Perspectives for CCSNe detection with the next generation of gravitational wave detectors

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on behalf of
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Outline

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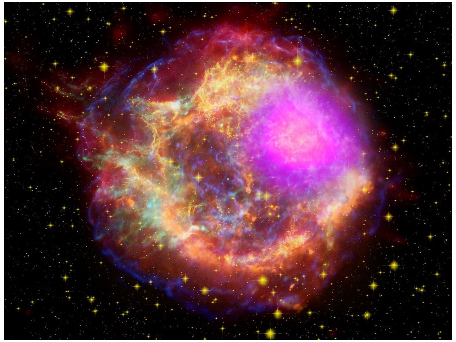
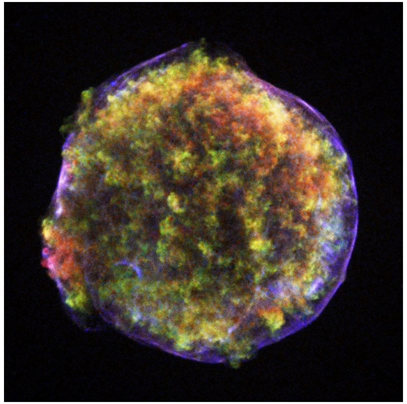
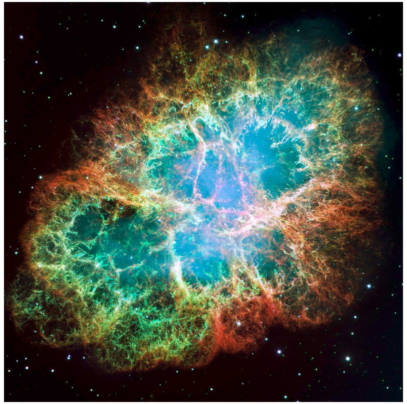
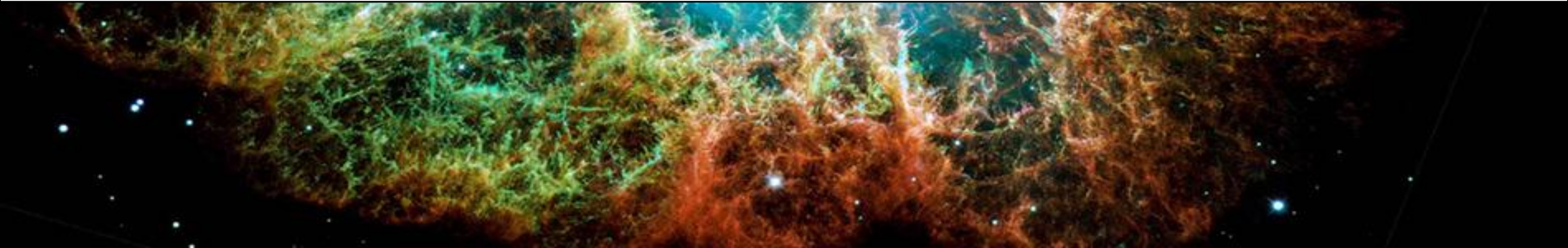
  - Stellar core collapse process
  - Neutrino-driven explosion
- Gravitational waves
  - GW signal in numerical simulations
  - Next generation GW detectors
- Methodology
  - Our method
  - Phenomenological waveforms
  - Neural network architecture
  - Dataset
- Results

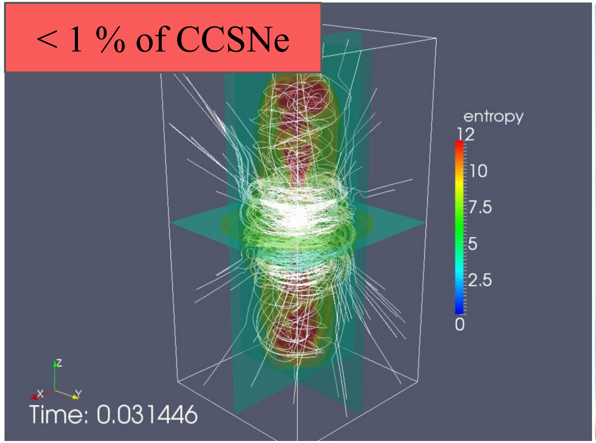
Stellar evolution paradigm



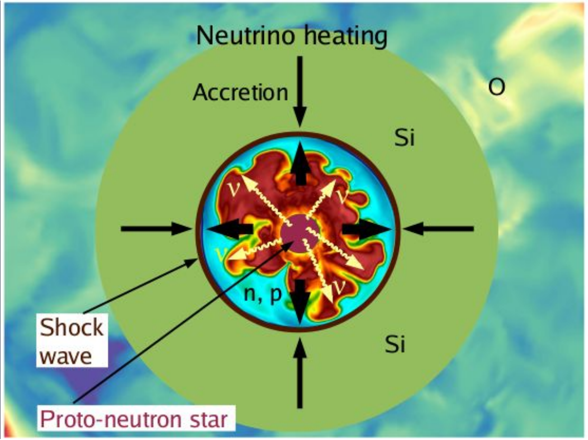
Stellar evolution paradigm

The life of a massive star (**M > 8 M$_\odot$**) can end up producing a core collapse supernova (CCSN), one of the most interesting target of the **multimessenger astronomy**.

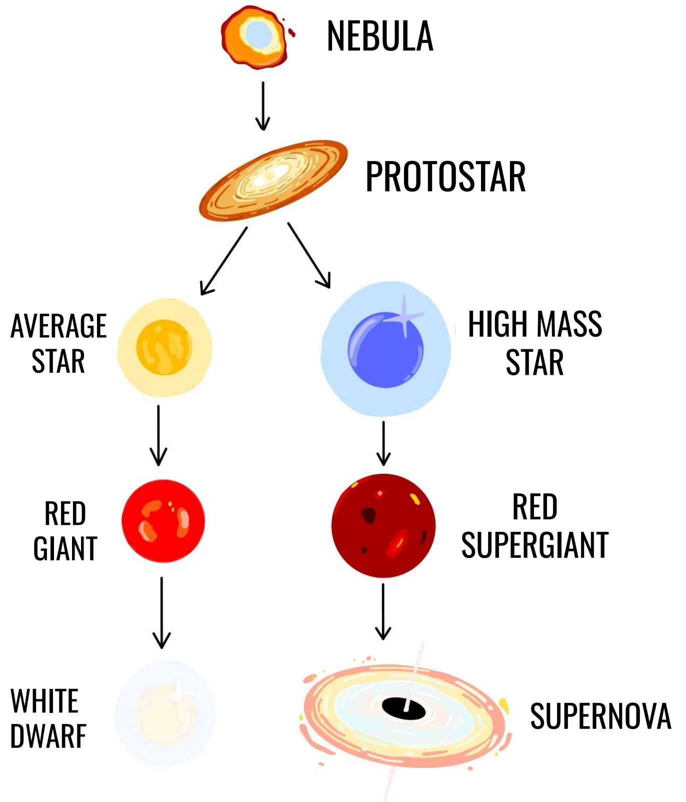
Due to the violent mass motion, we expect them to be a potential source of gravitational waves.



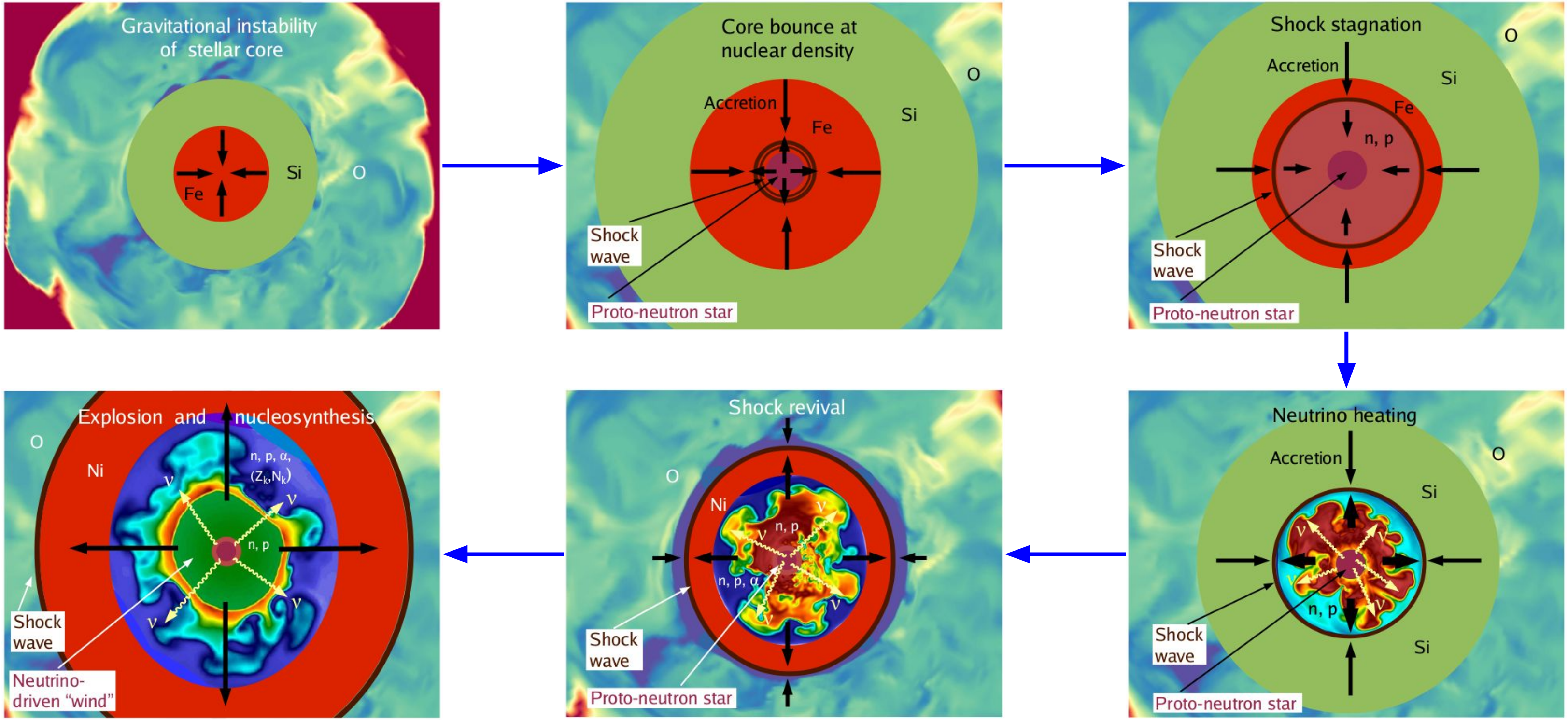
Magnetorotationally driven



Neutrino driven



Stellar core collapse process



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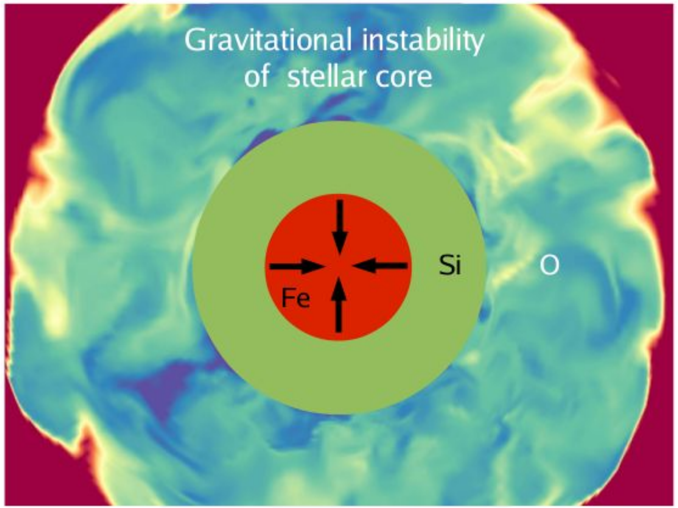
Core-collapse supernovae process

