542_Final

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Fossil Fuels & Economic Development

Rationale of our two questions

How do fossil fuels relate to social and economic development in different countries? * Can we identify groups of countries with similar oil production and GDP and if/how oil production impacts a country's GDP? * Can we identify groups of countries with similar population and fossil fuel usage and if/how population size affects fossil fuel usage?

Data: * Population * GDP per Capita * Oil Production (92 countries) * Fossil fuel use (as % of total electricity generating capacity)

QUESTION 1 CLUSTERING CODE START

RESEARCH QUESTION: 'Can we identify groups of countries with similar oil production and GDP and if/how oil production impacts a country's GDP?'

Data used: * Oil Production: [from U.S. Energy Information Administration] For calendar year 2019, on a comparable best-estimate basis * GDP per Capita: [from Wikipedia] Converted at market exchange rates to current U.S. dollars, divided by the population for the same year

Prep to cluster OilProduction and GDP_pc Getting data from github and initializing :

```
## Warning: package 'dplyr' was built under R version 3.6.3

##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

Removing rows where OilProduction == 0 :

Clustering Part

Preparing to cluster oil production & GDP :

```
##           OilProduction GDP_pc
## Albania           22915   5372
## Algeria         1348361   3980
## Angola          1769615   3037
## Argentina        510560   9887
```

```
## Australia         289749  53825
## Austria            15161  50022
```

This is for replicability of results.

Partitioning Technique: PAM

1. Apply function and indicate the amount of clusters required

2. Clustering results

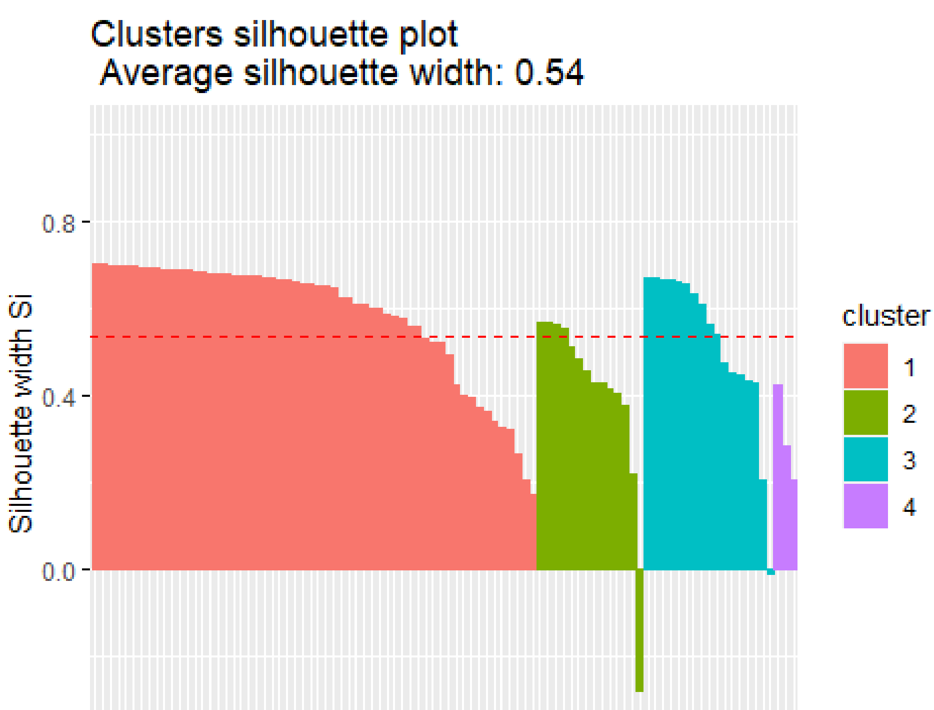
TABLE OF CLUSTERS：

```
## 
##  1  2  3  4 
## 58 14 17  3
```

3. Evaluate Results

AVG SILHOUETTES：

```
## Loading required package: ggplot2

## Warning: package 'ggplot2' was built under R version 3.6.3

## Welcome! Want to learn more? See two factoextra-related books at https://goo.gl/ve3WBa

##   cluster size ave.sil.width
## 1       1   58          0.58
## 2       2   14          0.41
## 3       3   17          0.52
## 4       4    3          0.30
```



DECTECTING ANOMALIES：

```
##                           cluster neighbor sil_width
## Vietnam                         1        3 0.7014283
## Congo, Republic of the          1        3 0.7006665
## Papua New Guinea                1        3 0.6977134
## Ghana                           1        3 0.6972409
## Timor-Leste                     1        3 0.6957549
## Tunisia                         1        3 0.6955229
```

Requesting negative silhouettes :

```
##          cluster neighbor    sil_width
## Italy          2        3 -0.277837863
## Romania        3        1 -0.008107932
```

Hierarchizing/Agglomerative Technique: AGNES

1. Apply function and indicate the amount of clusters required

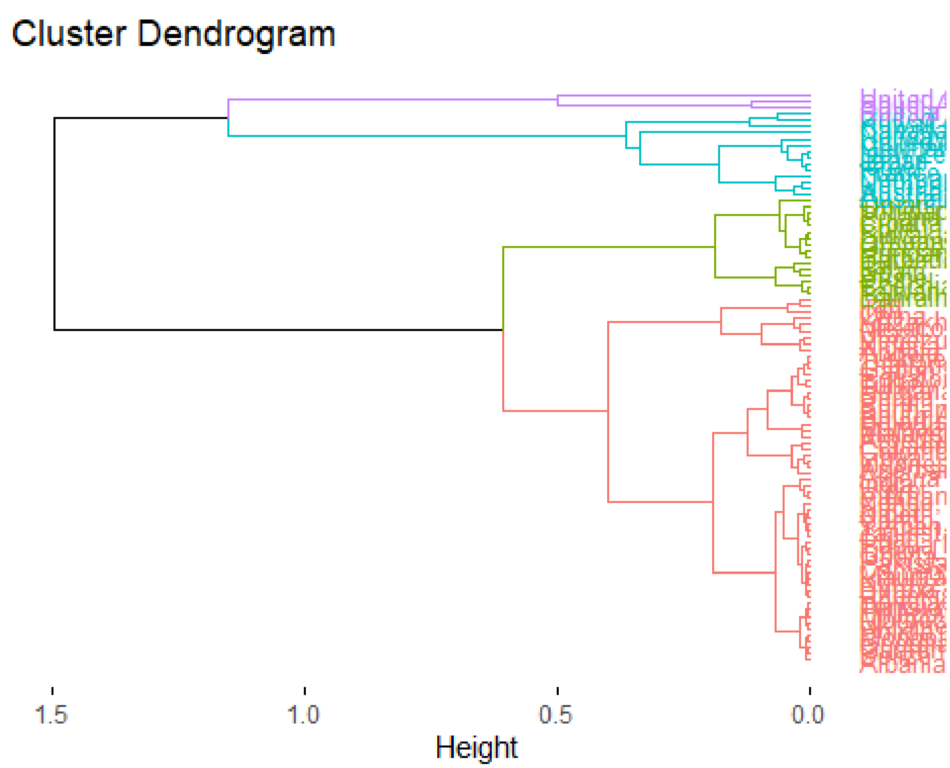
2. Clustering results

TABLE OF CLUSTERS:

```
## 
##  1  2  3  4 
## 59 14 16  3
```

3. Evaluate results

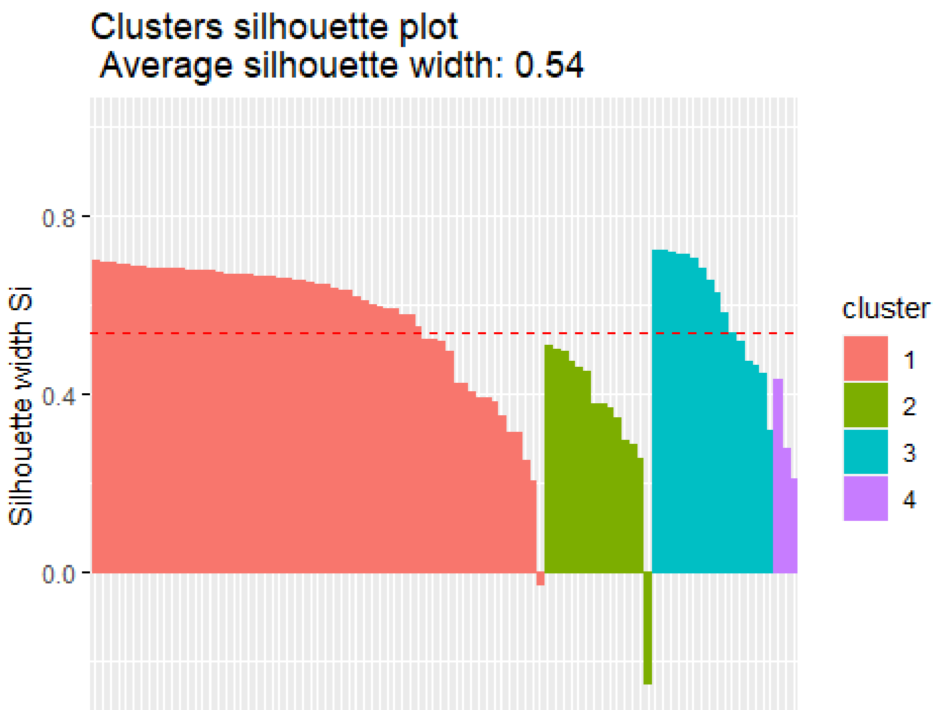
DENDOGRAM:



AVG SILHOUETTES:

```
##   cluster size ave.sil.width
## 1       1   59          0.57
## 2       2   14          0.35
```

```
## 3        3   16           0.60
## 4        4    3           0.30
```



DECTECTING ANOMALIES:

```
##                           cluster neighbor sil_width
## Vietnam                         1        3 0.6977023
## Congo, Republic of the          1        3 0.6970225
## Egypt                           1        3 0.6946234
## Ghana                           1        3 0.6884544
## Papua New Guinea                1        3 0.6880476
## Timor-Leste                     1        3 0.6860947
```

Requesting negative silhouettes:

```
##         cluster neighbor   sil_width
## Romania       1        3 -0.02769694
## Kuwait        2        3 -0.25164833
```

Hierarchizing/Divisive Technique: DIANA

1. Apply function and indicate the amount of clusters required

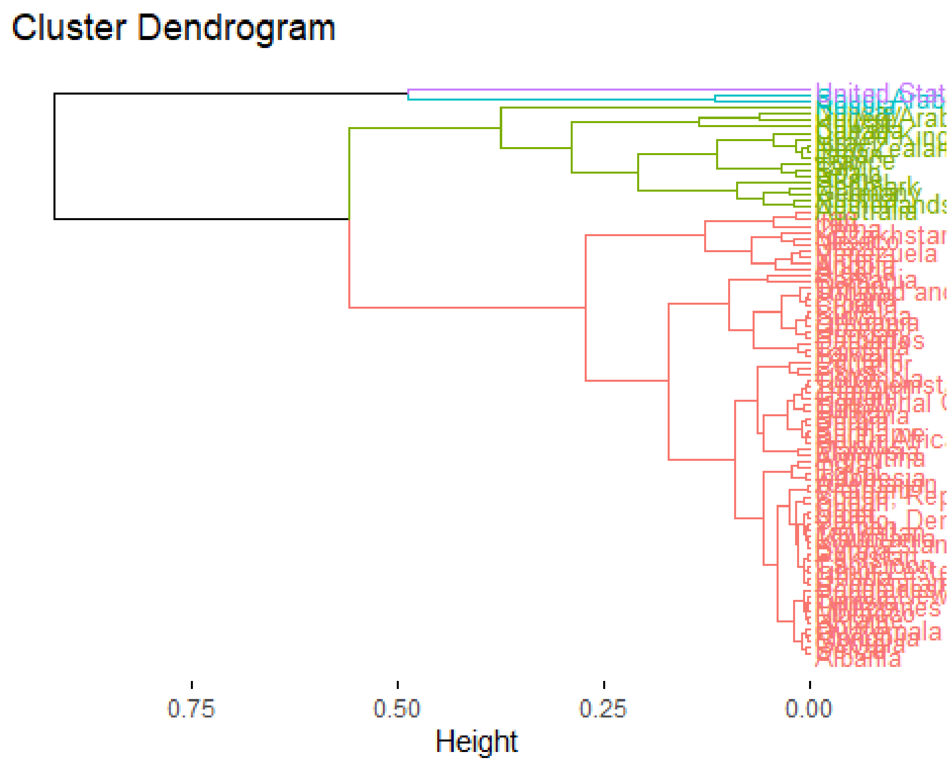
2. Clustering results

TABLE OF CLUSTERS:

```
## 
##  1  2  3  4 
## 72 17  2  1
```

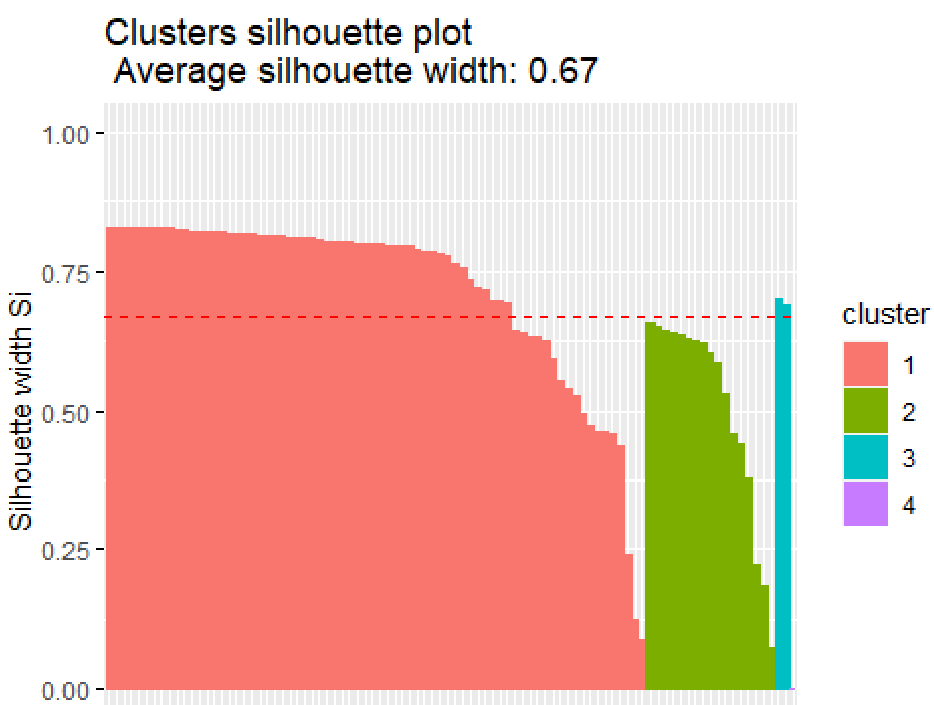
3. Evaluate results

DENDOGRAM:



AVG SILHOUETTES:

```
##   cluster size ave.sil.width
## 1       1   72          0.72
## 2       2   17          0.50
## 3       3    2          0.70
## 4       4    1          0.00
```



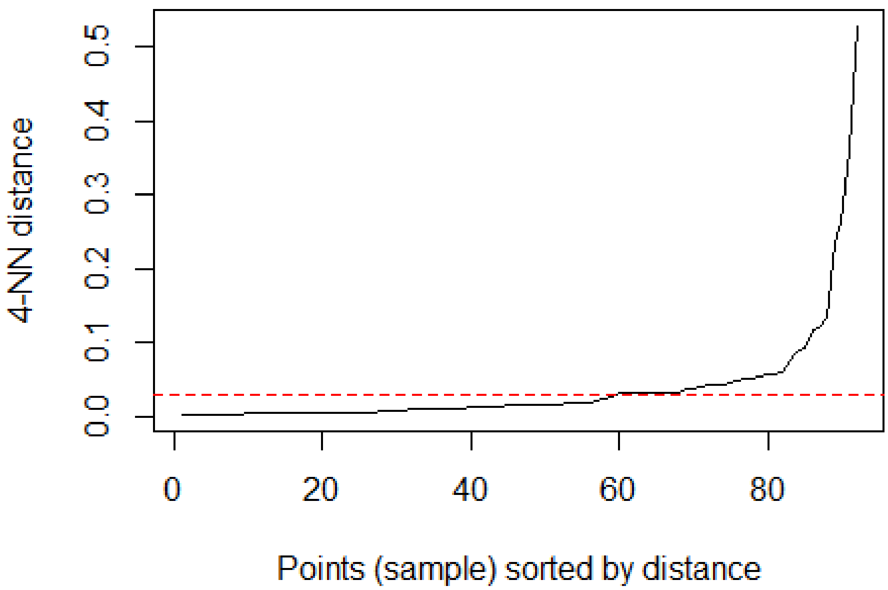
DECTECTING ANOMALIES:

```
##            cluster neighbor sil_width
## Mongolia        1        2 0.8295996
## Bolivia         1        2 0.8294036
## Ukraine         1        2 0.8291026
## Guatemala       1        2 0.8285038
## Tunisia         1        2 0.8284611
## Georgia         1        2 0.8284214
```

Requesting negative silhouettes:

```
## [1] cluster   neighbor  sil_width
## <0 rows> (or 0-length row.names)
```

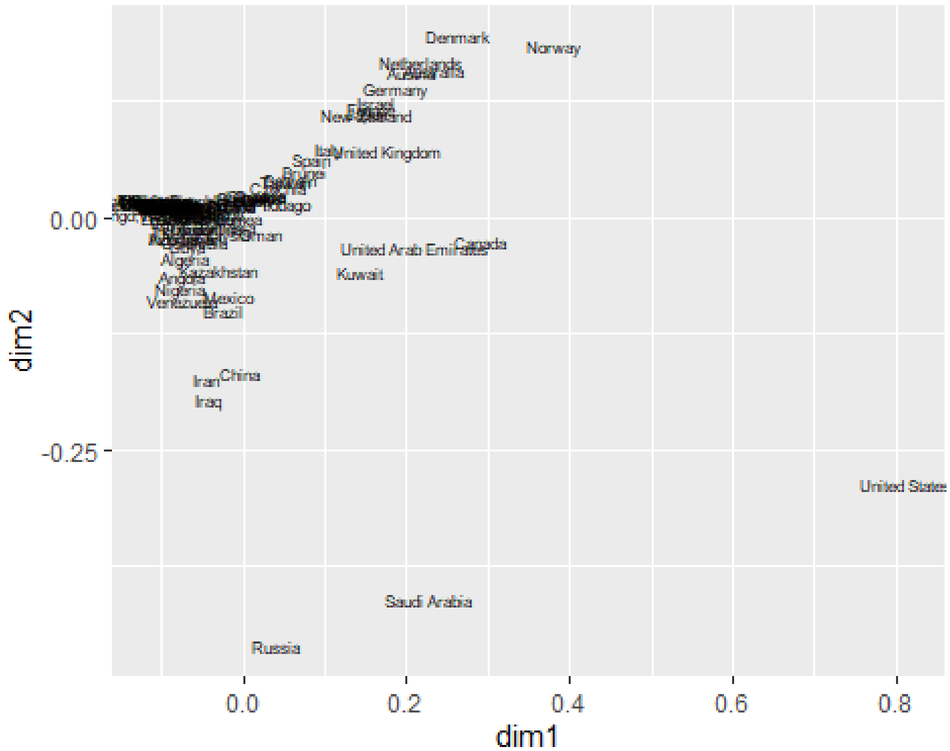
Density Based Clustering: DBSCAN



HOW MANY OUTLIERS? (0 identified outliers)

```
## DBSCAN clustering for 92 objects.
## Parameters: eps = 0.03, minPts = 4
## The clustering contains 3 cluster(s) and 20 noise points.
##
##  0  1  2  3
## 20 53 14  5
##
## Available fields: cluster, eps, minPts
```

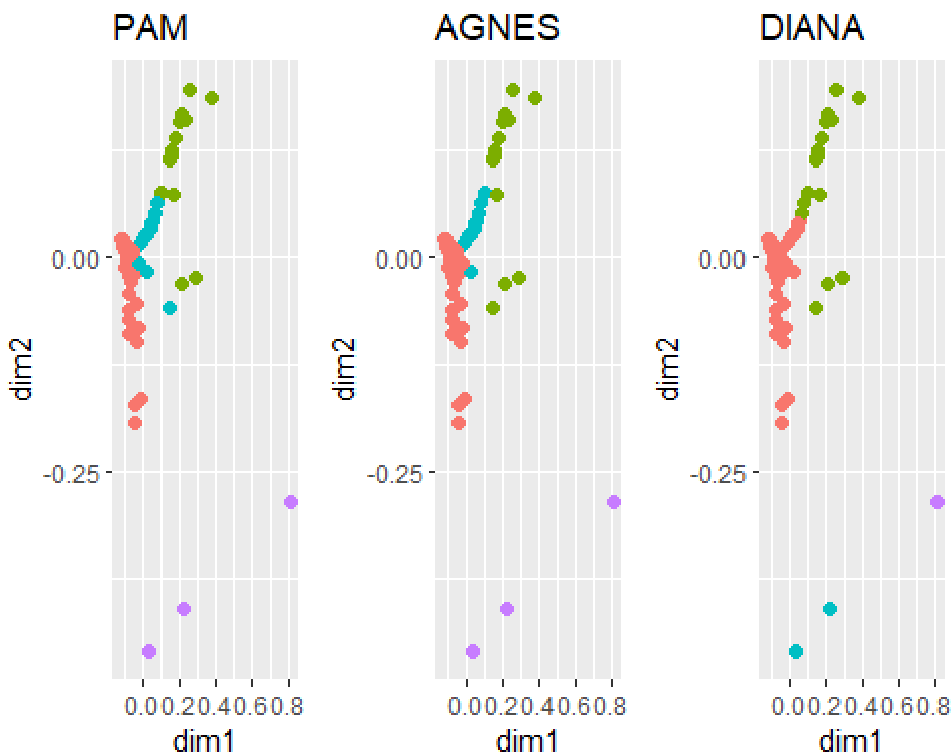
Save coordinates to original data frame:



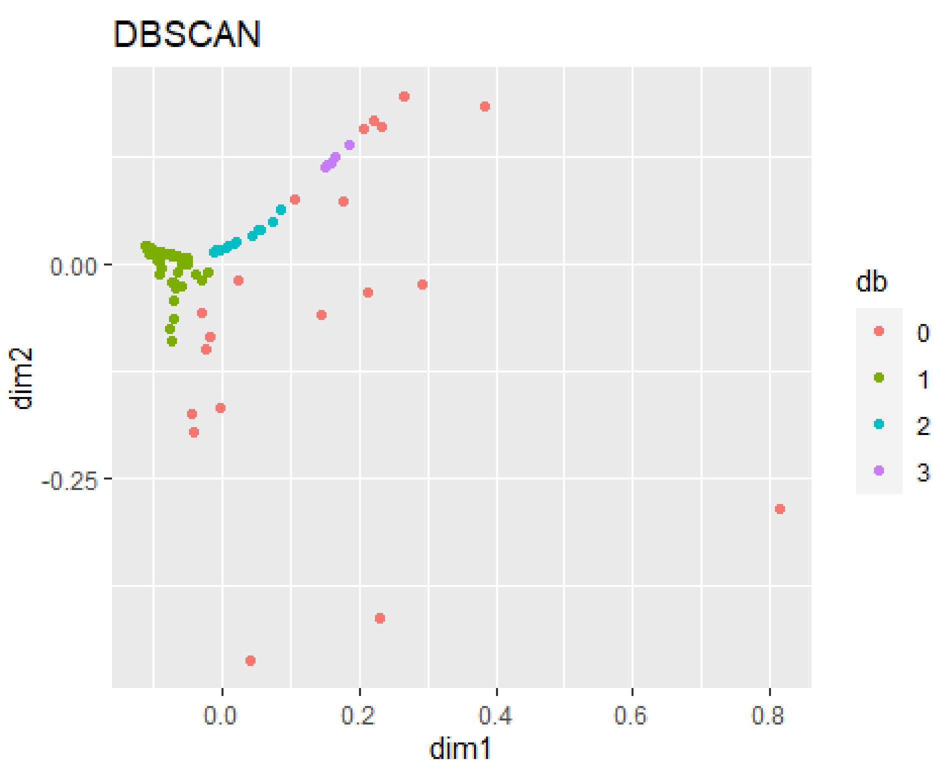
- Plot PAM :
- Plot AGNES :
- Plot DIANA :

Compare results visually :

