

Predictive Analytics, Classification, and Decision Trees

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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- **Introduction to predictive analytics**
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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!

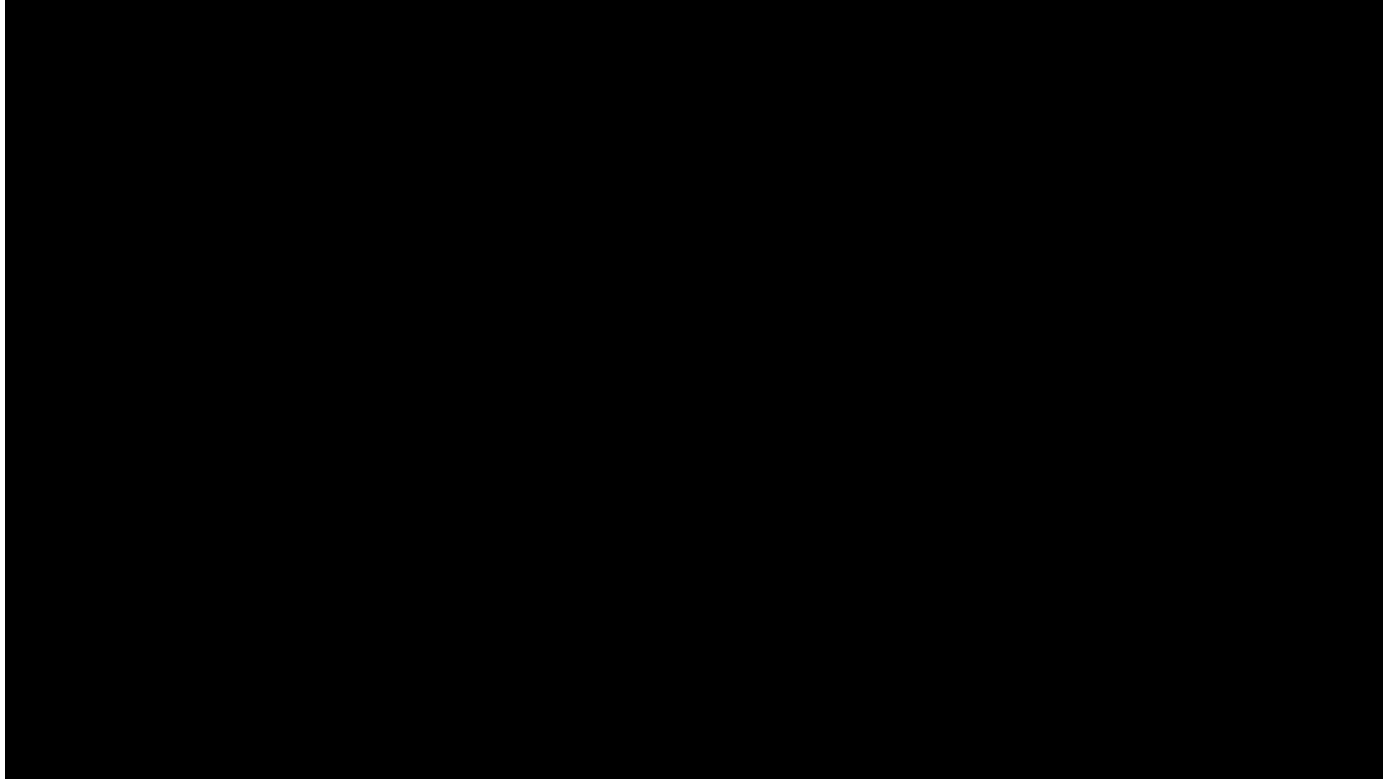
Direct Marketing

- 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

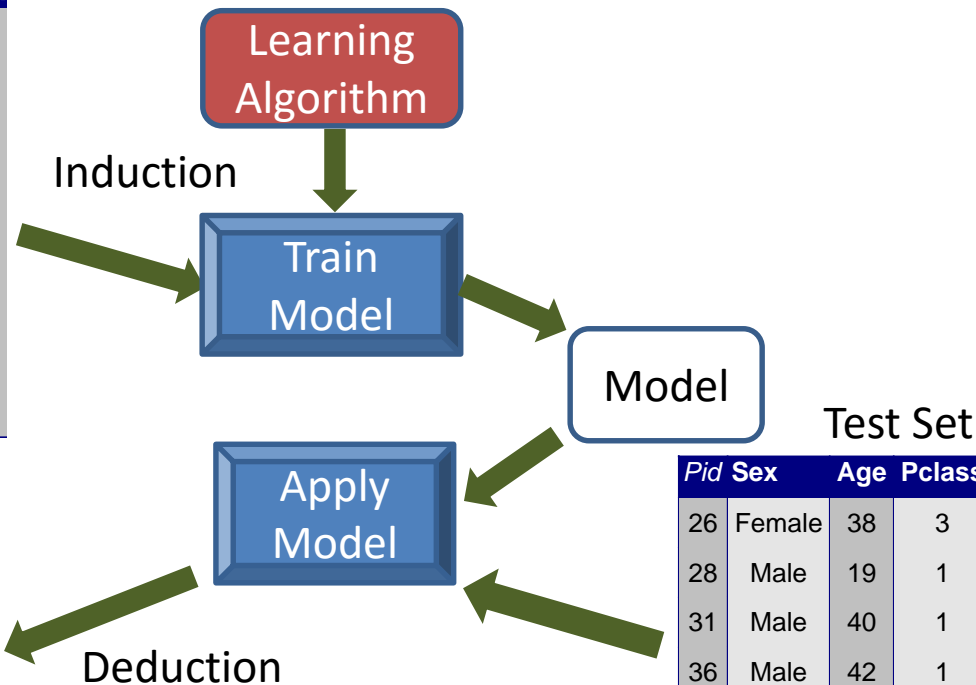
- Introduction to predictive analytics
- **Introduction to classification**
- Decision Tree Classifier
