

# Methods 3: Multilevel Statistical Modeling and Machine Learning

Week 5: *Evaluating and comparing models*  
October 12, 2021

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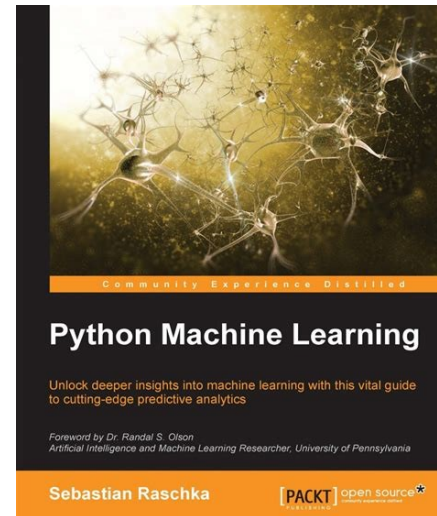
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# Study Cafe

# Python book in Stakbogladen

<https://www.stakbogladen.dk/soegning.asp?phrase=9781783555130>



**I still owe the answers to questions  
in the CryptPad  
Poisson and overdispersion,  
deviance in a logistic model, and the  
assumption of normality  
  
Code review – pair programming**

# Learning goals

*Evaluating and comparing models*

## 1) Learning tools for comparing models

- 1) Variance explained

- 2) Likelihood ratio tests

- 3) Information criteria

## 2) Bridging to out-of-sample

# Why are we modelling?

Remember Emil's slides from week 03

- To be able to understand the world
- To be able to predict and manipulate the world

$$F = G \frac{m_1 m_2}{r^2}$$

**EXPLANATION**



*NASA/Bill Ingalls*

**PREDICTION**

# What constitutes a good model?

Remember Emil's slides from week 03

- Accurate estimation of the underlying parameters of the population distribution
- Generalisation to new data

**EXPLANATION**

**PREDICTION**



Within an **explanatory** framework, how can we assess whether we have done a good job?

# 1) Variance explained?

# R summary

```
##  
## Call:  
## lm(formula = mpg ~ wt, data = mtcars)  
##  
## Residuals:  
##      Min       1Q   Median       3Q      Max   
## -4.5432 -2.3647 -0.1252  1.4096  6.8727   
##  
## Coefficients:  
##              Estimate Std. Error t value Pr(>|t|)      
## (Intercept)  37.2851     1.8776   19.858 < 2e-16 ***  
## wt          -5.3445     0.5591   -9.559 1.29e-10 ***  
## ---  
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1  
##  
## Residual standard error: 3.046 on 30 degrees of freedom  
## Multiple R-squared:  0.7528, Adjusted R-squared:  0.7446   
## F-statistic: 91.38 on 1 and 30 DF,  p-value: 1.294e-10
```

# $R^2$ (coefficient of determination)

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \mu_y)^2}$$

taking into account the number of parameters (p) and the number of observations (n).

number of p is BEYOND the constant term (intercept, what we call the mean)

lower than normal  $R^2$  (penalized)

# $R^2$ ; adjusted

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \mu_y)^2}$$

$$\bar{R}^2 = 1 - (1 - R^2) \frac{n-1}{n-p-1}$$

$n$ : number of observations

$p$ : number of predictors beyond the constant term

```
lm(formula = mpg ~ wt, data = mtcars)
```

Coefficients:

(Intercept)	wt
37.285	-5.344

---

"R-squared: 0.753"

"R-squared, adjusted: 0.745"

```
lm(formula = mpg ~ I(wt^2) + wt, data = mtcars)
```

Coefficients:

(Intercept)	I(wt^2)	wt
49.931	1.171	-13.380

---

"R-squared: 0.819"

"R-squared, adjusted: 0.807"

our explained variance increases (which is what we would expect due to physics...)

```
lm(formula = mpg ~ I(wt^3) + I(wt^2) + wt, data = mtcars)
```

Coefficients:

(Intercept)	I(wt^3)	I(wt^2)	wt
48.40370	0.04594	0.68938	-11.82598

---

"R-squared: 0.819"

"R-squared, adjusted: 0.8"

```
lm(formula = mpg ~ I(wt^4) + I(wt^3) + I(wt^2) + wt, data = mtcars)
```

Coefficients:

(Intercept)	I(wt^4)	I(wt^3)	I(wt^2)	wt
14.4558	-0.3863	5.2004	-23.7018	36.6195

---

"R-squared: 0.822"

"R-squared, adjusted: 0.796"

# R<sup>2</sup> – mixed models

$$R_{GLMM}(m)^2 = \frac{\sigma_f^2}{\sigma_f^2 + \sigma_\alpha^2 + \sigma_\epsilon^2}$$

here u only have  
the fixed effects  
(how much does  
the group effects  
explain of the  
variance?)

$$R_{GLMM}(c)^2 = \frac{\sigma_f^2 + \sigma_\alpha^2}{\sigma_f^2 + \sigma_\alpha^2 + \sigma_\epsilon^2}$$

combi of group and individual

$\sigma_f^2$ : variance of the fixed effects

$\sigma_\alpha^2$ : variance of the random effects

$\sigma_\epsilon^2$ : unexplained variance

# Variance explained

- Pros

- $R^2$  is intuitive we get numbers and percentages which we can easily interpret!

- Cons

- More complex models will always explain more variance ^we can use the adjusted  $R^2$  to deal w this a little
  - Hard to interpret in the case of collinearity covariance btw variables
  - $R^2$  doesn't give us what we want



$$y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \varepsilon_i. \quad (1)$$



$$\hat{y}_i = 1.6 + 0.35X_{1i} + 0.62X_{2i}.$$



$$R^2 = 0.750$$



Tempting interpretation: the parameter estimates are likely to be true, because  $R^2$  is large

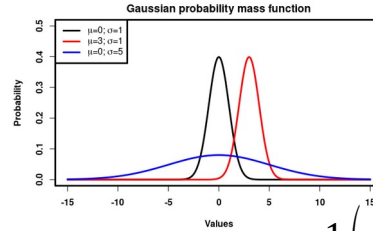
Correct interpretation:

“if one fits a model with the form of equation 1 in each new sample – *each time estimating new values of  $b_0$ ,  $b_1$ , and  $b_2$*  – what will be the average proportional reduction in the sum of squared errors?”  
(Yarkoni and Westfall 2017)

## 2) Likelihood ratios

# Maximum likelihood estimation

$$\text{PDF} = (2\pi\sigma^2)^{-1/2} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$



$$\text{Conditional PDF}(y_i|X) = (2\pi\sigma^2)^{-1/2} e^{-\frac{1}{2}\left(\frac{y_i - x_i\beta}{\sigma_0}\right)^2}$$

$$\text{Likelihood function: } L(\sigma^2, \epsilon) = (2\pi\sigma^2)^{-N/2} e^{-\left(\frac{1}{2\sigma^2} \sum_{i=1}^N (y_i - x_i\beta)^2\right)}$$

$$\text{Log-Likelihood function: } l(\sigma^2, \epsilon) = \log(L)$$

$y$ : dependent variable

$X\beta$ : linear predictor

$y - X\beta = \epsilon$ : residuals

$N$ : number of observations

```
model <- lmer(Reaction ~ days_deprived + (days_deprived | Subject),  
             data=sleepstudy)  
model.ranint <- lmer(Reaction ~ days_deprived + (1 | Subject),  
                   data=sleepstudy)
```

```
print(ll.m <- logLik(model))
```

```
## 'log Lik.' -702.0472 (df=6)
```

```
exp(ll.m)
```

```
## 'log Lik.' 1.272865e-305 (df=6)
```

```
print(ll.mr <- logLik(model.ranint))
```

```
## 'log Lik.' -715.01 (df=4)
```

```
exp(ll.mr)
```

```
## 'log Lik.' 2.986092e-311 (df=4)
```

# Likelihood-ratio test

$$LR = -2(l(\theta_2) - l(\theta_1))$$

```
anova(model.ranint, model.ranslope.and.int)
```

```
## Data: sleepstudy
## Models:
## model.ranint: Reaction ~ days_deprived + (1 | Subject)
## model.ranslope.and.int: Reaction ~ days_deprived + (days_deprived | Subject)
##
```

	Df	AIC	BIC	logLik	deviance	Chisq	Chi	Df
## model.ranint	4	1446.5	1458.4	-719.25	1438.5			
## model.ranslope.and.int	6	1425.2	1443.0	-706.58	1413.2	25.332		2

```
##
```

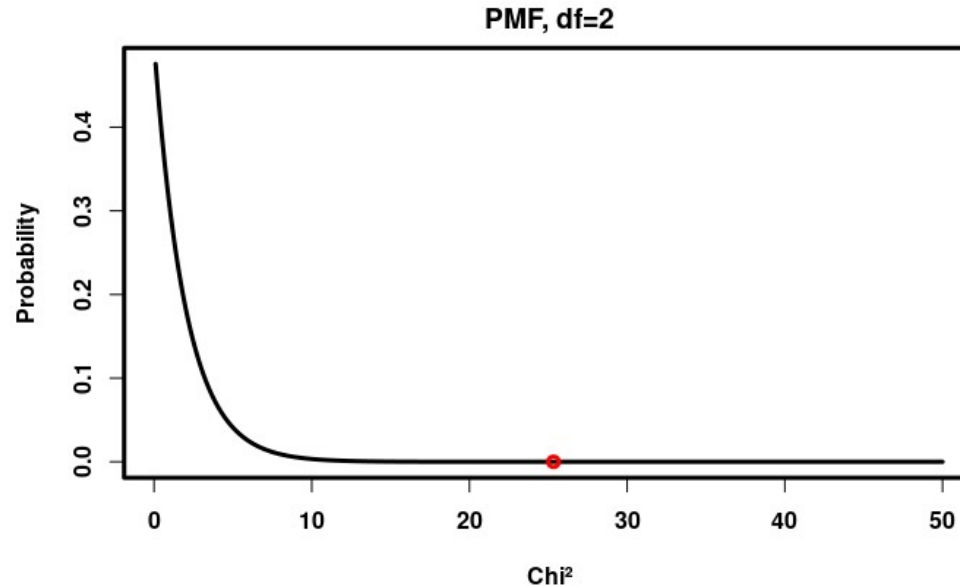
	Pr(>Chisq)
## model.ranint	
## model.ranslope.and.int	3.156e-06 ***

