# Tarea minería de datos y modelización predictiva

Pablo Benayas Penas

25/02/2020

- These are the different sections I am going to cover in this assignment:
  - Firstly, I am going to work with data from the Spanish National Elections. I will clean the dataset and then, will create linear and logistic regression models to predict variables thereof.
  - Secondly, Time Series Analysis will be conducted with US_monthly_unemployment_rate data.
  - Finally, I will carry out clustering analysis with the aforementioned Spanish National Elections Dataset.

**PART I**

To begin with, let's clean the dataset:

Columns are renamed

```
options(warn=-1)

elec=readxl::read_excel('C:/Users/pablo/Desktop/DatosEleccionesEsp.xlsx')
elec=as.data.frame(elec)

names(elec)=c('Name', 'ProvinceCode', 'Autonomous_Community', 'Population', 'TotalCensus',
              'AbstentionPtge', 'High_Abstention_rate', 'Left_wing_Pct', 'Right_wing_Pct',
              'Others_Pct', 'Left_wing', 'Right_wing', 'Age_0_4_Ptge', 'Age_under19_Ptge',
              'Age_19_65_pct', 'Age_over65_pct', 'FemalePopulationPtge', 'ForeignersPtge',
              'SameAutomComPtge', 'SameAutonComDiffProvPtge', 'DifAutonComPtge',
              'UnemployLess25_Ptge', 'Unemploy25_40_Ptge', 'UnemployMore40_Ptge',
              'AgricultureUnemploymentPtge', 'IndustryUnemploymentPtge',
              'ConstructionUnemploymentPtge', 'ServicesUnemploymentPtge', 'totalCompanies',
              'Industry', 'ConstructionInd', 'commerceNhostelry', 'ServiceInd',
              'MainActivity', 'RealProperty', 'Pob2010', 'SurfaceArea', 'Density',
              'PopChange_pct','People_RealProp_ratio', 'officesNfacilities')
```

If variable has few unique values, it should be converted to factor

```
sapply(elec, function(x) length(unique(x)))
```

```
##                         Name                 ProvinceCode
##                         8102                           52
##          Autonomous_Community                   Population
##                           19                         3597
##                  TotalCensus               AbstentionPtge
##                         3310                         5675
##          High_Abstention_rate                 Left_wing_Pct
##                            2                         6569
##               Right_wing_Pct                   Others_Pct
##                         6682                         4319
##                    Left_wing                   Right_wing
##                            2                            2
##                  Age_0_4_Ptge              Age_under19_Ptge
##                         3761                         5891
##                 Age_19_65_pct               Age_over65_pct
##                         6215                         6778
##          FemalePopulationPtge               ForeignersPtge
##                         4524                         2329
##              SameAutomComPtge      SameAutonComDiffProvPtge
##                         6151                         4207
##               DifAutonComPtge            UnemployLess25_Ptge
##                         5574                         2342
##            Unemploy25_40_Ptge            UnemployMore40_Ptge
##                         2681                         2751
##   AgricultureUnemploymentPtge      IndustryUnemploymentPtge
##                         2525                         2538
## ConstructionUnemploymentPtge      ServicesUnemploymentPtge
##                         2505                         2904
##               totalCompanies                     Industry
##                         1226                          308
##               ConstructionInd            commerceNhostelry
##                          457                          803
##                   ServiceInd                 MainActivity
##                          758                            5
##                  RealProperty                      Pob2010
##                         3088                         3625
##                  SurfaceArea                      Density
##                         8110                            4
##                PopChange_pct        People_RealProp_ratio
##                         3049                          283
##            officesNfacilities
##                          758
```

I set less than 10 unique values as benchmark for factor conversion

```
to_factor=elec[,sapply(elec, function(x) length(unique(x))) < 10]
elec[,sapply(elec, function(x) length(unique(x))) < 10] = lapply(to_factor, factor)

head(elec[,sapply(elec, function(x) length(unique(x))) < 10],2)
```

```
##   High_Abstention_rate Left_wing Right_wing MainActivity Density
## 1                    0         1          0         Otro MuyBaja
## 2                    0         1          0         Otro MuyBaja
```

for the sake of file length, dfplot() is not going to be displayed

```r
# function provided by my teacher
#dfplot <- function(data.frame){
#  df <- data.frame
#  ln <- length(names(data.frame))
#  for(i in 1:ln){
#    if(is.factor(df[,i])){
#      plot(df[,i],main=names(df)[i])} # 'main' argument: an overall title for the plot

#    # names(df)[i] returns its column name
#    else{hist(df[,i],main=names(df)[i])
#   boxplot(df[,i],main=names(df)[i])}
#  }
#}

#dfplot(elec)
```

Let's check the structure of the dataset

```r
str(elec)
```

```
## 'data.frame':    8119 obs. of  41 variables:
##  $ Name                        : chr  "Abadía" "Abertura" "Acebo" "Acehúche" ...
##  $ ProvinceCode                : num  10 10 10 10 10 10 10 10 10 10 ...
##  $ Autonomous_Community        : chr  "Extremadura" "Extremadura" "Extremadura" "Extremadura" ...
##  $ Population                  : num  336 429 569 822 623 ...
##  $ TotalCensus                 : num  282 364 569 704 540 ...
##  $ AbstentionPtge              : num  20.2 25.3 27.2 30.1 30.2 ...
##  $ High_Abstention_rate        : Factor w/ 2 levels "0","1": 1 1 1 2 2 1 2 1 1 1 ...
##  $ Left_wing_Pct               : num  60.4 54.8 44.2 50.8 44.6 ...
##  $ Right_wing_Pct              : num  35.6 44.1 53.1 45.3 49.9 ...
##  $ Others_Pct                  : num  1.778 0.368 0.966 0 0.796 ...
##  $ Left_wing                   : Factor w/ 2 levels "0","1": 2 2 1 2 1 2 2 1 1 1 ...
##  $ Right_wing                  : Factor w/ 2 levels "0","1": 1 1 2 1 2 1 1 2 2 2 ...
##  $ Age_0_4_Ptge                : num  3.87 1.63 1.23 4.26 3.53 ...
##  $ Age_under19_Ptge            : num  18.16 13.05 9.14 14.96 15.57 ...
##  $ Age_19_65_pct               : num  55.1 56.6 54.8 60.1 59.4 ...
##  $ Age_over65_pct              : num  26.8 30.3 36 24.9 25 ...
##  $ FemalePopulationPtge        : num  44 50.1 49 51.1 48.2 ...
##  $ ForeignersPtge              : num  0.89 1.63 0.7 0.12 0.64 0.56 0.98 3.56 2.04 1.95 ...
##  $ SameAutomComPtge            : num  79.8 90.9 78.9 93.9 93.3 ...
##  $ SameAutonComDiffProvPtge    : num  0.298 2.797 0.703 0.487 0.161 ...
##  $ DifAutonComPtge             : num  19.34 7.23 18.1 5.11 4.17 ...
##  $ UnemployLess25_Ptge         : num  2.38 16.22 8.2 7.41 15.38 ...
##  $ Unemploy25_40_Ptge          : num  54.8 32.4 36.1 61.1 48.1 ...
##  $ UnemployMore40_Ptge         : num  42.9 51.4 55.7 31.5 36.5 ...
##  $ AgricultureUnemploymentPtge : num  4.76 8.11 22.95 16.67 21.15 ...
##  $ IndustryUnemploymentPtge    : num  9.52 8.11 9.84 5.56 0 ...
##  $ ConstructionUnemploymentPtge: num  11.9 10.8 13.1 16.7 11.5 ...
##  $ ServicesUnemploymentPtge    : num  73.8 67.6 49.2 59.3 61.5 ...
##  $ totalCompanies              : num  15 11 49 50 22 90 45 26 82 7 ...
##  $ Industry                    : num  0 0 0 0 0 5 0 0 9 0 ...
##  $ ConstructionInd             : num  0 0 0 0 0 18 0 0 14 0 ...
##  $ commerceNhostelry           : num  0 0 0 0 0 56 0 0 32 0 ...
##  $ ServiceInd                  : num  0 0 0 0 0 11 0 0 27 0 ...
##  $ MainActivity                : Factor w/ 5 levels "ComercTTEHosteleria",..: 4 4 4 4 4 1 4 4 1 4 ...
##  $ RealProperty                : num  216 382 918 599 394 ...
##  $ Pob2010                     : num  326 459 674 842 625 ...
##  $ SurfaceArea                 : num  4508 6271 5702 9106 4008 ...
##  $ Density                     : Factor w/ 4 levels "?","Alta","Baja",..: 4 4 4 4 4 4 4 1 4 4 ...
##  $ PopChange_pct               : num  3.07 -6.54 -15.58 -2.38 -0.32 ...
##  $ People_RealProp_ratio       : num  1.56 1.12 0.62 1.37 1.58 1.39 2.18 0.83 1.26 0.78 ...
##  $ officesNfacilities          : num  28 67 74 66 96 ...
```

Let's check number of NAs per varaible

```r
sapply(elec, function(x) sum(is.na(x)))
```

```
##                       Name               ProvinceCode
##                          0                          0
##        Autonomous_Community                 Population
##                          0                          0
##                TotalCensus             AbstentionPtge
##                          0                          0
##        High_Abstention_rate              Left_wing_Pct
##                          0                          0
##              Right_wing_Pct                 Others_Pct
##                          0                          0
##                  Left_wing                 Right_wing
##                          0                          0
##               Age_0_4_Ptge           Age_under19_Ptge
##                          0                          0
##              Age_19_65_pct             Age_over65_pct
##                          0                          0
##        FemalePopulationPtge             ForeignersPtge
##                          0                          0
##            SameAutomComPtge    SameAutonComDiffProvPtge
##                          0                          0
##             DifAutonComPtge        UnemployLess25_Ptge
##                          0                          0
##          Unemploy25_40_Ptge        UnemployMore40_Ptge
##                          0                          0
##  AgricultureUnemploymentPtge    IndustryUnemploymentPtge
##                          0                          0
## ConstructionUnemploymentPtge    ServicesUnemploymentPtge
##                          0                          0
##              totalCompanies                   Industry
##                          5                        188
##             ConstructionInd          commerceNhostelry
##                        139                          9
##                  ServiceInd               MainActivity
##                         62                          0
##                RealProperty                    Pob2010
##                        138                          7
##                 SurfaceArea                    Density
##                          9                          0
##               PopChange_pct        People_RealProp_ratio
##                          7                        138
##           officesNfacilities
##                          0
```

- OBSERVATIONS:
  - 1. Check if 100 % is a valid max value for ‘Others_Pct’.
  - 2. ‘ForeignersPtge’ has negative values. Decide whether those values should be converted to positive or NA.
  - 3. Check if 127 % is a valid max value for ‘SameAutomComPtge’.
  - 4. ‘Density’ has ‘?’ values. Convert them to NAs.
  - 5. Check if 138.46 is a valid max value for ‘SameAutomComPtge’.
  - 6. ‘Offices&Facilities’: max value is ‘99999’, while median is 52.
  - 7. Explain 100 0 0 values in unemployment variables.

1. Check if 100 % is a valid max value for ‘Others_Pct’:
   Apart from national-oriented political parties, there are regional parties too. These political parties are particularly popular in Catolonia and the Basque Country.
   Thus, if max value of ‘Other_Pct’ is not a locality from the aforementioned Autonomous Communities, I will treat it as NA.
   As it is located in Catalonia, I assume this value is valid

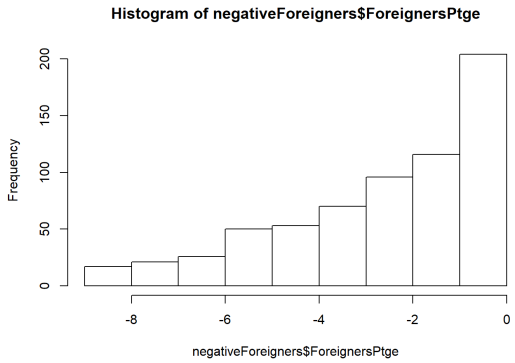
```
elec[elec$Others_Pct==max(elec$Others_Pct),c('Name','ProvinceCode',
                                            'Autonomous_Community','Others_Pct')]
```

```
##                     Name ProvinceCode Autonomous_Community Others_Pct
## 7699 Santa Maria de Merlès            8             Cataluña        100
```

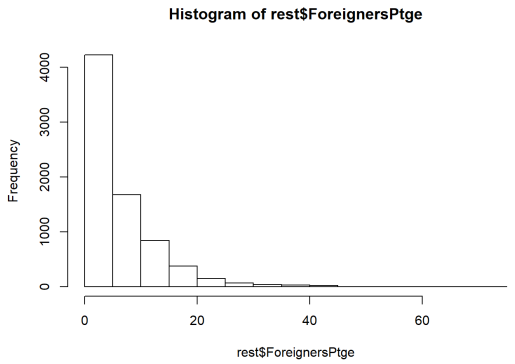
2) ‘ForeignersPtge’ has negative values. Decide whether those values should be converted to positive or NA.

I have decided to convert those values to positive since the distribution of both ‘negative’ and ‘rest’ are similar enough

```
negativeForeigners=elec[elec$ForeignersPtge<0,c('Name',
                             'ProvinceCode','Autonomous_Community','ForeignersPtge')]

rest=elec[elec$ForeignersPtge>=0,c('Name',
                             'ProvinceCode','Autonomous_Community','ForeignersPtge')]

hist(negativeForeigners$ForeignersPtge)
```




```
hist(rest$ForeignersPtge)
```




```
elec$ForeignersPtge=ifelse(elec$ForeignersPtge<0, -1*elec$ForeignersPtge, elec$ForeignersPtge)
```

3) Check if 127 % is a valid max value for ‘SameAutomComPtge’.
I assume percentages cannot be greater than 100% for ‘SameAutomComPtge’. Consequently, values greater than 100 are converted to NA

```
elec[elec$SameAutomComPtge>100,c('Name','Population',
                             'ProvinceCode','Autonomous_Community','SameAutomComPtge')]
```

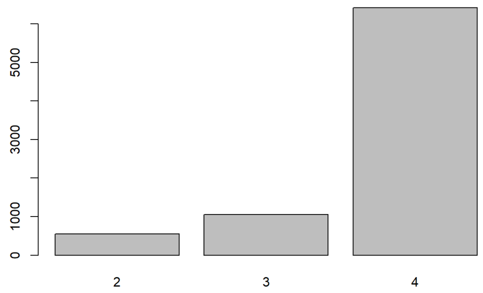
```
##                Name Population ProvinceCode Autonomous_Community
## 1148 Arenas del Rey       1241           18            Andalucía
## 1220       Iznalloz       5158           18            Andalucía
## 6883          Berja      12370            4            Andalucía
##      SameAutomComPtge
## 1148          127.156
## 1220          106.805
## 6883          102.401
```

```
elec$SameAutomComPtge=ifelse(elec$SameAutomComPtge>100, NA, elec$SameAutomComPtge)
summary(elec$SameAutomComPtge)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##    0.00   75.80   84.49   81.62   90.46  100.00       3
```

4) ‘Density’ has ‘?’ values. Convert them to NAs

```
elec$Density=as.factor(ifelse(elec$Density=='?', NA, elec$Density))
plot(elec$Density)
```



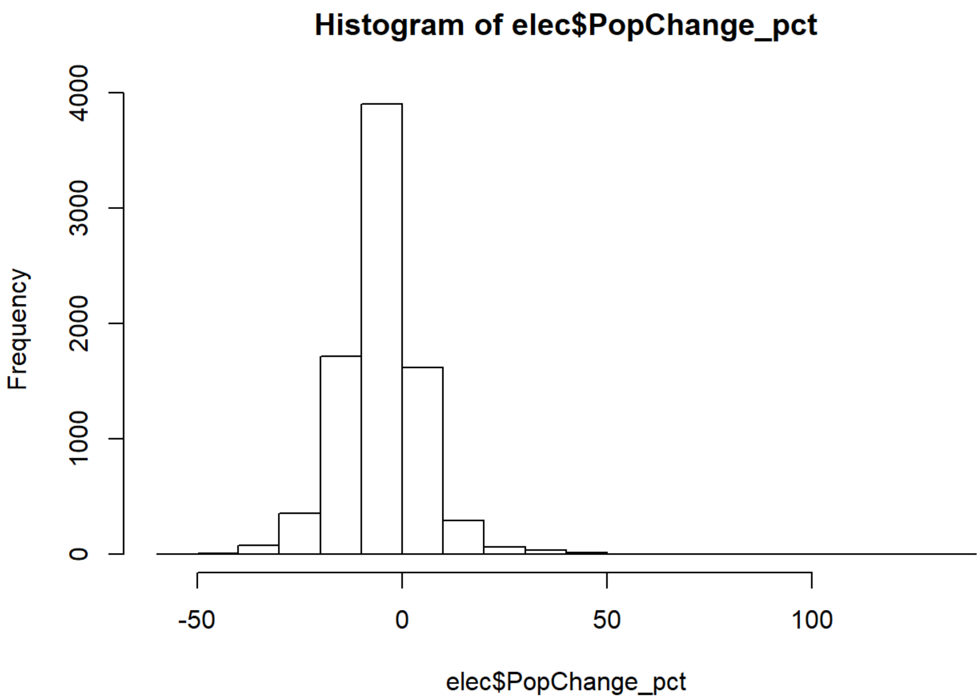

We have to pay special attention to outliers in this dataset. This is because some outliers are completely valid. For example, looking at the 'Population' variable there are two clear outliers ('Madrid and Barcelona') that should be included in the analysis. However, I cannot find any reasonable argument justifying a 138.46% population change in one year. Thus, we are going to modify those values.

