

ANCOVA with interactions in R

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1 ANCOVA with interactions in R

In this lesson, we will learn how to implement and interpret ANCOVA with interaction terms on real data in R.

Consider the data from a recent study on teacher training. The study was “designed to investigate the effect of a Facebook-based instructional approach on preservice teacher’s learning achievement and engagement.”

(C. Saini and J. Abraham (2019). “Implementing Facebook-Based Instructional Approach in Pre-Service Teacher Education: An Empirical Investigation,” Computers & Education, Vol. 128, pp. 243-255.)

The variables are:

1. `pre_lrn`: Pre-Treatment learning achievement score
2. `Trt`: 1=Facebook Group, 0=Control
3. `post_lrn`: Post-Treatment learning achievement score

```
[1]: # Load needed packages  
library(dplyr)
```

Attaching package: ‘dplyr’

The following objects are masked from ‘package:stats’:

`filter`, `lag`

The following objects are masked from ‘package:base’:

`intersect`, `setdiff`, `setequal`, `union`

```
[2]: # Load and format the data
fb = read.csv("facebook_teach.csv")

fb = fb %>%
  mutate(Trt = as.factor(Trt))

levels(fb$Trt) = c("control", "facebook")

head(fb);

fb %>%
  group_by(Trt) %>%
  summarise(n_pre = n(), mean_pre = mean(pre_lrn), n_post = n(), mean_post =
↪mean(post_lrn))
```

A data.frame: 6 × 3

	pre_lrn <dbl>	Trt <fct>	post_lrn <dbl>
1	28.973	facebook	28.502
2	17.533	facebook	21.033
3	28.995	facebook	20.734
4	31.416	facebook	28.960
5	15.897	facebook	47.417
6	37.776	facebook	51.461

