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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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!

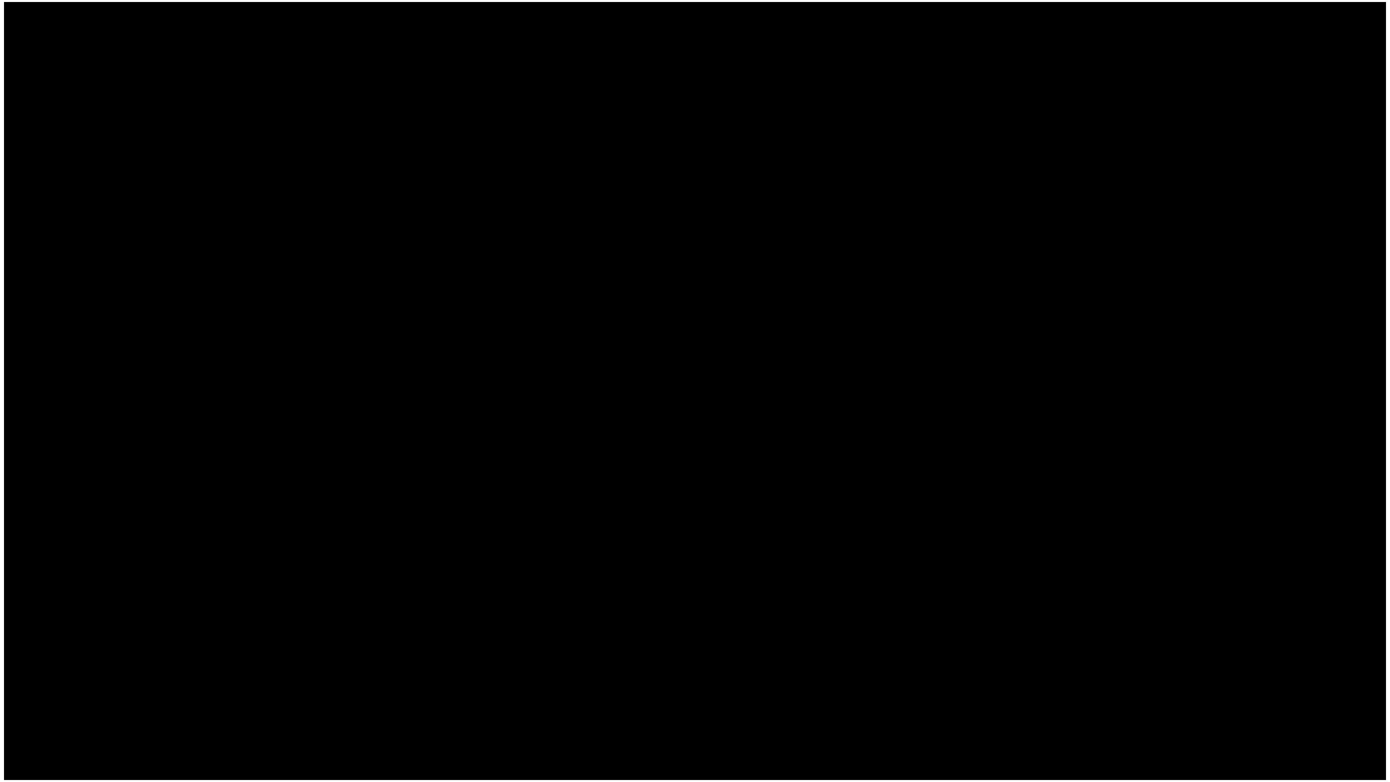
Direct Marketing

- 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

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

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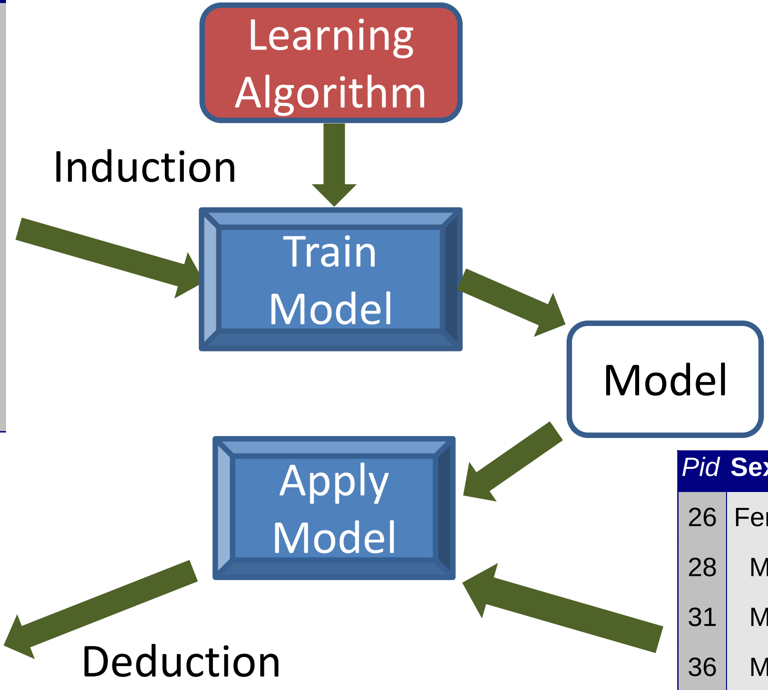
Decision Tree Application

