CrossWave: Detection and Parameterisation of Overlapping Compact Binary Coalescence Signals

We introduce CrossWave, a new attention-based neural network model for the identification and parameter estimation of overlapping CBC signals. CrossWave can with efficiencies matching that of more conventional matched filtering techniques, separate the case of overlapping mergers from lone mergers, but with considerably lower inference times and computational cost. We suggest CrossWave or a similar architecture may be used to augment existing CBC detection and parameter estimation infrastructure, either as a complementary confirmation of the presence of overlap or to extract the merger times of each signal in order to use other parameter estimation techniques on the separated parts of the signals.

Significant improvements to our gravitational wave detection capability are anticipated within the next decade, with improvements to existing detectors [cite], as well as future 3rd and 4th generation space and ground-based detectors such as the Einstein Telescope [cite] and Cosmic Explorer. Whilst the current rate of Compact Binary Coalescence (CBC) detection is too low (estimate) for any real concern about the possibility of overlapping detections, estimated rates for future networks (estimate) will render such events a significant percentage of detections.

Contemporary detection and parameter pipelines do not currently have any capabilities to deal with overlapping signals - and although, in many cases, detection would still be achieved [cite], it is likely that parameter estimation would be compromised by the presence of the overlap, especially if more detailed information about higher modes and spins [cite] are science goals.

We introduce CrossWave, two attention-based neural network models for the identification and parameter estimation of overlapping CBC signals. CrossWave consists of two complementary models, one for the separation of the overlapping case from the non-overlapping case and the second as a parameter estimation follow-up to extract the merger times of the overlapping signals in order to allow other parameter estimation methods to be performed.

Overlapnet

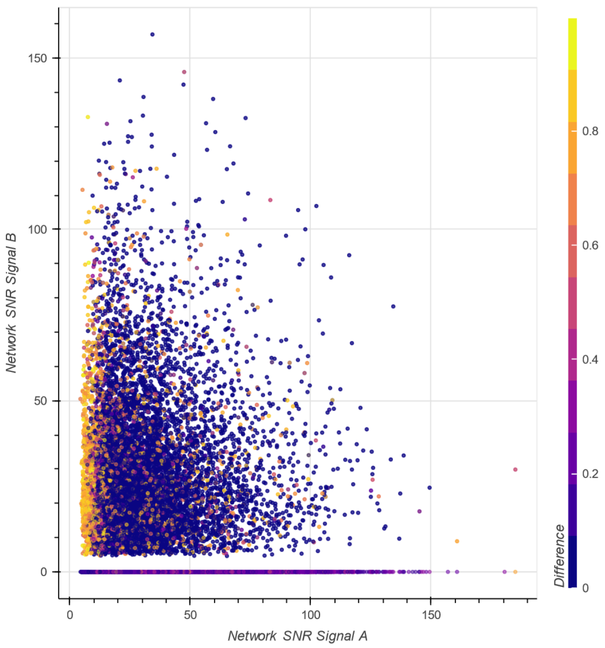


Figure 1:

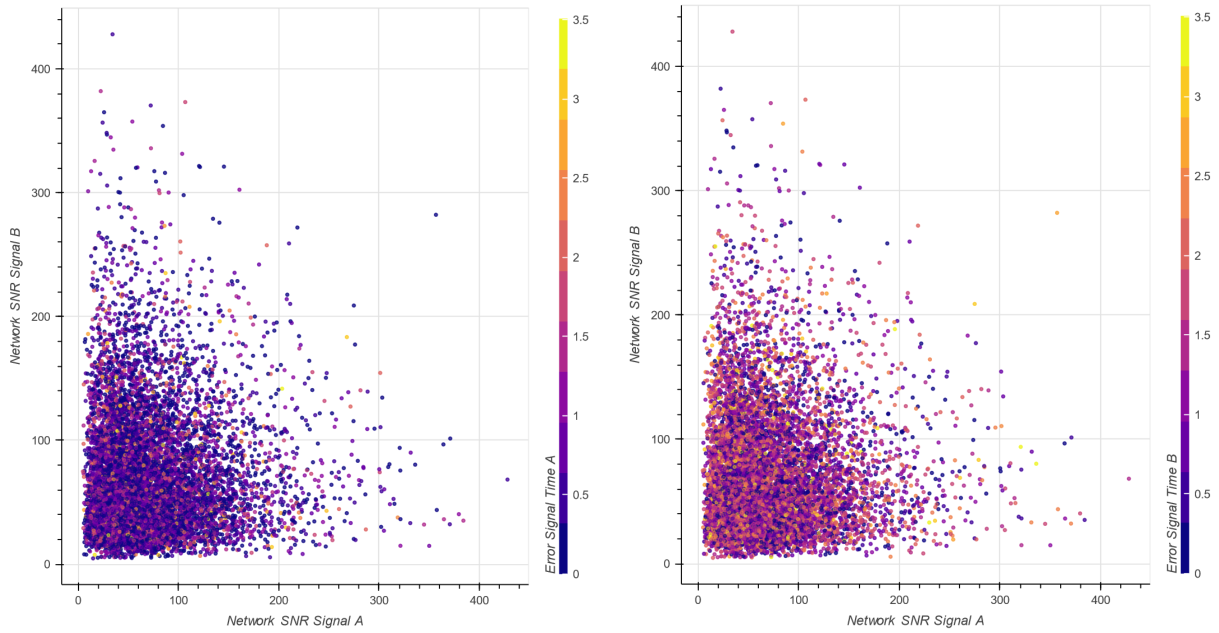
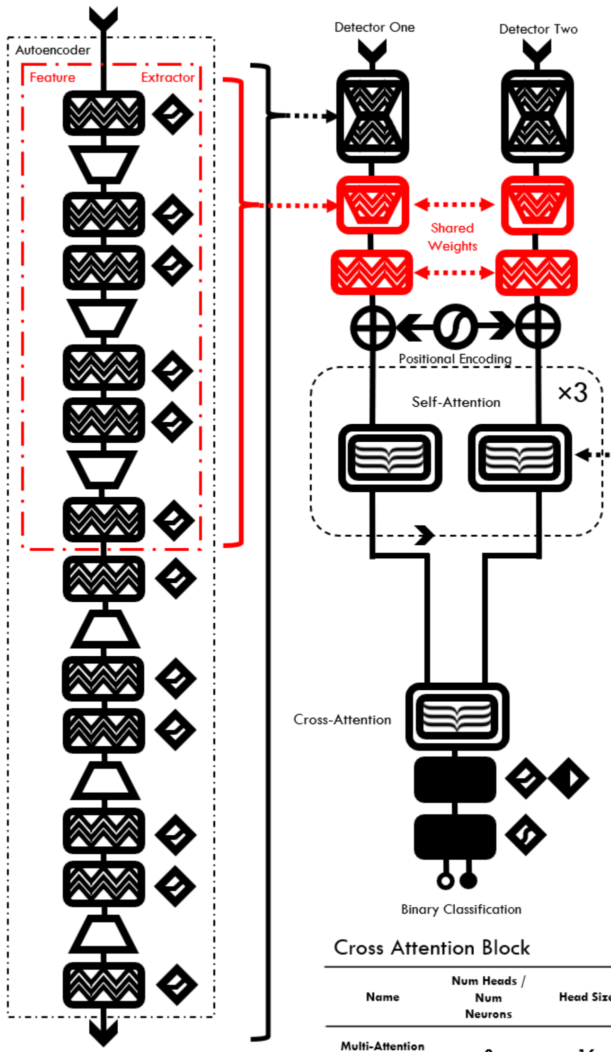


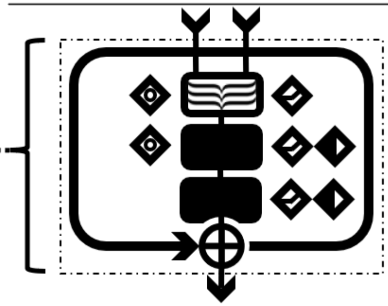
Figure 2:

CrossWave

Type	Num Filters	Filter / Pool Size	Stride	Activation Function
Convolutional	64	8	1	ReLU
MaxPooling	-	8	8	-
Convolutional	32	8	1	ReLU
Convolutional	32	16	1	ReLU
MaxPooling	-	6	6	-
Convolutional	16	16	1	ReLU
Convolutional	16	32	1	ReLU
MaxPooling	-	4	4	-
Convolutional	16	32	1	ReLU
Transpose Convolutional	16	32	1	ReLU
Upscaling	-	4	4	-
Transpose Convolutional	16	32	1	ReLU
Transpose Convolutional	16	16	1	ReLU
Upscaling	-	6	6	-
Transpose Convolutional	32	16	1	ReLU
Transpose Convolutional	32	8	1	ReLU
MaxPooling	-	8	8	-
Transpose Convolutional	64	8	1	ReLU



