

**The University of Chicago, Booth School of Business**  
Business 41202, Spring Quarter 2017, Mr. Ruey S. Tsay

**Final Exam**

**Booth Honor Code:**

*I pledge my honor that I have not violated the Honor Code during this examination.*

**Signature:**

**Name:**

**ID:**

Notes:

- This is a 3-hour, open-book, and open-note exam.
- Write your answer in the blank space provided for each question.
- The exam has 18 pages, including R output, and has FOUR (4) main parts (A to D).
- For simplicity, if not specified, all **risk-measure** calculations use 1% tail probability. Furthermore, unless specified, all value at risk (VaR) and expected shortfall (ES) are for the NEXT trading day. Also, unless specified, all tests use 5% type-I error.
- Round your answer to 3 significant digits.
- You may bring a PC or calculator to the exam, but **no Internet or email or any communication is allowed during the exam!**

**Problem A:** (40 points) Answer briefly the following questions.

1. Describe two characteristics commonly encountered in modeling high-frequency log returns in finance.
  
  
  
  
  
  
  
  
  
  
2. Give one nice feature and one drawback of using RiskMetrics in financial risk management.

3. Assume that  $x_t$  follows the stochastic diffusion equation  $dx_t = \mu x_t dt + \sigma x_t dw_t$ , where  $w_t$  is a Wiener process. Let  $G(x_t) = \sqrt{x_t}$ . Derive the stochastic diffusion equation for  $G(x_t)$ .
4. Describe two approaches to calculate value at risk using the extreme value theory.
5. Give two volatility models that can estimate the leverage effect in modeling daily asset returns.
6. Describe two statistics that can be used to specify the order of an autoregressive time series.
7. Describe two statistics that can be used to test for ARCH effects in the log returns of an asset.
8. Give two potential problems of overlooking the serial correlations in a linear regression model.
9. Describe two alternative approaches (vs econometric modeling) to calculate asset volatility.

10. Asset returns typically do not follow the Gaussian distribution. Provide two alternative statistical distributions that can improve volatility modeling.
11. Many statistical models have been introduced in this course. Describe two models that can be used to model the price changes in high-frequency financial trading.
12. Give one similarity and one difference between threshold autoregressive models and Markov switching models.
13. In empirical data analysis, one often encounters certain outliers. Describe two methods to mitigate the effects of outliers in financial time series analysis.
14. Describe two methods that can be used to compare different statistical models in analysis of financial data.
15. Give two reasons for analyzing two time series jointly.
16. Give two multivariate volatility models that always give positive-definite volatility matrices.
17. (**For Questions 17-20**). Consider the daily simple returns of Qualcomm (QCOM) stock and the S&P composite index for a period of 2769 trading days. Some analysis of

the data are given in the attached R output. Let  $\mu$  be the daily expected return of the S&P composite index. Test  $H_0 : \mu = 0$  versus  $H_a : \mu \neq 0$ . What is your conclusion? Why?

18. Is the CAPM model, **n1**, adequate for the QCOM return? Why?
19. A regression model with time series errors is entertained. After removing insignificant parameters. A final model is obtained. Write down the fitted model, **n3**.
20. Does the final model, **n3**, successfully capture the serial correlations in the residuals? Why?

**Problem B.** (12 points) Consider the daily exchange rates between U.S. Dollar and (a) Euro (Dollars per Euro) (b) Japanese Yen (Yens per Dollar) for a period of 2888 trading days. Let  $\mathbf{z}_t$  denote the daily exchange rates and  $\mathbf{x}_t$  denote the log returns of the exchange rates. Some analyses of  $\mathbf{x}_t$  and  $\mathbf{z}_t$  are given in the attached R output. Let  $\boldsymbol{\rho}_\ell$  be the lag- $\ell$  cross-correlation matrix of  $\mathbf{x}_t$ .

1. Write down the sample cross-correlation matrix of  $\mathbf{x}_t$ . Why is the correlation between the log returns of exchange rates negative?

2. The lag-1 sample cross-correlation matrix is

$$\boldsymbol{\rho}_1 = \begin{bmatrix} 0.0060 & 0.0109 \\ 0.0049 & -0.0169 \end{bmatrix}.$$

What is the meaning of the correlation  $-0.0169$ ? What is the meaning of the correlation  $0.0109$ ?

