

75 Minutes of Python

Alexander Clark

Columbia University - Stats 1101

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1 What is Python?

Python is a general-purpose programming language. Our purposes are statistical calculations and the occasional graph. We will run code in [Google Colaboratory](#) notebooks. This roughly mirrors running Jupyter notebooks on your own machine, but we skip the setup by running everything in the browser. If you master intro stats and become proficient in Python and SQL, there is a six-figure job waiting for you at any number of tech companies.¹

Python is popular because the code is readable. More specifically, “Pythonic” code is readable. Pythonic code not only gets you from point A to B, but it uses Python as it was intended and conforms to the standards of beauty described in *The Zen of Python* and [elsewhere](#).

Beautiful is better than ugly.
Explicit is better than implicit.
Simple is better than complex.
Complex is better than complicated.
Flat is better than nested.
Sparse is better than dense.
Readability counts.
Special cases aren't special enough to break the rules.
Although practicality beats purity.
Errors should never pass silently.
Unless explicitly silenced.
In the face of ambiguity, refuse the temptation to guess.
There should be one—and preferably only one—obvious way to do it.
Although that way may not be obvious at first unless you're Dutch.
Now is better than never.
Although never is often better than *right* now.
If the implementation is hard to explain, it's a bad idea.
If the implementation is easy to explain, it may be a good idea.
Namespaces are one honking great idea—let's do more of those!

The Zen of Python, by Tim Peters

Python can seem endlessly complex. *Fluent Python* is 1,012 pages. Luckily, we don't need to aspire to fluency. Let's learn just enough of the language to order off the kids' menu.

2 Can't ChatGPT do all of this for me?

Yes, you should use ChatGPT! ChatGPT and other AI tools write pretty good code. But you have the luxury of spending four years in college and I would suggest that beginners force themselves to write their own first draft. ChatGPT still hallucinates, so you can't yet depend on ChatGPT to do everything.

¹At least there was in early 2022. [Data scientists are over-represented in layoffs](#).

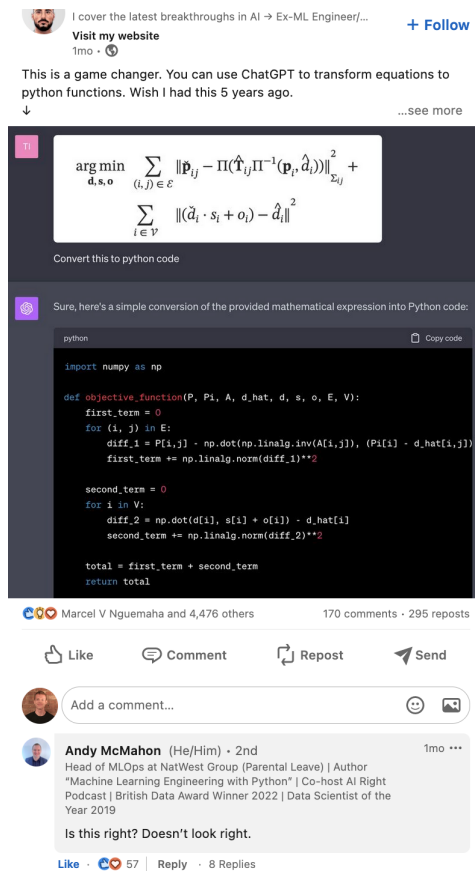


Figure 1: Misinformation spreading on the internets.

3 Python as a Calculator

3.1 Variables

A Python variable holds a value. It can be a string, a number, or perhaps a more complicated data type. Variable assignment is done with the equals sign, `=`. Below, we create a string variable called `greeting` and a integer variable called `my_favorite_number`.

```
1 greeting = "Hello, World!"
2 my_favorite_number = 91
```

`vars.py`

Now compare the output you get from the following.

```
1 print(greeting)
2 print("greeting")
3 print("Hello, World!")
4 print(91)
5 print(my_favorite_number)
6 print("my_favorite_number")
```

`print-vars.py`

Note that while $x = x + 1$ is nonsense as a mathematical equation, in Python `x = x+1` simply adds one to the value of `x`. What's the value of `x` at the end of the following program?²

Three.

```

1 x = 0
2 x = x + 1
3 x = x + 1
4 x += 1 # syntactic sugar
5 print(x)

```

reassignment.py

3.2 Comments

Commenting your code is helpful if you care about your colleagues or your future self. Comments should add clarity to the intention and workings of code. A comment is a piece of code that isn't actually executed—it's a comment left for the reader or the person who inherits and modifies your code. Everything after a `#` will be ignored by Python.

```

1 # This will print a greeting.
2 print("Hello, World!")

