# Gravitation Wave Identification

## Using Metropolis Hastings Algorithm

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# Problem Statement

# Problem Statement

Given a time series strain data with added noise with the structure of a gravitational wave as given below

$$h(t) = \alpha e^t [1 - \tanh\{2(t - \beta)\}] \sin(\gamma t)$$

$\alpha, \beta, \gamma$ are parameters that signify the physical properties of the given wave. There value ranges are

$$0 < \alpha < 2$$
$$1 < \beta < 10$$
$$1 < \gamma < 20$$

We need to determine the parameter values using a Metropolis Hastings Random walk algorithm in the 3 dimensional space.

# Understanding Wave Parameters

Let us visualize how the parameters α, β, and γ influence the waveform

1. α controls the amplitude of the signal
2. β shifts the signal in time
3. γ controls the oscillation frequency

Animation Paramater effects

# Methodology

# Random Walks

1. Initialization: We start with initial parameter values at the midpoints of the given ranges so

$$\alpha = 1, \beta = 5, \gamma = 10$$

2. Random Walk:

For each iteration we propose a new set of parameters using

$$\theta_{\text{new}} \sim N(\theta_{\text{initial}}, \sigma^2) \quad \text{where} \quad \sigma = [0.005, 0.081, 0.2]$$

The new value is discarded or chosen based on an Acceptance Probability defined as

$$A(\theta_{\text{new}}, \theta_{\text{initial}}) = \min\left(1, \frac{\text{Posterior}(\theta_{\text{new}})}{\text{Posterior}(\theta_{\text{initial}})}\right)$$

The Posterior function is defined as the following

$$\text{Posterior}(\theta_i) = P(\theta_i \mid \text{data}) \propto P(\text{data} \mid \theta_i)P(\theta_i)$$

Due to the assumptions taken, $P(\theta)$ has no effect on the acceptance ratio and our algorithm as a whole.

$$P(\theta) := \begin{cases} \text{constant if } \theta \in \theta_{\text{constraint}} \\ 0 \text{ everywhere else} \end{cases}$$

The only significant metric to consider is now the Likelihood Function $L(\theta)$ which we define as

$$L(\theta) = \exp\left(-\frac{1}{2N}\sum_i \frac{(y_i - f(\theta_i))^2}{\sigma_i^2}\right)$$

# Results

## Parameter Values

| Parameter | α (alpha) | β (beta) | γ (gamma) |
|---|---|---|---|
| Median Value | 1.38 | 3.91 | 10.00 |
| 95% Credibility Interval | 0.92 - 1.91 | 3.63 - 4.19 | 9.92 - 10.08 |
| Effective Sample Size | 25.0 | 61.1 | 1800.0 |
| MC Standard Error | 0.049 | 0.019 | 0.001 |

The MCMC Algorithm ran with Acceptance Ratio of 0.222.

The Global Signal to Noise Ratio was 0.97, with Local SNR of 0.99

# Measurement Metrics for Metropolis–Hastings

1.  Signal-to-Noise Ratio (SNR):

Measures how strongly the true signal stands out from the noise. A Global SNR of 0.97 indicates a moderately clean signal, while a Local SNR of 0.99 shows that the oscillatory region is highly informative.

1.  Effective Sample Size (ESS):

MCMC samples are correlated, so the true number of independent samples is smaller. ESS quantifies this:

$$\text{ESS} = \frac{N_{\text{samples}}}{1 + 2\sum_{k=1}^{\infty} \rho_{k}}$$

where $\rho_{k}$ is the autocorrelation at lag $k$.

1. Monte Carlo Standard Error (MCSE):

Estimates the uncertainty in the posterior mean due to sampling noise. It is defined as

