# Predictive Analytics, Classification, and Decision Trees

Data Science Dojo

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# Session Outline

- Introduction to predictive analytics
- Introduction to classification
- Decision Tree Classifier
- Hands-on Lab: Building a decision tree classifier using R

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# Family and Personal Life

- Location
  - Microsoft and Nokia predict future location based on cellular phone and location data
- Friendship and connection
  - Facebook and LinkedIn predict your personal connections
- Love
  - Every dating site tries to predict potential matches
  - OkCupid tracks which message content is most likely to elicit a response
- Life Events
  - Target predicts customer pregnancy
- Divorce and infidelity
  - University and clinical researchers can predict this as well!

# Direct Marketing

- Cox Communication
  - Tripled direct mail responses by predicting propensity to buy
- Harrah's Las Vegas
  - Predicts how much a customer will spend over the long term
- Target
  - Increased revenue 15-30 percent with predictive models
- PREMIER Bankcard
  - Reduced mailing cost by $12 million

# Telcos, Retail, and More

- Fedex
  - Predicts defection to a competitor with 65-90% accuracy
- Telcos
  - Predict cancellation, allowing targeted retention efforts
- Amazon
  - 35% sales come from product recommendation

# Even In Law Enforcement….

# Quick Review

- Unsupervised learning
  - Target values unknown
  - Training data unlabeled
  - Goal: Discover information hidden in the data
  - May precede supervised learning
- Supervised learning
  - Target values known
  - Training data labeled with target values
  - Goal: Find a way to map attributes to target value
  - Classification & Regression

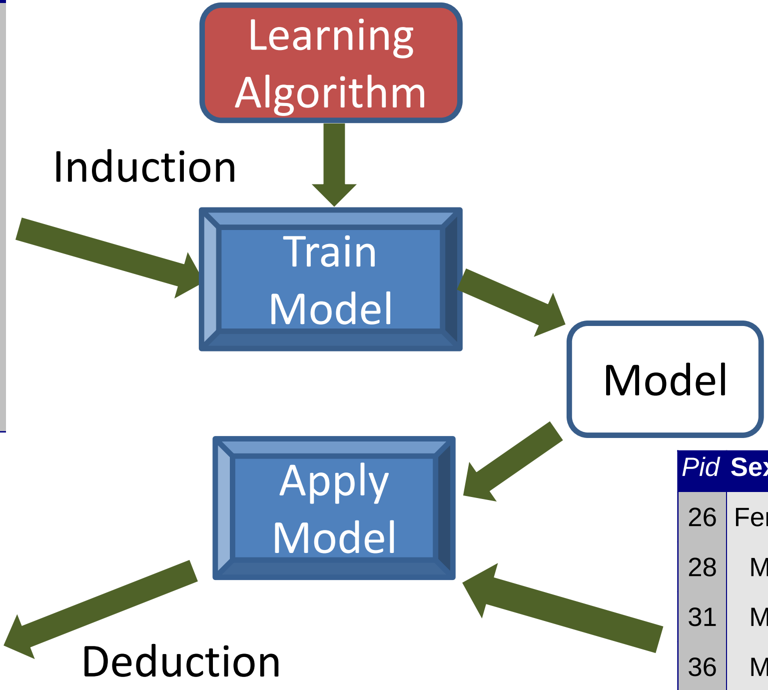
# Session Outline

- Introduction to predictive analytics
- **Introduction to classification**
- Decision Tree Classifier
- Hands-on Lab: Building a decision tree classifier using R

# Decision Tree Learning

| *Pid* | Sex | Age | Pclass | Survived |
|---|---|---|---|---|
| 2 | Female | 38 | 1 | Yes |
| 3 | Female | 26 | 3 | Yes |
| 5 | Male | 35 | 3 | No |
| 7 | Male | 54 | 1 | No |
| 13 | Male | 20 | 3 | No |
| 14 | Male | 39 | 3 | No |
| 21 | Male | 35 | 2 | No |
| 24 | Male | 28 | 1 | Yes |
| 34 | Male | 66 | 1 | No |
| 54 | Female | 29 | 2 | Yes |

Training Set




Test Set

| *Pid* | Sex | Age | Pclass | Survived |
|---|---|---|---|---|
| 26 | Female | 38 | 3 | ? |
| 28 | Male | 19 | 1 | ? |
| 31 | Male | 40 | 1 | ? |
| 36 | Male | 42 | 1 | ? |
| 71 | Male | 32 | 2 | ? |

| *Pid* | Survived |
|---|---|
| 26 | Yes |
| 28 | Yes |
| 31 | No |
| 36 | No |
| 71 | No |

# The Classification Task

- Given a collection of records (training set)
  - Two attribute types: **predictors** and **class**
  - Find a model to map predictor set to class
  - Class is
    - Categorical
    - Nominal (almost always)

