

# Data Analysis Project 1

MA8701

Group 5 : Yellow Submarine

15 February, 2021

## Note on Open Science

To pursue the idea of reproducible research, the chosen dataset as well as the code for our analysis are publicly accessible:

- dataset: <https://data.ub.uni-muenchen.de/2/1/miete03.asc>
- code: <https://github.com/FlorianBeiser/MA8701>

## Regression

We start with a vanilla LM regression for reference. Only significant coefficients are printed. Clearly, the area wfl is strongly related to the rent price. Surprisingly in the regression, the significance of different bjs and bezs varies a lot.

```
##          summary.lm_mod..coef.summary.lm_mod..coef...4.....0.05..4..1.4.
## (Intercept)                                6.944363e-09
## wfl                                           1.183420e-130
## rooms                                         4.474346e-02
## bj1924                                        3.936400e-07
```

## Ridge

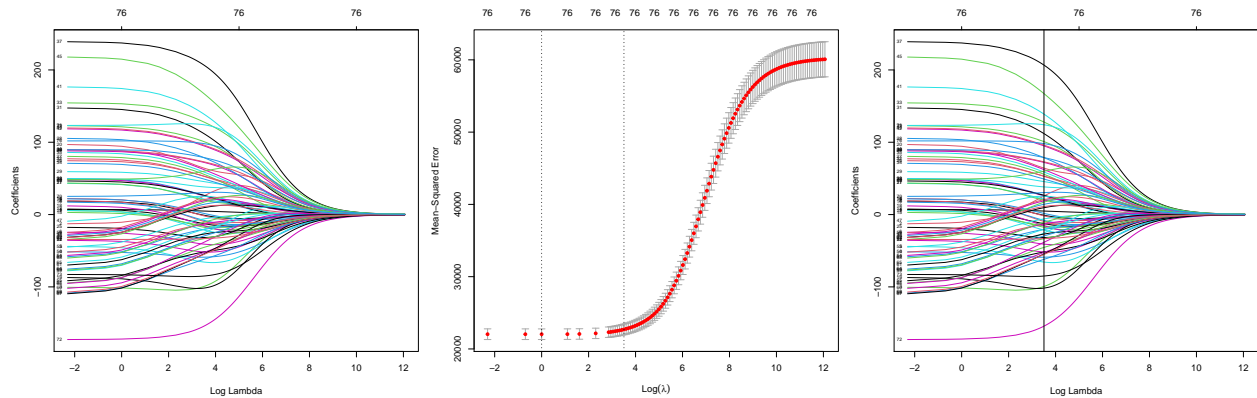
```
start <- glmnet(x = x_mod, y = y_mod, standardize = TRUE, alpha = 0)
autolambda <- start$lambda
newlambda <- c(autolambda, 10, 5, 3, 1, 0.5, 0.1) # add more to approach zero lambda
ridge_fit <- glmnet(x_mod, y_mod, standardize = TRUE, alpha = 0, lambda = newlambda)
cv.ridge <- cv.glmnet(x_mod, y_mod, standardize = TRUE, alpha = 0, lambda = newlambda)
print(paste("The lamda giving the smallest CV error", cv.ridge$lambda.min))
```

```
## [1] "The lamda giving the smallest CV error 1"
```

```
print(paste("The 1sd err method lambda", cv.ridge$lambda.1se))
```

```
## [1] "The 1sd err method lambda 33.2936676208139"
```

```
par(mfrow = c(1, 3), mar = c(4, 4, 4, 1), oma = c(0.5, 0.5, 0.5, 0))
plot(ridge_fit, xvar = "lambda", label = T)
plot(cv.ridge)
plot(ridge_fit, xvar = "lambda", label = T)
abline(v = log(cv.ridge$lambda.1se))
```



