

Simulated Data Regressions

The Normal Distribution

Read the indicated answers to these Quora questions:

- [Why do we use the normal distribution?](#) by Paul King, Ralph Winters and Peter Flom.
- [How would you explain the Gaussian distribution in layman's terms?](#) by Breno Sakaguti.

Then go through [Tutorial for the integration of the software, R, with introductory statistics](#) and [Chapter 3: The Normal Distribution](#).

Normal distributions and linear regression

The theory of linear regression applies when the variables involved are normally distributed. We'll be exploring this in the special case of two variables y and x that are normally distributed with mean 0 and standard deviation 1.¹

Suppose that $y = ax + \text{error}$, where:

- x is normally distributed with mean 0 and standard deviation 1, and
- error is normally distributed with mean 0 and standard deviation b such that $a^2 + b^2 = 1$.²

Then a is the *correlation* between x and y . The *percent variance in y explained by x* is just a^2 . This is also referred to as R^2 .

Regressions with simulated data

In this exercise we'll explore the approximations to a that come from applying ordinary least squares regression to a finite sample of data. In the material below, try $a = 0.1, 0.2, 0.3, \dots, 0.9$ and sample size $n = 100, 500, 2500, 10000$.

1. Write a function `getSamples(a, n)` that takes a value of a and a sample size n , returning a dataframe with two columns:
 - x , obtained using the `rnorm()` function, and
 - y as defined above.

¹Any normally distributed variable can be converted to such a variable using the `scale()` function in R.

²If distributions A and B have variances σ_A^2 and σ_B^2 , then their sum has variance $\sigma_A^2 + \sigma_B^2$ and therefore standard deviation $\sqrt{\sigma_A^2 + \sigma_B^2}$. (That is to say, *variances are additive*.) Therefore under the specified conditions y also has mean 0 and standard deviation 1.

2. Use `ggplot()` to make a scatter plot of y against x for various values of a and n to get intuition for what linear relationships between two normally distributed variables looks like. Graph a linear best fit line along with the points using `geom_smooth()` and the right choice for the `method` parameter.

The distributions of slope estimates

1. Write a function `estimateSlopes(a, n, numTrials = 500)` which returns an array of estimates of a for each of `numTrials` batches with sample size n . You'll want to call `coef()` on the output of `lm()`.
2. Using `geom_histogram()`, make histograms of the output of `estimateSlopes()` for some values of a and n . Based on your reading of the Quora answers above, speculate on why the values might be normally distributed.
3. Make a dataframe `dfSD` with rows corresponding to values of n and columns corresponding to values of a . You may find `rownames()` helpful for this. Fill the entries with the standard deviations of the outputs of `estimateSlopes()`. Do the answers depend on the value of a ?
4. Let $a = 0.1$. Determine how the standard deviations of the outputs of `estimateSlopes()` vary with n . You'll likely find it useful to make a dataframe `dfSD2` with a larger range of values of n , and plot the entries as a function of n .

p -values

1. Modify `estimateSlopes()` to make a function `estimateSlopesWithPVals()` to return a dataframe with estimated slopes and p -values associated with the slopes being nonzero. You'll have to figure out how to extract the latter from the `lm()` object in R.
2. Call the function with $a = 0.1$, $n = 500$, `numTrials = 10000`. Plot the slopes and the p -values. Compare the median p -value with the fraction of slopes that are less than or equal to zero.