

# Analysis of Covariance Tutorials: One-way and Factorial Analyses

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```
# Load in Required Libraries
library(psych)
library(tidyverse)
library(jmv)
library(ggpubr)
library(apaTables)
library(ez)
library(rstatix)
```

## ANCOVA | One-Way Research Context Prompt

### Research Context:

Researchers investigated the effect of exercises in reducing anxiety levels. Anxiety scores were measured from three groups of individuals practicing physical exercises at different levels ( low , moderate , and high ).

The anxiety score was measured pre- and 6-months post-exercise training programs. It is expected that any reduction in the anxiety by the exercises programs would also depend on the participant's baseline level of anxiety.

In this analysis we use the pre-test anxiety score as the covariate and are interested in possible differences between group with respect to the post-test anxiety score .

## One-way ANCOVA | Data

```
dat_anx <- read.csv("ancova1.csv")
```

## ANCOVA | Descriptive Stats (Baseline-test)

```
dat_anx$groupF <- factor(dat_anx$group,
                        levels = c("Low", "Moderate", "High"),
                        labels = c("Low", "Moderate", "High"))

# Descriptive Stats
describeBy(dat_anx$pretest,
           dat_anx$groupF,
           mat=TRUE)
```

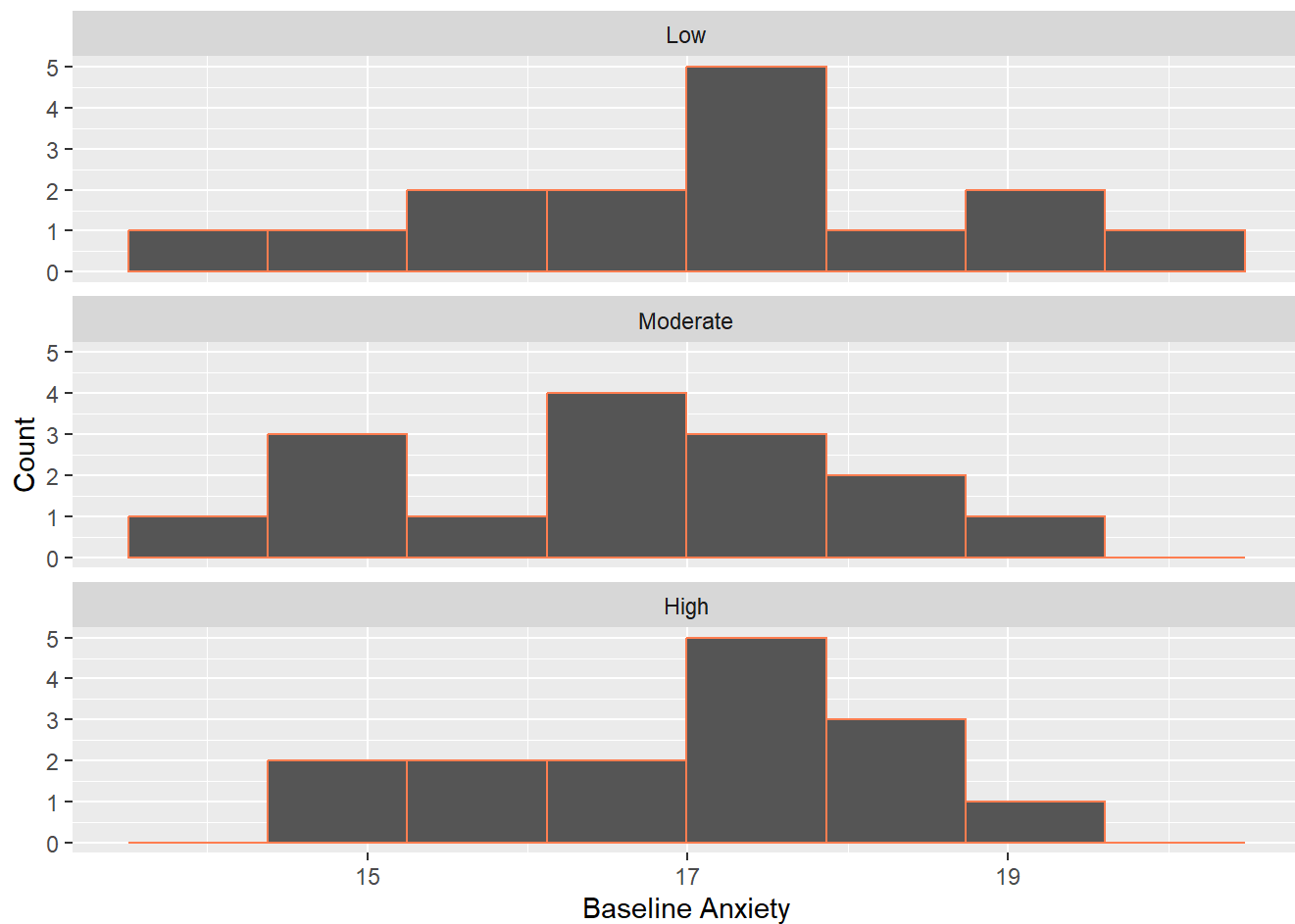
```
##      item  group1 vars  n    mean      sd median trimmed    mad min max
## X11     1      Low   1 15 17.08667 1.628701  17.0 17.10769 1.33434 14.1 19.8
## X12     2 Moderate  1 15 16.64667 1.565643  16.9 16.66923 1.63086 13.7 19.3
## X13     3      High  1 15 17.01333 1.321183  17.3 17.04615 1.33434 14.6 19.0
##      range      skew  kurtosis      se
## X11   5.7 -0.1029298 -0.8254734 0.4205288
## X12   5.6 -0.2002025 -1.0718963 0.4042473
## X13   4.4 -0.3718028 -1.1608155 0.3411279
```

```
describeBy(dat_anx$posttest,
           dat_anx$groupF,
           mat=TRUE)
```

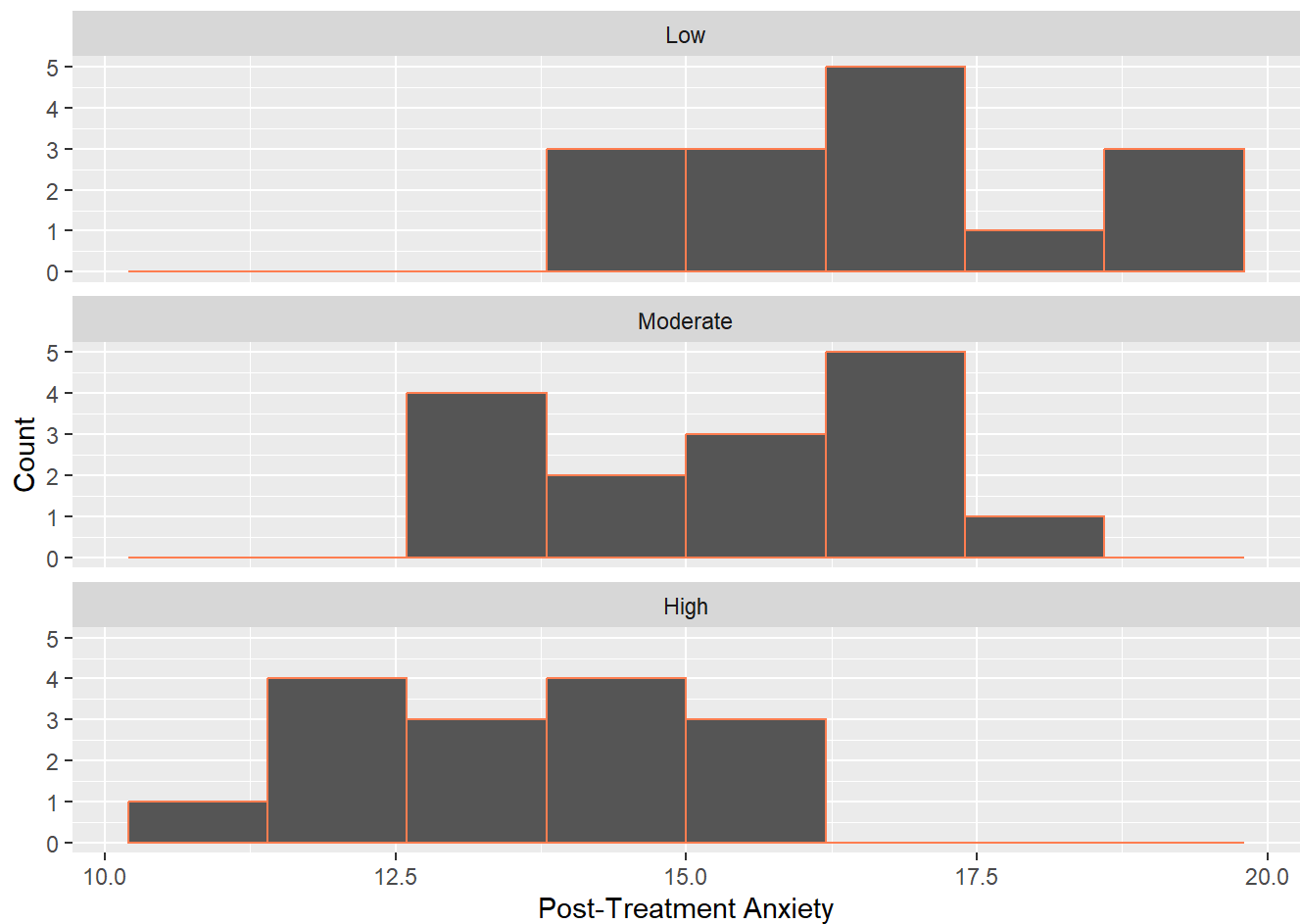
```
##      item  group1 vars  n    mean      sd median trimmed    mad min max
## X11     1      Low   1 15 16.62000 1.675538  16.5 16.60000 1.48260 14.1 19.4
## X12     2 Moderate  1 15 15.52667 1.702715  16.1 15.57692 1.77912 12.7 17.7
## X13     3      High  1 15 13.56000 1.422674  13.8 13.60769 1.92738 11.0 15.5
##      range      skew  kurtosis      se
## X11   5.3  0.2618597 -1.087983 0.4326221
## X12   5.0 -0.3236715 -1.539690 0.4396391
## X13   4.5 -0.3246574 -1.338458 0.3673327
```

## ANCOVA | EDA Visualiations

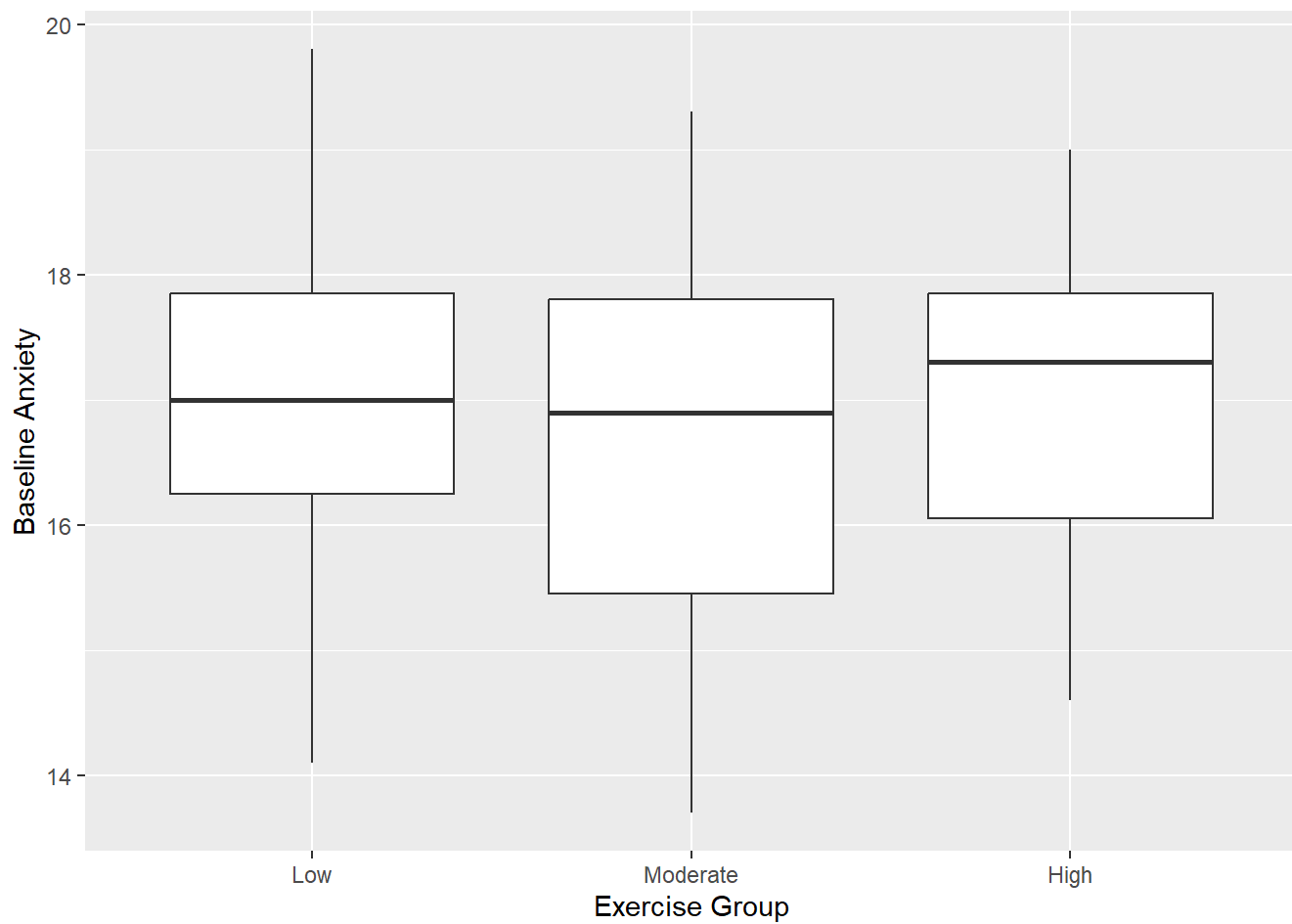
```
# Histograms
ggplot(data = dat_anx,
       mapping = aes(x = pretest)) +
  geom_histogram(bins = 8, color = "coral") +
  labs(y = "Count", x = "Baseline Anxiety")+
  facet_wrap(dat_anx$groupF, ncol=1)
```



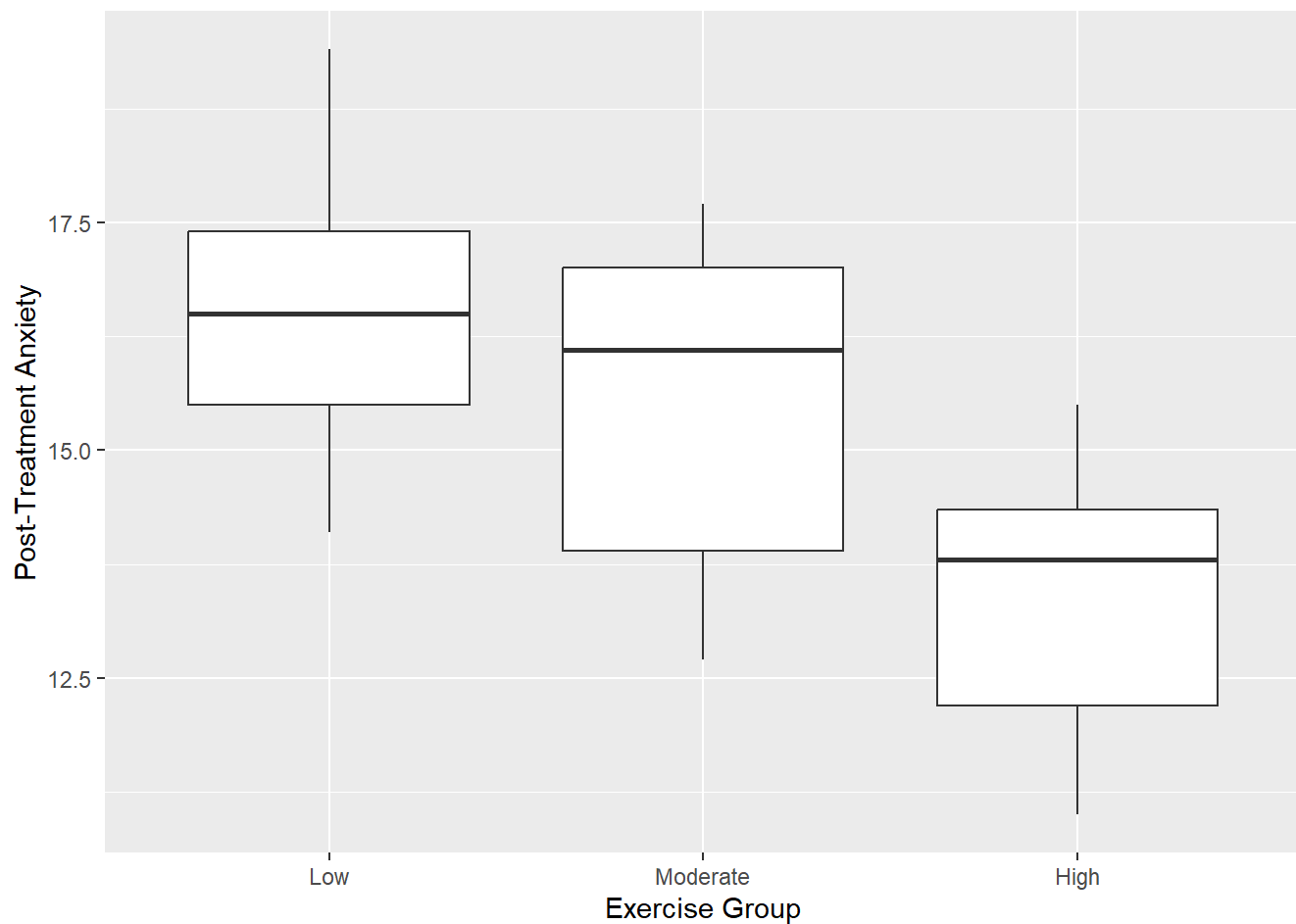
```
ggplot(data = dat_anx,
       mapping = aes(x = posttest)) +
  geom_histogram(bins = 8, color = "coral") +
  labs(y = "Count", x = "Post-Treatment Anxiety")+
  facet_wrap(dat_anx$groupF, ncol=1)
```



