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DETAILED LECTURE NOTES

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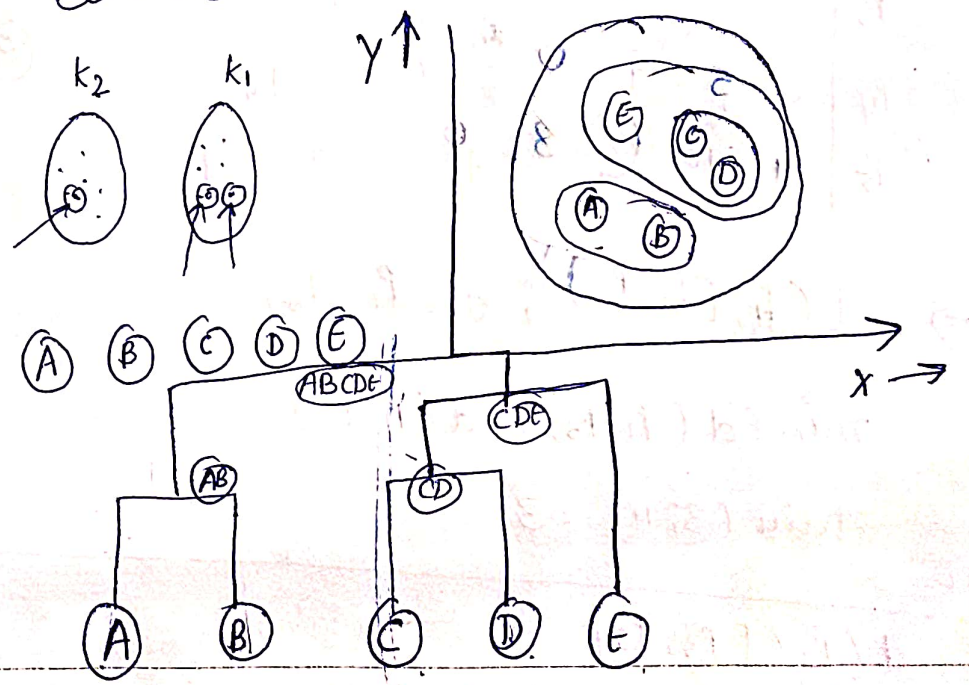
Regression is a statistical that helps us understand and predict the relationship between variables

Hierarchical clustering

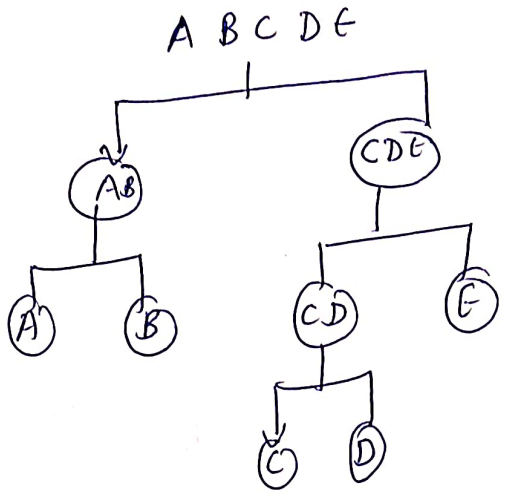
→ Agglomerative [Dendrogram]

→ Divise



Aggm bottom to Top.

→ Divise Algo:- Top to bottom.



