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

Session Outline

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

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!

datasciencedojo
unleash the data scientist in you

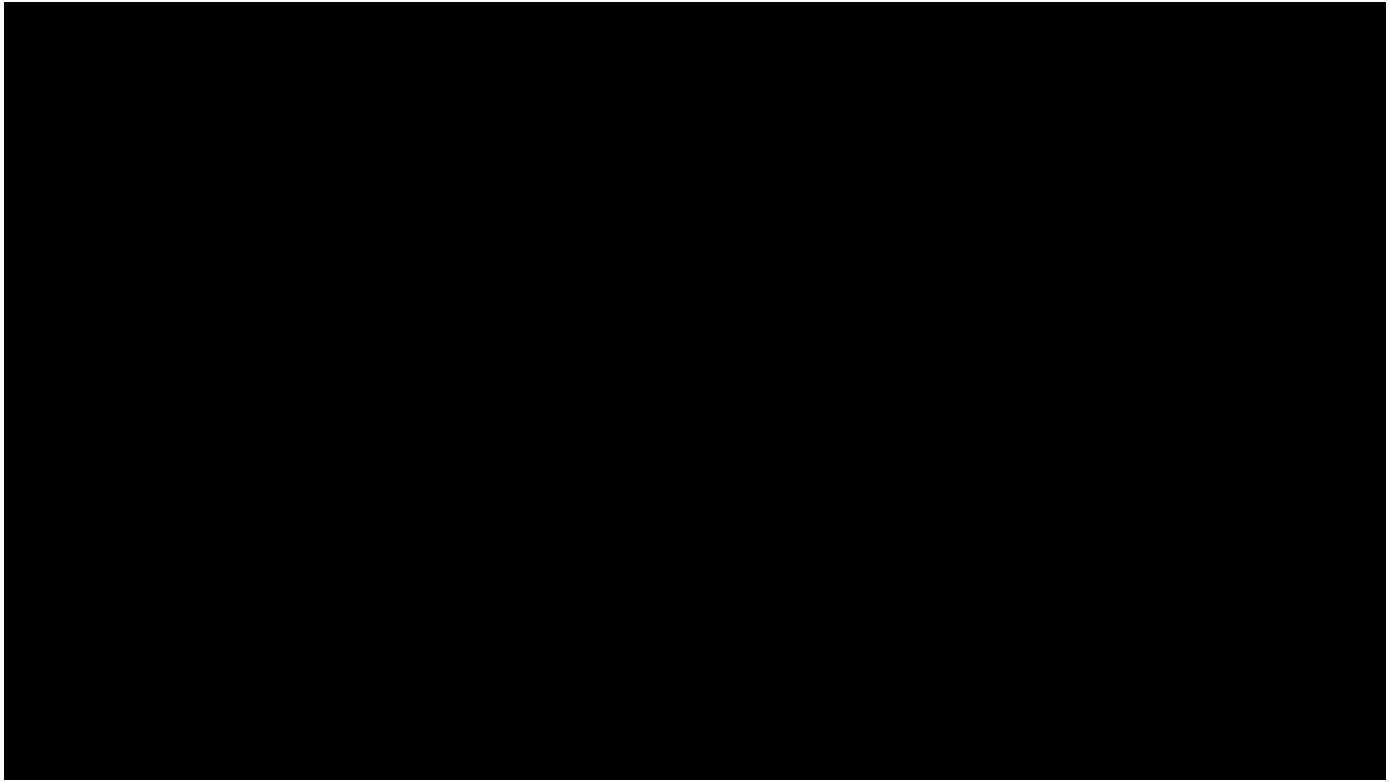
Direct Marketing

- 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….



