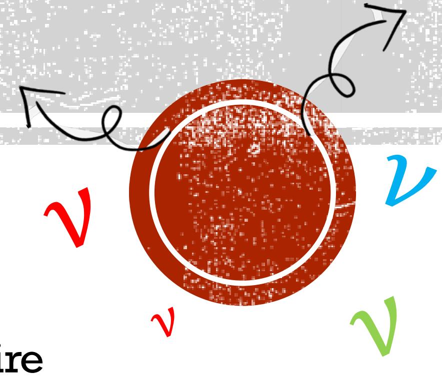
JOINT ANALYSIS OF CCSNE PHYSICS USING NEUTRINO AND GRAVITATIONAL WAVE SIGNALS

what can we learn from there?



Zidu Lin

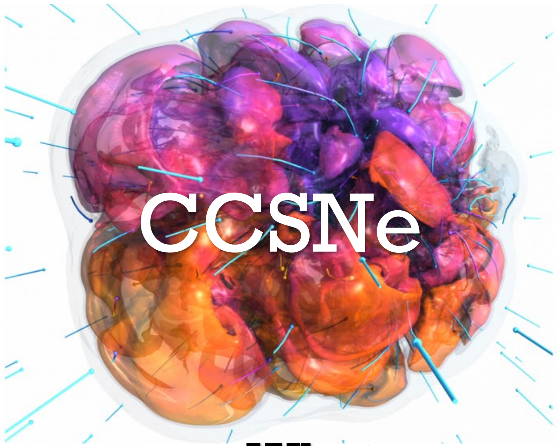
University of Tennessee, Knoxville and University of New Hampshire

@SN2025gw Symposium, 7/23/2025

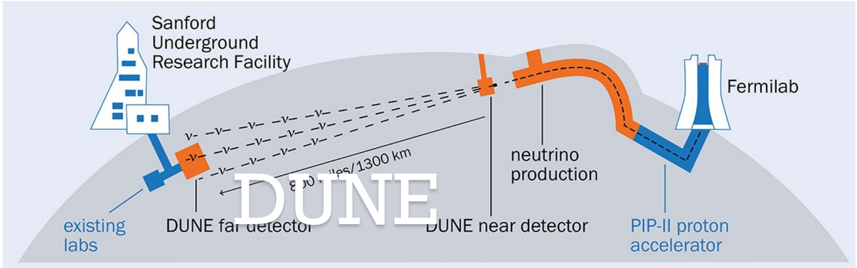
Collaborators: C. Lunardini (ASU), M. Zanolin (ERAU), K.Kotake (Fukuoka University), C. Richardson (UTK), A. Rijal (UTK), M. Morales (U of Guadalajara), S. Zha (CAS), E. O'Connor (Stockholm U), A. Steiner (UTK)

INFORMATION CONTENT OF CCSNE NEUTRINO MESSENGERS

Imagine a CCSN explode in our galaxy tomorrow…



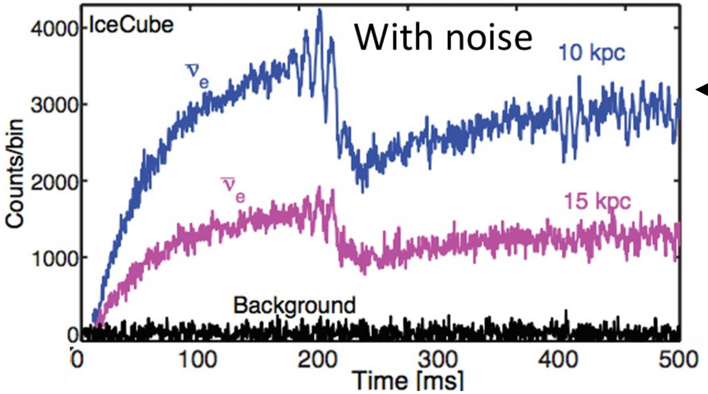
υ



Detectors

What can we say about this
star based on the data?

Tamborra
et al. 2013



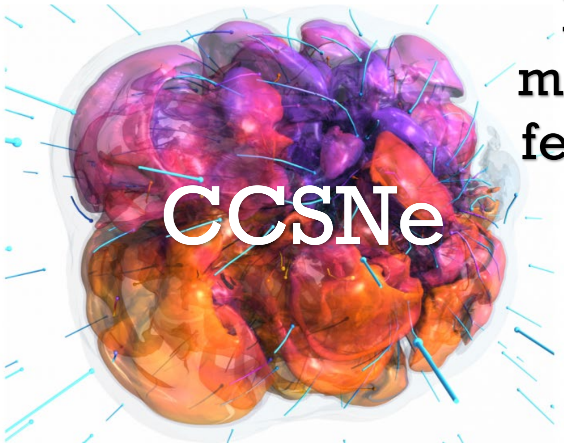
Signals

Is this the end of the story?

It's the beginning of the story…

A FEW NAÏVE FACTS

Not directly observable



How to reconstruct the microscopic/macroscopic features of a REAL CCSN?

Directly observable

Time- and **energy-** dependent neutrino events on **different detectors** and via **different neutrino reaction channels**

Microscopic nuclear physics

1. Finite-T EoSs
2. Exotic state of CCSNe matter (nuclear pasta, quark matter,…)
3. Many-body correction on neutrino-nucleon reactions
4. Neutrino flavor oscillations
5. Beyond standard model neutrino physics…

Macroscopic astro physics

1. The mass, compactness and structure of progenitor star
2. The proto-NS mass/radius
3. Rotation, magnetic fields…
4. The distance of the CCSN
5. The viewing angle of the CCSN

A PROBLEM: DEGENERACY

Candidate model A

Candidate model B

Candidate model C

...

Time and energy dependent features of neutrino events

1. What features of CCSNe neutrino signals suffer a degeneracy problem?

NO systematic study yet → Will talk （if we have time）

2. What features of CCSNe neutrino signals suffer less severe degeneracy problem?

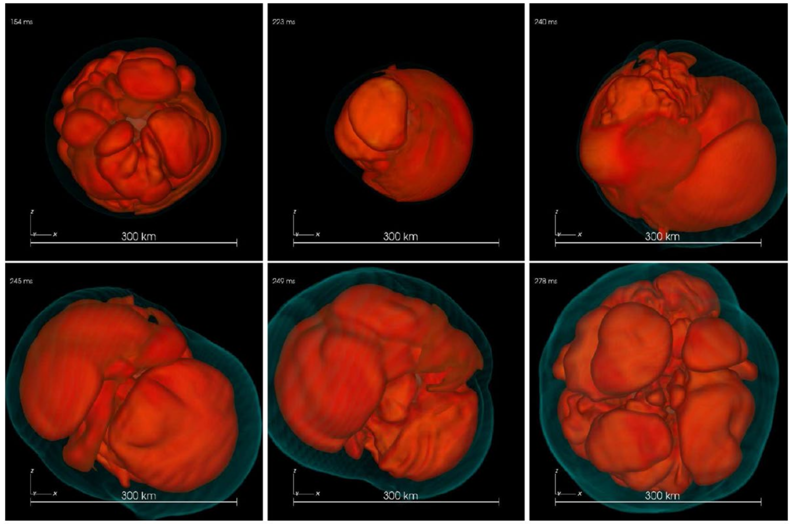
The oscillatory features, …

3. How to break the degeneracy?

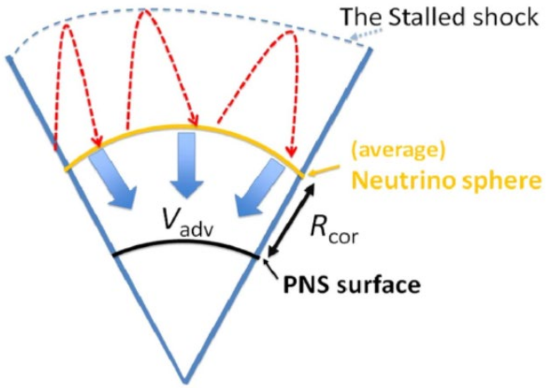
$\upsilon + GW$ analysis

This talk

OSCILLATORY υ SIGNALS: SASI



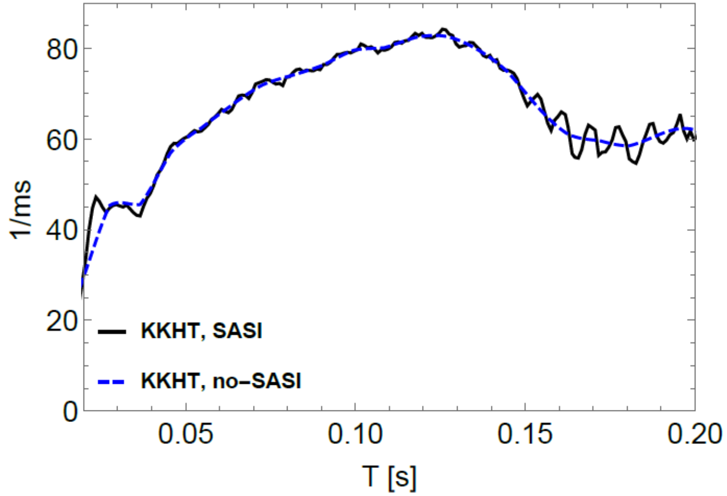
Hanke *et al.* (2013)



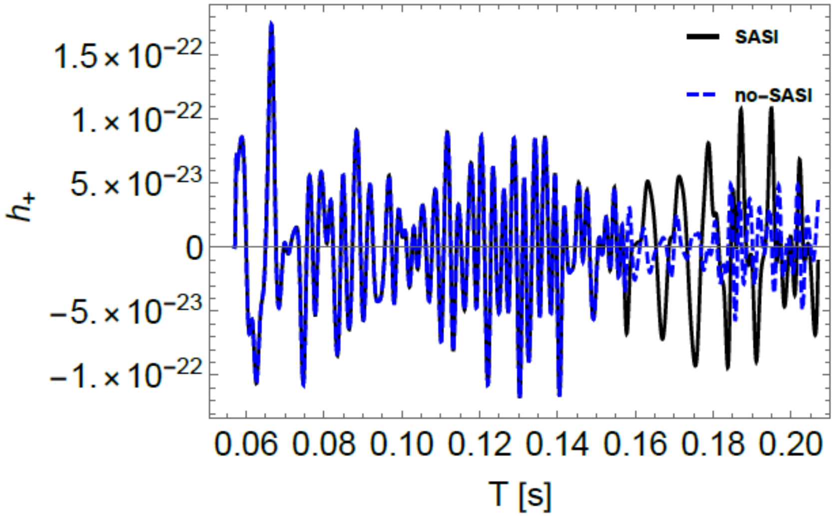
Kuroda *et al.* (2017)

