Software

# Introduction to Supervised Learning

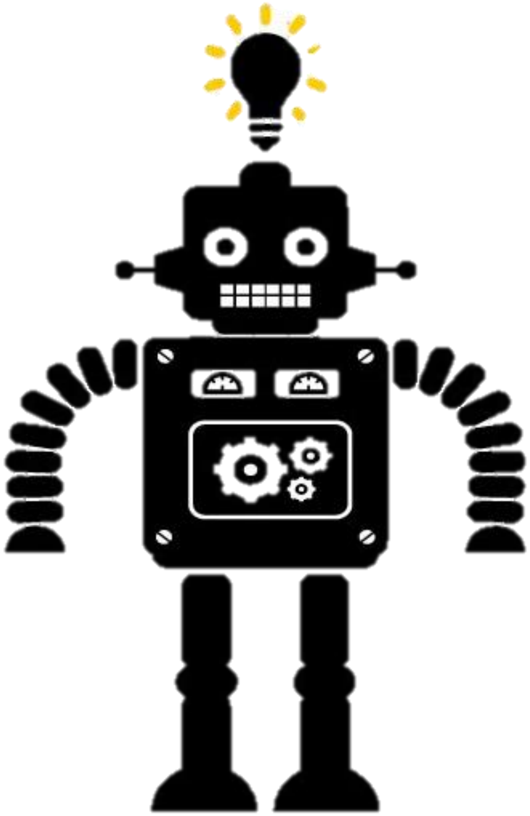
# Legal Notices and Disclaimers

# Learning Objectives

- Explain supervised learning and how it can be applied to regression and classification problems
- Apply K-Nearest Neighbor (KNN) algorithm for classification
- Apply Intel® Extension for Scikit-learn* to leverage underlying compute capabilities of hardware

# What is Machine Learning?

Machine learning allows computers to learn and infer from data.



# Machine Learning in Our Daily Lives

Spam Filtering

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Spam Filtering

Web Search

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Spam Filtering

Web Search

Postal Mail Routing

# Machine Learning in Our Daily Lives

| | | |
|---|---|---|
| Spam Filtering | Web Search | Postal Mail Routing |
| Fraud Detection | Movie Recommendations | Vehicle Driver Assistance |
| Web Advertisements | Social Networks | Speech Recognition |

# Types of Machine Learning

Supervised

data points have known outcome

# Types of Machine Learning

| | |
|---|---|
| Supervised | data points have known outcome |
| Unsupervised | data points have unknown outcome |

# Types of Machine Learning

**Supervised** data points have known outcome

**Unsupervised** data points have unknown outcome

# Types of Supervised Learning

| | |
|---|---|
| Regression | outcome is continuous (numerical) |

# Types of Supervised Learning

**Regression** — outcome is continuous (numerical)

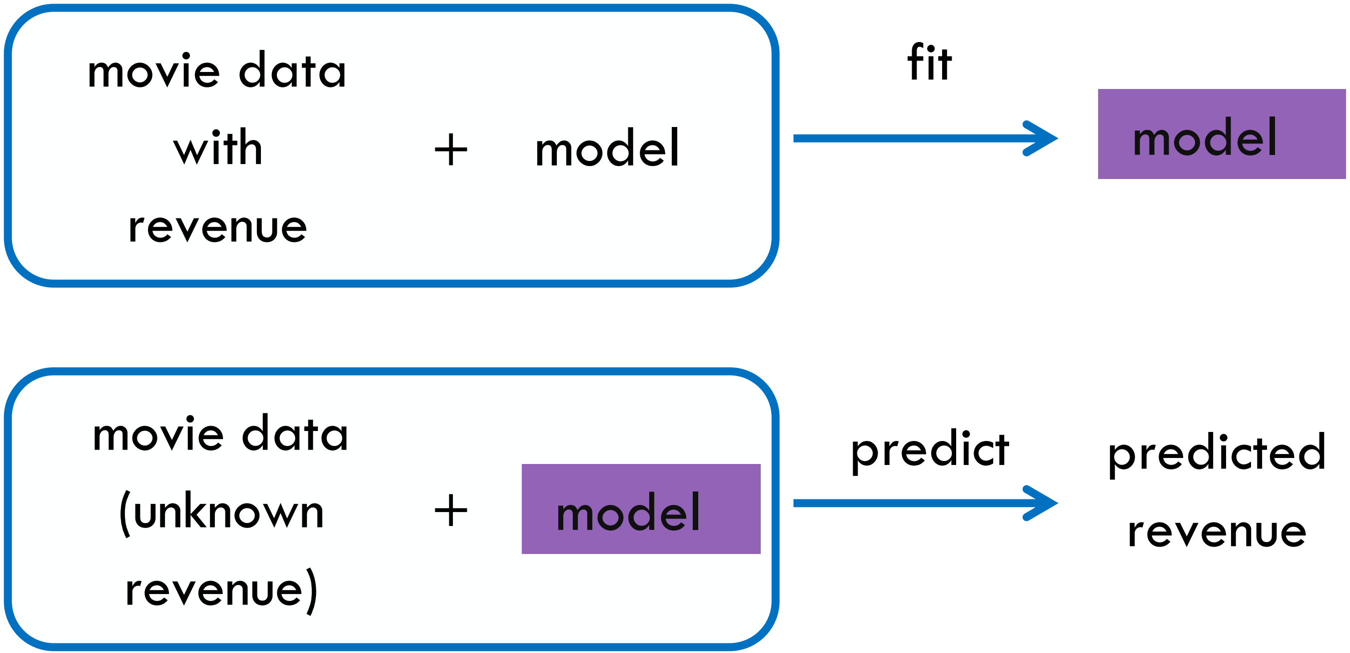
**Classification** — outcome is a category

# Supervised Learning Overview

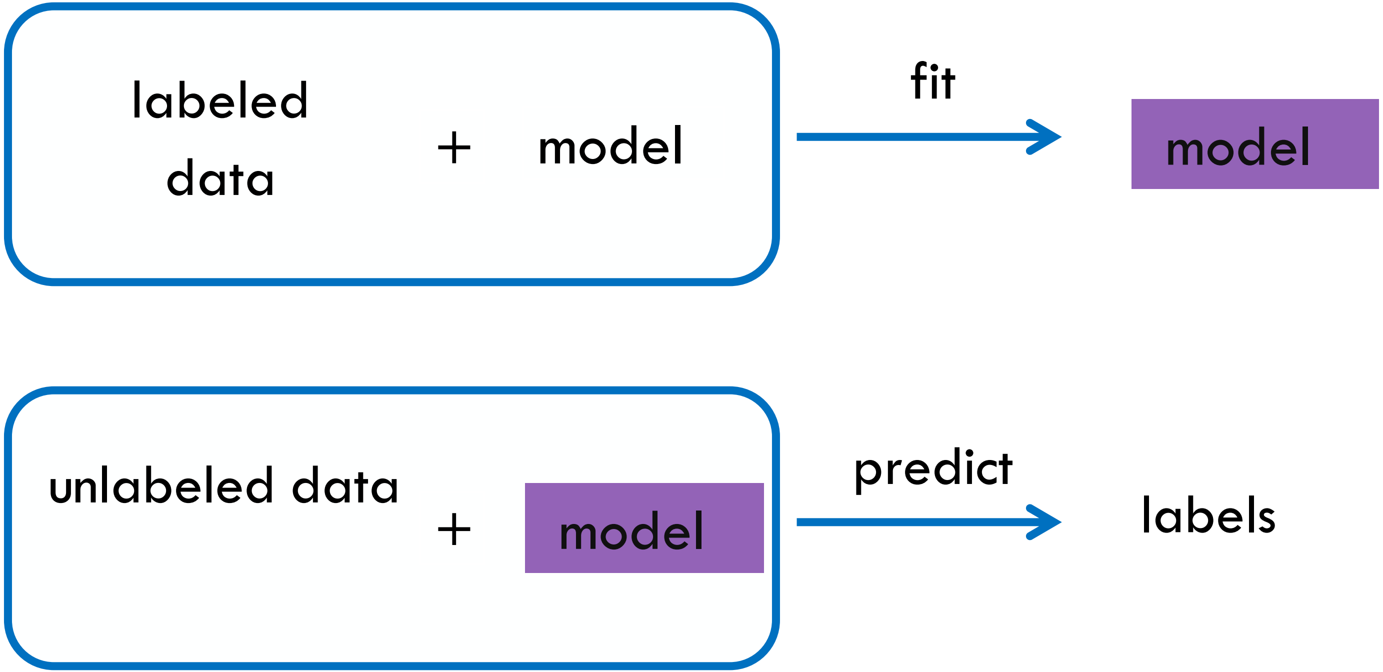
data with answers + model $\xrightarrow{\text{fit}}$ **model**

data without answers + **model** $\xrightarrow{\text{predict}}$ predicted answers

# Regression: Numeric Answers



# Classification: Categorical Answers



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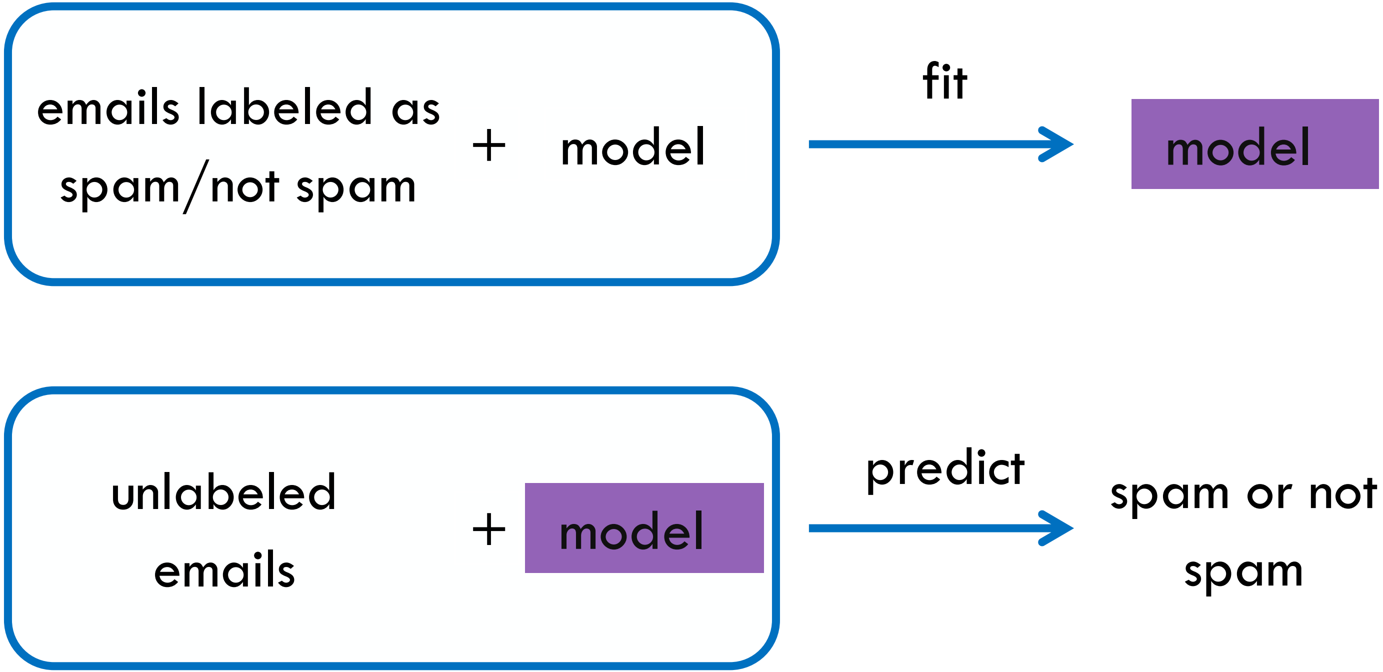

# Machine Learning Vocabulary

- **Target:** predicted category or value of the data (column to predict)

# Machine Learning Vocabulary

| sepal length | sepal width | petal length | petal width | species |
|---|---|---|---|---|
| 6.7 | 3.0 | 5.2 | 2.3 | virginica |
| 6.4 | 2.8 | 5.6 | 2.1 | virginica |
| 4.6 | 3.4 | 1.4 | 0.3 | setosa |
| 6.9 | 3.1 | 4.9 | 1.5 | versicolor |
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# Machine Learning Vocabulary

- **Target:** predicted category or value of the data (column to predict)
- **Features:** properties of the data used for prediction (non-target columns)

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# Machine Learning Vocabulary

- **Target:** predicted category or value of the data (column to predict)
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- **Example:** a single data point within the data (one row)

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# Machine Learning Vocabulary

- **Target:** predicted category or value of the data (column to predict)
- **Features**: properties of the data used for prediction (non-target columns)
- **Example:** a single data point within the data (one row)
- **Label:** the target value for a single data point

# Machine Learning Vocabulary

Label

| sepal length | sepal width | petal length | petal width | species |
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Software

# K – Nearest Neighbors

# What is Classification?

A flower shop wants to guess a customer's purchase from similarity to most recent purchase.

