Inferring core-collapse supernova physics with gravitational waves

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Outline

★ Introduction: Core-collapse supernovae

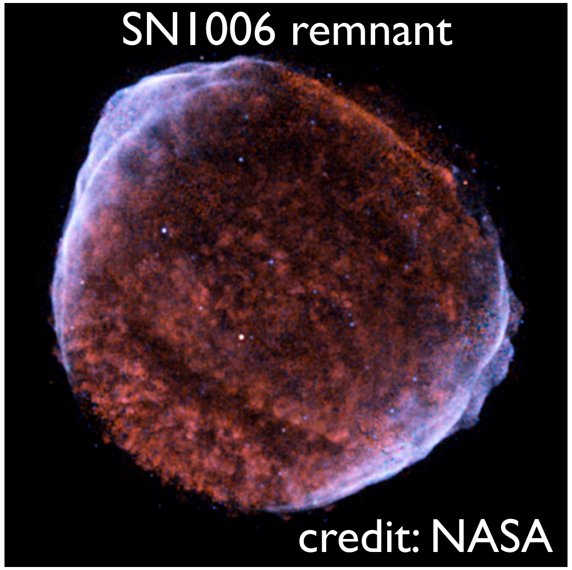
★ Supernova Model Evidence Extractor

- Singular Value Decomposition
- Bayesian model selection

★ Results

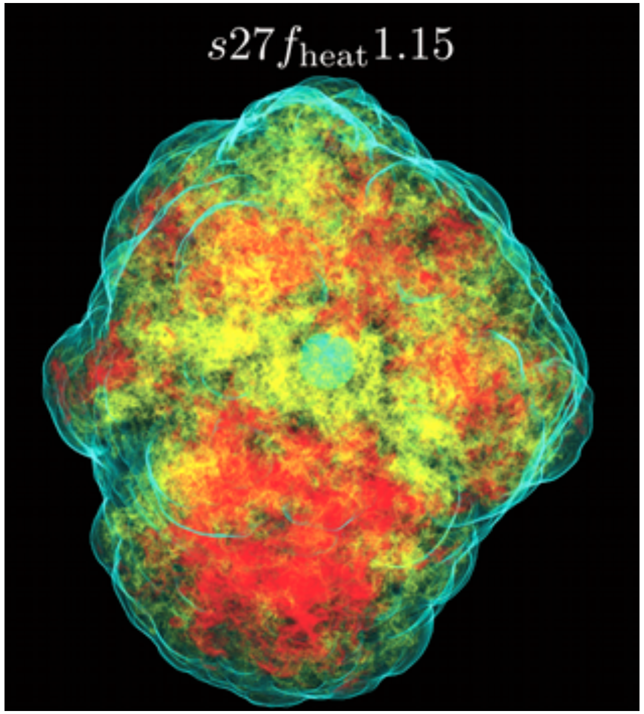
- Signal injections in Advanced LIGO noise
- Signal injections in ET noise

★ Summary and future work



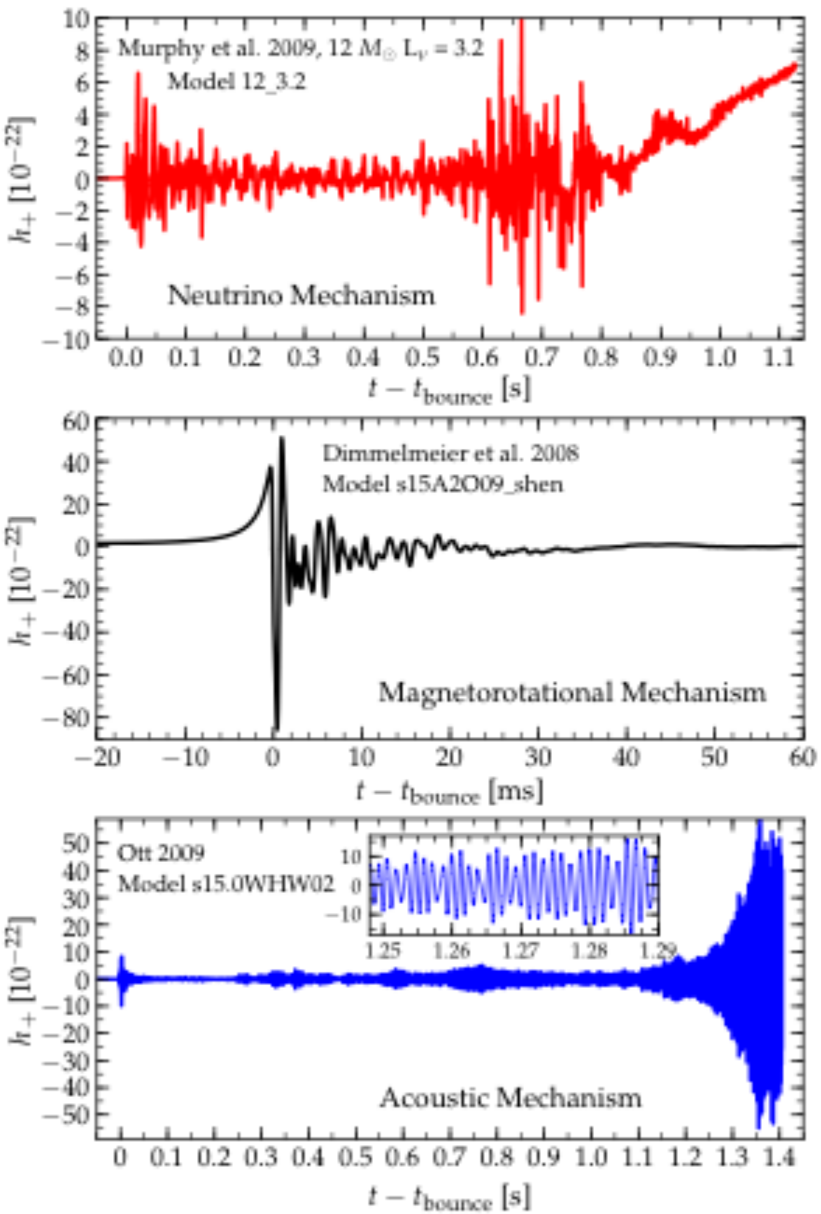
Core-collapse supernovae

- ★ Several models have been proposed to explain the processes behind core-collapse supernovae
- ★ These models lead to different gravitational wave emission mechanisms
- ★ Numerical simulations of the various mechanisms have produced catalogues of waveforms for the different mechanisms
- ★ Can we distinguish between the waveforms from the different catalogues and, thus, learn about the astrophysics behind core-collapse supernovae?



