Reconstruction in Super & Hyper-K

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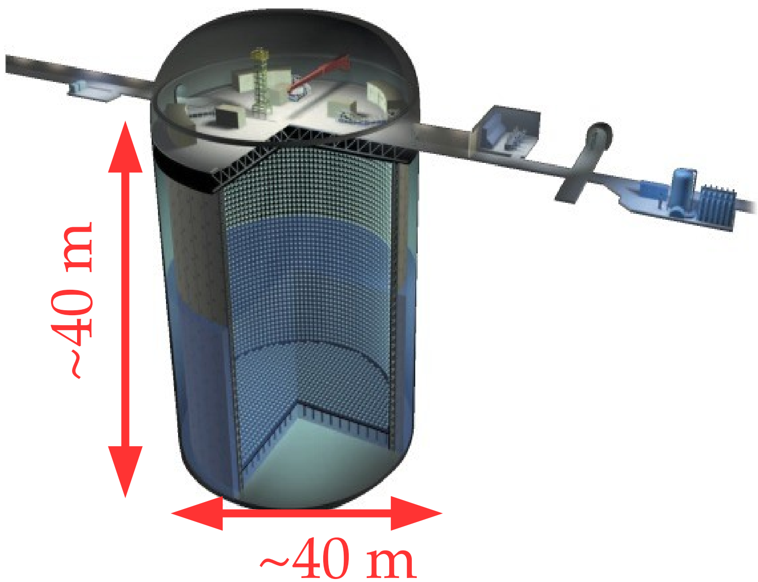
Super- and Hyper-Kamiokande detectors

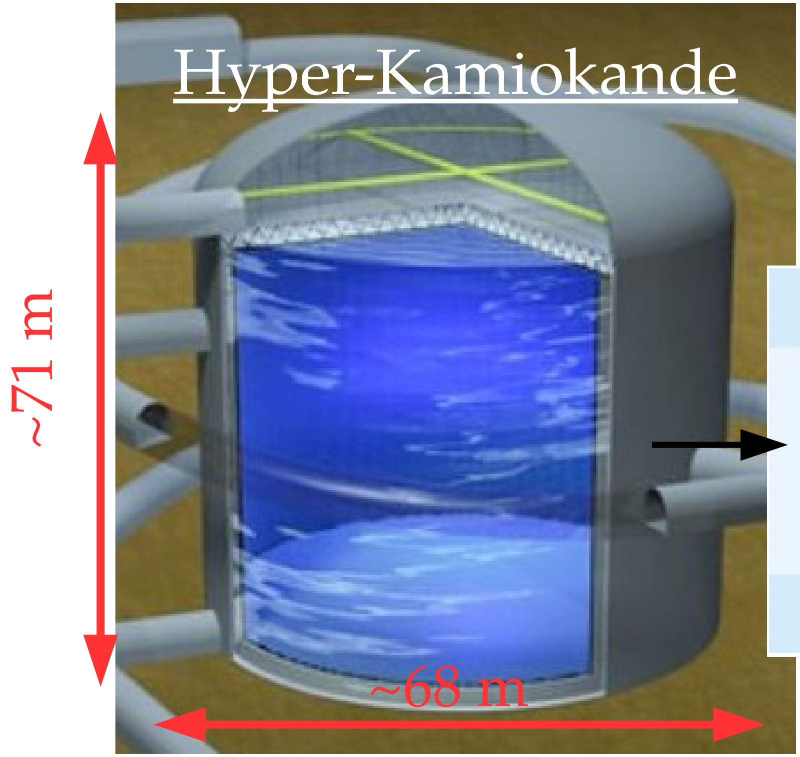
Neutrino observatories in Japan, based on water Cherenkov :

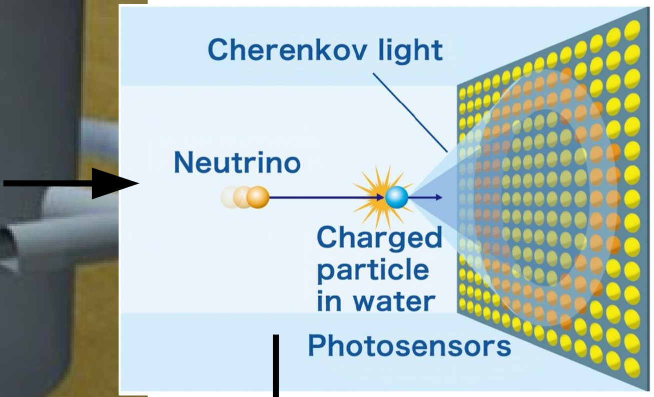
- SK (1996-Now) : current generation filled with 50kt of water.
- HK (in construction 2020-28) : next generation → Fiducial Mass ~ 8 x SK.

Super-Kamiokande

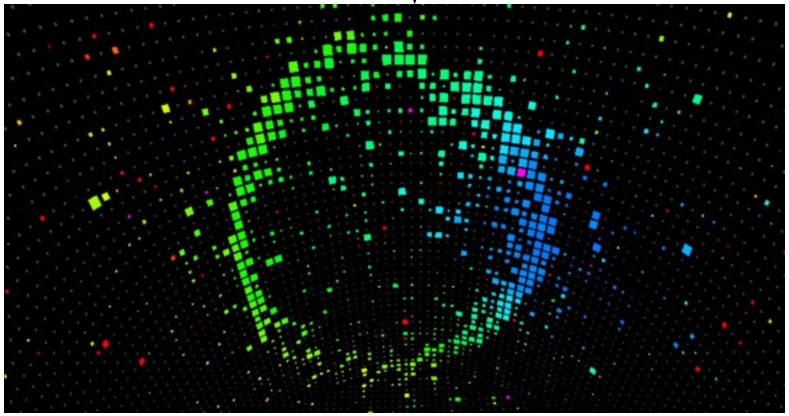


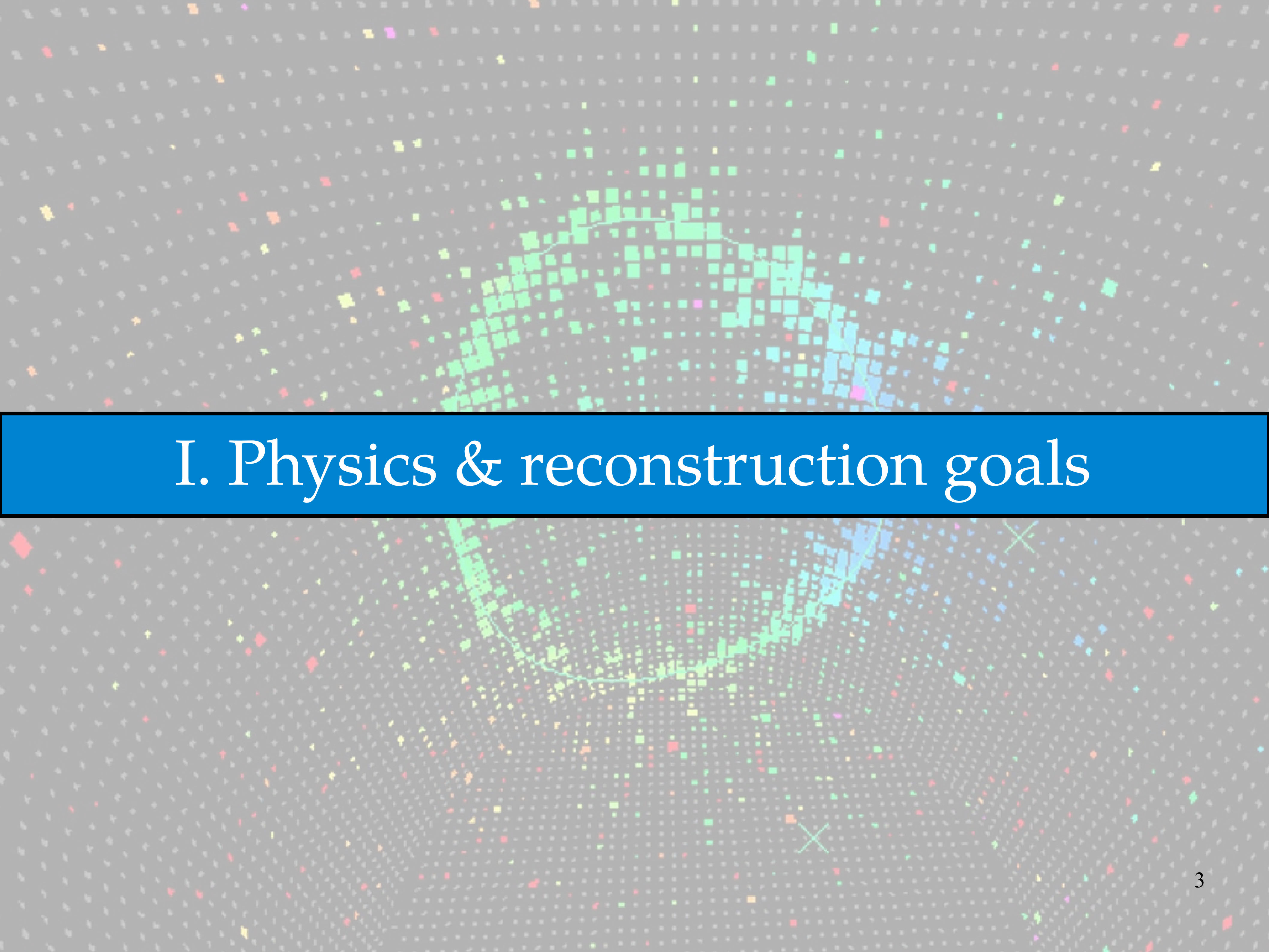
Hyper-Kamiokande





	Super-K	Hyper-K
Site	Mozumi	Tochibora
Overburden	2780 m.w.e.	1700 m.w.e.
Number of ID PMTs	11129	20000
Photo-coverage	40%	20% (×2 efficiency)
Mass / Fiducial Mass	50 kton / 22.5 kton	258 kton / 186 kton

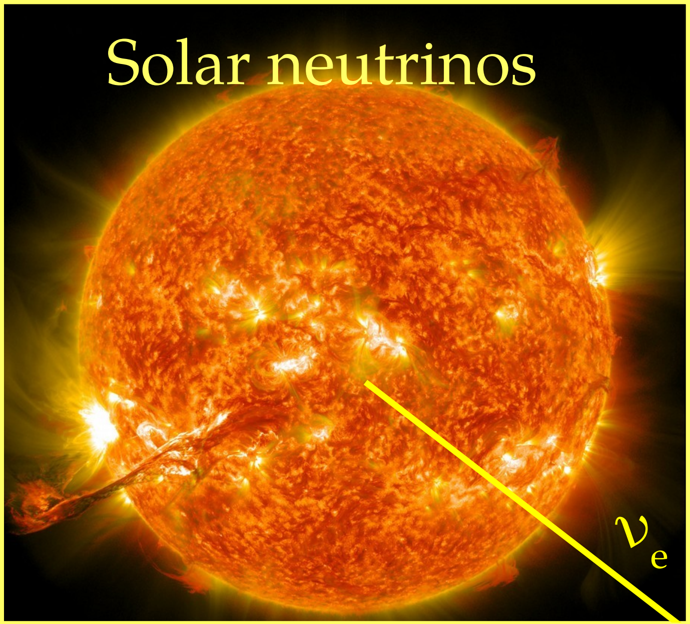




I. Physics & reconstruction goals

Physics case

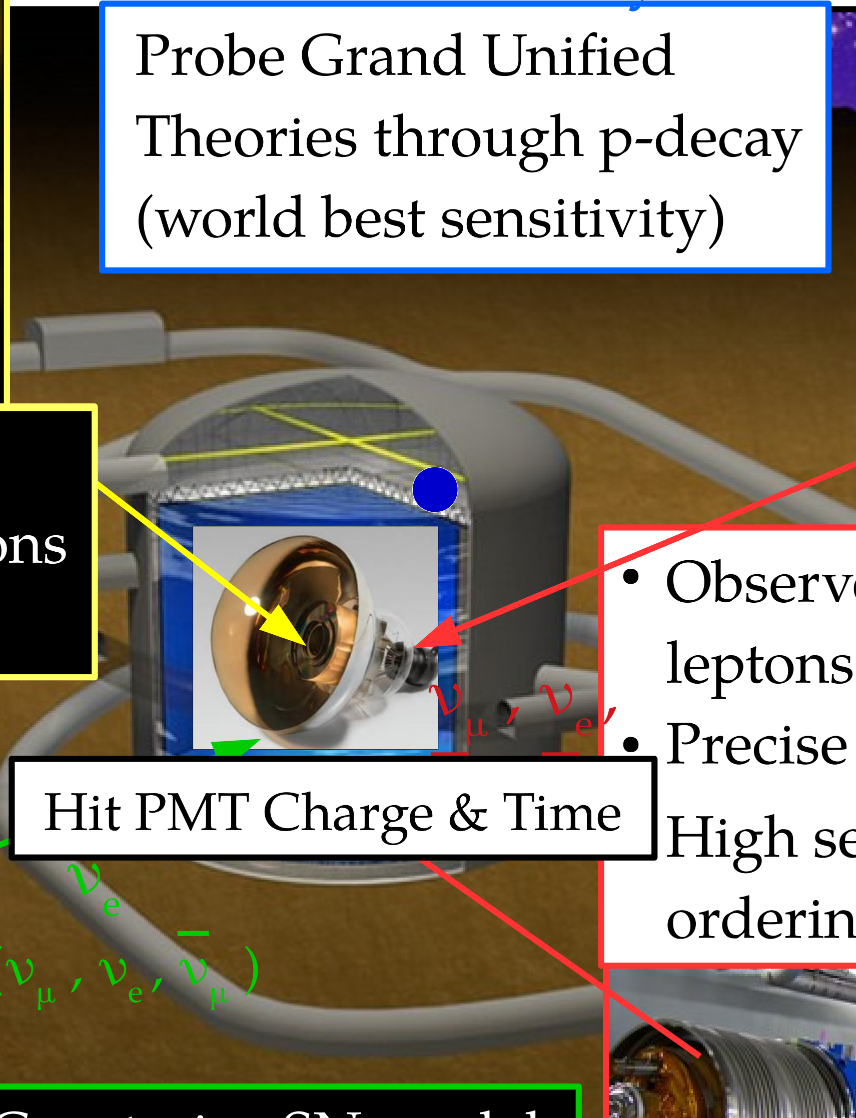
Solar neutrinos



- MSW effect in the Sun
- Non-standard interactions in the Sun.

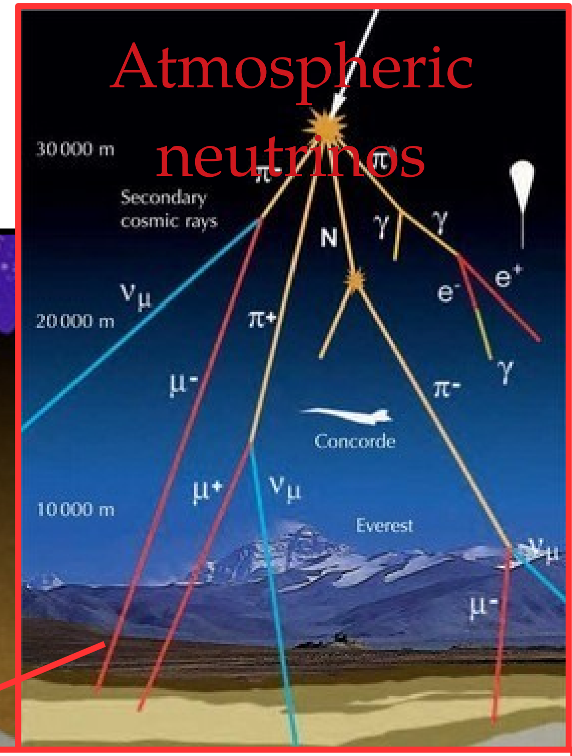
Proton decay

Probe Grand Unified Theories through p-decay (world best sensitivity)



Hit PMT Charge & Time

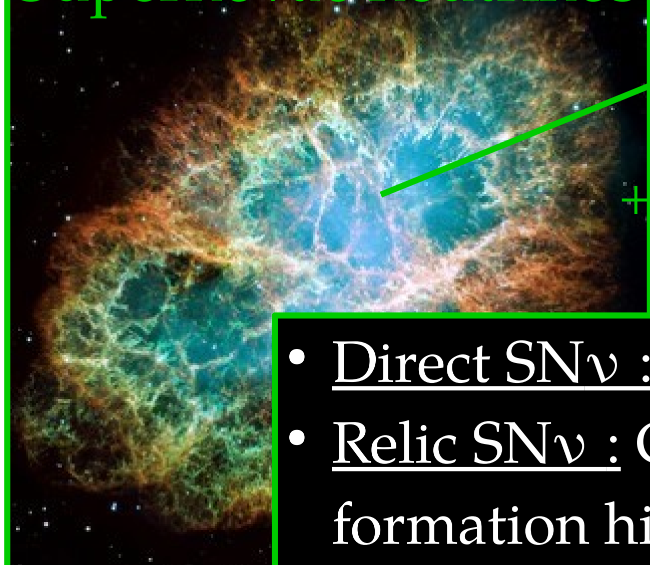
Atmospheric neutrinos



- Observe CP violation for leptons at 5σ
- Precise measurement of δ_{CP} .

High sensitivity to ν mass ordering.

Supernovae neutrinos

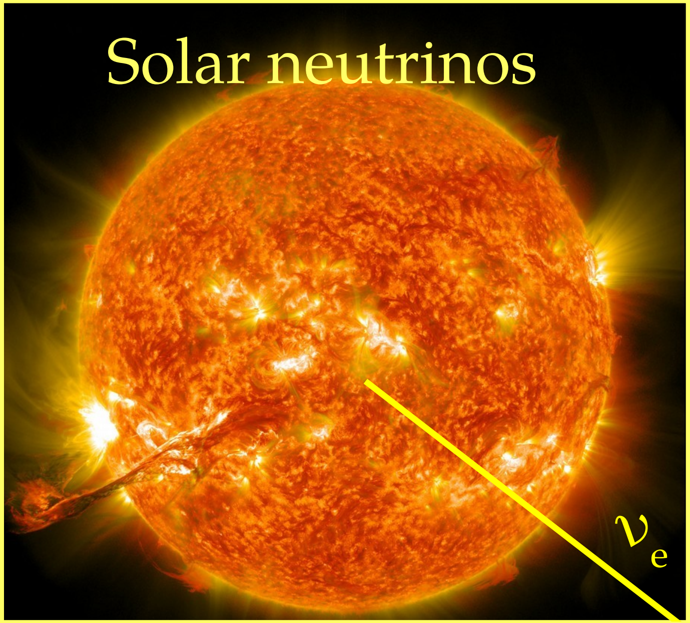


- Direct SNν : Constrains SN models.
- Relic SNν : Constrains cosmic star formation history

JPARC accelerator neutrinos

Physics case

Solar neutrinos



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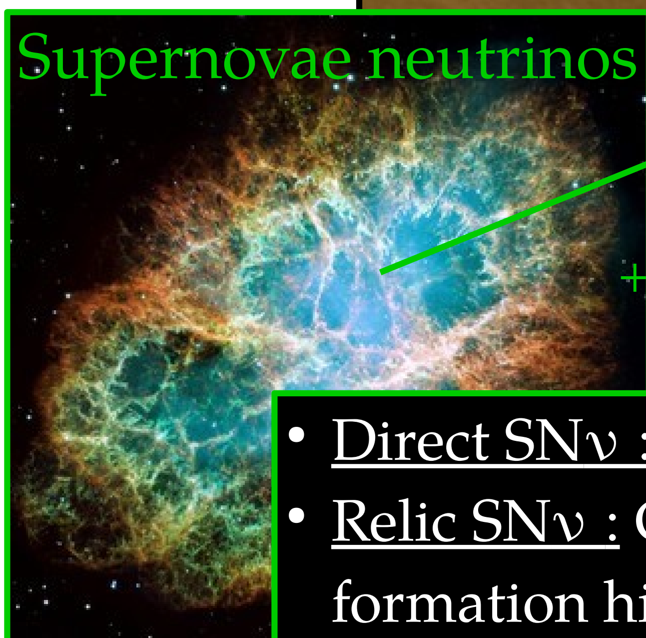
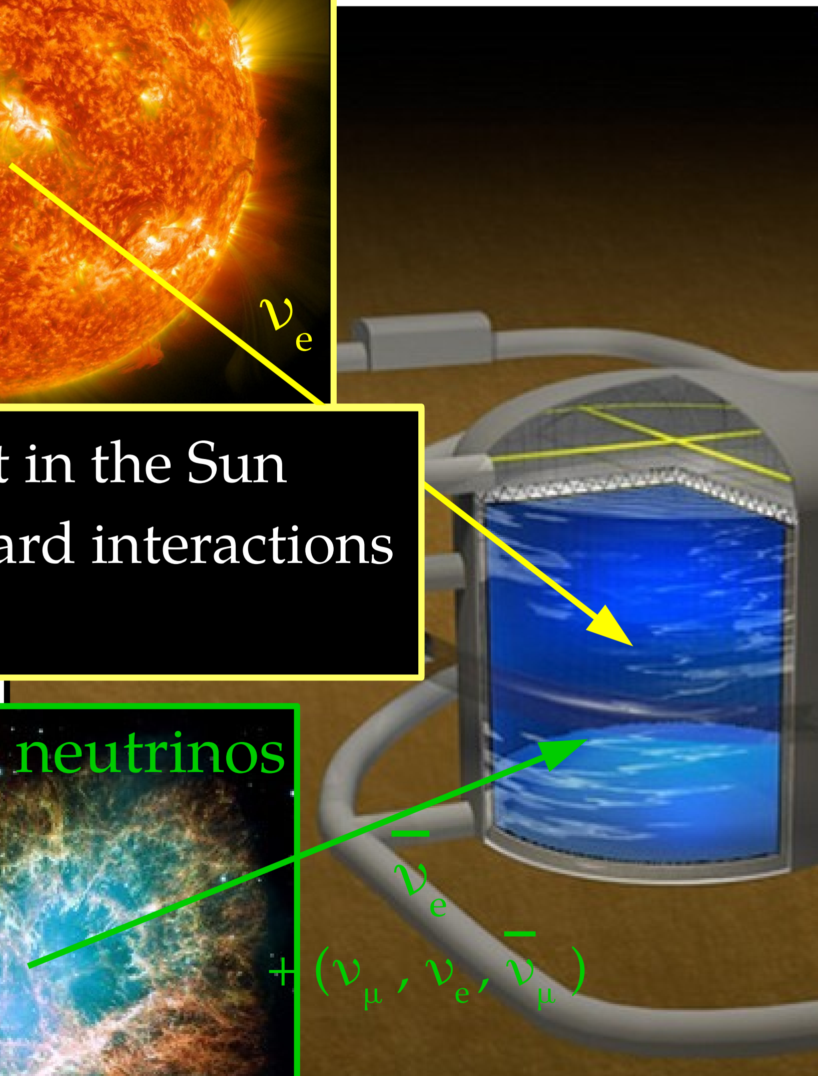
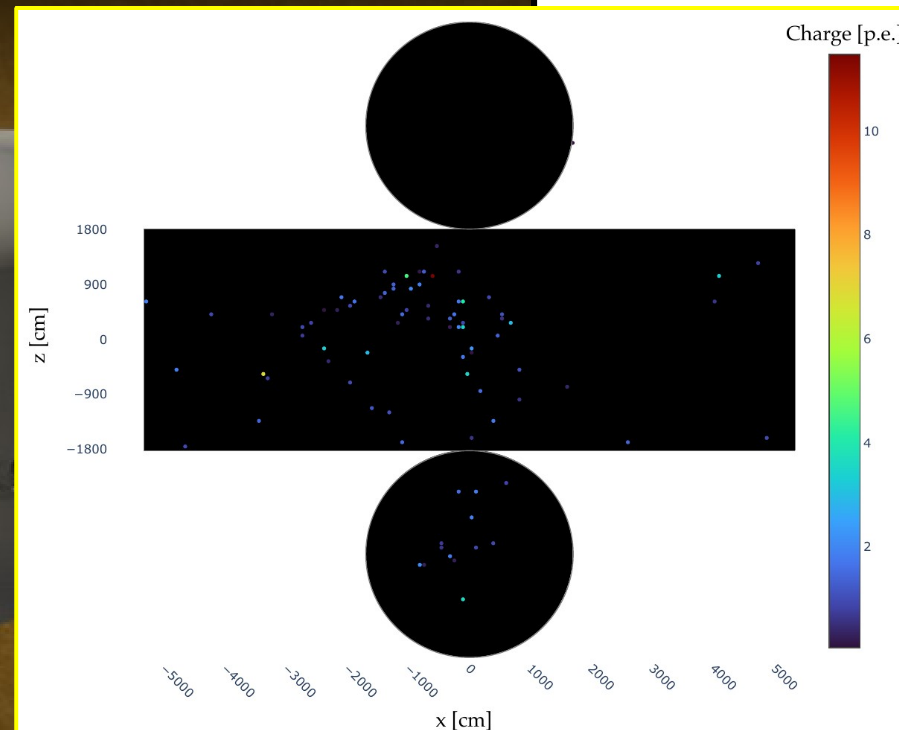
Supernovae neutrinos







