W10 practice

2023-03-01

1. height data

```r
  library(haven); library(psych); library(dplyr);
  library(magrittr); library(ggplot2); library(gridExtra)
  library(rstatix); library(multcomp); library(ggeffects)

# Read the data
  height = data.frame(
    child = c(1,1,1,2,2,2,3,3,3,4,4,4,5,5,5),
    age = c(6,7,8,6,7,8,6,7,8,6,7,8,6,7,8),
    height = c(46.3,49.5,51.7,46.0,47.8,50.5,42.5,44.0,45.6,47.0,50.2,52.2,45.5,47.2,49.1)
  )

# First run an OLS model predicting height by age
  ols_model =
    lm(height ~ age, data = height)
  summary(ols_model)
```

```
##
## Call:
## lm(formula = height ~ age, data = height)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -4.2533 -0.6133  0.5067  1.6667  2.5267
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  32.4133     4.9288   6.576 1.78e-05 ***
## age           2.1800     0.6994   3.117  0.00817 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.212 on 13 degrees of freedom
## Multiple R-squared:  0.4277, Adjusted R-squared:  0.3837
## F-statistic: 9.716 on 1 and 13 DF,  p-value: 0.008173
```

```r
# Then run a model accounting for the repeated measurements
  library(lme4)
  library(lmerTest)
  mixed_model =
    lmer(height ~ age + (1|child), data = height)
```

```r
summary(mixed_model)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: height ~ age + (1 | child)
##    Data: height
##
## REML criterion at convergence: 41.4
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -1.2820 -0.6088  0.1656  0.6987  1.0916
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  child    (Intercept) 4.9935   2.2346
##  Residual             0.2818   0.5308
## Number of obs: 15, groups:  child, 5
##
## Fixed effects:
##             Estimate Std. Error      df t value Pr(>|t|)
## (Intercept)  32.4133     1.5486 12.2203   20.93 6.07e-11 ***
## age           2.1800     0.1679  9.0000   12.99 3.92e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##     (Intr)
## age -0.759
```

```r
# Then transpose the data from long to wide
  library(tidyr)
  height_wide =
    spread(height, key = age, value = height)
  colnames(height_wide) =
    c("child", "height6", "height7", "height8")

# Check it
  print(height_wide)
```

```
##   child height6 height7 height8
## 1     1    46.3    49.5    51.7
## 2     2    46.0    47.8    50.5
## 3     3    42.5    44.0    45.6
## 4     4    47.0    50.2    52.2
## 5     5    45.5    47.2    49.1
```

```r
# Calculate means for the 3 height measurements
  colMeans(height_wide[,2:4])
```

```
## height6 height7 height8
##   45.46   47.74   49.82
```

```r
# Looking at the means at each time point to see if they are different
# Essentially our independent variable is time

# Repeated measures ANOVA
  height_anova =
    aov(height ~ age + Error(child), data = height)
  summary(height_anova)
```

```
##
## Error: child
##           Df Sum Sq Mean Sq F value Pr(>F)
## Residuals  1  1.323   1.323
##
## Error: Within
##           Df Sum Sq Mean Sq F value Pr(>F)
## age        1  47.52   47.52   9.159 0.0105 *
## Residuals 12  62.26    5.19
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

2. exone data

```r
# Create the exone dataset
  exone = data.frame(
    subjid = 1:10,
    asa = c(5, 5, 5, 6, 6, 4, 4, 4, 4, 5),
    apap = c(3, 4, 6, 4, 6, 2, 4, 5, 2, 3),
    ibp = c(2, 3, 5, 2, 6, 1, 3, 5, 2, 1)
  )

# Print the exone dataset
  print(exone)
```

```
##    subjid asa apap ibp
## 1       1   5    3   2
## 2       2   5    4   3
## 3       3   5    6   5
## 4       4   6    4   2
## 5       5   6    6   6
## 6       6   4    2   1
## 7       7   4    4   3
## 8       8   4    5   5
## 9       9   4    2   2
## 10     10   5    3   1
```

