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# Pattern Recognition

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# Summary

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- Decision Tree & Random Forests I
  - Hand on Labs: Data Classification using library
- Decision Tree & Random Forests II
  - Hand on Labs: Implementation of DT-RF



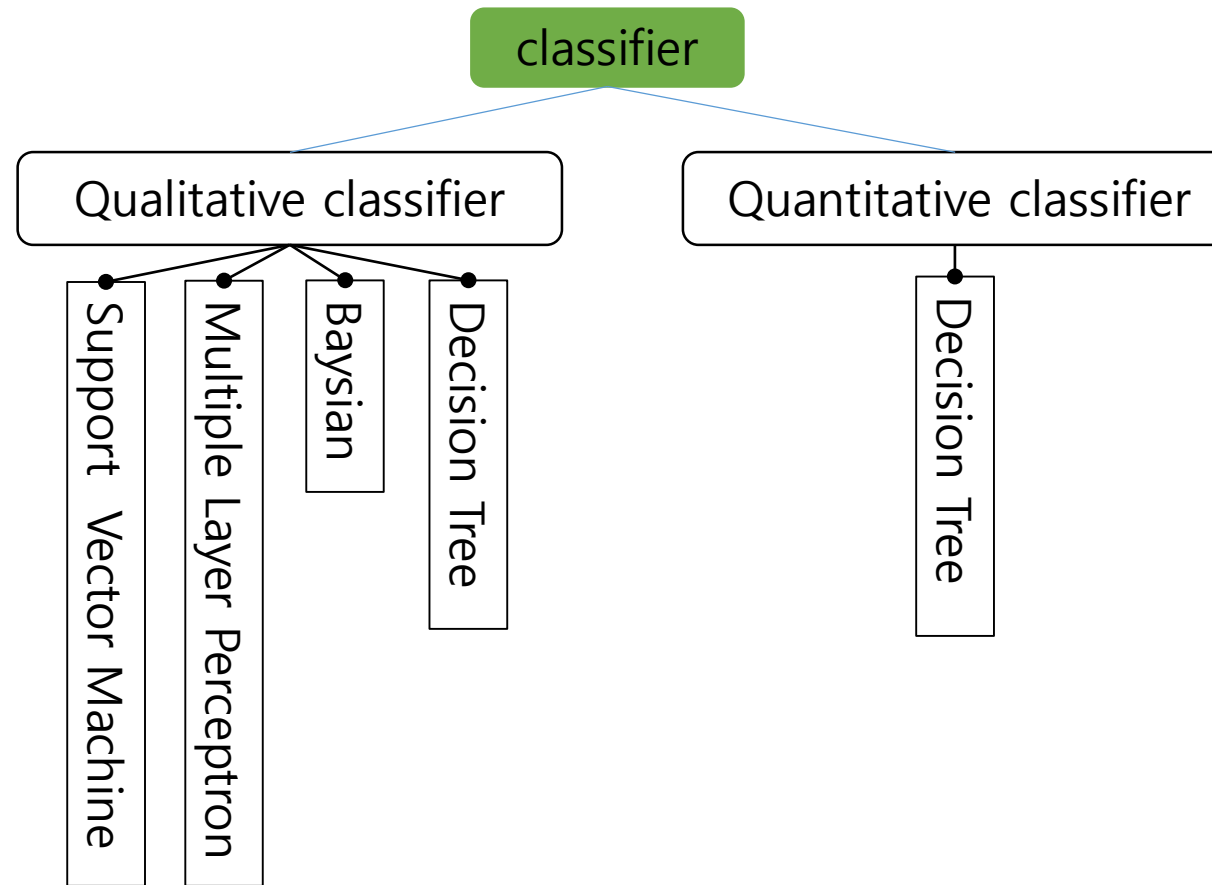
# Content

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- Decision Tree
- Random Decision Trees
- Random Forests
- Random Forests with discriminative decision tree