Agglomerative clustering:-

	P_1	P_2	P_3	P_4	P_5
P_1	0				
P_2	9	0			
P_3	3	7	0		
P_4	6	5	9	0	
P_5	11	10	2	8	0

⇒

	P_1	P_2	$[P_3\ P_5]$	P_4
P_1	0			
P_2	9	0		
$[P_3\ P_5]$	3	7	0	
P_4	6	5	8	0

⇒ ~~$d([P_1, [P_3\ P_5]), d(P_1, P_5)$~~

$\min(d(P_1, P_3), d(P_1, P_5))$

$\min(3, 11) = 3$

$d(P_2, [P_3, P_5])$

⇒ $\min(d(P_2, P_3), d(P_2, P_5))$

⇒ $\min(7, 10)$ ⇒ 7

$d(P_4[P_1\ P_3\ P_5)]$

$\Rightarrow \min(P_4,P_1), d(P_4,P_3), d(P_4,P_5]$

$\Rightarrow \min(6, 9, 8)$

$\Rightarrow \underline{6}$ ✓

	P_1	P_2	P_3	P_4	P_5
P_1	0				
P_2	9	0			
P_3	3	7	0		
P_4	6	5	9	0	
P_5	11	10	2	8	0

	$[P_1\ P_3\ P_5]$	P_2	P_4
$[P_1\ P_3\ P_5]$	0		
P_2	7	0	
P_4	6	5	0

	$[P_1\ P_3\ P_5]$	$[P_2\ P_4]$
$[P_1\ P_3\ P_5]$	0	
$[P_2\ P_4]$	6	0

$[P_1\ P_2\ P_3)\ [P_4\ P_5]$

9 [

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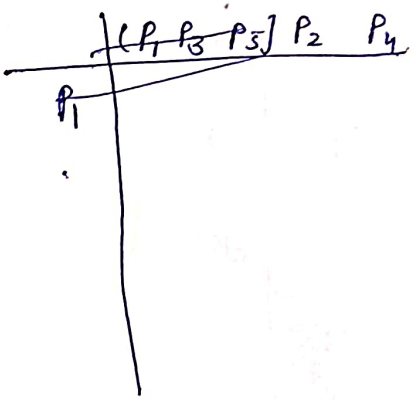
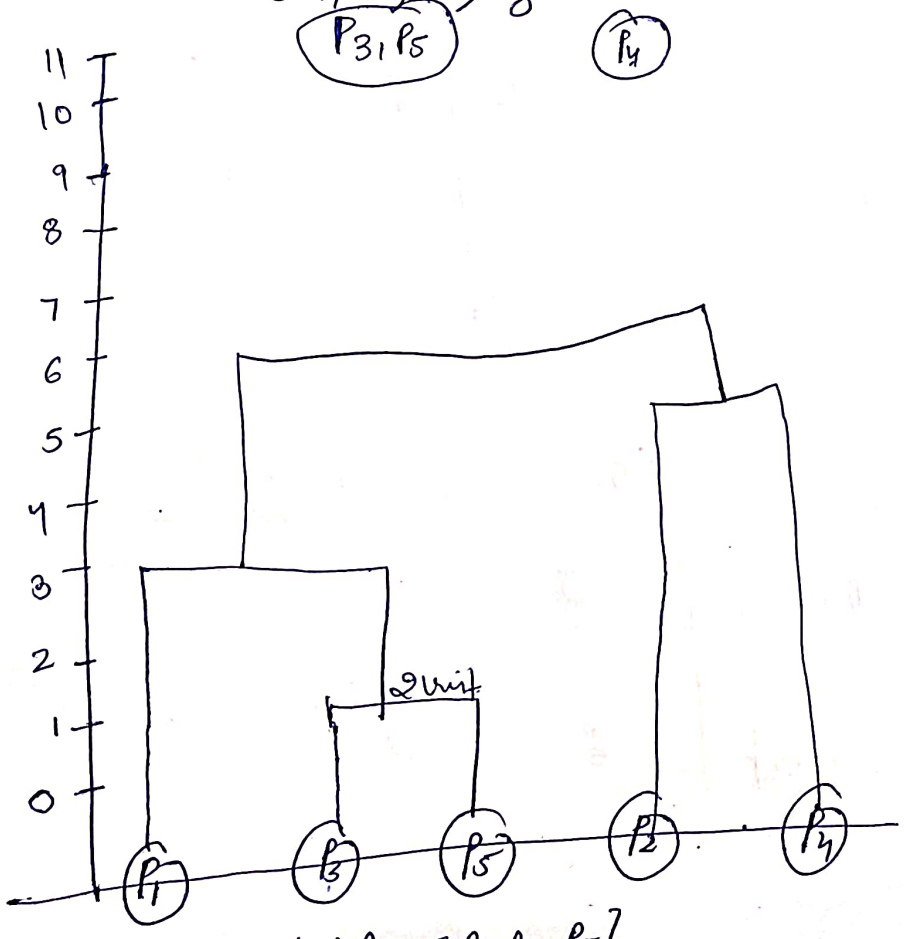
$\Rightarrow d[P_4, (P_3, P_5)]$

$\Rightarrow \min d(P_4, P_3), d(P_4, P_5)$

$\Rightarrow \min(9, 8) \Rightarrow 8$





$d[P_2, [P_1\ P_3\ P_5]$

$\min(d(P_2\ P_1), d(P_2, P_3), d(P_2, P_5))$

$\min(9, 7, 10) = 7$

	$P_1\ P_3\ P_5$	$(P_2\ P_4]$
$[P_1\ P_3\ P_5]$	0	
$(P_2\ P_4]$	⑥	0

$d[P_1\ P_3\ P_5][P_2\ P_4]$

$\Rightarrow \min d(P_2, P_1), d[P_3, P_3], d[P_2, P_5], d[P_4, P_1]$
$d[P_4, P_3), d[P_4, P_5)$

