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Introduction to Data Science
Classification and Prediction

- *The slides presented here are obtained from the authors of the books and from various other contributors. I hereby acknowledge all the contributors for their material and inputs.*
- *I have added and modified a few slides to suit the requirements of the course.*

Classification

predictive — most popular ML task

Classification

- Classification involves dividing up objects so that each is assigned to one of a number of mutually exhaustive and exclusive categories known as *classes*
- Many practical decision-making tasks can be formulated as classification problems
  - customers who are likely to buy or not buy a particular product in a supermarket
  - people who are at high, medium or low risk of acquiring a certain illness
  - student projects worthy of a distinction, merit, pass or fail grade
  - objects on a radar display which correspond to vehicles, people, buildings or trees
  - people who closely resemble, slightly resemble or do not resemble someone seen committing a crime
  - houses that are likely to rise in value, fall in value or have an unchanged value in 12 months' time
  - people who are at high, medium or low risk of a car accident in the next 12 months
  - people who are likely to vote for each of a number of political parties (or none)
  - the likelihood of rain the next day for a weather forecast (very likely, likely, unlikely, very unlikely).

will buy

will not buy

D M P F

Classification vs. Prediction

- Classification
  - predicts $\boxed{\text{categorical class labels}}$ (discrete or nominal)
  - classifies data (constructs a model) based on the training set and the values (class labels) in a classifying attribute and uses it in classifying new data

- Prediction
  - models continuous-valued functions, i.e., predicts unknown or missing values

1150 sft

1100 sft 50L

1200 sft 65L

900 sft 43L

Semi Supervised

Supervised vs. Unsupervised Learning

Supervised ML

- Supervised learning (classification)
  - Supervision: The training data (observations, measurements, etc.) are accompanied by labels indicating the class of the observations
  - New data is classified based on the training set

Association

- Unsupervised learning (clustering)
  - The class labels of training data is unknown
  - Given a set of measurements, observations, etc. with the aim of establishing the existence of classes or clusters in the data

People also talk about more forms of machine learning
https://www.gartner.com/smarterwithgartner/understand-3-key-types-of-machine-learning/
https://encrypted-tbn0.gstatic.com/images?q=tbn:ANd9GcQk6wDdKFf6owv5L902n1AMs6UB_dN4KiwC6w&usqp=CAU

Classification—A Two-Step Process

- Model construction: describing a set of predetermined classes
  - Each tuple/sample is assumed to belong to a predefined class, as determined by the class label attribute
  - The set of tuples used for model construction is training set
  - The model is represented as classification rules, decision trees, or mathematical formulae

Algo → M/C
Data → M/C
M/C → Model

- Model usage: for classifying future or unknown objects
  - Estimate accuracy of the model
    - The known label of test sample is compared with the classified result from the model
    - Accuracy rate is the percentage of test set samples that are correctly classified by the model
    - Test set is independent of training set, otherwise over-fitting will occur
  - If the accuracy is acceptable, use the model to classify data tuples whose class labels are not known

Test input → Model → predict label

Illustrating Classification Task

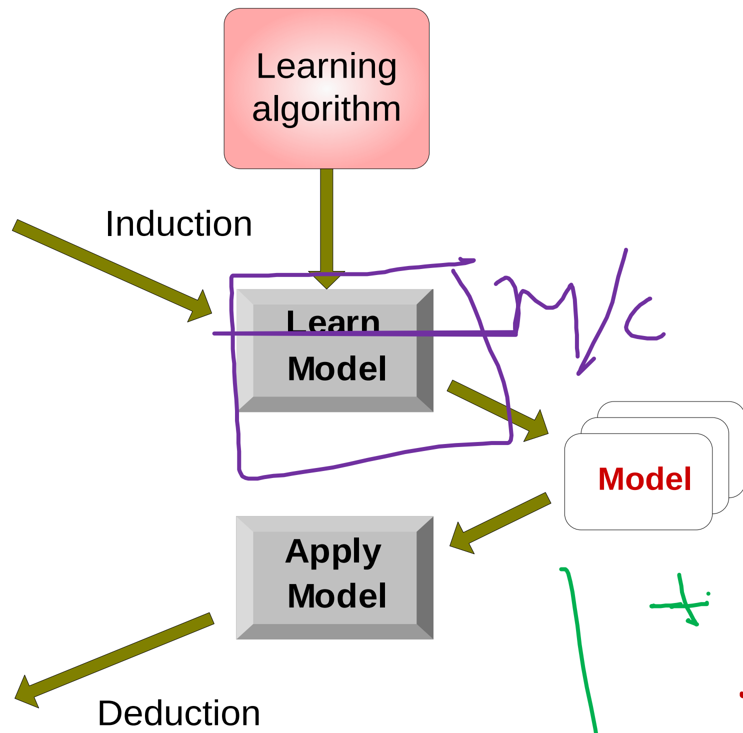
Training data

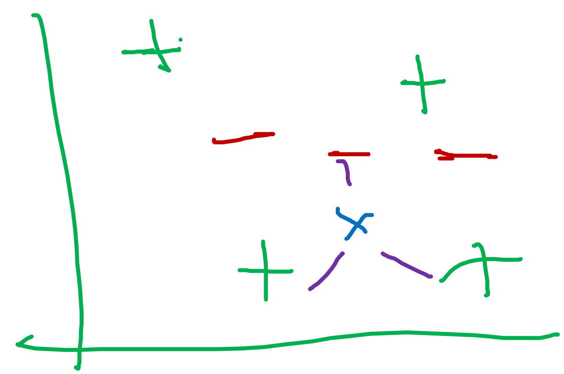
Tid	Attrib1	Attrib2	Attrib3	Class
1	Yes	Large	125K	No
2	No	Medium	100K	No
3	No	Small	70K	No
4	Yes	Medium	120K	No
5	No	Large	95K	Yes
6	No	Medium	60K	No
7	Yes	Large	220K	No
8	No	Small	85K	Yes
9	No	Medium	75K	No
10	No	Small	90K	Yes

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



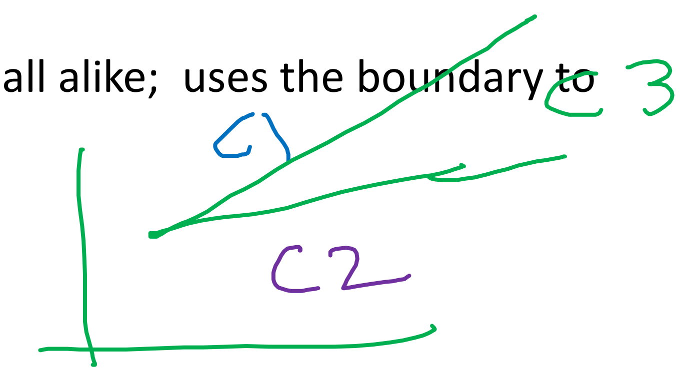


Classification Techniques

- Decision Tree based Methods
- Rule-based Methods
- Neural Networks
  - computational networks that simulate the decision process in neurons (networks of nerve cell)

ChatGPT Gemini
billions of parameters

- Naïve Bayes and Bayesian Belief Networks
  - uses the *probability theory* to find the most likely of the possible classifications
- Support Vector Machines
  - fits a boundary to a region of points that are all alike; uses the boundary to classify a new point



Lazy vs. Eager Learning

Test Tuple

Training Data

M/c

Label

- Lazy vs. eager learning
  - Lazy learning (e.g., instance-based learning): Simply stores training data (or only minor processing) and waits until it is given a test tuple
  - Eager learning (methods discussed in previous slide): Given a set of training set, constructs a classification model before receiving new (e.g., test) data to classify