Machine Learning Branches

- Supervised Learning
- Unsupervised Learning

Supervised Learning

- Supervised learning:
  - Target values known
  - Training data labeled with target values
  - Train model to map data object to target value

Unsupervised Learning

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

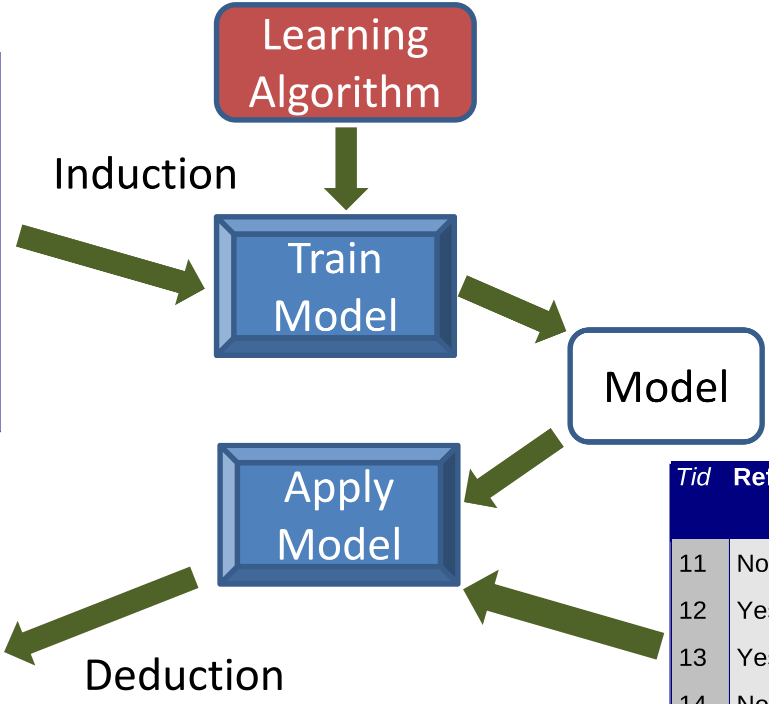
Session Outline

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

The Classification Task

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

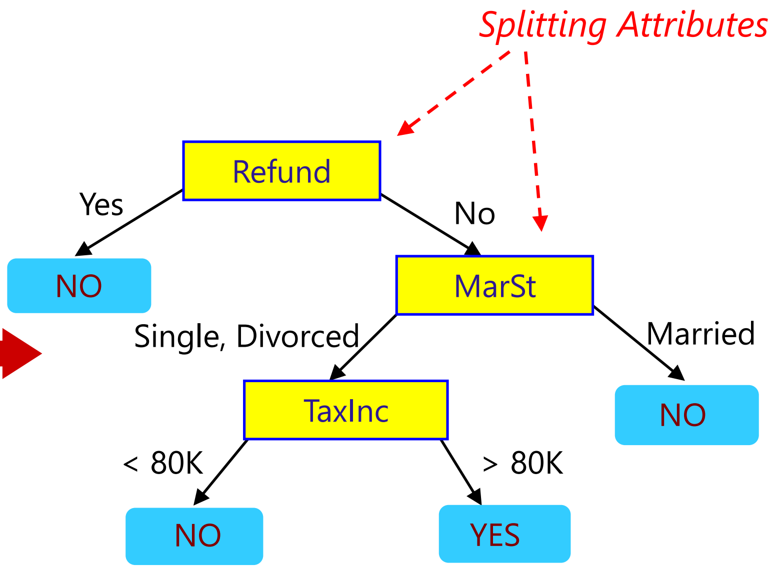
- Introduction to predictive analytics
- Introduction to classification
- **Decision Tree Classifier**
- Hands-on Lab: Building a decision tree classifier using R

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
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 Data

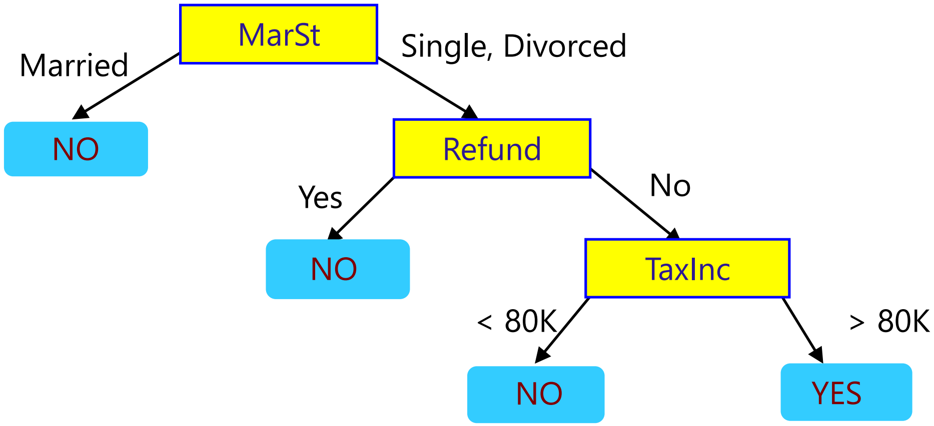


Model: Decision Tree

A Different Decision Tree

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
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