$\Rightarrow \min(9, 7, 10, 6, 9, 8)$

$\Rightarrow$ ⑥

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	S_1	S_2	S_3	S_4	S_5	S_6
S_1	0	3.16	2.82	5.09	6.32	2.23
S_2		0	3.16	4.47	7.07	5
S_3			0	7.07	8.94	3
S_4				0	3.16	7.28
S_5					0	8.06
S_6						0

$\{S_1, S_2, S_3\}$
$\{S_4, S_5\}$
$\{S_6\}$
3.17
3.17

Divise Algorithm:- (a, b, c, d, e)

	a	b	c	d	e
a	0	9	3	6	11
b	9	0	7	5	10
c	3	7	0	9	2
d	6	5	9	0	8
e	11	10	2	8	0

$C_i = \{a, b, c, d, e\}$

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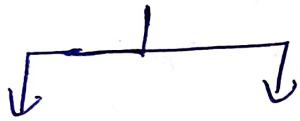
probabilistic clustering :-

Basic concept of probabilistic model-Based clustering.

mixture models for cluser analysis.

⇒ Gaussian mixture models.

⇒ the expectation-maximization Emalgo.



⇒ analysis of mixture model method.

what is probabilistic model :-

⇒ model the data from a generative procen.

⇒ Assume the data are generated by a mixture of underlying probability distribution.

⇒ Attempt to optimize the fit between the observed data and some mathmetical model using a probabilistic approach.

Probabilistic model-based clustering :-

⇒ each cluster can be represented mathematically by a parametric probability distribution (eg. a Gaussian or poisson distribution)

⇒ cluster : Data points (or objects) that most likely belongs to the same distribution.

⇒ clustering parameter estimation so that they will have a maximum likihood value to the model by a mixture of k component distribution (e.g k cluster)

Application :- image segmentation, document clustering.

Two type
mixture model

⇒ A very continous probability distribution is Gaussian distribution it is called as a bell curve. the eq. of one-dimension

$$P(X) = \frac{1}{\sqrt{2\pi\sigma \exp\left[-(x-\mu)^2/2\sigma^2\right]}}$$

σ → standrd μ → mean

Expectation-maximization algo.

A general techniques to find maximum likelihood estimation in mixture models.

Em algo. for Gaussian mixture model.

Example:-

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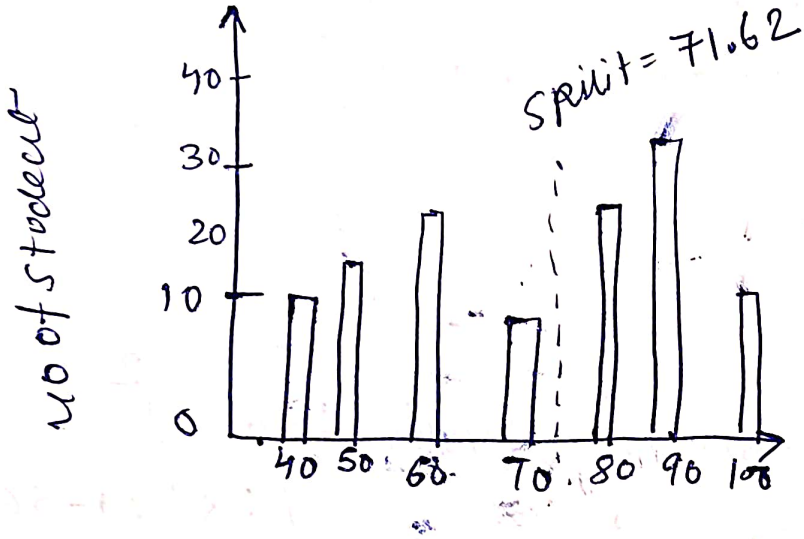
Histogram of exam score:-



score	num	$5 \times num$
40	10	
45	14	
50	19	
55	28	
60	22	
65	19	
70	16	
75	12	
80	30	
85	34	
90	24	
95	19	
100	12	
	Σf_i	$\Sigma x_i f_i$

total no student = 259

Step-① spirit the histogram:-

inial spirit point = $40 \times 10 + 45 \times 14 + 50 \times 19 + 55 \times 28 + 60 \times 22 + 65 \times 19 + 70 \times 16 \times 75 \times 12 + 80 \times 30 + 85 \times 34 + 90 \times 24 + 95 \times 19 + 100 \times 12$

total mean :- $\dfrac{}{10+14+19+28+22+19+16+12+30+34+24+19+12}$

$= 71.62$

itially, score less than 71.62 is treated as the first component.
score greater than 71.62 is treated as the second component.

