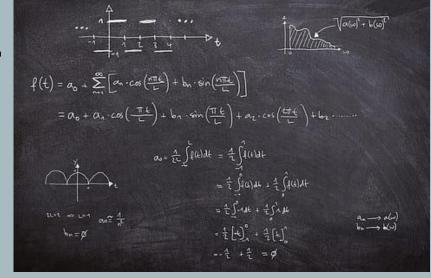
Python's Role in Actuarial $f(t) = a_0 + \sum_{n=1}^{\infty} \left[a_n \cdot cos\left(\frac{cn\pi t}{L}\right) + b_n \cdot sin\left(\frac{cn\pi t}{L}\right) \right]$ Science

By Chris Ixtabalan



Python's Background



- Guido Van Rossum created Python in 1991.
- Many languages at the time were complicated which meant they were less flexible and harder to read.
- Python was designed to be easy to read and write.

Why I picked Python

- Relevant to my actuarial career
- What actuaries do:
 - Analyze complex data sets
 - Build predictive models
 - Perform quantitative risk assessments
 - Usually by hand
- What Python offers:
 - Data analysis for mortality rates, insurance claims, financial projections
 - Many libraries for statistical modeling
 - Produce accurate data and avoid human error
 - Automate repetitive tasks



Python's Features

- Simplicity and readability:
 - Indentions used as code blocks
 - Prevents errors and data leaks
 - Variables type doesn't need to be declared
 - Interpreted
 - Debugging is made easier
 - "Batteries included"
 - Already comes with libraries which have modules and functions
 - Error handling
- Supports many ways of programming
 - Procedural programming
 - Object-oriented programming
 - Polymorphism
 - Functional Programming

```
print("Hello, world!")
```

```
#include <iostream>
using namespace std;
int main()
{
    cout << "Hello world!" << endl;
    return 0;
}</pre>
```

Python's Scorecard

Characteristic	Readability	Writability	Reliability
<u>Simplicity</u>	High	High	Moderate
<u>Orthogonality</u>	Moderate	Moderate	Moderate
<u>Data Types</u>	High	High	High
<u>Syntax Design</u>	High	High	High
Support for Abstraction	High	High	High
<u>Expressivity</u>	High	High	Moderate
Type Checking	Dynamic	Dynamic	Moderate
Exception Handling	Robust	Robust	High

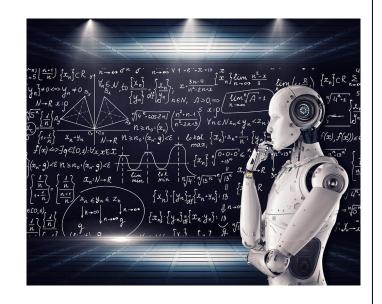
What Python is Typically Used For

<u>Data analysis</u>

 Gives efficient tools for data mining and numerical calculations

<u>Data visualization</u>

- Libraries can help with data cleaning for large datasets which prepares data visualization
- Machine learning and Artificial Intelligence
 - Help complex neural networking for deep learning



Why I Love Python

- How Python could apply to actuarial science:
 - OOP Could help with modeling insurance policies, financial instruments, and customer
 - Used to predict probabilities, customer behavior, and market trends
 - Functional programming simplifies data by processing collective data, so formulas could easily be applied
 - Complex mathematical calculations are made simple to solve
- Why other actuaries should adapt to the technology
 - Computational calculation is becoming trending
 - Easy to learn
 - They can work as teams
 - Actuarial models can be reused



How I Think it Should be Applied

Insurance Scenario:

An insurance company offers a special 5-year term life insurance policy. The policy pays a benefit based on the year of death within the term:

- Year 1: Pays \$1,000
- **Year 2**: Pays **\$2,000**
- **Year 3**: Pays **\$3,000**
- Year 4: Pays \$4,000
- **Year 5**: Pays **\$5,000**

The probability that the insured dies in any given year is **5%** (0.05), independent of other years.

Question: What is the **expected benefit** paid under this policy?

Coding Plan

- Make a Geometric Formula models for mathematical calculation
- Make a simulation of 1000 policyholders using threading, conditional statements, and classes
- Create exception handling in case of errors
- Use the "random" and "threading" libraries

Geometric Probability Distribution

$$P(X=n) = p(1-p)^{n-1}$$

$$P(X > n) = (1 - p)^n$$

Mean
$$\mu = \frac{1}{p}$$

Variance
$$\sigma^2 = \frac{1-p}{p^2}$$

p- probability of success

n- number of first successful trial

Demonstration

Importing Python Libraries

```
import random
#Imported to enabl
import threading
```

