A deep-learning solution to the gravitational-wave population problem

Davide Gerosa

University of Milano-Bicocca

arXiv:2203.03651

with M. Mould and S. Taylor

Jun 2, 2022 Black Hole Dynamics: From Gaseous Environments to Empty Space Copenhagen, Denmark





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90 waves and counting

Discovering are piling up! **About 90 black-hole binary mergers detected so far.** Will become millions in ~20 years!



Outline

- 1. The population problem
- 2. Current pipeline: hierarchical mergers
- 3. Current pipeline: machine learning
- 4. Things we (haven't) figured out (yet)



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How we put things together

Single-event parameters: masses, spins, redshifts

Population parameters: spectral index of mass distribution, cutoffs



What model for the Universe?

Option 1: Simple, parametrized functional forms

LIGO/Virgo and many others

Solution Evaluating $p_{\rm pop}(\theta|\lambda)$ is straightforward and can be done at each likelihood evaluation

But: Astrophysicists like you guys put a lot of effort in simulating stellar evolution, clusters, AGN, and all of that!

Option 2:

Can we instead interpret GW data using cool astro predictions *directly*?

Evaluating $p_{\mathrm{pop}}(\theta|\lambda)$ now is a costly simulation...

Ingredients in the blender

A population synthesis code

I'm not going to even try citing people here! So many excellent studies

- Early prototype with limited set of COMPAS runs Taylor DG 2018
- Current application: simple hierarchical merger populations Mould DG Taylor 2022
- Hopefully soon: full isolated formation channel inference
- (But can you help us doing dynamics?)
- 2. Design a training bank. Space filling algorithms



- Latin hypercubes
- Now working on implementing progressive hypercube sampling

Ingredients in the blender

- **3**. Some form of data compression
 - Used principal component analysis successfully Taylor, DG 2018
 - Tucker decomposition to avoid array raveling?
 - Non-linear dimensionality reduction schemes?

4 A powerful conditional density estimation scheme $p_{
m pop}(heta|\lambda)$

- Gaussian process regression
- Taylor, DG 2018, Wong, DG 2019
 FFT-based KDE and a multilayer perceptron

Mould **DG** Taylor 2022

 Autoregressive flows Wong, Contardo, Ho 2020



Ingredients in the blender

- **5** A model for the detector $p_{det}(\theta)$
 - A simple SNR cut? Finn Chernoff 1992
 - Pipeline injections? LIGO/Virgo 2019, 2021
 - Some attempts at machine-learn the GW detectability.
 DG Pratten Vecchio 2020, Talbot Thrane 2022
- **6** A sampler for $p(\lambda|d)$
 - A vanilla nested sampling for now... but should we?

...and of course the key player: the LIGO/Virgo data!

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Hierarchical black-hole mergers

DG Berti 2017



Orthogonal, but complementary, direction to the usual field vs. cluster debate

Spins: the magic number

DG Berti 2017, Fishbach+ 2017, Berti Volonteri 2008



Peculiar spin distribution peaked at **0.7**



An explosion of new predictions



- Masses in the pair-instability mass gap Heger+ 2003, Woosley+ 2007
- Peculiar spin distribution peaked at 0.7
 DG Berti 2017, Fishbach+ 2017
- But GW kicks require large escape speed
 DG Berti 2019
- Very frequent in AGNs
 Yang+ 2019, Tagawa+ 2020
- Promising for GW190412
 DG Vitale Berti 2020, Rogriguez+ 2020
- Leading explanation for GW190521
 LIGO/Virgo 2020
- Perhaps several events in the LIGO catalog?

Kimball+ 2021

• An exclusion region

DG Giacobbo Vecchio 2020

... but don't overdo it!
 Zevin Holz 2022

And many more! Enough for a dedicated review DG Fishbach 2021

Just balls of black holes for now....

We need a population that is easy enough for now but non-analytic...

Key idea: take a parametrized model but allow for hierarchical mergers

In this talk a cluster is... a "thing" with a given escape speed $v_{\rm esc}$ DG, Berti 2019, DG Giacobbo Vecchio 2021, Zevin Holz 2022

- Masses: $p(m) \propto m^{\gamma}$ $m \in [5M_{\odot}, m_{\max}]$
- Spins: $p(\chi) = \text{const}$ $\chi \in [0, \chi_{\max}]$

• Pairing: $p_{\mathrm{pair}}(m_1) \propto m_1^{\alpha}$ $p_{\mathrm{pair}}(m_2|m_1) \propto m_2^{\beta}$

• Clusters: $p(v_{\rm esc}) \propto v_{\rm esc}^{\delta}$

Here is a real expert on BH dynamics when hearing about my model



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Six population parameters

Here is a real expert on BH dynamics when hearing about my model



Out of the cluster, one kick at the time



Targeted populations



$\theta = \{M_c, q, \chi_{\text{eff}}, \chi_{\text{p}}\}$

Four representative hyperparameter locations

This is a hard problem!

Strong correlations, multimodalities, spikes, gaps, degeneracies

... and we keep track of the merger generation



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Simulations











Population neural network

Layer

Input

Dense 1

Dense 2

Dense 3

Dense 4

Dense 5 Output Neurons

10

128

128

128

128

128

1

Activation

RReLU

RReLU

RReLU

RReLU

RReLU

Absolute value

Parameters

0

1408

16,512

16,512

16,512

16,512

129

- A fully connected network
- A total of ~70k parameters!
- Implemented in Google's Tensorflow
- Fast (~days) training on GPU



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Full GWTC3 results



Inference and predictions



Masses

- Repeated mergers populate the upper mass gap
- 1g cutoff ok with pair instability SN?
- Additional structure in the gap due to higher generations



Inference and predictions

Escape speeds

- Easy to infer secondary population parameters (here the escape speed)
- But can go crazy! Metallicity, environments, etc



Generations

- If we allow for hierarchical mergers, the fit wants to go there! _{cf e.g. Kimball+ 2021}
- Easy to infer subchannels (here the generation)
- But can go crazy! Any label in the population...



Ready to go!

- A complete, highly optimized population inference pipeline designed to digest outputs of astrophysical simulations and GW data
- Deep learning is crucial here (no other way, I think)
- Current astrophysics is admittedly too simple...
- ...but we're ready to use this beast on state-of the art models!



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