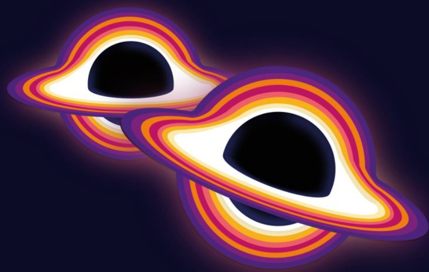


Deep Learning for the detection of Unmodelled Gravitational-Wave Transients

A deep learning approach

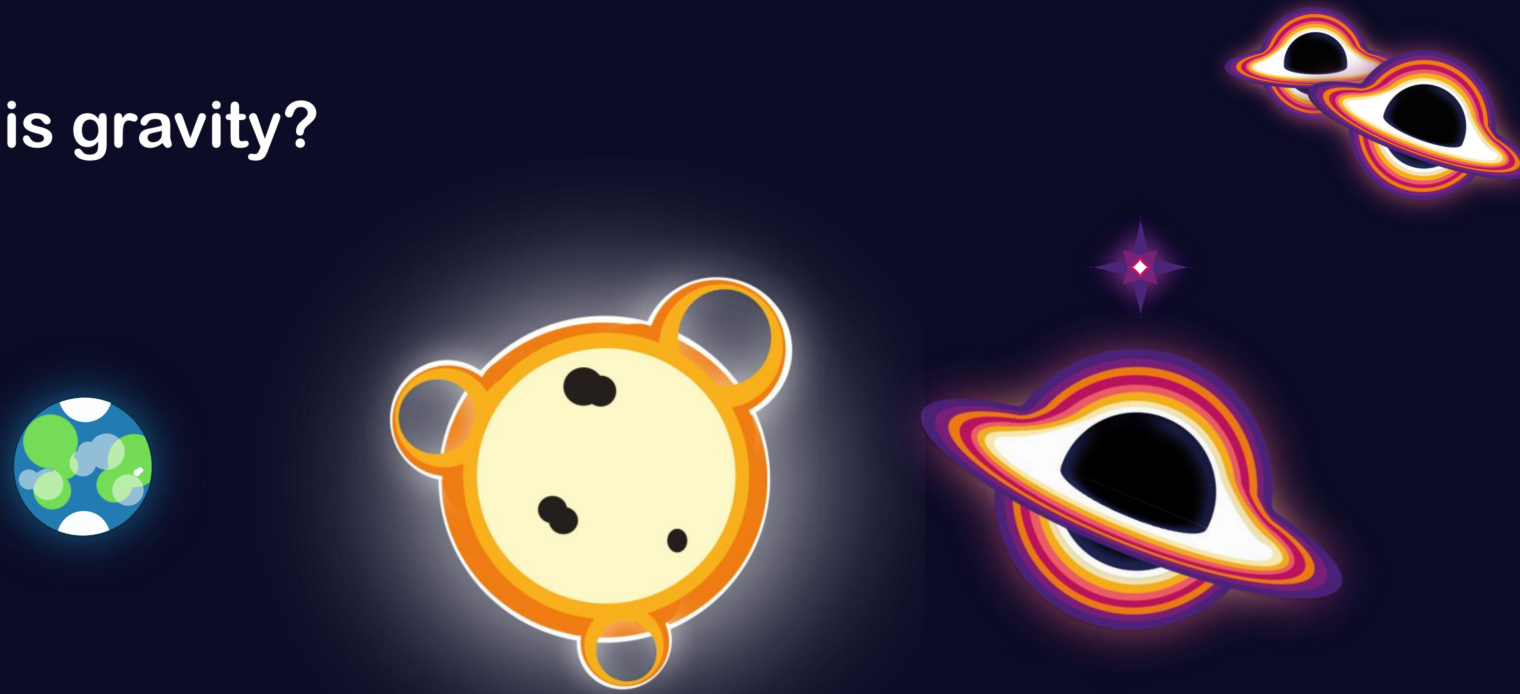
MLY PIPELINE

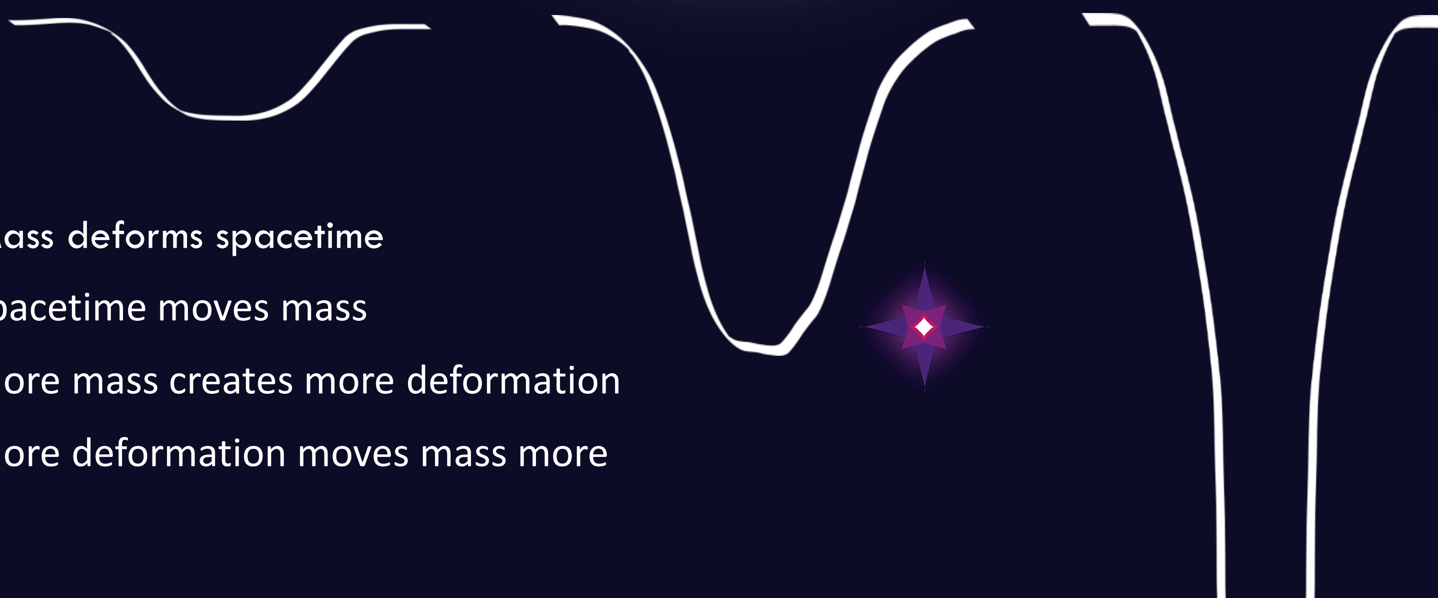
CARDIFF UNIVERSITY PRIFYSGOL CAERDYDD

LIGO

Michael Norman, Kyle Willets, Wasim Javed, Vasileios Skliris, Patrick Sutton

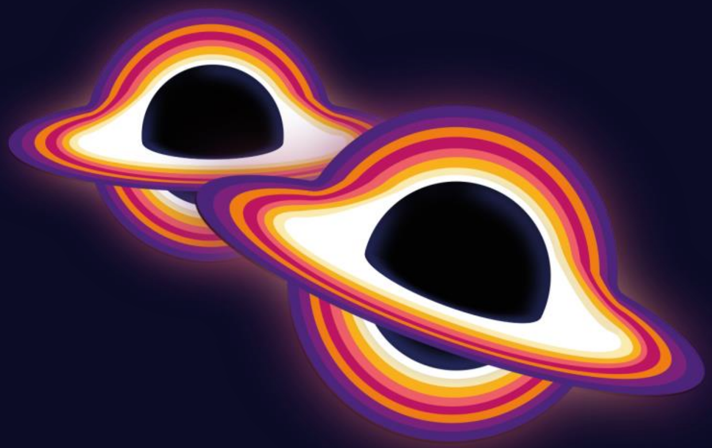
What is gravity?





1. Mass deforms spacetime
2. Spacetime moves mass
3. More mass creates more deformation
4. More deformation moves mass more

What are gravitational waves?



