## STAT 542 / CS 598: Project 2

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Due: Monday, Dec 16 by 11:59 PM Pacific Time

[10 Points, half a page] Project description and summary. This part should summerise your goal, your approach, and your results.

half page description goes here

[5 Points, half a page] Data processing for Question 1. Describe how you process the data so that it can be analyzed to answer question 1.

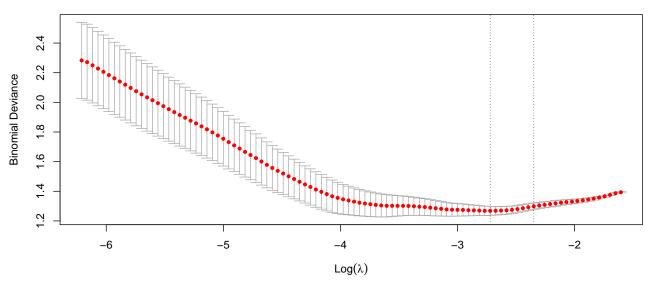
half page description goes here

[30 Points, within 5 pages] Classification models based on pixels.

```
# kable(results, caption = "KNN")
```

```
# use parallel for performace
registerDoMC(cores = 4)
cv_glmnet_model <- cv.glmnet(train.data[, -1], train.data[, 1], parallel = TRUE, alpha=1, family="binomi")</pre>
```

117 120 119 112 108 102 103 85 77 66 58 50 44 29 24 17 17 15 10 4 2 1 1



```
best_lambda = cv_glmnet_model$lambda.1se
# training with best lambda selected from the cv
train_glmnet_model <- glmnet(train.data[, -1], train.data[, 1], lambda = best_lambda, alpha=1, family="b
summary(train_glmnet_model)</pre>
```

Table 1: Lasso Regression Results

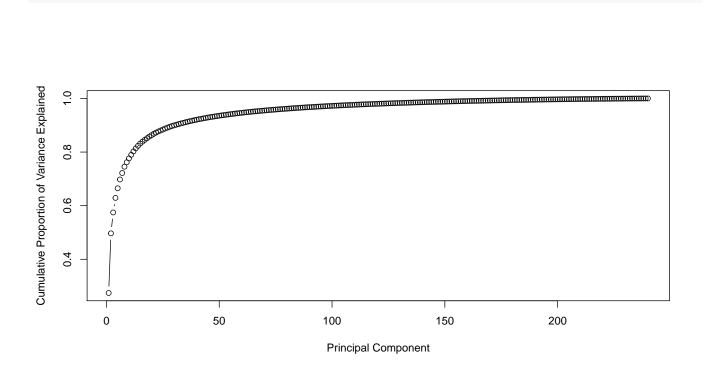
Best.lambda	Accuracy
0.0954646	0.6333333

```
Length Class
##
                                Mode
## a0
                  1 -none-
                                numeric
## beta
              30000 dgCMatrix S4
## df
                     -none-
                  1
                                numeric
                                numeric
## dim
                  2
                     -none-
## lambda
                  1
                     -none-
                                numeric
## dev.ratio
                  1
                     -none-
                                numeric
## nulldev
                     -none-
                  1
                                numeric
## npasses
                  1
                     -none-
                                numeric
## jerr
                  1
                     -none-
                                numeric
## offset
                                logical
                  1
                     -none-
## classnames
                  2
                     -none-
                                character
## call
                  6
                     -none-
                                call
## nobs
                  1
                                numeric
                     -none-
```

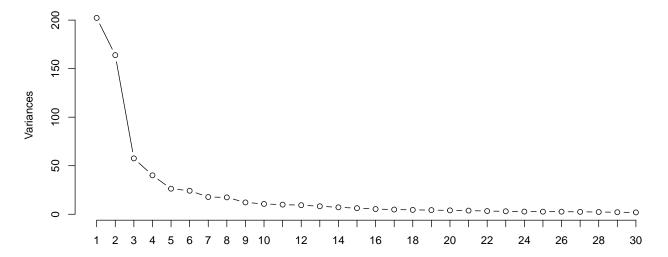
```
pred <- predict(train_glmnet_model, s = best_lambda, newx = test.data[, -1], type = "class")
accuracy = mean(test.data[, 1] == pred)

results = data.frame("Best lambda" = best_lambda, "Accuracy" = accuracy)</pre>
```

