

Problem 3

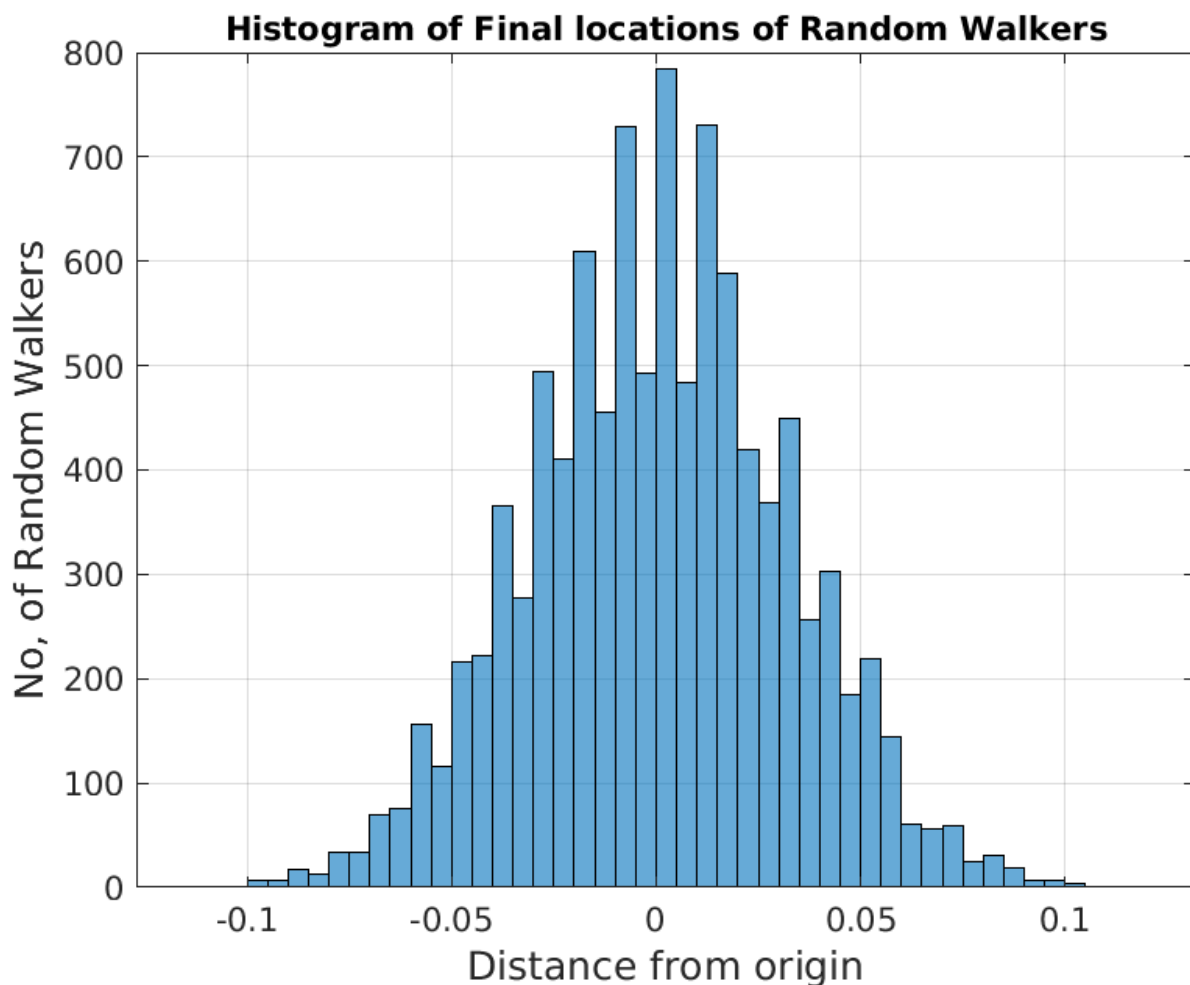
How to run code

- My submissions are live-scripts of matlab
- They are in zip format, don't unzip them
- Open matlab go to the folder of that zip and open the *.mlx files from matlab
- They would appear as jupyter notebook with markdown, codeblock and outputs.
- Press ctrl + enter to run each code block

