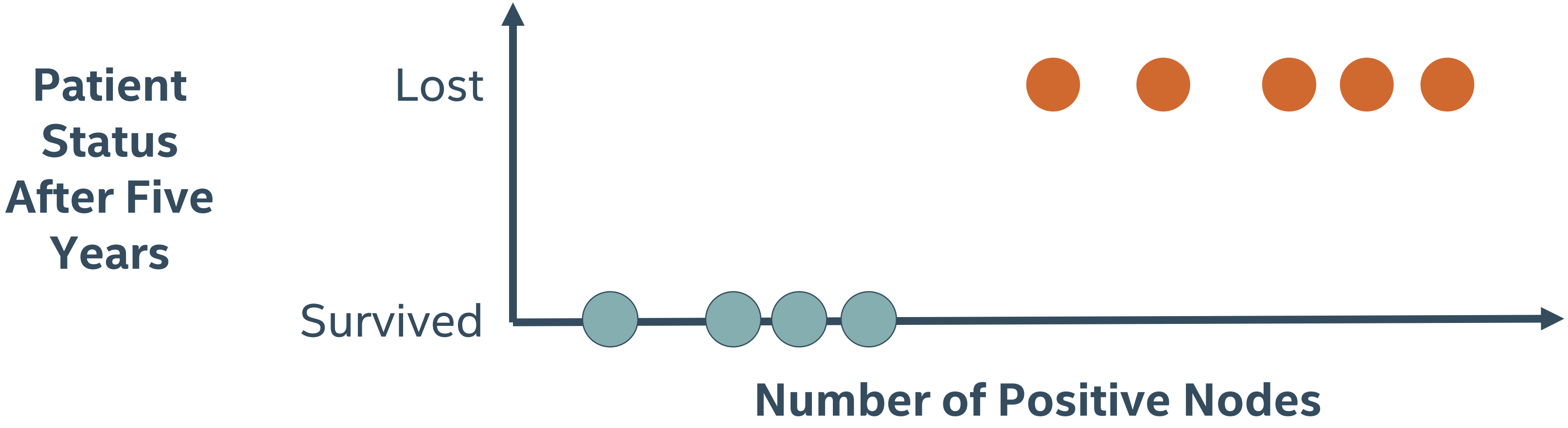
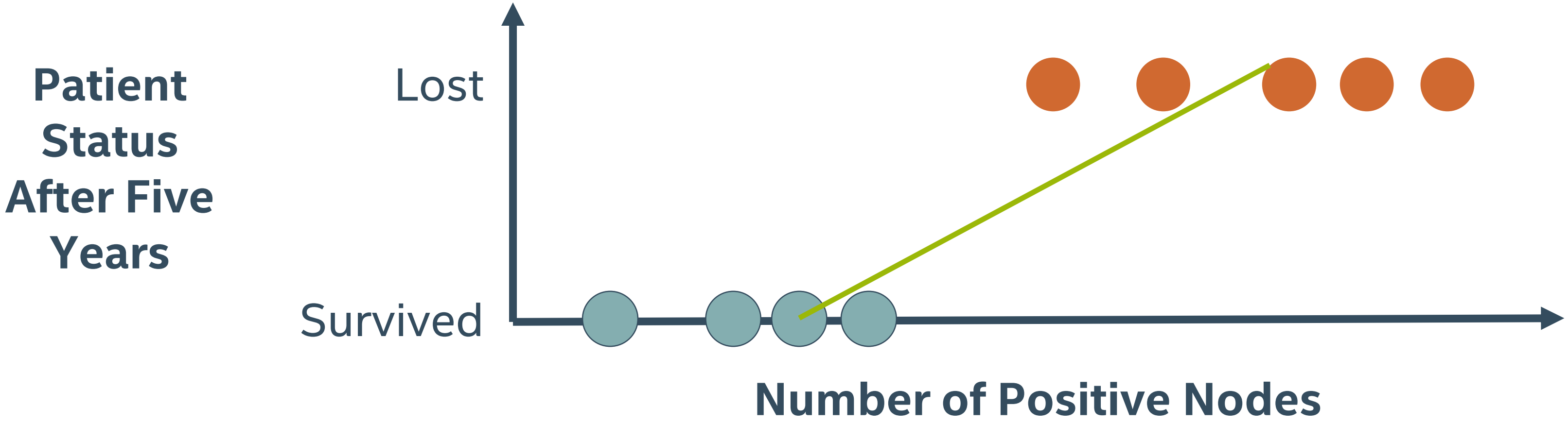
LOGISTIC REGRESSION

INTRODUCTION TO LOGISTIC REGRESSION



LINEAR REGRESSION FOR CLASSIFICATION?



$$y_\beta(x) = \beta_0 + \beta_1 x + \varepsilon$$

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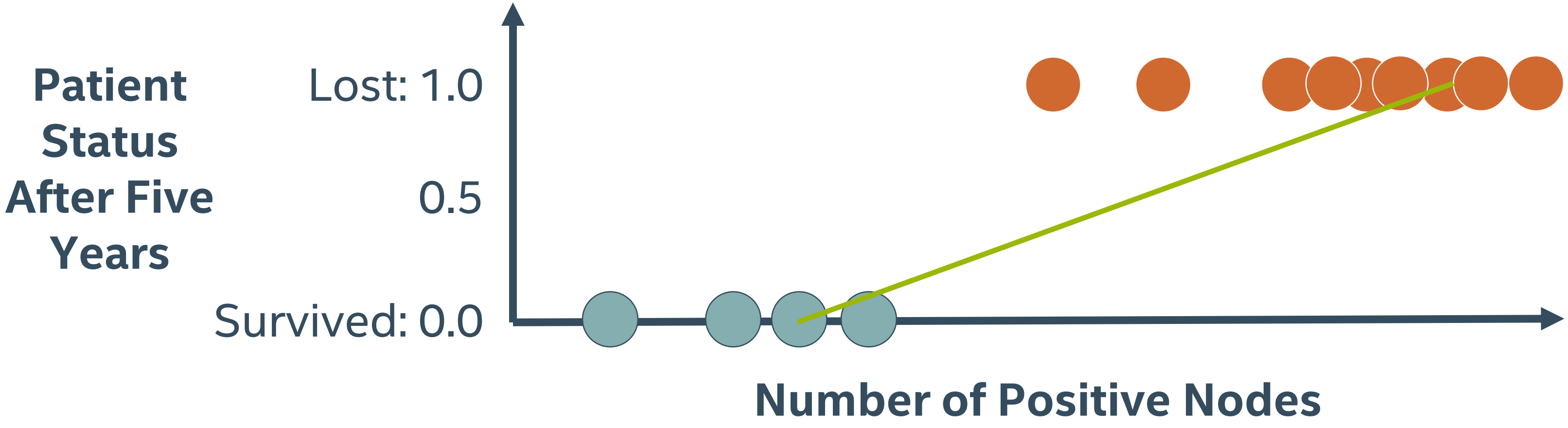

