## LSTM Autoencoder (encode-decode)

This example demonstrates the use of an LSTM-based Autoencoder to encode windows of a time series (p -> k) and reconstruct them (k -> p). This allows evaluation of reconstruction quality.

Prerequisites - Python with PyTorch accessible via reticulate - R packages: daltoolbox, tspredit, daltoolboxdp, ggplot2

# Installing example dependencies (if needed)  
#install.packages("tspredit")  
#install.packages("daltoolboxdp")

# Loading required packages  
library(daltoolbox)  
library(tspredit)  
library(daltoolboxdp)  
library(ggplot2)

# Example dataset (series -> windows)  
data(tsd)  
  
sw\_size <- 5 # sliding window size (p)  
ts <- ts\_data(tsd$y, sw\_size) # convert series into windows with p columns  
  
ts\_head(ts)

## t4 t3 t2 t1 t0  
## [1,] 0.0000000 0.2474040 0.4794255 0.6816388 0.8414710  
## [2,] 0.2474040 0.4794255 0.6816388 0.8414710 0.9489846  
## [3,] 0.4794255 0.6816388 0.8414710 0.9489846 0.9974950  
## [4,] 0.6816388 0.8414710 0.9489846 0.9974950 0.9839859  
## [5,] 0.8414710 0.9489846 0.9974950 0.9839859 0.9092974  
## [6,] 0.9489846 0.9974950 0.9839859 0.9092974 0.7780732

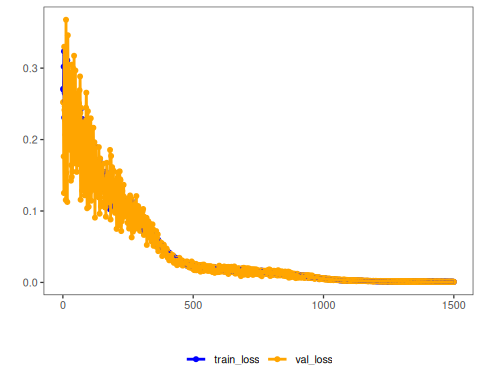
# Normalization (min-max by group)  
preproc <- ts\_norm\_gminmax()  
preproc <- fit(preproc, ts)  
ts <- transform(preproc, ts)  
  
ts\_head(ts)

## t4 t3 t2 t1 t0  
## [1,] 0.5004502 0.6243512 0.7405486 0.8418178 0.9218625  
## [2,] 0.6243512 0.7405486 0.8418178 0.9218625 0.9757058  
## [3,] 0.7405486 0.8418178 0.9218625 0.9757058 1.0000000  
## [4,] 0.8418178 0.9218625 0.9757058 1.0000000 0.9932346  
## [5,] 0.9218625 0.9757058 1.0000000 0.9932346 0.9558303  
## [6,] 0.9757058 1.0000000 0.9932346 0.9558303 0.8901126

# Train/test split  
samp <- ts\_sample(ts, test\_size = 10)  
train <- as.data.frame(samp$train)  
test <- as.data.frame(samp$test)

# Creating the LSTM autoencoder (encode-decode): 5 -> 3 -> 5 dimensions  
auto <- autoenc\_lstm\_ed(5, 3, num\_epochs = 1500)  
  
# Training the model  
auto <- fit(auto, train)

# Learning curves (train and validation loss per epoch)  
fit\_loss <- data.frame(  
 x = 1:length(auto$train\_loss),  
 train\_loss = auto$train\_loss,  
 val\_loss = auto$val\_loss  
)  
grf <- plot\_series(fit\_loss, colors = c('Blue', 'Orange'))  
plot(grf)



# Testing the autoencoder (reconstruction)  
# Show samples from the test set and the reconstruction (p columns)  
print(head(test))

## t4 t3 t2 t1 t0  
## 1 0.7258342 0.8294719 0.9126527 0.9702046 0.9985496  
## 2 0.8294719 0.9126527 0.9702046 0.9985496 0.9959251  
## 3 0.9126527 0.9702046 0.9985496 0.9959251 0.9624944  
## 4 0.9702046 0.9985496 0.9959251 0.9624944 0.9003360  
## 5 0.9985496 0.9959251 0.9624944 0.9003360 0.8133146  
## 6 0.9959251 0.9624944 0.9003360 0.8133146 0.7068409

result <- transform(auto, test)  
print(head(result))

## , , 1  
##   
## [,1]  
## [1,] 0.7378564  
## [2,] 0.8126957  
## [3,] 0.8700990  
## [4,] 0.9178955  
## [5,] 0.9581465  
## [6,] 0.9851200  
##   
## , , 2  
##   
## [,1]  
## [1,] 0.8634287  
## [2,] 0.9248940  
## [3,] 0.9594452  
## [4,] 0.9696572  
## [5,] 0.9553219  
## [6,] 0.9182859  
##   
## , , 3  
##   
## [,1]  
## [1,] 0.8978821  
## [2,] 0.9537579  
## [3,] 0.9818469  
## [4,] 0.9840649  
## [5,] 0.9600952  
## [6,] 0.9125356  
##   
## , , 4  
##   
## [,1]  
## [1,] 0.9661838  
## [2,] 0.9932855  
## [3,] 0.9918596  
## [4,] 0.9603509  
## [5,] 0.8976762  
## [6,] 0.8100237  
##   
## , , 5  
##   
## [,1]  
## [1,] 0.9945794  
## [2,] 0.9974468  
## [3,] 0.9715176  
## [4,] 0.9116393  
## [5,] 0.8156420  
## [6,] 0.6936240

# Reconstruction metrics per column: R2 and MAPE  
result <- as.data.frame(result)  
names(result) <- names(test)  
r2 <- c()  
mape <- c()  
for (col in names(test)){  
 r2\_col <- cor(test[col], result[col])^2  
 r2 <- append(r2, r2\_col)  
 mape\_col <- mean((abs((result[col] - test[col]))/test[col])[[col]])  
 mape <- append(mape, mape\_col)  
 print(paste(col, 'R2 test:', r2\_col, 'MAPE:', mape\_col))  
}

## [1] "t4 R2 test: 0.882281864100065 MAPE: 0.0353451365638885"  
## [1] "t3 R2 test: 0.967500316470969 MAPE: 0.0299000380813798"  
## [1] "t2 R2 test: 0.993576852261311 MAPE: 0.0465268674785365"  
## [1] "t1 R2 test: 0.999709995761421 MAPE: 0.0108679011522705"  
## [1] "t0 R2 test: 0.999277328331433 MAPE: 0.024465579264592"

print(paste('Means R2 test:', mean(r2), 'MAPE:', mean(mape)))

## [1] "Means R2 test: 0.96846927138504 MAPE: 0.0294211045081334"

### Method

An LSTM encoder summarizes each window into a compact state that a decoder uses to reconstruct the original sequence. Training minimizes reconstruction loss, encouraging the latent state to retain information about temporal dynamics in the window.

### References

* Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. Neural Computation, 9(8), 1735–1780.