Step-II initialization:-

First component

Score	num
40	10
45	14
50	19
55	28
60	22
65	19
70	16

$$\text{mean} = \frac{40\times10+45\times14+50\times19+55\times28+60\times22+65\times19+70\times16}{10+14+19+28+22+19+16}$$

$$m_1 = 56.21$$

$$\text{variance} = \sigma^2 = \frac{(x_i-\bar{x})^2}{n-1} = \frac{10\times(40-56.21)^2+14\times(45-56.21)^2+\cdots\cdots+16\times(70-56.21)^2}{(10+14+19+28+22+19+16)-1}$$

$$V_1 = 78.64$$

II component:- initialization:-

$$\text{mean} = \frac{75\times12+80\times30+85\times34+90\times24+95\times19+100\times12}{12+30+34+24+19+12}$$

$$m_2 = 86.68$$

$$\text{variance} = \frac{12\times(75-86.68)^2+30\times(80-86.68)^2+\cdots\cdots+12\times(100-86.68)^2}{(12+30+34+24+19+12)-1}$$

$$V_2 = 52.16$$

Step:-3 iteration (compute new weight)

this is the eq. to compute the new wight.

$$W_{k,new} = \frac{1}{N} \sum_{n=1}^{N} \frac{w_k \cdot G(x_n | m_k, v_k)}{w_k \cdot G(x_n | m_k, v_k)}$$

$N \rightarrow$ No. of students

$w_k \rightarrow$ weight (either w_1 or w_2) $= 0.5$

m_k — $m_1 = 56.21$ & $m_2 = 86.68$

v_k :- variance $v_1 = 78.64$

$v_2 = 52.16$

$x_n \rightarrow$ exam score (40, 45, ---100) from each of the student

259.

$k \rightarrow$ cluster value $= 2$

$$G(x | m_1, v_1) = \frac{1}{(2\pi)^{1/2} |v_1|^{1/2}} \exp\left[-\frac{1}{2}[x-m_1]^T v_1^{-1} [x-m_1]\right]$$

$$= \frac{1}{\text{(let solve numerator First)}}$$

$$= \frac{1}{(2\times 3.14\times 78.64)^{1/2}} \exp\left[-\frac{[X-56.21)\times[X-56.21}{2\times(78.64)}\right.$$

$X \rightarrow$ substitute!- 40, 45, 50, 55, 60, 65, 70, 75
80, 85, 90, 95, 100

$G(x_1|v_1) =$ -0.008, 0.002, 0.035, 0.045, 0.041, 0.028,
0.013, 0.005, 0.001, 0, 0, 0, 0

as II Component:-

$$\frac{1}{(2\times 3.14\times 52.16)^{1/2}} \exp\left[-\frac{(X-86.68)\times(X-86.68)}{2\times[52.16]}\right]$$

$X \rightarrow$ 40, ~~50~~ 45, 50, 55, 60, 65, 70, 75, 80, 85, 90, 95, 100
$\downarrow$
-0 0 0 0 0 0.001, 0.004, 0.015, 0.036,
0.054, 0.05, 0.028, 0.0

$$= \left[\frac{0.5\times 0.008}{0.5\times(0.008+0)} \times 10 + \frac{0.5\times 0.002}{0.5\times(0.002+0)} \times 14 + \frac{0.5\times 0.035}{0.5\times(0.035+0)} \times 19\right.$$

$$+ \frac{0.5\times 0.045}{0.5\times(0.045+0)} \times 28 + \frac{0.5\times 0.041}{0.5(0.041+0)} \times 22$$

$$\left. + \frac{0.5\times 0.028}{0.5(0.028+0.001)} \times 19 + \text{-------} \right] \times \frac{1}{259}$$

$$= 0.494$$

II Substitution:-

$$\left[\frac{0.5\times 0}{0.5\times(0.008+0)}\right]\times 10+\frac{0.5\times 0}{0.5\times(0.002+0}\Big]\times 14+\frac{0.5\times 0}{0.5\times(0.035+0}\times 19$$

$$+\frac{0.5\times 0}{0.5\times(0.045+0}\Big)\times 28+\frac{0.5\times 0}{0.5\times(0.041\times 0}\Big)\times 22$$

