# Nonlinear Scaling Normalization with NNS

#### **Install NNS**

We need the latest version of NNS available on GitHub.

```
require(devtools); install_github('OVVO-Financial/NNS',ref = "NNS-Beta-Version")
require(NNS)
```

# Nonlinear Scaling Normalization

NNS nonlinear scaling normalization involves using the degree of nonlinearity between variables to then transform the values to a shared range.

NNS's technique is different than linear scaling where all variables are assumed to have a perfect linear relationship (and by extension wind up with the same mean); and different than standardization  $(\frac{(x-\mu)}{\sigma})$  which does not consider variable relationships.

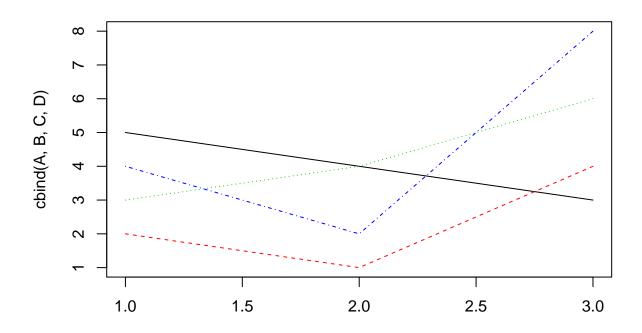
NNS is also different than quantile normalization, which as we'll show is not robust to different original scale values in multivariate problems.

# Examples

A multivariate example of each technique will highlight the differences.

We will use the quintessential quantile normalization example on Wikipedia as well as a more intricate financial variable example.

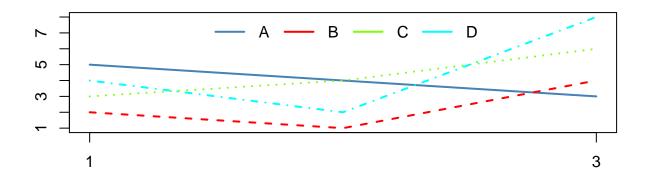
```
A=c(5,4,3);B=c(2,1,4);C=c(3,4,6);D=c(4,2,8)
matplot(cbind(A,B,C,D),type = 'l')
```

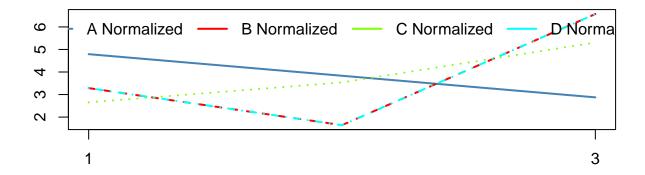


# **Linear Scaling**

NNS offers a linear scaling option which essentially sets the correlation between variables to 1.

lin.norm.variables=NNS.norm(cbind(A,B,C,D),chart.type='l',Linear=T)





A quick check verifies all of the means are equal for the linear scaling technique:

0.9583333 2.509506 1.351272 2.509506

```
t(lin.norm.variables)
```

```
## [,1] [,2] [,3]
## A 4.791667 3.833333 2.875000
## B 3.285714 1.642857 6.571429
## C 2.653846 3.538462 5.307692
## D 3.285714 1.642857 6.571429

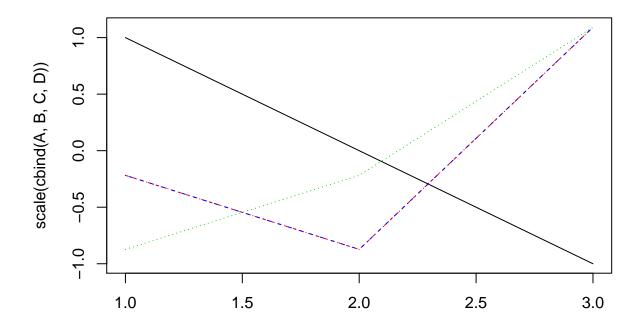
apply(lin.norm.variables,2,function(x) c(mean=mean(x),sd=sd(x)))

## A B C D
## mean 3.8333333 3.833333 3.833333 3.833333
```

### **Stadard Standarization**

Variables after going through a standard standardization technique will have a zero mean and unit variance. The following demonstrates the results.

```
matplot(scale(cbind(A,B,C,D)),type = 'l')
```



Means=0; variances=1...

