

# HW4

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April 23, 2017

```
## Q1

# Read in data
advertising <- read.csv("./Advertising.csv", header = TRUE)
# advertising <- read.csv("./Spring 2017/Machine Learning/Rmd files/HW4/Advertising.csv", header = TRUE)
advertising <- scale(advertising[, -1]) # standardize all inputs to have zero mean and unit variance

# Sample training and test sets
set.seed(1)
advertising.selection.id <- sample(1:nrow(advertising), 200)
advertising.train.id <- sample(advertising.selection.id, 150)
advertising.test.id <- advertising.selection.id[-advertising.train.id]
advertising.train <- advertising[advertising.train.id, ]
advertising.test <- advertising[advertising.test.id, ]
x.train <- advertising.train[, -4]
y.train <- advertising.train[, 4]
x.test <- advertising.test[, -4]
y.test <- advertising.test[, 4]

# a)
# Build a one-hidden-layer neural network
library(RSNNS)

## Warning: package 'RSNNS' was built under R version 3.3.3

## Loading required package: Rcpp

advertising.nn1 <- RSNNS::mlp(x=x.train, y=y.train, size = c(2), maxit = 10000, learnFuncParams = 0.01, 1,
summary(advertising.nn1)

## SNNS network definition file V1.4-3D
## generated at Sat Apr 29 17:12:30 2017
##
## network name : RSNNS_untitled
## source files :
## no. of units : 6
## no. of connections : 8
## no. of unit types : 0
## no. of site types : 0
##
##
## learning function : Std_Backpropagation
## update function   : Topological_Order
##
##
```

```

## unit default section :
##
## act      | bias      | st | subnet | layer | act func      | out func
## -----|-----|---|-----|-----|-----|-----
## 0.00000 | 0.00000 | i  |      0 |      1 | Act_Logistic | Out_Identity
## -----|-----|---|-----|-----|-----|-----
##
##
## unit definition section :
##
## no. | typeName | unitName      | act      | bias      | st | position | act func      | out func | s
## ---|-----|-----|-----|-----|---|-----|-----|-----|---
## 1 |      | Input_TV      | -0.82282 | -0.00831 | i  | 1,0,0     | Act_Identity |          |
## 2 |      | Input_Radio   | 0.23143  | -0.26172 | i  | 2,0,0     | Act_Identity |          |
## 3 |      | Input_Newspaper | -0.37900 | 0.17073  | i  | 3,0,0     | Act_Identity |          |
## 4 |      | Hidden_2_1    | 0.11825  | -2.89872 | h  | 1,2,0     | |||         |          |
## 5 |      | Hidden_2_2    | 0.06712  | -2.11667 | h  | 2,2,0     | |||         |          |
## 6 |      | Output_1      | -0.63844 | -238.62894 | o  | 1,4,0     | Act_Identity |          |
## ---|-----|-----|-----|-----|---|-----|-----|-----|---
##
##
## connection definition section :
##
## target | site | source:weight
## -----|-----|-----
##      4 |      | 3:-0.04908, 2:-0.04654, 1:-1.07166
##      5 |      | 3:-0.01779, 2: 1.44009, 1: 1.03937
##      6 |      | 5: 2.76215, 4:-6.96684
## -----|-----|-----