http://www.stellarcollapse.org/

Core-collapse supernova



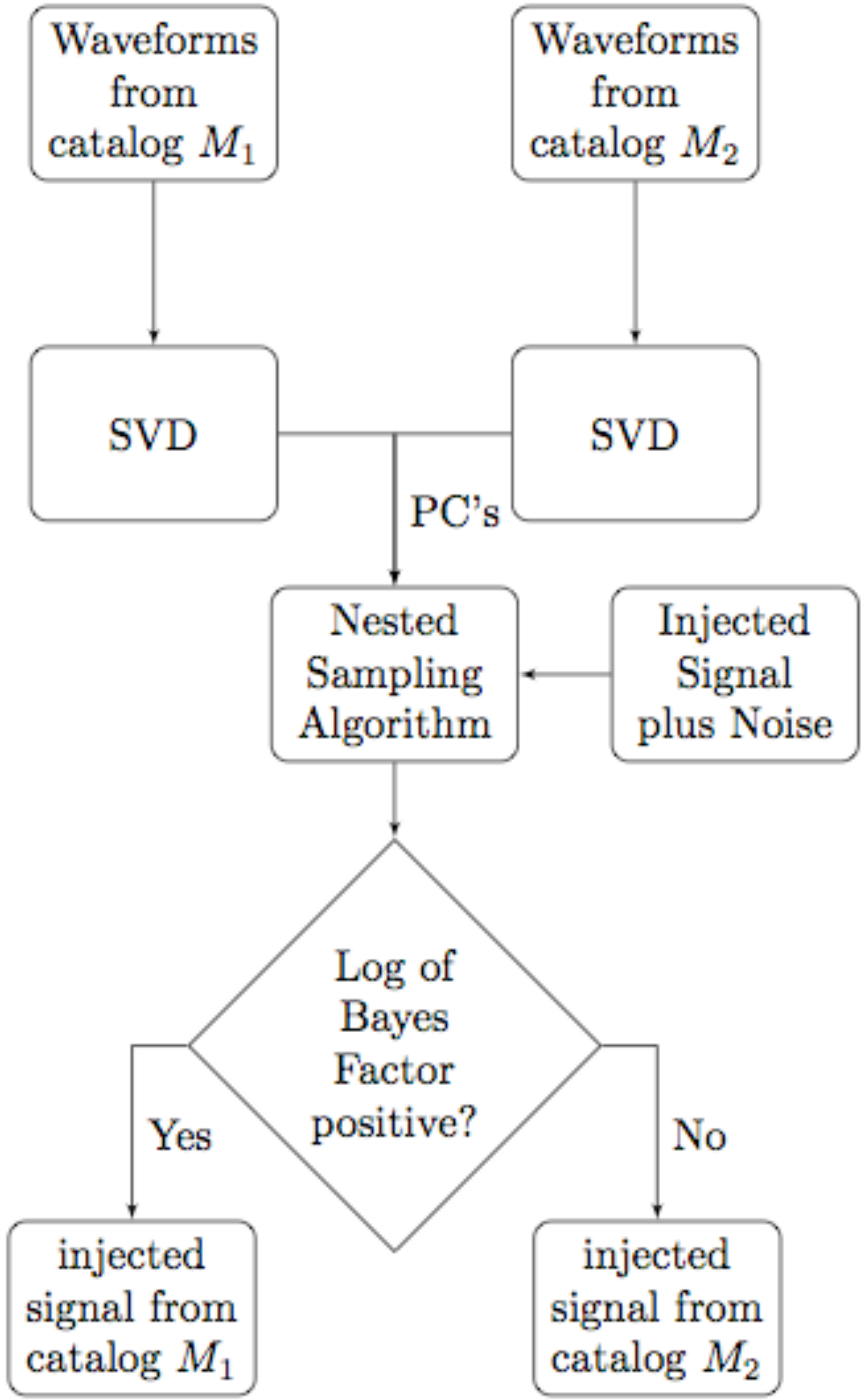
- ★ Chose 3 initial catalogues to develop analysis
- ★ Neutrino mechanism - use Murphy *et al.* 2009 catalogue with 16 waveforms
- ★ Magnetorotational mechanism - use Dimmelmeier *et al.* 2008 catalogue with 128 waveforms
- ★ Acoustic mechanism - use Ott *et al.* 2009 catalogue with 7 waveforms

SMEE

★ Use the Supernovae Model Evidence Extractor (SMEE) to distinguish between waveforms from different catalogues

★ SMEE:

1. reparameterises waveforms into a set of orthonormal basis vectors
2. uses Bayes factor to compare the likelihood that the observed signal belongs to one catalogue as opposed to another catalogue*

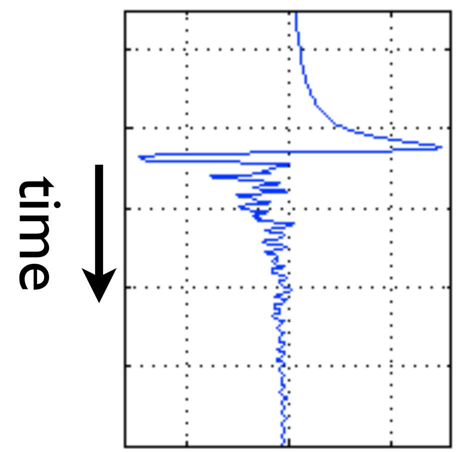


*the other "catalogue" could also be noise or a model for known spurious noise

Singular Value Decomposition

- ★ consider a catalogue of *M* waveforms, each *N* samples long

$$h_1 = \begin{bmatrix} h_1(t_1) \\ h_1(t_2) \\ \vdots \\ h_1(t_N) \end{bmatrix}$$



- ★ arranged into a matrix **A** (*N*x*M*) such that each column corresponds to one waveform

$$\mathbf{A} = \begin{bmatrix} h_1(t_1) h_2(t_1) \ldots h_M(t_1) \\ h_1(t_2) h_2(t_2) \ldots h_M(t_2) \\ \vdots \quad \ddots \quad \vdots \\ h_1(t_N) h_2(t_N) \ldots h_M(t_N) \end{bmatrix}$$

Singular Value Decomposition

★ Singular Value Decomposition (SVD) states that **A** can be factored into

$$\mathbf{A} = \mathbf{U\Sigma V}^{\mathrm{T}}$$

★ where **U** is *N*x*N*, **V** is *M*x*M* and **Σ** is *N*x*M*

★ **U** is a matrix where the columns are the eigenvectors of $\mathbf{AA}^{\mathrm{T}}$