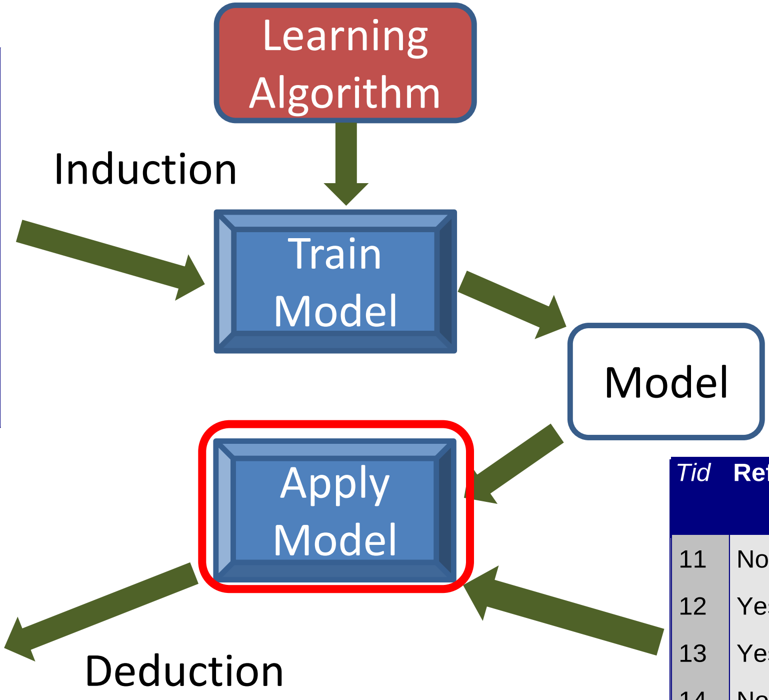


There could be more than one tree that fits the same data!

