SAND2020-2789O

Sandia National Laboratories

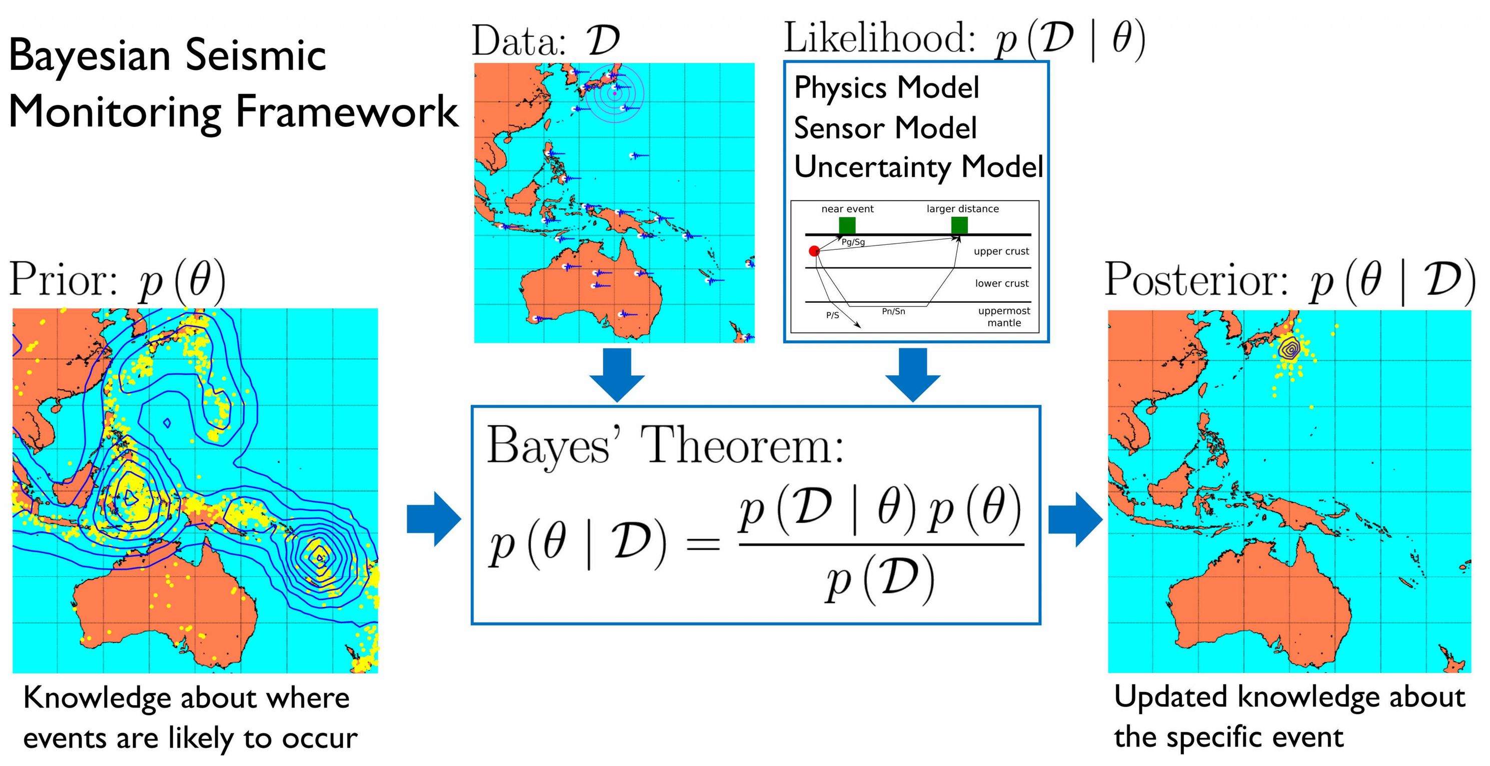
Seismic Monitoring with Feature-based Bayesian Inference

Thomas Catanach, Nathan Downey, and Christopher Young | Sandia National Laboratories

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 likelihood is based on comparing a predicted waveform to the observed waveform. This requires a complex predictive waveform model but can identity weak signals.

Our Approach:

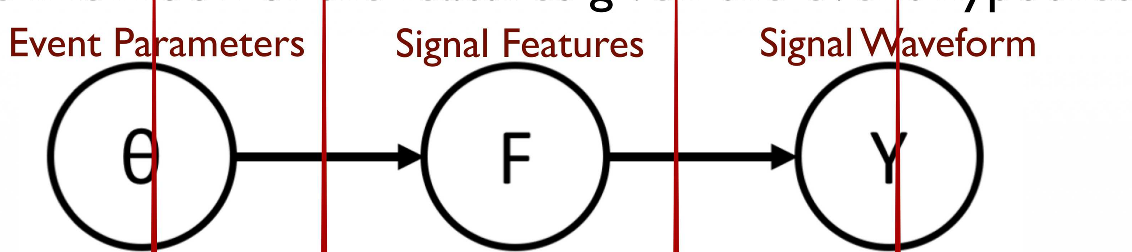
- Formulate an inference problem based on predicting waveform features instead of the waveforms themselves since this is more tractable
- Simulate waveforms[4] to build a statistical model of waveform features with uncertainty to accelerate inversion
- Use Sequential Tempered MCMC to sample posterior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

Feature-Based Inference

Inference Model:

- Feature-based inference requires building statistical models for the likelihood of a signal given features and the likelihood of the features given the event hypothesis

Graphical Model:

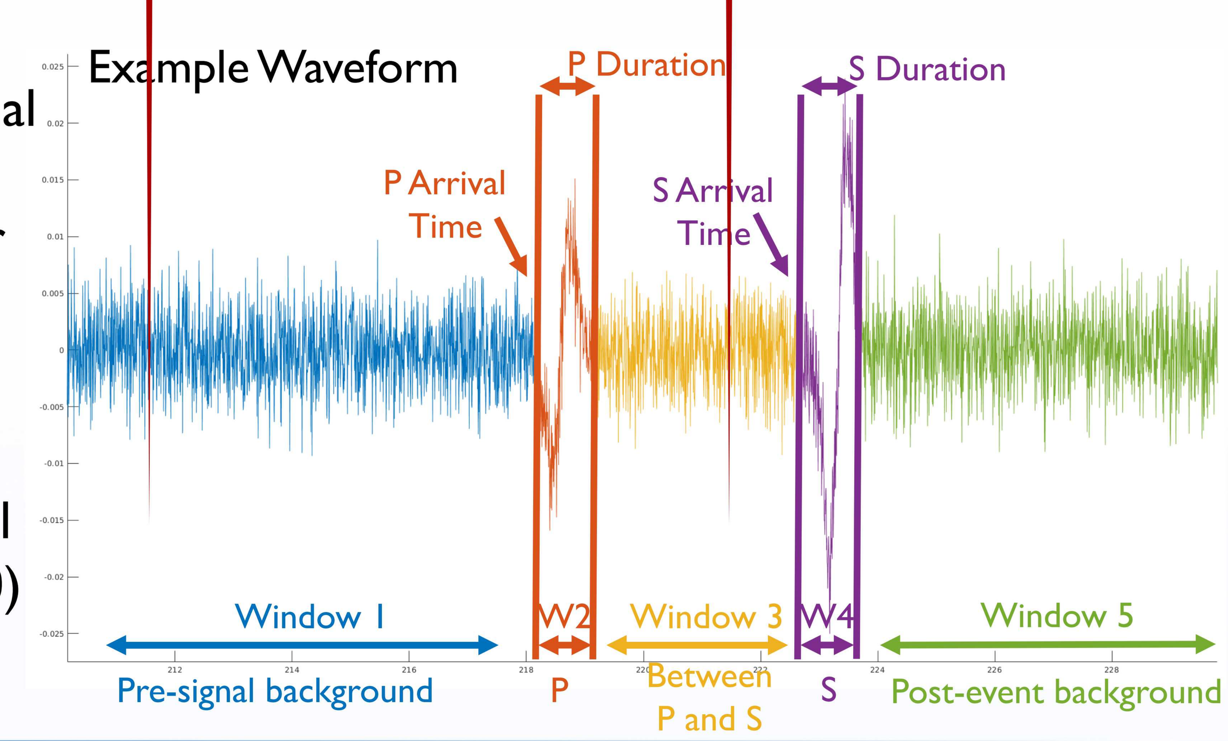


Mathematical Model:

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

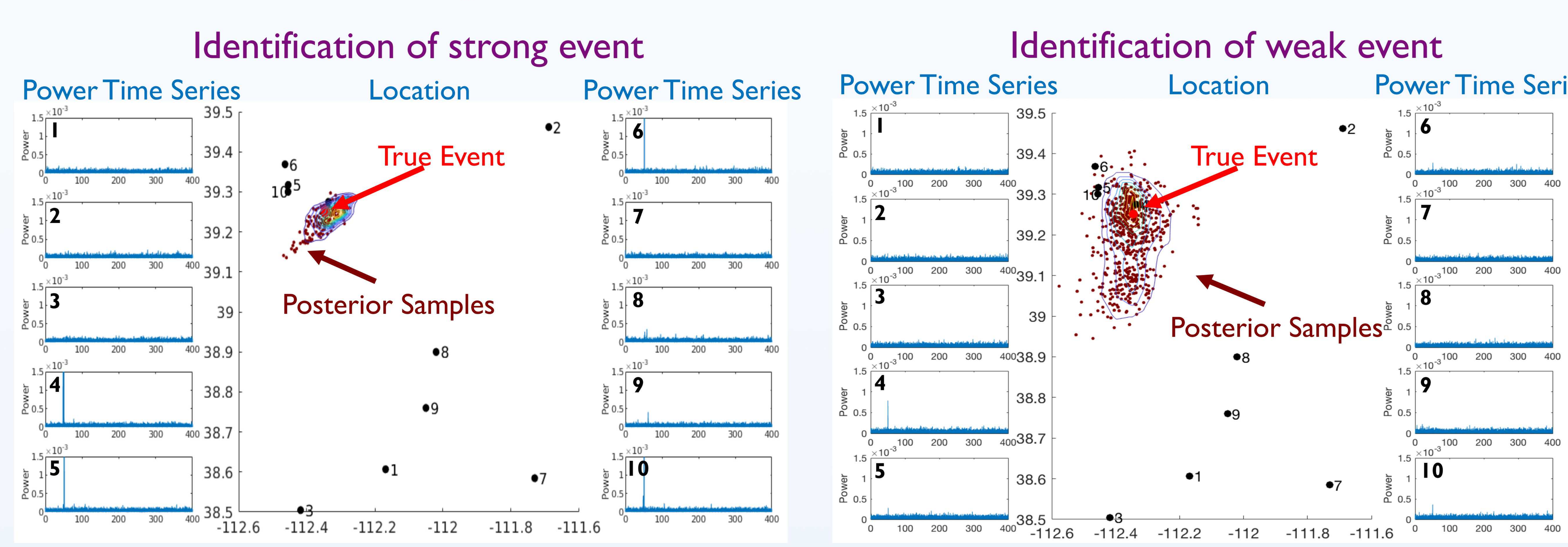
Waveform Features:

- P and S arrivals define five signal windows each with associated features e.g. total signal power within the window.
- P and S arrival times are estimate using AK135
- Statistical models for the signal power feature likelihood p(F|θ) come from simulations



Results

Identification of Synthetic Events:



Conclusion:

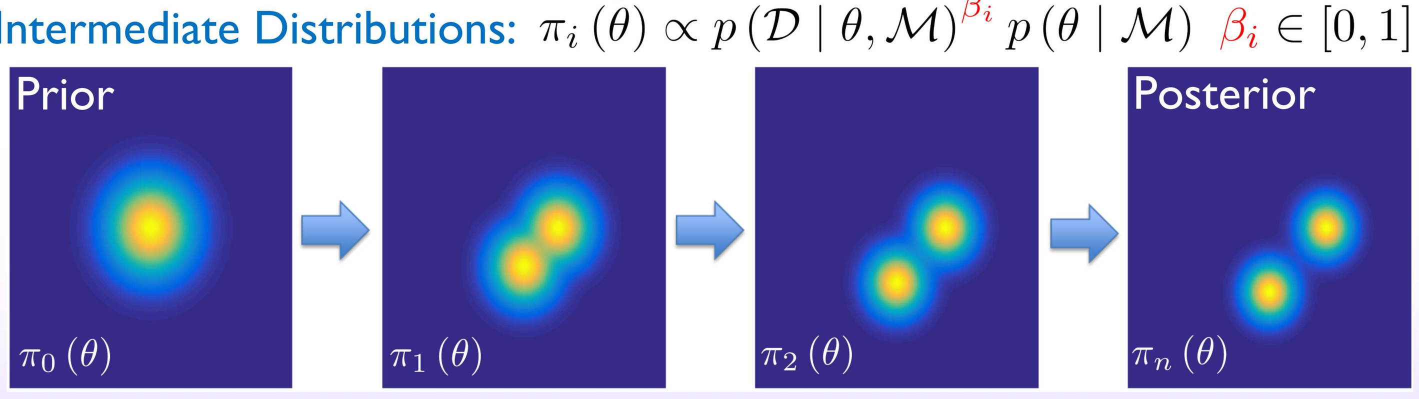
- Feature-based inference provides a promising approach to signal-based full waveform monitoring that reduces the complexity of the statistical problem
- Advanced MCMC techniques can be employed to reduce the computational burden and allow for the explicit integration of uncertainty
- Future work will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

Solving Bayesian Inference Problems with Markov Chain Monte Carlo

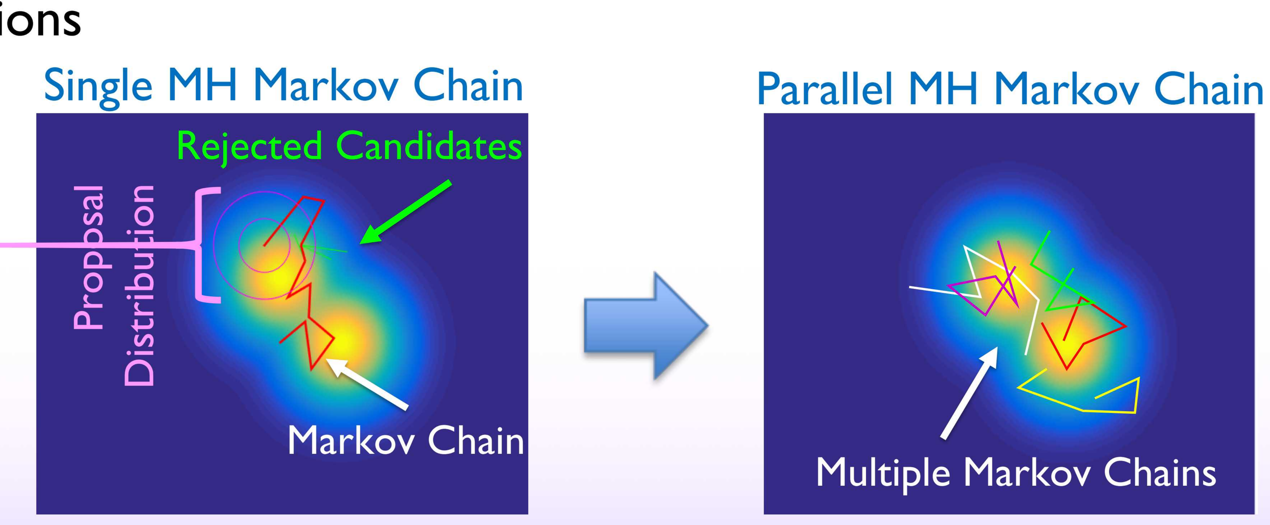
Sequential Tempered MCMC[5,6] (ST-MCMC) :

- 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



Sandia National Laboratories is a multimission laboratory managed and operated by National Technology & Engineering Solutions of Sandia, LLC, a wholly owned subsidiary of Honeywell International Inc., for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA0003525.
SAND No. SAND2019-9596 D

[1] Myers, S. C., et al. "BayesLoc: A robust location program for multiple seismic events given an imperfect earth model and error-corrupted seismic data" (2011)
[2] Arora, Nimar S. et al. "NET-VISA: Network processing vertically integrated seismic analysis" (2013)
[3] Moore, David A., and Stuart J. Russell. "Signal-based Bayesian seismic monitoring" (2017)
[4] Li, Dunzhu, et al. "Global synthetic seismograms using a 2-D finite-difference method." (2014)
[5] Catanach, T A., and J. L. Beck "Bayesian updating and uncertainty quantification using sequential tempered MCMC with the rank-one modified metropolis algorithm" (2018)
[6] Minson, S. E., M. Simons, and J. L. Beck "Bayesian inversion for finite fault earthquake source models I—Theory and algorithm" (2013)