Name	Number Filters	Filter Size	Activation Function	Dropout
Denoising Autoencoder (Independent Weights)	-	-	-	-
Feature Extractor (Weights Shared)	-	-	-	-
CNN Embedding (Weights Shared)	128	1	ReLU	-

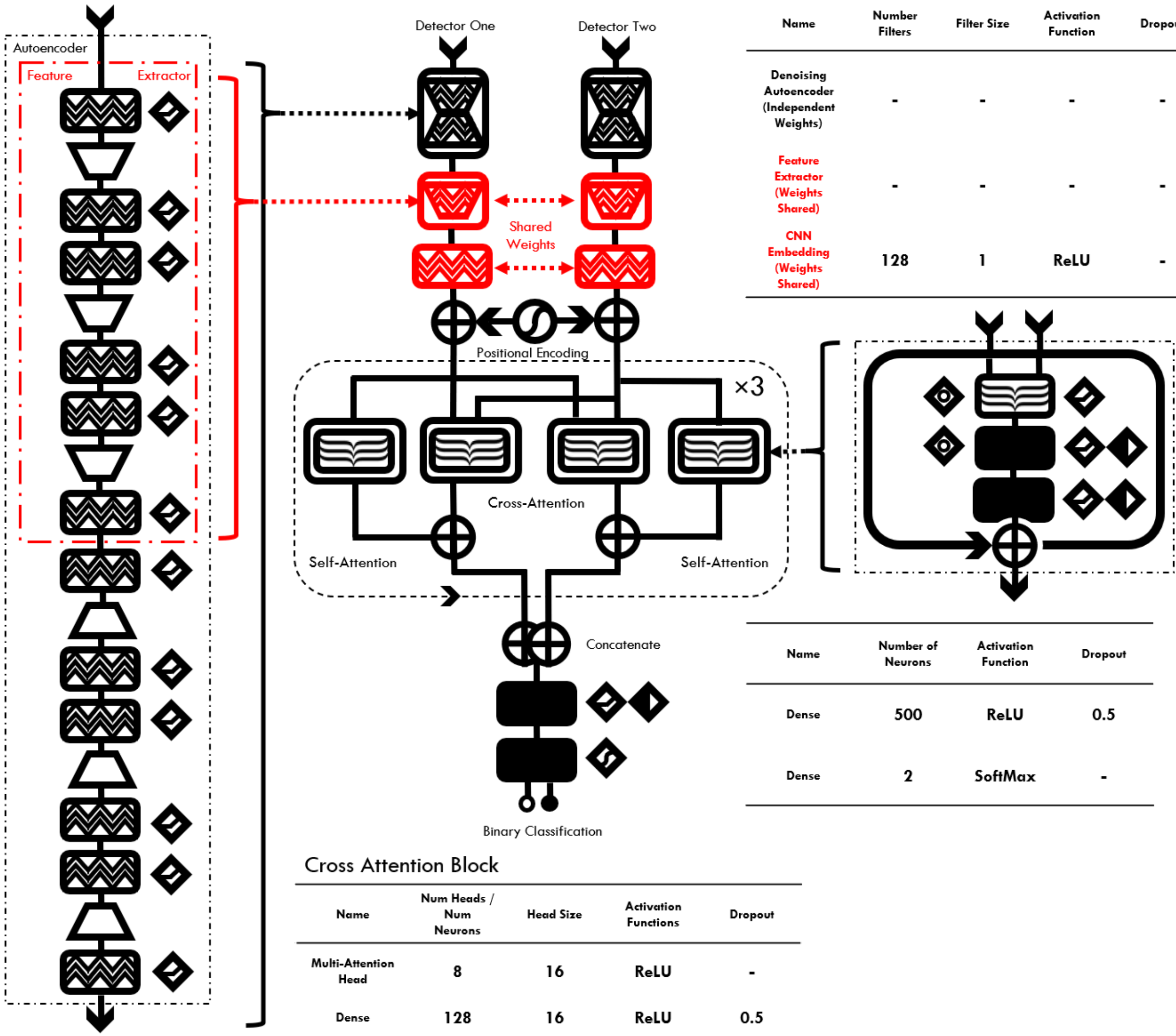


Name	Number of Neurons	Activation Function	Dropout
Attention Block	-	-	-
Dense	500	ReLU	0.5
Dense	2	SoftMax	-

