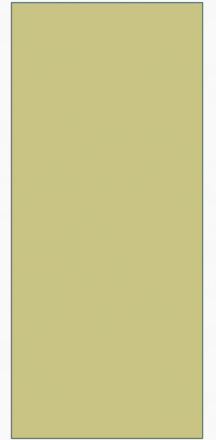


EDUCATION AND VOCABULARY

MULTIPLE REGRESSION IN ACTION



EDUCATION AND VOCABULARY

- 5-10 hours of input weekly is enough to pick up a new language (Schiff & Myers, 1988).
- Dutch children spend 5.5 hours/day in front of a screen (Valkenburg, 2013).
- Most of this input is in English.
- How much does education contribute?

RESEARCH QUESTION

Does the amount of time children are taught English weekly predict the size of their English vocabulary, or are there other factors – and if so, to what extent are they correlated with English vocabulary?

STUDY

- Participants
 - 72 Dutch children;
 - Primary school classes 5 and 6;
 - Age 8 – 10, but expressed in months ($m=113.5$);
 - 33 males, 39 females.
- Schools matched for
 - Low-risk;
 - High SES;
 - Urban environment;
 - No other official languages (like Frisian);
 - Cito scores.

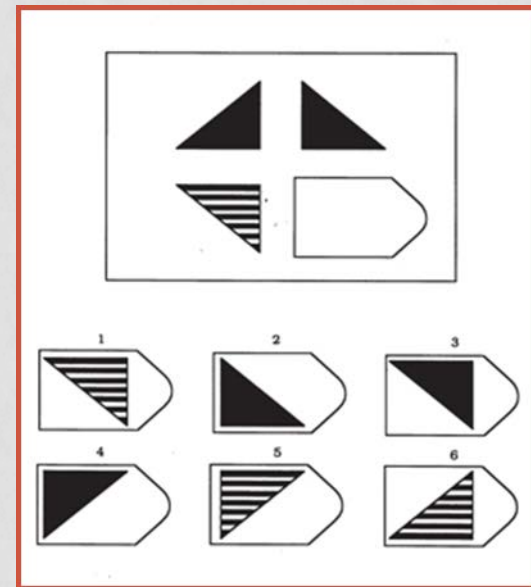
STUDY

- Hours of English:
 - School 1, which teaches 4 hours of English weekly. We tested 32 students, 4 of which were left out due to missing or unusable data*.
 - School 2, which teaches 2 hours of English weekly. We tested 34 students, 10 of which were left out .
 - School 3, which teaches no English in groups 5 and 6 (control). We tested 31 students, 11 of which were left out.

* Technical problems, learning disabilities, etc.

TOOLS

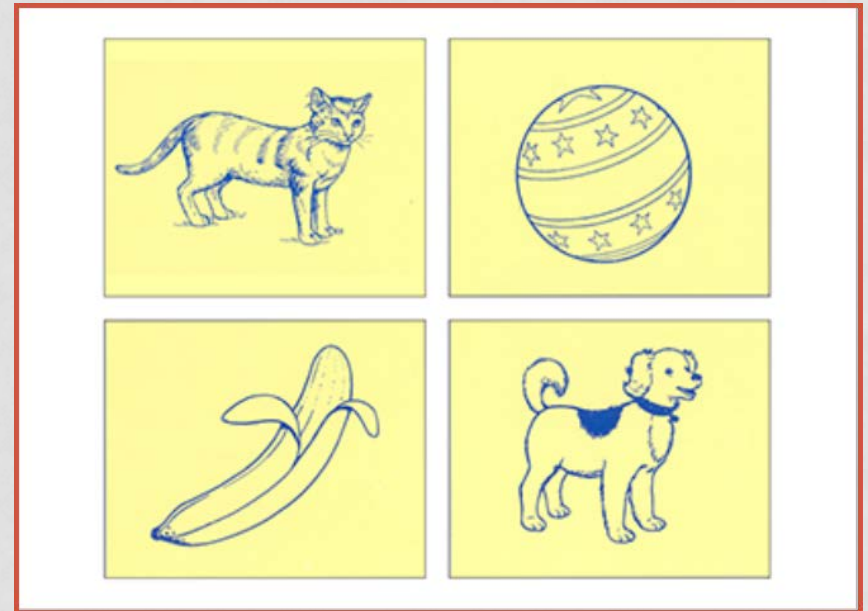
- Raven intelligence test, power version:
 - 48 questions;
 - 20 minutes;
 - Score = total correct.