```r
# Frequency of subjid
  table(exone$subjid)
```

```
##
##  1  2  3  4  5  6  7  8  9 10
##  1  1  1  1  1  1  1  1  1  1
```

```r
# Means of asa, apap, and ibp
  colMeans(exone[, c("asa", "apap", "ibp")])
```

```
##  asa apap  ibp
##  4.8  3.9  3.0
```

```r
# Convert the exone dataset to long format
  library(tidyr)
  exone_long =
    exone %>%
    pivot_longer(cols = c(asa, apap, ibp), names_to = "drug", values_to = "value")

# Perform the one-way ANOVA with repeated measures
  exone_anova =
    aov(value ~ drug + Error(subjid), data = exone_long)
  summary(exone_anova)
```

```
##
## Error: subjid
##           Df Sum Sq Mean Sq F value Pr(>F)
## Residuals  1  3.759   3.759
##
## Error: Within
##           Df Sum Sq Mean Sq F value Pr(>F)
## drug       2  16.20   8.100   4.321  0.024 *
## Residuals 26  48.74   1.875
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
  library(emmeans)
  lsmeans =
    emmeans(exone_anova, ~ factor(drug))

# Compare the means for the different levels of the drug factor
  pairs(lsmeans)
```

```
##  contrast    estimate    SE df t.ratio p.value
##  apap - asa      -0.9 0.612 26  -1.470  0.3215
##  apap - ibp       0.9 0.612 26   1.470  0.3215
##  asa - ibp        1.8 0.612 26   2.940  0.0181
##
## P value adjustment: tukey method for comparing a family of 3 estimates
```

```r
# Create exoneb dataset
  exoneb = data.frame(
    subjid = rep(1:10, each = 2),
    drug = rep(c(0, 1), 10),
    pscore = c(5, 3, 5, 4, 5, 6, 6, 4, 6, 6, 4, 2, 4, 4, 4, 5, 4, 2, 5, 1)
  )

# Fit mixed-effects models with lme4 package
```

```r
library(lme4)
model1 =
  lmer(pscore ~ drug + (1|subjid), data = exoneb)
summary(model1)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: pscore ~ drug + (1 | subjid)
##    Data: exoneb
##
## REML criterion at convergence: 65.2
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -1.91217 -0.54645  0.02901  0.45697  1.55754
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  subjid   (Intercept) 0.4889   0.6992
##  Residual             1.2722   1.1279
## Number of obs: 20, groups:  subjid, 10
##
## Fixed effects:
##             Estimate Std. Error      df t value Pr(>|t|)
## (Intercept)   4.8000     0.4197 16.7121  11.438 2.53e-09 ***
## drug         -1.1000     0.5044  9.0000  -2.181   0.0571 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##      (Intr)
## drug -0.601
```

3. ex2 data

```r
# Create ex2 dataset
ex2 = data.frame(
  subjid = c(1:10, 1:10),
  brand = c(rep(1, 10), rep(0, 10)),
  asa = c(5, 5, 5, 6, 6, 4, 4, 4, 4, 5, 4, 4, 5, 5, 5, 3, 4, 4, 4, 4),
  apap = c(3, 4, 6, 4, 6, 2, 4, 5, 2, 3, 3, 3, 6, 4, 6, 2, 4, 5, 2, 3),
  ibp = c(2, 3, 5, 2, 6, 1, 3, 5, 2, 1, 3, 3, 6, 3, 6, 1, 2, 5, 2, 2)
)

# Frequency table
table(ex2$subjid)
```

```
##
##  1  2  3  4  5  6  7  8  9 10
##  2  2  2  2  2  2  2  2  2  2
```

```r
table(ex2$asa)
```

```
##
##  3  4  5  6
##  1 10  7  2
```

```r
table(ex2$apap)
```

```
##
## 2 3 4 5 6
## 4 5 5 2 4
```

```r
table(ex2$ibp)
```

```
##
## 1 2 3 5 6
## 3 6 5 3 3
```

```r
# Convert data to long format
  ex2_long =
    ex2 %>%
    gather(key = "drug", value = "value", -subjid, -brand)

