TP2 MRR

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IV. Cookies Study

```
cookies_data <- read.csv("cookies.csv")
dim(cookies_data)
```

```
## [1]  32 701
```

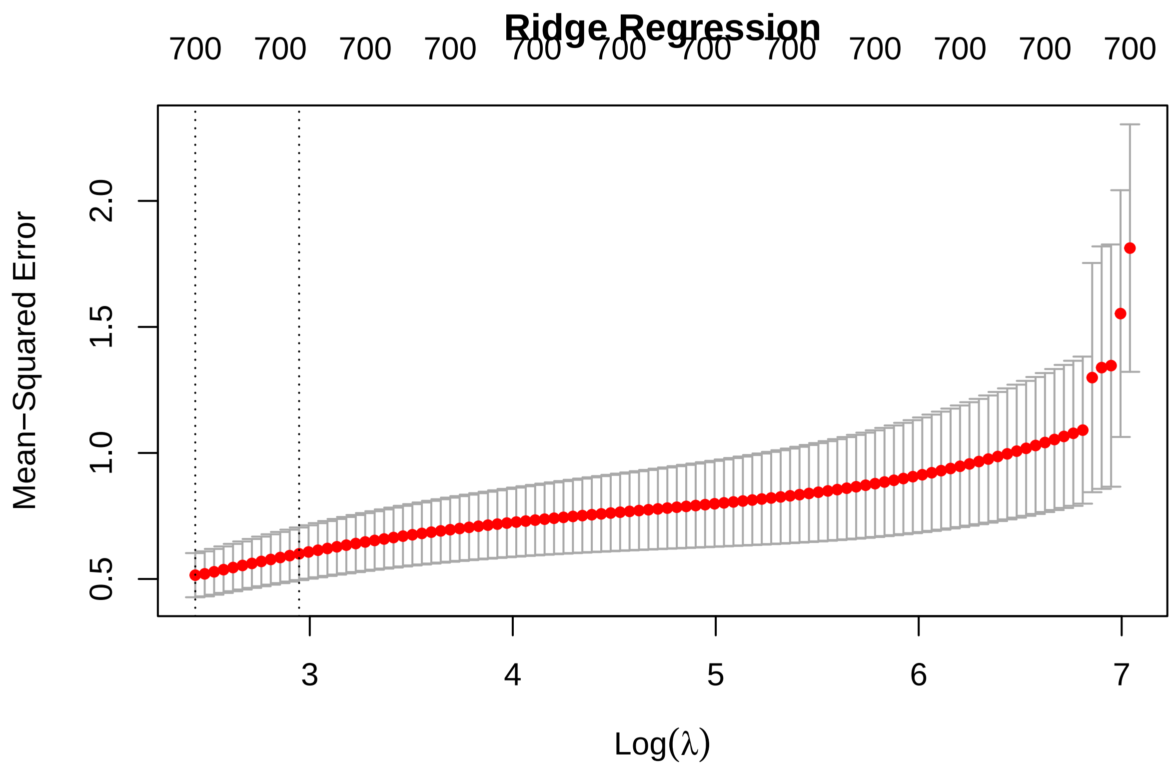
We see that there are 700 co-variables. We can assume that some of them are less important than the others. To see this, let's do a Ridge regression and look at the coefficient of each co-variables.

```
library(glmnet)
```

```
## Le chargement a nécessité le package : Matrix
```

```
## Loaded glmnet 4.1-8
```

```
y <- cookies_data[, 1]
X <- cookies_data[, -1]

cv_ridge_model <- cv.glmnet(as.matrix(X), y, alpha=0, standardize = TRUE)
plot(cv_ridge_model, main="Ridge Regression")
```



