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*UVA's Systems and Information Engineering*

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# SYS 3062: Lab 2

*Skewness, Kurtosis, and Retiring with Monte Carlo*

# Beyond the Average: Why Skewness and Kurtosis Matter

In Monte Carlo simulations, the Mean ( $\mu$ ) and Standard Deviation ( $\sigma$ ) only tell part of the story. To understand risk, we need to look at the shape of the data.

## Skewness (Asymmetry)

- Measures if the data is biased to the left or right.
- **Why it matters:** In retirement, we care if the uncertainty leans towards "making extra money" (positive skew) or "losing principal" (negative skew).

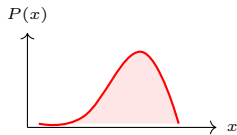
## Kurtosis (The Tails)

- Measures the "heaviness" of the tails (frequency of outliers).
- **Why it matters:** High kurtosis warns us of *extreme events*.

## Definition

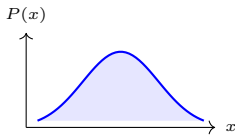
**Skewness** is a measure of the asymmetry of the probability distribution of a real-valued random variable about its mean.

### Negative Skew (Skew $< 0$ )



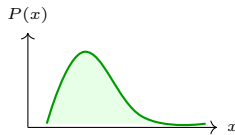
*"Tail is on the Left"*

### Symmetric (Skew $= 0$ )



*"Normal Distribution"*

### Positive Skew (Skew $> 0$ )



*"Tail is on the Right"*

## Fisher's Definition ( $\gamma_1$ )

The moment coefficient of skewness of a random variable  $X$  is the third standardized moment:

$$\gamma_1 = E \left[ \left( \frac{X - \mu}{\sigma} \right)^3 \right] = \frac{\mu_3}{\sigma^3} = \frac{E[(X - \mu)^3]}{(E[(X - \mu)^2])^{3/2}}$$

### Where:

- $\mu = E[X]$  is the mean.
- $\sigma$  is the standard deviation.
- $E[\cdot]$  is the expectation operator.
- $\mu_3$  is the third central moment.
- Sometimes denoted using cumulants:  $\frac{\kappa_3}{\kappa_2^{3/2}}$ .

If  $\mu$  and  $\sigma$  are finite, we can express skewness using non-central moments  $E[X^3]$ .

### Derivation

$$\begin{aligned}\gamma_1 &= E \left[ \left( \frac{X - \mu}{\sigma} \right)^3 \right] \\ &= \frac{E[X^3] - 3\mu E[X^2] + 3\mu^2 E[X] - \mu^3}{\sigma^3} \\ &= \frac{E[X^3] - 3\mu(E[X^2] - \mu E[X]) - \mu^3}{\sigma^3} \\ &= \frac{E[X^3] - 3\mu\sigma^2 - \mu^3}{\sigma^3}\end{aligned}$$

*This formula allows us to calculate skewness directly from the raw moments of the data.*

When dealing with a **sample** of data, we estimate skewness using the following formula:

## Sample Skewness Formula

$$b_1 = \frac{m_3}{s^3} = \frac{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^3}{\left[ \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2 \right]^{3/2}}$$

### Component Definitions:

- $n$ : Sample size.
- $\bar{x}$ : Sample mean.
- $m_3$ : The (biased) sample third central moment (Numerator).
- $s$ : The sample standard deviation (derived from the sample variance in the Denominator).

*Note: The denominator represents the sample variance raised to the power of 3/2 (which is the standard deviation cubed).*

**Dataset:**  $X = \{1, 1, 4\}$  ( $n = 3$ )

**Step 1: Mean ( $\bar{x}$ )**

$$\bar{x} = \frac{1 + 1 + 4}{3} = 2$$

**Step 2: Sample Variance Term (Denominator part)**

$$s^2 = \frac{1}{3-1} [(1-2)^2 + (1-2)^2 + (4-2)^2] = \frac{1}{2}[1 + 1 + 4] = 3$$

$$\text{Denominator } (s^3) = (3)^{3/2} \approx 5.196$$

**Step 3: Third Moment Term ( $m_3$ )**

$$m_3 = \frac{1}{3} [(1-2)^3 + (1-2)^3 + (4-2)^3] = \frac{1}{3}[-1 - 1 + 8] = \frac{6}{3} = 2$$

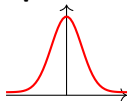
**Step 4: Final Skewness ( $b_1$ )**

$$b_1 = \frac{2}{5.196} \approx \mathbf{0.38} \quad (\text{Positively Skewed})$$

## What is Kurtosis?

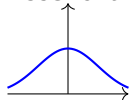
Kurtosis is a statistical measure that describes the shape of the tails of a probability distribution. It quantifies how often extreme values (outliers) occur compared to a normal distribution.

