1. Theoretical

Welford's Recursion

Welford's recursion is a practical and stable method to calculate the running mean and variance of a dataset incrementally. Unlike the standard approach, which recalculates mean and variance from scratch after each new data point, Welford's method updates these quantities using only a few variables. This makes it suitable for streaming data or large datasets where storing all observations is impractical.

Variables used:

- n: number of data points processed so far
- μ_n : running mean after nnn data points
- M2_n: running sum of squared differences from the current mean

Step-by-step update:

1. Initialization

$$n=0, \quad \mu_0=0, \quad M2_0=0$$

2. For each new data point Xn:

- Increment the counter: $n \leftarrow n+1$
- Compute the difference from the previous mean: $\delta = X_n \mu_n 1$
- Update the mean: $\mu_n = \mu_{n-1} + \delta/n$
- Adjust the difference: $\delta_2 = X_n \mu_n$
- Update the sum of squared differences: $M2_n=M2_{n-1}+\delta \cdot \delta_2$

3. Compute final variance and standard deviation (for n>1):

$$s^2=rac{M2_n}{n-1},\quad s=\sqrt{rac{M2_n}{n-1}}$$

Why this method is effective:

- **Efficient:** Each data point is processed only once.
- **Memory-friendly:** Only three variables are required, regardless of dataset size.
- **Stable:** Incremental updates reduce rounding errors.

• **Flexible:** Works with any dataset without modification.

In short, Welford's recursion provides a simple, robust, and elegant way to track running mean and variance.

2. Applications

Euler-Maruyama Simulator Refinement

To better study stochastic processes, I extended the Euler–Maruyama simulator with the following features:

A. Random Walk with Jumps

- Each step can increase or decrease the current state by 1, with probability p for a +1 and 1-p for a -1.
- This models a discrete-time random walk and allows analysis of systems where outcomes can both succeed and fail.

B. Absolute and Relative Frequency Trajectories

- **Absolute frequency (Bernoulli):** Counts total successes, always increasing with each success.
- **Absolute frequency (Random Walk):** Oscillates because outcomes can be positive or negative.
- **Relative frequency:** Normalized by the number of trials.
 - o Bernoulli relative frequency approaches ppp over time.
 - o Random walk relative frequency stabilizes around 2p-1, the expected drift.

C. Final and Intermediate Distributions

- The simulator can show the distribution of outcomes either at the end or at an intermediate time step selected by the user.
- For each case, it calculates the **mean** and **variance**, making it easy to compare different processes.
- A single interface controls all variants (absolute/relative frequency, Bernoulli/random walk, step number, probability p), allowing for flexible experimentation.

Observations on Mean and Variance

• Bernoulli model:

- Absolute frequency grows steadily; mean increases linearly (np) and variance as np(1-p).
- o Relative frequency converges to p, variance decreases with time.

• Random walk model:

- Absolute frequency fluctuates above and below zero; mean grows as n(2p-1).
- o Relative frequency remains near the expected drift; variance decreases with normalization but is higher than in the Bernoulli case.

Differences between absolute and relative frequencies:

- Absolute frequencies are integers and can have a wide range of values (0 to n in Bernoulli, –n to n in random walk).
- Relative frequencies are normalized, real-valued, and more concentrated around the expected value.

Summary:

- Bernoulli processes are predictable and steadily growing, both in absolute and relative terms.
- Random walks show oscillations in absolute frequencies but stabilized relative frequencies.
- Variance grows faster in random walks but relative normalization reduces its effect over time.

These observations give a clear understanding of how mean and variance evolve in different stochastic processes and highlight the value of parametric simulation tools for exploring such behaviors.