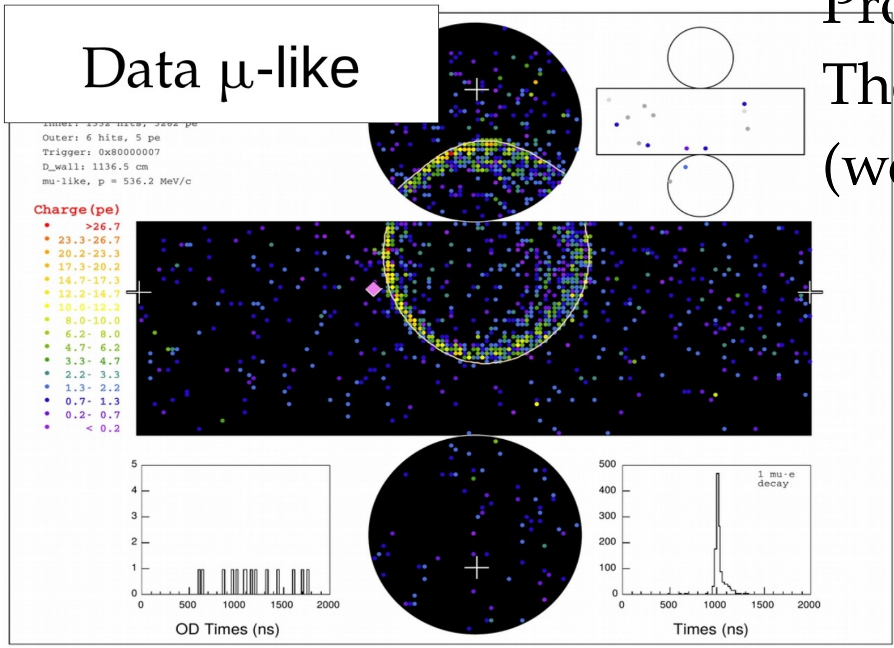
- Direct SNν : Constrains SN models
- Relic SNν : Constrains cosmic star formation history

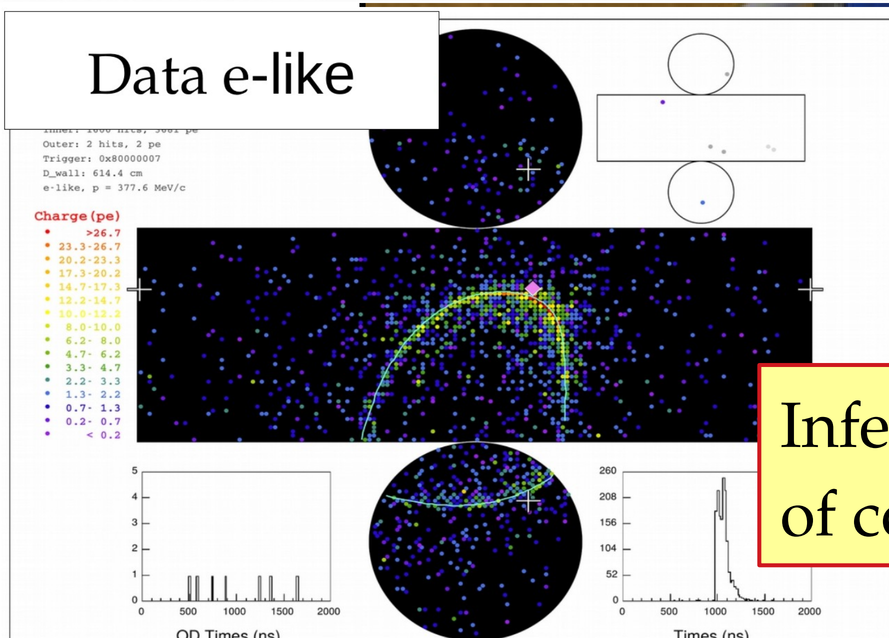
Reconstruct an event with very sparse information

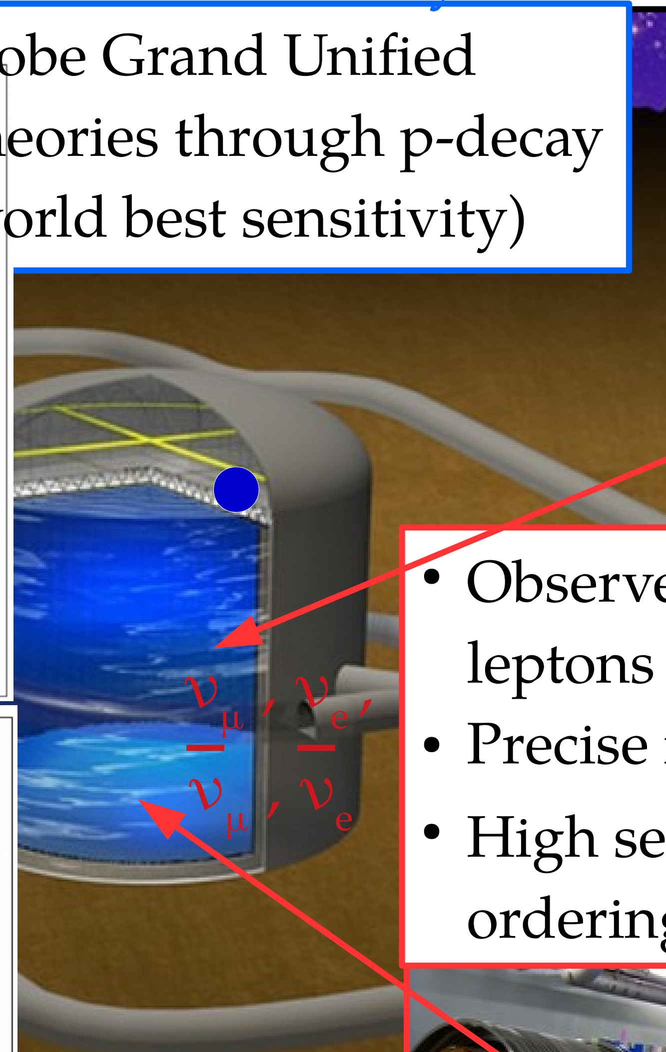
Physics case

Proton decay

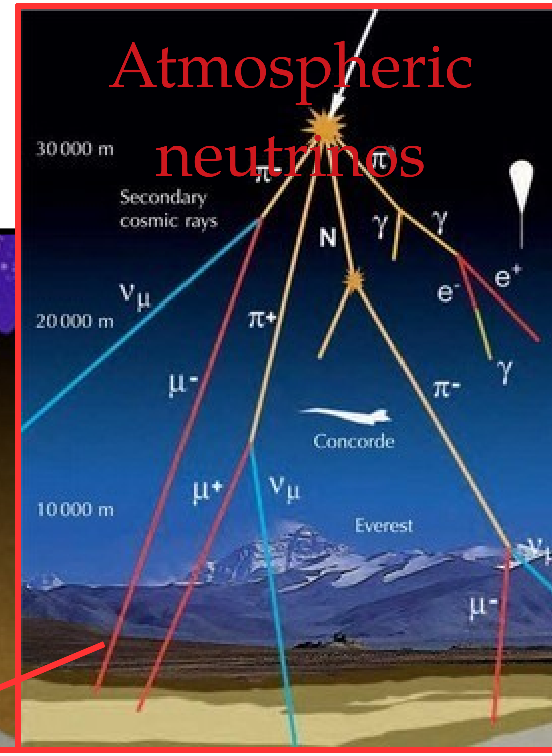
Probe Grand Unified Theories through p-decay (world best sensitivity)







Atmospheric neutrinos



- Observe CP violation for leptons at 5σ
- Precise measurement of δ_{CP} .
- High sensitivity to ν mass ordering.

Infer from a large amount of correlated information

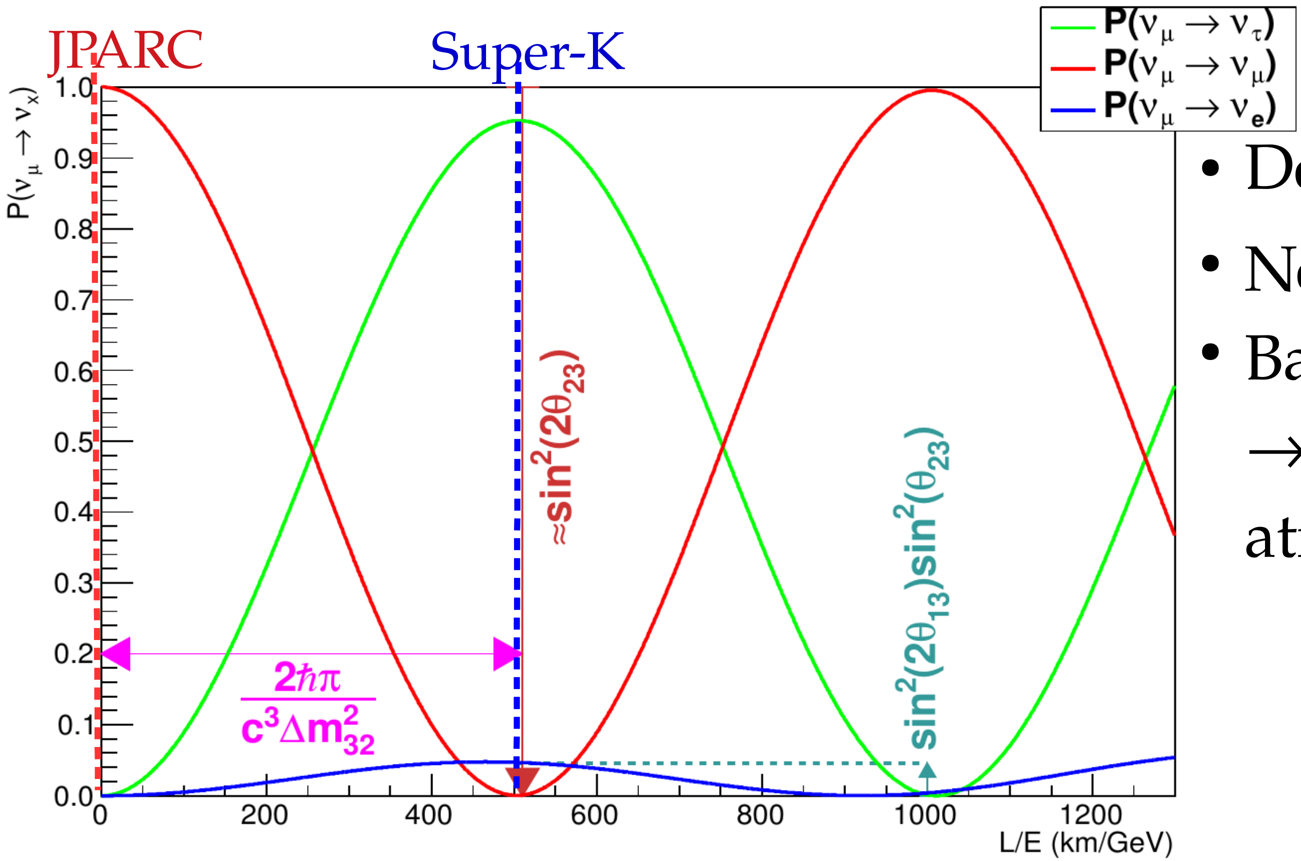
JPARC accelerator neutrinos

Principles of reconstruction

Hit PMT Charge & Time $\{q_i, t_i, x_i, y_i, z_i\}$	Reconstruction → Inference	Variables of interest for ν physics	What are they ?

- <u>Neutrino oscillates in L/E :</u>

<u>Example of T2K</u>



<u>Need to reconstruct the :</u>

- Detected flavour : ν_e/ν_μ.
- Neutrino energy.
- Baseline L : Fixed for T2K…
  → But variable for solar or atmospheric ν. How to do ?

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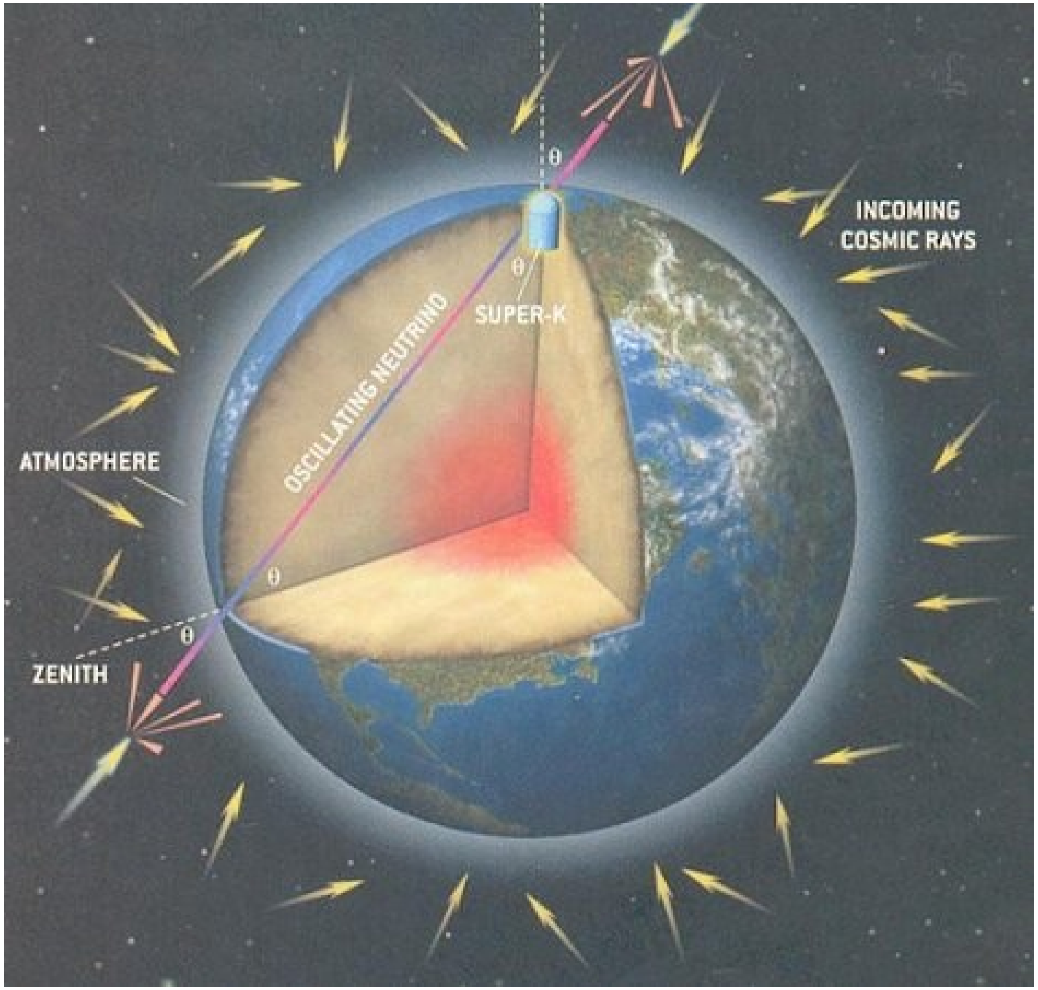
- <u>Neutrino oscillates in L/E :</u>

<u>Example of atmospherics</u>



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  → The ν direction (zenith angle θ) is a proxy for L.

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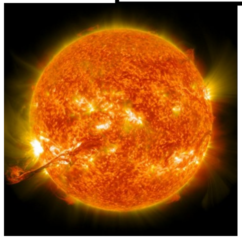
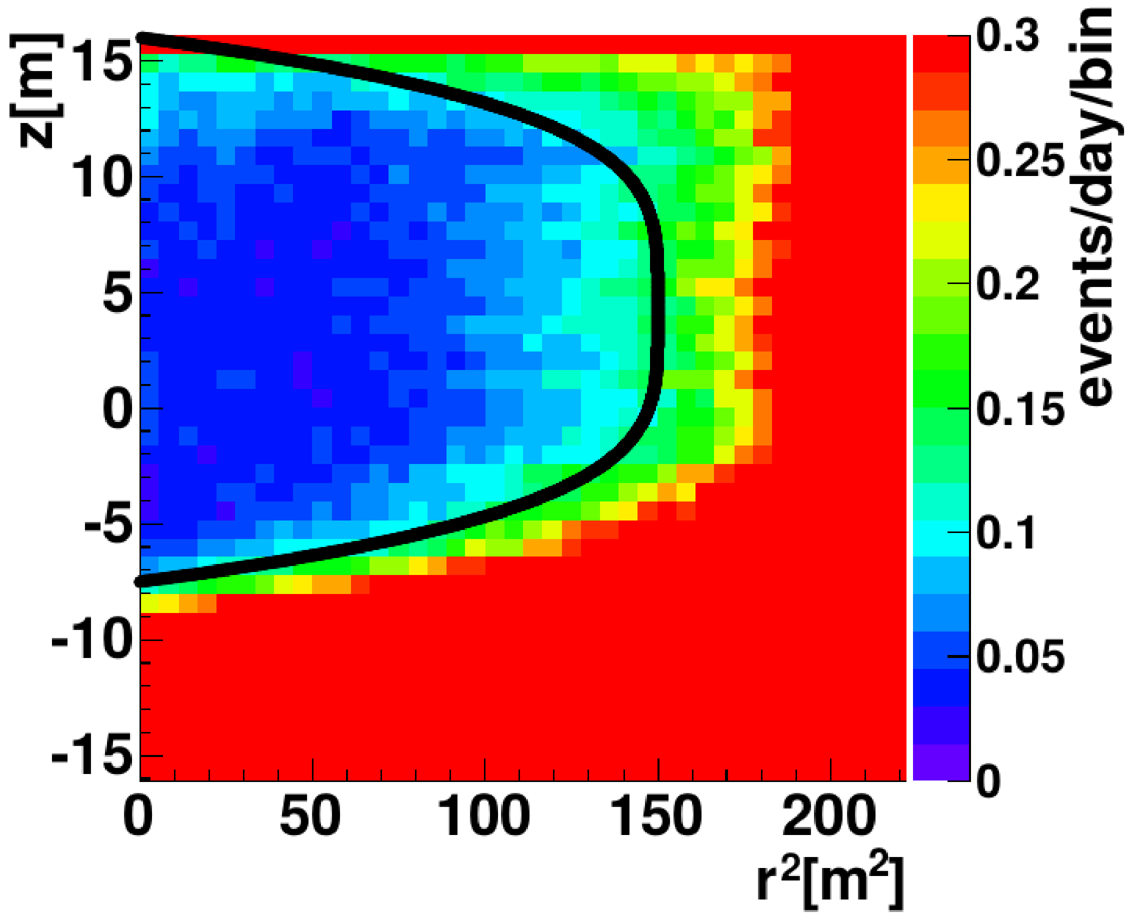


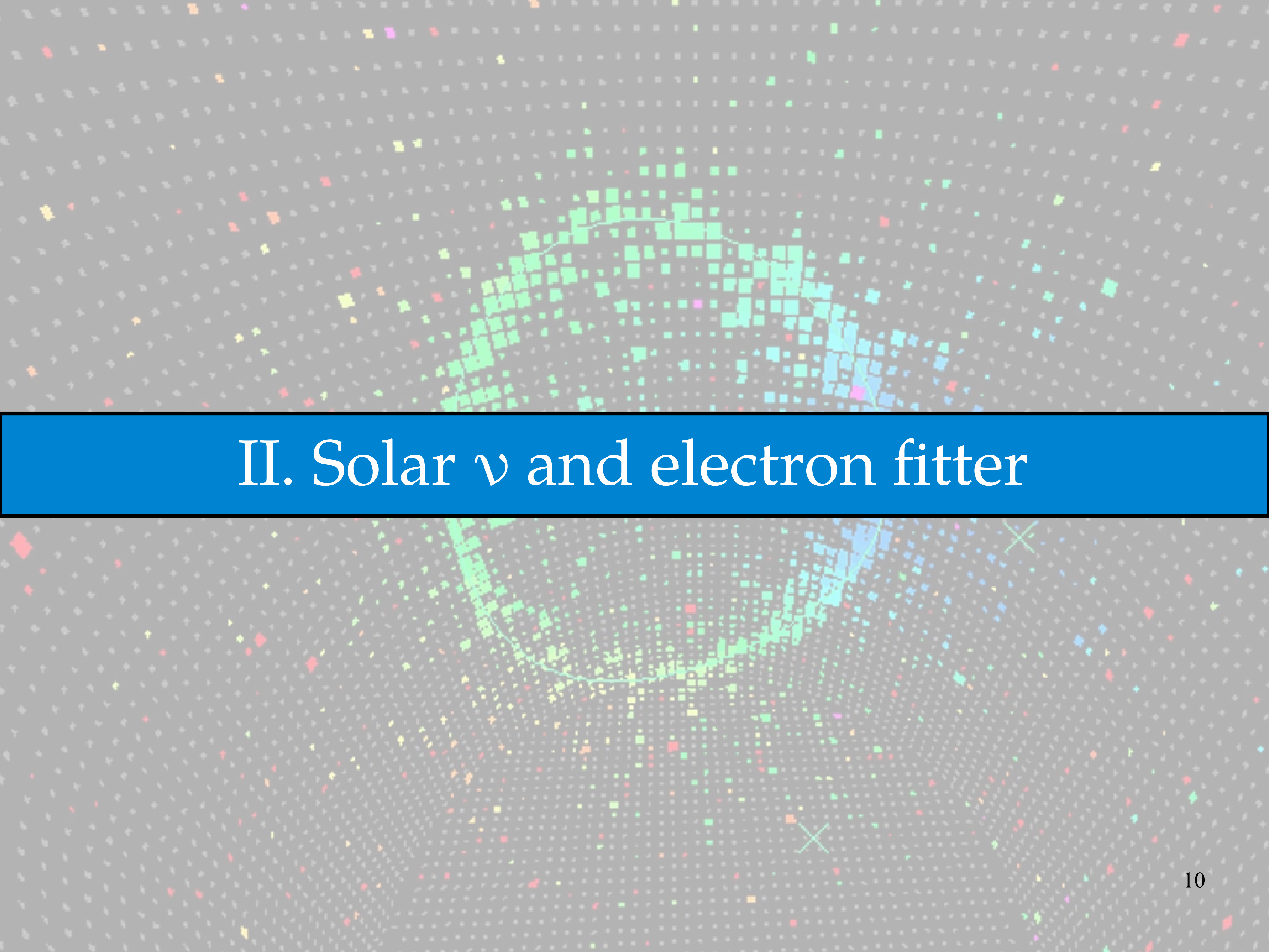
- <u>Neutrino oscillates in L/E :</u>

<u>Low energy event vertex</u>



<u>Need to reconstruct the :</u>

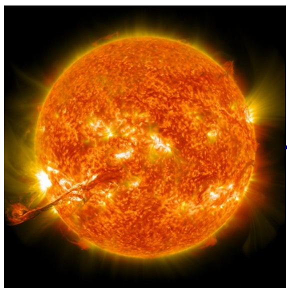
- Detected flavour : ν_e/ν_μ.
- Neutrino energy.
- Baseline L : Fixed for T2K…
  → But variable for solar or atmospheric ν. How to do ?
  → The ν direction (zenith angle θ) is a proxy for L.
- Interaction vertex (remove bkg etc.)

