
Decision Trees

HCL \Leftrightarrow AH.

↳ Emulate human decision.

Classification: Definition

→ Data.

- 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.

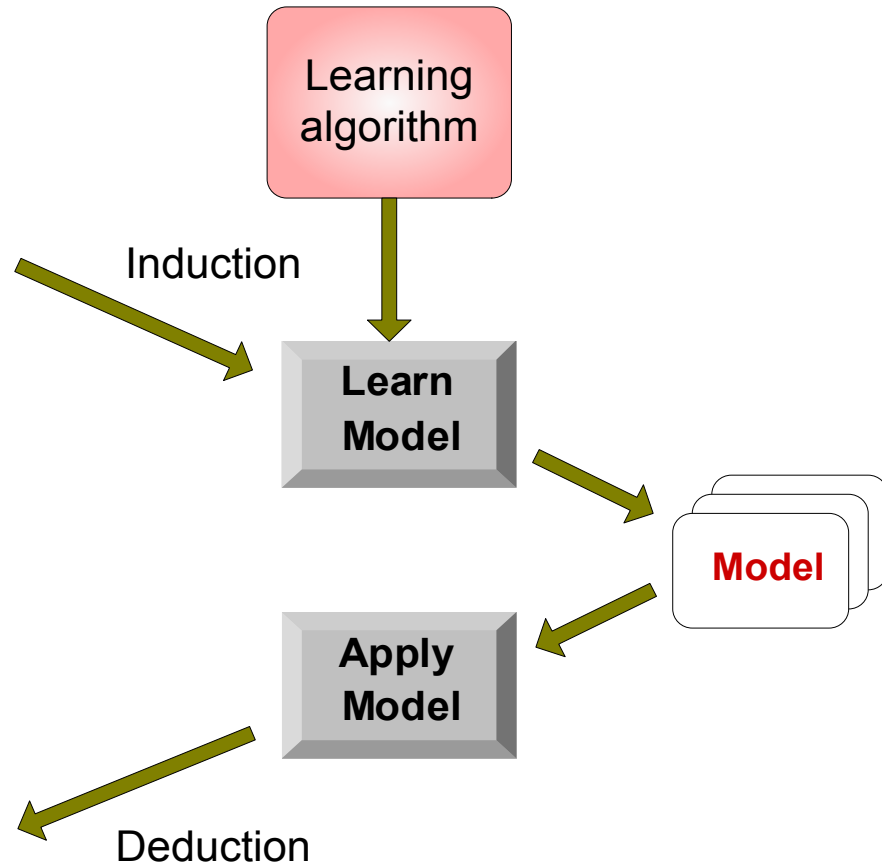
Illustrating Classification Task

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

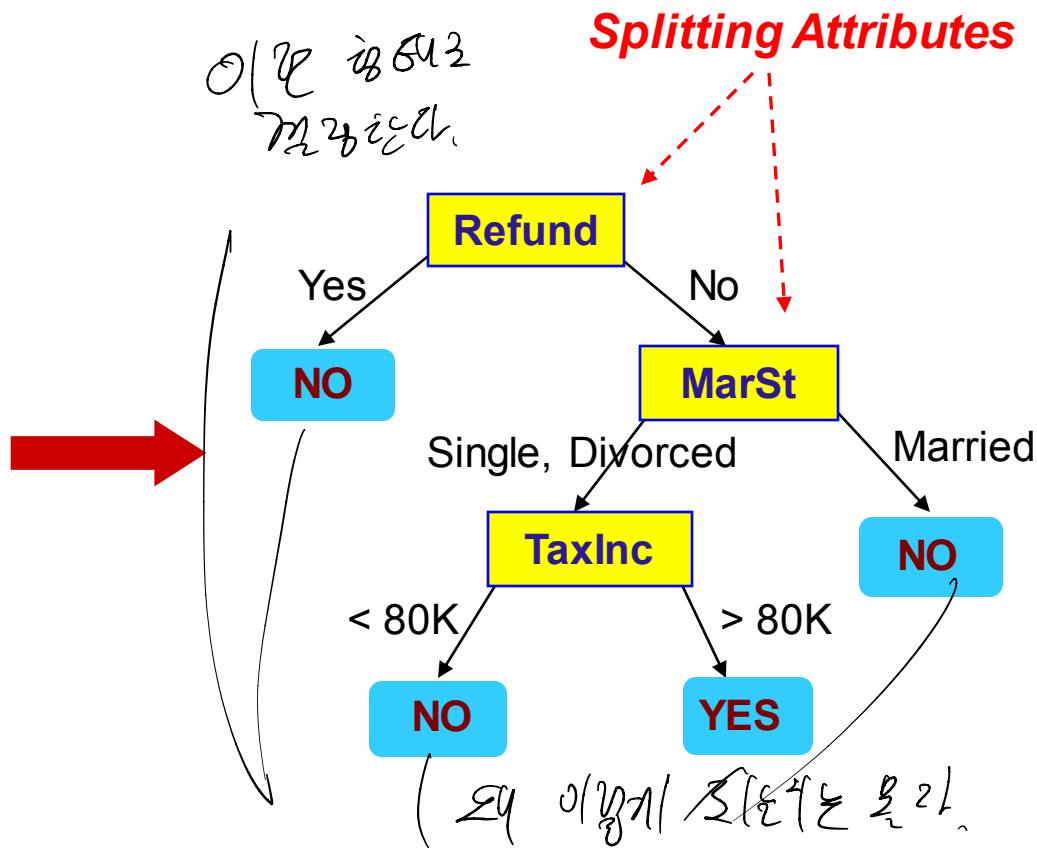


Example of a Decision Tree

