

# Stat 207 HW5

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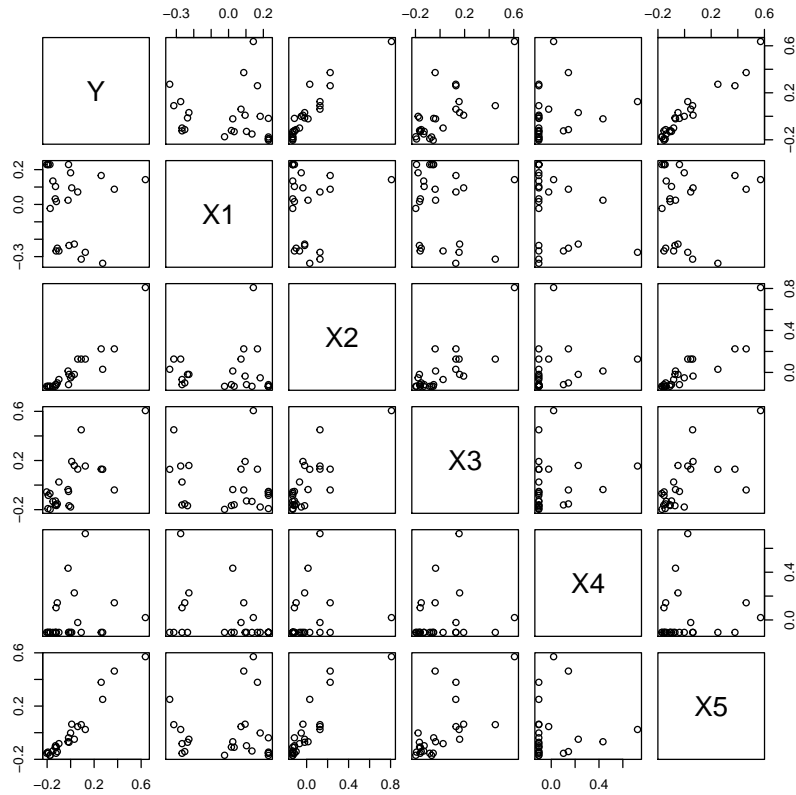
February 18, 2015



1 1

```
(a) require(gdata)
## Loading required package: gdata
## gdata: read.xls support for 'XLS' (Excel 97-2004) files ENABLED.
##
## gdata: read.xls support for 'XLSX' (Excel 2007+) files ENABLED.
##
## Attaching package: 'gdata'
##
## The following object is masked from 'package:stats':
##
##     nobs
##
## The following object is masked from 'package:utils':
##
##     object.size

dat1 = read.xls("apartment.xlsx", header = TRUE)
dat.stan = dat1
for(j in 1:ncol(dat1))
  dat.stan[,j] = (dat1[,j] - mean(dat1[,j]))/(sd(dat1[,j])*(sqrt(25-1)))
dat = dat.stan
plot(dat)
```



```
cor(dat)
```

```
##           Y           X1           X2           X3           X4           X5
## Y      1.0000000 -0.11453460  0.92345442  0.7413715  0.22497528 0.96813120
## X1 -0.1145346  1.00000000 -0.01415504 -0.1885895 -0.36265249 0.02700832
## X2  0.9234544 -0.01415504  1.00000000  0.8000696  0.22412565 0.87786360
## X3  0.7413715 -0.18858951  0.80006959  1.0000000  0.16609137 0.67269398
## X4  0.2249753 -0.36265249  0.22412565  0.1660914  1.00000000 0.08929658
## X5  0.9681312  0.02700832  0.87786360  0.6726940  0.08929658 1.00000000
```

We find that Y is highly correlated with X2, X3 and X5. and X2, X3 and X5 are highly correlated with each other, which means the multicollinearity is present.

(b) 

```
require(Matrix)
```

```
## Loading required package: Matrix
```

```
## Warning: package 'Matrix' was built under R version 3.1.2

X = dat[, 2:6]
X = as.matrix(X)
P = t(X) %*% X
eigen(P)

## $values
## [1] 2.63414515 1.33018568 0.65704211 0.29575194 0.08287513
##
## $vectors
##           [,1]      [,2]      [,3]      [,4]      [,5]
## [1,] -0.1012189  0.720376426  0.63332131 -0.25097092  0.08203814
## [2,]  0.5913231  0.122265531  0.09155295  0.08619205 -0.78713218
## [3,]  0.5475583  0.004633543 -0.24983677 -0.73925733  0.30205730
## [4,]  0.1893656 -0.646792392  0.72651658 -0.06042441  0.11967806
## [5,]  0.5517357  0.218511047  0.01665599  0.61598053  0.51781389
```

Some eigenvalues are not too close to zero, so that it does not exist serious multicollinearity.

```
(c) fit = lm(Y ~ 0 + ., data = dat)
summary(fit)

##
## Call:
## lm(formula = Y ~ 0 + ., data = dat)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.052406 -0.016609 -0.004069  0.014375  0.070701
##
## Coefficients:
##      Estimate Std. Error t value Pr(>|t|)
## X1 -0.10461     0.03556  -2.942  0.00807 **
## X2  0.24656     0.08636   2.855  0.00979 **
## X3  0.01854     0.05545   0.334  0.74159
## X4  0.06294     0.03581   1.758  0.09410 .
## X5  0.73642     0.06744  10.920 7.06e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.03121 on 20 degrees of freedom
## Multiple R-squared:  0.9805, Adjusted R-squared:  0.9757
## F-statistic: 201.4 on 5 and 20 DF, p-value: < 2.2e-16
```

```

anova(fit)

## Analysis of Variance Table
##
## Response: Y
##          Df Sum Sq Mean Sq  F value    Pr(>F)
## X1         1 0.01312  0.01312   13.4704 0.001519 **
## X2         1 0.84995  0.84995  872.7651 < 2.2e-16 ***
## X3         1 0.00073  0.00073    0.7458 0.398038
## X4         1 0.00061  0.00061    0.6247 0.438588
## X5         1 0.11612  0.11612  119.2409 7.064e-10 ***
## Residuals 20 0.01948  0.00097
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

In this multiple regression model, X1, X2, and X5 are more important to predict sale price.

(d)

