UNIT III - CLASSIFICATION

18CS54 – DATA MINING

Outline

- Recap
- Classification
  - *Definition*
  - *Illustrating Classification Task*
  - *Classification Techniques*
- Decision Tree
  - *Decision Tree Induction*
  - *Hunt's Algorithm*
  - *Measure of Node Impurity*
    - GINI
    - Entropy
    - Misclassification Error
  - *CART , SLIQ, SPRINT*
  - *C4.5*
- Rule based Classifiers
- Nearest Neighbor classifiers

LECTURE 14

Dr.Vani V

Recap & Moving forward

- Unit –I Data Mining: Introduction, KDD Process, Challenges, Data Mining Tasks, Data Mining Trends and Applications.
- Unit –II Data, Types of Data, Data Pre-processing, Measures of Similarity And Dissimilarity
- **Unit –III Classification: Basics, General Approach to Solve Classification Problem, Decision Tree Induction, Rule Based Classifiers, Nearest Neighbor Classifiers.**

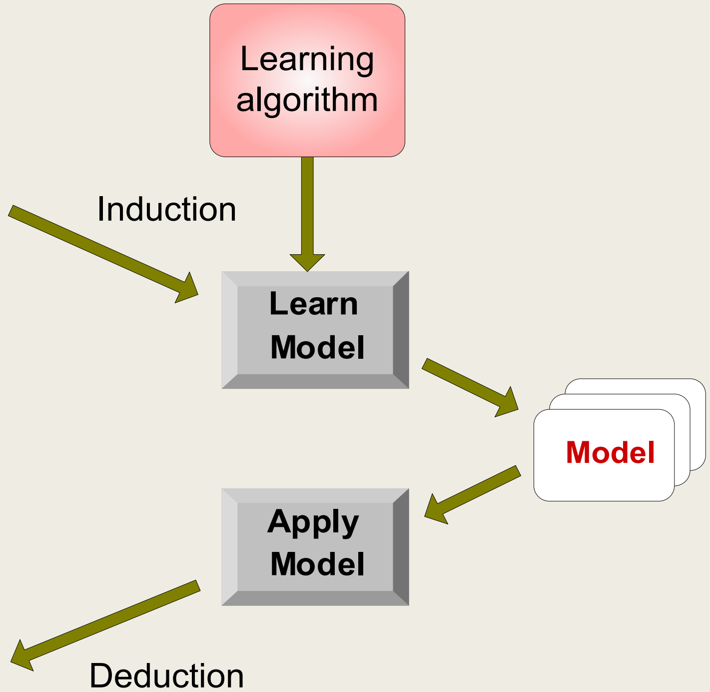
Classification: Definition

- Given a collection of records (*training set*)
  - *Each record contains a set of attributes, one of the attributes is the class.*
- Find a *model* for class attribute as a function of the values of other attributes.
- Goal: previously unseen records should be assigned a class as accurately as possible.
  - *A test set is used to determine the accuracy of the model. Usually, the given data set is divided into training and test sets, with training set used to build the model and test set used to validate it.*

Illustrating Classification Task

Tid	Attrib1	Attrib2	Attrib3	Class
1	Yes	Large	125K	No
2	No	Medium	100K	No
3	No	Small	70K	No
4	Yes	Medium	120K	No
5	No	Large	95K	Yes
6	No	Medium	60K	No
7	Yes	Large	220K	No
8	No	Small	85K	Yes
9	No	Medium	75K	No
10	No	Small	90K	Yes

Training Set

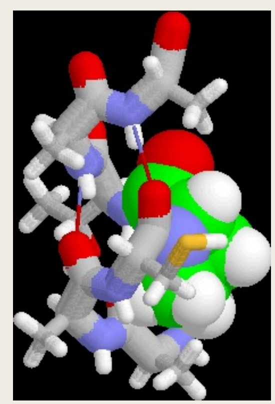


Tid	Attrib1	Attrib2	Attrib3	Class
11	No	Small	55K	?
12	Yes	Medium	80K	?
13	Yes	Large	110K	?
14	No	Small	95K	?
15	No	Large	67K	?

Test Set

Examples of Classification Task

- Predicting tumor cells as benign or malignant
- Classifying credit card transactions as legitimate or fraudulent
- Classifying secondary structures of protein as alpha-helix, beta-sheet, or random coil
- Categorizing news stories as finance, weather, entertainment, sports, etc



Classification Techniques

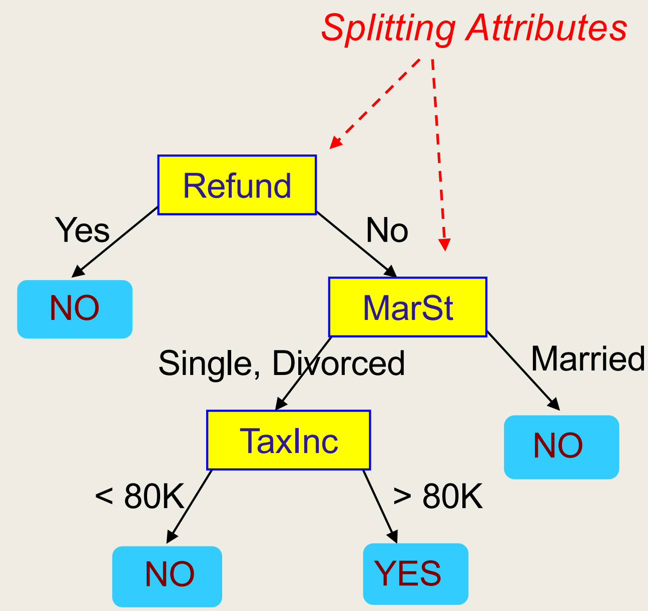
- Decision Tree based Methods
- Rule-based Methods
- Memory based reasoning
- Neural Networks
- Naïve Bayes and Bayesian Belief Networks
- Support Vector Machines