υ

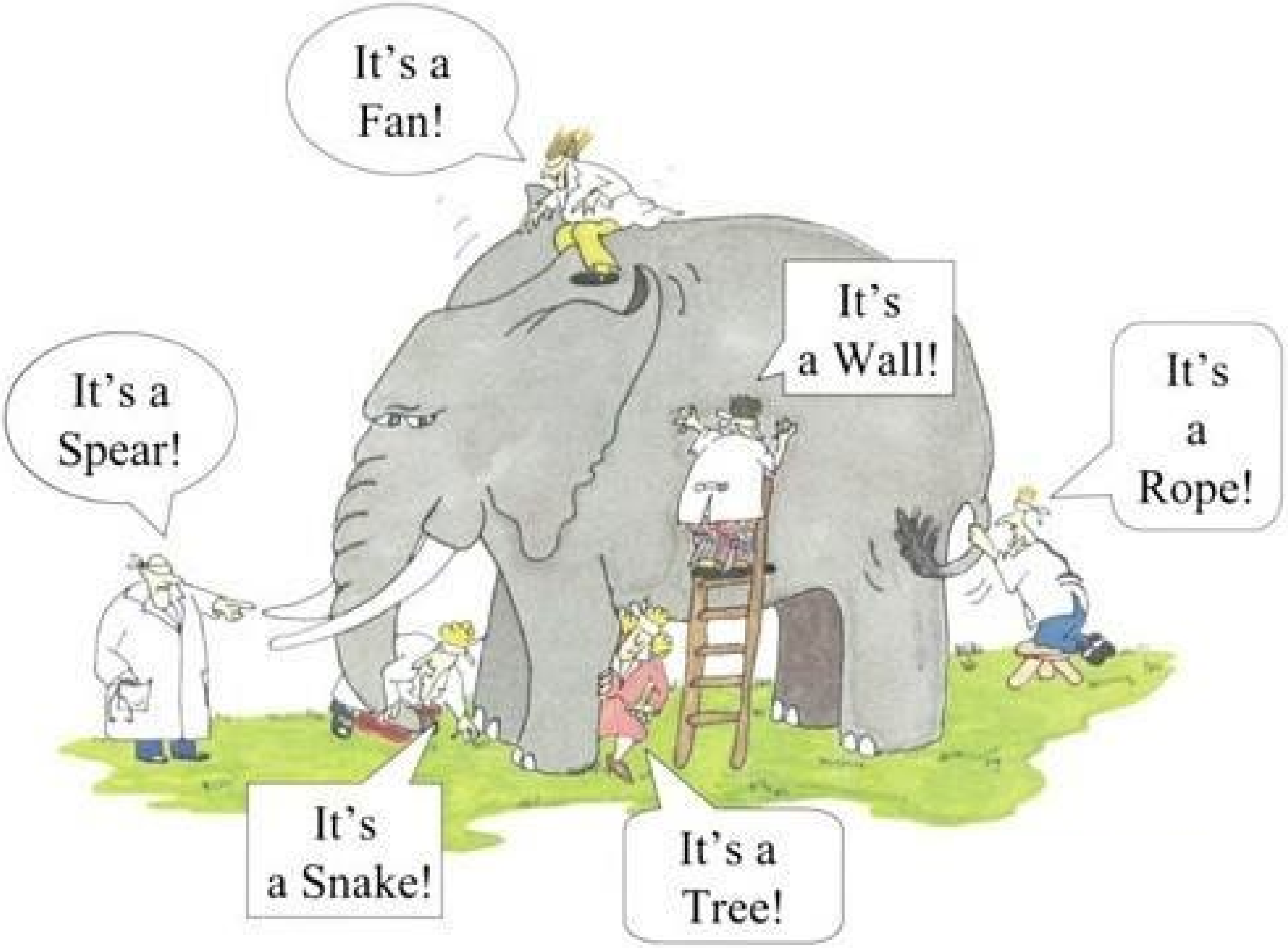
GW



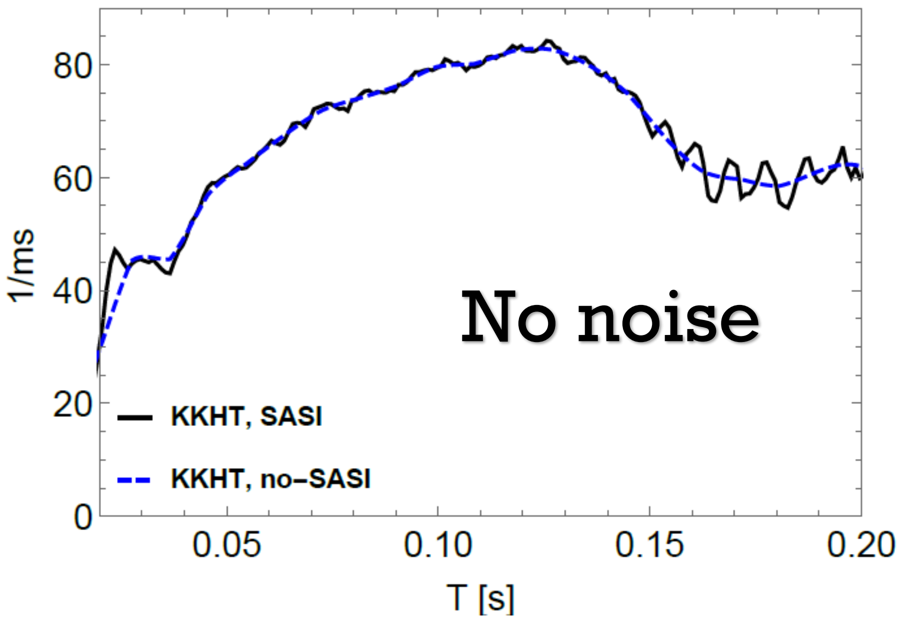
Phys. Rev. D **101**, 123028 (2020), **ZL**, CL, MZ, KK, CR
Phys. Rev. D **107**, 083017 (2023), ***ZL**, AR, CL, MM, and MZ*

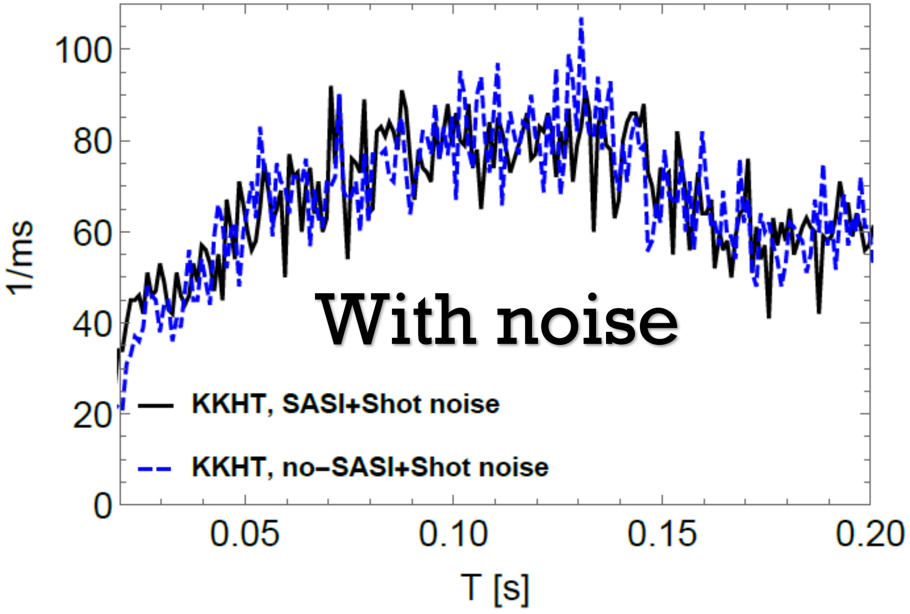


UNDERSTANDING SASI IN MULTI-MESSENGER CHANNELS



QUESTION: HOW TO CONFIRM SASI BASED ON REALISTIC ν SIGNALS?





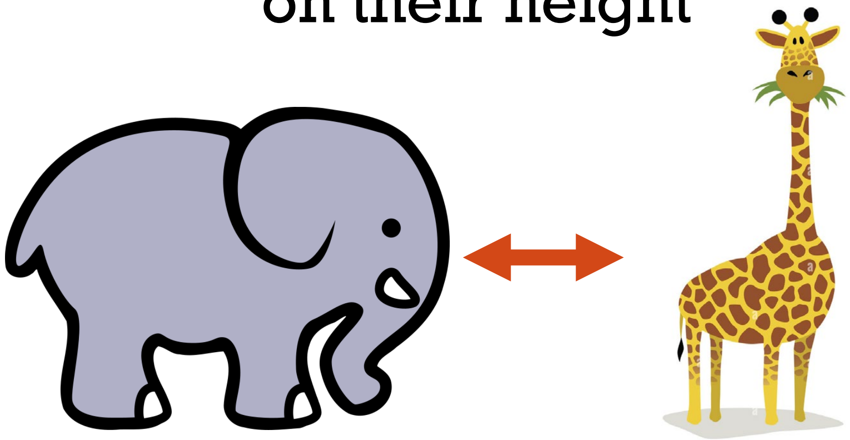
The noise comes from statistical fluctuation of ν signal itself: $\frac{Noise}{Signal} \approx \frac{\sqrt{N}}{N}$

The noise is **dependent** on the signal itself!

(note in GW case the noise is usually **independent** of the signal)

A new statistical tool quantifying υ oscillatory feature: SASI-meter

Basic idea: if you want to tell if an animal is an elephant or a giraffe based on their height

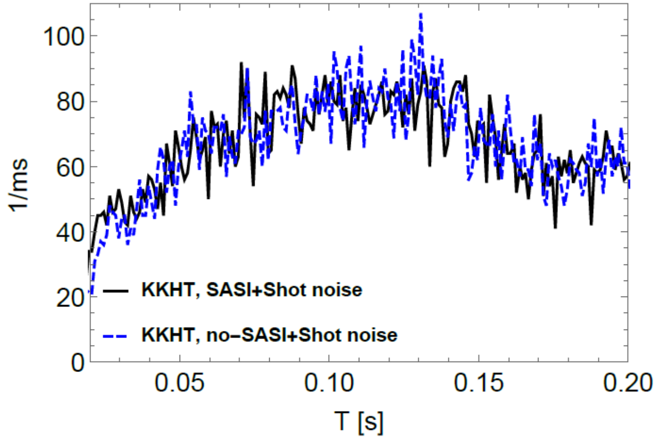


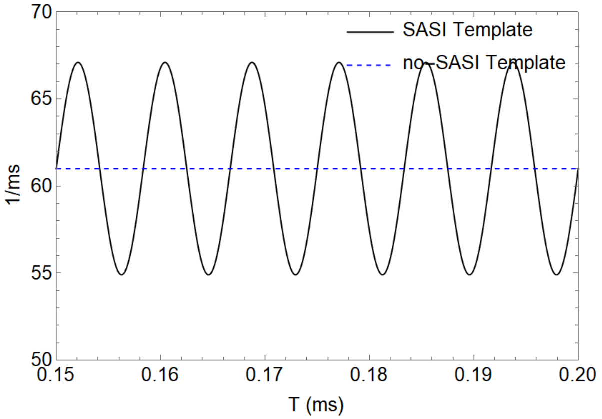
What you need is just a ruler that quantifies the height of an object…

$$N_{\mathrm{S}}(t) = (A - n)(1 + a\sin(2\pi f_{\mathrm{S}} t)) + n$$

$$N_{\mathrm{nS}}(t) = A$$

Directly comparing the oscillations on realistic υ events w/o SASI is difficult





Use a "SASI-meter" to quantify the occurrence possibility of oscillations on realistic υ events

