GSI Workshop, October 18, 2022

Fast Neutrino Flavor Conversions in Densa Neutrino Media: A Machine Learning Approach

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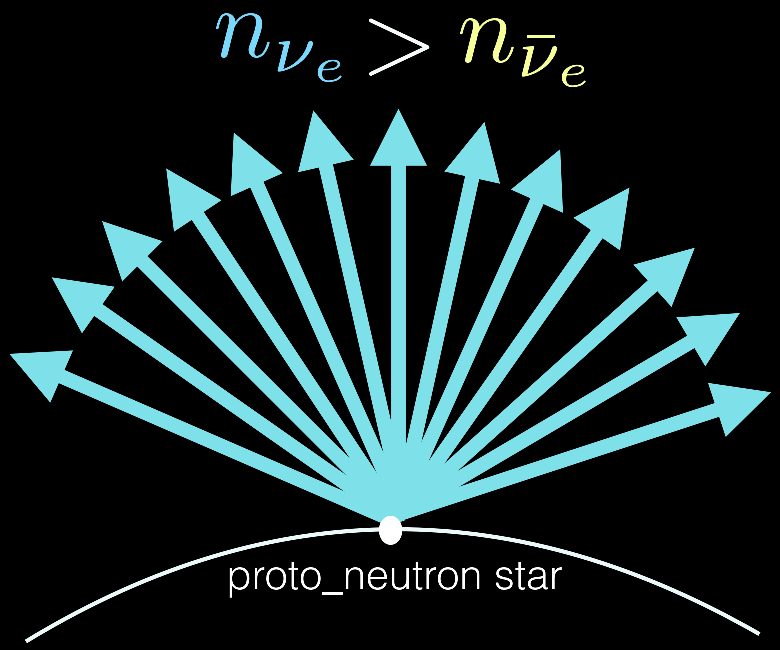
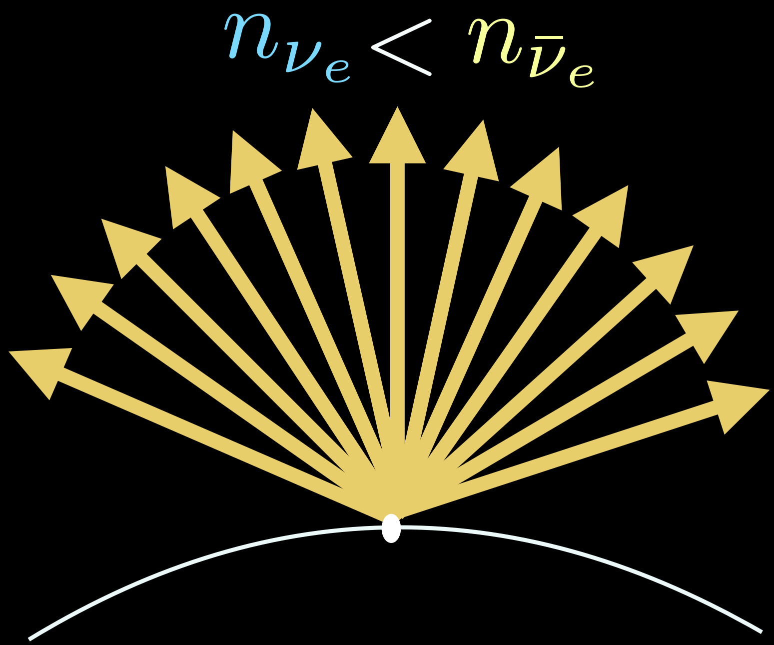
SFB 1258 | Neutrinos Dark Matter Messengers

Fast Flavor Conversion Modes

- We assumed that neutrinos and antineutrinos 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

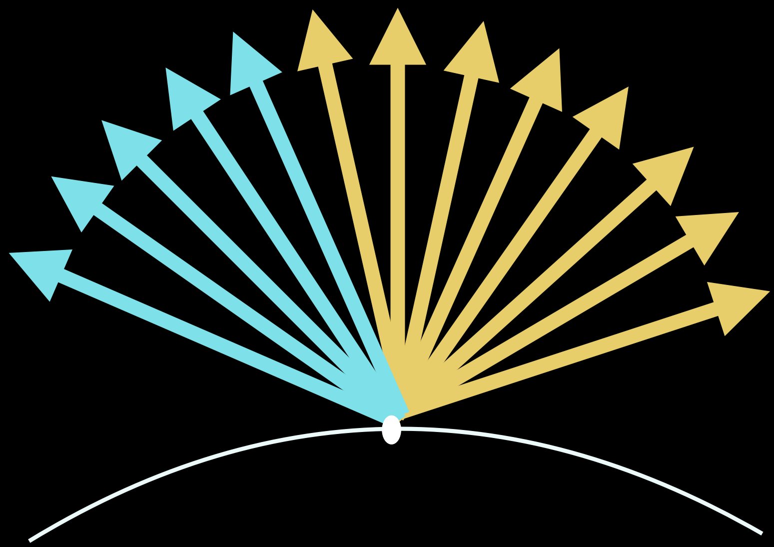




- This implies that the scales on which flavor conversion could occur are determined by vacuum frequency $\Delta m^2/2E \sim 1\ \mathrm{km}^{-1}$

Fast Flavor Conversion (FFC)

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

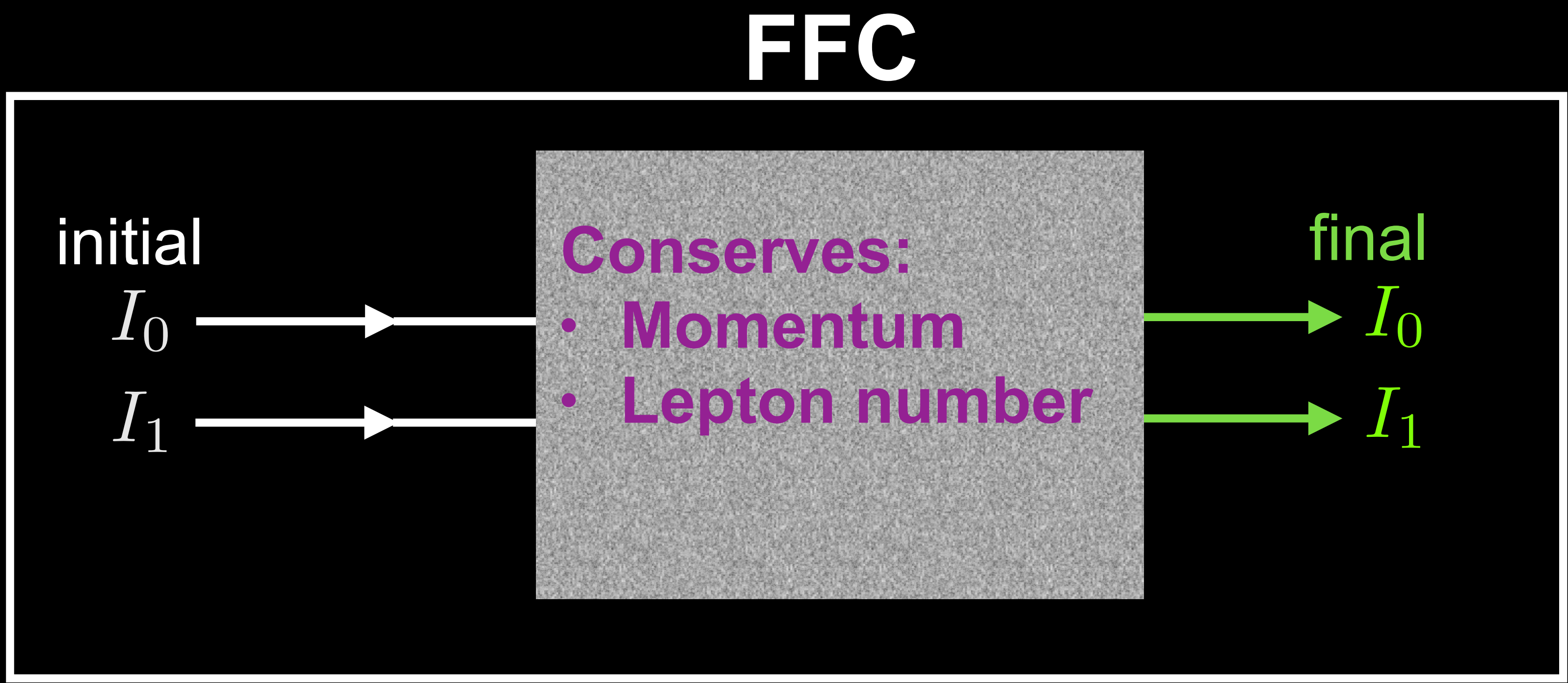


- Scales on which flavor conversion can occur is now proportional to n_ν and could be < 10 cm

