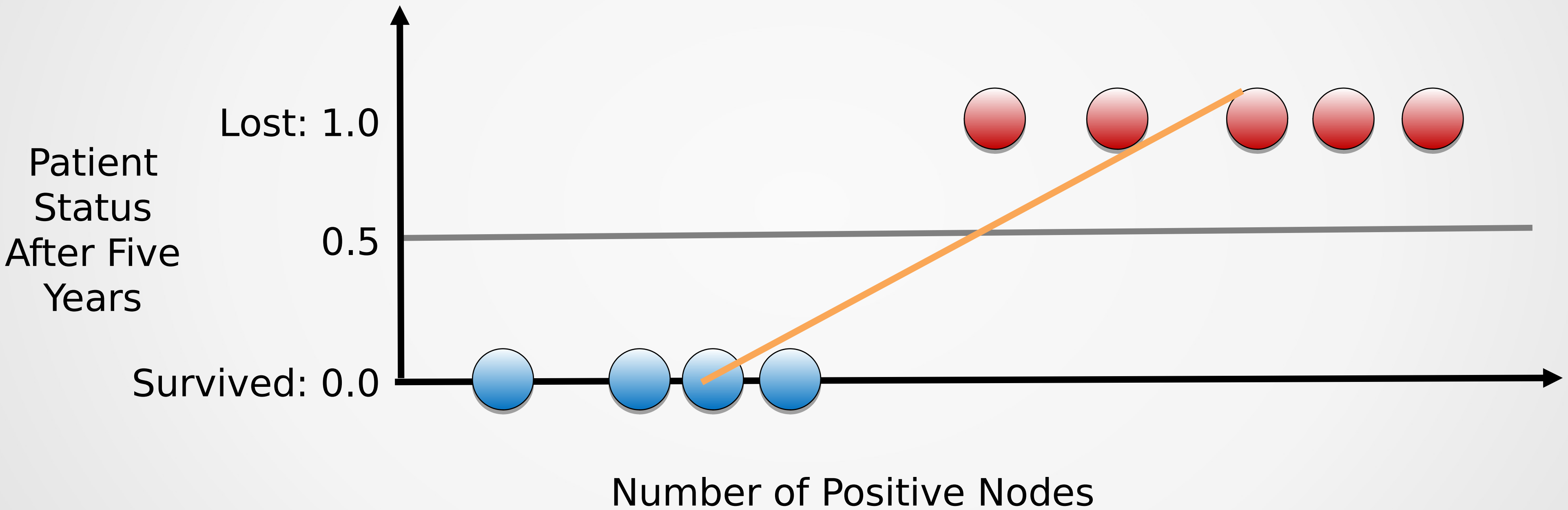
Logistic Regression And Classification Error Metrics

Learning Objectives

After completing this lecture, you will be able to:-

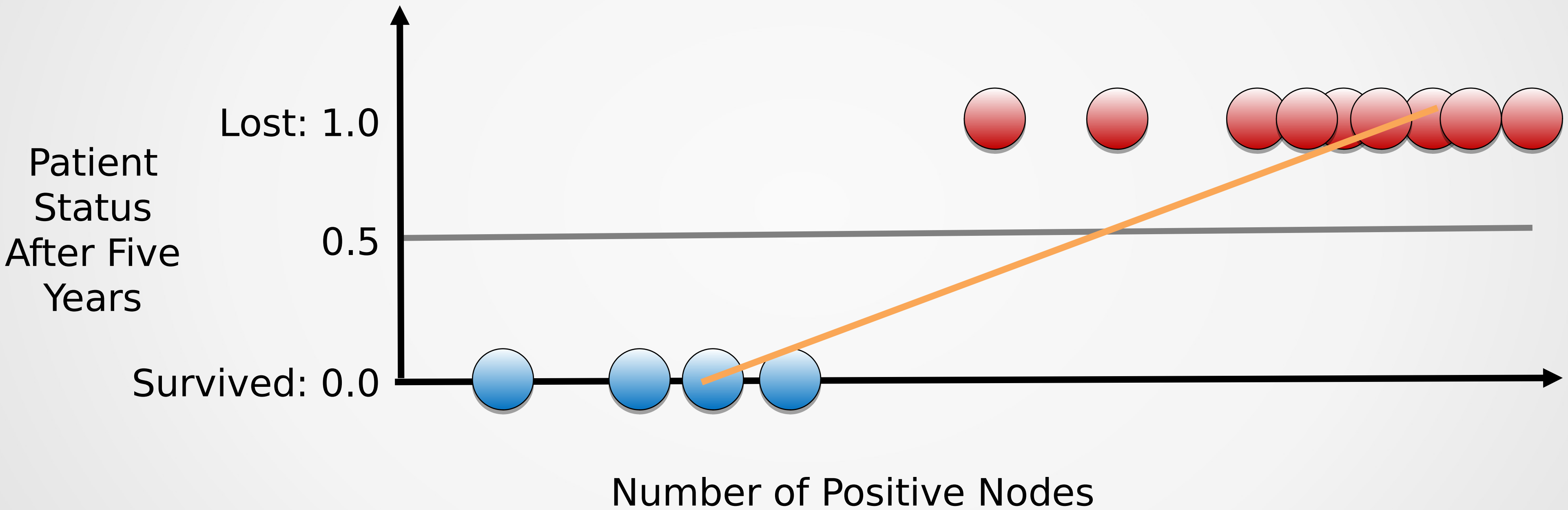
- Describe logistic regression
- Implement logistic function based optimization for any regression or classification problem
- Define and calculate the basic classification error metrics
- Utilize the advanced (compound) classification error metrics

