Inferring Core-Collapse Supernova Physics from Gravitational-Wave Observations

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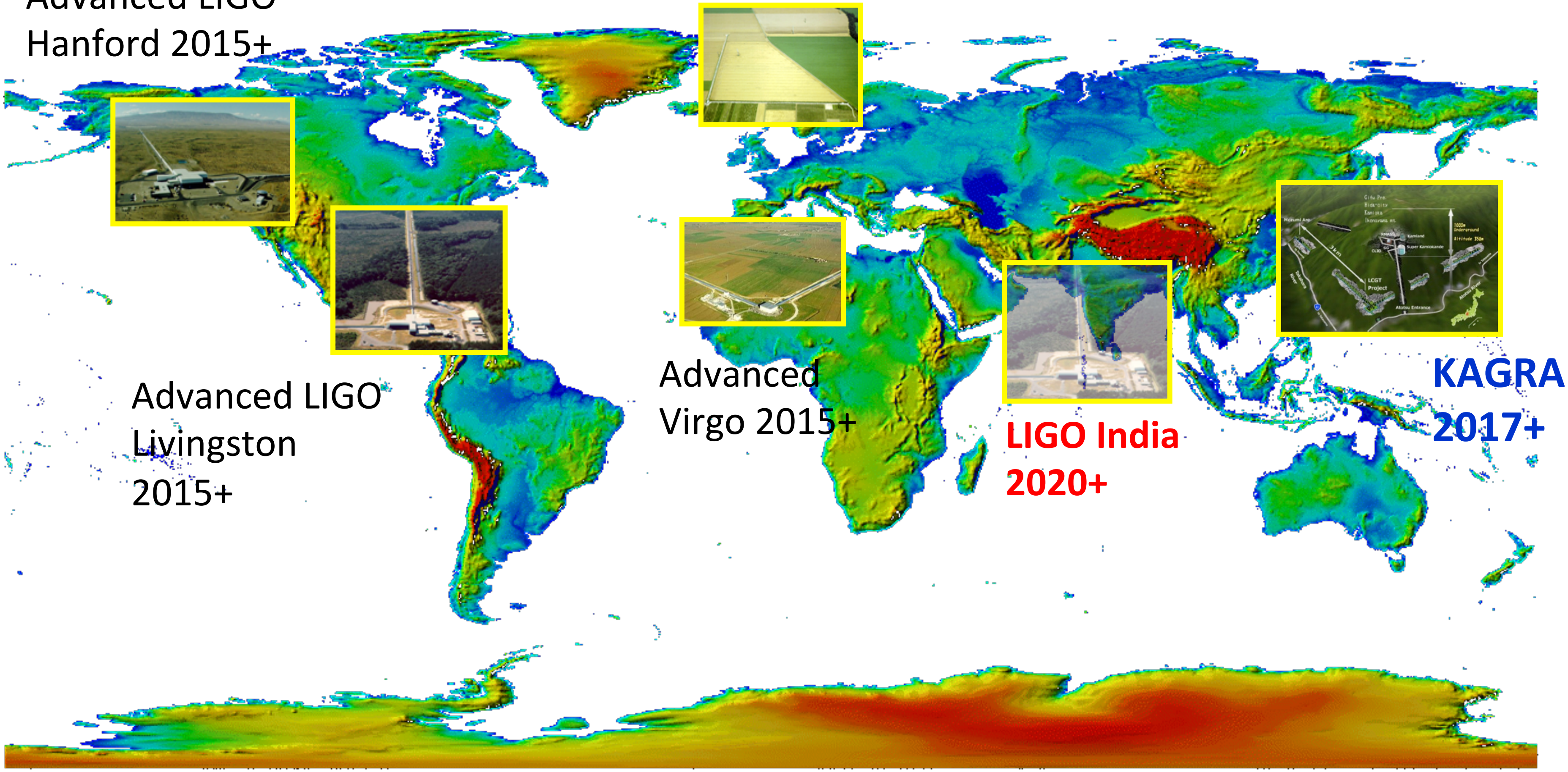
The Advanced GW Detector Network: 2020+



GEO 600 (HF) 2011

Advanced LIGO
Hanford 2015+

Advanced LIGO
Livingston
2015+

Advanced
Virgo 2015+

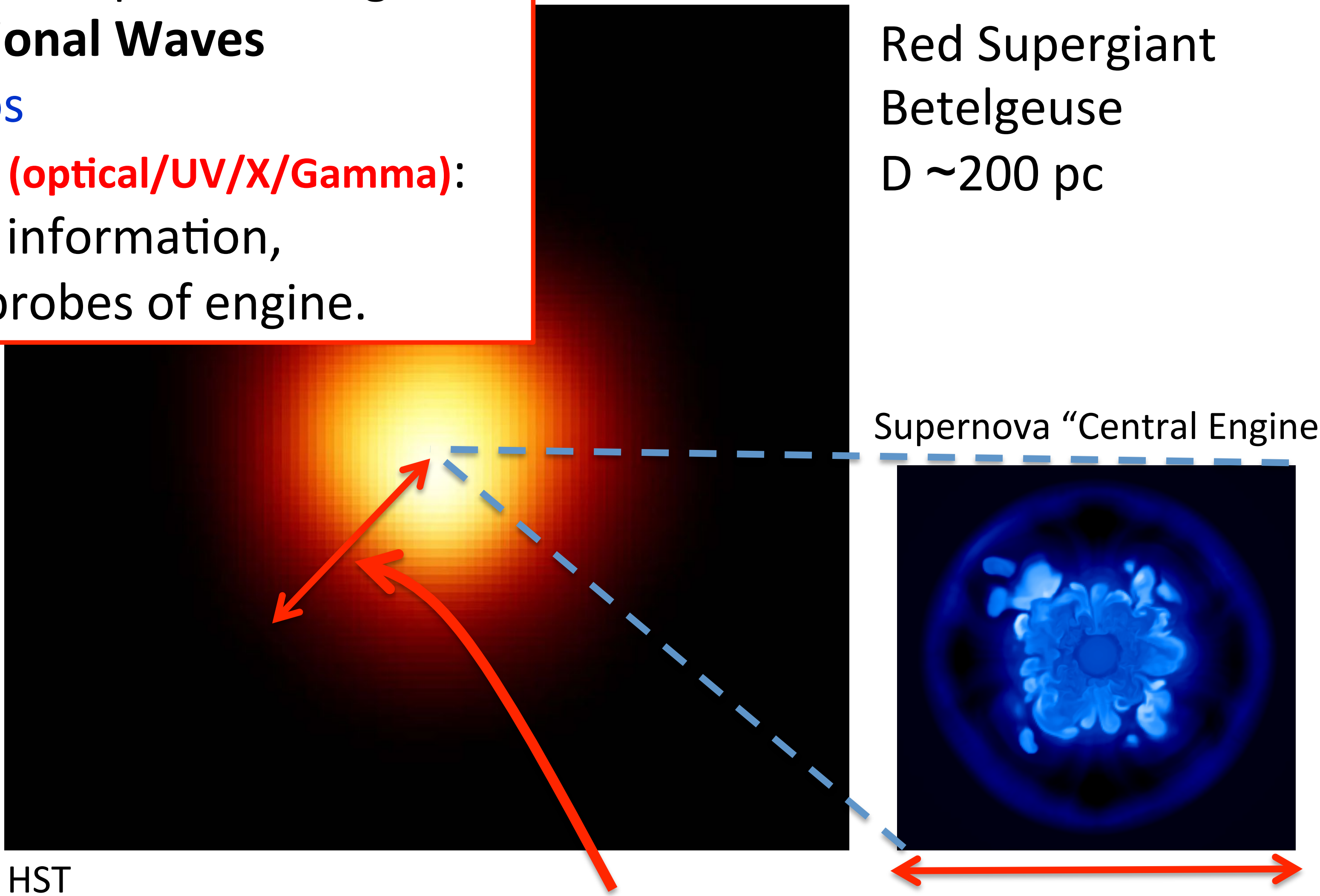
**LIGO India
2020+**

**KAGRA
2017+**

Observing the CCSN Mechanism

Probing the "Supernova Engine"
- **Gravitational Waves**
- Neutrinos

EM waves (optical/UV/X/Gamma): secondary information, late-time probes of engine.



