

# Linear models

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February, 2017

In this session we'll start to think about *modelling* the relationships between two or more variables

By modelling the relationship we are suggesting a means by which the data we collected might have originated

We won't be able to speak to *causation* in many cases because we have data collected as part of observational studies

But we can test hypotheses about the relationships between variables

## Linear Regression

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# Linear regression

Linear regression can be thought of as an extension of the ideas behind correlations

The linear regression model is a far more powerful statistical tool, however

Correlations tell us about the strength of the *linear relationship* between two variables  $x$  and  $y$

A linear regression provides a model, or equation, for the line of best fit placed through the data

Further, in the linear regression the roles played by  $x$  and  $y$  are different; we say the values of  $y$  depend, to some degree, on the values of  $x$  measured on the same entities

Hence  $x$  plays the role of the predictor variable and  $y$  is the response

Simple linear regression is a statistical model that assumes a linear relationship between a continuous response variable  $y$  and one or more, usually continuous, predictor variables,  $X = x_1, \dots, x_n$

Three major purposes of such models

- to describe the linear relationship between  $y$  and  $X$
- to determine how much variation (uncertainty) in  $y$  can be explained by the relationship with  $X$
- to predict new values of  $y$  from new values of  $X$

# Linear regression

In this section we'll consider the simplest case of a single predictor  $x$  & its relationship with  $y$

A suitable model for this linear relationship is

$$y_i = \underbrace{\beta_0 + \beta_1 x_i}_{\text{systematic}} + \underbrace{\varepsilon_i}_{\text{random}}$$

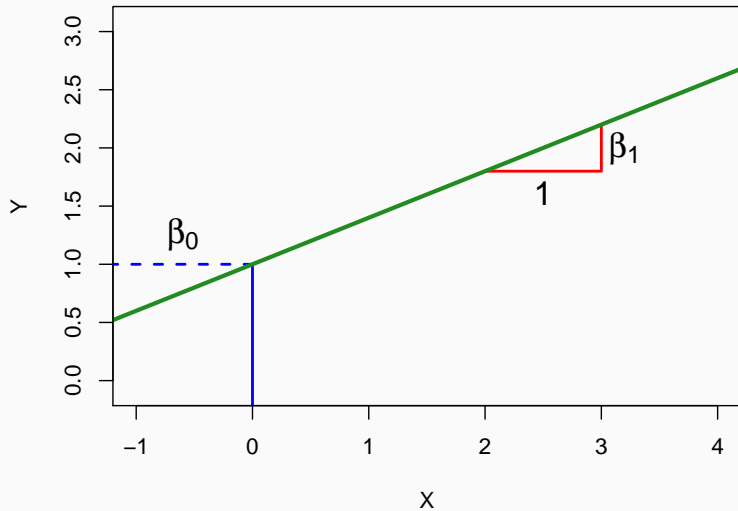
We have two knowns,  $x$  &  $y$ , & three unknowns,  $\beta_0$ ,  $\beta_1$ , &  $\varepsilon$ , although we only seek values for the first two

The  $\beta_j$  are the model **parameters**

$\beta_0$  is the intercept, the expected value of  $y$  when  $x$  is 0

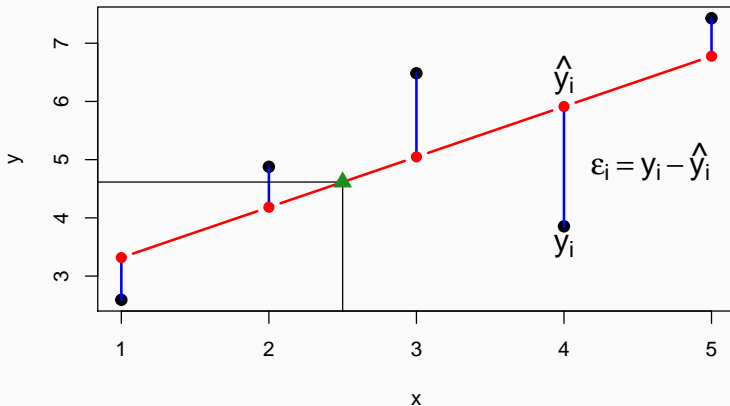
$\beta_1$  is often called the slope, it measures the rate of change in  $y$  for a unit change in  $x$

## Schematic of the linear regression line



# Linear regression

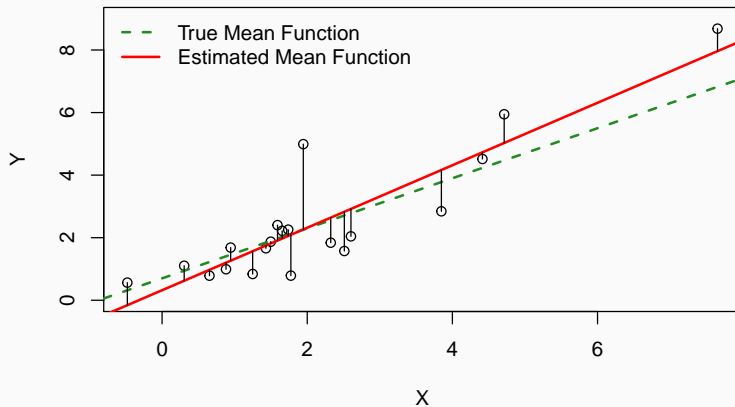
We estimate the two unknown parameters in the model using a procedure known as **least squares**, where we minimise the **Residual Sum of Squares**  $RSS = \sum_{i=1}^n \varepsilon_i$





# Linear regression

Estimates of parameters ( $\beta_j$ ) are for the *population* based on the fit to our *sample* of data



Data were 20 observations generated from the following model

$$y_i = 0.7 + 0.8x_i + \varepsilon_i \quad \varepsilon_i \sim N(\mu = 0, \sigma = 1)$$

Fitted model estimates are:  $\hat{\beta}_0 = 0.32$  and  $\hat{\beta}_1 = 0.999$

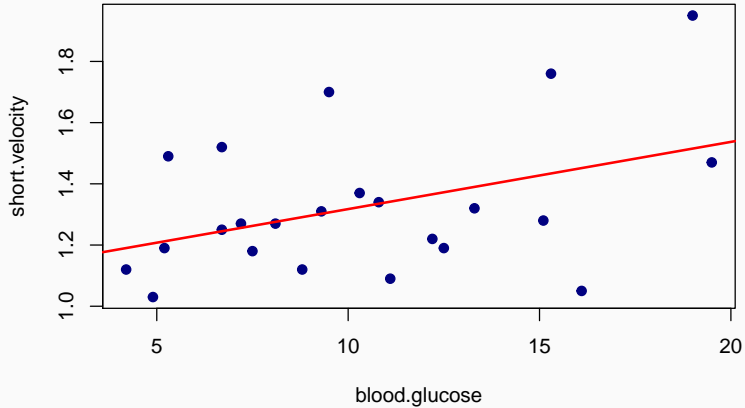
The parameters are means & the uncertainty in the estimated values is captured by their standard errors