Introduction to Logistic Regression



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

Introduction to Logistic Regression



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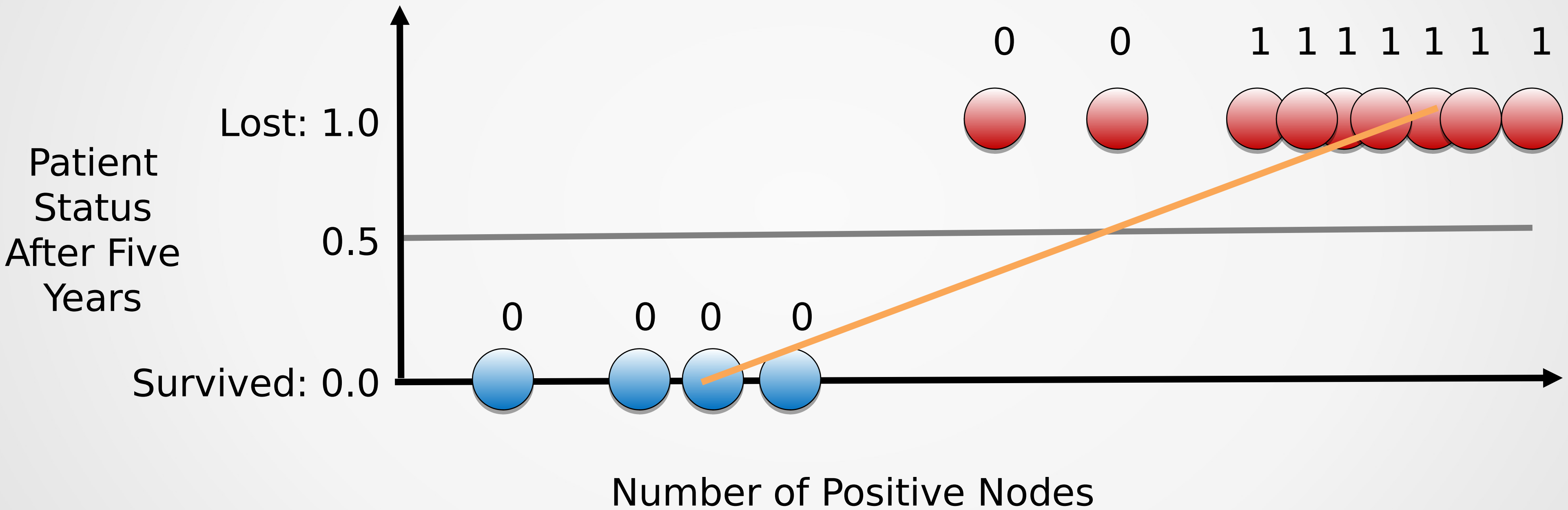
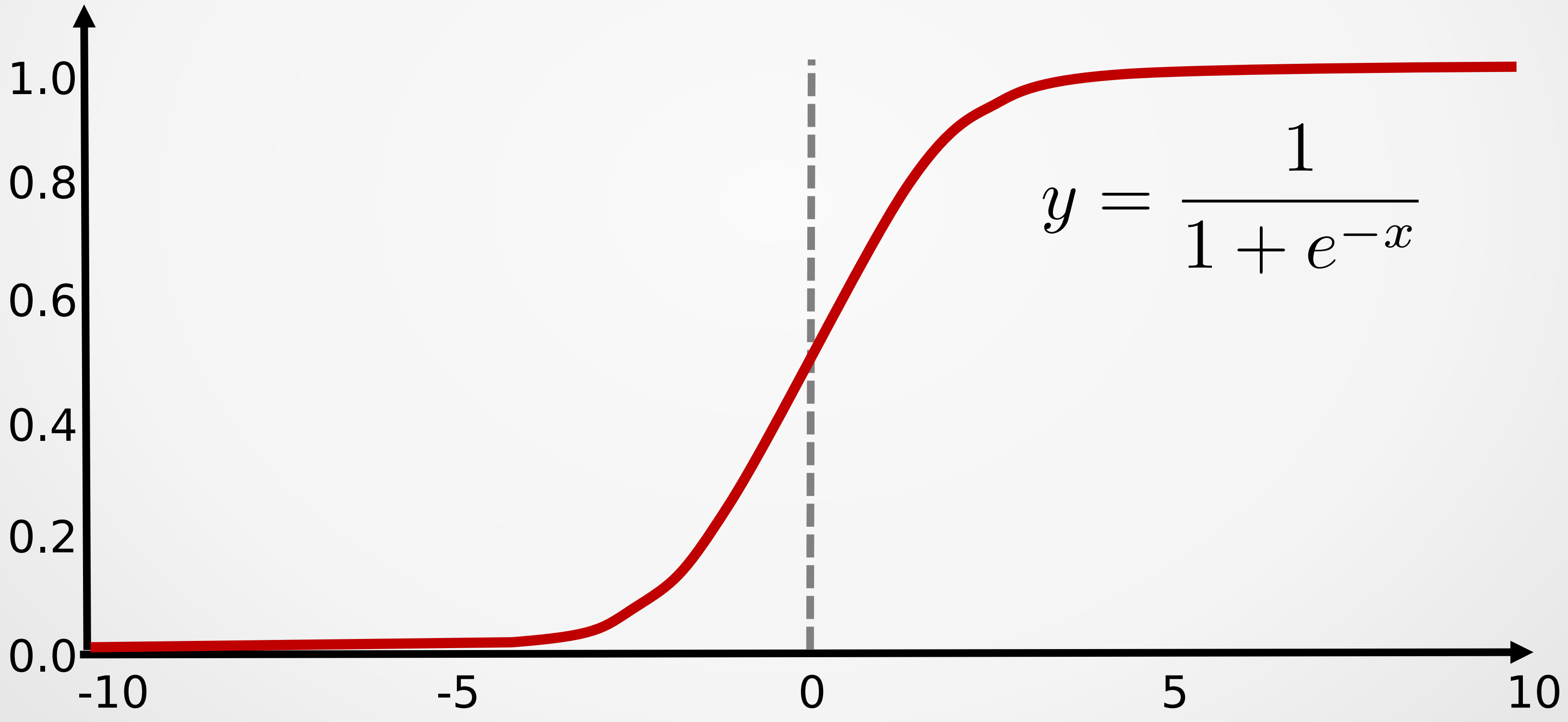
Introduction to Logistic Regression



