

Unsupervised Explore Analysis

Outline

- K-means clustering
- Hierarchical Clustering
- Principal component analysis (PCA)

k - means Clustering Analysis

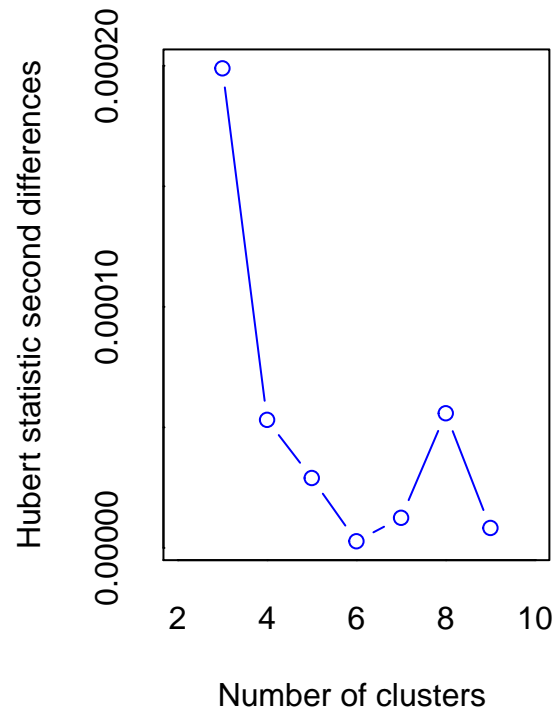
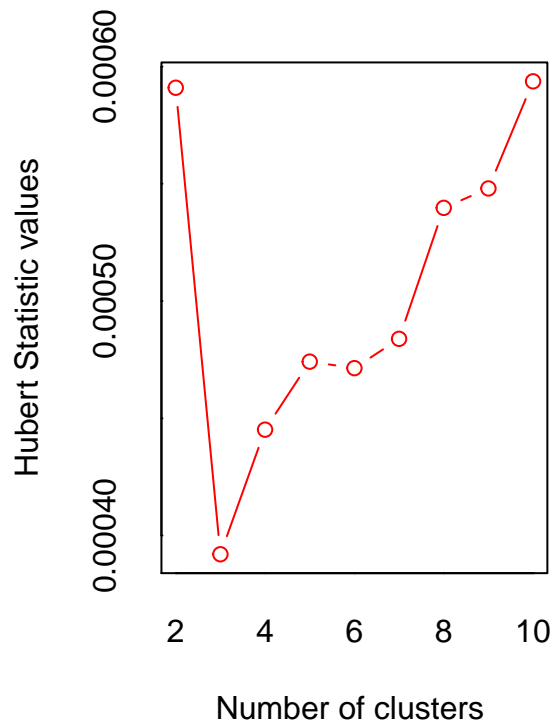
To Do Check List: - Data Updated?? from the changes in the website on May 2021 - Did I look at the correct variables? - What variables can I add? What variables can I take out?

Things that I should check when completing EDA: - Correlation Matrix - Did you need to scale the data? - What variables are important that are not numeric?

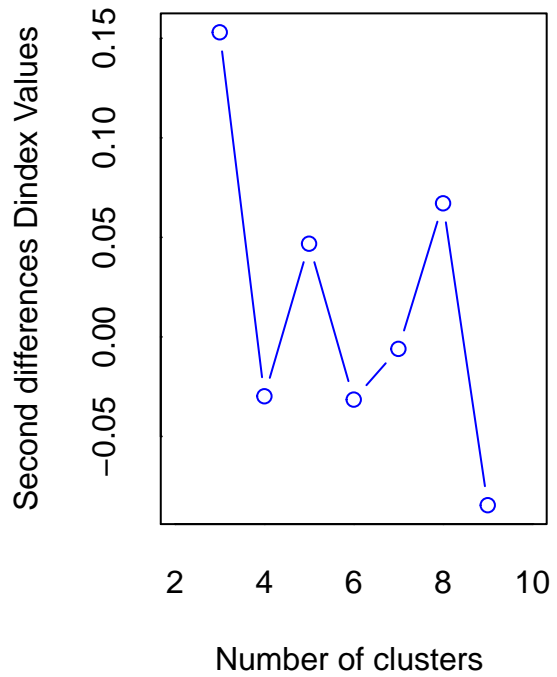
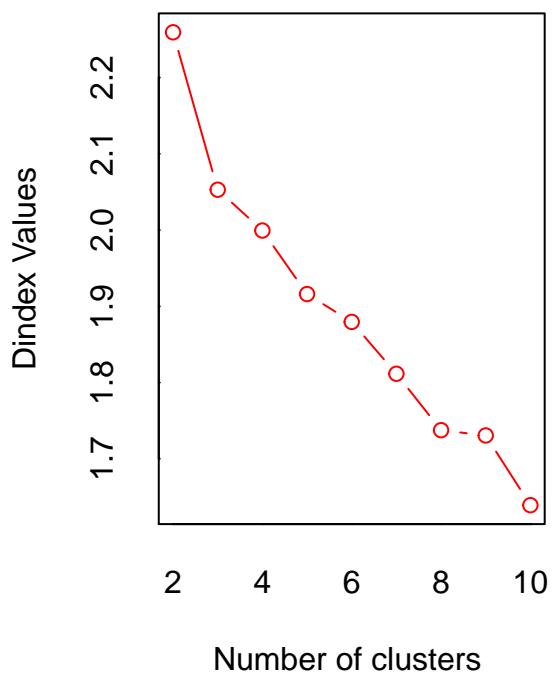
What issues am I having in the analysis for the K-means Analysis? -

Sourced methodology from https://cedric.cnam.fr/fichiers/art_2579.pdf

```
# ia.dist.data.nested <-  
#   ia.dist.data.nested %>%  
#   remove_rownames %>%  
#   column_to_rownames(var="City")  
#  
# scaled.ia.dist.data <- scale(ia.dist.data.nested[,-7])  
  
#Using the NBClust function to determine the number of clusters that are important to our data  
  
#Using the Euclidean Distance and Complete Method  
set.seed(26)  
clusterNo = NbClust(scaled.ia.dist.data,distance="euclidean",  
min.nc=2,max.nc=10,method="complete",index="all")
```



```
## *** : The Hubert index is a graphical method of determining the number of clusters.
##           In the plot of Hubert index, we seek a significant knee that corresponds to a
##           significant increase of the value of the measure i.e the significant peak in Hubert
##           index second differences plot.
##
```

