

Fast Neutrino Flavor Conversions in 1D Core-Collapse Supernova Simulations

CTAP Workshop, November 10, 2022
In honor of Georg Raffelt

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Neutrino Oscillations in Dense Media

- Neutrino evolution in dense neutrino media is **very different** from the one in vacuum and matter

$$i(\partial_t + \mathbf{v} \cdot \nabla)\rho = [H, \rho]$$

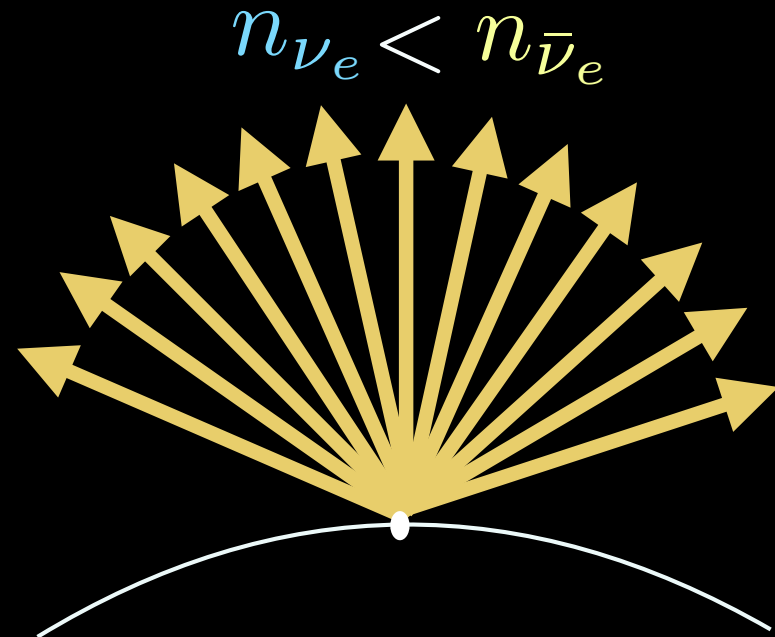
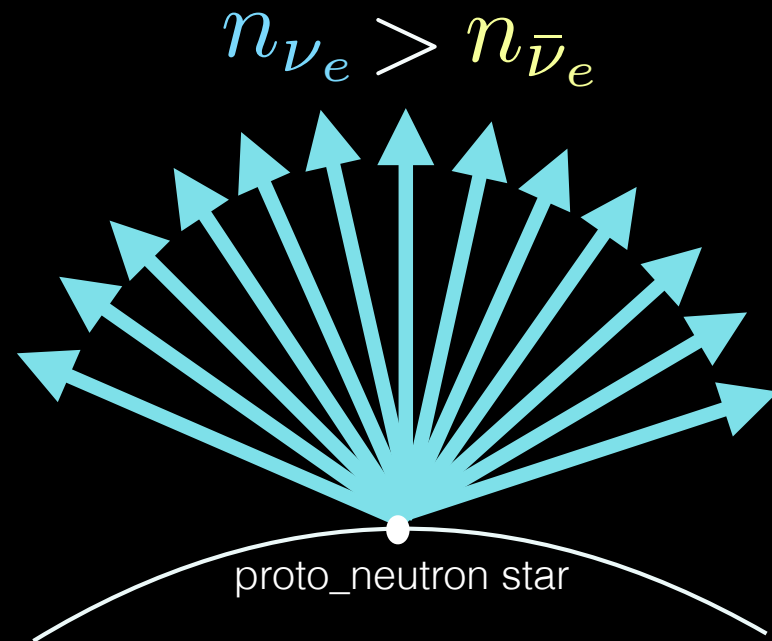
$$H = \frac{1}{2} \begin{bmatrix} -\omega \cos 2\theta + \sqrt{2}G_F n_e & \omega \sin 2\theta \\ \omega \sin 2\theta & \omega \cos 2\theta - \sqrt{2}G_F n_e \end{bmatrix} + H_{\nu\nu}$$

$$\sqrt{2}G_F \int \underbrace{d^3q}_{\text{coupling}} (1 - \mathbf{v}_P \cdot \mathbf{v}_q) \underbrace{(\rho_\nu - \rho_{\bar{\nu}})}_{\text{nonlinearity}}$$


- It is **important** to understand neutrino flavor evolution

Fast Flavor Conversions

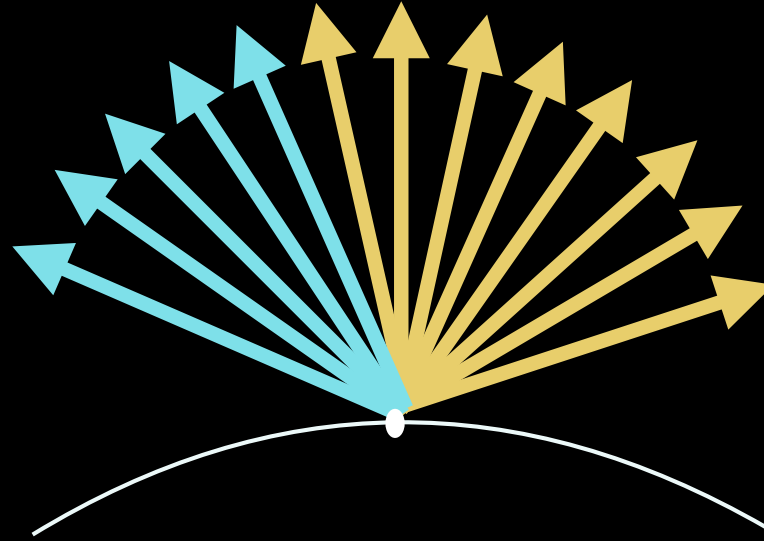
- In our traditional understanding, we assumed that neutrinos are emitted **isotropically** from the surface of the neutrino source
- $f_{\nu_e}(\theta) - f_{\bar{\nu}_e}(\theta)$ is either always **positive or negative**



- This implies that the **scales** on which flavor conversion could occur are determined by **vacuum frequency** $\Delta m^2 / 2E \sim 1 \text{ km}^{-1}$

Fast Flavor Conversions

- **FFC** could occur when there is **crossing** in $f_{\nu_e}(\theta) - f_{\bar{\nu}_e}(\theta)$

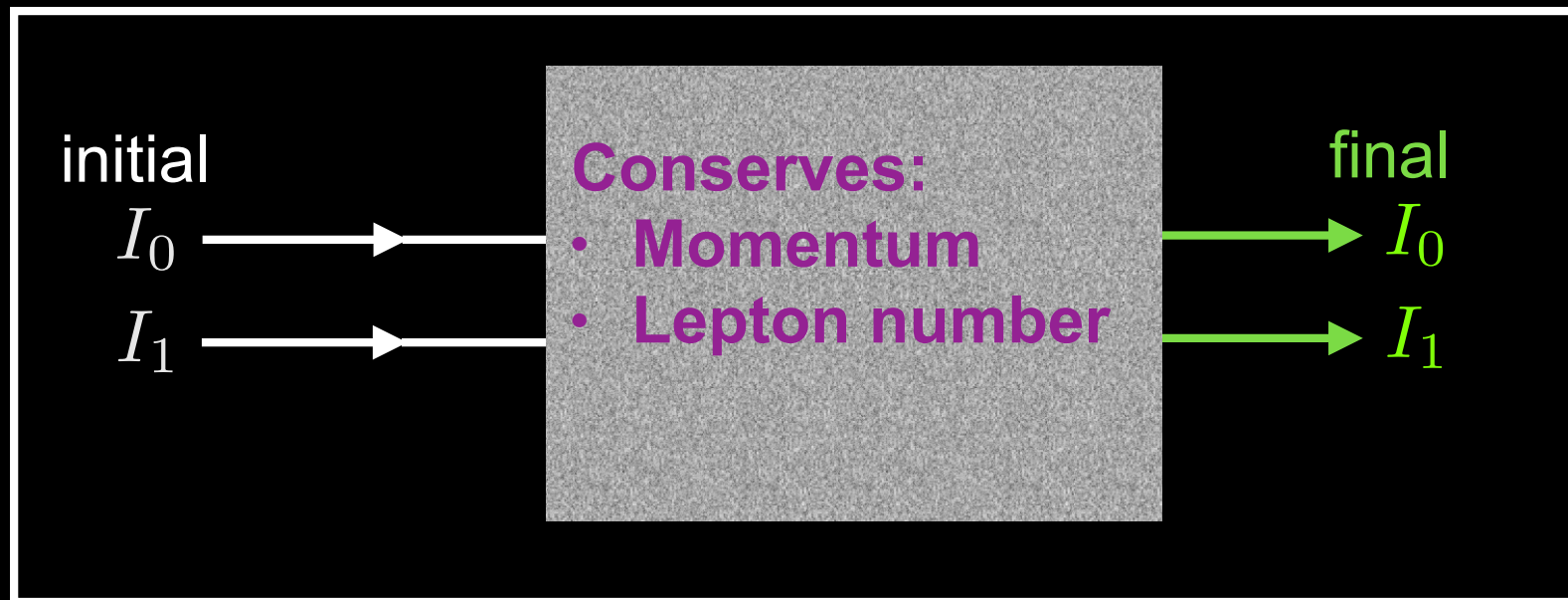


- **Scales** on which flavor conversion can occur is now proportional to n_ν and could be $< 10 \text{ cm}$
- Neutrino oscillations **can** now occur at densities that had been long thought to be the realm of collisional and scattering processes

Including FFC in CCSNe

- FFC **can not** be implemented **self-consistently**
- We assume FFC lead to a sort of flavor **equilibrium**