```

require(faraway)

## Loading required package: faraway

vif(fit)

## Warning in vif.lm(fit): No intercept term detected. Results
## may surprise.

##          X1          X2          X3          X4          X5
## 1.298654 7.657888 3.157590 1.316618 4.670186

```

All VIF >1 shows that each X variable has the intercorrelation with the rest of the X variables.

(e)

```

library('MASS')

## Warning: package 'MASS' was built under R version 3.1.2

select(lm.ridge(Y ~ 0 + ., data = dat,
               lambda = seq(0, 1, .001)))

## modified HKB estimator is 0.1181183
## modified L-W estimator is 0.07448998
## smallest value of GCV at 0.321

k = .321
require('ridge')

```

```
## Loading required package: ridge
## Warning: package 'ridge' was built under R version 3.1.2

model = linearRidge(Y ~ 0 + ., data = dat,
                    lambda = k, scaling = 'none'); model

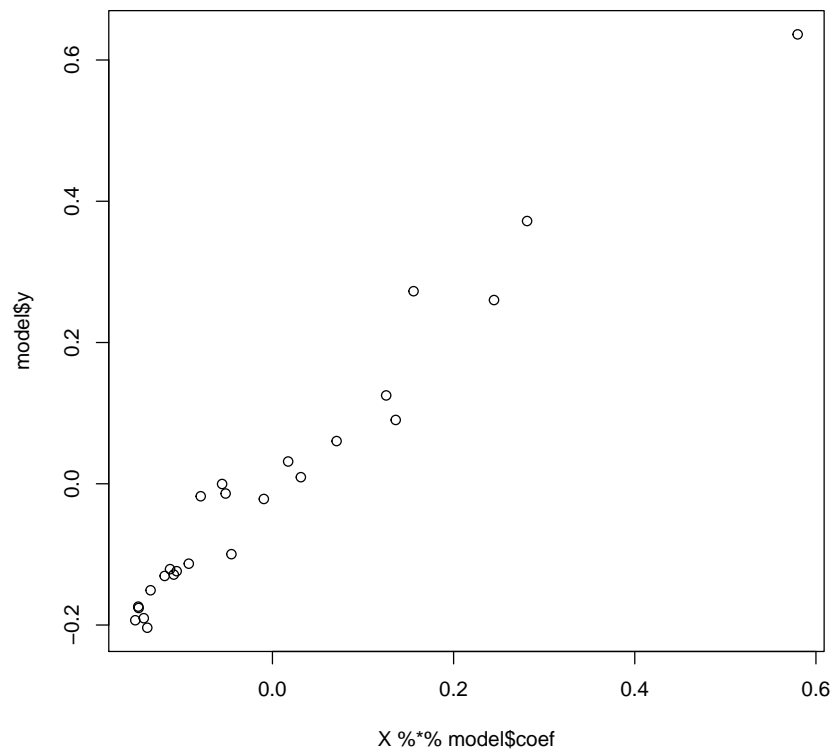
##
## Call:
## linearRidge(formula = Y ~ 0 + ., data = dat, lambda = k, scaling = "none")
##
##           X1           X2           X3           X4           X5
## -0.06004494  0.30522205  0.12451487  0.05500698  0.46414629

summary(model)

##
## Call:
## linearRidge(formula = Y ~ 0 + ., data = dat, lambda = k, scaling = "none")
##
##
## Coefficients:
##      Estimate Std. Error t value Pr(>|t|)
## X1 -0.06004    0.03763   1.596  0.11060
## X2  0.30522    0.03263   9.355 < 2e-16 ***
## X3  0.12451    0.03829   3.252  0.00114 **
## X4  0.05501    0.03774   1.457  0.14501
## X5  0.46415    0.03640  12.751 < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Ridge parameter: 0.321
##
## Degrees of freedom: model 3.053 , variance 2.167 , residual 3.94
```

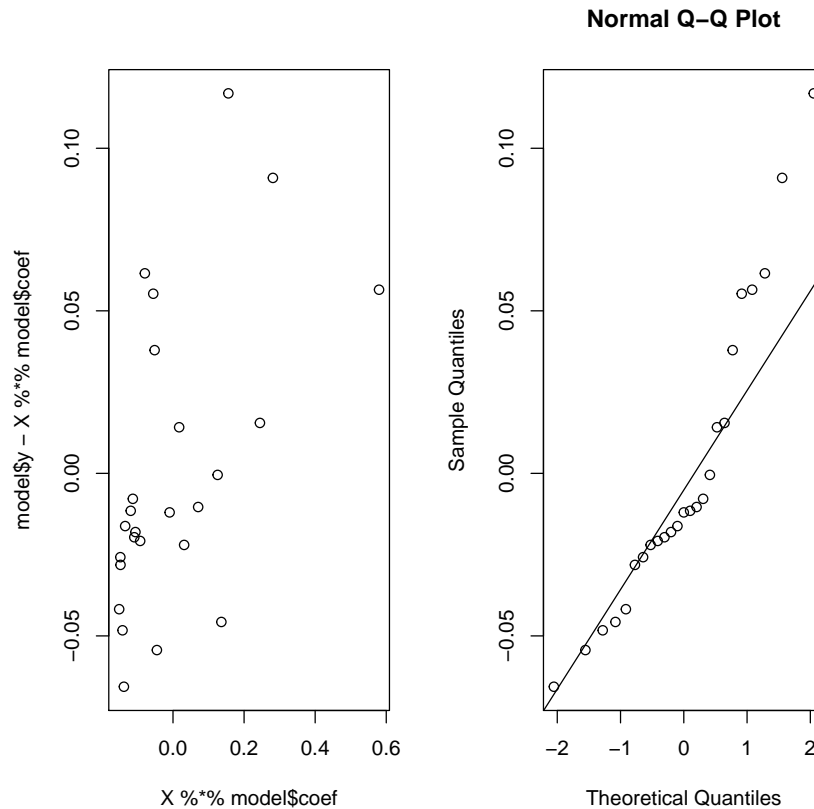
Parameter estimates and their standard errors are shown in the `summary(model)`.

(f) `plot(X%*%model$coef, model$y)`



