

Predictive Analytics, Classification, and Decision Trees

Data Science Dojo

Agenda

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

INTRODUCTION TO PREDICTIVE ANALYTICS

Family and Personal Life

- Location
 - Microsoft and Nokia predict future location based on cellular phone and location data
- Life Events
 - Target predicts customer pregnancy
- Divorce and infidelity
 - University and clinical researchers can predict this as well!

Friendship and Love

- 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

Telcos, Retail, and More

- FedEx
 - Predicts defection to a competitor with 65-90% accuracy
- Amazon
 - 35% sales come from product recommendation



Social Networks

Face recognition in Facebook posts

Performed better than humans

97% accuracy in recognizing faces

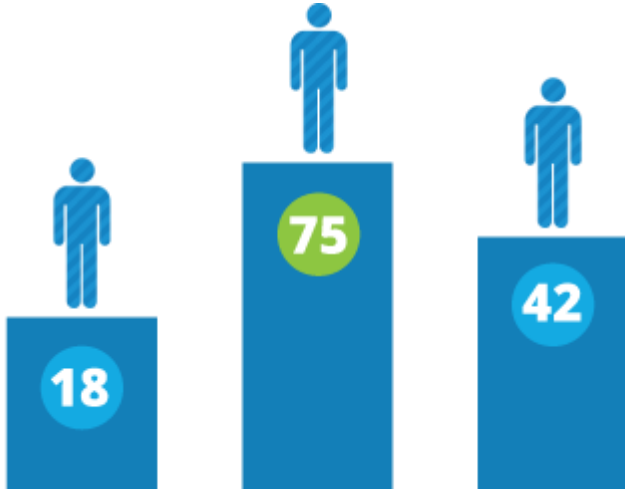


Customer Churn

Keep customers before they leave

Advanced detect allows for customer retention strategies to be employed

36% reduction in customer turnover

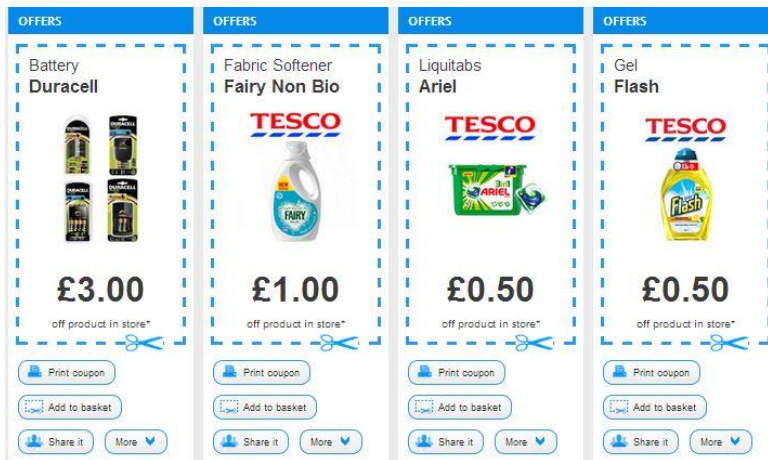


40% reduction in customer calls

Lead Scoring

Pin-pointing which leads to nurture

Allows sales resources to be more focused towards leads with higher probable conversions