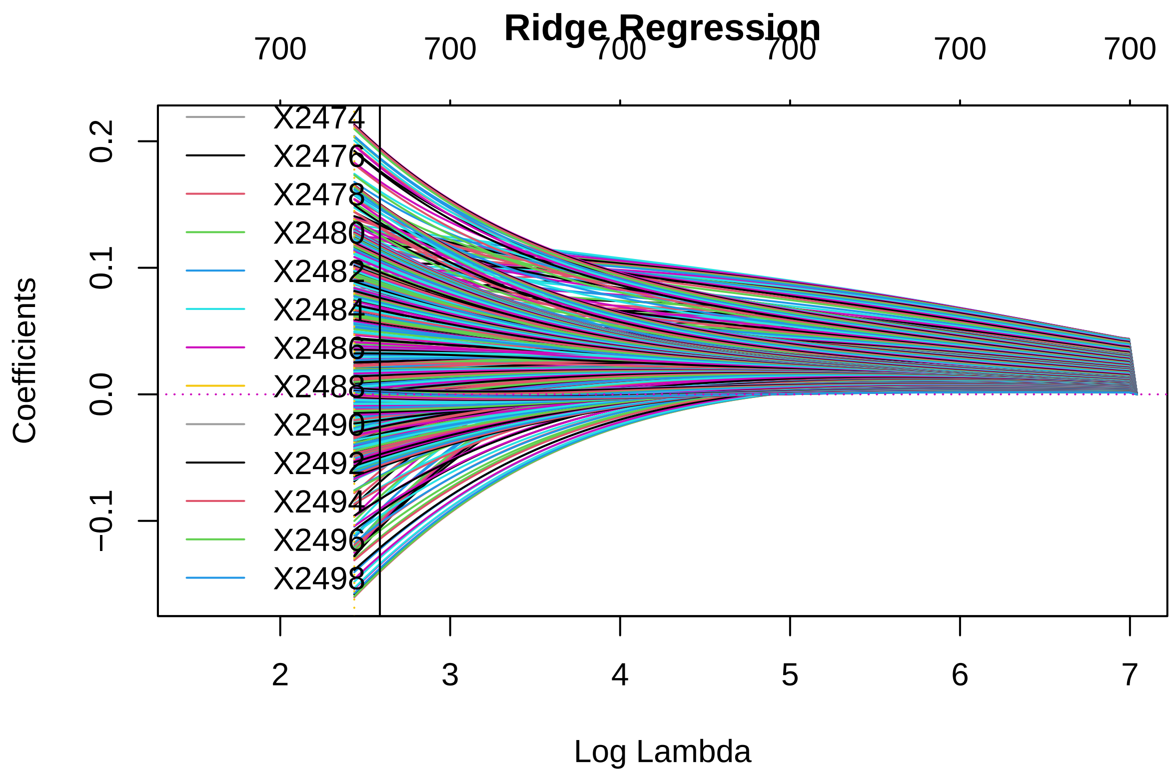

```r
print(cv_ridge_model)
```

```
##
## Call:  cv.glmnet(x = as.matrix(X), y = y, alpha = 0, standardize = TRUE)
##
## Measure: Mean-Squared Error
##
##     Lambda Index Measure     SE Nonzero
## min  11.42   100  0.5151 0.0876     700
## 1se  19.06    89  0.5999 0.1045     700
```

```r
best_lambda <- cv_ridge_model$lambda.min
best_lambda_ridge_model <- best_lambda
print(paste("Best lambda :", best_lambda))
```

```
## [1] "Best lambda : 11.4243191334971"
```

We can also plot the Regularization Path.