Algorithm

- Lazy: less time in training but more time in predicting
- Accuracy
  - Lazy method effectively uses a richer hypothesis space since it uses many local linear functions to form its implicit global approximation to the target function
  - Eager: must commit to a single hypothesis that covers the entire instance space

Lazy Learner: Instance-Based Methods

- Instance-based learning:
  - Store training examples and delay the processing ("lazy evaluation") until a new instance must be classified
- Typical approaches
  - *k*-nearest neighbor approach
    - Instances represented as points in a Euclidean space.
  - Locally weighted regression
    - Constructs local approximation
  - Case-based reasoning AI
    - Uses symbolic representations and knowledge-based inference

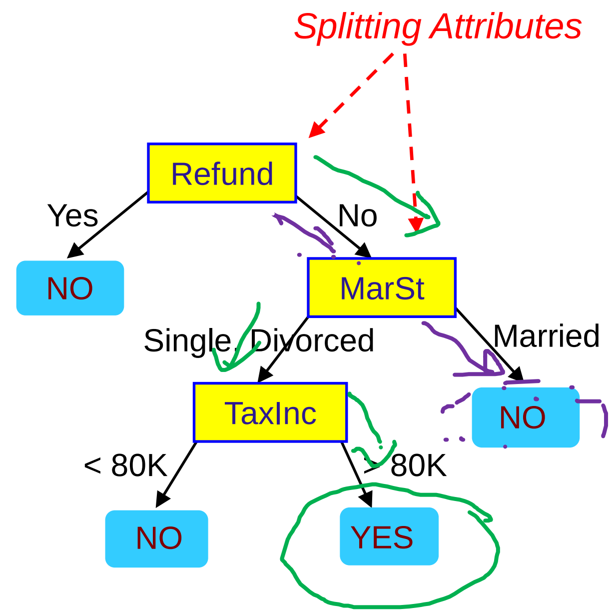
Eager classifier

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

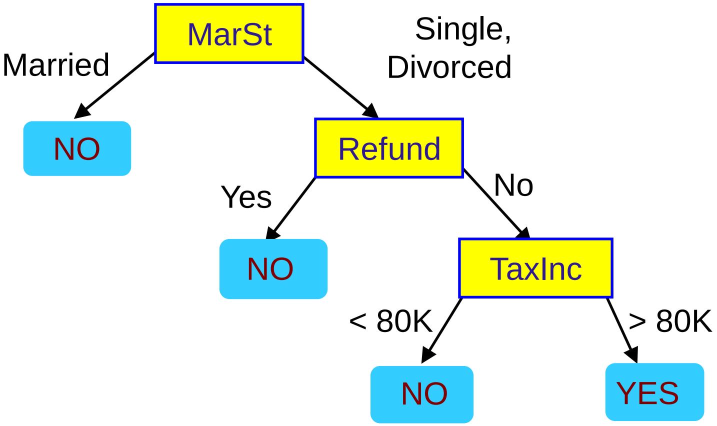


Model: Decision Tree

Another Example of Decision Tree

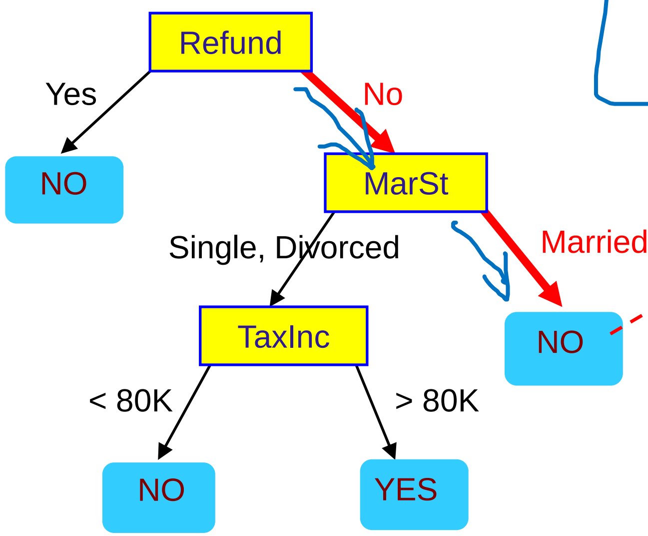
categorical categorical continuous class

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!

Apply Model to Test Data



Test Data

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

Assign Cheat to “No”

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
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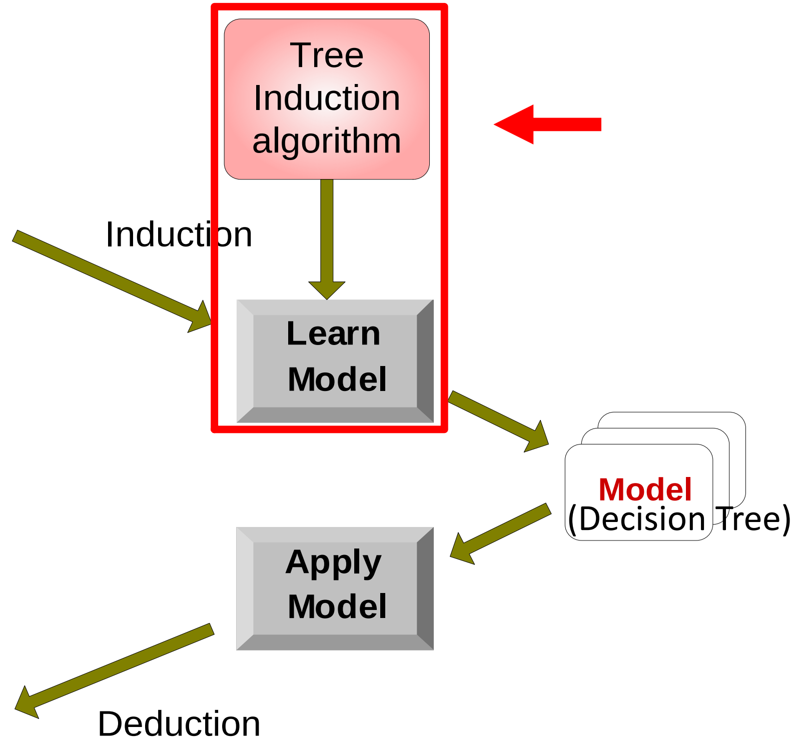
Training Set



Tid	Attrib1	Attrib2	Attrib3	Class
11	No	Small	55K	?
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14	No	Small	95K	?
15	No	Large	67K	?