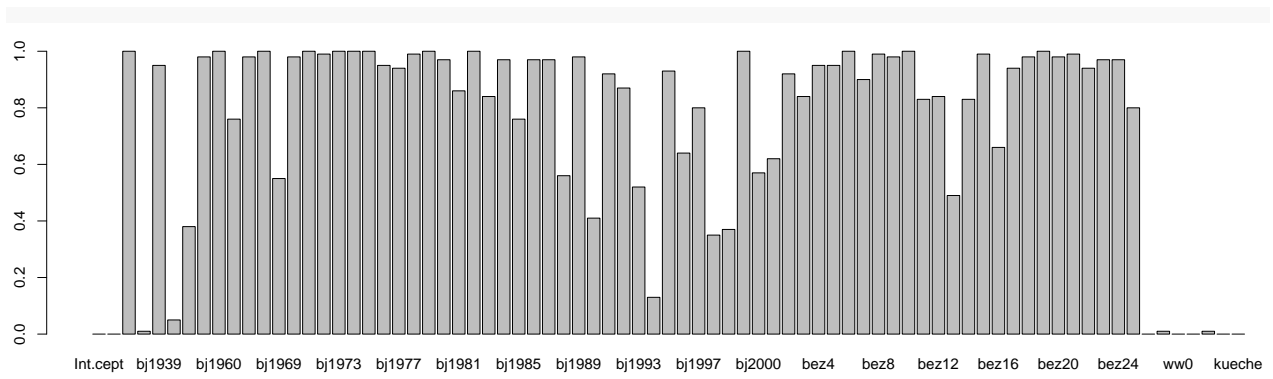
#Bootstrap validation Bootstrap can be applied here to find the proportion of times each element in the coefficients vector of being zero. So it is a way of validation.

```
# bootstrap loop
set.seed(2021)
B=100
n=nrow(x_mod)
p=ncol(x_mod)
lassomat=matrix(ncol=p+1,nrow=B)
ridgemat=matrix(ncol=p+1,nrow=B)

# no need or separate function for steps 1-6 since can use cv.glmnet
# and weight argument for giving the new bootstrapped data
for (b in 1:B)
{
  ids=sort(sample(1:n,replace=TRUE))
  wids=rep(0,n)
  for (i in 1:n)
    wids[i]=sum(ids==i)
  resl=cv.glmnet(x_mod,y_mod,weights=wids)
  resr=cv.glmnet(x_mod,y_mod,weights=wids,alpha=0)
  lassomat[b,]=as.vector(coef(resl)) #automatic lambda 1sd
