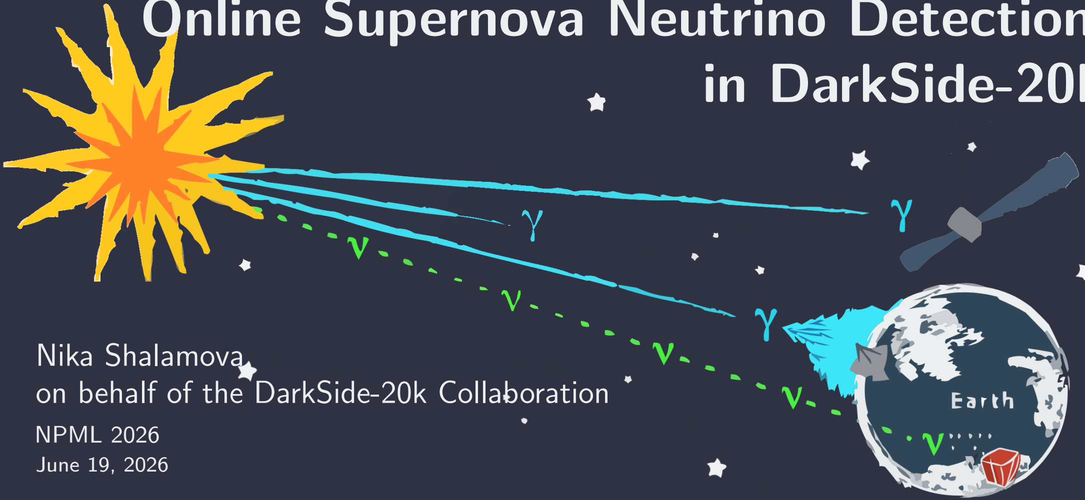
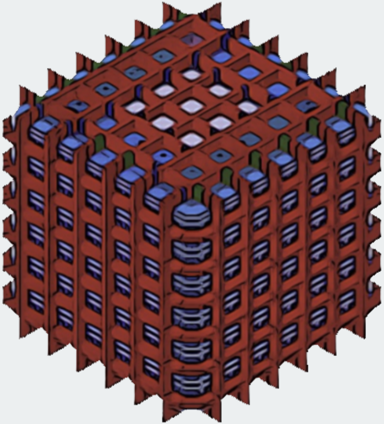
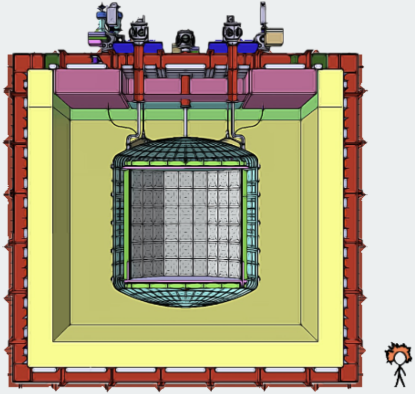
Machine Learning for Online Supernova Neutrino Detection in DarkSide-20k



Nika Shalamova
on behalf of the DarkSide-20k Collaboration

NPML 2026
June 19, 2026



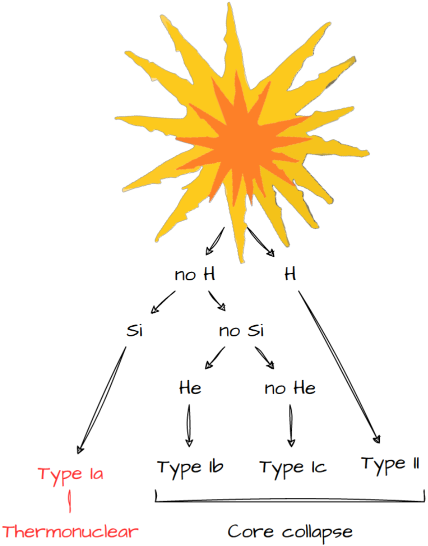


- 50 t liquid Ar TPC (Time Projection Chamber)
- Under construction at LNGS
- Underground Ar from the URANIA and ARIA

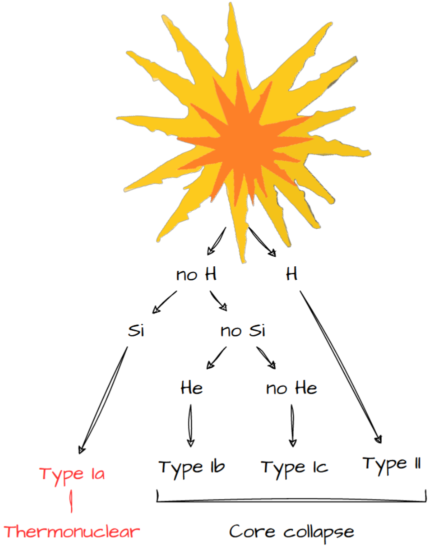
- 650 t atmospheric Ar Outer Veto + 32 t UAr Inner Veto
- $\sim 21\text{m}^2$ cryogenic SiPMs
- Scheduled to start operations in **2028** and run for 10 years

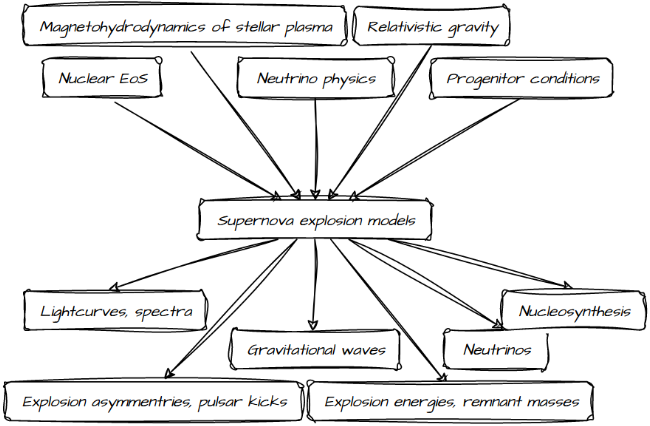
Supernovae and their neutrinos

Supernovae and their neutrinos

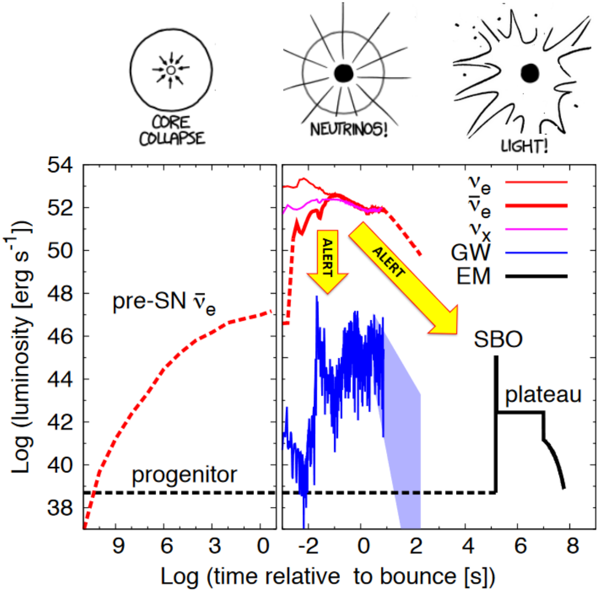


Supernovae and their neutrinos





pic: https://xkcd.com/ + NS



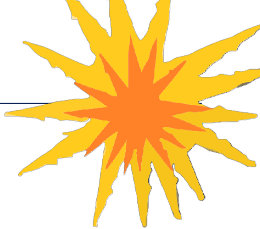
New J. Phys. 23 031201 (2021) "SNEWS 2.0: A Next-Generation SuperNova Early Warning System for Multi-messenger Astronomy"

SNEWS2.0

If several detectors report a potential SN within a small time window, SNEWS will issue an alert to its subscribers

- astronomical observatories
- neutrino detectors
- amateur astronomers and citizen scientists

Neutrino signal



$$E \sim 10^{53}\,\mathrm{erg} = 10^{46}\,\mathrm{J} \sim 10^{59}\,\mathrm{MeV}$$

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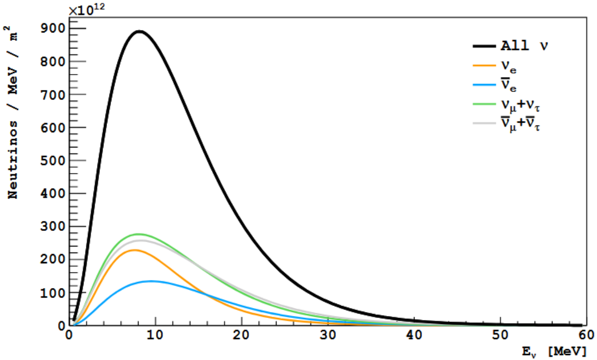

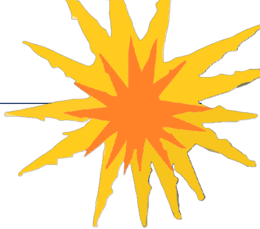

Left: *JCAP* 03 (2021) 043 "Sensitivity of future liquid argon dark matter search experiments to CCSN"