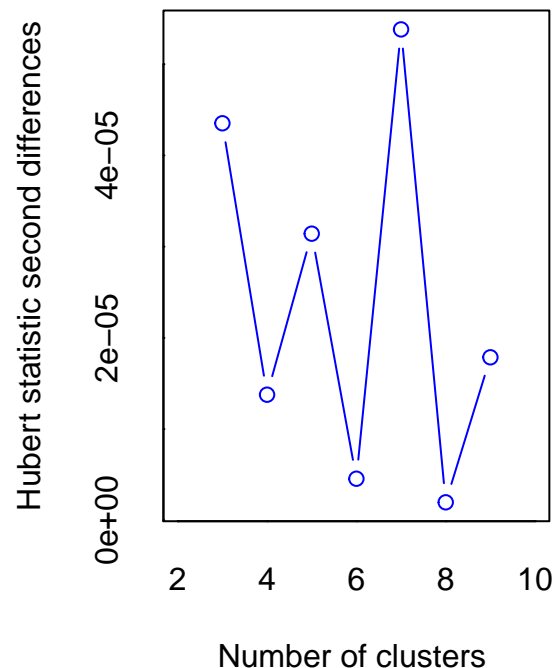
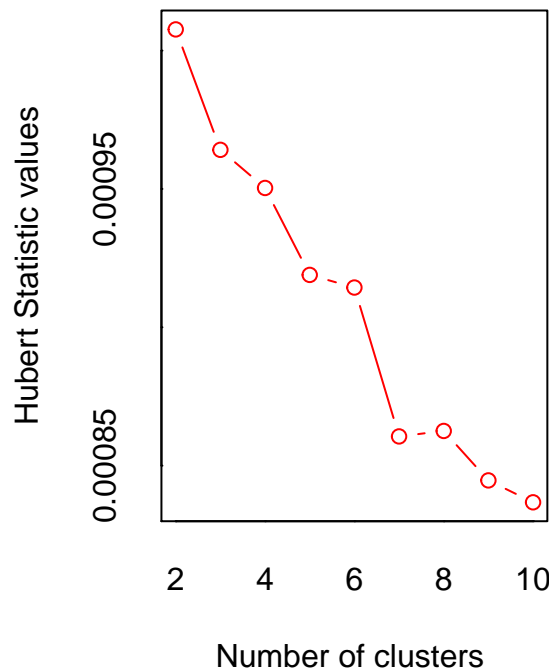


```
## *** : The D index is a graphical method of determining the number of clusters.
##           In the plot of D index, we seek a significant knee (the significant peak in Dindex
##           second differences plot) that corresponds to a significant increase of the value of
```

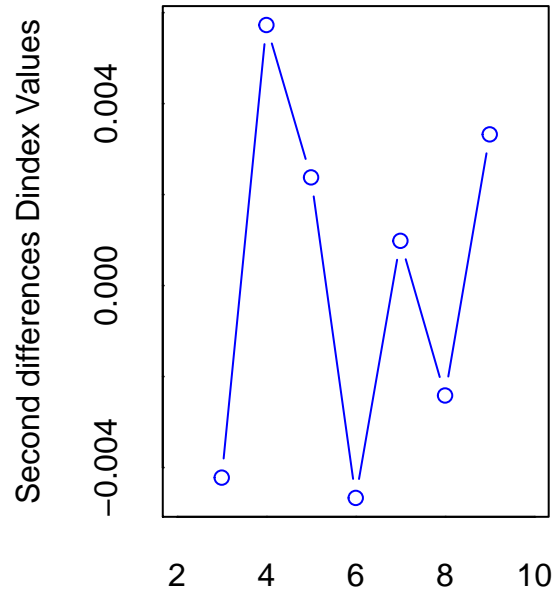
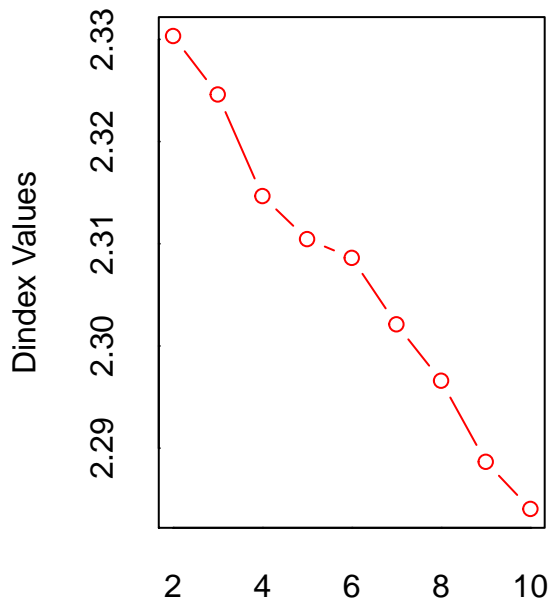
```
## the measure.
##
## *****
## * Among all indices:
## * 6 proposed 2 as the best number of clusters
## * 11 proposed 3 as the best number of clusters
## * 2 proposed 4 as the best number of clusters
## * 1 proposed 7 as the best number of clusters
## * 1 proposed 8 as the best number of clusters
## * 2 proposed 9 as the best number of clusters
## * 1 proposed 10 as the best number of clusters
##
## ***** Conclusion *****
##
## * According to the majority rule, the best number of clusters is 3
##
## *****
```

```
#Using the Euclidean Distance and Single Method (This may be the best method for our work, since we want
set.seed(26)
clusterNo = NbClust(scaled.ia.dist.data,distance="euclidean",
min.nc=2,max.nc=10,method="single",index="all")
```

```
## Warning in pf(beale, pp, df2): NaNs produced
```