Confidence intervals for the estimates:

- $\beta_0 \pm t_{0.975} \text{SE}_{\beta_0} = -0.401, 1.041$
- $\beta_1 \pm t_{0.975} \text{SE}_{\beta_1} = 0.741, 1.256$

## Ventricular shortening & Diabetes

Example data are from a study of the effects of blood glucose levels on heart function in diabetes patients



## Ventricular shortening & Diabetes: Model summary

Call:

```
lm(formula = short.velocity ~ blood.glucose, data = thuesen)
```

Residuals:

Min	1Q	Median	3Q	Max
-0.40141	-0.14760	-0.02202	0.03001	0.43490

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	1.09781	0.11748	9.345	6.26e-09 ***
blood.glucose	0.02196	0.01045	2.101	0.0479 *

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

Residual standard error: 0.2167 on 21 degrees of freedom

(1 observation deleted due to missingness)

Multiple R-squared: 0.1737, Adjusted R-squared: 0.1343

F-statistic: 4.414 on 1 and 21 DF, p-value: 0.0479

## Ventricular shortening & Diabetes: Model summary

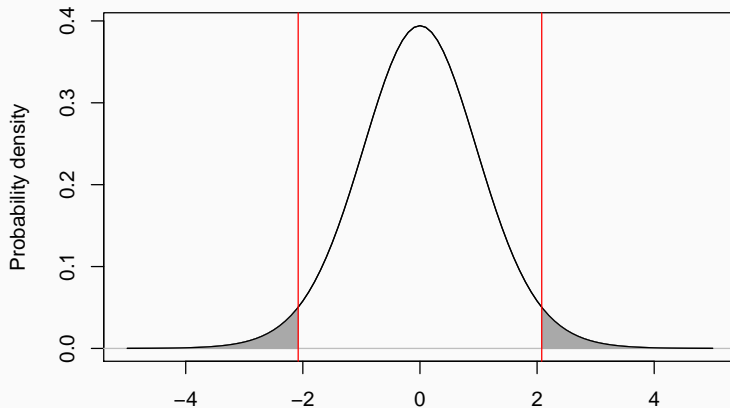
```
              Estimate Std. Error t value Pr(>|t|)
(Intercept)   1.09781    0.11748   9.345 6.26e-09 ***
blood.glucose  0.02196    0.01045   2.101  0.0479 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

- **Estimate** column contains the estimated parameters
- The intercept is 1.098, the ventricular shortening velocity (VSV) at a blood glucose level of 0 mmol/L
- For every increase of 1 mmol/L glucose in blood, VSV *increases* by 0.022
- Each row in the table is a statistical test of a parameter, with a null hypothesis  $\beta_j = 0$
- $t$  is the **test statistic** for the test  $t_j = \frac{\beta_j - 0}{SE_{\beta_j}}$
- *What is the probability of observing a value as extreme as  $\hat{\beta}_j$  if  $\beta_j = 0$ ?*
- *Is the observed coefficient expected if there was no relationship between  $x$  and  $y$*

## T tests

$n - 2$  degrees of freedom = 21

If  $t$  statistic lies in either rejection regions, reject  $H_0$  at  $\alpha = 0.05$  level



Linear regression can be seen as a partitioning of variance in the data in amounts explained by variables in the model & unexplained variance

Mean squares can only be positive; even a variable unrelated to response will explain some variance

Compare the ratio of Mean square (the SSq normalised by degrees of freedom) with an  $F$  distribution with 1 & 21 degrees of freedom

Analysis of Variance Table

Response: short.velocity

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
blood.glucose	1	0.207	0.207	4.41	0.048 *
Residuals	21	0.986	0.047		

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

$F$  is the  $F$ -ratio, the ratio of the regression and residual variances

$$F = \frac{\sum_{i=1}^n (\hat{y}_i - \bar{y})^2 / p}{\sum_{i=1}^n (y_i - \hat{y}_i)^2 / [n - (p + 1)]} = \frac{MS_{\text{reg}}}{MS_{\text{resid}}}$$

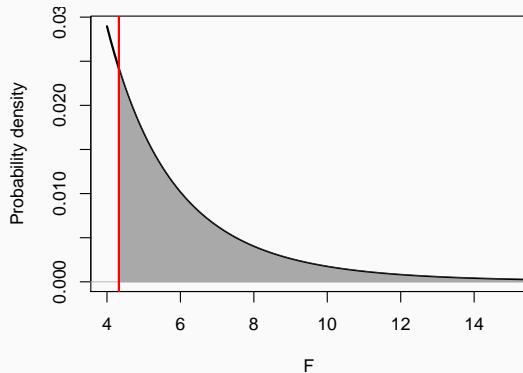
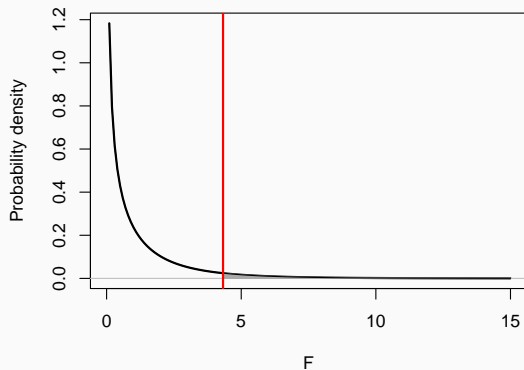
Probability of  $F$  greater than or equal to observed from  $F$ -distribution with  $p$  and  $n - (p + 1)$  degrees of freedom



## ANOVA table

Large values of  $F$  are evidence against the null hypothesis of no relationship

Reference distribution is  $F_{1,21}$ ; all rejection region is in upper tail



$R^2$  is a commonly reported measure of variance explained by the regression

$R^2$  is the **coefficient of determination**, the ratio of the variance explained to the total variance

$$R^2 = \frac{SS_{\text{reg}}}{SS_{\text{reg}} + \text{RSS}} = 1 - \frac{SS_{\text{resid}}}{SS_{\text{total}}}$$

One problem with  $R^2$  is that it increases as you add predictors to the model even if those predictors have no explanatory power

Adjusted  $R^2$  takes into account number of predictors in the model

