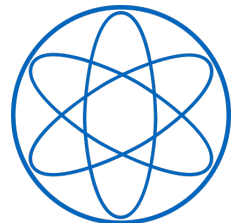


# Pulse Shape Discrimination for fast Neutrons and atmospheric NC Interactions in JUNO

DSNB Topical Workshop @ MITP, 2024-09-20

**Matthias Mayer**, Lothar Oberauer, Hans Steiger, Simon Basten, Raphael Stock

Physik-Department, TU München

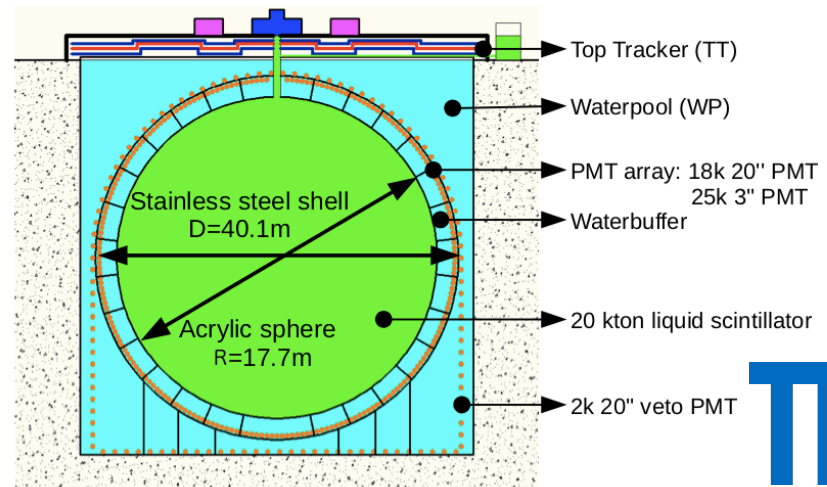


**PRISMA+**

Cluster of Excellence  
Precision Physics, Fundamental Interactions  
and Structure of Matter

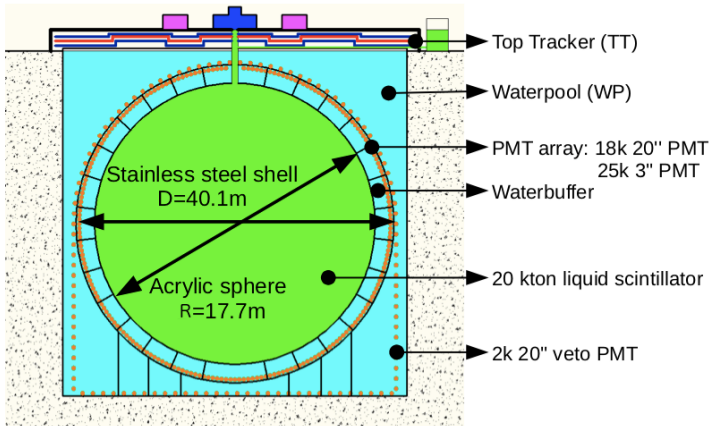
# Jiangmen Underground Neutrino Observatory (JUNO)

- Liquid scintillation detector using 20 kton of linear alkyl benzene (LAB)
- 17,612 20" PMTs and 25,600 3" PMTs observing the liquid scintillator volume
- 1600 PMTs are used for the water Cherenkov detector
- Shielded by  $\sim 1800\text{m.w.e.}$  of rock overburden
- Currently under construction, data taking starts Jan 2025



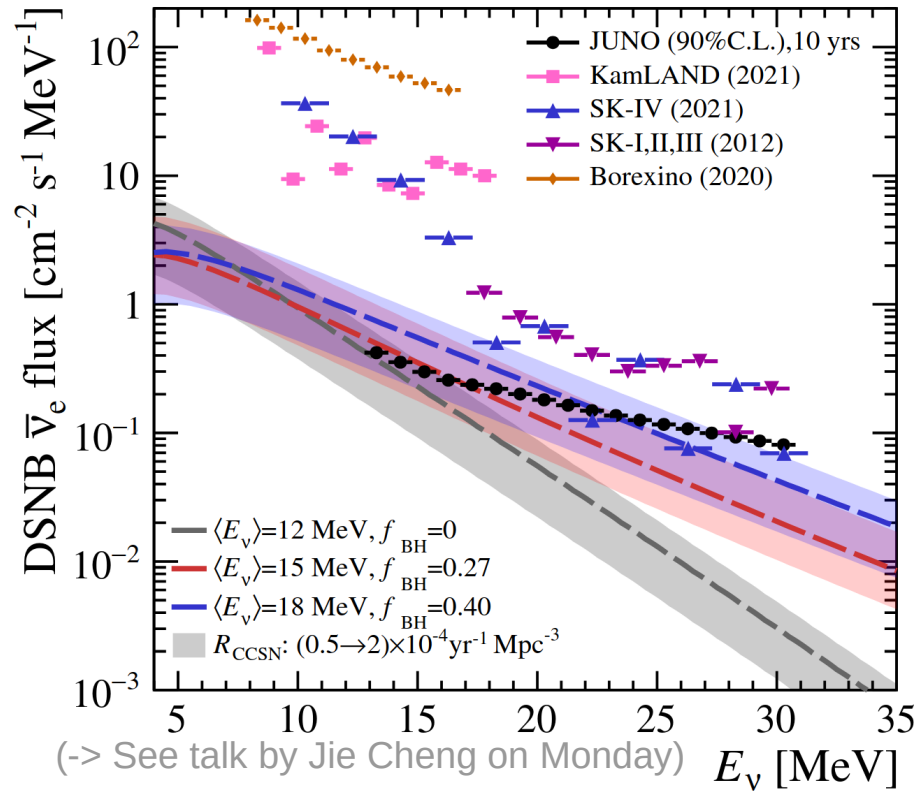
# Neutrino Physics with JUNO

(examples)



- Reactor neutrinos
  - > Neutrino mass ordering
  - > Oscillation parameters
- Solar neutrinos
- Atmospheric neutrinos
- Geoneutrinos
- Supernova burst neutrinos
- **Diffuse Supernova Neutrino Background**

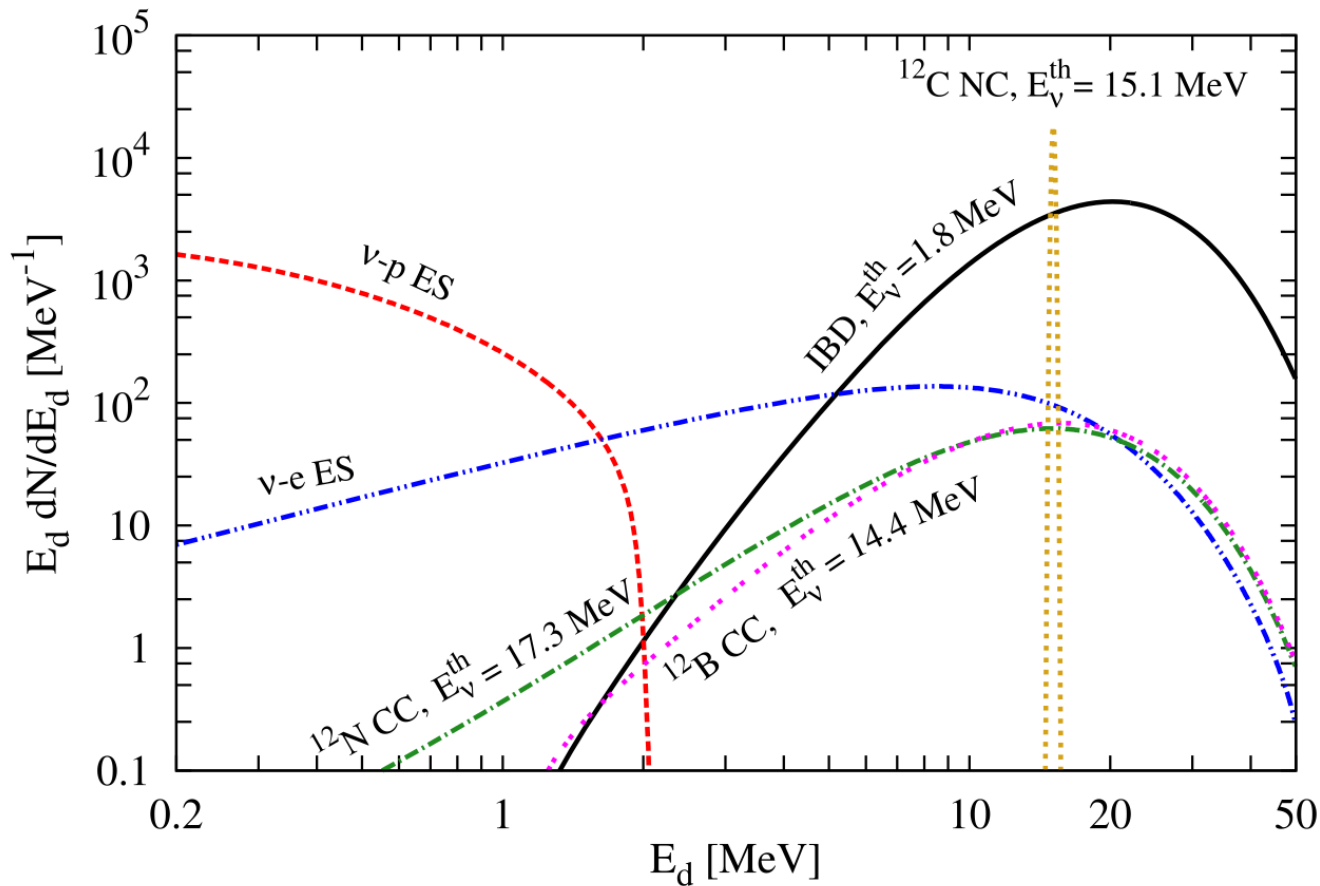
# DSNB Detection/Exclusion: Current Status



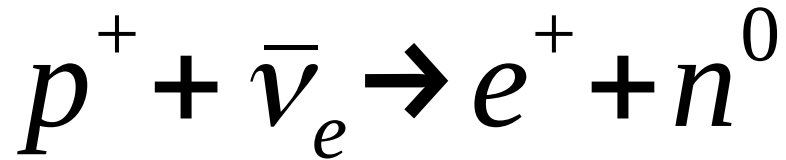
-> The detection of DSNB or the exclusion of various supernova models is possible within the lifetime of JUNO and HyperK!



For scintillation experiments, the inverse beta decay is the most suitable detection channel in the DSNB energy ROI:

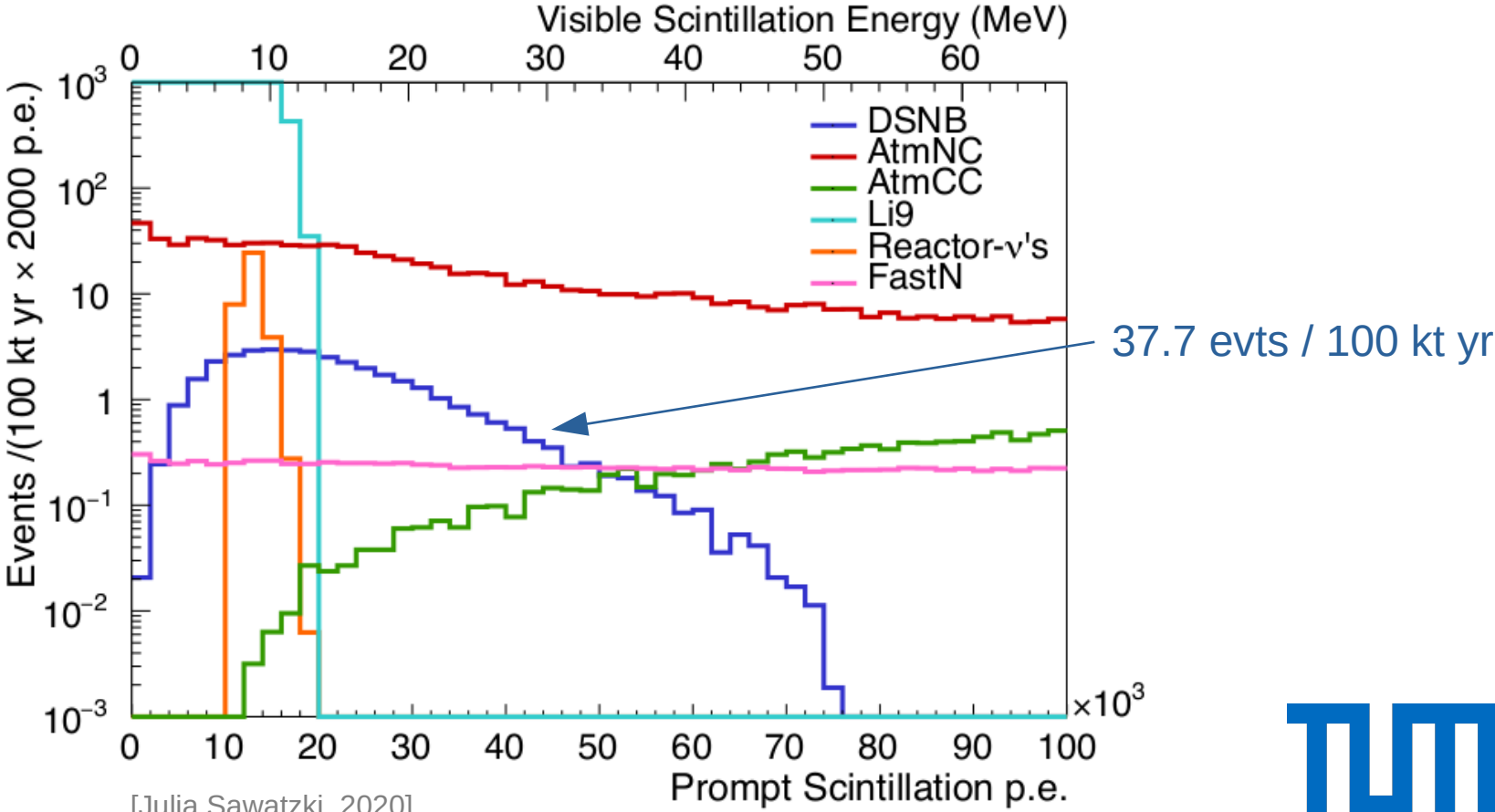


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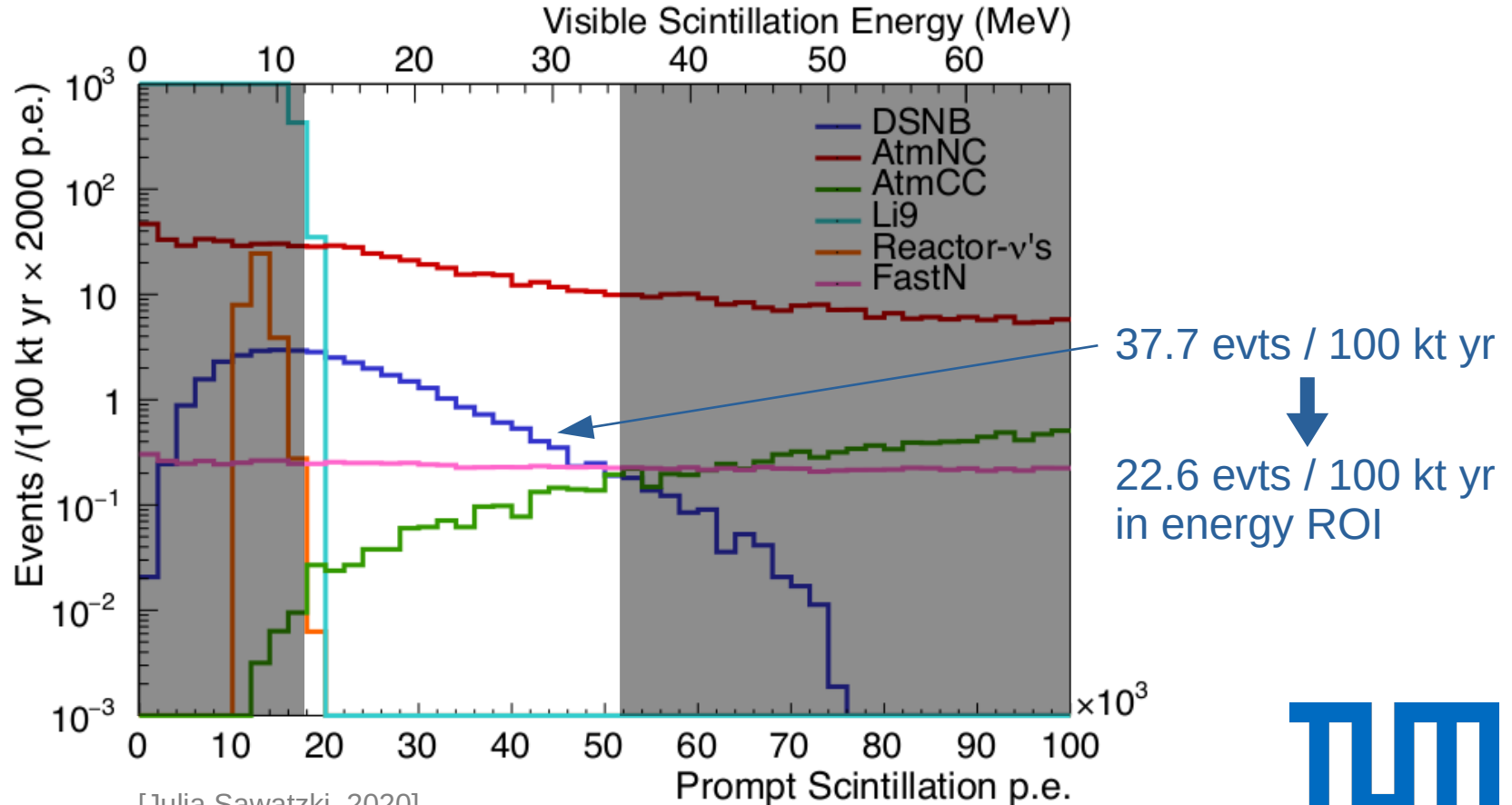


- Positron: Carries most of the kinetic energy,  
Capture within a few ns  
 $E_{\text{vis}} \approx E_{\nu} - 0.8 \text{ MeV}$
- Neutron: low kinetic energy,  
Capture with a lifetime of  $\sim 220 \mu\text{s}$ 
  - Capture on H: 2.2 MeV
  - Capture on C12: 4.9 MeV

Irreducible background is caused by  $\bar{\nu}_e$  from other sources reaching into the same energy range

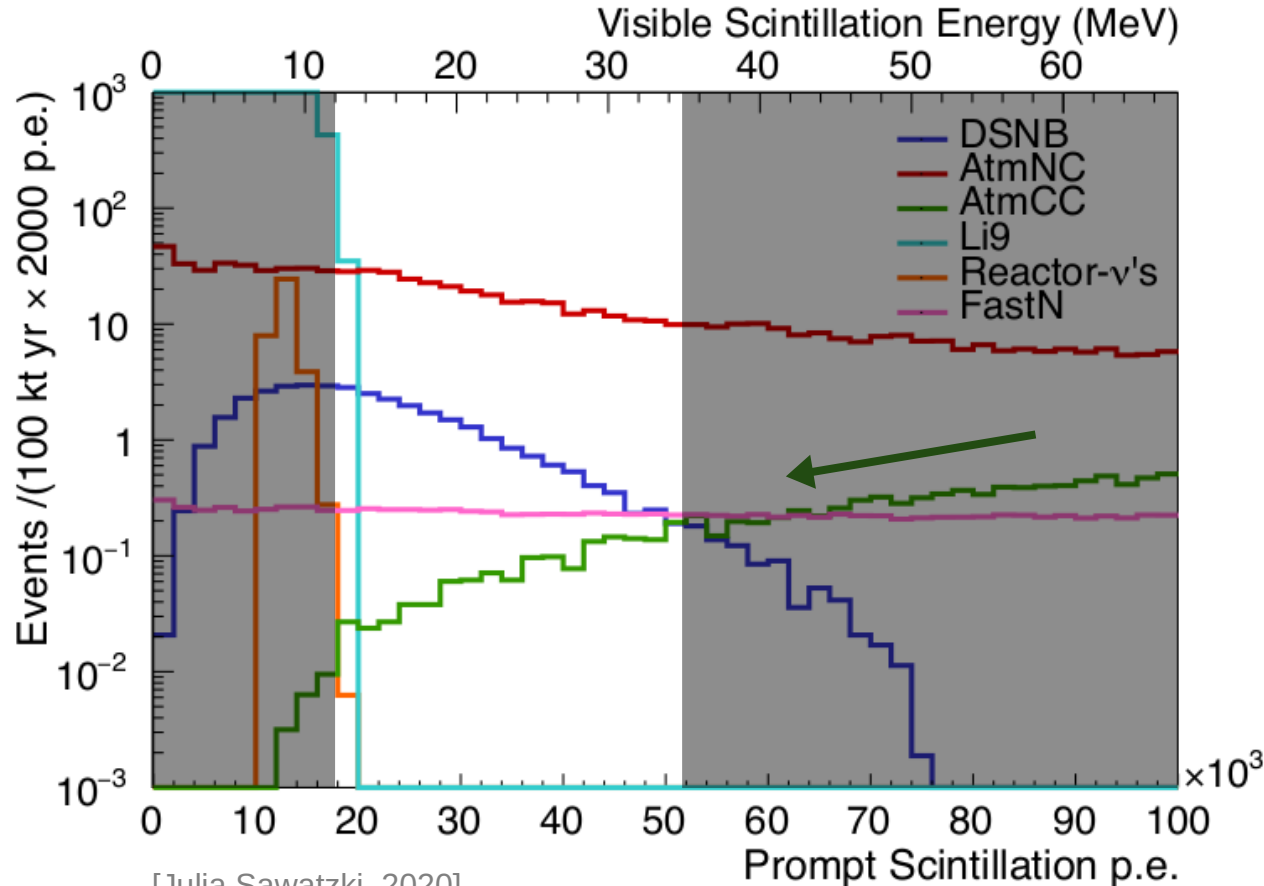


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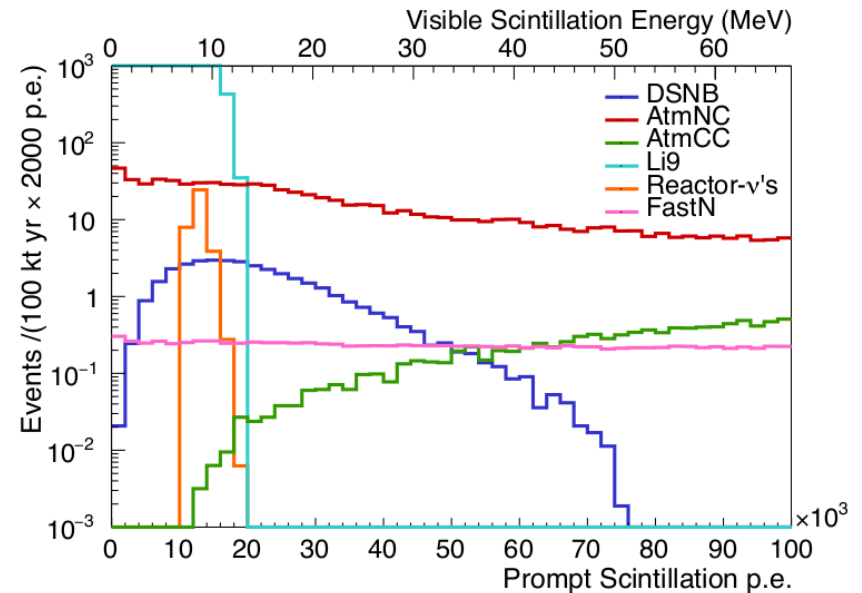


[Julia Sawatzki, 2020]



# NC interactions of all-flavour atmospheric neutrinos can create an event signature similar to an IBD event

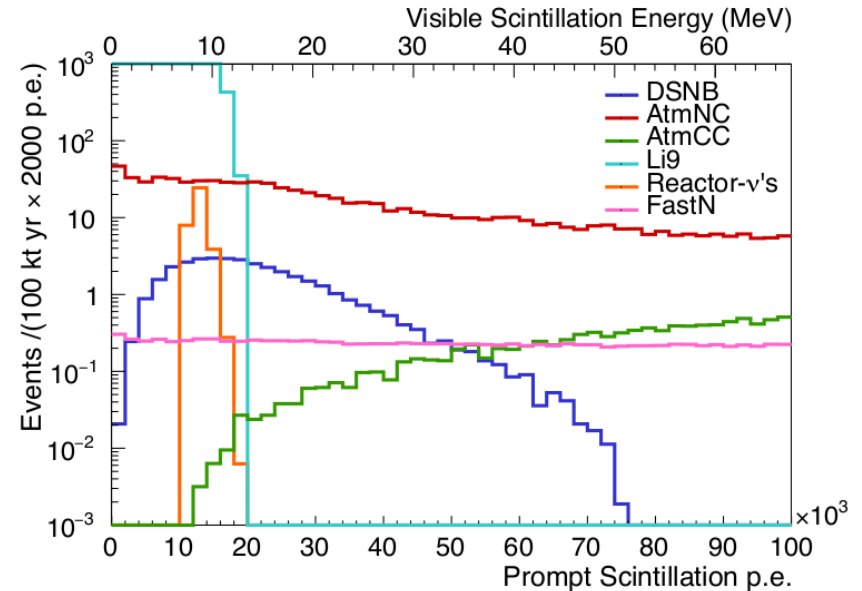
$\nu_x + {}^{12}\text{C} \longrightarrow \nu_x +$			
NC interactions in LS	[%]	after event selection	[%]
$p + {}^{11}\text{B}$	29.1	$n + {}^{11}\text{C}$	33.1
$n + {}^{11}\text{C}$	25.0	$n + p + {}^{10}\text{B}$	22.8
$n + p + {}^{10}\text{B}$	18.2	$n + 2p + {}^{10}\text{Be}$	9.3
$2p + {}^{10}\text{Be}$	4.2	$n + p + {}^2\text{H} + {}^8\text{Be}$	7.1
$2n + {}^{10}\text{C}$	4.0	$n + p + {}^4\text{He} + {}^6\text{Li}$	6.5
$n + 2p + {}^9\text{Be}$	1.1	$2n + {}^{10}\text{C}$	5.1
$2n + p + {}^9\text{B}$	1.1	$2n + 2p + {}^8\text{Be}$	2.8
$2n + 2p + {}^8\text{Be}$	1.0	$2n + p + {}^9\text{B}$	2.7
$3n + 3p + {}^6\text{Li}$	0.9	$n + 3p + {}^8\text{Li}$	2.0
other channels	15.4	other channels	8.6
30.8 / (kt yr)		7.8 / (kt yr)	



[Julia Sawatzki, 2020]

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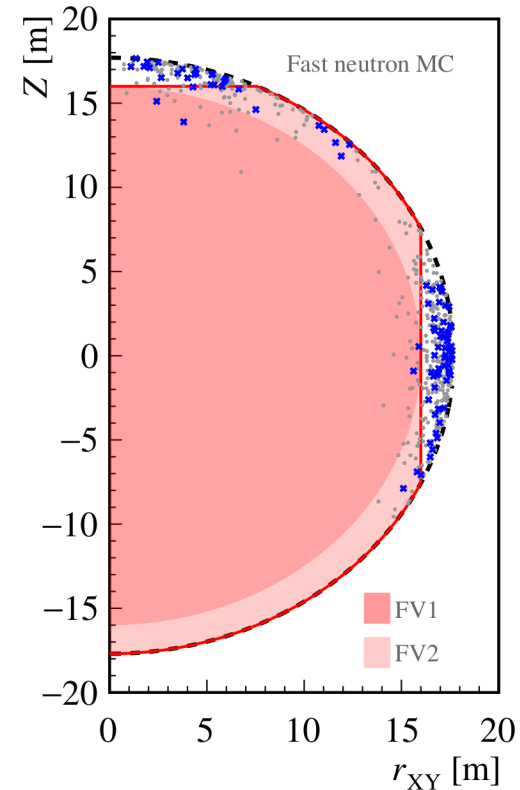
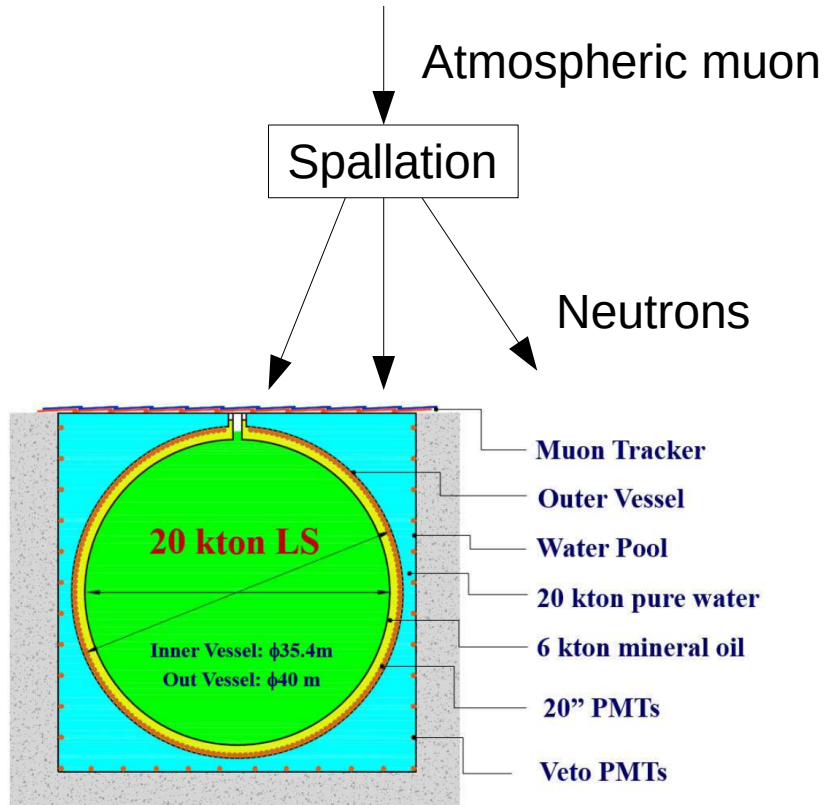