Example of a 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**

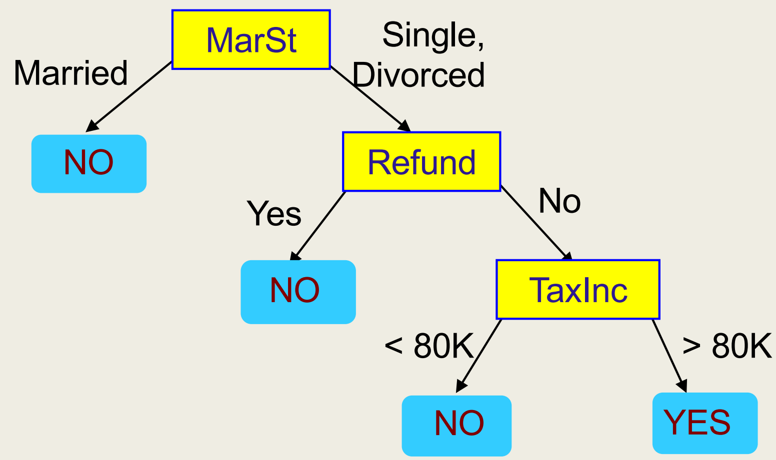
Training Data



Model: Decision Tree

Another Example of 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 Classification Task

Tid	Attrib1	Attrib2	Attrib3	Class
1	Yes	Large	125K	No
2	No	Medium	100K	No
3	No	Small	70K	No
4	Yes	Medium	120K	No
5	No	Large	95K	Yes
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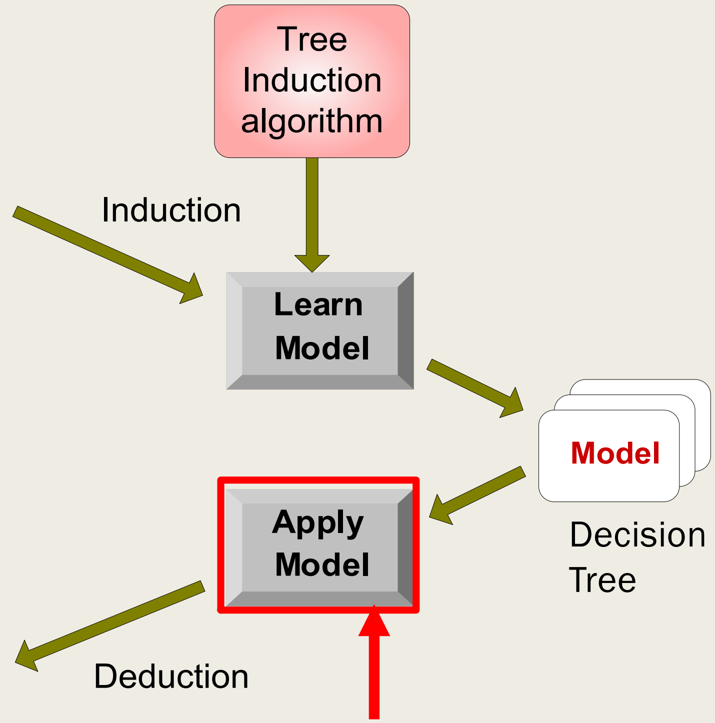
Training Set



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11	No	Small	55K	?
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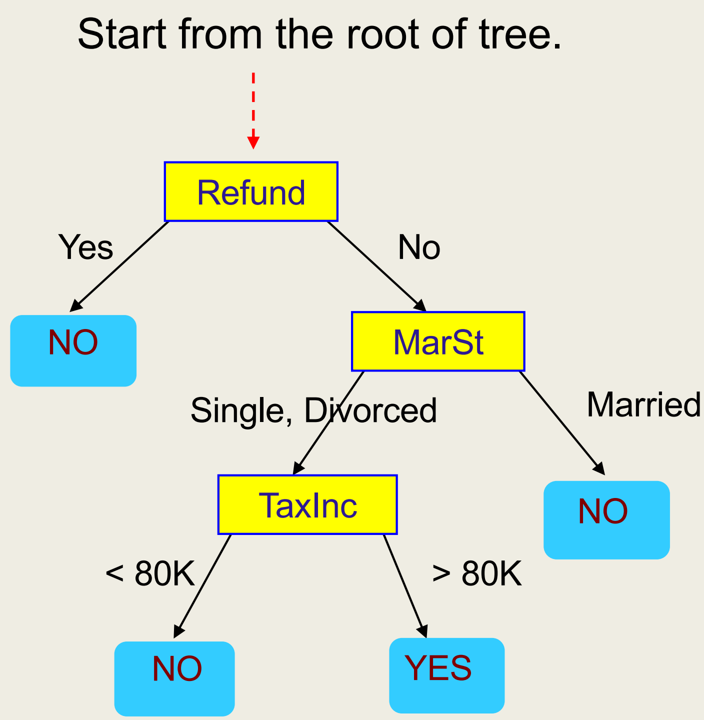
15	No	Large	67K	?