### Leptokurtic



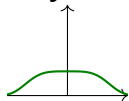
*Heavy tails, prone to outliers.*

### Mesokurtic



*Baseline (Gaussian).*

### Platykurtic



*Light tails, fewer outliers.*



# Calculating "Good Enough" Kurtosis

**Population Kurtosis** The fourth standardized moment:

$$\text{Kurt}[X] = E \left[ \left( \frac{X - \mu}{\sigma} \right)^4 \right] = \frac{\mu_4}{\sigma^4}$$

**Biased Sample Estimator ( $g_2$ )** For a sample, we often use a simpler, but **biased**, estimator:

**Biased Estimator Formula**

$$g_2 = \frac{m_4}{m_2^2} - 3 = \frac{\frac{1}{n} \sum (x_i - \bar{x})^4}{\left[ \frac{1}{n} \sum (x_i - \bar{x})^2 \right]^2} - 3$$

**Note on Bias:** An estimator is "biased" if its expected value differs from the true population parameter. This formula tends to underestimate kurtosis in small samples.

# Unbiased Kurtosis (A Common Formula)

To correct for bias (especially in small sample sizes), we use a significantly more complex formula. This is the version used by software like Excel, SPSS, and SAS.

## Unbiased Estimator ( $G_2$ )

$$G_2 = \underbrace{\frac{n(n+1)}{(n-1)(n-2)(n-3)} \sum_{i=1}^n \left( \frac{x_i - \bar{x}}{s} \right)^4}_{\text{Shape Adjustment}} - \underbrace{\frac{3(n-1)^2}{(n-2)(n-3)}}_{\text{Baseline Correction}}$$

### Why is it so complex?

- It accounts for the degrees of freedom lost by estimating the mean ( $\bar{x}$ ) and standard deviation ( $s$ ).
- It ensures that if the population is Normal, the expected value is exactly 0.

# Why Learn Kurtosis and Skewness?

**The Trap of Normality:** In simulation, relying solely on Mean and Standard Deviation (assuming a Normal distribution) can hide critical risks.

## Kurtosis: Assessing Extreme Risk

**Focus:** The "Tails" (Outliers).

- **Simulation Insight:** High kurtosis warns of "Black Swan" events, rare but catastrophic outcomes.
- **Key Applications:**
  - Financial Modeling (Market Crashes)
  - Weather Forecasting (Extreme Storms)
  - Network Traffic (Data Bursts)

## Skewness: Identifying Bias

**Focus:** Asymmetry.

- **Simulation Insight:** Outcomes are naturally biased in one direction. Symmetric confidence intervals will fail here.
- **Key Applications:**
  - Queuing Systems
  - Risk Assessment (Losses vs. Gains)
  - Reliability Engineering

## The Real-World Problem

Standard financial advice often uses simple, deterministic formulas ( $I = Prt$ ) to project retirement savings.

- **The Flaw:** This assumes returns are constant every single year.
- **The Reality:** Markets crash, interest rates fluctuate, and "average" returns can hide dangerous risks.

## Lab Objectives:

- 1 **Compare Models:** Contrast a static model against a stochastic (random) Monte Carlo model.
- 2 **Analyze Extreme Events:** Use simulation to find the likelihood of "tail risks" (e.g., running out of money) rather than just finding the mean ending balance.

### Primary Purpose

To demonstrate how Monte Carlo simulation improves upon deterministic models for retirement planning by introducing uncertainty and analyzing extreme events.