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

# Likelihood-ratio test

$$LR = -2(l(\theta_2) - l(\theta_1))$$

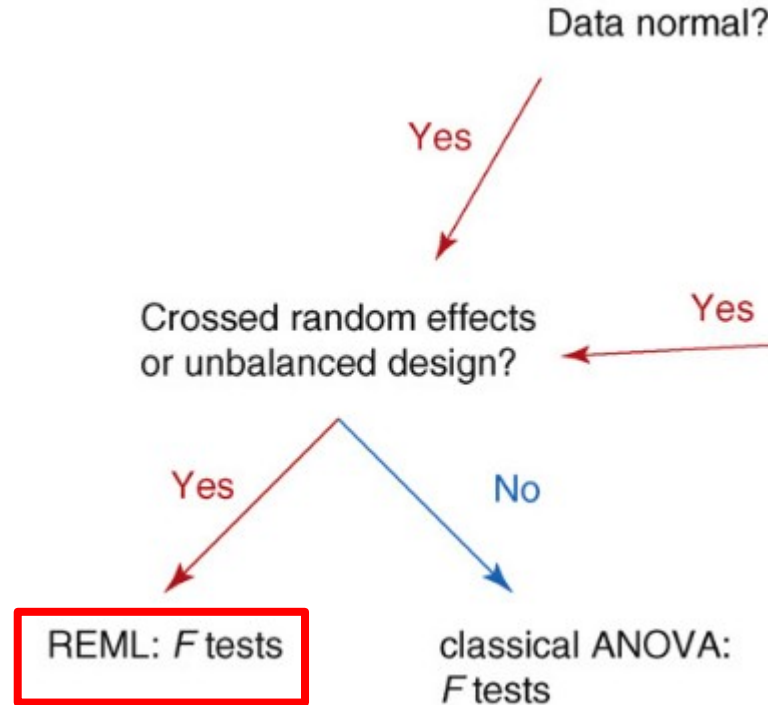
Chisq	Chi	Df
25.332		2
Pr(>Chisq)		
3.156e-06		



# Regarding GLMMs

“The LR test is only adequate for testing fixed effects when both the ratio of the total sample size to the number of fixed-effect levels being tested and the number of random-effect levels (blocks) are large. *We have found little guidance and no concrete rules of thumb in the literature [...]*” (my highlights, Bolker et al., 2008)

**Requires  
that  
degrees  
of  
freedom  
can be  
defined**



(Bolker et al., 2009)



# F-values – single level modelling

$$F = \frac{\left( \frac{RSS_1 - RSS_2}{p_2 - p_1} \right)}{\left( \frac{RSS_2}{n - p_2} \right)}$$

→ difference in unexplained variance between “null” model and “target” model

→ numerator degrees of freedom (difference in predictor variables)

→ unexplained variance by “target” model

→ denominator degrees of freedom (degrees of freedom for observations)

$RSS$ : Residual sum of squares  
 $p$ : number of predictor variables  
 $n$ : number of observations

# F-values – single level modelling

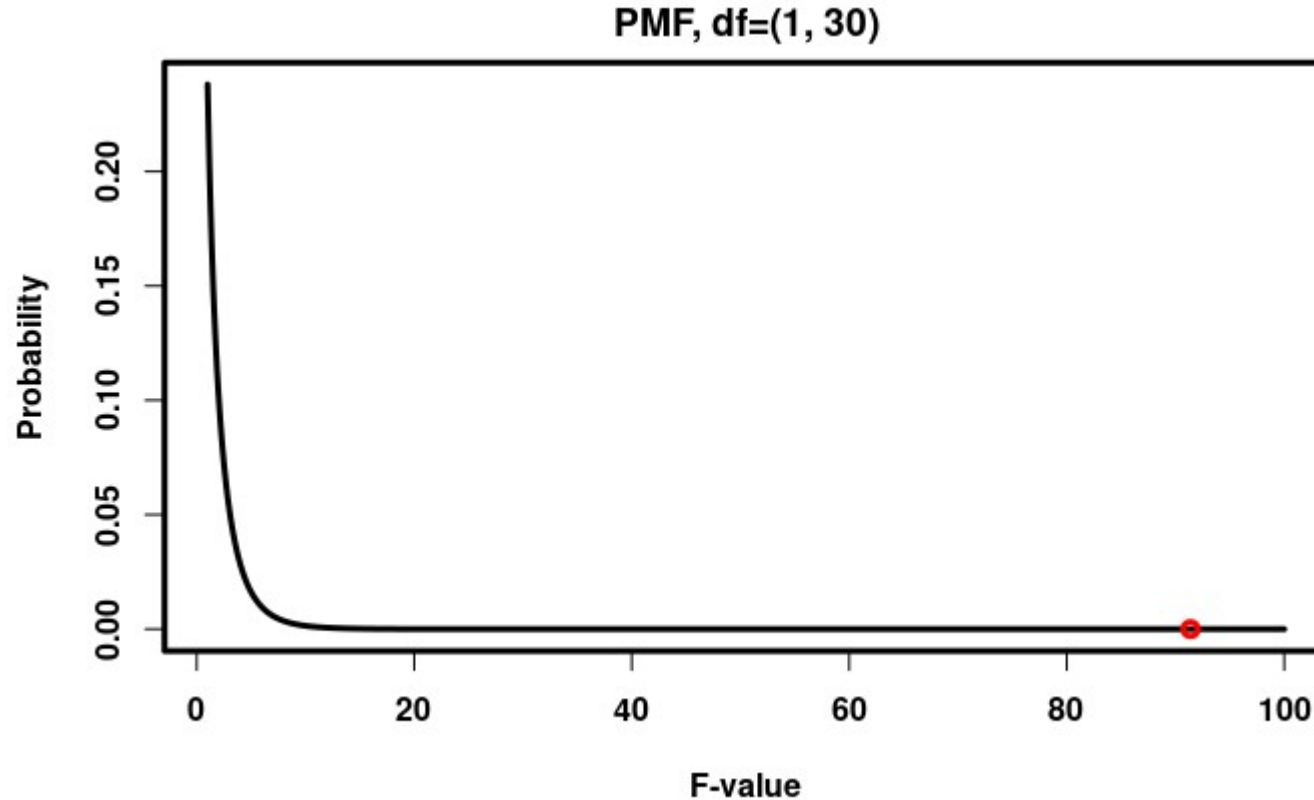
```
##  
## Call:  
## lm(formula = mpg ~ wt, data = mtcars) → Target model  
##  
## Residuals:  
##      Min       1Q   Median       3Q      Max   
## -4.5432 -2.3647 -0.1252  1.4096  6.8727   
##  
## Coefficients:  
##              Estimate Std. Error t value Pr(>|t|)      
## (Intercept)  37.2851     1.8776  19.858  < 2e-16 ***  
## wt          -5.3445     0.5591  -9.559 1.29e-10 ***  
## ---  
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1  
##  
## Residual standard error: 3.046 on 30 degrees of freedom  
## Multiple R-squared:  0.7528, Adjusted R-squared:  0.7446   
## F-statistic: 91.38 on 1 and 30 DF,  p-value: 1.294e-10
```

Call:  
lm(formula = mpg ~ 1, data = mtcars)



Null model

# F-values – single level modelling



```
## F-statistic: 91.38 on 1 and 30 DF,  p-value: 1.294e-10
```

# F-values – single level modelling

```
##  
## Call:  
## lm(formula = mpg ~ I(wt^2) + wt, data = mtcars)  
##  
## Residuals:  
##      Min       1Q   Median       3Q      Max   
## -3.483 -1.998 -0.773  1.462  6.238   
##  
## Coefficients:  
##              Estimate Std. Error t value Pr(>|t|)      
## (Intercept)  49.9308     4.2113   11.856 1.21e-12 ***  
## I(wt^2)       1.1711     0.3594    3.258 0.00286 **   
## wt           -13.3803     2.5140   -5.322 1.04e-05 ***  
## ---  
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1  
##  
## Residual standard error: 2.651 on 29 degrees of freedom  
## Multiple R-squared:  0.8191, Adjusted R-squared:  0.8066  
## F-statistic: 65.64 on 2 and 29 DF, p-value: 1.715e-11
```



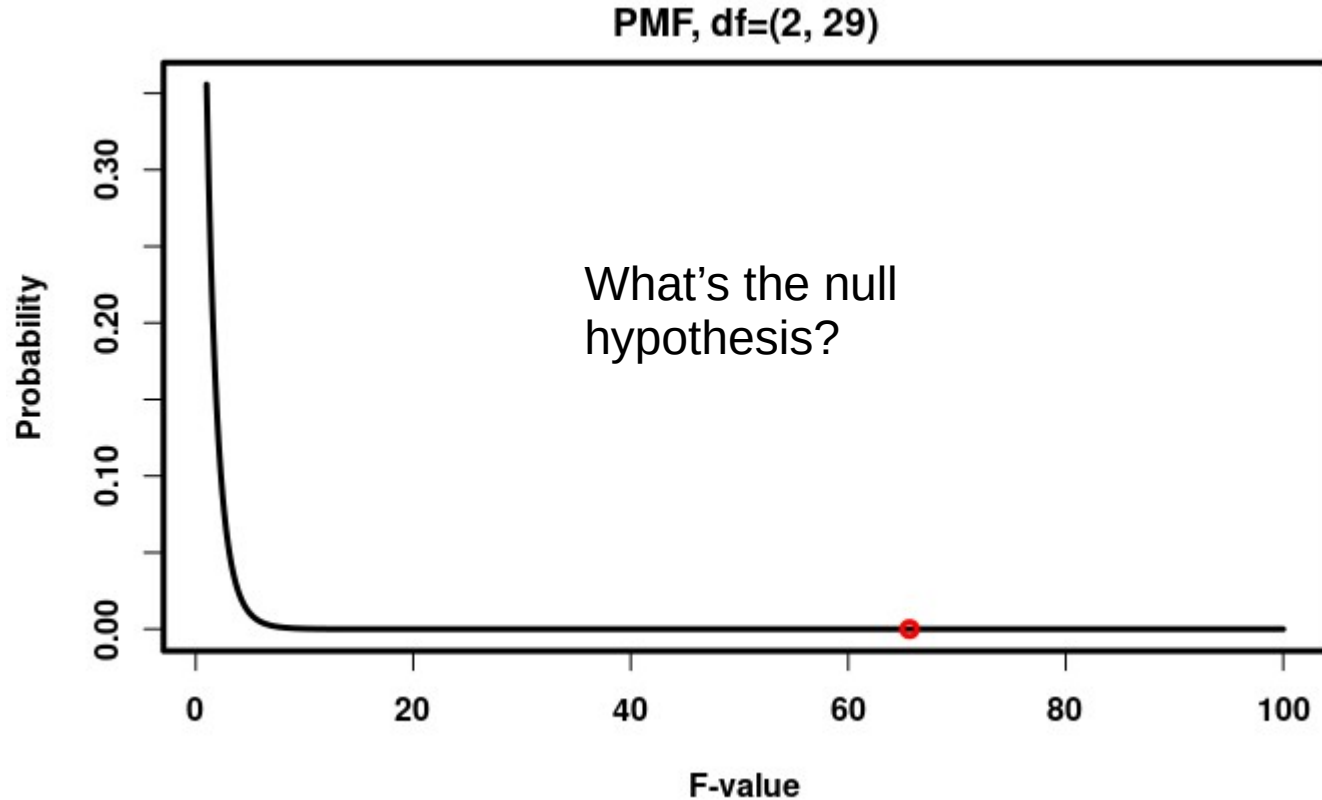
Target model

```
Call:  
lm(formula = mpg ~ 1, data = mtcars)
```



Null model,  
(still!)