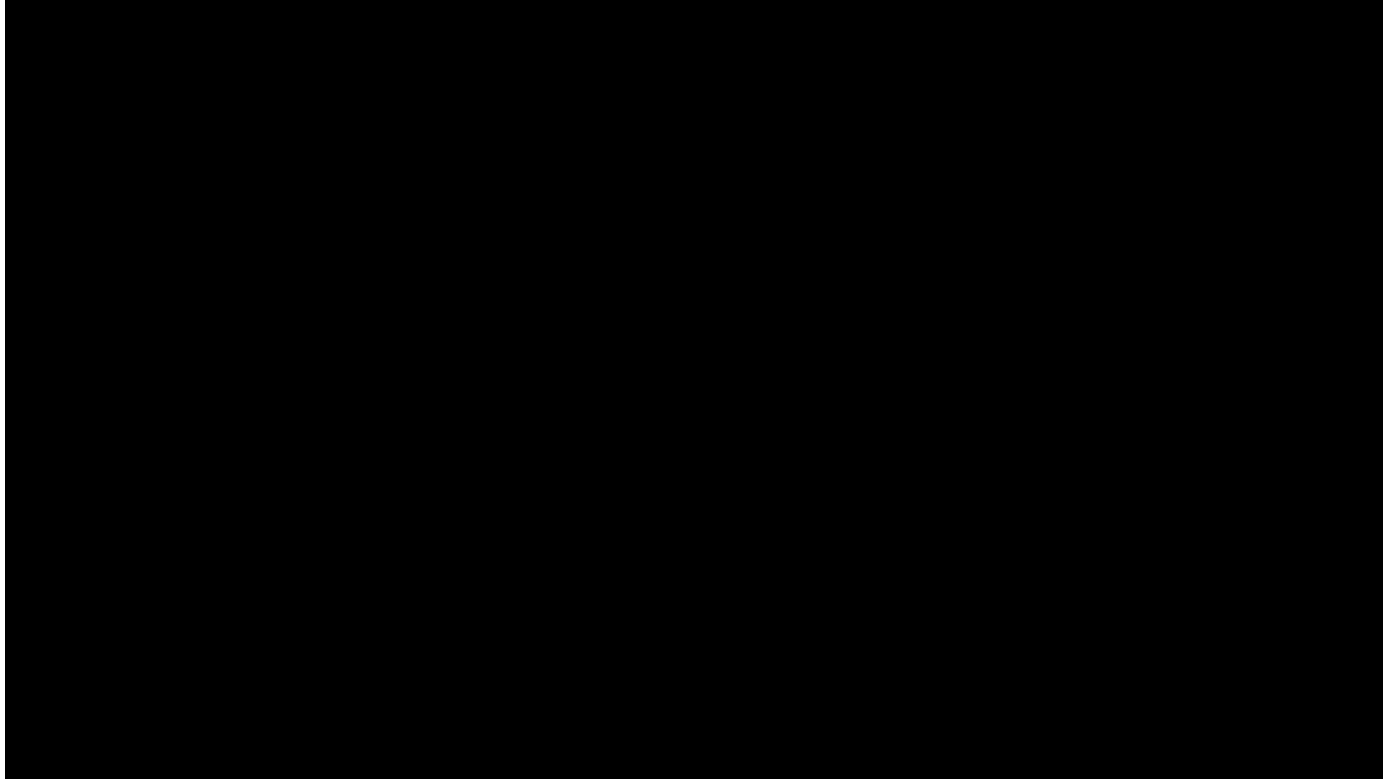
Coupon Redemption

Knowing the liability to bottom-line

Most coupons go un-redeemed. Knowing exactly how many allows you to plan more coupons by having less future liability.

3.6x more coupons than before are sent out

Even In Law Enforcement...



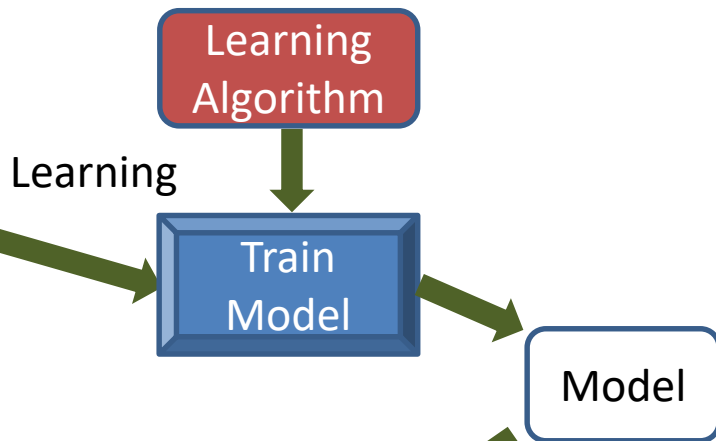
INTRODUCTION TO CLASSIFICATION

Supervised 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

Pid	Survived
26	Yes
28	Yes
31	No
36	No
71	No



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	?

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)

