BUS 41201 Big Data Midterm

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Setup

```
# Reddit news data
data = read.csv("RedditNews.csv", header = FALSE, skip = 1)
data[,2:3] = data[,1:2]
data[,1] = paste0("RedditNews_",rownames(data))
date<-data[2] # this is the day of the news

subset<-date=="7/1/16" # let's take a look at news headlines on 7/1/16
# data[subset,3] # we have 24 news headlines
```

```
# Read the DJIA data
dj<-read.csv("DJIA.csv")
head(dj) # Open price, highest, lowest and close price
```

```
##         Date     Open     High      Low    Close    Volume Adj.Close
## 1 2016-07-01 17924.24 18002.38 17916.91 17949.37  82160000  17949.37
## 2 2016-06-30 17712.76 17930.61 17711.80 17929.99 133030000  17929.99
## 3 2016-06-29 17456.02 17704.51 17456.02 17694.68 106380000  17694.68
## 4 2016-06-28 17190.51 17409.72 17190.51 17409.72 112190000  17409.72
## 5 2016-06-27 17355.21 17355.21 17063.08 17140.24 138740000  17140.24
## 6 2016-06-24 17946.63 17946.63 17356.34 17400.75 239000000  17400.75
```

```
ndays<-nrow(dj) # 1989 days
```

```
# Read the words
words<-read.csv("WordsFinal.csv",header=F)
words<-words[,1]
head(words)
```

```
## [1] "ab"      "abandon" "abba"    "abbott"  "abc"     "abduct"
```

```
length(words)
```

```
## [1] 5271
```

```
# Read the word-day pairings
doc_word<-read.table("WordFreqFinal.csv",header=F)

# Create a sparse matrix
spm<-sparseMatrix(
        i=doc_word[,1],
        j=doc_word[,2],
        x=doc_word[,3],
        dimnames=list(id=1:ndays,words=words))
dim(spm)
```

```
## [1] 1989 5271
```

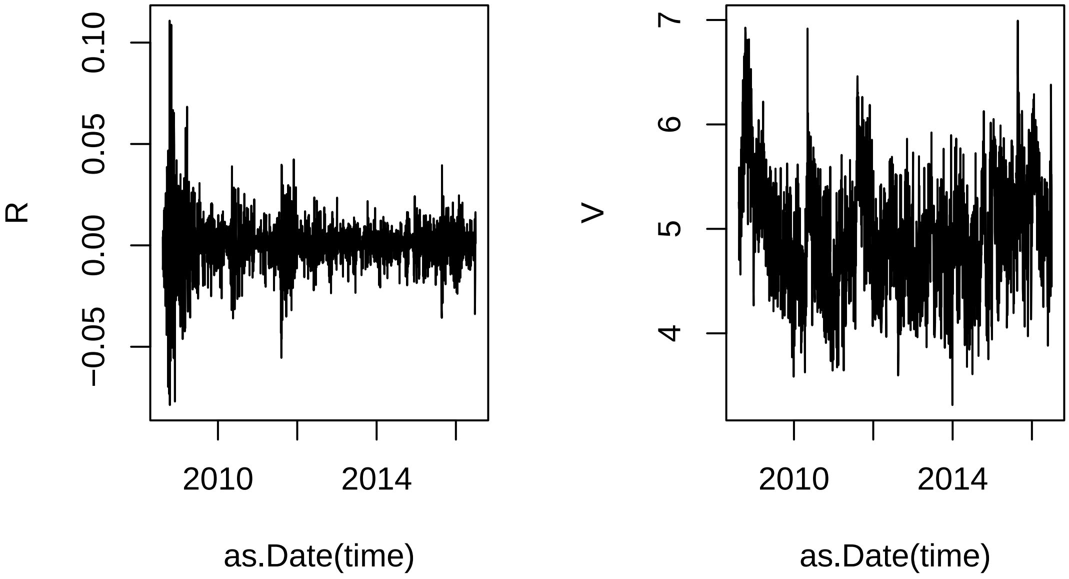
```
# We select only words at occur at least 5 times
cols<-apply(spm,2,sum)
index<-apply(spm,2,sum)>5
spm<-spm[,index]

# and words that do not occur every day
index<-apply(spm,2,sum)<ndays
spm<-spm[,index]

dim(spm) # we end up with 3183 words
```

```
## [1] 1989 3183
```

Question 1 Marginal Significance Screening and False Discovery

Setup

```
#  *** FDR *** analysis
spm<-spm[-ndays,]
time<-dj[-ndays,1]

# Take returns
par(mfrow=c(1,2))
R<-(dj[-ndays,7]-dj[-1,7])/dj[-1,7]
plot(R~as.Date(time),type="l")

# Take the log of the maximal spread
V<-log(dj[-ndays,3]-dj[-ndays,4])
plot(V~as.Date(time),type="l")
```