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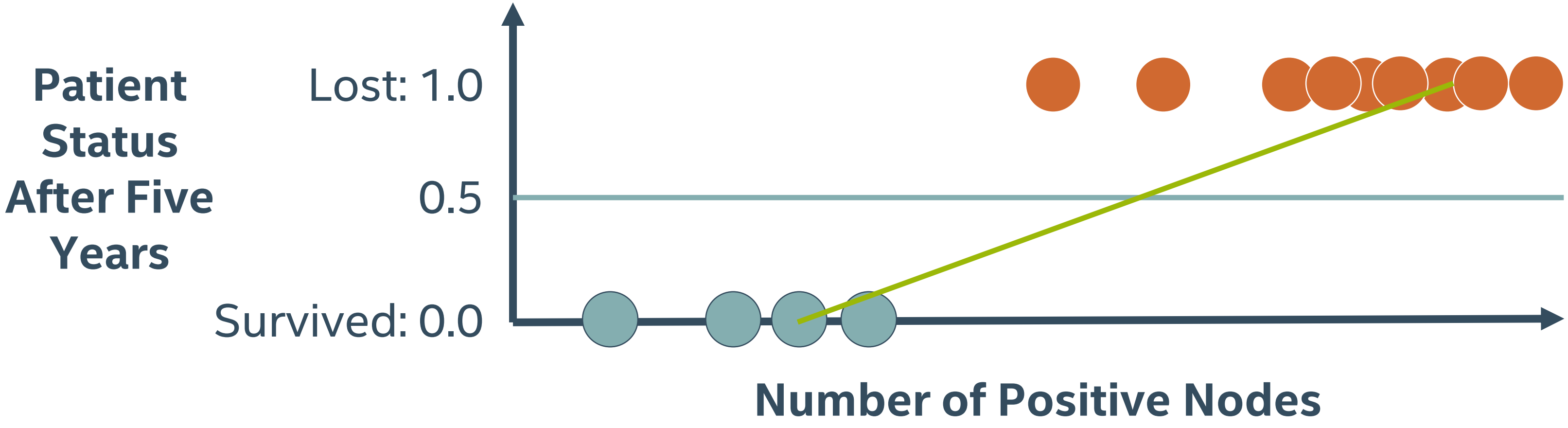
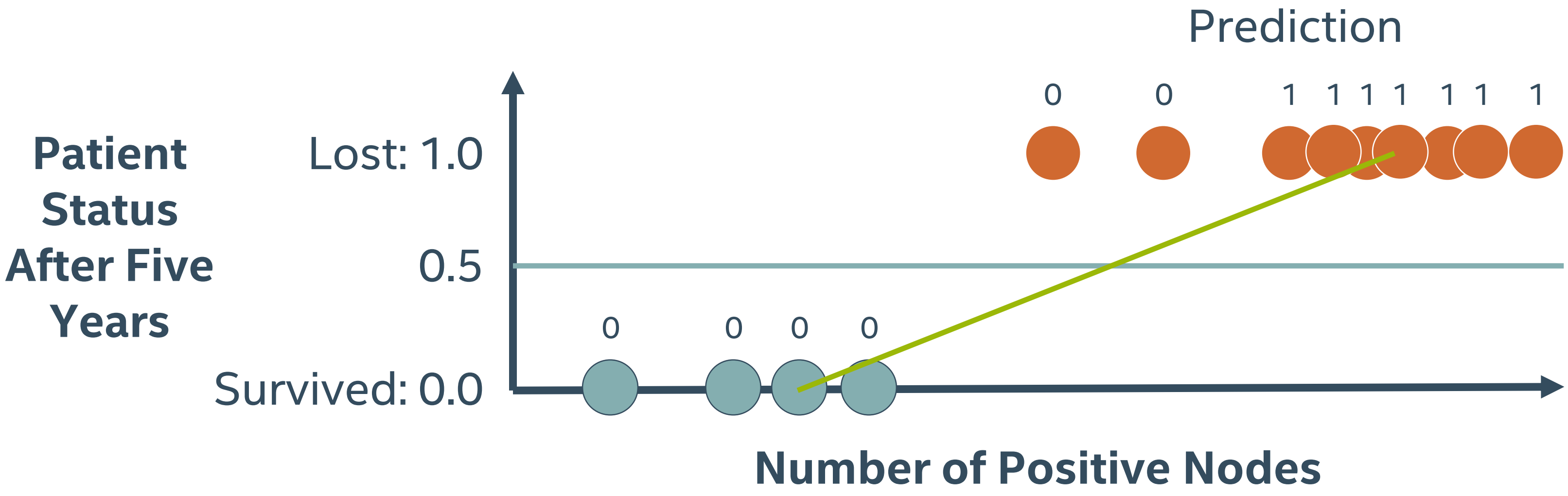


If model result > 0.5: predict lost
If model result < 0.5: predict survived

LINEAR REGRESSION FOR CLASSIFICATION?