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



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

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
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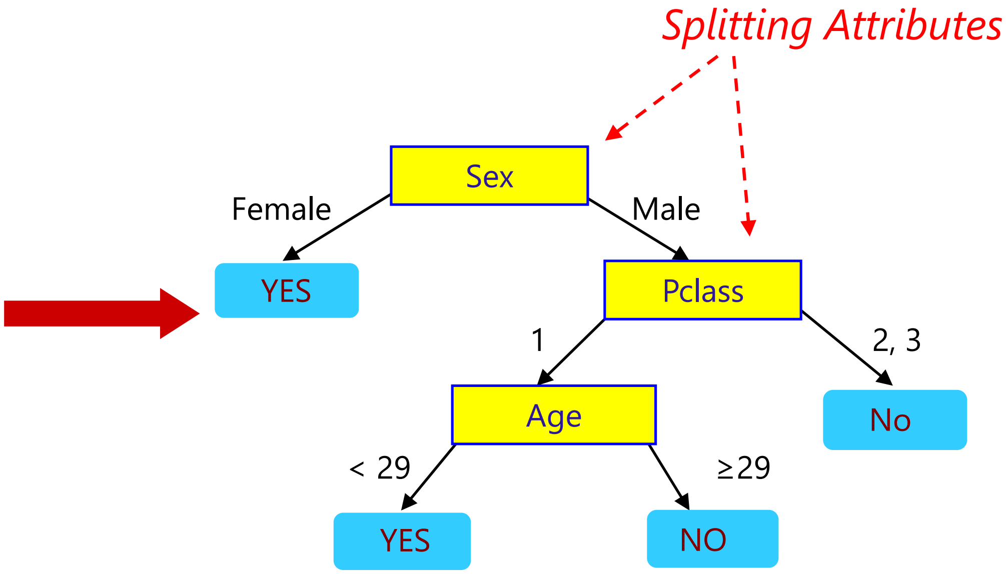
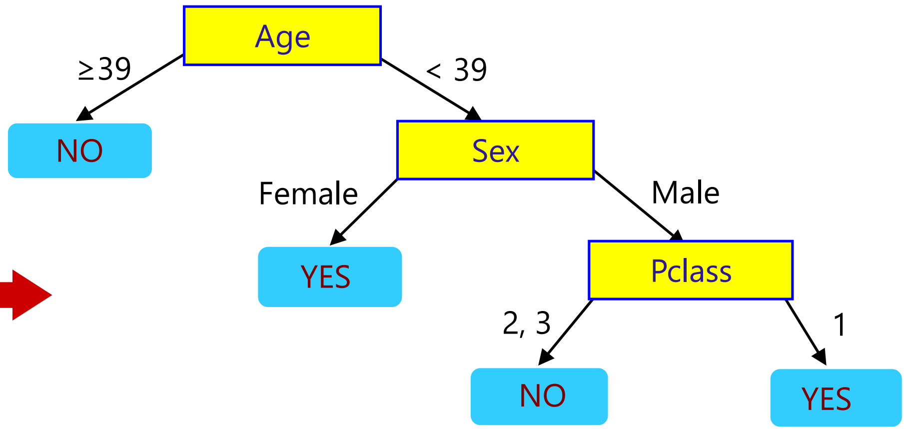


A Different Decision Tree

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**
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!