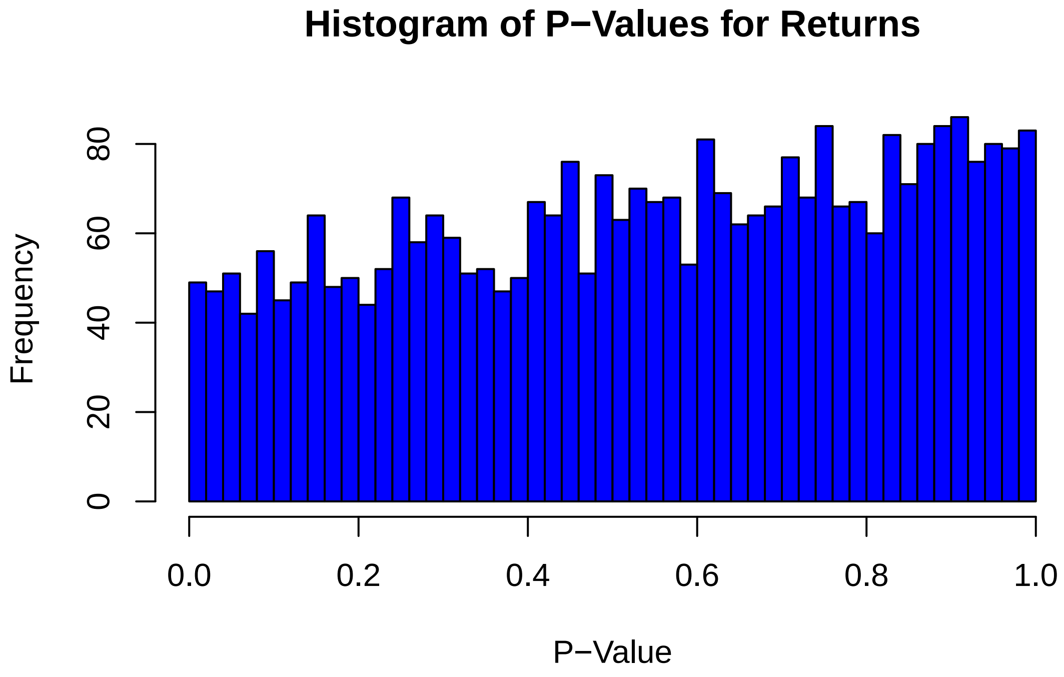


```
# FDR: we want to pick a few words that correlate with the outcomes (returns and volatility)

# create a dense matrix of word presence
P <- as.data.frame(as.matrix(spm>0))

# we will practice parallel computing now
margreg <- function(x){
    fit <- lm(Outcome~x)
    sf <- summary(fit)
    return(sf$coef[2,4])
}
```

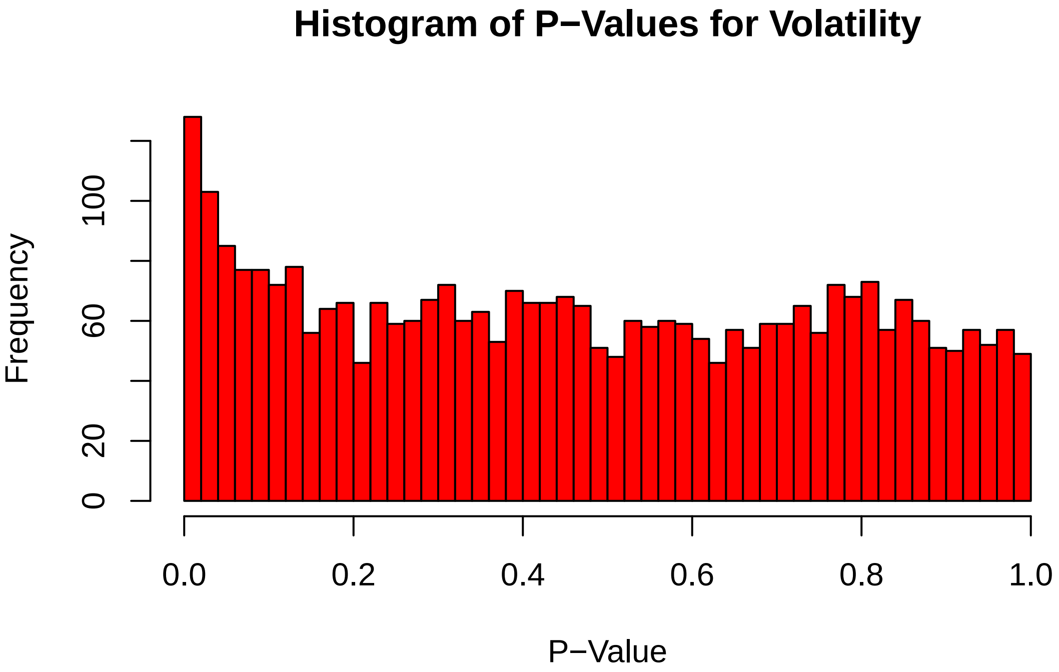
1.1 Plot the p-values and comment on their distributions (for both outcomes V and R). Is there enough signal to predict prices and volatility?

```r
# **** Analysis for Returns ****
cl <- makeCluster(detectCores())

Outcome<-R
clusterExport(cl,"Outcome")

# run the regressions in parallel
mrgpvals_R <- unlist(parLapply(cl,P,margreg))

stopCluster(cl)

# **** Analysis for Volatility ****
cl <- makeCluster(detectCores())

Outcome <- V
clusterExport(cl,"Outcome")

# run the regressions in parallel
mrgpvals_V <- unlist(parLapply(cl,P,margreg))

stopCluster(cl)
```

```r
# Combine the p-values into a data frame for easy plotting
pvals <- data.frame(Returns = mrgpvals_R, Volatility = mrgpvals_V)

# Plotting the p-values
# Plotting the histograms of p-values

# Histogram for Returns
hist(mrgpvals_R, breaks = 50, main = "Histogram of P-Values for Returns", xlab = "P-Value", ylab = "Fre
```



```r
# Histogram for Volatility
hist(mrgpvals_V, breaks = 50, main = "Histogram of P-Values for Volatility", xlab = "P-Value", ylab = "
```



