Hyper-fast gravitational wave parameter estimation

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PyData Edinburgh Meeting

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Talk Overview

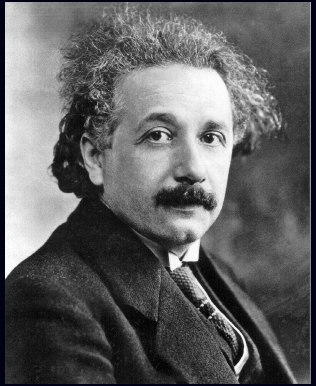
- What are gravitational waves?
- What are conditional variational autoencoders?
- What did we do?
- Where do we go from here?

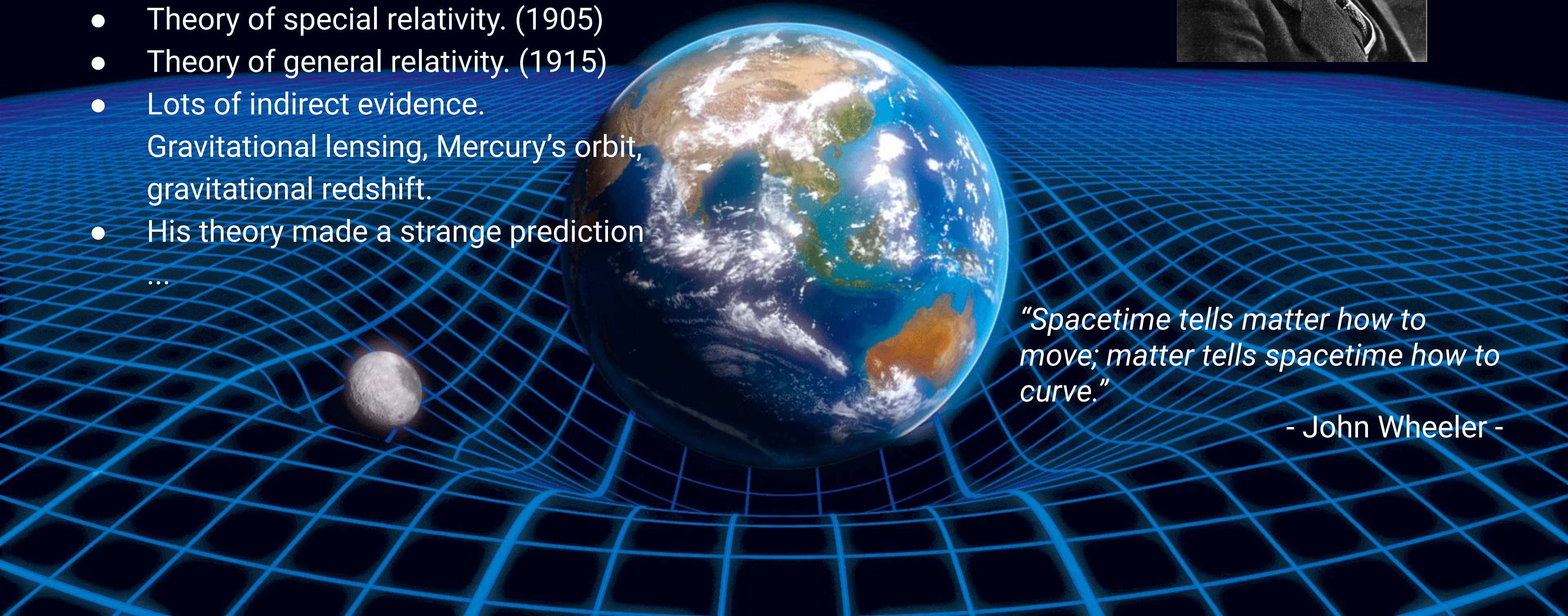
What are Gravitational Waves?

(things that go bump in the metric)

General Relativity

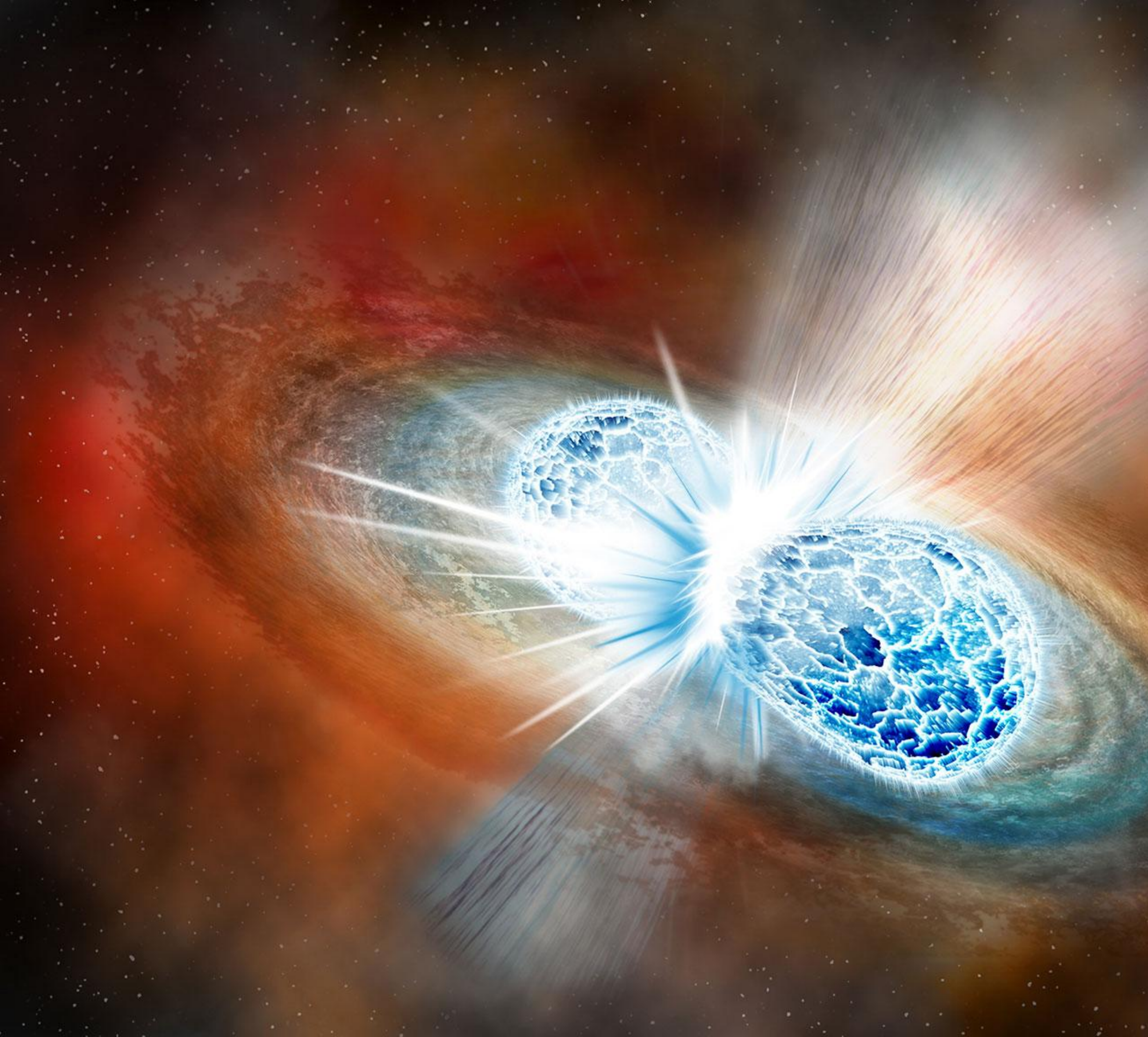
- Theory of special relativity. (1905)
- Theory of general relativity. (1915)
- Lots of indirect evidence.
  Gravitational lensing, Mercury’s orbit, gravitational redshift.
- His theory made a strange prediction
  ...