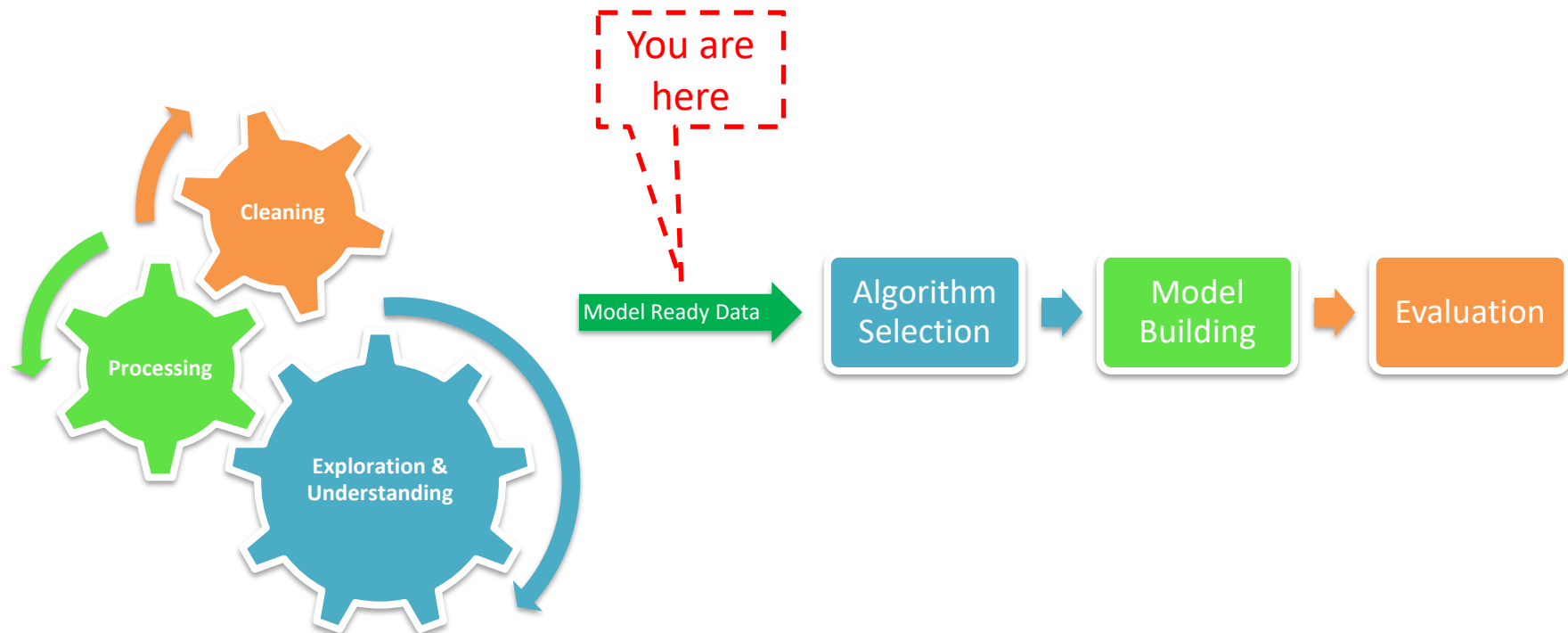
The Classification Task

- 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

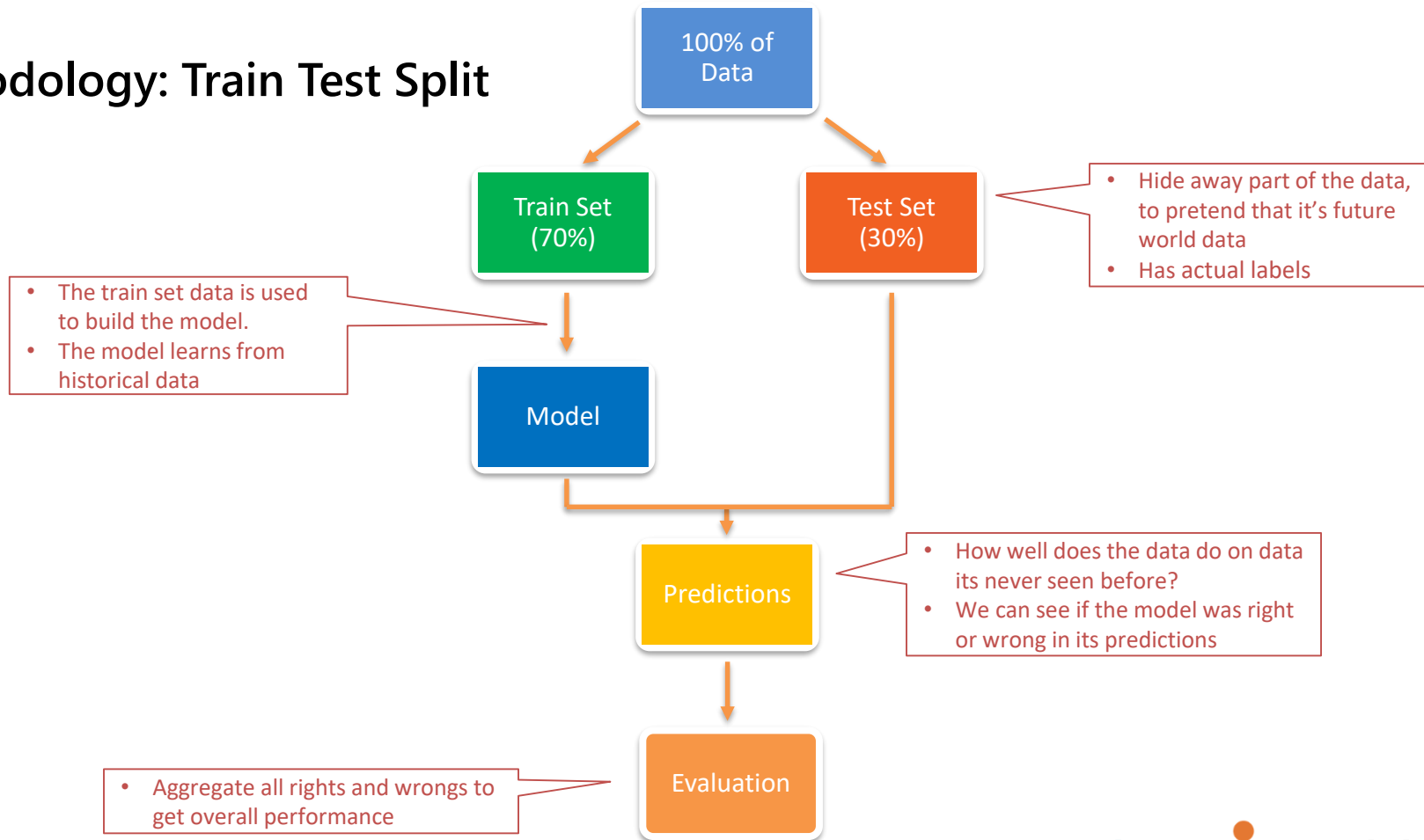
Train Test Split Methodology

- 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

Data Mining Framework



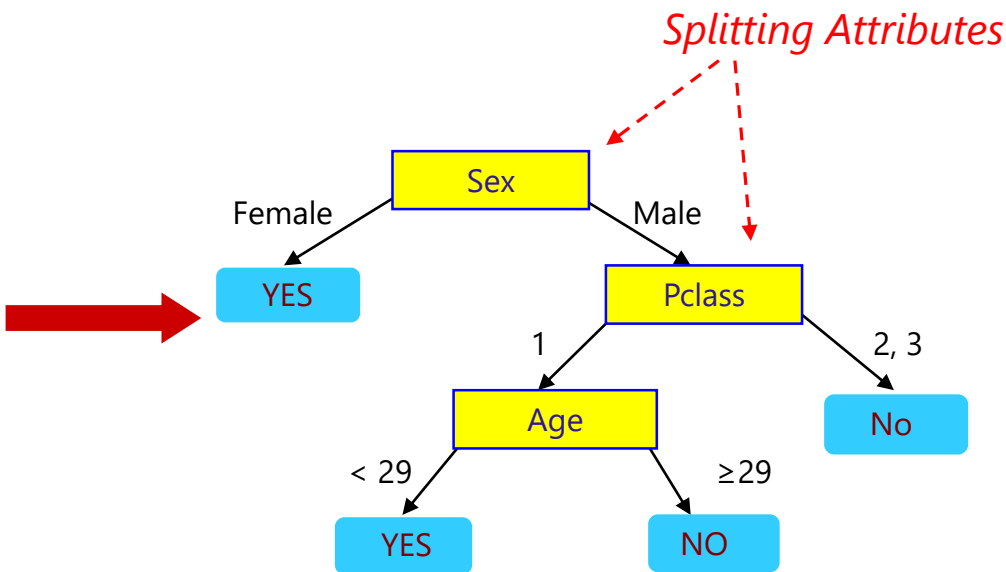
Methodology: Train Test Split



DECISION TREE LEARNING

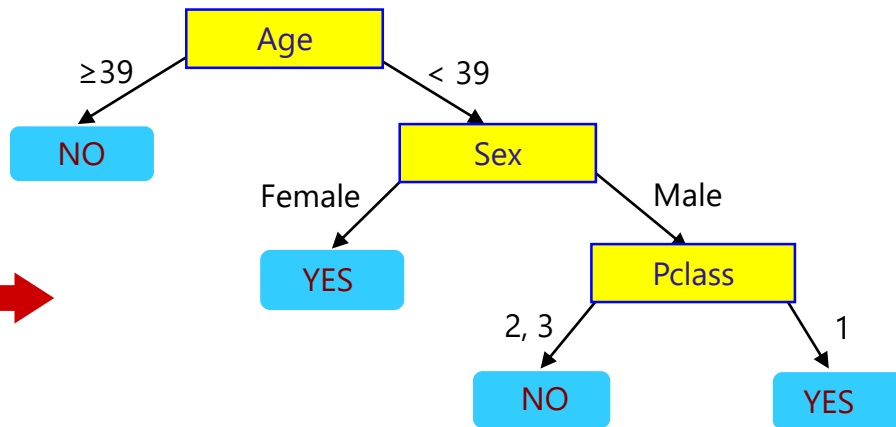
Decision Tree Learning