[Julia Sawatzki, 2020]

■ No or multiple neutrons produced



# Fast Neutron Events



# The Motivation behind PSD

Difference in fluorescence between neutrons, NC events, and IBD:

- IBD: Prompt scintillation caused by positron
- NC events and fast neutrons: no positron produced, most energy deposited by neutrons or protons

Difference in energy loss rate

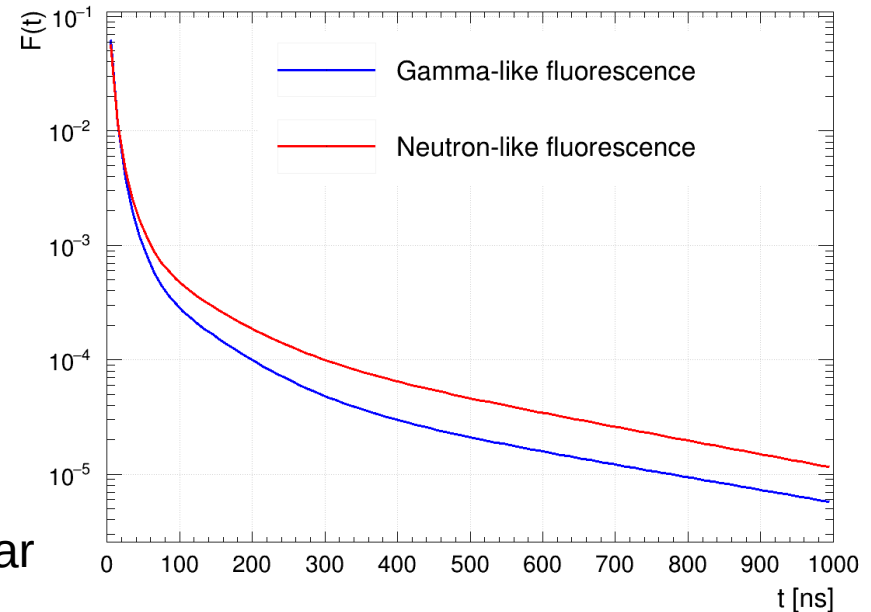
=> Difference in fluorescence spectra

We expect a difference between gamma-like and neutron-like fluorescence as already measured at MLL (Garching), Legnaro (ITA)

	Weights (%)				Decay-times (ns)				(ns)
	$n_1$	$n_2$	$n_3$	$n_4$	$\tau_1$	$\tau_2$	$\tau_3$	$\tau_4$	$\sigma$
	<b>LAB + 2.5 g/l PPO + 3 mg/l bisMSB</b>								
<b>Neutrons</b>	61.4 ±4.3	23.2 ±1.7	9.0 ±0.5	6.4 ±0.5	4.5 ±0.3	15.7 ±1.5	76.2 ±7.6	367 ±39	1.7 ±0.2
<b>Beam gammas</b>	70.7 ±6.0	20.5 ±2.5	6.0 ±0.4	2.8 ±0.4	4.6 ±0.4	15.1 ±1.9	76.1 ±10	397 ±91	1.9 ±0.1

[Raphael Stock, Hans Steiger, Neutrino 2020]

Neutron kinetic energies in measurements so far range from 1 to 11 MeV. -> Higher energies available in beamtimes in 2024/2025.



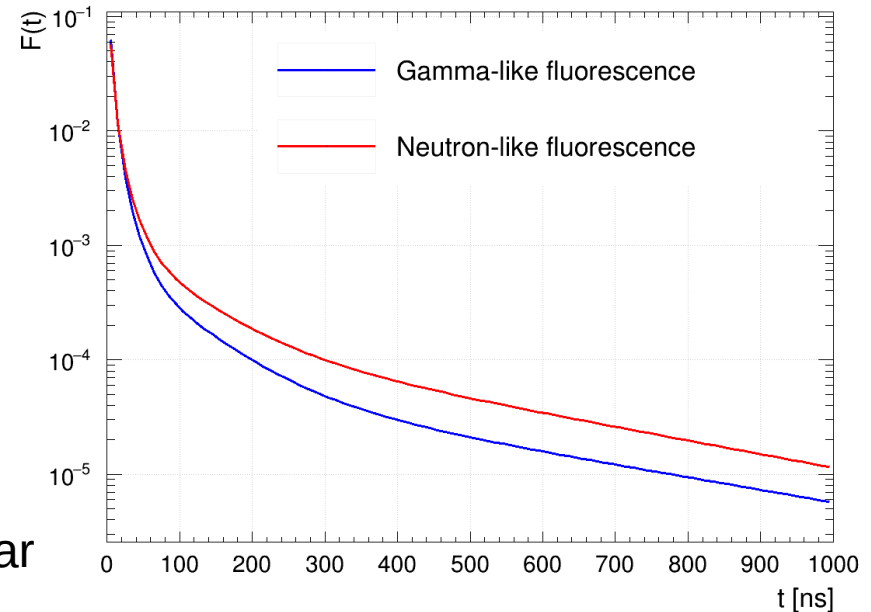
We expect a difference between gamma-like and neutron-like fluorescence as already measured at MLL (Garching), Legnaro (ITA)

Applies to IBD positrons

Applies to protons / recoil protons

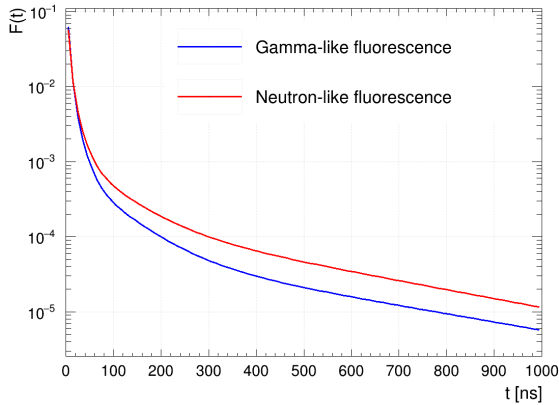
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<b>Beam gammas</b>	70.7 $\pm 6.0$	20.5 $\pm 2.5$	6.0 $\pm 0.4$	2.8 $\pm 0.4$	4.6 $\pm 0.4$	15.1 $\pm 1.9$	76.1 $\pm 10$	397 $\pm 91$	1.9 $\pm 0.1$

[Raphael Stock, Hans Steiger, Neutrino 2020]

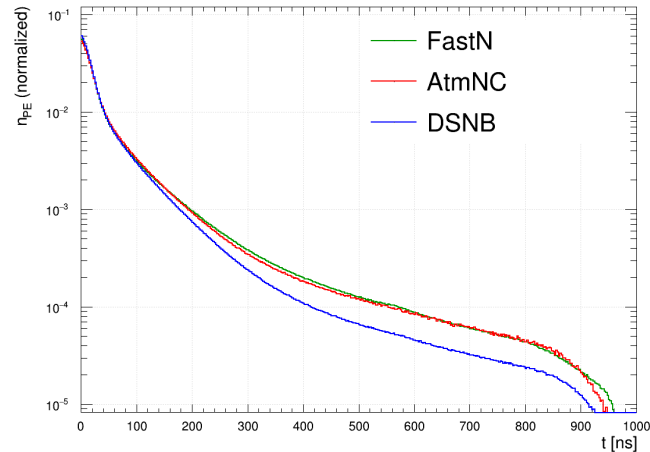


Neutron kinetic energies in measurements so far range from 1 to 11 MeV. -> Higher energies available in beamtimes in 2024/2025.

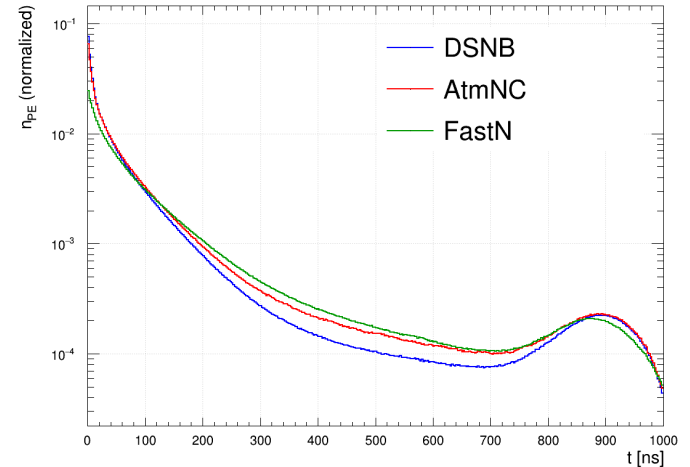
# The expected pulshape difference survives the full detector simulation -> We will use it for PSD



Detector Geometry

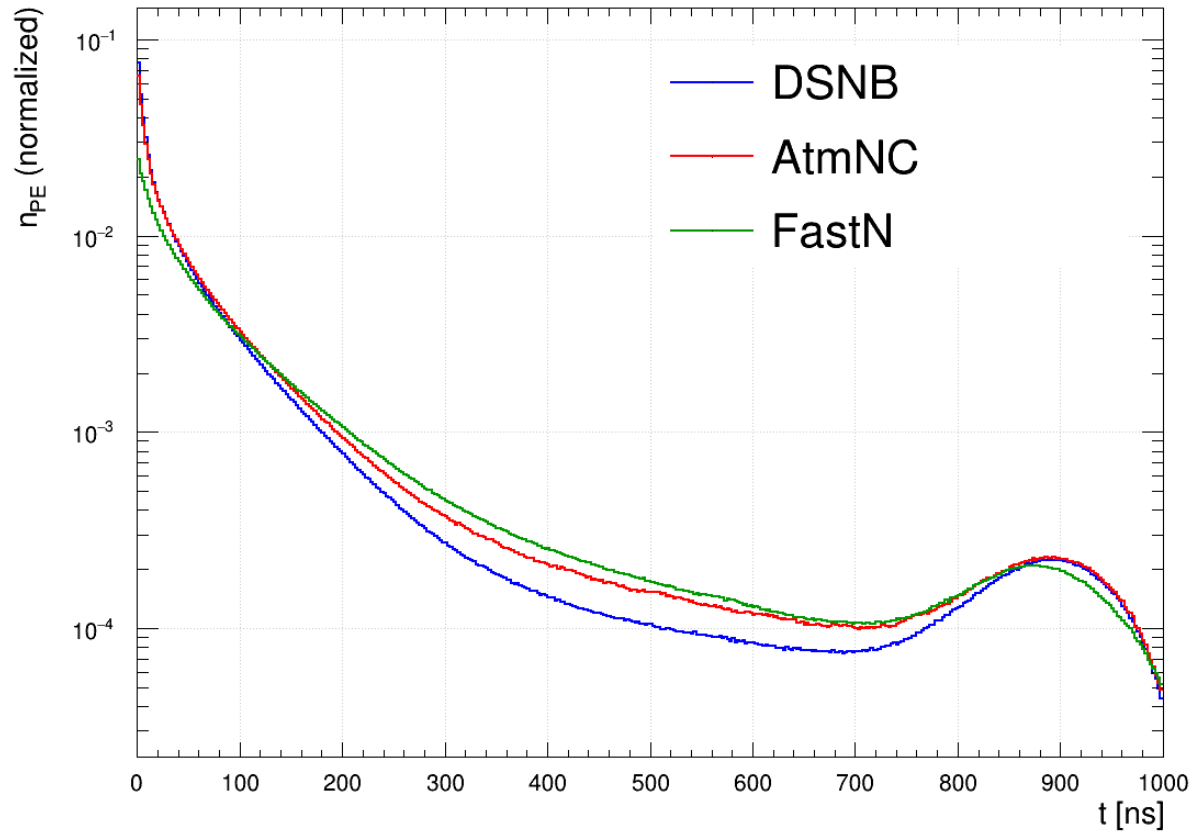


PMT Electronics

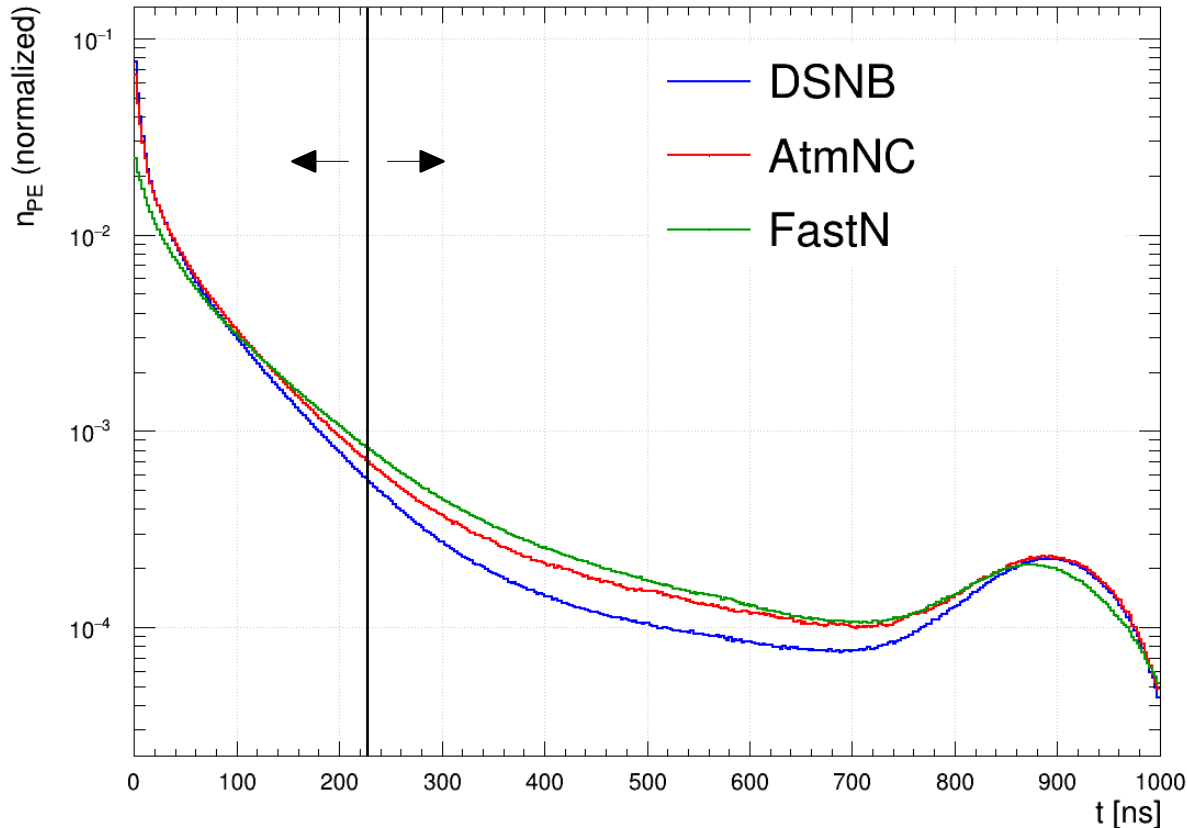




# Resulting pulseshapes from the full detector simulation



# Resulting pulseshapes from the full detector simulation



Traditional cut variable for PSD: Fraction of PE after a certain time  $t_{TTR}$   
-> 'Tail-to-Total ratio' (TTR)