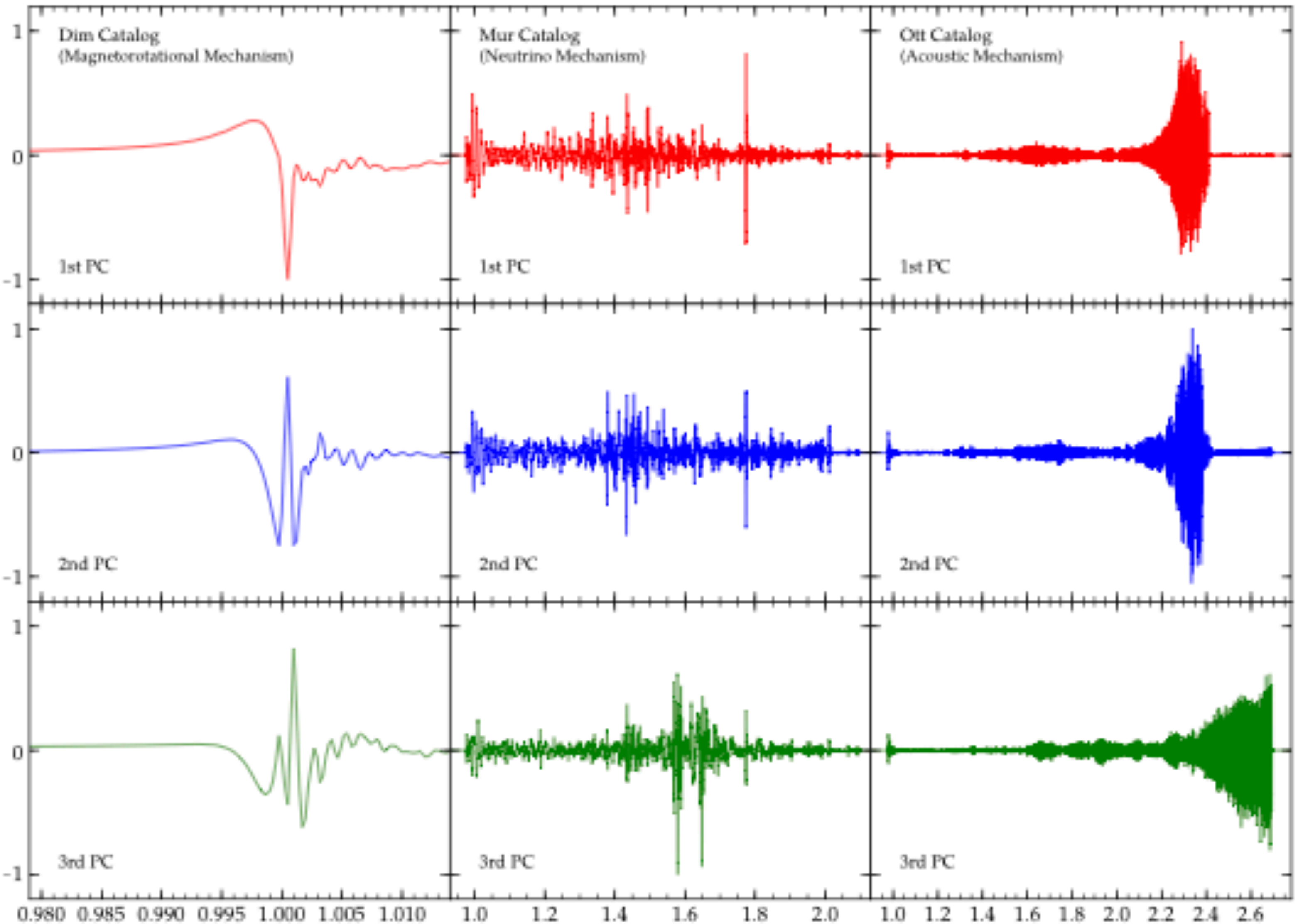
★ **V** is a matrix where the columns are the eigenvectors of $\mathbf{A}^{\mathrm{T}}\mathbf{A}$

★ **Σ** has the square roots of the eigenvalues on its diagonal

Principal Component Analysis

- ★ Note that $\mathbf{AA}^T$ is the covariance matrix for the data in $\mathbf{A}$
- ★ So, for our data matrix, $\mathbf{A}$, the eigenvectors in $\mathbf{U}$ (Principal Components) form an orthogonal basis than spans the parameter space defined by the data
- ★ The eigenvectors are ranked by their corresponding eigenvalue
- ★ The first Principal Component is the eigenvector with the largest corresponding eigenvalue
  - direction of the largest variance in the data set
- ★ The original set of waveforms that were used to construct $\mathbf{A}$ can now be described as a linear combination of the Principal Components in $\mathbf{U}$

Principal Component Analysis



Reconstructing the signal

- ★ If we use all *M* Principal Components, we can reconstruct all waveforms identically
- ★ The Principal Components are an efficient basis for spanning the parameter space described by the waveforms
- ★ One can approximate each waveform by taking a linear combination of *k* Principal Components, were *k* < *M*

$$h_i \approx \sum_{j=1}^{k} U_j \beta_j$$

- ★ Here, β*j* is the scalar coefficient for the *j*-th Principal Component
- ★ The corresponding eigenvalues indicate how well the choice of *k* Principal Components will reconstruct the original waveforms

Bayesian model selection

- ★ The Bayes factor is the ratio of the marginalised likelihoods for two competing models

$$B_{12} = \frac{p(D|M_1)}{p(D|M_2)}$$

- ★ If $B_{12} > 1$, M_1 is preferred. If $B_{12} < 1$, M_2 is preferred
- ★ If $B_{12} = 1$, then there is insufficient information in the data to support either model
  - noise introduces an uncertainty which enlarges this to a "region of ambiguity"
- ★ Here, M_1 and M_2 are the different core-collapse supernova mechanisms
  - these models can also be the ratio of the likelihood that the data contains a signal versus noise only

The signal model

★ Since simulated noise is used, we assume a Gaussian likelihood for our signal model, M_s,

$$p(D|\beta, M_s) \propto \exp\left[-\sum_{i=1}^{N} \frac{(D_i - h_i(\beta))^2}{2\sigma_i^2}\right]$$

★ Here, σ is the expected noise, D_i is the i-th data point, h_i is the reconstructed model signal from Principal Components and β are the amplitudes or coefficients for reconstructing the signal

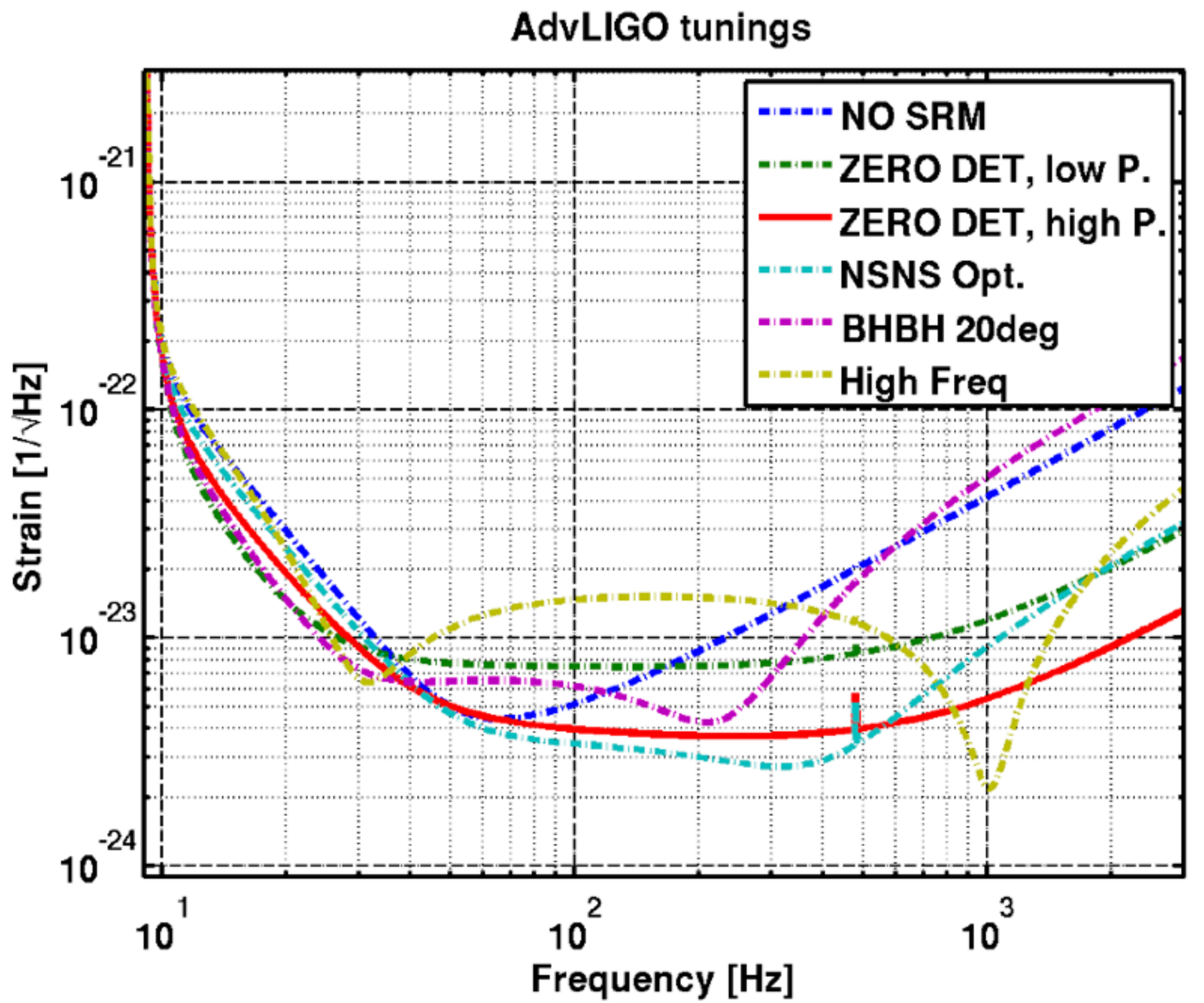
★ To obtain the evidence, marginalise over all expected values of β such that

