Project 1 - Shrinkage

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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 699 covariates 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 the 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. Instead of there being classes: hyperplasic, adenoma and serates, we have malignant and benign instead.
An observations made is 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 logistic regression, lasso and group lasso.

We will not be including the head or the top rows 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.

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

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

```
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
```

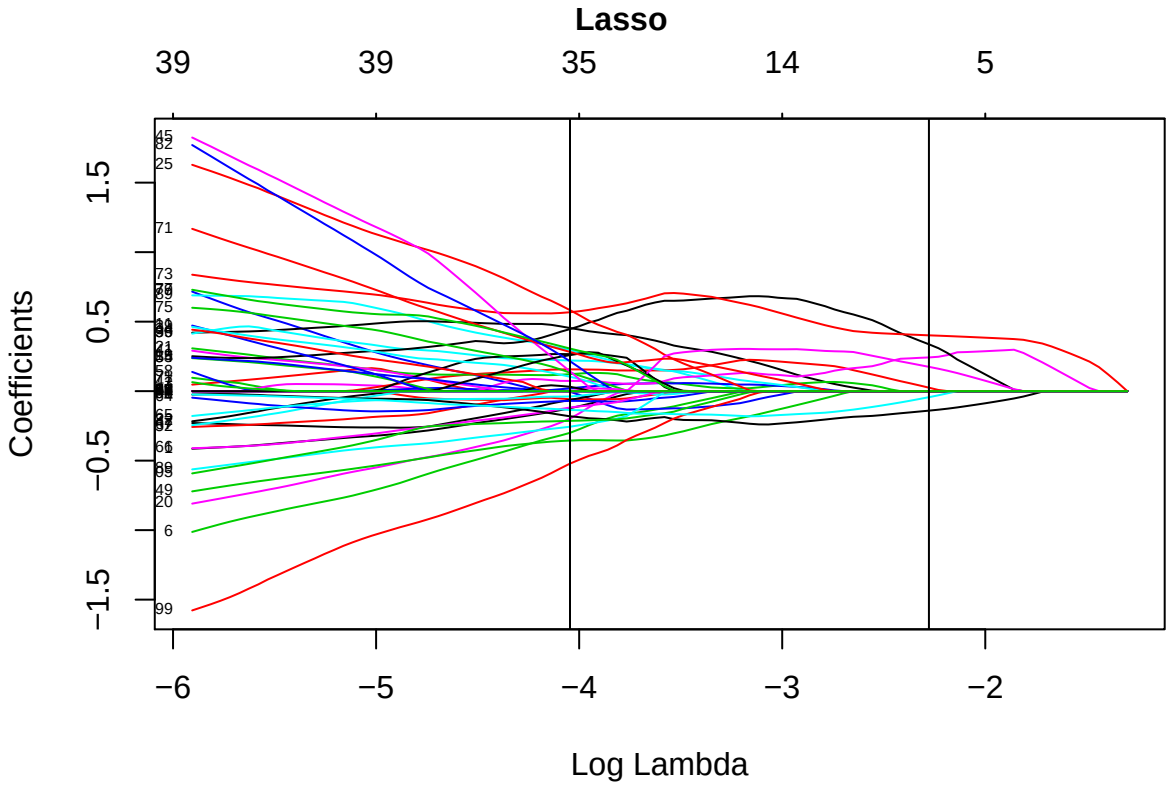
Unfortunately, the logistic regression did not manage to run, and we have recieved an error: does not converge, indicating that we most probably have multicollinearity issues and the issue with number of covariates being too large comapred to number of observations. We have attempted to surpass this by increasing the number of iterations, but eventho the it converged, it did not provide meaningful results, with very many coefficients being set to NA.