The null hypothesis is a uniform distribution of p-values which would mean all p-values having the same frequency.

The histogram of p-values for returns, R, seems to be fairly uniform but seems to be somewhat skewed to the left, which suggests that there is likely to be little signal to predict the returns.

However for volatility, V, the p-values have a clear spike near 0 and seem to be skewed towards the right. The large amount of p-values near 0 suggests there might indeed be a signal for some words to predict volatility.

1.2 What is the alpha value (p-value cutoff) associated with 10% False Discovery Rate? How many words are significant at this level? (Again analyze both outcomes V and R.) What are the advantages and disadvantages of FDR for word selection?

```r
# # To find the p-value cut off we first order the p values
mrgpvals_R_ordered <- mrgpvals_R[order(mrgpvals_R, decreasing=F)]
mrgpvals_V_ordered <- mrgpvals_V[order(mrgpvals_V, decreasing=F)]

source("fdr.R")

mgr_p_R = length(mrgpvals_R_ordered)
mrg_cutoff_R <- fdr_cut(mrgpvals_R_ordered, q=0.1)
mrg_cutoff_R
```

```
## [1] 1.026222e-05
```

```r
mgr_p_V = length(mrgpvals_V_ordered)
mrg_cutoff_V <- fdr_cut(mrgpvals_V_ordered, q=0.1)
mrg_cutoff_V
```

```
## [1] 0.0003571024
```

At the 10% False Discovery rate, the p-value cutoff is:

- 1.026×10^{-5} (4.s.f) for R
- 3.571×10^{-4} (4.s.f) for V

```
# Number of significant words at alpha level 0.1
significant_R <- sum(mrgpvals_R < mrg_cutoff_R)
significant_R
```

```
## [1] 0
```

```
significant_V <- sum(mrgpvals_V < mrg_cutoff_V)
significant_V
```

```
## [1] 11
```

At this FDR level, there are 0 words are significant for R and 11 words significant for V.

-

The main advantages of using FDR analysis for word selection is the ability to handle large datasets and do computations in parallel. So as an initial stage for analyzing which words are important, this method is computationally efficient compared to others. Further, as we are explicitly controlling the expected number of false discoveries, this method allows for a more reliable selection of significant results.

However, the FDR method relies on the assumption that each test is independent. This is not necessarily true for words in headlines as words can occur simultaneously. Further, we completely disregard the structure of groups of words / phrases by treating each word independently. Another disadvantage is that the FDR analysis only selects words based on the magnitude of the association but not their direction, so we cannot use this to select only words with positive or negative association.

1.3 Now, focus only on volatility V. Suppose you just mark the 20 smallest p-values as significant. How many of these discoveries do you expect to be false? Are the p-values independent? Discuss.

Just marking the 20 smallest p-values without using any testing correction like FDR lacks statistical control over the expected number of false discoveries. So we cannot estimate the expected number of false discoveries. However, if we used the discoveries using a 10% FDR from above, then we can expect 10% of the 11 words, i.e. 1.1 of them to be false discoveries.

