

# BAK3: Introduction to Quantitative Methods

## Week 6: Bivariate Descriptive Statistics

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# The Plan for today

- ▶ Statistics: Measuring association between ***two*** variables:
  - ▶ Easy: **cross-tabulations, mean comparisons.**
  - ▶ Hard(er): **covariance** and the **correlation coefficient.**
- ▶ Coding in R:
  - ▶ All this stuff, plus **scatter plots.**

# Review Quiz

- ▶ What does this formula compute for the variable  $x$  of length  $n$  ?

$$\sqrt{\frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2}$$

- ▶ What would be the formula for the **variance**?
- ▶ Let's compute together the **standard deviation** of this variable:

$$x = \{-4, 0, 2, 2, 4, 8\}$$

# Cross-Tabulations

- ▶ Imagine you had a hypothesis about the association between two categorical (i.e. **nominal** or strictly **ordinal**) variables.
- ▶ For instance:
  - ▶ Presidential systems are more likely to experience coups.
  - ▶ Black applicants are less likely to be offered a job interview.
  - ▶ Men are more likely than women to participate in demonstrations.
- ▶ What are the **independent variables** in these hypotheses? What are the **dependent variables**?

# Cross-Tabulations

- ▶ Because the values in these variables have no mathematical meaning, there's not much fancy math we can do with them.
- ▶ Just to count the frequency of the possible outcomes on the dependent variable across each category of the independent variable.
- ▶ This will return a table (known as **cross-tabulation**, **cross-tab** or **contingency table**) with as many rows as there are possible values for the independent variable and as many columns as there are possible values for the dependent variable.

# Cross-Tabulations

Government System	Experienced Coup	Did Not Experience Coup
Parliamentary	8	42
Semi-Presidential	6	24
Presidential	18	22

# Cross-Tabulations

Government System	Experienced Coup	Did Not Experience Coup
Parliamentary	16%	84%
Semi-Presidential	20%	80%
Presidential	45%	55%

**Conditional Proportions:** rows add up to 100%.

# Means Comparison

- ▶ Imagine now you had a hypothesis about the association between a categorical independent variable and a numerical dependent variable.
- ▶ For instance:
  - ▶ Proportional electoral systems lead to a higher share of women in parliament relative to mixed-member or majoritarian systems.
  - ▶ Incumbents receive more votes than non-incumbent candidates.
  - ▶ Unemployed people support higher levels of welfare spending.

# Means Comparison

- ▶ We've already seen in the R sessions and in the assignments what we do in these cases.
- ▶ We compute the mean (or, less commonly, some other representative descriptive statistic) separately for observations in each group.