```

```

nn1.pred <- predict(advertising.nn1,x.test)
mse <- sum((nn1.pred-y.test)^2)/length(y.test)
mse

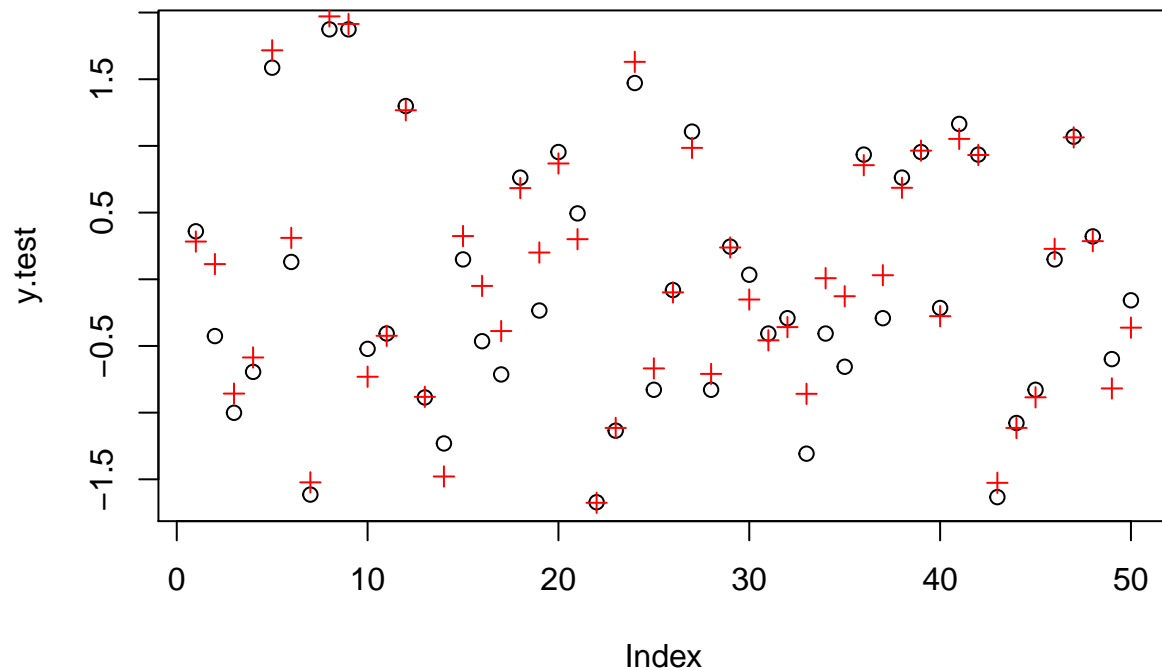
```

```
## [1] 0.04150914
```

```

# Plot the results
plot(y.test)
points(nn1.pred, col = "red", pch = 3)

```



1)

a) The results are shown from the R output above.

b) I chose 2 as the number of hidden units because there are 3 input units and 1 output unit, so 2, which is between 3 and 1, is an appropriate choice for the number of hidden units. Alternatively, I could choose 3 as the number of hidden units and look at the model results with regularization. For the learning parameter, I selected 0.01 after comparing model performance with different learning rates, but could use cross validation to select the best learning parameter as well.

```
## Q2

# Specify 9 kinds of hidden unit configurations
size_list <- list(c(2),c(3),c(3,3),c(3,2),c(2,2),c(3,3,3),c(3,3,2),c(3,2,2),c(2,2,2))
nn.pred <- nn1.pred

for (i in 1:9)
{
  for (j in 1:4) # Use 4 different starting values for each configuration
  {
    advertising.nn_temp <- RSNNs::mlp(x=x.train,y=y.train,size = size_list[[i]], maxit = 10000, learnFun =
    nn.pred <- cbind(nn.pred, predict(advertising.nn_temp,x.test))
  }
}
```

```

# Select 30 models from 36 models estimated
nn.pred <- nn.pred[,-1]
selection.id <- sample(1:36,30)
nn.pred <- nn.pred[,selection.id]

# Calculate the ensemble predictions and calculate MSE
nn_ensemble.pred <- rowMeans(nn.pred)
mse_ensemble <- sum((nn_ensemble.pred-y.test)^2)/length(y.test)
mse_ensemble

```

```
## [1] 0.007502991
```

2)

I selected 30 neural networks by varying both hidden layer configuration (number of hidden of layers and number of hidden units in each layer) and starting values. The MSE of the ensemble method turns out to be about 0.0075, which is much smaller than the MSE obtained from Q1, suggesting the ensemble method improves the predictive accuracy by a lot.

The reason for the improvement is perhaps because calibrated weights will depend on the chosen random starting points and averaging predictions with different starting points reduce the variance by a lot.

```
## Q3
```

```
library(rugarch)
```

```
## Warning: package 'rugarch' was built under R version 3.3.3
```

```
## Loading required package: parallel
```

```
##
```

```
## Attaching package: 'rugarch'
```

```
## The following object is masked from 'package:stats':
```

```
##
```

```
##      sigma
```

```
data("dji30ret")
```

```
summary(dji30ret)
```

```
##      AA      AXP      BA
## Min.   :-0.2745595 Min.   :-0.3034304 Min.   :-0.1938568
## 1st Qu.: -0.0114593 1st Qu.: -0.0109291 1st Qu.: -0.0098007
## Median : 0.0000000 Median : 0.0000000 Median : 0.0000000
## Mean   : 0.0001608 Mean   : 0.0001687 Mean   : 0.0003058
## 3rd Qu.: 0.0116377 3rd Qu.: 0.0114812 3rd Qu.: 0.0105709
## Max.   : 0.2087337 Max.   : 0.1712035 Max.   : 0.1439727
##      BAC      C      CAT
## Min.   :-0.3420588 Min.   :-0.3056056 Min.   :-0.244156
## 1st Qu.: -0.0093365 1st Qu.: -0.0111602 1st Qu.: -0.010575
## Median : 0.0000000 Median : 0.0000000 Median : 0.000000
```