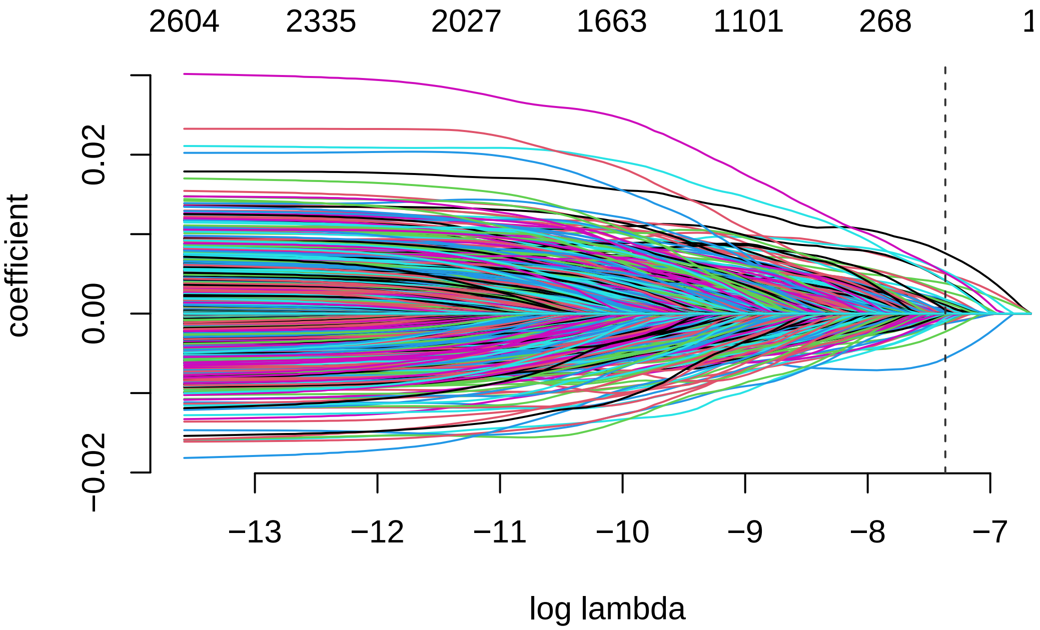
However, it is unlikely that the p-values are independent as words in language are usually correlated. So some words are likely to appear next to each other, and the presence of one word could mean that another word is more likely to appear. This is true with news headlines which often have common or repeated phrases, which means that some words appear frequently with other words.

So taking into account the lack of independence, we may assume that the expected number of false discoveries is even higher due to dependencies between words not being taken into account. So in conclusion, a more rigorous statistical method should be applied to find significant words rather than simply marking the smallest n as significant.

Question 2 LASSO Variable Selection and Bootstrapping

2.1 Use the LASSO method to come up with a combination of a few words that predict returns R. Pick a lambda and comment on the in-sample R^2. Is there enough evidence to conclude that headlines predict returns?

```
# First analyze returns
lasso1 <- gamlr(spm, y=R, lambda.min.ratio=1e-3)
plot(lasso1)
```



The top 10 most predictive words from this model are computed below:

```
betas <- drop(coef(lasso1)) # AICc default selection
non_zero_betas = betas[betas!=0][-1] # Exclude intercept and filter out zero betas

# Choose 10 most predictive words in this model
o<-order(non_zero_betas,decreasing=TRUE)
kable(non_zero_betas[o[1:10]])
```

	x
damn	0.0075899
theyll	0.0053115
elect	0.0051119
jamaican	0.0050146
kiss	0.0041769
trawler	0.0041643
paul	0.0038002
rift	0.0027937
grip	0.0024081
cctv	0.0018005

```
# Pick lambda using the AICc
lambda_1 = lasso1$lambda[which.min(AICc(lasso1))]
paste0("The AICc pick for lambda is: ", lambda_1[1])
```

```
## [1] "The AICc pick for lambda is: 0.000631890583514516"
```

```
# Compute the in-sample R2
dev <- lasso1$deviance[which.min(AICc(lasso1))] # deviance #of the AICc selected model
dev0<- lasso1$deviance[1] # null deviance
paste0("The in-sample $R^2$ is: ", 1-dev/dev0)
```

```
## [1] "The in-sample $R^2$ is: 0.07200122438874"
```

The in-sample $R^2$ is 0.07200122 which suggests there is not much signal. This means that approximately 7.2% of the variance in returns R is explained by the LASSO model based on word frequencies from the headlines. Having a low $R^2$ score suggests that is not sufficient evidence to conclude that headlines predict returns.

2.2 Repeat the analysis from (2.1) to predict Volatility instead of Returns.

```
# **** LASSO Analysis of volatility **** #
lasso2 <- gamlr(spm, y=V, lambda.min.ratio=1e-3)
betas2 <- drop(coef(lasso2)) # AICc default selection
non_zero_betas2 = betas2[betas2!=0][-1] # Exclude intercept and filter out zero betas

# Choose 10 most predictive words in this model
o <- order(non_zero_betas2,decreasing=TRUE)
kable(non_zero_betas2[o[1:10]])
```

	x
republican	0.1954297
chunk	0.1632192
fusion	0.1455132
govern	0.1123943
shed	0.0870666
august	0.0866411
bailout	0.0786730
barrel	0.0698835
hussein	0.0682012
medvedev	0.0658347

```
# Pick lambda using the AICc
lambda_2 = lasso2$lambda[which.min(AICc(lasso2))]
paste0("The AICc pick for lambda is: ", lambda_2[1])
```

```
## [1] "The AICc pick for lambda is: 0.0260163567306549"
```

```r
# Compute the in-sample R2
dev_2 <- lasso2$deviance[which.min(AICc(lasso2))] # deviance #of the AICc selected model
dev0_2<- lasso2$deviance[1] # null deviance
paste0("The in-sample $R^2$ is: ", 1-dev_2/dev0_2)
```

```
## [1] "The in-sample $R^2$ is: 0.161611573416107"
```

So the in-sample $R^2$ for this model to predict volatility is greater than the previous one for returns, which suggests a stronger signal for prediction.