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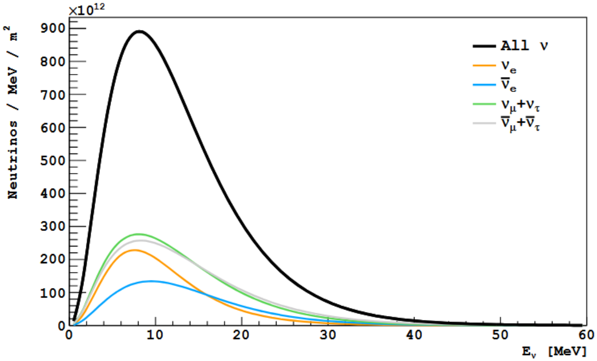

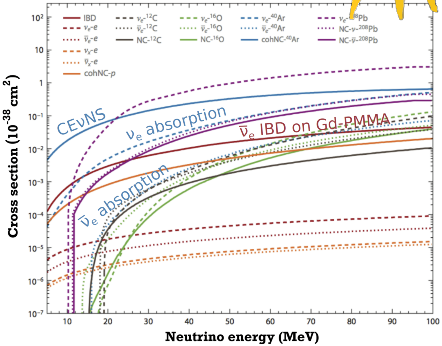

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Right: Kate Sholberg 2014 "Neutrino Cross-Section Experiments at the Spallation Neutron Source"

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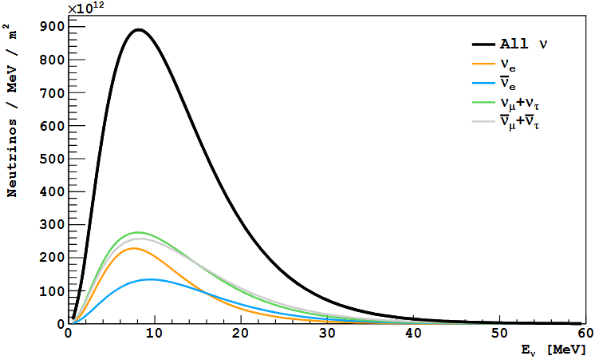

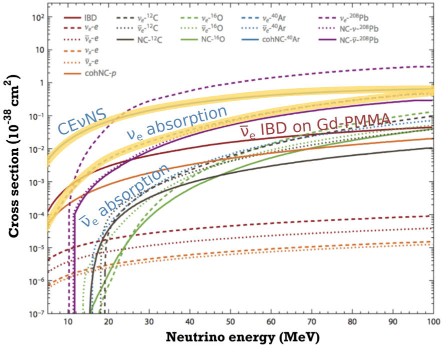

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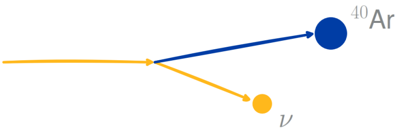
Detection channels

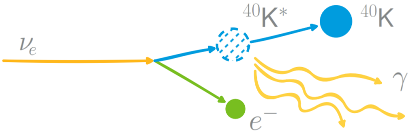
CEνNS: **coherent elastic neutrino nucleus scattering**



- High cross-section $\Longrightarrow$ high-statistics with a target mass of ∼50 tonnes
- S2 only
- Equally sensitive to all ν

  $\Longrightarrow$ Enables to measure the unoscillated SN ν flux
  $\Longrightarrow$ normalization of the total flux, potential measurement of the ν mass hierarchy
- Time resolution $\lesssim 3.3\,\mathbf{ms}$

CC: **charged current ^{40}Ar$(\nu_e, e)^{40}$K**



- Only ν_e
- Energy allows both Inner (32 t) and Outer Veto (650 t) to contribute
- Only scintillation light in IV and OV
- Allows to resolve neutrino interaction timing much more precisely (while CEνNS is limited by the electron drift time)

  $\Longrightarrow$ single photon time resolution **60 ns**

Detection channels

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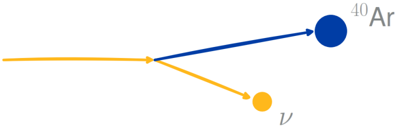

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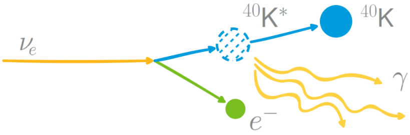

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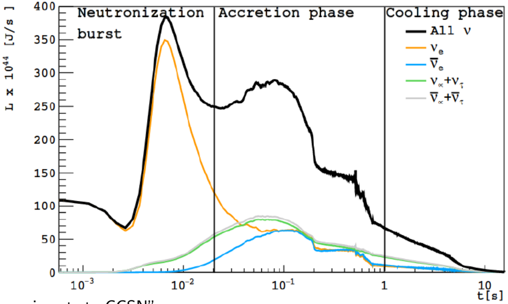

Veto to

n timing

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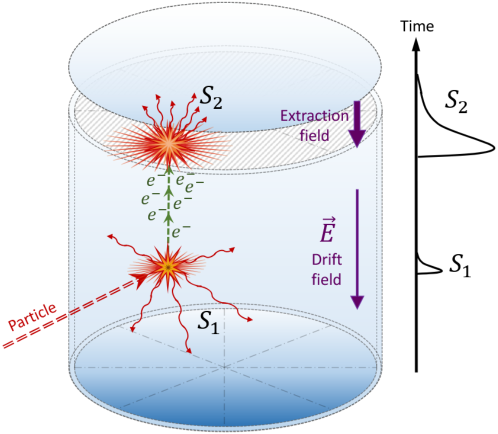
) ns

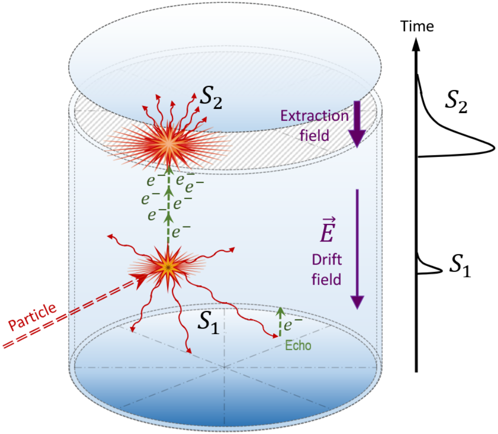
DarkSide-20k TPC and backgrounds



Backgrounds

- Ar-39 radioactivity
- Gammas
- Echo electrons
- Spurious electrons
- Neutrons
- Alpha decays

DarkSide-20k TPC and backgrounds



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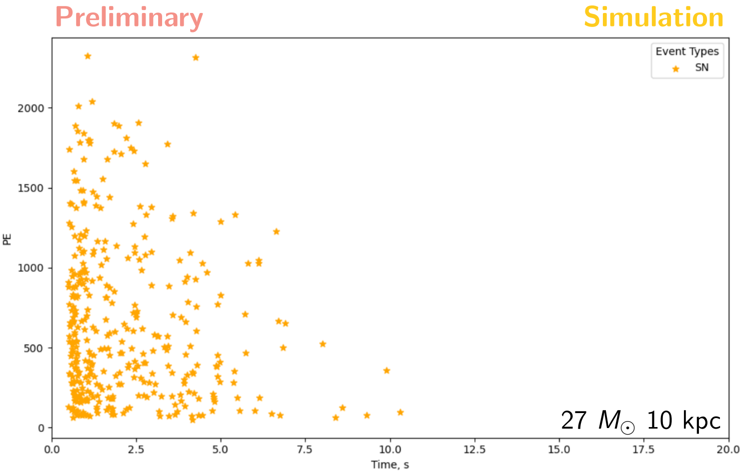
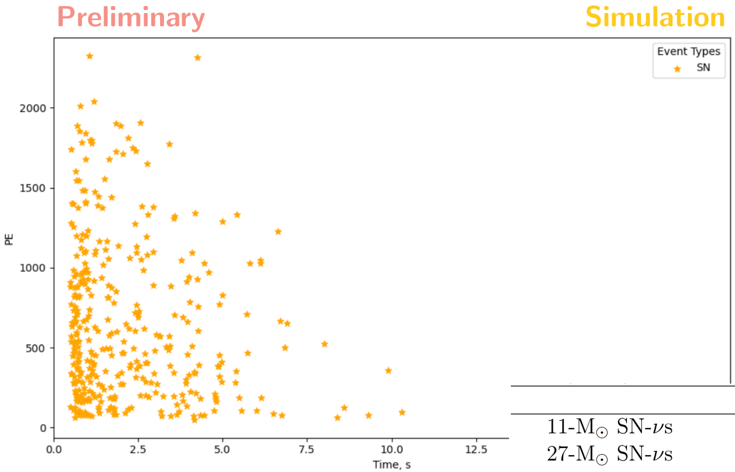
Neural Network Models for neutrino trigger