```
par( mfrow = c(1, 2))
plot(X %%% model$coef, model$y - X %%% model$coef)
qqnorm(model$y - X %%% model$coef)
qqline(model$y - X %%% model$coef)
```





The residuals versus fitted values plots shows no sign for unequal variance. And the QQ-plot indicates approximately normal distribution with heavy tail, so that normality assumption seems to be reasonable, we can use model here.

```
(g) ans = solve(P + diag(k,5,5)) %*% P %*% solve(P + diag(k,5,5))
      diag(ans)

##          X1          X2          X3          X4          X5
## 0.5841713 0.4390908 0.6045876 0.5875868 0.5465513
```

VIF of the estimated ridge regression are shown in the above. All VIF are smaller than 1, which means they have little intercorrelation between X variables.

2 2

```

(a) require(gdata)
dat = read.xls("ratdrink.xlsx")
dat = dat[, 1:4]
dat$wk = dat$weeks - mean(dat$weeks); dat$wk

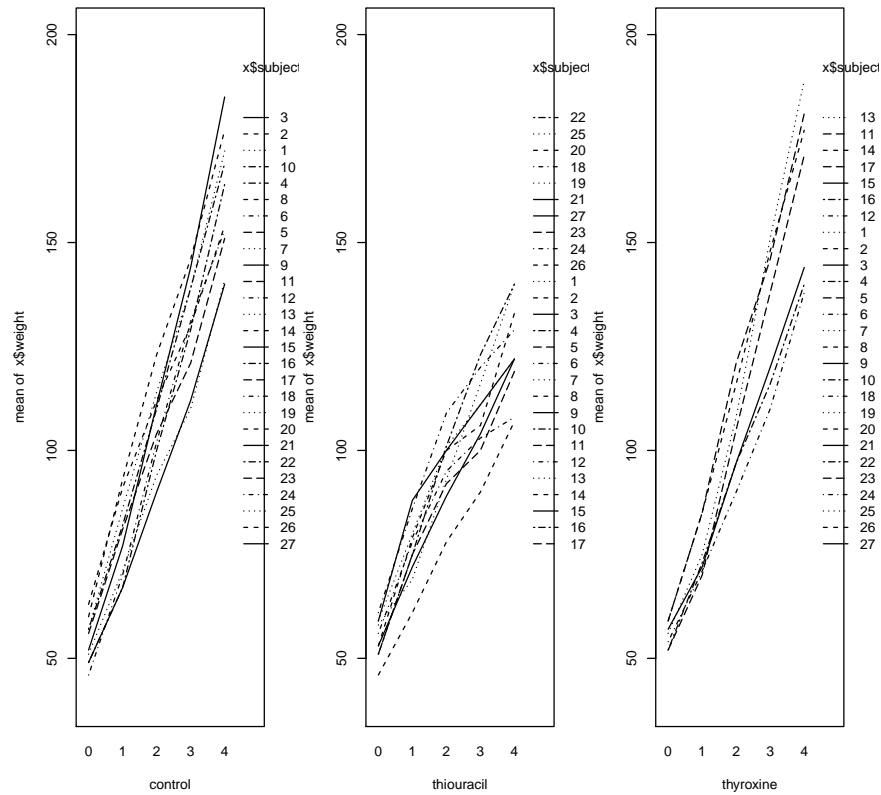
##      [1] -2 -1  0  1  2 -2 -1  0  1  2 -2 -1  0  1  2 -2 -1  0  1  2 -2 -1  0
##     [24]  1  2 -2 -1  0  1  2 -2 -1  0  1  2 -2 -1  0  1  2 -2 -1  0  1  2 -2
##     [47] -1  0  1  2 -2 -1  0  1  2 -2 -1  0  1  2 -2 -1  0  1  2 -2 -1  0  1
##     [70]  2 -2 -1  0  1  2 -2 -1  0  1  2 -2 -1  0  1  2 -2 -1  0  1  2 -2 -1
##     [93]  0  1  2 -2 -1  0  1  2 -2 -1  0  1  2 -2 -1  0  1  2 -2 -1  0  1  2
##    [116] -2 -1  0  1  2 -2 -1  0  1  2 -2 -1  0  1  2 -2 -1  0  1  2

dat$wk2 = dat$wk^2; dat$wk2

##      [1]  4  1  0  1  4  4  1  0  1  4  4  1  0  1  4  4  1  0  1  4  4  1  0  1  4
##     [36]  4  1  0  1  4  4  1  0  1  4  4  1  0  1  4  4  1  0  1  4  4  1  0  1  4
##     [71]  4  1  0  1  4  4  1  0  1  4  4  1  0  1  4  4  1  0  1  4  4  1  0  1  4
##    [106]  4  1  0  1  4  4  1  0  1  4  4  1  0  1  4  4  1  0  1  4

dat$weeks = as.factor(dat$weeks)
dat$subject = as.factor(dat$subject)
datt = split(dat, dat$treat)
par(mfrow = c(1, 3))
sapply(datt, function(x){interaction.plot(x$weeks, x$subject, x$weight, ylim = c(40, 2