IMPORTANT: We are not going to convert continuous variables to categorical. This is because we have several continuous variables and factorization will dramatically increase computational costs for 'lm' and 'glm' models. The main drawback of keeping continuous variables is that we might miss out non-linear relationships in our data.

Later on, we will see that it is possible to fix this problem by conducting mathematical transformations (e.g., x^2, log(x), …) in our continuous variables. By this way, linearity might be created with the target variable

5) Check if 138.46 is a valid max value for 'PobChange_pct'

```
hist(elec$PopChange_pct)
```




```
summary(elec$PopChange_pct)
```

```
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.     NA's
## -52.2700 -10.4000  -4.9600  -4.8974   0.0925 138.4600        7
```

```
# The following function counts the number of outliers and  transform it to missings
# (Function provided by my teacher)
outliersToMissing<-function(varaux){
  if (abs(skew(varaux))<1){
    criteria1<-abs((varaux-mean(varaux,na.rm=T))/sd(varaux,na.rm=T))>3
  } else {
    criteria1<-abs((varaux-median(varaux,na.rm=T))/mad(varaux,na.rm=T))>8
  }
  qnt <- quantile(varaux, probs=c(.25, .75), na.rm = T)
  H <- 3 * IQR(varaux, na.rm = T)
  criteria2<-(varaux<(qnt[1] - H))|(varaux>(qnt[2] + H))
  varaux[criteria1&criteria2]<-NA
  return(list(varaux,sum(criteria1&criteria2,na.rm=T)))
}


# (Function provided by my teacher)
quantVarNA_conversion<-function(vv,type){#type only accepts three possible values:'mean', 'median'
                                                                                   # or 'random'
  if (type=="mean"){
    vv[is.na(vv)]<-round(mean(vv,na.rm=T),4)
  } else if (type=="median"){
    vv[is.na(vv)]<-round(median(vv,na.rm=T),4)
  } else if (type=="random"){
    dd<-density(vv,na.rm=T,from=min(vv,na.rm = T),to=max(vv,na.rm = T))
    vv[is.na(vv)]<-round(approx(cumsum(dd$y)/sum(dd$y),dd$x,runif(sum(is.na(vv))))$y,4)
  }
  vv
}



elec$PopChange_pct=outliersToMissing(elec$PopChange_pct)[[1]]
elec$PopChange_pct=quantVarNA_conversion(elec$PopChange_pct,'random')
summary(elec$PopChange)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -52.270 -10.405  -4.970  -5.018   0.045  54.050
```

6) ‘officesNfacilities’: max value is ‘99999’, while median is 52
There is a clear significant difference between the greatest value (99999) and the second greatest (4759).
I am not going to make use of the previous outlier-detector function, but only convert 99999 values to NA.

```
unique(elec[elec$officesNfacilities>4000,c('Name','Population','ProvinceCode',
                                           'Autonomous_Community',
                                           'officesNfacilities')]$officesNfacilities)
```

```
## [1] 99999  4006  4759
```

```
elec$officesNfacilities=ifelse(elec$officesNfacilities==99999, median(elec$officesNfacilities),
                               elec$officesNfacilities)
summary(elec$officesNfacilities)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##     1.0    22.0    52.0   120.6   124.0  4759.0
```

7) Having a 100% Unemployment level at a specific age range is suspicious.  It is worth mentioning that if one of these variables (‘UnemployLess25_Ptge’, ‘Unemploy25_40_Ptge’, ‘UnemployMore40_Ptge’) have 100% as value, the remaining ones will be zero. (Collinearity).
I assume that having 100% in one of these categories is not valid.
For that reason, if there is a row having a value of 100% in one of the unemployment by age variables, I will convert them to NA. Then, I will pass the ‘quantVarNA_conversion’ function to them.

```
elec[(elec$UnemployLess25_Ptge==100|elec$Unemploy25_40_Ptge==100|elec$UnemployMore40_Ptge==100)
      | (elec$UnemployLess25_Ptge==0 & elec$Unemploy25_40_Ptge==0 & elec$UnemployMore40_Ptge==0),
                       c('UnemployLess25_Ptge', 'Unemploy25_40_Ptge','UnemployMore40_Ptge')] = NA


elec$UnemployLess25_Ptge=quantVarNA_conversion(elec$UnemployLess25_Ptge,'median')
elec$Unemploy25_40_Ptge=quantVarNA_conversion(elec$Unemploy25_40_Ptge,'median')
# elec$UnemployMore40_Ptge=quantVarNA_conversion(elec$UnemployMore40_Ptge,'random')

More40NA=elec[is.na(elec$UnemployMore40_Ptge),c('UnemployLess25_Ptge', 'Unemploy25_40_Ptge',
                                       'UnemployMore40_Ptge')]
More40NA=apply(More40NA[,c('UnemployLess25_Ptge', 'Unemploy25_40_Ptge')], 1,
               function(x) 100-sum(x)) #so that Unem_less_25 + Unem_25_40 + Unem_more_40 = 100

elec[is.na(elec$UnemployMore40_Ptge),c('UnemployMore40_Ptge')]=More40NA

summary(elec[,c('UnemployLess25_Ptge', 'Unemploy25_40_Ptge','UnemployMore40_Ptge')])
```

```
##  UnemployLess25_Ptge Unemploy25_40_Ptge UnemployMore40_Ptge
##  Min.   : 0.000      Min.   : 0.00      Min.   : 0.00
##  1st Qu.: 4.040      1st Qu.:35.00      1st Qu.:45.45
##  Median : 7.005      Median :40.93      Median :52.06
##  Mean   : 8.050      Mean   :40.32      Mean   :51.63
##  3rd Qu.:10.361      3rd Qu.:45.83      3rd Qu.:57.14
##  Max.   :80.000      Max.   :87.50      Max.   :94.74
```

Same idea with Unemployment by industry functions
I am going to convert these values to NAs and then pass the ‘quantVarNA_conversion’ function to those NA values.

```
elec[(elec$AgricultureUnemploymentPtge==100|elec$IndustryUnemploymentPtge==100|elec$ConstructionUnemployment
Ptge==100|elec$ServicesUnemploymentPtge==100)
      | (elec$AgricultureUnemploymentPtge==0 & elec$IndustryUnemploymentPtge==0 & elec$ConstructionUnemploym
entPtge==0 & elec$ServicesUnemploymentPtge==0),
                       c('AgricultureUnemploymentPtge','IndustryUnemploymentPtge',
                         'ConstructionUnemploymentPtge','ServicesUnemploymentPtge')] = NA



elec$ServicesUnemploymentPtge = quantVarNA_conversion(elec$ServicesUnemploymentPtge,'median')
elec$IndustryUnemploymentPtge = quantVarNA_conversion(elec$IndustryUnemploymentPtge,'median')
elec$ConstructionUnemploymentPtge = quantVarNA_conversion(elec$ConstructionUnemploymentPtge,'median')

AgricultureNA=elec[is.na(elec$AgricultureUnemploymentPtge),c('IndustryUnemploymentPtge',
                         'ConstructionUnemploymentPtge','ServicesUnemploymentPtge','AgricultureUnemployment
Ptge')]

AgricultureNA=apply(AgricultureNA[,c('IndustryUnemploymentPtge','ConstructionUnemploymentPtge',
                                     'ServicesUnemploymentPtge')], 1, function(x) 100-sum(x))

elec[is.na(elec$AgricultureUnemploymentPtge),c('AgricultureUnemploymentPtge')]=AgricultureNA

summary(elec[,c('AgricultureUnemploymentPtge','IndustryUnemploymentPtge',
                'ConstructionUnemploymentPtge','ServicesUnemploymentPtge')])
```

```
##  AgricultureUnemploymentPtge IndustryUnemploymentPtge
##  Min.   : 0.000              Min.   : 0.000
##  1st Qu.: 1.573              1st Qu.: 4.617
##  Median : 7.692              Median : 8.929
##  Mean   :10.813              Mean   :10.794
##  3rd Qu.:19.317              3rd Qu.:14.286
##  Max.   :90.909              Max.   :82.000
##  ConstructionUnemploymentPtge ServicesUnemploymentPtge
##  Min.   : 0.000               Min.   : 0.00
##  1st Qu.: 6.365               1st Qu.:53.85
##  Median : 9.849               Median :61.91
##  Mean   :11.703               Mean   :60.34
##  3rd Qu.:14.118               3rd Qu.:68.42
##  Max.   :86.486               Max.   :95.65
```

Let’s make sure there are no NAs in our debugged dataset.

I make a distinction between numeric and non_numeric variables that still include NAs

```
sapply(elec[,sapply(elec, function(x) sum(is.na(x))>0)],
                             function(x) is.numeric(x)) #We make distiction between
```

```
##      SameAutomComPtge        totalCompanies              Industry
##                  TRUE                  TRUE                  TRUE
##       ConstructionInd     commerceNhostelry            ServiceInd
##                  TRUE                  TRUE                  TRUE
##          RealProperty               Pob2010           SurfaceArea
##                  TRUE                  TRUE                  TRUE
##               Density People_RealProp_ratio
##                 FALSE                  TRUE
```

```
                                                          #numeric and non_numberic vars
```

variables with NAs are split into factor variables and numeric ones.
Now, there should be no NAs in the entire dataset

```
quantNAvars=rownames(data.frame(sapply(elec[,sapply(elec, function(x) sum(is.na(x))>0)],
function(x) is.numeric(x))))[!(rownames(data.frame(sapply(elec[,sapply(elec,
function(x) sum(is.na(x))>0)], function(x) is.numeric(x)))) %in% 'Density')]

elec[,quantNAvars]=sapply(quantNAvars, function(x) quantVarNA_conversion(elec[,x],'median'))

categNAvars='Density'
elec$Density[is.na(elec$Density)] = '4'
elec$Density=as.factor(elec$Density)

sapply(elec, function(x) sum(is.na(x)))
```

```
##                        Name                 ProvinceCode
##                           0                            0
##          Autonomous_Community                  Population
##                           0                            0
##                 TotalCensus              AbstentionPtge
##                           0                            0
##          High_Abstention_rate                Left_wing_Pct
##                           0                            0
##               Right_wing_Pct                  Others_Pct
##                           0                            0
##                   Left_wing                  Right_wing
##                           0                            0
##                 Age_0_4_Ptge              Age_under19_Ptge
##                           0                            0
##                Age_19_65_pct              Age_over65_pct
##                           0                            0
##          FemalePopulationPtge              ForeignersPtge
##                           0                            0
##              SameAutomComPtge      SameAutonComDiffProvPtge
##                           0                            0
##               DifAutonComPtge          UnemployLess25_Ptge
##                           0                            0
##             Unemploy25_40_Ptge          UnemployMore40_Ptge
##                           0                            0
##   AgricultureUnemploymentPtge      IndustryUnemploymentPtge
##                           0                            0
## ConstructionUnemploymentPtge      ServicesUnemploymentPtge
##                           0                            0
##               totalCompanies                    Industry
##                           0                            0
##              ConstructionInd             commerceNhostelry
##                           0                            0
##                   ServiceInd                MainActivity
##                           0                            0
##                 RealProperty                     Pob2010
##                           0                            0
##                  SurfaceArea                     Density
##                           0                            0
##                PopChange_pct          People_RealProp_ratio
##                           0                            0
##             officesNfacilities
##                           0
```

save file as RDS

```
saveRDS(elec, 'Debugged_elect_dataset')
```

**LINEAR MODELS**

LET'S DEFINE A BINARY TARGET VARIABLE FOR LOGISTIC REGRESSION AND CONTINUOUS TARGET VARIABLE FOR LINEAR REGRESSION

BINARY -> Right_wing
CONTINUOUS -> AbstentionPtge

Let's get rid of the other potential target variables that we are not going to use.
I am also going to remove 'Name' since each observation has a unique name.

```
options(warn=-1)

rowdata=as.data.frame(readRDS('C:/Users/pablo/Desktop/Debugged_elect_dataset'))

df=rowdata[,!(names(rowdata) %in% c('Left_wing_Pct','Right_wing_Pct','Others_Pct',
                                    'High_Abstention_rate','Left_wing','Right_wing','Name',
                                    'AbstentionPtge'))]
total_lm=as.data.frame(cbind(AbstentionPtge=rowdata$AbstentionPtge,df))

# head(total_lm,2)
```

IMPORTANT: there are collinearity issues in both unemployment and industry variables:
In order to avoid collinearity, We just have to remove one of the variables.