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Which flower is a customer most likely to purchase based on similarity to previous purchase?

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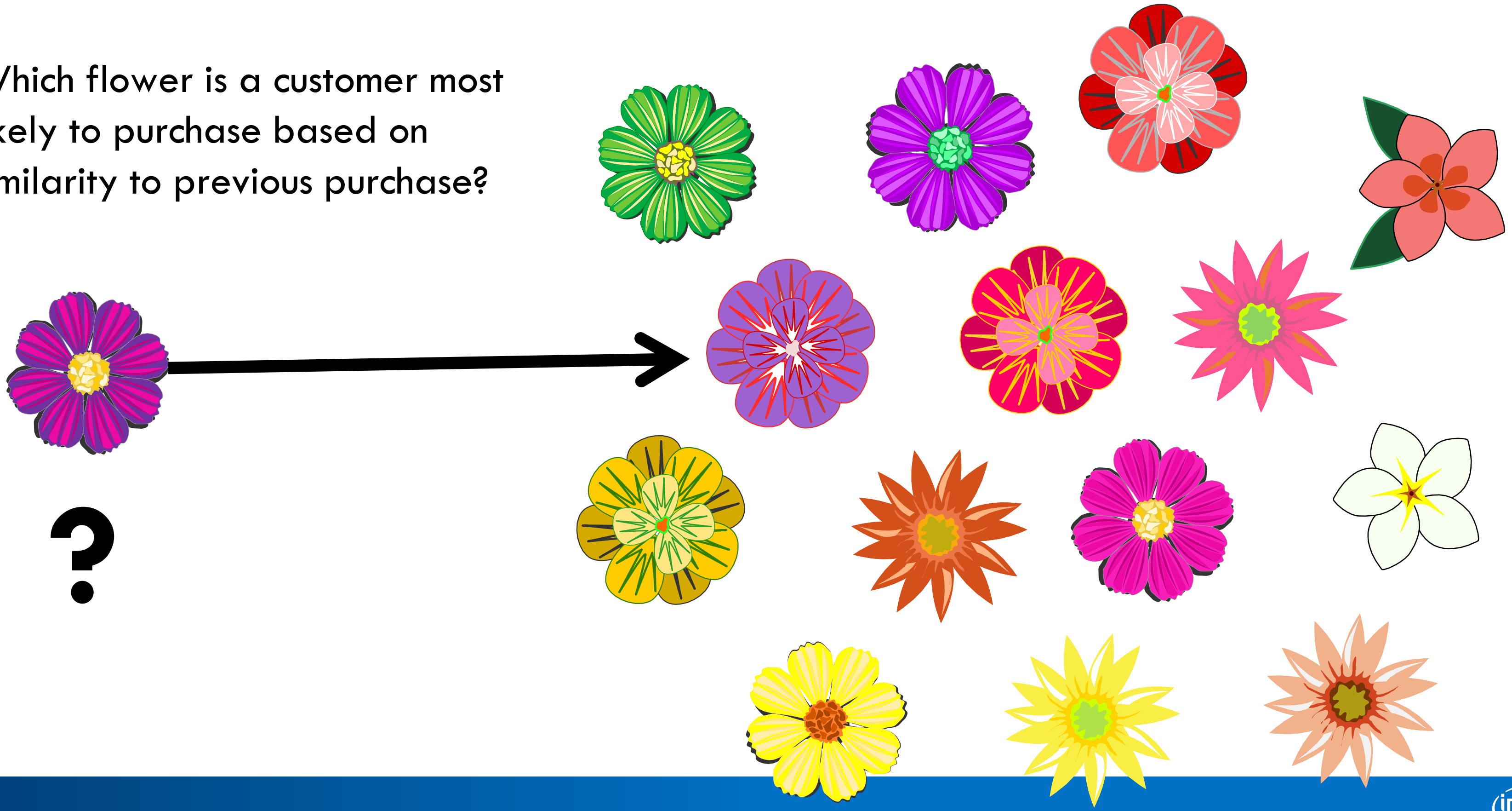

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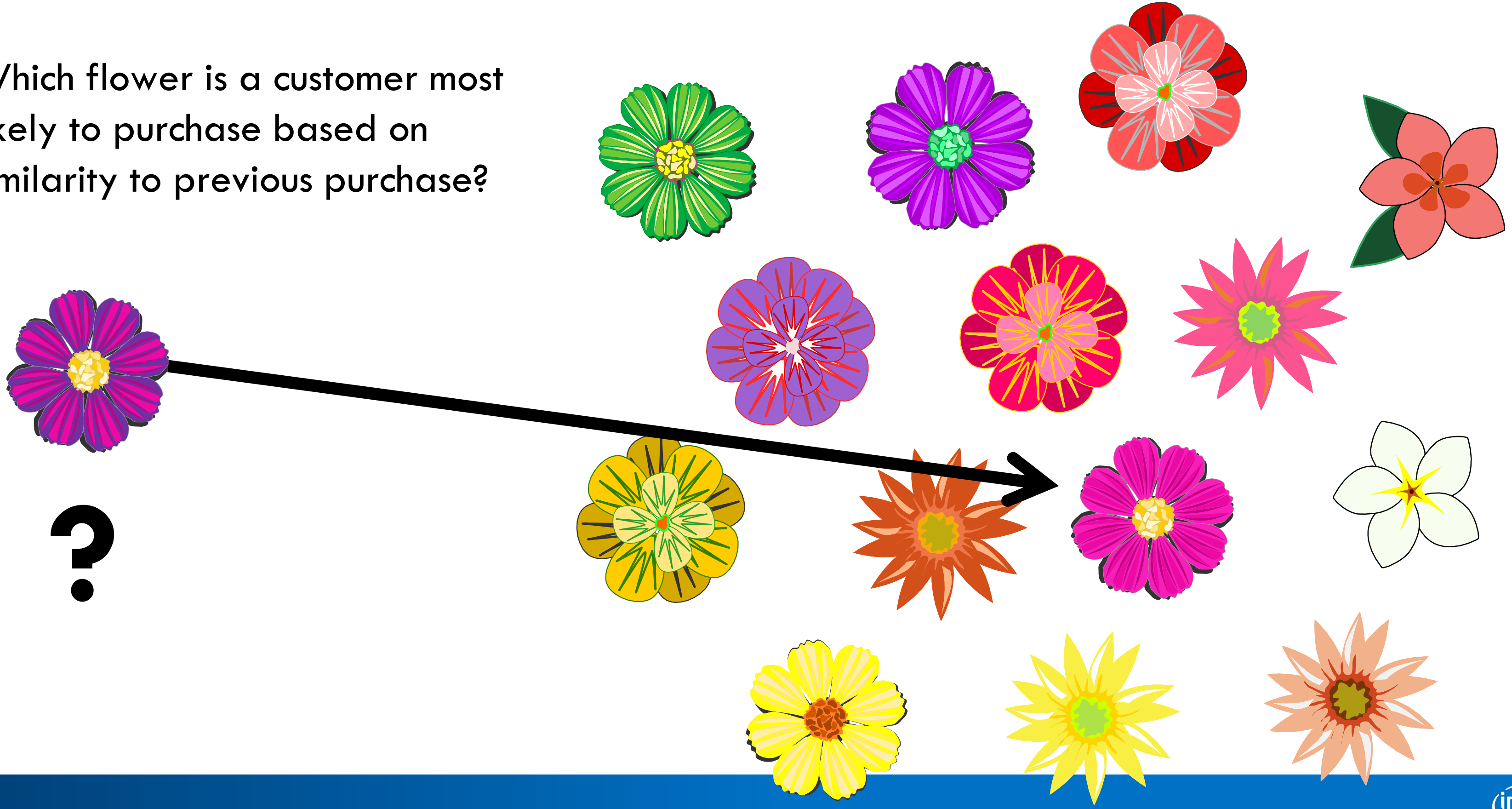

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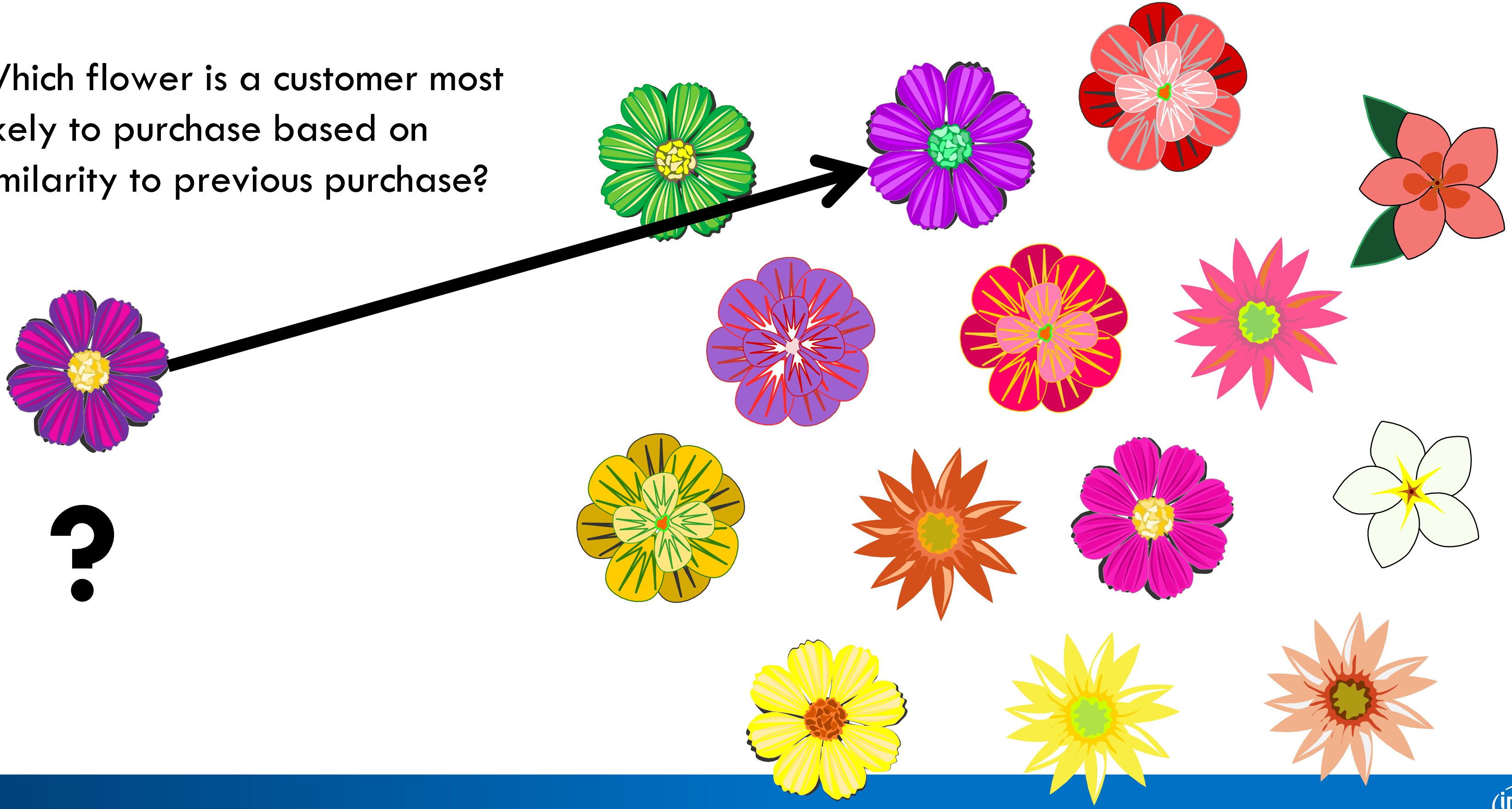

# What is Needed for Classification?

- Model data with:
  - Features that can be quantitated

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- Model data with:
  - Features that can be quantitated
  - Labels that are known
- Method to measure similarity