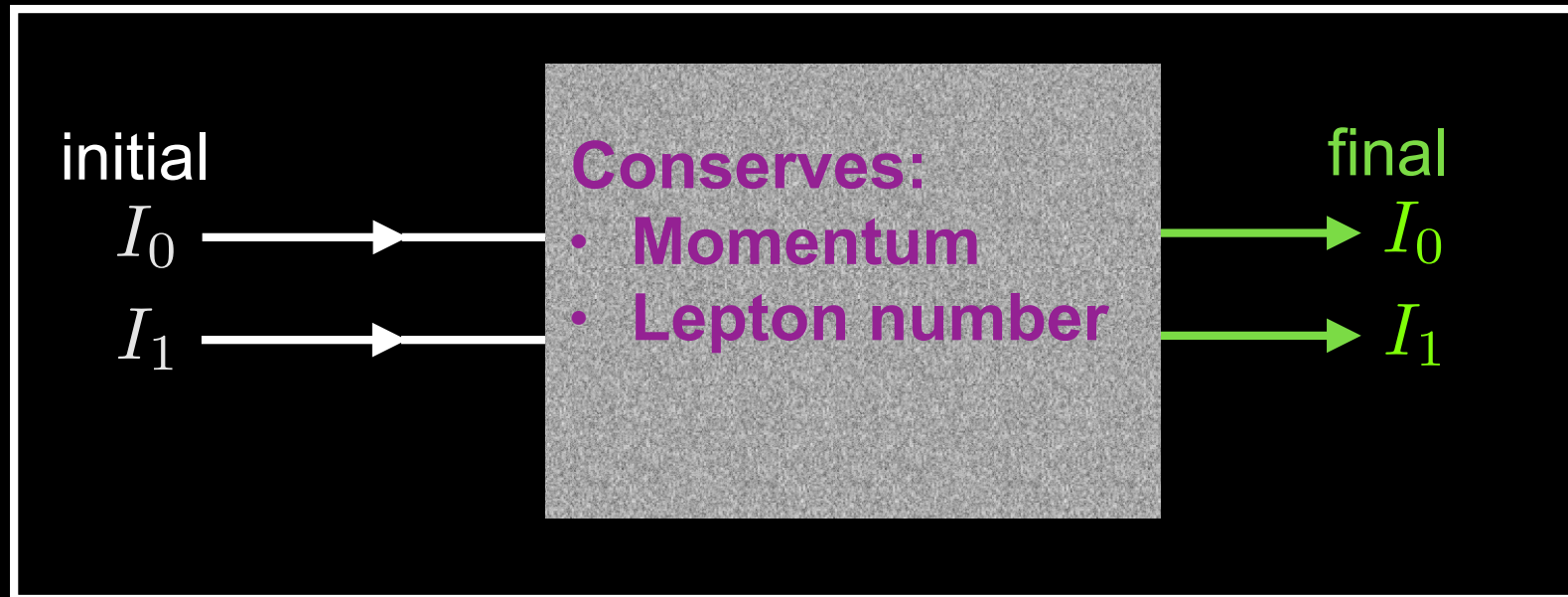
FFC



Including FFC in 1D CCSNe

- We perform SN simulations including FFC for a **1D** $20M_{\odot}$ model, in a **parametric** way
- We set a density **threshold** ($\rho_c = 10^9 - 10^{14} \text{ g cm}^{-3}$) below which FFC can occur

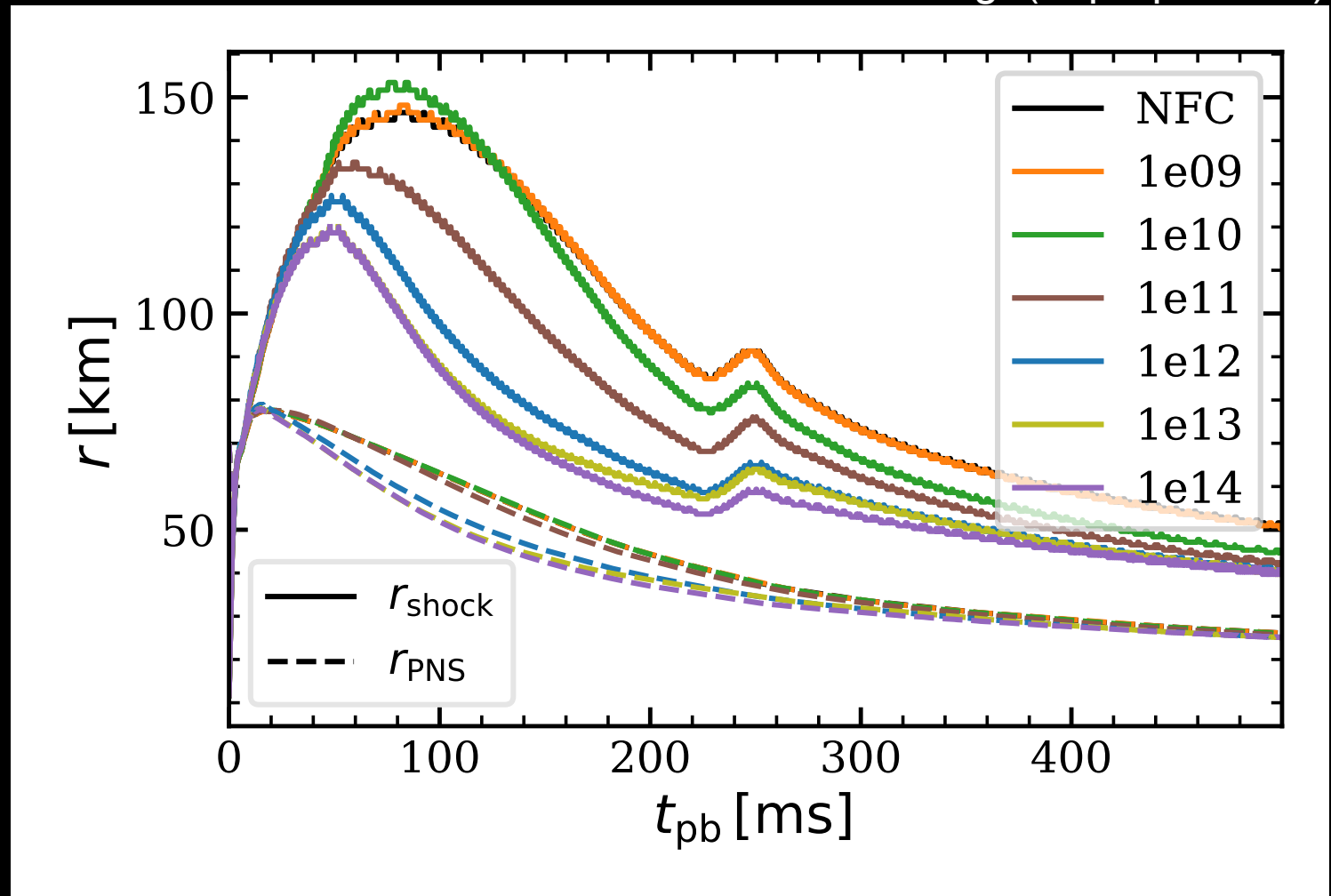
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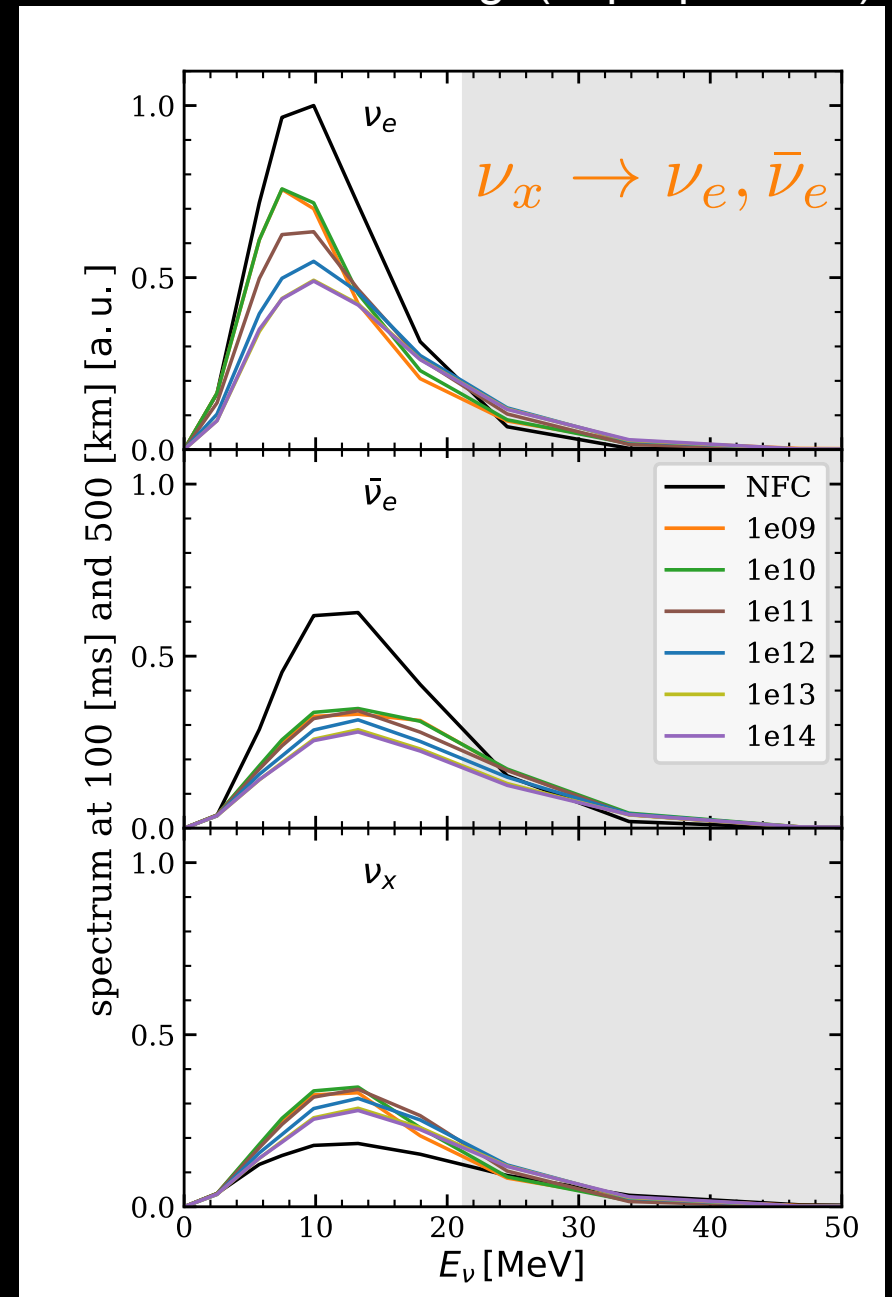
Ehring+(In preparation)