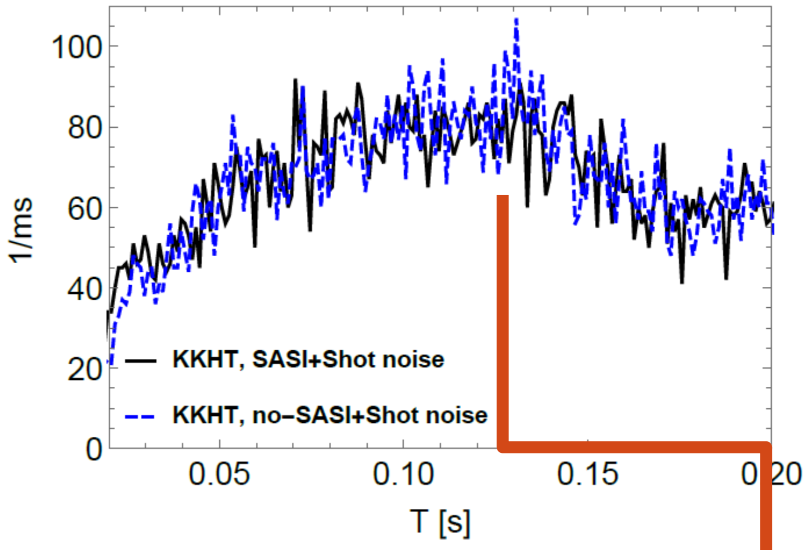
A: averaged # of neutrino events

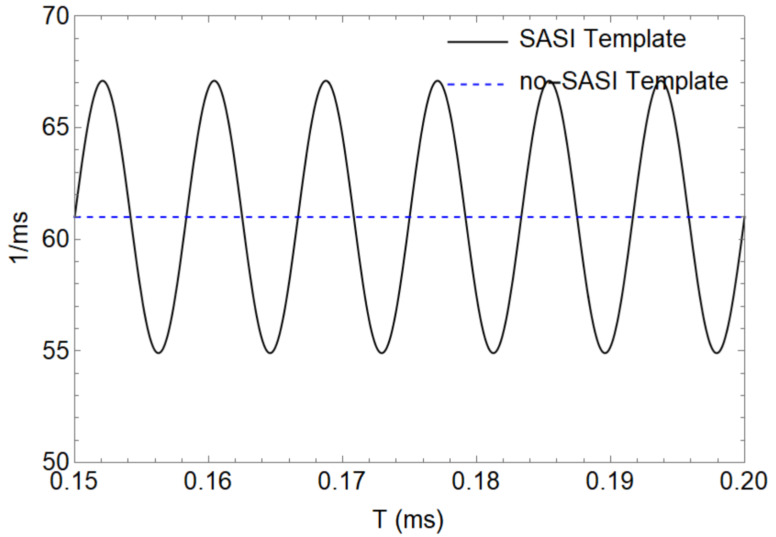
n: # of neutrino events from background

a: relative amplitude of SASI(PT)-induced oscillations

f_S: frequency of SASI(PT)-induced oscillations

Measure SASI-induced signals in υ channel





$$N_{\rm S}(t) = (A - n)(1 + a\sin(2\pi f_{\rm S} t)) + n$$

$$N_{\rm nS}(t) = A$$

SASI-Meter: $\mathcal{L}(\mathcal{P}) = \dfrac{\tilde{L}(\mathcal{P}, \tilde{\Omega}_{\rm S})}{\tilde{L}(\mathcal{P}, \tilde{\Omega}_{\rm nS})}$

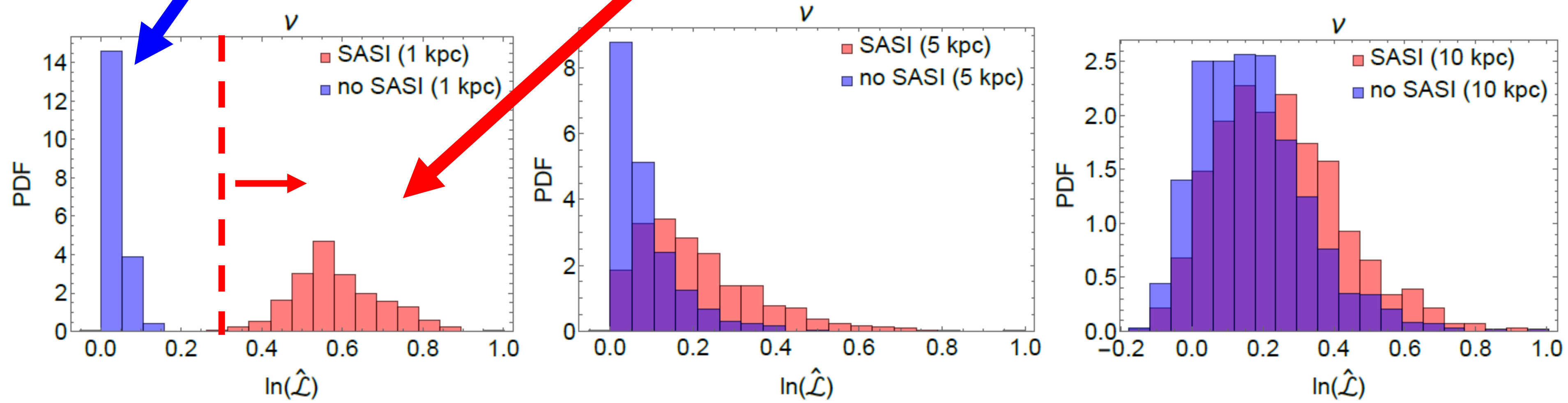
"Measure": It means to calculate the **likelihood ratio above,** which indicates the tendency that the power spectrum of realistic υ signals favoring SASI template over no-SASI template

$$\mathcal{L}(P_{nS}) = \frac{\tilde{L}(P_{nS}, \tilde{\Omega}_S)}{\tilde{L}(P_{nS}, \tilde{\Omega}_{nS})}$$

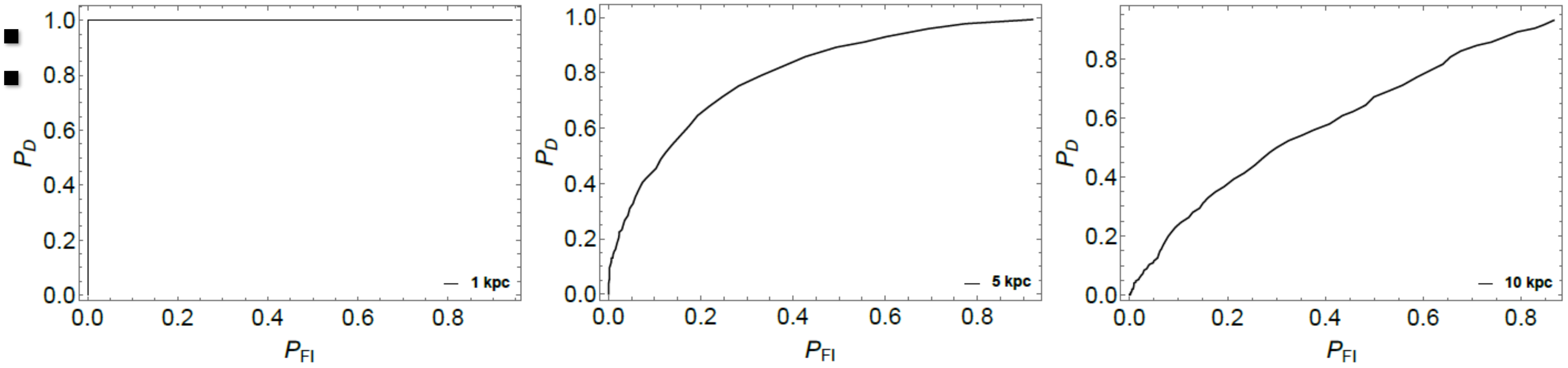
$$\mathcal{L}(P_S) = \frac{\tilde{L}(P_S, \tilde{\Omega}_S)}{\tilde{L}(P_S, \tilde{\Omega}_{nS})}$$

Phys. Rev. D **101**, 123028 (2020), **ZL**, CL, MZ, KK, CR

Phys. Rev. D **107**, 083017 (2023), ***ZL**, AR, CL, MM, and MZ*



ROC:



GW SASI-meter

H_1: waveform model with SASI

H_0: noise model without SASI

$$\Lambda(x) = \frac{\boxed{p(x|H_1)}}{\boxed{p(x|H_0)}}$$

$$\boxed{p(x|H_1) = \prod_{i=1}^{I} \frac{1}{\sqrt{2\pi\sigma}} e^{-\left(\frac{(x[i]-\xi[i])^2}{2\sigma^2}\right)}}$$

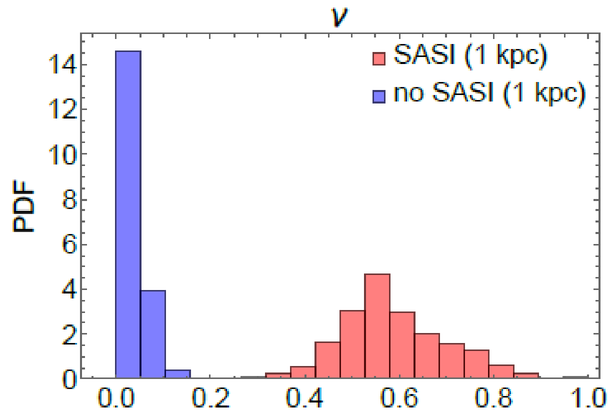
$$\boxed{p(x|H_0) = \prod_{i=1}^{I} \frac{1}{\sqrt{2\pi\sigma}} e^{-\left(\frac{x^2[i]}{2\sigma^2}\right)}}$$

$$\rho = \ln(\Lambda(x)) = \ln\left(\prod_{i=1}^{I} e^{\left(\frac{1}{\sigma^2}(x[i]\xi[i]-\frac{1}{2}\xi^2[i])\right)}\right)$$

$$= \sum_{i=1}^{I} \frac{1}{\sigma^2}\left(x[i]\xi[i] - \frac{1}{2}\xi^2[i]\right)$$

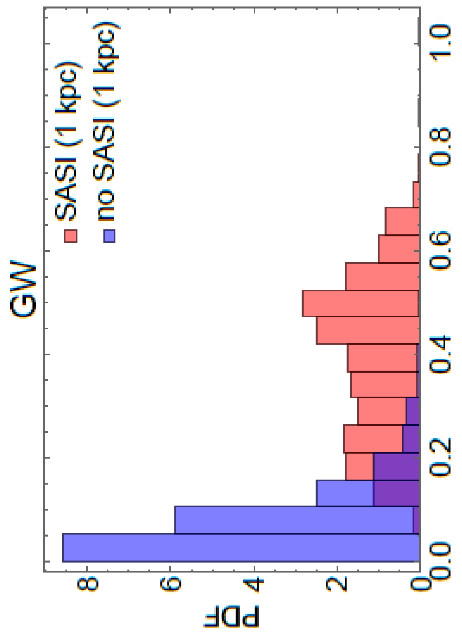
See Michele's talk yesterday for more details about the GW SASI-meter

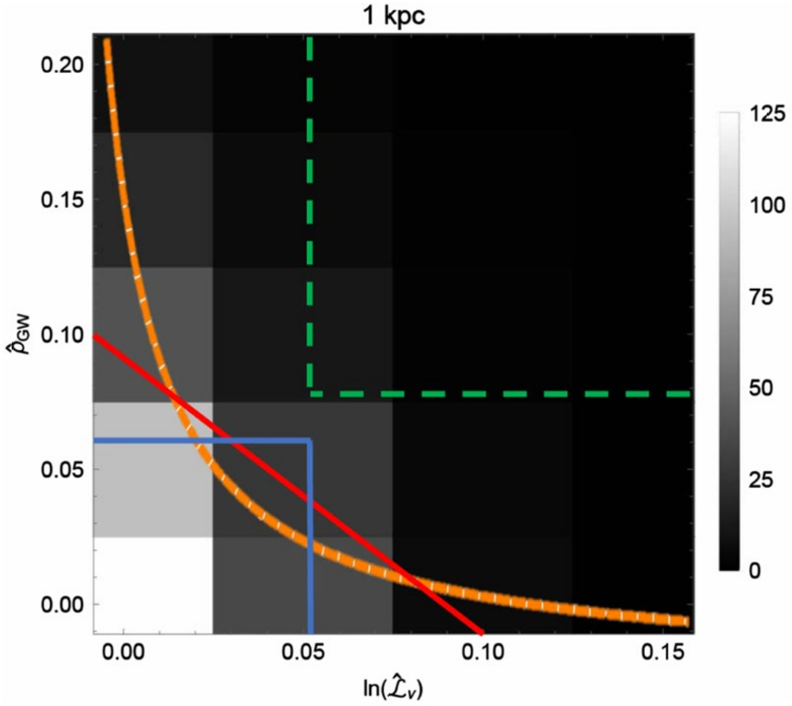
2-D PDF of Joint Likelihood Ratio



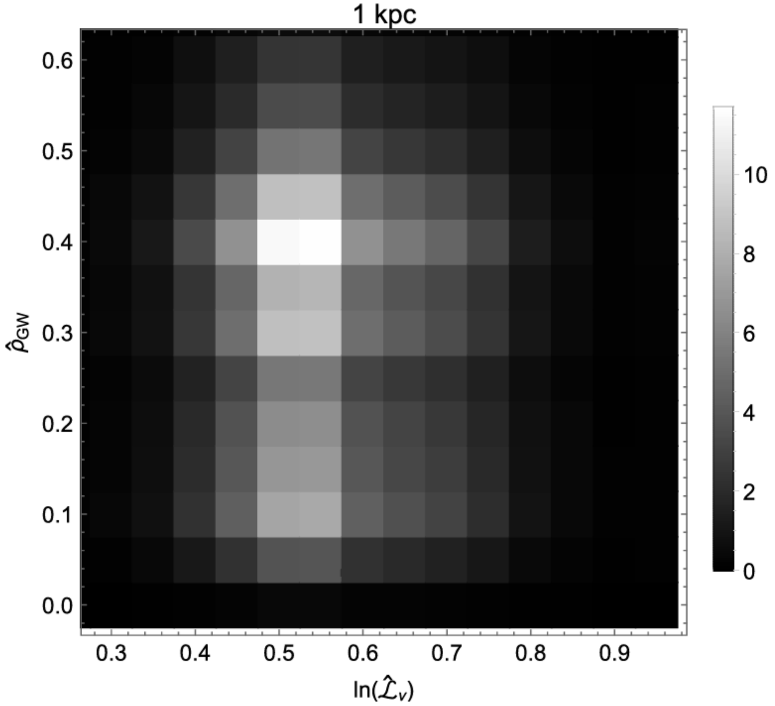
$$Prob_{\mathrm{S}}(ln(\mathcal{L}),\rho) = Prob_{\nu,\mathrm{S}}(ln(\mathcal{L}))Prob_{\mathrm{GW,S}}(\rho)$$

$$Prob_{\mathrm{nS}}(ln(\mathcal{L}),\rho) = Prob_{\nu,\mathrm{nS}}(ln(\mathcal{L}))Prob_{\mathrm{GW,nS}}(\rho)$$