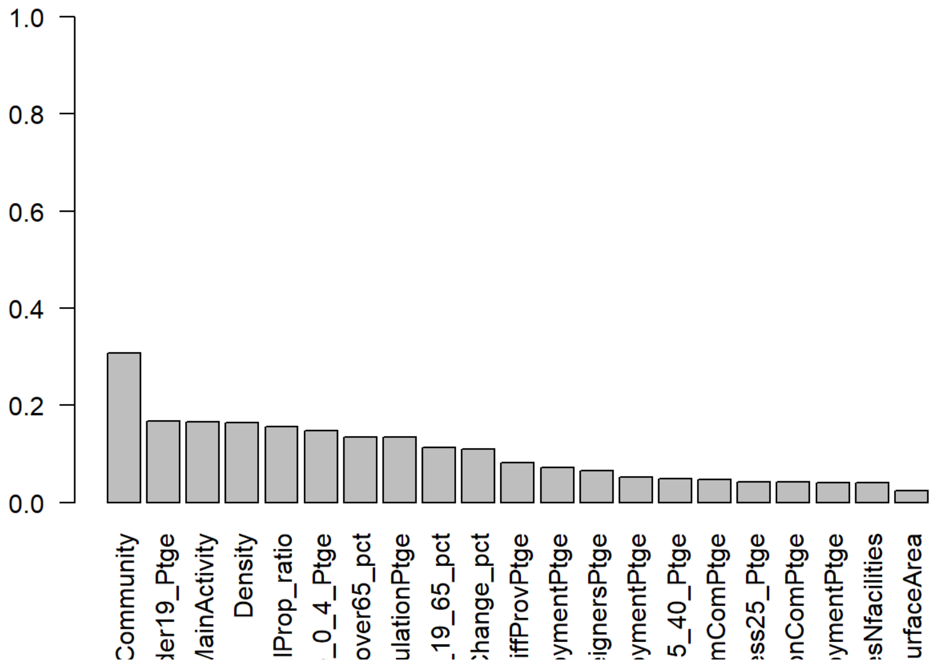
Let's make sure they have been successfully removed

```
total_lm=total_lm[, !(names(total_lm) %in% c('UnemployMore40_Ptge','AgricultureUnemploymentPtge'))]
total_lm[1:2, 14:20]
```

```
##   DifAutonComPtge UnemployLess25_Ptge Unemploy25_40_Ptge
## 1          19.345               2.381             54.762
## 2           7.226              16.216             32.432
##   IndustryUnemploymentPtge ConstructionUnemploymentPtge
## 1                    9.524                       11.905
## 2                    8.108                       10.811
##   ServicesUnemploymentPtge totalCompanies
## 1                   73.810             15
## 2                   67.568             11
```

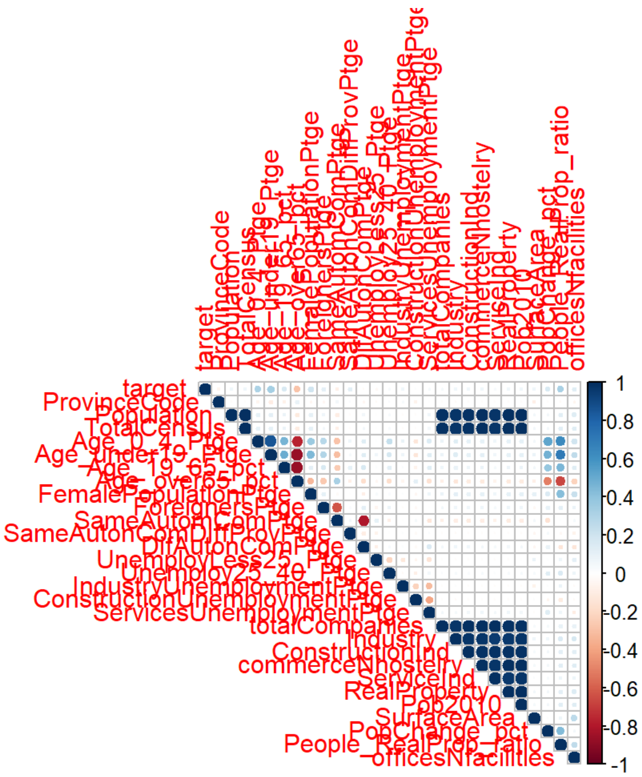
Significance of variables

```
# functions provided by my teacher
Vcramer<-function(v,target){
  if (is.numeric(v)){
    v<-cut(v,5)
  }
  if (is.numeric(target)){
    target<-cut(target,5)
  }
  cramer.v(table(v,target))
}

VcramerGraph<-function(matrix, target){
  outputVcramer<-sapply(matrix,function(x) Vcramer(x,target))
  barplot(sort(outputVcramer,decreasing =T),las=2,ylim=c(0,1))
}

VcramerGraph(total_lm[,3:ncol(total_lm)], total_lm$AbstentionPtge)
```




correlation among variables (only for numeric ones)

```
input=total_lm[,!(names(total_lm) %in% c('AbstentionPtge','Right_wing'))]
target=total_lm$AbstentionPtge

corrplot(cor(cbind(target,Filter(is.numeric, input)), use="pairwise",
             method="pearson"), method = "circle",type = "upper")
```




I am going to make mathematical transformations (e.g., x^2, log(x), …) in our continuous variables.
It is a good practice because these transformations sometimes help create linearity with the target variable.

```r
# function provided by my teacher
bestTransfCorr<-function(vv,target){
  vv<-scale(vv)
  vv<-vv+abs(min(vv,na.rm=T))*1.0001
  posiblesTransf<-data.frame(x=vv,logx=log(vv),expx=exp(vv),sqrx=vv^2,sqrtx=sqrt(vv),cuartax=vv^4,raiz4=vv^(1/4))
  return(list(colnames(posiblesTransf)[which.max(abs(cor(target,posiblesTransf, use="complete.obs")))],posiblesTransf[,which.max(abs(cor(target,posiblesTransf, use="complete.obs")))]))
}

only_numeric_vars=total_lm[,as.vector(sapply(total_lm, function(x) is.numeric(x))) & (!(names(total_lm) %in% 'AbstentionPtge'))]
transformed_total_lm=total_lm
transformed_total_lm[,as.vector(sapply(transformed_total_lm, function(x) is.numeric(x))) & (!(names(transformed_total_lm) %in% 'AbstentionPtge'))] =
sapply(only_numeric_vars, function(x) bestTransfCorr(x,total_lm$AbstentionPtge)[[2]])

#head(transformed_total_lm,2)
#head(total_lm,2)
```

Let’s check how useful these mathematical transformations have been.
To do so, R_square of both normal and transformed variables will be evaluated.
‘transformed_data’ will be used from now on

```r
# MY FIRST MODEL
# Function provided by my teacher
Rsq<-function(model,target,data){
  testpredicted<-predict(model, data)
  testReal<-data[,target]
  sse <- sum((testpredicted - testReal) ^ 2)
  sst <- sum((testReal - mean(testReal)) ^ 2)
  1 - sse/sst
}

model1=lm(total_lm$AbstentionPtge ~ ., total_lm)
paste('R_sq_normal_data', round(Rsq(model1,'AbstentionPtge', total_lm), digits=3), '%')
```

```
## [1] "R_sq_normal_data 0.382 %"
```

```
transformedModel=lm(total_lm$AbstentionPtge ~ ., transformed_total_lm)
paste('R_sq_transformed_data',round(Rsq(transformedModel,'AbstentionPtge',
                                        transformed_total_lm), digits=3), '%')
```

```
## [1] "R_sq_transformed_data 0.403 %"
```

Let’s create all possible combinations of variables

```
# function provided by teacher
#It generates all possible interactions
varInteractions<-function(data,position){ #position refers to index where target var is
  list_of_factors<-c()
  list_of_interactions<-paste(names(data)[position],'~')
  names<-names(data)
  for (i in (1:length(names))[-position]){
    list_of_interactions<-paste(list_of_interactions,names[i],'+')
    if (class(data[,i])=="factor"){
      list_of_factors<-c(list_of_factors,i)
      for (j in ((1:length(names))[-c(position,list_of_factors)])){
        list_of_interactions<-paste(list_of_interactions,names[i],':',names[j],'+')
      }
    }
  }
  list_of_interactions<-substr(list_of_interactions, 1, nchar(list_of_interactions)-1)
  list_of_interactions
}

transformed_interactions=varInteractions(transformed_total_lm, 1)
```

Let’s check R_sq of model including all possible interactions

```
# summary(lm(transformed_interactions, data_train))
Rsq(lm(transformed_interactions, transformed_total_lm), 'AbstentionPtge', transformed_total_lm) # a little b
it better
```

```
## [1] 0.4392858
```

This model only includes the most significant variables with no interactions

```
handmadeModel=lm(AbstentionPtge ~ Autonomous_Community + TotalCensus + FemalePopulationPtge + SameAutomComPt
ge + ConstructionUnemploymentPtge + totalCompanies + Industry + ConstructionInd + commerceNhostelry + Servic
eInd + MainActivity + RealProperty + SurfaceArea + PopChange_pct, transformed_total_lm)
# I only include the most significant variables with no interactions
# summary(handmadeModel)
Rsq(handmadeModel,'AbstentionPtge', transformed_total_lm)
```

```
## [1] 0.3944185
```

Most significant variables. Now including interactions

```
handmadeModel2=lm(AbstentionPtge ~ Autonomous_Community + TotalCensus + FemalePopulationPtge + SameAutomComP
tge + ConstructionUnemploymentPtge + totalCompanies + Industry + ConstructionInd + commerceNhostelry + Servi
ceInd + MainActivity + RealProperty + SurfaceArea + PopChange_pct + MainActivity : Population + MainActivity
: TotalCensus + MainActivity : totalCompanies + MainActivity : PopChange_pct, transformed_total_lm)

# Most significant variables. Now including interactions
# summary(handmadeModel2)
Rsq(handmadeModel2,'AbstentionPtge', transformed_total_lm)
```

```
## [1] 0.4059849
```

OUTPUT OF THIS CELL IS TOO LONG. THAT’S WHY IT IS NOT GOING TO BE RUN

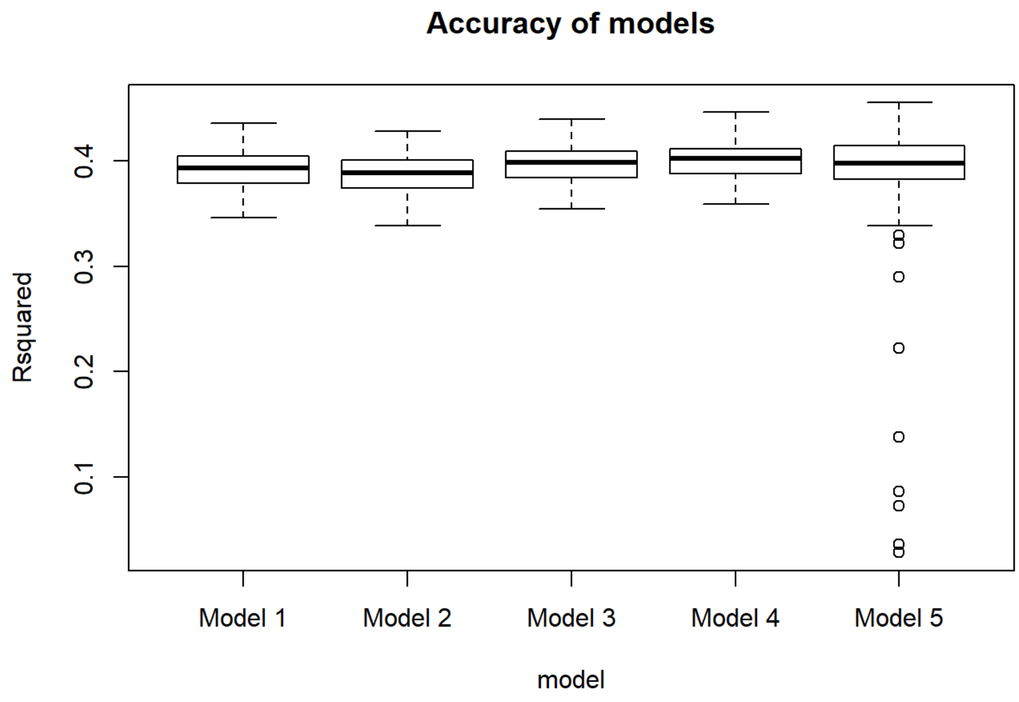
```
# nullmodel=lm(AbstentionPtge ~ 1, transformed_total_lm)
# fullmodel=lm(transformed_interactions, transformed_total_lm)

# BICmodel=step(nullmodel, scope=list(lower=nullmodel, upper=fullmodel), direction='both',
#               k=log(nrow(transformed_total_lm)))
# # summary(BICmodel)
# # Rsq(BICmodel, 'AbstentionPtge', transformed_total_lm) >>>0.407283270714246

# AICmodel=step(nullmodel, scope=list(lower=nullmodel, upper=fullmodel), direction='both')
# # summary(AICmodel)
# # Rsq(AICmodel, 'AbstentionPtge', transformed_total_lm) >>>0.420388579593511
```

THESE ARE THE LIST OF THE POTENTIAL MODELS:

```
nullmodel=lm(AbstentionPtge ~ 1, transformed_total_lm)
fullmodel=lm(transformed_interactions, transformed_total_lm)

model1=lm(AbstentionPtge ~ ., transformed_total_lm)

handmadeModel=lm(AbstentionPtge ~ Autonomous_Community + TotalCensus + FemalePopulationPtge +
                 SameAutomComPtge + ConstructionUnemploymentPtge + totalCompanies + Industry +
                 ConstructionInd + commerceNhostelry + ServiceInd + MainActivity + RealProperty +
                 SurfaceArea + PopChange_pct, transformed_total_lm)

handmadeModel2=lm(AbstentionPtge ~ Autonomous_Community + TotalCensus + FemalePopulationPtge +
                  SameAutomComPtge + ConstructionUnemploymentPtge + totalCompanies + Industry +
                  ConstructionInd + commerceNhostelry + ServiceInd + MainActivity +
                  RealProperty + SurfaceArea + PopChange_pct + MainActivity : Population +
                  MainActivity : TotalCensus + MainActivity : totalCompanies +
                  MainActivity : PopChange_pct, transformed_total_lm)

BICmodel=lm(AbstentionPtge ~ Autonomous_Community + Density + FemalePopulationPtge +
    Age_19_65_pct + Industry + People_RealProp_ratio + SameAutonComDiffProvPtge +
    Population + MainActivity + SurfaceArea + Density:People_RealProp_ratio +
    FemalePopulationPtge:MainActivity, transformed_total_lm)



AICmodel=lm(AbstentionPtge ~ Autonomous_Community + RealProperty + MainActivity +
    FemalePopulationPtge + Age_19_65_pct + ProvinceCode + SameAutonComDiffProvPtge +
    People_RealProp_ratio + Population + SurfaceArea + Industry +
    SameAutomComPtge + Age_under19_Ptge + ConstructionInd + Age_over65_pct +
    Autonomous_Community:MainActivity + RealProperty:MainActivity +
    MainActivity:FemalePopulationPtge + MainActivity:SameAutonComDiffProvPtge +
    MainActivity:Age_19_65_pct + MainActivity:Age_under19_Ptge, transformed_total_lm)
```

boxplot of models' accuracy.Data split method: cross validation
* BEST MODEL (in terms of R_squared_mean): MODEL4 -> BICmodel
* BEST MODEL (in terms of R_squared_standard_deviation): MODEL3 -> handmadeModel2

```
data=transformed_total_lm
# data$AbstentionPtge=make.names(data$AbstentionPtge) #this step is mandatory, otherwise
# train() will return an error

models=sapply(list(model1, handmadeModel, handmadeModel2, BICmodel, AICmodel),
              function(x) formula(x))

total=c()
for (i in 1:length(models)) {
    set.seed(652)
    cross_validation=train(as.formula(models[[i]]), data=data, method='lm',
                           trControl=trainControl(method="repeatedcv", number=5, repeats=20,
                                                  returnResamp="all"))
  total<-rbind(total,data.frame(cross_validation$resample,
                                model=rep(paste("Model",i),nrow(cross_validation$resample))))
}

# head(total,3)
boxplot(Rsquared~model,data=total,main="Accuracy of models")
```




```
sort_by_mean=as.data.frame(aggregate(Rsquared ~ model, data=total, mean))
by_mean=sort_by_mean[order(-sort_by_mean$Rsquared),]
names(by_mean)=c('Model','Rsquared_mean')
by_mean
```

```
##     Model Rsquared_mean
## 4 Model 4     0.4008136
## 3 Model 3     0.3974955
## 1 Model 1     0.3924420
## 2 Model 2     0.3884584
## 5 Model 5     0.3809804
```

```
sort_by_SD=as.data.frame(aggregate(Rsquared ~ model, data=total, sd))
by_SD=sort_by_SD[order(sort_by_SD$Rsquared),]
names(by_SD)=c('Model','Rsquared_SD')
by_SD
```

