# MNIST

## MNIST data prediction with PCA and SVM

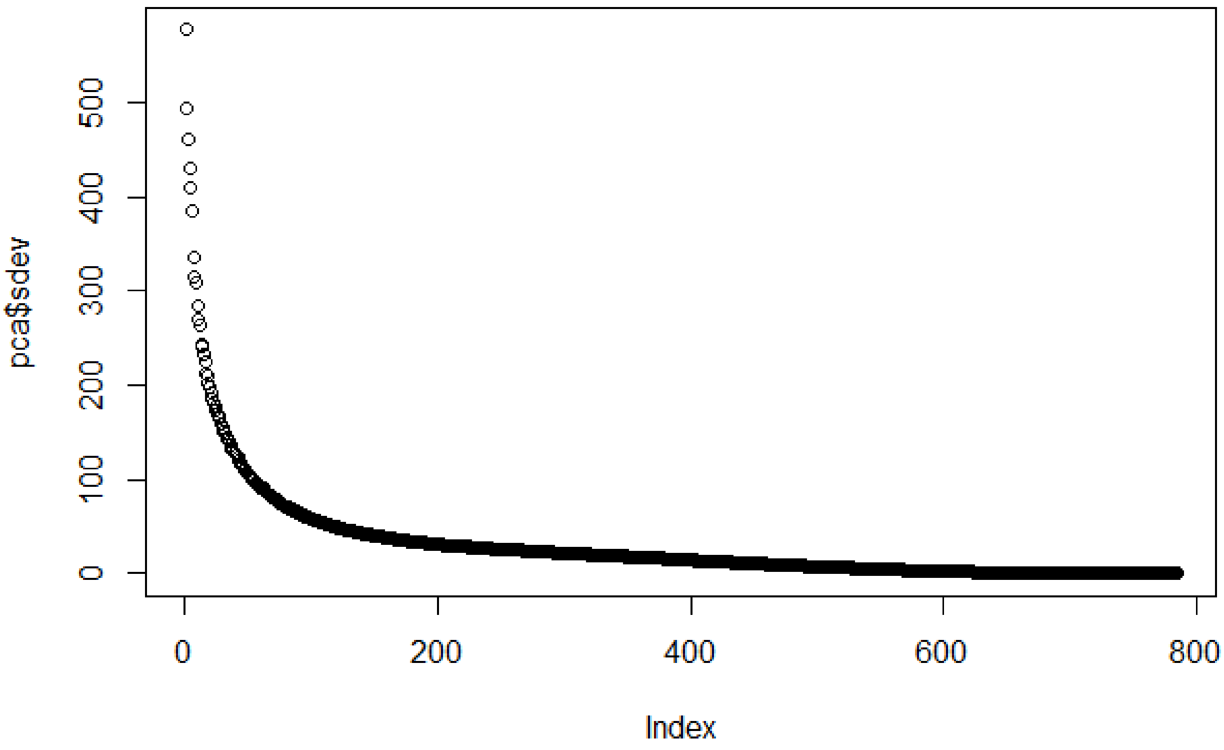
Load the data

```
mnist <- read_mnist()
```