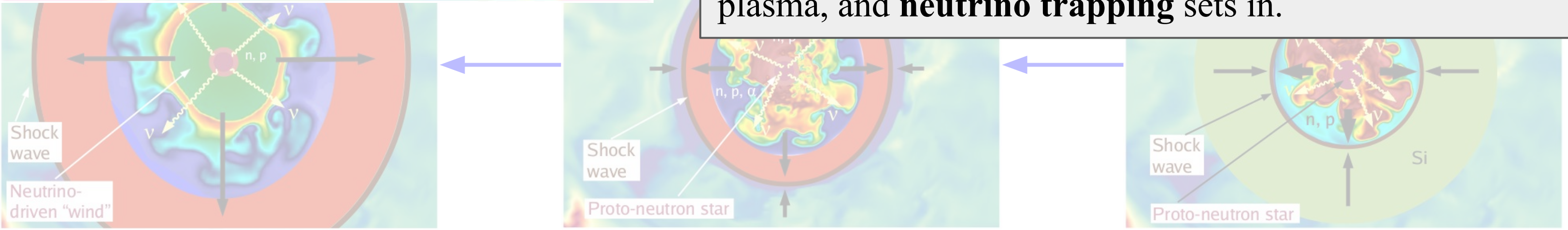


The gravitational instability of the degenerate O-Ne-Mg or iron core is initiated by electron captures on nuclei and free protons

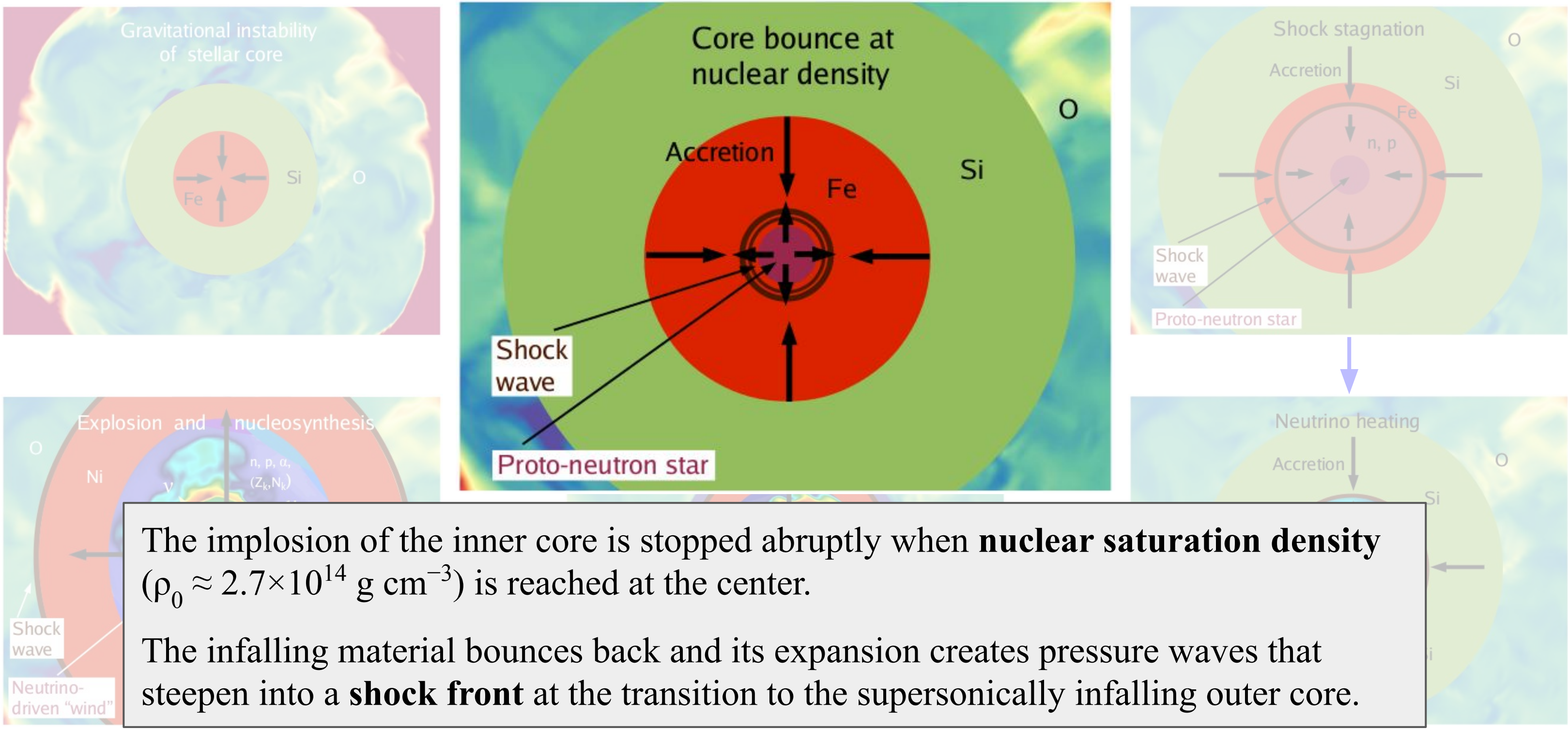
$$e^- + p \rightarrow \nu e + n$$
$$e^- + (A, Z) \rightarrow \nu e + (A, Z - 1)$$

and by the partial photodissociation of heavy nuclei to α particles and free nucleons.

At a density of about 10^{12} g cm^{-3} , the outward neutrino diffusion is slower than the accelerating infall of the stellar plasma, and **neutrino trapping** sets in.



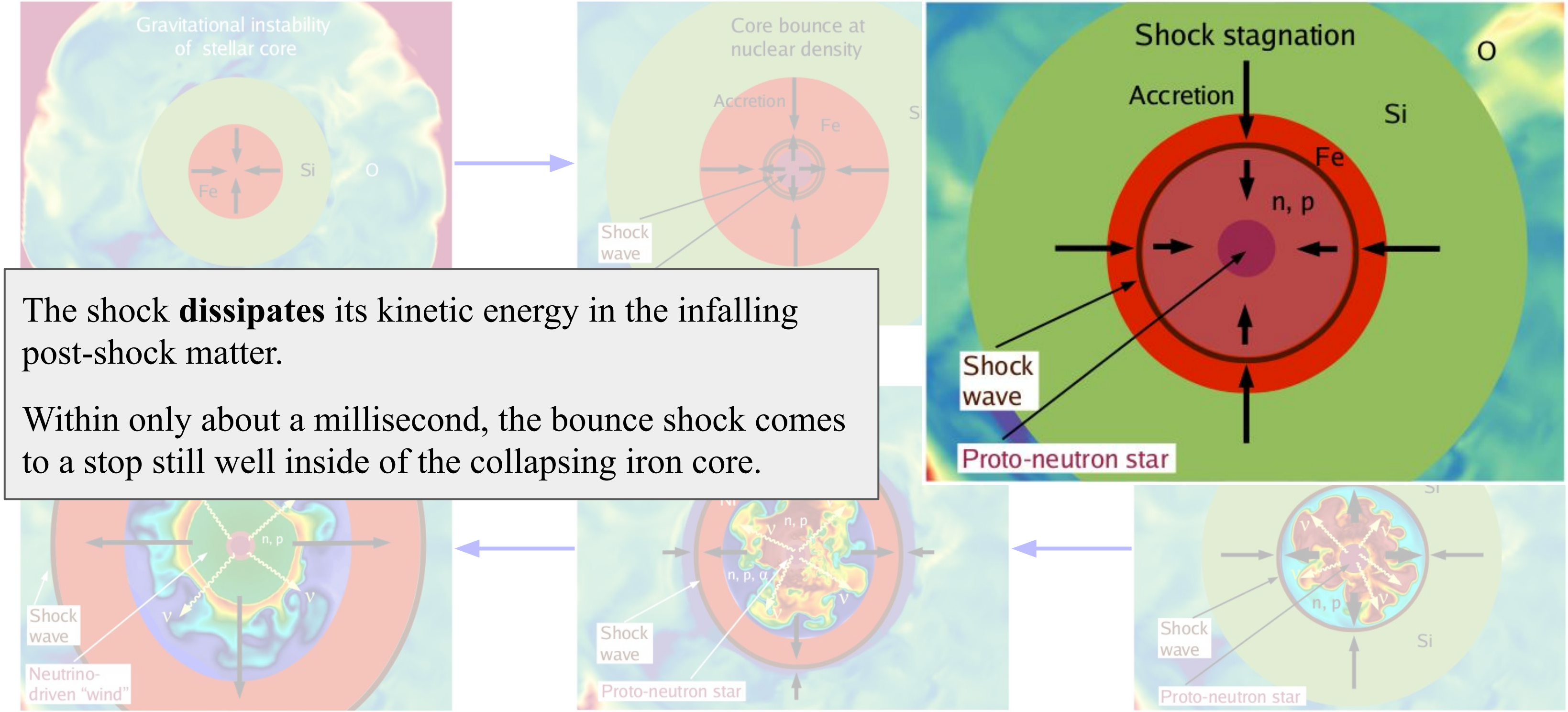
Core-collapse supernovae process



The implosion of the inner core is stopped abruptly when **nuclear saturation density** ($\rho_0 \approx 2.7\times10^{14}$ g cm^{-3}) is reached at the center.

The infalling material bounces back and its expansion creates pressure waves that steepen into a **shock front** at the transition to the supersonically infalling outer core.

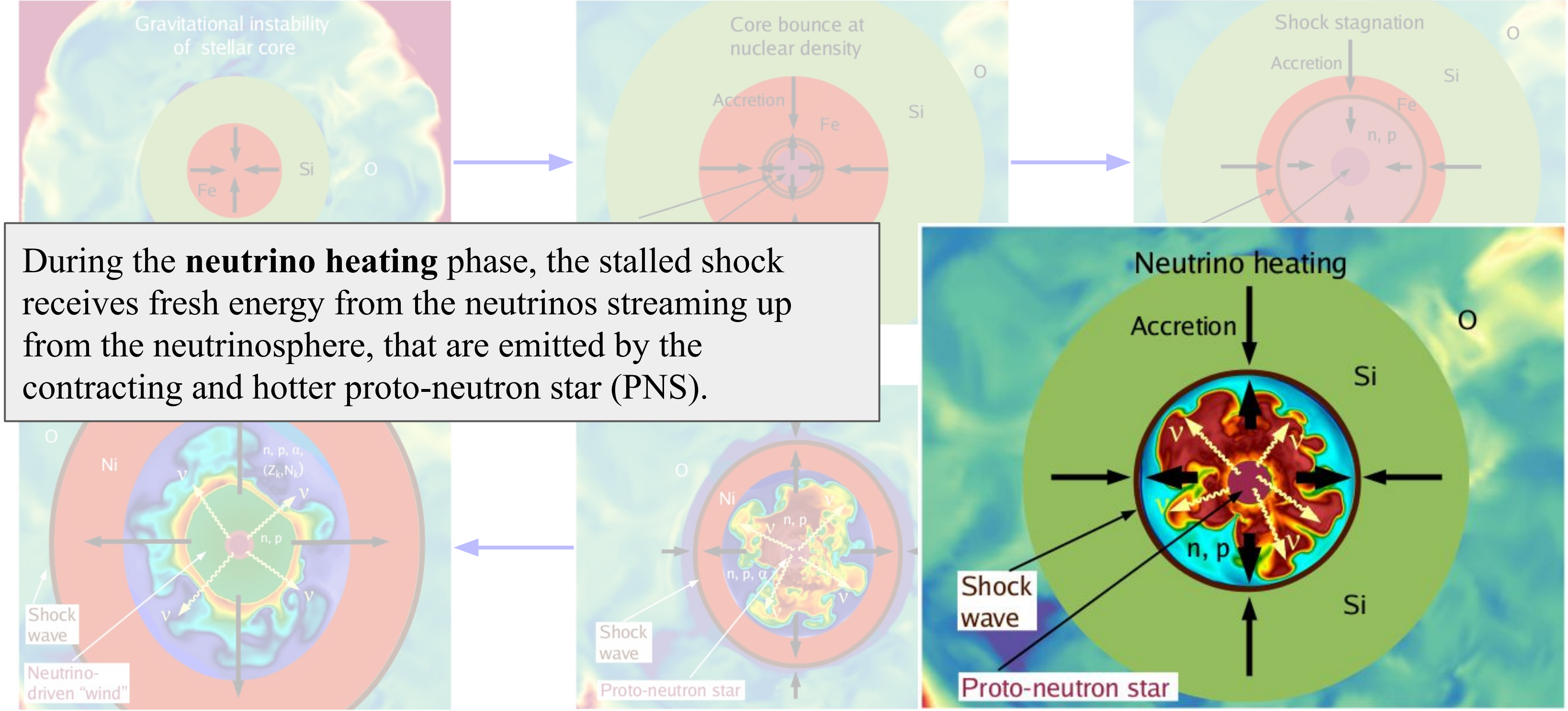
Core-collapse supernovae process



The shock **dissipates** its kinetic energy in the infalling post-shock matter.

Within only about a millisecond, the bounce shock comes to a stop still well inside of the collapsing iron core.

Neutrino-driven explosion

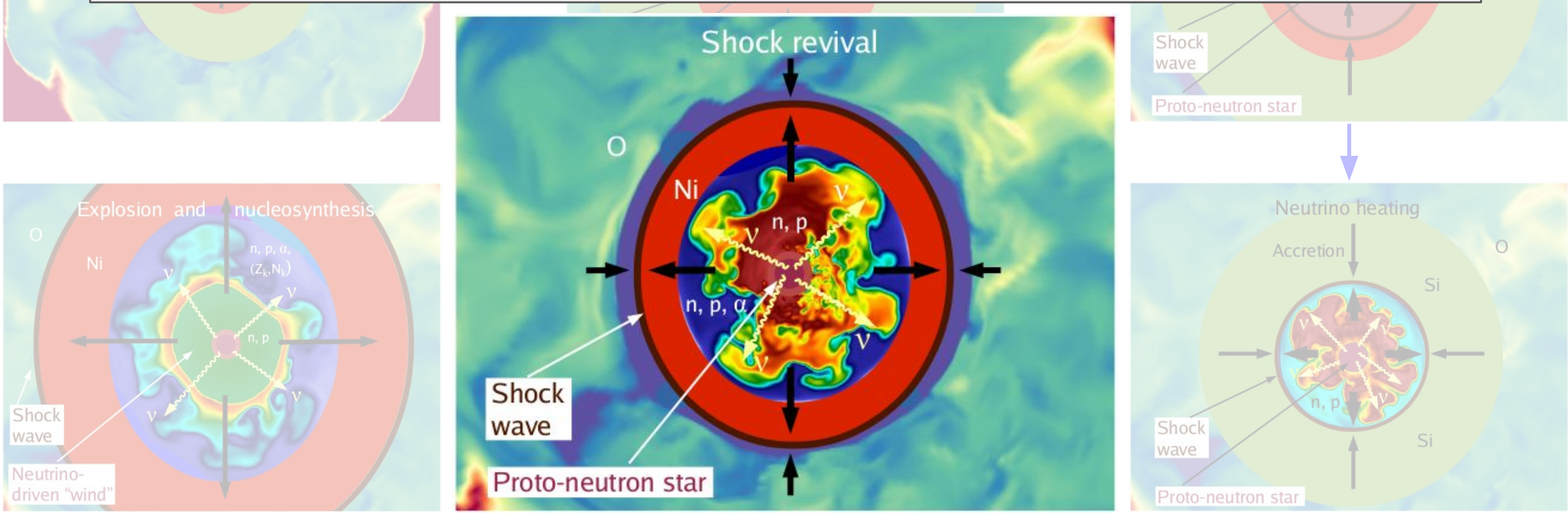


During the **neutrino heating** phase, the stalled shock receives fresh energy from the neutrinos streaming up from the neutrinosphere, that are emitted by the contracting and hotter proto-neutron star (PNS).

Neutrino-driven explosion

Neutrino-energy transfer to the shock raises the post-shock pressure. If the heating by neutrinos is strong enough, the shock can be pushed outwards and the SN explosion can be launched.

The non-radial fluid instabilities (buoyancy, convective overturn and the **SASI**) assist the neutrino-heating mechanism.



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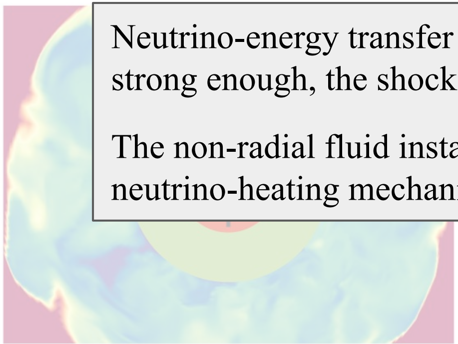
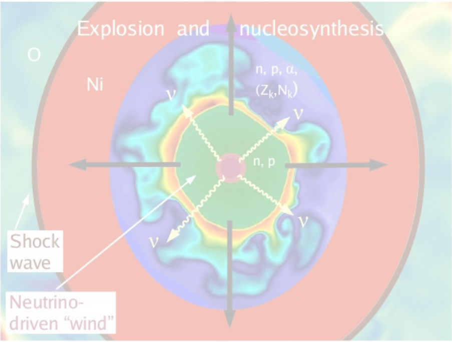
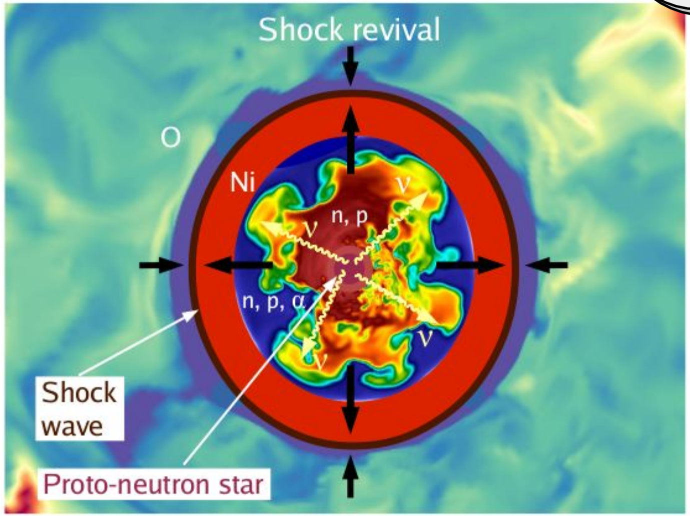