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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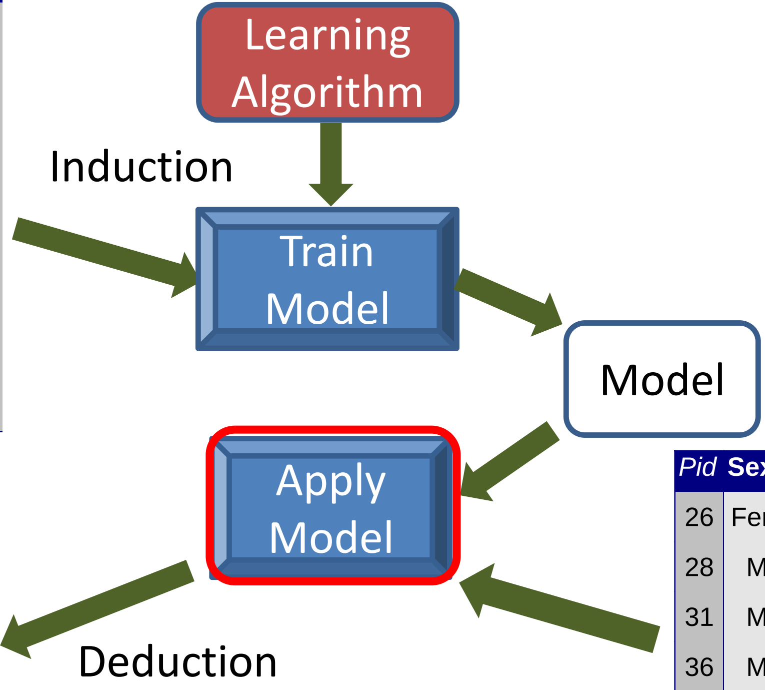
54	Female	29	2	Yes

Training Set



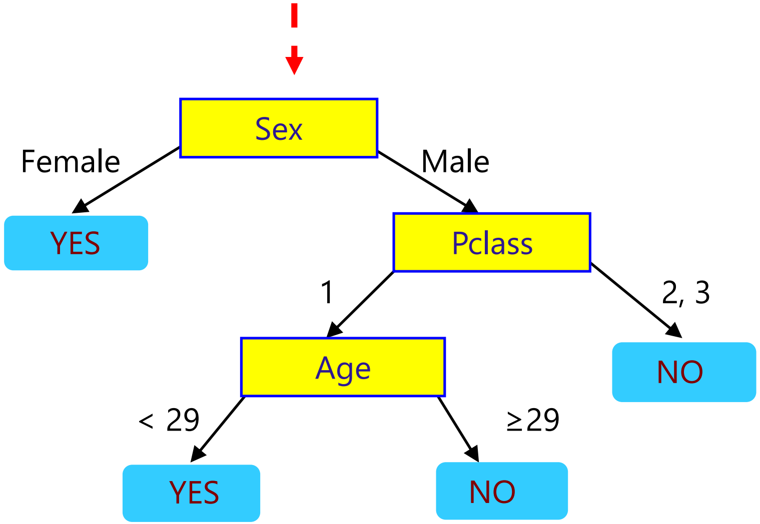
Test Set

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

Apply Model to Test Data

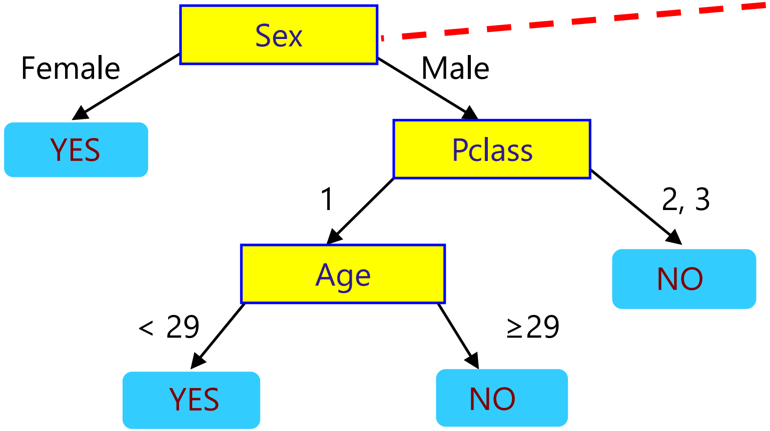
Start from the root of tree.



