Predictive Analytics, Classification, and Decision Trees

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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
- Love:
  - Match.com: Predict potential matches
  - OkCupid: Which message content is most likely to elicit a response
- Pregnancy: Target predicts customer pregnancy
- Divorce and infidelity: University and clinical researchers can predict this as well!

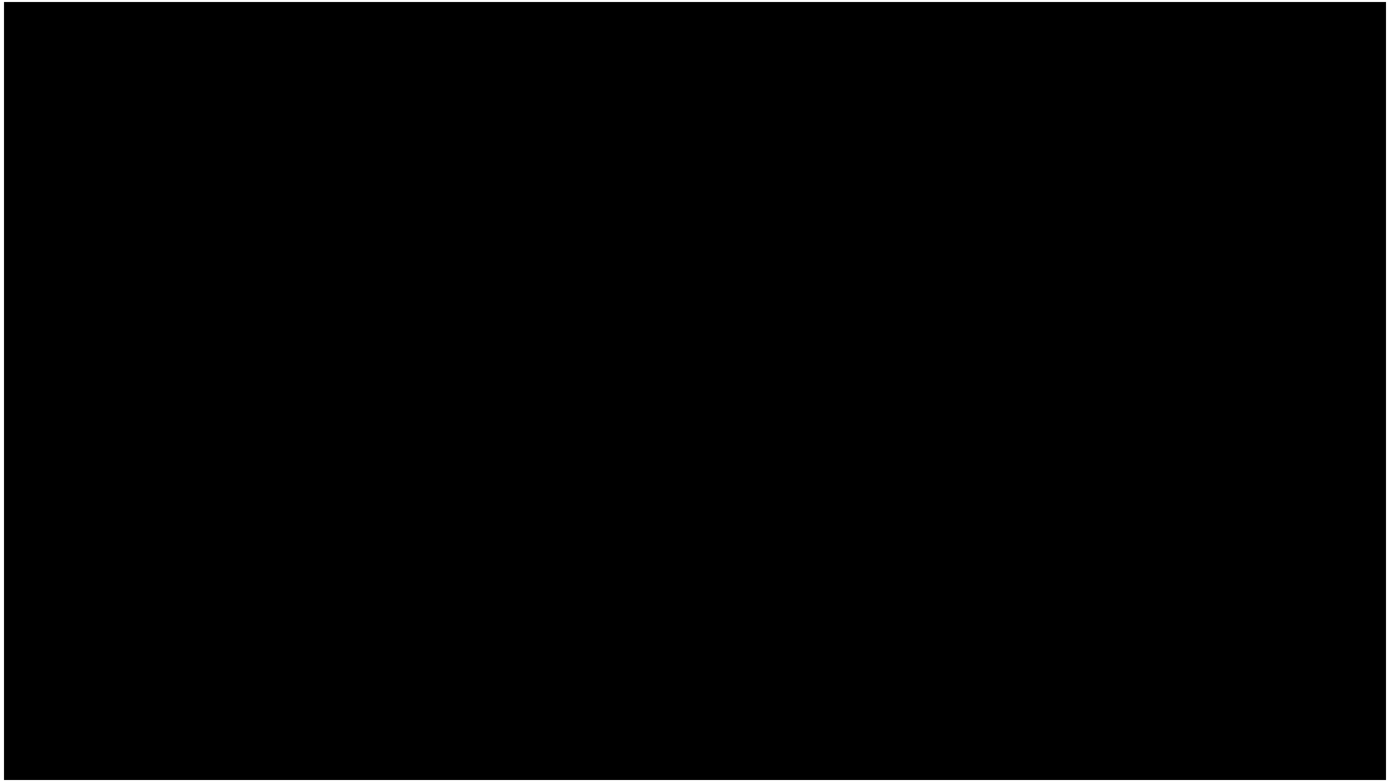
Direct Marketing

- Cox Communication: Tripled direct mail responses by predicting propensity to buy
- Harrah's Las Vegas: The casino 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: Optus (Australia), Sprint, Telenor(Norway), 2degrees (New Zealand)
- Amazon: 35% sales come from product recommendation

Even In Law Enforcement….