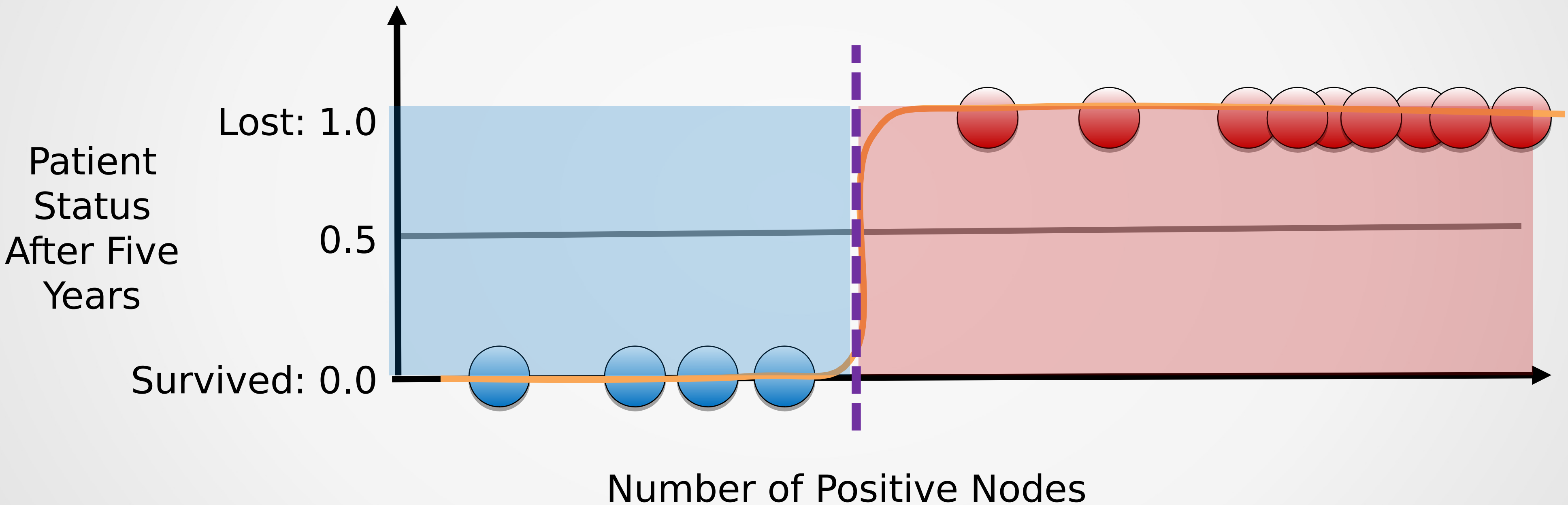
$$y_\beta(x) = \beta_0 + \beta_1 x + \varepsilon$$

Introduction to Logistic Regression

What is this function?



Classification with Logistic Regression



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

Relating to Linear Regression

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

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

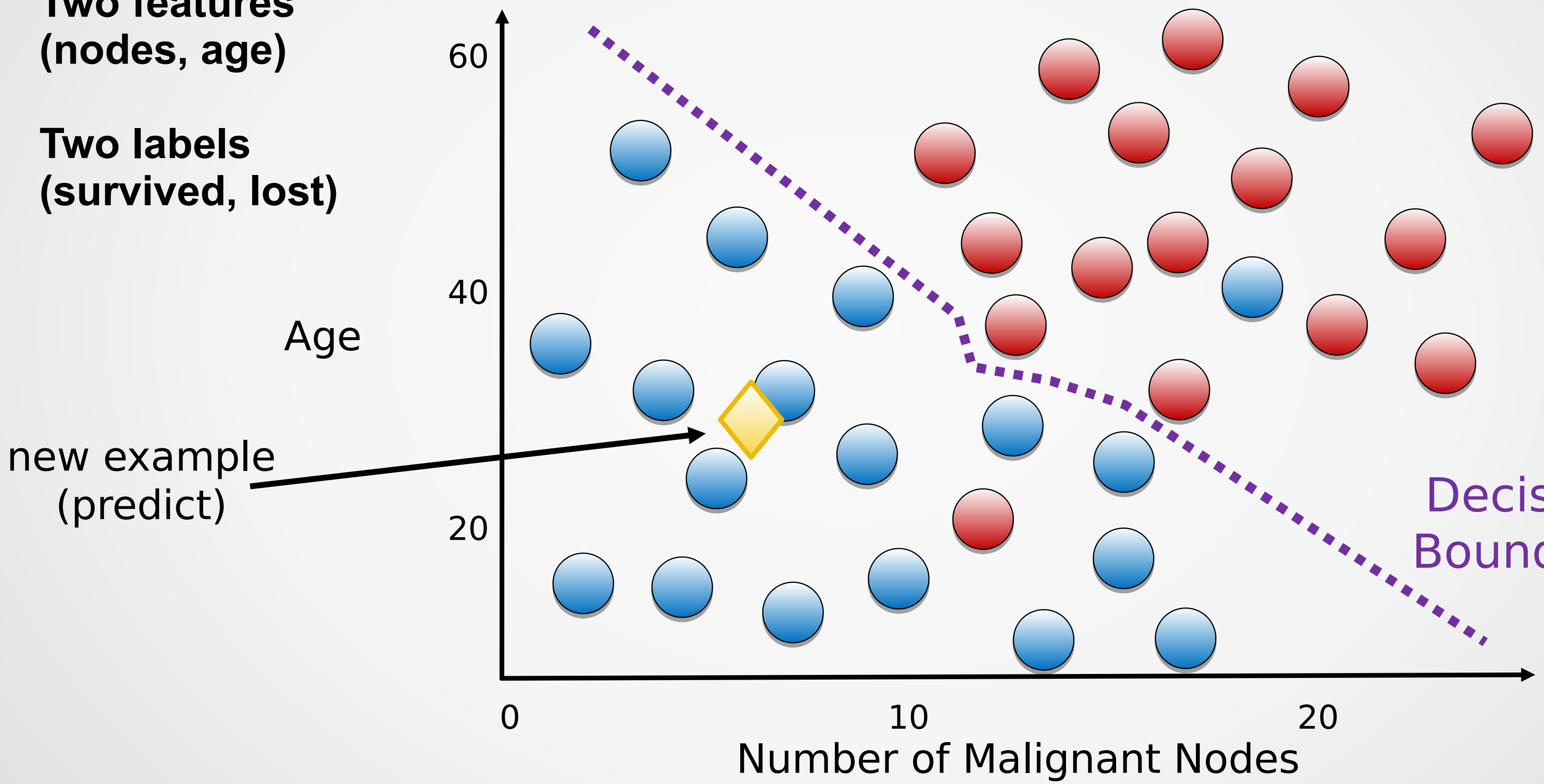
Odds Ratio
$$\frac{P(x)}{1 - P_x} = e^{(\beta_0 + \beta_1 x)}$$

