

Lecture - 1 : Supervised and Unsupervised Machine Learning Algorithms.

- Classification and regression : supervised learning
- Clustering and association : unsupervised learning.
- between sup and unsup is called semisupervised learning.

Supervised Machine Learning:

- Practical learning uses supervised learning. (for output file)
- Input variable (x) and output variable (y), use an algorithm to learn the mapping function from input to output.

$$y = f(x) \Rightarrow \text{mapping function}$$

new input data (x) can predict output (y) for data.

The process of an algorithm learning from the training dataset can be thought as a teacher supervising the learning process is called Supervised Learning.

* we know the correct ans, then algo makes prediction on training data.

Classification: output variable is a category.

Ex: red or blue ; 'disease' or 'no disease'

Regression: output variable is a real value.

Ex: dollars, weight

Example: of supervised ML:

recommendation, time series prediction.

① Linear regression
(regression problem)

② Random Forest
(regression ;
classification
problem)

③ SVM
(classification
problem)

Unsupervised Machine Learning:

UML is where only have input data (x) and no corresponding output variables.

Goal: underlying structure in the data, so it can learn more about the data.

There is no correct answer, no teacher. Algorithms are left to their own devices to discover and present to the interesting structure in the data. is called unsupervised learning.

UML further grouped into clustering and association problems.

Clustering: Discover the inherent groupings in the data,

Ex: grouping customers by purchasing behaviour.

சர்ட்டி, அர்ட்டி சர்ட்டி, லுர்ட்டி சர்ட்டி @

Association :

Discover rules that describe large portions of data.
(* data ko small rules me baat krna)

Ex: agar x buy krta, to y bhi buy krta or agar x nahi karta to y bhi nahi karta.

Example : ① k-means for clustering.

② Apriori " association.

③ Semi-supervised ml

A large amount of input data (x) and only some of the data is labeled (y) and are called semi-supervised learning problems.

Example: photo archive, some of images are labeled and majority are ~~unlabeled~~ unlabeled.

- unlabeled data is cheap and easy to collect and store.
- many world fall into this area.
- use SSML to discover and learn the structure in the input variables.

① Supervised: All data is labeled and algorithms learn to predict the output from the input data.

② Unsupervised: All data is ~~unlabeled~~ unlabeled and algorithms learn to inherent structure from the input.

③ Semi-supervised: some data is labeled but most of data is unlabeled, mixture of supervised and unsupervised techniques are used.

Lecture : 2

KDD = Knowledge data discovery.

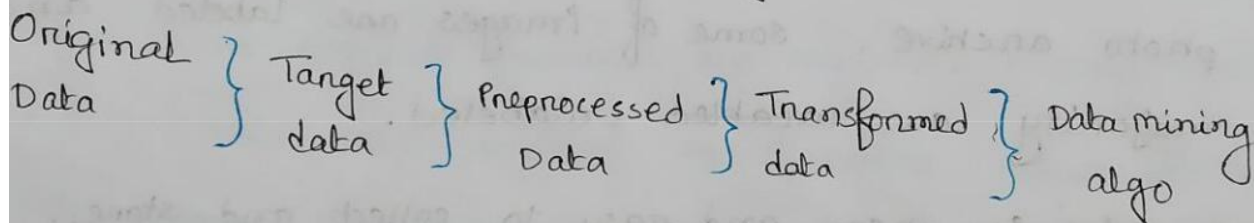


Fig: KDD processes.

Knowledge { Pattern

Lecture 2

Why we need to prepare data?

Data can be incomplete, inconsistent or noisy.

- ① Data entry, transmission, data collection problem solve error
- ② duplicate data remove error
- ③ incomplete missing data problem solve error
- ④ avoid contradictions in data.

When data can't be trusted:

- * difficult to make knowledge from untrusted site.
- * Better chance to discover new knowledge or pattern

when data is clean.