Test Set

Issues: Evaluating Classification Methods

>40 ⇒ C
<40 ⇒ M
Income (in K)
Vehicle

- Accuracy
  - classifier accuracy: predicting class label
  - predictor accuracy: guessing value of predicted attributes
- Speed
  - time to construct the model (training time)
  - time to use the model (classification/prediction time)
- Robustness: handling noise and missing values
- Scalability: efficiency in disk-resident databases
- Interpretability
  - understanding and insight provided by the model
- Other measures, e.g., goodness of rules, such as decision tree size or compactness of classification rules

Explainable AI

$w_1x_1 + w_2x_2 + w_3x_3 = w$

20 M
25 C
30 M
35 M
45 C
50 M
70 C
65 C

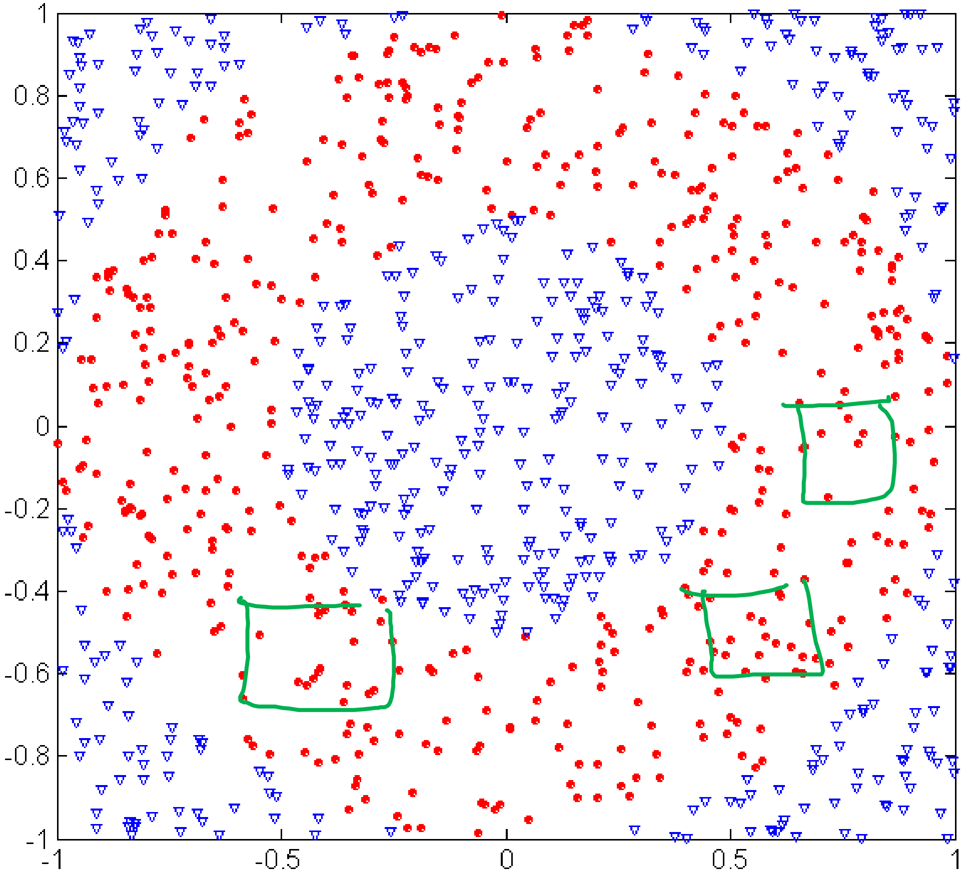
Data may have issues

2-D data 2 classes

Underfitting and Overfitting (Example)

Blue

Red



X_2 ↑

X_1 →

500 circular and 500 triangular data points.

Circular points: Red

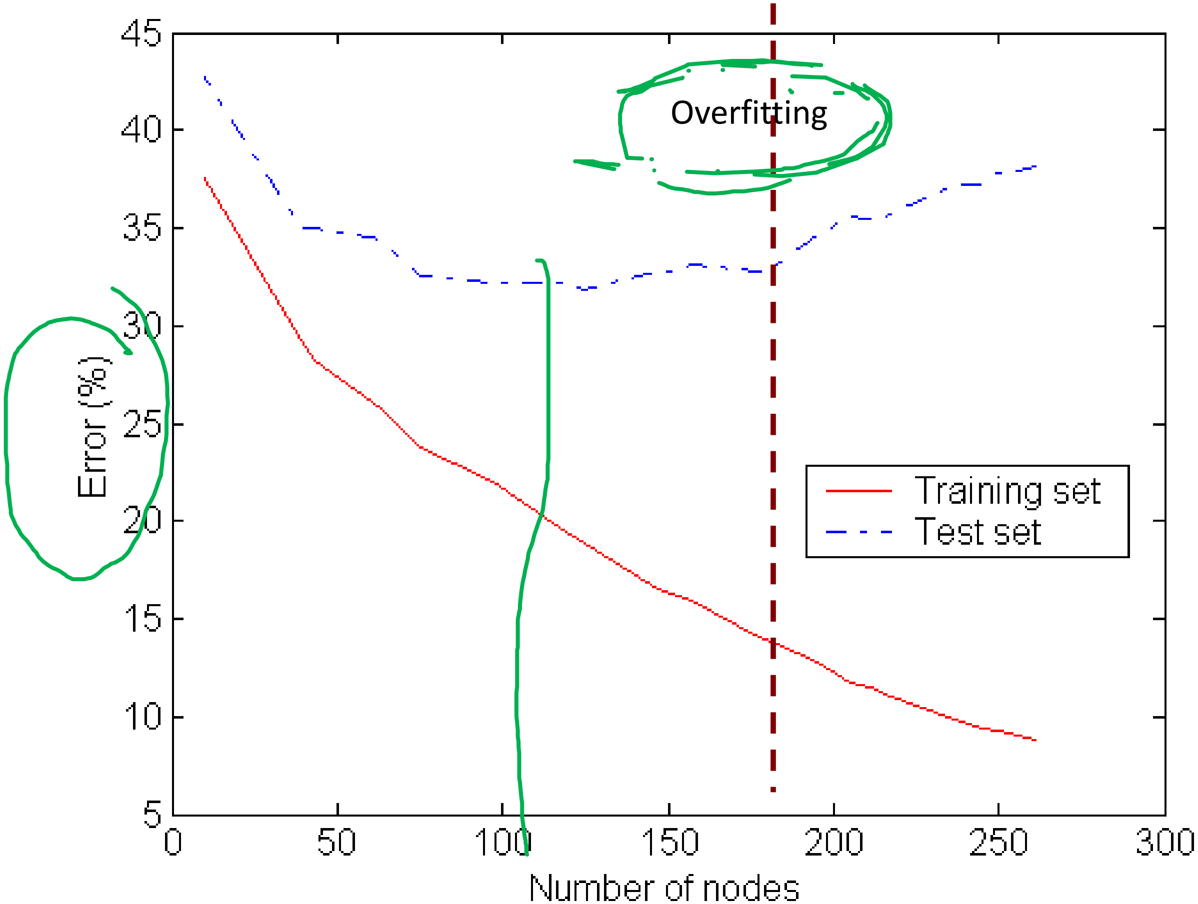
$0.5 \leq \text{sqrt}(x_1^2+x_2^2) \leq 1$

