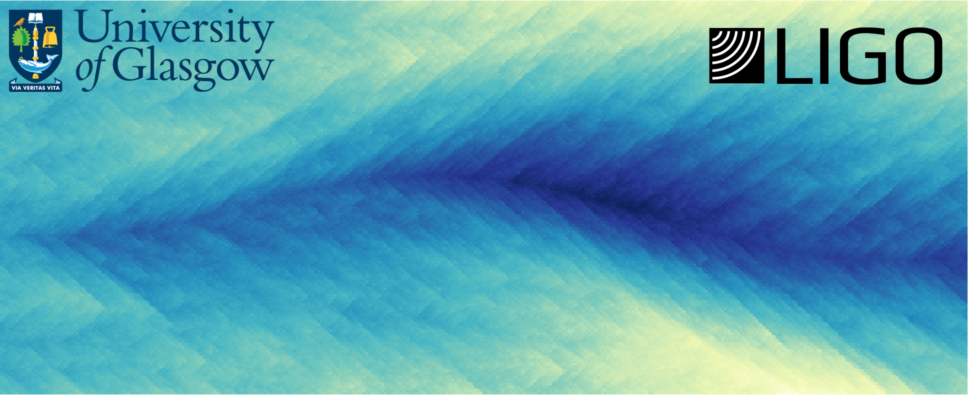


Rapidly searching for continuous gravitational waves

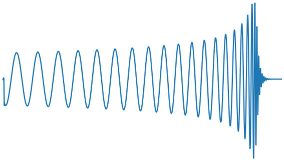
Joe Bayley - University of Glasgow

IPAM Workshop IV - 29th Nov 2021

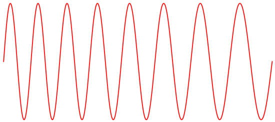
Summary

Gravitational wave searches

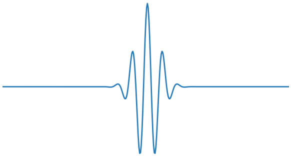
CBC signal



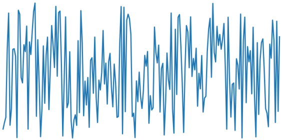
Continuous waves



Burst signals

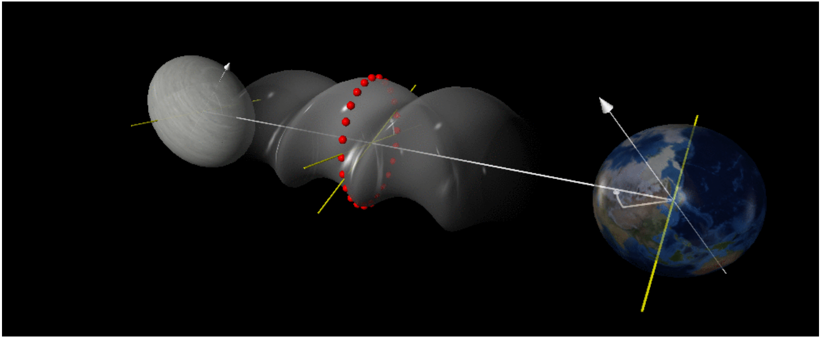


Stochastic signals



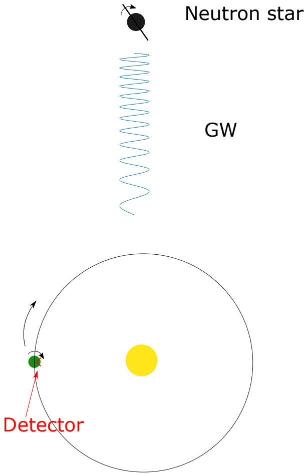
Continuous gravitational waves

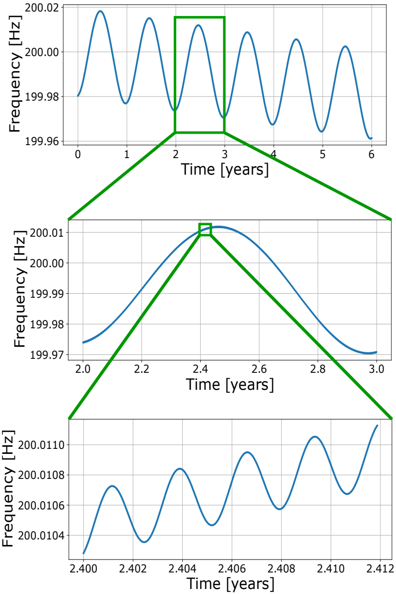
The key source of CW is thought to be rapidly rotating neutron stars which are not symmetric around their rotation axis.