# First (old) PSD Method: Tail-to-Total Ratio

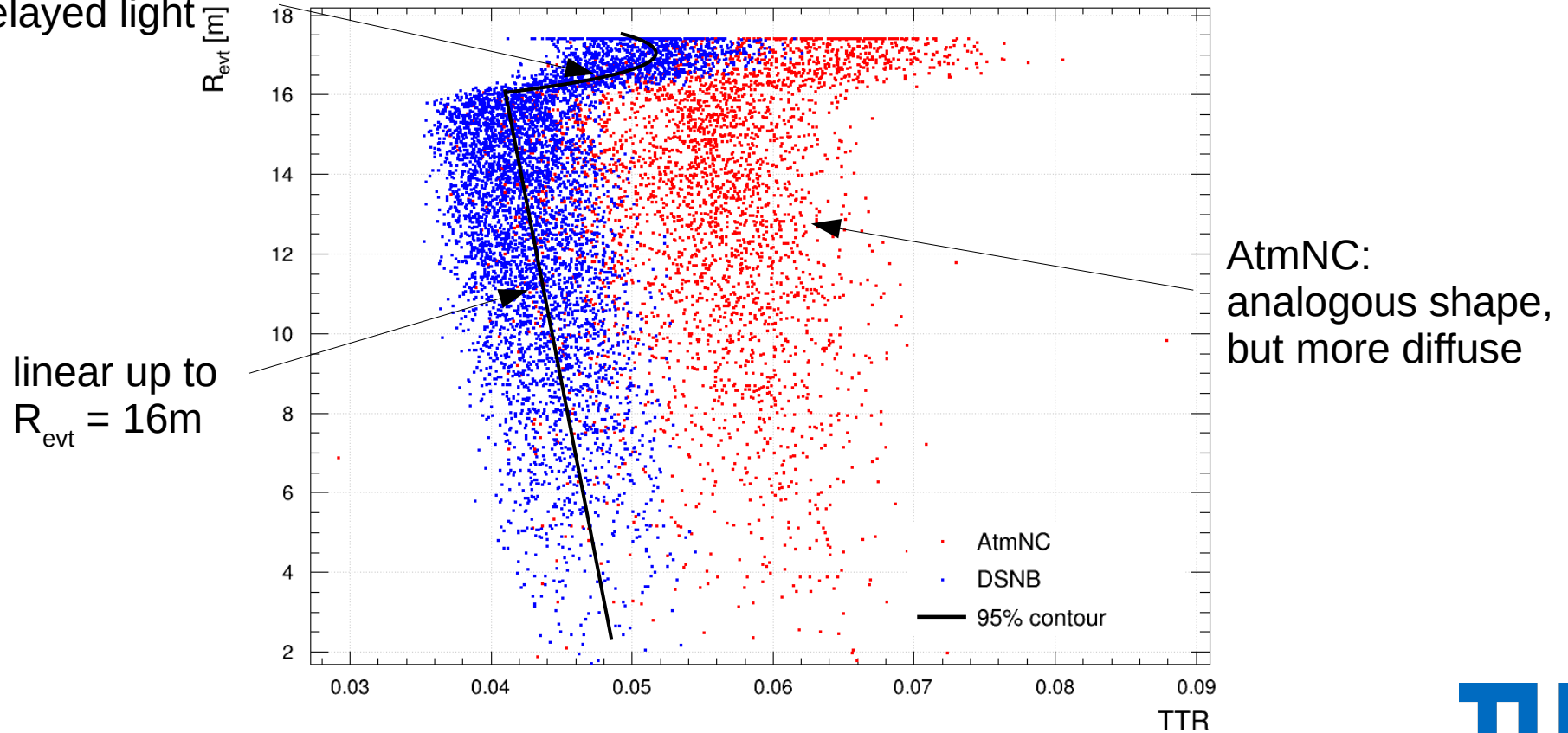
Cut variable for PSD: Fraction of PE after certain time  $t_{TTR}$   
-> 'Tail-to-Total ratio' (TTR)

$$TTR = \frac{nPE(t_{TTR} < t < 1000 \text{ ns})}{nPE(t < 1000 \text{ ns})}$$

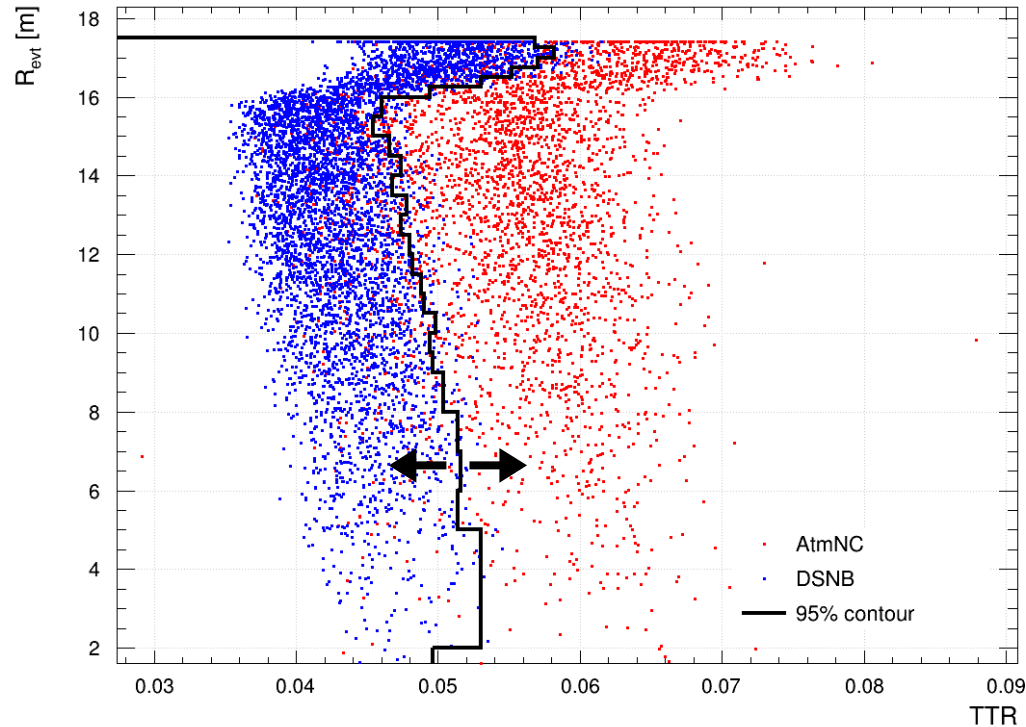
=> First variable for non-ML discrimination between IBD events (signal) and atmospheric NC events (background)

above 15.3m, light from the event position can undergo total reflection => more delayed light

## TTR vs. $R_{\text{evt}}$



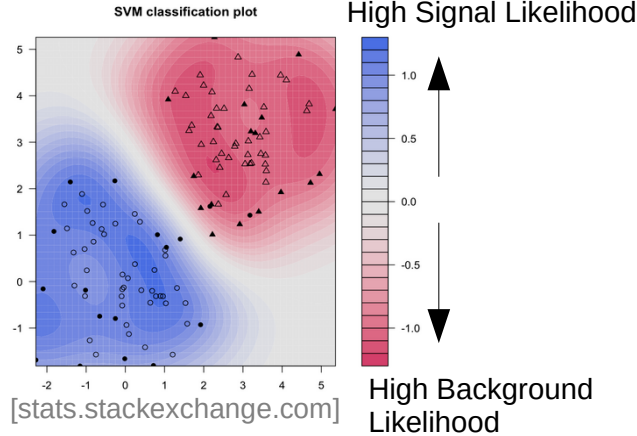
# Contour Cut in this 2D parameter space



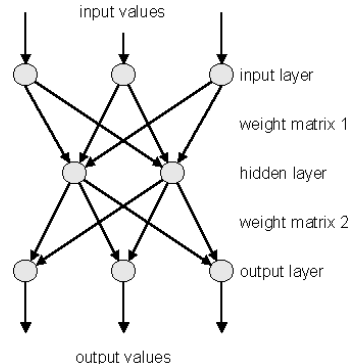
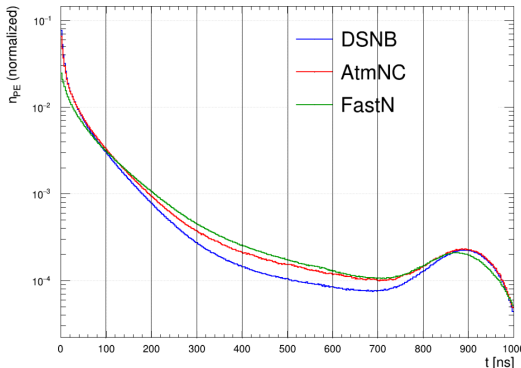
For each spherical shell, determine the TTR value, below which are 95% of signal events  $\Rightarrow$  contour function of variable resolution in  $R_{\text{evt}}$

# Using Machine Learning Methods for DSNB PSD

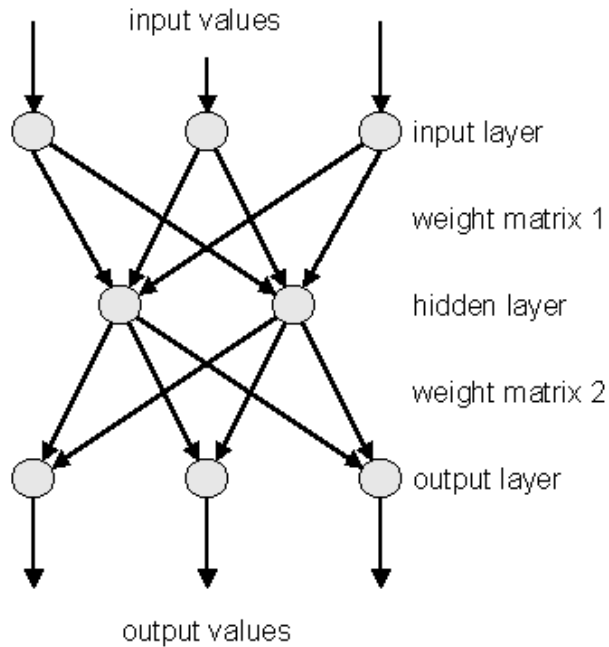
Generic Example of an SVM:



- ML implementations used here:
  - Feed-Forward Neural Networks (NN)
  - Boosted Decision Trees (BDT)
  - Support Vector Machines (SVM)
- Input given to the classifier about each event:
  - Total and prompt event energy
  - Event vertex radius
  - Ten 100ns-timebins
- Each classifier then gives an 'IBD likelihood' as output.



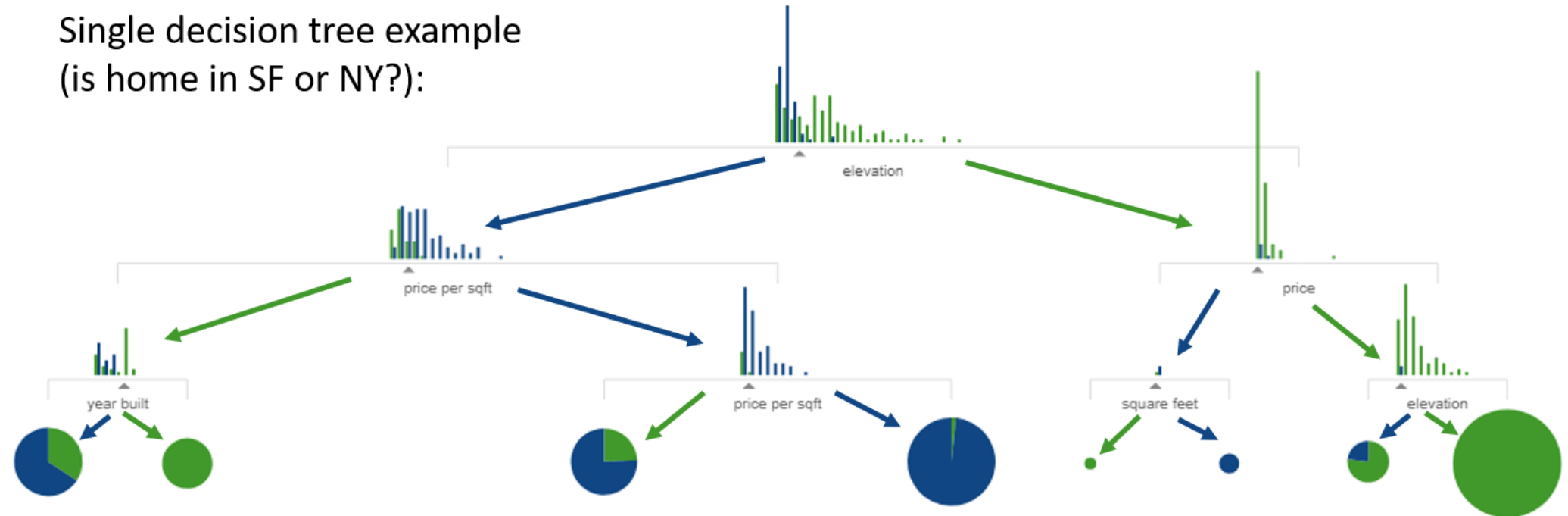
# Feed-forward Neural Networks



- Implementation used: Sequential model from Keras as provided by the TensorFlow package.
- Multiple input variables describing an event, 'IBD likelihood' as an output, variable number of hidden layers in between
- Neural Networks can provide great discrimination performance with the right parameters, but offer low transparency

# Boosted Decision Trees

Single decision tree example  
(is home in SF or NY?):



[<http://www.r2d3.us/visual-intro-to-machine-learning-part-1/>]

-> BDT: „Performance-weighted sum of trees“ -> Better training performance  
and continuous output from 0 to 1