Triangular points: Blue

$\text{sqrt}(x_1^2+x_2^2) > 0.5$ or

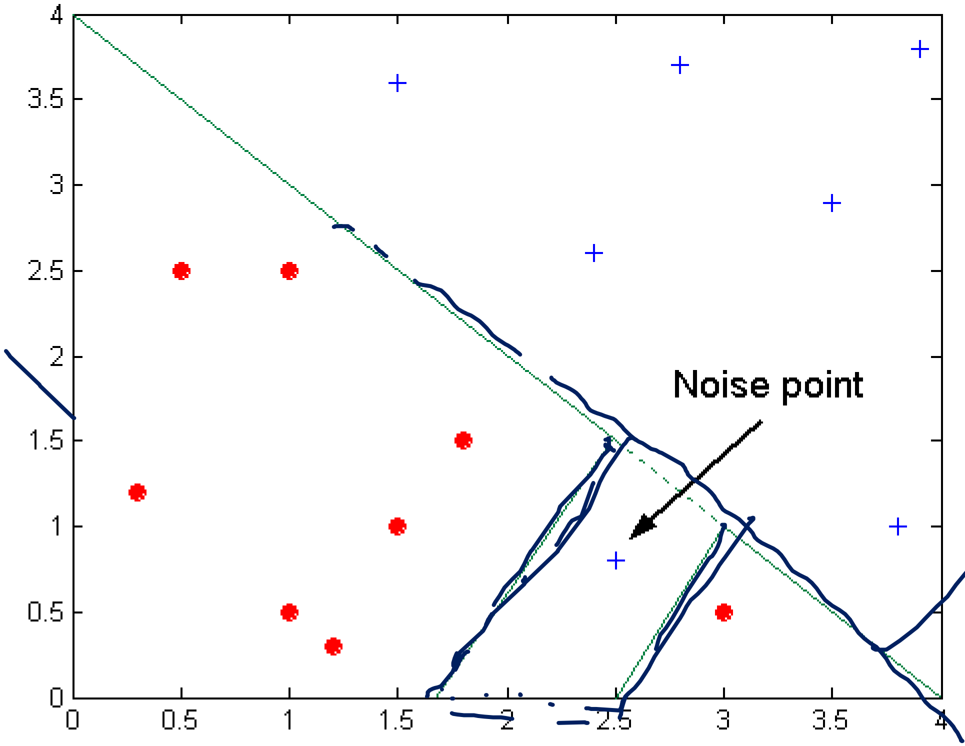
$\text{sqrt}(x_1^2+x_2^2) < 1$

Underfitting and Overfitting



Underfitting: when model is too simple, both training and test errors are large

Overfitting due to Noise



reason

boundary

Decision boundary is distorted by noise point

Decision Tree Based Classification

- Decision trees are intuitive and frequently used data mining technique for Classification
- For an analyst, they are easy to set up and for a business user they are easy to interpret.
- A decision tree model is a decision flowchart where an attribute is tested in each node and ends in a leaf node where a prediction is made.
- There are many algorithms for decision tree induction such as Hunt's Algorithm, CART, ID3, C4.5, SLIQ,SPRINT

partition train data so that we get purer subsets

Hunt's Algorithm - Structure

- Hunt's algorithm is among the earliest. More complex algorithms were built upon it.
- It grows a decision tree in a recursive fashion by partitioning the training records into successively purer subsets
- Let D_t be the set of training records that reach a node t
- General Procedure:
  - If D_t contains records that belong 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.

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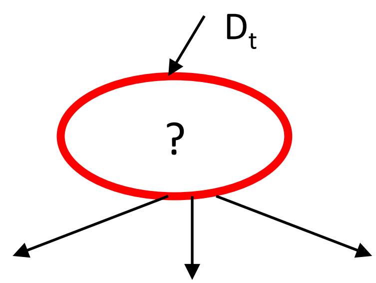
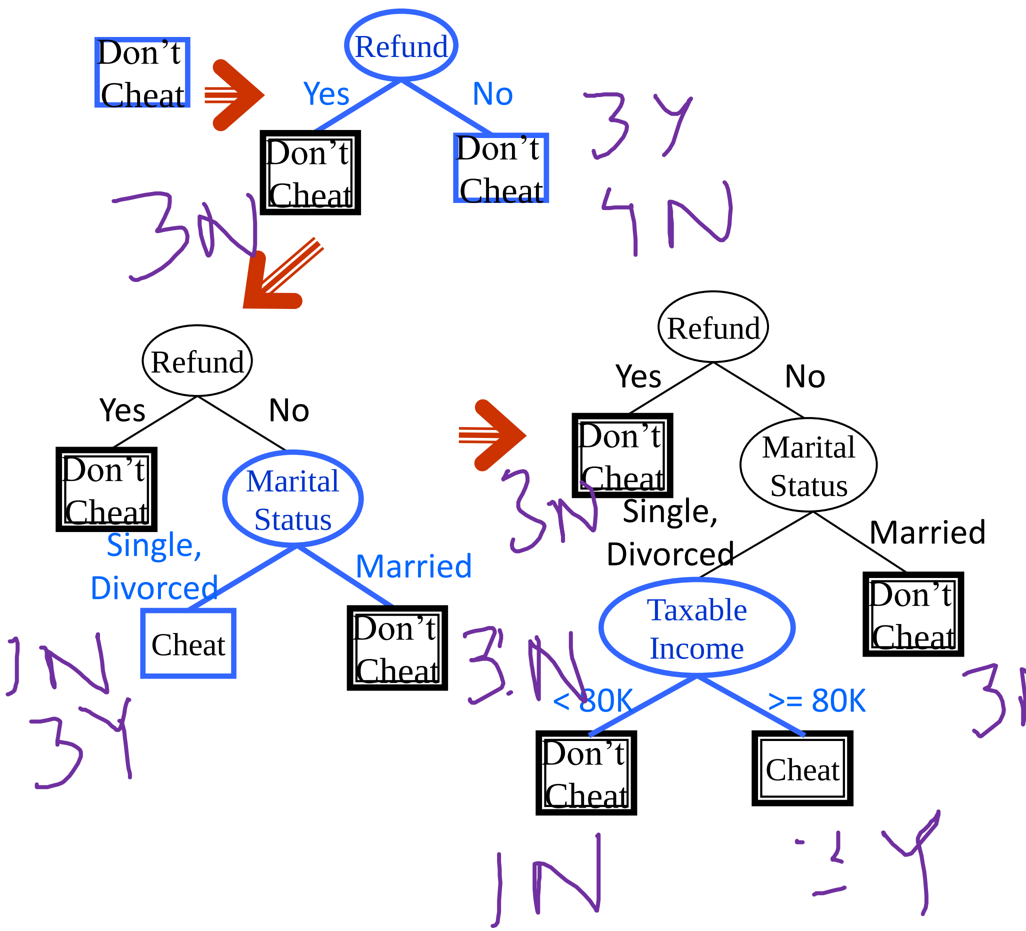
7	Yes	Divorced	220K	No
8	No	Single	85K	Yes
9	No	Married	75K	No
10	No	Single	90K	Yes

pure

impure



Hunt’s Algorithm - Example



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10	No	Single	90K	Yes

Tree Induction

At every point

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

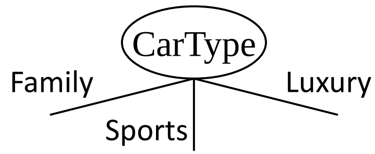
- Issues
  - Determine how to split the records
    - How to specify the attribute test condition?
    - How to determine the best split?
  - Determine when to stop splitting

How to Specify Test Condition?

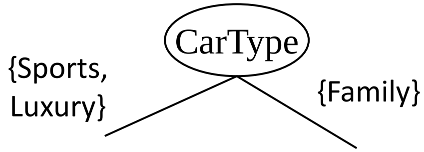
- Depends on attribute types
  - Nominal
  - Ordinal
  - Continuous
- Depends on number of ways to split
  - 2-way split
  - Multi-way split

Splitting Based on Nominal Attributes

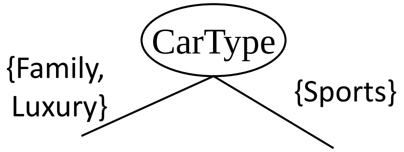
- Multi-way split: Use as many partitions as distinct values.