- 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

- We assume FFC lead to a sort of flavor equilibrium



Neutron Star Mergers

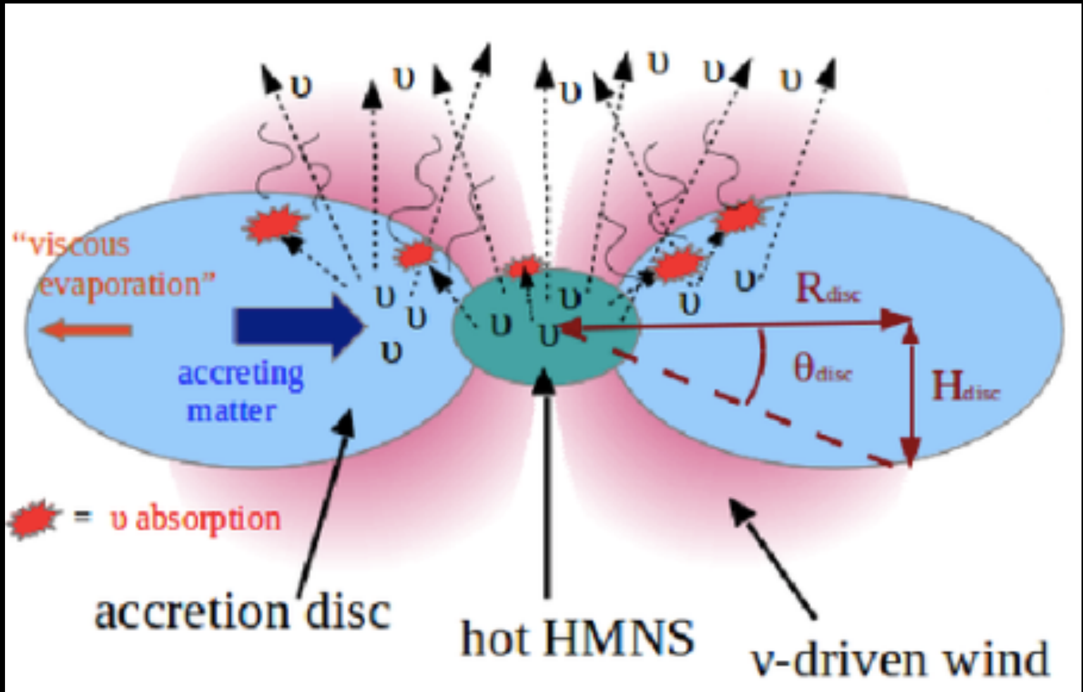
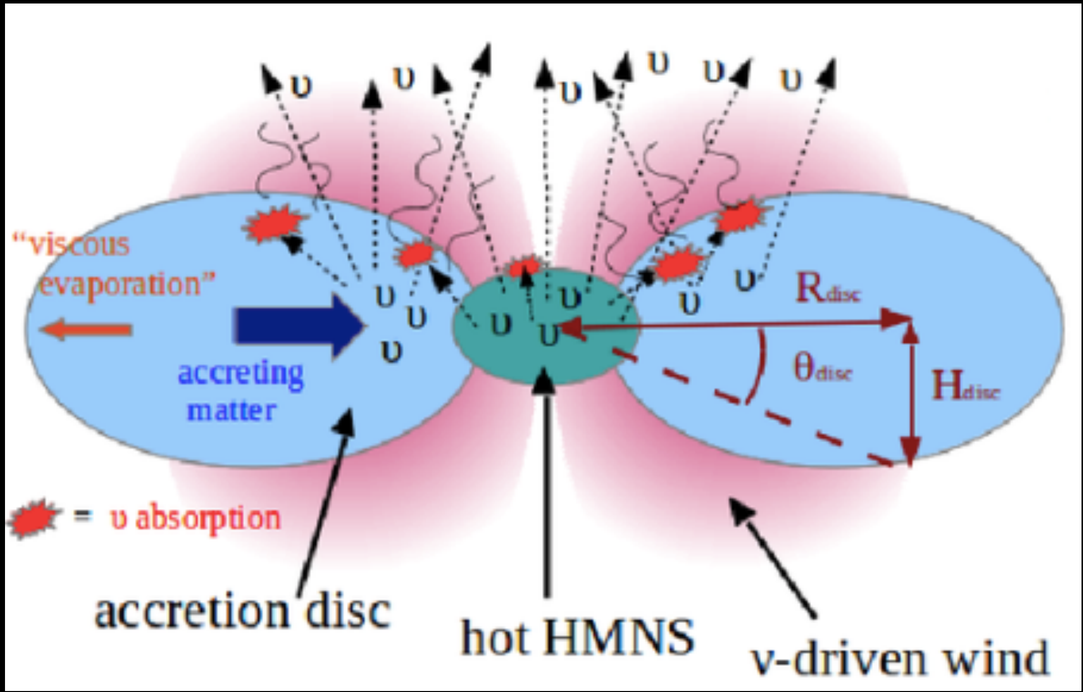


Figure from Perego et. al., arxiv: 1405.6730

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

Neutron Star Mergers



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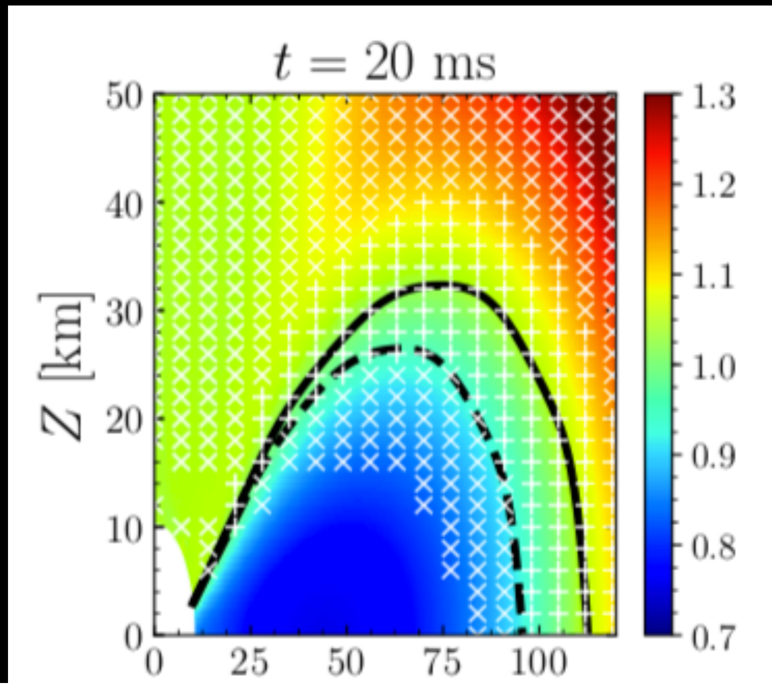
- Hot hyper massive NS and the accretion disk emit a huge number of neutrinos

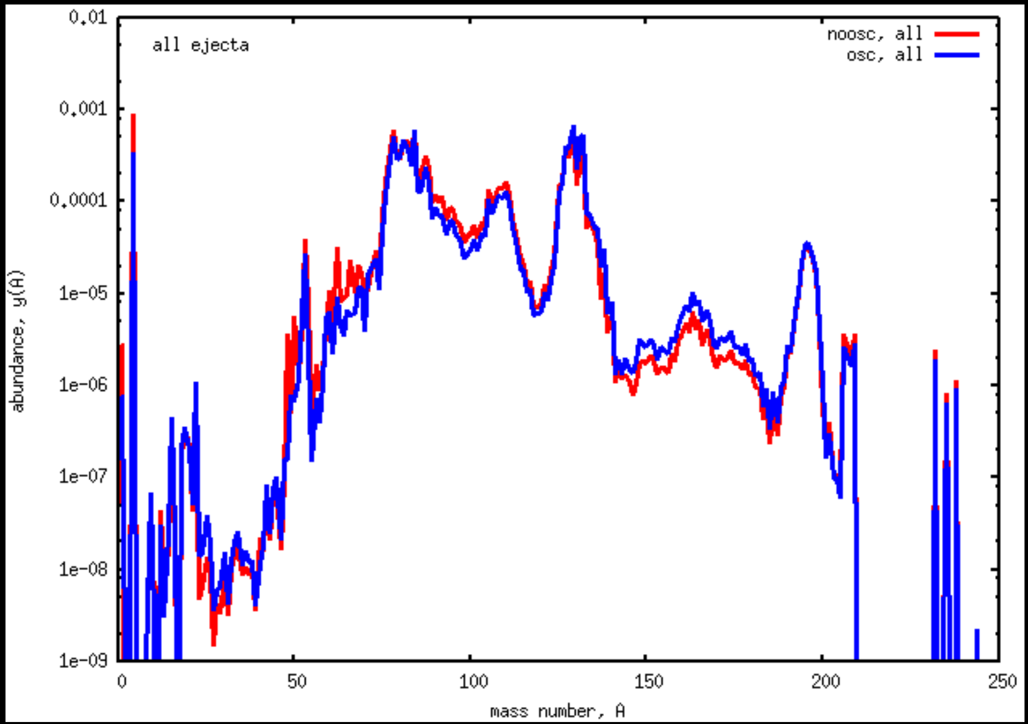
Just+2022 (also Li+2021, Fernandez+2022, Grohs+2022,)