# The Classification Task

- Goal: Assign new records a correct class
  - **Training set** used to create model
  - **Test set** used to check
  - Predict test set classes to assess correctness
  - Split data into training and test sets
    - 70/30, 60/40, 50/50

# Examples of Classification Tasks

- **Marketing:** Customer groups to target
- **Online:** Bot detection in web traffic
- **Medical:** Predicting tumor cells as benign or malignant
- **Finance:** Credit card fraud detection
- **Document Classification:** Categorizing news stories
- **Security/Surveillance:** Face and fingerprint recognition

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- **Decision Tree Learning**
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# Decision Tree Learning

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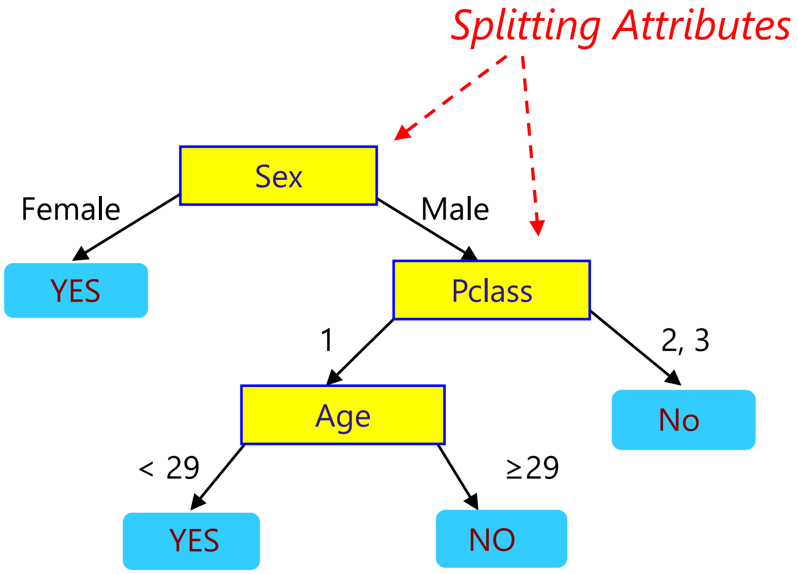

# A Different Decision Tree

| *Pid* | Sex | Age | Pclass | Survived |
|---|---|---|---|---|
| 2 | Female | 38 | 1 | Yes |
| 3 | Female | 26 | 3 | Yes |
| 5 | Male | 35 | 3 | No |
| 7 | Male | 54 | 1 | No |
| 13 | Male | 20 | 3 | No |
| 14 | Male | 39 | 3 | No |
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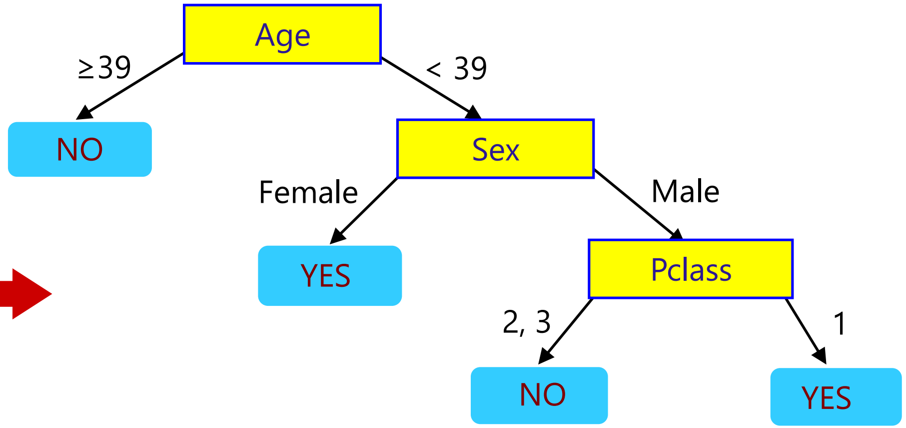


There could be more than one tree that fits the same data!