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



A Different Decision Tree

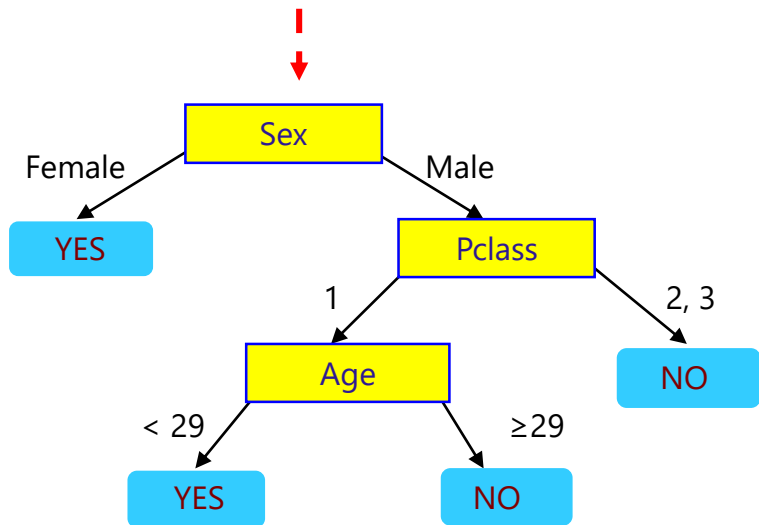
Pid	Sex	Age	Pclass	Survived
2	Female	38	1	Yes
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13	Male	20	3	No
14	Male	39	3	No
21	Male	35	2	No
24	Male	28	1	Yes
34	Male	66	1	No
54	Female	29	2	Yes



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

Apply Model to Test Data

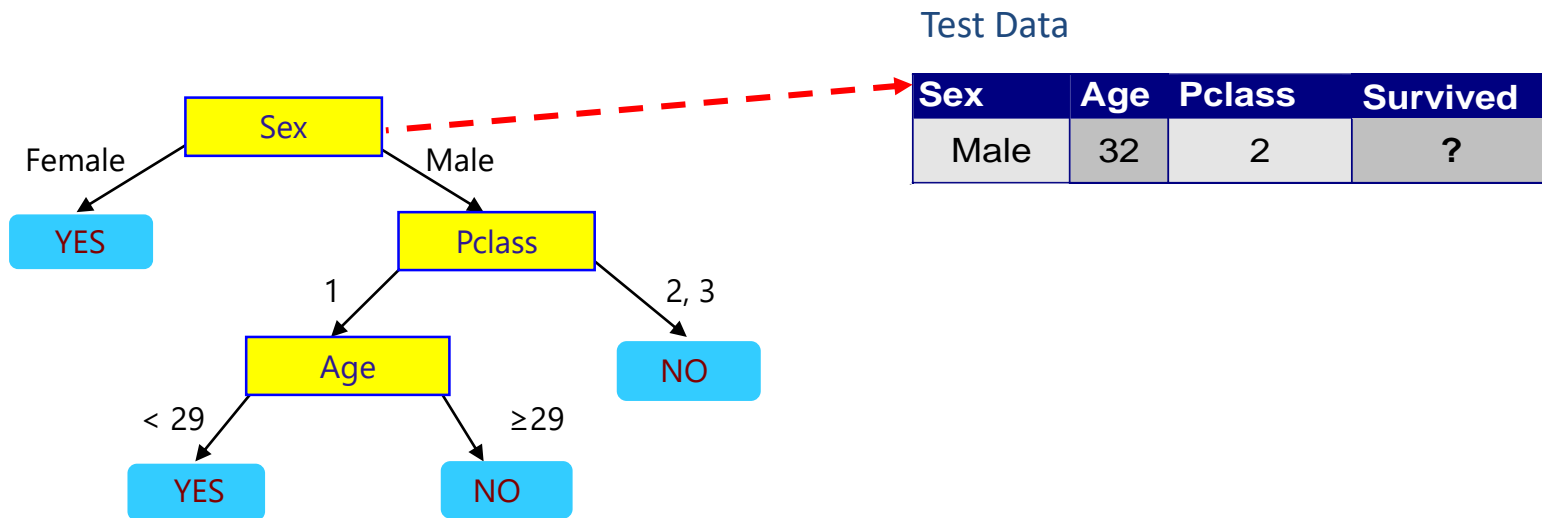
Start from the root of tree.



