

Assignment 2

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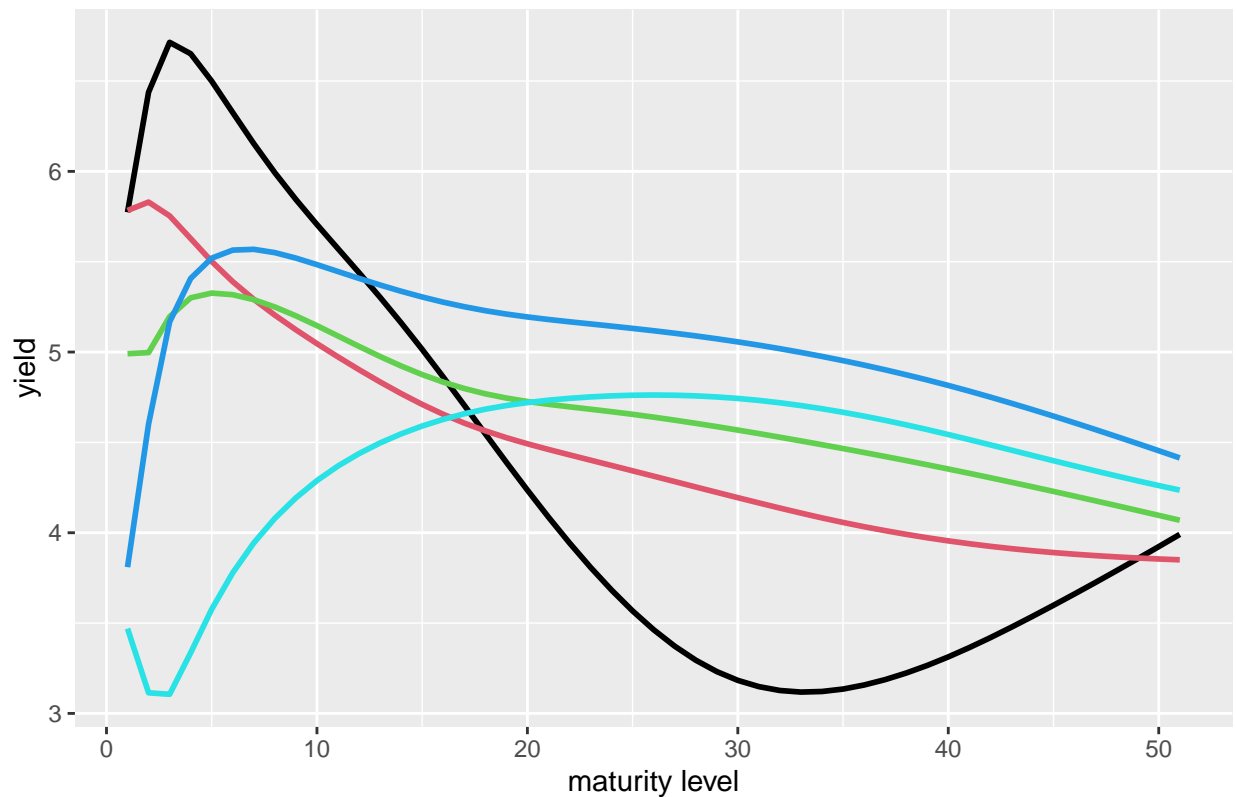
1.

```
Data=matrix(read.table("InterestRates.txt", header=FALSE))
```

Plot of the yield curve for day 1, day 200, day 400, day 600 and day 800:

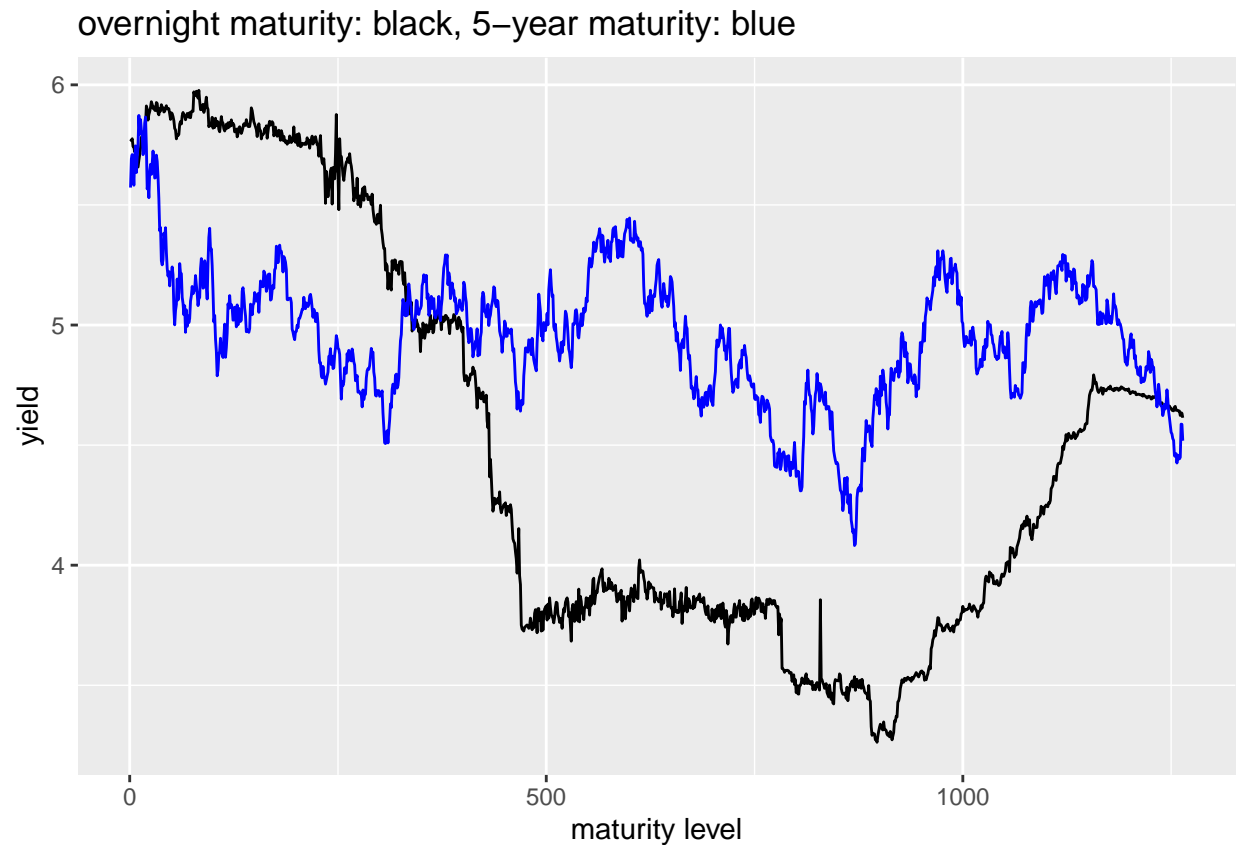
```
library(ggplot2)
d1 <- NULL
for (i in 1:ncol(Data)) {
  d1[i] <- Data[1,i]
}
d200 <- NULL
for (i in 1:ncol(Data)) {
  d200[i] <- Data[200,i]
}
d400<- NULL
for (i in 1:ncol(Data)) {
  d400[i] <- Data[400,i]
}
d600 <- NULL
for (i in 1:ncol(Data)) {
  d600[i] <- Data[600,i]
}
d800 <- NULL
for (i in 1:ncol(Data)) {
  d800[i] <- Data[800,i]
}
ggplot() +
  geom_line(mapping = aes(x=1:51, y=d1), col = 1, size = 1) +
  geom_line(mapping = aes(x=1:51, y=d200), col = 2, size = 1) +
  geom_line(mapping = aes(x=1:51, y=d400), col = 3, size = 1) +
  geom_line(mapping = aes(x=1:51, y=d600), col = 4, size = 1) +
  geom_line(mapping = aes(x=1:51, y=d800), col = 5, size = 1) +
  labs(x="maturity level", y="yield") +
  ggtitle("Yield curve for 5 different days")
```