Decision Tree Application

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

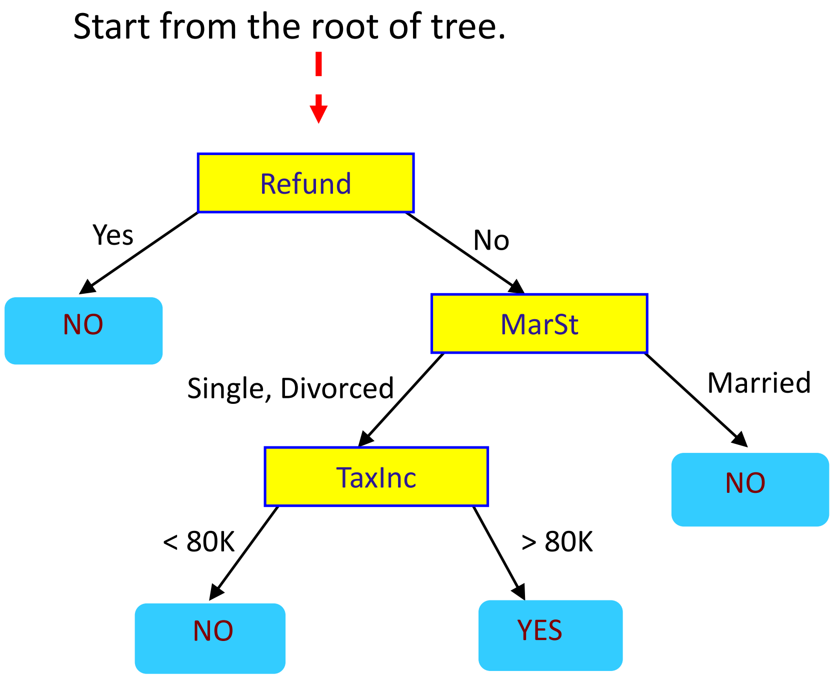


Test Set

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

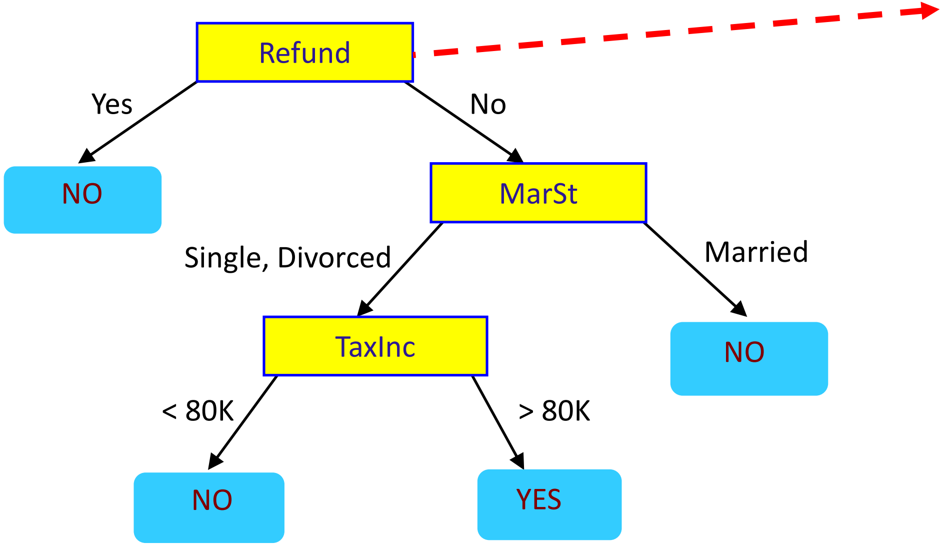
Apply Model to Test Data



Test Data

Refund	Marital Status	Taxable Income	Cheat
No	Married	80K	?

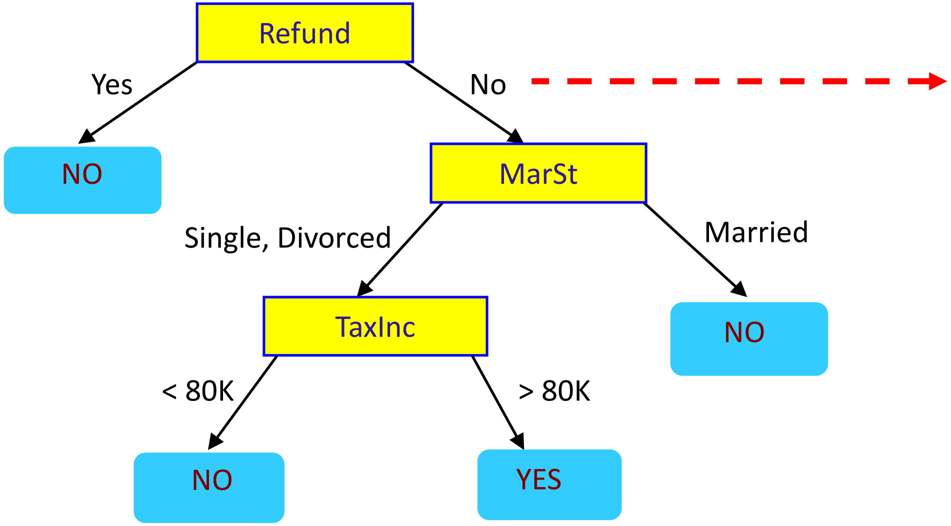
Apply Model to Test Data



Test Data

Refund	Marital Status	Taxable Income	Cheat
No	Married	80K	?

