Stat245_test1

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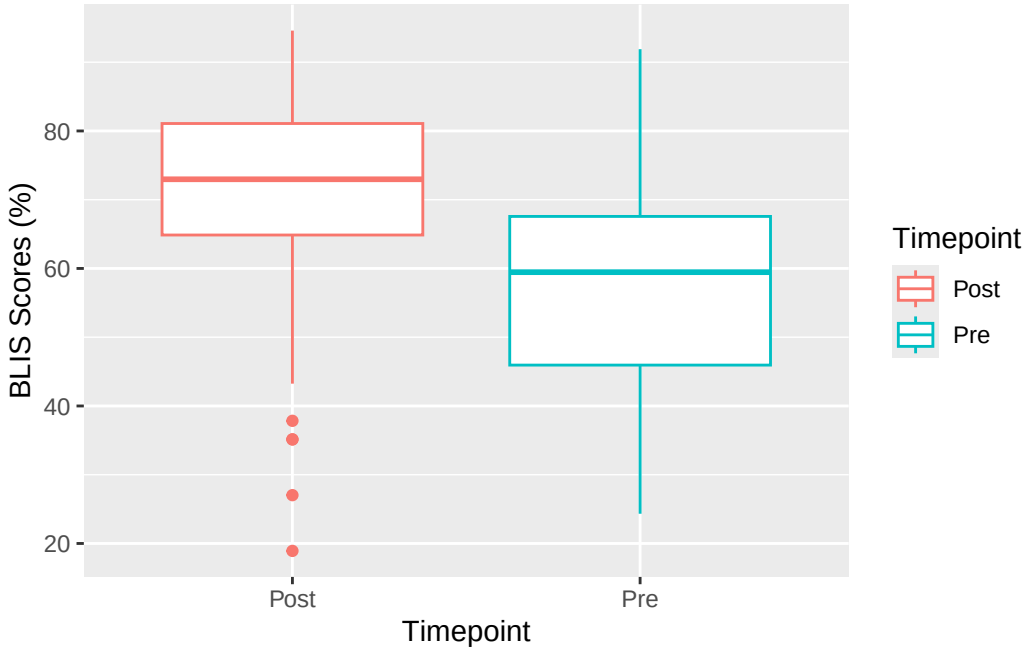
Plan

Question: Is there an association between Calvin students' BLIS scores and the Timepoint? Predictor: Timepoint Response: BLIS scores Confounding Variables: Colliders: Precision Covariates: courses and Duration. Courses may affect only the response variable, BLIS scores, but not the predictor, Timepoint. Duration (time the student took to complete the BLIS) may affect the response variable BLIS scores, but not the timepoint. And the dataset is big enough to satisfy the n/15 because there are more than 15 rows of data for each parameter. Mediation Chains:

Graphic

```
gf_boxplot(Percent~Timepoint, color = ~Timepoint, data = file) |>
gf_labs(
    x = "Timepoint",
    y = "BLIS Scores (%)"
  )
```

```
Warning: Removed 51 rows containing non-finite outside the scale range
(`stat_boxplot()`).
```



This boxplot graph shows a correlation between Timepoint and Blis Scores. The graph suggests that scores before courses (Timepoint = Pre) have lower mean than scores after courses (Timepoint = Post).

Fit

```
# create Model
mod <- lm(Percent ~ Timepoint
          + Duration
          + Course,
          data = cleaned_file)
summary(mod)
```

```
Call:
lm(formula = Percent ~ Timepoint + Duration + Course, data = cleaned_file)

Residuals:
    Min      1Q  Median      3Q     Max
-45.175  -8.712   1.448   9.027  34.761
```

```
Coefficients:
                Estimate Std. Error t value Pr(>|t|)
(Intercept)     63.09518    2.57537  24.499  < 2e-16 ***
TimepointPre   -13.89299    1.85624  -7.484  1.4e-12 ***
Duration         0.19708    0.06233   3.162  0.00177 **
CourseSTAT 243   3.28041    1.87966   1.745  0.08224 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 14.1 on 237 degrees of freedom
Multiple R-squared:  0.2313,    Adjusted R-squared:  0.2215
F-statistic: 23.77 on 3 and 237 DF,  p-value: 1.75e-13
```

Equation:

$$Percent = 63.095 - 13.89I_{[}pre] + 0.20Duration + 3.28I_{[}stat243] + \epsilon,$$
$$\epsilon \sim N(0, 14.1)$$

