project

January 9, 2025

[147]:
```r
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.

[148]:
```r
# 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.

[ ]:
```
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) %>%
```

```r
    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`)`
```

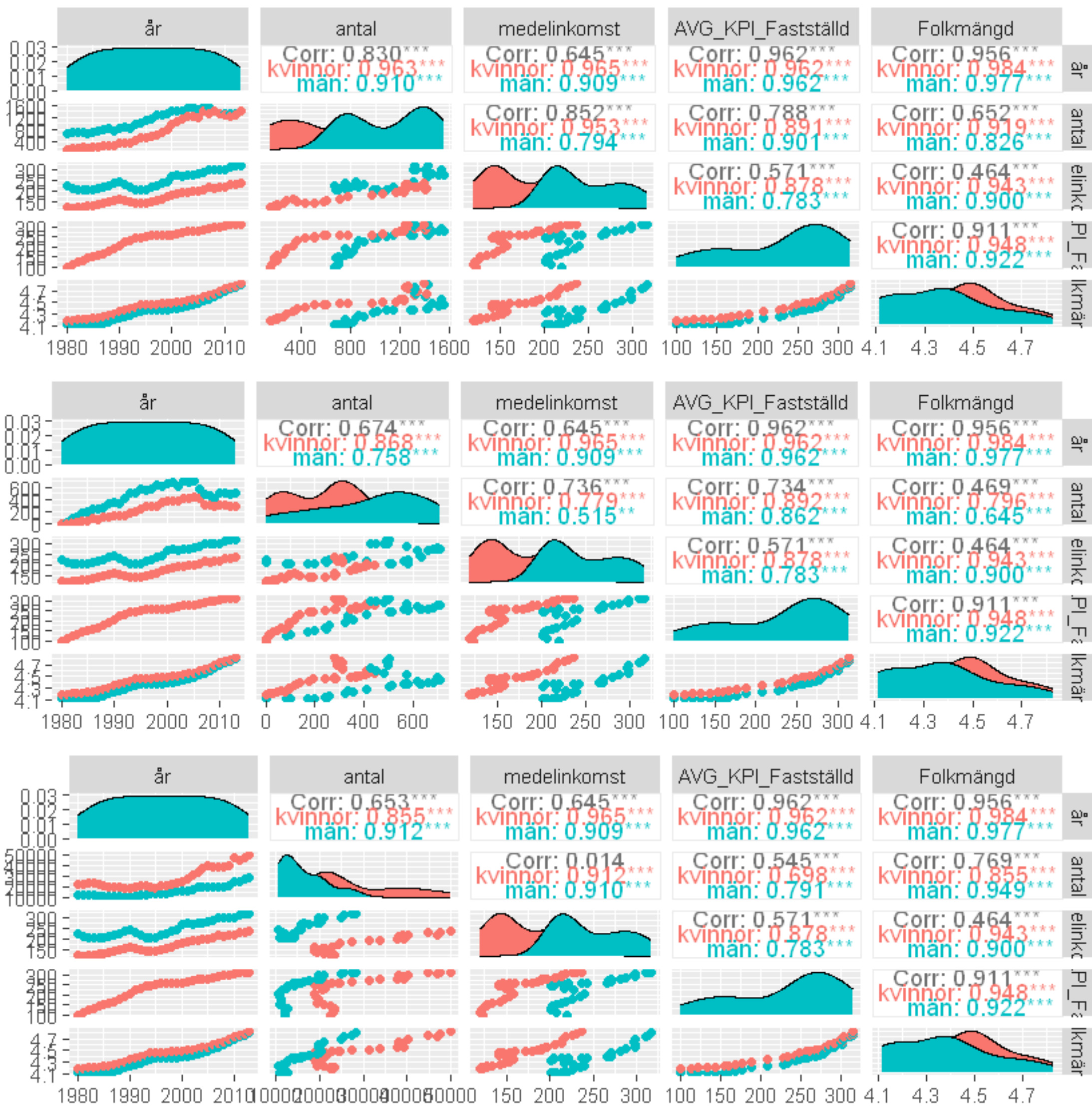
A tibble: 9 × 7

examen	år	kön	antal	medelinkomst	AVG_KPI_Fastställd	Folkmän
<fct>	<int>	<fct>	<dbl>	<dbl>	<dbl>	<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

