

Lab 2: Randomness

In this lab we will:

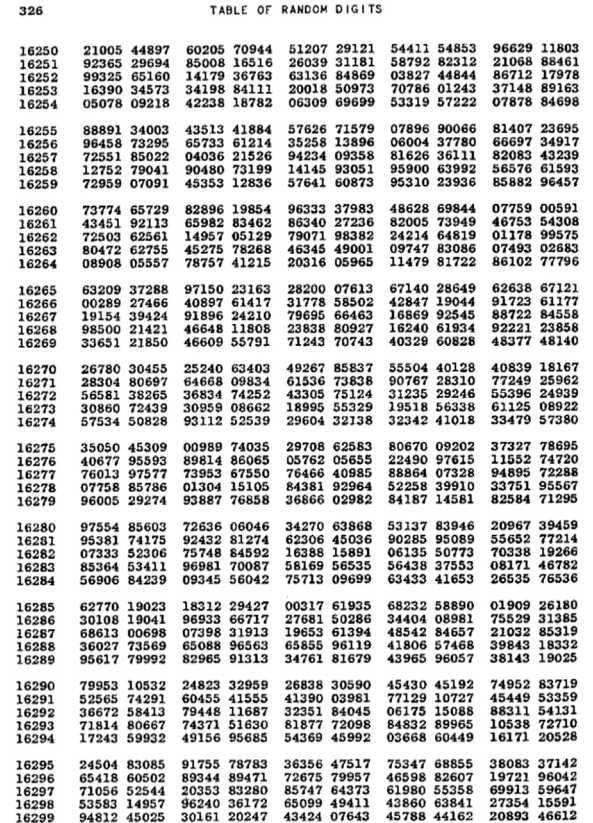
- review the main concepts about **randomness** in finance, including pseudo random number generators (PRNG) and quantum random number generators (QRNG)
- develop a **Python** computer programs to generate random numbers using classical computers and PRNG
- develop Python computer programs based on the **Qiskit** module in order to generate random numbers using quantum computers

The Problem: Tossing a Coin

In finance **randomness** is everywhere. There are many reasons for this. One is that we have incomplete information about the financial markets and some of the key parameters or variables are unknown or uncertain. Also, we do not know the future and we ought to make assumptions about the future behavior of key financial variables.



So how can we get computers to help use generate random numbers?



The Classical Solution

PRNG is a highly-sophisticated field (Gentle 2013; Glasserman 2013). There are different types of random numbers. These can be classified depending on where they come from. The most common are pseudo-random number generators (PRNG), which generate numbers that appear random, but are actually deterministic, as they are produced following some complex algorithm. They require the current state of the system to start their sequence, which is called the seed. A popular PRNG algorithm is the Mersenne Twister algorithm developed by Makoto Matsumoto and Takuji Nishimura in 1997. Another types of random number generators include quantum random number generators (QRNG), which we will discuss later.

The Quantum Solution

How can we generate random numbers using quantum computers?

The most direct way is to take advantage of the intrinsic nature of qubits.

Remember, in contrast to bits who can only take two states (i.e. 0 or 1), qubits can have a multiplicity of states.

The state of the qubit can be represented as a point in the Bloch Sphere.

So we can setup qubits to be in a state precisely in between $|0\rangle$ and $|1\rangle$ using a Hadamard gate (the H-Gate) we saw in Lecture 1). In other words, we put the qubit in a superposition of the two states $|0\rangle$ and $|1\rangle$.

And afterwards by measuring the actual location of the qubit, we force it to collapse to either the South Pole (0) or the North Pole (1).

Because the likelihood of finding them in either is equal, we can regard this as Tossing a Coin, and would find the qubit sometimes in state 0, and sometimes in state 1.

The probability of each is 50%. No need for PRNG or seeds, just the observed effects of quantum mechanics!



How do we do this in practice? We are going to start by generating random numbers from a single qubit that could be either pointing down (0) or pointing up (1). We are then going to take this as our building block and construct from this single measurement of a qubit a single bit of information. We will do this first in the IBM Quantum Experience using the visual tools from the website and then we will do it by write a computer program in Python with the help of the Qiskit module. Our goal is to generate various types of random numbers using quantum computing as follows:

Quantum Binary Random Numbers

Here is we directly observe a single quabit and after measuring it we transform it into a bit. We can repeat this process multiple times, say 8, and from the 8 measurements obtain 8 bits that would be useful to form a byte.

Quantum Integer Random Numbers

With the methodology above to generate bits and bytes from qubits, we can then transform the binary representations obtained into integers. For example, applying a H-Gate to the same qubit 8 times produces 8 states of information, say 0 1 0 0 1 1 0 1 that if we join them can be regarded as a byte (or 8-bit binary number) as 01001101 and transformed into the decimal integer 77.

Quantum Uniform Random Numbers

Then with a large enough set of integer numbers we can cover the domain $[0,1]$ and interpret these as samples from a uniform distribution. Of course too few would mean very few samples of the domain, like in the case of 8-bits representing 128 equidistant points between 0 and 1. Using 32 bits then the number increases significantly to $2^{32} = 4,294,967,296$.

Qiskit Lab

We start with a single qubit. This might seem too little, but as we will see, it will be the building block upon which we can construct much larger techniques to generate random numbers the quantum way.

LABORATORY 5: Quantum Binary Random Numbers in QISKIT

In this laboratory we will create our own Python programs in our computer based on the principles discussed before with the online service IBM Quantum Experience. We will do this in our own Python environment (I use Anaconda Individual and Jupyter Lab to run all the Labs). I run each code in Jupyter by simple copy and pasting it into a cell and pressing Shift+Enter. All the subsequent examples are based on the quantum random computer simulator offered by QISKIT, but the setting can be changed to use a real quantum computer as will be illustrated in the next chapter.