[Graham Woan - https://dcc.ligo.org/G2001983]

- Spin down from neutron star
- Doppler shift from earth orbit and rotation





Current searches

Targeted

Known frequency fdot and sky position
Templated matched filtering

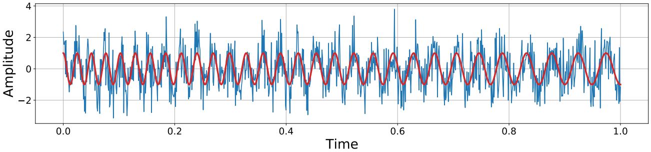
Directed

Known sky position

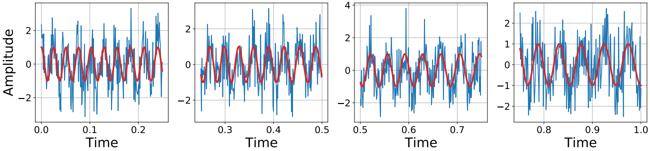
All-sky

Nothing known prior to search.
Mostly short coherence times - combined incoherently

- Targeted searches can use matched filter waveforms as they have prior knowledge of sky position and frequency evolution



- For all-sky searches one would need $\mathcal{O}(10^{14})$ templates to sufficiently cover the sky for 1 year of observation. Not accounting for $f, \dot{f}$ ...
- This is not feasible, so semi-coherent searches are used
  - Split the data up into small segments then analyse them coherently
  - results can then be incoherently combined

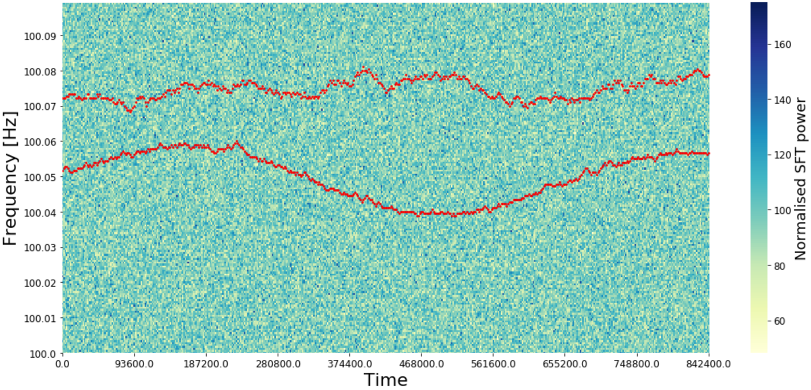


Semi-coherent techniques used in all-sky searches include

- Time domain F-stat - uses a matched filter over short duration segments $\mathcal{O}$(days), then finds coincidences between segments
- Hough searches based on sets of FFTs
  - Sky hough - Generates the hough transform on sky parameters for given frequencies
  - Frequency hough - Generates the hough transform for f and $\dot{f}$ for data demodulated for Doppler shifts
- SOAP - identifies the most probable frequency track in set of FFT power spectra

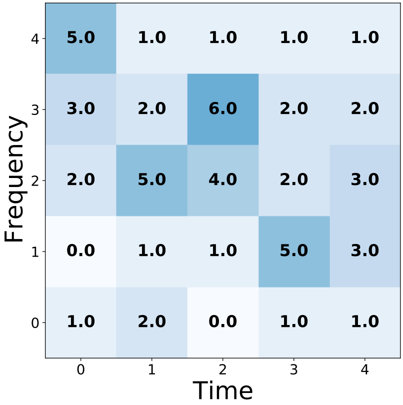
SOAP

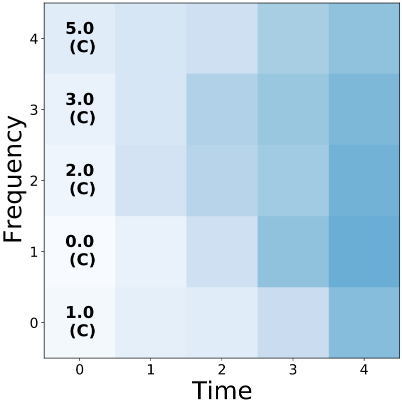
- SOAP is a rapid all sky search for continuous gravitational waves based on the Viterbi algorithm. 10.1103/PhysRevD.100.023006
- It identifies the track through a spectrogram which gives the highest sum of some statistic.