Test Set

Apply Model to Test Data



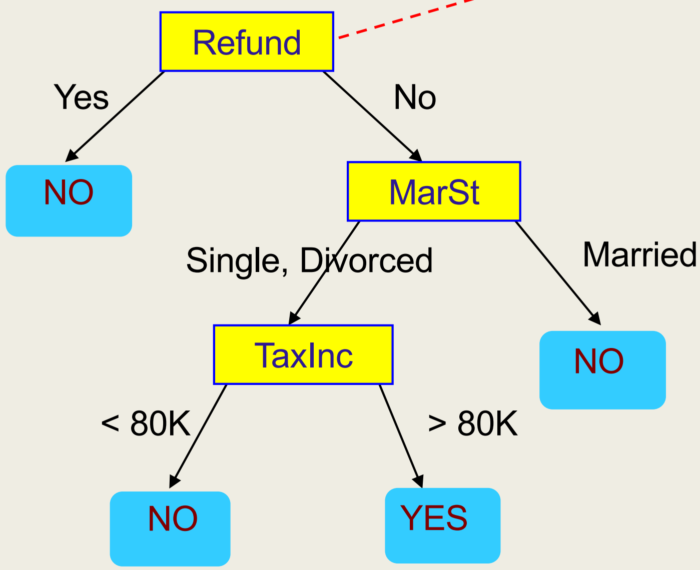
Test Data

Refund	Marital Status	Taxable Income	Cheat
No	Married	80K	**?**

Apply Model to Test Data

Test Data

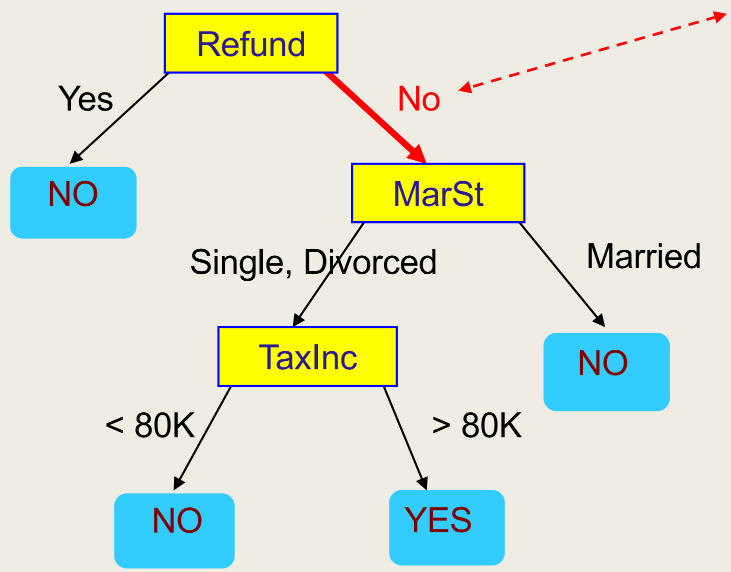
Refund	Marital Status	Taxable Income	Cheat
No	Married	80K	**?**



Apply Model to Test Data

Test Data

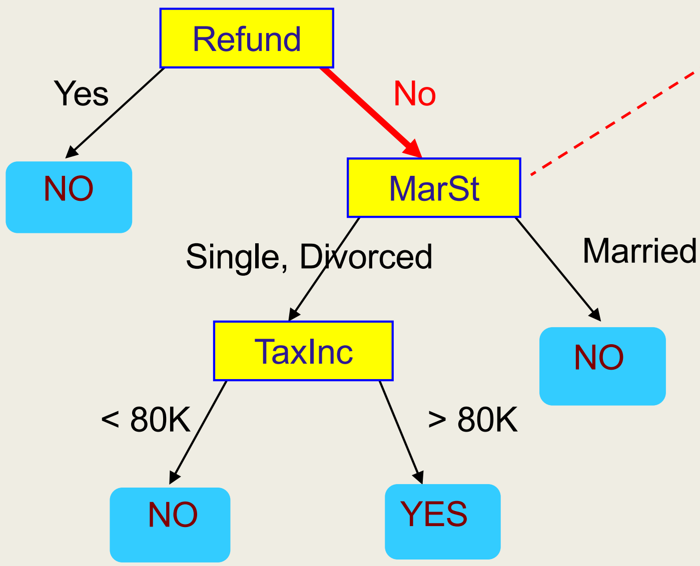
Refund	Marital Status	Taxable Income	Cheat
No	Married	80K	?



Apply Model to Test Data

Test Data

Refund	Marital Status	Taxable Income	Cheat
No	Married	80K	?



