

Analysis Bulgaria

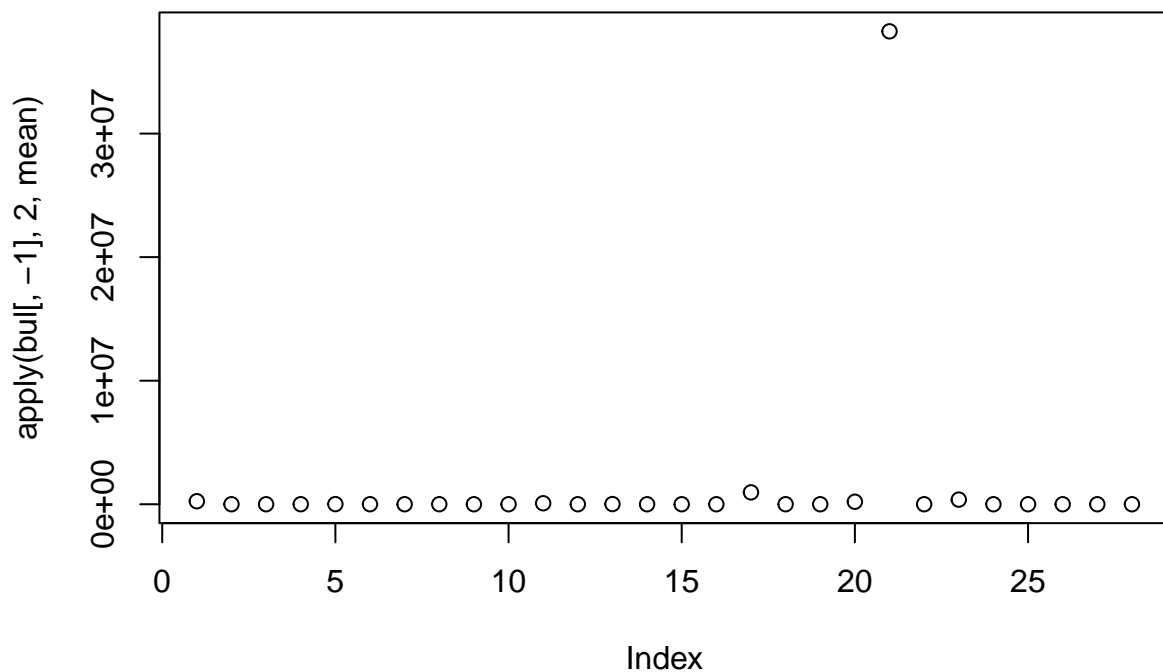
```
bul <- readxl::read_xlsx("C:/Users/User/Documents/UNITN/Computational social science/bulgaria/final_CIT")

bul$activity_rate <- as.double(bul$activity_rate)
bul$labour_force_thousands <- as.double(bul$labour_force_thousands)
bul$employment_rate <- as.double(bul$employment_rate)
bul$foreign_direct_investment_euro <- as.double(bul$foreign_direct_investment_euro)

apply(bul[,-1], 2, mean)
```

```
##          Population2021          fertility_rate
##          2.442478e+05          1.618992e+00
##          unis_colleges_number          teaching_staff
##          1.928571e+00          8.677089e+02
##          students_enrolled          graduates_uni
##          9.206643e+03          1.919709e+03
##          ratio_grad_enrolled_unis          TotalSchools
##          2.123366e-01          5.880000e+02
##          gradtotot57          gradtotot812
##          3.041211e-01          2.057127e-01
##          employees_laborcontract_avg          employees_laborcontract_avg_topop
##          7.899189e+04          2.633891e-01
##          avgwage          activity_rate
##          1.344071e+04          7.038571e+01
##          labour_force_thousands          employment_rate
##          1.126893e+02          6.527143e+01
##          foreign_direct_investment_euro          books_pamphlets
##          9.601554e+05          3.965956e+02
##          accommodation_establishments          arrivals_accommodation
##          1.191071e+02          2.017012e+05
##          revenue_accomm_lev          crimes
##          3.827540e+07          1.014286e+03
##          ecological_assets          water_supply2020
##          3.738583e+05          9.903214e+01
##          connected_to_wastewater_collecting          Pop_watersupplyregime
##          6.878750e+01          6.750714e+00
##          waste_thousandtons          hospitals2021
##          1.009150e+02          1.146429e+01
```

```
plot(apply(bul[,-1], 2, mean))
```



Taking a look at the correlation plot.

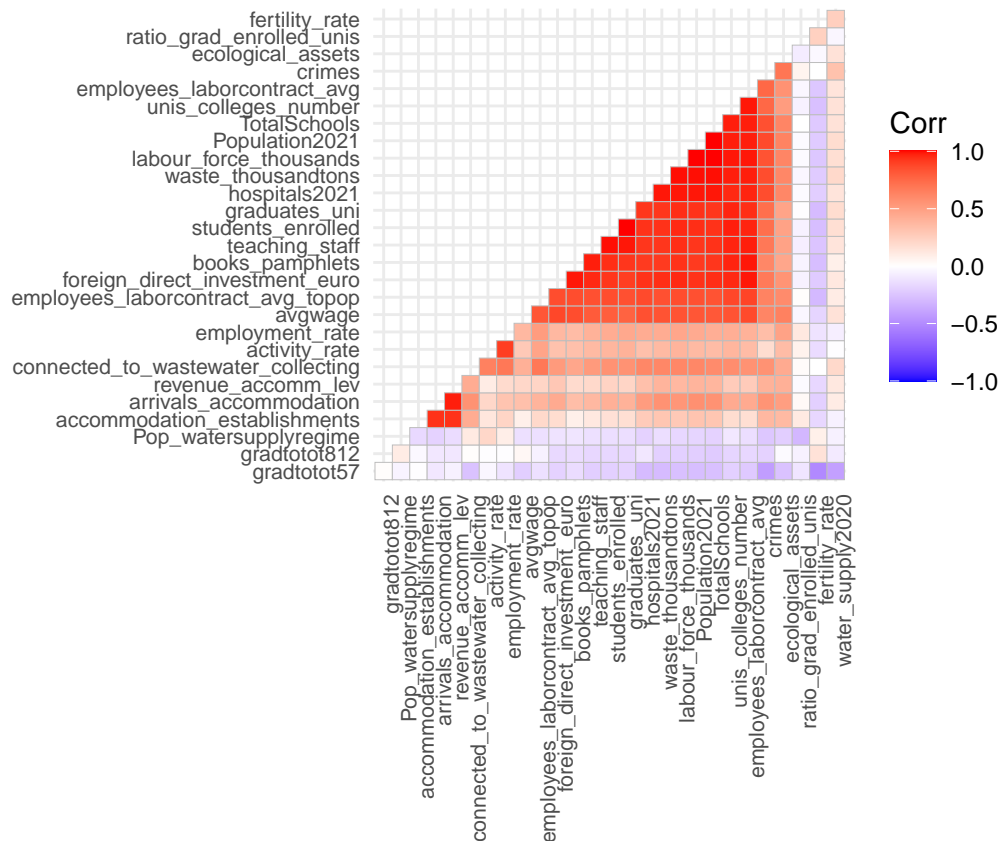
```
library(ggplot2)
```

```
## Warning: package 'ggplot2' was built under R version 4.1.2
```

```
library(ggcorrplot)
```

```
## Warning: package 'ggcorrplot' was built under R version 4.1.3
```

```
ggcorrplot(cor(bul[, -1]), hc.order = TRUE, type = "lower", tl.srt = 90, tl.cex = 8)
```



```
cor_pmat(bul[, -1])
```

```
##               Population2021 fertility_rate
## Population2021      0.000000e+00      0.250945796
## fertility_rate      2.509458e-01      0.000000000
## unis_colleges_number 8.548964e-17      0.162013246
## teaching_staff      2.811095e-12      0.196334207
## students_enrolled    2.308166e-13      0.154160412
## graduates_uni        1.616035e-12      0.134237146
## ratio_grad_enrolled_unis 9.174784e-01      0.222996596
## TotalSchools        2.362230e-29      0.241087324
## gradtotot57         1.418877e-01      0.006058911
## gradtotot812        2.952747e-01      0.440660293
## employees_laborcontract_avg 3.450719e-17      0.219037081
## employees_laborcontract_avg_topop 3.207855e-08      0.116461484
## avgwage             1.206978e-07      0.357018115
## activity_rate        6.364915e-02      0.448764218
## labour_force_thousands 1.353251e-30      0.221271236
## employment_rate      1.872476e-02      0.558539627
## foreign_direct_investment_euro 9.061431e-13      0.254730904
## books_pamphlets      2.923013e-11      0.142785867
## accommodation_establishments 1.060308e-01      0.397044789
## arrivals_accommodation 1.723961e-03      0.298147499
## revenue_accomm_lev    3.938970e-02      0.373134752
## crimes              2.896434e-09      0.999296010
```

## ecological_assets	3.074933e-04	0.870039025
## water_supply2020	3.588740e-01	0.193202583
## connected_to_wastewater_collecting	6.150684e-04	0.980647984
## Pop_watersupplyregime	3.555547e-01	0.675779887
## waste_thousandtons	5.810950e-27	0.262863431
## hospitals2021	5.654075e-20	0.279043553
##	unis_colleges_number	teaching_staff
## Population2021	8.548964e-17	2.811095e-12
## fertility_rate	1.620132e-01	1.963342e-01
## unis_colleges_number	0.000000e+00	1.344727e-16
## teaching_staff	1.344727e-16	0.000000e+00
## students_enrolled	2.963349e-17	9.052569e-24
## graduates_uni	7.621126e-16	1.695736e-19
## ratio_grad_enrolled_unis	7.723807e-01	7.054611e-01
## TotalSchools	5.813363e-17	1.524990e-12
## gradtotot57	2.997456e-01	2.866066e-01
## gradtotot812	3.694584e-01	3.912286e-01
## employees_laborcontract_avg	5.177584e-21	2.891258e-17
## employees_laborcontract_avg_topop	1.486333e-09	1.670977e-08
## avgwage	5.508042e-08	2.588742e-07
## activity_rate	4.367627e-02	5.718552e-02
## labour_force_thousands	7.430629e-19	1.547110e-13
## employment_rate	2.730561e-02	3.373584e-02
## foreign_direct_investment_euro	6.483622e-15	2.281280e-14
## books_pamphlets	3.378688e-16	1.202546e-16
## accommodation_establishments	3.461010e-01	5.396915e-01
## arrivals_accommodation	1.820738e-02	5.164016e-02
## revenue_accomm_lev	1.680250e-01	3.005860e-01
## crimes	5.074073e-06	7.564267e-05
## ecological_assets	5.287059e-03	1.023470e-02
## water_supply2020	4.360589e-01	4.689696e-01
## connected_to_wastewater_collecting	1.269101e-03	4.260336e-03
## Pop_watersupplyregime	6.193130e-01	5.005677e-01
## waste_thousandtons	1.387675e-17	4.264841e-12
## hospitals2021	3.580988e-15	6.870403e-12
##	students_enrolled	graduates_uni
## Population2021	2.308166e-13	1.616035e-12
## fertility_rate	1.541604e-01	1.342371e-01
## unis_colleges_number	2.963349e-17	7.621126e-16
## teaching_staff	9.052569e-24	1.695736e-19
## students_enrolled	0.000000e+00	1.258211e-27
## graduates_uni	1.258211e-27	0.000000e+00
## ratio_grad_enrolled_unis	7.565319e-01	9.563326e-01
## TotalSchools	5.619835e-13	3.669794e-12
## gradtotot57	3.003968e-01	3.201497e-01
## gradtotot812	3.886736e-01	3.829993e-01
## employees_laborcontract_avg	1.205652e-15	8.571757e-14
## employees_laborcontract_avg_topop	1.010958e-08	2.532003e-08
## avgwage	5.230809e-07	2.036097e-06
## activity_rate	4.697410e-02	3.275288e-02
## labour_force_thousands	2.481015e-14	2.384885e-13
## employment_rate	2.261861e-02	1.670390e-02
## foreign_direct_investment_euro	4.017206e-12	1.062732e-10
## books_pamphlets	1.613908e-13	3.004326e-12

## accommodation_establishments	4.090528e-01	3.989867e-01
## arrivals_accommodation	3.160789e-02	3.432386e-02
## revenue_accomm_lev	2.410499e-01	2.659196e-01
## crimes	1.284867e-05	1.496406e-05
## ecological_assets	8.930799e-03	1.209404e-02
## water_supply2020	3.875272e-01	3.687161e-01
## connected_to_wastewater_collecting	1.863047e-03	1.926984e-03
## Pop_watersupplyregime	4.765412e-01	4.816123e-01
## waste_thousandtons	3.808107e-13	4.320566e-12
## hospitals2021	1.332925e-12	8.246069e-12
##	ratio_grad_enrolled_unis	TotalSchools
## Population2021	0.9174784	2.362230e-29
## fertility_rate	0.2229966	2.410873e-01
## unis_colleges_number	0.7723807	5.813363e-17
## teaching_staff	0.7054611	1.524990e-12
## students_enrolled	0.7565319	5.619835e-13
## graduates_uni	0.9563326	3.669794e-12
## ratio_grad_enrolled_unis	0.0000000	9.952233e-01
## TotalSchools	0.9952233	0.000000e+00
## gradtotot57	0.5661728	1.687816e-01
## gradtotot812	0.7773340	2.667091e-01
## employees_laborcontract_avg	0.8296388	2.801606e-18
## employees_laborcontract_avg_topop	0.9407662	3.575026e-08
## avgwage	0.8241284	1.561710e-07
## activity_rate	0.7279581	6.969806e-02
## labour_force_thousands	0.9339930	2.023675e-29
## employment_rate	0.5405682	2.469519e-02
## foreign_direct_investment_euro	0.7656116	1.085266e-13
## books_pamphlets	0.7995991	5.028625e-12
## accommodation_establishments	0.5948895	1.178582e-01
## arrivals_accommodation	0.8841564	2.054524e-03
## revenue_accomm_lev	0.9095843	4.426235e-02
## crimes	0.7736133	1.959883e-08
## ecological_assets	0.6985980	4.419658e-04
## water_supply2020	0.8252628	4.413161e-01
## connected_to_wastewater_collecting	0.9128116	9.879394e-04
## Pop_watersupplyregime	0.1143659	3.332932e-01
## waste_thousandtons	0.8285402	1.372964e-22
## hospitals2021	0.9084748	6.089195e-19
##	gradtotot57	gradtotot812
## Population2021	0.141887698	0.2952747
## fertility_rate	0.006058911	0.4406603
## unis_colleges_number	0.299745563	0.3694584
## teaching_staff	0.286606596	0.3912286
## students_enrolled	0.300396829	0.3886736
## graduates_uni	0.320149717	0.3829993
## ratio_grad_enrolled_unis	0.566172818	0.7773340
## TotalSchools	0.168781606	0.2667091
## gradtotot57	0.000000000	0.9673395
## gradtotot812	0.967339496	0.0000000
## employees_laborcontract_avg	0.249296589	0.3918405
## employees_laborcontract_avg_topop	0.499404746	0.7780903
## avgwage	0.284910052	0.8371293
## activity_rate	0.838906739	0.9615401

## labour_force_thousands	0.172670229	0.3102730
## employment_rate	0.526816958	0.9459506
## foreign_direct_investment_euro	0.336302111	0.4206455
## books_pamphlets	0.435087034	0.4373995
## accommodation_establishments	0.961688540	0.8823993
## arrivals_accommodation	0.617980182	0.6007516
## revenue_accomm_lev	0.750597225	0.6186110
## crimes	0.025874115	0.3262990
## ecological_assets	0.174482585	0.9275258
## water_supply2020	0.030624543	0.6586801
## connected_to_wastewater_collecting	0.181640485	0.9485631
## Pop_watersupplyregime	0.818751436	0.6027330
## waste_thousandtons	0.127778512	0.2954185
## hospitals2021	0.138652510	0.6143097
##	employees_laborcontract_avg	
## Population2021		3.450719e-17
## fertility_rate		2.190371e-01
## unis_colleges_number		5.177584e-21
## teaching_staff		2.891258e-17
## students_enrolled		1.205652e-15
## graduates_uni		8.571757e-14
## ratio_grad_enrolled_unis		8.296388e-01
## TotalSchools		2.801606e-18
## gradtotot57		2.492966e-01
## gradtotot812		3.918405e-01
## employees_laborcontract_avg		0.000000e+00
## employees_laborcontract_avg_topop		7.707822e-10
## avgwage		4.769939e-09
## activity_rate		7.004113e-02
## labour_force_thousands		8.988365e-20
## employment_rate		3.689337e-02
## foreign_direct_investment_euro		4.961713e-21
## books_pamphlets		1.641697e-19
## accommodation_establishments		3.781604e-01
## arrivals_accommodation		2.008526e-02
## revenue_accomm_lev		1.697448e-01
## crimes		5.272764e-06
## ecological_assets		1.776650e-03
## water_supply2020		4.737079e-01
## connected_to_wastewater_collecting		2.169007e-03
## Pop_watersupplyregime		4.786344e-01
## waste_thousandtons		3.411883e-17
## hospitals2021		2.143765e-16
##	employees_laborcontract_avg_topop	
## Population2021		3.207855e-08
## fertility_rate		1.164615e-01
## unis_colleges_number		1.486333e-09
## teaching_staff		1.670977e-08
## students_enrolled		1.010958e-08
## graduates_uni		2.532003e-08
## ratio_grad_enrolled_unis		9.407662e-01
## TotalSchools		3.575026e-08
## gradtotot57		4.994047e-01
## gradtotot812		7.780903e-01

## employees_laborcontract_avg		7.707822e-10
## employees_laborcontract_avg_topop		0.000000e+00
## avgwage		8.347491e-08
## activity_rate		1.078904e-02
## labour_force_thousands		8.458678e-09
## employment_rate		5.876543e-03
## foreign_direct_investment_euro		8.777159e-09
## books_pamphlets		1.258685e-08
## accommodation_establishments		3.180112e-01
## arrivals_accommodation		3.902443e-02
## revenue_accomm_lev		2.676039e-01
## crimes		3.575331e-04
## ecological_assets		9.384480e-04
## water_supply2020		6.185624e-01
## connected_to_wastewater_collecting		8.133561e-05
## Pop_watersupplyregime		5.217981e-01
## waste_thousandtons		2.196234e-08
## hospitals2021		5.841520e-09
##	avgwage	activity_rate
## Population2021	1.206978e-07	6.364915e-02
## fertility_rate	3.570181e-01	4.487642e-01
## unis_colleges_number	5.508042e-08	4.367627e-02
## teaching_staff	2.588742e-07	5.718552e-02
## students_enrolled	5.230809e-07	4.697410e-02
## graduates_uni	2.036097e-06	3.275288e-02
## ratio_grad_enrolled_unis	8.241284e-01	7.279581e-01
## TotalSchools	1.561710e-07	6.969806e-02
## gradtotot57	2.849101e-01	8.389067e-01
## gradtotot812	8.371293e-01	9.615401e-01
## employees_laborcontract_avg	4.769939e-09	7.004113e-02
## employees_laborcontract_avg_topop	8.347491e-08	1.078904e-02
## avgwage	0.000000e+00	1.429699e-01
## activity_rate	1.429699e-01	0.000000e+00
## labour_force_thousands	4.202570e-08	4.039449e-02
## employment_rate	5.280930e-02	6.367707e-11
## foreign_direct_investment_euro	1.405608e-09	9.453520e-02
## books_pamphlets	1.104665e-08	8.302153e-02
## accommodation_establishments	6.795621e-01	5.216436e-01
## arrivals_accommodation	8.244060e-02	2.928131e-01
## revenue_accomm_lev	2.782676e-01	5.992890e-01
## crimes	4.245266e-04	3.577024e-01
## ecological_assets	2.631720e-04	7.052540e-02
## water_supply2020	4.354830e-01	9.766521e-01
## connected_to_wastewater_collecting	3.166612e-02	2.207454e-04
## Pop_watersupplyregime	4.976932e-01	2.840861e-01
## waste_thousandtons	5.226491e-08	6.244443e-02
## hospitals2021	3.258252e-08	8.721927e-02
##	labour_force_thousands	employment_rate
## Population2021	1.353251e-30	1.872476e-02
## fertility_rate	2.212712e-01	5.585396e-01
## unis_colleges_number	7.430629e-19	2.730561e-02
## teaching_staff	1.547110e-13	3.373584e-02
## students_enrolled	2.481015e-14	2.261861e-02
## graduates_uni	2.384885e-13	1.670390e-02

## ratio_grad_enrolled_unis	9.339930e-01	5.405682e-01
## TotalSchools	2.023675e-29	2.469519e-02
## gradtotot57	1.726702e-01	5.268170e-01
## gradtotot812	3.102730e-01	9.459506e-01
## employees_laborcontract_avg	8.988365e-20	3.689337e-02
## employees_laborcontract_avg_topop	8.458678e-09	5.876543e-03
## avgwage	4.202570e-08	5.280930e-02
## activity_rate	4.039449e-02	6.367707e-11
## labour_force_thousands	0.000000e+00	1.334995e-02
## employment_rate	1.334995e-02	0.000000e+00
## foreign_direct_investment_euro	2.669757e-14	5.607410e-02
## books_pamphlets	8.989825e-13	6.397558e-02
## accommodation_establishments	1.426862e-01	2.716921e-01
## arrivals_accommodation	2.782551e-03	1.099995e-01
## revenue_accomm_lev	5.256686e-02	3.221385e-01
## crimes	4.605281e-08	7.418199e-02
## ecological_assets	4.022472e-04	9.965846e-03
## water_supply2020	3.921588e-01	7.231720e-01
## connected_to_wastewater_collecting	5.677852e-04	6.673639e-05
## Pop_watersupplyregime	4.004869e-01	6.414645e-01
## waste_thousandtons	5.224098e-25	2.178014e-02
## hospitals2021	6.634480e-19	2.258016e-02
##	foreign_direct_investment_euro	
## Population2021	9.061431e-13	
## fertility_rate	2.547309e-01	
## unis_colleges_number	6.483622e-15	
## teaching_staff	2.281280e-14	
## students_enrolled	4.017206e-12	
## graduates_uni	1.062732e-10	
## ratio_grad_enrolled_unis	7.656116e-01	
## TotalSchools	1.085266e-13	
## gradtotot57	3.363021e-01	
## gradtotot812	4.206455e-01	
## employees_laborcontract_avg	4.961713e-21	
## employees_laborcontract_avg_topop	8.777159e-09	
## avgwage	1.405608e-09	
## activity_rate	9.453520e-02	
## labour_force_thousands	2.669757e-14	
## employment_rate	5.607410e-02	
## foreign_direct_investment_euro	0.000000e+00	
## books_pamphlets	1.659138e-19	
## accommodation_establishments	3.555852e-01	
## arrivals_accommodation	1.815019e-02	
## revenue_accomm_lev	1.302487e-01	
## crimes	9.553139e-05	
## ecological_assets	2.698625e-03	
## water_supply2020	5.529411e-01	
## connected_to_wastewater_collecting	4.749950e-03	
## Pop_watersupplyregime	5.582831e-01	
## waste_thousandtons	3.161996e-13	
## hospitals2021	7.493611e-13	
##	books_pamphlets accommodation_establishments	
## Population2021	2.923013e-11	1.060308e-01
## fertility_rate	1.427859e-01	3.970448e-01

