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Neural likelihood estimators for flexible gravitational wave data anlysis

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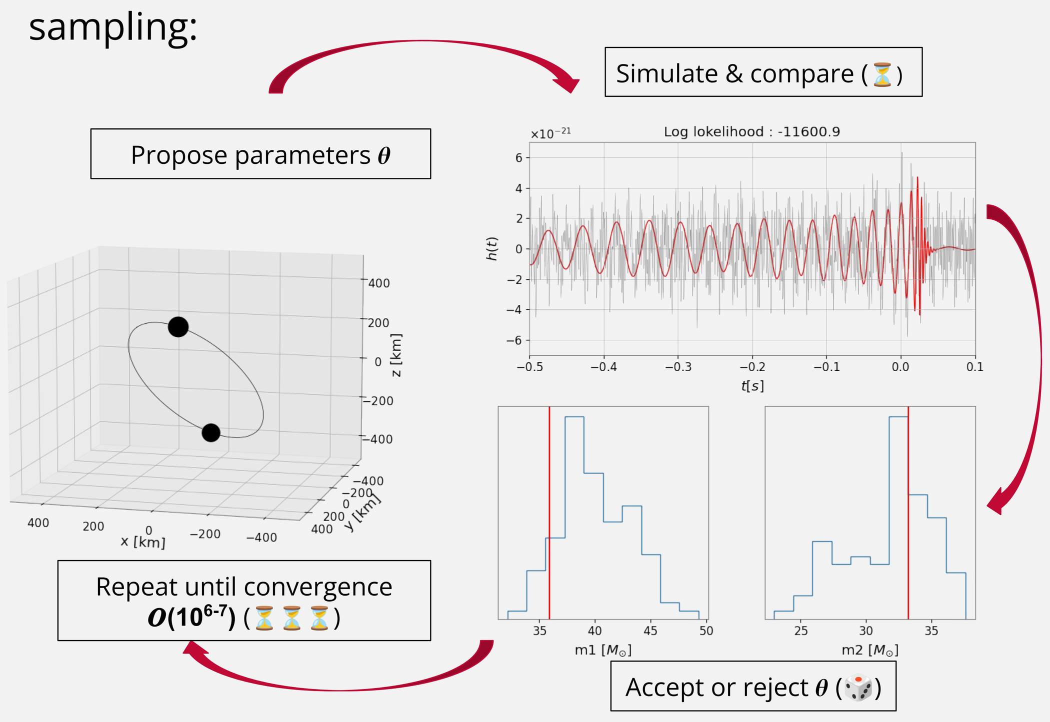
1. Parameter estimation is expensive!

Parameters probability distribution found trough MCMC sampling:



3rd generation of interferometers will come with new challenges:

⏳ ~1000 more signals
⏳ Louder & longer signals
⏳ More complex models

We are not ready to analyze ET data [1]

A big chunk of the science output and the costs of running current analysis comes from "unique" events, that requires multiple PE runs to test different models, different priors, different ways to deal with the noise ...

We want a machine learning approach that is capable of dealing with these challenges

- Flexible
- Easily adaptable
- No special hardware requirements, any scientist should be able to run it

2. What can machine learning do for you?

Many different approaches exists, we will try and use **Neural Likelihood Estimators.**

(Tested before in [2], but not retried ever since)

Basic idea:

$$p(\vec{\theta}|y,\mathcal{M}) = \frac{p(y|\vec{\theta},\mathcal{M})\,p(\vec{\theta}|\mathcal{M})}{p(y|\mathcal{M})},$$ Takes ms to s to evaluate

$$p(\vec{\theta}|y,\mathcal{M}) = \frac{\text{NN}\;p(\vec{\theta}|\mathcal{M})}{p(y|\mathcal{M})},$$ Takes less than a μs even on modest hardware

PROs :

✅ **Speedup** of single likelihood evaluation of factor ~10^5
✅ **FLEXibility**! You can use any sampler, waveform or prior you want with the neural likelihood, no expensive pretraining

BUT ... :

😕 New NN trained on the fly for every signal
😕 Need to generate training data (⏳)
😕 Training add time to full inference
😕 Can NNs even be accurate enough?