Next, add one extra predictor, Volatility on a previous day. In other words, fit a LASSO model for predicting today's volatility V_t using word counts and yesterday's volatility V_{t-1}.

$V_t = a + bV_{t-1} + x_t'\beta + \epsilon_t$

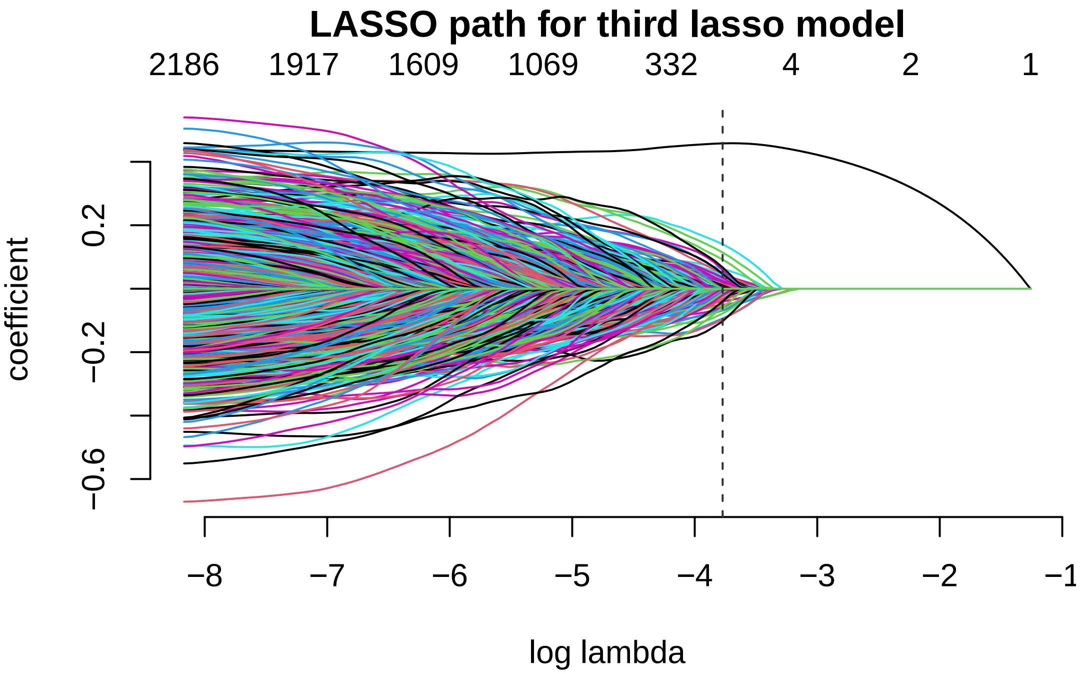
What is the in-sample R2 now? Describe the LASSO path and pick the top 10 strongest coefficients. What is the interpretation of the coefficient of word "terrorist" and of V_{t-1}?

```r
# predict future volatility from past volatility
Previous <- log(dj[-1,3]-dj[-1,4]) # remove the last return
spm2 <- cbind(Previous,spm) # add the previous return to the model matrix
colnames(spm2)[1]<-"previous" # the first column is the previous volatility
lasso3 <- gamlr(spm2, y=V, lambda.min.ratio=1e-3)

# Pick lambda using the AICc
lambda_3 = lasso3$lambda[which.min(AICc(lasso3))]

# Compute the in-sample R2
dev_3 <- lasso3$deviance[which.min(AICc(lasso3))] # deviance #of the AICc selected model
dev0_3 <- lasso3$deviance[1] # null deviance
paste0("The in-sample $R^2$ is: ", 1-dev_3/dev0_3)
```

```
## [1] "The in-sample $R^2$ is: 0.331584990647596"
```

So the in-sample $R^2$ of the third model is much greater than the previous 2 models, and suggests an even stronger signal, so adding the previous day's volatility increased our predictive power.

```r
plot(lasso3)
title("LASSO path for third lasso model")
```



From the plot of the coefficients vs lambda, we observe that the model iteratively selects coefficients of different words to become 0 as the value of lambda increases. The dotted vertical line corresponds to the log value of the lambda selected by the AICc. The coefficients all tend to 0 fairly sequentially as lambda decreases, however there is one coefficient that remains non-zero as lambda increases, and only drops to 0 after a significant rise in lambda. This is likely to be the coefficient for the previous day's volatility (V_{t-1}).

```
# Choose top 10 strongest coefficients in this model
betas3 <- drop(coef(lasso3)) # AICc default selection
non_zero_betas3 = betas3[betas3!=0][-1] # Exclude intercept and filter out zero betas

# Choose 10 most predictive words in this model
o <- order(non_zero_betas3,decreasing=TRUE)
kable(non_zero_betas3[o[1:10]])
```

	x
previous	0.4580944
shed	0.1401080
fusion	0.1141525
republican	0.0920512
pioneer	0.0670934
lowest	0.0629167
chunk	0.0581594
ton	0.0491526
william	0.0463384
medvedev	0.0450435

