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Seismic Monitoring with Feature-based Bayesian Inference and Sequential Tempered MCMC

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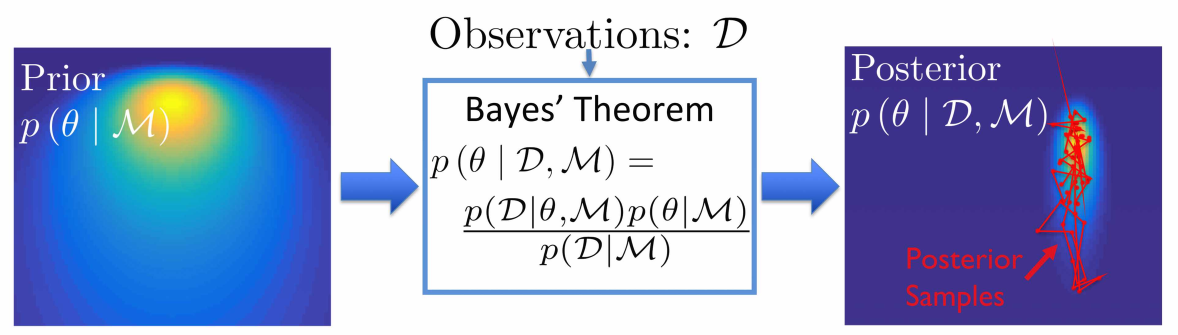
Bayesian Inference Problems

The Bayesian Perspective:

We update uncertainty as information or observations (D) are added (Bayes' Theorem)



Applications
- Calibrate model parameters p(θ|D)
- Compare model structures p(M|D)

Challenges of Bayesian Methods:

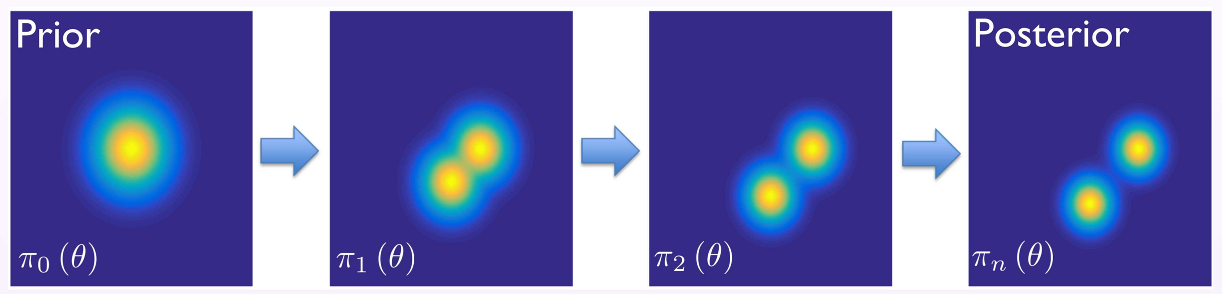
- Markov Chain Monte Carlo (MCMC) is often used to sample the posterior in these applications
- We desire methods that quickly explore the posterior, require little tuning, can be parallelized, and leverage multifidelity models

MCMC Solver

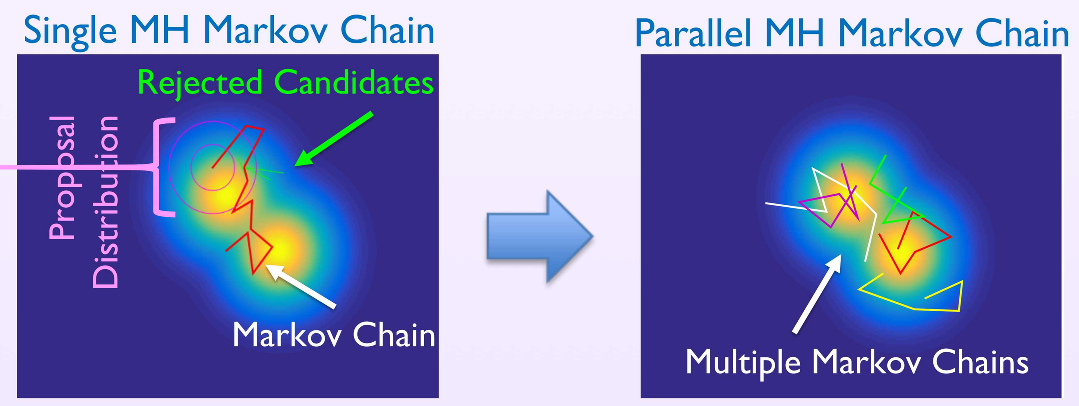
Sequential Tempered MCMC[5,6] (ST-MCMC) :