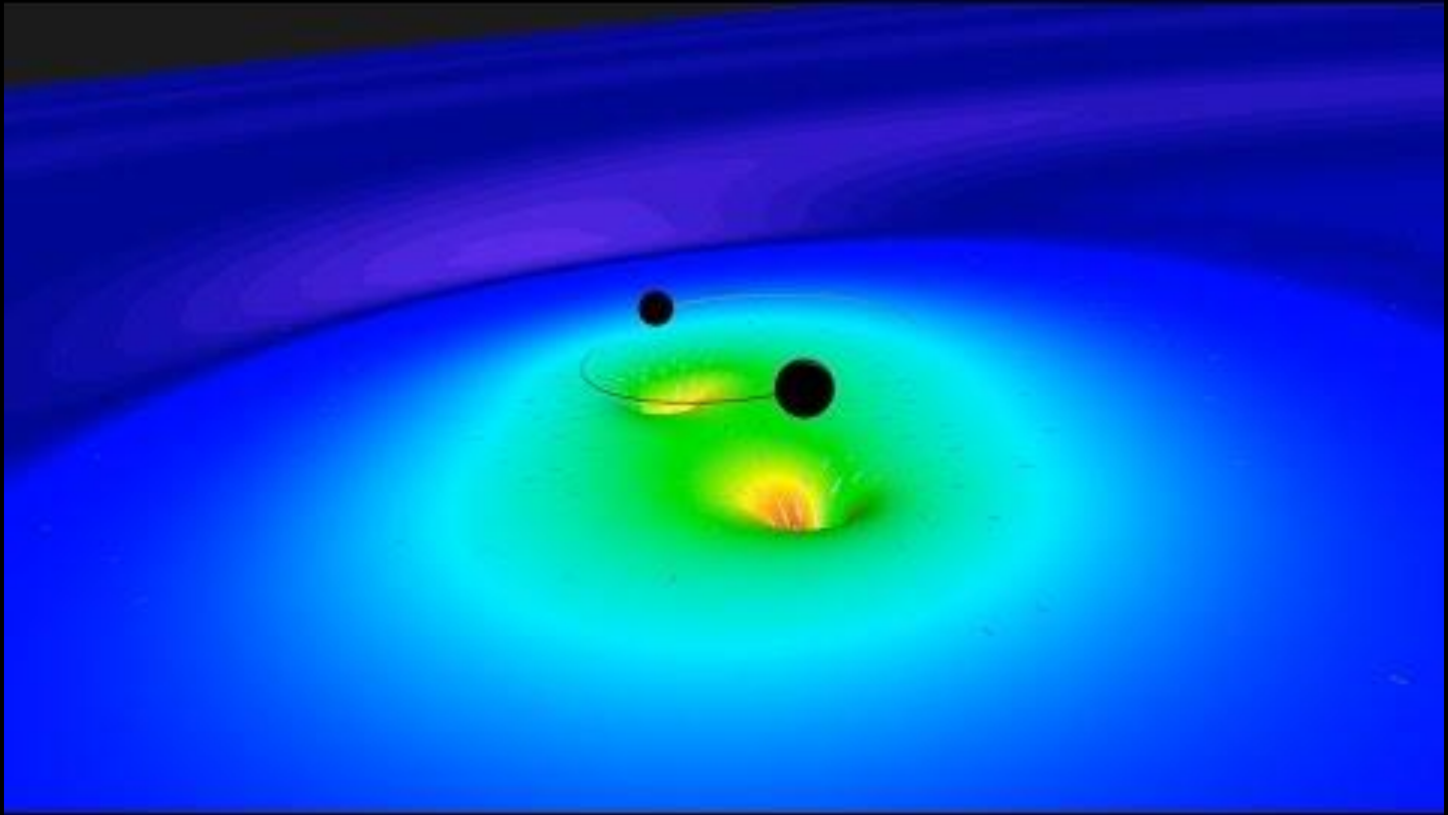
“Spacetime tells matter how to move; matter tells spacetime how to curve.”

- John Wheeler -



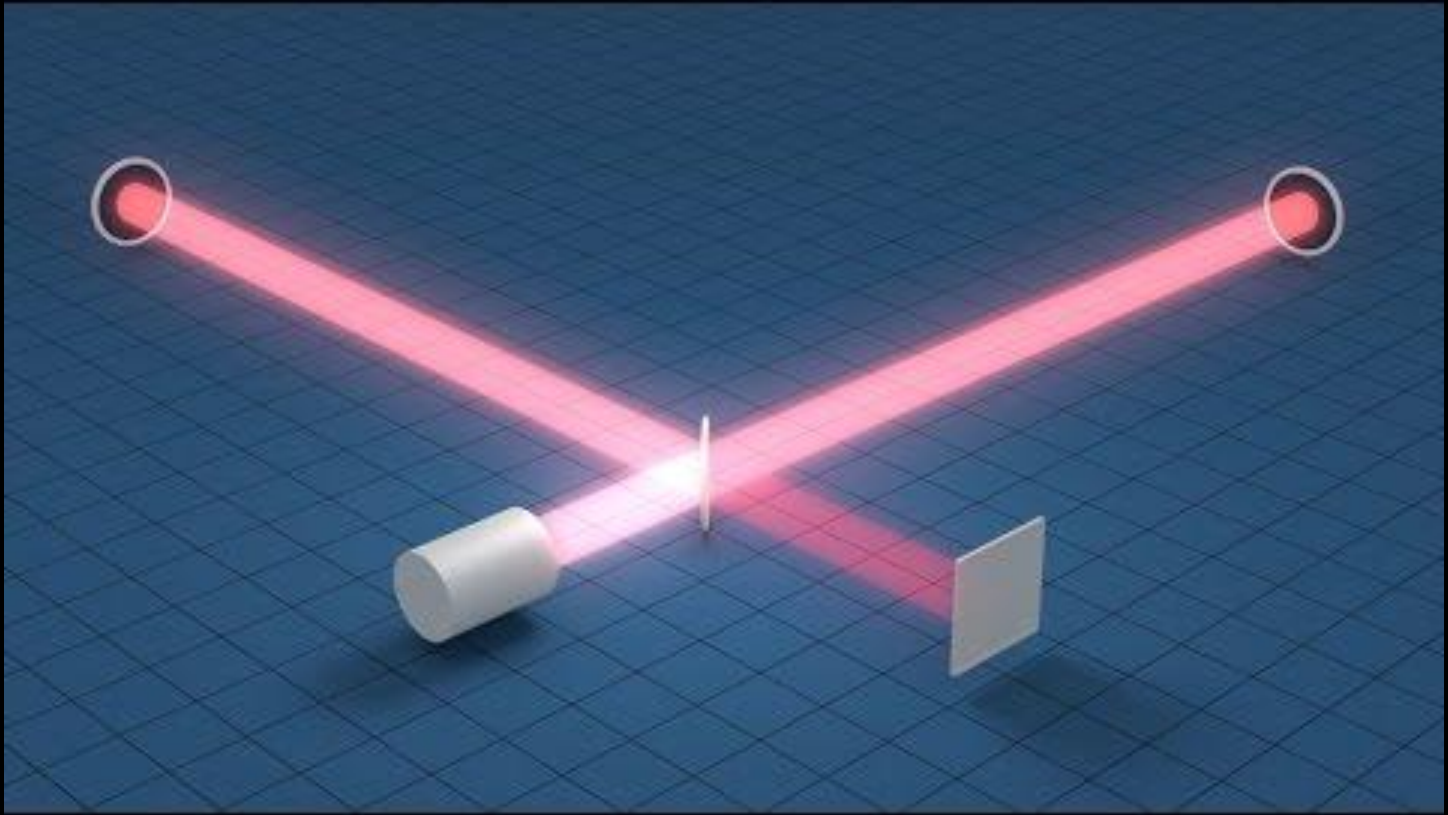
Gravitational waves

- Predicted by Einstein in 1916.
- Result from some of the most violent events in the known universe.
- Potential sources: binary black holes, binary neutron stars, supernovae, the big bang … other unknown?
- If detected, can do whole new form of astronomy without using light!



How do we detect them?