Example Raven exercise, from
<http://www.talentlens.nl>

TOOLS

- Peabody NL (language aptitude):
 - Dutch words presented over headphone;
 - Subjects must click on matching picture out of 4;
 - Score = total correct;
 - Increasing difficulty;
 - Max score = 204.



Example Peabody NL exercise. Test developed by Pearson and software developed by Dr. Claire Stevenson, University of Leiden.

TOOLS

- Peabody EN (English vocabulary):
 - English words presented over headphone;
 - Subjects must click on matching picture out of 4;
 - Score = total correct;
 - Increasing difficulty;
 - Max score = 228.



Example Peabody EN exercise. Test developed by Pearson and software developed by Dr. Claire Stevenson, University of Leiden.

FORMULA

Peabody EN score_{*i*} = ($b_0 + b_1 \text{ hours}_i + b_2 \text{ aptitude}_i + b_3 \text{ age}_i + b_4 \text{ intelligence}_i$) + ε_i

SIMPLE REGRESSION

R Output

```
> englishSR<-lm(pben ~ hours, data=english)
> summary(englishSR)
```

```
Call:
lm(formula = pben ~ hours, data = english)
```

```
Residuals:
    Min     1Q  Median     3Q     Max
-36.87 -25.34 -15.32  20.57 110.91
```

```
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  31.318     6.886  4.548 2.21e-05 ***
hours         4.388     2.505  1.752  0.0842 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Residual standard error: 34.39 on 70 degrees of freedom
Multiple R-squared:  0.04199, Adjusted R-squared:  0.0283
F-statistic: 3.068 on 1 and 70 DF, p-value: 0.08424
```

Interpretation

- Hours of English explains only 4.2% of the variation in PBEN.
- Not significant.

MULTIPLE REGRESSION

R Output

```
> englishMR<-lm(pben ~ hours + age + raven + pbnl, data=english)
> summary(englishMR)
```

```
Call:
lm(formula = pben ~ hours + age + raven + pbnl, data = english)
```

Residuals:

Min	1Q	Median	3Q	Max
-46.274	-15.792	-3.031	18.155	58.196

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-275.7125	46.2748	-5.958	1.05e-07 ***
hours	-0.3710	2.2422	-0.165	0.869098
age	1.2612	0.3471	3.633	0.000543 ***
raven	1.2722	0.4780	2.661	0.009732 **
pbnl	1.4268	0.2486	5.739	2.51e-07 ***

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

Residual standard error: 25.55 on 67 degrees of freedom
Multiple R-squared: 0.4939, Adjusted R-squared: 0.4637
F-statistic: 16.34 on 4 and 67 DF, p-value: 2.172e-09

Interpretation

- Age, intelligence and aptitude account for an extra 45%.
- Adjusted R² is 3% less.
- Highly significant at P < 0.001.

INTERPRETATION

- As hours increases by one unit, PBEN decreases by 0.37 units (!)
 - However, the contribution of this variable to the model is highly insignificant at $P = 0.87$.
- As age increases by one unit, PBEN increases by 1.25 units.
 - Highly significant contribution at $P < 0.001$
- As intelligence increases by one unit, PBEN increases by 1.19 units.
 - Highly significant contribution at $P < 0.01$
- As aptitude increases by one unit, PBEN increases by 1.5 units.
 - Highly significant contribution at $P < 0.001$

STANDARDIZED B-VALUES

R Output

```
> lm.beta(englishMR)
hours      age      raven      pbnl
-0.01732222  0.31904493  0.27639488  0.51697292
```

Interpretation

- Number of SDs by which PBEN will change as each of the predictors changes by 1 SD (all other predictors being equal!).
- Directly comparable;
- Better insight into weight of each variable.

CONFIDENCE INTERVALS

R Output

```
> confint(englishMR)
                2.5 %      97.5 %
(Intercept) -368.0773784 -183.347680
hours       -4.8464871   4.104587
age         0.5683334   1.954122
raven      0.3180700   2.226378
pbnl       0.9305210   1.923057
```

Interpretation

- The confidence bands for each of the predictors is small, except for hours.
- Hours crosses 0: sometimes the relationship is positive, sometimes negative.
- BAD.