3. Consider the null hypothesis  $H_0 : \boldsymbol{\rho}_1 = \cdots = \boldsymbol{\rho}_{10} = \mathbf{0}$  versus  $H_a : \boldsymbol{\rho}_i \neq \mathbf{0}$  for some  $1 \leq i \leq 10$ . Perform a proper test and state the  $p$ -value of the test statistic. Also, draw your conclusion.
4. State the implication of the conclusion of the hypothesis testing of Question (3).
5. (3 points) A vector autoregressive model of order 1 is entertained for  $\mathbf{z}_t$ . Write down the fitted model, including the residual covariance matrix.
6. (1 point) Is the VAR(1) model adequate? Why?

**Problem C.** (38 points) Consider the daily log returns of Qualcomm (QCOM) and Pfizer (PFE) stocks. A recent time span with 2769 trading days is employed. R output of certain analyses of the two log returns are given. Unless stated otherwise, assume that the portfolio of interest consists of holding 1-million dollars of stocks of each company.

1. (**Questions 1 to 4**) What are the VaR of the individual stocks using RiskMetrics?
2. What is the VaR of the portfolio using RiskMetrics?
3. What is the VaR of the portfolio for the next 10 trading days using RiskMetrics?
4. Suppose the position on Pfizer stock is changed to a short position. What is the VaR of the portfolio for the next trading day?
5. A Gaussian GARCH(1,1) model is fitted to the QCOM returns, **m3**. What are the VaR and expected shortfall of the stock?
6. A Gaussian GARCH(1,1) model is also fitted to the PFE returns, **m4**. What are the VaR and expected shortfall of the stock?
7. What is the VaR of the portfolio for the next trading day using the Gaussian GARCH(1,1) models?

8. A GARCH(1,1) model with standardized Student- $t$  innovations is entertained for the QCOM stock returns, **m5**. What are the VaR and expected shortfall of the QCOM position?
9. What are the VaR and expected shortfall of QCOM position for the next five (5) trading days?
10. A GARCH(1,1) model with standardized Student- $t$  innovations is also fitted to the PFE stock returns, **m6**. What are the VaR and expected shortfall of PFE position?
11. What is the VaR of the portfolio for the next trading day using Student- $t$  GARCH(1,1) models?
12. Turn to extreme value theory. A extreme value distribution is fitted to the QCOM stock returns with block size 21, **m8**. Write down the three parameter estimates.
13. Let  $\xi$  be the shape parameter. Consider the null hypothesis  $H_0 : \xi = 0$  versus  $H_a : \xi \neq 0$ . Perform a proper test and draw your conclusion.
14. Based on the fitted EVT, calculate the VaR for the QCOM position for the next trading day. What is the VaR for the next ten (10) trading days?

15. A peaks over the threshold approach is used. With threshold 0.02, we fit a POT model to the QCOM stock returns, **m9**. Write down the estimate of the shape parameter  $\xi$ . What are the VaR and expected shortfall for the QCOM position under the fitted POT mode (next trading day).
16. The threshold is changed to 0.03, **m10**. What are the VaR and expected shortfall for the QCOM position for the next trading day?
17. A generalized Pareto distribution with threshold 0.02 is also fitted to the QCOM returns, **m11**. What are the VaR and expected shortfall for the QCOM position? Compared with results of model **m9**. Is there any significant difference? Why?
18. Turn to quantile regression. The daily log returns of the S&P composite index during the sample period is used to obtain a proxy of market volatility; see the model **W1** in the R output. We then employ a quantile regression for QCOM returns using (1) squares of lag-1 return, (2) lag-1 market volatility and (3) lag-1 QCOM volatility as explanatory variables. However, the lag-1 squared return appears to be statistically insignificant; see model **mm**. A simplified quantile regression is fitted, **mm1**. Based on the fitted model, is the lag-1 S&P volatility helpful in estimating the 95 percentiles of QCOM returns? Why?
19. Given that lag-1 volatilities of the QCOM return and market index are 0.0163 and 0.00609, respectively, what is the fitted value of the 95th percentile?



**Problem D.** (10 points) Consider, again, the daily log returns of Qualcomm stock of Problem C. Let  $r_t$  and  $m_t$  be the daily log returns of QCOM and S&P composite index. Define

$$Q_t = \begin{cases} 1 & \text{if } r_t > 0 \\ 0 & \text{otherwise,} \end{cases} \quad M_t = \begin{cases} 1 & \text{if } m_t > 0 \\ 0 & \text{otherwise.} \end{cases}$$

The goal is to predict  $Q_t$  using  $Q_{t-i}$  and  $M_{t-j}$ , where  $i, j > 0$ .