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

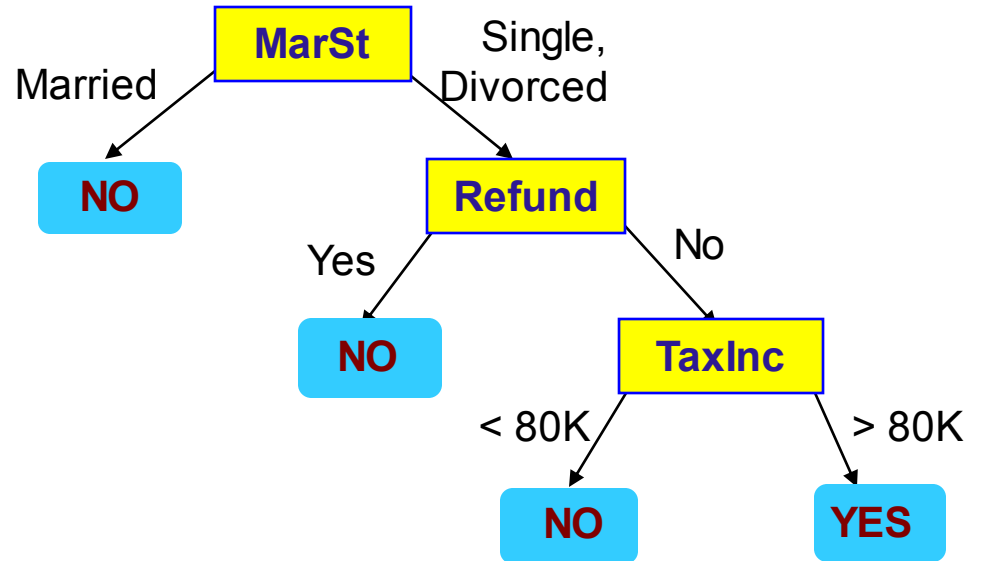


Model: Decision Tree

Another Example of Decision Tree

categorical
categorical
continuous
class

<i>Tid</i>	Refund	Marital Status	Taxable Income	Cheat
1	Yes	Single	125K	No
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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!