## unis_colleges_number	3.378688e-16	3.461010e-01
## teaching_staff	1.202546e-16	5.396915e-01
## students_enrolled	1.613908e-13	4.090528e-01
## graduates_uni	3.004326e-12	3.989867e-01
## ratio_grad_enrolled_unis	7.995991e-01	5.948895e-01
## TotalSchools	5.028625e-12	1.178582e-01
## gradtotot57	4.350870e-01	9.616885e-01
## gradtotot812	4.373995e-01	8.823993e-01
## employees_laborcontract_avg	1.641697e-19	3.781604e-01
## employees_laborcontract_avg_topop	1.258685e-08	3.180112e-01
## avgwage	1.104665e-08	6.795621e-01
## activity_rate	8.302153e-02	5.216436e-01
## labour_force_thousands	8.989825e-13	1.426862e-01
## employment_rate	6.397558e-02	2.716921e-01
## foreign_direct_investment_euro	1.659138e-19	3.555852e-01
## books_pamphlets	0.000000e+00	6.906769e-01
## accommodation_establishments	6.906769e-01	0.000000e+00
## arrivals_accommodation	7.783529e-02	3.501127e-13
## revenue_accomm_leve	3.425449e-01	3.621872e-13
## crimes	5.219904e-04	5.478229e-02
## ecological_assets	1.407395e-02	5.726460e-02
## water_supply2020	6.856924e-01	7.621771e-01
## connected_to_wastewater_collecting	1.346303e-02	2.252809e-02
## Pop_watersupplyregime	5.816912e-01	4.308826e-01
## waste_thousandtons	2.055625e-11	1.153675e-01
## hospitals2021	3.117799e-11	1.567887e-01
##	arrivals_accommodation	revenue_accomm_leve
## Population2021	1.723961e-03	3.938970e-02
## fertility_rate	2.981475e-01	3.731348e-01
## unis_colleges_number	1.820738e-02	1.680250e-01
## teaching_staff	5.164016e-02	3.005860e-01
## students_enrolled	3.160789e-02	2.410499e-01
## graduates_uni	3.432386e-02	2.659196e-01
## ratio_grad_enrolled_unis	8.841564e-01	9.095843e-01
## TotalSchools	2.054524e-03	4.426235e-02
## gradtotot57	6.179802e-01	7.505972e-01
## gradtotot812	6.007516e-01	6.186110e-01
## employees_laborcontract_avg	2.008526e-02	1.697448e-01
## employees_laborcontract_avg_topop	3.902443e-02	2.676039e-01
## avgwage	8.244060e-02	2.782676e-01
## activity_rate	2.928131e-01	5.992890e-01
## labour_force_thousands	2.782551e-03	5.256686e-02
## employment_rate	1.099995e-01	3.221385e-01
## foreign_direct_investment_euro	1.815019e-02	1.302487e-01
## books_pamphlets	7.783529e-02	3.425449e-01
## accommodation_establishments	3.501127e-13	3.621872e-13
## arrivals_accommodation	0.000000e+00	7.767479e-17
## revenue_accomm_leve	7.767479e-17	0.000000e+00
## crimes	2.267126e-03	3.641935e-02
## ecological_assets	6.520253e-03	3.008247e-02
## water_supply2020	6.180186e-01	5.459912e-01
## connected_to_wastewater_collecting	1.890579e-03	2.239572e-02
## Pop_watersupplyregime	3.271437e-01	4.597803e-01
## waste_thousandtons	2.053488e-03	4.125734e-02

## hospitals2021	5.226827e-03	8.942890e-02
##	crimes	ecological_assets
## Population2021	2.896434e-09	3.074933e-04
## fertility_rate	9.992960e-01	8.700390e-01
## unis_colleges_number	5.074073e-06	5.287059e-03
## teaching_staff	7.564267e-05	1.023470e-02
## students_enrolled	1.284867e-05	8.930799e-03
## graduates_uni	1.496406e-05	1.209404e-02
## ratio_grad_enrolled_unis	7.736133e-01	6.985980e-01
## TotalSchools	1.959883e-08	4.419658e-04
## gradtotot57	2.587411e-02	1.744826e-01
## gradtotot812	3.262990e-01	9.275258e-01
## employees_laborcontract_avg	5.272764e-06	1.776650e-03
## employees_laborcontract_avg_topop	3.575331e-04	9.384480e-04
## avgwage	4.245266e-04	2.631720e-04
## activity_rate	3.577024e-01	7.052540e-02
## labour_force_thousands	4.605281e-08	4.022472e-04
## employment_rate	7.418199e-02	9.965846e-03
## foreign_direct_investment_euro	9.553139e-05	2.698625e-03
## books_pamphlets	5.219904e-04	1.407395e-02
## accommodation_establishments	5.478229e-02	5.726460e-02
## arrivals_accommodation	2.267126e-03	6.520253e-03
## revenue_accomm_lev	3.641935e-02	3.008247e-02
## crimes	0.000000e+00	4.909495e-05
## ecological_assets	4.909495e-05	0.000000e+00
## water_supply2020	9.173999e-02	4.478699e-01
## connected_to_wastewater_collecting	2.148812e-03	1.783444e-02
## Pop_watersupplyregime	2.115819e-01	2.952266e-01
## waste_thousandtons	1.060412e-08	5.035568e-04
## hospitals2021	1.050377e-08	5.082737e-04
##	water_supply2020	
## Population2021	0.35887402	
## fertility_rate	0.19320258	
## unis_colleges_number	0.43605885	
## teaching_staff	0.46896957	
## students_enrolled	0.38752721	
## graduates_uni	0.36871610	
## ratio_grad_enrolled_unis	0.82526279	
## TotalSchools	0.44131607	
## gradtotot57	0.03062454	
## gradtotot812	0.65868014	
## employees_laborcontract_avg	0.47370794	
## employees_laborcontract_avg_topop	0.61856240	
## avgwage	0.43548300	
## activity_rate	0.97665210	
## labour_force_thousands	0.39215879	
## employment_rate	0.72317200	
## foreign_direct_investment_euro	0.55294114	
## books_pamphlets	0.68569244	
## accommodation_establishments	0.76217711	
## arrivals_accommodation	0.61801859	
## revenue_accomm_lev	0.54599119	
## crimes	0.09173999	
## ecological_assets	0.44786989	

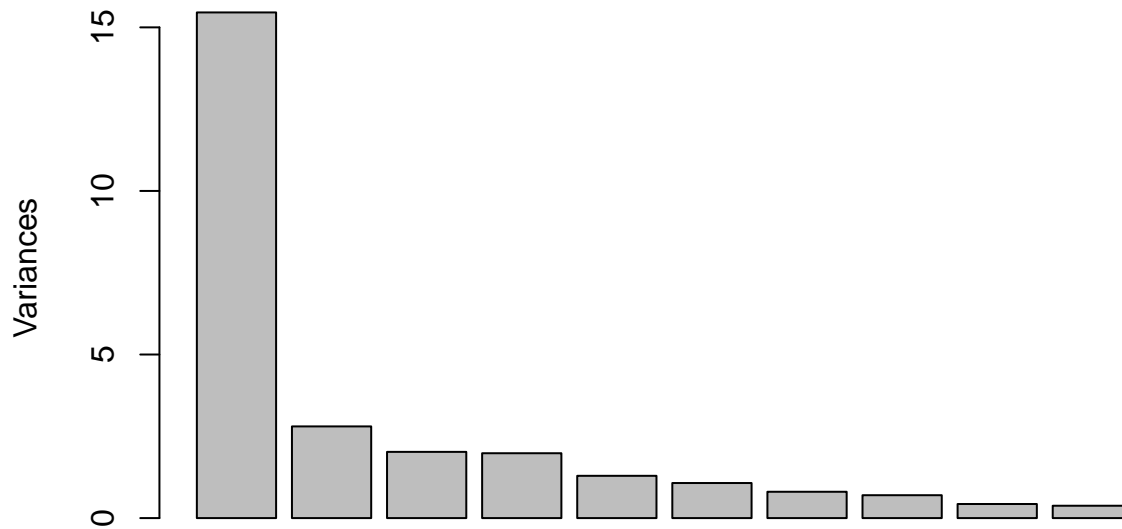
## water_supply2020	0.00000000
## connected_to_wastewater_collecting	0.30767670
## Pop_watersupplyregime	0.74842448
## waste_thousandtons	0.31990552
## hospitals2021	0.46762118
##	connected_to_wastewater_collecting
## Population2021	6.150684e-04
## fertility_rate	9.806480e-01
## unis_colleges_number	1.269101e-03
## teaching_staff	4.260336e-03
## students_enrolled	1.863047e-03
## graduates_uni	1.926984e-03
## ratio_grad_enrolled_unis	9.128116e-01
## TotalSchools	9.879394e-04
## gradtotot57	1.816405e-01
## gradtotot812	9.485631e-01
## employees_laborcontract_avg	2.169007e-03
## employees_laborcontract_avg_topop	8.133561e-05
## avgwage	3.166612e-02
## activity_rate	2.207454e-04
## labour_force_thousands	5.677852e-04
## employment_rate	6.673639e-05
## foreign_direct_investment_euro	4.749950e-03
## books_pamphlets	1.346303e-02
## accommodation_establishments	2.252809e-02
## arrivals_accommodation	1.890579e-03
## revenue_accomm_lev	2.239572e-02
## crimes	2.148812e-03
## ecological_assets	1.783444e-02
## water_supply2020	3.076767e-01
## connected_to_wastewater_collecting	0.000000e+00
## Pop_watersupplyregime	5.816404e-01
## waste_thousandtons	5.890266e-04
## hospitals2021	6.313287e-04
##	Pop_watersupplyregime waste_thousandtons
## Population2021	0.3555547 5.810950e-27
## fertility_rate	0.6757799 2.628634e-01
## unis_colleges_number	0.6193130 1.387675e-17
## teaching_staff	0.5005677 4.264841e-12
## students_enrolled	0.4765412 3.808107e-13
## graduates_uni	0.4816123 4.320566e-12
## ratio_grad_enrolled_unis	0.1143659 8.285402e-01
## TotalSchools	0.3332932 1.372964e-22
## gradtotot57	0.8187514 1.277785e-01
## gradtotot812	0.6027330 2.954185e-01
## employees_laborcontract_avg	0.4786344 3.411883e-17
## employees_laborcontract_avg_topop	0.5217981 2.196234e-08
## avgwage	0.4976932 5.226491e-08
## activity_rate	0.2840861 6.244443e-02
## labour_force_thousands	0.4004869 5.224098e-25
## employment_rate	0.6414645 2.178014e-02
## foreign_direct_investment_euro	0.5582831 3.161996e-13
## books_pamphlets	0.5816912 2.055625e-11
## accommodation_establishments	0.4308826 1.153675e-01

## arrivals_accommodation	0.3271437	2.053488e-03
## revenue_accomm_lev	0.4597803	4.125734e-02
## crimes	0.2115819	1.060412e-08
## ecological_assets	0.2952266	5.035568e-04
## water_supply2020	0.7484245	3.199055e-01
## connected_to_wastewater_collecting	0.5816404	5.890266e-04
## Pop_watersupplyregime	0.0000000	4.781744e-01
## waste_thousandtons	0.4781744	0.000000e+00
## hospitals2021	0.3212510	6.523838e-19
##	hospitals2021	
## Population2021	5.654075e-20	
## fertility_rate	2.790436e-01	
## unis_colleges_number	3.580988e-15	
## teaching_staff	6.870403e-12	
## students_enrolled	1.332925e-12	
## graduates_uni	8.246069e-12	
## ratio_grad_enrolled_unis	9.084748e-01	
## TotalSchools	6.089195e-19	
## gradtotot57	1.386525e-01	
## gradtotot812	6.143097e-01	
## employees_laborcontract_avg	2.143765e-16	
## employees_laborcontract_avg_topop	5.841520e-09	
## avgwage	3.258252e-08	
## activity_rate	8.721927e-02	
## labour_force_thousands	6.634480e-19	
## employment_rate	2.258016e-02	
## foreign_direct_investment_euro	7.493611e-13	
## books_pamphlets	3.117799e-11	
## accommodation_establishments	1.567887e-01	
## arrivals_accommodation	5.226827e-03	
## revenue_accomm_lev	8.942890e-02	
## crimes	1.050377e-08	
## ecological_assets	5.082737e-04	
## water_supply2020	4.676212e-01	
## connected_to_wastewater_collecting	6.313287e-04	
## Pop_watersupplyregime	3.212510e-01	
## waste_thousandtons	6.523838e-19	
## hospitals2021	0.000000e+00	

PCA

```
pr.out <- prcomp(bul[, -1] , scale = TRUE)
plot(pr.out)
```

pr.out



pr.out\$rotation

##	PC1	PC2	PC3
## Population2021	0.251140229	-0.005046812	0.052035616
## fertility_rate	-0.061933786	0.004236421	0.443056816
## unis_colleges_number	0.246977988	-0.100950594	-0.019287931
## teaching_staff	0.239559270	-0.144548347	-0.017635288
## students_enrolled	0.242020761	-0.116779470	-0.019543819
## graduates_uni	0.239369553	-0.112562813	-0.028872779
## ratio_grad_enrolled_unis	-0.005262813	0.082745242	0.141708436
## TotalSchools	0.250129175	-0.013680735	0.045314795
## gradtotot57	-0.066483530	-0.011406212	-0.461880847
## gradtotot812	-0.041952643	0.003572495	-0.058022670
## employees_laborcontract_avg	0.247939032	-0.105909278	0.009054059
## employees_laborcontract_avg_topop	0.226481280	-0.065514636	-0.110787032
## avgwage	0.215023672	-0.118080001	0.024551632
## activity_rate	0.110739683	0.056607059	-0.375160411
## labour_force_thousands	0.252312426	-0.023844442	0.024538549
## employment_rate	0.129915368	0.111185559	-0.314809366
## foreign_direct_investment_euro	0.240654010	-0.101108177	-0.003687789
## books_pamphlets	0.234898285	-0.170648060	-0.042960180
## accommodation_establishments	0.082140331	0.538786847	-0.041966539
## arrivals_accommodation	0.145251001	0.470908872	0.001131015
## revenue_accomm_lev	0.101725203	0.507921078	0.015530774
## crimes	0.207845520	0.097844232	0.249667957

## ecological_assets	0.165723426	0.160041012	0.068263378
## water_supply2020	0.045534485	0.007033836	0.416155456
## connected_to_wastewater_collecting	0.168502577	0.194519974	-0.106008313
## Pop_watersupplyregime	-0.040172150	-0.077565432	-0.215900135
## waste_thousandtons	0.250515857	-0.012492624	0.050882951
## hospitals2021	0.247929971	-0.034340547	0.048643960
##	PC4	PC5	PC6
## Population2021	-0.04016222	1.405881e-03	-0.026670081
## fertility_rate	0.37475711	-3.609576e-02	0.103935000
## unis_colleges_number	-0.04174413	2.652159e-02	-0.034809698
## teaching_staff	-0.04685187	1.025979e-02	-0.027435736
## students_enrolled	-0.03959269	4.495466e-03	-0.045609725
## graduates_uni	-0.02697869	-3.164669e-02	-0.065203828
## ratio_grad_enrolled_unis	0.11278802	-7.418846e-01	0.013598332
## TotalSchools	-0.05623542	-1.941028e-02	-0.027090775
## gradtotot57	-0.33887249	-8.712085e-02	0.041488149
## gradtotot812	0.17981239	1.652511e-01	0.837895553
## employees_laborcontract_avg	-0.05237174	7.969481e-03	0.014758752
## employees_laborcontract_avg_topop	0.04736688	-5.897516e-02	0.105921510
## avgwage	-0.01160603	3.114401e-02	0.271902878
## activity_rate	0.44251861	-1.249495e-01	-0.141843819
## labour_force_thousands	-0.02995947	-6.659888e-03	-0.025058190
## employment_rate	0.42421384	-1.925941e-01	-0.058761222
## foreign_direct_investment_euro	-0.07187571	3.242673e-02	0.039920946
## books_pamphlets	-0.08357866	3.638601e-05	0.022444782
## accommodation_establishments	-0.12261989	2.032362e-02	0.039670130
## arrivals_accommodation	-0.11912516	7.387451e-02	-0.005329358
## revenue_accomm_lev	-0.14676286	1.449268e-01	-0.025052242
## crimes	0.02072875	-1.468744e-02	-0.027129525
## ecological_assets	0.10532497	2.038307e-02	0.231521726
## water_supply2020	0.15655341	2.256034e-01	-0.246563843
## connected_to_wastewater_collecting	0.33698932	5.638967e-02	-0.067358955
## Pop_watersupplyregime	0.30400210	5.196688e-01	-0.184599379
## waste_thousandtons	-0.03224516	3.517184e-02	-0.036443026
## hospitals2021	-0.02989101	-3.166684e-03	0.080688532
##	PC7	PC8	PC9
## Population2021	0.02019425	-0.059980228	0.06275423
## fertility_rate	0.23468104	-0.176219808	-0.03654949
## unis_colleges_number	0.09120326	0.051452197	0.01717751
## teaching_staff	0.08183814	0.070820986	0.08810036
## students_enrolled	0.05543924	0.110100735	0.14526978
## graduates_uni	0.06115848	0.146203307	0.14627099
## ratio_grad_enrolled_unis	0.33129749	0.177025021	-0.36766992
## TotalSchools	0.04673119	-0.071525175	0.03656808
## gradtotot57	-0.14720072	0.210109707	-0.22699371
## gradtotot812	0.09945341	0.327153104	0.14803643
## employees_laborcontract_avg	0.07032260	-0.008784486	-0.04867281
## employees_laborcontract_avg_topop	-0.06585973	0.109364831	-0.11445501
## avgwage	-0.10297619	-0.049047887	-0.45033635
## activity_rate	-0.16466121	0.080136405	-0.02264198
## labour_force_thousands	0.02609689	-0.040365356	0.01983792
## employment_rate	-0.18778716	-0.101407142	0.09128334
## foreign_direct_investment_euro	0.10711059	-0.018436774	-0.18727399
## books_pamphlets	0.12651227	0.030829900	-0.11940666

## accommodation_establishments	0.17436277	0.009984262	0.02076352
## arrivals_accommodation	0.09251497	0.056889976	-0.03328867
## revenue_accomm_lev	0.07528513	0.066001173	-0.15934926
## crimes	-0.12063551	-0.160887415	0.20309459
## ecological_assets	-0.50307637	-0.437299225	-0.28397969
## water_supply2020	-0.38587557	0.636274968	-0.25644061
## connected_to_wastewater_collecting	0.07506431	0.221115544	0.25165095
## Pop_watersupplyregime	0.44588949	-0.140510827	-0.40255136
## waste_thousandtons	0.04099822	-0.049472640	0.02010311
## hospitals2021	0.03824365	-0.041886813	0.13040802
##	PC10	PC11	PC12
## Population2021	-0.0168836459	-0.093225382	0.1018160596
## fertility_rate	0.6380286887	0.231486672	0.1769750710
## unis_colleges_number	0.0239611255	-0.016547933	0.0514600322
## teaching_staff	0.0307476342	0.183442531	0.0886325014
## students_enrolled	0.0004004975	0.047319915	0.1187740551
## graduates_uni	-0.0519972274	-0.005348873	0.1794255872
## ratio_grad_enrolled_unis	-0.1729083306	-0.243545964	0.0309737448
## TotalSchools	0.0004006340	-0.057788246	0.0874262960
## gradtotot57	0.6080084393	-0.275306719	0.2913052930
## gradtotot812	-0.1370303922	-0.081850435	0.1925188825
## employees_laborcontract_avg	0.0520653695	0.055411878	-0.0180460264
## employees_laborcontract_avg_topop	0.0743572849	-0.115109404	-0.6083186280
## avgwage	-0.0737695150	0.131985939	-0.1103068998
## activity_rate	-0.0552838685	0.208197337	0.1974823402
## labour_force_thousands	-0.0129917572	-0.034755837	0.0901811381
## employment_rate	-0.0950562059	0.125241648	0.1968395523
## foreign_direct_investment_euro	0.1153390853	0.212229917	-0.0412527522
## books_pamphlets	0.0219390341	0.214055832	0.0007111605
## accommodation_establishments	-0.0288290821	0.001390045	0.0014814354
## arrivals_accommodation	0.0015191893	0.098974325	0.0447057764
## revenue_accomm_lev	-0.0305071498	0.237413108	0.0492522367
## crimes	0.0055588757	-0.558573276	0.2035447627
## ecological_assets	0.0362582972	-0.118389589	-0.0181203832
## water_supply2020	-0.0395601061	-0.040884384	0.1182334671
## connected_to_wastewater_collecting	0.3340814174	-0.186116166	-0.4763904399
## Pop_watersupplyregime	-0.1151861273	-0.345360056	0.0969978774
## waste_thousandtons	-0.0238408894	-0.076750683	0.0650278689
## hospitals2021	-0.0146156027	-0.133726558	0.0104478511
##	PC13	PC14	PC15
## Population2021	-0.1321722330	0.093474052	0.027638529
## fertility_rate	0.0549335456	-0.076049052	0.190349517
## unis_colleges_number	-0.0266267429	0.084927756	0.170125690
## teaching_staff	0.3296591037	-0.129434155	-0.131896564
## students_enrolled	0.3223717184	-0.277026611	-0.009374319
## graduates_uni	0.3849009164	-0.265605969	0.009411193
## ratio_grad_enrolled_unis	0.0724045786	0.052040906	-0.141319676
## TotalSchools	-0.1279401565	0.216749460	-0.026143983
## gradtotot57	-0.0371149842	-0.042851029	-0.003079070
## gradtotot812	0.0093051158	0.120481589	-0.053755583
## employees_laborcontract_avg	-0.0231376124	0.178184628	-0.112819185
## employees_laborcontract_avg_topop	0.2170818491	-0.049027191	0.361194174
## avgwage	-0.3529072840	-0.499788252	0.222815066
## activity_rate	-0.0004909334	0.385773942	0.437424253

## labour_force_thousands	-0.1159618891	0.130856611	-0.020306794
## employment_rate	-0.1840850669	-0.403153160	-0.266385818
## foreign_direct_investment_euro	-0.0864655962	0.183398640	-0.235351122
## books_pamphlets	-0.0047737436	0.186571537	-0.194218466
## accommodation_establishments	0.2539483214	-0.035968977	0.315486202
## arrivals_accommodation	-0.0492190213	-0.006592734	-0.022878872
## revenue_accomm_lev	-0.0958276207	-0.069414221	-0.135651369
## crimes	-0.1215066743	-0.125571328	0.107171134
## ecological_assets	0.4243591003	0.189530657	-0.249992143
## water_supply2020	0.0095962307	0.040162578	-0.031193869
## connected_to_wastewater_collecting	-0.1314769442	-0.009570540	-0.339207667
## Pop_watersupplyregime	0.1155992369	-0.038622851	-0.047841014
## waste_thousandtons	-0.1791533385	0.062930152	0.175946231
## hospitals2021	-0.1848429727	0.048135287	0.050536760
##	PC16	PC17	PC18
## Population2021	-0.07710523	-0.129364489	-0.089701395
## fertility_rate	0.06228573	-0.092578349	-0.035614218
## unis_colleges_number	-0.07346819	-0.429518433	-0.005901009
## teaching_staff	-0.02108584	0.122618706	0.159107017
## students_enrolled	-0.14704734	0.030368022	-0.017382224
## graduates_uni	-0.17604598	0.057034704	-0.155396774
## ratio_grad_enrolled_unis	-0.06764702	0.004709447	-0.015114569
## TotalSchools	-0.09965398	-0.140541976	-0.176573630
## gradtotot57	0.03332089	-0.011601388	-0.021399049
## gradtotot812	0.02071715	-0.078409544	0.023349072
## employees_laborcontract_avg	0.08927507	-0.016014067	0.083869565
## employees_laborcontract_avg_topop	0.34620346	-0.297320462	0.027079306
## avgwage	-0.32614332	0.210215987	0.039521141
## activity_rate	-0.21066731	0.218805084	0.163734938
## labour_force_thousands	-0.12483484	-0.167052338	-0.093584807
## employment_rate	0.43301928	-0.224043524	-0.088335975
## foreign_direct_investment_euro	0.28397734	0.386075077	-0.048628070
## books_pamphlets	0.15495621	-0.072691756	0.419308568
## accommodation_establishments	0.23366748	0.268961521	0.025040531
## arrivals_accommodation	-0.06783844	-0.100581051	-0.379495289
## revenue_accomm_lev	-0.07092829	-0.205087305	0.375331896
## crimes	0.09112184	0.104875484	0.510061856
## ecological_assets	-0.13413661	-0.008209166	-0.096416008
## water_supply2020	0.16314088	0.009875505	-0.076672278
## connected_to_wastewater_collecting	-0.34457527	0.155615575	0.035396129
## Pop_watersupplyregime	0.04406206	-0.009788759	-0.039430295
## waste_thousandtons	-0.02390299	-0.093289450	-0.178665815
## hospitals2021	0.30159797	0.403833928	-0.286367833
##	PC19	PC20	PC21
## Population2021	-0.154503748	-0.043549917	0.307144277
## fertility_rate	-0.032124130	0.046450253	0.068674807
## unis_colleges_number	0.568141129	0.184904978	-0.523078719
## teaching_staff	-0.242905710	-0.036666200	-0.400488598
## students_enrolled	-0.052205906	-0.221050665	0.061306063
## graduates_uni	0.103326338	0.205780106	0.281957120
## ratio_grad_enrolled_unis	0.022881560	-0.023021262	-0.025539591
## TotalSchools	-0.408376680	0.267115180	-0.154543141
## gradtotot57	-0.016054830	0.002050614	0.031113915
## gradtotot812	-0.038771104	-0.064049526	-0.012397133