Including FFC in 1D CCSNe

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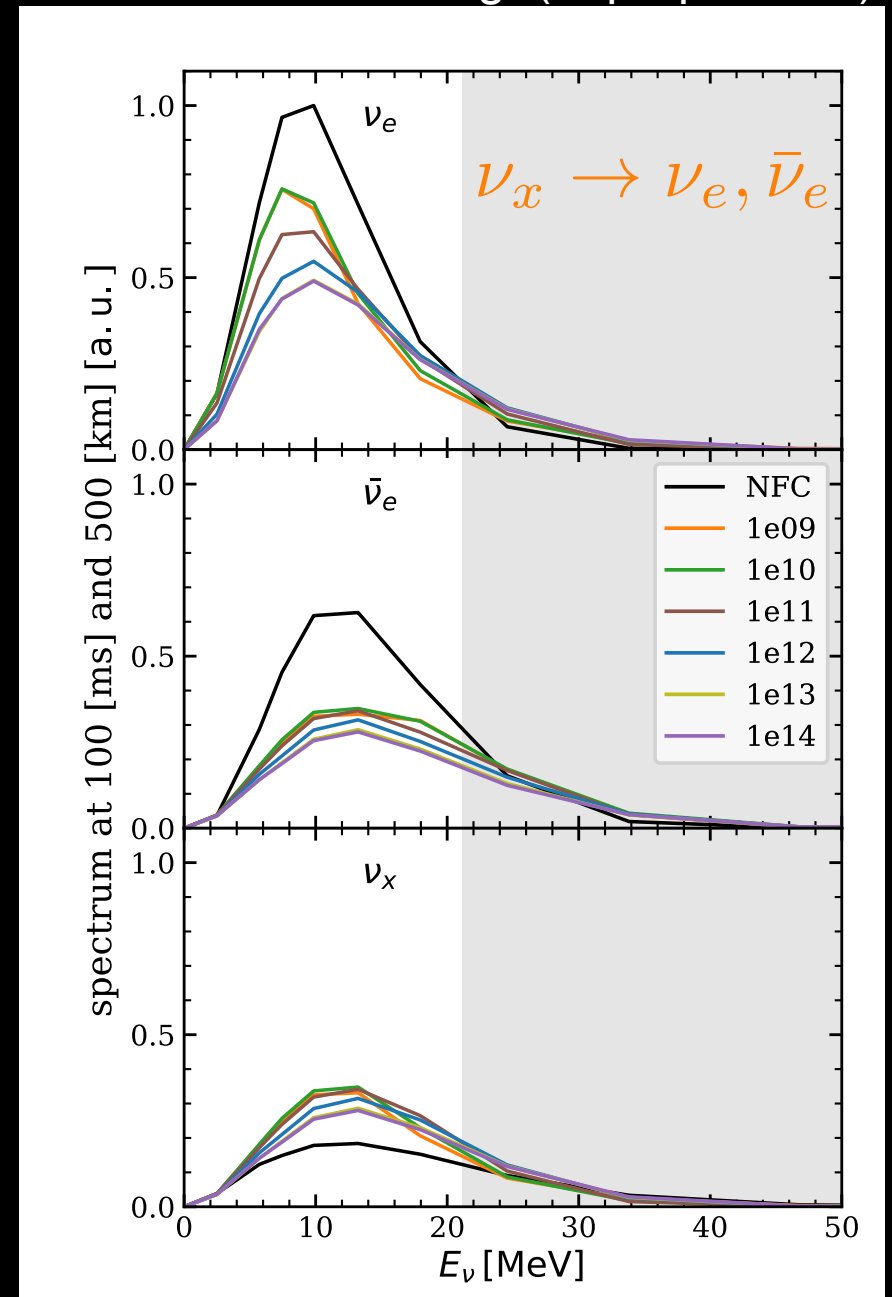
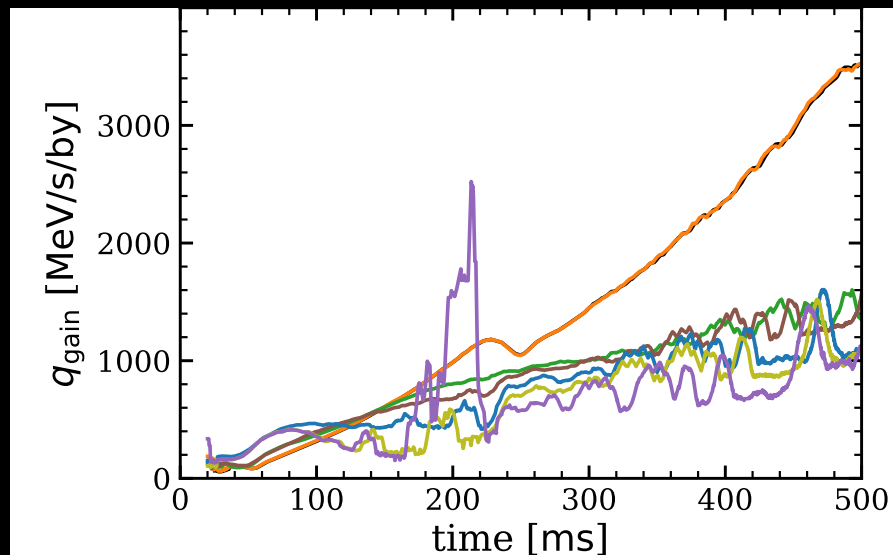
- Two competing effects here
 - $\nu_x \rightarrow \nu_e, \bar{\nu}_e$ at the tail **increases** heating