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

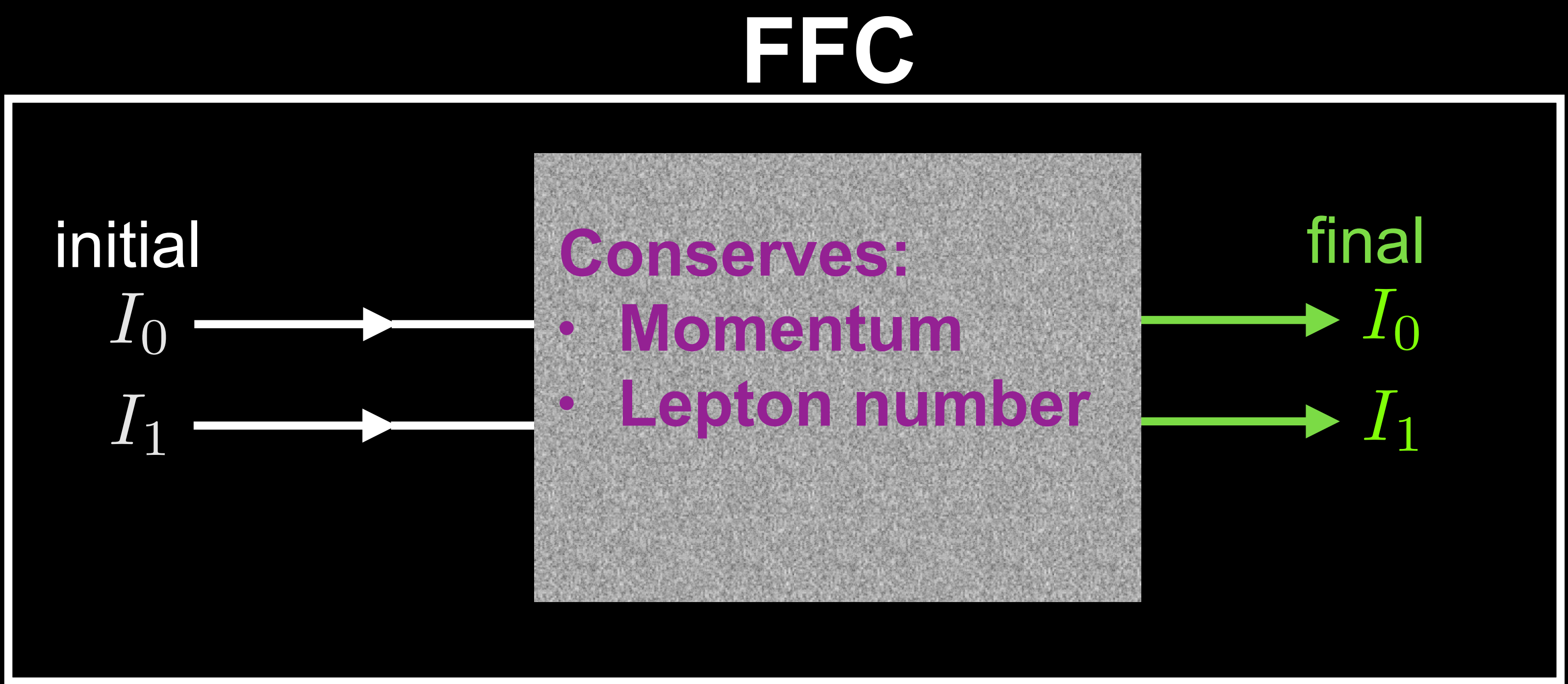
Neutron Star Mergers

- 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 Ye due to a sort of self-regulating mechanism



Including FFC in CCSNe

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



Including FFC in CCSNe

Ehring+(In preparation)

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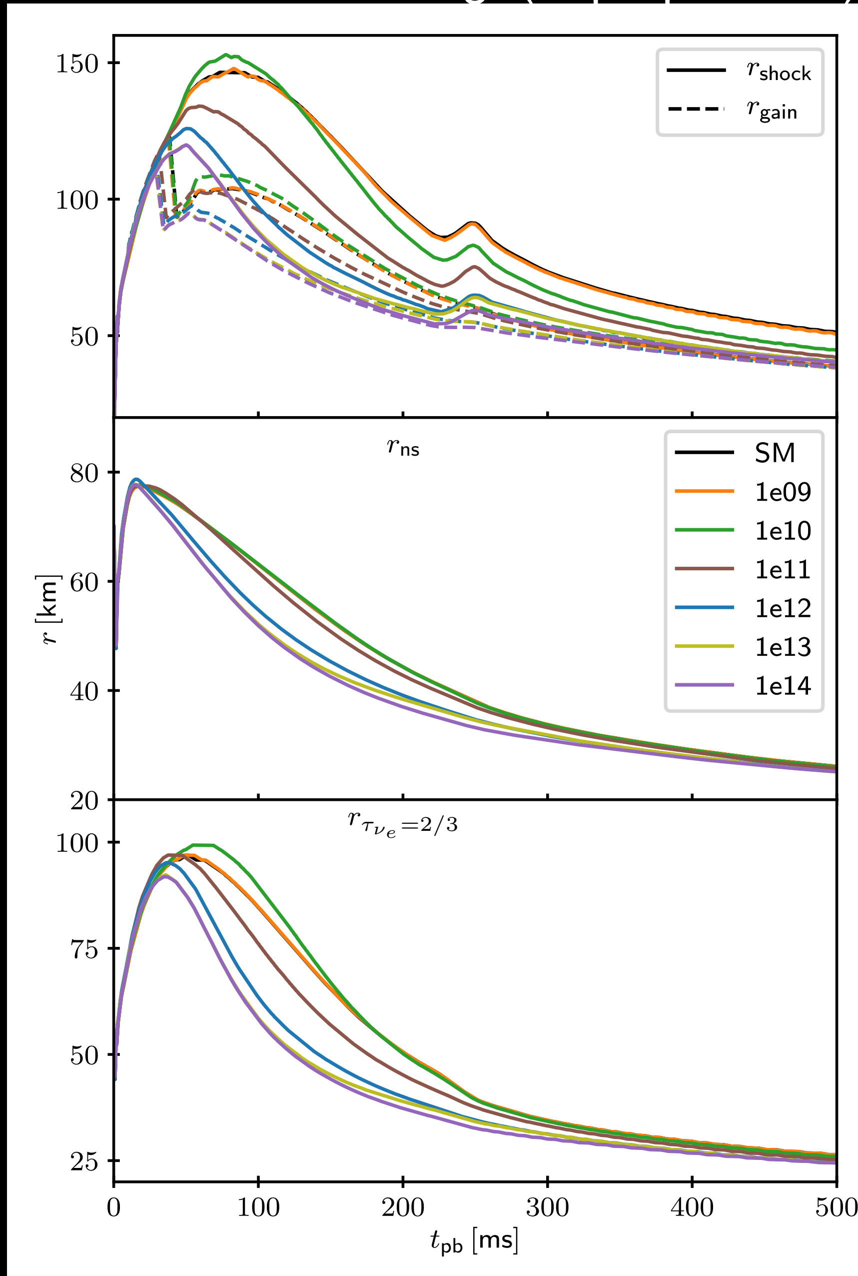
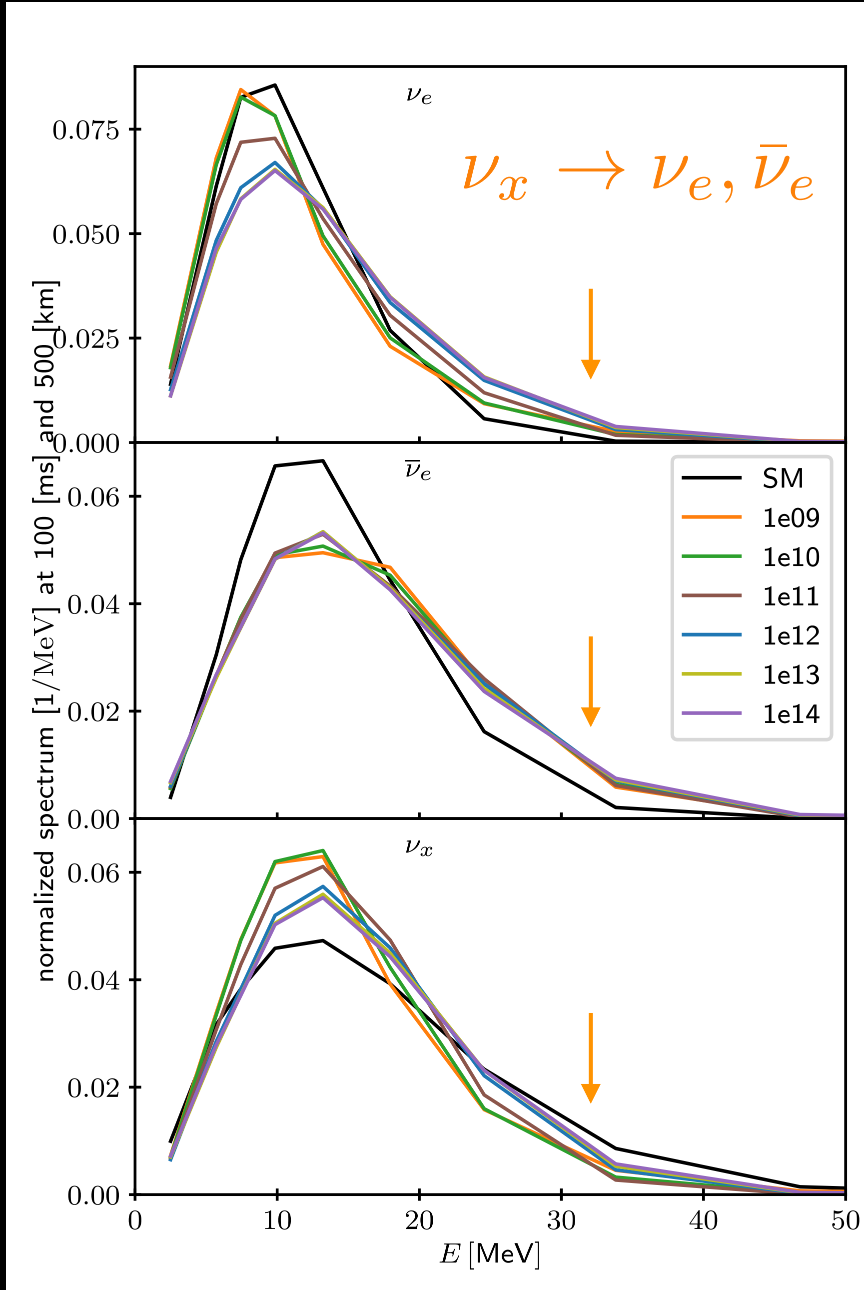


Including FFC in CCSNe

Ehring+(In preparation)