(the world’s most precise ruler)

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By DENNIS OVERBYE
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Courted Hard in South Carolina, Loyalists Listen Closely
By RICHARD FAUSSET
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Kosmische Kollision
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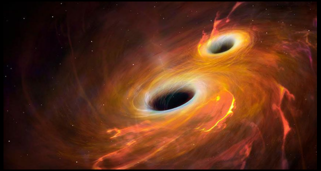
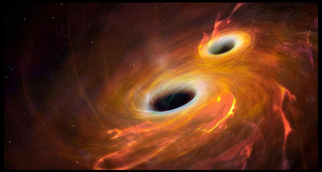
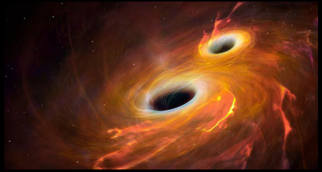
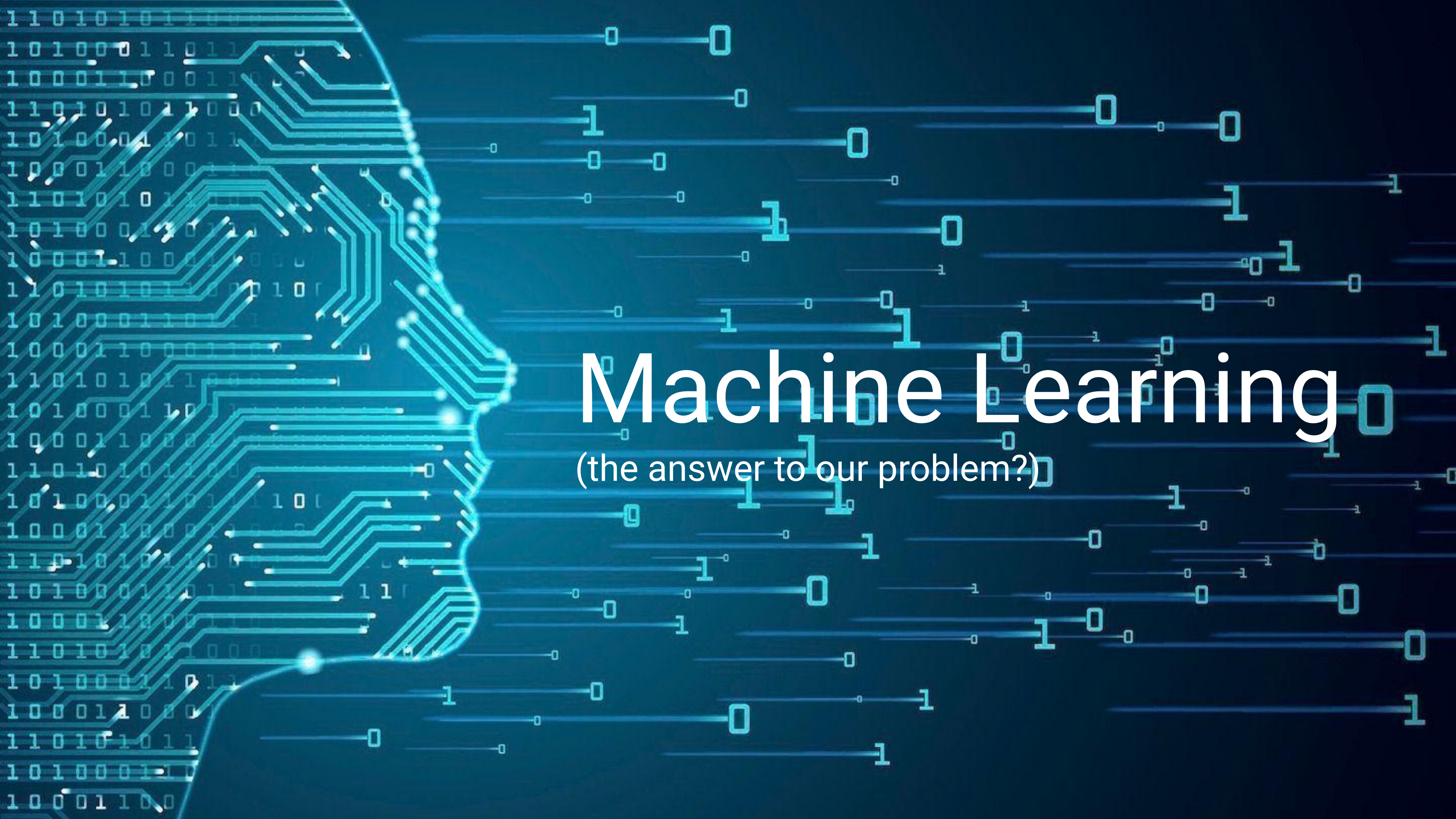
So what now? ...







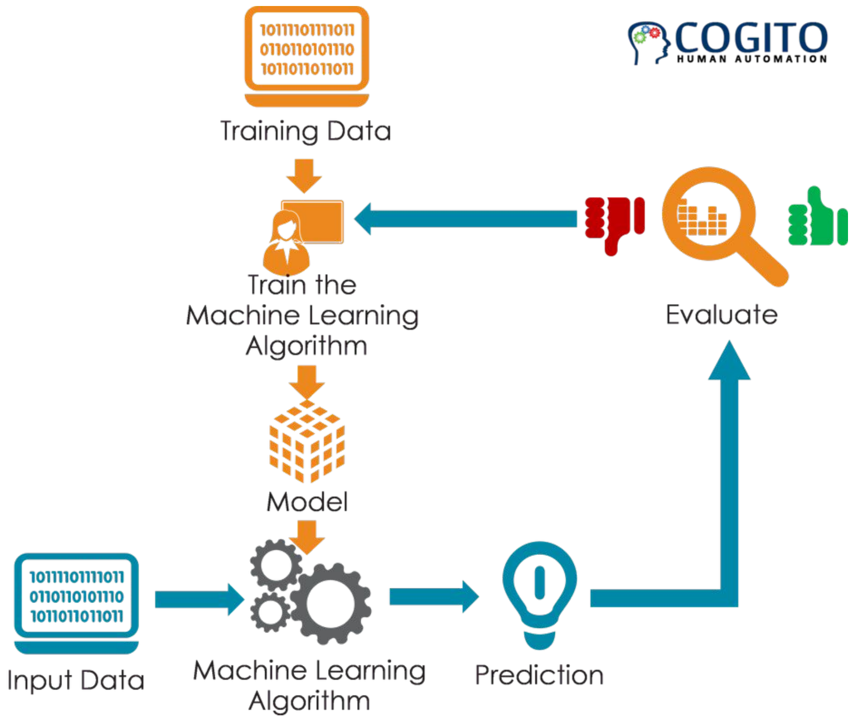


Machine Learning

(the answer to our problem?)