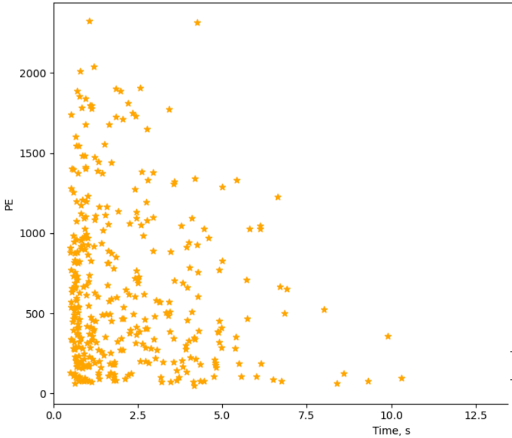
NNs for neutrino trigger



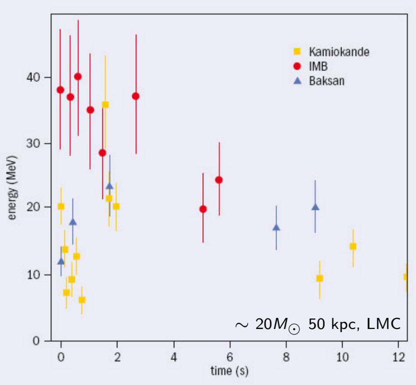
	DarkSide-20k	Argo
11-$M_\odot$ SN-νs	181.4	1396.6
27-$M_\odot$ SN-νs	336.5	2591.6

NNs for neutrino trigger

Preliminary



Simulat



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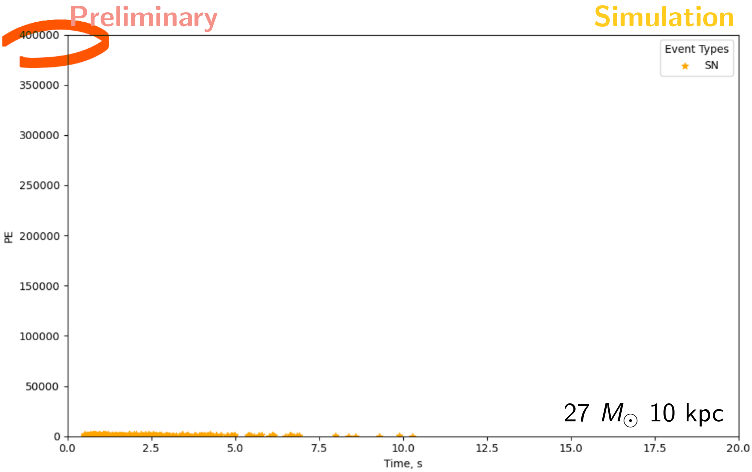
CERN Courier 30 January 2007 Nakahata M

NNs for neutrino trigger



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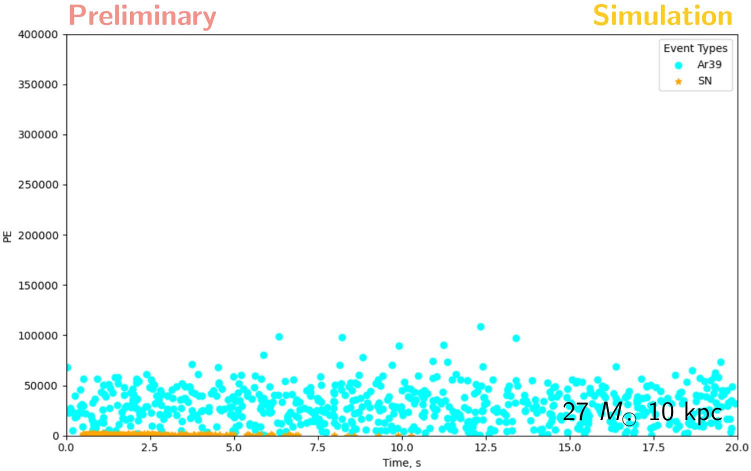

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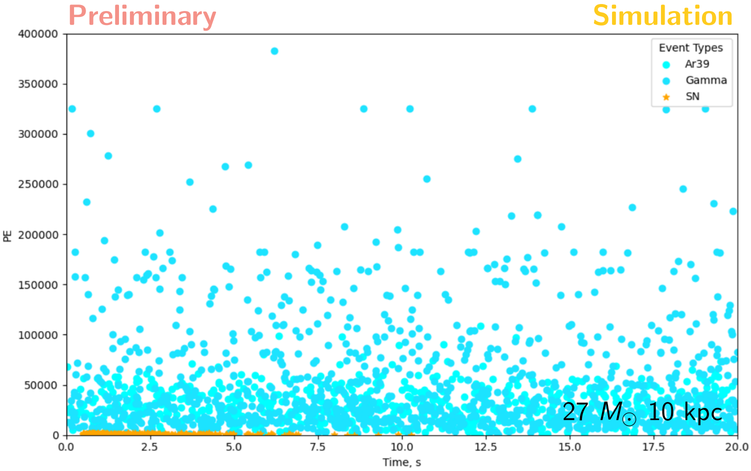

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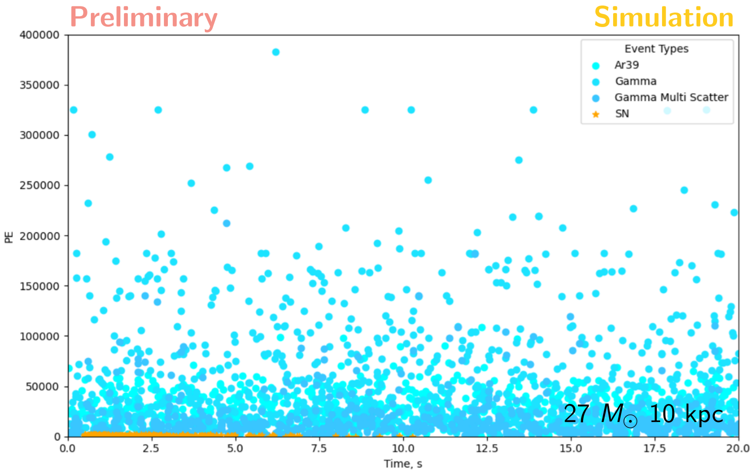

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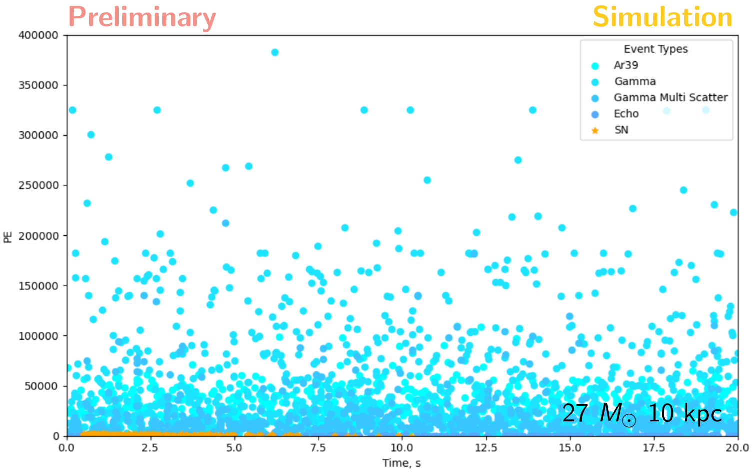

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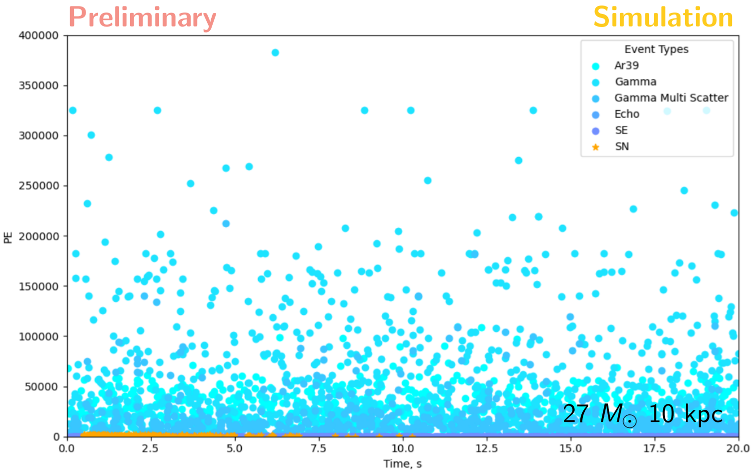

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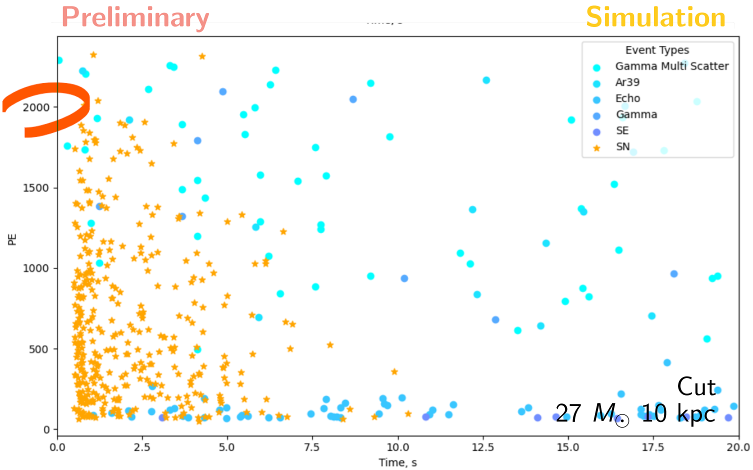