Yield curve for 5 different days



2. Plot of the overnight yield and 5-year maturity yield:

```
v1 <- NULL
for (i in 1:nrow(Data)) {
  v1[i] <- Data[i, 1]
}
v11 <- NULL
for (i in 1:nrow(Data)) {
  v11[i] <- Data[i, 11]
}
ggplot() +
  geom_line(mapping = aes(x=1:nrow(Data), y=v1), col = "black") +
  geom_line(mapping = aes(x=1:nrow(Data), y=v11), col = "blue") +
  labs(x="maturity level", y="yield") +
  ggtitle("overnight maturity: black, 5-year maturity: blue")
```

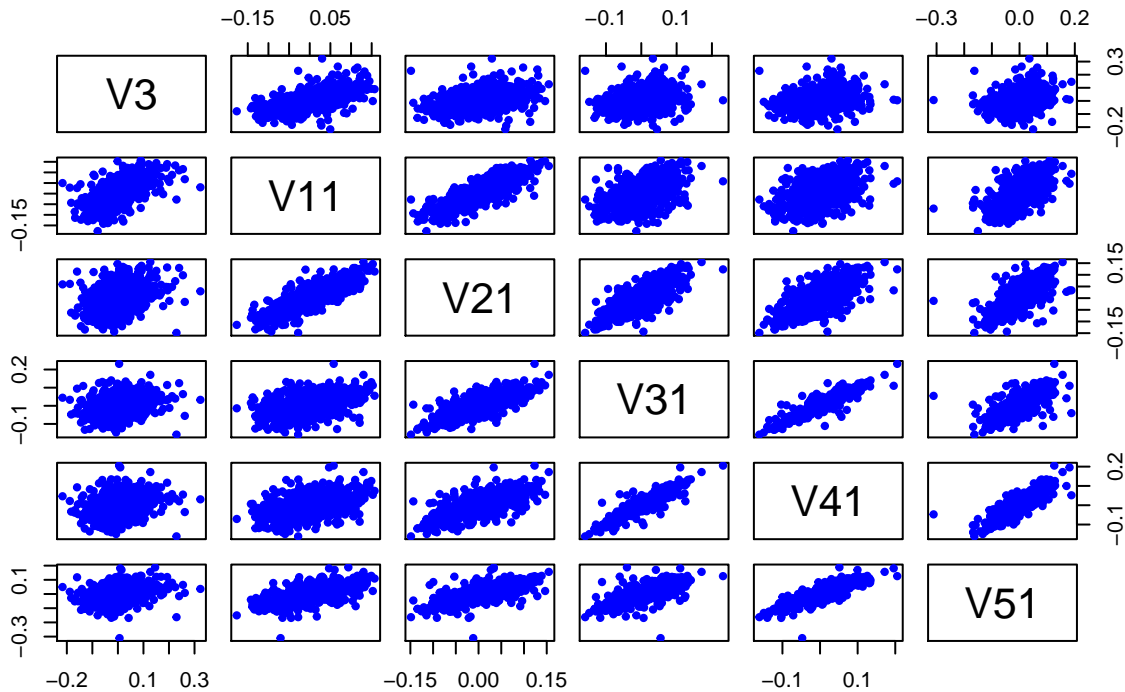


The overnight yield fluctuates heavily. It decreases from 5.773 to a minimum at 3.263, then increases to 4.614 in the end. The 5-year yield decreases overall, with the starting value of 5.572 and the end value of 4.518.

