Midterm 2

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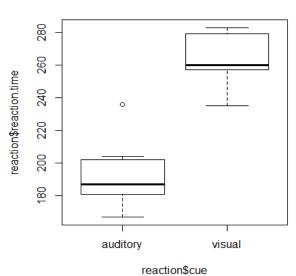
1.1

- > plot(reaction.time~elapsed.time,main="Reaction Time versus Elapsed Time")
 > plot(reaction.time~reaction\$cue,main="Reaction Time versus Cue")

Reaction Time versus Elapsed Time

280 260 reaction\$reaction.time 240 220 200 8 2 3 reaction\$elapsed.time

Reaction Time versus Cue



1.2

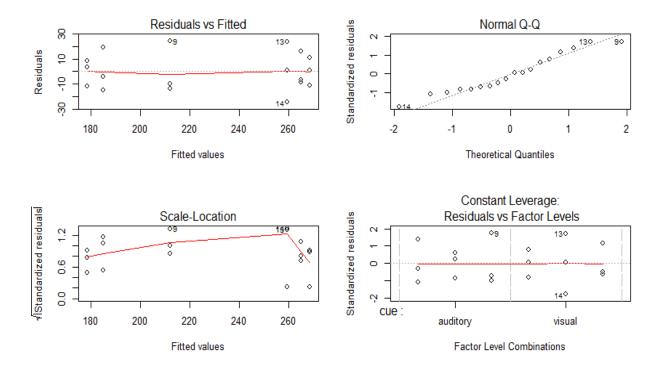
First, we want to set up the 2-way complete model:

$$Y_{ijt} = \mu + \alpha_i + \beta_j + (\alpha\beta)_{ij} + \epsilon_{ijt}, \epsilon_{ijt} \sim N(0,\sigma^2)$$
 with iid

 Y_{ijt} = the reaction time with i^{th} cue and j^{th} elapsed time.

i = auditory, visual j = 1, 2, 3 $t = 1, ..., r_i$

- > lsm.reaction=aov(reaction.time~cue+elapsed.time+cue:elapsed.time,data=react ion)
- > par(mfrow=c(2,2))
- > plot(lsm.reaction)



The plots show that in the residuals plot of the 2-way complete model, constant variance is satisfied, and the Q-Q plot shows the normality. In this case, we do not need to do transformation. All assumptions are satisfied. We can do further study with this model.

```
> anova(lsm.reaction)
Analysis of Variance Table
Response: reaction.time
                 Df
                     Sum Sq Mean Sq F value
                                                 Pr(>F)
                  1 23544.5 23544.5 81.3750 1.077e-06 ***
elapsed.time
                  2
                                      2.0013
                     1158.1
                               579.1
                                                 0.1778
                  2
                       846.3
                               423.2
                                      1.4626
                                                 0.2701
cue:elapsed.time
Residuals
                 12
                      3472.0
                               289.3
                0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Signif. codes:
```

For Interaction term:

 H_0 : combination of cue and elapsed time has no impact on the mean reaction time

Test Statistic $F_{2,12} = 1.4626$

p-value = $0.2701 > \alpha = 0.05$

Since the p-value of the interaction term is larger than 0.05, we fail to reject null hypothesis and conclude that different combinations of cue and elapsed time have no impact on mean reaction time.

For Cue:

H₀: cue has no impact on reaction time

```
Test Statistic F_{1,12} = 81.3750
```

```
p-value = 1.077 \times 10^{-6} < \alpha = 0.05
```

Since the p-value of the cue is smaller than 0.05, we reject null hypothesis and conclude that different cues have impacts on mean reaction time.

```
> cld(reaction.cue,alpha=0.05)
cue    lsmean    SE df lower.CL upper.CL .group
auditory 191.8889 5.669934 12 179.5352 204.2426 1
visual    264.2222 5.669934 12 251.8685 276.5759    2

Results are averaged over the levels of: elapsed.time
Confidence level used: 0.95
significance level used: alpha = 0.05
```

By observing the chart and graph above, we can see that the <u>visual cue</u> has more impacts on the mean reaction time than the <u>auditory cue</u> has.