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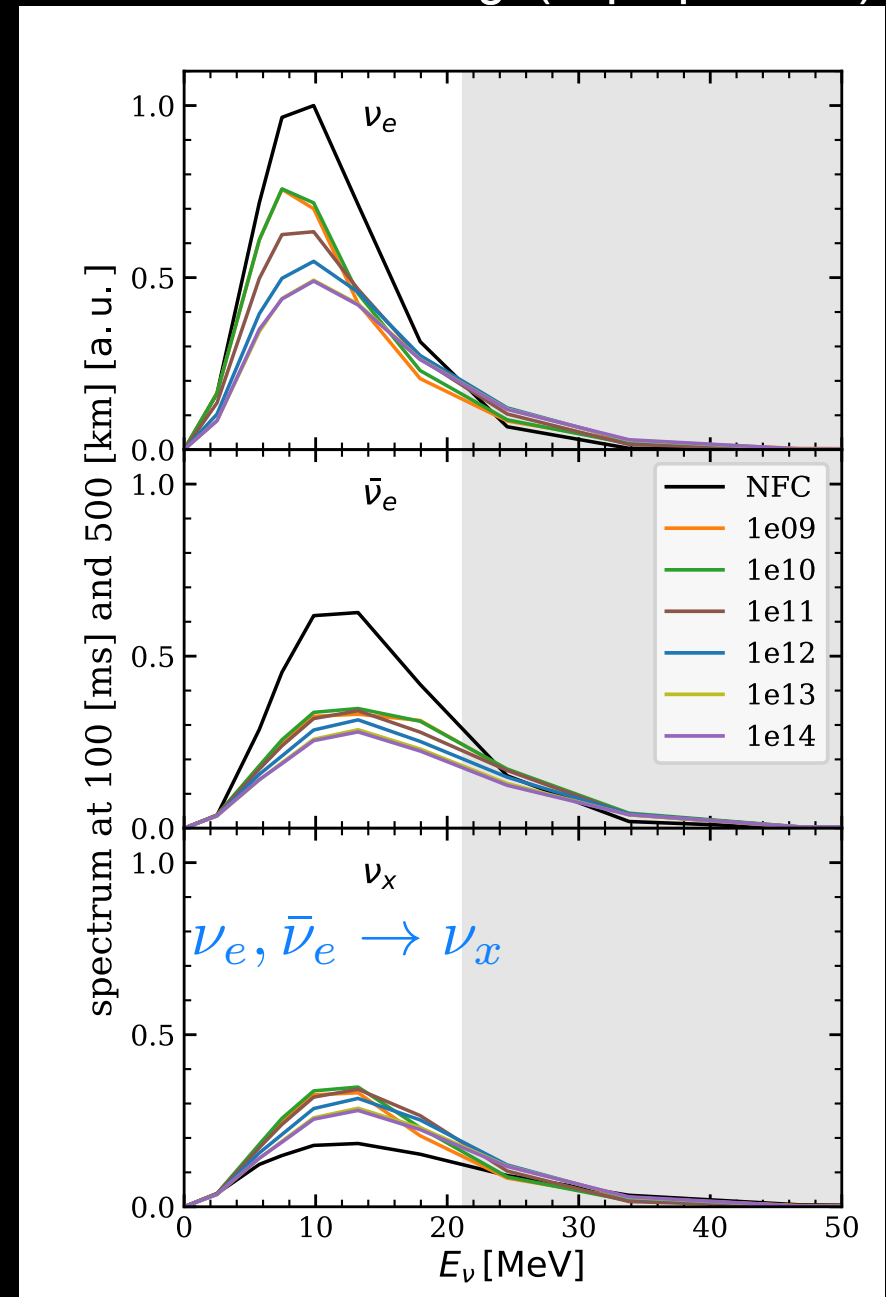
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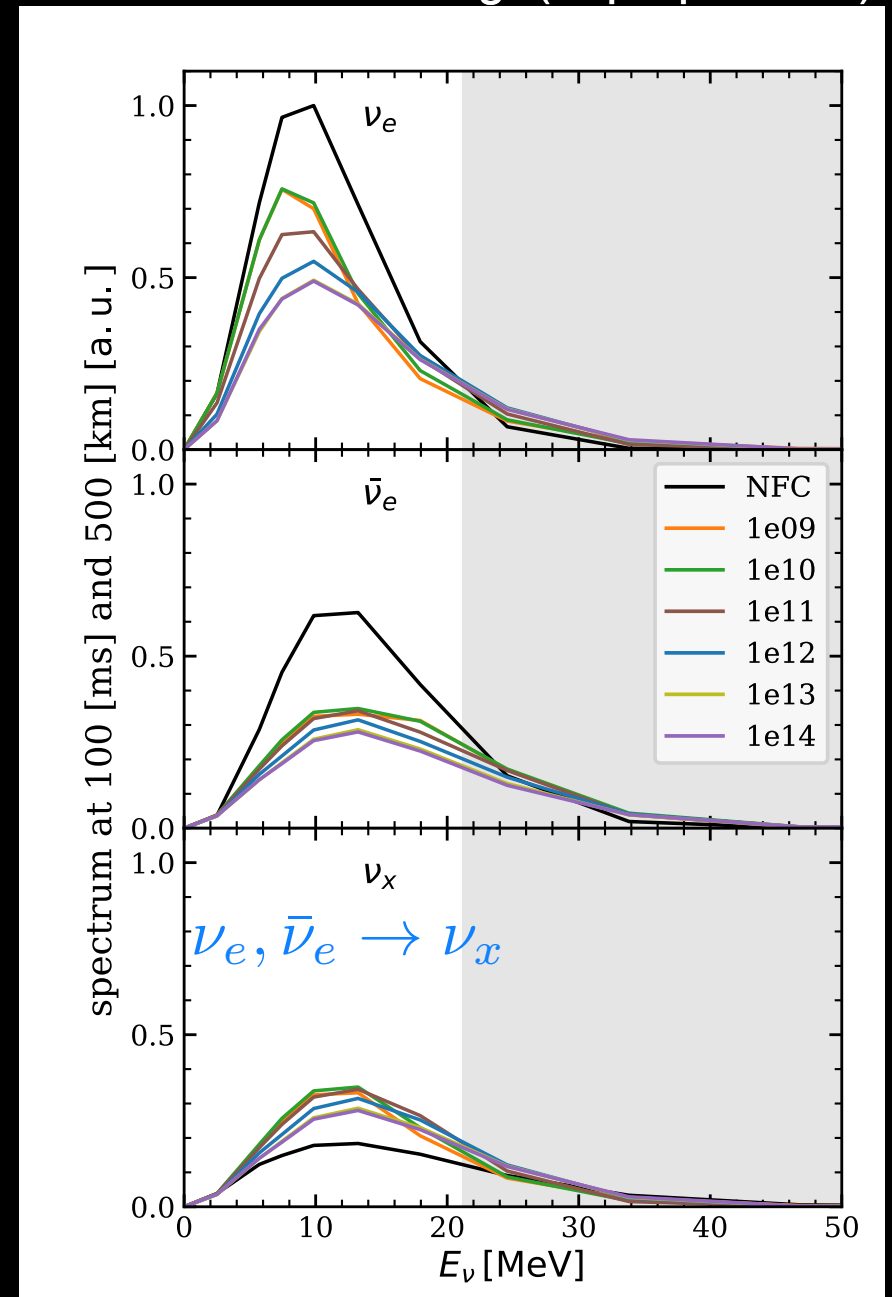
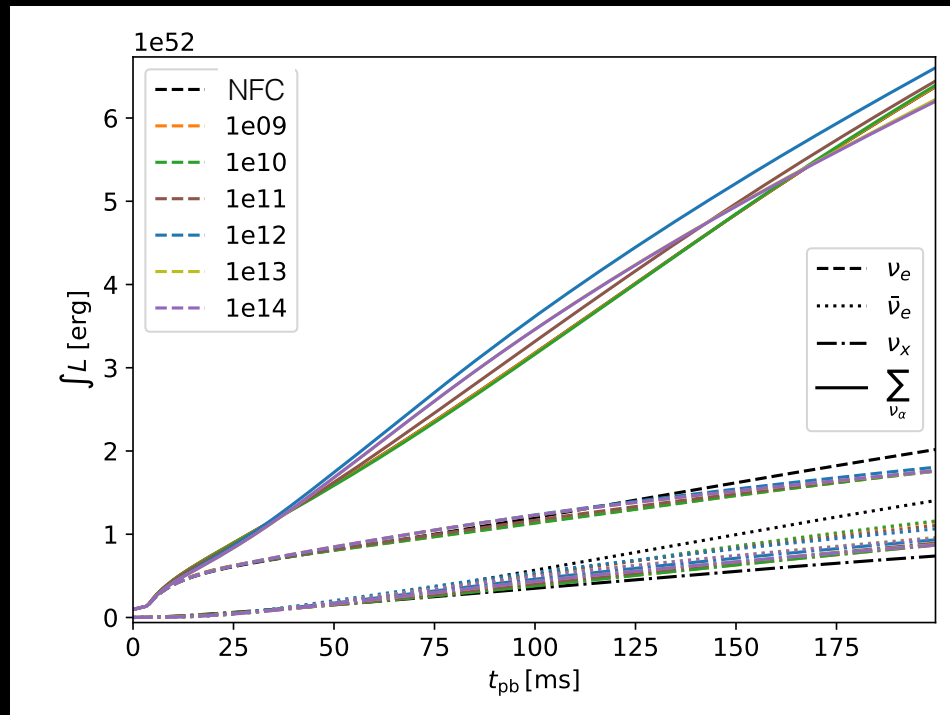
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Neutron Star Mergers

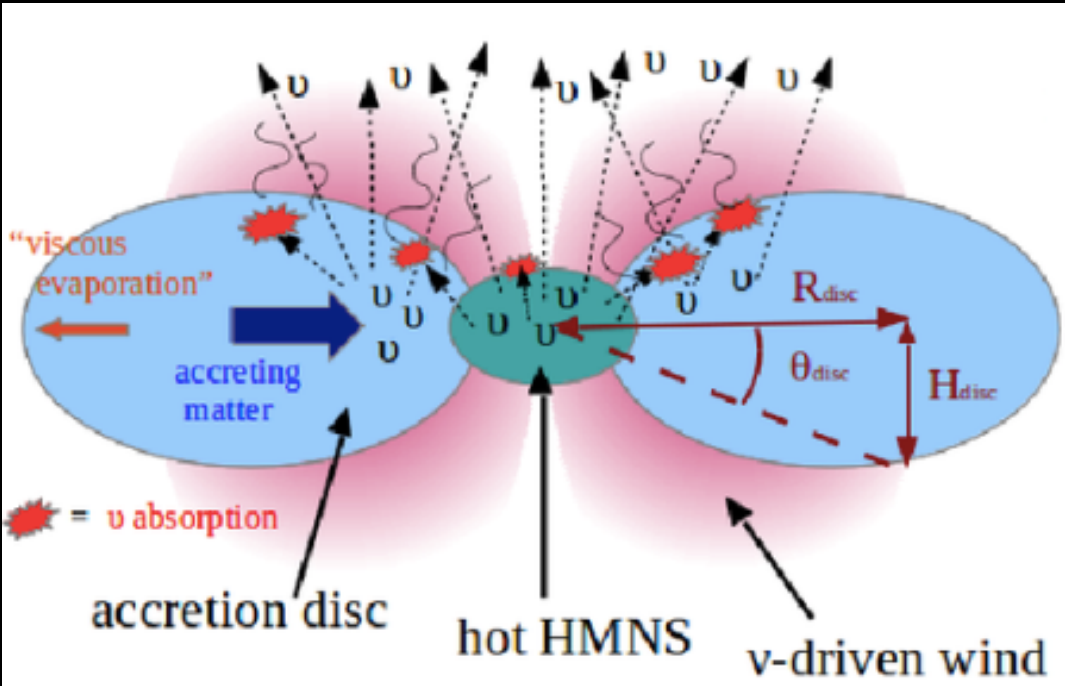


Figure from Perego et. al., arxiv: 1405.6730

- Hot **hyper massive NS** and the **accretion disc** emit a huge number of neutrinos