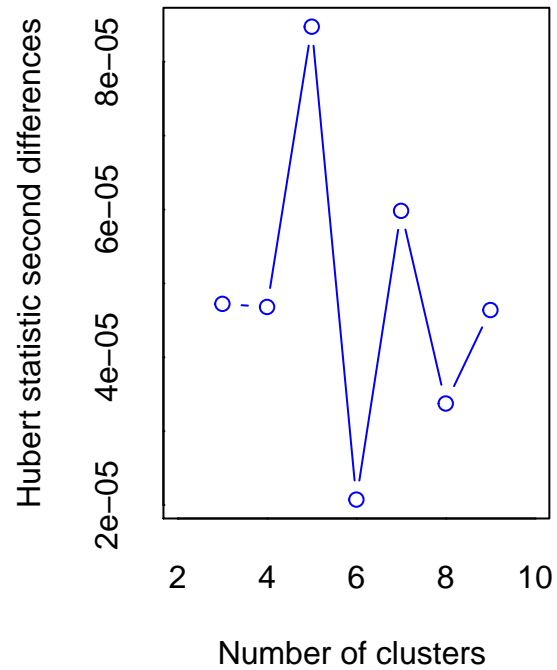
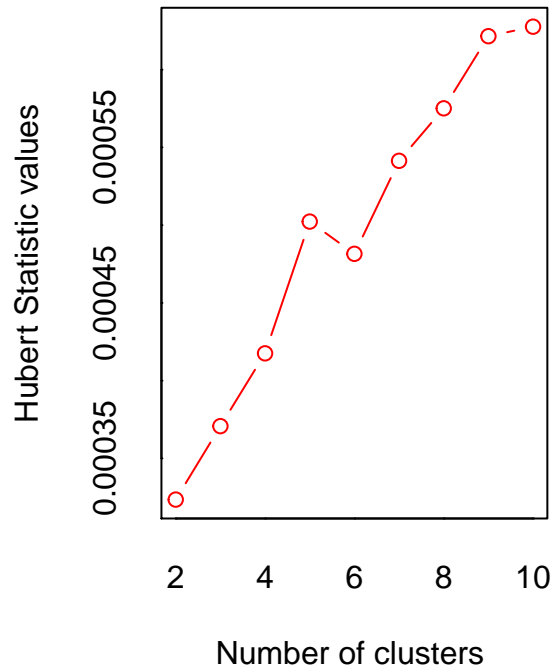
```
## *** : The Hubert index is a graphical method of determining the number of clusters.
## In the plot of Hubert index, we seek a significant knee that corresponds to a
## significant increase of the value of the measure i.e the significant peak in Hubert
## index second differences plot.
##
```



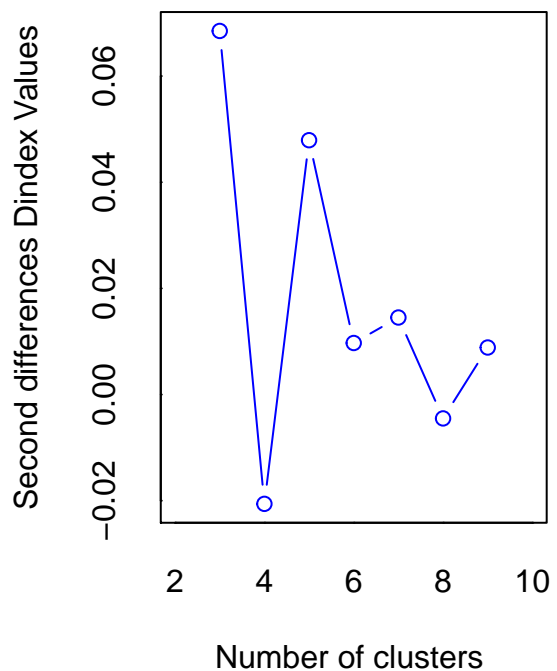
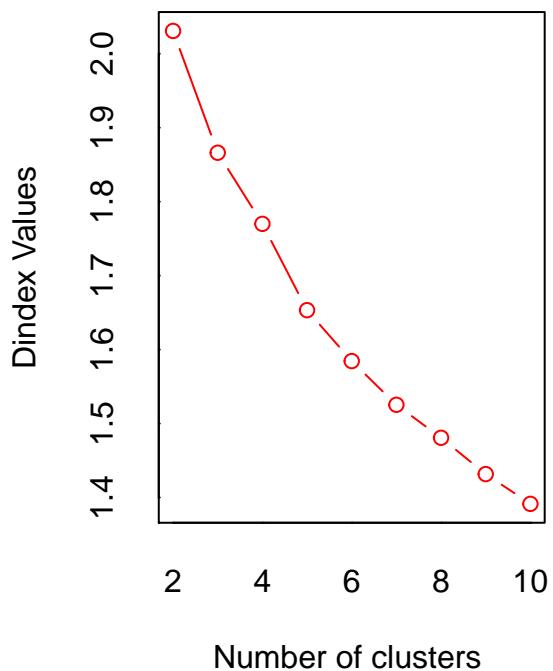
Number of clusters

Number of clusters

```
## *** : The D index is a graphical method of determining the number of clusters.
##           In the plot of D index, we seek a significant knee (the significant peak in Dindex
##           second differences plot) that corresponds to a significant increase of the value of
##           the measure.
##
## *****
## * Among all indices:
## * 9 proposed 2 as the best number of clusters
## * 1 proposed 3 as the best number of clusters
## * 7 proposed 4 as the best number of clusters
## * 1 proposed 5 as the best number of clusters
## * 1 proposed 9 as the best number of clusters
## * 5 proposed 10 as the best number of clusters
##
##           ***** Conclusion *****
##
## * According to the majority rule, the best number of clusters is 2
##
## *****
## Using the Euclidean Distance and Kmeans Method
## set.seed(13)
## clusterNo = NbClust(scaled.ia.dist.data,distance="euclidean",
## min.nc=2,max.nc=10,method="kmeans",index="all")
```



```
## *** : The Hubert index is a graphical method of determining the number of clusters.
##       In the plot of Hubert index, we seek a significant knee that corresponds to a
##       significant increase of the value of the measure i.e the significant peak in Hubert
##       index second differences plot.
##
```



```
## *** : The D index is a graphical method of determining the number of clusters.
##       In the plot of D index, we seek a significant knee (the significant peak in Dindex
##       second differences plot) that corresponds to a significant increase of the value of
##       the measure.
##
```

```
## *****
## * Among all indices:
## * 6 proposed 2 as the best number of clusters
## * 6 proposed 3 as the best number of clusters
## * 4 proposed 5 as the best number of clusters
## * 1 proposed 6 as the best number of clusters
## * 1 proposed 8 as the best number of clusters
## * 1 proposed 9 as the best number of clusters
## * 4 proposed 10 as the best number of clusters
##
```

```
##          ***** Conclusion *****
```

```
## * According to the majority rule, the best number of clusters is 2
```

```
## *****
```

```
#Using the Euclidean Distance and Centroid Method
```

```
#set.seed(78)
```

```
#clusterNo = NbClust(scaled.ia.dist.data,distance="euclidean",
```

```
#min.nc=2,max.nc=10,method="centroid",index="all")
```

```
#Let's look at the distance differences in the hospitals only
```

```
#scaled.hosp.dist.data <- scale(ia.dist.data.nested[,-7]) # Scaling the data by removing the city name
```

```
# View the first 3 rows of the data
```

```
#head(scaled.ia.dist.data, n = 3)
```

```
# Compute k-means with k = 4
```

```
set.seed(123)
```

```
km.res <- kmeans(scaled.ia.dist.data, 2, nstart = 25)
```

```
print(km.res)
```

```
## K-means clustering with 2 clusters of sizes 484, 525
```

```
##
```

```
## Cluster means:
```

```
## hosp.dist.mi fire.dist.mi dist.public.Elementary dist.public.Middle
```

```
## 1 -0.2809237 -0.1132019 -0.7223146 -0.7809283
```

```
## 2 0.2589849 0.1043614 0.6659052 0.7199415
```

```
## dist.public.High postoff.dist.mi
```

```
## 1 -0.5786003 0.04602256
```

```
## 2 0.5334144 -0.04242841
```

```
##
```

```
## Clustering vector:
```

```
## Ackley Ackworth Adair
```

```
## 1 1 2
```

```
## Adel Afton Agency
```

```
## 1 1 1
```

```
## Ainsworth Akron Albert City
```

```
## 2 1 2
```

```
## Albia Albion Alburnett
```

```
## 2 1 1
```

```
## Alden Alexander Algona
```

```
## 1 1 2
```

```
## Alleman Allerton Allison
```

