ML challenges in Theia and WBLS

Presented by

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on behalf of the THEIA collaboration

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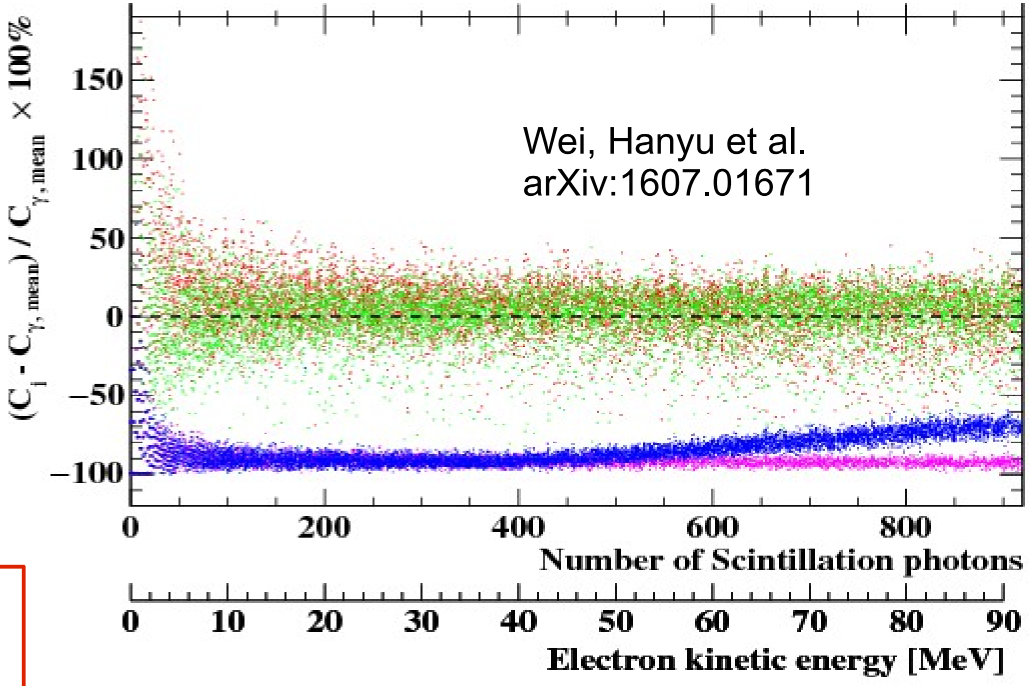
Universität Hamburg
DER FORSCHUNG | DER LEHRE | DER BILDUNG

Theia Concept/Motivation

- **New-generation of large-scale, low-threshold, directional detectors**
- **Combine advantages of Water-Cherenkov- and liquid scintillator-detectors** ASDC Whitepaper October 2014 arxiv:1409.5864

- **Advantages:**
  - **Scintillation:** High light yield
    → Good energy resolution + low threshold
  - **Cherenkov-light:** Non-isotropic emission
    → Directional information
    + Particle identification by ring-characteristic
  - **Combined:** C/S-ratio
    → Improved particle discrimination

Crucial: Need to be able to separate both light species!



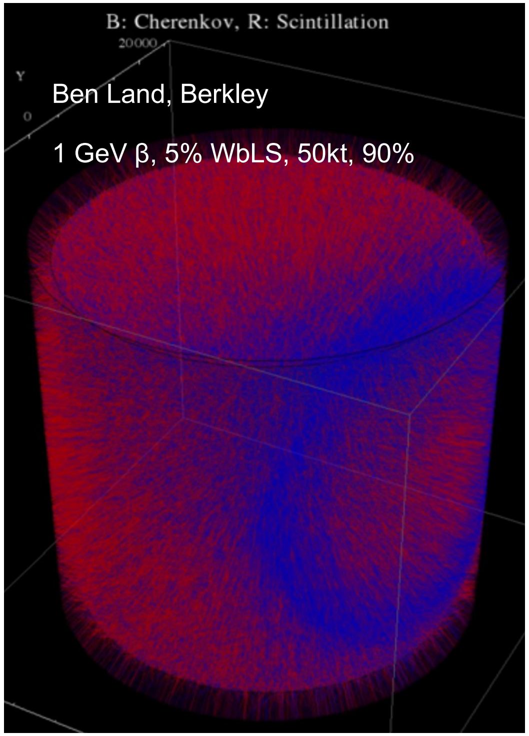
Number of Cherenkov- and scintillation photons for different particles in LAB

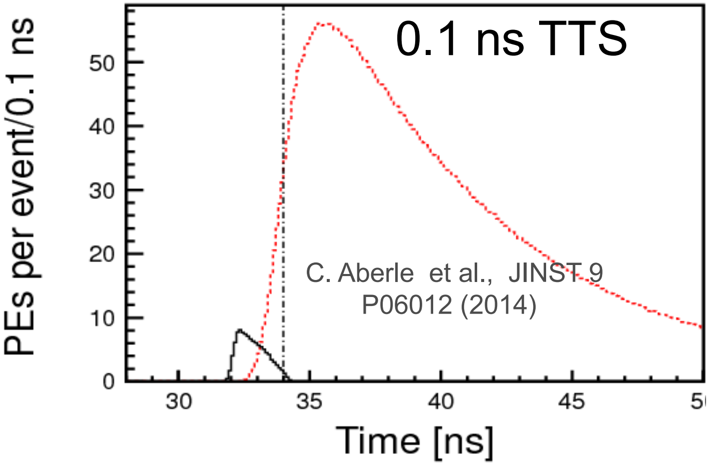
Also important:
Low cost & high transparency of water

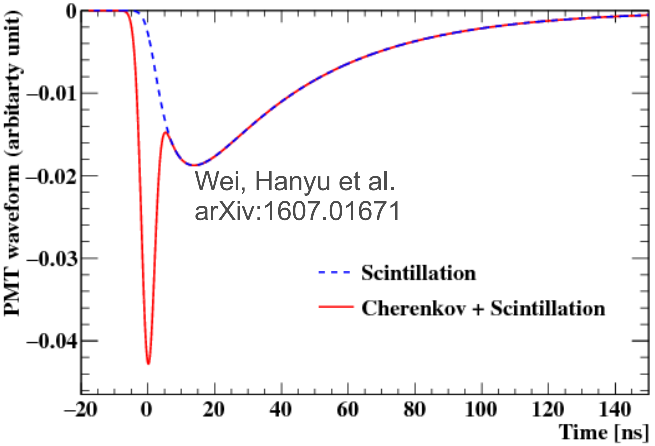
Cherenkov-/Scintillation Light Separation

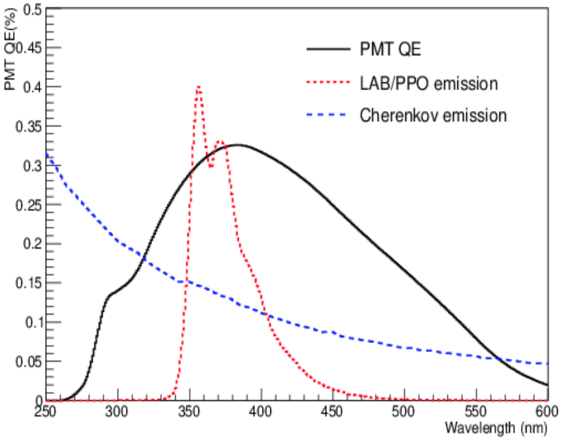
- **Three different signatures + new technologies**
  - Cherenkov-rings → optimize light ratio
    → Water-Based-Liquid-Scintilator (WBLS)/low light yield scintillator
  - Emission time profile
    → fast timing (sensors)/slow scintillator (cocktail)
  - Wavelength
    → filtering/optimized sensors

  + Advanced reconstruction methods





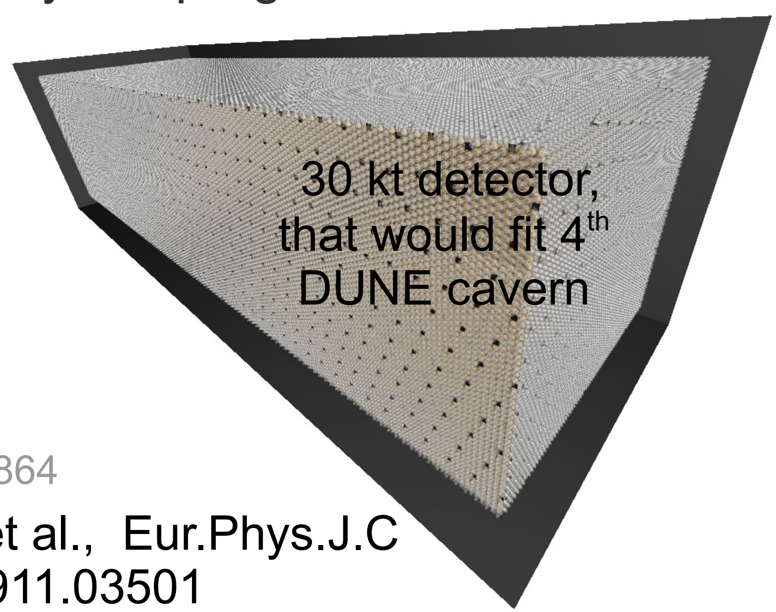


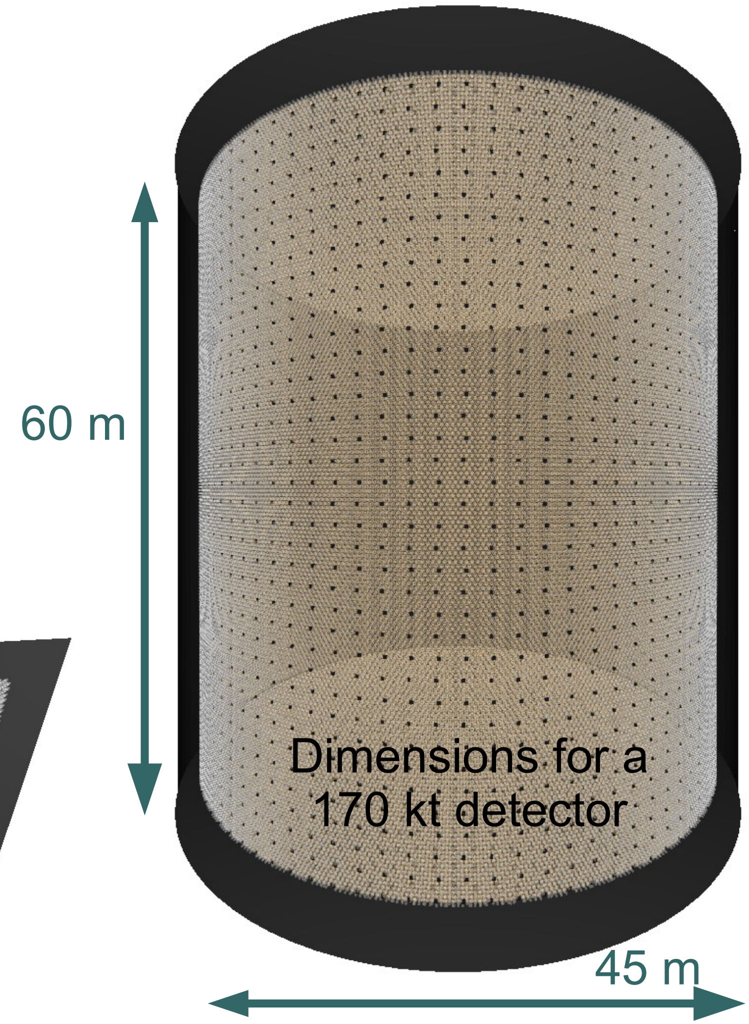


The THEIA Detector

- Large-scale detector (30-100 kton)
- Water-based LS target
- Fast, high-efficiency photon detection with high coverage
- Deep underground (e.g. Homestake)
- Isotope loading (Gd, Te, Li...)
- **Flexible!** Target, loading, configuration

➡ Broad physics program!



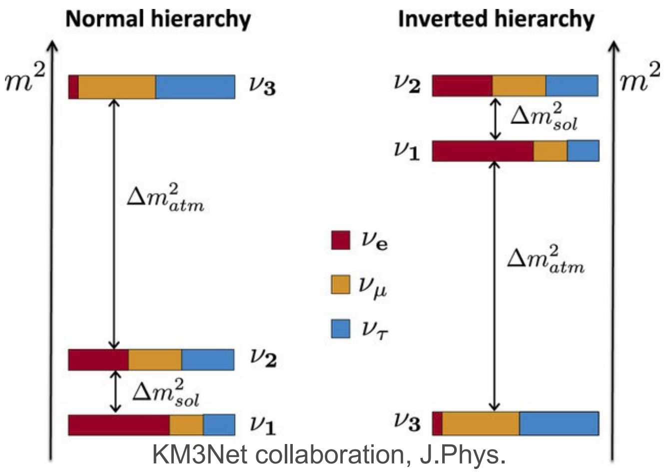


Concept paper: arXiv:1409.5864

White paper: M. Askins et al., Eur.Phys.J.C 80 (2020) 5, 416, arXiv:1911.03501

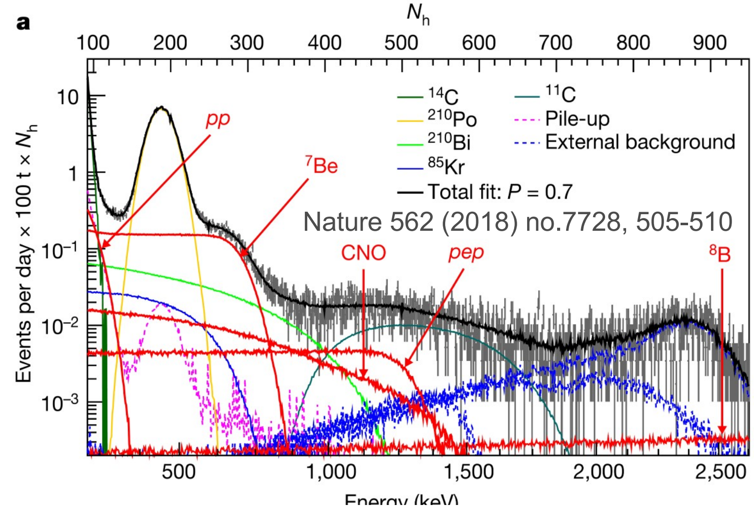
Theia Physics Program

Long-baseline physics



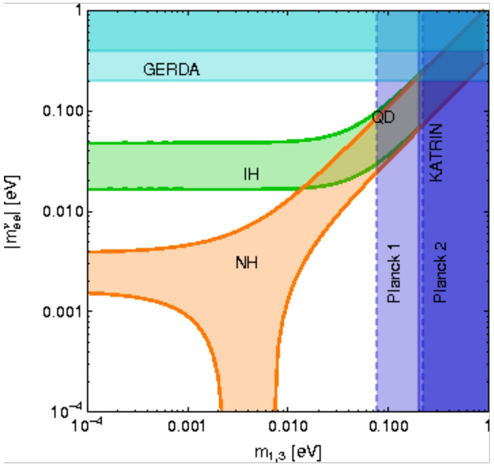
KM3Net collaboration, J.Phys. G43 (2016) no.8, 084001

Solar neutrinos



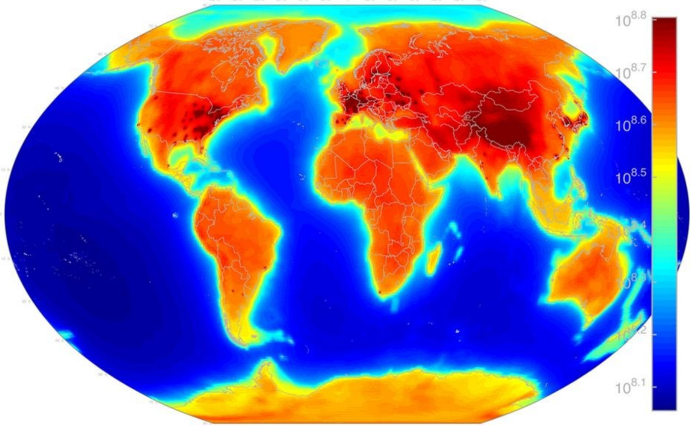
Supernova burst neutrinos & DSNB

Neutrinoless double beta decay



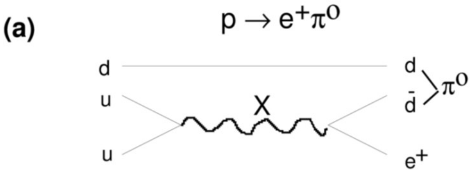
Ge, Shao-Feng, et al. JHEP 1510 (2015) 077

Geo-neutrinos

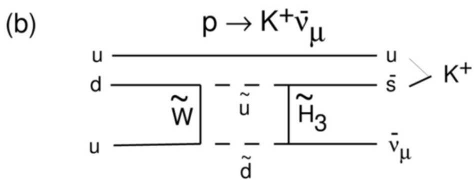


S.M. Usman, et al., Scientific Rep. 5, 13945 (2015)