3. The pairwise scatterplot for the changes in the yield for the 1-year, 5-year, 10-year, 15-year, 20-year and 25-year maturity:

```
Change <- Data[2:1264,] - Data[1:1263,]
pairs(~V3 + V11 + V21 + V31 + V41 + V51, data=Change, pch=20, col="blue",
      main = "Dependencies between yield changes")
```

Dependencies between yield changes



Dependency can be explained by the pairwise scatterplot, and based on the scatterplot, the linear relation to each variable to the subsequent Year 5, 10, 15, 20 and 25 can be observed. The dependency of Year 5 to the subsequent years is shown above and a pattern can be observed, where the dependency of the Year 5 to Year 10 is strongest and the subsequent years decreases as it approaches Year 25, which is depicted by the linear relationship of the scatterplot. On the other hand, there are further findings that can be observed:

- Observation 1: Year 1 has a stronger dependency to Year 5, as compared to the subsequent years later as the dependency decreases, which can be observed from the linearity of the scatterplot.
- Observation 2: Year 5 has a stronger dependency to Year 10, as compared to the subsequent years later and its dependency is much more prominent than Observation 1.
- Observation 3: Year 15 has the strongest dependency to Year 20, as compared to the previous two observations.

The correlation between the yield changes of 1-year (black), 5-year (red), 10-year (green), 15-year (blue), 20-year (teal) and 25-year (teal) maturity and every other maturities:

```
a1<- NULL
for (i in 3:51) {
  a1[i] <- cor(Change[,3], Change[,i])
}
a11<- NULL
for (i in 3:51) {
  a11[i] <- cor(Change[,11], Change[,i])
}
a21<- NULL
```

```

for (i in 3:51) {
  a21[i] <- cor(Change[,21], Change[,i])
}
a31<- NULL
for (i in 3:51) {
  a31[i] <- cor(Change[,31], Change[,i])
}
a41<- NULL
for (i in 3:51) {
  a41[i] <- cor(Change[,41], Change[,i])
}
a51<- NULL
for (i in 3:51) {
  a51[i] <- cor(Change[,51], Change[,i])
}
ggplot() +
  geom_line(mapping = aes(x=1:51, y=a1), col = 1, size = 1) +
  geom_line(mapping = aes(x=1:51, y=a11), col = 2, size = 1) +
  geom_line(mapping = aes(x=1:51, y=a21), col = 3, size = 1) +
  geom_line(mapping = aes(x=1:51, y=a31), col = 4, size = 1) +
  geom_line(mapping = aes(x=1:51, y=a41), col = 5, size = 1) +
  geom_line(mapping = aes(x=1:51, y=a51), col = 6, size = 1) +
  ggtitle("Correlation between yield changes of 1-year, 5-year, 10-year, 15-year, 20-year and 25-year \

```

```
## Warning: Removed 2 row(s) containing missing values (geom_path).
```

```
## Warning: Removed 2 row(s) containing missing values (geom_path).
```

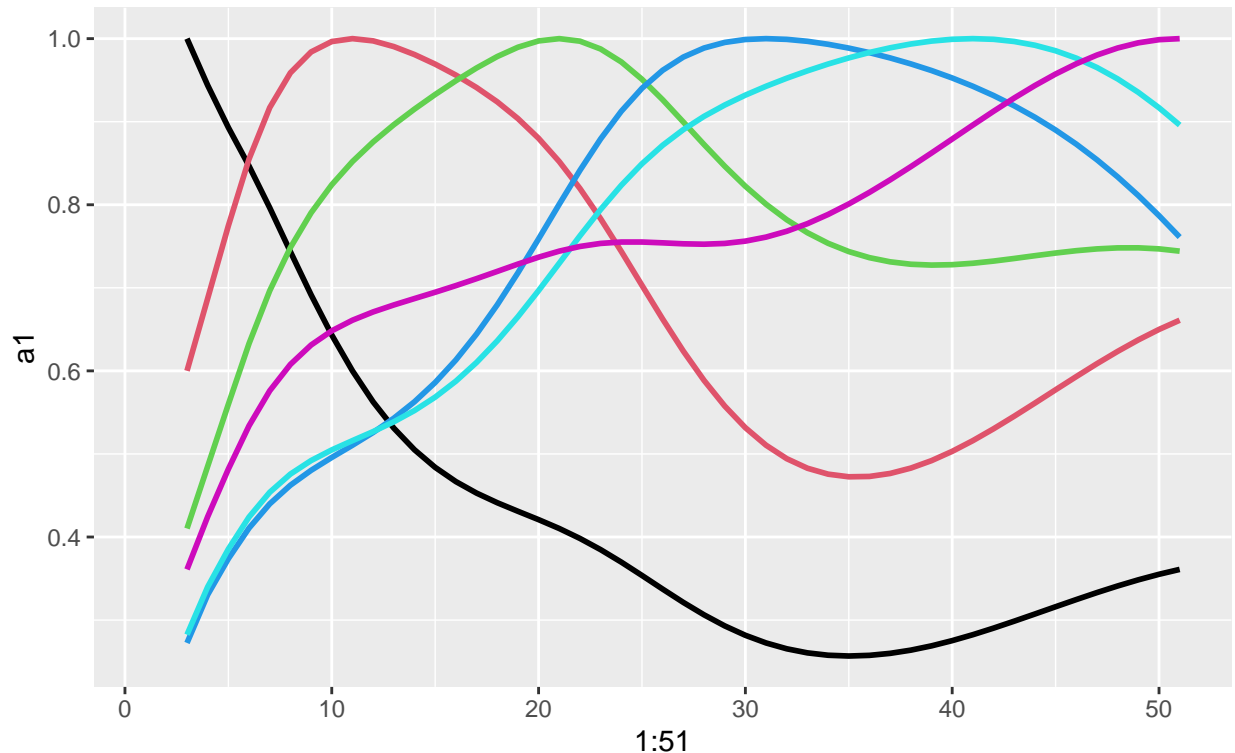
```
## Warning: Removed 2 row(s) containing missing values (geom_path).
```

```
## Warning: Removed 2 row(s) containing missing values (geom_path).
```

```
## Warning: Removed 2 row(s) containing missing values (geom_path).
```

```
## Warning: Removed 2 row(s) containing missing values (geom_path).
```