##	1	2	2
##	Alta	Alta Vista	Alton
##	1	2	1
##	Altoona	Alvord	Amana
##	1	1	1
##	Ames	Anamosa	Anderson
##	1	1	2
##	Andover	Andrew	Anita
##	2	2	2
##	Ankeny	Anthon	Aplington
##	1	2	1
##	Arcadia	Archer	Aredale
##	1	1	2
##	Arion	Arispe	Arlington
##	2	2	2
##	Armstrong	Arnolds Park	Arthur
##	2	2	2
##	Asbury	Ashton	Aspinwall
##	1	1	1
##	Atalissa	Athelstan	Atkins
##	1	2	1
##	Atlantic	Auburn	Audubon
##	2	1	2
##	Aurelia	Aurora	Avoca
##	1	1	2
##	Ayrshire	Badger	Bagley
##	2	1	2
##	Baldwin	Balltown	Bancroft
##	2	1	2
##	Bankston	Barnes City	Barnum
##	1	2	1
##	Bartlett	Bassett	Batavia
##	2	2	2
##	Battle Creek	Baxter	Bayard
##	1	1	2
##	Beacon	Beaconsfield	Beaman
##	2	2	1
##	Beaver	Beaverdale	Bedford
##	2	1	2
##	Belle Plaine	Bellevue	Belmond
##	1	2	1
##	Bennett	Bentley	Benton
##	2	1	2
##	Berkley	Bernard	Bertram
##	2	1	1
##	Bettendorf	Bevington	Birmingham
##	1	1	2
##	Blairsburg	Blairstown	Blakesburg
##	2	1	2
##	Blanchard	Blencoe	Blockton
##	2	2	2
##	Bloomfield	Blue Grass	Bode
##	1	1	2
##	Bolan	Bonaparte	Bondurant

##	1	2	1
##	Boone	Bouton	Boxholm
##	1	1	2
##	Boyden	Braddyville	Bradford
##	1	2	1
##	Bradgate	Brandon	Brayton
##	2	1	2
##	Breda	Bridgewater	Brighton
##	1	2	2
##	Bristow	Britt	Bronson
##	2	2	1
##	Brooklyn	Brunsville	Buck Grove
##	2	1	2
##	Buckeye	Buffalo	Buffalo Center
##	2	1	2
##	Burchinal	Burlington	Burr Oak
##	1	1	2
##	Burt	Bussey	Calamus
##	2	2	1
##	California Junction	Callender	Calmar
##	1	1	1
##	Calumet	Camanche	Cambridge
##	1	1	1
##	Cantril	Carbon	Carlisle
##	2	2	1
##	Carpenter	Carroll	Carson
##	1	1	2
##	Carter Lake	Cascade	Casey
##	1	1	2
##	Castalia	Castana	Cedar Falls
##	1	2	1
##	Cedar Rapids	Center Junction	Center Point
##	1	1	1
##	Centerville	Central City	Centralia
##	2	1	1
##	Chapin	Chariton	Charles City
##	1	1	2
##	Charlotte	Charter Oak	Chatsworth
##	2	2	1
##	Chelsea	Cherokee	Chester
##	2	1	2
##	Chillicothe	Churdan	Cincinnati
##	2	2	2
##	Clare	Clarence	Clarinda
##	1	2	1
##	Clarion	Clarksville	Clayton
##	1	1	2
##	Clear Lake	Clearfield	Cleghorn
##	1	2	1
##	Clemons	Clermont	Climbing Hill
##	2	1	2
##	Clinton	Clio	Clive
##	1	2	1
##	Clutier	Coalville	Coburg

##	1	1	2
##	Coggon	Coin	Colesburg
##	2	1	1
##	Colfax	College Springs	Collins
##	1	1	1
##	Colo	Columbus City	Columbus Junction
##	1	2	2
##	Colwell	Conesville	Conrad
##	2	2	1
##	Conroy	Conway	Coon Rapids
##	1	2	1
##	Coppock	Coralville	Corley
##	2	1	2
##	Corning	Correctionville	Corwith
##	2	2	2
##	Corydon	Cotter	Coulter
##	2	2	1
##	Council Bluffs	Craig	Crawfordsville
##	1	1	2
##	Crescent	Cresco	Creston
##	1	2	1
##	Cromwell	Crystal Lake	Cumberland
##	1	2	2
##	Cumming	Curlew	Cushing
##	1	2	2
##	Cylinder	Dakota City	Dallas Center
##	2	1	1
##	Dana	Danbury	Danville
##	2	2	1
##	Davenport	Davis City	Dawson
##	1	2	2
##	Dayton	De Soto	Decatur City
##	2	1	2
##	Decorah	Dedham	Deep River
##	1	1	2
##	Defiance	Delaware	Delhi
##	2	1	1
##	Delmar	Deloit	Delphos
##	2	2	2
##	Delta	Denison	Denmark
##	2	2	1
##	Denver	Derby	Des Moines
##	1	2	1
##	DeWitt	Dexter	Diagonal
##	1	2	2
##	Diamondhead Lake	Dickens	Dike
##	2	2	1
##	Dixon	Dolliver	Donahue
##	1	2	1
##	Donnellson	Doon	Douds
##	2	1	2
##	Dougherty	Dow City	Dows
##	1	2	1
##	Drakesville	Dubuque	Dumont