$$\text{MCSE} = \frac{\sigma}{\sqrt{\text{ESS}}}$$

Low MCSE indicates that the chain produced enough effective samples for reliable estimation of parameter statistics.
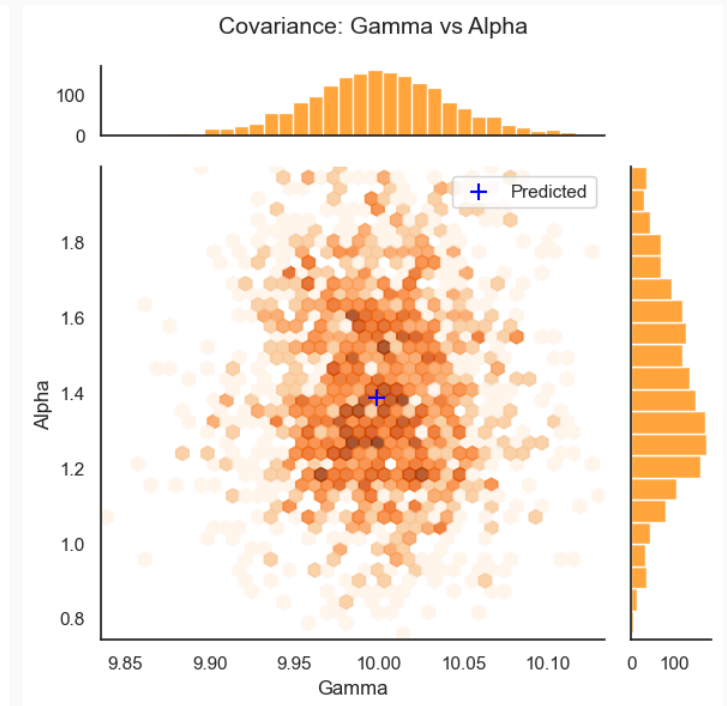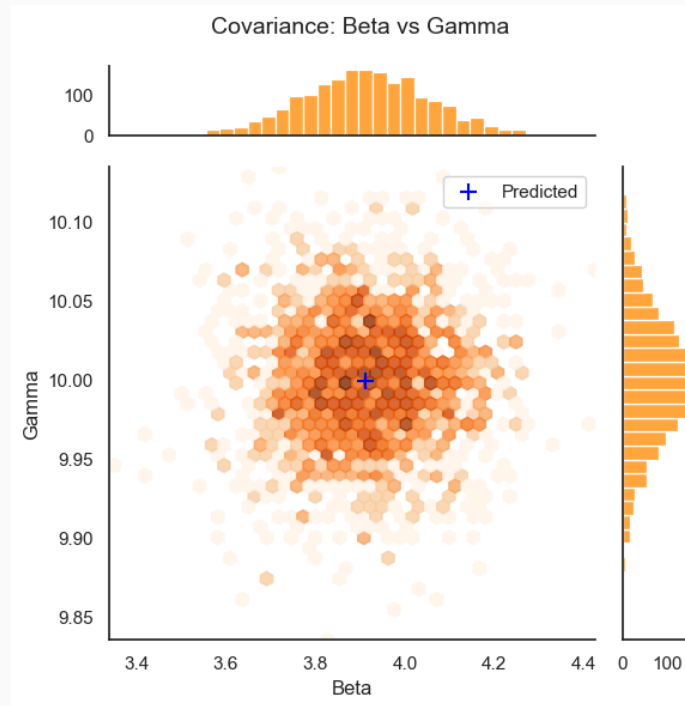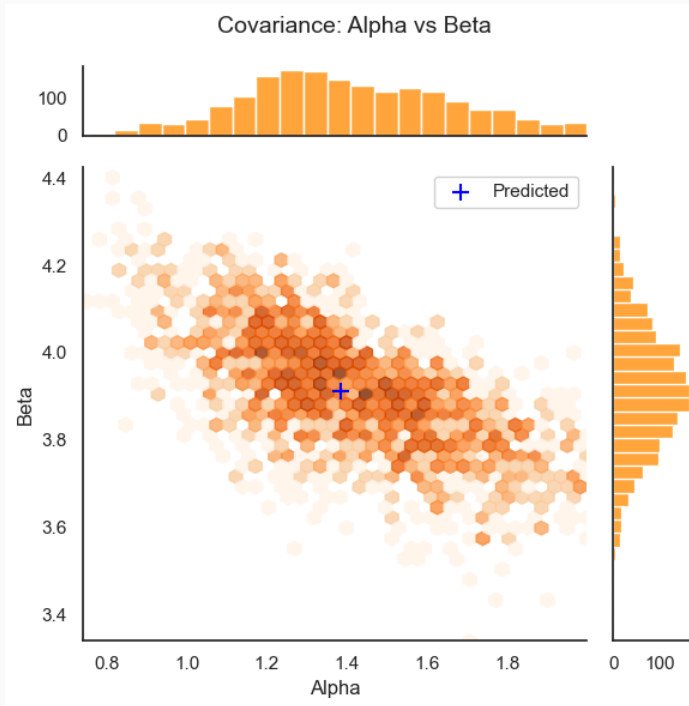
1. Autocorrelation:

Measures how strongly each MCMC sample depends on earlier samples. High autocorrelation means slow exploration and fewer effectively independent samples, directly reducing ESS and increasing MCSE.
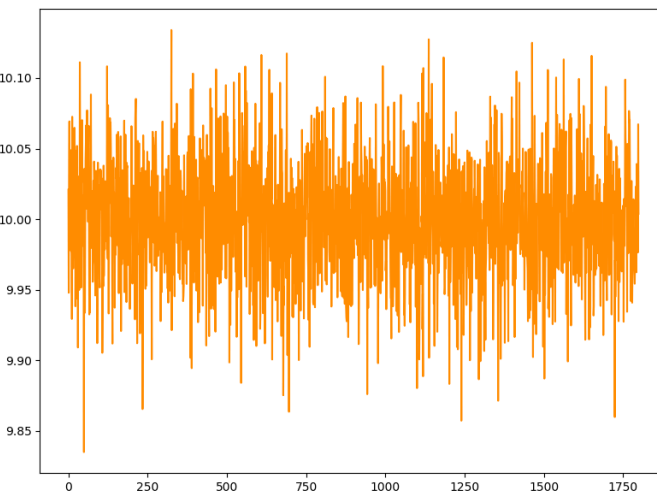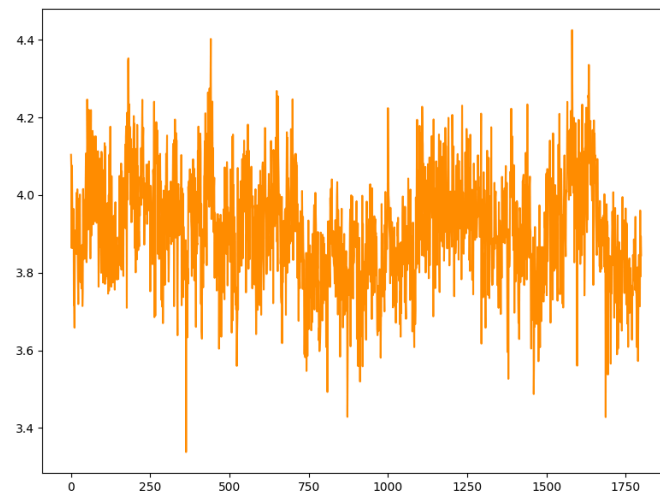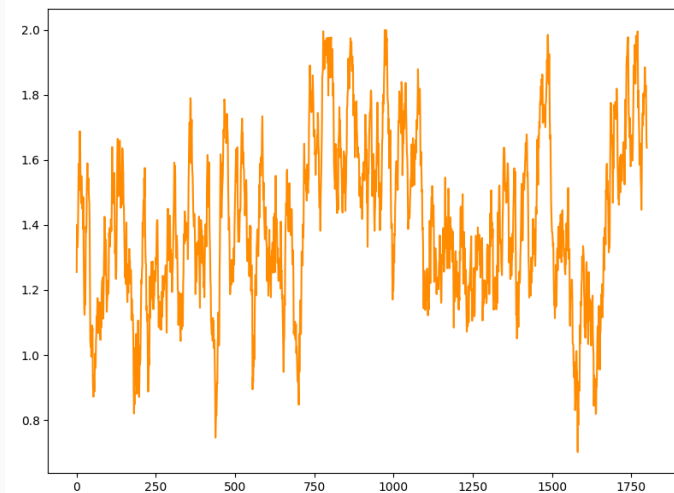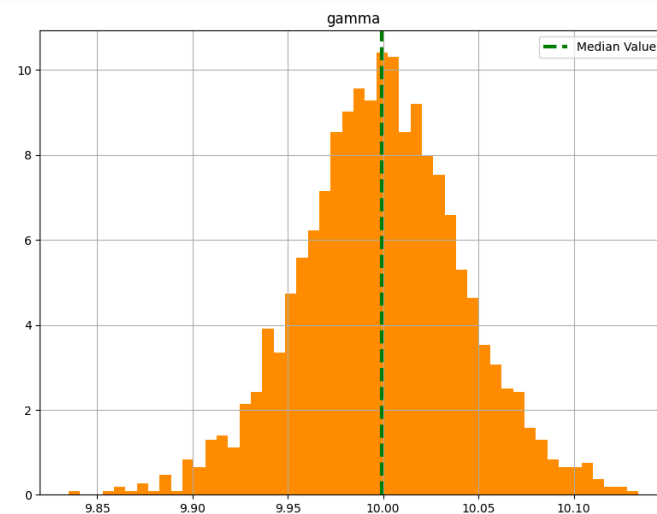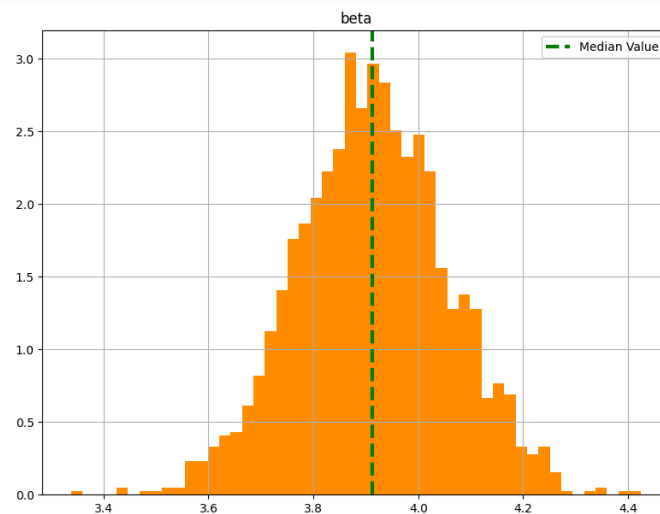
Predicted Model with Noisy Datapoints
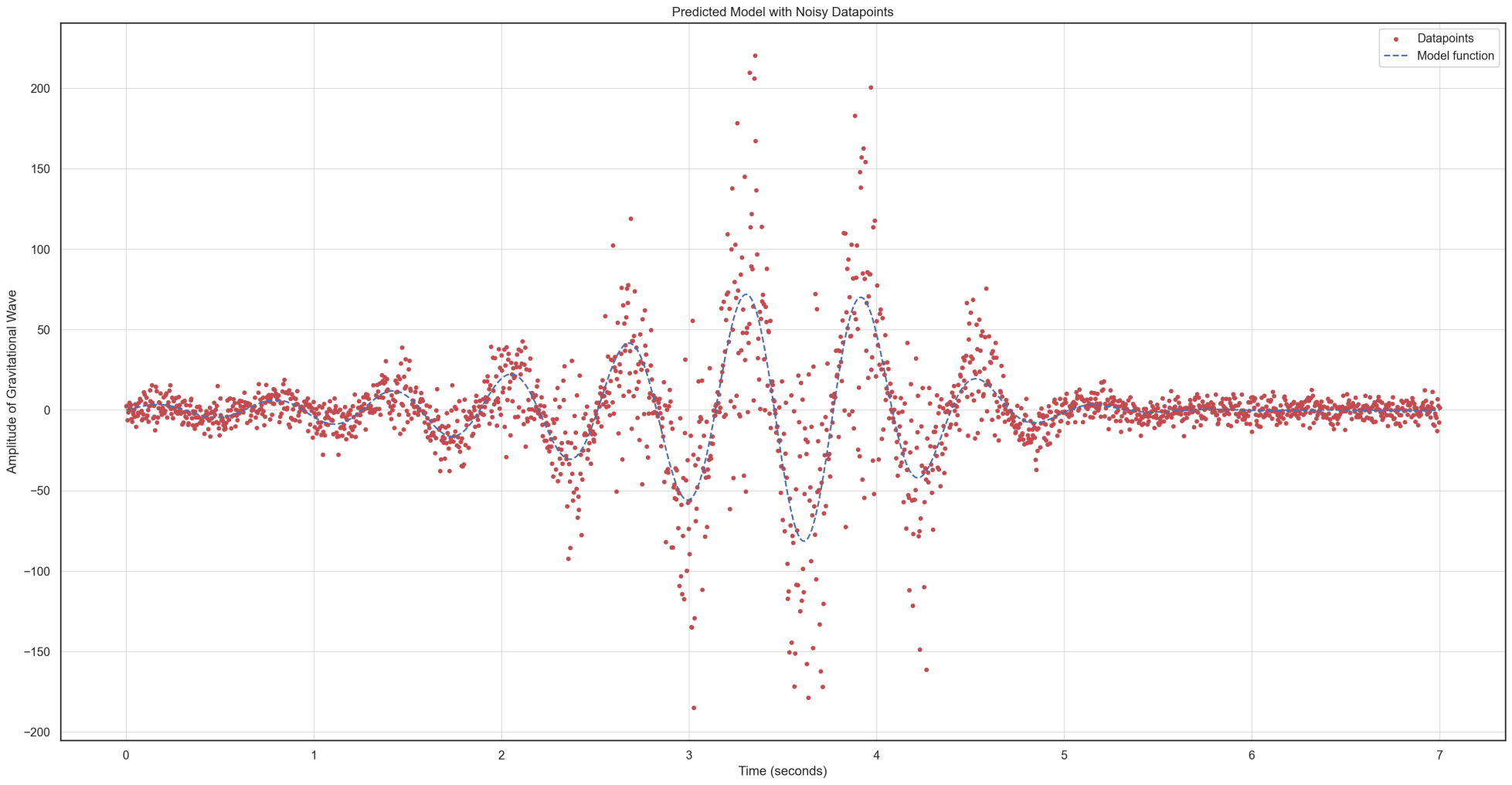
# Covariance Scatter Plots

