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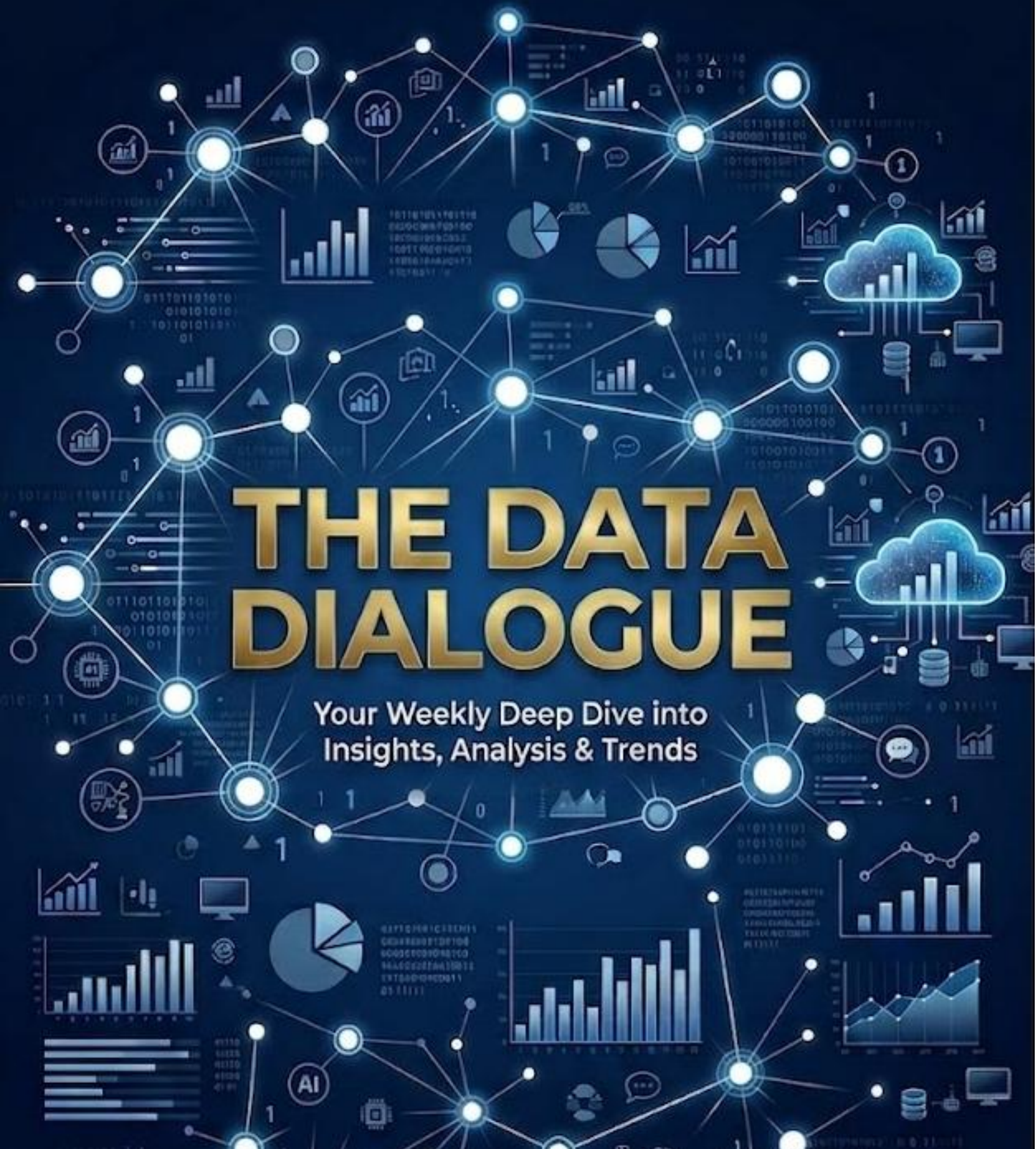

The Data Dialogue.

Simplified. Not Simplistic

July. 15th. 2026 | Vol.1 | Issue 1 | Probability Theory

In-Focus

Probability Theory: Their Gambling Hobby became Your Headache

Back in 1654, a French nobleman and serious gambler known as the Chevalier de Méré) found himself in a sticky situation. A betting game had to be cut short before anyone could win the pot, leaving them wondering how to split the money fairly.

Chevalier reached out to his buddy, the mathematician Blaise Pascal, who then confided in his friend Pierre de Fermat to solve the problem. Instead of just dividing the pot based on how many rounds each player had *already* won, the duo had a brilliant (and revolutionary) idea: figure out a fair split based on future expectations.