Nucleon decay

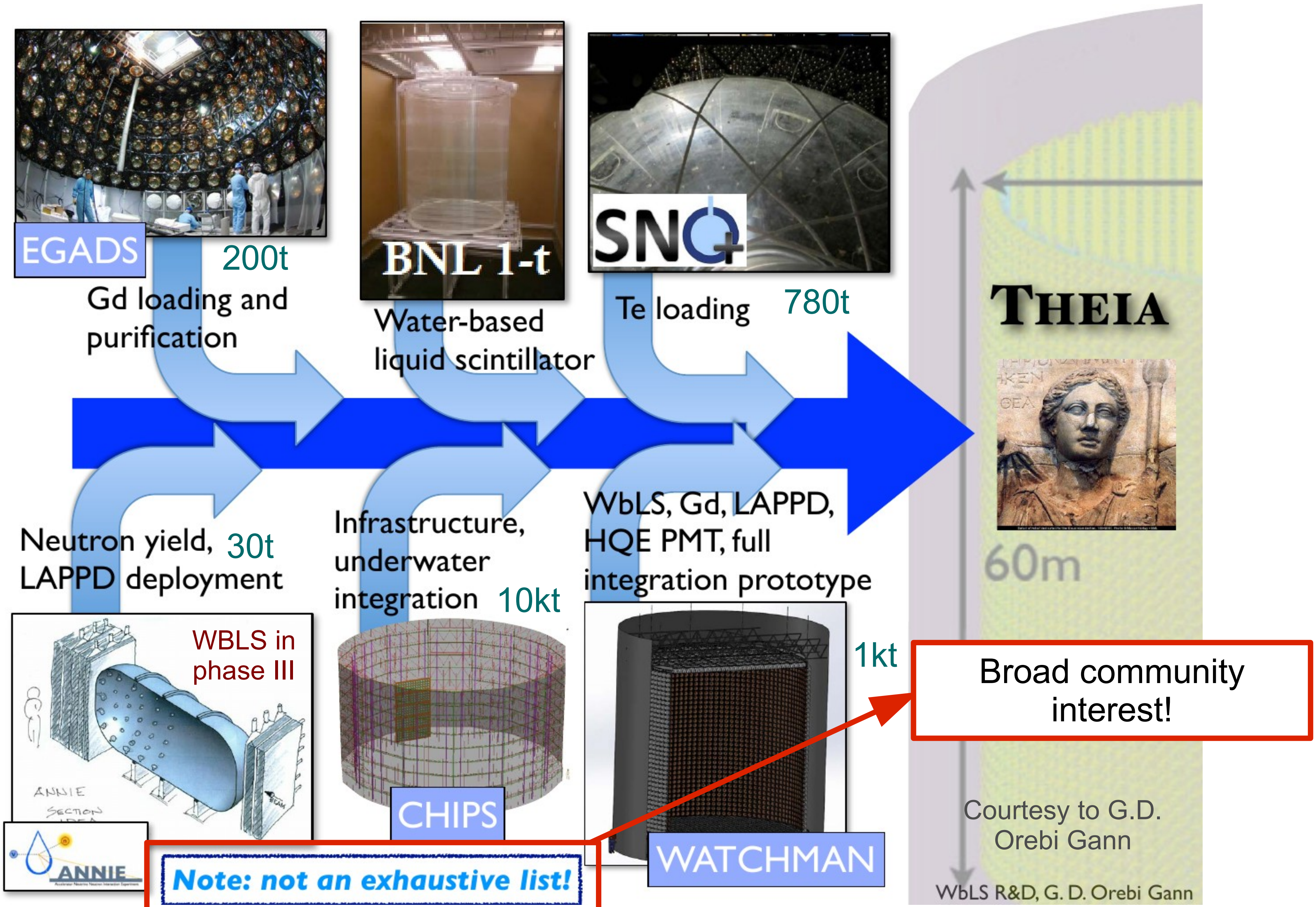


Jorge L. Lopez, Rept.Prog.Phys. 59 (1996) 819-865

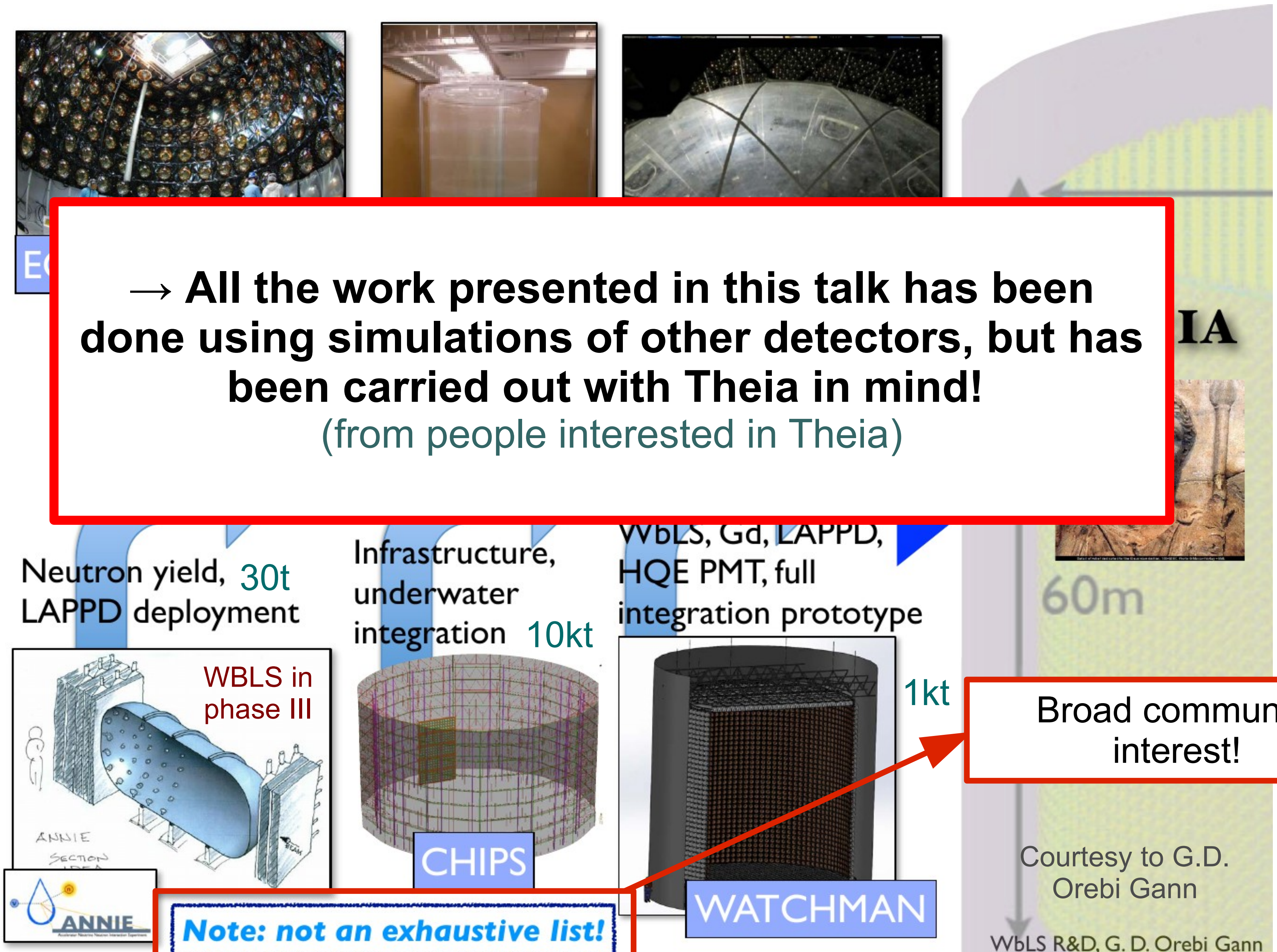


and more ...

Using Other Experiments as R&D Testbeds



Using Other Experiments as R&D Testbeds



→ All the work presented in this talk has been done using simulations of other detectors, but has been carried out with Theia in mind!
(from people interested in Theia)

Broad community interest!

Note: not an exhaustive list!

How can Theia profit from ML?

- **Make the most from the data:**
  - Particle identification
  - Cherenkov-Separation
    - Ring counting/analysis
      → Particle identification
  - Direction analysis
  - Topological reconstruction

- **Speeding up MC production**
  - Maybe combine reconstruction & simulation in an invert-able network
- **Optimizing the detector design**
  - Requires understanding how data quality and performance are related to detector properties!

Will not cover this here!

How can Theia profit from ML?

- **Make the most from the data:**
  - Particle identification
  - Cherenkov-Separation
    - Ring counting/analysis

      → Particle identification
  - Direction analysis

Many different design options

→ Reconstruction algorithms need to be portable

→ This is easier for ML

(Once I have architecture, I can train on many different data sets)

in an invert-able network

Will not cover this here!

- **Optimizing the detector design**
  - Requires understanding how data quality and performance are related to detector properties!

Particle Identification at MeV Energies

- **Detector environment:**
  - JUNO full MC

    → 20kt LAB-PPO + bis-MSB (pure LS)

    → **~3% Cherenkov-light** (2/3 of this is scatter)

    total coverage ~80%

    ~5000 dynode PMTs (σ_{TTS} = 1.27 ns)

    ~12000 MCP PMTs (σ_{TTS} = 5.1 ns)

    → Much worse TTS than Theia and no WBLS

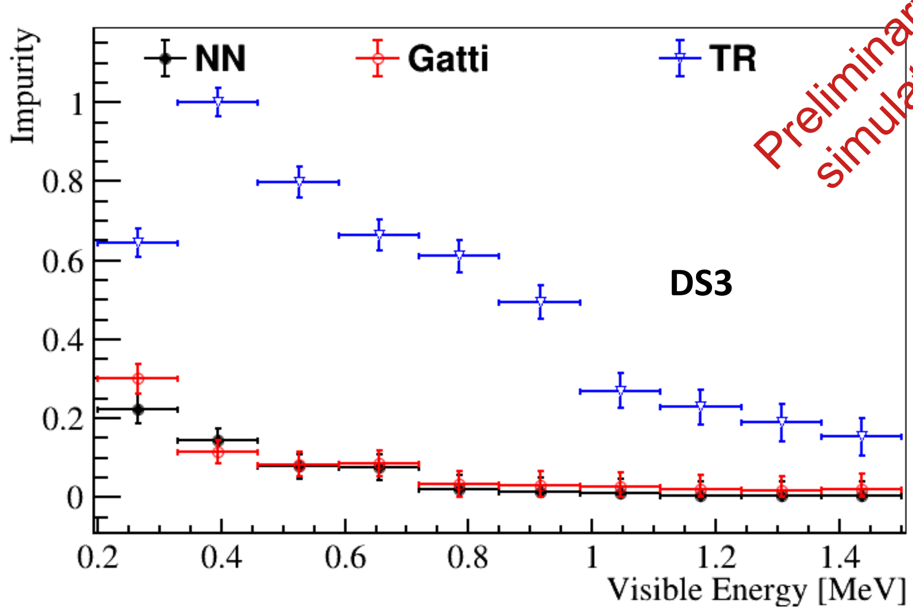
- **Assumptions:**
  - Know vertex from previous reconstruction methods
- **Compared three methods:**
  - **Gatti:** Time of Flight (ToF) corrected time spectrum of all hits
  - **ML:** Uses the same data (1D-data)
  - **Topological reconstruction (TR):** 3D picture of event signature (+ cut based analyses / ML on 3D)

    (TR: Optimized for electron events)

Results Particle Identification I

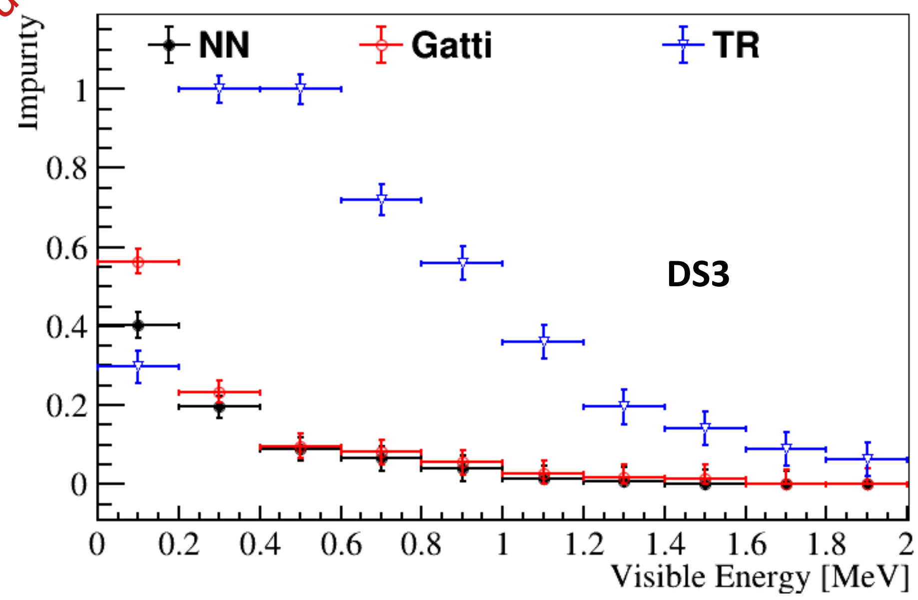
- Discrimination based on long tail of α and proton time spectrum

α/β discrimination at 90 %efficiency



Preliminary JUNO simulation used

p/β discrimination at 90 %efficiency



L. Ludhova et al. arXiv:2007.02687

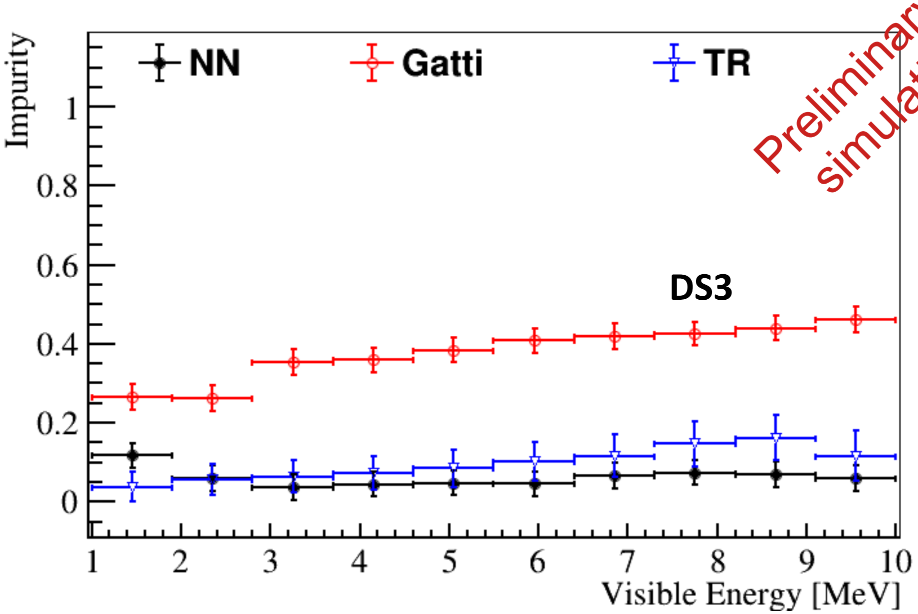
- ML slightly better than Gatti
- TR not compatible (but also not optimized for this)

Results Particle Identification II

- Discrimination based on topological differences

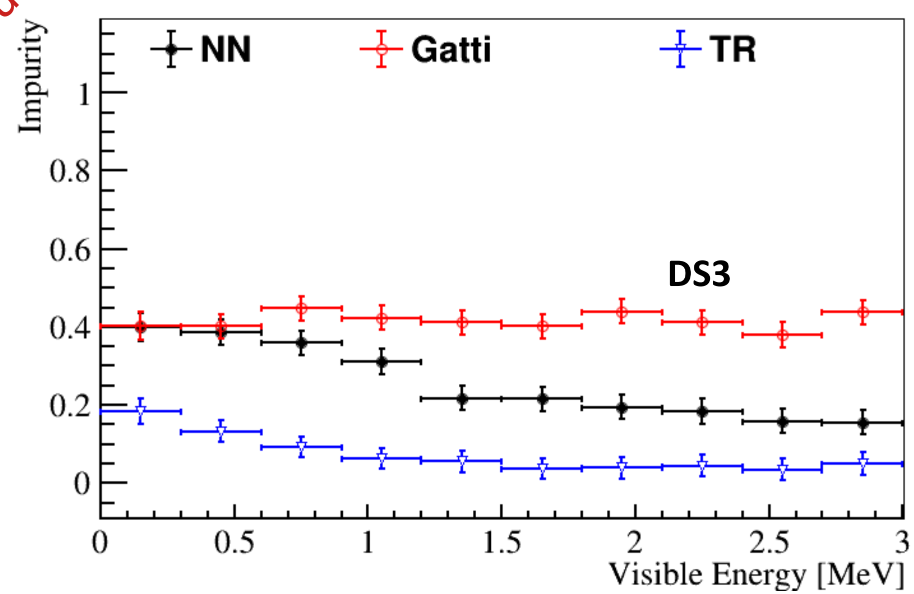
  (additional γ, several Compton scattering points, etc.)