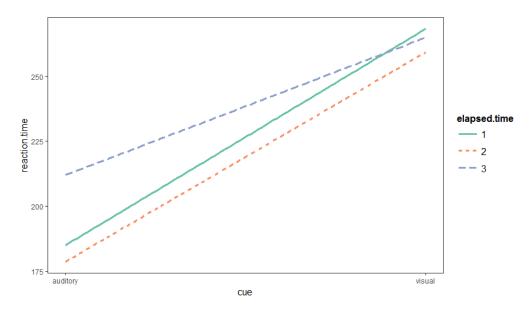
For Elapsed Time:

H₀: elapsed time has no impact on reaction time

Test Statistic $F_{1,14} = 1.3470$

p-value = $0.2652 > \alpha = 0.05$

Since the p-value of the elapsed time is larger than 0.05, we fail to reject null hypothesis and conclude that different elapsed time have no impact on mean reaction time.



By observing the graph above, we can see that:

For auditory cue, elapsed time 1 and 2 have similar effect on reaction time but elapsed time 3 has a little bit more effects on reaction time than elapsed time 1 and 2 have.

For visual cue, elapsed time 1 and 3 have same effects on reaction time but elapsed time 2 has a little bit less effects on reaction time than elapsed time 1 and 3 have.

In general, combinations of cue and elapsed have no significant effects on reaction time.

For cue, auditory cue has less effects on reaction time than visual cue has.

For elapsed time, even though the elapsed time 2 has the smallest effects on reaction time, there is no significant different between elapsed times.

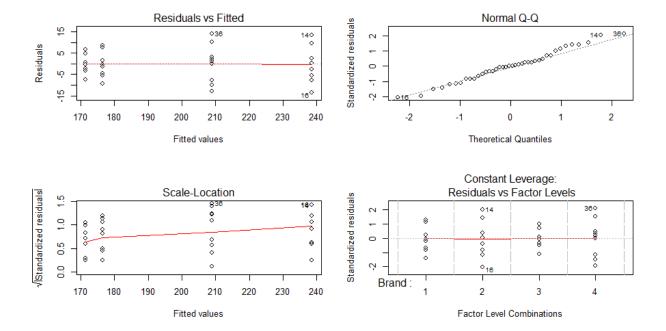
2.

Model: $Y_{it} = \mu + \tau_i + \epsilon_{it}$, $\epsilon_{it} \sim N(0, \sigma^2)$ with iid

 Y_{it} = melting time of t^{th} butter of i^{th} brand.

$$i = 1, 2, 3, 4$$
 $t = 1, ..., r_i$

- > lsm.melt=aov(Times~Brand,data=melt)
- > par(mfrow=c(2,2))
- > plot(lsm.melt)



By observing the graph above, we can see that the residual plot shows a constant variance and the Q-Q plot shows the normality. Thus, all assumptions are satisfied. We can do further study.

H₀: Brand has no significant effect to the mean melting time.

H₁: Brand has significant effects to the mean melting time.

```
Test-Statistic = F_{3,36} = 200.35
p-value < 2.2 × 10<sup>-16</sup> < \alpha =0.05
```

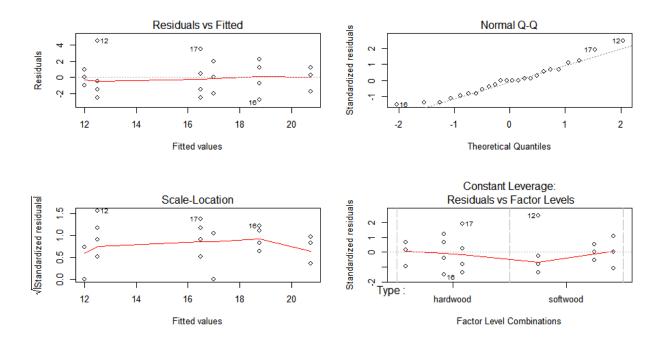
Since the p-value is smaller than 0.05, we reject null hypothesis and conclude that butter brands do have significant effect to the mean melting time.