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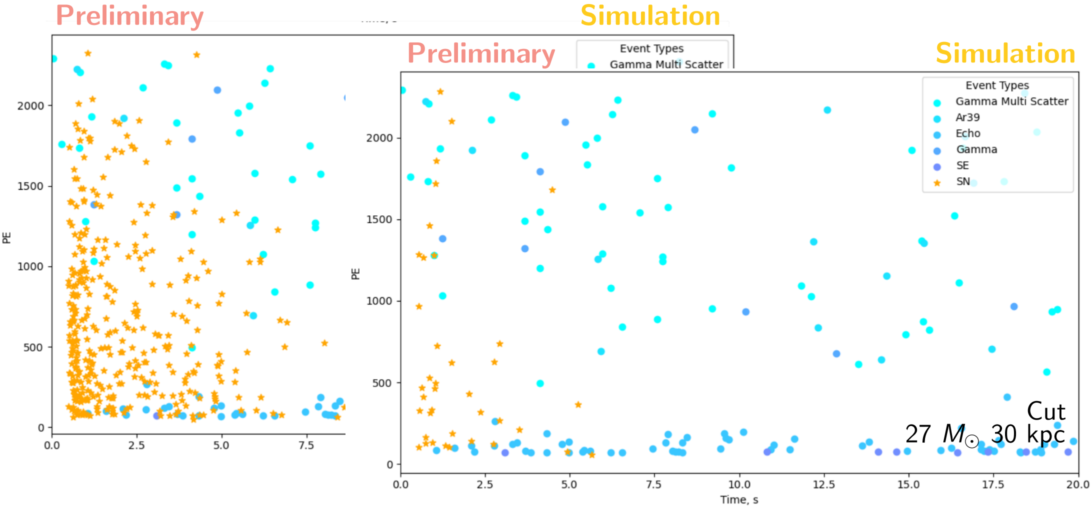

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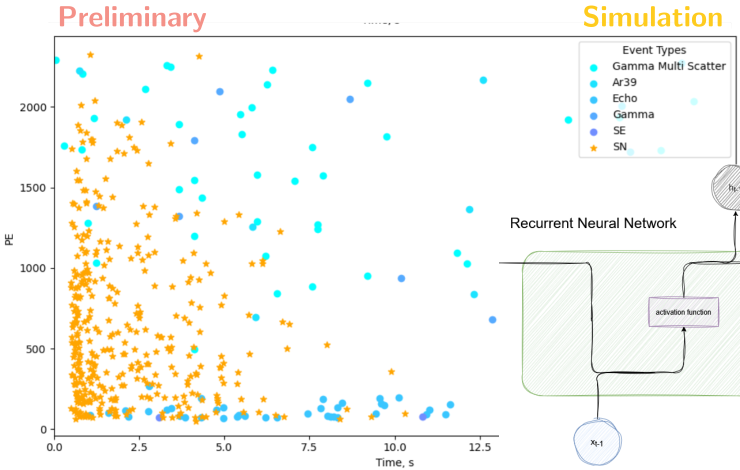
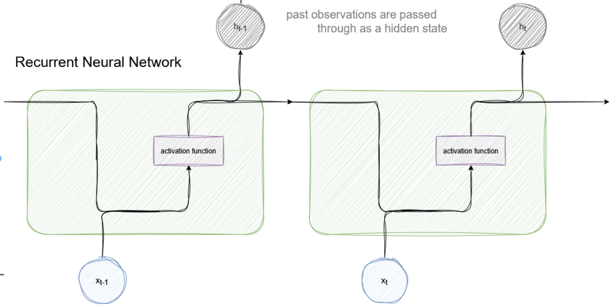
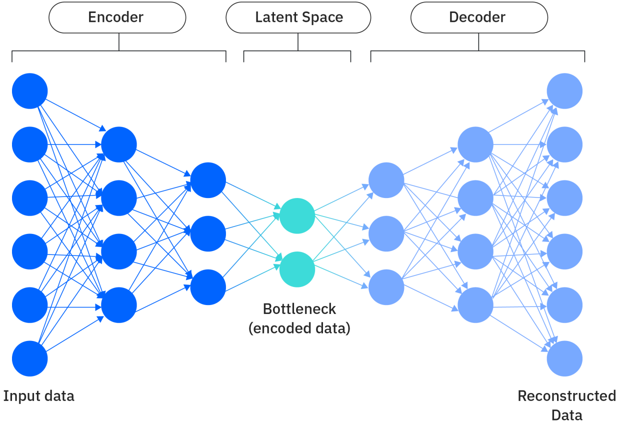




Autoencoders



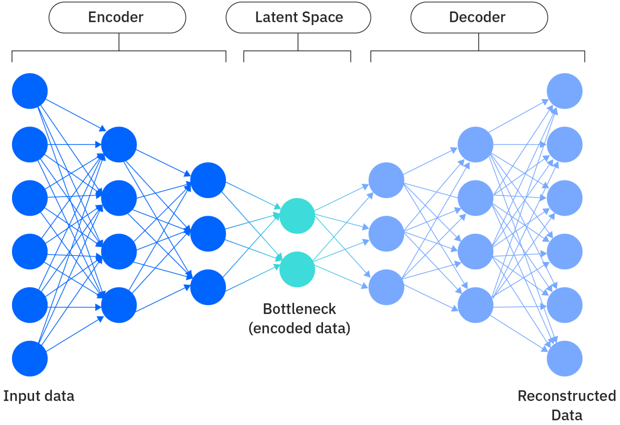
- Train AE on "normal" data = known backgrounds $\implies$ it learns to compress and reconstruct typical signals accurately
- When fed anomalous data = backgrounds + signal, the AE struggles to reconstruct it well

$\implies$ The reconstruction loss increases for anomalous inputs

- Anomalies are detected by comparing reconstruction loss to a threshold.

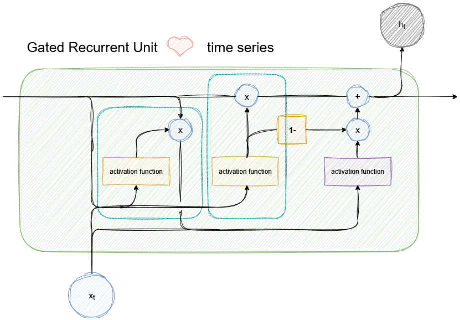
pic: `ibm.com`

Autoencoders + Gated Recurrent Unit



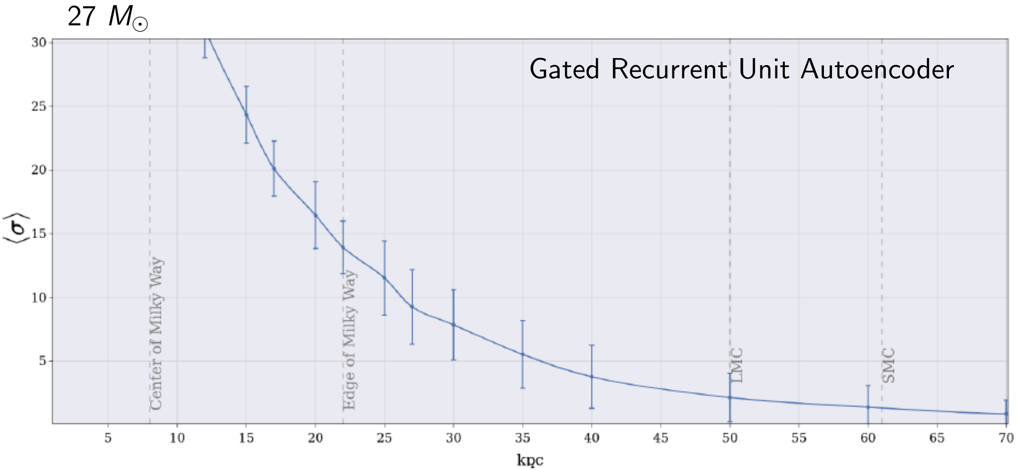
- Dependency between data points

$\Longrightarrow$ We need memory! $\Longrightarrow$ RNN, GRU



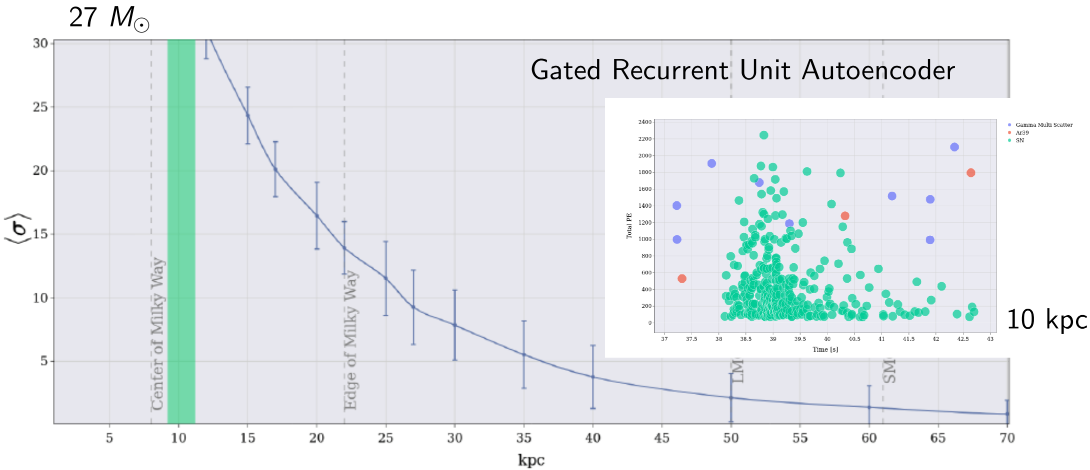
GRU AE with 2 GRU Layers for both encoder and decoder (baby NN model)