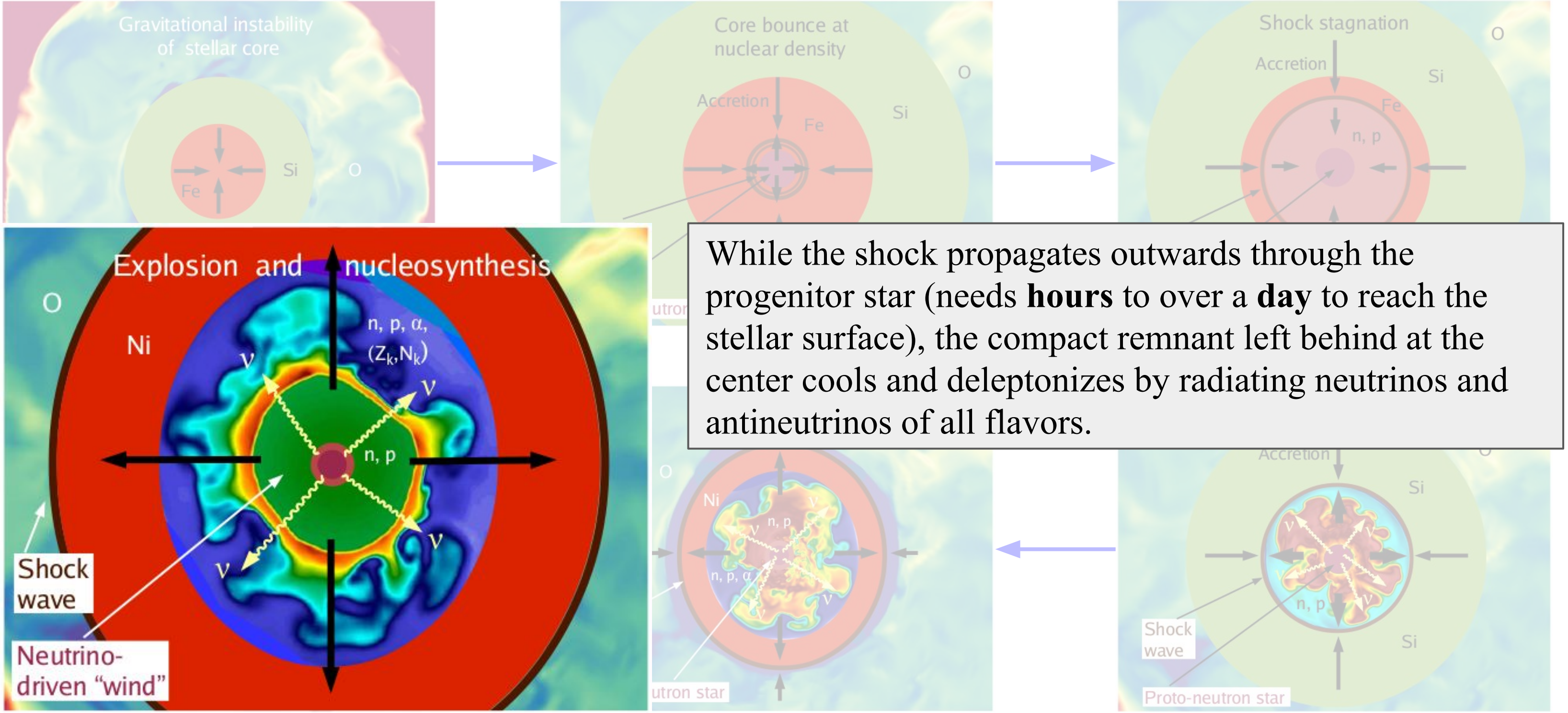




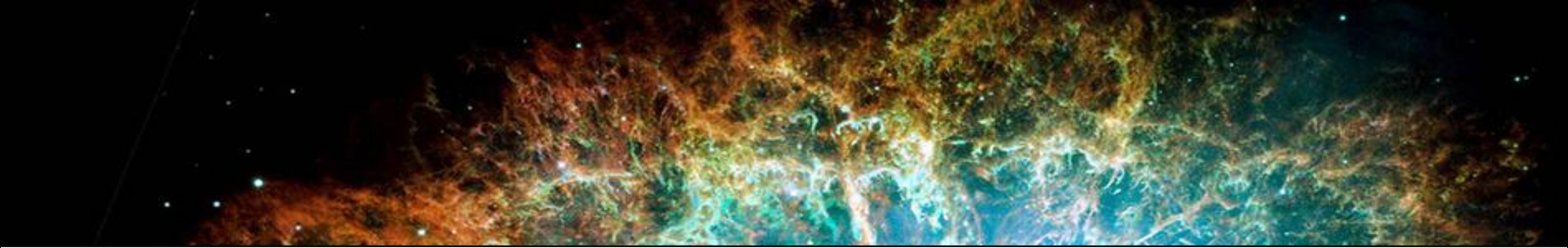
Standing Accretion Shock Instability

A cycle in which a perturbation at the location of the shock is advected downwards by the subsonically accreting fluid until it reaches the surface of the PNS,where it can excite sound waves that travel upwards, further exciting the shock.

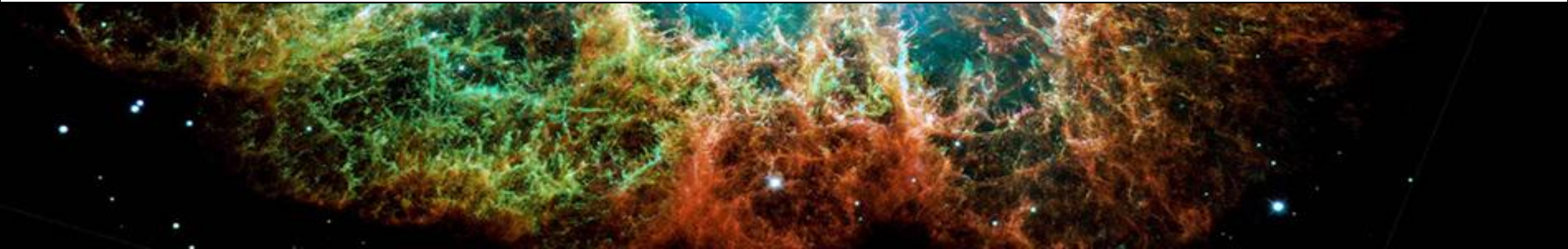
Core-collapse supernovae process



While the shock propagates outwards through the progenitor star (needs **hours** to over a **day** to reach the stellar surface), the compact remnant left behind at the center cools and deleptonizes by radiating neutrinos and antineutrinos of all flavors.

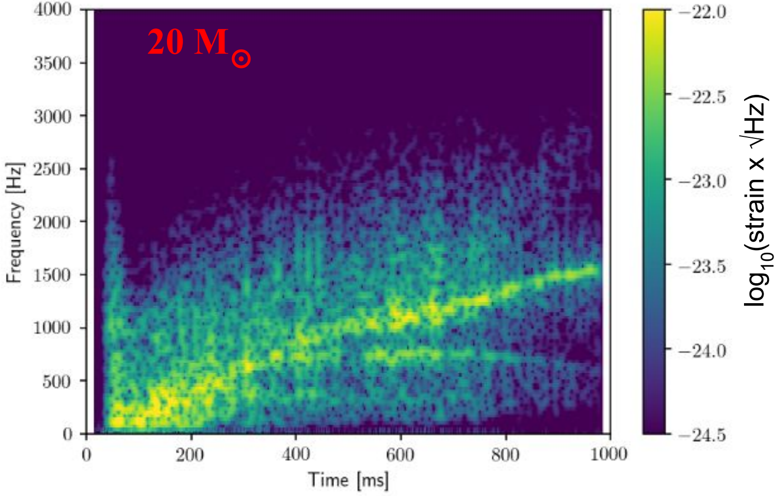


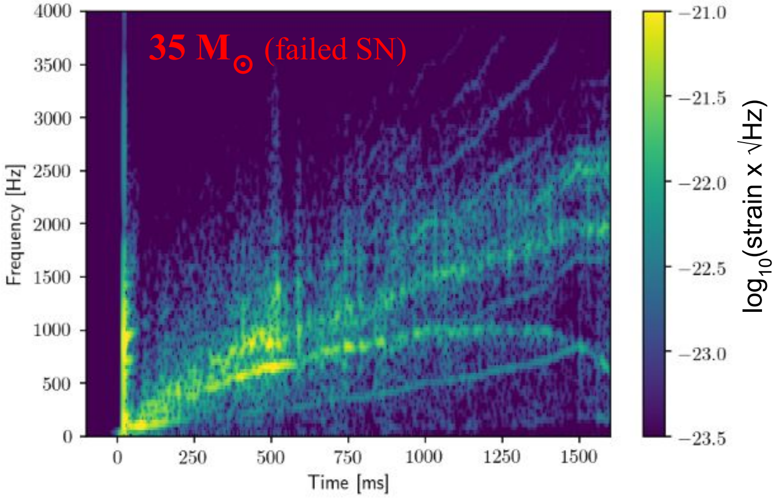
Gravitational waves



GW signal from numerical simulation

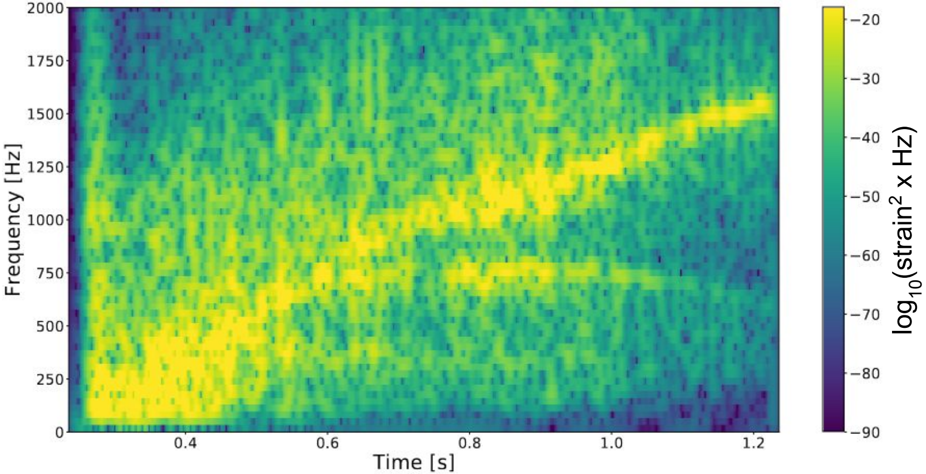
Despite of the problem complexity, numerical simulations give acceptable remnant neutron-star masses and predicted already few distinct signatures of GW signals in both the time and frequency domains.
The most interesting and well understood part of the signal is the one associated with the **post-bounce** evolution of the newly formed proto-neutron star (PNS).