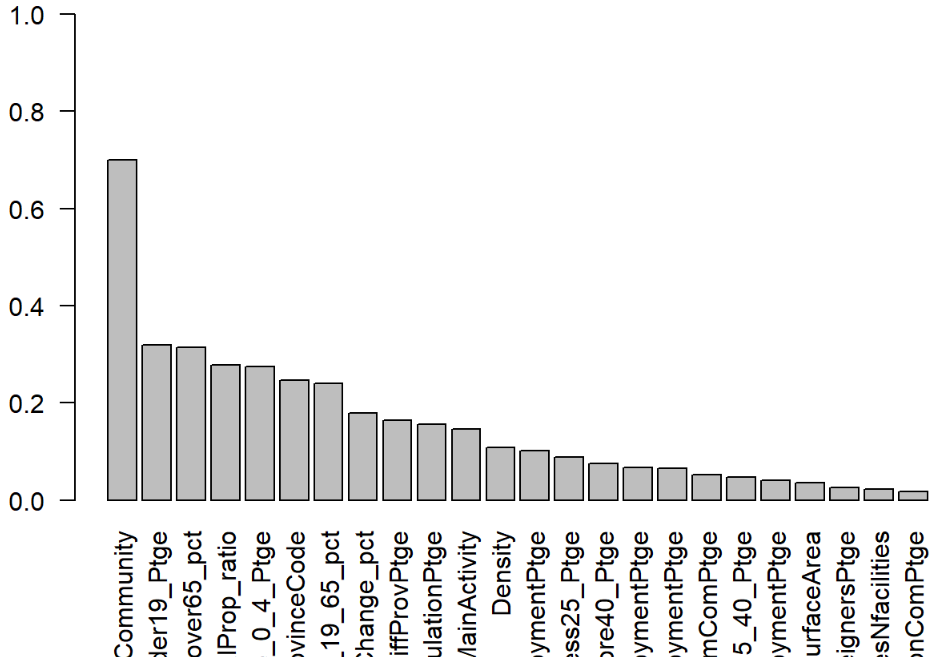
```
##     Model Rsquared_SD
## 3 Model 3  0.01806530
## 2 Model 2  0.01841971
## 1 Model 1  0.01853401
## 4 Model 4  0.01867398
## 5 Model 5  0.07810699
```

**Logistic regression models**
BINARY (our targer var for glm) -> Right_wing
CONTINUOUS (previous lm model) -> AbstentionPtge

```
### LOGISTIC REGRESSION MODEL FOR BINARY TARGET VARIABLE
# Let's get rid of the other potential target variables we havent used
noTargetVars=rowdata[,!(names(rowdata) %in% c('Name','Left_wing_Pct','Right_wing_Pct','Others_Pct',
                                     'High_Abstention_rate','Left_wing','AbstentionPtge',
                                     'Right_wing'))]

# BINARY (our targer var for glm) -> Right_wing
# CONTINUOUS (previous lm model) -> AbstentionPtge

total_glm=cbind(Right_wing=rowdata$Right_wing, noTargetVars)
#head(total_glm,2)
```

Significance of variables using Cramer's V graph

```
VcramerGraph(total_glm[,2:ncol(total_glm)], total_glm$Right_wing)
```




(In the following cell I am going to select the mathematical transformation that maximizes Cramer's V with the target variable)

```
# function provided by my teacher
bestTransfVcramer<-function(vv,target){
  vv<-scale(vv)
  vv<-vv+abs(min(vv,na.rm=T))*1.0001
  possibleTransf<-data.frame(x=vv,logx=log(vv),expx=exp(vv),sqrx=vv^2,sqrtx=sqrt(vv),cuartax=vv^4,raiz4=vv^(
1/4))
  return(list(colnames(possibleTransf)[which.max(apply(possibleTransf,2,function(x) cramersV(x,target)))],po
ssibleTransf[,which.max(apply(possibleTransf,2,function(x) cramersV(x,target)))]))
}

only_numeric_vars=total_glm[,as.vector(sapply(total_glm, function(x) is.numeric(x))) & (!(names(total_glm) %
in% 'Right_wing'))]


transfData=total_glm
transfData[,as.vector(sapply(total_glm, function(x) is.numeric(x))) & (!(names(total_glm) %in% 'Right_wing')
)]=sapply(only_numeric_vars,
                     function(x) bestTransfVcramer(x,total_glm$Right_wing)[[2]])
```

We obtain same accuracy with transfData. We will use 'transfData' from now on, even though it does not matter using 'total_glm'

```
# Function provided by my teacher
#Evaluate logistic_regression_pseudo-R2 in any data set
pseudoR2<-function(modelo,dd,nombreVar){
  pred.out.link <- predict(modelo, dd, type = "response")
  mod.out.null <- glm(as.formula(paste(nombreVar,"~1")), family = binomial, data = dd)
  pred.out.linkN <- predict(mod.out.null, dd, type = "response")
  1-sum((dd[,nombreVar]==1)*log(pred.out.link)+log(1 -pred.out.link)*(1-(dd[,nombreVar]==1)))/
    sum((dd[,nombreVar]==1)*log(pred.out.linkN)+log(1 -pred.out.linkN)*(1-(dd[,nombreVar]==1)))
}

previousModel=glm(Right_wing ~ ., data=total_glm, family=binomial)
paste('pseudoR2_normal_data',round(pseudoR2(previousModel,total_glm,"Right_wing"),
                                        digits=3), '%')
```

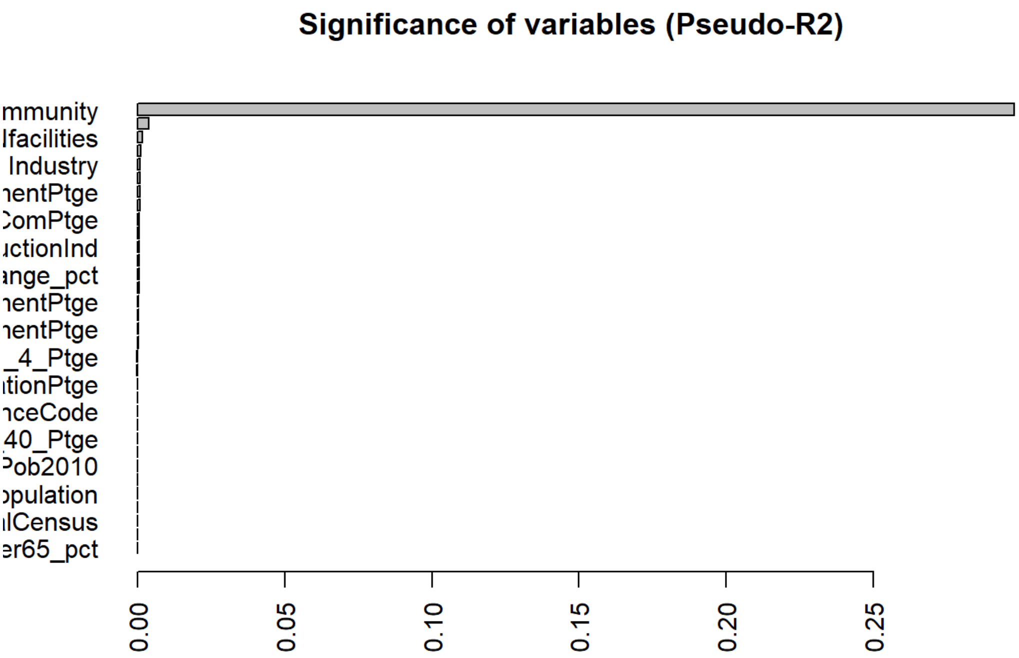
```
## [1] "pseudoR2_normal_data 0.449 %"
```

```
transfModel=glm(Right_wing ~ ., data=transfData, family=binomial)
paste('pseudoR2_transfData',round(pseudoR2(transfModel,transfData,"Right_wing"),
                                        digits=3), '%')
```

```
## [1] "pseudoR2_transfData 0.449 %"
```

Graph displyaing input features' significance in the 'transfModel'

```
# function provided by my teacher
impVariablesLog<-function(modelo,nombreVar,dd=data_train){
  null<-glm(as.formula(paste(nombreVar,"~1")),data=dd,family=binomial)
  aux2<-capture.output(aux<-step(modelo, scope=list(lower=null, upper=modelo), direction="backward",k=0,step
s=1))
  aux3<-read.table(textConnection(aux2[grep("-",aux2)]))[,c(2,5)]
  aux3$V5<-(aux3$V5-modelo$deviance)/modelo$null.deviance
  barplot(aux3$V5,names.arg = aux3$V2,las=2,horiz=T,main="Significance of variables (Pseudo-R2)")
}

impVariablesLog(transfModel, 'Right_wing', transfData)
```




As may be inferred, 'Autonomous_Community' is clearly the most significant variable (This pseudoR2 confirms what we have already observed in the 'impVariablesLog' graph )

```
AACCmodel=glm(Right_wing ~ Autonomous_Community, data=transfData, family=binomial)
pseudoR2(AACCmodel, transfData, 'Right_wing')
```

```
## [1] 0.4279396
```

Best score at the moment. Then main drawback is that it includes a lot of variables and we are not looking for super complex models. We want something easier to interpret.

```
transformed_interactions=varInteractions(transfData, 1)
fullmodel=glm(transformed_interactions, family=binomial, data=transfData)
pseudoR2(fullmodel, transfData, 'Right_wing')
```

```
## [1] 0.4929482
```

handmadeModel: including those interactions with the lowest p-value. (Selected interactions at least have '**' as significance level)

```
formula=as.formula('Right_wing ~ . + totalCompanies:MainActivity + Industry:Density + ConstructionInd:Density + SameAutonComDiffProvPtge:Density +
UnemployLess25_Ptge:MainActivity + Unemploy25_40_Ptge:MainActivity + UnemployMore40_Ptge:MainActivity')
handmadeModel=glm(formula, data=transfData, family=binomial)
# handmadeModel
pseudoR2(handmadeModel, transfData, 'Right_wing')
```

```
## [1] 0.457309
```

The following cell is not going to be run, since output gets too long

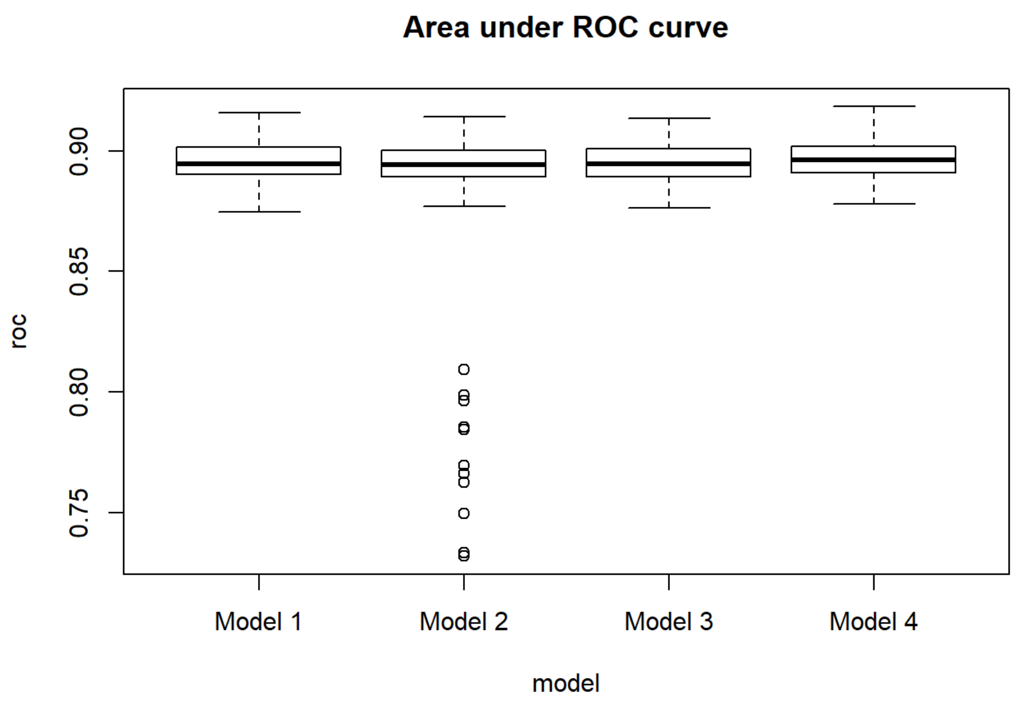
```
# nullmodel=glm(Right_wing ~ 1, family=binomial, data=transfData)

# fullmodel=glm(transformed_interactions, family=binomial, data=transfData)


# BICmodel=step(nullmodel, scope=list(lower=nullmodel, upper=fullmodel), direction='both',
#                k=log(nrow(transfData)))

# AICmodel=step(nullmodel, scope=list(lower=nullmodel, upper=fullmodel), direction='both')
```

MODELS:

```
firstmodelFormula=as.formula('Right_wing ~ .')

handmadeModelFormula=as.formula('Right_wing ~ . + totalCompanies:MainActivity + Industry:Density +
    ConstructionInd:Density + SameAutonComDiffProvPtge:Density +
    UnemployLess25_Ptge:MainActivity + Unemploy25_40_Ptge:MainActivity +
    UnemployMore40_Ptge:MainActivity')

BICmodelFormula=as.formula('Right_wing ~ Autonomous_Community + Age_19_65_pct +
    officesNfacilities + MainActivity + ServiceInd + RealProperty + ForeignersPtge +
    commerceNhostelry')

AICmodelFormula=as.formula('Right_wing ~ Autonomous_Community + MainActivity + ServiceInd +
    Age_19_65_pct + ForeignersPtge + RealProperty + officesNfacilities +
    commerceNhostelry + SameAutonComDiffProvPtge + People_RealProp_ratio +
    PopChange_pct + UnemployLess25_Ptge + SurfaceArea + ServicesUnemploymentPtge +
    IndustryUnemploymentPtge + Autonomous_Community:MainActivity +
    MainActivity:ForeignersPtge + MainActivity:officesNfacilities +
    MainActivity:UnemployLess25_Ptge + MainActivity:SameAutonComDiffProvPtge')

model1=glm(firstmodelFormula, family=binomial, data=transfData)
model2=glm(handmadeModelFormula, family=binomial, data=transfData)
model3=glm(BICmodelFormula, family=binomial, data=transfData)
model4=glm(AICmodelFormula, family=binomial, data=transfData)
```

boxplot of models' accuracy. (Data split mehtod: cross validation)
* BEST MODEL: MODEL4 -> AICmodel

```r
data=transfData
# data$AbstentionPtge=make.names(data$AbstentionPtge) #this step is mandatory, otherwise
# train() will return an error

data$Right_wing=make.names(data$Right_wing) #convert target to character: values -> 'X0' and 'X1'

models=sapply(list(model1, model2, model3, model4), function(x) formula(x))

total=c()
for (i in 1:length(models)) {
    set.seed(192)
    cross_validation=train(as.formula(models[[i]]), data=data, method='glm', family='binomial',
                           metric='ROC', trControl=trainControl(method="repeatedcv", number=5,
                                                                repeats=20,
                                                                summaryFunction=twoClassSummary,
                                                                classProbs=TRUE,
                                                                returnResamp="all"))

  total<-rbind(total,data.frame(roc=cross_validation$resample[,1],
                                model=rep(paste("Model",i),nrow(cross_validation$resample))))
}

boxplot(roc~model,data=total,main="Area under ROC curve")
```




```r
sort_by_mean=as.data.frame(aggregate(roc ~ model, data=total, mean))
sort_by_mean=sort_by_mean[order(-sort_by_mean$roc),]
names(sort_by_mean)=c('Model','Rsquared_mean')
sort_by_mean
```

