

A NOVEL APPROACH TO DISCOVER UNMODELLED FEATURES IN GRAVITATIONAL WAVE SIGNALS

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Gravitational signals from CBC



Parameter estimations



Residual analyses



Machine learning

GRAVITATIONAL WAVE SIGNALS

Different sources: focus on CBC

Goal: find parameters of the objects

For example: masses, spin, position in the sky

Start with simulated signals



Inspiral

Merger

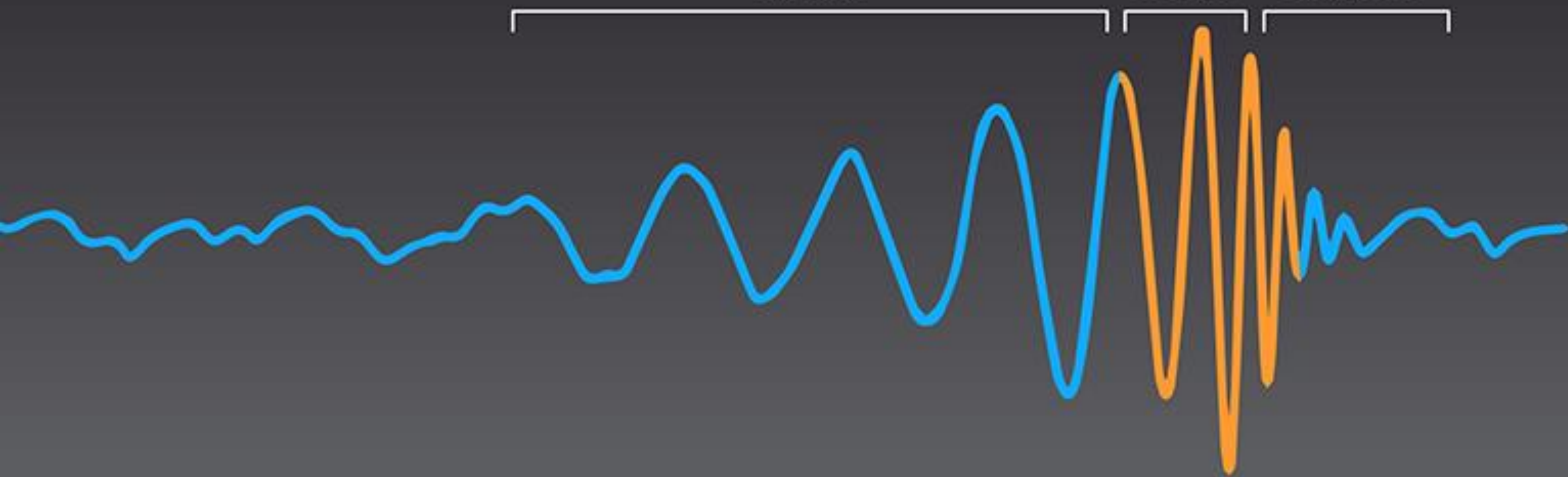
Ringdown



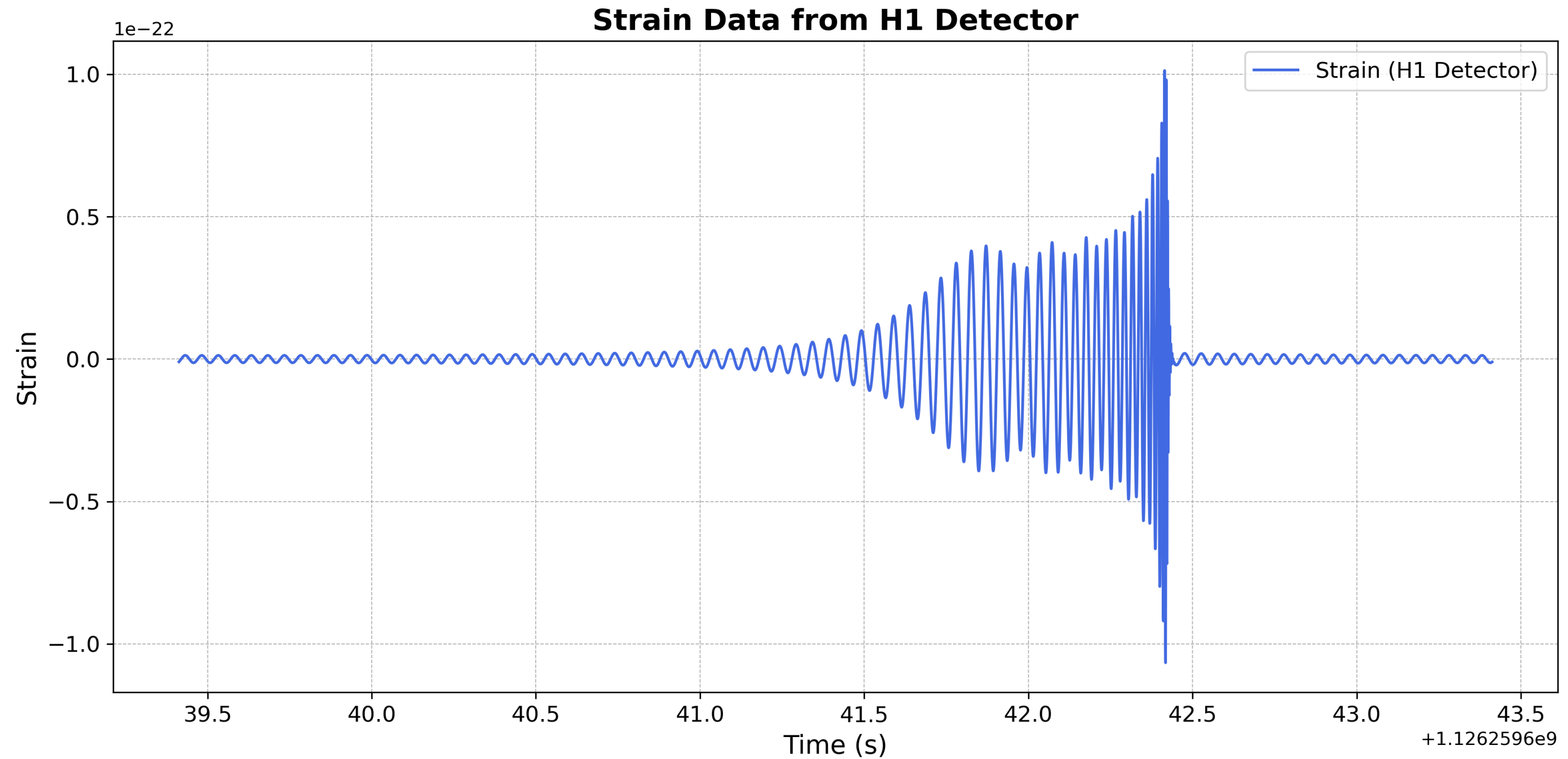
Inspiral

Merger

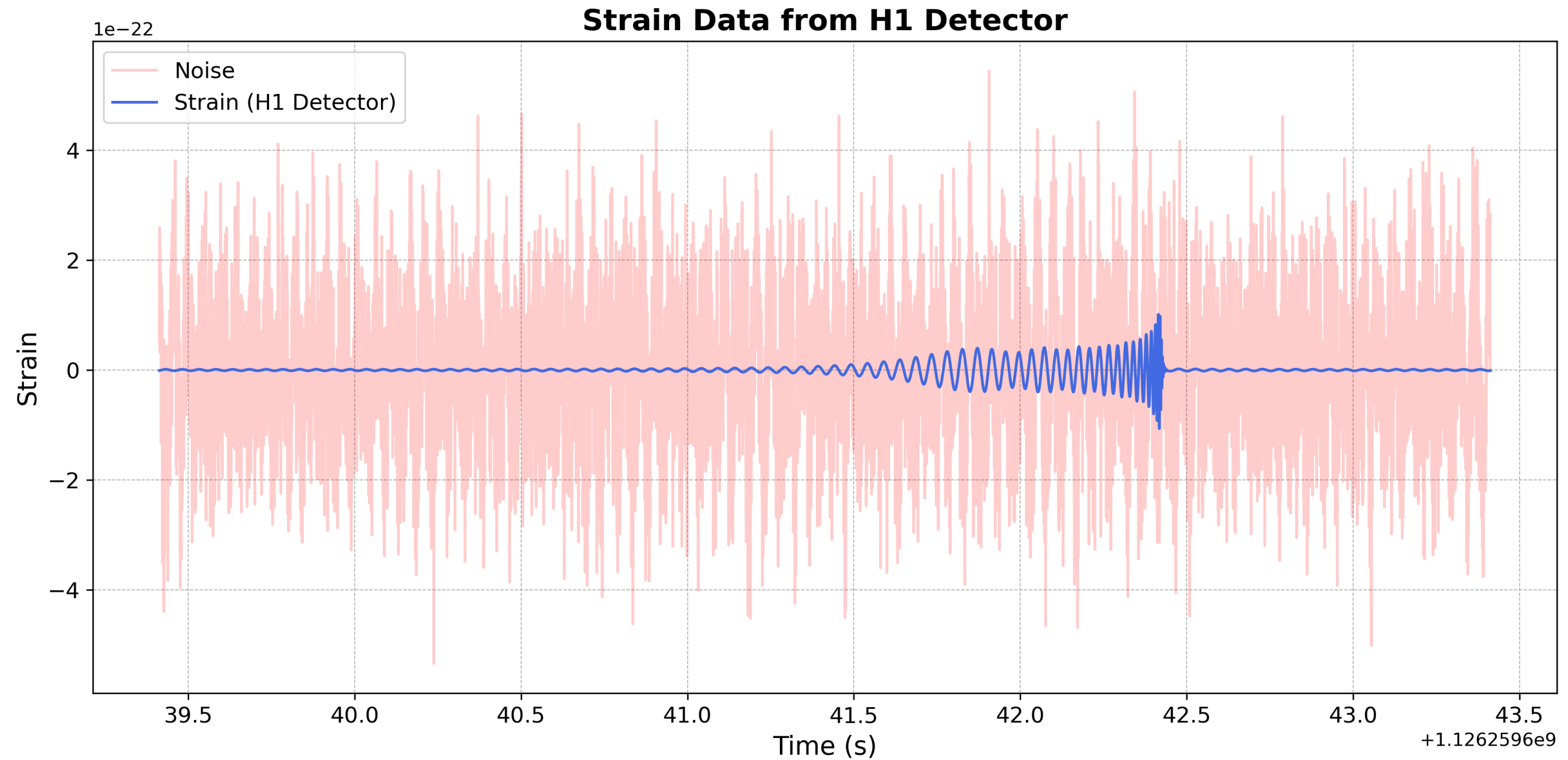
Ringdown



SIMULATED SIGNAL



ADDING THE NOISE



PARAMETER ESTIMATION

BAYESIAN PARAMETER ESTIMATION

Bilby

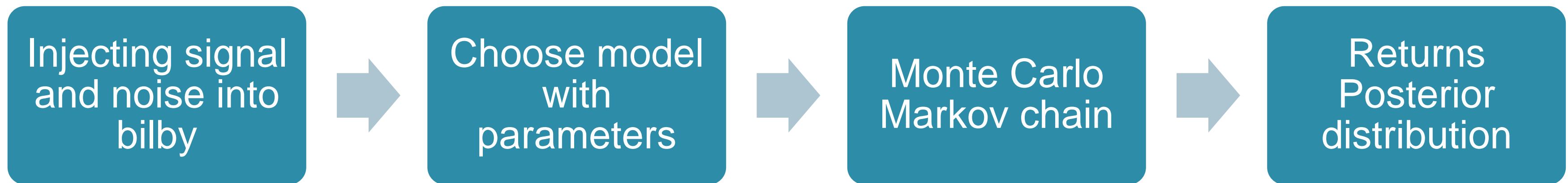


Result: posterior
distribution

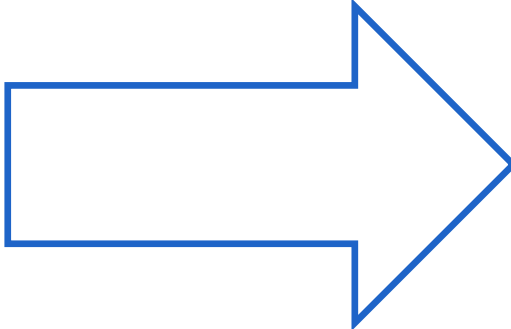
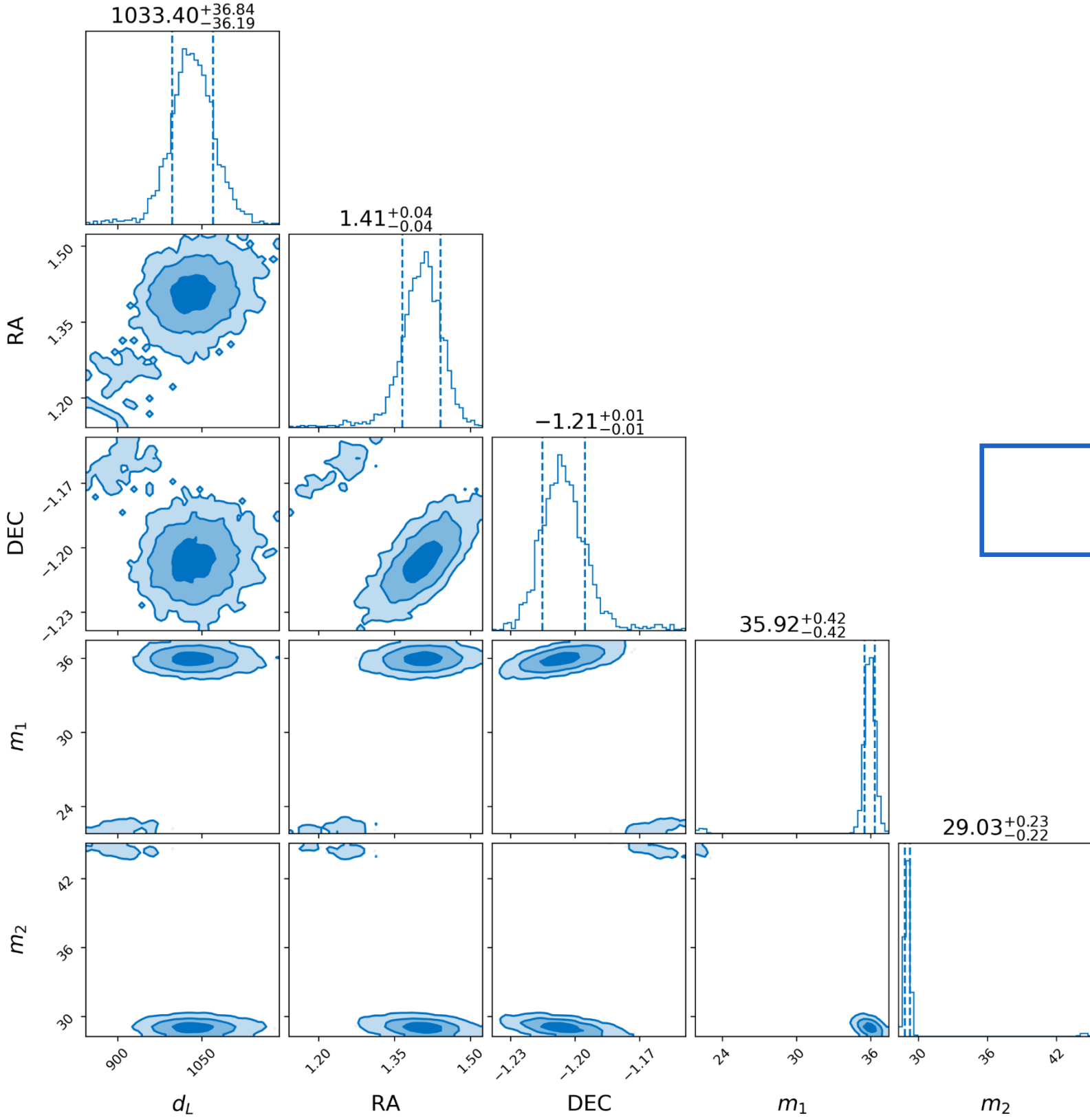
$$P(A | B) = \frac{P(B | A) P(A)}{P(B)}$$

BILBY WORKFLOW

- Inference: figuring out the model parameters θ given some model M



POSTERIOR DISTRIBUTION



$m_1 = \dots$
 $m_2 = \dots$
 $DEC = \dots$
 $RA = \dots$

PROBLEMS WITH PARAMETER ESTIMATIONS

- Advancing detectors → More data
- Curse of dimensionality → long runtimes
- Less advanced waveforms → less parameters
- Sounds nice but is it still good enough?
- To check this, create ML algorithm

