Competition Problem Statement

The Solar Flare Pulse: Stochastic Signal Recovery

Competition Committee

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1 Background & Scenario

The Solar Dynamics Observatory (SDO) has captured a high-cadence time series of a localized magnetic reconnection event. This "Stellar Flare" exhibits a characteristic oscillation that grows exponentially as the plasma heats up, followed by a rapid quenching (shutdown) as the magnetic loop ruptures.

Your task is to extract the physical parameters of this flare from the noise-corrupted sensor data to predict the energetics of the event.

2 The Analytical Model

The intensity $S(t)$ of the flare is modeled by the following analytical template:

$$S(t) = A \cdot e^t \cdot \{1 - \tanh[2(t - \tau)]\} \cdot \sin(\omega t) \tag{1}$$

Where the parameters represent physical properties of the system:

- A : Intensity Scale (Amplitude). Range: $0 < A < 2$
- τ (tau) : Quench Time (Event Peak). Range: $1 < \tau < 10$
- ω (omega) : Angular Frequency. Range: $1 < \omega < 20$

3 The Challenge

You are provided with a dataset `flare_data.csv` containing two columns: time (t) and sensor intensity (y_{data}). The data is heavily corrupted by noise.

Your goal is to perform a **Bayesian Parameter Estimation** by implementing a Random Walk in the 3D parameter space (A, τ, ω) using the **Metropolis-Hastings algorithm**.

Statistical Assumptions

1. **Prior $P(\theta)$:** Assume uniform (flat) priors within the ranges specified above for all parameters.
2. **Likelihood $P(D|\theta)$:** Assume a relative error of 20% at each data point. The probability of the data given the parameters is estimated as proportional to $\exp(\mathcal{L})$, where the Log-Likelihood $\mathcal{L}$ is defined as:

$$\mathcal{L} = -\sum_i \frac{(y_{\mathrm{data},i} - y_{\mathrm{model},i})^2}{\sigma_i^2} \tag{2}$$

Where the error σ_i is defined relative to the signal strength:

$$\sigma_i = 0.2 \cdot |y_{\mathrm{data},i}|$$

Hint: *Participants should consider how to handle numerical stability when the signal y_{data} crosses zero.*

4 Deliverables

Participants must submit a report containing the following:

1. **Trace Plots:** Graphs showing the evolution of each parameter (A, τ, ω) versus iteration number. Use these to demonstrate that your MCMC chain has converged.
2. **Posterior Distributions:** Plot the histograms for the posterior distributions of each parameter.
3. **Best Fit Values:** Report the Maximum A Posteriori (MAP) estimates for A, τ, and ω.
4. **Source Code:** The Python script (or notebook) used to generate the results.