# project

January 9, 2025

[128]:
```
library(tidyr)
library("pxweb")
library("tidyverse")
library("GGally")
library("ggpubr")
library(gridExtra)
library(cowplot)
```

We are going to explore if it is reasonable to use a MLR model to predict the number of people graduating from three different levels of education. We will also explore if the model performs better for the entire population or for men and women separately.

[129]:
```
#d <- pxweb_interactive("https://api.scb.se/OV0104/v1/doris/sv/ssd/UF/UF0550/
↪UF0550C/Historisk11bN")
API_wait<-1e-3
pxq_edu <-
  list(
    "Examen" = c("*"), # Use "*" to select all
    "Kon" = c("*"),
    "ContentsCode" = c("000004NE"),
    "Tid" = c("*")
  )
pxg_edu<-pxweb_get("https://api.scb.se/OV0104/v1/doris/sv/ssd/START/UF/UF0550/
↪UF0550C/Historisk11bN",pxq_edu)
Sys.sleep(API_wait)
pxq_pop <-
  list(
    "Kon" = c("*"),
    "ContentsCode" = c("000000LV"),
    "Tid" = c("*")
  )

pxg_pop<-pxweb_get("https://api.scb.se/OV0104/v1/doris/sv/ssd/START/BE/BE0101/
↪BE0101G/BefUtvKon1749",pxq_pop)
Sys.sleep(API_wait)
#https://api.scb.se/OV0104/v1/doris/sv/ssd/START/HE/HE0103/HE0103A/ArbInk28
pxq_income<-list(
```

```
  "Kon" = c("*"),
  "Tid" = c("*"),
  "ContentsCode" = c("HE0103CL")
          #"HE0103CM")
)
pxg_income<-pxweb_get("https://api.scb.se/OV0104/v1/doris/sv/ssd/START/HE/
 ↪HE0103/HE0103A/ArbInk28",pxq_income)

Sys.sleep(API_wait)
pxq_kpi<-list(
  "Tid" = c("*"),
  "ContentsCode" = c("000004VU")
)
pxg_kpi<-pxweb_get("https://api.scb.se/OV0104/v1/doris/sv/ssd/START/PR/PR0101/
 ↪PR0101A/KPItotM",pxq_kpi)
```

We start by gathering data from SCB about education,income,KPI and population. Then we clean and modify the data to fit our needs.

[130]:
```
edu_df<-as.data.frame(pxg_edu)
edu_df<-as_tibble(edu_df)

doktor_df<-edu_df%>%
filter(examen%in%c("Doktorsgrad","Doktorsexamen"))%>%
group_by(läsår,kön)%>%
mutate(`Utfärdade examina vid universitet och högskolor`=sum(`Utfärdade examina␣
 ↪vid universitet och högskolor`))%>%
filter(examen=="Doktorsexamen")%>%
ungroup()


licenciat_df<-edu_df%>%
filter(examen%in%c("Licentiatexamen","Licentiatexamen (Äldre)"))%>%
group_by(läsår,kön)%>%
mutate(`Utfärdade examina vid universitet och högskolor`=sum(`Utfärdade examina␣
 ↪vid universitet och högskolor`))%>%
filter(examen=="Licentiatexamen")%>%
ungroup()


edu_df<-edu_df%>%
filter(examen=="Examen från grundutbildning")%>%
full_join(licenciat_df)%>%
full_join(doktor_df)%>%
pivot_wider(names_from=kön,values_from = `Utfärdade examina vid universitet och␣
 ↪högskolor`)%>%
mutate(läsår=as.integer(str_extract(läsår,"^\\w*")))%>%rename(år=läsår)%>%
```

```
pivot_longer(!c(år,examen),names_to = "kön",values_to = "antal")%>%
mutate(kön=str_replace(kön,"båda könen","totalt"),
    examen=factor(examen,
    ordered = FALSE,
    levels = c(
    "Examen från grundutbildning","Licentiatexamen","Licentiatexamen␣
  ↪(Äldre)","Doktorsgrad","Doktorsexamen"
    ),
    labels=c(
       ␣
  ↪"Grundutbildning","Licentiatexamen","Licentiatexamen","Doktorsexamen","Doktorsexamen"
)))

pop_df<-as.data.frame(pxg_pop)
pop_df<-as_tibble(pop_df)%>%mutate(år=as.integer(år))#%>%



income_df<-as.data.frame(pxg_income)
income_df<-as_tibble(income_df)%>%filter(år>=1936)%>%mutate(år=as.integer(år))


kpi_df<-as.data.frame(pxg_kpi)
kpi_df<-as_tibble(kpi_df)%>%
mutate(månad=str_extract(månad,"(20|19)[\\d]{2}"))%>%
rename("år"="månad")%>%
group_by(år)%>%mutate(år=as.integer(år))%>%
summarize(`AVG_KPI_Fastställd` = mean(`KPI, fastställda tal`))%>%
ungroup()


final_df<-edu_df%>%
left_join(income_df,by=join_by("år",kön==kön))%>%
left_join(kpi_df,by="år")%>%
left_join(pop_df,by=join_by("år",kön==kön))%>%rename(medelinkomst=`Medelvärde,␣
  ↪tkr`)%>%
mutate(kön=factor(kön,levels=c("totalt","kvinnor","män"),ordered = FALSE))%>%
drop_na()

final_df%>%filter(år==1980)
```