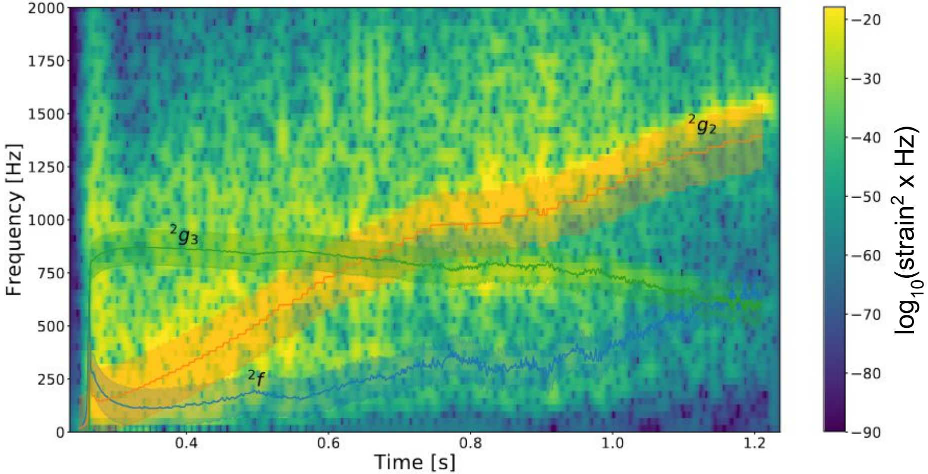




GW signal from numerical simulation

Recent works has converged in identifying the so-called **g-modes** (gravity modes) as the common feature of all models, responsible for the bulk of the GW signal in the post-bounce evolution of the PNS.
While, the **fundamental ^2f mode** seems to be excited in cases with strong SASI activity.

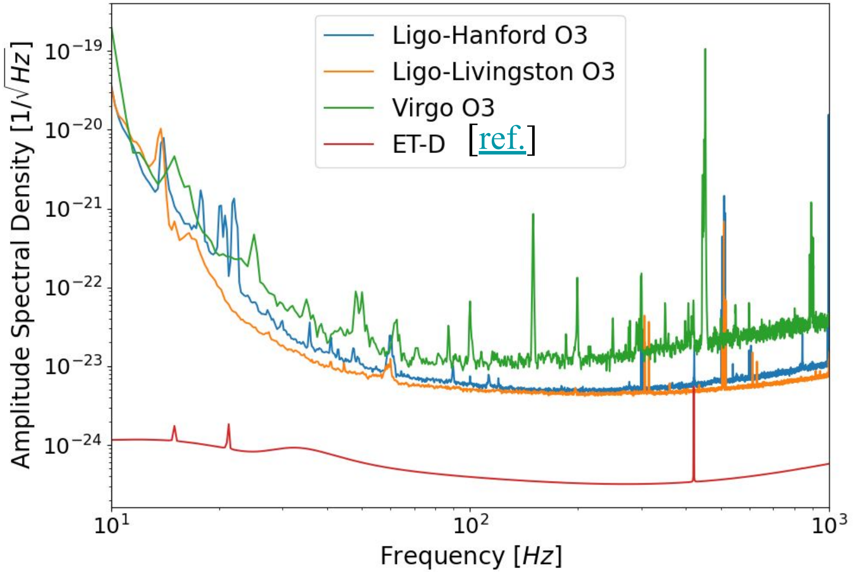


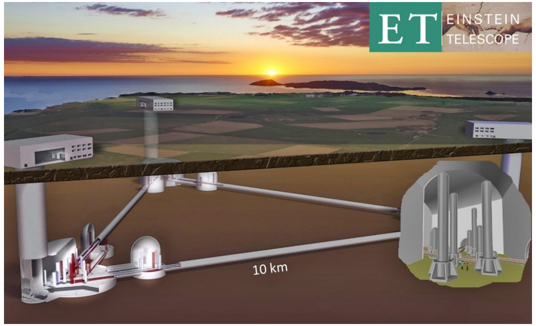


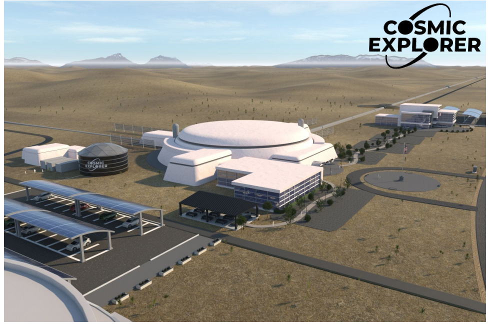
[ref.]

Next generation GW detectors

LIGO and Virgo have opened a new window in the multimessenger astronomy field allowing us to add gravitational wave as a new piece of information of the astrophysical sources.
More than 90 GW sources have been detected in total up to now. However, all the observed GW signals have been produced at the merger of compact binary systems.







Third-generation gravitational-wave detectors (e.g. Einsten Telescope and Cosmic Explorer) will be many times **more sensitive** than current detectors and could thus provide a range of new insights into the invisible side of the universe.

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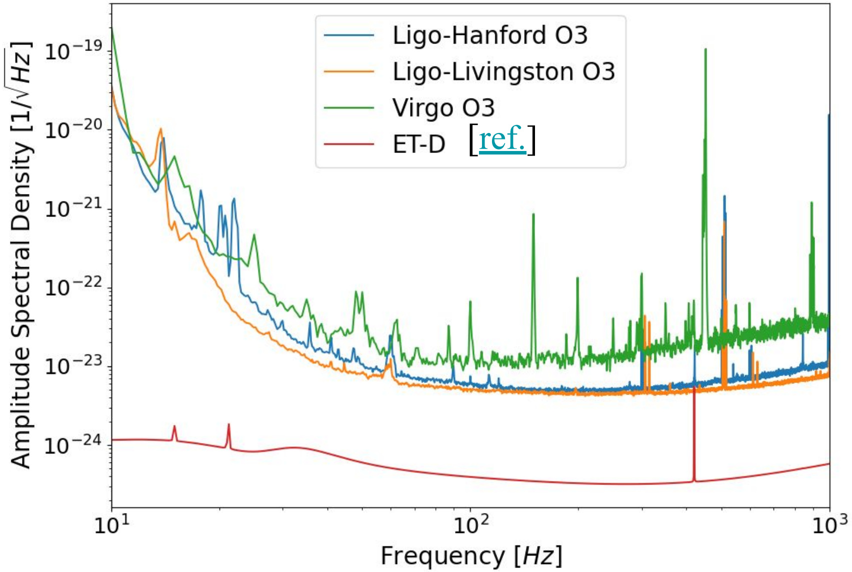

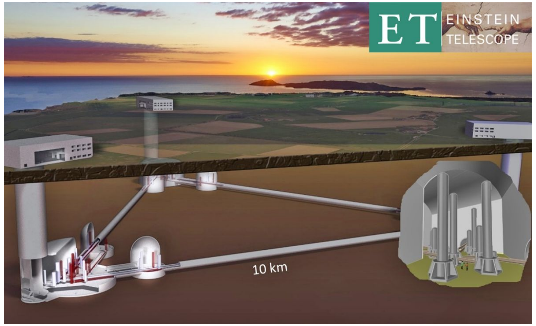

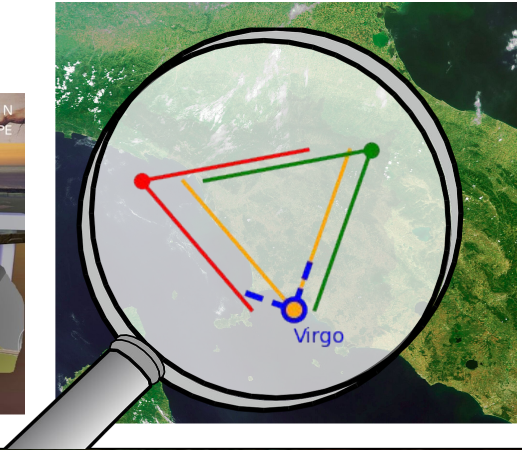

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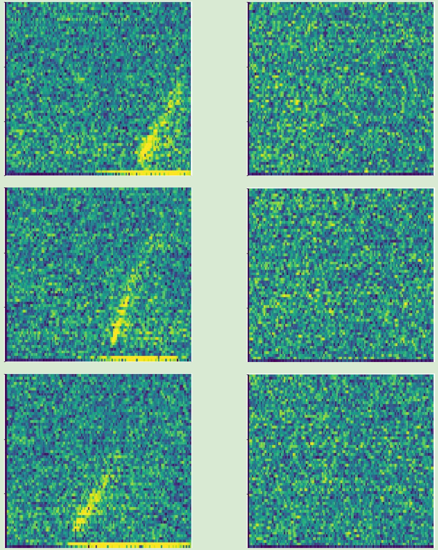
Methodology

Our method

Input dataset

signal + noise | noise



→ **Convolutional Neural Network** →

θ

probability of containing the signal

A large bunch of data is needed for training the neural network

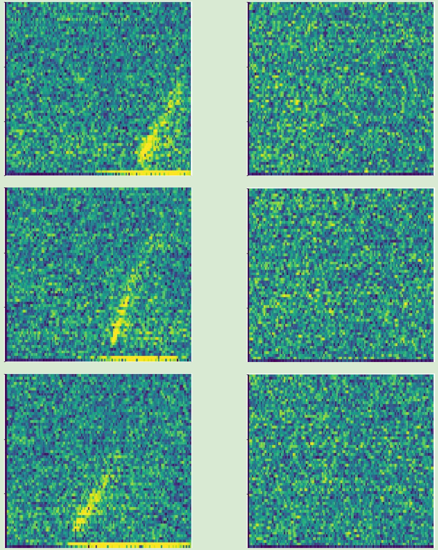
BUT

the set of available waveforms from numerical simulations is limited.