# Decision Tree Application

| *Pid* | Sex | Age | Pclass | Survived |
|---|---|---|---|---|
| 2 | Female | 38 | 1 | Yes |
| 3 | Female | 26 | 3 | Yes |
| 5 | Male | 35 | 3 | No |
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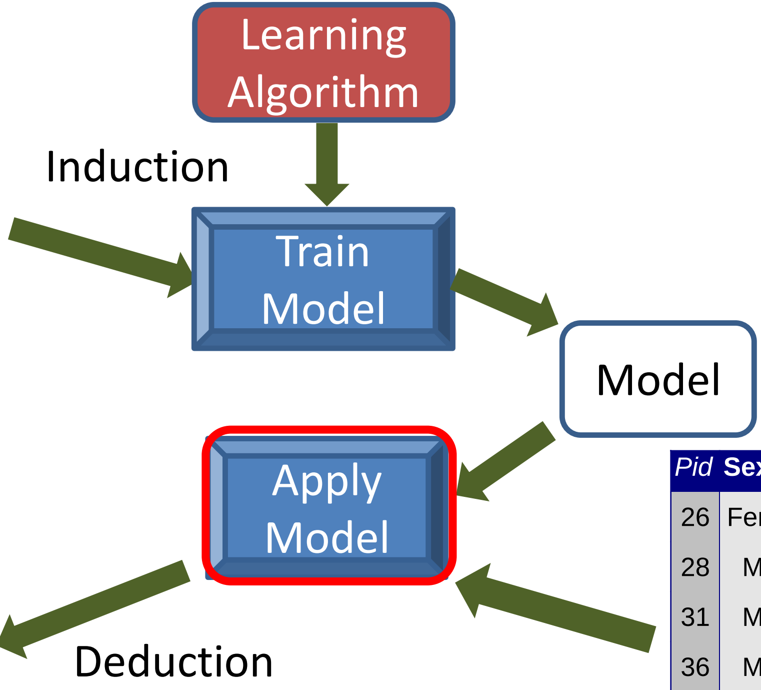
Training Set

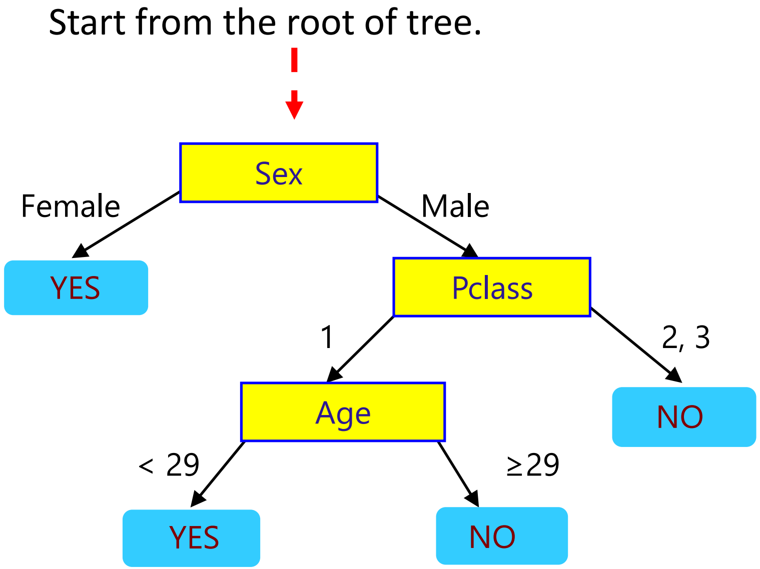



Test Set

| *Pid* | Sex | Age | Pclass | Survived |
|---|---|---|---|---|
| 26 | Female | 38 | 3 | ? |
| 28 | Male | 19 | 1 | ? |
| 31 | Male | 40 | 1 | ? |
| 36 | Male | 42 | 1 | ? |
| 71 | Male | 32 | 2 | ? |

| *Pid* | Survived |
|---|---|
| 26 | Yes |
| 28 | Yes |
| 31 | No |
| 36 | No |
| 71 | No |