Viterbi algorithm

The Viterbi algorithm rapidly identifies an optimum set of states. Finds the optimal path with $3 \times N_f \times N_t$ calculations rather than $N_f \times 3^{N_t}$





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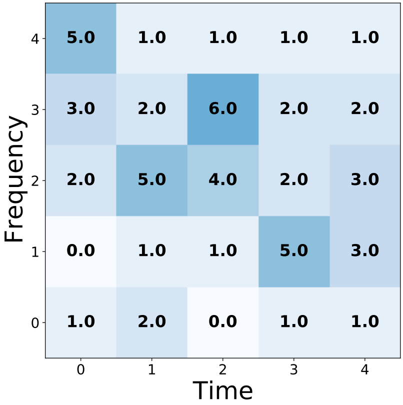

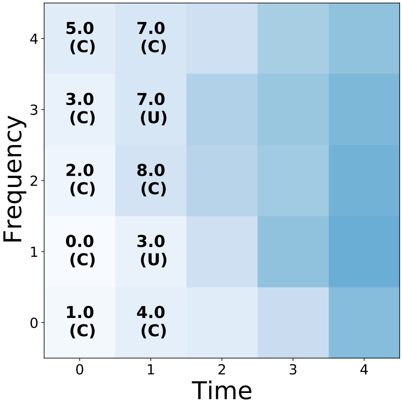

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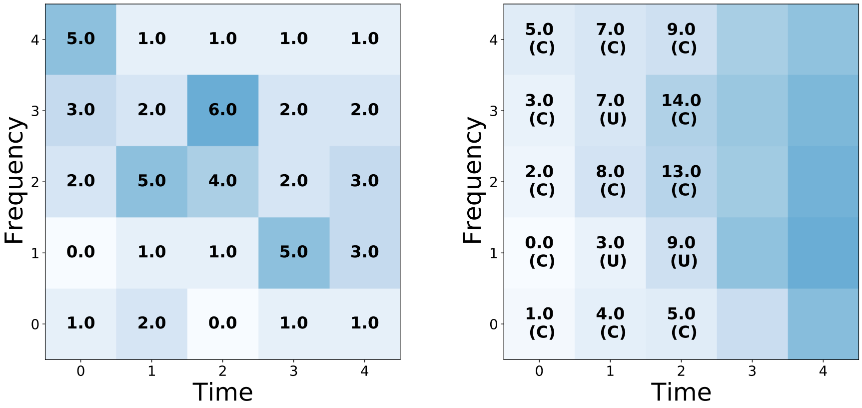

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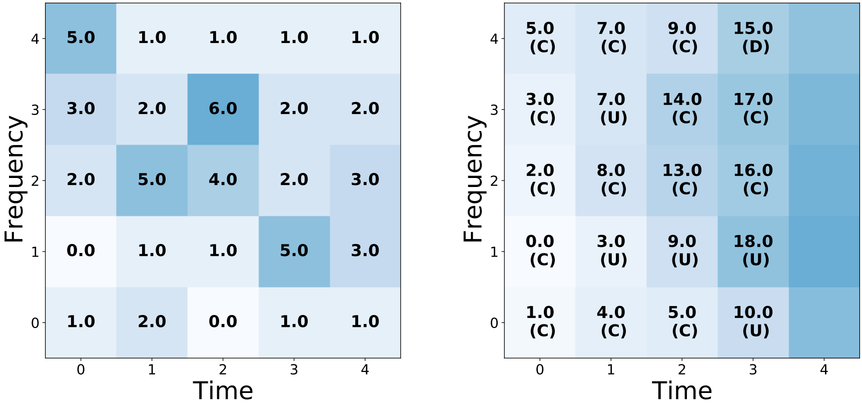

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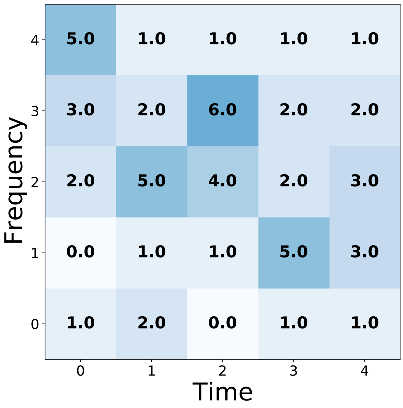