e+/e- discrimination at 50% efficiency



Preliminary JUNO simulation used

e-/γ discrimination at 50% efficiency



L. Ludhova et al. arXiv:2007.02687

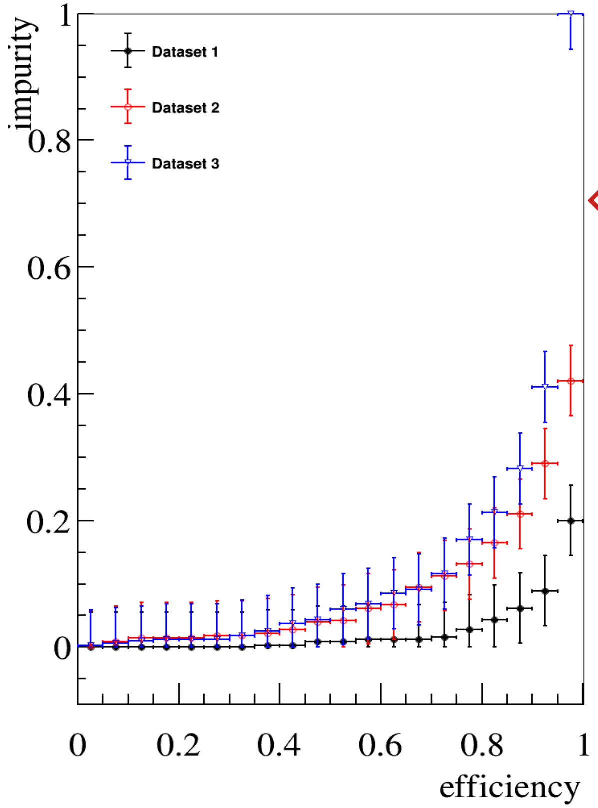
- ML best for e+/e- but TR best for e-/γ
- Gatti not compatible (but also not optimized for this)

Results Particle Identification III

- **Data-set 1:** No TTS, perfect vertex, no DCR
- **Data-set 2:** Added TTS and realistic vertex
- **Data-set 3:** Added Dark Count Rate (DCR)

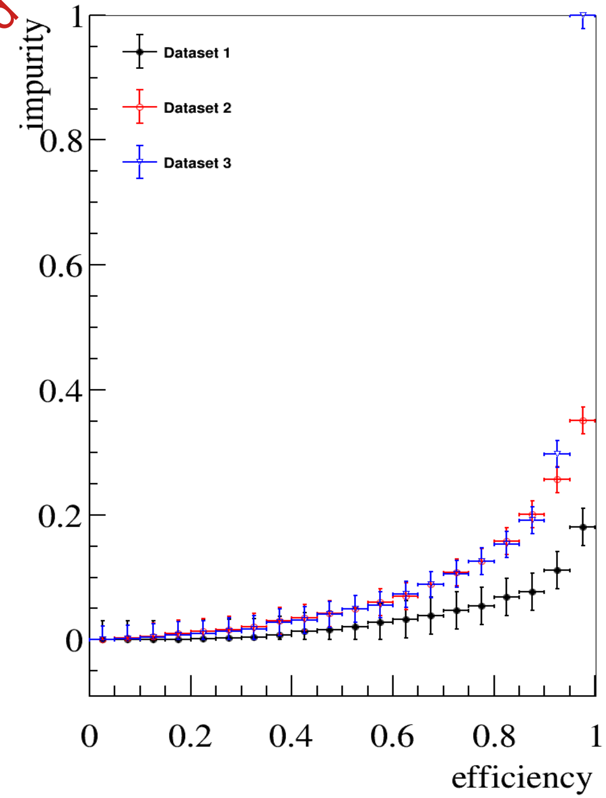
L. Ludhova et al. arXiv:2007.02687

e+e- discrimination



Preliminary JUNO simulation used

e-/γ discrimination

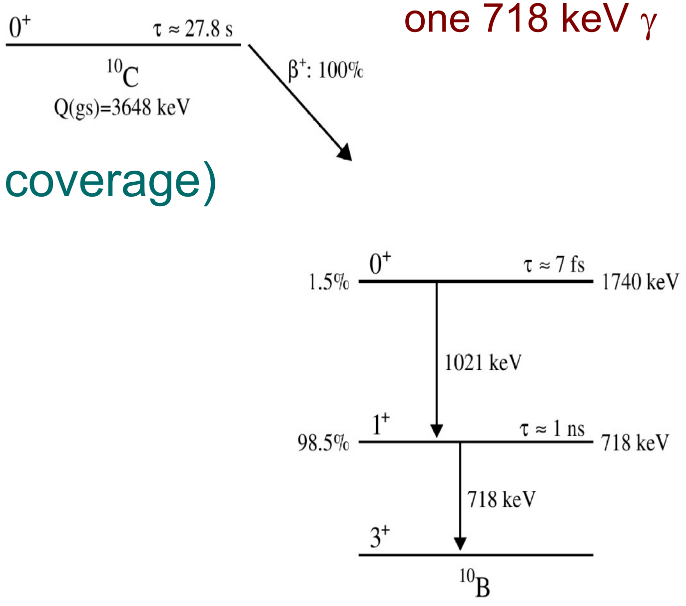


Gap between data-set 1 and 2 indicates huge potential of good TTS

(good TTS will also affect the vertex resolution)

Machine Learning Example: C-10

One positron + at least one 718 keV γ



- Studied in A. Li et al. , arXiv:1812.02906
- Using a Convolutional Neural Network (CNN)
- In KamLAND-like detector (~1ns σ_T, 23% QE, 16% coverage)

→ 62% bkg reduction at 90% signal efficiency

83.5% for JUNO-like coverage and QE,

98% for perfect light collection

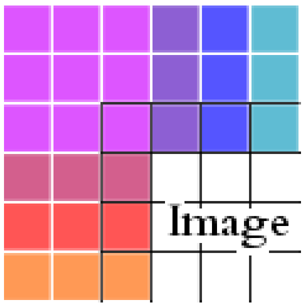
(time delay of ortho-positronium decay not used)

- C-10 is background (bkg) for solar-ν and $0\nu\beta\beta$
- I see similar potential for I-130 & Cs-136 ($0\nu\beta\beta$ bkg)

Conclusion: High granularity and statistics (coverage) are important!

Directional Reconstruction: What Kind of Network do we Use?

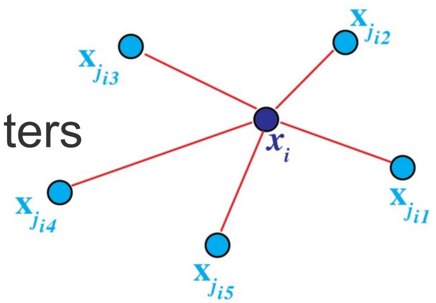
- **CNN:**
  - CNN use structured data in Cartesian space
  - Converting unstructured and sparse 3D Data (our PMT-positions) can lead to loss of information and quantization problems
  - Computation intensive if volume approach or a combination of several views is used to handle 3D point clouds



- **Graph-Neural-Networks**
  - Use unsorted nodes + connections (edges)

    → All operations need to be invariant against permutation

    (like max or average)
  - Nodes and edges can have features (color, id, ...)
  - Nodes usually not equidistant → hard to use kernel based filters
  - Hard to get power of convolution integrated

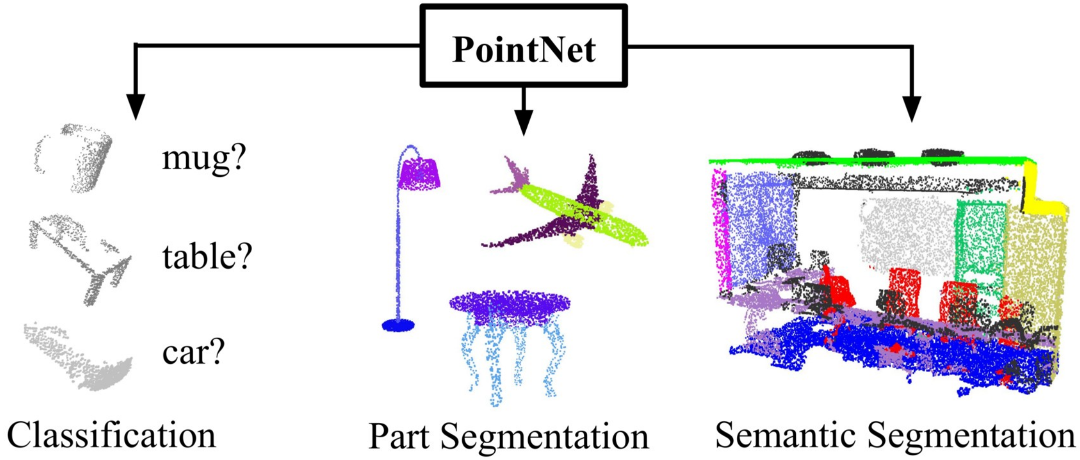


Choice of ML-Tool: PointNet

- **PointNet:**
  - Optimized for point clouds
  - Can do classification and segmentation
  - Each point is a vector (x,y,z) + features (no edges)
  - Operating on each point independently
  - Subsequently applying a symmetric function to accumulate features (max pooling)

    → Invariant against permutation by using max pooling

    + not so good in capturing local features
  - Robust to various kinds of input corruptions



Charles R. Qi et al.: https://arxiv.org/abs/1612.00593v2

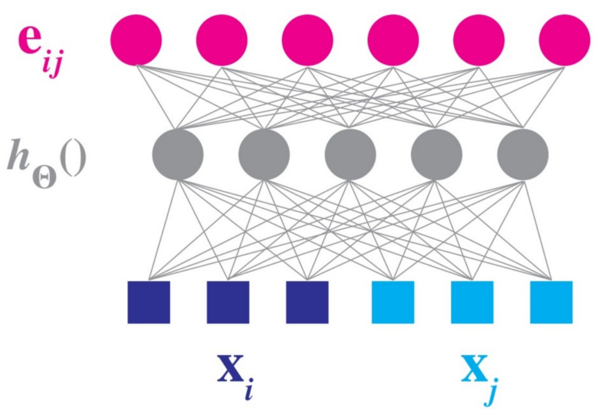
Choice of ML-Tool: DGCNN

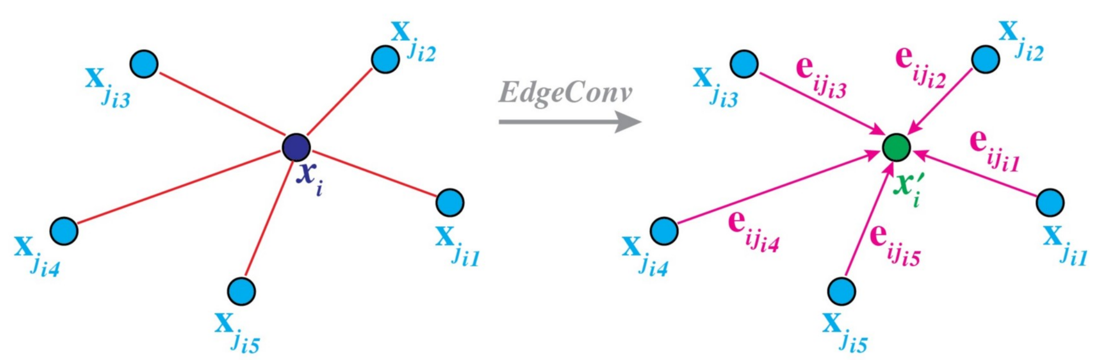
- **Dynamic Graph CNN (DGCNN):** Yue Wang et al.: https://arxiv.org/abs/1801.07829
  - Independent neural network module
  - Can be used with PointNet (also has been in original publication)
  - Also uses only symmetric aggregation function (like the max pooling in PointNet)
  - Constructs local neighborhood graph using closed k-points in (feature) space

    (→ Needs to define metric to measure distances in feature space)
  - Applying convolution-like operations on the edges connecting neighboring pairs of points (called EdgeConvolution)
  - The neighborhood graph is rebuild (in feature space) after each layer

    → Graph changes dynamically

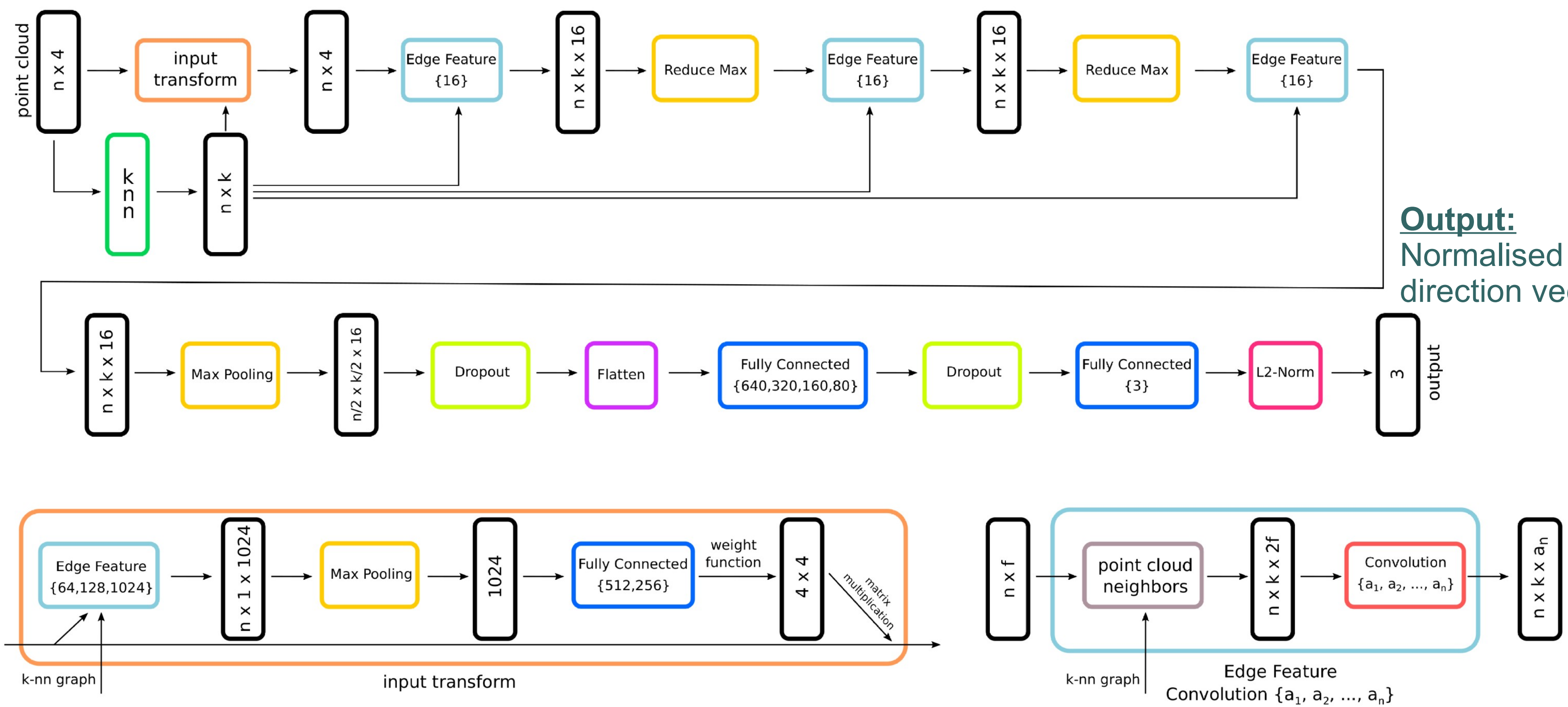
    → No deterministic neighborhood relation
  - Stacking this propagates local features over long distances and thus enables connection to global features





Our Network

- Use always the same k-neighbors
- Instead of finding neighbors in the feature space of each layer
- Made 'static' again by using always same neighborhood graph