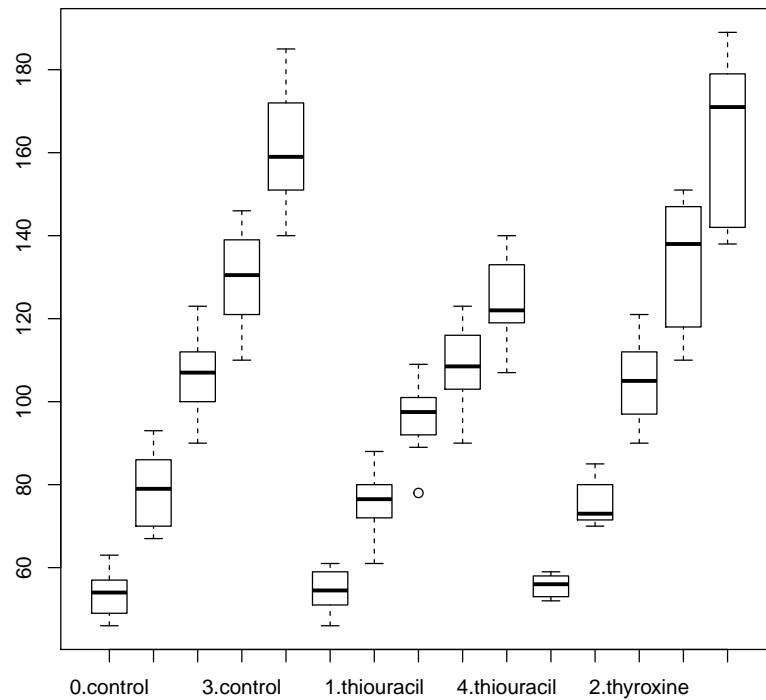
```



```
## $control
## NULL
##
## $thiouracil
## NULL
##
## $thyroxine
## NULL
```

(b)

```
par(mfrow = c(1, 1))
boxplot(weight ~ factor(weeks)*treat, data = dat)
```

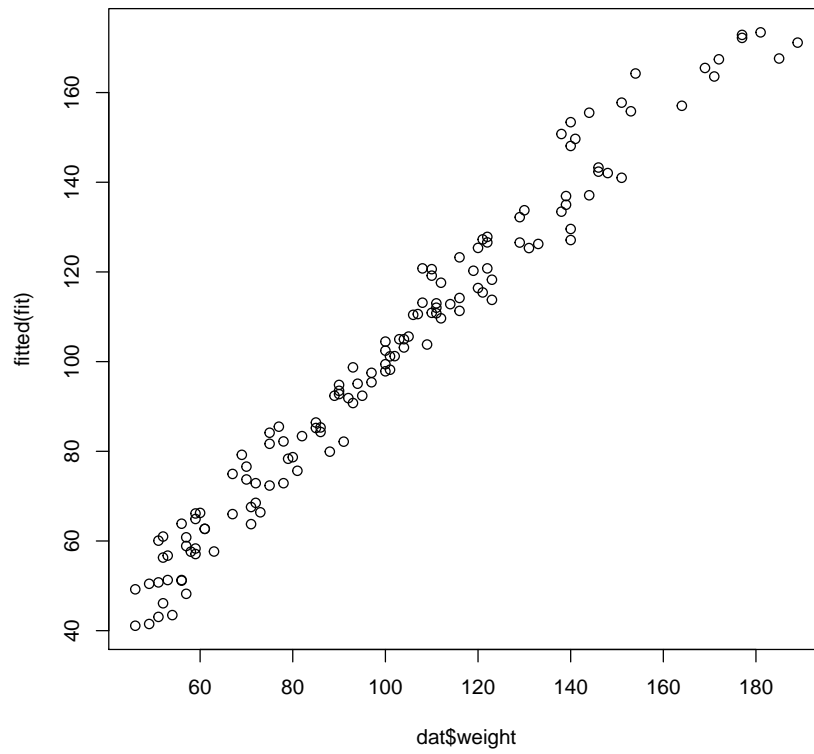


The mean weight becomes larger over time. And the variability of weight change over time gets bigger, treatment thyroxine has the biggest variability over time.

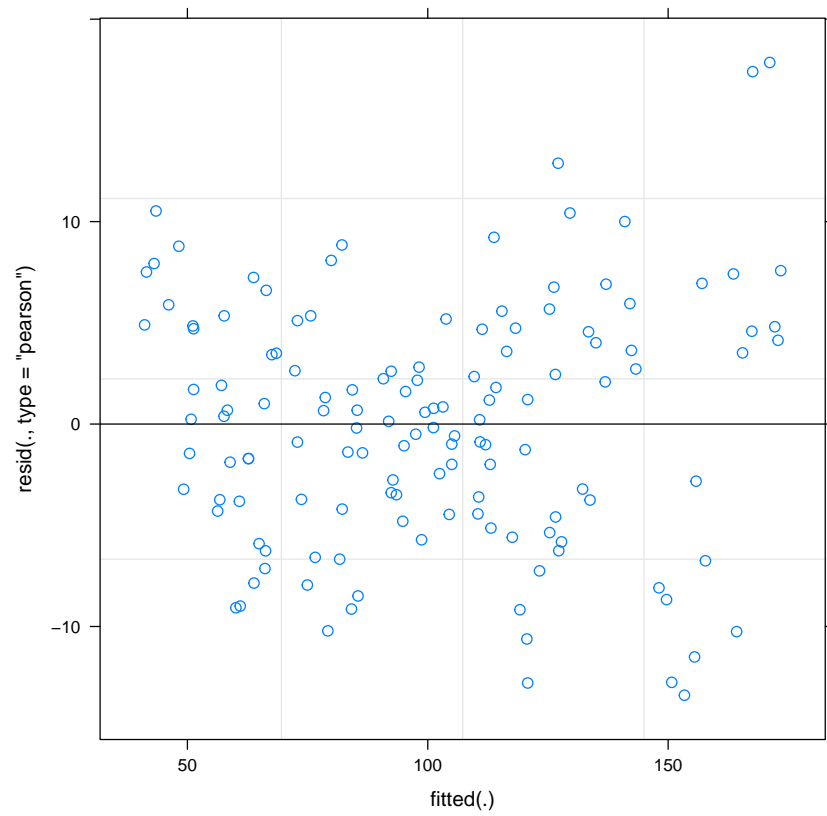
(c)