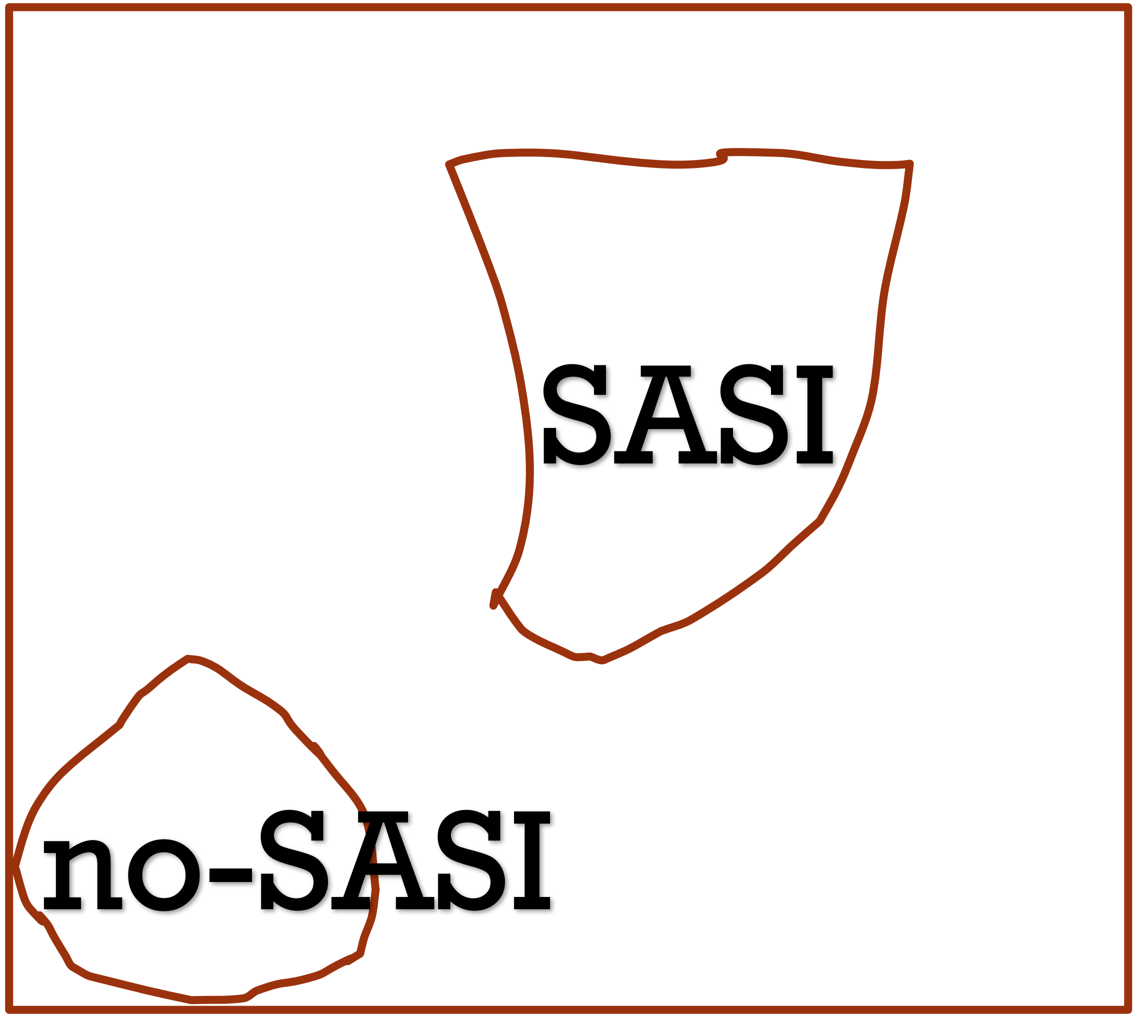




no-SASI



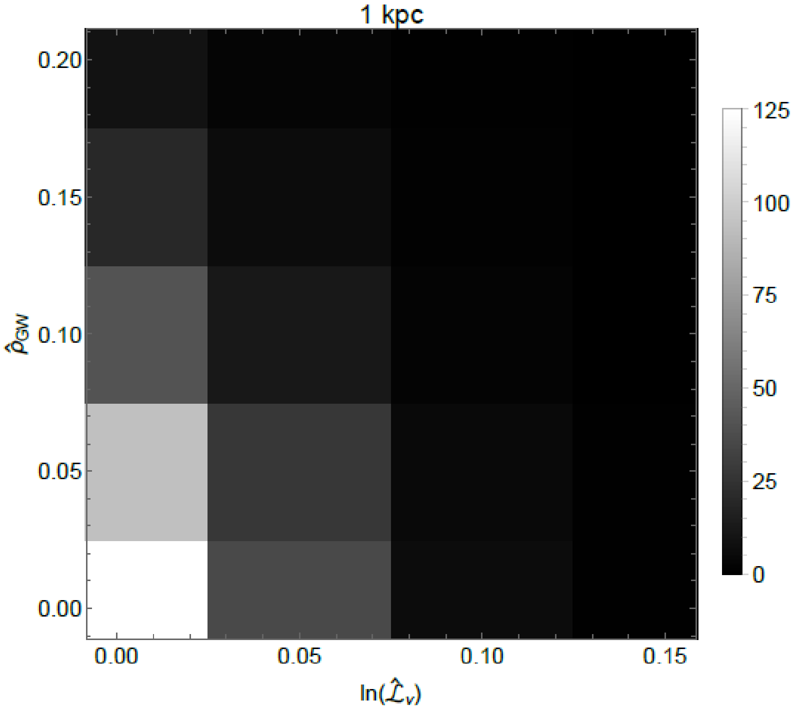
SASI

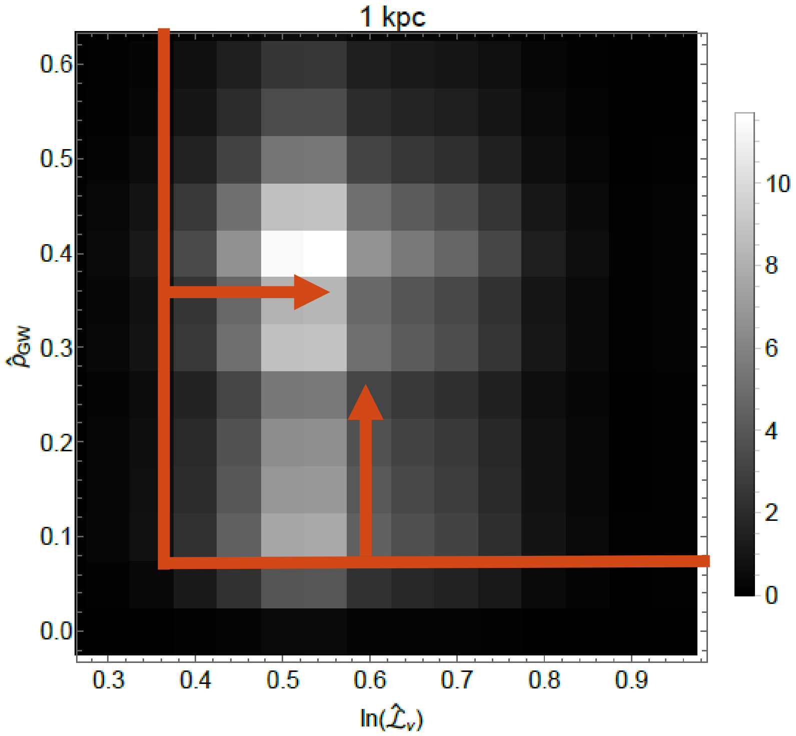


In **1-D**, the threshold distinguishing SASI and no-SASI PDF is a **value**.
In **2-D**, the threshold distinguishing SASI and no-SASI PDF is a **curve**, and there can be more than one ways to define the 2-D threshold.

How to distinguish PDF of SASI from PDF of no-SASI in a 2-D map?

1: Logical "And"

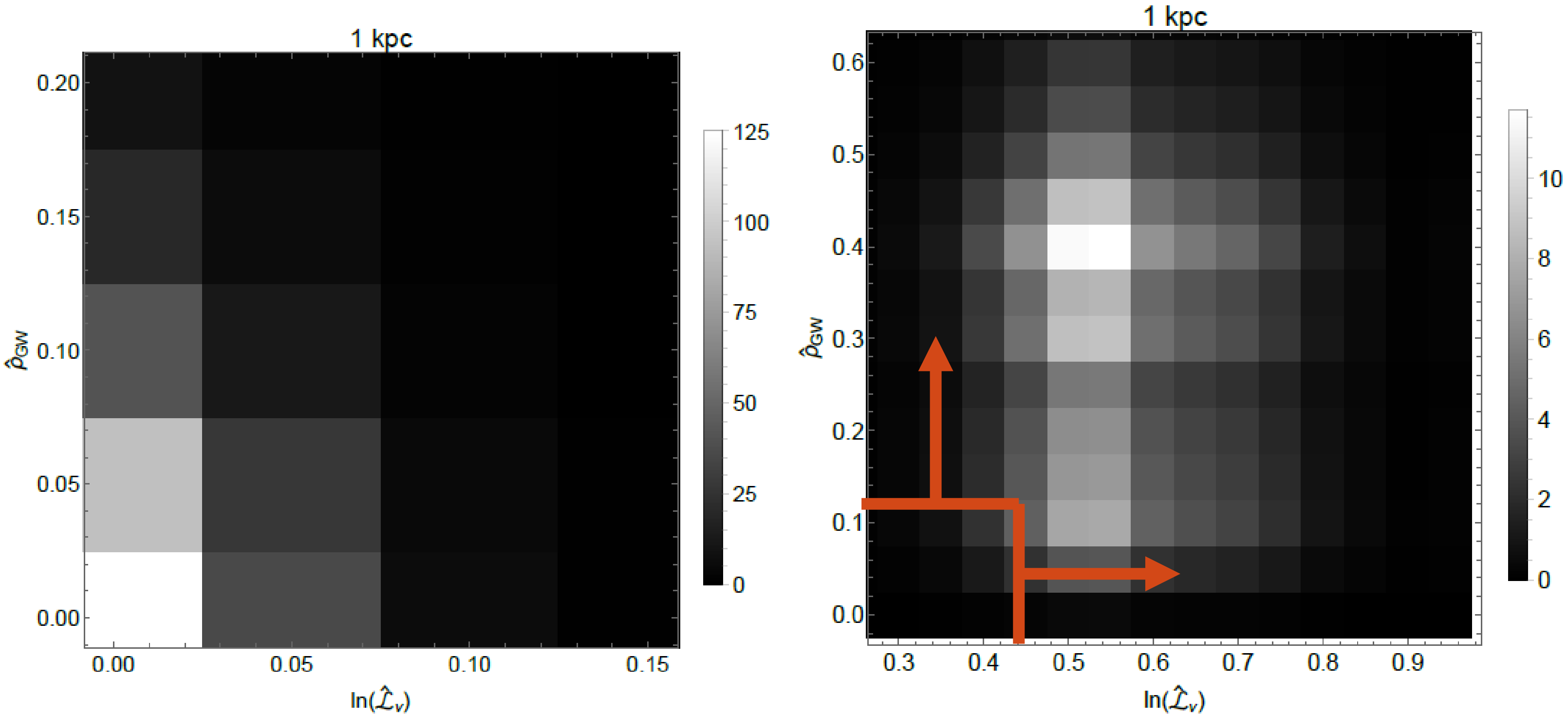




$$P_{\mathrm{D}}^{comb} = P_{\mathrm{D}}^{\nu} \times P_{\mathrm{D}}^{GW}$$
$$= \int_{\Lambda_\nu}^{\infty} \int_{\Lambda_{GW}}^{\infty} dln(\mathcal{L}) d\rho Prob_{\nu,\mathrm{S}}(ln(\mathcal{L})) Prob_{\mathrm{GW,S}}(\rho)$$

How to distinguish PDF of SASI from PDF of no-SASI in a 2-D map?