To start with, I this laboratory we will start by generating binary numbers, i.e. bits and bytes.

Code 2.7 Quantum 1-bit generator

In this code we construct a simple 1 qubit circuit with a H-Gate and repeat its measurement 8 times (using 8 shots).

```
# CODE_2_7_QISKIT_1_qubit_8_shots

# QISKIT generate 1-bit binary (0,1) with 1 qubit 8 shots


from qiskit import QuantumCircuit, execute, Aer, IBMQ

from qiskit.visualization import *

from qiskit.tools.jupyter import *


# Create a quantum circuit with 1 qubits and 1 classic bits
qcircuit = QuantumCircuit(1,1)


# Add an Hadamard gate to the qubit
qcircuit.h(0)


# Measure and link qubit into classical bit
qcircuit.measure([0],[0])


# Execute the circuit
backend = Aer.get_backend('qasm_simulator')

result = execute(qcircuit, backend, shots=8, memory = True).result()

counts = result.get_counts(qcircuit)


# Get individual shot results
shotlist = result.get_memory()


# Output

print(counts)

print(shotlist)

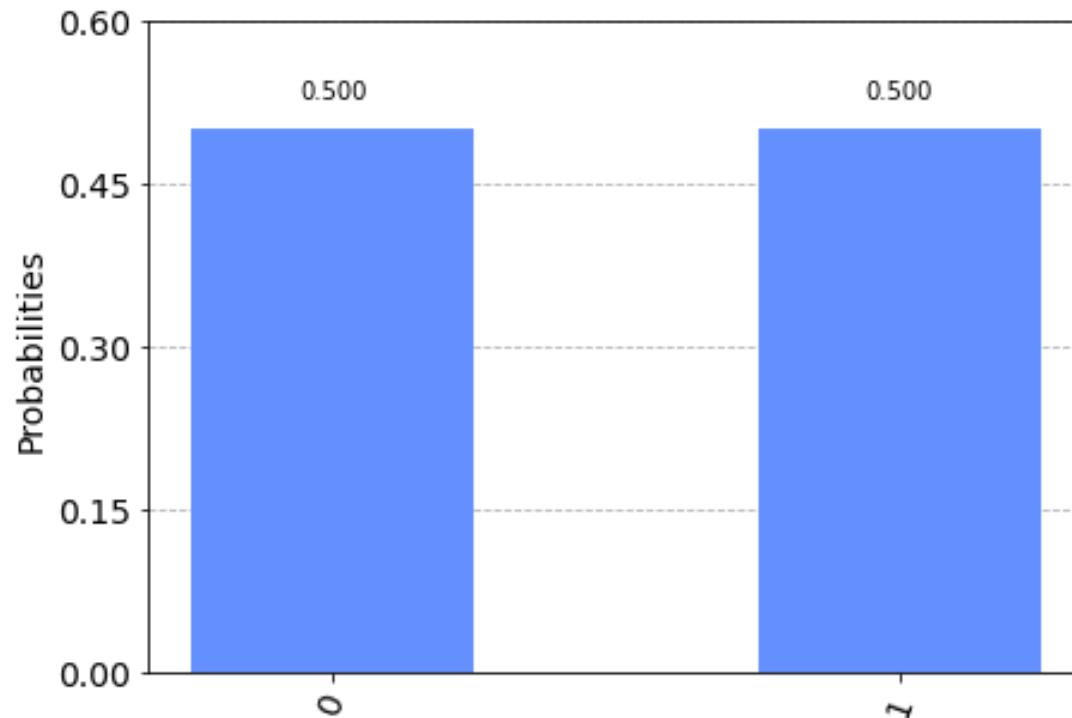
plot_histogram(counts)
```

Running this circuit in Jupyter results in the following numerical results. Of the eight runs (shots), 4 times the qubit measured gave a zero (i.e. pointing up in the Bloch Sphere) and 4 times the qubit measured gave a one (i.e. pointing down in the Bloch Sphere). The results from the individual runs are given in the second row.

```
{ '0': 4, '1': 4 }  
[ '1', '0', '0', '0', '0', '1', '1', '1' ]
```

OUTPUT Code 2.7: numerical results

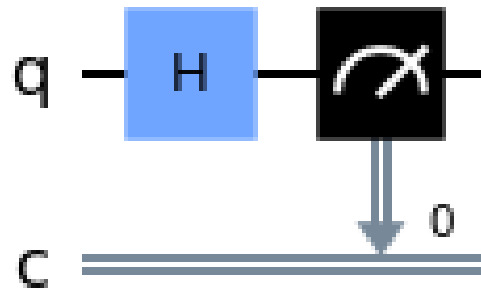
These values can be further summarized in terms of an histogram:



OUTPUT Code 2.7: histogram

Finally, if in Jupyter Lab we write in the next cell and execute (Shift+Enter) we can obtain a graph of our circuit:

```
# Draw the circuit  
qcircuit.draw()
```



OUTPUT Code 2.7: circuit

References

James E. Gent. Random Number Generation and Monte Carlo Methods. Springer, 2013.

Paul Glasserman. Monte Carlo Methods in Financial Engineering. Springer, 2010.

Matsumoto, M.; Nishimura, T. (1998). "Mersenne twister: a 623-dimensionally equidistributed uniform pseudo-random number generator". ACM Transactions on Modeling and Computer Simulation. 8 (1): 3–30.

Christian Kollmitzer, Stefan Schauer, Stefan Rass. Quantum Random Number Generation: Theory and Practice. Springer, 2020.