

# Machine Learning - Midterm

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```
#Machine Learning - Midterm Assignment#  
#Email: msasnur@kent.edu#  
#Date:31/10/2019#
```

```
library(readr)  
library(ISLR)  
library(tidyverse)
```

```
## -- Attaching packages ----- tidyverse 1.2.1 --
```

```
## v ggplot2 3.2.1      v purrr   0.3.2  
## v tibble  2.1.3      v dplyr   0.8.3  
## v tidyr   0.8.3      v stringr 1.4.0  
## v ggplot2 3.2.1      v forcats 0.4.0
```

```
## -- Conflicts ----- tidyverse_conflicts() --  
## x dplyr::filter() masks stats::filter()  
## x dplyr::lag()    masks stats::lag()
```

```
library(factoextra)
```

```
## Welcome! Related Books: `Practical Guide To Cluster Analysis in R` at https://goo.gl/13EFCZ
```

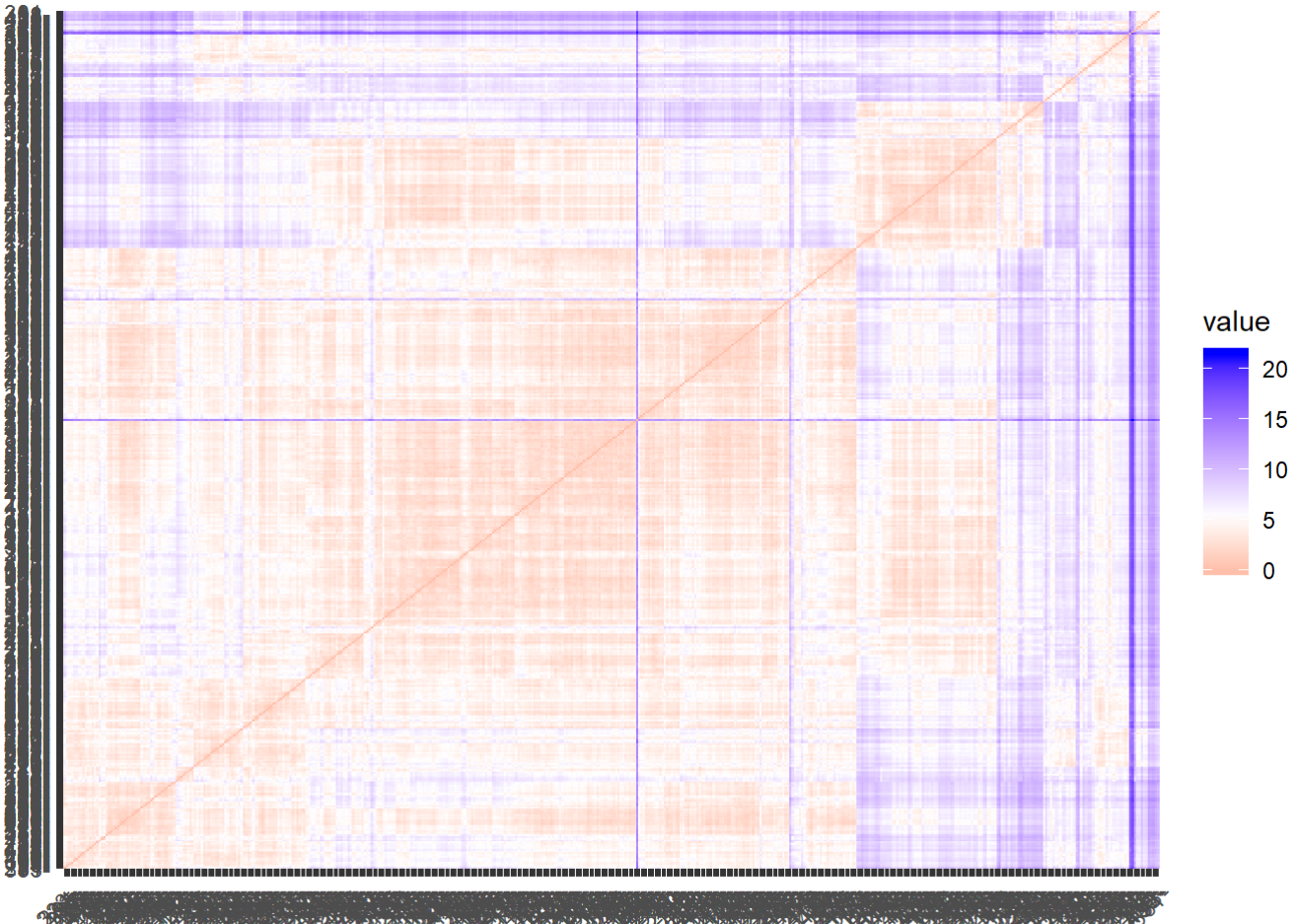
```
univ<-read_csv("Universities.csv")
```