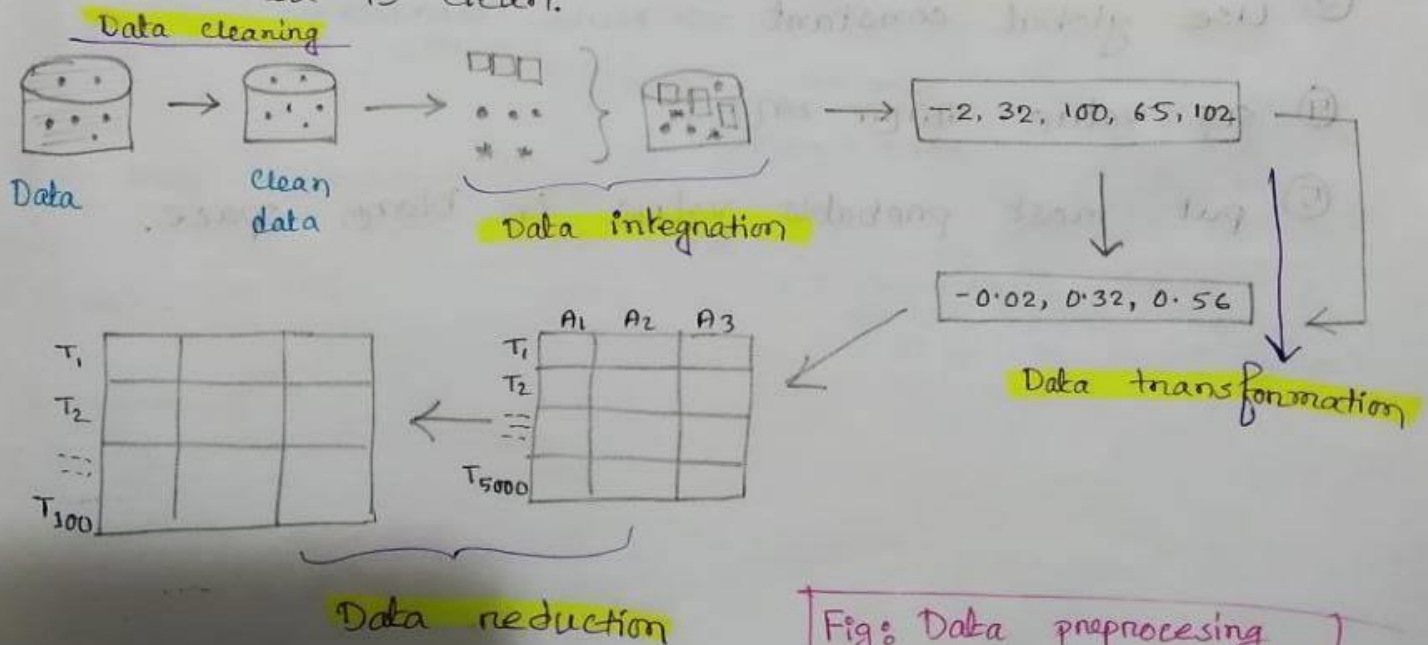


Fig: Data preprocessing

Data cleaning:

real world data is noisy, incomplete, inconsistent etc.

- some attribute has no value
- random error
- irrelevant records

data cleaning
etc.

Data cleaning steps:

- ① fill in missing values
- ② pull out noisy data
- ③ correct inconsistencies
- ④ remove irrelevant data

Solving missing data problem:

- ① ignore the record with missing value
- ② fill the missing value manually.
- ③ Use global constant $\Rightarrow$ NULL, unknown
- ④ use value other than zero
- ⑤ put most probable value in blank space.

plate

Something Noisy Data 3 methods

① Binning method.

Avg Boundaries

② Clustering

③ Regression

④ Binning method technique

- ① Data sort ascending
- ② k bins k integer value given, when limit is given = 3
- ③ " " " " " "
- ④ k bin k integer value sort then replace ID
- ⑤ in case of float, keep the nearest int value.
- ⑥ Then put the value according to ID in data table.

Data Transformation Nonnormalization

① Min max method $\rightarrow v' = \frac{v - \min}{\max - \min}$ when range is 0-1

② Z-score normalization

$$v' = \frac{(v - \text{mean})}{\text{Stdv (Standard Deviation)}}$$

$$\text{Stdv} = \sqrt{\frac{\sum (\text{mean} - x_i)^2}{N}}$$

$$\frac{\sum (\text{mean} - x_i)^2}{N} = \text{variance}$$

$$\text{Stdv} = \sqrt{\text{variance}}$$

Data transformation: Discretization

methods

Nominal = values from unordered list

Ordinal = " " ordered list

Numeric = real numbers.