Run PCA

```
pca <- prcomp(mnist$train$images)

plot(pca$sdev)
```

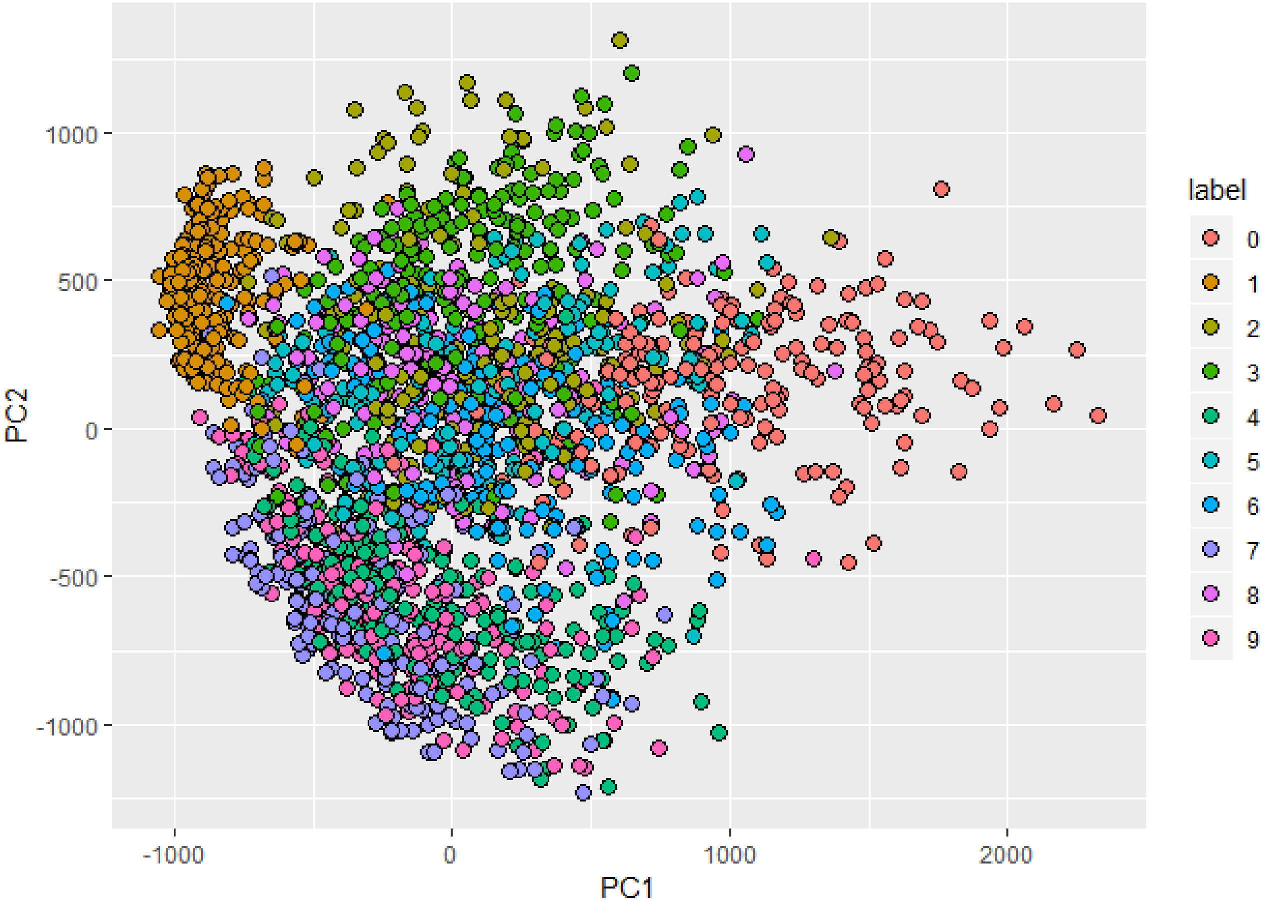


```
summary(pca)$importance[,1:5] %>% knitr::kable()
```

| | PC1 | PC2 | PC3 | PC4 | PC5 |
|---|---|---|---|---|---|
| Standard deviation | 576.82291 | 493.23822 | 459.89930 | 429.85624 | 408.56680 |
| Proportion of Variance | 0.09705 | 0.07096 | 0.06169 | 0.05389 | 0.04869 |
| Cumulative Proportion | 0.09705 | 0.16801 | 0.22970 | 0.28359 | 0.33228 |

Plot 2000 samples digits with PC1 and PC2

```
data.frame(PC1 = pca$x[,1], PC2 = pca$x[,2],
           label=factor(mnist$train$label)) %>%
  sample_n(2000) %>%
  ggplot(aes(PC1, PC2, fill=label))+
  geom_point(cex=3, pch=21)
```



Taking 36 principal components to analyse the data create train and test sets with x & y components

```
K <- 36
x_train <- pca$x[,1:K]
y <- factor(mnist$train$labels)

col_means <- colMeans(mnist$test$images)
x_test <- sweep(mnist$test$images, 2, col_means) %*% pca$rotation
x_test <- x_test[,1:K]
```

Model with Support vector machine algorithm

```
svm.linear <- ksvm(y~x_train, scale =FALSE, kernel="vanilladot")
```

```
##  Setting default kernel parameters
```