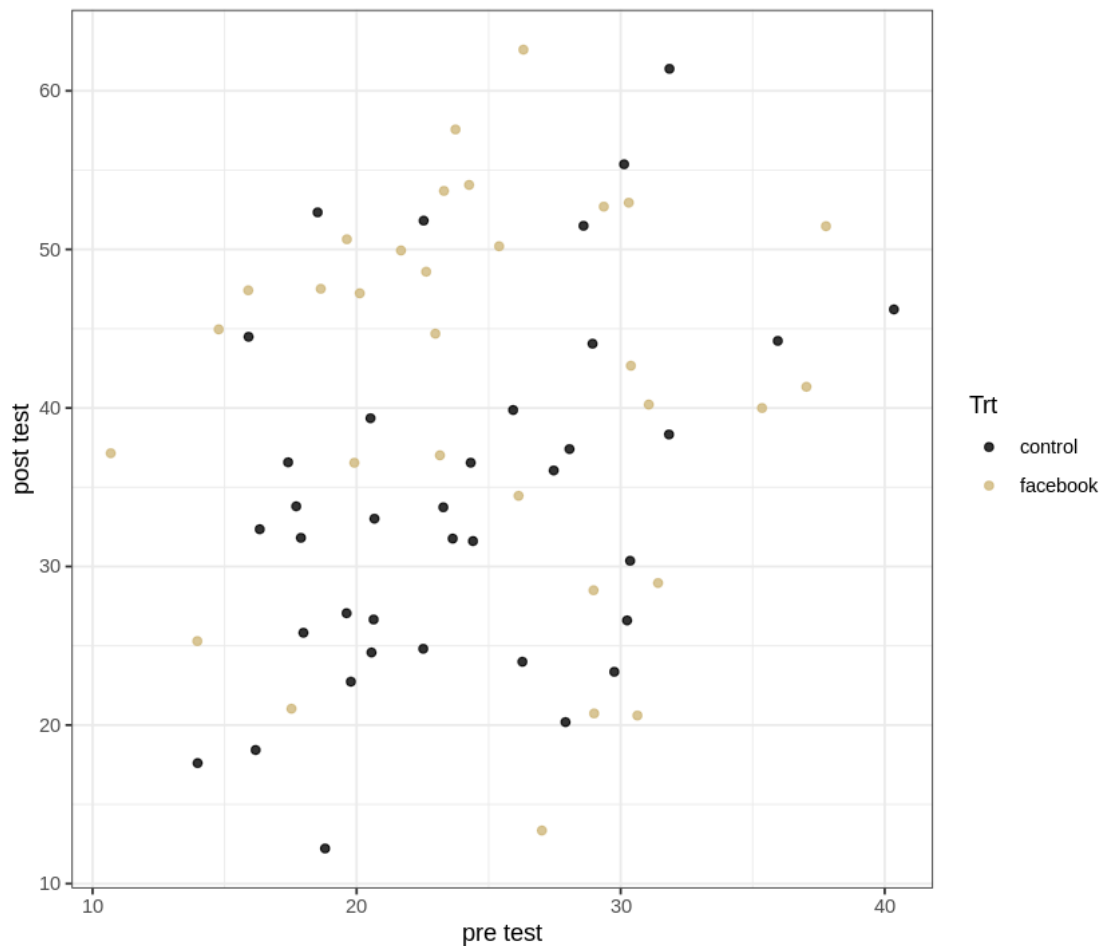
A tibble: 2 × 5

Trt <fct>	n_pre <int>	mean_pre <dbl>	n_post <int>	mean_post <dbl>
control	37	23.96995	37	34.26997
facebook	31	24.80997	31	41.42006

```
[3]: library(ggplot2)

p2 = ggplot(data = fb, aes(x = pre_lrn, y = post_lrn, color = Trt))
p2 = p2 + geom_point(alpha = 0.8)
p2 = p2 + scale_color_manual(values=c('black', '#CFB87C'))
p2 = p2 + xlab("pre test") + ylab("post test") + theme_bw() + coord_fixed(ratio
↪= 0.6)
#p2 = p2 + ggsave(filename = file.path("~/CU Google Drive/fig1.pdf"))

p2
```



Plotting the data by group, we do not get a great sense as to whether the least squares line going through the black points should have the same slope as the one going through the gold points. So, we can fit an ANCOVA model (in the regression form) with an interaction term. Here, we use the `lm()` function with the same formula as normal linear regression. Our interaction term enters that formula with `Trt : pre_lrn`.

```
[4]: ancova = lm(post_lrn ~ Trt + pre_lrn + Trt:pre_lrn, data = fb)
      summary(ancova)
```

Call:

```
lm(formula = post_lrn ~ Trt + pre_lrn + Trt:pre_lrn, data = fb)
```

Residuals:

Min	1Q	Median	3Q	Max
-----	----	--------	----	-----

```
-28.0246 -7.4198 0.0964 7.3837 22.1946
```

Coefficients:

```

              Estimate Std. Error t value Pr(>|t|)
(Intercept)    16.0895     7.6817   2.095  0.0402 *
Trtfacebook    25.8308    11.0997   2.327  0.0231 *
pre_lrn         0.7585     0.3106   2.442  0.0174 *
Trtfacebook:pre_lrn -0.7786    0.4403  -1.768  0.0818 .

```

```
---
```

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 11.49 on 64 degrees of freedom

Multiple R-squared: 0.1633, Adjusted R-squared: 0.1241

F-statistic: 4.165 on 3 and 64 DF, p-value: 0.009307

Let's use the default $\alpha = 0.05$. First, our full F-test is significant, which suggests that we need *some* of the terms in the model. Now, let's decide whether we need the interaction term. The t-test associated with the interaction term is not significant at the 0.05 level. That suggests that we could leave the interaction term out. The `anova()` function would yield the same result.

```
[5]: anova(ancova)
```

		Df <int>	Sum Sq <dbl>	Mean Sq <dbl>	F value <dbl>	Pr(>F) <dbl>
A anova: 4 × 5	Trt	1	862.3384	862.3384	6.527611	0.01300978
	pre_lrn	1	375.0380	375.0380	2.838911	0.09687739
	Trt:pre_lrn	1	413.1494	413.1494	3.127402	0.08175182
	Residuals	64	8454.8020	132.1063	NA	NA

Now let's consider a plot of the lines over the data.