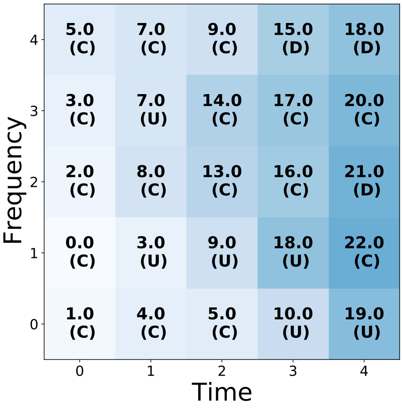

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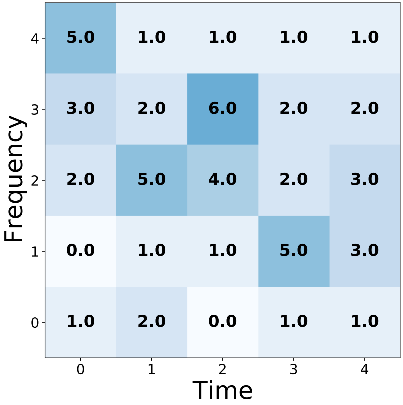
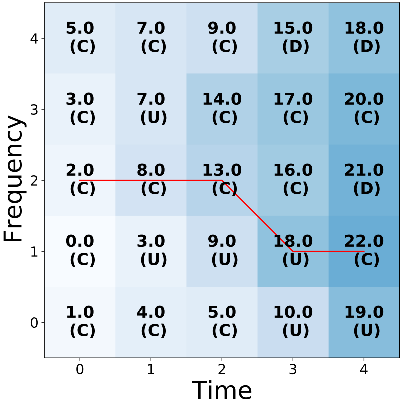
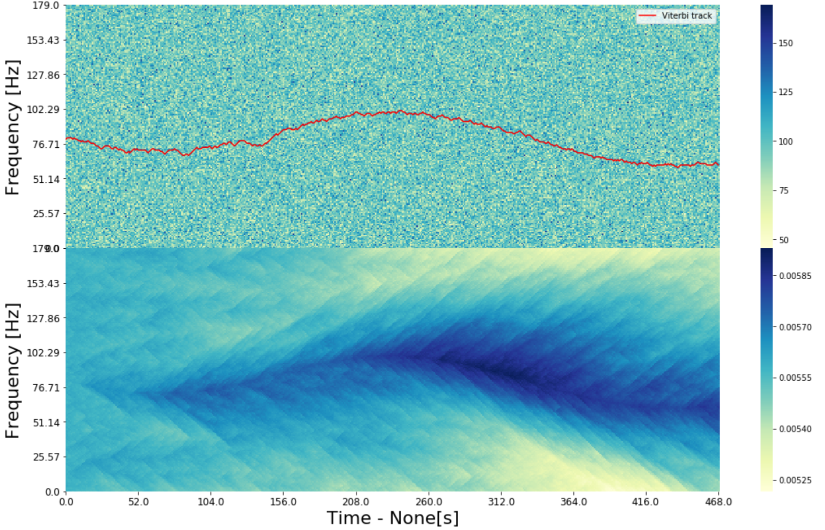
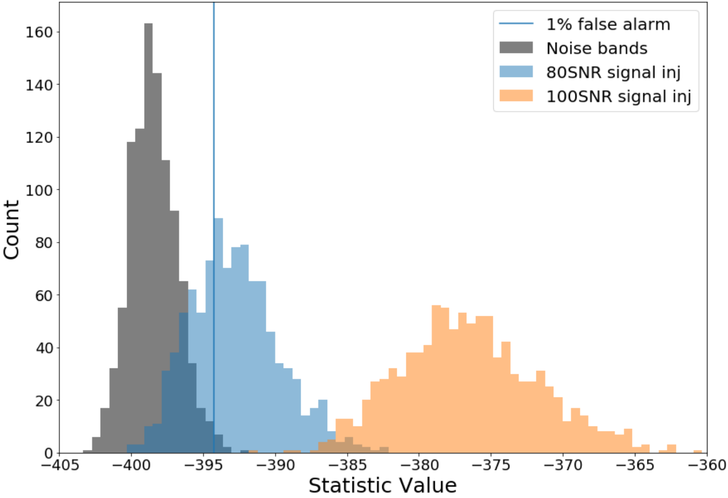




The inputs and outputs of the search are then the Viterbi statistic, Viterbi track and Viterbi map