- Hands-on Lab: Building a decision tree classifier using R

Decision Tree 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
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



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

Examples of Classification Tasks

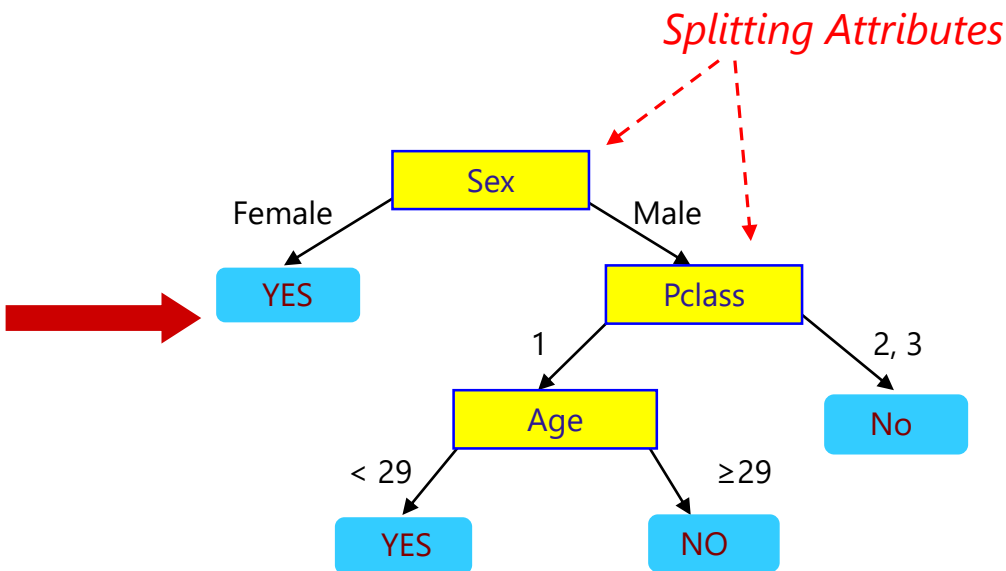
- **Marketing:** Customer groups to target
- **Online:** Bot detection in web traffic
- **Medical:** Predicting tumor cells as benign or malignant
- **Finance:** Credit card fraud detection
- **Document Classification:** Categorizing news stories
- **Security/Surveillance:** Face and fingerprint recognition