Output:
Normalised direction vector

Data Treatment

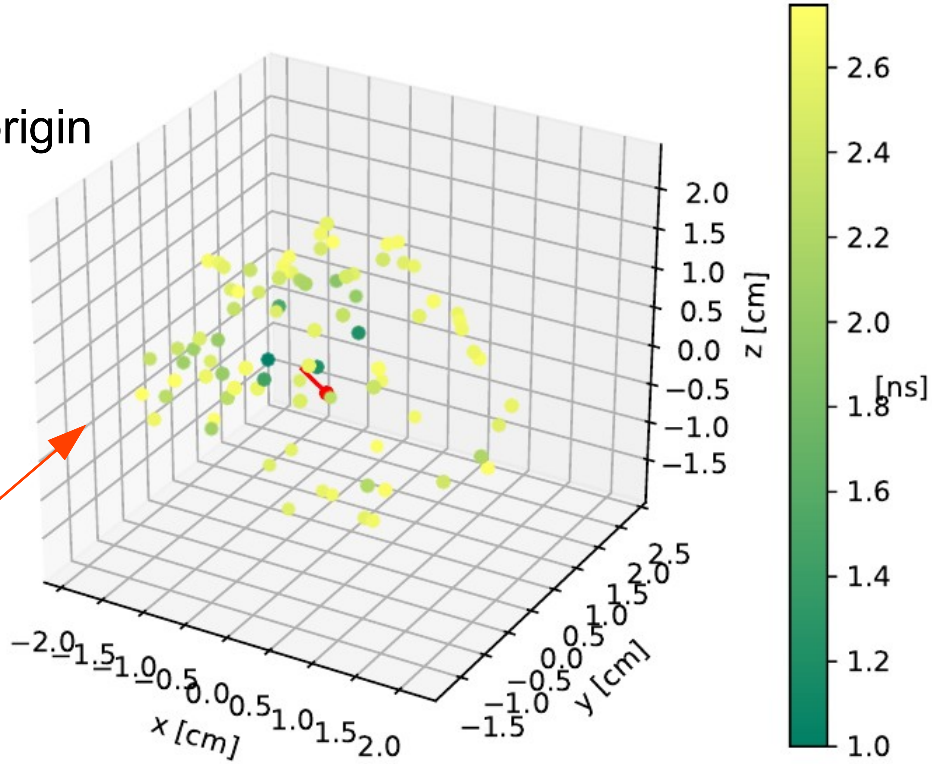
- **Assume vertex to be known by other methods!**

  Use this to correct signals for time of flight

- **Use special projection on unit-sphere:**

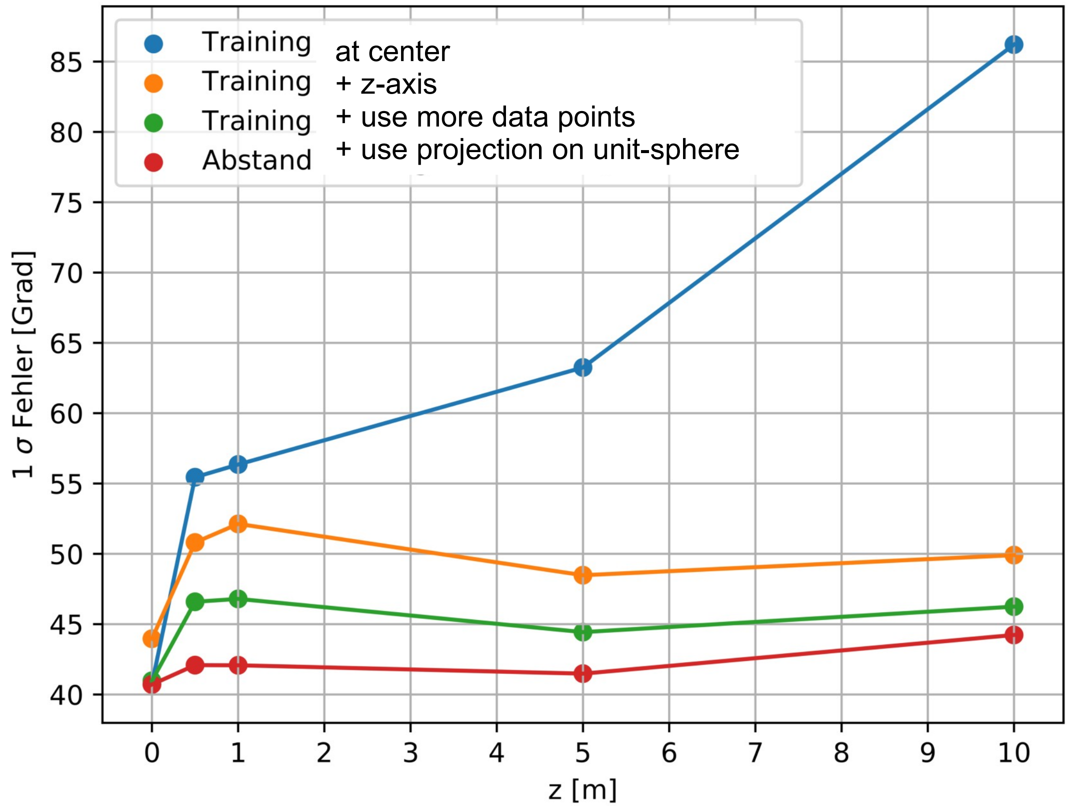
  Project PMT-position on unit sphere around vertex
  → Angular position for each signal

  Use time to modulate distance of point to origin
  → Time deformed sphere around vertex



All signals surviving 2.75 ns time cut projected on unit sphere around vertex (red)

Influence of Training-Data



First three colors:

No projection on unit sphere

set	count	energy	position
training	210,000	3 MeV	center and z-axis *
validation	5,200	4 MeV	center
energy evaluation	8 x 5,200	1 - 8 MeV	center
vertex evaluation	5 x 5,200	4 MeV	z-axis: 0 to 10 meters

* 100,000 events at detector center, rest evenly distributed along z-axis

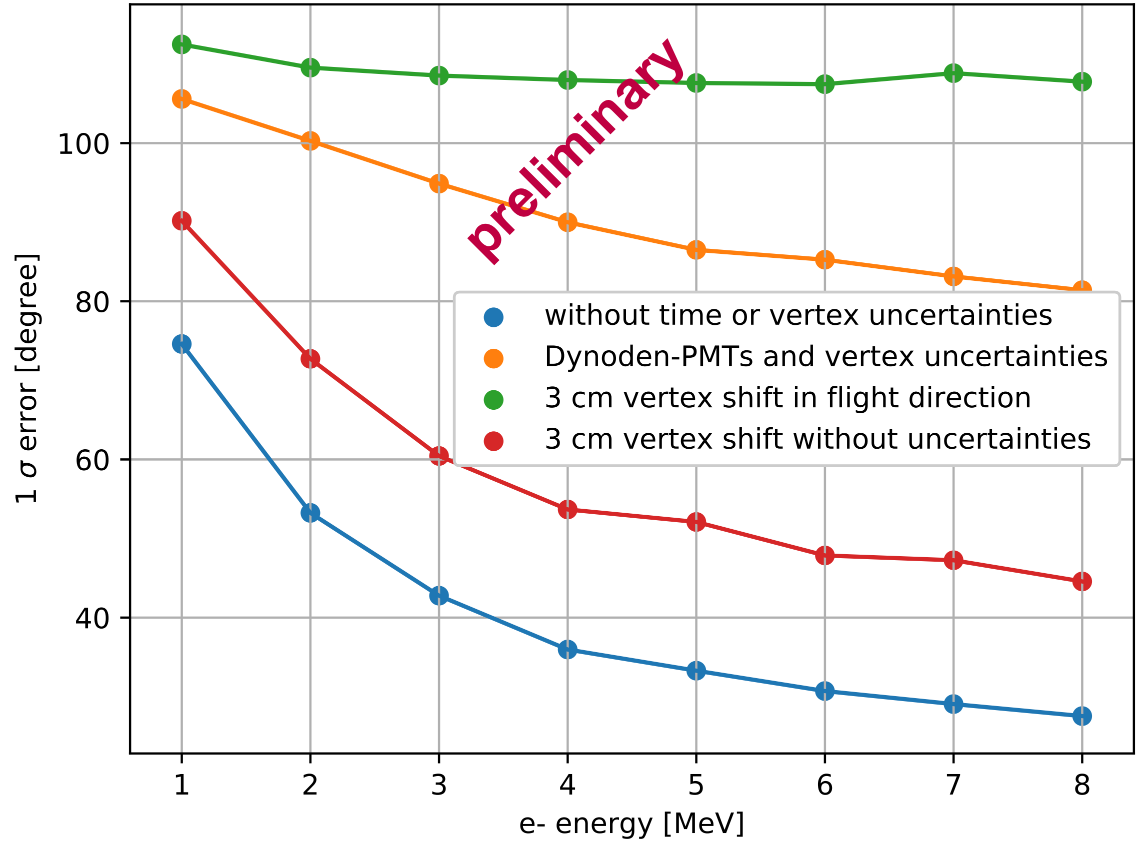
Final Results: JUNO

3 cm bias of vertex in flight direction is included (green):
As expected from vertex reconstruction (that assumes only scintillation light)

Blue & red line:
All PMTs used (80% coverage)

Green & yellow line:
Only dynode PMTs (25% coverage)

Preliminary JUNO simulation used



Conclusion:

- Not much directional information in JUNO
- But a change of strategy might help to improve (do not rely on vertex)

Results with better TTS

- **Assuming 1 ns TTS for all PMTs** (80% coverage)

  → Theia-like instrumentation

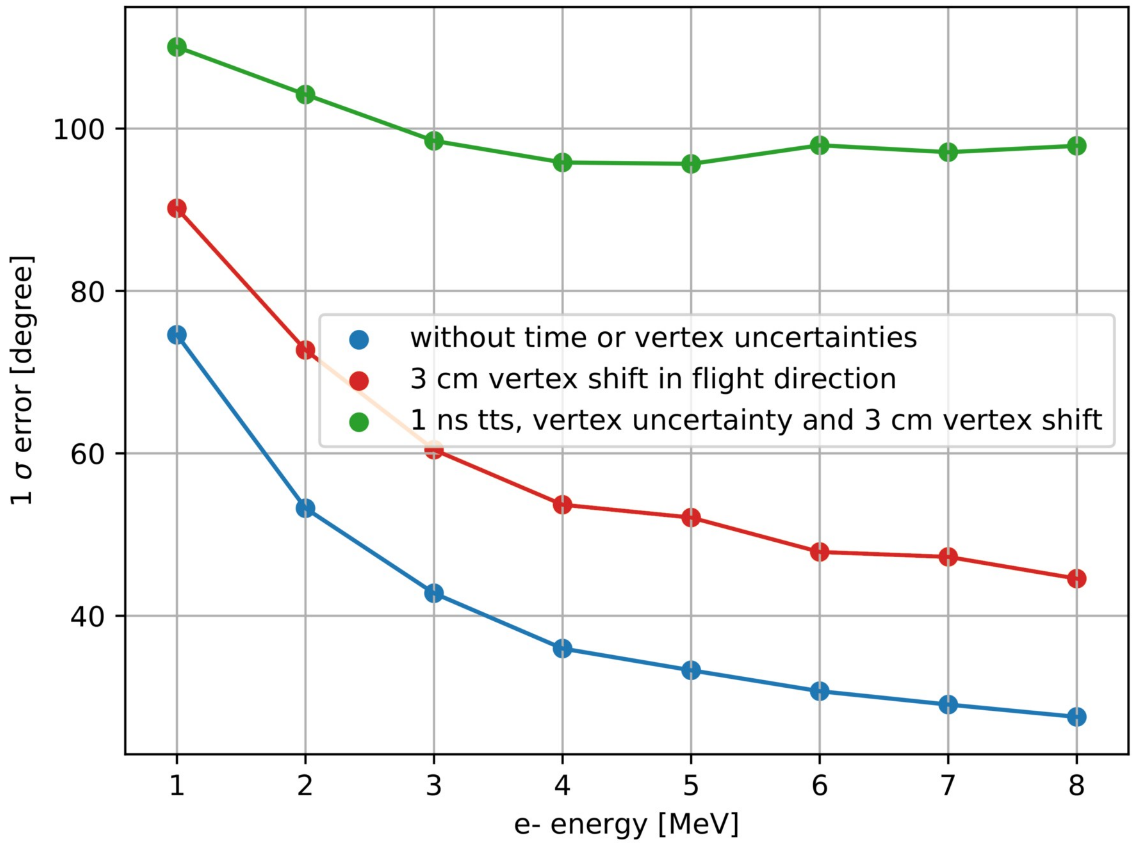
Green line:

1 ns TTS, 80% coverage,
3 cm vertex bias,
6 cm/√E vertex resolution
0.1 ns vertex time resolution

Blue & red line:

The same as before

Preliminary JUNO simulation used



Probably need to extract vertex and direction simultaneously to further improve this!

Results with better TTS

- **Assuming 1 ns TTS for all PMTs** (80% coverage)

  → Theia-like instrumentation

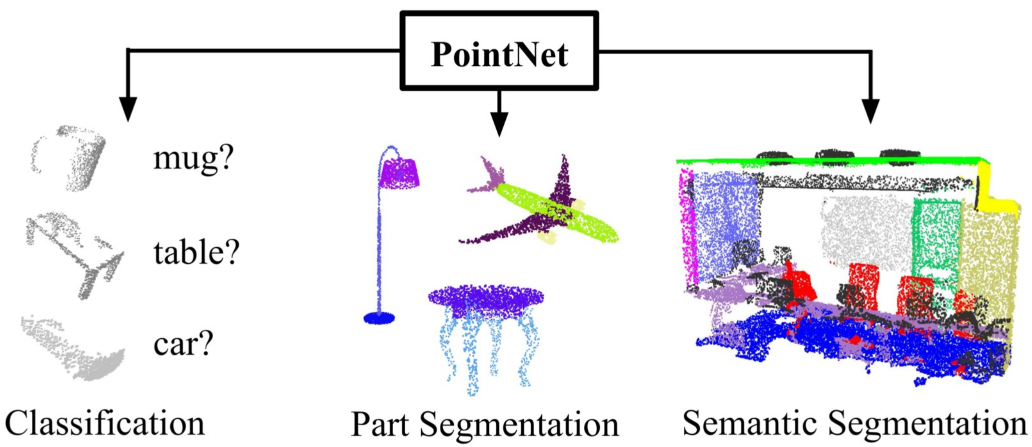
Gre

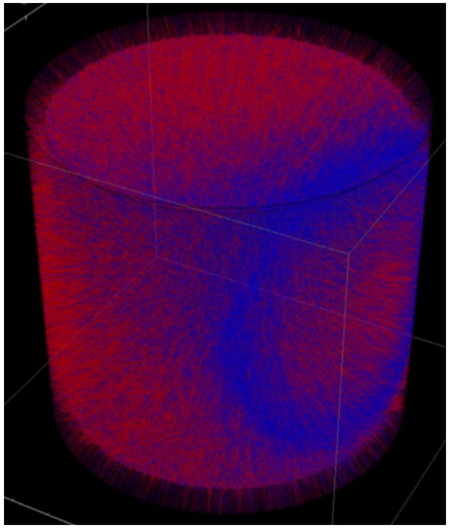
Blue

Remark: Here only 3% Cherenkov-light
(in WBLS much higher ratio)

→ Should be much easier in WBLS (work in progress!)
(but will also depend on how fast the scintillation is in WBLS)

- The same DG-CNN could also be used to separate Cherenkov from scintillation signals