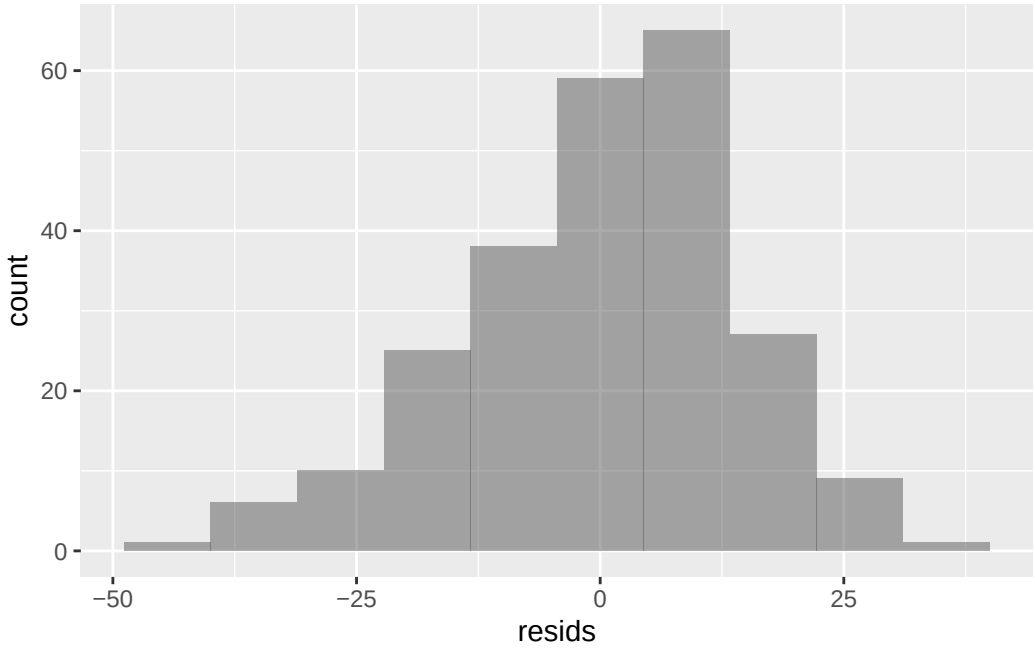
R_squared

$R^2 = 0.2215$ (adjusted R-Square) The porpotion of the varience in response variable, BLIS score, that is explained by the predictors are 0.2215.

Assessment

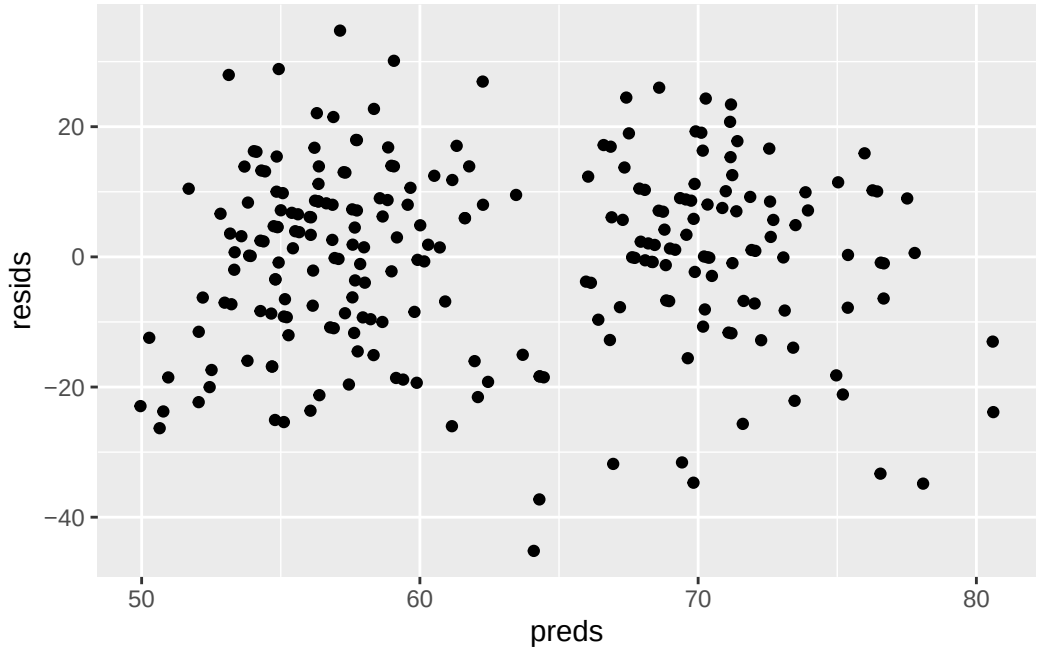
```
cleaned_file <- cleaned_file |>
  mutate(preds = predict(mod),
         resids = resid(mod))
```

```
# Residual Normal: Histogram
gf_histogram(~resids, data = cleaned_file, bins = 10)
```