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- **Decision Tree Learning**
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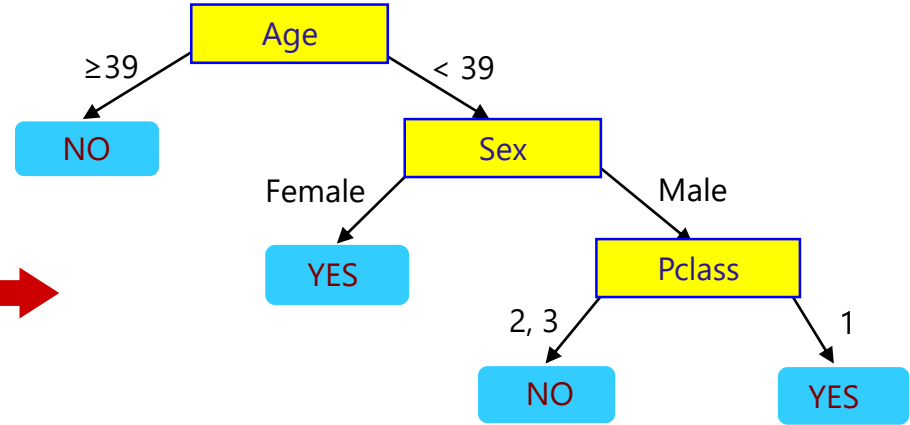
A Different Decision Tree

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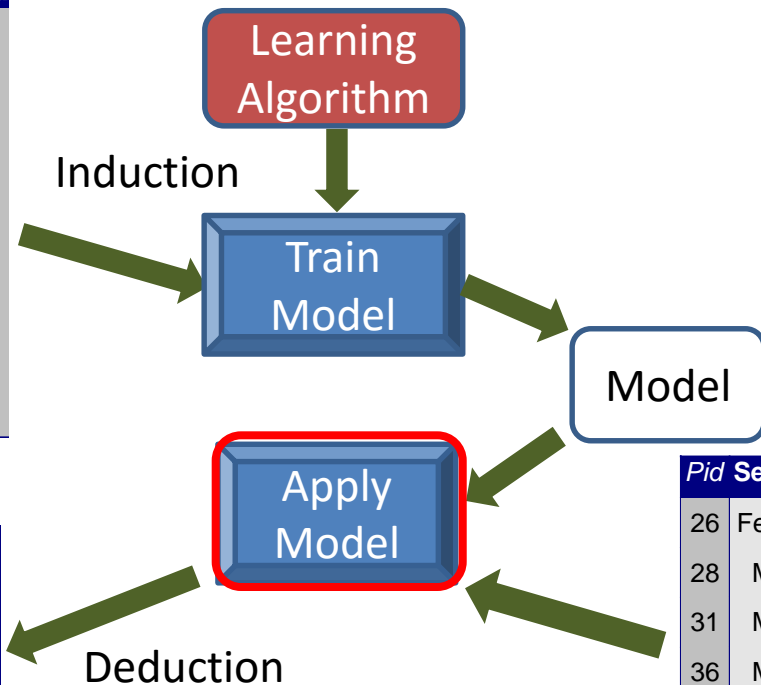
There could be more than one tree that fits the same data!

Decision Tree Application

Pid	Sex	Age	Pclass	Survived
2	Female	38	1	Yes
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Training Set

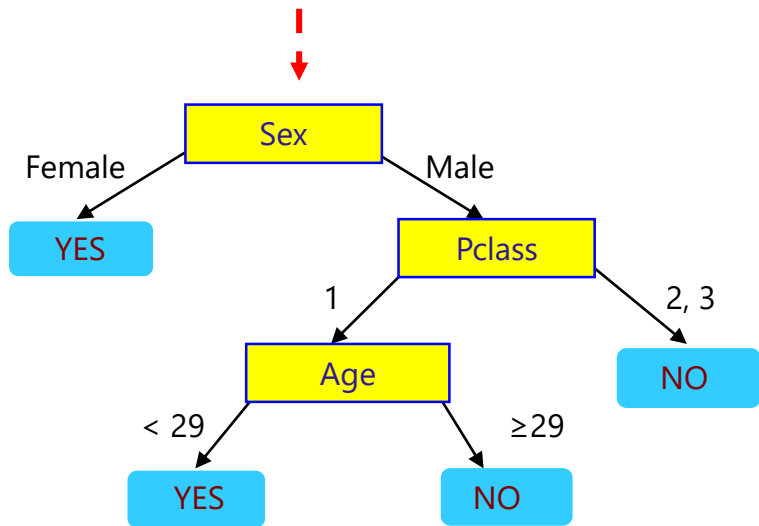
Pid	Survived
26	Yes
28	Yes
31	No
36	No
71	No



