Experimental design

Chapter 14

Goals of experiments

- Eliminate bias
- Reduce sampling error (increase precision and power)

Design features that reduce bias

- Controls
- Random assignment to treatments
- Blinding

Controls

A group which is identical to the experimental treatment in all respects aside from the treatment itself

Example: placebo

Some illnesses, e.g. pain and depression, respond to fact of treatment, even with no pharmaceutically active ingredients.

Control: "sugar pills"

Random assignment averages out the effects of confounding variables

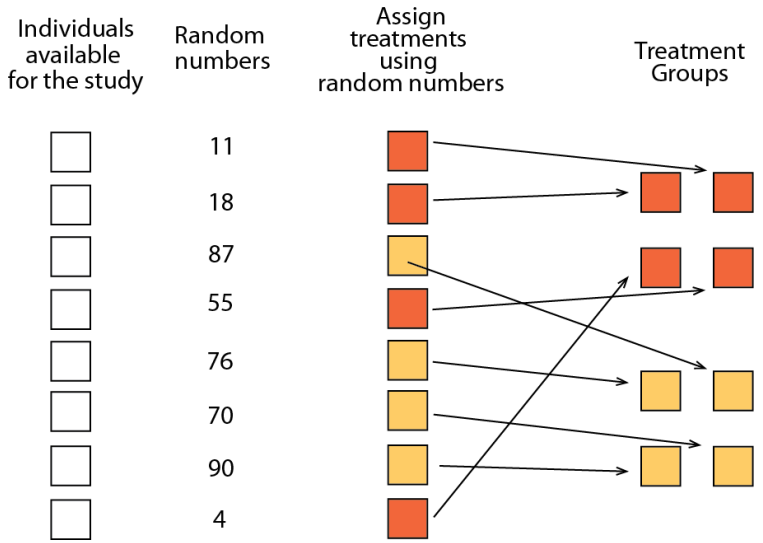
Example: independent recovery

Patients tend to seek treatment when they feel very bad

As a result, they often visit the doctor when they are at their worst. Improvement may be inevitable, even without treatment

Therefore, we need a control, untreated group to compare with, if we want to measure the effects of a new therapy

Experiment: individuals are randomly assigned to treatments



Blinding

Preventing knowledge of experimenter (or patient) of which treatment is given to whom

Unblinded studies usually find much larger effects (sometimes threefold higher), showing the bias that results from lack of blinding.

Reducing sampling error

Increasing the signal to noise ratio

$$t = \frac{\bar{Y}_1 - \bar{Y}_2}{\sqrt{s_p^2\left(\frac{1}{n_1} + \frac{1}{n_2}\right)}}$$

"Signal"

"Noise"

Reducing sampling error

Increasing the signal to noise ratio

If the "noise" $\sqrt{s_p^2\left(\frac{1}{n_1} + \frac{1}{n_2}\right)}$ is smaller, it is easier to detect a given "signal".

Can be achieved with smaller *s* or larger *n*.

Design features that reduce the effects of sampling error

Replication: carry out study on multiple independent objects.

Balance: nearly equal sample sizes in each treatment.

Blocking: grouping of experimental unit; within each group, different experimental treatments are applied to different units.

Extreme treatments: stronger treatments can increase the signal-to-noise ratio.

Balance increases precision

$$SE_{\overline{Y_1}-\overline{Y_2}} = \sqrt{s_p^2\left(\frac{1}{n_1}+\frac{1}{n_2}\right)}$$

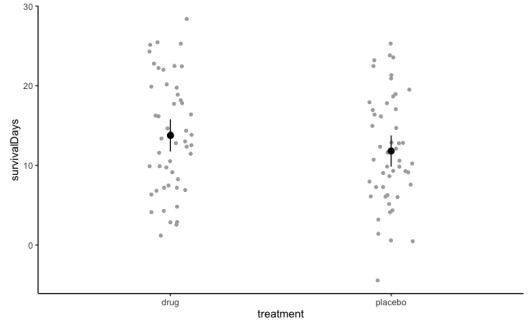
For a given total sample size ($n_1 + n_2$), the standard error is smallest when $n_1 = n_2$.

The value of blocking

Imagine we are testing the effects of a new drug (compared to a placebo) on survival time.

We've done the study on multiple patients spread over 5 hospitals.

No significant effect of the drug when just comparing treatment and controls

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Analysis of Variance Table
Response: survivalDays
           Df Sum Sq Mean Sq  F value  Pr(>F)
treatment   1   95.3  95.328   1.9334  0.1675
Residuals  98 4831.9  49.305
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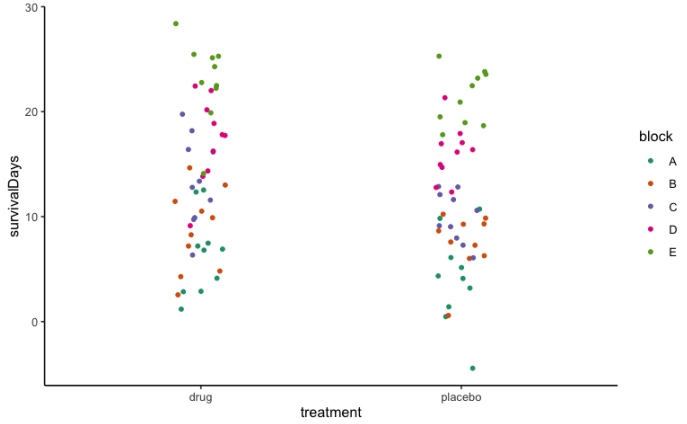
But let's look at which hospital they were at:



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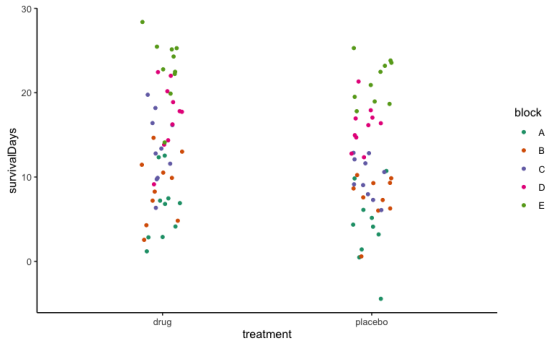

	numDF	denDF	F-value	p-value
	<int>	<dbl>	<chr>	<chr>
(Intercept)	1	94	17.779530	0.0001
treatment	1	94	7.741927	0.0065

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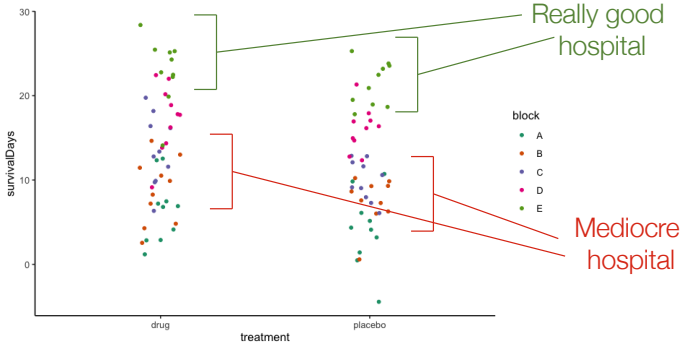

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Blocking allows extraneous variation to be accounted for.

It is therefore easier to see the signal through the remaining noise.