# K Nearest Neighbors Classification

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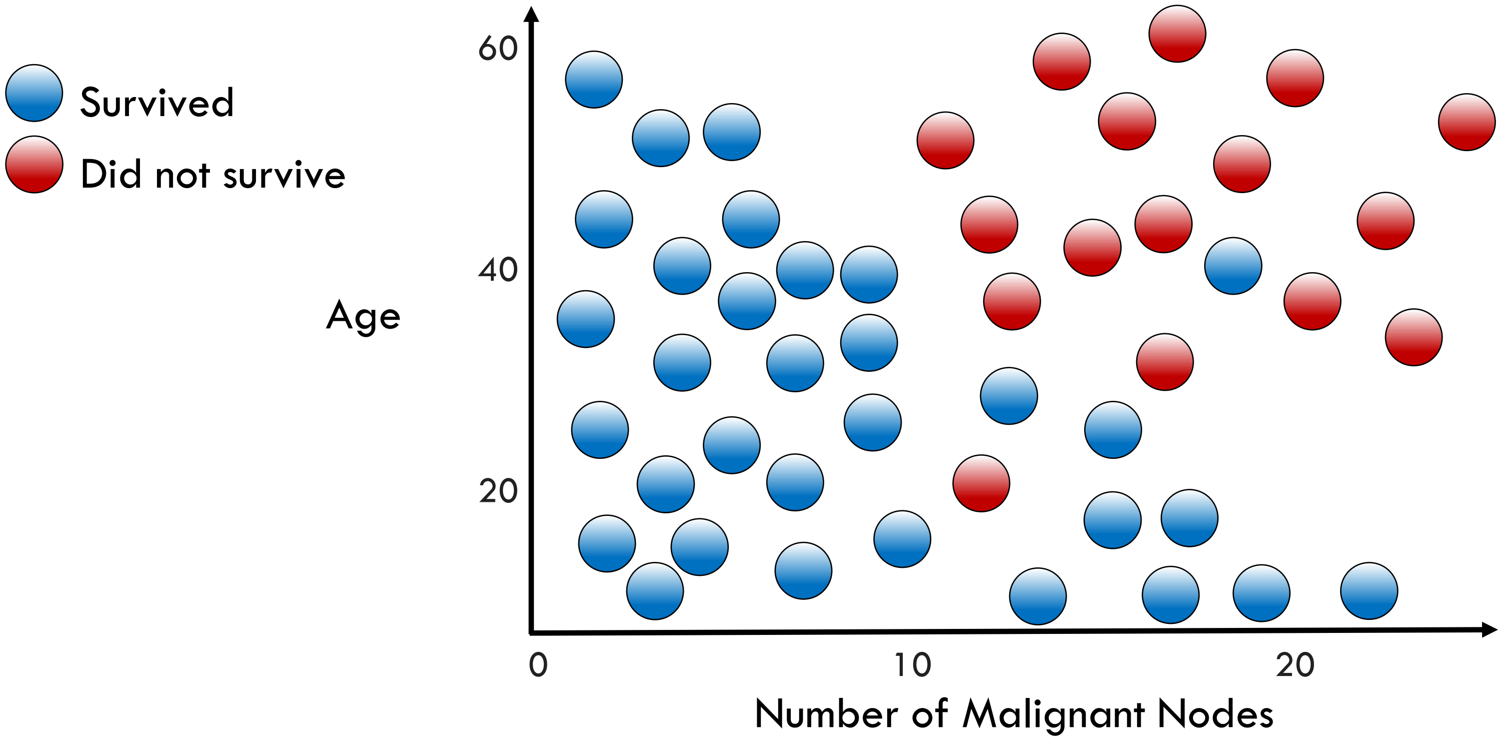

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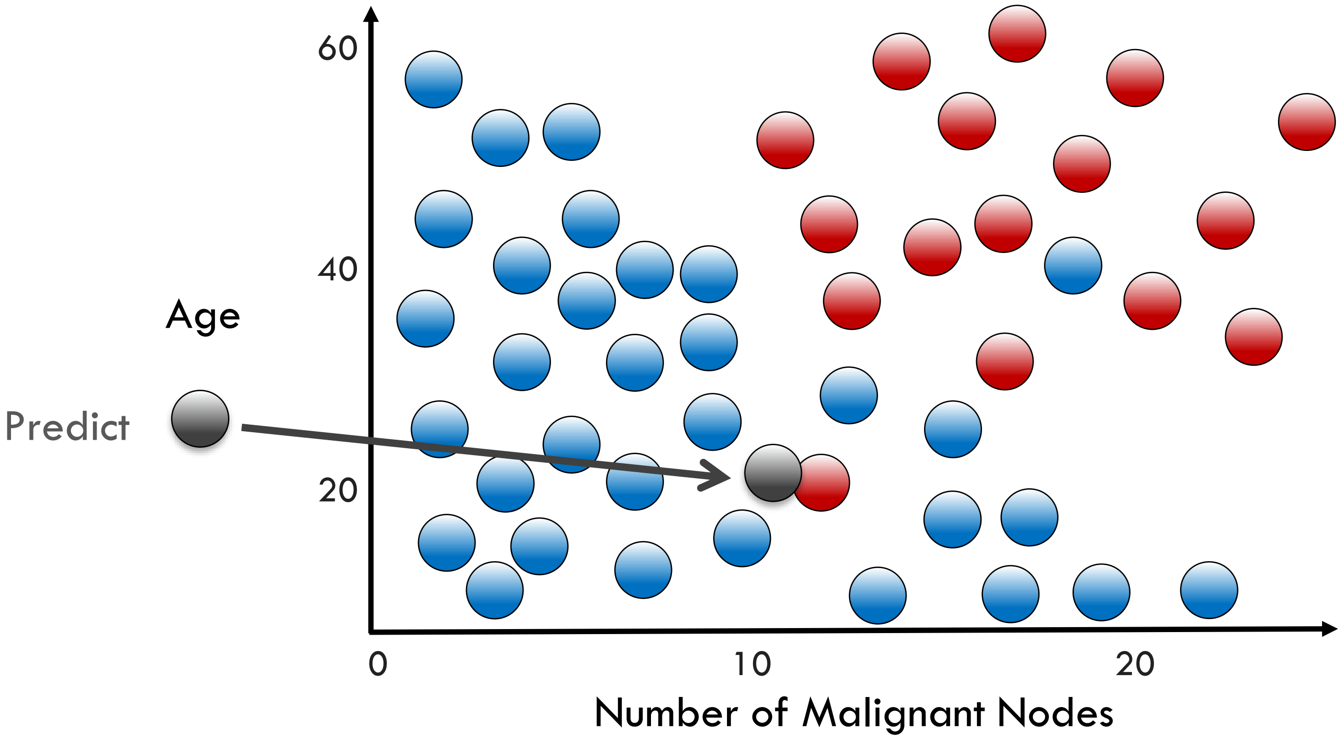

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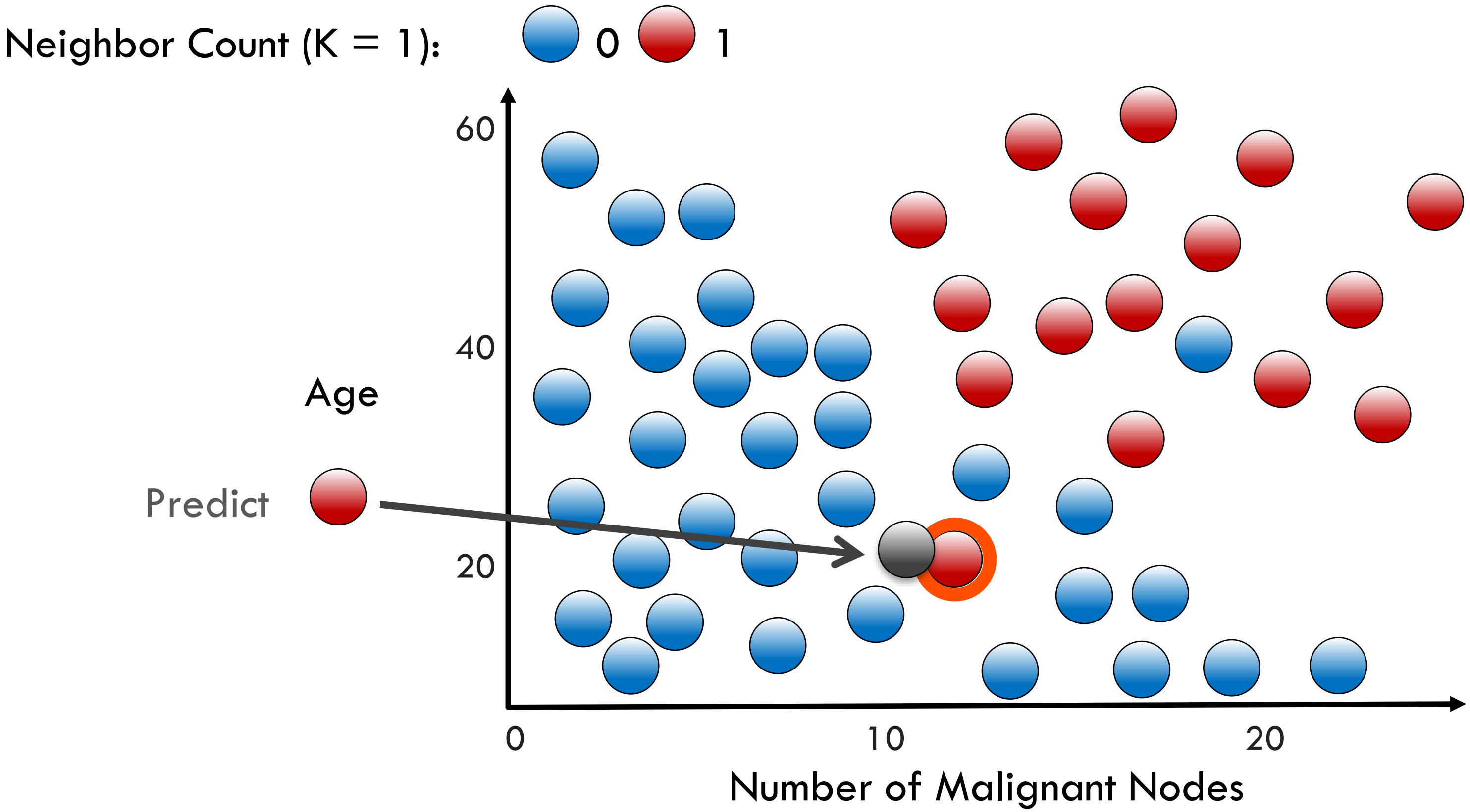