RESIDUAL ANALYSES

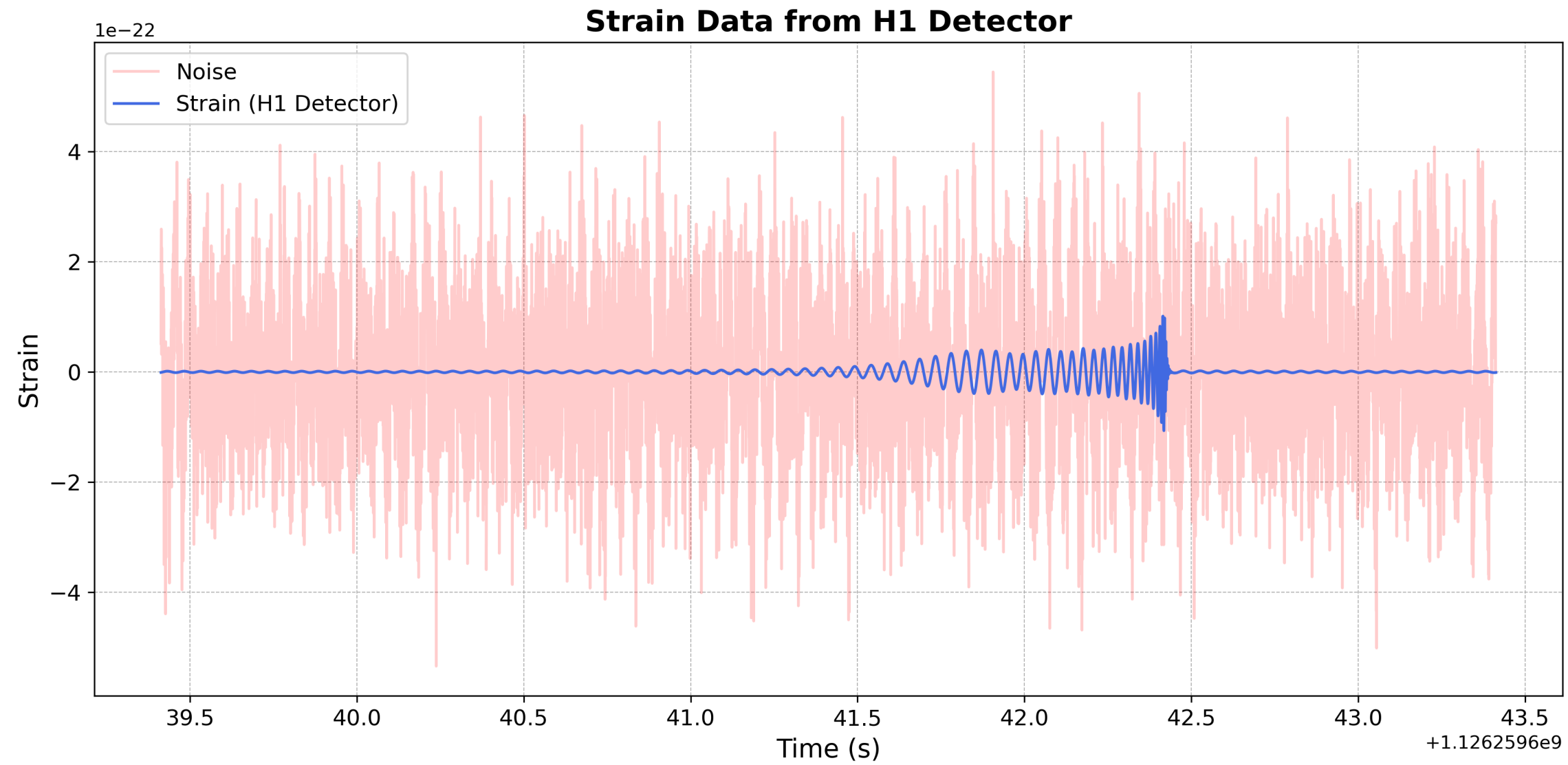
GOING TO THE RESIDUAL

Extract best parameters

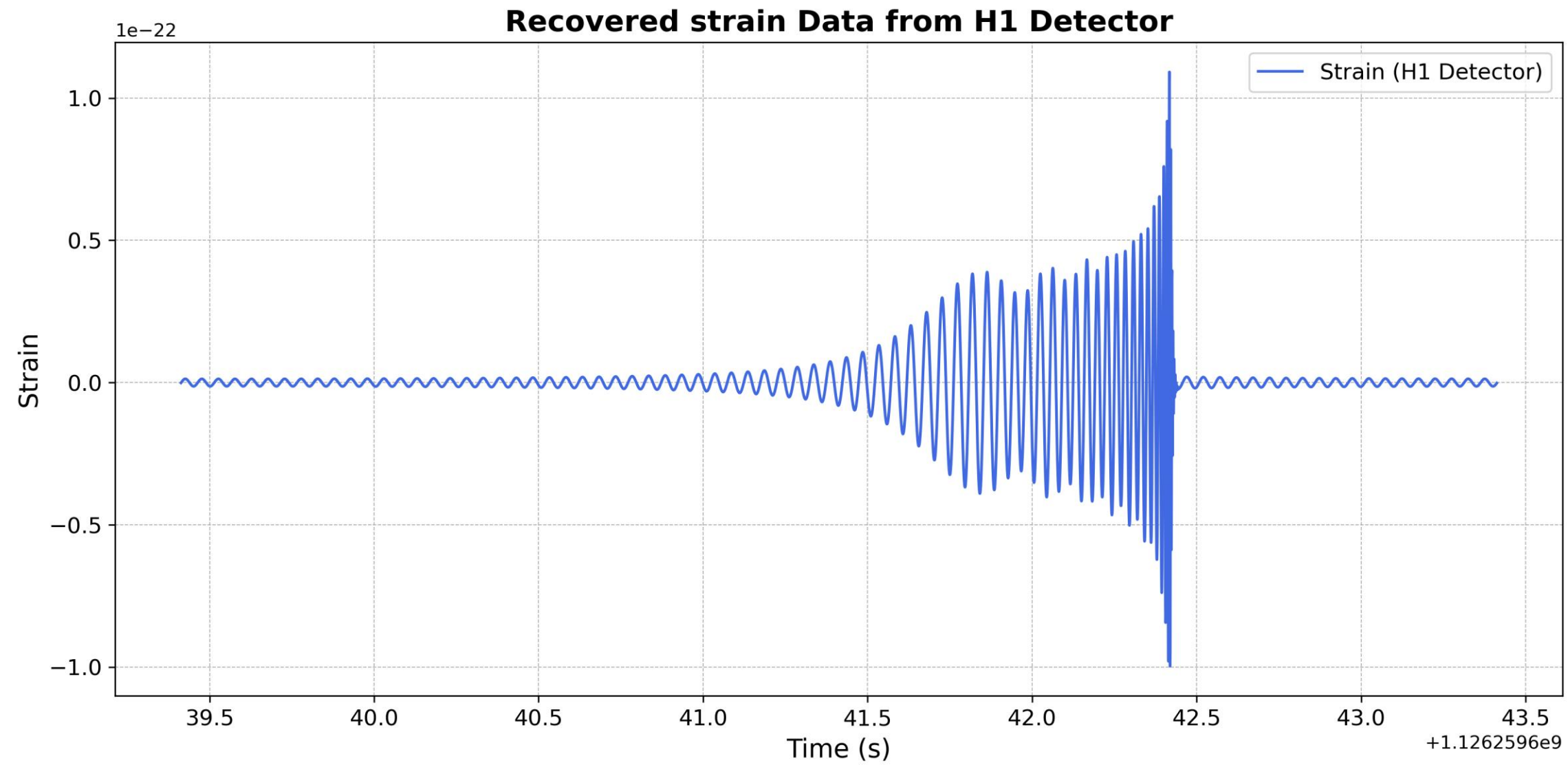
Residual = Observed Data – Best-fit Signal