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



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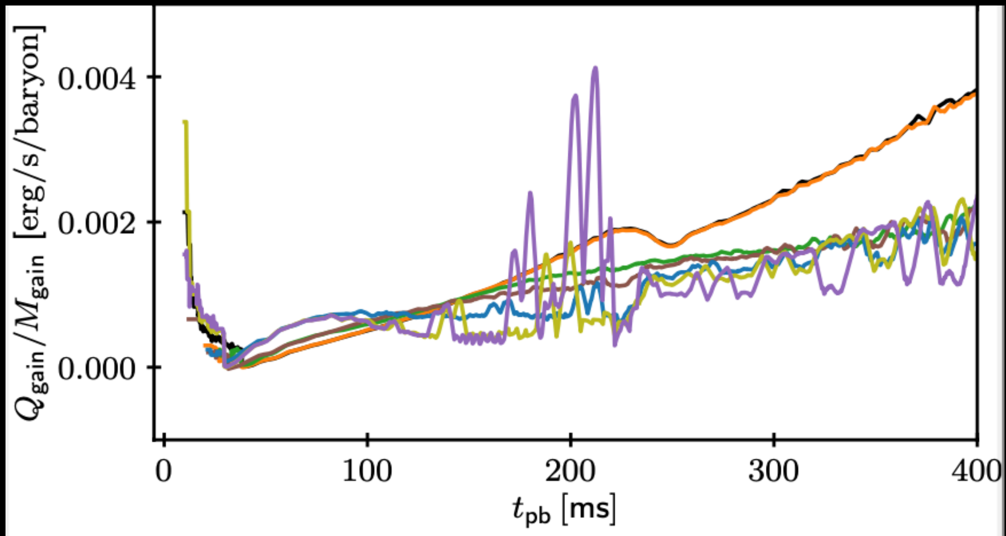

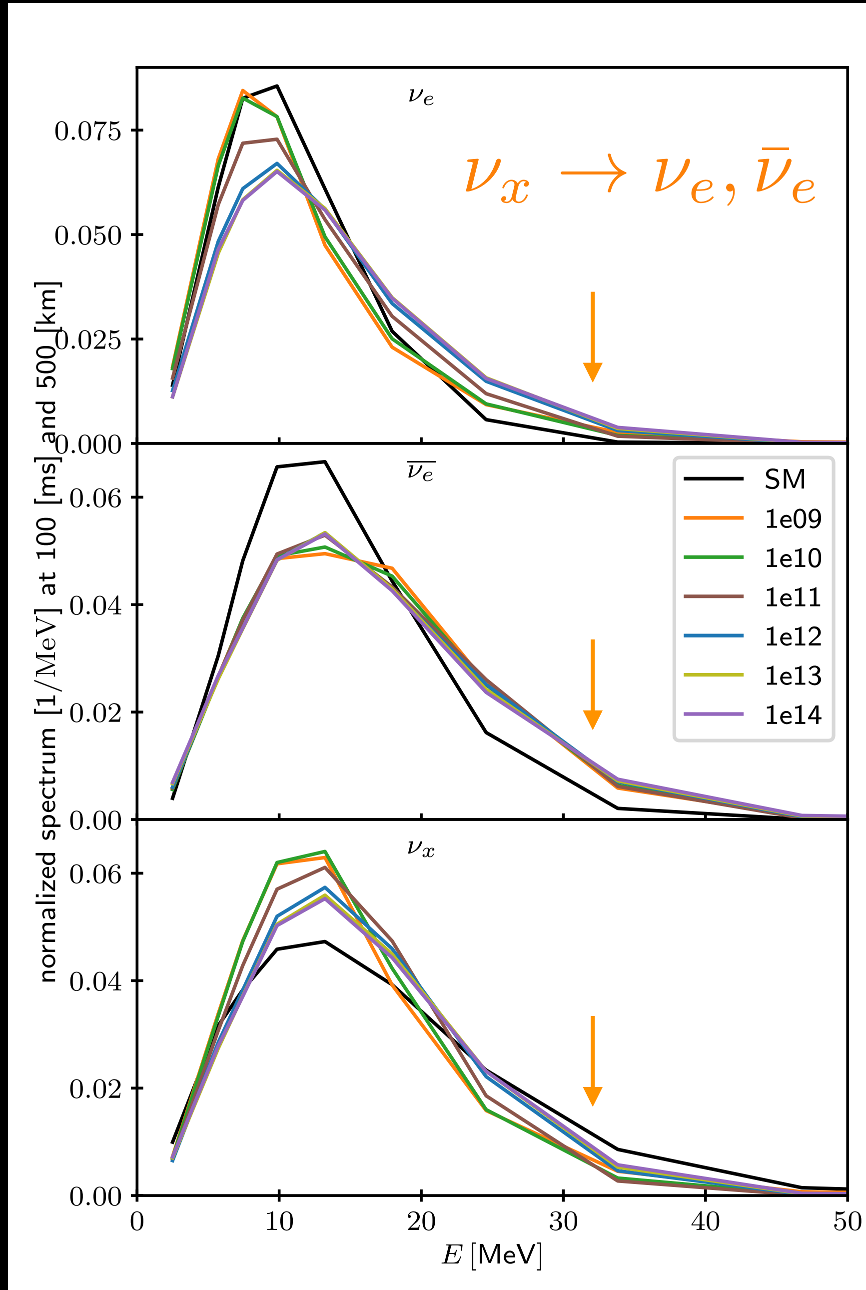

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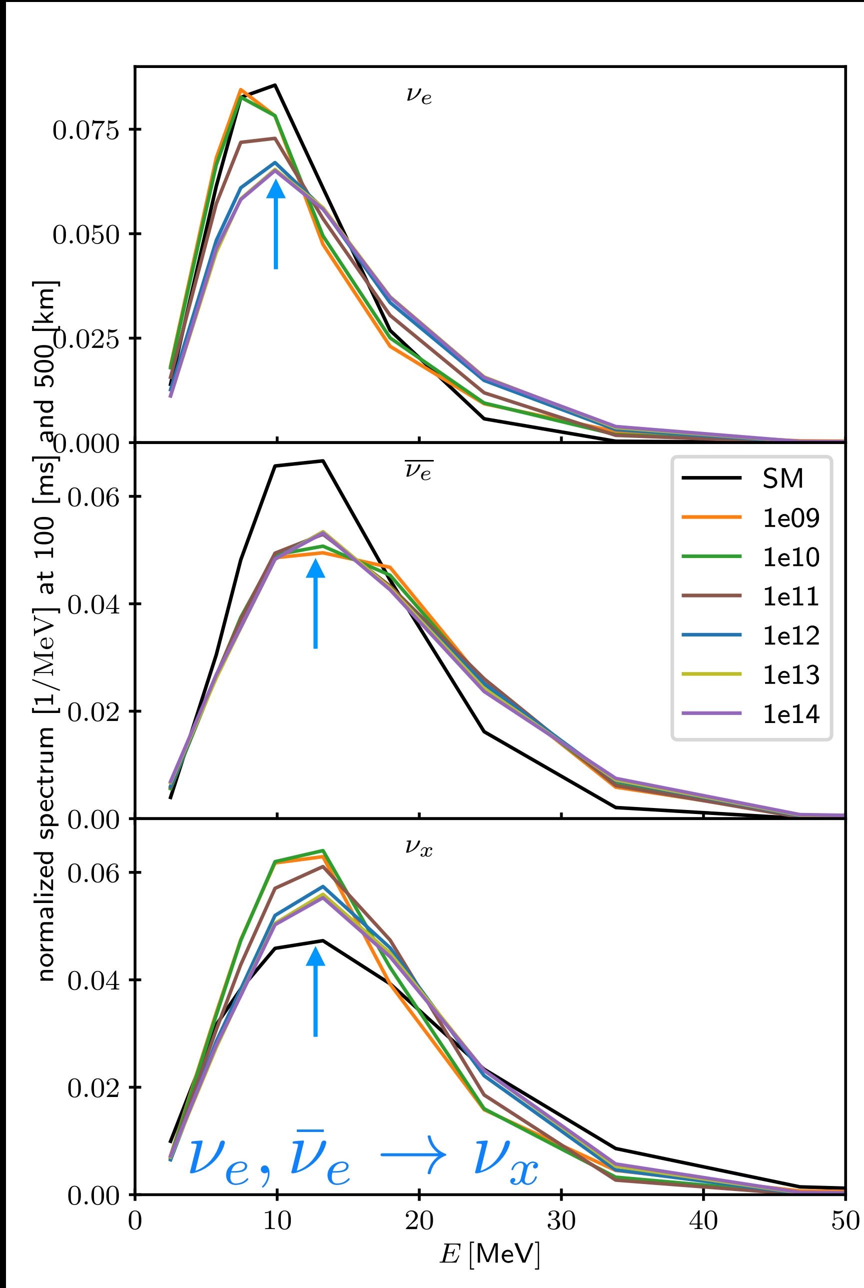
- Two competing effects here
  - $\nu_x \rightarrow \nu_e, \bar{\nu}_e$ at the tail increases heating
  - $\nu_e, \bar{\nu}_e \rightarrow \nu_x$ at the peak increases total neutrino luminosity