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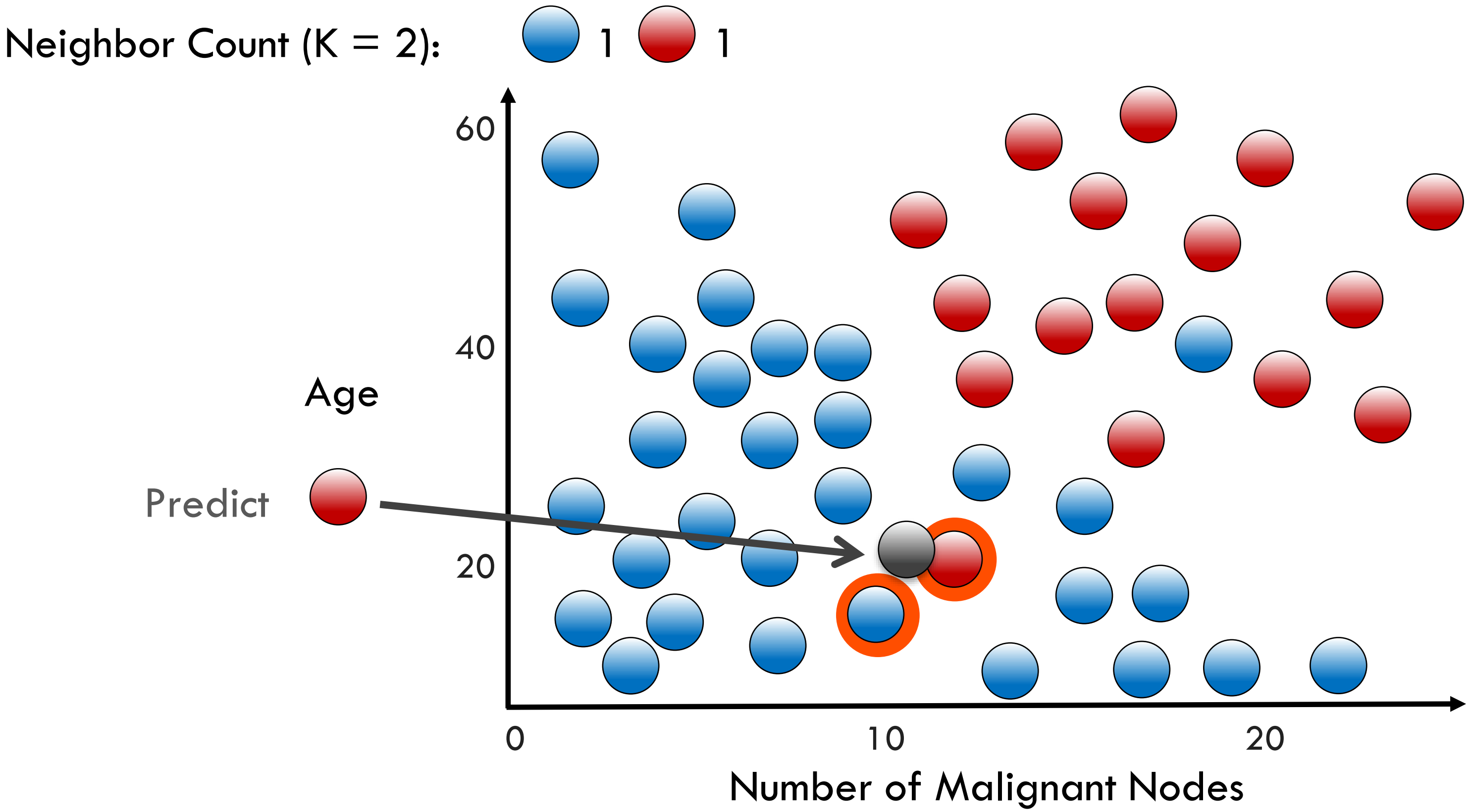
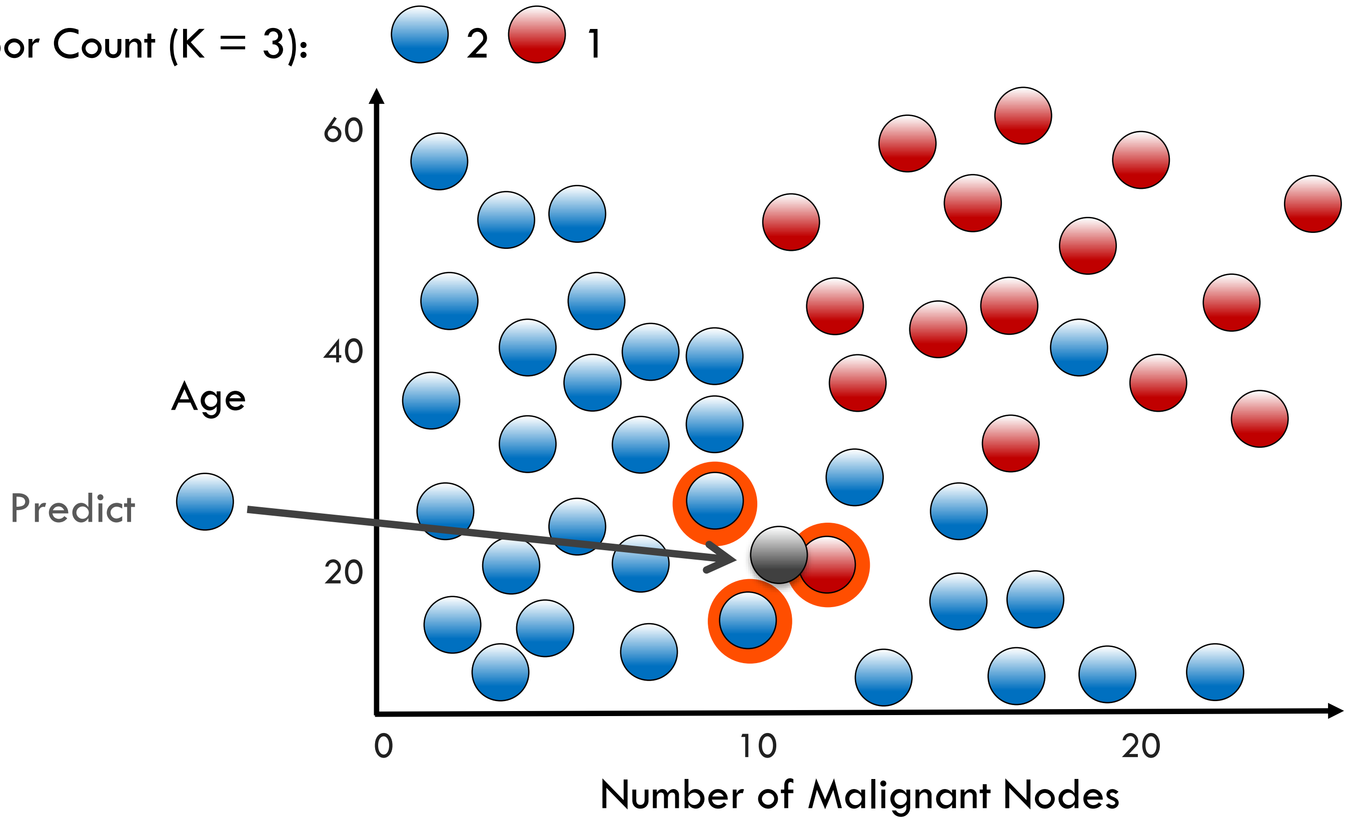


# K Nearest Neighbors Classification

Neighbor Count (K = 3):



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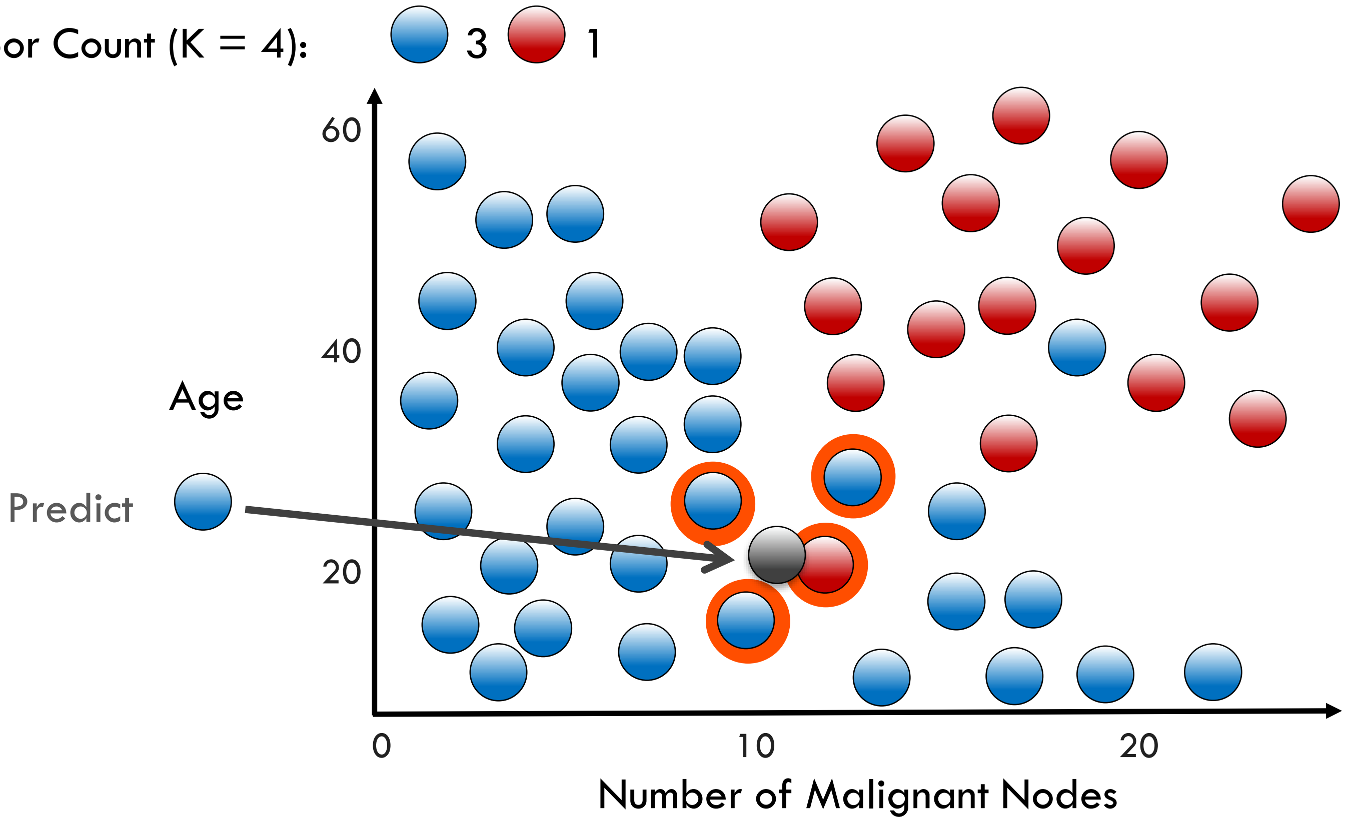

# What is Needed to Select a KNN Model?

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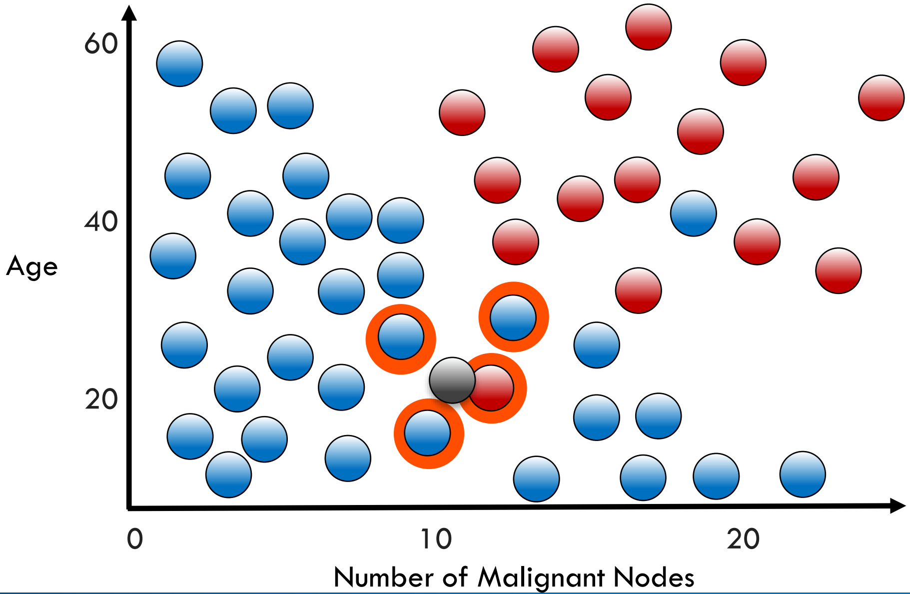
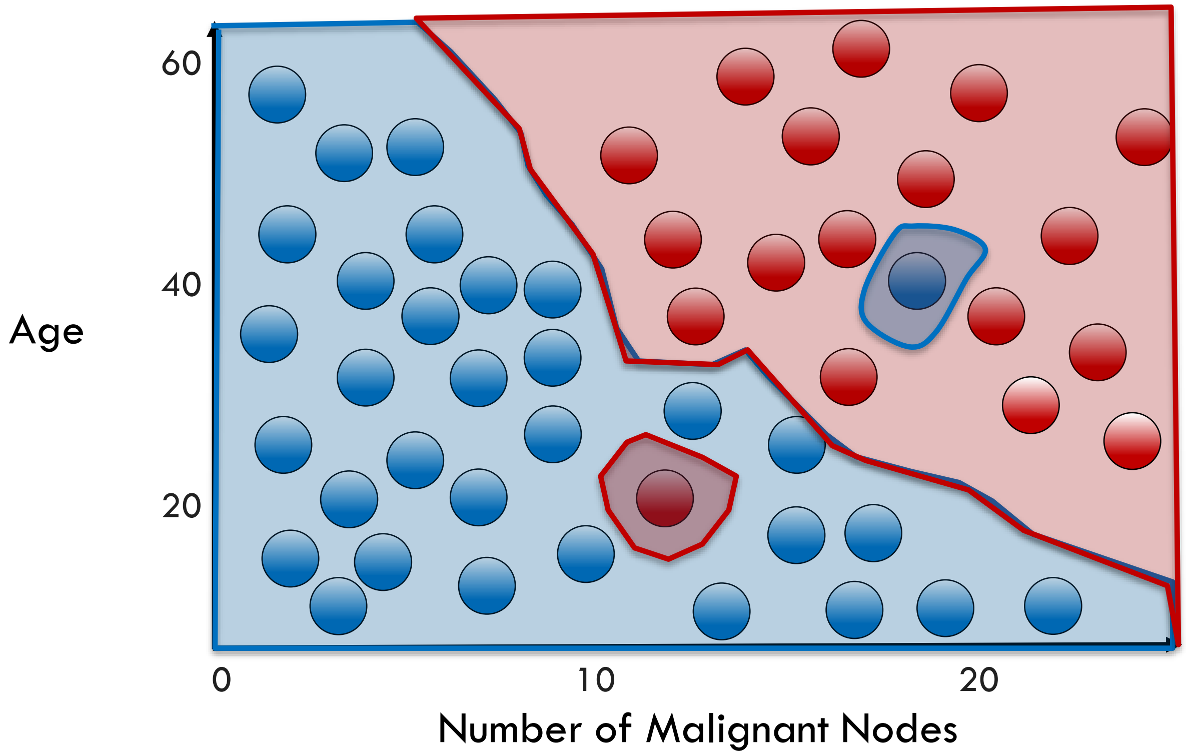
- Correct value for 'K'
- How to measure closeness of neighbors?