$$\cdots\cdots\cdots\cdots\frac{0.5\times 0.01}{0.5\times(1+0.01)}\times 12\Big]\times\frac{1}{259}$$

$$= 0.506$$

$w_1 = 0.5$

$w_2 = 0.5$

$w_1 = 0.494$

$w_2 = 0.506$

$w_1 = 0.494$, $m_1 = 56.45$, $v_1 = 85.95$

$w_2 = 0.506$, $m_2 = 86.46$, $v_2 = 57.64$

Em algorithm:- em algo is a problem in which the data d is a set of instances generated by probability distribution that is mixure of k district normal distribution. the case where k=2 and where the ~~distance~~ instances are the point x axis. Each instance is generated using a two-step proces.

First one, k normal distribution is seted at random. Second a single random instance x_i is generated according to this seted attributed.

where each of k-normal distribution has a same variance σ^2

the learning task is ouput H

$$= \{ u_1 \cdots u_k \}$$

the mean of each of the k distribution.

it is easily calculated max. likelihood hypothesis for the mean of a single normal distribution observed data instance $x_1, x_2 \cdots x_n$

n → training instance

$$u_{ML} = \underset{u}{\operatorname{argmin}} \sum_{i=1}^{n} (x_i - u)^2$$

in case the sum of sequred error is minimized by sample mean.

DETAILED LECTURE NOTES

Campus: ..... Course: ..... Class/Section: ..... Date: .....
Name of Faculty: ..... Name of Subject: ..... Code: .....

$$\mu_{ML} = \frac{1}{M}\sum_{i=1}^{m} x_i$$

Step-I :- Calculate the expected value $E[z_i]$ of each hidden variable z_{ij}, assuming the current hypothesis $h = (\mu_1, \mu_2)$

Step 2 :- Calculate a new maximum likelihood $h = (\mu_1, \mu_2)$ assuming the value taken on by each hidden z_{ij}.

$$E[z_{ij}] = \frac{P(x = x_i) \mid \mu = \mu_j]}{\sum_{n=1}^{2} P(x = x_i) \mid \mu = \mu_n]}$$

Association rule mining :-

~~ARM also called as market~~

Association rule mining is one of the ways to find pattern in data.

- feature (dimension) which occur together
- feature (ee) which are correlated.

Association rule in any dataset where feature take only two values 0/1.

- market Basket analysis is a popular application of association rule mining.

set of item is transaction is called market Basket.

Example:- For the following given transaction Data-set Generate rule using

Support = 50% Confidence = 75%.

measure of effectiveness of the Rule:-

- support
- Confidence
- lift
- other Affinity, leverage

DETAILED LECTURE NOTES

Campus: ..... Course: ..... Class/Section: ..... Date: .....
Name of Faculty: ..... Name of Subject: ..... Code: .....

Transaction item

ID	Purchased
1	Bread, Cheese, Egg, Juice
2	Bread, ~~milk~~, Cheese, Juice
3	Bread, milk, Yogurt
4	Bread, Juice, milk
5	Cheese, Juice, milk

Support = $\frac{\text{no. of times item}}{\text{total no. of transaction}}$

Frequent item set:-

items	Frequency	Support
Bread	→ 4	$\frac{4}{5}$ = 80%
Cheese	→ 3	$\frac{3}{5}$ = 60%
Egg	→ 1	$\frac{1}{5}$ = 20%
Juice	→ 4	$\frac{4}{5}$ = 80%
milk	→ 3	$\frac{3}{5}$ = 60%
Yogurt	→ 1	$\frac{1}{5}$ = 20%

minimum support 50%

we will Remove these two then support is less than 50%.

make 2 - item candidate set and wrote their fequany.

item pair	Fequany	support
(Bread, cheese)	→ 2	→ 2/5 = 40%
(Bread, Juice)	→ 3	→ 3/5 = 60%
(Bread, milk)	→ 2	→ 2/5 = 40%
(cheese, Juice)	→ 3	→ 3/5 = 60%
(cheese, milk)	→ 1	→ 1/5 = 20%
(Juice, milk)	→ 2	→ 2/5 = 40%

There support ≥ 50%

For Rules make
- (Bread, Juice) — (I)
- (cheese, Juice) — (II)

(I) (Bread, Juice)

(Bread → Juice) (Juice → Bread)

Confidence :-

$(A \to B) = \frac{\text{support of } A \cup B}{\text{suppor}(A)}$

(1) Bread → Juice.