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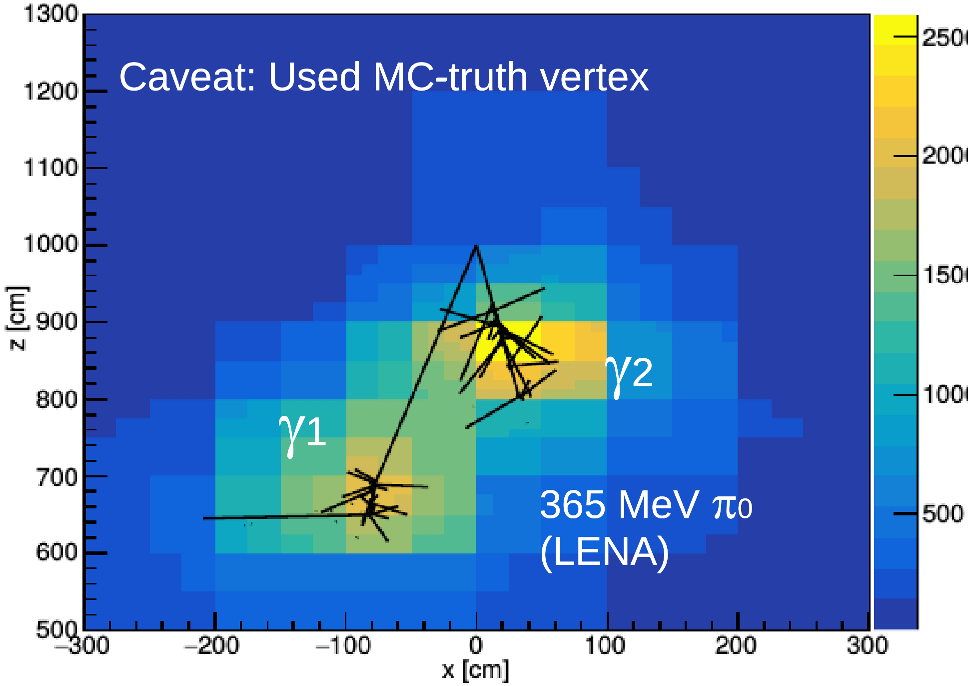
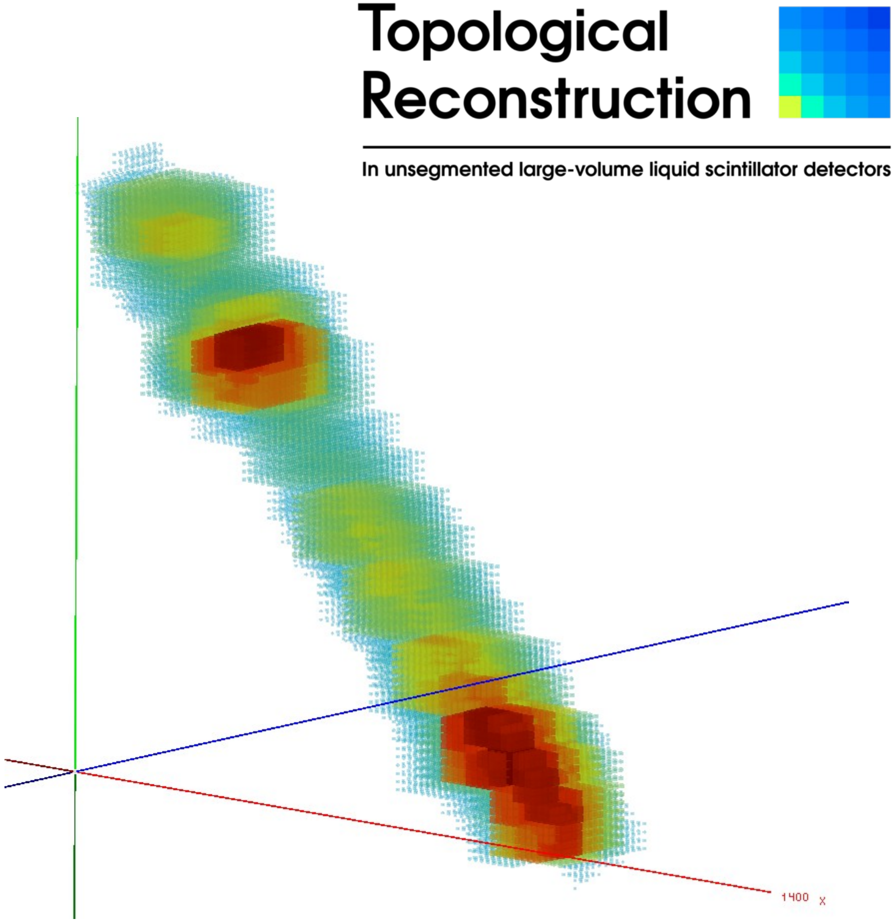
improve this!

Goals at GeV Energies

- **Non-ML methods:** Full topological reconstruction can reveal many details
- **But:** Very computing intensive & lack robustness in some cases
- **Question:** Can ML do better?

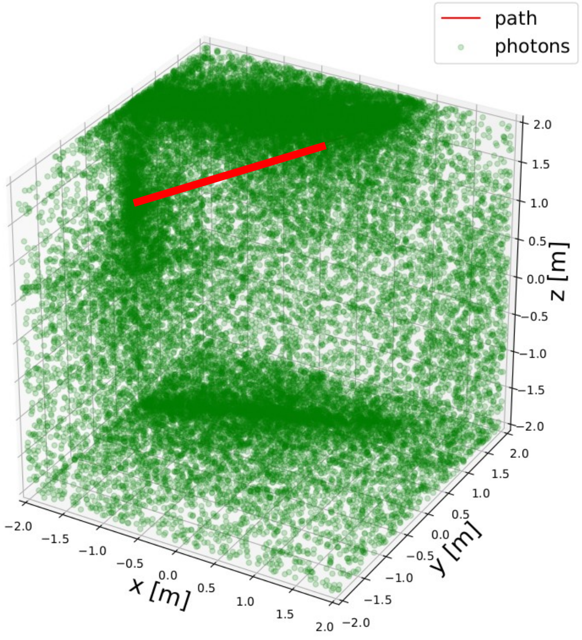


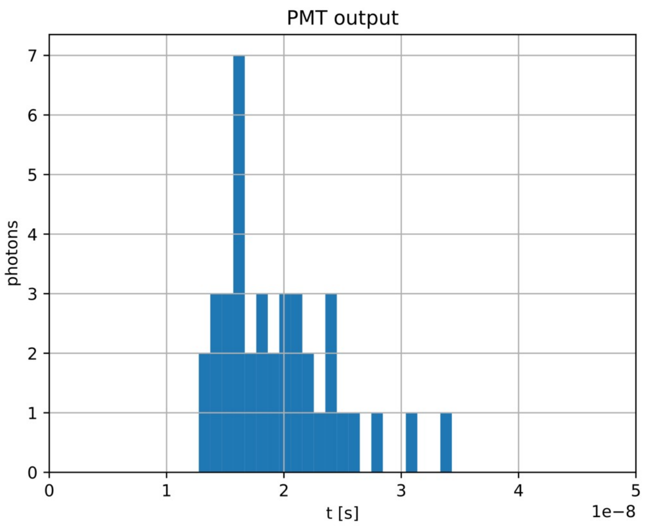


How to do Something Similiar with ML?

- **Scenario used:**
  - Toy-MC simulating scintillation along random track with a high emission point (peak)
  - No light attenuation or scattering (otherwise full LS model)
  - Cubic detector with 4m edge length
  - 100 PMTs with 1ns time resolution per wall (full coverage)

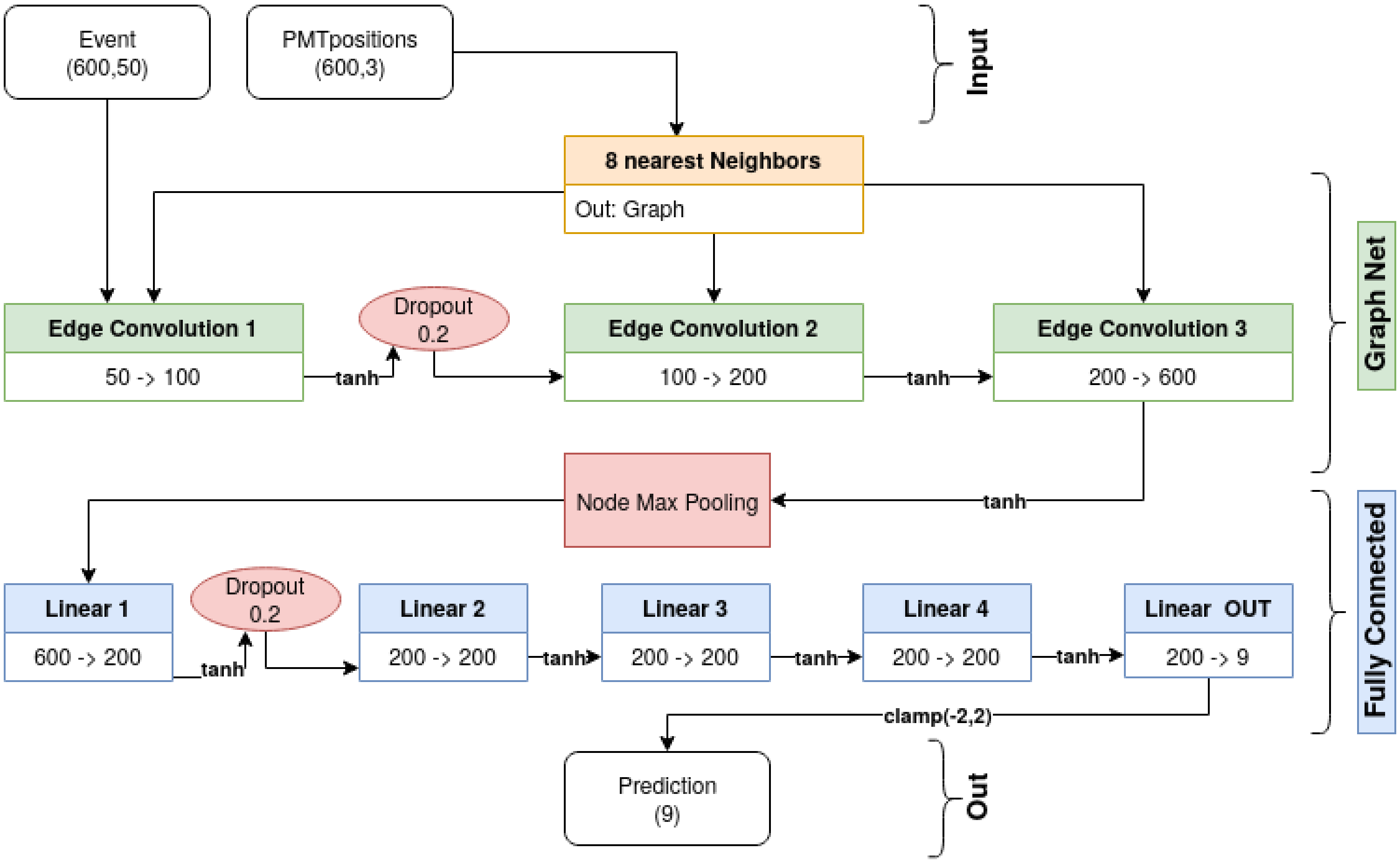
- **Two output goals:**
  - Coordinates of start-, end- and peak-position
  - Voxel reconstruction





ML Architecture For Shower Reconstruction

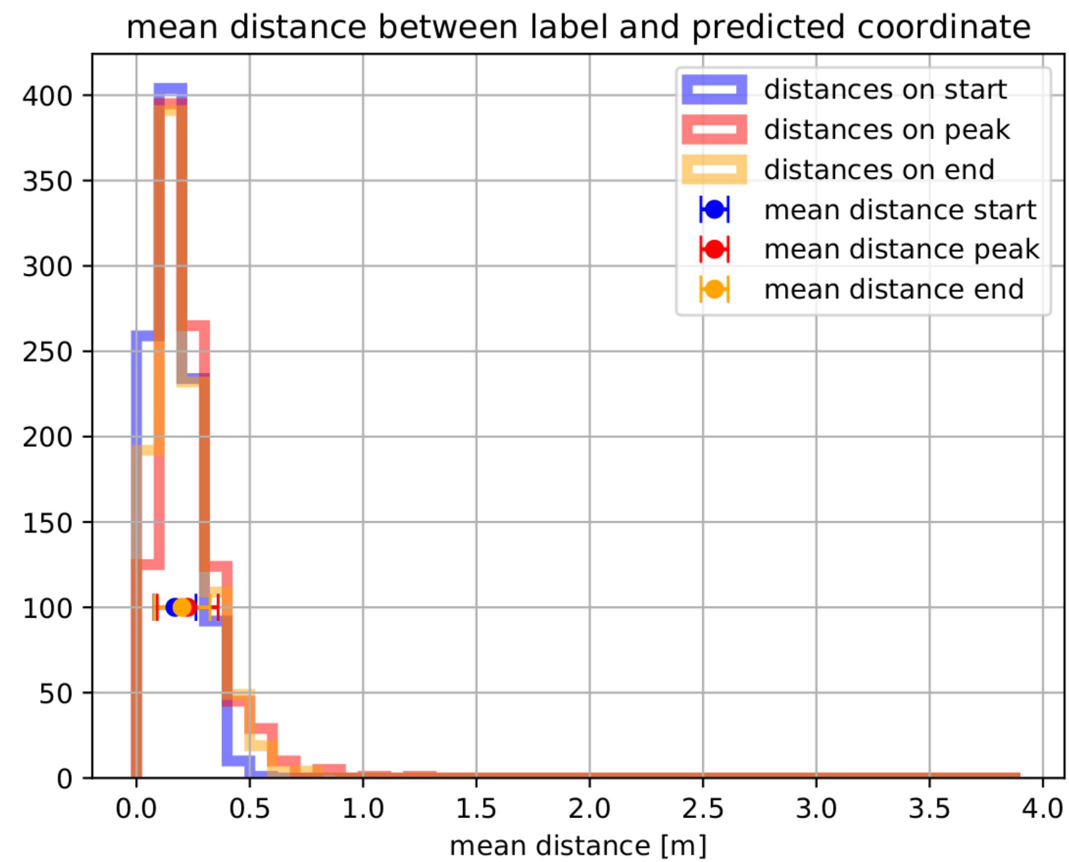
- **First stage:** Dynamic Graph CNN
- **Second stage:** Fully connected layers (standard CNN)



First Results: Shower (Peak) Finding

Promising first results:

Position	Mean distance
Entrance	$0.16 \pm 0.09\,\mathrm{m}$
Peak	$0.22 \pm 0.14\,\mathrm{m}$
Exit	$0.20 \pm 0.12\,\mathrm{m}$



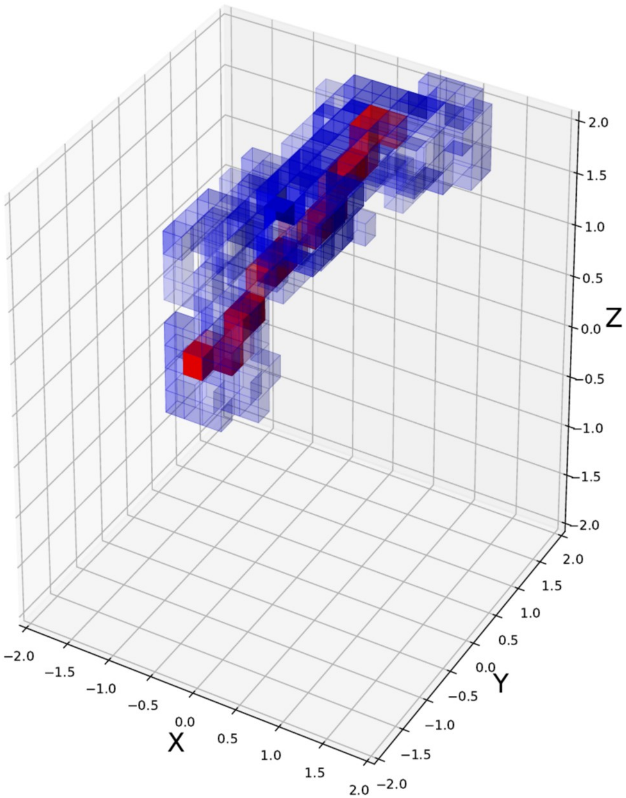
Next steps:

- Go to more realistic detector/simulation
- Look at more complicated events

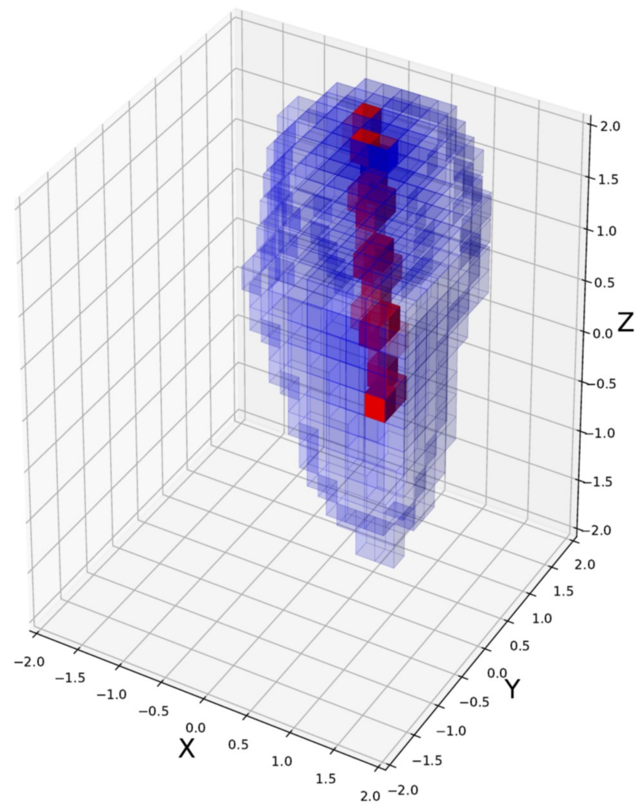
Outlook: First Results Voxel Reconstruction