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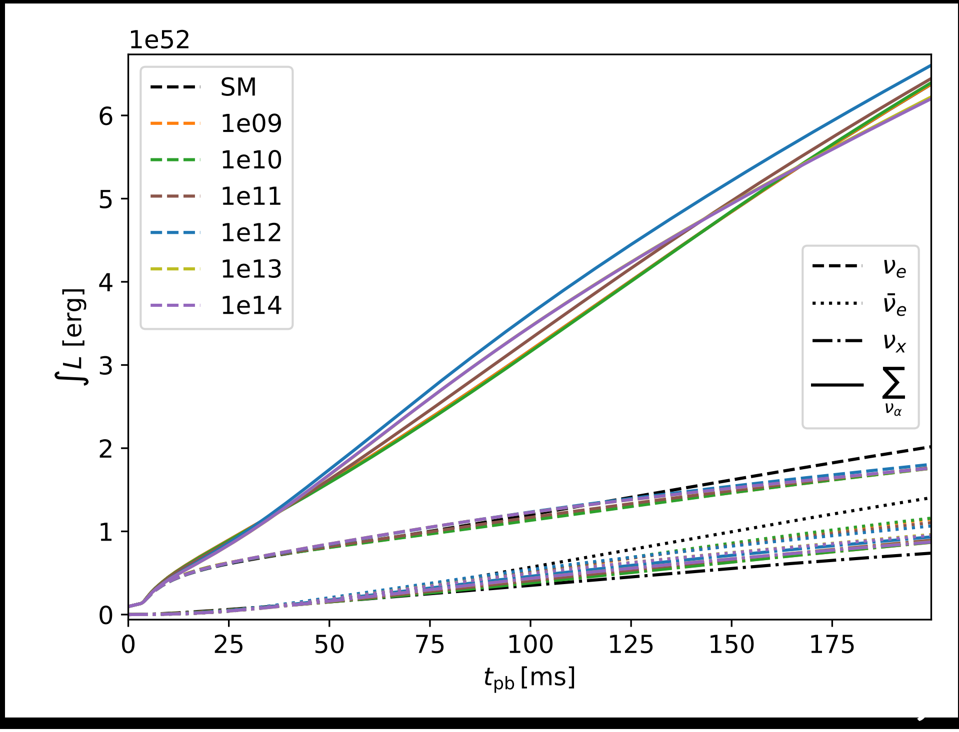

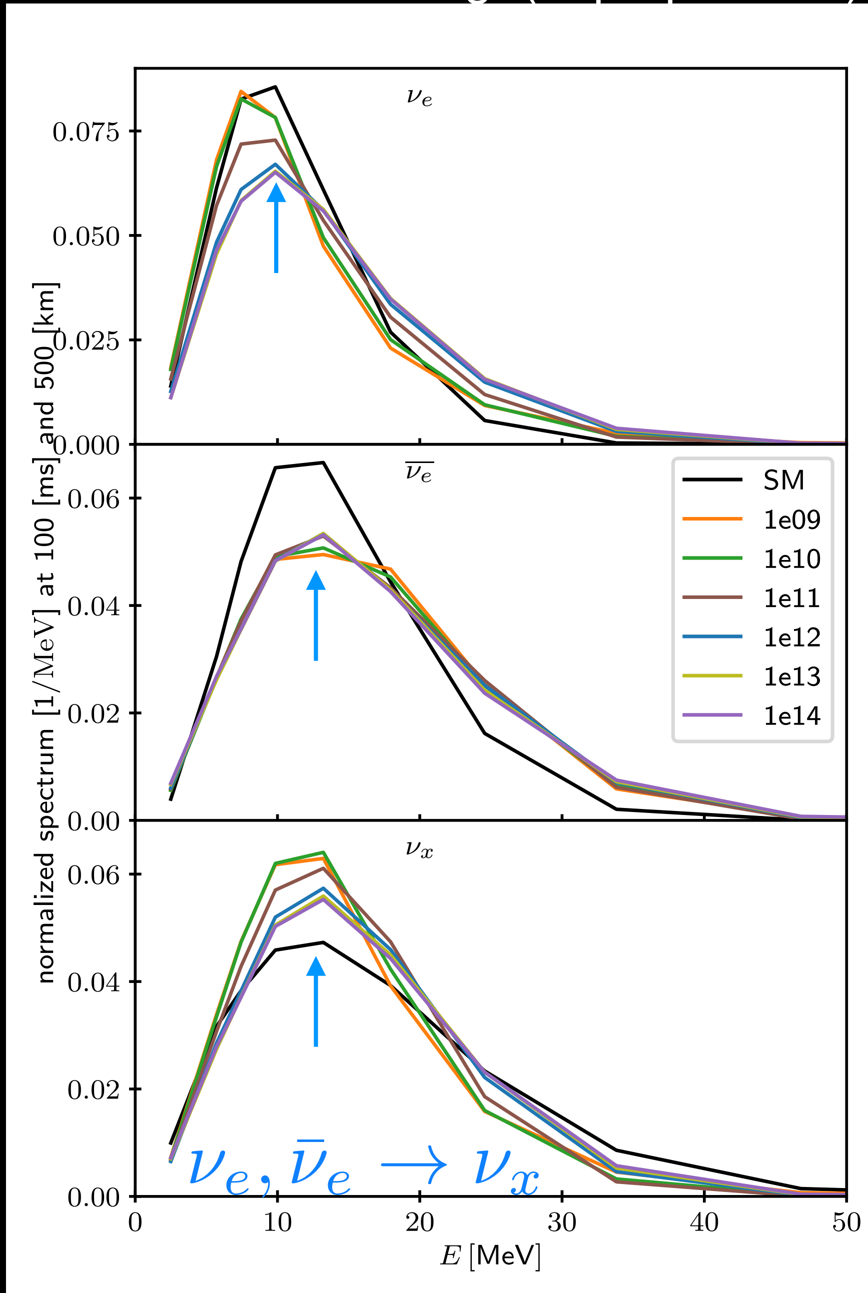

Fast Flavor Conversion (FFC)

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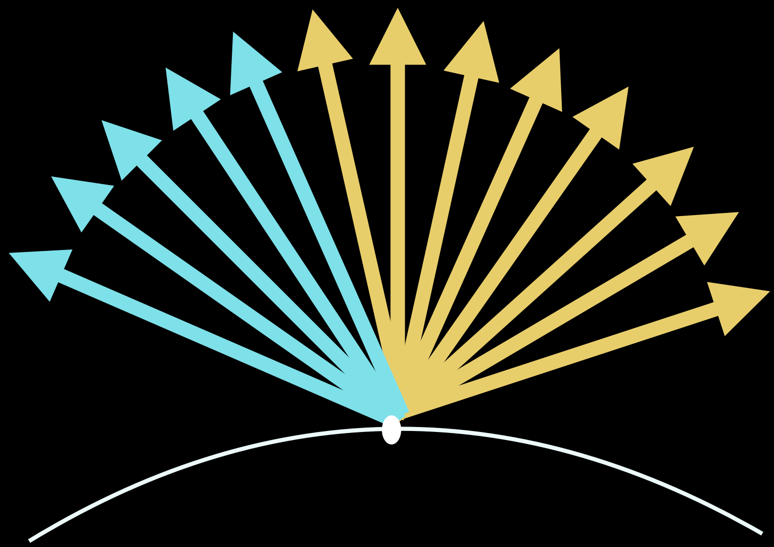


Fast Flavor Conversion (FFC)

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

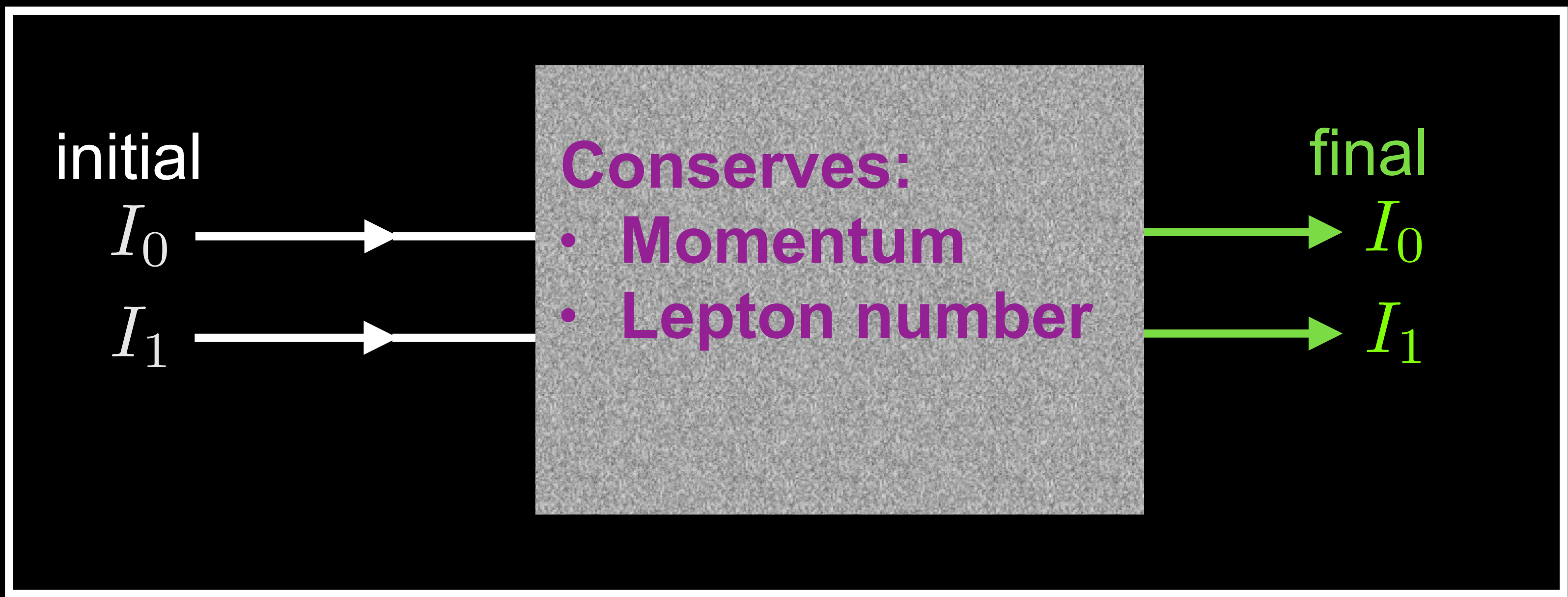
$$I_n = \int \mathrm{d}\cos\theta_\nu \;\; \cos^n\theta_\nu \;\; f_\nu(\cos\theta_\nu)$$

- We can still make progress!