# F-values – single level modelling



## F-statistic: 65.64 on 2 and 29 DF, p-value: 1.715e-11

```
anova(model.1, model.2)
```

```
## Analysis of Variance Table
```

```
##
```

```
## Model 1: mpg ~ wt
```



Null model

```
## Model 2: mpg ~ I(wt^2) + wt
```



Target model

```
##   Res.Df  RSS Df Sum of Sq    F Pr(>F)
```

```
## 1      30 278.32
```

```
## 2      29 203.75  1    74.576 10.615 0.00286 **
```

```
## ---
```

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

What's the null hypothesis?

that the decrease in the highlighted blue is surprising

# Likelihood ratio

- Pros
  - Models can be compared in a principled way by reference to a theoretical distribution,  $\chi^2$ . (In the single level case,  $F$  can be calculated)
- Cons
  - Models have to be nested in one another
  - Maximum likelihood fitting may be biased for complex models
  - Requires large sample sizes
  - Be careful if collinearity is high

# **3) Information criteria**



# Information criteria

$$\text{deviance} = -2l(\hat{\theta})$$

$$\text{AIC} = \text{deviance} + 2k$$


$k$ : number of predictors

When we add  $k$  predictors that are pure noise, deviance is reduced by an amount corresponding to a  $\chi^2$  distribution with  $k$  degrees of freedom.

(Gelman and Hill, 2006)

“On average, a predictor needs to reduce the deviance by 2 in order to improve the fit to new data”