1. A logistic regression is employed using  $\{Q_{t-i}, M_{t-i} | i = 1, 2, 3\}$  as explanatory variables. It turns out that only  $Q_{t-2}$  is statistically significant. See models **g1** and **g3**. Write down the fitted model **g3**.
  
2. What is the meaning of the fitted coefficient  $-0.275$ ?
  
3. What is  $P(Q_t = 1 | Q_{t-2} = 1)$ ?
  
4. A 6-2-1 neural network with inputs  $\{Q_{t-i}, M_{t-i} | i = 1, 2, 3\}$  is applied. See **g4**. Write down the model for the hidden node  $h_1$ .
  
5. Write down the model for the output node.

## R output

```
### Problem A #####
> dim(da)
[1] 2769    9
> head(da)
  PERMNO    date  PRC    VOL OPENPRC ASKHI  BIDLO    RET    sprtrn
1  77178 xxxxxxxxx 44.00 15840983   43.25 44.35 42.910  0.021356  0.016430
> sp <- da$sprtrn; qcom <- da$RET
> require(fBasics)
> basicStats(sp)

              sp
nobs          2769.000000
NAs            0.000000
...
Mean           0.000292
Median         0.000680
SE Mean        0.000242
LCL Mean       -0.000182
UCL Mean       0.000765
Variance       0.000162
Stdev          0.012710
Kurtosis       10.839450
> n1 <- lm(qcom~sp)
> summary(n1)
Call:lm(formula = qcom ~ sp)
Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.0001301  0.0002867   0.454    0.65
sp           0.9923800  0.0225527  44.003 <2e-16 ***
---
Residual standard error: 0.01508 on 2767 degrees of freedom
Multiple R-squared:  0.4117,    Adjusted R-squared:  0.4115

> Box.test(n1$residuals,lag=10,type="Ljung")
      Box-Ljung test
data:  m1$residuals
X-squared = 19.024, df = 10, p-value = 0.03996
> n2 <- arima(qcom,order=c(0,0,2),xreg=sp)
> n2
Call:arima(x = qcom, order = c(0, 0, 2), xreg = sp)
Coefficients:
      ma1      ma2  intercept      sp
      0.0116 -0.0469      1e-04  0.9901
s.e.  0.0190  0.0197      3e-04  0.0226
sigma^2 estimated as 0.0002268:
> c1 <- c(0,NA,NA)
```

```

> n3 <- arima(qcom,order=c(0,0,2),xreg=sp,include.mean=F,fixed=c1)
> n3
Call:arima(x=qcom,order=c(0,0,2),xreg=sp,include.mean=F,fixed=c1)
Coefficients:
      ma1      ma2      sp
      0 -0.0472  0.9900
s.e.    0   0.0197  0.0226
sigma^2 estimated as 0.0002268:log likelihood=7688.74,aic=-15371.48
> Box.test(m3$residuals,lag=10,type="Ljung")
      Box-Ljung test
data:  m3$residuals
X-squared = 14.249, df = 10, p-value = 0.1619

#### Problem B #####
> zt <- cbind(eu,jp)  ### exchange rate series
> dim(zt)
[1] 2888      2
> reu <- diff(log(eu))  ### log returns
> rjp <- diff(log(jp))
> xt <- cbind(reu,rjp)  #### return series
> colnames(xt) <- c("eu","jp")
> ccm(xt,lag=2,level=T)
[1] "Covariance matrix:"
      eu      jp
eu    3.97e-05 -1.04e-05
jp   -1.04e-05  4.58e-05
CCM at lag:  0
      [,1] [,2]
[1,]  1.000 -0.245
[2,] -0.245  1.000
CCM at lag:  1
Correlations:
      [,1] [,2]
[1,] 0.00604 0.0109
[2,] 0.00489 -0.0169
> mq(xt,lag=10)  ### Ljung-Box statistics
Ljung-Box Statistics:
      m      Q(m)      df      p-value
[1,]  1.00      1.22      4.00      0.87
[2,]  2.00      2.69      8.00      0.95
[3,]  3.00      9.69     12.00      0.64
[4,]  4.00     15.48     16.00      0.49
[5,]  5.00     27.02     20.00      0.13
[6,]  6.00     27.85     24.00      0.27
[7,]  7.00     29.38     28.00      0.39
[8,]  8.00     35.44     32.00      0.31