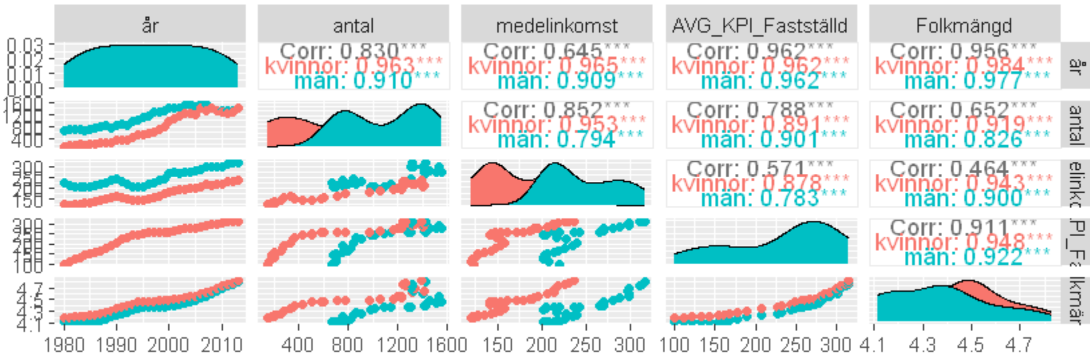
```
Joining with `by = join_by(examen, kön, läsår, `Utfärdade examina vid
universitet och högskolor`)`
Joining with `by = join_by(examen, kön, läsår, `Utfärdade examina vid
universitet och högskolor`)`
```