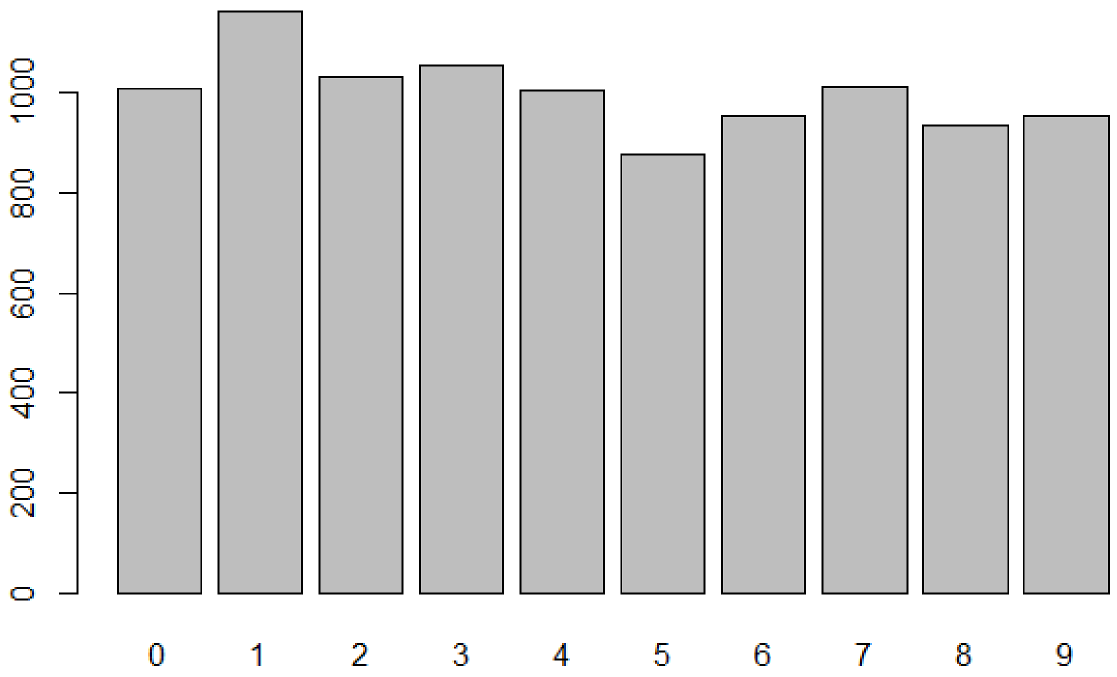
```
predict <- predict(svm.linear, x_test)
confusionMatrix(predict, factor(mnist$test$labels))
```

```
## Confusion Matrix and Statistics
## 
##           Reference
## Prediction    0    1    2    3    4    5    6    7    8    9
##          0  967    0    8    3    2   10    7    2    7    4
##          1    0 1123    6    2    0    5    3    9    5   10
##          2    2    1  951   13    5   11   10   26    8    4
##          3    2    2   13  938    0   53    2    5   26   15
##          4    0    0   10    1  933    6    7    8    6   33
##          5    5    3    6   22    3  783   12    0   34   11
##          6    2    1   11    1    5    8  916    0   10    1
##          7    1    0    9   11    4    2    1  958    3   25
##          8    1    5   18   15    2   11    0    4  869    9
##          9    0    0    0    4   28    3    0   16    6  897
## 
## Overall Statistics
## 
##                Accuracy : 0.9335
##                  95% CI : (0.9284, 0.9383)
##     No Information Rate : 0.1135
##     P-Value [Acc > NIR] : < 2.2e-16
## 
##                   Kappa : 0.9261
##  Mcnemar's Test P-Value : NA
```

```
## 
## Statistics by Class:
## 
##                      Class: 0 Class: 1 Class: 2 Class: 3 Class: 4 Class: 5
## Sensitivity            0.9867   0.9894   0.9215   0.9287   0.9501   0.8778
## Specificity            0.9952   0.9955   0.9911   0.9869   0.9921   0.9895
## Pos Pred Value         0.9574   0.9656   0.9224   0.8883   0.9293   0.8908
## Neg Pred Value         0.9986   0.9986   0.9910   0.9919   0.9946   0.9880
## Prevalence             0.0980   0.1135   0.1032   0.1010   0.0982   0.0892
## Detection Rate         0.0967   0.1123   0.0951   0.0938   0.0933   0.0783
## Detection Prevalence   0.1010   0.1163   0.1031   0.1056   0.1004   0.0879
## Balanced Accuracy      0.9910   0.9925   0.9563   0.9578   0.9711   0.9336
##                      Class: 6 Class: 7 Class: 8 Class: 9
## Sensitivity            0.9562   0.9319   0.8922   0.8890
## Specificity            0.9957   0.9938   0.9928   0.9937
## Pos Pred Value         0.9592   0.9448   0.9304   0.9403
## Neg Pred Value         0.9954   0.9922   0.9884   0.9876
## Prevalence             0.0958   0.1028   0.0974   0.1009
## Detection Rate         0.0916   0.0958   0.0869   0.0897
## Detection Prevalence   0.0955   0.1014   0.0934   0.0954
## Balanced Accuracy      0.9759   0.9628   0.9425   0.9413
```

## Plot the predictions

```
plot(predict)
```


0
200
400
600
800
1000
0
1
2
3
4
5
6
7
8
9