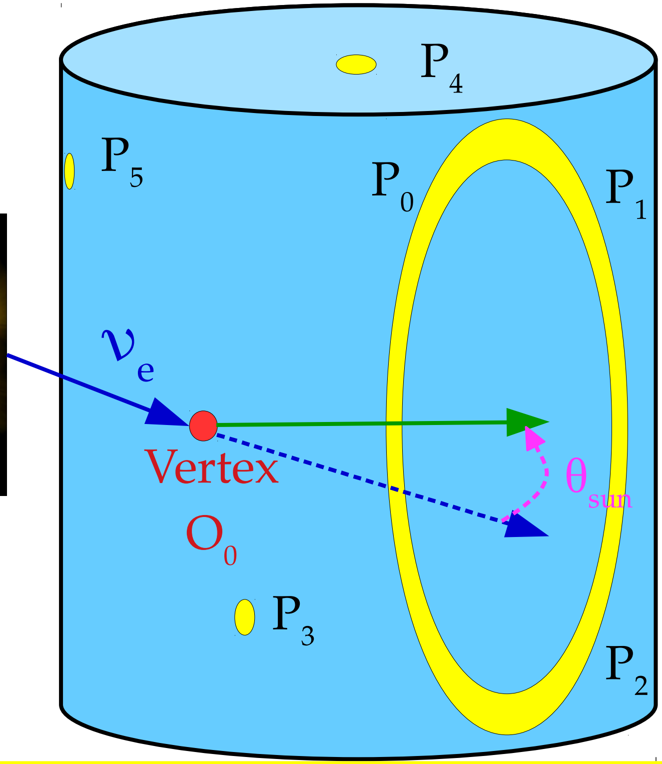


II. Solar ν and electron fitter

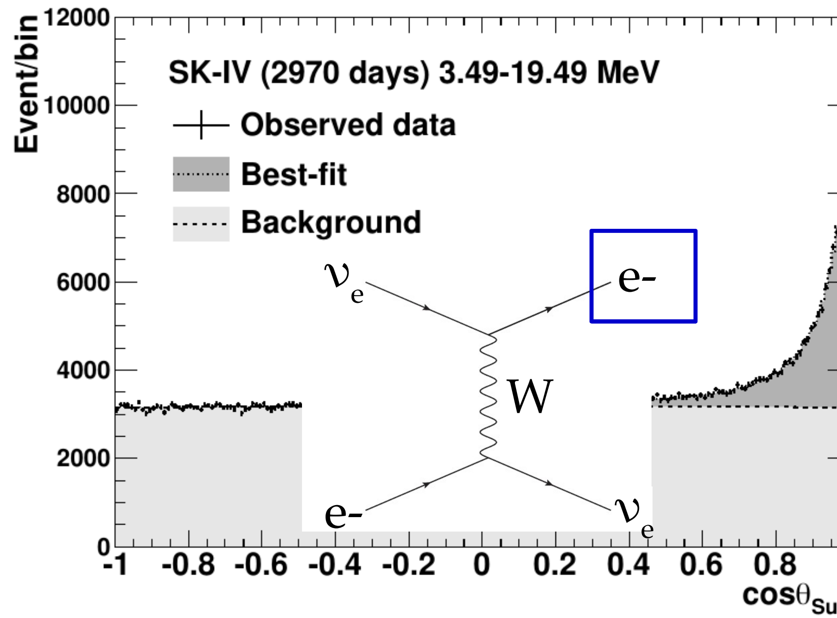
Low energy reconstruction

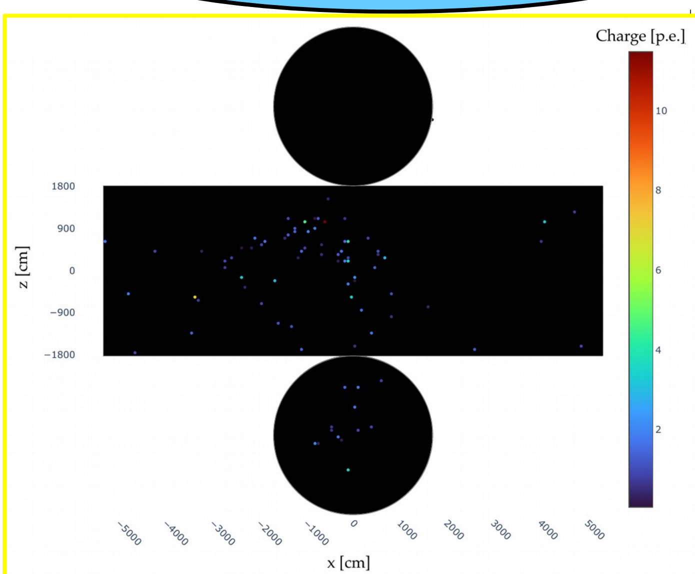
- How to identify solar neutrinos ? ~10 events / day.





Rely on elastic scattering : reconstruct θ_{sun} to remove background.





How to reconstruct low E electrons ?

→ Very faint ring.

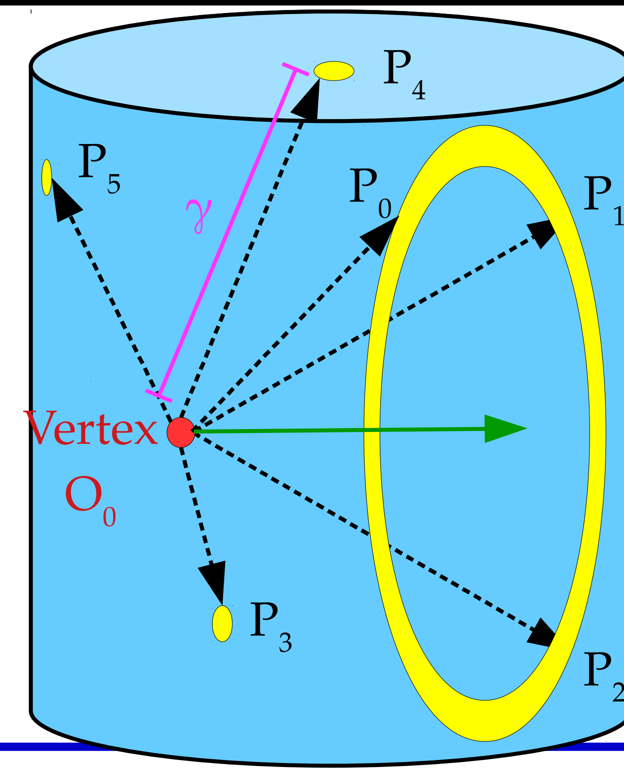
→ e- crosses ≤ 5-10 cm before passing < Cherenkov threshold. Sequential fitter

→ vertex resolution ~50cm

⇒ Light emitted from single point.

Vertex reconstruction

- This single point reconstruction is based on time triangulation ⇒ BONSAI
  → Uses <u>time residual :</u> $\boxed{t_{res} = \text{time} - \text{tof} - t_{vertex}}$.

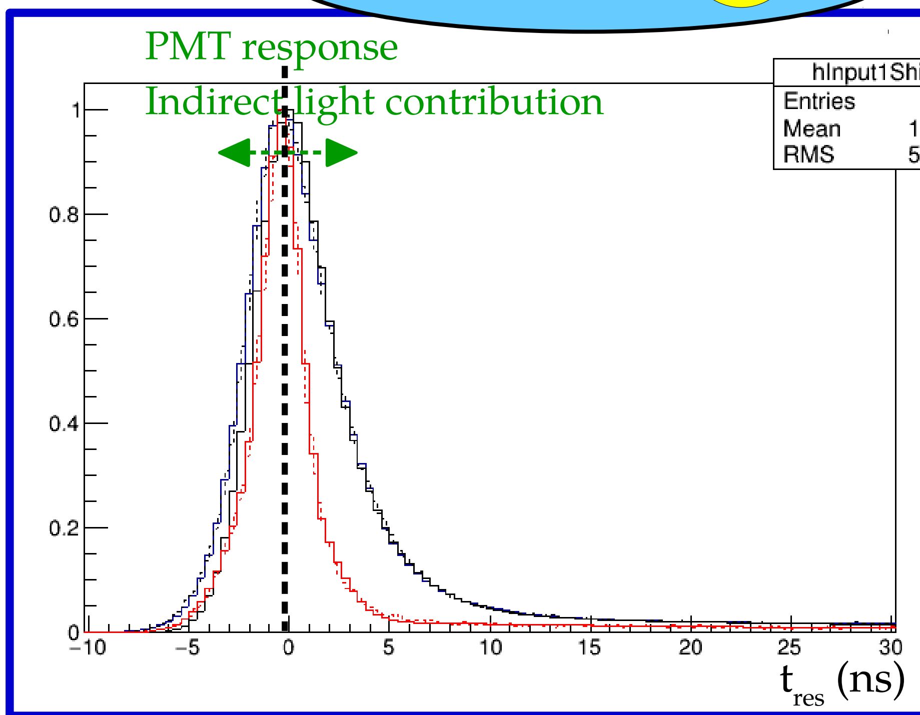


- <u>Vertex finding using the following likelihood :</u>

$$\boxed{L(Vtx|[hits]) = \prod_{i=0}^{nhits} P([t_{res}]|Vtx)}$$

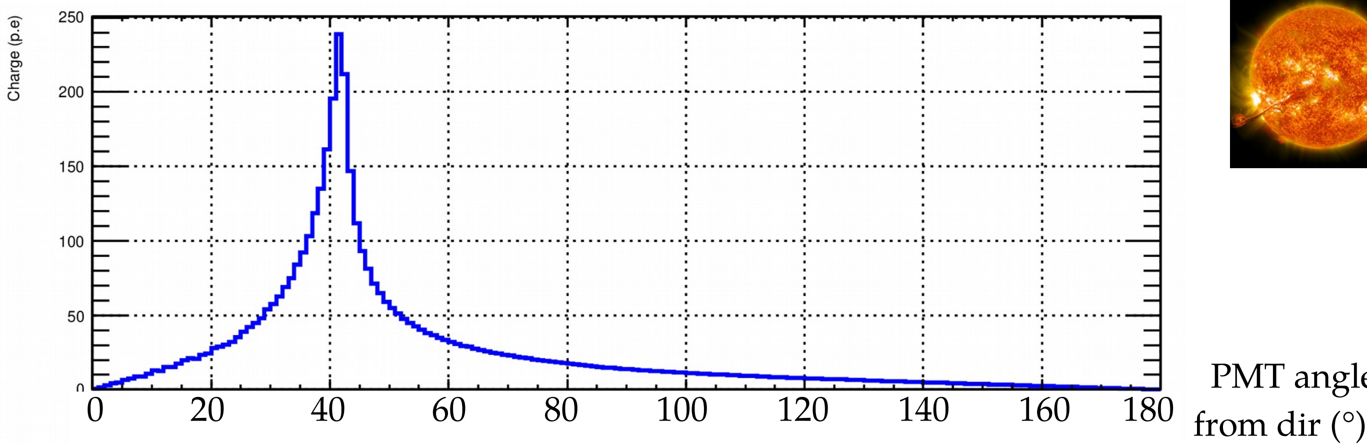
Time residual likelihood

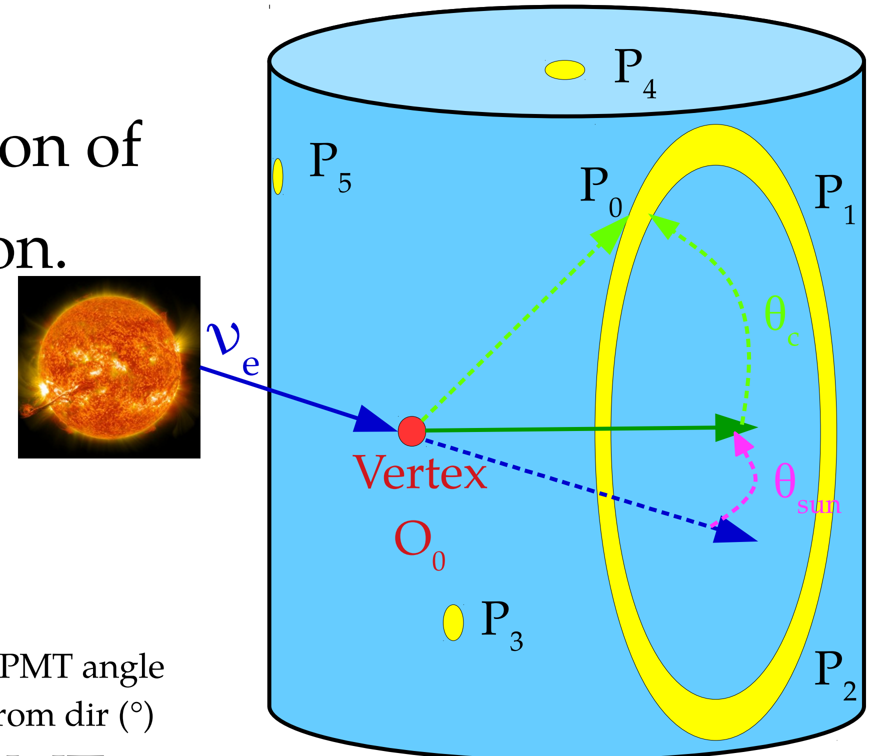
- Likelihood is minimized to find the vertex.



Direction & momentum reconstruction

- Start from the fitted vertex.
- <u>Rely on « charge profile » (θ_c) :</u> distribution of vertex-to-hit PMT direction wrt e- direction.

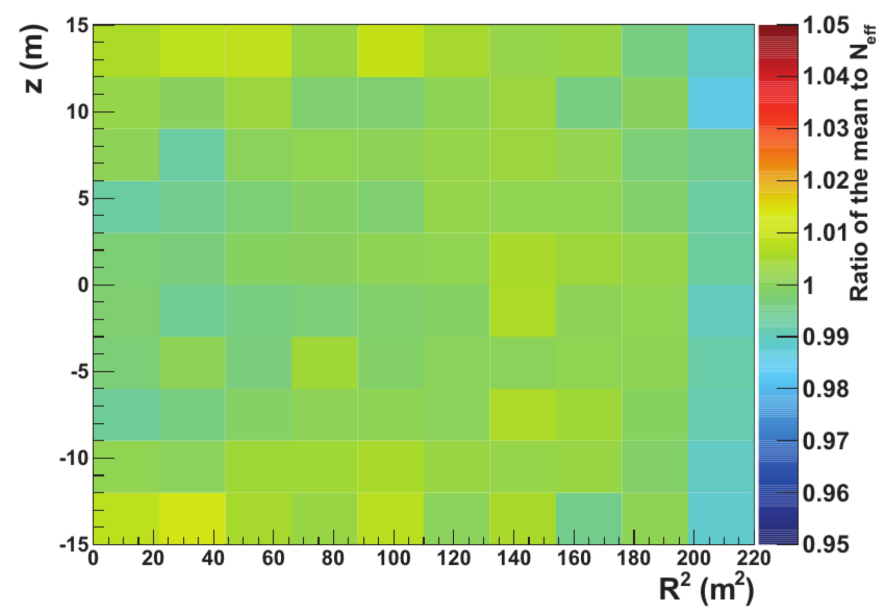




→ Uses unbinned likelihood over all hit PMT :

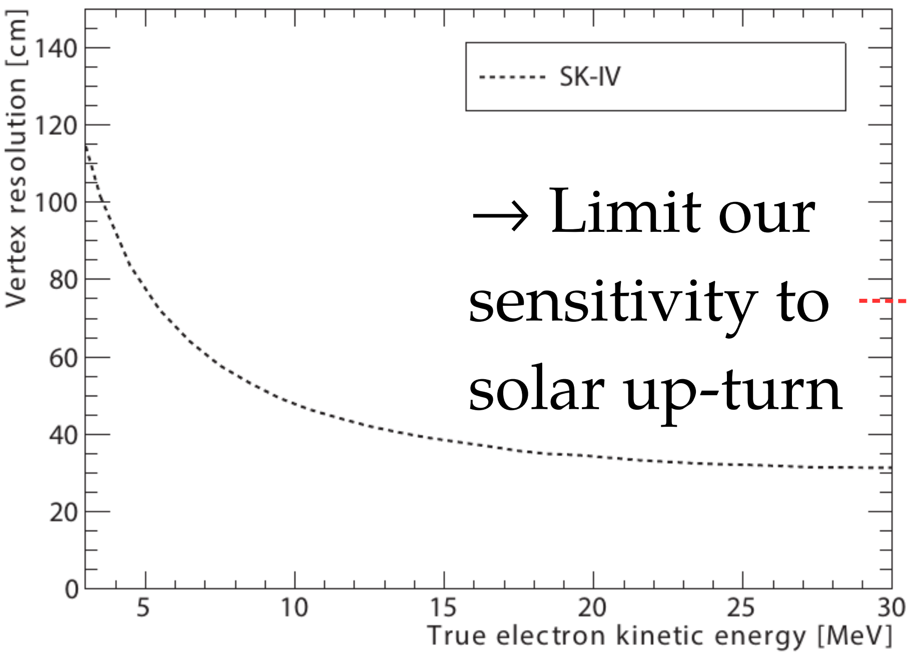
$$L(\vec{d}) = \sum_{i}^{N_{30}} \log\left[f(\cos\theta_{\mathrm{dir},i}, E)\right] \times \frac{\cos\theta_i}{a(\theta_i)}$$

- Momentum inferred from the total number of hits deposited in the detector & in-time wrt vertex.

