Quick Start with **Rdimtools** Package

Kisung You

In this vignette, we will demonstrate basic functionalities of **Rdimtools** package by walking through from installation to analysis with the famous *iris* dataset.

1. Install and Load

Rdimtools can be installed in two handy options. A release version from CRAN can be installed

```
install.packages("Rdimtools")
```

or a development version is available from GitHub with `devtools` package.

```
## install.packages("devtools")
devtools::install_github("kyoustat/Rdimtools")
```

Now we are ready to go by loading the library.

```
library(Rdimtools)
```

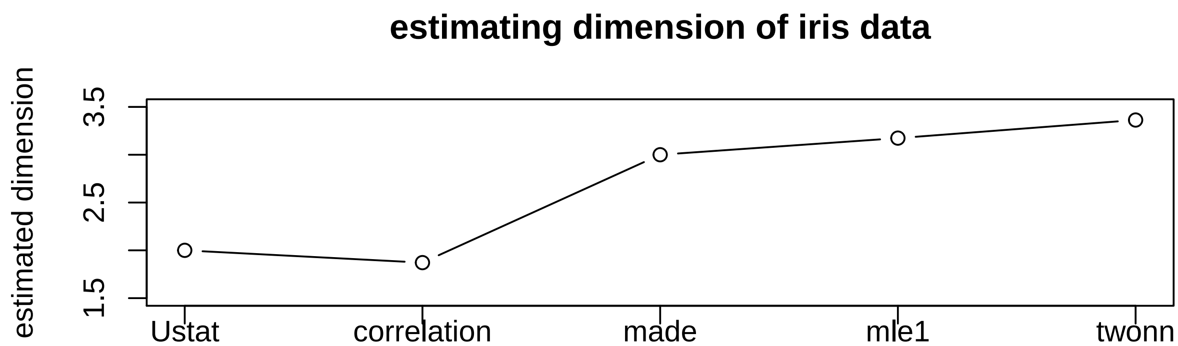
2. Dimension Estimation

As of version 0.1.2, there are 17 intrinsic dimension estimation (IDE) algorithms. In the following example, we will only show 5 methods' performance.

```
# load the iris data
X   = as.matrix(iris[,1:4])
lab = as.factor(iris[,5])

# we will compare 5 methods (out of 17 methods from version 1.0.0)
vecd = rep(0,5)
vecd[1] = est.Ustat(X)$estdim       # convergence rate of U-statistic on manifold
vecd[2] = est.correlation(X)$estdim # correlation dimension
vecd[3] = est.made(X)$estdim        # manifold-adaptive dimension estimation
vecd[4] = est.mle1(X)$estdim        # MLE with Poisson process
vecd[5] = est.twonn(X)$estdim       # minimal neighborhood information

# let's visualize
plot(1:5, vecd, type="b", ylim=c(1.5,3.5),
     main="estimating dimension of iris data",
     xaxt="n",xlab="",ylab="estimated dimension")
xtick = seq(1,5,by=1)
axis(side=1, at=xtick, labels = FALSE)
text(x=xtick,  par("usr")[3],
     labels = c("Ustat","correlation","made","mle1","twonn"), pos=1, xpd = TRUE)
```



As the true dimension is not known for a given dataset, different methods bring about heterogeneous estimates. That's why we deliver 17 methods at an unprecedented scale to provide a broader basis for your decision.

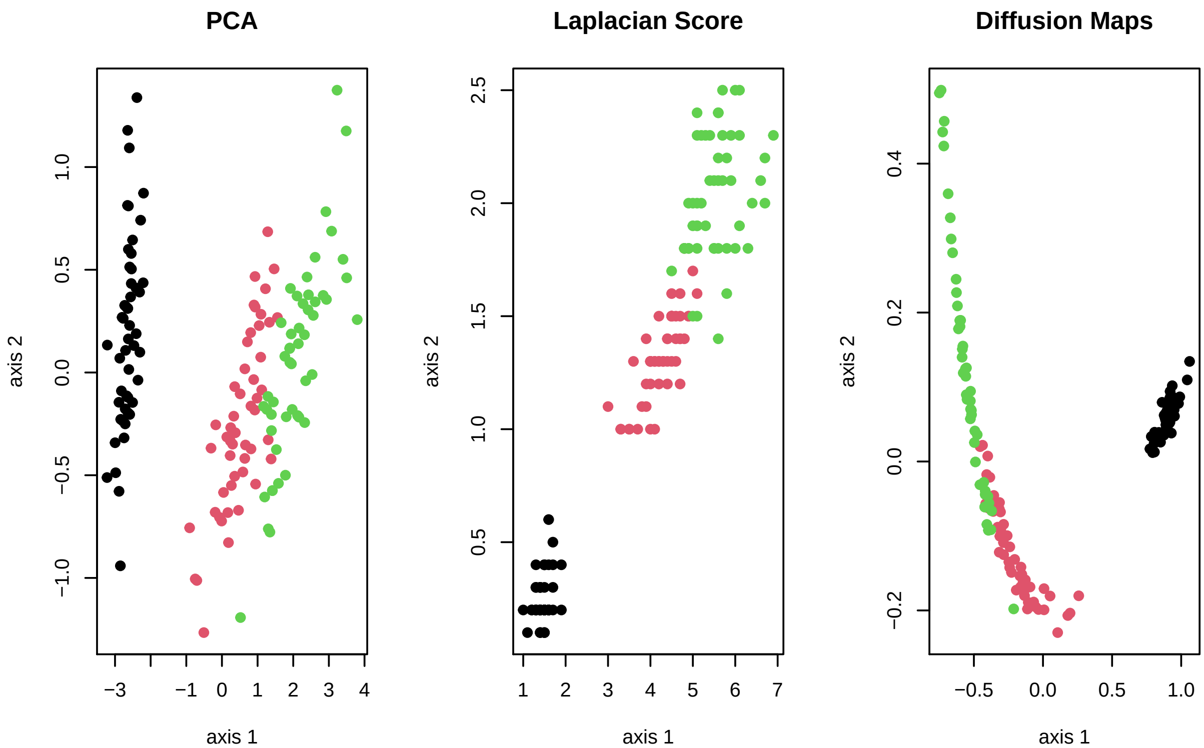
3. Dimension Reduction

In this section, we compare Principal Component Analysis (`do.pca`), Laplacian Score (`do.lscore`), and Diffusion Maps (`do.dm`) are compared, each from a family of algorithms for linear reduction, feature extraction, and nonlinear reduction.

```
# run 3 algorithms mentioned above
mypca = do.pca(X, ndim=2)
mylap = do.lscore(X, ndim=2)
mydfm = do.dm(X, ndim=2, bandwidth=10)

# extract embeddings from each method
Y1 = mypca$Y
Y2 = mylap$Y
Y3 = mydfm$Y

# visualize
par(mfrow=c(1,3))
plot(Y1, pch=19, col=lab, xlab="axis 1", ylab="axis 2", main="PCA")
plot(Y2, pch=19, col=lab, xlab="axis 1", ylab="axis 2", main="Laplacian Score")
plot(Y3, pch=19, col=lab, xlab="axis 1", ylab="axis 2", main="Diffusion Maps")
```



As the figure above shows, in general, different algorithms show heterogeneous nature of the data. We hope **Rdimtools**, with 133 dimension reduction methods as of version 0.1.2, be a valuable toolset to help practitioners and scientists discover many facets of the data.