

Replication

BIOE 498/598 PJ

Spring 2022

Why replication?

1. Reduce noise effects.
2. Estimate confidence intervals for effect sizes.
3. Analyze dispersion effects.

Does noise matter?

```
data <- read.csv("LeafSpring.csv")  
data1 <- data[ 1:16, ]  
data2 <- data[17:32, ]  
data3 <- data[33:48, ]
```

Effect sizes differ for each replicate

Replicate 1

##	B	.09937
##	C	.09313
##	Q	-.08688
##	C:Q	-.07563
##	B:Q	.07313
##	E	.07312
##	B:D:Q	-.06687
##	D	.05688
##	C:D	.04313
##	D:Q	.02312

Replicate 2

##	Q	-.14688
##	B	.12937
##	C	.11063
##	C:Q	-.07688
##	D:Q	.06687
##	E	.06312
##	C:D:Q	-.05063
##	B:Q	.04438
##	B:C	.04187
##	C:D	-.02812

Duplicates vs. Replicates

- ▶ We use replicates to estimate **confidence intervals** for effect sizes.
- ▶ More replicates = narrower confidence intervals
- ▶ Treating duplicates as replicates artificially narrows the confidence intervals for two reasons.
 1. Inflating the degrees of freedom fakes additional statistical power
 2. Duplicates typically have less variation than replicates

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 1. Inflating the degrees of freedom fakes additional statistical power
 2. Duplicates typically have less variation than replicates
- ▶ Statistical significance \neq Practical significance

Sample variance across replicates

If a run is replicated r times with responses y_1, y_2, \dots, y_r and mean \bar{y} ,

$$\text{sample variance} = s^2 = \frac{\sum_i^n (y_i - \bar{y})^2}{r - 1}$$

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For a factorial design with N *unreplicated* runs ($N = 2^k$ for a full factorial or $N = 2^{k-p}$ for a fractional factorial),

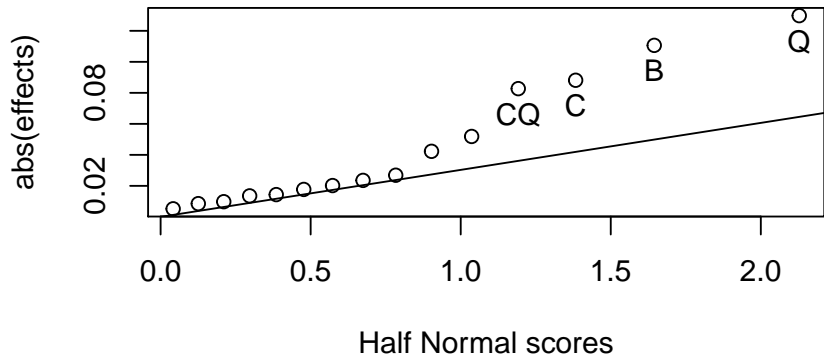
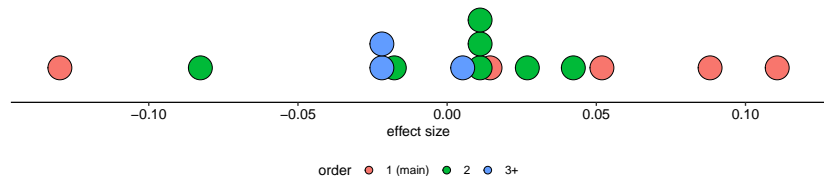
$$\text{standard error of effects} = SE(\beta_i) = \sqrt{\frac{\text{mean}(s^2)}{rN}}$$

Linear models find the “best fit” effect sizes

```
model <- lm(height ~ B*C*D*E*Q, data=data)
show_model(model, n_coefs=17, show_fit=FALSE)
```

	Estimate	Std. Error	t value	Pr(> t)	
## (Intercept)	7.636042	0.018571	411.183	< 2e-16	***
## Q	-0.129792	0.018571	-6.989	6.42e-08	***
## B	0.110625	0.018571	5.957	1.23e-06	***
## C	0.088125	0.018571	4.745	4.16e-05	***
## C:Q	-0.082708	0.018571	-4.454	9.64e-05	***
## E	0.051875	0.018571	2.793	0.00874	**
## B:Q	0.042292	0.018571	2.277	0.02959	*
## D:Q	0.026875	0.018571	1.447	0.15758	
## C:D:Q	-0.023542	0.018571	-1.268	0.21406	
## B:D:Q	-0.020208	0.018571	-1.088	0.28465	
## C:D	-0.017708	0.018571	-0.954	0.34746	
## D	0.014375	0.018571	0.774	0.44458	
## E:Q	0.013542	0.018571	0.729	0.47119	
## B:D	0.009792	0.018571	0.527	0.60165	
## B:C	0.008542	0.018571	0.460	0.64866	
## B:C:Q	0.005208	0.018571	0.280	0.78093	
## B:E	NA	NA	NA	NA	
## ---					
## Signif. codes:	0 '***'	0.001 '**'	0.01 '*'	0.05 '.'	0.1 ' ' 1

Half-normal & dot plots — significance based only on effect size



zscore= 0.0417893 0.1256613 0.2104284 0.2967378 0.3853205 0.4770404