공인 회계사, 차관관 521

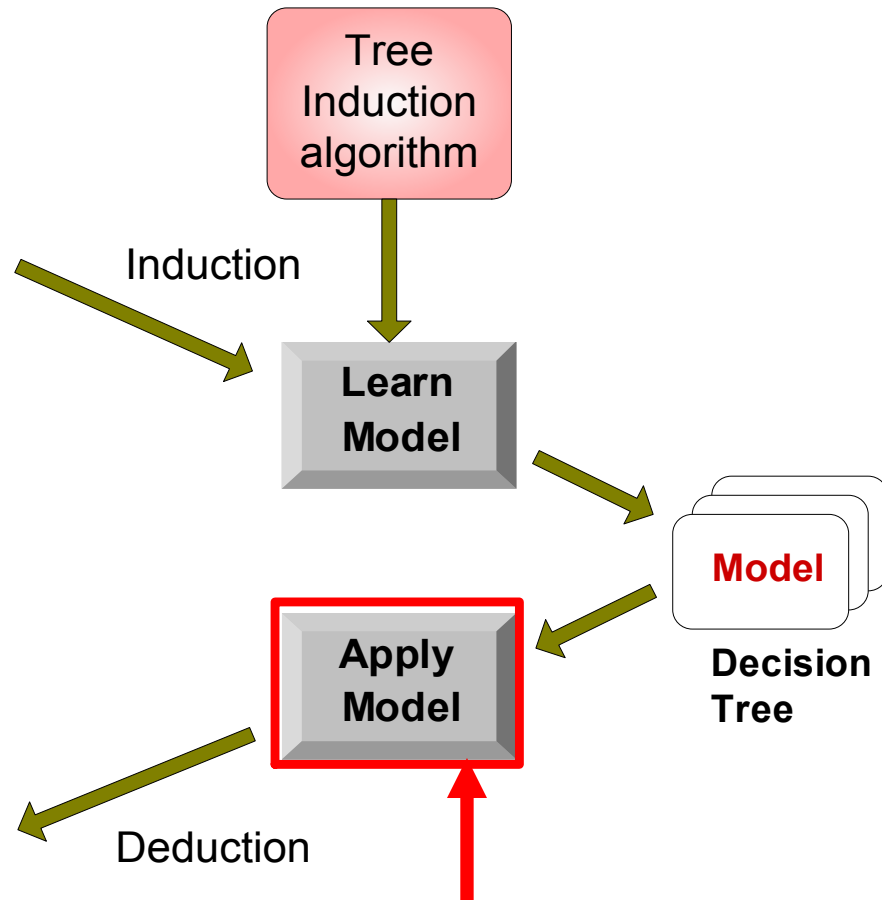
Decision Tree Classification Task

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Test Set



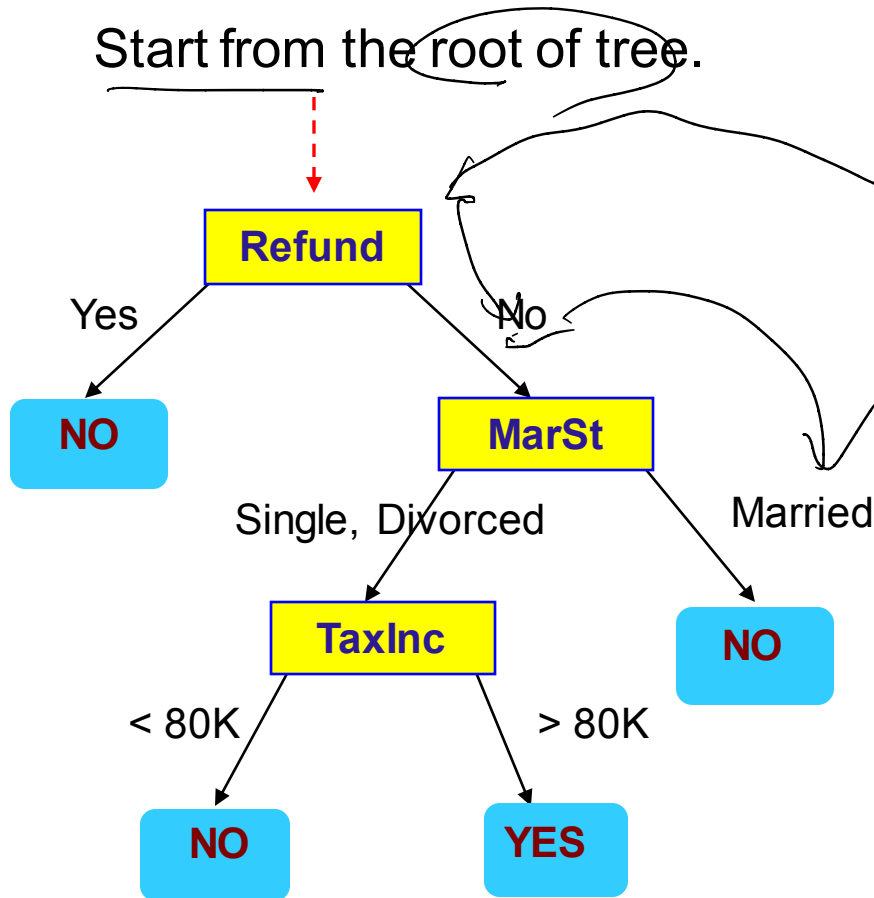
Apply Model to Test Data

Test Data

Refund	Marital Status	Taxable Income	Cheat
No	Married	80K	?

NO!

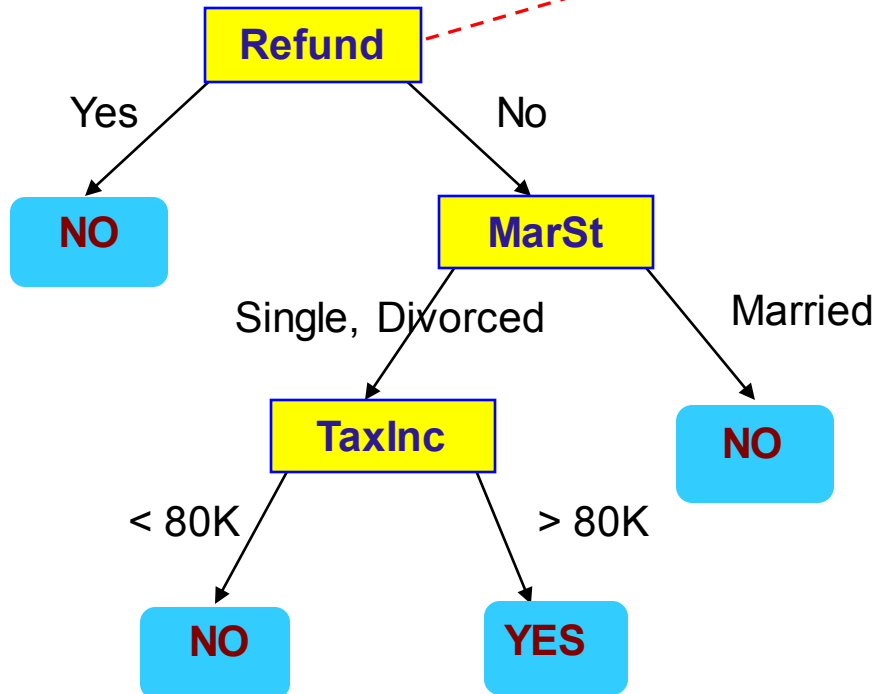
Start from the root of tree.



