# Rainfall Example

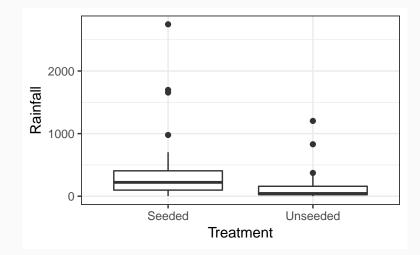
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Here, we work through the rainfall analysis

library(Sleuth3)
library(ggplot2)
data("case0301")

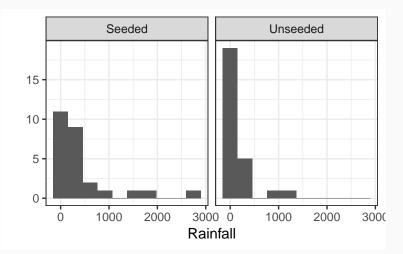
#### qplot(x = Treatment, y = Rainfall,

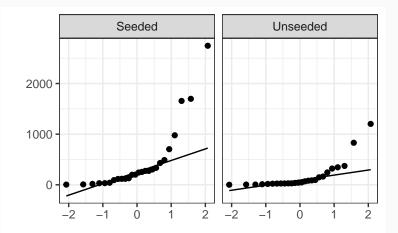
data = case0301, geom = "boxplot")



#### qplot(x = Rainfall, facets = . ~ Treatment,

data = case0301, geom = "histogram", bins = 10)



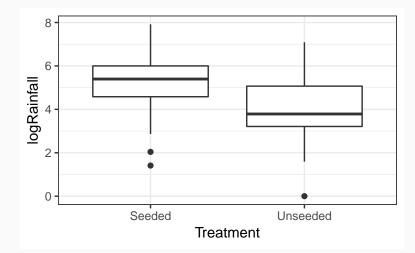


#### case0301\$logRainfall <- log(case0301\$Rainfall)</pre>

## Rain EDA

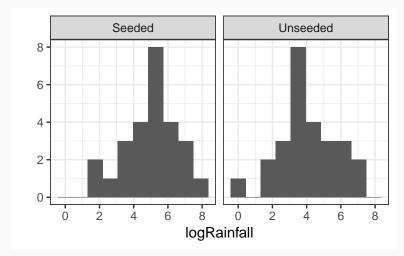
qplot(x = Treatment, y = logRainfall,

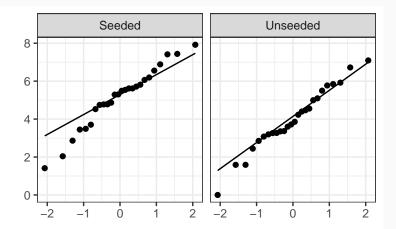
data = case0301, geom = "boxplot")



qplot(x = logRainfall, facets = . ~ Treatment,

data = case0301, geom = "histogram", bins = 10)





Interpretation

- $Z_i$  = rainfall on unseeded days.
- $Y_i = \log$  rainfall on unseeded days.
- $Z_i^*$  = rainfall on seeded days.
- $Y_i^* = \log$  rainfall on seeded days.
- $Y_i^* = Y_i + \delta$ .
- $Z_i^* = e^{\delta} Z_i$ .
- $e^{\delta}$  is the multiplicative effect of seeding on rainfall.
- $e^{\delta} = 2$  means rainfall is twice as large on seeded days.
- $e^{\delta} = 3$  means rainfall is three times as large on seeded days.

- $H_0: \delta = 0$
- $H_a: \delta \neq 0$

### Run t-test

tout <- t.test(logRainfall ~ Treatment, data = case0301)
tout</pre>

##	
##	Welch Two Sample t-test
##	
##	data: logRainfall by Treatment
##	t = 2.5, df = 50, p-value = 0.01
##	alternative hypothesis: true difference in means is not
##	95 percent confidence interval:
##	0.2408 2.0467
##	sample estimates:
##	mean in group Seeded mean in group Unseeded
##	5.134 3.990

exp(tout\$estimate[1] - tout\$estimate[2])

## mean in group Seeded
## 3.139

```
exp(tout$conf.int)
```

## [1] 1.272 7.742
## attr(,"conf.level")
## [1] 0.95

- We estimate that that seeding results in a 3.1 factor increase in rainfall (*p*-value 0.01, 95% confidence interval of 1.3 to 7.7).
- Note the causal language because this is a randomized experiment. I will deduct many points if you use causal language in an observational study.