##	1	1	2
##	Duncan	Duncombe	Dundee
##	2	1	1
##	Dunkerton	Dunlap	Durango
##	1	2	1
##	Durant	Dyersville	Dysart
##	1	1	1
##	Eagle Grove	Earlham	Earling
##	2	2	2
##	Earlville	Early	East Amana
##	1	2	1
##	East Peru	Eddyville	Edgewood
##	2	2	1
##	Elberon	Eldon	Eldora
##	1	2	1
##	Eldridge	Elgin	Elk Horn
##	1	1	2
##	Elk Run Heights	Elkader	Elkhart
##	1	2	1
##	Elkport	Elliott	Ellston
##	1	2	2
##	Ellsworth	Elma	Ely
##	2	2	1
##	Emerson	Emmetsburg	Epworth
##	2	2	1
##	Essex	Estherville	Evansdale
##	1	2	1
##	Everly	Exira	Exline
##	2	2	2
##	Fairbank	Fairfax	Fairfield
##	1	1	1
##	Farley	Farmersburg	Farmington
##	1	2	2
##	Farnhamville	Farragut	Fayette
##	2	2	2
##	Fenton	Ferguson	Fertile
##	2	1	1
##	Floris	Floyd	Fonda
##	1	2	2
##	Fontanelle	Forest City	Fort Atkinson
##	2	2	1
##	Fort Dodge	Fort Madison	Fostoria
##	1	1	2
##	Franklin	Fraser	Fredericksburg
##	2	2	2
##	Frederika	Fredonia	Fremont
##	2	2	2
##	Fruitland	Frytown	Galt
##	1	1	1
##	Galva	Garber	Garden City
##	1	1	2
##	Garden Grove	Garnavillo	Garner
##	2	2	2
##	Garrison	Garwin	Geneva

##	1	1	1
##	George	Gibson	Gilbert
##	1	2	1
##	Gilbertville	Gillett Grove	Gilman
##	1	2	1
##	Gilmore City	Gladbrook	Glenwood
##	2	1	1
##	Glidden	Goldfield	Goodell
##	1	2	1
##	Goose Lake	Gowrie	Graettinger
##	2	2	2
##	Graf	Grafton	Grand Junction
##	1	1	2
##	Grand Mound	Grand River	Grandview
##	1	2	2
##	Granger	Grant	Granville
##	1	2	1
##	Gravity	Gray	Greeley
##	2	1	1
##	Green Mountain	Greene	Greenfield
##	1	2	2
##	Greenville	Grimes	Grinnell
##	2	1	1
##	Griswold	Grundy Center	Gruver
##	2	1	2
##	Guernsey	Guthrie Center	Guttenberg
##	2	2	1
##	Halbur	Hamburg	Hamilton
##	1	2	2
##	Hampton	Hancock	Hanlontown
##	1	2	1
##	Hansell	Harcourt	Hardy
##	1	2	2
##	Harlan	Harper	Harpers Ferry
##	2	2	2
##	Harris	Hartford	Hartley
##	2	1	1
##	Hartwick	Harvey	Hastings
##	2	2	2
##	Havelock	Haverhill	Hawarden
##	2	1	1
##	Hawkeye	Hayesville	Hayfield
##	2	2	2
##	Hazleton	Hedrick	Henderson
##	1	2	2
##	Hepburn	Hiawatha	High Amana
##	1	1	1
##	Hills	Hillsboro	Hinton
##	1	2	1
##	Holiday Lake	Holland	Holstein
##	2	1	2
##	Holy Cross	Homestead	Hopkinton
##	1	1	1
##	Hornick	Hospers	Houghton

##	2	1	2
##	Hubbard	Hudson	Hull
##	2	1	1
##	Humboldt	Humeston	Hutchins
##	1	2	2
##	Huxley	Ida Grove	Imogene
##	1	1	2
##	Independence	Indianola	Inwood
##	1	1	1
##	Ionia	Iowa City	Iowa Falls
##	2	1	1
##	Ireton	Irvington	Irwin
##	1	2	2
##	Jackson Junction	Jacksonville	Jamaica
##	2	2	2
##	Janesville	Jefferson	Jesup
##	1	2	1
##	Jewell Junction	Johnston	Joice
##	2	1	1
##	Jolley	Kalona	Kamrar
##	2	1	2
##	Kanawha	Kellerton	Kelley
##	2	2	1
##	Kellogg	Kensett	Kent
##	1	1	1
##	Keokuk	Keomah Village	Keosauqua
##	2	2	2
##	Keota	Keswick	Keystone
##	2	2	1
##	Kimballton	Kingsley	Kinross
##	2	1	2
##	Kirkman	Kirkville	Kiron
##	2	2	2
##	Klemme	Knierim	Knoxville
##	2	2	2
##	La Motte	La Porte City	Lacona
##	1	1	1
##	Ladora	Lake City	Lake Mills
##	2	1	2
##	Lake Panorama	Lake Park	Lake View
##	2	2	1
##	Lakeside	Lakota	Lambs Grove
##	1	2	1
##	Lamoni	Lamont	Lanesboro
##	2	2	1
##	Lansing	Larchwood	Larrabee
##	2	1	1
##	Latimer	Laurel	Laurens
##	1	1	2
##	Lawler	Lawton	Le Claire
##	2	1	1
##	Le Grand	Le Mars	Le Roy
##	1	1	2
##	Leando	Ledyard	Lehigh