Pid	Sex	Age	Pclass	Survived
26	Female	38	3	?
28	Male	19	1	?
31	Male	40	1	?
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71	Male	32	2	?

Apply Model to Test Data

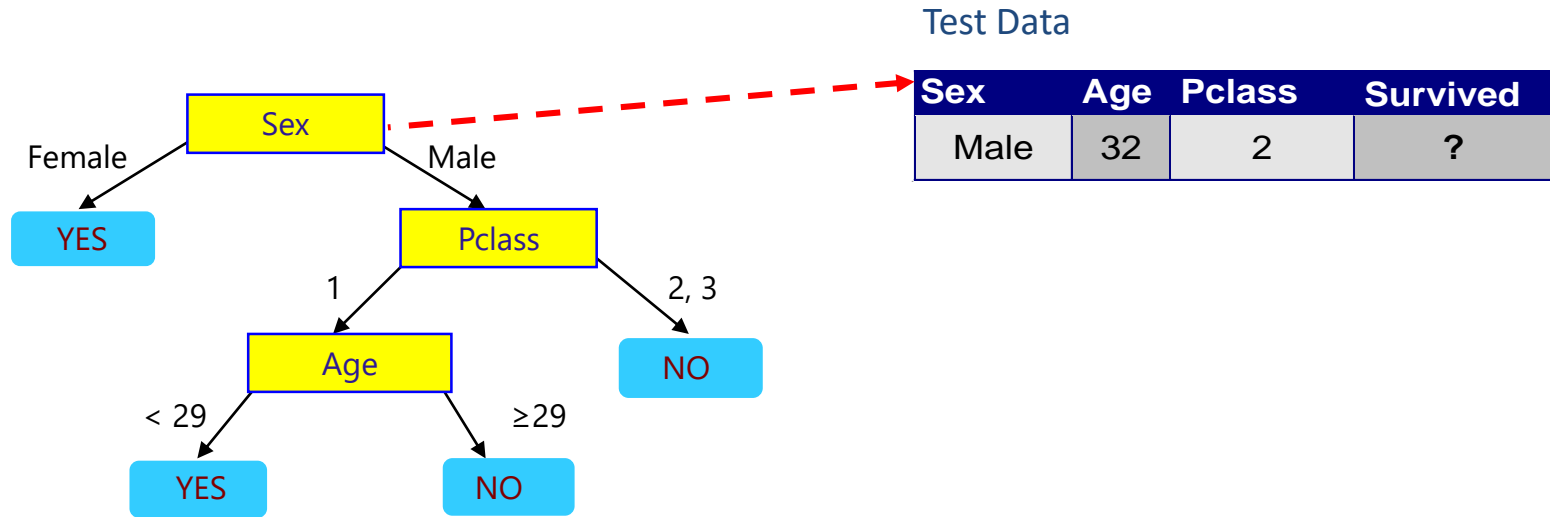
Start from the root of tree.