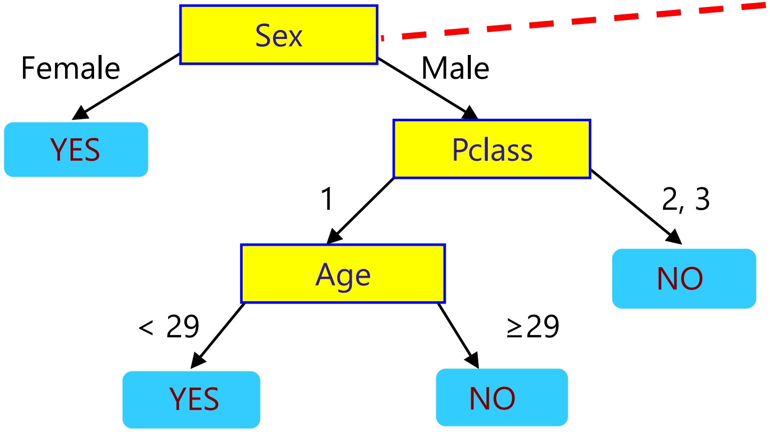
# Apply Model to Test Data




Test Data

| Sex | Age | Pclass | Survived |
|---|---|---|---|
| Male | 32 | 2 | ? |

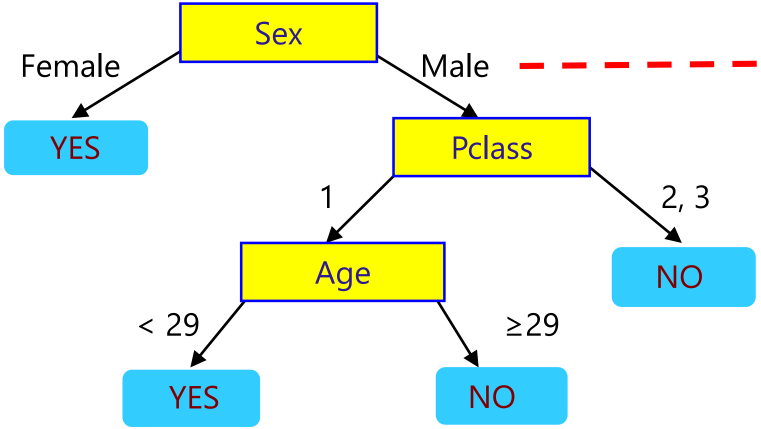
# Apply Model to Test Data




Test Data

| Sex | Age | Pclass | Survived |
|---|---|---|---|
| Male | 32 | 2 | ? |

# Apply Model to Test Data




Test Data

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| Male | 32 | 2 | ? |

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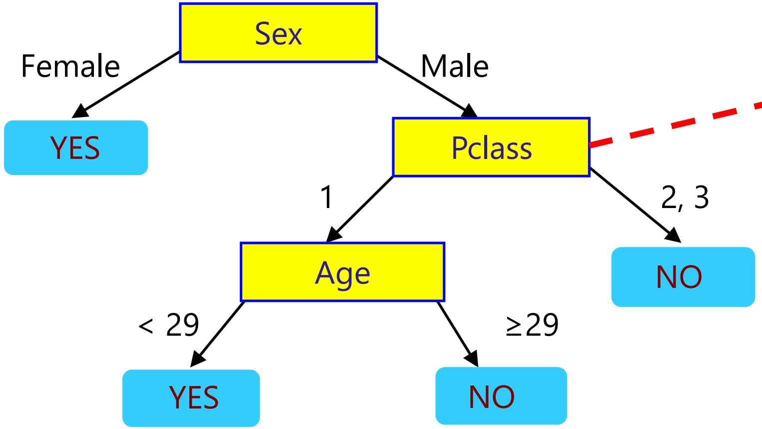


Test Data

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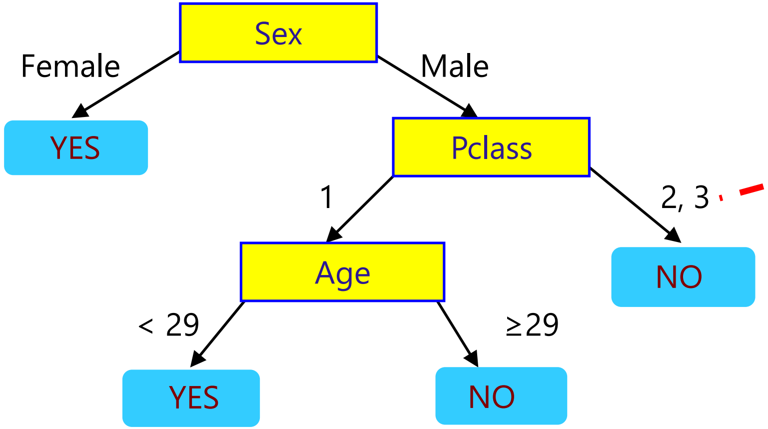
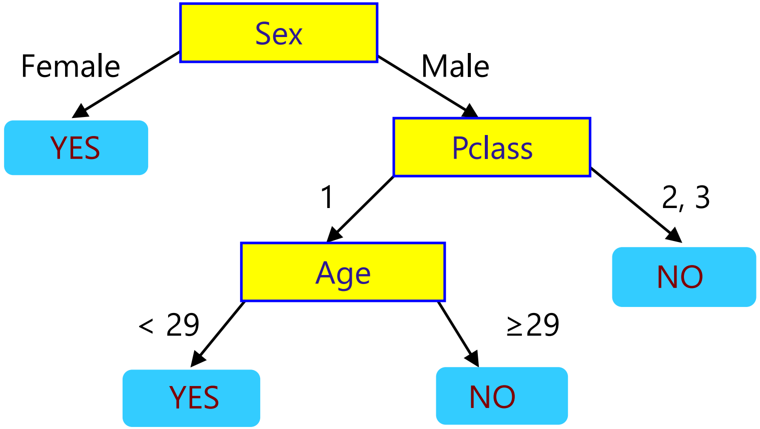



Test Data

| Sex | Age | Pclass | Survived |
|---|---|---|---|
| Male | 32 | 2 | ? |

# Apply Model to Test Data




Test Data

| Sex | Age | Pclass | Survived |
|---|---|---|---|
| Male | 32 | 2 | ? |

Survived = “No”