Log Odds
$$\log\left(\frac{P(x)}{1 - P_x}\right) = \beta_0 + \beta_1 x$$

Classification with Logistic Regression

Two features (nodes, age)

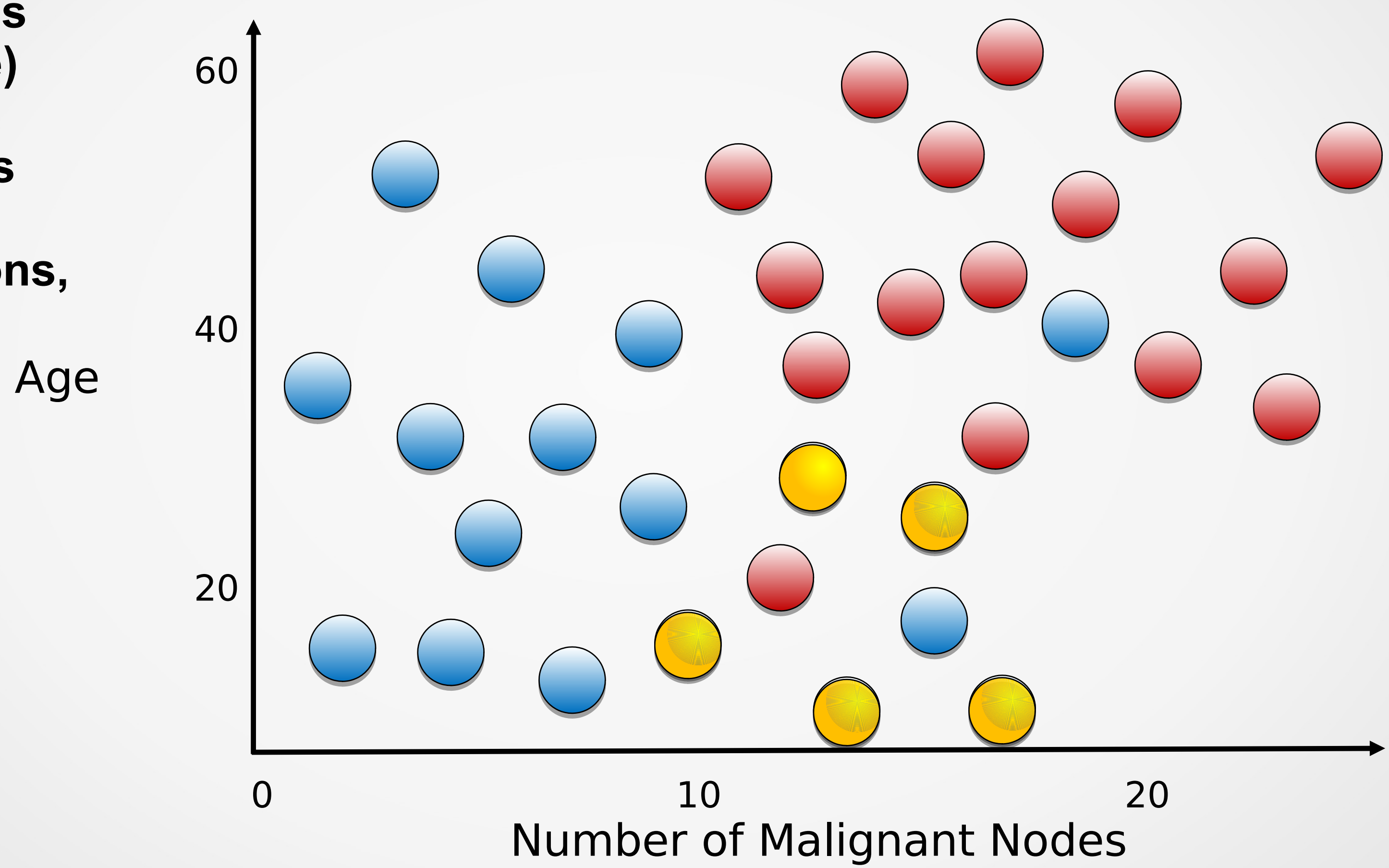
Two labels (survived, lost)



Classification with Logistic Regression

Two features (nodes, age)

Three labels (survived, complications, lost)