(Gelman and Hill, 2006, p. 525)

```
## Data: sleepstudy
## Models:
## model.ranint: Reaction ~ days_deprived + (1 | Subject)
## model.ranslope.and.int: Reaction ~ days_deprived + (days_deprived | Subject)
##
##           Df      AIC      BIC  logLik deviance  Chisq Chi Df
## model.ranint      4 1446.5 1458.4 -719.25   1438.5
## model.ranslope.and.int 6 1425.2 1443.0 -706.58   1413.2 25.332      2
##
##           Pr(>Chisq)
## model.ranint
## model.ranslope.and.int 3.156e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

## How are the degrees of freedom calculated?

Hints: **Likelihood function**:  $L(\sigma^2, \epsilon)$

$$\hat{\sigma}^2 = \frac{1}{N} \sum_{i=1}^N (y_i - x_i \hat{\beta}_N)^2$$

# How to estimate $k$ ?

# With $J$ parameters

- Complete pooling
  - all  $J$  parameters collapsed into 1 parameter, ( $k = 1$ )
- No pooling
  - each of the  $J$  parameters is estimated, ( $k = J$ )
- Partial pooling
  - the number of effective parameters may be estimated by sampling and the *Deviance Information Criterion* can be estimated (beyond this course)
  - the number of parameters, loosely speaking, depend on whether the parameters are estimated mostly by the group average or the individual's own average ( $k = ?$ )

# Information criteria

- Pros
  - Models can be compared even though one is not nested within the other (response data has to be the same though)
- Cons
  - Number of effective parameters not well defined for multilevel models
  - Maximum likelihood fitting may be biased for complex models

# Did you learn? (it's not easy)

*Evaluating and comparing models*

## 1) Learning tools for comparing models

- 1) Variance explained

- 2) Likelihood ratio tests

- 3) Information criteria

## 2) Bridging to out-of-sample

# Learning goals

*Explanation and prediction*

- 1) Understanding that fitting (explaining) often leads to overfitting
- 2) Learning methods to prevent overfitting by introducing *bias*
- 3) Understanding how the error can be decomposed into *bias* and *variance*

$$\hat{\beta} = (X^T X)^{-1} X^T Y$$

maximises the likelihood of

$$Y = X\beta + \epsilon$$

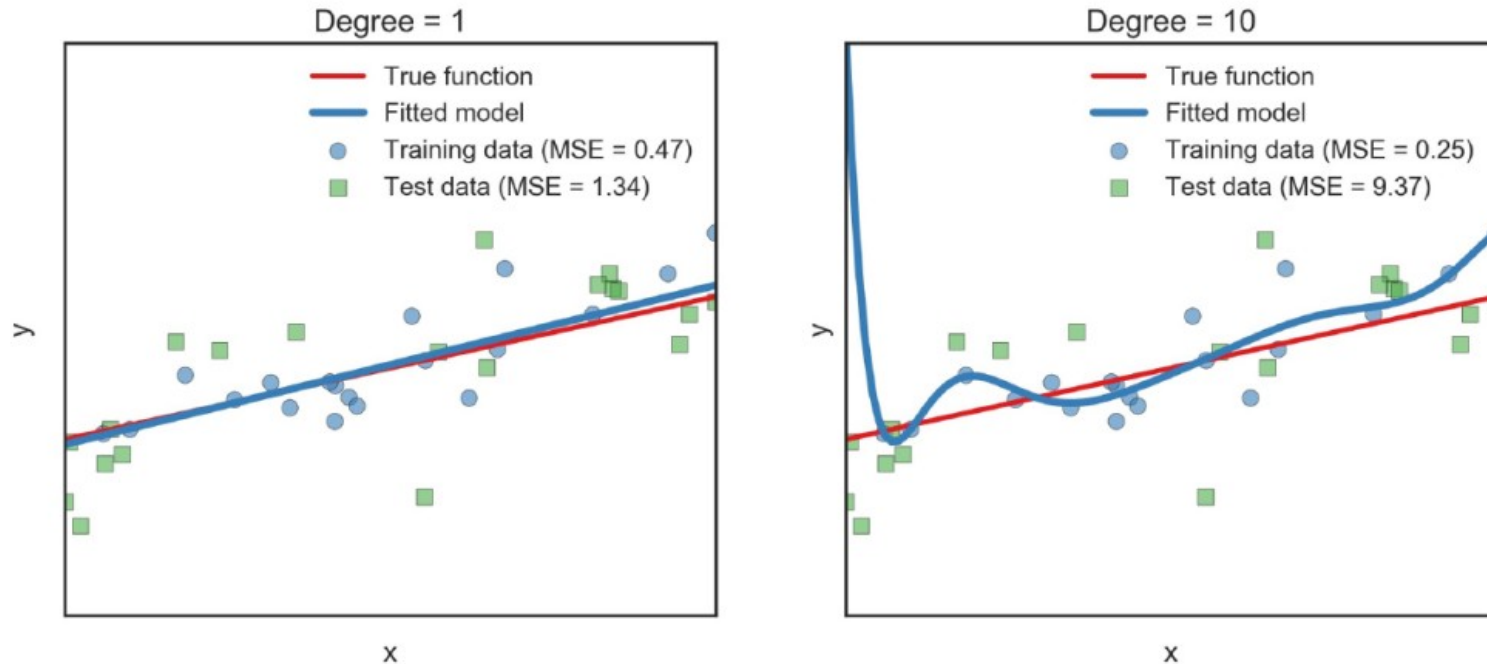
for which link function?



# To fit is to overfit

(Yarkoni and Westfall, 2017)

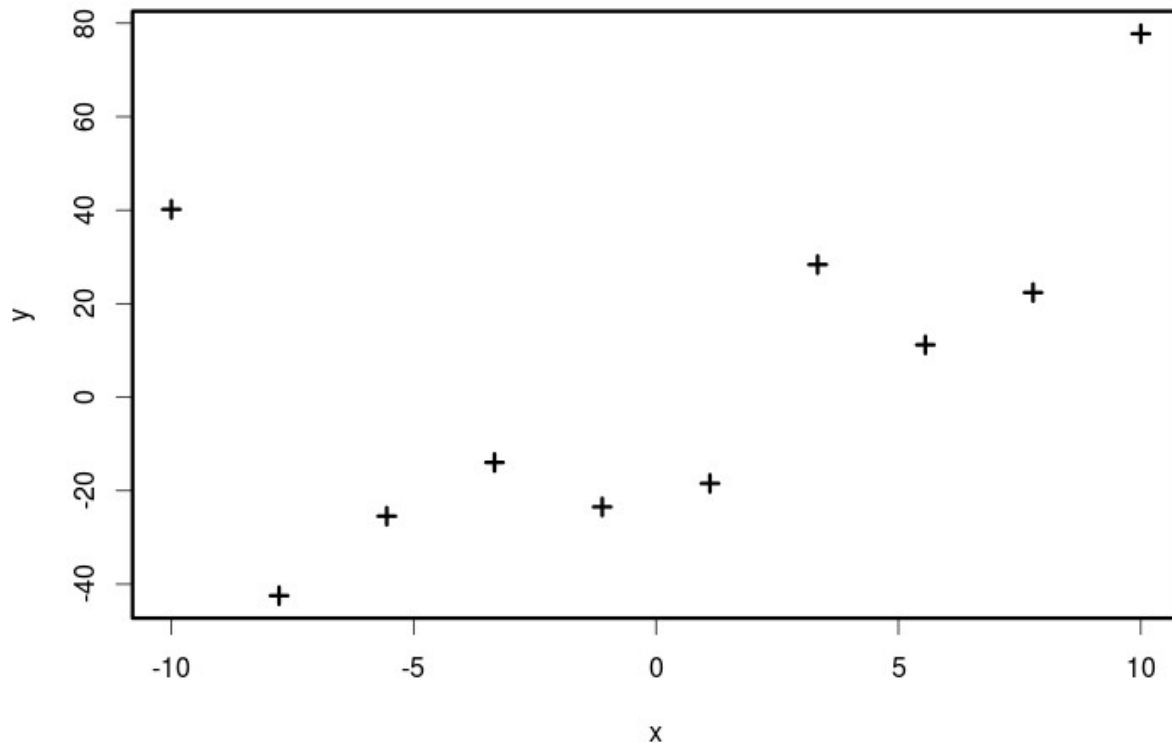
**Overfitting:** fitting sample-specific noise,  
which is thus not representative of the  
population



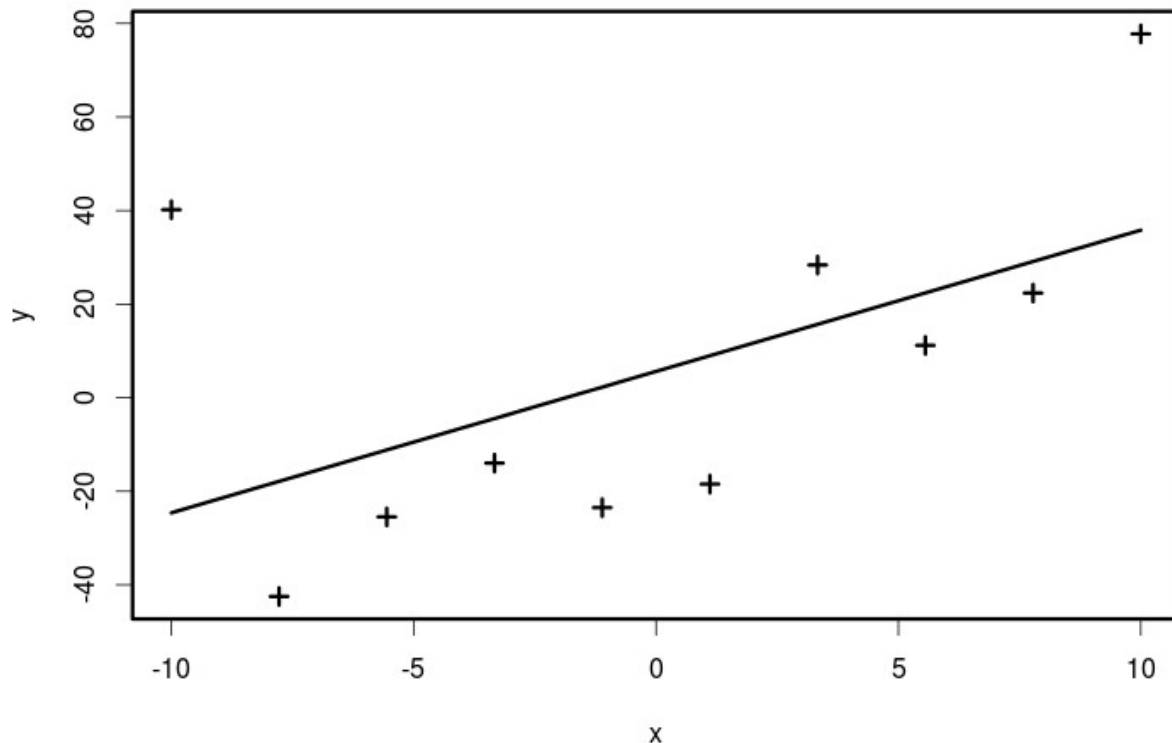
**Fig. 1.** Training and test error produced by fitting either a linear regression (left) or a 10th-order polynomial regression (right) when the true relationship in the population (red line) is linear. In both cases, the test data (green) deviate more from the model's predictions (blue line) than the training data (blue). However, the flexibility of the 10th-order polynomial model facilitates much greater overfitting, resulting in lower training error but much higher test error than the linear model. MSE = mean squared error.

(Yarkoni and Westfall, 2017)

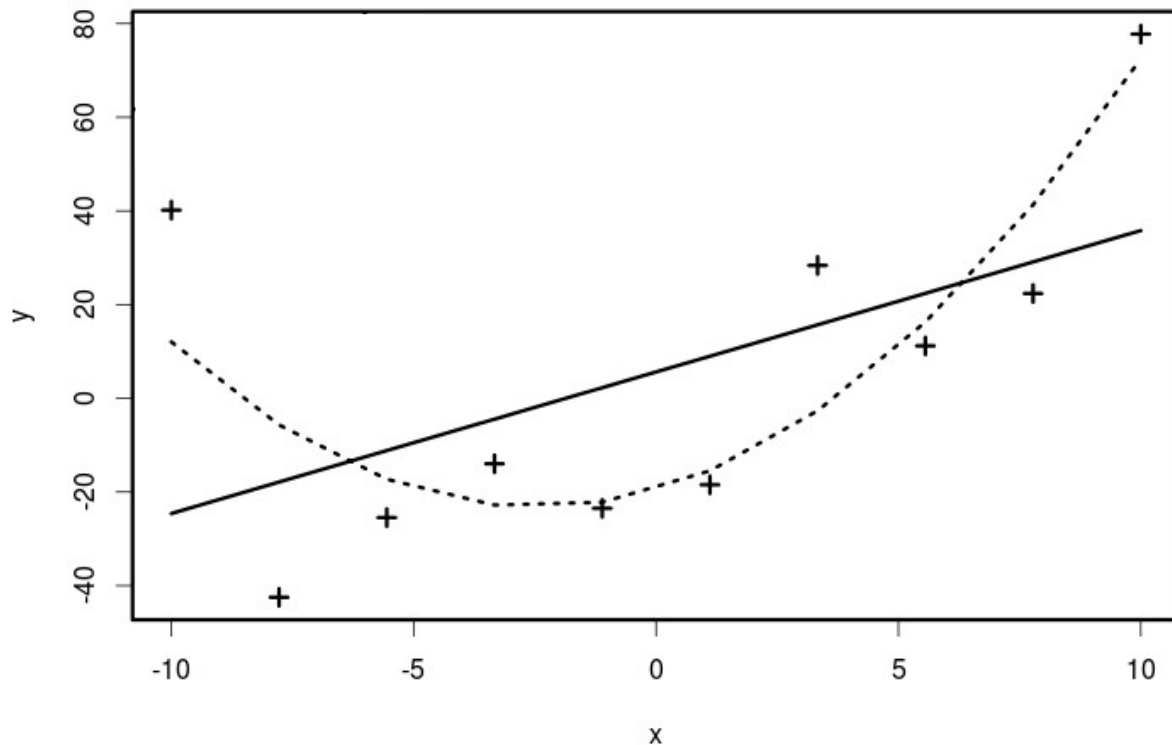
# A sample of 10 linear or quadratic?



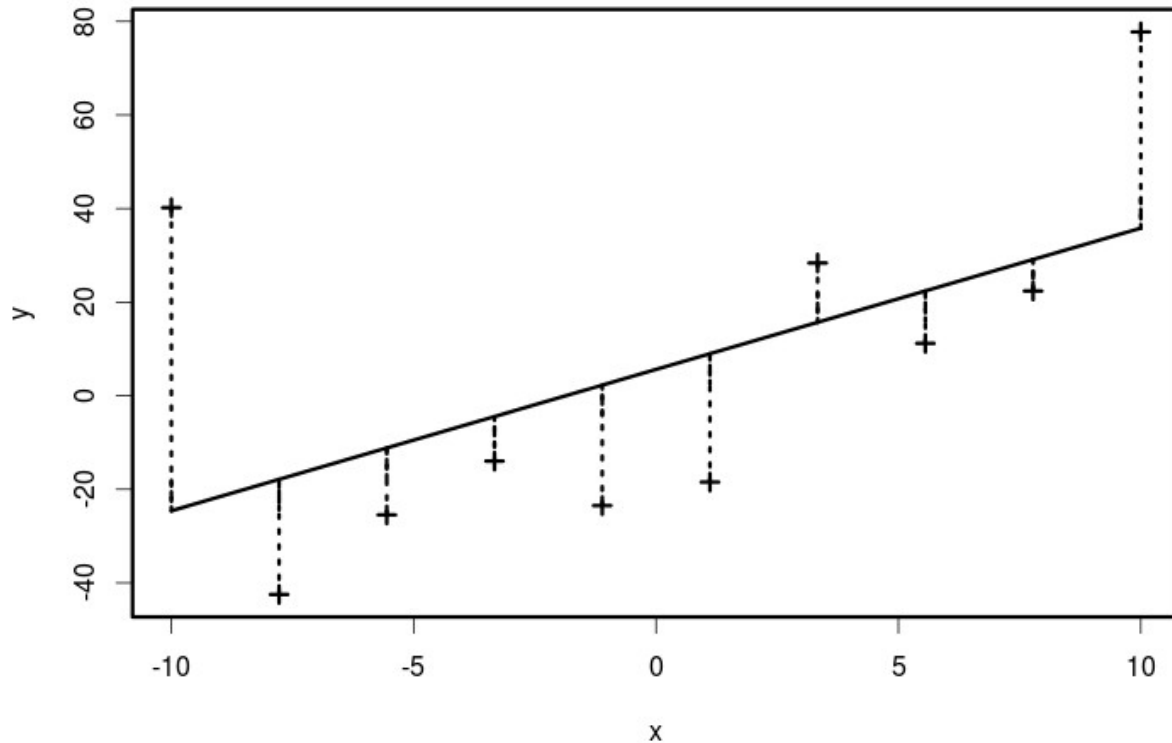
# A sample of 10 linear or quadratic?



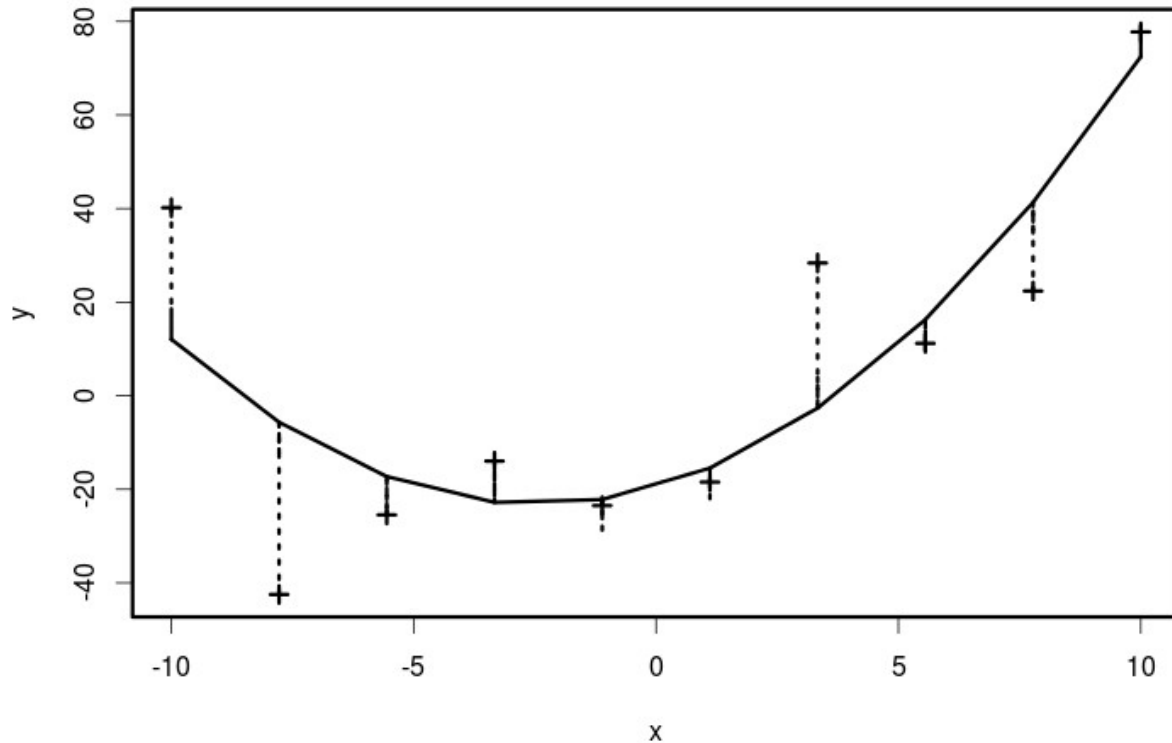
# A sample of 10 linear or quadratic?



# Residuals (linear)



# Residuals (quadratic)



Quadratic:

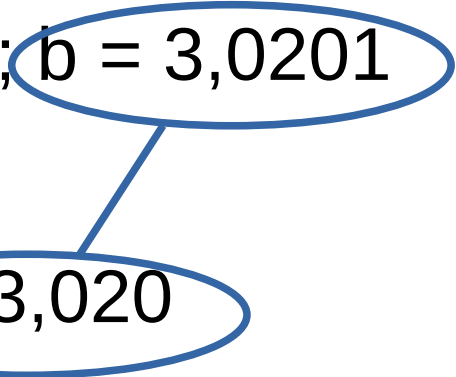
$$ax^2 + bx + c$$

Linear:

$$bx + c$$

Estimates

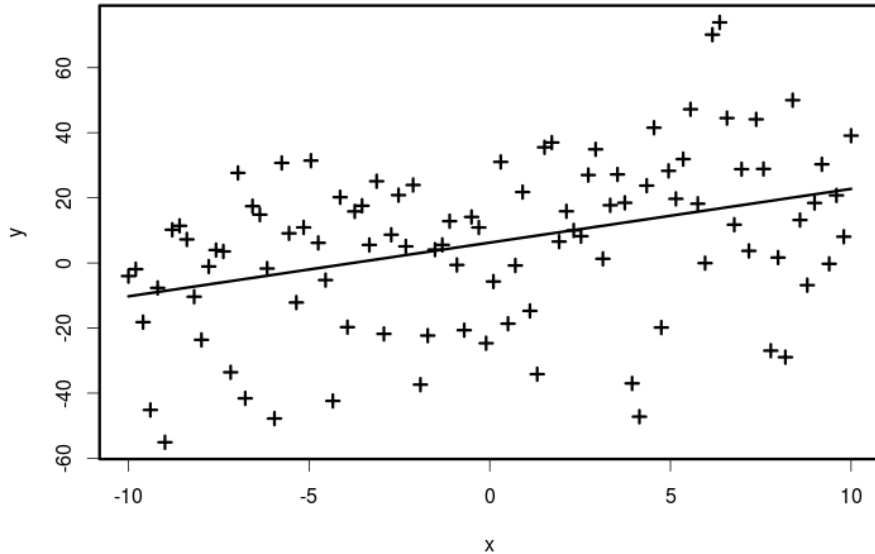
$a = 0,6184; b = 3,0201$



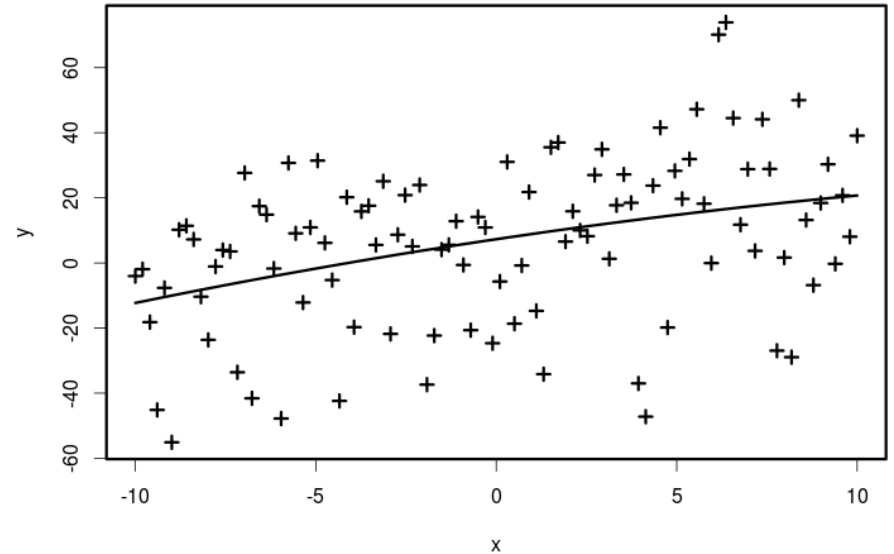
$b = 3,020$



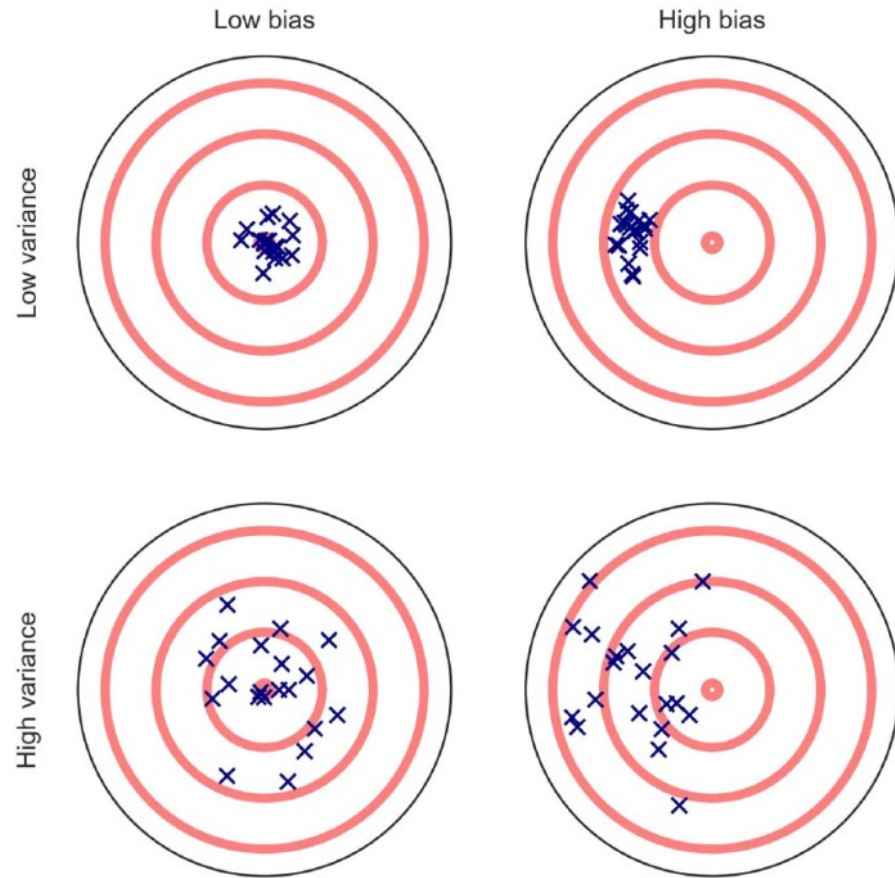
# Now a sample of 100



$$b = 1,650$$



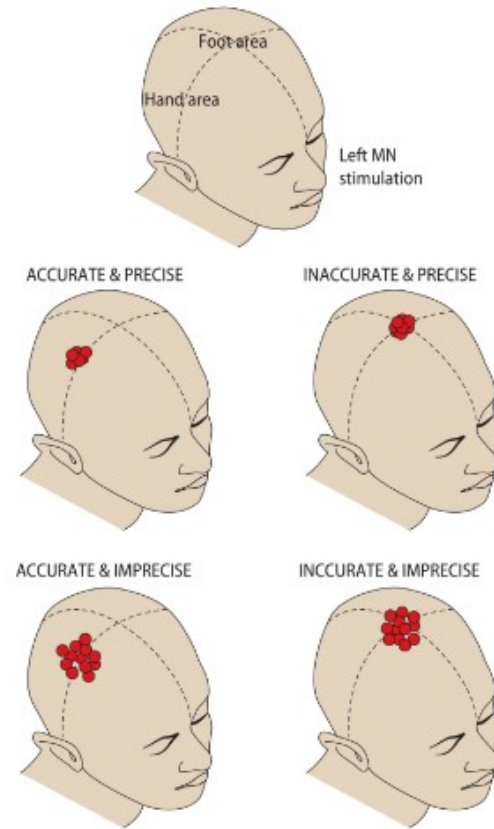
$$a = -0,03074 \approx 0; b = 1,650$$