```
require(lme4)
## Loading required package: lme4
## Warning: package 'lme4' was built under R version 3.1.2
## Loading required package: Rcpp
## Warning: package 'Rcpp' was built under R version 3.1.2

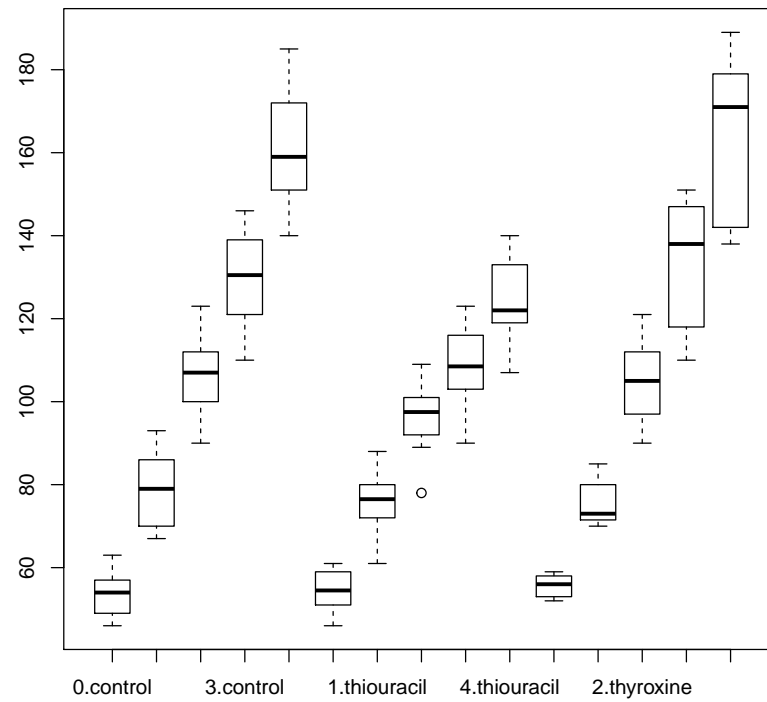
fit = lmer(weight ~ factor(weeks) + treat + factor(weeks):treat + (1|subject), data =
par(mfrow = c(1, 1))
plot(dat$weight, fitted(fit))
```



```
plot(fit, which = 1)
```



```
par(mfrow = c(1, 1))  
boxplot(weight ~ weeks*treat, data = dat)
```



The residuals versus fitted values plots shows no sign for unequal variance.

```
(d) summary(fit)

## Linear mixed model fit by REML ['lmerMod']
## Formula:
## weight ~ factor(weeks) + treat + factor(weeks):treat + (1 | subject)
## Data: dat
##
## REML criterion at convergence: 892.1
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -1.90369 -0.60408  0.03345  0.64957  2.53828
##
## Random effects:
```

```

## Groups      Name      Variance Std.Dev.
## subject (Intercept) 71.55      8.459
## Residual          49.51      7.036
## Number of obs: 135, groups:  subject, 27
##
## Fixed effects:
##
##              Estimate Std. Error t value
## (Intercept)      54.0000      3.4794  15.52
## factor(weeks)1      24.5000      3.1468   7.79
## factor(weeks)2      52.0000      3.1468  16.52
## factor(weeks)3      76.1000      3.1468  24.18
## factor(weeks)4     106.6000      3.1468  33.88
## treatthiouracil      0.7000      4.9206   0.14
## treatthyroxine      1.5714      5.4222   0.29
## factor(weeks)1:treatthiouracil -2.9000      4.4503  -0.65
## factor(weeks)2:treatthiouracil -10.9000      4.4503  -2.45
## factor(weeks)3:treatthiouracil -22.4000      4.4503  -5.03
## factor(weeks)4:treatthiouracil -37.1000      4.4503  -8.34
## factor(weeks)1:treatthyroxine  -4.2143      4.9039  -0.86
## factor(weeks)2:treatthyroxine  -2.7143      4.9039  -0.55
## factor(weeks)3:treatthyroxine   1.0429      4.9039   0.21
## factor(weeks)4:treatthyroxine   0.6857      4.9039   0.14
##
## Correlation of Fixed Effects:
##              (Intr) fct()1 fct()2 fct()3 fct()4 trtthr trtthy
## factr(wks)1      -0.452
## factr(wks)2      -0.452  0.500
## factr(wks)3      -0.452  0.500  0.500
## factr(wks)4      -0.452  0.500  0.500  0.500
## treatthirc1      -0.707  0.320  0.320  0.320  0.320
## treatthyrxn      -0.642  0.290  0.290  0.290  0.290  0.454
## fctr(wks)1:trtthr  0.320 -0.707 -0.354 -0.354 -0.354 -0.452 -0.205
## fctr(wks)2:trtthr  0.320 -0.354 -0.707 -0.354 -0.354 -0.452 -0.205
## fctr(wks)3:trtthr  0.320 -0.354 -0.354 -0.707 -0.354 -0.452 -0.205
## fctr(wks)4:trtthr  0.320 -0.354 -0.354 -0.354 -0.707 -0.452 -0.205
## fctr(wks)1:trtthy  0.290 -0.642 -0.321 -0.321 -0.321 -0.205 -0.452
## fctr(wks)2:trtthy  0.290 -0.321 -0.642 -0.321 -0.321 -0.205 -0.452
## fctr(wks)3:trtthy  0.290 -0.321 -0.321 -0.642 -0.321 -0.205 -0.452
## fctr(wks)4:trtthy  0.290 -0.321 -0.321 -0.321 -0.642 -0.205 -0.452
## fctr(wks)1:trtthr fctr(wks)2:trtthr fctr(wks)3:trtthr
## factr(wks)1
## factr(wks)2
## factr(wks)3
## factr(wks)4
## treatthirc1

```