```

```

[9,] 9.00    36.50   36.00    0.45
[10,] 10.00   42.00   40.00    0.38
> K1 <- VAR(zt,p=1,include.mean=F) ## Fit a VAR(1) model without constant
AR coefficient matrix
AR( 1 )-matrix
      [,1]      [,2]
[1,] 0.9993 8.85e-06
[2,] 0.0514 9.99e-01
standard error
      [,1]      [,2]
[1,] 0.000587 7.45e-06
[2,] 0.049113 6.24e-04

```

```

Residuals cov-mtx:
      [,1]      [,2]
[1,] 6.748664e-05 -0.001420639
[2,] -1.420639e-03 0.473086159

```

```

> mq(K1$residuals,lag=5) ## Model checking
Ljung-Box Statistics:

```

	m	Q(m)	df	p-value
[1,]	1.00	1.53	4.00	0.82
[2,]	2.00	2.92	8.00	0.94
[3,]	3.00	9.87	12.00	0.63
[4,]	4.00	15.72	16.00	0.47
[5,]	5.00	27.57	20.00	0.12

##### Problem C #####

```

> QCOM <- read.table("d-qcom-xxxx.txt",header=T)
> PFE <- read.table("d-pfe-xxxx.txt",header=T)
> qcom <- log(QCOM$RET+1)
> pfe <- log(PFE$RET+1)

```

```

> cor(qcom,pfe) ### correlation
[1] 0.4201796
>

```

```

> m1 <- RMfit(qcom,estim=F)
Default beta = 0.96 is used.

```

```

Risk measure based on RiskMetrics:
      prob      VaR      ES
[1,] 0.950 0.02508961 0.03146338
[2,] 0.990 0.03548471 0.04065357
[3,] 0.999 0.04713654 0.05135956

```

```

> m2 <- RMfit(pfe,estim=F)
Default beta = 0.96 is used.

```

```

Risk measure based on RiskMetrics:
      prob      VaR      ES
[1,] 0.950 0.02036793 0.02554221
[2,] 0.990 0.02880676 0.03300288
[3,] 0.999 0.03826581 0.04169409
>
> xt <- -qcom
> m3 <- garchFit(~garch(1,1),data=xt,trace=F)
> summary(m3)
Title: GARCH Modelling
Call: garchFit(formula=~garch(1,1),data=xt,trace=F)
Mean and Variance Equation:
  data ~ garch(1, 1); [data = xt]
Conditional Distribution: norm
Error Analysis:
      Estimate Std. Error t value Pr(>|t|)
mu      -4.797e-04  3.216e-04  -1.492   0.136
omega    1.312e-05  3.128e-06   4.196 2.71e-05 ***
alpha1   6.889e-02  1.466e-02   4.698 2.63e-06 ***
beta1    8.982e-01  2.003e-02  44.840 < 2e-16 ***
---
> predict(m3,1)
      meanForecast meanError standardDeviation
1 -0.0004797206 0.01618072      0.01618072

> yt <- -pfe
> m4 <- garchFit(~garch(1,1),data=yt,trace=F)
> summary(m4)
Title: GARCH Modelling
Call: garchFit(formula=~garch(1,1),data=yt,trace=F)
Mean and Variance Equation:
  data ~ garch(1, 1); [data = yt]
Conditional Distribution: norm
Error Analysis:
      Estimate Std. Error t value Pr(>|t|)
mu      -3.924e-04  2.160e-04  -1.817 0.069293 .
omega    4.217e-06  1.118e-06   3.773 0.000161 ***
alpha1   8.234e-02  1.482e-02   5.558 2.73e-08 ***
beta1    8.972e-01  1.790e-02  50.112 < 2e-16 ***
---
> predict(m4,1)
      meanForecast meanError standardDeviation
1 -0.0003923808 0.01026344      0.01026344
>
> m5 <- garchFit(~garch(1,1),data=xt,trace=F,cond.dist="std")
> summary(m5)