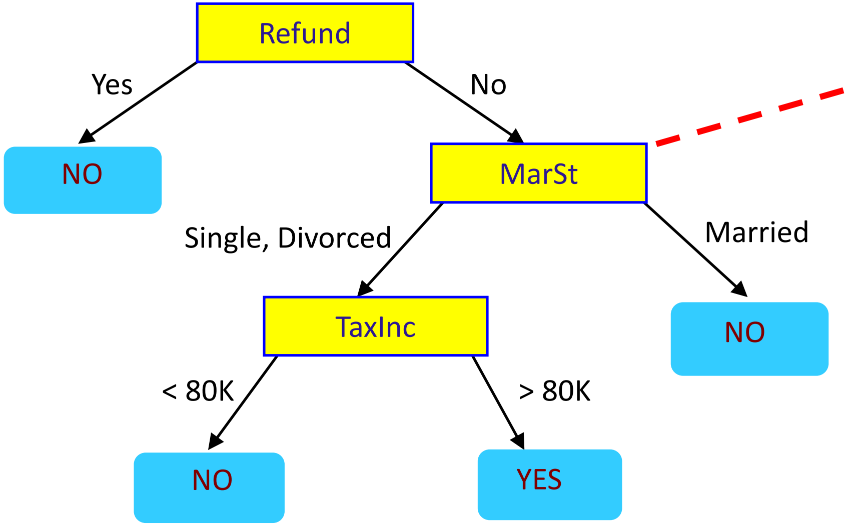
Apply Model to Test Data



Test Data

Refund	Marital Status	Taxable Income	Cheat
No	Married	80K	?

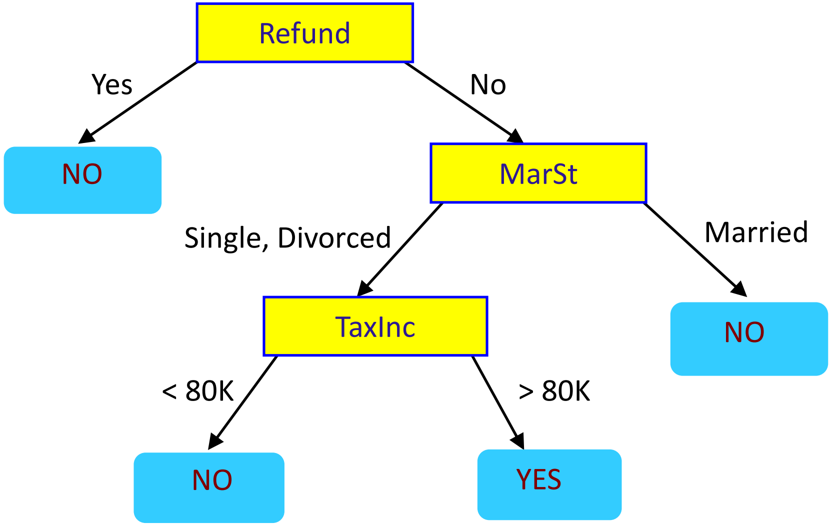
Apply Model to Test Data



Test Data

Refund	Marital Status	Taxable Income	Cheat
No	Married	80K	?

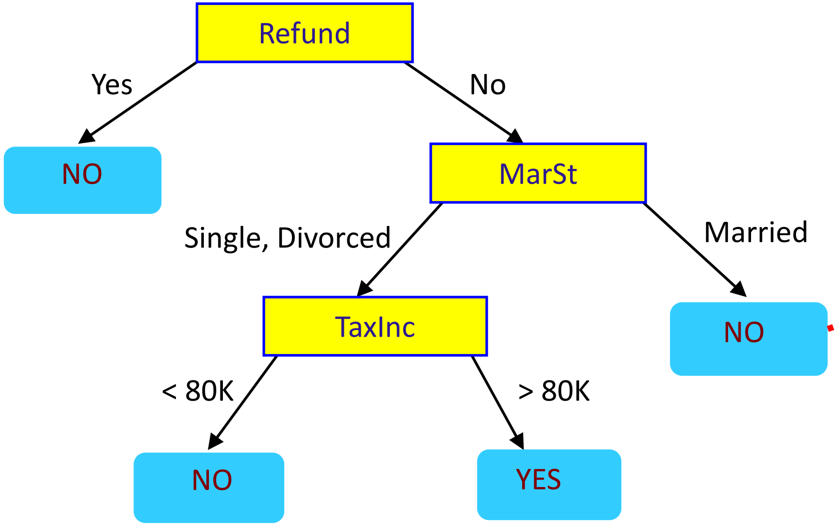
Apply Model to Test Data



Test Data

Refund	Marital Status	Taxable Income	Cheat
No	Married	80K	?