Correlation between yield changes of 1–year, 5–year, 10–year, 15–year, 20 maturity and every other maturities



Based on the line graph, these are the findings that can be observed:

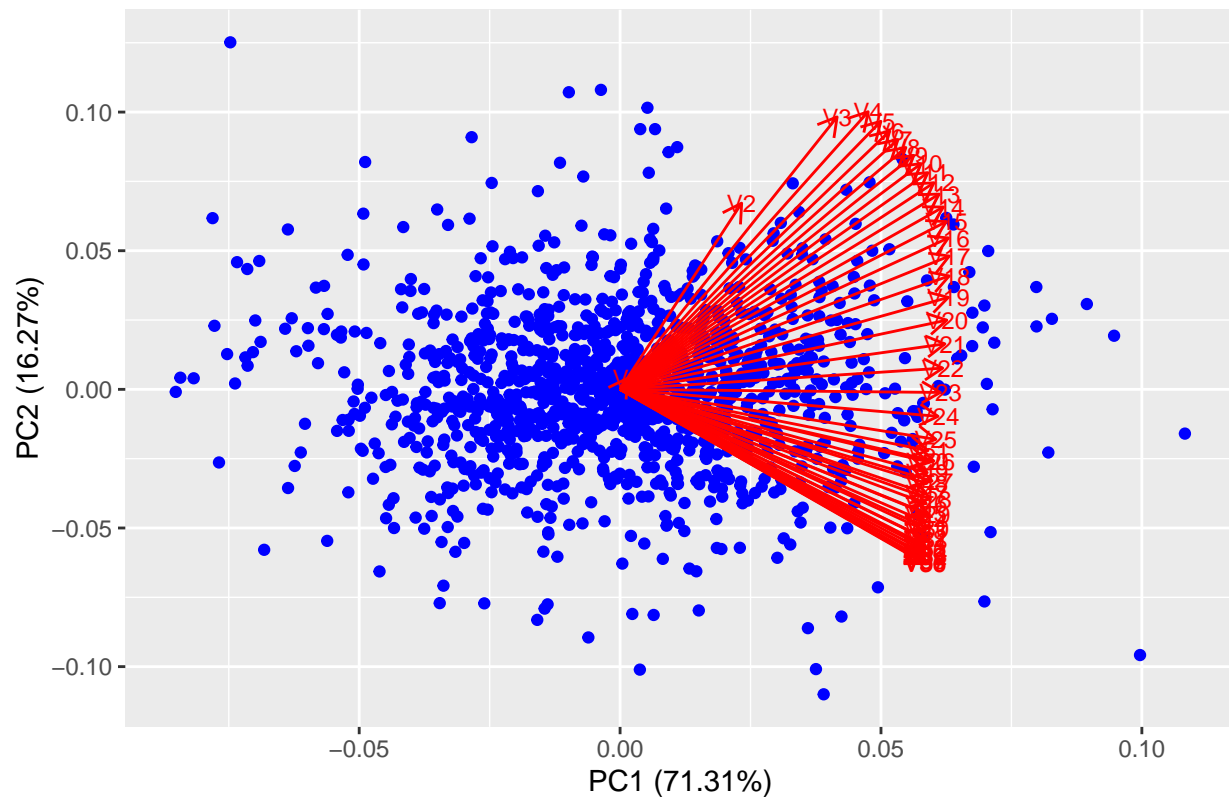
- Observation 1: With a comparison from Year 1 to the subsequent years, it can be seen that the correlation decreases to below 0.5 in Year 25.
- Observation 2: With a comparison from Year 15 to subsequent years, it can be seen that the correlation is decreasing as well, however, it's higher than Observation 1 which is 0.75 at Year 25.
- Observation 3: With a comparison from Year 20 to subsequent years, it can be seen that the correlation decreases, however, it's higher than Observation 1 and Observation 2 at 0.9 at Year 25.

Therefore, based on the observation, a pattern can be concluded. The closer the base year we used for comparison, to the year of maturity, the higher the correlation is.

4. Principal component analysis on the original “Change” dataset:

```
Change.PCA <- prcomp(Change)
library(ggfortify)
autoplot(Change.PCA, loadings = TRUE, loadings.label = TRUE, loadings.label.size = 3, col = "blue",
         main = "PCA for changes in the yield curve (original data)")
```

PCA for changes in the yield curve (original data)



