

**CSE3506: Essentials of Data Analytics**

**Ex-08: Hierarchical clustering**

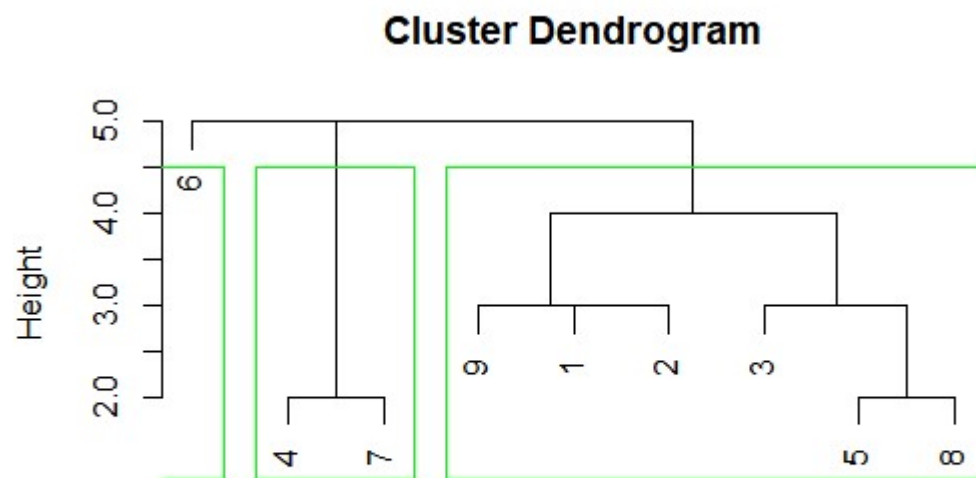
**Aim:** to perform hierarchical clustering using manhattan and euclidean distance with both single and complete linkage methods.

**Tools:** R studio

**Method-1:**

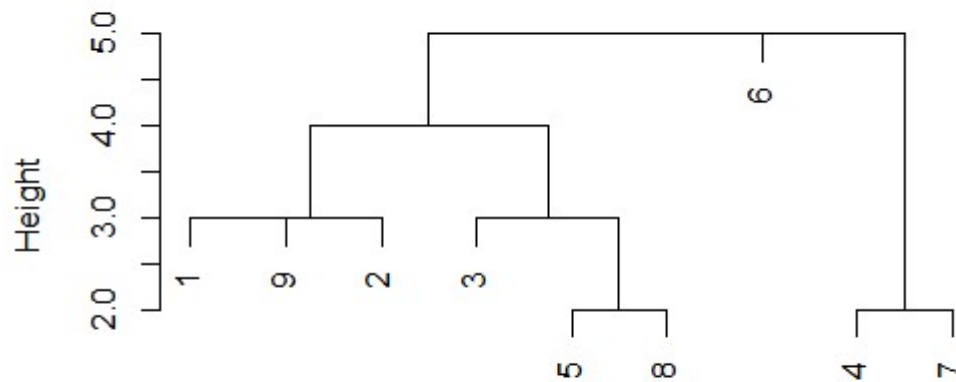
##Manhattan Distance ,single linkage method

PLOTS:



Activate Windows  
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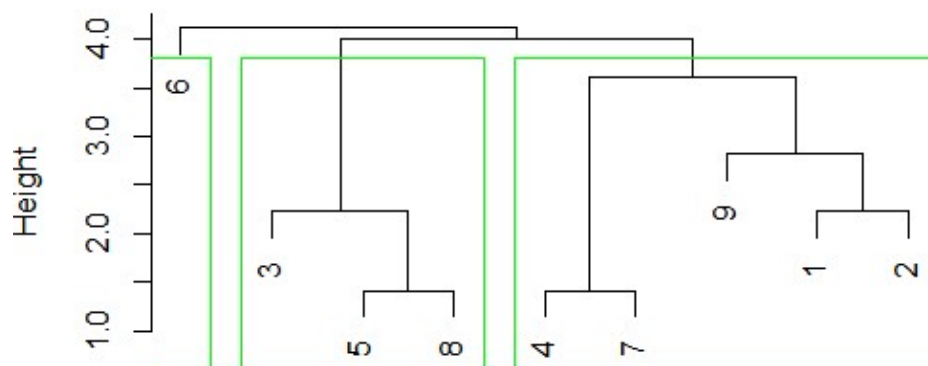
```
distance_mat  
hclust (*, "single")
```