Problem 3.1

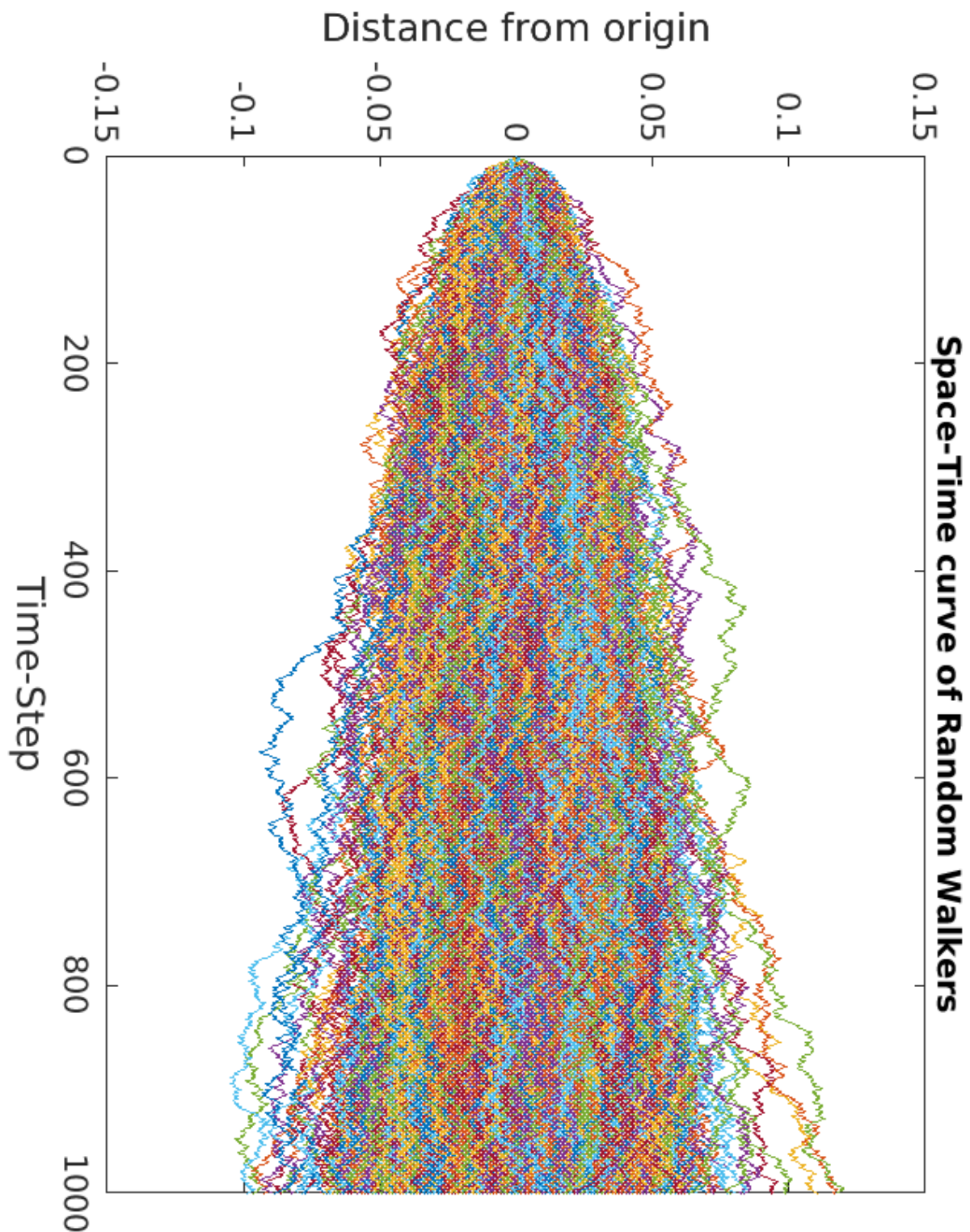
Part 1

- We have $N = 10^4$ random walkers.
- Further suppose within each timeframe Δt , walkers take either a $\Delta z = 10^{-3}$ step right with probability p (say 0.5 for simplicity), OR a Δz step left with probability $q := 1 - p$ ($= 0.5$)
- If in an event a walker took ' x ' steps right and ' $n-x$ ' steps left then random walker's final location is at $z = \Delta z(2x - n)$
- Where variable x can be obtained using `binornd()` in matlab for various random walkers $N_i \in N$, because x is the result of repeated Bernoulli trial (Number of success(here taking right step) in n trials with success probability p) and hence has a binomial distribution.
- Now we can find final location and plot the histogram



Part 2

- A 2D matrix is made to contain location of each random walker after each step 1,2,3....n
- This was done by running a loop and then adding to the previous row, 10^3 Bernoulli random variables for left and right steps, to obtain the next row.



Part 3

[code]

Problem 3.2

a) Law of large numbers:- For all $\epsilon > 0$, as $N \rightarrow \infty$, $P(|\hat{M} - E[X]| \geq \epsilon) \rightarrow 0$

By Markov inequality, we write as $N \rightarrow \infty$ for all $\epsilon > 0$

$$P(|\hat{M} - E[X]| \geq \epsilon) \leq \frac{E(|\hat{M} - E[X]|)}{\epsilon}$$

So we have

$$E(|\hat{M} - E[X]|) \rightarrow 0 \text{ as } N \rightarrow \infty$$

$$\text{So } \hat{M} := E[X] \text{ as } N \rightarrow \infty$$

b) Replacing X_i by X_i^2 in the above proof, we have

$$\frac{X_1^2 + X_2^2 + \dots + X_N^2}{N^2} := E[X^2] \text{ as } N \rightarrow \infty$$