Classification with Logistic Regression

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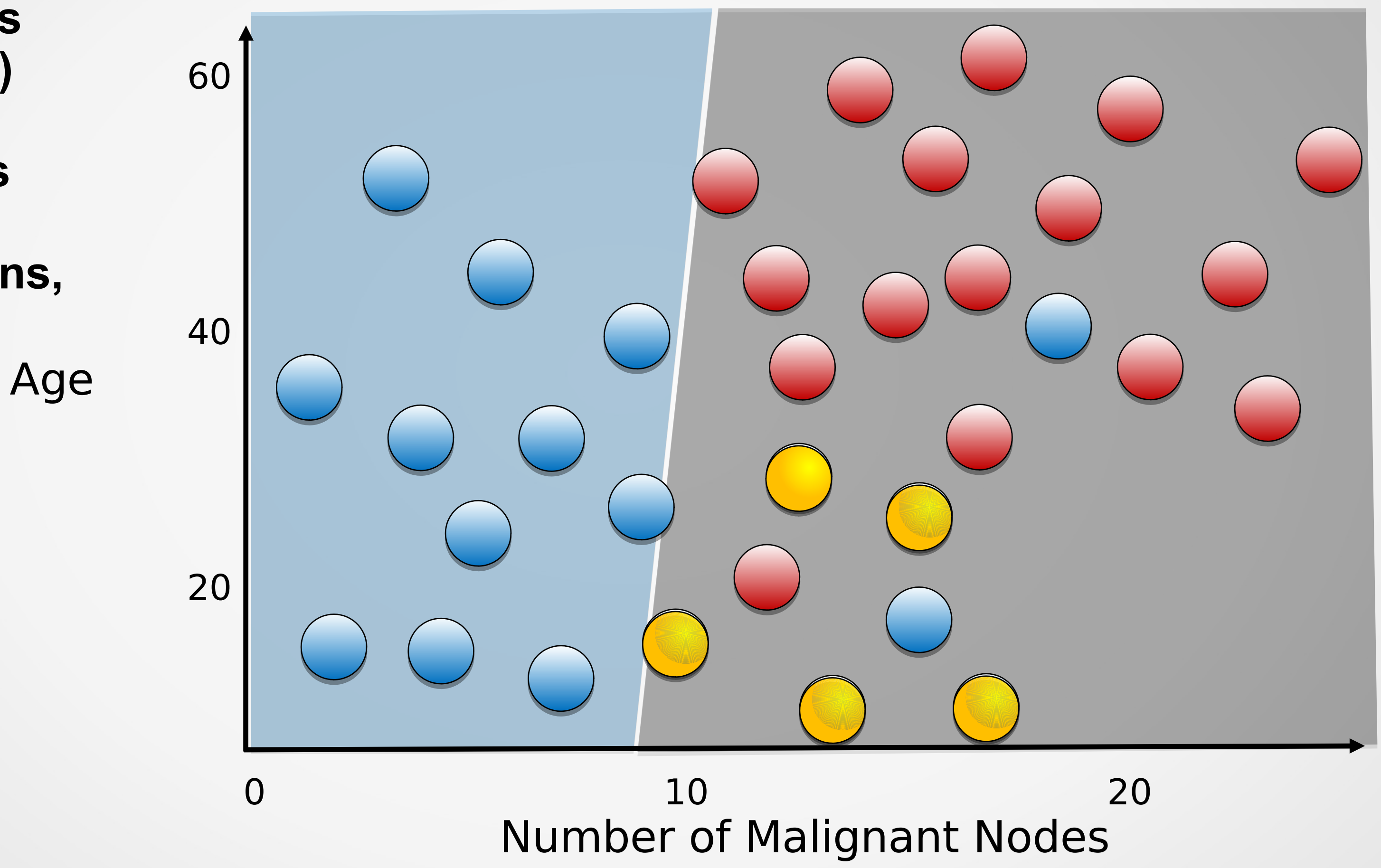

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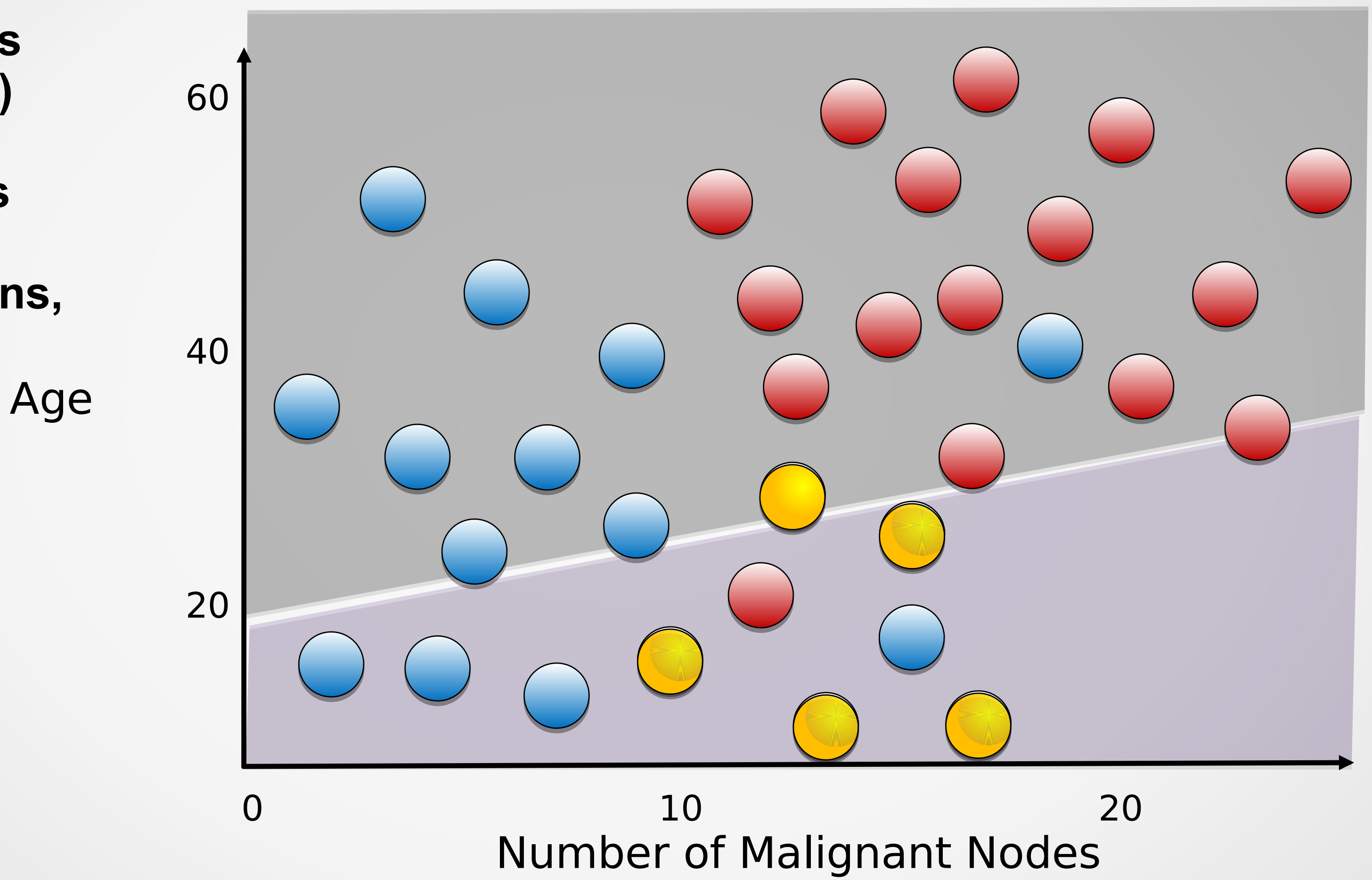