COMPARING MODELS

R Output

```
> anova(englishSR, englishMR)
Analysis of Variance Table

Model 1: pben ~ hours
Model 2: pben ~ hours + age + raven + pbnl
```

	Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
1	70	82790				
2	67	43739	3	39051	19.94	2.401e-09 ***

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

Interpretation

- EnglishMR is a significantly better fit to the data compared to EnglishSR, $F(3, 67) = 19.94$, $p < 0.001$.

DIAGNOSTICS

R Output

```
> english$standardized.residuals<-rstandard(englishMR)
> english$large.residual<-english$standardized.residuals > 2 |
english$standardized.residuals < -2
sum(english$large.residual)
[1] 3

> english[english$large.residual, c("pben", "age", "raven", "pbnl", "hours",
"standardized.residuals")]
  pben age raven pbnl hours standardized.residuals
1  149 128  39   110    4      2.389620
48  151 117  41   121    2      2.285620
56   92 109  27    99    0      2.198725
```

Interpretation

- Sample = 72
- 95% of residuals should be within +/- 2 (SD).
- 5% should be outside.
- 5% of 72 = 3.6
- 3 or 4 outliers
- We have 3.
- Fine.

DIAGNOSTICS

R Output

```
> english$cooks<-cooks.distance(englishMR)
> english$leverage<-hatvalues(englishMR)
> english$covariance<-covratio(englishMR)
> english[english$large.residual, c("cooks", "leverage", "covariance")]
```

	cooks	leverage	covariance
1	0.11501253	0.09149260	0.7601336
48	0.12934210	0.11015771	0.8073542
56	0.05533664	0.05413405	0.7837935

Interpretation

- Cook's distance should be < 1 .
- Leverage should be $< 2(k + 1/n)$;
 - $2(5/72) = 0.14$
- Covariance ratio
 - $CVR_i < 1 + [3(k + 1)/n]$
 - $CVR_i < 1 + [3(4 + 1)/72] = 1.08$
 - $CVR_i > 1 - [3(k + 1)/n]$
 - $CVR_i > 1 - [3(4 + 1)/72] = 0.79$
- #1 is lowish, but see Cook's distance.

INDEPENDENCE

R Output

```
> dwt(englishMR)
lag Autocorrelation D-W Statistic p-value
 1  0.07124528  1.778073 0.228
Alternative hypothesis: rho != 0
```

Interpretation

- Durbin-Watson tests assumption of independent errors.
- Should be close to 2 and not <1 or >3 .
- Fine at 1.78.

NO MULTICOLLINEARITY

R Output

```
> vif(englishMR)
hours      age      raven      pbnl
1.451289   1.020795  1.427768  1.074327

> 1/vif(englishMR)
hours      age      raven      pbnl
0.6890425  0.9796286  0.7003941  0.9308155

> mean(vif(englishMR))
[1] 1.243545
```

Interpretation

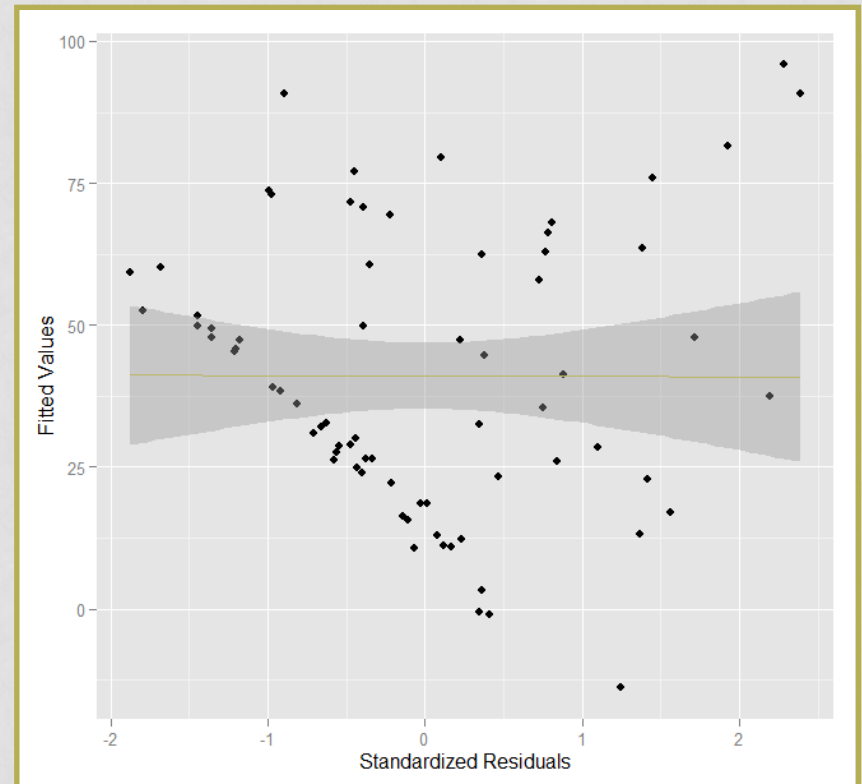
- VIF to assess multicollinearity.
- Tolerance = $1/\text{VIF}$.
- Largest VIF > 10 means problem.
- Mean VIF much > 1 means problem.
- Tolerance < 0.2 means potential problem.
- All fine.

