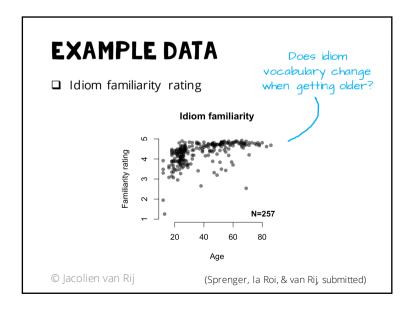
# ADVANCED STATISTICAL MODELING

Version 1, 2018

Jacolien van Rij [j.c.van.rij@rug.nl] Hermine Berberyan, and Stefan Huijser Today's topic

# INTRODUCTION LINEAR MODEL



### **HYPOTHESIS TESTING**

- ☐ Statistical hypothesis ≠ research hypothesis
- ☐ Example:
  - RH: Idiom vocabulary increases with age.

Older participants will know more idioms than younger participants.

• SH: Difference idiom vocabulary<sub>old</sub> – Idiom vocabulary<sub>young</sub> is larger than 0.

 $\circ$  Hn = 0

older participants

o H<sub>1</sub> > 0

← know more idioms

 $\circ H_2 < 0$ 

younger participantsknow more idioms

### STATISTICAL TEST

- $\Box$  Calculates the probability that  $H_0$  is true
  - $\alpha$  : significance level of test
- ☐ Errors in statistical conclusions:

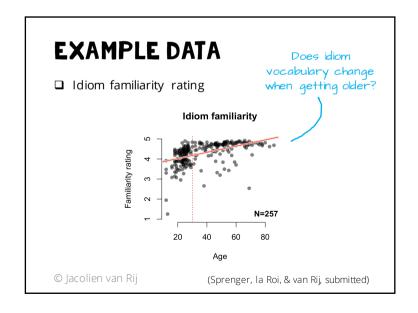
	decision:	
	retain H <sub>0</sub>	reject H₀
H <sub>0</sub> is true	correct decision	type I error
H <sub>0</sub> is false	type II error	correct decision

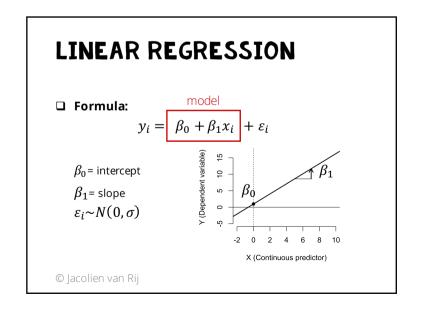
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## STATISTICAL TEST

- $\Box$  Calculates the probability that  $H_0$  is true
  - $\alpha$  : significance level of test
  - **β**: power of test
- ☐ Errors in statistical conclusions:

	decision:	
	retain H₀	reject H₀
H <sub>0</sub> is true	1 – α	<mark>α</mark> (type l error)
H <sub>0</sub> is false	β (type II error)	$1-\beta$
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### LINEAR REGRESSION

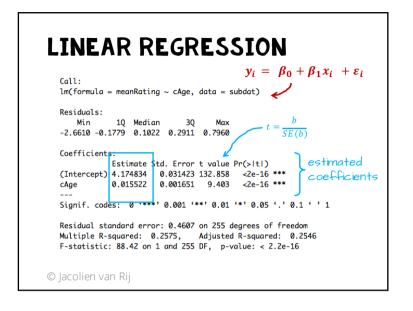
m1 <- lm(Rating ~ Age, data=subdat)
summary(m1)</pre>

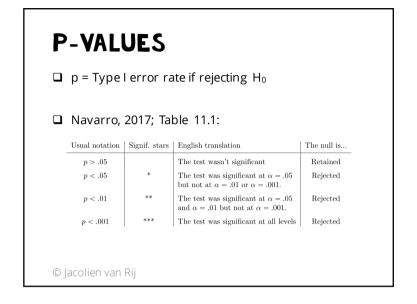
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# LINEAR REGRESSION y = 3.709 + 0.0155\*Age Idiom familiarity Idiom familiarity N=257 20 40 60 80 Age © Jacolien van Rij (Sprenger, la Roi, & van Rij, submitted)