1. Asymmetric motion of mass creates ripples in spacetime

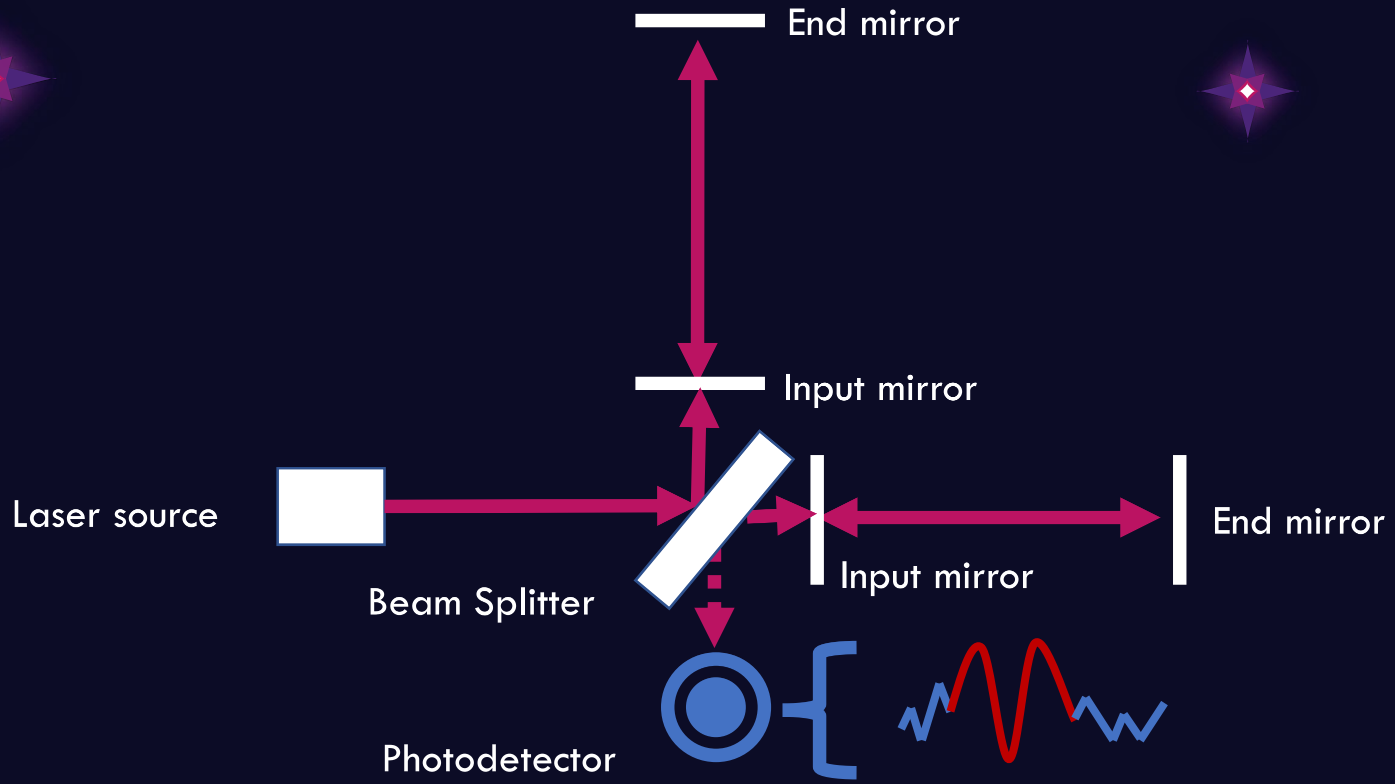
2. Therefore objects in orbit create gravitational waves

3. And more massive objects in orbit create larger waves

How do we detect gravitational waves?

1. Deformations in spacetime changes the real distance between freely floating points
2. If we can measure changes in the distance between two freely floating points we can measure changes in spacetime

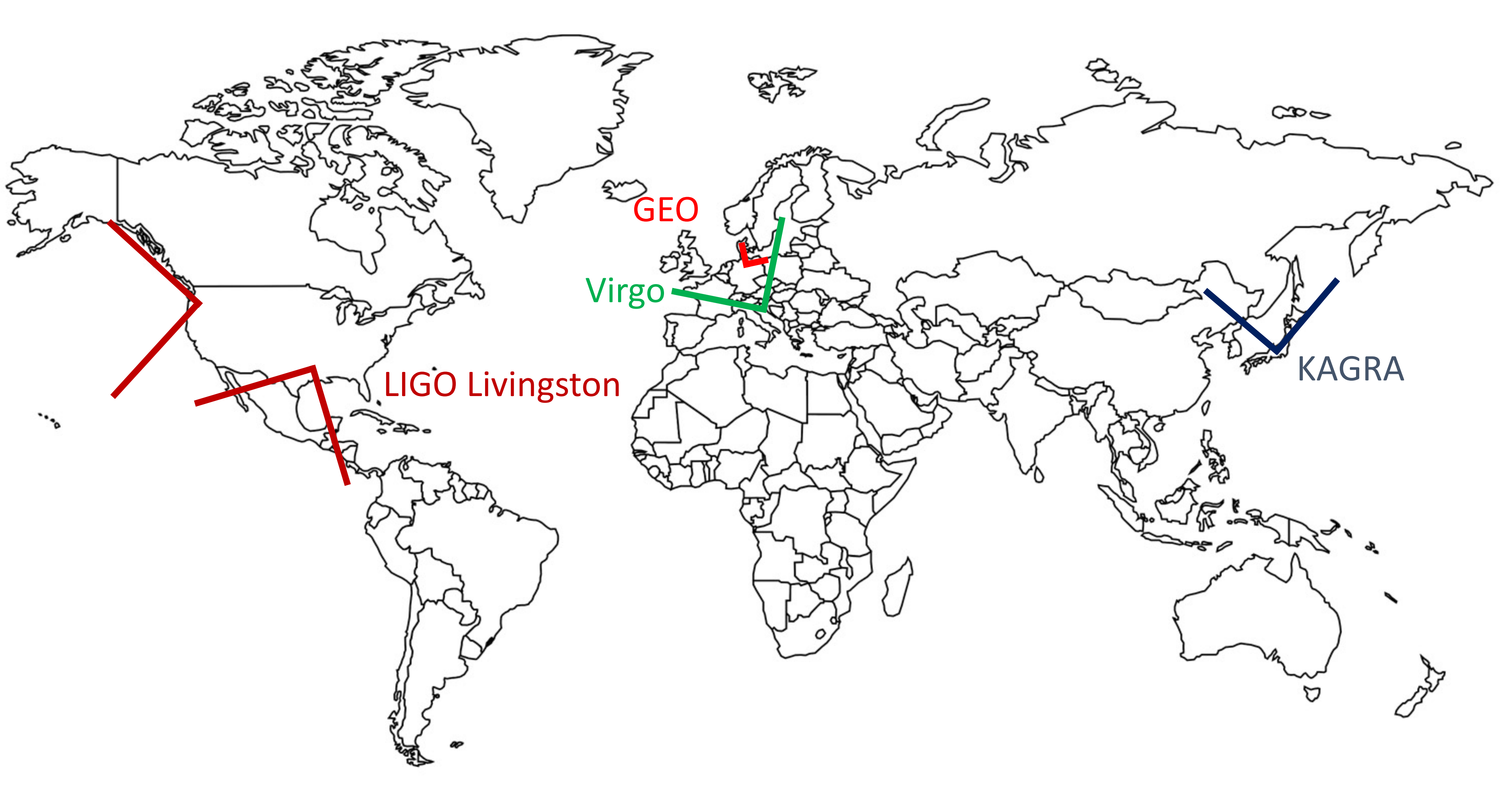
How do we detect gravitational waves?



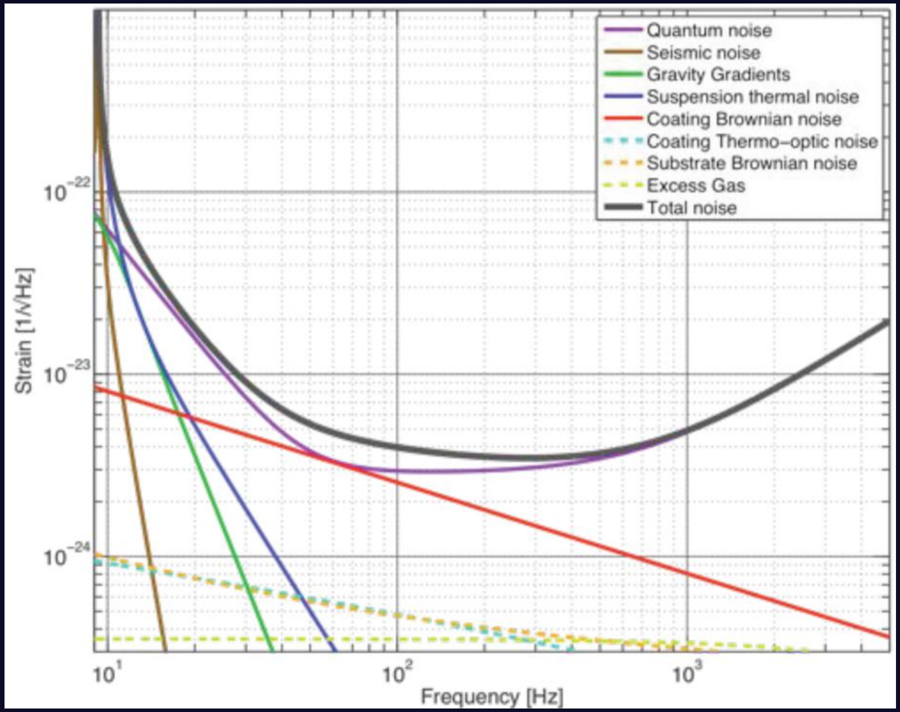
1. We can do this using interferometers
2. A laser is split into two orthogonal cavities, and reflected back to destructively interfere
3. A photodiode reads the resulting power

How do we detect gravitational waves?

