

Part I

More than one independent variable

Fully factorial designs

In a fully factorial design you are interested in the effect of two or more factors on the dependent variable.

Every level of each factor is run with every level of the others. These combinations may or may not be replicated

As the numbers of factors increases, these experiments become unwieldy. When $f = 5$ running a fully factorial experiment is difficult to implement.

Interactions

Factorial designs allow the estimation of effects due to the main factors as well as *interactions* among those factors.

- Interactions occur when the response variable for a level in factor 'A' changes with changes of the level in factor 'B'. This is known as
 - A X B interaction
 - A *by* B interaction

Guinea pig tooth growth

The `ToothGrowth` dataframe is available in R base. It outlines the growth of guinea pig teeth under various vitamin C dosages administered in 2 ways. This is a balanced design with 10 replicates per combination of treatment levels.

Teeth, cont.

```
> data(ToothGrowth)
> names(ToothGrowth)

[1] "len" "supp" "dose"

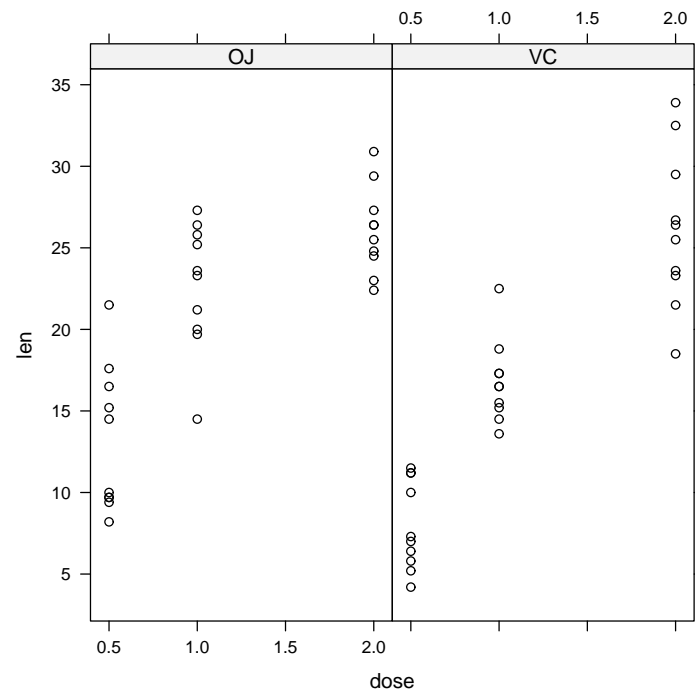
> ToothGrowth[1:12, ]

      len supp dose
1   4.2   VC  0.5
2  11.5   VC  0.5
3   7.3   VC  0.5
```

4	5.8	VC	0.5
5	6.4	VC	0.5
6	10.0	VC	0.5
7	11.2	VC	0.5
8	11.2	VC	0.5
9	5.2	VC	0.5
10	7.0	VC	0.5
11	16.5	VC	1.0
12	16.5	VC	1.0

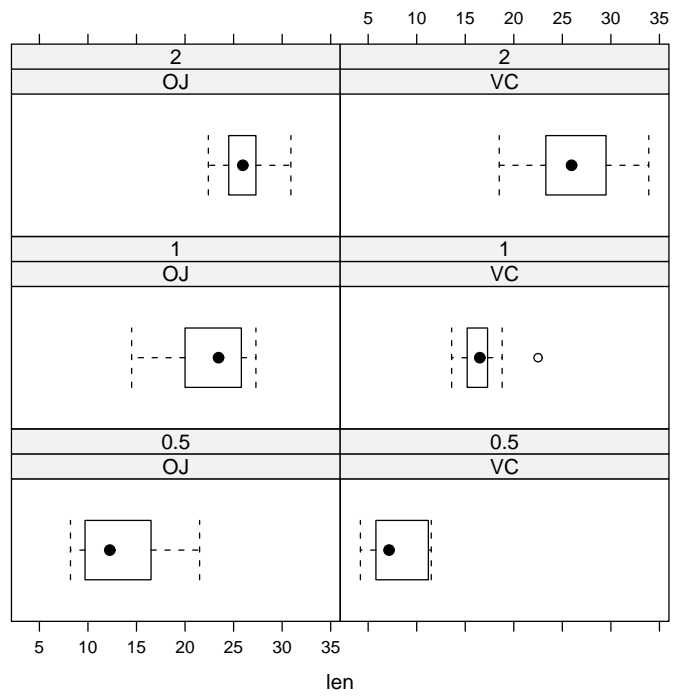
Teeth, cont.

```
> library(lattice)
> print(xyplot(len ~ dose | supp, data = ToothGrowth))
```



