Precept 3

Can Television be Educational?

In this precept we're going to look at the effect of a daily educational television program The Electric Company on children's reading ability. The program was targeted at the first through fourth grades. Here we'll focus on whether and how much it increased the reading ability of its target audience.

As we discussed in lecture, the gold standard for policy evaluation is the *randomized trial*. This was a two location trial that randomized at the level of school classes, but for now we'll simplify a little and ignore the location of the trial and some supplementary treatment details. For more details of the experiment see Cooney (1976).

The dataset `electric-company.csv` in the `data` folder contains the following variables:

Name	Description
`pair`	The index of the treated and control pair (ignored here).
`city`	The city: Fresno ("F") or Youngstown ("Y")
`grade`	Grade (1 through 4)
`supp`	Whether the program replaced ("R") or supplemented ("S") a reading activity
`treatment`	"T" if the class was treated, "C" otherwise
`pre.score`	Class reading score *before* treatment, at the beginning of the school year
`post.score`	Class reading score at the end of the school year

In our data, every observation is a class of students, which was either *treated*, if the program was shown to them, or *control* if the program was not shown as part of their studies. The outcome of interest, our 'dependent variable', is the class's average score on a reading test at the end of the year. We've called that `post.score`. Every observation in our data is a separate class, so no class got the treatment more than once.

Part 1: Study Design

Question 1.1

What kind of experiment is this? What is the treatment and what is the outcome? What *kind* of a variable is `pre.score`? What about `grade`?

Answer 1.1

Question 1.2

Define the average treatment effect (ATE) of watching the Electric Company. Do you think this is the same for all grades? If not, how do you think it might differ?

Answer 1.2

Question 1.3

A *conditional average treatment effect* (CATE) is an average treatment effect for a particular value of pre-treatment variable. What are the possible CATEs in this experiment?

Answer 1.3

Part 2: Analyzing the Data

Question 2

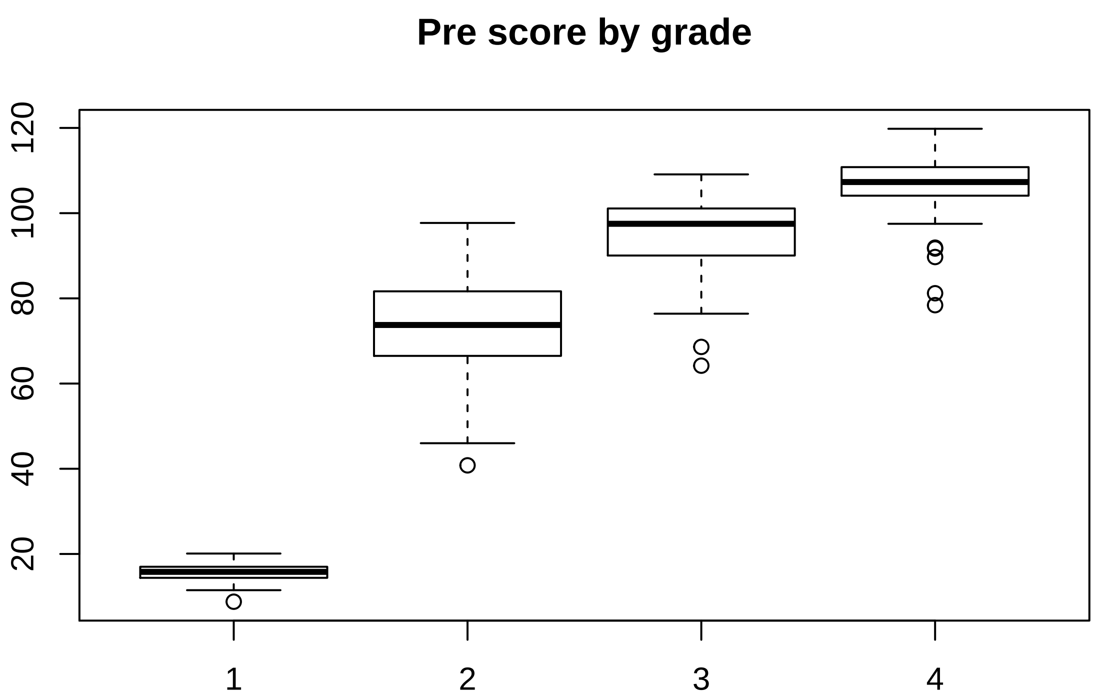
Read the data into an object named `electric`. How many classes were treated and how many not? Make a boxplot of class `pre.scores` (the reading scores before seeing the program) for each grade. What do you see?

