# Linear Regression Examples

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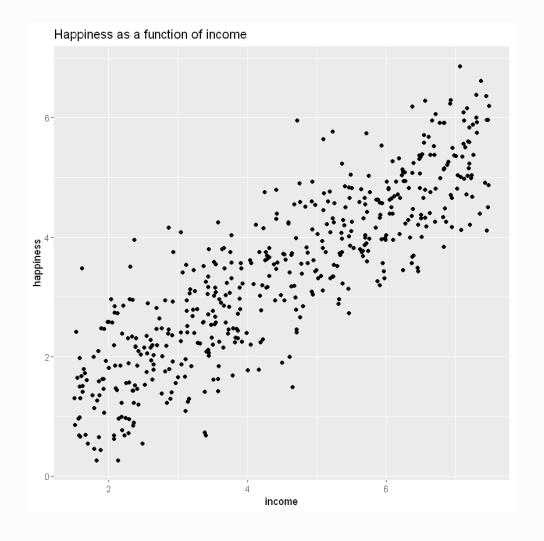
# Example 1 Income and Happiness

# Road Map

- Explore the dataset
- Split the dataset into training and test, randomly (50-50 split)
- Use the training dataset to fit the model
- Use the test dataset to evaluate the model
- Interpret the results and extract knowledge/advice.

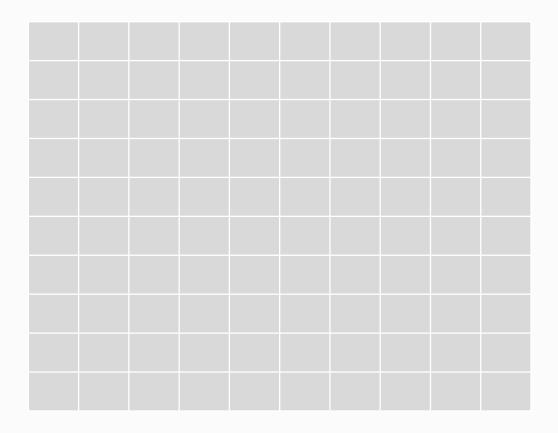
# Income Happiness Dataset

| income   | happiness |
|----------|-----------|
| 3.862647 | 2.314489  |
| 4.979381 | 3.433490  |
| 4.923957 | 4.599373  |
| 3.214372 | 2.791114  |
| 7.196409 | 5.596398  |
| 3.729643 | 2.458556  |



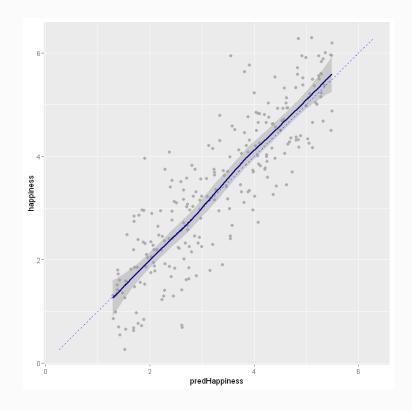
### Residuals

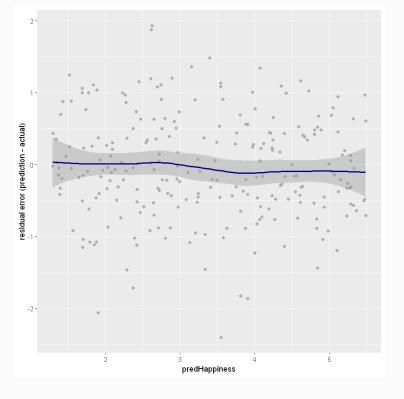
- Prediction Quality
  - Systematic errors?



# Analyse the Residuals

Residuals:
Min 1Q Median 3Q Max
-1.99990 -0.47966 -0.01526 0.48223 2.11681





#### R-Squared

$$R^{2} = 1 - \frac{\sum_{i=1}^{n} (p - o)^{2}}{\sum_{i=1}^{n} (\mu - o)^{2}}$$

- Over the training dataset: 0.7445
- Over the test dataset: 0.7531



# Interpreting Coefficients

- The interpretation of the slope (value = 0.70245) is that happiness rate increases 0.70 units, on average, for each one unit (one percent) increase in the income.
- The interpretation of the intercept (value=0.23226) is that if income = 0, the predicted average happiness rate would be 0.23

# Example 2 Predict Income

# Linear Regression

Suppose you want to predict personal income of any individual in the general public, within some relative percent, given their age, education, and other demographic variables. In addition to predicting income, you also have a secondary goal: to determine the effect of a bachelor's degree on income, relative to having no degree at all.

• From: Practical Data Science with R, 2<sup>nd</sup> Edition. Nina Zumel and John Mount. [Chapter 7]