- Update prior to posterior through intermediate distributions to aid exploration through an annealing factor β to gradually introduce data, sensors, or adjust model fidelity

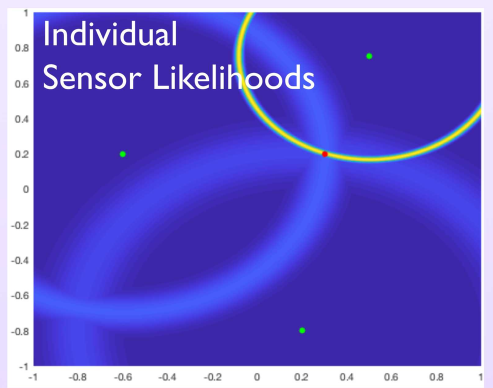
Intermediate Distributions: $\pi_i(\theta) \propto p(\mathcal{D} \mid \theta, \mathcal{M})^{\beta_i}\, p(\theta \mid \mathcal{M}) \quad \beta_i \in [0,1]$



- A population of parallel MCMC chains quickly explore and sample the intermediate distributions



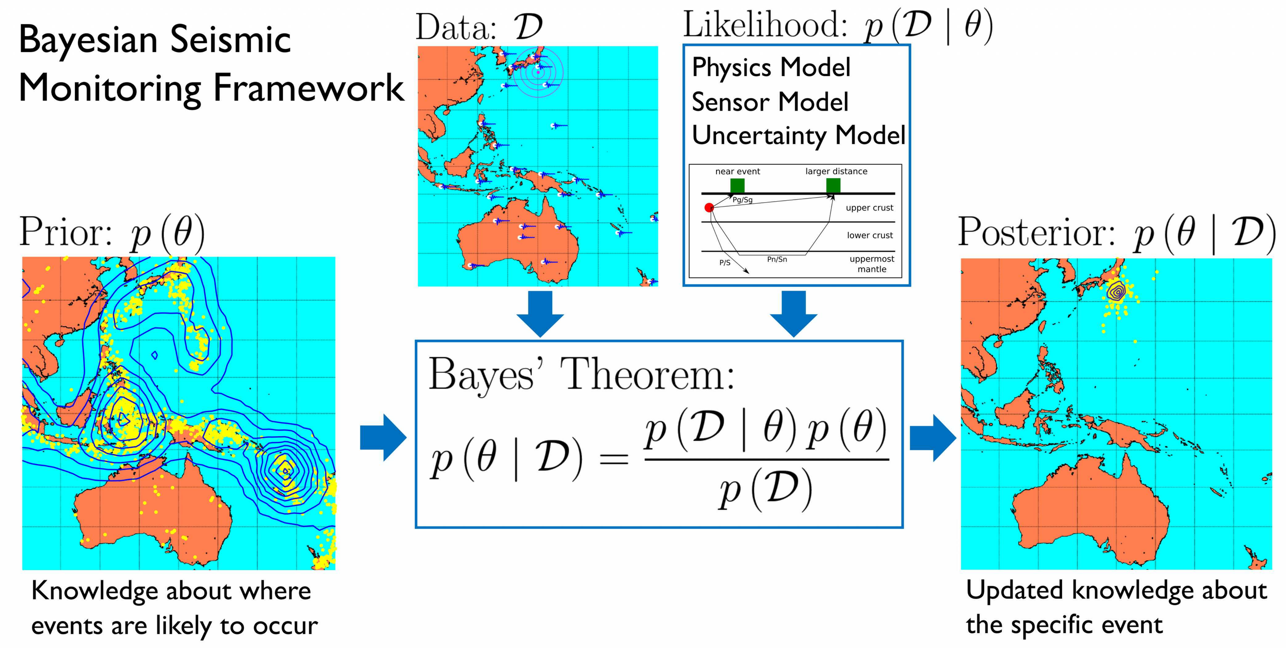
- ST-MCMC adapts online based on statistics from the intermediate samples with little user tuning e.g. adaptively weight sensors to avoid difficult to sample intermediate distributions
- Pseudo-Marginal MCMC[7] can be used to marginalize over sources of uncertainty using an unbiased likelihood estimate



Bayesian Seismic Monitoring

Problem Set up:

- Infer the event parameters: Longitude, Latitude, Depth, Magnitude, Time
- Observations: Seismometer waveforms at various locations
- Uncertainty to integrate: Travel time uncertainty, earth structure heterogeneity, event focal mechanism, background noise process