Red: MC Truth
Blue: Network output

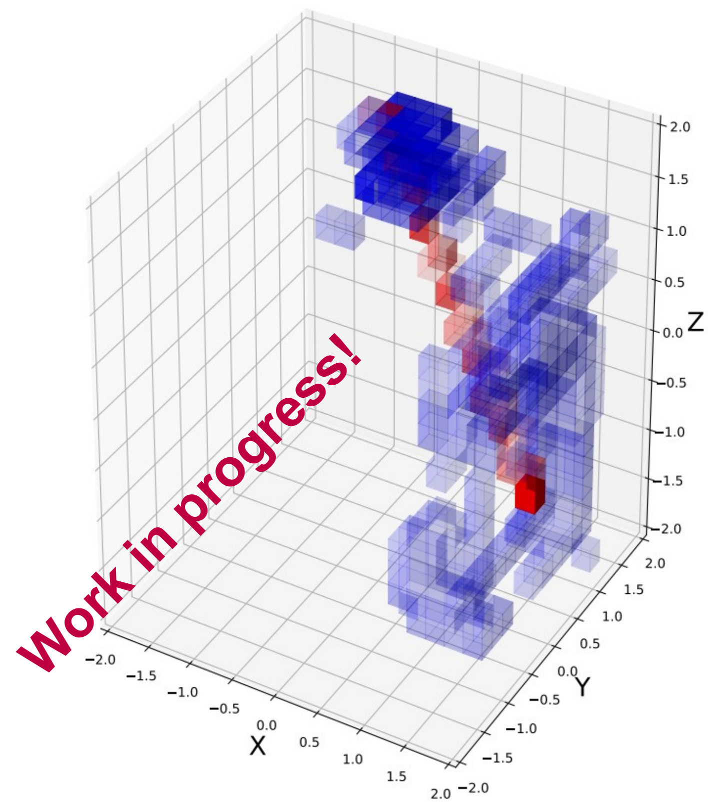
Using L1-regularization in loss function



Result of homogeneous network



Result after propagation layers

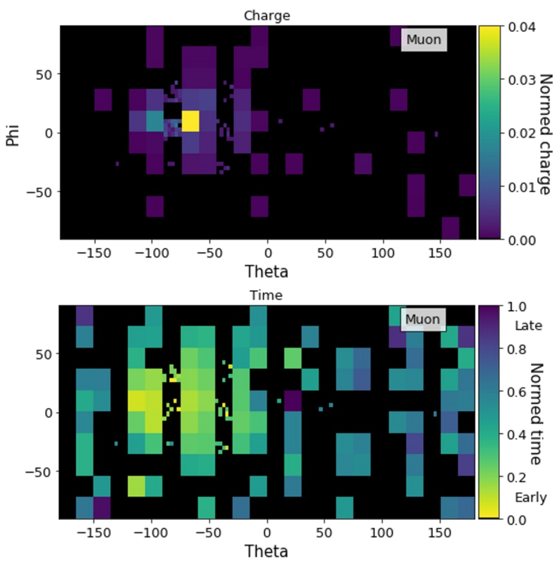


Result heterogeneous network (after training)

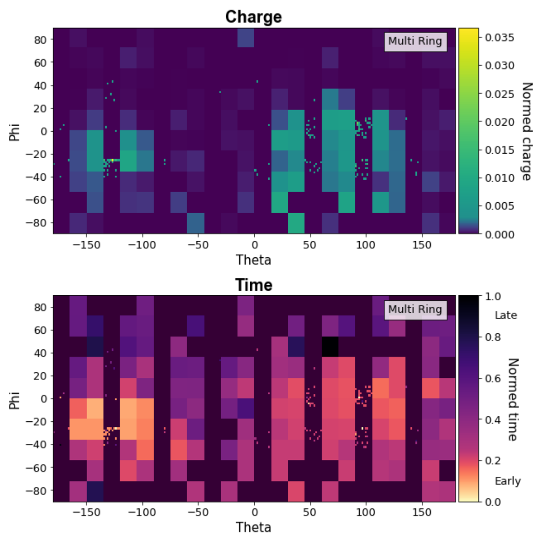
Event Classification with CNNs in ANNIE

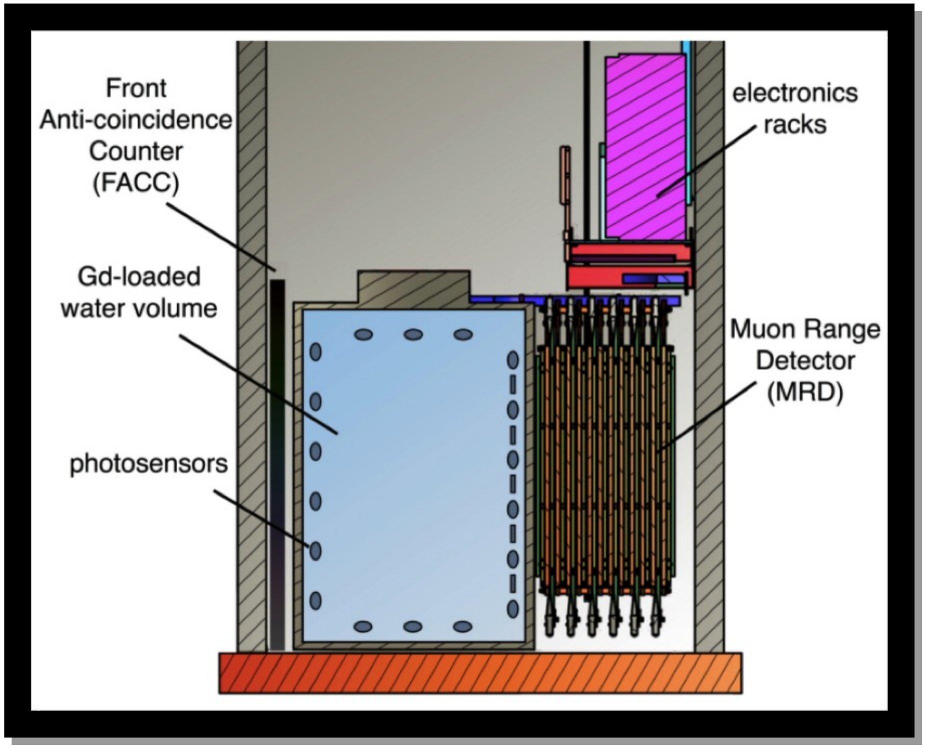
- **Water-Cherenkov detector (26 ton) operated in Booster-neutrino beam (at Fermilab)**
- **First neutrino experiment using LAPPDs**
  - → TTS ~ 0.1 ns, spatial resolution ~ 1mm
  - Assumed 24 LAPPDs in simulation for this study

Single ring/disk



Multi rings/disks

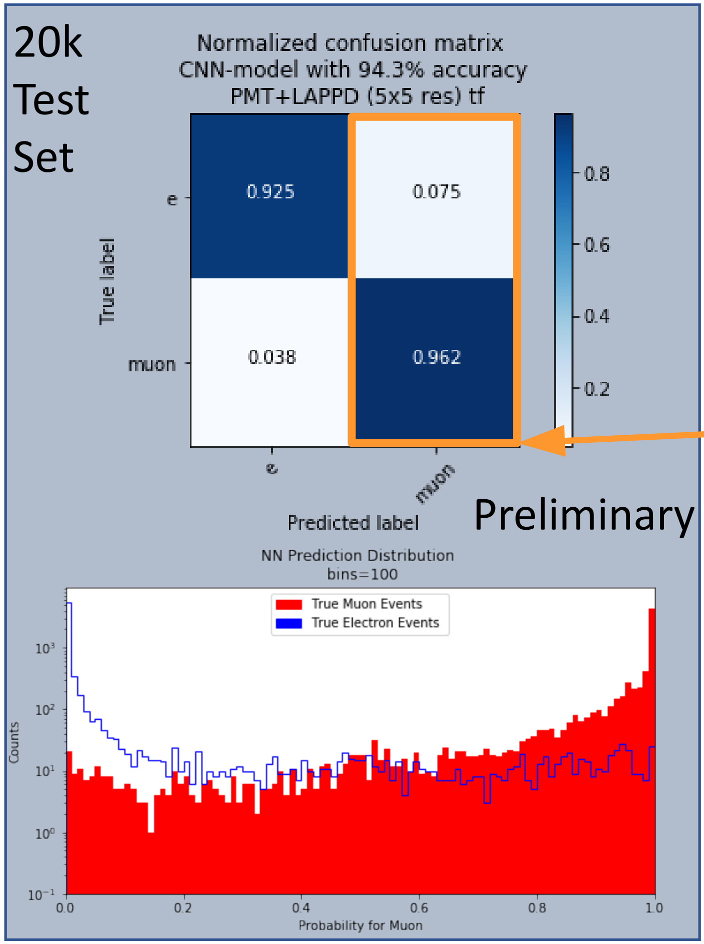




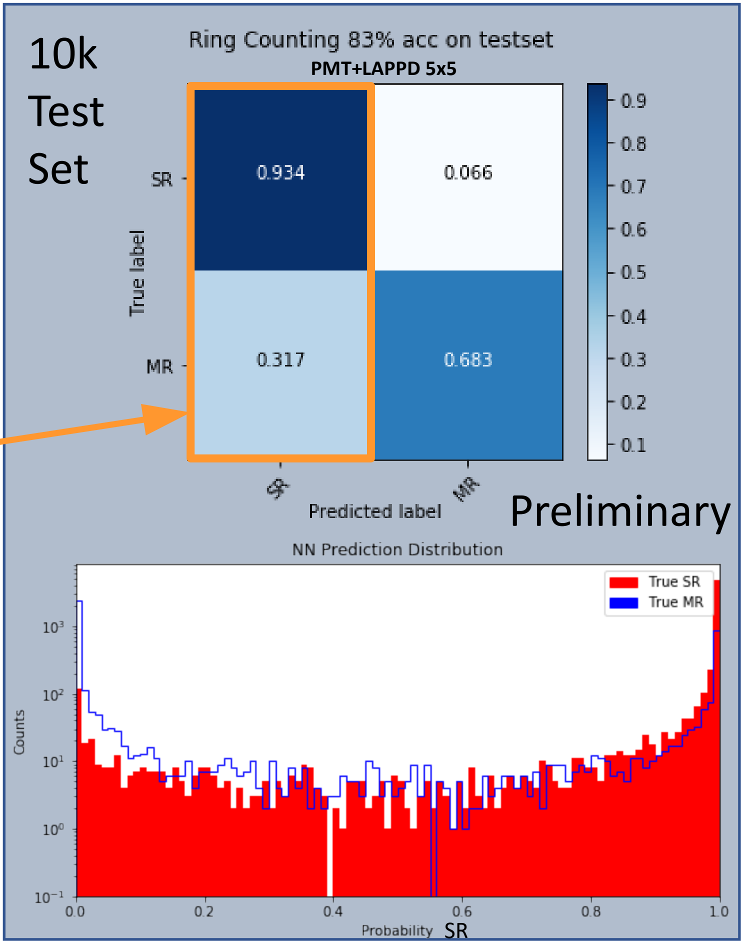
Identifying CCQE-0π Events

- **Two classification tasks:**

Electron vs. muon



Single ring (SR) vs. multi ring (MR)



CCQE-0π candidates

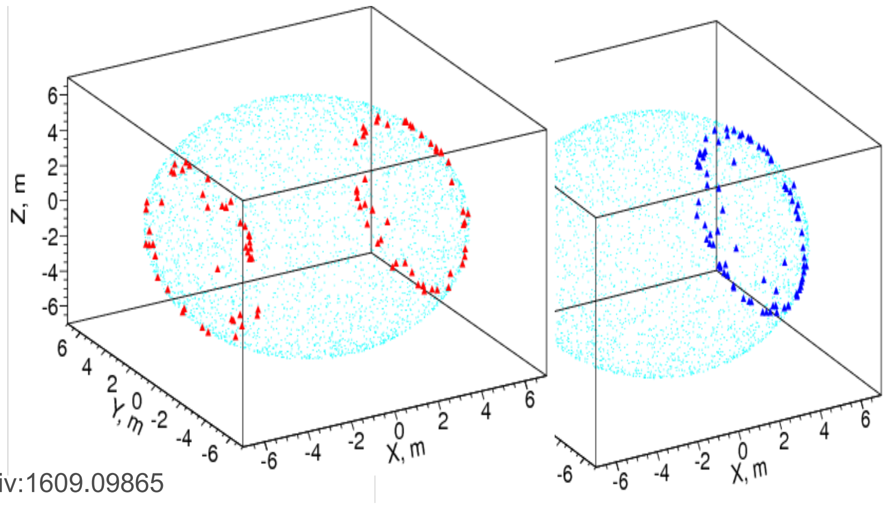
Result: Up to 5% **increases** of accuracy compared to classical methods
→ Efficiency > 92% for each task (impurity <0.3%)

Summary/Conclusion

- **Theia is a proposed detector**
  - Large community interest, collaboration has been formed
  - **White paper:** M. Askins et al., Eur.Phys.J.C 80 (2020) 5, 416, arXiv:1911.03501

- **ML learning is a central to reach its full potential**
  - Particle Identification in pure LS already very successful
    - Profits a lot from fast timing, high granularity and large coverage
    - Separating Cherenkov-light will increase potential further
  - Directional reconstruction difficult in LAB+PPO+bis-MSB (MeV energies)
    → The right cocktail (WBLS, slow LS, ...) will help a lot!

- **Goal:** Unlock power of C/S-ratio and ring-counting



A. Elagin et al., arXiv:1609.09865

Backup slides

Theia Interest Group

Canada
Alberta
Laurentian
Queens
Toronto

China
Tsinghua

Finland
Jyvaskyla
Oulu

Germany
Aachen
Dresden
Juelich
Mainz
TU Munich
U. Hamburg

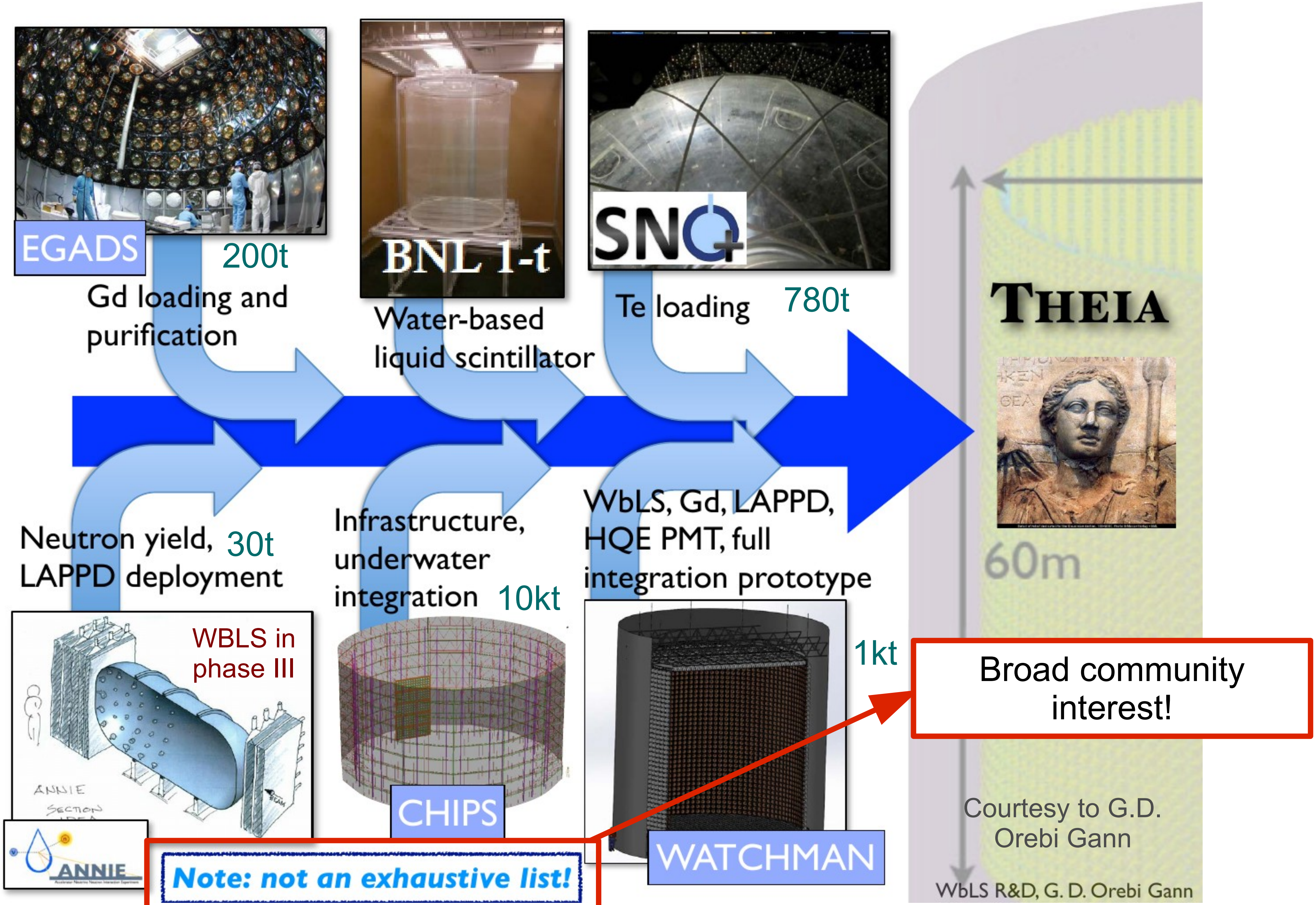
Portugal
LIP

UK
Sheffield

US
Brookhaven NL
Boston U.
U. Chicago
Colorado U.
Cornell U.
U. Hawaii
Iowa State
Lawrence
Berkeley NL
LSU
MIT
U. Penn
Stony Brook
SURF
Temple
UC Berkeley
UC Davis

Most of these institutes joint the Theia proto-collaboration!