The top 10 strongest coefficients are listed above.

```
# coefficients
coef_terrorist = betas3[names(betas3)=="terrorist"]
paste0("The coefficient of the word terrorist is: ", coef_terrorist)
```

```
## [1] "The coefficient of the word terrorist is: 0.0178389418998624"
```

```
# V_{t-1}
coef_prev_v = betas3[names(betas3)=="previous"][1]
paste0("The coefficient of $V_{t-1}$ is: ", coef_prev_v)
```

```
## [1] "The coefficient of $V_{t-1}$ is: 0.458094444835972"
```

So the coefficient of the word “terrorist” suggests a small but positive association between the word appearing in headlines and market volatility that day. So the appearance of the word “terrorist” suggest that the market will increase in volatility by ≈ 0.0178 units keeping everything else constant. This may be

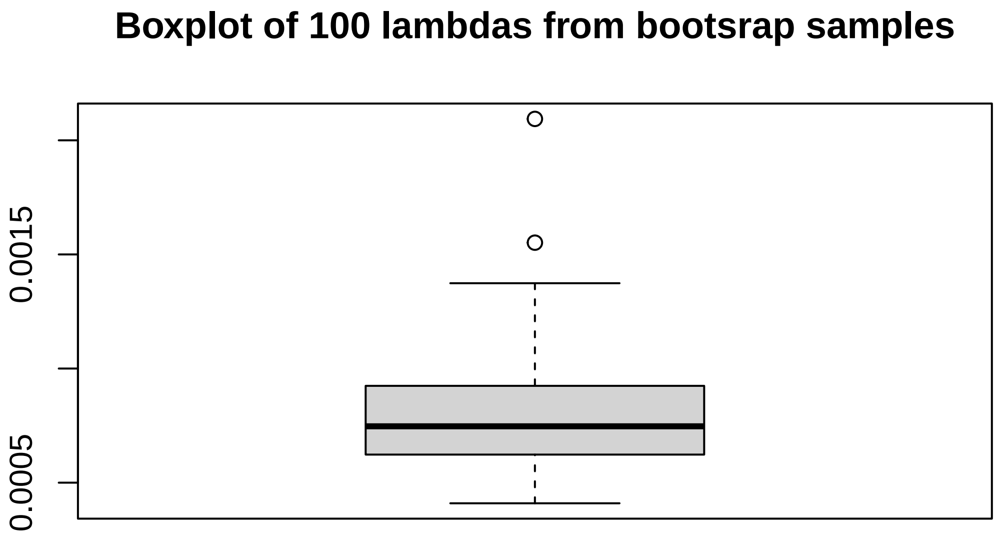
The coefficient of the previous day’s volatility is positive and large suggesting that the previous day’s volatility has a strong positive effect on the current day’s volatility. That is, a increase in the yesterday’s volatility by 1 unit leads to an expected increase in today’s volatility by ≈ 0.458 units, keeping other factors fixed. So $V_{t-1}$ is a critical component in forecasting V_t .

2.3 Consider the estimated of lambda selected by AICc in the model from (2.2) (using both words and $V_{t-1}$). We want to know how variable this estimate is. The starter script has code to bootstrap the sampling distribution for the λ selected by AICc in this regression.

– What is the standard error for the selected λ?

– Find the 95% CI for λ?

```
# Bootstrap to obtain s.e. of 1.s.e. chosen lambda

# We apply bootstrap to approximate the sampling distribution of lambda selected by AICc

# export the data to the clusters
cl <- makeCluster(detectCores())

Outcome<-V
clusterExport(cl,"spm2")
clusterExport(cl,"V")

# run 100 bootstrap resample fits
boot_function <- function(ib){
    require(gamlr)
    fit <- gamlr(spm2[ib,],y=V[ib], lambda.min.ratio=1e-3)
    fit$lambda[which.min(AICc(fit))]
}

boots <- 100
n <- nrow(spm2)
resamp <- as.data.frame(
            matrix(sample(1:n,boots*n,replace=TRUE),
            ncol=boots))

lambda_samp <- unlist(parLapply(cl,resamp,boot_function))
stopCluster(cl)

boxplot(lambda_samp)
title("Boxplot of 100 lambdas from bootsrap samples")
```



The summary statistics for the bootstrap samples are:

```
summary(lambda_samp)
```

```
##      Min.   1st Qu.    Median      Mean   3rd Qu.      Max. 
## 0.0004097 0.0006231 0.0007469 0.0007979 0.0009178 0.0020937
```

```
# Original estimate of lambda
paste0("The original estimated lambda from 2.2 is: ", lambda_3)
```

```
## [1] "The original estimated lambda from 2.2 is: 0.0230003726568119"
```

```
# Compute Standard Error
se = sqrt(mean((lambda_samp - lambda_3)**2))
paste0("The standard error for the selected lambda is: ", se)
```

```
## [1] "The standard error for the selected lambda is: 0.02220395911209"
```