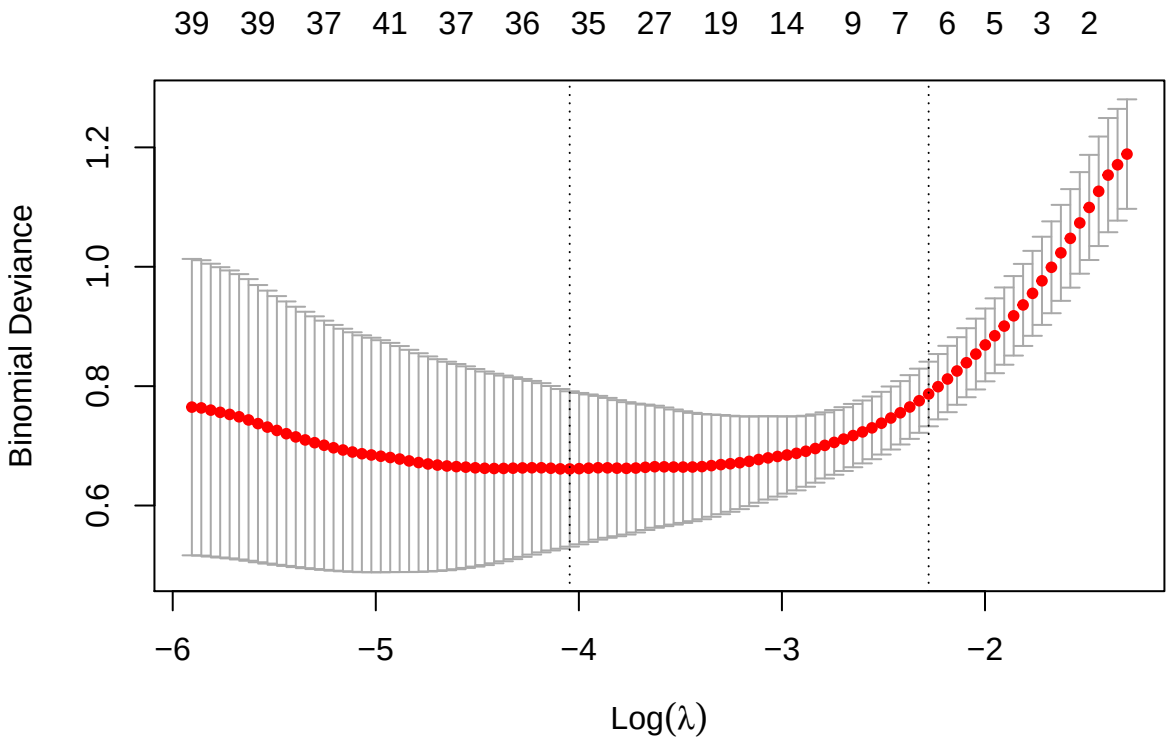
Lasso

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"
```



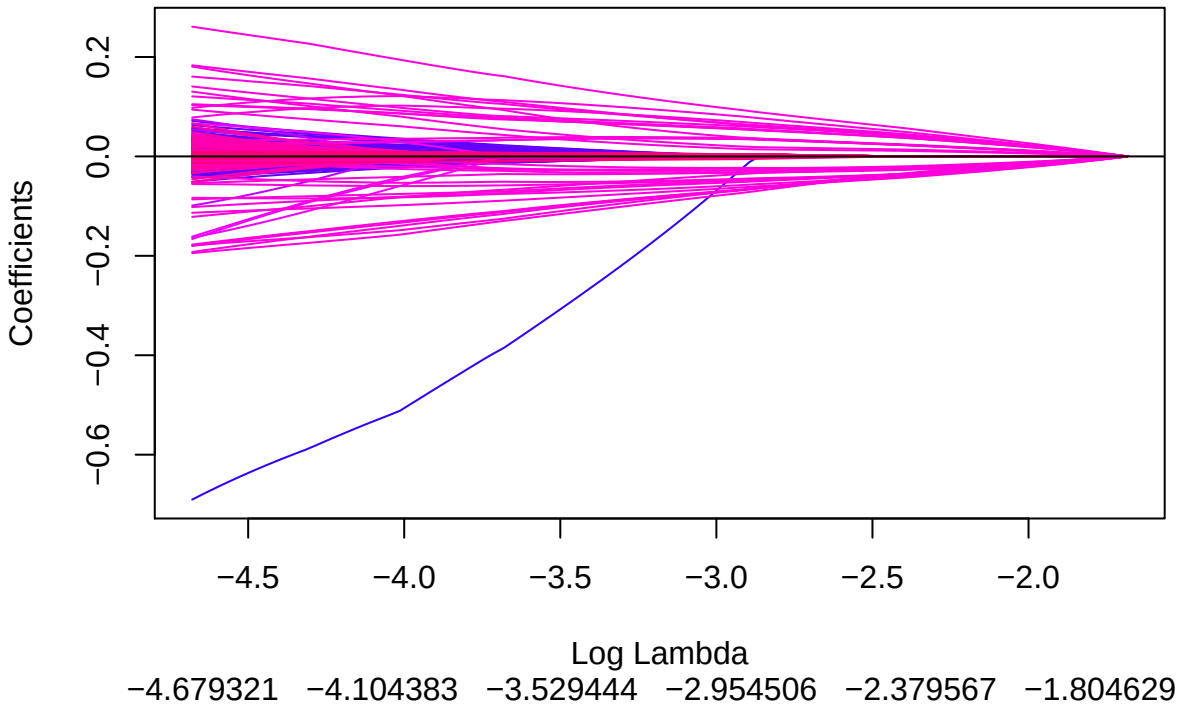


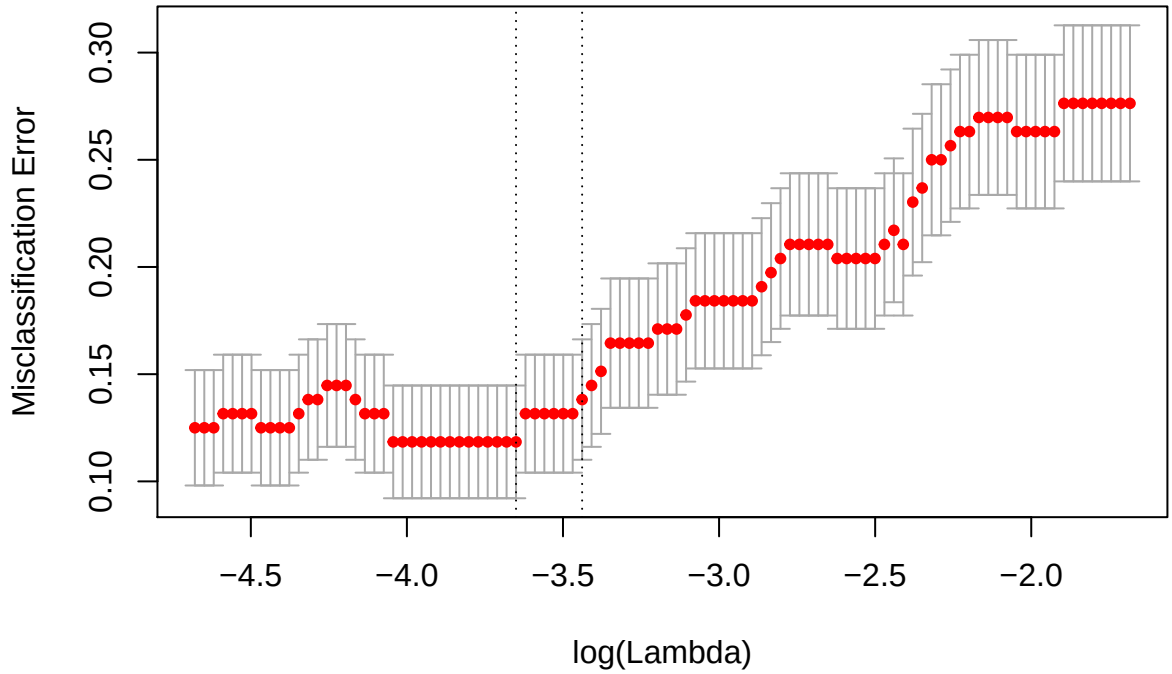
We can see the covariates picked with the lasso method. These are: textural feature AHT number 110, rotationally invariante LBP number 4 and 52. In addition three of the covariates realted to the level of grayscale are included as well. Finally a KPCA number 2 is included. It is rather difficult to say whether these results were as expected, considering the lack of knowledge about the covariates.