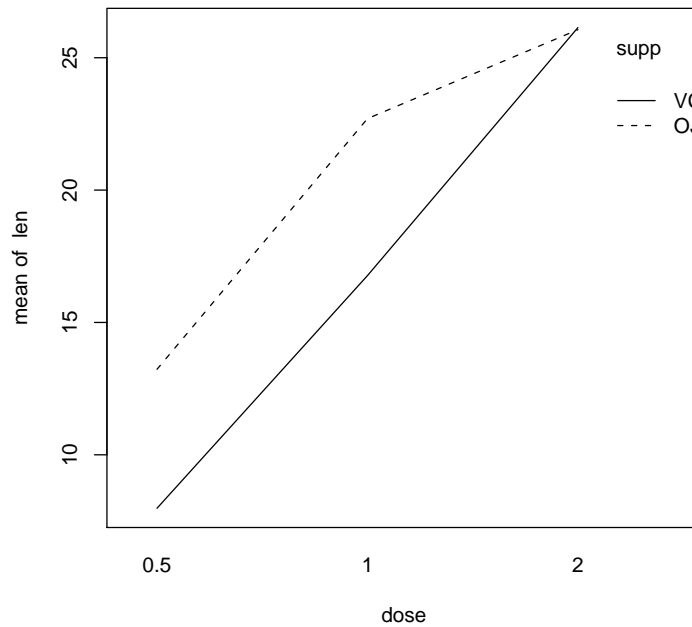
Teeth, cont.

```
> print(bwplot(~len | as.factor(supp) + as.factor(dose), data = ToothGrowth))
```



Teeth, “official” interaction plot

```
> attach(ToothGrowth)
> interaction.plot(dose, supp, len)
> detach(ToothGrowth)
```



Linear Model 2-way

$$Y_{ilj} = \mu + \tau_i + \beta_l + \gamma_{li} + \epsilon_{lij} \quad (1)$$

- The τ_i term represents the deviance of the first factor
- The β_l term represents the second factor deviance
- The γ_{li} term represents the interaction deviance

2-way anova (main and int)

```
> ToothGrowth$supp <- as.factor(ToothGrowth$supp)
> ToothGrowth$dose <- as.factor(ToothGrowth$dose)
> tooth.main <- aov(len ~ supp + dose, data = ToothGrowth)
> summary(tooth.main)
```

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
supp	1	205.35	205.35	14.017	0.0004293 ***
dose	2	2426.43	1213.22	82.811	< 2.2e-16 ***
Residuals	56	820.43	14.65		

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

```
> tooth.int <- aov(len ~ supp + dose + supp * dose, data = ToothGrowth)
> summary(tooth.int)
```

```
          Df Sum Sq Mean Sq F value    Pr(>F)
supp       1  205.35   205.35   15.572 0.0002312 ***
dose       2 2426.43  1213.22   92.000 < 2.2e-16 ***
supp:dose   2  108.32    54.16    4.107 0.0218603 *
Residuals  54   712.11    13.19
---
```

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

Some things to notice

- d.f.
 - $SS_{\text{total}} = N - 1$
 - $SS_{\text{supp}} = k_{\text{supp}} - 1 = 1$
 - $SS_{\text{dose}} = k_{\text{dose}} - 1 = 2$
 - $SS_{\text{supp:dose}} = (k_{\text{supp}} - 1) \times (k_{\text{dose}} - 1) = 2$
 - $SS_{\text{resid}} = k_{\text{supp}} \times k_{\text{dose}} \times (n - 1)$ (only true for balanced designs)