Quick Review

- Supervised Learning
- Unsupervised Learning

Unsupervised Learning

- Unsupervised learning:
  - Target values unknown
  - Training data unlabeled
  - Goal: Discover information hidden in the data
  - May precede supervised learning

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 classification**
- Decision Tree Classifier
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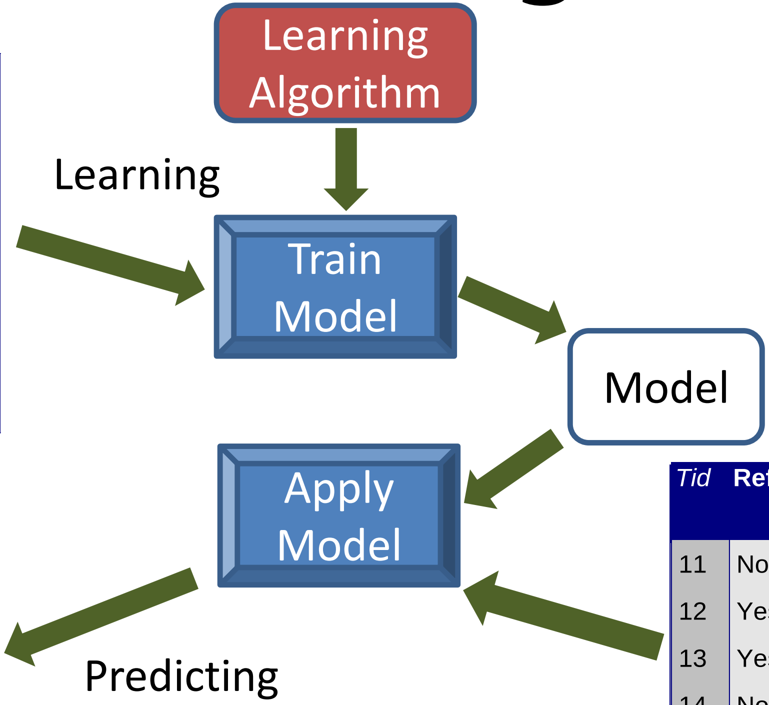
Supervised Learning

Tid	Refund	Marital Status	Taxable Income	Cheat
1	Yes	Single	125K	No
2	No	Married	100K	No
3	No	Single	70K	No
4	Yes	Married	120K	No
5	No	Divorced	95K	Yes
6	No	Married	60K	No
7	Yes	Divorced	220K	No
8	No	Single	85K	Yes
9	No	Married	75K	No
10	No	Single	90K	Yes

Training Set



Test Set

Tid	Refund	Marital Status	Taxable Income	Cheat
11	No	Married	125K	?
12	Yes	Divorced	100K	?
13	Yes	Single	70K	?
14	No	Married	120K	?
15	No	Single	95K	?

Tid	Cheat
11	No
12	Yes
13	No
14	No
15	Yes

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

Session Outline

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

Decision Tree Classification

categorical categorical continuous class

Tid	**Refund**	**Marital Status**	**Taxable Income**	**Cheat**
1	Yes	Single	125K	**No**
2	No	Married	100K	**No**
3	No	Single	70K	**No**
4	Yes	Married	120K	**No**
5	No	Divorced	95K	**Yes**
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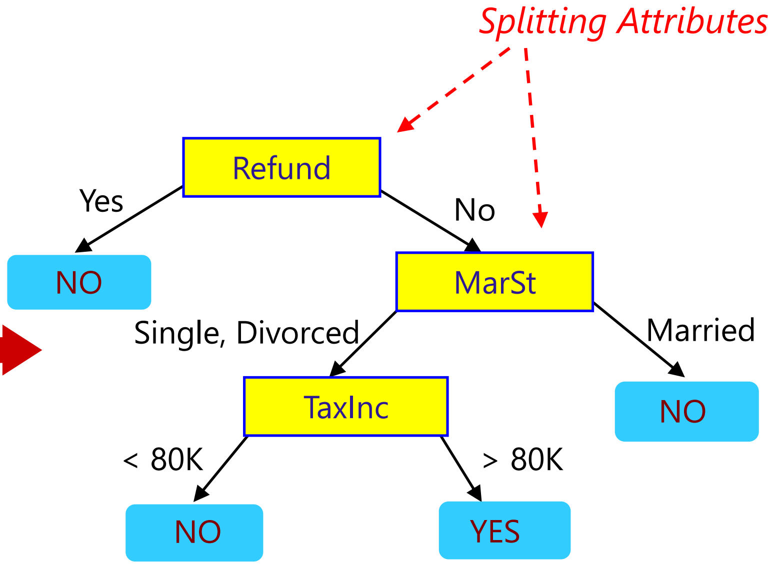
7	Yes	Divorced	220K	**No**
8	No	Single	85K	**Yes**
9	No	Married	75K	**No**
10	No	Single	90K	**Yes**