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
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

Induction

Learning Algorithm

Train Model

Model

Apply Model

Deduction

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

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

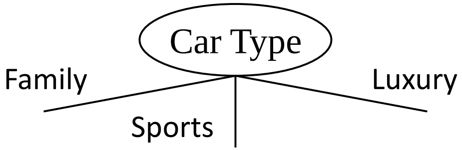
- Greedy strategy
  - Split based attribute test that optimizes a criterion
- Issues
  - How to split the records
    - **What attribute test criterion?**
    - How to determine the best split?
    - When do we stop?

How to Specify Test Condition?

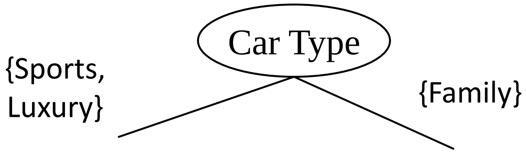
- Attribute types
  - Nominal
  - Ordinal
  - Continuous
- Order of split
  - 2-way split
  - Multi-way split

Splitting: Nominal Attributes

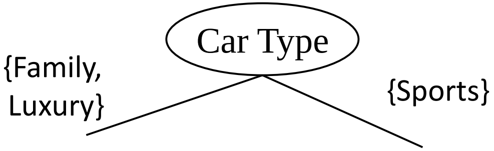
- Multi-way split: As many partitions as distinct values.



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

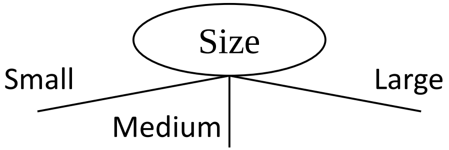


OR

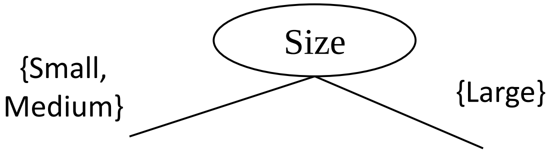


Splitting: Ordinal Attributes

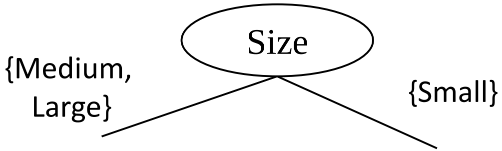
- Multi-way split: As many partitions as distinct values.



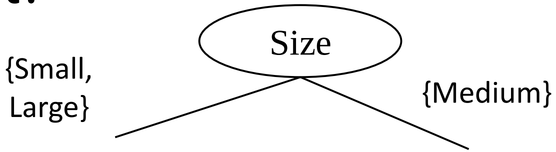
- Binary split: Divides values into two subsets. Need to find optimal partitioning.



OR



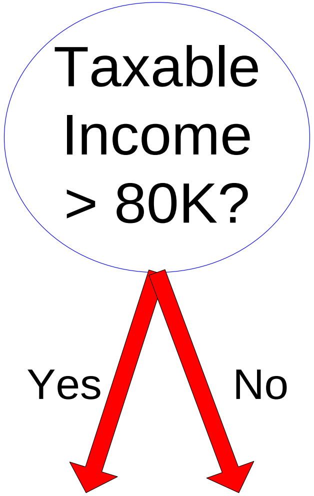
- What about this split?



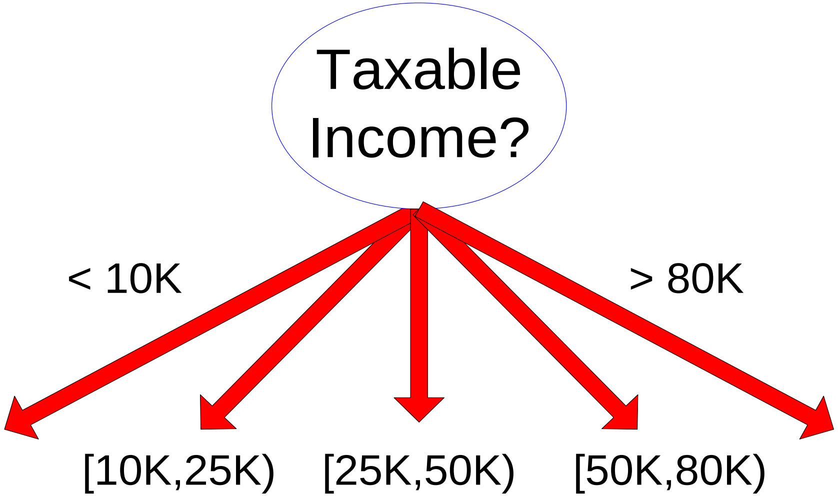
Splitting: Continuous Attributes

- 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.
- Binary Decision: $(A < v)$ or $(A \geq v)$
  - Consider all possible splits and finds the best cut value
  - Can be more computationally intensive