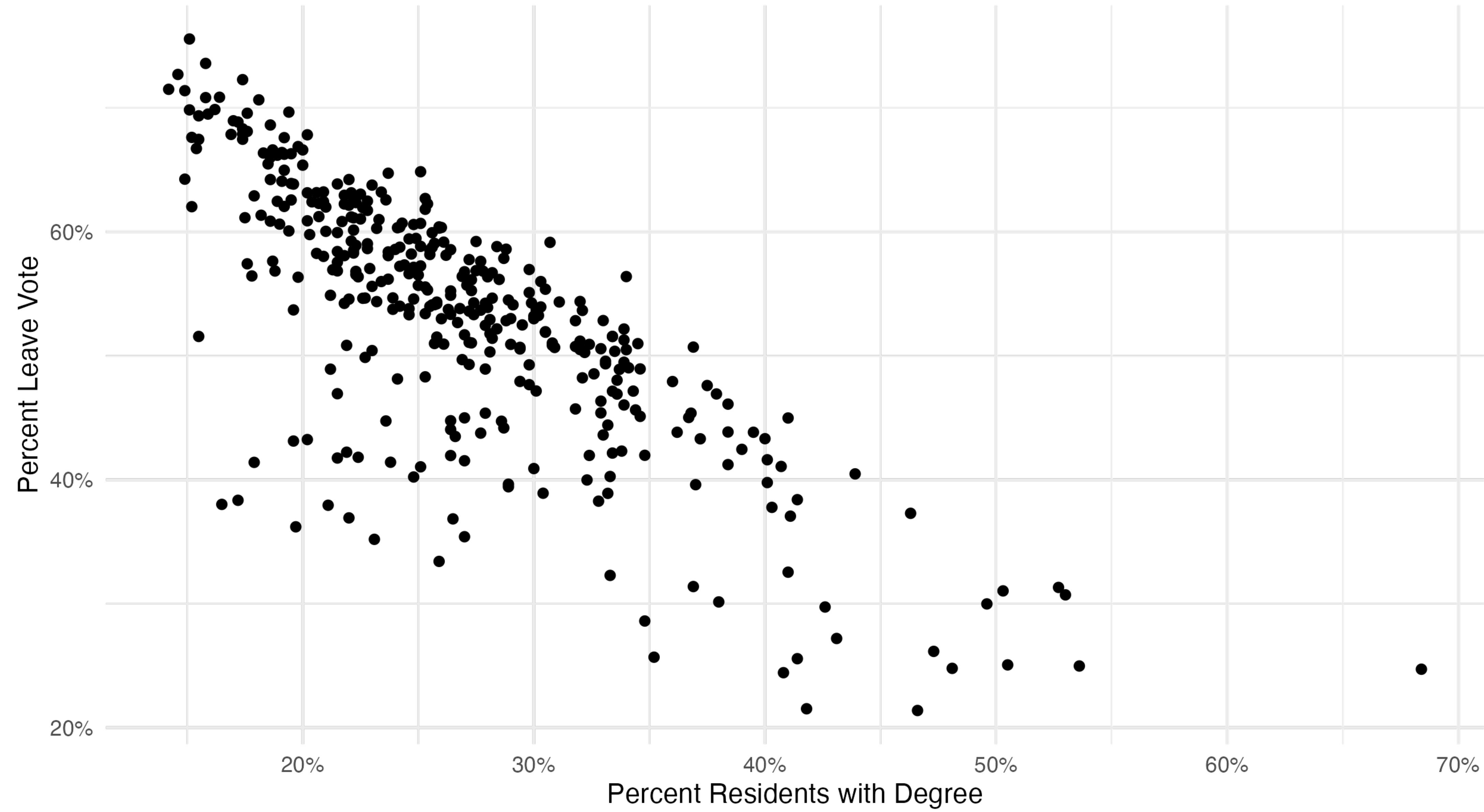
# Means Comparison

Electoral system	Number of countries (N)	Mean % women in parliament	Minimum	Maximum
Majoritarian	22	18.5%	5%	33%
Mixed	17	24.1%	8%	39%
Proportional	21	34.2%	17%	49%
Total	60	25.9%	5%	49%

# Two Numerical Variables

- ▶ When you have a hypothesis linking two numerical variables, it's often useful to start with a visualisation: the **scatter plot**.
- ▶ The scatter plot shows observations as points in a space, with coordinates  $(x_i, y_i)$ , where  $x_i$  is the value of the **independent** variable for observation  $i$ , and  $y_i$  is the value of the **dependent** variable.
- ▶ It's a convention (and not clear-cut in all cases), but remember to put the 'cause' variable on the  $x$  axis, and the 'effect' on the  $y$  axis.

# Some Scatter Plots



# Covariance

- One way of quantifying direction (and strength) of associations is the **covariance**. The covariance of  $X$  and  $Y$  is given by...

$$\text{Cov}(X, Y) = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{n - 1}$$

- Can take **any value**. If positive, the association is positive. If negative, the association is negative.

# Covariance

- ▶ Why does this work? Imagine having only two people in your data: A weights 60kg and is 165cm; B weights 80kg and is 175cm.
- ▶ The mean weight is 70, the mean height is 170.

$$\text{Cov}(W, H) = \frac{(w_A - 70)(H_A - 170) + (w_B - 70)(H_B - 170)}{n - 1}$$

$$\text{Cov}(W, H) = \frac{(-10)(-5) + (10)(5)}{2 - 1} = 50 + 50 = 100$$

- ▶ Weight and height are positively associated (groundbreaking!).

# Covariance

- Another basic example: person A works 10 hours a day, and has 2 hours of leisure time. Person B works 4 hours a day, and has 6 hours of leisure time.
- The mean work-time is 7, the mean leisure-time is 4.

$$\text{Cov}(W, L) = \frac{(w_A - 7)(l_A - 4) + (w_B - 7)(l_B - 4)}{n - 1}$$

$$\text{Cov}(W, L) = \frac{(3)(-2) + (-3)(2)}{2 - 1} = -6 + (-6) = -12$$

- Work-time and leisure-time are negatively associated.

# Covariance

- ▶ Order doesn't matter.  $\text{Cov}(X, Y) = \text{Cov}(Y, X)$ .
- ▶ The covariance is a close relative of the **variance**. In fact,  $\text{Cov}(X, X) = \text{Var}(X)$ .
- ▶ ***Unlike the variance***, it can take positive **or negative** values. The sign refers to the direction of the association.
- ▶ Like the variance, it's **hard to interpret in terms of 'size'**. But it's the stepping stone to better measures of association (today: the **correlation coefficient**, week 11: the regression coefficient).

# Correlation Coefficient

- ▶ A more widely used measure of correlation is the Pearson correlation coefficient (a.k.a. Pearson's  $r$  or Pearson product-moment correlation coefficient, or just the correlation coefficient).
- ▶ It's the covariance of  $X$  and  $Y$  divided by the product of the standard deviation of  $X$  and the standard deviation of  $Y$ :

$$r_{X,Y} = \frac{\text{Cov}(X, Y)}{s_X s_Y}$$

- ▶ It's a **unit-less** quantity. If you measure time in hours, minutes or seconds, if you measure weight in kgs, pounds or grams, it will still be the same.