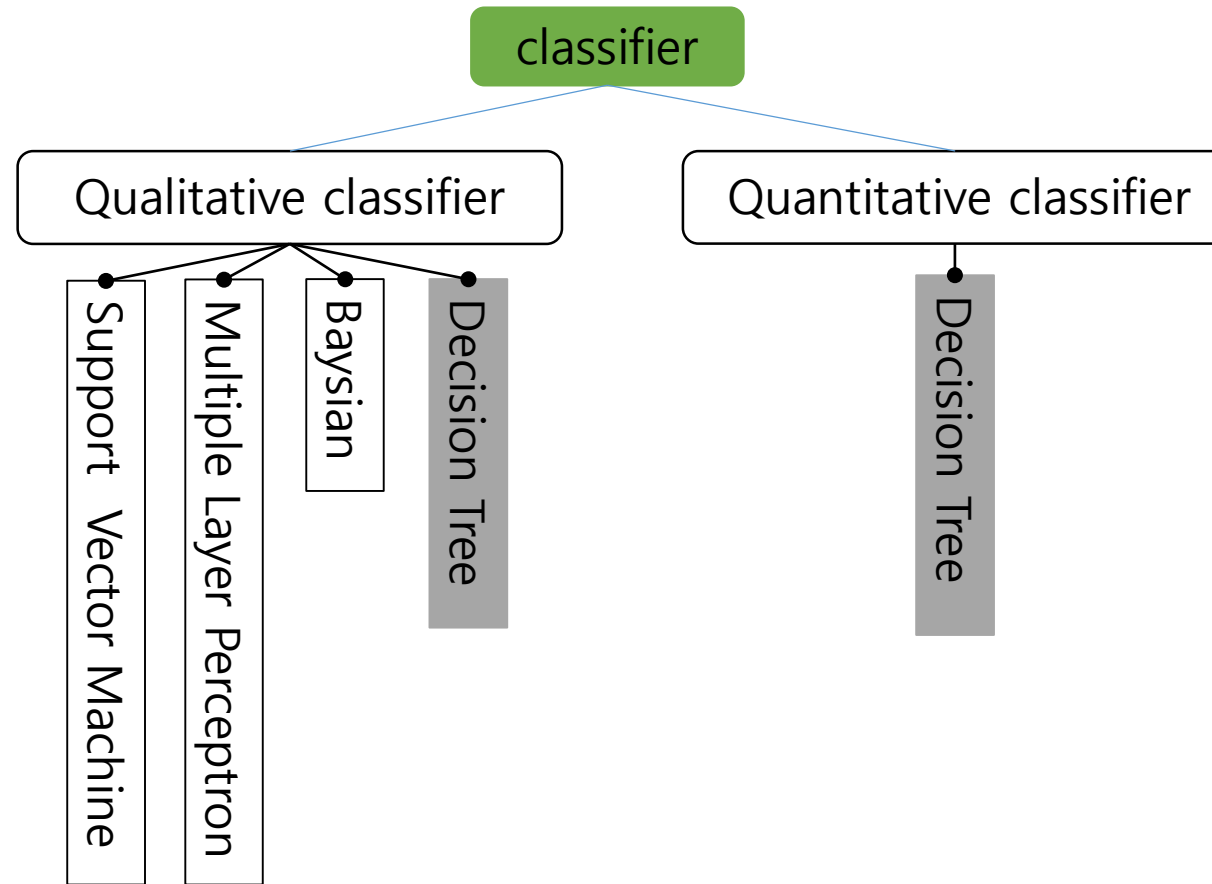
# Classifier



Metric/Non-Metric data : 어떤 사물이나 개념을 양적/질적 으로 표시한 데이터



# Classifier



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# Decision Tree

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## Definition

*Tree structure* based Classifier

Classification method by using **several rules** and **constrains**.



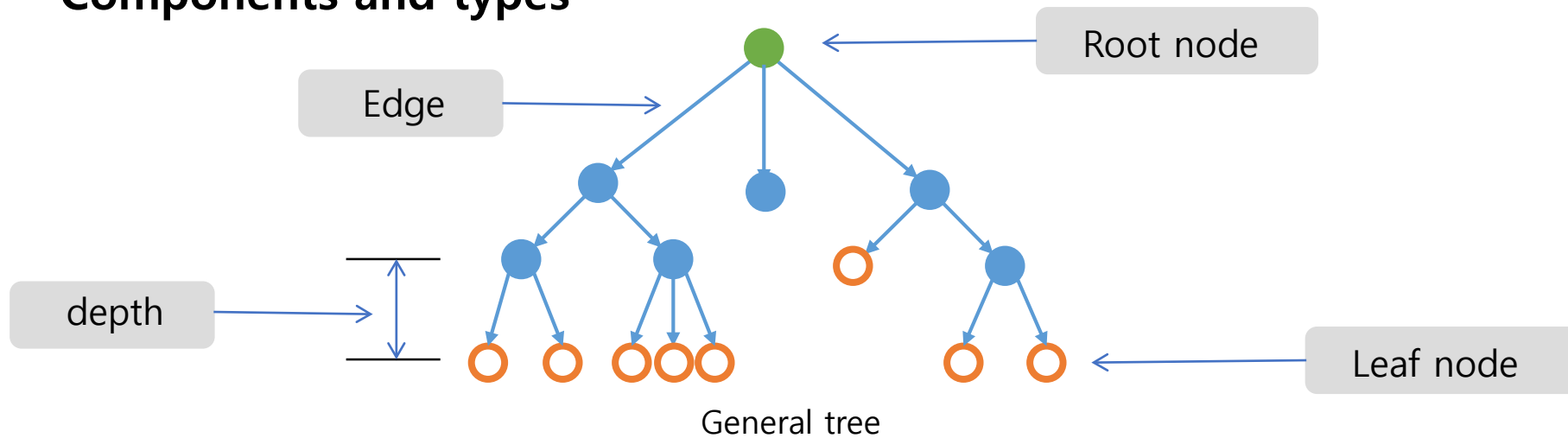
# Decision Tree

## Definition

Tree structure based Classifier

Classification method by using several rules and constrains.