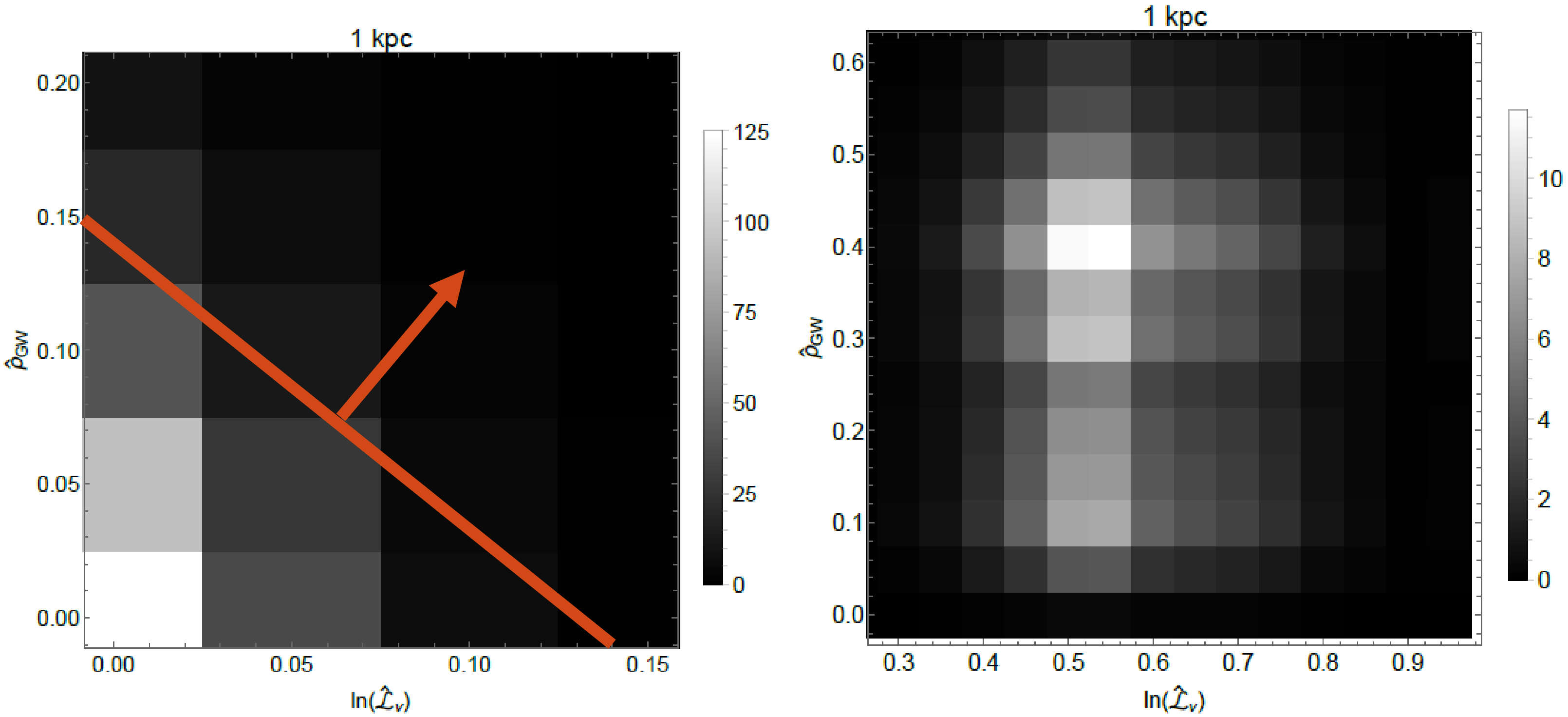
2: Logical "Or"



$$P_{\rm D}^{comb} = 1 - (1 - P_{\rm D}^{\nu}) \times (1 - P_{\rm D}^{GW})$$
$$= 1 - \int_0^{\Lambda_\nu} \int_0^{\Lambda_{GW}} dln(\mathcal{L}) d\rho Prob_{\nu,\rm S}(ln(\mathcal{L})) Prob_{\rm GW,S}(\rho)$$

How to distinguish PDF of SASI from PDF of no-SASI in a 2-D map?

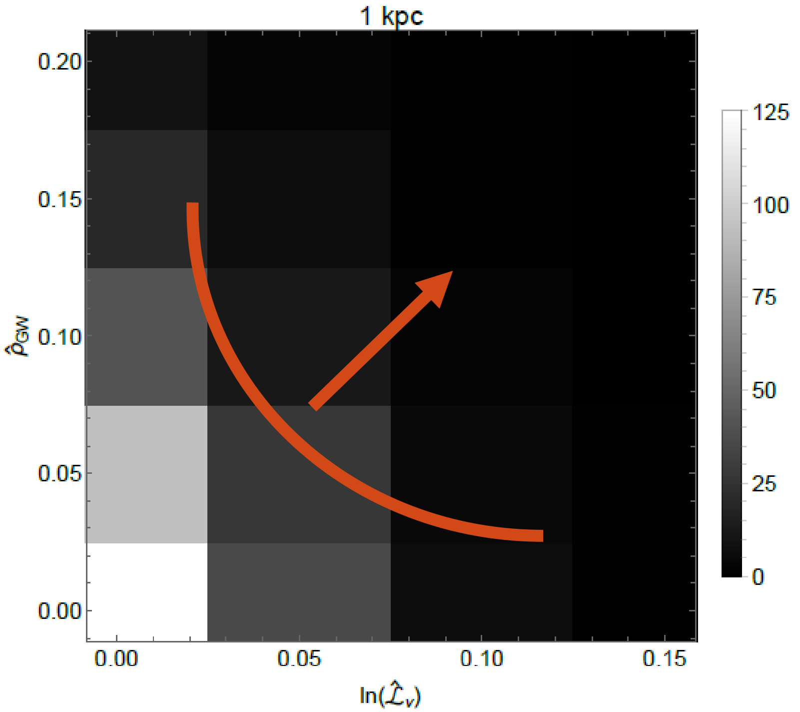
3:X+Y=const

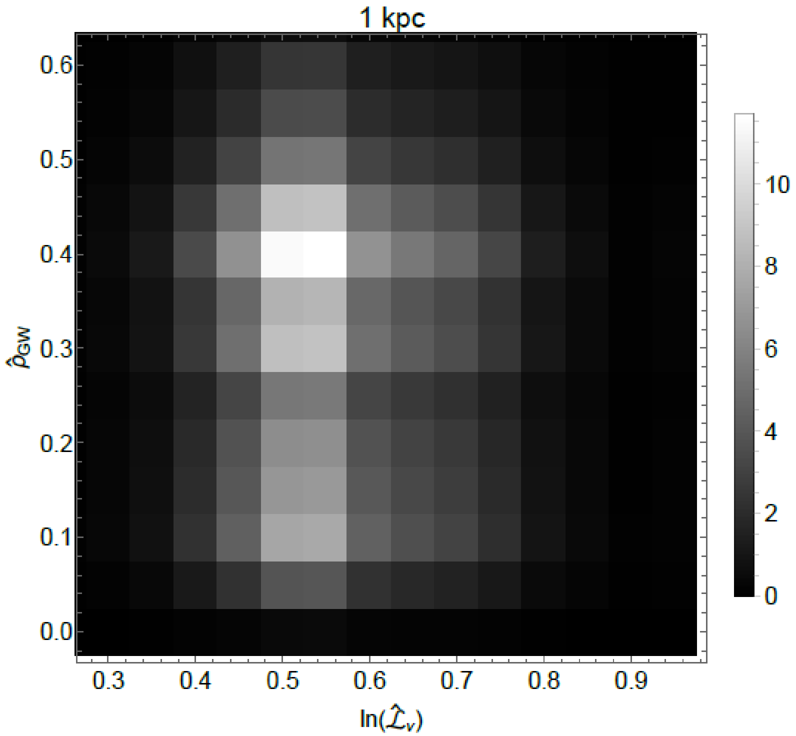


$$P_{\mathrm{D}}^{comb,x+y} = \int_{\mathcal{L}+\rho>\Lambda}^{\infty} dln(\mathcal{L}) d\rho Prob_{\nu,\mathrm{S}}(ln(\mathcal{L})) Prob_{\mathrm{GW},\mathrm{S}}(\rho)$$

How to distinguish PDF of SASI from PDF of no-SASI in a 2-D map?