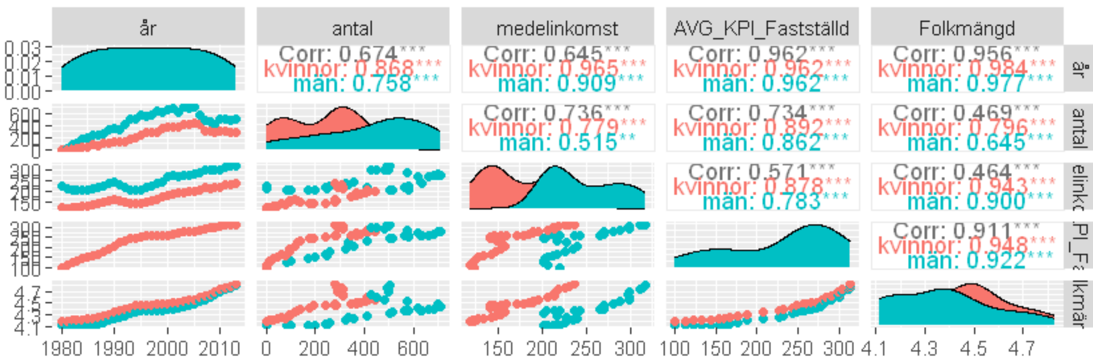
A tibble: 9 × 7

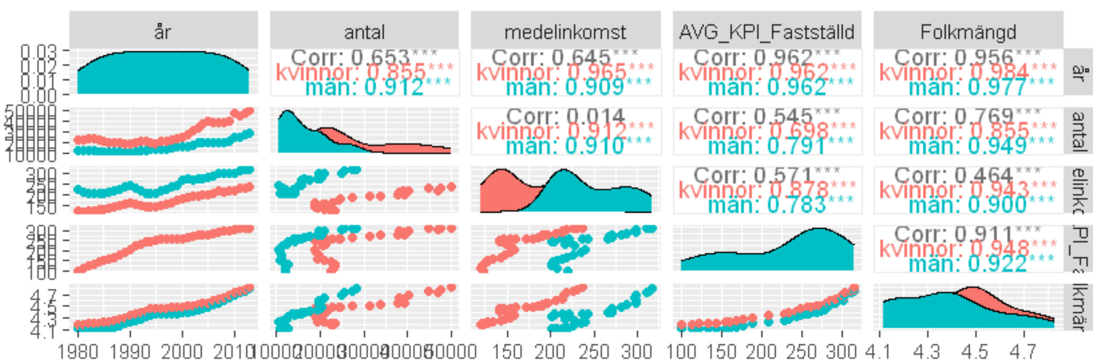
| examen <fct> | år <int> | kön <fct> | antal <dbl> | medelinkomst <dbl> | AVG_KPI_Fastställd <dbl> | Folkmän <dbl> |
|---|---|---|---|---|---|---|
| Grundutbildning | 1980 | totalt | 34536 | 172.3 | 100 | 8317937 |
| Grundutbildning | 1980 | män | 12110 | 220.4 | 100 | 4119822 |
| Grundutbildning | 1980 | kvinnor | 22426 | 122.9 | 100 | 4198115 |
| Licentiatexamen | 1980 | totalt | 1 | 172.3 | 100 | 8317937 |
| Licentiatexamen | 1980 | män | 1 | 220.4 | 100 | 4119822 |
| Licentiatexamen | 1980 | kvinnor | 0 | 122.9 | 100 | 4198115 |
| Doktorsexamen | 1980 | totalt | 812 | 172.3 | 100 | 8317937 |
| Doktorsexamen | 1980 | män | 666 | 220.4 | 100 | 4119822 |
| Doktorsexamen | 1980 | kvinnor | 146 | 122.9 | 100 | 4198115 |

We then do some eploratory data analysis on the collected data

[131]:
```
dok_df<-final_df%>%
filter(examen=="Doktorsexamen",kön!="totalt")%>%
mutate(Folkmängd=1e-6*Folkmängd)

lic_df<-final_df%>%
filter(examen=="Licentiatexamen",kön!="totalt")%>%
mutate(Folkmängd=1e-6*Folkmängd)

grund_df<-final_df%>%
filter(examen=="Grundutbildning",kön!="totalt")%>%
mutate(Folkmängd=1e-6*Folkmängd)

dok_pairs<-ggpairs(data=dok_df,
columns=c("år","antal","medelinkomst","AVG_KPI_Fastställd","Folkmängd"),
mapping=aes(color=kön))

lic_pairs<-ggpairs(data=lic_df,columns=c("år","antal","medelinkomst","AVG_KPI_Fastställd","Fol
 ↪
mapping=aes(color=kön))

grund_pairs<-ggpairs(data=grund_df,columns=c("år","antal","medelinkomst","AVG_KPI_Fastställd",
mapping=aes(color=kön))

plot_grid(
    ggmatrix_gtable(dok_pairs), ggmatrix_gtable(lic_pairs),␣
 ↪ggmatrix_gtable(grund_pairs),
    ncol=1)
```




We can see that there is some collinearity between some of the columns and that it differs between different types of degrees.