# Decision Tree Application

| *Pid* | Sex | Age | Pclass | Survived |
|---|---|---|---|---|
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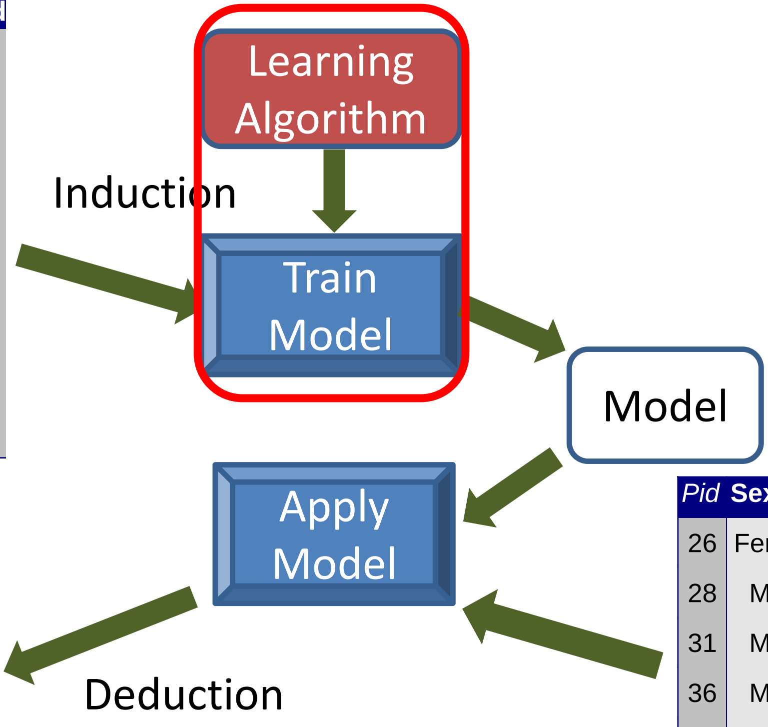
Training Set

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# How Do We Get A Tree?

- Exponentially many decision trees are possible
- Finding the optimal tree is infeasible
- Greedy methods that find near-optimal solutions do exist

# Tree Induction

- Greedy strategy
  - Split based attribute test that optimizes a criterion
- Issues
  - How to split the records
    - What attribute test condition?
    - How to determine the best split?
    - When do we stop?

# Tree Induction

- Greedy strategy
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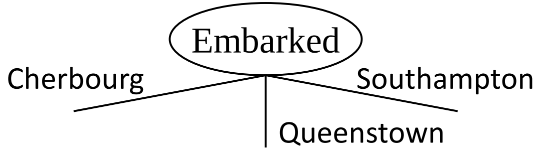
- Issues
  - How to split the records
    - **What attribute test criterion?**
    - How to determine the best split?
    - When do we stop?

# How to Specify Test Condition?

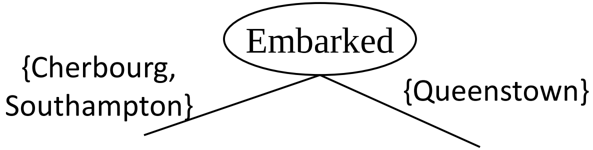
- Attribute types
  - Nominal
  - Ordinal
  - Continuous
- Order of split
  - 2-way split
  - Multi-way split

# Splitting: Nominal Attributes

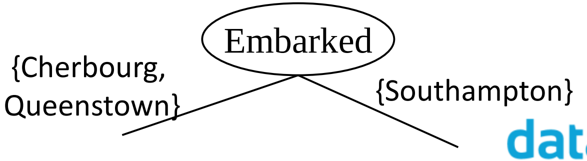
- Multi-way split: As many partitions as distinct values.




- Binary split: Divide values into two subsets. Need to find optimal partitioning.

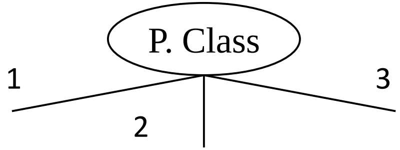



OR

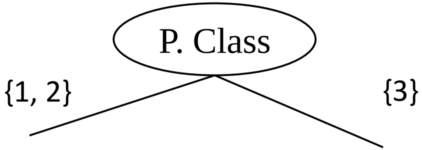


# Splitting: Ordinal Attributes

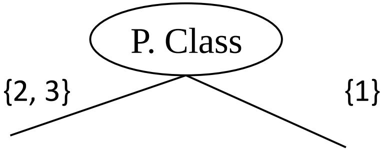
- Multi-way split: As many partitions as distinct values.



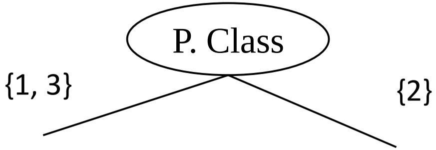

- Binary split:  Divides values into two subsets. Need to find optimal partitioning.




OR




- What about this split?