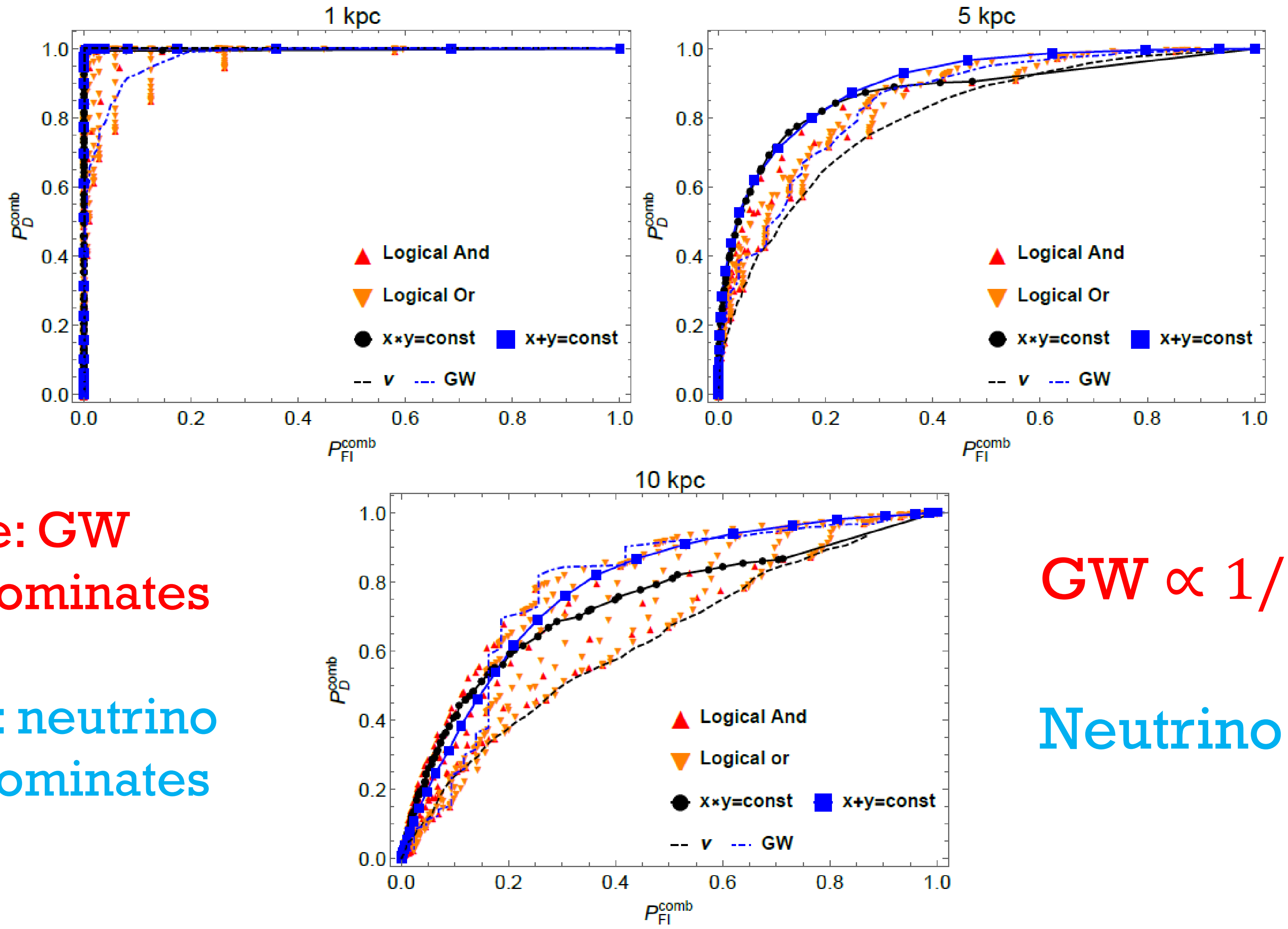
3:X*Y=const





$$P_{\rm D}^{comb,x\times y} = \int_{\mathcal{L}\times\rho>\Lambda}^{\infty} dln(\mathcal{L})d\rho Prob_{\nu,\rm S}(ln(\mathcal{L}))Prob_{\rm GW,S}(\rho)$$

ROC from Multi-messenger analysis



High distance: GW messenger dominates

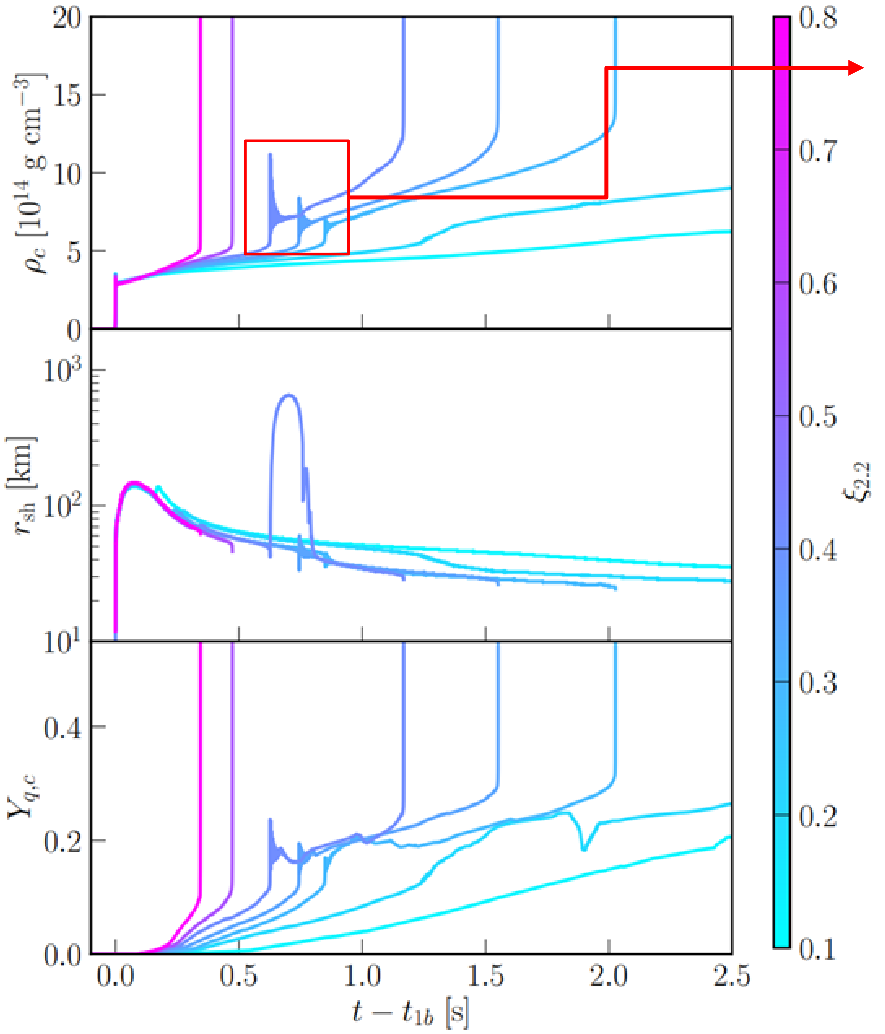
Low distance: neutrino messenger dominates

GW ∝ 1/D

Neutrino ∝ $1/D^2$

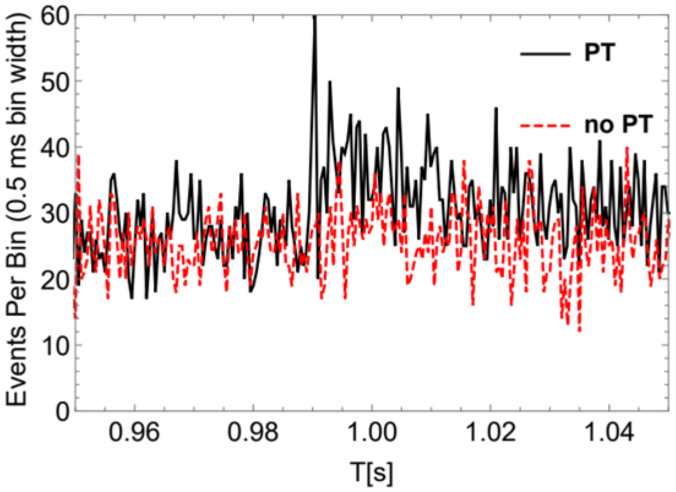
OSCILLATORY ν SIGNALS: PHASE TRANSITION

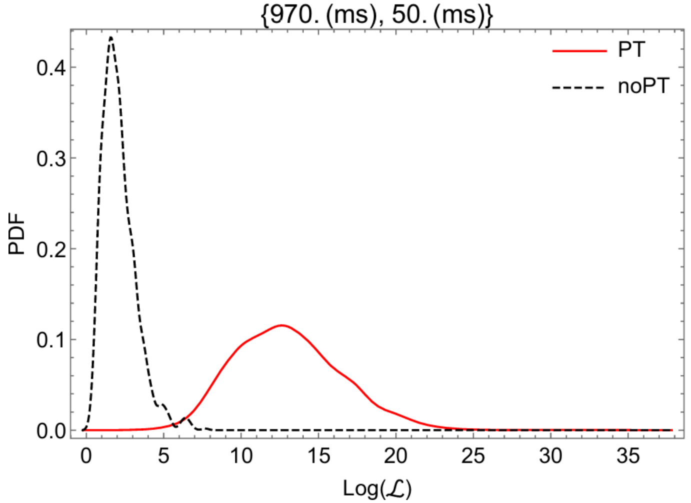
Shuai Zha *et al* 2021 ApJ 911 74



The oscillation of proto-compact star after the 2nd bounce due to hadron-quark phase transition

Phys. Rev. D 109, 023005 (2024), **ZL**, SZ, EPO, AWS





Use a **PT-meter** to analyze the **detectability, the frequency, the starting time, the duration** of the PT-induced oscillation, the damping of PT-induced oscillation is related to **bulk viscosity** of the hybrid star.

What features of CCSNe neutrino signals suffer a degeneracy problem?

$< \mathrm{E}_{\upsilon} >, L_{\nu}(t), \ldots$

Could be influenced by many micro/macroscopic physics and the approximations made in neutrino transport equations

How to systematically analyze the degeneracy of CCSNe models?

A BAYESIAN INFERENCE WITH A GAUSSIAN MIXTURE MODEL AS THE PRIOR OF υ FLUENCE

$$Prior\left(\vec{F}(E)\right) = \sum_{i}^{CCSNe\ models} w_i \times G(\vec{F}(E)|\vec{F}_{i,Mean}, Cov_i + Cov_{noise})$$

First layer of hyper-parameters: w_i is the weight of CCSNe models; Cov_{noise} is the uncertainty of CCSNe models

Second layer of hyper-parameters: l_i and σ_i characterizing the kernel $\sigma_i^2 \exp(-\frac{(E-E')^2}{2l_i^2})$ of Cov_i

Given the Prior distribution:

(1) Draw a realization of $\vec{F}(E)$ from the prior;
(2) Calculate the corresponding likelihood of $\vec{F}(E)$ $\mathcal{L}(\vec{F}(E)|\{F_{exp}, \Delta F_{exp}\})$ given (discrete) experimental data and uncertainties
(3) Repeat until sample size is sufficient

A GAUSSIAN MIXTURE MODEL AS THE PRIOR OF $F_v(E)$

$$Prior\left(\vec{F}(E)\right) = \sum_{i}^{CCSNe\ models} w_i \times G(\vec{F}(E)|\vec{F}_{i,Mean}, Cov_i + Cov_{noise})$$

First layer of hyper-parameters: w_i is the weight of CCSNe models; Cov_{noise} is the uncertainty of CCSNe models

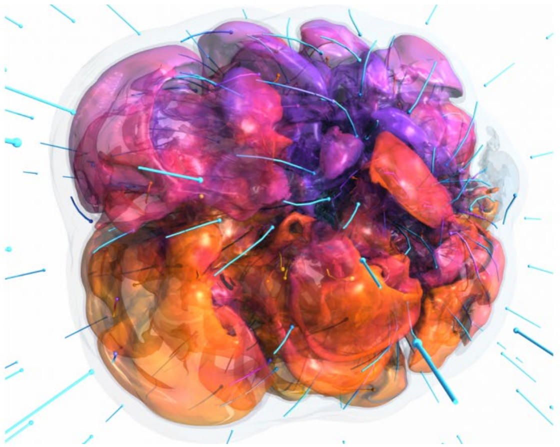
Second layer of hyper-parameters: l_i and σ_i characterizing the kernel $\sigma_i^2 \exp(-\frac{(E-E')^2}{2l_i^2})$ of Cov_i

Given the Prior distribution:

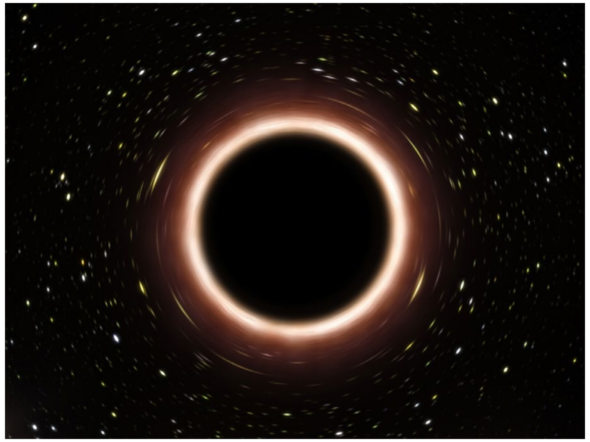
We have posterior distribution of not only $\vec{F}(E)$, **but also w_i and Cov_{noise}.**

Posterior distribution of w_i and Cov_{noise} are useful to **identify the CCSNe models** and **quantify their errors** given experimental observations in this new framework.