```
## Parsed with column specification:  
## cols(  
##   .default = col_double(),  
##   `College Name` = col_character(),  
##   State = col_character()  
## )
```

```
## See spec(...) for full column specifications.
```

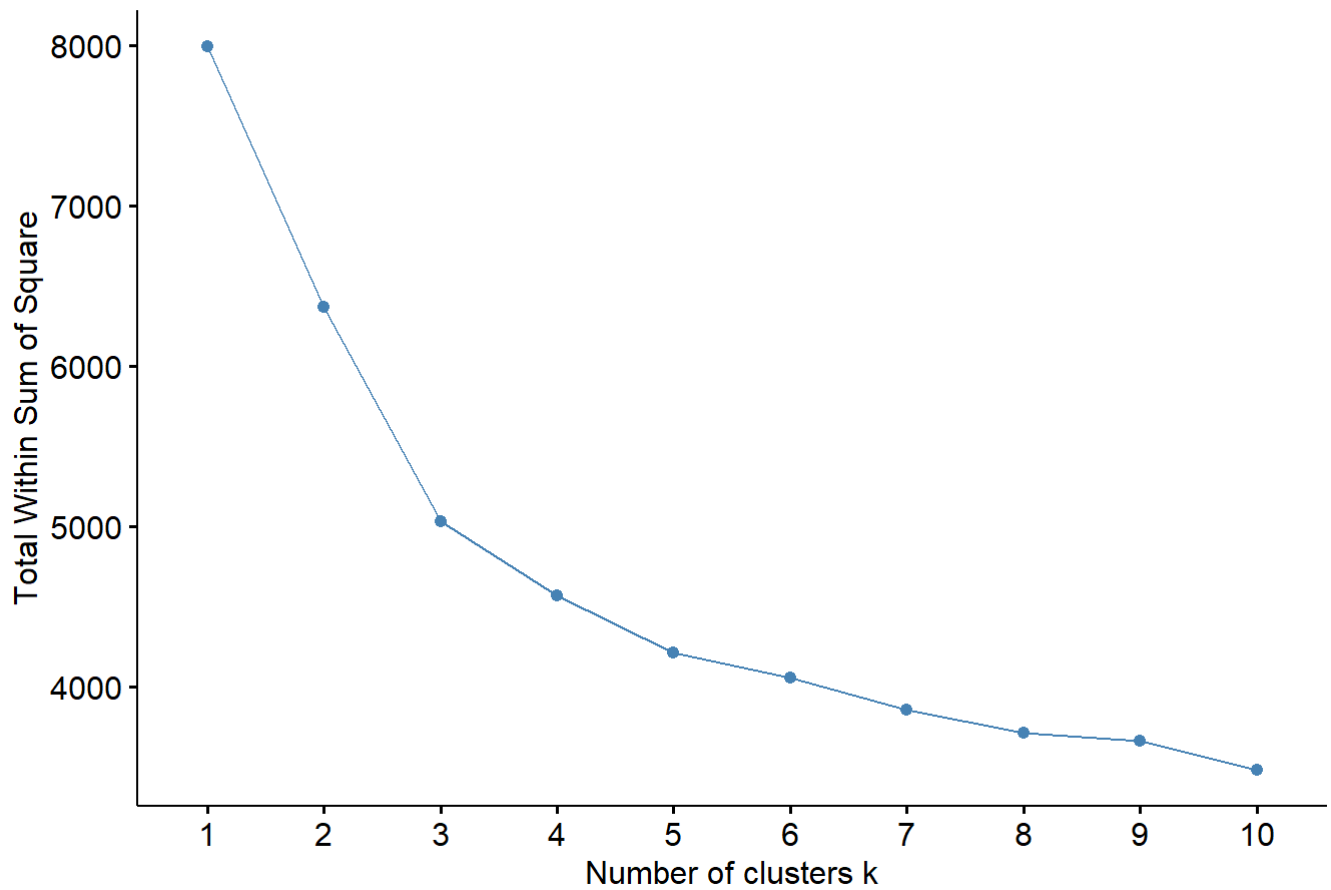
```
#Removing all records with missing measurements from the dataset
univ1<-na.omit(univ)
View(univ1)
```