Depends on waveform

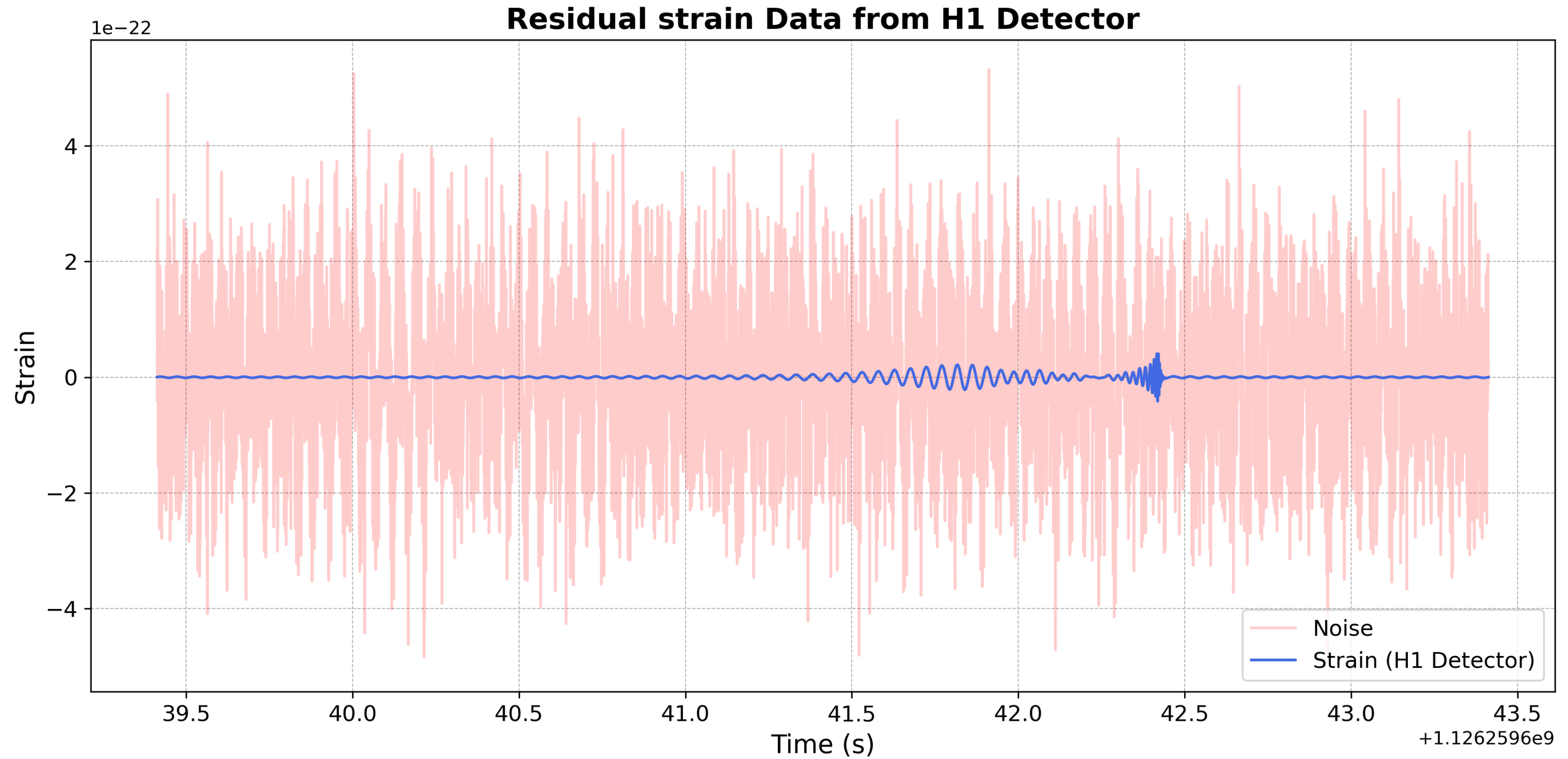
ORIGINAL SIGNAL



RECOVERED SIGNAL