# Perform two-way ANOVA with repeated measures
  ex2_anova =
    aov(value ~ drug * brand + Error(subjid), data = ex2_long)

# Print the results
  summary(ex2_anova)
```

```
##
## Error: subjid
##           Df Sum Sq Mean Sq F value Pr(>F)
## Residuals  1  6.796   6.796
##
## Error: Within
##            Df Sum Sq Mean Sq F value Pr(>F)
## drug        2  18.23   9.117   4.981 0.0104 *
## brand       1   0.27   0.267   0.146 0.7042
## drug:brand  2   2.03   1.017   0.555 0.5771
## Residuals  53  97.00   1.830
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
# Least square means
  library(emmeans)
  lsmeans_result =
    emmeans(ex2_anova, ~drug)
  summary(lsmeans_result)
```

```
##   drug emmean    SE   df lower.CL upper.CL
##   apap   3.92 0.453 3.23     2.53     5.30
##   asa    4.57 0.453 3.23     3.18     5.95
##   ibp    3.22 0.453 3.23     1.83     4.60
##
## Results are averaged over the levels of: brand
## Warning: EMMs are biased unless design is perfectly balanced
## Confidence level used: 0.95
```

```
# Create extwo dataset
  extwo = data.frame(
    subjid = rep(1:10, each = 6),
    drug = rep(rep(0:2, each = 2), 10),
    brand = rep(rep(0:1, 3), 10),
    pscore = c(
      5, 3, 2, 4, 3, 3, 5, 4, 3, 4, 3, 3, 5, 6, 5, 5, 6, 6, 6, 4, 2, 5, 4, 3,
      6, 6, 6, 5, 6, 6, 4, 2, 1, 3, 2, 1, 4, 4, 3, 4, 4, 2, 4, 5, 5, 4, 5, 5,
      4, 2, 2, 3, 2, 3, 5, 3, 1, 4, 3, 2
    )
  )

# Frequency table
  table(extwo$drug)
```

```
##
##  0  1  2
## 20 20 20
```

```
  table(extwo$brand)
```

```
##
##  0  1
## 30 30
```

```
  table(extwo$subjid)
```

```
##
##  1  2  3  4  5  6  7  8  9 10
##  6  6  6  6  6  6  6  6  6  6
```

```
# Two-way ANOVA with repeated measures
  extwo_aov =
    lmer(
    pscore ~ drug * brand + (1 | subjid),
    data = extwo,
    REML = FALSE)

# Summary of the model
  summary(extwo_aov)
```

```
## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
```

```
##   method [lmerModLmerTest]
## Formula: pscore ~ drug * brand + (1 | subjid)
##    Data: extwo
##
##      AIC      BIC   logLik deviance df.resid
##    191.0    203.6    -89.5    179.0       54
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.3796 -0.6443  0.1269  0.7444  1.6658
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  subjid   (Intercept) 1.1399   1.0677
##  Residual             0.7937   0.8909
## Number of obs: 60, groups:  subjid, 10
##
## Fixed effects:
##             Estimate Std. Error      df t value Pr(>|t|)
## (Intercept)   4.3667     0.4244 19.3773  10.289 2.71e-09 ***
## drug         -0.5000     0.1992 50.0000  -2.510   0.0154 *
## brand        -0.3167     0.3637 50.0000  -0.871   0.3881
## drug:brand    0.2500     0.2817 50.0000   0.887   0.3791
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##            (Intr) drug   brand
## drug       -0.469
## brand      -0.428  0.548
## drug:brand  0.332 -0.707 -0.775
```

```r
# Fitting the model without interaction
  extwo_aov_no_interaction =
    lmer(
    pscore ~ drug + brand + (1 | subjid),
    data = extwo,
    REML = FALSE)

# Summary of the model without interaction
  summary(extwo_aov_no_interaction)
```

```
## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula: pscore ~ drug + brand + (1 | subjid)
##    Data: extwo
##
##      AIC      BIC   logLik deviance df.resid
##    189.8    200.3    -89.9    179.8       55
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -2.36264 -0.64346  0.03253  0.77726  1.79232
##
```