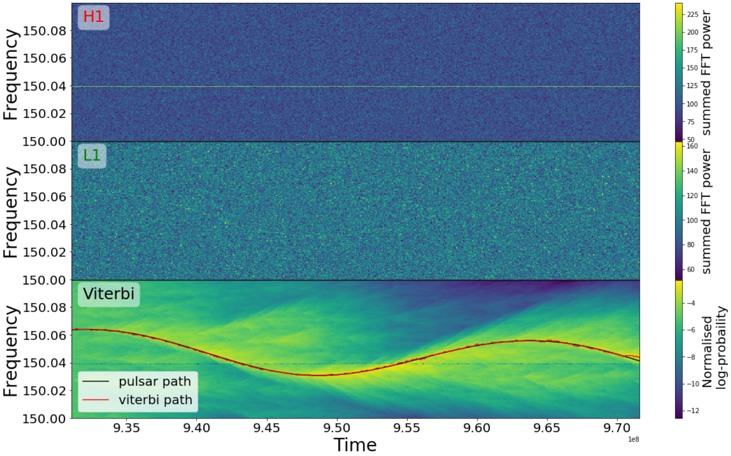
By taking the sum of the values along the Viterbi track, one can build a detection statistic.



Multiple detectors

- SOAP searches for a consistent track between the detectors using a Bayesian 'line aware statistic'

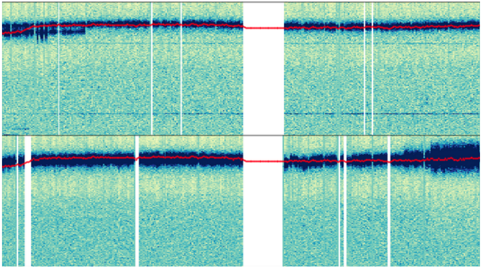
$$\mathrm{Odds} = \mathrm{p}_{\mathrm{signal}}/(\mathrm{p}_{\mathrm{noise}} + \mathrm{p}_{\mathrm{line}}) \quad (1)$$

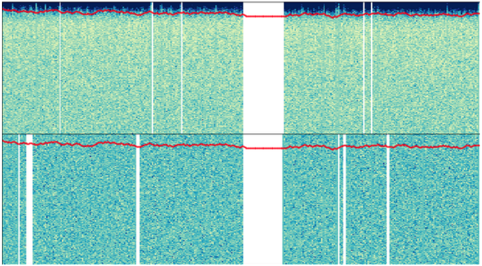


Instrumental lines

Instrumental lines are still a large issue for SOAP

- If they appear in both detectors
- In single detectors the track can follow the edge of a line where it finds consistent high power





Convolutional neural networks

To address the issue of noise contamination in the output statistics, we can combine the output information of the Viterbi search. 10.1103/PhysRevD.102.083024

Viterbi statistic

Sum of statistics along path

Downsampled Viterbi map

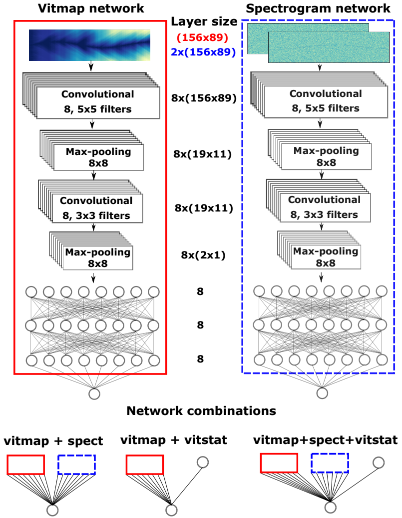
Map of normalised Viterbi statistic in each time-frequency bin

Downsampled spectrograms

Downsample the input spectrograms such that the spectrograms are 1/6 of original size

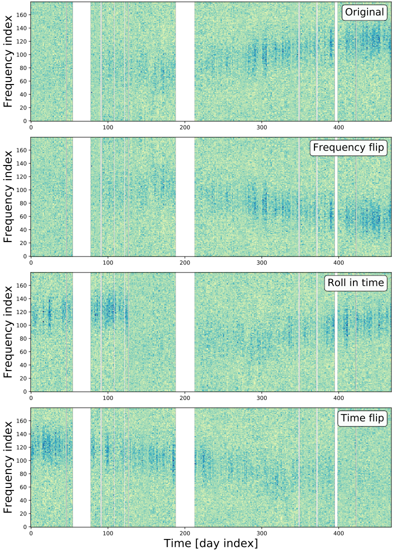
Network structure

- The final statistic is made of the outputs separate networks combined together.
- Train the Vitmap and Spectrogram networks separately
- Then strip the output layers of each and join to final output
- Retrain network