Interferometer Locations



How do we detect find signals from noise?



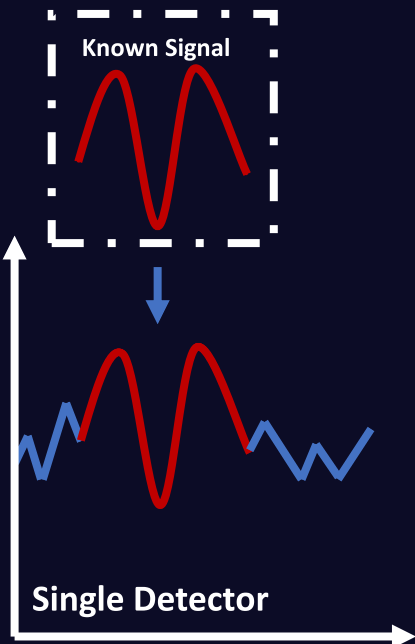
The output of the photodetector takes the form of a 1D timeseries at 16kHz

Care is taken to insulate detectors from noise, but noise is still present at various frequencies

Thus a method is needed to extract real gravitational wave signals from terrestrial noise

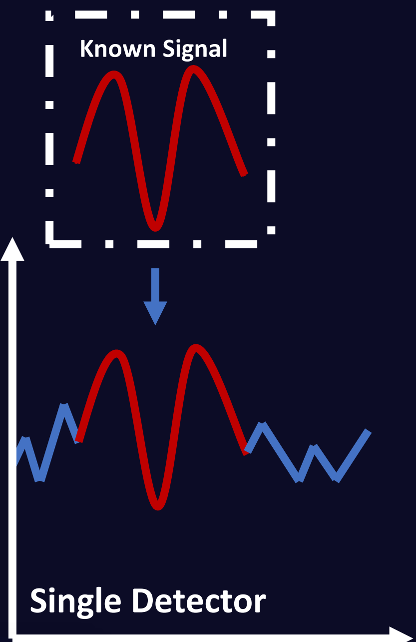
How do we detect find signals from noise?

Matched Filtering

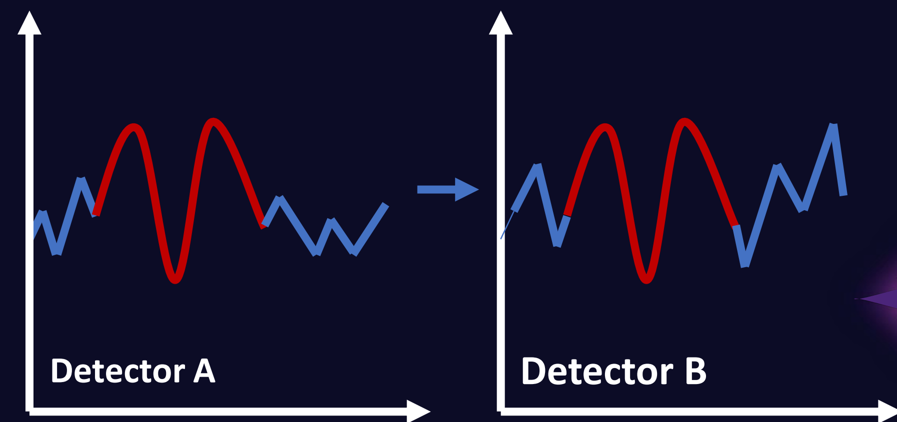


What about other signal types?

Matched Filter



Coherence detection



COHERENCE DETECTION

Pros

- Doesn’t require prior knowledge of (exact) signal shape

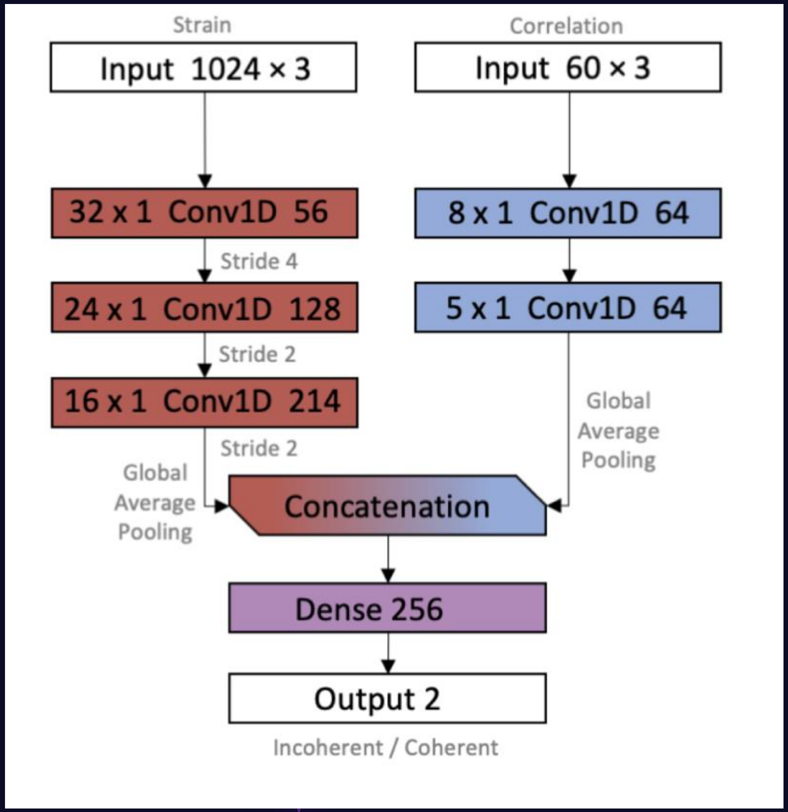
Cons

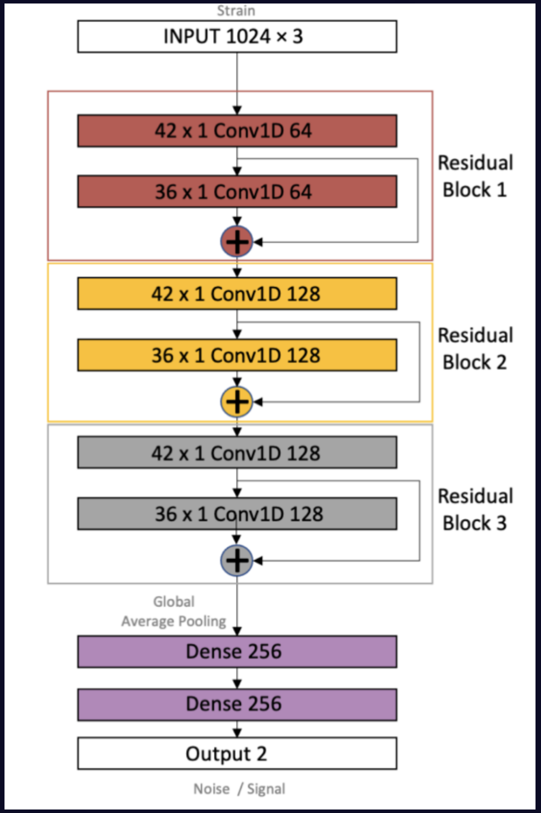
- Is not as sensitive as matched filtering
- Existing pipelines can be quite slow

MLy PIPELINE

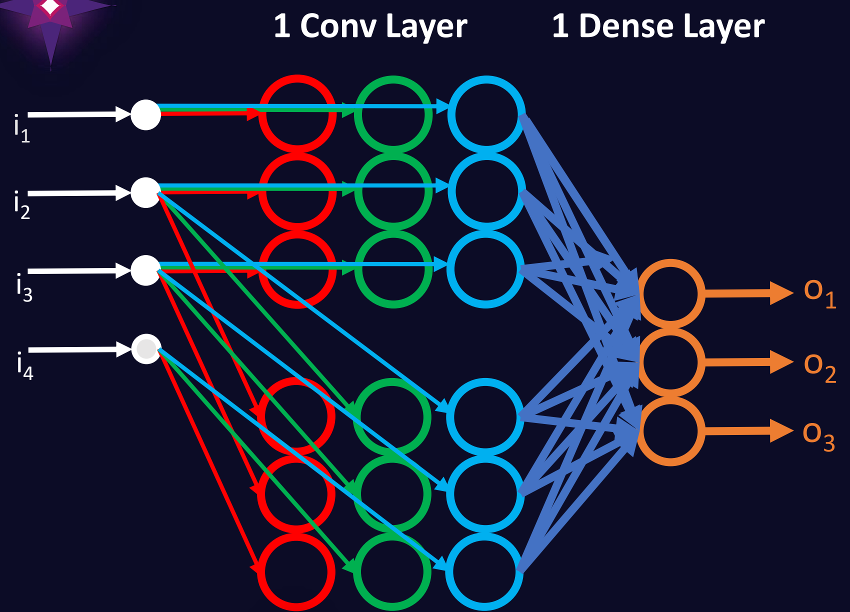
- **Team:** Vasileios Skliris, Wasim Javed, Kyle Willets, **Michael Norman**, Patrick Sutton
- Machine learning pipeline
- Low-latency, unmodelled burst detection for use in Multi-messenger astronomy
- CNN for detection, basic PE, and localization
- Currently in review for deployment in O4
- Methods paper: https://arxiv.org/abs/2009.14611

CURRENT MLy ARCHITECTURE





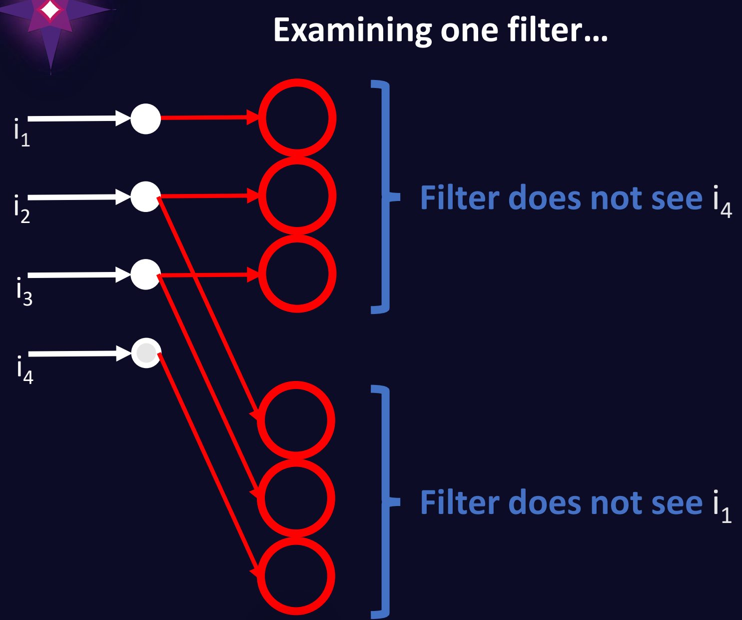
THE PROBLEM WITH CNNs



Toy example:

- Input Size = 4
- Output Size = 3
- Filter Size = 3
- Number of filters = 3

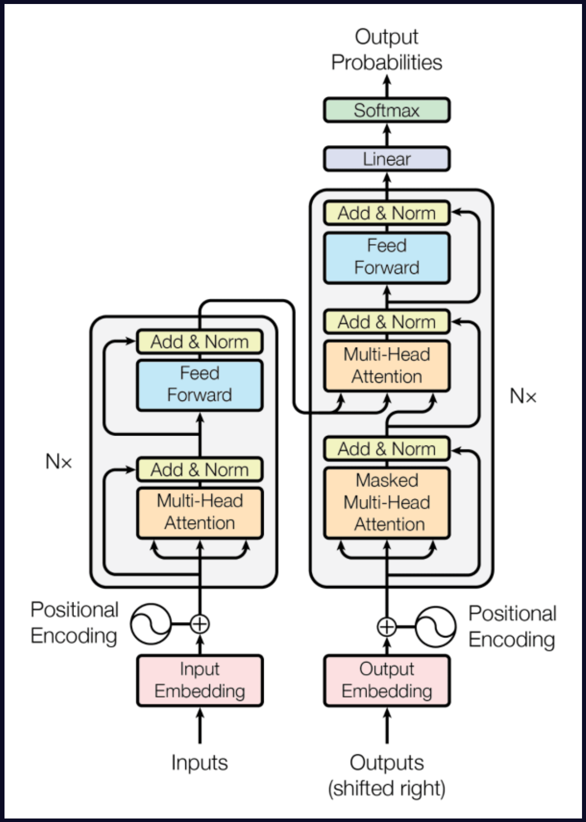
A DRAWBACK OF CNNs



Receptive field size = 3:

- Conv layers are best for focusing on local features not global features
- For multi-detector case unknown arrival time difference between detectors disrupts local features

INTRODUCING TRANSFORMER MODELS



[1] https://arxiv.org/abs/1706.03762

Transformers embed global context locally using **attention**

NATURAL LANGUAGE PROCESSING (NLP)
A quick foray…

The quick brown fox jumped over the lazy dog

NATURAL LANGUAGE PROCESSING (NLP)
A quick foray…

is brown　　has jumped

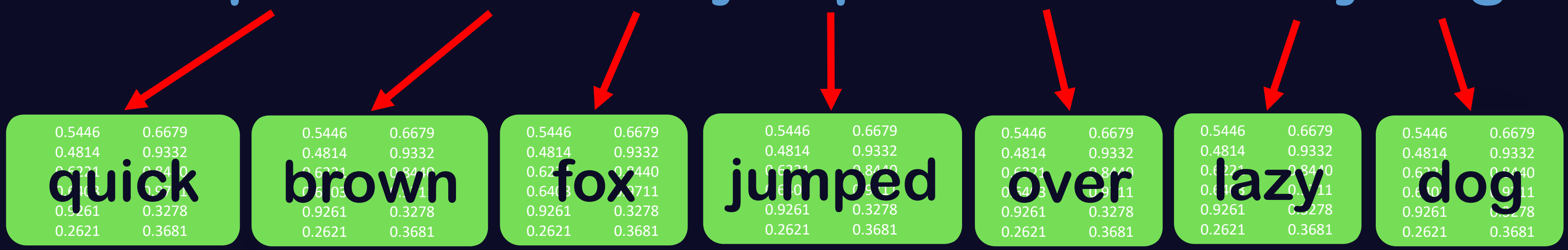
The quick brown fox jumped over the lazy dog