① Binning

② Histogram Analysis

③ Clustering "

④ Decision-tree "

⑤ Correlation "

⑥ Discretization use ex: continuous attribute reduce to discrete

* some DM algo allow only categorical data/ Attribute, cannot handle continuous attribute value.

** Discretization can also used to generate high level concepts.

age continuous value convert high level concept to

convert to discretization or simple,

Example: young, middle age, old $\rightarrow$ category error into age class.

(*** Continuous value to discrete convert)

Age
25
38
51
75
86

low = 25 - 40

MA = 41 - 60

old = 60 <

Age
Low
Low
MA
old
old

Data reduction

Often Data become too large, reduce data for improve performance.

- ① dimensionally reduce ~~not~~ ^{size}
- ② Discretization
- ③ Regression / clustering reduction.

Chap = 9

- ① continuous value ~~array~~ dynamically define new discrete value with range / intervals.
- ② missing = assign probable value (possible)
= most common value.

● Lecture = 3

Confusion Matrix

TP = Dengue $\pi\pi\pi$,
test positive } actual result.

FN = Dengue $\pi\pi\pi$,
test negative

TN = Dengue $\pi\pi\pi$,
test negative } actual result

FP = Dengue $\pi\pi\pi$,
test positive.

Original Class	Predicted Class	
	test	
Dengue	1 Yes a	0 No b
	1 Yes a	0 No b
Original Class	test	
	1 Yes a	0 No b
Dengue	1 Yes a	0 No b
	1 Yes a	0 No b
Original Class	test	
	1 Yes a	0 No b
Dengue	1 Yes a	0 No b
	1 Yes a	0 No b

	1	0
1	TP	FN
0	FP	TN

Classification

first group, rule
after,
(Supervise)

Clustering

first group, rules $\pi\pi\pi\pi$,
(unsupervise)

Confusion Matrix

● Accuracy = $\frac{TP + TN}{ALL}$

● Error rate = 1 - accuracy

or = $\frac{FN + FP}{ALL}$

● Sensitivity = $\frac{TP}{P}$ (TP rate)

● Specificity = $\frac{TN}{N}$

● bayes - rate should be = 60 - 40

↓ ↓
pslv neglv

P = Actual true
N = Negative

other classifier evaluation metrics.

▣ Precision: original 20% positive cases, machine says 20% correct predict cases.

Example: original 70% correct heart diseases cases, but machine predict 95% correct heart disease cases.

▣ machine says positive cases = $TP + FP$.

$$\text{Precision} = \frac{TP}{TP + FP} \xrightarrow{0} \text{original } 70$$

on
m

$\xrightarrow{F} 95\%$, machine says, where HD has or not, but machine says yes.

▣ Recall: machine says predict correct cases, originally correct cases positive cases.

~~70%~~ 50% originally samsung use cases, but machine predict 30% correct cases.

m
on

$$\text{Recall} = \frac{TP}{TP + FN} \xrightarrow{F} \text{machine predict actual users} = 30$$
$$\xrightarrow{0} \text{original} = 50$$

▣ Perfect score for both is 1.0, but there is often a

a trade-off between precision and recall.

F measure : (F_1 or F-score)

harmonic mean of precision and recall,

$$F = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}}$$

$$\text{Overall correct rate} = \frac{TP + FN}{TP + FP + TN + FN}$$

Association Analysis

Now, find, after buying Bread, how many prob to buy milks.

TID	Items
1	Bread, milk
2	Bread, Diapers, Beer, Egg
3	milk, Diapers, Beer, Cola
4	Bread, milk, Diapers, Beer
5	Bread, milk, Diapers, Cola.

$$\boxed{\text{Support}} = \frac{(x \cup y)}{N}$$

$x \rightarrow y$

$$\boxed{\text{Confidence}} = \frac{(x \cup y)}{\sigma(x)}$$

$x \rightarrow y$

* $x \cup y$ = x aur y dono ka union.