$\frac{S(B \cup J)}{S(B)} = \frac{3 \times 5}{5 \cdot 4} = 75\%$

(2) Juice → Bread

$\frac{S(J \cup B)}{S(J)} = \frac{3}{5} \cdot \frac{5}{4} = 75\%$

Both rule are good enough to be implement.

(2) Cheese → Juice)
Juice → cheese.

$\frac{S(C \cup J)}{S(C)} =$

$\frac{S(J \cup C)}{S(J)} =$ $3/5 \cdot \frac{5}{3} = 100\%$

$\frac{3 \cdot 5}{5 \cdot 4} = 75\%$

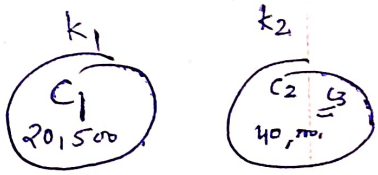
All rule are good.

K-Mean clustering :-

Sr NO	age	amount
C1	20	500
C2	40	1000
C3	30	800
C4	18	300
C5	28	1200
C6	35	1400
C7	45	1800

Euclidean Distance :-

$$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$



$$C_3 = \sqrt{(30-20)^2 + (800-500)^2}$$

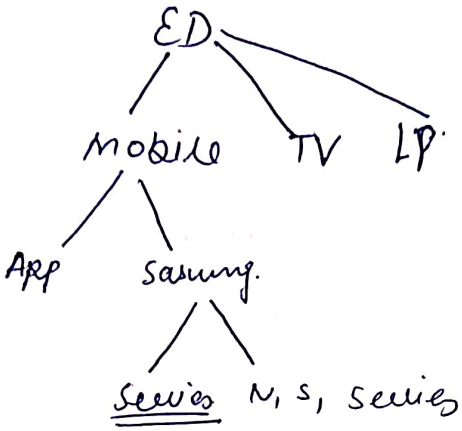
$$\sqrt{(10)^2 + (300)^2} = \underline{3000}$$

$$C_3 = \sqrt{(30-40)^2 + (800-1000)^2} = \underline{200}$$

K-mean clustering :-

Central, Hirarchy.

Tree divided.



Step-1 Take mean value.

Step 2 Find nearest no. of mean and put in cluster.

Step 3 :- Report one and two until we get same mean.

K = { 2, 3, 4, 10, 11, 12, 20, 25, 30 }

K = 2,

$M_1 = 4$ $M_2 = 12$

K_1 K_2

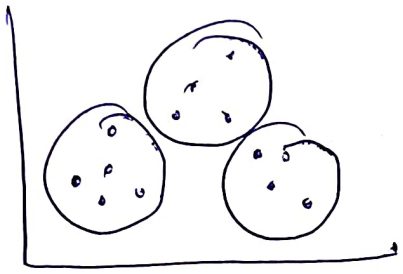
$K_1 = \{2, 3, 4\} \Rightarrow M_1 = 9/3 = 3$ (average)

$K_2 = \{10, 11, 12, 20, 25, 30\}$

$M_2 = \frac{108}{6} = 18$

Numerical:-

- k-mean clustering is an unsupervise iterative clustering technique
- it partitians the given data set into k predefined distuict cluster.
- A cluster is defined as a collection of data points cuttain similarties



O(n k t)

- n → no. of instance
  k → no. of cluster.
  t → no. of iteration

$A_1(2,10)$, $A_2(2,5)$, $A_3(8,3)$ $A_4(5,8)$
$A_5(7,5)$, $A_6(6,4)$, $A_7(1,2)$, $A_8(4,9)$

intial cluster $A(2,10)$, $A_4(5,8)$ and $A_7(1,2)$

$$P(a,b) = \sqrt{(x_2-x_1)^2 + (y_2-y_1)^2}$$

iteration 01:- $A_1(2,10)$, $C_1(2,10)$

$(2-2) + (10-10)$
$= 0$

$A_1(2,10)$ and $C_2(5,8)$
$(5-2| + |8-10| = 3+2 = 5$

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$M_1 = 3$, $M_2 = 18$

$k_1 = \{2, 3, 4, 10\}$

$k_2 = \{11, 12, 20, 25, 30\}$

$M_1 = 4.75 (5)$, $M_2 = 19.6 = (20)$

$k_1 = \{2, 3, 4, 10, 11, 12\}$

$k_2 = \{20, 25, 30\}$

$m_1 = 7$, $M_2 = 25$

$k_1 = \{2, 3, 4, 10, 11, 12\}$

$k_2 = \{20, 25, 30\}$

$m_1 = 7$, $M_2 = 25$

Thus we are getting same mean we have to stop.