```
# Scaling the data frame (z-score)
uni<-univ1[,c(-1,-2,-3)]
uni<-scale(uni)
distance <- get_dist(uni)
fviz_dist(distance)
```



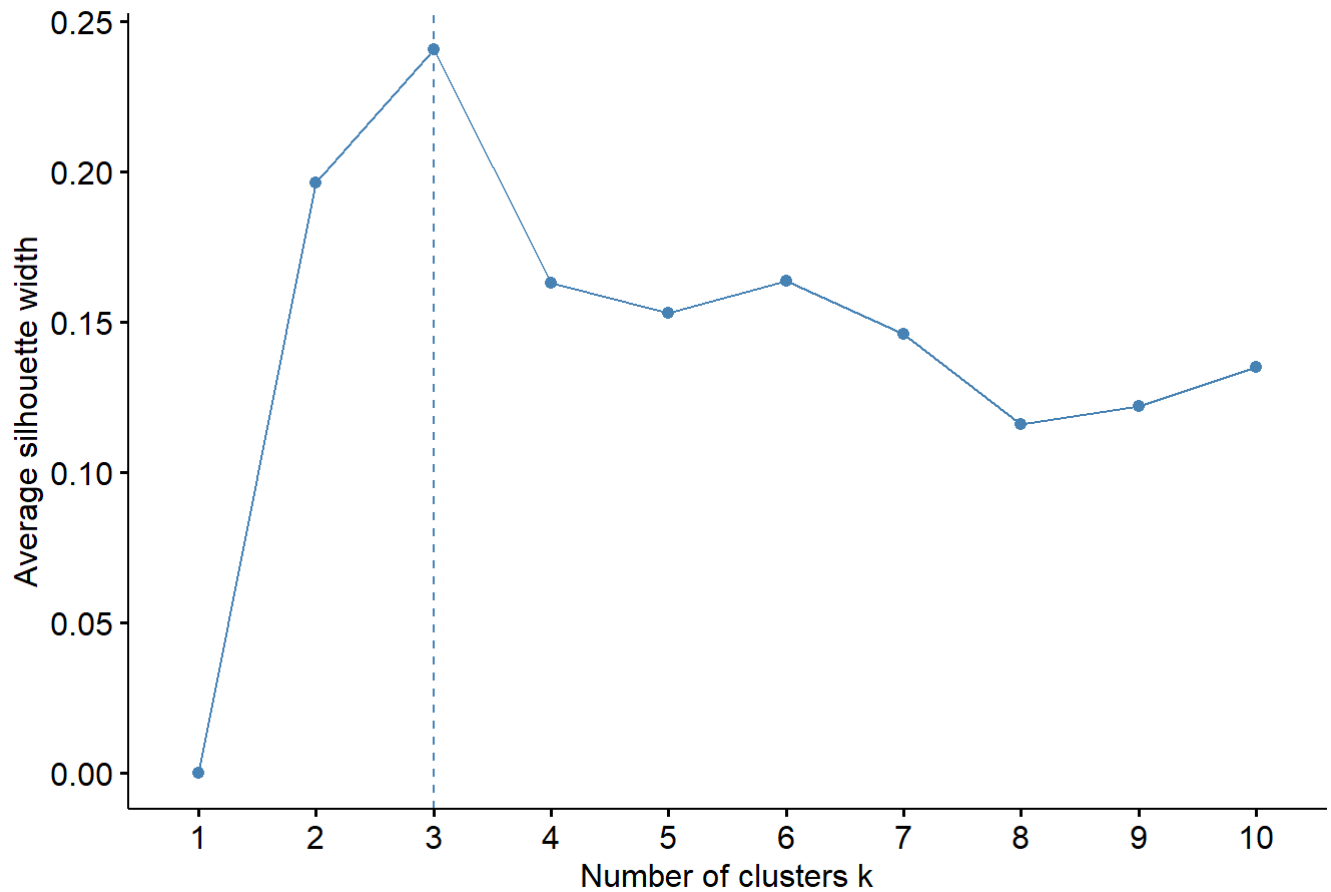
```
# To find the best K value using Elbow Method and Silhouette Method
fviz_nbclust(uni,kmeans,method = "wss")
```

Optimal number of clusters