Our method

Input dataset

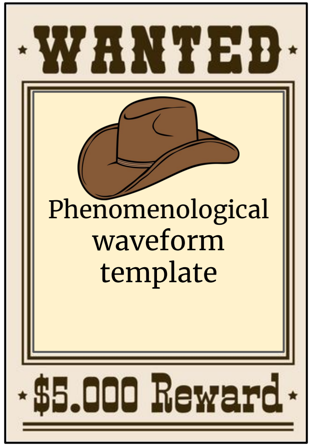
signal + noise | noise



Convolutional Neural Network

θ

probability of containing the signal



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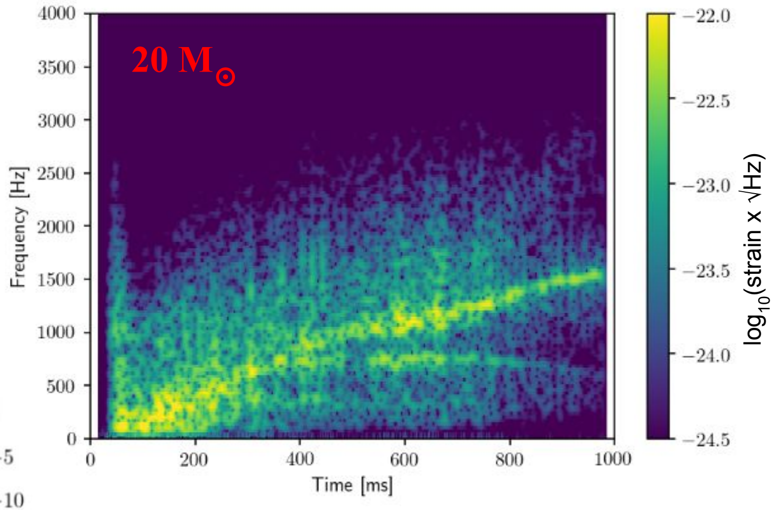
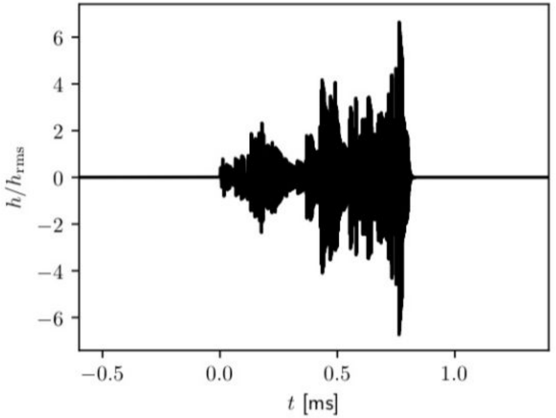
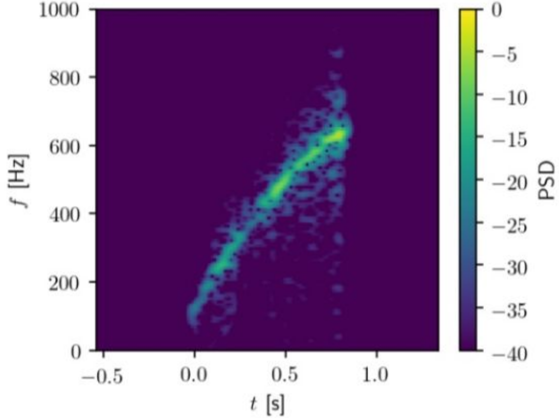
Phenomenological waveforms

The aim is reproducing the dominant feature observed from numerical simulations, i.e. the lowest order g-mode responsible for the monotonically raising arch in the time vs frequency domain.

The frequency evolution is modelled as **splines** interpolation to a series of discrete points.



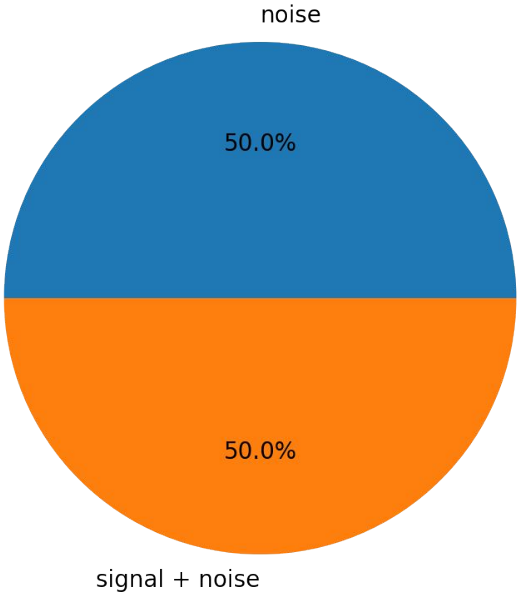


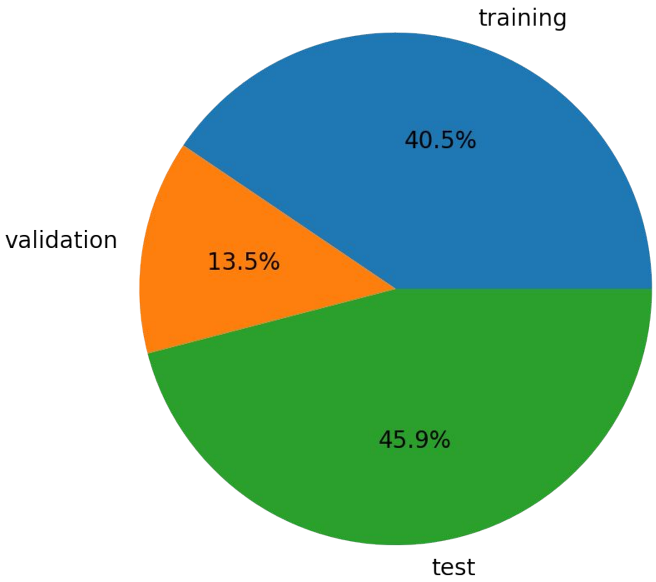


With this approach, a wider parameter space can be explored wrt using only numerical simulations results.

Dataset

The training of the network was performed using *curriculum learning*, where we start training with the easiest data sets, and then gradually the task difficulty is increased.





Training set = 180k phenomenological waveforms from a distance in [0, 100] kpc

Validation set = 60k phenomenological waveforms from a distance in [0, 100] kpc

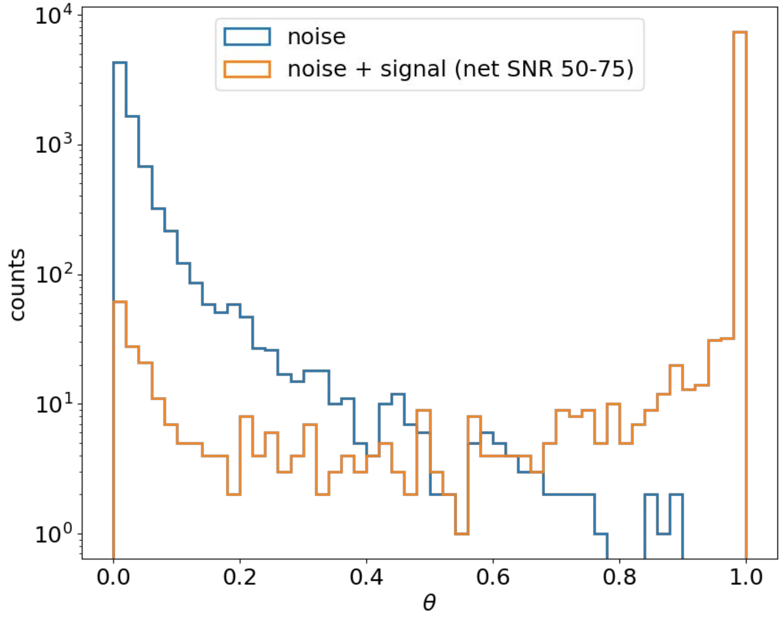
Test set = 208k numerical waveforms (from the literature) from a distance in [0, 100] kpc

Results

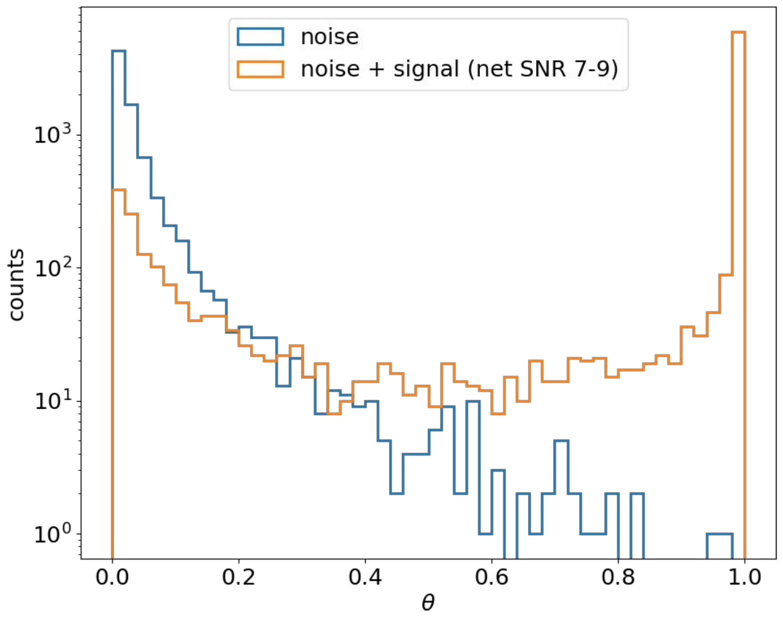
✔

Test set θ distribution

θ is the probability for a given image of containing the signal

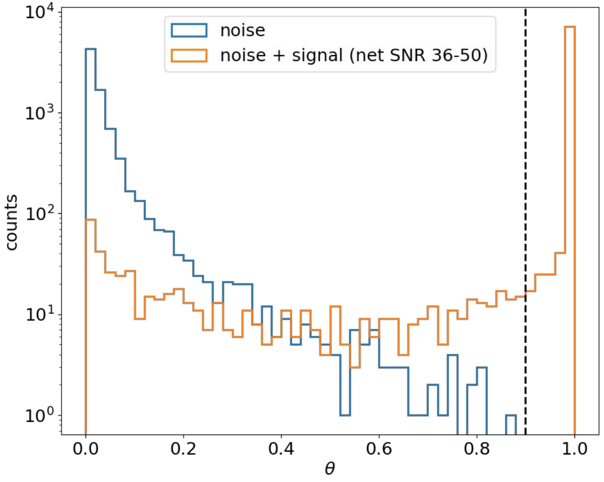


High network SNR



Low network SNR

How can we compute the efficiency?



Confusion matrix is a very popular measure used while solving classification problems. It can be applied to binary classification (as in our case) as well as for multiclass classification problems.