### LINEAR REGRESSION $y_i = \beta_0 + \beta_1 x_i + \varepsilon_i$ lm(formula = meanRating ~ Age, data = subdat) Residuals: Min 1Q Median 3Q Max -2.6610 -0.1779 0.1022 0.2911 0.7960 Coefficients: estimated Estimate 5td. Error t value Pr(>|t|) coefficients 0.015522 0.001651 9.403 <2e-16 \*\*\* Signif. codes: 0 '\*\*\* 0.001 '\*\* 0.01 '\* 0.05 '.' 0.1 ' 1 Residual standard error: 0.4607 on 255 degrees of freedom Multiple R-squared: 0.2575, Adjusted R-squared: 0.2546 F-statistic: 88.42 on 1 and 255 DF, p-value: < 2.2e-16 © Jacolien van Rij

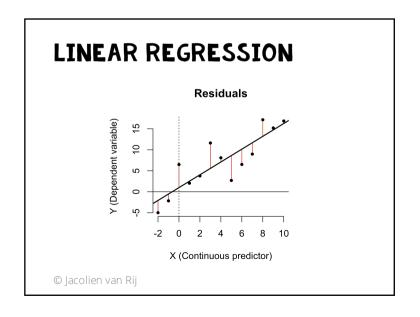
### **CENTERING**







- Selection coefficients
  - minimizing sum of squared residuals:  $\sum_{i=1}^{N} (Y_i \hat{Y}_i)^2$
  - residuals = unexplained part of data



### **REGRESSION ANALYSIS**

DATA = MODEL + RESIDUALS

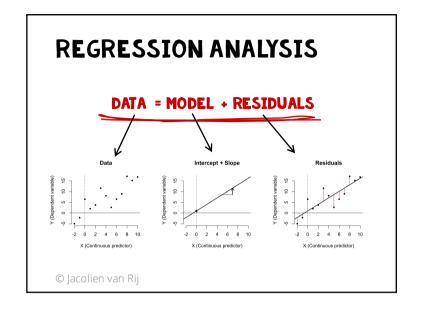
### ■ Model:

- Explanation / description of data
- Fitted effects, model estimates

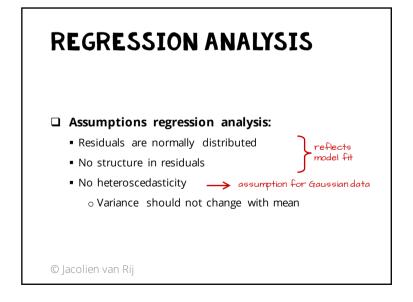
### ☐ Error:

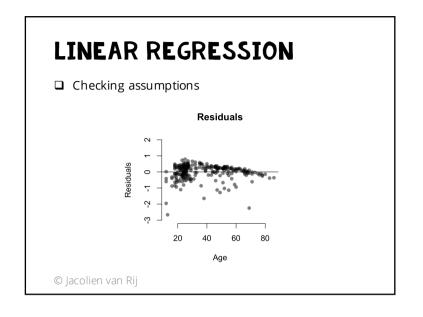
- Unexplained part of data
- Residuals

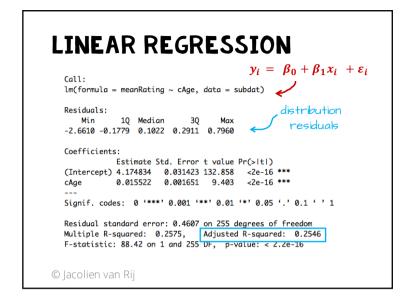
© Jacolien van Rij



# LINEAR REGRESSION model $y_i = \beta_0 + \beta_1 x_i + \epsilon_i$ Call: $lm(formula = meanRating \sim cAge, data = subdat)$ Residuals: $min \quad 10 \quad Median \quad 30 \quad Max \\ -2.6610 \quad -0.1779 \quad 0.1022 \quad 0.2911 \quad 0.7960$ Coefficients: $Estimate \quad Std. \quad Error \quad t \quad value \quad Pr(>|t|) \\ (Intercept) \quad 4.174834 \quad 0.031423 \quad 132.858 \quad <2e-16 \quad *** \\ cAge \quad 0.015522 \quad 0.001651 \quad 9.403 \quad <2e-16 \quad *** \\ cAge \quad 0.015522 \quad 0.001651 \quad 9.403 \quad <2e-16 \quad *** \\ cAge \quad 0.015522 \quad 0.001651 \quad 9.403 \quad <2e-16 \quad *** \\ cAge \quad 0.015522 \quad 0.001651 \quad 9.403 \quad <2e-16 \quad *** \\ cAge \quad 0.015522 \quad 0.001651 \quad 9.403 \quad <2e-16 \quad *** \\ cAge \quad 0.015522 \quad 0.001651 \quad 9.403 \quad <2e-16 \quad *** \\ cAge \quad 0.015522 \quad 0.001651 \quad 9.403 \quad <2e-16 \quad *** \\ cAge \quad 0.015522 \quad 0.001651 \quad 9.403 \quad <2e-16 \quad *** \\ cAge \quad 0.015522 \quad 0.001651 \quad 9.403 \quad <2e-16 \quad *** \\ cAge \quad 0.015522 \quad 0.001651 \quad 9.403 \quad <2e-16 \quad *** \\ cAge \quad 0.015522 \quad 0.001651 \quad 9.403 \quad <2e-16 \quad *** \\ cAge \quad 0.015522 \quad 0.001651 \quad 9.403 \quad <2e-16 \quad *** \\ cAge \quad 0.015522 \quad 0.001651 \quad 9.403 \quad <2e-16 \quad *** \\ cAge \quad 0.015522 \quad 0.001651 \quad 9.403 \quad <2e-16 \quad *** \\ cAge \quad 0.015522 \quad 0.001651 \quad 9.403 \quad <2e-16 \quad *** \\ cAge \quad 0.015522 \quad 0.001651 \quad 9.403 \quad <2e-16 \quad *** \\ cAge \quad 0.015522 \quad 0.001651 \quad 9.403 \quad <2e-16 \quad *** \\ cAge \quad 0.015522 \quad 0.001651 \quad 9.403 \quad <2e-16 \quad *** \\ cAge \quad 0.015522 \quad 0.001651 \quad 9.403 \quad <2e-16 \quad *** \\ cAge \quad 0.015522 \quad 0.001651 \quad 9.403 \quad <2e-16 \quad *** \\ cAge \quad 0.015522 \quad 0.001651 \quad 9.403 \quad <2e-16 \quad *** \\ cAge \quad 0.015522 \quad 0.001651 \quad 9.403 \quad <2e-16 \quad *** \\ cAge \quad 0.015522 \quad 0.001651 \quad 9.403 \quad <2e-16 \quad *** \\ cAge \quad 0.015522 \quad 0.001651 \quad 9.403 \quad <2e-16 \quad *** \\ cAge \quad 0.015522 \quad 0.001651 \quad 9.403 \quad <2e-16 \quad *** \\ cAge \quad 0.015522 \quad 0.001651 \quad 9.403 \quad <2e-16 \quad *** \\ cAge \quad 0.015522 \quad 0.001651 \quad 9.403 \quad <2e-16 \quad *** \\ cAge \quad 0.015522 \quad 0.001651 \quad 9.403 \quad <2e-16 \quad *** \\ cAge \quad 0.015522 \quad 0.001651 \quad 9.403 \quad <2e-16 \quad *** \\ cAge \quad 0.015522 \quad 0.001651 \quad 9.403 \quad <2e-16 \quad *** \\ cAge \quad 0.015522 \quad 0.001651 \quad 9.403 \quad <2e-16 \quad *** \\ cAge \quad 0.015522 \quad 0.001651 \quad 9.403 \quad <2e-16 \quad *** \\ cAge \quad 0.015522 \quad 0.001651 \quad 9.403 \quad <2e-16 \quad *** \\ cAge \quad 0$









- $\square$  sum of squared residuals:  $SS_{res} = \sum_{i=1}^{N} (Y_i \hat{Y}_i)^2$
- $\label{eq:sstot} \ \ \, \square \ \ \, \text{total variability:} \qquad \qquad SS_{\text{tot}} = \sum_{i=1}^N (Y_i Y)^2$
- $\square R^2 = 1 \frac{ssres}{sstot}$
- $\Box$  adjusted  $R^2 = 1 \left(\frac{SSres}{SStot} \times \frac{N-1}{N-K-1}\right)$

degrees of freedom of model (K=number of predictors)

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## CATEGORICAL PREDICTOR

m2 <- lm(Rating ~ cAge+gender, data=subdat)
summary(m2)</pre>

Semester Ib 2018/2019

### CATEGORICAL PREDICTOR

### **MODEL COMPARISONS**

```
anova(m1, m2)
```

```
Analysis of Variance Table
```

```
Model 1: meanRating ~ cAge
Model 2: meanRating ~ cAge + gender
Res.Df RSS Df Sum of Sq F Pr(>F)
1 255 54.111
2 254 54.109 1 0.0023534 0.011 0.9164
```

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### **MODEL COMPARISONS**

```
m0 <- lm(Rating ~ 1, data=subdat)
anova(m0, m1)</pre>
```

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### **MODEL COMPARISONS**

```
anova(m2) — Do not use the function like this, order matters!
```

```
Analysis of Variance Table
```