Red Supergiant
Betelgeuse
D ~200 pc

Supernova "Central Engine"

HST

800 million km

300 km

Gravitational-Waves from Core-Collapse Supernovae

Recent reviews: Ott '09, Kotake '11, Fryer & New '11

Need:

$$h_{jk}^{TT}(t,\vec{x}) = \left[\frac{2}{c^4}\frac{G}{|\vec{x}|}\ddot{I}_{jk}\left(t-\frac{|\vec{x}|}{c}\right)\right]^{TT} \rightarrow$$

accelerated aspherical (quadrupolar) mass-energy motions

Candidate Emission Processes:

- Neutrino-driven Convection and SASI
- Prompt convection
- Protoneutron star convection
- Rotating collapse & bounce
- Rotational 3D instabilities
- Black hole formation
- Pulsations of the protoneutron star
- Anisotropic neutrino emission
- Aspherical accelerated outflows
- Magnetic stresses

Tasks:

(1) Determine GW signals from these emission processes.
(2) Connect GW emission processes to CCSN Mechanism.
(3) Detection: How far out can we detect GWs from CCSNe and can we infer the explosion mechanism (and other physics)?

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(2) Connecting GW Signals and Explosion Mechanisms

Ott '09, CQG
see also Kotake '11, Kotake et al.'12

Connecting GW Signals and Explosion Mechanisms

Ott '09, CQG 26, 063001

Dominant GW Emission Processes

Neutrino Mechanism

[e.g. Yakunin et al. '10, Müller et al. '12ab]

→ Turbulent convection,
Standing-**A**ccretion-**S**hock **I**nstability

Magnetorotational Mechanism

[e.g. Burrows et al. '07, Takiwaki & Kotake '11]

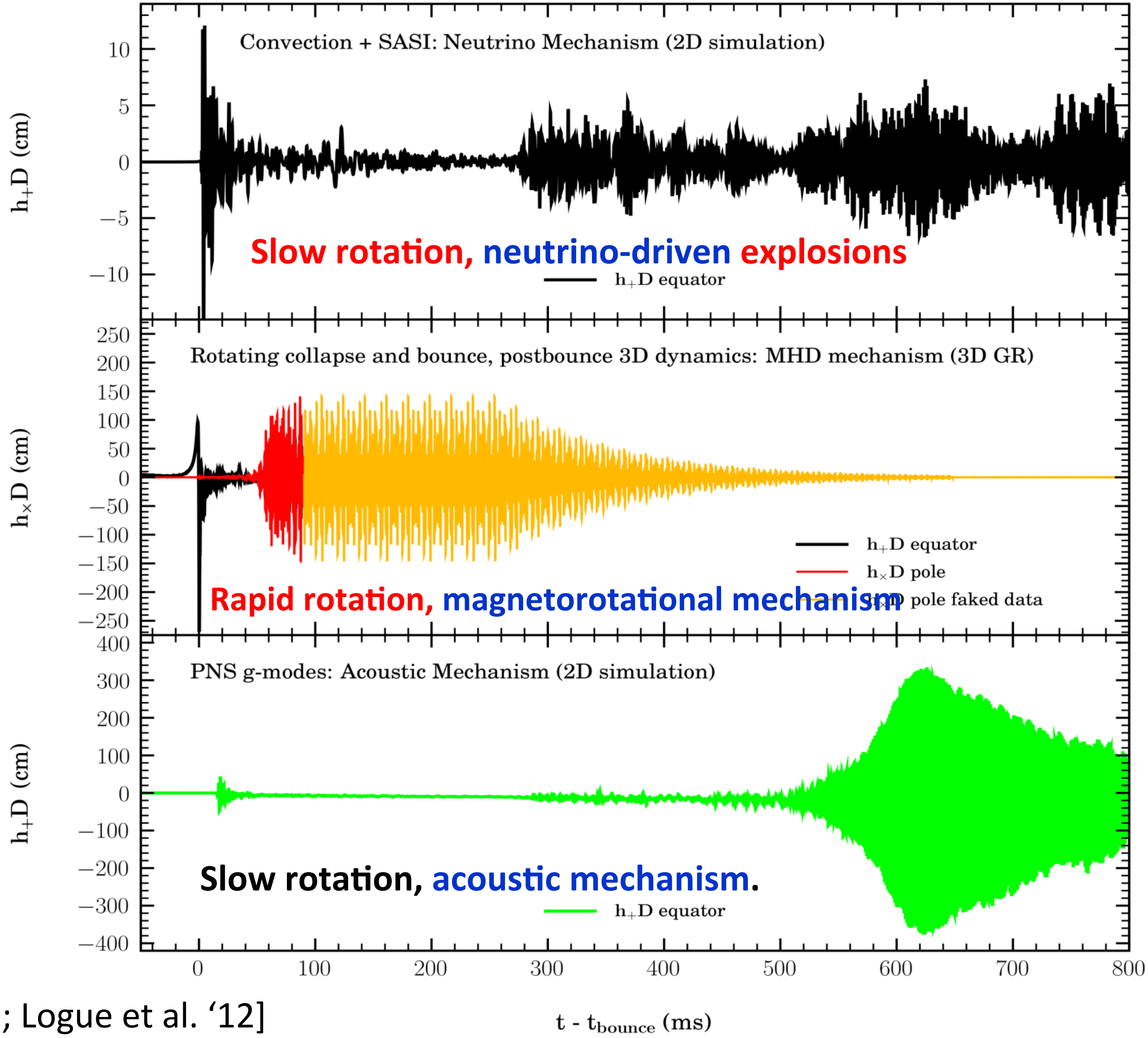
→ Rotating core collapse & bounce,
rotational 3D instabilities.

Acoustic Mechanism

[e.g. Burrows et al. 06, Ott et al. '06]

→ Protoneutron star pulsations.
(Caveat: Weinberg & Quataert '08,
Marek & Janka '09 -> may not
occur in nature)

Connecting GW Signals and Explosion Mechanisms



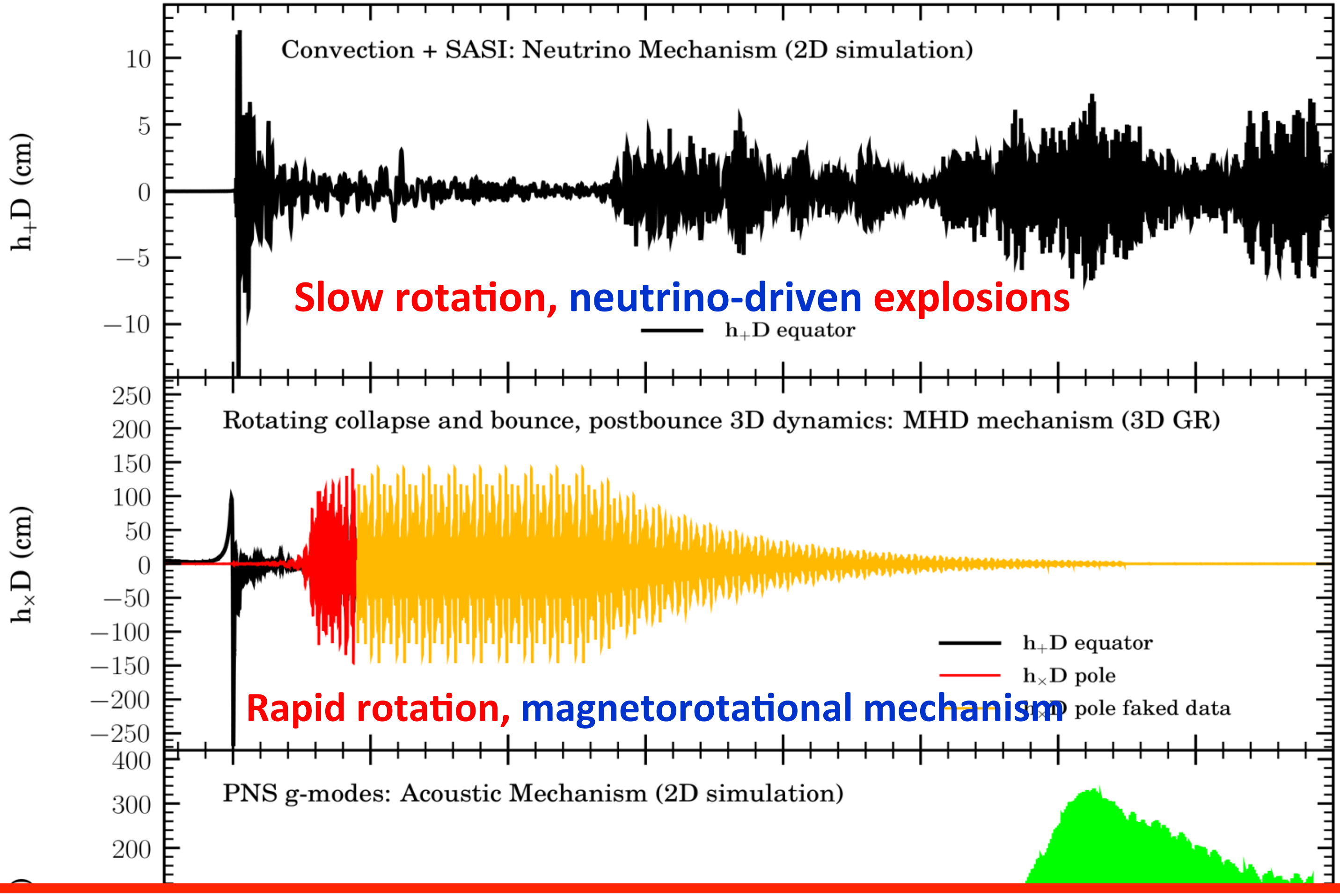
Slow rotation, neutrino-driven explosions