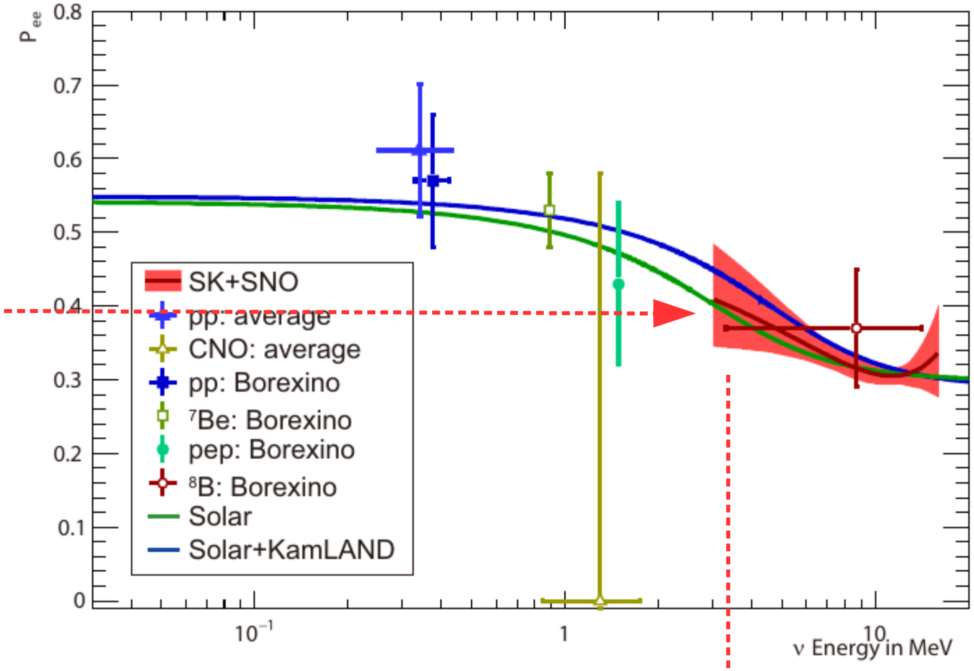


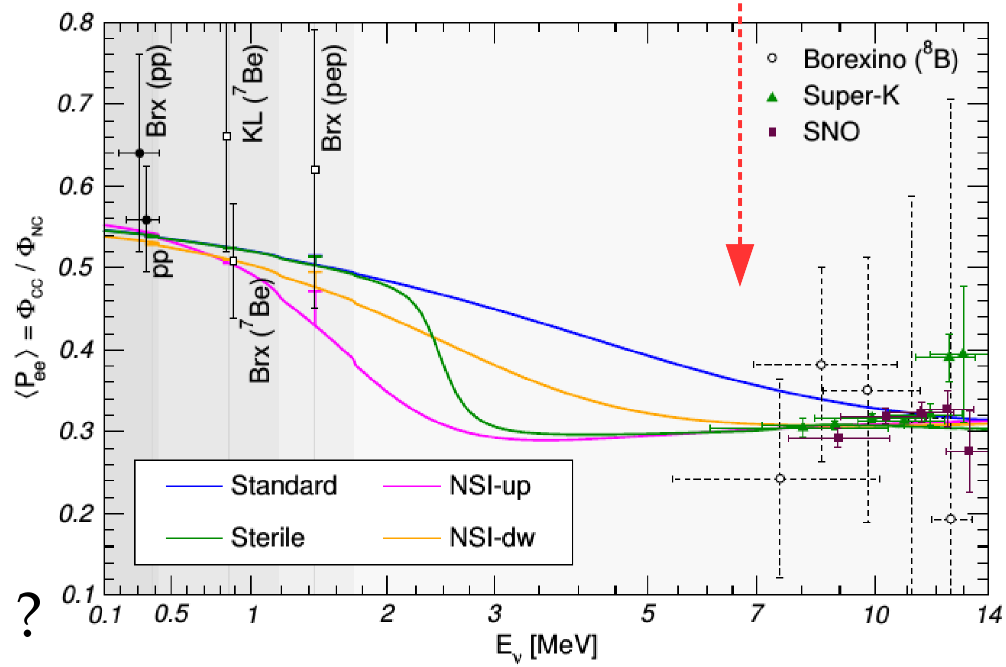
Performances in SK and impact on upturn

- Vertex resolution in SK : Reconstruction threshold @3 MeV



→ Limit our sensitivity to solar up-turn



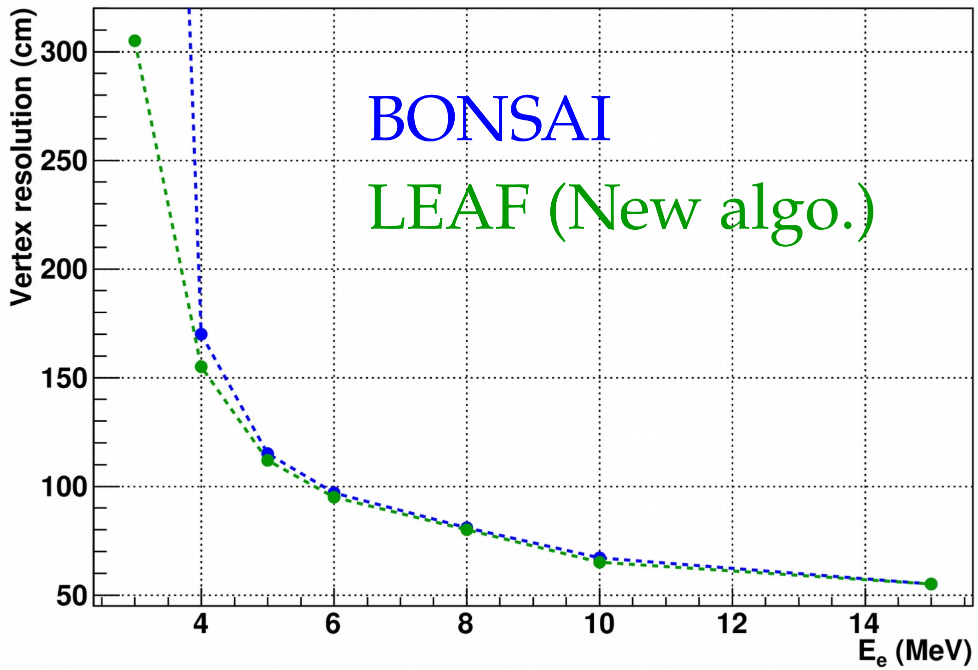


- Up-turn determination :
  - Solar parameter measurement.
  - Light sterile ν ?
  - Non-standard interaction in the dense core of the Sun

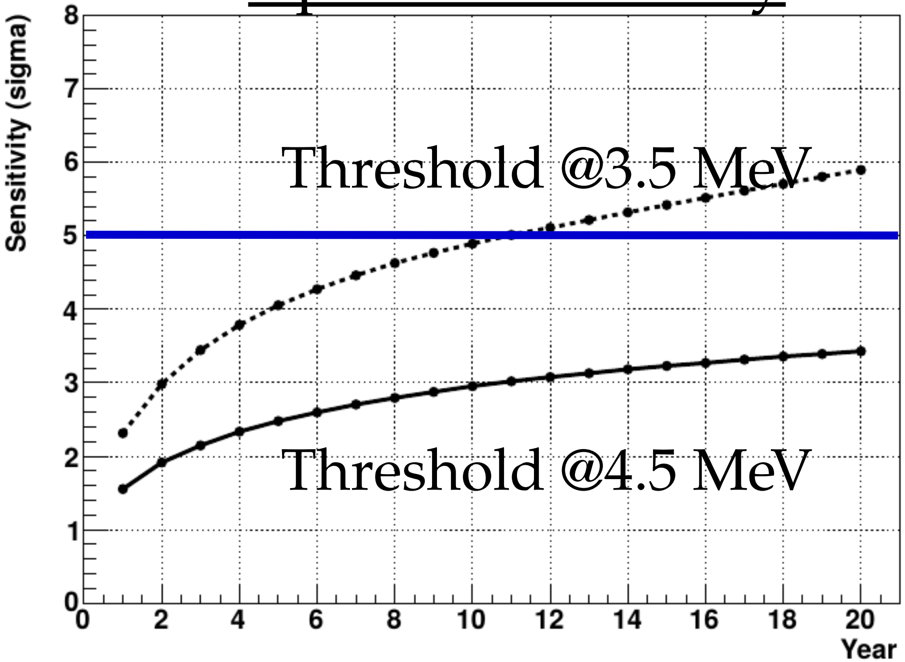
- Can we do equal or better in HK ?

Performances in HK

- BONSAI ported to HK → At the moment, E threshold ~4.5 MeV/c²



Up-turn sensitivity



- Limited sensitivity in upturn determination due to mis-tuning

⇒ Ported BONSAI → LEAF (C++) based on MINUIT minimizer

→ More flexible & improved : ↓ E threshold to @3-3.5 MeV.

→ Work-in progress to reach 2 MeV, using LEAF.

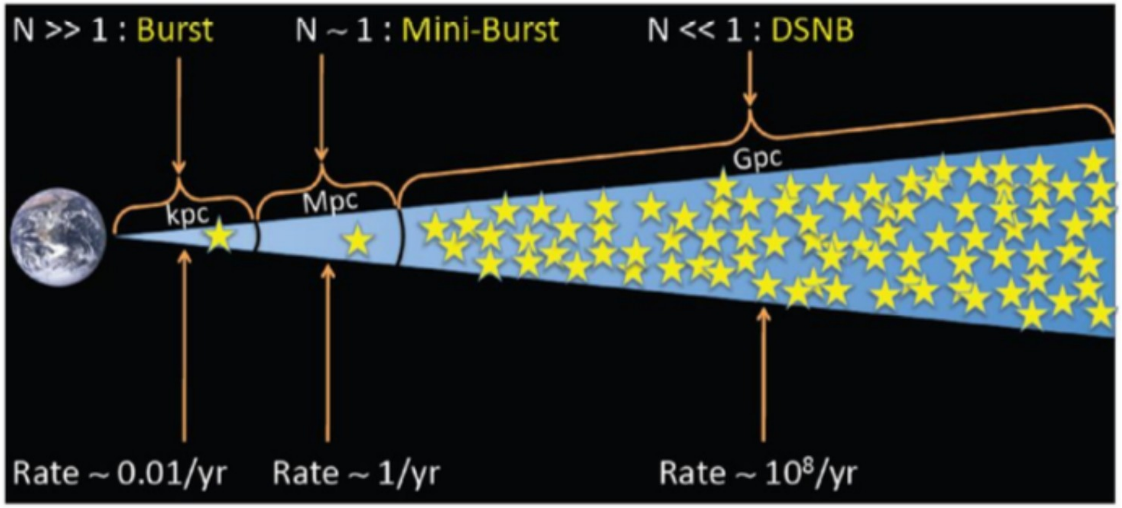
→ Real data will likely be even more tough → Prepare for it.

- ML-based algorithm are also developed (PETAL…) *→ L. Almagro's presentation*

III. DSNB search and n-tagging

Diffuse Supernovae Neutrino Background

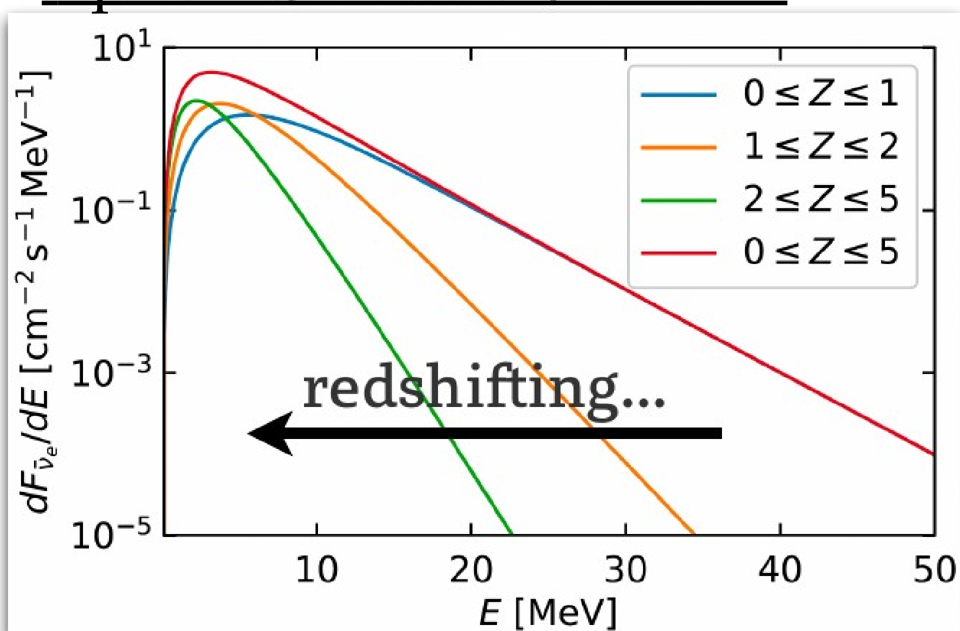
- Background from ν emitted by all SN from the start of the universe.

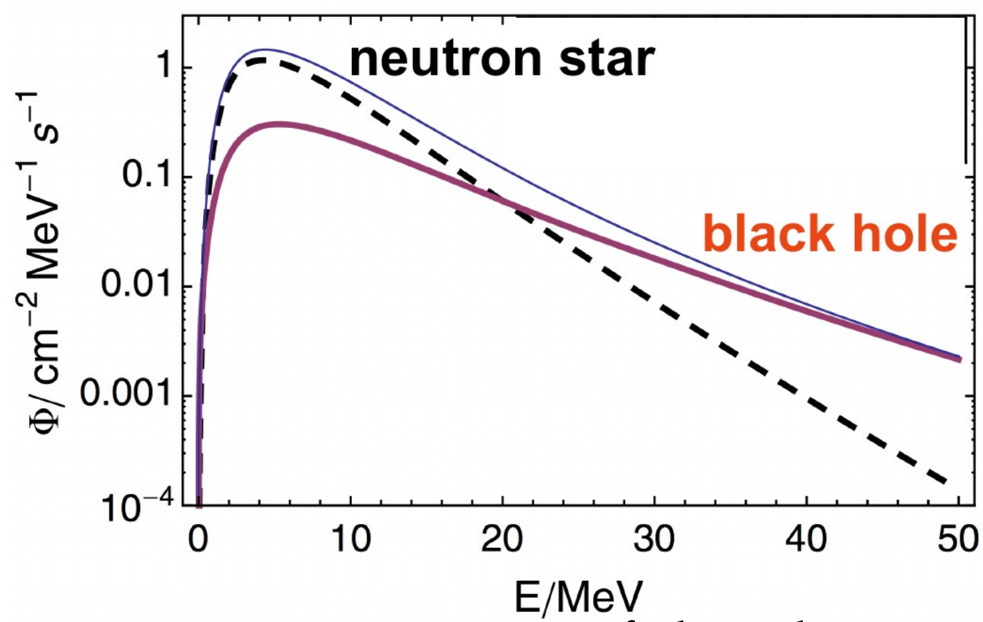


- 1 SN/s in observable universe
  → Constraint SN spectra.
  → But also, cosmic star history !

- Spectrum determination : Low energy ↔ Probe older stars

S.Ando et al., Proc. Jpn. Acad., Ser. B, Phys. 99(2023) 10

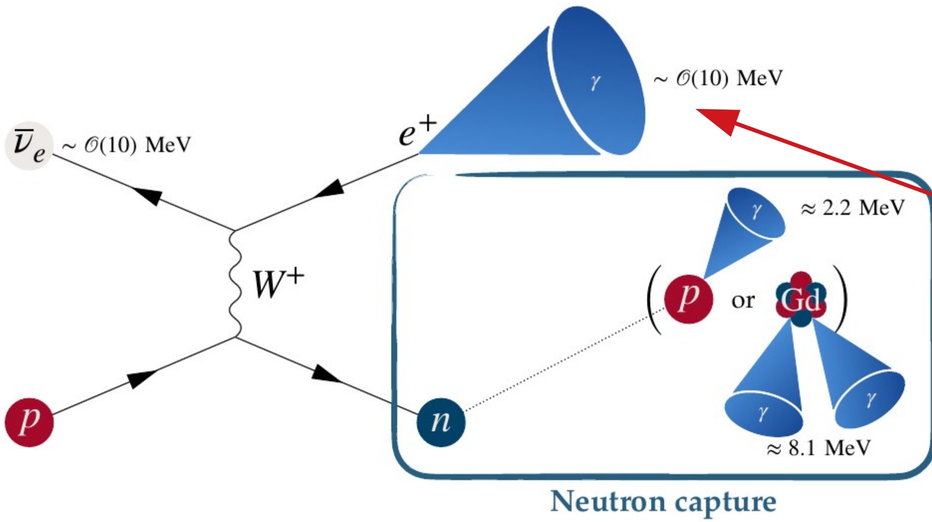




- SK-Gd, then JUNO & HK are the pioneer experiments of this domain !

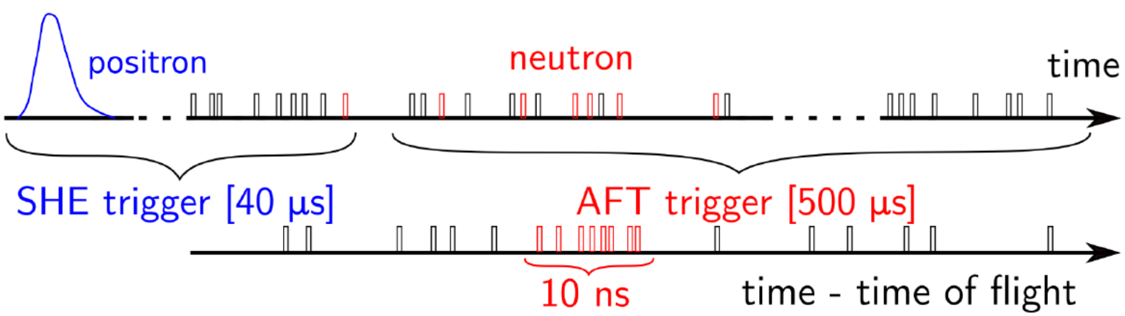
Detection method & neutron tagging

- How to identify DSNB as we expect ~3 events/year in SK… ?



- Uses the ν_e IBD channel…
- .. and rely on coincident detection of prompt positron and late neutrons.
  → Neutron capture on H or Gd.
- How to identify neutrons ?

- Search neutrons in a 500 µs time window after the trigger [-5, 35 µs] :

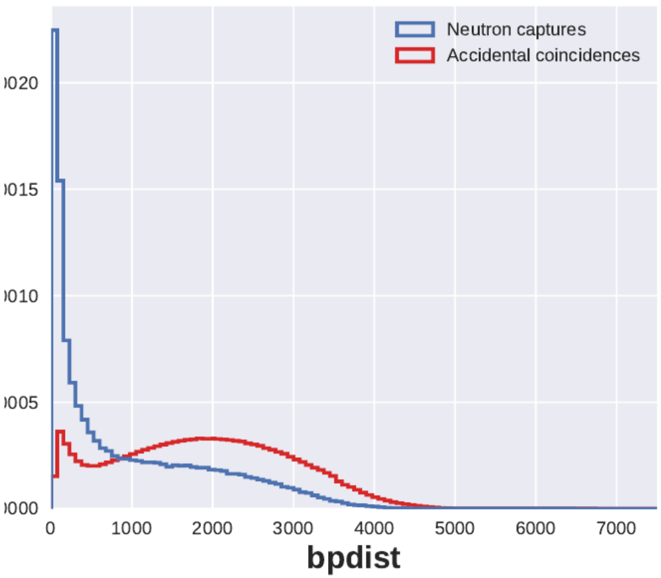


	H-capture	Gd-capture
γ energy	2.2 MeV	8 MeV
Capture time λ	205 µs	30 µs

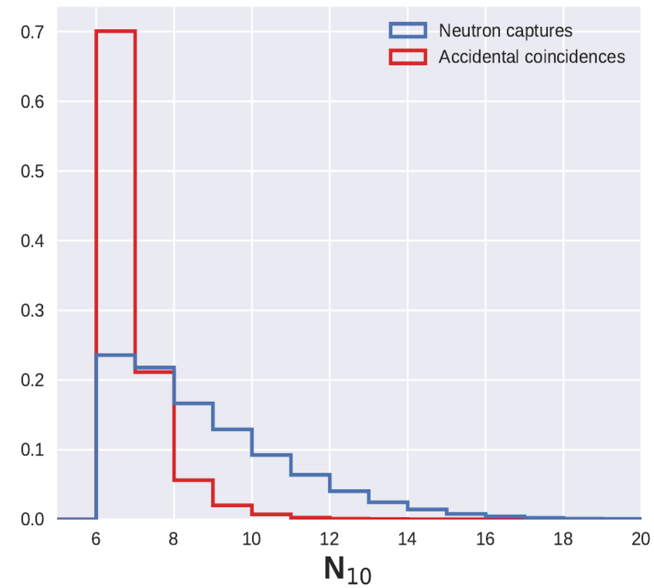
- How to eliminate remaining background after prompt+late detection ?

DSNB reconstruction in SK

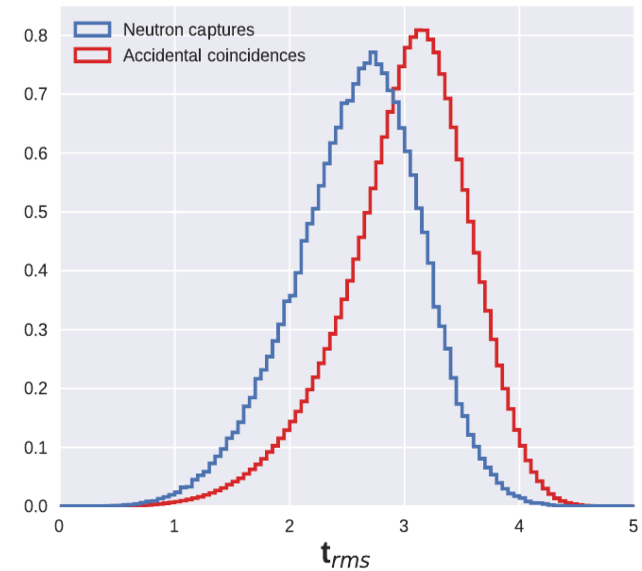
- <u>22 variables in total :</u> Reconstruct neutron vertex using BONSAI/LEAF.