is quick

NATURAL LANGUAGE PROCESSING (NLP)
A quick foray…

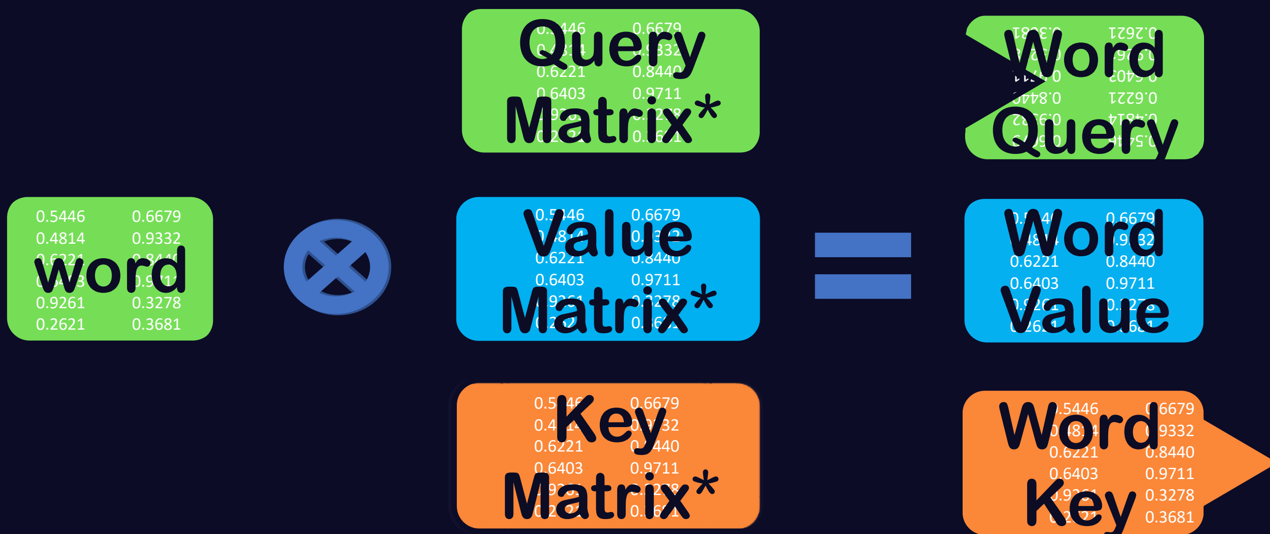
embedding

The quick brown fox jumped over the lazy dog



NATURAL LANGUAGE PROCESSING (NLP)
A quick foray…

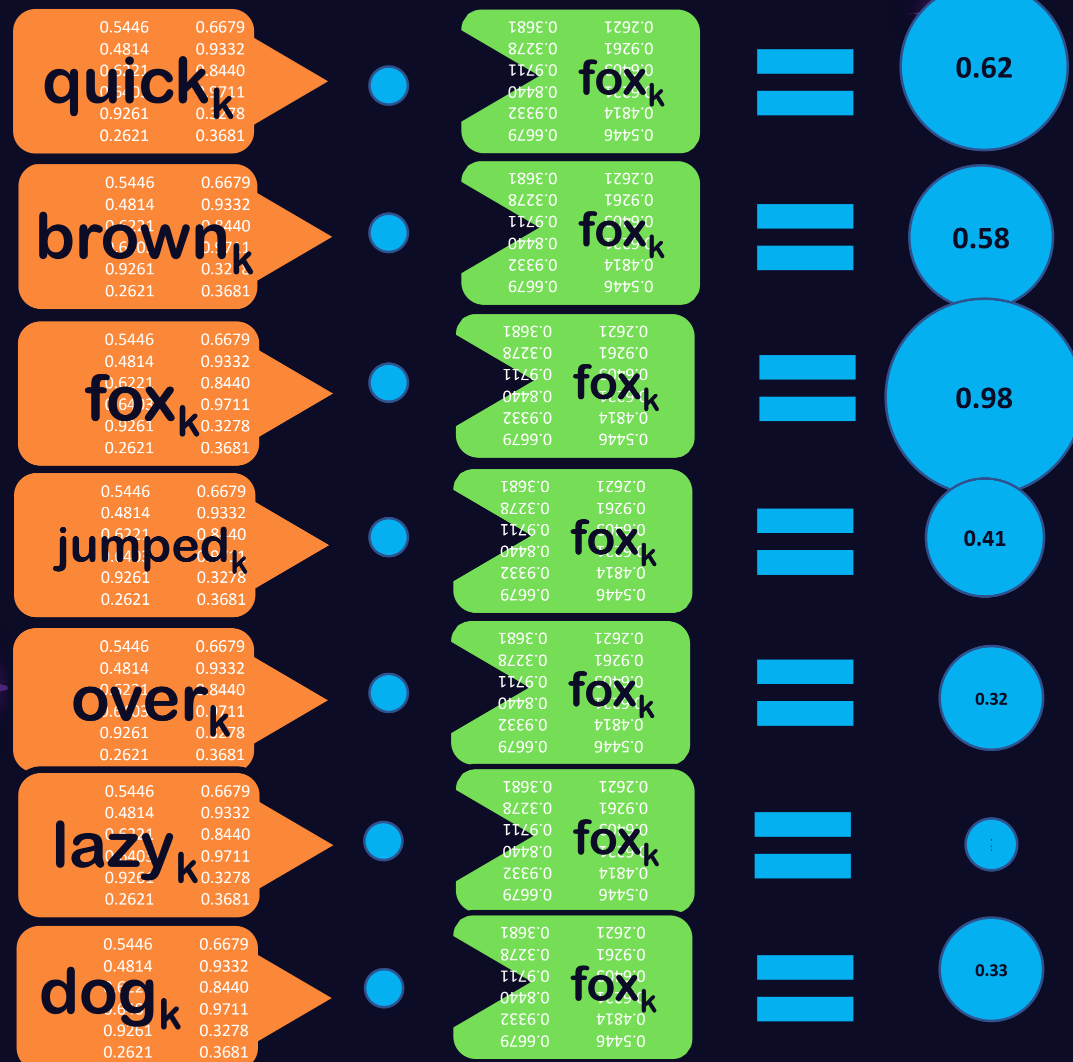
for each token…



*weights matrices are learned, identical for each token

NATURAL LANGUAGE PROCESSING (NLP)
A quick foray…

NATURAL LANGUAGE PROCESSING (NLP)
A quick foray…



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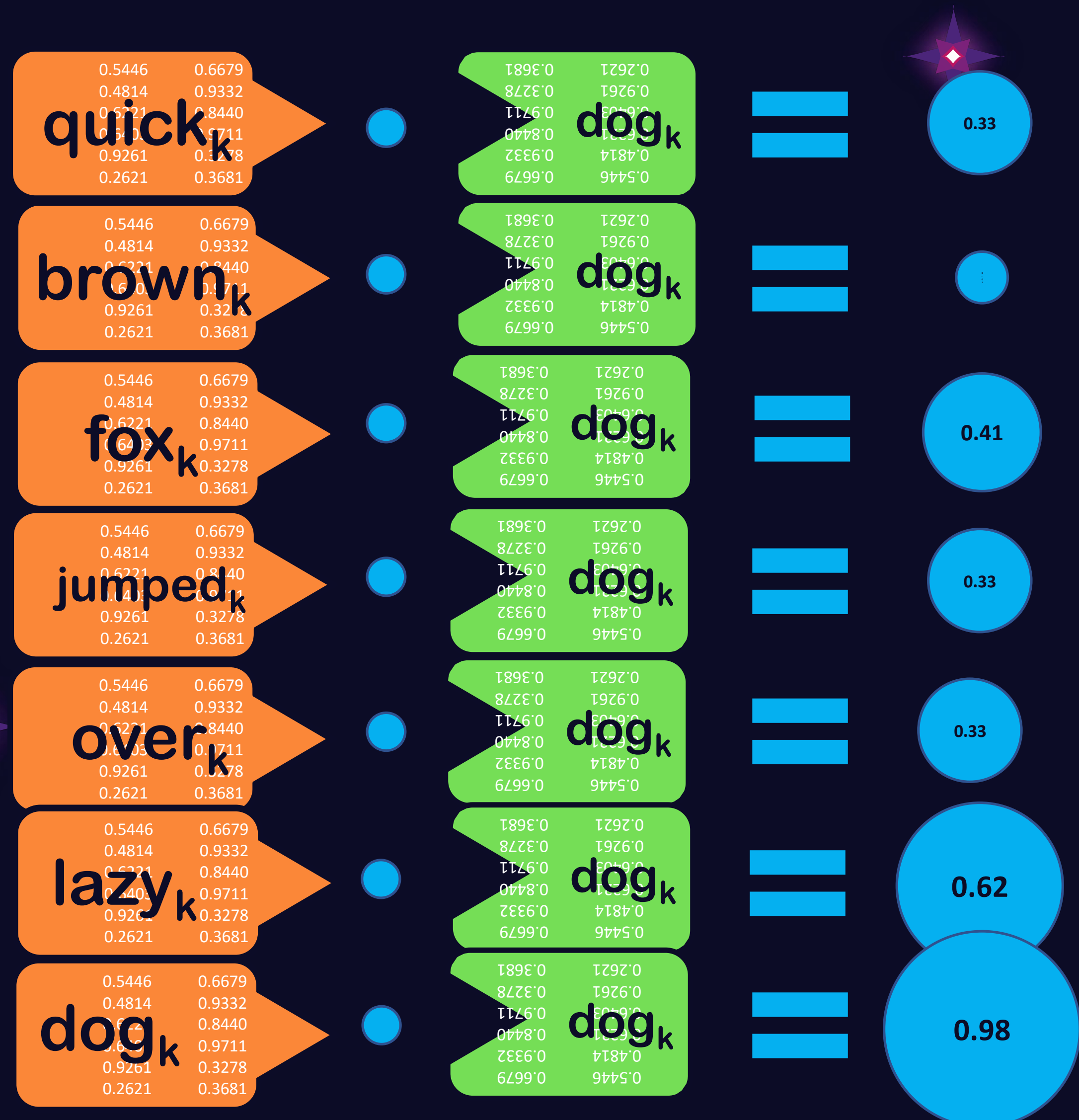