They realized that the past didn't matter; what mattered was counting exactly how many rounds were still needed for each player to win. By mapping out all the possible future scenarios, they could calculate everyone's true chance of winning.

Since then, a chain reaction of mathematical developments: Bernoulli took things a step further, proving that repeating an experiment reveals hidden patterns in chaos, Bayes introduced conditional probability to figure out how things change when new information is added to the mix, Gauss brought us the bell curve (normal distribution), and Pearson and Fisher built the statistical tests we still use constantly.

It’s an incredible story of how brilliant theories are born out of everyday problems, passed along from a friend to a friend of a friend. It's exactly why statistics is the beating heart of data science and analysis today—while computer software is just there to crunch the numbers**.**

Isn’t it ironic how one man’s gambling hobby became some students’ nightmare. Anway, next time a friend asks for your advice, take it seriously it might be your ticket to a great theory, who knows!

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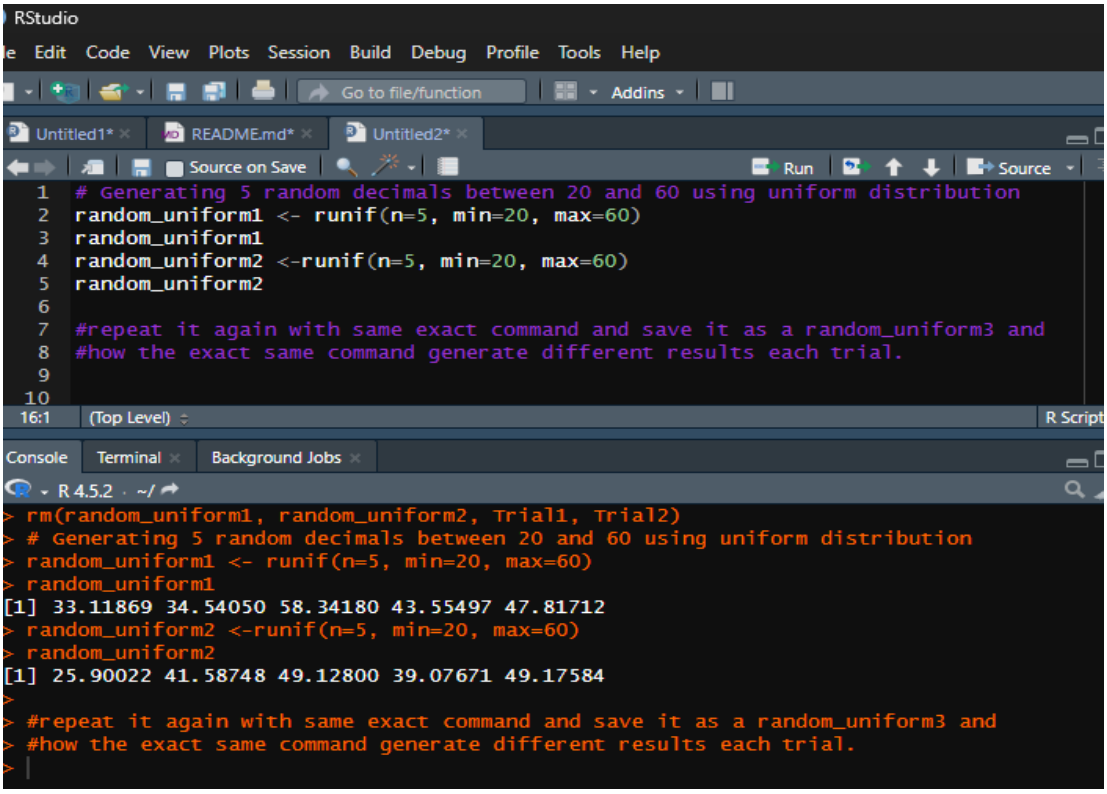
Tools

You Reap what you Sow? Set.seed() in R

- **When will you need it?** when writing a code that requires generating variable with random values.
- **Why would an analysis require generating variables with random values**? Simply when the idea of uncertainty is part of the analysis, and more specifically in: Monte Carlo Simulations, Resampling methods (bootstrapping & premutation tests), Power analysis, Bayesian analysis, and finally Machine Learning using Synthetic data generation.
- How set.seed() works? It tells the computer to pick the same random values every time you (or any one else) run the code. This secures reproducibility of results.

What difference will it make?(See for yourself)



This is the results of generating values for a variable without using the command set.seed()

You can notice that with each trial, you get a totally different result despite the fact that you use the same command.