Training Data



Model: Decision Tree

A Different Decision Tree

categorical categorical continuous class

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1	Yes	Single	125K	No
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4	Yes	Married	120K	No
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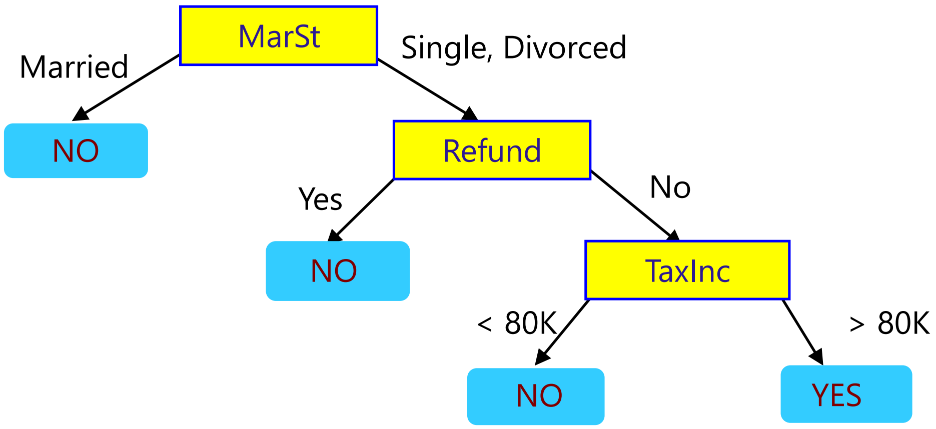

There could be more than one tree that fits the same data!

Decision Tree Application

Tid	Refund	Marital Status	Taxable Income	Cheat
1	Yes	Single	125K	No
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Training Set

Learning Algorithm

Induction

Train Model

Model

Apply Model

Deduction

Test Set

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11	No	Married	125K	?
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13	Yes	Single	70K	?
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Tid	Cheat
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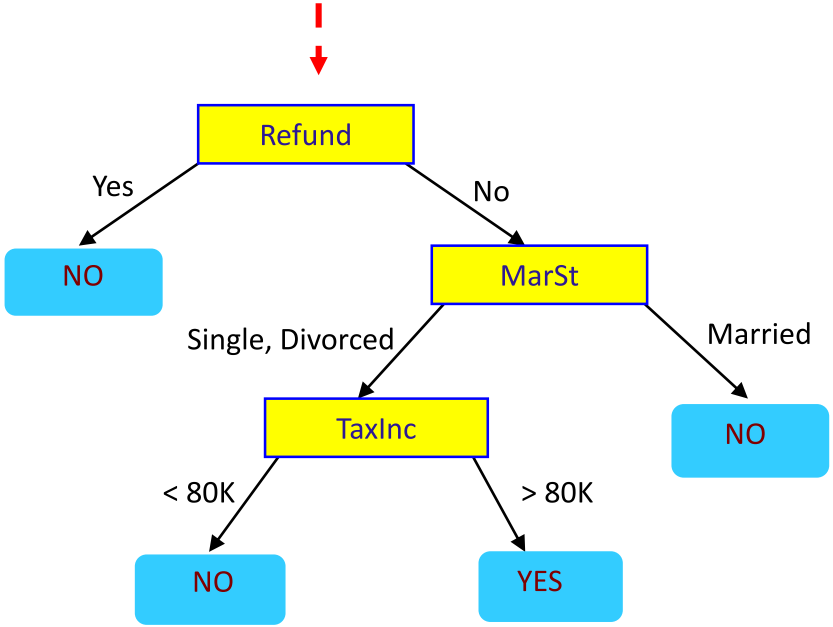
Apply Model to Test Data

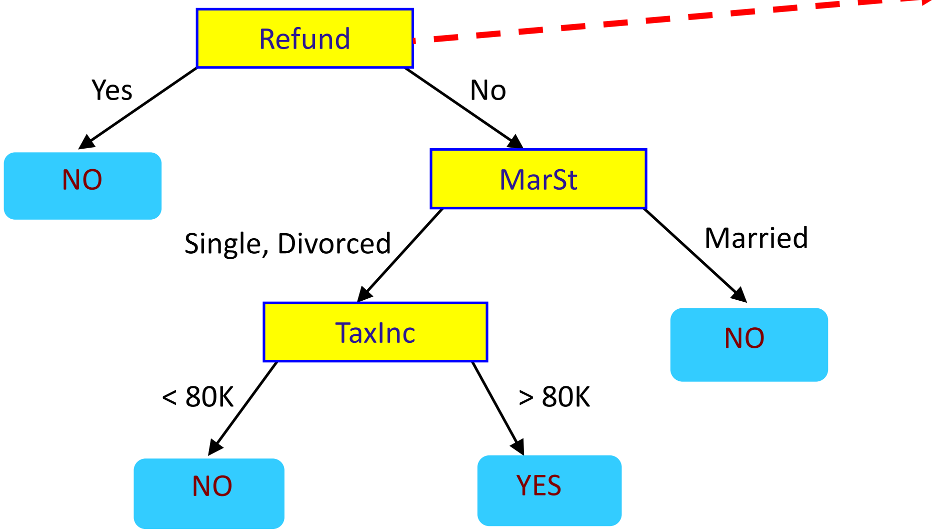
Start from the root of tree.