```
# Boxplots
ggplot(data = dat_anx,
       mapping = aes(y = pretest, x = groupF)) +
  geom_boxplot() +
  labs(y = "Baseline Anxiety",
       x = "Exercise Group")
```

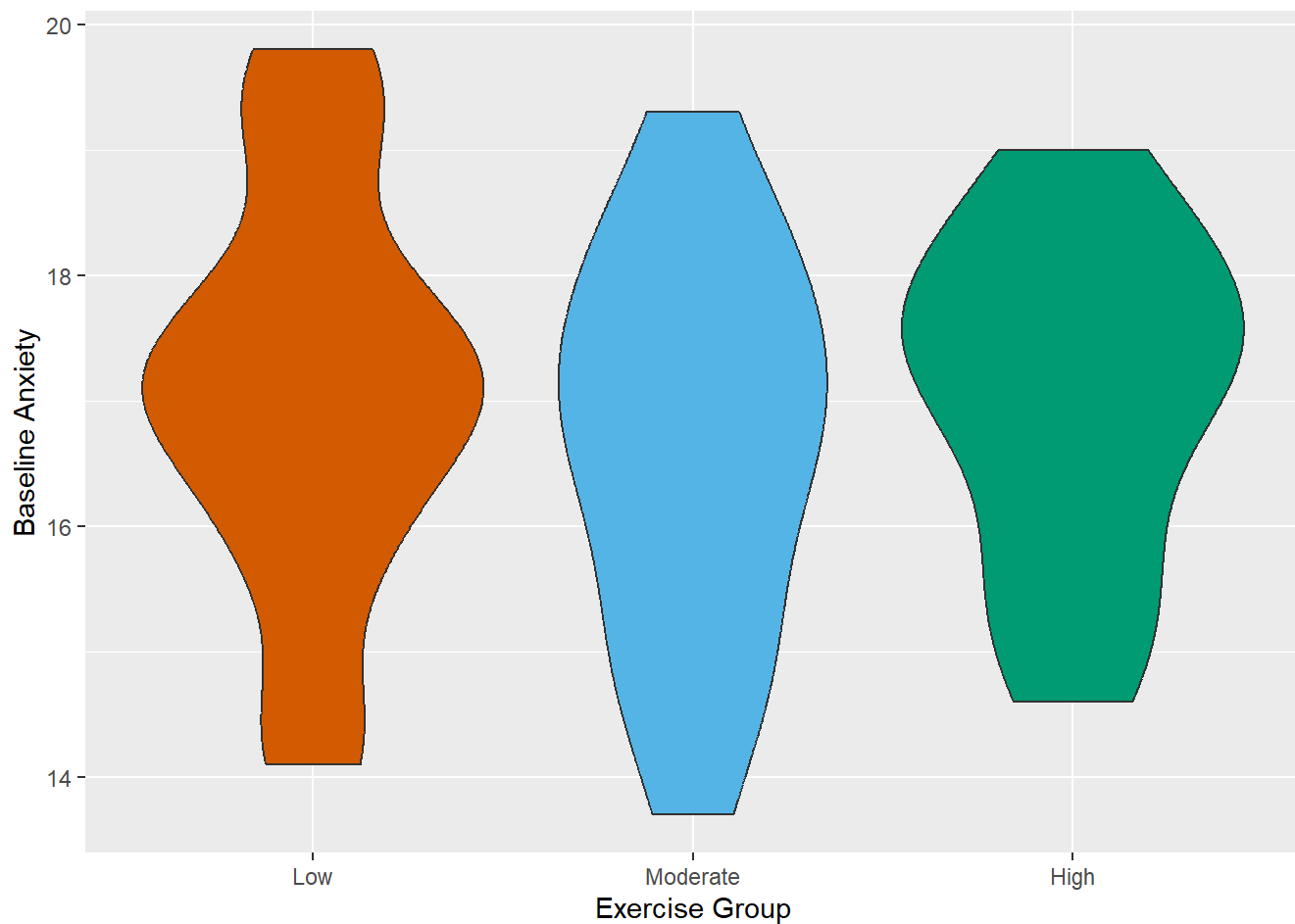


```
ggplot(data = dat_anx,  
       mapping = aes(y = posttest, x = groupF)) +  
  geom_boxplot() +  
  labs(y = "Post-Treatment Anxiety",  
       x = "Exercise Group")
```

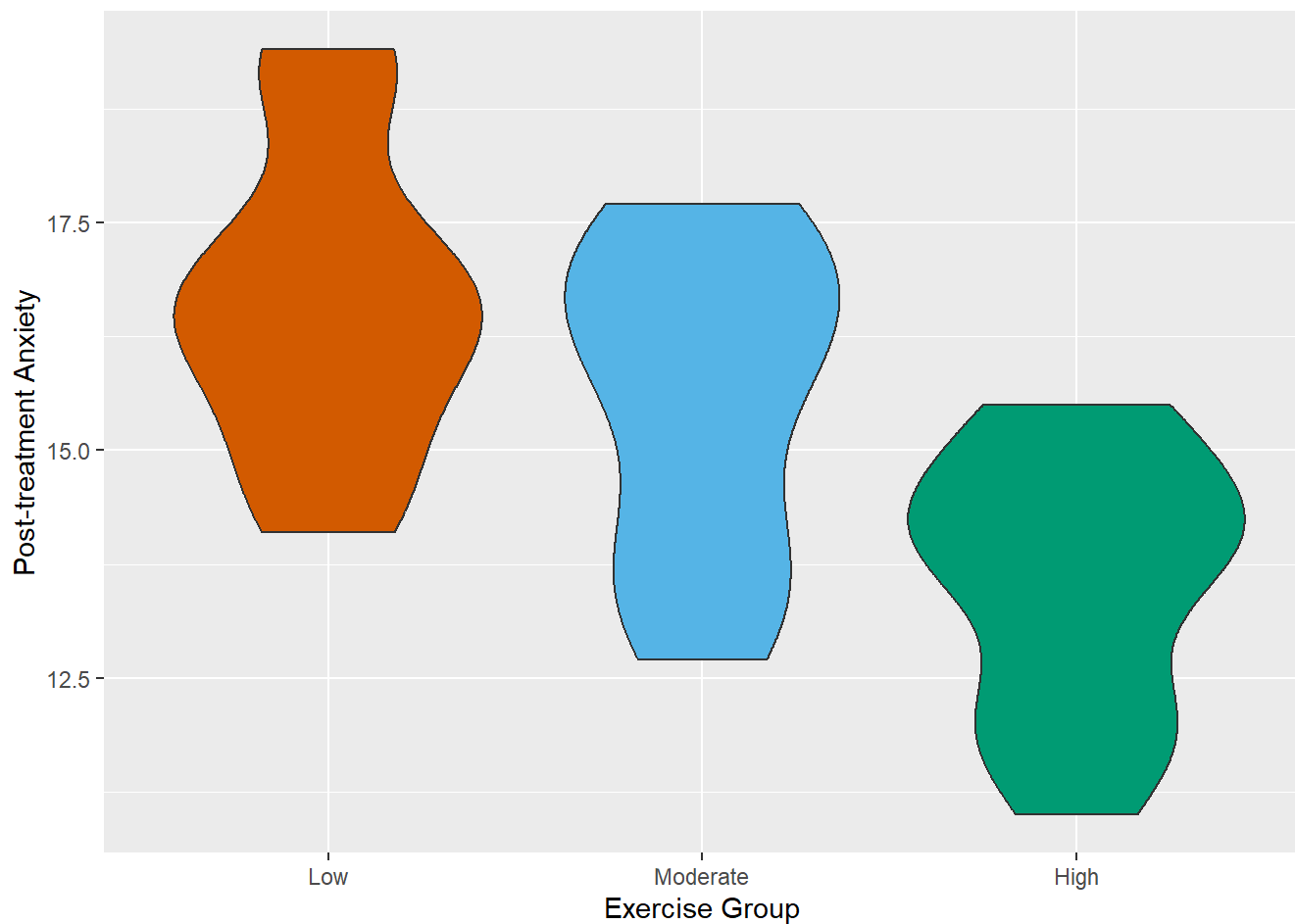


*# Violin Plots*