Classification with Logistic Regression

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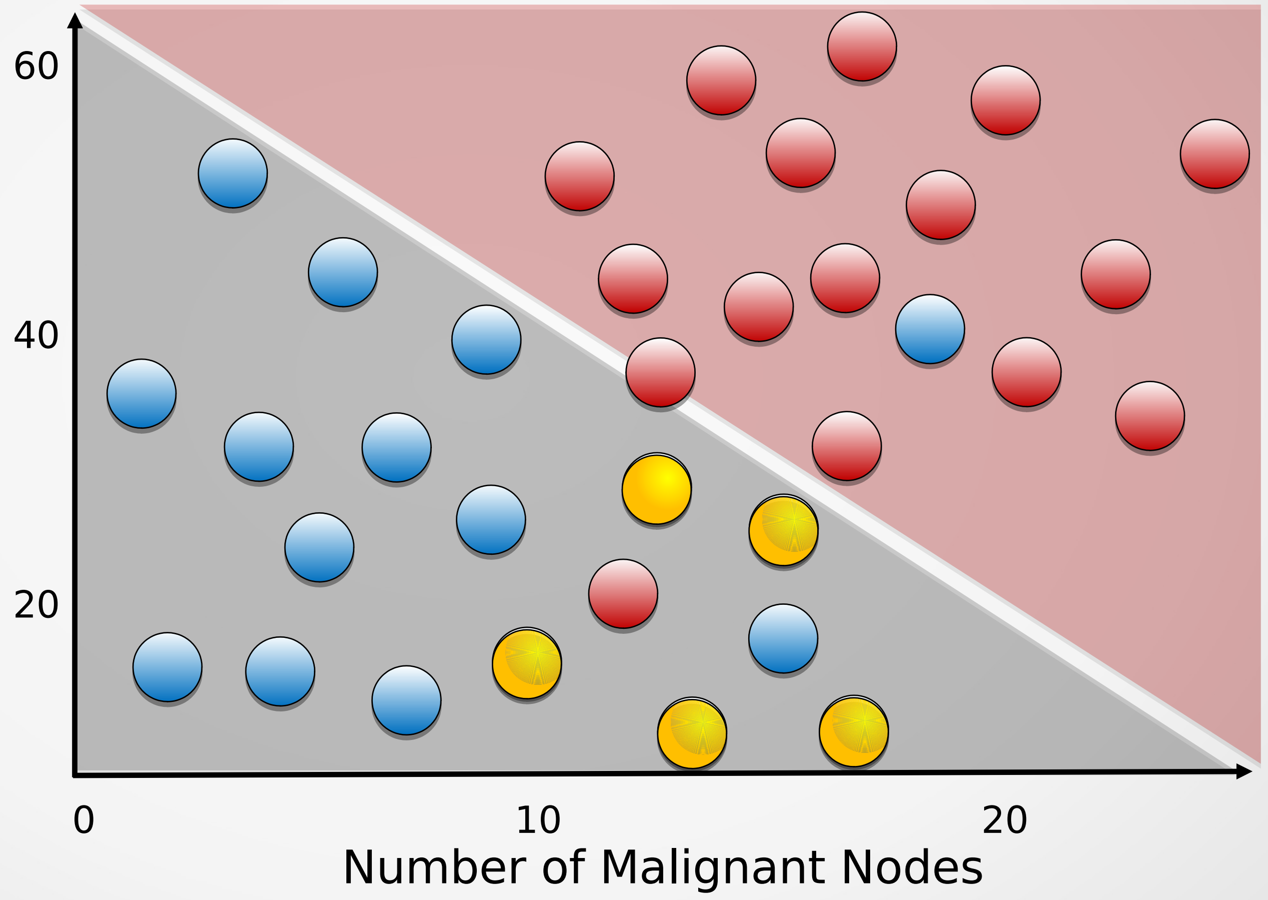

Classification with Logistic Regression

Two features (nodes, age)

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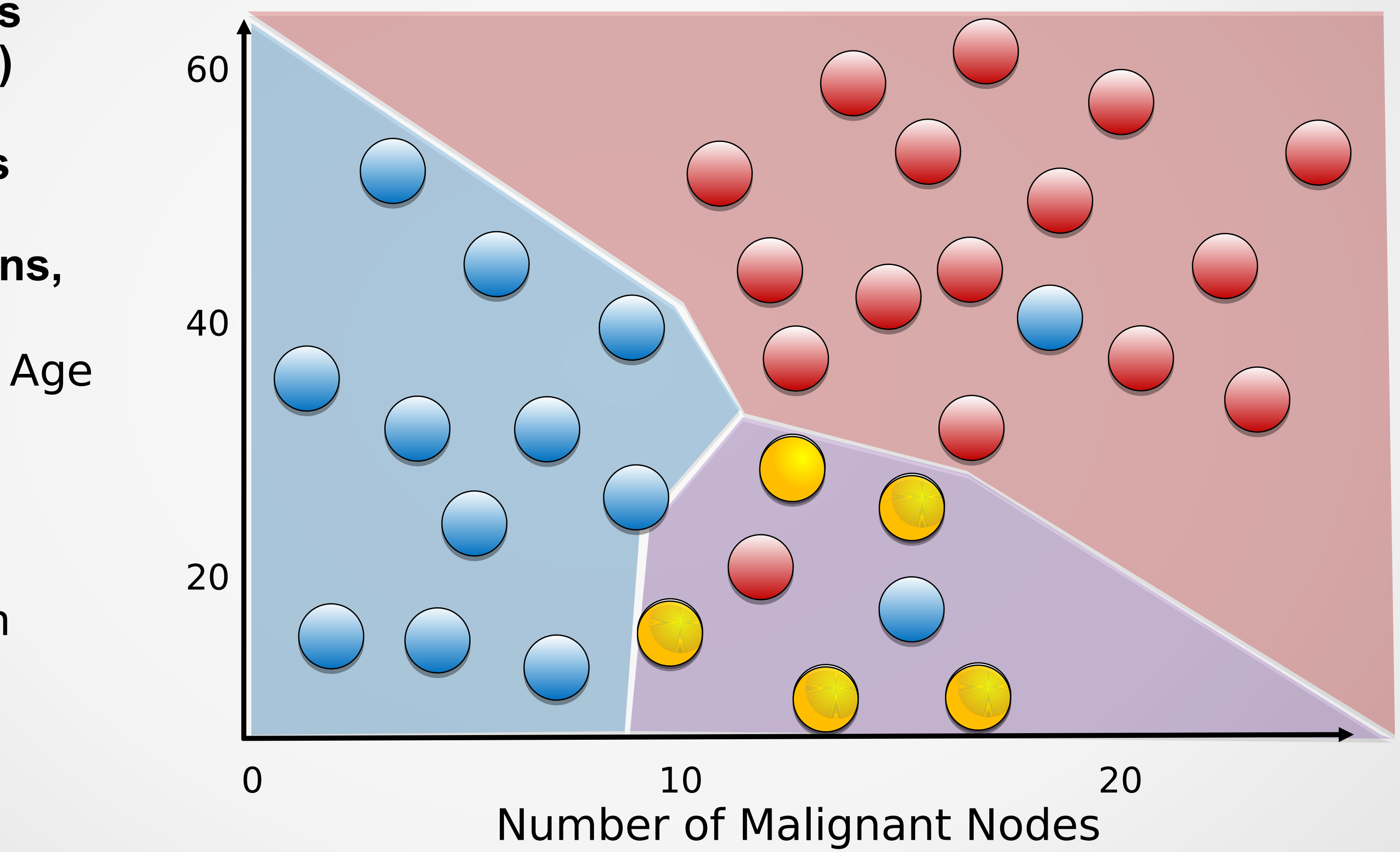