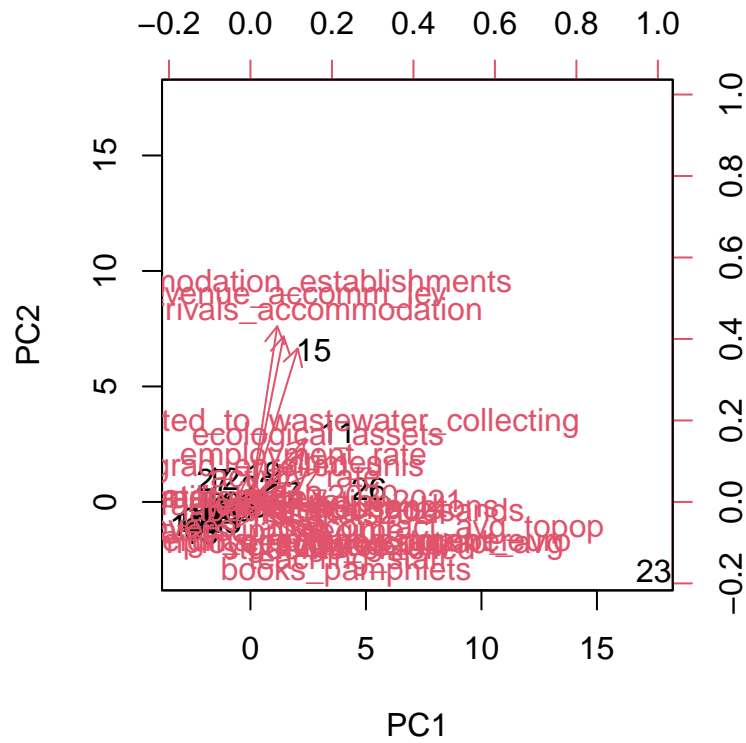
## employees_laborcontract_avg	-0.092580596	-0.128446268	0.099117046
## employees_laborcontract_avg_topop	-0.263475459	0.003936368	0.048354880
## avgwage	0.007355372	0.072237077	-0.033152913
## activity_rate	-0.083426973	0.025488912	-0.017970142
## labour_force_thousands	-0.173409321	-0.040669704	0.168902664
## employment_rate	0.024620222	-0.031351816	-0.014868603
## foreign_direct_investment_euro	-0.032736532	-0.292591009	-0.283526928
## books_pamphlets	0.242799215	0.224201731	0.356753583
## accommodation_establishments	0.193322154	-0.051909938	0.042794921
## arrivals_accommodation	-0.169503103	0.046030539	-0.164336350
## revenue_accomm_lev	-0.062085362	0.078478970	0.104313837
## crimes	-0.114871456	-0.038966560	-0.166695216
## ecological_assets	0.156851129	0.018053772	0.010619666
## water_supply2020	0.020320334	0.011650100	0.009907705
## connected_to_wastewater_collecting	0.142264473	-0.008082126	0.005050094
## Pop_watersupplyregime	-0.050101597	0.030905604	0.009886265
## waste_thousandtons	0.280639863	-0.639668990	0.169182685
## hospitals2021	0.159588451	0.457352796	0.107564439
##	PC22	PC23	PC24
## Population2021	0.0654777324	0.129373772	0.2056324324
## fertility_rate	-0.0147515380	-0.024175158	0.0088349658
## unis_colleges_number	0.0935155690	0.040487740	0.1601170253
## teaching_staff	-0.4235288127	0.189444768	-0.2642041725
## students_enrolled	-0.0749515978	-0.125239102	0.3446037987
## graduates_uni	0.2969064949	-0.192220169	-0.0413222425
## ratio_grad_enrolled_unis	-0.0783260913	-0.026990899	0.0295704684
## TotalSchools	-0.0974739992	0.257173572	-0.0490972126
## gradtotot57	-0.0583458729	0.022290446	-0.0071334339
## gradtotot812	0.0071975926	-0.009401281	0.0138215150
## employees_laborcontract_avg	0.0698125332	0.098498150	-0.2036714506
## employees_laborcontract_avg_topop	-0.0173954920	-0.155161872	0.0541945783
## avgwage	0.0605070198	0.126376805	-0.0927488122
## activity_rate	-0.0093185886	-0.154101205	0.0185061973
## labour_force_thousands	0.2084576409	0.321884996	0.1884395674
## employment_rate	0.0350099916	0.121002701	-0.0275185552
## foreign_direct_investment_euro	0.3593413316	-0.167835736	0.3169568145
## books_pamphlets	0.0794464067	-0.040725454	-0.3663331120
## accommodation_establishments	0.1344548124	0.532507548	-0.0448983418
## arrivals_accommodation	0.2046641657	-0.425390708	-0.4230215589
## revenue_accomm_lev	-0.3052001492	-0.194673668	0.3861106586
## crimes	0.1827975908	-0.199822382	-0.0917694112
## ecological_assets	-0.0688416826	-0.002826552	0.0190181672
## water_supply2020	-0.0069660492	0.115550268	-0.0261962050
## connected_to_wastewater_collecting	0.0008689237	0.101992718	-0.0298507629
## Pop_watersupplyregime	-0.0376494657	-0.012086685	-0.0002683304
## waste_thousandtons	-0.3756266036	-0.099145235	-0.2242676573
## hospitals2021	-0.4142926457	-0.165538552	0.1523689554
##	PC25	PC26	PC27
## Population2021	0.0852439902	0.0791172178	0.5237957371
## fertility_rate	0.0039106427	-0.0100638217	-0.0112871421
## unis_colleges_number	0.0940721568	0.0612522096	0.0449362052
## teaching_staff	0.1595717161	-0.2937024411	0.1966910357
## students_enrolled	-0.2195476356	0.4823372638	0.2154143092
## graduates_uni	0.0468161826	-0.2505286199	-0.4165989338

## ratio_grad_enrolled_unis	0.0184181622	0.0003378177	0.0274883073
## TotalSchools	-0.5061210677	0.2040150164	-0.3805876949
## gradtotot57	0.0016714399	-0.0129735898	0.0048694753
## gradtotot812	-0.0178018727	-0.0146793820	-0.0156542432
## employees_laborcontract_avg	0.6374265376	0.5066078164	-0.3091993501
## employees_laborcontract_avg_topop	-0.0199160070	-0.0901447228	-0.0160736699
## avgwage	-0.0002416359	0.0497526207	0.0112651718
## activity_rate	0.0304196767	0.0104378016	0.0151691322
## labour_force_thousands	0.2059455108	-0.4880843239	0.0715377025
## employment_rate	-0.0236621077	0.0276649174	-0.0302060041
## foreign_direct_investment_euro	-0.1478529298	-0.1345584531	-0.0755563930
## books_pamphlets	-0.3309351305	0.0005716673	0.2163856320
## accommodation_establishments	-0.0869148748	0.0788331992	-0.0041964401
## arrivals_accommodation	0.0491793992	0.0452399615	0.2645186511
## revenue_accomm_lev	0.0842382901	-0.0894831851	-0.2268662044
## crimes	-0.0169318943	-0.0260631710	-0.0123735264
## ecological_assets	-0.0093271296	0.0069688993	0.0192815211
## water_supply2020	-0.0235685186	0.0244925727	0.0239466505
## connected_to_wastewater_collecting	-0.0369812432	0.0027659737	-0.0007149752
## Pop_watersupplyregime	0.0075788807	0.0007935117	0.0234186248
## waste_thousandtons	-0.1628121185	-0.1551360420	-0.1940579176
## hospitals2021	0.1525697717	-0.0086488525	0.0585809637
##	PC28		
## Population2021	0.6128476922		
## fertility_rate	-0.0080424509		
## unis_colleges_number	0.0448730022		
## teaching_staff	0.1287858709		
## students_enrolled	-0.3805720960		
## graduates_uni	0.2583817625		
## ratio_grad_enrolled_unis	-0.0031092368		
## TotalSchools	0.0610317081		
## gradtotot57	0.0002864466		
## gradtotot812	0.0171326853		
## employees_laborcontract_avg	-0.0301864303		
## employees_laborcontract_avg_topop	0.0110645654		
## avgwage	0.0056638971		
## activity_rate	-0.0134870268		
## labour_force_thousands	-0.5563890778		
## employment_rate	0.0157154941		
## foreign_direct_investment_euro	0.1343258793		
## books_pamphlets	-0.1272072325		
## accommodation_establishments	0.0135119023		
## arrivals_accommodation	-0.1302307766		
## revenue_accomm_lev	0.0718153138		
## crimes	-0.0386269751		
## ecological_assets	-0.0044437954		
## water_supply2020	-0.0061153737		
## connected_to_wastewater_collecting	0.0236414166		
## Pop_watersupplyregime	-0.0134082821		
## waste_thousandtons	0.0380803984		
## hospitals2021	-0.1371227048		

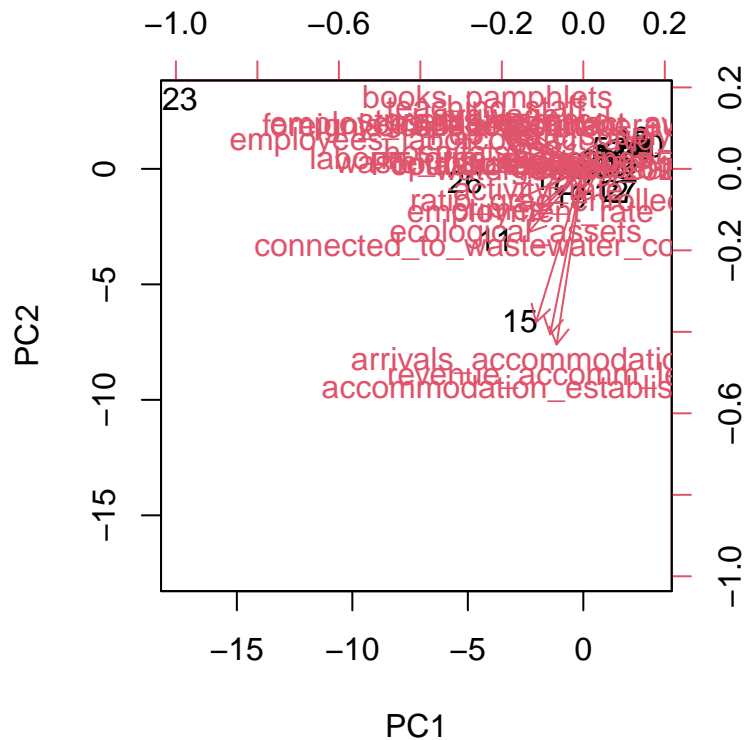
```
dim(pr.out$x)
```

```
## [1] 28 28
```

```
biplot(pr.out , scale = 0)
```



```
pr.out$rotation = -pr.out$rotation
pr.out$x = -pr.out$x
biplot(pr.out , scale = 0)
```



```
pr.out$sdev
```

```
## [1] 3.931517e+00 1.673940e+00 1.422777e+00 1.408069e+00 1.136550e+00
## [6] 1.035448e+00 8.969773e-01 8.363943e-01 6.559477e-01 6.144131e-01
## [11] 5.910615e-01 5.221696e-01 3.894370e-01 3.322988e-01 2.626092e-01
## [16] 1.989281e-01 1.607195e-01 1.192726e-01 1.019228e-01 8.704966e-02
## [21] 5.928014e-02 4.905328e-02 3.665443e-02 1.696045e-02 1.030414e-02
## [26] 5.546134e-03 2.585343e-03 1.228443e-15
```

*#The variance explained by each principal component is obtained by squaring
#these:*

```
pr.var <- pr.out$sdev^2
pr.var
```

```
## [1] 1.545683e+01 2.802075e+00 2.024294e+00 1.982658e+00 1.291747e+00
## [6] 1.072152e+00 8.045683e-01 6.995555e-01 4.302674e-01 3.775034e-01
## [11] 3.493538e-01 2.726611e-01 1.516612e-01 1.104225e-01 6.896358e-02
## [16] 3.957237e-02 2.583074e-02 1.422594e-02 1.038825e-02 7.577643e-03
## [21] 3.514135e-03 2.406225e-03 1.343547e-03 2.876568e-04 1.061753e-04
## [26] 3.075960e-05 6.684000e-06 1.509072e-30
```

#explained var

```
pve <- pr.var / sum(pr.var)
pve
```

```
## [1] 5.520296e-01 1.000741e-01 7.229622e-02 7.080921e-02 4.613381e-02
## [6] 3.829113e-02 2.873458e-02 2.498412e-02 1.536669e-02 1.348227e-02
## [11] 1.247692e-02 9.737897e-03 5.416470e-03 3.943661e-03 2.462985e-03
## [16] 1.413299e-03 9.225266e-04 5.080694e-04 3.710089e-04 2.706301e-04
## [21] 1.255048e-04 8.593659e-05 4.798382e-05 1.027346e-05 3.791974e-06
## [26] 1.098557e-06 2.387143e-07 5.389545e-32
```

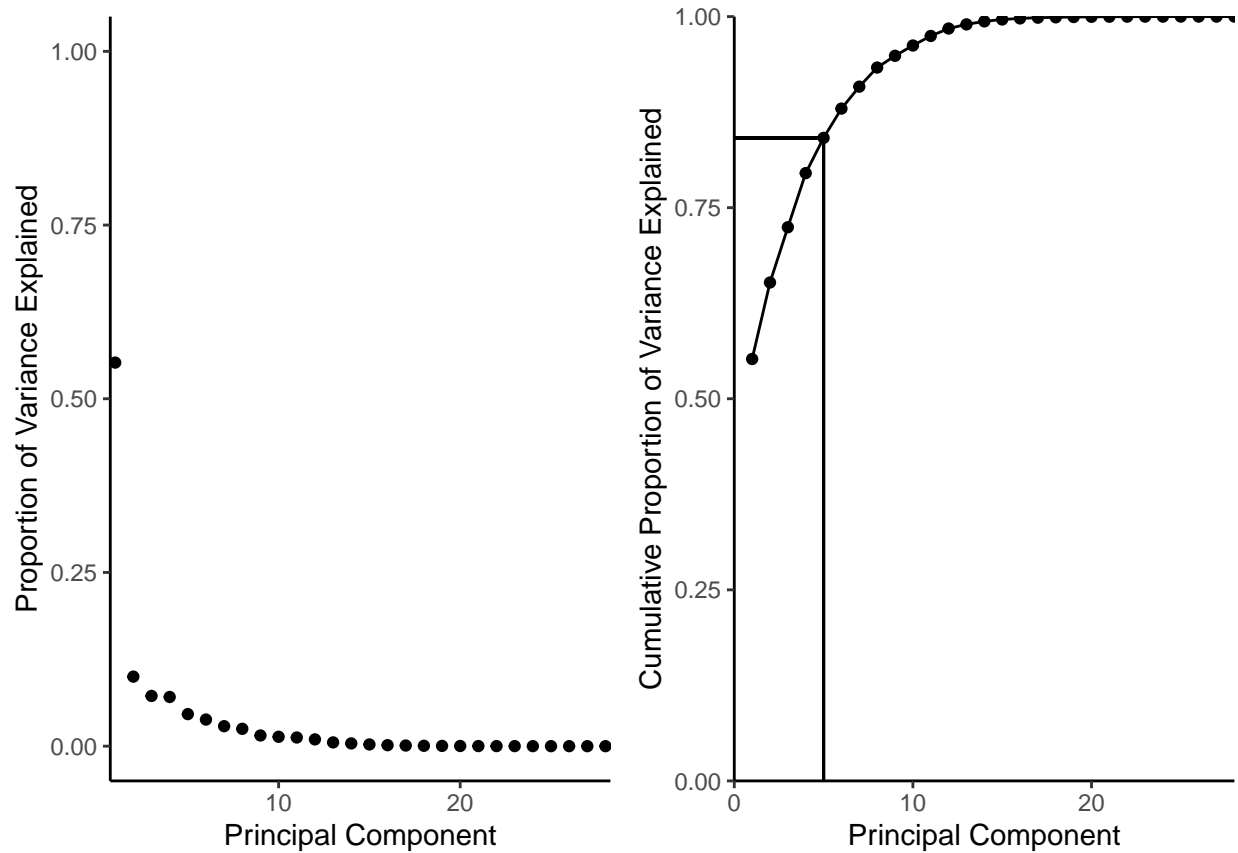
```
library(ggpubr)
```

```
## Warning: package 'ggpubr' was built under R version 4.1.3
```

```
p1 <- ggplot(data = as.data.frame(pve), aes(x = seq(1:28), y = pve)) +
  geom_point() +
  #geom_line() +
  #geom_segment(aes(x = 5, y = 0, xend = 5, yend = pve[5])) +
  #geom_segment(aes(x = 0, y = pve[5], xend = 5, yend = pve[5])) +
  xlab("Principal Component") +
  ylab("Proportion of Variance Explained") +
  scale_x_continuous(expand = c(0.01,0)) +
  scale_y_continuous(expand = c(0.05, 0), limits = c(0,1)) +
  theme_classic()

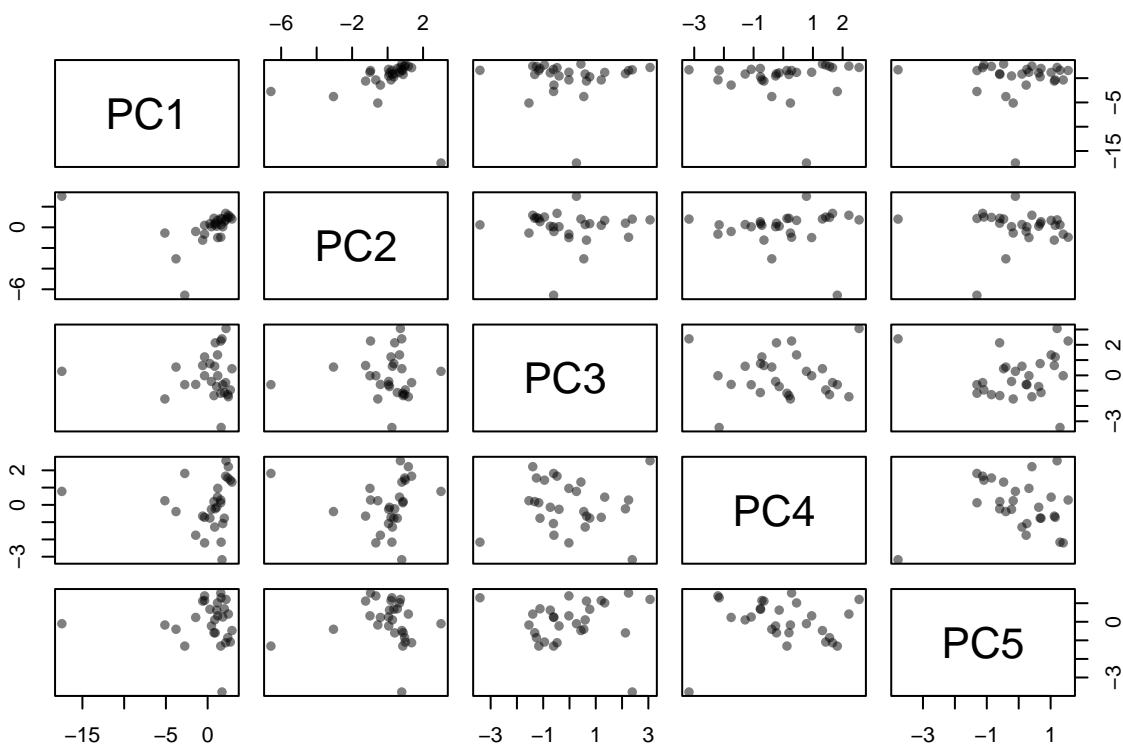
p2 <- ggplot(data = as.data.frame(cumsum(pve)), aes(x = seq(1:28), y = cumsum(pve))) +
  geom_point() +
  geom_line() +
  geom_segment(aes(x = 5, y = 0, xend = 5, yend = cumsum(pve)[5])) +
  geom_segment(aes(x = 0, y = cumsum(pve)[5], xend = 5, yend = cumsum(pve)[5])) +
  xlab("Principal Component") +
  ylab("Cumulative Proportion of Variance Explained") +
  scale_x_continuous(expand = c(0,0)) +
  scale_y_continuous(expand = c(0, 0)) +
  theme_classic()

ggarrange(p1, p2)
```



```
comp <- data.frame(pr.out$x[,1:5])

#write.csv(comp, "C:/Users/User/Documents/UNITN/Computational social science/bulgariafirst5PCs.csv")
plot(comp, pch=16, col=rgb(0,0,0,0.5))
```



#outlier in all the dimensions, and some grouping in the different projections.

```
summary(pr.out)
```

```
## Importance of components:
##              PC1    PC2    PC3    PC4    PC5    PC6    PC7
## Standard deviation  3.932 1.6739 1.4228 1.40807 1.13655 1.03545 0.89698
## Proportion of Variance 0.552 0.1001 0.0723 0.07081 0.04613 0.03829 0.02873
## Cumulative Proportion 0.552 0.6521 0.7244 0.79521 0.84134 0.87963 0.90837
##              PC8    PC9    PC10    PC11    PC12    PC13    PC14
## Standard deviation  0.83639 0.65595 0.61441 0.59106 0.52217 0.38944 0.33230
## Proportion of Variance 0.02498 0.01537 0.01348 0.01248 0.00974 0.00542 0.00394
## Cumulative Proportion 0.93335 0.94872 0.96220 0.97468 0.98442 0.98983 0.99378
##              PC15    PC16    PC17    PC18    PC19    PC20    PC21
## Standard deviation  0.26261 0.19893 0.16072 0.11927 0.10192 0.08705 0.05928
## Proportion of Variance 0.00246 0.00141 0.00092 0.00051 0.00037 0.00027 0.00013
## Cumulative Proportion 0.99624 0.99765 0.99858 0.99908 0.99945 0.99973 0.99985
##              PC22    PC23    PC24    PC25    PC26    PC27
## Standard deviation  0.04905 0.03665 0.01696 0.0103 0.005546 0.002585
## Proportion of Variance 0.00009 0.00005 0.00001 0.0000 0.000000 0.000000
## Cumulative Proportion 0.99994 0.99998 0.99999 1.0000 1.000000 1.000000
##              PC28
## Standard deviation  1.228e-15
## Proportion of Variance 0.000e+00
## Cumulative Proportion 1.000e+00
```

```
bul_transform <- as.data.frame(-pr.out$x[,1:5])
```

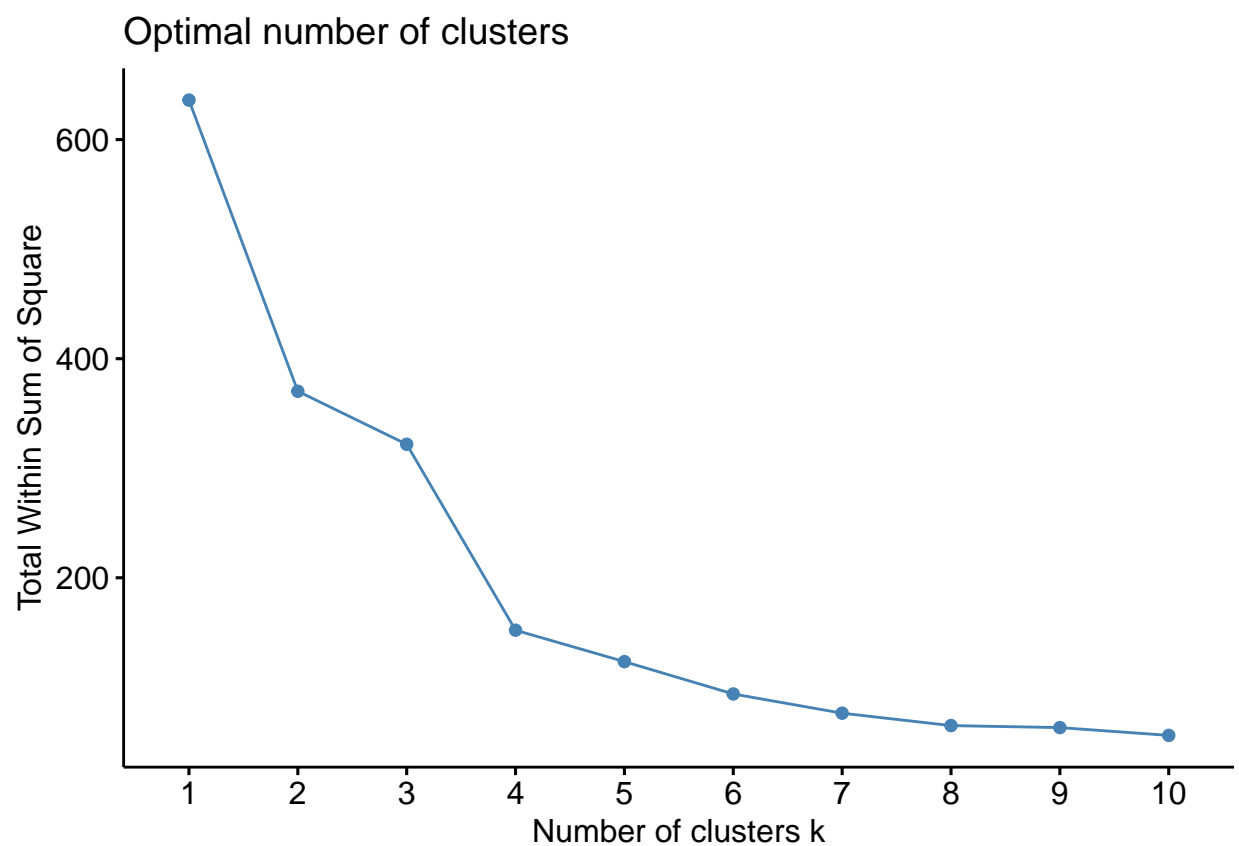
```
#Clustering k-means
```

```
library(factoextra)
```