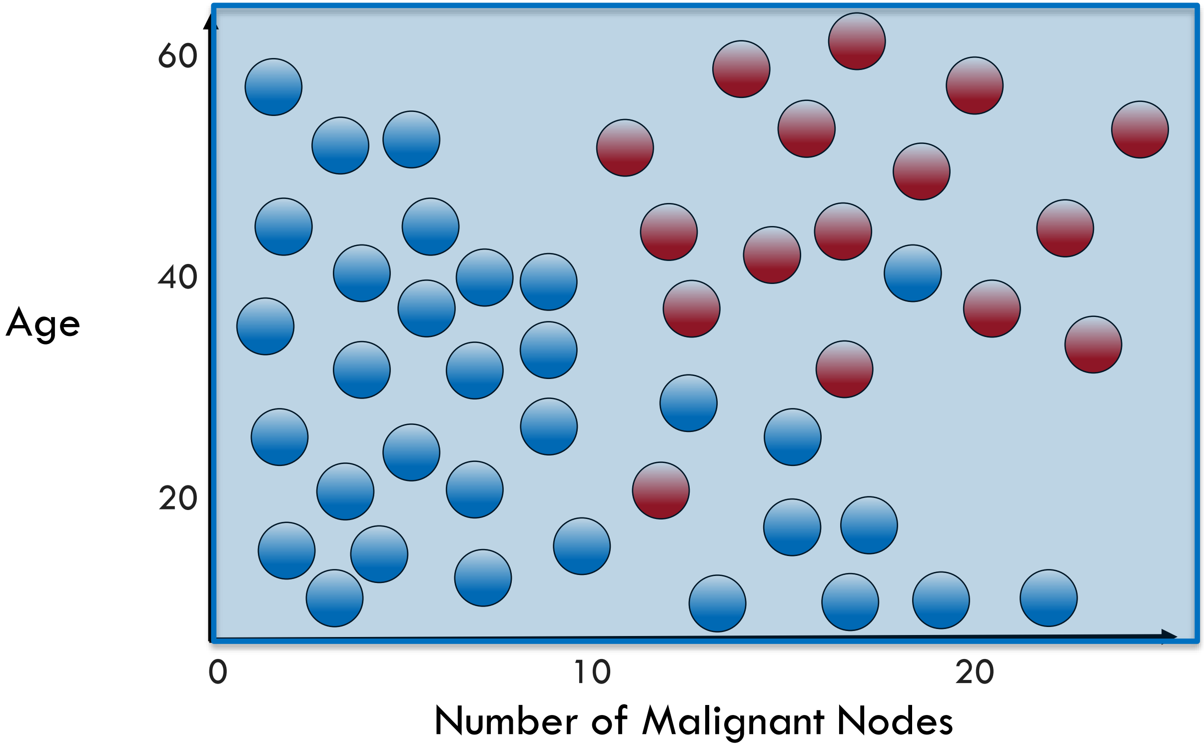
# K Nearest Neighbors Decision Boundary

K = 1

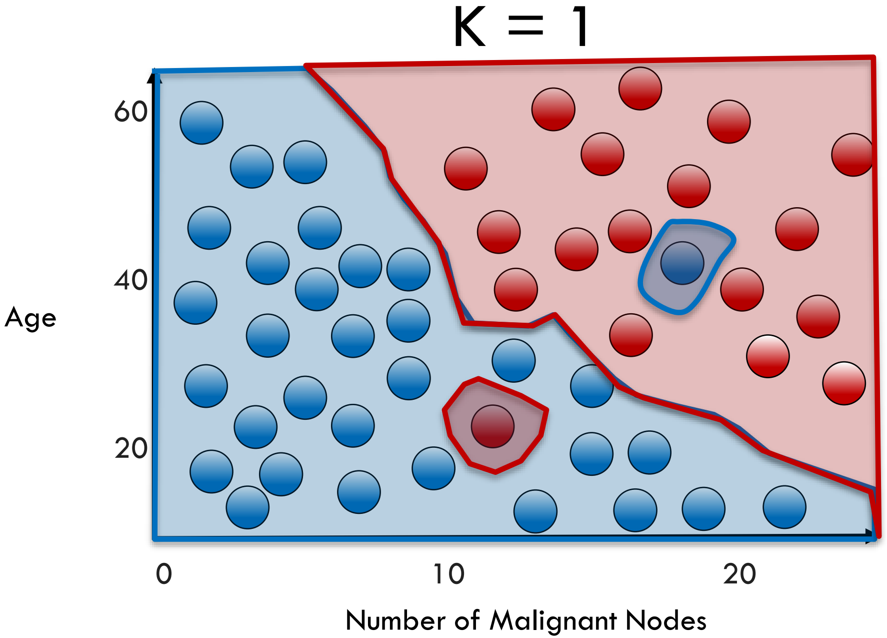


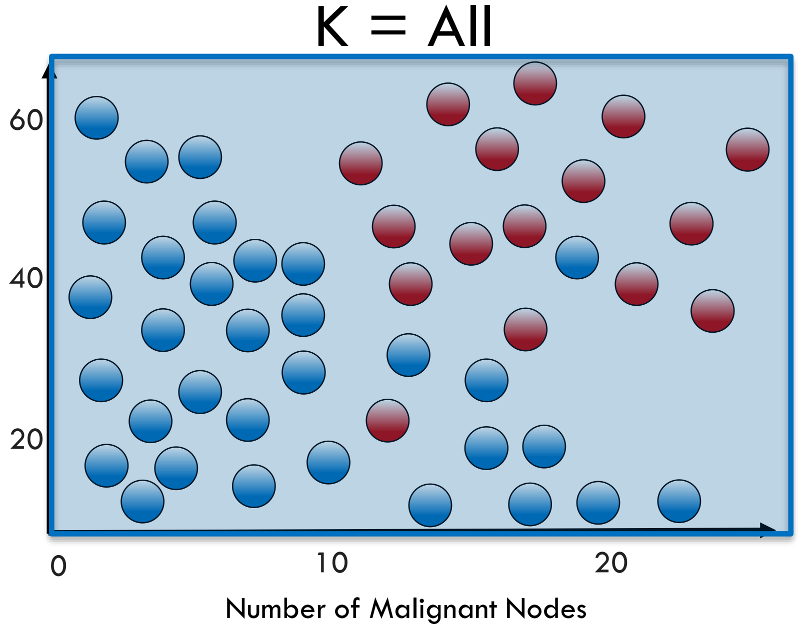
# K Nearest Neighbors Decision Boundary

K = All



# Value of 'K' Affects Decision Boundary



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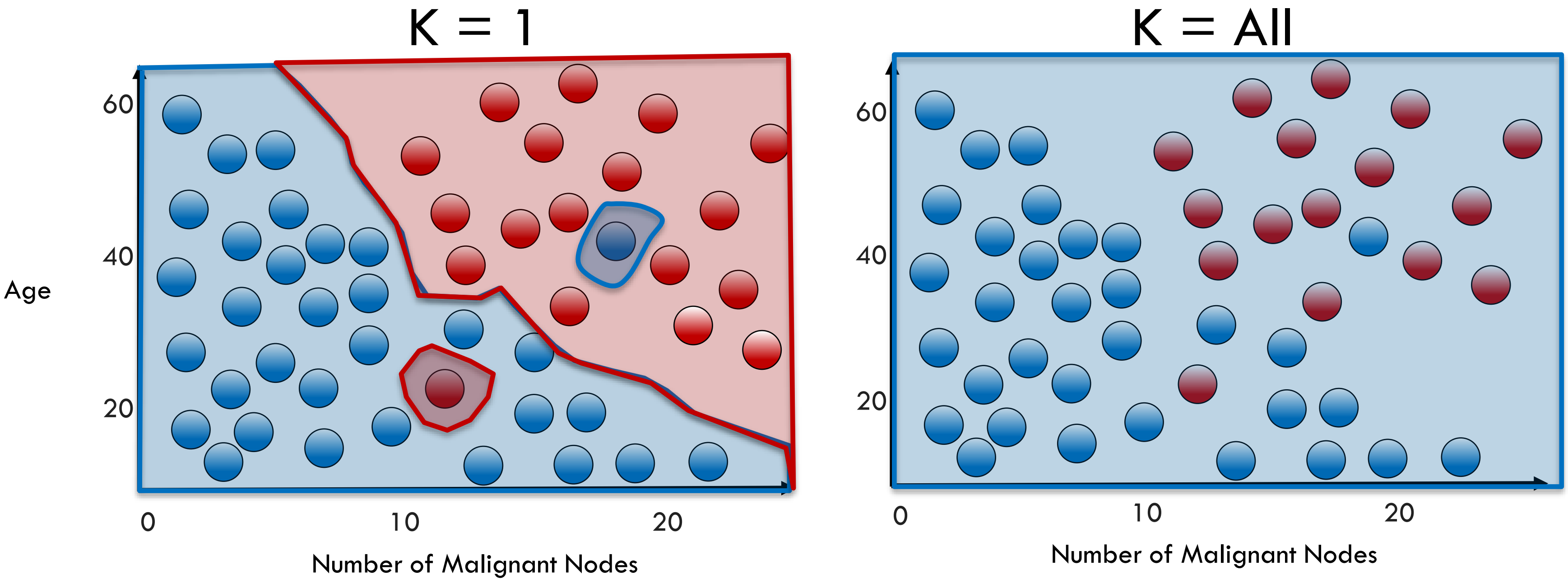
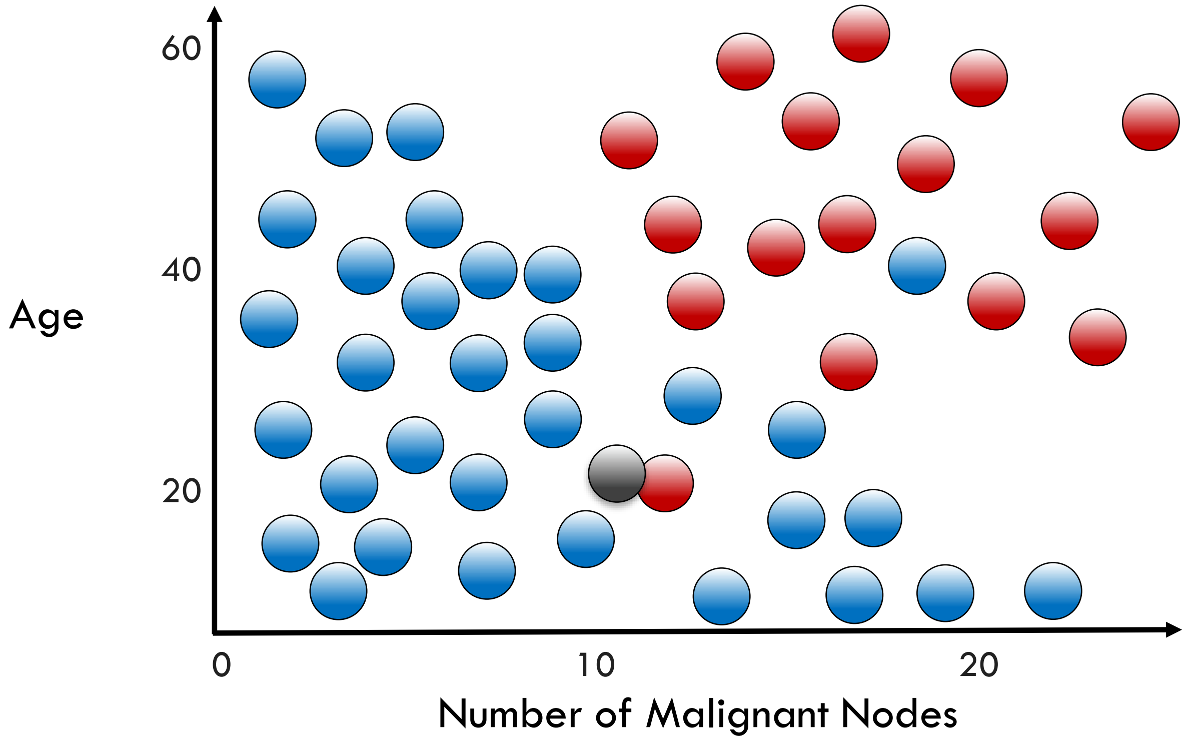