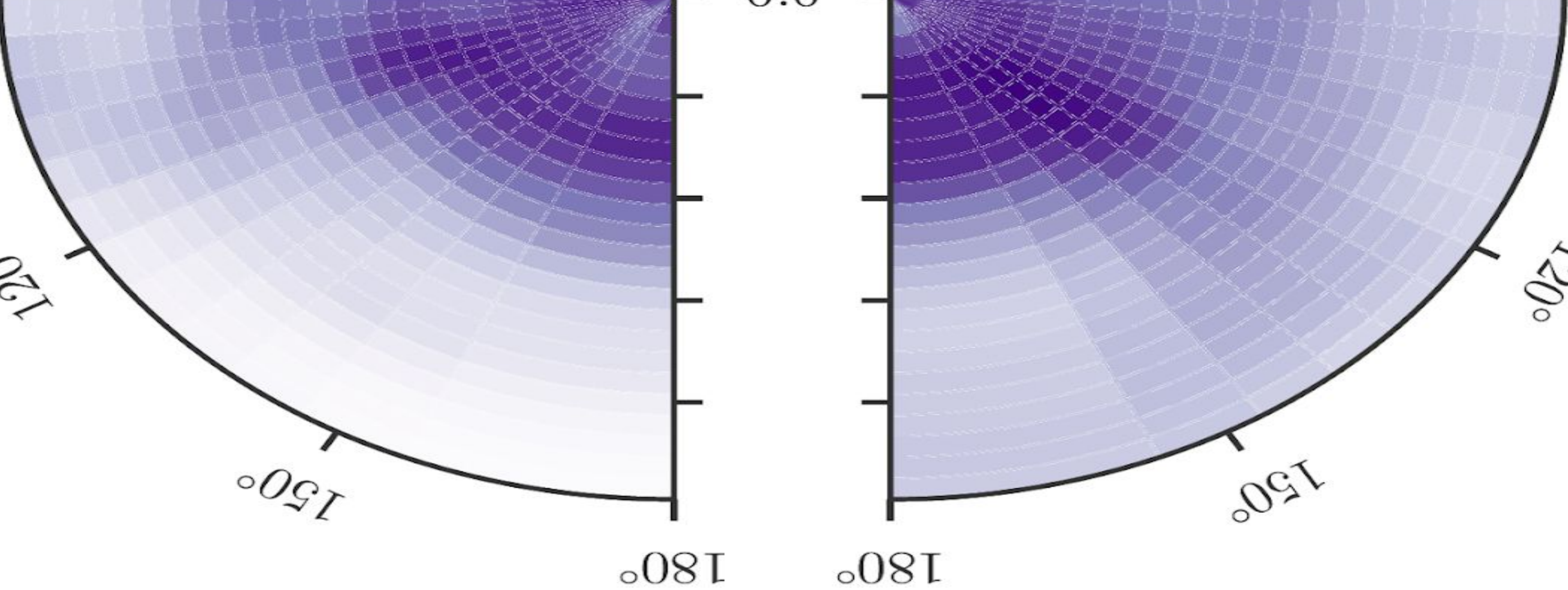
What is Machine Learning?

- Good question Hunter!
- Is it just a useful black box? NO!
- It is a complex system composed of simple operations that is initially “stupid”. Through the initial choice of incentive the system can be trained to do certain tasks.
- Often referred to as a simple function approximator.



Why use machine learning?

- Speed
    - Front loading the cost - leads to rapid real-time analysis.
    - Simply saves CPU cycles and therefore cold hard cash.
    - Allows us to keep up with the detections.
- It’s just better (maybe)
    - Existing techniques are (near) optimal when you know your model (signal and noise).
    - ML has the potential to learn what we have approximated or incorrectly assumed.
    - If faster than computationally limited searches - can be made more sensitive.



Parameter estimation

(what exactly did we just detect?)

Bayesian Inference

- We rely heavily on Bayesian parameter estimation.

$$\underbrace{p(\boldsymbol{\theta}|\boldsymbol{x},I)}_{\text{posterior}} = \frac{\overbrace{p(\boldsymbol{x}|\boldsymbol{\theta},I)}^{\text{likelihood}}\,\overbrace{p(\boldsymbol{\theta}|I)}^{\text{prior}}}{\underbrace{p(\boldsymbol{x}|I)}_{\text{evidence}}}$$

- We must make (motivated) assumptions regarding our noise distribution and the prior values of of the parameters.

$$\log p(\boldsymbol{x}|\boldsymbol{\theta},I) = \exp\left[-\sum_{j=0}^{N-1}\frac{|\tilde{x}_j-\tilde{h}_j(\boldsymbol{\theta})|^2}{TS_h(f_j)}\right] + \text{const}$$

- In practice, obtaining posterior probability densities on system parameters is done via Monte-Carlo techniques (MCMC, nested sampling).

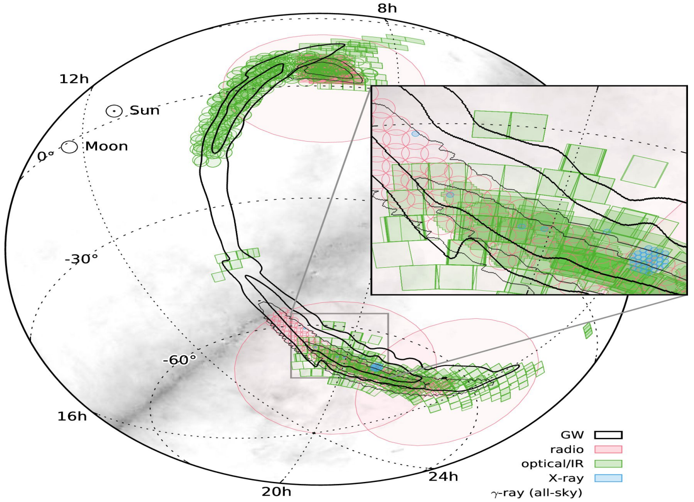
https://lscsoft.docs.ligo.org/bilby/

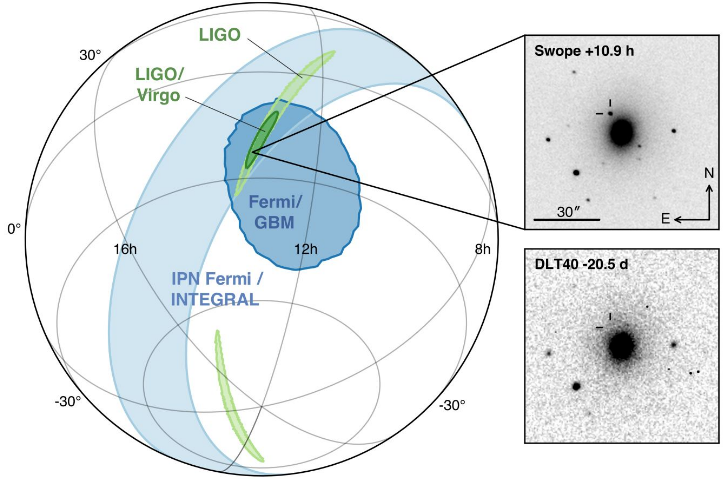
L. Singer & L. Price, PRD 93, 2, 024013 (2016)

Motivation

- Existing Bayesian parameter estimation is optimal but very slow
- For transient GW events and multi-messenger astronomy it is crucial that we produce data products very quickly.

LIGO-Virgo Collaboration, ApJ 848, 2, L12, 59 (2017)





LIGO-Virgo Collaboration, ApJ Volume 826, 1, L13, 8 (2016)

Conditional Variational Autoencoders

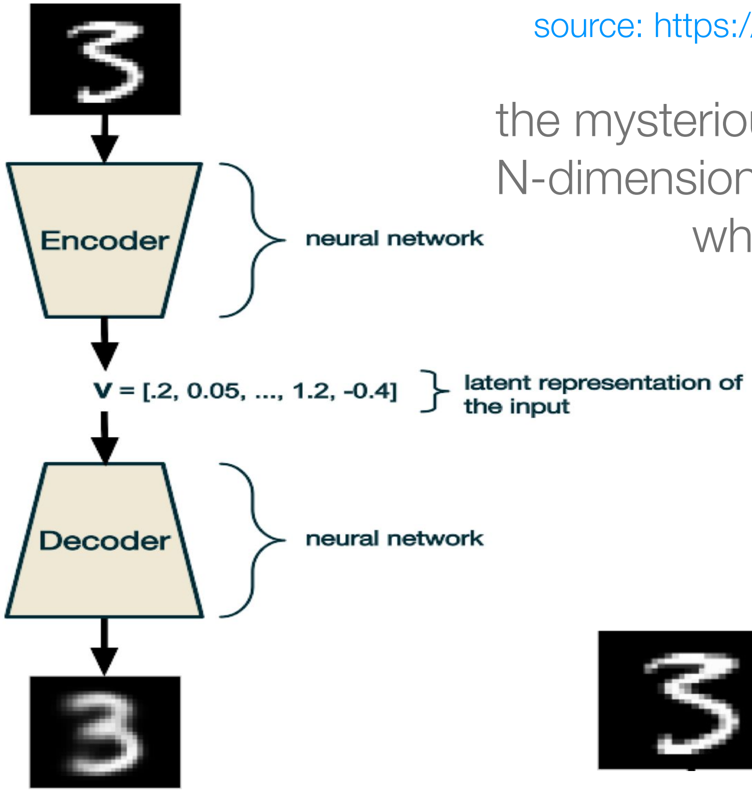
(it’s not magic, I promise)