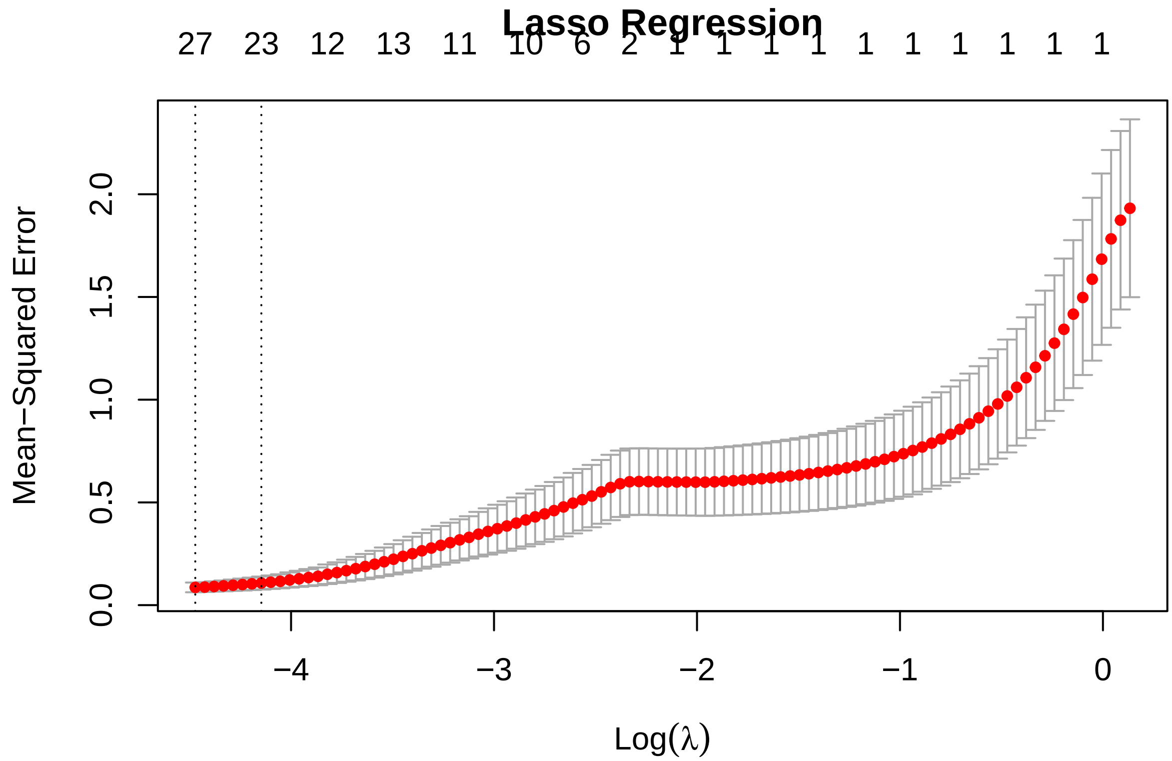
Now let's take a look at the coefficients of the best model we've managed to get.

```
final_ridge_model <- glmnet(as.matrix(X), y, alpha=0, lambda=best_lambda)

abs_coef <- abs(coef(final_ridge_model)[-1])
```

```
## [1] 2.232542e-05

## [1] "Number of value higher than 10^-1 :  178"

## [1] "Number of value higher than 10^-2 :  629"

## [1] "Number of value higher than 10^-3 :  693"

## [1] "Number of value higher than 10^-4 :  699"
```

We can see that the majority of the coefficients are lower than 10^{-1}. Then, we could think that a lot of our co-variables are useless to predict the target variable. (We scaled the data when doing the Ridge regression)

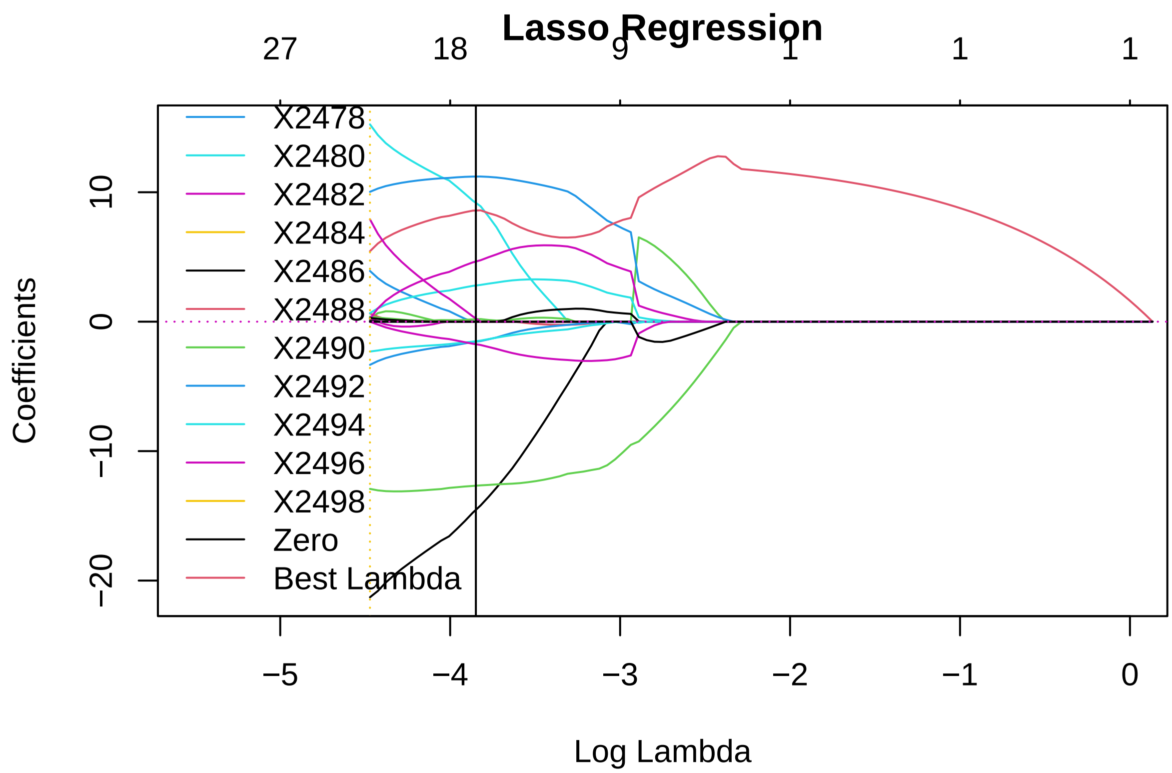
Let's do a Lasso regression to see if there are less co-variables that are actually useful to predict the fat :




```
##
## Call:  cv.glmnet(x = as.matrix(X), y = y, alpha = 1)
##
## Measure: Mean-Squared Error
##
##      Lambda Index Measure      SE Nonzero
## min 0.01142   100 0.08637 0.02358      27
## 1se 0.01582    93 0.10752 0.03138      23
```