A TOY MODEL



A successful CCSN explosion (15.01 $M_\odot$)
Model A

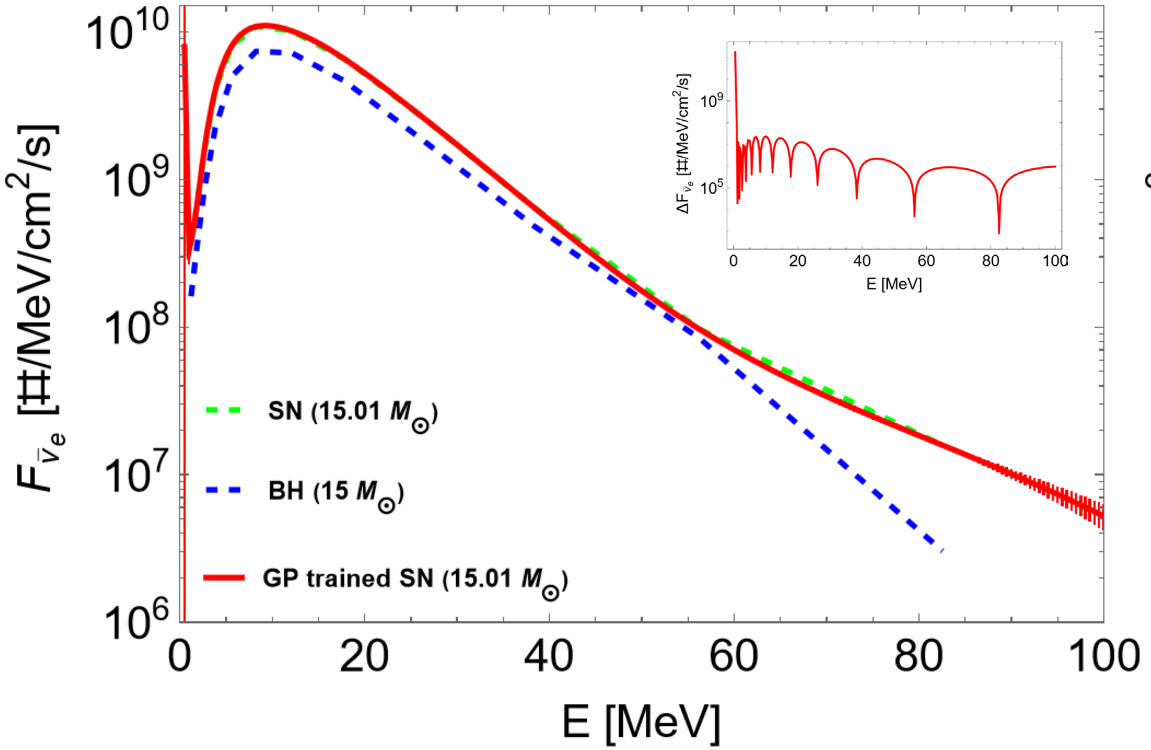


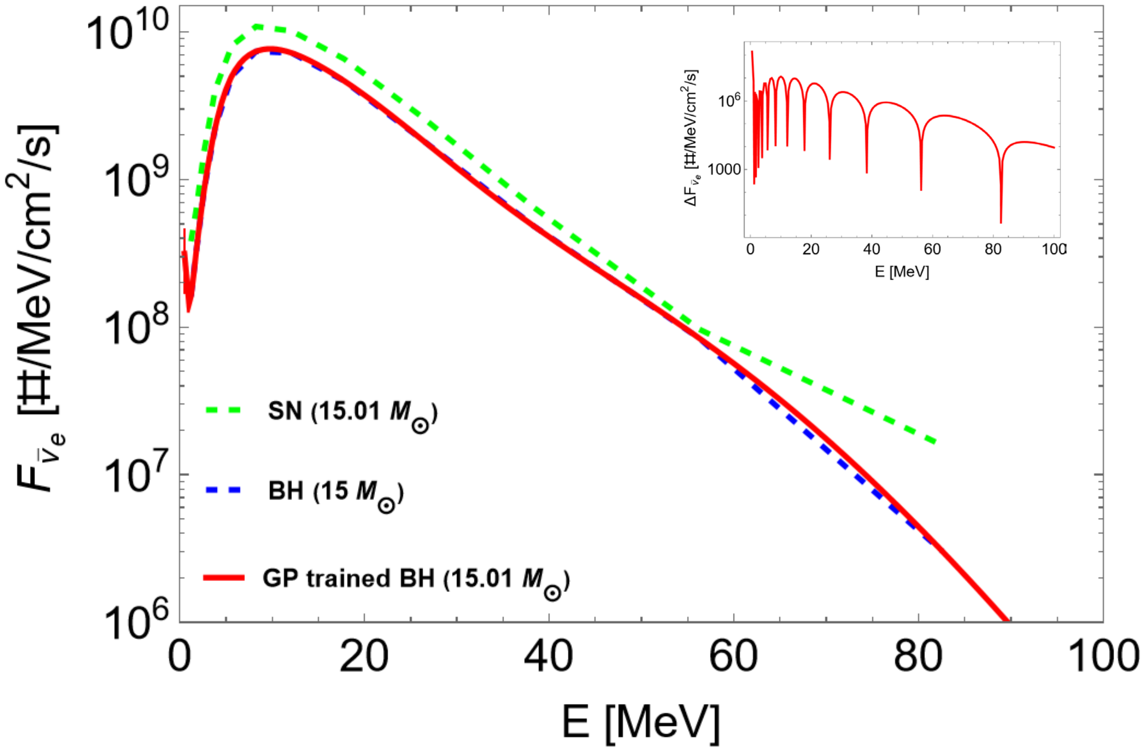
A failed CCSN explosion (15 $M_\odot$) that collapse to a BH
Model B

From MNRAS, Volume 526, Issue 4 (2023) D. Vartanyan, and A. Burrows

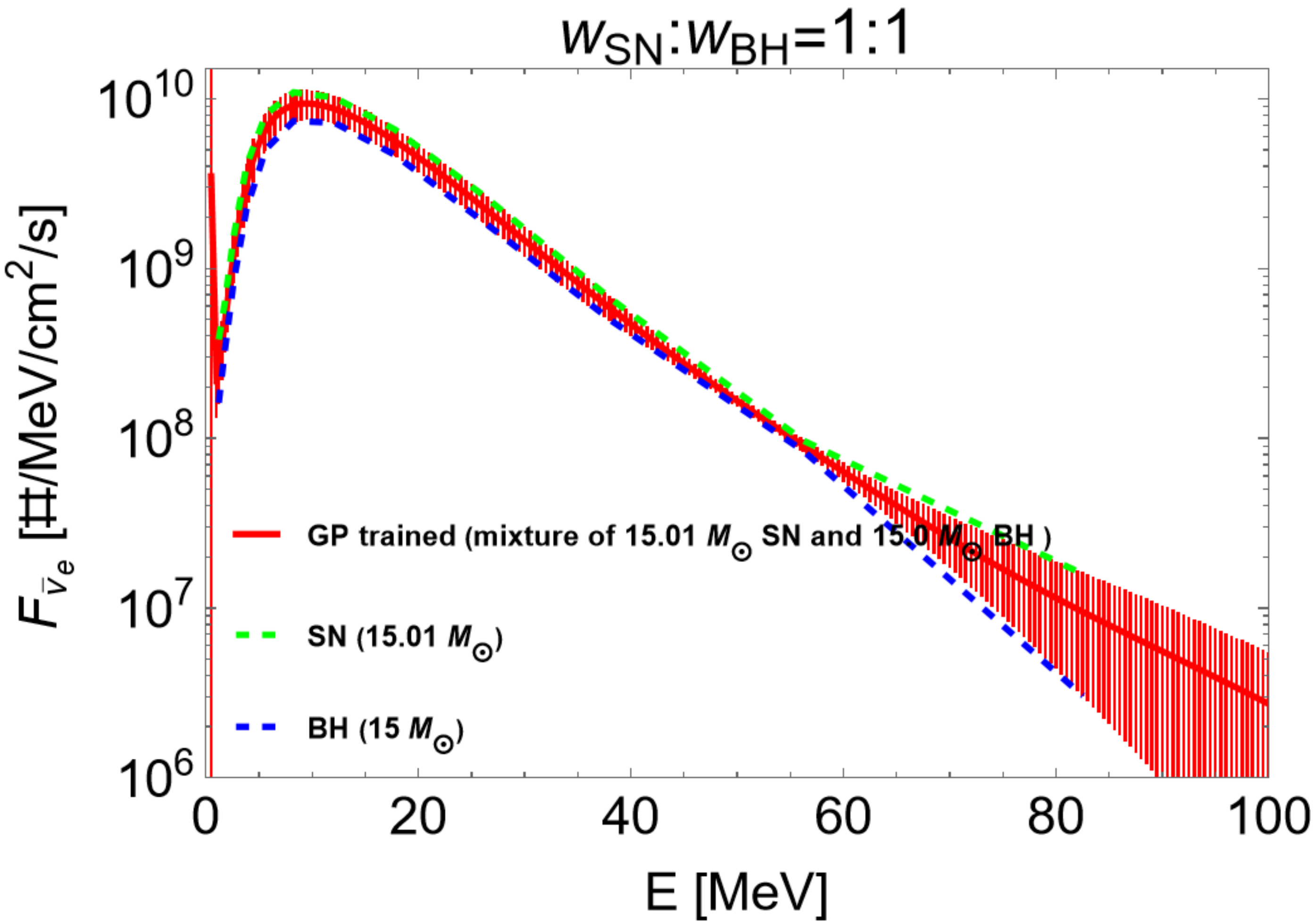
We train the GP and create a **Gaussian mixture model** as the prior of neutrino fluences based on model A and B

TRAINED GP NEUTRINO FLUENCES (WITHOUT NOISE)



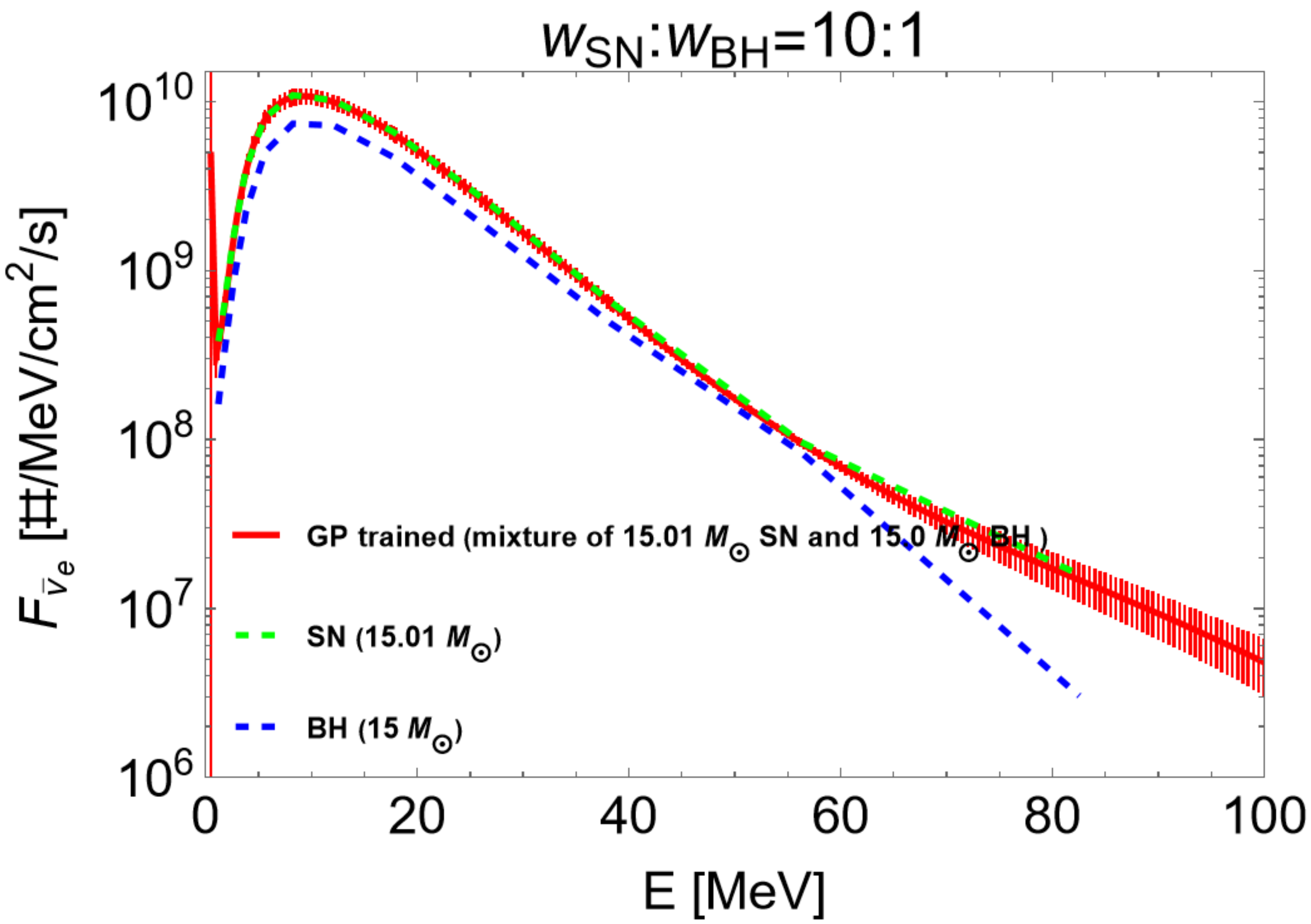


TRAINED GP MIXTURE MODEL (WITHOUT NOISE)