`summary(Change.PCA)`

```
## Importance of components:
##              PC1      PC2      PC3      PC4      PC5      PC6      PC7
## Standard deviation  0.2837 0.1355 0.08059 0.05801 0.04499 0.03599 0.02471
## Proportion of Variance 0.7131 0.1627 0.05753 0.02980 0.01793 0.01148 0.00541
## Cumulative Proportion 0.7131 0.8758 0.93332 0.96312 0.98105 0.99253 0.99794
##              PC8      PC9      PC10      PC11      PC12      PC13
## Standard deviation  0.01245 0.007596 0.003981 0.001753 0.0009451 0.0005199
## Proportion of Variance 0.00137 0.000510 0.000140 0.000030 0.0000100 0.0000000
## Cumulative Proportion 0.99931 0.999820 0.999960 0.999990 1.0000000 1.0000000
##              PC14      PC15      PC16      PC17      PC18      PC19
## Standard deviation  0.0002852 0.0001816 0.0001124 8.21e-05 6.92e-05 5.7e-05
## Proportion of Variance 0.0000000 0.0000000 0.0000000 0.00e+00 0.00e+00 0.0e+00
## Cumulative Proportion 1.0000000 1.0000000 1.0000000 1.00e+00 1.00e+00 1.0e+00
##              PC20      PC21      PC22      PC23      PC24
## Standard deviation  4.299e-05 3.097e-05 2.243e-05 1.763e-05 1.271e-05
## Proportion of Variance 0.000e+00 0.000e+00 0.000e+00 0.000e+00 0.000e+00
## Cumulative Proportion 1.000e+00 1.000e+00 1.000e+00 1.000e+00 1.000e+00
##              PC25      PC26      PC27      PC28      PC29
## Standard deviation  1.019e-05 8.428e-06 6.523e-06 4.986e-06 3.655e-06
## Proportion of Variance 0.000e+00 0.000e+00 0.000e+00 0.000e+00 0.000e+00
## Cumulative Proportion 1.000e+00 1.000e+00 1.000e+00 1.000e+00 1.000e+00
##              PC30      PC31      PC32      PC33      PC34
## Standard deviation  3.389e-06 2.886e-06 2.834e-06 2.189e-06 1.972e-06
```

```
## Proportion of Variance 0.000e+00 0.000e+00 0.000e+00 0.000e+00 0.000e+00
## Cumulative Proportion 1.000e+00 1.000e+00 1.000e+00 1.000e+00 1.000e+00
##          PC35      PC36      PC37      PC38      PC39
## Standard deviation 1.703e-06 1.524e-06 1.411e-06 1.337e-06 1.299e-06
## Proportion of Variance 0.000e+00 0.000e+00 0.000e+00 0.000e+00 0.000e+00
## Cumulative Proportion 1.000e+00 1.000e+00 1.000e+00 1.000e+00 1.000e+00
##          PC40      PC41      PC42      PC43      PC44
## Standard deviation 1.092e-06 8.902e-07 7.583e-07 5.866e-07 5.147e-07
## Proportion of Variance 0.000e+00 0.000e+00 0.000e+00 0.000e+00 0.000e+00
## Cumulative Proportion 1.000e+00 1.000e+00 1.000e+00 1.000e+00 1.000e+00
##          PC45      PC46      PC47      PC48      PC49
## Standard deviation 4.617e-07 4.099e-07 3.164e-07 2.243e-07 9.994e-08
## Proportion of Variance 0.000e+00 0.000e+00 0.000e+00 0.000e+00 0.000e+00
## Cumulative Proportion 1.000e+00 1.000e+00 1.000e+00 1.000e+00 1.000e+00
##          PC50      PC51
## Standard deviation 8.623e-08 4.153e-08
## Proportion of Variance 0.000e+00 0.000e+00
## Cumulative Proportion 1.000e+00 1.000e+00
```

According to the summary, we should keep the first 4 principal components to explain 96.31% of the variance.

```
PC <- Change.PCA$rotation
round(PC[,1], digits = 3)
```

```
##      V1      V2      V3      V4      V5      V6      V7      V8      V9      V10     V11     V12     V13
## 0.004 0.057 0.101 0.116 0.122 0.126 0.129 0.133 0.137 0.140 0.143 0.146 0.149
##      V14     V15     V16     V17     V18     V19     V20     V21     V22     V23     V24     V25     V26
## 0.151 0.152 0.153 0.153 0.153 0.153 0.152 0.151 0.150 0.149 0.148 0.147 0.146
##      V27     V28     V29     V30     V31     V32     V33     V34     V35     V36     V37     V38     V39
## 0.145 0.145 0.144 0.143 0.143 0.143 0.142 0.142 0.142 0.142 0.142 0.142 0.142
##      V40     V41     V42     V43     V44     V45     V46     V47     V48     V49     V50     V51
## 0.142 0.142 0.142 0.142 0.142 0.143 0.143 0.143 0.143 0.143 0.143 0.144
```

For PC1, all the variable has the same direction, however, V1 (overnight) and V2 (6-month) has the lowest magnitude, while the rest has a similar magnitude that ranges from 0.1 to 0.15.

```
round(PC[,2], digits = 3)
```

```
##      V1      V2      V3      V4      V5      V6      V7      V8      V9      V10     V11
## 0.010 0.163 0.239 0.243 0.235 0.227 0.219 0.212 0.205 0.198 0.190
##      V12     V13     V14     V15     V16     V17     V18     V19     V20     V21     V22
## 0.181 0.171 0.160 0.147 0.133 0.117 0.099 0.081 0.061 0.040 0.019
##      V23     V24     V25     V26     V27     V28     V29     V30     V31     V32     V33
## -0.003 -0.024 -0.044 -0.063 -0.080 -0.096 -0.110 -0.122 -0.132 -0.140 -0.146
##      V34     V35     V36     V37     V38     V39     V40     V41     V42     V43     V44
## -0.150 -0.152 -0.153 -0.152 -0.150 -0.147 -0.142 -0.137 -0.131 -0.124 -0.116
##      V45     V46     V47     V48     V49     V50     V51
## -0.109 -0.100 -0.091 -0.082 -0.073 -0.063 -0.054
```

For PC2, the variable V3 to V9 (1-year to 4-year) dominates in PC2 with an approximation of the same magnitude in the 0.2 scale, on the other hand, from V23 (11-year) onwards, it has an opposite direction compared to the previous years.


```
round(PC[,3], digits = 3)
```

```
##      V1      V2      V3      V4      V5      V6      V7      V8      V9      V10     V11
## -0.001  0.273  0.402  0.356  0.275  0.196  0.125  0.062  0.007 -0.041 -0.083
##      V12     V13     V14     V15     V16     V17     V18     V19     V20     V21     V22
## -0.119 -0.148 -0.170 -0.186 -0.196 -0.199 -0.198 -0.192 -0.181 -0.168 -0.152
##      V23     V24     V25     V26     V27     V28     V29     V30     V31     V32     V33
## -0.134 -0.114 -0.095 -0.075 -0.056 -0.037 -0.020 -0.003  0.012  0.025  0.037
##      V34     V35     V36     V37     V38     V39     V40     V41     V42     V43     V44
##  0.048  0.057  0.065  0.072  0.077  0.081  0.084  0.086  0.086  0.087  0.086
##      V45     V46     V47     V48     V49     V50     V51
##  0.085  0.083  0.080  0.077  0.074  0.070  0.066
```