Methods for determining 'K' will be discussed in next lesson

# Measurement of Distance in KNN



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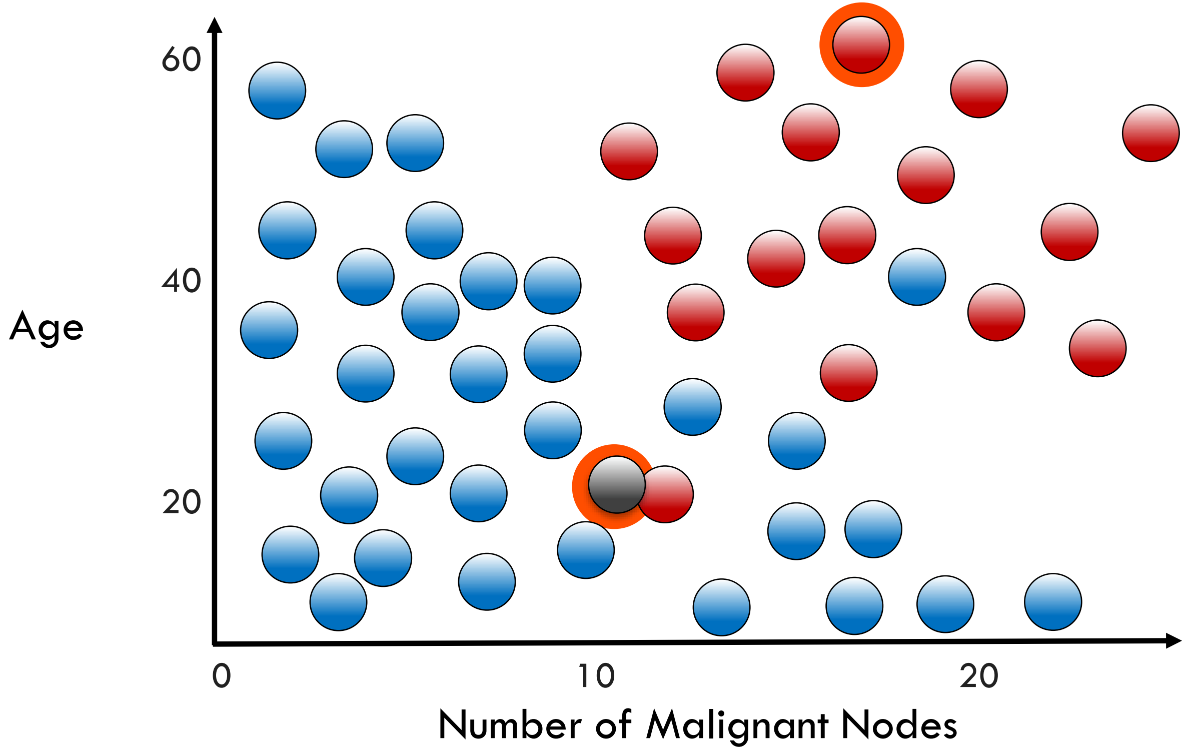
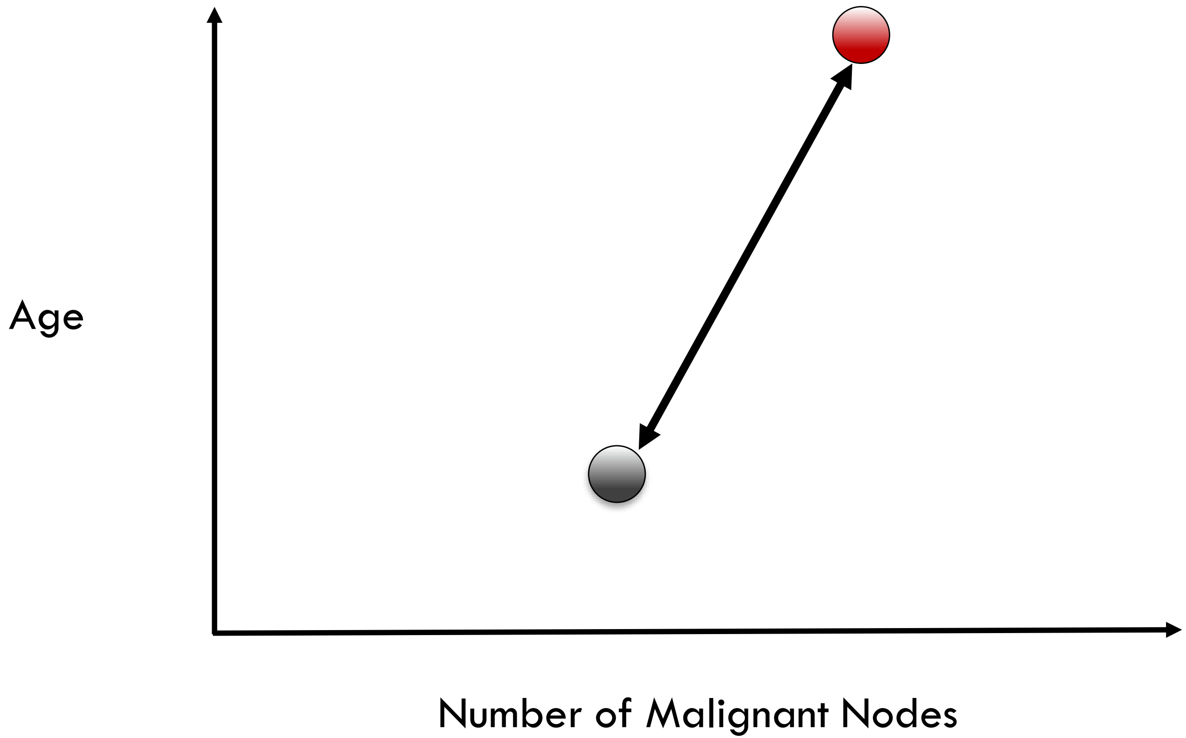
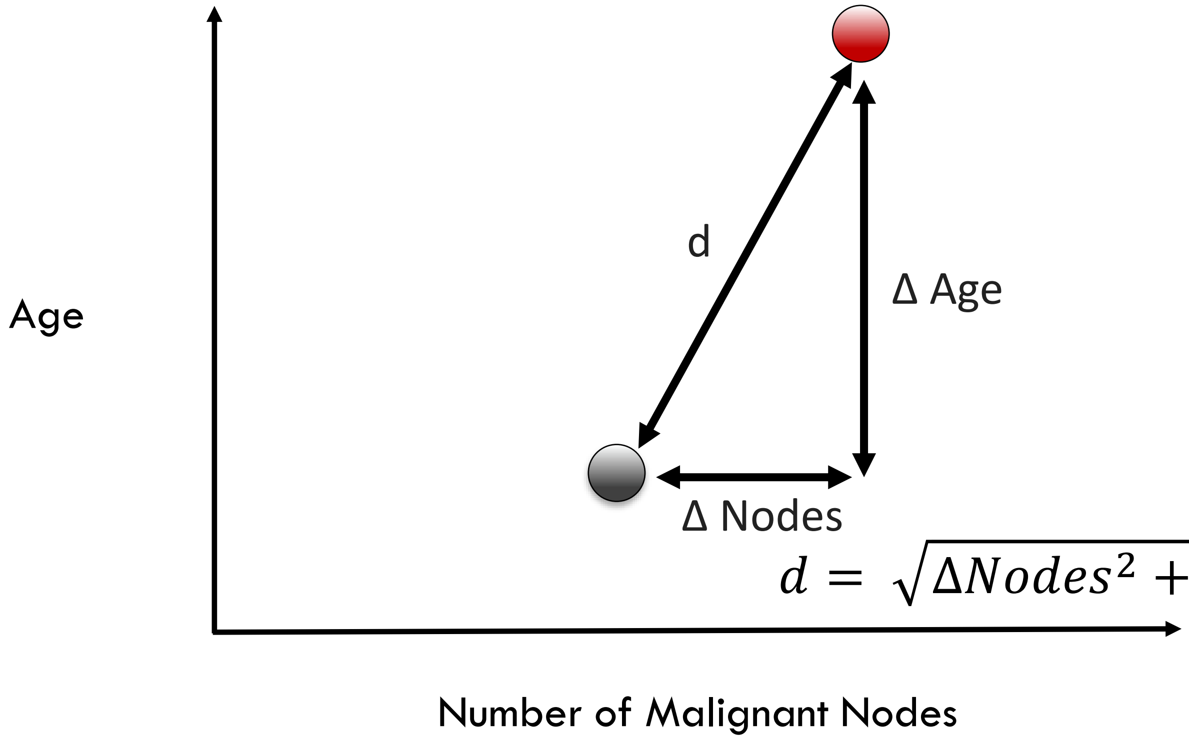


