Project 1 - Shrinkage

2NN: Bjerke, Martin & Spremic, Mina

2/15/2021

Introduction

The goal of the project is to apply the shrinkage methods to a dataset of the groups choice. As one of the main methods of the first part of the course has been lasso, applied in cases when the number of covariates is much larger than number of observations, in addition to there being very few observations. Hence, we have chosen a dataset satisfying these criteria.

Dataset

The dataset in question is a Gastrointestinal Lesions in Regular Colonoscopy dataset, which can be accessed at https://archive.ics.uci.edu/ml/datasets/Gastrointestinal+Lesions+in+Regular+Colonoscopy.

This dataset contains a response variable, which is one of the three types of lesions (growth): hyperplasic, adenoma and serates, with the firts one being benign and the latter two malignant. The rest of the covariates, 699 of them, have been extracted from video and represent different aspects it through rotation, texture, colour, contrast etc. They are divided roughly in three groups being: textural features, color features and shape features, all having multiple subgroups.

This dataset had to be labeled all over again, as the txt file including the data, did not have a header. The relabeled dataset is available in the git-repo. In this dataset, majority of the 701 covaraites have not been easy to decipher, both due to the large number and the lack of information on them, both on the webpage of the dataset, but also in the paper. Most of the information about the variables have been references to other papers which do analysis and describe the process of extracting some of these variables. We will include references to some of these articles in the end of the report. The dataset is connected to a published paper Computer-Aided Classification of Gastrointestinal Lesions in Regular Colonoscopy.

The names of the covariates, which have been used as labels are the following:

Group	Subgroup	Number of covariates
Type of light used for recording*		1
2D textural features		422
	AHT - Autocorrelation Homogeneous Texture (Invariant Gabor Texture)	166
	Rotational Invariant LBP	256
2D COLOR FEATURES		76
	Color naming	16
	Discriminative Color	13
	Hue	7
	Opponent	7
	Color gray-level co-occurence matrix	33
3D shape features		200

Group	Subgroup	Number of covariates
	shapeDNA	100
	KPCA	100

*Types of light are 1=WL (White Light), 2=NBI(Narrow Band Imaging)

We wish to specify that this is a classification problem. Provided in the dataset are three clases of the response. We have chosen not to use all of the three classes in our problem, and have instead merged two of the classes. Meaning, instead of there being classes: hyperplasic, adenoma and serates, we have malignant and benign instead.
An observations made is also that some of the covariates had only zero entries, but due to lack of documentation on the cause of this, we have chosen to keep all the covariates in the dataset.

Analysis

For this classification problem, we wish to use a logistic regression, lasso and group lasso. The reason behind using group lasso was due to there being, from our point of view, clear groupings of the variables.

We will not be including the head of the dataset as it is rather large, with 699 covariates, and it takes up too many pages. If the reader is interested, he/she can insepct it on their own initiative.

```r
table(test_ds$type_of_lesion)
```

```
##
##   0   1
##  42 110
```

```r
summary(test_ds[,c(1,2,3,169,425,441,454,461,468,501,601)])
```