Apply Model to Test Data

Test Data

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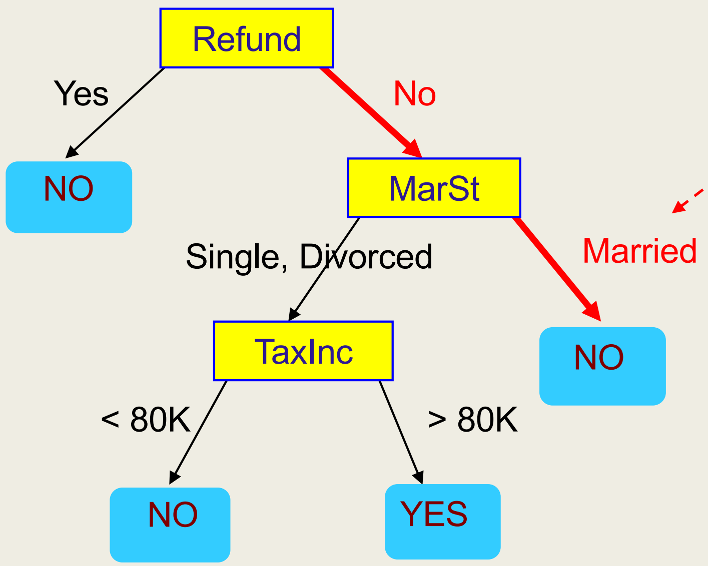
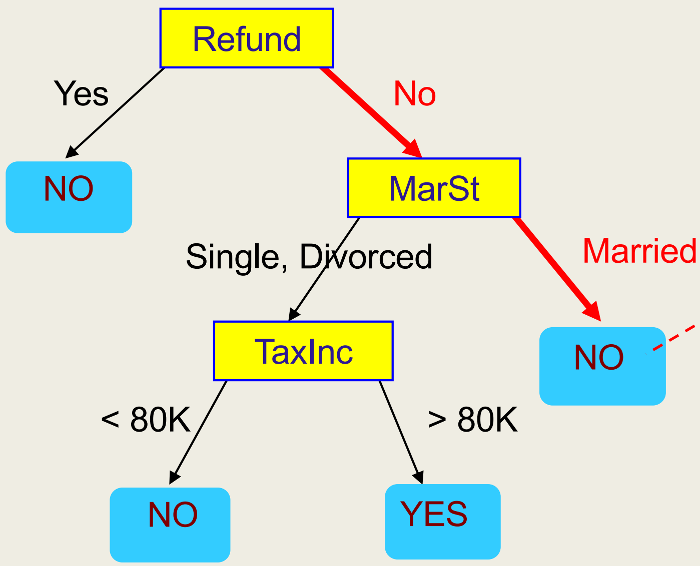


Apply Model to Test Data



Test Data

Refund	Marital Status	Taxable Income	Cheat
No	Married	80K	?

Assign Cheat to “No”

Decision Tree Classification Task

Tid	Attrib1	Attrib2	Attrib3	Class
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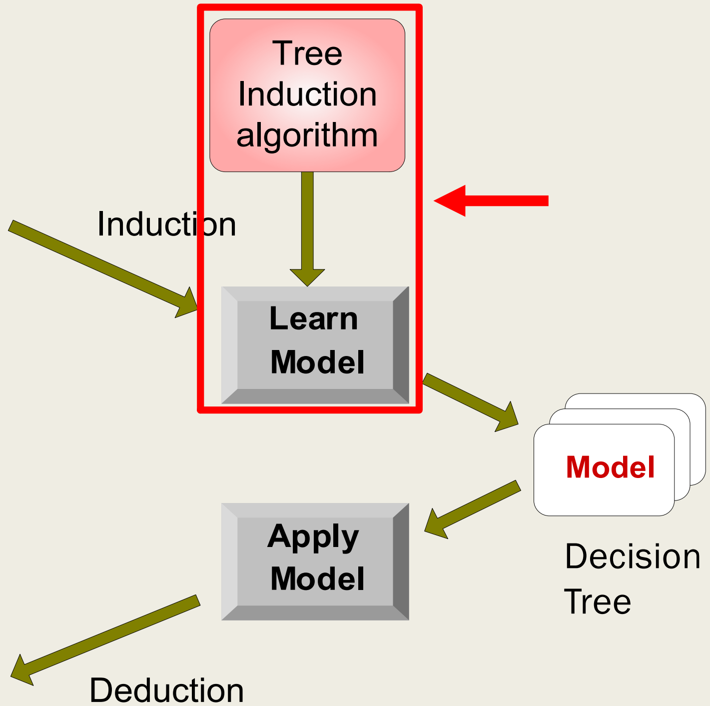
Training Set



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Test Set

Decision Tree Induction

- Many Algorithms:
  - *Hunt’s Algorithm (one of the earliest)*
  - *CART*
  - *ID3, C4.5*
  - *SLIQ,SPRINT*

General Structure of Hunt's Algorithm

- Let D_t be the set of training records that reach a node t
- General Procedure:
  - *If D_t contains records that belong to the same class y_t, then t is a leaf node labeled as y_t*
  - *If D_t is an empty set, then t is a leaf node labeled by the default class, y_d*
  - *If D_t contains records that belong to more than one class, use an attribute test to split the data into smaller subsets. Recursively apply the procedure to each subset.*