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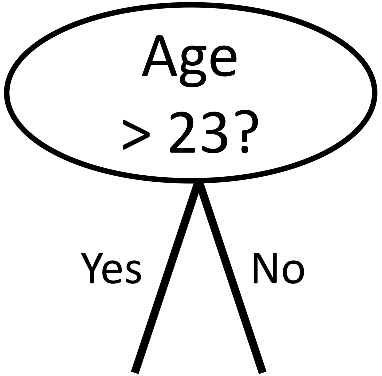
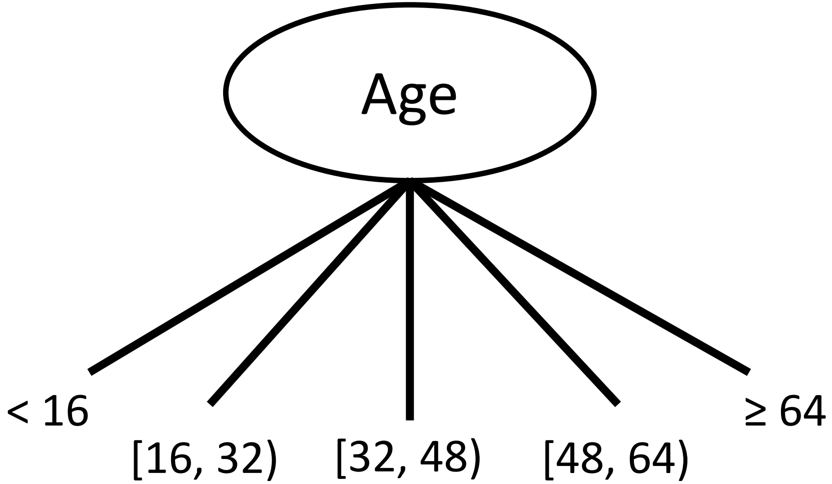
# Splitting: Continuous Attributes

- Discretize: transform to ordinal categorical attribute
  - Static – “bucket” once at the beginning
  - Dynamic – “bucket” at each node
    - Equal interval bucketing
    - Equal frequency bucketing (percentiles)
    - Clustering
    - Sweep – Consider all possible splits
      - Usually more computationally intensive

# Splitting on Continuous Attributes




Binary Split




Multi-way Split

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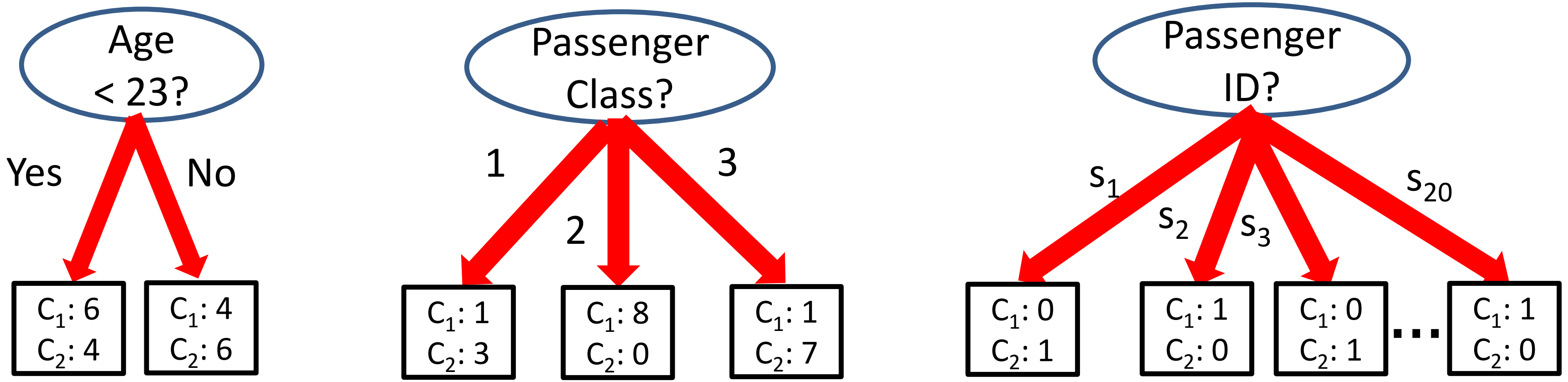
# Tree Induction

- Greedy strategy
  - Split based attribute test that optimizes a criterion
- Issues
  - How to split the records
    - What attribute test criterion?
    - **How to determine the best split?**
    - When do we stop?

$C_1$: Dead
$C_2$: Survived

# What is The Best Split?

Before Splitting: 10 records of class 1, 10 records of class 2




Which test condition is the best?