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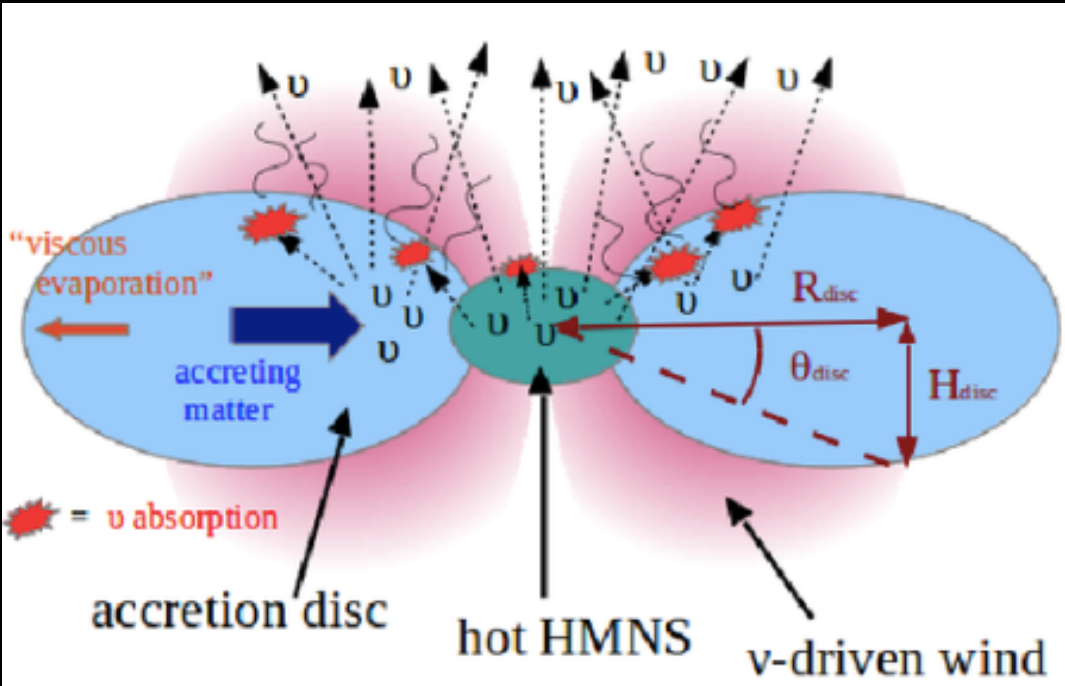
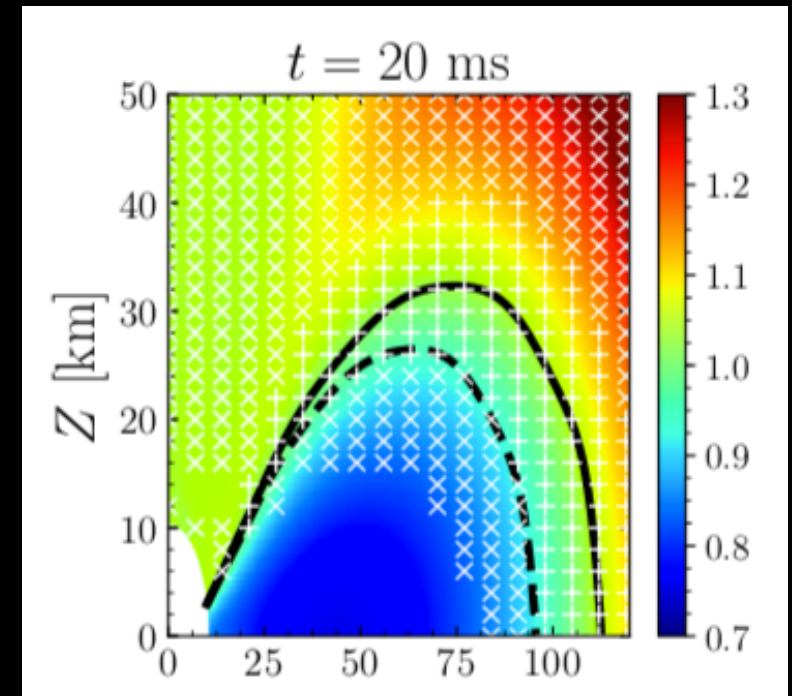


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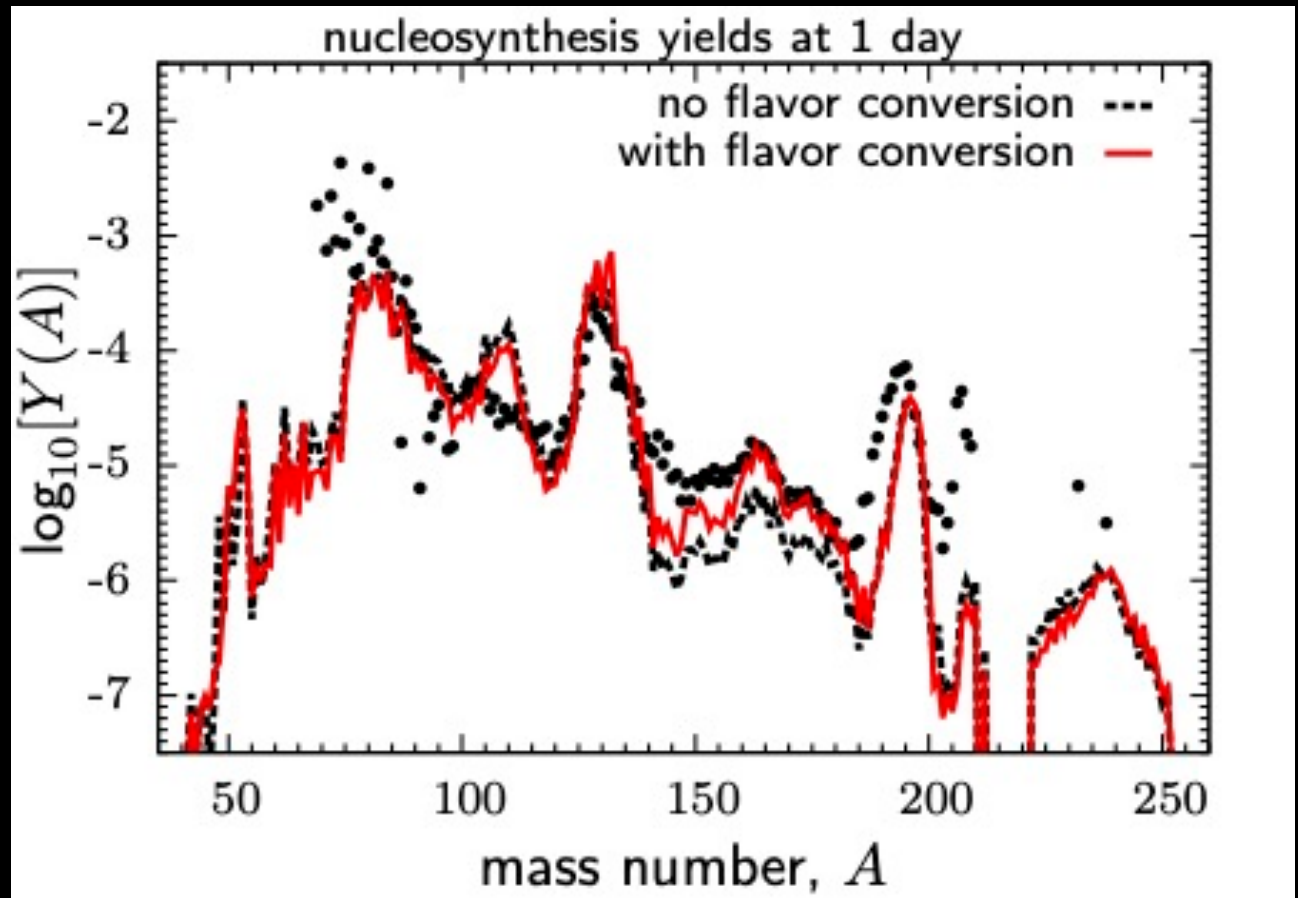
Just+2022 (also Li+2021, Fernandez+2022, Grohs+2022,)

- Fast modes can occur in a wide region even **inside** the disk
- Any self-consistent neutrino transport should **implement** fast conversions.



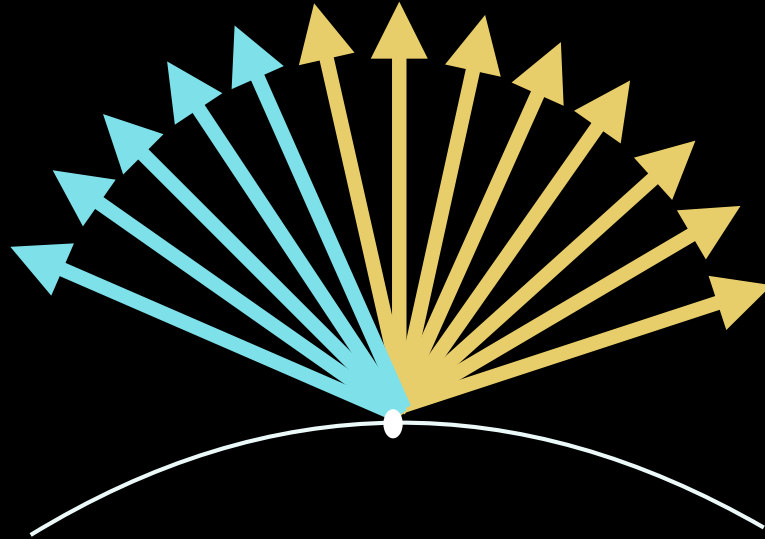
Neutron Star Mergers

- We perform simulations with **self-consistent** neutrino transport
- The presence of fast conversions inside the torus opens up a new **cooling channel**
- The impact of the fast modes remains **small** on the Y_e due to a sort of **self-regulating** mechanism



Fast Flavor Conversions

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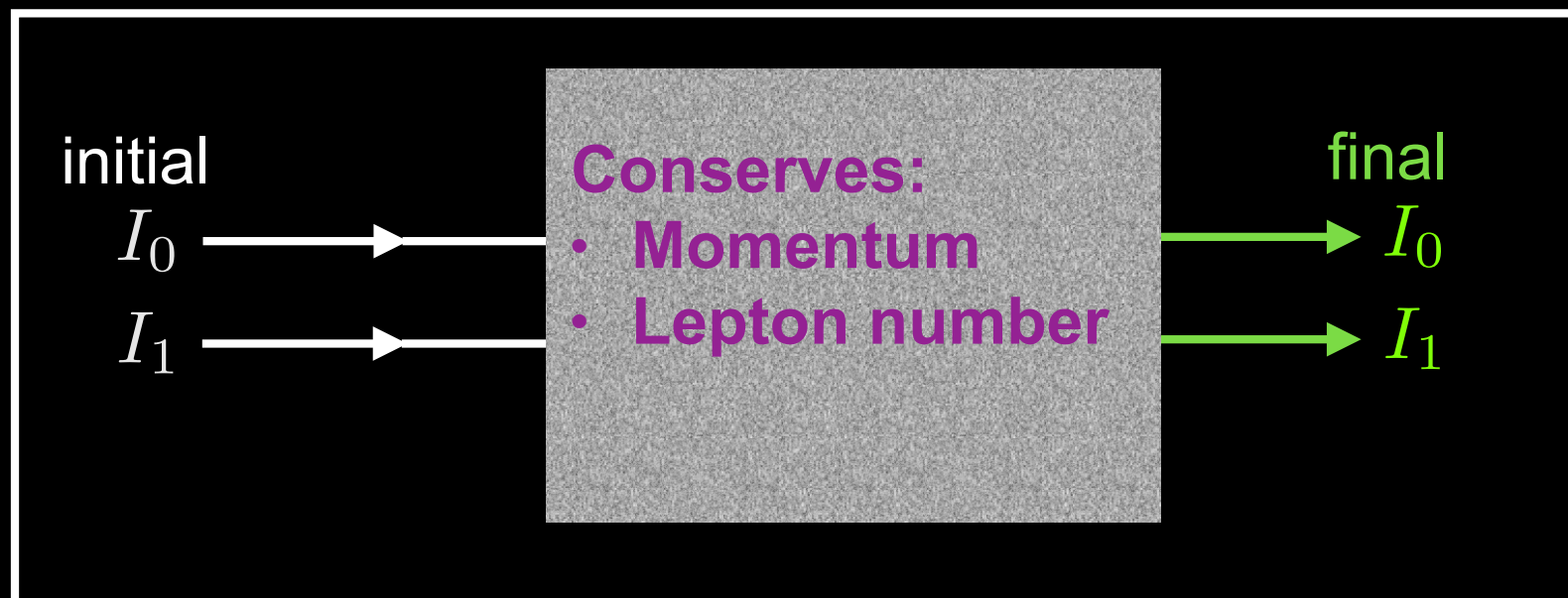