* N = total num of transaction

* $\sigma(x)$ = transaction x milke

TID	Bread	milk	Diaper	Beer	Egg	Cola
1	1	1	0	0	0	0
2	1	0	1	1	1	0
3	0	1	1	1	0	1
4	1	1	1	1	0	0
5	1	1	1	0	0	1

0/1 binary representation

Q: For Bread $\rightarrow$ Milk.

$$\text{Support} : \frac{3}{5} ; \quad \text{confidence} = \frac{3}{4}$$

* Total num of combination : $R = 2^d - 2^{d+1} + 1$

brute force approach for
mining s & c for every
possible rule.

d = Num of item.

B, D $\rightarrow$ M

D, M $\rightarrow$ B etc.

C, D $\rightarrow$ M

Threshold = 50%

①

TID	Items
001	1 3 4
002	2 3 5
003	1 2 3 5
004	2 5

from item purchase info

②

Item	sup
{1}	2
{2}	3
{3}	3
{4}	①
{5}	3

each item name/oid

item support

③

Item	sup
{1}	2
{2}	3
{3}	3
{5}	3

maximum product sell = 3
threshold = 50%
so, we not accept
(3 × 50%) = 1.5
so, item 4 out.

⑤

itemset	sup
{1, 2}	①
{1, 3}	2
{1, 5}	①
{2, 3}	2
{2, 5}	3
{3, 5}	2

set of product info

④

itemset
{1, 2}
{1, 3}
{1, 5}
{2, 3}
{2, 5}
{3, 5}

item of combination

this combination also available in table 1

⑥

item	sup
1, 3	2
2, 3	2
2, 5	3
3, 5	2

remove, 1, 5 > item

⑦

itemset
2 3 5

Here, 1 3 5 is not available in table 1.
(2, 3, 5) available

⑧

item	sup
{2 3 5}	2

Here (2, 3, 5) combination occur 2 times in table 1.

final stage.

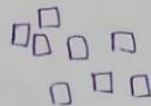
K-mean clustering

Clustering: Clustering is a task of grouping set of object in such way that objects in the same group are more similar to each other.

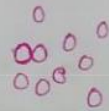
* same group ko cluster khte hai. Har cluster ko objects ko ekhane same, kahan kahan kahan kahan.

* distance measure ko grouping karte hai.

Example:



3 cluster



Type of clustering:

① Hierarchical Algorithm: Hierarchy cluster / ranking cluster build karte hai. Clustering fall into two types

① bottom-up

Small → Big

② top-down

Big → Small

② Partitional clustering: determine cluster at once.

⇒ k-means and derivatives

⇒ fuzzy c-means clustering.

⇒ OT clustering.

③ Common distance measure: distance first similarity measure
for cluster shape or influence

① The Euclidean distance $\Rightarrow d = \sqrt{\sum |x_i - y_i|^2}$

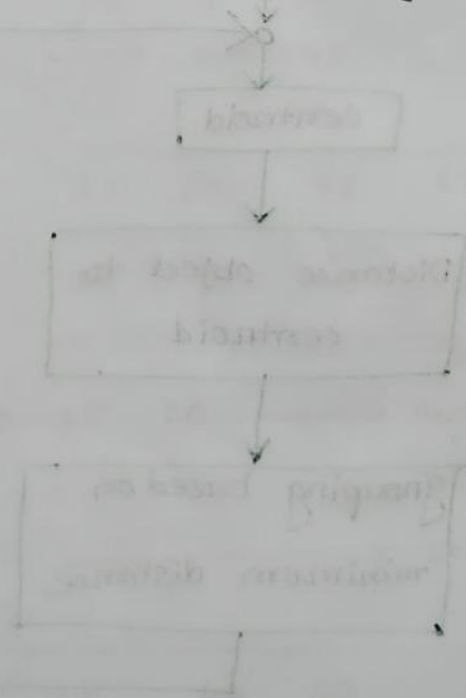
② The Manhattan Distance $\Rightarrow d = \sum |x_i - y_i|$

③ Maximum norm $\Rightarrow d = \max |x_i - y_i|$

④ Mahalanobis distance

⑤ Inner product space

⑥ Hamming distance.