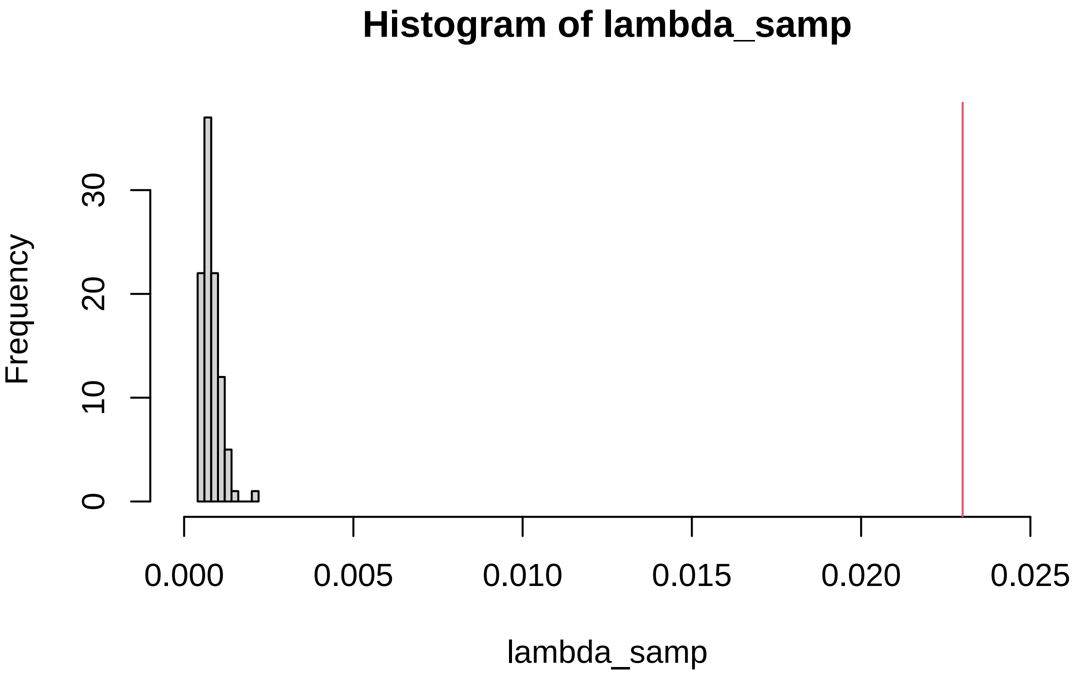
```
# Compute the 95% confidence interval
lower = lambda_3 - 1.96 * se
upper = lambda_3 + 1.96 * se

print(paste0("The confidence interval for the selected lambda is: [", lower, ",", upper, "]"))
```

```
## [1] "The confidence interval for the selected lambda is: [-0.0205193872028844,0.0665201325165083]"
```

However we note that the original lambda selected in (2.2) is significantly different from the mean of the bootstrapped samples.

So we can repeat the same calculations using the mean of the bootstraps as new estimate for lambda

```r
hist(lambda_samp, xlim=c(0, 0.025))
abline(v=lambda_3, col=2)
```



The red line on the histogram indicates the estimated lambda from the full sample in (2.2). This shows that our estimated lambda is very far from our bootstrap sampling distribution, which suggest

The picture shows that our full sample AICc estimate is near the low end of the sampling distribution; there is high variability in the estimator and this leads us to question the robustness and reliability of the original estimate.

Question 3 High-dimensional Controls and Double LASSO

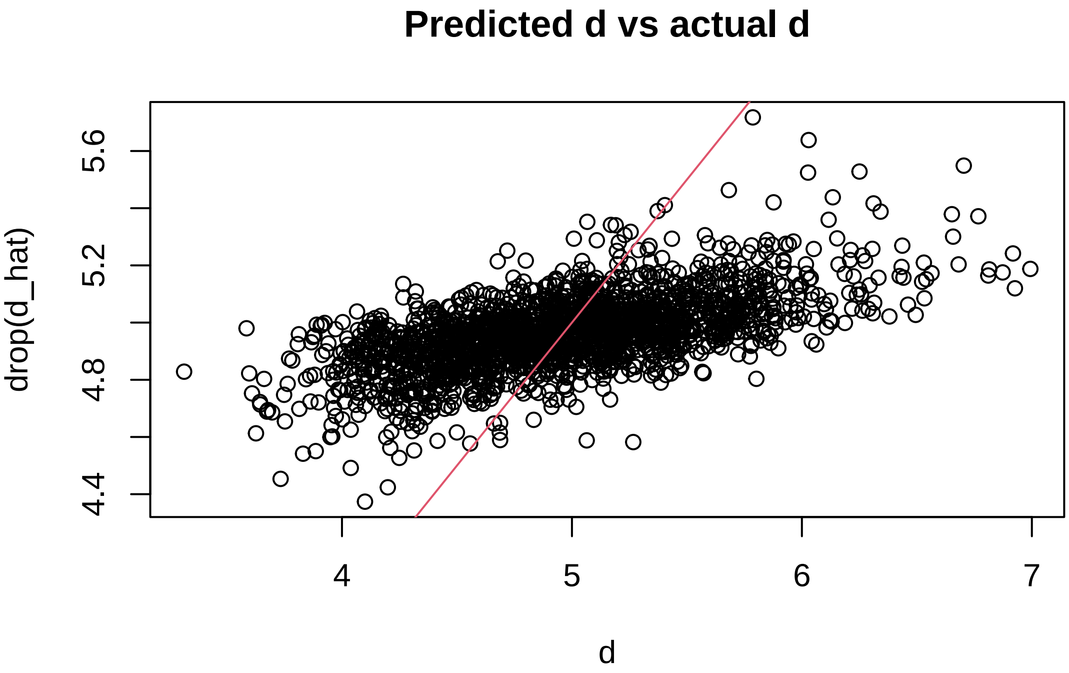
3.1 Explore a marginal regression (just a regression of V_t on V_{t-1}) to see if there is any correlation. Predict d from x (headlines words), and comment on the degree of confounding we can expect. Is there any information in d independent of x?

```r
# High-dimensional Covariate Adjustment
d <- Previous # this is the treatment

# marginal effect of past on present volatility
summary(glm(V~d))
```

```
##
## Call:
## glm(formula = V ~ d)
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  2.42168    0.09620   25.17   <2e-16 ***
## d            0.51195    0.01926   26.58   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 0.2262754)
##
##     Null deviance: 609.23  on 1987  degrees of freedom
## Residual deviance: 449.38  on 1986  degrees of freedom
## AIC: 2691.5
##
## Number of Fisher Scoring iterations: 2
```