For a binary classification, the matrix entries contains the following information:

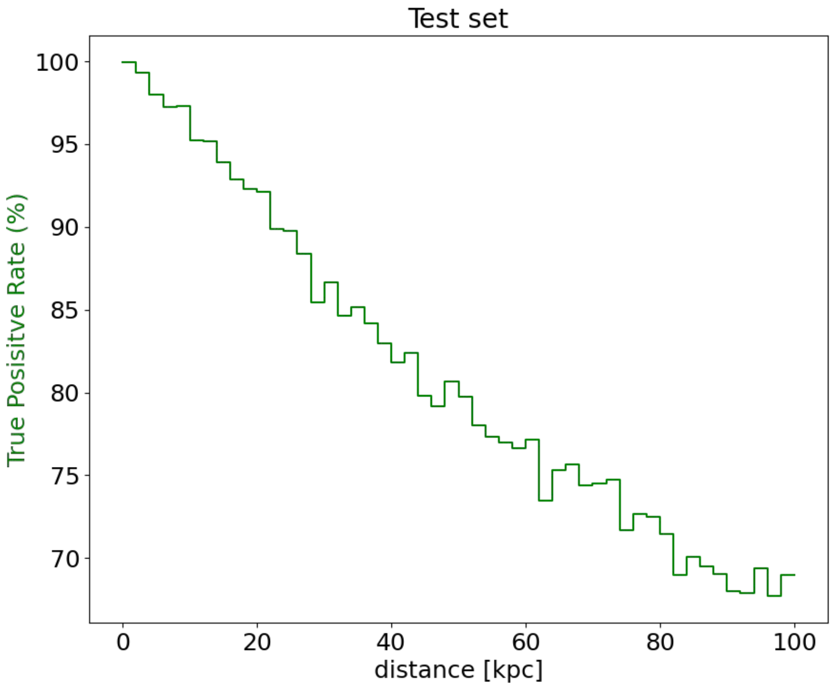
- **True Positive** (TP) = # "*signal+noise*" classified as "*signal+noise*"
- **False Positive** (FP) = # "*noise*" classified as "*signal+noise*"
- **True Negative** (TN) = # "*noise*" classified as "*noise*"
- **False Negative** (FN) = # "*signal+noise*" classified as "*noise*"

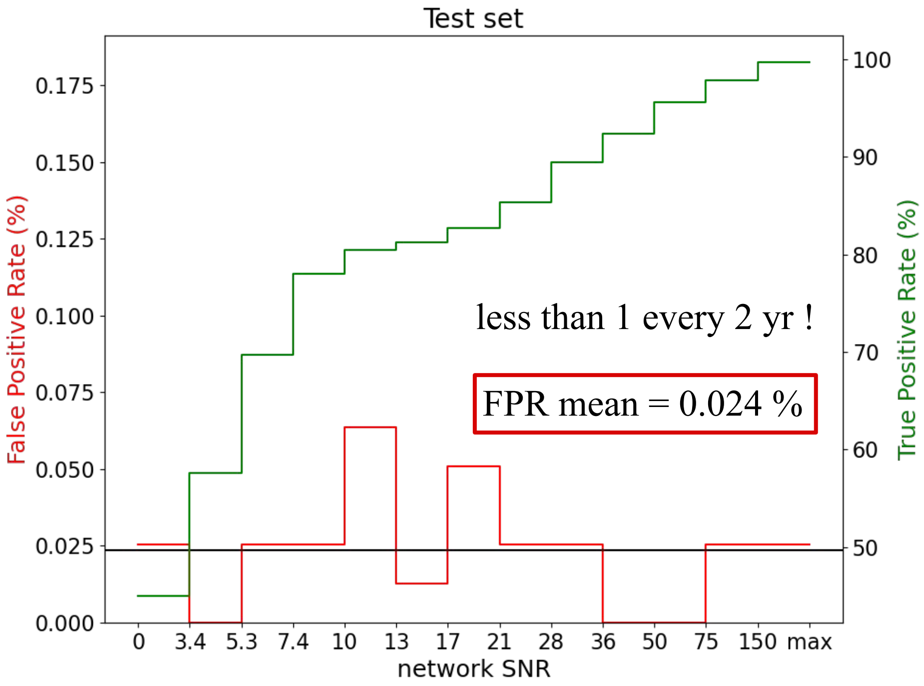
$$TruePositiveRate = \frac{TP}{TP + FN}$$

$$FalsePositiveRate = \frac{FP}{FP + TN}$$

$\theta^* = 0.9$	Pred *signal+noise*	Pred *noise*
True *signal+noise*	TP = 7246	FN = 600
True *noise*	FP = 0	TN = 7846

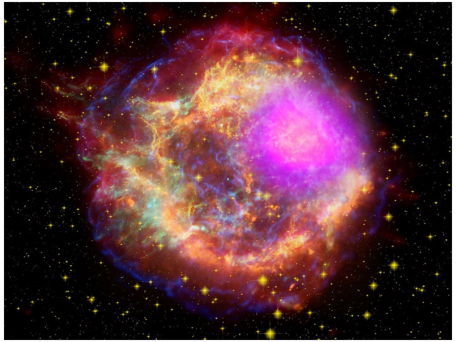
Test results ($\theta^{*} = 0.9$)

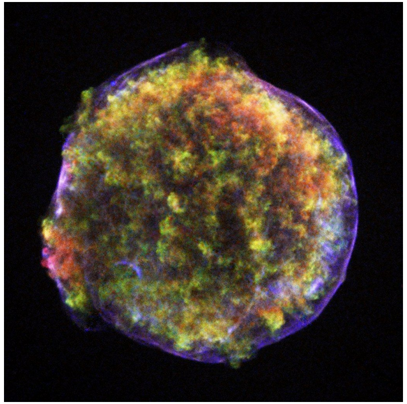


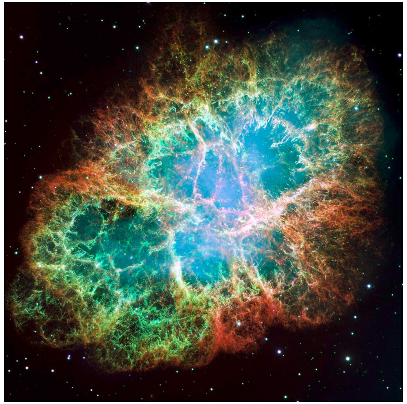


Summary

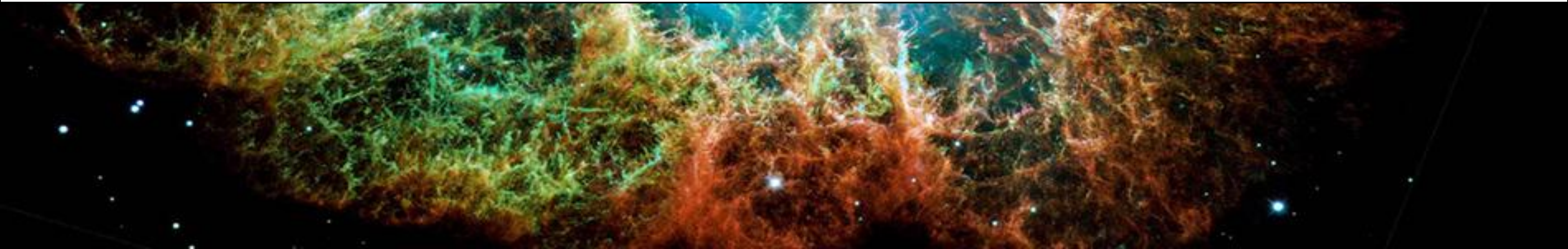
- The complex and dynamic evolution of CCSNe makes them a suitable GW source candidate.
- Multidimensional numerical simulations are not yet finally conclusive with respect to the possibility of explaining explosions for wider sets of progenitors.
- In order to cover a wider parameter space, we need to rely on a phenomenological waveform template that can mimic the main features of the GW emission from a CCSN.
- Our method, applied to the next generation gravitational wave detectors should allow us to extract the unique GW feature expected from a CCSN up to 100 kpc with an efficiency around 70 %.







Thank you for your attention!



Backup slides

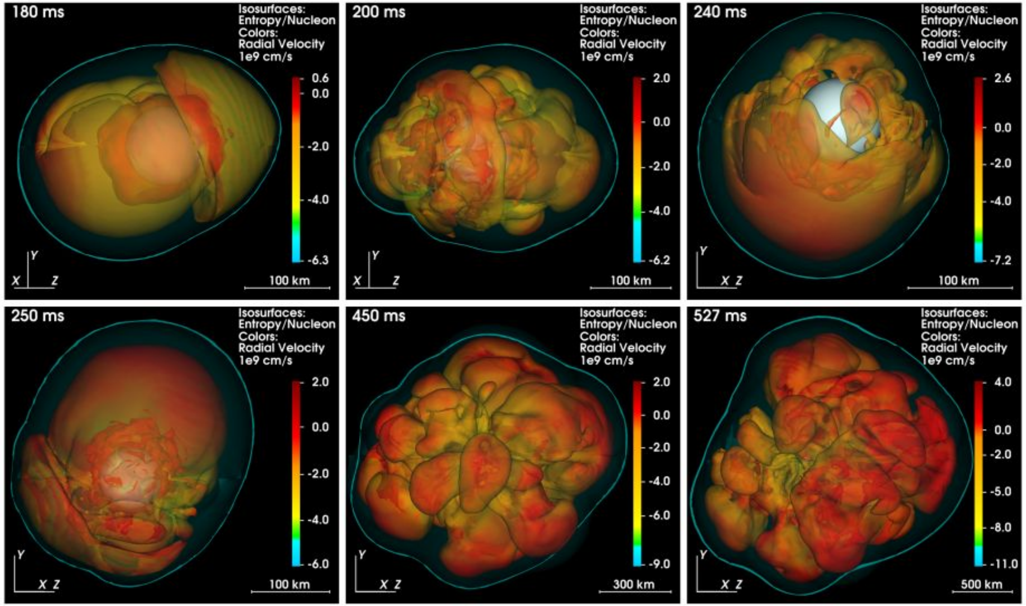
State-of-the-art numerical simulation

The numerical modelling of the core-collapse scenario is computationally challenging and even today, with the use of the largest scientific supercomputing facilities available, we are only starting to understand the physics involved.

The main algorithmic as well as computational challenges are:

1. the neutrino propagation in the six-dimensional phase space;
2. the neutrino-matter interactions

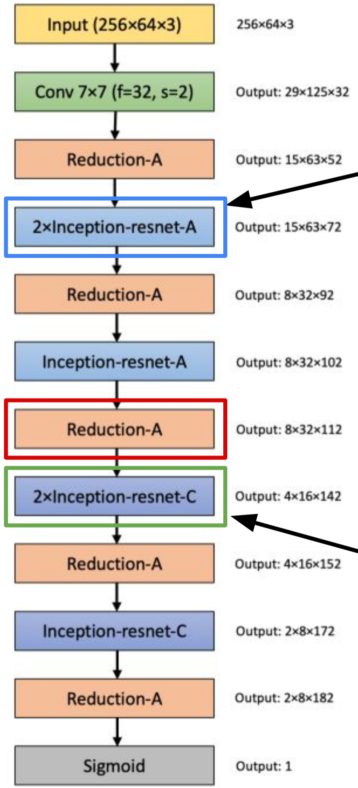
Up to now, no one has carried out a definitive 3D simulation including all the physical ingredients and with sufficiently high resolution to give the world-wide community confidence in the results.