NNs for neutrino trigger: Offline



Sebastian Torres-Lara thesis: `https://inspirehep.net/literature/2830076`

NNs for neutrino trigger: Offline



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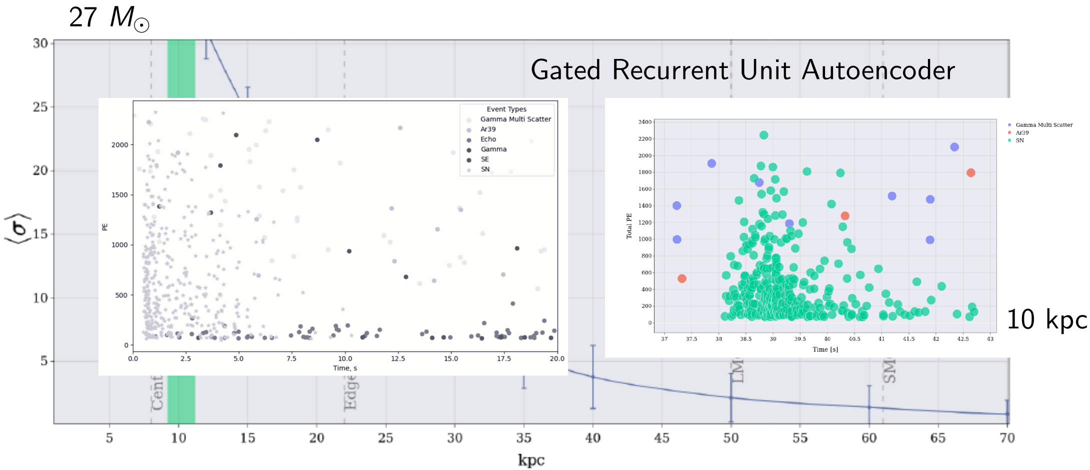
NNs for neutrino trigger: Offline vs Online



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Developing a Real-Time Supernova Trigger

Current proof-of-concept workflow

1. Generate one year of background-only data
2. Apply only fast online-quality selection cuts
3. Construct simple features:
   - PE
   - Events occurring within a window after the current event
4. Train a lightweight 2-layer neural network
5. Run the model continuously on rolling windows

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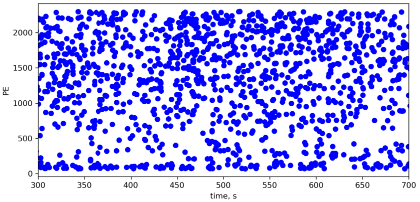

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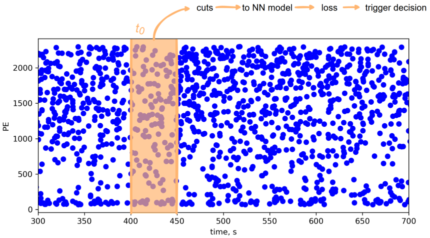

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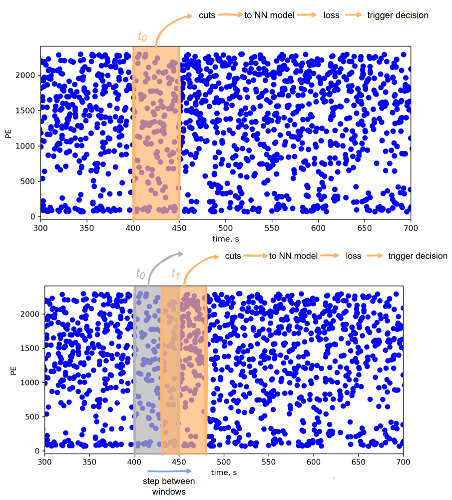

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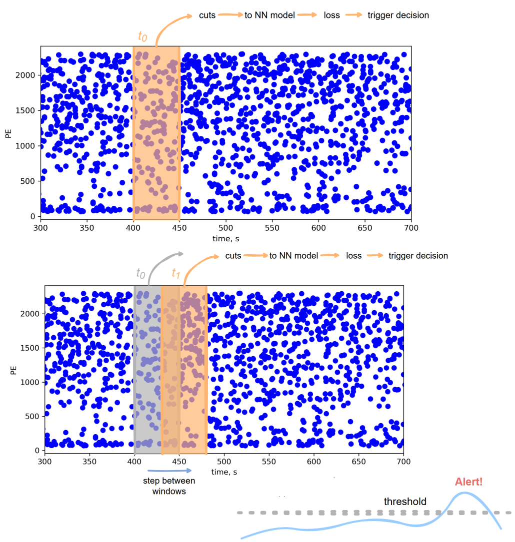
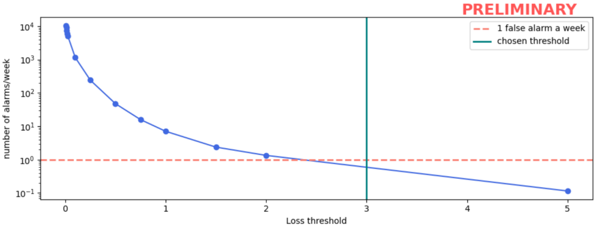


Meeting False Alarm Requirements

Threshold:

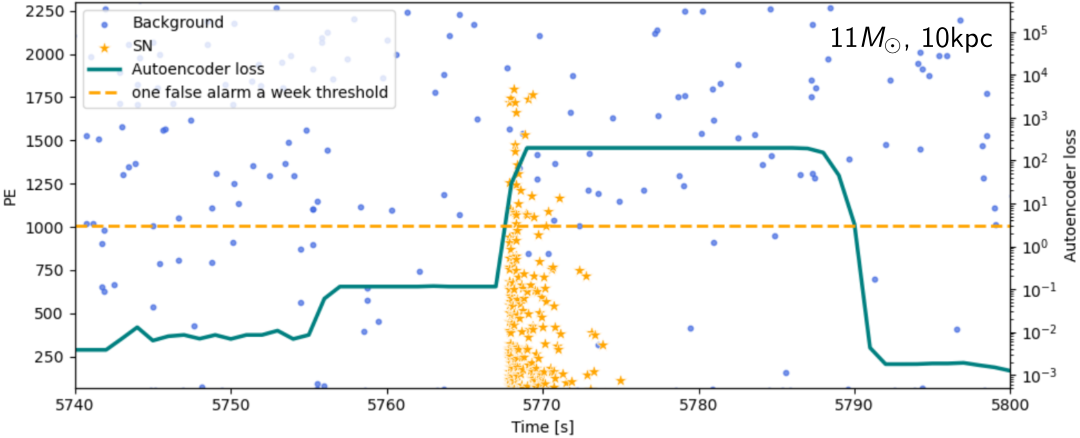
- Process one year of background-only data.
- Evaluate the loss for every rolling window.
- Measure the background trigger rate as a function of threshold.
- Choose the threshold to satisfy the required false alarm rate.

We can now inject supernova signals and evaluate sensitivity!