  ridgemat[b,]=as.vector(coef(resr)) #automatic lambda 1sd
}
colnames(lassomat)=colnames(ridgemat)=c("Int.cept",colnames(x_mod))
# plotting boxplots
lassomatUI=lassomat[,-1]
lassods=reshape2::melt(lassomatUI,
  variable.name ="variable",value.name="value")
lassopp=ggplot(lassods,aes(x=Var2,y=value))+
  geom_boxplot()+ggtitle("Boxplots for bootstrapped lasso for diabetes data")
# lassopp

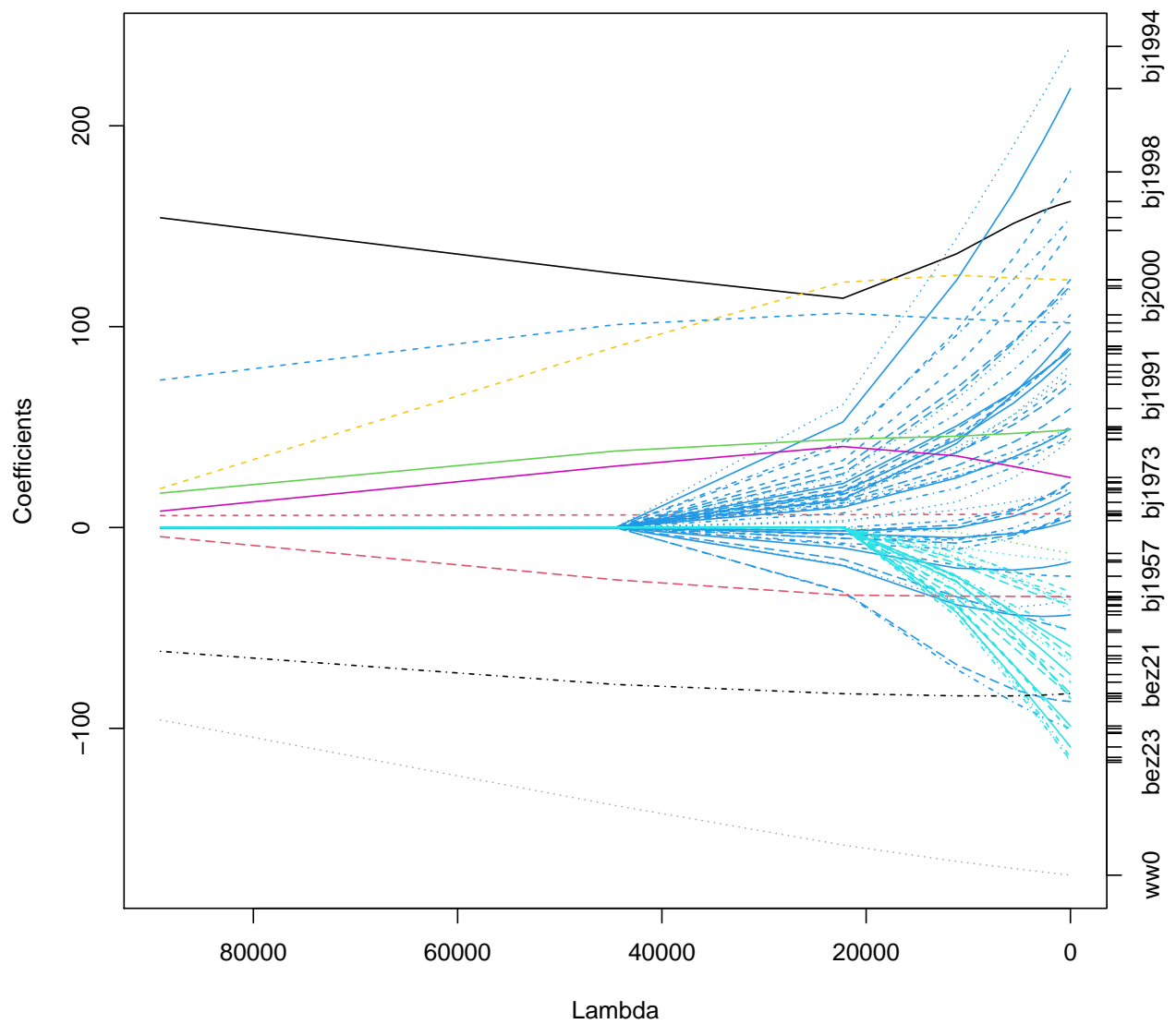
ridgematUI=ridgemat[,-1]
ridgeds=reshape2::melt(ridgematUI,variable.name="variable",value.name="value")
ridgepp=ggplot(ridgeds,aes(x=Var2,y=value))+
  geom_boxplot()+ggtitle("Boxplots for bootstrapped ridge for diabetes data")
# ridgepp

lasso0perc=apply(abs(lassomat)< .Machine$double.eps,2,mean)
par(mfrow = c(1, 1))
barplot(lasso0perc)
```