```
ggplot(data = dat_anx,
       aes(x = groupF, y = pretest,
           fill = groupF))+
  geom_violin(show.legend=FALSE)+
  ylab("Baseline Anxiety")+
  xlab("Exercise Group")+
  scale_fill_manual(values=c("#D55e00", "#56B4E9", "#009E73"))
```



```
ggplot(data = dat_anx,  
       aes(x = groupF, y = posttest,  
           fill = groupF))+  
geom_violin(show.legend=FALSE)+  
ylab("Post-treatment Anxiety")+  
xlab("Exercise Group")+  
scale_fill_manual(values=c("#D55e00", "#56B4E9", "#009E73"))
```



## ANCOVA | Omnibus Assumption Check

```
ancova(data = dat_anx,  
        dep = posttest,  
        factors = groupF,  
        covs = pretest,  
        effectSize = "eta",  
        homo = TRUE,  
        qq = TRUE,  
        norm = TRUE)
```



```
##
## ANCOVA
##
## ANCOVA - posttest
##
```

	Sum of Squares	df	Mean Square	F	p	$\eta^2$
groupF	74.022594	2	37.0112970	218.6293	< .0000001	0.4061553
pretest	101.288528	1	101.2885278	598.3210	< .0000001	0.5557611
Residuals	6.940805	41	0.1692879			

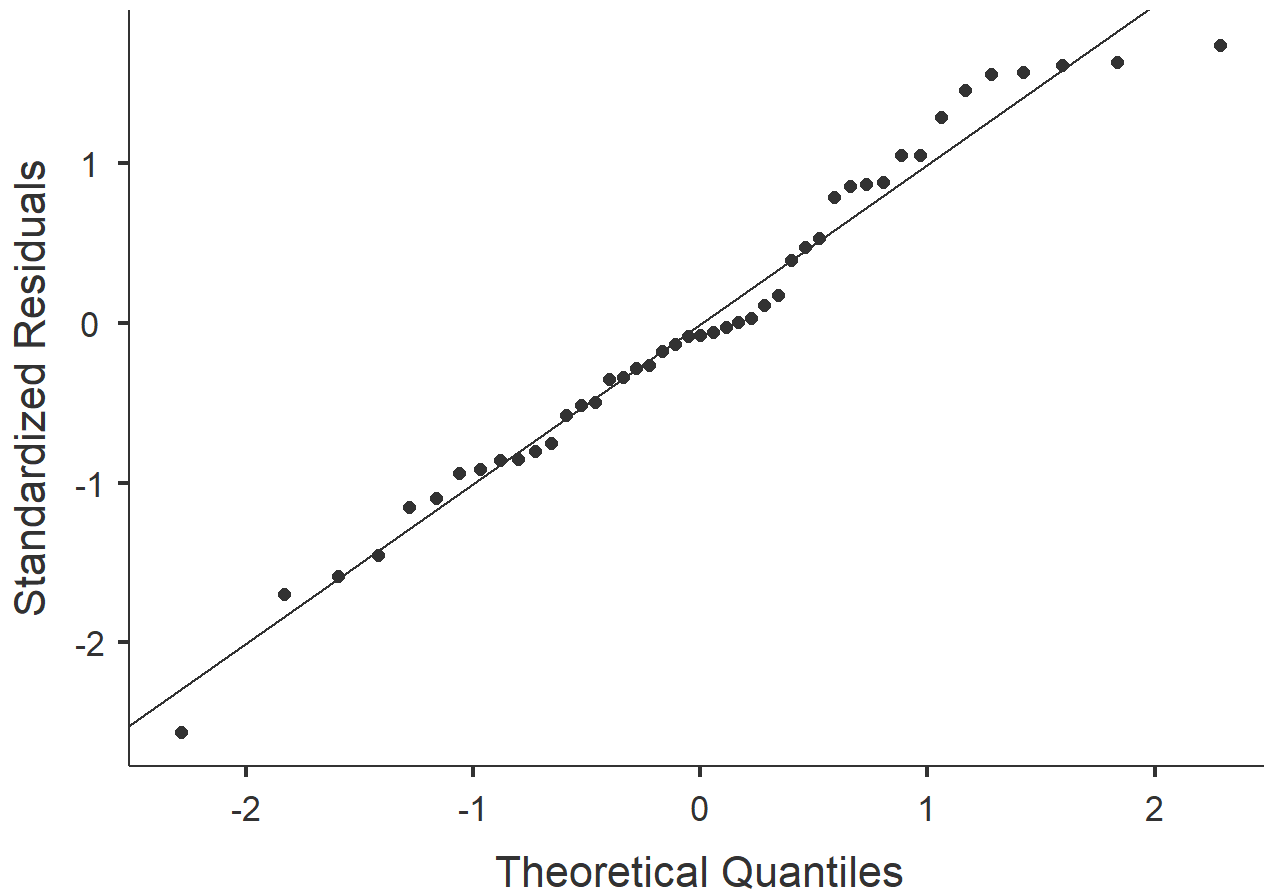
```
##
##
## ASSUMPTION CHECKS
##
## Homogeneity of Variances Test (Levene's)
##
```

F	df1	df2	p
2.339315	2	42	0.1088316

```
##
##
## Normality Test (Shapiro-Wilk)
##
```

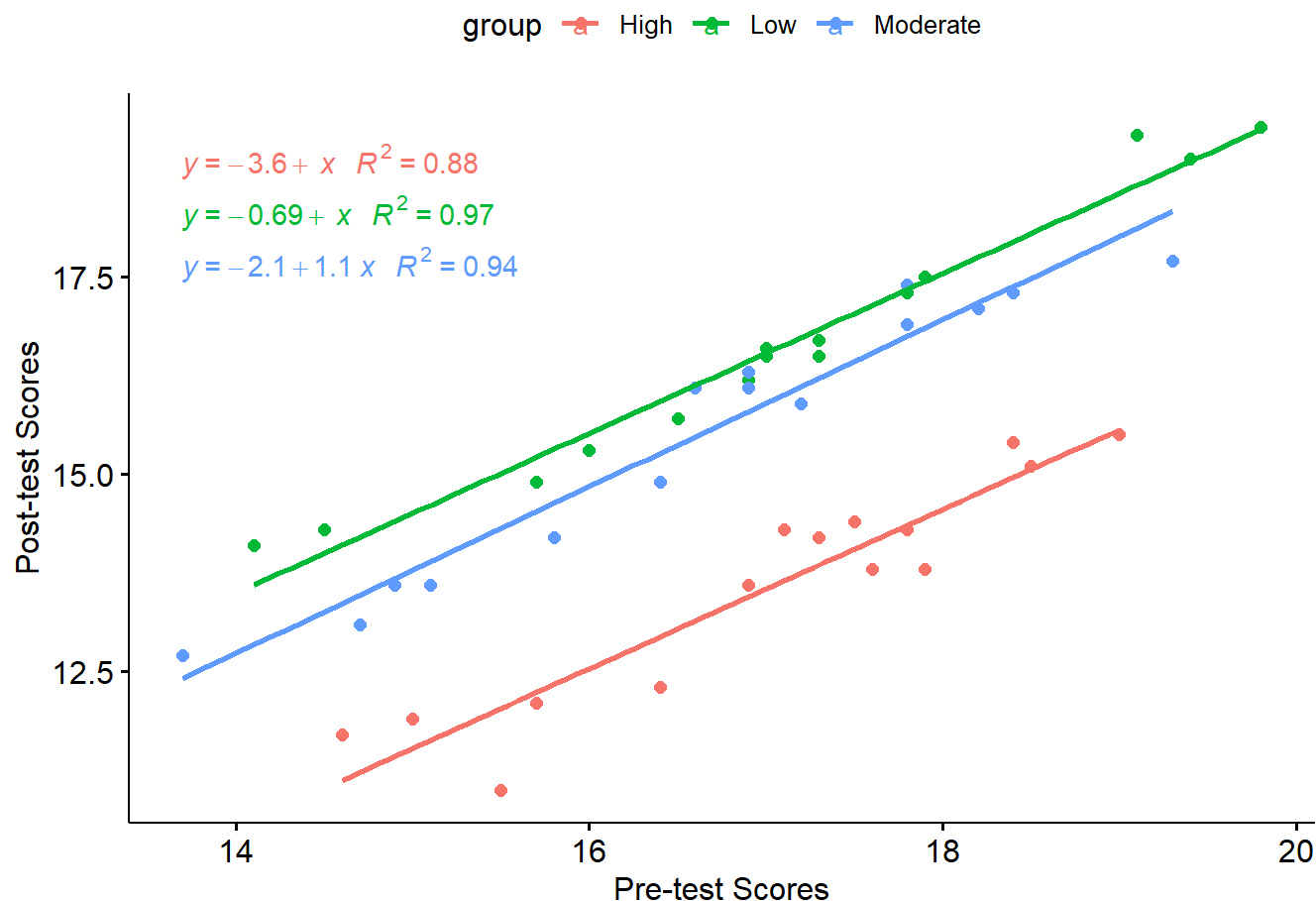
Statistic	p
0.9753224	0.4440646

```
##
```



## ANCOVA | Linearity Assumption Check

```
ggscatter(dat_anx,
  x = "pretest",
  y = "posttest",
  color = "group",
  add = "reg.line",
  xlab = "Pre-test Scores",
  ylab = "Post-test Scores")+
stat_regline_equation(
  aes(label = paste(after_stat(eq.label),
                    after_stat(rr.label),
                    sep = "~~~"),
  color = group))
```



## ANCOVA | Homogeneity of Regression Slopes Assumption Check

```
dat_anx %>%
  anova_test(posttest ~ groupF*pretest)
```

```
## ANOVA Table (type II tests)
```

```
##
##      Effect DFn DFd      F      p p<.05 ges
## 1      groupF   2   39 209.314 1.40e-21 * 0.915
## 2      pretest   1   39 572.828 6.36e-25 * 0.936
## 3 groupF:pretest  2   39   0.127 8.81e-01    0.006
```

```
# Since  $p > .05$  for the interaction we can assume homogeneity of regression slopes
```

# ANCOVA | Normality of Residuals

```
lm<-lm(posttest~pretest + groupF,
      dat_anx)

model.metrics <- augment(lm)

shapiro_test(model.metrics$.resid)
```

```
## # A tibble: 1 × 3
##   variable      statistic p.value
##   <chr>          <dbl>   <dbl>
## 1 model.metrics$.resid    0.975    0.444
```

*# Lack of statistical significant implies that normality of residuals has been achieved*

# ANCOVA | Homogeneity of Variances