Additivity

- Additivity for SS

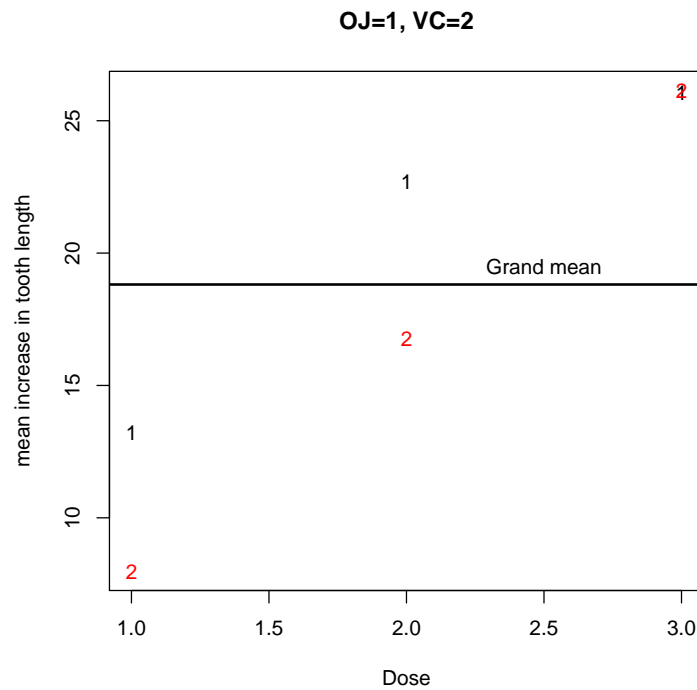
$$SS_{\text{total}} = SS_{\text{supp}} + SS_{\text{dose}} + SS_{\text{supp:dose}} + SS_{\text{resid}}$$

More detail

- means:

```
> tapply(ToothGrowth$len, list(ToothGrowth$dose, ToothGrowth$supp),
+       mean)
```

```
      0J      VC
0.5 13.23  7.98
1    22.70 16.77
2    26.06 26.14
```



more More detail

- Testing components of the model

```
> lm(len ~ supp * as.factor(dose), data = ToothGrowth)
```

Call:

```
lm(formula = len ~ supp * as.factor(dose), data = ToothGrowth)
```

Coefficients:

(Intercept)	suppVC	as.factor(dose)1
13.23	-5.25	9.47
as.factor(dose)2	suppVC:as.factor(dose)1	suppVC:as.factor(dose)2
12.83	-0.68	5.33

more more More detail

```
> summary(lm(len ~ supp * as.factor(dose), data = ToothGrowth))
```

Call:

```
lm(formula = len ~ supp * as.factor(dose), data = ToothGrowth)
```

Residuals:

Min	1Q	Median	3Q	Max
-8.20	-2.72	-0.27	2.65	8.27

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	13.230	1.148	11.521	3.60e-16	***
suppVC	-5.250	1.624	-3.233	0.00209	**
as.factor(dose)1	9.470	1.624	5.831	3.18e-07	***
as.factor(dose)2	12.830	1.624	7.900	1.43e-10	***
suppVC:as.factor(dose)1	-0.680	2.297	-0.296	0.76831	
suppVC:as.factor(dose)2	5.330	2.297	2.321	0.02411	*

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

Residual standard error: 3.631 on 54 degrees of freedom

Multiple R-Squared: 0.7937, Adjusted R-squared: 0.7746

F-statistic: 41.56 on 5 and 54 DF, p-value: < 2.2e-16

Shrimp data

A multiway shrimp culture experiment was conducted. The design was full factorial with three factors. Three replicate aquaria were set up for each combination of factor levels. The factors were:

- Temperature (25C, 35C)
- Density (80 or 160 per 40 liter tank)
- Salinity (10, 25, or 40 ppt)

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These data are in 'shrimp.csv'

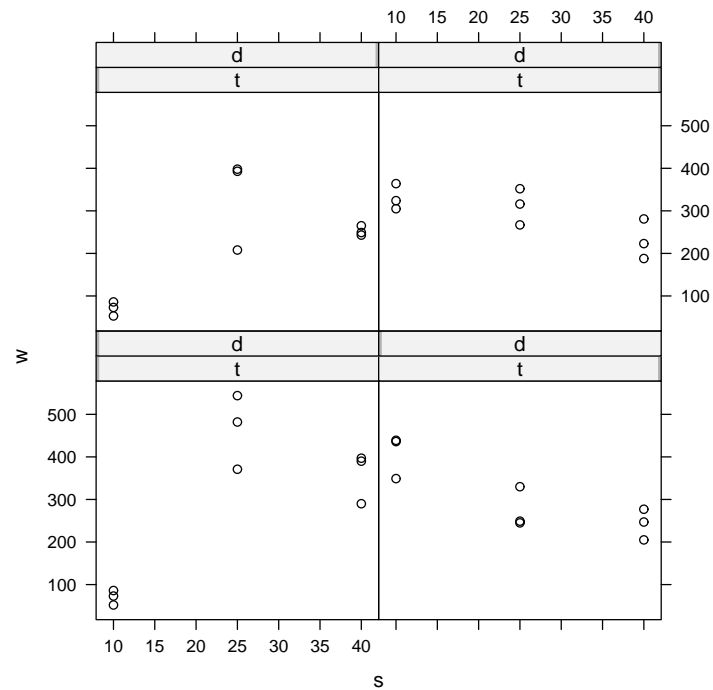
Shrimp data cont

```
> shrimp <- read.csv("shrimp.csv")
> shrimp[1:10, ]
```