```
fviz_nbclust(uni,kmeans,method = "silhouette")
```

Optimal number of clusters



```
# From above two methods we have found out that the Best K value for cluster analysis is 3.
```

```
# To run kmeans clustering analysis
k3<- kmeans(uni, centers = 3, nstart = 25)
k3$centers #summary of cluster analysis
```

```
## # appli. rec'd # appl. accepted # new stud. enrolled
## 1 -0.35953828 -0.34918455 -0.3171053
## 2 0.05140256 -0.04367128 -0.1683551
## 3 1.98179657 2.22992267 2.4447222
## % new stud. from top 10% % new stud. from top 25% # FT undergrad
## 1 -0.5020886 -0.5128195 -0.2952142
## 2 0.8795798 0.8620961 -0.2324464
## 3 0.1334215 0.2545856 2.5228452
## # PT undergrad in-state tuition out-of-state tuition room
## 1 -0.1217682 -0.4036544 -0.5263964 -0.3588740
## 2 -0.3130216 1.0620416 1.1158839 0.6698444
## 3 1.7486849 -1.0500277 -0.4918168 -0.0388330
## board add. fees estim. book costs estim. personal $ % fac. w/PHD
## 1 -0.3938990 -0.05832646 -0.06621454 0.05935933 -0.5322257
## 2 0.7756859 -0.04496556 0.07122705 -0.39665857 0.7659627
## 3 -0.1745795 0.49531762 0.16358567 0.93858632 0.6840794
## stud./fac. ratio Graduation rate
## 1 0.2810858 -0.4171456
## 2 -0.7036167 0.8426062
## 3 0.6139980 -0.2538234
```