```
model.metrics %>%
  levene_test(.resid ~ groupF)
```

```
## # A tibble: 1 × 4
##   df1  df2 statistic    p
##   <int> <int>   <dbl> <dbl>
## 1     2    42     2.27 0.116
```

*# Lack of statistical significance here implies that residual variances are homogeneous across b etween-subject groups*

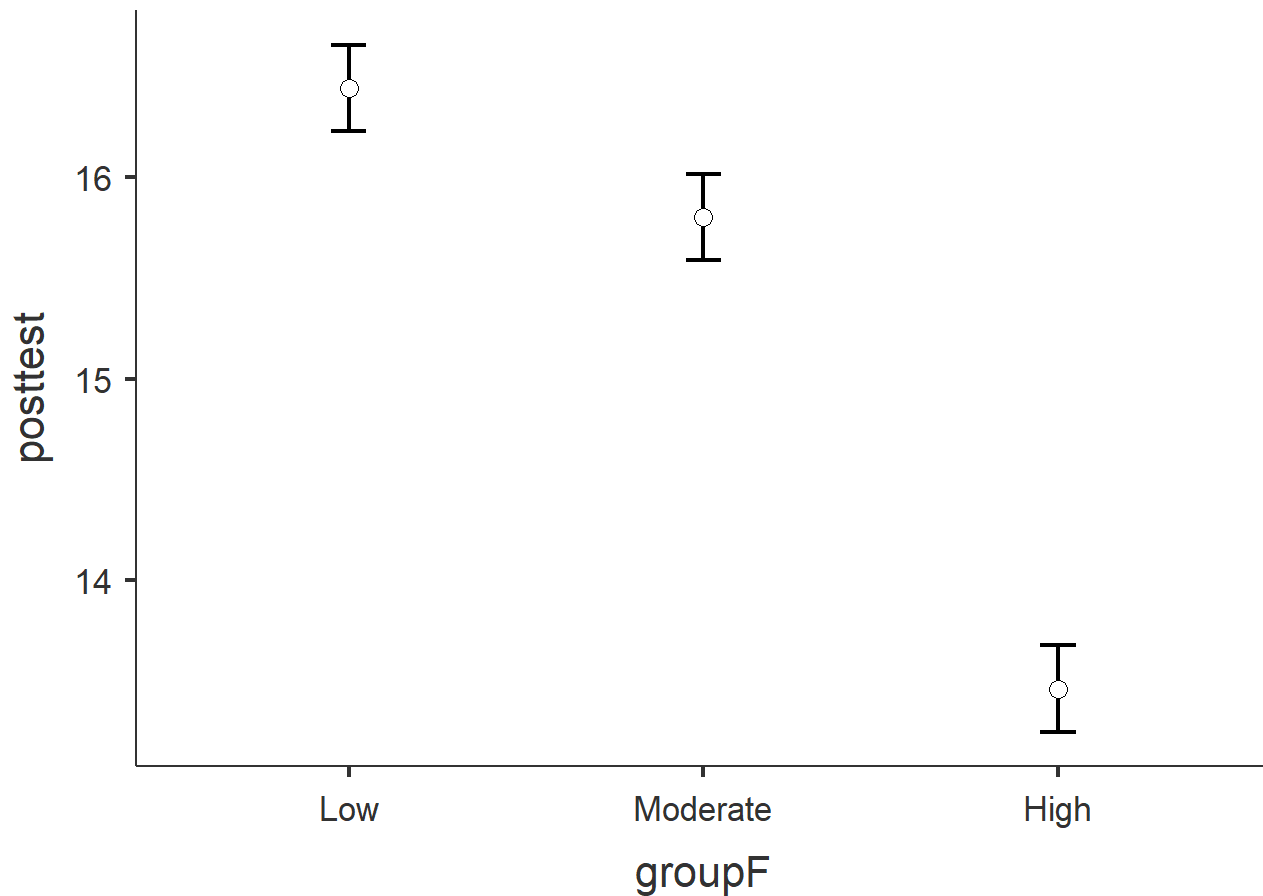
# ANCOVA | Conducting the ANCOVA

```
options(digits = 3)
ancova(data = dat_anx,
      dep = posttest,
      factors = groupF,
      covs = pretest,
      effectSize = "eta",
      postHoc = 'groupF',
      postHocCorr = 'bonf',
      postHocES = 'd',
      postHocEsCi = TRUE,
      emMeans=list(
        list('groupF')),
      emmTables=TRUE,
      emmPlots=TRUE)
```

```

##
## ANCOVA
##
## ANCOVA - posttest
##
##
## Sum of Squares    df    Mean Square    F    p    η²
##
## groupF            74.02     2      37.011    219    < .001    0.406
## pretest          101.29     1     101.289    598    < .001    0.556
## Residuals         6.94    41       0.169
##
##
##
## POST HOC TESTS
##
## Post Hoc Comparisons - groupF
##
##
## groupF            groupF    Mean Difference    SE    df    t    p-bonferroni
Cohen's d    Lower    Upper
##
##
## Low            -    Moderate    0.641    0.151    41.0    4.24    < .001
1.56    0.738    2.38
##            -    High    2.985    0.150    41.0    19.86    < .001
7.25    5.476    9.03
## Moderate    -    High    2.344    0.151    41.0    15.52    < .001
5.70    4.225    7.17
##
##
## Note. Comparisons are based on estimated marginal means
##
##
## ESTIMATED MARGINAL MEANS
##
## GROUPF
##
## Estimated Marginal Means - groupF
##
## groupF    Mean    SE    Lower    Upper
##
## Low        16.4    0.106    16.2    16.7
## Moderate    15.8    0.107    15.6    16.0
## High        13.5    0.106    13.2    13.7
##

```



## ANCOVA | Professional ANCOVA Visualization

```
res.aov<- dat_anx %>%
  anova_test(dv = posttest,
             between= group,
             covariate = pretest,
             effect.size = 'ges')

# Generates Marginal Means for Visualization
pwc <- dat_anx %>%
  emmeans_test(posttest ~ group,
               covariate = pretest,
               p.adjust.method = "bonferroni") %>%
  add_xy_position(x = "group")

pwc
```

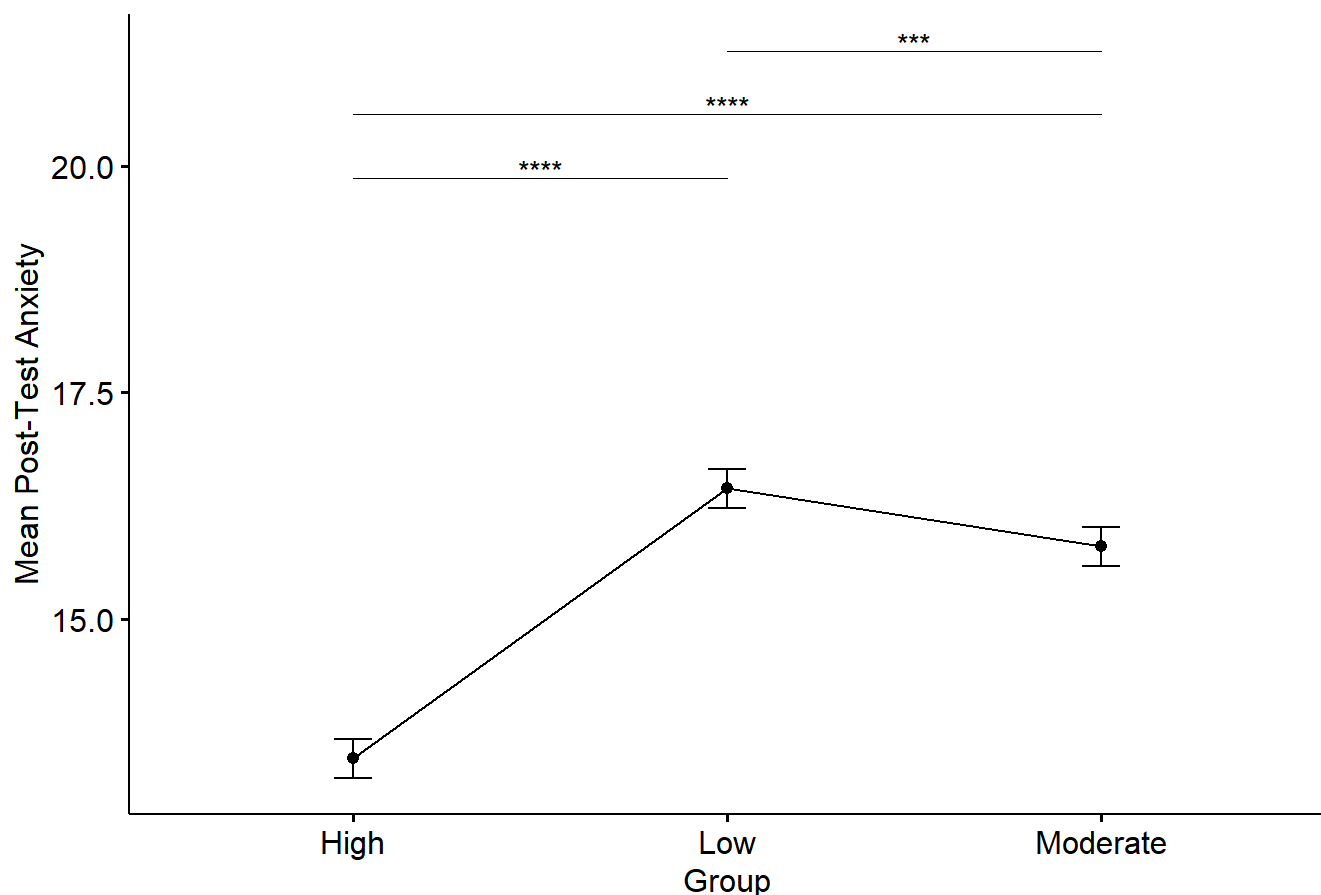
```
## # A tibble: 3 × 13
##   term      .y. group1 group2   df statistic      p    p.adj p.adj.signif
##   <chr>    <chr> <chr> <chr> <dbl>    <dbl>    <dbl>    <dbl> <chr>
## 1 pretest*gr... post... High   Low     41    -19.9  1.19e-22  3.58e-22 ****
## 2 pretest*gr... post... High   Moder... 41    -15.5  9.21e-19  2.76e-18 ****
## 3 pretest*gr... post... Low    Moder... 41     4.24  1.26e- 4  3.77e- 4 ***
## # i 4 more variables: y.position <dbl>, groups <named list>, xmin <dbl>,
## #   xmax <dbl>
```

## ANCOVA | Professional ANCOVA Visualization

```
get_emmeans(pwc)
```

```
## # A tibble: 3 × 8
##   pretest group   emmean    se    df conf.low conf.high method
##   <dbl> <fct>    <dbl> <dbl> <dbl>    <dbl>    <dbl> <chr>
## 1  16.9 High     13.5 0.106   41    13.2     13.7 Emmeans test
## 2  16.9 Low      16.4 0.106   41    16.2     16.7 Emmeans test
## 3  16.9 Moderate 15.8 0.107   41    15.6     16.0 Emmeans test
```

```
ggline(get_emmeans(pwc),
      x = "group",
      y = "emmean") +
  geom_errorbar(aes(ymin = conf.low,
                    ymax = conf.high),
                width = 0.1) +
  stat_pvalue_manual(pwc,
                    hide.ns = TRUE,
                    tip.length = FALSE) +
  ylab("Mean Post-Test Anxiety") +
  xlab("Group") +
  labs(caption = get_pwc_label(pwc))
)
```



## ANCOVA | Factorial Research Context Prompt

Your local sports psychologist and stress research enthusiast found out you were learning various quantitative statistical methods and reached out to offer you a consulting/analytics opportunity. They gathered data from 60 participants to attempt to evaluate the effect of a new protein treatment and exercise on experienced stress levels in a group of older adults. The data set ( `dat_stress` ) contains five variables:

- `id` — Participant identification number
- `score` — Stress score collected from each participant
- `treatment` — Treatment variable with two levels ( `yes` — Received protein treatment; `no` — Received placebo treatment)
- `exercise` — Level of exercise employed by participants ( `low` , `moderate` , `high` )
- `age` — Age of participant when data was collected

The goal for this final research question was: Does adjusting for the age of participants impact how stress scores fluctuate across treatment and exercise variables?

## Factorial ANCOVA | Data

```
dat_stress <- read.csv("ancova2.csv")
```



# Factorial ANCOVA | Descriptive Stats (Baseline-test)

```
# Descriptive Stats
dat_stress$Treatment <- factor(dat_stress$treatment,
                              levels = c("no", "yes"),
                              labels = c("No Treatment", "Protein Treatment"))