```
## Warning: package 'ggpubr' was built under R version 3.6.3

## Loading required package: magrittr
```

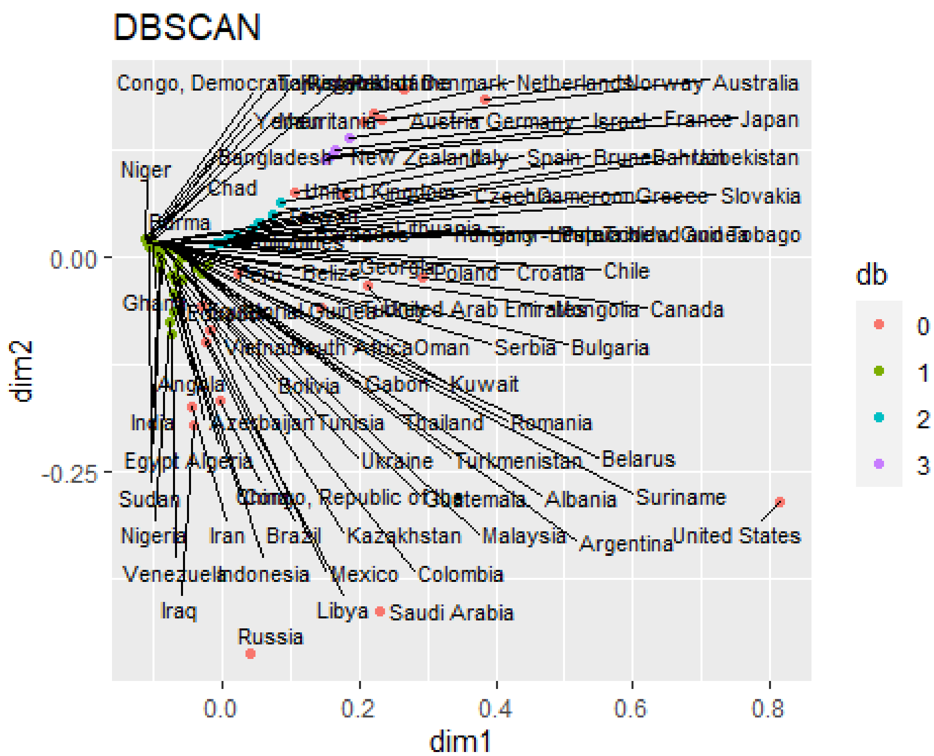


- Plot DBSCAN：

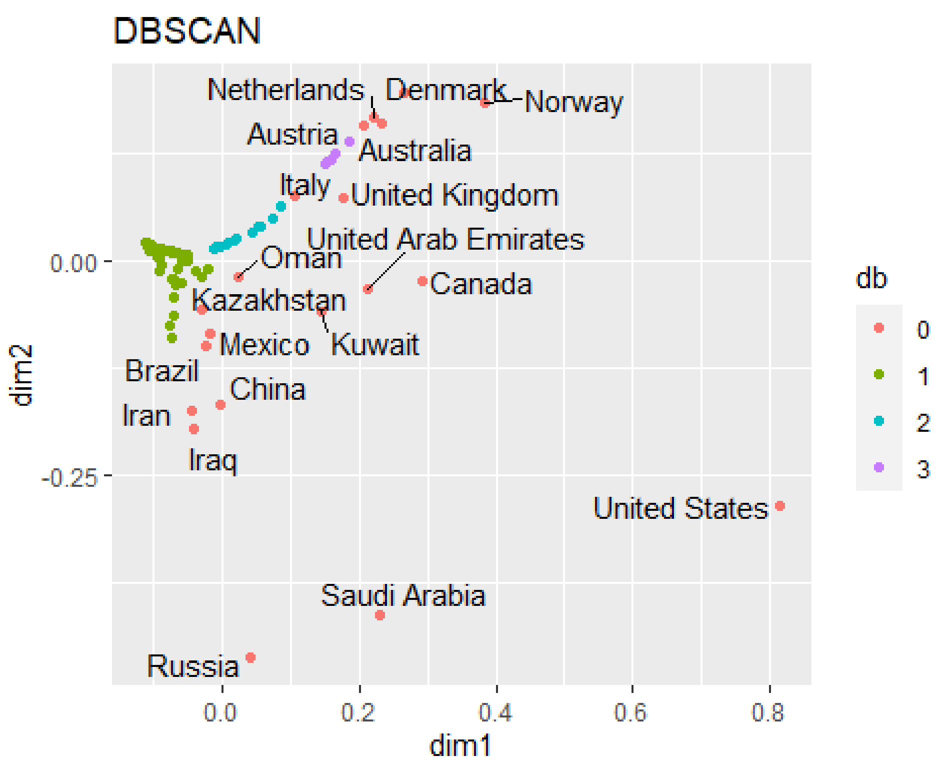


Annotating:

```
## Warning: package 'ggrepel' was built under R version 3.6.3
```



Annotating Outliers:



BASED ON CLUSTERING, WE WILL USE DBSCAN. This cluster had high production &/OR high GDP (outliers).

```
##  [1] "Australia"            "Austria"              "Brazil"
##  [4] "Canada"               "China"                "Denmark"
##  [7] "Iran"                 "Iraq"                 "Italy"
## [10] "Kazakhstan"           "Kuwait"               "Mexico"
```

```
## [13] "Netherlands"          "Norway"               "Oman"
## [16] "Russia"               "Saudi Arabia"         "United Arab Emirates"
## [19] "United Kingdom"       "United States"
```

This cluster had higher production & lower GDP.

```
##  [1] "Albania"                            "Algeria"
##  [3] "Angola"                             "Argentina"
##  [5] "Azerbaijan"                         "Bangladesh"
##  [7] "Belarus"                            "Belize"
##  [9] "Bolivia"                            "Bulgaria"
## [11] "Burma"                              "Cameroon"
## [13] "Chad"                               "Colombia"
## [15] "Congo, Democratic Republic of the" "Congo, Republic of the"
## [17] "Ecuador"                            "Egypt"
## [19] "Equatorial Guinea"                  "Gabon"
## [21] "Georgia"                            "Ghana"
## [23] "Guatemala"                          "India"
## [25] "Indonesia"                          "Kyrgyzstan"
## [27] "Libya"                              "Malaysia"
## [29] "Mauritania"                         "Mongolia"
## [31] "Morocco"                            "Niger"
## [33] "Nigeria"                            "Pakistan"
## [35] "Papua New Guinea"                   "Peru"
## [37] "Philippines"                        "Romania"
## [39] "Serbia"                             "South Africa"
## [41] "Sudan"                              "Suriname"
## [43] "Tajikistan"                         "Thailand"
## [45] "Timor-Leste"                        "Tunisia"
## [47] "Turkey"                             "Turkmenistan"
## [49] "Ukraine"                            "Uzbekistan"
## [51] "Venezuela"                          "Vietnam"
## [53] "Yemen"
```

This cluster had lower production & lower GDP.

```
##  [1] "Bahrain"             "Barbados"            "Brunei"
##  [4] "Chile"               "Croatia"             "Czechia"
##  [7] "Greece"              "Hungary"             "Lithuania"
## [10] "Poland"              "Slovakia"            "Spain"
## [13] "Taiwan"              "Trinidad and Tobago"
```

This cluster had lower production & higher GDP.

```
## [1] "France"      "Germany"     "Israel"      "Japan"       "New Zealand"
```

QUESTION 1 REGRESSION START

- Hypothesis:
  - Model 1: GDP Per Capita ~ Oil Production
  - Model 2: GDP Per Capita ~ Oil Production + Continent
- Continuous Outcome – – GDP Per Capita
- Independent variable – – Oil Production

- Control variable – – Continent
- Rationale for hypothesis
    - Oil infrastructure supports GDP
    - OPEC // many economies heavily rely on oil income
    - Oil price wars (like now with Saudi Arabia and Russia) impact oil prices and thus GDP

Preparing to regress Oil Production & GDP

```
## 'data.frame':    92 obs. of  12 variables:
##  $ Country                : chr  "Albania" "Algeria" "Angola" "Arge"..
##  $ fossilFuel_PctTotalElec: num  0.05 0.96 0.34 0.69 0.72 0.25 0.84 ..
##  $ OilProduction          : num  22915 1348361 1769615 510560 289749..
##  $ Population             : int  2880917 43053054 31825295 44780677 ..
##  $ GDP_pc                 : int  5372 3980 3037 9887 53825 50022 468..
##  $ Continent              : Factor w/ 7 levels "Africa","Asia",..: 3..
##  $ pam                    : Factor w/ 4 levels "1","2","3","4": 1 1 ..
##  $ agn                    : Factor w/ 4 levels "1","2","3","4": 1 1 ..
##  $ dia                    : Factor w/ 4 levels "1","2","3","4": 1 1 ..
##  $ db                     : Factor w/ 4 levels "0","1","2","3": 2 2 ..
##  $ dim1                   : num  -0.0795 -0.0701 -0.0722 -0.0399 0.2..
##  $ dim2                   : num  0.0111 -0.0435 -0.063 -0.0116 0.159..
```

EXPLANATORY APPROACH

1.State the hypotheses

```
hypo1=formula(GDP_pc ~ OilProduction)
hypo2=formula(GDP_pc ~ OilProduction + Continent)
```

2.Save colums needed and varify data types

```
## 'data.frame':    92 obs. of  3 variables:
##  $ OilProduction: num  22915 1348361 1769615 510560 289749 ...
##  $ GDP_pc       : int  5372 3980 3037 9887 53825 50022 4689 25273 1905 18069 ...
##  $ Continent    : Factor w/ 7 levels "Africa","Asia",..: 3 1 1 7 6 3 4 2 2 5 ...
```

3.Compute regression models

4.Hypothesis results

- First Hypothesis:

```
## 
## Call:
## glm(formula = hypo1, family = "gaussian", data = DataRegGauss)
## 
## Deviance Residuals: 
##    Min      1Q  Median      3Q     Max  
## -20272  -11232   -7177    5968   61852  
## 
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)    
## (Intercept)   1.337e+04  1.882e+03   7.103 2.76e-10 ***
## OilProduction 1.673e-03  7.318e-04   2.286   0.0246 *  
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## (Dispersion parameter for gaussian family taken to be 280755365)
##
##     Null deviance: 2.6736e+10  on 91  degrees of freedom
## Residual deviance: 2.5268e+10  on 90  degrees of freedom
## AIC: 2054.7
##
## Number of Fisher Scoring iterations: 2
```

- Second Hypothesis:

```
summary(gauss2)

##
## Call:
## glm(formula = hypo2, family = "gaussian", data = DataRegGauss)
##
## Deviance Residuals:
##    Min      1Q  Median      3Q     Max
## -29507   -8171   -1380    5466   47217
##
## Coefficients:
##                          Estimate Std. Error t value Pr(>|t|)
## (Intercept)             2.227e+03  3.288e+03   0.677 0.500143
## OilProduction           2.140e-03  6.498e-04   3.294 0.001448 **
## ContinentAsia           7.450e+03  4.231e+03   1.761 0.081897 .
## ContinentEurope         2.500e+04  4.421e+03   5.656 2.09e-07 ***
## ContinentEurope/Asia   -2.640e+02  7.171e+03  -0.037 0.970725
## ContinentNorth America  1.499e+04  6.409e+03   2.340 0.021675 *
## ContinentOceania        2.990e+04  8.669e+03   3.449 0.000882 ***
## ContinentSouth America  3.519e+03  5.678e+03   0.620 0.537102
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 193147596)
##
##     Null deviance: 2.6736e+10  on 91  degrees of freedom
## Residual deviance: 1.6224e+10  on 84  degrees of freedom
## AIC: 2026
##
## Number of Fisher Scoring iterations: 2
```

5.Searching for a better model

```
## Analysis of Deviance Table
##
## Model 1: GDP_pc ~ OilProduction
## Model 2: GDP_pc ~ OilProduction + Continent
##   Resid. Df Resid. Dev Df   Deviance Pr(>Chi)
## 1        90 2.5268e+10
## 2        84 1.6224e+10  6 9043584826 2.03e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

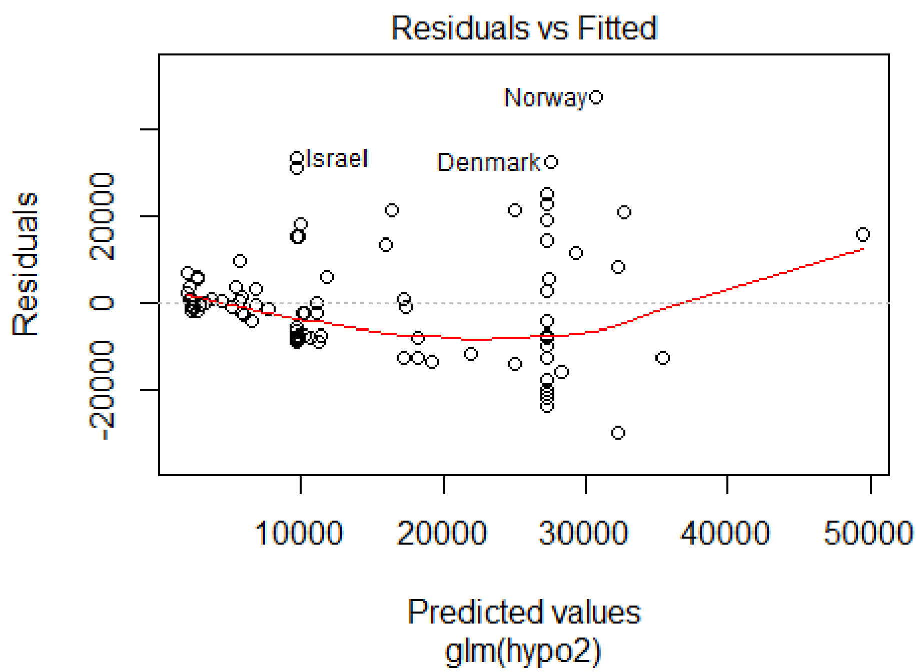
Model for the Second hypothesis is chosen. This is the RSquared:

```
## Warning: package 'rsq' was built under R version 3.6.3
```

```
## [1] 0.3425815
```

6.Verify the situation of chosen model:

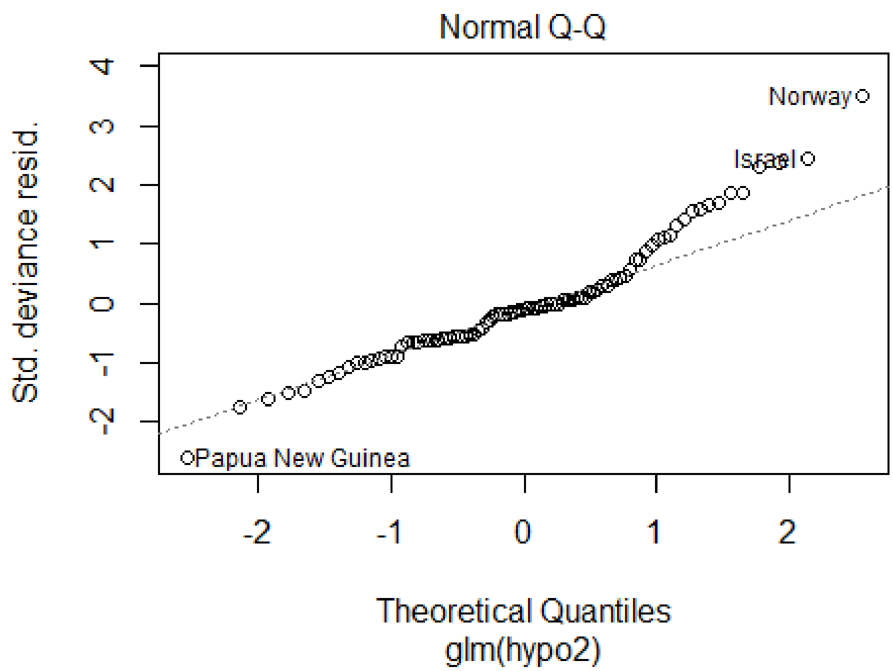
6.1. Linearity between dependent variable and predictors is assumed, then these dots should follow a linear and horizontal trend:



The linear trend is not obvious, and the distribution range goes wider when the predicted values increase. I'd like to say it represents the linearity between our variables in a certain level. Further research upon outliers are necessary.

6.2. Normality of residuals is assumed:

Visual exploration

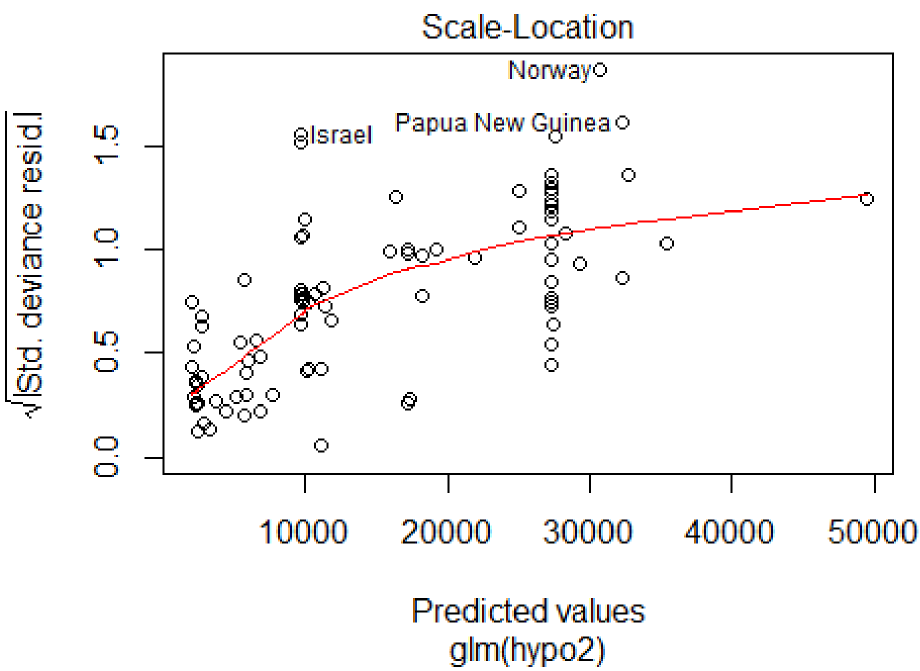


Mathematical exploration:

```
##
##  Shapiro-Wilk normality test
##
## data:  gauss2$residuals
## W = 0.94464, p-value = 0.000681
```

6.3. Homoscedasticity is assumed, so check if residuals are spread equally along the ranges of predictors

Visual exploration:



Mathematical exploration:

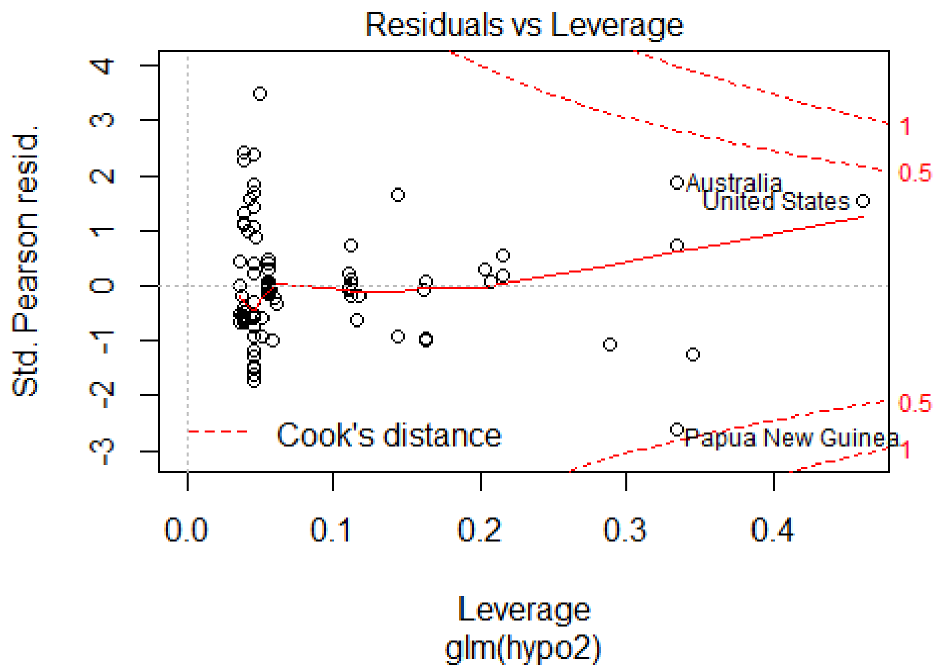
```
## Loading required package: zoo

##
## Attaching package: 'zoo'

## The following objects are masked from 'package:base':
##
##     as.Date, as.Date.numeric

##
##  studentized Breusch-Pagan test
##
## data:  gauss2
## BP = 19.735, df = 7, p-value = 0.006171
```

6.4. We assume that there is no colinearity, that is, that the predictors are not correlated.

```
## Warning: package 'car' was built under R version 3.6.3

## Loading required package: carData

##
## Attaching package: 'car'

## The following object is masked from 'package:dplyr':
##
##     recode

##                   GVIF Df GVIF^(1/(2*Df))
## OilProduction 1.146212  1        1.070613
## Continent     1.146212  6        1.011437
```