## Mean : 0.0001149	Mean : 0.0000796	Mean : 0.000378
## 3rd Qu.: 0.0100293	3rd Qu.: 0.0116803	3rd Qu.: 0.011141
## Max. : 0.2698774	Max. : 0.4572902	Max. : 0.137371
## CVX	DD	DIS
## Min. : -0.1812526	Min. : -0.2018984	Min. : -0.3426451
## 1st Qu.: -0.0082829	1st Qu.: -0.0093255	1st Qu.: -0.0102932
## Median : 0.0000000	Median : 0.0000000	Median : 0.0000000
## Mean : 0.0004538	Mean : 0.0001774	Mean : 0.0002886
## 3rd Qu.: 0.0095239	3rd Qu.: 0.0095836	3rd Qu.: 0.0105821
## Max. : 0.1894765	Max. : 0.1086964	Max. : 0.1756133
## GE	GM	HD
## Min. : -0.1947441	Min. : -0.3727220	Min. : -0.3386365
## 1st Qu.: -0.0083683	1st Qu.: -0.0119502	1st Qu.: -0.0115889
## Median : 0.0000000	Median : 0.0000000	Median : 0.0000000
## Mean : 0.0002751	Mean : -0.0002715	Mean : 0.0006922
## 3rd Qu.: 0.0093459	3rd Qu.: 0.0115692	3rd Qu.: 0.0127656
## Max. : 0.1275967	Max. : 0.3009365	Max. : 0.1315251
## HPQ	IBM	INTC
## Min. : -0.2263815	Min. : -0.268161	Min. : -0.2488610
## 1st Qu.: -0.0125577	1st Qu.: -0.009243	1st Qu.: -0.0139915
## Median : 0.0000000	Median : 0.000000	Median : 0.0000000
## Mean : 0.0003792	Mean : 0.000249	Mean : 0.0005553
## 3rd Qu.: 0.0135366	3rd Qu.: 0.009469	3rd Qu.: 0.0158734
## Max. : 0.1591410	Max. : 0.123635	Max. : 0.2265276
## JNJ	JPM	AIG
## Min. : -0.2043813	Min. : -0.3234769	Min. : -0.9362581
## 1st Qu.: -0.0078036	1st Qu.: -0.0111299	1st Qu.: -0.0089217
## Median : 0.0000000	Median : 0.0000000	Median : 0.0000000
## Mean : 0.0004993	Mean : 0.0002586	Mean : -0.0002978
## 3rd Qu.: 0.0084695	3rd Qu.: 0.0111094	3rd Qu.: 0.0094814
## Max. : 0.1153126	Max. : 0.2239172	Max. : 0.3585320
## KO	MCD	MMM
## Min. : -0.2828628	Min. : -0.1827990	Min. : -0.2257926
## 1st Qu.: -0.0080020	1st Qu.: -0.0093024	1st Qu.: -0.0074074
## Median : 0.0000000	Median : 0.0000000	Median : 0.0000000
## Mean : 0.0004333	Mean : 0.0004514	Mean : 0.0003322
## 3rd Qu.: 0.0089027	3rd Qu.: 0.0099834	3rd Qu.: 0.0082499
## Max. : 0.1791113	Max. : 0.1030806	Max. : 0.1049975
## MRK	MSFT	PFE
## Min. : -0.3119154	Min. : -0.379490	Min. : -0.1892420
## 1st Qu.: -0.0090772	1st Qu.: -0.010643	1st Qu.: -0.0096386
## Median : 0.0000000	Median : 0.000000	Median : 0.0000000
## Mean : 0.0003447	Mean : 0.000787	Mean : 0.0003885
## 3rd Qu.: 0.0100307	3rd Qu.: 0.012848	3rd Qu.: 0.0107528
## Max. : 0.1224923	Max. : 0.178465	Max. : 0.0989399
## PG	T	UTX
## Min. : -0.3598917	Min. : -0.1352280	Min. : -0.3029024
## 1st Qu.: -0.0074074	1st Qu.: -0.0087377	1st Qu.: -0.0083770
## Median : 0.0000000	Median : 0.0000000	Median : 0.0000000
## Mean : 0.0004917	Mean : 0.0003364	Mean : 0.0004517
## 3rd Qu.: 0.0085107	3rd Qu.: 0.0096619	3rd Qu.: 0.0098064
## Max. : 0.1980376	Max. : 0.1505242	Max. : 0.1278841
## VZ	WMT	XOM
## Min. : -0.1931448	Min. : -0.1249721	Min. : -0.2676996

```
## 1st Qu.: -0.0087802 1st Qu.: -0.0100137 1st Qu.: -0.0078818
## Median : 0.0000000 Median : 0.0000000 Median : 0.0000000
## Mean : 0.0002848 Mean : 0.0004985 Mean : 0.0004964
## 3rd Qu.: 0.0089366 3rd Qu.: 0.0104713 3rd Qu.: 0.0090419
## Max. : 0.1365130 Max. : 0.1146918 Max. : 0.1653925
```

```
# Construct the data matrix with Ys and one-lag Xs
dji30ret$AVG <- rowMeans(dji30ret)
summary(dji30ret)
```