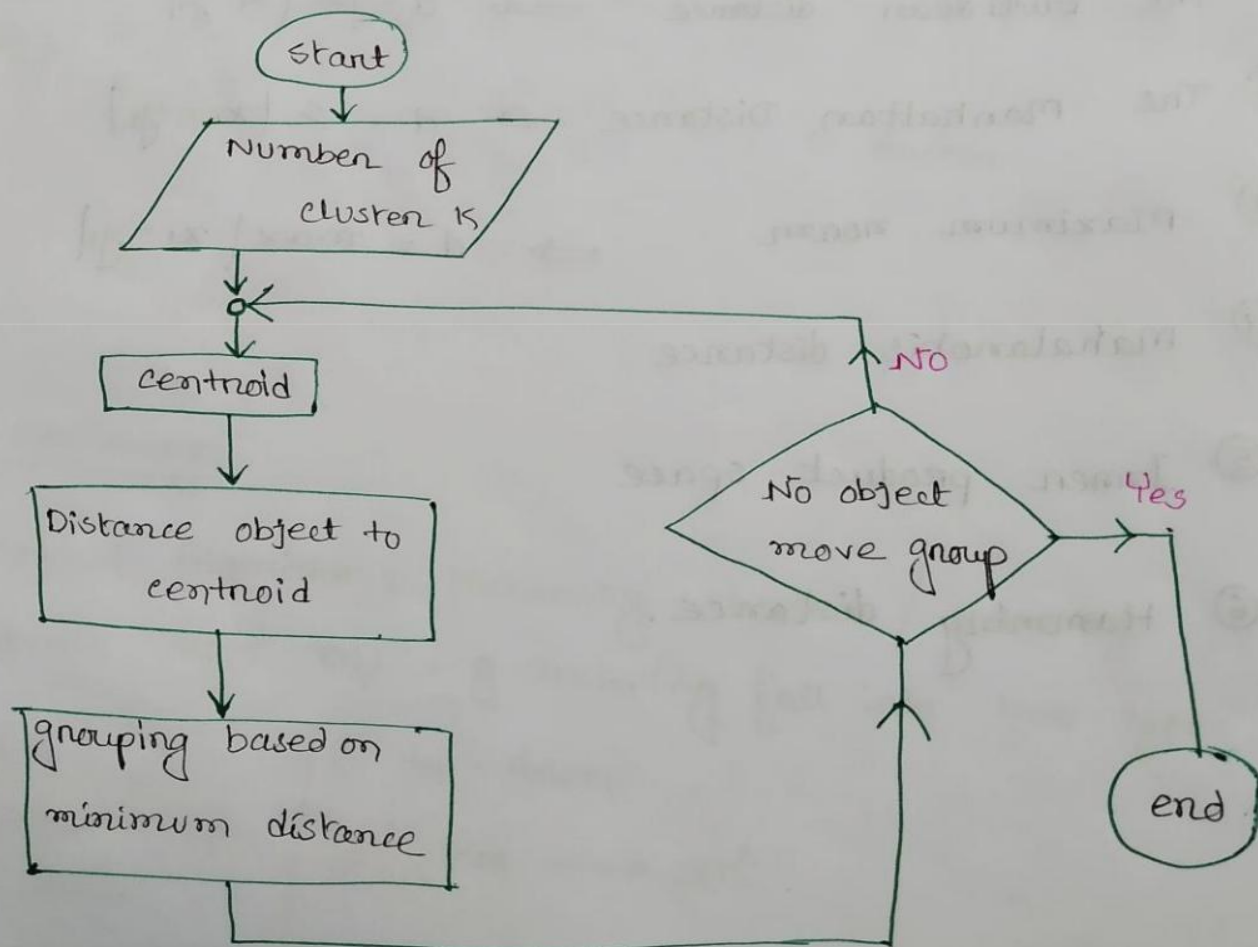


K-mean clustering

n = object number, K = partition, $n > K$.

randomly select n or more objects g_1, g_2 first, then, group close objects into clusters, distance measure used, next g_1, g_2 are group objects' average.

centroid values change up; when center g_1, g_2 move same way then clustering done.



1 5 9 15 20 25 35 50 70

Hence $K = 2$.