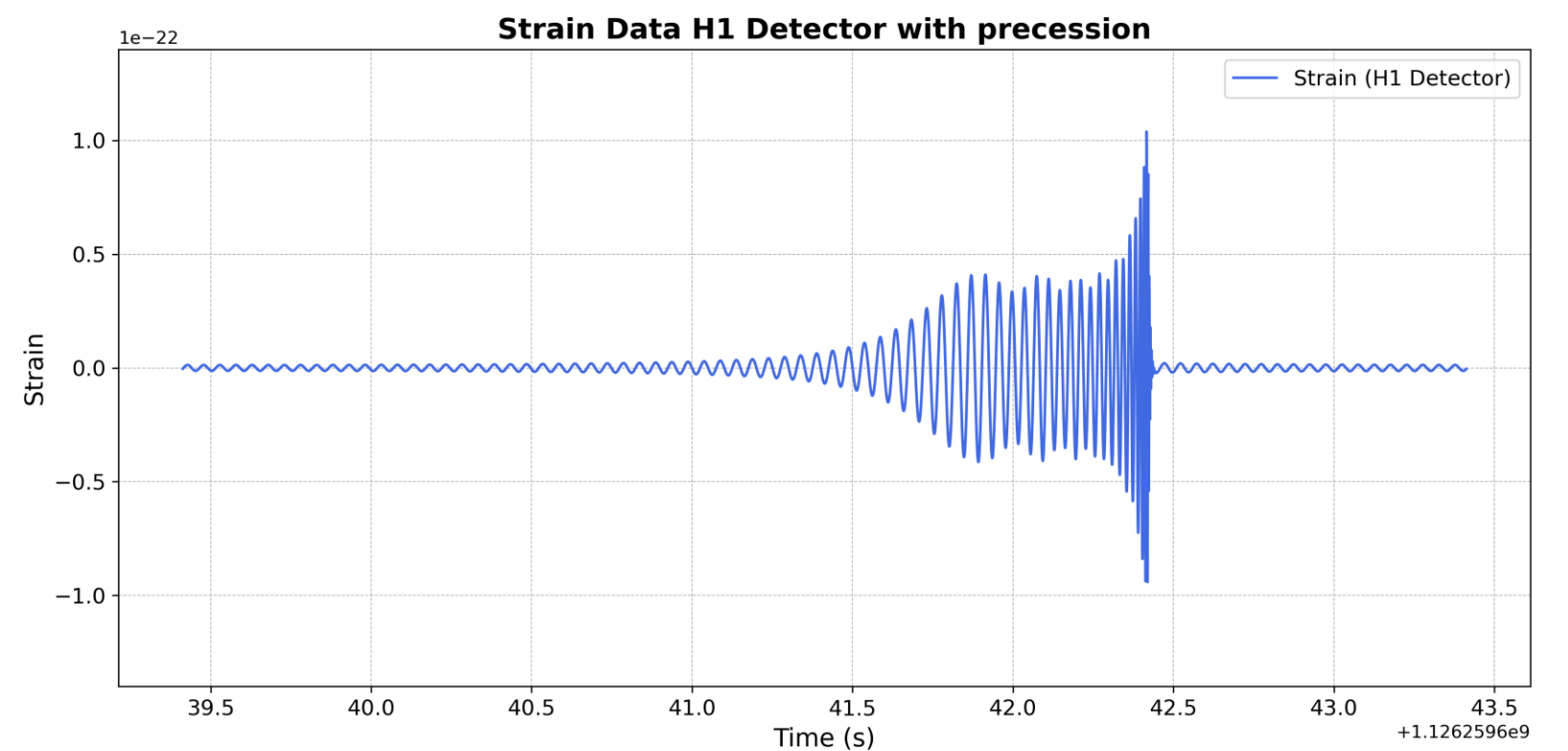
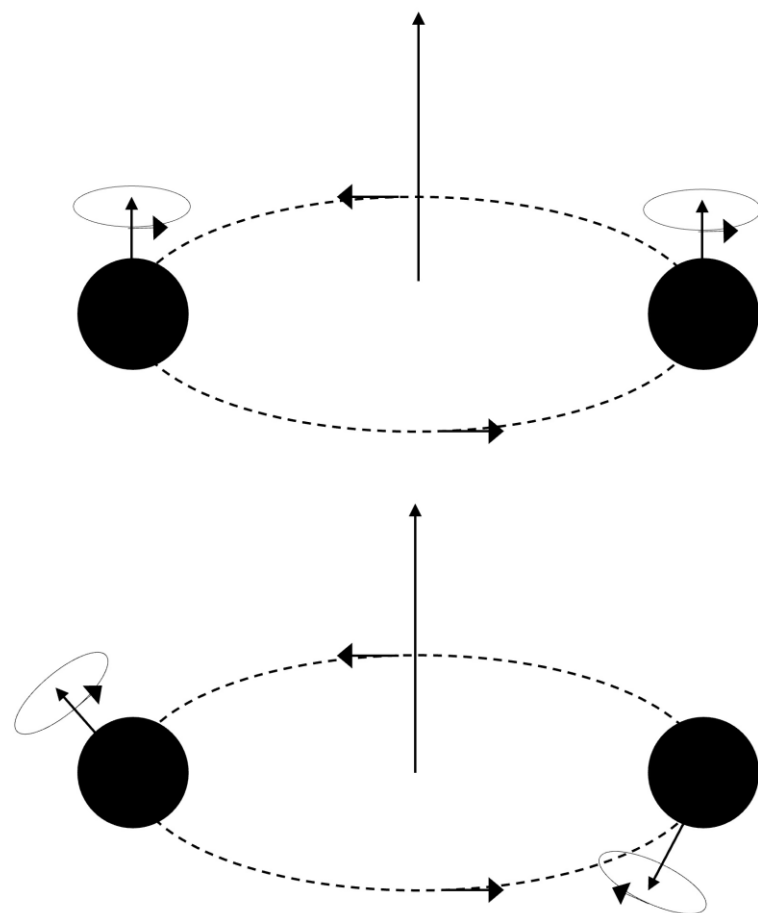
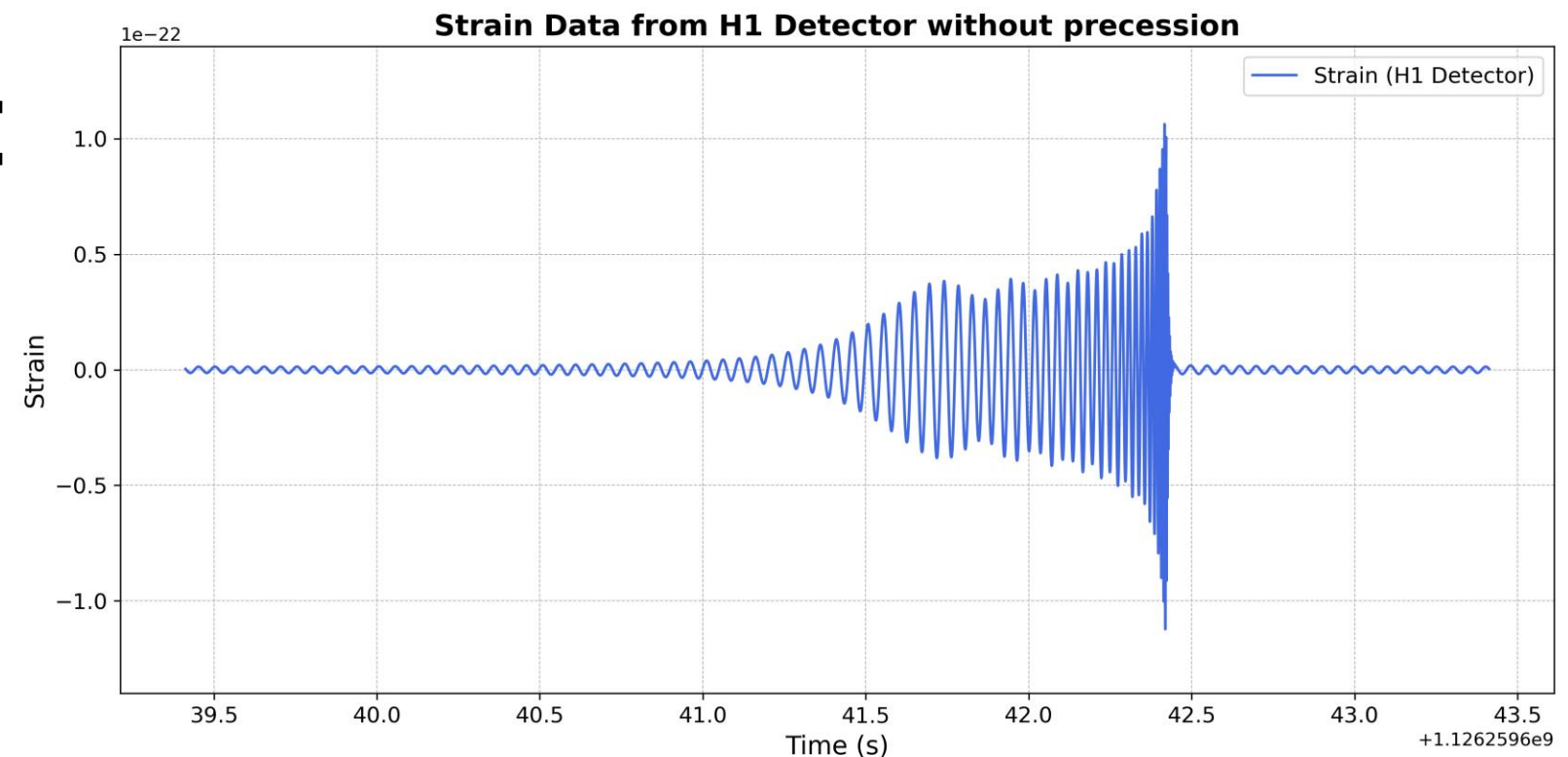