(NEXT SLIDE)

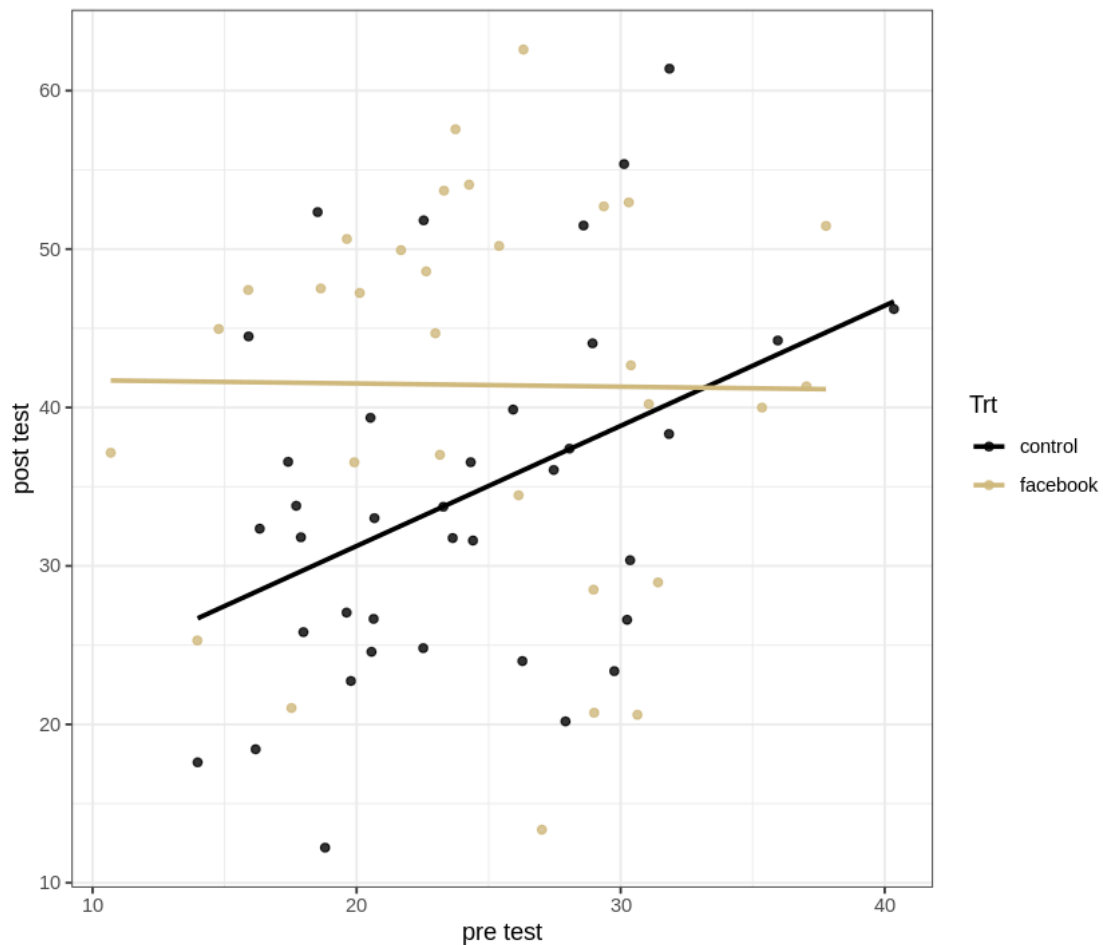
```
[6]: p2 = ggplot(data = fb, aes(x = pre_lrn, y = post_lrn, color = Trt))
p2 = p2 + geom_point(alpha = 0.8)
p2 = p2 + scale_color_manual(values=c('black', '#CFB87C'))
p2 = p2 + geom_smooth(method = "lm", se = F, alpha = 0.3)
p2 = p2 + xlab("pre test") + ylab("post test") + theme_bw() + coord_fixed(ratio_
  ↳ 0.6)

p2

#plot separate regression lines without ggplot
#with(fb, plot(pre_lrn, post_lrn, pch = 16, col = c("#CFB87C", "#565A5C")[Trt]))
#abline(coef(lm(post_lrn[Trt == "control"] ~ pre_lrn[Trt == "control"], data = f
  ↳ b)), col = "#CFB87C")
```

```
#abline(coef(lm(post_lrn[Trt == "facebook"] ~ pre_lrn[Trt == "facebook"], data_
↪ = fb)), col = "#565A5C")
```

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



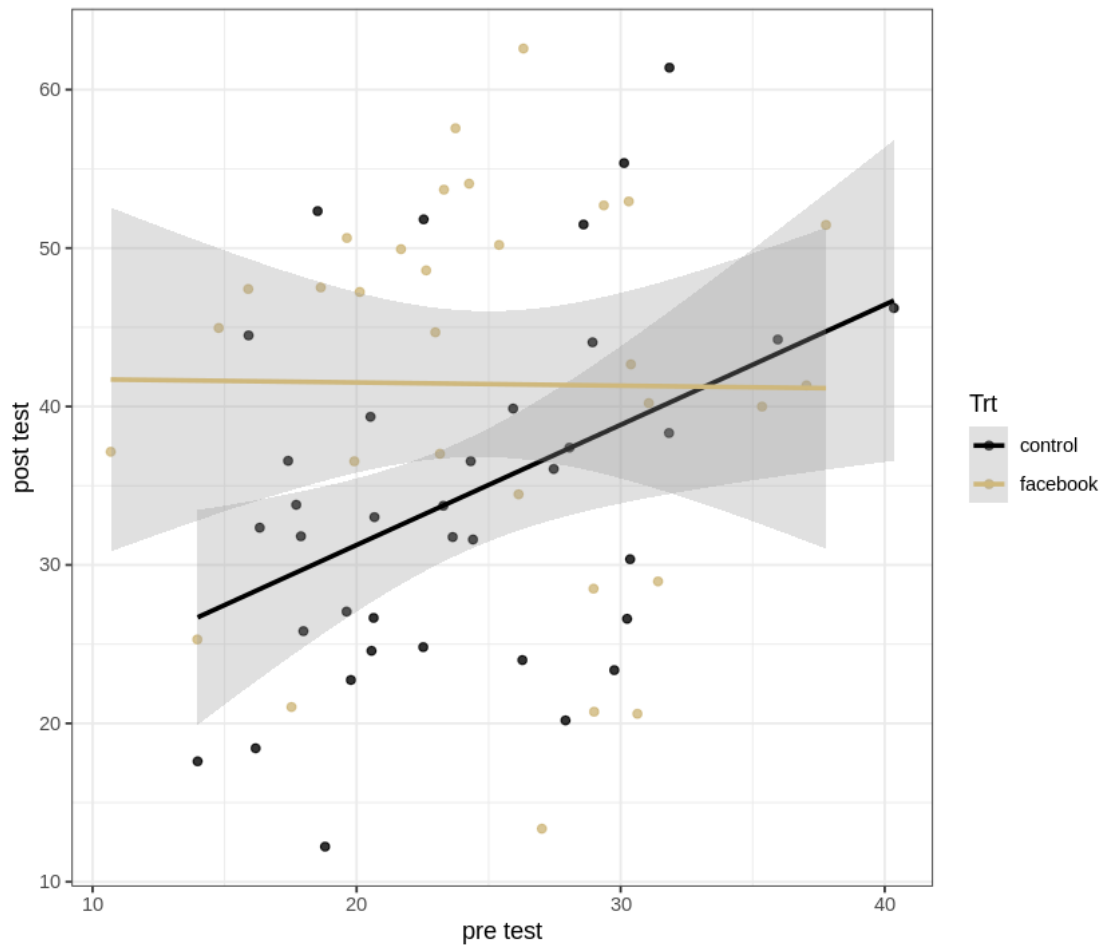
This result might seem inconsistent with the test above! These lines clearly aren't parallel! However, let's plot the lines with the corresponding confidence bands:

```
[7]: p2 = ggplot(data = fb, aes(x = pre_lrn, y = post_lrn, color = Trt))
p2 = p2 + geom_point(alpha = 0.8)
p2 = p2 + scale_color_manual(values=c('black', '#CFB87C'))
p2 = p2 + geom_smooth(method = "lm", se = T, alpha = 0.3)
```

```
p2 = p2 + xlab("pre test") + ylab("post test") + theme_bw() + coord_fixed(ratio_u
  ↪ = 0.6)
```

```
p2
```

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



Here, we notice that the confidence bands are relatively wide, which reflects the relatively high variability in the data (vertical stretch). Recall the interpretation of these confidence bands: if we resampled the post-test data (at the same values of the pre-test data and same values of the treatment), then we would get a different confidence band. If we did this over and over, then 95% of the bands would cover the true line.

Now, suppose that *this* band covers the true interval (after all, before calculating it, there was a 0.95 probability...). That suggests that any line that we could draw within the band is “plausible”. And, notice that it is possible to redraw the gold line and the black line so that they are parallel! So, while it seems as though the visual and statistical results are inconsistent, in a way, they’re not.

[]: