STOR 590 HW7 Solution

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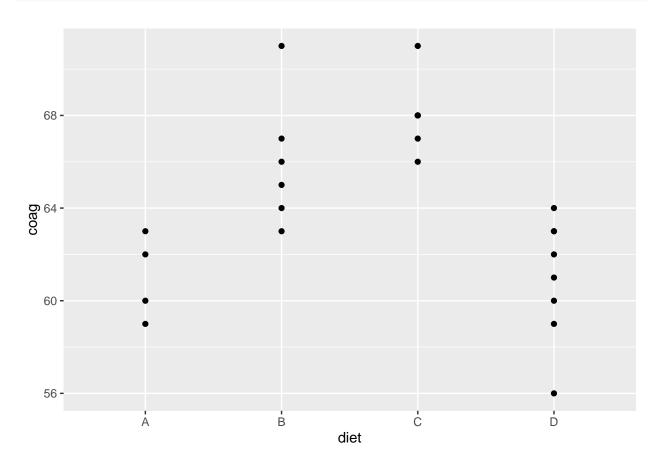
Part (a)

We plot the data.

```
library(faraway)
library(ggplot2)
```

Warning: package 'ggplot2' was built under R version 3.6.2

```
data(coagulation)
ggplot(coagulation, aes(diet, coag)) + geom_point()
```



We can observe that diet A and D leads to less blood coagulation times than other diets.

Part (b)

We fit a fixed effects model and construct a prediction together with a 95% prediction interval for the response of a new animal assigned to diet D.

```
lmod <- aov(coag ~ diet, coagulation)</pre>
summary(lmod)
##
               Df Sum Sq Mean Sq F value
                                            Pr(>F)
## diet
                3
                     228
                            76.0
                                   13.57 4.66e-05 ***
## Residuals
               20
                     112
                             5.6
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
predict(lmod, newdata=data.frame(diet="D"), interval = "predict")
##
     fit
              lwr
                       upr
```

We can see that the predicted value of coag is 61 and the prediction interval is [55.76427, 66.23573].

Part (c)

1 61 55.76427 66.23573

We fit a random effects model using REML. Then we predict the blood coagulation time for a new animal assigned to diet D along with a 95% prediction interval.

```
library(lme4)

## Loading required package: Matrix

mmod <- lmer(coag ~ 1 + (1|diet), coagulation)
summary(mmod)</pre>
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: coag ~ 1 + (1 | diet)
      Data: coagulation
##
##
## REML criterion at convergence: 115.8
##
## Scaled residuals:
##
        Min
                  1Q
                       Median
                                    3Q
                                             Max
## -2.18491 -0.59921 0.09332 0.54078 2.17508
##
## Random effects:
## Groups
                         Variance Std.Dev.
## diet
             (Intercept) 11.692
                                  3.419
## Residual
                          5.599
                                  2.366
## Number of obs: 24, groups: diet, 4
##
## Fixed effects:
               Estimate Std. Error t value
## (Intercept)
                  64.01
                              1.78
                                     35.96
```

```
group.sd <- as.data.frame(VarCorr(mmod))$sdcor[1]</pre>
resid.sd <- as.data.frame(VarCorr(mmod))$sdcor[2]
predict(mmod, newdata=data.frame(diet="D"))
##
## 61.17017
pv <- numeric(1000)
set.seed(590)
for(i in 1:1000){
  y <- unlist(simulate(mmod))</pre>
 bmod <- refit(mmod, y)</pre>
 pv[i] <- predict(bmod, newdata=data.frame(diet="D"))</pre>
  + rnorm(n=1,sd=resid.sd)
## boundary (singular) fit: see ?isSingular
## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl =
## control$checkConv, : Model failed to converge with max|grad| = 0.0103843
## (tol = 0.002, component 1)
## boundary (singular) fit: see ?isSingular
## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl =
## control$checkConv, : Model failed to converge with max|grad| = 0.00232904
## (tol = 0.002, component 1)
## boundary (singular) fit: see ?isSingular
## boundary (singular) fit: see ?isSingular
## boundary (singular) fit: see ?isSingular
```

```
## boundary (singular) fit: see ?isSingular
```

2.5% 97.5% ## 57.33823 71.43798

The predicted value of the blood coagulation time for a new animal assigned to diet D is 61.17017 and the prediction interval is [57.33823, 71.43798].