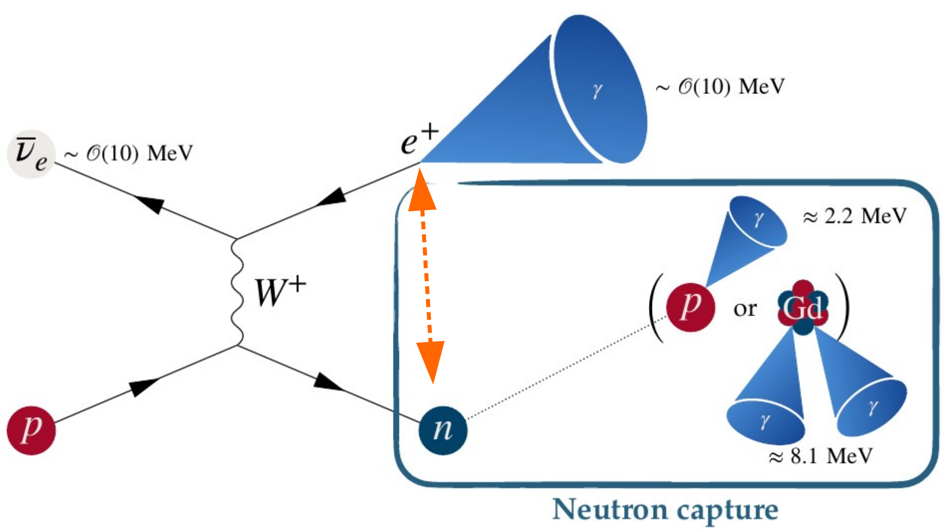
Distance between e+ & n vertex

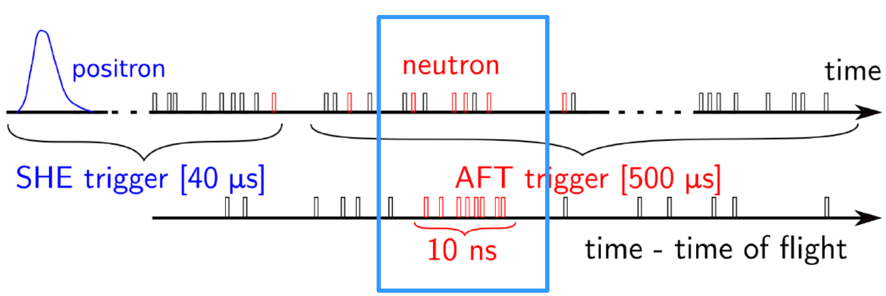


Number of hits in ±10ns around n-vertex



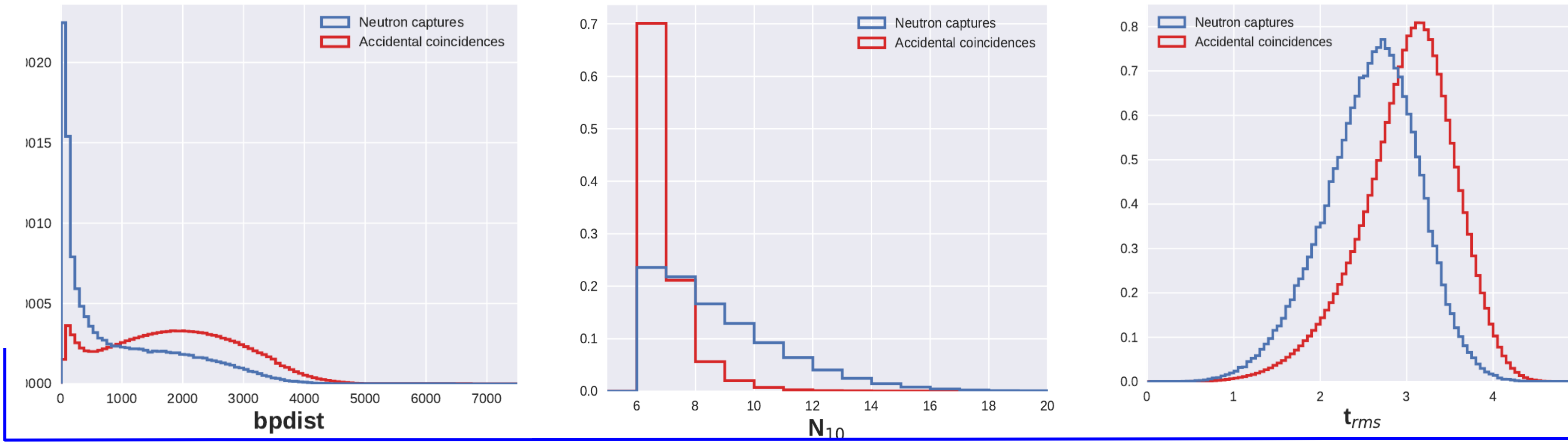
Time spread of hits around e+ vertex



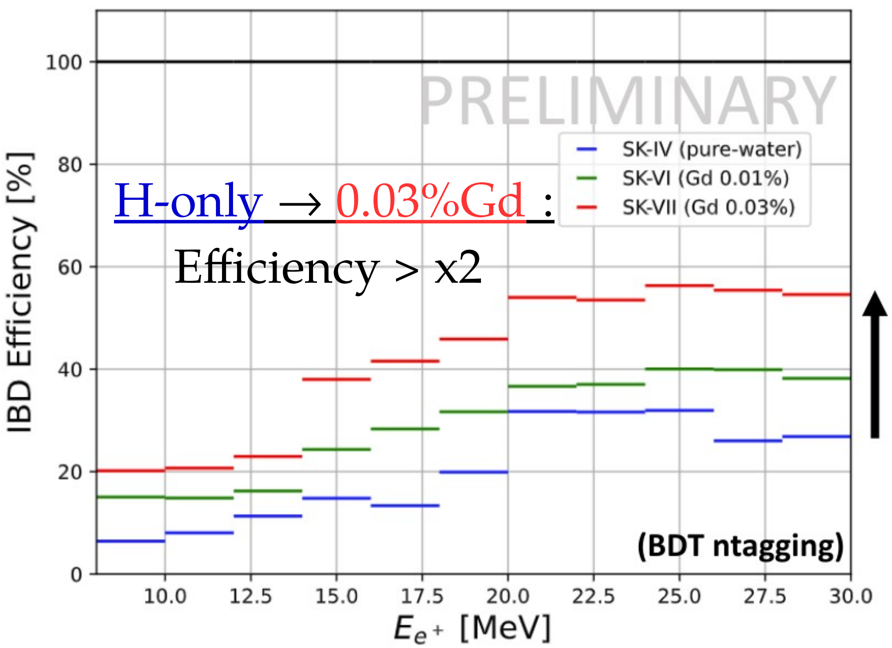


DSNB reconstruction in SK

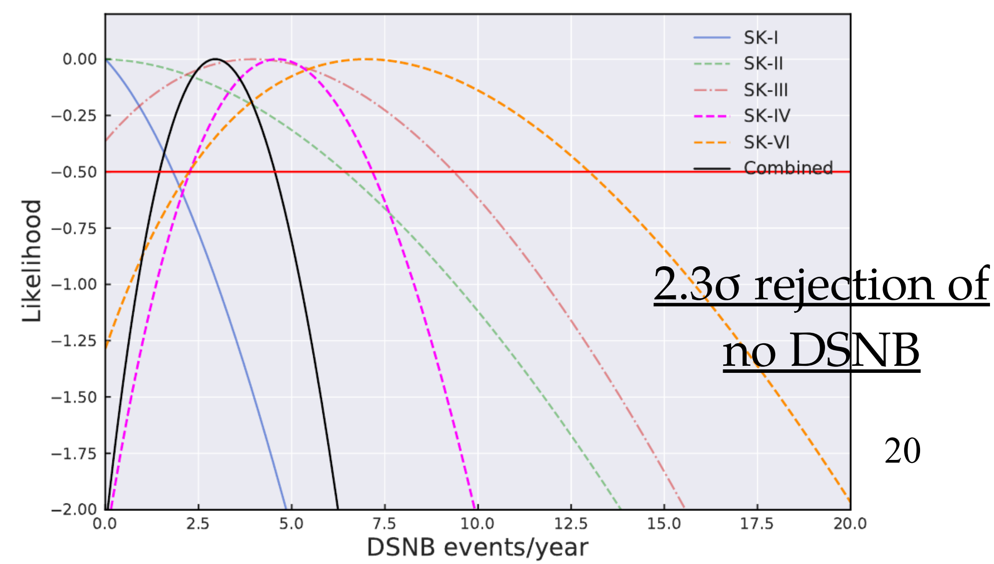
- How to eliminate remaining background after prompt+late detection ?



Boosted Decision Tree & Neural Network

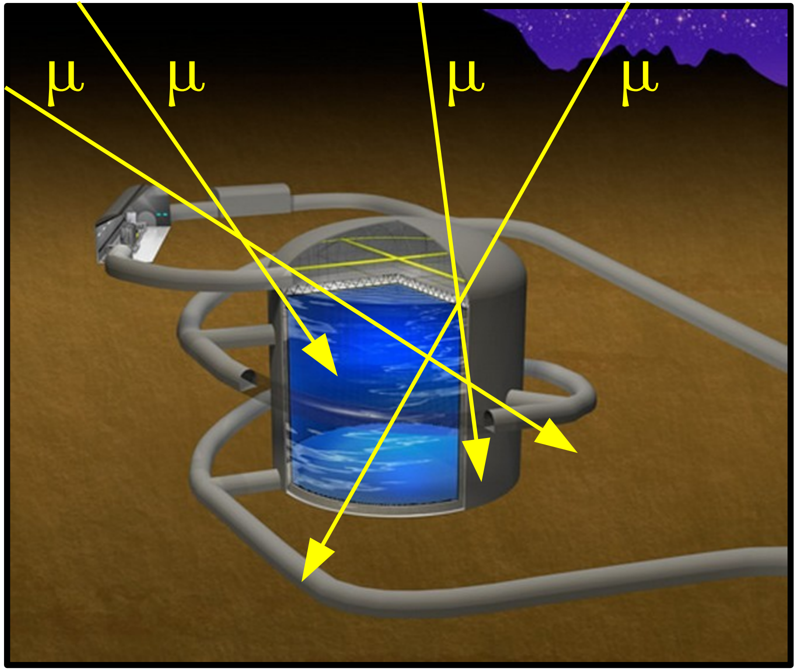


World-leading results on DSNB search



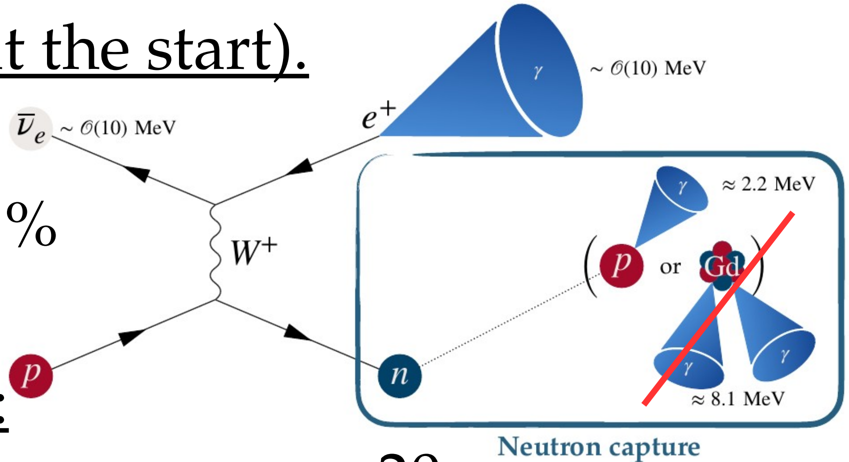
DSNB search in HK

- Hyper-K, though having 8x larger volume, will have several limitations



- Water only (at the start).

  → Efficiency ↓ 50 % → 25 %

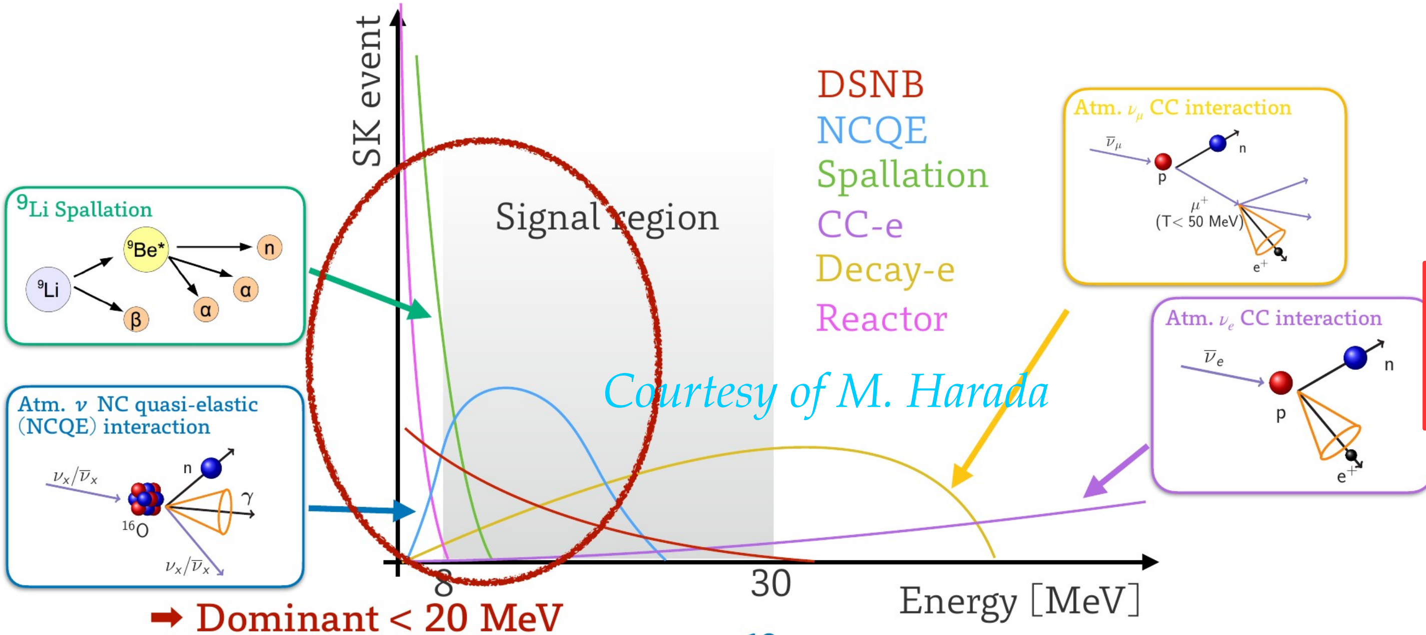


- Overburden :

  1000 mwe → 650 mwe.

  ⇒ 20x more spallation

- Larger surface

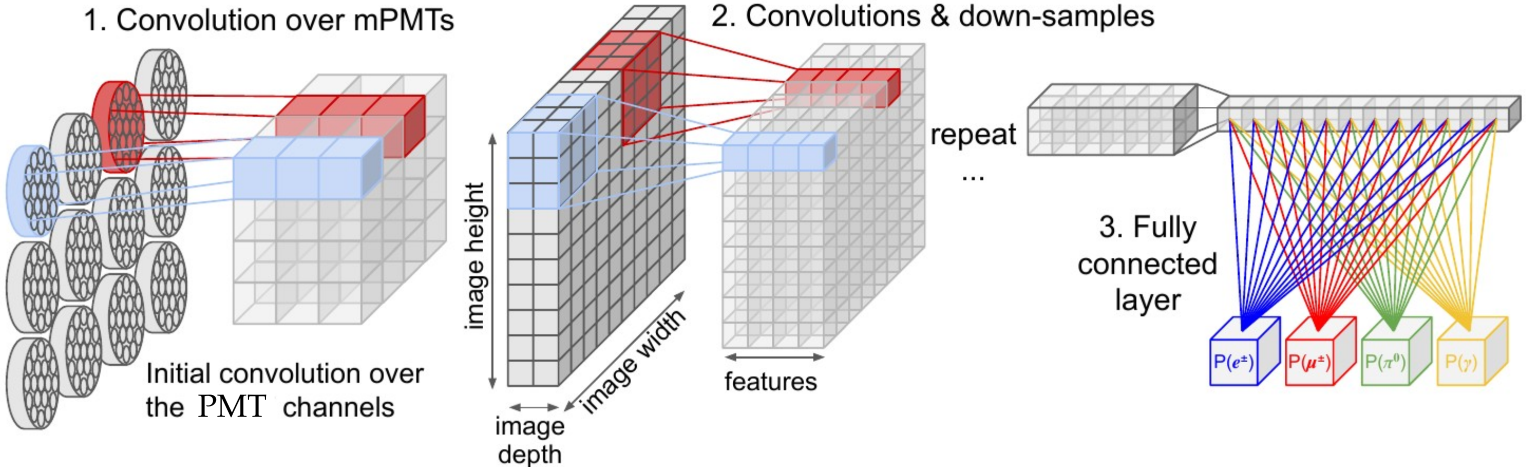


Need to urgently step up in :

- ↑ neutron detection efficiency on H.
- ↑ spallation model & identification cut

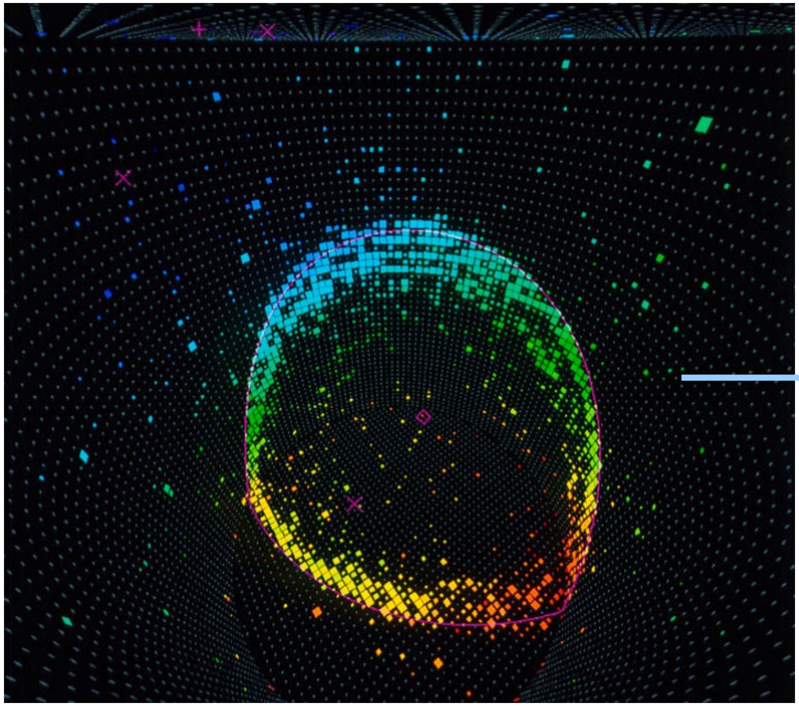
ML-based reconstruction in SK/HK

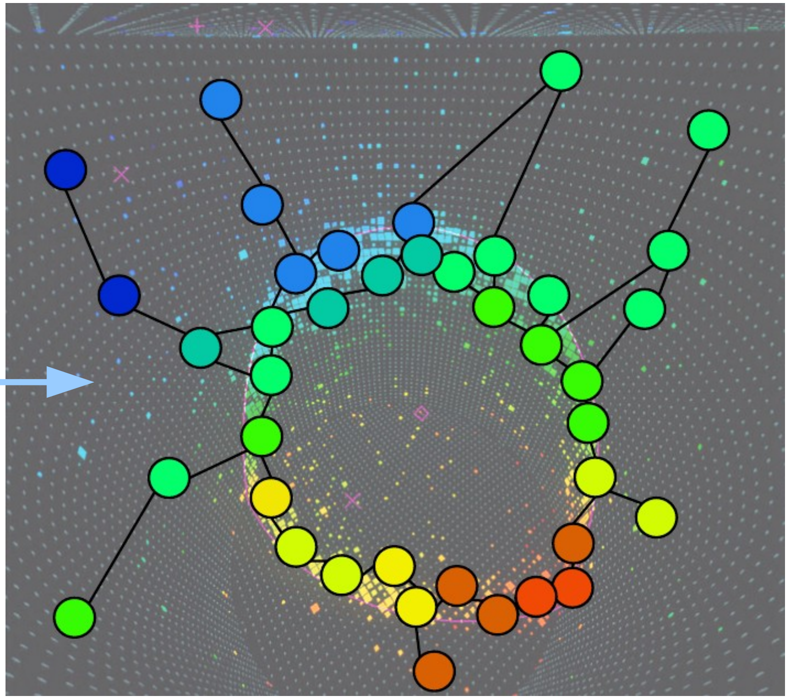
- Convolutional neural networks (WatChMaL) → *A. Atta, K. Joseph, N. Prouse*



- Graph neural networks (CAVERNS-WatChMaL) → *E. Le Blevec, M. Ferey*

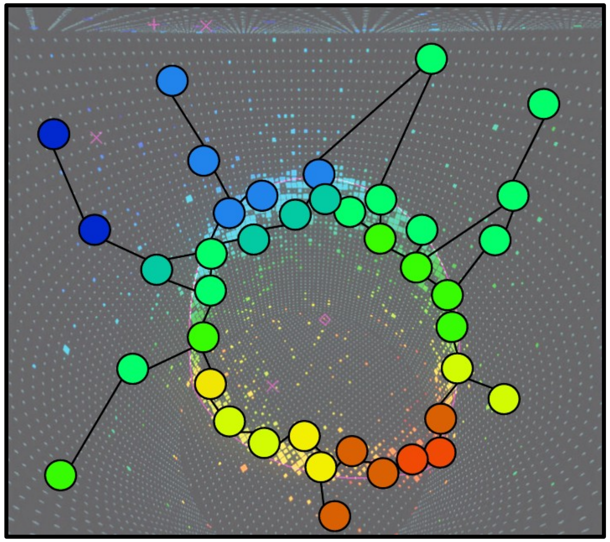
  → Rely on node & edges : Each hit PMT = a node of the GNN.

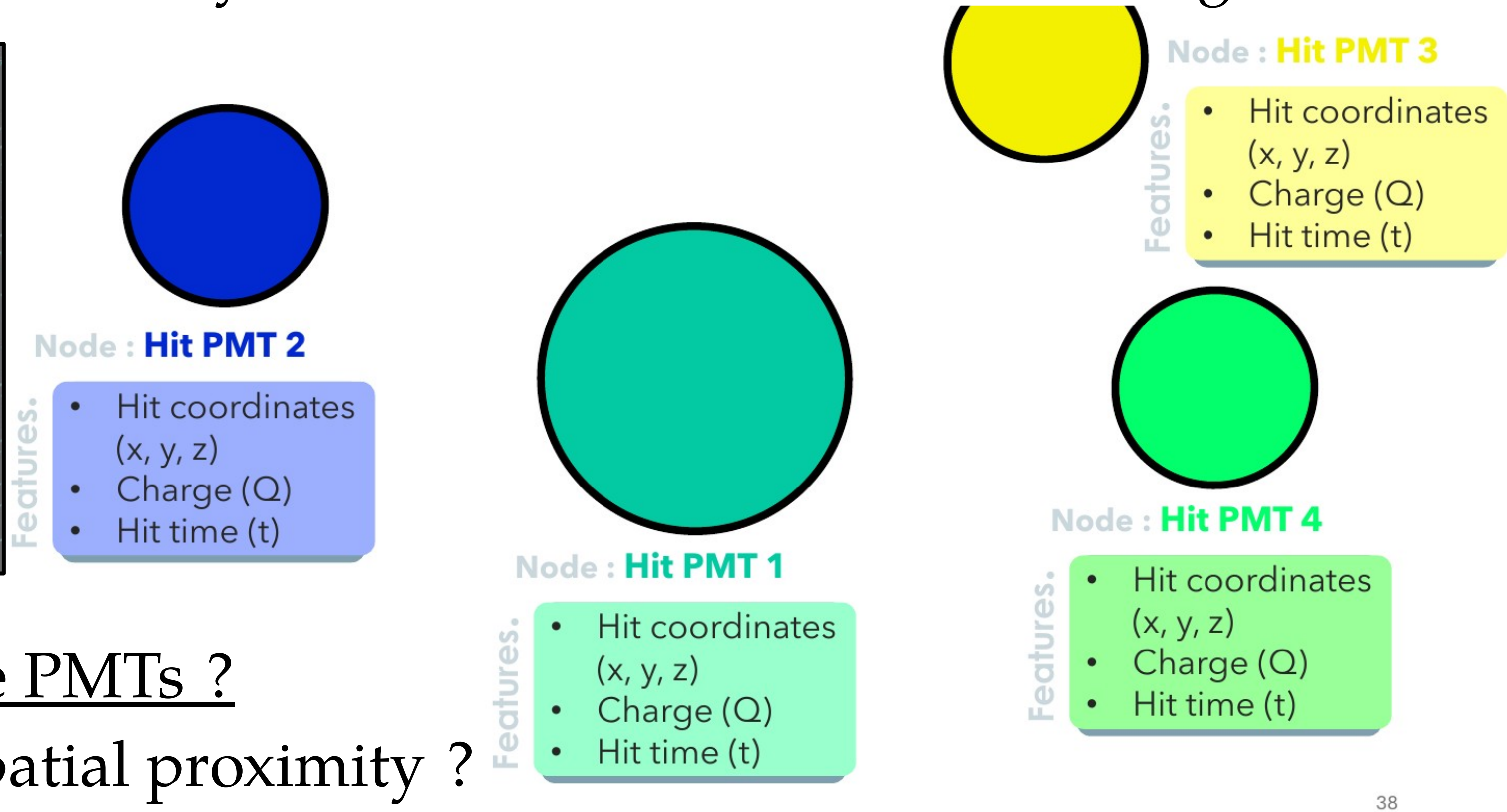




Basic principles of GNN

- Use hit PMT informations (position, hit charge&time) to construct a Graph i.e. a connected array of PMTs → <u>To reconstruct the ring or vertex.</u>





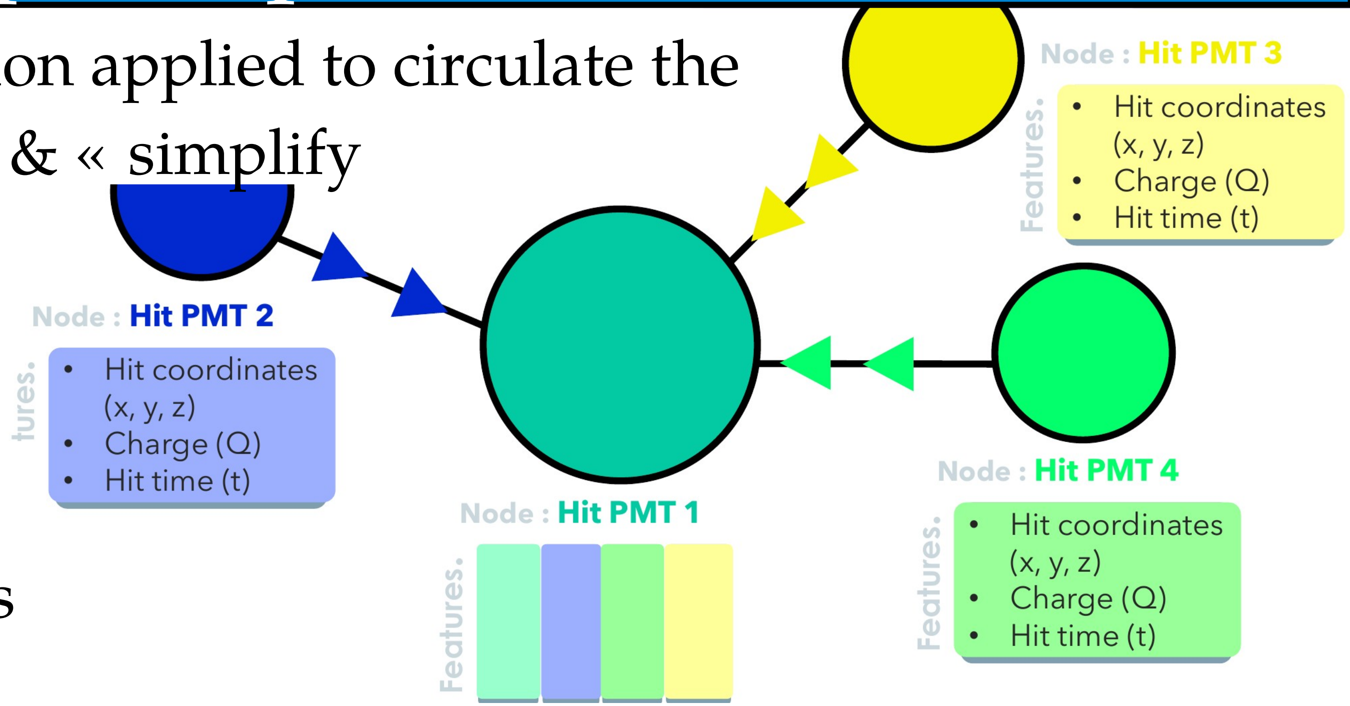
- <u>How to connect the PMTs ?</u>

1. Based on their spatial proximity ?
→ Clear image of a ring.
2. Based on their « charge deposit » proximity ?
3. Based on their hit time proximity ?
→ Great to reconstruct vertex through triangulation.
4. All at once ?

→ Answers depends on the task we wish to accomplish.

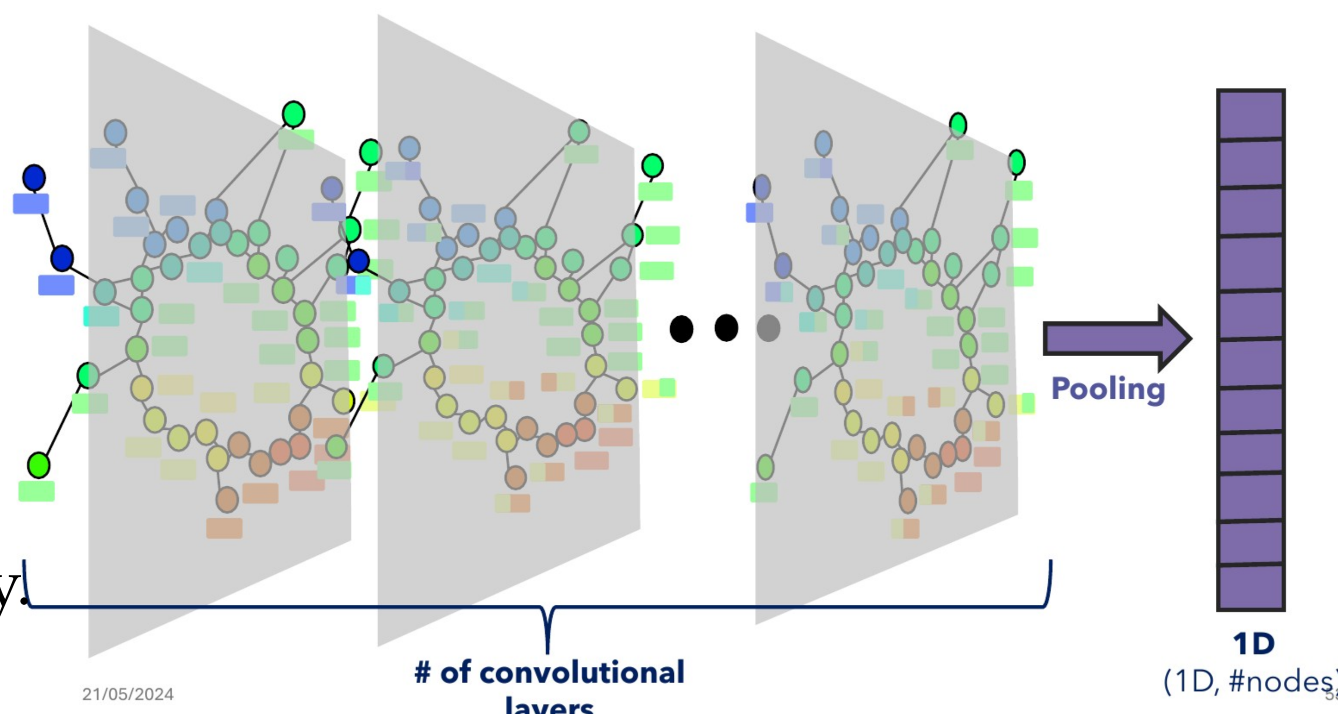
Basic principles of GNN

- Aggregation + Convolution applied to circulate the information along nodes & « simplify it » using convolution.
  = a convolutional layer



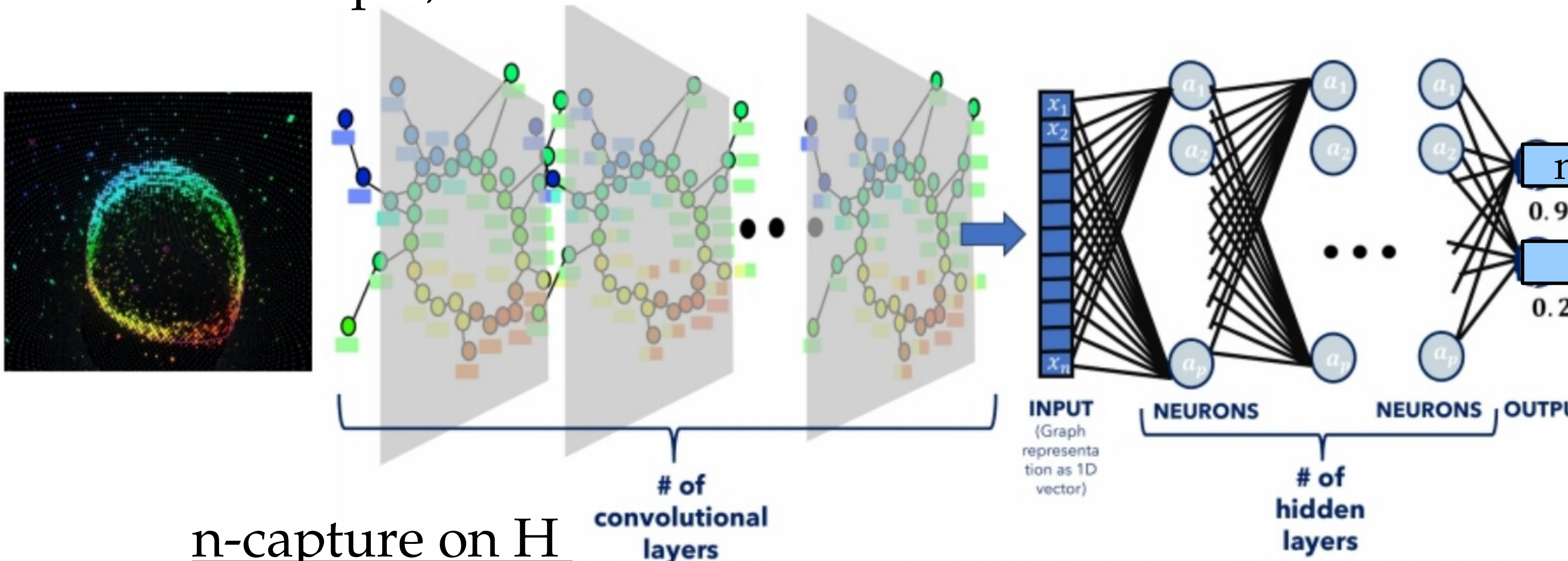
- To optimise : number of connected nodes & layers should be optimized.
  → Problem dependent.
  → Optimized it through minimum gradient descent.

- Graph output is then aggregated in a 1D array.

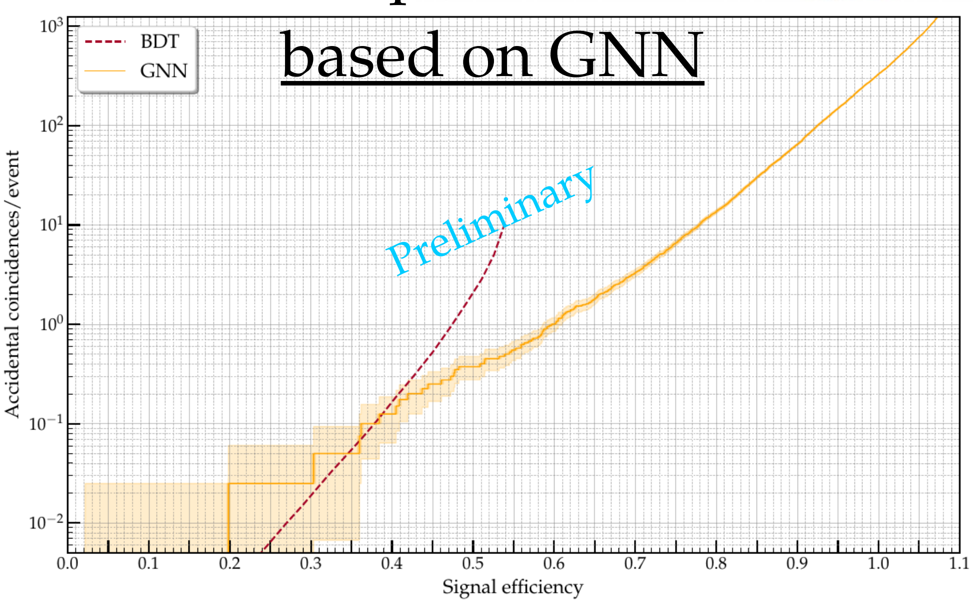


Classification using GNN

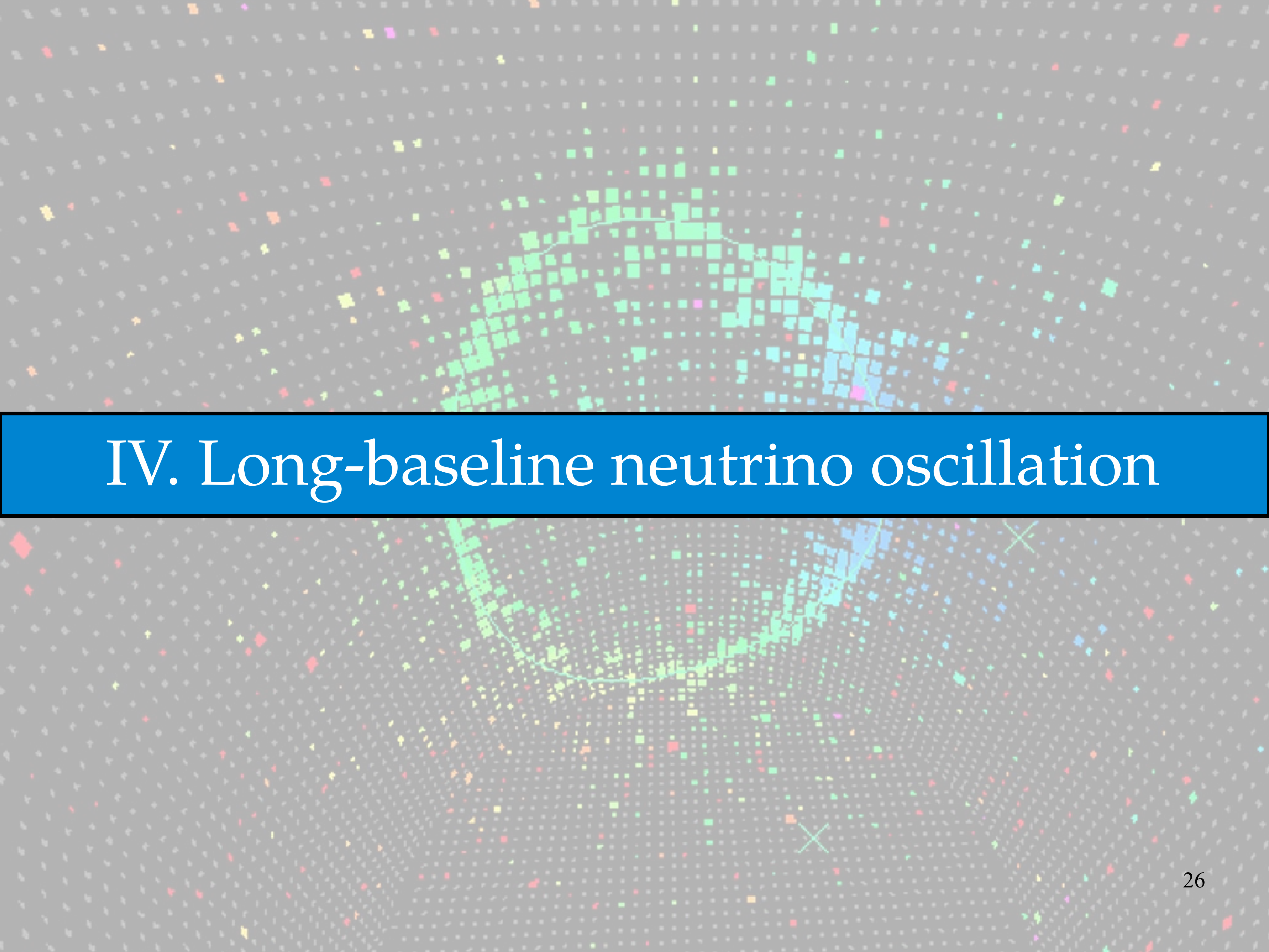
- A multi-layer perceptron basically does the final classification task
  → In our example, the neutron identification



n-capture on H based on GNN

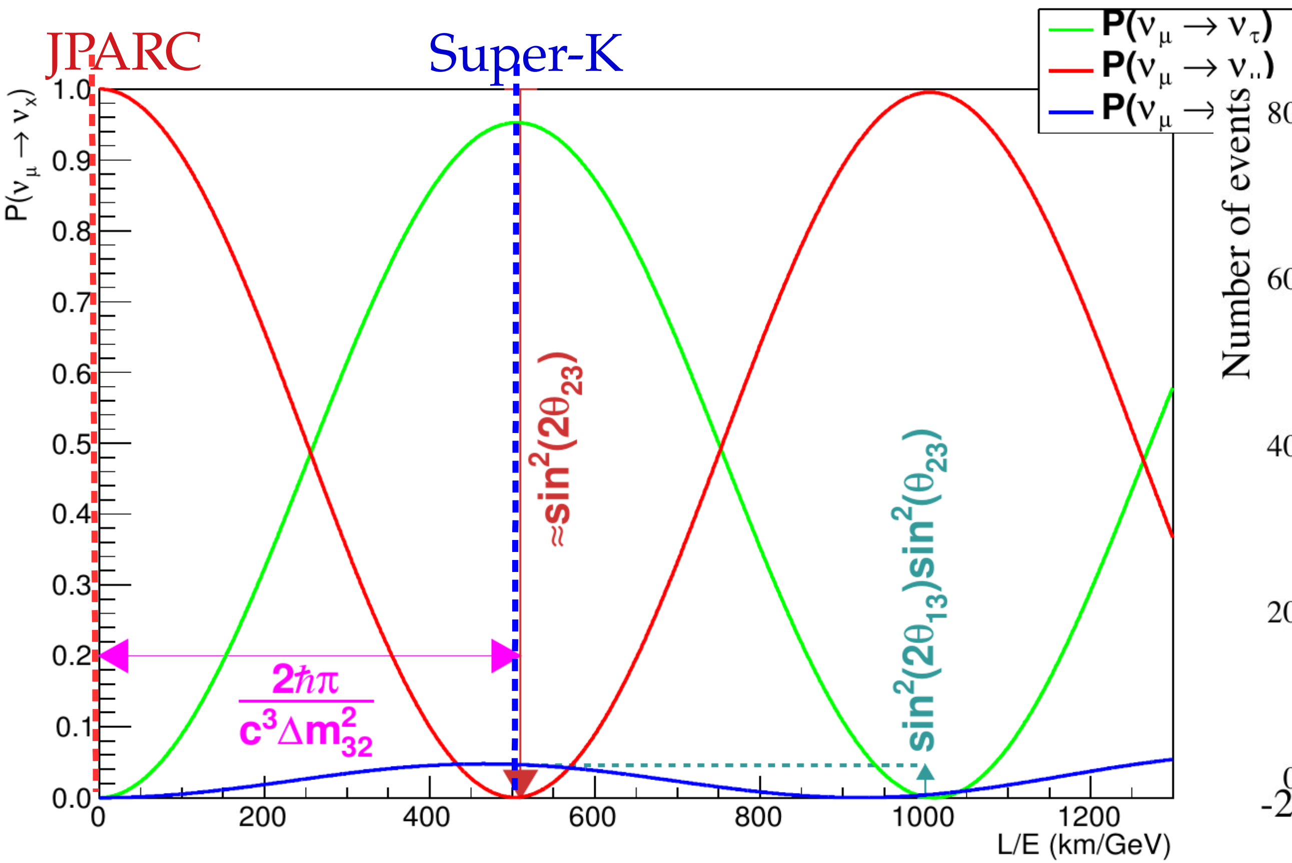


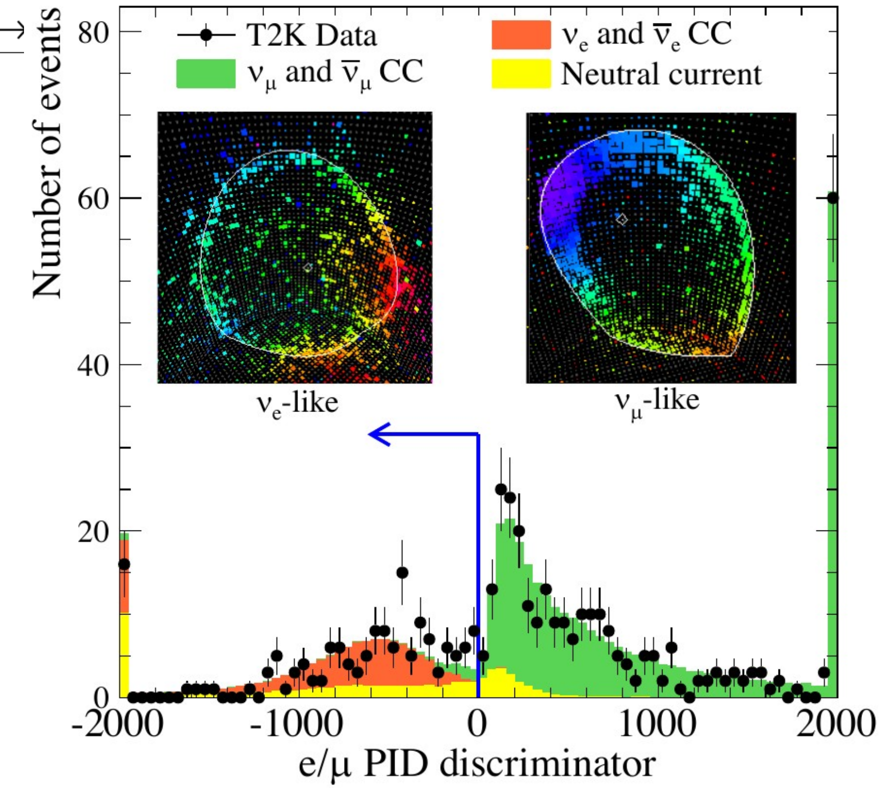
- High background acceptance : GNN signficantly outperforms BDT (+20%).
- Low background acceptance : GNN performs same as BDT.
  → Starting and on-going effort.