Dasgupta+2018; Abbar2020; Johns+2021; Richers2022;

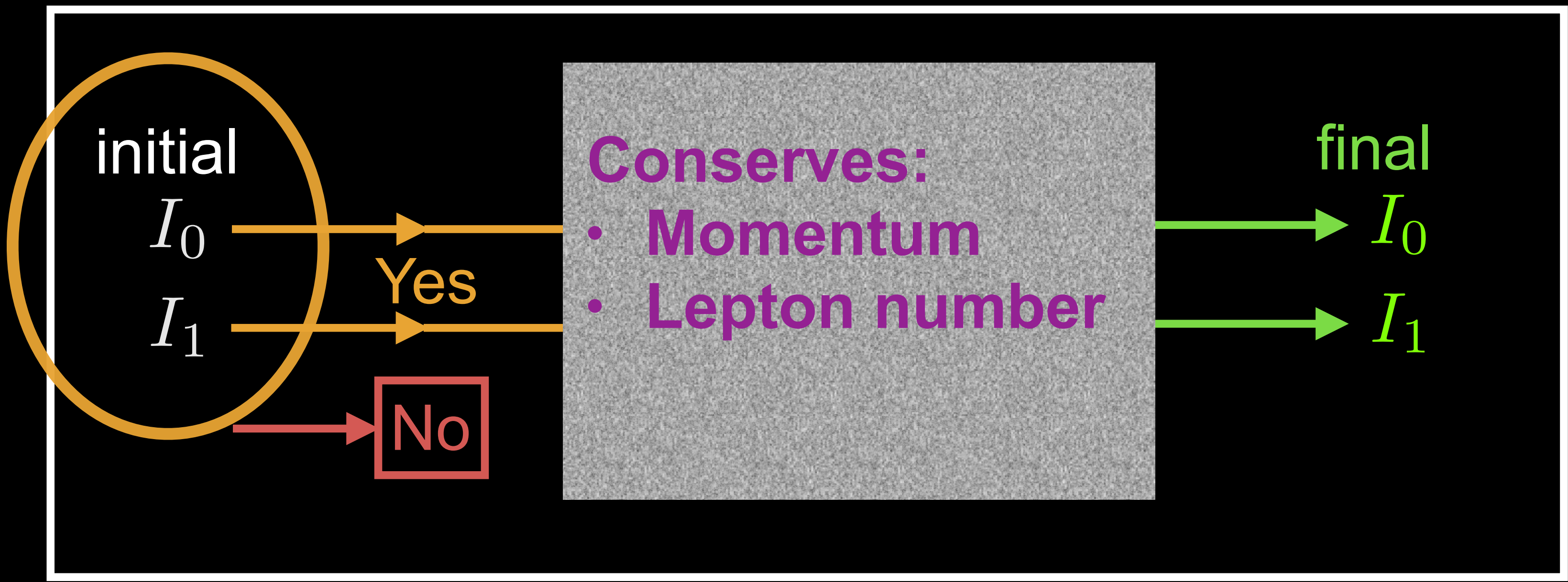
- But these methods are normally inefficient and very slow

- FFC can not be detected on the fly



Fast Flavor Conversion (FFC)

- A classification problem!



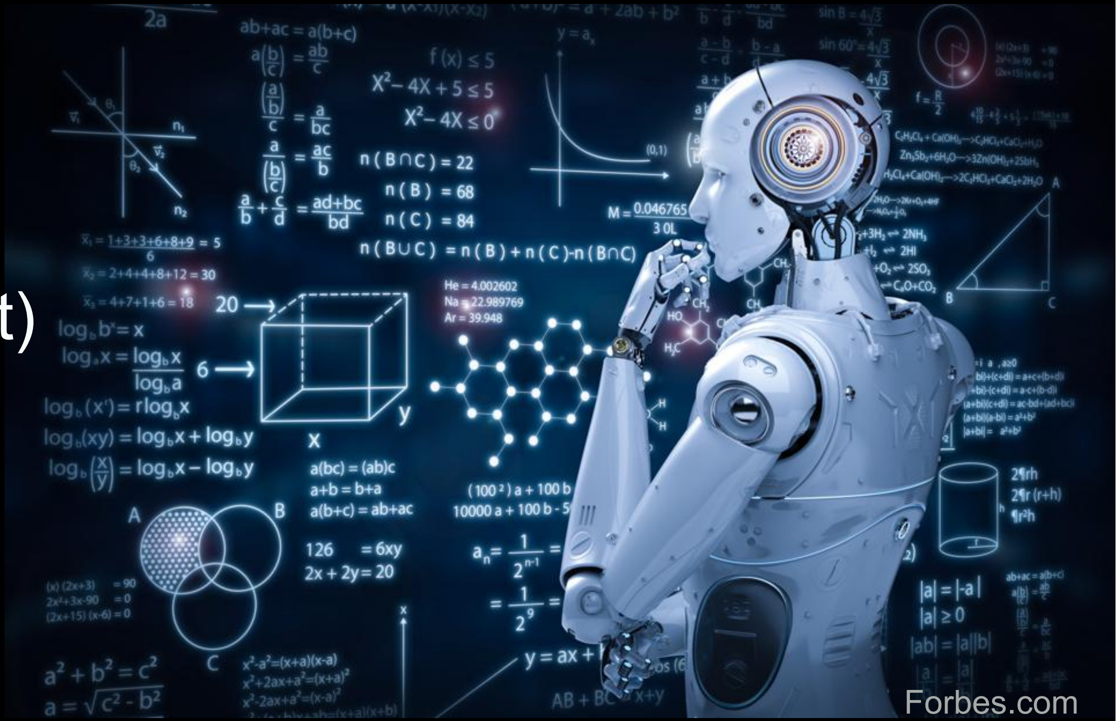
Fast Flavor Conversion (FFC)

- Machine learning can help us

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

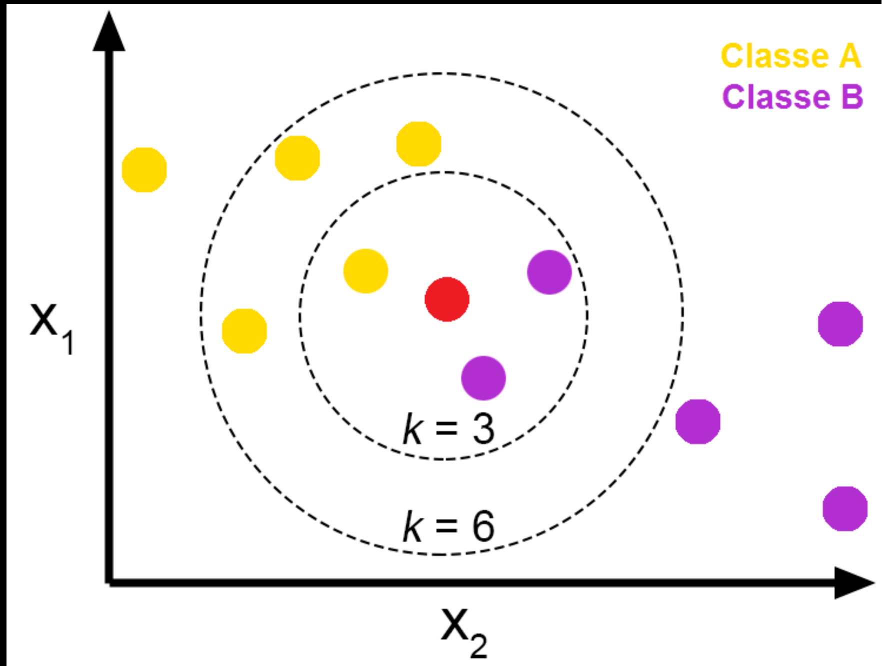
- A number of ML algorithms out there. I here introduce:

    - KNN
    - Decision Tree
    - Naive Bayes
    - SVM
    - Logistic Regression



Including FFC in CCSNe

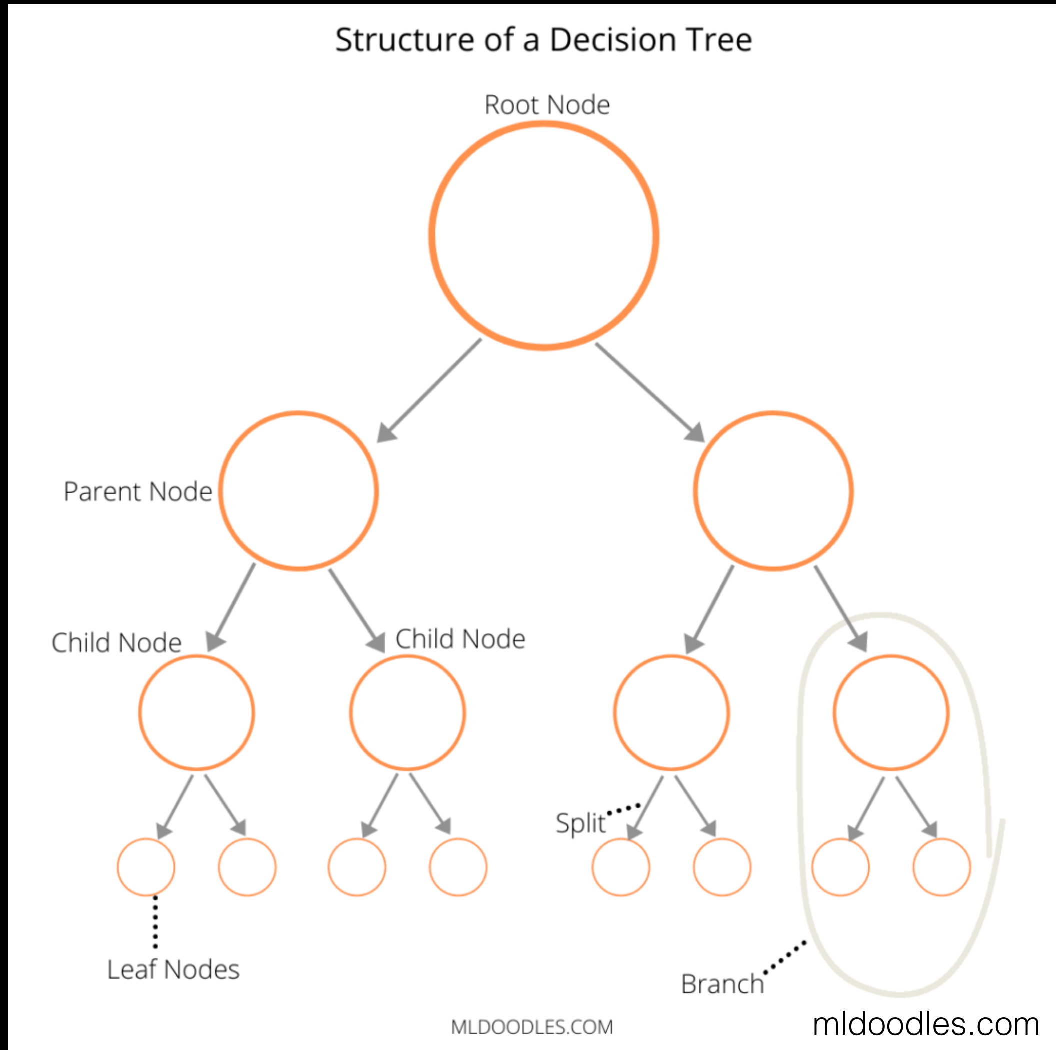
- KNN is one of the simplest forms of machine learning algorithms mostly used for classification. It **classifies the data point on how its neighbor is classified**.



townrdsdatascience.com

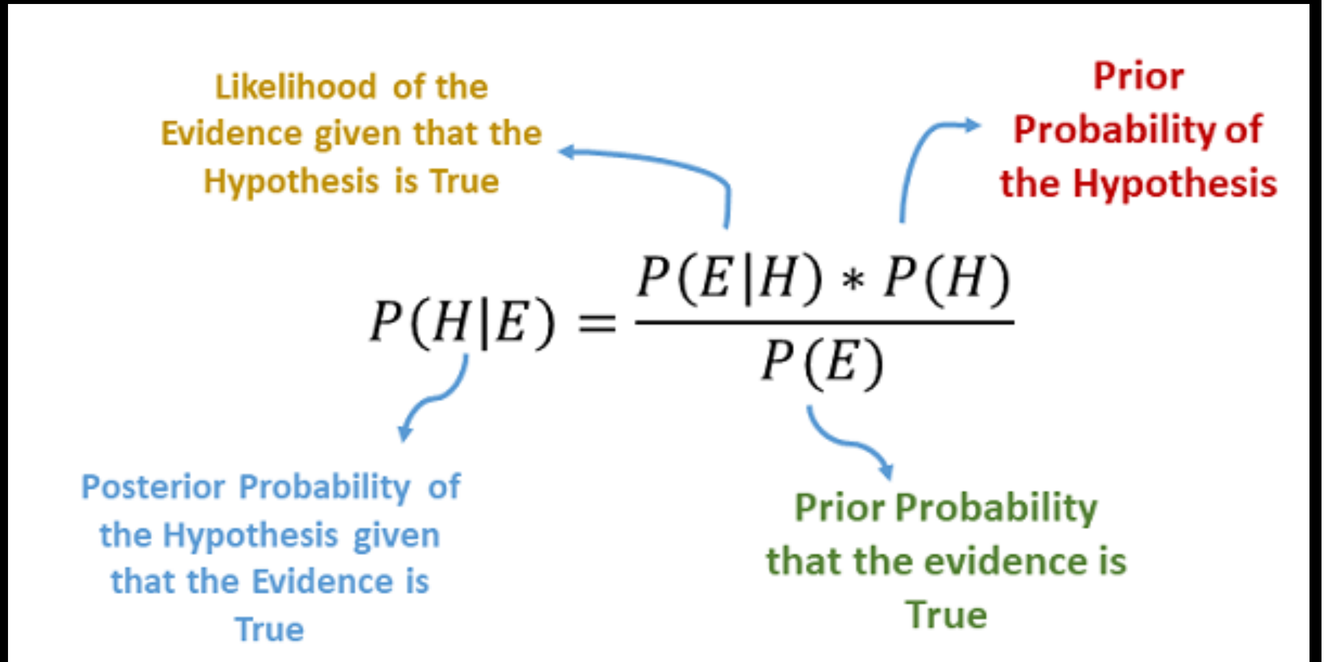
Decision Tree

- 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

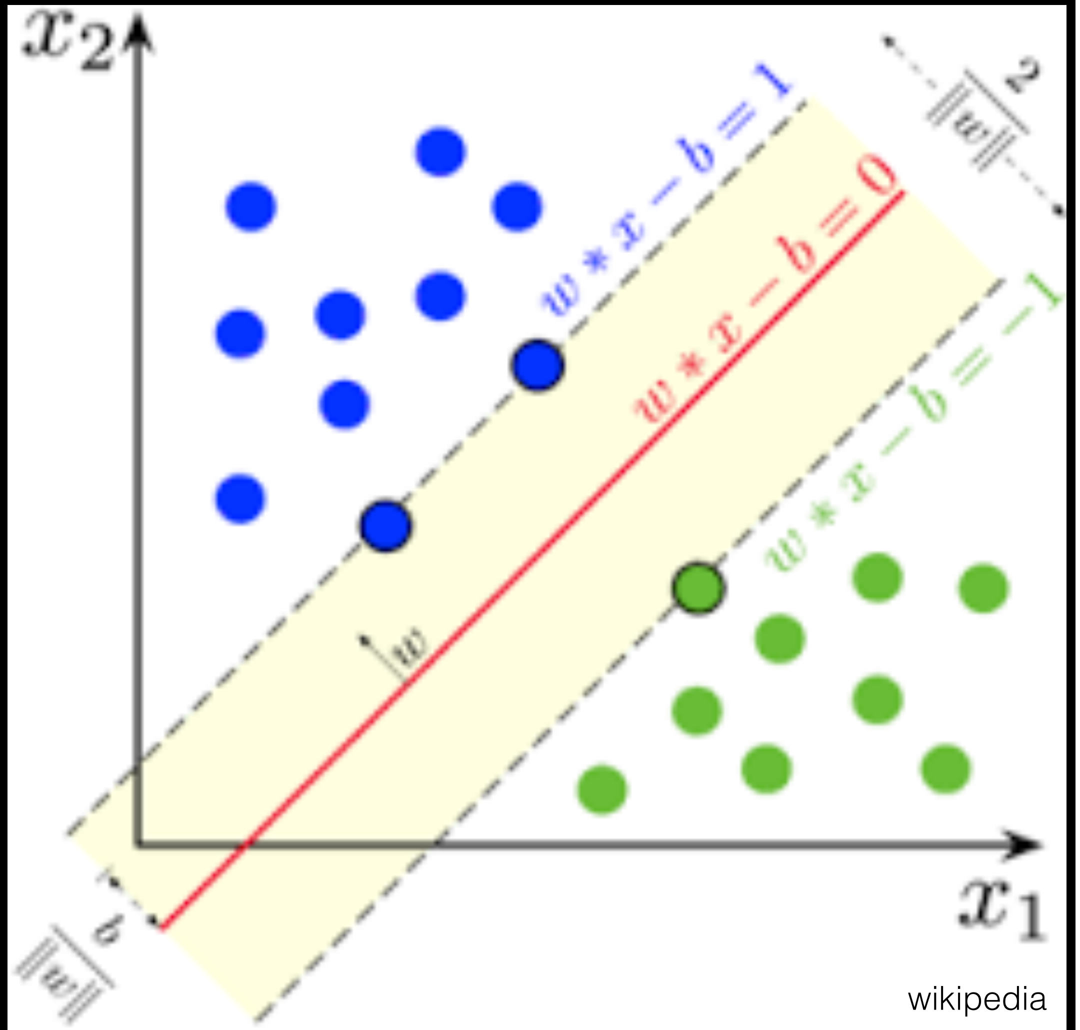
- Naive Bayes cassifier is a probabilistic machine learning model which is based on the Bayes theorem



medium.com

SVM

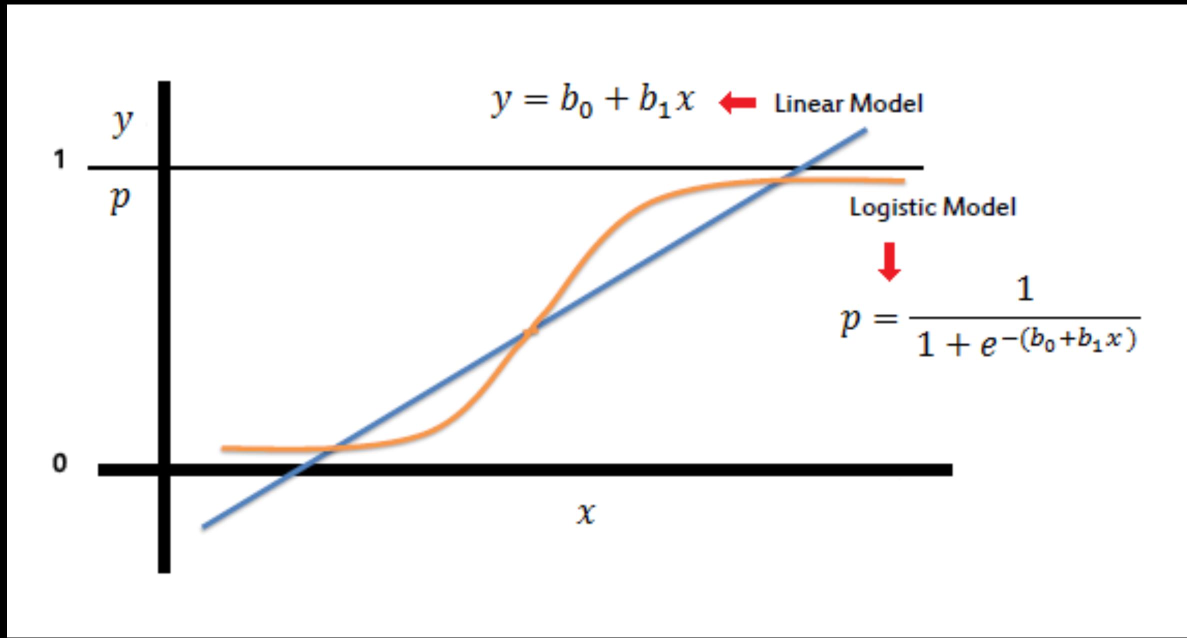
- Support Vector Machine is a classification based on finding a line that classifies the data points, maximises the margins