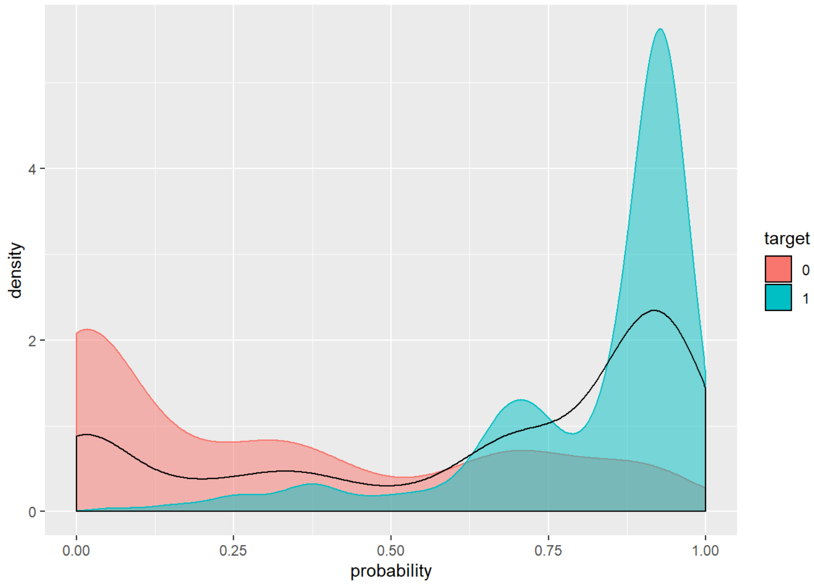
```
##     Model Rsquared_mean
## 4 Model 4     0.8963939
## 1 Model 1     0.8956538
## 3 Model 3     0.8950435
## 2 Model 2     0.8821663
```

```r
sort_by_SD=as.data.frame(aggregate(roc ~ model, data=total, sd))
sort_by_SD=sort_by_SD[order(sort_by_SD$roc),]
names(sort_by_SD)=c('Model','Rsquared_sd')
sort_by_SD
```

```
##      Model Rsquared_sd
## 4 Model 4 0.007489163
## 3 Model 3 0.007617589
## 1 Model 1 0.007643041
## 2 Model 2 0.040582090
```

distribution of values of the binary target variable (Right_wing)

```
options(repr.plot.width=4, repr.plot.height=3)
data=transfData

trainIndex=createDataPartition(data$Right_wing, p=0.8, list=FALSE)  #we make this transformation before visu
alizing models' boxplots
data_train=data[trainIndex,]
data_test=data[-trainIndex,]

winner_model=model4


# function provided by my teacher
hist_binaryTarget=function(var, target, title_of_x_axis) {
    values=data.frame(variable=var, target=target)
    ggplot(values, aes(x=var)) +
        geom_density(aes(colour=target, fill=target), alpha=0.5) +
        geom_density(lty=1) +
        xlab(title_of_x_axis)
}

set.seed(4545)
trainIndex=createDataPartition(data$Right_wing, p=0.8, list=FALSE)
data_train=data[trainIndex,]
data_test=data[-trainIndex,]

y_pred=predict(winner_model, newdata=data_test, type='response')
hist_binaryTarget(y_pred, data_test$Right_wing,'probability')
```




The by default partition point is 0.5 in logistic regressions. Let’s check whether 0.5 is actually the optimal partition value
We are going to maintain 0.5 as partition value since the model presents the greatest accuracy score at 0.5 and the Youden metric is good enough at this value.

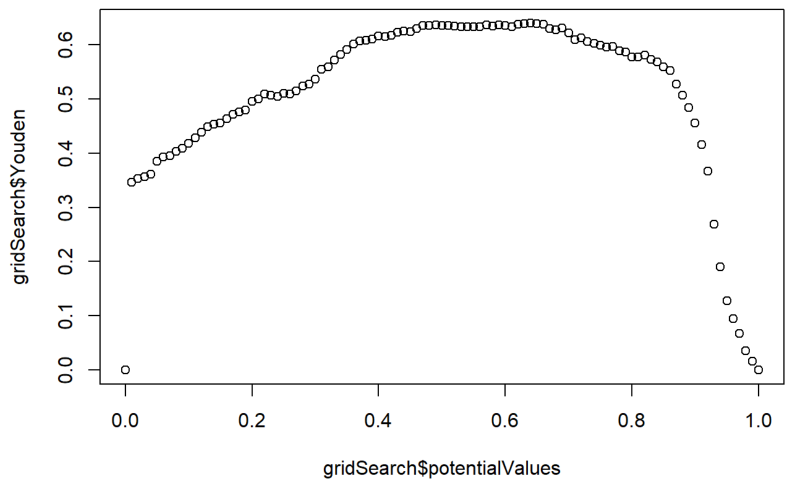
```
# function provided by my teacher
partitionPointMetrics=function(model, dataset, target_var_as_string,
                               partitionValue, positive_class) {
    probs=predict(model, newdata=dataset, type='response')
    cm=confusionMatrix(data=factor(ifelse(probs > partitionValue, 1, 0)),
                       reference=dataset[, target_var_as_string], positive=positive_class)
    c(cm$overall[1], cm$byClass[1:4])
}

# Let's test values
potentialValues=seq(0,1,0.01) #sequence of 0.01 evenly splitted values between 0 and 1.

# data_test[,'Right_wing']
gridSearch=data.frame(cbind(potentialValues, t(sapply(potentialValues, function(x)
    partitionPointMetrics(winner_model, data_test, 'Right_wing',x,'1')))))


gridSearch$Youden=gridSearch$Sensitivity + gridSearch$Specificity - 1 #we have included a new
                                                                      #accuracy method

# optimal values
gridSearch[gridSearch$Youden==max(gridSearch$Youden),c('potentialValues','Youden')]
```

```
##    potentialValues    Youden
## 65            0.64 0.6393099
```

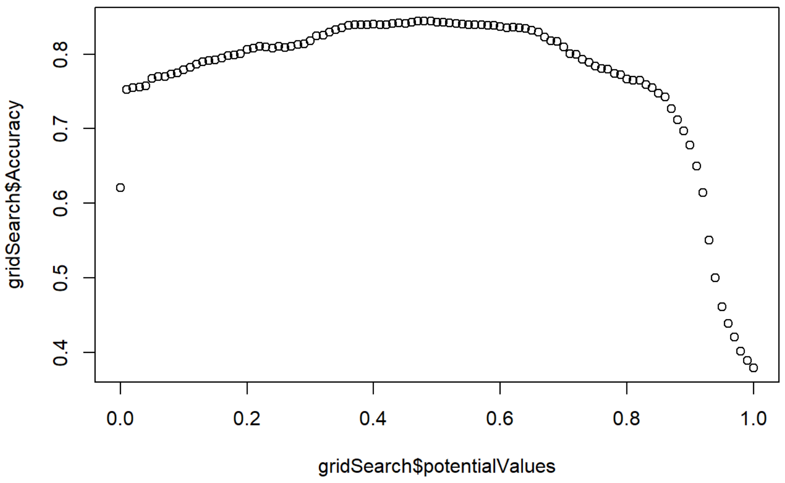
```
gridSearch[gridSearch$Accuracy==max(gridSearch$Accuracy),c('potentialValues','Accuracy')]
```

```
##    potentialValues  Accuracy
## 48            0.47 0.8441158
## 49            0.48 0.8441158
## 50            0.49 0.8441158
```

```
# GRAPHS
plot(gridSearch$potentialValues, gridSearch$Youden)
```




```
plot(gridSearch$potentialValues, gridSearch$Accuracy)
```




**PART II**

Time Series: US monthly unemployment rate from 2007-08 to present moment

```
options(warn=-1)

data=read.csv('C:/Users/pablo/Desktop/US_unemployment.csv')
names(data)=c('Date','Unemployment_rate')
data=data[(nrow(data)-149):nrow(data),] #we want 150 observations
nrow(data)
```

```
## [1] 150
```

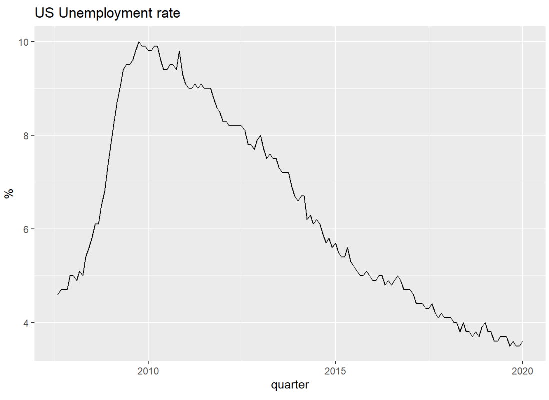
```
head(data,2)
```

```
##           Date Unemployment_rate
## 716 2007-08-01               4.6
## 717 2007-09-01               4.7
```

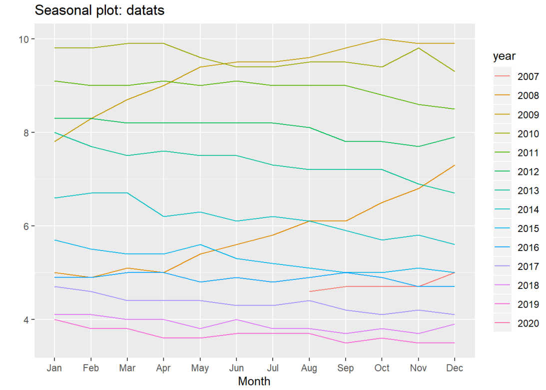
Convert dataframe to timeseries object

As may be inferred in ggseasonplot(), there is no clear seasonal behaviour

```
datats=ts(data[,-1], start=c(2007,8), frequency=12) #monthly frequency

autoplot(datats) + ggtitle('US Unemployment rate') + xlab('quarter') + ylab('%')
```

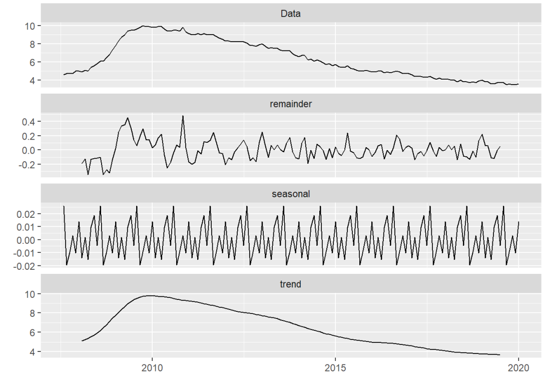



```
ggseasonplot(datats)
```




This time series is clearly non-seasonal

```
data_desc=decompose(datats)#,type=c("multiplicative"))
autoplot(data_desc)
```

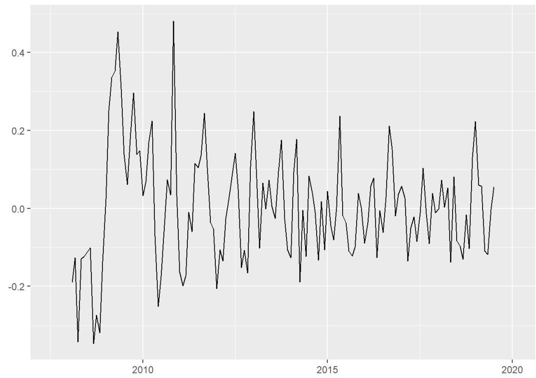



```
data_desc$figure
```

```
##  [1]  0.026060080 -0.019394465 -0.009167193  0.002954019 -0.010303556
##  [6]  0.013938868 -0.013933607  0.001691393 -0.015322496  0.009330282
## [11]  0.018705282 -0.004558607
```

Normality test for residuals: small p-values -> errors dont follow normal distribution. Thus, there is no white noise

```
autoplot(data_desc$random)
```




```
ks.test(data_desc$random,'pnorm')
```

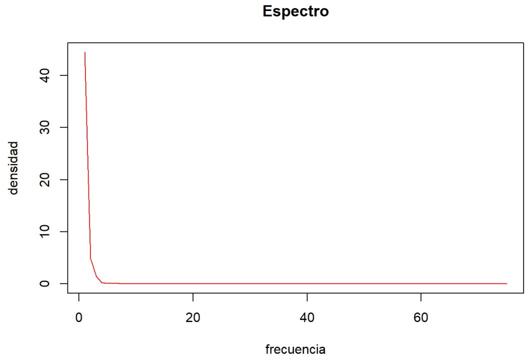
```
##
##  One-sample Kolmogorov-Smirnov test
##
## data:  data_desc$random
## D = 0.38232, p-value < 2.2e-16
## alternative hypothesis: two-sided
```

```
shapiro.test(data_desc$random) #small p-value. errors dont follow a normal distribution.
```

```
##
##  Shapiro-Wilk normality test
##
## data:  data_desc$random
## W = 0.97707, p-value = 0.02
```

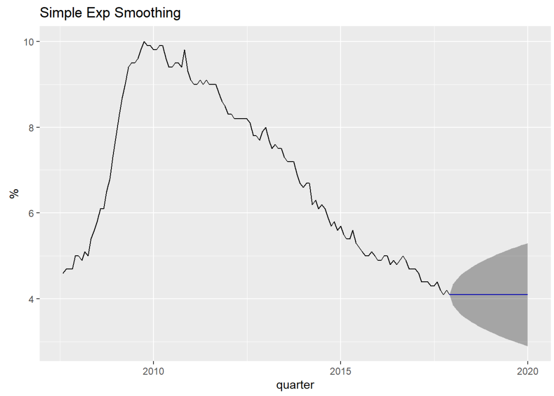
A periodogram calculates the significance of different frequencies in time-series. Its main goal is identifying any intrinsic periodic signal.

```
# peridiogram
gperiodograma(datats)
```

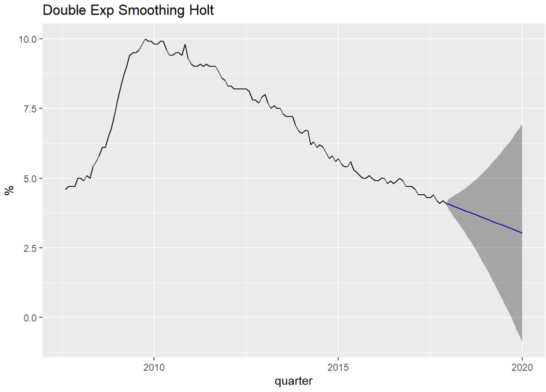



BEST SMOOTHING METHOD FOR THIS DATASET: Holt-Winters Additive method (graph legend: 'fitted_hwAdd')
It is the best method because its prediction is graphically closer to the actual value.