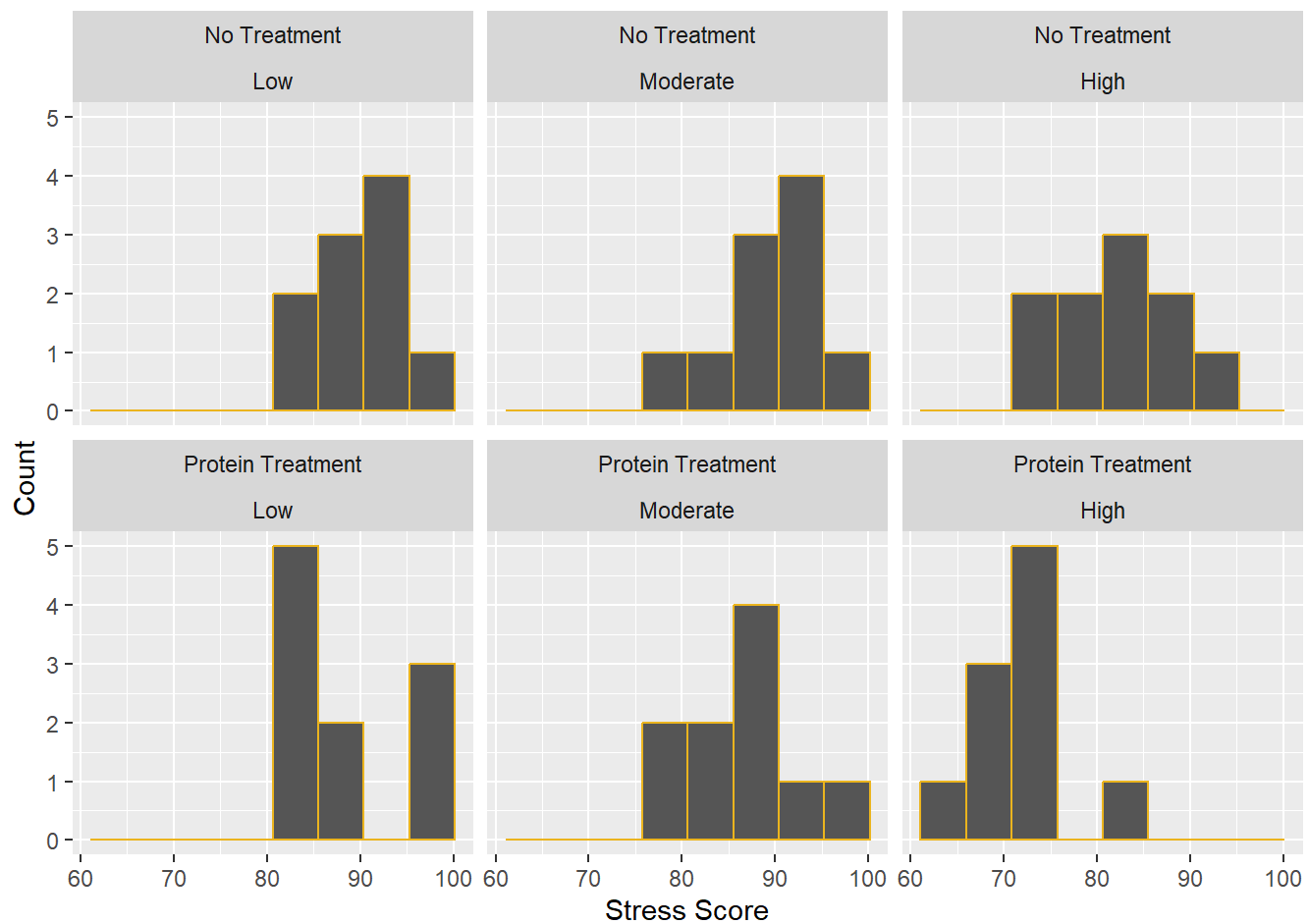
dat_stress$Exercise <- factor(dat_stress$exercise,
                              levels = c("low", "moderate", "high"),
                              labels = c("Low", "Moderate", "High"))

describeBy(dat_stress$score,
            list(dat_stress$Treatment, dat_stress$Exercise),
            mat=TRUE)
```

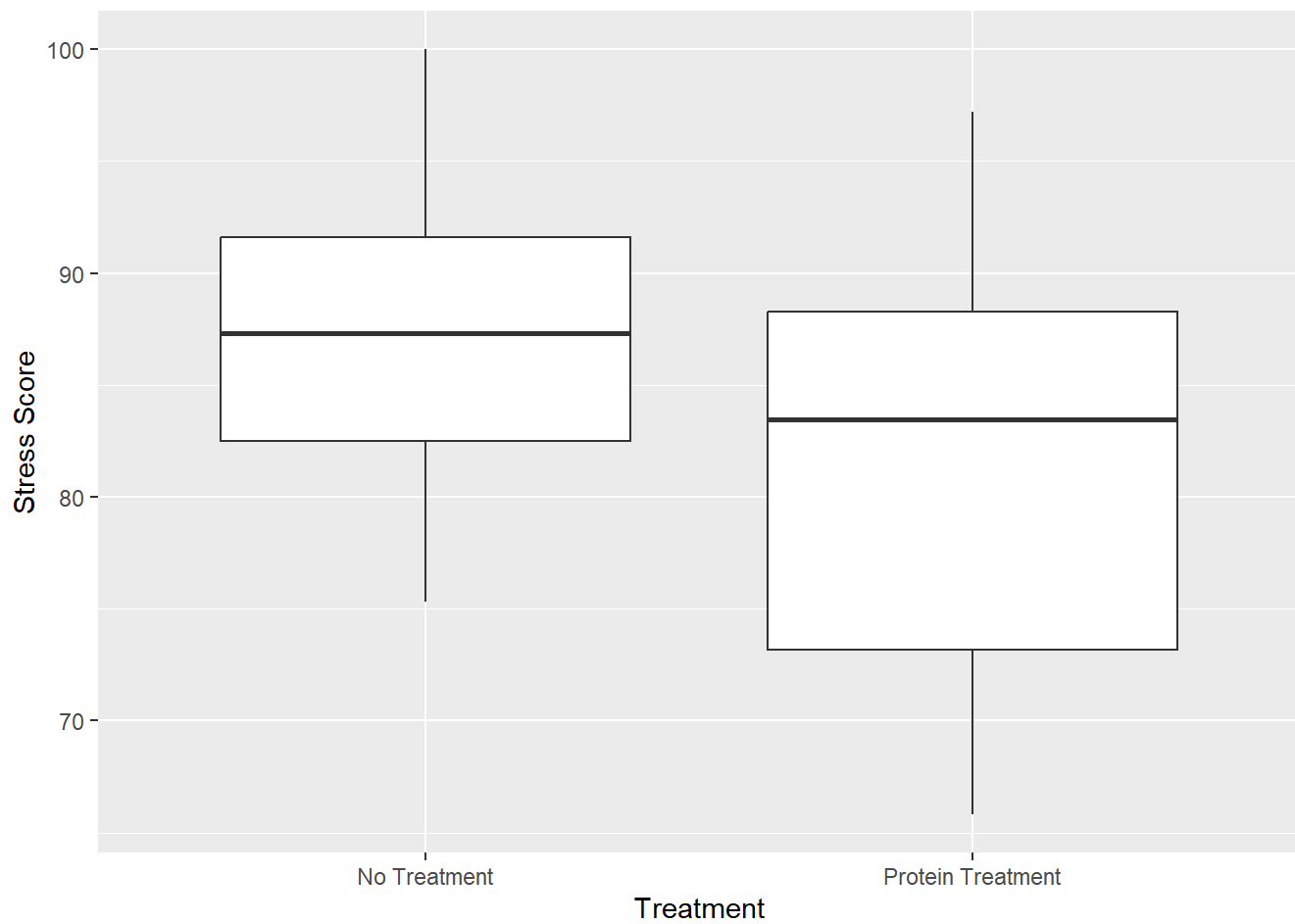
```
##      item      group1  group2 vars  n mean  sd median trimmed  mad  min
## X11    1      No Treatment    Low   1 10 89.6 4.49   89.2   89.7 5.49 82.5
## X12    2 Protein Treatment    Low   1 10 87.9 6.29   84.8   87.5 4.37 81.4
## X13    3      No Treatment Moderate  1 10 89.4 5.42   89.8   89.2 4.23 80.5
## X14    4 Protein Treatment Moderate  1 10 86.8 5.69   87.1   86.6 4.23 78.2
## X15    5      No Treatment    High   1 10 82.0 5.58   82.1   81.6 7.56 75.3
## X16    6 Protein Treatment    High   1 10 71.8 4.33   71.2   71.3 1.93 65.8
##      max range  skew kurtosis  se
## X11  96.1 13.6 -0.0335 -1.565 1.42
## X12  97.2 15.8  0.4837 -1.702 1.99
## X13 100.0 19.5  0.2159 -0.670 1.72
## X14  97.2 19.0  0.0618 -0.916 1.80
## X15  91.7 16.4  0.2737 -1.345 1.77
## X16  81.8 16.0  0.9351  0.303 1.37
```

## Factorial ANCOVA | EDA Visualizations

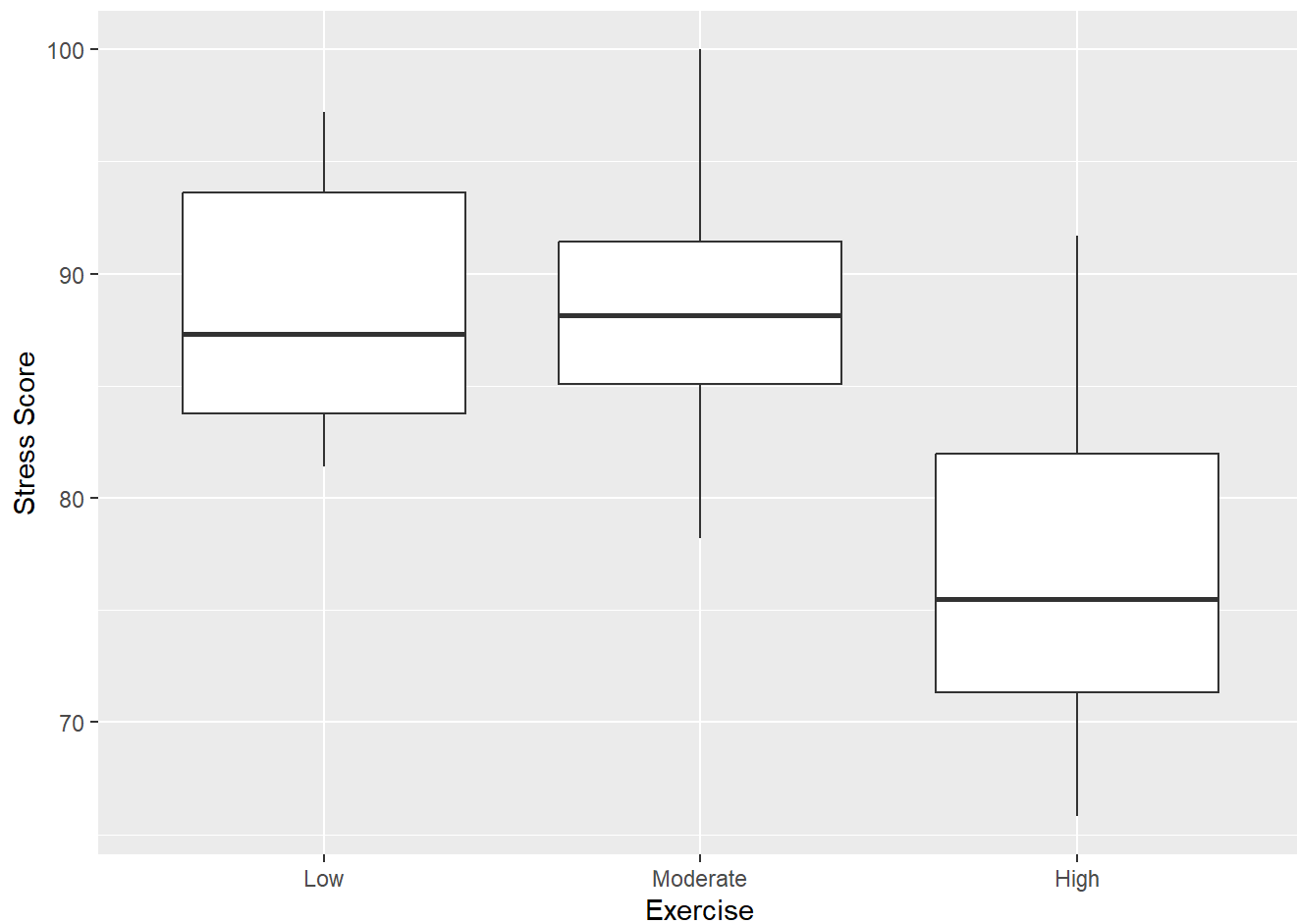
```
# Histogram
ggplot(data = dat_stress,
        mapping = aes(x = score)) +
  geom_histogram(bins = 8, color = "goldenrod2") +
  labs(y = "Count", x = "Stress Score")+
  facet_wrap(~dat_stress$Treatment + dat_stress$Exercise)
```



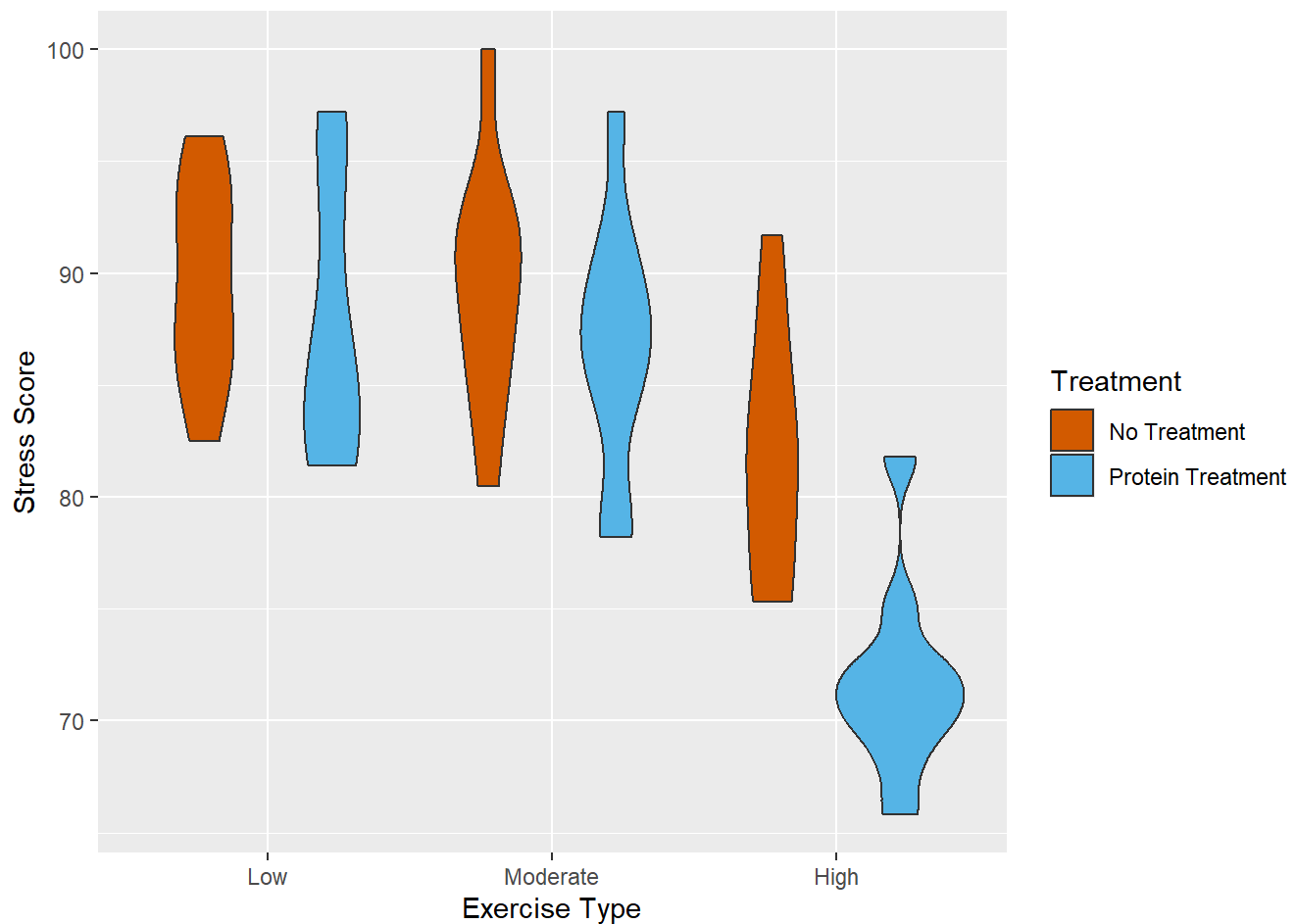
```
# Boxplots
ggplot(data = dat_stress,
       mapping = aes(y = score, x = Treatment)) +
  geom_boxplot() +
  labs(y = "Stress Score")
```