Again, here's the regularization path :

```
plot(cv_lasso_model$glmnet.fit, xvar = "lambda", main="Lasso Regression", xlim=c(-5.5, 0))
abline(h = 0, col = 6, lty = 3)
abline(v = log(best_lambda_lasso), col = 7, lty = 3)
legend("bottomleft", legend = c(colnames(X), "Zero", "Best Lambda"), col = 1:7, lty = 1)
```




```r
print(log(best_lambda_lasso))
```

```
## [1] -4.472011
```

Now, let's see how many co-variables we have left :

```
##    non_zero_spectra non_zero_coefficients
## 1              X1406          7.037482e-01
## 2              X1408          2.940229e-01
## 3              X1410          1.336872e+00
## 4              X1720         -9.926792e+00
## 5              X1722         -1.355581e+01
## 6              X1882          1.061205e+01
## 7              X1884          7.755343e+00
## 8              X1886          3.492588e+00
## 9              X1888          5.762739e+00
## 10             X1890          5.224832e+00
## 11             X1892          5.554246e-01
## 12             X1894          4.179640e-01
## 13             X1966          7.299027e+00
## 14             X1968          6.783323e-04
## 15             X1970          1.990190e-03
## 16             X1972          6.091168e-04
## 17             X1974          1.477502e-03
## 18             X1976          2.118964e-03
```

```
## 19            X1978          1.855211e-03
## 20            X1980          2.782265e-03
## 21            X1982          2.921429e-04
## 22            X1984          1.729233e-04
## 23            X1986          2.473668e-04
## 24            X1988          8.019437e-04
## 25            X1990          4.819718e-05
## 26            X2068         -2.840478e-03
## 27            X2070         -5.620257e-03
## 28            X2072         -5.550826e+00
## 29            X2074         -9.807742e+00
## 30            X2076         -9.603172e-04
## 31            X2302         -2.810737e+00
```

```
##
## Call:  glmnet(x = as.matrix(X), y = y, alpha = 1, lambda = best_lambda_lasso)
##
##   Df  %Dev  Lambda
## 1 31 98.09 0.01142
```

We can see that our model is pretty accurate (deviance of 98.09%) with only 31 co-variables used among the 700 existant.

Actually, we've shown that even less co-variables are useless than what we thought.