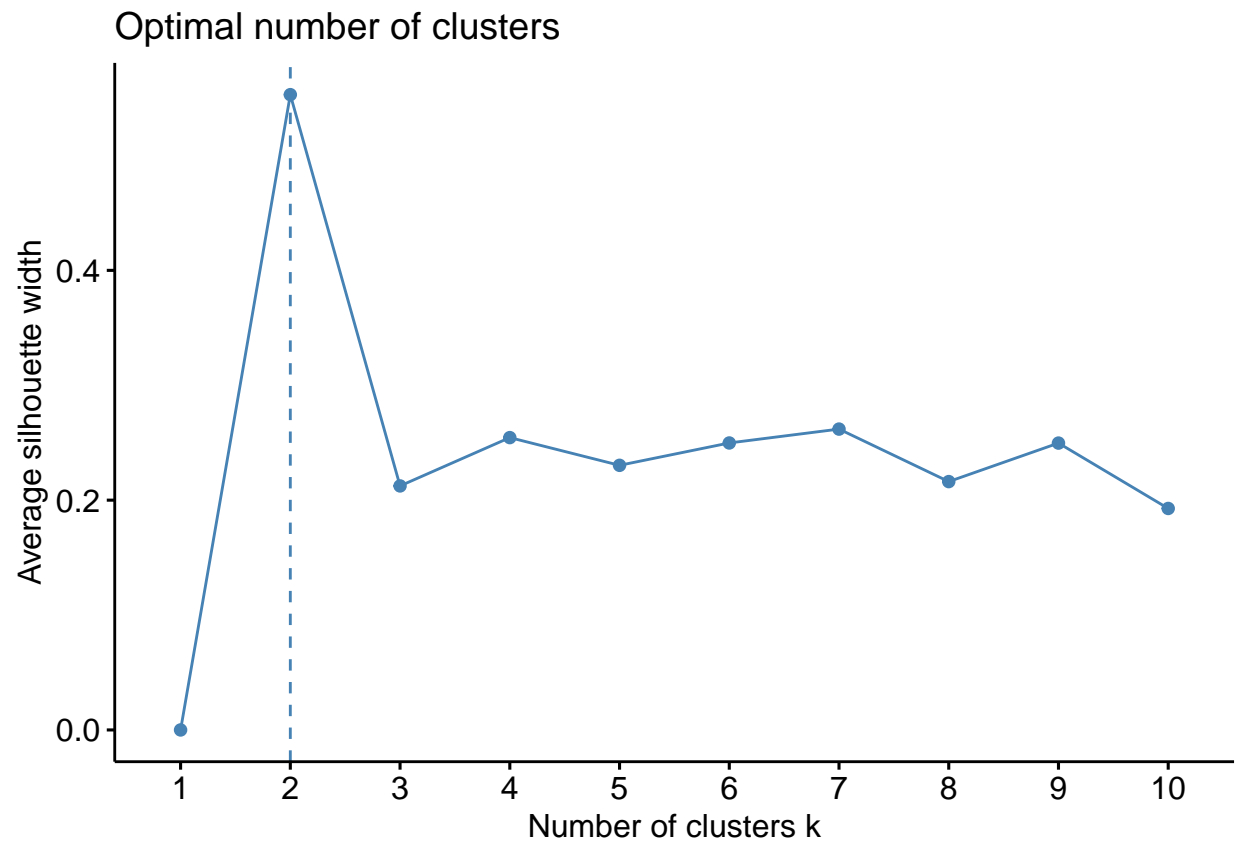
```
## Warning: package 'factoextra' was built under R version 4.1.3
```

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

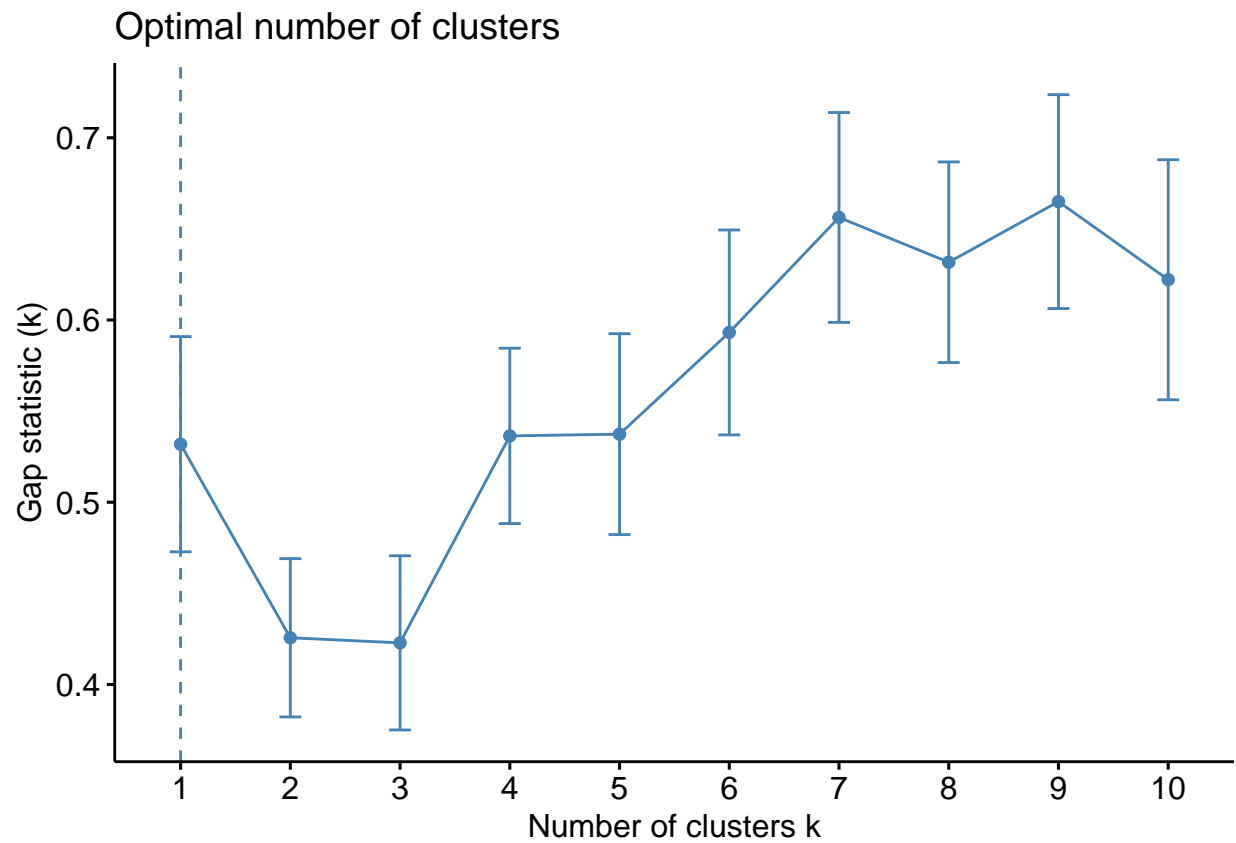
```
fviz_nbclust(bul_transform, kmeans, method = 'wss')
```



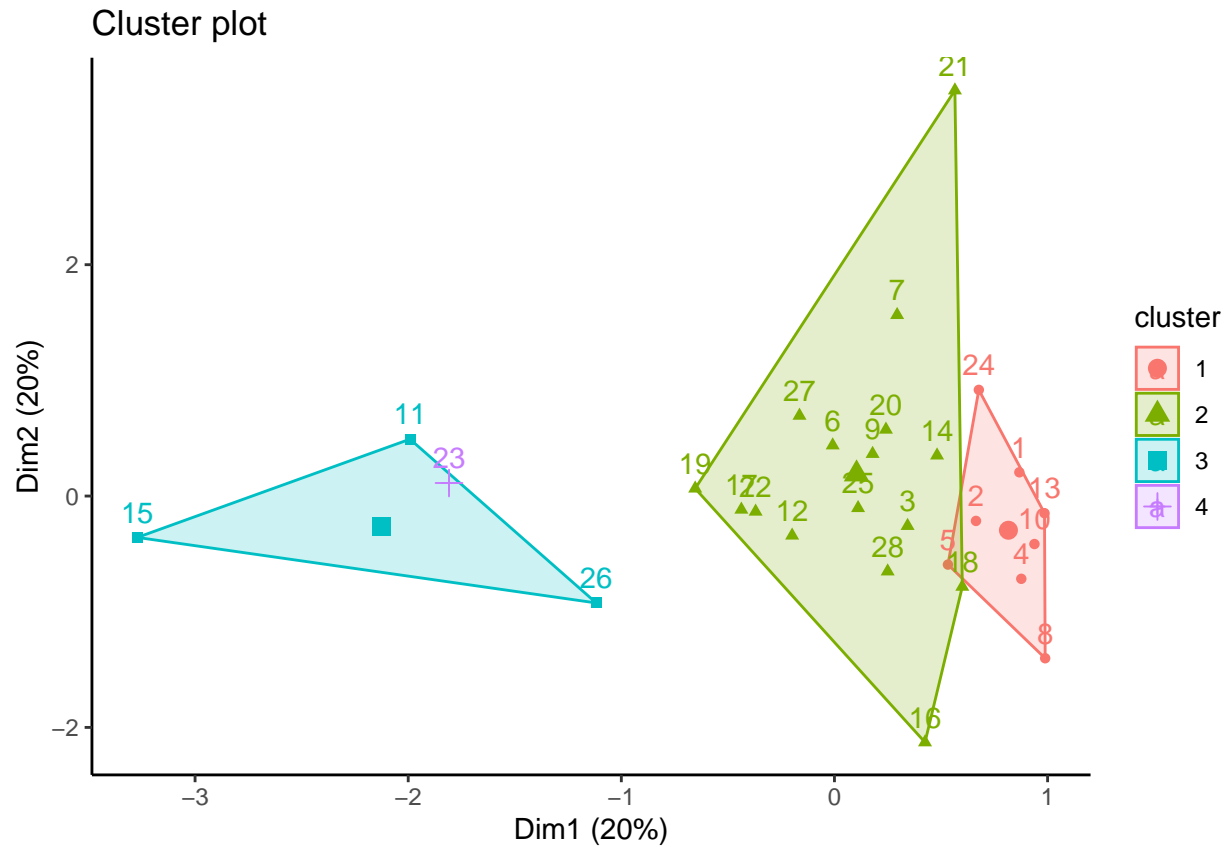
```
fviz_nbclust(bul_transform, kmeans, method = 'silhouette')
```

```
fviz_nbclust(bul_transform, kmeans, method = 'gap_stat')
```



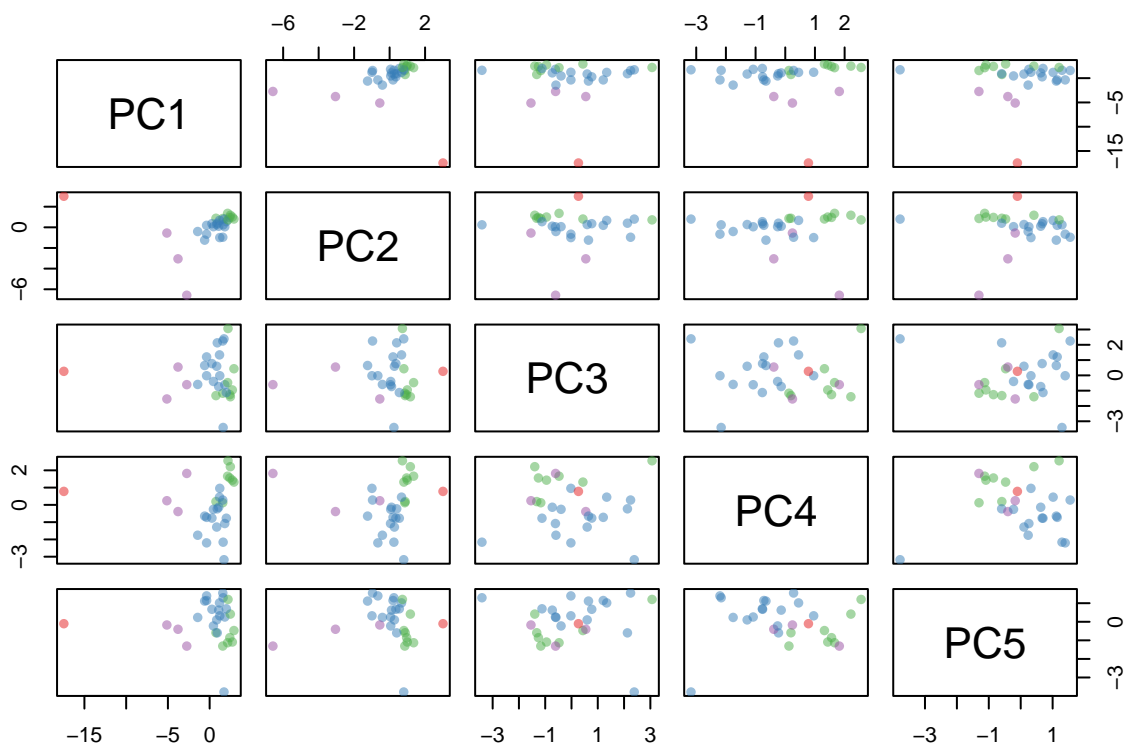
```
k = 4
kmeans_bul = kmeans(bul_transform, centers = k, nstart = 20)
fviz_cluster(kmeans_bul, data = bul_transform) + theme_classic()
```



```
set.seed(21)
k <- kmeans(comp, 4, nstart=25, iter.max=1000)
library(RColorBrewer)
library(scales)
```

```
## Warning: package 'scales' was built under R version 4.1.2
```

```
palette(alpha(brewer.pal(9,'Set1'), 0.5))
plot(comp, col=k$clust, pch=16)
```



```
clusters_kmeans4 <- k$cluster
```

```
bul_with_labels <- bul[,]
bul_with_labels$kmeans4 <- as.factor(clusters_kmeans4)

scaled <- as.data.frame(scale(bul_with_labels[, -c(1, 30)]))
scaled$Region <- bul$Region
scaled$kmeans4 <- as.factor(clusters_kmeans4)
```

Random forest with previously found clusters. Turning to supervised method to see variable importance

```
library(randomForest)
```

```
## Warning: package 'randomForest' was built under R version 4.1.3
```

```
## randomForest 4.7-1
```

```
## Type rfNews() to see new features/changes/bug fixes.
```

```
##
```

```
## Attaching package: 'randomForest'
```

```
## The following object is masked from 'package:ggplot2':
```

```
##
```

```
## margin
```

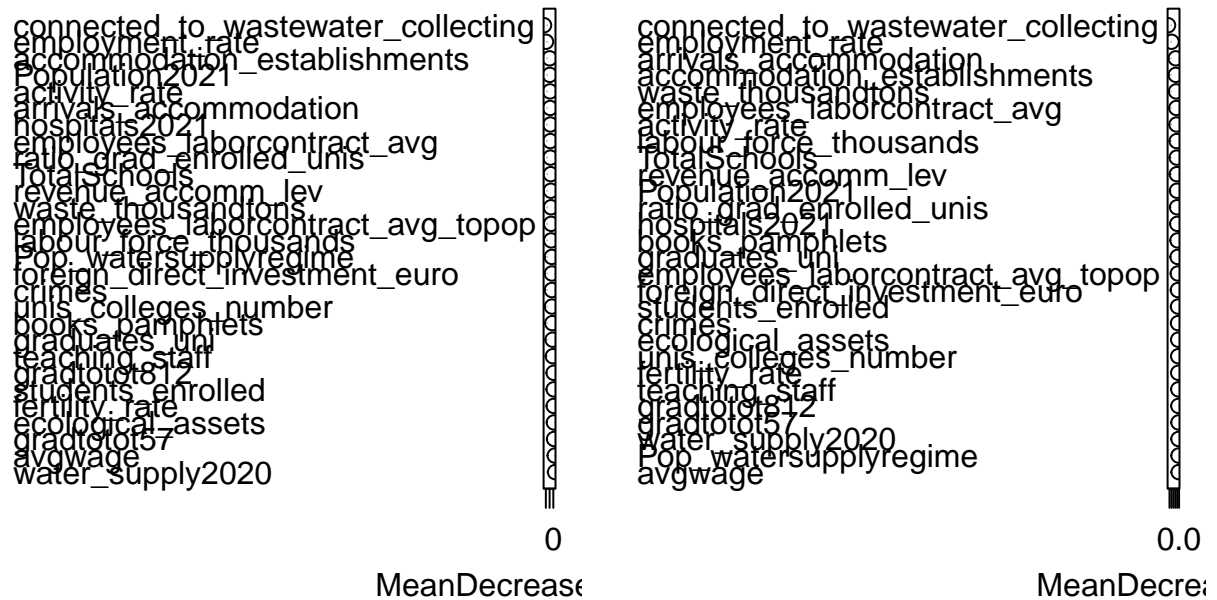
```
set.seed(21)
rf_bul <- randomForest(kmeans4 ~.-Region, data = scaled, mtry = 9, importance = TRUE)
importance(rf_bul)
```

##	1	2	3	4
## Population2021	0	3.0944974	2.2348611	4.9154188
## fertility_rate	0	1.3806214	-1.7026641	0.8170415
## unis_colleges_number	0	-0.3044071	1.8447912	2.2107259
## teaching_staff	0	1.2794980	-1.0010015	1.3440623
## students_enrolled	0	-1.3137853	-0.2116132	1.7372705
## graduates_uni	0	-1.7851431	2.2977510	1.9042342
## ratio_grad_enrolled_unis	0	3.7999063	3.4299788	0.7750618
## TotalSchools	0	2.4348926	-0.5582108	4.5349450
## gradtotot57	0	-0.2055544	-1.6759457	-0.7849477
## gradtotot812	0	-0.8278552	0.6871270	0.8170415
## employees_laborcontract_avg	0	1.7473011	0.9631427	4.2273121
## employees_laborcontract_avg_topop	0	-0.4520301	3.5997366	0.0000000
## avgwage	0	-1.8574279	-1.0010015	-0.4473031
## activity_rate	0	2.8721927	4.7805602	0.5775428
## labour_force_thousands	0	2.1372957	0.3838362	3.3709993
## employment_rate	0	7.8748633	10.1021484	3.3013910
## foreign_direct_investment_euro	0	0.9513106	0.4544046	2.8072960
## books_pamphlets	0	0.6398717	-1.6373653	3.1168189
## accommodation_establishments	0	-0.7969141	5.5761435	3.5213750
## arrivals_accommodation	0	1.7293872	3.5332769	3.4417392
## revenue_accomm_lev	0	-0.4388249	4.3726237	2.5461701
## crimes	0	1.1874604	1.7372705	0.8534238
## ecological_assets	0	-1.0268032	-1.8828449	2.3702273
## water_supply2020	0	-1.7963290	-1.7213102	-1.5109947
## connected_to_wastewater_collecting	0	9.3916299	12.8024755	3.9666081
## Pop_watersupplyregime	0	1.3522689	-0.8170415	1.9488101
## waste_thousandtons	0	1.9889544	0.4222991	4.6249729
## hospitals2021	0	3.2940716	1.6973247	3.3709993
##	MeanDecreaseAccuracy		MeanDecreaseGini	
## Population2021		4.7267958		0.5494781
## fertility_rate		-0.5044853		0.2170927
## unis_colleges_number		1.8436906		0.2270247
## teaching_staff		0.6849340		0.2004856
## students_enrolled		-0.4151720		0.2761430
## graduates_uni		0.9804711		0.3907602
## ratio_grad_enrolled_unis		3.8596197		0.5313134
## TotalSchools		3.4875730		0.6096154
## gradtotot57		-0.9716918		0.1587595
## gradtotot812		-0.4082056		0.1773898
## employees_laborcontract_avg		3.9413252		0.7016275
## employees_laborcontract_avg_topop		2.9257927		0.3366603
## avgwage		-1.8354708		0.1150994
## activity_rate		4.4702664		0.6711244
## labour_force_thousands		2.8507184		0.6261772
## employment_rate		9.7666767		1.9700773
## foreign_direct_investment_euro		1.9833337		0.3112777
## books_pamphlets		1.4089195		0.4152488
## accommodation_establishments		4.9813727		0.8607068

## arrivals_accommodation	4.2169647	0.8758904
## revenue_accomm_lev	3.3142306	0.5875183
## crimes	1.9780300	0.2709768
## ecological_assets	-0.7022895	0.2333642
## water_supply2020	-2.3102545	0.1524638
## connected_to_wastewater_collecting	12.4128684	2.8783794
## Pop_watersupplyregime	2.0780875	0.1480691
## waste_thousandtons	3.1034616	0.7865394
## hospitals2021	3.9628511	0.4757368

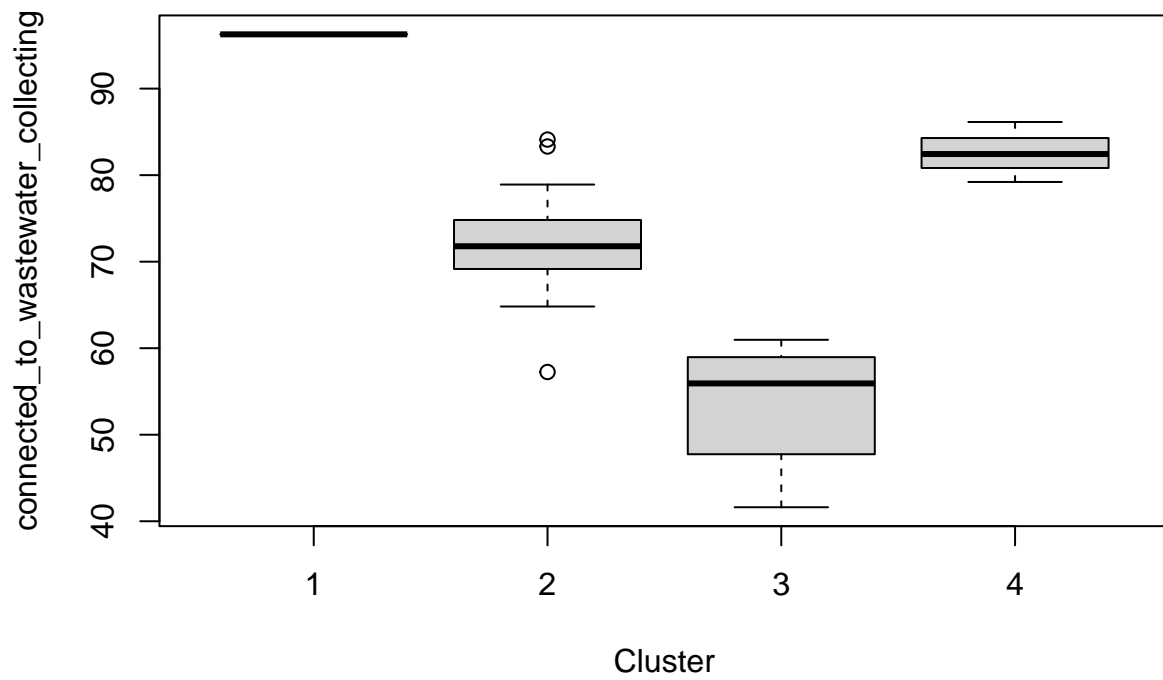
```
varImpPlot(rf_bul)
```

rf_bul



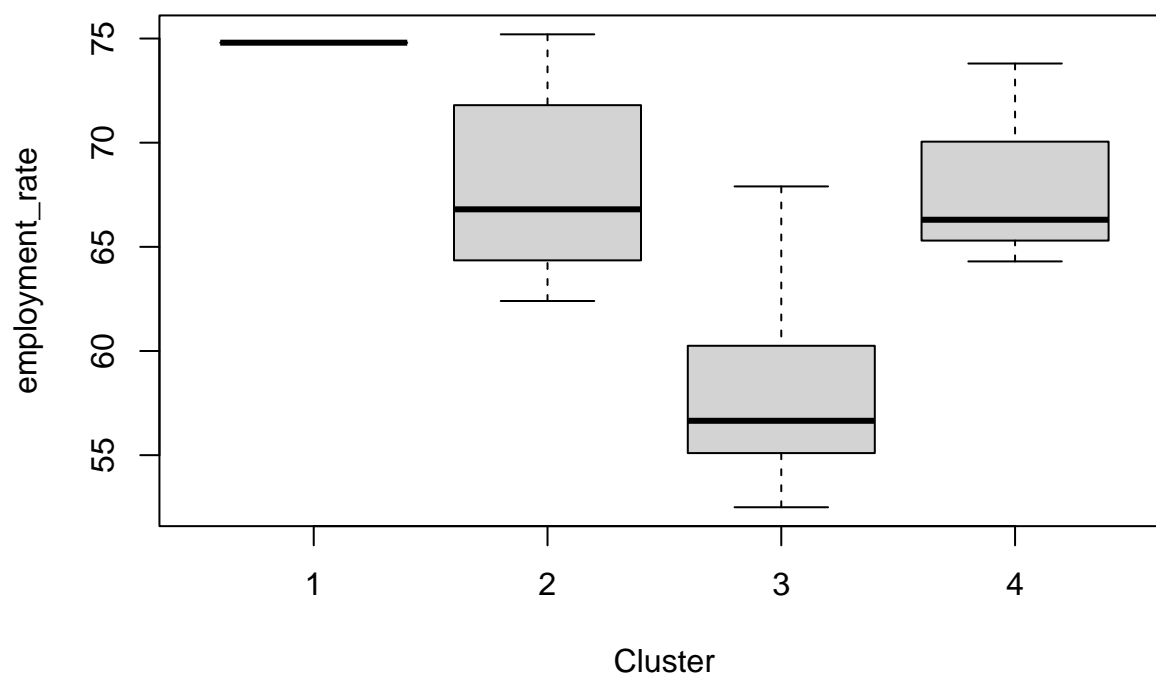
```
boxplot(bul_with_labels$connected_to_wastewater_collecting ~ bul_with_labels$kmeans4,
        xlab='Cluster', ylab='connected_to_wastewater_collecting',
        main='connected_to_wastewater_collecting by Cluster')
```