Test Data

Refund	Marital Status	Taxable Income	Cheat
No	Married	80K	?

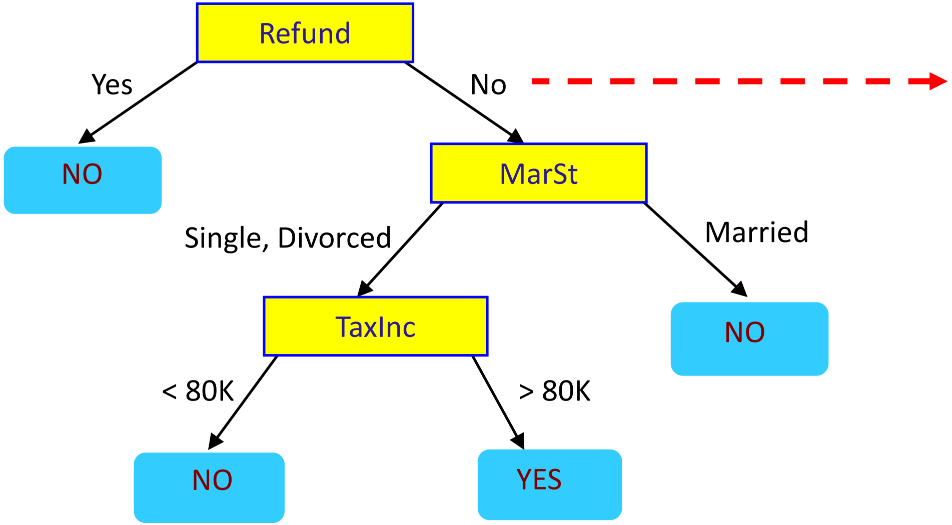
Apply Model to Test Data



Test Data

Refund	Marital Status	Taxable Income	Cheat
No	Married	80K	?

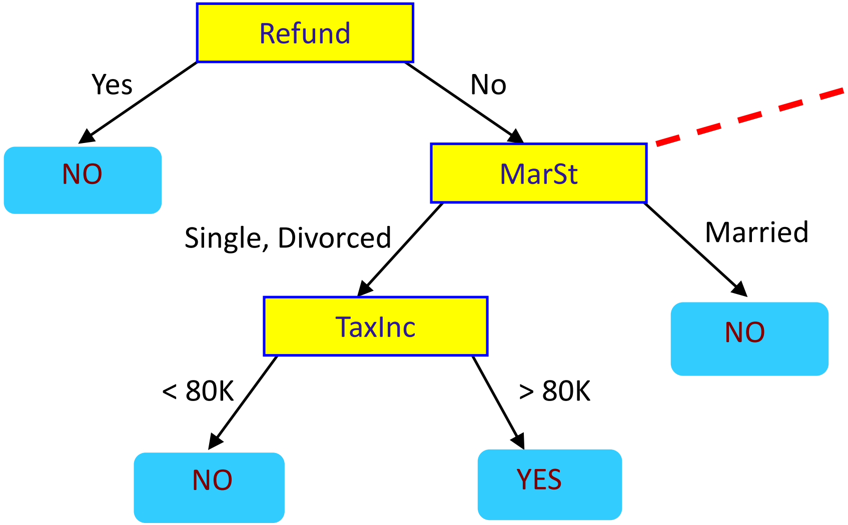
Apply Model to Test Data



Test Data

Refund	Marital Status	Taxable Income	Cheat
No	Married	80K	?