```

## treatthyrxn
## fctr(wks)1:trtthr
## fctr(wks)2:trtthr 0.500
## fctr(wks)3:trtthr 0.500 0.500
## fctr(wks)4:trtthr 0.500 0.500 0.500
## fctr(wks)1:trtthy 0.454 0.227 0.227
## fctr(wks)2:trtthy 0.227 0.454 0.227
## fctr(wks)3:trtthy 0.227 0.227 0.454
## fctr(wks)4:trtthy 0.227 0.227 0.227
## fctr(wks)4:trtthr fctr(wks)1:trtthy fctr(wks)2:trtthy
## factr(wks)1
## factr(wks)2
## factr(wks)3
## factr(wks)4
## treatthirc1
## treatthyrxn
## fctr(wks)1:trtthr
## fctr(wks)2:trtthr
## fctr(wks)3:trtthr
## fctr(wks)4:trtthr
## fctr(wks)1:trtthy 0.227
## fctr(wks)2:trtthy 0.227 0.500
## fctr(wks)3:trtthy 0.227 0.500 0.500
## fctr(wks)4:trtthy 0.454 0.500 0.500
## fctr(wks)3:trtthy
## factr(wks)1
## factr(wks)2
## factr(wks)3
## factr(wks)4
## treatthirc1
## treatthyrxn
## fctr(wks)1:trtthr
## fctr(wks)2:trtthr
## fctr(wks)3:trtthr
## fctr(wks)4:trtthr
## fctr(wks)1:trtthy
## fctr(wks)2:trtthy
## fctr(wks)3:trtthy
## fctr(wks)4:trtthy 0.500

anova(fit)

## Analysis of Variance Table
## Df Sum Sq Mean Sq F value
## factor(weeks) 4 145188 36297 733.0981

```

```
## treat          2    770    385    7.7774
## factor(weeks):treat  8   6403    800   16.1641

fit1 = lm(weight ~ factor(weeks) + treat + factor(weeks):treat, data = dat )
fit2 = lmer(weight ~ treat + factor(weeks):treat + (1|subject), data = dat )
fit3 = lmer(weight ~ factor(weeks) + factor(weeks):treat + (1|subject), data = dat )
fit4 = lmer(weight ~ factor(weeks) + treat + (1|subject), data = dat )
AIC(fit)

## [1] 926.1398

AIC(fit1)

## [1] 1046.712

AIC(fit2)

## [1] 926.1398

AIC(fit3)

## [1] 926.1398

AIC(fit4)