$$p(D|M_s) = \int_{\beta_{\min}}^{\beta_{\max}} p(\beta|M_s)p(D|\beta, M_s)d\beta$$

Investigations with Advanced LIGO noise

★ Simulate noise for Advance LIGO in "zero detuning, high power" configuration

- ZERO_DET_high_P.txt, publicly available from LIGO DCC



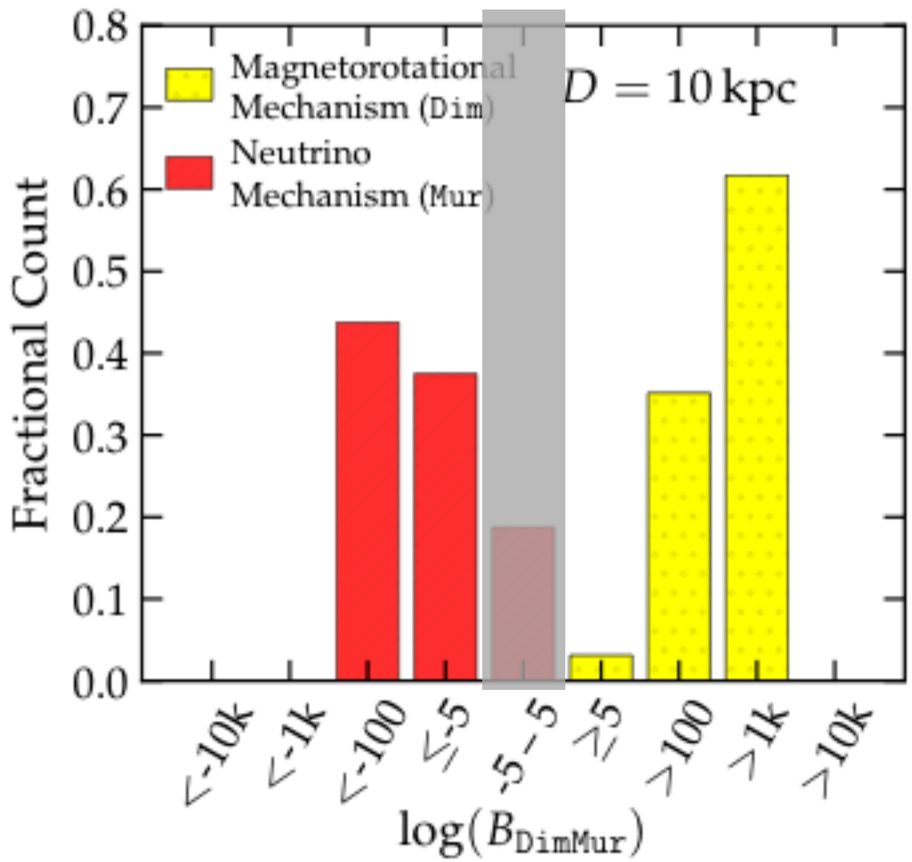
https://dcc.ligo.org/cgi-bin/DocDB/ShowDocument?docid=T0900288