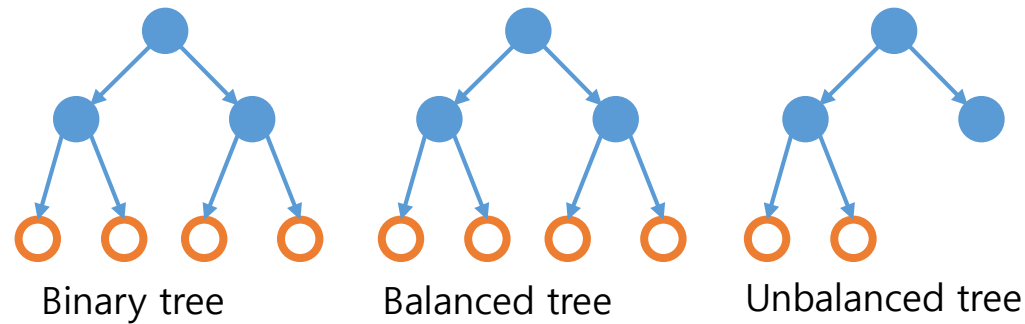
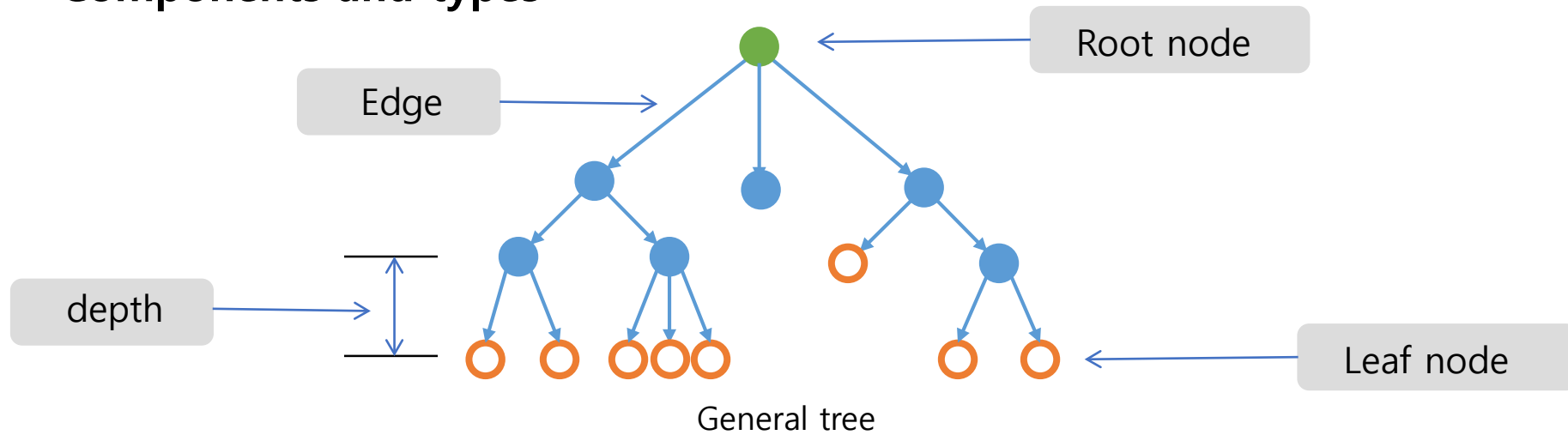
## Components and types





# Decision Tree

## Components and types







# Decision Tree

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## Training

build the tree

## Consideration in this step

- 1) How many splits should there be at each node?
- 2) How to select the query attribute?
- 3) When to stop growing the tree?
- 4) Which class to allow leaf nodes?



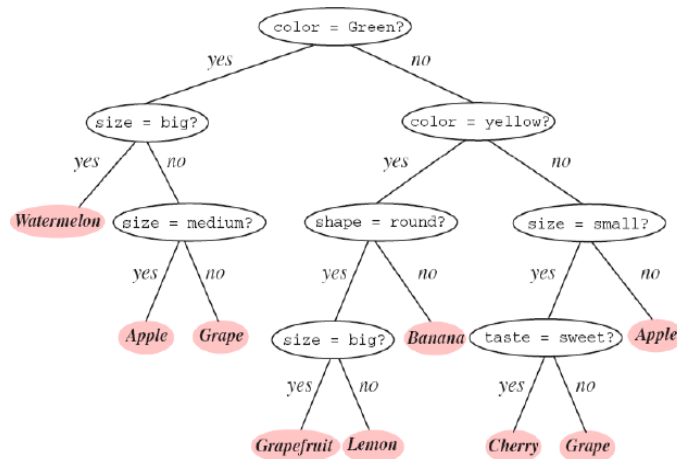
# Decision Tree

## Training

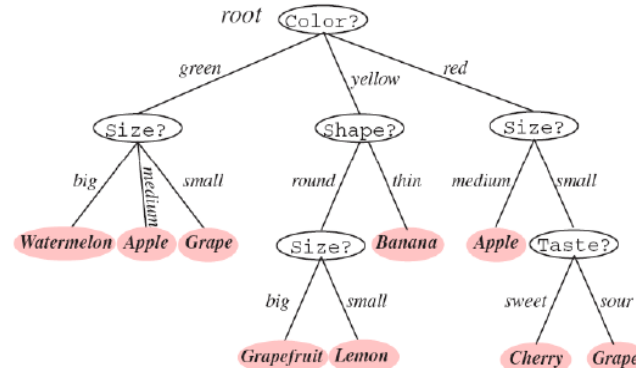
build the tree

## Consideration in this step

1) How many splits should there be at each node?