The coefficient of d is 0.51195 is positive and significant (p-value <2e-16) which suggests a strong positive correlation between d and V. That is, for a one-unit increase in yesterday's volatility, we can expect an increase of ≈ 0.512 units in today's volatility.

```r
# LASSO model to predict d from x
treat <- gamlr(spm, d, lambda.min.ratio=1e-4)

# Isolate d_hat (the part of treatment that we can predict with x's)
d_hat = predict(treat, spm)

# Plot d_hat against d
plot(d, drop(d_hat))
abline(a=0, b=1, col=2)
title("Predicted d vs actual d")
```



```
# In-sample R2
print(paste0("R2: ", cor(d, drop(d_hat))^2))
```

```
## [1] "R2: 0.364826258601986"
```

From the graph we observe that the predictions are fairly close to the actual values, but the slope of the trend differs from what we expect.

Also the in-sample R^2 suggests that $\approx$ 36.5 % of the variance in d is explained by x (the words in the headlines).

As the words explain more than 1/3 of the amount of variance in V_{t-1}, we can expect a moderate degree of confounding effect that should be controlled.

However, there is still $\approx$ 63.5% of unexplained variance in V_{t-1} which suggests that there is significant information in d that is independent of x.

3.2 Isolate the effect of V_{t-1} by running the causal (double) LASSO. Interpret this effect and compare it to the effect obtained from the naive LASSO.

```
# Second Stage LASSO
causal <-  gamlr(cbind(d, d_hat, spm), V, free=2)
print(paste0("The coefficient of d from 2-stage LASSO is: ", coef(causal)["d",]))
```

```
## [1] "The coefficient of d from 2-stage LASSO is: 0.360282069419024"
```

```
# Naive LASSO
naive <- gamlr(cbind(d, spm), V)
print(paste0("The coefficient of d from naive LASSO is: ", coef(naive)["d",]))
```

```
## [1] "The coefficient of d from naive LASSO is: 0.457421796653875"
```

The effect of V_{t-1} from the causal LASSO is ≈ 0.36 which is fairly large, thus suggests that there is evidence that the previous day's volatility does have a moderate effect on the current day's volatility. So after controlling for confounding effects of the headline words, a 1 unit increase in yesterday's volatility leads to an increase of approximately 0.36 units in today's volatility.

However we also observe that there is an effect when running naive LASSO, and in fact it is greater in magnitude (≈ 0.46). This difference in magnitude might be attributed to the confounding influence of the words in the headlines.

3.3 Can we safely claim that the effect is causal?

By implementing a double LASSO, we did manage to effectively control for the observed confounders x (the words in the headlines that might influence both V_t and V_{t-1}), and the coefficient we obtained was not insignificant.

However, this is just one part of the picture, as we have not controlled for all confounders, namely the unobserved ones that are not included in our datasets. These may still influence both V_t and V_{t-1} so we cannot conclude with certainty that there is a causal effect.

Further, as with all statistical analyses, we need to make sure the model is correctly specified, and statistical assumptions are met. As discussed in question 1, the independence of words in the headlines may not be a reasonable assumption to make. And as we are dealing with financial data, it is unclear whether the assumption of normality for error terms still holds, which is necessary to interpret the model output.

Finally, in order reach a stronger conclusion about causality, we should ideally implement further analyses that can either strengthen or disprove our claim, such as the use of instrumental variables, or more advanced LASSO methods.

Thus although we cannot claim for certain the effect is causal, we can claim that there is a statistically significant association and so our double LASSO model suggests that there could be a potential causal effect.

Bonus Freestyle Analysis

Provide additional analysis of the data. Points will handed out only for insightful use of data mining tools, not for scattershot application of techniques.