Rapid rotation, magnetorotational mechanism

Slow rotation, acoustic mechanism.

[Ott ’09; Logue et al. ‘12]

Connecting GW Signals and Explosion Mechanisms



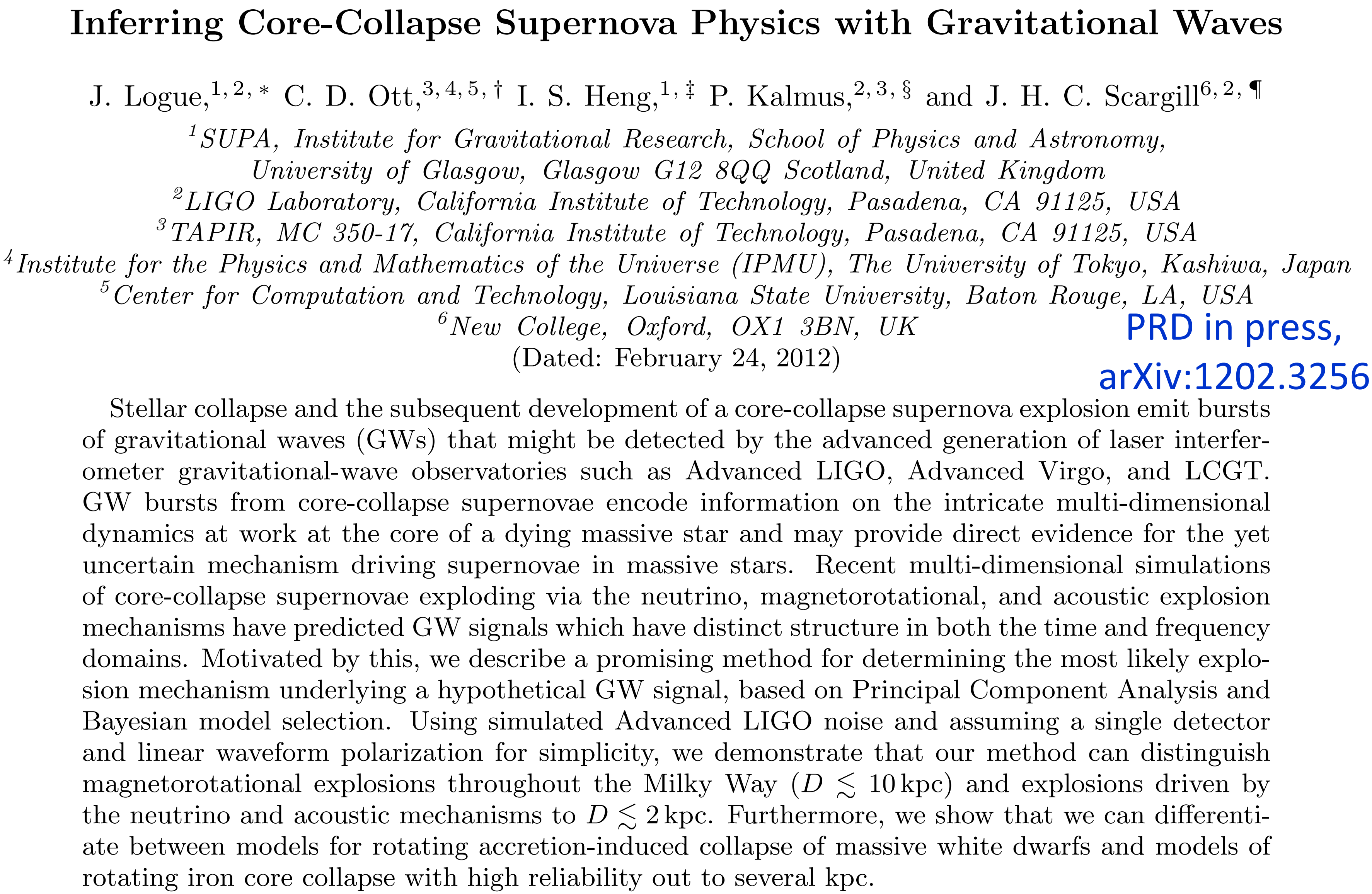
Slow rotation, neutrino-driven explosions

Rapid rotation, magnetorotational mechanism

Caveats:

- GW signal predictions still mostly based on 2D simulations.
- Advanced LIGO sensitivity:
  Need core-collapse supernova in the Milky Way.

(3) Inferring Physics from GW Observations of Core-Collapse Supernovae



Inferring Core-Collapse Supernova Physics with Gravitational Waves

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[5] *Center for Computation and Technology, Louisiana State University, Baton Rouge, LA, USA*
[6] *New College, Oxford, OX1 3BN, UK*

(Dated: February 24, 2012)

PRD in press,
arXiv:1202.3256

Stellar collapse and the subsequent development of a core-collapse supernova explosion emit bursts of gravitational waves (GWs) that might be detected by the advanced generation of laser interferometer gravitational-wave observatories such as Advanced LIGO, Advanced Virgo, and LCGT. GW bursts from core-collapse supernovae encode information on the intricate multi-dimensional dynamics at work at the core of a dying massive star and may provide direct evidence for the yet uncertain mechanism driving supernovae in massive stars. Recent multi-dimensional simulations of core-collapse supernovae exploding via the neutrino, magnetorotational, and acoustic explosion mechanisms have predicted GW signals which have distinct structure in both the time and frequency domains. Motivated by this, we describe a promising method for determining the most likely explosion mechanism underlying a hypothetical GW signal, based on Principal Component Analysis and Bayesian model selection. Using simulated Advanced LIGO noise and assuming a single detector and linear waveform polarization for simplicity, we demonstrate that our method can distinguish magnetorotational explosions throughout the Milky Way ($D \lesssim 10\,\mathrm{kpc}$) and explosions driven by the neutrino and acoustic mechanisms to $D \lesssim 2\,\mathrm{kpc}$. Furthermore, we show that we can differentiate between models for rotating accretion-induced collapse of massive white dwarfs and models of rotating iron core collapse with high reliability out to several kpc.