	t	d	s	w
1	25	80	10	86
2	25	80	25	544
3	25	80	40	390
4	25	160	10	53
5	25	160	25	393
6	25	160	40	249
7	35	80	10	439
8	35	80	25	249
9	35	80	40	247
10	35	160	10	324

Shrimp data cont

```
> library(lattice)
> print(xyplot(w ~ s | t + d, data = shrimp))
```

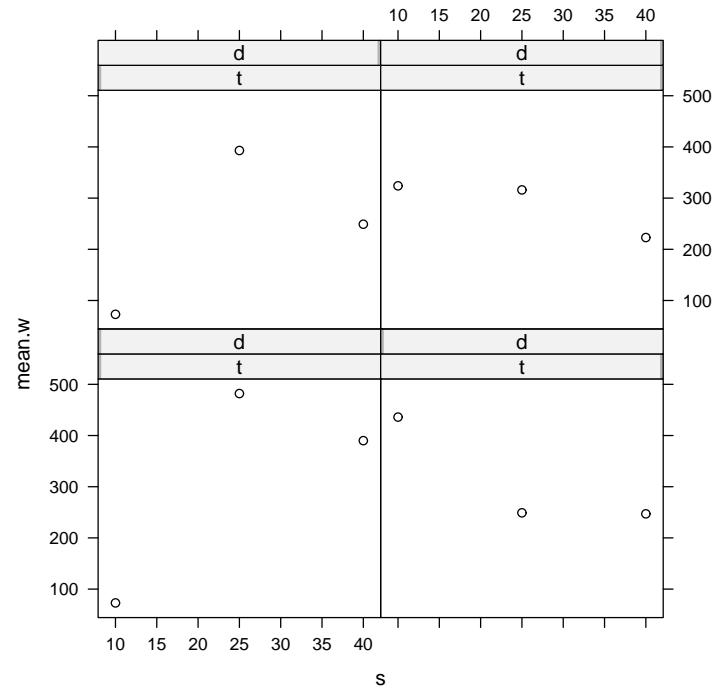


Shrimp data cont

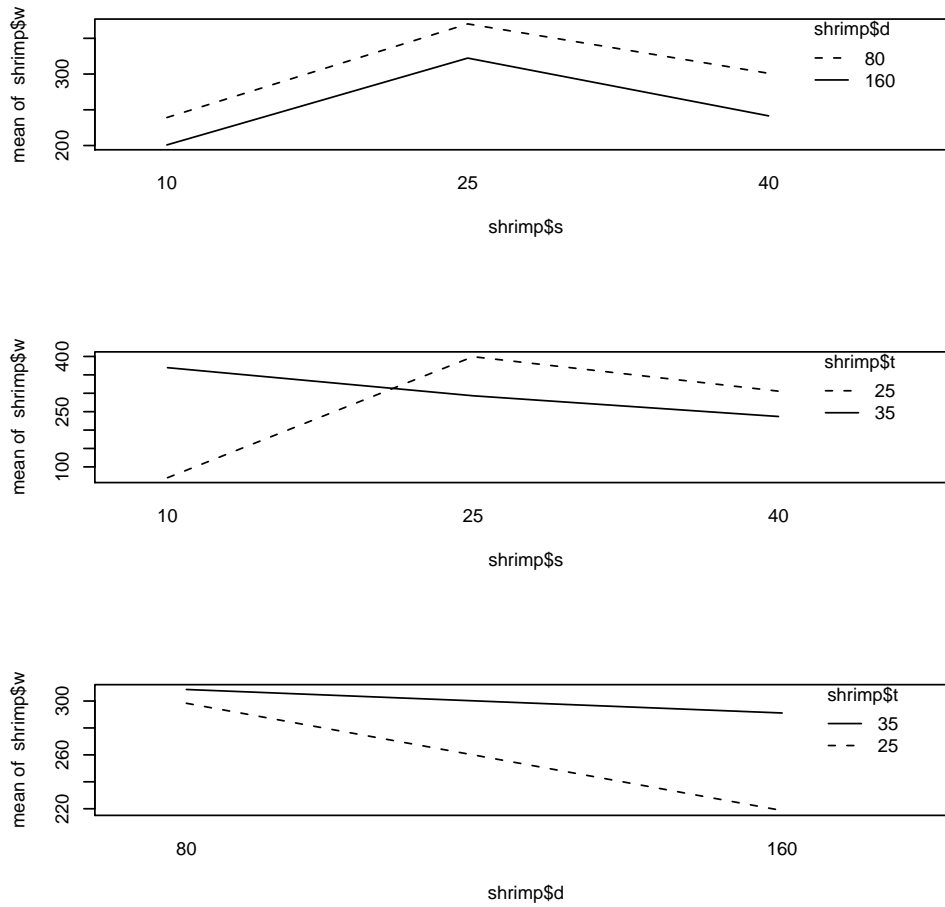
```
> shrimp.mean <- aggregate(shrimp$w, list(t = shrimp$t, d = shrimp$d,
+     s = shrimp$s), median)
> names(shrimp.mean)[4] <- "mean.w"
> shrimp.mean[1:10, ]
```