Multi-valued tree



Binary tree



# Decision Tree

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## Training

build the tree

### Consideration in this step

2) How to select the query attribute?

**Ready to Candidate query attributes :**

Collect all possible attributes



# Decision Tree

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## Training

build the tree

### Consideration in this step

2) How to select the query attribute?

**Ready to Candidate query attributes :**

Collect all possible attributes

**Select the best query attributes :**

Find the maximal decrease in *impurity(entropy)*



# Decision Tree

## Training

build the tree

## Consideration in this step

2) How to select the query attribute?

**Ready to Candidate query attributes :**

Collect all possible attributes

**Select the best query attributes :**

Find the maximal decrease in *impurity(entropy)*

$$\Delta im(T) = im(T) - \frac{|X_{Tleft}|}{|X_T|} im(T_{left}) - \frac{|X_{Tright}|}{|X_T|} im(T_{right})$$

$$\Delta im(T) = \frac{|X_{Tleft}|}{|X_T|} \frac{|X_{Tright}|}{|X_T|} \left( \sum_{i=1}^M |p(w_i | T_{left}) - p(w_i | T_{right})| \right)^2$$



# Decision Tree

## Training

build the tree

## Consideration in this step

2) How to select the query attribute?

## Impurity functions

Entropy, Gini, Misclassification

Entropy	$im(T) = 1 - \sum_{i=1}^M p(w_i   T)^2 = \sum_{i \neq j} p(w_i   T) p(w_j   T)$
Gini	$im(T) = - \sum_{i=1}^M p(w_i   T) \log_2 p(w_i   T)$
Misclassification	$im(T) = 1 - \max_i p(w_i   T)$



# Decision Tree

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## Training

build the tree

## Consideration in this step

3) When to stop growing the tree?

## Stop conditions

$$im(T) = 0$$



**Overfitting**



# Decision Tree

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## Training

build the tree

## Consideration in this step

3) When to stop growing the tree?

### Stop conditions

$$im(T) = 0$$

the number of  $X_t \leq \text{threshold}$

$\arg\max \triangle im(T) \leq \text{threshold}$



**Overfitting**



**Premature  
convergence**





# Decision Tree

## Training

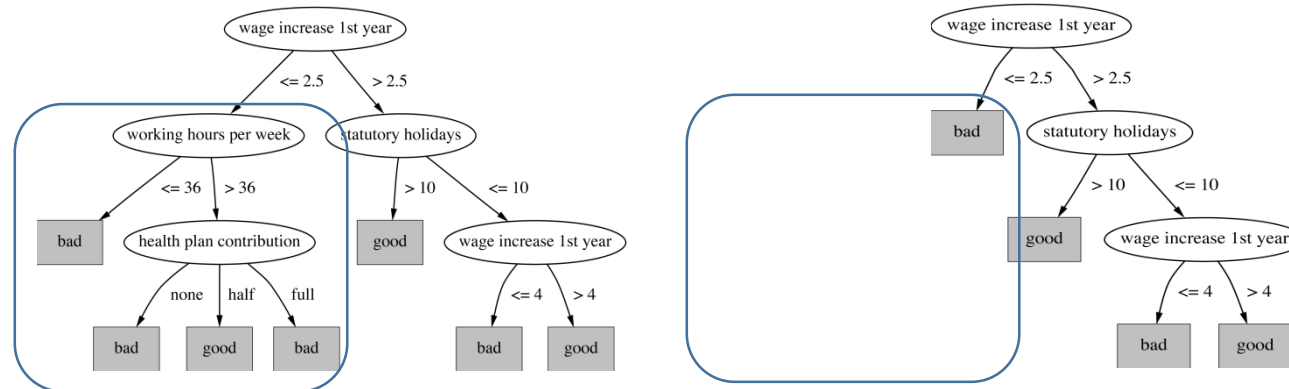
build the tree

## Consideration in this step

3) When to stop growing the tree?