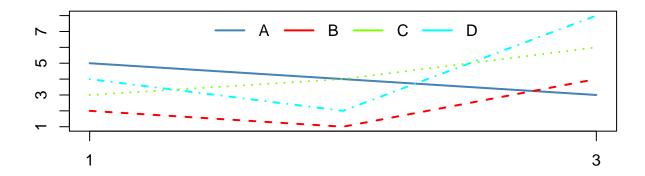
```
apply(scale(cbind(A,B,C,D)),2,function(x) c(mean=mean(x),sd=sd(x)))
```

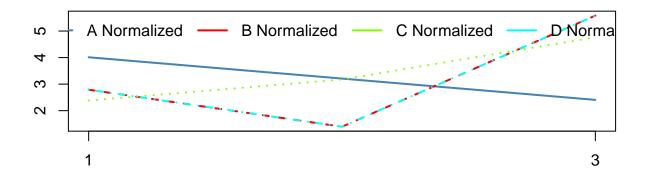
```
## mean 0 -7.401487e-17 2.035409e-16 -7.401487e-17 ## sd 1 1.000000e+00 1.000000e+00 1.000000e+00
```

# NNS Nonlinear Scaling

We can now compare the noninear scaling normalization technique.

```
nonlin.norm.variables=NNS.norm(cbind(A,B,C,D),chart.type='l',Linear=F)
```





And we note the difference in means along with the smaller standard deviation for each transformed variable versus the other methods.

#### t(nonlin.norm.variables)

```
## [,1] [,2] [,3]
## A 4.011820 3.209456 2.407092
## B 2.790724 1.395362 5.581447
## C 2.381756 3.175674 4.763511
## D 2.790724 1.395362 5.581447

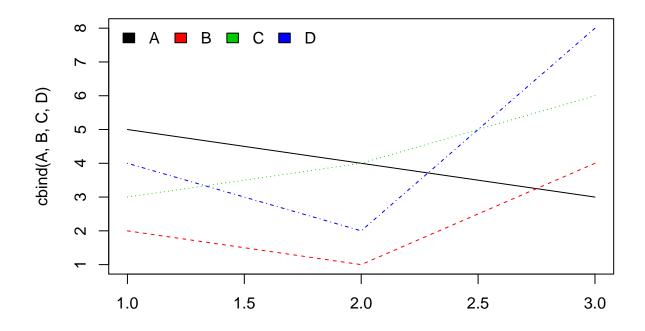
apply(nonlin.norm.variables,2,function(x) c(mean=mean(x),sd=sd(x)))

## A B C D
## mean 3.209456 3.255844 3.440314 3.255844
## sd 0.802364 2.131450 1.212731 2.131450
```