Solution: let, centroid 1 = 1, centroid 2 = 20.

distance from 1: 0 4 8 14 19 24 34 49 69

" " 20: 19 15 11 5 0 5 15 30 50

Now, (1) group 1: 1 5 9 $\longrightarrow$ avg = 5

(20) group 2: 15 20 25 35 50 70 $\longrightarrow$ avg = 35.

distance from 5: 4 0 4 10 15 20 30 45 65

" " 35: 34 30 26 20 15 10 0 15 35

(5) group: 1 5 9 15 $\longrightarrow$ avg = 8

(35) group: 20 25 35 50 70 $\longrightarrow$ avg = 40

d.f 8: 7 3 1 7 12 17 27 42 62

d.f 40: 39 35 31 25 20 15 5 10 30

(8) group: ~~1~~ ~~5~~ ~~9~~ ~~15~~ 1 5 9 15 20 $\longrightarrow$ avg = 10

(40) group: 25 35 50 70 $\longrightarrow$ avg = 45

d.f 10 = 9 5 1 5 10 15 25 40 60

d.f 45 = 44 40 36 20 25 20 5 5 25

1 5 9 15 20 25 35 50 70

$$(10) \text{ group} = 1 \ 5 \ 9 \ 15 \ 20 \ 25 \rightarrow 12.5$$

$$(45) \text{ group} = 35 \ 50 \ 70. \rightarrow 51.66$$

d.f 13 : 12 8 4 2 7 12 22 37 57

d.f 52 : 51 47 43 37 32 27 17 2 18

$$(13) \text{ group} = 1 \ 5 \ 9 \ 15 \ 20 \ 25$$

$$(52) \text{ group} = 35 \ 50 \ 70.$$

as repeat 2 time so, group / clustering
done.

$$\text{Ans: } \begin{bmatrix} 1 & 5 & 9 & 15 & 20 & 25 \end{bmatrix}$$

$$\begin{bmatrix} 35 & 50 & 70 \end{bmatrix}$$

A

Example of 2D data (x, y) .

$$\text{Euclidean Distance} = \sqrt{(x - x_1)^2 + (y - y_1)^2}$$

given that,

$$K = 2$$

$$m_1 = 1.0, 1.0$$

$$m_2 = 5.0, 7.0$$

indv	x_1	y_1
1	1.0	1.0
2	1.5	2.0
3	3.0	4.0
4	5.0	7.0
5	3.5	5.0
6	4.5	5.0
7	3.5	4.5

Now, calculate distance,

for m_1 :

$$1 = \sqrt{(1.0 - 1.0)^2 + (1.0 - 1.0)^2} = 0$$

$$2 = \sqrt{(1.0 - 1.5)^2 + (1.0 - 2.0)^2} = 1.12$$

$$3 = \sqrt{(1.0 - 3.0)^2 + (1.0 - 4.0)^2} = 3.60$$

$$4 = \sqrt{(1.0 - 5.0)^2 + (1.0 - 7.0)^2} = 7.21$$

$$5 = \sqrt{(1.0 - 3.5)^2 + (1.0 - 5.0)^2} = 4.72$$

$$6 = \sqrt{(1.0 - 4.5)^2 + (1.0 - 5.0)^2} = 5.31$$

$$7 = \sqrt{(1.0 - 3.5)^2 + (1.0 - 4.5)^2} = 4.30$$

for m2:

$$1 = \sqrt{(5.0 - 1.0)^2 + (7.0 - 1.0)^2} = 7.21$$

$$2 = \sqrt{(5.0 - 1.5)^2 + (7.0 - 2.0)^2} = 6.10$$

$$3 = \sqrt{(5.0 - 3.0)^2 + (7.0 - 4.0)^2} = 3.61$$

$$4 = \sqrt{(5.0 - 5.0)^2 + (7.0 - 7.0)^2} = 0$$

$$5 = \sqrt{(5.0 - 3.5)^2 + (7.0 - 5.0)^2} = 2.5$$

$$6 = \sqrt{(5.0 - 4.5)^2 + (7.0 - 5.0)^2} = 2.06$$

$$7 = \sqrt{(5.0 - 3.5)^2 + (7.0 - 4.5)^2} = 2.92$$

Now

	cen 1	cen 2
1	0	7.21
2	0 1.12	6.10
3	3.61	3.61
4	7.21	0
5	4.72	2.5
6	5.31	2.06
7	4.30	2.92

group 1

group-2

Weakness of K-mean:

- ① data points are grouping to cluster 20,
- ② cluster, k must be determined before 20, cluster depends on initial assignment
- ③ never know the real cluster,
- ④ different initial condition or has different cluster 20.