connected_to_wastewater_collecting by Cluster

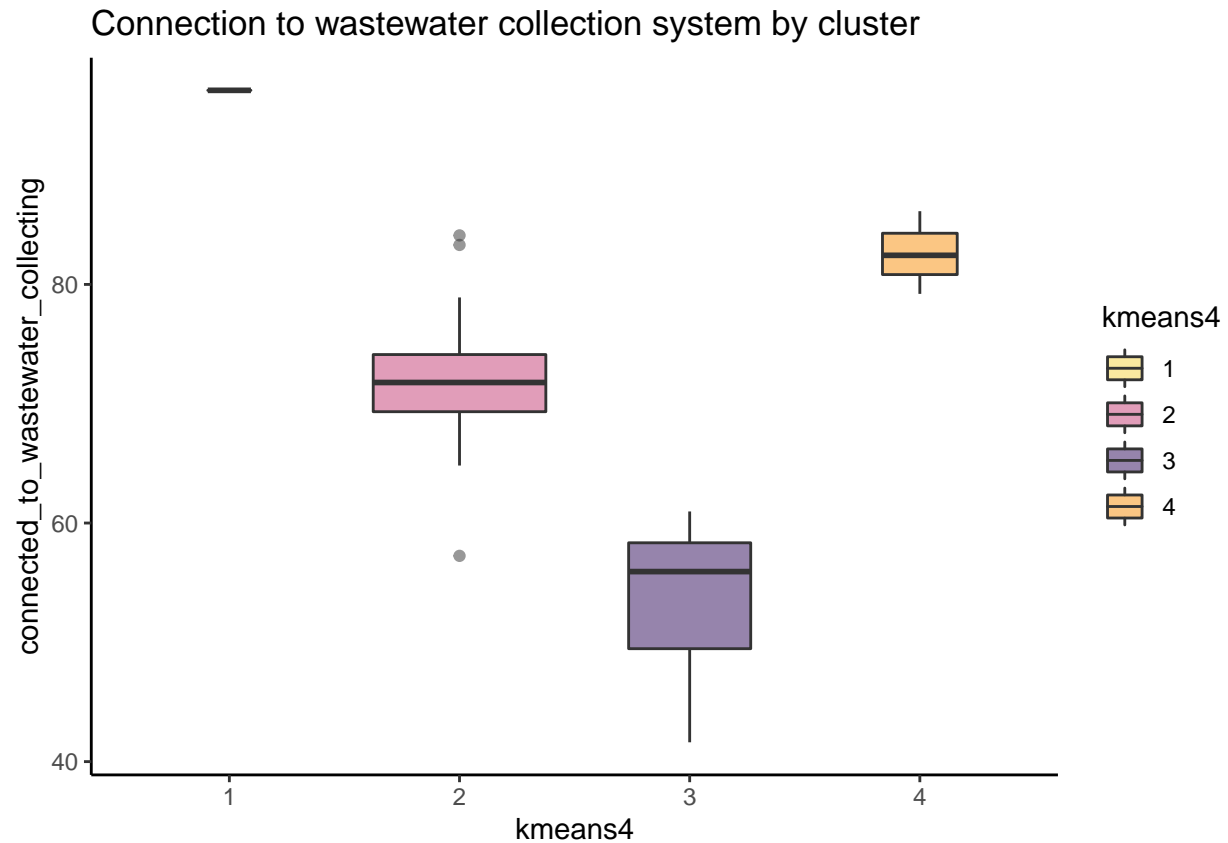


```
boxplot(bul$employment_rate ~ bul_with_labels$kmeans4,  
        xlab='Cluster', ylab='employment_rate',  
        main='employment_rate by Cluster')
```

employment_rate by Cluster



```
ggplot(bul_with_labels, aes(x=kmeans4, y=connected_to_wastewater_collecting, fill = kmeans4)) +  
  geom_boxplot(varwidth = TRUE, alpha=0.5) +  
  theme(legend.position="none") +  
    scale_fill_manual(values = c("#f6d543", "#c53c74", "#2f0a5b", "#f98e09")) +  
    theme_classic() +  
    ggtitle("Connection to wastewater collection system by cluster")
```

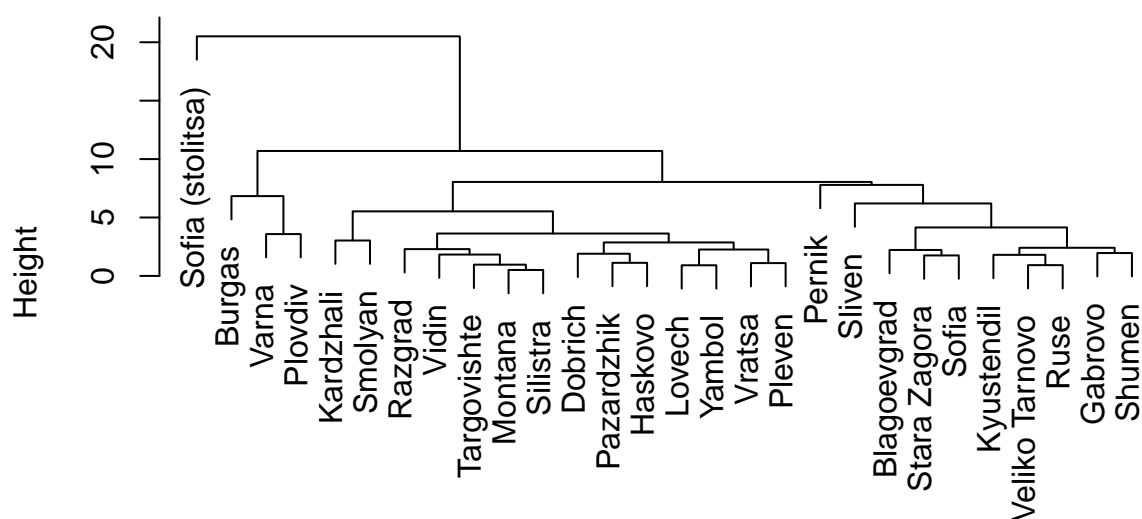



```
rownames(scaled) <- scaled$Region  
rownames(bul_transform) <- scaled$Region
```

#Hierarchical clustering

```
set.seed(21)  
distmatrix2 <- dist(bul_transform)  
hc2 <- hclust(distmatrix2, method = "complete")  
plot(hc2, labels = scaled$Region)
```

Cluster Dendrogram



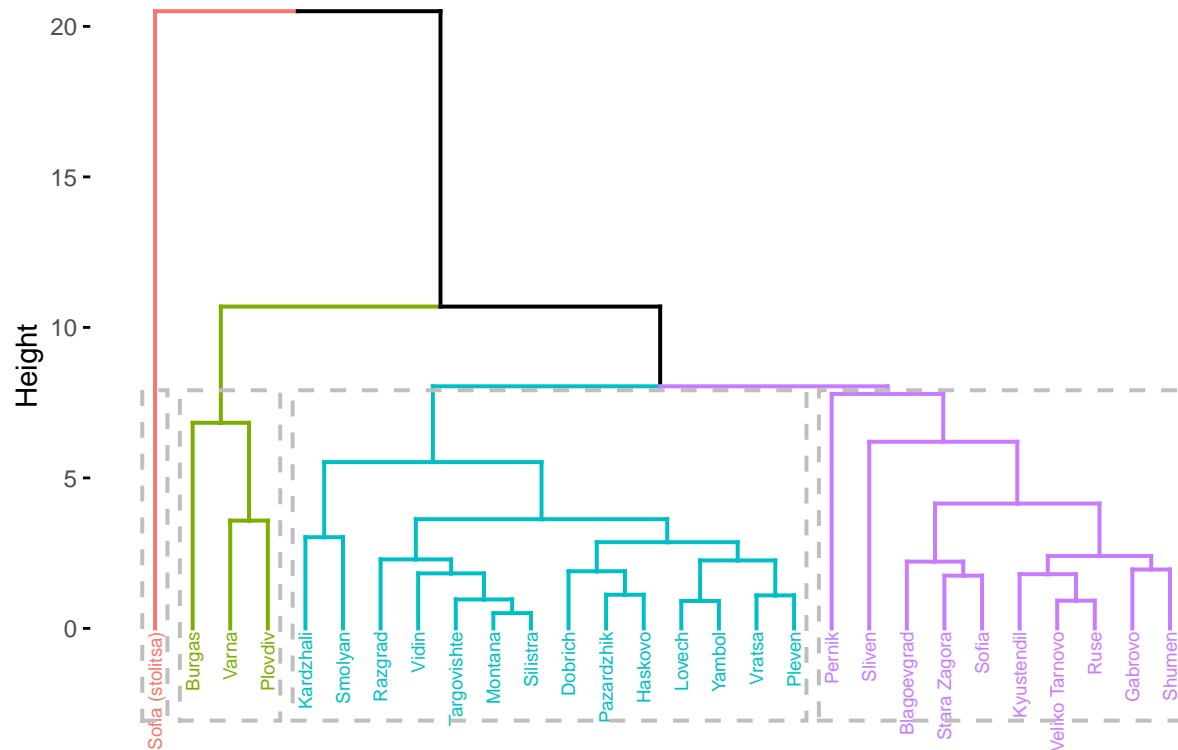
```
distmatrix2
hclust (*, "complete")
```

```
labs_pca_hc4 <- cutree(hc2, 4)
```

```
#hc2$labels <- as.vector(bul_with_labels[hc2$order, 'Region'])
fviz_dend(hc2, cex = 0.5, k = 4, rect = TRUE)
```

```
## Warning: 'guides(<scale> = FALSE)' is deprecated. Please use 'guides(<scale> =
## "none")' instead.
```

Cluster Dendrogram



```
#See var importance when hclust
set.seed(21)
rf_bul2 <- randomForest(labs_pca_hc4 ~.-Region - kmeans4, data = scaled, mtry = 9, importance = TRUE)
```

```
## Warning in randomForest.default(m, y, ...): The response has five or fewer
## unique values. Are you sure you want to do regression?
```

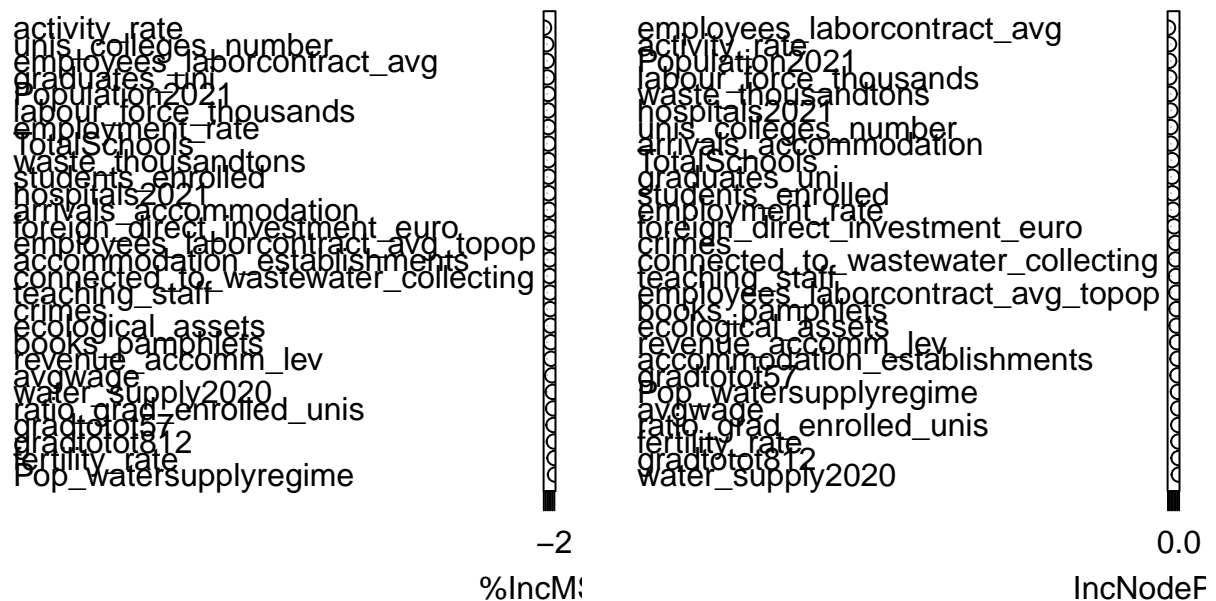
```
importance(rf_bul2)
```

	%IncMSE	IncNodePurity
## Population2021	5.2033142	1.24951975
## fertility_rate	-2.2233084	0.08464824
## unis_colleges_number	7.2046531	1.07999555
## teaching_staff	2.9962718	0.40954240
## students_enrolled	4.6460614	0.84295702
## graduates_uni	6.1058844	0.88974869
## ratio_grad_enrolled_unis	-0.6388594	0.10222527
## TotalSchools	4.7879051	0.89658836
## gradtotot57	-1.0865686	0.20081573
## gradtotot812	-1.4547252	0.06458656
## employees_laborcontract_avg	6.5768174	1.39392990
## employees_laborcontract_avg_topop	3.4811170	0.35114744
## avgwage	0.5529313	0.11122043
## activity_rate	9.7289770	1.26258297
## labour_force_thousands	5.0603443	1.22931283

## employment_rate	5.0000539	0.78126165
## foreign_direct_investment_euro	4.0084955	0.63736012
## books_pamphlets	2.0376067	0.33069871
## accommodation_establishments	3.4290073	0.20594652
## arrivals_accommodation	4.1233131	1.06373374
## revenue_accomm_lev	1.7112880	0.26007155
## crimes	2.7466196	0.44704275
## ecological_assets	2.2691104	0.32256053
## water_supply2020	-0.1584301	0.03034158
## connected_to_wastewater_collecting	3.4168809	0.44510818
## Pop_watersupplyregime	-2.8136707	0.14672062
## waste_thousandtons	4.7640144	1.17588837
## hospitals2021	4.4972784	1.09049692

```
varImpPlot(rf_bul2)
```

rf_bul2



Align clusters of the two methods

```
i = labs_pca_hc4 == 1
j = labs_pca_hc4 == 3
v = labs_pca_hc4 == 4
labs_pca_hc4[i] = 3
labs_pca_hc4[j] = 4
labs_pca_hc4[v] = 1
```

```
labs_pca_hc4 == clusters_kmeans4
```

```
##          Vidin          Vratsa          Lovech          Montana
##          TRUE          TRUE          FALSE          TRUE
##      Pleven  Veliko Tarnovo  Gabrovo  Razgrad
##          TRUE          TRUE          TRUE          TRUE
##          Ruse          Silistra  Varna  Dobrich
##          TRUE          TRUE          TRUE          FALSE
##      Targovishte  Shumen  Burgas  Sliven
##          TRUE          TRUE          TRUE          TRUE
##      Stara Zagora  Yambol  Blagoevgrad  Kyustendil
##          TRUE          FALSE          TRUE          TRUE
##          Pernik  Sofia Sofia (stolitsa)  Kardzhali
##          TRUE          TRUE          TRUE          TRUE
##      Pazardzhik  Plovdiv  Smolyan  Haskovo
##          FALSE          TRUE          FALSE          FALSE
```

```
sum(labs_pca_hc4 == clusters_kmeans4)
```

```
## [1] 22
```

```
table(labs_pca_hc4, clusters_kmeans4)
```

```
##          clusters_kmeans4
## labs_pca_hc4  1  2  3  4
##          1  1  0  0  0
##          2  0 10  0  0
##          3  0  6  8  0
##          4  0  0  0  3
```

```
bul_with_labels$labs_pca_hc4 <- as.factor(labs_pca_hc4)
scaled$labs_pca_hc4 <- as.factor(labs_pca_hc4)
```

```
mclust::adjustedRandIndex(clusters_kmeans4, labs_pca_hc4)
```

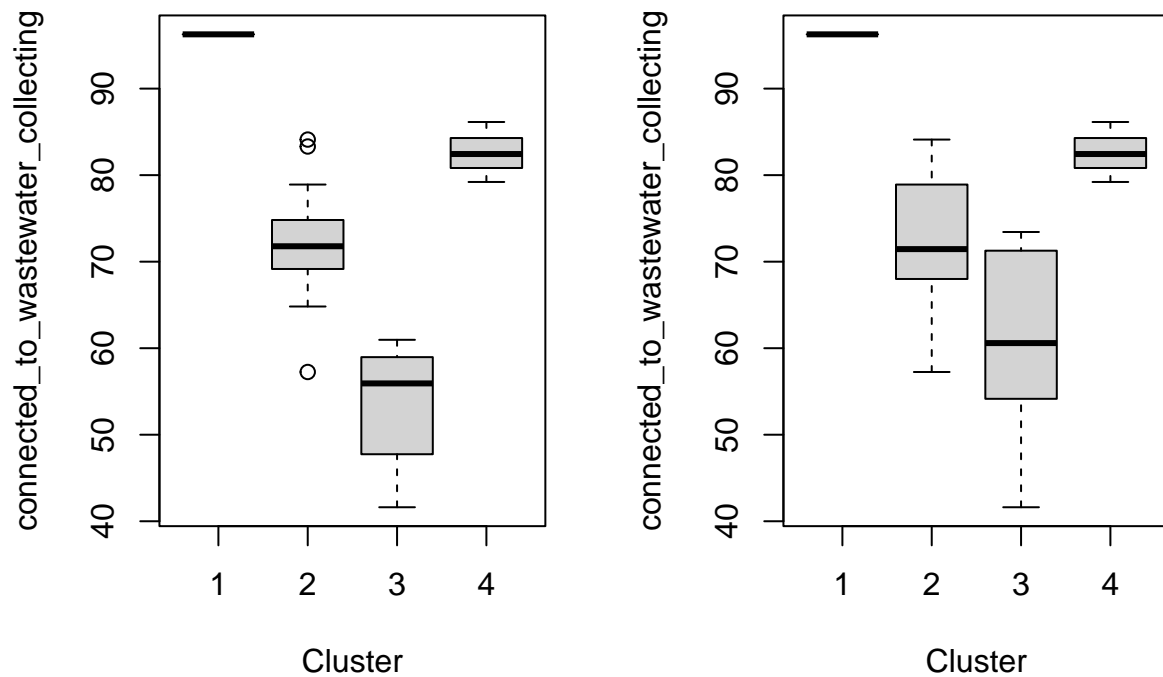
```
## [1] 0.3964696
```

```
#describe what it is and how it is calculated
```

```
par(mfrow = c(1,2))
```

```
boxplot(bul_with_labels$connected_to_wastewater_collecting ~ bul_with_labels$kmeans4,
        xlab='Cluster', ylab='connected_to_wastewater_collecting',
        main='connected_to_wastewater_collecting by Cluster kmeans')
boxplot(bul_with_labels$connected_to_wastewater_collecting ~ bul_with_labels$labs_pca_hc4,
        xlab='Cluster', ylab='connected_to_wastewater_collecting',
        main='connected_to_wastewater_collecting by Cluster hclust')
```

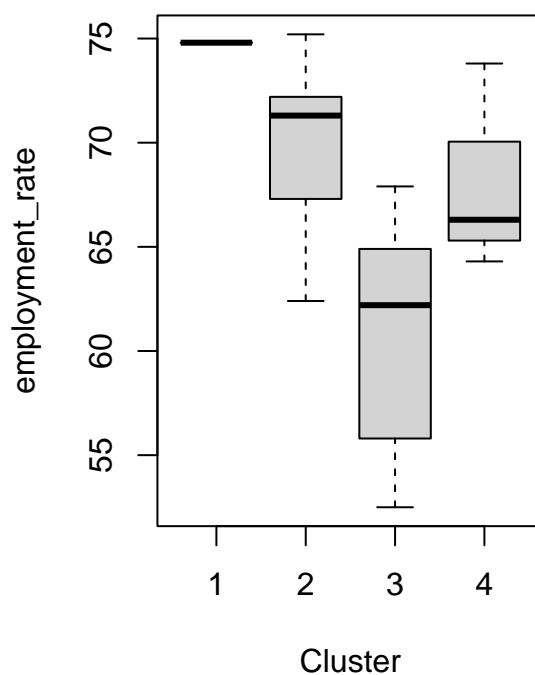
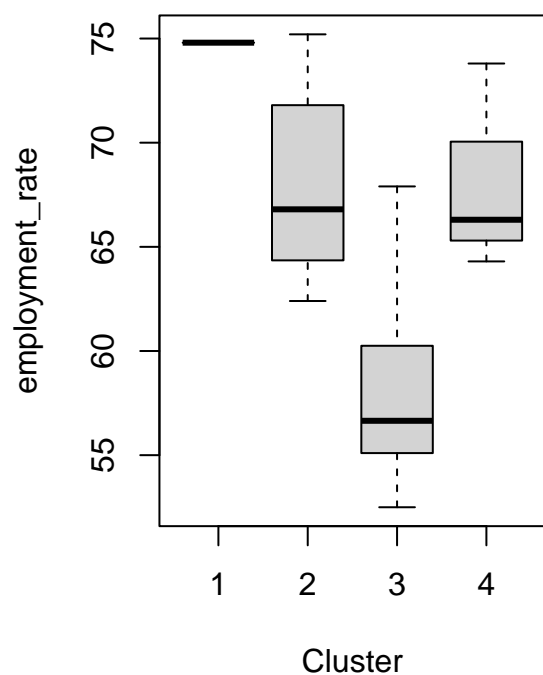
ed_to_wastewater_collecting by Cluted_to_wastewater_collecting by Cl



```
boxplot(bul$employment_rate ~ bul_with_labels$kmeans4,
        xlab='Cluster', ylab='employment_rate',
        main='employment_rate by Cluster kmeans')

boxplot(bul$employment_rate ~ bul_with_labels$labs_pca_hc4,
        xlab='Cluster', ylab='employment_rate',
        main='employment_rate by Cluster hclust')
```

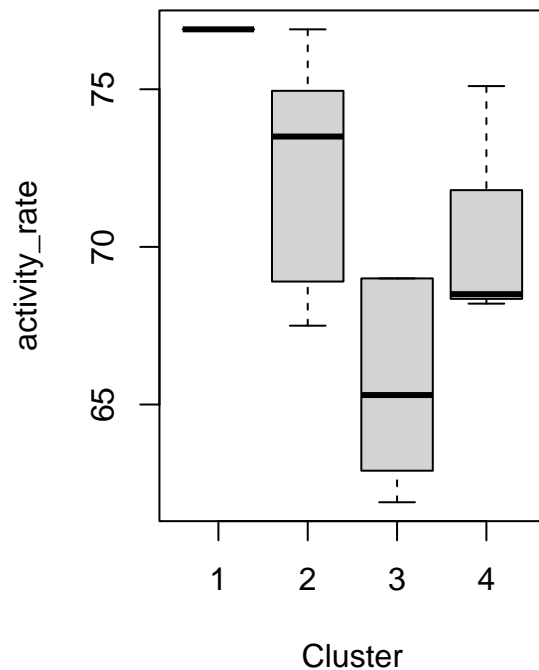
employment_rate by Cluster kmeans employment_rate by Cluster hclu