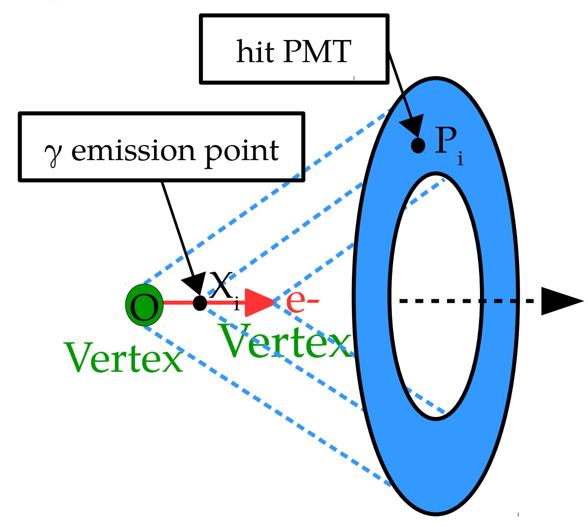
IV. Long-baseline neutrino oscillation

Long-baseline experiment





- Need to reconstruct : detected flavour (ν_e/ν_μ) & E.
- Particles cross several meters while emitting Cherenkov light :
  → Not point-like source & correlated parameters.
  → Momentum can be reconstructed using total charge &/or ring-width



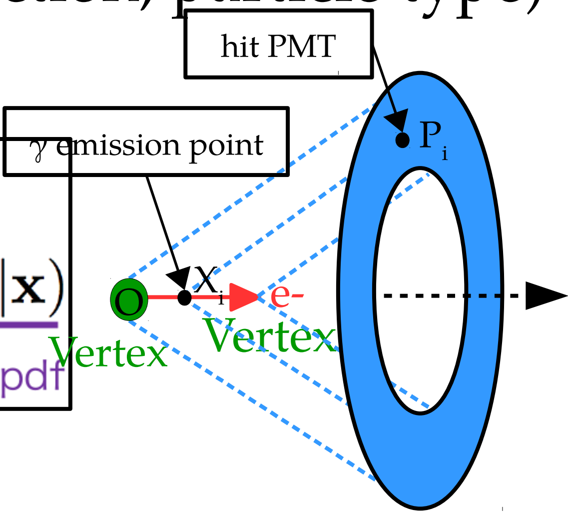
FiTQun high-energy algorithm

- Simulatenous fit of **8 parameters** using all PMTs charge&time:

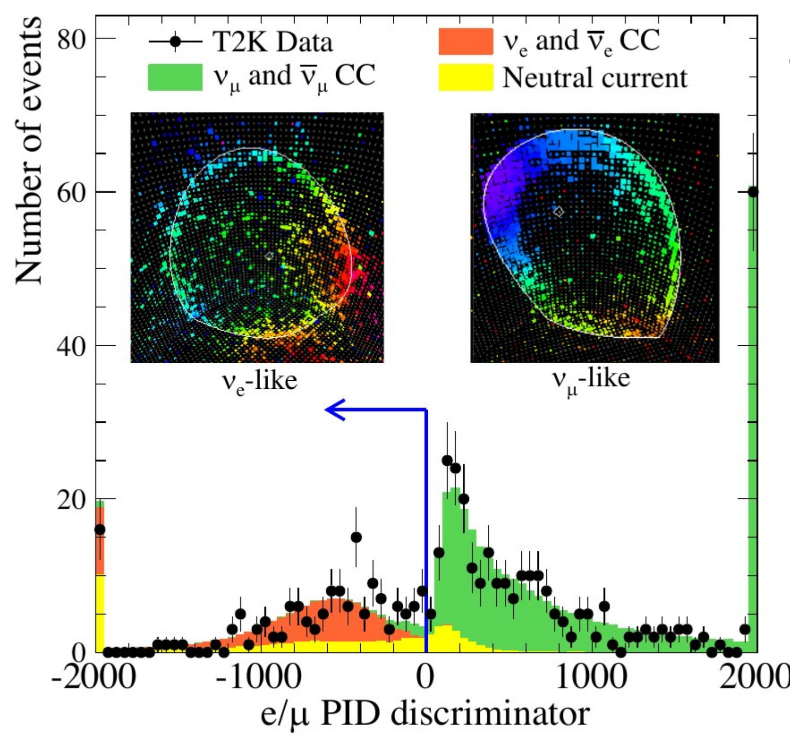
  $\{X\}_i$ = (vertex position, vertex time, momentum, direction, particle type)

- Likelihood-based fitter :

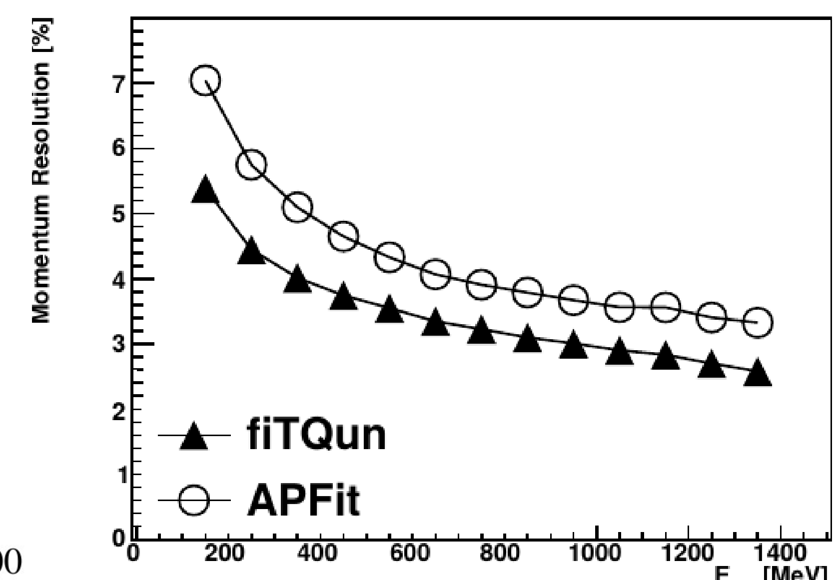
$$L(\mathbf{x}) = \prod_j^{\text{unhit}} \underbrace{P_j(\text{unhit}|\mu_j)}_{\text{PMT unhit probability}} \prod_i^{\text{hit}} \underbrace{\{1 - P_i(\text{unhit}|\mu_i)\}}_{\text{PMT hit probability}} \underbrace{f_q(q_i|\mu_i)}_{\text{PMT charge pdf}} \underbrace{f_t(t_i|\mathbf{x})}_{\text{PMT timing pdf}}$$

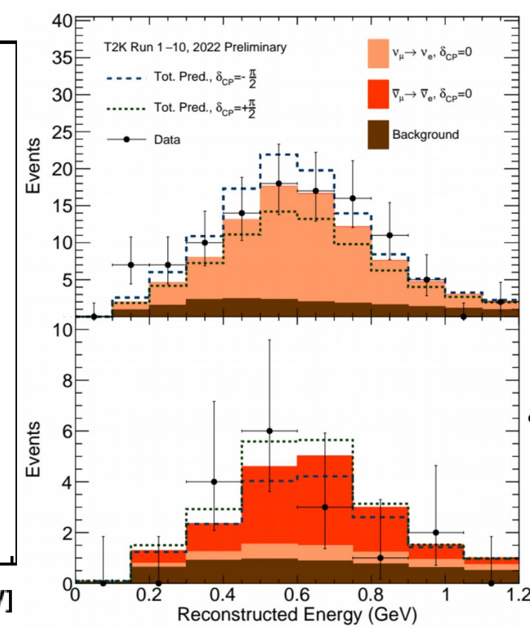


- Excellent e/μ separation (mis-ID < 1%)

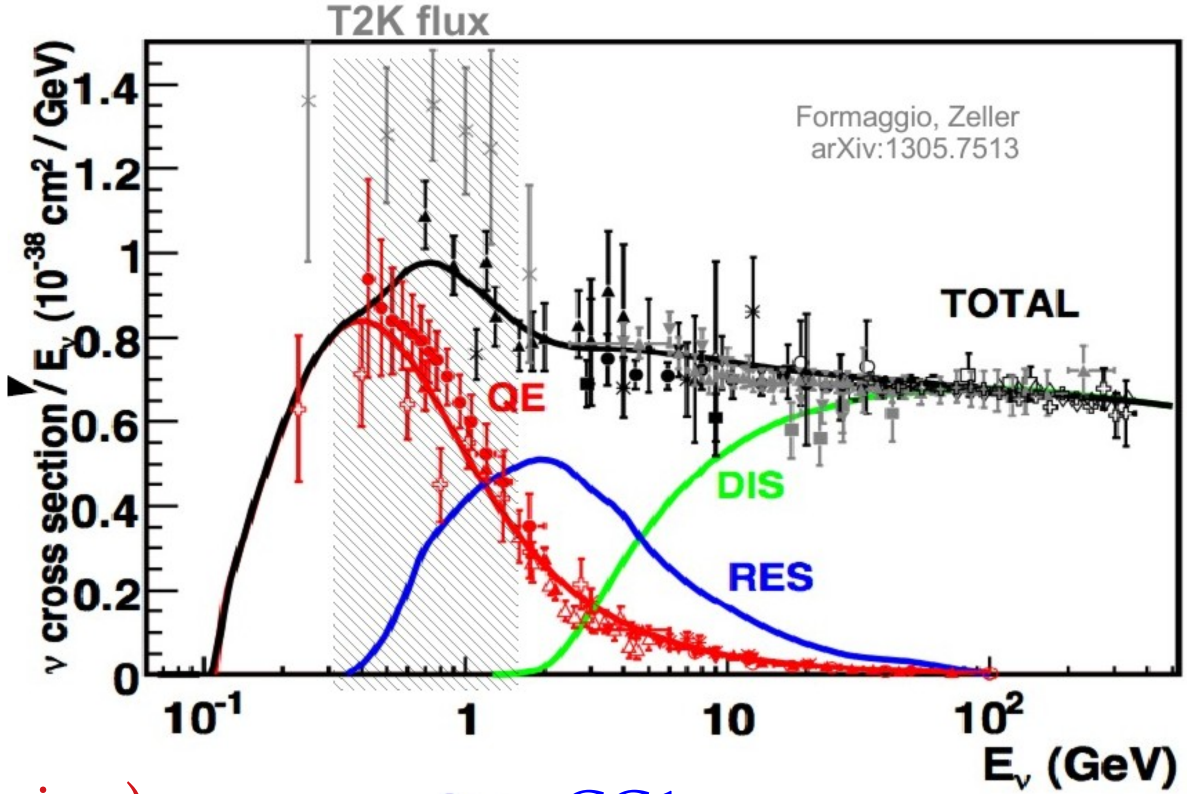


& momentum resolution (<4 % for e-)



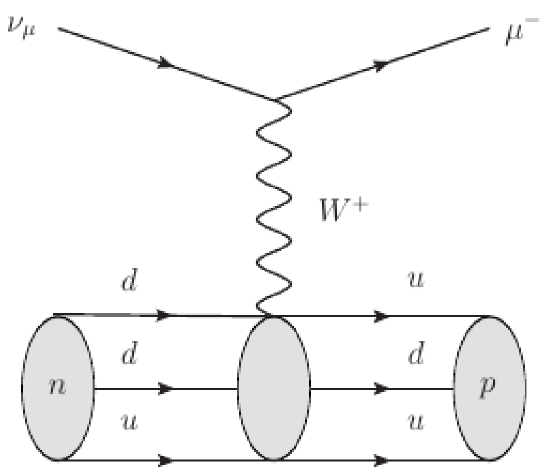


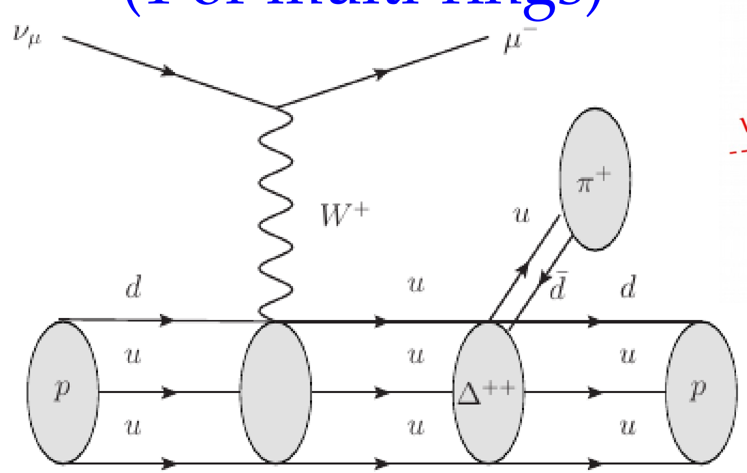
Multiple ring reconstruction

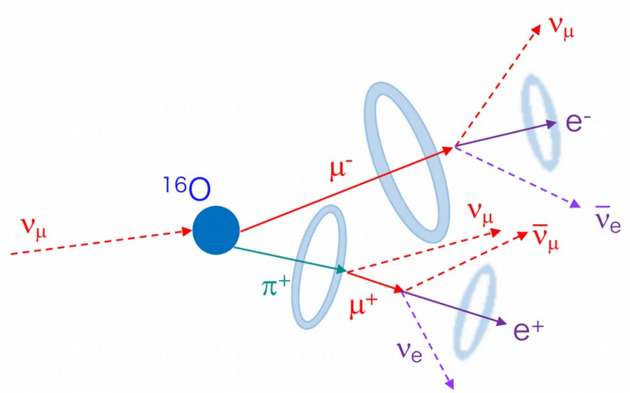


<u>CCQE (1 ring)</u>
dominant channel

<u>CC1π</u>
(1 or multi-rings)



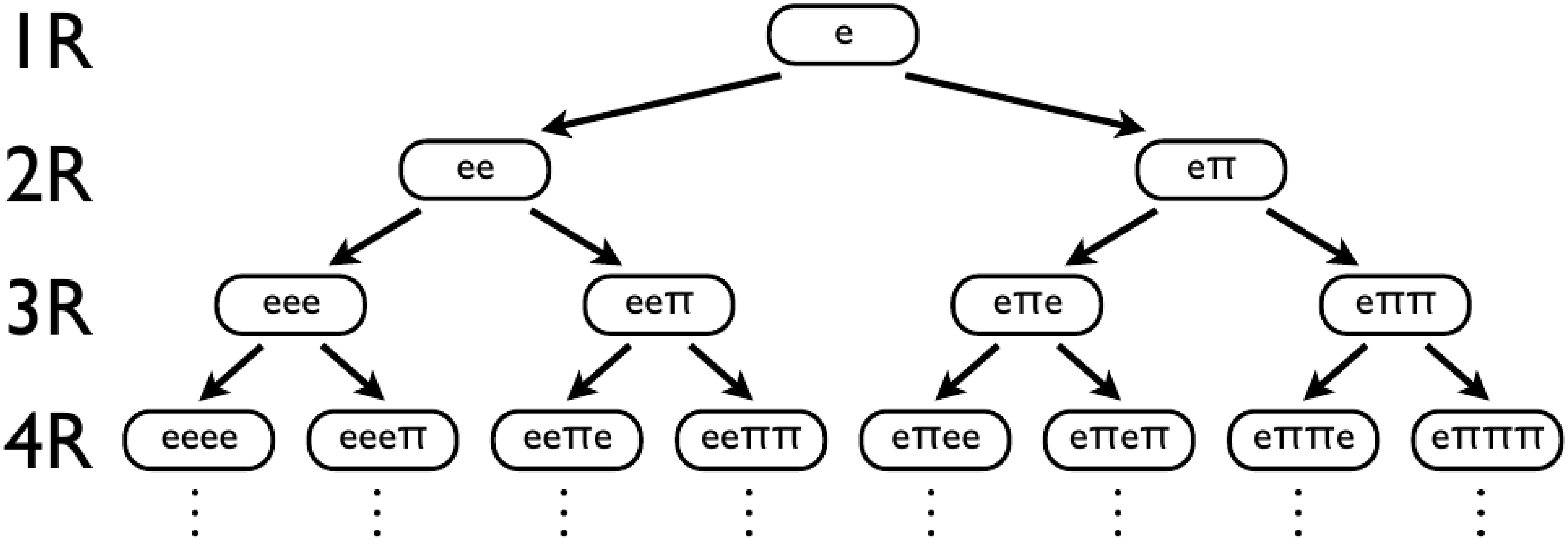




How the new ring is accepted / rejected

Let's assume that the real event is e+π

1. First ring fitted as e-like & π-like (π-like not shown here)

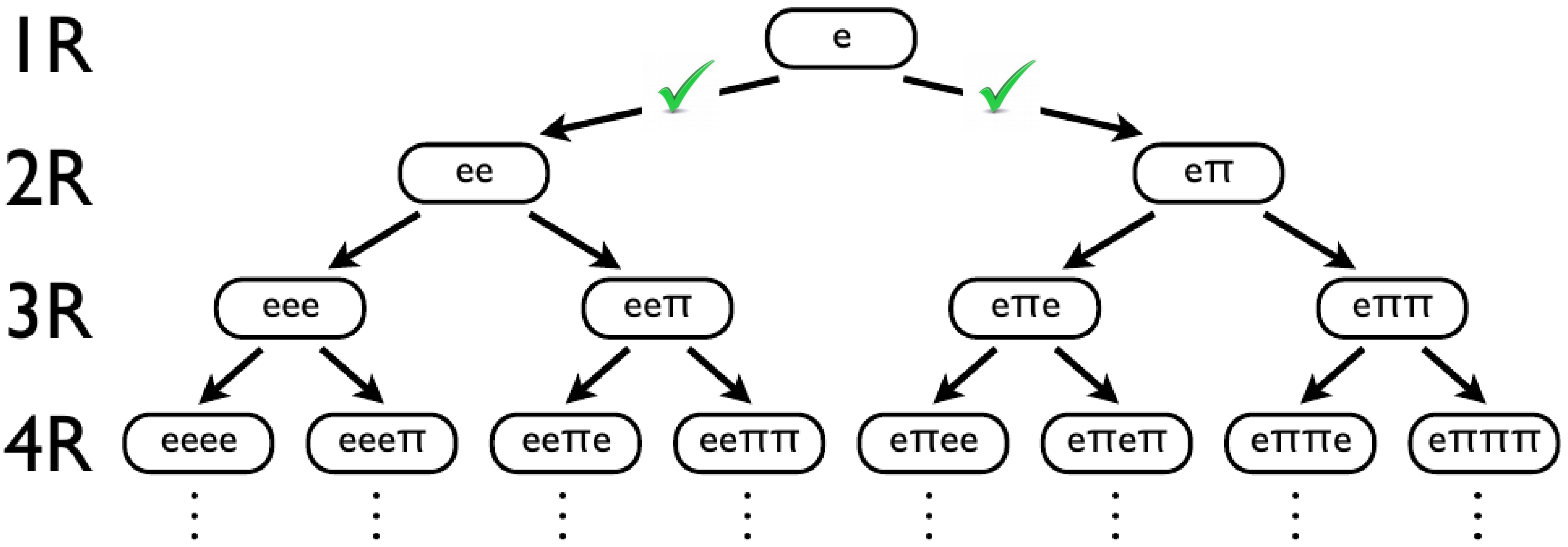


How the new ring is accepted / rejected

Let's assume that the real event is e+π

1. First ring fitted as e-like & π-like (π-like not shown here)
2. Let's focus on 1st ring e-like. 2nd ring fitted as e-like & π-like

→ Let's assume both hypotheses pass the cut (Likelihood improved)



How the new ring is accepted / rejected

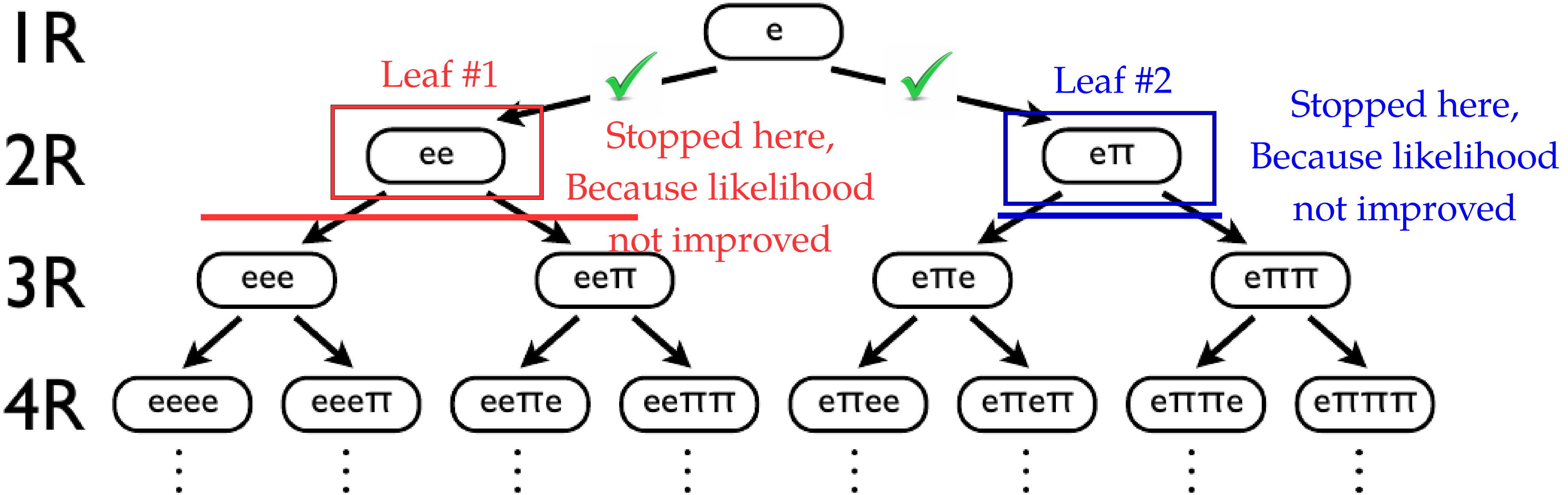
Let's assume that the real event is e+π

1. First ring fitted as e-like & π-like (π-like not shown here, but same).
2. Let's focus on 1st ring e-like. 2nd ring fitted as e-like & π-like

→ Let's assume both hypotheses pass the cut (Likelihood improved)

3. 3rd ring is fitted as e-like & π-like

→ Let's assume that no 3 ring hypothesis pass the cut.



→ The fit is stopped here.

How the new ring is accepted/rejected

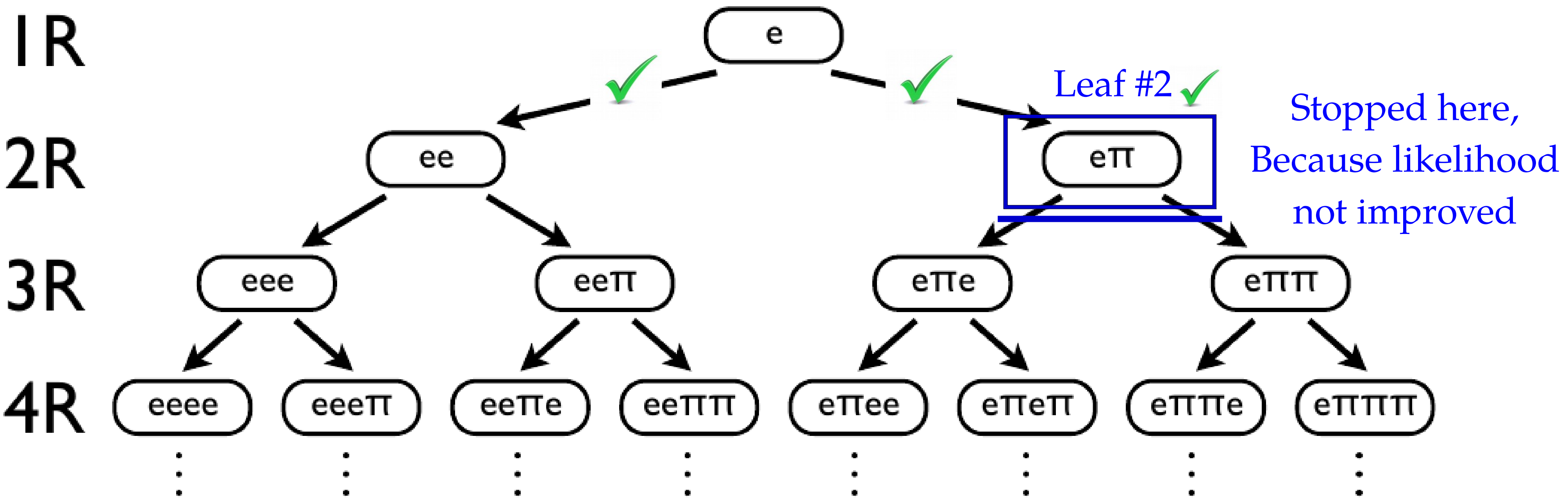
4. The Likelihood of the 2 leaves are compared

→ The higher becomes the fit result.

→ If everything works well, the winner should be Leaf #2.

5. Note that we have not shown the graph where 1st ring is π-like

⇒ More leaves in this case in reality ⇒ Very time consuming !