3.1

This experiment is a completely randomized design because for each treatment (softwood and hardwood), 4 trees are randomly selected from a larger population of each species.

3.2

```
Model: Y_{ijt} = \mu + \alpha_i + \beta_{j(i)} + \epsilon_{ijt}, \epsilon_{ijt} \sim N(0,\sigma^2) with iid Y_{ijt} = \text{nitrogen content of } t^{th} \text{ tree of } i^{th} \text{ type and } j^{th} \text{ species.} i = \text{hardwood}, softwood j = \text{oak}, ash, maple, pine, spruce, fir t = 1, \dots, r_i \text{span} = 1, \dots, r_i
```



The plots show that the residuals of the 2-way nested model satisfy constant variance and the Q-Q plot shows the normality. Thus, assumptions are satisfied. No transformation is needed at this time. We can do further study with this model.

```
> anova(1sm.wood)
Analysis of Variance Table
Response: Nconc
             Df
                 Sum Sq Mean Sq F value
                                            Pr(>F)
              1 140.167 140.167 31.7358 2.408e-05 ***
                         24.208
                                  5.4811
                 96.833
                                         0.004574
Type:Species
              4
                 79.500
Residuals
             18
                           4.417
                0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Signif. codes:
```

For Interaction term:

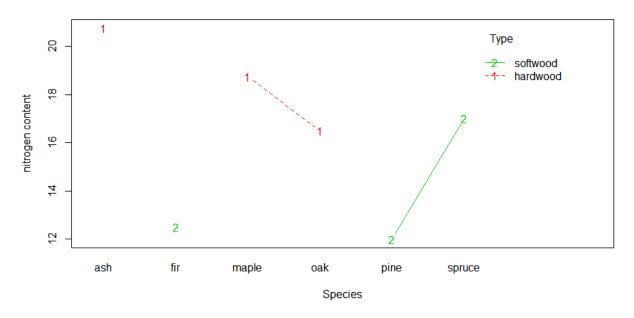
H₀: combination of Type and Species has no impact on the mean reaction time

Test Statistic $F_{4,18} = 5.4811$

p-value = $0.004574 < \alpha = 0.05$

Since the p-value of the interaction term is smaller than 0.05, we reject null hypothesis and conclude that different combinations of Type and Species have impact on mean nitrogen content.

Then we will do pairwise comparison:



```
contrast(wood.ST, method="pairwise")
 contrast
                                   estimate
                                                   SE df t.ratio p.value
 ash, hardwood - maple, hardwood
                                       2.00 1.486046 18
                                                           1.346
                                                                  0.7567
 ash, hardwood - oak, hardwood
                                       4.25 1.486046 18
                                                           2.860
                                                                  0.0923
 ash, hardwood - fir, softwood
                                       8.25 1.486046 18
                                                           5.552
                                                                  0.0004
 ash, hardwood - pine, softwood
                                       8.75 1.486046 18
                                                           5.888
                                                                  0.0002
 ash, hardwood - spruce, softwood
                                       3.75 1.486046 18
                                                           2.523
                                                                  0.1689
 maple, hardwood - oak, hardwood
                                       2.25 1.486046 18
                                                           1.514
                                                                   0.6602
 maple,hardwood - fir,softwood
                                       6.25 1.486046 18
                                                           4.206
                                                                   0.0060
 maple,hardwood - pine,softwood
                                       6.75 1.486046 18
                                                           4.542
                                                                   0.0029
 maple,hardwood - spruce,softwood
                                       1.75 1.486046 18
                                                           1.178
                                                                  0.8416
 oak, hardwood - fir, softwood
                                       4.00 1.486046 18
                                                           2.692
                                                                   0.1257
 oak, hardwood - pine, softwood
                                       4.50 1.486046 18
                                                           3.028
                                                                  0.0670
 oak, hardwood - spruce, softwood
                                      -0.50 1.486046 18
                                                          -0.336
                                                                  0.9993
fir,softwood - pine,softwood
                                       0.50 1.486046 18
                                                           0.336
                                                                  0.9993
 fir,softwood - spruce,softwood
                                      -4.50 1.486046 18
                                                          -3.028
                                                                  0.0670
 pine,softwood - spruce,softwood
                                      -5.00 1.486046 18
                                                          -3.365
                                                                  0.0344
P value adjustment: tukey method for comparing a family of 6 estimates
```

By observing the chart above, we can conclude that:

- Species of <u>fir</u> in <u>soft wood</u> category has less impact on mean nitrogen content than species of ash in hard wood category has.
- Species of <u>pine</u> in <u>soft wood</u> category has less impact on mean nitrogen content than species of <u>ash</u> in <u>hard wood</u> category has.
- Species of <u>fir</u> in <u>soft wood</u> category has less impact on mean nitrogen content than species of maple in hard wood category has.
- Species of <u>pine</u> in <u>soft wood</u> category has less impact on mean nitrogen content than species of <u>maple</u> in <u>hard wood</u> category has.

- Species of <u>pine</u> in <u>soft wood</u> category has more impact on mean nitrogen content than species of <u>spruce</u> in <u>soft wood</u> category has.
- No other comparisons are significantly different than zero based on the p-values.

For Type:

H₀: Type has no impact on reaction time

```
Test Statistic F_{1,18} = 31.7358
```

```
p-value = 2.408 \times 10^{-5} < \alpha = 0.05
```

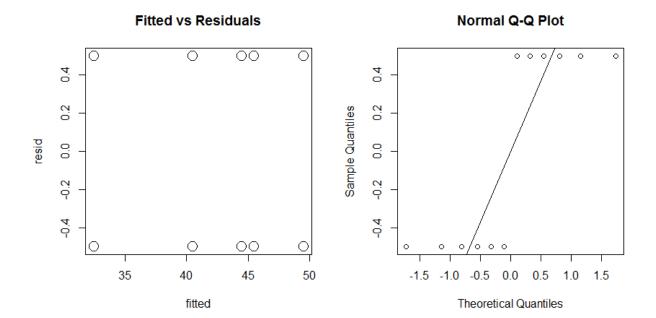
Since the p-value of the Type is smaller than 0.05, we reject null hypothesis and conclude that Type has impacts on mean nitrogen content.

By observing the chart above, we can see that <u>soft wood</u> has less impacts on mean nitrogen content than hard wood has.

4.1

In this experiment, beans from each crocks are divided into 3 jars. This implies that each kind of beans in different crocks only have one jar. Then, it is not necessary to treat jar as a factor. Instead, we simply treat jar as a replicate.

(crocks nested in soak time, crocks crossed with recipes, response = reating, jars = replicates)



By observing the graph above, we can see that the constant variance is satisfied, but the Q-Q plot shows no normality. Thus, we want to try some transformations.

By trying transformation of 1/Rating, log(Rating), sqrt(Rating), the Q-Q plot gets better but the residual plots then show non-constant variance (transformations are not shown in the report but are included in the R code). Thus, we will still use the original model. Since not all assumptions are satisfied, we need to be careful with the p-value.

```
> Anova(lsm.taste,type="III")
Analysis of Deviance Table (Type III Wald chisquare tests)
Response: Rating
                   Chisq Df Pr(>Chisq)
                          1 < 2.2e-16 ***
(Intercept)
               42672.667
                             < 2.2e-16 ***
SoakTim
                 450.667
                          1
                          2
                             < 2.2e-16 ***
Recipe
                 145.333
SoakTim:Recipe
                          2
                             < 2.2e-16 ***
                  81.333
                0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Signif. codes:
```

For fixed Interaction between Soak Time and Recipes:

H₀: the interaction between Soak Time and Recipes has no effect on mean taste rating score

Test Statistic =
$$\chi^2_2$$
 = 81.333
p-value < 2.2 × 10⁻¹⁶ < α = 0.05

Since the p-value of the interaction between Soak Time and Recipes is smaller than 0.05, we reject null hypothesis and conclude that interaction between Soak Time and Recipes has significant effects on mean taste rating score. Also, since the interaction term has significant effects, we do not need to look at the main effect lines.

By observing the chart above, we can conclude that:

- Beans with Short soaking time and Barbecue recipes have less impacts on the mean taste rating score than beans with Long soaking time and Barbecue recipes.
- Beans with Long soaking time and Original recipes have less impacts on the mean taste rating score than beans with Long soaking time and Barbecue recipes.
- Beans with Short soaking time and Original recipes have less impacts on the mean taste rating score than beans with Long soaking time and Barbecue recipes.
- Beans with Long soaking time and Refried recipes have less impacts on the mean taste rating score than beans with Long soaking time and Barbecue recipes.
- Beans with Short soaking time and Refried recipes have less impacts on the mean taste rating score than beans with Long soaking time and Barbecue recipes.
- Beans with Short soaking time and Barbecue recipes have less impacts on the mean taste rating score than beans with Long soaking time and Original recipes.
- Beans with Short soaking time and Original recipes have less impacts on the mean taste rating score than beans with Short soaking time and Barbecue recipes.
- Beans with Short soaking time and Barbecue recipes have less impacts on the mean taste rating score than beans with Long soaking time and Refried recipes.
- Beans with Short soaking time and Original recipes have less impacts on the mean taste rating score than beans with Long soaking time and Original recipes.
- Beans with Short soaking time and Refried recipes have less impacts on the mean taste rating score than beans with Long soaking time and Original recipes.
- Beans with Short soaking time and Original recipes have less impacts on the mean taste rating score than beans with Long soaking time and Refried recipes.

- Beans with Short soaking time and Original recipes have less impacts on the mean taste rating score than beans with Short soaking time and Refried recipes.
- Beans with Short soaking time and Refried recipes have less impacts on the mean taste rating score than beans with Long soaking time and Refried recipes.
- No other comparisons are significantly different than zero based on the p-values.

For random Interaction between Soak Time and Crock:

```
H<sub>0</sub>: \sigma^2_{crock} = 0
Test Statistic = \chi^2_1 = -8.55
p-value = 1 > \alpha = 0.05
```

Since the p-value of the interaction between Soak Time and Crock is larger than 0.05, we fail to reject null hypothesis and conclude that there are no differences between Crock.

R code:

```
#install.packages("ImerTest")
#install.packages("Ismeans")
#install.packages("car")
#install.packages("multcompView")
#install.packages("Ime4")
#install.packages("jtools")
library(Ismeans)
library(car)
library(multcompView)
library(lme4)
library(ImerTest)
library(jtools)
options(contrasts =c("contr.sum", "contr.poly"))
cue=c(rep("auditory",9),rep("visual",9))
elapsed.time=rep(rep(1:3,each=3),2)
reaction.time=c(204,170,181,167,182,187,202,198,236,257,279,269,283,235,260,256,281,258)
reaction=data.frame(cue=cue,elapsed.time=as.factor(elapsed.time),reaction.time=reaction.time)
par(mfrow=c(1,2))
plot(reaction$reaction.time~reaction$elapsed.time,main="Reaction Time versus Elapsed Time")
plot(reaction$reaction.time~reaction$cue,main="Reaction Time versus Cue")
Ism.reaction=aov(reaction.time~cue+elapsed.time+cue:elapsed.time,data=reaction)
par(mfrow=c(2,2))
plot(lsm.reaction)
anova(Ism.reaction)
interact_plot(lsm.reaction,pred="cue",modx="elapsed.time")
unloadNamespace("ImerTest")
library(Ismeans)
reaction.cue=Ismeans(Ism.reaction,~cue)
cld(reaction.cue,alpha=0.05)
```

```
Brand<-c(rep(1,10), rep(2, 10), rep(3,10), rep(4, 10))
Times<-c(167, 171, 178, 175, 184, 176, 185, 172, 178, 178,
    231, 233, 236, 252, 233, 225, 241, 248, 239, 248,
    176, 168, 171, 172, 178, 176, 169, 164, 169, 171,
    201, 199, 196, 211, 209, 223, 209, 219, 212, 210)
melt=data.frame(Brand=as.factor(Brand),Times=Times)
lsm.melt=aov(Times~Brand,data=melt)
summary(Ism.melt)
par(mfrow=c(2,2))
plot(lsm.melt)
anova(Ism.melt)
#3.2-----
wood=read.table("wood.csv",header=TRUE)
wood
lsm.wood=aov(Nconc~Type/Species,data=wood)
par(mfrow=c(2,2))
plot(lsm.wood)
anova(Ism.wood)
par(mfrow=c(1,1))
interaction.plot(x.factor = wood$Species, trace.factor = wood$Type, response = wood$Nconc,
        type ="b",col = 2:3,xlab ="Species", ylab ="nitrogen content", trace.label ="Type")
wood.ST=Ismeans(Ism.wood, ~Species:Type)
contrast(wood.ST, method="pairwise")
wood.T=Ismeans(Ism.wood, ~Type)
cld(wood.T, alpha=0.05)
beans=read.table("Beans.csv",header=TRUE)
beans
Crock=as.factor(beans$Crock)
SoakTim=beans$SoakTim
Recipe=beans$Recipe
Jar=as.factor(beans$Jar)
```

```
Rating=beans$Rating
beans.frame=data.frame(Crock=Crock,SoakTim=SoakTim,Recipe=Recipe,Jar=Jar,Rating=Rating)
library(ImerTest)
lsm.taste=lmer(Rating~SoakTim+(1|Crock:SoakTim)+Recipe+SoakTim:Recipe,data=beans.frame)
par(mfrow=c(1,2))
fitted=fitted(lsm.taste)
resid=residuals(lsm.taste)
plot(fitted,resid,main="Fitted vs Residuals",pch=1,cex=2)
qqnorm(resid)
qqline(resid)
lsm.taste1=lmer(1/(Rating)~SoakTim+(1|Crock:SoakTim)+Recipe+SoakTim:Recipe,data=beans.frame)
fitted1=fitted(lsm.taste1)
resid1=residuals(lsm.taste1)
plot(fitted1,resid1,main="Fitted vs Residuals",pch=1,cex=2)
qqnorm(resid1)
qqline(resid1)
lsm.taste2=lmer(sqrt(Rating)~SoakTim+(1|Crock:SoakTim)+Recipe+SoakTim:Recipe,data=beans.frame
fitted2=fitted(lsm.taste2)
resid2=residuals(lsm.taste2)
plot(fitted2,resid2,main="Fitted vs Residuals",pch=1,cex=2)
qqnorm(resid2)
qqline(resid2)
lsm.taste3=lmer(log(Rating)~SoakTim+(1|Crock:SoakTim)+Recipe+SoakTim:Recipe,data=beans.frame)
fitted3=fitted(lsm.taste3)
resid3=residuals(lsm.taste3)
plot(fitted3,resid3,main="Fitted vs Residuals",pch=1,cex=2)
qqnorm(resid3)
qqline(resid3)
```

Anova(lsm.taste,type="III")

difflsmeans(lsm.taste, "SoakTim:Recipe")

rand(lsm.taste)