Now,

$$\begin{aligned} \hat{V} &= \frac{\sum_{i=1}^N (X_i - \hat{M})^2}{N} = \frac{\sum_{i=1}^N X_i^2}{N} - \frac{2\hat{M} \sum_{i=1}^N X_i}{N} + \frac{\hat{M}^2 \cdot N}{N} \\ &= \frac{\sum_{i=1}^N X_i^2}{N} - \hat{M}^2 \end{aligned}$$

The first term tends to $E[X^2]$ and second tends to $E[X]^2$ as $N \rightarrow \infty$ by part A.

So,

$$\hat{V} \rightarrow E[X^2] - E[X]^2 \text{ as } N \rightarrow \infty$$

$$\text{or } \hat{V} := \text{Var}(X) \text{ as } N \rightarrow \infty$$

Part 1

Empirically-computed mean $\hat{M} = 3.9120\text{e-}04$

Empirically-computed variance $\hat{V} = 9.9757\text{e-}04$

Part 2

$$\begin{aligned}\text{True mean} &= \frac{\sum_{N_i=1}^N z_i}{N} \\ &= \frac{\sum_{N_i=1}^N \Delta z(2x_i - n)}{N} \\ &= \Delta z \left(2 \frac{\sum_{N_i=1}^N x_i}{N} - n \right)\end{aligned}$$

Now since x is a binomial distribution with success probability p and number of trials n its mean is simply np .

Thus :=

$$\begin{aligned}\text{True Mean} &= \Delta z \cdot n(2p - 1) \\ &= 0\end{aligned}$$

$$\begin{aligned}\text{True mean} &= \text{Var}(z) \\ &= \text{Var}(\Delta z(2x_i - n)) \\ &= 4(\Delta z)^2 \text{Var}(x)\end{aligned}$$

Now since x is a binomial distribution with success probability p and number of trials n its variance is simply $np(1-p)$.

Thus :=

$$\begin{aligned}\text{True Variance} &= 4(\Delta z)^2 \cdot np(1 - p) \\ &= 1.0000\text{e-}03\end{aligned}$$

Part 3

$$\text{error_mean} = |\text{True mean} - \text{Empirical mean}| = 3.9120\text{e-}04$$

$$\text{error_variance} = |\text{True variance} - \text{Empirical variance}| = 2.4314\text{e-}06$$