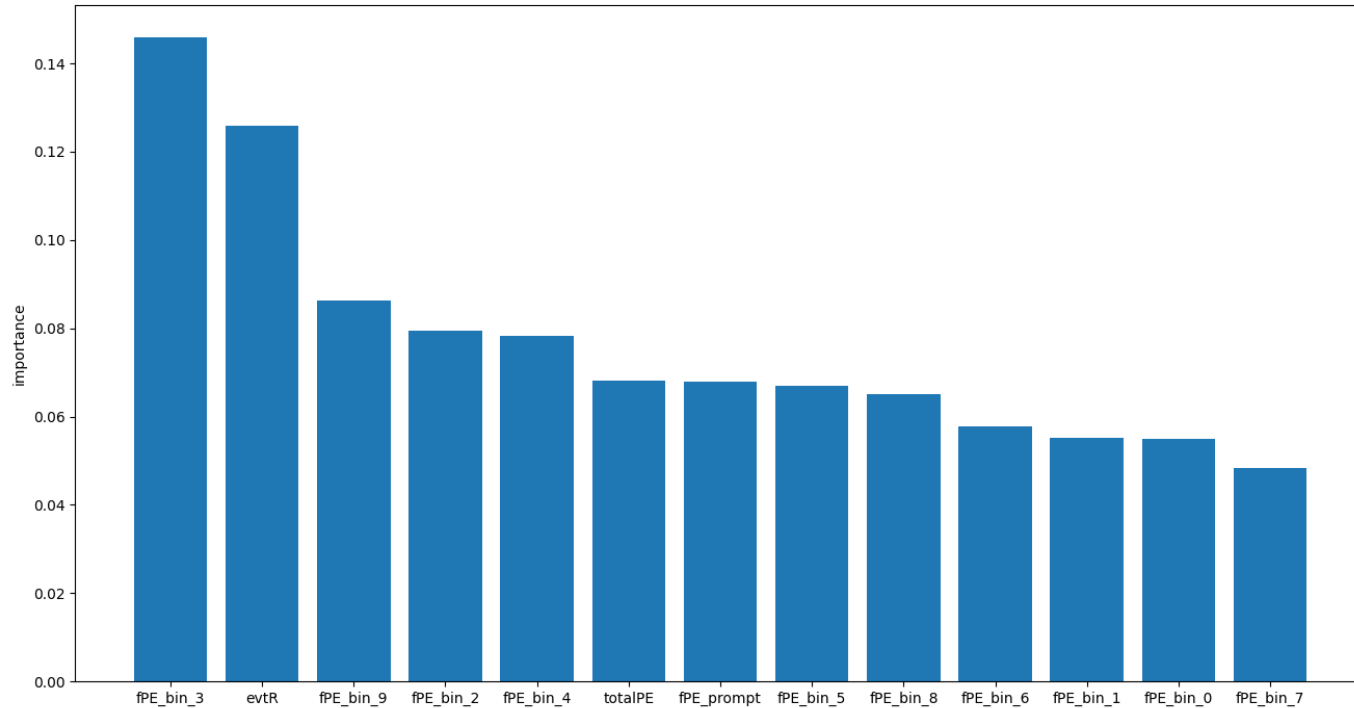


# Boosted Decision Trees

-> BDT: „Performance-weighted sum of trees“ -> Better training performance and continuous output from 0 to 1

- Implementation used: DecisionTreeClassifier from scikit-learn, boosted by AdaBoostClassifier
- Easy to set up, but not many options for parameter tuning
- Far more transparent than neural networks, leading to better insight into the discrimination power of individual variables
- Limited overall performance due to the nature of linear cuts

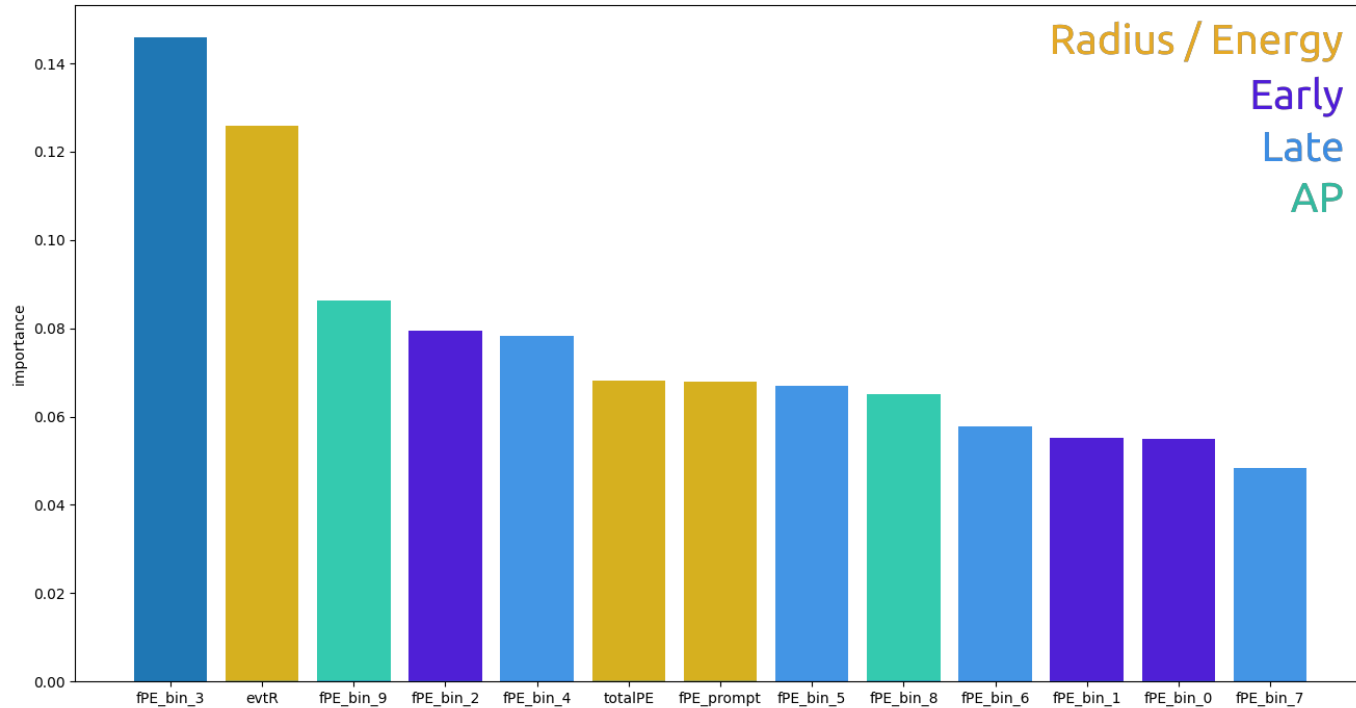
# BDT Parameter Comparison: Frequency of each Variable as a branch in a decision tree



(Only one example training run drawn)



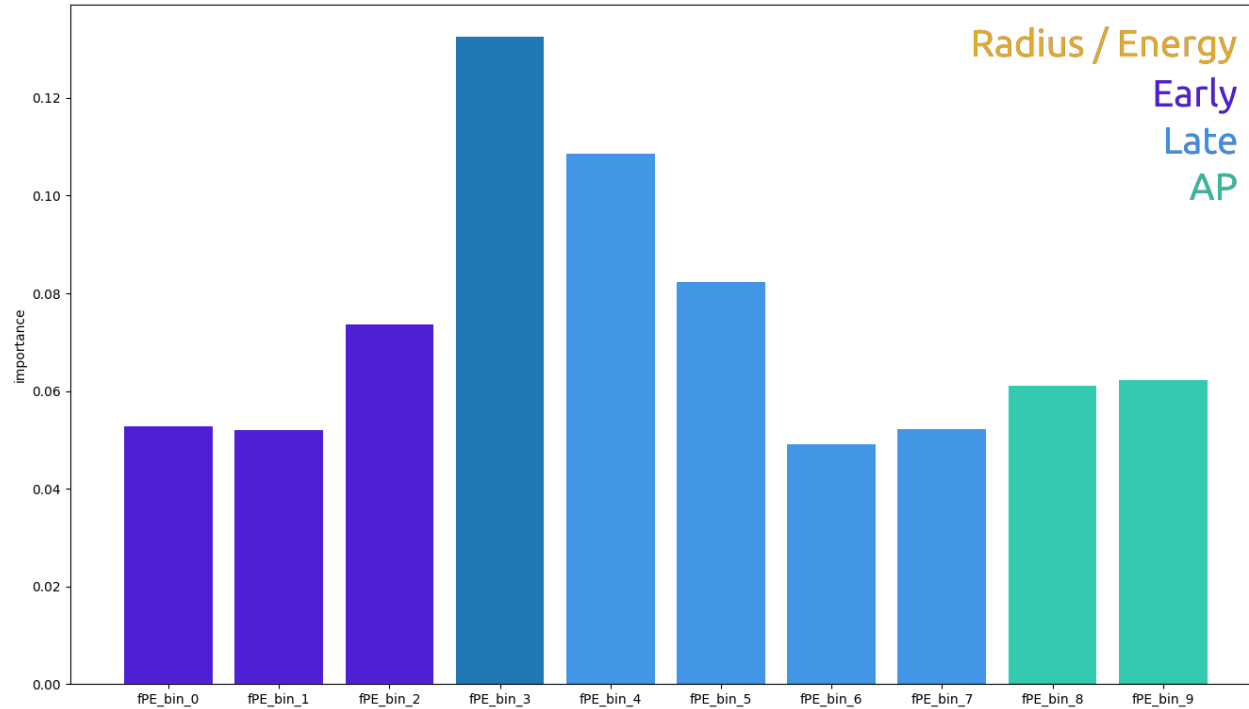
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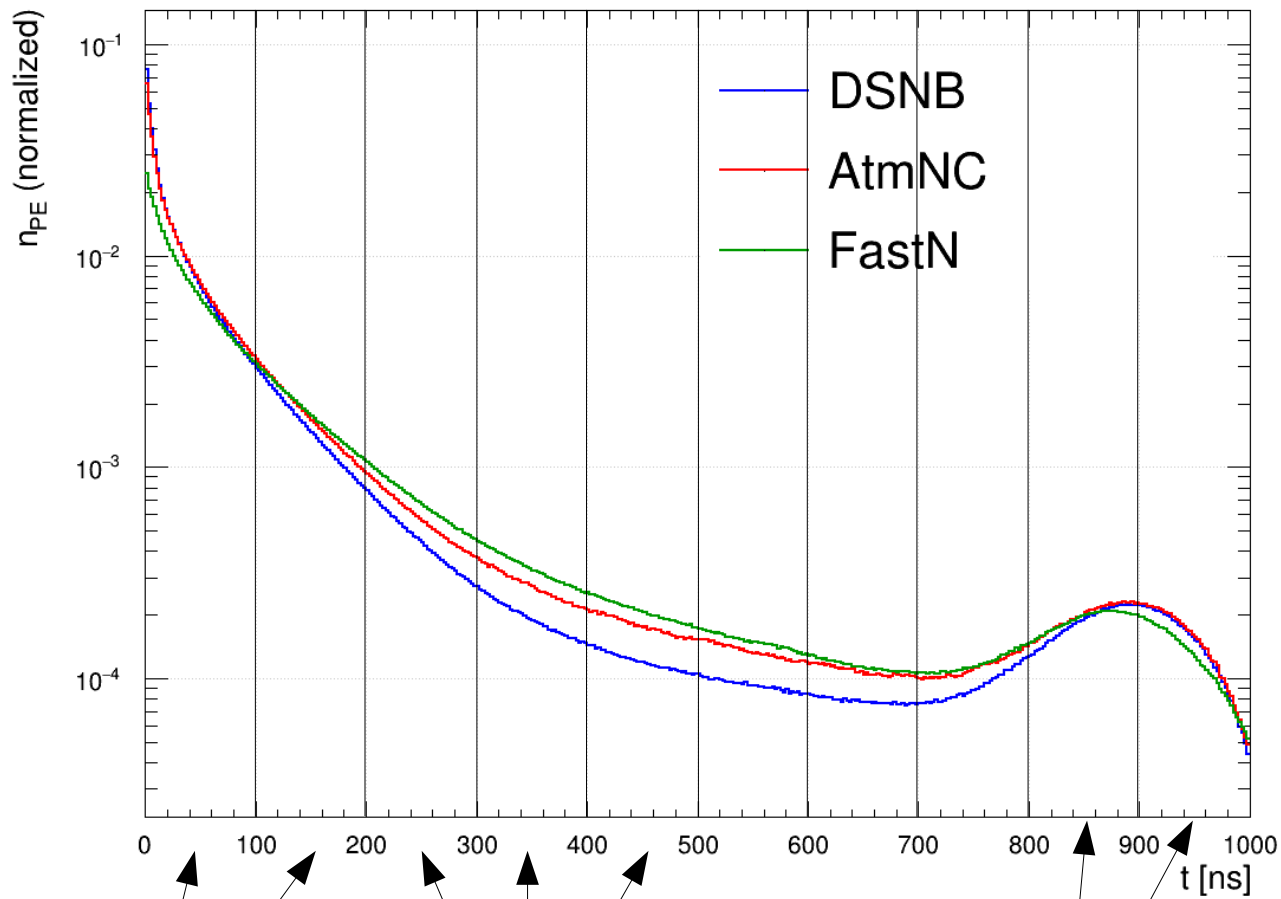
# BDT Parameter Comparison: Frequency of each Variable as a branch in a decision tree



=> Importance of different time regimes of the detector event readout window!

(Only one example training run drawn)





Not enough  
separation

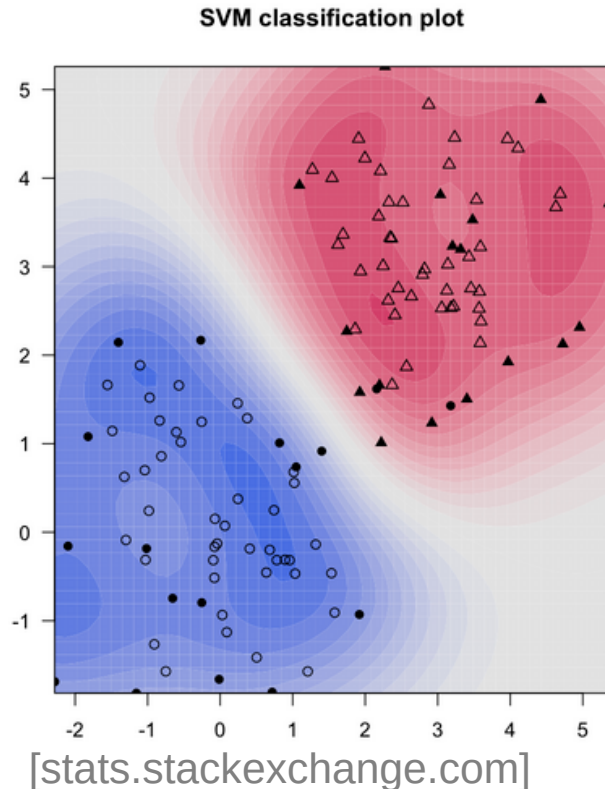
sufficient separation  
and PE count

Afterpulsing

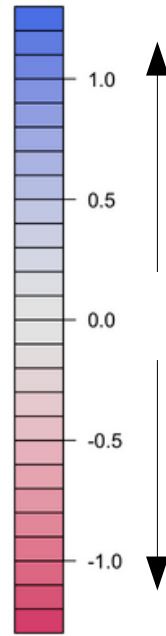


# Support Vector Machines

Generic Example:



High Signal Likelihood

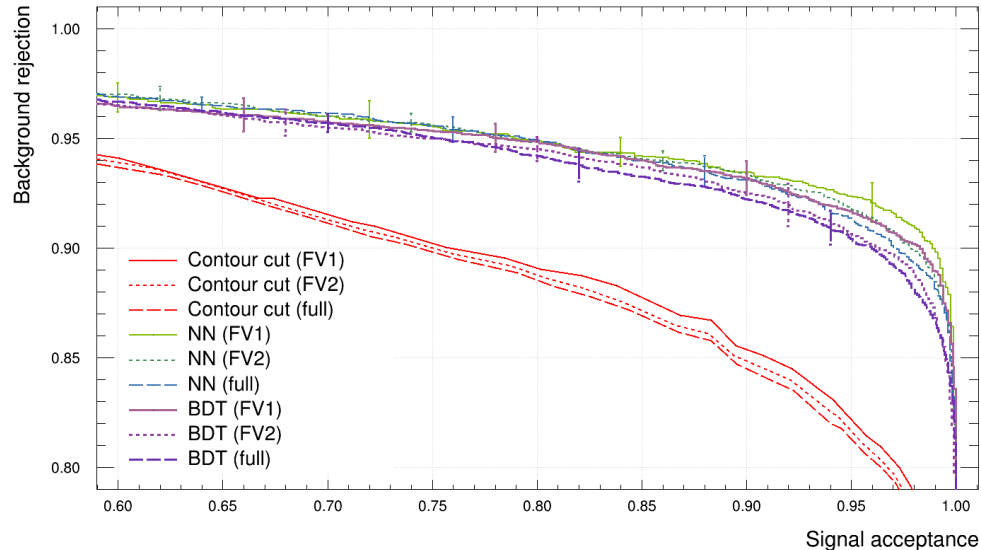


High Background Likelihood

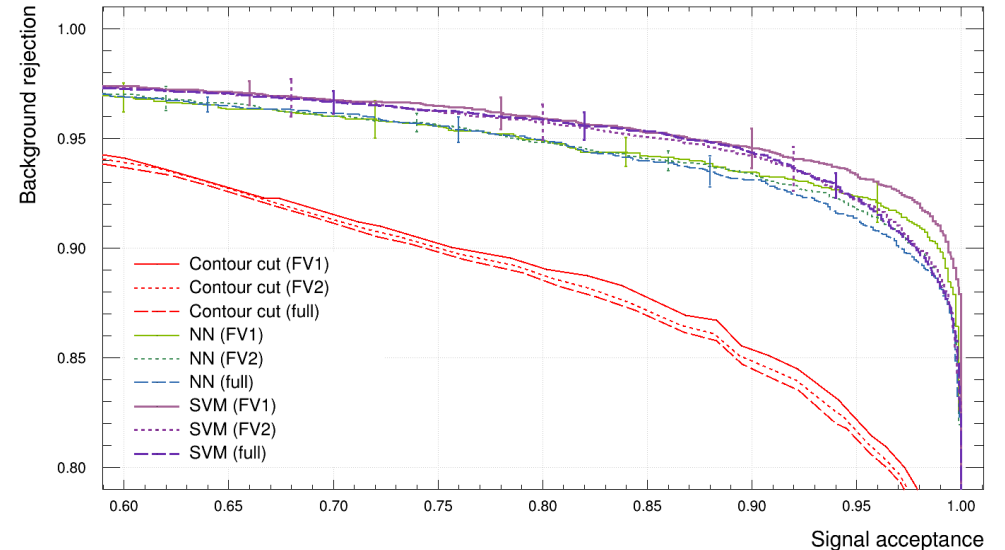
- Implementation used: SVC by scikit-learn
- SVMs try to find the ideal hypersurface cut between two event populations by transforming the input parameter space and classify input events by a resulting distance metric
- Best performance achievable with the 'radial basis function' kernel
- Usually better performance compared to boosted decision trees, but less transparency

# Machine learning methods can significantly outperform conventional TTR analysis

Compared with BDT:

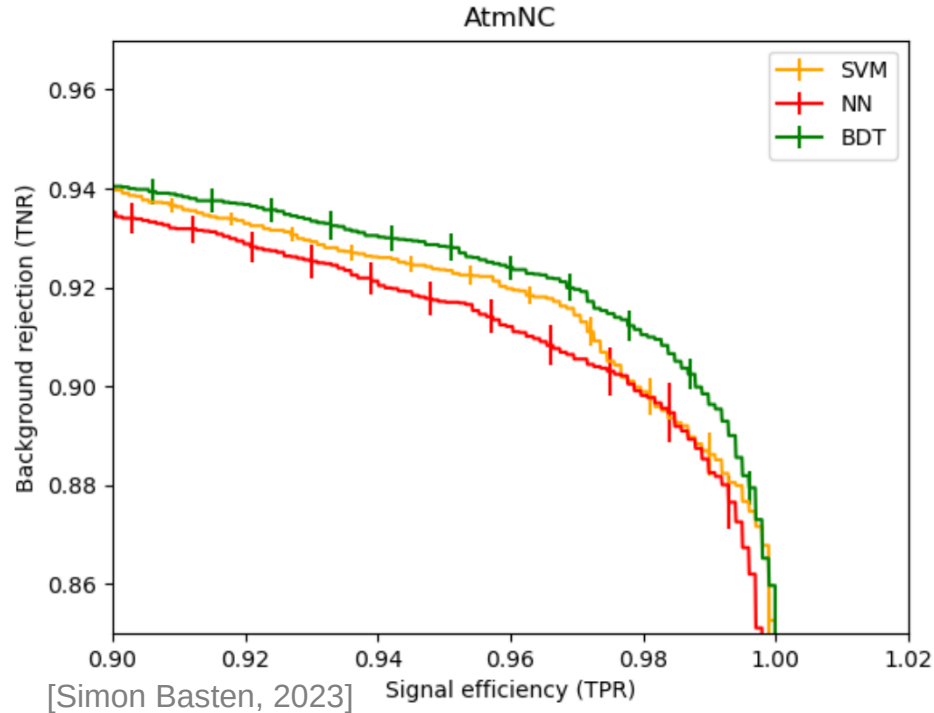


Compared with SVM:



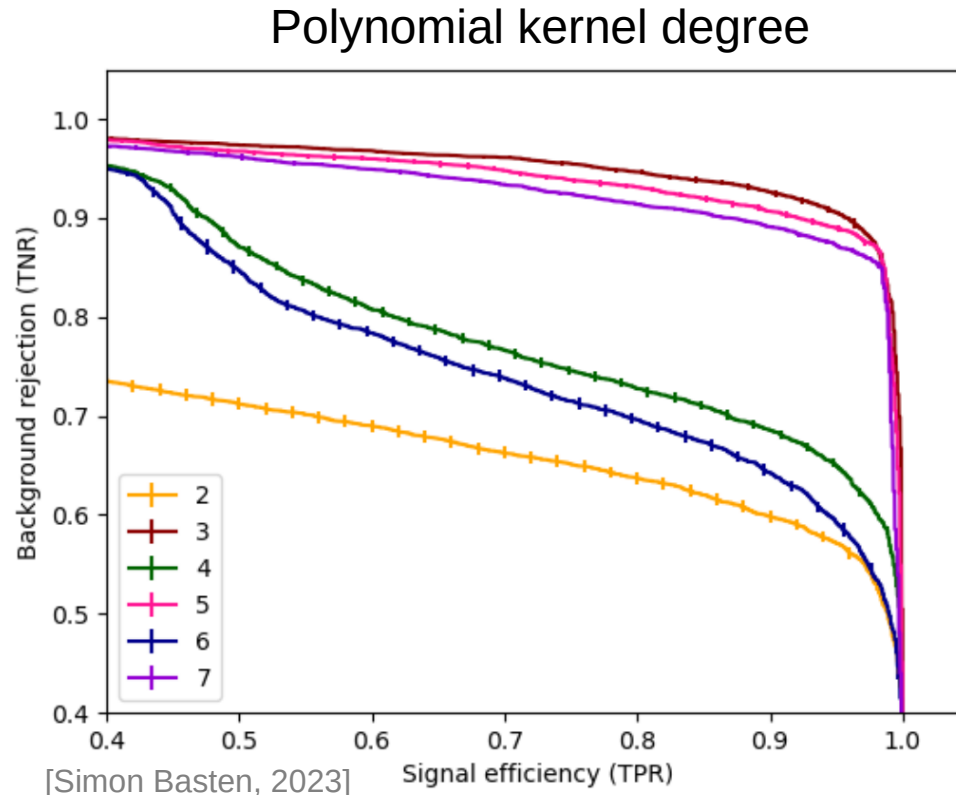
(Shown here: Discrimination against AtmNC background)

=> TUMKolleg student Simon Basten further improving BDT and SVM performance by careful hyper-parameter tuning





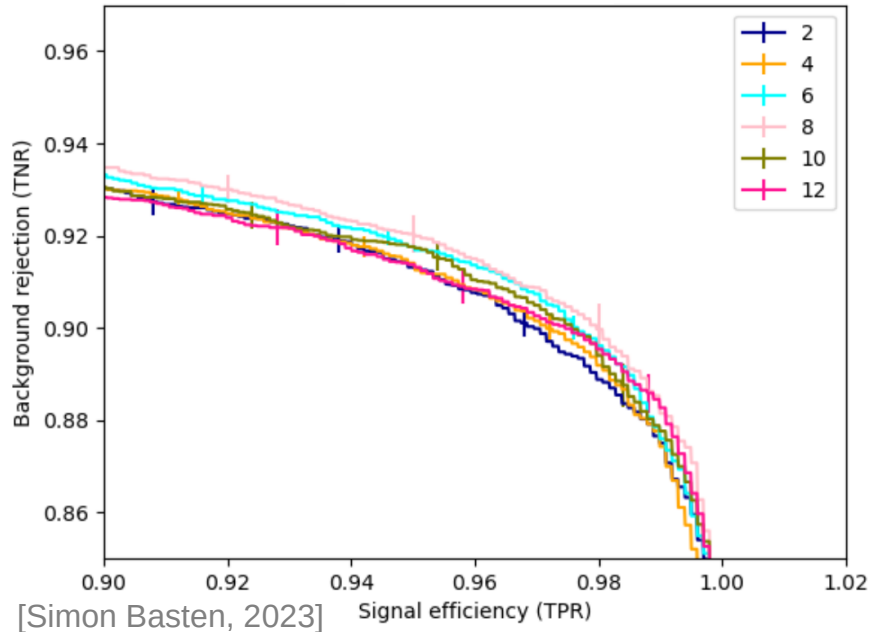
Interesting observations: SVM performance with a polynomial kernel function is highly dependent on its degree.



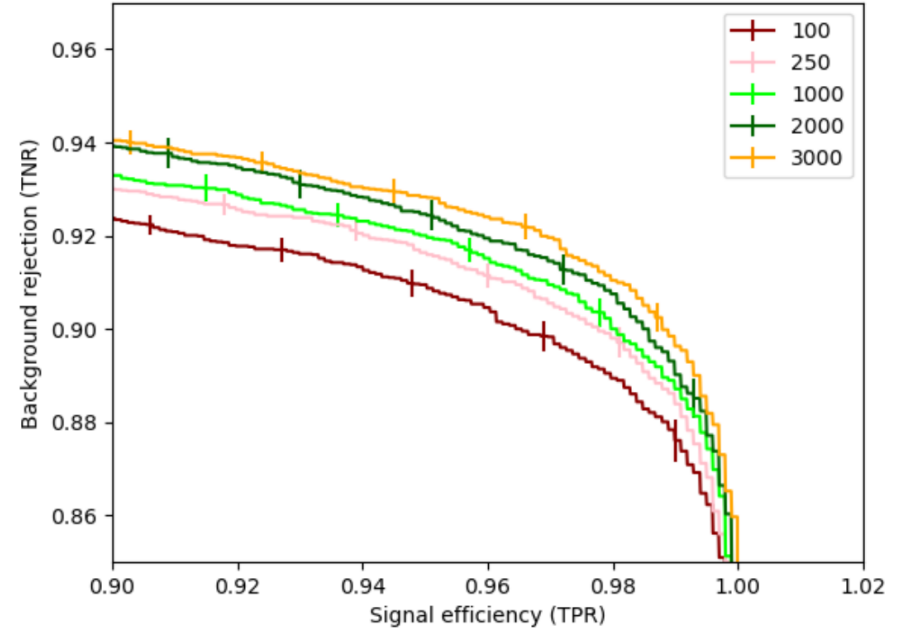
=> Small insight into 'shape' of multi-dimensional event populations.

# Interesting observations: BDTs can reach greater performance as 'weak learners'

## SDT depth

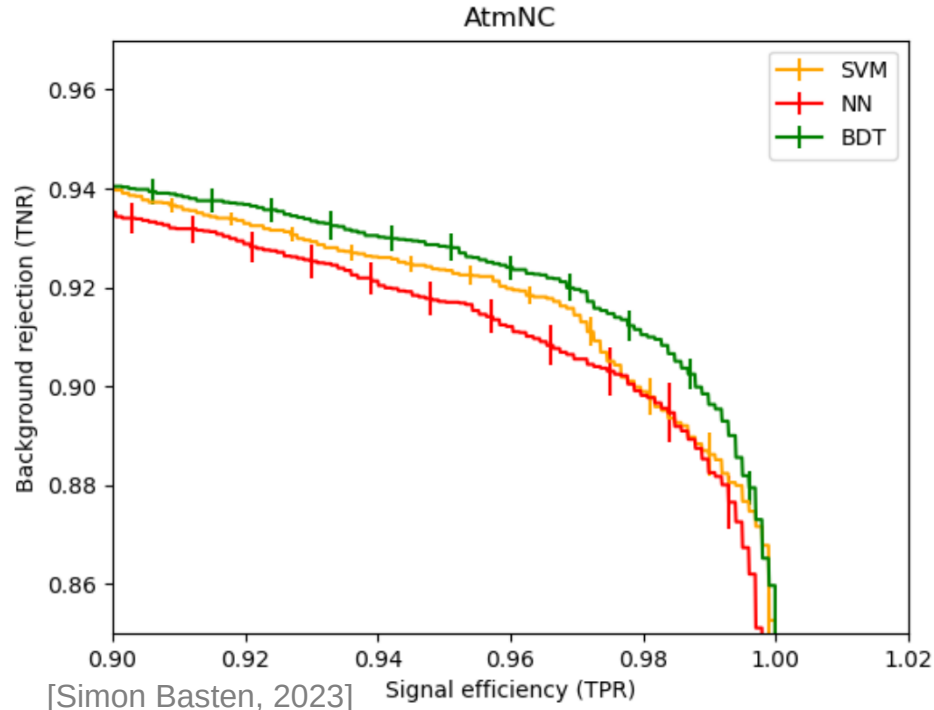


## Number of SDTs per BDT



=> No notable performance gain from increased tree depth after a certain point, but greater performance increase from added SDTs.

=> TUMKolleg student Simon Basten further improving BDT and SVM performance by careful hyper-parameter tuning



=> BDT using 'weak learner' technique is now the best performing of the three studied ML tools.

# Conclusions / Outlook

- Our main background comes from atmospheric NC events, but machine learning can greatly help our pulse shape discrimination.
- Careful parameter optimization can notably improve the discrimination performance of our machine learning tools.
- Liquid scintillator particle identification PSD has not been done at such high energies in previous experiments.
- Depending on our recent/future beamtime results, we might have a more challenging PSD task at these high energies than estimated from low-MeV results.