# Euclidean Distance

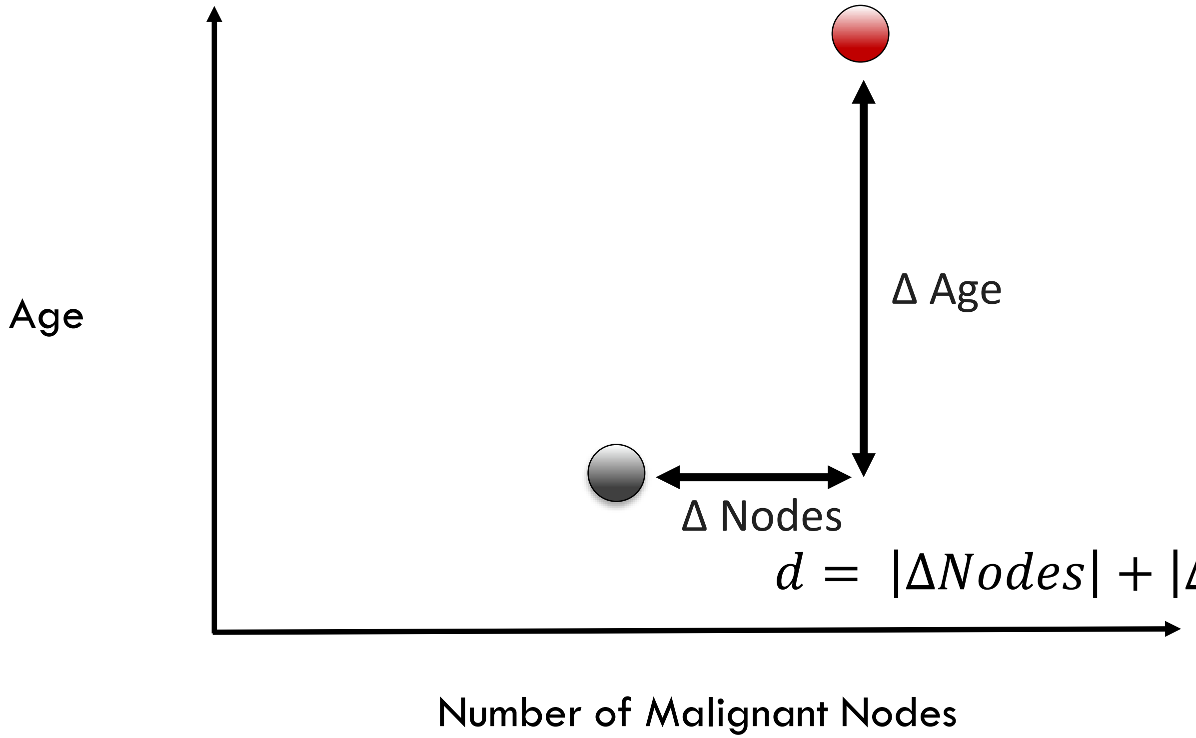


# Euclidean Distance (L2 Distance)



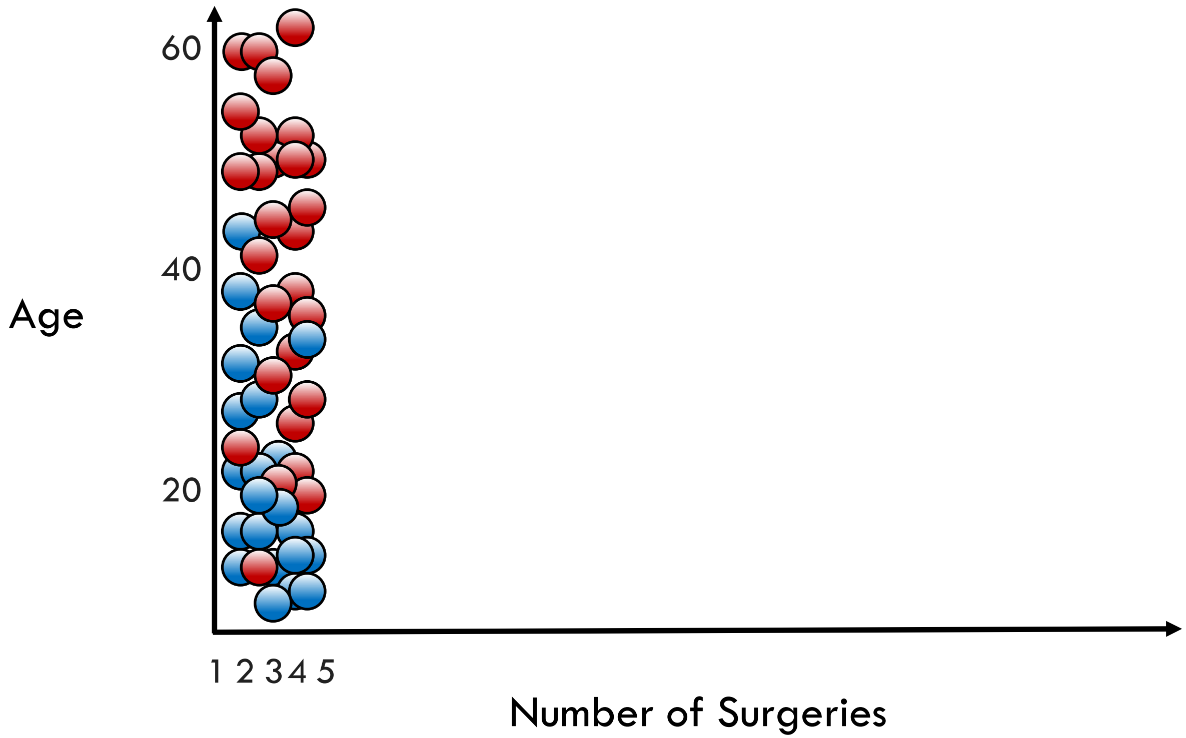

$$d = \sqrt{\Delta Nodes^2 + \Delta Age^2}$$

# Manhattan Distance (L1 or City Block Distance)




$$d = |\Delta Nodes| + |\Delta Age|$$

# Scale is Important for Distance Measurement



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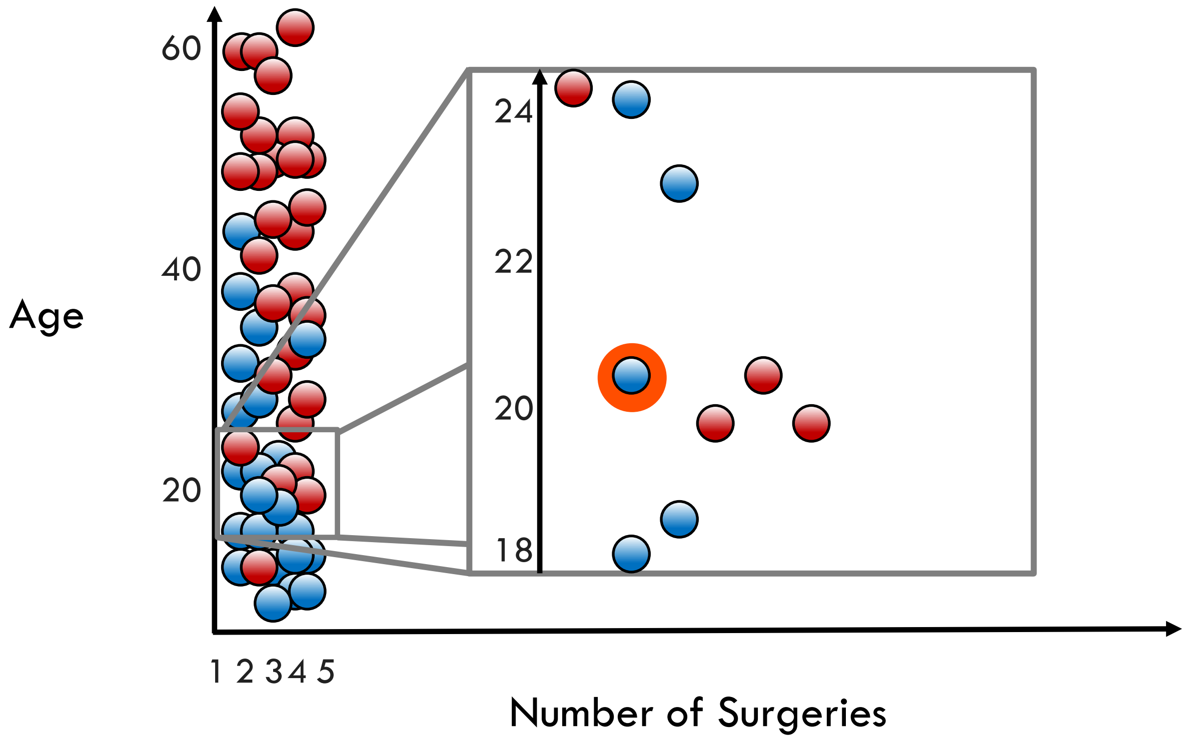

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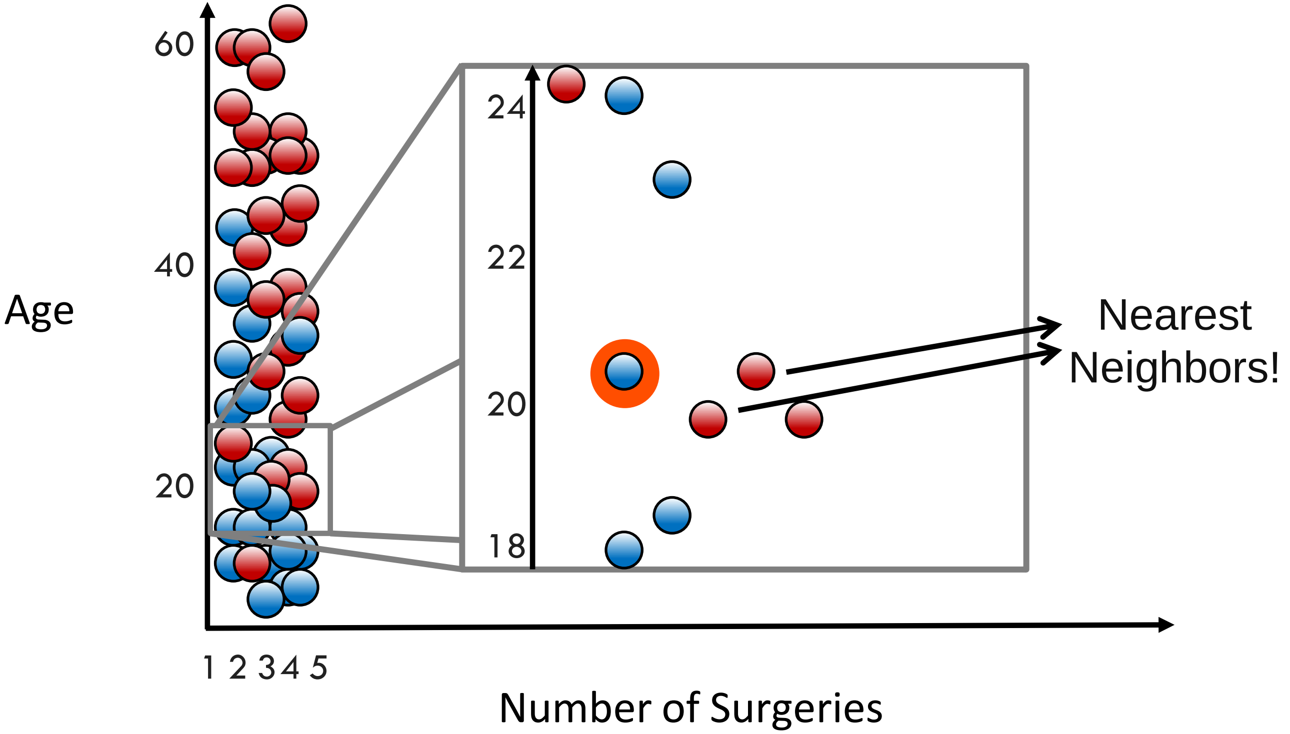
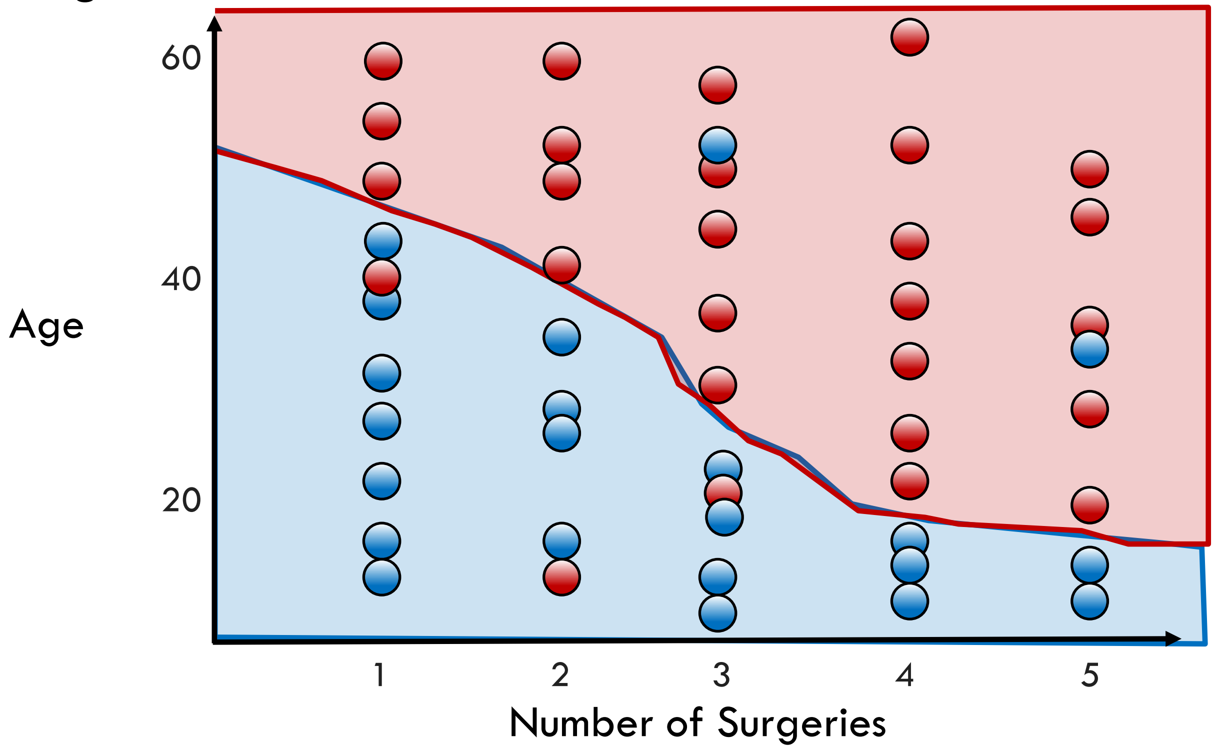