High-energy reconstruction in HK

- fiTQun is powerful and has been ported to HK… but is relatively slow

	1 ring e/μ	1 ring e/π0	Multi-ring atmospheric
CPU time / event	30s	50s	up to 600s

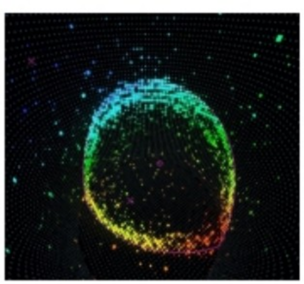
- <u>For HK :</u> aim to reach ≤ 1% stat. and syst. uncertainties

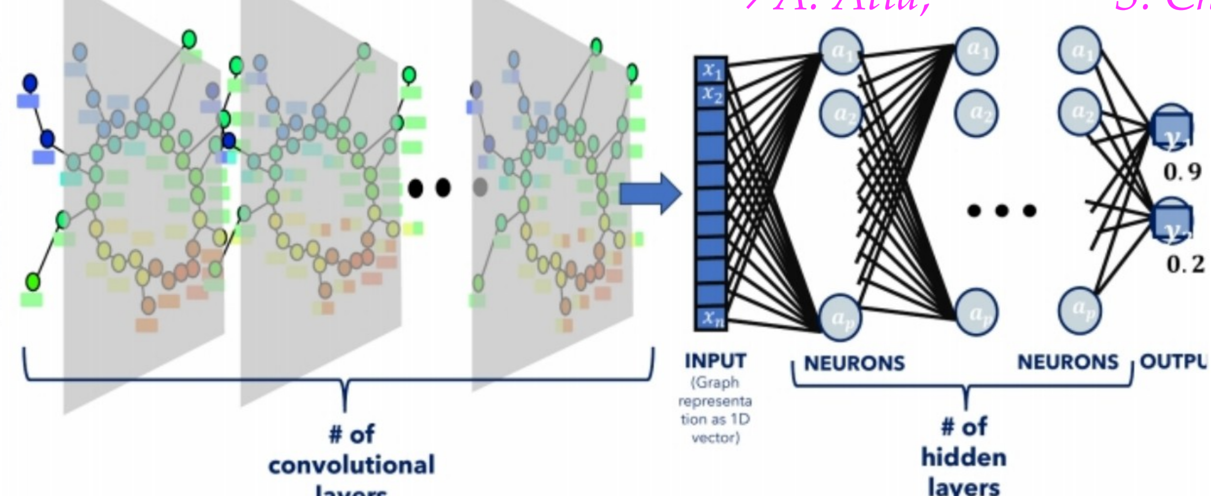
  ⇒ Huge data processing & large MC generation to constrain our syst.

  ⇒ Need a faster algorithm (and potentially more physics powerful).
- <u>3 efforts are on-going :</u>
  - Improve fiTQun efficiency.
  - Port fiTQun to GPU : computation time ↓ by 100.
  - Machine learning development : CNN, Visual transformers, GNN

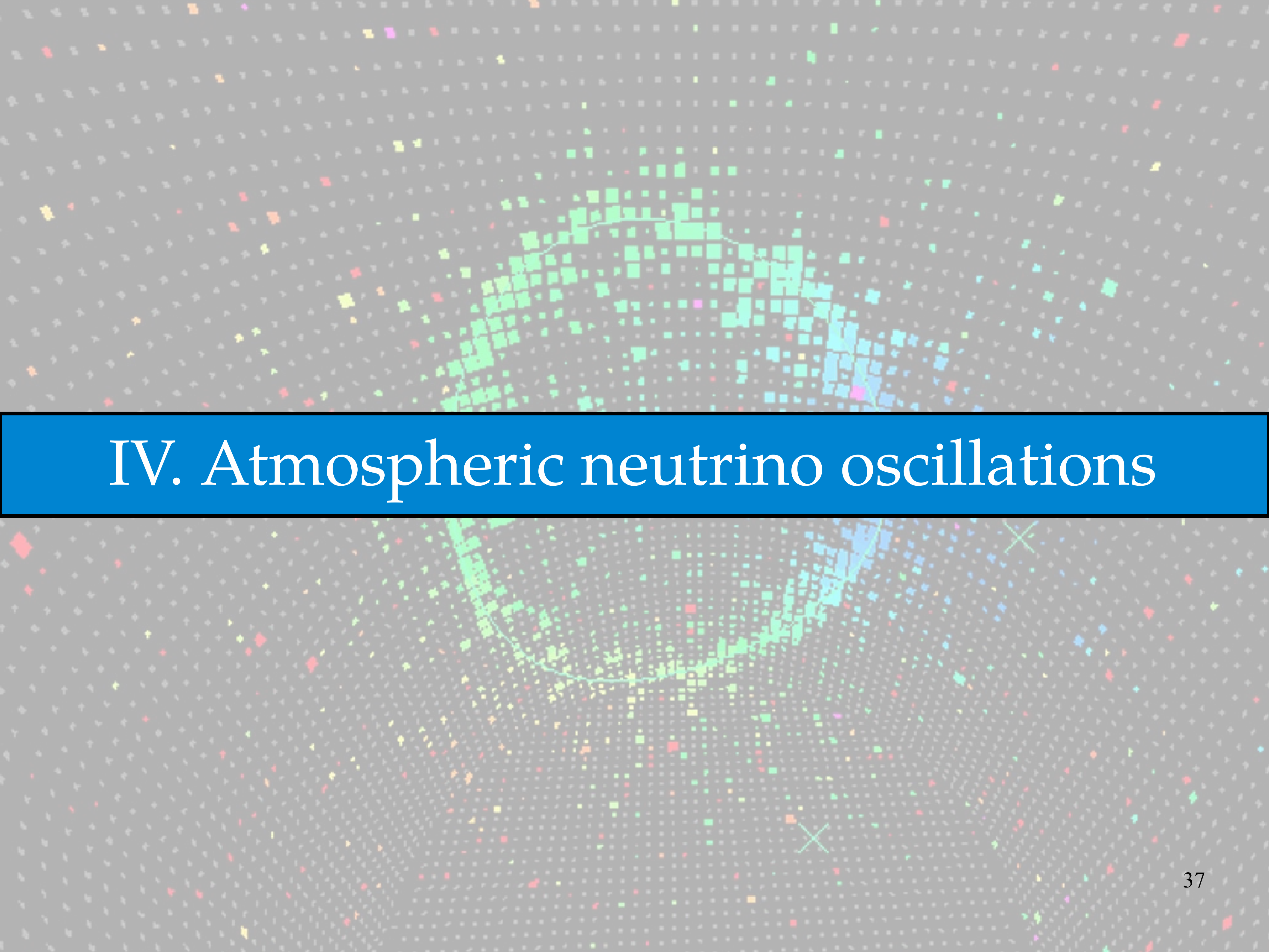
Work in-progress before officialization

→ A. Atta, S. Chen, E. Le Blevec





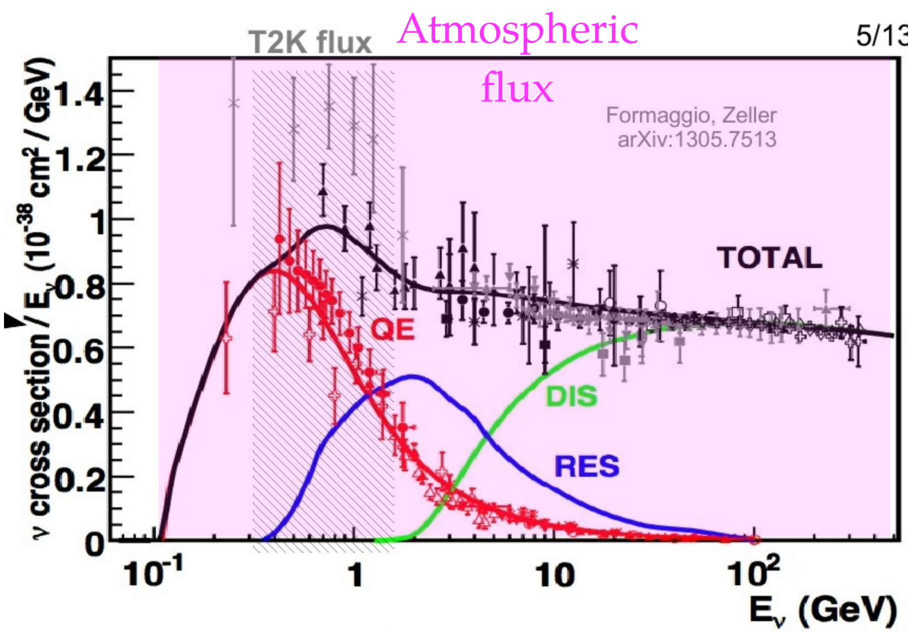
- PID e/μ
- PID e/π0
- E-reconstruction
- Vertex reconstruction



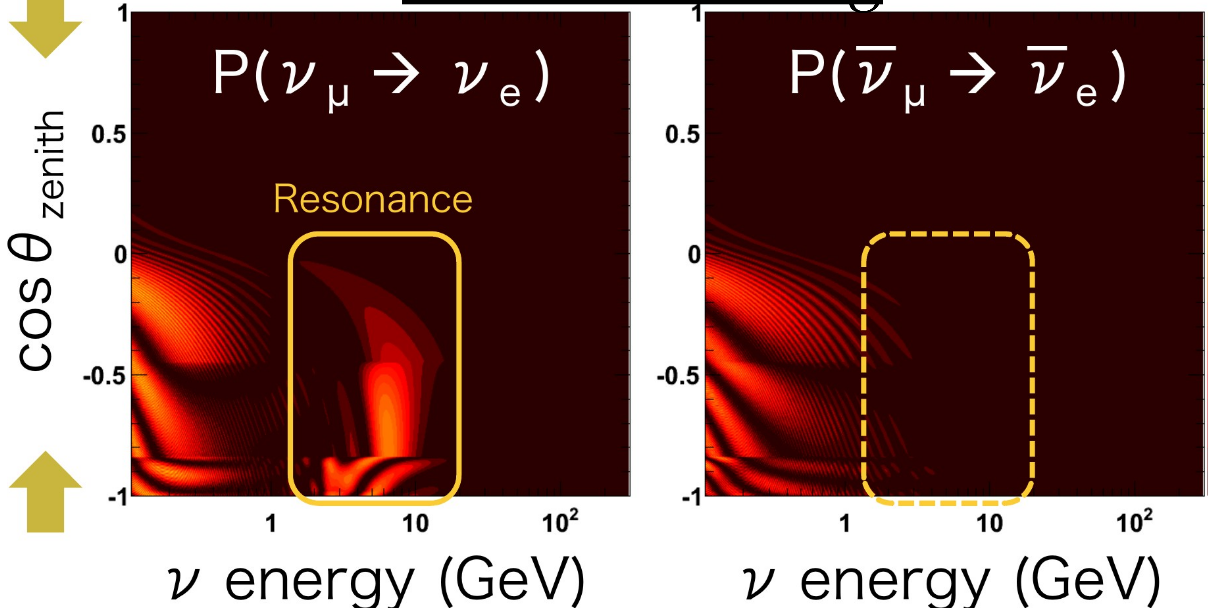
IV. Atmospheric neutrino oscillations

Atmospheric neutrinos

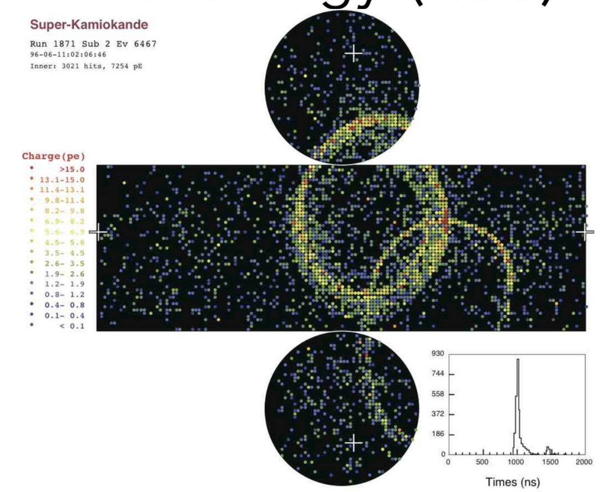
- Very broad spectrum ranging from few MeV to TeV.
- <u>Mass ordering dominantly determined with upward-going multi-GeV ν_e sample :</u> → CC-resonant and DIS dominates ⇒ Multi-ring domain.



Normal ordering



- <u>A fast and reliable ring counting algorithm is the key for atmospheric neutrino</u>
  → Historical Super-K fitter : APFit



The APFit algorithm

- APFit is a sequential algorithm :

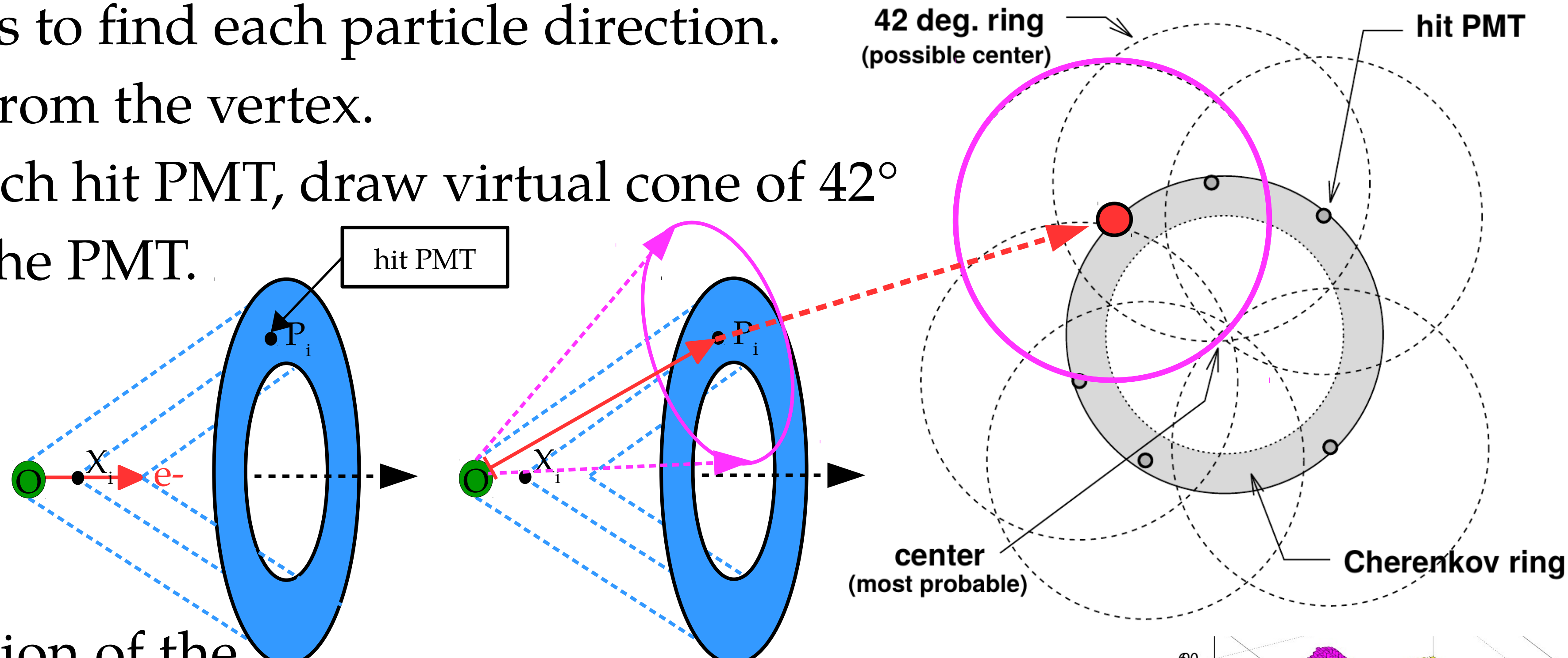
Vertex & direction → Ring counting → PID → Momentum → Refine ring counting

- Ring counting much faster than fiTQun, based on Hough transform

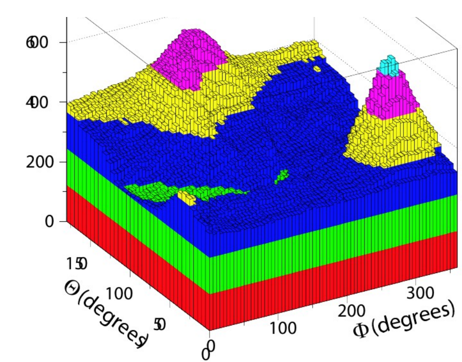
  → Goal is to find each particle direction.

  → Start from the vertex.

  → For each hit PMT, draw virtual cone of 42° around the PMT.



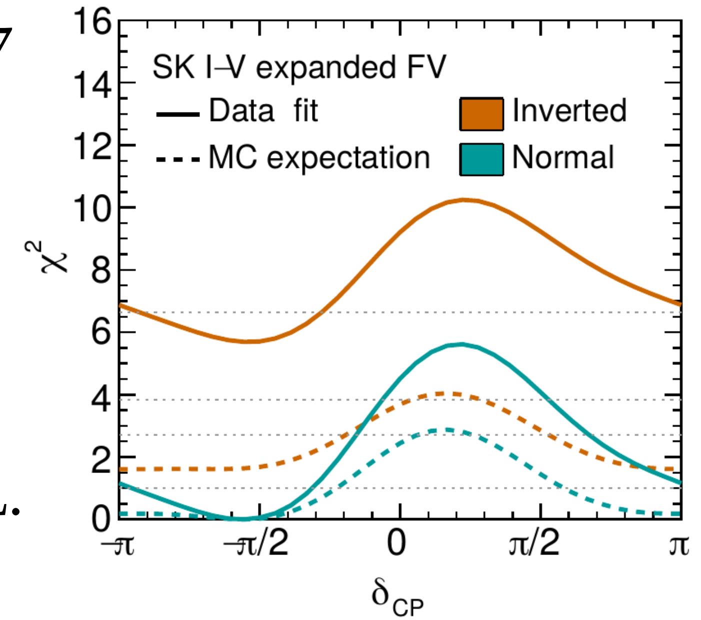
  → Direction of the particle is region with higher density virtual cone.



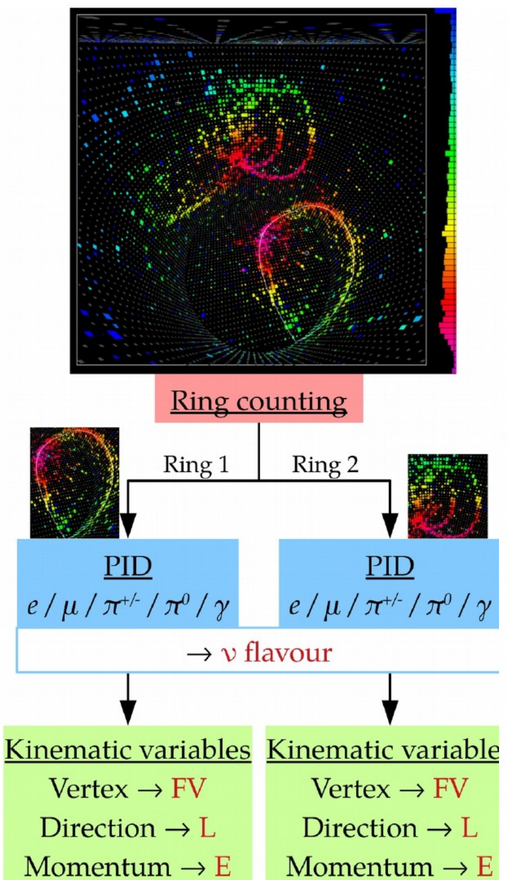
- PID is based on charge distribution only

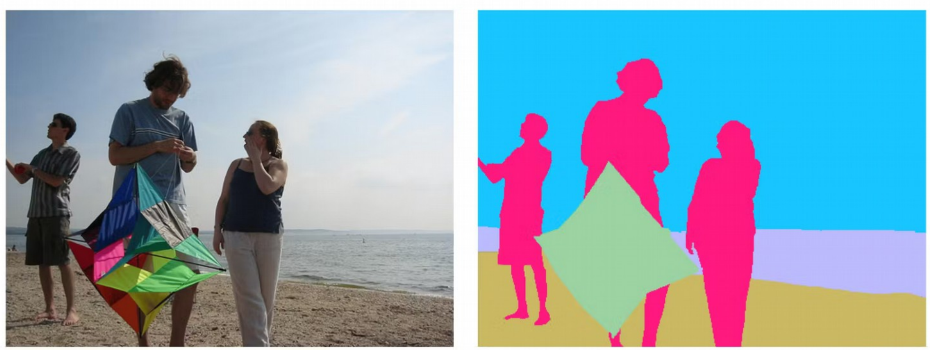
Perspectives of improvement

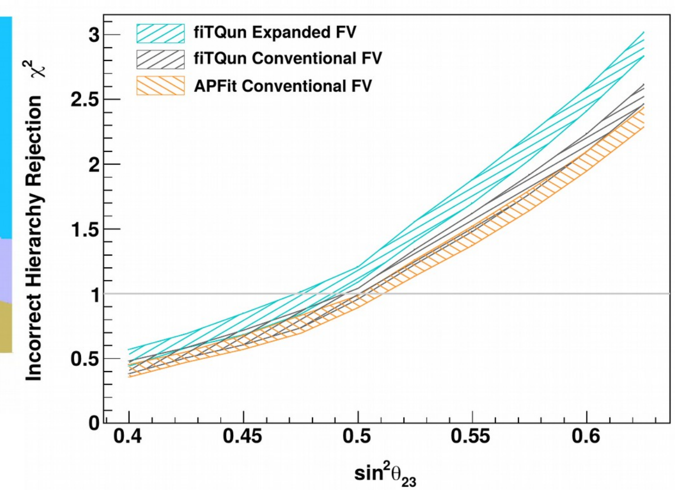
- <u>Provide mass-ordering determination :</u> $\Delta\chi^2 = 5.7$



- <u>Perspective for improvement :</u>
  - Adapt fiTQun to atmospheric ν (now only SK-IV) → More performant in FV-size &PID.
  - Develop a ring counting algorithm using ML.




(a) Image (b) Semantic segmentation



Conclusions

- Super- and Hyper-K covers a large range of physics : MeV → TeV
  → At low energy : reconstructed event from a sparse&noisy information.
  → At high-energy : reconstructed very correlated information.

- Significant challenges ahead of us, esp. for Hyper-K
  → Low energy, especially for DSNB search, will be very challenging.
  ⇒ Improve our n-tag algorithm performances.
  → At high-energy : ↓ computational time while ↑ physics performances.

- ML-based algorithms are a new key to open these doors.
  → Many developments on SK/HK presented after this talk.
  → They are not the sole keys : developed as a complementary approach to our existing algorithms.
  → A complementary approach helps to learn from ML-algorithm to feed « traditional »reconstruction, and vice-versa.
  → Hope NPML could be an ideal place for these fruitful discussions.

Additional slides

DSNB search with pre-selection cuts