Test Data

Sex	Age	Pclass	Survived
Male	32	2	?

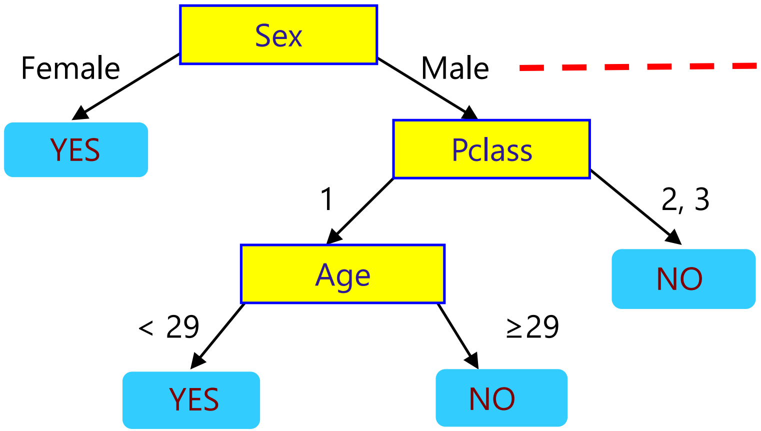
Apply Model to Test Data



Test Data

Sex	Age	Pclass	Survived
Male	32	2	?

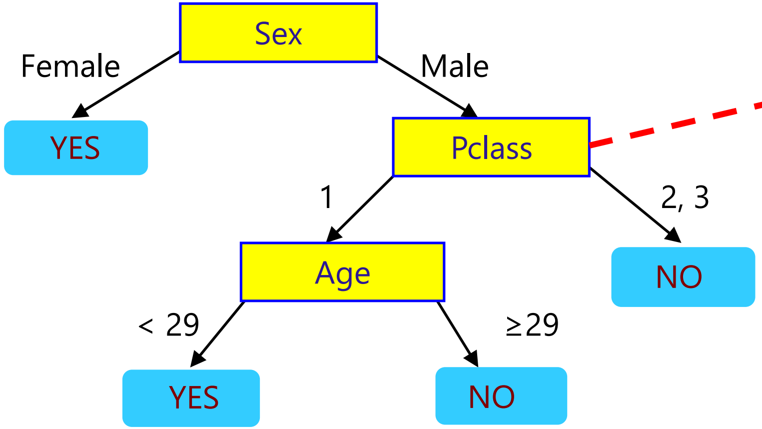
Apply Model to Test Data



Test Data

Sex	Age	Pclass	Survived
Male	32	2	?

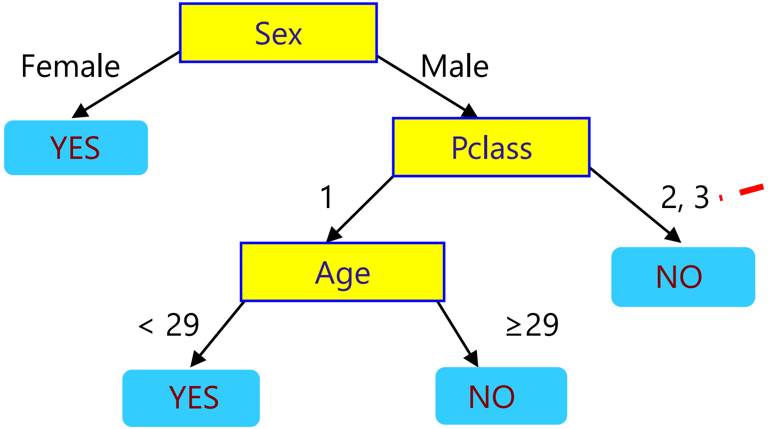
Apply Model to Test Data



Test Data

Sex	Age	Pclass	Survived
Male	32	2	?