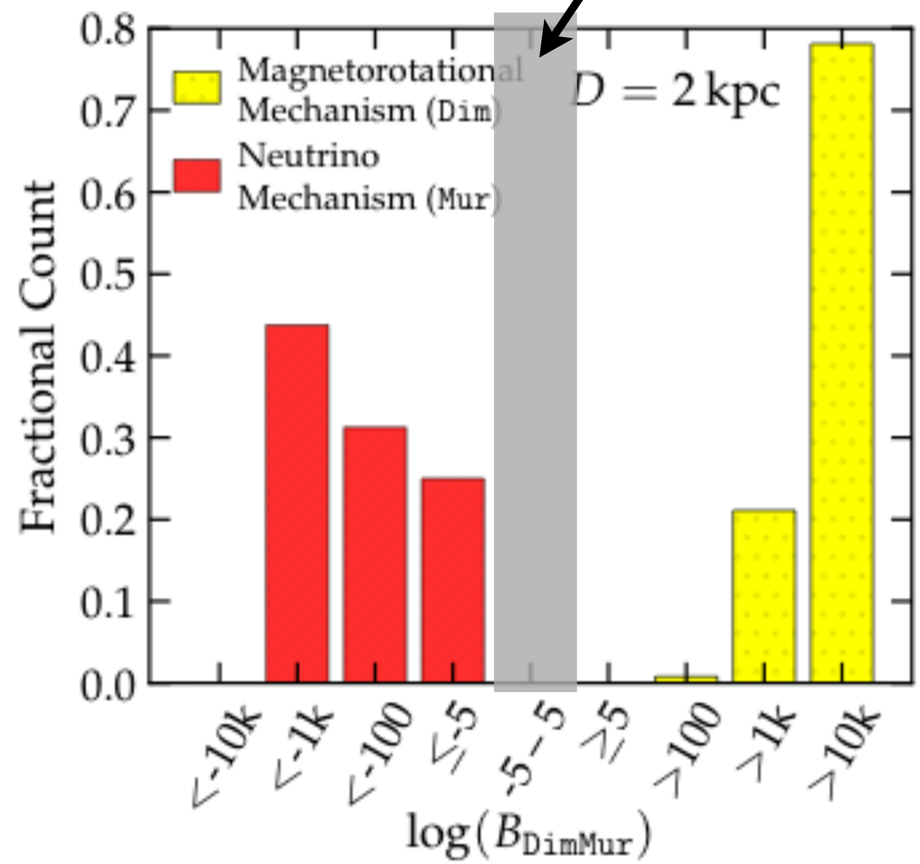
Distinguishing SNe models

$$\log(B_{\mathrm{DimMur}}) = \log B_{\mathrm{Dim}} - \log B_{\mathrm{Mur}}$$

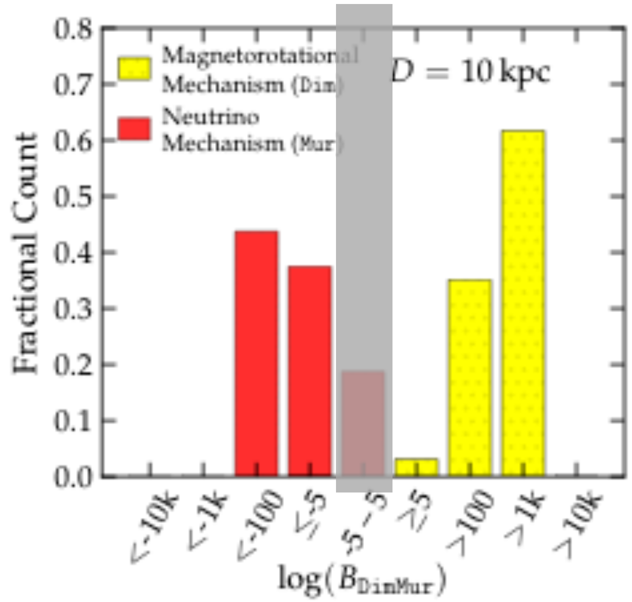
$$B_i = p(D|M_i)$$

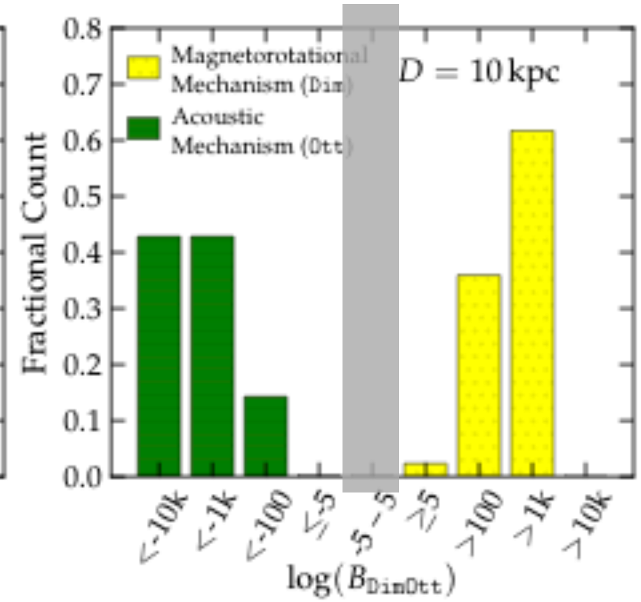
cannot distinguish between models





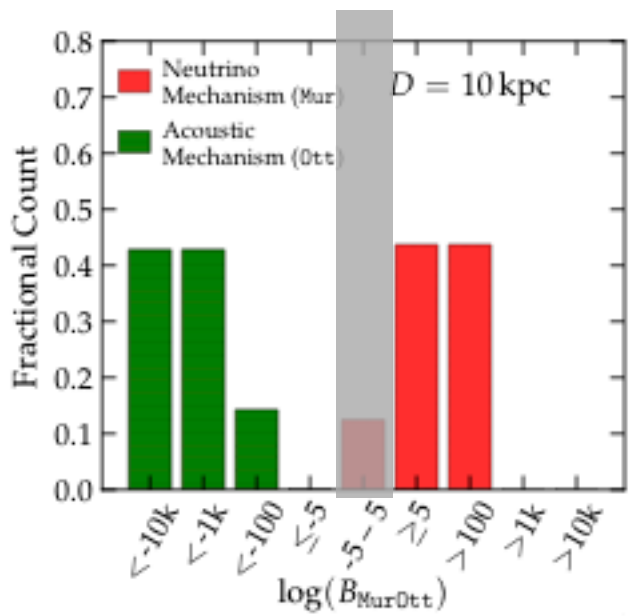
Distinguishing SNe models





Most signals are correctly identified!

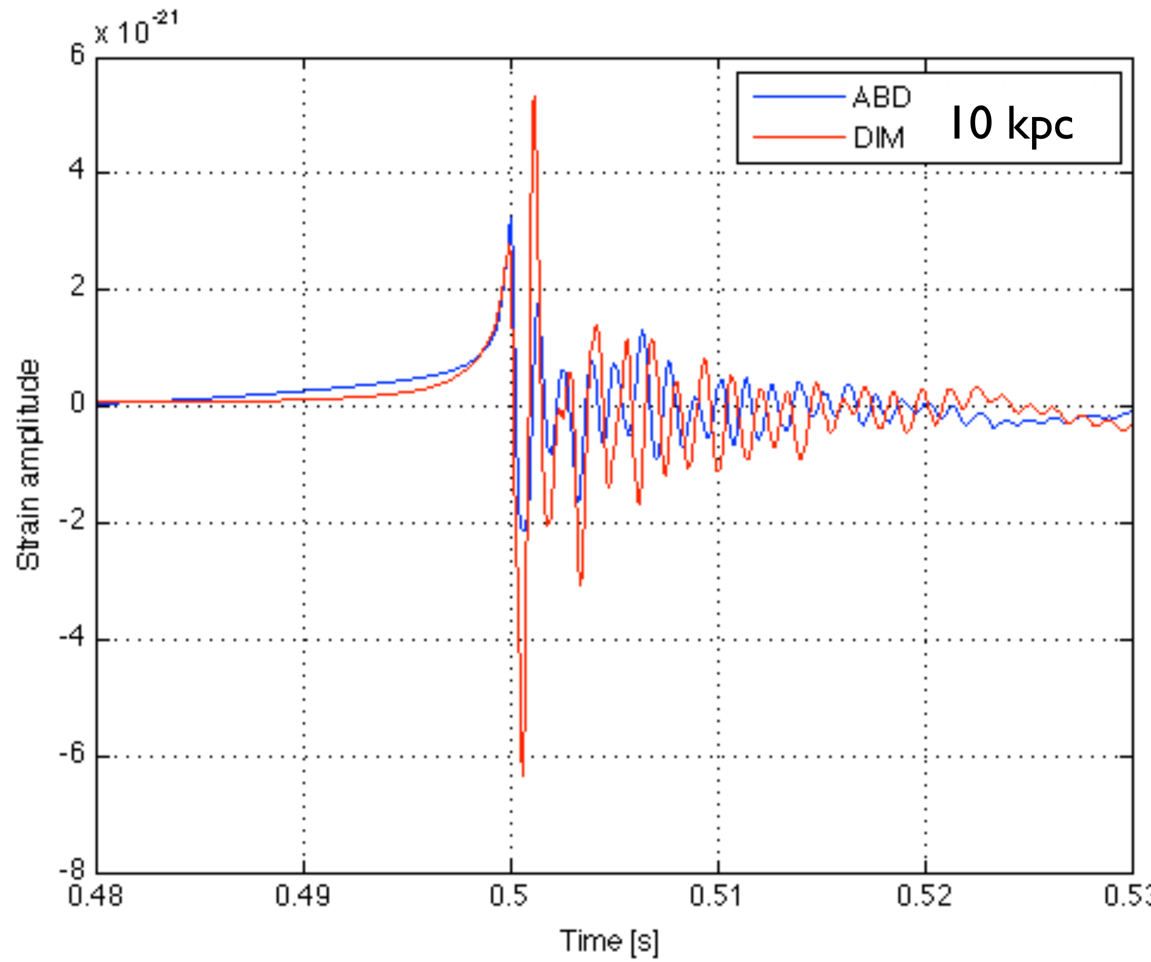
Only a small fraction of neutrino mechanism waveforms returning an ambiguous Bayes factor



Results are published in Phys. Rev. D **86** (4) 044023 (arXiv:1202.3256)