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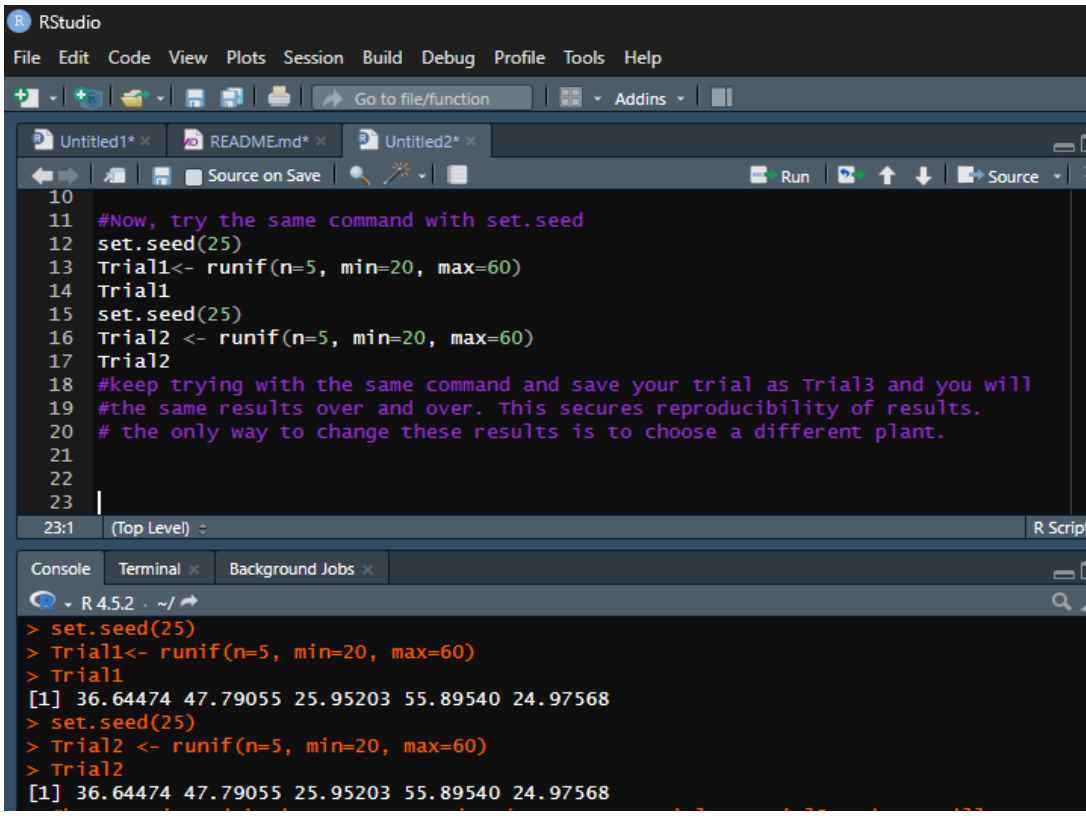
Here, when using set.seed() before the command, it gives back the same exact results.

Notice that we have to repeat the command in line 12 and in line 15 of the script. Each time you attempt reproducing the results, you should use it.



Pitfall Patrol

- Using loop when modifying data in R using command: for ()
- Using vectorization instead, which either available as built-in functions or using packages such as mutate.

Why?

Assume that you want a variable's values to be multiplied the entry x 3.
Loop command is like a security guard that has to check on every person one by one and follow your instructions (any function. In this case it is multiplication) on every single value one-by-one.

Vectorization is like a facial recognition camera that can check on all the individuals simultaneously. Loops take way more time than vectorization and slow your software and laptop down.

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Pandora's Box

Is synthetic data the same as data fabrication?

Synthetic data are usually used in machine learning applications. It is when you ask the software (usually R) to create data using specific attributes. This might be completely synthetic or partially synthetic when you give it some data collected from human participants.

Skeptic voices argue against synthetic data and call it fabricated data. For them, fake data is not different from fake news and it will lead to fake conclusions. Training AI on old data to get new data and claim new insights is similar to your mother recycling bread into a cake and claiming baking you a new dessert. Allowing synthetic data, they argue, lowers the bar for researchers who would love to escape academic audit. Finally, opponents argue that using synthetic data breaks down the scientific wheel where theoretical expectations should be checked against real world empirics not unrealistic data.

On the other hand, proponents of synthetic data admire it for canceling out concerns about human privacy and confidentiality compared to having your name or ID masked or anonymized and stored somewhere on a student's laptop. For them, it is noise-free, highly precise data, and this it is not fake.

Before you Go

Did it happen that you made a mistake while conducting data analysis? If so, send us a punchy 250 words describing this mistake and how you fixed it.

If it's humanized, we'll publish it next week with your name, title and link to your profile.

Disclaimer: *"We reserve the right to edit all submissions for conversational tone, length, and formatting to ensure it matches the Data Dialogue voice"*

You will find the submission button on my website.