```
k3$size #Size of each cluster
```

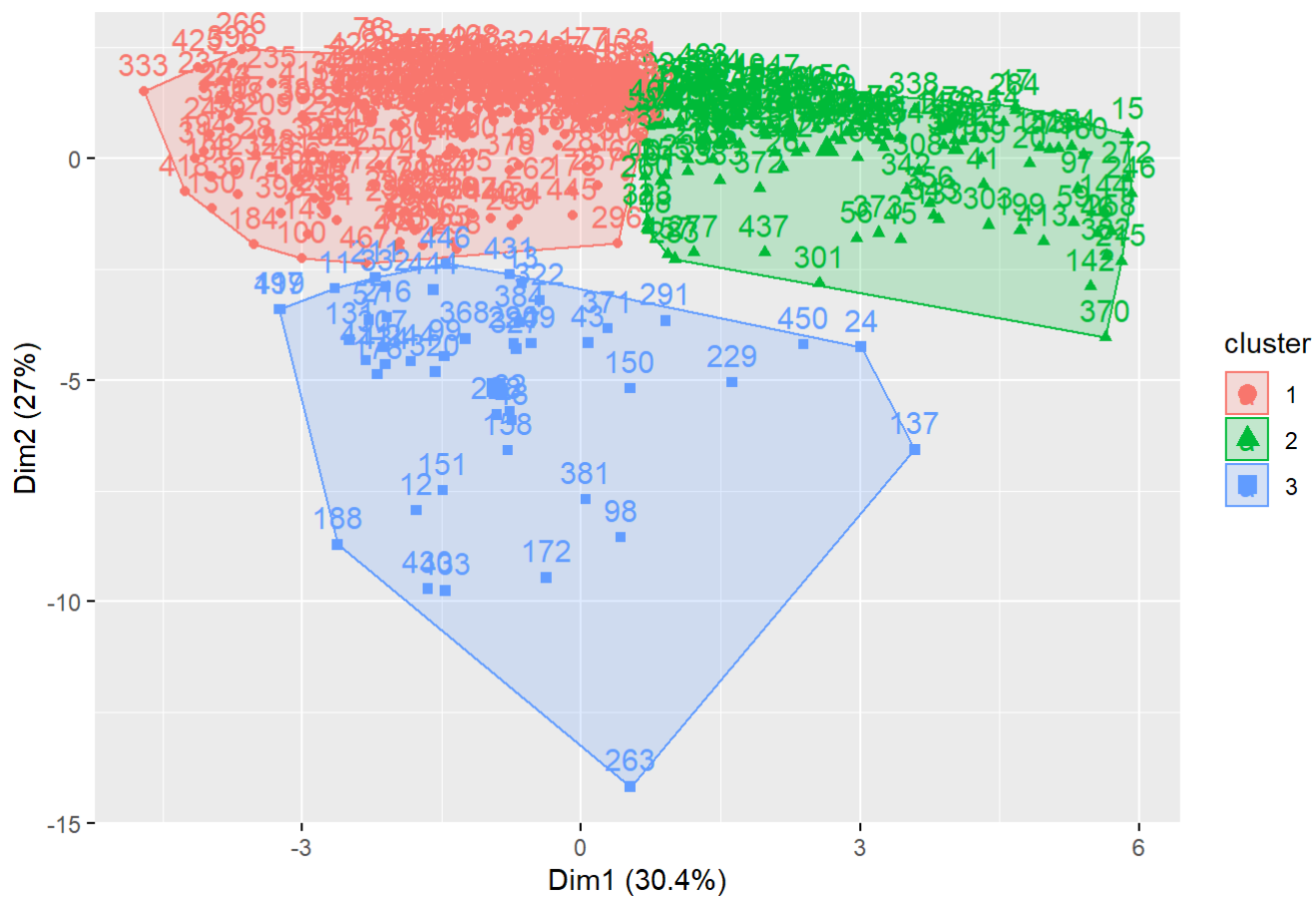
```
## [1] 275 150 46
```

```
k3$cluster[99] # To see which Cluster does 99th record belong to
```

```
## [1] 3
```

```
fviz_cluster(k3, data = uni) #Drawing cluster graph
```

Cluster plot



### #Question 3

# As seen above from summary of k3\$centers, we can observe the values for three different clusters.

```
# In cluster 3,  
# Columns (Application Rejected,  
#           Application Accepted,  
#           New Student Enrolled,  
#           Full Time underGrad,  
#           Part Time underGrad,  
#           Additional fees,  
#           book costs,  
#           estimated personal expenses,  
#           student to faculty ratio)  
#           have higher values and we can discern this pattern in cluster 3.
```

```
#In cluster 2,  
# Columns (New student from 10%,  
#           New student from top 25%,  
#           in-state tuition,  
#           out-of-station tuition,  
#           Room,  
#           Board,  
#           Percentage of faculty with PhD,  
#           Graduation Rate)  
#           have higher values and we can discern that in Cluster 2.
```

```
#In cluster 1,  
# Columns (Application Rejected,  
#           Application Accepted,  
#           New Student Enrolled,  
#           New student from 10%,  
#           New student from top 25%,  
#           Full Time underGrad,  
#           Part Time underGrad,  
#           in-state tuition,  
#           out-of-station tuition,  
#           Room,  
#           Board,)  
#           have lower values and we can discern that in Cluster 1.
```

### #Question 4

```
cat<-cbind(univ1[,c(1,2,3)],k3$cluster)  
head(cat)
```

College Name <chr>	State <chr>	Public (1)/ Private (2) <dbl>	k3\$cluster <int>
1 Alaska Pacific University	AK	2	1
2 University of Alaska Southeast	AK	1	1
3 Birmingham-Southern College	AL	2	2
4 Huntingdon College	AL	2	1
5 Talladega College	AL	2	1

College Name <chr>	State <chr>	Public (1)/ Private (2) <dbl>	k3\$cluster <int>
6 University of Alabama at Birmingham	AL	1	1

6 rows

```
cat<-as.data.frame(cat)
cat$`Public (1)/ Private (2)`<-factor(univ1$`Public (1)/ Private (2)`, levels=c("1","2"), lab
els = c("Public","Private"))
Cluster1 <- cat[cat$k3$cluster` == 1,]
View(Cluster1)
Cluster2 <- cat[cat$k3$cluster` == 2,]
View(Cluster2)
Cluster3 <- cat[cat$k3$cluster` == 3,]
View(Cluster3)
```

*#After binding the categorical columns with clusters, we observe that*  
*# Cluster 1 has data of both Public and Private Universities*  
*# Cluster 2 has data belonging to Private universities*  
*# Cluster 3 has data belonging to Public Universities mostly*

*# Using Pivot table we can get detailed information on number of universities belonging to ea*  
*ch cluster,*  
*# represented according to states. Separated by Public and Private Universities.*  
*# We can also see the total number of Public and Private universities in each state.*

```
library(pivottabler)
pt<-PivotTable$new()
pt$addData(cat)
pt$addColumnDataGroups('Public (1)/ Private (2)')
pt$addColumnDataGroups('k3$cluster')
pt$addRowDataGroups('State')
pt$defineCalculation(calculationName= 'Total', summariseExpression = 'n()')
pt$renderPivot()
```

	Public				Private				Total
	1	2	3	Total	1	2	3	Total	
AK	1			1	1			1	2
AL	1			1	2	1		3	4
AR					4			4	4
AZ			2	2					2
CA		1	1	2	3	9	1	13	15
CO	5			5		1		1	6
CT	2		1	3	1	6		7	10
DC						4		4	4
DE					1		1	2	2
FL			1	1	3	4		7	8
GA			1	1	4	2		6	7
HI	1			1					1
IA	1			1	15	2		17	18
ID					2			2	2
IL	2		2	4	5	6		11	15
IN	1			1	7	7		14	15
KS					7			7	7

KY	1			1	3	2		5	6
LA	1		1	2	1	2		3	5
MA	4		1	5	3	12	2	17	22
MD	1		1	2		1		1	3
ME	3			3	1	2		3	6
MI	1		2	3	6	4		10	13
MN	2		1	3	4	4		8	11
MO	2		1	3	10	2		12	15
MS	3			3	2			2	5
MT	1			1	1			1	2
NC	6		4	10	10	3		13	23
ND	4			4	1			1	5
NE	2		1	3	3	1		4	7
NH	1		1	2	3	1		4	6
NJ	6		1	7	3	3		6	13
NM					2			2	2
NY	10		2	12	8	18		26	38
OH			4	4	13	7		20	24
OK	2		1	3	3			3	6
OR					1	4		5	5
PA	4		3	7	15	20		35	42
RI			1	1	1	2		3	4
SC	2			2	5	2		7	9
SD	2			2	2			2	4
TN			1	1	11	3		14	15
TX	4		3	7	10	2	1	13	20
UT			1	1	1			1	2
VA	2	1	3	6	6	3		9	15
VT	3	1		4	2	1		3	7
WA						2		2	2
WI	2			2	3	4		7	9
WV					2			2	2
WY	1			1					1
Total	84	3	41	128	191	147	5	343	471

*#Question 5*

*# Using cluster.stats() function, we can get statistics of the all the clusters.*

*# This Statistics include Number of Cluster, Cluster Size, Diameter of each cluster, distance, Separation.*

**library(fpc)**

**cluster.stats(distance,k3\$cluster)**



```
## $n
## [1] 471
##
## $cluster.number
## [1] 3
##
## $cluster.size
## [1] 275 150 46
##
## $min.cluster.size
## [1] 46
##
## $noisen
## [1] 0
##
## $diameter
## [1] 15.72735 10.83931 17.38478
##
## $average.distance
## [1] 4.102453 4.113867 6.235578
##
## $median.distance
## [1] 4.019750 3.907029 5.489743
##
## $separation
## [1] 1.054636 1.054636 2.106758
##
## $average.toother
## [1] 6.102039 5.977532 7.918952
##
## $separation.matrix
##      [,1]      [,2]      [,3]
## [1,] 0.000000 1.054636 2.106758
## [2,] 1.054636 0.000000 2.769109
## [3,] 2.106758 2.769109 0.000000
##
## $ave.between.matrix
##      [,1]      [,2]      [,3]
## [1,] 0.000000 5.598819 7.742976
## [2,] 5.598819 0.000000 8.241575
## [3,] 7.742976 8.241575 0.000000
##
## $average.between
## [1] 6.344849
##
## $average.within
## [1] 4.314419
##
## $n.between
## [1] 60800
##
## $n.within
## [1] 49885
##
## $max.diameter
## [1] 17.38478
##
```

```
## $min.separation
## [1] 1.054636
##
## $within.cluster.ss
## [1] 5031.914
##
## $clus.avg.silwidths
##          1          2          3
## 0.2503594 0.2484554 0.1560818
##
## $avg.silwidth
## [1] 0.2405454
##
## $g2
## NULL
##
## $g3
## NULL
##
## $pearsongamma
## [1] 0.4736057
##
## $dunn
## [1] 0.06066437
##
## $dunn2
## [1] 0.897883
##
## $entropy
## [1] 0.9057607
##
## $wb.ratio
## [1] 0.6799877
##
## $ch
## [1] 137.5604
##
## $cwidegap
## [1] 8.247873 6.747930 9.655971
##
## $widestgap
## [1] 9.655971
##
## $sindex
## [1] 1.523979
##
## $corrected.rand
## NULL
##
## $vi
## NULL
```

### #Question 6

# Replacing the NA value

```
univ$`# PT undergrad`[is.na(univ$`# PT undergrad`)] <- mean(univ$`# PT undergrad`,na.rm = TRUE)
tuftuni<-univ[476,]
summary(univ$`# PT undergrad`)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      1.0   136.5   487.5  1081.5  1286.0 21836.0
```

```
x<- rbind(univ1,tuftuni) #Binding the Tuft University record to our Dataset without NA values
y<- scale(x[,c(-1,-2,-3)]) #Normalizing the dataset
k.tuft<-kmeans(y,centers = 3,nstart = 25) #Performing Cluster Analysis on Dataset
k.tuft$cluster
```