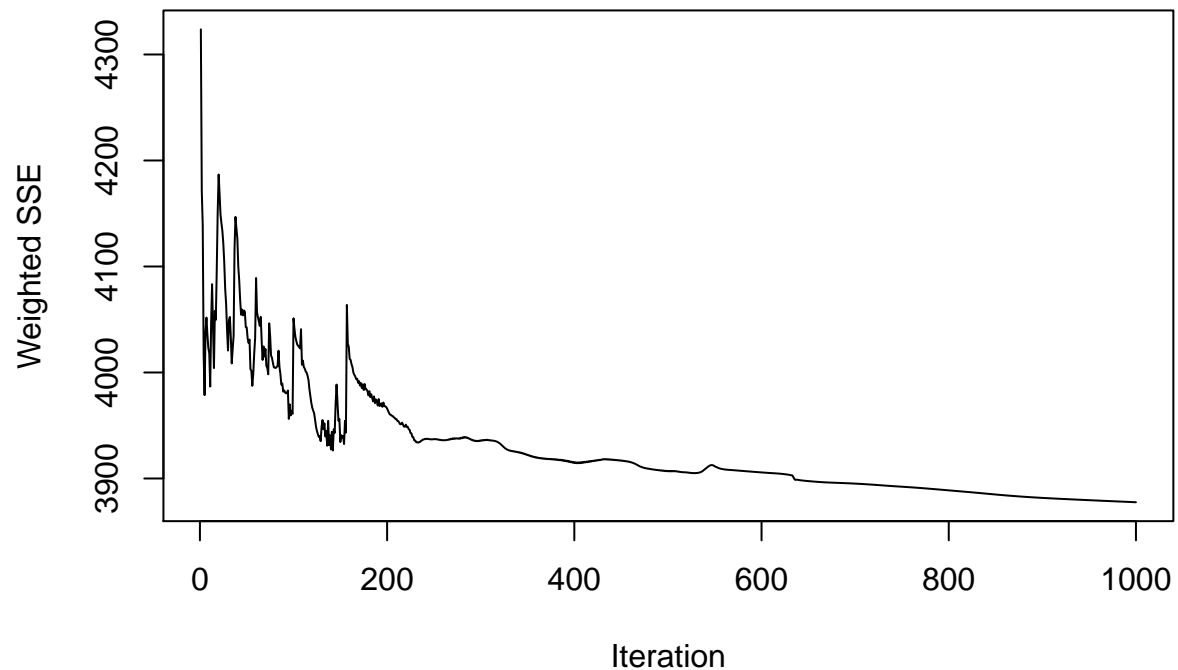
```
##      AA      AXP      BA
## Min.   : -0.2745595 Min.   : -0.3034304 Min.   : -0.1938568
## 1st Qu.: -0.0114593 1st Qu.: -0.0109291 1st Qu.: -0.0098007
## Median : 0.0000000 Median : 0.0000000 Median : 0.0000000
## Mean   : 0.0001608 Mean   : 0.0001687 Mean   : 0.0003058
## 3rd Qu.: 0.0116377 3rd Qu.: 0.0114812 3rd Qu.: 0.0105709
## Max.   : 0.2087337 Max.   : 0.1712035 Max.   : 0.1439727
##      BAC      C      CAT
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## Median : 0.0000000 Median : 0.0000000 Median : 0.0000000
## Mean   : 0.0001149 Mean   : 0.0000796 Mean   : 0.000378
## 3rd Qu.: 0.0100293 3rd Qu.: 0.0116803 3rd Qu.: 0.011141
## Max.   : 0.2698774 Max.   : 0.4572902 Max.   : 0.137371
##      CVX      DD      DIS
## Min.   : -0.1812526 Min.   : -0.2018984 Min.   : -0.3426451
## 1st Qu.: -0.0082829 1st Qu.: -0.0093255 1st Qu.: -0.0102932
## Median : 0.0000000 Median : 0.0000000 Median : 0.0000000
## Mean   : 0.0004538 Mean   : 0.0001774 Mean   : 0.0002886
## 3rd Qu.: 0.0095239 3rd Qu.: 0.0095836 3rd Qu.: 0.0105821
## Max.   : 0.1894765 Max.   : 0.1086964 Max.   : 0.1756133
##      GE      GM      HD
## Min.   : -0.1947441 Min.   : -0.3727220 Min.   : -0.3386365
## 1st Qu.: -0.0083683 1st Qu.: -0.0119502 1st Qu.: -0.0115889
## Median : 0.0000000 Median : 0.0000000 Median : 0.0000000
## Mean   : 0.0002751 Mean   : -0.0002715 Mean   : 0.0006922
## 3rd Qu.: 0.0093459 3rd Qu.: 0.0115692 3rd Qu.: 0.0127656
## Max.   : 0.1275967 Max.   : 0.3009365 Max.   : 0.1315251
##      HPQ      IBM      INTC
## Min.   : -0.2263815 Min.   : -0.268161 Min.   : -0.2488610
## 1st Qu.: -0.0125577 1st Qu.: -0.009243 1st Qu.: -0.0139915
## Median : 0.0000000 Median : 0.0000000 Median : 0.0000000
## Mean   : 0.0003792 Mean   : 0.000249 Mean   : 0.0005553
## 3rd Qu.: 0.0135366 3rd Qu.: 0.009469 3rd Qu.: 0.0158734
## Max.   : 0.1591410 Max.   : 0.123635 Max.   : 0.2265276
##      JNJ      JPM      AIG
## Min.   : -0.2043813 Min.   : -0.3234769 Min.   : -0.9362581
## 1st Qu.: -0.0078036 1st Qu.: -0.0111299 1st Qu.: -0.0089217
## Median : 0.0000000 Median : 0.0000000 Median : 0.0000000
## Mean   : 0.0004993 Mean   : 0.0002586 Mean   : -0.0002978
## 3rd Qu.: 0.0084695 3rd Qu.: 0.0111094 3rd Qu.: 0.0094814
## Max.   : 0.1153126 Max.   : 0.2239172 Max.   : 0.3585320
##      KO      MCD      MMM
## Min.   : -0.2828628 Min.   : -0.1827990 Min.   : -0.2257926
```

```