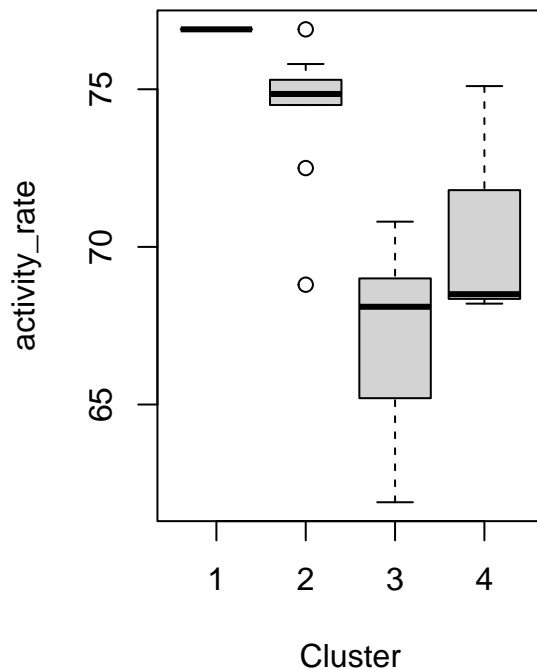
```
boxplot(bul$activity_rate ~ bul_with_labels$kmeans4,
        xlab='Cluster', ylab='activity_rate',
        main='activity_rate by Cluster kmeans')

boxplot(bul$activity_rate ~ bul_with_labels$labs_pca_hc4,
        xlab='Cluster', ylab='activity_rate',
        main='activity_rate by Cluster hclust')
```

activity_rate by Cluster kmeans

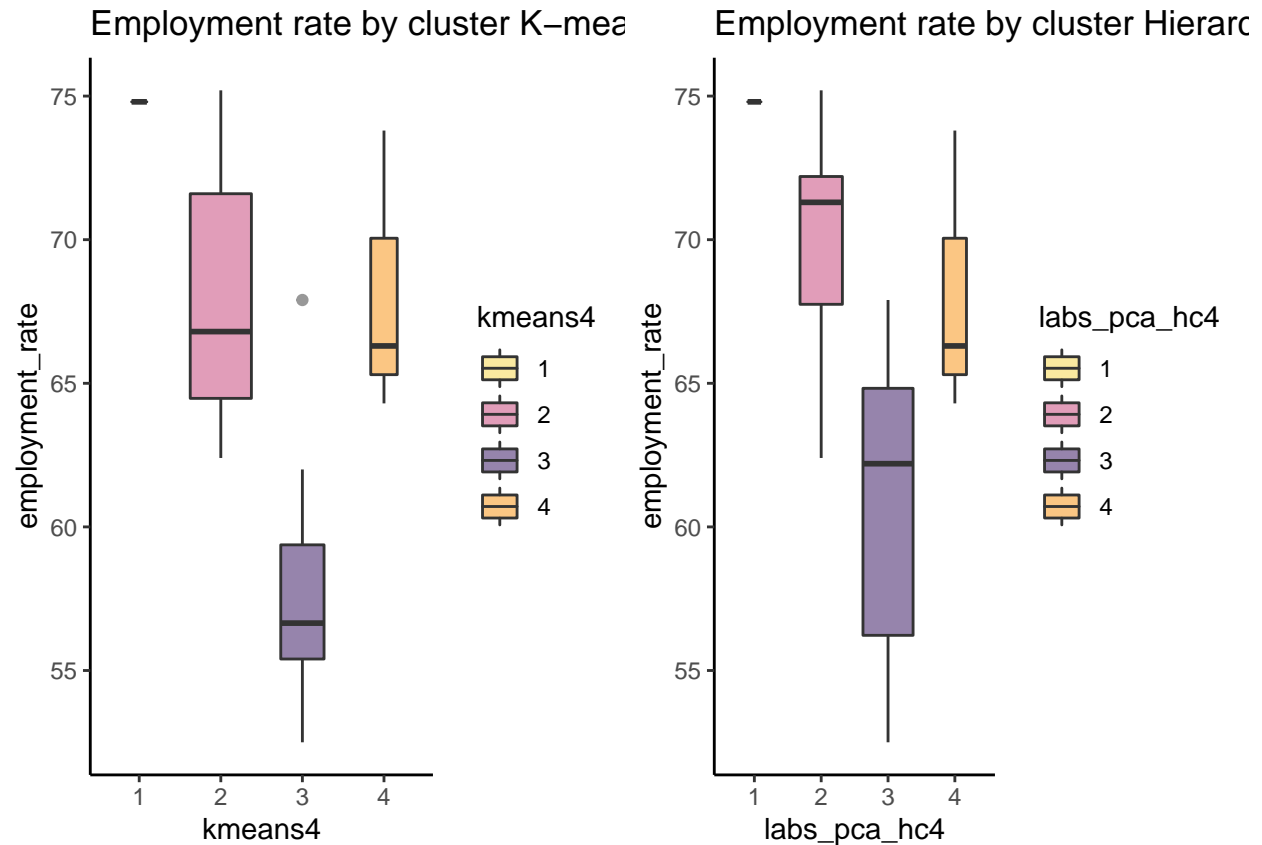


activity_rate by Cluster hclust



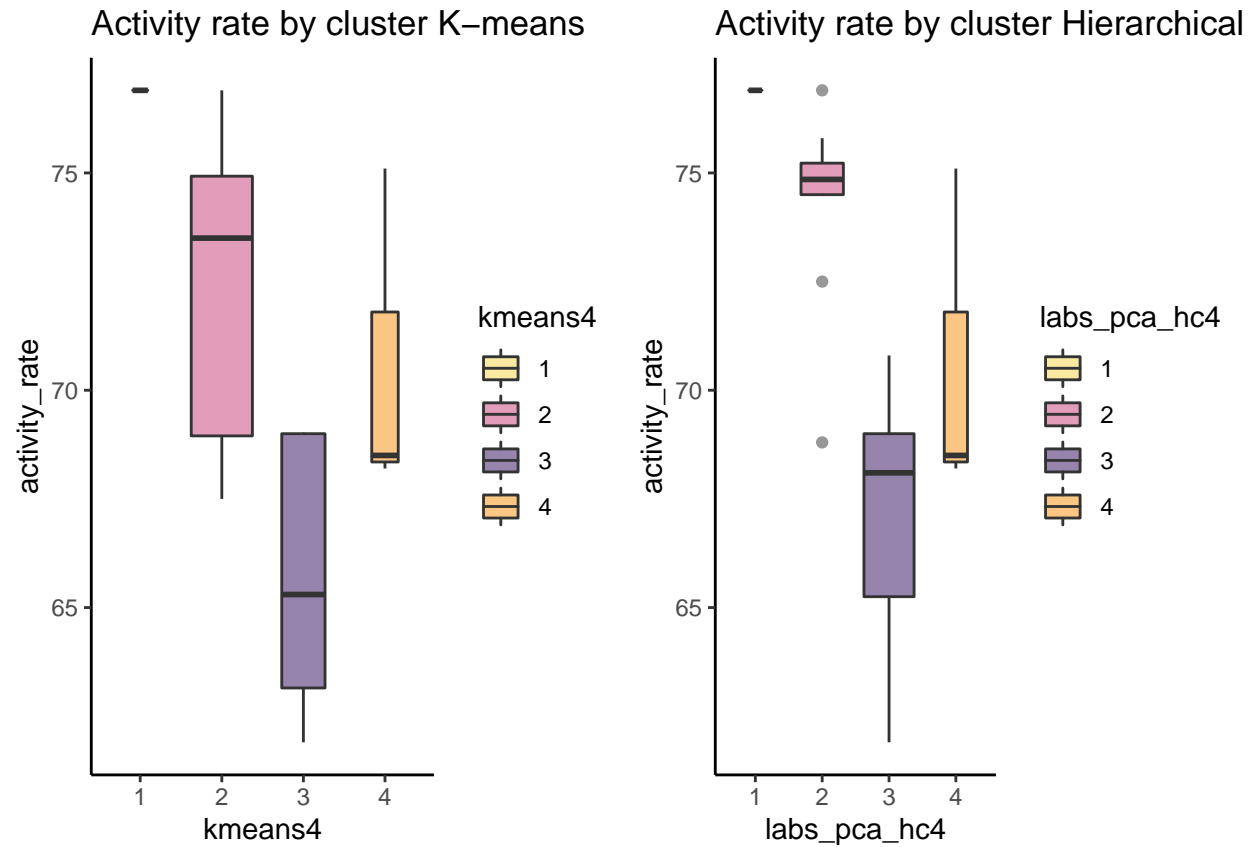
```
par(mfrow = c(1,1))
```

```
p1 <- ggplot(bul_with_labels, aes(x=kmeans4, y=employment_rate, fill = kmeans4)) +
  geom_boxplot(varwidth = TRUE, alpha=0.5) +
  theme(legend.position="none") +
  scale_fill_manual(values = c("#f6d543", "#c53c74", "#2f0a5b", "#f98e09")) +
  theme_classic() +
  ggtitle("Employment rate by cluster K-means")
p2 <- ggplot(bul_with_labels, aes(x=labs_pca_hc4, y=employment_rate, fill = labs_pca_hc4)) +
  geom_boxplot(varwidth = TRUE, alpha=0.5) +
  theme(legend.position="none") +
  scale_fill_manual(values = c("#f6d543", "#c53c74", "#2f0a5b", "#f98e09")) +
  theme_classic() +
  ggtitle("Employment rate by cluster Hierarchical clustering")
ggarrange(p1, p2)
```

```
p1 <- ggplot(bul_with_labels, aes(x=kmeans4, y=activity_rate, fill = kmeans4)) +
  geom_boxplot(varwidth = TRUE, alpha=0.5) +
  theme(legend.position="none") +
  scale_fill_manual(values = c("#f6d543", "#c53c74", "#2f0a5b", "#f98e09")) +
  theme_classic() +
  ggtitle("Activity rate by cluster K-means")
p2 <- ggplot(bul_with_labels, aes(x=labs_pca_hc4, y=activity_rate, fill = labs_pca_hc4)) +
  geom_boxplot(varwidth = TRUE, alpha=0.5) +
  theme(legend.position="none") +
  scale_fill_manual(values = c("#f6d543", "#c53c74", "#2f0a5b", "#f98e09")) +
  theme_classic() +
  ggtitle("Activity rate by cluster Hierarchical clustering")

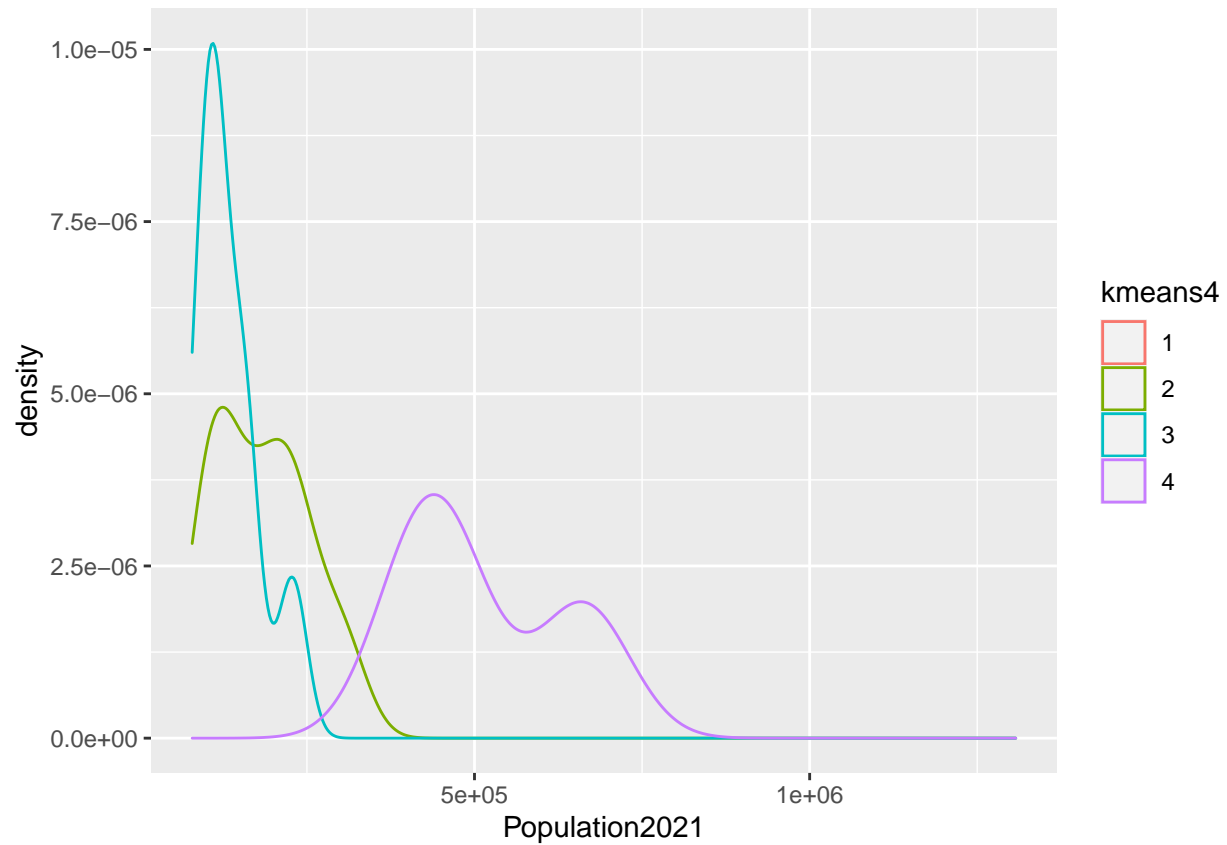
ggarrange(p1, p2)
```



```
ggplot(bul_with_labels, aes(Population2021, colour = kmeans4)) +
  geom_density()
```

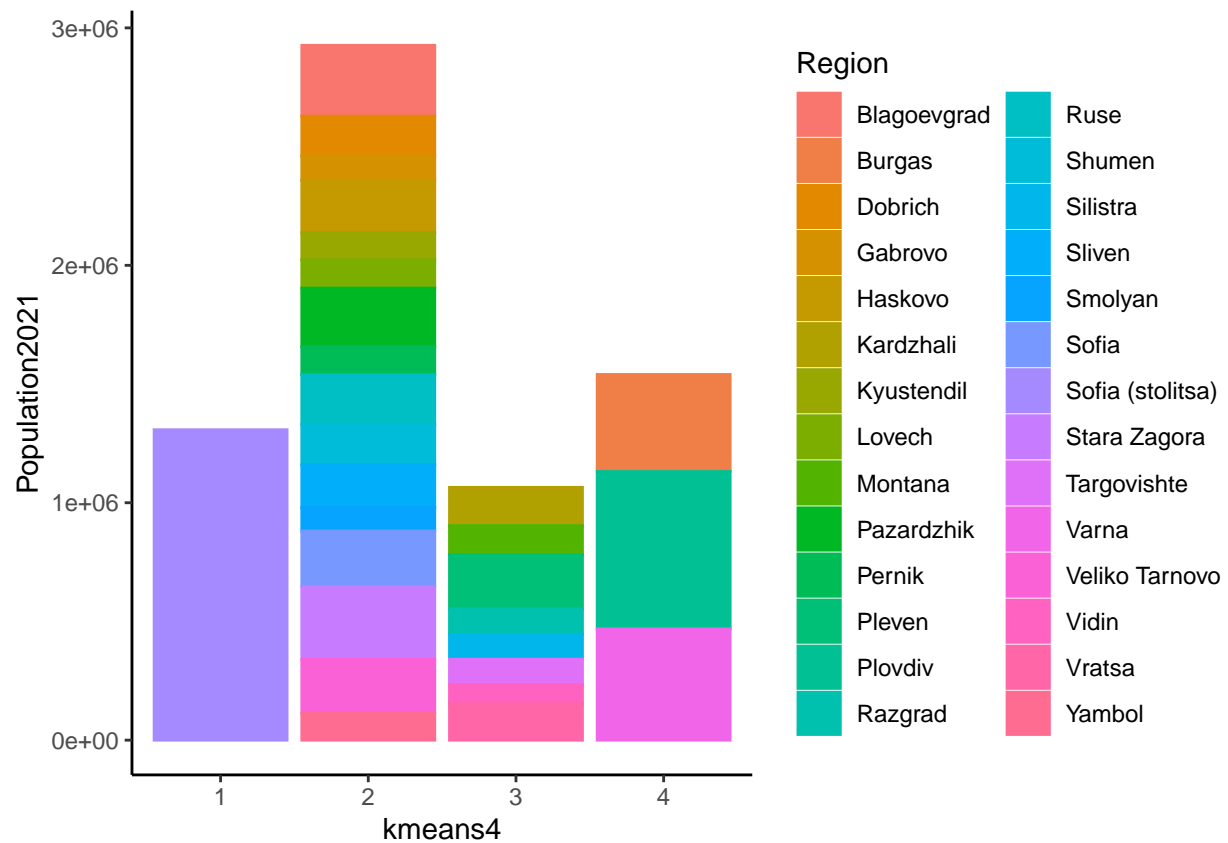
```
## Warning: Groups with fewer than two data points have been dropped.
```

```
## Warning in max(ids, na.rm = TRUE): no non-missing arguments to max; returning
## -Inf
```



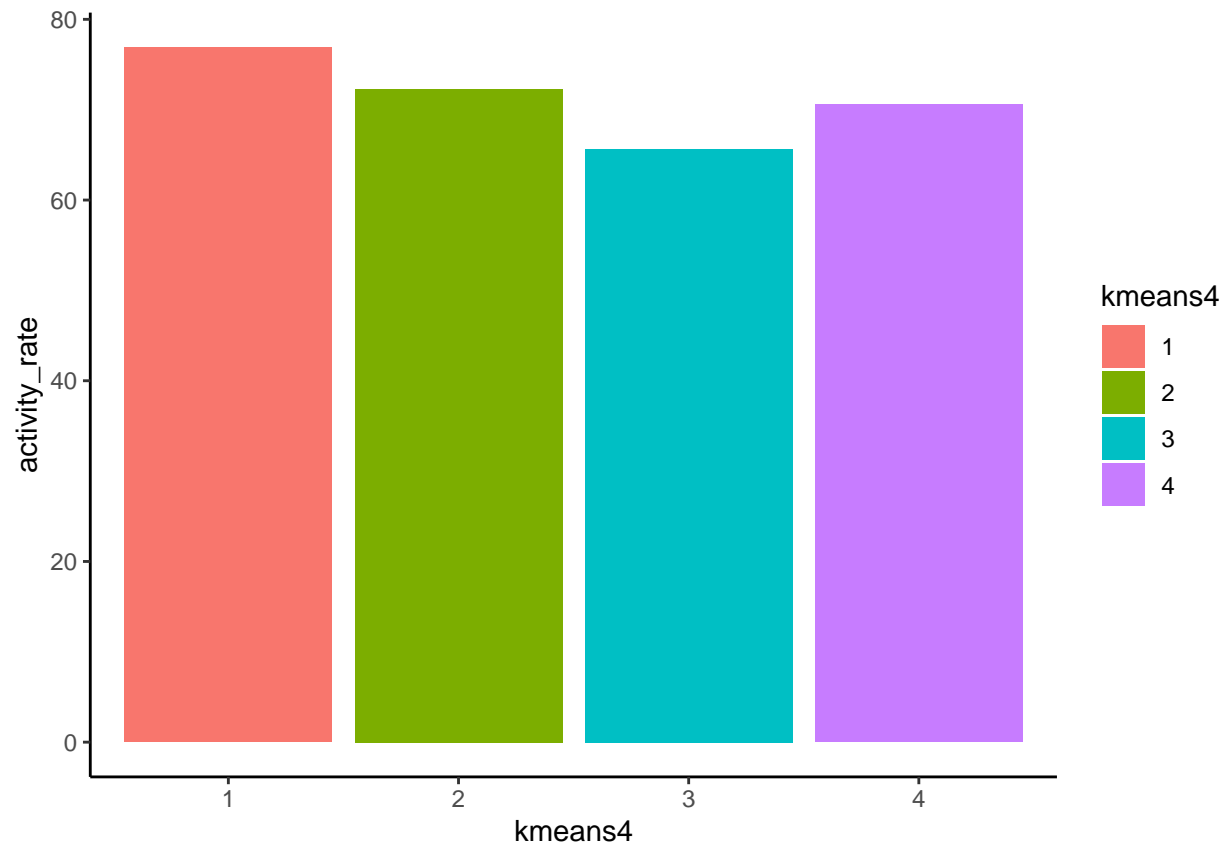
```
ggplot(bul_with_labels, aes(x = kmeans4, y = Population2021)) +
  geom_bar(
    aes(color = Region, fill = Region),
    stat = "summary", position = position_stack()
  ) +
  theme_classic()
```

```
## No summary function supplied, defaulting to 'mean_se()'
```



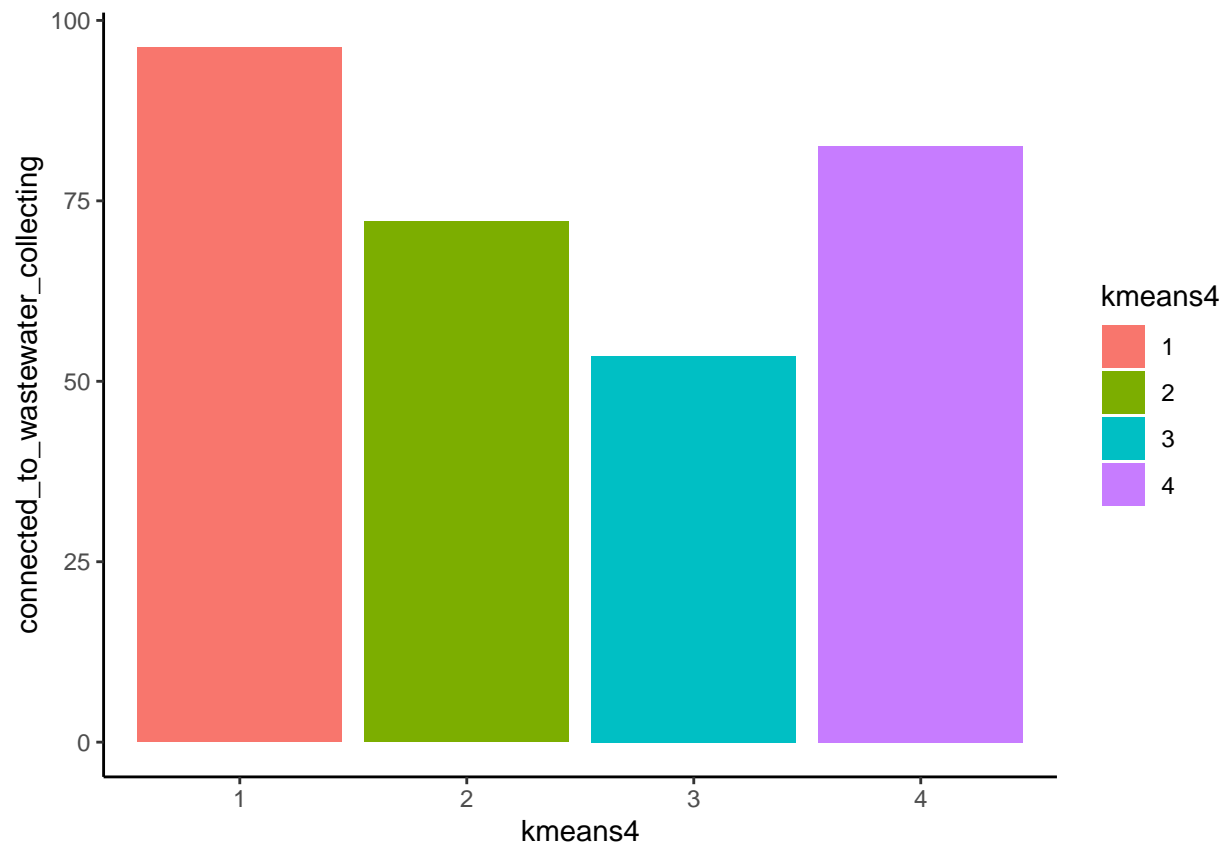
```
ggplot(bul_with_labels, aes(x = kmeans4, y = activity_rate)) +
  geom_bar(
    aes(fill = kmeans4),
    #aes(color = Region, fill = Region),
    stat = "summary", position = position_stack()
  ) +
  theme_classic()
```

```
## No summary function supplied, defaulting to 'mean_se()'
```



```
ggplot(bul_with_labels, aes(x = kmeans4, y = connected_to_wastewater_collecting)) +  
  geom_bar(  
    aes(fill = kmeans4),  
    #aes(color = Region, fill = Region),  
    stat = "summary", position = position_stack()  
  ) +  
  theme_classic()
```

```
## No summary function supplied, defaulting to 'mean_se()'
```



#To see which cities are classified differently

```
bul_with_labels$Region[bul_with_labels$kmeans4 == 2 & bul_with_labels$labs_pca_hc4 == 3]
```

```
## [1] "Lovech"      "Dobrich"     "Yambol"      "Pazardzhik" "Smolyan"
## [6] "Haskovo"
```