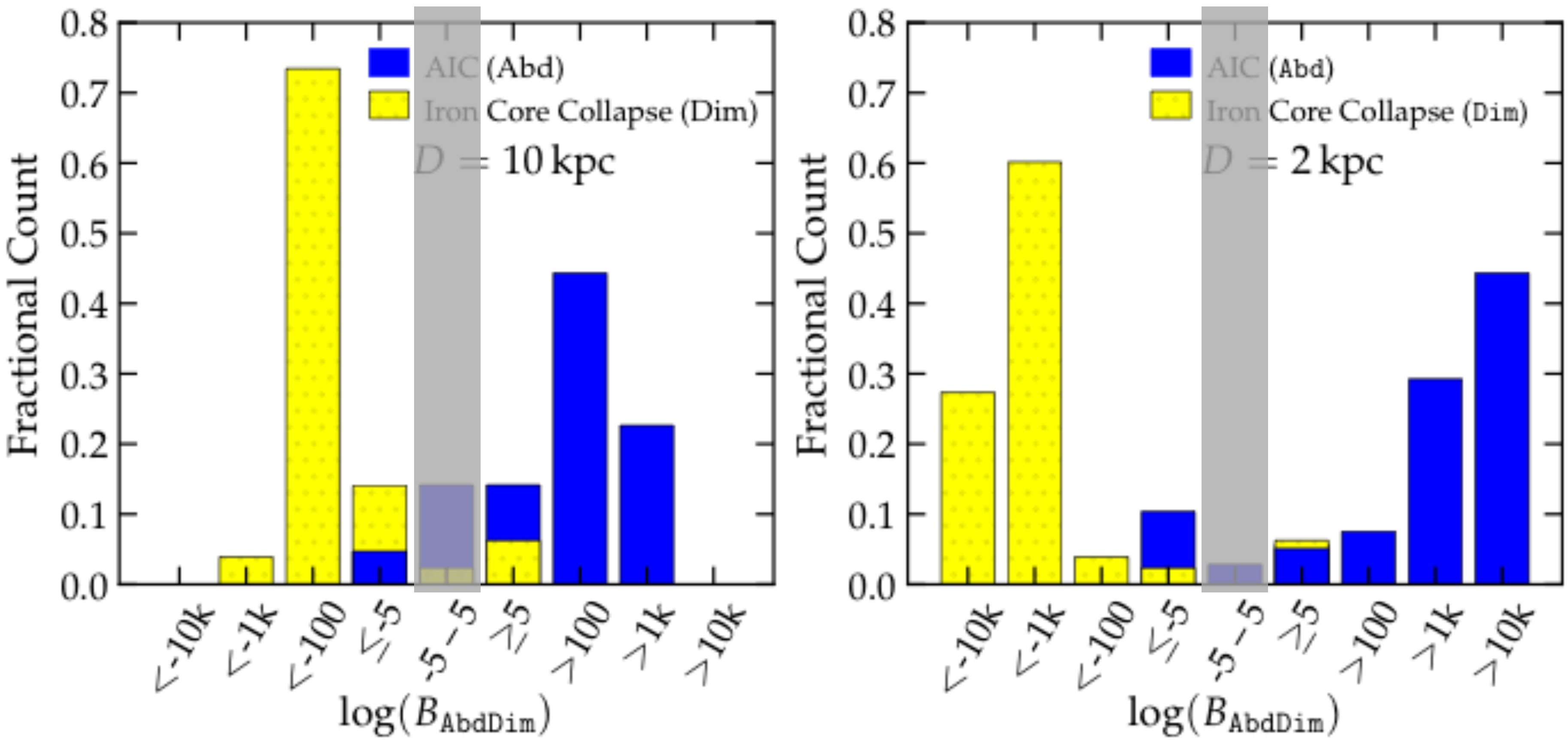
Distinguishing SNe models

- ★ The mechanisms examined so far produce quite different waveforms
- ★ Also compared Dimmelmeier waveforms to Accretion Induced Collapse (AIC) waveforms
- ★ AIC: collapse of accreting carbon white dwarfs
- ★ Use catalogue by Abdikamalov *et al.* 2010