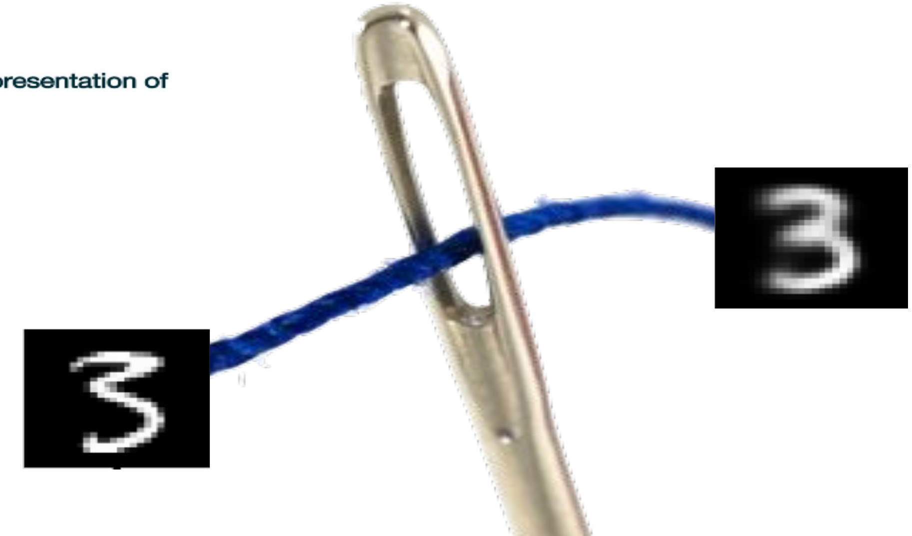
First - an autoencoder

source: https://ijdykeman.github.io/ml/2016/12/21/cvae.html

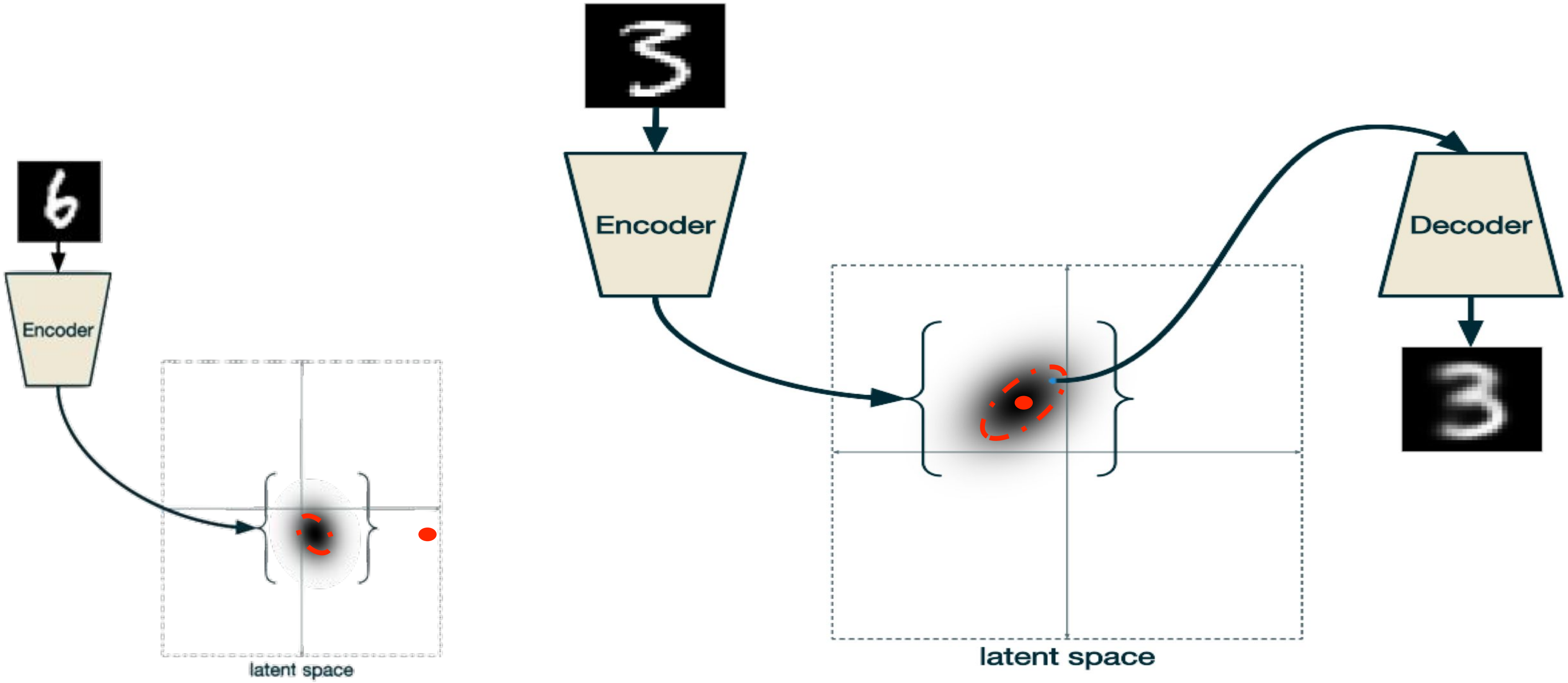
the mysterious “latent” space is jargon for some N-dimensional non-physical parameter space in which to represent your data

loss based on input/output similarity





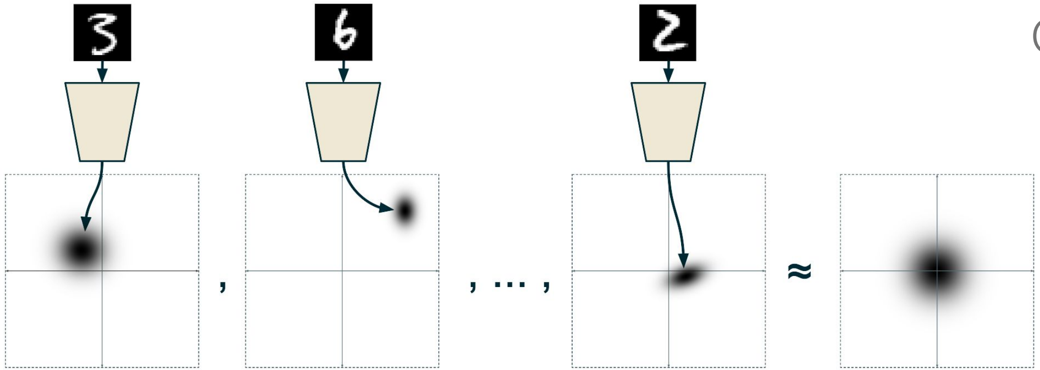
Next - a variational autoencoder

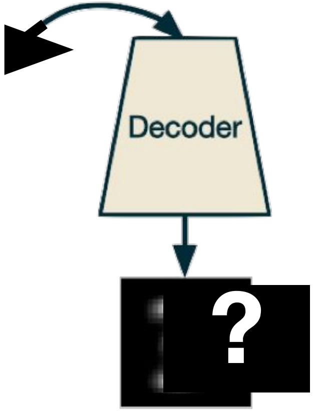


source: https://ijdykeman.github.io/ml/2016/12/21/cvae.html

Next - a variational autoencoder

The loss function incorporates a KL-divergence term testing the Gaussianity of the total distribution in the latent space