Supernova Model Evidence Extractor (SMEE)

Logue et al. '12, arXiv:1202.3256, PRD in press

- Can we really tell these signals apart in a noisy detector?
- Approach: Bayesian Model Selection

M: Model
D: Data
I: Prior information

Bayes Theorem:

$$P(M|D,I) = \frac{P(M|I)P(D|M,I)}{P(D|I)}$$

"Posterior Probability"

"Prior Probability"

Normalization

"Evidence (Likelihood)"

- For model selection: When comparing two models, odds ratio is sufficient:

$$O_{ij} = \frac{P(M_i|I)P(D|M_i,I)}{P(M_j|I)\underbrace{P(D|M_j,I)}_{B_{ij}}}$$

Ratio of Priors

Bayes Factor

"Marginal Likelihood"

$$P(D|M,I) = \int_\theta p(\theta|M,I)p(D|\theta,M)d\theta$$

θ: Model Parameters

$$\log B_{ij} = \log P(D|M_i,I) - \log P(D|M_j,I)$$

SMEE: Signal Models

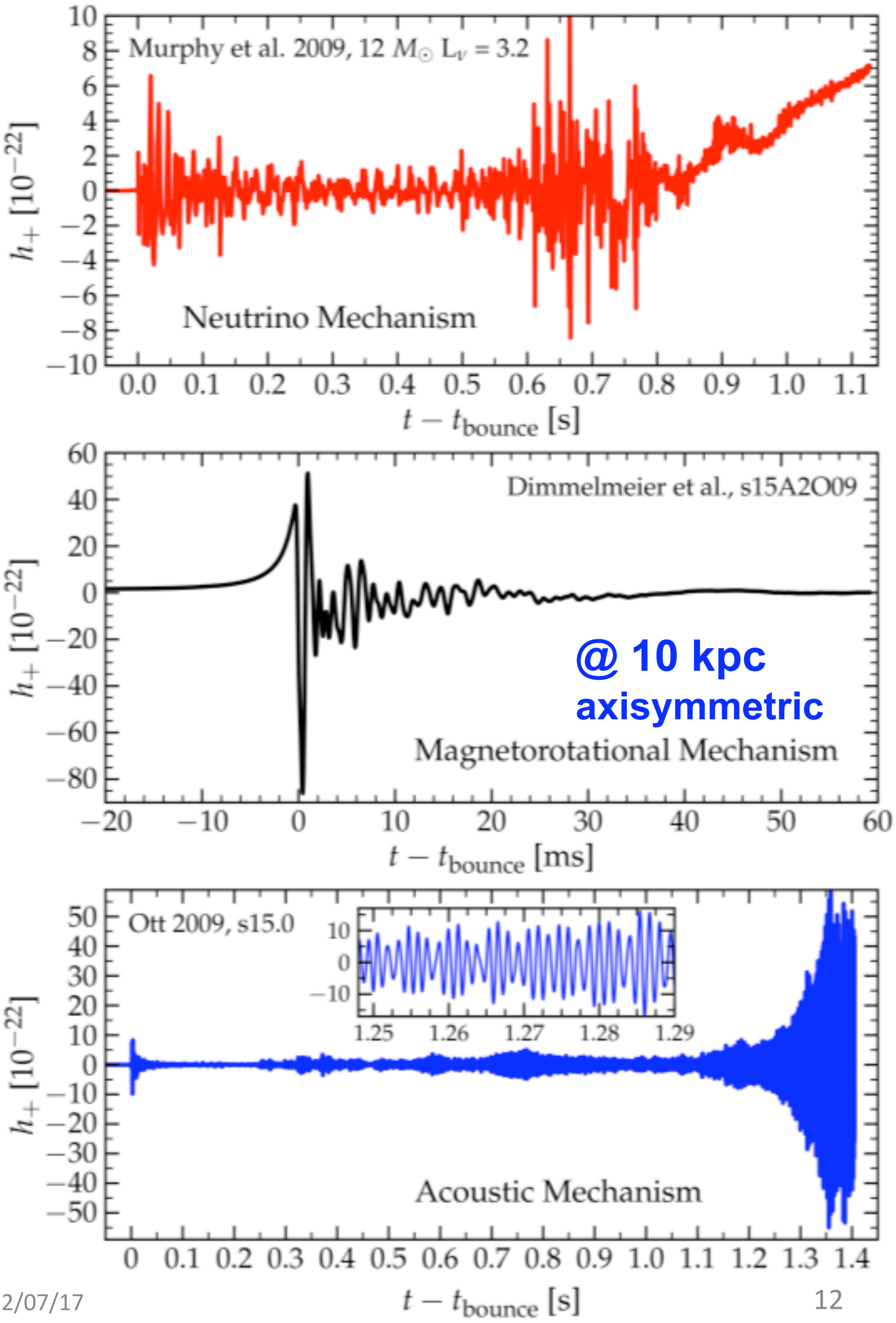
Logue et al. ‘12, arXiv:1202.3256, PRD in press

Consider waveforms representative for:

Neutrino Mechanism

Magnetorotational Mechanism

Acoustic Mechanism



@ 10 kpc
axisymmetric

SMEE: Signal Models

Logue et al. ‘12, arXiv:1202.3256, PRD in press

Consider waveforms representative for:

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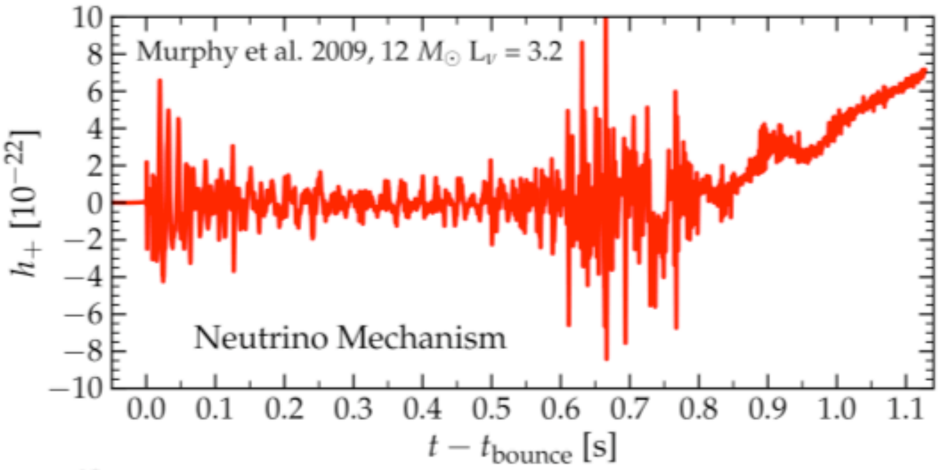
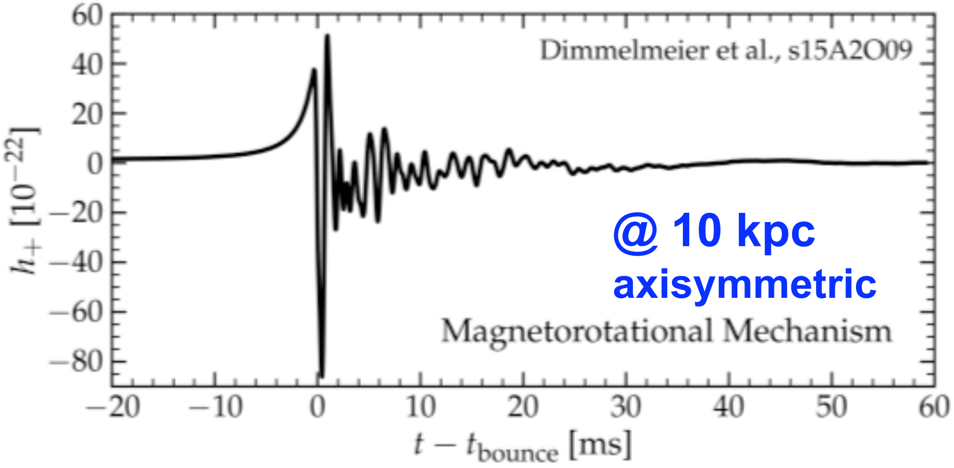
Magnetorotational Mechanism

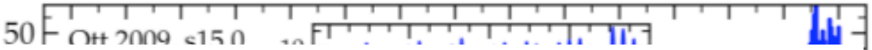
Acoustic Mechanism

What are the parameters to marginalize over?