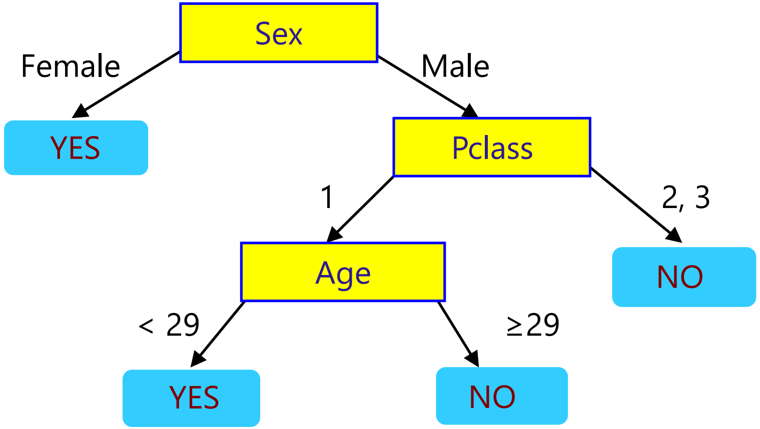
Apply Model to Test Data



Test Data

Sex	Age	Pclass	Survived
Male	32	2	?

Apply Model to Test Data



Test Data

Sex	Age	Pclass	Survived
Male	32	2	?

Survived = “No”

Decision Tree Application

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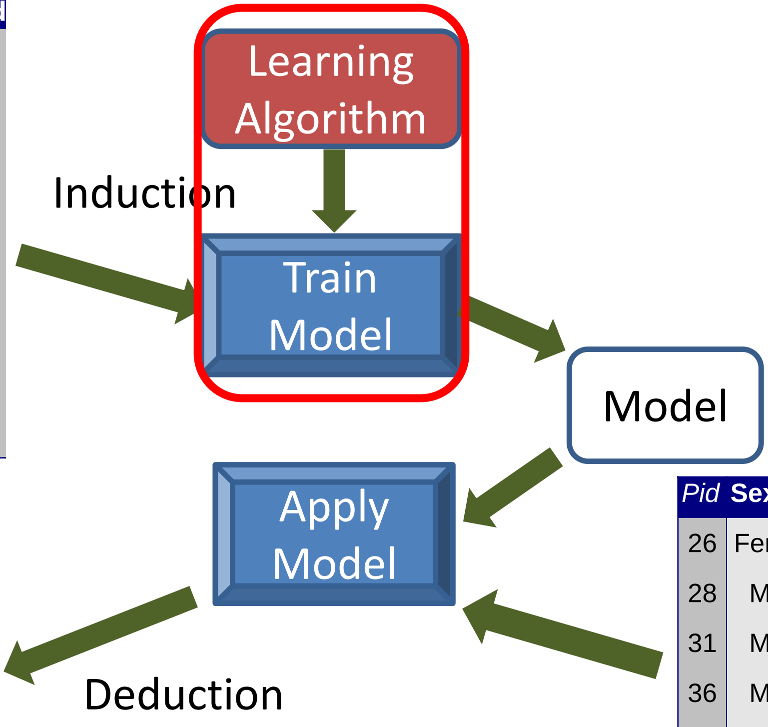

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26	Female	38	3	?
28	Male	19	1	?
31	Male	40	1	?
36	Male	42	1	?
71	Male	32	2	?

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

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

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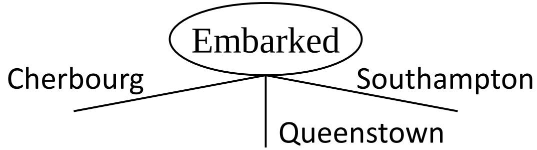
How to Specify Test Condition?

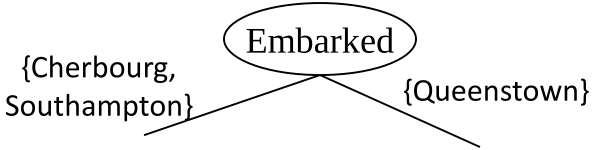
- Attribute types
  - Nominal
  - Ordinal
  - Continuous
- Order of split
  - 2-way split
  - Multi-way split

Splitting: Nominal Attributes

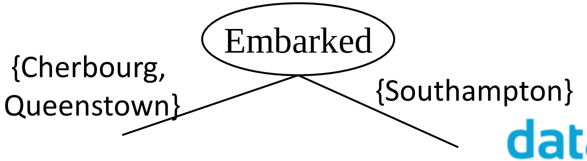
- Multi-way split: As many partitions as distinct values.