Tid	Refund	Marital Status	Taxable Income	Cheat
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3	No	Single	70K	No
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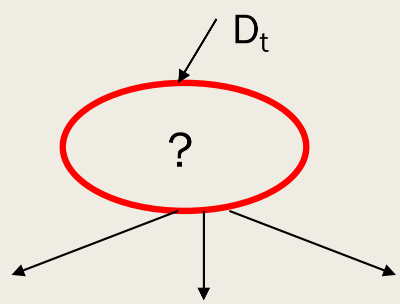
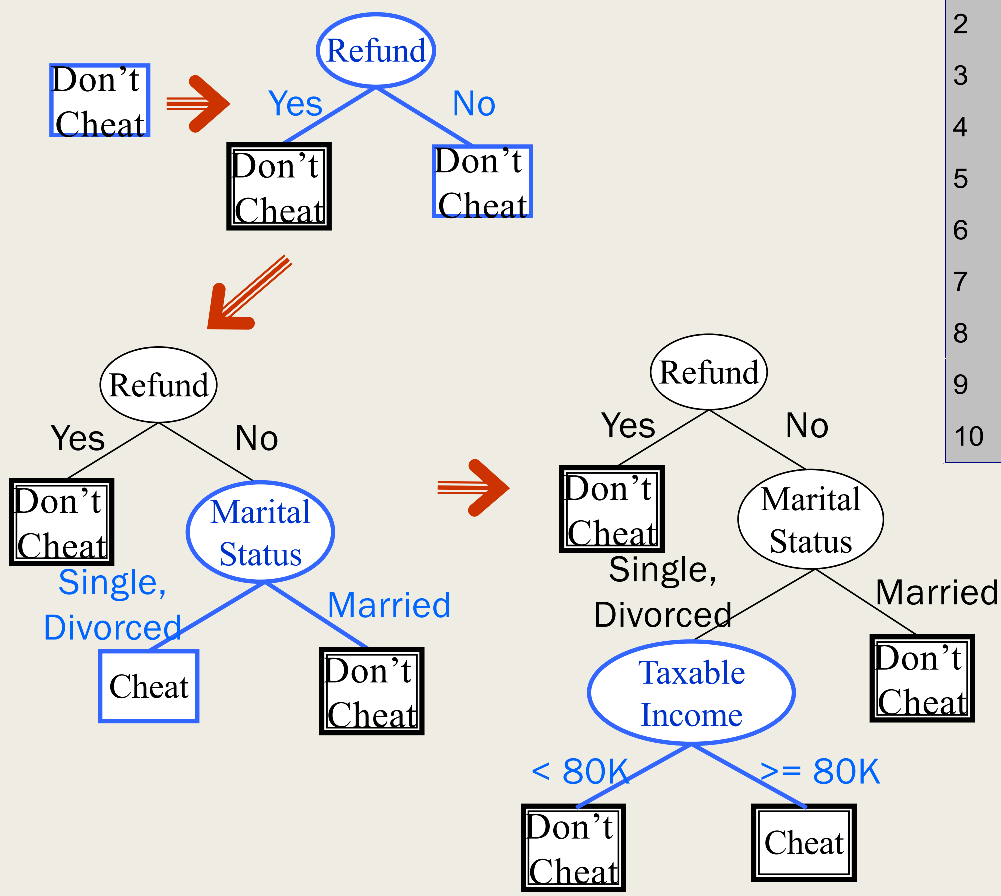
8	No	Single	85K	Yes
9	No	Married	75K	No
10	No	Single	90K	Yes



Hunt's Algorithm



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7	Yes	Divorced	220K	No
8	No	Single	85K	Yes
9	No	Married	75K	No
10	No	Single	90K	Yes

Tree Induction

- Greedy strategy.
  - *Split the records based on an attribute test that optimizes certain criterion.*

- Issues
  - *Determine how to split the records*
    - How to specify the attribute test condition?
    - How to determine the best split?
  - *Determine when to stop splitting*

Tree Induction

- Greedy strategy.
  - *Split the records based on an attribute test that optimizes certain criterion.*

- Issues
  - *Determine how to split the records*
    - How to specify the attribute test condition?
    - How to determine the best split?
  - *Determine when to stop splitting*

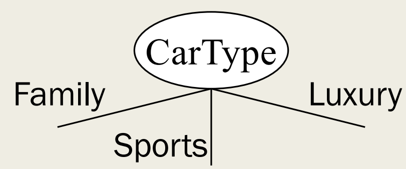
How to Specify Test Condition?

- Depends on attribute types
  - *Nominal*
  - *Ordinal*
  - *Continuous*

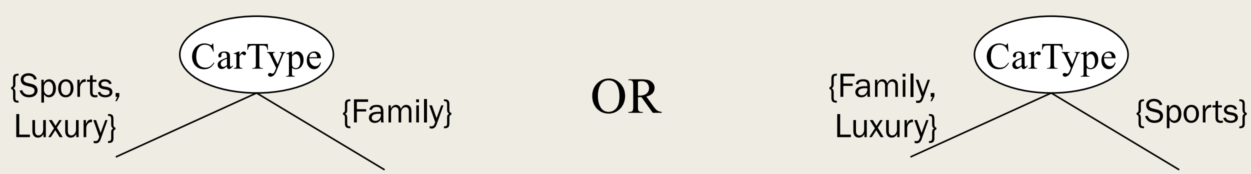
- Depends on number of ways to split
  - *2-way split*
  - *Multi-way split*

Splitting Based on Nominal Attributes

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

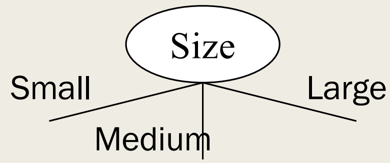


- Binary split: Divides values into two subsets.
  Need to find optimal partitioning.