Challenge:

- Detecting and locating very weak seismic signals requires sensor fusion and utilizing more information signal waveforms
- Uncertainty quantification is essential since there is limited knowledge about the complexities of models, sensors, and data
- Historic data or simulations will need to be used to understand these complexities and synthesize them into tractable models

Potential Impact:

- Provide event information with well calibrated confidences for decisions
- Provide a framework to fuse multi fidelity and phenomenology data
- Enable experimental design methods to quantify a network's ability to detect events and test improvements to the processing system

Existing Methods:

- Detection-Based (e.g. BayesLoc[1], NET-VISA[2]): The event likelihood is based on comparing the predicted seismic wave arrival time to the observed arrival time. This uses a simple travel time model but has difficulty with weak signals when it is hard to detect the arrival.
- Signal-Based (e.g. SIG-VISA[3]): The event likelihood is based on comparing the predicted waveform to the observed waveform. This requires a complex predictive waveform model but can identity weak signals.

Our Approach:

- Formulate an inference problem based upon predicting waveform features instead of the waveforms themselves since this is more tractable
- Simulate waveforms[4] to build a statistical model of waveform features with uncertainty to accelerate inversion
- Use Sequential Tempered MCMC to sample posterior event parameters

Feature-Based Inference

Inference Model:

- Feature-based inference requires building statistical models for the likelihood of a signal given certain features and the likelihood of those features given an hypothesized event

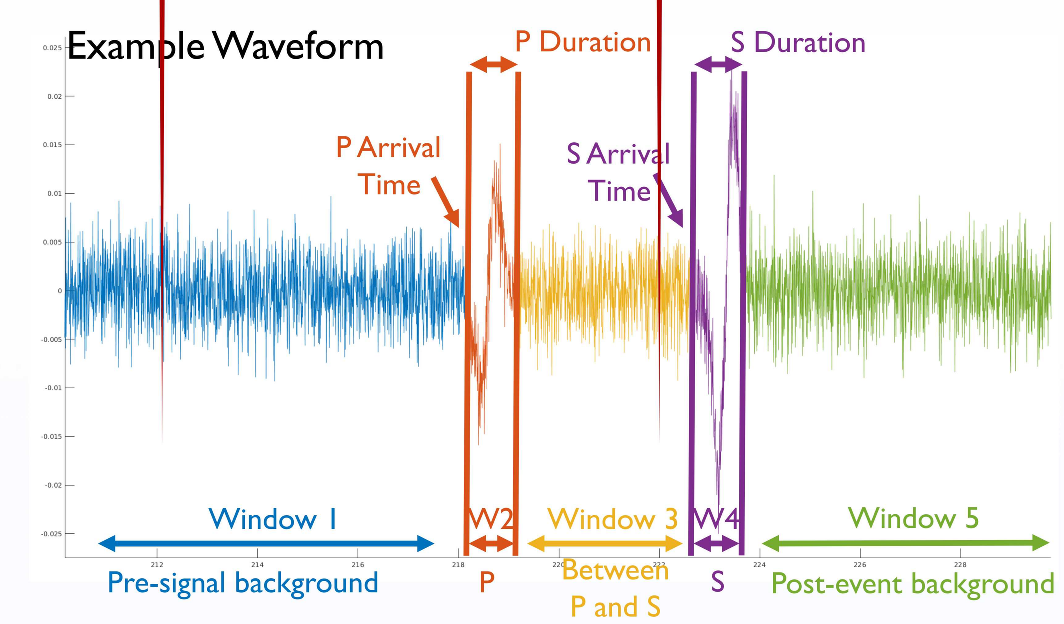
Graphical Model: $\underbrace{\theta}_{\text{Event Parameters}} \rightarrow \underbrace{F}_{\text{Signal Features}} \rightarrow \underbrace{Y}_{\text{Signal Waveform}}$

Mathematical Model:

$$\underbrace{p(\theta \mid Y)}_{\text{Posterior}} = \frac{\overbrace{p(Y \mid \theta)}^{\text{Likelihood}}\,\overbrace{p(\theta)}^{\text{Prior}}}{\underbrace{p(Y)}_{\text{Evidence}}} = \underbrace{\left(\int \overbrace{p(Y \mid F)}^{\text{Signal Likelihood}}\,\overbrace{p(F \mid \theta)}^{\text{Feature Likelihood}}\, dF\right)}_{\text{Marginalize over features}} \frac{p(\theta)}{p(Y)}$$