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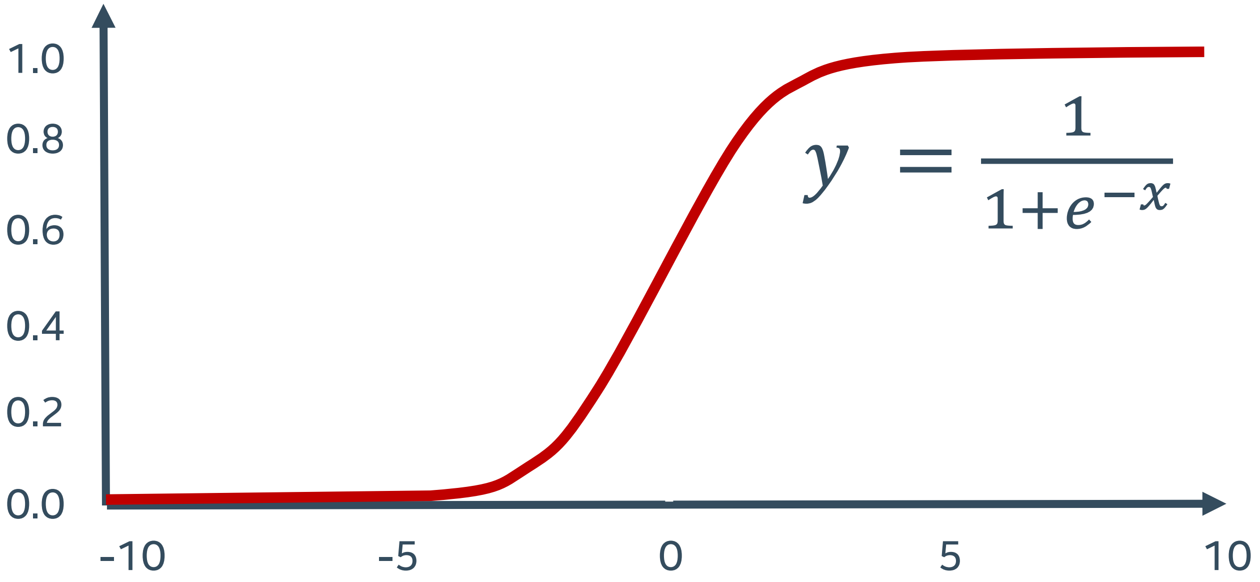
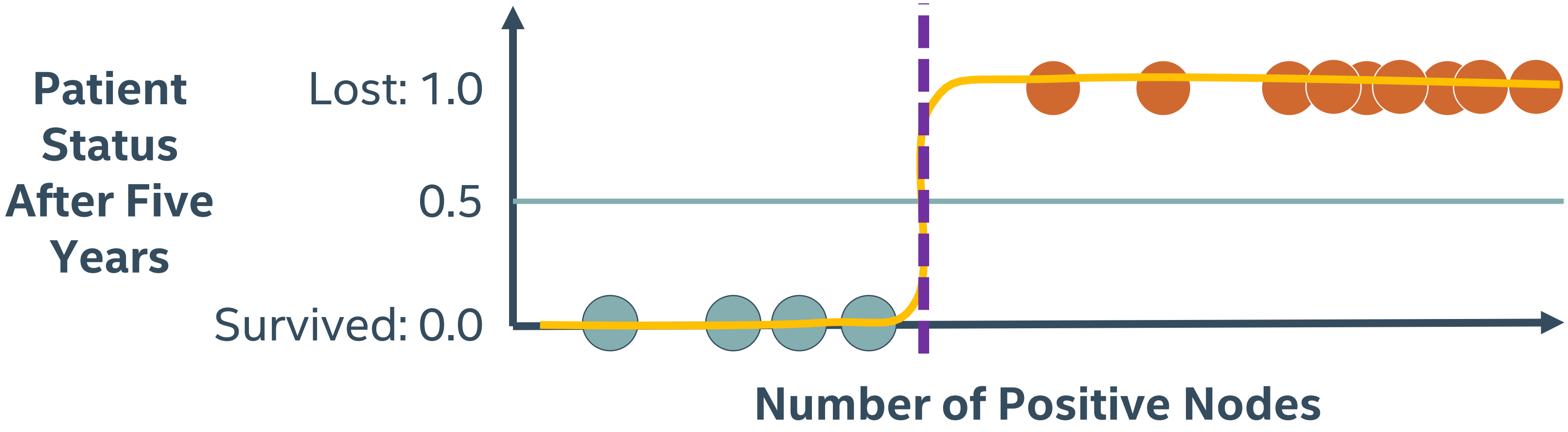
WHAT IS THIS FUNCTION?

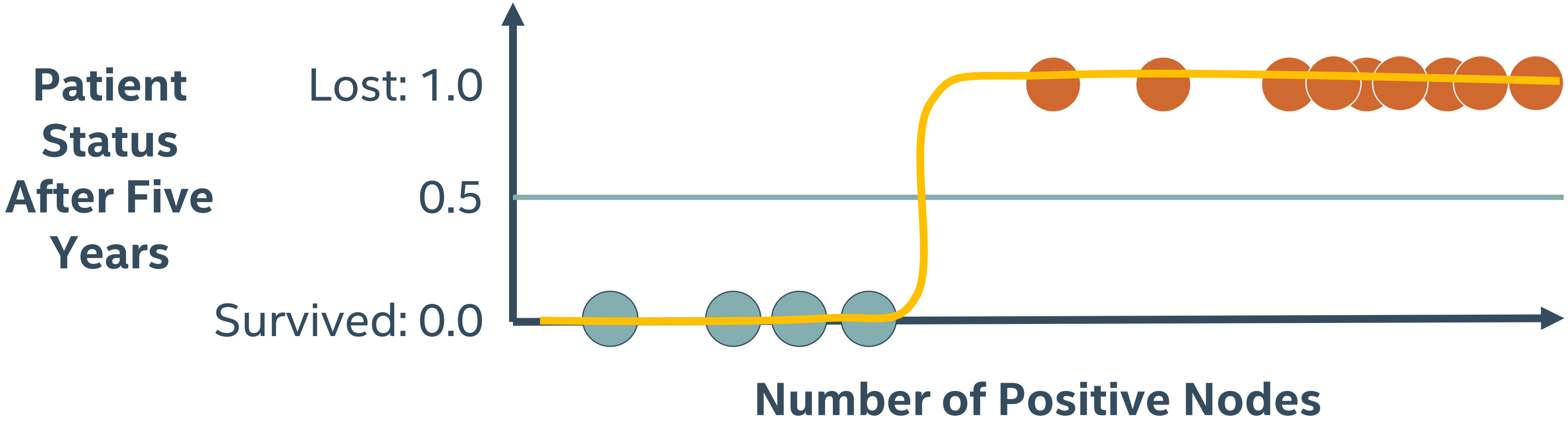


THE DECISION BOUNDARY



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

LOGISTIC REGRESSION



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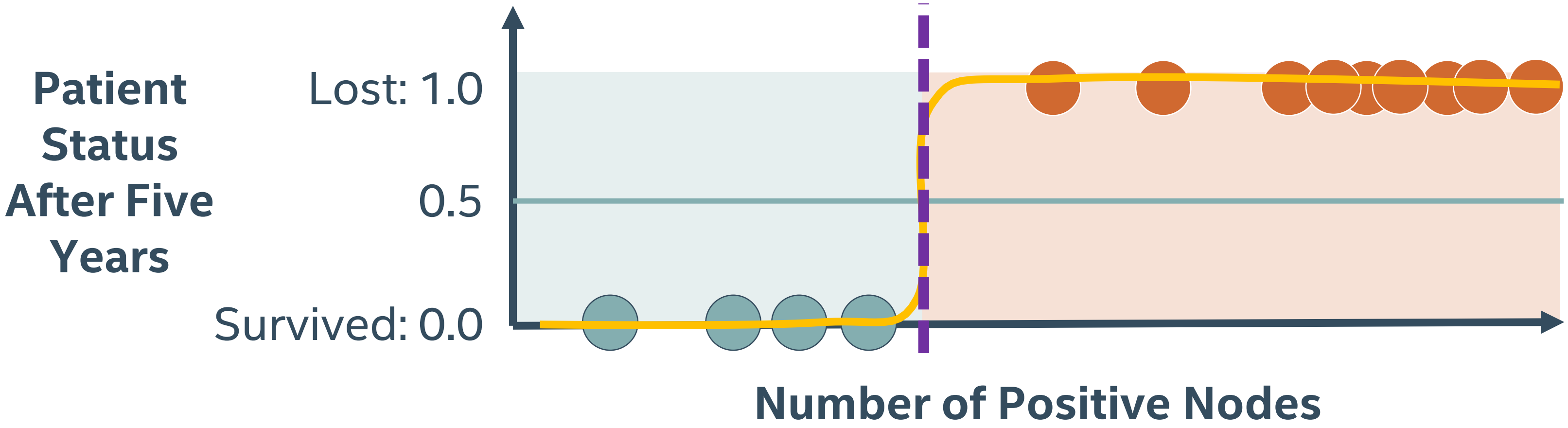