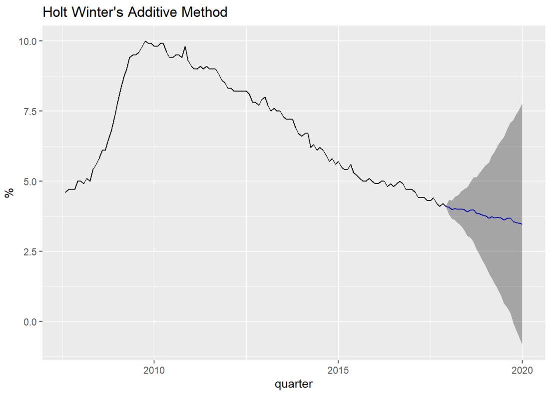
```
# TRAIN TEST SPLIT
datats_tr<-as.ts(window(x = datats, end = c(2017,12)))
datats_tst<-as.ts(window(x = datats, start = c(2018,1)))



# ### SIMPLE EXPONENTIAL SMOOTHING
datats_s1=ses(datats_tr, h=length(datats_tst))


###  DOUBLE EXPOENENTIAL SMOOTHING HOLT
datats_sh <- holt(datats_tr, h=length(datats_tst))


#### Holt-Winters

# ADDITIVE AND MULTIPLICATIVE
datats_hw_add <- hw(datats_tr, h=length(datats_tst),level = c(80, 95))
datats_hw_mul <- hw(datats_tr, h=length(datats_tst), seasonal="multiplicative",level = c(80, 95))


autoplot(datats_s1) + ggtitle('Simple Exp Smoothing') + xlab('quarter') + ylab('%')
```



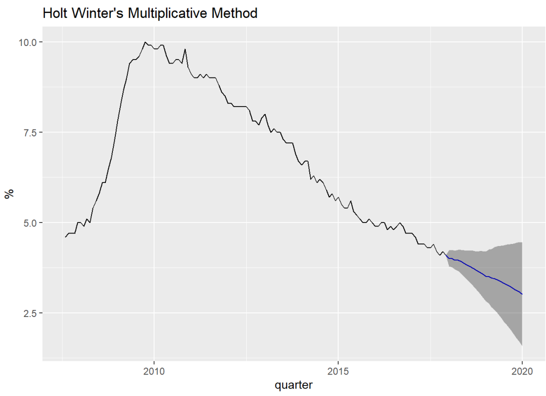

```
autoplot(datats_sh) + ggtitle("Double Exp Smoothing Holt") + xlab('quarter') + ylab('%')
```



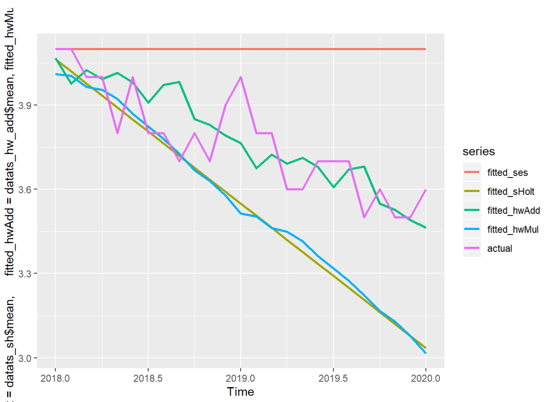

```r
autoplot(datats_hw_add) + ggtitle("Holt Winter's Additive Method") + xlab('quarter') +
    ylab('%')
```




```r
autoplot(datats_hw_mul) + ggtitle("Holt Winter's Multiplicative Method") + xlab('quarter') +
    ylab('%')
```

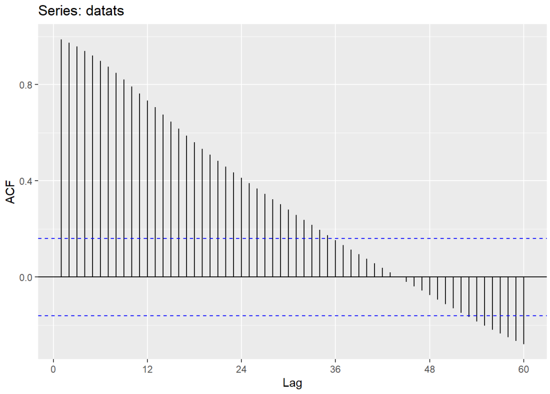



```r
autoplot(cbind(fitted_ses=datats_s1$mean, fitted_sHolt=datats_sh$mean,
               fitted_hwAdd=datats_hw_add$mean, fitted_hwMul=datats_hw_mul$mean,
               actual=datats_tst), size=1)
```

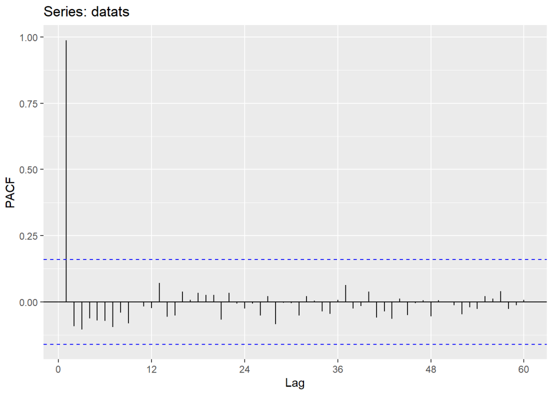



ACF & PACF confirm that datats does not have seasonal patters

```
ggAcf(datats, lag=60)
```



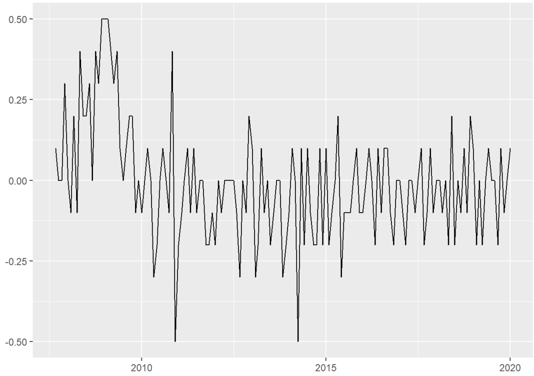

```
ggPacf(datats, lag=60)
```



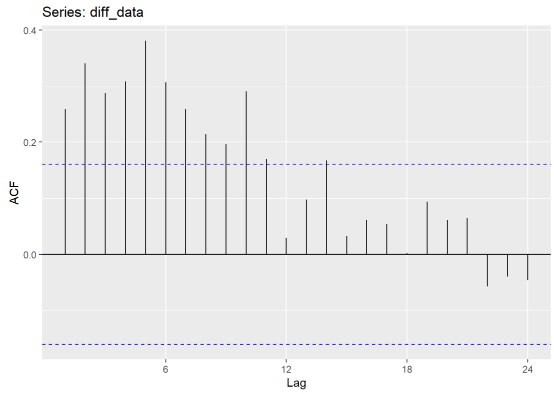

First order difference (t-1)
Even though there are spikes in lag 12 & 24 in PACF. We don't have any spike at that lags in ACF.
* Spikes occurs at the first lags in both PACF and ACF. For that reason, my proposed ARIMA model is ARIMA(2,1,2)(0,0,0)
* Before showing the formula of my Arima model: ARIMA(2,1,2)(0,0,0). Let's explain some notation first:
$By_t = y_{t-1}$
$B\epsilon_t = \epsilon_{t-1}$, where $\epsilon$ refers to the error
Thus, $(1-B)y_t = y_t - By_t = y_t - y_{t-1}$

* Formula: $(1-\phi_1 B - \phi_2 B^2)(1-B)y_t = c + (1+\theta_1 B + \theta_2 B^2)\epsilon$

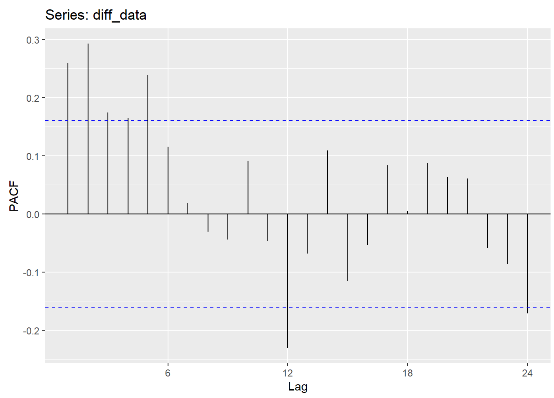
```
diff_data = datats %>% diff()
autoplot(diff_data)
```



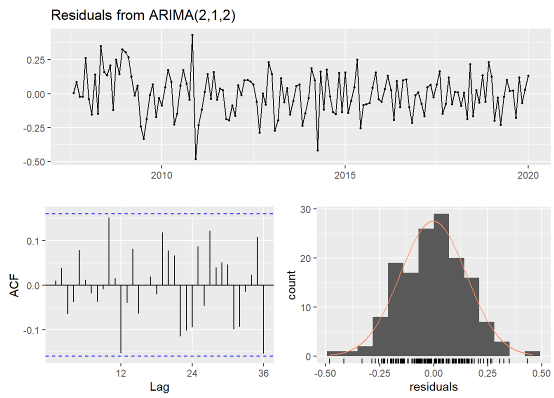

```
ggAcf(diff_data)
```




```
ggPacf(diff_data)
```



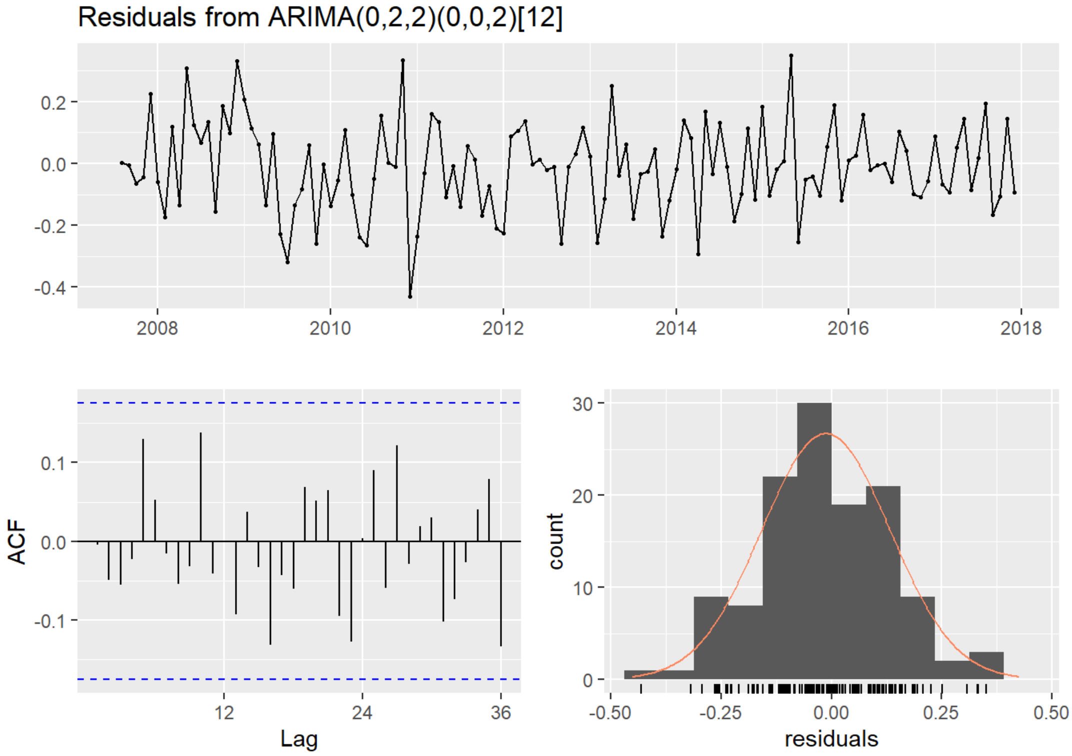

```
checkresiduals(datats %>% Arima(order=c(2,1,2), seasonal=c(0,0,0)))
```




```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(2,1,2)
## Q* = 22.463, df = 20, p-value = 0.3159
##
## Model df: 4.   Total lags used: 24
```

LET'S CREATE AN AUTOARIMA MODEL AND CHECK IF IT OUTPERFORMS MY PROPOSED MODELS:

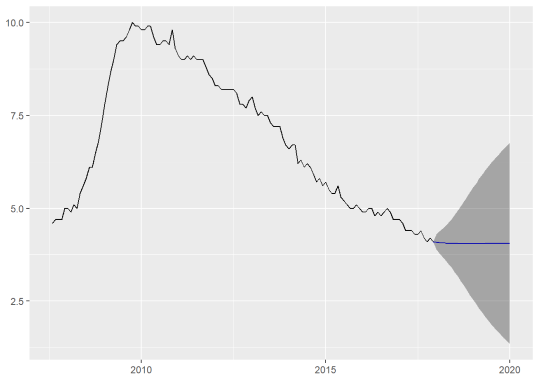
```
model1=datats_tr %>% Arima(order=c(2,1,2), seasonal=c(0,0,0))
model2=datats_tr %>% Arima(order=c(1,1,1), seasonal=c(0,0,0))

# datats_tr %>% Arima(order=c(2,1,2), seasonal=c(0,0,0))
# checkresiduals(datats_tr %>% Arima(order=c(1,1,1), seasonal=c(0,0,0)))

autoModel=datats_tr %>% auto.arima(seasonal=T)
checkresiduals(autoModel)
```



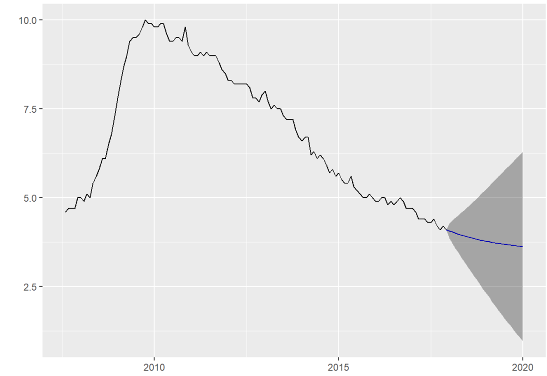

```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(0,2,2)(0,0,2)[12]
## Q* = 17.387, df = 20, p-value = 0.6277
##
## Model df: 4.   Total lags used: 24
```

VISUALIZATION OF ARIMA MODELS' PERFORMANCE IN TEST SET BEST MODEL FOR THIS DATASET: ARIMA(1,1,1)(0,0,0) (graph legend: 'pred2')
It is the best model since its prediction is graphically closer to the actual value.