Answer 2

```r
electric <- read.csv("data/electric-company.csv")

table(electric$treatment)
```

```

 C  T 
96 96 
```

```r
boxplot(pre.score ~ grade, data = electric, main = "Pre score by grade")
```

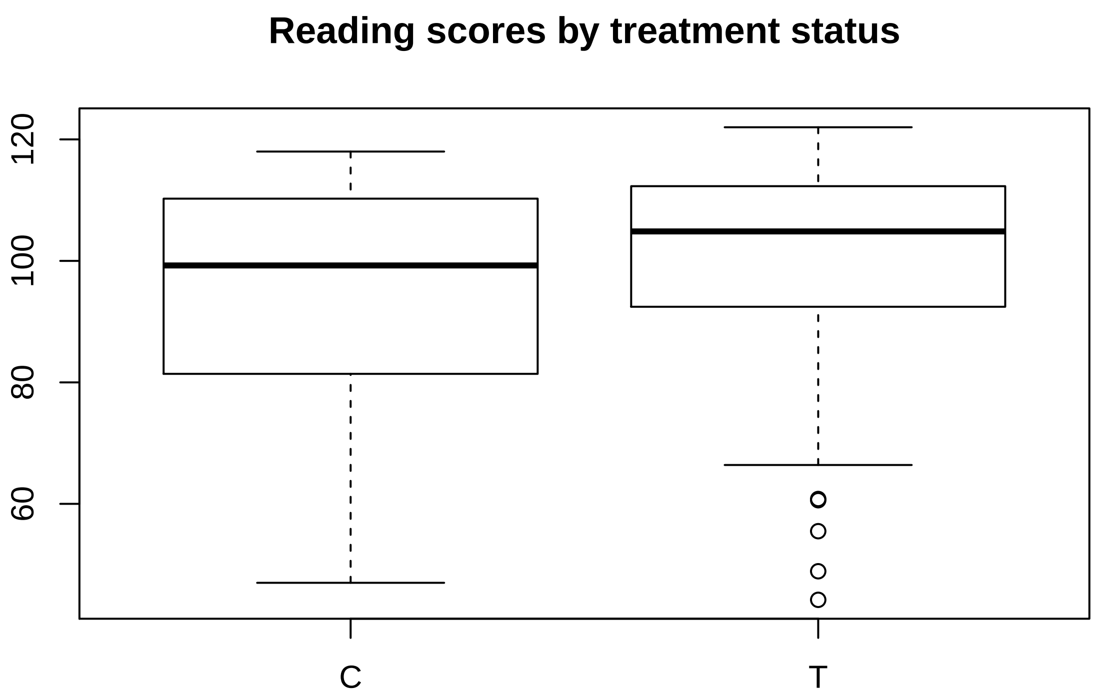


Question 3

Now let's consider the effect of the program. Make boxplot plot of `post.score` for treated and non-treated classes. Does it seem like the program had an effect? How big does it seem to be? Be clear about the units.

Answer 3

```r
boxplot(post.score ~ treatment, data = electric, main = "Reading scores by treatment status")
```




```r
mean(electric$post.score[electric$treatment == "T"]) -
  mean(electric$post.score[electric$treatment == "C"])
```

```
[1] 5.657292
```