```
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  subjid   (Intercept) 1.1379   1.0667
##  Residual             0.8062   0.8979
## Number of obs: 60, groups:  subjid, 10
##
## Fixed effects:
##             Estimate Std. Error       df t value Pr(>|t|)
## (Intercept)  4.24167    0.40101 15.75798  10.577 1.46e-08 ***
## drug        -0.37500    0.14197 50.00000  -2.641    0.011 *
## brand       -0.06667    0.23183 50.00000  -0.288    0.775
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##       (Intr) drug
## drug  -0.354
## brand -0.289  0.000
```

4. exercise

```
# Data input
  exercise = tribble(
    ~id, ~exertype, ~diet, ~time1, ~time2, ~time3,
  1 ,  1,  1,   85,   85,   88,
  2 ,  1,  1,   90,   92,   93,
  3 ,  1,  1,   97,   97,   94,
  4 ,  1,  1,   80,   82,   83,
  5 ,  1,  1,   91,   92,   91,
  6 ,  1,  2,   83,   83,   84,
  7 ,  1,  2,   87,   88,   90,
  8 ,  1,  2,   92,   94,   95,
  9 ,  1,  2,   97,   99,   96,
  10,  1,  2,  100,   97,  100,
  11,  2,  1,   86,   86,   84,
  12,  2,  1,   93,  103,  104,
  13,  2,  1,   90,   92,   93,
  14,  2,  1,   95,   96,  100,
  15,  2,  1,   89,   96,   95,
  16,  2,  2,   84,   86,   89,
  17,  2,  2,  103,  109,   90,
  18,  2,  2,   92,   96,  101,
  19,  2,  2,   97,   98,  100,
  20,  2,  2,  102,  104,  103,
  21,  3,  1,   93,   98,  110,
  22,  3,  1,   98,  104,  112,
  23,  3,  1,   98,  105,   99,
  24,  3,  1,   87,  132,  120,
  25,  3,  1,   94,  110,  116,
  26,  3,  2,   95,  126,  143,
  27,  3,  2,  100,  126,  140,
```

```r
  28,  3,  2,  103,  124,  140,
  29,  3,  2,   94,  135,  130,
  30,  3,  2,   99,  111,  150
  )

# Convert the data to long format
  exercise_long =
    exercise %>%
    pivot_longer(cols = starts_with("time"),
                 names_to = "time",
                 values_to = "pulse")

# Fit the ANOVA model with repeated measures
  exercise_aov1 =
    aov(pulse ~ factor(diet) * time + Error(id), data = exercise_long)
  summary(exercise_aov1)
```

```
##
## Error: id
##              Df Sum Sq Mean Sq
## factor(diet)  1   9059    9059
##
## Error: Within
##                   Df Sum Sq Mean Sq F value   Pr(>F)
## factor(diet)       1     70    70.4   0.707    0.403
## time               2   2067  1033.3  10.383 9.45e-05 ***
## factor(diet):time  2    193    96.4   0.969    0.384
## Residuals         83   8260    99.5
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
cat("Looking at the results from the manova test
    the effect of time is significant but the
    interaction of time and diet is not significant.
    The between subject test of the effect of diet
    is also not significant. Consequently, in the graph
    we have lines that are not flat, in fact, they are
    actually increasing over time, which was expected
    since the effect of time was significant.
    Furthermore, the lines are approximately parallel
    which was anticipated since the interaction was
    not significant.")
```

```
## Looking at the results from the manova test
##     the effect of time is significant but the
##     interaction of time and diet is not significant.
##     The between subject test of the effect of diet
##     is also not significant. Consequently, in the graph
##     we have lines that are not flat, in fact, they are
##     actually increasing over time, which was expected
##     since the effect of time was significant.
##     Furthermore, the lines are approximately parallel
```

```
##     which was anticipated since the interaction was
##     not significant.
```

```r
# Fit the ANOVA model with repeated measures using exertype as the group variable
  exercise_aov2 =
    aov(pulse ~ factor(exertype) * time + Error(id), data = exercise_long)