## 1st Qu.: -0.0080020 1st Qu.: -0.0093024 1st Qu.: -0.0074074
## Median : 0.0000000 Median : 0.0000000 Median : 0.0000000
## Mean : 0.0004333 Mean : 0.0004514 Mean : 0.0003322
## 3rd Qu.: 0.0089027 3rd Qu.: 0.0099834 3rd Qu.: 0.0082499
## Max. : 0.1791113 Max. : 0.1030806 Max. : 0.1049975
## MRK MSFT PFE
## Min. : -0.3119154 Min. : -0.379490 Min. : -0.1892420
## 1st Qu.: -0.0090772 1st Qu.: -0.010643 1st Qu.: -0.0096386
## Median : 0.0000000 Median : 0.0000000 Median : 0.0000000
## Mean : 0.0003447 Mean : 0.000787 Mean : 0.0003885
## 3rd Qu.: 0.0100307 3rd Qu.: 0.012848 3rd Qu.: 0.0107528
## Max. : 0.1224923 Max. : 0.178465 Max. : 0.0989399
## PG T UTX
## Min. : -0.3598917 Min. : -0.1352280 Min. : -0.3029024
## 1st Qu.: -0.0074074 1st Qu.: -0.0087377 1st Qu.: -0.0083770
## Median : 0.0000000 Median : 0.0000000 Median : 0.0000000
## Mean : 0.0004917 Mean : 0.0003364 Mean : 0.0004517
## 3rd Qu.: 0.0085107 3rd Qu.: 0.0096619 3rd Qu.: 0.0098064
## Max. : 0.1980376 Max. : 0.1505242 Max. : 0.1278841
## VZ WMT XOM
## Min. : -0.1931448 Min. : -0.1249721 Min. : -0.2676996
## 1st Qu.: -0.0087802 1st Qu.: -0.0100137 1st Qu.: -0.0078818
## Median : 0.0000000 Median : 0.0000000 Median : 0.0000000
## Mean : 0.0002848 Mean : 0.0004985 Mean : 0.0004964
## 3rd Qu.: 0.0089366 3rd Qu.: 0.0104713 3rd Qu.: 0.0090419
## Max. : 0.1365130 Max. : 0.1146918 Max. : 0.1653925
## AVG
## Min. : -0.2259355
## 1st Qu.: -0.0053170
## Median : 0.0005850
## Mean : 0.0003255
## 3rd Qu.: 0.0061890
## Max. : 0.1151826
```

```
xfactors <- dji30ret[,-nrow(dji30ret),-ncol(dji30ret)]
yfactors <- dji30ret[-1,ncol(dji30ret)]
dji_data <- as.matrix(cbind(xfactors,yfactors))
dji_data <- scale(dji_data)

# a)
# Split into training and test sets
split_date.id <- which(dji_data[,1]==dji_data["2005-12-30",1]) + 1
dji_train <- dji_data[1:split_date.id,]
dji_test <- dji_data[split_date.id:nrow(dji_data),]

# Fit a Elman neural network
library(RSNNS)
x_train <- dji_train[,-ncol(dji_train)]
y_train <- dji_train[,ncol(dji_train)]
dji.elman <- elman(x_train, y_train, size = c(5), learnFuncParams = c(0.1), maxit = 1000)
plotIterativeError(dji.elman)
```



```
summary(dji.elman)
```

```
## SNNS network definition file V1.4-3D
## generated at Sat Apr 29 17:14:51 2017
##
## network name : RSNNS_untitled
## source files :
## no. of units : 41
## no. of connections : 190
## no. of unit types : 0
## no. of site types : 0
##
##
## learning function : JE_BP
## update function   : JE_Order
##
##
## unit default section :
##
## act      | bias      | st | subnet | layer | act func      | out func
## -----|-----|----|-----|-----|-----|-----
## 1.00000 | 0.00000 | i  |      0 |      1 | Act_Logistic | Out_Identity
## -----|-----|----|-----|-----|-----|-----
##
##
```