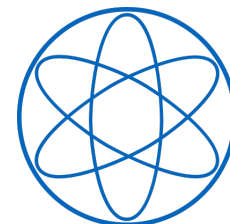
**Thank you for your attention!**

**DFG**

Deutsche  
Forschungsgemeinschaft

SFB 1258

Neutrinos  
Dark Matter  
Messengers

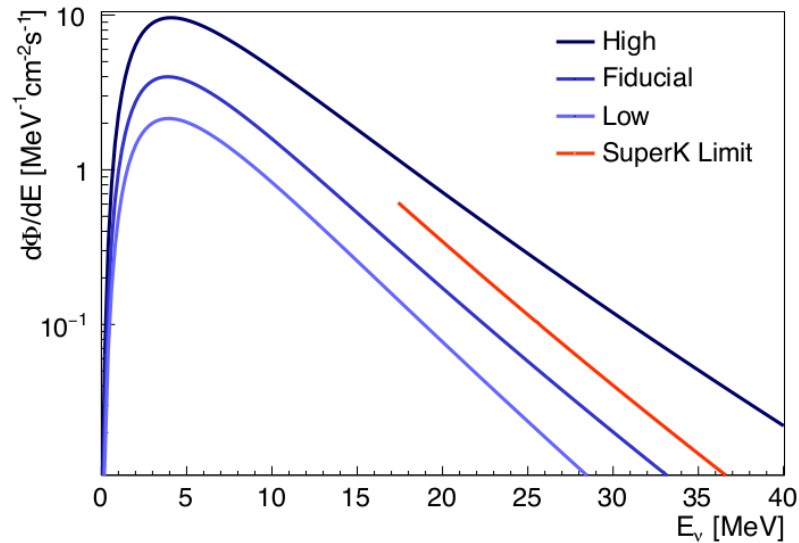


# Backup Slides

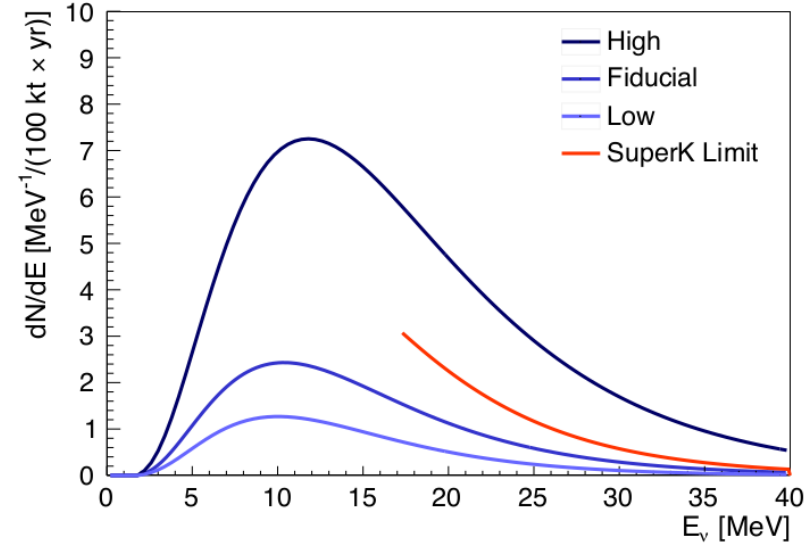
DSNB

# DSNB - Expected Signal

DSNB  $\bar{\nu}_e$  Flux



DSNB  $\bar{\nu}_e$  Spectra



[Julia Sawatzki, 2020]

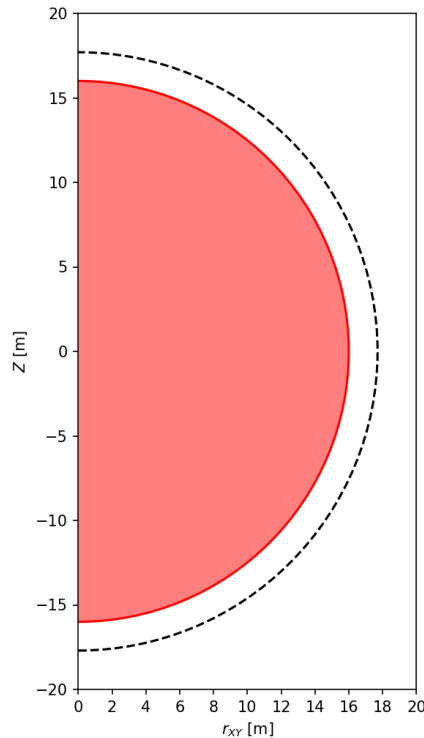
~6 orders of magnitude below solar <sup>8</sup>B neutrino flux

# Data Preparation / Setup



# There are different fiducial volume options available for the DSNB event search in the JUNO LS

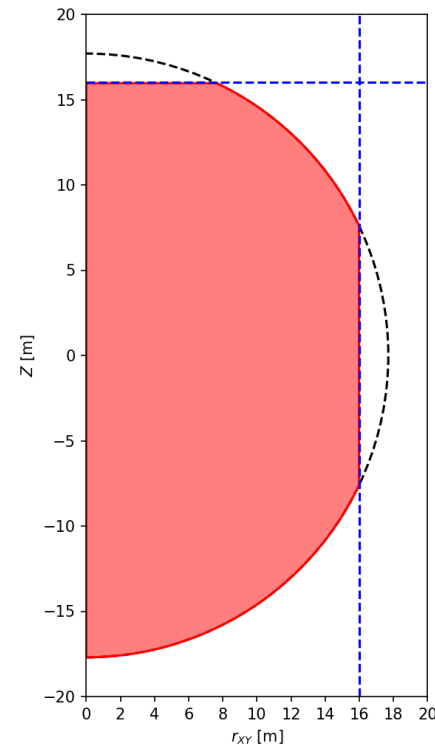
FV1:



73.9 % of the  
detector volume

$$R_{evt} < 16 \text{ m}$$

FV2:



~ 92 % of the  
detector volume

$$\sqrt{x^2 + y^2} < 16 \text{ m}$$

$$z < 16 \text{ m}$$

Joint project:

- Technical University of Munich
- JGU Mainz with **PRISMA+**
- UC and LBNL Berkeley

Study:

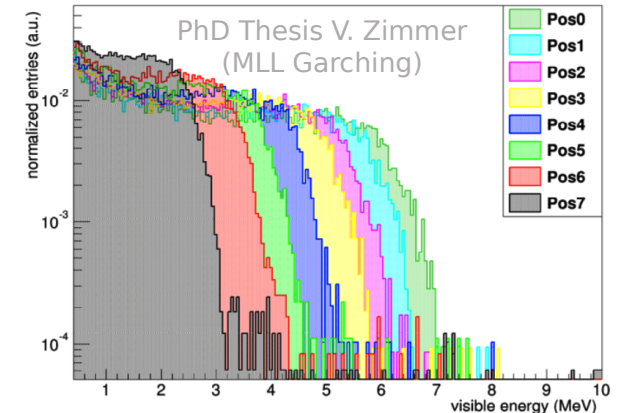
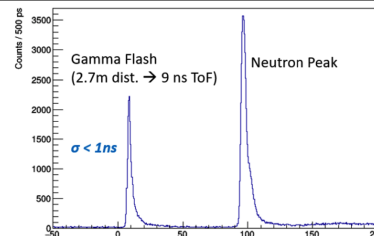
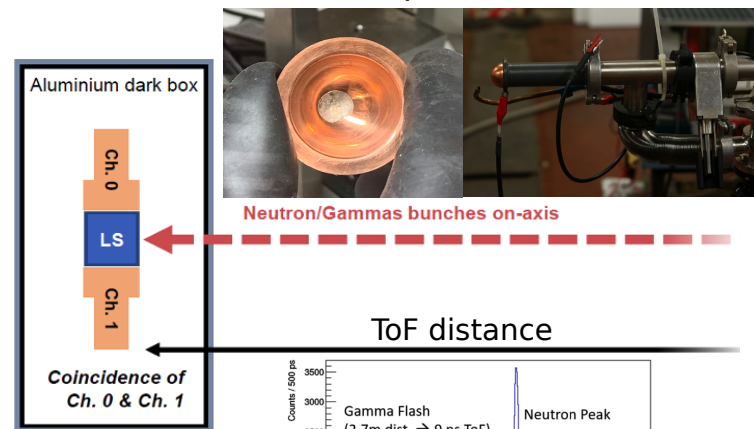
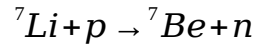
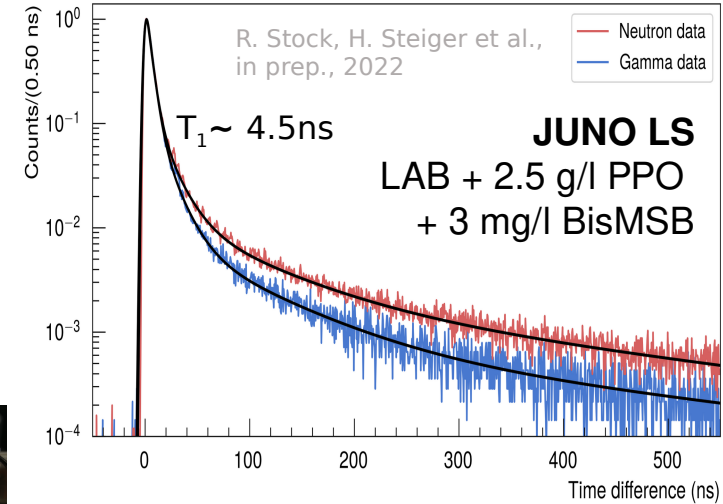
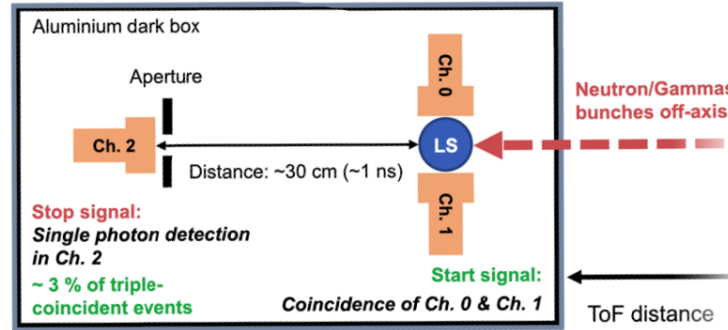
- **time profiles** for gamma and neutron excitation
- **QFs** for gamma and **neutron** interactions

Successfully measuring the scintillation time profiles and quenching factors for JUNO and JUNO-TAO LSs allows us to **improve our understanding of the energy transfer mechanisms!**

Measurements provide valuable input data for **JUNO and TAO**:

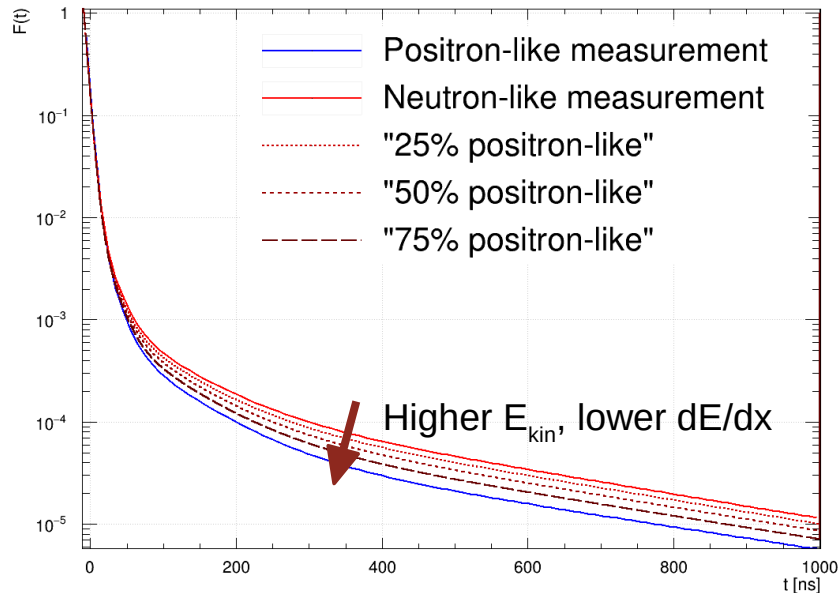
- Basis **for reliable Monte Carlo simulations**
- Development of **event reconstruction algorithms and PSD techniques**

Beamtimes at the LNL in June 2021, December 2021, April/May 2022 ⇒ Data analysis ongoing!



Proton recoil spectra for different initial n energies

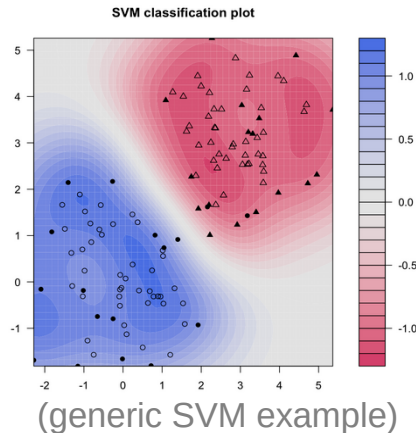
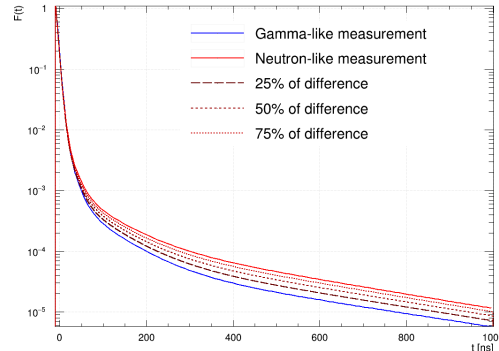
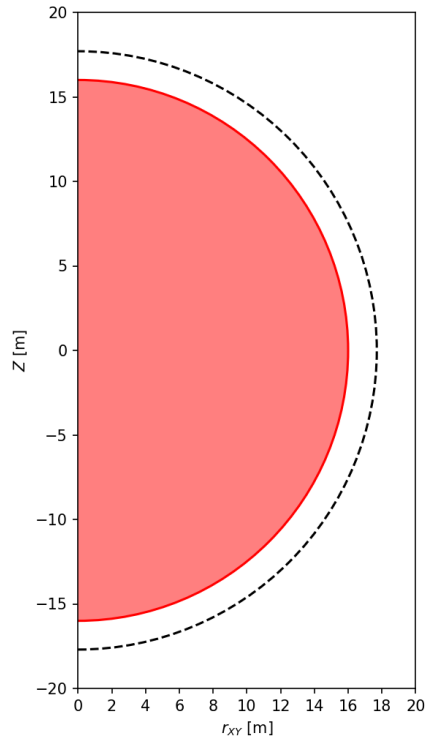
We expect the scintillation time profile of background neutrons/protons to become more signal-like at higher energies:



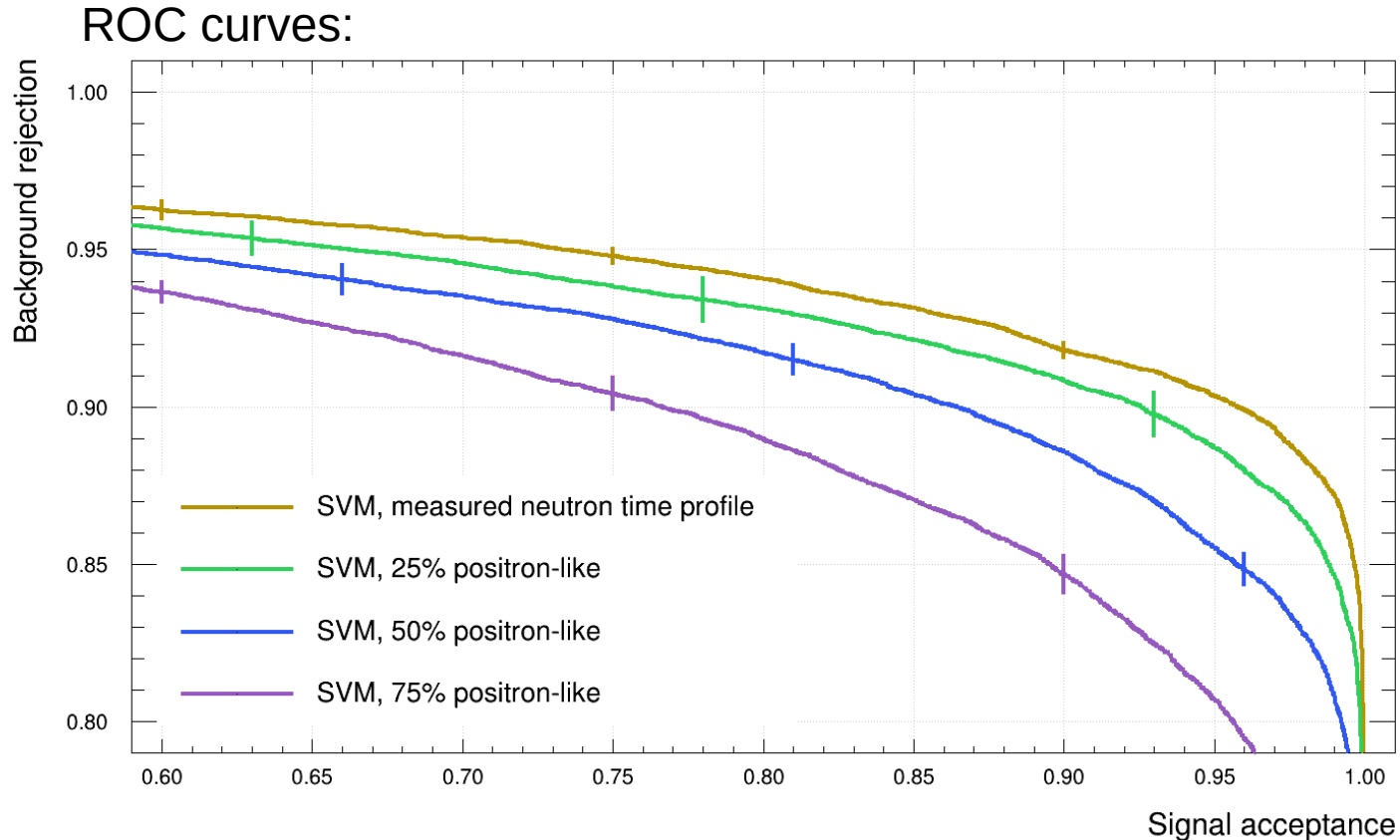
- The scintillation time profile caused by a particle in LAB mostly depends on its energy loss rate  $dE/dx$ .
- At lower energies ( $< 10$  MeV): background neutrons/protons lose significantly more energy per distance than signal positrons.
- At higher energies: neutrons/protons lose **less** energy per distance than at lower energies.
  - Closer to the  $dE/dx$  of positrons
- We plan to measure this effect at beamtimes at LNL Legnaro.

# Setup

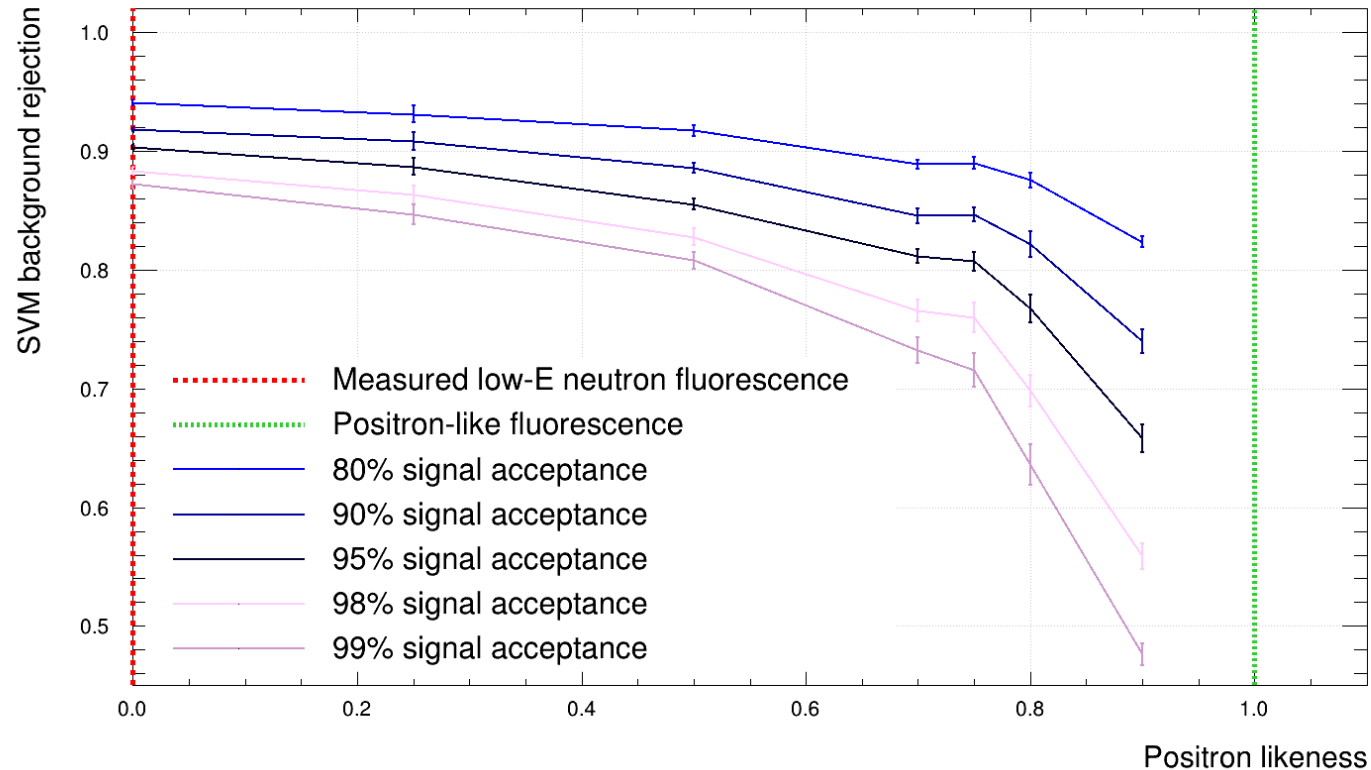
- IBD signal positrons and background neutrons in the DSNB energy ROI (12-35 MeV)
- Multiple sets of background neutrons for different linear combinations between n and e+ time profiles
- Then: SVM discrimination between each neutron time profile set and the IBD positron set.



As the high-energy neutron time profile approaches the positron time profile, we steadily lose discrimination performance.

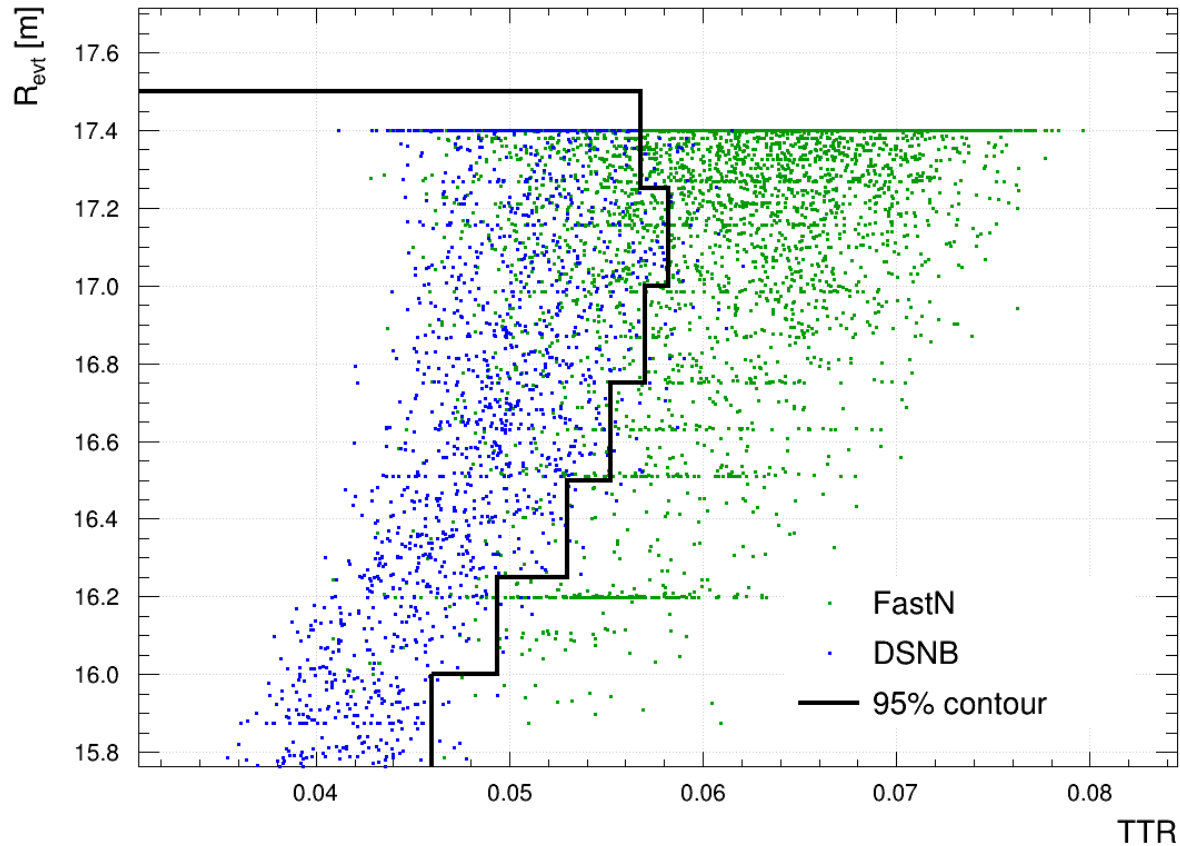


After the half-way point between both time profiles we see an even stronger decrease in PSD performance.



# TTR Analysis

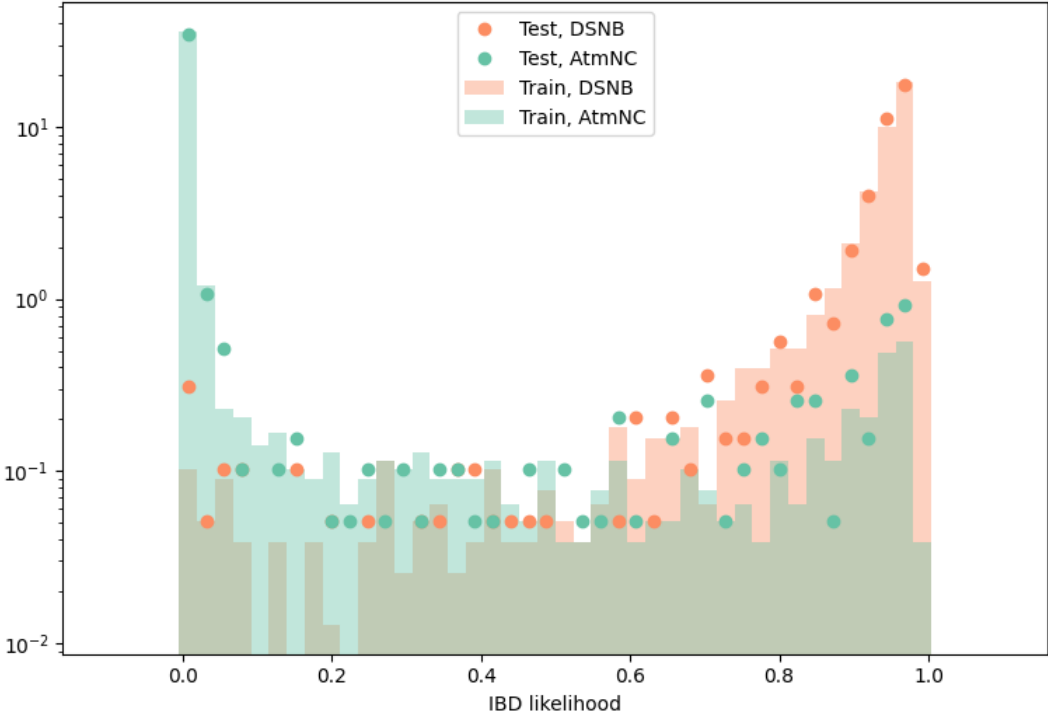
# The same contour cut can also be applied in the rejection of FastN Events



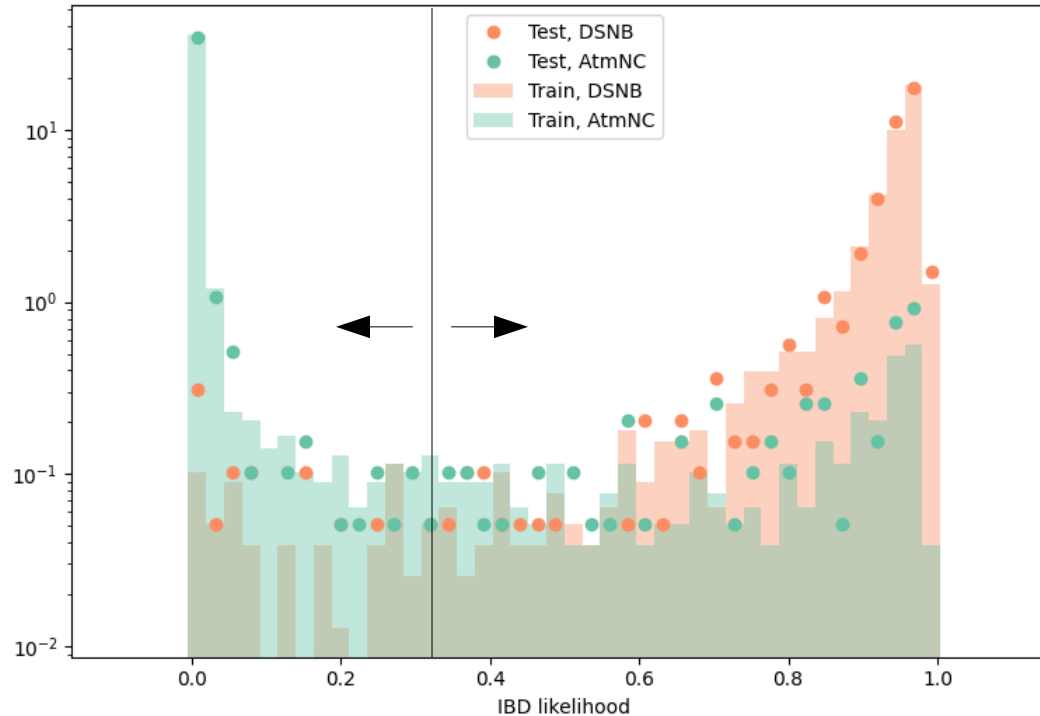


# Machine Learning

# Training results – Example Output



# Training results – Example Output



-> Alternating IBD likelihood cutoff to vary background rejection against signal acceptance (e.g. in an ROC curve)