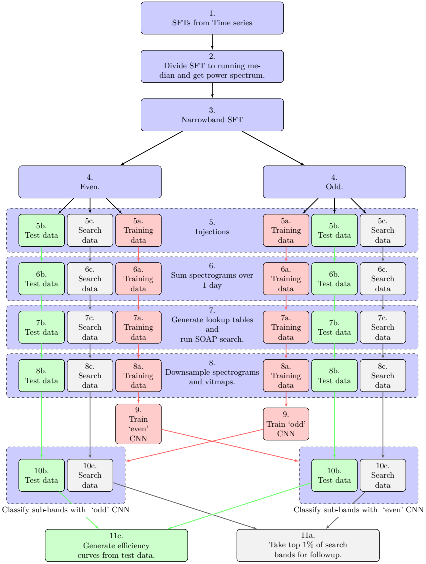


Training data

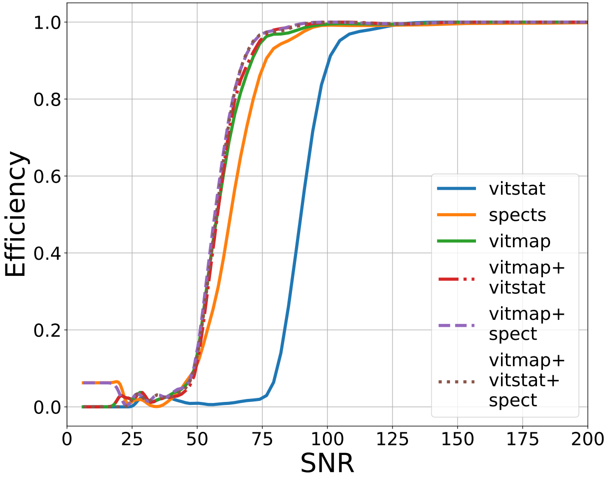
- We split real detector sub-bands into two categories odd and even
  - ‘even’ sub-bands are 100.0, 100.2, 100.4 ......
  - ‘odd’ sub-bands are 100.1,100.3,100.5 ......
- This allows us to train and test on different sets of data
- We can ‘augment’ the data
- For each piece of noise we can duplicate and inject a CW signal into one



- Full pipeline generates training, testing and search data for each odd and even bands
- Trained networks test and search on opposite band category



Example of sensitivity to signals injected into LIGO's second observing run O2 with 1% false alarm



- Time taken for different parts of the search
- Data generation is easily parallelised
- 5000 - 10000 times faster than existing all-sky searches

Generating data on single CPU

	Time [hrs]
Narrow-banding	~ 9
Training data	~ 240
Testing data	~ 75
Search data	~ 40

Training CNN on single GPU

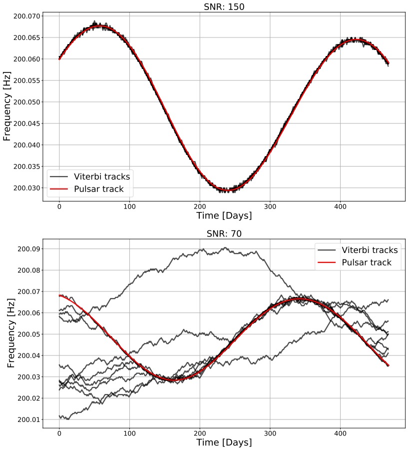
	Training time [hrs]	Loading time [hrs]
Viterbi statistic	0.03	0.2
Viterbi map	0.8	0.7
spectrogram	9	1
Viterbi map + Viterbi statistic	1	0.7
Viterbi map + spectrogram	1.4	1.6
Viterbi map + Viterbi statistic + spectrogram	1.5	2

Testing CNN on real data on GPU

	Testing [s]	Loading [s]
All CNN	5	$60 - 160$

Parameter estimation

- Once we have a detection, we would then like to know astrophysical parameters about the source.
- We would like to estimate the sky position, frequency and frequency derivative.
- It becomes very difficult to define a likelihood for these tracks.



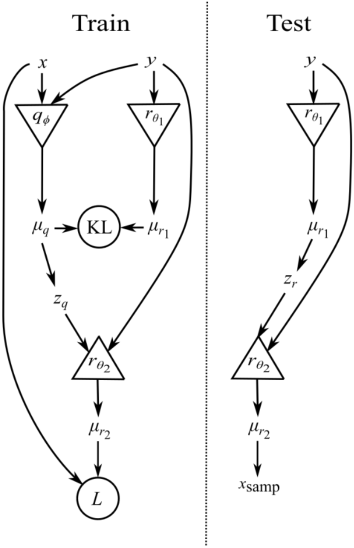
Conditional Variational Autoencoders

- We looked into likelihood free methods
- Conditional Variational Auto Encoders
  - Initially used for CBC parameter estimation to generate Bayesian posteriors
  - VItamin paper accepted into nature
  - Gabbard et al https://arxiv.org/abs/1909.06296
- This technique minimises the cross-entropy between the true posterior p and a posterior estimate r_θ

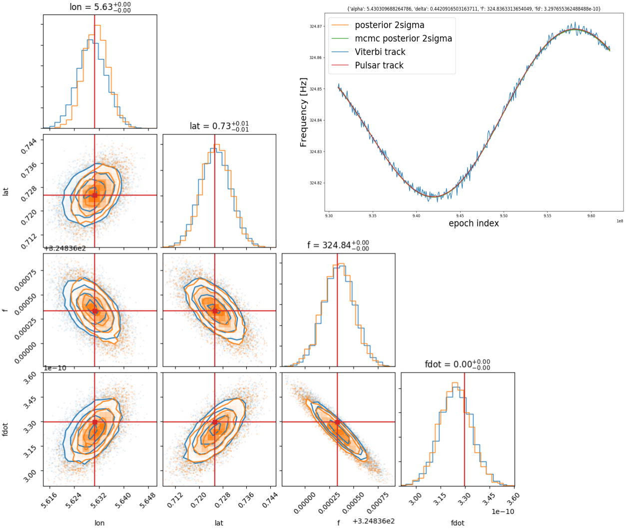
$$H(p, r) = -\int p(x \mid y) \log r_\theta(x \mid y) dx \tag{2}$$

- The structure of the CVAE allows the posterior to be estimated without the network ever seeing a true posterior
- The cross entropy can be rewritten as

$$H \lesssim \frac{1}{N}\sum_{n=1}^{N_b}\left[-\log r_{\theta_2}(x_n \mid z_n, y_n) + \mathrm{KL}\left[q_\phi(z_n \mid x_n, y_n) || r_{\theta_1}(z_n \mid y_n)\right]\right]. \tag{3}$$

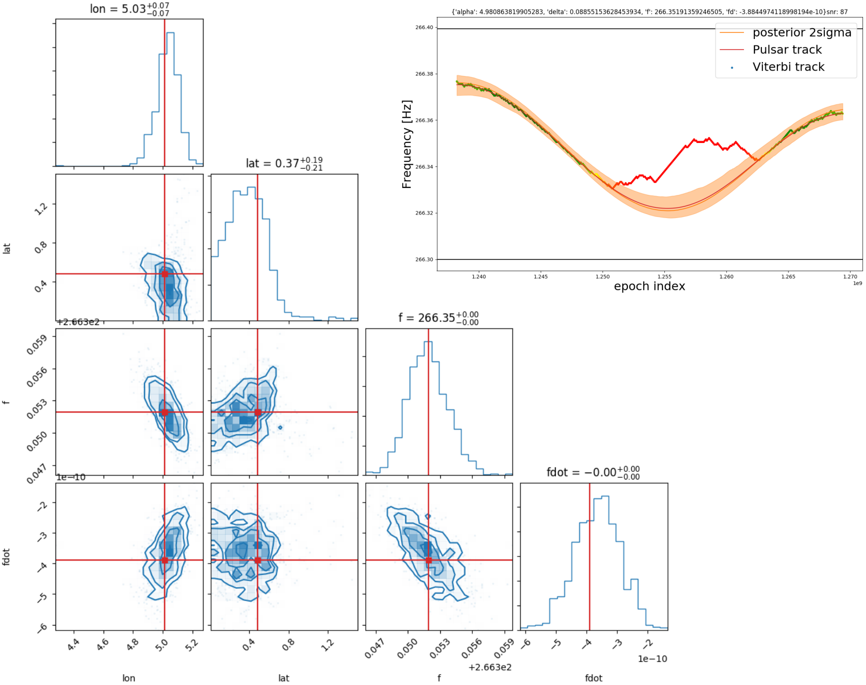


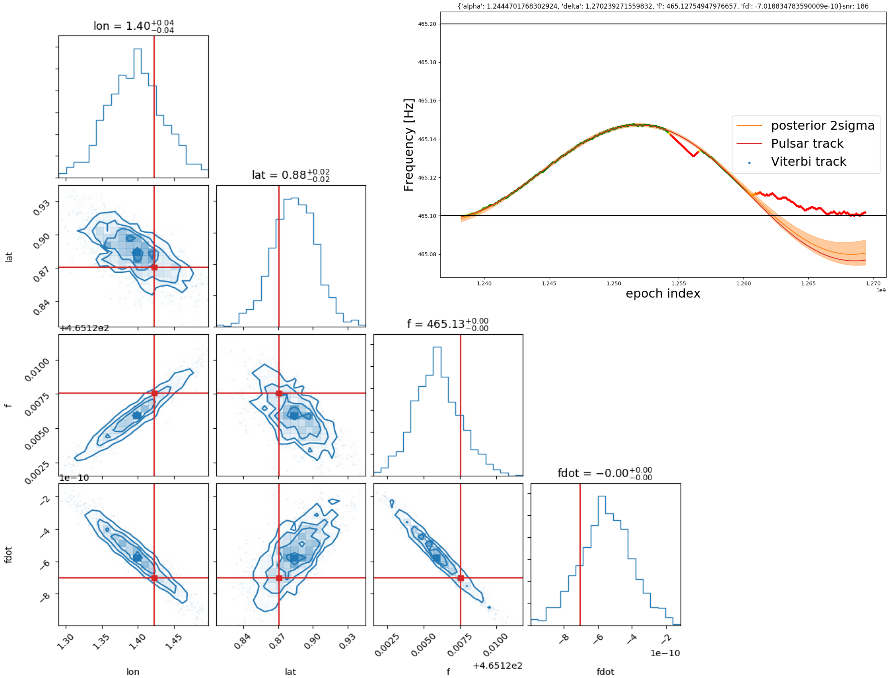
To compare this technique to traditional samplers (nested samplers, mcmc samplers) We do with by adding Gaussian noise to the CW frequency evolution (not physical)



Viterbi tracks

- To train on Viterbi tracks we run the SOAP search on many spectrograms containing continuous gravitational wave signals ($\sim 1 \times 10^6$)
- There are two main outputs to the network
  - The four Doppler parameters $\alpha, \delta, f, \dot{f}$
  - The probability that a sample from the track is associated with an astrophysical signal
- It returns samples from the posterior distribution on these 360 + 4 parameters


lon = $5.03^{+0.07}_{-0.07}$
lat = $0.37^{+0.19}_{-0.21}$
f = $266.35^{+0.00}_{-0.00}$
fdot = $-0.00^{+0.00}_{-0.00}$
+2.663e2
1e−10
lon
lat
f
fdot
4.4 4.6 4.8 5.0 5.2
0.4 0.8 1.2
0.047 0.050 0.053 0.056 0.059
−6 −5 −4 −3 −2
1e−10
{'alpha': 4.980863819905283, 'delta': 0.08855153628453934, 'f': 266.35191359246505, 'fd': -3.8844974118998194e-10}snr: 87
posterior 2sigma
Pulsar track
Viterbi track
Frequency [Hz]
epoch index
1e9


lon = $1.40^{+0.04}_{-0.04}$
lat = $0.88^{+0.02}_{-0.02}$
f = $465.13^{+0.00}_{-0.00}$
fdot = $-0.00^{+0.00}_{-0.00}$
+4.6512e2
1e−10
lon
lat
f
fdot
{'alpha': 1.2444701768302924, 'delta': 1.270239271559832, 'f': 465.12754947976657, 'fd': -7.018834783590009e-10}snr: 186
Frequency [Hz]
epoch index
posterior 2sigma
Pulsar track
Viterbi track

Summary

- To identify a CW signal we need to search through a large parameter space and large amount of data.
- Semi-coherent techniques can be used to make all-sky analyses feasible
- SOAP is a semi coherent pipeline which can rapidly identify candidates
- CNNs help improve the search sensitivity to neutron star signals by classifying SOAP outputs and inputs
- CVAEs allow us to return some astrophysical parameters about the source