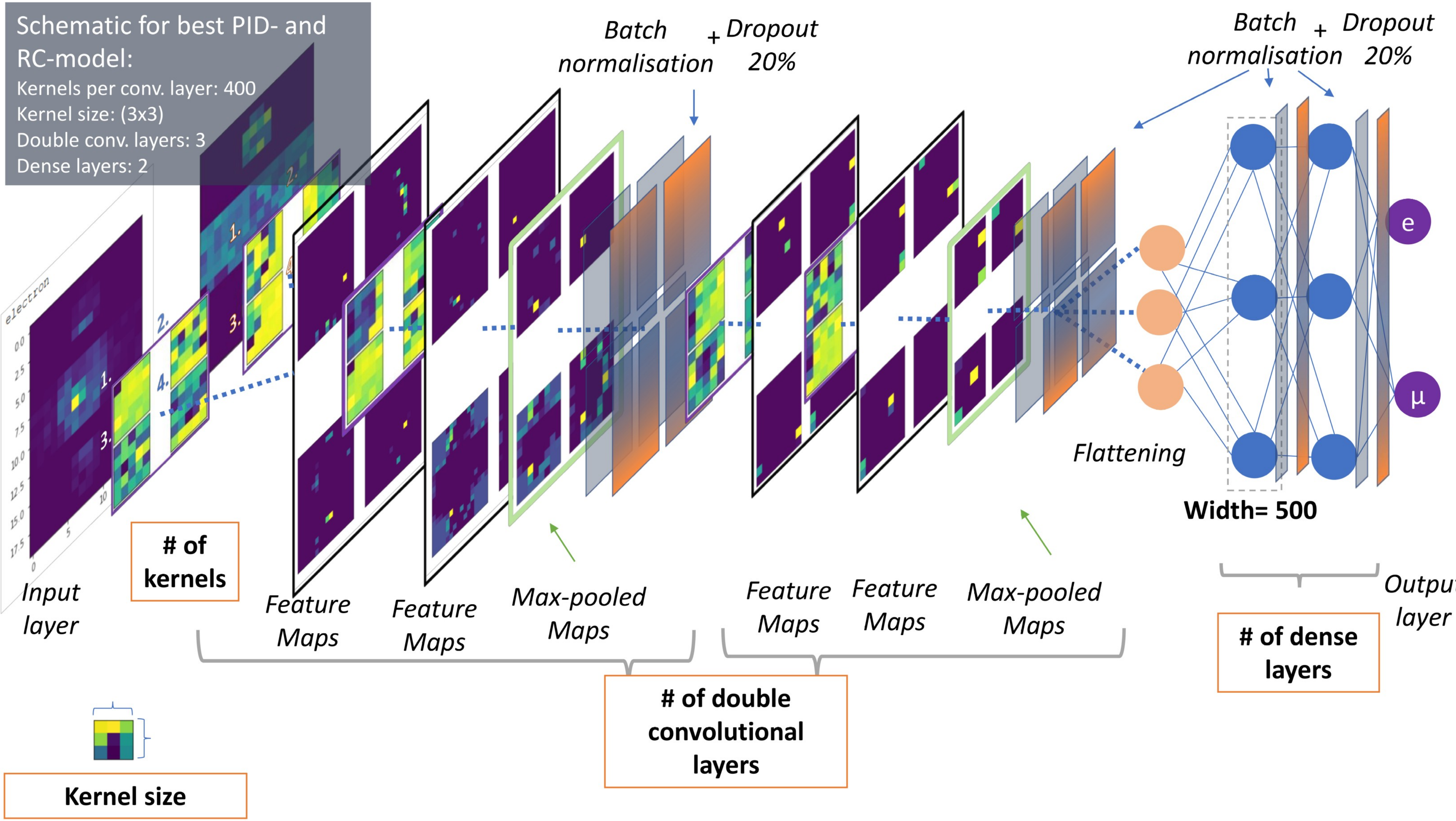
Bringing everything together



Community Interest

Site	Scale	Target	Measurements	Timescale
UChicago	bench top	H2O	fast photodetectors	Exists
CHIPS	10 kton	H2O	electronics, readout, mechanical infrastructure	2019
EGADS	200 ton	H2O+Gd	isotope loading, fast photodetectors	Exists
ANNIE	30 ton	H2O+Gd	isotope loading, fast photodetectors	Exists
WATCHMAN	1 kton	H2O+Gd	isotope loading, fast photodetectors	2020
NuDot	1 ton	LS	directionality	2018
Penn	30 L	(Wb)LS	light yield, timing, loading	Exists
SNO+	780 ton	(Wb)LS	light yield, timing, loading	2018
CHESS (LBNL)	bench top	WbLS	signal separation, tracking, reconstruction / light yield, loading, attenuation	Exists
BNL	1 ton	WbLS	signal separation, tracking, reconstruction / light yield, loading, attenuation	Exists

ANNIE CNN:Architecture

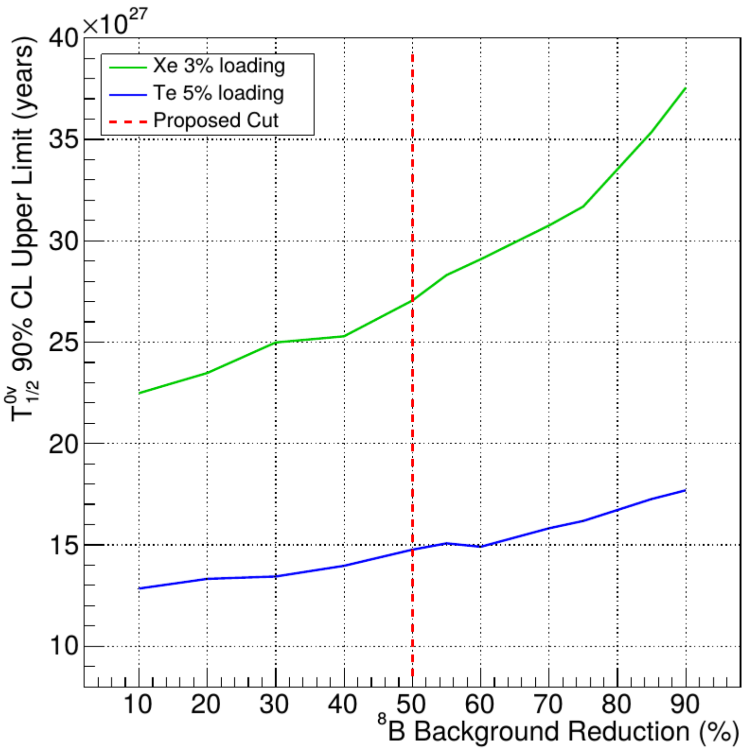


Influence of Directionality/Particle ID

- Cherenkov-light
  - Can reveal direction of solar neutrino events
  - And help particle identification
- Cutting events pointing away from sun reduces bkg
- Efficiency will strongly depend on scintillator & detector properties

(MC-simulations for 50% coverage in water show 80% rejection of B-8 bkg with 75% signal efficiency)

(R. Jiang & A. Elagin, arXiv:1902.06912: 65% coverage in LAB → >50% rejection with 70% signal efficiency)



Which events do we want to discriminate - and why?

$\boldsymbol{\alpha/\beta}$:

- α-background from natural radioactivity

$\boldsymbol{p/\beta}$:

- **supernova**: e.g. elastic scattering channel with protons (signal) vs β^- decay from ^{85}Kr, ^{210}Bi and ^{14}C
- elastic scattering channel with protons vs elastic scattering channel with electrons
- **geo-neutrino**: suppress background from ^{13}C(α,n)^{16}O interactions, which can result in elastic scattering on proton

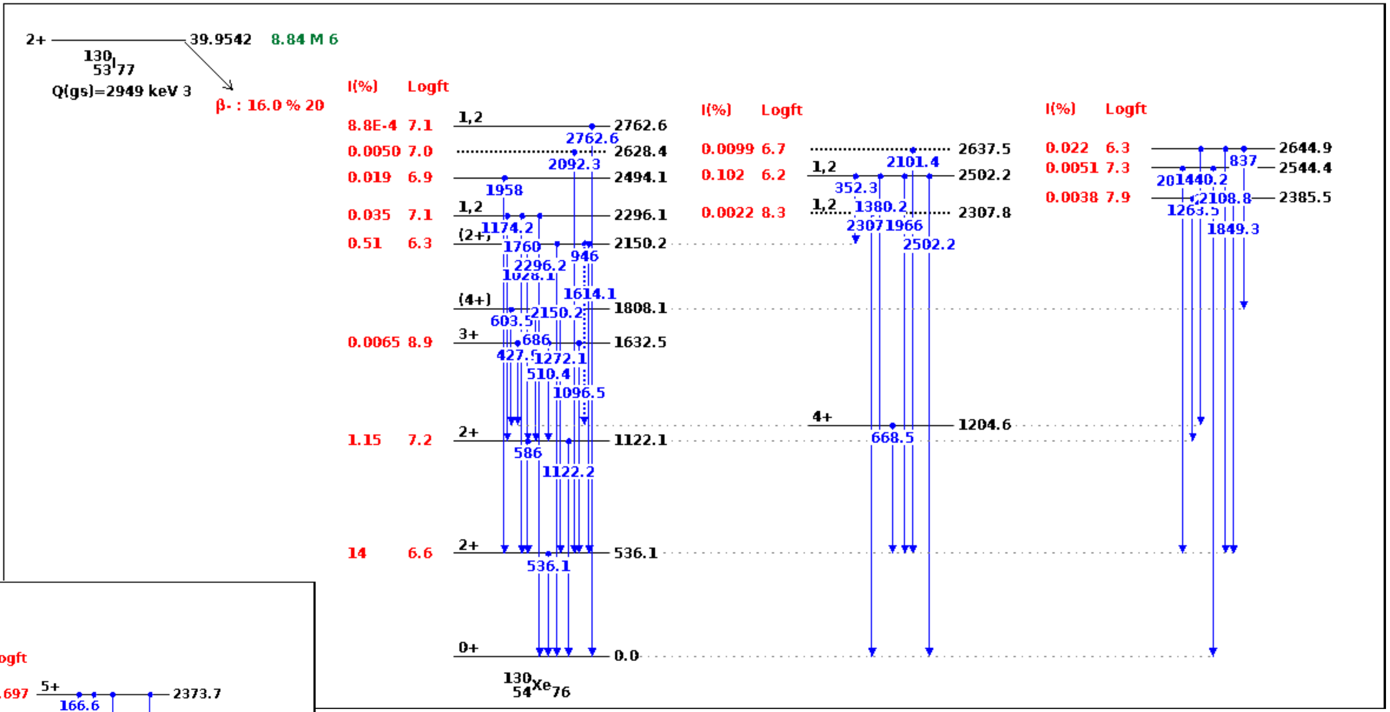
$\boldsymbol{e^+/e^-}$:

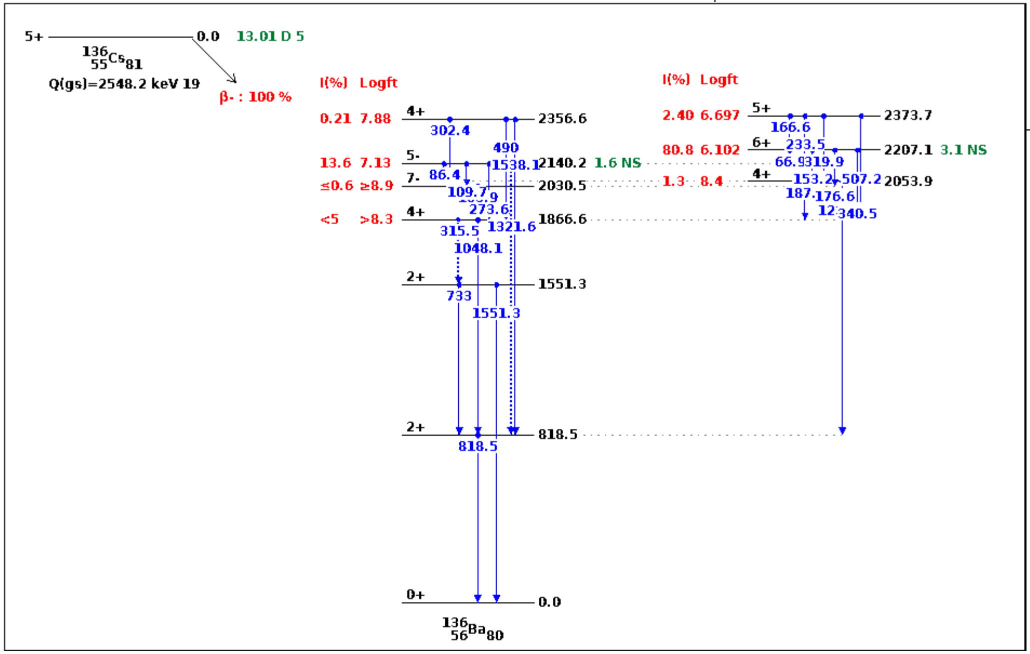
- **IBD**: measure **^{8}He and ^{9}Li yield** in interactions with cosmic muons (both β^-)
- **solar**: MSW-transition region (2 MeV – 4 MeV) partly dominated by β^+ decays from **^{10}C**

$\boldsymbol{e^-/\gamma}$:

- **solar**: external gammas from outside of the CD, high loss of exposure due to deep fiducial volume cut

Decay Schemes I-130 & Cs-136





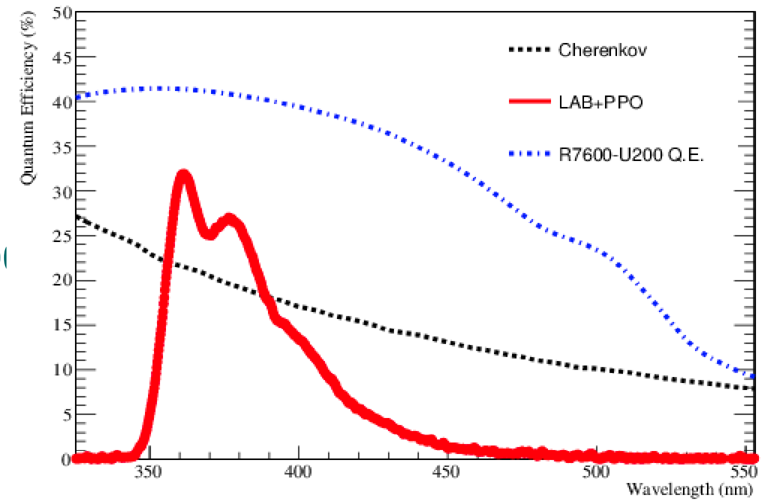
https://www.nndc.bnl.gov/nudat2

Cherenkov-Light Separation by Wavelength

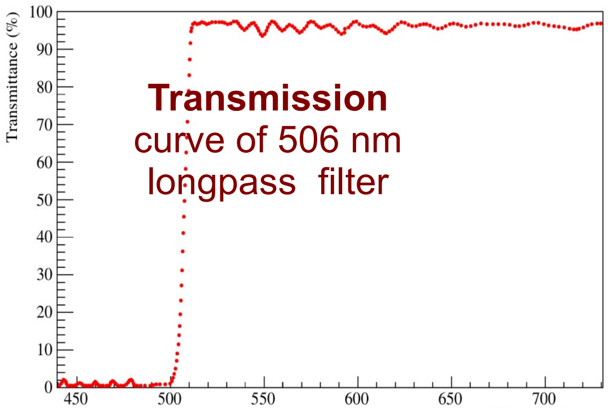
- Using dichroic filter

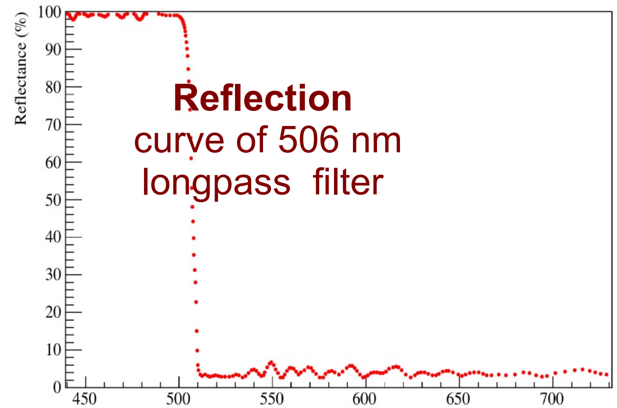
  (transmitting above or below a certain threshold, reflecting the rest)
- Optimal Cut for LAB-PPO (2g/l): 450 nm