Fast Flavor Conversions

- The angular distributions are **not available**, instead we have only access to their moments

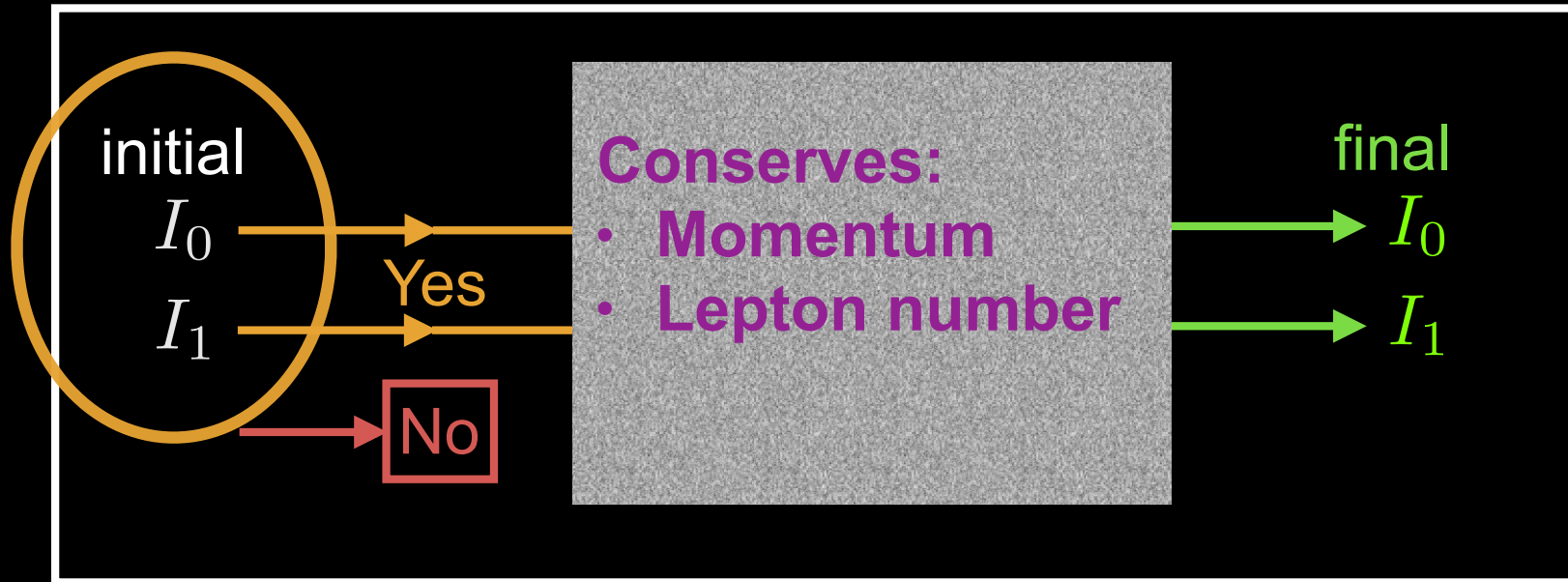
$$I_n = \int d \cos \theta_\nu \cos^n \theta_\nu f_\nu(\cos \theta_\nu)$$

- We can still make progress! Dasgupta+2018; Abbar2020; Johns+2021; Richers2022;
- But these methods are normally **inefficient** and **very slow**
- FFC can not be detected **on the fly**



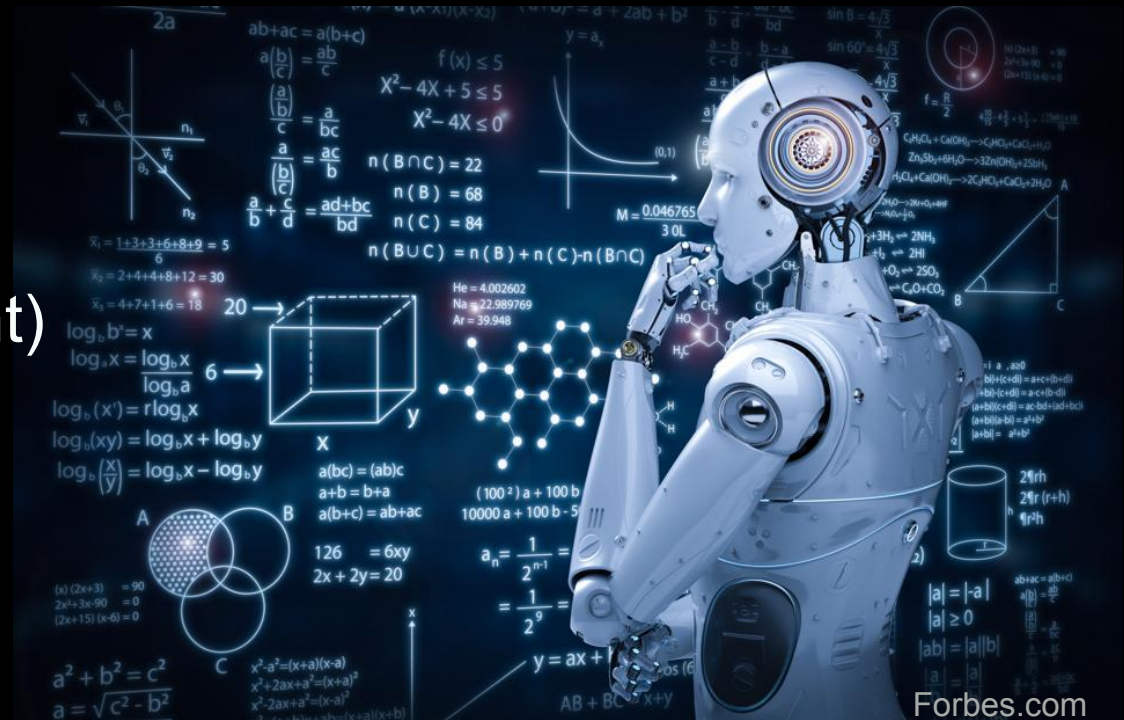
Application of Machine Learning

- A **classification** problem!



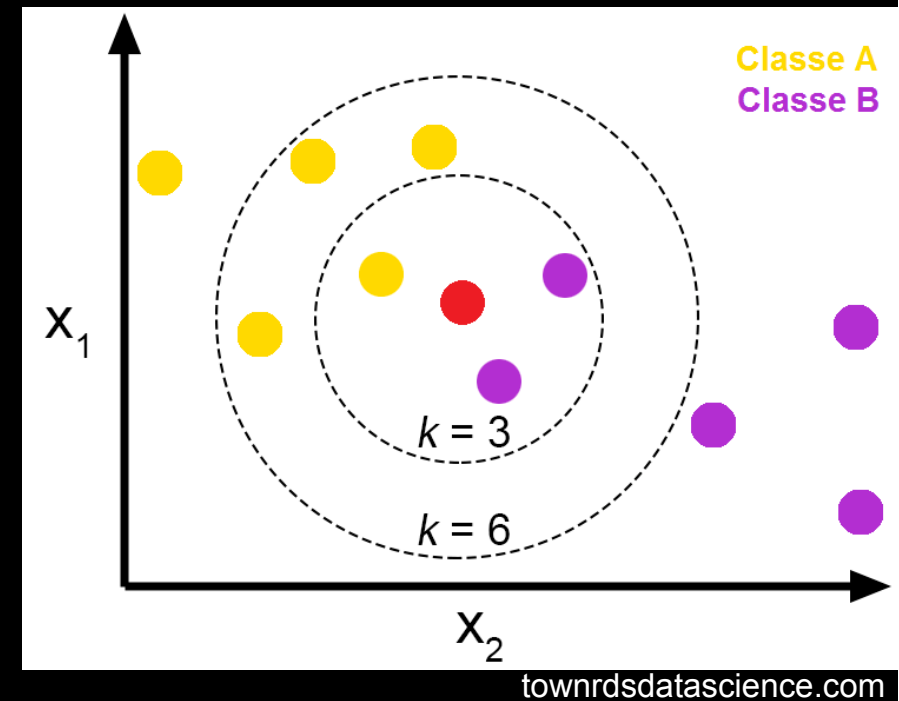
Application of Machine Learning

- Machine learning can help us
- We have four feature here: I_0 and I_1 for neutrinos and antineutrinos (one is redundant)
- A number of ML algorithms out there. I here introduce:
 - KNN
 - Decision Tree
 - Naive Bayes
 - SVM
 - Logistic Regression