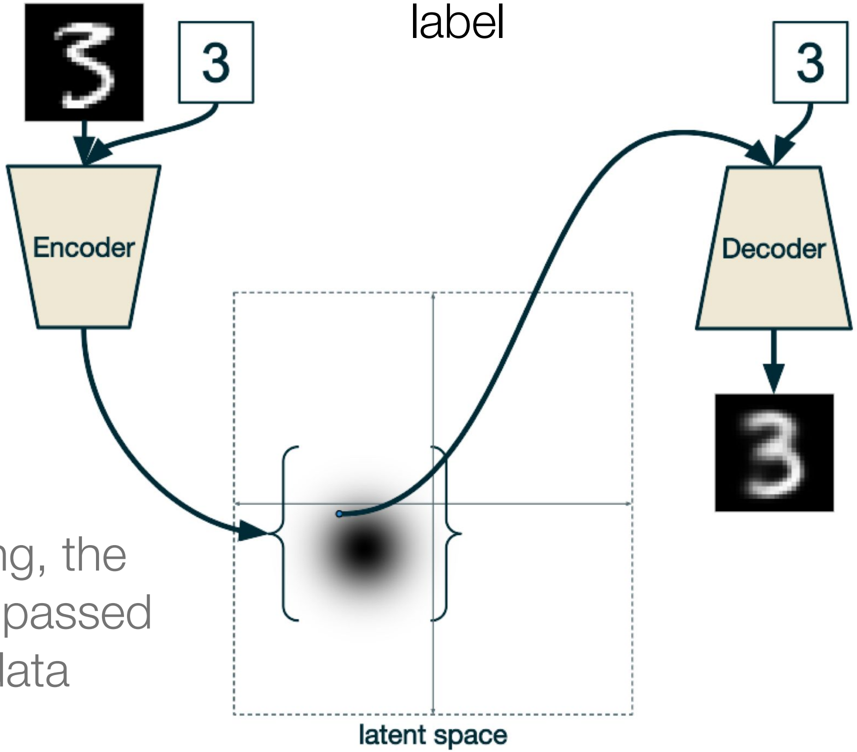
random draw
can’t produce particular numbers on command

source: https://ijdykeman.github.io/ml/2016/12/21/cvae.html

Then - a conditional variational autoencoder

label

label



Within training, the true “label” is passed with the data

now you can ask for a random “7” or “4”, etc…

source: https://ijdykeman.github.io/ml/2016/12/21/cvae.html

Some of the components of our scheme

The GW data y

we generate lots of these

The GW parameters x

from this

The prior $p(x)$

we never have to evaluate this

The likelihood $p(y|x)$

we want this

The latent space parameters z

The posterior $p(x|y)$

we are going to use 3 neural networks to model each of these 3 functions

The recognition function $q_\phi(z|x,y)$

The target distribution $p_\theta(x|y) = \int dz\, r_{\theta_1}(z|y) r_{\theta_2}(x|z,y)$

Gabbard *et al*, arXiv:1909.06296 (2019)

The scheme

Loss function:

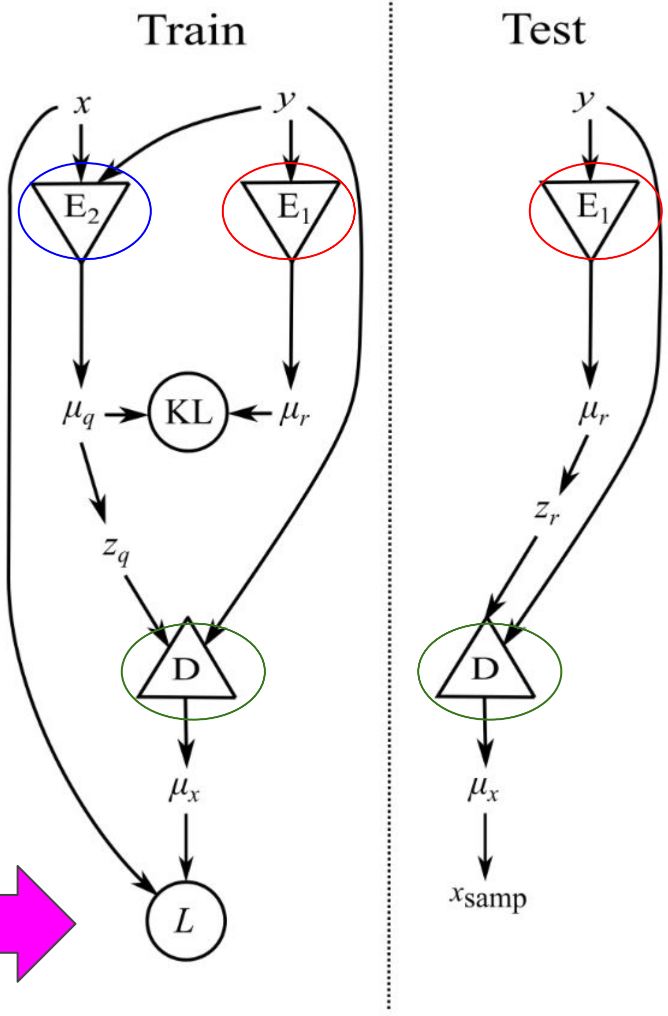
- Start of derivation

$$H(p,r) = -\int dx\, p(x|y)\log r_\theta(x|y)$$

... Here be math dragons ...

- End of derivation

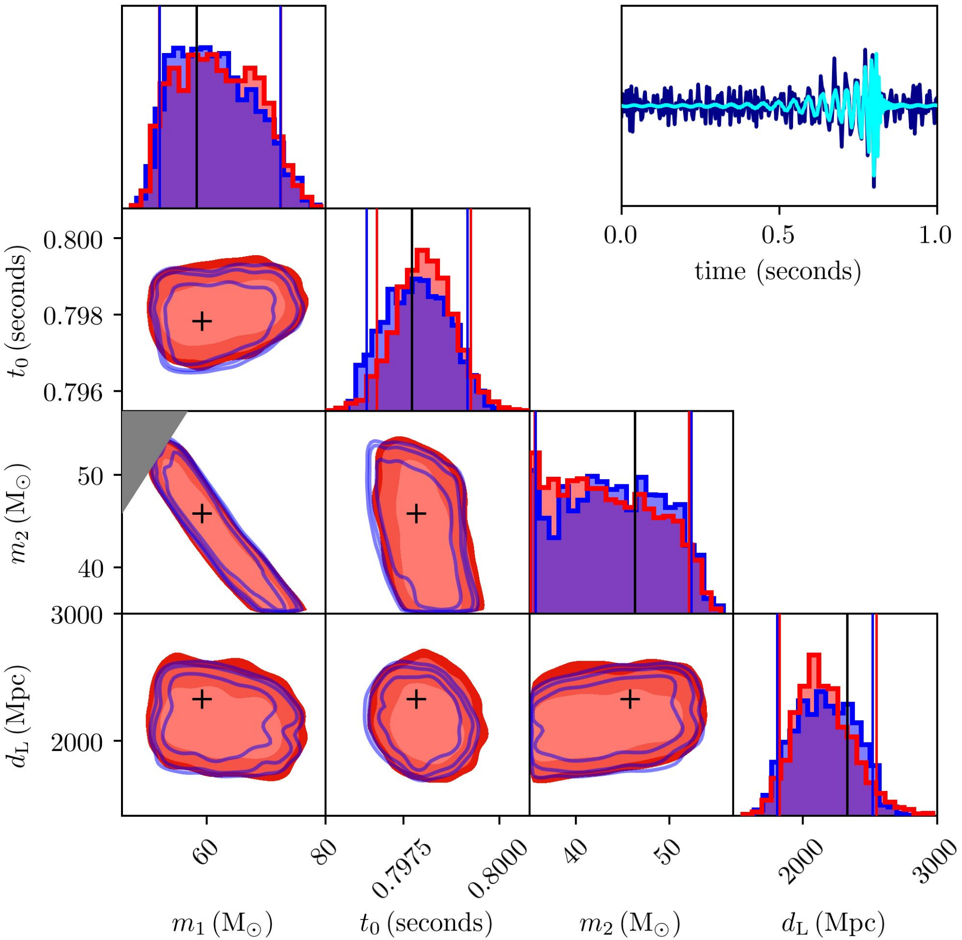
$$H \lesssim -\frac{1}{N}\sum_{n=1}^{N}\left[\log r_{\theta_2}(x_n|z_n,y_n)\right. \\ \left. -\mathrm{KL}\left[q_\phi(z|x_n,y_n)\|r_{\theta_1}(z|y_n)\right]\right].$$



What did we find out?