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



OR



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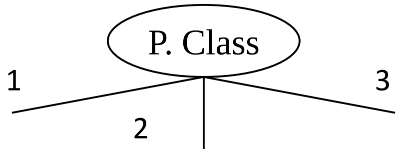
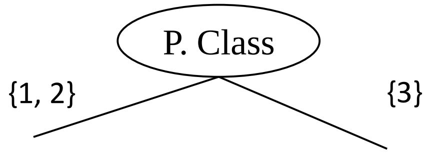
Splitting: Ordinal Attributes

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



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



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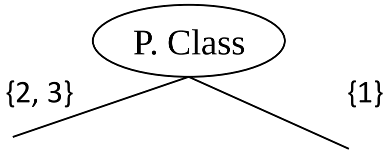
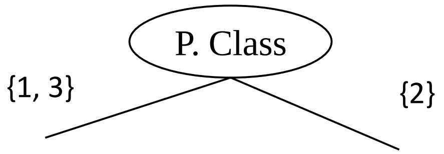


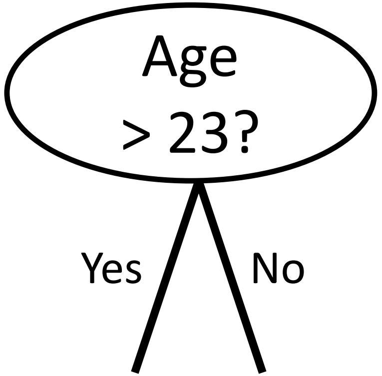
- What about this split?



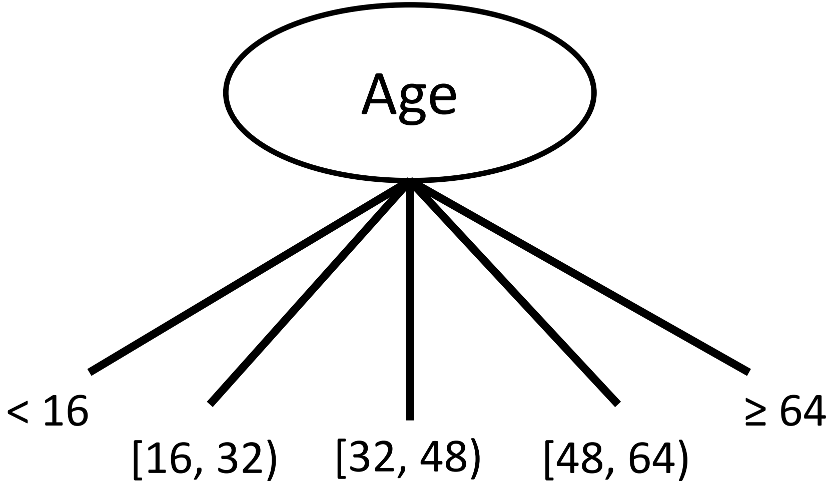
Splitting: Continuous Attributes

- 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

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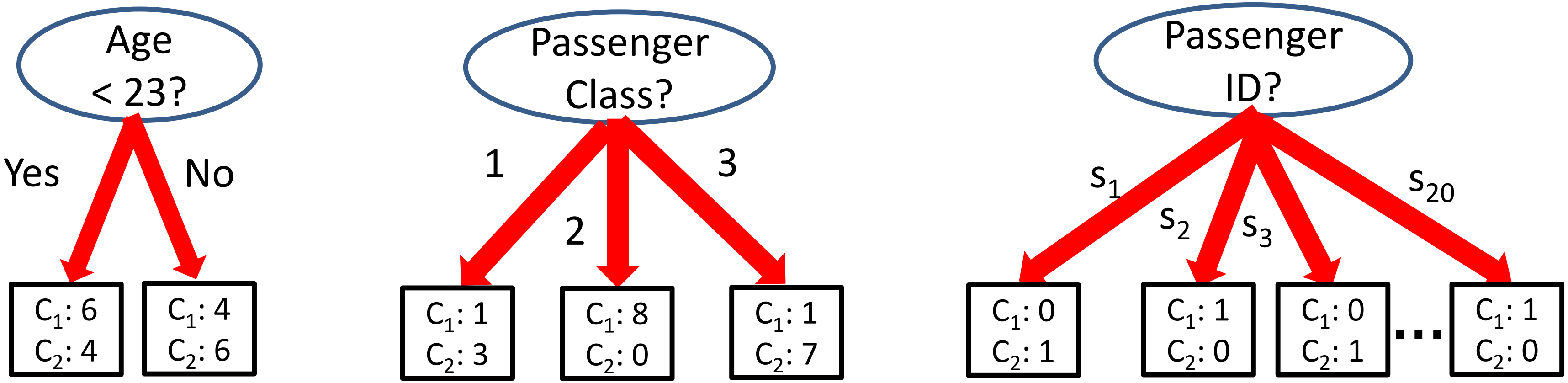
Tree Induction

- 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?