### The Three Sub-models:

- 1 **Sub-model 1 (Deterministic):** A fixed growth formula ( $I = Prt$  style) using constant rates.
- 2 **Sub-model 2 (Single Stochastic):** Introduces randomness to the interest rate ( $r$ ) for a single run.
- 3 **Sub-model 3 (Full Monte Carlo):**
  - » Randomizes **Principal** ( $P_0$ ) per experiment.
  - » Randomizes **Interest Rate** ( $r$ ) per year.
  - » Runs  $N$  experiments to analyze **Skewness** and **Kurtosis**.

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**Algorithm 1** Monte Carlo Retirement Simulation

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```
1:  $Results \leftarrow []$ 
2:  $N \leftarrow 1000$                                 ▷ Number of experiments
3: for  $i = 1$  to  $N$  do
4:    $P \leftarrow \text{Triangular}(15k, 25k, 35k)$         ▷ Sample Principal once
5:   for  $t = 1$  to 40 do
6:      $r \leftarrow \text{Normal}(\mu = 0.10, \sigma = 0.12)$     ▷ Sample Rate annually
7:      $P \leftarrow P \times (1 + r) + 10,000$             ▷ Apply Interest + Contribution
8:   end for
9:   Append  $P$  to  $Results$ 
10: end for
11: Calculate Skewness( $Results$ )
12: Calculate Kurtosis( $Results$ )
```

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The code maps directly to the algorithm. Note the separation of the **Experiment Loop** and the **Yearly Projection Loop**.

```
def run_pattern_3(params):
    n = params['n_experiments']
    t = params['years_t']
    s = params['contribution_s']
    final_values = []

    # 1. Experiment Loop
    for i in range(n):
        # Sample Stochastic Principal ONCE per experiment
        p_current = np.random.triangular(
            params['p_tri_min'], params['p_tri_mode'], params['p_tri_max'])

        # 2. Yearly Projection Loop
        for _ in range(t):
            # Sample Stochastic Rate EACH year
            r = np.random.normal(params['mean_r'], params['sigma_r'])
            p_current = p_current * (1 + r) + s

        final_values.append(p_current)
    return np.array(final_values)
```

# Going Further: Sensitivity Analysis

How does volatility ( $\sigma$ ) affect the shape of our outcomes? We can sweep through sigma values to see how Skewness and Kurtosis react.

## Code Concept:

- Wrap the experiment in a loop over 'sigma-range'.
- Collect Mean, Skew, and Kurtosis for each level of volatility.

## Why it matters:

- High Kurtosis = Higher risk of extreme poverty or extreme wealth.
- Helps clients understand "Tail Risk" beyond just the "Average Return."

## Key Output Metrics

Use `scipy.stats.skew` and `scipy.stats.kurtosis` on the final array of results to quantify these risks.



Now, it's your turn to implement a retirement plan in Python or using XLRisk! Good Luck!

# How to Naively Pick a Distribution

## Discrete Data (Counts/Integers)

Can you estimate outcomes & probs?

- › Yes: Use an **Empirical Distribution**.
- › No: Check Symmetry.

Is the data **Symmetric**?

- › Yes:
  - ›› Clustered around center? → **Binomial**
  - ›› Equal probability? → **Uniform Discrete**
- › No:
  - ›› Outliers positive? → **Geometric, Negative Binomial**

## Continuous Data (Measurements)

Is the data **Symmetric**?

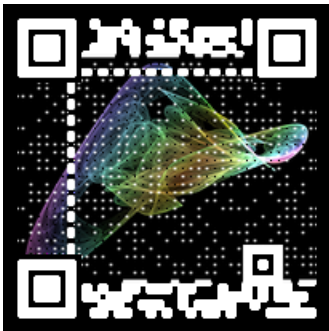
- › Yes:
  - ›› Clustered around center? → **Normal, Logistic**
  - ›› No central cluster? → **Uniform, Triangular**

Is the data **Asymmetric**?

- › Where are the outliers?
  - ›› Only Positive? → **Exponential, Lognormal, Gamma, Weibull**
  - ›› Mostly Negative? → **Min. Extreme Value**

Throughout the course, I may ask for your feedback on:

- **Course Materials**
- **Lecture & Lab**
- **Assignments**



First, I will thank you all again for coming to lab at 5 pm on a Tuesday!

And now, you need to do the following tasks:

- **Submit** your Python file to Gradescope by next week's lab!
- **Read** Prelab 3 for next week!

Let's keep on moving forward!