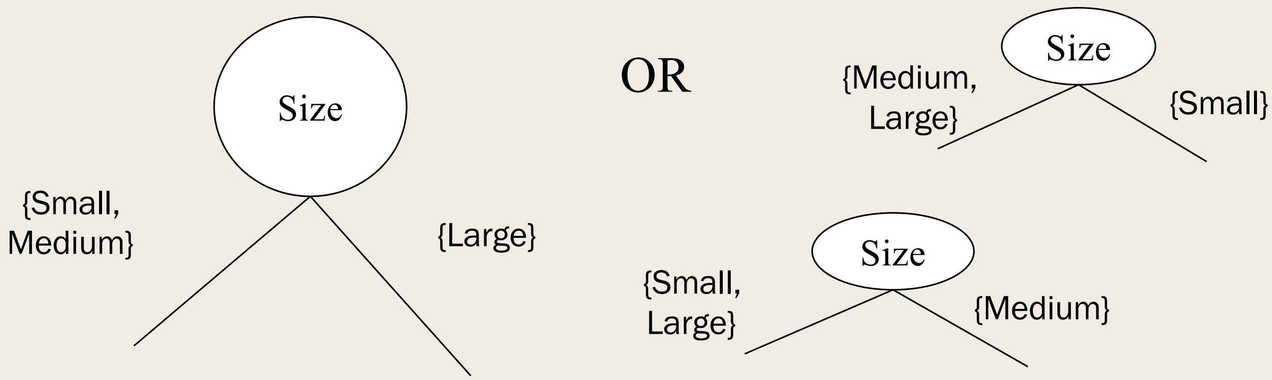
Splitting Based on Ordinal Attributes

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



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

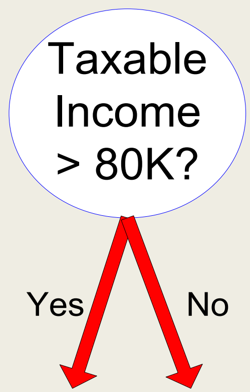
- What about this split?



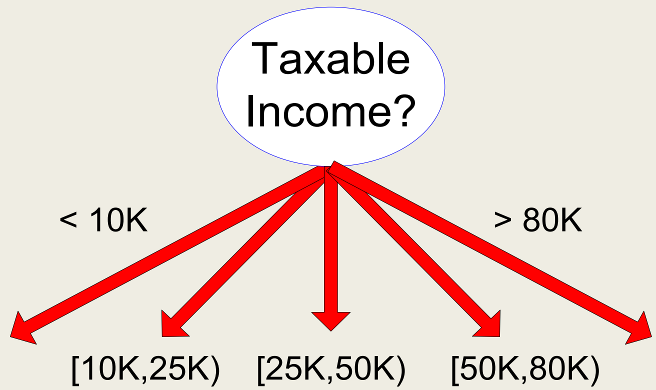
Splitting Based on Continuous Attributes

- Different ways of handling
  - *Discretization to form an ordinal categorical attribute*
    - Static – discretize once at the beginning
    - Dynamic – ranges can be found by equal interval bucketing, equal frequency bucketing
      (percentiles), or clustering.
  - *Binary Decision: $(A < v)$ or $(A \geq v)$*
    - consider all possible splits and finds the best cut
    - can be more compute intensive

Splitting Based on Continuous Attributes



(i) Binary split



(ii) Multi-way split

LECTURE 15

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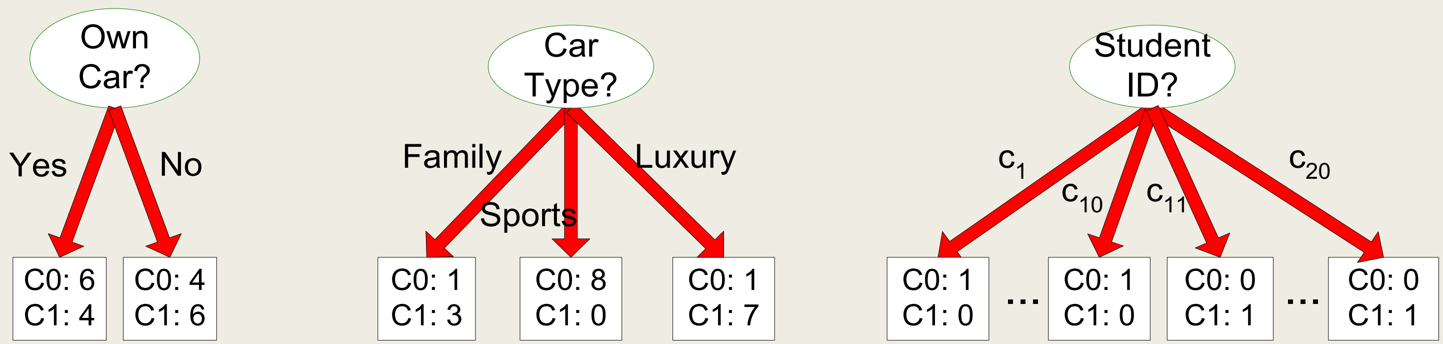
Tree Induction

- Greedy strategy.
  - *Split the records based on an attribute test that optimizes certain criterion.*

- Issues
  - *Determine how to split the records*
    - How to specify the attribute test condition?
    - How to determine the best split?
  - *Determine when to stop splitting*

How to determine the Best Split

Before Splitting: 10 records of class 0,
10 records of class 1



Which test condition is the best?