```

comment.py

You might also use end-line comments like the following

```

1 print("Hello, World!") # Prints a greeting

```

inline.py

Perfect comment technique does not correct for bad code though. Compare the following blocks of code.

```

1 x = 90 # Wins
2 y = 10 # Losses
3 a = 100 * x/(y+x) # Winning Percentage

```

compensation.py

```

1 wins = 90
2 losses = 10
3 winning_percentage = 100 * wins / (losses + wins)

```

good-names.py

The first block is commented and the second is not. Still, the second code block is better because the variable names are chosen so you don't *need* comments. Good naming becomes even more important as the program becomes longer and variables are used over and over.

3.3 Calculations

Below is a list of some typical operations. What might stand out is that exponentiation is done with `**` and not `^`. It happens that `^` still works, but it does something else.

Operator	Description
+	Addition
-	Subtraction
*	Multiplication
/	Floating point (normal) division
**	Exponentiation

We can use parenthesis for readability and to order operations in the usual way.

```

1 a = 1 - 1 * 0
2 b = (1 - 1) * 0
3 print(a, b)

```

parens.py

For our first substantive program, let's calculate the test statistic for $\hat{p} = 0.34$ with $n = 116$ if we assume a null hypothesis of $p = \frac{1}{3}$. We will obtain $z = 0.15231546211727914$.

```
1 p_hat = 0.34
2 p = 1/3
3 n = 116
4 sd = (p*(1-p) / n)**0.5 # st dev from sampling distribution
5 z = (p_hat - p)/sd # test stat
```

z-stat.py

3.4 Truth and Decision Structures

You'll notice the test statistic we just calculated is small. For a 95% confidence level and a two-sided test, we would fail to reject the null hypothesis because $|z| < 1.96$. It would be nice if Python could make that call without us even having to look at the statistic. We can do that with if statements. If statements are based on truth statements, or boolean expressions.

```
1 if True:
2     print(1)
3 else:
4     print(0)
```

if-true.py

```
1 if False:
2     print(4)
3 else:
4     print(5)
```

if-false.py

We don't work directly with `True` and `False` in practice. We have to make use of comparison operators.

Operator	Description
<code>==</code>	Equality, $1 == 1$
<code>></code>	Greater Than, $1 > 0$
<code><</code>	Less Than, $1 < 2$
<code>>=</code>	Greater Than or Equal, $1 >= 1$
<code><=</code>	Less Than or Equal, $9 - 1 <= 7 + 1$

Observe.

```
1 if 1 == abs(-1):
2     print("Equality in absolute value")
3 else:
4     print("Inequality")
```

if-calc.py

Using the `abs()` function above to take an absolute value, Python knows $1 = |-1|$ and executes only the first print statement. Finally, let's have Python make the call on our hypothesis test.

```
1 if abs(z) < 1.96:
2     print("Fail to reject.")
3 else:
4     print("Reject.")
```

reject-rule.py

4 Libraries for Statistical Functions and Graphs

We've hit a ceiling in Python's usefulness. You, the coder, supplied the critical value 1.96 in the previous program and we couldn't calculate a P-value. To go further, we have to import additional libraries that contain the stuff we want to use. SciPy, and specifically the stats module, will replace a *z*-table and then some. Below, we import the SciPy stats module and use it to calculate $P(Z < 1.96)$, using the standard normal CDF.

```
1 import scipy.stats as stats
2
3 z_table_value = stats.norm.cdf(1.96)
4 print(z_table_value)
```

scipy-norm.py

We can go in the opposite direction with `stats.norm.ppf`.

```
1 # Two-sided Critical Value
2 confidence_level = 0.9
3 alpha = 1 - confidence_level
4 critical_value = stats.norm.ppf(1 - alpha/2)
5 print(critical_value)
```

crit-val.py

Occasionally, it's useful to simulate data. SciPy again suits this purpose. For this call, we make use of keyword parameter `size`, specifying that we want 75 iid draws from the standard normal distribution.

```
1 # Normal random variables
2 random_draws = stats.norm.rvs(size = 75)
3 random_draws
```