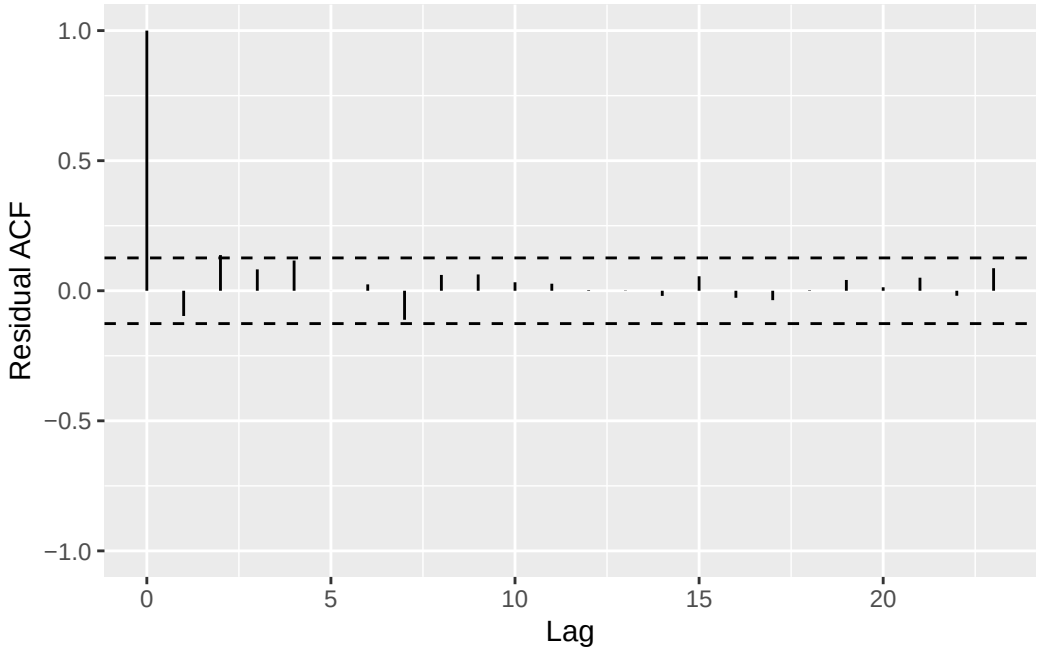
Histogram helps us check if our dataset is normally distributed, which is a requirement for fitting linear model. I think this condition is met because the residuals look unimodal, symmetrical, and loosely fit like a normal bell curve with the middle has higher counts than the left and right.

```
# Residuals VS Fitted Plot
gf_point(resids~preds, data = cleaned_file)
```



Residuals VS Fitted Plot helps us check if the dataset satisfies the lack of non-linearity and constant Residual Variance. I think both of these conditions are met because there are many points scattered randomly to indicate this graph as no trend and the points fit loosely into a rectangle between resids (-40,30), despite some outlier points that exceeds the rectangle.

```
s245::gf_acf(~mod) |>
  gf_lims(y = c(-1,1))
```



The ACF plot checks the independence of residuals. I think this condition is met, because all lines except Lag(0) are within or slightly touching the confidence bounds.

Overall, I think all conditionals are met, so the model passes assessment and can be used to draw conclusions.