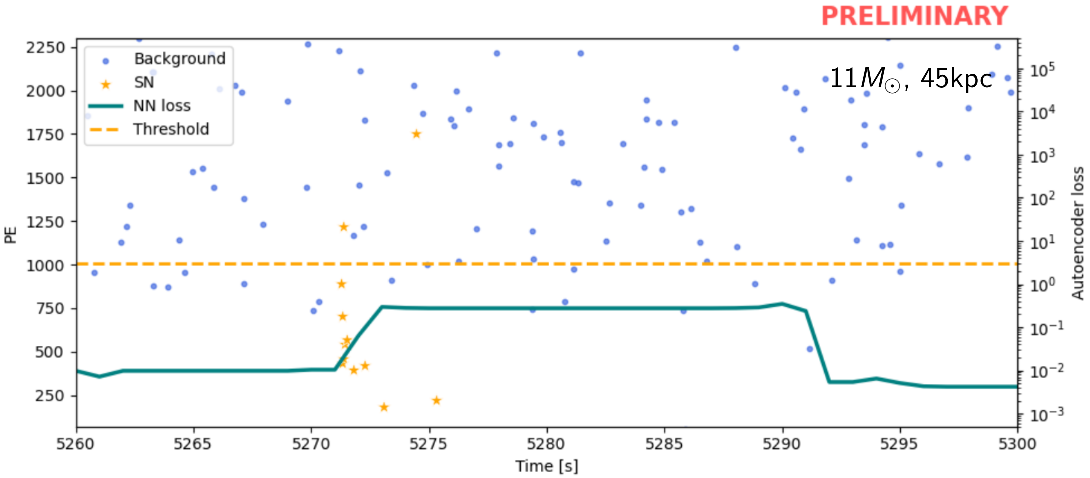


Supernova signal detection

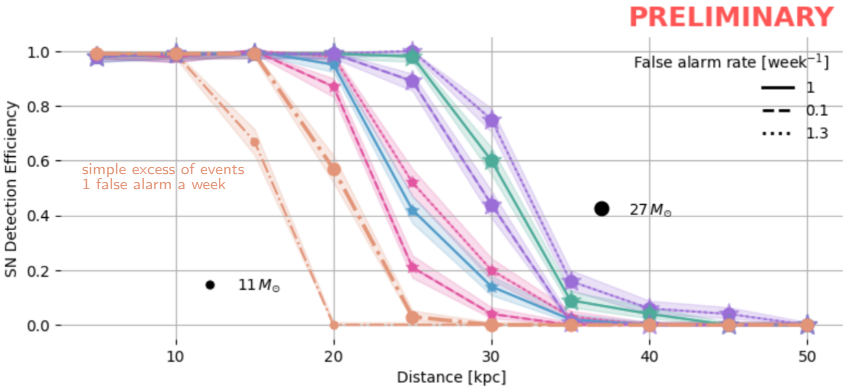
PRELIMINARY



Supernova signal detection

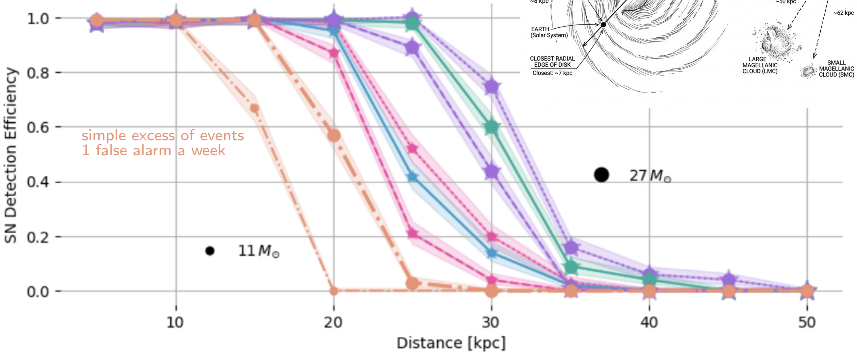


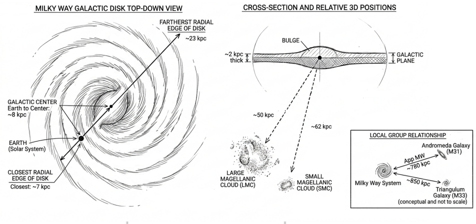
Supernova signal detection efficiency



Small toy 2-layer autoencoder model allows us to reach the farthest edge of Milky Way disk!

Supernova signal detection efficiency





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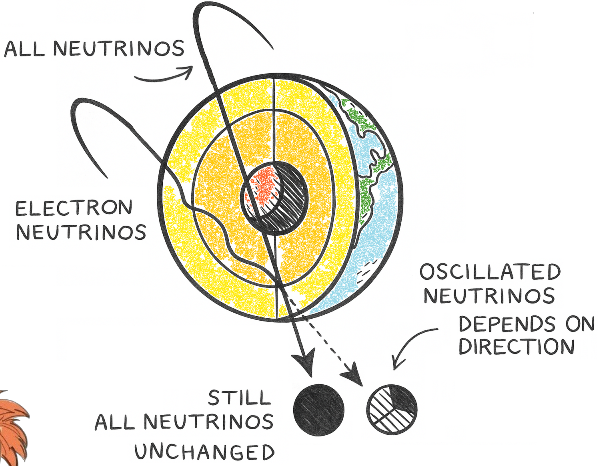
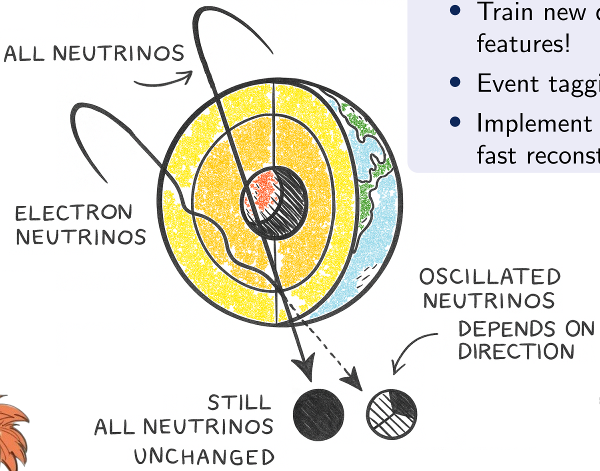
MSW effect pointing and next steps



pic: ChatGPT + NS

MSW effect pointing and next steps

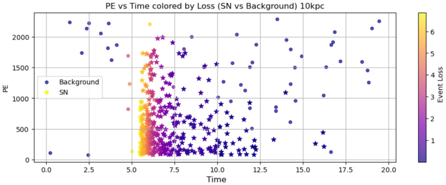


pic: ChatGPT + NS

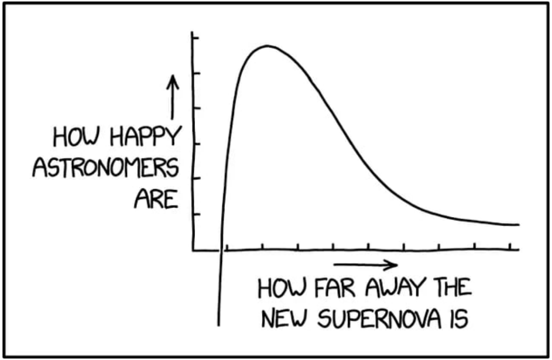
Next steps

- Train new dragons with burst-sensitive set of features!
- Event tagging
- Implement more data: neutronization burst, fast reconstructed data

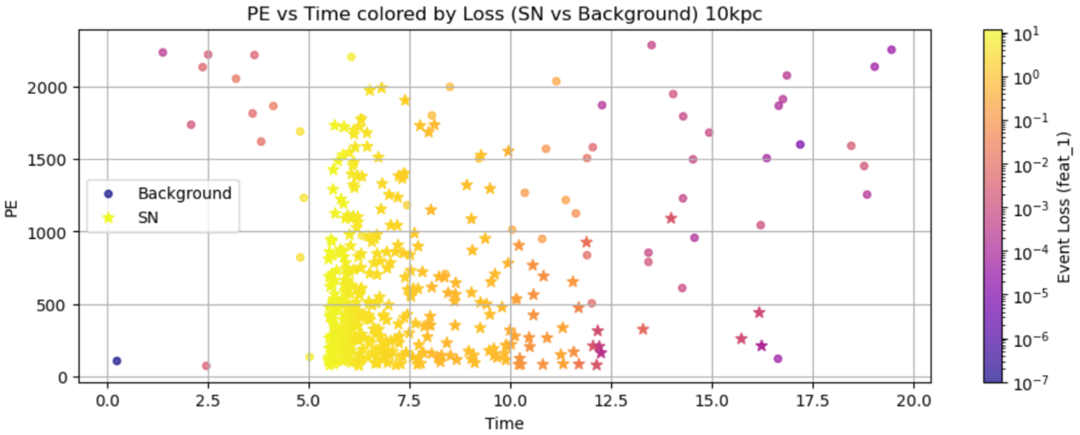
- MSW effect pointing
- Progenitor properties: mass, distance