For PC3, the variable V2 to V5 (6-month to 2-year) dominates with the highest magnitude in the positive direction, and in the negative direction, V12 to V24 (5.5-year to 11.5-year) has the highest magnitude.

```
round(PC[,4], digits = 3)
```

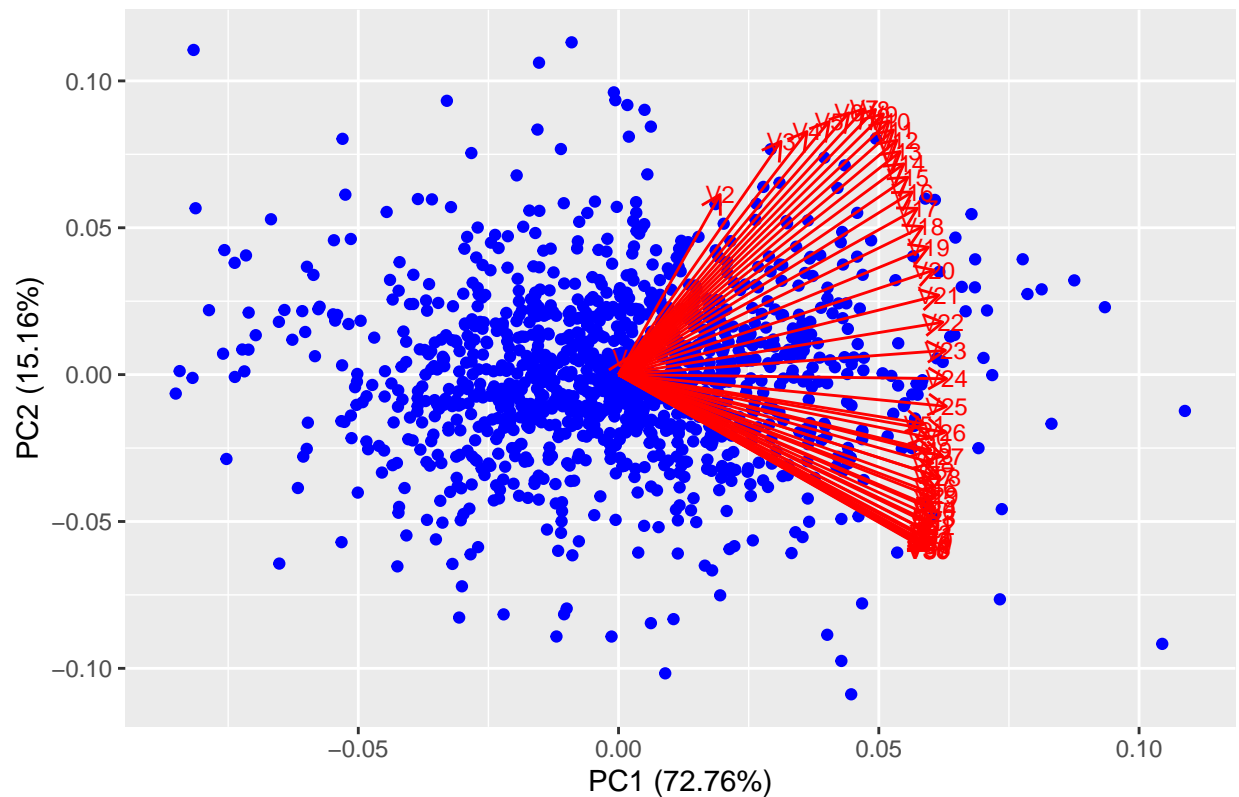
```
##      V1      V2      V3      V4      V5      V6      V7      V8      V9      V10     V11
## -0.013 -0.127 -0.198 -0.148 -0.087 -0.035  0.007  0.040  0.065  0.083  0.093
##      V12     V13     V14     V15     V16     V17     V18     V19     V20     V21     V22
##  0.098  0.095  0.087  0.072  0.053  0.029  0.003 -0.026 -0.056 -0.085 -0.112
##      V23     V24     V25     V26     V27     V28     V29     V30     V31     V32     V33
## -0.137 -0.158 -0.174 -0.186 -0.192 -0.194 -0.190 -0.182 -0.169 -0.154 -0.134
##      V34     V35     V36     V37     V38     V39     V40     V41     V42     V43     V44
## -0.113 -0.089 -0.065 -0.039 -0.013  0.014  0.041  0.067  0.094  0.120  0.145
##      V45     V46     V47     V48     V49     V50     V51
##  0.171  0.196  0.220  0.245  0.269  0.293  0.317
```

For PC4, the variable V47 to V51 (23-year to 25-year) dominates with a magnitude of 0.22 to 0.317 with a positive direction, however, there is a change of direction from V1 to V38 (overnight to 18.5-year).