**Dendrogram of agnes(x = distance\_mat, method = "single")**

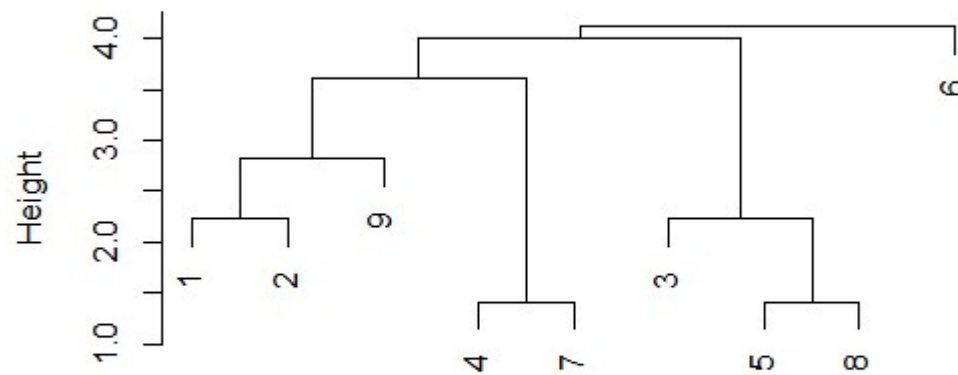
Activate Windows  
Go to Settings to activate Windows.  
distance\_mat  
agnes (\*, "single")

**Method-2:**

##Euclidean Distance ,single linkage method

**Cluster Dendrogram**

Activate Windows  
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distance\_mat  
hclust (\*, "single")

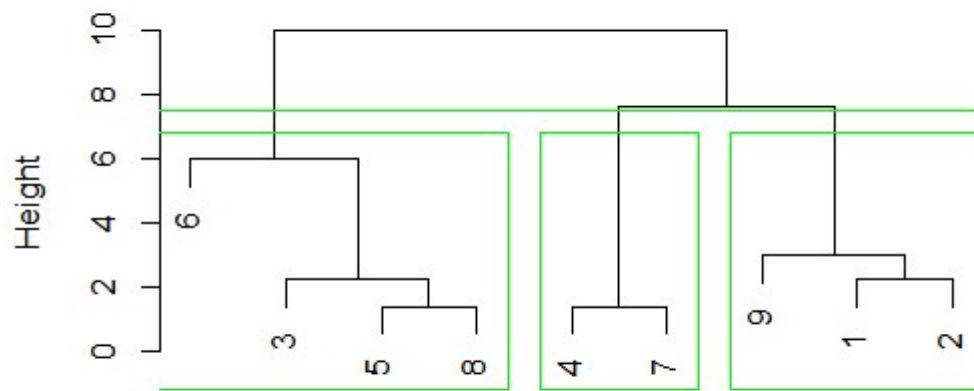
**Dendrogram of agnes(x = distance\_mat, method = "single")**

Activate Windows  
Go to Settings to activate Windows.  
distance\_mat  
agnes (\*, "single")