Part (d)

We predict the blood coagulation time for a new animal given a new diet along with a 95% prediction interval.

```
predict(mmod, re.form=~0)[1]
##
## 64.01266
pv <- numeric(1000)</pre>
set.seed(590)
for(i in 1:1000){
  y <- unlist(simulate(mmod))</pre>
  bmod <- refit(mmod, y)</pre>
 pv[i] <- predict(bmod, re.form=~0)[1]</pre>
 + rnorm(n=1,sd=group.sd)
  + rnorm(n=1,sd=resid.sd)
## boundary (singular) fit: see ?isSingular
## boundary (singular) fit: see ?isSingular
## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl =
## control$checkConv, : Model failed to converge with max|grad| = 0.00593833
## (tol = 0.002, component 1)
## boundary (singular) fit: see ?isSingular
## boundary (singular) fit: see ?isSingular
```

```
## boundary (singular) fit: see ?isSingular
## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl =
## control$checkConv, : Model failed to converge with max|grad| = 0.00571489
## (tol = 0.002, component 1)
## boundary (singular) fit: see ?isSingular
## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl =
## control$checkConv, : Model failed to converge with max|grad| = 0.00359389
## (tol = 0.002, component 1)
## boundary (singular) fit: see ?isSingular
## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl =
## control$checkConv, : Model failed to converge with max|grad| = 0.00204675
## (tol = 0.002, component 1)
## boundary (singular) fit: see ?isSingular
quantile(pv, c(0.025, 0.975))
##
       2.5%
               97.5%
```

The predicted value is 64.01266 and the 95% prediction interval is [60.63008, 67.45680].

60.63008 67.45680

Part (e)

We predict the blood coagulation time for the first animal in the dataset given a new diet along with a 95% prediction interval.

```
predict(mmod, re.form=~0)[1]
##
## 64.01266
pv <- numeric(1000)</pre>
set.seed(590)
for(i in 1:1000){
  y <- unlist(simulate(mmod))</pre>
  bmod <- refit(mmod, y)</pre>
  pv[i] <- predict(bmod, re.form=~0)[1]</pre>
  + rnorm(n=1,sd=group.sd)
## boundary (singular) fit: see ?isSingular
## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl =
## control$checkConv, : Model failed to converge with max|grad| = 0.0103843
## (tol = 0.002, component 1)
## boundary (singular) fit: see ?isSingular
## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl =
## control$checkConv, : Model failed to converge with max|grad| = 0.00232904
## (tol = 0.002, component 1)
## boundary (singular) fit: see ?isSingular
## boundary (singular) fit: see ?isSingular
## boundary (singular) fit: see ?isSingular
```

```
## boundary (singular) fit: see ?isSingular
quantile(pv, c(0.025, 0.975))
##
       2.5%
               97.5%
## 60.80694 67.75822
```

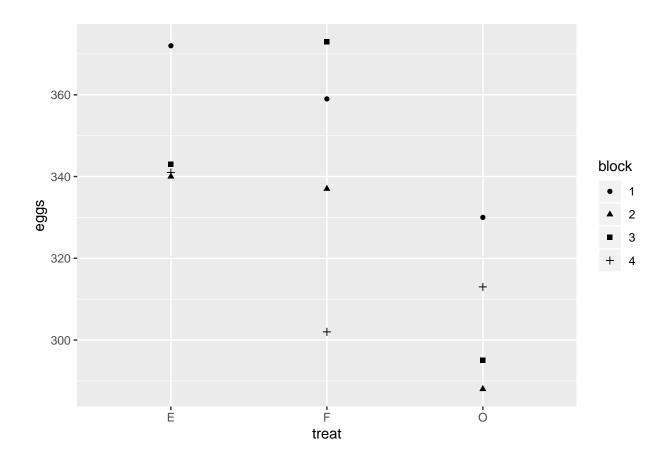
The predicted value is 64.01266 and the predicted interval is [60.80694, 67.75822].

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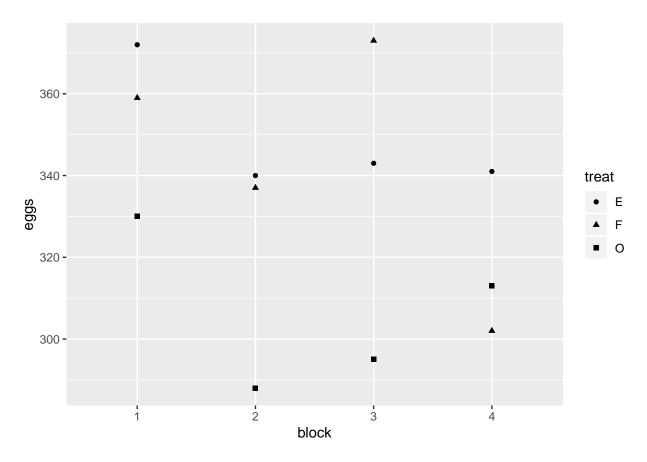
Part (a)

We make suitable plots of the eggprod data.

```
data(eggprod)
ggplot(eggprod, aes(treat, eggs, shape = block)) + geom_point()
```



ggplot(eggprod, aes(block, eggs, shape = treat)) + geom_point()