$$R_{\text{adj}}^2 = 1 - \frac{\text{SS}_{\text{resid}}/[n - (p + 1)]}{\text{SS}_{\text{total}}/(n - 1)}$$

Neither measure is a particularly *useful* summary; don't indicate how the regression model will predict new observations

The **effect size**, the size of the model coefficients, is far more useful

## Assumptions of the linear model

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# Assumptions of the linear model

To fit the model, we don't need to make any assumptions, beyond linearity

Statistical inference on the estimated parameters depends on a number of assumptions

1. The linear model correctly describes the functional relationship between  $y$  and  $x$
2. The  $x_i$  are measured without error
3. For any given value of  $x_i$ , the sampled  $y_i$  values are independent with normally distributed errors
4. Variances are constant along the regression line/model

# Assumptions of the linear model I

The linear model correctly describes the functional relationship between  $y$  and  $x$

Effectively, this assumption is about whether the model we've fitted represents the true underlying relationship between  $x$  and  $y$

*Is the relationship well approximated via a straight line?*

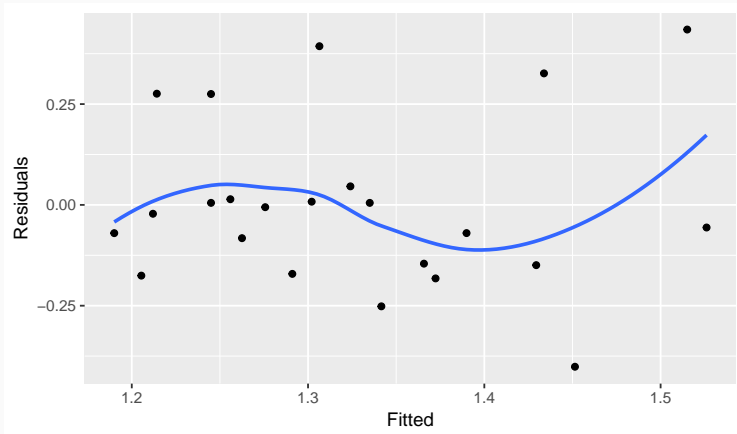
*Would a curved line (*polynomial*) be better?*

If we have the model form wrong, our model will be **biased**; fitted values different appreciably from the true values

If violated the estimate of predictor variances ( $\sigma^2$ ) will be inflated

Incorrect model specification can show itself as patterns in the residuals

## Assumptions of the linear model I



## Assumptions of the linear model II

$x_i$  are measured without error

This assumption states that we know the values of the predictor variable(s)  $x$  *exactly*

Allows us to isolate the error component ( $\varepsilon_i$ ) as random variation in  $y$

Estimates  $\hat{\beta}_j$  will be biased if there is error in  $x$

This is often ignored in data analysis, but modern, advanced approaches can account for this extra source of variation



## Assumptions of the linear model III

For any  $x_i$ , the sampled  $y_i$  are **independent** with normally distributed errors

Variances are constant along the regression line/model

These 2 assumptions relate to distribution of the residuals ( $\varepsilon_i$ ), or, *conditional upon* the values of  $x$ , of  $y$   
 $\varepsilon_i$  are assumed to follow a **Normal** distribution with zero mean and constant variance

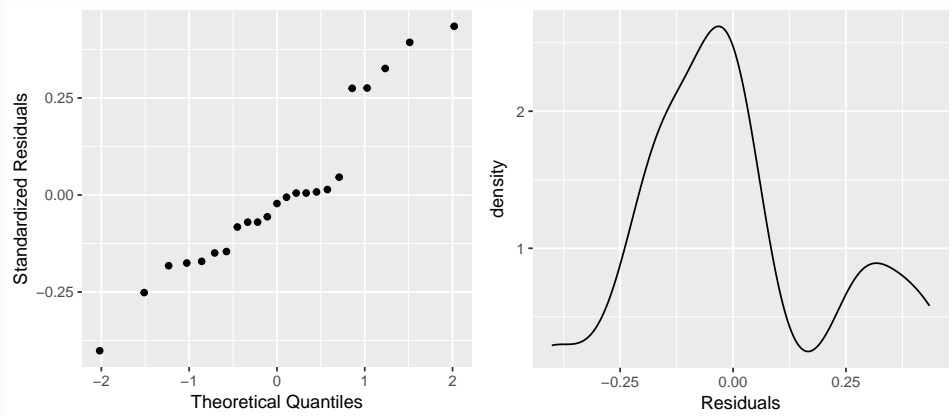
Independence and normality of errors allows us to use parametric theory for confidence intervals and hypothesis tests on the  $F$ -ratio.

Allows a single constant variance  $\sigma^2$  for the variance of the regression line/model

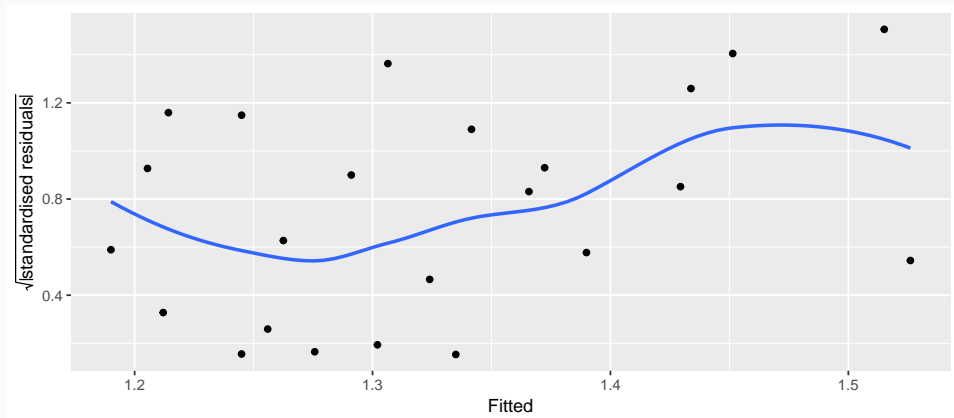
Each residual is drawn from the same distribution; Normal with mean zero, variance  $\hat{\sigma}^2$

Non-constant variances can be recognised through plots of residuals (among others); residuals get wider as the values of  $y$  increase

## Assumptions of the linear model III



## Assumptions of the linear model III



**Independence** is a key assumption; knowing the value of one residual tells use nothing about another

Data that have spatial or temporal components, or represent repeated observations on the same set of individuals are commonly encountered & violate this assumption

## Outliers, Leverage & Influence

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# Outliers, Leverage & Influence

An **outlier** is an observation which is inconsistent with the rest of a sample

An observation can be an outlier due to the response variable(s) or one or more of the predictor variables having values outside their expected limits