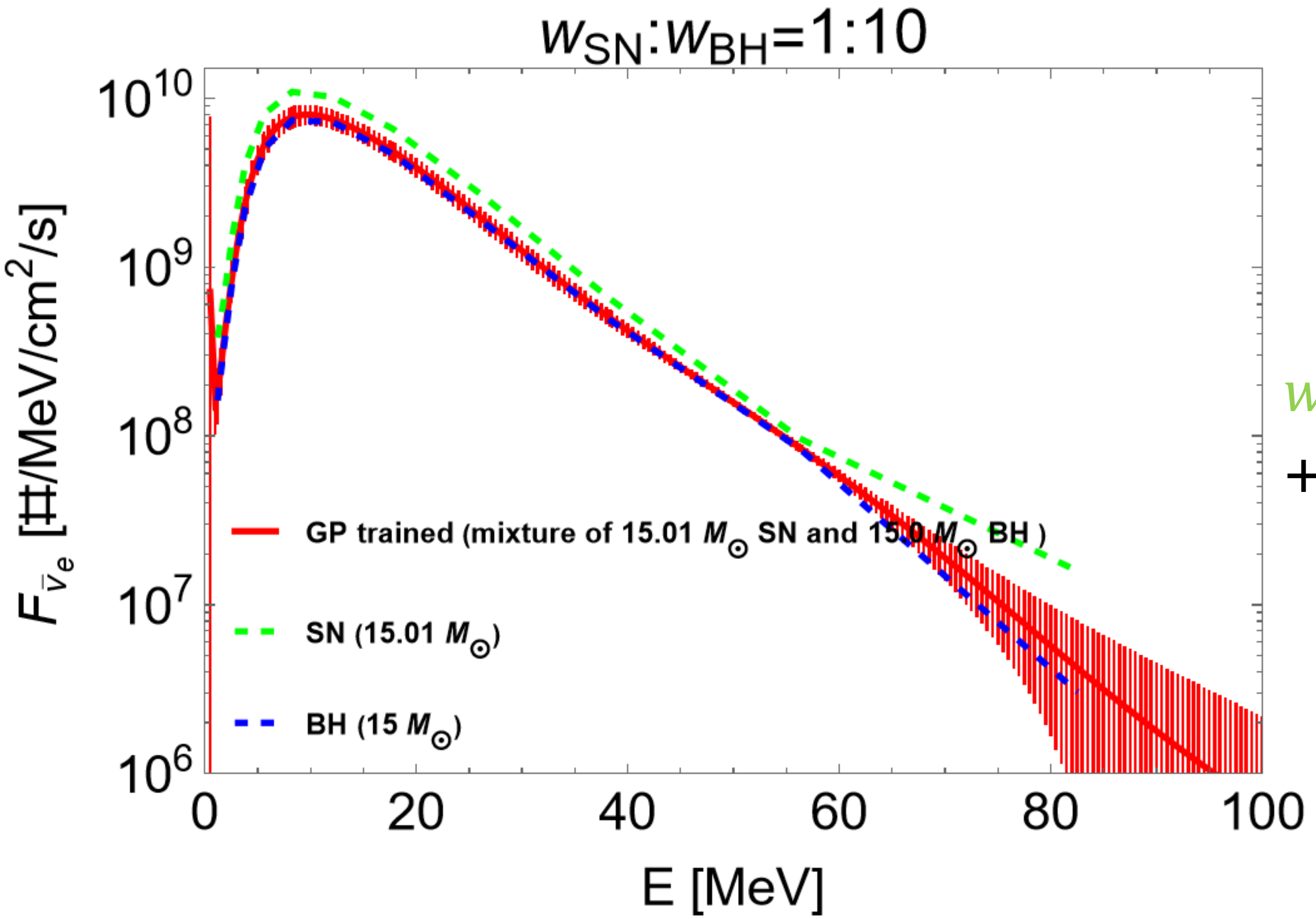
$$Prior\left(\vec{F}(E)\right) =$$
$$w_{SN} \times G(\vec{F}(E)|\vec{F}_{SN,Mean}, Cov_{SN})$$
$$+\, w_{BH} \times G(\vec{F}(E)|\vec{F}_{BH,Mean}, Cov_{BH})$$

TRAINED GP MIXTURE MODEL (WITHOUT NOISE)



$$Prior\left(\vec{F}(E)\right) =$$
$$w_{SN} \times G(\vec{F}(E)|\vec{F}_{SN,Mean}, Cov_{SN})$$
$$+ w_{BH} \times G(\vec{F}(E)|\vec{F}_{BH,Mean}, Cov_{BH})$$

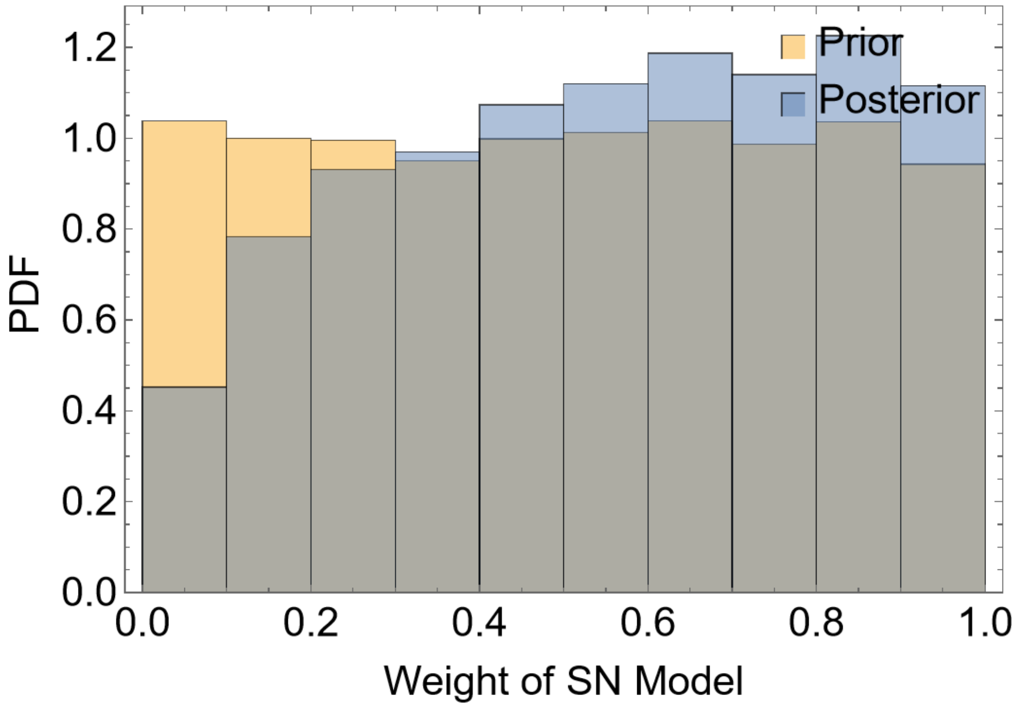
TRAINED GP MIXTURE MODEL (WITHOUT NOISE)

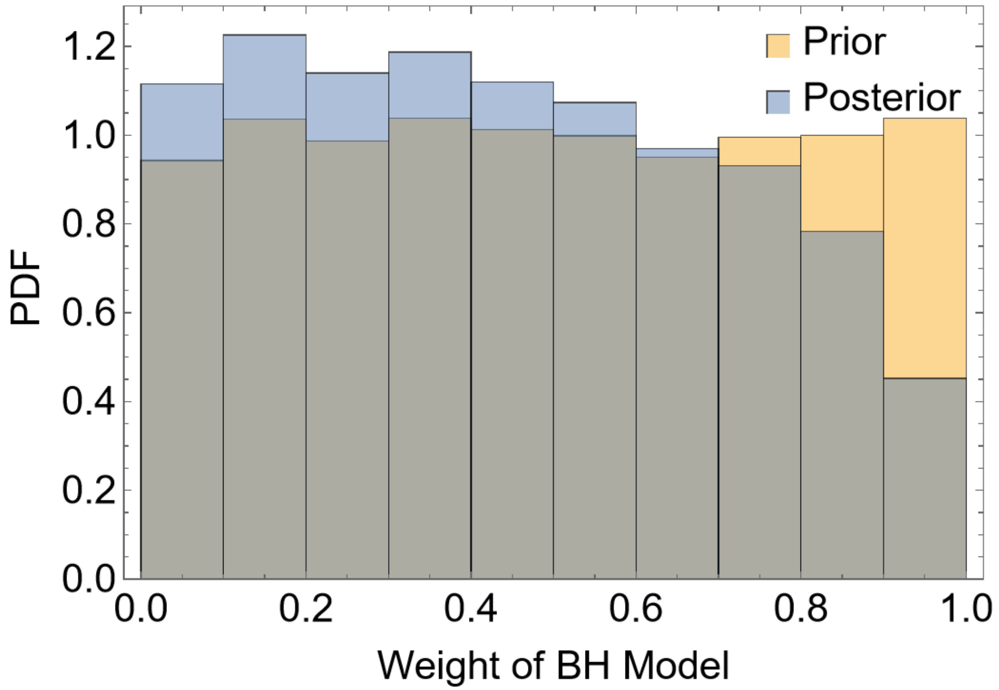


$$Prior\left(\vec{F}(E)\right) =$$
$$w_{SN} \times G(\vec{F}(E)|\vec{F}_{SN,Mean}, Cov_{SN})$$
$$+\, w_{BH} \times G(\vec{F}(E)|\vec{F}_{BH,Mean}, Cov_{BH})$$

POSTERIOR OF MODEL WEIGHTS

Assuming we have a pseudo observation
coming from SN model





CONCLUSION

1. An effective way (SASI/PT-meter) that statistically analyze the oscillatory features on the CCSNe neutrino signals

2. The detectability of SASI can be improved (in a specific range of CCSN distance) by jointly analyzing neutrino and GW signatures

3. Bayesian inference method based on Gaussian mixing model to study the degeneracy problem in CCSNe model identification

QUESTIONS

(1)How to build the prior of CCSNe models?
(2)How to jointly use neutrino, GW and EM constraints from the next galactic CCSNe in a Bayesian inference?

ACKNOWLEDGEMENT:

I thank all my collaborators (listed in the 1st page) and

(1)A. Burrows and D. Vartanyan for the discussion of CCSNe simulations and providing the CCSNe neutrino data,

(2) K. Scholberg for the discussion of neutrino detectors,

(3) P. Landry for the discussion of GP

(4) Y. Saito for the discussion of Ensemble Bayesian model averaging

Thank you!