@ 10 kpc
axisymmetric



-> Waveforms impossible to predict exactly.

-> Parameter studies of GW emission in CCSNe provide waveform catalogs.

-> Approach: Try to isolate robust features present in waveform catalogs and parameterize waveforms according to these.

Principal Component Analysis

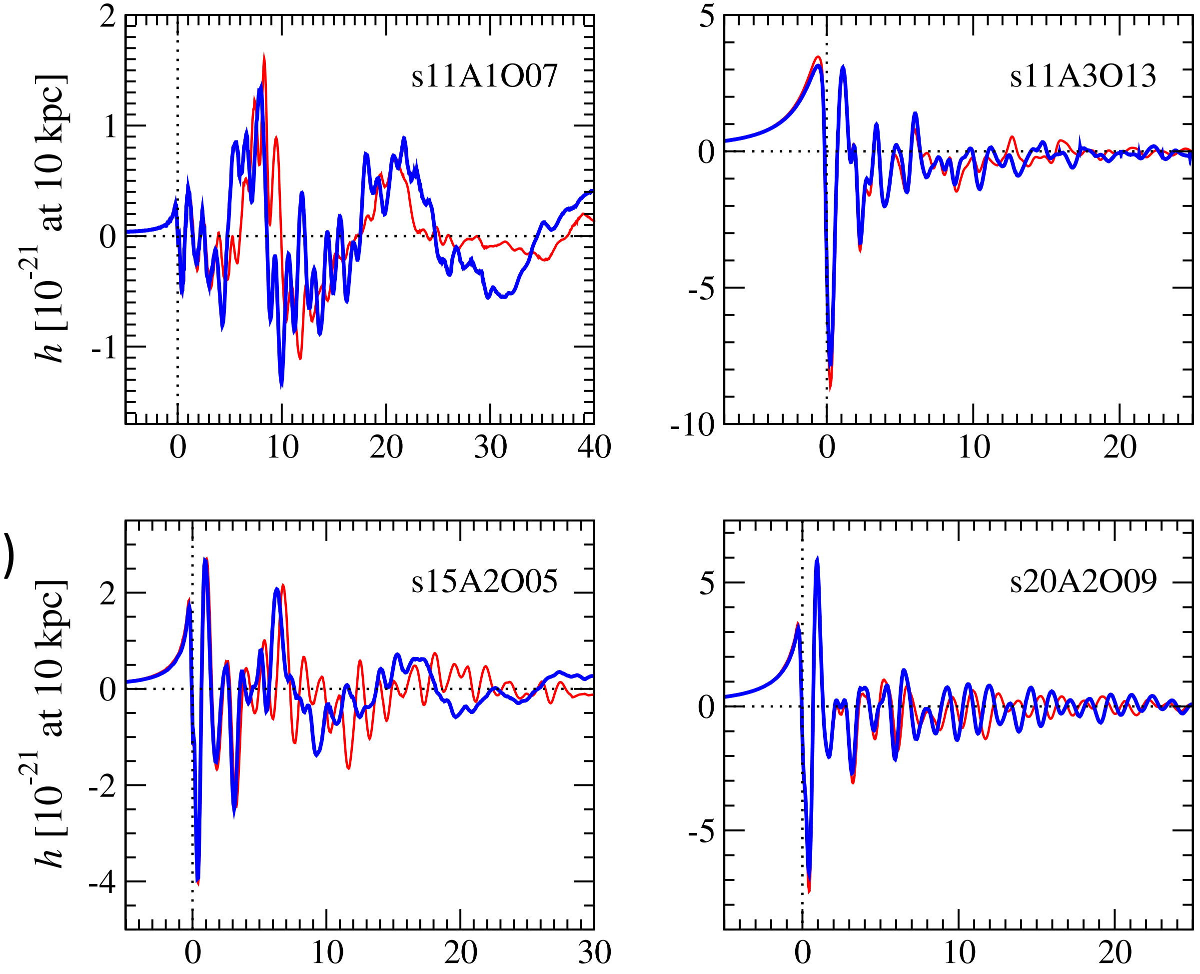
Logue et al. '12, arXiv:1202.3256, PRD in press,
previously applied to GWs by Heng '09, Roever+ '09

Assumption:

Gravitational wave signals have certain robust features in their time series or power spectra that can be isolated.

Example:

Rotating
core collapse
waveforms from
Dimmelmeier+ '08
(128 waveforms total)



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Assumption:

Gravitational wave signals have certain robust features in their time series or power spectra that can be isolated.

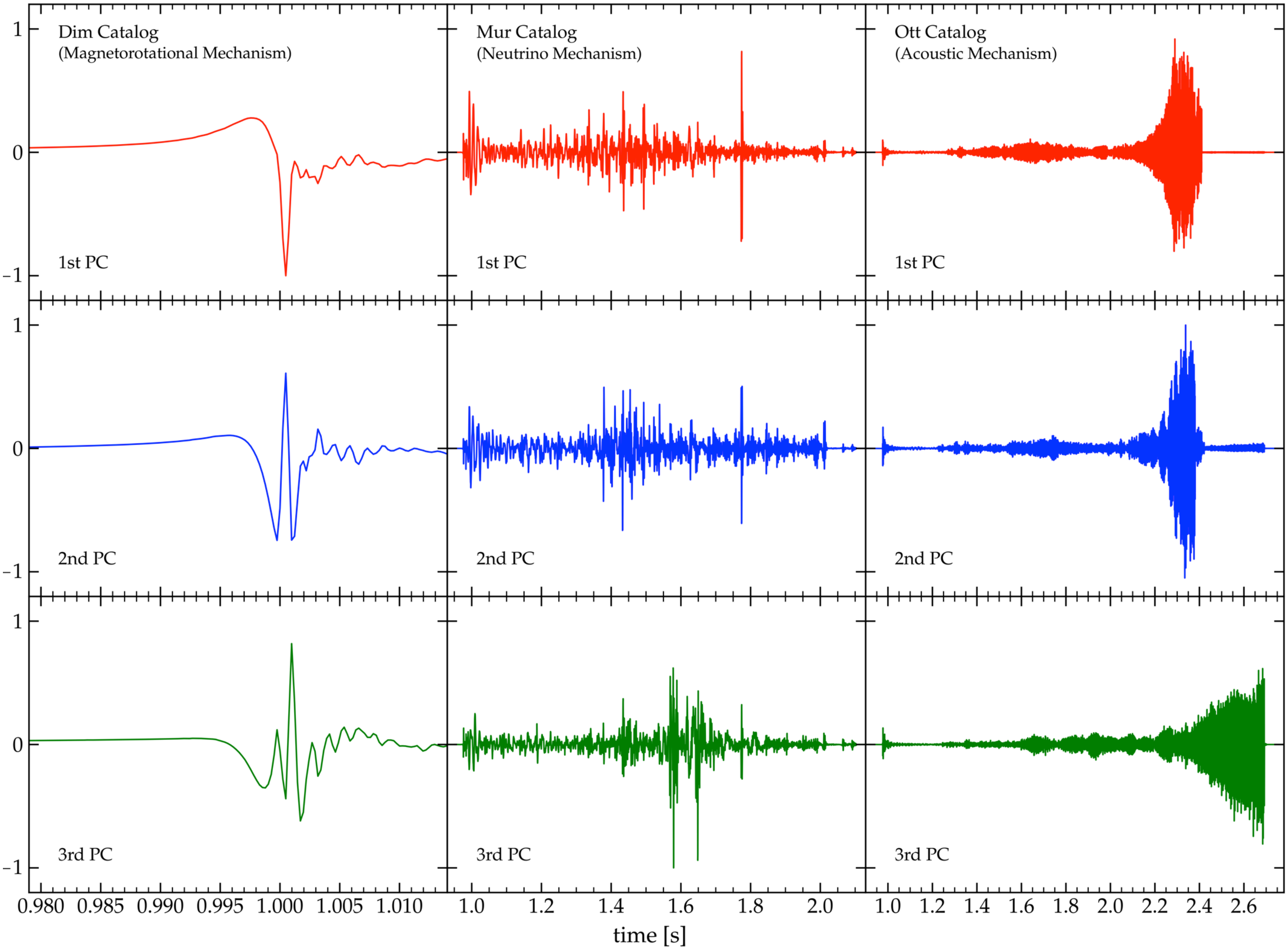
Procedure for feature isolation:

en.wikipedia.org/wiki/Principal_component_analysis

- Take m waveforms of length n that span the m-dimensional parameter space and construct n x m matrix A.
- One can show (->linear algebra) that the eigenvectors U_i of AA^T are orthorgonal basis vectors of the m-dimensional parameter space. They are the principal components (PCs).
- The PCs are ordered according to the values of their eigenvalues λ_i, which indicate the importance of any given PC in the parameter space spanned by m waveforms.
- If the PCA works efficiently, only k << m PCs are needed to reconstruct any waveform of the catalog with good accuracy.