**Fig. 2.** An estimator's predictions can deviate from the desired outcome (or true scores) in two ways. First, the predictions may display a systematic tendency (or *bias*) to deviate from the central tendency of the true scores (compare right panels with left panels). Second, the predictions may show a high degree of *variance*, or imprecision (compare bottom panels with top panels).

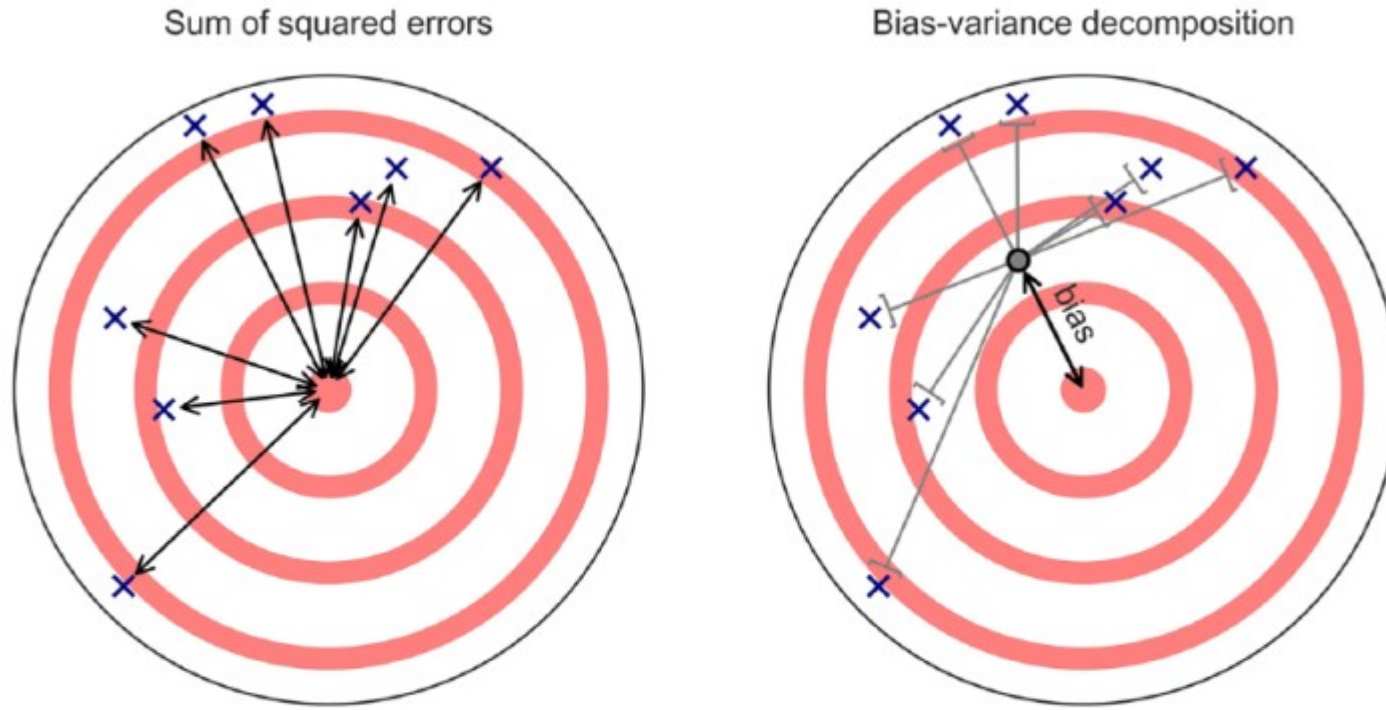
(Yarkoni and Westfall, 2017)

Which two of these does our least-squares solution prefer?



**FIGURE 3.7.** Accuracy versus precision. A schematic illustration of the differences between accuracy and precision of source localization. After left median-nerve stimulation, activations is expected in the right-hemisphere hand region of the primary somatosensory cortex. The foot area is shown at the top of the head. See text for further explanation.

(Hari and Puce, 2017)



**Fig. 3.** Schematic illustration of the bias-variance decomposition. (Left) Under the classical error model, prediction error is defined as the sum of squared differences between true scores and observed scores (black lines). (Right) The bias-variance decomposition partitions the total sum of squared errors into two separate components: a bias term that captures a model's systematic tendency to deviate from the true scores in a predictable way (black line) and a variance term that represents the deviations of the individual observations from the model's expected prediction (gray lines).

# Multilevel modelling as a *bias* introducer

*“For example, some readers may be surprised to learn that multilevel modeling approaches to analyzing clustered data—which have recently seen a dramatic increase in adoption in psychology—improve on ordinary least squares (OLS) approaches to estimating individual cluster effects by deliberately biasing (through “shrinking” or “pooling”) the cluster estimates toward the estimated population average”*

(Yarkoni and Westfall, 2017)

# Introducing *bias*

*“In a widely used form of penalized regression called lasso regression (Tibshirani, 1996, 2011), this leastsquares criterion is retained, but the overall cost function that the estimation seeks to minimize now includes an additional penalty term that is proportional to the sum of the absolute values of the coefficients.”*

(Yarkoni and Westfall, 2017)

# Penalised regression

$$\text{RSS} = \sum (y_i - \hat{y}_i)^2 \text{ (minimise to obtain least squares solution)}$$

$$\text{lasso regression: } \text{RSS} + \lambda \sum_{j=1}^p |\beta_j| \text{ (minimise this sum)}$$

$$\text{ridge regression: } \text{RSS} + \lambda \sum_{j=1}^p (\beta_j^2) \text{ (minimise this sum)}$$

$i$ : observations

$p$ : predictor variables

$\lambda$ : a constant

# Penalised regression

$RSS = \sum (y_i - \hat{y}_i)^2$  (minimise to obtain least squares solution)

lasso regression :  $RSS + \lambda \sum_{j=1}^p |\beta_j|$  (minimise this sum)

ridge regression :  $RSS + \lambda \sum_{j=1}^p (\beta_j^2)$  (minimise this sum)

$i$ : observations

$p$ : predictor variables

$\lambda$ : a constant

## Group discussion

In each case: what happens when?

1.  $\lambda$  increases?
2.  $\lambda$  decreases?
3.  $\lambda$  is 0?
4.  $\lambda$  goes towards infinity?

# Penalised regression

$$\text{RSS} = \sum (y_i - \hat{y}_i)^2 \text{ (minimise to obtain least squares solution )}$$

$$\underset{\lambda}{\text{argmin}} = \text{RSS} + \lambda \sum_{j=1}^p |\beta_j|$$

$$\underset{\lambda}{\text{argmin}} = \text{RSS} + \lambda \sum_{j=1}^p (\beta_j^2)$$

$i$ : observations

$p$ : predictor variables

$\lambda$ : a constant



# How to choose $\lambda$ ?