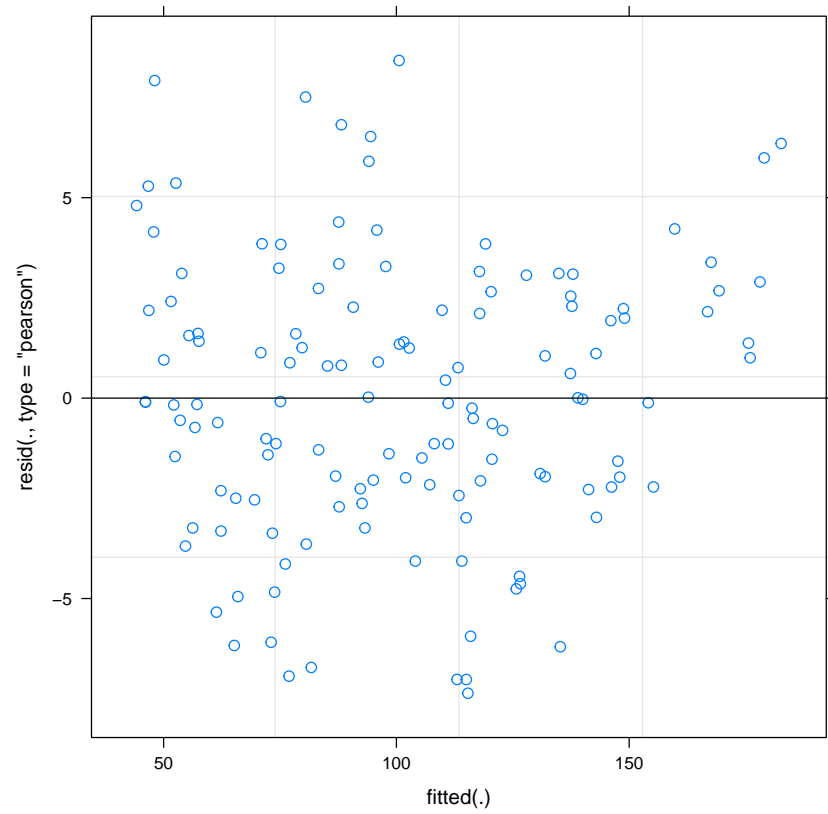
## [1] 1034.661
```

The AIC of the full model is 926.1398, which means it's the smallest AIC of all. So there's no need to drop the terms.

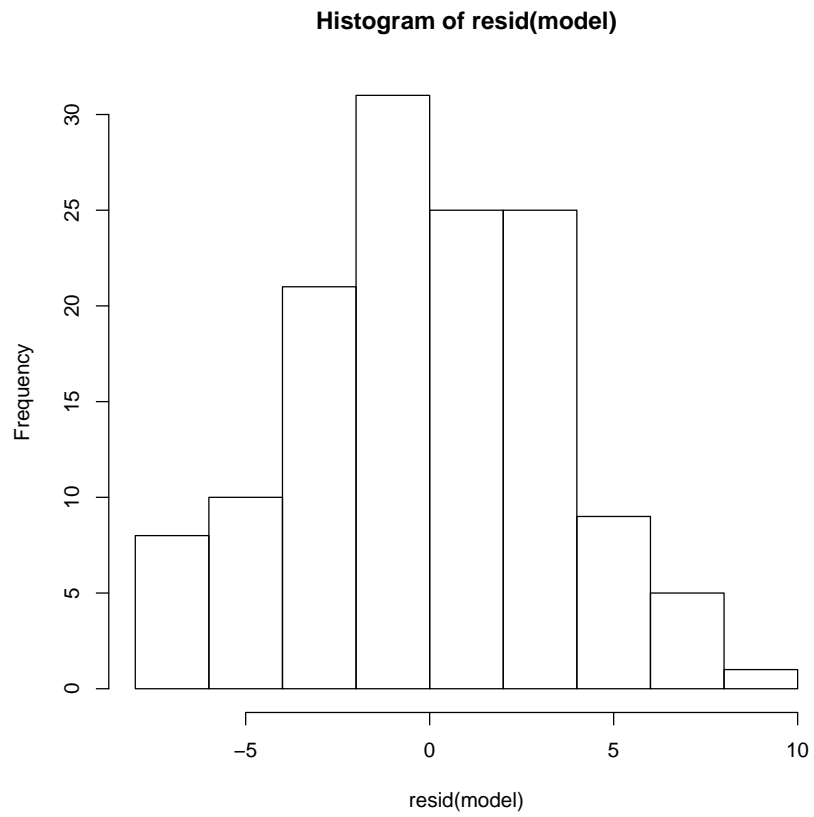
### 3 3

- (a) 

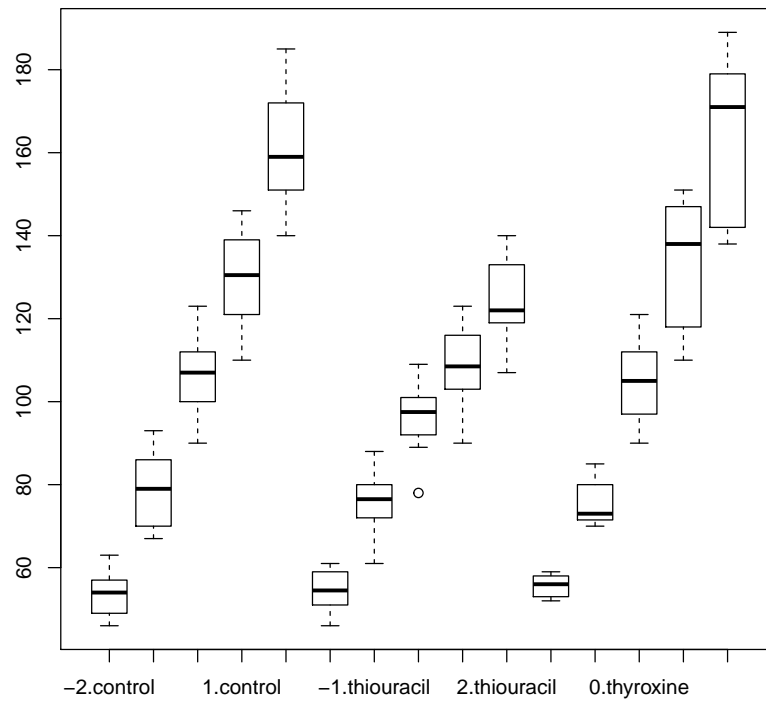
```
model = lmer(weight ~ wk + treat + (1|subject) + (0 + wk|subject), data = dat)
par( mfrow = c(1, 1))
plot(model, which = 1)
```



```
hist(resid(model))
```



```
boxplot(weight ~ wk*treat, data = dat)
```



```
(b) model2 = lmer(weight ~ wk + wk2 + treat + (1|subject)+ (0 + wk|subject)+ (0 + wk2|subject)
summary(model2)

## Linear mixed model fit by REML ['lmerMod']
## Formula: weight ~ wk + wk2 + treat + (1 | subject) + (0 + wk | subject) +
##      (0 + wk2 | subject)
##      Data: dat
##
## REML criterion at convergence: 908.3
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -2.4904 -0.4034  0.0611  0.3895  1.7395
##
## Random effects:
##      Groups      Name      Variance Std.Dev.
##      subject      (Intercept) 87.138   9.335
```

```
## subject.1 wk      36.444    6.037
## subject.2 wk2     2.042    1.429
## Residual          9.402    3.066
## Number of obs: 135, groups:  subject, 27
##
## Fixed effects:
##              Estimate Std. Error t value
## (Intercept)  104.87487    3.02136   34.71
## wk           23.18148    1.17669   19.70
## wk2          0.08201    0.31704    0.26
## treatthiouracil -11.04663    4.26709   -2.59
## treatthyroxine  -0.54055    4.70210   -0.11
##
## Correlation of Fixed Effects:
##              (Intr) wk      wk2      trtthr
## wk           0.000
## wk2          -0.052  0.000
## treatthircl -0.706  0.000  0.000
## treatthyrxn -0.641  0.000  0.000  0.454
```

No, they seems to be different, the second model has term  $I(weeks^2)$ .

(c) `AIC(model)`