#Lasso and Ridge regression

Nested Cross Validation: model selection and model assessment. To choose the optimal lambda, and to have a picture of the medium test error rate.

```
library(caret)
```

```
## Warning: package 'caret' was built under R version 4.1.3
```

```
## Loading required package: lattice
```

```
library(glmnet)
```

```
## Warning: package 'glmnet' was built under R version 4.1.3
```

```
## Loading required package: Matrix
```

```
## Loaded glmnet 4.1-4
```

```

set.seed(21)
outfolds <- caret::createFolds(scaled$employment_rate ,k = 5, returnTrain = FALSE)
errors_folds_las <- c()
errors_folds_rid <- c()

for (outfold in outfolds){
  tr <- scaled[-outfold,]
  ts <- scaled[outfold,]
  y_test <- scaled[outfold,16]
  y_train <- scaled[-outfold,16]

  #taking a as a variable the region according to kmeans
  x_train <- model.matrix(employment_rate ~ .-Region - labs_pca_hc4, data = tr) #[, -c(16,29,30,31)]
  x_test <- model.matrix(employment_rate ~ .-Region - labs_pca_hc4, data = ts) #[, -c(16,29,30,31)]
  #print(colnames(x_train))
  cv.las <- cv.glmnet(x_train, y_train, alpha = 1, nfolds = 5)

  las <- glmnet(x_train, y_train, alpha = 1)

  plot(cv.las)
  bestlam = cv.las$lambda.min

  las_predict <- predict(las, s = bestlam, newx = x_test)
  #print(las_predict)
  #print(dim(las_predict))
  #print(y_test)
  #print(length(y_test))
  err <- mean((as.data.frame(las_predict)$s1 - y_test)^2)
  print(err)
  errors_folds_las <- c(errors_folds_las, err)

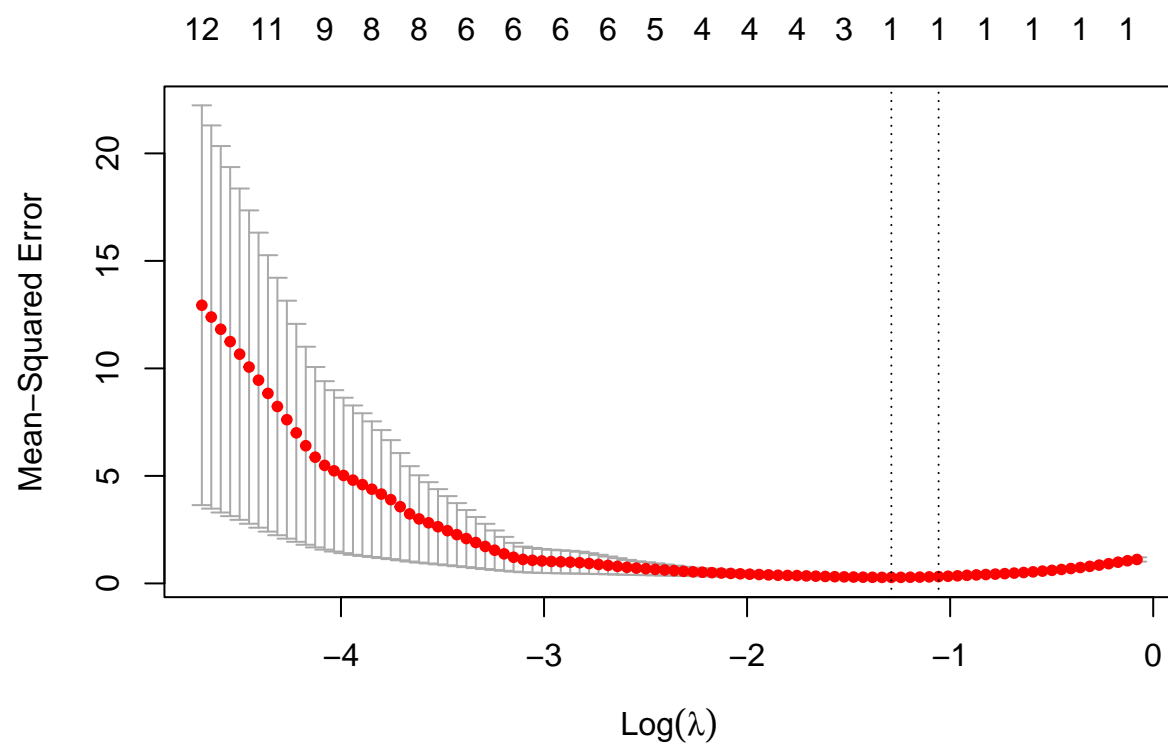
  #RIDGE
  cv.rid <- cv.glmnet(x_train, y_train, alpha = 0, nfolds = 5)

  rid <- glmnet(x_train, y_train, alpha = 0)

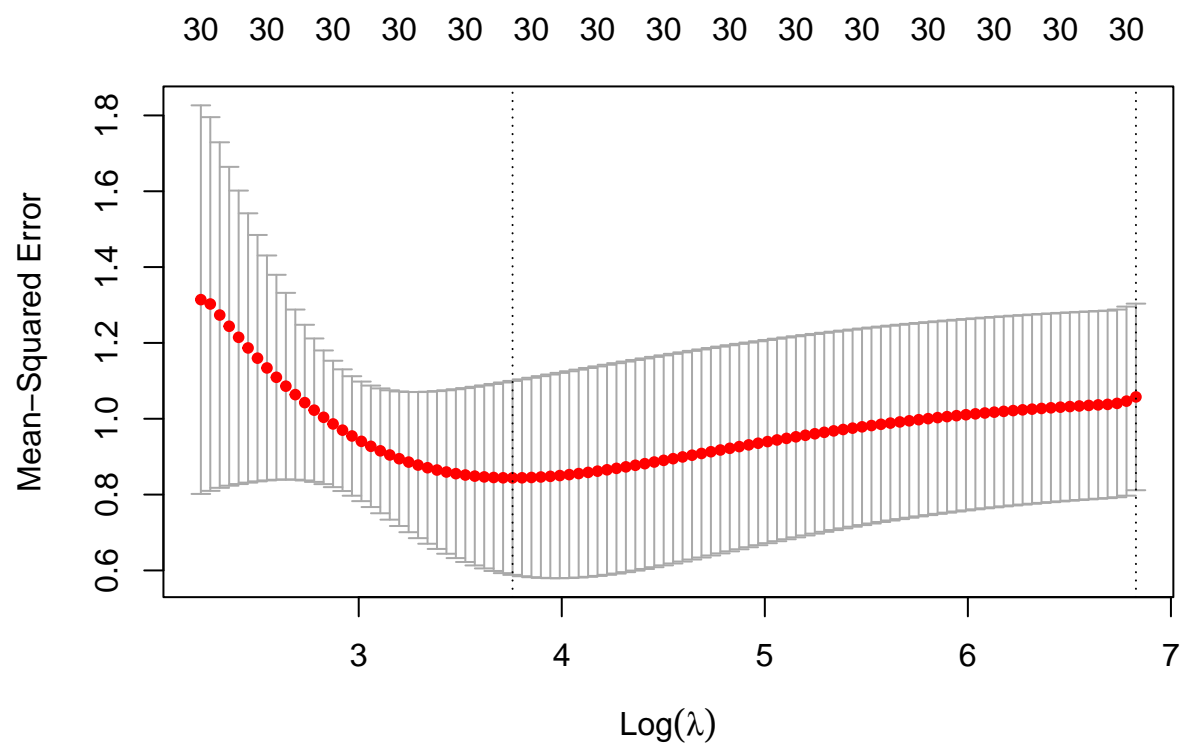
  plot(cv.rid)
  bestlam = cv.rid$lambda.min

  rid_predict <- predict(rid, s = bestlam, newx = x_test)
  #print(las_predict)
  #print(dim(las_predict))
  #print(y_test)
  #print(length(y_test))
  err2 <- mean((as.data.frame(rid_predict)$s1 - y_test)^2)
  print(err2)
  errors_folds_rid <- c(errors_folds_rid, err2)
}

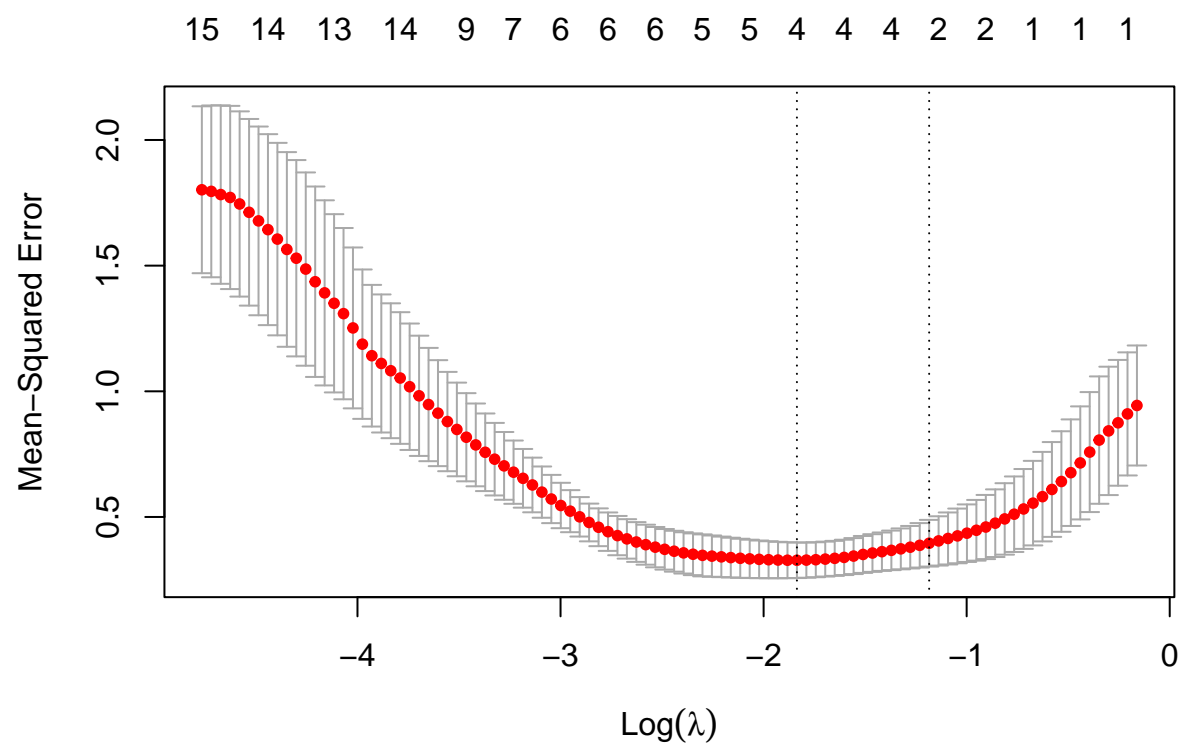
```