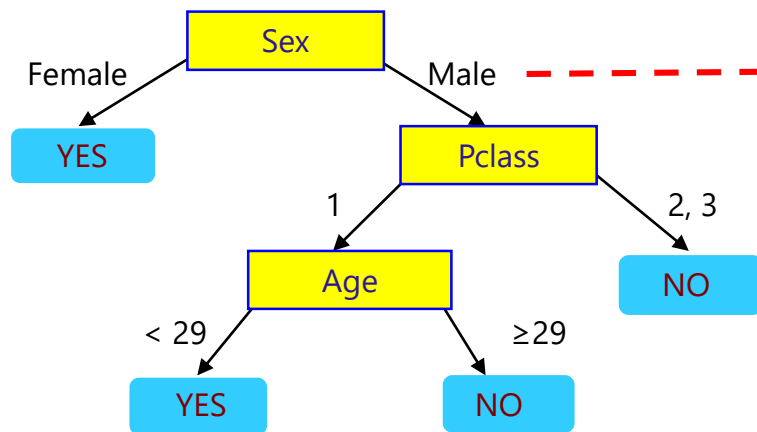
Test Data

Sex	Age	Pclass	Survived
Male	32	2	?

Apply Model to Test Data



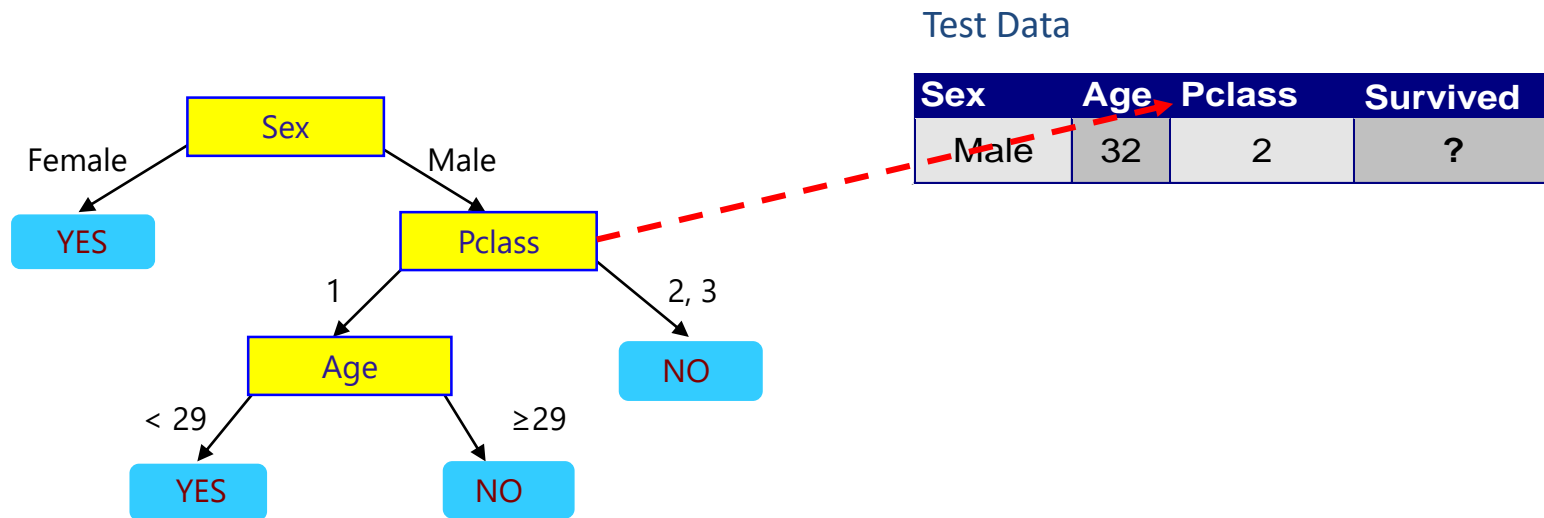
Apply Model to Test Data



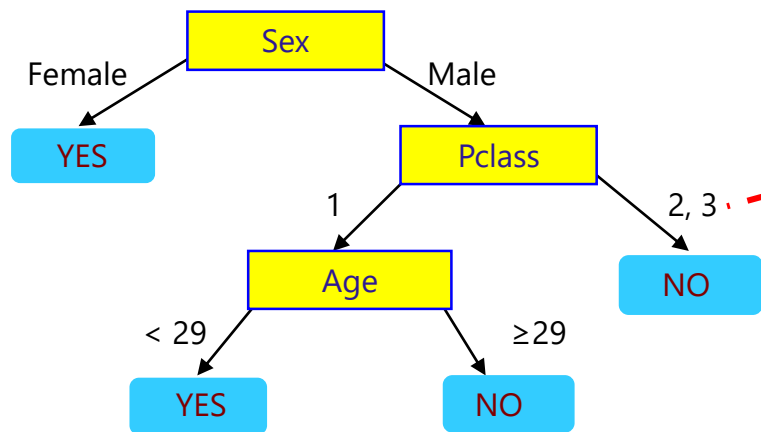
Test Data

Sex	Age	Pclass	Survived
Male	32	2	?