```
##      [1] 1 1 3 1 1 1 1 1 1 1 2 2 3 3 3 3 3 1 3 1 3 3 2 3 3 1 1 3 1 1 1 1 1 3
##      [36] 1 3 3 3 3 3 1 2 3 3 3 3 2 1 1 3 1 1 3 3 3 2 1 3 1 3 2 1 1 1 1 1 1 3 1
##      [71] 1 1 3 1 1 1 1 1 1 1 1 1 1 1 1 3 1 3 3 3 1 3 1 1 1 1 3 2 2 1 1 3 3 3 1
##     [106] 1 1 1 1 1 1 3 3 3 3 1 1 1 1 1 1 1 1 3 1 1 1 3 1 1 2 3 3 3 3 3 2 1 3 3
##     [141] 1 3 1 3 1 1 1 1 3 2 2 3 3 3 3 3 1 2 1 3 3 1 1 1 1 3 3 1 3 3 1 2 1 1 1
##     [176] 2 1 3 1 1 3 3 3 1 1 1 1 2 1 1 1 1 1 1 1 1 2 3 3 1 1 1 1 1 1 1 1 1 1 1
##     [211] 2 1 1 3 3 2 1 1 1 1 1 1 1 1 1 3 2 2 1 1 1 1 1 1 1 1 1 1 3 1 1 1 1 2 1
##     [246] 3 1 1 2 1 1 3 1 1 1 1 1 3 1 3 1 1 2 1 1 1 3 1 1 3 3 3 3 1 3 3 3 1 3 3
##     [281] 1 1 3 3 3 3 1 1 3 2 2 1 1 1 1 1 1 1 1 3 3 3 1 1 1 2 3 1 1 1 3 1 3 1
##     [316] 3 1 1 3 2 1 2 3 1 3 1 2 1 1 1 1 2 1 1 1 3 3 3 3 3 3 3 3 3 3 1 3 1 1
##     [351] 3 3 1 3 3 3 1 1 3 3 1 1 1 1 1 1 3 2 1 3 2 3 3 3 1 1 1 1 1 2 3 3 2 1
##     [386] 1 1 1 1 1 3 1 1 3 1 1 1 1 1 1 1 1 1 1 1 1 3 1 1 2 3 3 1 1 1 1 1 2 1
##     [421] 1 1 1 1 1 1 3 3 1 2 2 1 2 2 1 1 3 1 3 1 3 1 1 2 1 2 1 1 3 2 1 1 1 1 3
##     [456] 1 3 3 3 3 1 3 3 3 1 1 1 1 1 1 1 1 3
```

```
k.tuft$centers
```

```
##      # appli. rec'd # appl. accepted # new stud. enrolled
## 1      -0.36178481      -0.35072087      -0.3183527
## 2       1.97905301       2.23008958       2.4457813
## 3       0.05598931      -0.04063498      -0.1652911
##      % new stud. from top 10% % new stud. from top 25% # FT undergrad
## 1      -0.5046909      -0.5153888      -0.2959828
## 2       0.1294809       0.2505136       2.5249258
## 3       0.8796945       0.8623066      -0.2301411
##      # PT undergrad in-state tuition out-of-state tuition      room
## 1      -0.1222831      -0.4065412      -0.5289356 -0.36118215
## 2       1.7500917      -1.0512232      -0.4944827 -0.04124618
## 3      -0.3104396       1.0606299       1.1139304  0.67034712
##      board      add. fees estim. book costs estim. personal $ % fac. w/PHD
## 1 -0.3964868 -0.05911977      -0.06694360      0.0605963 -0.5347161
## 2 -0.1774061  0.49504158      0.16307690      0.9404620  0.6797982
## 3  0.7761229 -0.04313891      0.07223809      -0.3968559  0.7667298
##      stud./fac. ratio Graduation rate
## 1       0.2831120      -0.4197344
## 2       0.6160664      -0.2566056
## 3      -0.7032771      0.8425881
```

```
which(grepl("Tufts University",x$`College Name`)) #To find the index of Tuft University record
```

```
## [1] 472
```

```
k.tuft$cluster[472] #To find cluster value in which Tuft University belongs to, using the index value
```

```
## [1] 3
```

```
# From above results, we can see that Tufts University belongs to Cluster 3 and its indexed at 472nd record.
```