Assign most probable class to each region

Logistic Regression Syntax

- Import the class containing the classification method

```
from sklearn.linear_model import LogisticRegression
```

- Create an instance of the class

```
LR = LogisticRegression(penalty='l2', c=10.0)
```

- Fit the instance on the data and then predict the expected value

```
LR = LR.fit(x_train, y_train)
y_predict = LR.predict(x_test)
```

- Tune regularization parameters with cross-validation using `LogisticRegressionCV`

Classification Error Metrics

- Task: 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)
Actual Negative	False Positive (FP)	True Negative (TN)

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)
Actual Negative	False Positive (FP)	True Negative (TN)

$$\text{Recall (sensitivity)} = \frac{TP}{TP + FN}$$

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)

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

Confusion Matrix Error Measurements

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

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

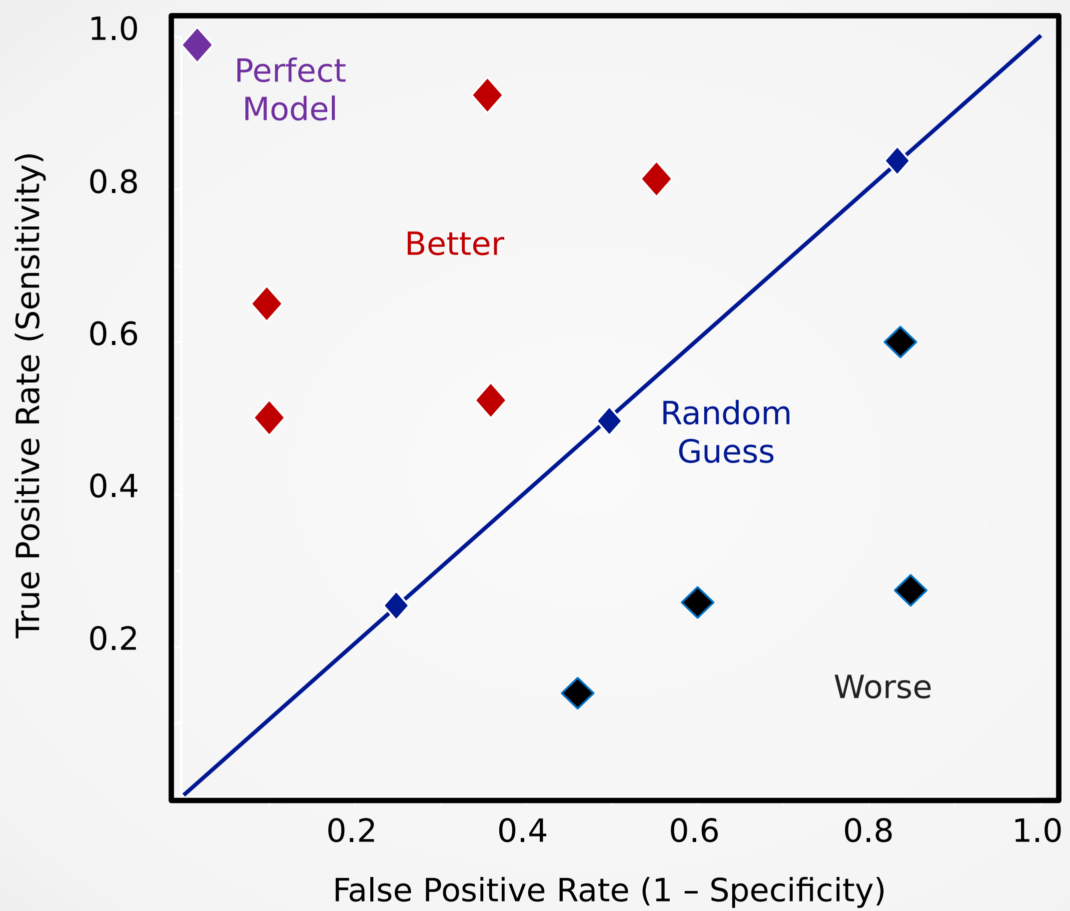
$$\text{Recall or Sensitivity} = \frac{TP}{TP + FN}$$

