

Math6373 Homework 3

An application of MLP AutoEncoders

1 Prediction Task :

Select 50 major companies $Comp_1 \dots Comp_{50}$ on the US stockmarket

We consider $Comp_{50}$ as a "target" company

On each day "t" we want to *predict* the future stock price of our target on day (t+1) given the past evolution of our 50 stocks observed up to time "t"

2 Data Set

Denote TIMPER the time period 2014-2015-2016-2017

Let $t=1, 2, \dots, N$ be the days on which the US stock exchange was open during TIMPER

you will have N roughly in the range 1005- 1010

For day "t", let $S_j(t)$ be the stock price of company $Comp_j$ (at closing time)

On each day "t", we want to predict the unknown target stock price $S_{50}(t+1)$ given the evolution of our 50 stock prices over the last 5 days up to day "t", with day "t" included.

Download the 50 time series $S_1 \dots S_{50}$ (which have the same length N)

2 PreProcessing of time series

Replace *isolated* missing values $S_j(t)$ by the mean of two actual values closest to time t


If there are too many missing values in S_j , discard the stock $Comp_j$ and download another stock

Compute the moving mean of each series $avS_j(t) = [S_j(1) + \dots + S_j(t)] / t$

Normalize each series $S_j(t)$ by $Y_j(t) = S_j(t) / avS_j(t)$

We now only use the time series $Y_1 \dots Y_{50}$

3 Create Training and Test sets for an MLP predictor :

On each day $t \geq 10$ 

the *recent past* of the series Y_j will be the 1×5 line vector $[Y_j(t-4) \ Y_j(t-3) \ Y_j(t-2) \ Y_j(t-1) \ Y_j(t)]$

the *recent past* of our 50 time series $Y_1 \dots Y_{50}$ will be recorded by a 50×5 matrix M_t

each row "j" of M_t will be the line vector $[Y_j(t-4) \ Y_j(t-3) \ Y_j(t-2) \ Y_j(t-1) \ Y_j(t)]$

The $50 \times 5 = 250$ coefficients of M_t can be "flattened" into a long 1×250 line vector X_t

for $5 \leq t \leq N-1$ the vectors X_t will be the original *input vectors*

the MLP predictor to be trained later on (see question 5 below) will have the X_t as inputs, and a *single* output neuron with state Z_t .

Z_t will be the MLP prediction of the *target* $TARG_t = S_{50}(t+1)$, which is not known at time t .

Now construct a data set of $(N-5)$ "cases" for the prediction task :

Case₁₀ Case₁₁ Case₁₂ ... Case_{N-1}, indexed by $t = 5, 6, 7, \dots, N-1$

each Case_t is described by 250 features = 250 coordinates of vector X_t

for Case t , the TRUE output to be predicted at time t is the yet unknown $TARG_t = S_{50}(t+1)$

Define the data set of $(N-5)$ cases for prediction learning by

$PredCases = \{ \text{all pairs } (X_t, TARG_t) \text{ with } t = 5, 6, 7, \dots, N-1 \}$

Randomly Split the set $PredCases$ with proportions (90%,10%)

90% for the training set $PredTRAIN$, and 10 % for the test set $PredTEST$

4 AutoEncoder to compress the input vectors X_t

Consider an MLP Auto Encoder with architecture

INPUT ==> HiddenLayer H ==> OUTPUT

where $\dim(\text{INPUT}) = \dim(\text{OUTPUT}) = 250$

$\dim(H) = h < 250$

Ideally for each input X_t we want the autoencoder to compute an output Y_t very close to X_t .

First step will be to compute a reasonable value for h , as follows

4.1 Compute a plausible dimension h for H

Implement PCA on the set of all input vectors X_t , with $t = 10, 11, \dots, N$

Plot the 250 eigenvalues $\lambda_1 > \lambda_2 > \dots > \lambda_{250}$ associated to the 250 principal components

Plot the ratios $R(k) = (\lambda_1 + \dots + \lambda_k) / (\lambda_1 + \dots + \lambda_{250})$

Determine the number h of principal components which preserves 90% of the variance

Fix $\dim(H) = h$.

4.2 AutoEncoder Training

Define the training and test sets for the MLP auto encoder by

$AutoTrain = \text{all } (X_t, X_t) \text{ where } X_t \text{ is in } PredTRAIN$

$AutoTest = \text{all } (X_t, X_t) \text{ where } X_t \text{ is in } TestTRAIN$

Use the RELU response function and the Loss function "Mean Squared Error"

Use Stochastic Gradient Descent, Batch Learning, and Early Stopping based on comparing MSE on AutoTrain and AutoTest

Plot $MSE(AutoTrain)$ and $MSE(AutoTest)$ versus the number of batches

4.4 Compute Compressed Inputs

For each X_t in PredTRAIN or PredTEST compute the vector H_t (of dimension h) which gathers the states of all the neurons in the hidden layer H of the trained AutoEncoder

H_t will be called a *compressed input vector* (dimension h)

The H_t generated by X_t in PredTRAIN define a new training set *NewTrain*

$NewTrain = \text{all } (H_t, TARG_t) \text{ such that } X_t \text{ is in } PredTRAIN$

$NewTest = \text{all } (H_t, TARG_t) \text{ such that } X_t \text{ is in } PredTEST$

5 MLP predictor (deep learning method)

Deep Learning methodology suggests to construct an MLP predictor (*MLPpred*)

which will have the H_t as inputs, and a 3 layers architecture :

input $H \Rightarrow$ hidden layer $K \Rightarrow$ Output, with $\text{size}(H) = h$ and $\text{size}(\text{Output}) = 1$

On day t , the *MLPpred* input is the compressed vector H_t computed by auto encoding of X_t ,

and the MLP output is Z_t , which should be close $TARG_t = S_{50}(t+1)$

The training and test sets of MLPpred will be NewTrain and NewTest

5.1 Selection of size(K)

Let $numcases$ = number of cases in NewTrain

Let $k = \text{size}(\text{hidden layer } K)$. Compute $numwth = \{\text{number of weights \& thresholds}\}$ in *MLPpred*.

This should give a linear formula of the type $numwth = u \cdot k + v$ with explicit values for u and v

Select for k the largest integer such that $numwth < numcases$

Intuitive justification for this choice of k ?

5.2 Training of MLPpred

Implement an automatic training of MLPpred, with the same options used above :

RELU response, Loss = "MSE", Stochastic Gradient Descent, Batch Learning, Early Stopping

Plot MSE(NewTrain) and MSE(NewTest) versus the number of batches

5.3 Evaluation of Results

Comment on the comparison MSE(NewTrain) versus MSE(NewTest)

Plot on the same graph the true values $TARG_t$ and the predicted values Z_t

Comments on the graph?

Compute the Mean Relative Errors of Prediction MREP on NewTrain , using the formula

$MREP(NewTrain) = \text{average} (| Z_t - TARG_t | / TARG_t)$ over all cases in NewTrain

Compute similarly MREP(NewTest). Comments ?