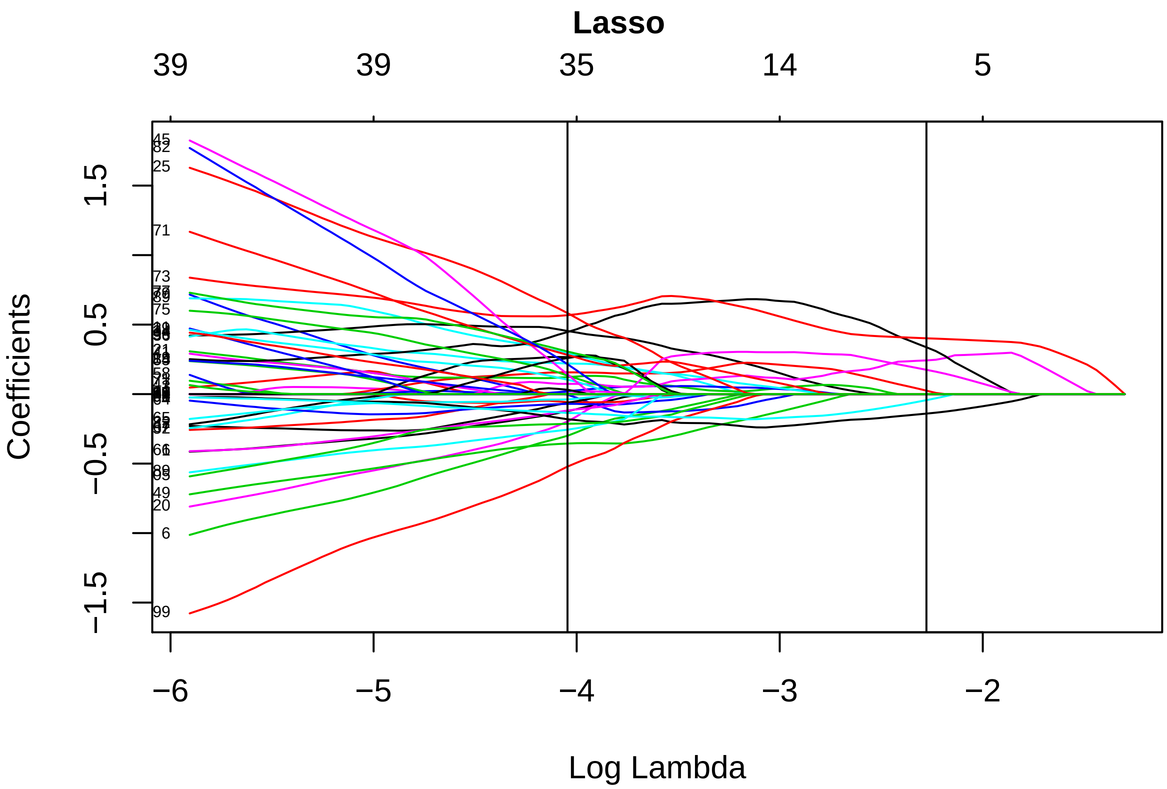
```
##  type_of_lesion   type_of_light_1_WL_2_NBL Textural_feature_AHT1
##  Min.   :0.0000   Min.   :1.0              Min.   : 65.18
##  1st Qu.:0.0000   1st Qu.:1.0              1st Qu.:107.46
##  Median :1.0000   Median :1.5              Median :128.84
##  Mean   :0.7237   Mean   :1.5              Mean   :128.24
##  3rd Qu.:1.0000   3rd Qu.:2.0              3rd Qu.:147.23
##  Max.   :1.0000   Max.   :2.0              Max.   :204.53
##  Rot_invariant_LBP1 Color_naming1   Discriminative_color1      Hue1
##  Min.   :  82.0     Min.   : 44.0   Min.   :0             Min.   :0
##  1st Qu.: 400.5     1st Qu.: 77.5   1st Qu.:0             1st Qu.:0
##  Median : 820.0     Median :111.5   Median :0             Median :0
##  Mean   : 993.8     Mean   :118.5   Mean   :0             Mean   :0
##  3rd Qu.:1479.2     3rd Qu.:149.2   3rd Qu.:0             3rd Qu.:0
##  Max.   :3906.0     Max.   :279.0   Max.   :0             Max.   :0
##    Opponent1 Col_gray_lvl_co-occurr_mx1   shapeDNA1     KPCA1
##  Min.   :0   Min.   : 72.73            Min.   :0   Min.   :0.2977
##  1st Qu.:0   1st Qu.:142.13            1st Qu.:0   1st Qu.:0.4865
##  Median :0   Median :168.01            Median :0   Median :0.6080
##  Mean   :0   Mean   :167.47            Mean   :0   Mean   :0.5898
##  3rd Qu.:0   3rd Qu.:198.54            3rd Qu.:0   3rd Qu.:0.6892
##  Max.   :0   Max.   :253.03            Max.   :0   Max.   :0.9049
```