```

```

Title: GARCH Modelling
Call: garchFit(formula=~garch(1,1),data=xt,cond.dist="std",trace=F)
Mean and Variance Equation:
  data ~ garch(1, 1); [data = xt]
Conditional Distribution: std
Error Analysis:
      Estimate Std. Error t value Pr(>|t|)
mu      -5.681e-04  2.605e-04  -2.181 0.029200 *
omega    4.826e-06  2.142e-06   2.254 0.024223 *
alpha1   6.931e-02  1.818e-02   3.812 0.000138 ***
beta1    9.211e-01  2.053e-02  44.875 < 2e-16 ***
shape    4.311e+00  3.440e-01  12.532 < 2e-16 ***
---
> pm5 <- predict(m5,5)
> pm5
      meanForecast meanError standardDeviation
1 -0.0005680794 0.01571565      0.01571565
2 -0.0005680794 0.01579346      0.01579346
3 -0.0005680794 0.01587014      0.01587014
4 -0.0005680794 0.01594572      0.01594572
5 -0.0005680794 0.01602022      0.01602022
> sum(pm5$meanForecast)
[1] -0.002840397
> sqrt(sum(pm5$meanError^2))
[1] 0.03548506
> m6 <- garchFit(~garch(1,1),data=yt,trace=F,cond.dist="std")
> summary(m6)
Title: GARCH Modelling
Call: garchFit(formula=~garch(1,1),data=yt,cond.dist="std")
Mean and Variance Equation:
  data ~ garch(1, 1); [data = yt]
Conditional Distribution: std
Error Analysis:
      Estimate Std. Error t value Pr(>|t|)
mu      -3.608e-04  2.019e-04  -1.788 0.073853 .
omega    4.893e-06  1.445e-06   3.385 0.000711 ***
alpha1   8.724e-02  1.703e-02   5.121 3.04e-07 ***
beta1    8.869e-01  2.150e-02  41.257 < 2e-16 ***
shape    5.940e+00  6.512e-01   9.123 < 2e-16 ***
---
> pm6 <- predict(m6,5)
> pm6
      meanForecast meanError standardDeviation
1 -0.0003608439 0.009946404      0.009946404
2 -0.0003608439 0.010063303      0.010063303
....

```

```

5 -0.0003608439 0.010388997      0.010388997
> sum(pm6$meanForecast)
[1] -0.001804219
> sqrt(sum(pm6$meanError^2))
[1] 0.02274752
>
> m8 <- gev(xt,21)
> m8
$n.all: 2769
$n: 132
$block: 21
$par.ests
      xi      sigma      mu
0.29821631 0.01298859 0.02379390
$par.ses
      xi      sigma      mu
0.079596178 0.001043204 0.001295292
>
> m9 <- pot(xt,thres=0.02)
> m9
$n: 2769
$period: 1 2769
$span: 2768
$threshold: 0.02
$p.less.thresh: 0.8992416
$n.exceed: 279
$par.ests
      xi      sigma      mu      beta
2.506414e-01 6.432637e-03 4.861427e-05 1.143328e-02
$par.ses
      xi      sigma      mu
0.0444796461 0.0007849947 0.0016659266
> riskmeasures(m9,c(0.95,0.99,0.999))
      p quantile      sfall
[1,] 0.950 0.02875788 0.04694459
[2,] 0.990 0.05577594 0.08299950
[3,] 0.999 0.11933559 0.16781824
> m10 <- pot(xt,thres=0.03)
> m10
$n: 2769
$period: 1 2769
$threshold: 0.03
$p.less.thresh: 0.9566631
$n.exceed: 120
$par.ests
      xi      sigma      mu      beta

```

```

0.2697388483 0.0061190532 -0.0002079986 0.0142673240
$par.ses
      xi      sigma      mu
0.055425686 0.001138747 0.003509789
> riskmeasures(m10,c(0.95,0.99,0.999))
      p  quantile  sfall
[1,] 0.950 0.02799838 0.04679633
[2,] 0.990 0.05566382 0.08468063
[3,] 0.999 0.12329879 0.17729815
>
> m11 <- gpd(xt,thres=0.02)
> m11
$n: 2769
$threshold: 0.02
$p.less.thresh: 0.8992416
$n.exceed: 279
$par.ests
      xi      beta
0.25077309 0.01142907
$par.ses
      xi      beta
0.072973159 0.001045189
> riskmeasures(m11,c(0.95,0.99,0.999))
      p  quantile  sfall
[1,] 0.950 0.02875507 0.04693995
[2,] 0.990 0.05576871 0.08299531
[3,] 0.999 0.11933484 0.16783759

### Quantile regression
> sp <- log(QCOM$sprtrn+1)
> W1 <- garchFit(~garch(1,1),data=sp,trace=F,cond.dist="std")
> spVol <- volatility(W1)
> xtVol <- volatility(m5)
> length(xt)
[1] 2769
> Yt <- xt[2:2769]; Ytm1 <- xt[1:2768]
> xtVolm1 <- xtVol[1:2768]; spVolm1 <- spVol[1:2768]
> require(quantreg)
> mm <- rq(Yt~Ytm1^2+xtVolm1+spVolm1,tau=0.95)
> summary(mm)
Call: rq(formula=Yt~Ytm1^2+xtVolm1+spVolm1,tau=0.95)
tau: 0.95
Coefficients:
      Value Std. Error t value Pr(>|t|)
(Intercept) 0.00541 0.00292   1.85385 0.06387
Ytm1        0.04119 0.05410   0.76144 0.44646