(it’s fast)

Posterior comparisons



Red: Our method
Blue: Other method

The speed

TABLE I. Durations required to produce samples from each of the different posterior sampling approaches.

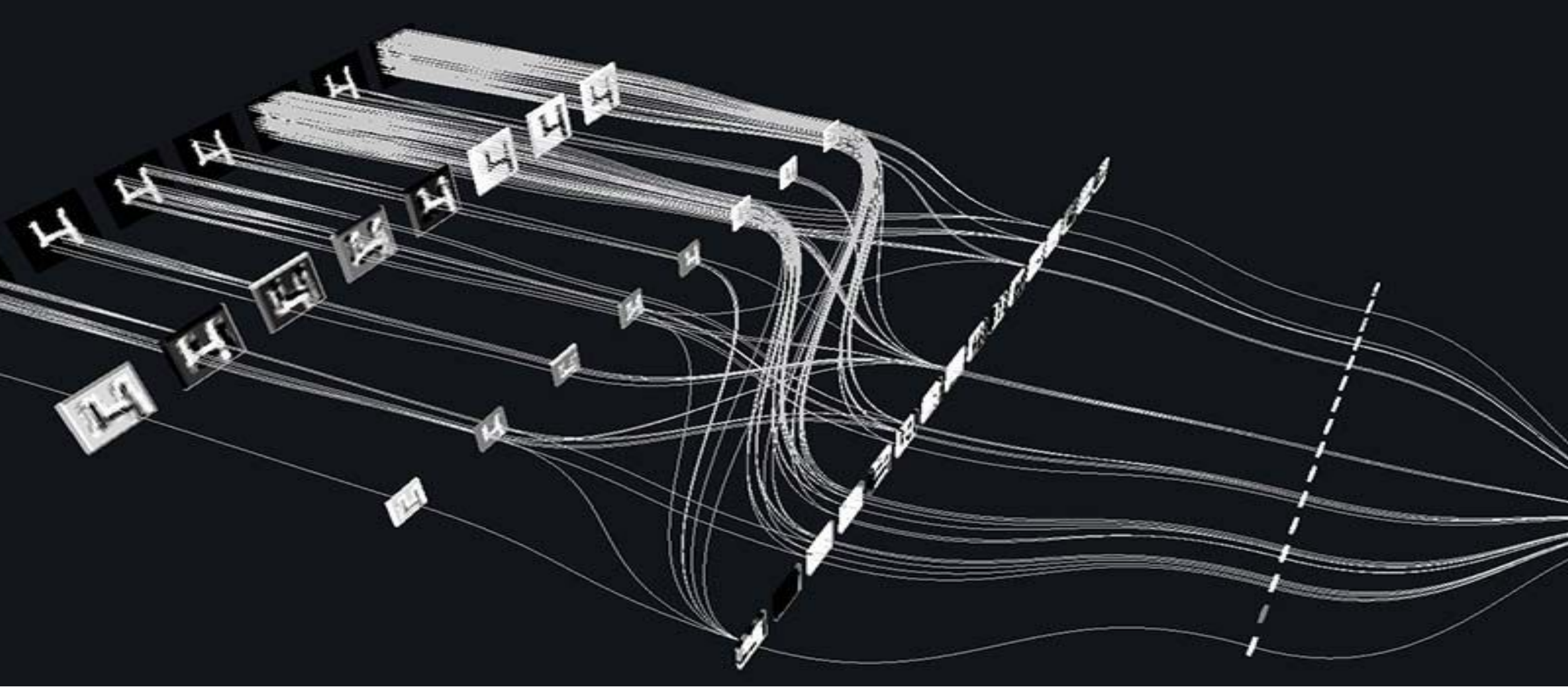
sampler	run time (seconds) min	max	median	ratio $\frac{\tau_{\text{VItamin}}}{\tau_X}$
Dynesty[a]	602	1538	774[b]	2.6×10^{-6}
Emcee	2005	11927	4351	4.6×10^{-7}
Ptemcee	3354	12771	4982	4.0×10^{-7}
Cpnest	1431	5405	2287	8.8×10^{-7}
`VItamin`[c]		$\mathbf{2 \times 10^{-3}}$		1

[a] The benchmark samplers all produced $\mathcal{O}(3000 - 10000)$ samples dependent on the default sampling parameters used.

[b] The reader may note that benchmark sampler run times are a few orders of magnitude lower than what is typical of a complete BBH analysis ($\mathcal{O}(10^5 - 10^6)$ seconds). This is primarily due our use of a reduced parameter space, low sampling rate and choice of sampler hyperparameters.

[c] For the `VItamin` sampler 3000 samples are produced as representative of a typical posterior. The run time is independent of the signal content in the data and is therefore constant for all test cases.

Gabbard *et al*, arXiv:1909.06296 (2019)



Conclusions

The take home message

Variational Inference - Future work

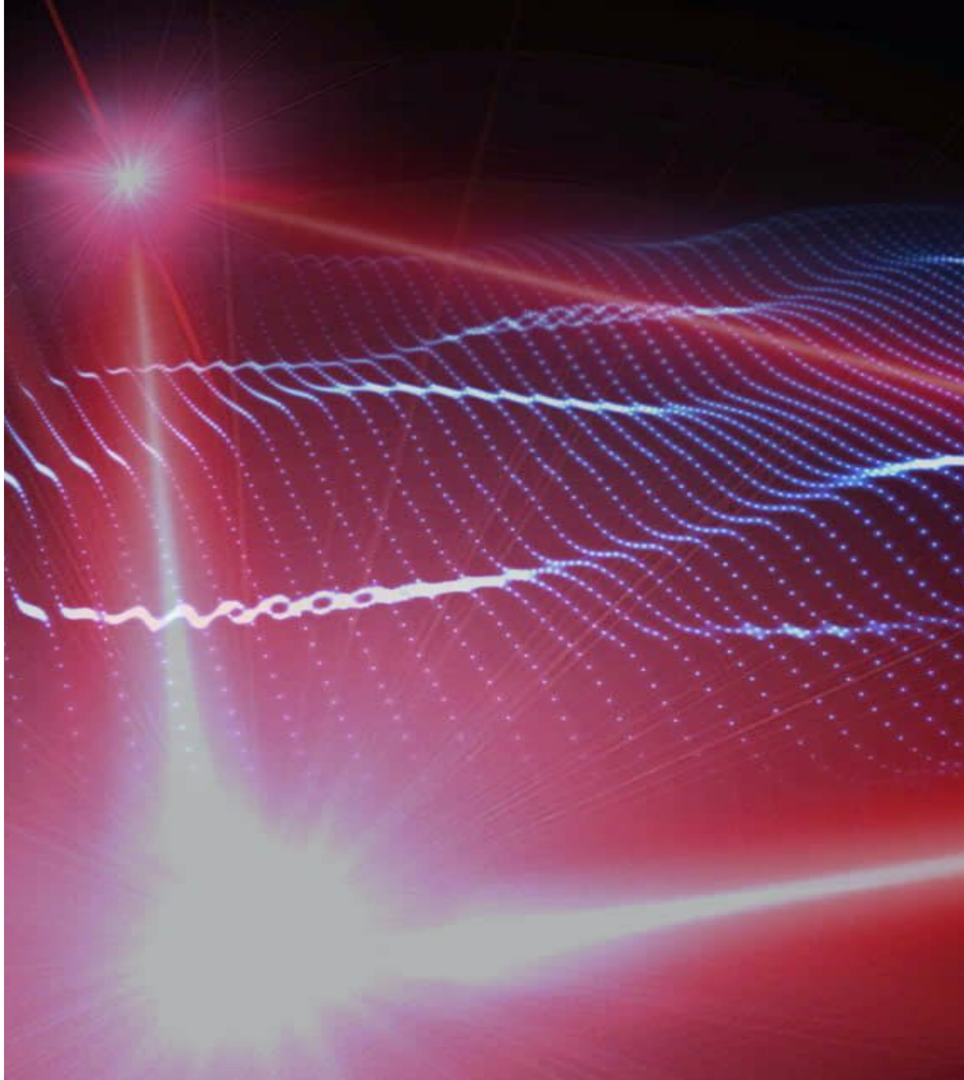
- We've shown (and so have another group) [Chua & Valisneri, arXiv:1909.05966 (2019)] that variational inference is a powerful tool.