# Histograms and Trace Plots
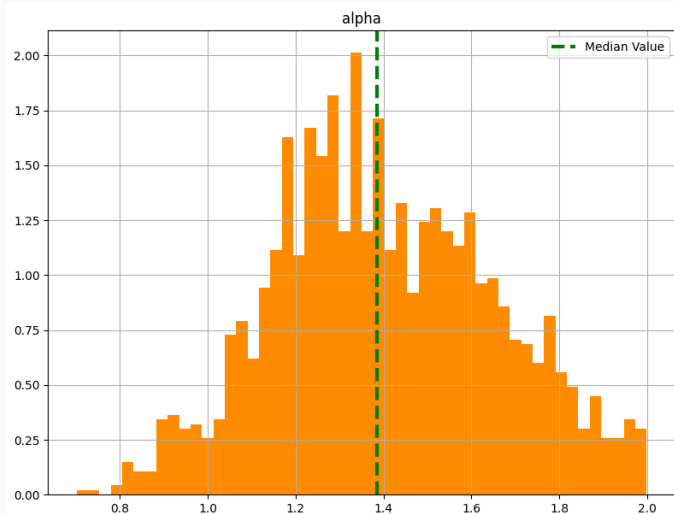
# Optimization

# Scale Selection



Metropolis–Hastings: Accuracy & Acceptance vs Scale Multiplier
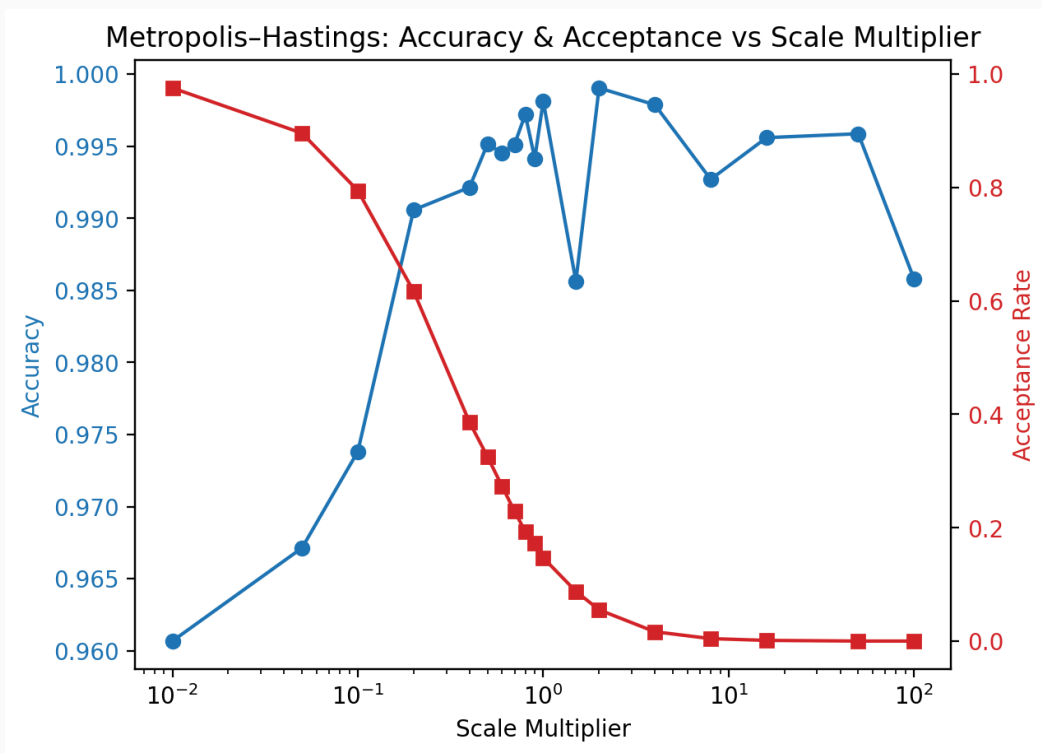
- Small Scales ($< 10^{-1}$)
  - ‣ Chain barely moves $\rightarrow$ strong autocorrelation $\rightarrow$ low accuracy.