6.5. Analize the effect of atypical values. Determine if outliers (points that are far from the rest, but still in the trend) or high-leverage points (far from the trend but close to the rest) are influential

Visual exploration:

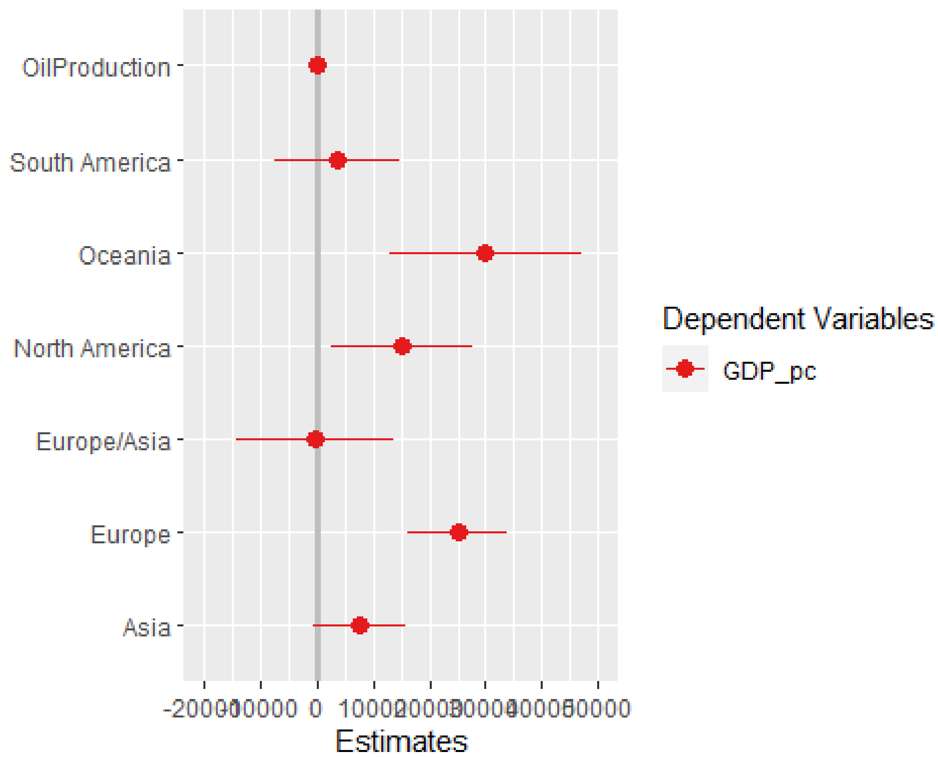


Querying:

```
gaussInf=as.data.frame(influence.measures(gauss2)$is.inf)
gaussInf[gaussInf$cook.d,]

##  [1] dfb.1_   dfb.OlPr dfb.CntA dfb.CntE dfb.CE/A dfb.CnNA dfb.CntO dfb.CnSA
##  [9] dffit    cov.r    cook.d   hat
## <0 rows> (or 0-length row.names)
```

7. Finally, a nice summary plot of our work

```
## Warning: package 'sjPlot' was built under R version 3.6.3

## Registered S3 methods overwritten by 'lme4':
##   method                          from
##   cooks.distance.influence.merMod car
##   influence.merMod                car
##   dfbeta.influence.merMod         car
##   dfbetas.influence.merMod        car

## Learn more about sjPlot with 'browseVignettes("sjPlot")'.
```



PREDICTIVE APPROACH

1. Splitting the data set

```
## Warning: package 'caret' was built under R version 3.6.3

## Loading required package: lattice
```

2. Regress with train data

```
##
## Call:
## NULL
##
## Deviance Residuals:
##    Min      1Q  Median      3Q     Max
## -29470   -9388   -1480    7635   44909
##
## Coefficients:
##                           Estimate Std. Error t value Pr(>|t|)
## (Intercept)              2.204e+03  4.180e+03   0.527  0.59982
## OilProduction            2.670e-03  8.371e-04   3.189  0.00221 **
## ContinentAsia            8.393e+03  5.127e+03   1.637  0.10657
## ContinentEurope          2.646e+04  5.685e+03   4.655 1.68e-05 ***
## `ContinentEurope/Asia`  -1.646e+03  8.083e+03  -0.204  0.83925
## `ContinentNorth America` 1.532e+04  7.708e+03   1.988  0.05109 .
## ContinentOceania         2.986e+04  9.604e+03   3.109  0.00280 **
## `ContinentSouth America` 3.651e+03  7.890e+03   0.463  0.64509
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 224537488)
##
##     Null deviance: 2.3585e+10  on 71  degrees of freedom
## Residual deviance: 1.4370e+10  on 64  degrees of freedom
```

```
## AIC: 1598.4
##
## Number of Fisher Scoring iterations: 2
```

3. Evaluate performance

```
##          RMSE     Rsquared          MAE
## 10322.575720     0.536489  7547.290591
```

QUESTION 2 CLUSTERING START

RESEARCH QUESTION: 'Can we identify groups of countries with similar population and fossil fuel usage and if/how population size affects fossil fuel usage?'

Data used: * fossilFuel_PctTotalElec: [from CIA World Factbook] percentage of total electricity generating capacity that comes from fossil fuels * Population: [UN Dept of Economic and Social Affairs] World population estimates

Prep to cluster fossilFuel_PctTotalElec and Population

```
##           fossilFuel_PctTotalElec Population
## Albania                      0.05    2880917
## Algeria                      0.96   43053054
## Angola                       0.34   31825295
## Argentina                    0.69   44780677
## Australia                    0.72   25203198
## Austria                      0.25    8955102
```

Set random seed for replicability of results:

Setting distance matrix:

Defining number of clusters for each method (NumCluster = 5) Clustering via pam method:

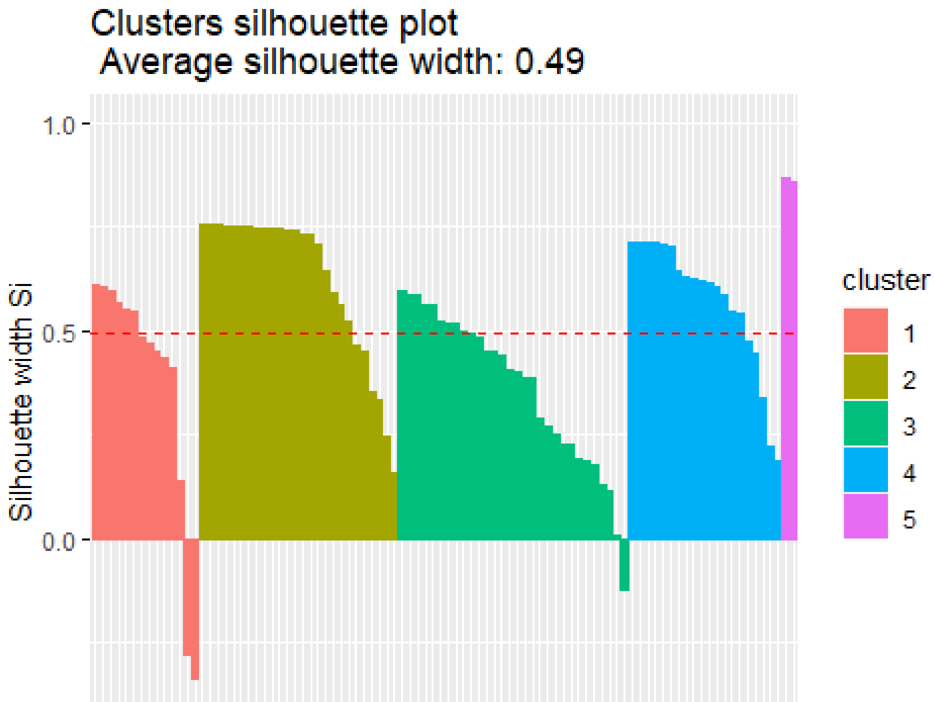
Adding pam results to original DF (DFnew1)

REPORT: Table of Cluster:

```
##
##  1  2  3  4  5
## 14 26 30 20  2
```

REPORT: Evaluate Results:

```
##   cluster size ave.sil.width
## 1       1   14          0.38
## 2       2   26          0.63
## 3       3   30          0.36
## 4       4   20          0.57
## 5       5    2          0.86
```



REPORT: Detecting Anomalies

Saving individual silhouettes

```
##                                     cluster neighbor sil_width
## Tajikistan                                1        4 0.6090716
## Albania                                   1        4 0.6060691
## Norway                                    1        4 0.5978116
## Timor-Leste                               1        4 0.5667970
## Congo, Democratic Republic of the         1        4 0.5525901
## France                                    1        4 0.5468275
```

Requesting negative silhouettes:

```
##         cluster neighbor  sil_width
## Angola        1        4 -0.2800818
## Georgia       1        4 -0.3377824
## Ghana         3        4 -0.1223473
```

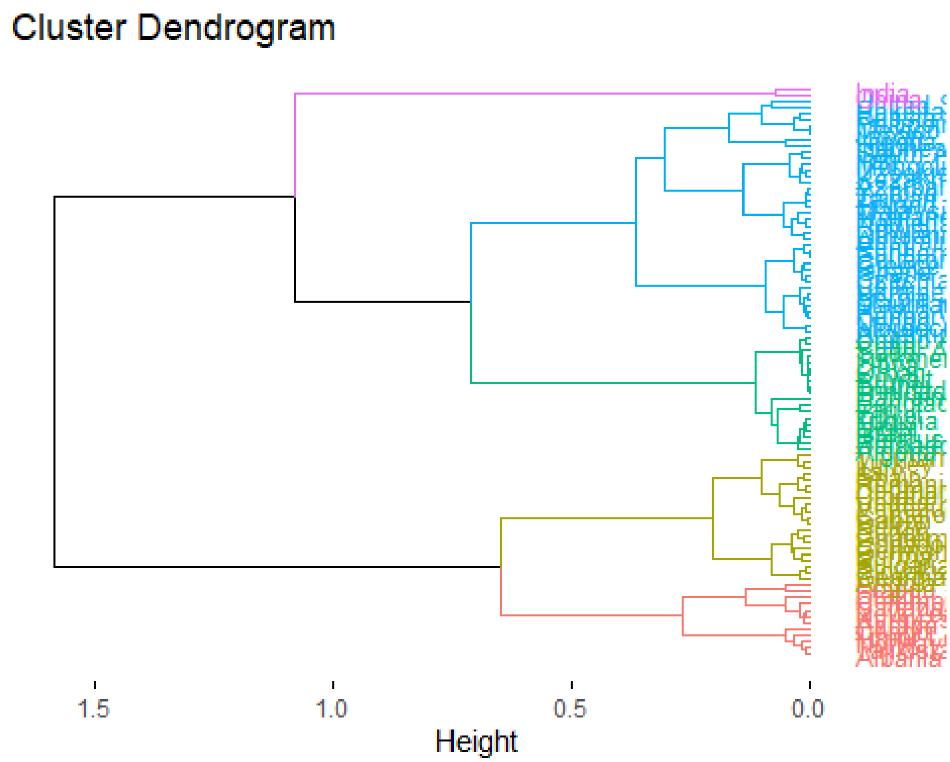
Cluster via agnes method; indicate number of clusters (NumCluster):

Adding agn results to original DF (DFnew1)

REPORT: Table of clusters:

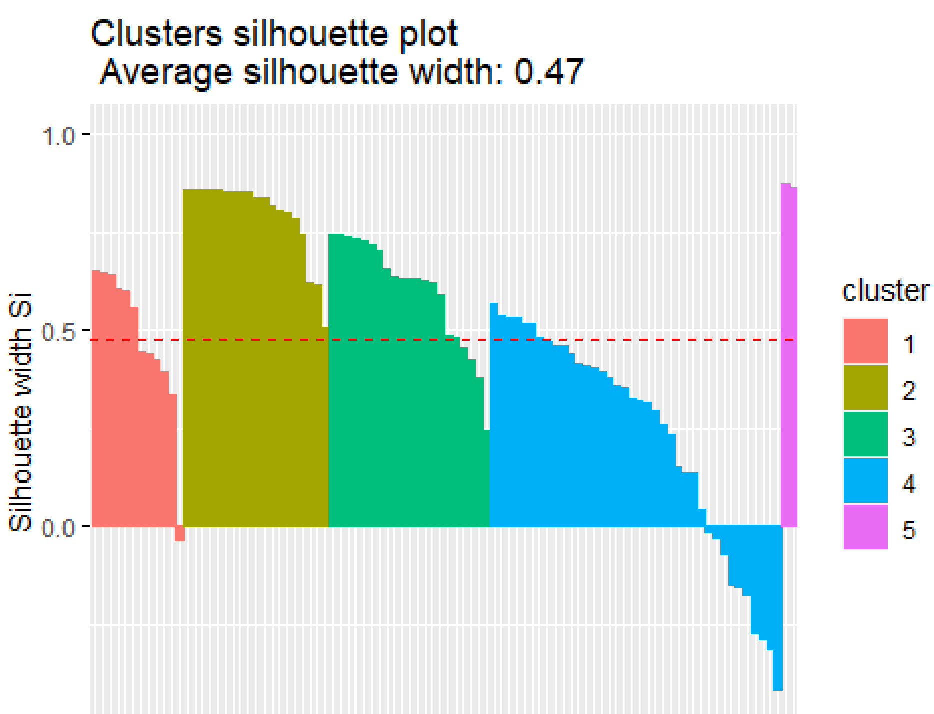
```
## 
##  1  2  3  4  5 
## 12 19 21 38  2
```

Evaluating results:



REPORT: Average silhouettes

```
##   cluster size ave.sil.width
## 1       1   12          0.47
## 2       2   19          0.79
## 3       3   21          0.60
## 4       4   38          0.23
## 5       5    2          0.87
```



REPORT: Detecting anomalies

```
##                                     cluster neighbor sil_width
## Tajikistan                                1        3 0.6486823
## Albania                                   1        3 0.6461141
## Norway                                    1        3 0.6392016
## Timor-Leste                               1        3 0.6056001
## Congo, Democratic Republic of the         1        3 0.5963339
## France                                    1        3 0.5571241
```

Requesting negative silhouettes:

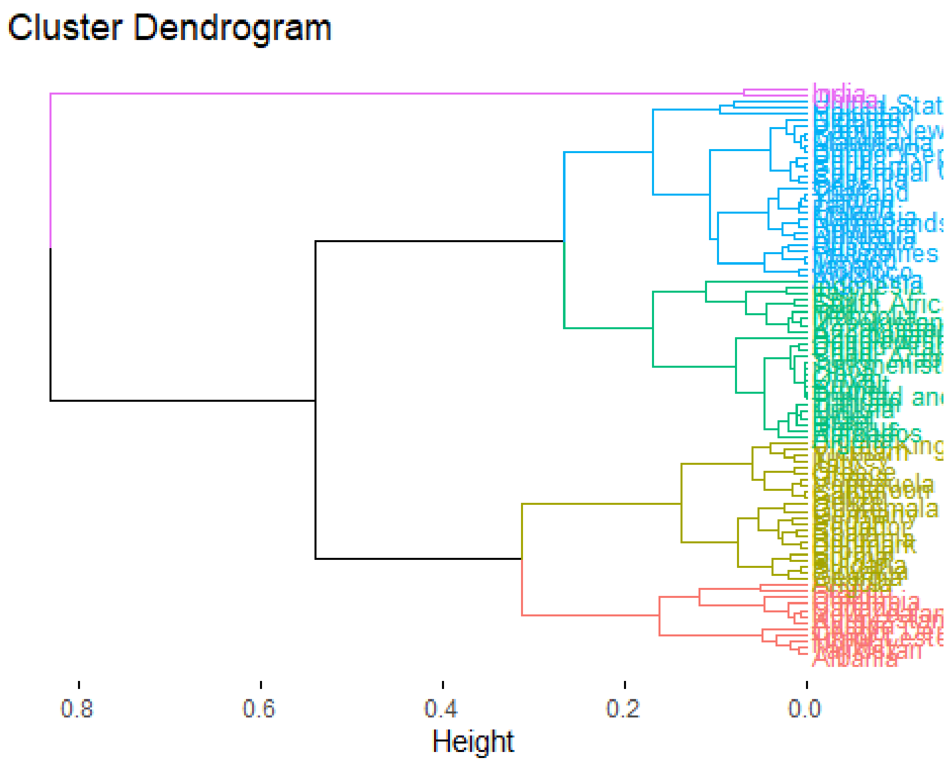
```
##              cluster neighbor   sil_width
## Colombia           1        3 -0.03279474
## Indonesia          4        2 -0.01212078
## Iran               4        2 -0.03057378
## Chile              4        3 -0.06866262
## Azerbaijan         4        2 -0.14697731
## South Africa       4        2 -0.15226216
## Ghana              4        3 -0.17299110
## Greece             4        3 -0.27237486
## Uzbekistan         4        2 -0.28525827
## Kazakhstan         4        2 -0.31159271
## Mongolia           4        2 -0.41514761
```

Cluster via diana method; indicate number of clusters (NumCluster):

Adding diana results to original DF (DFnew1):

REPORT: Table of clusters

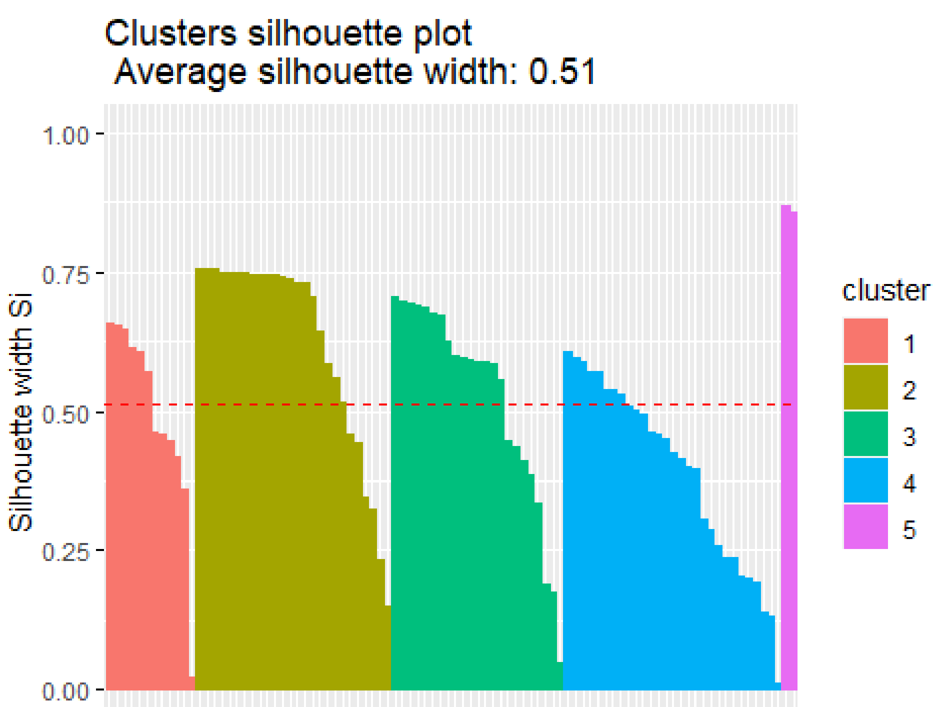
```
## 
##  1  2  3  4  5 
## 12 26 23 29  2
```



REPORT: Dendrogram

REPORT: Average silhouettes

```
##   cluster size ave.sil.width
## 1       1   12          0.49
## 2       2   26          0.62
## 3       3   23          0.52
## 4       4   29          0.39
## 5       5    2          0.86
```



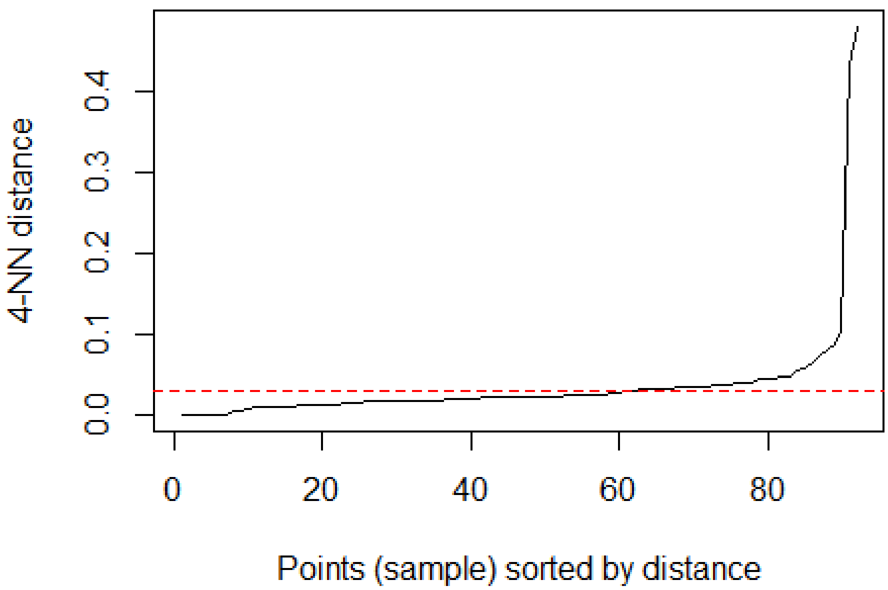
REPORT: Detecting anomalies:

```
##                                    cluster neighbor sil_width
## Tajikistan                                1        3 0.6564827
## Albania                                   1        3 0.6539019
## Norway                                    1        3 0.6467797
## Timor-Leste                               1        3 0.6133818
## Congo, Democratic Republic of the         1        3 0.6057145
## France                                    1        3 0.5720875
```

Requesting negative silhouettes:

```
## [1] cluster   neighbor  sil_width
## <0 rows> (or 0-length row.names)
```

Cluster via DBSCAN method; indicate minimum neighbors (4):



Setting distance (epsilon):