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

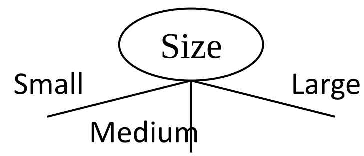


OR



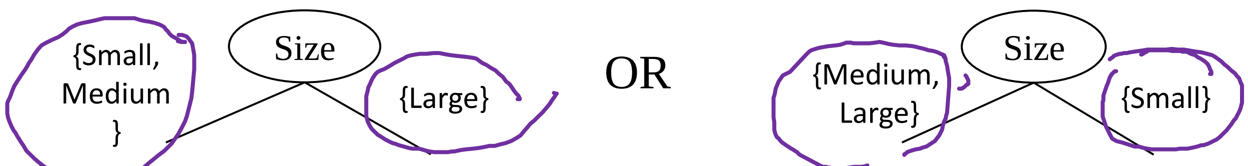
Splitting Based on Ordinal Attributes

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

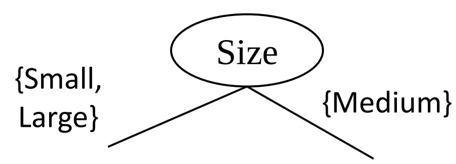


- Binary split: Divides values into two subsets. Need to find optimal partitioning.

more likely



- What about this split?



specific domain based

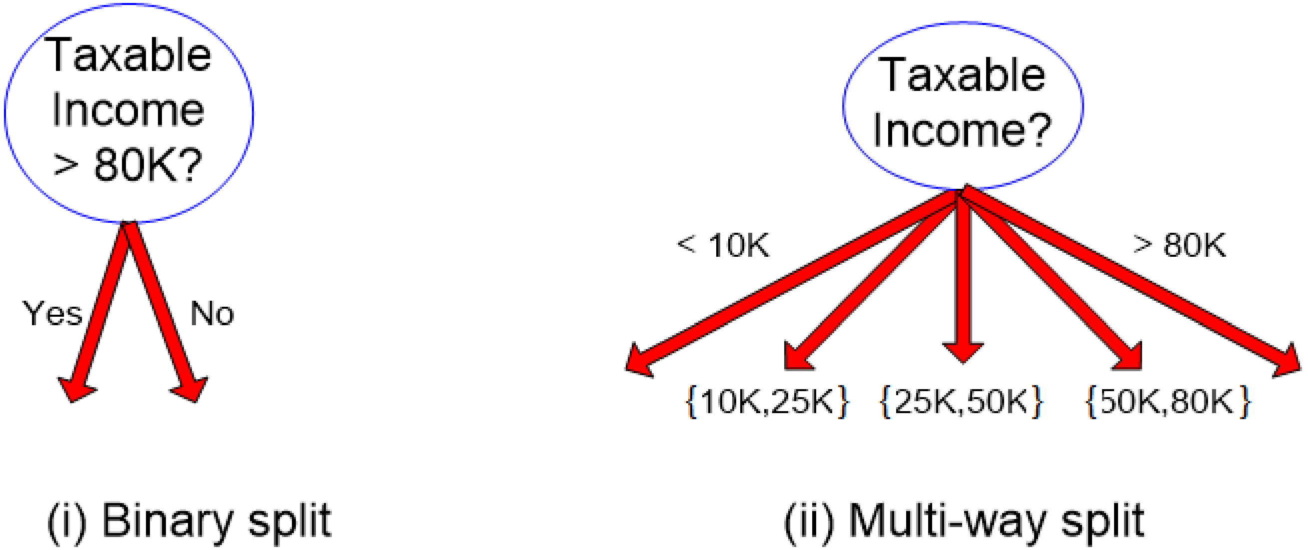
Splitting Based on Continuous Attributes

Income

Low Mid High

- 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 ≥ v)
    - consider all possible splits and finds the best cut
    - can be more compute intensive

Splitting Based on Continuous Attributes



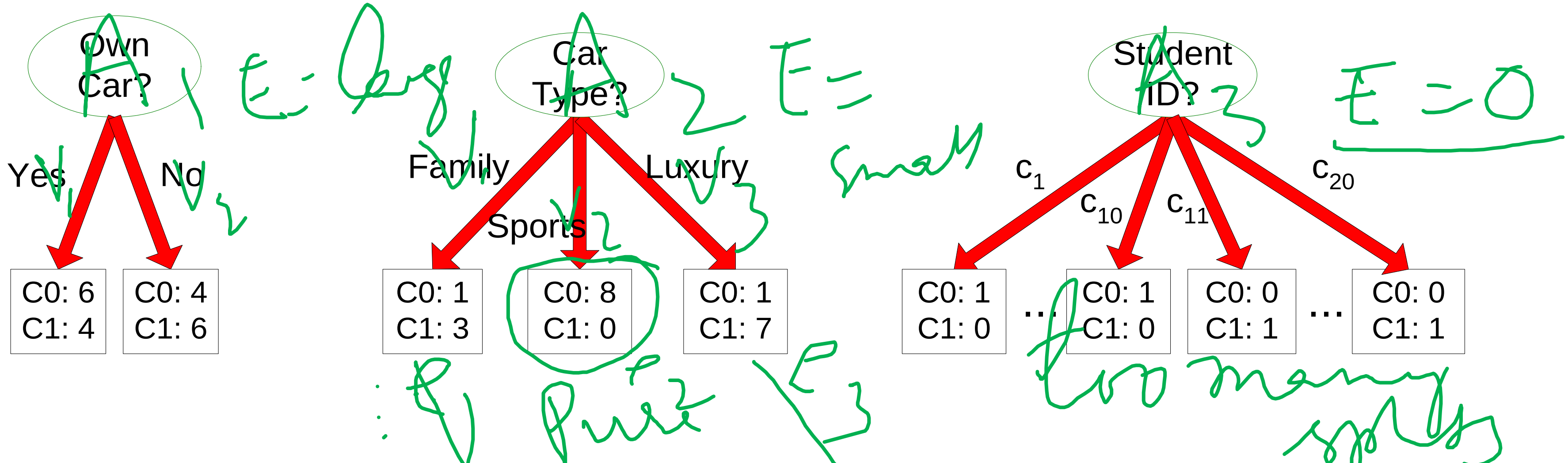
20 training tuples

How to determine the Best Split

$\frac{4}{20} e_1 + \frac{8}{20} e_2 + \frac{8}{20} e_3$ 3 attributes

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

completely impure



Which test condition is the best?

nearly pure

How to determine the Best Split

- Greedy approach:
  - Nodes with homogeneous class distribution are preferred

- Need a measure of node impurity:

Bad

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

Good

Non-homogeneous,	Homogeneous,
High degree of impurity	Low degree of impurity

Measures of Node Impurity

- Gini Index
- Entropy
- Misclassification error

Finding the Best Split

D_0 I_0

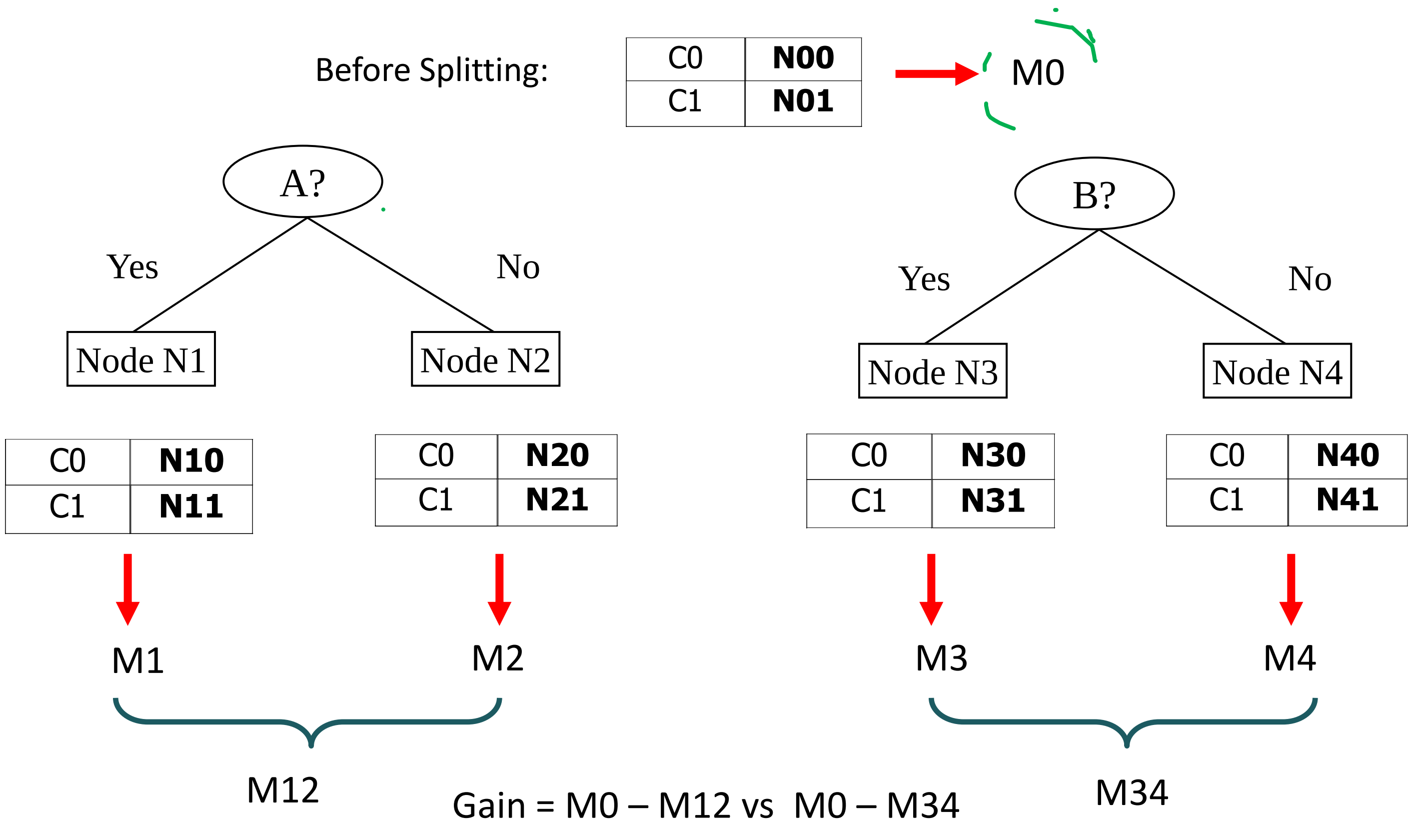
D_1 I_1 D_2 I_2

1. Compute impurity measure (M_0) before splitting
2. Compute impurity measure (M) after splitting
   - Compute impurity measure of each child node
   - M is the weighted impurity of children
3. Choose the attribute test condition that produces the highest gain

$$\text{Gain} = M_0 - M$$

or equivalently, lowest impurity measure after splitting (M)

How to Find the Best Split



Gain = M0 – M12 vs M0 – M34

Measure of Impurity: GINI

$1 - \sum_j p_j^2$

- Gini Index for a given node t :

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

(NOTE: *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
- 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	

$p(C_1) = 1/6$ $p(C_2) = 5/6$

Examples for computing GINI

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

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

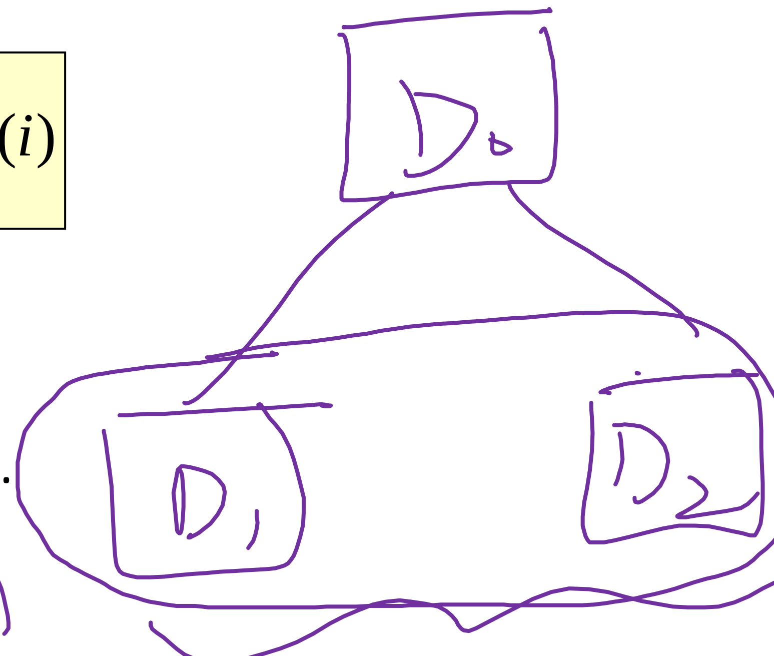
C_1 3
C_2 3

$1 - (3/6)^2 - (3/6)^2 = 0.5$

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,

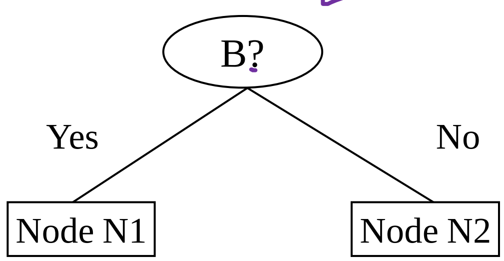
n = number of records at node p.

$$\frac{\|D_1\|}{\|D_1\| + \|D_2\|} * G_1 + \frac{\|D_2\|}{\|D_1\| + \|D_2\|} * G_2$$

Binary Attributes: Computing GINI Index

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

12



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

Gini(N1)
$= 1 - (5/7)^2 - (2/7)^2$
$= 0.408$

Gini(N2)
$= 1 - (1/5)^2 - (4/5)^2$
$= 0.32$

	N1	N2
C1	**5**	**1**
C2	**2**	**4**
Gini=0.37		

Gini(Children)
$= 7/12 * 0.408 +$
$\quad 5/12 * 0.32$
$= 0.37$

Weighted Sum

$0.5 - 0.37 = 0.13$

Categorical Attributes: Computing Gini Index

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

Go to

Multi-way split

more complex tree

	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	

less complex tree

Greatest gain

Income

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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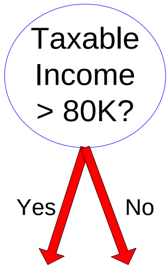


4 < 4N 0Y

6 < 3Y 3N

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	

Keep trying multiple split points

0 to 2 8 classes 0-3

Alternative Splitting Criteria

- Entropy at a given node t:

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

(NOTE: *p(j | 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

$0 \text{ to } \log_2 n_c$

Examples for computing Entropy

$p(C_1) \times \log_2(p(C_1)) + p(C_2) \times \log_2(p(C_2))$

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

$\log_2 p = \dfrac{\log p}{\log 2}$

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

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

Entropy = – 0 * $\log_2$ 0 – 1 * $\log_2$ 1 = – 0 – 0 = 0

$\log_2 1 = 0$

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

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

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

−2.59   −.26

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

$1/6 \times 2.59 + 5/6 \times 0.26$

$0.43 + 0.22 = 0.65$

Splitting Criteria based on Classification Error

- Classification error at a node t :

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

- Measures misclassification error made by a node.
  - 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

$1 - \max(0, 1) = 0$

Classification

Examples for Computing Error

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

0

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

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

Error = 1 – max (0, 1) = 1 – 1 = 0

$1 -$

1/6

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

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

Error = 1 – max (1/6, 5/6) = 1 – 5/6 = $\boxed{1/6}$

1/3

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

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

Error = 1 – max (2/6, 4/6) = 1 – 4/6 = $\boxed{1/3}$

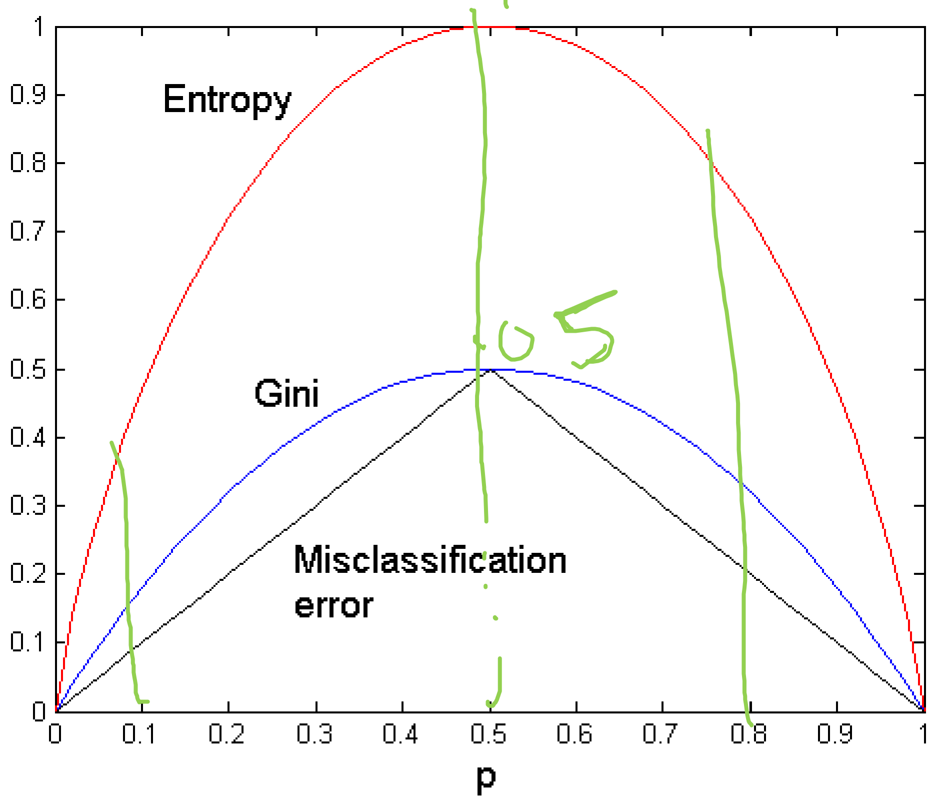
Comparison among Splitting Criteria

For a 2-class problem:

Better

0.1, 0.5

0.3, 0.7



Gain Ratio

Going beyond entropy

Attribute Selection Measure: Information Gain (ID3/C4.5)

- Select the attribute with the highest information gain
- Let p_i be the probability that an arbitrary tuple in D belongs to class C_i, estimated by $|C_{i,D}|/|D|$
- Expected information (entropy) needed to classify a tuple in D:

$$Info(D) = -\sum_{i=1}^{m} p_i \log_2(p_i)$$

- Information needed (after using A to split D into v partitions) to classify D:

$$Info_A(D) = \sum_{j=1}^{v} \frac{|D_j|}{|D|} \times Info(D_j)$$

- Information gained by branching on attribute A

$$Gain(A) = Info(D) - Info_A(D)$$

Attribute Selection: Information Gain

age	income	student	credit_rating	buys_computer
<=30	high	no	fair	no
<=30	high	no	excellent	no
31…40	high	no	fair	yes
>40	medium	no	fair	yes
>40	low	yes	fair	yes
>40	low	yes	excellent	no
31…40	low	yes	excellent	yes
<=30	medium	no	fair	no
<=30	low	yes	fair	yes
>40	medium	yes	fair	yes
<=30	medium	yes	excellent	yes
31…40	medium	no	excellent	yes
31…40	high	yes	fair	yes
>40	medium	no	excellent	no

- Class P: buys_computer = "yes"
- Class N: buys_computer = "no"

$$Info(D) = I(9,5) = -\frac{9}{14}\log_2\left(\frac{9}{14}\right) - \frac{5}{14}\log_2\left(\frac{5}{14}\right) = 0.940$$

Attribute Selection: Information Gain

$$Info_{age}(D) = \frac{5}{14}I(2,3) + \frac{4}{14}I(4,0) + \frac{5}{14}I(3,2)$$
$$= 0.694$$

age	p_i	n_i	$I(p_i, n_i)$
<=30	2	3	0.971
31…40	4	0	0
>40	3	2	0.971

$\frac{5}{14}I(2,3)$ means "age <=30" has 5 out of 14 samples, with 2 yes'es and 3 no's. Hence

$$Gain(age) = Info(D) - Info_{age}(D) = 0.246$$

Similarly,

$$Gain(income) = 0.029$$
$$Gain(student) = 0.151$$
$$Gain(credit\_rating) = 0.048$$

16 paths dividing data equally

Gain Ratio for Attribute Selection (C4.5)

- Information gain measure is biased towards attributes with a large number of values
- C4.5 (a successor of ID3) uses gain ratio to overcome the problem (normalization to information gain)
  - GainRatio(A) = Gain(A)/SplitInfo(A)

$$\boxed{SplitInfo_A(D) = -\sum_{j=1}^{v} \frac{|D_j|}{|D|} \times \log_2\left(\frac{|D_j|}{|D|}\right)}$$

$$-\sum_{}^{16} \frac{1}{16} \times \log_2 \frac{1}{16} =$$

- Ex.

$$SplitInfo_{income}(D) = -\frac{4}{14} \times \log_2\left(\frac{4}{14}\right) - \frac{6}{14} \times \log_2\left(\frac{6}{14}\right) - \frac{4}{14} \times \log_2\left(\frac{4}{14}\right) = 1.557$$

  - gain_ratio(income) = 0.029/1.557 = 0.019

$$16 \times \frac{1}{16} \times 4$$

- The attribute with the maximum gain ratio is selected as the splitting attribute

$$= 4$$

Refining Decision Tree Model

Stopping Criteria for Tree Induction

- Stop expanding a node when all the records belong to the same class
- Stop expanding a node when all the records have similar attribute values
- Early termination

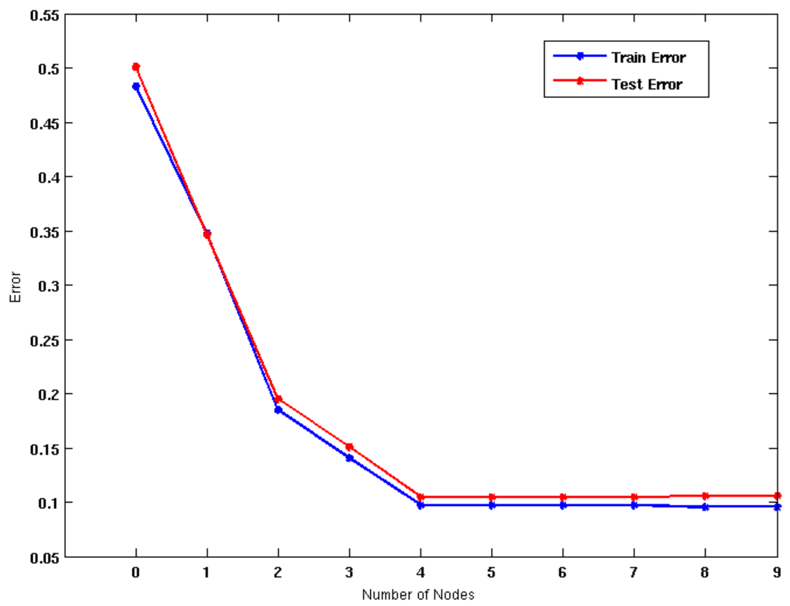
Practical Issues of Classification

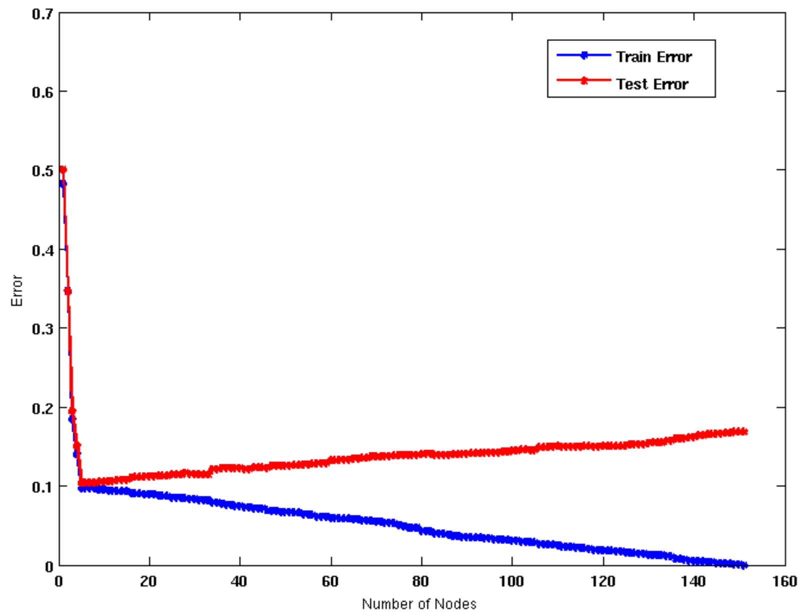
- Underfitting and Overfitting
- Missing Values
- Costs of Classification

Underfitting vs. Overfitting

- Underfitting results in decision trees that are too simple to solve the problem. They may offer superior interpretability.
- Overfitting results in decision trees that are more complex than necessary
  - Training error no longer provides a good estimate of how well the tree will perform on previously unseen records
  - Need new ways for estimating errors

Model Overfitting





Underfitting: when model is too simple, both training and test errors are large

Overfitting: when model is too complex, training error is small but test error is large

How to Address Overfitting

- Pre-Pruning (Early Stopping Rule)
  - Stop the algorithm before it becomes a fully-grown tree
  - General stopping conditions for a node:
    - Stop if all instances belong to the same class
    - Stop if all the attribute values are the same
  - More restrictive conditions (for pre-pruning) :
    - Stop if number of instances is less than some user-specified threshold
    - Stop if class distribution of instances are independent of the available features (e.g., using χ^2 test)
    - Stop if expanding the current node does not improve impurity measures (e.g., Gini or information gain).

How to Address Overfitting…

- Post-pruning
  - Grow decision tree to its entirety
  - Trim the nodes of the decision tree in a bottom-up fashion
  - If generalization error(i.e. expected error of the model on previously unseen records) improves after trimming, replace sub-tree by a leaf node.
  - Class label of leaf node is determined from majority class of instances in the sub-tree

Decision Tree Based Classification

- Advantages:
  - Inexpensive to construct
  - Extremely fast at classifying unknown records
  - Easy to interpret for small-sized trees
  - Accuracy is comparable to other classification techniques for many simple data sets

Prescribed Text Books

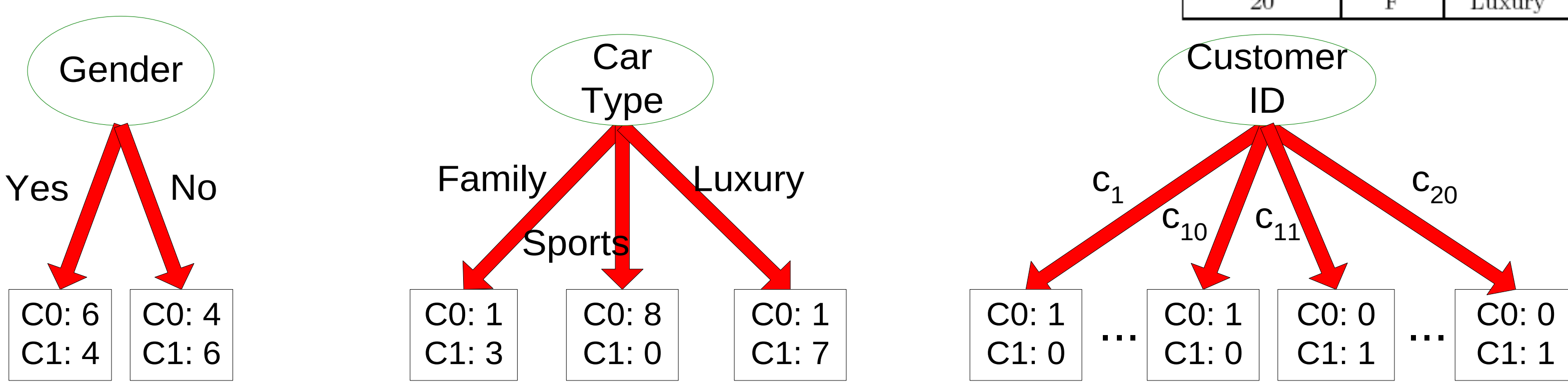
	Author(s), Title, Edition, Publishing House
T1	Tan P. N., Steinbach M & Kumar V. "Introduction to Data Mining" Pearson Education
T4	Data Mining: Concepts and Techniques, Third Edition by Jiawei Han, Micheline Kamber and Jian Pei Morgan Kaufmann Publishers
	Principles of Data Mining, Second Edition by Max Bramer Springer © 2013

Thank You

How to determine the Best Split

Customer Id	Gender	Car Type	Shirt Size	Class
1	M	Family	Small	C0
2	M	Sports	Medium	C0
3	M	Sports	Medium	C0
4	M	Sports	Large	C0
5	M	Sports	Extra Large	C0
6	M	Sports	Extra Large	C0
7	F	Sports	Small	C0
8	F	Sports	Small	C0
9	F	Sports	Medium	C0
10	F	Luxury	Large	C0
11	M	Family	Large	C1
12	M	Family	Extra Large	C1
13	M	Family	Medium	C1
14	M	Luxury	Extra Large	C1
15	F	Luxury	Small	C1
16	F	Luxury	Small	C1
17	F	Luxury	Medium	C1
18	F	Luxury	Medium	C1
19	F	Luxury	Medium	C1
20	F	Luxury	Large	C1

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



Which test condition is the best?