Apply Model to Test Data

Test Data

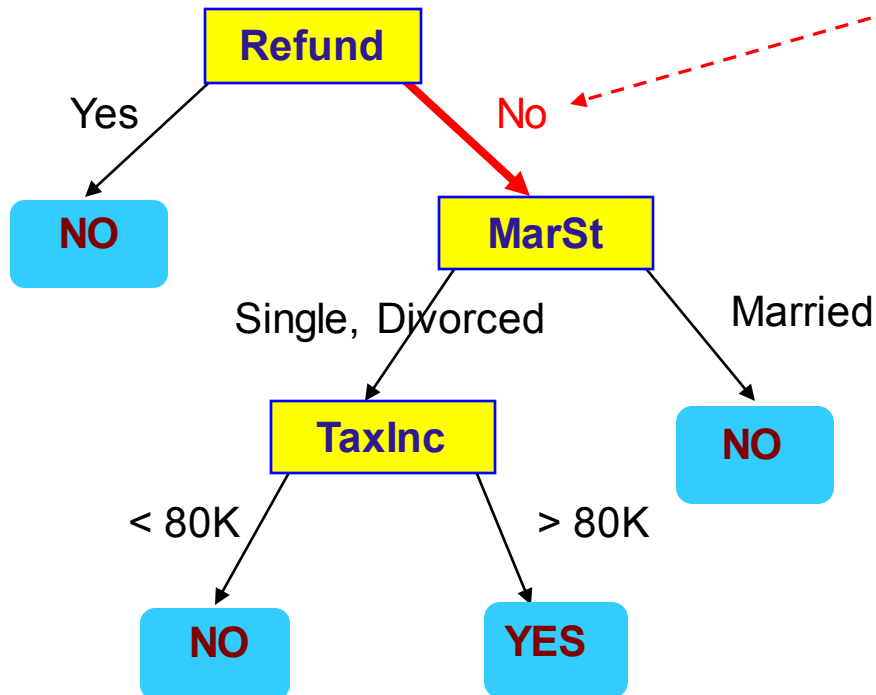
Refund	Marital Status	Taxable Income	Cheat
No	Married	80K	?



Apply Model to Test Data

Test Data

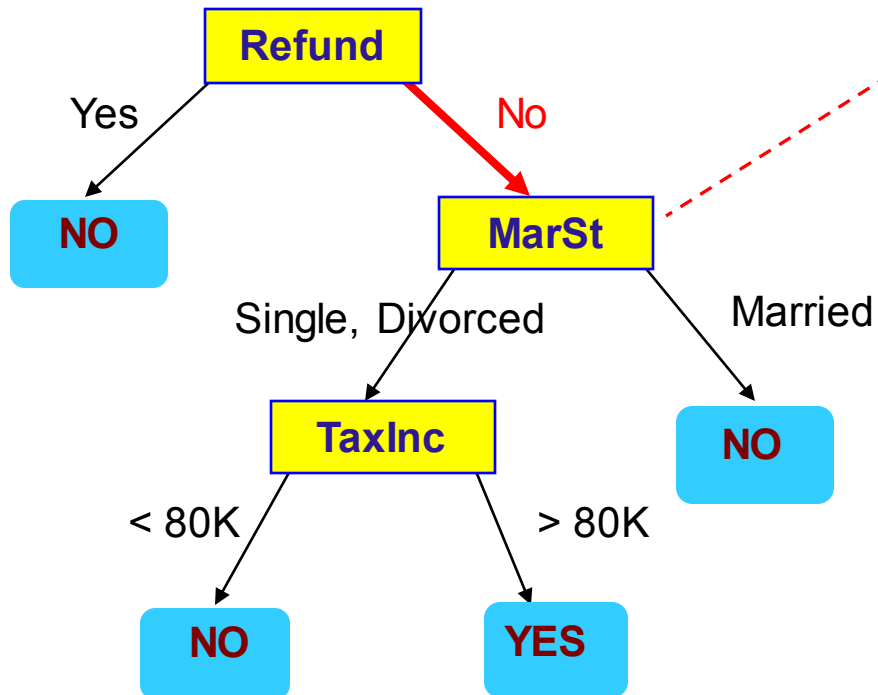
Refund	Marital Status	Taxable Income	Cheat
No	Married	80K	?



Apply Model to Test Data

Test Data

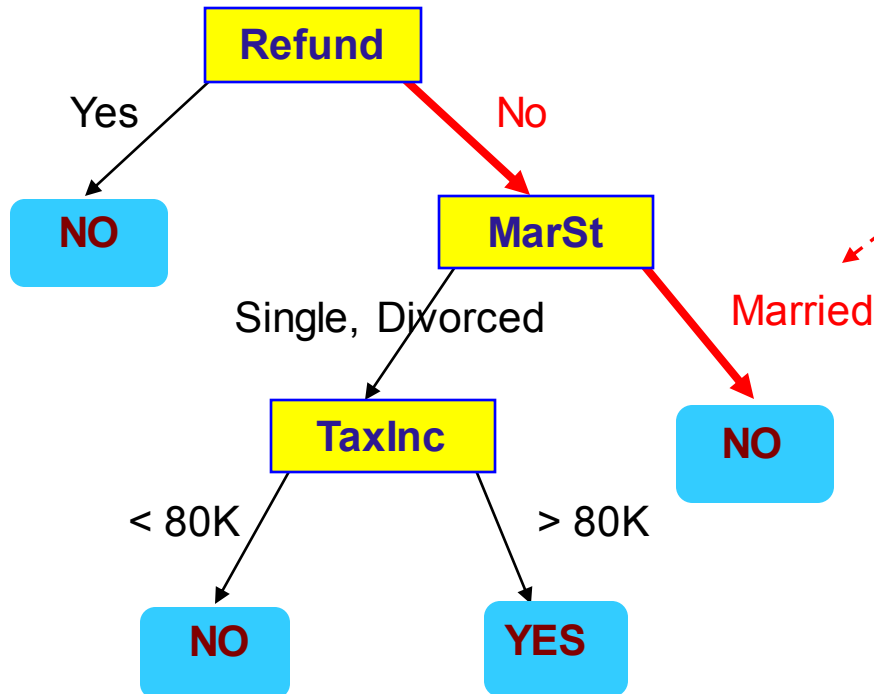
Refund	Marital Status	Taxable Income	Cheat
No	Married	80K	?