# Correlation Coefficient

- ▶ Properties of Pearson's  $r$ :
  - ▶ It is always comprised between -1 and 1, where -1 is a perfect negative correlation, 1 is a perfect positive correlation and 0 is no correlation.
  - ▶ So we can interpret both **direction** (positive or negative) and **size** of the association (0.7 is larger than 0.2, whatever the units of your variables).
- ▶ BUT:
  - ▶ It only tells us about **linear** associations. Use scatter plots to detect if there are non-linear patterns in your data.
  - ▶ As usual, **correlation  $\neq$  causation**, no matter how 'big' the coefficient.

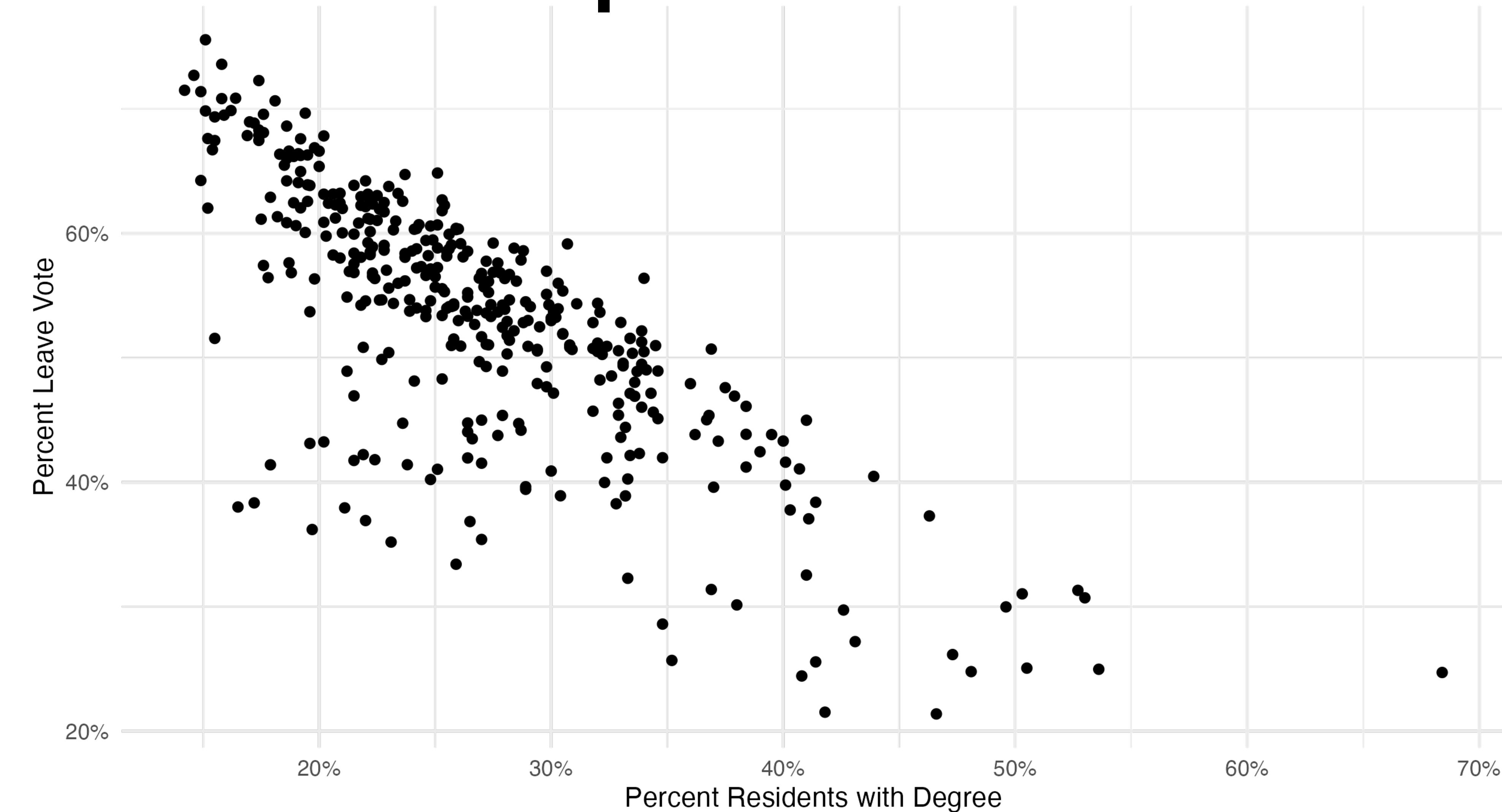
# Examples

$r = -0.77$

$r = 0.91$

$r = 0.57$

$r = -0.36$



# Summing Up...

- ▶ When you have two categorical variables, show the association via a **cross-tabulation**.
- ▶ When you have one categorical variable and one numerical variable, show the association via a **means comparison**.
- ▶ When you have two numerical variables, measure the association with the **correlation coefficient** (show it with a **scatter plot**).
- ▶ And now, let's open RStudio...



R