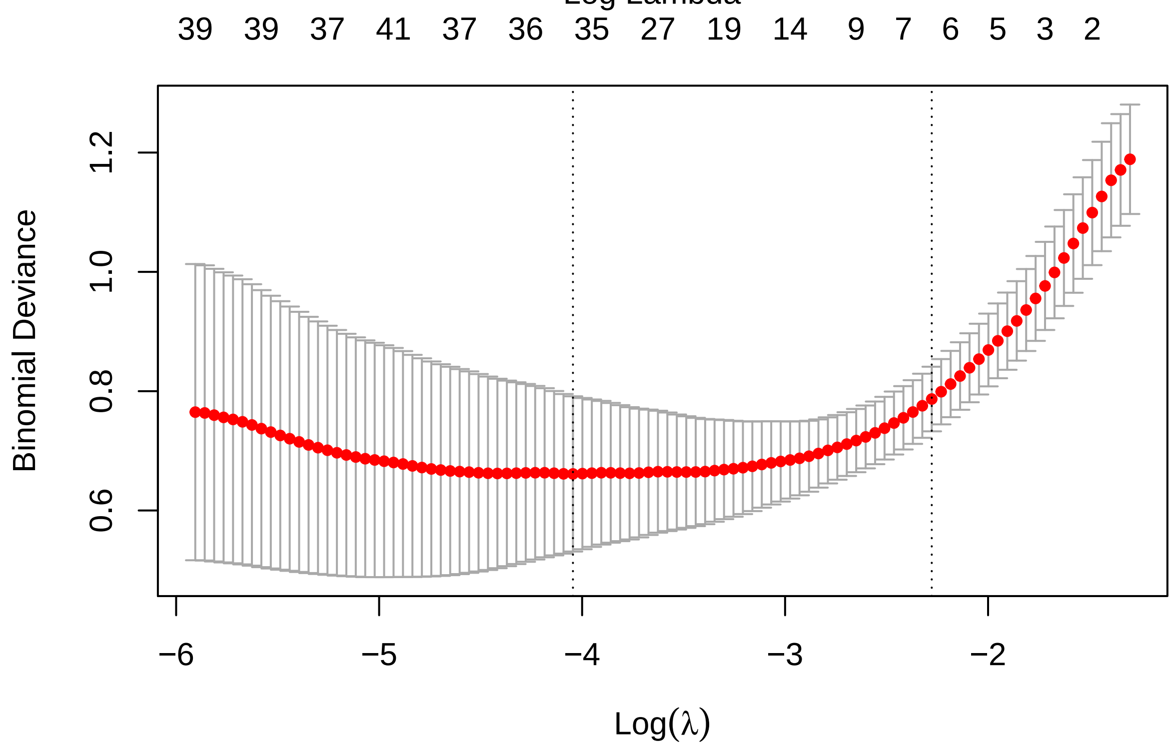
Unfortunately, the logistic regression did not manage to run, and we have recieved an error: does not converge, indicating that we most probably have multicollinearity issues and the issue with number covariates being too large comapred to number of observations.

We proceed using the lasso, using the glmnet packaget. We perform cross-validation using the cv.lasso function from glmnet package to find the optimal lambda. We plot the lasso-plot, visualising at which λs the coefficients get shrunk to zero.

Additionally we show the minimum λ as well as one standard deviation λ.

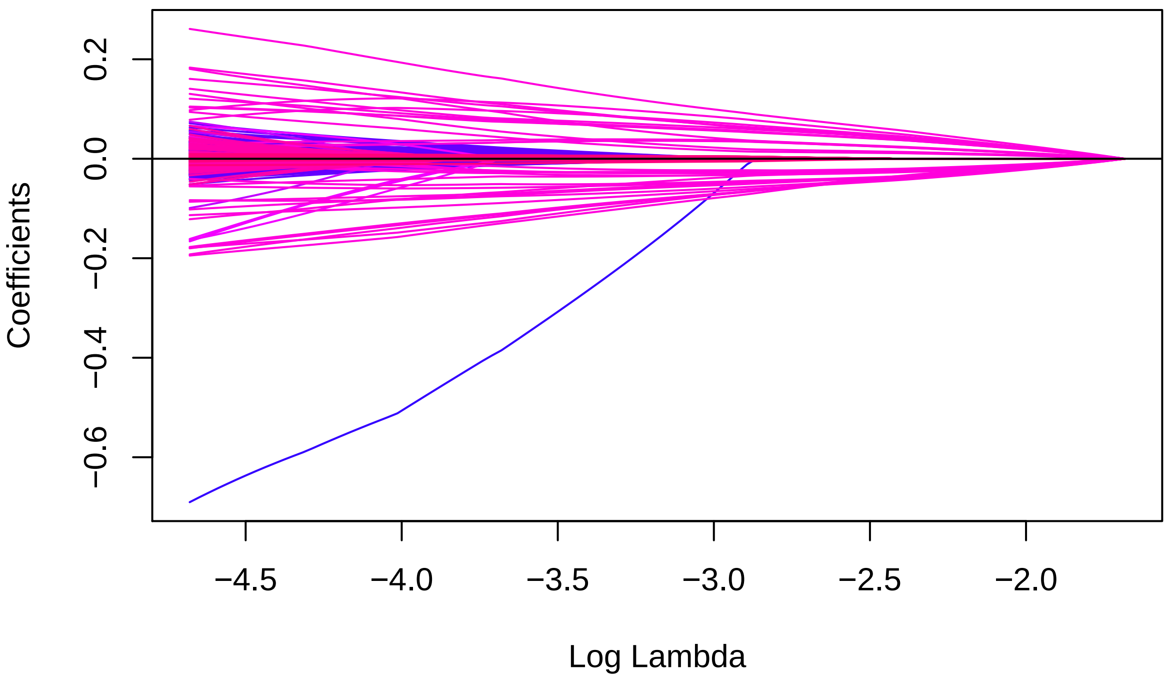
```
## [1] "The lamda giving the smallest CV error 0.0175077054824553"
```