##	2	2	1
##	Leighton	Leland	Lenox
##	2	2	2
##	Leon	Lester	Letts
##	2	1	2
##	Lewis	Libertyville	Lidderdale
##	2	1	1
##	Lime Springs	Lincoln	Linden
##	2	1	2
##	Lineville	Linn Grove	Lisbon
##	2	2	1
##	Liscomb	Little Cedar	Little Rock
##	1	2	2
##	Little Sioux	Livermore	Lockridge
##	2	2	2
##	Logan	Lohrville	Lone Rock
##	2	2	2
##	Lone Tree	Long Grove	Lorimor
##	1	1	2
##	Lost Nation	Loveland	Lovilia
##	2	1	2
##	Low Moor	Lowden	Lu Verne
##	1	2	2
##	Luana	Lucas	Luther
##	2	1	1
##	Luxemburg	Luzerne	Lynnville
##	1	1	1
##	Lytton	Macedonia	Macksburg
##	2	2	2
##	Madrid	Magnolia	Maharishi Vedic City
##	1	2	1
##	Malcom	Mallard	Maloy
##	1	2	2
##	Malvern	Manchester	Manilla
##	2	1	2
##	Manly	Manning	Manson
##	1	1	2
##	Mapleton	Maquoketa	Marathon
##	2	2	2
##	Marble Rock	Marcus	Marengo
##	2	1	1
##	Marion	Marne	Marquette
##	1	2	2
##	Marshalltown	Martelle	Martensdale
##	1	1	1
##	Martinsburg	Marysville	Mason City
##	2	2	1
##	Masonville	Massena	Matlock
##	2	2	1
##	Maurice	Maxwell	Maynard
##	1	1	1
##	Maysville	McCallsburg	McCausland
##	1	2	1
##	McClelland	McGregor	McIntire

##	1	2	2
##	Mechanicsville	Mediapolis	Melbourne
##	2	2	2
##	Melcher-Dallas	Melrose	Melvin
##	1	2	1
##	Menlo	Meriden	Merrill
##	2	1	1
##	Meservey	Meyer	Middle Amana
##	1	2	1
##	Middletown	Miles	Milford
##	1	2	2
##	Miller	Millersburg	Millerton
##	2	2	2
##	Milo	Milton	Minburn
##	1	2	1
##	Minden	Mineola	Mingo
##	1	1	1
##	Missouri Valley	Mitchell	Mitchellville
##	1	1	1
##	Modale	Mona	Mondamin
##	2	2	2
##	Monmouth	Monona	Monroe
##	2	2	1
##	Montezuma	Monticello	Montour
##	2	1	1
##	Montrose	Moorhead	Moorland
##	2	2	1
##	Moravia	Morley	Morning Sun
##	2	2	2
##	Morrison	Moulton	Mount Auburn
##	1	2	1
##	Mount Ayr	Mount Pleasant	Mount Sterling
##	2	2	2
##	Mount Union	Mount Vernon	Moville
##	2	1	1
##	Murray	Muscatine	Mystic
##	2	1	2
##	Nashua	Nemaha	Neola
##	2	2	1
##	Nevada	New Albin	New Hampton
##	1	2	2
##	New Hartford	New Haven	New Liberty
##	1	2	1
##	New London	New Market	New Providence
##	2	1	2
##	New Sharon	New Vienna	New Virginia
##	2	1	1
##	Newell	Newhall	Newton
##	1	1	1
##	Nichols	Nodaway	Nora Springs
##	2	2	1
##	North Buena Vista	North English	North Liberty
##	1	2	1
##	North Washington	Northboro	Northwood

##	2	2	1
##	Norwalk	Norway	Numa
##	1	1	2
##	Oakland	Oakland Acres	Oakville
##	2	1	2
##	Ocheyedan	Odebolt	Oelwein
##	2	2	1
##	Ogden	Okoboji	Olds
##	2	2	2
##	Olin	Ollie	Onawa
##	2	2	2
##	Onslow	Orange City	Orchard
##	1	1	2
##	Orient	Orleans	Osage
##	1	2	1
##	Osceola	Oskaloosa	Ossian
##	2	2	1
##	Osterdock	Otho	Oto
##	1	1	2
##	Otranto	Ottosen	Ottumwa
##	1	2	1
##	Owasa	Oxford	Oxford Junction
##	1	1	2
##	Oyens	Pacific Junction	Packwood
##	1	1	2
##	Palmer	Palo	Panama
##	1	1	2
##	Panora	Panorama Park	Park View
##	2	1	1
##	Parkersburg	Parnell	Paton
##	1	2	2
##	Patterson	Paullina	Pella
##	1	1	2
##	Peosta	Percival	Perry
##	1	2	1
##	Persia	Peterson	Pierson
##	1	2	2
##	Pilot Mound	Pioneer	Pisgah
##	2	2	2
##	Plainfield	Plano	Pleasant Hill
##	1	2	1
##	Pleasant Plain	Pleasanton	Pleasantville
##	2	2	1
##	Plover	Plymouth	Pocahontas
##	2	1	1
##	Polk City	Pomeroy	Popejoy
##	1	2	1
##	Portland	Portsmouth	Postville
##	1	2	1
##	Prairie City	Prairieburg	Prescott
##	1	1	2
##	Preston	Primghar	Princeton
##	2	1	1
##	Promise City	Protivin	Pulaski

##	2	2	2
##	Quasqueton	Quimby	Radcliffe
##	1	1	2
##	Rake	Ralston	Randalia
##	2	1	2
##	Randall	Randolph	Rathbun
##	2	2	2
##	Raymond	Readlyn	Reasnor
##	1	1	1
##	Red Oak	Redding	Redfield
##	2	2	2
##	Reinbeck	Rembrandt	Remsen
##	1	2	1
##	Renwick	Rhodes	Riceville
##	2	2	2
##	Richland	Rickardsville	Ricketts
##	2	1	2
##	Ridgeway	Rinard	Ringsted
##	2	2	2
##	Rippey	River Sioux	Riverdale
##	2	2	1
##	Riverside	Riverton	Robins
##	1	2	1
##	Rochester	Rock Falls	Rock Rapids
##	2	1	1
##	Rock Valley	Rockford	Rockwell
##	1	1	1
##	Rockwell City	Rodman	Rodney
##	2	2	2
##	Roland	Rolfe	Rome
##	2	2	2
##	Rose Hill	Roseville	Rossie
##	2	2	2
##	Rowan	Rowley	Royal
##	1	1	2
##	Rudd	Runnells	Russell
##	1	1	2
##	Ruthven	Rutland	Ryan
##	2	2	2
##	Sabula	Sac City	Sageville
##	2	2	1
##	Salem	Salix	Sanborn
##	2	1	1
##	Sandyville	Saylorville	Scarville
##	1	1	2
##	Schaller	Schleswig	Scranton
##	2	2	1
##	Searsboro	Sergeant Bluff	Sexton
##	1	1	2
##	Seymour	Shambaugh	Shannon City
##	2	1	2
##	Sharpsburg	Sheffield	Shelby
##	2	1	2
##	Sheldahl	Sheldon	Shell Rock