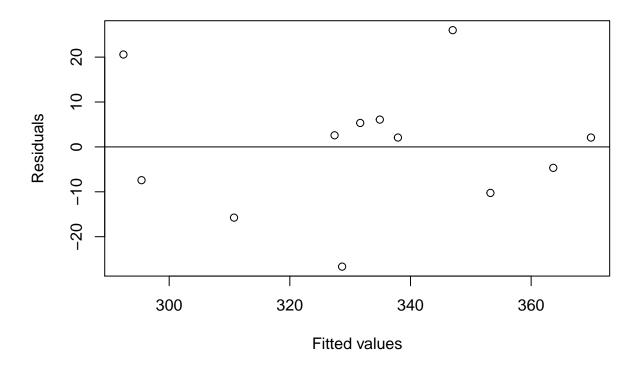


We can observe that the number of eggs produced is large for treatment E and small for treatment O, while it is evenly distributed across different blocks.

Part (b)

We fit a fixed effects model for the number of eggs produced with the treatments and blocks as predictors. We also determine the significance of the two predictors and perform a basic diagnostic check.

```
lmod <- aov(eggs ~ treat + block, eggprod)</pre>
summary(lmod)
##
               Df Sum Sq Mean Sq F value Pr(>F)
## treat
                2
                    4212
                          2106.2
                                   5.444 0.0449 *
                3
                    2330
                           776.8
                                   2.008 0.2145
## block
## Residuals
                    2322
                           386.9
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
plot(residuals(lmod) ~ fitted(lmod), xlab = "Fitted values", ylab = "Residuals")
abline(h = 0)
```



The result shows that treat is the only significant predictor at 5% significance level. The diagnostic plot show no problem in the model.

Part (c)

We fit a model for the number of eggs produced with the treatments as fixed effects and the bloacks as random effects.

```
mmod <- lmer(eggs ~ treat + (1|block), eggprod)
sumary(mmod)</pre>
```

```
## Fixed Effects:
##
               coef.est coef.se
## (Intercept) 349.00
                          11.37
  treatF
                 -6.25
##
                          13.91
##
  treat0
               -42.50
                          13.91
##
## Random Effects:
##
    Groups
                          Std.Dev.
             Name
    block
              (Intercept) 11.40
##
    Residual
                          19.67
## ---
## number of obs: 12, groups: block, 4
## AIC = 95.4, DIC = 124.4
## deviance = 104.9
```

We can see that treatE has the largest coefficient (=0), which implies that treatment E maximizes the estimated egg production. We are not sure if it is better than treatment F since the difference between the coefficient of treatE and treatFis smaller than the estimated standard error.

Part (d)

We use the Kenward-Roger approximation for an F-test to check for differences between the treatments.

```
library(pbkrtest)
## Warning: package 'pbkrtest' was built under R version 3.6.3
amod <- lmer(eggs ~ treat + (1|block), eggprod, REML = FALSE)
nmod <- lmer(eggs ~ 1 + (1|block), eggprod, REML = FALSE)
## boundary (singular) fit: see ?isSingular
KRmodcomp(amod, nmod)
## F-test with Kenward-Roger approximation; time: 0.11 sec
## large : eggs ~ treat + (1 | block)
## small : eggs ~ 1 + (1 | block)
                         ddf F.scaling p.value
##
          stat
                  ndf
## Ftest 5.4438 2.0000 6.0000
                                     1 0.04485 *
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
```

Since the p-value of the F-test is smaller than 0.05, we conclude that treat is significant. We can make the same conclusion with the fixed effects model.

Part (e)

We perform the same test using a bootstrap method.

```
set.seed(590)
pmod <- PBmodcomp(amod, nmod)

## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl =
## control$checkConv, : Model failed to converge with max|grad| = 0.00561394
## (tol = 0.002, component 1)

summary(pmod)

## Bootstrap test; time: 16.95 sec;samples: 1000; extremes: 68;
## large : eggs ~ treat + (1 | block)
## small : eggs ~ 1 + (1 | block)
## stat df ddf p.value
## LRT 8.4245 2.0000 0.01481 *</pre>
```

Since the p-value of PBtest is larger than 0.05, we conclude that treat is not significant. The result is different from (f). (This part might vary for different seeds.)

Part (f)

We test for significance of the blocks.

RLRT = 0.51536, p-value = 0.2156

```
## Warning: package 'RLRsim' was built under R version 3.6.3

set.seed(590)
exactRLRT(mmod)

##
## simulated finite sample distribution of RLRT.
##
## (p-value based on 10000 simulated values)
##
## data:
```

Since the p-value is larger than 0.05, we conclude that block is not significant. Note that the outcome is similar to the fixed effects model.