An outlier may also result from: incorrect measurement, incorrect data entry, transcription error, recording error

Two main concepts

- **Leverage**: Potential for an outlier to be influential
- **Influence**: Observation is influential if its deletion substantially changes the results

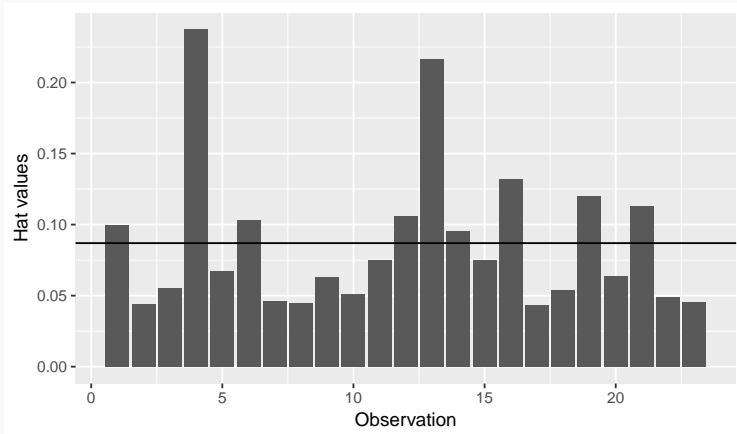
**Leverage** measures the degree to which individual observations affect the the fitted value for that observation

Leverage values are also known as **hat values**, as they are the values on the diagonal of the *hat matrix*, which projects the observed values onto the fitted values of the model

Hat matrix is so called because it puts a **hat on Y**:  $\hat{Y} = HY$

Leverage ranges from  $1/n$  to 1

Observation has high leverage if its hat value is 2–3 times the average hat value:  $h = (p + 1)/n$ , where  $p + 1$  is number of coefficients (inc. the intercept)





An observation that combines *outlyingness* with high leverage exerts an **influence** on the estimated regression coefficients

If an influential observation is deleted from the model, the *estimated coefficients change substantially*

$dfbeta_{ij}$  assesses the impact on the  $j$ th coefficient of deleting the  $i$ th observation

$$dfbeta_{ij} = \beta_{j(-i)} - \beta_j$$

The  $dfbeta_{ij}$  are expressed in the metric of the coefficient

A standardised version,  $dfbetas_{ij}$  divides  $dfbeta_{ij}$  by the standard error of  $\beta_j$

Influential observations have  $dfbetas_{ij} \geq 2/\sqrt{n}$

## Outliers, Leverage & Influence: Cook's Distance

One problem with  $\text{dfbetas}_{ij}$  is that there are so many numbers!

One for each observation for every  $\beta_j$ :  $n \times (p + 1)$

**Cook's Distance**,  $D_i$ , is a scale invariant measure of distance between  $\beta_j$  and  $\beta_{j(-i)}$

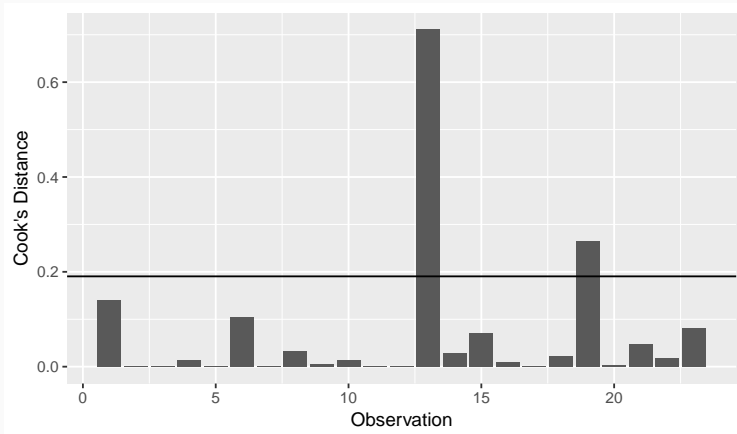
$$D_i = \frac{e_i^2}{s^2(p+1)} \times \frac{h_i}{1-h_i}$$

where  $e_i^2$  is the squared residual &  $h_i$  is the hat value for  $x_i$ ;  $s^2$  is the variance of the residuals

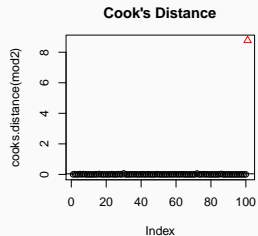
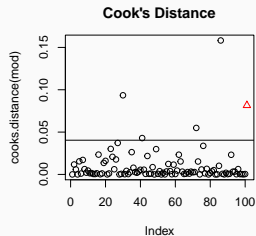
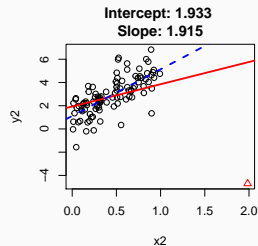
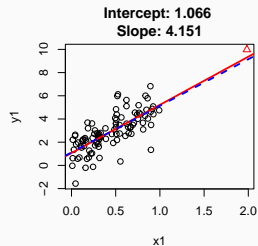
The first fraction is a measure of **outlyingness**, the second of **leverage**

$D_i \geq 4/(n - p - 1)$  suggested as a cutoff for high values of  $D_i$

## Outliers, Leverage & Influence: Cook's Distance



# Outliers, Leverage & Influence: Example



## Multiple Regression

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The simple regression model readily generalises to the situation where we have  $m$  predictors not just one

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_m x_{im} + \varepsilon_i$$

Now we have  $m + 1$  parameters to estimate, one for intercept and one each for the  $m$  predictors  $x_m$ . Can have as many as  $m = n - 1$  predictor variables

Simple description as a regression lines starts to be blurred; with  $m = 2$  we have a *regression plane*

But in other respects the model fitting, assumptions, etc remain the same

We do now have the problem of deciding which of the  $m$  predictors are related to  $y$

## Multiple regression: lung function in cystic fibrosis patients

**pemax** is *maximal expiratory pressure*, a measure of lung function

A number of predictor variables thought to affect **pemax**

- Age, sex, height, weight, & body mass (**bmp**) of each patient
- Forced expiratory (**fev1**) & residual (**rv**) volume
- Functional residual capacity (**frc**) & total lung capacity (**tlc**)

# Multiple regression: lung function in cystic fibrosis patients

## Typical statistical output for the full model

Call:

```
lm(formula = pemax ~ age + sex + height + weight + bmp + fev1 +  
    rv + frc + tlc, data = cystfibr)
```

Residuals:

Min	1Q	Median	3Q	Max
-37.34	-11.53	1.08	13.39	33.41

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	176.058	225.891	0.78	0.45
age	-2.542	4.802	-0.53	0.60
sexFemale	-3.737	15.460	-0.24	0.81
height	-0.446	0.903	-0.49	0.63
weight	2.993	2.008	1.49	0.16
bmp	-1.745	1.155	-1.51	0.15
fev1	1.081	1.081	1.00	0.33
rv	0.197	0.196	1.00	0.33
frc	-0.308	0.492	-0.63	0.54
tlc	0.189	0.500	0.38	0.71

Residual standard error: 25.5 on 15 degrees of freedom

Multiple R-squared: 0.637, Adjusted R-squared: 0.42

F-statistic: 2.93 on 9 and 15 DF, p-value: 0.032



## Multiple regression: lung function in cystic fibrosis patients

No  $t$  tests are significant, but this is only a reflection of what would happen if you removed that variable from model leaving others in the model

However, the joint  $F$  test is significant, indicating that there is an effect in there somewhere

### Analysis of Variance Table

Model 1: pemax ~ 1

Model 2: pemax ~ age + sex + height + weight + bmp + fev1 + rv + frc +  
tlc

	Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
1	24	26833				
2	15	9731	9	17101	2.929	0.032 *

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

# Multiple regression: lung function in cystic fibrosis patients

## Sequential sums of squares (Type I), ordering matters & changes results

### Analysis of Variance Table

Response: pemax

	Df	Sum Sq	Mean Sq	F value	Pr(>F)	
age	1	10098	10098	15.566	0.0013	**
sex	1	955	955	1.473	0.2437	
height	1	155	155	0.239	0.6321	
weight	1	632	632	0.975	0.3392	
bmp	1	2862	2862	4.412	0.0530	.
fev1	1	1549	1549	2.388	0.1431	
rv	1	562	562	0.866	0.3668	
frc	1	195	195	0.300	0.5920	
tlc	1	92	92	0.142	0.7112	
Residuals	15	9731	649			

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## Model selection

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# Model selection

Where we have several candidate covariates for inclusion in a model, we face the problem of selecting a **minimal, adequate model**

A minimal, adequate model is one that is complex enough to provide sufficient fit to the observed response but no more complex than is necessary

Several automated techniques available to help

1. Best subsets regression
2. Forward selection
3. Backwards elimination
4. Stepwise regression (forward selection and backward elimination)

Regardless of method used to select a minimal model there's no free lunch

$p$  values from tests on the selected model do not account for the selection procedure; anti-conservative, too many variables selected

Model or subset selection often used for 2 reasons

1. **Interpretation**: Smaller subset of predictors with strongest effects on response  $y$  may be easier to interpret and explain
2. **Prediction accuracy**: least squares estimates have low **bias** but large **variance**  
Can sometimes improve prediction accuracy by shrinking the coefficients or setting some to zero. In doing so we sacrifice a bit of **bias**

Subset selection leads to a small set of interpretable predictors, with possibly lower error (MSE) than the full model

Subset selection is a discrete process — predictors are either *in* the model, or *not*

**Akaike information criterion** (AIC) is an index of fit that takes account of the parsimony of the model by penalising the number of parameters

The more parameters in the model the better the fit — if you have as many parameters as data points then the fit is perfect but the model has no explanatory power! A Trade-off

AIC is useful as it explicitly penalises any superfluous parameters in the model by adding  $2p$  to the variance or deviance of the model

$$\text{AIC} = -2 \times \log(\text{likelihood}) + 2p$$

Associated is Bayes information criterion (BIC), which applies a stronger penalty of  $p \log n$ , where  $n$  is number of observations

For linear regression the  $-2 \times \log(\text{likelihood})$  is  $n \log(\text{RSS}/n) + \text{constant}$

We can use AIC and BIC to compare two or more **nested** models

Nested means that one model is a subset of the other

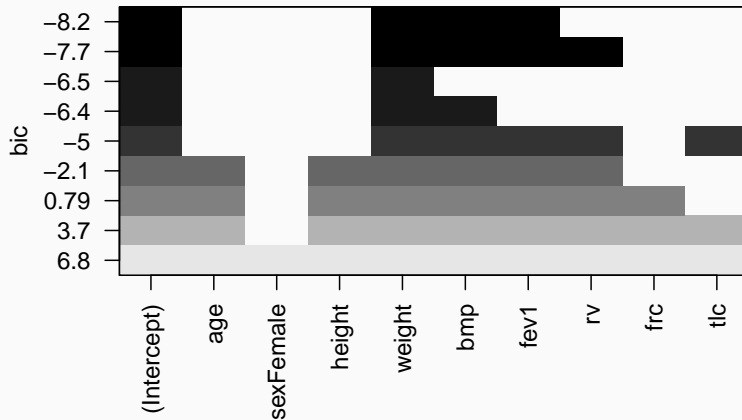
The model with the *smallest* AIC or BIC is to be preferred

Note that you can get negative values for AIC and BIC. This is fine, just go for the smallest value: -21.5 is better than -15.4

Difference in AIC of 2 is expected with a redundant parameter. Models with AIC differing by 2 or less are effectively the same

## Best subsets

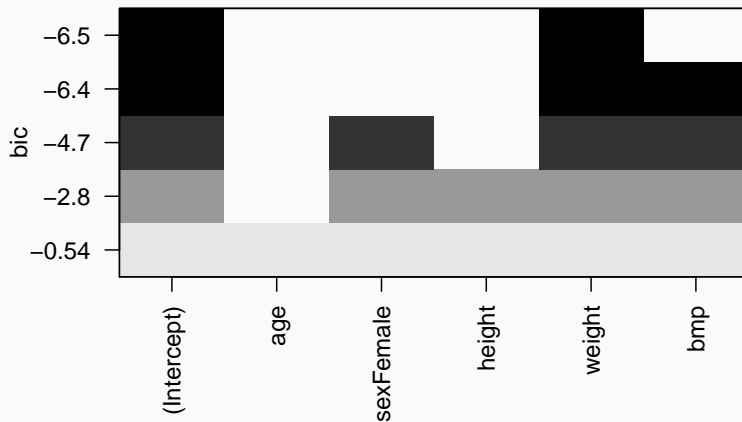
**Best subsets** identifies the *best* model of each *size*, & compare models via a statistic; **AIC** and **BIC** are commonly used





## Best subsets

Having some manual control is handy; might want to remove the other lung function variables first



# Forwards, backwards, and stepwise selection

Stepwise selection is a combination of **forward** selection & **backward** elimination steps

## Forward selection

1. Start with only the constant term
2. Fit  $m$  models, each adding one of the  $m$  predictors to the current model
3. Identify the *best* model from the set of models
4. Add the predictor from this *best* model to the current model **if** this results in a significant improvement in model fit
5. Repeat 3–4 until no further addition results in a better model

Forward selection starts with only the intercept term & adds variables until no improvement can be made

AIC used to assess improvement as terms added; notice that the inclusion of **rv** is probably unwarranted

	Step	Df	Deviance	Resid. Df	Resid. Dev	AIC
1		NA	NA	24	26832.64	176.4625
2	+ weight	-1	10827.159	23	16005.48	165.5453
3	+ bmp	-1	1914.939	22	14090.54	164.3596
4	+ fev1	-1	2552.354	21	11538.19	161.3635
5	+ rv	-1	1183.588	20	10354.60	160.6578

## Backwards elimination

Backwards elimination starts with the full model & removes variables until no improvement can be made

Can only fit the full model if you have fewer variables than observations

	Step	Df	Deviance	Resid. Df	Resid. Dev	AIC
1		NA	NA	15	9731.250	169.1055
2	- sex	1	37.90214	16	9769.152	167.2027
3	- tlc	1	115.94265	17	9885.094	165.4977
4	- frc	1	133.15598	18	10018.250	163.8322
5	- age	1	145.33646	19	10163.587	162.1923
6	- height	1	191.01331	20	10354.600	160.6578

Call:

```
lm(formula = pemax ~ weight + bmp + fev1 + rv, data = cystfibr)
```

Coefficients:

(Intercept)	weight	bmp	fev1	rv
63.9467	1.7489	-1.3772	1.5477	0.1257

## Stepwise selection

Stepwise selection starts with either the intercept or the full model & adds or removes variables at each step until no improvement can be made

	Step	Df	Deviance	Resid. Df	Resid. Dev	AIC
1		NA	NA	24	26832.64	176.4625
2	+ weight	-1	10827.159	23	16005.48	165.5453
3	+ bmp	-1	1914.939	22	14090.54	164.3596
4	+ fev1	-1	2552.354	21	11538.19	161.3635
5	+ rv	-1	1183.588	20	10354.60	160.6578

Call:

```
lm(formula = pemax ~ weight + bmp + fev1 + rv, data = cystfibr)
```

Coefficients:

(Intercept)	weight	bmp	fev1	rv
63.9467	1.7489	-1.3772	1.5477	0.1257

Here AIC used to assess improvement, but often  $p$  values & formal statistical tests are used to test improvement

Multiple testing is then a major problem, but AIC may be too liberal

No guarantee that selection will find the best model or that they will agree on the best model

$p$  values of terms in the selected models no longer have their usual meaning

Model coefficients ( $\hat{\beta}_j$ ) are biased

## Interactions

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Up to now we've only considered the **main effects** of the variables in our model

There, terms are **additive**, each variable contributing an amount to the model irrespective of the values of the other predictors

But what if the effect of one variable depends upon the value of one or more other variables?

This is where **interaction terms** come in



Two explanatory variables **interact** when the **partial** effect of one depends on the *value* of the other

**Marginal effect** — effect of  $x_1$  on  $y$  *ignoring* the effects on  $y$  of the other variables  $x_j$

**Partial effect** — effect of  $x_1$  on  $y$  *accounting for* the effects on  $y$  of the other variables  $x_j$

Interactions occur in several types

- continuous — factor interactions
- continuous — continuous interactions
- factor — factor interactions

### PTSD in adult female survivors of childhood sexual abuse

45 women treated at a clinic who reported childhood sexual abuse (CSA) were measured for PTSD & childhood physical abuse (CPA) on standardised scales

31 women at same clinic but did not report CSA were also assessed

Two models

$$\text{PTSD}_i = \beta_0 + \beta_1 \text{CSA}_i + \beta_2 \text{CPA}_i + \varepsilon_i \quad (1)$$

$$\text{PTSD}_i = \beta_0 + \beta_1 \text{CSA}_i + \beta_2 \text{CPA}_i + \beta_3 (\text{CSA}_i \times \text{CPA}_i) + \varepsilon_i \quad (2)$$

## Interaction Terms: Continuous—factor interactions

PTSD in adult female survivors of childhood sexual abuse



## Interaction Terms: Continuous—factor interactions

Call:

```
lm(formula = ptsd ~ cpa * csa, data = sexab)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-8.1999	-2.5313	-0.1807	2.7744	6.9748

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	3.6959	0.7107	5.201	1.79e-06 ***
cpa	0.7640	0.3038	2.515	0.0142 *
csaAbused	6.8612	1.0747	6.384	1.48e-08 ***
cpa:csaAbused	-0.3140	0.3685	-0.852	0.3970

---

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

Residual standard error: 3.279 on 72 degrees of freedom

Multiple R-squared: 0.5828, Adjusted R-squared: 0.5654

F-statistic: 33.53 on 3 and 72 DF, p-value: 1.133e-13

## Interaction Terms: Continuous—factor interactions

Interactions between factors can be represented as **dummy** variables, indicating group/combination membership

Reference level (**NotAbused**) absorbed into the intercept term

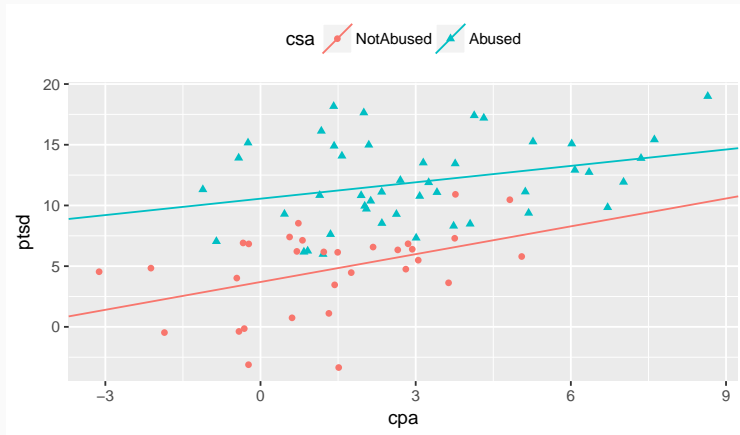
Model is parameterised in terms of differences of means from the reference level

	(Intercept)	cpa	csaAbused	cpa:csaAbused
1	1	2.04786	1	2.04786
2	1	0.83895	1	0.83895
3	1	-0.24139	1	-0.24139

	(Intercept)	cpa	csaAbused	cpa:csaAbused
74	1	-1.85753	0	0
75	1	2.85253	0	0
76	1	0.81138	0	0