##	1	1	1
##	Shellsburg	Shenandoah	Sherrill
##	1	2	1
##	Shueyville	Sibley	Sidney
##	1	1	2
##	Sigourney	Silver City	Sioux Center
##	2	1	1
##	Sioux City	Sioux Rapids	Slater
##	1	2	1
##	Sloan	Smithland	Soldier
##	1	2	2
##	Solon	Somers	South Amana
##	1	2	1
##	South English	Spencer	Spillville
##	2	2	1
##	Spirit Lake	Spragueville	Spring Hill
##	2	2	1
##	Springbrook	Springville	St. Ansgar
##	2	1	1
##	St. Anthony	St. Benedict	St. Charles
##	2	2	1
##	St. Donatus	St. Joseph	St. Lucas
##	1	2	1
##	St. Marys	St. Olaf	St. Paul
##	1	2	2
##	Stacyville	Stanhope	Stanley
##	2	2	1
##	Stanton	Stanwood	State Center
##	2	2	2
##	Steamboat Rock	Stockport	Stockton
##	1	2	1
##	Stone City	Storm Lake	Story City
##	1	1	1
##	Stout	Stratford	Strawberry Point
##	1	2	2
##	Struble	Stuart	Sully
##	1	2	1
##	Sumner	Sun Valley Lake	Superior
##	1	2	2
##	Sutherland	Swaledale	Swan
##	1	1	1
##	Swea City	Swisher	Tabor
##	2	1	2
##	Tama	Templeton	Tennant
##	1	1	2
##	Terril	Thayer	Thompson
##	2	2	2
##	Thor	Thornburg	Thornton
##	2	2	1
##	Thurman	Tiffin	Tingley
##	2	1	2
##	Tipton	Titonka	Toeterville
##	2	2	2
##	Toledo	Toronto	Traer

##	1	2	1
##	Treynor	Tripoli	Truesdale
##	1	1	1
##	Truro	Turin	Twin Lakes
##	2	2	2
##	Udell	Underwood	Union
##	2	1	1
##	Unionville	University Heights	University Park
##	2	1	2
##	Urbana	Urbandale	Ute
##	1	1	2
##	Vail	Valeria	Van Horne
##	1	1	1
##	Van Meter	Van Wert	Varina
##	1	2	2
##	Ventura	Victor	Villisca
##	1	2	2
##	Vincent	Vining	Vinton
##	1	2	1
##	Volga	Wadena	Wahpeton
##	2	2	2
##	Walcott	Walford	Walker
##	1	1	2
##	Wall Lake	Wallingford	Walnut
##	1	2	2
##	Wapello	Washburn	Washington
##	2	1	2
##	Washta	Waterloo	Waterville
##	2	1	2
##	Watkins	Waucoma	Waukee
##	1	2	1
##	Waukon	Waverly	Wayland
##	2	1	2
##	Webb	Webster	Webster City
##	2	2	2
##	Weldon	Wellman	Wellsburg
##	2	1	1
##	Welton	Wesley	West Amana
##	2	2	1
##	West Bend	West Branch	West Burlington
##	2	1	1
##	West Chester	West Des Moines	West Liberty
##	2	1	1
##	West Okoboji	West Point	West Union
##	2	1	1
##	Westfield	Westgate	Weston
##	2	1	1
##	Westphalia	Westside	Westwood
##	2	1	2
##	What Cheer	Wheatland	Whiting
##	2	2	2
##	Whittemore	Whitten	Willey
##	2	1	1
##	Williams	Williamsburg	Williamson

```
##           2           2           1
##           Wilton      Windsor Heights      Winfield
##           1           1           2
##           Winterset      Winthrop      Wiota
##           1           1           2
##           Woden         Woodbine      Woodburn
##           2           2           2
##           Woodward      Woolstock      Worthington
##           1           2           1
##           Wyoming       Yale          Yetter
##           2           2           1
##           Yorktown      Zearing       Zwingle
##           1           2           1
##           Millville
##           1
##
## Within cluster sum of squares by cluster:
## [1] 1933.607 2663.077
## (between_SS / total_SS =  24.0 %)
##
## Available components:
##
## [1] "cluster"      "centers"      "totss"        "withinss"     "tot.withinss"
## [6] "betweenss"    "size"         "iter"         "ifault"
aggregate(ia.dist.data.nested[,-7], by=list(cluster=km.res$cluster), mean)

## cluster hosp.dist.mi fire.dist.mi dist.public.Elementary dist.public.Middle
## 1      1      7.966303      2.063298      9.189214      10.75561
## 2      2     10.589195      2.705587     22.221631     27.41758
## dist.public.High postoff.dist.mi
## 1      19.40729      2.051503
## 2      38.16582      1.811753

#Add the original data to the clustering
dd <- cbind(ia.dist.data.nested[,-7], cluster = km.res$cluster)
head(dd)

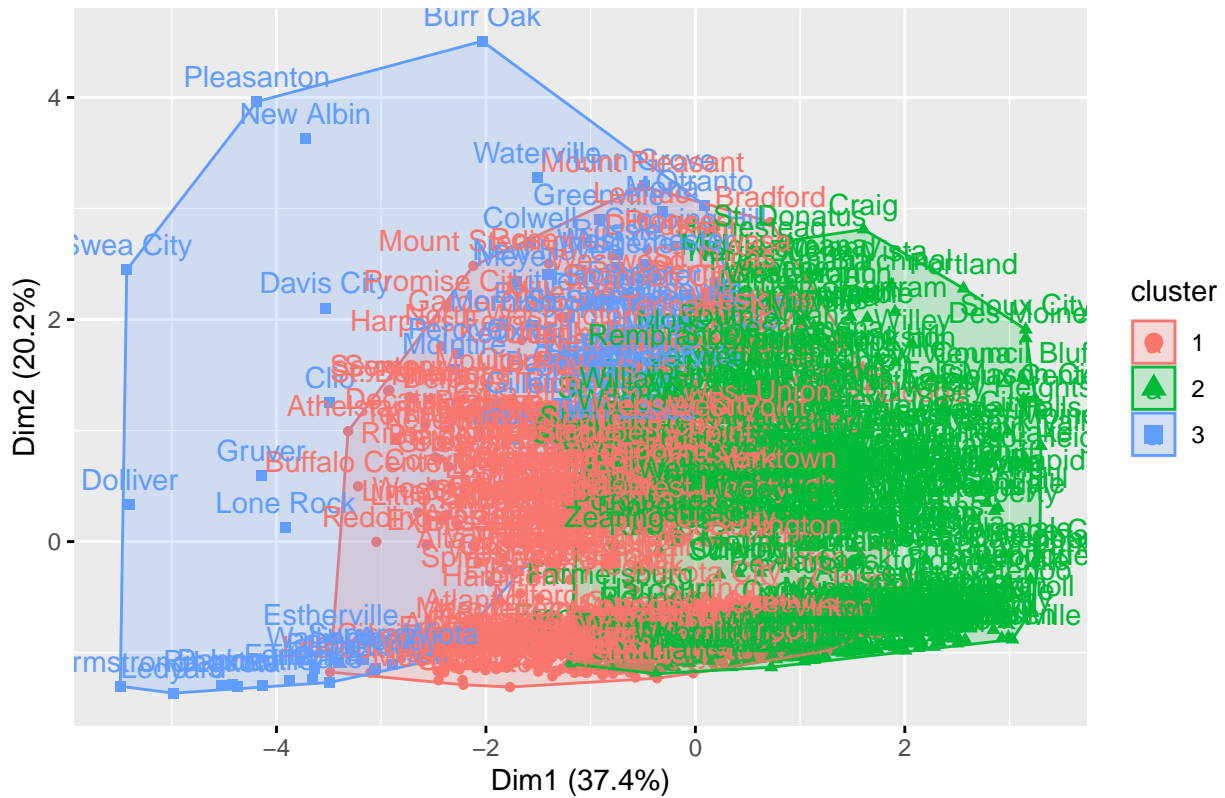
## hosp.dist.mi fire.dist.mi dist.public.Elementary dist.public.Middle
## Ackley      10.752386      0.20964318      9.364122      9.364122
## Ackworth    17.557559      4.50931622      5.485392      3.532412
## Adair       14.901110      0.08292593     33.958287     33.958287
## Adel        11.767396      0.17697943      9.757398     16.300612
## Afton       10.228697      0.10101117      8.988911      8.988911
## Agency      5.589762      0.10893199      5.027100     17.518109
## dist.public.High postoff.dist.mi cluster
## Ackley      36.67893      0.01265446      1
## Ackworth    14.15004      4.82660575      1
## Adair       40.28068      0.06610386      2
## Adel        16.10238      0.45052746      1
## Afton       45.89492      0.06887685      1
## Agency      46.24354      0.06961048      1

# Cluster number for each of the observations
head(km.res$cluster, 10)
```