This approach needs to balance:

N of initial training samples ⚖ Accuracy of final results

4. Ok but is it good?

Tests done on GW150914-like signals:

- High mass BBHs
- HL/HLV networks
- Phase & distance marginalized
- aligned spin
- Medium-low SNR

} Easiest signals to analyze. Posterior has "only" 9 dimensions

4.1 Yes!

Posteriors match with standard analysis methods for GW150914. Analysis run around ×50 faster on 4 CPUs. 🏍️ 🏍️

Model	Time (on same-ish hardware)	Number of Waveforms
Dynesty	~12 hours	~ 1e7
FLEX	~18 minutes	~ 1.4e5

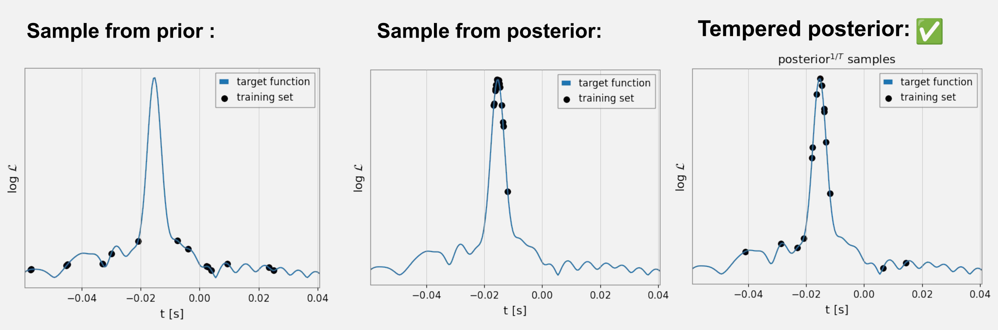
× 70 reduction

still much room for optimization!

3. The Neural Likelihood Estimator.

How does the **F**ast **L**ikelihoods for **E**vidence appro**X**imation (**FLEX**) NLE gets trained? There are 4 phases:

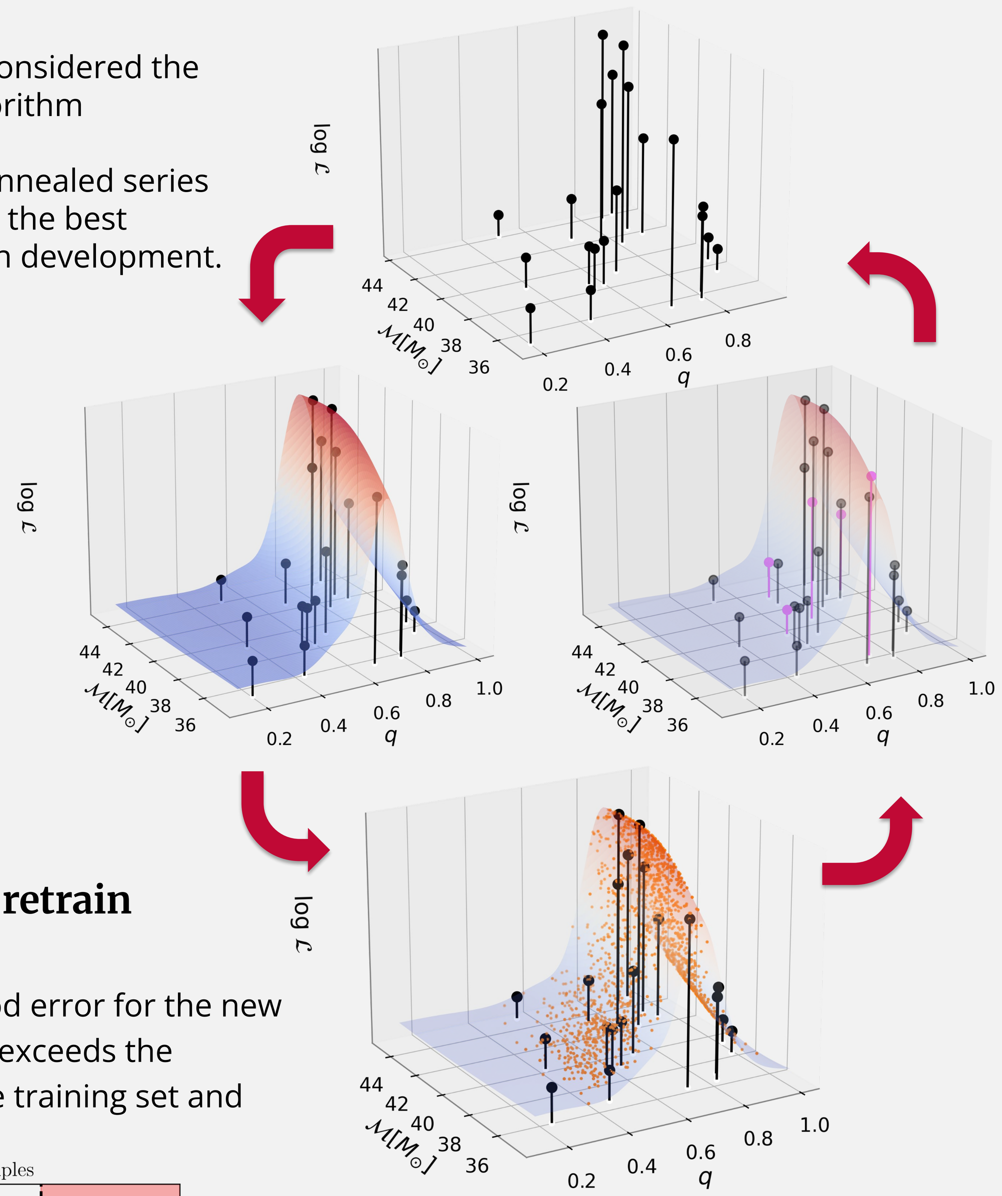
Phase 1: Generate training data



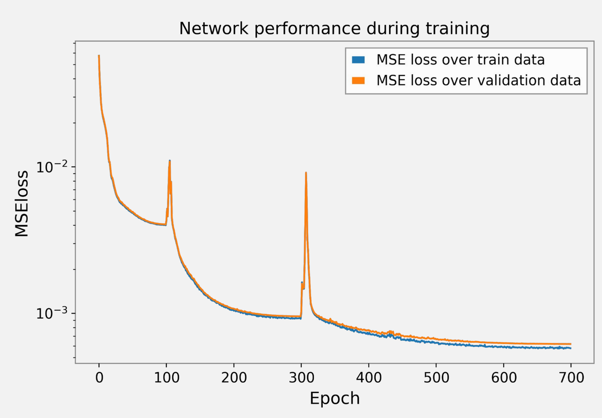
$\theta_i \sim p(\theta|y,\mathcal{M})^{1/T}$

This phase can be considered the "Burn in" of the algorithm

Sampling from an annealed series of posteriors is now the best method, more are in development.



Phase 2: Train the neural likelihood

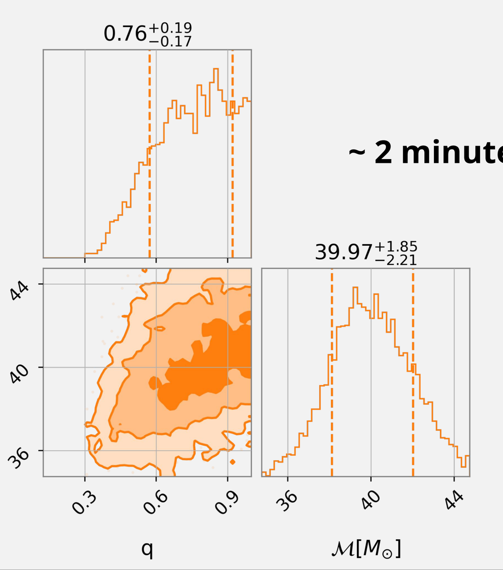


Small Neural Network (~15 k parameters) is used to approximate the real log likelihood.

Loss function $= (e^{\log(\mathcal{L}(\theta))} - e^{\mathrm{FLEX}(\theta)})^2$

Phase 3: Run MCMC on the Neural Likelihood

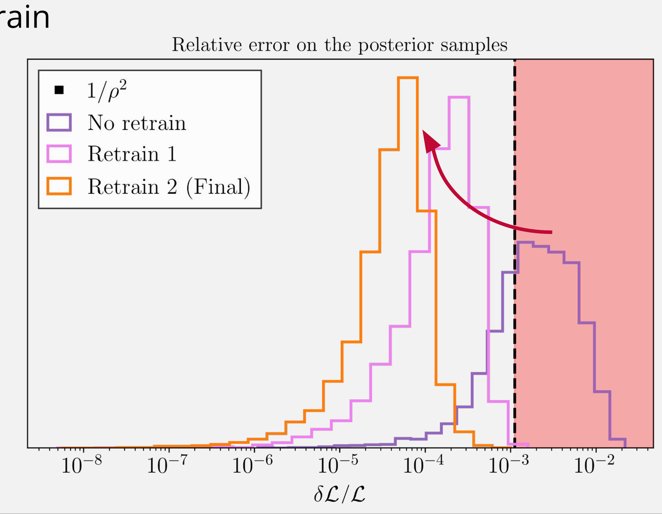
Standard MCMC run. Parallel tempering and affine moves used to help reach convergence.