As a naive approach the first model will contain all available data in the multiple linear regression for the amount of graduates.

[132]:

```
naive_model<-lm(antal~år+kön+examen+medelinkomst+Folkmängd+AVG_KPI_Fastställd,data=final_df%>%
  ↪="totalt"))
summary(naive_model)
```

```
Call:
lm(formula = antal ~ år + kön + examen + medelinkomst + Folkmängd +
    AVG_KPI_Fastställd, data = final_df %>% filter(kön != "totalt"))
```

```
Residuals:
    Min      1Q  Median      3Q     Max 
-7336.1 -2820.9  -343.8  2509.4 20567.5 

Coefficients:
                         Estimate Std. Error t value Pr(>|t|)    
(Intercept)            -1.674e+06  6.974e+05  -2.400  0.01733 *  
år                      8.648e+02  3.656e+02   2.365  0.01898 *  
könmän                 -1.241e+03  3.123e+03  -0.397  0.69157    
examenLicentiatexamen -2.188e+04  8.268e+02 -26.464  < 2e-16 ***
examenDoktorsexamen   -2.129e+04  8.268e+02 -25.744  < 2e-16 ***
medelinkomst           -3.498e+01  3.875e+01  -0.903  0.36787    
Folkmängd              -1.050e-03  8.651e-03  -0.121  0.90357    
AVG_KPI_Fastställd     -7.788e+01  2.982e+01  -2.611  0.00972 ** 
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 4821 on 196 degrees of freedom
Multiple R-squared:  0.836,	Adjusted R-squared:  0.8301 
F-statistic: 142.7 on 7 and 196 DF,  p-value: < 2.2e-16
```

[133]:

```
naive_model2<-lm(antal~år+kön+examen+medelinkomst+AVG_KPI_Fastställd,data=final_df%>%filter(kö
↪="totalt"))
summary(naive_model2)
```

```
Call:
lm(formula = antal ~ år + kön + examen + medelinkomst + AVG_KPI_Fastställd, 
    data = final_df %>% filter(kön != "totalt"))

Residuals:
   Min     1Q Median     3Q    Max 
 -7296  -2807   -362   2527  20515 

Coefficients:
                         Estimate Std. Error t value Pr(>|t|)    
(Intercept)            -1.628e+06  5.878e+05  -2.770  0.00613 ** 
år                      8.397e+02  3.006e+02   2.793  0.00573 ** 
könmän                 -1.184e+03  3.080e+03  -0.384  0.70108    
examenLicentiatexamen -2.188e+04  8.247e+02 -26.531  < 2e-16 ***
examenDoktorsexamen   -2.129e+04  8.247e+02 -25.809  < 2e-16 ***
medelinkomst           -3.458e+01  3.852e+01  -0.898  0.37042    
AVG_KPI_Fastställd     -7.729e+01  2.934e+01  -2.634  0.00911 ** 
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Residual standard error: 4809 on 197 degrees of freedom
Multiple R-squared:  0.8359,	Adjusted R-squared:  0.8309
F-statistic: 167.3 on 6 and 197 DF,  p-value: < 2.2e-16
```

This naive model results in a relatively high $R^2$ and $R^2_{adj}$ values of $R^2 = 0.836, R^2_{adj} = 0.830$. The most significant regressors were the average KPI that year and if the degree was a "Licenciat" or PH. That the type of degree was significant is not at all unexpected as a Bachelor's level degree is a prerequesite for further studies. That KPI was significant could hint at the state of the economy being important in people studying or not. But the model is quite hard to interpret as a person, because of the large amount of explanatory variables. Because of this the regressor with the highest $p$-value was removed from the model, this being the population variable.