Application of K-mean:

- ① efficient & fast. time = $O(tkn)$

n = number of object

k = " " cluster

t = " " iteration.

- ② machine learning & data mining @ use 20.
- ③ wave $\rightarrow k$ category @ use 20, wave, speech data @ use 20.
- ④ color plot & graphical display @ use 20.

Lecture = 5 Classification

Classification process: 3 steps

① model construction (learning) pre defined class & record
target, to determine target attribute value,
value of target attribute = class labels,

Training set = learning & use set.

② Model Evaluation: (Accuracy) estimate accuracy rate
based on test set.

③ Model use: (classification) model is used to
classify unseen instances. Predict value.

Classification method: ① Decision tree

② Bayesian classification

③ K-Nearest neighbor

④ Neural network

⑤ SVM

⑥ Genetic Algorithm.

Naive Bayesian learning

Naive bayes play important role on prediction.

$$P(H|x) = \frac{P(x|H) \cdot P(H)}{P(x)}$$

$P(A|B)$ = prob of A, given B.

B is known,

$$P(A \wedge B) = P(A|B) \cdot P(B). \quad \boxed{****}$$

Bayes's rule = $P(A \wedge B) = P(A|B) \cdot P(B)$

$$P(B \wedge A) = P(B|A) \cdot P(A).$$

but, $P(A \wedge B) = P(B \wedge A).$

$$\therefore P(A|B) \cdot P(B) = P(B|A) \cdot P(A).$$

$$\Rightarrow P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B)}.$$

So, $P(H|E) = \frac{P(E|H) \cdot P(H)}{P(E)}$

$$P(A|B) = P(A) \quad ; \quad P(B|A) = P(B)$$

two constraints are logically equal.

$$P(A|B) = \frac{P(A \wedge B)}{P(B)} = P(A)$$

$$P(A \wedge B) = \cancel{P(A)} P(A|B) \cdot P(B) = P(A) \cdot P(B)$$

$$P(C_i|E) = \frac{P(C_i) \cdot P(E|C_i)}{P(E)}$$

math

Problem: Too many possible combination.

Estimate = Estimated based on training data.

= compute mean & standard deviation

Smoothing: small training set, $\hat{P}$ estimate smooth $\hat{P}$

$$P(\text{Yes}) = \frac{9}{14} \quad \begin{array}{l} \text{--- yes} \\ \text{--- all} \end{array}$$

$$P(\text{sunny} | \text{Yes}) = \frac{2}{9} \quad \begin{array}{l} \text{sunny} \rightarrow \text{yes} \\ \text{--- total yes.} \end{array}$$

$$P(\text{humidity} | \text{No}) = P(\text{high} | \text{No}) = \frac{4}{5}$$

4 for high, 5 for actual no.

outlook	P	N
Sunny	2/9	3/5
Overcast	4/9	0
rain	3/9	2/5

Humid.	P	N
high	3/9	4/5
normal	6/9	1/5

Temp	P	N
hot	2/9	2/5
mild	4/9	2/5
cool	3/9	1/5

wind	P	N
true	3/9	3/5
false	6/9	2/5

given,

$$x = \langle \text{sunny, mild, high, true} \rangle$$

$$P(x | \text{No}) = \frac{3}{5} \times \frac{2}{5} \times \frac{4}{5} \times \frac{3}{5} = \frac{72}{625}$$

$$P(x | \text{Yes}) = \frac{2}{9} \times \frac{4}{9} \times \frac{3}{9} \times \frac{3}{9} = \frac{72}{6561}$$

Now,

$$P(x | \text{No}) \cdot P(\text{No}) = \frac{72}{625} \times \frac{5}{14} = 0.041$$

$$P(x | \text{Yes}) \cdot P(\text{Yes}) = \frac{72}{6561} \times \frac{9}{14} = 0.007$$

convert in probabilities,

$$P(\text{No} | x) = \frac{0.04}{0.04 + 0.007} = 0.85$$

$$P(\text{Yes} | x) = \frac{0.007}{0.04 + 0.007} = 0.15$$

Ans: Not play. classified as No.