Apply Model to Test Data

Test Data

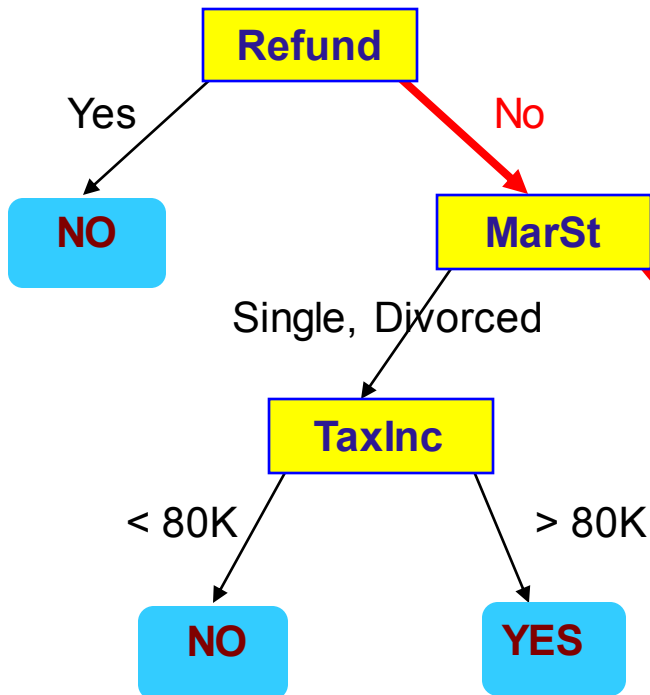
Refund	Marital Status	Taxable Income	Cheat
No	Married	80K	?



Apply Model to Test Data

Test Data

Refund	Marital Status	Taxable Income	Cheat
No	Married	80K	?



Assign Cheat to "No"

Classification (cheat or not?)

~ **"Search" ?**

~ **"Solving a problem" ?**

~ **"Searching for an answer"?**

Find me answer for:

"Will this person with these attributes cheat?"

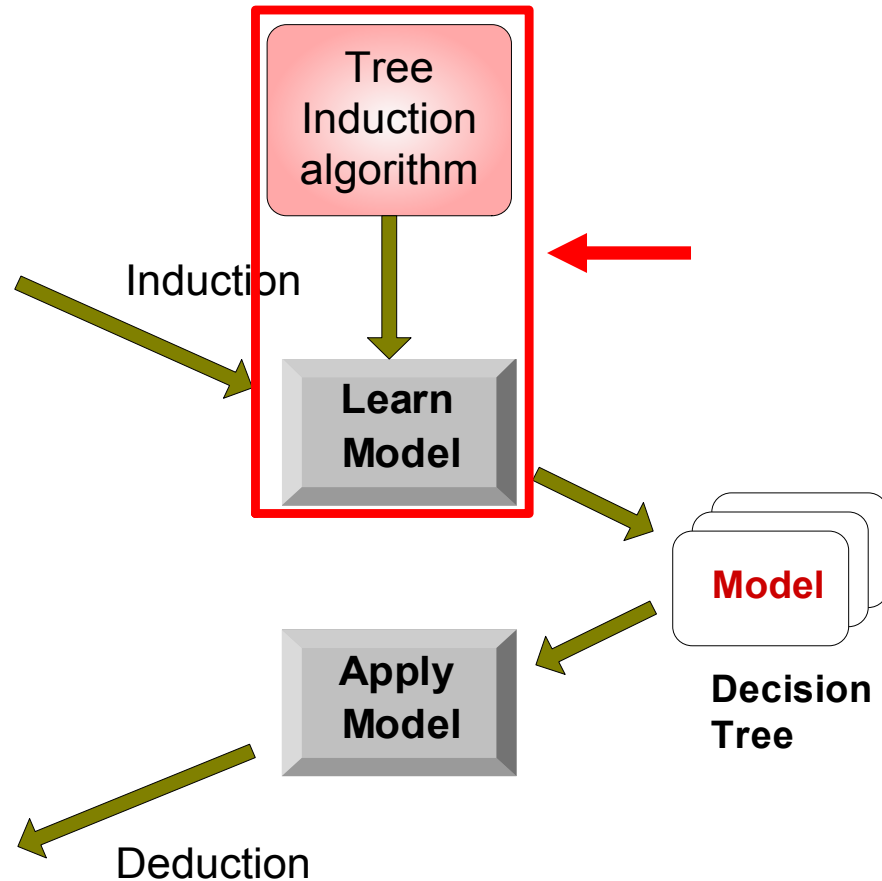
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Test Set