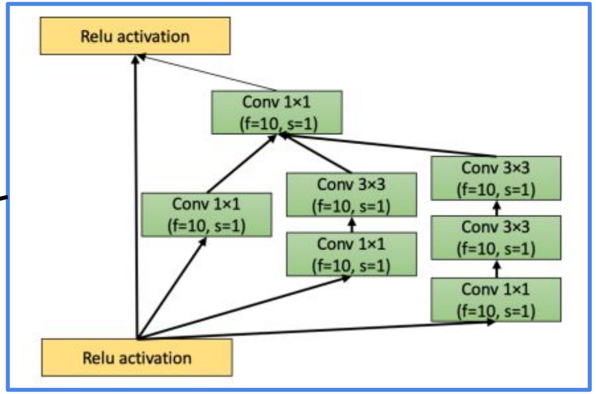


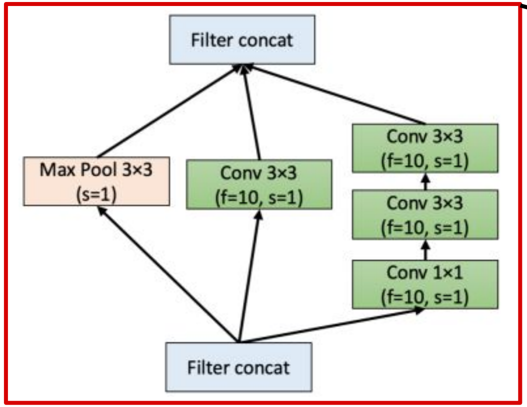
Neural network architecture

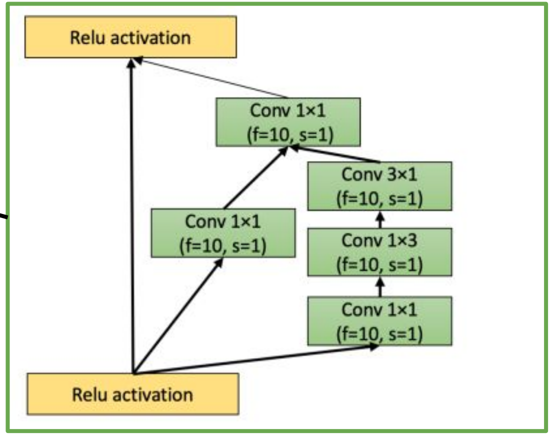
In order to exploit the peculiar structure of the input data, i.e. 2D spectrogram, we decide to use a **Convolutional Neural Network** (CNN).

The CNN developed for this scope is a **reduced version** of Inception-Resnet v1.



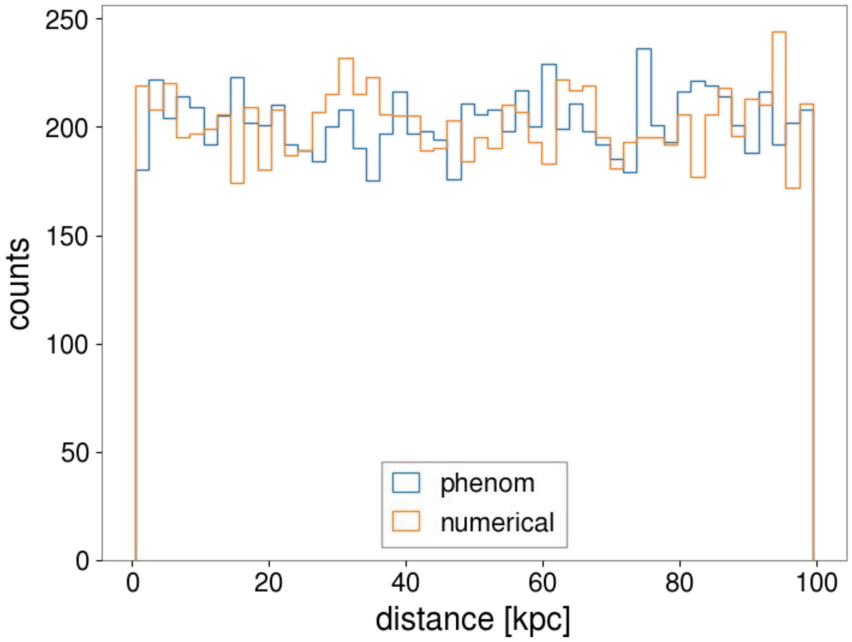




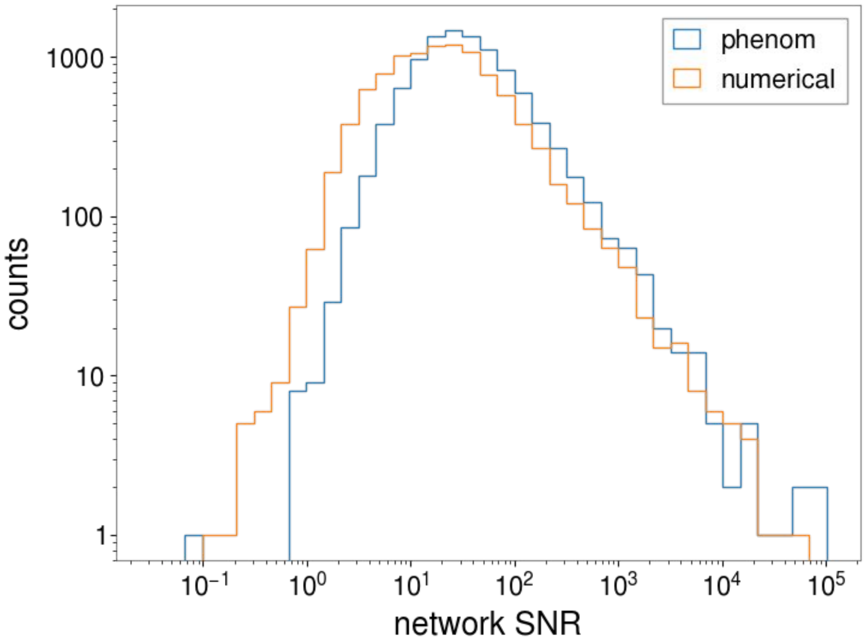


Injected waveforms

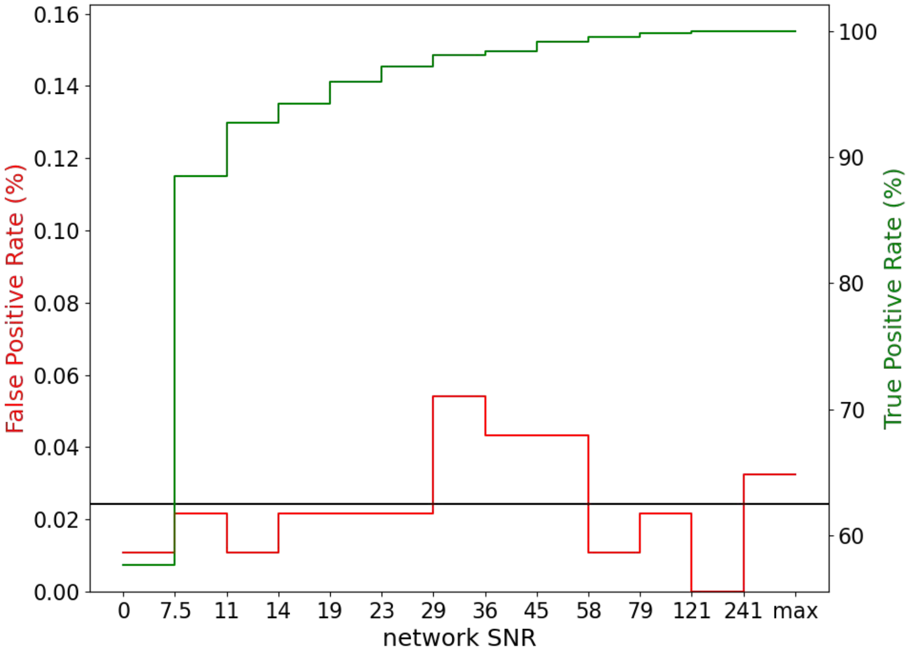
1. Sample uniformly the distance (and the sky location) between 0 and 100 kpc



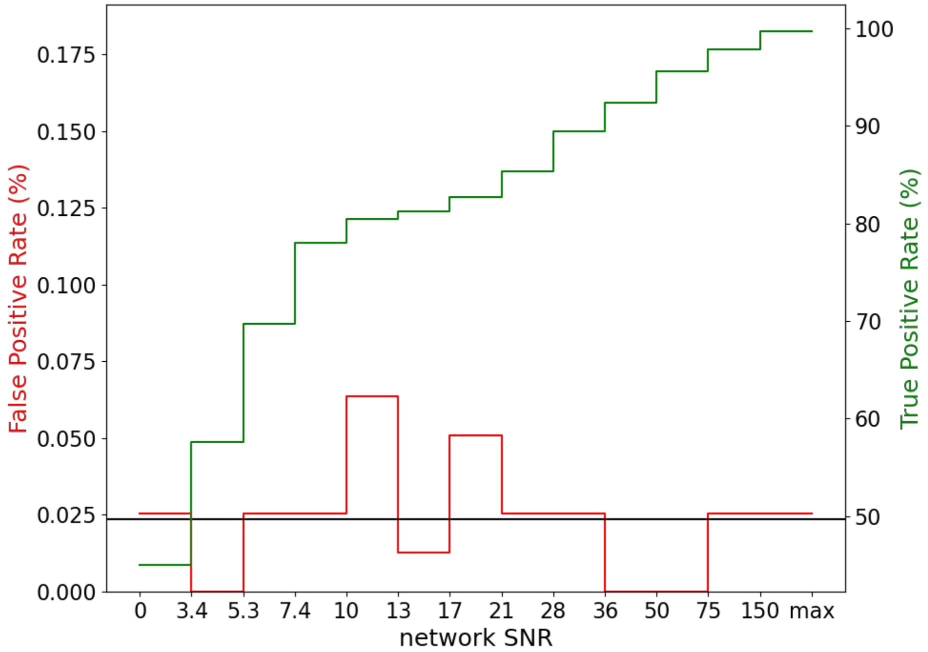
2. Compute the signal-to-noise ratio for the given detector configuration



Blind dataset ($\theta^* = 0.9$)



Test dataset ($\theta^* = 0.9$)



Blind & Test datasets ($\theta^* = 0.9$)