New cluster will be

$k_1 = \{2, 3, 4, 10, 11, 12\}$

$k_2 = \{20, 25, 30\}$

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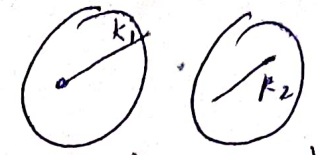
Height weight.

185	72
170	56
168	60
179	68
182	72
188	77
180	71
180	70
183	84
180	88
180	67
177	76



(185, 72) (170, 56)

$k_1 \rightarrow \sqrt{(168-185)^2+(60-72)^2}$

$= 26.82$

$k_2 \rightarrow \sqrt{(168-170)^2+(60-56)^2}$

$= 4.48$

New centraid:-

$k_2 = \left(\frac{170+168}{2}\right), \left(\frac{60+56}{2}\right) = (169, 58)$

(185, 72) (169, 58)

$k_1 \rightarrow \{1, 4, 5, 6, 7, 9, 10, 11, 12\}$

$k_2 \rightarrow \{2, 3\}$

$k_1 = \sqrt{(179-185)^2 + (168-72)^2}$

$\Rightarrow \sqrt{(6.32)}$

$k_2 = \sqrt{(179-169)^2+(168-58)^2}$

$= 14.14$

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$A_1(2,10)$, and $C_3(1,2)$ =

$|1-2| + |2-10|$

$1 + 8 = 9$

Given Points	Distance (2,10) clus 01	Distance (5,8) clus 02	Distance (1,2) clus 03	Point belongs to clus-
A1 (2,10)	0	5	9	C1
A2 (2,5)	5	6	4	C3
A3 (8,4)	12	7	9	C2
A4 (5,8)	5	0	10	C2
A5 (7,5)	10	5	9	C2
A6 (6,4)	10	5	7	C2
A7 (1,2)	9	10	0	C3
A8 (4,9)	3	2	10	C2

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suppose = 50%.
confidence = 75%.

Transaction ID	items purchased
1	Bread, cheese, egg, juice
2	Bread, cheese, juice.
3	Bread, milk, Yogurt.
4	Bread, juice, milk
5	cheese, juice, milk

Frequent itemset.

support → $\frac{\text{Bread}}{4}$

items	Frequency.	
Bread	4	4/5 x 100 = 80%.
cheese	3	3/5 x 100 = 60%.
egg	1	1/5 = 20%.
juice	4	4/5 = 80%.
milk	3	3/5 = 60%.
Yogurt	1	1/5 = 20%.

Item pairs	Frequency	support
(Bread, cheese)	2	2/5 = 40%
(Bread, juice)	3	3/5 = 60%
(Bread, milk)	2	2/5 = 40%
(cheese, juice)	3	3/5 = 60%
(cheese, milk)	1	1/5 = 20%
(juice, milk)	2	2/5 = 40%

For Rules → (Bread, juice)
→ (cheese, juice)

(i) (Bread, juice)

(Bread → juice) (juice → Bread

Confidence (A → B) = $\frac{\text{support}(A \cup B)}{\text{support } A}$

1) Bread → juice = $\frac{S(B \cup j)}{S(B)} = \frac{3}{5} \cdot \frac{5}{4} = \frac{3}{4}$ = 75%