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

Principal Components



Supernova Model Evidence Extractor (SMEE)

Logue et al. '12, arXiv:1202.3256, PRD in press

Must compute the likelihood that the data is consistent with model M.

$$P(D|M,I) = \int_\theta p(\theta|M,I)p(D|\theta,M)d\theta \qquad h_i \approx \sum_{j=1}^{k} U_j \beta_j$$

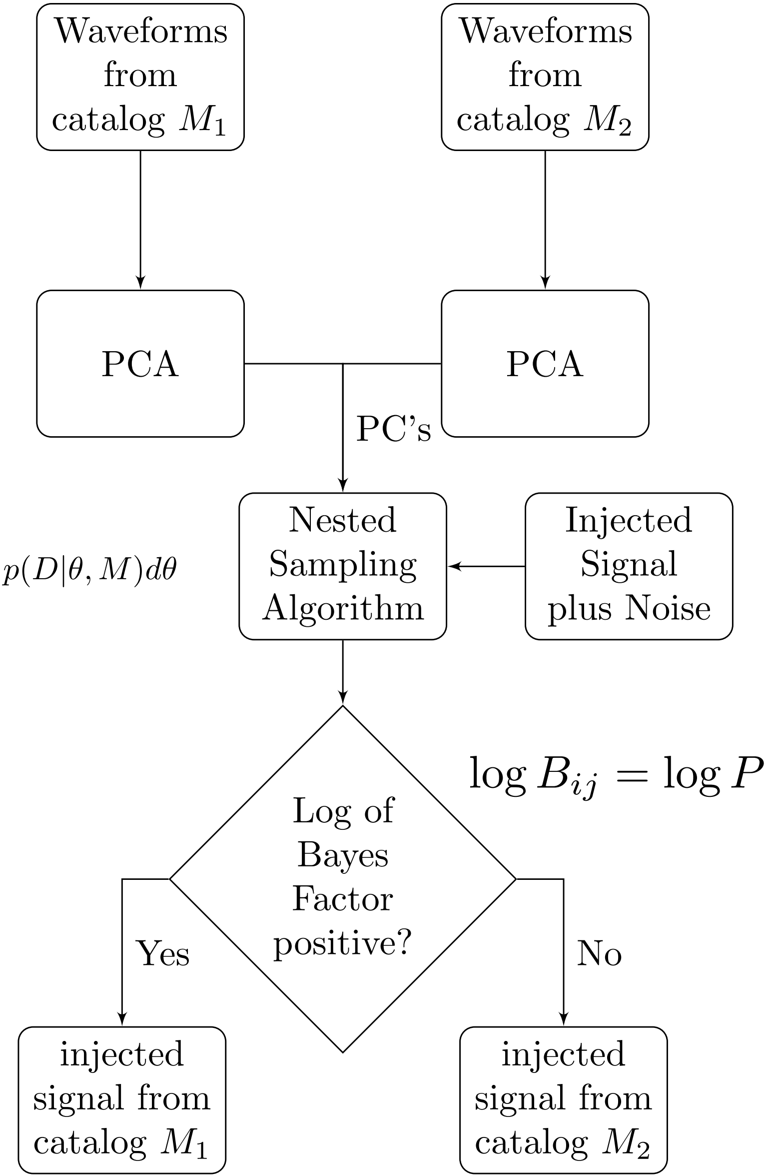
θ: Set of Model Parameters -> coefficients of the PCs

In SMEE:

- Uniform prior on the β_i.
- Ranges set by ranges found for each signal catalog.
- Usually use 3 or 7 PCs -> marginalization integral is multi-dimensional.
- Efficient integration technique: "Nested Sampling" (Skilling '04) http://en.wikipedia.org/wiki/Nested_sampling_algorithm (similar to Markov-Chain Monte Carlo)

Supernova Model Evidence Extractor (SMEE)

Logue et al. ‘12, arXiv:1202.3256, PRD in press



Waveforms from catalog M_1

Waveforms from catalog M_2

PCA

PCA

PC’s

Nested Sampling Algorithm

Injected Signal plus Noise

Log of Bayes Factor positive?

Yes

No

injected signal from catalog M_1

injected signal from catalog M_2

$$P(D|M,I) = \int_\theta p(\theta|M,I)p(D|\theta,M)d\theta$$

$$\log B_{ij} = \log P(D|M_i,I) - \log P(D|M_j,I)$$

Supernova Model Evidence Extractor (SMEE)

Logue et al. ‘12, arXiv:1202.3256, PRD in press

Must consider two cases:

(1) Is signal different from noise?

$$\log B_{SN} = \log P(D|M_S, I) - \log P(D|M_N, I)$$

M_S signal model M_N noise model (here: Gaussian,stationary)

(note: real detector noise: non-Gaussian, non-stationary)

(2) Comparison of signal models

$$\log B_{ij} = \log P(D|M_i, I) - \log P(D|M_j, I)$$

Problem: How to describe signal mode? GW signals cannot be predicted exactly (turbulence! + unknown physics).