The new model had $R^2 = 0.836, R^2_{adj} = 0.831$ meaning it performed slightly better than the naive model. Altough it should be noted that all of the $p$-values barely changed.

In order to increase the interpretability of the model and to more easily choose our variables, we will instead create two new models one for the amount of people graduating with a Bachelor's level degree and another for the amount of people graduating with either a "Licenciat" or PHD.

We will also aproach the problem of choosing variables in the opposite way from what was done to the naive model, that is we will add one variable at a time instead of removing them.

[134]:
```r
bachelor_model<-lm(antal~.,data=final_df%>%filter(examen=="Grundutbildning",kön!
 ↪="totalt")%>%select(!examen))
ols_step_forward_p(bachelor_model)
```

```
                                   Stepwise Summary
-------------------------------------------------------------------------------------
Step    Variable                AIC         SBC         SBIC         R2         Adj.
 ↪ R2
-------------------------------------------------------------------------------------
 0      Base Model            1447.805    1452.244    1251.378    0.00000    0.
 ↪00000
 1      Folkmängd             1388.922    1395.580    1191.690    0.59153    0.
 ↪58534
 2      kön                   1339.183    1348.061    1142.668    0.80914    0.
 ↪80326
 3      medelinkomst          1327.645    1338.743    1131.189    0.84359    0.
 ↪83626
 4      AVG_KPI_Fastställd    1320.904    1334.221    1124.602    0.86246    0.
 ↪85373
 5      år                    1291.093    1306.629    1099.260    0.91385    0.
 ↪90690
-------------------------------------------------------------------------------------

Final Model Output
```

```
------------------

                           Model Summary
----------------------------------------------------------------------
R                          0.956       RMSE                  2897.053
R-Squared                  0.914       MSE                8392914.012
Adj. R-Squared             0.907       Coef. Var               13.662
Pred R-Squared             0.896       AIC                   1291.093
MAE                     2360.274       SBC                   1306.629
----------------------------------------------------------------------
 RMSE: Root Mean Square Error
 MSE: Mean Square Error
 MAE: Mean Absolute Error
 AIC: Akaike Information Criteria
 SBC: Schwarz Bayesian Criteria

                                   ANOVA
------------------------------------------------------------------------------
                     Sum of
                    Squares        DF       Mean Square       F          Sig.
------------------------------------------------------------------------------
Regression    6053846173.952        5    1210769234.790    131.532    0.0000
Residual       570718152.798       62       9205131.497
Total         6624564326.750       67
------------------------------------------------------------------------------

                                              Parameter Estimates
----------------------------------------------------------------------------------------------------
             model               Beta    Std. Error    Std. Beta       t        Sig
 ↪           lower              upper
----------------------------------------------------------------------------------------------------
       (Intercept)    -4744231.247    760146.820                   -6.241    0.000
 ↪    -6263743.089    -3224719.405
         Folkmängd           0.001         0.009        0.021     0.113    0.911
 ↪          -0.018           0.020
            könmän       -4492.417      3404.323       -0.228    -1.320    0.192
 ↪      -11297.563        2312.728
      medelinkomst         -98.245        42.241       -0.536    -2.326    0.023
 ↪        -182.683         -13.807
AVG_KPI_Fastställd        -231.133        32.509       -1.486    -7.110    0.000
 ↪        -296.118        -166.148
                år        2423.482       398.513        2.409     6.081    0.000
 ↪        1626.866        3220.097
----------------------------------------------------------------------------------------------------
```

The variable selection algorithm for the Bachelor's level model resulted in the following choices: 1. Population 2. Gender 3. Average income 4. Average KPI 5. Year

On first glance this result was surprising to me as the first variable it chose was population in contrast to the naive model were it had the largest $p$-values, and that the variable with the lowest $p$-value except type of degree was added second to last.

Altough from the pairs plot we knew that there was collinearity between some of the variables so it is to be excpected that they would interact in nonintuitive ways.