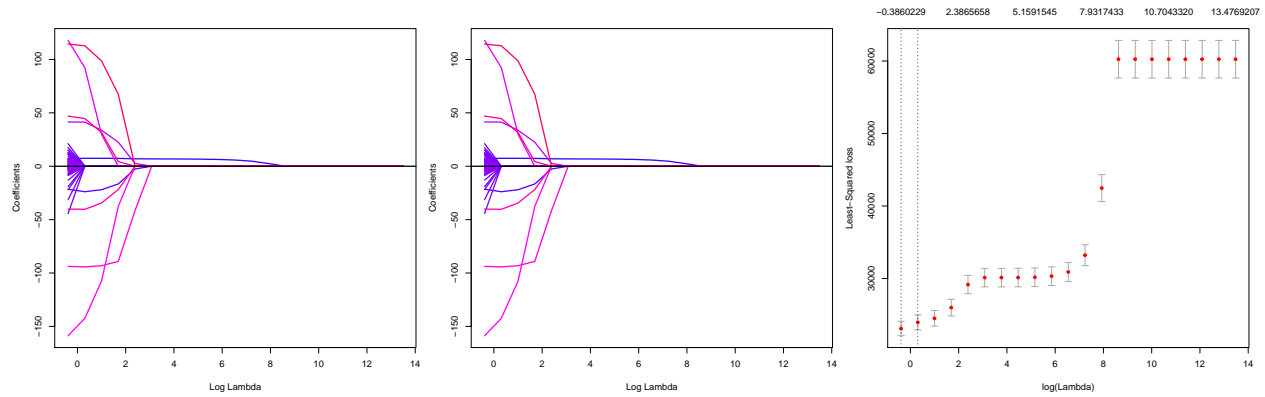
## Group lasso

### Coefficient paths



In the grouped lasso, the `bj` and `bez` are all shrunk or are all included, respectively. This coincides better with our intuition, that this criterion is considered or not considered. Whereas in the regression and lasso before, just some years of construction and some areas were significant.

```
## [1] 1.35951
```



```
## 77 x 4 sparse Matrix of class "dgCMatrix"
##          vanilla LS      ridge general lasso group lasso
## (Intercept) 162.310441 168.4715817    122.673487 106.107086
## wfl          6.921638   4.8629070     6.342412  7.413067
## rooms       -12.919931  25.7264339      .        -23.871982
## bj1924      -100.109344 -99.4046212    -73.446432  .
## bj1939      -51.082040 -58.9465412      .        .
## bj1948      -43.469920 -65.6687241    -37.034493  .
## bj1957      -24.238117 -40.8564769    -10.676323  .
## bj1957.5     18.713838  -0.9125516      .        .
## bj1960       19.561674  -9.5305143      .        .
## bj1966        5.920349 -17.5316242      .        .
## bj1967       17.432638  -7.9666613      .        .
## bj1968        6.161898 -21.3940887      .        .
## bj1969      -35.123926 -51.6304994    -14.711354  .
## bj1970        8.146714 -12.6099436      .        .
## bj1971       22.738843  -1.7844297      .        .
## bj1972        3.464200 -15.6345329      .        .
## bj1973       22.219275   1.6222145      .        .
## bj1974       43.700203  21.5328485      .        .
## bj1975       12.564953 -15.3913215      .        .
## bj1976      -86.605034 -101.6647975      .        .
## bj1977       97.644285  64.2430125      .        .
## bj1978       44.068520  19.8998308      .        .
## bj1979       50.112745  26.2832574      .        .
## bj1980       49.937326  38.2516186      .        .
## bj1981       88.509713  72.1350495      .        .
## bj1982      -17.165153 -31.7554851      .        .
## bj1983       74.815843  52.9317513      .        .
## bj1984       80.953167  55.7123009      .        .
## bj1985      105.867818  78.7009273      .        .
## bj1986       59.225499  45.5847650      .        .
## bj1987       49.115827  25.9989203      .        .
## bj1988      147.915666 111.9539126    16.588404  .
## bj1989       77.648956  53.1657915      .        .
## bj1990      154.290945 127.9670624    34.664189  .
```

## bj1991	71.347309	49.1283501	.	.
## bj1992	86.541067	58.8138218	.	.
## bj1993	90.312924	62.1667748	8.340729	.
## bj1994	239.532748	206.6996228	117.656488	.
## bj1995	90.135389	72.9381986	.	.
## bj1996	123.421116	100.8788309	10.486620	.
## bj1997	88.819228	78.8415667	.	.
## bj1998	177.049378	138.9134856	43.126355	.
## bj1998.5	119.079298	94.9563515	29.919294	.
## bj1999	47.001514	26.6754469	.	.
## bj2000	120.284699	96.0137413	20.408401	.
## bj2001	218.551590	167.2567758	19.861128	.
## bez2	-35.985131	14.1742602	.	.
## bez3	-16.274425	25.3125976	.	.
## bez4	-34.474015	18.7801598	.	.
## bez5	-38.466358	9.5381755	.	.
## bez6	-59.243092	-13.2742914	.	.
## bez7	-101.994969	-45.4102319	.	.
## bez8	-65.397522	-20.4966813	.	.
## bez9	-52.053469	-5.9794115	.	.
## bez10	-63.833161	-12.9174696	.	.
## bez11	-98.831306	-51.7946291	.	.
## bez12	-32.035394	20.6130943	.	.
## bez13	-41.710326	17.1253215	6.729042	.
## bez14	-115.863027	-61.9261117	.	.
## bez15	-85.041679	-25.4459111	.	.
## bez16	-109.255107	-52.4098604	-2.965043	.
## bez17	-76.998642	-26.9632238	.	.
## bez18	-39.053201	11.1194434	.	.
## bez19	-67.355571	-10.6046787	.	.
## bez20	-82.574987	-29.6472488	.	.
## bez21	-73.198994	-20.4163988	.	.
## bez22	-102.468535	-38.3224415	.	.
## bez23	-116.883323	-54.4625628	.	.
## bez24	-114.417039	-55.0778235	.	.
## bez25	-83.937882	-33.2424724	.	.
## wohngut	24.911148	30.3952336	34.414495	41.318858
## wohnbest	123.264686	124.1723666	101.928210	92.318048
## ww0	-173.087458	-154.3111090	-146.292424	-142.415965
## zh0	-82.624164	-84.9891552	-78.010891	-94.286712
## badkach0	-34.489575	-33.1824107	-29.551194	-40.350166
## badextra	48.627634	59.9369537	37.441777	44.631976
## kueche	101.861941	98.1190664	102.748488	112.865650