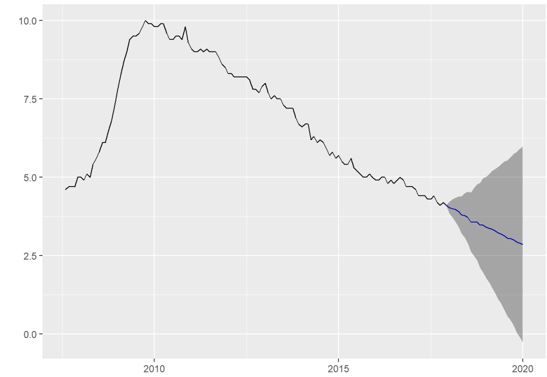
```
pred1=forecast(model1, h=length(datats_tst))
pred2=forecast(model2, h=length(datats_tst))
pred3=forecast(autoModel, h=length(datats_tst))

autoplot(pred1)
```



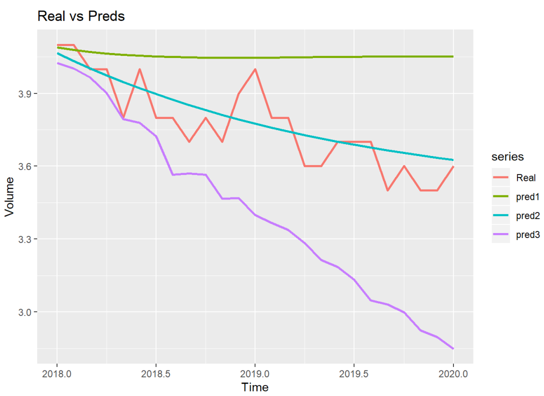

```
autoplot(pred2)
```




```
autoplot(pred3)
```




```
autoplot(cbind(Real=datats_tst, pred1=pred1$mean, pred2=pred2$mean, pred3=pred3$mean),
        size=1, ylab='Volume') + ggtitle('Real vs Preds')
```




**Last Section: CLUSTERING**
(Dataset: Again, Spanish National elections)
10 numeric variables are going to be selected for this analysis.

```
allColumns=readRDS('Debugged_elect_dataset')
data=allColumns[,c('Autonomous_Community', 'Population', 'Left_wing_Pct', 'Right_wing_Pct',
             'ForeignersPtge', 'SurfaceArea' ,'FemalePopulationPtge', 'Others_Pct',
             'Age_19_65_pct', 'Age_over65_pct', 'totalCompanies')]
```

```
library(dplyr)
```

Let's group values by Autonomous_Community to calculate its mean and sum.
This is going to be our dataset from now on

```
agg = data %>% group_by(Autonomous_Community) %>% summarise_all(list(~mean(.), ~sum(.))) %>%
        mutate_at(vars(2:ncol(data)), function(x) round(x, digits=3))

head(agg,2)
```

```
## # A tibble: 2 x 21
##   Autonomous_Comm~ Population_mean Left_wing_Pct_m~ Right_wing_Pct_~
##   <chr>                      <dbl>            <dbl>            <dbl>
## 1 Andalucía                 10858.             55.2             41.4
## 2 Aragón                     1803.             41.6             54.7
## # ... with 17 more variables: ForeignersPtge_mean <dbl>,
## #   SurfaceArea_mean <dbl>, FemalePopulationPtge_mean <dbl>,
## #   Others_Pct_mean <dbl>, Age_19_65_pct_mean <dbl>, Age_over65_pct_mean <dbl>,
## #   totalCompanies_mean <dbl>, Population_sum <dbl>, Left_wing_Pct_sum <dbl>,
## #   Right_wing_Pct_sum <dbl>, ForeignersPtge_sum <dbl>, SurfaceArea_sum <dbl>,
## #   FemalePopulationPtge_sum <dbl>, Others_Pct_sum <dbl>,
## #   Age_19_65_pct_sum <dbl>, Age_over65_pct_sum <dbl>, totalCompanies_sum <dbl>
```

Normalization of values

```
z = as.data.frame(agg[,-1])

rownames(z) = agg$Autonomous_Community

means = apply(z,2,mean) # '2' because we want to use 'apply' by columns
sd = apply(z,2,sd)

z = scale(z, means, sd)
#head(z,3)
```

Distance is going to measured by the Euclidean method It is worth mentionning that if Euclidean distance is chosen, then observations with high values of features will be clustered together. The same holds true for observations with low values of features. If we want to identify clusters of observations with the same overall profiles regardless of their magnitudes, then we should go with correlation-based distance as a dissimilarity measure.

```
distance=dist(z, method='euclidean')

#print(distance, digits=3)
```

LET'S SELECT WHICH LINKAGE METHOD IS THE BEST for K=4

```
methods <- c("single", "complete", "average", "mcquitty", "ward.D2")
st = as.data.frame(t((sapply(methods,
        function(x) cluster.stats(distance, cutree(hclust(distance, method= x), 4))))))
# head(st,2)
```

DEPENDING ON THE NUMBER OF CLUSTERS SELECTED, WE MIGHT GET DIFFERENT SOLUTIONS.
THUS WE HAVE TO REPEAT THIS PROCESS, ONCE THE K-MEANS wss (elbow method) plot is done.

```
both=as.data.frame(cbind(avg.silwidth=as.numeric(st$avg.silwidth),
                         within.cluster.ss=as.numeric(st$within.cluster.ss)))
rownames(both)= rownames(st)
round(both, digits=3)
```

```
##          avg.silwidth within.cluster.ss
## single          0.167           192.386
## complete        0.173           163.601
## average         0.167           192.386
## mcquitty        0.167           192.386
## ward.D2         0.190           160.834
```

IMPORTANT: The silhouette ranges from −1 to +1, where a high value indicates that the object is well matched to its own cluster and poorly matched to neighboring clusters.
BEST LINKAGE METHODS: 'ward.D2' for number of clusters = 4

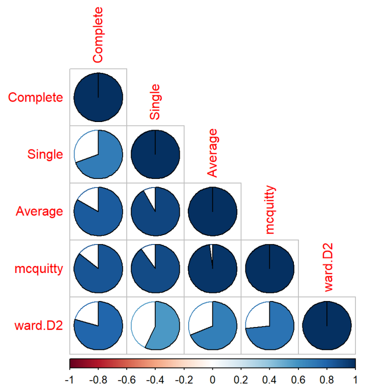
```
library(dendextend)
```

Correlation matrix of dendograms

```r
# Create multiple dendrograms by chaining
dend1 <- z %>% dist %>% hclust("complete") %>% as.dendrogram
dend2 <- z %>% dist %>% hclust("single") %>% as.dendrogram
dend3 <- z %>% dist %>% hclust("average") %>% as.dendrogram
dend4 <- z %>% dist %>% hclust("mcquitty") %>% as.dendrogram
dend5 <- z %>% dist %>% hclust("ward.D2") %>% as.dendrogram
# Compute correlation matrix
dend_list <- dendlist("Complete" = dend1, "Single" = dend2,
"Average" = dend3, "mcquitty" = dend4, "ward.D2" = dend5)
cors <- cor.dendlist(dend_list)
# Print correlation matrix
round(cors, 2)
```

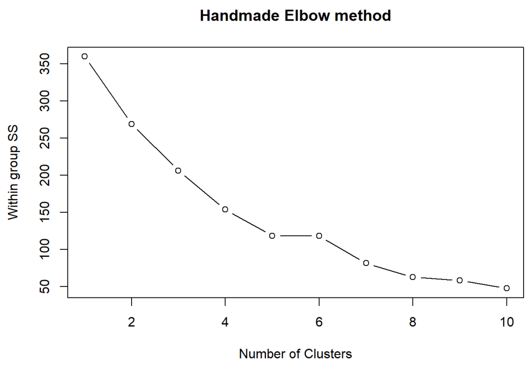
```
##          Complete Single Average mcquitty ward.D2
## Complete     1.00   0.70    0.83     0.86    0.79
## Single       0.70   1.00    0.92     0.90    0.57
## Average      0.83   0.92    1.00     0.98    0.69
## mcquitty     0.86   0.90    0.98     1.00    0.73
## ward.D2      0.79   0.57    0.69     0.73    1.00
```

```r
corrplot(cors, "pie", "lower")
```

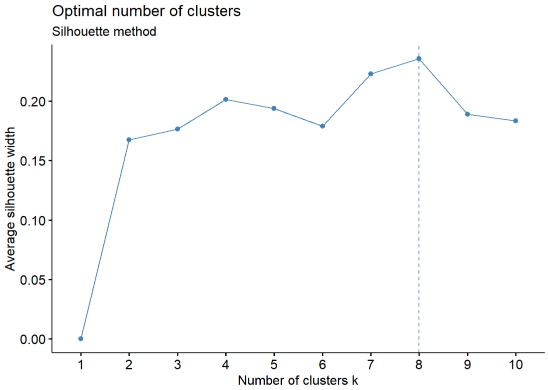



Withing group SS (elbow) method and Silhouette method

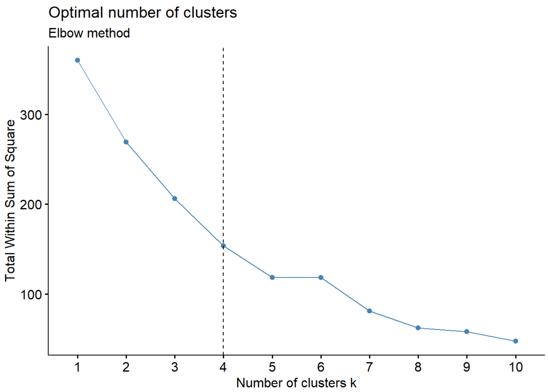
```r
set.seed(123)
# Scree Plot
z=as.data.frame(z)
wss=(nrow(z)-1)*sum(apply(z,2,var))

# for (i in 1:(nrow(z)-1)) wss[i] = sum(kmeans(z, centers=i)$withinss)
# plot(1:(nrow(z)-1),wss, type='b',xlab='Number of Clusters',
#       ylab='Within group SS', main='Handmade Elbow method')

for (i in 1:10) wss[i] = sum(kmeans(z, centers=i)$withinss) #maximum number of clusters created:10
plot(1:10,wss, type='b',xlab='Number of Clusters',
     ylab='Within group SS', main='Handmade Elbow method')
```




```r
fviz_nbclust(z, kmeans, method = "silhouette")+
labs(subtitle = "Silhouette method")
```




```
fviz_nbclust(z, kmeans, method = "wss") +
geom_vline(xintercept = 4, linetype = 2)+
labs(subtitle = "Elbow method")
```



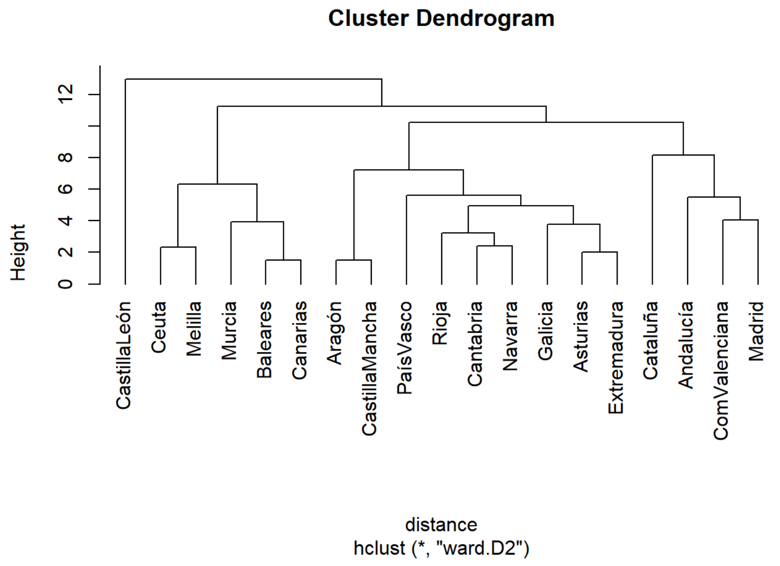

I SELECT K=4 BECAUSE IT IS THE BEST VALUE ACCORDING TO THE ‘ELBOW METHOD’. ADDITIONALY, K=4 HAS THE GREATEST AVERAGE SILHOUETTE WIDTH FOR THE FIRST 6 ‘number of clusters k’.
It is worth mentioning that there are less than 20 observations and, consequently, we are not interested in creating many groups.
LET’S IDENTIFY THE MOST SUITABLE LINKAGE METHOD

```
methods <- c("single", "complete", "average", "mcquitty", "ward.D2")
st = as.data.frame(t((sapply(methods,
        function(x) cluster.stats(distance, cutree(hclust(distance, method= x), 4))))))

both=as.data.frame(cbind(avg.silwidth=as.numeric(st$avg.silwidth),
                         within.cluster.ss=as.numeric(st$within.cluster.ss)))
rownames(both)= rownames(st)
round(both, digits=3)    #ward.D2 is the best linkage for k=4
```

```
##          avg.silwidth within.cluster.ss
## single          0.167           192.386
## complete        0.173           163.601
## average         0.167           192.386
## mcquitty        0.167           192.386
## ward.D2         0.190           160.834
```

Dendogram using ‘ward.D2’ as linkage method

```
plot(hclust(distance, method='ward.D2'), labels=agg$Autonomous_Community, hang=-1)
```




hybrid_k_means method with parameters we have already selected vs kmeans with k=4

```
set.seed(443)
hybrid=hkmeans(x=z, k=4, hc.metric = "euclidean", hc.method = "ward.D2")
random_Kmeans=kmeans(z,4)

paste('hybrid_withinss_mean: ', round(mean(hybrid$withinss), digits=3))
```

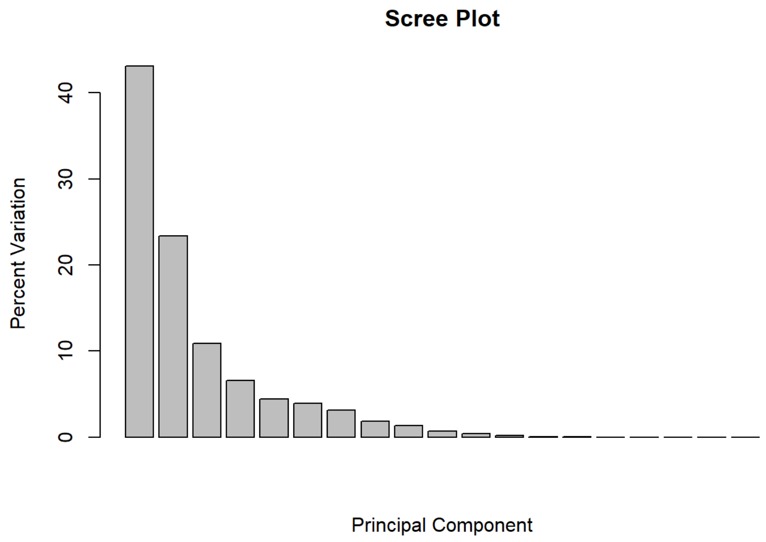
```
## [1] "hybrid_withinss_mean:  37.784"
```

```
paste('random_Kmeans_withinss_mean: ', round(mean(random_Kmeans$withinss), digits=3))
```

```
## [1] "random_Kmeans_withinss_mean:  38.378"
```

**Principal Component Analysis**
# the first PC accounts for the most variation in the original data, and so forth.
# As we want to plot a 2-D graph, we will use the first two PCs.

```
# PCA
z.pca <- prcomp(t(z))

## LET'S PLOT THE FIRST TWO PRINCIPAL COMPONENTS
#plot(z.pca$x[,1], z.pca$x[,2])


z.pca.var=z.pca$sd^2
z.pca.var.per=round(z.pca.var/sum(z.pca.var)*100, digits=3)
barplot(z.pca.var.per, main='Scree Plot', xlab='Principal Component', ylab='Percent Variation')
```




Let’s check how variables are distributed under PC1 and PC2
* In the ggbiplot graph, the correlation circle has a scale from -1 to 1 and it is useful to compare the first two PCs in relation to variables

As may be inferred, ‘Age_over_65_pct_sum’,‘FemalePopulationPtge_sum’, ‘Surface_Area_sum’ have large POSITIVE loadings on component one, while ‘Age_19_65_pct_mean’, ‘totalCompanies_mean’ present large NEGATIVE loadings on component one.