Cross Attention Block

Name	Num Heads / Num Neurons	Head Size	Activation Functions	Dropout
Multi-Attention Head	8	16	ReLU	-
Dense	128	16	ReLU	0.5
Dense	8	16	ReLU	0.5

Type	Num Filters	Filter / Pool Size	Stride	Activation Function
Convolutional	64	8	1	ReLU
MaxPooling	-	8	8	-
Convolutional	32	8	1	ReLU
Convolutional	32	16	1	ReLU
MaxPooling	-	6	6	-
Convolutional	16	16	1	ReLU
Convolutional	16	32	1	ReLU
MaxPooling	-	4	4	-
Convolutional	16	32	1	ReLU
Transpose Convolutional	16	32	1	ReLU
Upscaling	-	4	4	-
Transpose Convolutional	16	32	1	ReLU
Transpose Convolutional	16	16	1	ReLU
Upscaling	-	6	6	-
Transpose Convolutional	32	16	1	ReLU
Transpose Convolutional	32	8	1	ReLU
MaxPooling	-	8	8	-
Transpose Convolutional	64	8	1	ReLU



Name	Number Filters	Filter Size	Activation Function	Dropout
Denoising Autoencoder (Independent Weights)	-	-	-	-
Feature Extractor (Weights Shared)	-	-	-	-
CNN Embedding (Weights Shared)	128	1	ReLU	-

Name	Number of Neurons	Activation Function	Dropout
Dense	500	ReLU	0.5
Dense	2	SoftMax	-

Cross Attention Block

Name	Num Heads / Num Neurons	Head Size	Activation Functions	Dropout
Multi-Attention Head	8	16	ReLU	-
Dense	128	16	ReLU	0.5
Dense	8	16	ReLU	0.5

Arrival Time Parameter Estimation:

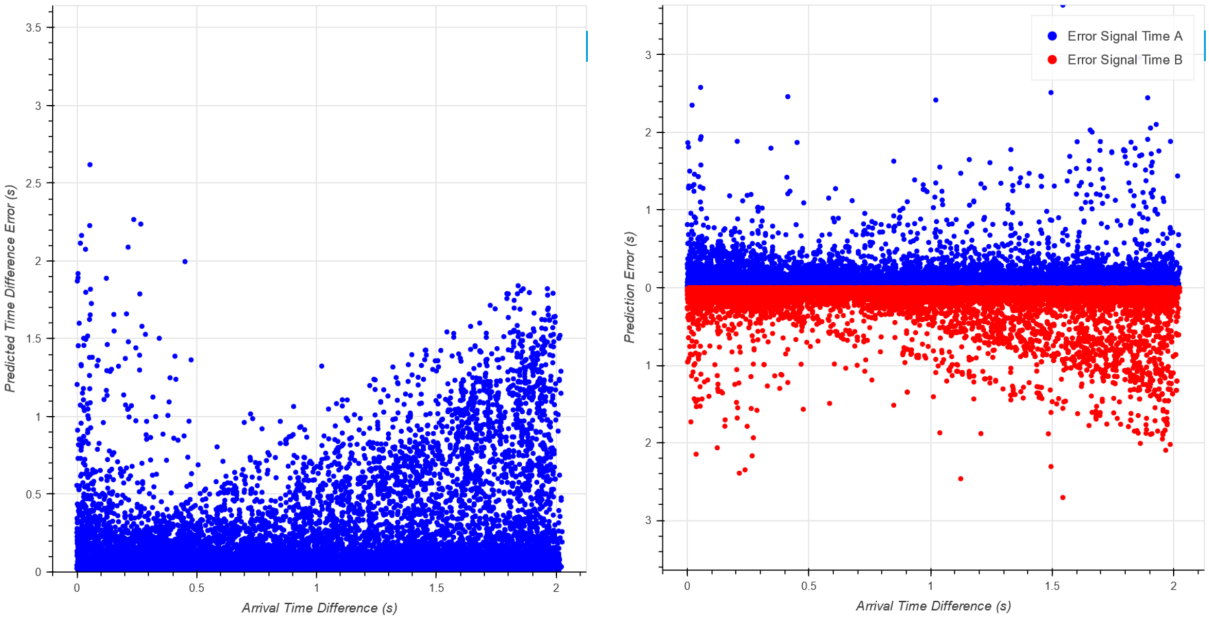


Figure 3:

Other Parameter Results

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