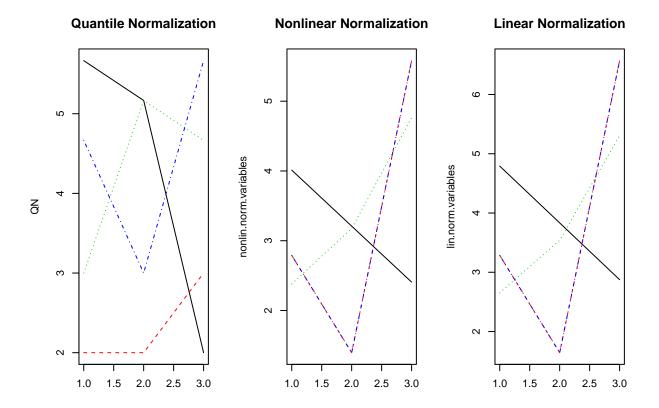
### Quantile Normalization

Quantile normalization is a technique for making two or more distributions identical in statistical properties. This is the antithesis of NNS.norm as we seek to retain the uniqueness of each distribution while creating a shared range of observations.

```
#install if necessary
#install.packages("BiocInstaller",
# repos="http://bioconductor.org/packages/3.4/bioc")
require(BiocInstaller)
## Loading required package: BiocInstaller
## Bioconductor version 3.4 (BiocInstaller 1.24.0), ?biocLite for help
#if necessary...
#biocLite('preprocessCore')
require(preprocessCore)
## Loading required package: preprocessCore
#the function expects a matrix
#create a matrix using the same example
mat \leftarrow matrix(c(5,2,3,4,4,1,4,2,3,4,6,8),
\#mat \leftarrow matrix(c(20,1,5,13,19,2,6,12,17,3,8,10),
             ncol=3)
row.names(mat)=c("A","B","C","D")
mat
##
     [,1] [,2] [,3]
## A
        5
            4
                  3
## B
        2
                  4
             1
## C
        3
             4
                  6
qn.mat=apply(normalize.quantiles(mat),1,function(x) c(mean=mean(x),sd=sd(x)))
colnames(qn.mat)=c("A","B","C","D")
QN=normalize.quantiles(mat)
Comparing all methods with the original dataset yields:
### Rotate matrix for plotting as QN is row based variables
QN=t(QN[1:nrow(QN),])
#Plot
matplot(cbind(A,B,C,D),type = '1')
legend('topleft',legend=c("A","B","C","D"),col = seq_len(4),fill=seq_len(4),horiz = T,bty='n')
```



```
par(mfrow=c(1,3))
matplot(QN,type = 'l')
title(main = "Quantile Normalization")
matplot(nonlin.norm.variables,type = 'l')
title(main = "Nonlinear Normalization")
matplot(lin.norm.variables,type = 'l')
title(main = "Linear Normalization")
```



### Financial Series Example

Let's load some financial variables that have overlapping prices...

```
require(quantmod)
getSymbols(c("SPY","GLD","TLT","FXE"),src='yahoo')

## [1] "SPY" "GLD" "TLT" "FXE"

SPY<- Ad(to.monthly(SPY))
GLD<- Ad(to.monthly(GLD))
TLT<- Ad(to.monthly(TLT))
FXE<- Ad(to.monthly(FXE))

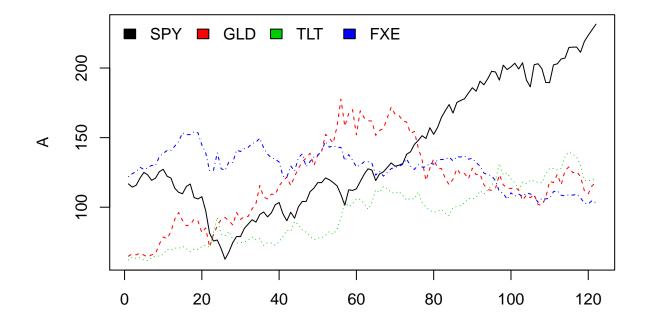
A<- as.matrix(cbind(SPY,GLD,TLT,FXE))
A<- A[complete.cases(A),]

# Rotate matrix to variables by row for QN
qn.mat=t(A[1:nrow(A),])
QN=normalize.quantiles(qn.mat)
nonlin.norm.variables=NNS.norm(A,Linear = F)
lin.norm.variables=NNS.norm(A,Linear = T)</pre>
```