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

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

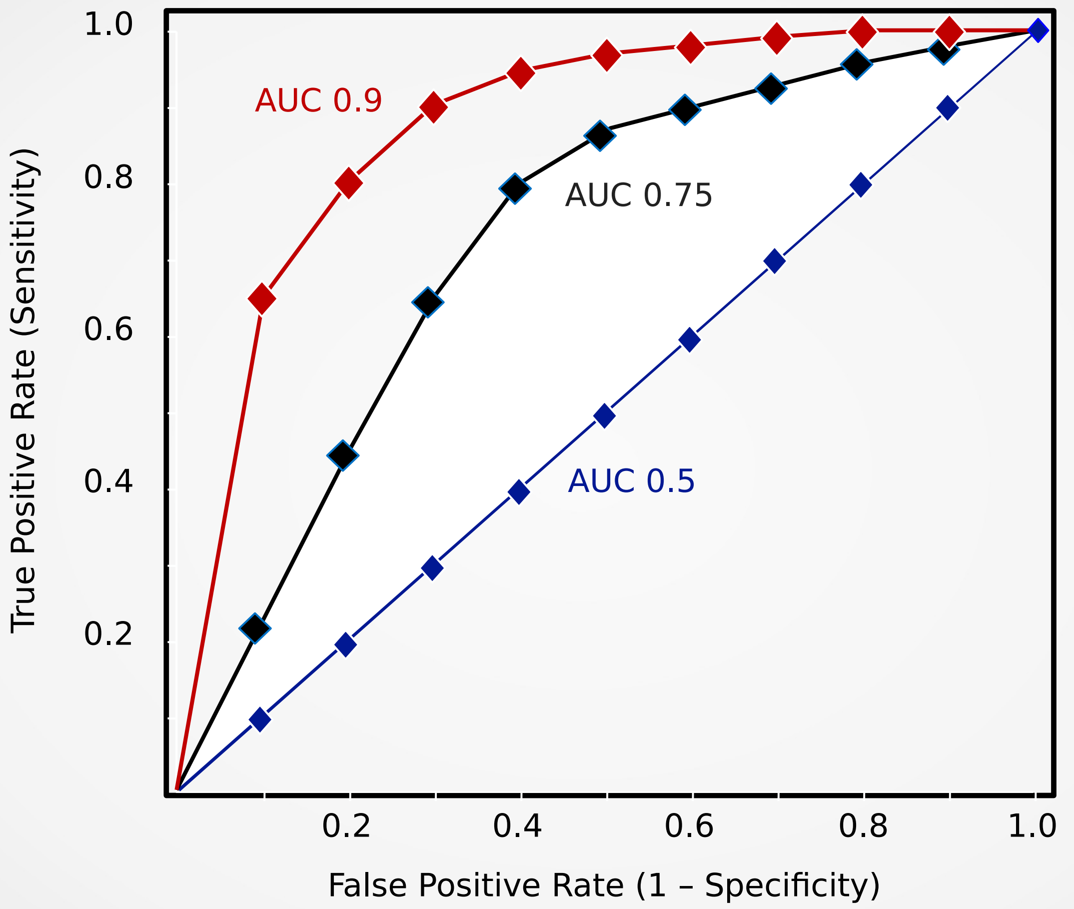
$$\text{Specificity} = \frac{TN}{FP + TN}$$

Receiver Operating Characteristic (ROC)



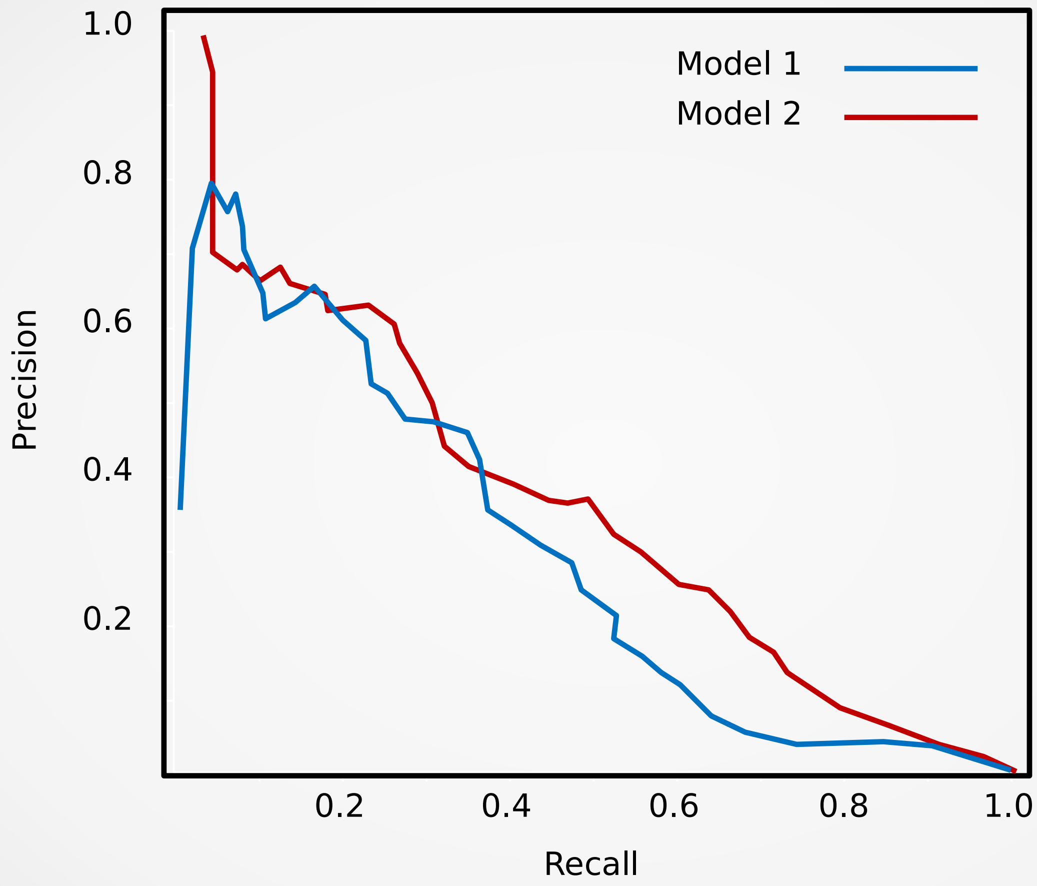
Evaluation of model at all possible thresholds

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

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

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

Classification Error Metrics Syntax

- Import the desired error function

```
from sklearn.metrics import accuracy_score
```

- Calculate the error on the test and predicted data sets

```
accuracy_value = accuracy_score(y_test, y_pred)
```

- 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)
```

End of Lecture

Many thanks to Intel Software for providing a variety of resources for this lecture series