```
## [1] 939.0791
```

`AIC(model2)`

```
## [1] 926.3378
```

The AIC of the first model is 939.0791, which is bigger than 926.3378(second model). So that, we should choose the first model with wk2.

`summary(model2)`

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: weight ~ wk + wk2 + treat + (1 | subject) + (0 + wk | subject) +
##          (0 + wk2 | subject)
## Data: dat
##
## REML criterion at convergence: 908.3
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
```

```
## -2.4904 -0.4034 0.0611 0.3895 1.7395
##
## Random effects:
## Groups      Name      Variance Std.Dev.
## subject    (Intercept) 87.138   9.335
## subject.1 wk          36.444   6.037
## subject.2 wk2          2.042   1.429
## Residual                9.402   3.066
## Number of obs: 135, groups:  subject, 27
##
## Fixed effects:
##              Estimate Std. Error t value
## (Intercept)  104.87487    3.02136   34.71
## wk           23.18148    1.17669   19.70
## wk2           0.08201    0.31704    0.26
## treatthiouracil -11.04663    4.26709   -2.59
## treatthyroxine  -0.54055    4.70210   -0.11
##
## Correlation of Fixed Effects:
##              (Intr) wk      wk2      trtthr
## wk              0.000
## wk2             -0.052  0.000
## treatthircl    -0.706  0.000  0.000
## treatthyrxn    -0.641  0.000  0.000  0.454
```

(d) `model3 = lmer(weight ~ weeks + I(weeks^2) + treat + (1|subject) + (0 + weeks|subject))`  
 ## Warning in Ops.factor(weeks, 2): ^ not meaningful for factors  
 ## Error: Invalid grouping factor specification, subject

It seems that the slopes may depend on the treatment.

(e) `summary(model3)`  
 ## Error in summary(model3): error in evaluating the argument 'object'  
 in selecting a method for function 'summary': Error: object 'model3'  
 not found  
  
`drop1(model3, )`  
 ## Error in drop1(model3, ): object 'model3' not found

4 4

(a)

$$\begin{aligned}
E(Y_{ij}) &= E(\mu + \rho_i + \beta_1 x_i + \gamma_1 t_j + \epsilon_{ij}) \\
&= \mu + \beta_1 x_i + \gamma_1 t_j \\
\text{Var}(Y_{ij}) &= \text{var}(\mu + \rho_i + \beta_1 x_i + \gamma_1 t_j + \epsilon_{ij}) \\
&= \text{var}(\rho_i + \epsilon_{ij}) \\
&= \sigma_\rho^2 + \sigma^2 (\text{since } \rho_i \text{ and } \epsilon_{ij} \text{ are independent}) \\
\text{Cov}(Y_{ij}, Y_{ij'}) &= E((Y_{ij} - E(Y_{ij}))(Y_{ij'} - E(Y_{ij'}))) \\
&= E((\rho_i + \epsilon_{ij})(\rho_i + \epsilon_{ij'})) \\
&= E(\rho_i^2) (\text{since } \rho_i \text{ and } \epsilon_{ij} \text{ and } \epsilon_{ij'} \text{ are independent}) \\
&= \text{Var}(\rho_i) + (E(\rho_i))^2 \\
&= \sigma_\rho^2 \\
\text{Corr}(Y_{ij}, Y_{ij'}) &= \frac{\text{Cov}(Y_{ij}, Y_{ij'})}{\sqrt{\text{Var}(Y_{ij}) * \text{Var}(Y_{ij'})}} \\
&= \frac{\sigma_\rho^2}{\sigma_\rho^2 + \sigma^2}
\end{aligned}$$

(b)

$$\begin{aligned}
E(Y_{ij}) &= E(\mu + \rho_i + \beta_1 x_i + \gamma_1 t_j + \gamma_{i1} t_j + \epsilon_{ij}) \\
&= \mu + \beta_1 x_i + \gamma_1 t_j \\
\text{Var}(Y_{ij}) &= \text{var}(\mu + \rho_i + \beta_1 x_i + \gamma_1 t_j + \gamma_{i1} t_j + \epsilon_{ij}) \\
&= \text{var}(\rho_i + \gamma_{i1} t_j + \epsilon_{ij}) \\
&= \sigma_\rho^2 + t_j^2 \sigma_{\gamma_1}^2 + \sigma^2 (\text{since } \rho_i, \gamma_{i1} \text{ and } \epsilon_{ij} \text{ are independent}) \\
\text{Cov}(Y_{ij}, Y_{ij'}) &= E((Y_{ij} - E(Y_{ij}))(Y_{ij'} - E(Y_{ij'}))) \\
&= E((\rho_i + \gamma_{i1} t_j + \epsilon_{ij})(\rho_i + \gamma_{i1} t_{j'} + \epsilon_{ij'})) \\
&= E(\rho_i^2 + \gamma_{i1}^2 t_j * t_{j'}) (\text{since } \rho_i, \gamma_{i1}, \epsilon_{ij} \text{ and } \epsilon_{ij'} \text{ are independent}) \\
&= E(\rho_i^2) + (t_j * t_{j'}) * E(\gamma_{i1}^2) \\
&= \sigma_\rho^2 + (t_j * t_{j'}) \sigma_{\gamma_1}^2 \\
\text{Corr}(Y_{ij}, Y_{ij'}) &= \frac{\text{Cov}(Y_{ij}, Y_{ij'})}{\sqrt{\text{Var}(Y_{ij}) * \text{Var}(Y_{ij'})}} \\
&= \frac{\sigma_\rho^2 + (t_j * t_{j'}) \sigma_{\gamma_1}^2}{\sqrt{(\sigma_\rho^2 + t_j^2 \sigma_{\gamma_1}^2 + \sigma^2)(\sigma_\rho^2 + t_{j'}^2 \sigma_{\gamma_1}^2 + \sigma^2)}}
\end{aligned}$$