Splitting on Continuous Attributes



(i) Binary split



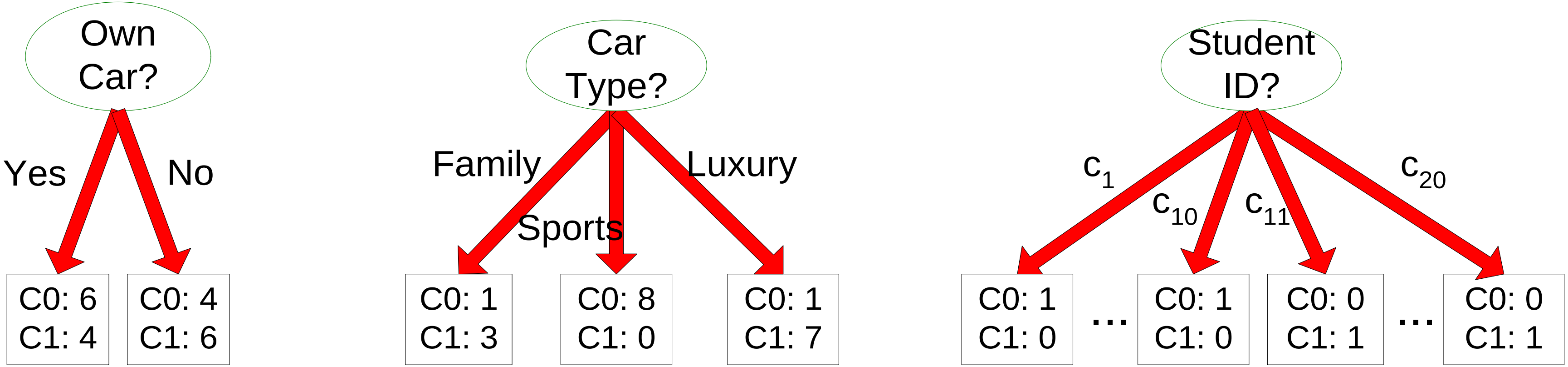
(ii) Multi-way split

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 0, 10 records of class 1



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:

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

where,

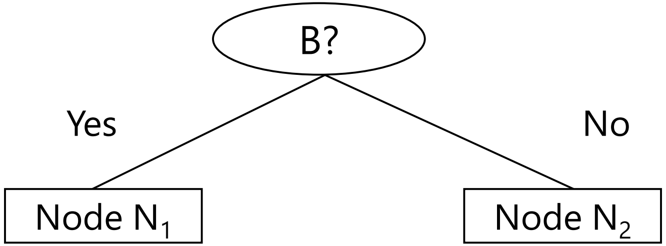
n_i = number of records at child i,

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)
$= 1 - (5/6)^2 - (2/6)^2$
$= 0.194$

Gini(N_2)
$= 1 - (1/6)^2 - (4/6)^2$
$= 0.528$

	N_1	N_2
C_1	**5**	**1**
C_2	**2**	**4**
Gini=0.333		

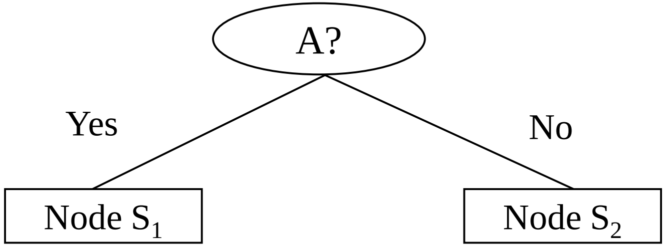
Gini(N_1 + N_2)
$= 7/12 * 0.194 +$
$5/12 * 0.528$
$= 0.333$

A or B?