Principal component analysis on the standardized “Change” dataset:

```
Change_scaled <- scale(Change)
Change_scaled.PCA <- prcomp(Change_scaled)
autoplot(Change_scaled.PCA, loadings = TRUE, loadings.label = TRUE, loadings.label.size = 3,
         col = "blue", main = "PCA for changes in the yield curve (standardized data)")
```

PCA for changes in the yield curve (standardized data)

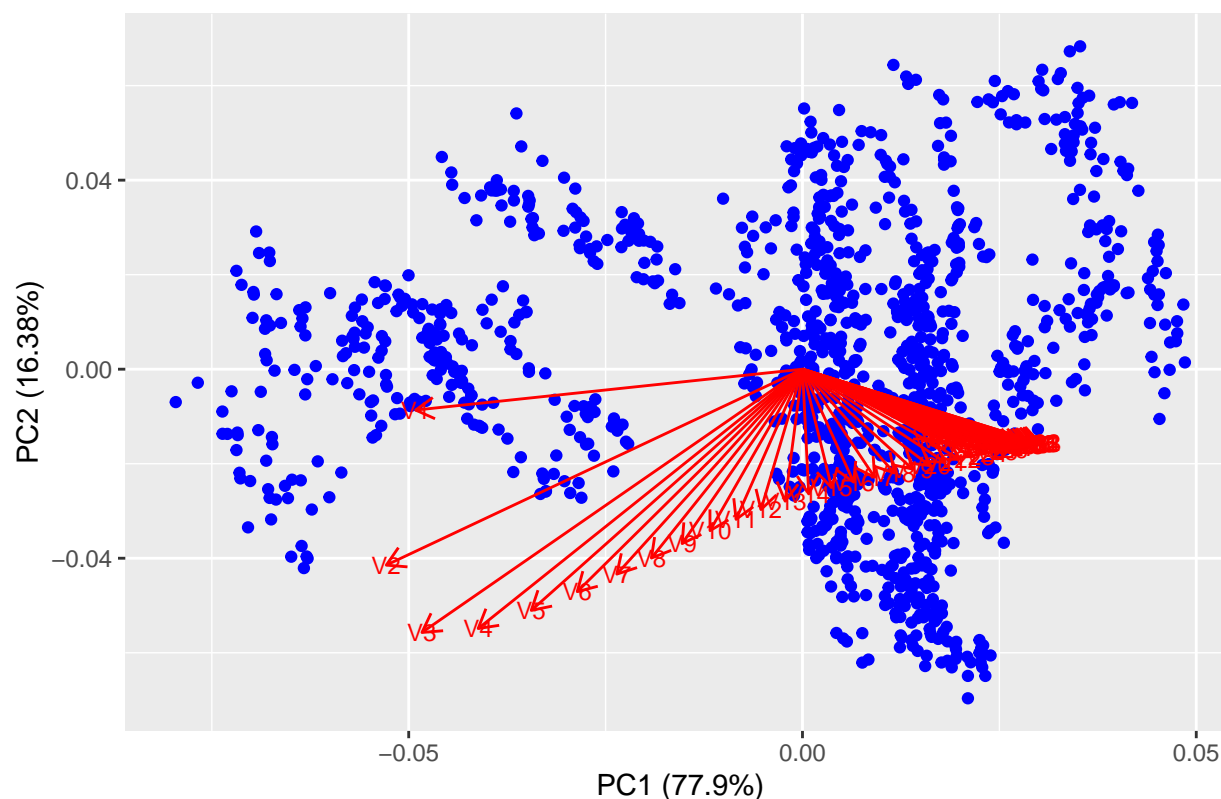


Standardisation is not required because this transformation is done for data of different scale, however, the data that we currently have is of the same scale. Moreover, it can be seen that the biplot of the original data and the standardized data is similar. This further solidify that the data is standardised, and transformation is not required to standardise the given data.

5. Principal component analysis on the original dataset:

```
Data.PCA <- prcomp(Data)
autoplot(Data.PCA, loadings = TRUE, loadings.label = TRUE, loadings.label.size = 3, col = "blue",
         main = "PCA (original data)")
```

PCA (original data)



```
summary(Data.PCA)
```

```
## Importance of components:
##              PC1      PC2      PC3      PC4      PC5      PC6      PC7
## Standard deviation  2.854  1.3087  0.5401  0.42852  0.2999  0.16059  0.06611
## Proportion of Variance 0.779  0.1638  0.0279  0.01756  0.0086  0.00247  0.00042
## Cumulative Proportion 0.779  0.9428  0.9707  0.98825  0.9969  0.99932  0.99974
##              PC8      PC9      PC10     PC11     PC12     PC13
## Standard deviation  0.04252  0.02679  0.01231  0.007842  0.004507  0.002125
## Proportion of Variance 0.00017  0.00007  0.00001  0.000010  0.000000  0.000000
## Cumulative Proportion 0.99991  0.99998  0.99999  1.000000  1.000000  1.000000
##              PC14     PC15     PC16     PC17     PC18
## Standard deviation  0.001039  0.0008103  0.000538  0.0003512  0.0002524
## Proportion of Variance 0.000000  0.0000000  0.000000  0.0000000  0.0000000
## Cumulative Proportion 1.000000  1.0000000  1.000000  1.0000000  1.0000000
##              PC19     PC20     PC21     PC22     PC23
## Standard deviation  0.0002044  0.0001516  0.0001084  6.661e-05  4.686e-05
## Proportion of Variance 0.0000000  0.0000000  0.0000000  0.000e+00  0.000e+00
## Cumulative Proportion 1.0000000  1.0000000  1.0000000  1.000e+00  1.000e+00
##              PC24     PC25     PC26     PC27     PC28
## Standard deviation  4.439e-05  3.435e-05  2.998e-05  2.035e-05  1.692e-05
## Proportion of Variance 0.000e+00  0.000e+00  0.000e+00  0.000e+00  0.000e+00
## Cumulative Proportion 1.000e+00  1.000e+00  1.000e+00  1.000e+00  1.000e+00
##              PC29     PC30     PC31     PC32     PC33
## Standard deviation  1.225e-05  1.09e-05  9.527e-06  8.849e-06  6.782e-06
```

```
## Proportion of Variance 0.000e+00 0.00e+00 0.000e+00 0.000e+00 0.000e+00
## Cumulative Proportion 1.000e+00 1.00e+00 1.000e+00 1.000e+00 1.000e+00
##          PC34      PC35      PC36      PC37      PC38
## Standard deviation  6.299e-06 5.631e-06 5.359e-06 5.166e-06 4.7e-06
## Proportion of Variance 0.000e+00 0.000e+00 0.000e+00 0.000e+00 0.0e+00
## Cumulative Proportion 1.000e+00 1.000e+00 1.000e+00 1.000e+00 1.0e+00
##          PC39      PC40      PC41      PC42      PC43
## Standard deviation  3.651e-06 3.185e-06 2.684e-06 2.158e-06 2.002e-06
## Proportion of Variance 0.000e+00 0.000e+00 0.000e+00 0.000e+00 0.000e+00
## Cumulative Proportion 1.000e+00 1.000e+00 1.000e+00 1.000e+00 1.000e+00
##          PC44      PC45      PC46      PC47      PC48
## Standard deviation  1.898e-06 1.265e-06 1.077e-06 8.829e-07 6.081e-07
## Proportion of Variance 0.000e+00 0.000e+00 0.000e+00 0.000e+00 0.000e+00
## Cumulative Proportion 1.000e+00 1.000e+00 1.000e+00 1.000e+00 1.000e+00
##          PC49      PC50      PC51
## Standard deviation  2.609e-07 2.272e-07 1.015e-07
## Proportion of Variance 0.000e+00 0.000e+00 0.000e+00
## Cumulative Proportion 1.000e+00 1.000e+00 1.000e+00
```