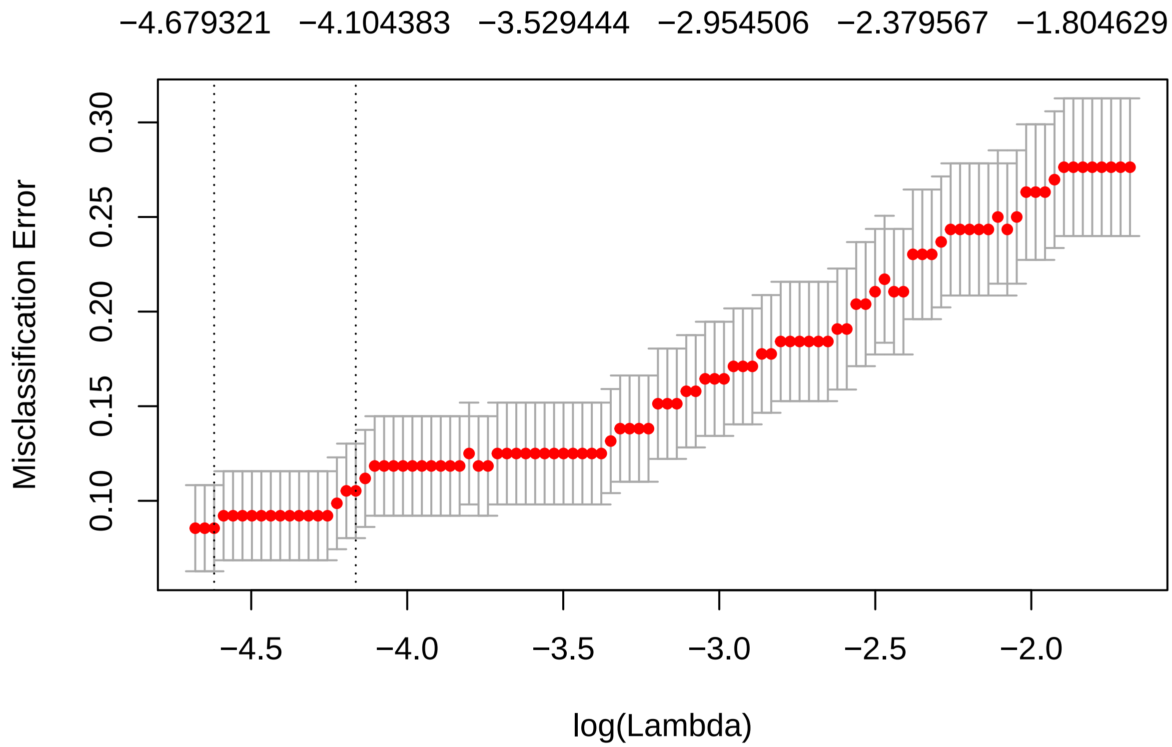




We can see the covariates picked with the lasso method.

```
##      [,1]                          [,2]
## [1,] "Intercept"                   "1.18465841574577"
## [2,] "Textural_feature_AHT110"     "0.0249186745724624"
## [3,] "Rot_invariant_LBP4"          "0.242568780505343"
## [4,] "Rot_invariant_LBP52"         "0.337142751439206"
## [5,] "Col_gray_lvl_co-occurr_mx7"  "0.401557814164094"
## [6,] "Col_gray_lvl_co-occurr_mx25" "0.174812809230365"
## [7,] "Col_gray_lvl_co-occurr_mx32" "-0.140210001687806"
## [8,] "KPCA2"                       "-0.0435275366316781"
```






```
##      [,1]
## [1,] "type_of_light_1_WL_2_NBL"
## [2,] "Textural_feature_AHT1"
## [3,] "Discriminative_color3"
## [4,] "`Col_gray_lvl_co-occurr_mx20`"
```

- Group lasso has been attempted, gives similar results

Inference

- we have chosen to do bootstrapping on lasso only, as both lasso and group lasso produced similar results.

Discussion

After the analysis has been conducted, and inference has been performed, and the results were rather surprising. We did not know exactly what to expect due to the large number of covariates, most of which have been extracted from videos, as mentioned previously. Hence, the meaning and significanc are rather difficult to interpret. We could speculate whether the results would have been different have we had opted out for a classification problem with three classes.

References

- dataset source
- paper using the dataset
- additional links to papers describing different covariates
- reference to matrix, glmnet, grplasso, gglasso packages