# Print the summary
  summary(exercise_aov2)
```

```
##
## Error: id
##                  Df Sum Sq Mean Sq
## factor(exertype)  1   9059    9059
##
## Error: Within
##                       Df Sum Sq Mean Sq F value   Pr(>F)
## factor(exertype)       2   1034   517.0   8.679 0.000388 ***
## time                   2   2067  1033.3  17.346 5.53e-07 ***
## factor(exertype):time  4   2723   680.8  11.429 2.19e-07 ***
## Residuals             80   4766    59.6
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
cat("The interaction of time and exertype is significant
    as is the effect of time.  The between subject test
    of the effect of exertype is also significant.
    Consequently, in the graph we have lines that are
    not parallel which we expected since the interaction
    was significant. Furthermore, we see that some of the
    lines that are rather far apart and at least one line
    is not horizontal which was anticipated since exertype
    and time were both significant.")
```

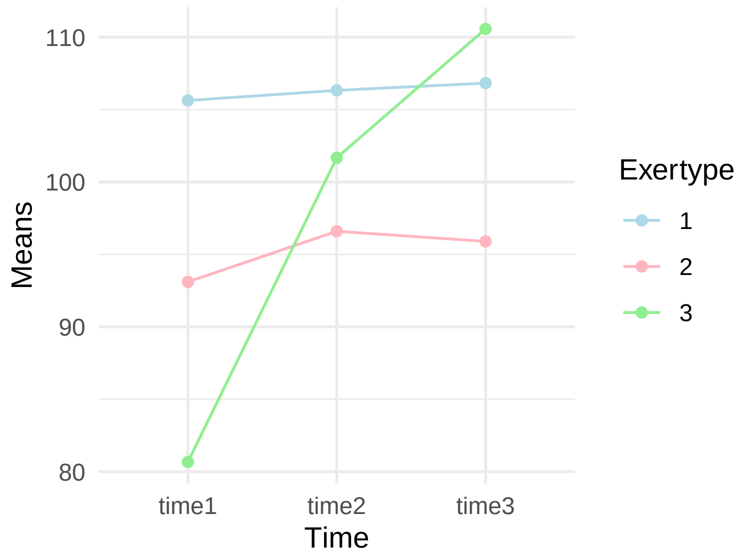
```
## The interaction of time and exertype is significant
##     as is the effect of time.  The between subject test
##     of the effect of exertype is also significant.
##     Consequently, in the graph we have lines that are
##     not parallel which we expected since the interaction
##     was significant. Furthermore, we see that some of the
##     lines that are rather far apart and at least one line
##     is not horizontal which was anticipated since exertype
##     and time were both significant.
```

```r
  ls_means =
    emmeans(exercise_aov2, ~ exertype | time)

  means_df =
    as.data.frame(ls_means)

  ggplot(means_df, aes(x = time, y = emmean,
                       group = exertype, color = as.factor(exertype))) +
```

```r
    geom_line() +
    geom_point() +
    scale_color_manual(values = c("lightblue", "lightpink", "lightgreen")) +
    labs(x = "Time", y = "Means", color = "Exertype") +
    theme_minimal()
```




```r
# Fit the linear mixed-effects model
  exercise_mixed1 =
    lmer(pulse ~ factor(exertype) * time + (1 | id), data = exercise_long)
  summary(exercise_mixed1)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: pulse ~ factor(exertype) * time + (1 | id)
##    Data: exercise_long
##
## REML criterion at convergence: 590.8
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -2.73661 -0.37409 -0.02086  0.37126  2.87404
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  id       (Intercept) 36.76    6.063
##  Residual             43.89    6.625
## Number of obs: 90, groups:  id, 30
##
## Fixed effects:
##                             Estimate Std. Error     df t value Pr(>|t|)
## (Intercept)                   90.200      2.840 57.222  31.761  < 2e-16 ***
## factor(exertype)2              2.900      4.016 57.222   0.722    0.473
## factor(exertype)3              5.900      4.016 57.222   1.469    0.147
```