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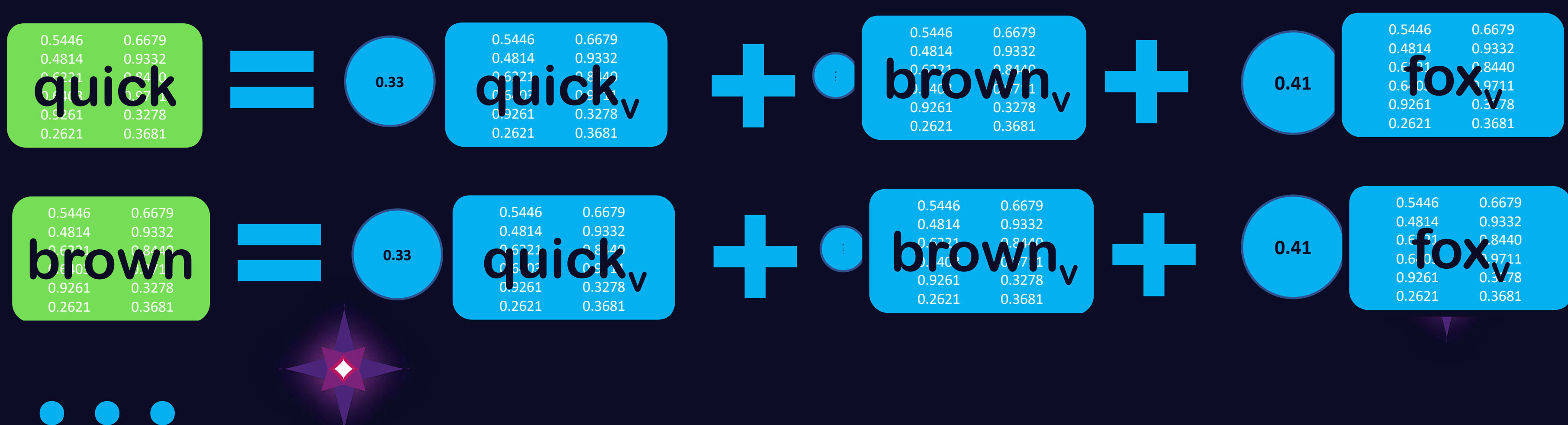

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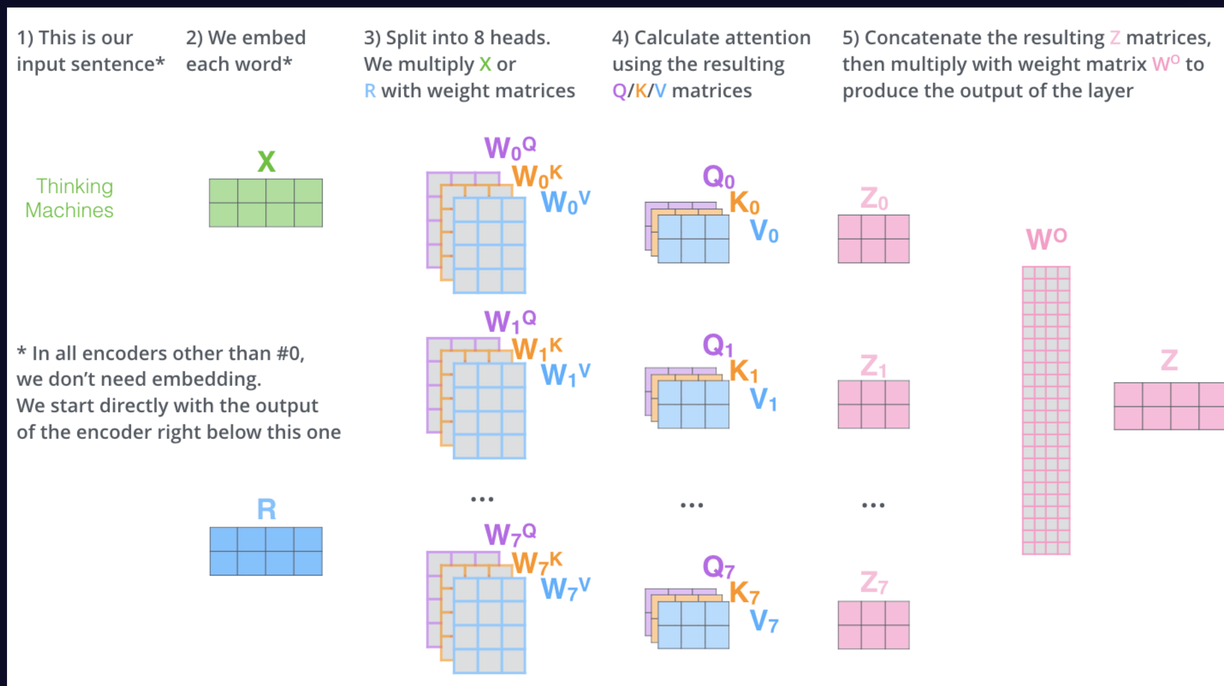
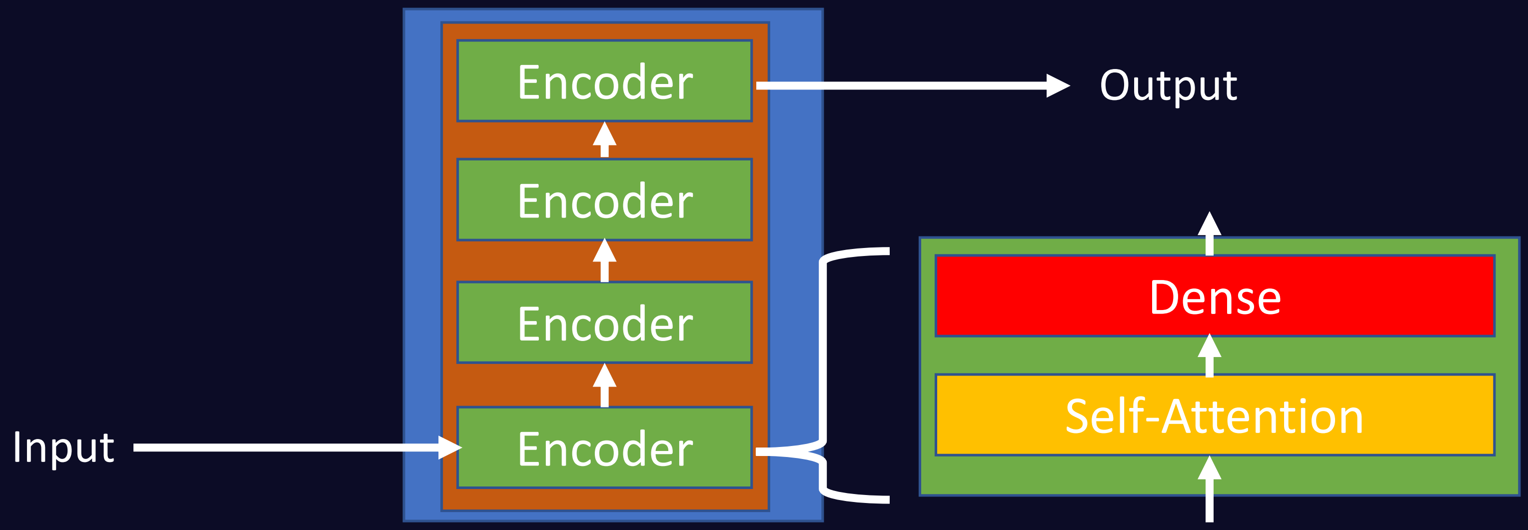
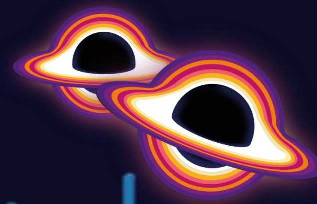
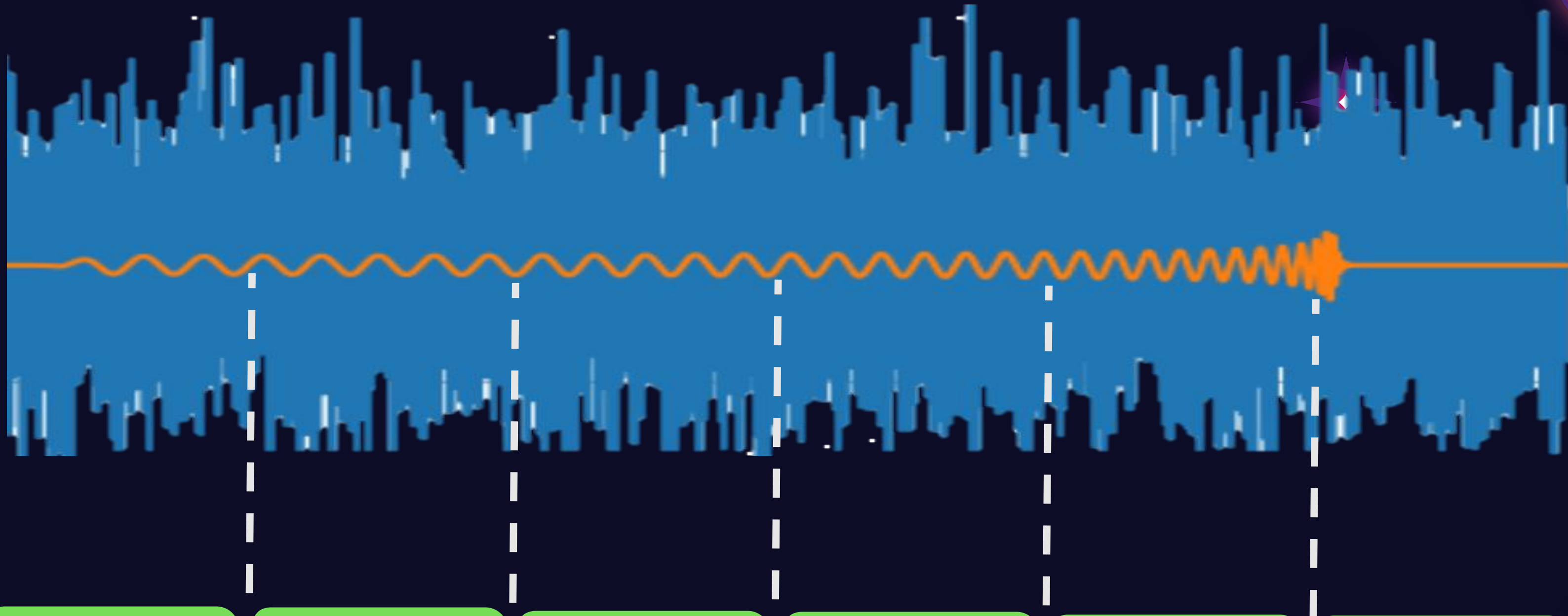