## Avoiding overfitting & premature convergence

Make the largest tree and then do *pruning*



Example of pruning



# Decision Tree

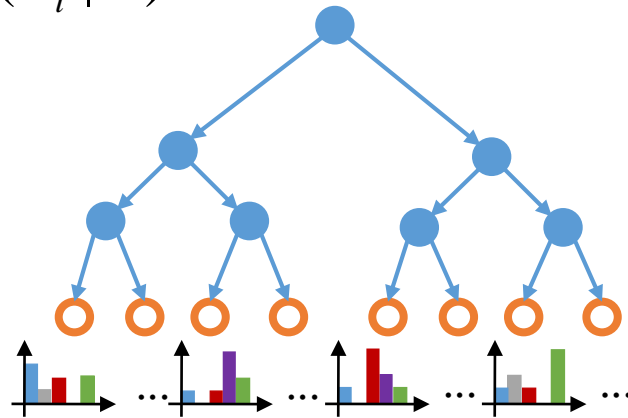
## Training

build the tree

## Consideration in this step

4) Which class to allocate leaf nodes?

$$K = \arg \max_i p(w_i | T)$$





# Decision Tree

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## **Classification**

recognize the sample



# Decision Tree

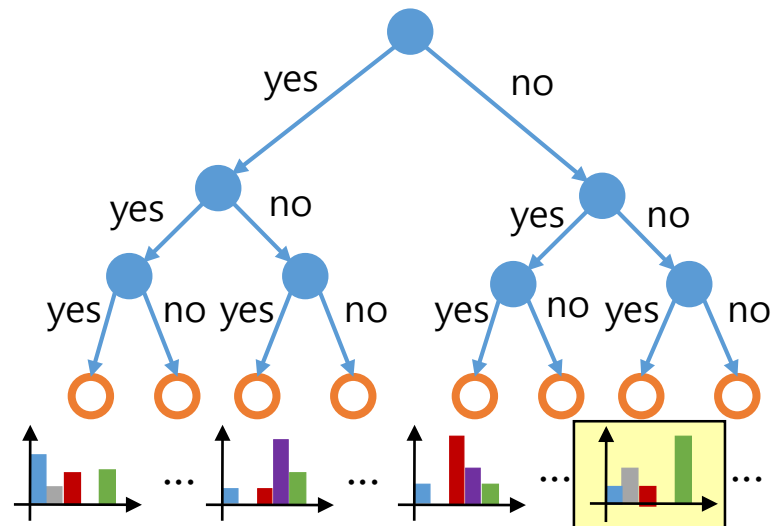
## Classification

recognize the sample

## Advantages

Very fast "Yes/NO" operation

Just  $h-1$  times comparison (  $h$  : depth level )



Example of classification

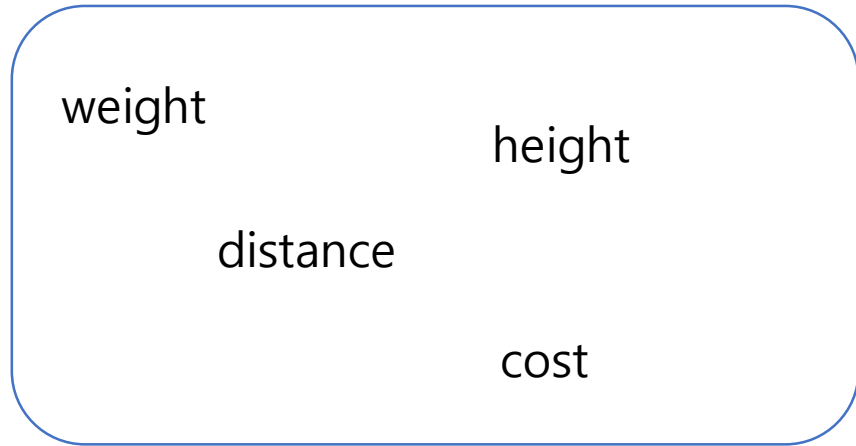


# Decision Tree

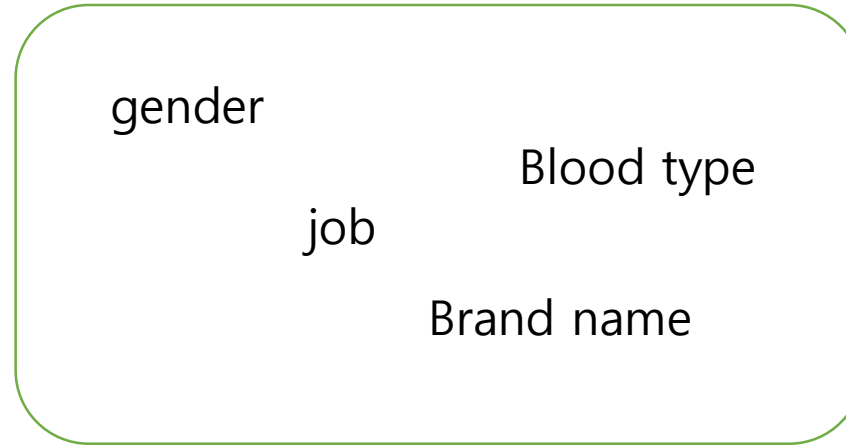
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## Characteristics