rand-draws.py

If you display `random_draws`, you'll see we have an array—a new data type.

```
array([ 0.26670047,  0.90571598,  0.58999261, -0.11483403, -0.11317713,
        0.24380578, -1.34662353, -2.38132282, -1.06133942, -0.51280499,
       -0.20017384, -0.99053684,  1.39045452, -0.03411639,  0.86640634,
       -0.58858272, -0.07981447, -1.15327852,  0.75582911,  0.6196648 ,
       -1.21089585,  0.71239498,  0.53601251, -0.60518285,  0.81547665,
        0.87444887,  0.17482955, -0.30222337,  0.70213597, -0.48985895,
        0.58287787,  0.43369743,  0.47753534,  0.4218932 ,  1.28159422,
        0.98054053,  0.47001209,  0.63269663,  1.48985604, -2.17641724,
        0.70551392,  0.65769517, -0.19576411,  0.09185508, -0.53660252,
       -0.15239094,  1.01012891,  0.52824524,  1.28593209, -1.12874119,
        1.4837867 ,  1.11762774, -1.44385417, -0.54467961,  2.1815505 ,
        0.82446247,  1.52427836, -0.89112124,  0.79242734,  0.81785614,
       -0.11150023, -0.24244312,  0.66204106,  1.46663459,  1.30903711,
        1.49169821, -0.36590489, -0.16852676,  2.11081052, -0.45121903,
        0.88317932, -0.55096038,  0.6298471 , -0.1914023 , -0.71709689])
```

We'll sneak in a histogram. The standard data visualization library for Python is matplotlib. We use the pyplot module for a bare-bones histogram in Figure 2.

```
1 import matplotlib.pyplot as plt
2 plt.hist(random_draws)
3 plt.title("Random Draws from the Standard Normal Distribution")
4 plt.savefig("first_histogram.pdf")
5 plt.show()
```

mpl-hist.py

We can simulate Bernoulli draws and run a hypothesis test. Python has a small selection of mathematical functions available apart from any library. Previously, we used `abs()`. Below, we use `sum()` and then `len()` which counts the number of elements in an array.

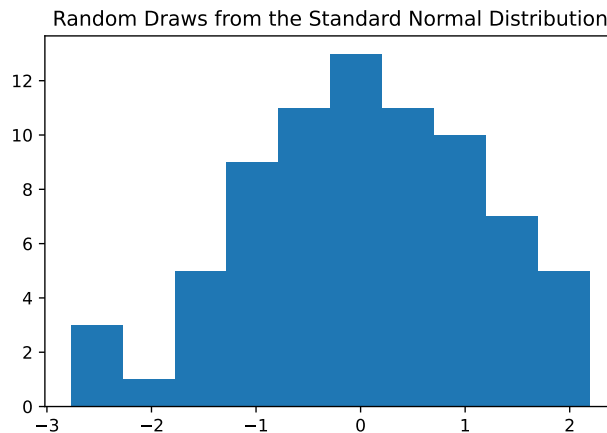


Figure 2: Our first histogram.

```
1 data = stats.bernoulli.rvs(p = .52, size = 30)
2 p = 0.5 # null hypothesis
3 p_hat = sum(data) / len(data)
4 sd = (p*(1-p) / n)**0.5 # st dev from sampling distribution
5 z = (p_hat - p)/sd # test stat
```

bernoulli.py

We can run many with the help of a special repetition structure called a *for loop*. The code below simulates 30 flips of a fair coin 10,000 times. `k` records how often our test statistic, under a null of $p = 0.5$, would lead us to incorrectly reject the null hypothesis using $\alpha = 0.05$ and a two-sided alternative. What value do you expect for k/N ?³

```
1 N = 10_000
2 k = 0
3
4 n = 30
5 p = 0.5 # null hypothesis
6 sd = (p*(1-p) / n)**0.5 # st dev from sampling distribution
7
8 for sim in range(N):
9     data = stats.bernoulli.rvs(p = .5, size = n)
10    p_hat = sum(data) / len(data)
11    z = (p_hat - p)/sd
12    if abs(z) > 1.96:
13        k += 1
14
15 print(k/N)
```

simulation.py

5 Libraries for Data

The main library for data wrangling and anything tabular (like a spreadsheet) is `pandas`. `Pandas` is famous—it's no wonder the bear is named after this library. Primarily, we will read `csv` and `xlsx` files into *DataFrames*. *DataFrames* can also be constructed by hand like in the program below.

```
1 import pandas as pd
2
3 atus_df = pd.read_csv("ATUS_activity_2019.csv")
```

³ `k/N` should be close to 0.05, using a Normal approximation. Large simulations will show this approximation to be inexact.

```

4 other_df = pd.read_excel("helper.xlsx")
5
6 data = {'day' : ['Monday', 'Tuesday'],
7         'frosty_expenditure' : [0,2],
8         'mcflurry_expenditure': [3,0]}
9 df = pd.DataFrame(data)

```

[pandas-df.py](#)

Individual columns can be accessed as a *Series* with `df['frosty_expenditure']` or `df.frosty_expenditure`.⁴ We can then create new columns based on existing columns.

```

1 df['total_expenditure'] = df.frosty_expenditure + df.mcflurry_expenditure

```

[new-column.py](#)

DataFrames and Series also have special *methods* available.

```

1 df = pd.read_csv('file.csv')
2
3 mean = df.response_variable.mean()
4 grouped_means = df.groupby("assignment").response_variable.mean()
5
6 var = df.var() # variance of each column
7 corr = df.corr() # correlation table

```

[pd-methods.py](#)

6 A Two-Sample t -Test

```

1 import numpy as np
2 import scipy.stats as stats
3 np.random.seed(1)
4
5 x = np.random.normal(1, 1, size = 25) # 25 draws from N(1,1)
6 y = np.random.normal(0, 1, size = 10) # 10 draws from N(0,1)
7 stats.ttest_ind(x, y, equal_var = False)

```

[two-samp-t.py](#)

7 A χ^2 -Test

We'll use the `marital_status_party_affiliation.csv` file to conduct a test of independence for the variables *marital status* and *political party affiliation*. It's generally known that married people lean Republican and that single people lean Democrat. With our dummy data, we'll see if we have enough evidence to reject the possibility of this being only noise.

```

1 df = pd.read_csv("marital_status_party_affiliation.csv")
2
3 # inspect the data using value_counts()
4 df.value_counts()
5
6 # repeat with crosstab
7 pd.crosstab(df['Marital Status'], df['Party Affiliation'], margins = True)

```

[pd-ctab.py](#)

With the `crosstab`, we have everything we need for a test of independence. The SciPy library offers the appropriate functions.

```

1 import scipy.stats as stats
2 ctab = pd.crosstab(df['Marital Status'], df['Party Affiliation'], margins = False)
3 stats.chi2_contingency(ctab, correction = False)

```

[chi2.py](#)

⁴This pattern will not work if there is a space in the column name or if the column doesn't adhere to other naming requirements.

```
pd.crosstab(df['Marital Status'], df['Party Affiliation'], margins = True)
```

Party Affiliation	All	Day Breakfast Party	Democrat	Republican	All
Marital Status					
Married	2	22	26	50	
Single	2	26	22	50	
All	4	48	48	100	

Figure 3: A `crosstab` as displayed in Google Colab.

8 Further Resources and Caution

8.1 Resources

I got my start with [DataCamp](#) courses. DataCamp uses a subscription model that is affordable. You can have ChatGPT quiz you. There are also many excellent, free resources available that will help you learn Python. *Python for Data Analysis* by Wes McKinney was updated in 2022, making it one of the most current resources. I also recommend Jake VanderPlas's *Whirlwind Tour of Python* and *Python Data Science Handbook*. For plotting with matplotlib, try [my book](#).

8.2 Caution

Recall when we calculated sample variance as $\sum_{i=1}^n \frac{(x_i - \bar{x})^2}{n-1}$ and sample standard deviation as the square root of this quantity. We used $n - 1$ instead of n in the denominator as correction for unbiasedness. Not all Python libraries do this by default! NumPy is one such library that does not use the correction by default. The lesson here is that, for this class, do your research if you are using other libraries and functions. There are many ways to do what sounds like the same thing in statistics and some disjointedness across all of the Python libraries.

Below is another example where default behavior in the StatsModels library does not match our intro conventions. For now, our calculations are simple enough that I don't recommend finding random libraries and functions to shorten your code.

```
1 from statsmodels.stats.proportion import proportions_ztest
2
3 # Hypothesis testing with null of p = 0.6
4
5 # Wrong/Different
6 z1, pval1 = proportions_ztest(10, 20, value = .6)
7
8 # Correct/Matches Textbook
9 z2, pval2 = proportions_ztest(10, 20, value = .6, prop_var = .6)
10
11 # By hand
12 p_hat = 0.5
13 p = .6
14 n = 20
15 sd = (p*(1-p) / (n))*0.5 # st dev from sampling distribution
16 z3 = (p_hat - p)/sd # test stat
```

[prop-ztest.py](#)