How to determine the Best Split

- Greedy approach:
  - *Nodes with homogeneous class distribution are preferred*
- Need a measure of node impurity:

C0: 5	C0: 9
C1: 5	C1: 1

Non-homogeneous,

High degree of impurity

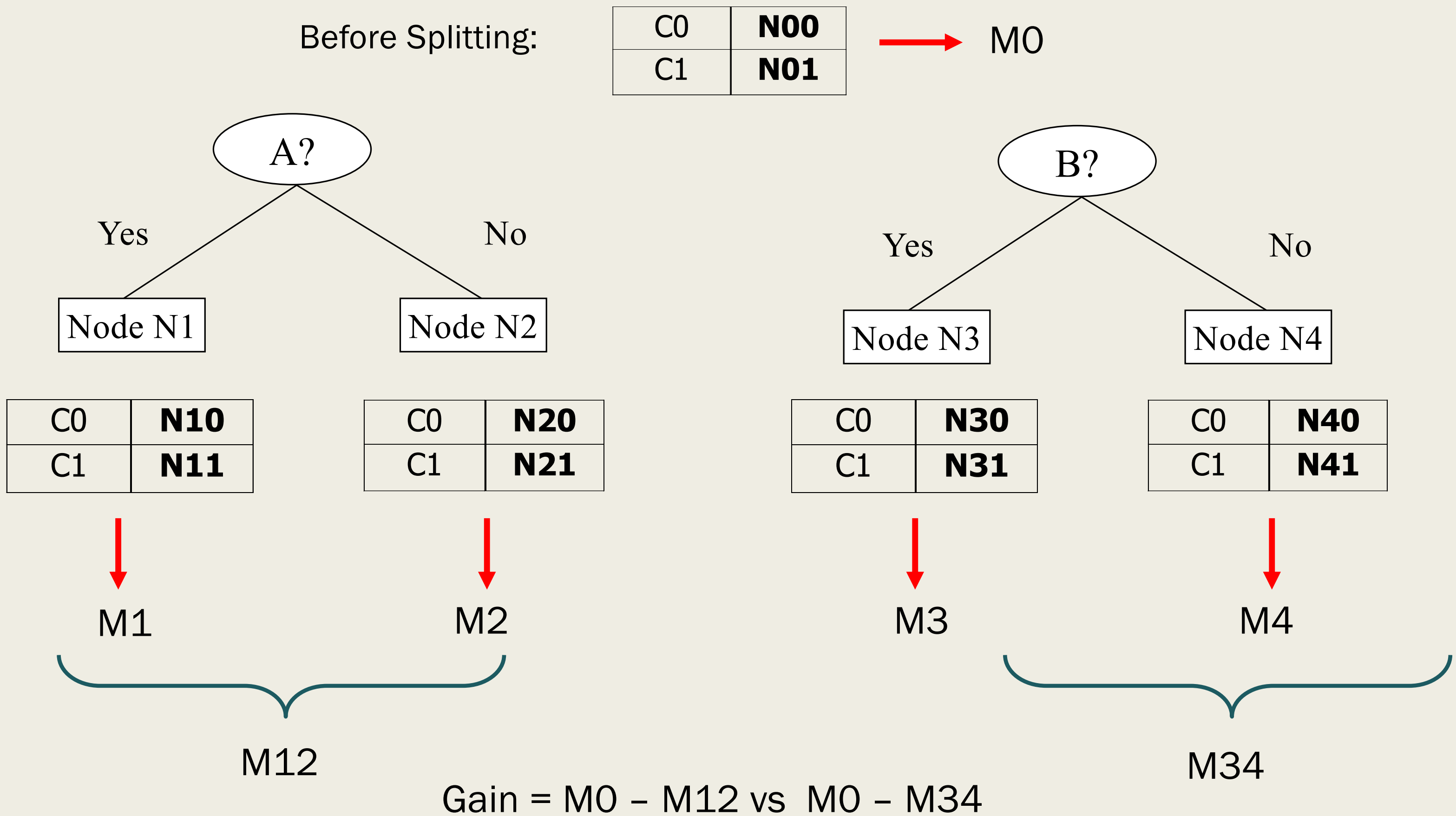
Homogeneous,

Low degree of impurity

Measures of Node Impurity

- Gini Index
- Entropy
- Misclassification error

How to Find the Best Split



Measure of Impurity: GINI

- Gini Index for a given node t :

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

(NOTE: $p(j \mid t)$ 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*
  – *Minimum (0.0) when all records belong to one class, implying most interesting information*