- Chosen Scales ($\alpha$: 0.005, $\beta$: 0.1, $\gamma$: 0.2)
  - ‣ (Roberts & Rosenthal, 2004) predicts optimal acceptance $\approx 0.234$ for high-dimensional targets.
  - ‣ Accuracy peaks — this is the optimal region for efficient sampling.

- Large Scales ($> 5$)
  - ‣ Acceptance rate falls $\rightarrow$ chain stagnates $\rightarrow$ accuracy degrades.

# Likelihood Function

-> The original likelihood makes even tiny parameter changes look catastrophically unlikely, driving acceptance to near zero. The new version fixes this by taking a mean instead of summation, keeping acceptance stable.



Effect of Likelihood Definition on Acceptance Probability
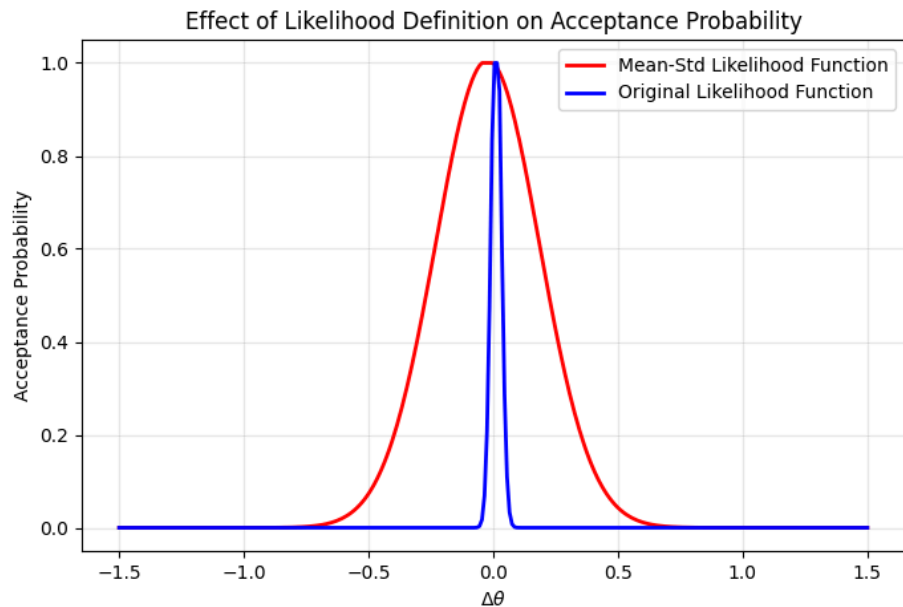
```
def likelihood_new(y_data, y_prior):
    y_err = 0.1 * np.std(y_data)
    Y = np.mean((y_data-y_prior)**2)/y_err**2
    return -0.5 * Y

def likelihood_original(y_datay, y_priory):
    y_err = 0.1 * (y_data + y_prior) + 1e-6
    Y = np.sum(((y_data - y_prior)/y_err) ** 2 )
    return -0.5 * Y
```

# Data Generation for Better Inference

## System Overview

The data generation pipeline accepts an analytical gravitational wave model function and produces a CSV file containing noisy observations at discrete time points. This system serves two primary purposes:

- Algorithm Validation: Generate data with known ground truth parameters to verify MCMC recovery accuracy
- Sensitivity Analysis: Test algorithm performance under varying noise conditions and proposal scales
- Robustness Check : Validate algorithm stability under heteroscedastic noise to assess reliability across signal regimes.