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)



Fast Flavor Conversion (FFC)

- For training, we use analytical maximum-entropy distribution

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

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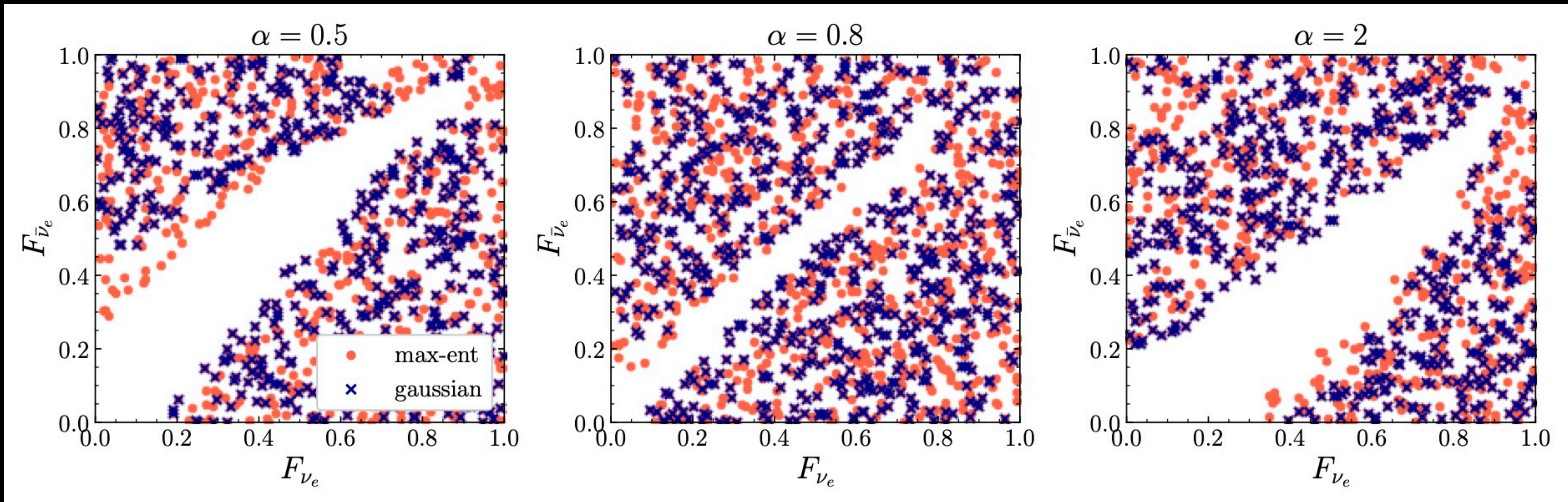
$$f_\nu(\cos\theta_\nu) = \exp(-\eta + a\cos\theta_\nu)$$

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

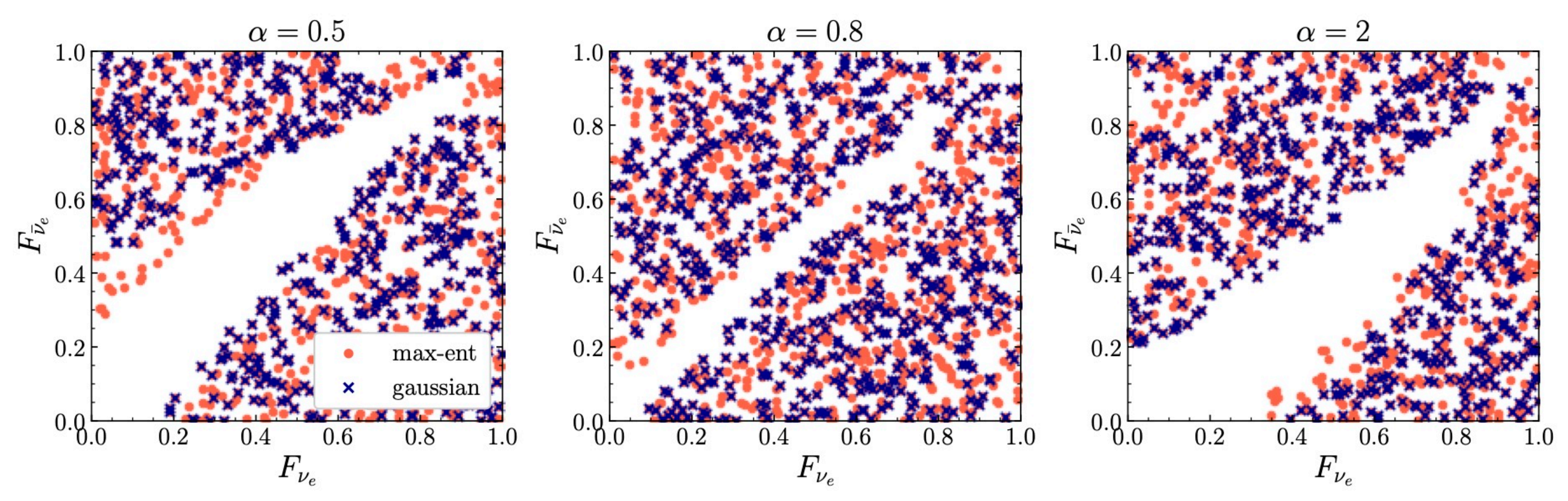
- We have four feature here: I_0 and I_1 for neutrinos and antineutrinos (one is redundant)

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



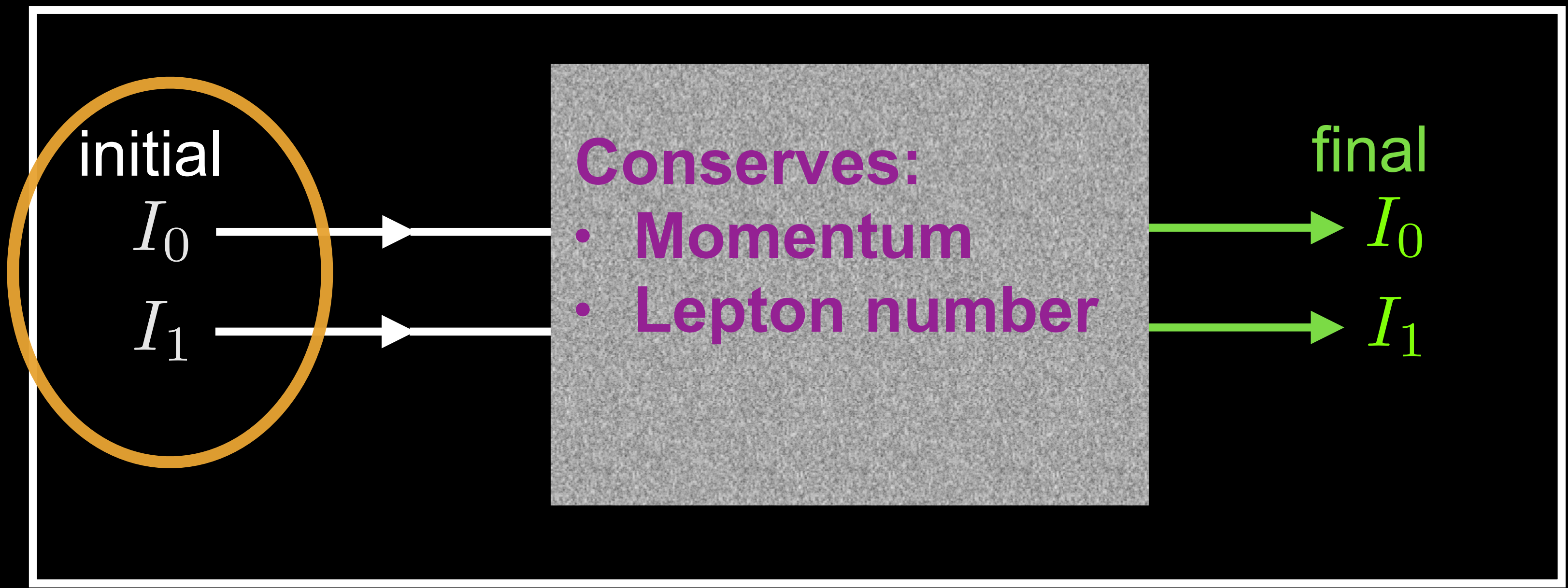
Fast Flavor Conversion (FFC)

	accuracy
• KNN	~ 95%
• Decision Tree	~ 92%
• Naive Bayes	~ 90%
• SVM	~ 94%
• Logistic Regression	~ 94%



Machine Learning

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



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