~ **2 minutes** on 1 CPU.

Phase 4: Check and (maybe) retrain

Recompute the relative log likelihood error for the new posterior samples. If the max error exceeds the threshold, add these samples to the training set and retrain



Re-training samples are again obtained from tempered MCMC chains, which area direct output of the parallel tempering MCMC algorithm.

This will help to have full coverage of the parameter space and not only the posterior's peak.

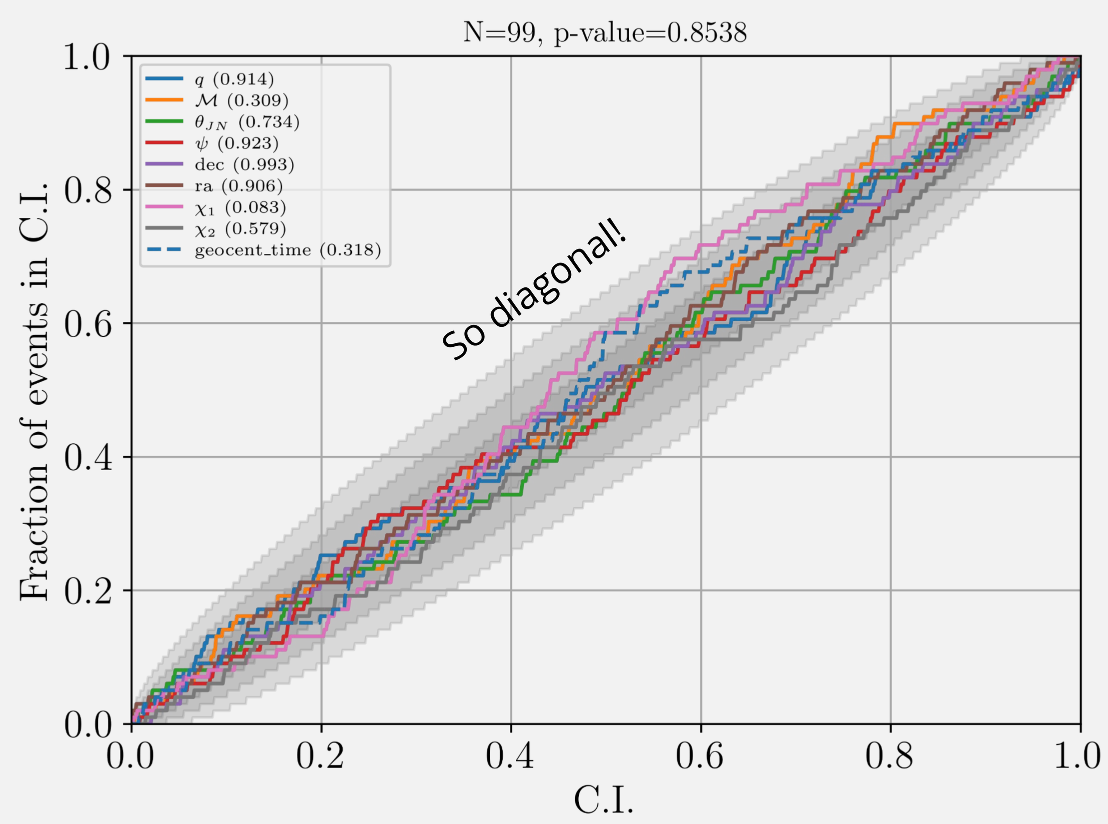
5. Conclusions

Neural likelihood estimators are a viable option for speeding up gravitational wave parameter estimation. PP plots and comparisons with standard PE methods show the robustness of the Neural Likelihood, and that Neural Networks can be accurate enough to act as "surrogate" likelihoods.

The analysis was fully run on CPUs, with no pretraining on the network. So the method can be instantly applied on any prior, waveform model, noise model ... you just need to define a likelihood!

Where to go next?

- Binary Neutron Stars
- Precessing signals
- 3G
- ...



References

1. **Q. Hu *et al.* ; 2024; Costs of Bayesian Parameter Estimation in Third-Generation Gravitational Wave Detectors: a Review of Acceleration Methods**
2. **P. Graff *et al.* ; 2012: BAMBI: Blind accelerated multimodal Bayesian inference**

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