Question 4

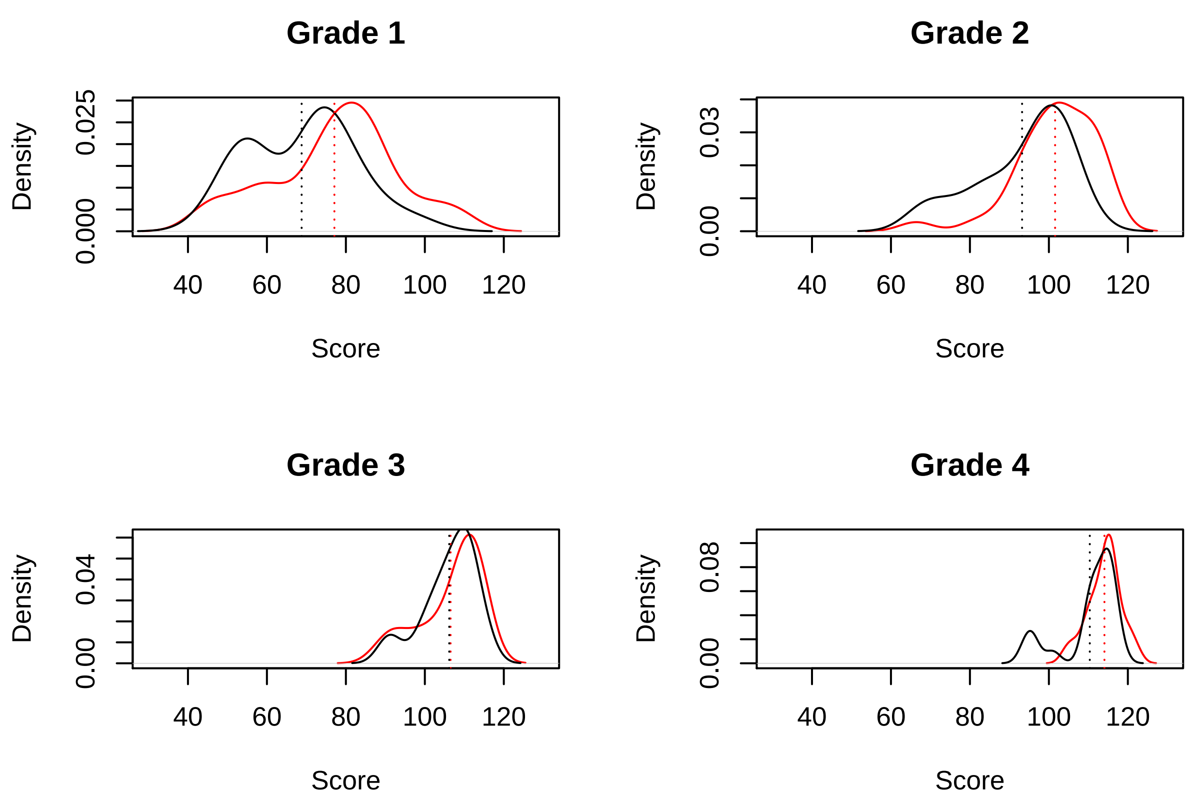
Now let's consider the effect of treatment within in each grade. We'll use density plots to visualize this. For each grade plot the density of the `post.scores` of the treated classes in red and the density of the `post.scores` of the untreated classes in black. Within each grade, mark the mean `post.score` in each experimental condition with dotted vertical line of the appropriate color. Make sure that all these plots share the same x-axis, e.g. scores from 30 to 130.

Which grade seems to show the largest effect of treatment? How about the smallest effect?

Answer 4

```r
par(mfrow = c(2,2))

grade1 <- electric[electric$grade == 1,]
grade2 <- electric[electric$grade == 2,]
grade3 <- electric[electric$grade == 3,]
grade4 <- electric[electric$grade == 4,]

plot(density(grade1$post.score[grade1$treatment == "T"]),
     col = "red", main = "Grade 1", xlab = "Score",
     xlim = c(30, 130))
lines(density(grade1$post.score[grade1$treatment == "C"]))
abline(v = mean(grade1$post.score[grade1$treatment == "T"]),
       col = "red", lty = "dotted")
abline(v = mean(grade1$post.score[grade1$treatment == "C"]),
       lty = "dotted")
```

```r
plot(density(grade2$post.score[grade2$treatment == "T"]),
     col = "red", main = "Grade 2", xlab = "Score",
     xlim = c(30, 130))
lines(density(grade2$post.score[grade2$treatment == "C"]))
abline(v = mean(grade2$post.score[grade2$treatment == "T"]),
       col = "red", lty = "dotted")
abline(v = mean(grade2$post.score[grade2$treatment == "C"]),
       lty = "dotted")

plot(density(grade3$post.score[grade3$treatment == "T"]),
     col = "red", main = "Grade 3", xlab = "Score",
     xlim = c(30, 130))
lines(density(grade3$post.score[grade3$treatment == "C"]))
abline(v = mean(grade3$post.score[grade3$treatment == "T"]),
       col = "red", lty = "dotted")
abline(v = mean(grade3$post.score[grade3$treatment == "C"]),
       lty = "dotted")

plot(density(grade4$post.score[grade4$treatment == "T"]),
     col = "red", main = "Grade 4", xlab = "Score",
     xlim = c(30, 130))
lines(density(grade4$post.score[grade4$treatment == "C"]))
abline(v = mean(grade4$post.score[grade4$treatment == "T"]),
       col = "red", lty = "dotted")
abline(v = mean(grade4$post.score[grade4$treatment == "C"]),
       lty = "dotted")
```



```r
par(mfrow = c(1,1))
```