- Extending this to more realistic cases is the next step.

- The ultimate aim is to have this working on CBC signals containing matter.

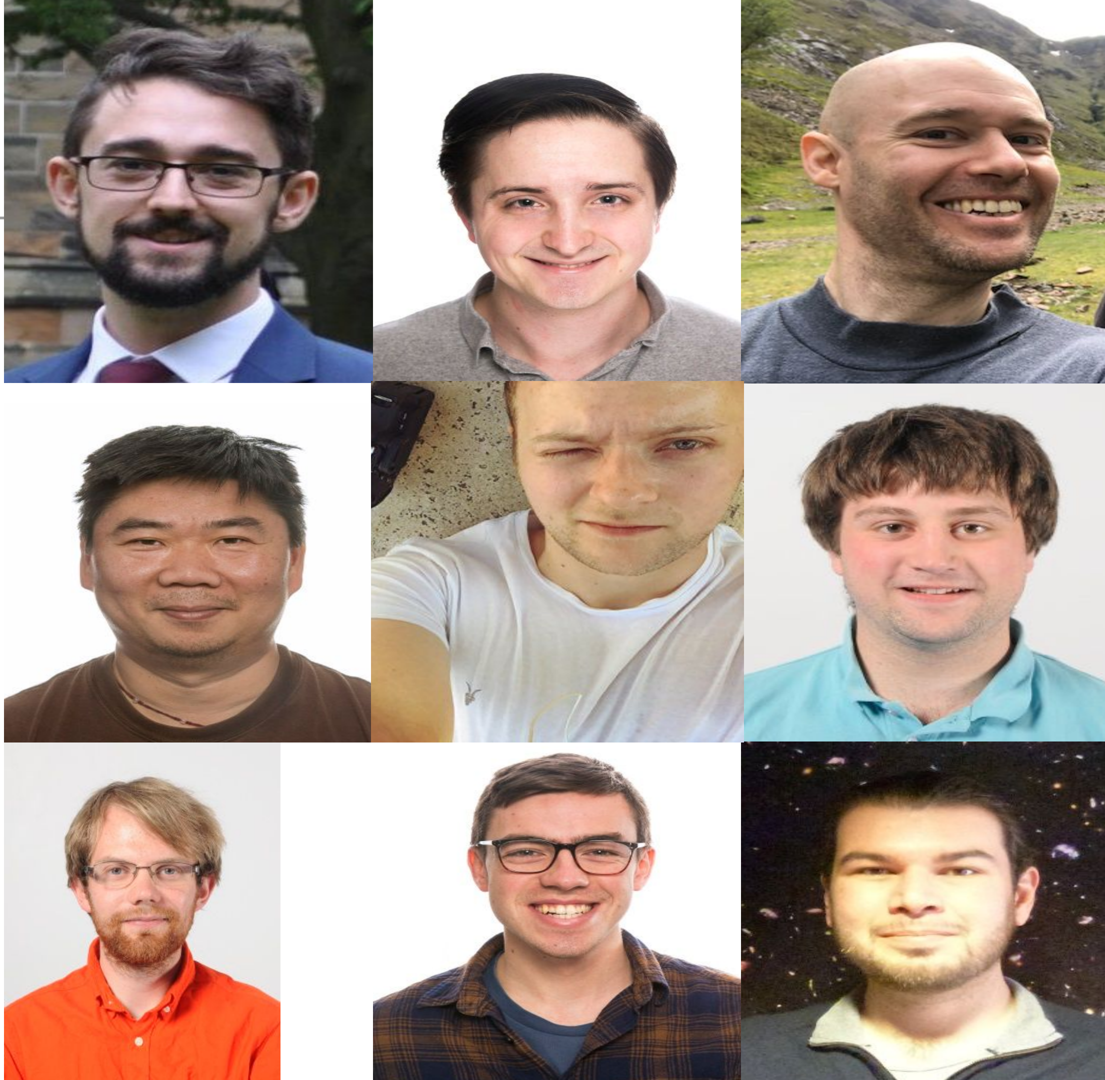
- Our pipeline is called VItamin and is available to play with here

https://github.com/hagabbar/VItamin



Summary

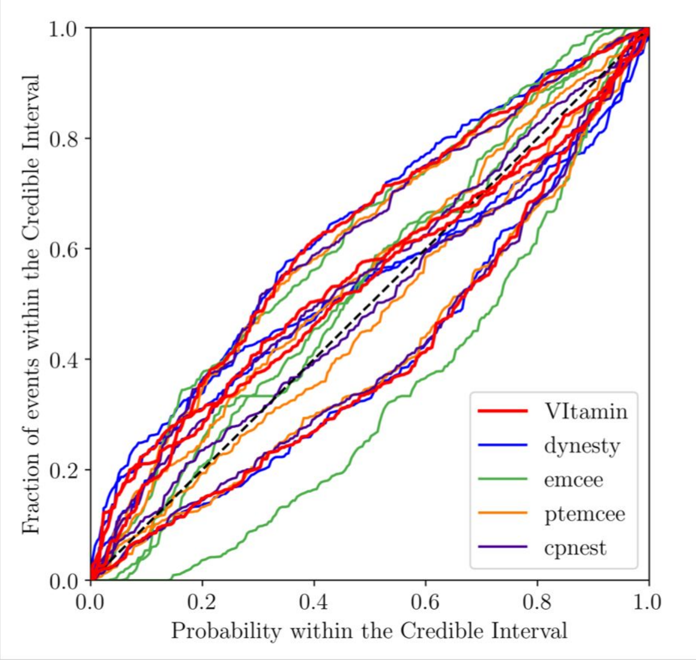
- We covered the basics of gravitational wave astronomy
- We then covered some ML basics
- We covered variational autoencoders
- We finished off with variational inference for Bayesian parameter estimation.



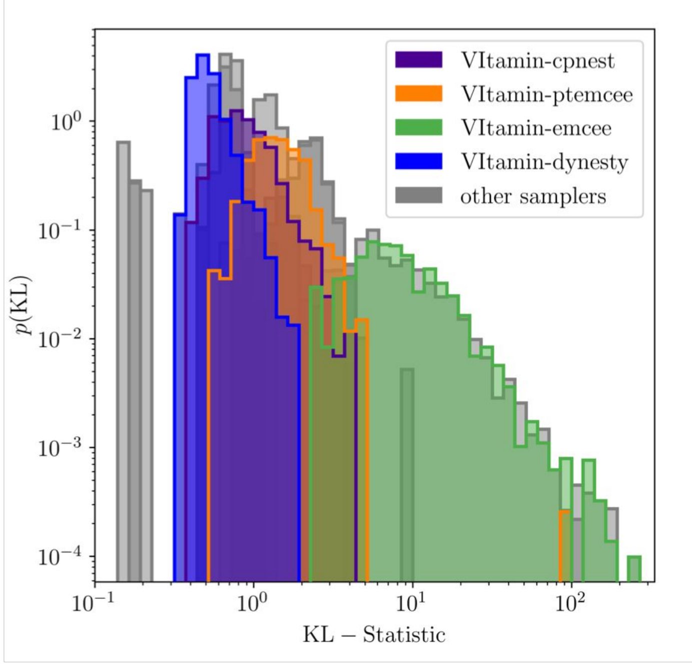
Thank you for your attention!

Validation

p-p plot



KL-divergence distributions



Gabbard ***et al***, arXiv:1909.06296 (2019)