+Handling the metric and non-metric data



Metric data



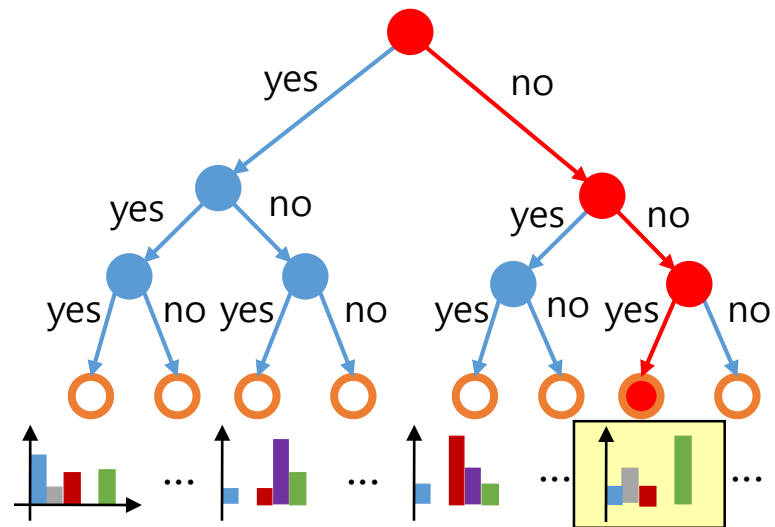
Non-Metric data



# Decision Tree

## Characteristics

- +Handling the metric and non-metric data
- +Visualization





# Decision Tree

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## Characteristics

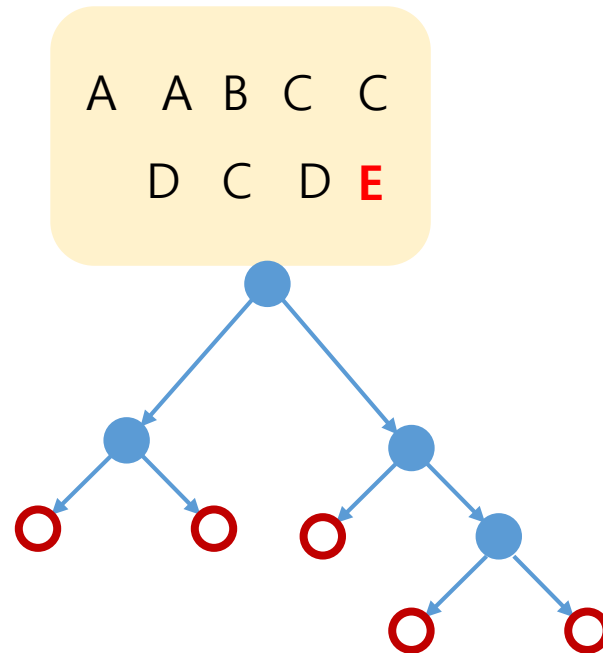
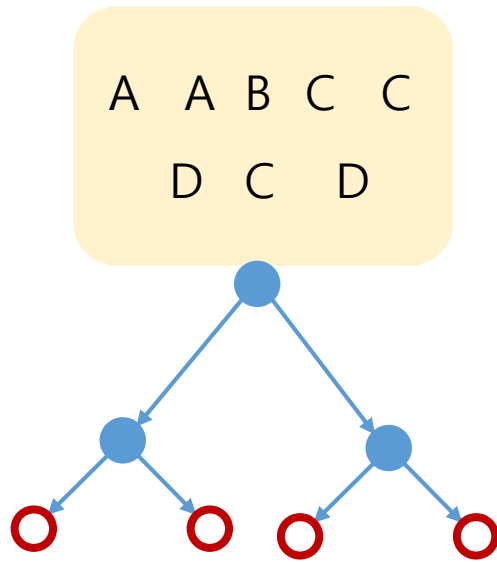
- +Handling the metric and non-metric data
- +Visualization
- +Fast recognition



# Decision Tree

## Characteristics

- +Handling the metric and non-metric data
- +Visualization
- +Fast recognition
- Instability







# Decision Tree

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## Characteristics

- + Handling the metric and non-metric data
- + Visualization
- + Fast recognition
- Instability
- Greedy algorithms



# Decision Tree

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## Characteristics

- +Handling the metric and non-metric data
- +Visualization
- +Fast recognition
- Instability
- Greedy algorithms
- +Handling the missing data