NATURAL LANGUAGE PROCESSING (NLP)
A quick foray…





BACK TO GRAVITATIONAL WAVES



0.5446	0.6679
0.4814	0.9332
0.6221	0.8440
0.6403	0.9711
0.9261	0.3278
0.2621	0.3681

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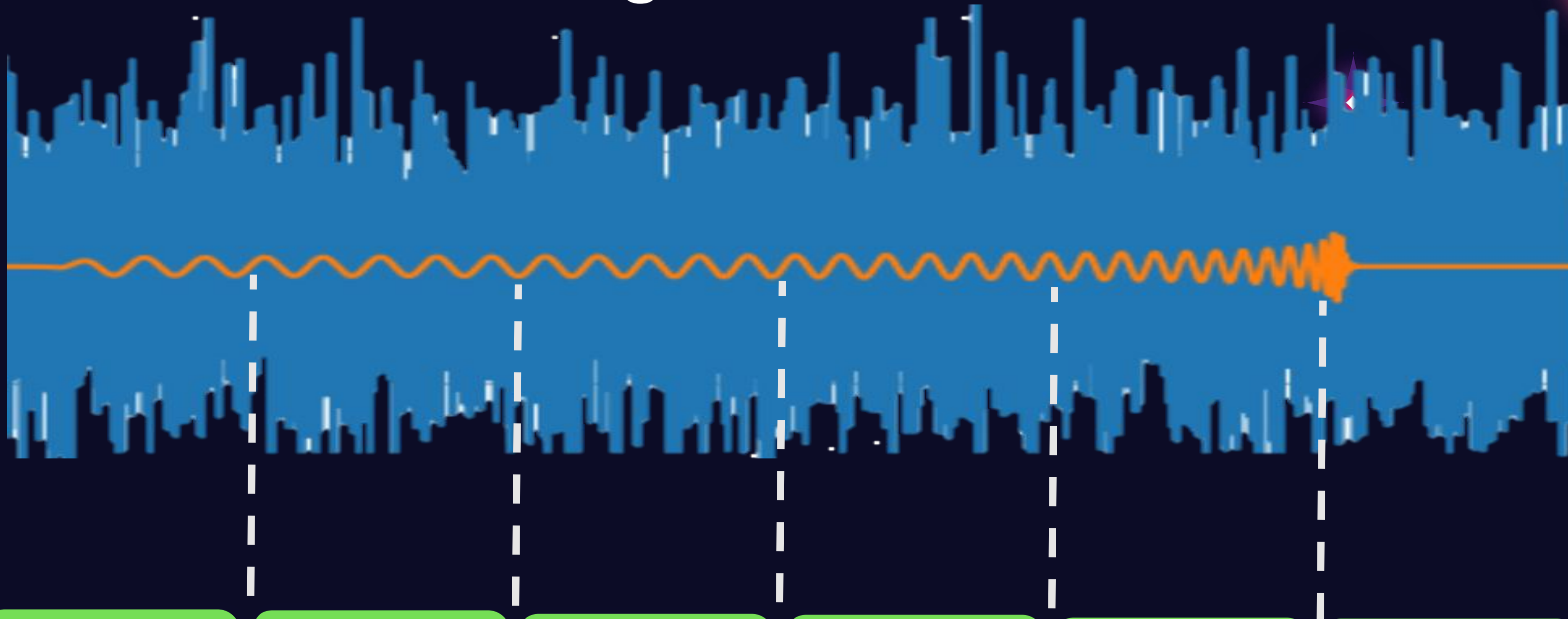
SINGLE DETECTOR BBH DETECTION AS PROOF OF CONCEPT
EXPAND TO COHERENT CASE IN FUTURE WORK

Positional Encoding



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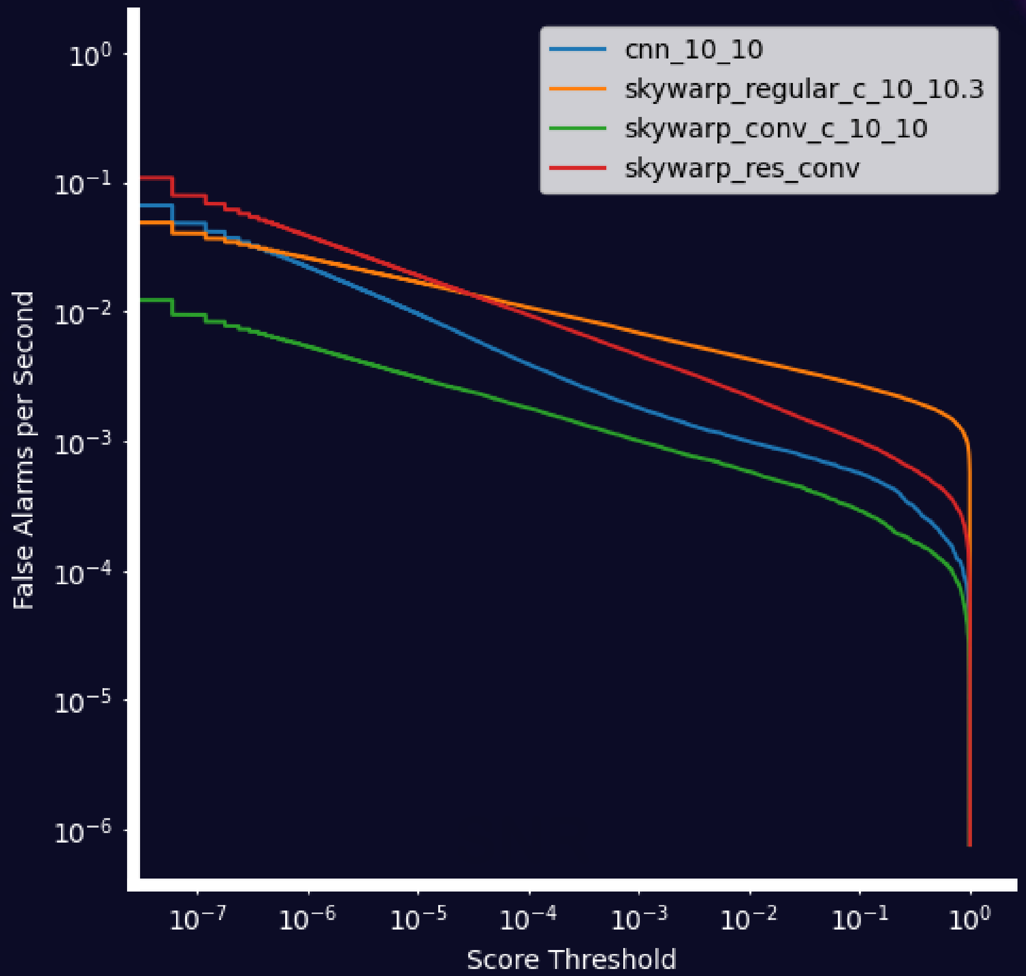
0.2621	0.3681