## unit definition section :

##

## no.	typeName	unitName	act	bias	st	position	act func	out func	sites
##	----	-----	-----	-----	----	-----	-----	-----	-----
## 1		inp1	0.47778	-0.91907	i	1, 1, 0	Act_Identity		
## 2		inp2	0.92574	-0.12462	i	1, 2, 0	Act_Identity		
## 3		inp3	0.13042	-0.48560	i	1, 3, 0	Act_Identity		
## 4		inp4	0.81756	0.06269	i	1, 4, 0	Act_Identity		
## 5		inp5	0.56515	-0.87587	i	1, 5, 0	Act_Identity		
## 6		inp6	0.00867	0.36288	i	1, 6, 0	Act_Identity		
## 7		inp7	2.39554	0.89557	i	1, 7, 0	Act_Identity		
## 8		inp8	0.71180	0.24236	i	1, 8, 0	Act_Identity		
## 9		inp9	0.85728	-0.75426	i	1, 9, 0	Act_Identity		
## 10		inp10	0.49591	0.53197	i	1,10, 0	Act_Identity		
## 11		inp11	-1.04595	-0.73817	i	1,11, 0	Act_Identity		
## 12		inp12	0.79020	-0.01690	i	1,12, 0	Act_Identity		
## 13		inp13	0.18284	-0.88500	i	1,13, 0	Act_Identity		
## 14		inp14	-0.09957	0.06298	i	1,14, 0	Act_Identity		
## 15		inp15	0.84702	0.48217	i	1,15, 0	Act_Identity		
## 16		inp16	1.58807	-0.88437	i	1,16, 0	Act_Identity		
## 17		inp17	0.48330	0.24819	i	1,17, 0	Act_Identity		
## 18		inp18	0.70600	0.76945	i	1,18, 0	Act_Identity		
## 19		inp19	0.84114	-0.84202	i	1,19, 0	Act_Identity		
## 20		inp20	-0.36057	0.84574	i	1,20, 0	Act_Identity		
## 21		inp21	1.31152	0.08409	i	1,21, 0	Act_Identity		
## 22		inp22	1.55195	0.97354	i	1,22, 0	Act_Identity		
## 23		inp23	1.04920	0.17025	i	1,23, 0	Act_Identity		
## 24		inp24	1.02713	-0.06105	i	1,24, 0	Act_Identity		
## 25		inp25	0.89237	0.96711	i	1,25, 0	Act_Identity		
## 26		inp26	0.48688	-0.98152	i	1,26, 0	Act_Identity		
## 27		inp27	0.58224	-0.57759	i	1,27, 0	Act_Identity		
## 28		inp28	0.49715	-0.77045	i	1,28, 0	Act_Identity		
## 29		inp29	-0.67272	0.74644	i	1,29, 0	Act_Identity		
## 30		inp30	2.44071	0.74061	i	1,30, 0	Act_Identity		
## 31		hid1	0.00000	-29.75155	h	7, 1, 0			
## 32		hid2	0.00000	-36.35191	h	7, 2, 0			
## 33		hid3	0.00000	-40.83426	h	7, 3, 0			
## 34		hid4	0.00000	-30.64052	h	7, 4, 0			
## 35		hid5	0.00000	-34.01869	h	7, 5, 0			
## 36		out1	-0.00000	6470.86182	o	13, 1, 0	Act_Identity		
## 37		con1	0.00780	0.50000	sh	4,32, 0	Act_Identity		
## 38		con2	0.00000	0.50000	sh	4,33, 0	Act_Identity		
## 39		con3	0.00000	0.50000	sh	4,34, 0	Act_Identity		
## 40		con4	0.00042	0.50000	sh	4,35, 0	Act_Identity		
## 41		con5	0.00000	0.50000	sh	4,36, 0	Act_Identity		
##	----	-----	-----	-----	----	-----	-----	-----	-----

##

##

## connection definition section :

##

## target | site | source:weight

##	-----	-----	-----	-----	-----	-----	-----	-----	-----
## 31		41:-2.17612, 40:-4.18329, 39: 4.19223, 38: 6.08403, 37: 0.07002, 30:-5.80402, 29:-3.9							
##		26:-4.21796, 25: 0.82071, 24:-1.59751, 23:-1.13426, 22:-10.43551, 21:-6.95692, 20:-2							

```
##          17:-6.51633, 16: 5.45805, 15: 1.60647, 14:-2.99970, 13:-1.76194, 12:-1.55023, 11:-0.8
##          8: 0.98661, 7: 3.63648, 6: 0.10857, 5:-3.29318, 4: 3.19364, 3:-9.52617, 2:-6.4
##    32 |      | 41:-3.29806, 40:-9.51252, 39:-2.22531, 38: 7.07721, 37: 4.13384, 30: 8.99229, 29: 4.9
##          26:-9.90123, 25:-2.40001, 24:-8.01598, 23:-3.72813, 22:-2.20097, 21:-3.96336, 20: 1.6
##          17:-4.47132, 16: 0.21522, 15:-7.95894, 14:-6.05867, 13: 0.47383, 12:-3.47754, 11:-2.2
##          8:-1.59087, 7: 0.21432, 6:-3.64856, 5: 7.08441, 4: 3.94321, 3:-2.52364, 2:-0.0
##    33 |      | 41: 6.21000, 40:-0.27678, 39:-1.78365, 38: 6.19060, 37: 2.29166, 30:-0.10326, 29: 1.6
##          26:-4.37074, 25:-3.78208, 24:-6.97006, 23:-5.20621, 22:-3.23019, 21:-3.53245, 20: 5.3
##          17:-9.63702, 16:-0.08717, 15:-7.80373, 14:-0.47953, 13: 2.31084, 12:-7.66372, 11:-5.7
##          8: 1.80991, 7: 6.45970, 6: 4.16970, 5: 1.45316, 4:-3.56986, 3: 1.69088, 2: 5.8
##    34 |      | 41:-3.10743, 40: 1.11616, 39:-7.36880, 38:-4.51558, 37:-5.85712, 30:-7.11287, 29:-1.7
##          26:-6.51610, 25: 0.24658, 24:-5.01959, 23:-5.46858, 22:-3.33413, 21: 0.88455, 20: 0.0
##          17:-3.74158, 16:-2.89301, 15:-2.27218, 14:-0.65667, 13:-1.36925, 12:-7.86950, 11:-6.0
##          8:-3.91973, 7: 0.57402, 6:-0.96416, 5: 3.77501, 4: 0.75505, 3:-0.10111, 2:-6.0
##    35 |      | 41: 7.26769, 40:-6.66623, 39:-6.61548, 38:10.34146, 37:-7.16306, 30:-4.06458, 29:-7.1
##          26:-5.05459, 25:-1.70842, 24: 0.14433, 23:-7.31349, 22:-3.02293, 21:-0.95516, 20: 1.0
##          17:-3.43398, 16:-6.01401, 15:-4.77596, 14: 0.15178, 13:-2.53260, 12:-3.01854, 11:-2.9
##          8: 3.45483, 7: 7.31434, 6: 5.43265, 5: 1.12381, 4:-5.09163, 3: 1.55712, 2:-0.0
##    36 |      | 35:-0.66226, 34:-0.07983, 33: 1.65654, 32:-1.49724, 31: 0.42017
##    37 |      | 37: 0.30000, 31: 1.00000
##    38 |      | 38: 0.30000, 32: 1.00000
##    39 |      | 39: 0.30000, 33: 1.00000
##    40 |      | 40: 0.30000, 34: 1.00000
##    41 |      | 41: 0.30000, 35: 1.00000
## -----|-----|-----
```

```
# b)
# Make predictions and calculate MSE
x_test <- dji_test[,ncol(dji_test)]
y_test <- dji_test[,ncol(dji_test)]
elman.pred <- predict(dji.elman, x_test)
mse_elman <- sum((elman.pred-y_test)^2)/length(y_test)
mse_elman
```

```
## [1] 2.19211
```