Distinguishing SNe models

$$\log(B_{\mathrm{AbdDim}}) = \log B_{\mathrm{Abd}} - \log B_{\mathrm{Dim}}$$

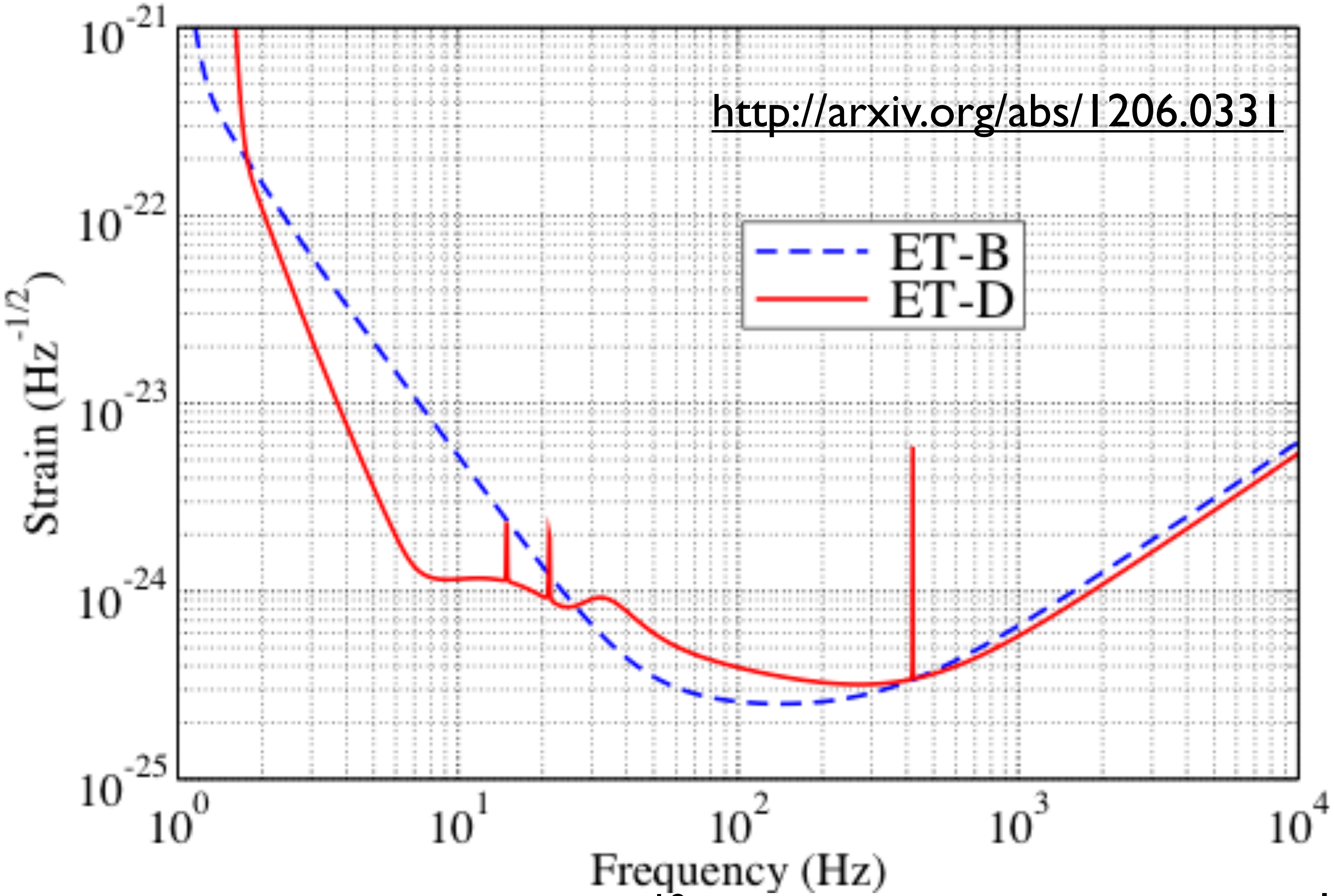


Again, most signals are correctly identified for a supernova at 10 kpc

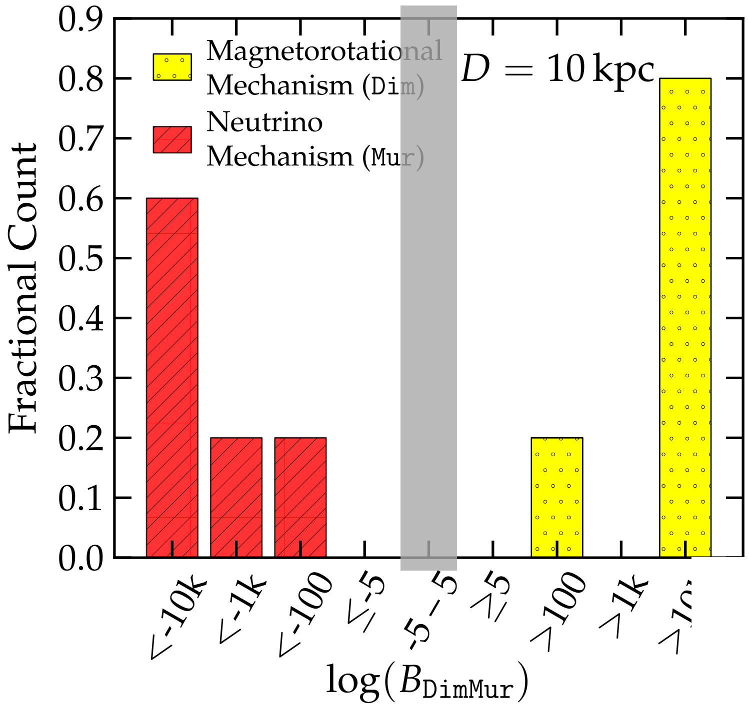
Investigations with ET noise

★ We injected the signals at 10 kpc and 778 kpc (Andromeda) into the ET-B noise curve

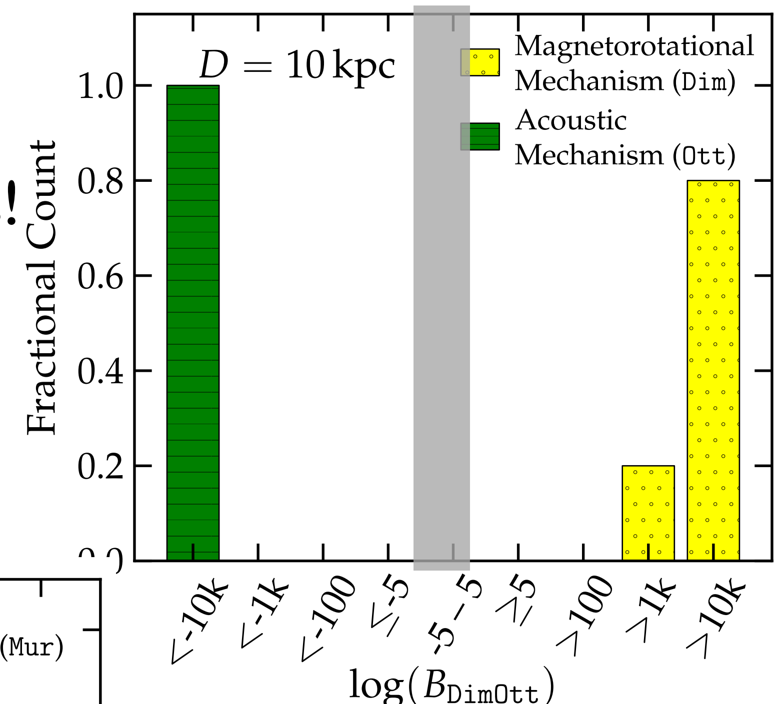
- we will use something more current next time...

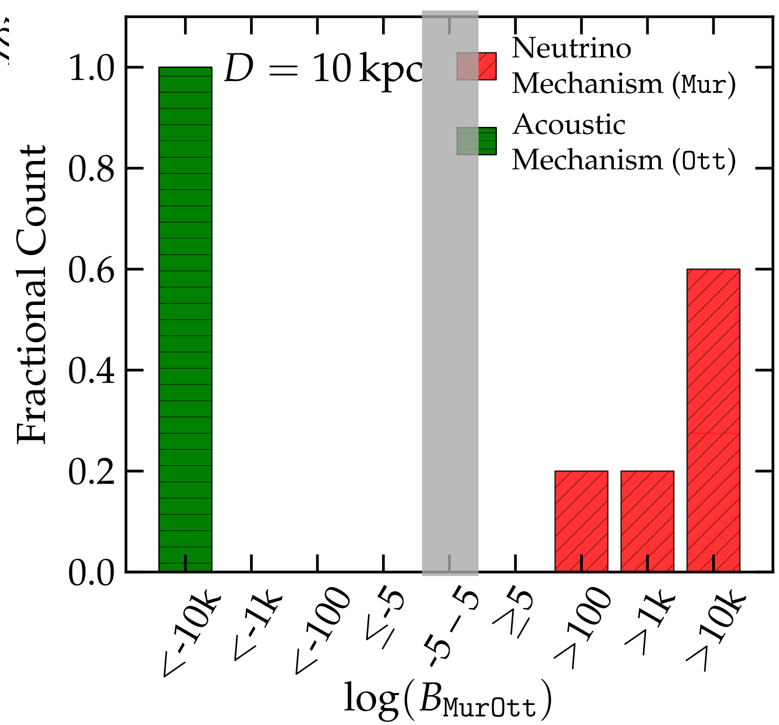


Supernova in Galactic Centre (ET)



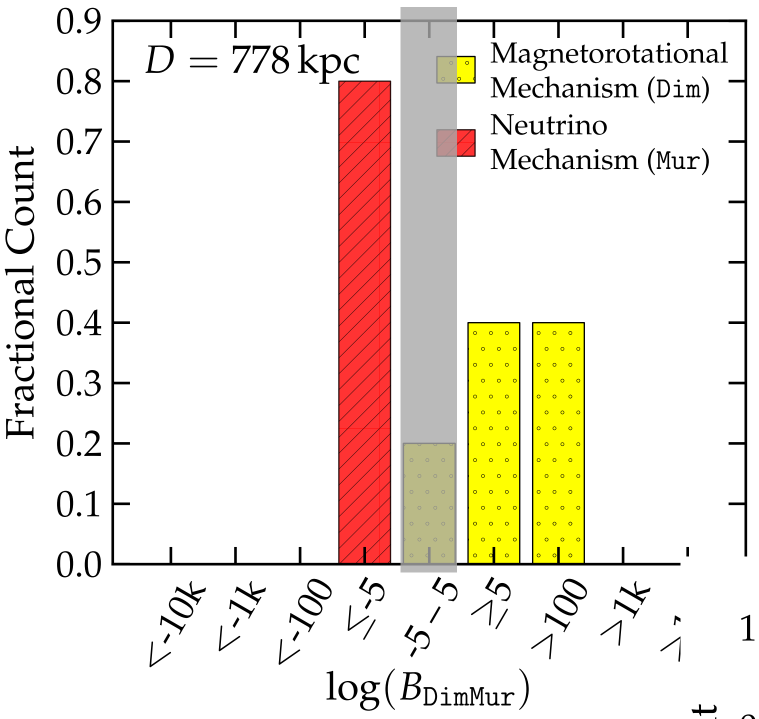
There is no ambiguity when identifying the supernova mechanisms!