```
##  
## Call:  
## lm(formula = hp ~ mpg + wt + drat + qsec, data = mtcars)  
##  
## Coefficients:  
## (Intercept)          mpg           wt          drat          qsec  
##      473.779       -2.877       26.037        4.819       -20.751
```

What is  $\lambda$  equal to here?

```
sum.of.squares.total <- sum((y - mean(y))^2)  
sum.of.squared.errors.lm <- sum(residuals(linear_model)^2)  
print(r.squared.lm <- 1 - sum.of.squared.errors.lm/sum.of.squares.total)
```

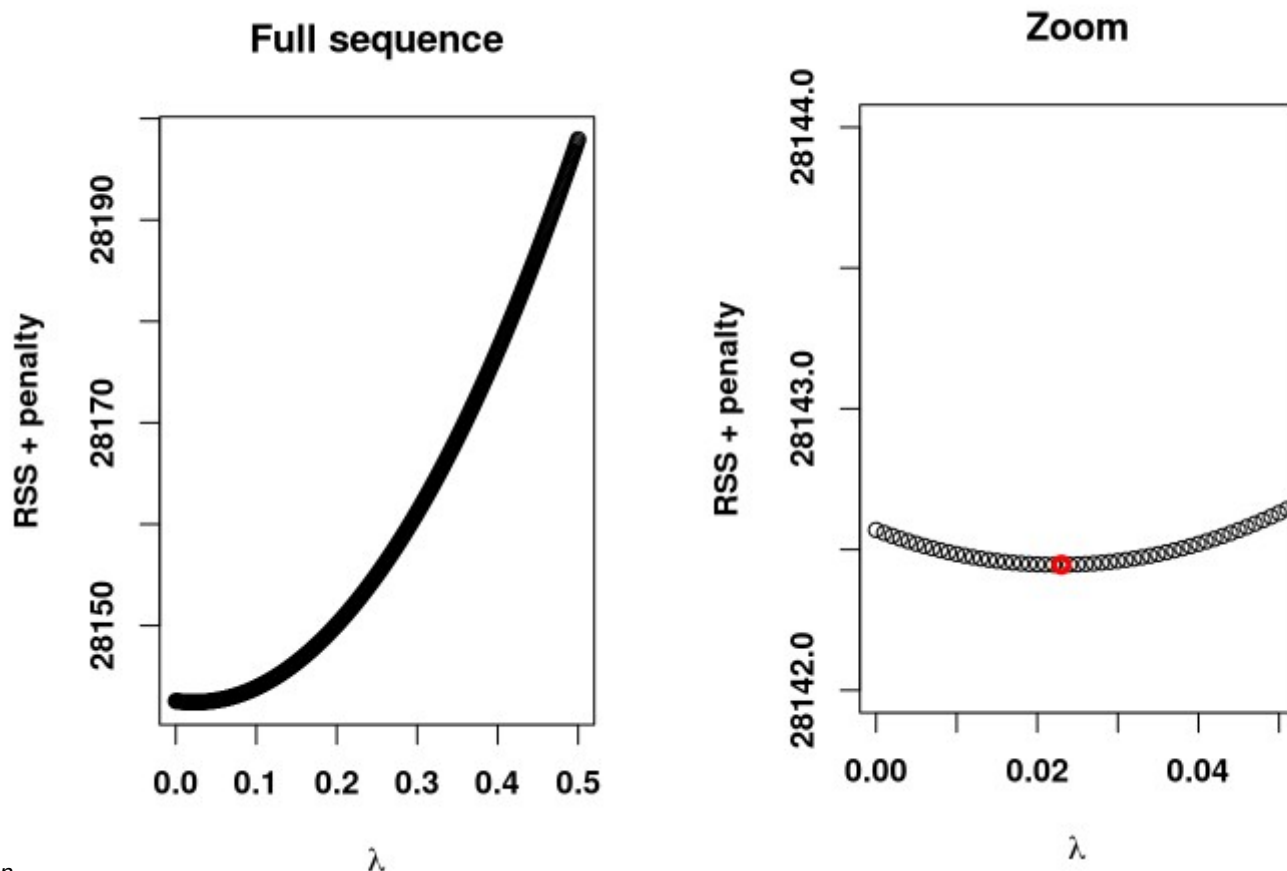
```
## [1] 0.8072553
```

# How to choose $\lambda_{(lasso)}$ ?

