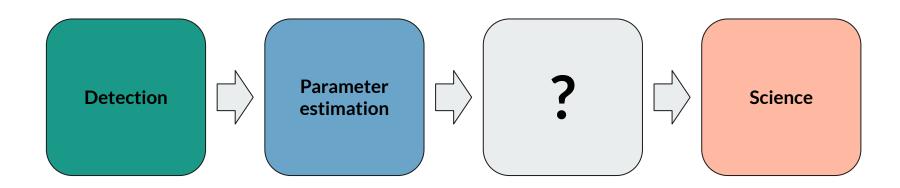
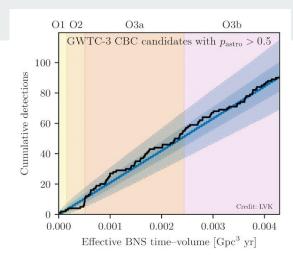


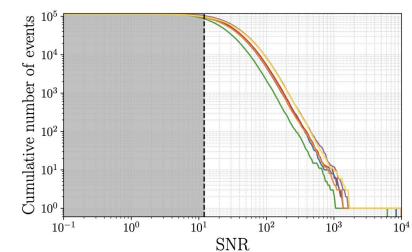
Gravitational-wave astrophysics



Challenges

- Detection
 - More robust
 - Find more and find new stuff
- Parameter estimation
 - Currently close to the limit
 - o O(1000) more events in 3G

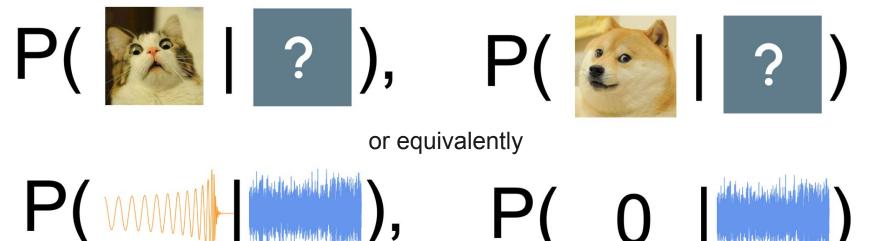




Detection of transient GW signals



Melissa Lopez

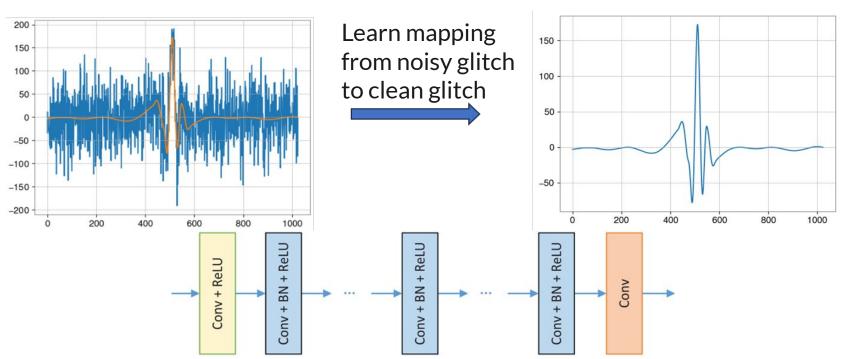


Detection of compact binary coalescence and supernovae, with background mitigation (ResNet-based, WaveNet, autoencoder, GAN)

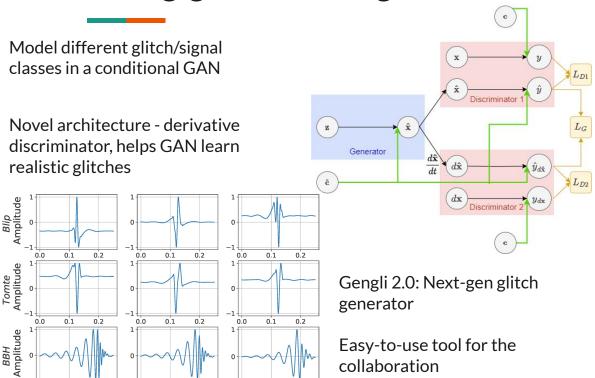
Extracting the glitch



Tom Dooney



Modelling glitches in a generative model (cDVGAN)



0.1

Time (s)

0.1

Time (s)

Training data

0.0

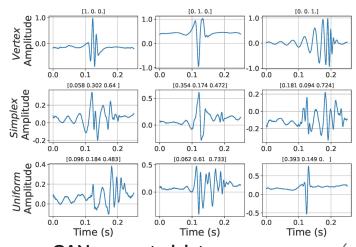
0.1

Time (s)

Tom Dooney

We can generate specific classes (top), or hybrid samples.

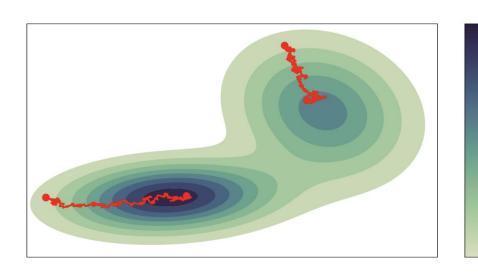
Can be useful for testing pipelines



GAN-generated data

Parameter estimation (PE)

$$egin{aligned} p(ec{ heta}|d) &= rac{p(d|ec{ heta})p(ec{ heta})}{p(d)} \ &= rac{ ext{likelihood} imes ext{prior}}{ ext{evidence}} \end{aligned}$$



Traditionally slow: ~1 - 2 months on a single CPU core for binary neutron star signal

Posterior

Parameter estimation (PE)

Accelerate with:

- Machine learning: Use normalizing flows to enhance the robustness and speed of MCMC
- JAX: Python with auto-differentiation, JIT-compilation and hardware acceleration (GPU/TPU)

Results

- PE on BNS in < 30 minutes [paper], O(1000) speed-up
- Speed up waveform evaluation with deep learning [paper, Github]
- On-going work
 - Bridging theoretical gap between nuclear physics and astrophysics
 [Github]
 - Combining telescopes' data: accelerated multi-messenger astrophysics [Github]







Stefano Schmidt

Conclusion

- A lot more effort for AI in GW within NL not covered
 - Simulation-based inference
 - Detections on early inspiral
 - And more...
- Various tools used
 - JAX
 - Normalizing flows
 - "Vanilla" deep learning
- Dream
 - More GPU resources
 - More cross-group collaboration