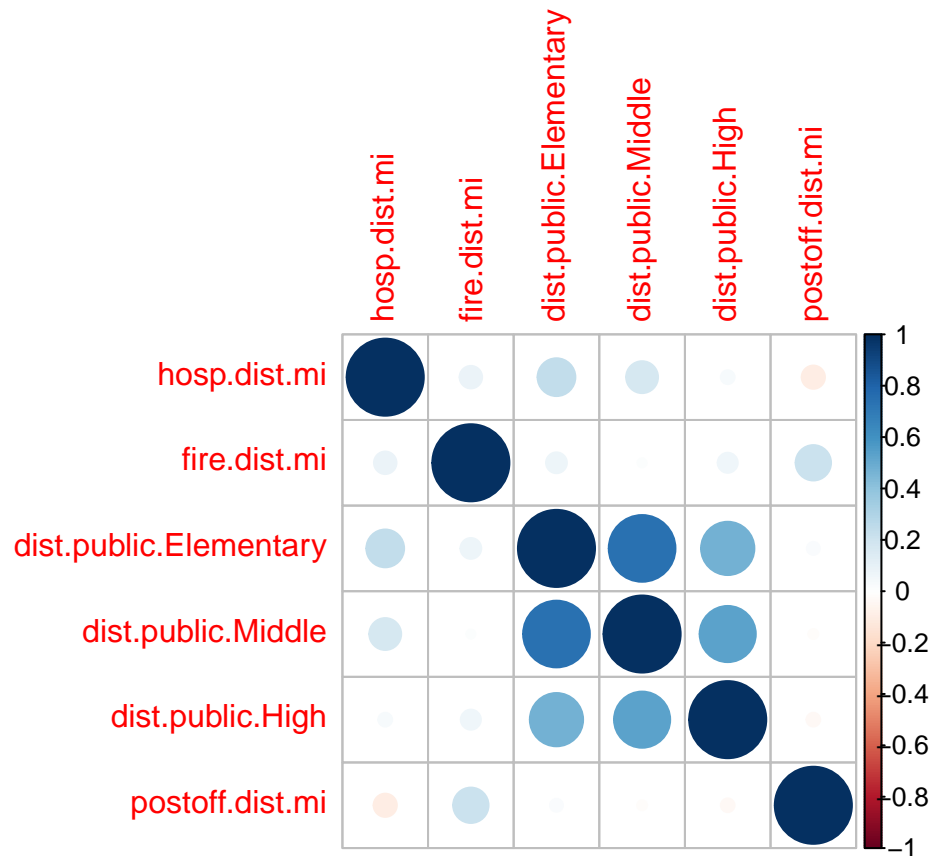
```
# Hierarchical clustering
# ++++++
# Use hcut() which compute hclust and cut the tree
hc.cut <- hcut(scaled.ia.dist.data, k = 3, hc_method = "complete")
# Visualize dendrogram
#fviz_dend(hc.cut, show_labels = FALSE, rect = TRUE)
# Visualize cluster
fviz_cluster(hc.cut, ellipse.type = "convex")
```

Cluster plot



Principal component analysis (PCA)

```
M <- cor(scaled.ia.dist.data)
corrplot(M, method = "circle")
```



```
allpca <- prcomp(scaled.ia.dist.data)
summary(allpca)
```

```
## Importance of components:
##              PC1    PC2    PC3    PC4    PC5    PC6
## Standard deviation  1.4987 1.1008 1.0094 0.8756 0.71719 0.49224
## Proportion of Variance 0.3743 0.2019 0.1698 0.1278 0.08573 0.04038
## Cumulative Proportion 0.3743 0.5763 0.7461 0.8739 0.95962 1.00000
```

```
# PAM clustering
# *****
require(cluster)
pam.res <- pam(scaled.ia.dist.data, 4)
# Visualize pam clustering
fviz_cluster(pam.res, geom = "point", ellipse.type = "norm")
```