RESIDUAL

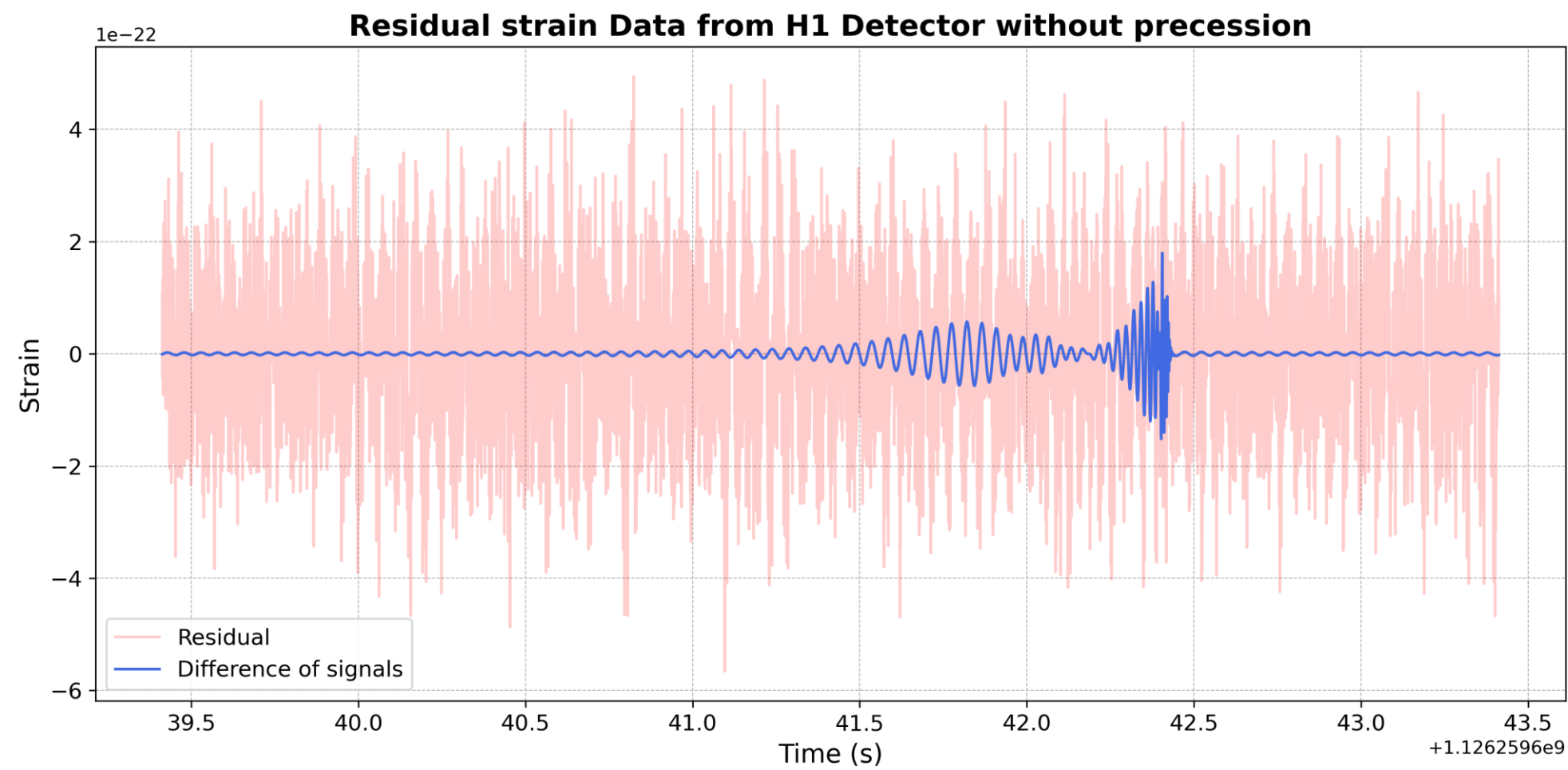
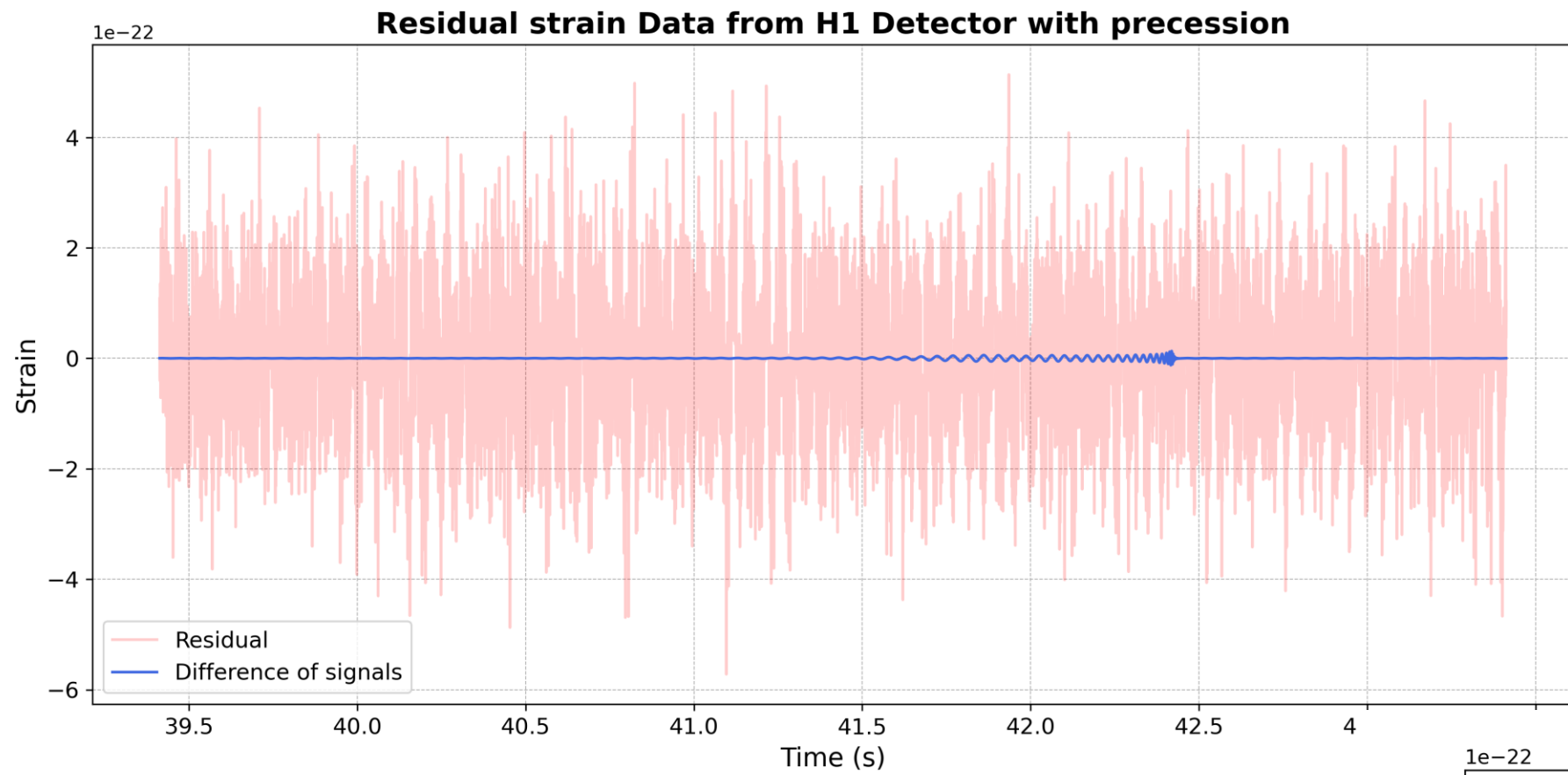