```
##      [,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"
```

Group Lasso

We attempt the group lasso now. The groups chosen are structured such that the covariates belonging to the group of variables presented in the begining, are in the same group in this analysis as well. This has been the only sensible decision of group split, taken into considerationg the number of covariates and the difficulties considering their origin.



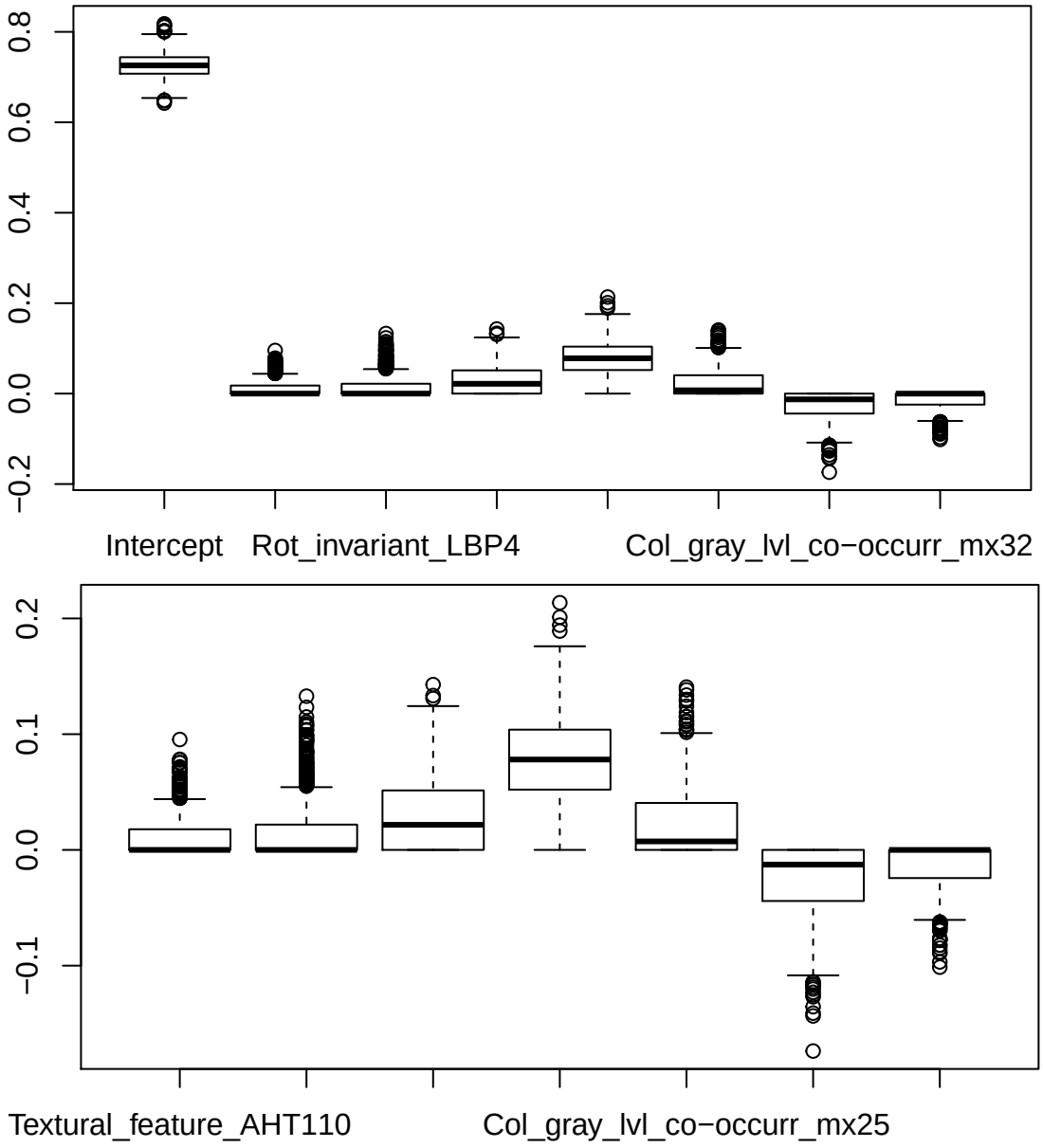


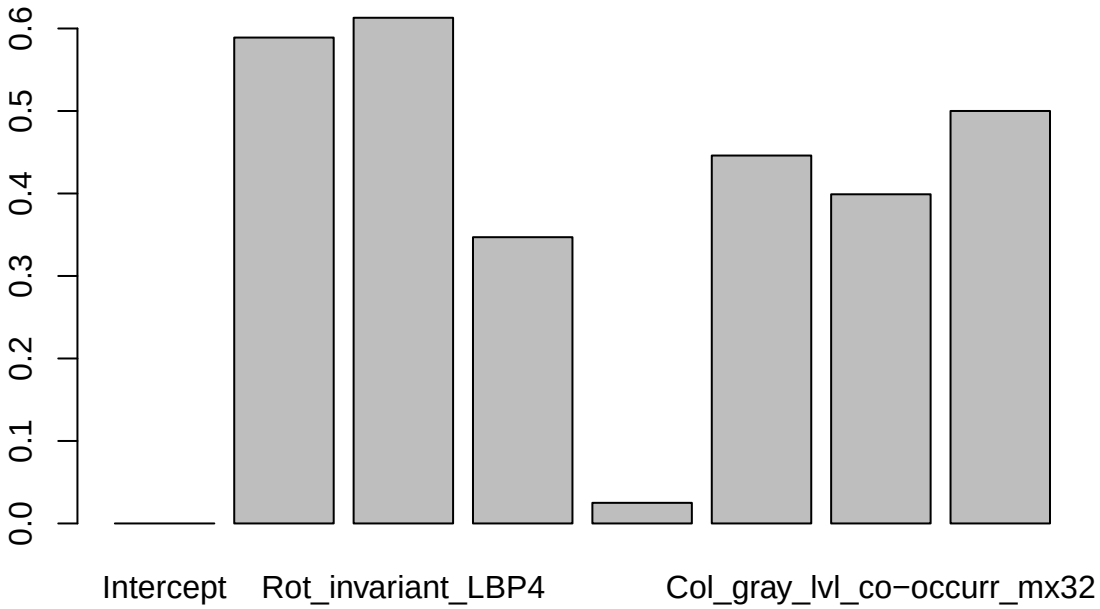