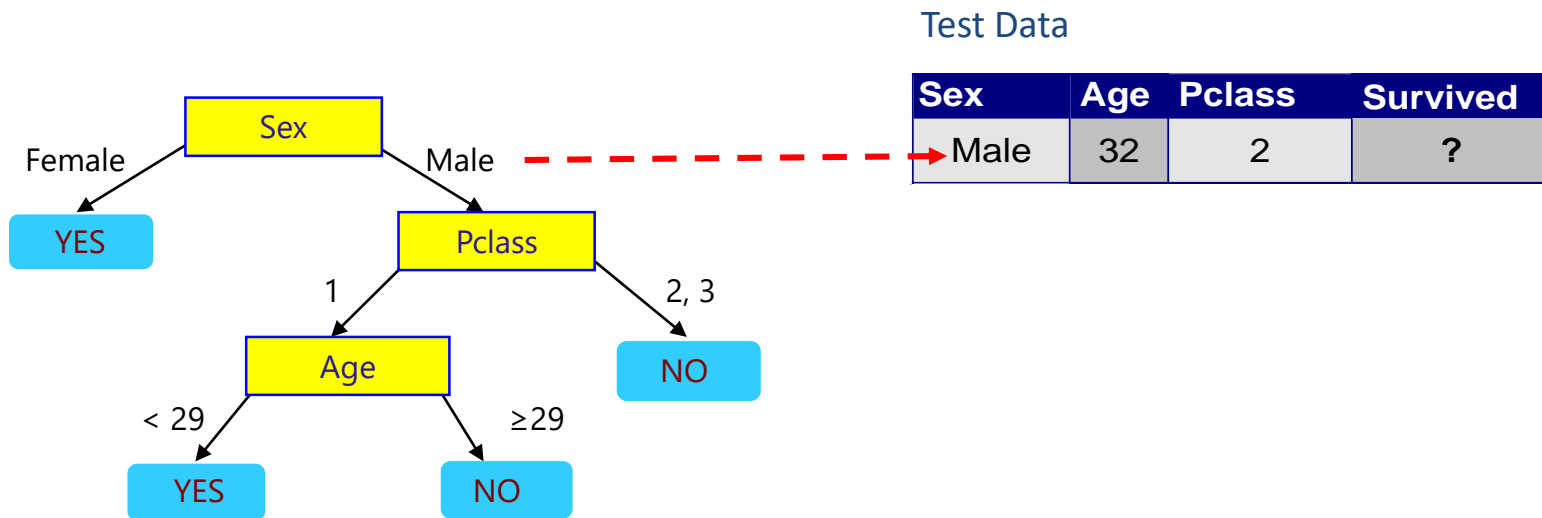
Test Data

Sex	Age	Pclass	Survived
Male	32	2	?

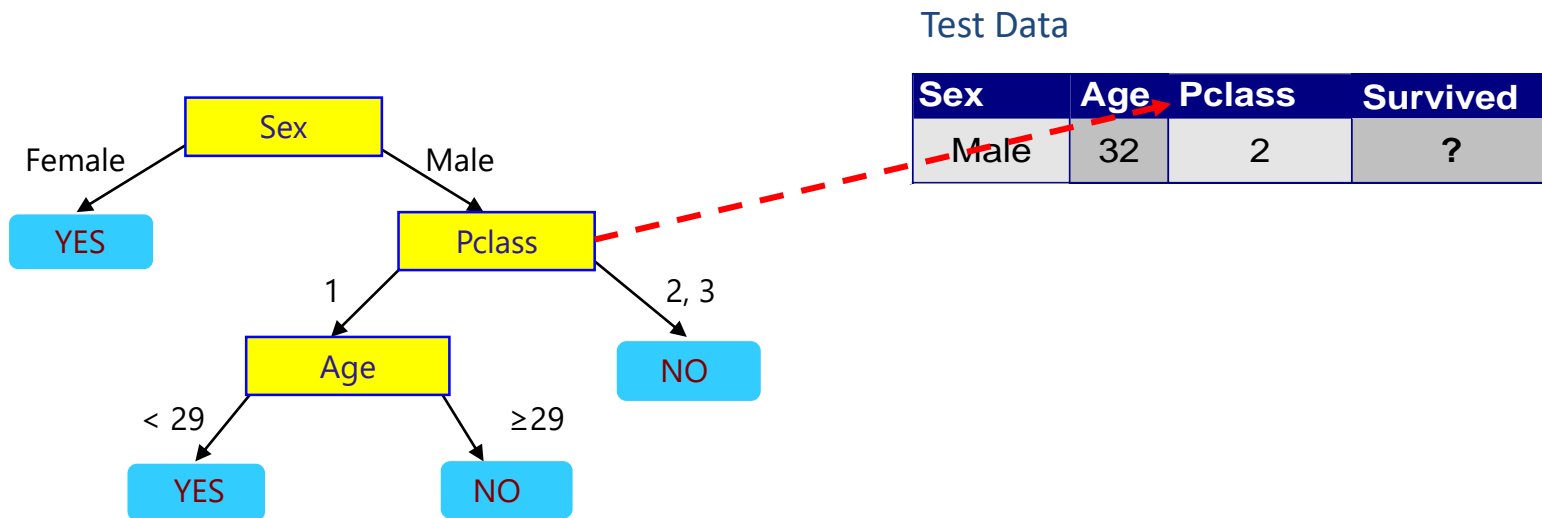
Apply Model to Test Data



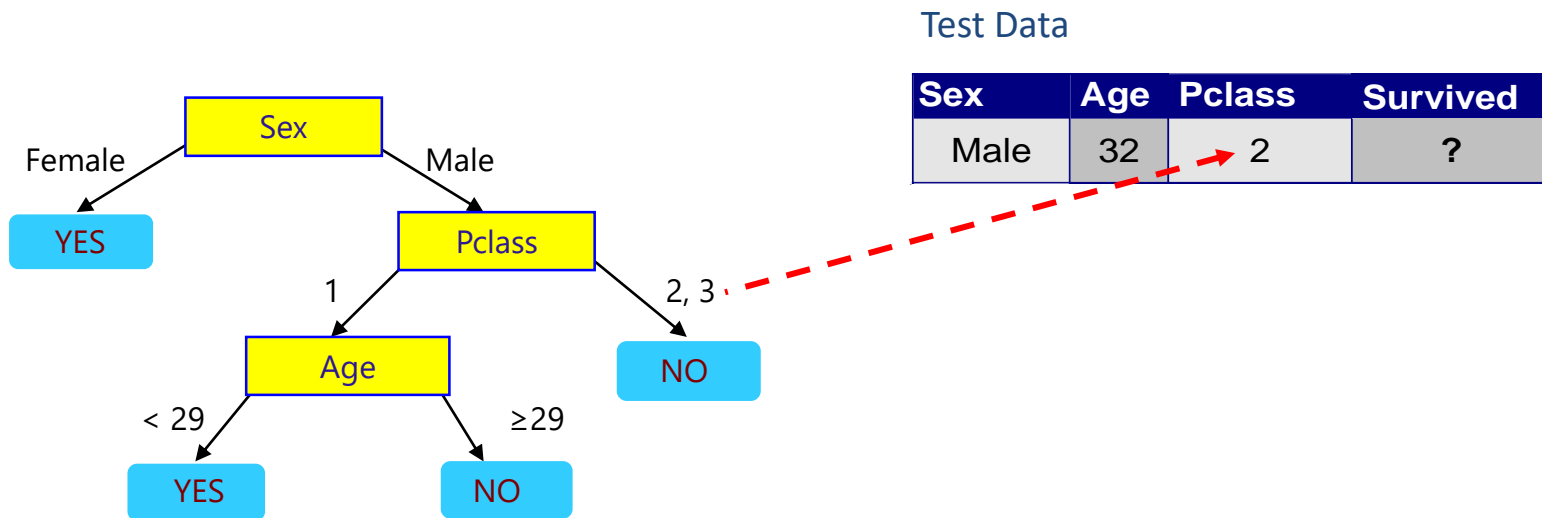
Apply Model to Test Data



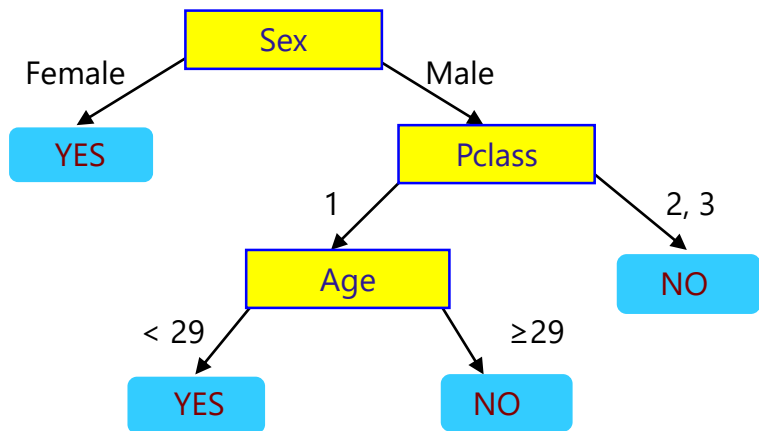
Apply Model to Test Data



Apply Model to Test Data



Apply Model to Test Data



Test Data

Sex	Age	Pclass	Survived
Male	32	2	?

Survived = "No"

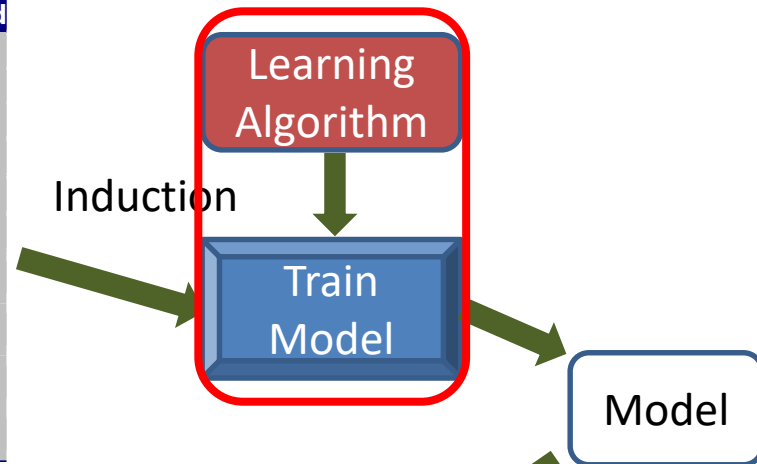
Decision Tree Application

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
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54	Female	29	2	Yes

Training Set

Pid	Survived
26	Yes
28	Yes
31	No
36	No
71	No

Induction



Deduction



Test Set

Pid	Sex	Age	Pclass	Survived
26	Female	38	3	?
28	Male	19	1	?
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36	Male	42	1	?
71	Male	32	2	?

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 on 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

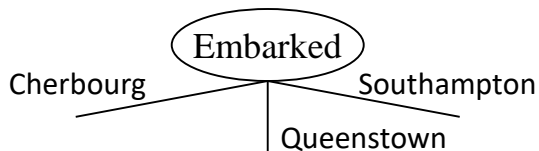
- Greedy strategy
 - Split based attribute test that optimizes a criterion
- Issues
 - How to split the records
 - **What attribute test criterion?**
 - How to determine the best split?
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How to Specify Test Condition?

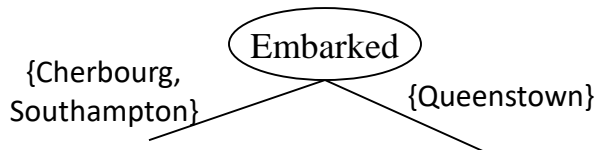
- Attribute types
 - Nominal
 - Ordinal
 - Continuous
- Order of split
 - 2-way split
 - Multi-way split

Splitting: Nominal Attributes

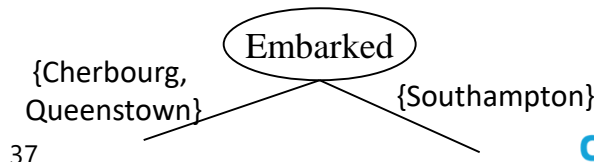
- Multi-way split: As many partitions as distinct values.



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

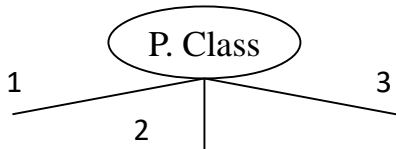


OR

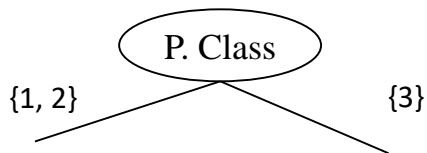


Splitting: Ordinal Attributes

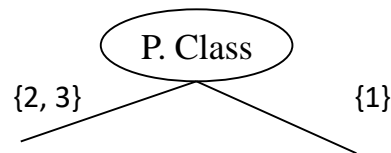
- Multi-way split: As many partitions as distinct values.



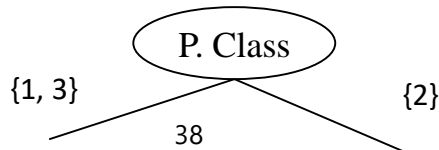
- Binary split: Divides values into two subsets. Need to find optimal partitioning.



OR



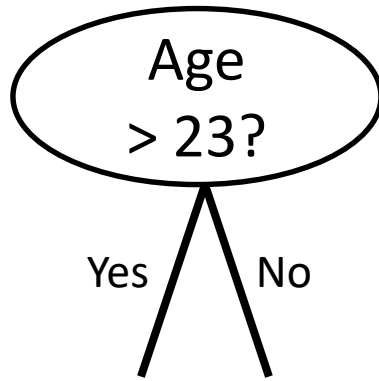
- What about this split?



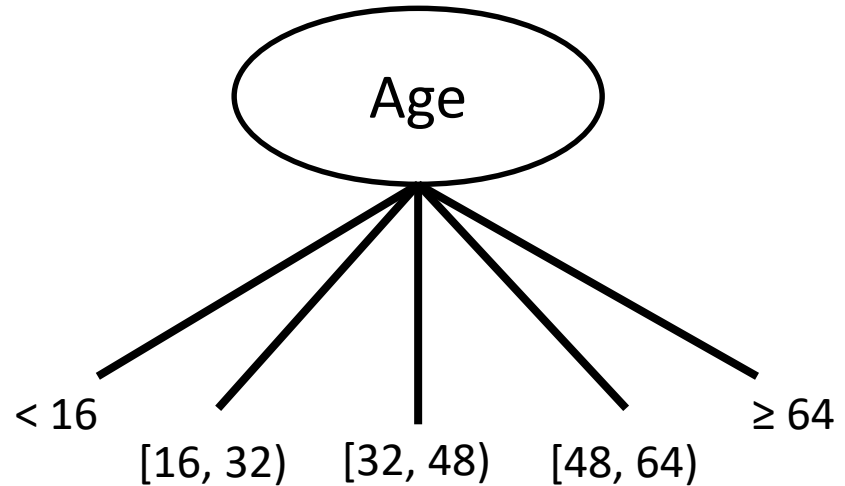
Splitting: Continuous Attributes

- 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

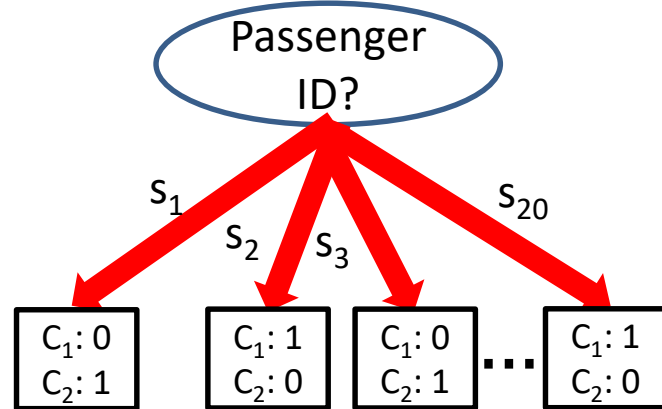
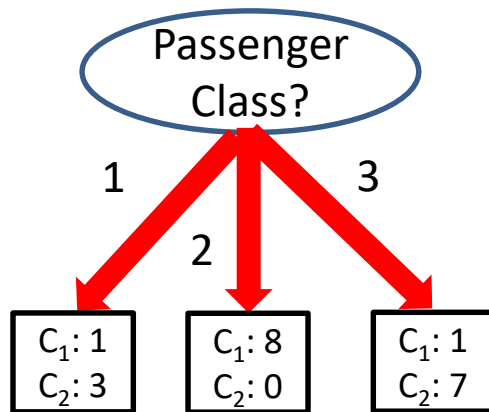
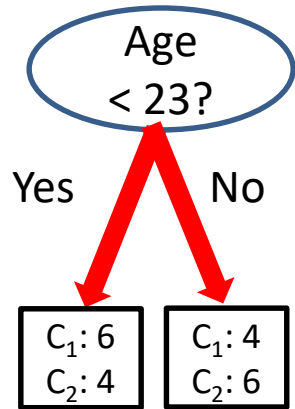
Tree Induction

- 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?