	t	d	s	mean.w
1	25	80	10	73
2	35	80	10	436
3	25	160	10	73
4	35	160	10	324
5	25	80	25	482
6	35	80	25	249
7	25	160	25	393
8	35	160	25	316
9	25	80	40	390
10	35	80	40	247


```
> shrimp.mean$s <- as.numeric(as.character(shrimp.mean$s))
> print(xyplot(mean.w ~ s | t + d, data = shrimp.mean))
```



Shrimp data interaction plot 1



Linear Model 3-way

$$Y_{lhij} = \mu + \tau_i + \beta_l + \alpha_h + \gamma_{li} + \lambda_{ih} + \beta_{lh} + \eta_{ilh} + \epsilon_{lhij} \quad (2)$$

- The τ_i term represents the effect of the first factor
- The β_l term represents the effect of the second factor
- The α_l term represents the effect of the third factor
- The $\gamma_{li}, \beta_{lh}, \lambda_{ih}$ terms represent the interaction deviances among pairs of terms.
- The η_{ilh} term represents the three-way interaction

Shrimp Anova

```

> shrimp$d <- as.factor(shrimp$d)
> shrimp$t <- as.factor(shrimp$t)
> shrimp$s <- as.factor(shrimp$s)
> shrimp2way <- aov(w ~ t + d + s + t:s + t:d + s:d, data = shrimp)
> summary(shrimp2way)

```

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
t	1	15376	15376	4.2652	0.04900 *
d	1	21219	21219	5.8860	0.02250 *
s	2	96763	48381	13.4207	9.908e-05 ***
t:s	2	300855	150428	41.7279	7.666e-09 ***
t:d	1	8711	8711	2.4164	0.13216
d:s	2	674	337	0.0935	0.91101
Residuals	26	93729	3605		

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

Shrimp Anova-threeway interaction

```

> shrimp3way <- aov(w ~ t + d + s + t:s + t:d + s:d + s:d:t, data = shrimp)
> summary(shrimp3way)

```

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
t	1	15376	15376	5.2952	0.03038 *
d	1	21219	21219	7.3073	0.01242 *
s	2	96763	48381	16.6615	2.901e-05 ***
t:s	2	300855	150428	51.8041	1.959e-09 ***
t:d	1	8711	8711	2.9999	0.09610 .
d:s	2	674	337	0.1161	0.89086
t:d:s	2	24038	12019	4.1392	0.02855 *
Residuals	24	69691	2904		

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

Shrimp Anova another parameterization

```

> shrimp3way <- aov(w ~ d * s * t, data = shrimp)
> summary(shrimp3way)

```

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
d	1	21219	21219	7.3073	0.01242 *
s	2	96763	48381	16.6615	2.901e-05 ***

t	1	15376	15376	5.2952	0.03038	*
d:s	2	674	337	0.1161	0.89086	
d:t	1	8711	8711	2.9999	0.09610	.
s:t	2	300855	150428	51.8041	1.959e-09	***
d:s:t	2	24038	12019	4.1392	0.02855	*
Residuals	24	69691	2904			

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