DIFFERENT WAVEFORMS

- Gravitational wave features:
 - Precession
 - Higher-Order Modes
 - Other exotic features



DIFFERENCE IN RESIDUAL



FIRST STEP

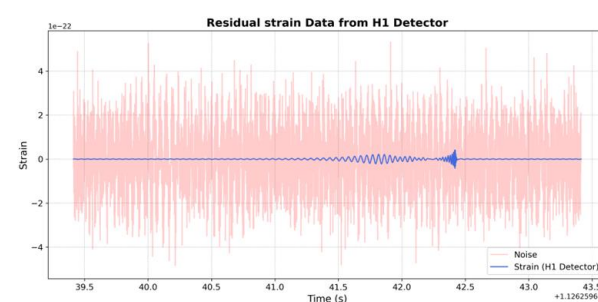
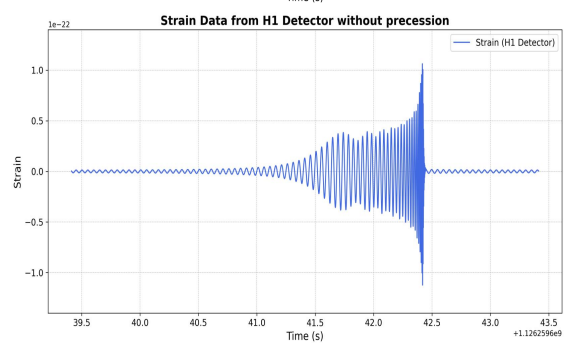
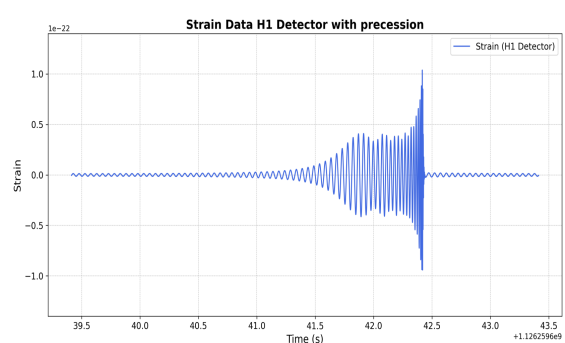
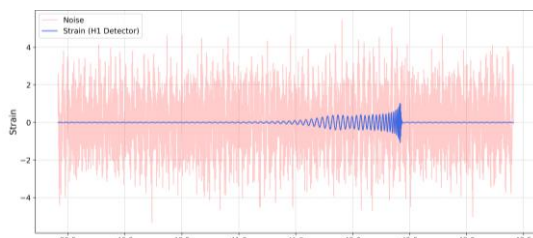
Parameter estimation on simulated GW

Chose waveform for reconstruction

Create residual

Train ML model

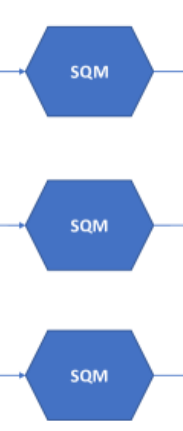
Test classifier with simulated signals not in the training set



0.3	0.1	0.5
0.2	0.6	0.4
-0.5	0.2	1.1
3.6	1.2	-0.1

SAX or SFA

- (36,4,3)
 - accb ccba
 - ccca bbca
 - bbbc cbca
 - dccd caac
- (30,5,4)
 - abbbc dddab
 - accdd bbcca
 - ddccb dddac
 - baccd daaac
- (52,5,6)
 - efcbc ffedd
 - abbeff faaac
 - affca eeeed
 - fafaa ddeff



	acc	cdd	faa	ddda
accb ccba	1	1	0	0
ccca bbca	0	1	1	0
bbbc cbca	0	0	0	1
dccd caac	0	0	1	0

Logistic Regression

NEXT STEPS

Experimenting with different ML algorithms

Extending to more features

Unmodelled features