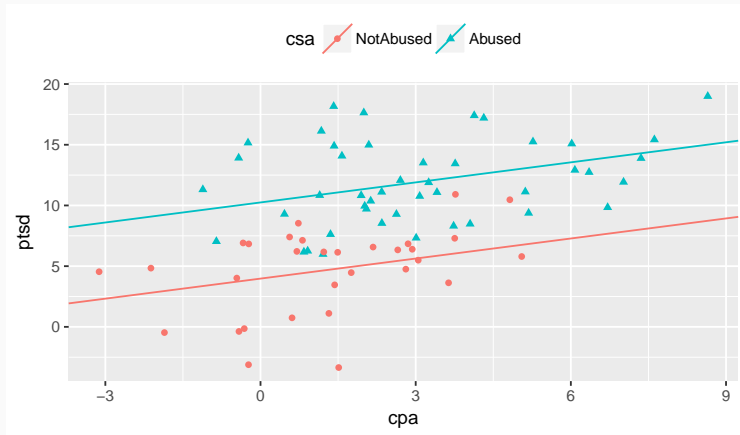
# Interaction Terms: Continuous—factor interactions

Model fits *with* interaction



# Interaction Terms: Continuous—factor interactions

Model fits *without* interaction



## Interaction Terms: Continuous—continuous interactions

In continuous—continuous interactions we don't need to worry about coding

This type of interaction is represented by a new variable that is the product of the two variables

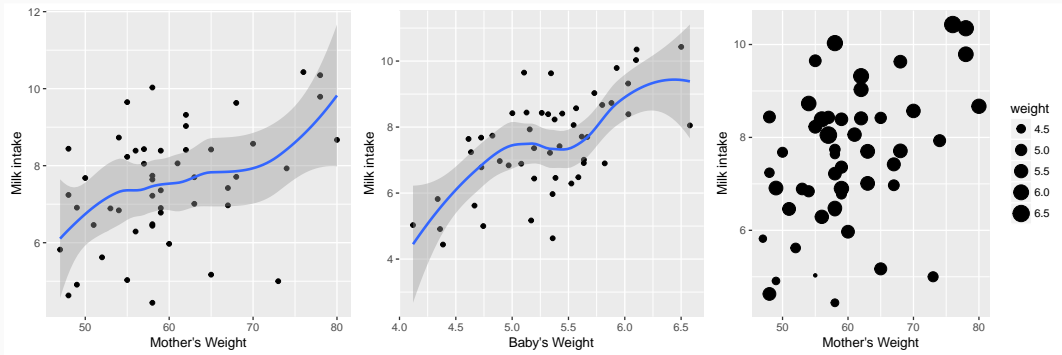
If we have  $x_1$  and  $x_2$ , the interaction would be  $(x_1 \times x_2)$



## Interaction Terms: Continuous—continuous interactions

50 infants of age approximately 2 months were weighed immediately before & after each breast feeding

Measured the intake of breast milk (dL) along with various other data



## Interaction Terms: Continuous—continuous interactions

Call:

```
lm(formula = dl.milk ~ mat.weight * weight, data = kfm)
```

Residuals:

Min	1Q	Median	3Q	Max
-2.45005	-0.73689	0.09775	0.80987	2.67499

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	15.68279	10.79790	1.452	0.1532
mat.weight	-0.27868	0.18354	-1.518	0.1358
weight	-1.89188	1.99057	-0.950	0.3469
mat.weight:weight	0.05797	0.03340	1.736	0.0893 .

---

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

Residual standard error: 1.13 on 46 degrees of freedom

Multiple R-squared: 0.4755, Adjusted R-squared: 0.4413

F-statistic: 13.9 on 3 and 46 DF, p-value: 1.389e-06

## Interaction Terms: Continuous—continuous interactions

Testing whether the interaction term is required via an  $F$  test

Marginally significant; effect looks small

Analysis of Variance Table

Model 1: `dl.milk ~ mat.weight + weight`

Model 2: `dl.milk ~ mat.weight * weight`

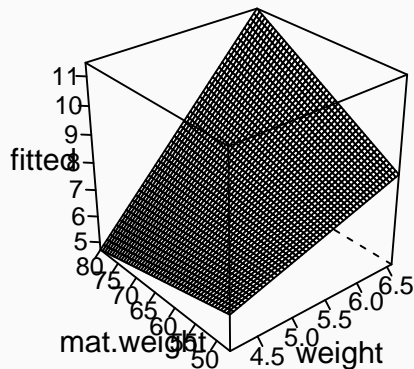
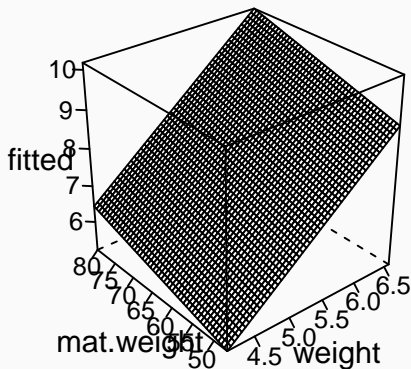
	Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
1	47	62.562				
2	46	58.716	1	3.8456	3.0128	0.08931 .

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

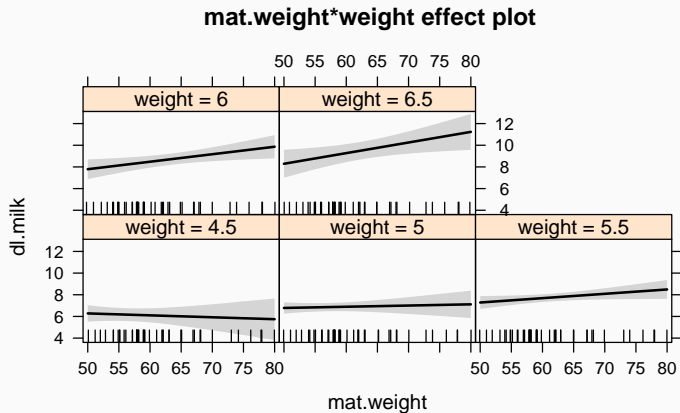
## Interaction Terms: Continuous—continuous interactions

Visualisation of the effect of continuous—continuous interactions



## Interaction Terms: Effects displays

Focus on high-order terms in the model; each high-order term is allowed to vary over its range, while other variables are held at some average values



## Interaction terms: Principal of Marginality

The *partial (main)* effects of variables in a model are **marginal** to any interaction terms in which they participate

Partial effects of CPA & CSA are *marginal* to the CPA  $\times$  CSA interaction

In general, should not test partial effects that are marginal to an interaction term

Can test the partial effects if we can remove the interaction on empirical or theoretical grounds

Also doesn't make sense to fit models with interaction terms without including the main effects of terms participating in the interaction

## Analysis of Variance

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**Analysis of Variance** (ANOVA) is the classic name for a linear model where the predictor (explanatory) variables are *categorical*

Earlier ANOVA used to partition variance in  $y$  into components explained by  $x_j$  & a residual component not explained by the regression model

A slightly more restricted view of ANOVA is that it is a technique for partitioning the variation in  $y$  into that explained by one or more categorical predictor variables

The categories of each factor are the groups or experimental treatments



ANOVA considers the different sources of variation that might arise on a data set

Of particular interest is on the differences in the mean value of  $y$  between groups

We can think of *within-group* and *between-group* variances

- **Between-group** variance is that due to the treatment (group) effects
- **Within-group** variance is that due to the variability of individuals & measurement error

There Will always be variation between individuals but is this within-group variance large or small, relative to the variance *between* groups?