```
ggplot(data = dat_stress,  
       mapping = aes(y = score, x = Exercise)) +  
  geom_boxplot() +  
  labs(y = "Stress Score")
```



```
# Violin Plot
ggplot(data = dat_stress,
       aes(x = Exercise, y = score,
           fill = Treatment))+
  geom_violin(show.legend=TRUE)+
  ylab("Stress Score")+
  xlab("Exercise Type")+
  scale_fill_manual(values=c("#D55e00", "#56B4E9", "#009E73"))
```



## Factorial ANCOVA | Assumption Check: Omnibus and Grouped Level

*# Check Assumptions using techniques described in class*

```
ancova(data = dat_stress,
       dep = score,
       factors = c(Treatment, Exercise),
       covs = age,
       effectSize = "partEta",
       homo = TRUE,
       qq = TRUE,
       norm = TRUE)
```

```
##
## ANCOVA
##
## ANCOVA - score
##
```

	Sum of Squares	df	Mean Square	F	p	$\eta^2p$
Treatment	275	1	275.0	11.07	0.002	0.173
Exercise	1029	2	514.7	20.71	< .001	0.439
age	226	1	226.4	9.11	0.004	0.147
Treatment:Exercise	221	2	110.5	4.45	0.016	0.144
Residuals	1317	53	24.8			

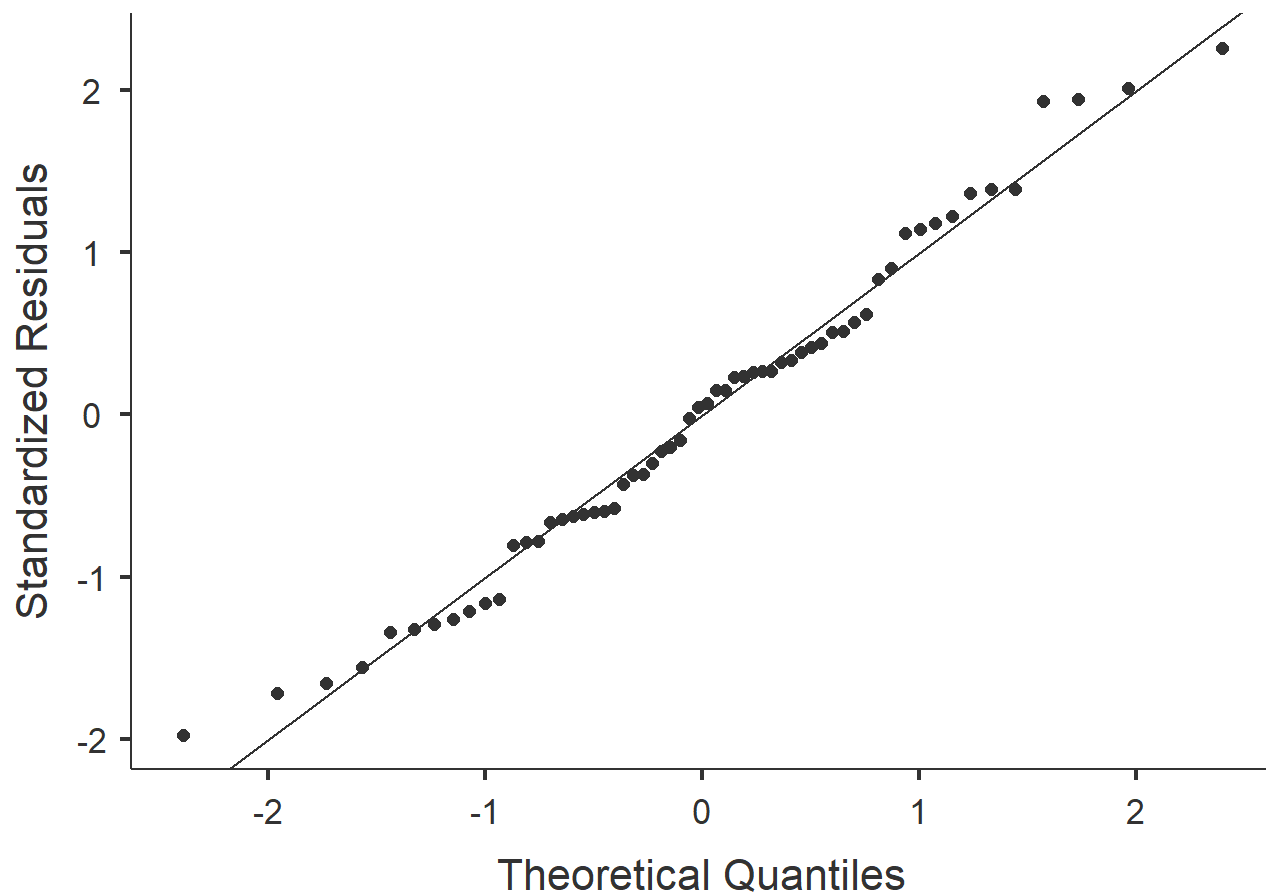
```
##
##
## ASSUMPTION CHECKS
##
## Homogeneity of Variances Test (Levene's)
##
```

F	df1	df2	p
0.955	5	54	0.453

```
##
##
## Normality Test (Shapiro-Wilk)
##
```

Statistic	p
0.982	0.531

```
##
```

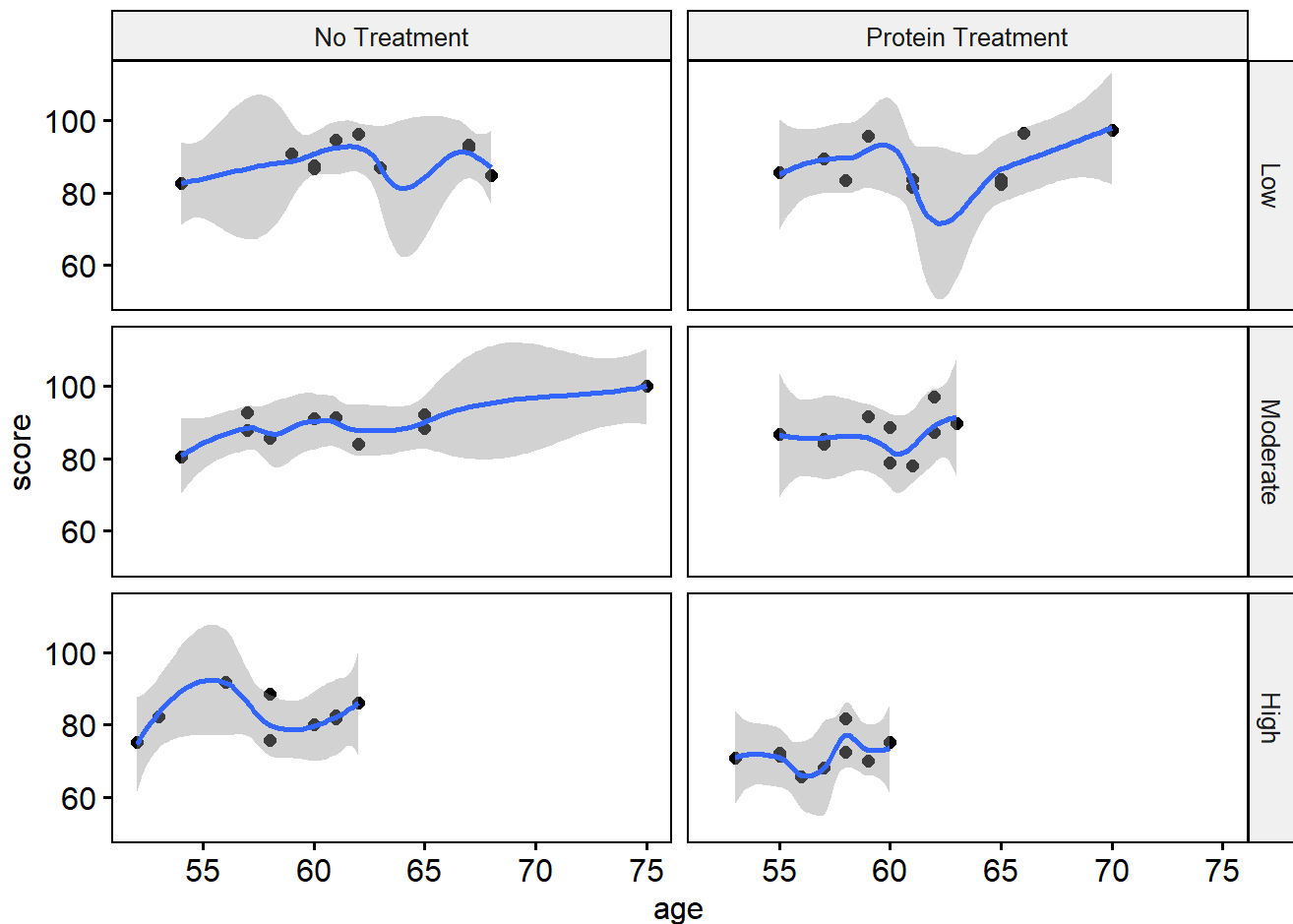


```
# Grouped Assumption Checks
```

```
# Linear relationship based on age and IVs
```

```
ggscatter(dat_stress,
          x = "age",
          y = "score",
          facet.by = c("Exercise", "Treatment")) +
  stat_smooth(method = "loess")
```