### Noise Formula

The noise standard deviation for each data point is calculated as:

```
f_error = noise x f_points + 0.1 x std(f_points)
f_noisy = f_points +
        np.random.normal(0, np.abs(f_error), num)
```
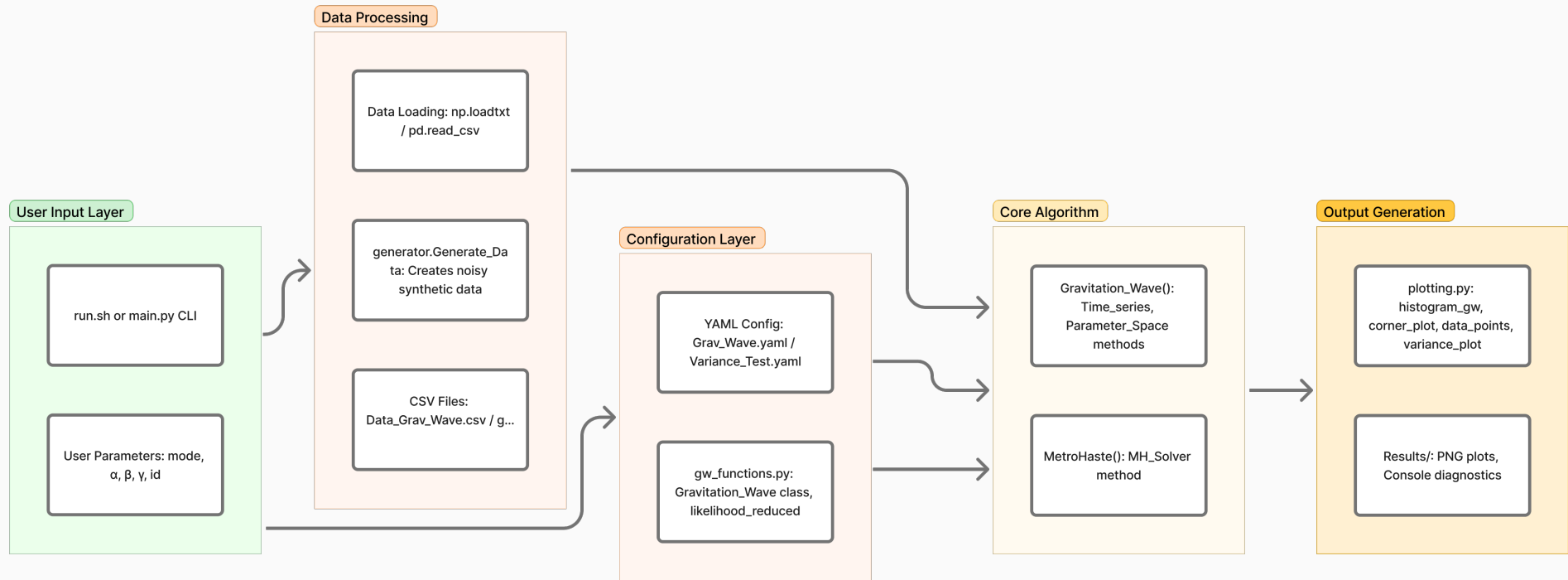
This creates heteroscedastic noise where measurement error grows with signal amplitude.

### Noise Characteristics

| Component | Purpose | Typical Magnitude |
|---|---|---|
| Proportional | Scales with signal amplitude | Dominant near peaks |
| Baseline | Constant floor noise | 4–8 for typical signals |

# Code Structure

**User Input Layer**

- run.sh or main.py CLI
- User Parameters: mode, $\alpha$, $\beta$, $\gamma$, id

**Data Processing**

- Data Loading: np.loadtxt / pd.read_csv
- generator.Generate_Data: Creates noisy synthetic data
- CSV Files: Data_Grav_Wave.csv / g...

**Configuration Layer**

- YAML Config: Grav_Wave.yaml / Variance_Test.yaml
- gw_functions.py: Gravitation_Wave class, likelihood_reduced

**Core Algorithm**

- Gravitation_Wave(): Time_series, Parameter_Space methods
- MetroHaste(): MH_Solver method

**Output Generation**

- plotting.py: histogram_gw, corner_plot, data_points, variance_plot
- Results/: PNG plots, Console diagnostics

# Thank You