Question 5

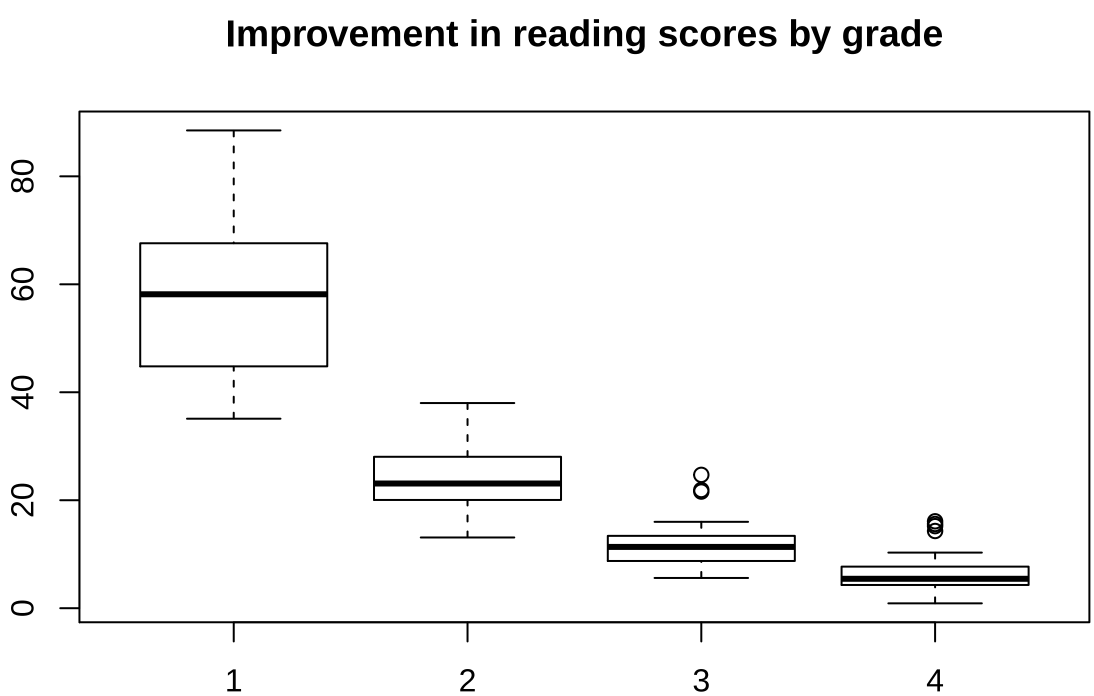
So far we have ignored the possible effect of a class *starting* a grade with a low or high `pre.score`. To take into account possible effects of starting with a high or low `pre.score` we will construct an index `score.diff`, defined as

`score.diff` = `post.score` - `pre.score`

Add this new variable to `electric` and show its distribution within each grade in a boxplot, ignoring treatment status. What does this suggest about progression in reading scores across the grades?

Answer 5

```r
electric$score.diff <- electric$post.score - electric$pre.score

boxplot(score.diff ~ grade, data = electric,
        main = "Improvement in reading scores by grade")
```



Question 6

In the previous question we saw that `post.score` was predictable using `pre.score` ignoring treatment status, so now let's consider the effect of treatment in the light of this relationship. That is, we'll look at the effect of treatment on `score.diff` rather than `post.score`.

Calculate the effect of treatment on `score.diff` over all grades together and also within each grade separately. How does the effect of treatment vary across grades? What is the relationship between the overall treatment effect and the grade-specific treatment effects? Why is that? Why might we prefer this estimate of treatment effects over those in earlier questions?

Answer 6

```r
# subset again
grade1 <- electric[electric$grade == 1,]
grade2 <- electric[electric$grade == 2,]
grade3 <- electric[electric$grade == 3,]
grade4 <- electric[electric$grade == 4,]

eff.1 <- mean(grade1$score.diff[grade1$treatment == "T"]) -
         mean(grade1$score.diff[grade1$treatment == "C"])

eff.2 <- mean(grade2$score.diff[grade2$treatment == "T"]) -
         mean(grade2$score.diff[grade2$treatment == "C"])

eff.3 <- mean(grade3$score.diff[grade3$treatment == "T"]) -
         mean(grade3$score.diff[grade3$treatment == "C"])

eff.4 <- mean(grade4$score.diff[grade4$treatment == "T"]) -
         mean(grade4$score.diff[grade4$treatment == "C"])

overall <- mean(electric$score.diff[electric$treatment == "T"]) -
           mean(electric$score.diff[electric$treatment == "C"])

# the overall effect
overall
```

```
[1] 3.65
```

```r
# grade-specific effects
c(eff.1, eff.2, eff.3, eff.4)
```

```
[1] 8.395238 3.170588 2.635000 0.647619
```

References

Cooney, Joan G. 1976. "The Electric Company: Television and Reading,1971-1980: A Mid-Experiment Appraisal." New York: Children's Television Network.