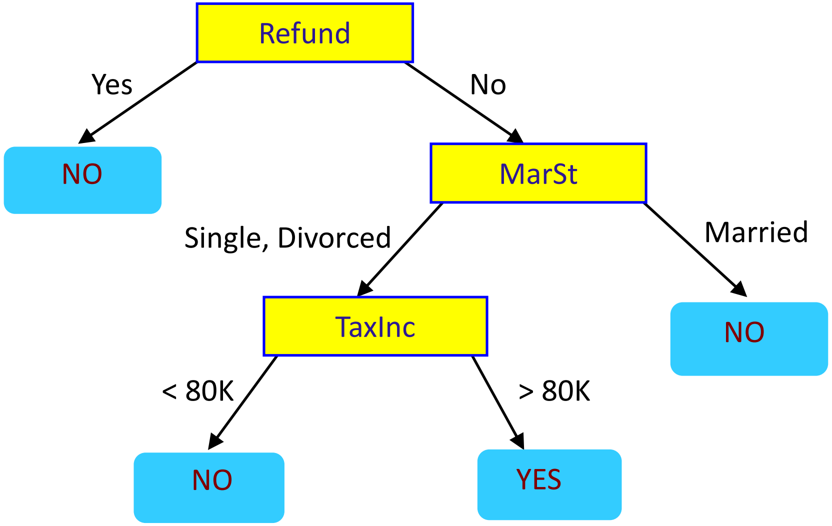
Apply Model to Test Data



Test Data

Refund	Marital Status	Taxable Income	Cheat
No	Married	80K	?

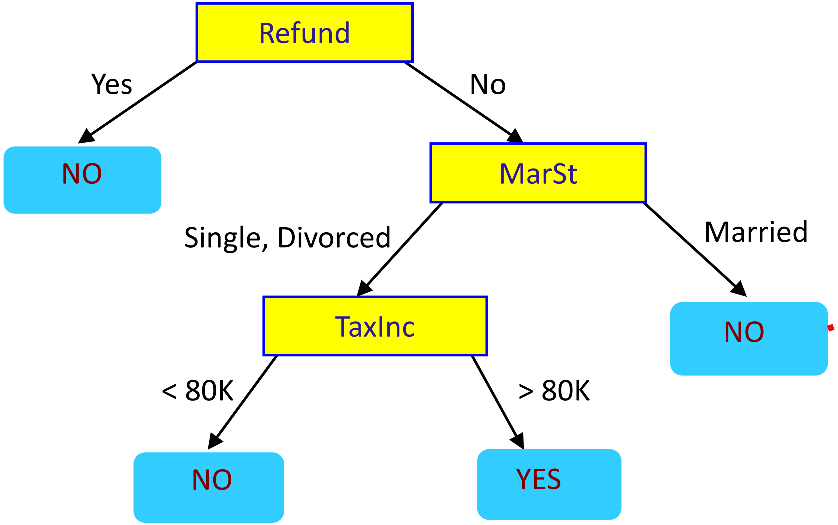
Apply Model to Test Data



Test Data

Refund	Marital Status	Taxable Income	Cheat
No	Married	80K	?

Apply Model to Test Data



Test Data

Refund	Marital Status	Taxable Income	Cheat
No	Married	80K	?

Cheat = "No"

Decision Tree Training

Tid	Refund	Marital Status	Taxable Income	Cheat
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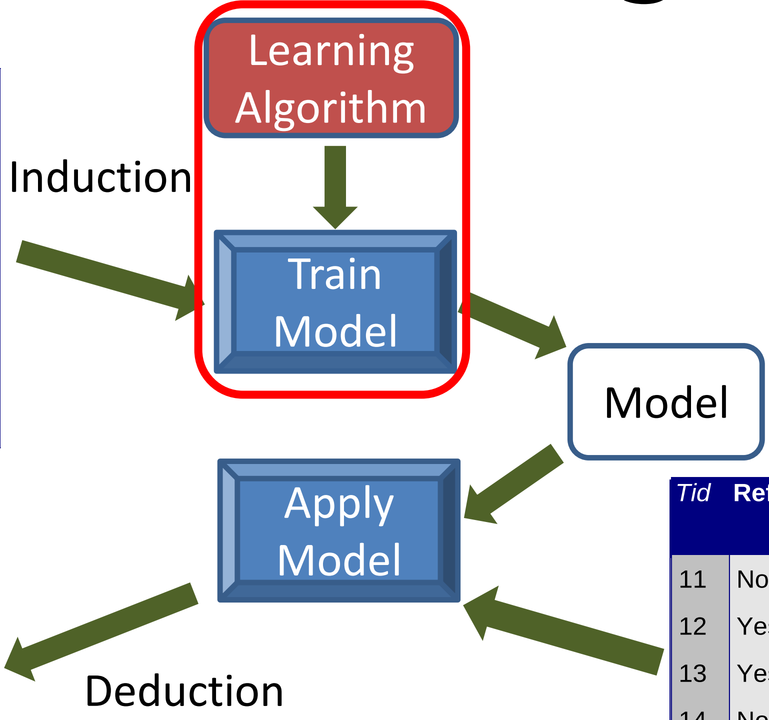
Training Set



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14	No
15	Yes

How Do We Get A Tree?

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

Tree Induction

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

Tree Induction

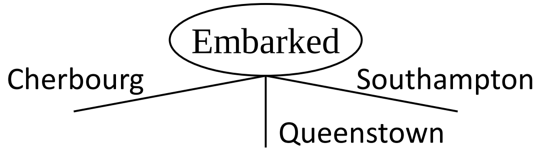
- Greedy strategy
  - Split based attribute test that optimizes a criterion
- Issues
  - How to split the records
    - **What attribute test criterion?**
    - How to determine the best split?
    - When do we stop?

How to Specify Test Condition?

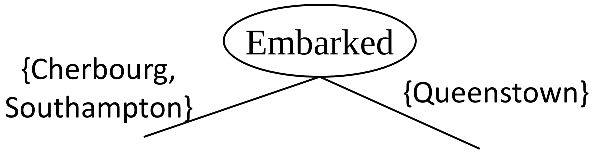
- Attribute types
  - Nominal
  - Ordinal
  - Continuous
- Order of split
  - 2-way split
  - Multi-way split

Splitting: Nominal Attributes

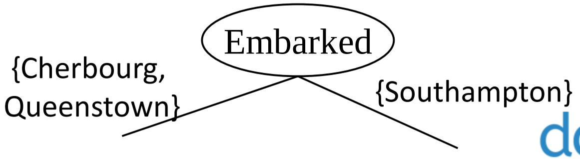
- Multi-way split: As many partitions as distinct values.



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



OR



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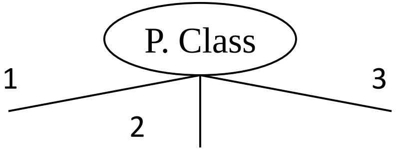
Splitting: Ordinal Attributes

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



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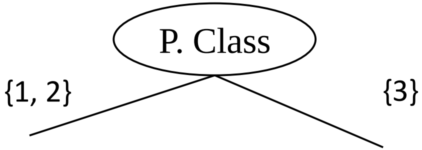

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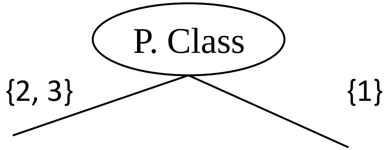
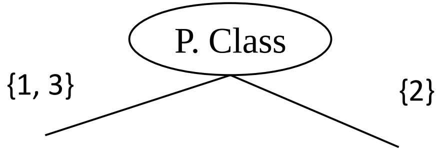


- What about this split?



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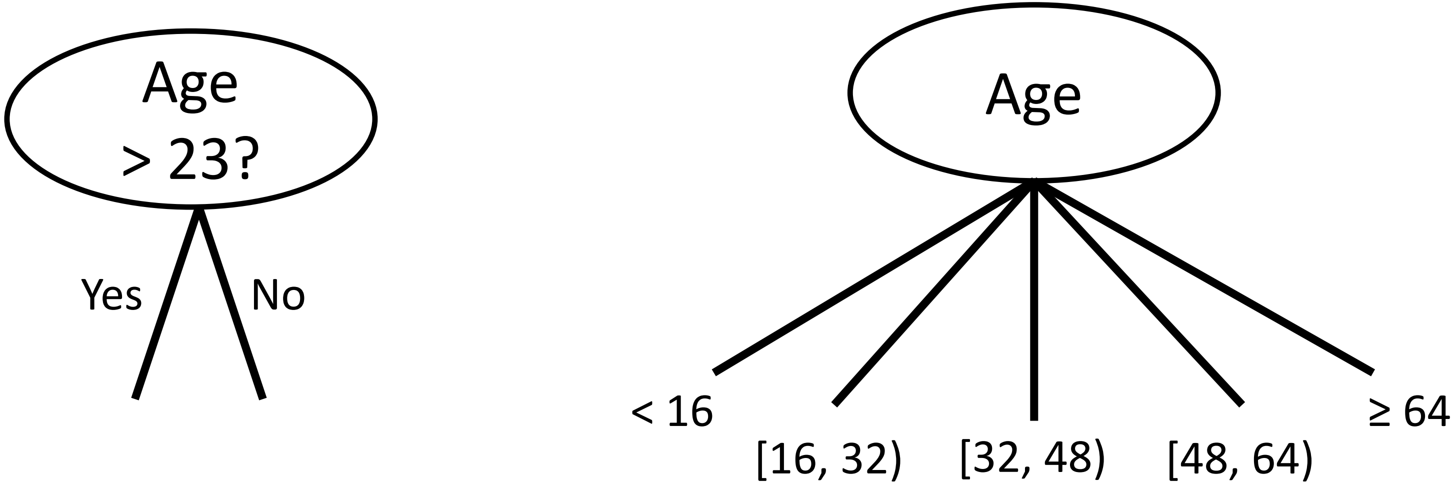
Splitting: Continuous Attributes

- 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
      - Can be more computationally intensive

Splitting on Continuous Attributes



Binary Split

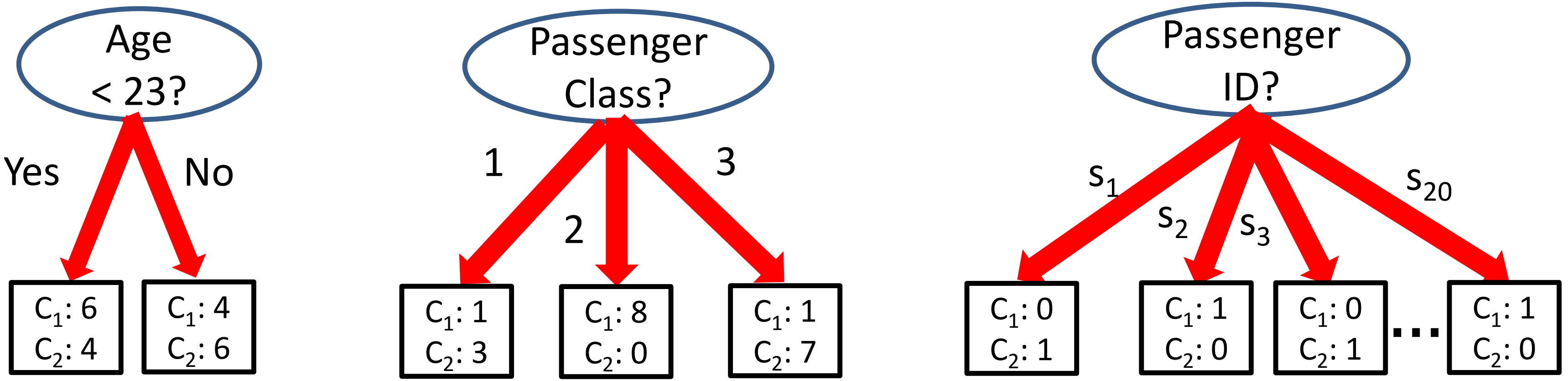
Multi-way Split

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?

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**:

C0: 5 C1: 5	C0: 9 C1: 1
Non-homogeneous	Homogeneous
High degree of impurity	Low degree of impurity

Measures of Node Impurity

- Gini Index
- Entropy
- Misclassification error

Impurity Measure: GINI

- Gini Index for a given node t :

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

  - 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

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

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,

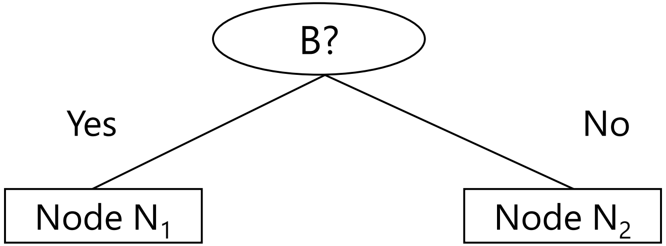
n_i = number of records at child i,

n = number of records at node p

Impurity Measure: Computing GINI Index

- Splits into two partitions
- Effect of Weighing partitions:
  - 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)
$= 1 – (1/6)^2 – (4/6)^2$
$= 0.320$

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

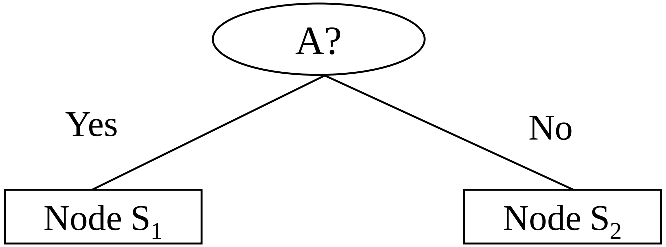
Gini(B?, Parent)
$= 7/12 * 0.408 +$
$5/12 * 0.320$
$= 0.371$

A or B?

Parent

C_1	$\mathbf{N_{0,1}}$
C_2	$\mathbf{N_{0,2}}$

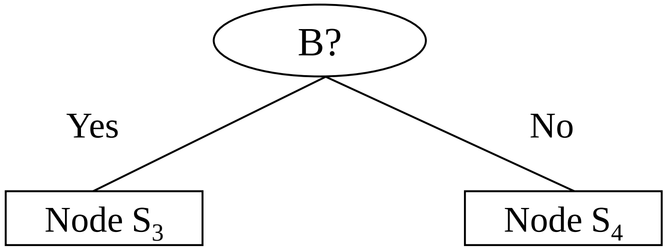
M_0



C_1	$\mathbf{N_{1,1}}$
C_2	$\mathbf{N_{1,2}}$

C_1	$\mathbf{N_{2,1}}$
C_2	$\mathbf{N_{2,2}}$

$\underbrace{M_1 \qquad M_2}_{M_{12}}$



C_1	$\mathbf{N_{3,1}}$
C_2	$\mathbf{N_{3,2}}$

C_1	$\mathbf{N_{4,1}}$
C_2	$\mathbf{N_{4,2}}$

$\underbrace{M_3 \qquad M_4}_{M_{34}}$

Gain

$M_0 - M_{12}$ vs $M_0 - M_{34}$

Impurity Measure: Entropy

- Entropy at a given node t:

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

  - 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

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

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) $\log_2$ (1/6) = 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

- Information Gain:

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

  - 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

- Classification error at a node t :

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

  - 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

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

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

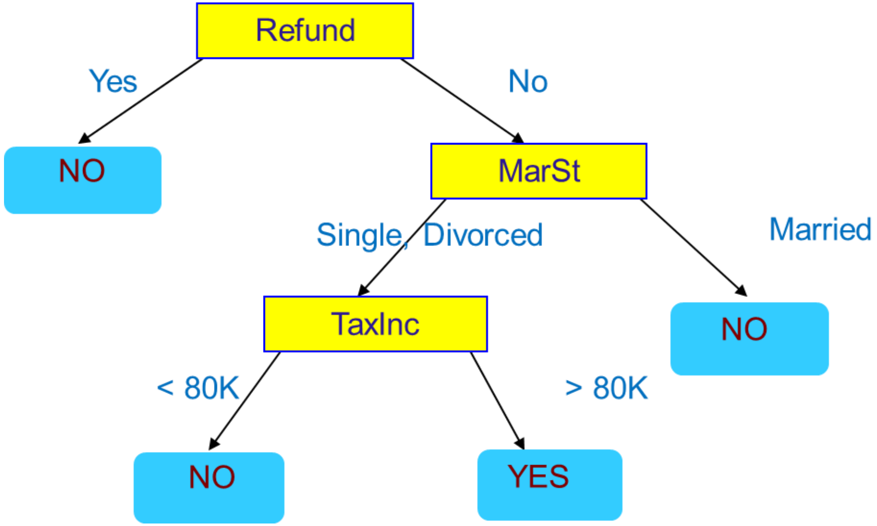
- Greedy strategy
  - Split based attribute test that optimizes a criterion
- Issues
  - How to split the records
    - What attribute test criterion?
    - How to determine the best split?
    - **When do we stop?**

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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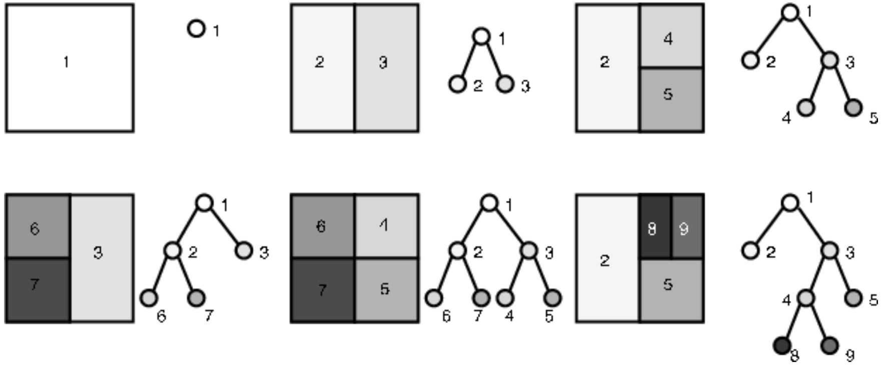
Decision Trees - CONS

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



QUESTIONS

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