Decision Tree Induction

□ Many Algorithms

- Hunt's Algorithm (one of the earliest)
- CART
- ID3, C4.5
- SLIQ, SPRINT

Deriving the interaction model (search process, solution process)

→ Manually through user research

→ We also see that this is somewhat possible with just data


→ Of course data comes from the humans anyway

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

→ 이 때 질문은 그만 해야 하는가? // attribute가 부족하거나 많을 때
가장 좋은 split을 찾지 못했는지

Stopping Criteria for Tree Induction

- Stop expanding a node when all the records belong to the same class $\frac{10}{20} \frac{0}{2} \frac{24}{20} \frac{5}{2}$
- Stop expanding a node when all the records have similar attribute values
 $\frac{10}{20} \frac{5}{20} \frac{24}{20}$
- Early termination (to be discussed later)

Decision Tree Based Classification

□ Advantages:

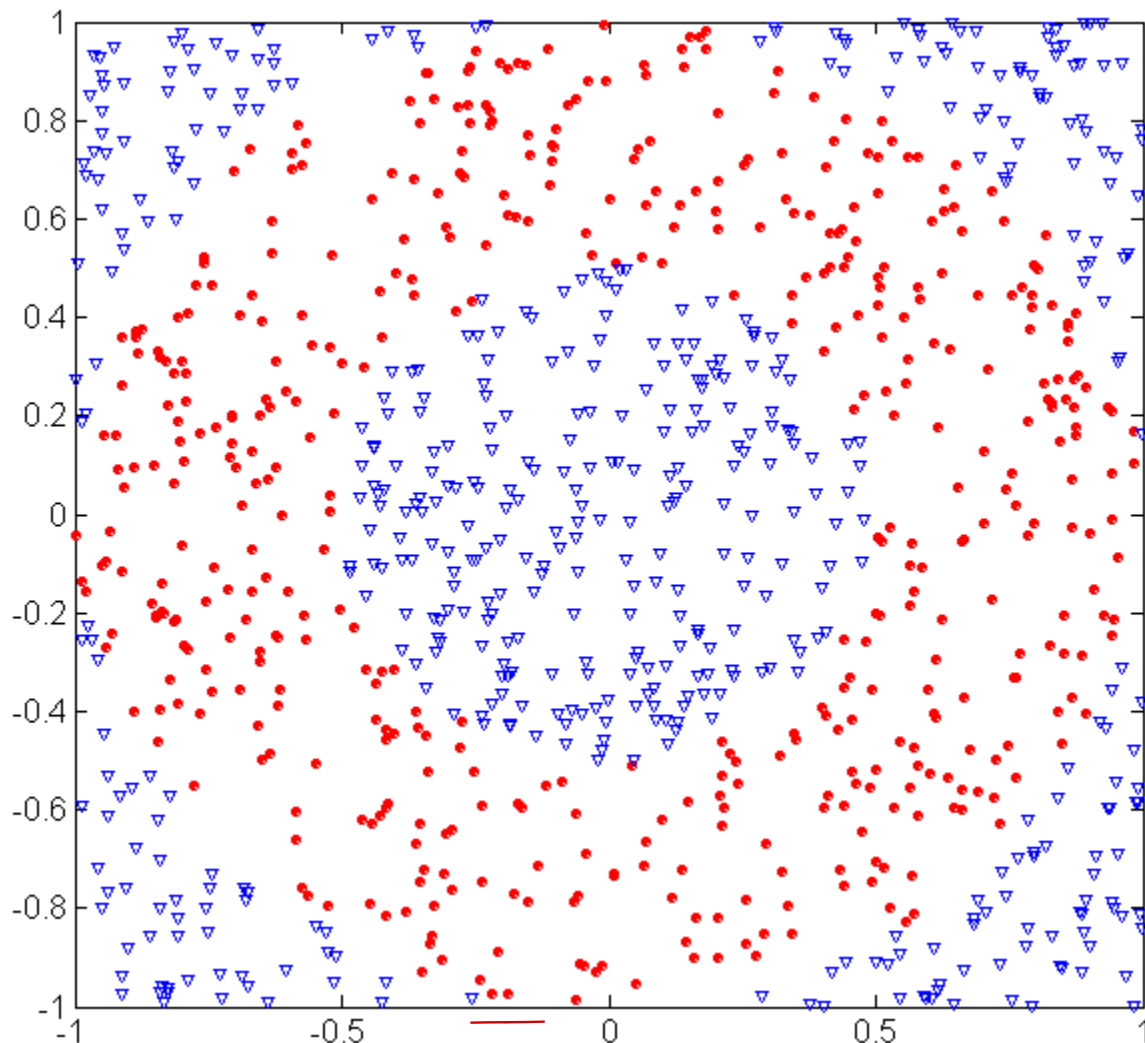
- Inexpensive to construct
- Extremely fast at classifying unknown records
- Easy to interpret for small-sized trees
- Accuracy is comparable to other classification techniques for many simple data sets

Practical Issues of Classification

- Underfitting and Overfitting
- Missing Values
- Costs of Classification

Underfitting and Overfitting (Example)

2차원 데이터 분포 = 2개의 클래스를 가진 데이터



500 circular and 500 triangular data points.