First SMEE Study

Logue et al. ‘12, arXiv:1202.3256, PRD in press

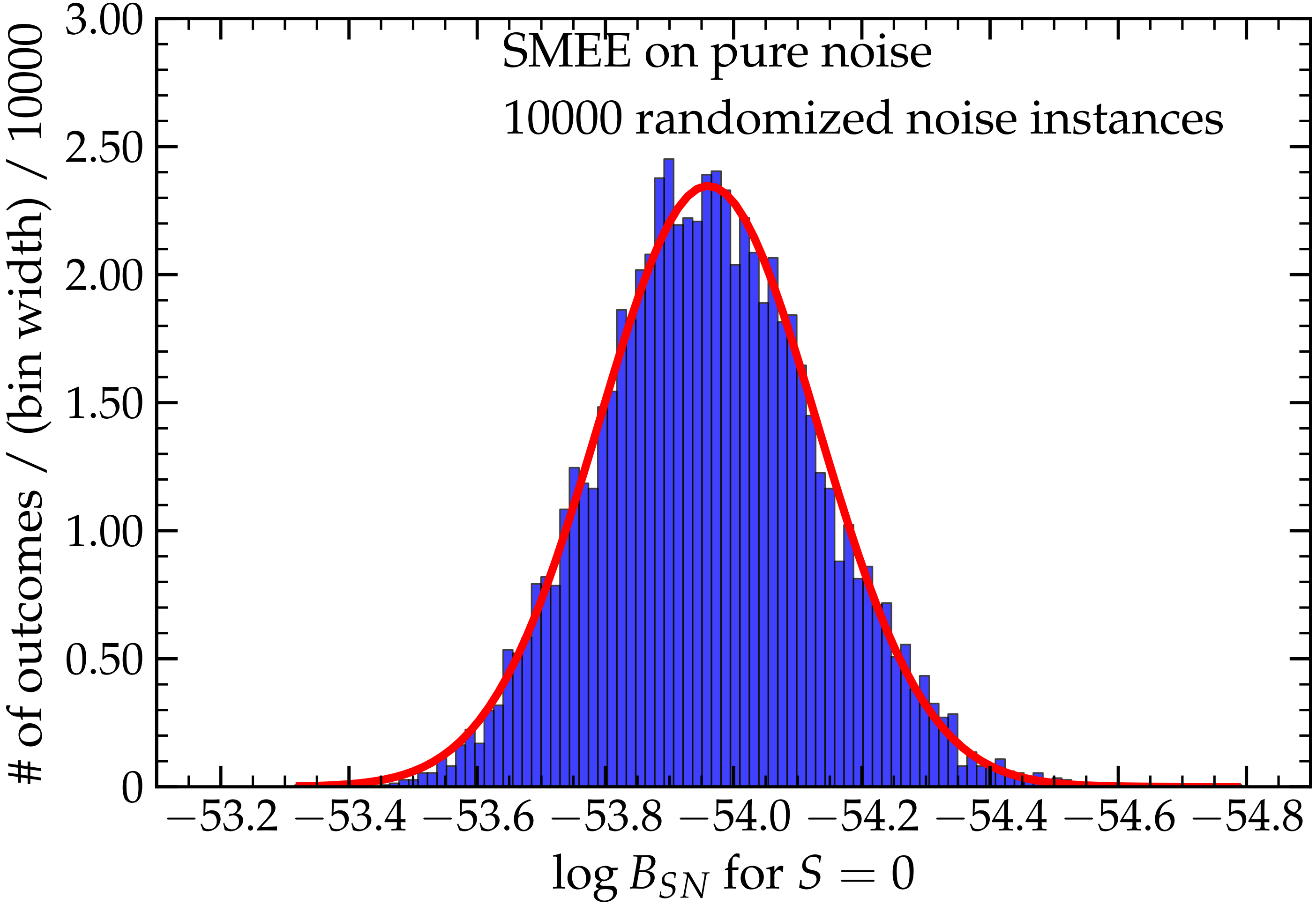
Magnetorotational Mechanism	128 waveforms from Dimmelmeier et al. 2008
Neutrino Mechanism	16 waveforms from Murphy et al. 2009
Acoustic Mechanism	7 waveforms from Ott 2009

Simplifications:

- Single detector.
- Gaussian noise.
- Linearly polarized waves.
- Optimally oriented source.

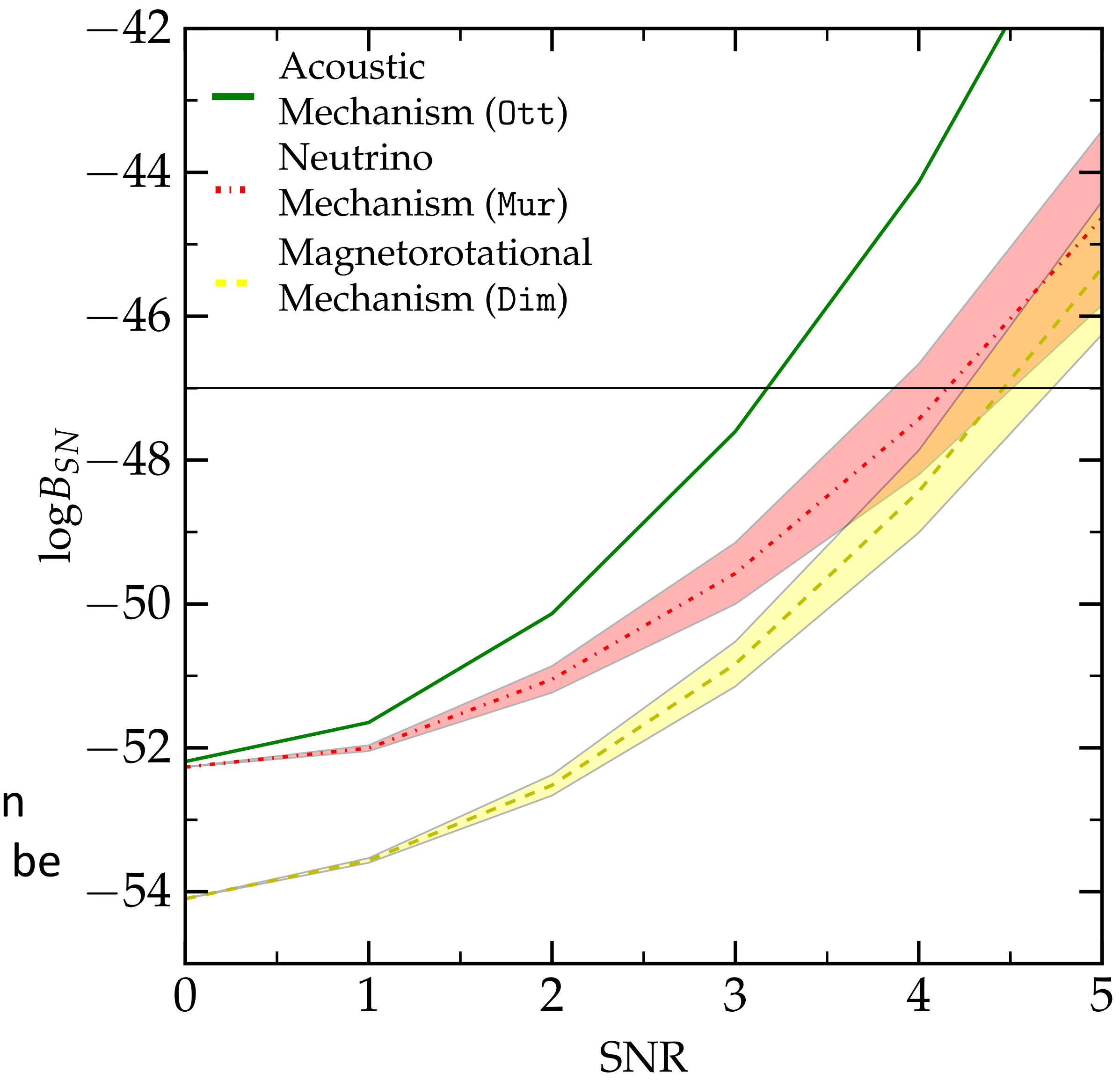
Results: Pure Noise

Logue et al. '12, arXiv:1202.3256, PRD in press



Agrees with analytic calculation based on noise model.

Results: Signal vs. Noise

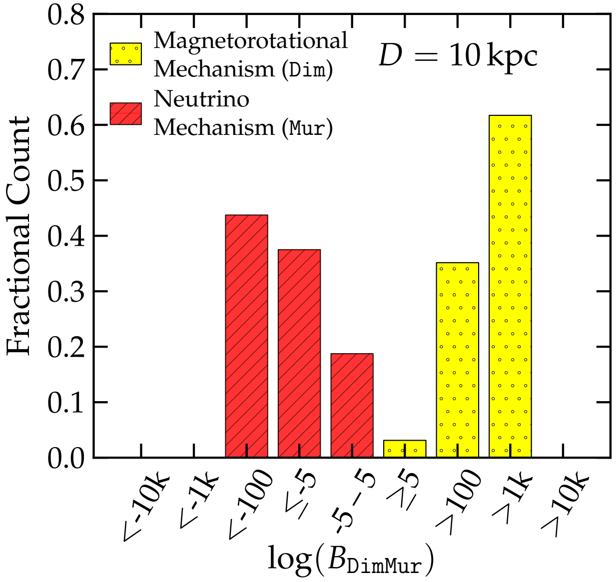


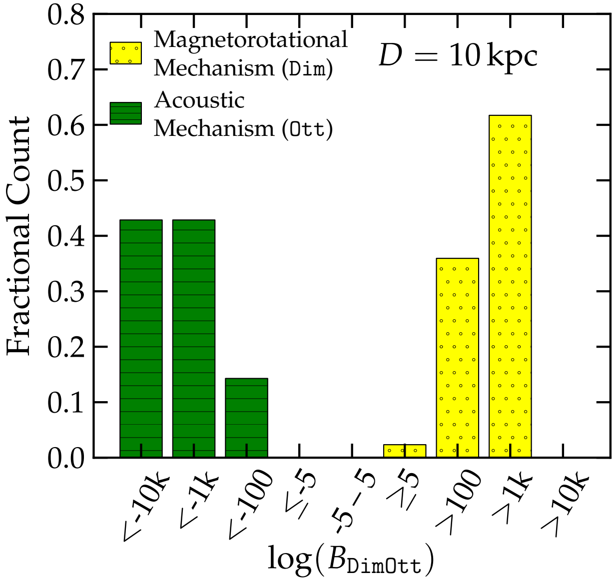
Note:
Real SNR
for detection
will need to be
> 8-10.