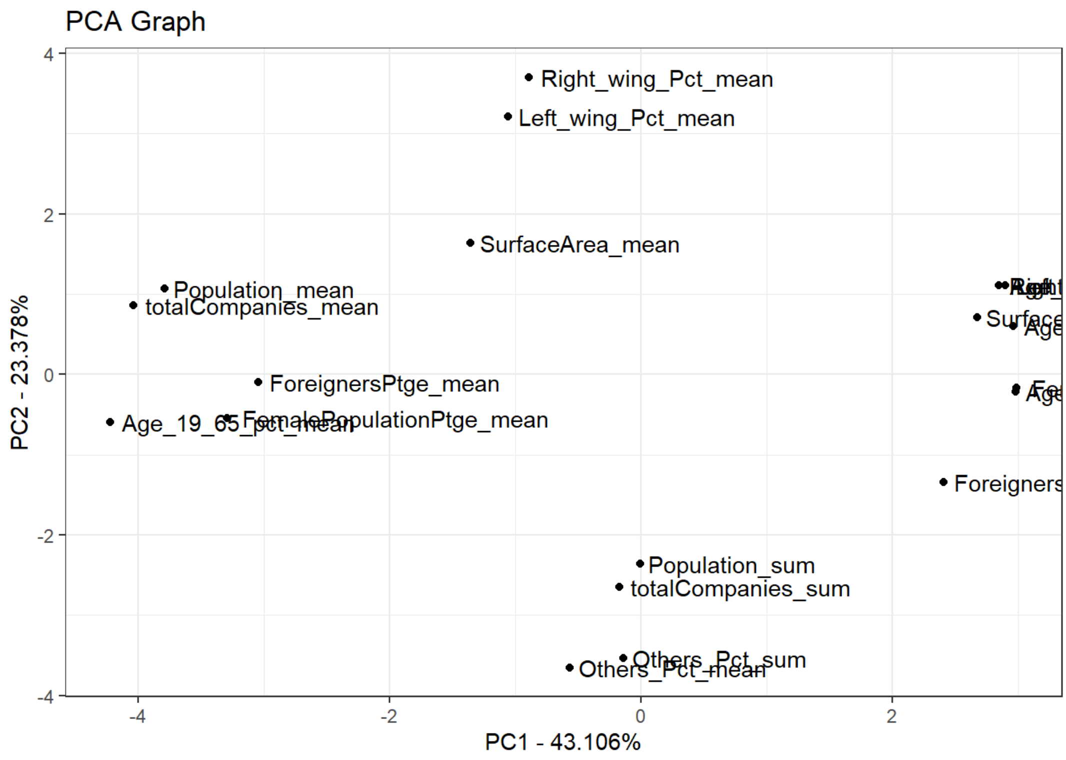
Looking at Component two, ‘Right_wing_Pct_mean’,‘Left_wing_Pct_mean’ have the greatest loadings and ‘Others_Pct_mean’,‘Others_Pct_sum’ the lowest ones.

Because of that, it can be claimed that PC1 measures demographics such as age, gender, population, number of foreigners. PC2, on the other hand, accounts for political variables such as ‘Right_wing_Pct_mean’, ‘Left_wing_Pct_mean’ or ‘Others_Pct_mean’.

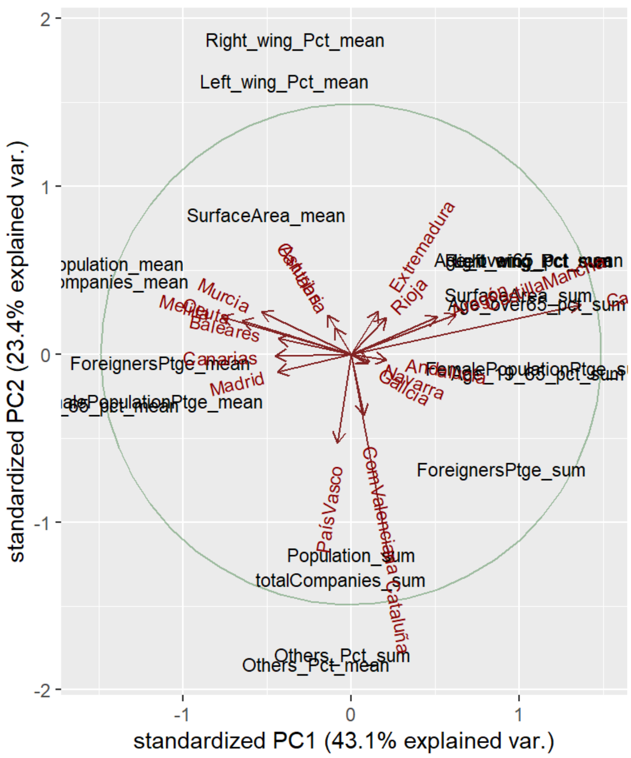
```
pca.data=data.frame(X=z.pca$x[,1], Y=z.pca$x[,2])
head(pca.data,3)
```

```
##                              X        Y
## Population_mean     -3.7879128 1.066871
## Left_wing_Pct_mean  -1.0595904 3.215874
## Right_wing_Pct_mean -0.8916274 3.704902
```

```
library(plyr)
ggplot(pca.data, aes(x=X, y=Y, label=rownames(pca.data))) +
       geom_text(aes(label=rownames(pca.data)),hjust=-0.05, vjust=0.5) +
       xlab(paste('PC1 - ', z.pca.var.per[1], '%', sep='')) +
       ylab(paste('PC2 - ', z.pca.var.per[2], '%', sep='')) +
       theme_bw() +
       geom_point() +
       ggtitle('PCA Graph')
```



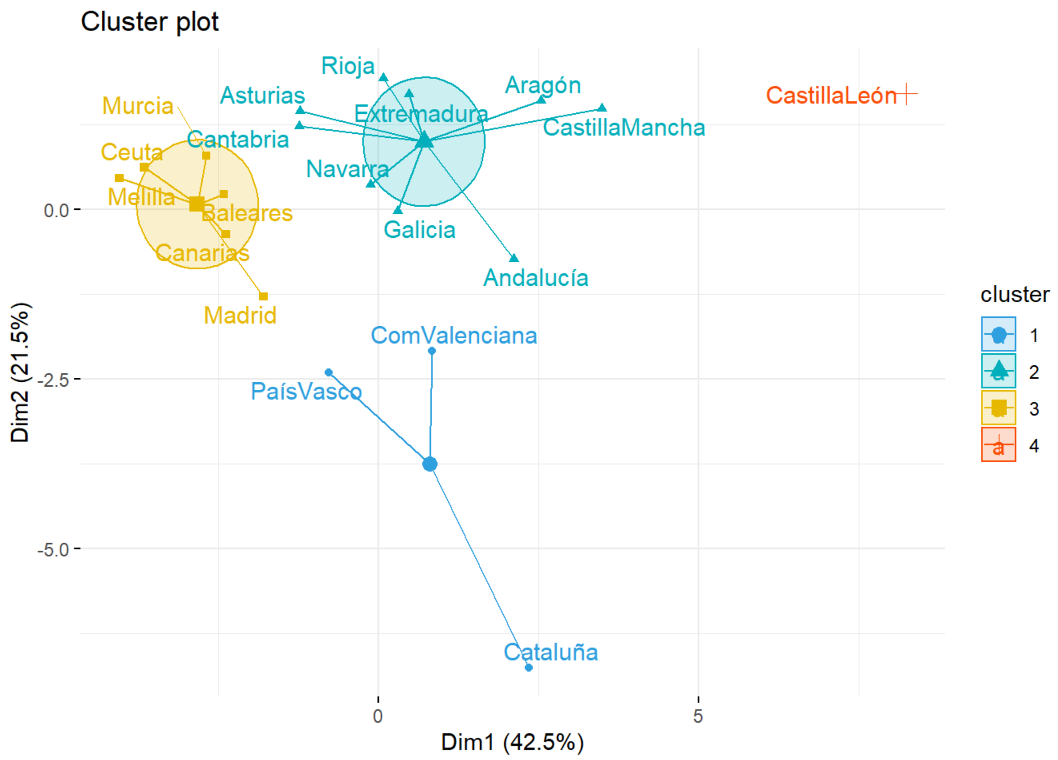

```
ggbiplot::ggbiplot(z.pca, labels = rownames(pca.data), ellipse = TRUE, circle = TRUE)
```




Cluster plot

```
hybrid=hkmeans(x=z, k=4, hc.metric = "euclidean", hc.method = "ward.D2")

fviz_cluster(hybrid, data = z,
palette = c("#2E9FDF", "#00AFBB", "#E7B800", "#FC4E07"),
ellipse.type = "euclid", # Concentration ellipse
star.plot = TRUE, # Add segments from centroids to items
repel = TRUE, # Avoid label overplotting (slow)
ggtheme = theme_minimal()
)
```

```
## Too few points to calculate an ellipse
## Too few points to calculate an ellipse
```




PCA_hybrid_withinss_mean vs PCA_by_defualt_kmeans

```
PCA_z=princomp(z[,11:ncol(z)])$score[,1:2]

PCA_hybrid=hkmeans(x=PCA_z, k=4, hc.metric = "euclidean", hc.method = "ward.D2")
PCA_random_Kmeans=kmeans(PCA_z,4)

paste('PCA_hybrid_withinss_mean: ', round(mean(PCA_hybrid$withinss), digits=3))
```

```
## [1] "PCA_hybrid_withinss_mean:  5.453"
```

```
paste('PCA_random_Kmeans_withinss_mean: ', round(mean(PCA_random_Kmeans$withinss), digits=3))
```

```
## [1] "PCA_random_Kmeans_withinss_mean:  5.453"
```

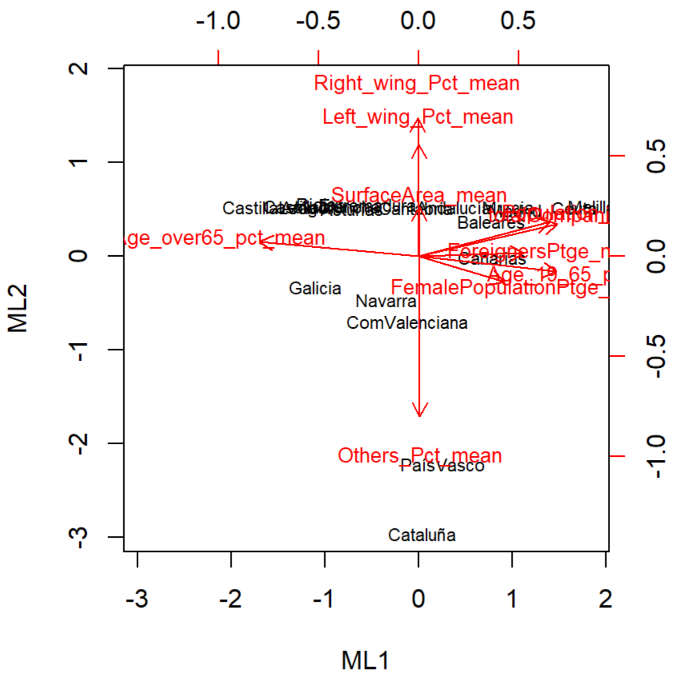
**FACTOR ANALYSIS**

In Factor Analysis, variables are grouped by their correlations, this implies that all variables in a particular group will have a high correlation among themselves, but a low correlation with variables of other group(s). Here, each group is known as a factor. These factors are small in number as compared to the original dimensions of the data. However, it is important to highlight that these factors are difficult to observe and interpret.

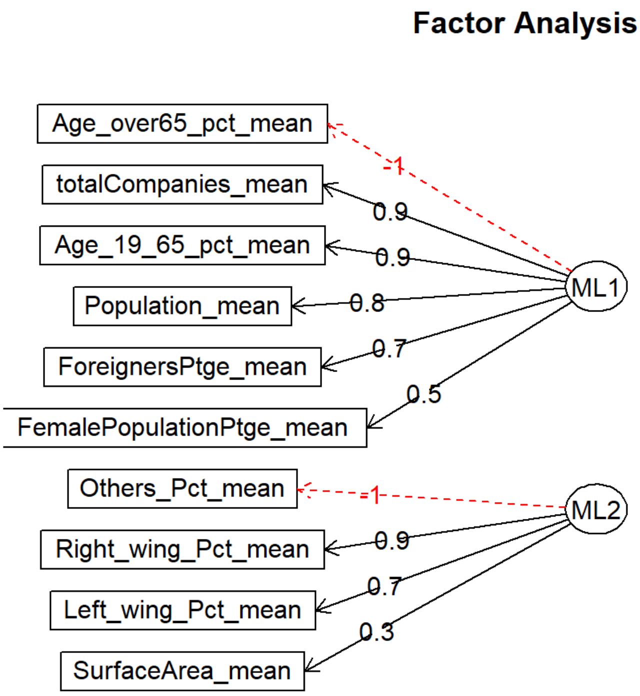
```
z.fa=z[,1:10] #var_mean is a linear combination of var_sum. Thus, we must get rid of one
              #of them

head(z.fa[,c(1,10)],2)
```

```
##           Population_mean totalCompanies_mean
## Andalucía      -0.3089806          -0.3733671
## Aragón         -0.6652714          -0.7728934
```

```
z.fa1=psych::fa(z.fa, nfactors=2, fm="ml", rotate="varimax")
FA_z=z.fa1$scores


biplot(z.fa1$scores, loadings(z.fa1), cex=c(0.7,0.8))
```



```
psych::fa.diagram(z.fa1, simple=FALSE) #
```




Let's call ML1 & ML2 with more technical names
Based on the previuos graph, ML1 is related to demographic variables such as 'Age_16_65_pct_mean', 'ForeignersPtge_mean' or 'FemalePopulationPtge_mean'. For that reason, ML1 will be renamed as 'Demographics'.
ML2 will be renamed as 'Political preferences' since, based on the Factor Analysis graph, it is more related to political variables such as 'Others_Pct_mean', 'Right_wing_Pct_mean' or'Left_wing_Pct_mean'.

```
head(FA_z,2)
```

```
##                    ML1       ML2
## Andalucía   0.3765881 0.523554
## Aragón     -1.1687773 0.510747
```

```
colnames(FA_z)=c('Demographics', 'Political preferences')
head(FA_z,2)
```

```
##            Demographics Political preferences
## Andalucía     0.3765881              0.523554
## Aragón       -1.1687773              0.510747
```

withingss_mean check

```
FA_hybrid=hkmeans(x=FA_z, k=4, hc.metric = "euclidean", hc.method = "ward.D2")
FA_random_Kmeans=kmeans(FA_z,4)

paste('FA_hybrid_withinss_mean:', round(mean(FA_hybrid$withinss), digits=3))
```

```
## [1] "FA_hybrid_withinss_mean: 1.07"
```

```
paste('FA_random_Kmeans_withinss_mean:', round(mean(FA_random_Kmeans$withinss), digits=3))
```

```
## [1] "FA_random_Kmeans_withinss_mean: 1.086"
```

cluster plot

```
fviz_cluster(FA_hybrid, data = FA_z,
palette = c("#2E9FDF", "#00AFBB", "#E7B800", "#FC4E07"),
ellipse.type = "euclid", # Concentration ellipse
star.plot = TRUE, # Add segments from centroids to items
repel = TRUE, # Avoid label overplotting (slow)
ggtheme = theme_minimal()
)
```

```
## Too few points to calculate an ellipse
## Too few points to calculate an ellipse
```