+ Positional Encoding

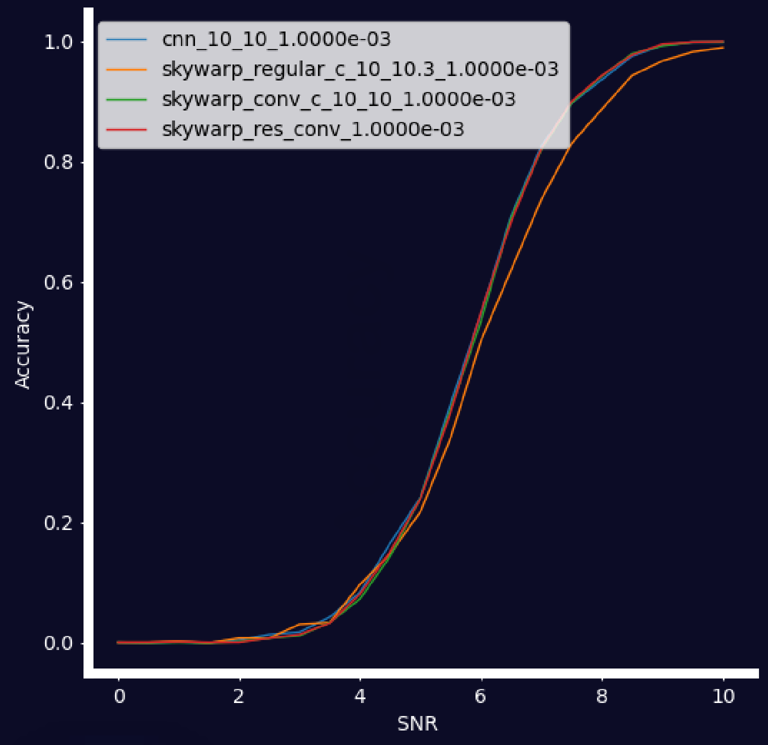
CNN*	Transformer	Conv Transformer
Conv 64, 8	Conv 1, 128	Conv 64, 8
Conv 32, 8	+ positional encoding	Conv 32, 8
Conv 32, 16	Transformer Encoder	Conv 32, 16
Conv 16, 16	Dense 512	Conv 16, 16
Conv 16, 32	Dense 2	Conv 16, 32
Conv 16, 32		Conv 16, 128
Dense 64		+ positional encoding
Dense 2		Transformer Encoder
		Dense 512
		Dense 2

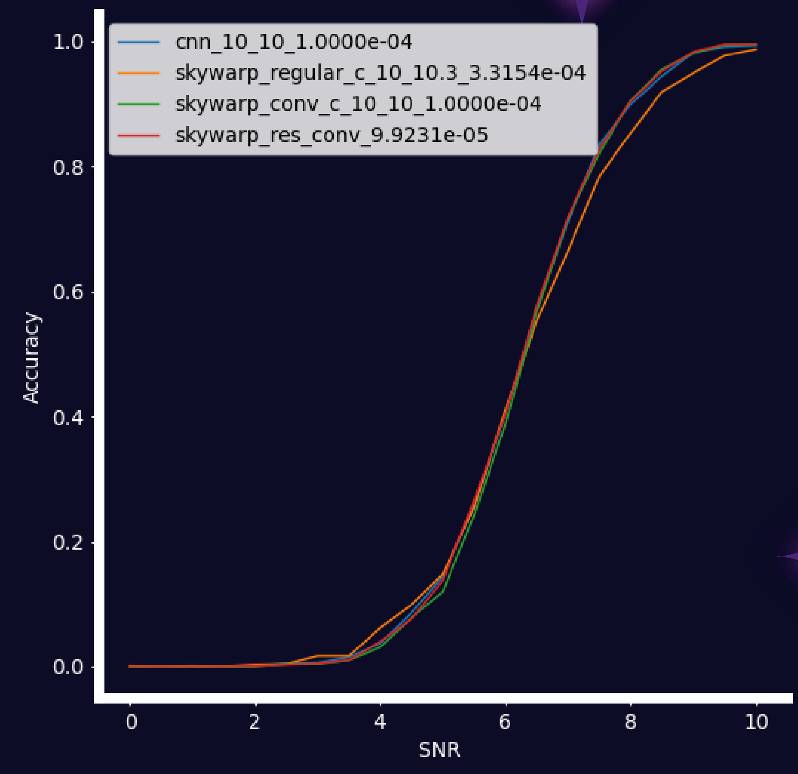
***Architecture from Gabbard et al.**
https://journals.aps.org/prl/abstract/10.1103/PhysRevLett.120.141103

Preliminary Results

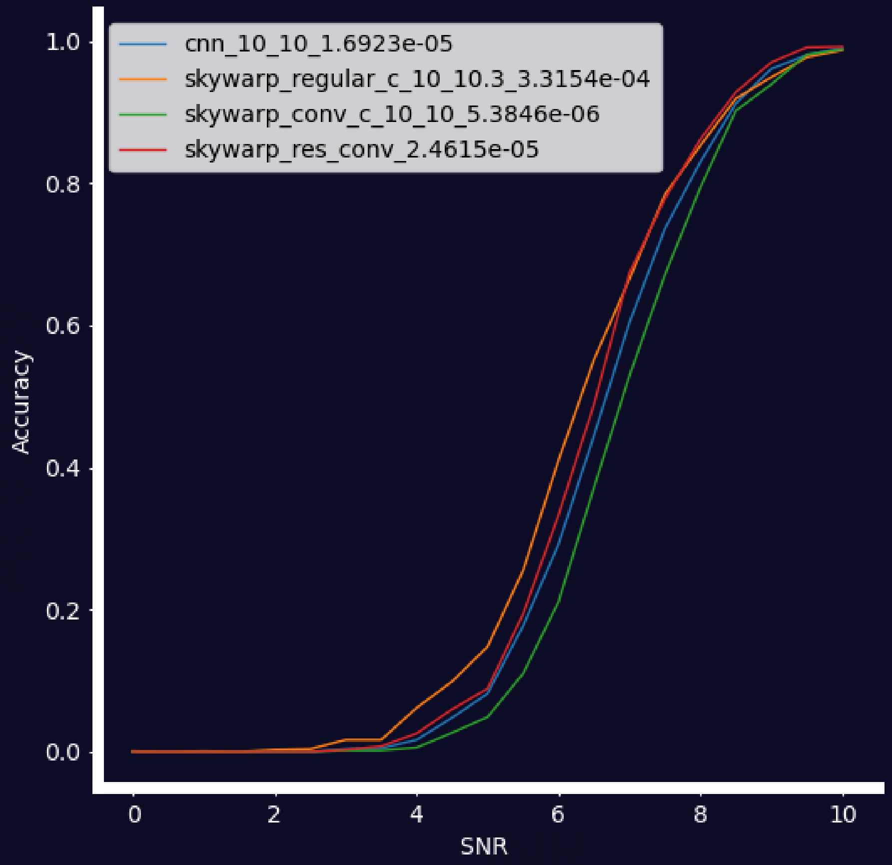


Preliminary Results





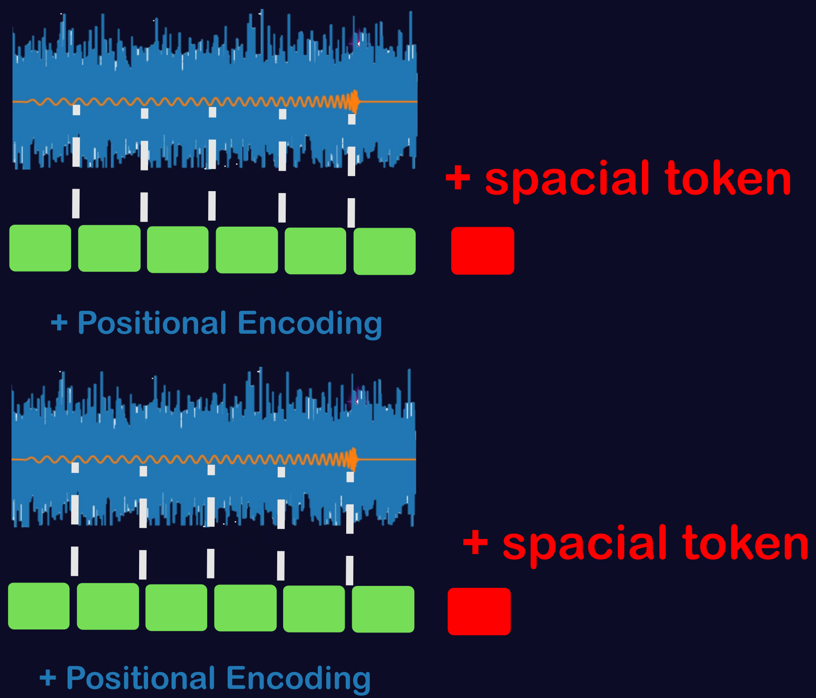
Preliminary Results



FUTURE PLANS

- Extend to multi detector case for coherent analysis
- Special encoding as well as temporal
- Detector agonistic - spatially and perhaps also conditioned on PSD

FUTURE PLANS – UNICRON

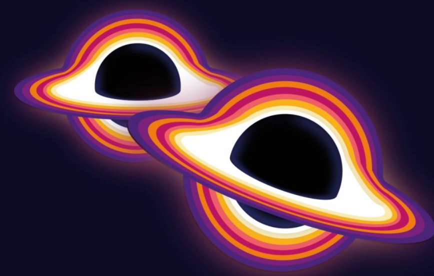


UNICRON

Classification

Signal reconstruction at earth centre coordinates?

Vary detector positions during training



ANY QUESTIONS?