```



```
xtVolm1      0.51409 0.18735      2.74409 0.00611
spVolm1      1.17486 0.23880      4.91982 0.00000
```

```
> mm1 <- rq(Yt~xtVolm1+spVolm1,tau=0.95)
> summary(mm1)
Call: rq(formula=Yt~xtVolm1+spVolm1,tau=0.95)
tau: 0.95
Coefficients:
```

	Value	Std. Error	t value	Pr(> t )
(Intercept)	0.00602	0.00276	2.18367	0.02907
xtVolm1	0.53592	0.14511	3.69312	0.00023
spVolm1	1.07361	0.22871	4.69430	0.00000

```
> xtVolm1[2768]
[1] 0.01626298
> spVolm1[2768]
[1] 0.006088562
```

```
##### Problem D #####
```

```
> idx <- c(1:2769)[qcom > 0]
> Qt <- rep(0,2769)
> Qt[idx] <- 1
> idx <- c(1:2769)[sp > 0]
> Mt <- rep(0, 2769)
> Mt[idx] <- 1
> dqcom <- Qt[4:2769]; dqm1 <- Qt[3:2768]; dqm2 <- Qt[2:2767]; dqm3 <- Qt[1:2766]
> qm1 <- qcom[3:2768]; qm2 <- qcom[2:2767]; qm3 <- qcom[1:2766]
> Mtm1 <- Mt[3:2768]; Mtm2 <- Mt[2:2767]; Mtm3 <- Mt[1:2766]
>
> g1 <- glm(dqcom~dqm1+dqm2+dqm3+Mtm1+Mtm2+Mtm3,family=binomial)
> summary(g1)
```

```
Call:
glm(formula = dqcom ~ dqm1 + dqm2 + dqm3 + Mtm1 + Mtm2 + Mtm3, family = binomial)
Coefficients:
```

	Estimate	Std. Error	z value	Pr(> z )
(Intercept)	0.20241	0.09264	2.185	0.028899 *
dqm1	-0.08002	0.08587	-0.932	0.351397
dqm2	-0.30609	0.08586	-3.565	0.000364 ***
dqm3	-0.02902	0.08593	-0.338	0.735605
Mtm1	-0.02655	0.08613	-0.308	0.757910
Mtm2	0.06188	0.08651	0.715	0.474376
Mtm3	-0.01395	0.08618	-0.162	0.871432

```
---
> g3 <- glm(dqcom~dqm2,family=binomial)
> summary(g3)
```

```
Call:
```

```
glm(formula = dqcom ~ dqm2, family = binomial)
```

```
Coefficients:
```

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	0.14383	0.05400	2.664	0.007729	**
dqm2	-0.27524	0.07624	-3.610	0.000306	***

```
---
```

```
> require(nnet)
```

```
> X <- cbind(dqm1,dqm2,dqm3,Mtm1,Mtm2,Mtm3)
```

```
> g4 <- nnet(X,dqcom,size=2,linout=F,skip=T)
```

```
# weights: 23
```

```
initial value 748.070119
```

```
iter 10 value 688.549909
```

```
.....
```

```
final value 681.800425
```

```
stopped after 100 iterations
```

```
> g4
```

```
a 6-2-1 network with 23 weights
```

```
options were - skip-layer connections
```

```
> summary(g4)
```

```
a 6-2-1 network with 23 weights
```

```
options were - skip-layer connections
```

```
b->h1 i1->h1 i2->h1 i3->h1 i4->h1 i5->h1 i6->h1
```

```
-20.18 -2.78 16.90 -4.62 8.16 8.08 12.04
```

```
b->h2 i1->h2 i2->h2 i3->h2 i4->h2 i5->h2 i6->h2
```

```
-30.84 -20.16 9.92 -18.02 0.70 15.89 22.89
```

```
b->o h1->o h2->o i1->o i2->o i3->o i4->o i5->o i6->o
```

```
0.29 0.74 -0.68 -0.15 -0.82 -0.03 -0.10 -0.04 -0.03
```