[150]:
```
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", "Folkmängd"),
    mapping = aes(color = kön)
)

grund_pairs <- ggpairs(
    data = grund_df, columns = c("år", "antal", "medelinkomst",
 ↪"AVG_KPI_Fastställd", "Folkmängd"),
    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.

[151]:
```
naive_model <- lm(antal ~ år + kön + examen + medelinkomst + Folkmängd +
    AVG_KPI_Fastställd, data = final_df %>% filter(kön != "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
```

[152]:
```
naive_model2 <- lm(antal ~ år + kön + examen + medelinkomst +
    AVG_KPI_Fastställd, data = final_df %>% filter(kön != "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.

[153]:
```r
bachelor_model <- lm(antal ~ ., data = final_df %>% filter(examen ==
  "Grundutbildning", kön != "totalt") %>% select(!examen))
ols_step_forward_p(bachelor_model)

higher_ed_model <- lm(antal ~ ., data = final_df %>% filter(examen !=
  "Grundutbildning", kön != "totalt") %>% mutate(examen = factor(examen)))
ols_step_forward_p(higher_ed_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
----------------------------------------------------------------------------------------------
```

```
                                   Stepwise Summary
------------------------------------------------------------------------------------
Step    Variable                 AIC          SBC          SBIC          R2        Adj.
 ↪ R2
------------------------------------------------------------------------------------
 0      Base Model             2054.785     2060.611     1665.554     0.00000     0.
 ↪00000
 1      examen                 1980.883     1989.621     1590.585     0.42771     0.
 ↪42344
 2      medelinkomst           1863.077     1874.728     1473.845     0.76284     0.
 ↪75928
 3      AVG_KPI_Fastställd     1817.731     1832.294     1429.629     0.83257     0.
 ↪82876
 4      Folkmängd              1804.162     1821.638     1416.537     0.85068     0.
 ↪84612
 5      år                     1784.163     1804.551     1398.030     0.87298     0.
 ↪86809
 6      kön                    1776.912     1800.214     1391.715     0.88133     0.
 ↪87581
------------------------------------------------------------------------------------

Final Model Output
------------------

                           Model Summary
-------------------------------------------------------------------
R                         0.939       RMSE                 156.805
R-Squared                 0.881       MSE                24587.845
Adj. R-Squared            0.876       Coef. Var             25.765
Pred R-Squared            0.868       AIC                 1776.912
MAE                     132.207       SBC                 1800.214
-------------------------------------------------------------------
 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	24834911.666	6	4139151.944	159.677	0.0000
Residual	3343946.892	129	25922.069		
Total	28178858.559	135			

Parameter Estimates

model	Beta	Std. Error	Std. Beta	t	Sig	lower	upper
(Intercept)	-160197.705	28523.471		-5.616	0.000	-216632.090	-103763.320
examenDoktorsexamen	595.382	27.612	0.654	21.563	0.000	540.752	650.013
medelinkomst	-3.341	1.585	-0.395	-2.108	0.037	-6.477	-0.205
AVG_KPI_Fastställd	-1.257	1.220	-0.175	-1.030	0.305	-3.670	1.157
Folkmängd	-0.002	0.000	-0.905	-5.951	0.000	-0.003	-0.001
år	85.460	14.954	1.842	5.715	0.000	55.874	115.046
könmän	384.918	127.743	0.423	3.013	0.003	132.176	637.660

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.

For the model of the other two degrees, forward selection resulted in the choices: