A Hierarchical Approach to Rapid Gravitational Wave Parameter Estimation

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LIGO-G1301137
Parameter Estimation w/ MCMC

- Stochastically walks through parameter space.
- Produces samples with density $\propto$ posterior
  $$p(\theta|d) \propto p(d|\theta)p(\theta)$$
- 9-D for non-spinning circularized compact binary

$$\tilde{\theta} = \{m_1, m_2, t, \nu, d, \alpha, \delta, \phi, \psi\}$$
Timeline of a GW Deliverables

- **Online Detection**
- **Low-Latency Sky Localization**
- **Parameter Estimation**

- Minutes
- Hours
- Days

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A Better Timeline

Online Detection

Low-Latency Sky Localization

Sky Localization & Distance Estimates

Better Localization (intrinsic/extrinsic correlations)

Better Localization (spin correlations)

Mass Estimates

Spins Estimates

Parameter Estimation
Parameter Correlations

- Strong correlations within intrinsic/extrinsic subspaces.
- Weak correlations between subspaces.
Hierarchical Approach

- Low-Latency Localization
  - Intrinsic Analysis
- Pipeline Trigger Values
  - Extrinsic Analysis

Full Analysis
Educating an MCMC

• Can be done through jump proposals.

• Kernel Density Estimators (KDEs):
  + Estimates distribution from samples.
  + Easily draw samples from result.
  + Continuous (helps with detailed balance).
  - Over-smoothes multimodal distributions.

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Educating an MCMC

- Use a density-based clustering algorithm (OPTICS) to extract clusters.
- Estimate posterior in each mode with a KDE.
- Weight KDEs by cluster size.
Hierarchical Performance

- Tested on 20 NS-NS injections in simulated aLIGO noise.
- Intrinsic parameters matter (~50% changes in sky area).
- “Educated” MCMC ~4x more efficient at sampling posterior.
Remaining Work

- Leverage low-latency results.
- Test on 2-detector data.
- Extend to the spinning parameter space.