Since the model met all assessment conditions, we can proceed to making predictions:

Interpretation

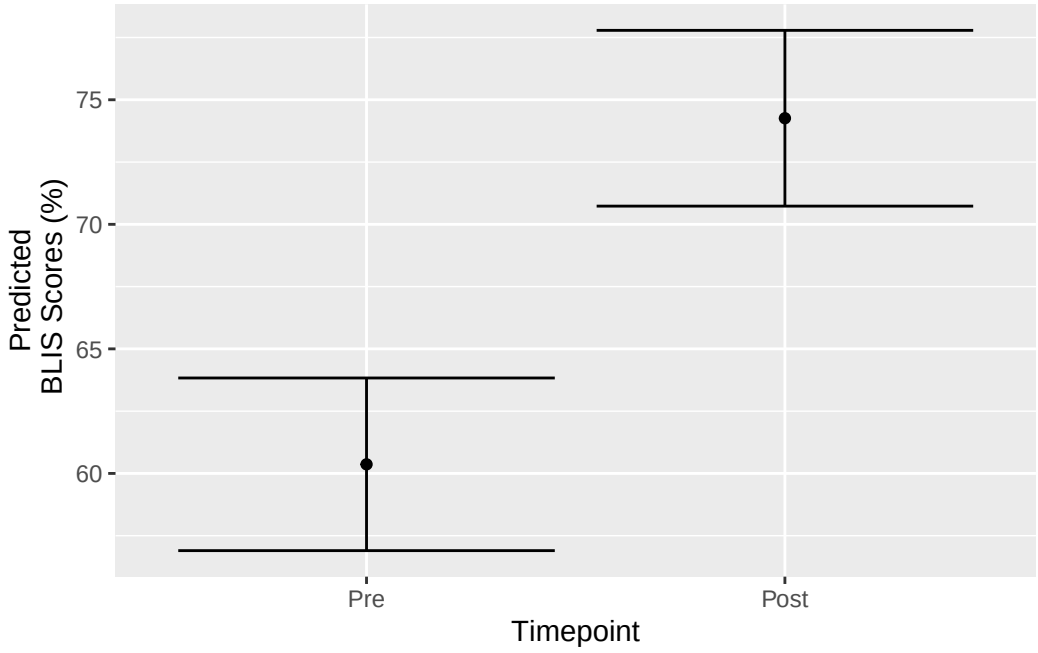
Prediction plot

```
# Create hypothetical data in which all others are kept constant.
fake_data <-
  expand.grid(Duration = 40,
              Course = "STAT 243",
              Timepoint = c('Pre','Post'))
preds <- predict(mod,
                 newdata = fake_data,
                 se.fit = TRUE)
```

```
fake_data <- fake_data |>
 mutate(pred = preds$fit,
 pred.se = preds$se.fit,
 CI_lower = pred - 1.96*pred.se,
 CI_upper = pred + 1.96*pred.se)
glimpse(fake_data)
```

```
Rows: 2
Columns: 7
$ Duration  <dbl> 40, 40
$ Course    <fct> STAT 243, STAT 243
$ Timepoint <fct> Pre, Post
$ pred      <dbl> 60.36596, 74.25894
$ pred.se   <dbl> 1.768142, 1.799738
$ CI_lower  <dbl> 56.90040, 70.73146
$ CI_upper  <dbl> 63.83152, 77.78643
```

```
gf_point(pred ~ Timepoint,
 data = fake_data) |>
 gf_labs(y='Predicted\n BLIS Scores (%)') |>
 gf_errorbar(CI_lower + CI_upper ~ Timepoint)
```



Explanation for the prediction plot: This is a prediction plot that BLIS scores(%) from categorical predictor Timepoint, while keeping the other variables constant. The variables are kept constant as the following: Duration = 40 and Course = "STAT 243".

Any relevant model selection result

```
# get Confident Intervals
confint(mod)
```

```
                     2.5 %      97.5 %
(Intercept)     58.02163544  68.1687214
TimepointPre   -17.54983090 -10.2361425
Duration         0.07429648   0.3198712
CourseSTAT 243  -0.42256070   6.9833843
```

```
# Hypothesis Test
car::Anova(mod)
```

```
Anova Table (Type II tests)

Response: Percent
          Sum Sq  Df F value    Pr(>F)
Timepoint  11133   1 56.0172 1.402e-12 ***
Duration    1987   1  9.9986  0.001771 **
Course       605   1  3.0458  0.082243 .
Residuals  47100 237
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The Anova inference suggests that there is very strong evidence (p_value = 1.402e-12) that BLIS score is associated with Timepoint, decreases 13.89 if Timepoint is Pre course (95% CI: -17.55 to -10.24) when other predictors are kept constant.

```
# AIC
AIC(mod)
```

```
[1] 1965.261
```

```r
# BIC
BIC(mod)
```

```
[1] 1982.685
```