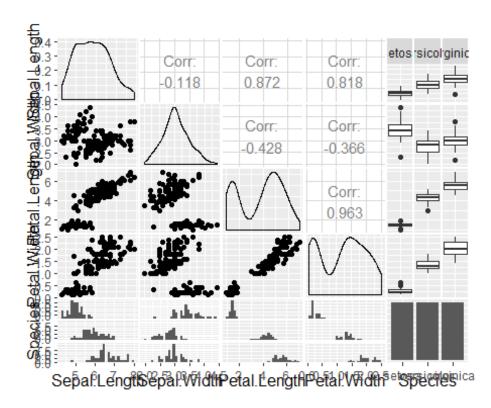
PCA

Pratik Gandhi

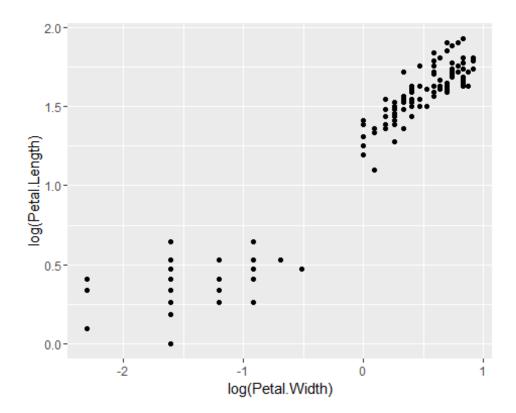
May 16, 2016

```
library(GGally)
## Warning: package 'GGally' was built under R version 3.2.5
library(ggplot2)
## Warning: package 'ggplot2' was built under R version 3.2.4
# Loading the data:
data("iris")
# Looking at first few observations of the dataset:
head(iris)
     Sepal.Length Sepal.Width Petal.Length Petal.Width Species
##
              5.1
## 1
                          3.5
                                       1.4
                                                   0.2 setosa
## 2
              4.9
                          3.0
                                       1.4
                                                   0.2 setosa
              4.7
## 3
                          3.2
                                       1.3
                                                   0.2 setosa
## 4
              4.6
                          3.1
                                       1.5
                                                   0.2 setosa
## 5
              5.0
                          3.6
                                       1.4
                                                   0.2 setosa
## 6
              5.4
                          3.9
                                                   0.4 setosa
                                       1.7
# Looking at the class type of all variables:
str(iris)
## 'data.frame':
                    150 obs. of 5 variables:
## $ Sepal.Length: num 5.1 4.9 4.7 4.6 5 5.4 4.6 5 4.4 4.9 ...
## $ Sepal.Width : num 3.5 3 3.2 3.1 3.6 3.9 3.4 3.4 2.9 3.1 ...
## $ Petal.Length: num 1.4 1.4 1.3 1.5 1.4 1.7 1.4 1.5 1.4 1.5 ...
## $ Petal.Width : num 0.2 0.2 0.2 0.2 0.4 0.3 0.2 0.2 0.1 ...
                  : Factor w/ 3 levels "setosa", "versicolor", ...: 1 1 1 1 1 1
## $ Species
1 1 1 1 ...
# Tabling them by Species:
table(iris$Species)
##
##
       setosa versicolor virginica
##
           50
                      50
                                 50
# Looking at the variables in pairs to look at the correlations:
ggpairs(iris)
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
## `stat bin()` using `bins = 30`. Pick better value with `binwidth`.
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



Looking at one of the pairs with highest correlation:
qplot(log(Petal.Width), log(Petal.Length), data = iris)

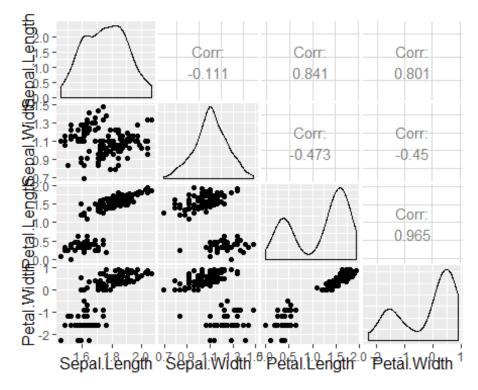


Calculating PCA step by step:

```
# Applying log to all the continuous variables:
log.iris <- log(iris [, 1:4])</pre>
head(log.iris)
##
     Sepal.Length Sepal.Width Petal.Length Petal.Width
## 1
         1.629241
                      1.252763
                                   0.3364722
                                              -1.6094379
## 2
         1.589235
                      1.098612
                                  0.3364722
                                              -1.6094379
                                  0.2623643 -1.6094379
## 3
         1.547563
                      1.163151
## 4
         1.526056
                      1.131402
                                  0.4054651
                                              -1.6094379
## 5
         1.609438
                      1.280934
                                   0.3364722
                                              -1.6094379
## 6
         1.686399
                      1.360977
                                   0.5306283
                                              -0.9162907
# Storing the discrete variable in another one:
iris.species <- iris [,5]</pre>
iris.species
##
     [1] setosa
                                setosa
                                            setosa
                                                        setosa
                     setosa
                                                                    setosa
##
     [7] setosa
                     setosa
                                setosa
                                            setosa
                                                        setosa
                                                                    setosa
##
    [13] setosa
                     setosa
                                setosa
                                            setosa
                                                        setosa
                                                                    setosa
##
    [19] setosa
                     setosa
                                setosa
                                            setosa
                                                        setosa
                                                                    setosa
##
    [25] setosa
                     setosa
                                setosa
                                            setosa
                                                        setosa
                                                                    setosa
##
    [31] setosa
                     setosa
                                setosa
                                            setosa
                                                        setosa
                                                                    setosa
    [37] setosa
##
                     setosa
                                setosa
                                            setosa
                                                        setosa
                                                                   setosa
##
    [43] setosa
                     setosa
                                setosa
                                            setosa
                                                        setosa
                                                                    setosa
##
    [49] setosa
                                versicolor versicolor versicolor
                     setosa
```

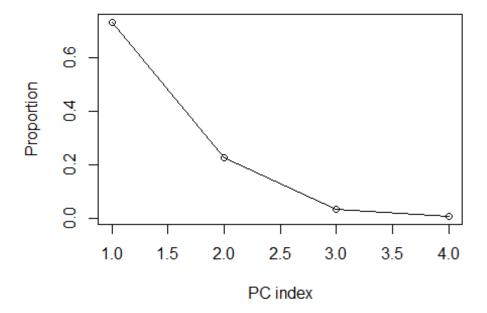
```
[55] versicolor versicolor versicolor versicolor versicolor
   [61] versicolor versicolor versicolor versicolor versicolor
##
   [67] versicolor versicolor versicolor versicolor versicolor
##
   [73] versicolor versicolor versicolor versicolor versicolor
##
   [79] versicolor versicolor versicolor versicolor versicolor
##
   [85] versicolor versicolor versicolor versicolor versicolor
##
   [91] versicolor versicolor versicolor versicolor versicolor
   [97] versicolor versicolor versicolor virginica virginica
## [103] virginica virginica virginica virginica virginica
                                                         virginica
## [109] virginica virginica virginica
                                     virginica virginica
                                                         virginica
## [115] virginica virginica virginica virginica virginica
                                                         virginica
## [121] virginica virginica virginica virginica virginica
                                                         virginica
## [127] virginica virginica virginica virginica virginica
                                                         virginica
## [133] virginica virginica virginica virginica virginica virginica
## [139] virginica virginica virginica
                                     virginica virginica
                                                         virginica
                                     virginica virginica virginica
## [145] virginica virginica virginica
## Levels: setosa versicolor virginica
```

#pairs(log.iris) ggpairs(log.iris)



```
# Scaling the continuous variables:
log.iris.scaled <- scale(log.iris, center = TRUE, scale = TRUE)
## Here scale = (log.iris - colMeans(log.iris)) / apply(log.iris, 2, sd)
## In other words : (log.iris - mu) / sd</pre>
```

```
# Performing SVD on our matrix:
log.iris.svd <- svd (log.iris.scaled)</pre>
names(log.iris.svd)
## [1] "d" "u" "v"
# SVD is performed to find the eigenvalues and eigenvectors of any data. We
get three matrices when we run SVD.
# U represents the left singular vectors
# V represents the right singular vectors - Eigen Vectors
# D represents the diagonal vectors
U <- log.iris.svd$u
V <- log.iris.svd$v # PC Loadings</pre>
D <- log.iris.svd$d # Strength of each component
# Multiplication of Scaled Data with the loadings:
# Final Data (PCs) = RowFeatureVector (V) x RowZeroMeanData (log.iris.scaled)
Z <- log.iris.scaled %*% V # This are our PCs</pre>
head(Z)
##
             [,1]
                        [2,]
                                     [,3]
                                                  [,4]
## [1,] -2.406639 -0.3969554 0.19396467 0.004779476
## [2,] -2.223539 0.6901804 0.35000151 0.048868378
## [3,] -2.581105 0.4275418 0.01889761 0.049909545
## [4,] -2.450869 0.6860074 -0.06874595 -0.149646465
## [5,] -2.536853 -0.5082516 0.02932259 -0.040048202
## [6,] -1.841495 -1.2899381 -0.25276831 0.163890597
## We have changed our original data in terms of the eigenvectors. This will
reorient the data in the direction where the data is having maximum variance.
## Variance explained by each PC:
var.exp \leftarrow D^2 / sum(D^2)
var.exp
## [1] 0.73312837 0.22675677 0.03325206 0.00686280
## Cummulative Sum of the Variation Explained:
cum.var.exp <- cumsum(var.exp)</pre>
# Plotting the PCs for both with and without Cummulative Sum:
plot(var.exp, xlab = "PC index", ylab = "Proportion")
lines(var.exp)
```



plot(cum.var.exp, xlab = "PC index", ylab = "Cummulative Proportion")
lines(cum.var.exp)