RESIDUALS

R Output

```
> english$fitted <- englishMR$fitted.values  
> scatterResiduals<-ggplot(english, aes(standardized.residuals, fitted))  
> scatterResiduals<-scatterResiduals + geom_point() +  
geom_smooth(method="lm", colour="darkkhaki") + labs(x="Standardized  
Residuals", y="Fitted Values")  
> scatterResiduals
```

Visualizing residuals

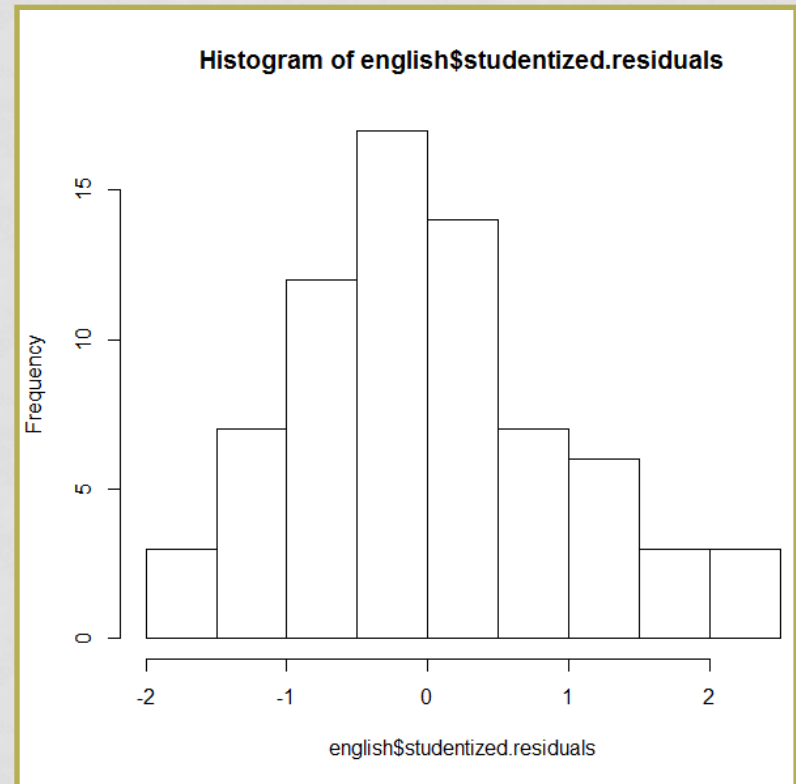


RESIDUALS

R Output

```
> hist(english$studentized.residuals)
```

Visualizing residuals



INTERPRETING RESIDUALS

- Some heteroscedascity and non-linearity.
- Distribution of residuals seems normal.

CONCLUSION

- Assumption of homoscedascity and linearity of residuals violated.
- Findings cannot be generalized beyond sample (yet).
- Options:
 - Logistic regression
 - Robust regression

CONCLUSION

- Hours of education does not predict PBEN score.
- Rather, a combination of age, intelligence and language aptitude does.

REFERENCES

- Field, A. et al (2012). *Discovering statistics using R*. London: Sage Publications Ltd.
- Moore, D. S. et al (2012). *Introduction to the practice of statistics*. New York: W. H. Freeman and Company.
- Schiff-Myers, N., Klein, H. (1985). Some phonological characteristics of the speech of normal-hearing children of Deaf parents. *Journal of Speech and Hearing Research*, 28(4), 466-474.
- Valkenburg, P. et al. (2013). Developing and validating the perceived parental media mediation scale: A self-determination perspective. *Human Communication Research*, 39. 445-469.