# What is The Best Split?

$C_1$: Dead
$C_2$: Survived

- Greedy approach
  - Homogeneous class distribution preferred
- Need a measure of **node impurity**

| $C_1$: 5<br>$C_2$: 5 | $C_1$: 9<br>$C_2$: 1 |
|---|---|
| Non-homogeneous | Homogeneous |
| High degree of impurity | Low degree of impurity |

# Measures of Node Impurity

- Gini Index
- Entropy
- Misclassification error

# Impurity Measure: GINI

$C_1$: Dead
$C_2$: Survived

$$GINI(t) = 1 - \sum_j [p(j \mid t)]^2$$

- p( j | t) is the relative frequency of class j at node t

- Maximum ($1 - 1/n_c$) when records are equally distributed among all classes, implying least interesting information
    - $n_c$=number of classes
- Minimum (0.0) when all records belong to one class, implying most interesting information

| | |
|---|---|
| $C_1$ | **0** |
| $C_2$ | **6** |
| **Gini=0.000** | |

| | |
|---|---|
| $C_1$ | **1** |
| $C_2$ | **5** |
| **Gini=0.278** | |

| | |
|---|---|
| $C_1$ | **2** |
| $C_2$ | **4** |
| **Gini=0.444** | |

| | |
|---|---|
| $C_1$ | **3** |
| $C_2$ | **3** |
| **Gini=0.500** | |

# Impurity Measure: GINI

$C_1$: Dead
$C_2$: Survived

$$GINI(t) = 1 - \sum_j [p(j \mid t)]^2$$

| | |
|---|---|
| $C_1$ | **0** |
| $C_2$ | **6** |

P(C1) = 0/6 = 0 P(C2) = 6/6 = 1

Gini = $1 - P(C1)^2 - P(C2)^2 = 1 - 0 - 1 = 0$

| | |
|---|---|
| $C_1$ | **1** |
| $C_2$ | **5** |

P(C1) = 1/6 P(C2) = 5/6

Gini = $1 - (1/6)^2 - (5/6)^2 = 0.278$

| | |
|---|---|
| $C_1$ | **2** |
| $C_2$ | **4** |

P(C1) = 2/6 P(C2) = 4/6

Gini = $1 - (2/6)^2 - (4/6)^2 = 0.444$

# Impurity Measure: GINI

- When a node p is split into k partitions (children), the quality of split is computed as:

$$GINI(split, p) = \sum_{i=1}^{k} \frac{n_i}{n} GINI(i)$$

where

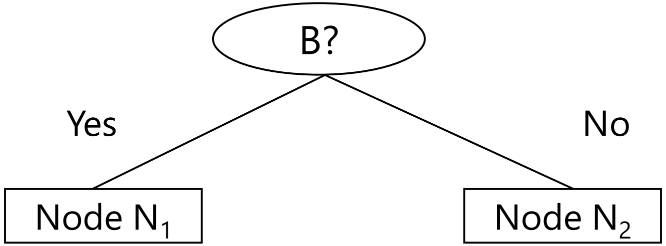
$n_i$ = number of records at child i

$n$ = number of records at node p

# Impurity Measure: GINI

| |
|---|
| $C_1$: Dead |
| $C_2$: Survived |

- Split data into two partitions
- Partition measurements are weighted
  - Larger and purer partitions are sought after




| | **Parent** |
|---|---|
| $C_1$ | **6** |
| $C_2$ | **6** |
| **Gini = 0.500** | |

Gini($N_1$)
$= 1 - (5/7)^2 - (2/7)^2$
$= 0.408$

Gini($N_2$)
$= 1 - (1/5)^2 - (4/5)^2$
$= 0.320$

| | **$N_1$** | **$N_2$** |
|---|---|---|
| $C_1$ | **5** | **1** |
| $C_2$ | **2** | **4** |
| **Gini=0.371** | | |

Gini(B?, Parent)
$= 7/12 * 0.408 +$
$5/12 * 0.320$
$= 0.371$

# Impurity Measure: Entropy

$$Entropy(t) = -\sum_{j} p(j \mid t) \log_2 (p(j \mid t))$$

- $p(j|t)$ is the relative frequency of class j at node t

- Maximum: records equally distributed
- Minimum: all records belong to one class

# Impurity Measure: Entropy

$C_1$: Dead
$C_2$: Survived

$$Entropy(t) = -\sum_j p(j|t)\log_2 p(j|t)$$

| | |
|---|---|
| $C_1$ | **0** |
| $C_2$ | **6** |

P(C1) = 0/6 = 0    P(C2) = 6/6 = 1

Entropy = – 0 log 0 – 1 log 1 = – 0 – 0 = 0

| | |
|---|---|
| $C_1$ | **1** |
| $C_2$ | **5** |

P(C1) = 1/6    P(C2) = 5/6

Entropy = – (1/6) $\log_2$ (1/6) – (5/6) $\log_2$ (5/6) = 0.65

| | |
|---|---|
| $C_1$ | **2** |
| $C_2$ | **4** |

P(C1) = 2/6    P(C2) = 4/6

Entropy = – (2/6) $\log_2$ (2/6) – (4/6) $\log_2$ (4/6) = 0.92

# Impurity Measure: Information

$$GAIN_{split} = Entropy(p) - \left( \sum_{i=1}^{k} \frac{n_i}{n} Entropy(i) \right)$$

- Node p is split into k partitions
- $n_i$ is number of records in partition i

- Measures reduction in entropy
- Choose split that maximizes GAIN
- Tends to prefer splits with large number of partitions