```
## `geom_smooth()` using formula = 'y ~ x'
```



# Homogeneity of Regression slopes

```
dat_stress %>%
  anova_test(score ~ age + Treatment + Exercise + Treatment*Exercise + age*Treatment + age*Exercise + age*Exercise*Treatment)
```

## ANOVA Table (type II tests)

##	Effect	DFn	DFd	F	p	p<.05	ges
## 1	age	1	48	8.359	6.00e-03	*	0.148000
## 2	Treatment	1	48	9.907	3.00e-03	*	0.171000
## 3	Exercise	2	48	18.197	1.31e-06	*	0.431000
## 4	Treatment:Exercise	2	48	3.303	4.50e-02	*	0.121000
## 5	age:Treatment	1	48	0.009	9.25e-01		0.000189
## 6	age:Exercise	2	48	0.235	7.91e-01		0.010000
## 7	age:Treatment:Exercise	2	48	0.073	9.30e-01		0.003000

# Normality assessments

```
lm<-lm(score~age + Exercise*Treatment, dat_stress)
model.metrics <- augment(lm)
shapiro_test(model.metrics$.resid)
```



```
## # A tibble: 1 × 3
##   variable      statistic p.value
##   <chr>          <dbl>   <dbl>
## 1 model.metrics$.resid    0.982   0.531
```

```
# Homogeneity of variance assessments
model.metrics %>%
  levene_test(.resid ~ Exercise*Treatment)
```

```
## # A tibble: 1 × 4
##   df1  df2 statistic      p
##   <int> <int>   <dbl> <dbl>
## 1     5    54    0.829 0.535
```

## Factorial ANCOVA | Conducting the ANCOVA

```
options(digits=3)
ancova(data = dat_stress,
       dep = score,
       factors = c(Treatment, Exercise),
       covs = age,
       effectSize = "partEta",
       postHoc = ~Exercise + Treatment:Exercise,
       postHocCorr = 'bonf',
       postHocES = 'd',
       postHocEsCi = TRUE,
       emMeans = ~ Exercise + Treatment + Exercise:Treatment,
       emmTables=TRUE,
       emmPlots=TRUE)
```

```
## NOTE: Results may be misleading due to involvement in interactions
```

```

##
## ANCOVA
##
## ANCOVA - score
##
##
## Sum of Squares    df    Mean Square    F        p        η²p
##
## Treatment          275      1        275.0    11.07    0.002    0.173
## Exercise          1029      2        514.7    20.71    < .001    0.439
## age                226      1        226.4     9.11    0.004    0.147
## Treatment:Exercise  221      2        110.5     4.45    0.016    0.144
## Residuals         1317     53         24.8
##
##
## POST HOC TESTS
##
## Post Hoc Comparisons - Exercise
##
##
## Exercise          Exercise    Mean Difference    SE    df    t        p-bonferroni
Cohen's d    Lower    Upper
##
##
## Low          -    Moderate    -0.0950    1.59    53.0    -0.0596    1.000
-0.0191    -0.660    0.622
##
##          -    High    9.5942    1.74    53.0    5.5063    < .001    1.
9247    1.130    2.720
##
## Moderate    -    High    9.6892    1.66    53.0    5.8495    < .001    1.
9438    1.177    2.710
##
##
## Note. Comparisons are based on estimated marginal means
##
##
## Post Hoc Comparisons - Treatment:Exercise
##
##
## Treatment          Exercise    Treatment    Exercise    Mean Difference
SE    df    t        p-bonferroni    Cohen's d    Lower    Upper
##
##
## No Treatment    Low    -    No Treatment    Moderate    -0.1725
2.23    53.0    -0.07727    1.000    -0.03460    -0.933    0.864
##
##          -    No Treatment    High    5.4851
2.34    53.0    2.34727    0.340    1.10037    0.136    2.065
##
##          -    Protein Treatment    Low    1.5286
2.23    53.0    0.68538    1.000    0.30665    -0.593    1.206
##
##          -    Protein Treatment    Moderate    1.5111
2.27    53.0    0.66630    1.000    0.30315    -0.611    1.218
##
##          -    Protein Treatment    High    15.2319
2.39    53.0    6.38354    < .001    3.05569    1.926    4.185

```

##			Moderate	-	No Treatment	High	5.6576
2.30	53.0	2.45505	0.261	1.13497	0.182	2.088	
##			-	Protein Treatment	Low		1.7011
2.23	53.0	0.76287	1.000	-0.34125	-1.241	0.558	
##			-	Protein Treatment	Moderate		1.6836
2.25	53.0	0.74847	1.000	0.33775	-0.570	1.245	
##			-	Protein Treatment	High		15.4044
2.35	53.0	6.56340	< .001	3.09029	1.970	4.210	
##			High	-	Protein Treatment	Low	-3.9565
2.32	53.0	-1.70712	1.000	0.79372	-0.152	1.739	
##			-	Protein Treatment	Moderate		-3.9740
2.25	53.0	-1.76839	1.000	0.79722	-0.120	1.715	
##			-	Protein Treatment	High		9.7468
2.23	53.0	4.36234	< .001	1.95532	0.979	2.932	
##	Protein Treatment	Low	-	Protein Treatment	Moderate		-0.0175
2.26	53.0	-0.00774	1.000	-0.00350	-0.912	0.905	
##			-	Protein Treatment	High		13.7033
2.36	53.0	5.79876	< .001	2.74904	1.658	3.840	
##			Moderate	-	Protein Treatment	High	13.7208
2.27	53.0	6.04155	< .001	2.75254	1.693	3.812	
##							

## Note. Comparisons are based on estimated marginal means

##

##

## ESTIMATED MARGINAL MEANS

##

## EXERCISE

##

## Estimated Marginal Means - Exercise

##

##	Exercise	Mean	SE	Lower	Upper
##	Low	87.7	1.16	85.4	90.1
##	Moderate	87.8	1.12	85.6	90.1
##	High	78.1	1.19	75.8	80.5

##

##

## TREATMENT

##

## Estimated Marginal Means - Treatment

##

##	Treatment	Mean	SE	Lower	Upper
##	No Treatment	86.7	0.914	84.9	88.6
##	Protein Treatment	82.4	0.914	80.6	84.3

##

##

##

## EXERCISE:TREATMENT

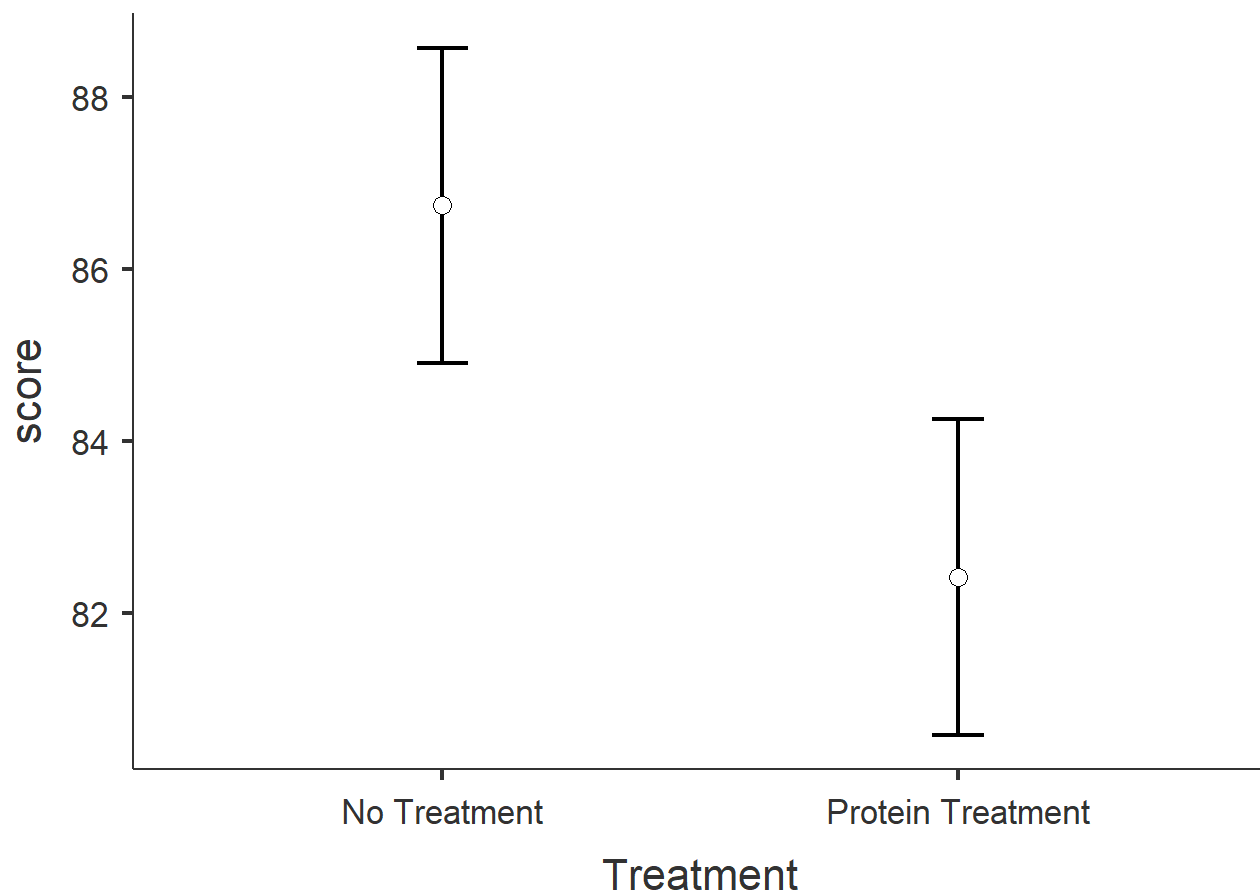
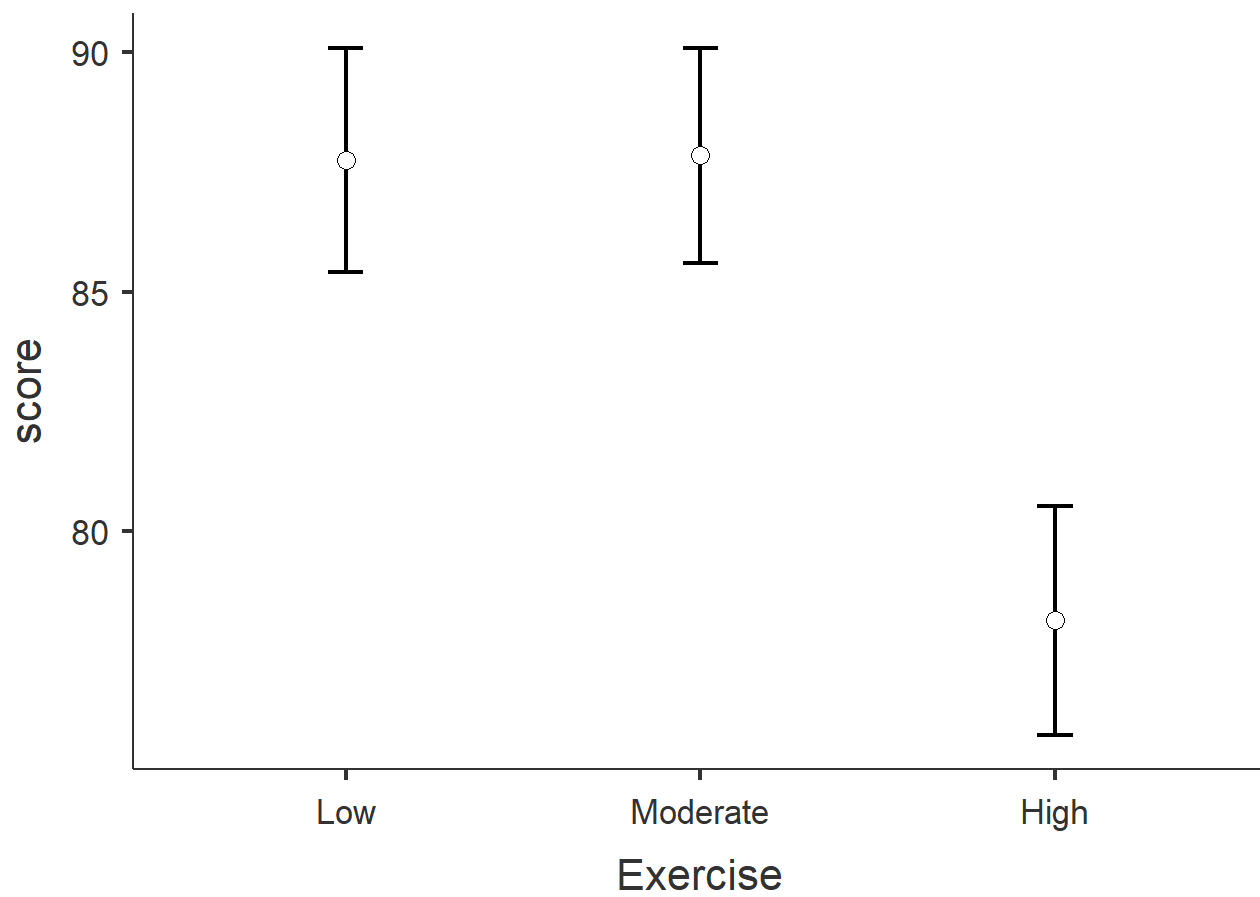
##

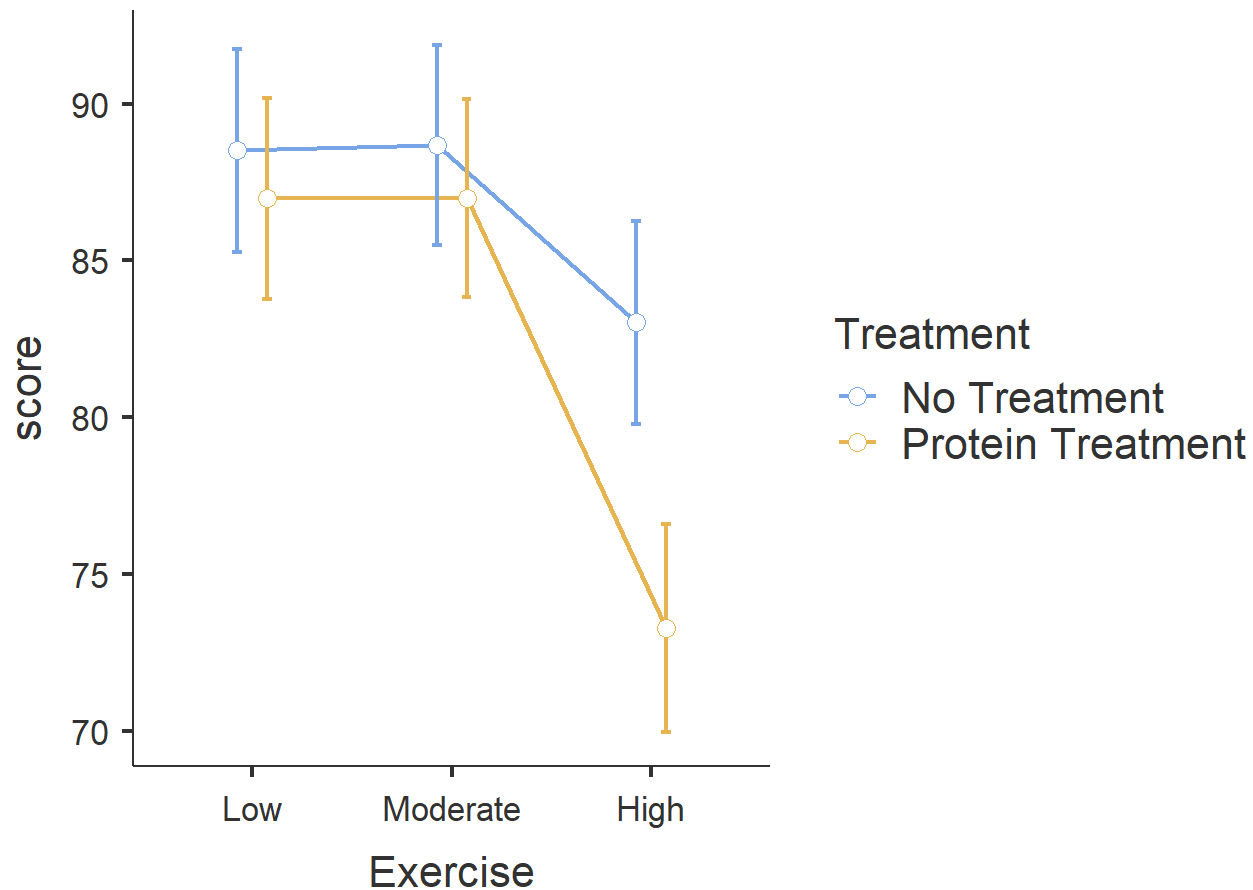
```
## Estimated Marginal Means - Exercise:Treatment
```