C1	**0**
C2	**6**
Gini=0.000	

C1	**1**
C2	**5**
Gini=0.278	

C1	**2**
C2	**4**
Gini=0.444	

C1	**3**
C2	**3**
Gini=0.500	

Examples for computing GINI

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

C1	**0**
C2	**6**

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

Gini = 1 – P(C1)^2 – P(C2)^2 = 1 – 0 – 1 = 0

C1	**1**
C2	**5**

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

Gini = 1 – (1/6)^2 – (5/6)^2 = 0.278

C1	**2**
C2	**4**

P(C1) = 2/6 P(C2) = 4/6

Gini = 1 – (2/6)^2 – (4/6)^2 = 0.444

Splitting Based on GINI

- Used in CART, SLIQ, SPRINT.
- When a node p is split into k partitions (children), the quality of split is computed as,

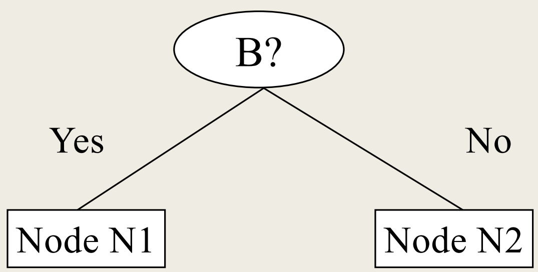
$$GINI_{split} = \sum_{i=1}^{k} \frac{n_i}{n} GINI(i)$$

where, n_i = number of records at child i,

n = number of records at node p.

Binary Attributes: Computing GINI Index

- Splits into two partitions
- Effect of Weighing partitions:
  - Larger and Purer Partitions are sought for.



	Parent
C1	**6**
C2	**6**
Gini = 0.500	

Gini(N1)
$= 1 - (5/6)^2 - (2/6)^2$
$= 0.194$

Gini(N2)
$= 1 - (1/6)^2 - (4/6)^2$
$= 0.528$

	N1	**N2**
C1	**5**	**1**
C2	**2**	**4**
Gini=0.333		

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

Categorical Attributes: Computing Gini Index

- For each distinct value, gather counts for each class in the dataset
- Use the count matrix to make decisions

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

Multi-way split

	CarType		
	Family	Sports	Luxury
C1	1	2	1
C2	4	1	1
Gini	0.393		

Two-way split
(find best partition of values)

	CarType	
	{Sports, Luxury}	{Family}
C1	3	1
C2	2	4
Gini	0.400	

	CarType	
	{Sports}	{Family, Luxury}
C1	2	2
C2	1	5
Gini	0.419	

Continuous Attributes: Computing Gini Index

- Use Binary Decisions based on one value
- Several Choices for the splitting value
  - *Number of possible splitting values = Number of distinct values*
- Each splitting value has a count matrix associated with it
  - *Class counts in each of the partitions, A < v and A $\geq$ v*
- Simple method to choose best v
  - *For each v, scan the database to gather count matrix and compute its Gini index*
  - *Computationally Inefficient! Repetition of work.*

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1	Yes	Single	125K	**No**
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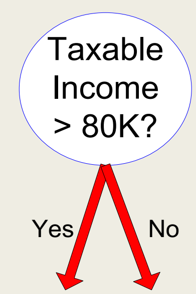

Continuous Attributes: Computing Gini Index...

- For efficient computation: for each attribute,
  - *Sort the attribute on values*
  - *Linearly scan these values, each time updating the count matrix and computing gini index*
  - *Choose the split position that has the least gini index*

Cheat	No	No	No	Yes	Yes	Yes	No	No	No	No
	Taxable Income									
Sorted Values	60	70	75	85	90	95	100	120	125	220

Split Positions	55		65		72		80		87		92		97		110		122		172		230	
	<=	>	<=	>	<=	>	<=	>	<=	>	<=	>	<=	>	<=	>	<=	>	<=	>	<=	>
Yes	0	3	0	3	0	3	0	3	1	2	2	1	3	0	3	0	3	0	3	0	3	0
No	0	7	1	6	2	5	3	4	3	4	3	4	3	4	4	3	5	2	6	1	7	0
Gini	0.420		0.400		0.375		0.343		0.417		0.400		*0.300*		0.343		0.375		0.400		0.420	

Alternative Splitting Criteria based on INFO

- Entropy at a given node t:

$$\boxed{Entropy(t) = -\sum_{j} p(j \mid t) \log p(j \mid t)}$$

(NOTE: $p(j \mid t)$ is the relative frequency of class j at node t).

– *Measures homogeneity of a node.*
  - Maximum ($\log n_c$) when records are equally distributed among all classes implying least information
  - Minimum (0.0) when all records belong to one class, implying most information

– *Entropy based computations are similar to the GINI index computations*

Examples for computing Entropy

$$Entropy(t) = -\sum_{j} p(j\,|\,t)\log_{2} p(j\,|\,t)$$

C1	**0**
C2	**6**

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

Entropy = – 0 log 0 – 1 log 1 = – 0 – 0 = 0

C1	**1**
C2	**5**

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

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

C1	**2**
C2	**4**

P(C1) = 2/6 P(C2) = 4/6

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

References

TEXTBOOKS :

1. Pang-Ning Tan, Vipin Kumar, Michael Steinbach: **Introduction to Data Mining**, Pearson, 2012.
2. Jiawei Han and Micheline Kamber: **Data Mining - Concepts and Techniques**, 3rd Edition, MorganKaufmann Publisher, 2014