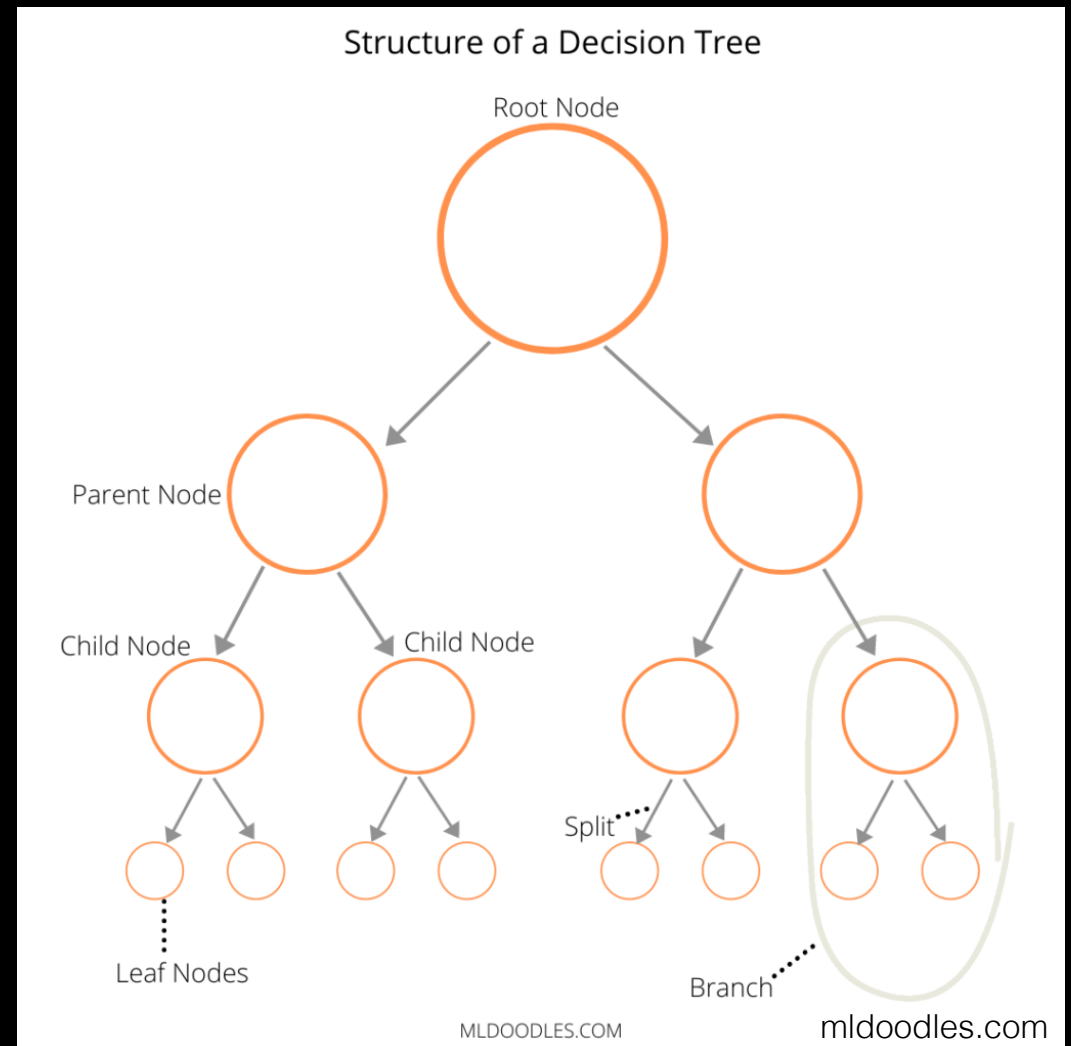
KNN

- KNN is one of the simplest forms of machine learning algorithms mostly used for classification. It **classifies the data point on how its neighbor is classified.**



Decision Tree

- In decision tree, one makes decision using a tree-like structure. At each node, one of the features is selected and the branching occurs.



Naive Bayes

- Naive Bayes classifier is a probabilistic machine learning model which is based on the Bayes theorem

The diagram illustrates Bayes' Theorem with the following components and labels:

- Likelihood of the Evidence given that the Hypothesis is True** (orange text, top left): Points to $P(E|H)$ in the numerator.
- Prior Probability of the Hypothesis** (red text, top right): Points to $P(H)$ in the numerator.
- Posterior Probability of the Hypothesis given that the Evidence is True** (blue text, bottom left): Points to $P(H|E)$ on the left side of the equation.
- Prior Probability that the evidence is True** (green text, bottom right): Points to $P(E)$ in the denominator.

$$P(H|E) = \frac{P(E|H) * P(H)}{P(E)}$$

medium.com

Figure from wikipedia

SVM

- **Support Vector Machine** is a classification based on finding a line that classifies the data points, maximises the margins

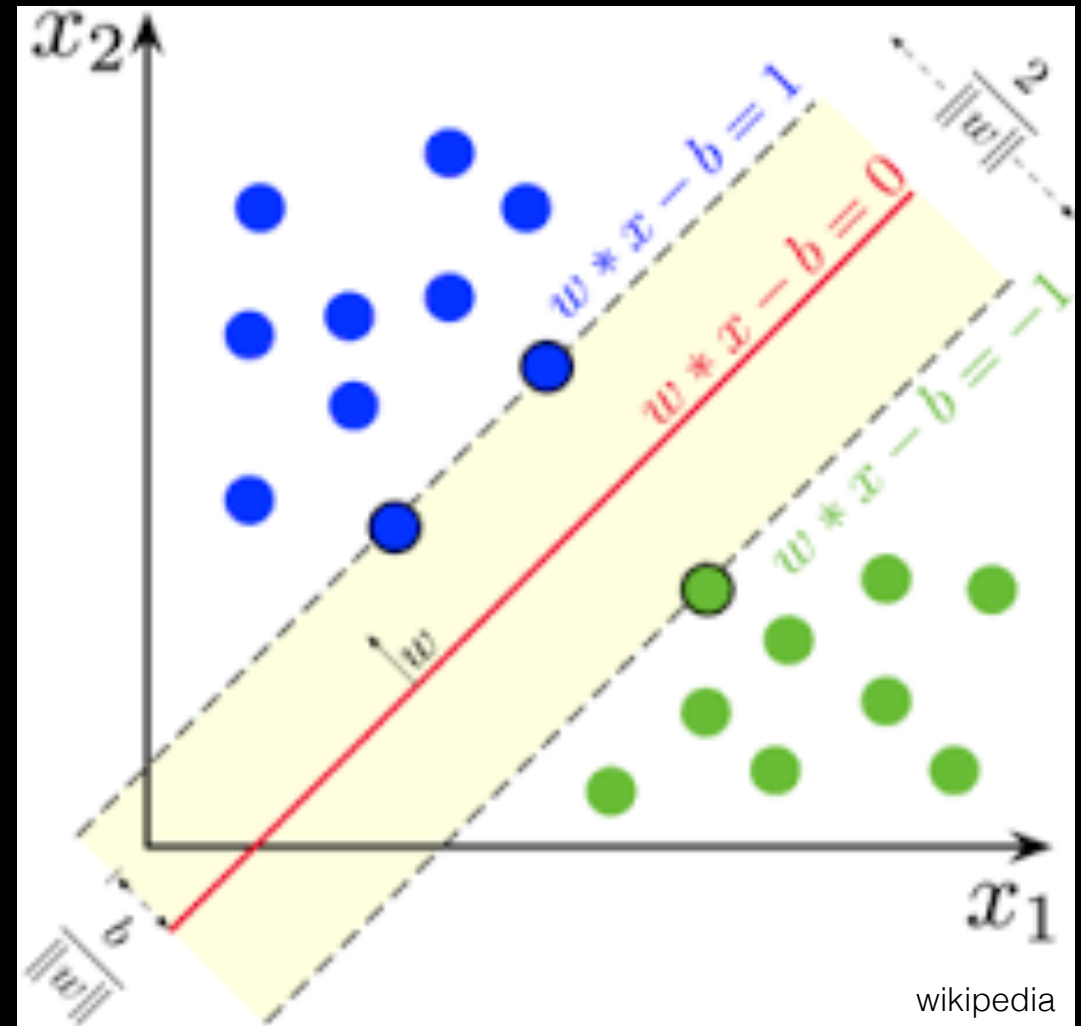
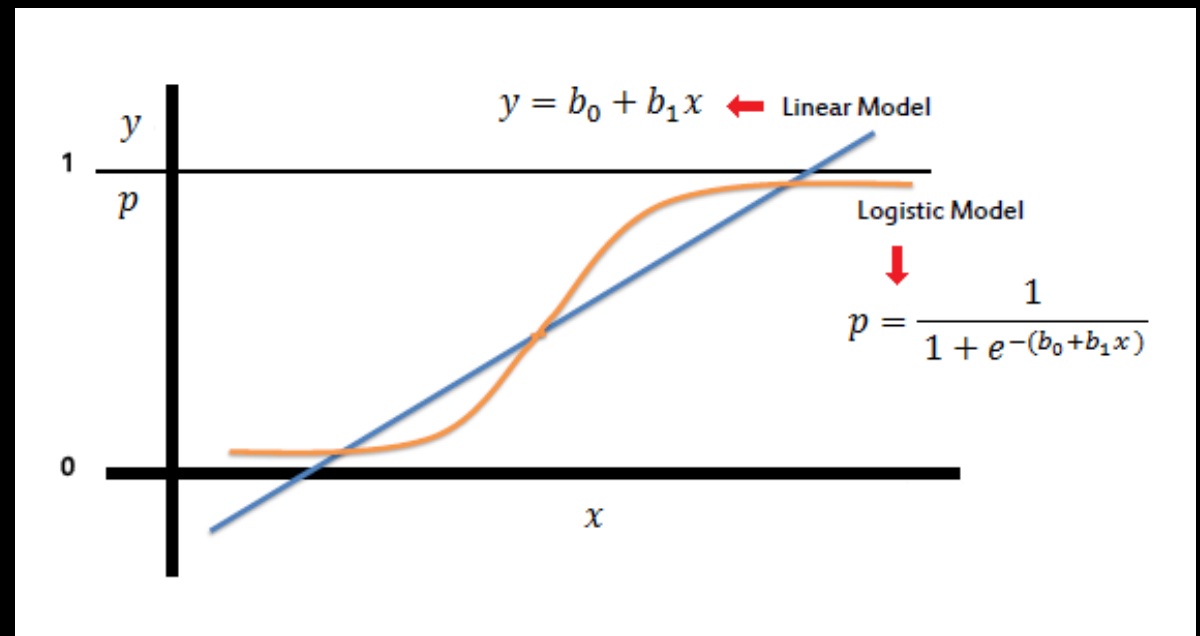


Figure from wikipedia

Logistic Regression

- Based on finding a line that separates the data points, in which a **logistic** function is applied on the top of the linear one so that one can decide on the basis of some final values which are in (0,1)



<http://www.elusives.eu>

Figure from wikipedia

Application of Machine Learning

- For training, we use analytical **maximum-entropy** distribution

$$f_{\nu}(\cos \theta_{\nu}) = \exp(-\eta + a \cos \theta_{\nu})$$

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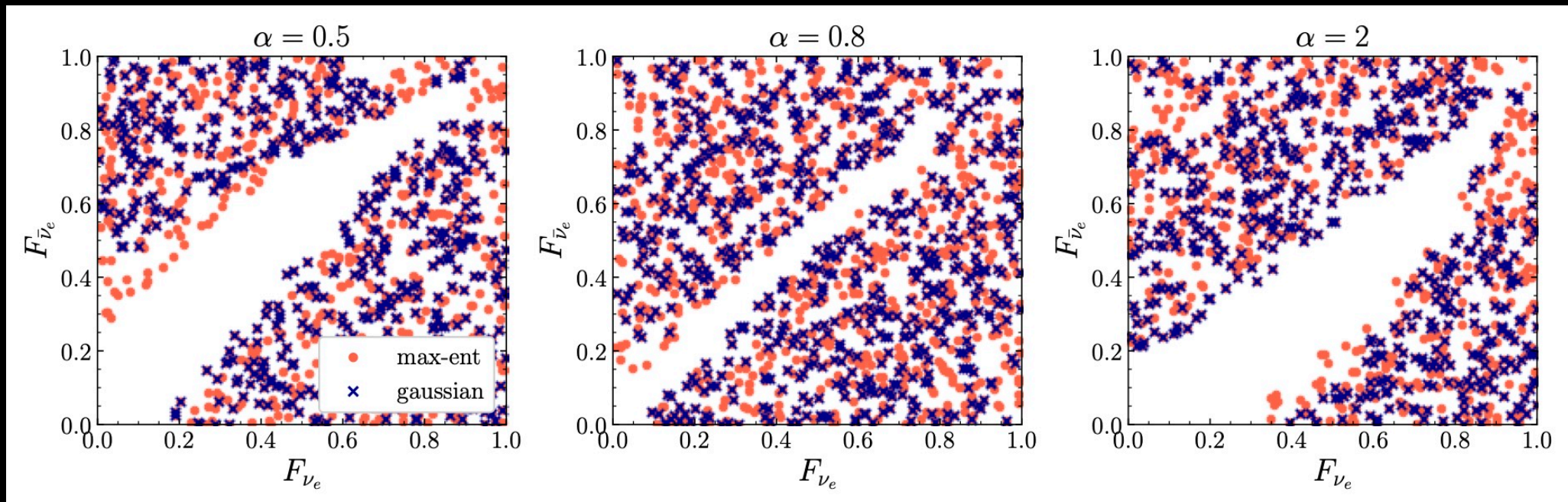
$$f_\nu(\cos \theta_\nu) = \exp(-\eta + a \cos \theta_\nu)$$

gaussian

$$f_\nu(\cos \theta_\nu) = \exp[-a(1 - \cos \theta_\nu)^2 + b]$$

- We have **four** feature here: I_0 and I_1 for neutrinos and antineutrinos (one is **redundant**)

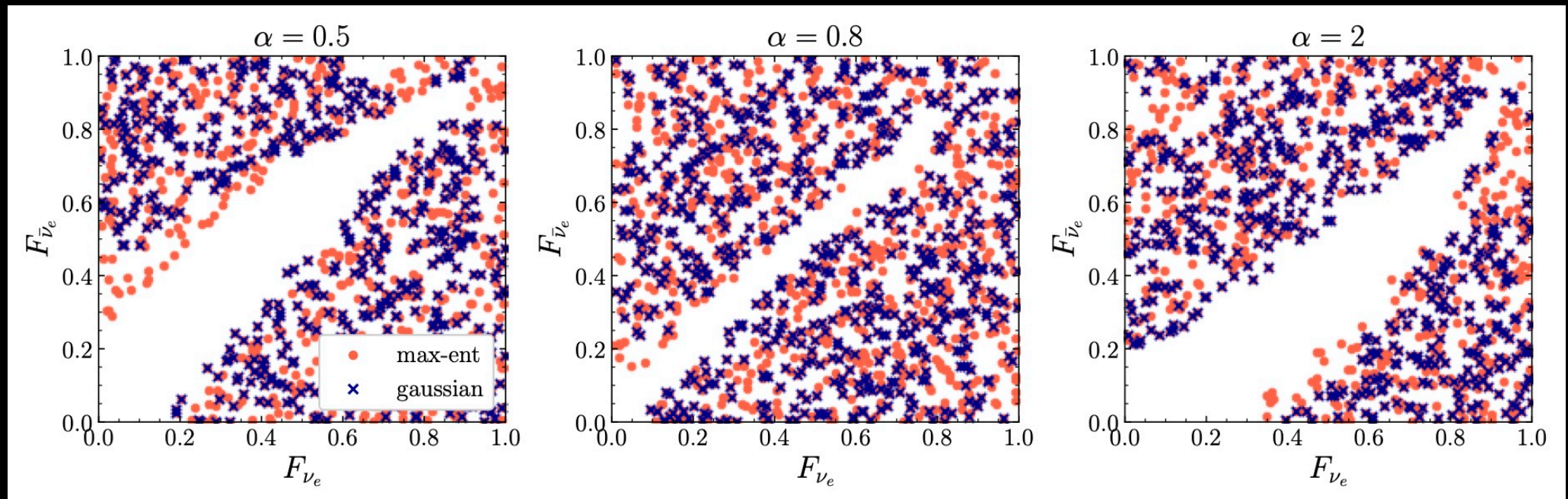
$$\alpha = \frac{I_0^{\bar{\nu}_e}}{I_0^{\nu_e}} \quad F_\nu = \frac{I_1}{I_0}$$



Application of Machine Learning

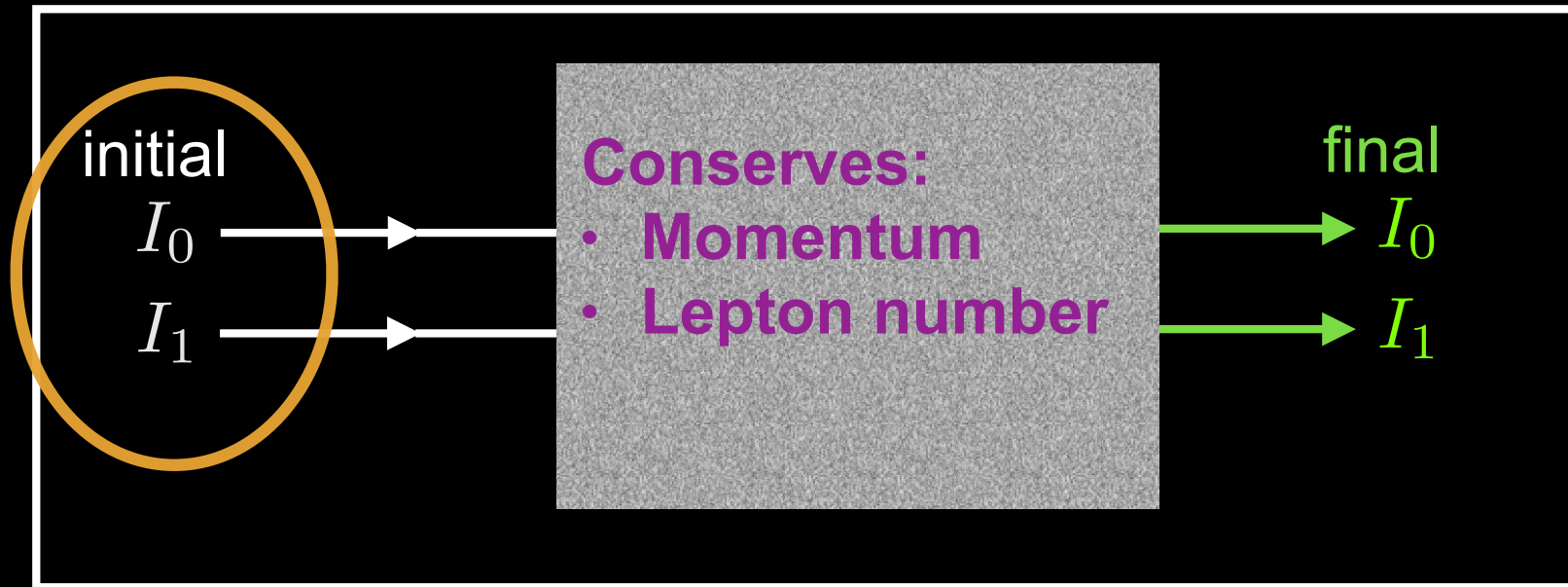
accuracy

- KNN $\sim 95\%$
- Decision Tree $\sim 92\%$
- Naive Bayes $\sim 90\%$
- SVM $\sim 94\%$
- Logistic Regression $\sim 94\%$



Application of Machine Learning

- Machine learning methods prove to be very promising regarding the detection of FFI



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