REPORT: Number of clusters and outliers produced

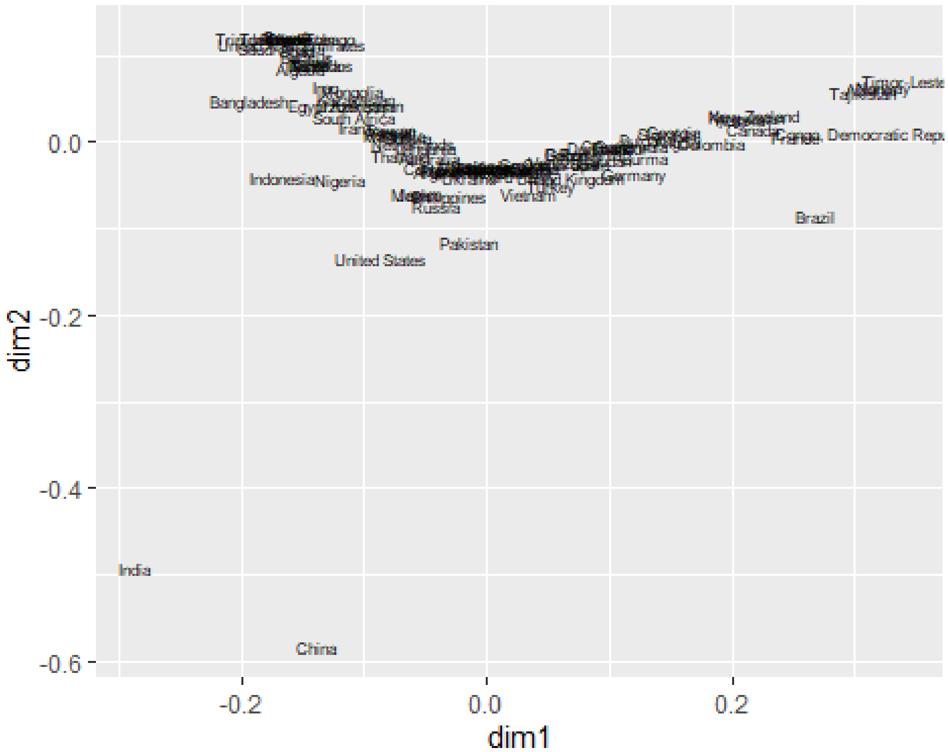
```
## DBSCAN clustering for 92 objects.
## Parameters: eps = 0.03, minPts = 4
## The clustering contains 4 cluster(s) and 11 noise points.
##
##  0  1  2  3  4
## 11  4 52  4 21
##
## Available fields: cluster, eps, minPts
```

Saving results:

Comparing clusters

Prepare a bidimensional map:

View bidimensional map:



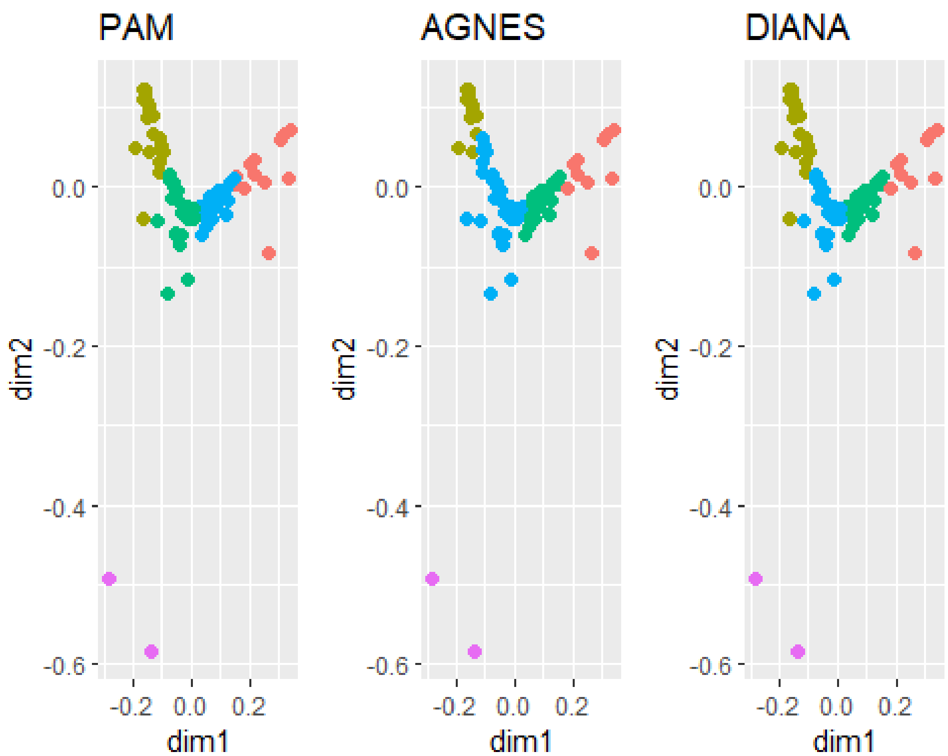
Results from pam:

Results from agnes:

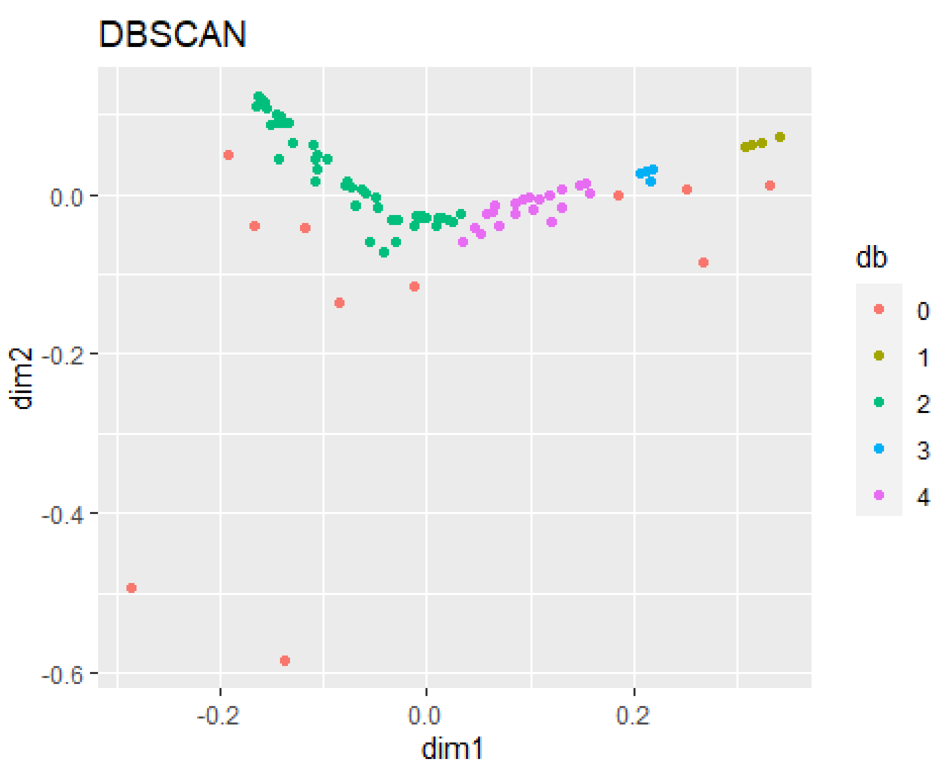
Results from diana :

Compare visually:

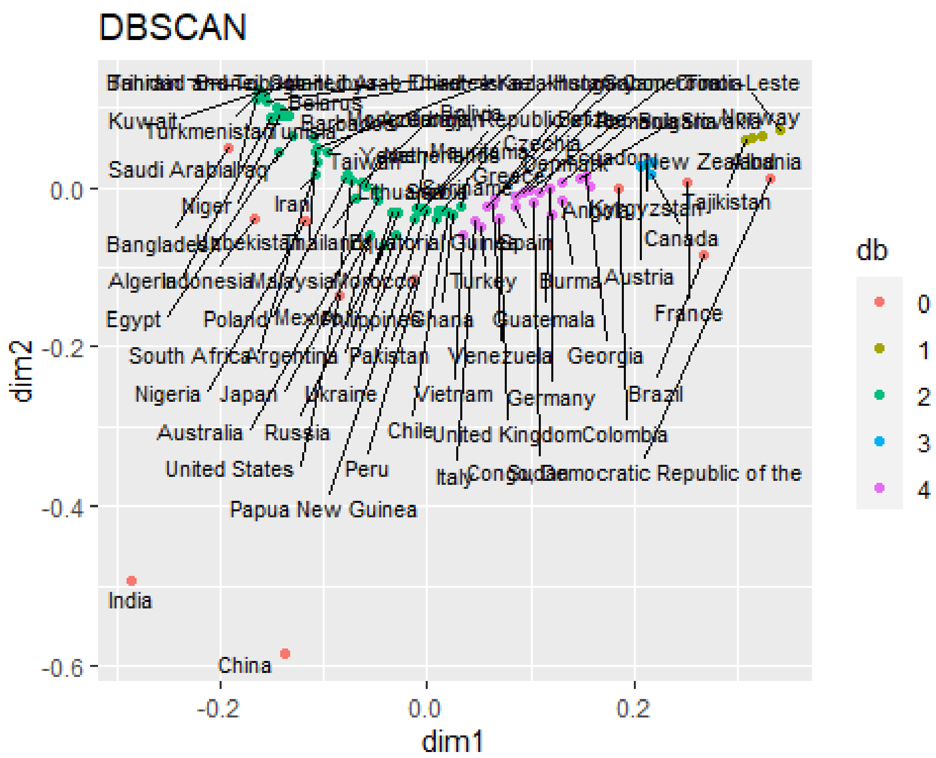
Viewing pam, agnes, and diana plots side by side



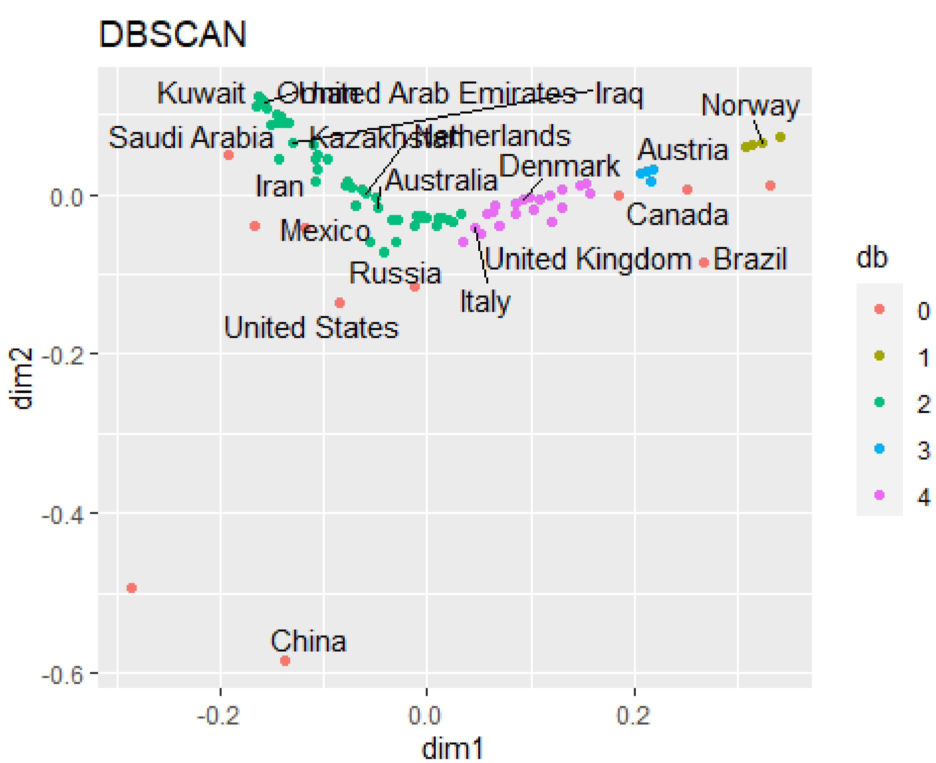
Plot results from DBSCAN :



Annotating graph with country names :



Annotating just the outlier countries：



CHOOSING DIANA METHOD DUE TO HAVING ZERO NEGATIVE SILHOUETTES。

QUESTION 2 REGRESSION CODE START

- Hypothesis:
  - Model 1: FF ~ Population
  - Model 2: FF ~ Population + Developed