$$y_\beta(x) = \frac{1}{1+e^{-(\beta_0+\beta_1 x+\varepsilon)}}$$

RELATIONSHIP OF LOGISTIC TO LINEAR REGRESSION

Logistic Function

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

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Odds Ratio

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

RELATIONSHIP OF LOGISTIC TO LINEAR REGRESSION

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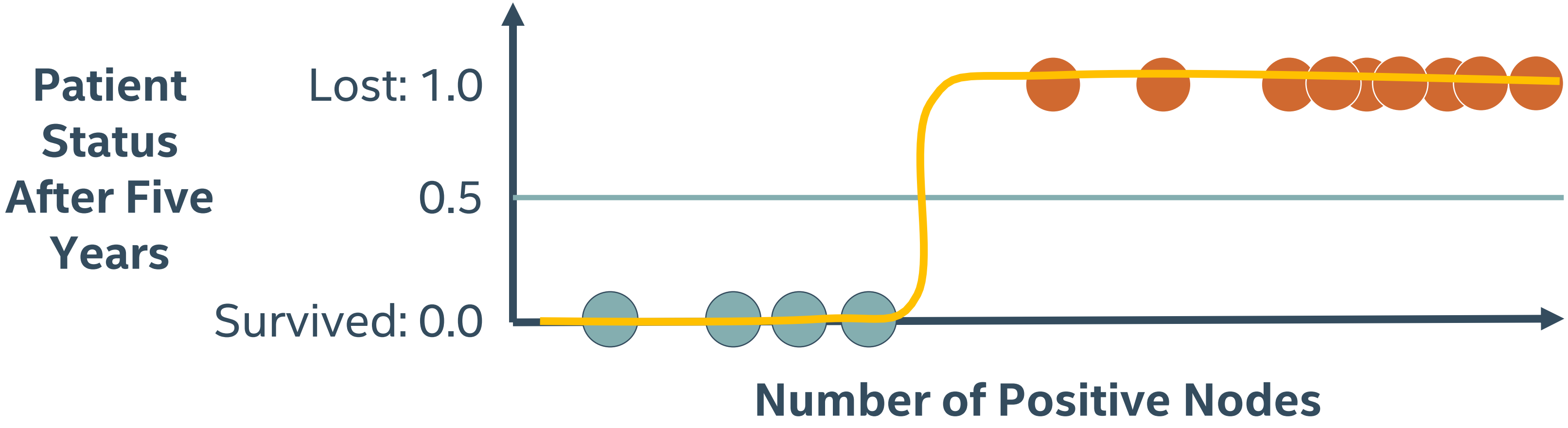
CLASSIFICATION WITH LOGISTIC REGRESSION

One feature (nodes)
Two labels (survived, lost)



CLASSIFICATION WITH LOGISTIC REGRESSION

Two features (nodes, age)
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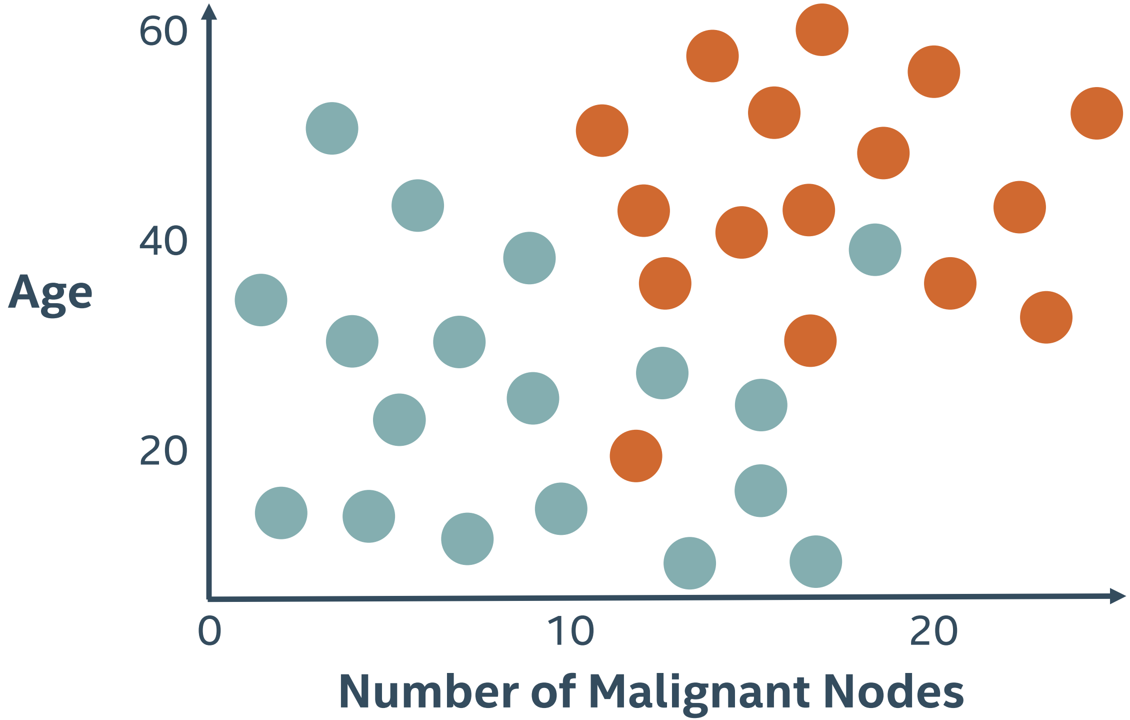