What is The Best Split?

C_1: Dead
C_2: Survived

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 C_2: 5	C_1: 9 C_2: 1
Non-homogeneous	Homogeneous
High degree of impurity	Low degree of impurity

Measures of Node Impurity

- Gini Index
- Entropy
- Misclassification error

C_1: Dead
C_2: Survived

Impurity Measure: GINI

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

- 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	

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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

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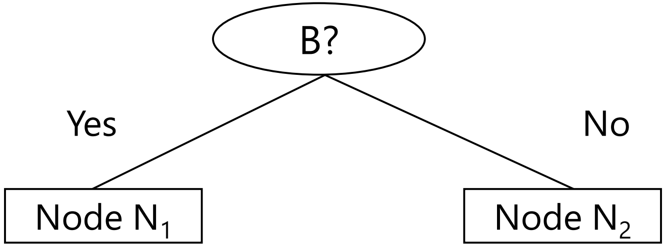
C_1: Dead
C_2: Survived

Impurity Measure: GINI

- 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**

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

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

C_1	**1**
C_2	**5**

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

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

C_1	**2**
C_2	**4**

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

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

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

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

- 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

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

C_1	**0**
C_2	**6**

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

Error = 1 – max (0, 1) = 1 – 1 = 0

C_1	**1**
C_2	**5**

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

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

Error = 1 – max (2/6, 4/6) = 1 – 4/6 = 1/3

Tree Induction

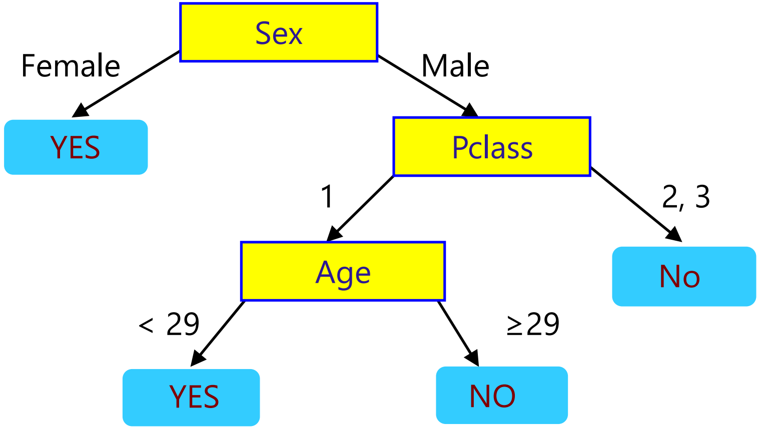
- Greedy strategy
  - Split based attribute test that optimizes a criterion
- Issues
  - How to split the records
    - What attribute test criterion?
    - How to determine the best split?
    - **When do we stop?**

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



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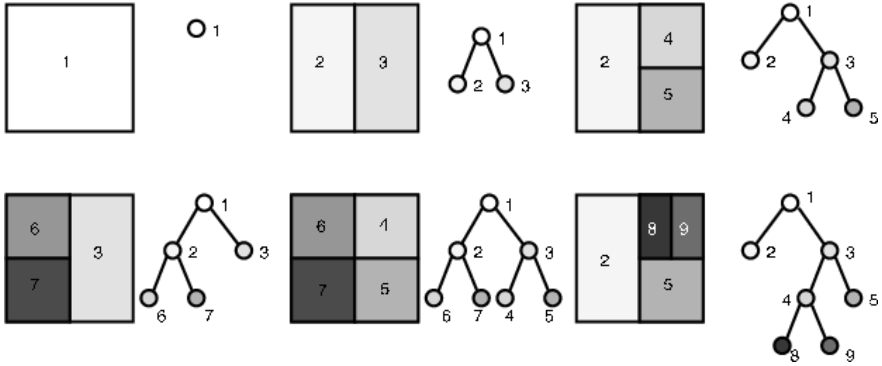
Decision Trees - CONS

- 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**