Now let's try to split our dataset into train and test dataset:

Ridge :

```
# We split into 2 dataframe randomly
indice_train <- sample(1:nrow(cookies_data), 0.8 * nrow(cookies_data))
train_data <- cookies_data[indice_train, ]
test_data <- cookies_data[-indice_train, ]

# We define X & y for both dataframe
y_train <- train_data[, 1]
X_train <- train_data[, -1]
y_test <- test_data[, 1]
X_test <- test_data[, -1]

# We train the model with the best value for lambda
cv_ridge_model <- cv.glmnet(as.matrix(X_train), y_train, alpha = 0, grouped = FALSE)
best_lambda_ridge <- cv_ridge_model$lambda.min
ridge_model <- glmnet(as.matrix(X_train), y_train, lambda = best_lambda_ridge, alpha = 0)

predictions_ridge <- predict(ridge_model, s = best_lambda_ridge, newx = as.matrix(X_test))

error_ridge <- sqrt(mean((predictions_ridge - y_test)^2))
print(paste("RMSE Ridge :", round(error_ridge, 2)))
```

```
## [1] "RMSE Ridge : 0.83"
```

Lasso :

```r
# We split into 2 dataframe randomly
indice_train <- sample(1:nrow(cookies_data), 0.8 * nrow(cookies_data))
train_data <- cookies_data[indice_train, ]
test_data <- cookies_data[-indice_train, ]

# We define X & y for both dataframe
y_train <- train_data[, 1]
X_train <- train_data[, -1]
y_test <- test_data[, 1]
X_test <- test_data[, -1]

# We train the model with the best value for lambda
cv_lasso_model <- cv.glmnet(as.matrix(X_train), y_train, alpha = 1, grouped = FALSE)
best_lambda <- cv_lasso_model$lambda.min
lasso_model <- glmnet(as.matrix(X_train), y_train, lambda = best_lambda, alpha = 1)

# We make prediction on the X_test
predictions_lasso <- predict(lasso_model, s = best_lambda, newx = as.matrix(X_test))

# We compute the RMSE
error_lasso  <- sqrt(mean((predictions_lasso - y_test)^2))
print(paste("RMSE Lasso :", round(error_lasso, 2)))
```

```
## [1] "RMSE Lasso : 0.25"
```

We see that the RMSE for the Lasso regression is way better than for the Ridge one.

Finally, let's verify if only 31 co-variables are useful for our prediction by using a Step forward selection :

```
##
## Call:  glm(formula = fat ~ X1980 + X2128 + X1416 + X1716 + X2200 + X1428 +
##     X1976 + X2224 + X1978 + X2202 + X1468 + X2252 + X2018 + X2242 +
##     X2192 + X1564 + X2164 + X1718 + X2176 + X2216 + X1878 + X1144 +
##     X1566 + X2186 + X2244 + X2196 + X2346 + X1502 + X2246 + X1346 +
##     X2398, family = gaussian, data = cookies_data)
##
## Coefficients:
## (Intercept)        X1980        X2128        X1416        X1716        X2200
##   1.554e+01   -1.658e+02    2.891e+01    8.449e+01   -4.707e+02    5.583e+02
##       X1428        X1976        X2224        X1978        X2202        X1468
##  -8.572e+01   -3.285e+02   -9.854e+01    4.724e+02   -3.391e+02    3.288e+00
##       X2252        X2018        X2242        X2192        X1564        X2164
##   1.213e+02    4.101e+01   -1.714e+02    4.322e+01    1.270e+02   -1.991e+02
##       X1718        X2176        X2216        X1878        X1144        X1566
##   4.175e+02    1.244e+02   -6.102e+01    4.573e+01   -5.264e+00   -9.188e+01
##       X2186        X2244        X2196        X2346        X1502        X2246
##  -2.245e+01    1.672e+01   -4.137e+01    4.972e-01    2.369e-01    2.554e-01
##       X1346        X2398
##  -5.883e-03    3.412e-06
##
## Degrees of Freedom: 31 Total (i.e. Null);  0 Residual
## Null Deviance:       56.37
## Residual Deviance: 1.382e-23     AIC: -1638
```

We see that we also get only 31 degrees of freedom, the same as the lasso regression.

Conclusion

Because we had 700 covariables, which is way greater than the number of observation (32), the matrix $X^T X$ is not invertible and the covariables might be correlated. Therefore, we can't use the OLS method to find the best coefficients. We had to use a Ridge regression or a Lasso regression to find the best coefficients and a correct number of covariables. We've seen that the Lasso regression was way better than the Ridge one. This is because the Lasso regression is a method that is used to get a sparse solution, which is what we wanted. We've also seen that only 31 co-variables were useful to predict the fat. We've also seen that the RMSE of the Lasso regression was very low comapred to the ridge one, which is really good: the model is really accurate and predictive.