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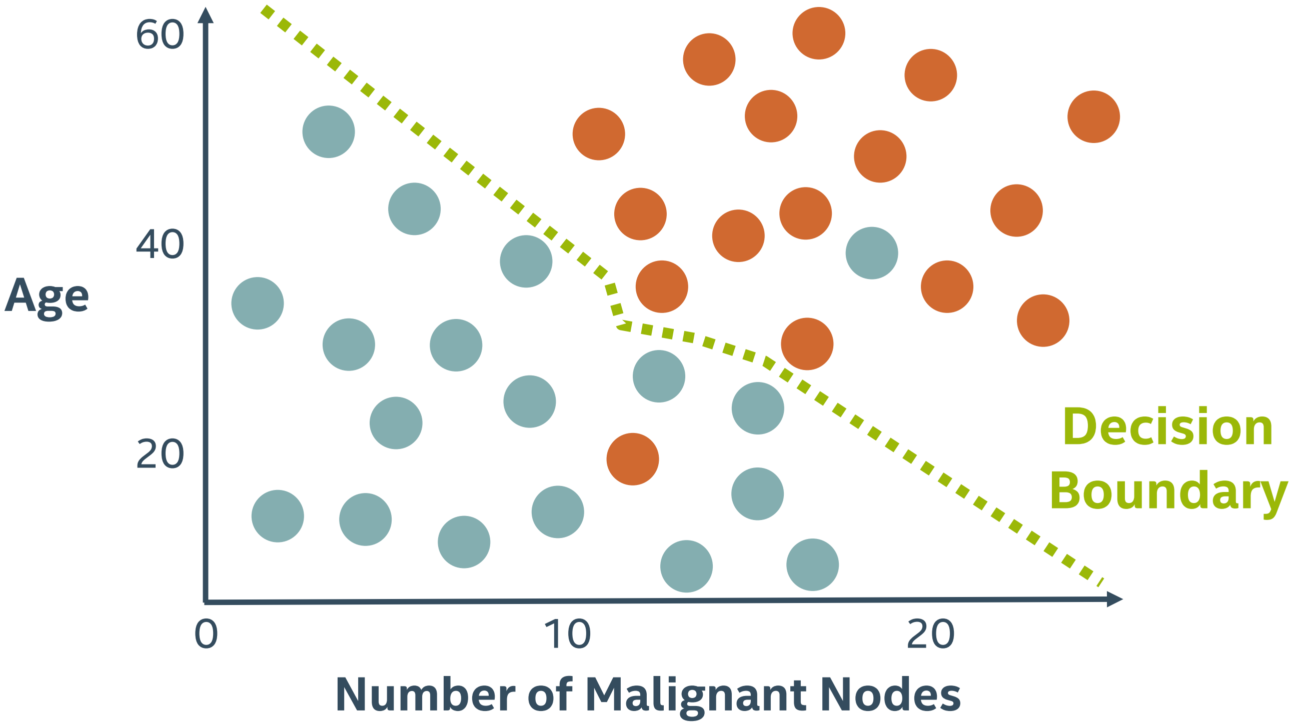

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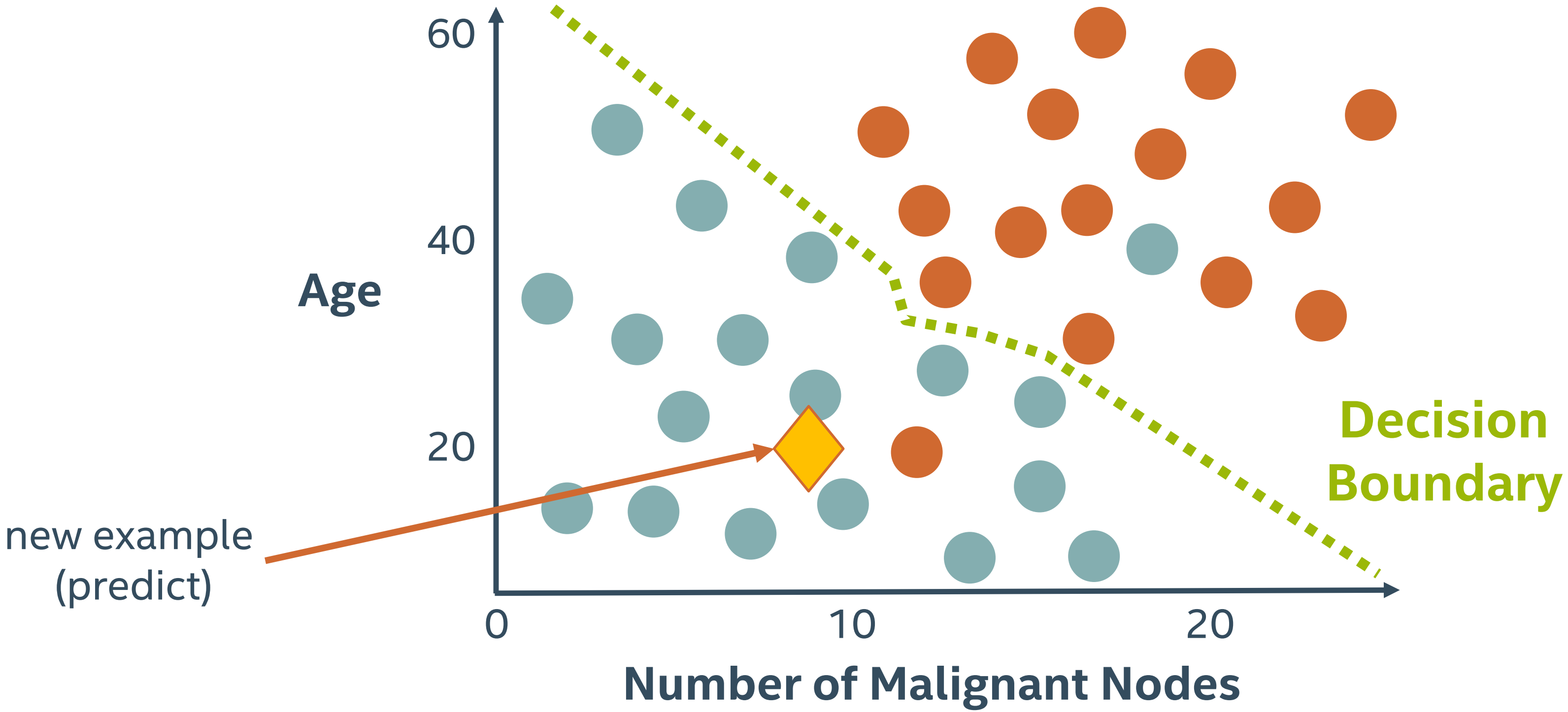
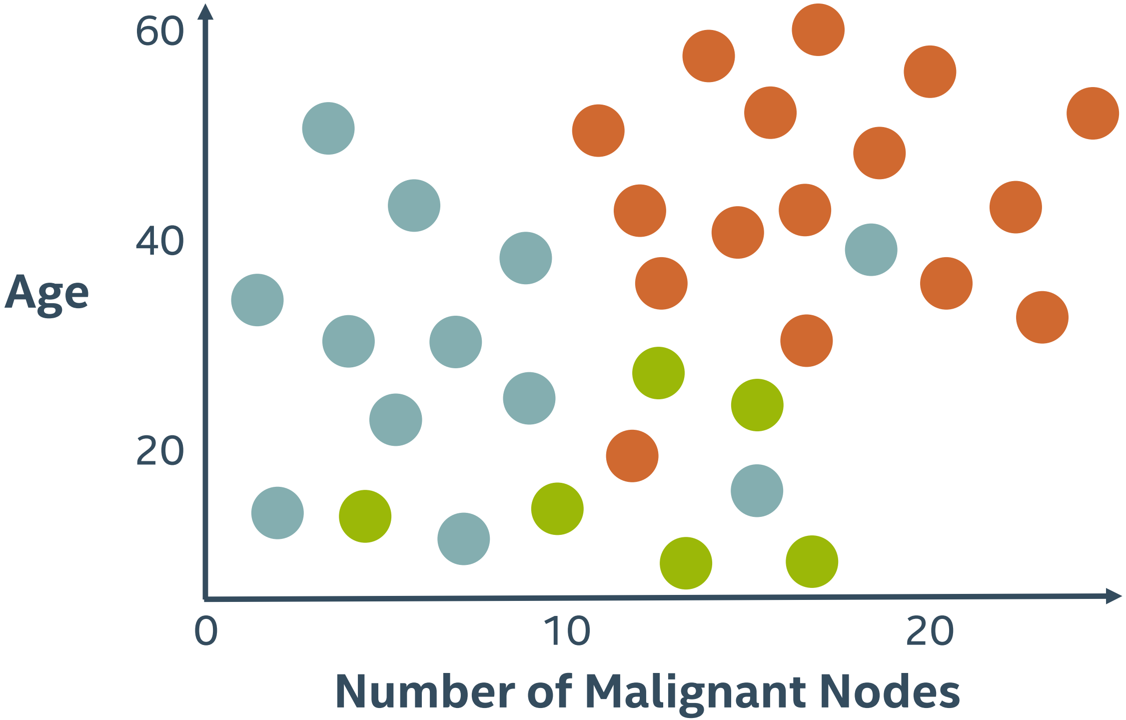
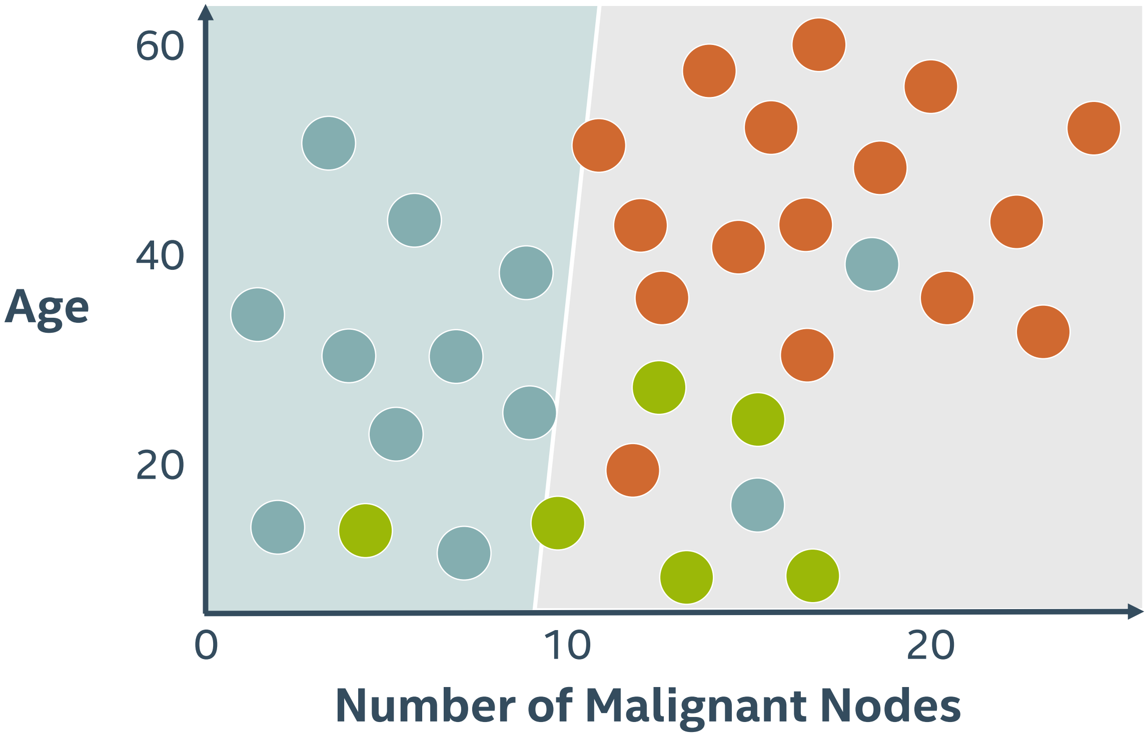


MULTICLASS CLASSIFICATION WITH LOGISTIC REGRESSION

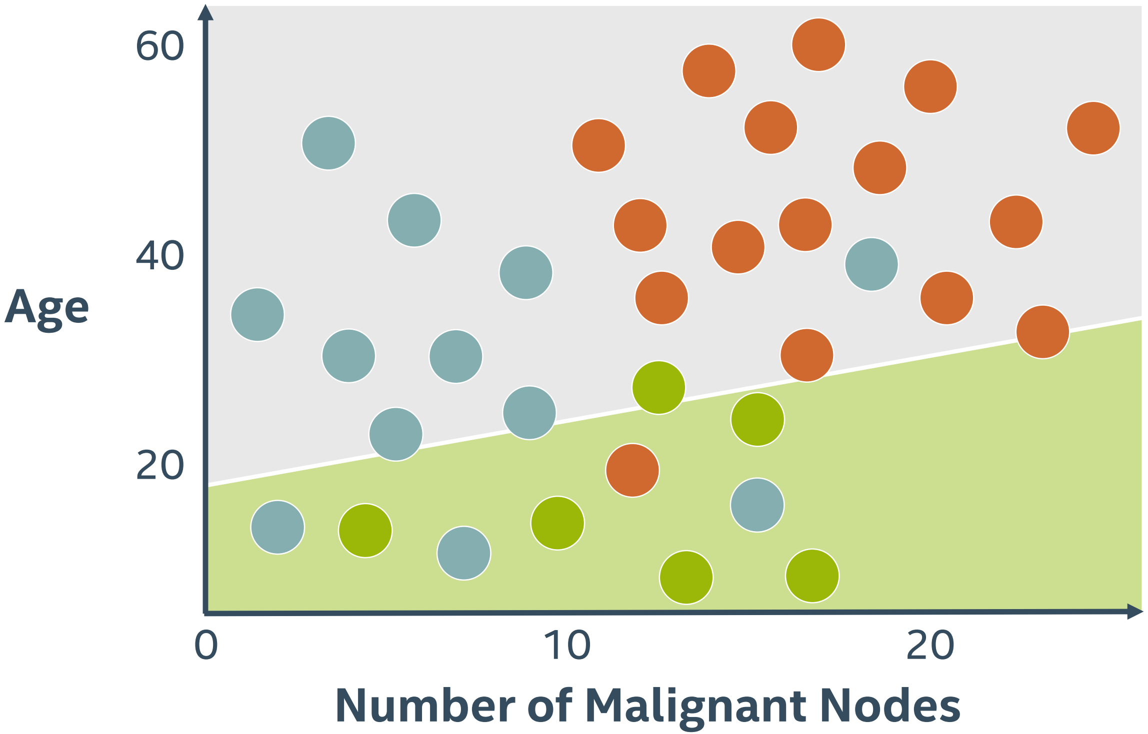
Two features (nodes, age)
Three labels (survived, complications, lost)



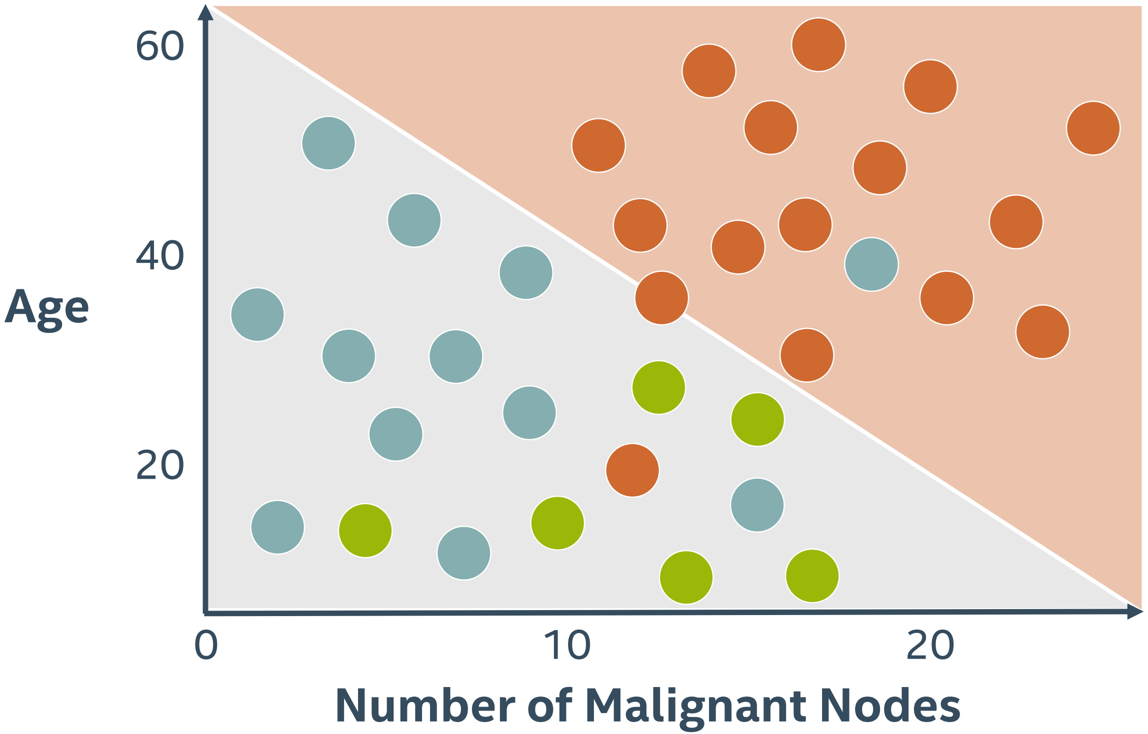
ONE VS ALL: SURVIVED VS ALL



ONE VS ALL: COMPLICATIONS VS ALL

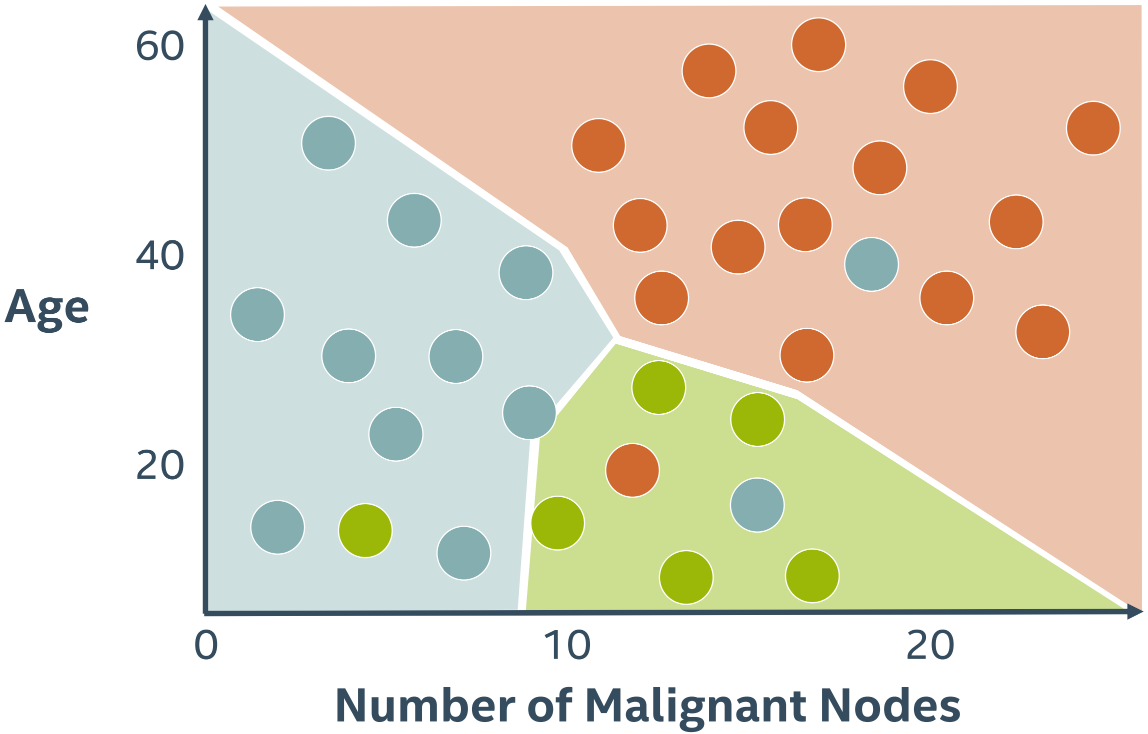


ONE VS ALL: LOSS VS ALL



MULTICLASS DECISION BOUNDARY

Assign most probable class to each region



LOGISTIC REGRESSION: THE SYNTAX

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from sklearn.linear_model import LogisticRegression
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regularization parameters

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y_predict = LR.predict(X_test)
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Tune regularization parameters with cross-validation: LogisticRegressionCV.