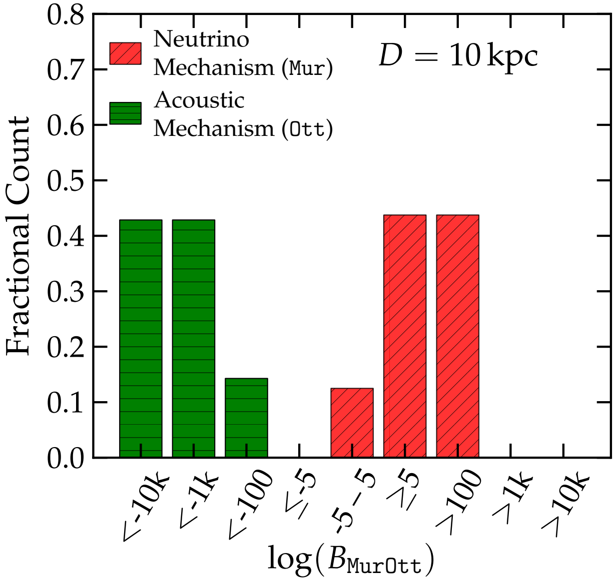
Results: Ideal Case

Logue et al. ‘12, arXiv:1202.3256, PRD in press

Injected “known” waveforms from catalogs that were used to generate principle components (PCs); use first 7 PCs.







$$\log B_{ij} = \log P(D|M_i, I) - \log P(D|M_j, I)$$

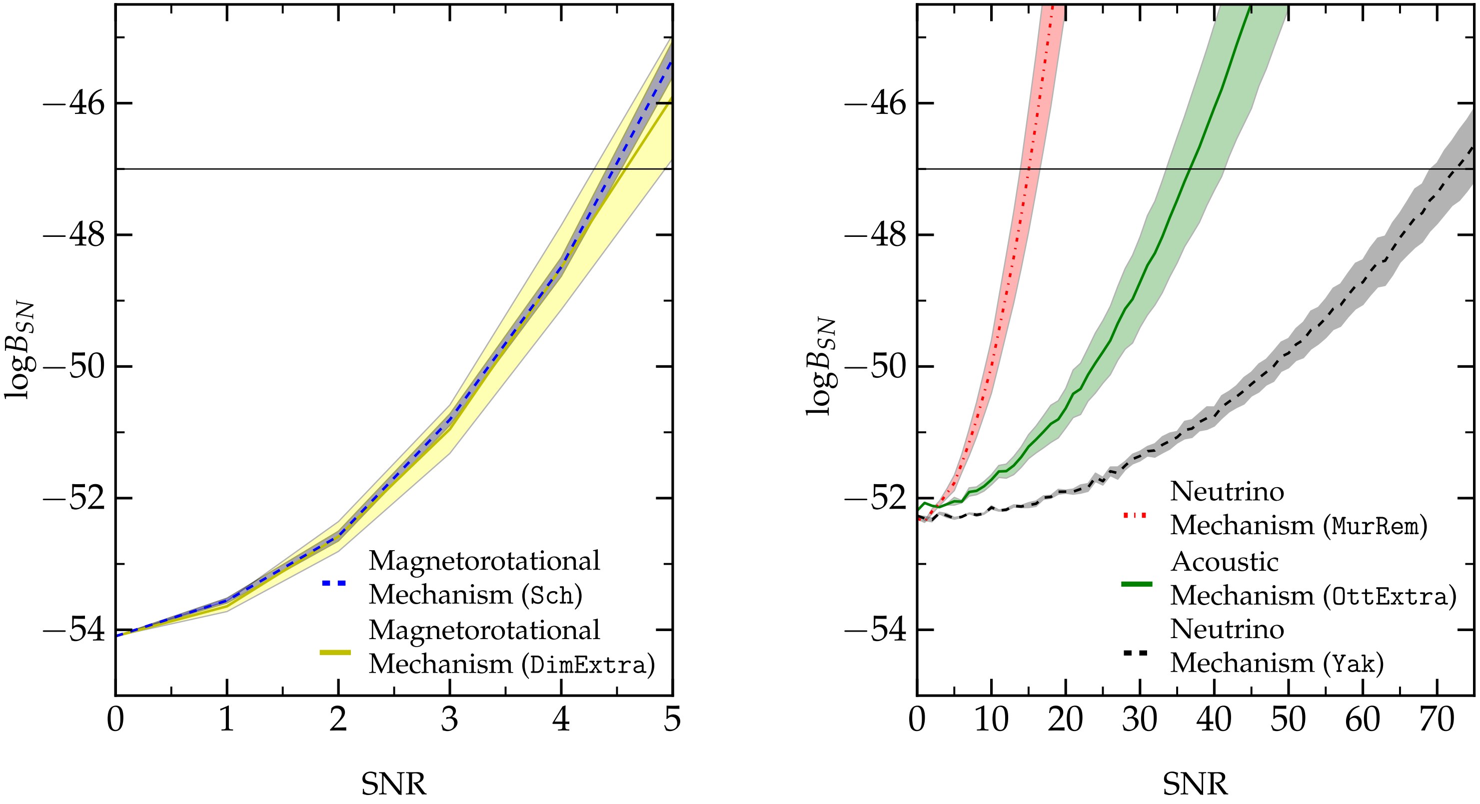
Results: More realistic case

Logue et al. ‘12, arXiv:1202.3256, PRD in press

Use **unknown waveforms** from different studies modeling the same physics.

Scheidegger et al. ‘10: magnetorotational mechanism.

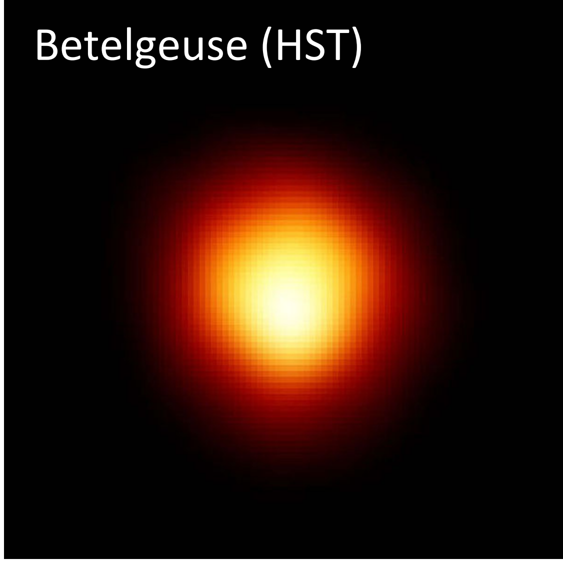
Yakunin et al. ‘10: neutrino mechanism



-> Method robust for magnetorotational mechanism out to 10 kpc.

-> Can identify neutrino mechanism out to ~2 kpc (using Murphy+ 09 PCs).

Summary


Betelgeuse (HST)

- Magnetorotational, neutrino-driven, and **acoustically-driven** CCSN explosions are likely to have distinct GW signatures.

- Provided (a) that this is the case, and, (b) robust large catalogs of waveform predictions are available, The Supernova Model Evidence Extractor (SMEE) can determine the core-collapse supernova explosion mechanism based on the GW signal alone.

- Need nearby event (< 2 – 10 kpc).

- Neutrinos will provide additional information (to be explored).

- Many Limitations: PCA not good for some signal types, so far only considered ideal case of Gaussian noise, single detector, optimal orientation, linear polarization, catalogs with limited predictive power.