(2) juice → Bread = $\frac{3 \cdot 5}{5 \cdot 4}$ = 75%

(ii) cheese → juice

$3/5 \cdot 5/3 = 100\%$

juice → cheese

$3/5 \cdot 5/4 = 75\%$

A. Frequent pattern set (L) is built which will contain all element whose frequny is greater than or equal to the

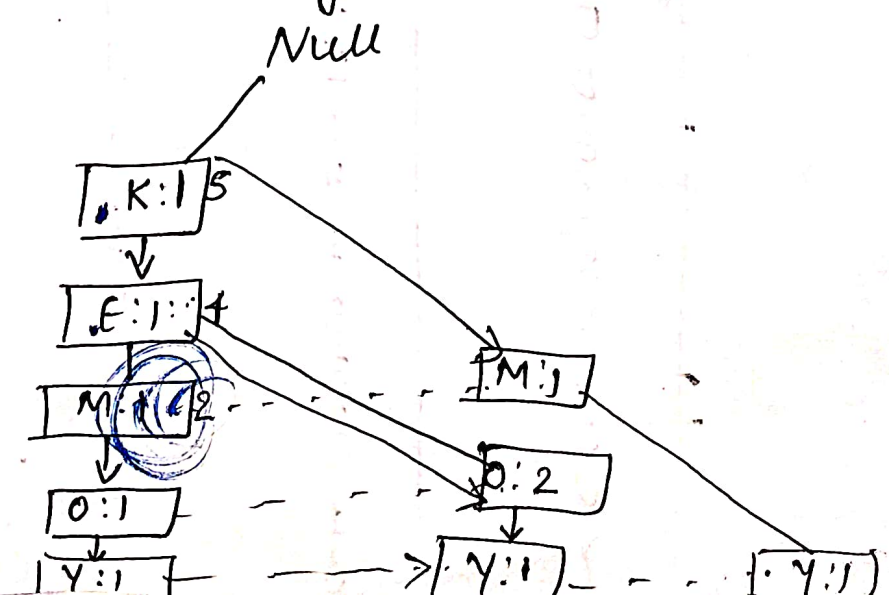
These elements are stored in desending order of their respectives.

$L = \{K:5, E:4, M:3, O:3, Y:3\}$

Frequnt pattern set $L = \{K:5, E:4, M:3, O:3, Y:3\}$

Transaction ID	items	ordered-itemset
T1	{E, K, M, N, O, Y}	~~{K, E, M, O, Y}~~ {K, E, M, O, Y}
T2	{D, E, K, N, O, Y}	~~{K, E, O, Y}~~ {K, E, O, Y}
T3	{A, E, K, M}	~~{A, E, K, M}~~ {K, E, M}
T4	{C, K, M, U, Y}	~~{C, K, M, U, Y}~~ {K, M, Y}
T5	{C, E, I, K, O, O}	~~{C, E, I, K, O, O}~~ {K, E, O}

a) inserting the set {K, E, O, Y}



DETAILED LECTURE NOTES

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Frequent pattern (FP growth):-

Transaction ID	items
T1	{E, K, M, N, O, Y}
T2	{D, E, K, N, O, Y}
T3	{A, E, K, M}
T4	{C, K, M, U, Y}
T5	{C, E, I, K, O, O}

the above-given data is a hypothetical dataset of transaction with each letter representing an item

- Let the minimum support is 3.

item	Frequency
A	1
C	2
D	1
E	4
I	1
K	5
M	3
N	2
O	3
U	1
Y	3

DETAILED LECTURE NOTES

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Y	{K, E, M, O : 1}, {K, E, O : 1} [K, M : 1]
O	{ K, E, M : 1], { K, E : 2]
M	{ K E : 2], { K : 1]
E	{ K : 4]
K	

Y	{K, E, M, O : 1}, {K, E, O : 1} { K, M : 1]	Condition fever {K : 3]
O	{[K, E, M : 1], { K, E : 2]	{ K, E : 3]
M	{ K, E : 2], { K = 1]	{ K : 3)
E	{ K = 4]	{ K : 4]
K		

Y	{<K, Y : 3 >
O	{< K, O : 3 >, < E, O : 3 >, < E, K, O : 3 >
M	{< K, M : 3 >]
E	{< E, K : 3 >]
K	

DETAILED LECTURE NOTES

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Association rule Mining :-

min support

Transcation ID	items
T1	HOTDOGS, Buns, ketchup
T2	HOTDogs, Buns
T3	HOTDogs, coke, chips
T4	chips, cake
T5	chips, ketchup
T6	HOTDogs, cake, chips

2. Transcation. Threshold = 33.34 %.

Q.2

T-ID	itemset
T=1000	M, O, N, K, E, Y
T=1001	D, O, N, K E, Y
T=1002	M, A, K, E
T=1003	M, U, C, K y
T=1004	C, O, O, K E

Min Support 60%

Confidence = 80%

=

Support = $\frac{60}{100} \times 5 = 3$

itemset	Supp. count
M	3
O	4
K	5
E	4
Y	3

MO	1
MK	3
ME	2
MY	2
OK	3
O, E	3
O, Y	2
K, E	4
K, Y	3
E, Y	2

→

Now again C_2 in min support

M, K	3
O, K	3
O, E	3
K, Y	3
K, E	4

↓

MOK	1
MKE	2
MKY	2
OKE	3
OK, Y	2

OKE = 3

O∧K = E
O∧E = K
} marked Basket

O∧K=E	3	100
O∧K=K	3	100

→

1 { Bread, Butter, Milk }
2 { Bread, Butter }
3) { Beer, cookies, Diapers }
4) { milk, Diapers, Bread, Butter }
5) { Beer, Diapers }