Annual Progression Review

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LITERATURE REVIEW

Gravitational waves (GWs) are perturbations of spacetime generated by mass distributions with non-null second derivative of the quadrupole mass-moment. Binary systems of stellar objects are exemplary GW emitters and the more compact the object, the bigger the wave produced, making the system more suitable for detection.

The LIGO-Virgo-KAGRA (LVK) collaboration uses a system of interferometers to detect gravitational waves. The latest complete catalogue published by the LVK collaboration is the third gravitational-wave transient catalogue (GWTC-3) and contains about a hundred signals generated by the coalescence of binaries of neutron stars (NSs) and stellar-mass black holes (BHs).

When LVK detect an astrophysical signal, they analyze the data to infer the properties of the event, such as the masses of the objects in the binary, their spins, the distance from the observer and its sky localization. The statistical framework used for individual event analysis is Bayesian inference. With the number of events growing, it becomes crucial to do population analyses, as they allow to set further constraints on the astrophysics underlying stellar objects. To do so, one uses Hierarchical Bayesian statistics.

The models used have multi-dimensional parameters, resulting in probability distributions computationally prohebitive. Traditional methods rely on stochastic sampling methods, such as Markov Chain Monte Carlo (MCMC) or Nested sampling, to infer the probability distribution. However powerful, these methods are expensive, as probability distributions have to be evaluated million of times for each individual event analysis. Each evaluation requires to generate a waveform on the fly, which heavily contributes to the overall costs. Machine learning approaches have the advantage of moving most of the costs in the training stage, dramatically speeding up inference time. Several attempts have been made in this direction, from architectures that model the noise more realistically than traditional methods, to architectures that employ models without an analytical expression, which is unfeasible with stochastic samplers.

0.1 BAYESIAN STATISTICS

Let us refer to the vector of binary parameters as θ. It consists of intrinsic parameters, such as the masses and the spins, and extrinsic parameters, such as the redshift and the binary orientation. The goal of the analysis is to infer the posterior distribution $p(\theta|d)$, which associates to each point in the binary-parameter space the probability of that binary to generate the observed data d. Observed data is the sum of the astrophysical signal, which is assumed to be deterministic and a function of binary-parameters, and a noise realization in the detector, which is assumed to be stochastic. To evaluate the posterior one needs a prior $\pi(\theta)$ and a Likelihood $\mathcal{L}(d|\theta)$. The prior is the probability distribution that an event with parameters θ takes place in the Universe. A possiblility is to use knowledge from theory or previous experiments to build it. Nevertheless, the preferred approach is often conservative, and uninformative priors are used. These priors have constant probability in the binary-parameters dominium and zero outside. The Likelihood is the probability in the data space, given θ parameters. To evaluate the Likelihood one needs to generate waveforms for θ, and a noise model, which is often assumed to be stationary and Gaussian. Bayes theorem links the posterior to the prior and the Likelihood:

$$p(\theta|d) \propto \pi(\theta) \times \mathcal{L}(d|\theta). \tag{1}$$

0.2 HIERARCHICAL BAYESIAN STATISTICS

COMPLETED WORK

a descripiton of work completed to date - small project description

Transfer learning is a series of techniques used in machine learning to transfer knowledge from a neural network to another. Each time one modifies a neural network, for instance changing the model assumed in the analysis, the neural network needs to be trained again. The goal of transfer learning is to fine tune a new training run using some knowledge acquired during a previous training. These strategies allow to reduce training time, and, more importantly, could even improve the results respect to training the new run without any information from previous trainings.

WORK PLAN

a plan of work for the next 12 months - pop growing pains for sure - we talked about using astrophysical models as pop models. We need to understand better. Surely something more astro - another idea is to keep developing the current project (NR simulations, beyond GR models)

PERSONAL DEVELOPMENT PLAN

Copy of personal development plan summary and a statement of progress made towards those training goals