## ANOVA how *many* ways?

One of the complications surrounding ANOVA is the convoluted nomenclature used describe variants of the method

Variants commonly distinguished by the number of categorical variables in the model

- One-way ANOVA contains a single categorical variable
- Two-way ANOVA contains two categorical variables
- Three-way ANOVA contains three categorical variables
- ...

Two-way and higher ANOVA potentially involve the consideration of *factor—factor* interactions

In a **One-way ANOVA** we have a single categorical variable  $x$  with *two or more* levels With two levels we have the same analysis as the  $t$  test

If we consider differences between patients with different illnesses, we might use an **illness-group** factor whose *levels* might be

- Multiple Sclerosis,
- Irritable Bowel Syndrome, &
- Chronic Fatigue Syndrome

If we're testing the 5 doses of a drug on Multiple Sclerosis patients, the factor might be **dose** with levels: placebo, 5 mg, 10 mg, 15 mg, & 20 mg

## One-way ANOVA

Assume we have a single categorical variable  $x$  with three levels. The One-way ANOVA model using dummy coding or treatment contrasts is

$$y_i = \beta_0 + \beta_1 D_{i1} + \beta_2 D_{i2} + \varepsilon_i$$

Where  $D_{ij}$  is the coding for the  $j$ th level (group) for the  $i$ th observation

Group	$D_1$	$D_2$
1	0	0
2	1	0
3	0	1

Measure the **between-group** variance as the *regression sums of squares*

The **within-group** variance is the *residual sums of squares*

An **omnibus test** F statistic is used to test the null hypothesis of *no differences among population group means*

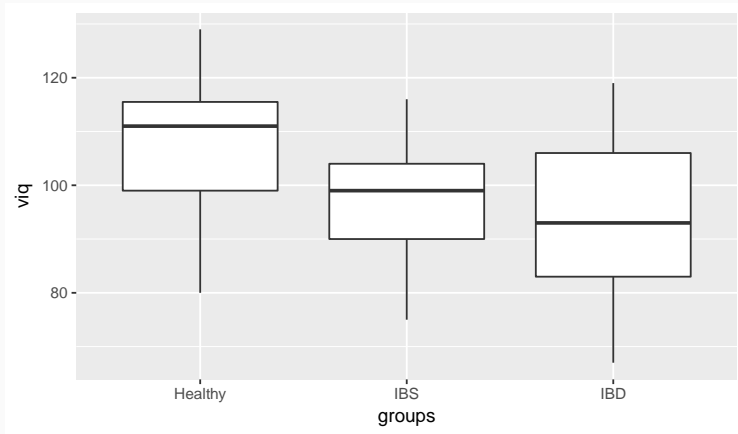
$$H_0 : \beta_1 = \beta_2 = 0$$

Attree & colleagues (2003, *Applied Neurophysiology* **10**(2)) conducted a study of variation in cognitive function in patients with *Inflammatory Bowel Disease* (IBD) & *Irritable Bowel Syndrome* (IBS) relative to health controls (Healthy)

Response variable was the *Verbal IQ Score* (VIQ)

Previous studies had shown that VIQs were impaired in other patient groups relative to healthy controls

# One-way ANOVA



Results of fitting one-way ANOVA to the verbal IQ score data

Analysis of Variance Table

Response: viq

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
groups	2	3365.4	1682.70	11.403	4.103e-05 ***
Residuals	85	12543.5	147.57		

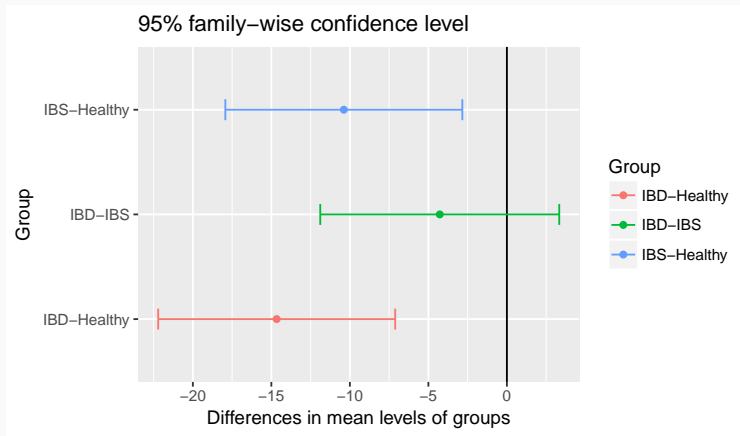
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Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1



# One-way ANOVA

## Multiple comparisons



## Example

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Human exposure to polychlorinated biphenyls (PCBs) from consumption of fish is a health concern in the Great Lakes region of the US

- Exposure limits based on fish tissue concentrations; anglers can not easily determine this concentration
- Can size of fish be used to infer PCB tissue concentration?
- Data are PCB concentrations in lake trout (1974–2003)



- *Estimate* is  $\beta_j$ , the model coefficients, on log scale
- For 1 cm increase in fish length, PCB tissue concentration increases by  $1.3 \text{ mg kg}^{-1}$
- *t-value* is the  $t$  statistic, the ratio of the estimate and its standard error

$$t = \frac{\hat{\beta}_j}{\hat{\text{se}}_j}$$

- Probability of achieving a  $t$  as large or larger than the observed
- Intercept of no biological interest — PCB concentration of a length 0 fish

- $F$  is the  $F$ -ratio, the ratio of the regression and residual variances

$$F = \frac{\sum_{i=1}^n (\hat{y}_i - \bar{y})^2 / p}{\sum_{i=1}^n (y_i - \hat{y}_i)^2 / [n - (p + 1)]} = \frac{MS_{\text{reg}}}{MS_{\text{resid}}}$$

- Probability of  $F$  greater than or equal to observed from  $F$ -distribution with  $p$  and  $n - (p + 1)$  degrees of freedom

```
#anova(pcb.m1)
```

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