Apply Model to Test Data



Apply Model to Test Data

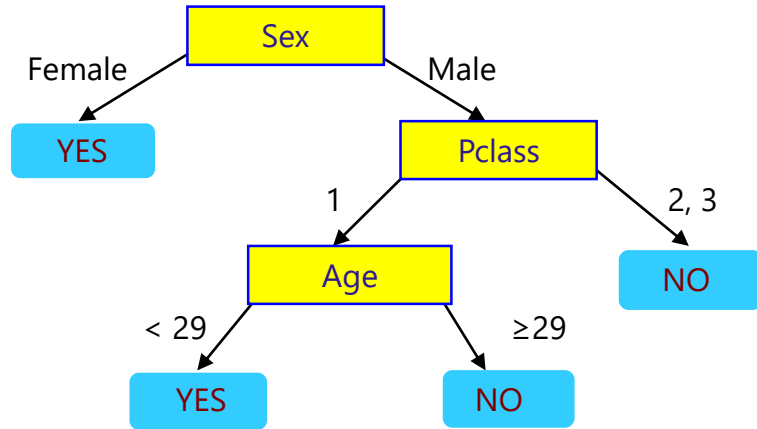


Test Data

Sex	Age	Pclass	Survived
Male	32	2	?



Apply Model to Test Data



Test Data

Sex	Age	Pclass	Survived
Male	32	2	?

Survived = "No"

Decision Tree Application

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Training Set

Pid	Survived
26	Yes
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36	No
71	No

Induction

Learning
Algorithm

Train
Model

Model

Test Set

Pid	Sex	Age	Pclass	Survived
26	Female	38	3	?
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Apply
Model

Deduction

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

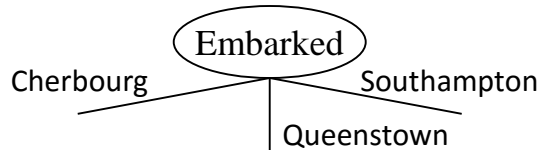
- Greedy strategy
 - Split based attribute test that optimizes a criterion
- Issues
 - How to split the records
 - **What attribute test criterion?**
 - How to determine the best split?
 - When do we stop?

How to Specify Test Condition?

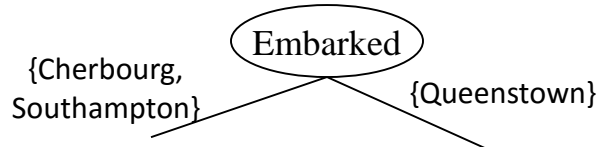
- Attribute types
 - Nominal
 - Ordinal
 - Continuous
- Order of split
 - 2-way split
 - Multi-way split

Splitting: Nominal Attributes

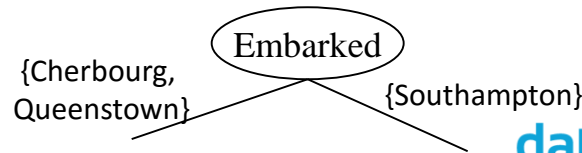
- Multi-way split: As many partitions as distinct values.



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

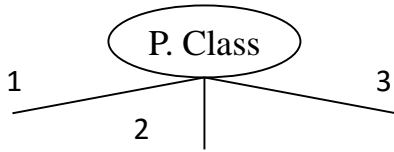


OR

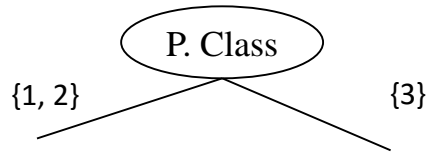


Splitting: Ordinal Attributes

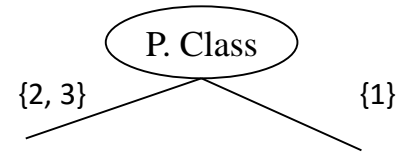
- Multi-way split: As many partitions as distinct values.



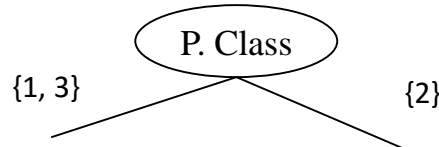
- Binary split: Divides values into two subsets. Need to find optimal partitioning.



OR



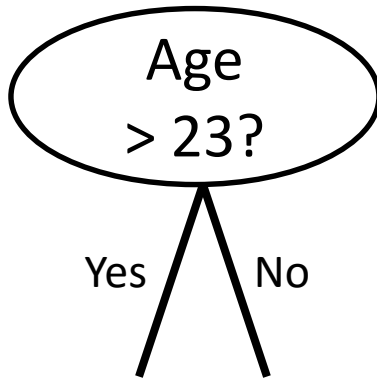
- What about this split?



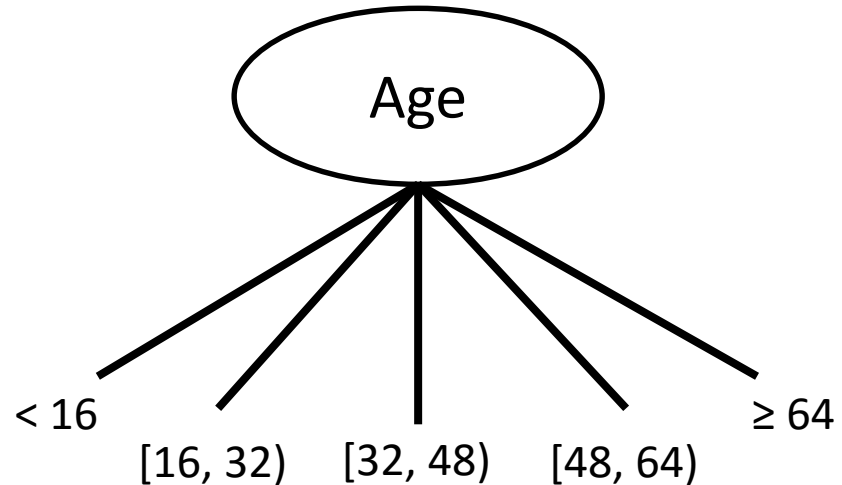
Splitting: Continuous Attributes

- 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

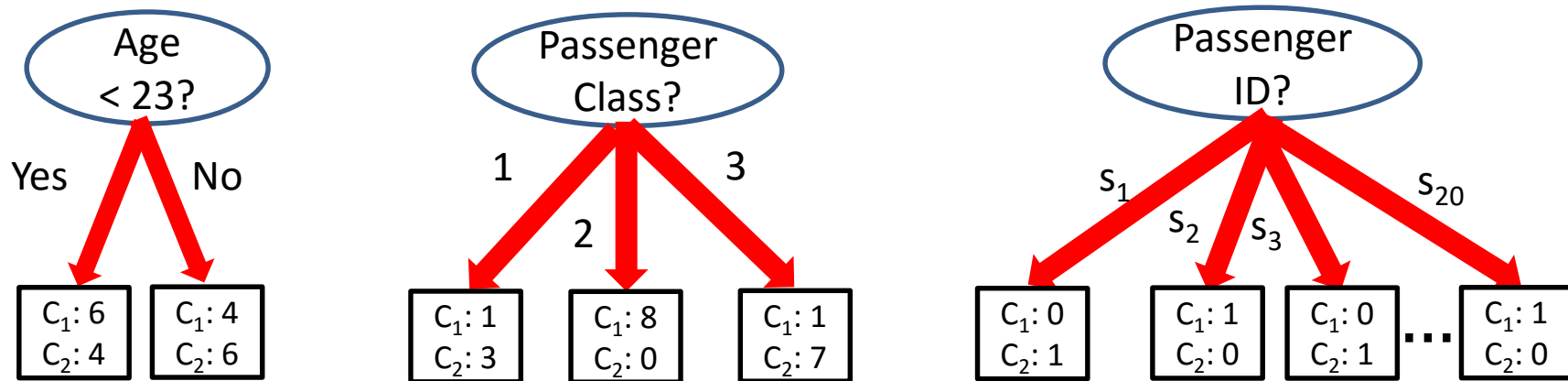
Tree Induction

- 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?

C_1 : Dead
 C_2 : Survived

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

C_1 : Dead
 C_2 : 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	

C_1 : Dead
 C_2 : 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

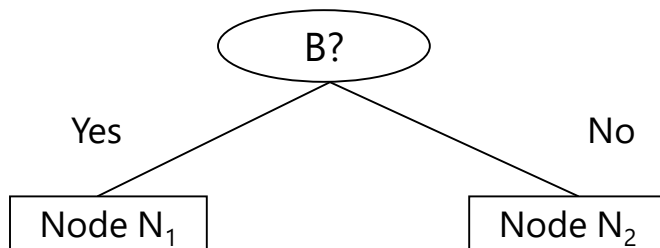
n_i = number of records at child i

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

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

- $p(j | t)$ 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: 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

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

- 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

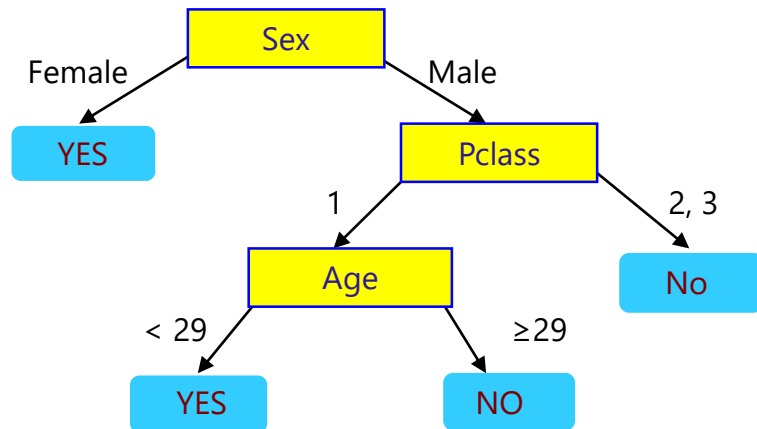
- Greedy strategy
 - Split based attribute test that optimizes a criterion
- Issues
 - How to split the records
 - What attribute test criterion?
 - How to determine the best split?
 - **When do we stop?**

Sample Stopping Criteria

- All the records belong to the same class
- All the records have similar attribute values
- Fixed termination
 - Number of Levels
 - Number in Leaf Node

Decision Trees - PROS

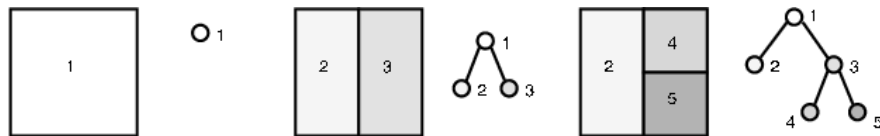
- Intuitive
 - Easy interpretation for small trees
- Non parametric
 - Incorporate both numeric and categorical attributes
- Fast
 - Once rules are developed, prediction is rapid
- Robust to outliers



Decision Trees - CONS

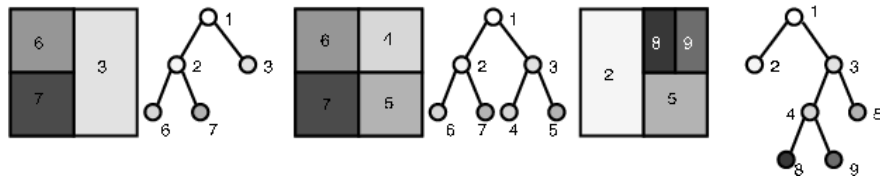
- Overfitting

- Must be trained with great care



- Rectangular Classification

- Recursive partitioning of data may not capture complex relationships



QUESTIONS

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- **Hands-on Lab: Building a decision tree classifier using R**