# Scale is Important for Distance Measurement

"Feature Scaling"



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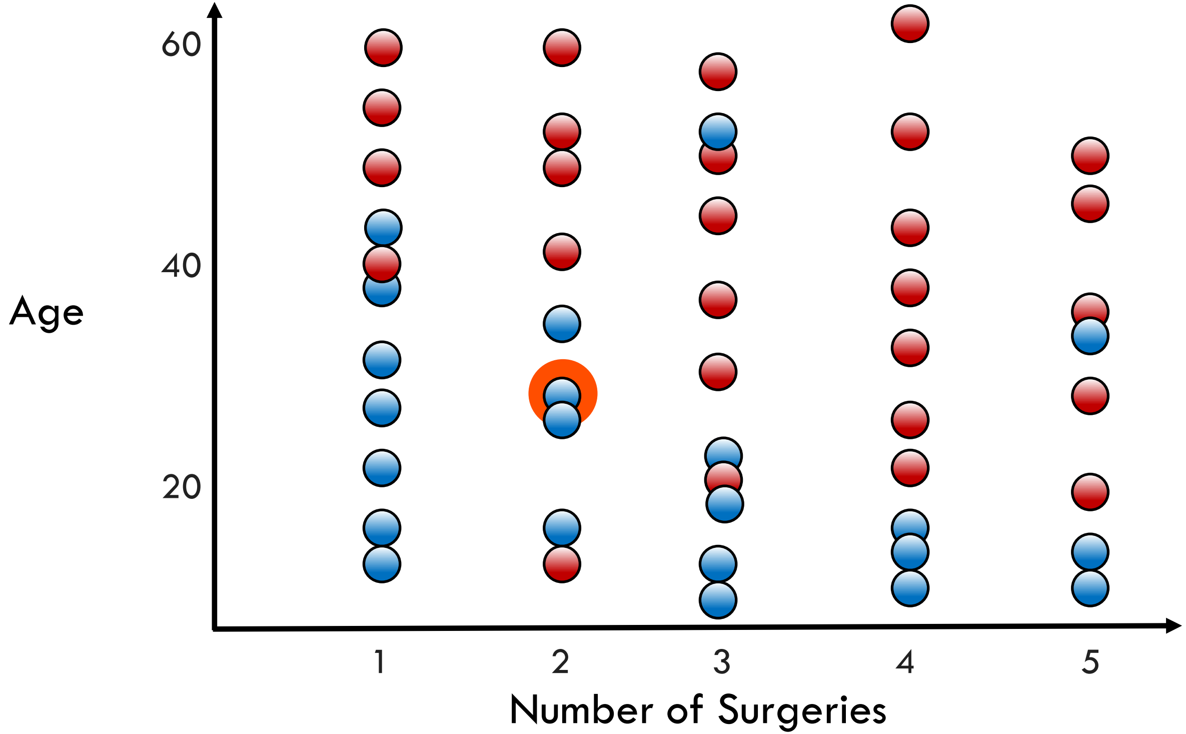

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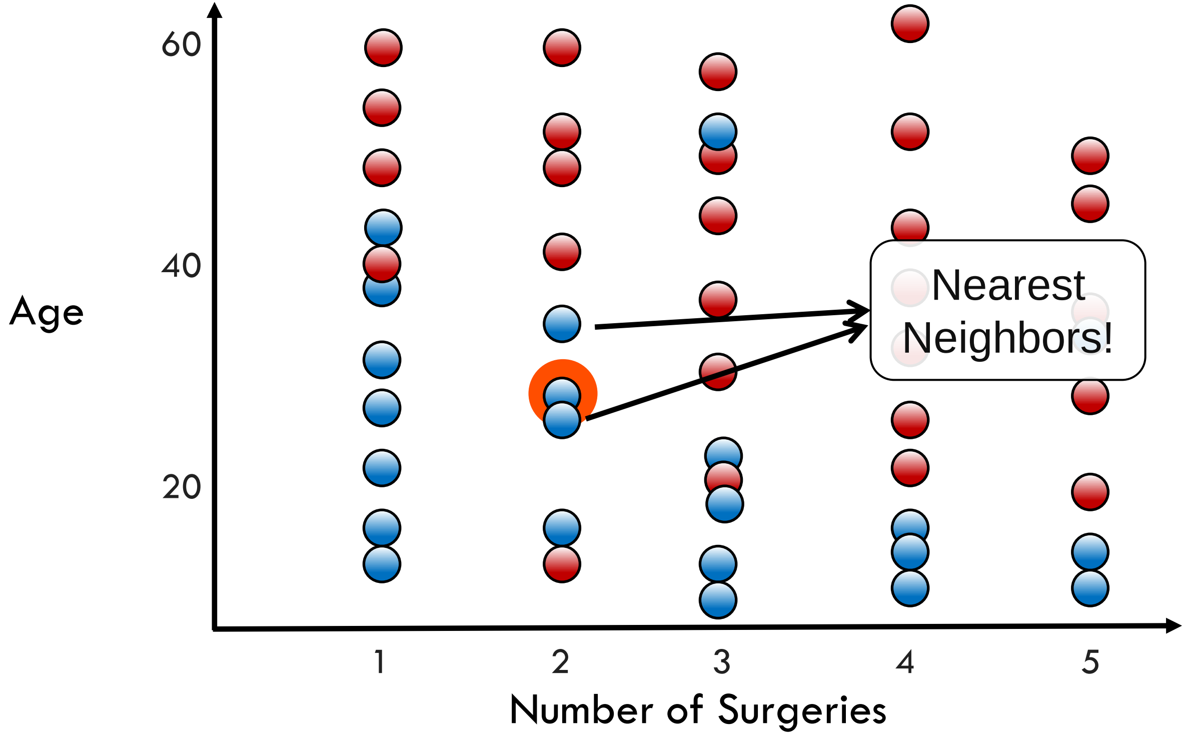

# Comparison of Feature Scaling Methods

- **Standard Scaler:** mean center data and scale to unit variance
- **Minimum-Maximum Scaler:** scale data to fixed range (usually 0–1)
- **Maximum Absolute Value Scaler:** scale maximum absolute value

# Feature Scaling: The Syntax

**Import the class containing the scaling method**

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StdSc = StdSc.fit(X_data)

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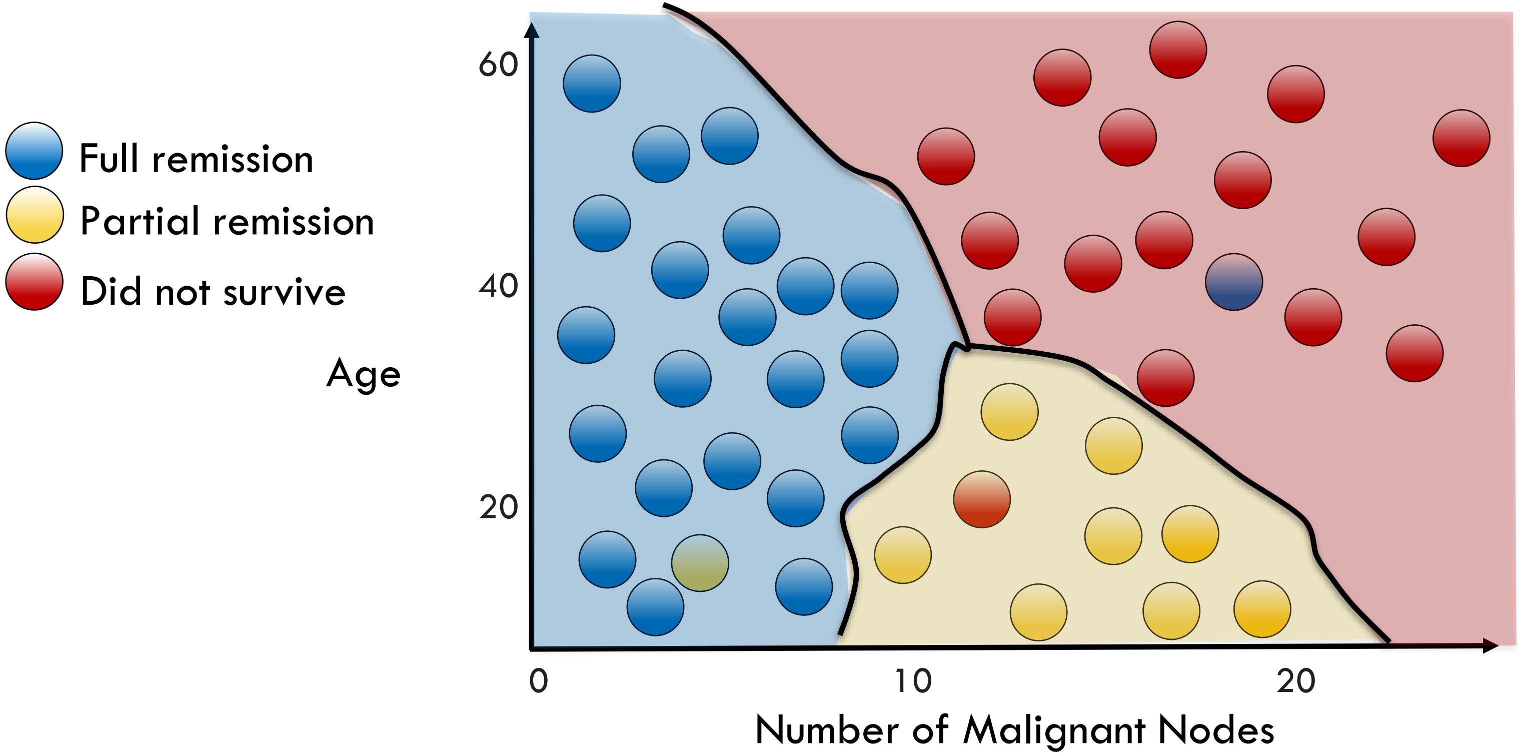
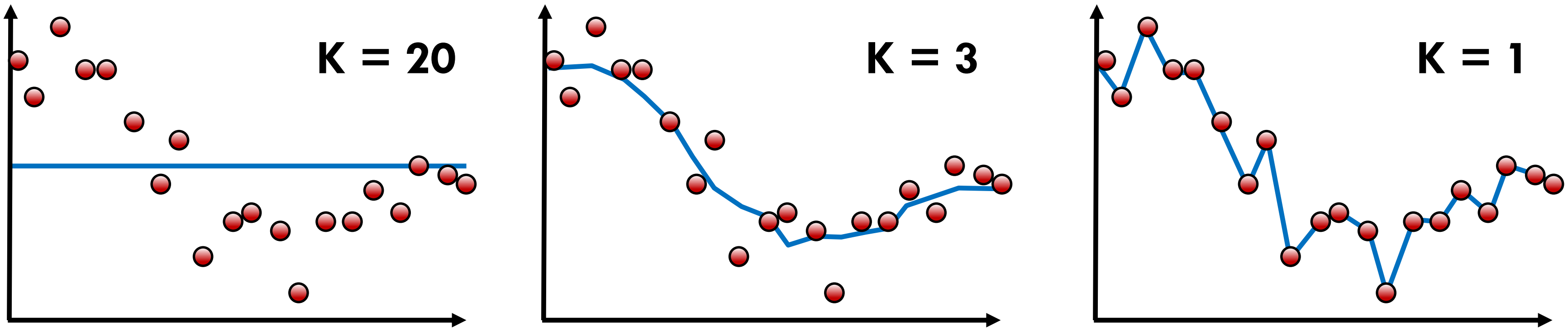
**Other scaling methods exist: MinMaxScaler, MaxAbsScaler.**

# Multiclass KNN Decision Boundary

K = 5



# Regression with KNN



# Characteristics of a KNN Model

- Fast to create model because it simply stores data

- Slow to predict because many distance calculations

- Can require lots of memory if data set is large

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**To use the Intel® Extension for Scikit-learn* variant of this algorithm:**

- **Install Intel® oneAPI AI Analytics Toolkit (AI Kit)**

**Add the following two lines of code after the above code:**

```
import patch_sklearn
patch_sklearn()
```

# K Nearest Neighbors: The Syntax

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**Create an instance of the class**

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KNN = KNeighborsClassifier(n_neighbors=3)
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```
KNN = KNN.fit(X_data, y_data)

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**The fit and predict/transform syntax will show up throughout the course.**

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**Regression can be done with KNeighborsRegressor.**

Software