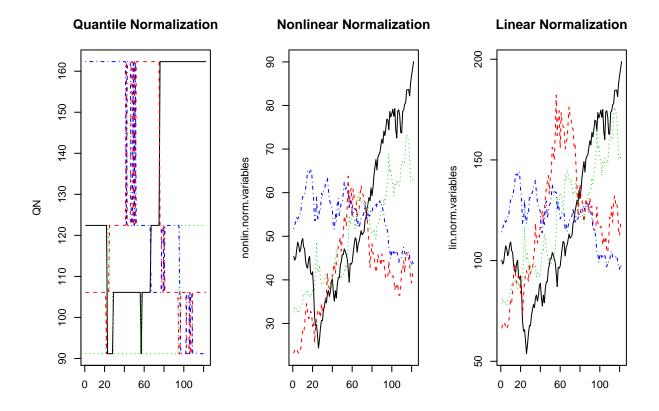
Comparing all methods with the original dataset yields:

```
#Rotate QN results so matplot can use columns
QN=t(QN[1:nrow(QN),])

#Plot
matplot(A,type = '1')
legend('topleft',legend=c("SPY","GLD","TLT","FXE"),col = seq_len(ncol(A)),fill=seq_len(ncol(A)),horiz =
```



```
par(mfrow=c(1,3))
matplot(QN,type = 'l')
title(main = "Quantile Normalization")
matplot(nonlin.norm.variables,type = 'l')
title(main = "Nonlinear Normalization")
matplot(lin.norm.variables,type = 'l')
title(main = "Linear Normalization")
```



Note the tighter overall range for NNS.norm.

### Non-overlapping variables

When the variables do not share any ranges of observations, quantile normalization merely reports the mean value for that variable.

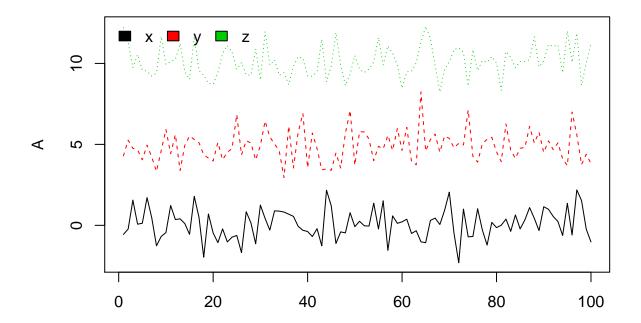
```
set.seed(123)
x=rnorm(100);y=rnorm(100)+5;z=rnorm(100)+10
A=as.matrix(cbind(x,y,z))
nonlin.norm.variables=NNS.norm(A,Linear = F)
lin.norm.variables=NNS.norm(A,Linear = T)

# Rotate matrix to variables by row for QN
qn.mat=t(A[1:nrow(A),])
QN=normalize.quantiles(qn.mat)
```

Quantiles have a problem...

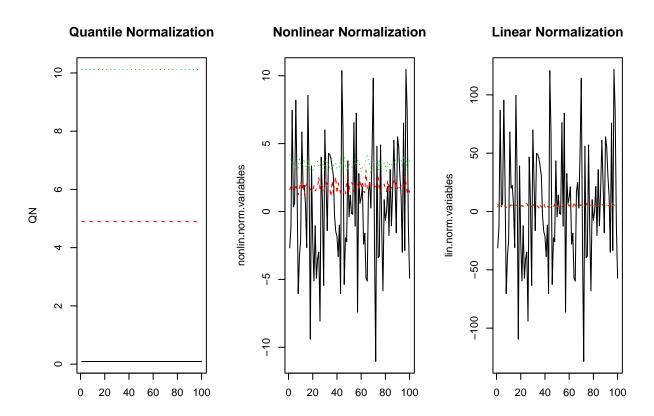
```
#Rotate QN results so matplot can use columns
QN=t(QN[1:nrow(QN),])

#Plot
matplot(A,type = 'l')
legend('topleft',legend=colnames(A),col = seq_len(ncol(A)),fill=seq_len(ncol(A)),horiz = T,bty='n')
```



```
par(mfrow=c(1,3))
matplot(QN,type = 'l')
title(main = "Quantile Normalization")
matplot(nonlin.norm.variables,type = 'l')
```