3)

a) The results are shown from the R output above.

b) The results are shown from the R output above.

c) Elman neural network is an appropriate model for time-series prediction, as the context layer within the Elman neural network “remember” the previous internal state of the network by storing hidden layer neuron values. The number of hidden units chosen for the model is 5, much fewer than the number of input units, which is 30, suggesting that overfitting may not occur. We could also use regularization to minimize the risk of overfitting.

```
## Q4
# Build transformed dataset with 5 lagged returns
library(ISLR)
data("Weekly")
summary(Weekly)
```

```
##      Year      Lag1      Lag2      Lag3
## Min.   :1990   Min.   :-18.1950   Min.   :-18.1950   Min.   :-18.1950
## 1st Qu.:1995   1st Qu.: -1.1540   1st Qu.: -1.1540   1st Qu.: -1.1580
## Median :2000   Median :  0.2410   Median :  0.2410   Median :  0.2410
## Mean   :2000   Mean    :  0.1506   Mean    :  0.1511   Mean    :  0.1472
## 3rd Qu.:2005   3rd Qu.:  1.4050   3rd Qu.:  1.4090   3rd Qu.:  1.4090
## Max.   :2010   Max.    : 12.0260   Max.    : 12.0260   Max.    : 12.0260
##      Lag4      Lag5      Volume
## Min.   :-18.1950   Min.   :-18.1950   Min.   :0.08747
## 1st Qu.: -1.1580   1st Qu.: -1.1660   1st Qu.:0.33202
## Median :  0.2380   Median :  0.2340   Median :1.00268
## Mean    :  0.1458   Mean    :  0.1399   Mean    :1.57462
## 3rd Qu.:  1.4090   3rd Qu.:  1.4050   3rd Qu.:2.05373
## Max.    : 12.0260   Max.    : 12.0260   Max.    :9.32821
##      Today      Direction
## Min.   :-18.1950   Down:484
## 1st Qu.: -1.1540   Up  :605
## Median :  0.2410
## Mean    :  0.1499
## 3rd Qu.:  1.4050
## Max.    : 12.0260
```

```
# Split into training and test sets
```

```
sp_500.x_train <- head(scale(as.matrix(Weekly[,2:6])),889)
```

```
sp_500.y_train <- head(scale(as.matrix(Weekly[,8])),889)
```

```
# Build the Deep Belief Net (DBN)
```

```
library(deepnet)
```

```
sp_500.dbn <- dbn.dnn.train(sp_500.x_train, sp_500.y_train, hidden = c(4,3), output = "linear", learning
```

```
## begin to train dbn .....
```

```
## training layer 1 rbm ...
```

```
## training layer 2 rbm ...
```

```
## dbn has been trained.
```

```
## begin to train deep nn .....
```

```
## #####loss on step 10000 is : 0.326920
```

```
## #####loss on step 20000 is : 0.838359
```

```
## #####loss on step 30000 is : 0.258900
```

```
## #####loss on step 40000 is : 0.733237
```

```
## #####loss on step 50000 is : 0.559317
```

```
## #####loss on step 60000 is : 0.395439
```

```
## ####loss on step 70000 is : 0.722998
```

```
## ####loss on step 80000 is : 0.297470
```

```
## deep nn has been trained.
```

```
# Make predictions and calculate MSE
sp_500.x_test <- tail(scale(as.matrix(Weekly[,2:6])),200)
sp_500.y_test <- tail(scale(as.matrix(Weekly[,8])),200)
dbn.pred <- nn.predict(sp_500.dbn, sp_500.x_test)
mse_dbn <- sum((dbn.pred-sp_500.y_test)^2)/length(sp_500.y_test)
mse_dbn
```

```
## [1] 2.04773
```

4)

a) The results are shown from the R output above.

b) The results are shown from the R output above.

c) I used c(4,3) as the number of hidden units because the number of inputs is 5, so I want to make the number of hidden units smaller or equal to 5 to extract meaningful features from the input. I also tried many other hidden layer configurations that satisfy this rule. Overall, My finding is that after trying 100+ set of parameters for the Deep Belief Network, the DBN still produces predictions that do not make much sense. Specifically, the distribution of the predictions do not align very closely with the distribution of the y\_test variable. This might be because the package has some problem handling this dataset.