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

C_1 : 5
 C_2 : 5

Non-homogeneous

High degree of impurity

C_1 : 9
 C_2 : 1

Homogeneous

Low degree of impurity

Measures of Node Impurity

- Gini Index
- Entropy
- Misclassification error

C₁: Dead
C₂: Survived

Impurity Measure: GINI

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

- $p(j | t)$ 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	

C₁: Dead
C₂: Survived

Impurity Measure: GINI

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

C ₁	0
C ₂	6

$$P(C_1) = 0/6 = 0 \quad P(C_2) = 6/6 = 1$$

$$Gini = 1 - P(C_1)^2 - P(C_2)^2 = 1 - 0 - 1 = 0$$

C ₁	1
C ₂	5

$$P(C_1) = 1/6 \quad P(C_2) = 5/6$$

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

C ₁	2
C ₂	4

$$P(C_1) = 2/6 \quad P(C_2) = 4/6$$

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

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

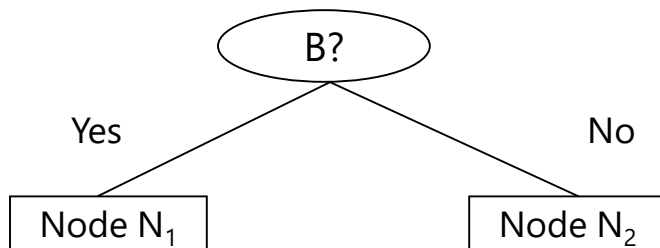
n_i = number of records at child i

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



$$\begin{aligned} \text{Gini}(N_1) &= 1 - (5/7)^2 - (2/7)^2 \\ &= 0.408 \end{aligned}$$

$$\begin{aligned} \text{Gini}(N_2) &= 1 - (1/5)^2 - (4/5)^2 \\ &= 0.320 \end{aligned}$$

	N₁	N₂
C_1	5	1
C_2	2	4
Gini=0.371		

	Parent
C_1	6
C_2	6
Gini = 0.500	

$$\begin{aligned} \text{Gini}(B?, \text{Parent}) &= 7/12 * 0.408 + \\ &\quad 5/12 * 0.320 \\ &= 0.371 \end{aligned}$$

Impurity Measure: Entropy

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

- $p(j|t)$ 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

$$P(C_1) = 0/6 = 0 \quad P(C_2) = 6/6 = 1$$

$$Entropy = -0 \log 0 - 1 \log 1 = -0 - 0 = 0$$

C_1	1
C_2	5

$$P(C_1) = 1/6 \quad P(C_2) = 5/6$$

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

C_1	2
C_2	4

$$P(C_1) = 2/6 \quad P(C_2) = 4/6$$

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

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: Classification Error

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

- 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

C_1 : Dead
 C_2 : Survived

Impurity Measure: Classification Error

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

C_1	0
C_2	6

$$P(C_1) = 0/6 = 0 \quad P(C_2) = 6/6 = 1$$

$$Error = 1 - \max(0, 1) = 1 - 1 = 0$$

C_1	1
C_2	5

$$P(C_1) = 1/6 \quad P(C_2) = 5/6$$

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

C_1	2
C_2	4

$$P(C_1) = 2/6 \quad P(C_2) = 4/6$$

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

Tree Induction

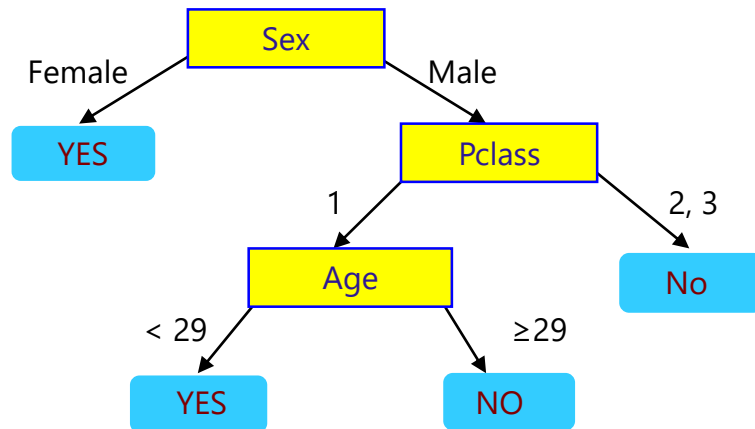
- Greedy strategy
 - Split based attribute test that optimizes a criterion
- Issues
 - How to split the records
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 - How to determine the best split?
 - **When do we stop?**

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 of Leaf Nodes
 - Minimum samples per leaf node

Decision Trees - PROS

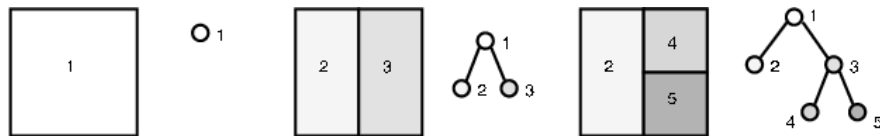
- Intuitive
 - Easy interpretation for small trees
- Non parametric
 - Incorporate both numeric and categorical attributes
- Fast
 - Once rules are developed, prediction is rapid
- Robust to outliers



Decision Trees - CONS

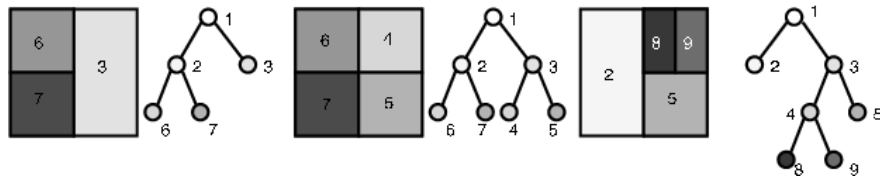
■ Overfitting

- Must be trained with great care



■ Rectangular Classification

- Recursive partitioning of data may not capture complex relationships



QUESTIONS

HANDS-ON LAB: BUILDING A DECISION TREE CLASSIFIER USING R