# Decision Tree

## Algorithms

CART, ID3, C4.5

L.Breiman

CART

R.Quinlan

ID3



C4.5



C5.0

extension

commercialization

## Comparisons

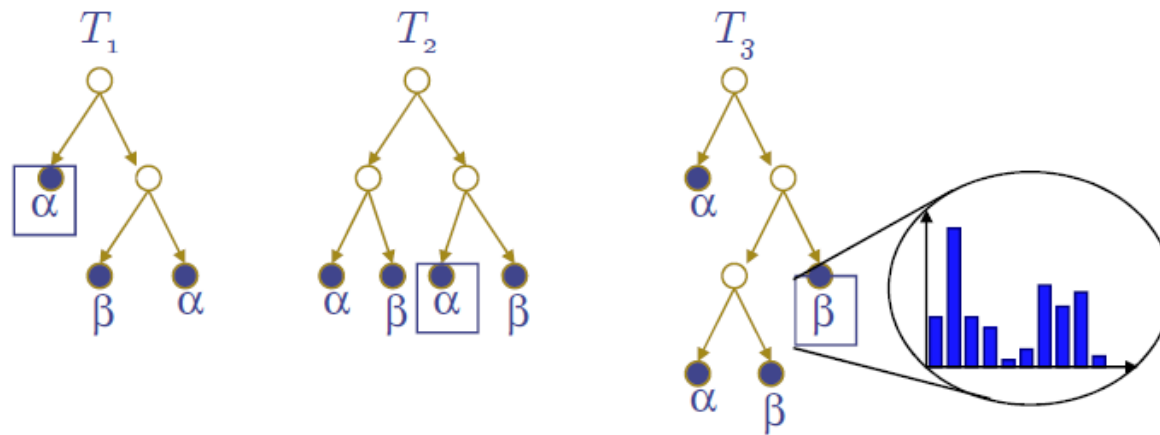
Property	CART	ID3	C4.5
Float data	O	X	O
Tree type	Binary	Multi	Multi
Prune	O	X	O
Classification	O	O	O
Regression	O	X	X
Missing data	Surrogate split	X	skip
Multi variable	O	X	X



# Randomized Decision Trees

**Randomized Decision Trees** ( Amit & German 1997 )

Multiple classifier of several trees



Randomized decision trees



# Randomized Decision Trees

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**Randomized Decision Trees** ( Amit & German 1997 )

Multiple classifier of several trees

Idea : **randomized attribute selection**



# Randomized Decision Trees

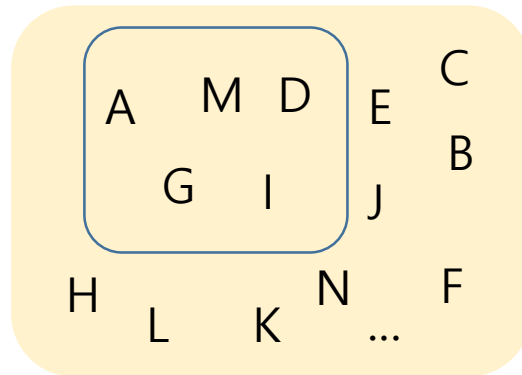
**Randomized Decision Trees** ( Amit & German 1997 )

Multiple classifier of several trees

**Idea : randomized attribute selection**

Instead **randomly use subset** of  $K$  attributes (  $K \ll \text{All cases}$  )

- Reduce correlation between different trees
- Typical choice :  $K = 10$  for root node,  $K = 100*d$  (  $d$  : depth level )



All cases of possible  
attributes



# Randomized Decision Trees

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**Randomized Decision Trees** ( Amit & German 1997 )

Multiple classifier of several trees

## **Idea : randomized attribute selection**

Instead randomly use subset of  $K$  attributes (  $K \ll \text{All cases}$  )

- Typical choice :  $K = 10$  for root node,  $K = 100*d$  (  $d$  : depth level )
- Reduce correlation between different trees.

Choose best splitting attribute

- **Minimizing entropy** ( impurity )



# Randomized Forests

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**Randomized Forests** ( Breiman 2001 )

Multiple classifier of several trees





# Randomized Forests

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**Randomized Forests** ( Breiman 2001 )

Multiple classifier of several trees

Idea : Randomness = <sup>1)</sup>**Bootstrap sampling** + <sup>2)</sup>randomized attribute selection



# Randomized Forests

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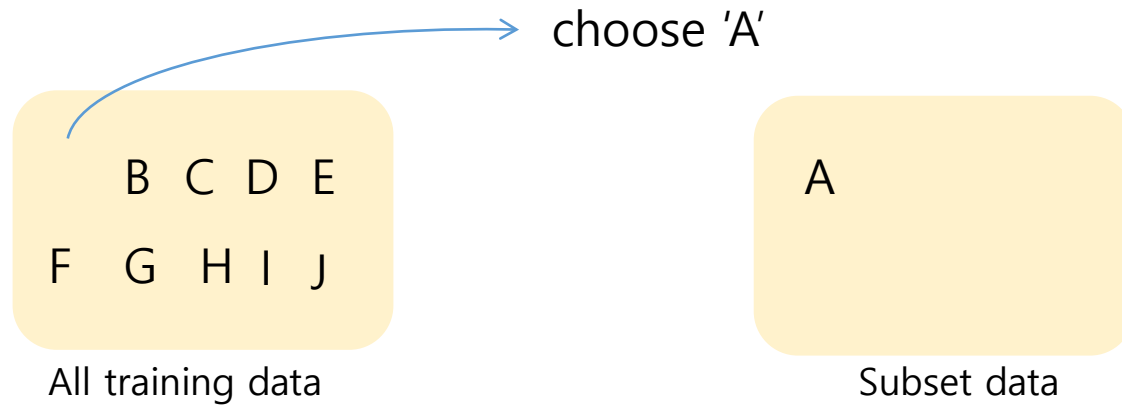
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Multiple classifier of several trees

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**Bootstrap sampling**

Select a subset by choosing N times with replacement from all training data.