According to the summary, we should keep the first 3 principal components to explain 97.07% of the variance.

```
Data.PC <- Data.PCA$rotation
round(Data.PC[,1], digits = 3)
```

```
##      V1      V2      V3      V4      V5      V6      V7      V8      V9      V10     V11
## -0.269 -0.289 -0.265 -0.225 -0.189 -0.157 -0.129 -0.105 -0.084 -0.064 -0.046
##      V12     V13     V14     V15     V16     V17     V18     V19     V20     V21     V22
## -0.029 -0.012  0.004  0.020  0.036  0.050  0.064  0.077  0.088  0.099  0.109
##      V23     V24     V25     V26     V27     V28     V29     V30     V31     V32     V33
##  0.119  0.127  0.135  0.142  0.148  0.153  0.158  0.161  0.163  0.165  0.165
##      V34     V35     V36     V37     V38     V39     V40     V41     V42     V43     V44
##  0.165  0.163  0.161  0.159  0.156  0.152  0.148  0.144  0.139  0.134  0.129
##      V45     V46     V47     V48     V49     V50     V51
##  0.124  0.119  0.113  0.108  0.103  0.097  0.092
```

For PC1, the variable V21 to V51 (10-year to 25-year) dominates with the equal magnitude in the positive direction, and in the negative direction, V1 to V13 (overnight to 6-year) has the highest magnitude.

```
round(Data.PC[,2], digits = 3)
```

```
##      V1      V2      V3      V4      V5      V6      V7      V8      V9      V10     V11
## -0.047 -0.227 -0.305 -0.300 -0.279 -0.258 -0.237 -0.219 -0.202 -0.187 -0.174
##      V12     V13     V14     V15     V16     V17     V18     V19     V20     V21     V22
## -0.163 -0.153 -0.145 -0.137 -0.131 -0.125 -0.120 -0.116 -0.112 -0.108 -0.104
##      V23     V24     V25     V26     V27     V28     V29     V30     V31     V32     V33
## -0.101 -0.098 -0.095 -0.093 -0.090 -0.089 -0.087 -0.086 -0.086 -0.085 -0.085
##      V34     V35     V36     V37     V38     V39     V40     V41     V42     V43     V44
## -0.086 -0.086 -0.086 -0.087 -0.087 -0.088 -0.088 -0.088 -0.088 -0.088 -0.087
##      V45     V46     V47     V48     V49     V50     V51
## -0.087 -0.086 -0.085 -0.084 -0.083 -0.081 -0.080
```

For PC2, all the values are negative. This implies a negative effect on the yield.

```
round(Data.PC[,3], digits = 3)
```

```
##      V1      V2      V3      V4      V5      V6      V7      V8      V9      V10     V11
## -0.583 -0.373 -0.167 -0.041  0.038  0.086  0.116  0.133  0.144  0.150  0.153
##      V12     V13     V14     V15     V16     V17     V18     V19     V20     V21     V22
##  0.155  0.154  0.152  0.147  0.141  0.133  0.122  0.109  0.095  0.079  0.063
##      V23     V24     V25     V26     V27     V28     V29     V30     V31     V32     V33
##  0.047  0.031  0.015  0.001 -0.014 -0.027 -0.040 -0.051 -0.062 -0.072 -0.080
##      V34     V35     V36     V37     V38     V39     V40     V41     V42     V43     V44
## -0.088 -0.094 -0.100 -0.104 -0.107 -0.109 -0.110 -0.111 -0.110 -0.109 -0.107
##      V45     V46     V47     V48     V49     V50     V51
## -0.105 -0.102 -0.099 -0.096 -0.092 -0.088 -0.084
```

For PC3, the variable V1 (overnight) and V2 (6-month) dominates with the highest magnitude in the negative direction.

The PC1 explains roughly 77.9% of the variance, PC2 explains 16.38% of the variance, and PC3 explains 2.79% of the variance. In sum, the first 3 PC's explain 97.07% of the variance. As a consequence, the yield curve movements can be approximated linear combination of the first three loadings, with small relative error. In other words, a three or four factor model will do a very good job in fitting the time-series yield curve. By looking at the principal components, it can be seen that different maturities impact the yield in different extents. Therefore, there exists the changes in the yield over time.