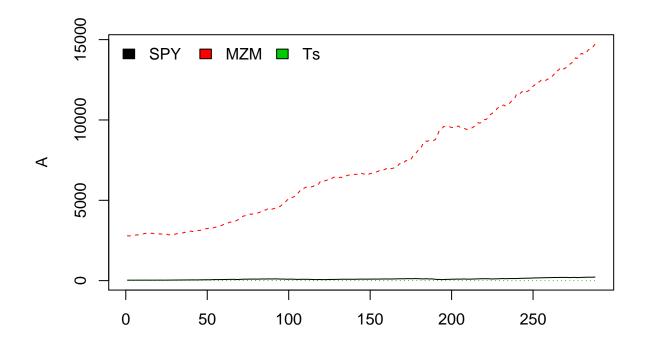
```
title(main = "Nonlinear Normalization")
matplot(lin.norm.variables,type = 'l')
title(main = "Linear Normalization")
```



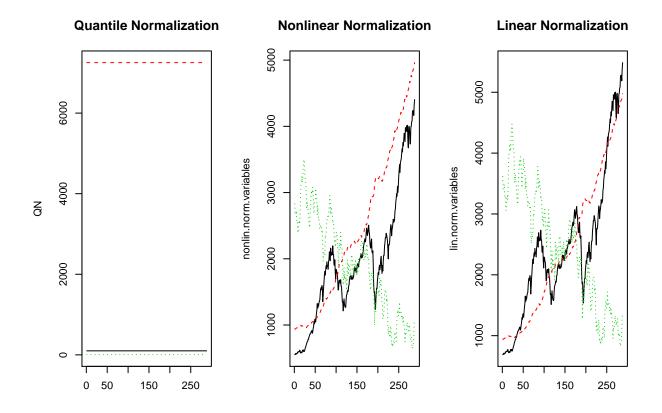
### Orders of Magnitude Reduced

We can successfully remove orders of magnitude differences between variables. Here is a financial example using money supply (MZM) measured in billions of dollars, the S&P 500 (SPY) closing prices measured in points and US 10-year Treasury yields (Ts) measured in percentage points.

```
getSymbols("SPY",src='yahoo',from="1965-01-01")
getSymbols(c("MZMNS","DGS10"),src='FRED',from="1965-01-01")
SPY<- Ad(to.monthly(SPY['1962::']))
MZM<- MZMNS['1962::']
Ts<- Cl(to.monthly(DGS10['1962::']))
## Warning in to.period(x, "months", indexAt = indexAt, name = name, ...):
## missing values removed from data
A=as.matrix(cbind(SPY,MZM,Ts))
A<- A[complete.cases(A),]
# Rotate matrix to variables by row for QN
qn.mat=t(A[1:nrow(A),])
nonlin.norm.variables=NNS.norm(A,Linear = F)
lin.norm.variables=NNS.norm(A,Linear = T)
QN=normalize.quantiles(qn.mat)
#Rotate QN results so matplot can use columns
QN=t(QN[1:nrow(QN),])
#Plot
matplot(A, type = '1')
legend('topleft',legend=c("SPY","MZM","Ts"),col = seq_len(ncol(A)),fill=seq_len(ncol(A)),horiz = T,bty=
```



```
par(mfrow=c(1,3))
matplot(QN,type = 'l')
title(main = "Quantile Normalization")
matplot(nonlin.norm.variables,type = 'l')
title(main = "Nonlinear Normalization")
matplot(lin.norm.variables,type = 'l')
title(main = "Linear Normalization")
```



# **Practical Applications**

Normalization eliminates the need for multiple y-axis charts and prohibits the misuse thereof. Furthermore, placing variables on the same axes with shared ranges permits a more relevant conditional probability analysis, which along with time normalization is used in the NNS.caus routine for identifying causal relationships between variables.

To learn more about NNS statistics and their theoretical foundations, see "Nonlinear Nonparametric Statistics: Using Partial Moments" available on Amazon: http://a.co/5bpHvUg

Check back to see more NNS examples posted on GitHub:

https://github.com/OVVO-Financial/NNS/tree/NNS-Beta-Version/examples