Using Classes to represent a policyholder

```
class PolicyHolder:
    #Used to represent a policyholder
    def __init__(self, policy_id):
        self.policy_id = policy_id #Their ID
        self.benefit = 0 #Their starting benefit

#Simulates life of policyholder
    def simulate_life(self):
        probability_of_death = 0.05 # 5% chance of deafor year in range(1, 6): # Years 1 to 5
        #Generates random number 0-1, if number is
        if random.random() < probability_of_death:
            self.benefit = 1000 * year # Benefit in break # Policyholder dies; exit the lower than the self.benefit = 1000 * year # Benefit in break # Policyholder dies; exit the lower than the self.benefit = 1000 * year # Benefit in break # Policyholder dies; exit the lower than the self.benefit = 1000 * year # Benefit in break # Policyholder dies; exit the lower than the self.benefit = 1000 * year # Benefit in break # Policyholder dies; exit the lower than the self.benefit = 1000 * year # Benefit in break # Policyholder dies; exit the lower than the self.benefit = 1000 * year # Benefit in break # Policyholder dies;</pre>
```

Simulation Function

```
def simulate_policies_threaded(num_simulations, num_threads=4):
   total benefit = 0 #Total sum of all benefits for all policyholders
   benefits = [] #List to store individual beneftis of each policyholder
    lock = threading.Lock() # Lock: To make sure threadts don't interfere with each
   #Worker function that will be runned in each thread
   def worker(simulations per thread, thread id):
        nonlocal total_benefit, benefits #Allows variable modification from outer function
        thread_benefit = 0 #Total benefit for each specific thread
        thread benefits = [] #Lists of each benefit
        #Ran for each simulation
        for i in range(simulations per thread):
            policyholder = PolicyHolder(f"Policy_{thread_id}_{i}") #Creates ID
            policyholder.simulate_life() #Simulate life of policyholder
            thread_benefit += policyholder.benefit #Add policyholder's benefit to thre
           thread benefits.append(policyholder.benefit) #Then stores it into the thre
            total benefit += thread benefit #Adds a threads benefit to overall total L
            benefits.extend(thread_benefits) #Same thing but to overall list
   simulations_per_thread = num_simulations // num_threads #Divides total simulation
    threads = [] #List to store all threads
    #Creates and start threads
    for thread id in range(num threads):
       t = threading. Thread(target=worker, args=(simulations per thread, thread id))
       threads.append(t) #Add thread to list of threads
       t.start() #Starts thread
    # Wait for all threads to complete
    for t in threads:
       t.join() #Waits until thread "t" finishes
   #Calculates average beneftt
   expected_benefit = total_benefit / num_simulations
   #Returns all individuals outputs
   return expected benefit, benefits
```

Demonstration

Geometric Probability Function

```
def calculate_analytical_expected_benefit():
    probability_of_death = 0.05
    expected_benefit = 0
    for year in range(1, 6): # Years 1 to 5
        benefit = 1000 * year
        # Calculate the probability of dying in a specific year
        prob = (1 - probability_of_death) ** (year - 1) * probability_of_death
        expected_benefit += benefit * prob # Sum up the expected benefits
    return expected_benefit
```

Geometric Probability Distribution

$$P(X = n) = p(1-p)^{n-1}$$

 $P(X > n) = (1-p)^n$

Mean
$$\mu = \frac{1}{p}$$

Variance
$$\sigma^2 = \frac{1-p}{p^2}$$

p — probability of success n- number of first successful trial

Main Function w/ other formulas

```
def main():
      num simulations = 100000 # Number of simulations
       #Calculate using simulation with threads
       expected_benefit_simulation, benefits = simulate_policies_threaded(num_simulations)
       #Calculate using Geometric Distribution
       expected_benefit_analytical = calculate_analytical_expected_benefit()
       print(f"Expected Benefit Using Math Concepts: ${expected benefit analytical:.2f}")
       print(f"Expected Benefit Using Simulations: ${expected_benefit_simulation:.2f}")
      # Additional analysis using the benefits list
       # Calculate variance and standard deviation
      mean = expected benefit simulation
      variance = sum((x - mean) ** 2 for x in benefits) / num simulations
       std dev = variance ** 0.5
       print(f"Simulated Variance: ${variance:.2f}")
      print(f"Simulated Standard Deviation: ${std dev:.2f}")
      #Exception Handling
   except Exception as e:
      print("An error occurred during the simulation.")
       print("Error message:", str(e))
```

Conclusion

Final Outcome

```
Expected Benefit Using Math Concepts: $655.48
Expected Benefit Using Simulations: $650.35
Simulated Variance: $1906334.88
Simulated Standard Deviation: $1380.70
christopherixtabalan@Chris-OIs-Mac Codes %
```

- Python is a versatile and flexible programming language for professionals
- It has changed the way people do problem solving
- Making actuarial models can help create accurate data and find probabilities
- Great for mathematical computations and data analysis