# Impurity Measure: Information

- Gain Ratio

$$GainRATIO_{split} = \frac{GAIN_{Split}}{SplitINFO}$$

$$SplitINFO = -\sum_{i=1}^{k} \frac{n_i}{n} \log \frac{n_i}{n}$$

  - Node p is split into k partitions
  - $n_i$ is the number of records in partition i
- Penalizes GAIN metric for extra splits
- Counters tendency towards many splits

# Impurity Measure: Classification Error

$$Error(t) = 1 - \max_i P(i \mid t)$$

- Maximum: records are equally distributed
- Minimum: all records belong to one class
- Similar to information gain
  - Less sensitive for > 2 or 3 splits
  - Less prone to overfitting

# Impurity Measure: Classification Error

$C_1$: Dead
$C_2$: Survived

$$Error(t) = 1 - \max_i P(i|t)$$

| | |
|---|---|
| $C_1$ | **0** |
| $C_2$ | **6** |

$P(C1) = 0/6 = 0$ $P(C2) = 6/6 = 1$

$\text{Error} = 1 - \max(0, 1) = 1 - 1 = 0$

| | |
|---|---|
| $C_1$ | **1** |
| $C_2$ | **5** |

$P(C1) = 1/6$ $P(C2) = 5/6$

$\text{Error} = 1 - \max(1/6, 5/6) = 1 - 5/6 = 1/6$

| | |
|---|---|
| $C_1$ | **2** |
| $C_2$ | **4** |

$P(C1) = 2/6$ $P(C2) = 4/6$

$\text{Error} = 1 - \max(2/6, 4/6) = 1 - 4/6 = 1/3$

# Tree Induction

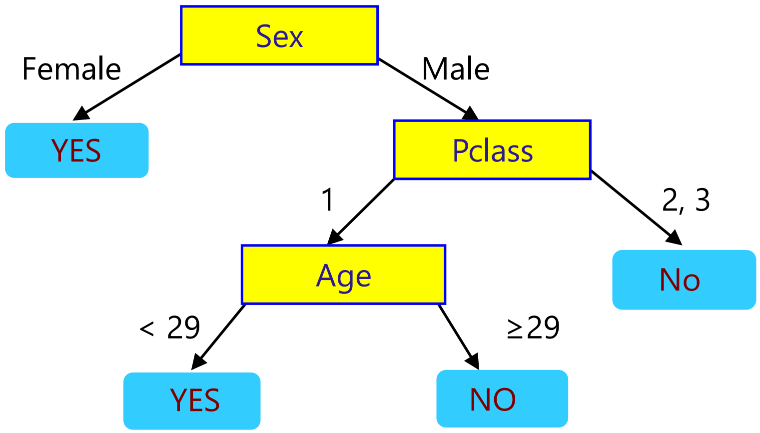
- Greedy strategy
  - Split based attribute test that optimizes a criterion
- Issues
  - How to split the records
    - What attribute test criterion?
    - How to determine the best split?
    - **When do we stop?**

# Sample Stopping Criteria

- All the records belong to the same class
- All the records have similar attribute values
- Fixed termination or pruning
  - Number of Levels
  - Number in Leaf Node
  - Minimum samples per leaf node

# Decision Trees - PROS

- Intuitive
  - Easy interpretation for small trees
- Non parametric
  - Incorporate both numeric and categorical attributes
- Fast
  - Once rules are developed, prediction is rapid
- Robust to outliers

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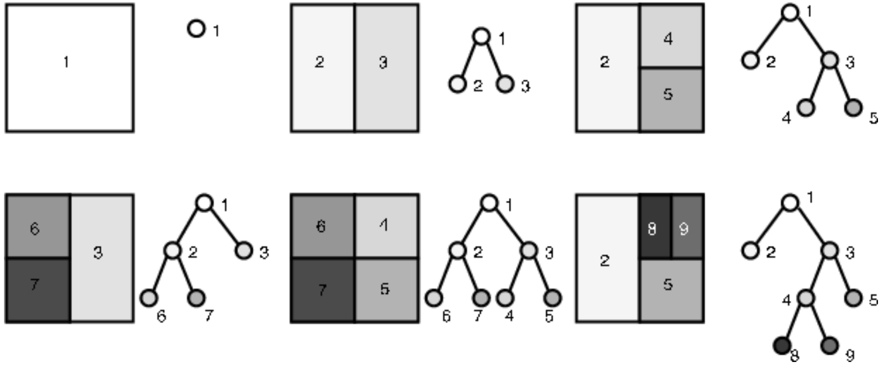
# Decision Trees - CONS

- Overfitting
  - Must be trained with great care
- Rectangular Classification
  - Recursive partitioning of data may not capture complex relationships

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# QUESTIONS

# Session Outline

- Introduction to predictive analytics
- Introduction to classification
- Decision Tree Classifier
- **Hands-on Lab: Building a decision tree classifier using R**