```
##
## Call:  glmnet(x = x, y = y, alpha = 1, lambda = c(0, 0.2, 2, 4, 20,
100))
##
```

				lambda	RSS	penalty	sum
##	Df	%Dev	Lambda				
## 1	0	0.0000	100.0	100.0	145726.9	0.0	145726.9
## 2	2	0.6567	20.0	20.00000	50025.64218	14.05496	50039.69714
## 3	3	0.8004	4.0	4.00000	29082.92003	41.34363	29124.26366
## 4	3	0.8051	2.0	2.00000	28408.50683	44.99057	28453.49740
## 5	4	0.8072	0.2	0.20000	28097.60764	52.47741	28150.08505
## 6	4	0.8073	0.0	0.00000	28088.09951	54.46997	28142.56948

# How to choose $\lambda$ ?



# What does $\lambda$ do?

$$\hat{\beta}_{ridge} = (X^T X + \lambda I)^{-1} X^T y$$

$I$ : an identity matrix with  $p$  predictor variables

$\lambda$ : a constant

# What is $X^T X$ ?

```
head(X)
```

```
##                (Intercept)  mpg    wt drat  qsec
## Mazda RX4                1 21.0 2.620 3.90 16.46
## Mazda RX4 Wag            1 21.0 2.875 3.90 17.02
## Datsun 710                 1 22.8 2.320 3.85 18.61
## Hornet 4 Drive             1 21.4 3.215 3.08 19.44
## Hornet Sportabout         1 18.7 3.440 3.15 17.02
## Valiant                    1 18.1 3.460 2.76 20.22
```

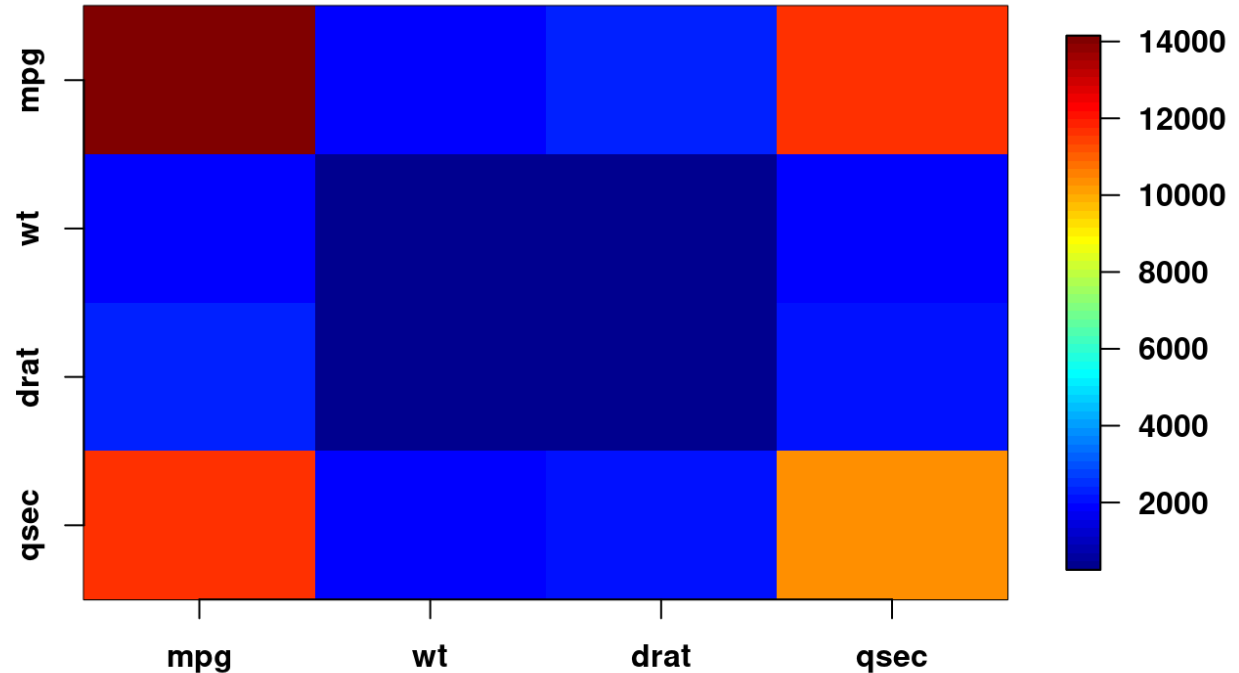
```
print(cov.X)
```

$$X_{COV} = X^T X$$