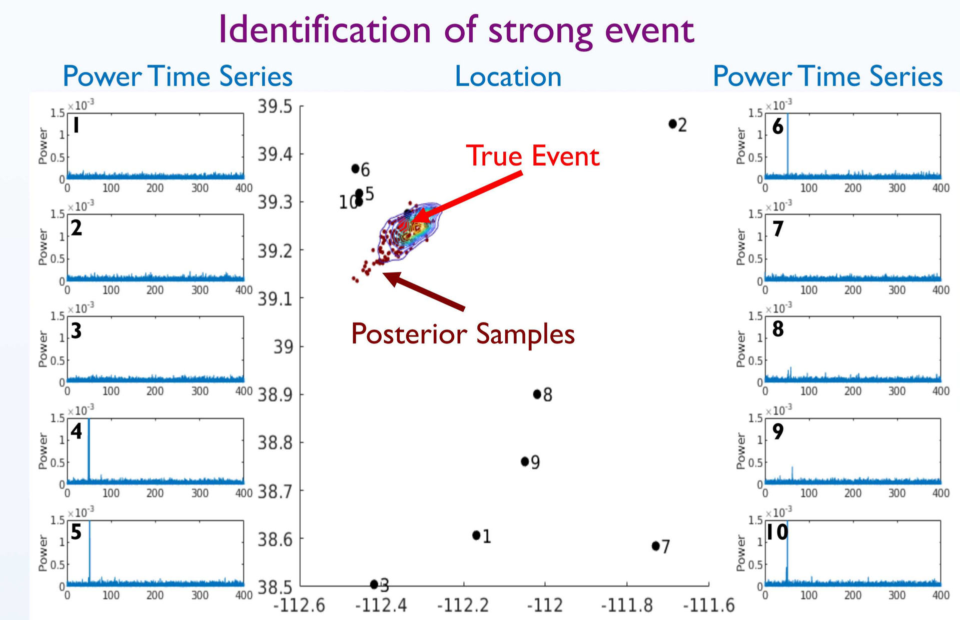
Waveform Features:

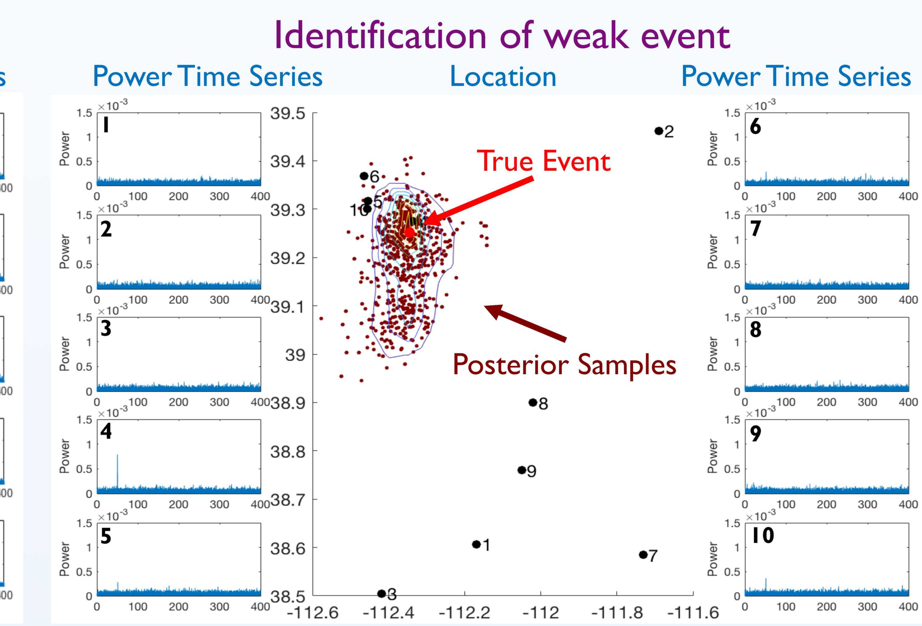
- The arrival times of P and S waves define five signal windows each with associated features e.g. total signal power within the window.
- P and S arrival times and uncertainty can be found using models like AK135
- Build a statistical model for the signal power feature likelihood p(F|θ) using simulations and the signal noise model



Results

Identification of Synthetic Events:





Conclusion:

- Feature-based inference provides a promising approach to signal-based full waveform monitoring that reduces the complexity of the statistical problem
- Advanced MCMC techniques can be employed to reduce the computational burden of the Bayesian inference problem and allow for the explicit integration of uncertainty
- Future work will focus on developing a richer set of features to better isolate information from the seismic event and integrating more complex uncertainty models

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References

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