- Method:
  - Binary Outcome – – FF usage (Median percentage FF use of total electricity capacity)
- Control variable – – Developed (Median GDP per capita)
- Independent variable – – Population
- Rationale for hypothesis:
  - Larger populations would exhibit higher fossil fuel usage as a percent of total electricity capacity

Changing dtype for population :

```
##                Country fossilFuel_PctTotalElec           OilProduction
##            "character"               "numeric"               "numeric"
##             Population                  GDP_pc
##              "numeric"               "integer"
```

Changing dtype for GDP_pc(gdp):

```
##                Country fossilFuel_PctTotalElec           OilProduction
##            "character"               "numeric"               "numeric"
##             Population                  GDP_pc
##              "numeric"               "numeric"
```

Filtering out non-oil producing countries & creating new DF (teamnew):

```
##                              Country fossilFuel_PctTotalElec OilProduction
## 2                            Albania                    0.05         22915
## 3                            Algeria                    0.96       1348361
## 4                             Angola                    0.34       1769615
## 6                          Argentina                    0.69        510560
## 9                          Australia                    0.72        289749
## 10                           Austria                    0.25         15161
## 11                        Azerbaijan                    0.84        833538
## 13                           Bahrain                    1.00         40000
## 14                        Bangladesh                    0.97          4189
## 15                          Barbados                    0.93          1000
## 16                           Belarus                    0.96         25000
## 18                            Belize                    0.51          2000
## 21                           Bolivia                    0.76         58077
## 24                            Brazil                    0.17       2515459
## 25                            Brunei                    1.00        109117
## 26                          Bulgaria                    0.39          1000
## 28                             Burma                    0.39         15000
## 32                          Cameroon                    0.52         93205
## 33                            Canada                    0.23       3662694
## 35                              Chad                    0.98        110156
## 36                             Chile                    0.59          4423
## 37                             China                    0.62       3980650
## 38                          Colombia                    0.29        897784
## 40  Congo, Democratic Republic of the                    0.02         20000
## 41             Congo, Republic of the                    0.64        308363
## 43                           Croatia                    0.45         13582
## 45                           Czechia                    0.60          2333
## 46                           Denmark                    0.46        140637
## 50                           Ecuador                    0.43        548421
## 51                             Egypt                    0.91        490000
```

```
## 53                       Equatorial Guinea                     0.61       227000
## 60                                  France                     0.17        16418
## 61                                   Gabon                     0.51       210820
## 63                                 Georgia                     0.35          400
## 64                                 Germany                     0.41        46839
## 65                                   Ghana                     0.58       100549
## 66                                  Greece                     0.57         3172
## 68                               Guatemala                     0.41         8977
## 75                                 Hungary                     0.64        13833
## 77                                   India                     0.71       715459
## 78                               Indonesia                     0.85       833667
## 79                                    Iran                     0.84      3990956
## 80                                    Iraq                     0.91      4451516
## 82                                  Israel                     0.95          390
## 83                                   Italy                     0.54        70675
## 85                                   Japan                     0.71         3918
## 87                              Kazakhstan                     0.86      1595199
## 91                                  Kuwait                     1.00      2923825
## 92                              Kyrgyzstan                     0.24         1000
## 98                                   Libya                     1.00      1003000
## 99                               Lithuania                     0.73         2000
## 104                               Malaysia                     0.78       661240
## 109                             Mauritania                     0.65         5000
## 111                                 Mexico                     0.71      2186877
## 114                               Mongolia                     0.87        23426
## 116                                Morocco                     0.68          160
## 121                            Netherlands                     0.75        18087
## 122                            New Zealand                     0.23        35574
## 124                                  Niger                     0.95        13000
## 125                                Nigeria                     0.80      1999885
## 127                                 Norway                     0.03      1647975
## 128                                   Oman                     1.00      1006841
## 129                               Pakistan                     0.62        80000
## 131                       Papua New Guinea                     0.63        56667
## 133                                   Peru                     0.61        40266
## 134                            Philippines                     0.67        20000
## 135                                 Poland                     0.79        20104
## 139                                Romania                     0.47       504000
## 140                                 Russia                     0.68     10800000
## 147                           Saudi Arabia                     1.00     12000000
## 149                                 Serbia                     0.65        20000
## 153                               Slovakia                     0.36          200
## 156                           South Africa                     0.85         2000
## 158                                  Spain                     0.47         2667
## 160                                  Sudan                     0.44       255000
## 161                               Suriname                     0.61        17000
## 164                                 Taiwan                     0.79          196
## 165                             Tajikistan                     0.06          180
## 167                               Thailand                     0.76       257525
## 168                            Timor-Leste                     0.00        60661
## 171                    Trinidad and Tobago                     1.00        60090
## 172                                Tunisia                     0.94        48757
## 173                                 Turkey                     0.53        49497
## 174                           Turkmenistan                     1.00       230779
## 177                                Ukraine                     0.65        31989
```

```
## 178             United Arab Emirates                       0.99       3106077
## 179                   United Kingdom                       0.50        939760
## 180                    United States                       0.70      15043000
## 182                       Uzbekistan                       0.86         52913
## 184                        Venezuela                       0.51       2276967
## 185                          Vietnam                       0.56        301850
## 186                            Yemen                       0.79         22000
##     Population GDP_pc
## 2      2880917   5372
## 3     43053054   3980
## 4     31825295   3037
## 6     44780677   9887
## 9     25203198  53825
## 10     8955102  50022
## 11    10047718   4689
## 13     1641172  25273
## 14   163046161   1905
## 15      287025  18069
## 16     9452411   6603
## 18      390353   4925
## 21    11513100   3670
## 24   211049527   8796
## 25      433285  27871
## 26     7000119   9518
## 28    54045420   1244
## 32    25876380   1514
## 33    37411047  46212
## 35    15946876    861
## 36    18952038  15399
## 37  1433783686  10098
## 38    50339443   6508
## 40    86790567    500
## 41     5380508   2534
## 43     4130304  14949
## 45    10689209  23213
## 46     5771876  59795
## 50    17373662   6249
## 51   100388073   3046
## 53     1355986   8927
## 60    65129728  41760
## 61     2172579   8112
## 63     3996765   4289
## 64    83517045  46563
## 65    28833629   2223
## 66    10473455  19974
## 68    17581472   4616
## 75     9684679  17463
## 77  1366417754   2171
## 78   270625568   4163
## 79    82913906   5506
## 80    39309783   5738
## 82     8519377  42823
## 83    60550075  32946
## 85   126860301  40846
## 87    18551427   9139
```

```
## 91     4207083  29266
## 92     6415850   1292
## 98     6777452   5019
## 99     2759627  19266
## 104   31949777  11136
## 109    4525696   1392
## 111  127575529  10118
## 114    3225167   4132
## 116   36471769   3345
## 121   17097130  52367
## 122    4783063  40634
## 124   23310715    405
## 125  200963599   2222
## 127    5378857  77975
## 128    4974986  17791
## 129  216565318   1388
## 131    8776109   2742
## 133   32510453   7046
## 134  108116615   3294
## 135   37887768  14901
## 139   19364557  12482
## 140  145872256  11162
## 147   34268528  22865
## 149    8772235   7397
## 153    5457013  19547
## 156   58558270   6100
## 158   46736776  29961
## 160   42813238    714
## 161     581372   6310
## 164   23773876  24827
## 165    9321018    877
## 167   69037513   7791
## 168    1293119   2262
## 171    1394973  16365
## 172   11694719   3287
## 173   83429615   8957
## 174    5942089   7816
## 177   43993638   3592
## 178    9770529  37749
## 179   67530172  41030
## 180  329064917  65111
## 182   32981716   1831
## 184   28515829   2547
## 185   96462106   2740
## 186   29161922    943
```

Converting USDollar to a factor variable

Calling new variable 'Developed'

Converting fossilFuel_PctTotalElec to a factor variable

Calling new variable 'FF'

Checking dtypes:

```
## 'data.frame':    92 obs. of  7 variables:
##  $ Country                 : chr  "Albania" "Algeria" "Angola" "Arge"..
##  $ fossilFuel_PctTotalElec: num  0.05 0.96 0.34 0.69 0.72 0.25 0.84 ..
##  $ OilProduction          : num  22915 1348361 1769615 510560 289749..
##  $ Population             : num  2880917 43053054 31825295 44780677 ..
##  $ GDP_pc                 : num  5372 3980 3037 9887 53825 ...
##  $ Developed              : Factor w/ 2 levels "0","1": 1 1 1 2 2 2 ..
##  $ FF                     : Factor w/ 2 levels "0","1": 1 2 1 2 2 1 ..
```

Defining 'Population' as independent variable:

Defining columns needed :

Verify dtypes for colsNeededDico:

```
## 'data.frame':    92 obs. of  3 variables:
##  $ FF        : Factor w/ 2 levels "0","1": 1 2 1 2 2 1 2 2 2 2 ...
##  $ Population: num  2880917 43053054 31825295 44780677 25203198 ...
##  $ Developed : Factor w/ 2 levels "0","1": 1 1 1 2 2 2 1 2 1 2 ...
```

Create subset

Rename indexes by country

Define & compute regression models

Results of hypo3:

At p-value of 0.634, this model is not statistically significant

```
## 
## Call:
## glm(formula = hypo3, family = "binomial", data = DataRegLogis)
## 
## Deviance Residuals: 
##    Min      1Q  Median      3Q     Max  
## -1.436  -1.129  -1.126   1.223   1.230  
## 
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept) -1.231e-01  2.217e-01  -0.555    0.579
## Population   4.972e-10  1.045e-09   0.476    0.634
## 
## (Dispersion parameter for binomial family taken to be 1)
## 
##     Null deviance: 127.37  on 91  degrees of freedom
## Residual deviance: 127.13  on 90  degrees of freedom
## AIC: 131.13
## 
## Number of Fisher Scoring iterations: 4
```

Results of hypo4:

At p-values of 0.631 and 0.673, this model also is not statistically significant:

```
## 
## Call:
## glm(formula = hypo4, family = "binomial", data = DataRegLogis)
```

```
##
## Deviance Residuals:
##    Min      1Q  Median      3Q     Max
## -1.479  -1.141  -1.089   1.192   1.268
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept) -2.120e-01  3.063e-01  -0.692    0.489
## Population   5.028e-10  1.048e-09   0.480    0.631
## Developed1   1.768e-01  4.184e-01   0.422    0.673
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 127.37  on 91  degrees of freedom
## Residual deviance: 126.95  on 89  degrees of freedom
## AIC: 132.95
##
## Number of Fisher Scoring iterations: 4
```

Analysis of variance between models:

```
## Analysis of Deviance Table
##
## Model 1: FF ~ Population
## Model 2: FF ~ Population + Developed
##   Resid. Df Resid. Dev Df Deviance Pr(>Chi)
## 1        90     127.13
## 2        89     126.95  1  0.17869   0.6725
```

Recommendations

First Question

Oil production could be an important component of GDP, but higher oil production rate does not lead to higher GDP. If we want to evaluate the relationship between GDP and oil production, we also need to know what is the percentage of the GDP generated by oil production.

- *Same level variables are more easy to be compared*
- Too many countries that their oil production is close to zero
- *Try other control variables like export/import*
- Higher oil production does not lead to higher GDP necessarily

Second Question

Neither model is statistically significant; no further analysis required.

Recommendations for future analysis of question #2 include:

- *Incorporate country-specific income levels as an additional variable*
- Remove major outliers from sample population
- Use actual fossil fuel usage data in lieu of ratios