```
##
```

		Mean	SE	Lower	Upper
Treatment					
Exercise					
No Treatment	Low	88.5	1.62	85.3	91.7
	Moderate	88.7	1.59	85.5	91.9
	High	83.0	1.61	79.8	86.3
Protein Treatment	Low	87.0	1.60	83.8	90.2
	Moderate	87.0	1.58	83.8	90.2
	High	73.3	1.65	70.0	76.6

```
##
```





```
# Assessment of Simple Main Effects
dat_stress %>%
  group_by(Exercise) %>%
  anova_test(score ~ age + Treatment)
```

```
## # A tibble: 6 x 8
##   Exercise Effect      DFn  DFd      F      p `p<.05` ges
## * <fct>      <chr>    <dbl> <dbl> <dbl> <dbl> <chr> <dbl>
## 1 Low        age         1    17  2.25  0.152 ""    0.117
## 2 Low        Treatment    1    17  0.437 0.517 ""    0.025
## 3 Moderate age         1    17  6.65  0.02  "*"   0.281
## 4 Moderate Treatment    1    17  0.419 0.526 ""    0.024
## 5 High       age         1    17  0.794 0.385 ""    0.045
## 6 High       Treatment    1    17 18.7   0.000455 "*"   0.524
```

```
dat_stress %>%
  group_by(Treatment) %>%
  anova_test(score ~ age + Exercise)
```

```
## # A tibble: 4 × 8
##   Treatment      Effect    DFn  DFd    F      p `p<.05` ges
## * <fct>      <chr>    <dbl> <dbl> <dbl>    <dbl> <chr>    <dbl>
## 1 No Treatment    age         1    26  7.26 0.012    "*"    0.218
## 2 No Treatment  Exercise     2    26  3.99 0.031    "*"    0.235
## 3 Protein Treatment age         1    26  2.37 0.136    ""     0.083
## 4 Protein Treatment Exercise     2    26 17.3  0.0000164 "*"    0.572
```

## Factorial ANCOVA | Professional ANCOVA Visualization

```
# Pairwise Comparisons
pwc <- dat_stress %>%
  group_by(Exercise) %>%
  emmeans_test(score ~ Treatment,
                covariate = age,
                p.adjust.method = "bonferroni")

pwc %>% filter(Exercise == "High")
```

```
## # A tibble: 1 × 10
##   Exercise term      .y. group1 group2 df statistic      p p.adj
##   <fct>    <chr>    <chr> <chr>    <chr> <dbl>    <dbl>    <dbl>    <dbl>
## 1 High    age*Treatment score No Treatm... Prote...    53      4.36 5.97e-5 5.97e-5
## # i 1 more variable: p.adj.signif <chr>
```

```
pwc2 <- dat_stress %>%
  group_by(Treatment) %>%
  emmeans_test(score ~ Exercise,
                covariate = age,
                p.adjust.method = "bonferroni")

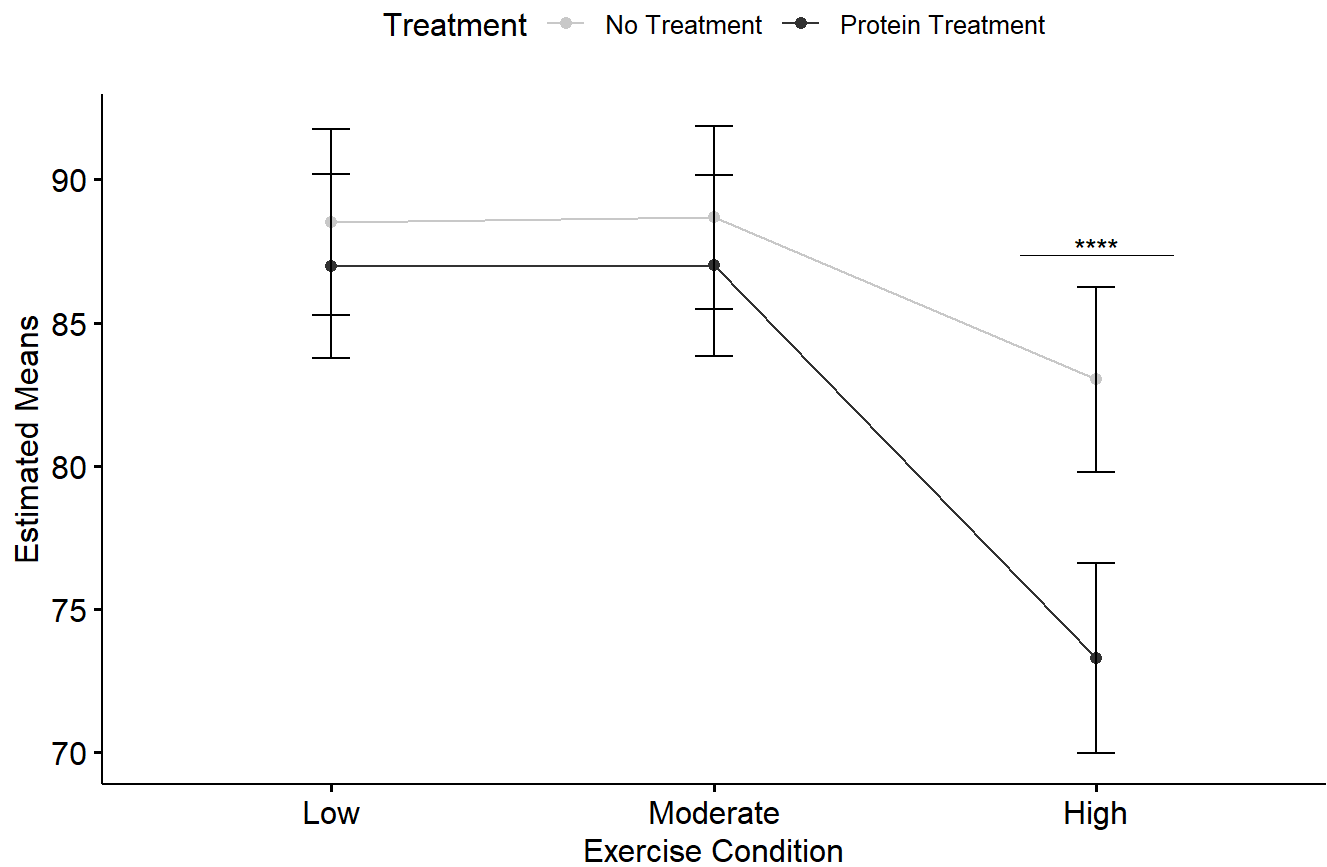
pwc2 %>% filter(Treatment == "Protein Treatment")
```

```
## # A tibble: 3 × 10
##   Treatment      term      .y. group1 group2 df statistic      p p.adj
##   <fct>      <chr>    <chr> <chr>    <chr> <dbl>    <dbl>    <dbl>    <dbl>
## 1 Protein Treatment age*Exe... score Low    Moder...    53   -0.00774 9.94e-1 1 e+0
## 2 Protein Treatment age*Exe... score Low    High      53    5.80    3.78e-7 1.13e-6
## 3 Protein Treatment age*Exe... score Moder... High      53    6.04    1.55e-7 4.66e-7
## # i 1 more variable: p.adj.signif <chr>
```

```
lp <- ggline(  
  get_emmeans(pwc),  
  x = "Exercise",  
  y = "emmean",  
  color = "Treatment",  
  palette = "grey") +  
  geom_errorbar(  
    aes(ymin = conf.low,  
        ymax = conf.high),  
    width = 0.1)
```

```
pwc <- pwc %>% add_xy_position(x = "Exercise",  
                             fun = "mean_se",  
                             step.increase = 0.2)  
  
pwc.filtered <- pwc %>% filter(Exercise == "High")  
  
lp + stat_pvalue_manual(pwc,  
                        hide.ns = TRUE,  
                        tip.length = 0) +  
  labs(  
    y = "Estimated Means",  
    x = "Exercise Condition",  
    color = "Treatment",  
    caption = get_pwc_label(pwc)  
  )
```





pwc: **Emmeans test**; p.adjust: **Bonferroni**

```
pwc2 <- pwc2 %>% add_xy_position(x = "Exercise",
                                fun = "mean_se")

pwc2.filtered <- pwc2 %>% filter(Treatment == "Protein Treatment")

lp + stat_pvalue_manual(pwc2,
                        hide.ns = TRUE,
                        tip.length = 0) +

labs(
  y = "Estimated Means",
  x = "Exercise Condition",
  color = "Treatment",
  caption = get_pwc_label(pwc)
)
```