CLASSIFICATION ERROR METRICS

CHOOSING THE RIGHT ERROR MEASUREMENT

- You are asked to build a classifier for leukemia
- **Training data:** 1% patients with leukemia, 99% healthy
- **Measure accuracy:** total % of predictions that are correct

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- You are asked to build a classifier for leukemia
- **Training data:** 1% patients with leukemia, 99% healthy
- **Measure accuracy:** total % of predictions that are correct
- Build a simple model that always predicts “healthy”
- Accuracy will be 99%...

CONFUSION MATRIX

	Predicted Positive	Predicted Negative
Actual Positive	True Positive (TP)	False Negative (FN)
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Type II Error

Type I Error

ACCURACY: PREDICTING CORRECTLY

	Predicted Positive	Predicted Negative
Actual Positive	True Positive (TP)	False Negative (FN)
Actual Negative	False Positive (FP)	True Negative (TN)

$$\text{Accuracy} = \frac{TP + TN}{TP + FN + FP + TN}$$

RECALL: IDENTIFYING ALL POSITIVE INSTANCES

	Predicted Positive	Predicted Negative
Actual Positive	True Positive (TP)	False Negative (FN)
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$$\text{Recall or Sensitivity} = \frac{TP}{TP + FN}$$

PRECISION: IDENTIFYING ONLY POSITIVE INSTANCES

	Predicted Positive	Predicted Negative
Actual Positive	True Positive (TP)	False Negative (FN)
Actual Negative	False Positive (FP)	True Negative (TN)

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

SPECIFICITY: AVOIDING FALSE ALARMS

	Predicted Positive	Predicted Negative
Actual Positive	True Positive (TP)	False Negative (FN)
Actual Negative	False Positive (FP)	True Negative (TN)

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

ERROR MEASUREMENTS

	Predicted Positive	Predicted Negative
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$$\text{Accuracy} = \frac{TP + TN}{TP + FN + FP + TN}$$

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ERROR MEASUREMENTS

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$$\text{Accuracy} = \frac{TP + TN}{TP + FN + FP + TN}$$

$$\text{Recall or Sensitivity} = \frac{TP}{TP + FN}$$

$$F1 = 2\ \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

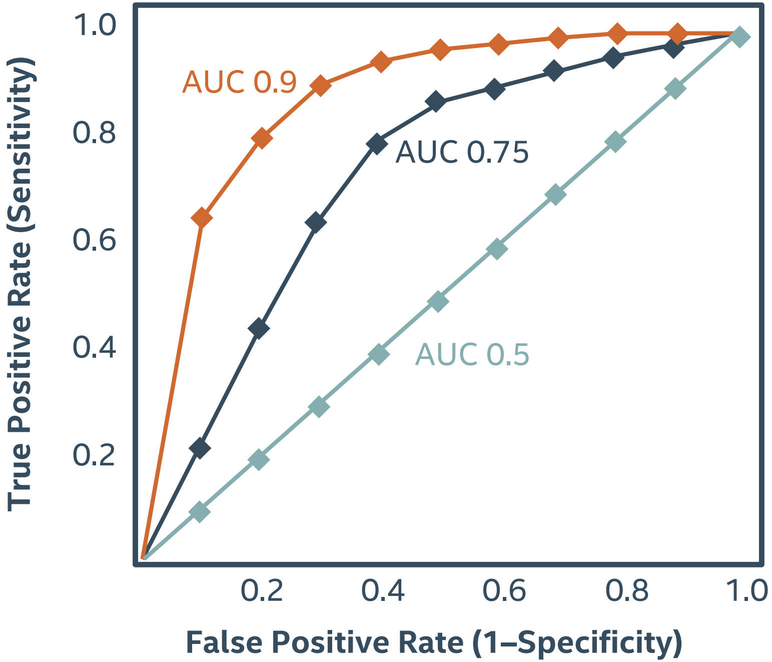
$$\text{Precision} = \frac{TP}{TP + FP}$$

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

RECEIVER OPERATING CHARACTERISTIC (ROC)

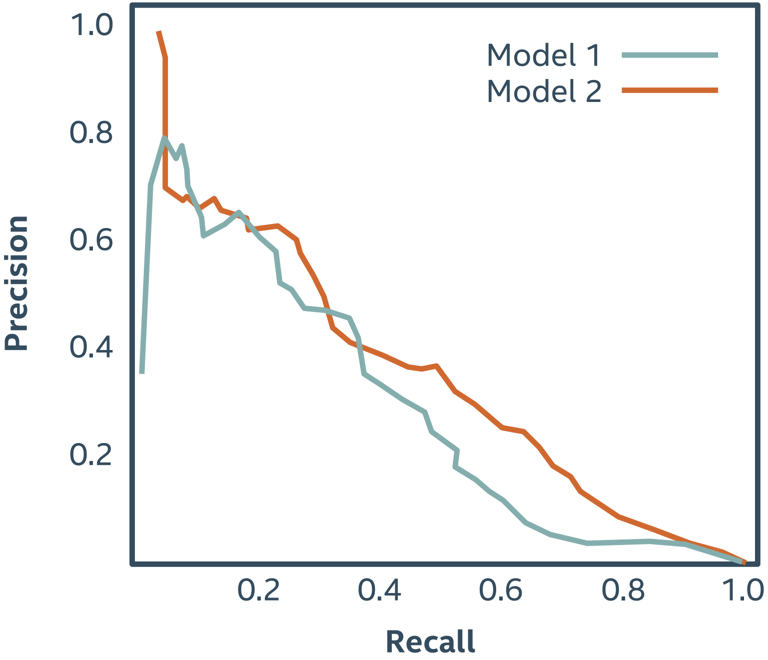
Evaluation of model at all possible thresholds

AREA UNDER CURVE (AUC)



Measures total area under ROC curve

PRECISION RECALL CURVE (PR CURVE)



Measures trade-off between precision and recall

MULTIPLE CLASS ERROR METRICS

	Predicted Class 1	Predicted Class 2	Predicted Class 3
Actual Class 1	TP1		
Actual Class 2		TP2	
Actual Class 3			TP3

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$$\text{Accuracy} = \frac{\text{TP1} + \text{TP2} + \text{TP3}}{\text{Total}}$$

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Actual Class 1	TP1		
Actual Class 2		TP2	
Actual Class 3			TP3

$$\text{Accuracy} = \frac{TP1 + TP2 + TP3}{\text{Total}}$$

Most multi-class error metrics are similar to binary versions—just expand elements as a sum

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Lots of other error metrics and diagnostic tools:

```
from sklearn.metrics import precision_score, recall_score,
    f1_score, roc_auc_score,
    confusion_matrix, roc_curve,
    precision_recall_curve
```

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