Additional (advanced) exercises

1 Brownian motion

Write a function that simulates a random walk:

- 1. From a starting position of x = 0 and y = 0, move a virtual particle by a distance of 1 in a random direction.
- 2. Repeat n = 1000 times and plot the track of the particle as a line.
- 3. Repeat steps 1 and 2 for N = 500 virtual particles and visualise their final positions on a scatter plot.

2 Diffusion

Using the code from exercise 1:

- 1. Repeat step 1.3 for n=250, 500, 1000 and 2000 iterations and visualise the final positions on a 2×2 panel grid of scatter plots. Adjust the axis limits so that all four panels are plotted at the same scale.
- 2. Plot the marginal distributions of the x-values as kernel density estimates and empirical cumulative distribution functions.
- 3. Visualise the bivariate datasets as 2-dimensional KDEs.

3 Summary statistics

Using the code from the previous exercises:

- 1. Construct a table with the means, medians, standard deviations and interquartile ranges of the synthetic datasets (x-values) of exercise 2.
- 2. Plot the four datasets as box plots.

4 Probability

Suppose that a password needs to contain exactly 8 characters and must include at least one lowercase letter, uppercase letter and digit. How many such passwords are possible?

5 Bernoulli variables

- 1. Draw a random number from a uniform distribution between 0 and 1 and store this number in a variable (p, say).
- 2. draw n = 20 additional numbers from the same uniform distribution and count how many of these values are less than p.
- 3. Repeat steps 1 and 2 N = 100 times, store the results in a vector (x, say), and plot the results as a histogram.

- 4. Suppose that you did not know the value of p, then you could estimate it (as a new variable \hat{p} , say) from the data x. To this end, compute the binomial density (or 'likelihood') of all values in x for $\hat{p} = 0.5$ and sample size n.
- 5. Now take the sum of the logarithms of the binomial likelihoods of x. Call this sum LL (for 'log-likelihood').
- 6. Repeat step 5 for a regularly spaced sequence of \hat{p} -values. Then plot the resulting LL-values against those \hat{p} -values.
- 7. Approximately which value of \hat{p} corresponds to the maximum value for LL? How does this compare to the true value of p?

By completing this exercise, you have numerically extended the procedure described in Section 5.1 of the notes.

6 Type-2 errors

- 1. Draw a random number from a binomial distribution with n = 20 and p = 0.52.
- 2. Apply a binomial test comparing $H_o: p = 0.5$ with $H_a: p \neq 0.5$. Do the data pass the test?
- 3. Repeat steps 1 and 2 N = 1000 times. What percentage of the datasets pass the test?
- 4. Repeat steps 1 through 3 for n = 200.
- 5. Repeat step 4 for a range of values from n=20 to n=2000. Plot the probability of rejection against n.
- 6. Compare the results of step 5 with a manual calculation of the probability of committing a Type-2 error as a function of sample size.

7 Confidence intervals

- 1. Draw N=10 random numbers from a binomial distribution with p=0.55 and n=20. Construct 95% confidence intervals for p for each of these numbers.
- 2. Plot these confidence intervals against n as error bars using R's arrows() function.
- 3. How many of the confidence intervals in step 2 overlap with $p_0 = 0.5$?
- 4. Repeat step 2 for n = 200. How many of these new confidence intervals fall outside p = 0.5? Do so again for n = 2000.

8 Random sampling in 2D

- 1. Generate two vectors (x and y, say) of 1000 random numbers between 0 and 500 and visualise them on a scatter plot. Add a grid of lines at every 20 units of x and y.
- 2. Count the number of items falling in each square bin of the graticule contained in the interval from x = 0 to x = 100 and from y = 0 to y = 100. Plot these numbers as a histogram.
- 3. Calculate the mean and variance of the resulting dataset of counts. Repeat steps 1 and 2 several times before drawing conclusions.

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