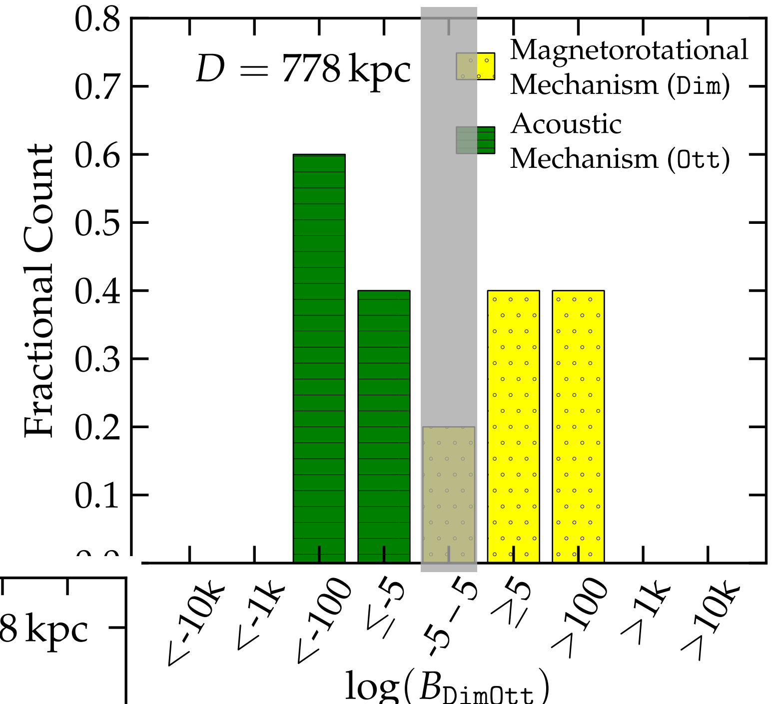


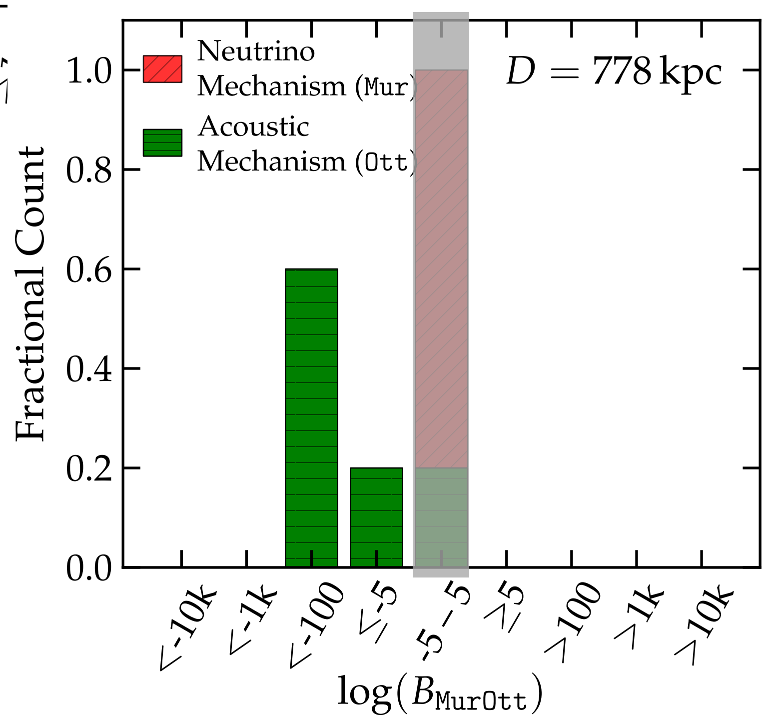
SNRs: Dim ~1000, Mur ~200, Ott ~1500

Supernova at Andromeda (ET)



Most waveforms can still correctly identified.



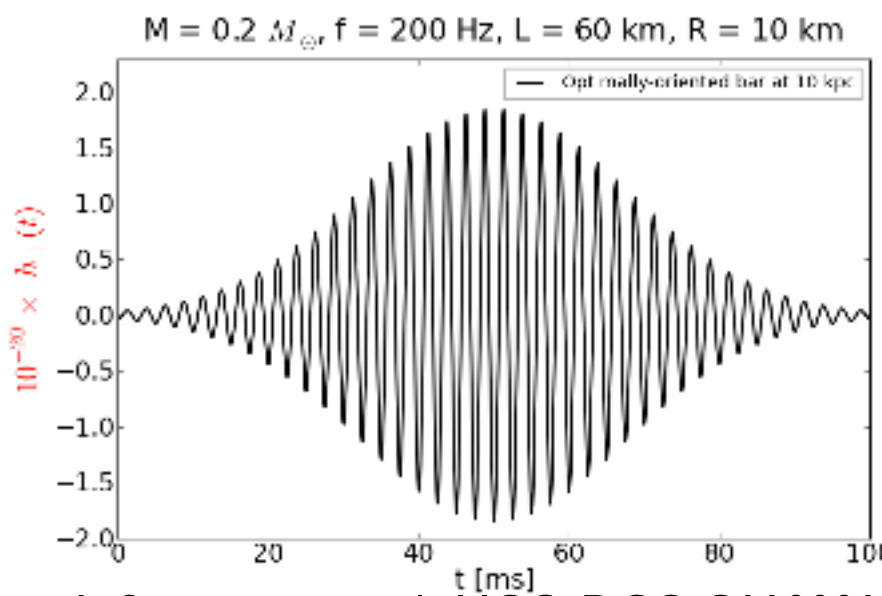


SNRs: Dim ~13, Mur ~2, Ott ~20

Note: We have assumed that the signal is detected and GW signal time is known. ie false alarm rate is not considered!

ET MDC

- ★ Two supernova waveforms were injected into the latest ET Mock Data Challenge (MDC)
- ★ One from Dimmelmeier *et al.* 2008 catalogue and the other is a long bar waveform using the waveform proposed by Fryer, Hughes, Holz 2002
- ★ SMEE will be run on these injections
  - need to include long bar signal model



L. Santamaria et al., LIGO-DCC-G1100014

Summary and future work

- ★ The proposed method, SMEE, has demonstrated its ability to associate an observed core-collapse supernova gravitational wave signal with the correct waveform catalogue
- ★ This allows us to infer the astrophysics behind the core-collapse supernova from the detected gravitational wave signal
- ★ Further features are required for SMEE and work is underway to implement them
  - analyse multi-detector data, incorporate time uncertainty and antenna patterns, use power spectra or time-frequency data,.....
- ★ Investigate waveform reconstruction from SMEE outputs
- ★ Extend SMEE framework for analysis towards a broader Burst parameter estimation and glitch classification