# Randomized Forests

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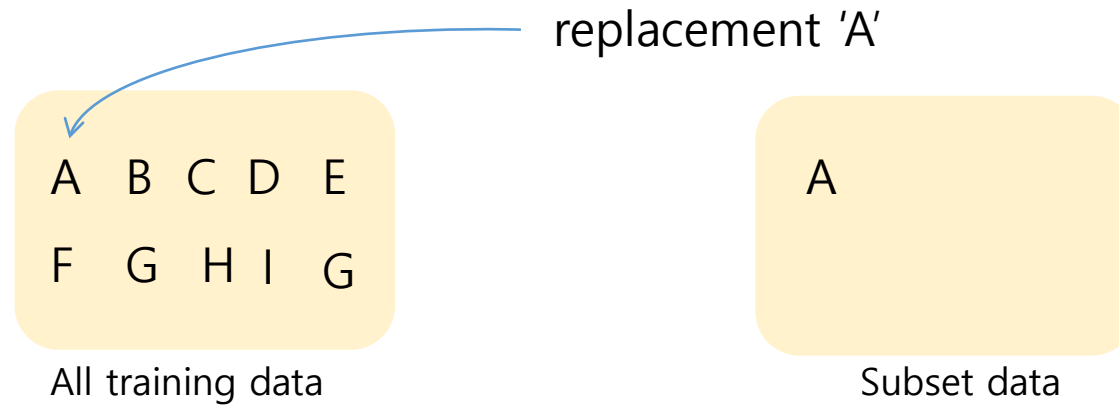
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Multiple classifier of several trees

**Idea : Randomness = <sup>1)</sup>Bootstrap sampling + <sup>2)</sup>randomized attribute selection**

## **Bootstrap sampling**

Select a subset by choosing N times with replacement from all training data.





# Randomized Forests

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**Randomized Forests** ( Breiman 2001 )

Multiple classifier of several trees

**Idea : Randomness = <sup>1)</sup>Bootstrap sampling + <sup>2)</sup>randomized attribute selection**

**Bootstrap sampling**

Select a subset by choosing N times with replacement from all training data.

**Randomized attribute selection**

Instead **randomly use subset of K** attributes

- Typical choice :  $K = \sqrt{N}$  ( N : the number of subset )



# Randomized Forests

---

**Randomized Forests** ( Breiman 2001 )

Multiple classifier of several trees

**Idea : Randomness = <sup>1)</sup>Bootstrap sampling + <sup>2)</sup>randomized attribute selection**

**Advantage**

Resistant to Overfitting



# Randomized Forests

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**Randomized Forests** ( Breiman 2001 )

Multiple classifier of several trees

**Idea : Randomness = <sup>1)</sup>Bootstrap sampling + <sup>2)</sup>randomized attribute selection**

## **Advantage**

Resistant to Overfitting

Well suited for large training data



# Randomized Forests

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**Randomized Forests** ( Breiman 2001 )

Multiple classifier of several trees

**Idea : Randomness = <sup>1)</sup>Bootstrap sampling + <sup>2)</sup>randomized attribute selection**

## **Advantage**

Resistant to Overfitting

Well suited for large training data

Empirically very good results. (  $\geq$  SVM,  $\geq$  Boosting )



# Randomized Forests

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**Randomized Forests** ( Breiman 2001 )

Multiple classifier of several trees

**Idea : Randomness = <sup>1)</sup>Bootstrap sampling + <sup>2)</sup>randomized attribute selection**

## **Advantage**

Resistant to Overfitting

Well suited for problems with large training data

Empirically very good results. (  $\geq$  SVM,  $\geq$  Boosting )

## **Disadvantage**

Memory consumption



# Comparison with various classifier

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- CIFAR-10: Image Classification
- Comparison with various classifier
  - <https://github.com/PhilippeCodes/Image-Classifier>
  - <https://github.com/PhilippeCodes/Image-Classifier/blob/master/Decision%20trees%20and%20random%20forests.ipynb>

	Estimator	Test Accuracy	
0	Baseline (dummy)	0.222	
1	KNeighbors	0.776	
2	DecisionTree	0.646	
3	RandomForest	0.800	
4	LogisticRegression	0.840	
5	SVM Linear Kernel	0.817	
6	SVM RBF Kernel	0.823	
7	Multilayer Neural Network	0.821	
8	Convolutional Neural Network	0.777	

# Hands on Lab

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- Decision Tree from scratch
- Random Forests from scratch

# Application

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- Titanic: Machine Learning from Disaster
- Solution: **Random Forests**
  - <https://www.kaggle.com/mukultiwari/titanic-top-14-with-random-forest>

# Application

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- Bike Sharing Demand
- Solution: **Random Forests**
  - <https://www.kaggle.com/kwonyoung234/for-beginner>