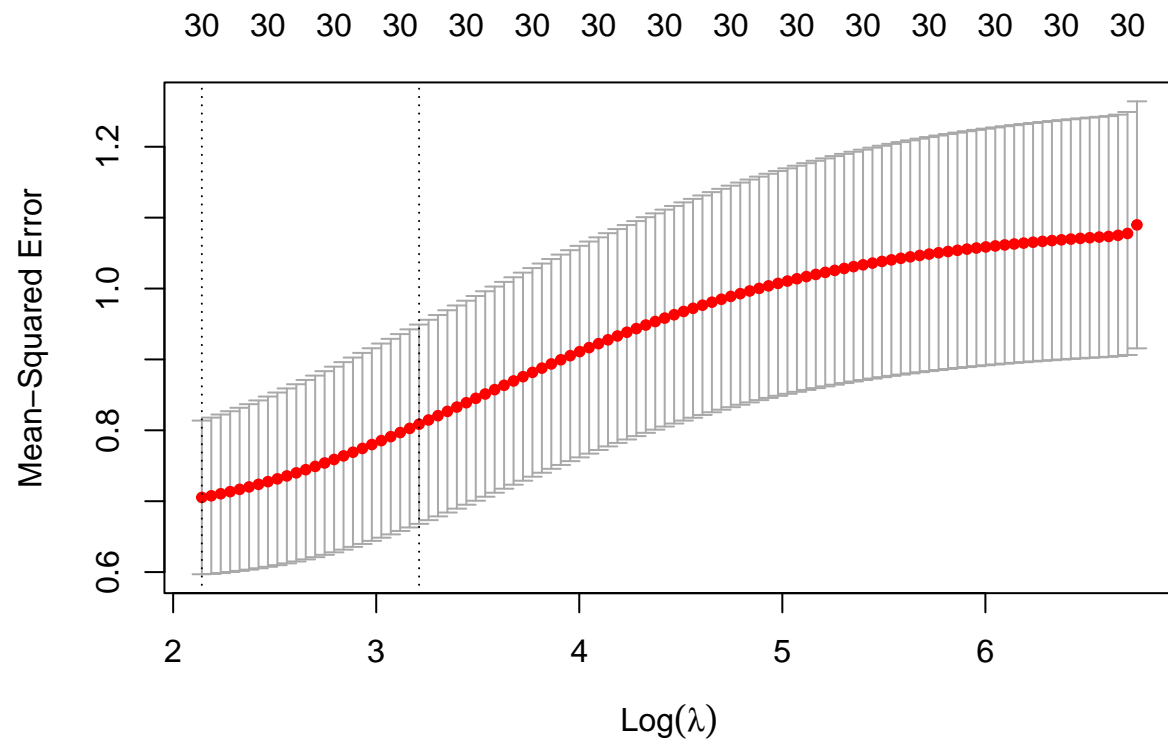
```
## [1] 0.3414291
```

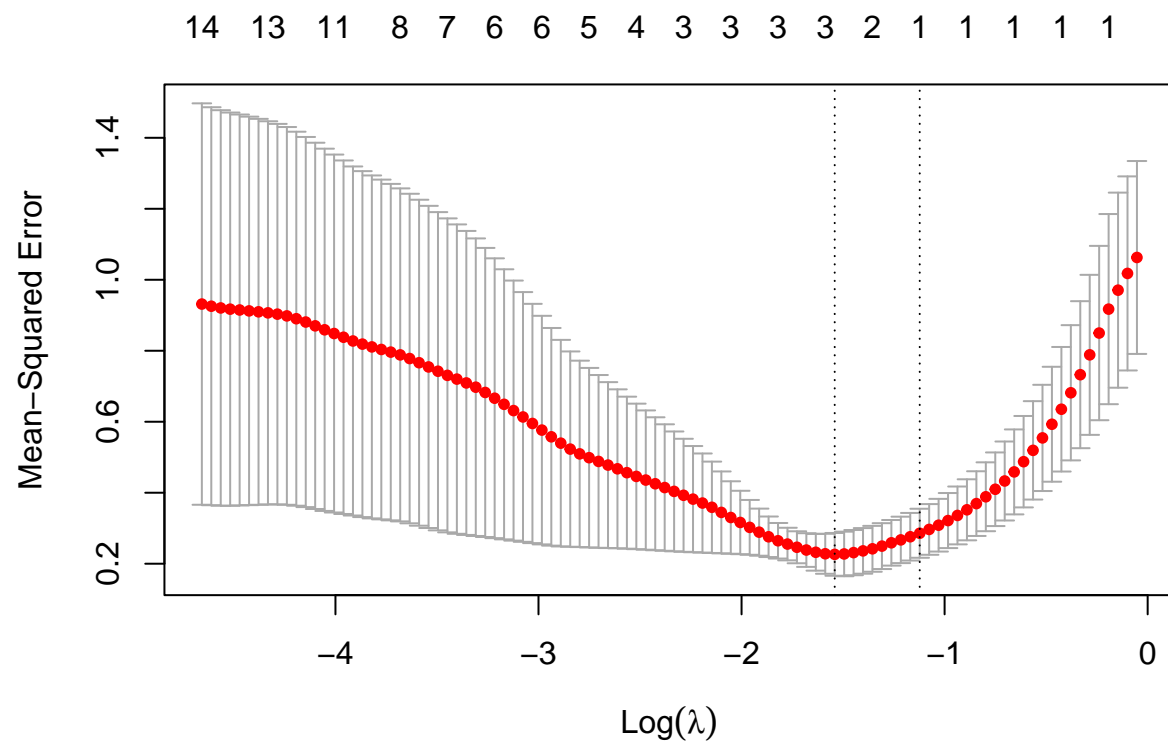
[1] 0.7286646



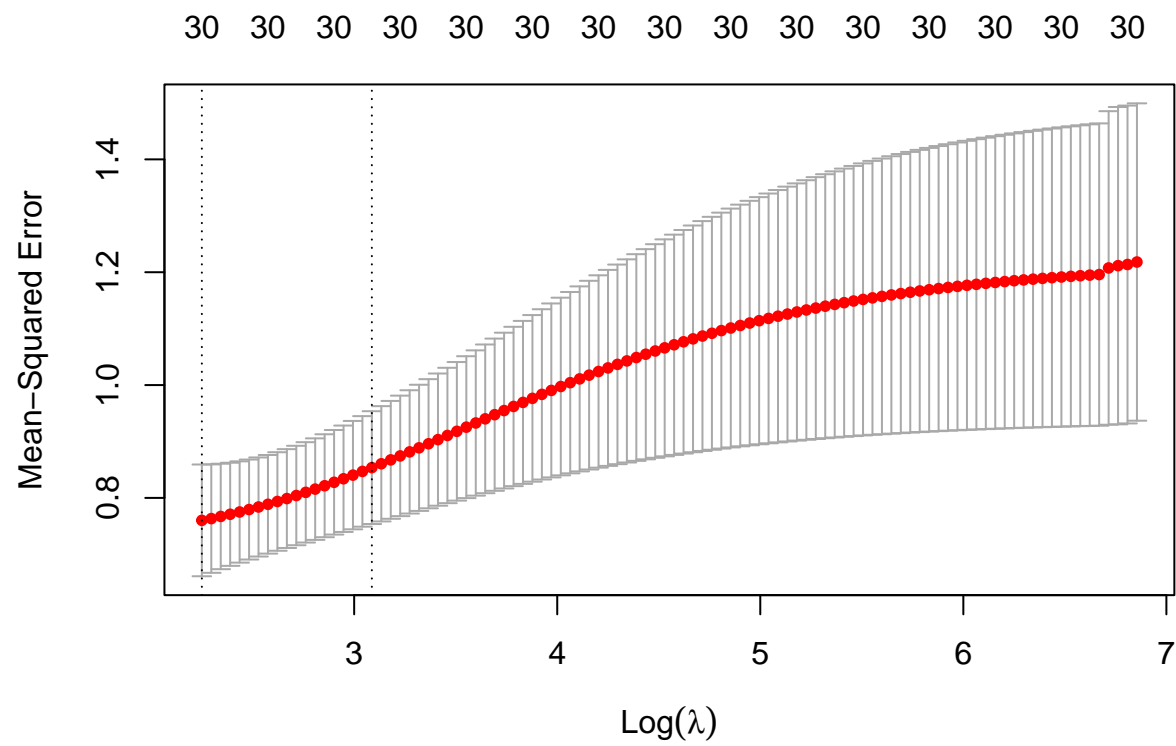
[1] 0.2142669



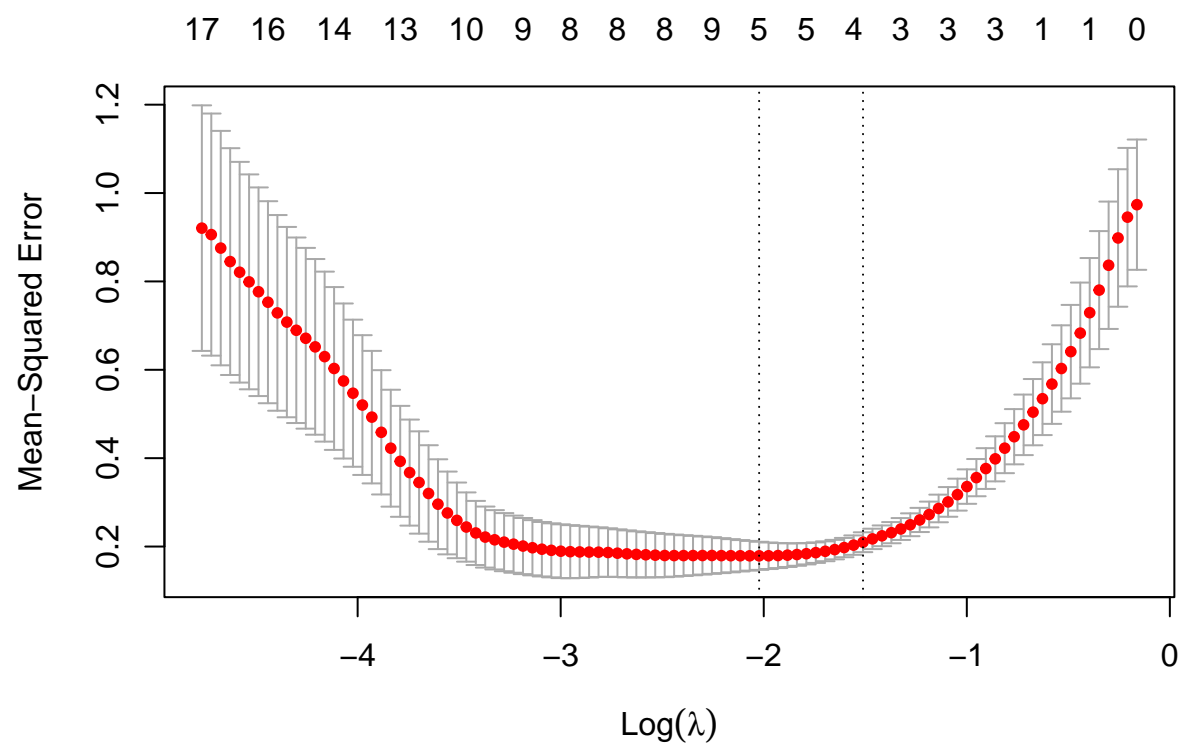
[1] 0.7627827



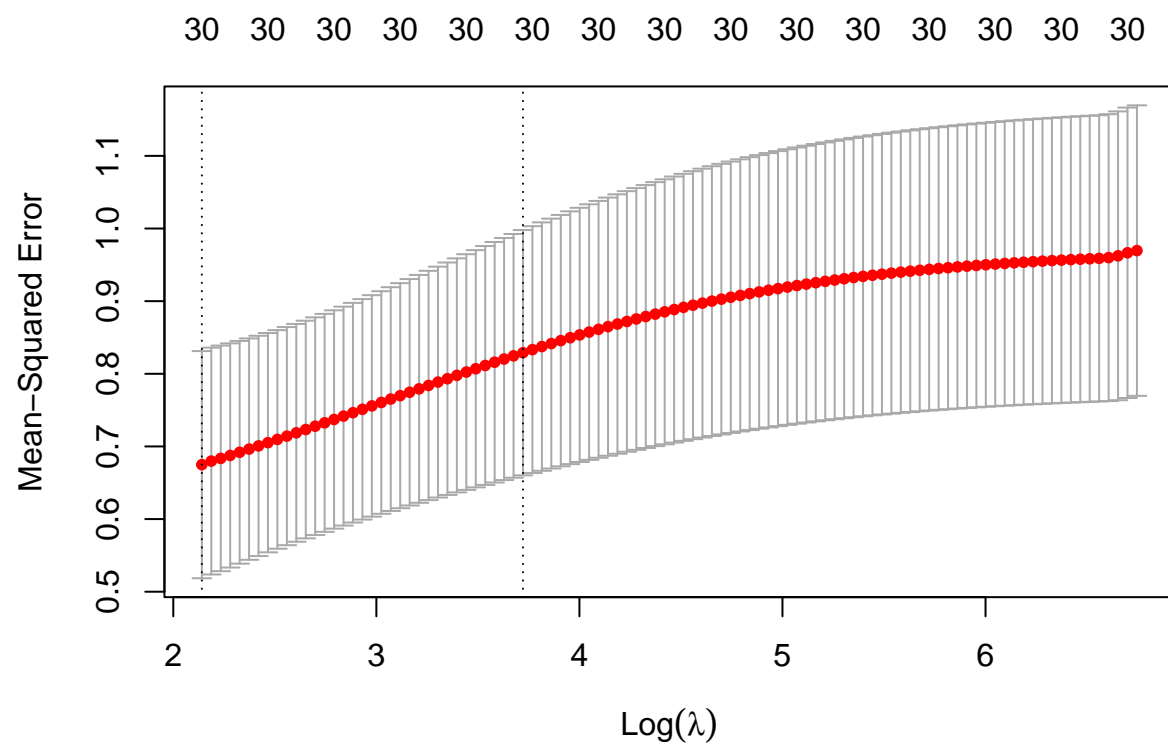
[1] 0.2482378



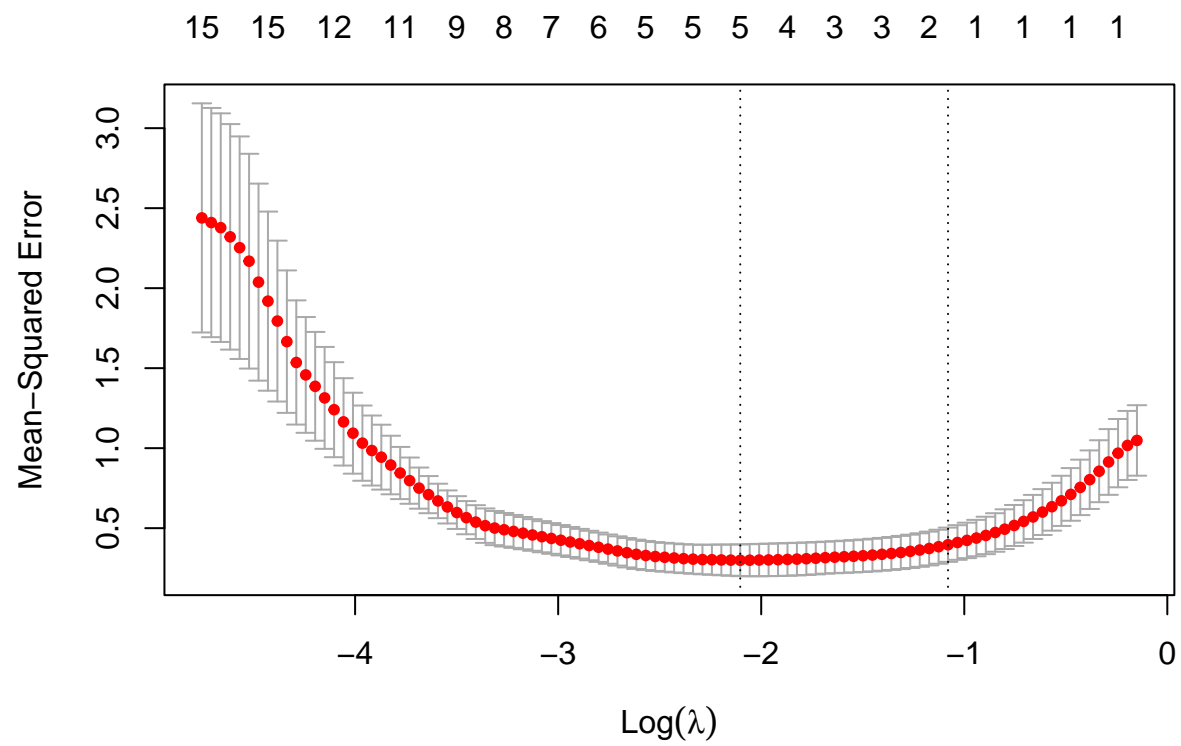
[1] 0.4553804



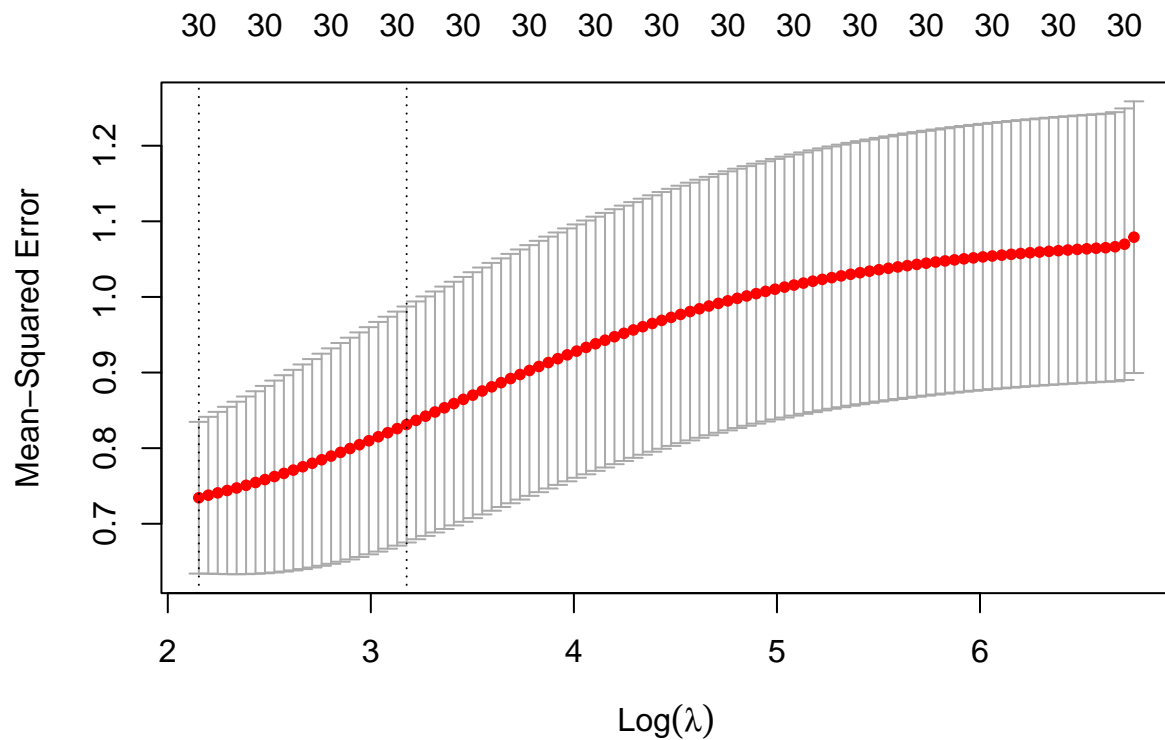
[1] 0.4159981



```
## [1] 1.310944
```



[1] 0.1472002



```
## [1] 0.660005
```

```
#The estimate of the error of the models are:
mean(errors_folds_las)
```

```
## [1] 0.2734264
```

```
mean(errors_folds_rid)
```

```
## [1] 0.7835553
```

Just one train-test separation

```
y <- scaled$employment_rate
```

```
set.seed(21)
```

```
tr <- sample(1:nrow(scaled), 0.8*nrow(scaled))
```

```
ts <- -tr
```

```
y_test <- y[ts]
```

```
y_train <- y[tr]
```

```
x <- model.matrix(employment_rate ~ .-Region-labs_pca_hc4, data = scaled) #[, -c(16,29,30,31)]
```

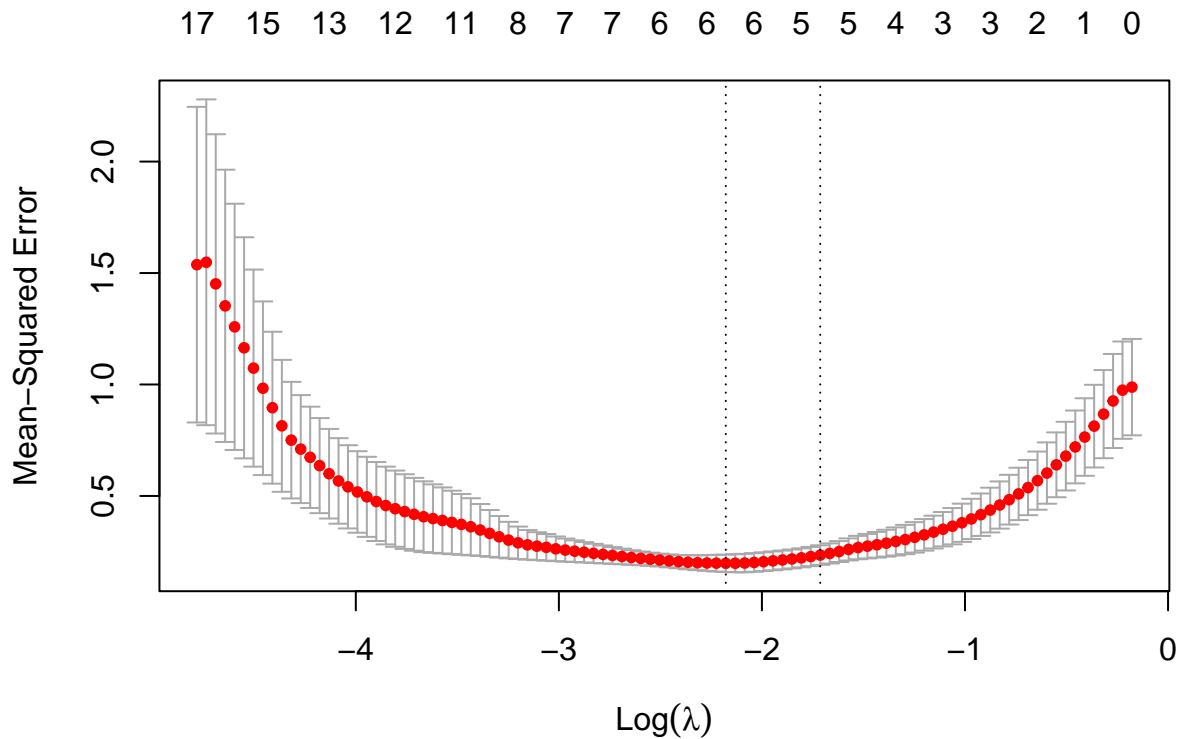
```
x_train <- model.matrix(employment_rate ~ .-Region-labs_pca_hc4, data = scaled[tr,]) #[, -c(16,29,30,31)]
```

```
x_test <- model.matrix(employment_rate ~ .-Region-labs_pca_hc4, data = scaled[ts,]) #[, -c(16,29,30,31)]
```

```
set.seed(21)
cv.las <- cv.glmnet(x_train, y_train, alpha = 1, nfolds = 5)

las <- glmnet(x_train, y_train, alpha = 1)

plot(cv.las)
```



```
bestlam = cv.las$lambda.min

las_predict <- predict(las, s = bestlam, newx = x_test)
mean((las_predict - y_test)^2) #test error based on just one split train-test
```

```
## [1] 0.4242374
```

Fit lasso on full dataset, final model to be used

```
out.cv <- cv.glmnet(x, y, alpha = 1, nfolds = 5)
bestlam <- out.cv$lambda.min
out <- glmnet(x, y, alpha = 1)

las_pred <- predict(out, type = "coefficients", s = bestlam)[1:32,]
las_pred
```

```
##                (Intercept)                (Intercept)
```

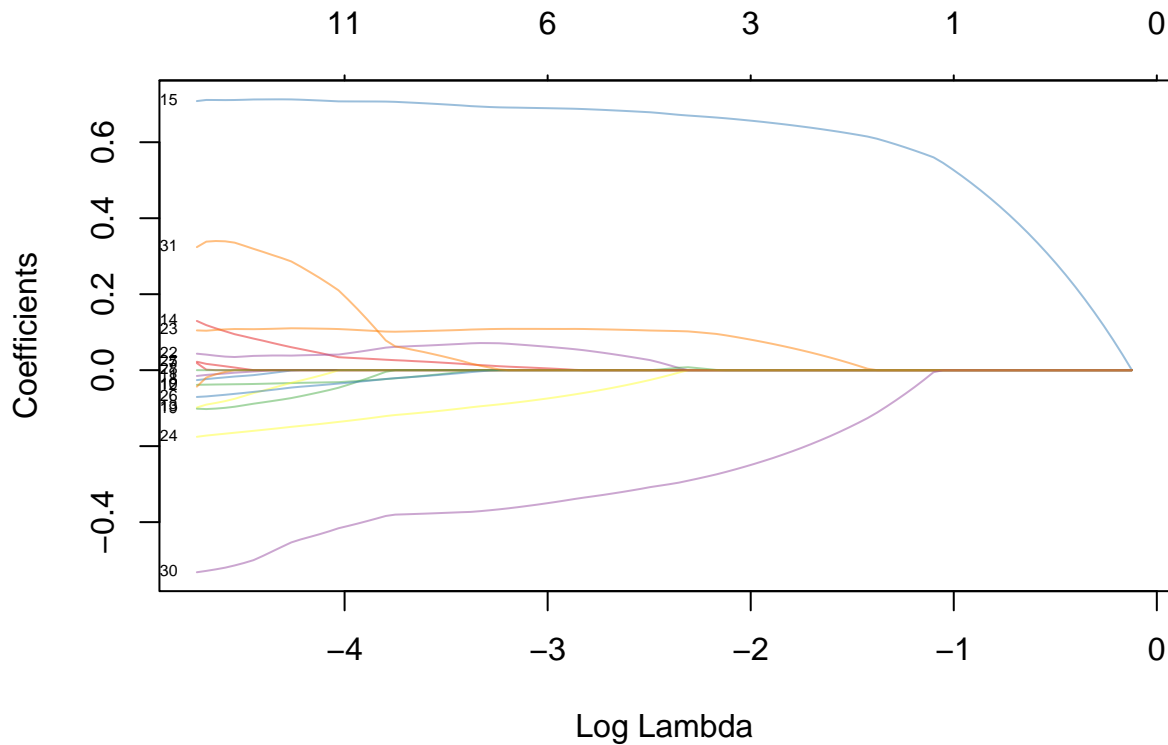
```
##          0.06605187          0.00000000
##          Population2021          fertility_rate
##          0.00000000          0.00000000
##          unis_colleges_number          teaching_staff
##          0.00000000          0.00000000
##          students_enrolled          graduates_uni
##          0.00000000          0.00000000
##          ratio_grad_enrolled_unis          TotalSchools
##          0.00000000          0.00000000
##          gradtotot57          gradtotot812
##          0.00000000          0.00000000
##          employees_laborcontract_avg employees_laborcontract_avg_topop
##          0.00000000          0.00000000
##          avgwage          activity_rate
##          0.00000000          0.65052093
##          labour_force_thousands          foreign_direct_investment_euro
##          0.00000000          0.00000000
##          books_pamphlets          accommodation_establishments
##          0.00000000          0.00000000
##          arrivals_accommodation          revenue_accomm_lev
##          0.00000000          0.00000000
##          crimes          ecological_assets
##          0.00000000          0.06891589
##          water_supply2020 connected_to_wastewater_collecting
##          0.00000000          0.00000000
##          Pop_watersupplyregime          waste_thousandtons
##          0.00000000          0.00000000
##          hospitals2021          kmeans42
##          0.00000000          0.00000000
##          kmeans43          kmeans44
##          -0.23118154          0.00000000
```

```
print(las_pred[las_pred != 0]) # These are the most important variables
```

```
##          (Intercept)          activity_rate ecological_assets          kmeans43
##          0.06605187          0.65052093          0.06891589          -0.23118154
```

```
#Again we see that activity rate is very important, but also ecological assets
#also region cluster!
```

```
plot(out, xvar = "lambda", label = TRUE)
```



Some predictions

```
one_x <- model.matrix(employment_rate ~ .-Region - labs_pca_hc4, data = scaled)[1,] #[1,-c(16,29,30,31)]
prediction_new_observation <- predict(out, s = bestlam, newx = one_x)
#This is normalized, so to get employment rate, need to "de-normalize"
mean_empl_rate <- mean(bul_with_labels$employment_rate)
stdev_empl_rate <- sqrt(var(bul_with_labels$employment_rate))
one_y <- prediction_new_observation*stdev_empl_rate + mean_empl_rate
(prediction_new_observation - scaled[1,16])^2 #error for this one
```

```
##          s1
## [1,] 0.6266015
```

```
#Let's see what will happen if we increase the activity rate with say 10%
new_x <- bul_with_labels[c(1,2,3),]
new_x$activity_rate <- new_x$activity_rate + 10
new_x_scaled <- scaled[c(1,2,3),]
new_x_scaled$activity_rate <- (new_x$activity_rate - mean(bul_with_labels$activity_rate))/sqrt(var(bul_with_labels$activity_rate))
new_x_scaled_mm <- model.matrix(employment_rate ~ .-Region-labs_pca_hc4, data = new_x_scaled) #[-c(16,29,30,31)]
new_scaled_predictions <- predict(out, s = bestlam, newx = new_x_scaled_mm)
new_predictions <- new_scaled_predictions*stdev_empl_rate + mean_empl_rate

#To see the change in the first three cities for example:
bul_with_labels[c(1,2,3),c(1,17)] #this would be before
```

```
## # A tibble: 3 x 2
```

```
## Region employment_rate
## <chr> <dbl>
## 1 Vidin 57.5
## 2 Vratsa 58.5
## 3 Lovech 65
```

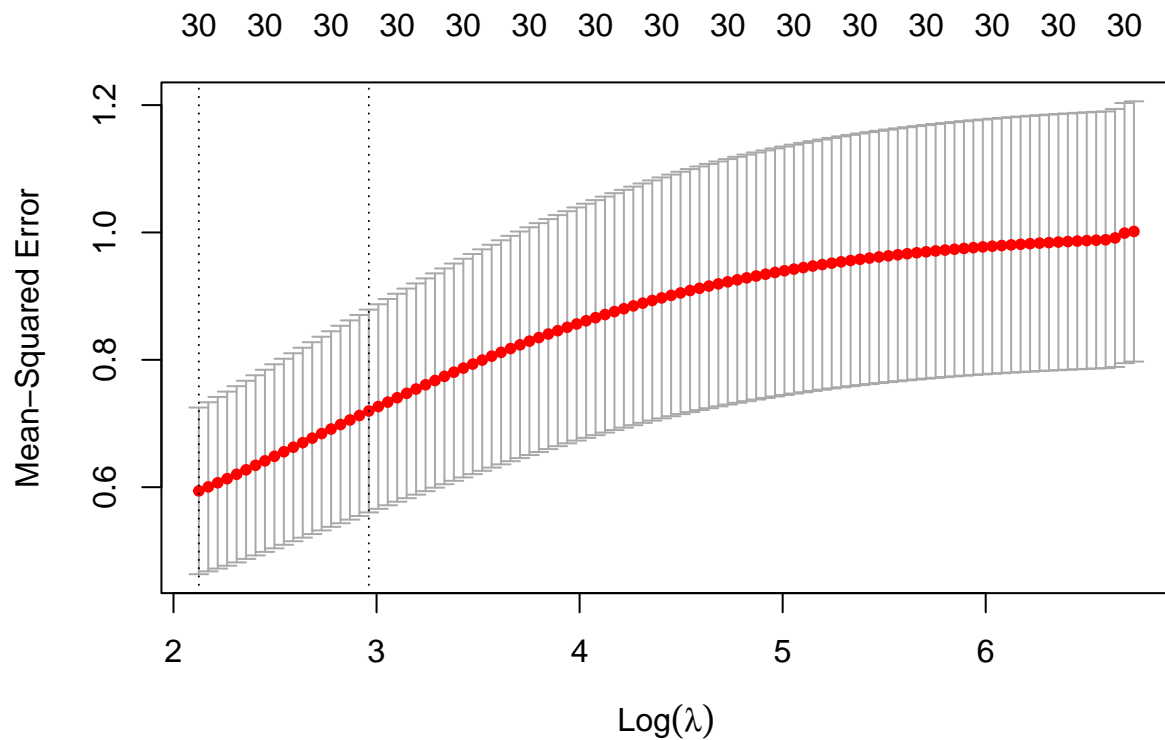
```
new_predictions #after increase in activity rate with 10%
```

```
## s1
## Vidin 71.96609
## Vratsa 68.86956
## Lovech 73.60174
```

```
set.seed(21)
cv.ridge <- cv.glmnet(x_train, y_train, alpha = 0, nfolds = 5)

ridge <- glmnet(x_train, y_train, alpha = 0)

plot(cv.ridge)
```



```
bestlam = cv.ridge$lambda.min

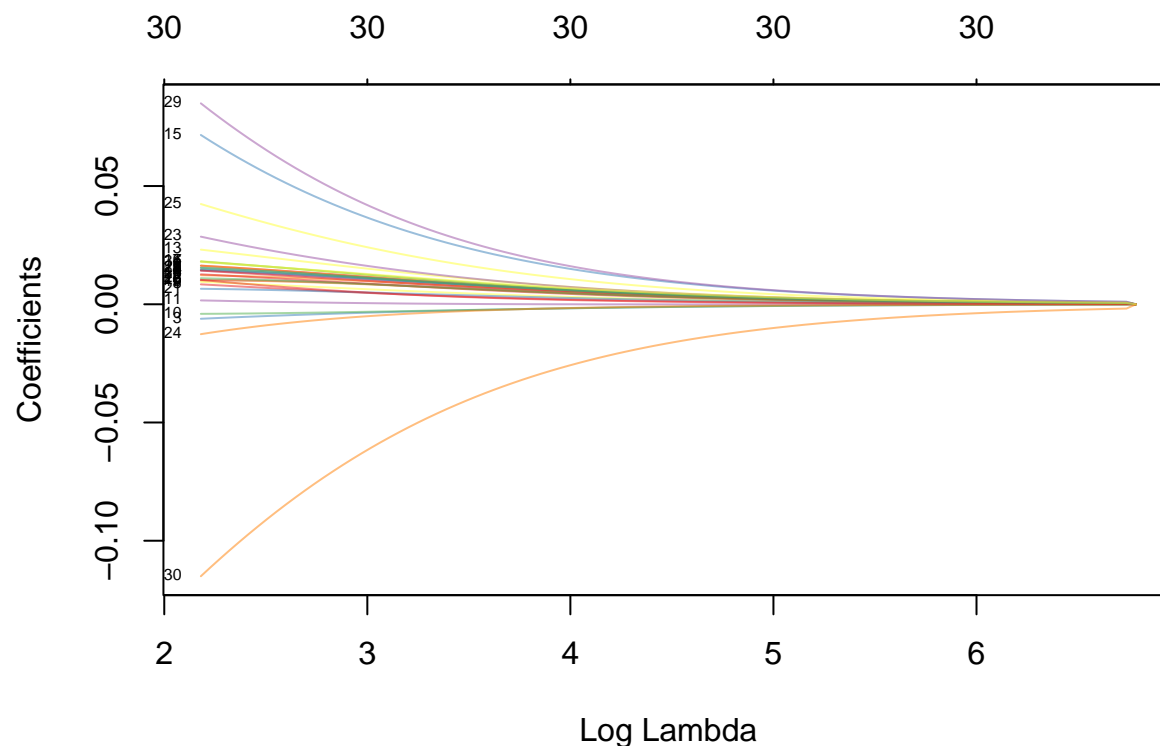
ridge_predict <- predict(ridge, s = bestlam, newx = x_test)
mean((ridge_predict - y_test)^2)
```

```
## [1] 1.075523
```

```
out.cv <- cv.glmnet(x, y, alpha = 0, nfolds = 5)
bestlam <- out.cv$lambda.min
out <- glmnet(x, y, alpha = 0)
ridg_pred <- predict(out, type = "coefficients", s = bestlam)[1:32,]
ridg_pred
```

```
##              (Intercept)              (Intercept)
##              -0.014789244              0.000000000
##              Population2021              fertility_rate
##              0.015362616              -0.005438623
##              unis_colleges_number              teaching_staff
##              0.013832112              0.013491261
##              students_enrolled              graduates_uni
##              0.015340629              0.016959348
##              ratio_grad_enrolled_unis              TotalSchools
##              0.007554291              0.013980163
##              gradtotot57              gradtotot812
##              -0.003937786              0.001309550
##              employees_laborcontract_avg employees_laborcontract_avg_topop
##              0.011953325              0.021273243
##              avgwage              activity_rate
##              0.013270576              0.061892025
##              labour_force_thousands foreign_direct_investment_euro
##              0.016882316              0.010119465
##              books_pamphlets accommodation_establishments
##              0.010012730              0.008819129
##              arrivals_accommodation              revenue_accomm_lev
##              0.011821126              0.006309441
##              crimes              ecological_assets
##              0.010624529              0.025302893
##              water_supply2020 connected_to_wastewater_collecting
##              -0.010337282              0.037679052
##              Pop_watersupplyregime              waste_thousandtons
##              0.008863088              0.014585569
##              hospitals2021              kmeans42
##              0.014642704              0.073110296
##              kmeans43              kmeans44
##              -0.100762630              0.016811707
```

```
plot(out, xvar = "lambda", label = TRUE)
```



```
ridg_pred[order(abs(ridg_pred))] #ordering of the coefficients of variables
```

```
##          (Intercept)          gradtotot812
##          0.000000000          0.001309550
##          gradtotot57          fertility_rate
##          -0.003937786          -0.005438623
##          revenue_accomm_lev          ratio_grad_enrolled_unis
##          0.006309441          0.007554291
##          accommodation_establishments          Pop_watersupplyregime
##          0.008819129          0.008863088
##          books_pamphlets          foreign_direct_investment_euro
##          0.010012730          0.010119465
##          water_supply2020          crimes
##          -0.010337282          0.010624529
##          arrivals_accommodation          employees_laborcontract_avg
##          0.011821126          0.011953325
##          avgwage          teaching_staff
##          0.013270576          0.013491261
##          unis_colleges_number          TotalSchools
##          0.013832112          0.013980163
##          waste_thousandtons          hospitals2021
##          0.014585569          0.014642704
##          (Intercept)          students_enrolled
##          -0.014789244          0.015340629
##          Population2021          kmeans44
```

##	0.015362616	0.016811707
##	labour_force_thousands	graduates_uni
##	0.016882316	0.016959348
##	employees_laborcontract_avg_topop	ecological_assets
##	0.021273243	0.025302893
##	connected_to_wastewater_collecting	activity_rate
##	0.037679052	0.061892025
##	kmeans42	kmeans43
##	0.073110296	-0.100762630

```
write.csv(bul_with_labels, "C:/Users/User/Documents/UNITN/Computational social science/bulgaria/bul_with_labels.csv")
```