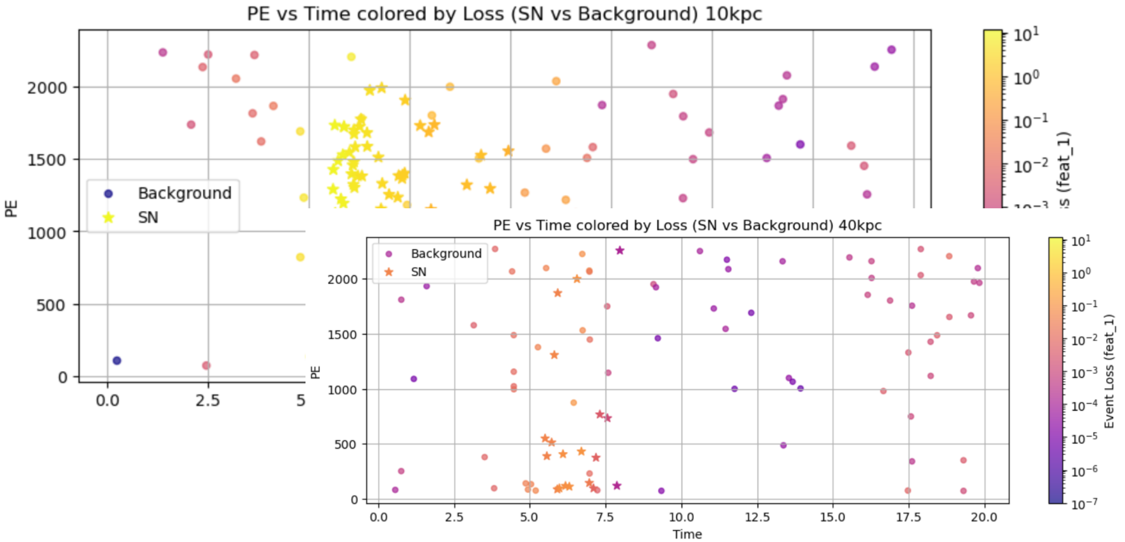


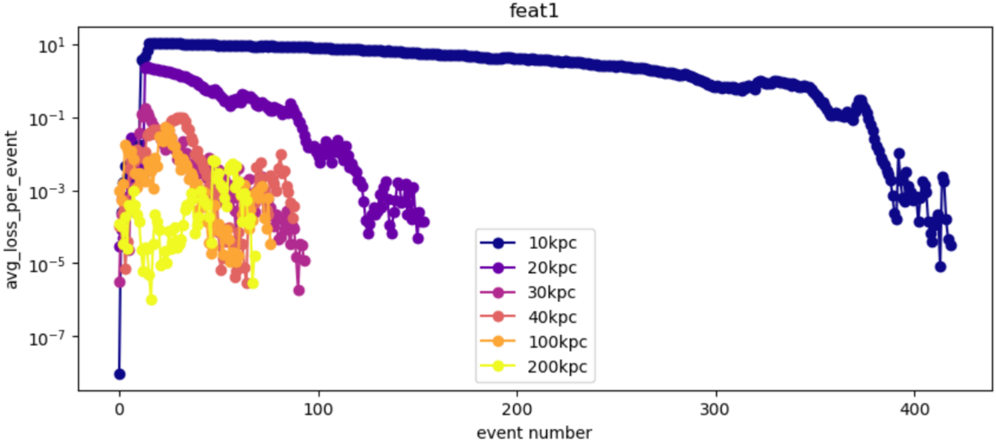
Thank you for attention :)

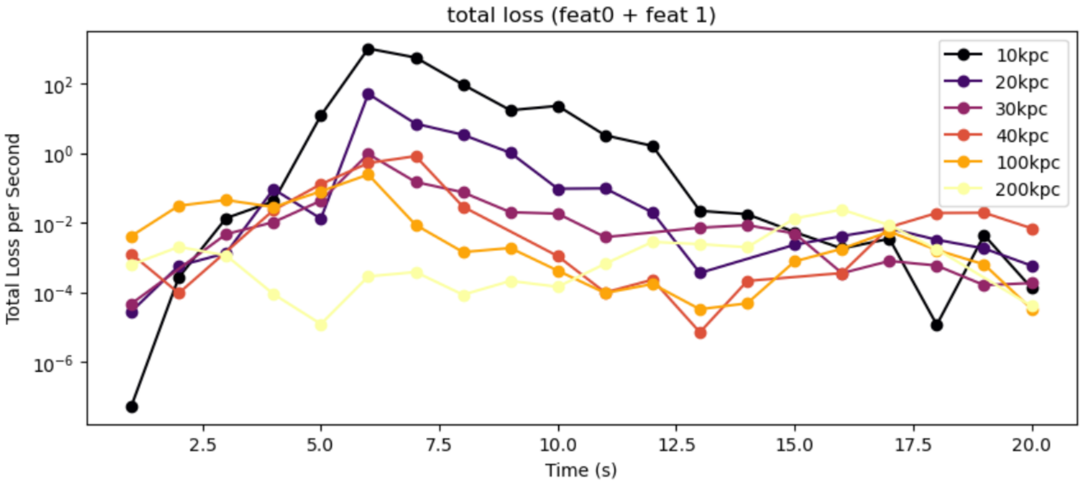


https://xkcd.com/

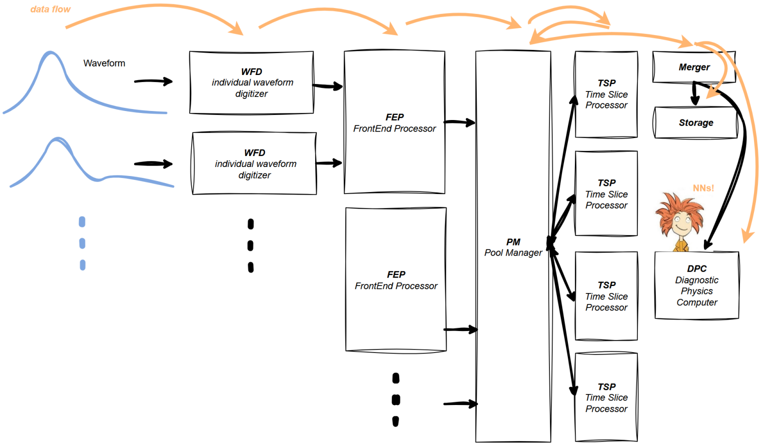

PE vs Time colored by Loss (SN vs Background) 10kpc
PE
2000
1500
1000
500
0
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
Time
Background
SN
Event Loss (feat_1)
10^{1}
10^{0}
10^{-1}
10^{-2}
10^{-3}
10^{-4}
10^{-5}
10^{-6}
10^{-7}


PE vs Time colored by Loss (SN vs Background) 10kpc
PE
Background
SN
2000
1500
1000
500
0
0.0
2.5
5
10^1
10^0
10^{-1}
10^{-2}
PE vs Time colored by Loss (SN vs Background) 40kpc
Background
SN
PE
Time
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
10^1
10^0
10^{-1}
10^{-2}
10^{-3}
10^{-4}
10^{-5}
10^{-6}
10^{-7}
Event Loss (feat_1)

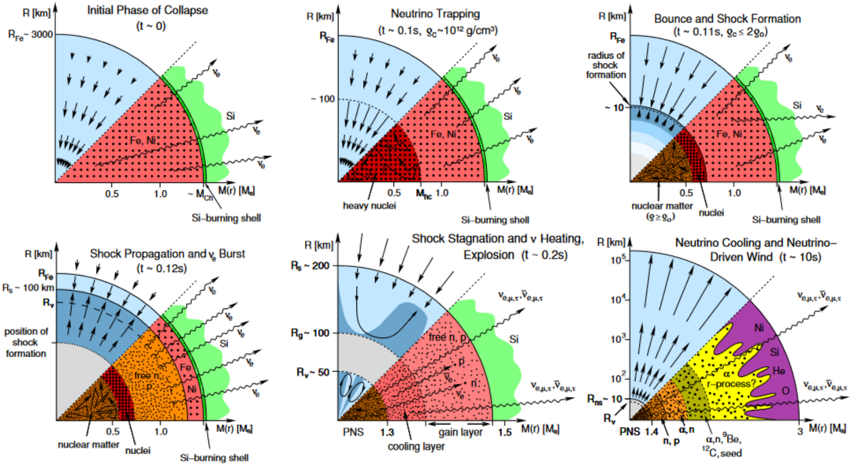

feat1
avg_loss_per_event
event number
10kpc
20kpc
30kpc
40kpc
100kpc
200kpc



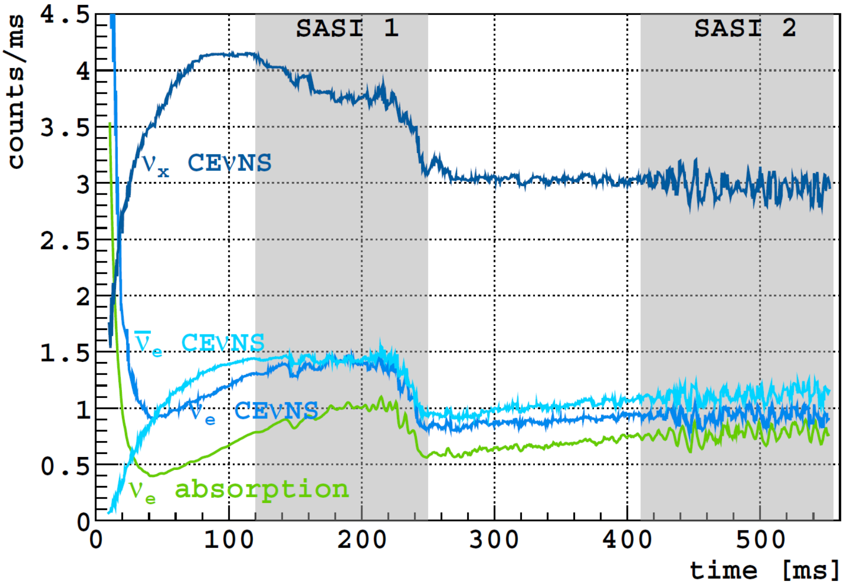
total loss (feat0 + feat 1)
10kpc
20kpc
30kpc
40kpc
100kpc
200kpc
Total Loss per Second
10^2
10^0
10^{-2}
10^{-4}
10^{-6}
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
Time (s)


data flow
Waveform
WFD
individual waveform
digitizer
WFD
individual waveform
digitizer
FEP
FrontEnd Processor
FEP
FrontEnd Processor
PM
Pool Manager
TSP
Time Slice
Processor
TSP
Time Slice
Processor
TSP
Time Slice
Processor
TSP
Time Slice
Processor
Merger
Storage
NNs!
DPC
Diagnostic
Physics
Computer