**Method-3:**

##Euclidean Distance ,complete linkage method

### Cluster Dendrogram

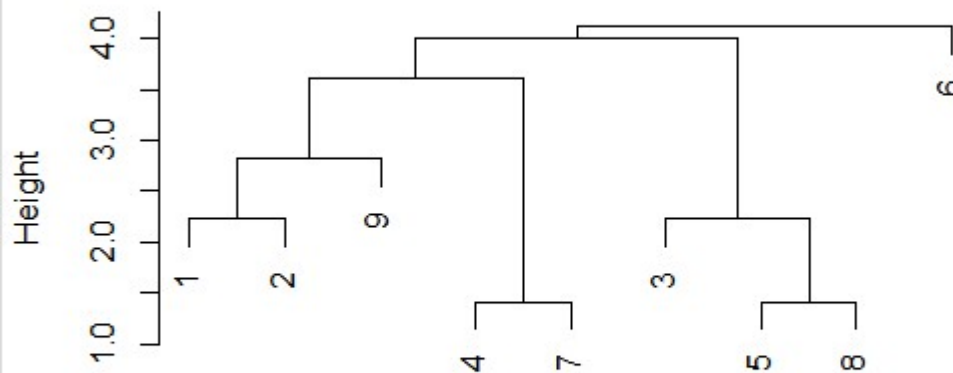


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```
distance_mat
hclust (*, "complete")
```

### Dendrogram of agnes(x = distance\_mat, method = "single")



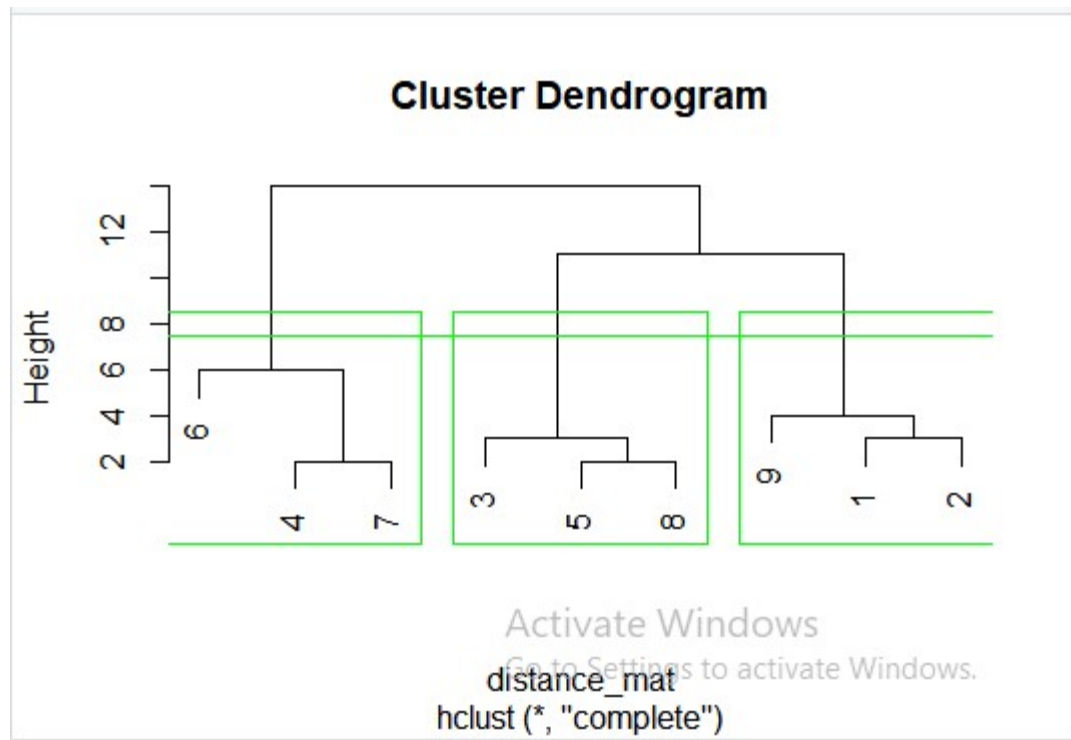
Activate Windows

Go to Settings to activate Windows.

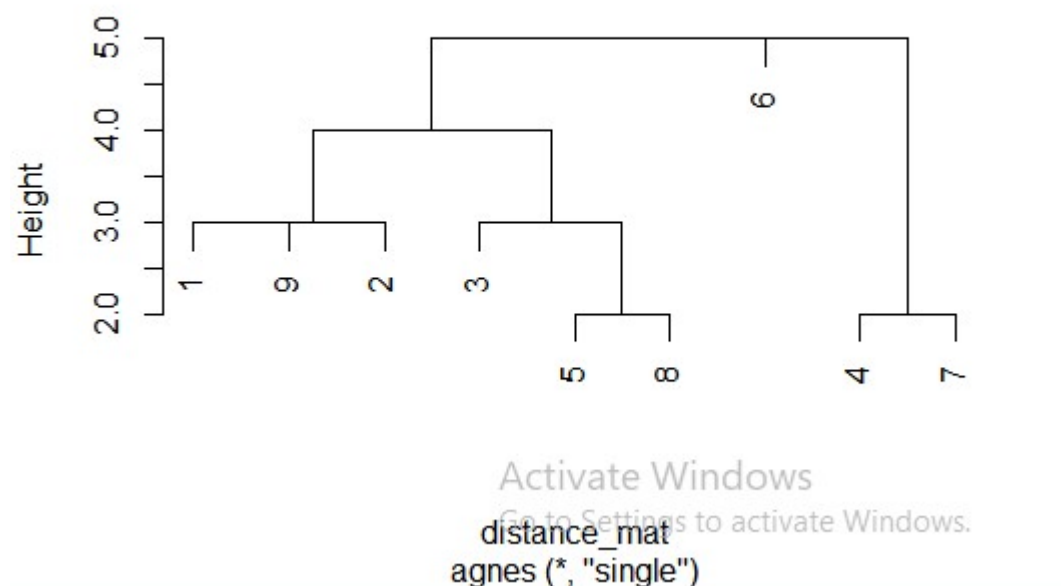
```
distance_mat
agnes (*, "single")
```

#### Method-4:

```
##Manhattan Distance ,complete linkage method
```



### Dendrogram of agnes(x = distance\_mat, method = "single")



### Inference:

Here we saw, the difference between dendrograms when different methods were chosen.

In case of single linkage, the manhattan distance, we check for farthest points and vice versa.

In case of complete linkage, the manhattan distance, we check for closest points and vice versa.

### **#ANNEX**

#Code

```
rm(list=ls())
```

```
library(cluster)
```

```
library(dplyr)
```

```
v2=c(1,2,1,7,2,7,8,3,4)
```

```
v1=c(1,3,9,3,7,9,4,8,1)
```

```
df=data.frame(v1,v2)
```

```
#DO FOR ALL POSSIBLE COMBN
```

```
#manhattan, euclidean
```

```
#single, complete
```

```
distance_mat =dist(df,method = 'manhattan')
```

```
distance_mat
```

```
hierar_cl=hclust(distance_mat,method= "single")
```

```
hierar_cl
```

```
plot(hierar_cl)
```

```
#choosing no of clusters
```

```
#cutting tree by height
```

```
abline(h=7.5 ,col ="green")
```

```
#cutting tree by no of clusters
```

```
fit = cutree(hierar_cl, k=3)
```

```
fit
```

```
table(fit) # frq of occurence
```

```
rect.hclust(hierar_cl, k=3 ,border = "green")
```

```
## euclidian ,single
```

```
rm(list=ls())
```

```
library(cluster)
```

```
library(dplyr)
```



```
v2=c(1,2,1,7,2,7,8,3,4)
```

```
v1=c(1,3,9,3,7,9,4,8,1)
```

```
df=data.frame(v1,v2)
```

```
#DO FOR ALL POSSIBLE COMBN
```

```
#manhattan, euclidean
```

```
#single, complete
```

```
distance_mat =dist(df,method = 'euclidean')
```

```
distance_mat
```

```
hierar_cl=hclust(distance_mat,method= "single")
```

```
hierar_cl
```

```
plot(hierar_cl)
```

```
#choosing no of clusters
```

```
#cutting tree by height
```

```
abline(h=7.5 ,col ="green")
```

```
#cutting tree by no of clusters
```

```
fit = cutree(hierar_cl, k=3)
```

```
fit
```

```
table(fit) # frq of occurence
```

```
rect.hclust(hierar_cl, k=3 ,border = "green")
```

```
#-----
```

```
Hierar_agnes<-agnes(distance_mat,method="single")
```

```
pltree(Hierar_agnes)
```