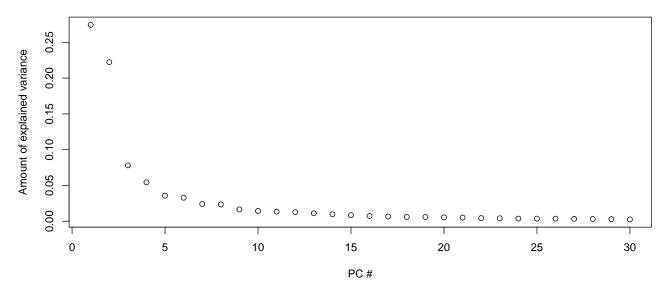
```
kable(results, caption = "Lasso Regression Results")
```

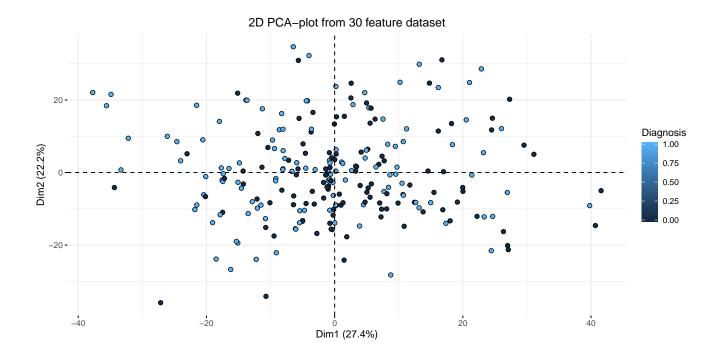


## Screeplot of the first 30 PCs



## **Cumulative variance plot**





[10 Points, 1 page] Literature review. You should search and read existing literature and summarize clinically relevant characteristics that could be used for skin cancer image diagnosis. There is no limitation on what type of literature you could use. However, the goal should be motivating your feature engineering approaches from a clinical and analytic point of view. Please give appropriate citations to the literature you read.

1 page description goes here

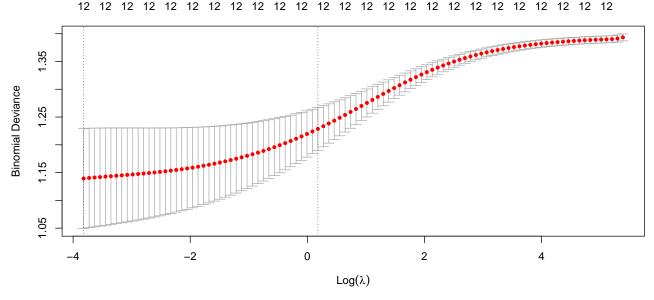
[10 Points, 1 page] Feature engineering. Motivated by what you have read (or your understanding), process the data in a reasonable way such that the new variables are more intuitive to your collaborator/clinicians. You need to describe clearly what is your data processing criteria and how your variables are calculated.

1 page description goes here

[20 Points, 2 page] Classification models based on new features. Fit two different classification models to identify malignant moles. You can either use the ones from Question 1 or use some new models if you believe they may perform better on the new features. Same requirements of Question 1 apply to this part. Besides, you should focus more on variable selection and interpretation.

```
# use parallel for performace
registerDoMC(cores = 4)

# Ridge Regression
cv_glmnet_model <- cv.glmnet(train.data[, -1], train.data[, 1], parallel = TRUE, alpha=0, family="binomi"</pre>
```



```
best_lambda = cv_glmnet_model$lambda.1se
# training with best lambda selected from the cv
train_glmnet_model <- glmnet(train.data[, -1], train.data[, 1], lambda = best_lambda, alpha=0, family="b
summary(train_glmnet_model)
```

```
##
               Length Class
                                  Mode
## a0
                1
                       -none-
                                  numeric
                       {\tt dgCMatrix} \ {\tt S4}
## beta
               12
## df
                1
                       -none-
                                  numeric
## dim
                2
                       -none-
                                  numeric
## lambda
                1
                       -none-
                                  numeric
## dev.ratio
                       -none-
                1
                                  numeric
## nulldev
                       -none-
                                  numeric
## npasses
                       -none-
                1
                                  numeric
## jerr
                1
                       -none-
                                  numeric
## offset
                1
                                  logical
                       -none-
## classnames
                2
                       -none-
                                  character
## call
                6
                                  call
                       -none-
## nobs
                       -none-
                                  numeric
```

```
pred <- predict(train_glmnet_model, s = best_lambda, newx = test.data[, -1], type = "class")</pre>
accuracy = mean(test.data[, 1] == pred)
results = data.frame("Best lambda" = best_lambda, "Accuracy" = accuracy)
```

kable(results, caption = "Ridge Regression Results")

Table 2: Ridge Regression Results

Best.lambda	Accuracy
1.198349	0.7