```
##                mpg          wt          drat          qsec
## mpg  14042.310 1909.7528 2380.2770 11614.745
## wt   1909.753  360.9011  358.7190  1828.095
## drat 2380.277  358.7190  422.7907  2056.914
## qsec 11614.745 1828.0946 2056.9140 10293.480
```

$$X_{COV} = X^T X$$

Covariance matrix



The fact that the off-diagonal  $> 0$ , indicates that there is **collinearity**

# Collinearity can be bad

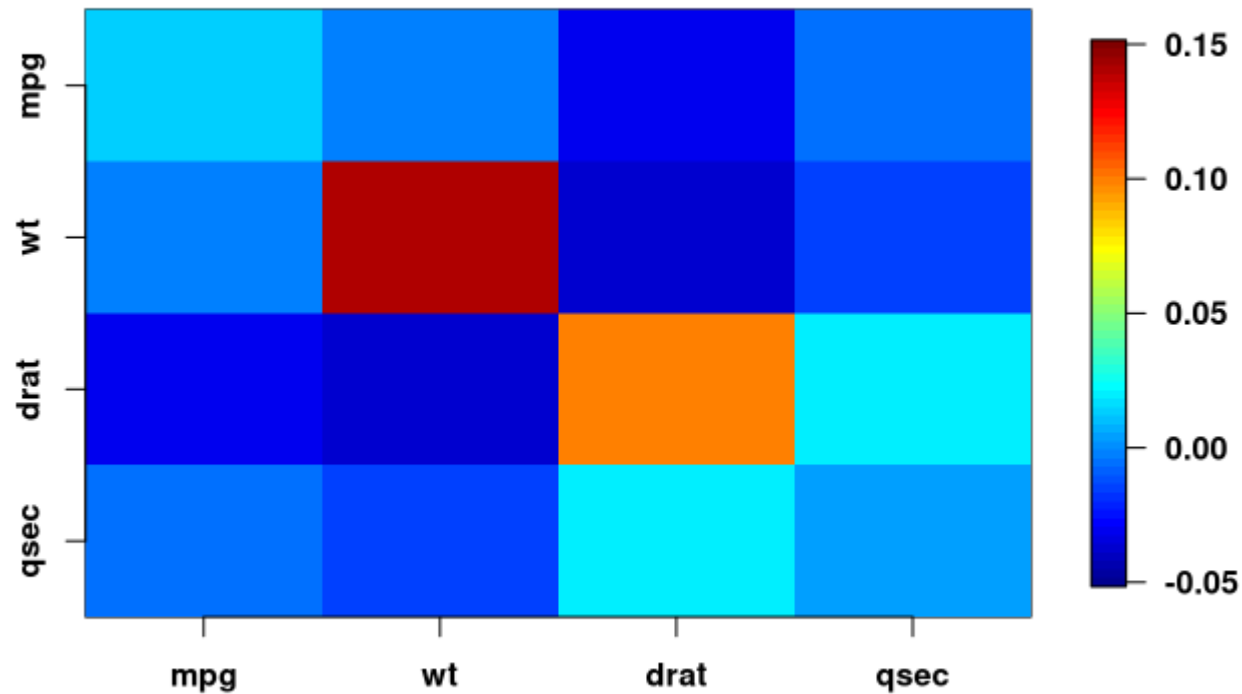
```
##  
## Call:  
## lm(formula = hp ~ mpg + wt + drat + qsec, data = mtcars)  
##  
## Coefficients:  
## (Intercept)          mpg           wt          drat          qsec  
##      473.779       -2.877       26.037        4.819       -20.751
```

Assuming no collinearity, what is the interpretation of the coefficients?  
With collinearity, is that interpretation possible?



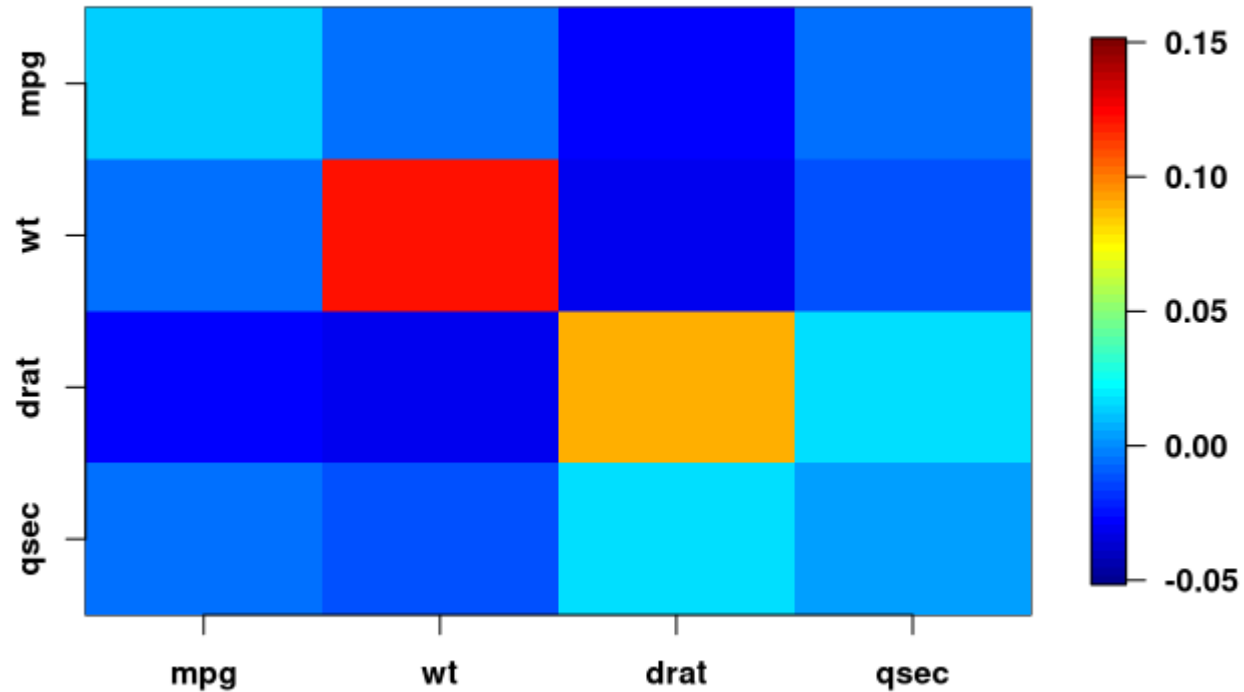
$$\hat{\beta}_{ridge} = (X^T X + \lambda I)^{-1} X^T y$$

Inverted Covariance matrix, regularized:(lambda= 0 )



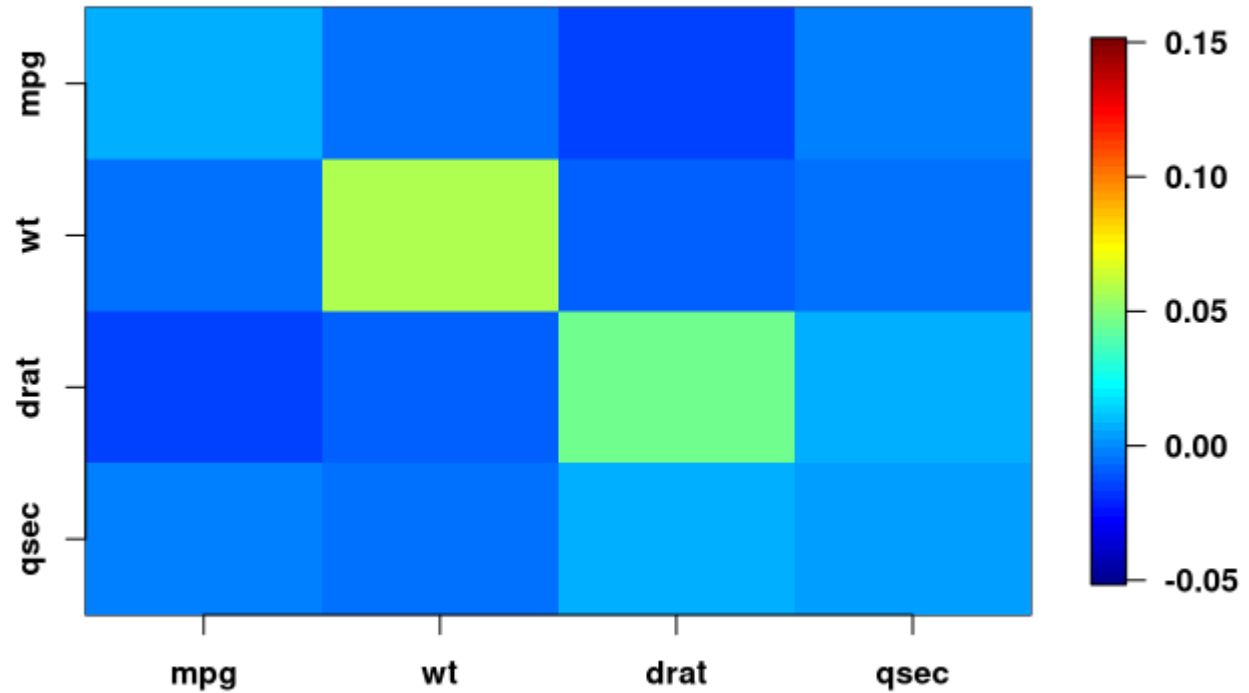
$$\hat{\beta}_{ridge} = (X^T X + \lambda I)^{-1} X^T y$$

Inverted Covariance matrix, regularized:(lambda= 1 )



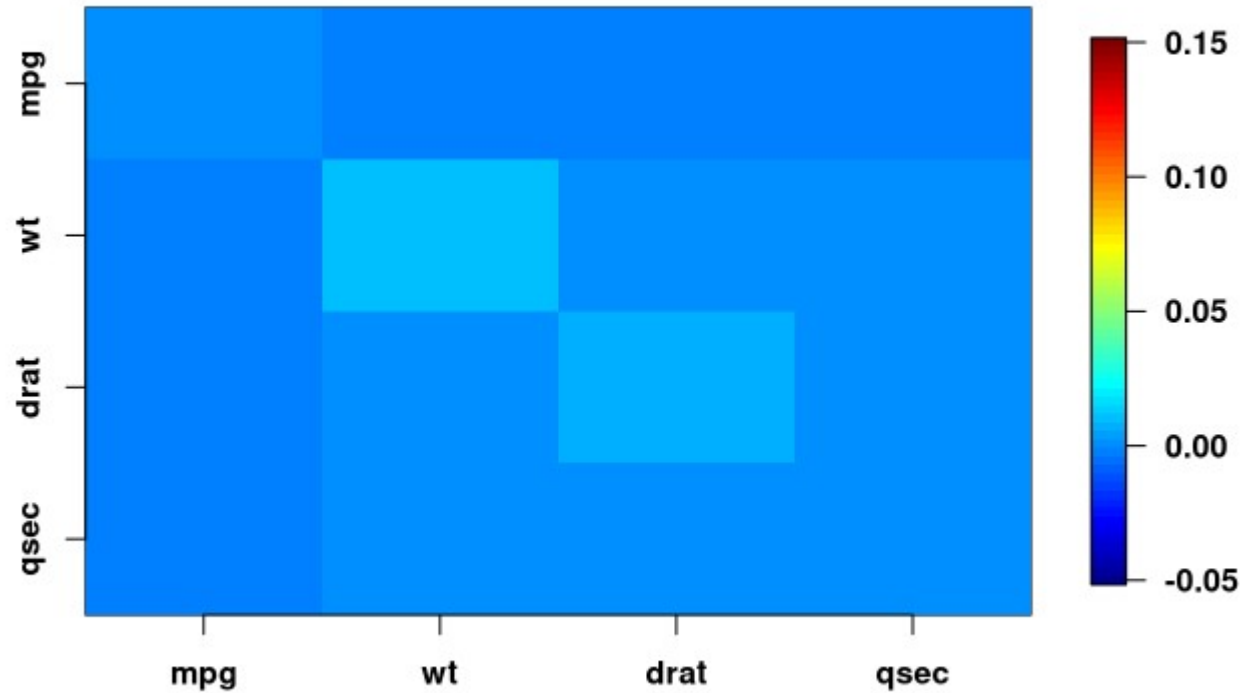
$$\hat{\beta}_{ridge} = (X^T X + \lambda I)^{-1} X^T y$$

Inverted Covariance matrix, regularized:(lambda= 10 )



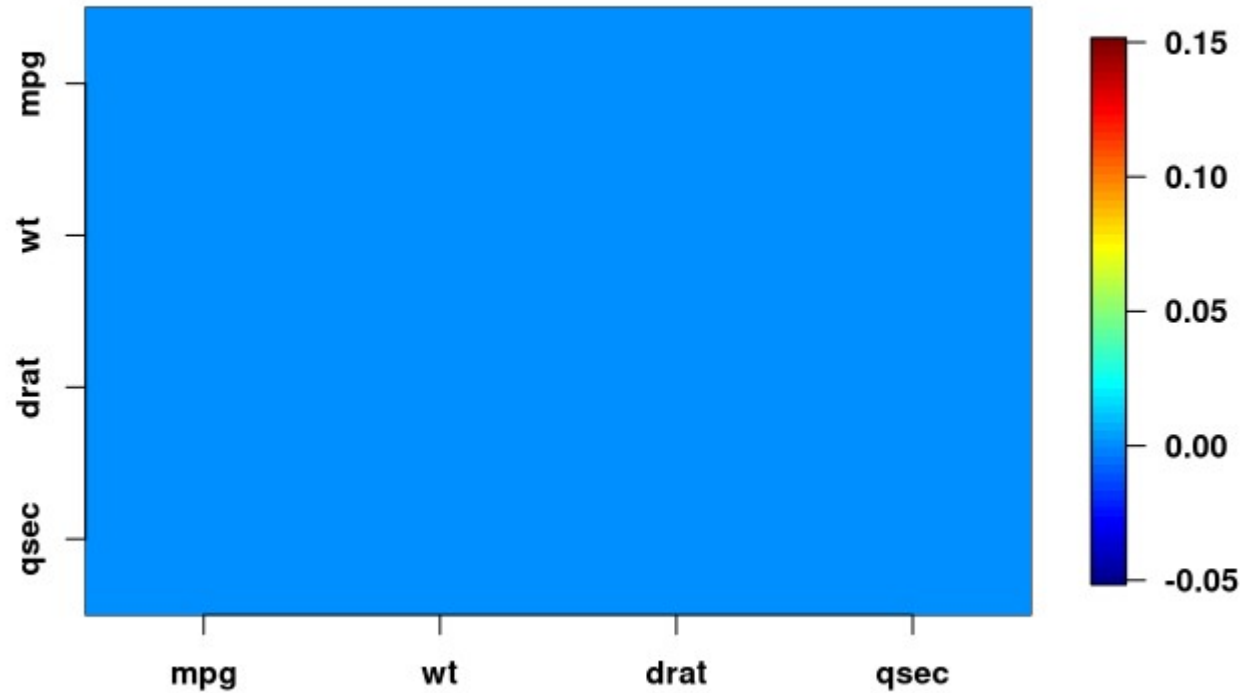
$$\hat{\beta}_{ridge} = (X^T X + \lambda I)^{-1} X^T y$$

Inverted Covariance matrix, regularized:(lambda= 100 )



$$\hat{\beta}_{ridge} = (X^T X + \lambda I)^{-1} X^T y$$

Inverted Covariance matrix, regularized:(lambda= 1000 )



**So why is it called  
regularisation?**

# Two notes about the inverted matrix:

with increase of  $\lambda$

1. Diagonal shrinks (bias is added)
2. Off-diagonal shrinks (collinearity is reduced, which improves the stability of the model)

# Stability of a model:

Feeding new data or adding new predictor variables will not change the parameter estimates a lot



We have succeeded in finding a  $\lambda$  making our model more stable (improved **in-sample** validity), but we haven't found a  $\lambda$  that optimises predictive power – (**out-of-sample**) – week 6)

# Did you learn?

*Explanation and prediction*

- 1) Understanding that fitting (explaining) often leads to overfitting
- 2) Learning methods to prevent overfitting by introducing *bias*
- 3) Understanding how the error can be decomposed into *bias* and *variance*

# References

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