Parent

C_1	**$N_{0,1}$**
C_2	**$N_{0,2}$**

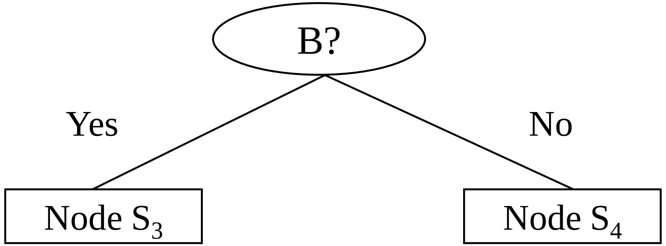
M_0



C_1	**$N_{1,1}$**
C_2	**$N_{1,2}$**

C_1	**$N_{2,1}$**
C_2	**$N_{2,2}$**

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



C_1	**$N_{3,1}$**
C_2	**$N_{3,2}$**

C_1	**$N_{4,1}$**
C_2	**$N_{4,2}$**

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

Gain

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

datasciencedojo
unleash the data scientist in you

Impurity Measure: Entropy

- Entropy at a given node t:

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

  - 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

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

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 :

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

  - 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

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

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

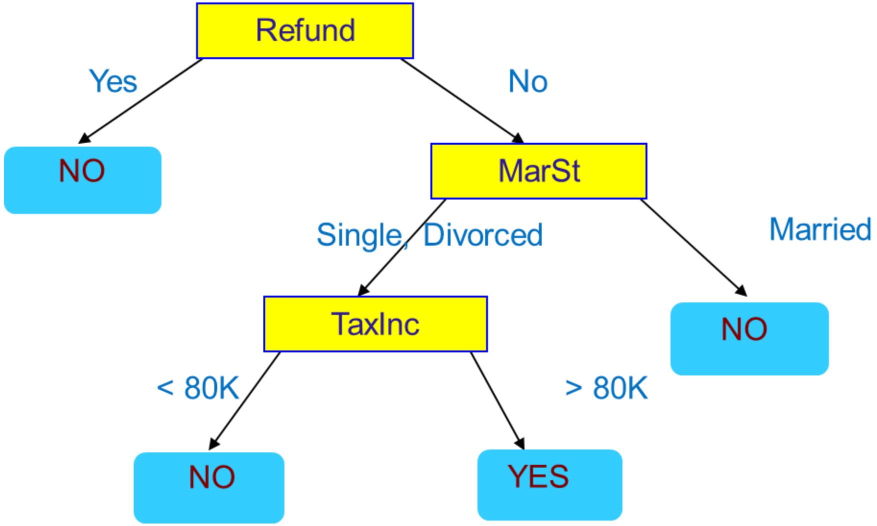
- Greedy strategy
  - Split based attribute test that optimizes a criterion
- Issues
  - How to split the records
    - What attribute test criterion?
    - How to determine the best split?
    - **When do we stop?**

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

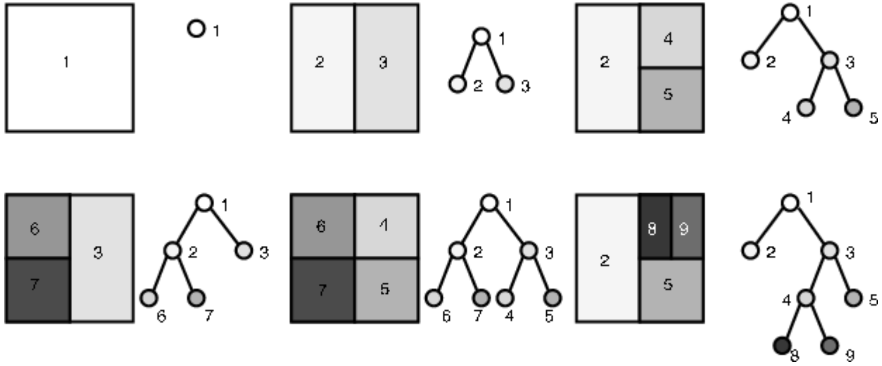
- Intuitive
  - Easy interpretation for small trees
- Non parametric:
  - Incorporate both numeric and categorical attributes
- Fast
  - Once rules are developed, prediction is rapid
- Robust to outliers



datasciencedojo
unleash the data scientist in you

Decision Trees - CONS

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



QUESTIONS

Session Outline

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