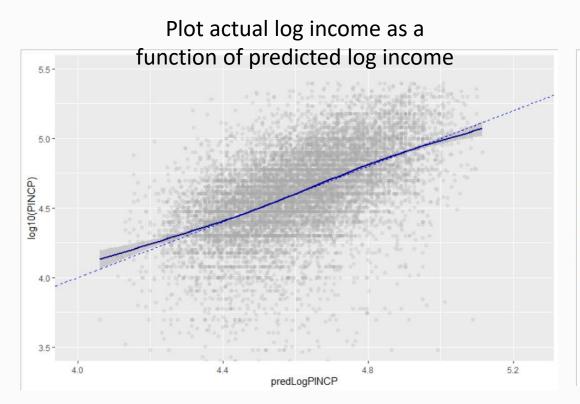
# The dataset

Formula: log10(PINCP) ~ AGEP + SEX + COW + SCHL

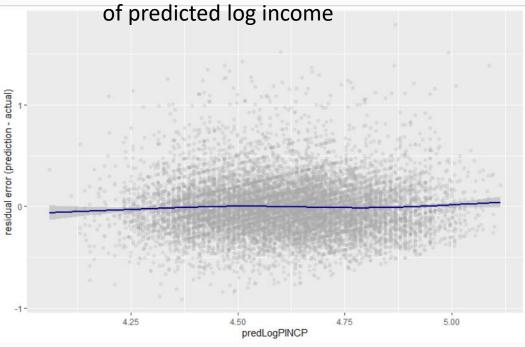
- Records = 22241
- Features = 204

| RT | SERIALNO  | SPORDER | PUMA  | ST         | ADJINC  | AGEP | CIT                       | CITWP | COW                                       | <br>FSEXP | FSSIP | FSSP | FWAGP | FWKHP | FWKLP |
|----|-----------|---------|-------|------------|---------|------|---------------------------|-------|---|-----------|-------|------|-------|-------|-------|
| Р  | 000006646 | 03      | 02400 | Alabama/AL | 1007588 | 24   | Born<br>in<br>the<br>U.S. | NA    | Employee<br>of a<br>private for<br>profit | <br>No    | Yes   | Yes  | Yes   | Yes   | Yes   |
| Р  | 000008359 | 04      | 02702 | Alabama/AL | 1007588 | 31   | Born<br>in<br>the<br>U.S. | NA    | Private<br>not-for-<br>profit<br>employee | <br>No    | No    | No   | Yes   | No    | No    |
| Р  | 000015018 | 01      | 00400 | Alabama/AL | 1007588 | 26   | Born<br>in<br>the<br>U.S. | NA    | Employee<br>of a<br>private for<br>profit | <br>No    | No    | No   | No    | No    | No    |
| Р  | 000017383 | 04      | 02400 | Alabama/AL | 1007588 | 27   | Born<br>in<br>the<br>U.S. | NA    | Employee<br>of a<br>private for<br>profit | <br>No    | No    | No   | No    | No    | No    |
| Р  | 000030038 | 02      | 02100 | Alabama/AL | 1007588 | 27   | Born<br>in<br>the<br>U.S. | NA    | Private<br>not-for-<br>profit<br>employee | <br>No    | No    | No   | No    | No    | No    |
| Р  | 000033559 | 02      | 02500 | Alabama/AL | 1007588 | 47   | Born<br>in<br>the<br>U.S. | NA    | Employee<br>of a<br>private for<br>profit | <br>No    | No    | No   | No    | No    | No    |

# Analysing the Residuals



#### Plot residuals income as a function



#### Extract Relations and Knowledge

• Examples:

```
Coefficients:
                                    Estimate Std. Error t value Pr(>|t|)
(Intercept)
                                   4.0058856 0.0144265 277.676 < 2e-16 ***
AGEP
                                   0.0115985 0.0003032 38.259
SEXFemale
                                  -0.1076883
                                             0.0052567 -20.486
COWFederal government employee
                                                         4.055 5.06e-05 ***
                                   0.0638672 0.0157521
COWLocal government employee
                                  -0.0297093
                                             0.0107370
                                                        -2.767 0.005667 **
COWPrivate not-for-profit employee -0.0330196
                                             0.0102449
                                                        -3.223 0.001272 **
COWSelf employed incorporated
                                   0.0145475 0.0164742
                                                         0.883 0.377232
COWSelf employed not incorporated
                                  -0.1282285 0.0134708
                                                        -9.519 < 2e-16 ***
COWState government employee
                                  -0.0479571
                                             0.0123275
                                                        -3.890 0.000101 ***
SCHLRegular high school diploma
                                   0.1135386 0.0107236 10.588
SCHLGED or alternative credential
                                             0.0173038
                                   0.1216670
                                                         7.031 2.17e-12 ***
SCHLsome college credit, no degree
                                  0.1838278
                                             0.0106461 17.267 < 2e-16 ***
SCHLAssociate's degree
                                   0.2387045 0.0123568 19.318
SCHLBachelor's degree
                                   0.3637114 0.0105810 34.374
SCHLMaster's degree
                                   0.4445777
                                             0.0127100 34.978 < 2e-16 ***
SCHLProfessional degree
                                   0.5111167
                                             0.0201800 25.328 < 2e-16 ***
                                   0.4818700 0.0245162 19.655 < 2e-16 ***
SCHLDoctorate degree
Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
```

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### Residuals Summary

Over the training dataset

```
Min. 1st Qu. Median Mean 3rd Qu. Max.
-1.5038 -0.1354 0.0187 0.0000 0.1710 0.9741
```

Over the test dataset

```
Min. 1st Qu. Median Mean 3rd Qu. Max. -1.789150 -0.130733 0.027413 0.006359 0.175847 0.912646
```

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#### Linear Regression

- Linear regression assumes that the outcome is a linear combination of the input variables.
- If you want to use the coefficients of your model for advice, you should only trust the coefficients that appear statistically significant
- Overly large coefficient magnitudes, overly large standard errors on the coefficient estimates, and the wrong sign on a coefficient could be indications of correlated inputs.
- Linear regression can predict well even in the presence of correlated variables, but correlated variables lower the quality of the advice.
- Linear regression will have trouble with problems that have a very large number of variables, or categorical variables with a very large number of levels.

# Try the following

- Measure R-square for the following:
  - O = (1,2,3,4,5,9,10)
  - P = (0.5, 0.5, 0.5, 0.5, 0.5, 9, 10)

# Reference

• Practical Data Science with R, 2<sup>nd</sup> Edition. Nina Zumel and John Mount. [Chapter 7]

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