```
## timetime2                        0.700      2.963 54.000   0.236    0.814
## timetime3                        1.200      2.963 54.000   0.405    0.687
## factor(exertype)2:timetime2    2.800      4.190 54.000   0.668    0.507
## factor(exertype)3:timetime2   20.300      4.190 54.000   4.845 1.11e-05 ***
## factor(exertype)2:timetime3    1.600      4.190 54.000   0.382    0.704
## factor(exertype)3:timetime3   28.700      4.190 54.000   6.850 7.23e-09 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##              (Intr) fct()2 fct()3 timtm2 timtm3 f()2:2 f()3:2 f()2:3
## fctr(xrty)2 -0.707
## fctr(xrty)3 -0.707  0.500
## timetime2   -0.522  0.369  0.369
## timetime3   -0.522  0.369  0.369  0.500
## fctr(xr)2:2  0.369 -0.522 -0.261 -0.707 -0.354
## fctr(xr)3:2  0.369 -0.261 -0.522 -0.707 -0.354  0.500
## fctr(xr)2:3  0.369 -0.522 -0.261 -0.354 -0.707  0.500  0.250
## fctr(xr)3:3  0.369 -0.261 -0.522 -0.354 -0.707  0.250  0.500  0.500
```

```
# Fit the autoregressive model
  library(nlme)
  exercise_mixed2 =
    lme(pulse ~ factor(exertype) * time,
        random = ~ 1 | id,
        correlation = corAR1(form = ~ 1 | id),
        data = exercise_long)
  summary(exercise_mixed2)
```

```
## Linear mixed-effects model fit by REML
##   Data: exercise_long
##      AIC      BIC   logLik
##   613.73 642.4634 -294.865
##
## Random effects:
##  Formula: ~1 | id
##         (Intercept) Residual
## StdDev:    4.679625 7.638338
##
## Correlation Structure: AR(1)
##  Formula: ~1 | id
##  Parameter estimate(s):
##       Phi
## 0.3141089
## Fixed effects:  pulse ~ factor(exertype) * time
##                              Value Std.Error DF  t-value p-value
## (Intercept)                   90.2  2.832721 54 31.84217  0.0000
## factor(exertype)2              2.9  4.006073 27  0.72390  0.4754
## factor(exertype)3              5.9  4.006073 27  1.47276  0.1524
## timetime2                      0.7  2.829055 54  0.24743  0.8055
## timetime3                      1.2  3.243076 54  0.37002  0.7128
## factor(exertype)2:timetime2    2.8  4.000888 54  0.69984  0.4870
## factor(exertype)3:timetime2   20.3  4.000888 54  5.07387  0.0000
## factor(exertype)2:timetime3    1.6  4.586402 54  0.34886  0.7286
```

```
## factor(exertype)3:timetime3  28.7  4.586402 54  6.25763  0.0000
##  Correlation:
##                              (Intr) fct()2 fct()3 timtm2 timtm3 f()2:2 f()3:2
## factor(exertype)2            -0.707
## factor(exertype)3            -0.707  0.500
## timetime2                    -0.499  0.353  0.353
## timetime3                    -0.572  0.405  0.405  0.573
## factor(exertype)2:timetime2  0.353 -0.499 -0.250 -0.707 -0.405
## factor(exertype)3:timetime2  0.353 -0.250 -0.499 -0.707 -0.405  0.500
## factor(exertype)2:timetime3  0.405 -0.572 -0.286 -0.405 -0.707  0.573  0.287
## factor(exertype)3:timetime3  0.405 -0.286 -0.572 -0.405 -0.707  0.287  0.573
##                              f()2:3
## factor(exertype)2
## factor(exertype)3
## timetime2
## timetime3
## factor(exertype)2:timetime2
## factor(exertype)3:timetime2
## factor(exertype)2:timetime3
## factor(exertype)3:timetime3  0.500
##
## Standardized Within-Group Residuals:
##          Min           Q1          Med           Q3          Max
## -2.828064206 -0.538654484 -0.000337104  0.504262310  2.661367863
##
## Number of Observations: 90
## Number of Groups: 30
```

```r
# plot
  ggpredict(exercise_mixed1, c("time", "exertype")) %>%
    plot(connect.line = T, color = c("lightblue", "lightpink", "lightgreen"))
```