```
##       [,1]
## [1,] "type_of_light_1_WL_2_NBL"
## [2,] "Textural_feature_AHT1"
## [3,] "`Col_gray_lvl_co-occurr_mx1`"
## [4,] "KPCA1"
```

The covariate groups chosen by the group lasso are as given above. If we compare it to the ones chosen by the lasso, we observe that the covariates chosen by the lasso come from the three of groups picked by the group lasso. The differene between the two is that the group lasso picks type of light covariate but not the rotational invariance.

Inference

We choose to do the bootstrapping on the lasso only.





From the boxplots we observe that majority of the boxes have median at zero, or are very close to zero. This is further confirmed throught the barplot. In the barplot we can see that almost all of the coefficients are zero at 40% of the time. The only coefficient that is noticeably different, and is almost never zero, is one of the coefficients for the gray-level contrast.

Discussion and concluding words

After the analysis has been conducted, and inference has been performed, the results were slightly suprising. Eventhough 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, it was rather suprising only one of the coefficients was non-zero less than 40% of the time. We could speculate whether the results would have been different have we had opted out for a classification problem with three classes.

References

[1]: "Gastrointestinal Lesions in Regular Colonoscopy Data Set" - https://archive.ics.uci.edu/ml/datasets/Gastrointestinal+Lesions+in+Regular+Colonoscopy
[2]: "Computer-Aided Classification of Gastrointestinal Lesions in Regular Colonoscopy" https://pubmed.ncbi.nlm.nih.gov/28005009/
[3]: R. Nava, G. Cristo bbal, and B. Escalante-Ramiırez, "Invariant texture analysis through local binary patterns," CoRR, vol. abs/1111.7271, 2011.
[4]: F. Riaz, F. B. Silva, M. Dinis-Ribeiro, and M. T. Coimbra, "Invariant gabor texture descriptors for classification of gastroenterology images," IEEE Trans. Biomed. Engineering, vol. 59, no. 10, pp. 2893–2904, 2012.
[5]: M. Reuter, F.-E. Wolter, and N. Peinecke, "Laplace–beltrami spectra as shape-dnaof surfaces and solids," Computer-Aided Design, vol. 38, no. 4, pp. 342–366, 2006.
[6]:C. M. Bishop, Pattern recognition and machine learning. Springer, 2006.
[7]: grplasso package https://cran.r-project.org/web/packages/grplasso/grplasso.pdf
[8]: gglasso package https://cran.r-project.org/web/packages/gglasso/gglasso.pdf
[9]: glmnet package https://cran.r-project.org/web/packages/glmnet/glmnet.pdf
[10]: matrix package https://cran.r-project.org/web/packages/Matrix/Matrix.pdf