Circular points:

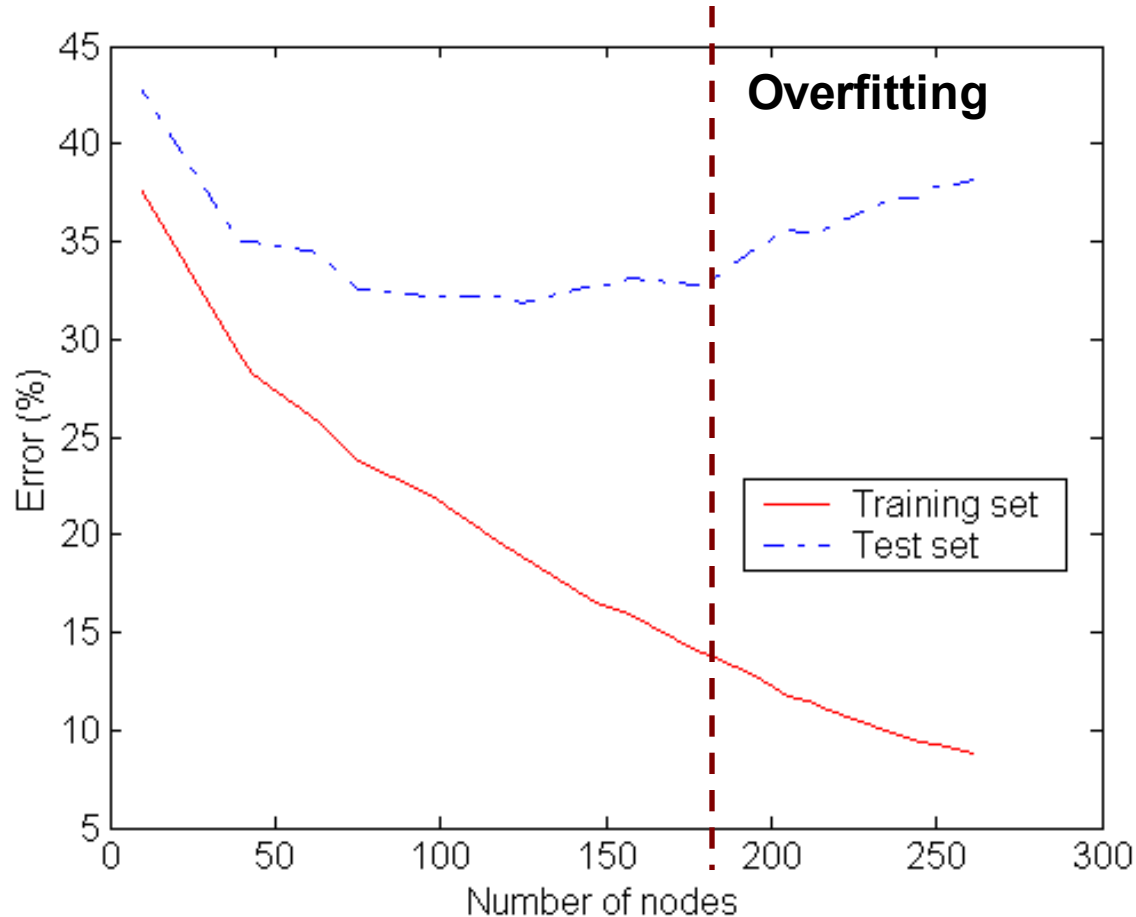
$$0.5 \leq \sqrt{x_1^2 + x_2^2} \leq 1$$

Triangular points:

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

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

Underfitting and Overfitting

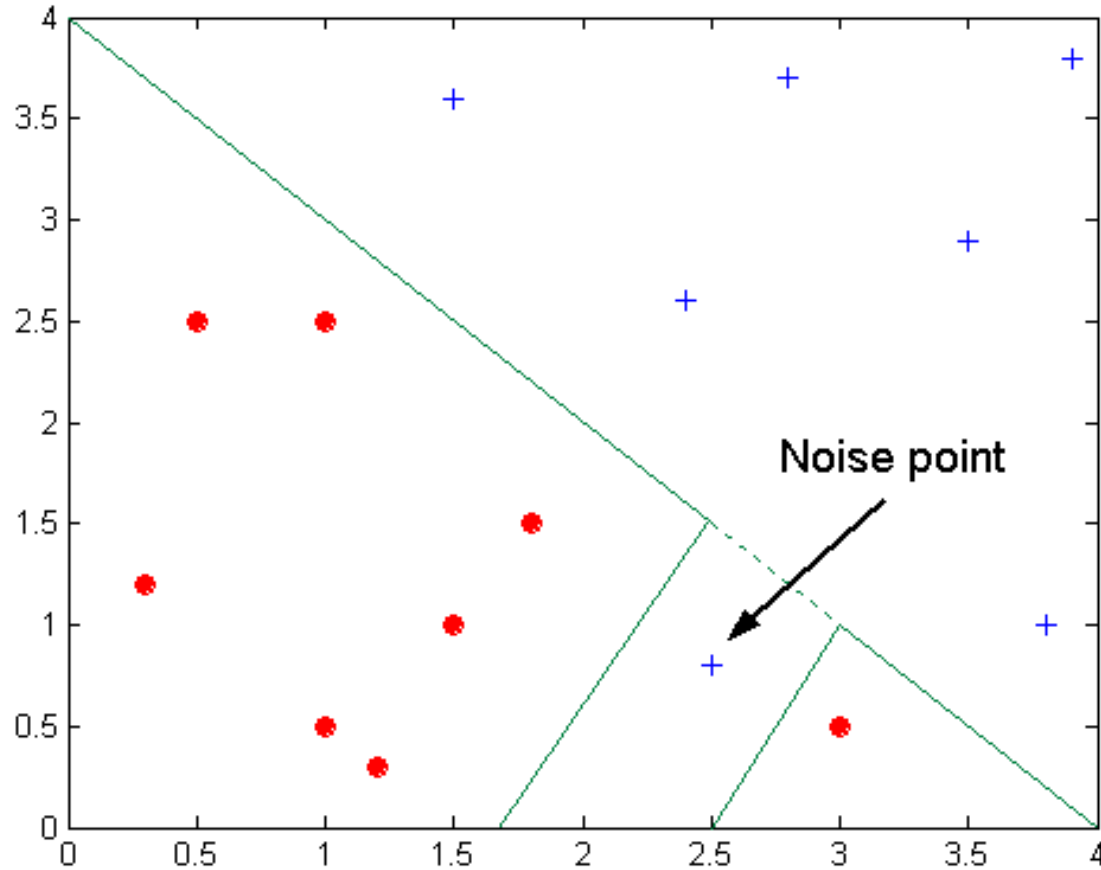


Underfitting: when model is too simple, both training and test errors are large
모델이 너무 단순하다.

Overfitting due to Noise



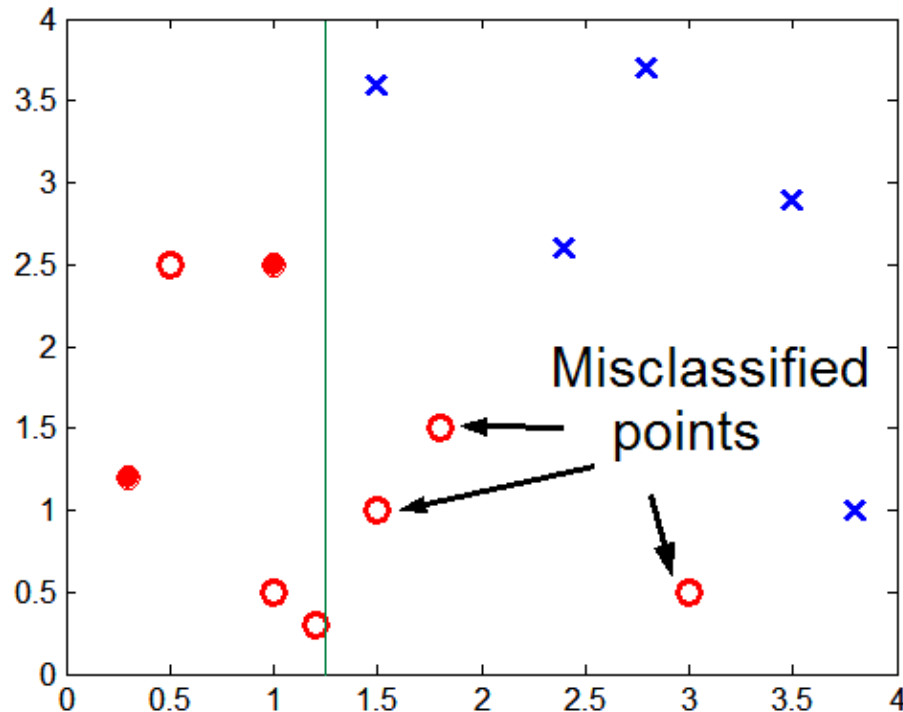
데이터의 노이즈
가 많을수록



Decision boundary is distorted by noise point

Overfitting due to Insufficient Examples

only one line
⇒ overfitting



Lack of data points in the lower half of the diagram makes it difficult to predict correctly the class labels of that region

- Insufficient number of training records in the region causes the decision tree to predict the test examples using other training records that are irrelevant to the classification task**

Notes on Overfitting

- 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

How to Address Overfitting

⇒ 문제가 너무 복잡하거나 많은 경우.

□ Pre-Pruning (Early Stopping Rule)

- Stop the algorithm before it becomes a fully-grown tree
- Typical 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:
 - ◆ 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).

이런 경우를 방지.

2가지.

→ 각 노드의 깊이를 제한하는 등.

How to Address Overfitting...

→ 8213, 2021, 2021

□ Post-pruning

- Grow decision tree to its entirety
- Trim the nodes of the decision tree in a bottom-up fashion
- If generalization error 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

How to Address Overfitting...

□ Post-pruning

- Grow decision tree to its entirety
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- If generalization error improves after trimming, replace sub-tree by a leaf node.
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