CCSN mechanism

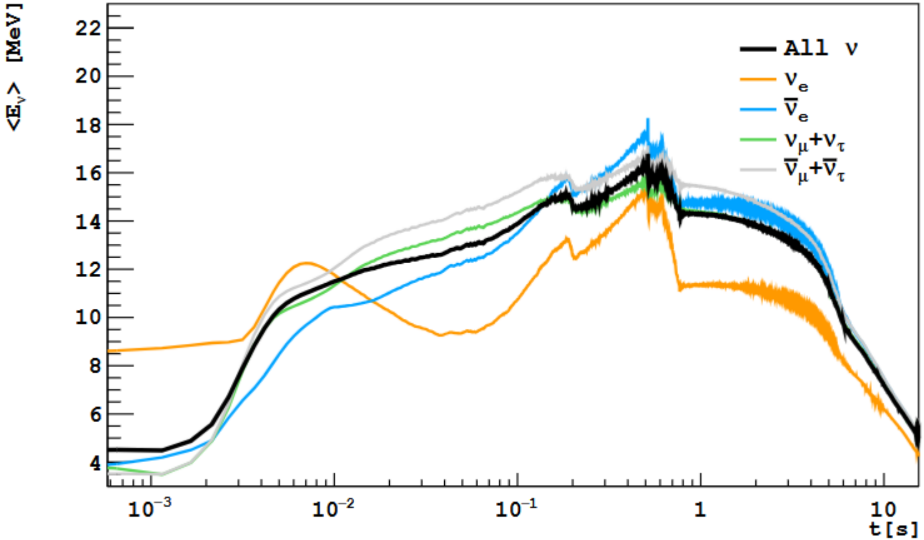


Phys. Rept. 442:38-74, 2007 "Theory of core-collapse supernovae"



SASI 1
SASI 2
counts/ms
time [ms]
ν_x CEνNS
$\bar{\nu}_e$ CEνNS
ν_e CEνNS
ν_e absorption

Mean energy of SN neutrinos



Data flow through GRU layers

- **Input:** one waveform

$$X \in \mathbb{R}^{1\times 100\times 1} \quad (\text{batch} = 1,\ \text{timesteps} = 100,\ \text{features} = 1)$$

- **Step-wise input:** At timestep t:

$$x_t \in \mathbb{R}^{1\times 1}$$

- **First GRU layer (64 units):** Processes all 100 steps $\longrightarrow$ returns hidden states

$$H^{(1)} \in \mathbb{R}^{1\times 100\times 64}$$

- **Second GRU layer (32 units):** Takes sequence of 64-dim states as input

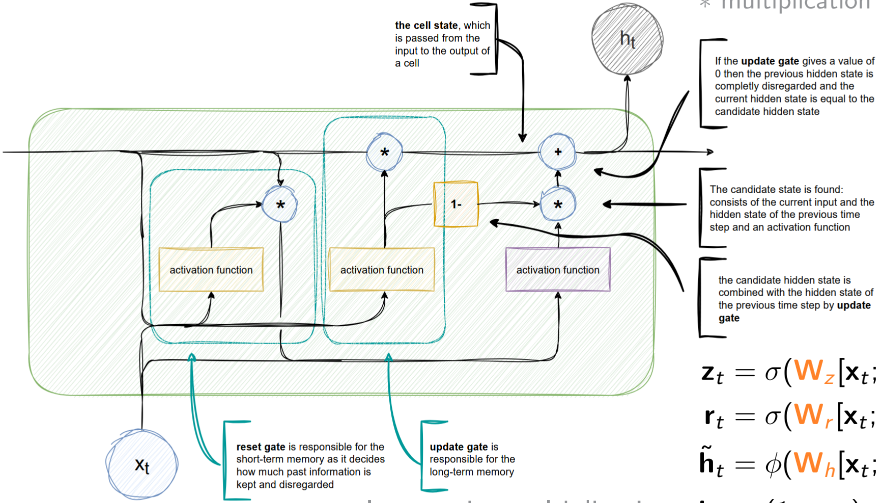
$$H^{(2)} \in \mathbb{R}^{1\times 100\times 32}$$

- **(Optional)** If you only keep the last state:

$$h_{100}^{(2)} \in \mathbb{R}^{1\times 32}$$

Autoencoders + Gated Recurrent Unit

$*$ multiplication



trained parameters

$$\mathbf{z}_t = \sigma(\mathbf{W}_z[\mathbf{x}_t; \mathbf{h}_{t-1}] + \mathbf{b}_z)\,,$$

$$\mathbf{r}_t = \sigma(\mathbf{W}_r[\mathbf{x}_t; \mathbf{h}_{t-1}] + \mathbf{b}_r)\,,$$

$$\tilde{\mathbf{h}}_t = \phi(\mathbf{W}_h[\mathbf{x}_t;\ \mathbf{r}_t \odot \mathbf{h}_{t-1}] + \mathbf{b}_h)\,,$$

$$\mathbf{h}_t = (1 - \mathbf{z}_t) \odot \mathbf{h}_{t-1} + \mathbf{z}_t \odot \tilde{\mathbf{h}}_t$$

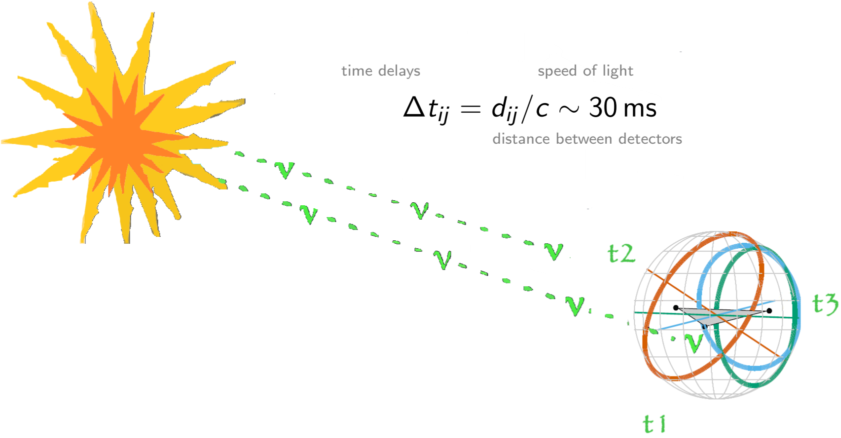
$\odot$ elementwise multiplication

SNEWS2.0: Triangulation

time delays — speed of light

$$\Delta t_{ij} = d_{ij}/c \sim 30\,\text{ms}$$

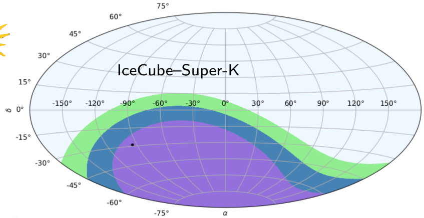
distance between detectors

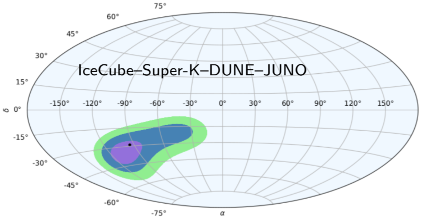


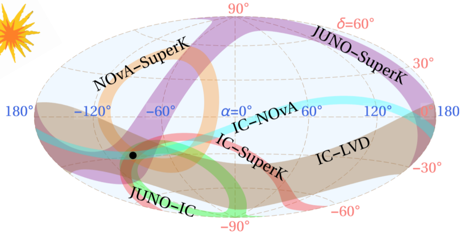
Pic: `https://doi.org/10.1007/s41114-018-0012-9`: "Prospects for observing and localizing gravitational-wave transients with Advanced LIGO, Advanced Virgo and KAGRA" + NS

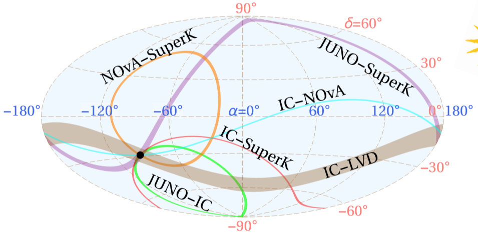
SNEWS2.0: Triangulation

10 kpc









New J. Phys. 23 031201 (2021) "SNEWS 2.0: A Next-Generation SuperNova Early Warning System for Multi-messenger Astronomy"