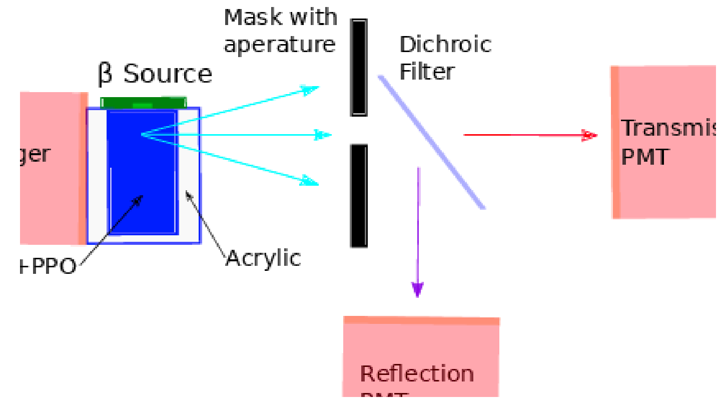
  Full description in T. Kaptanoglu et al., JINST 14 (2019) no.05, T050

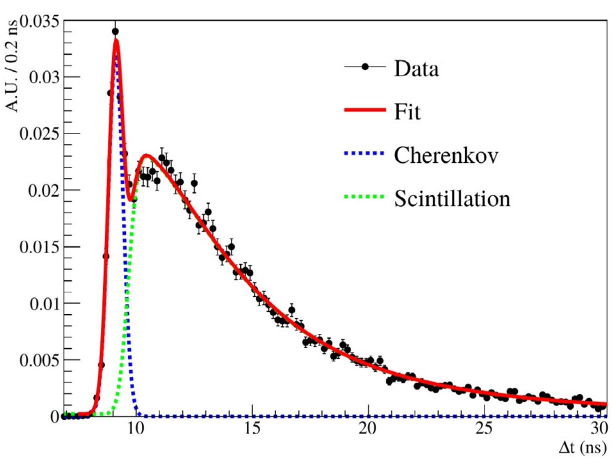


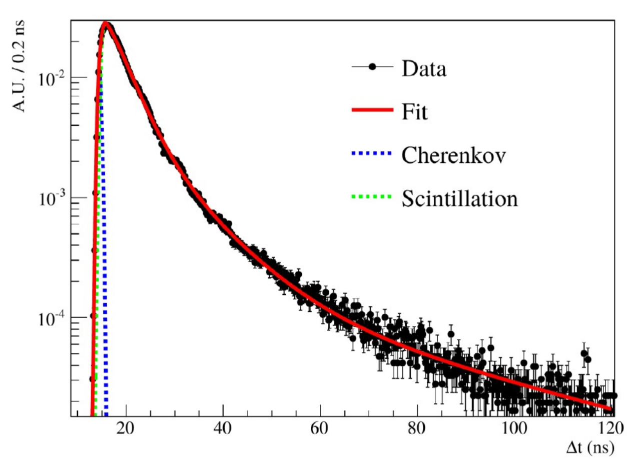
T. Kaptanoglu et al., JINST 14 (2019) no.05, T05001











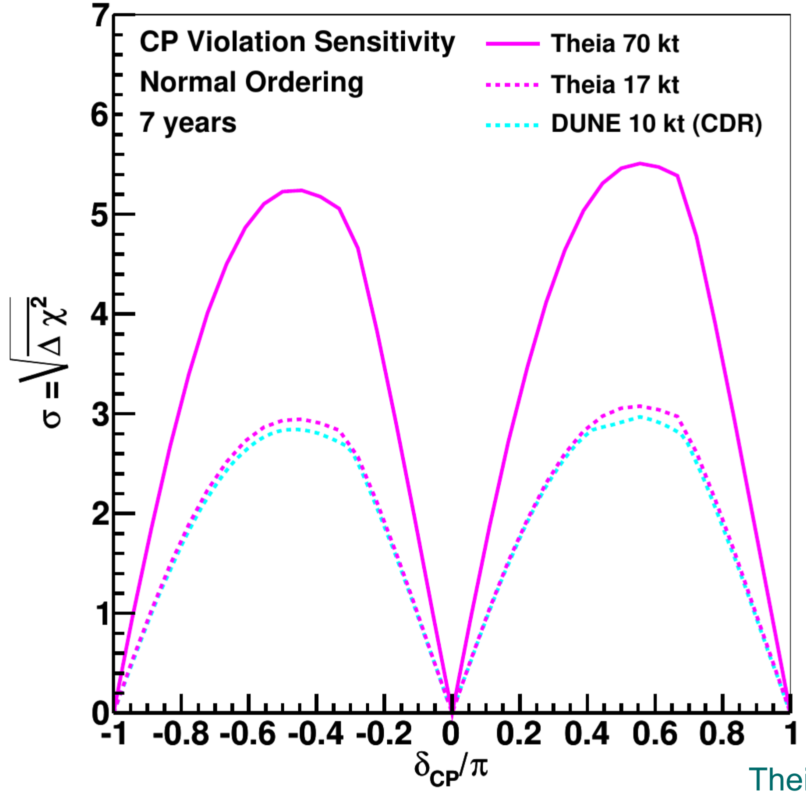
Measured time profile of **transmitted (left)** and **reflected (right)** light from LAB-PPO

Long-Baseline Physics with Theia

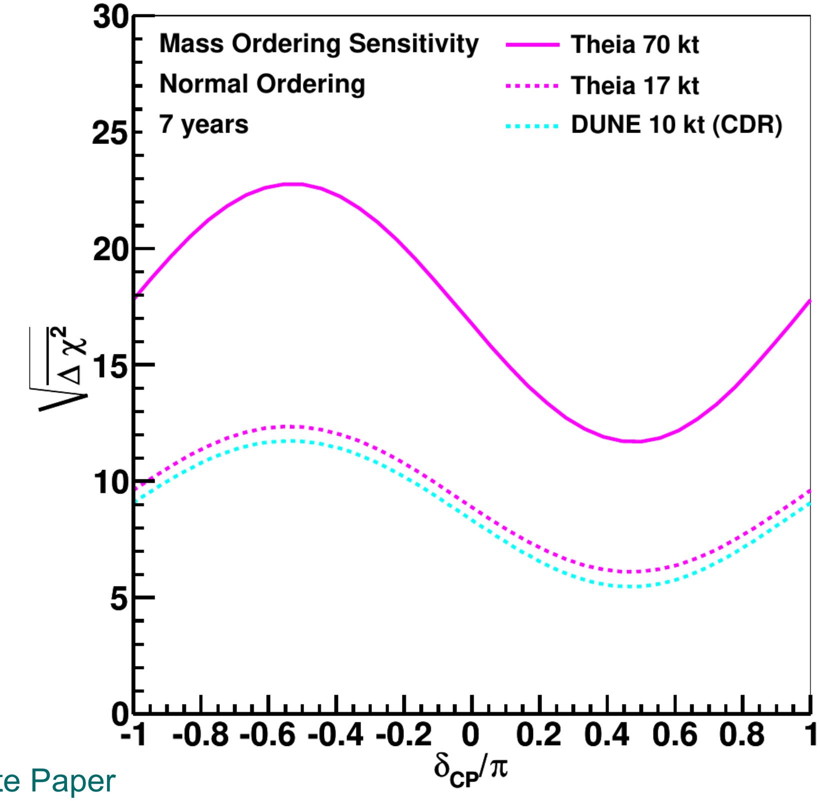
- Ring-imaging for long-baseline physics
- SK & HK improved reconstruction methods a lot

  → Theia competitive long-baseline

CP Violation Sensitivity



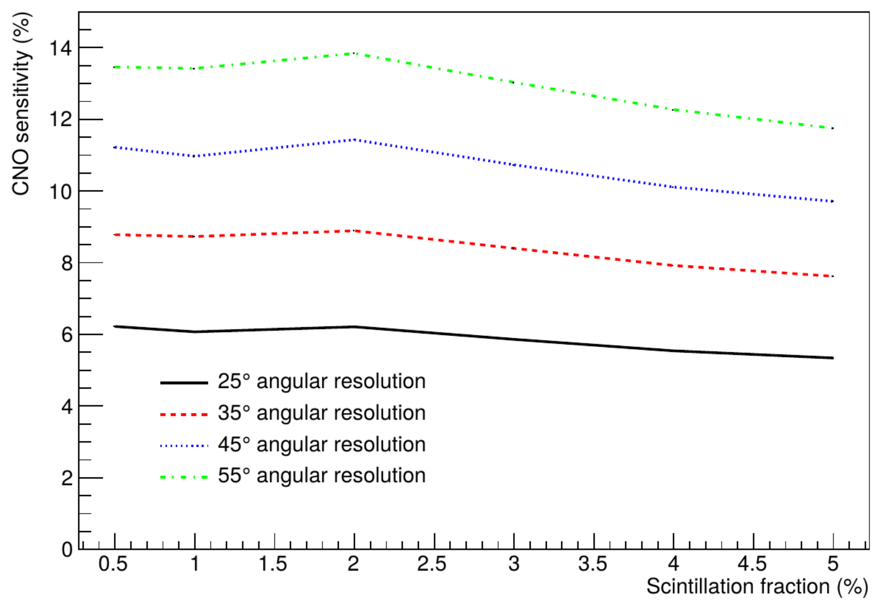
Mass Ordering Sensitivity



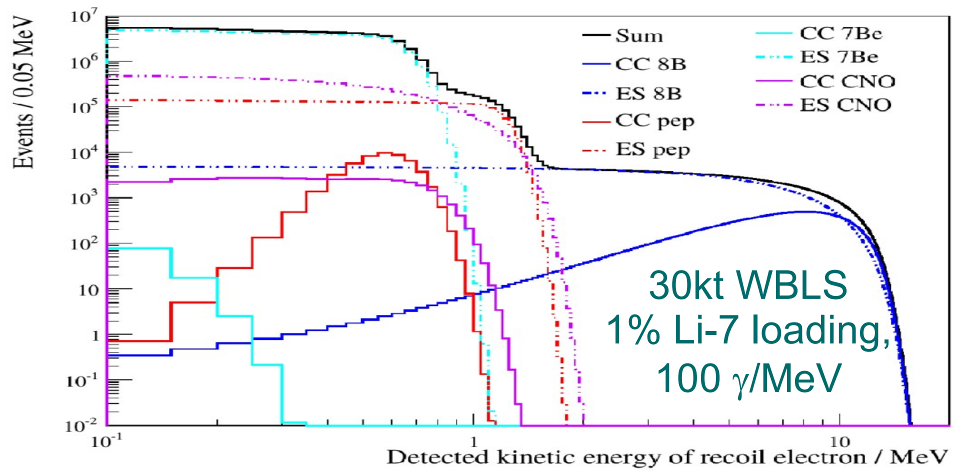
Theia White Paper

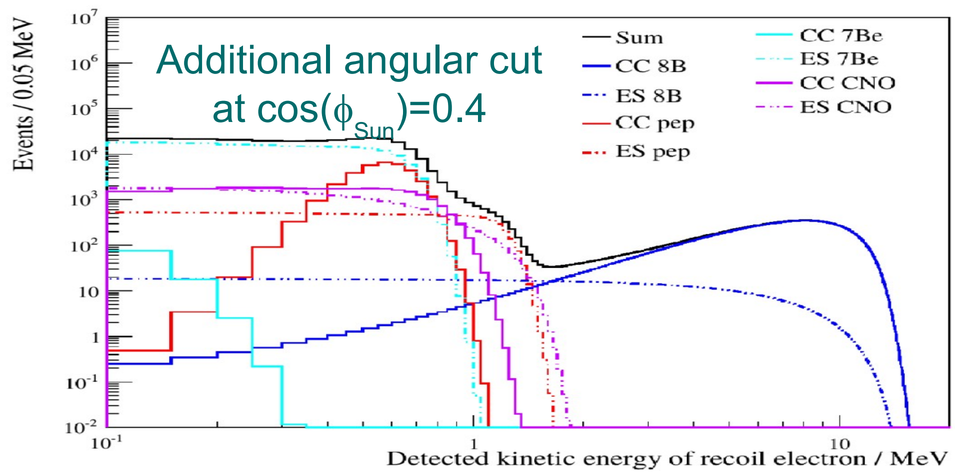
Solar Neutrinos with Theia

- **Directionality** very potent tool
- **Also powerful:** Discrimination point-like & non-point-like events (like C-10)
- **Li-loading** can make CC-channels accessible $^7Li + \nu_e \rightarrow {}^7Be + e^- \quad (\mathrm{Q} = 862\ \mathrm{keV})$



Dependence of CNO-Sensitivity on angular resoultion





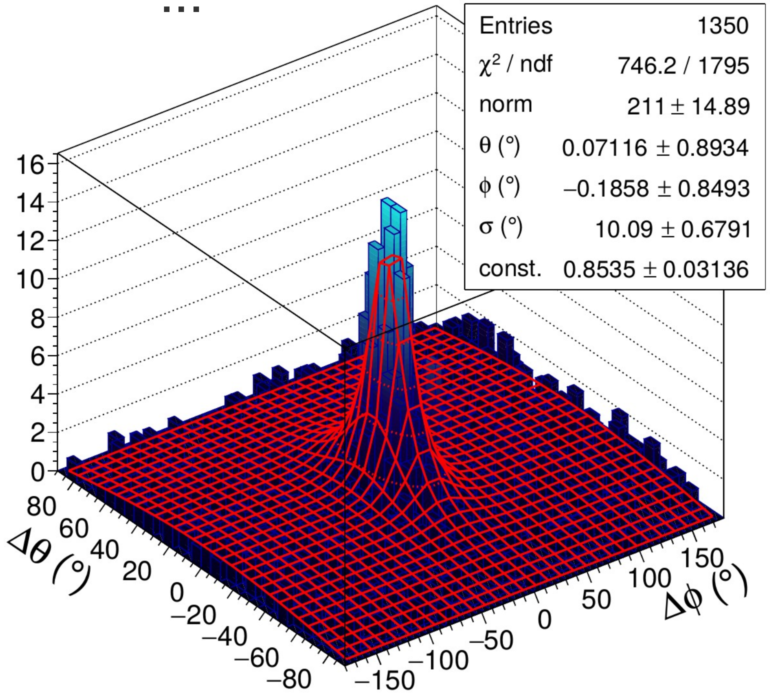
Theia White Paper, to be published soon (Courtesy to R. Bonventre &G.D. Orebi Gann)

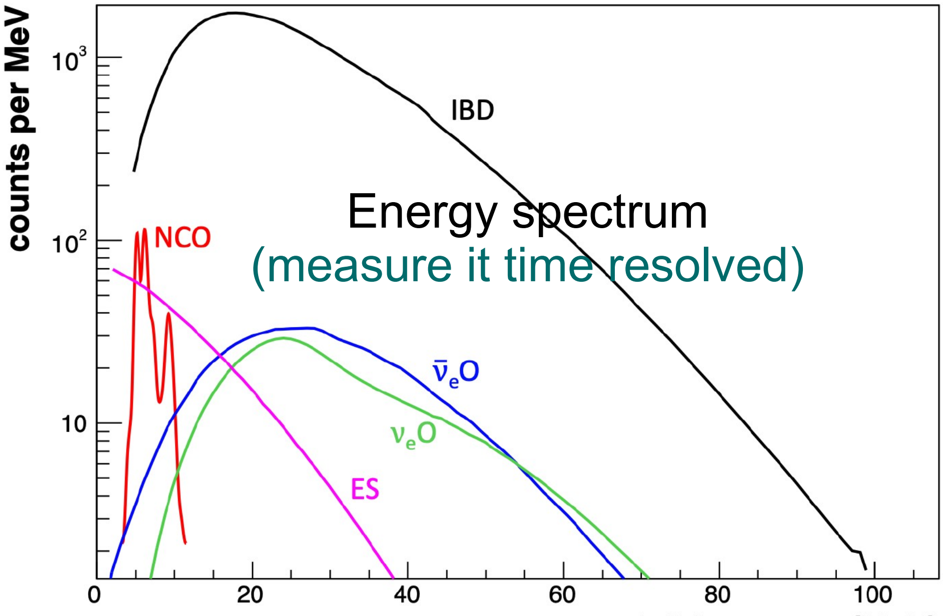
Supernova Neutrinos in Theia

- **Core-collapse SN at 10kpc**
- **Opens new physics window:**
  - Test SN models
  - Information about MH
  - Multi-messenger astronomy
  - Early warning with precise pointing (< 1°)
  - ...

Huge statistics + Flavour information

Reaction		Rate
(IBD)	$\bar{\nu}_e + p \to n + e^+$	19,800
(ES)	$\nu + e \to e + \nu$	960
(ν_eO)	$^{16}O(\nu_e, e^-)^{16}F$	340
($\bar{\nu}_e$O)	$^{16}O(\bar{\nu}_e, e^+)^{16}N$	440
(NCO)	$^{16}O(\nu, \nu)^{16}O^*$	1,100





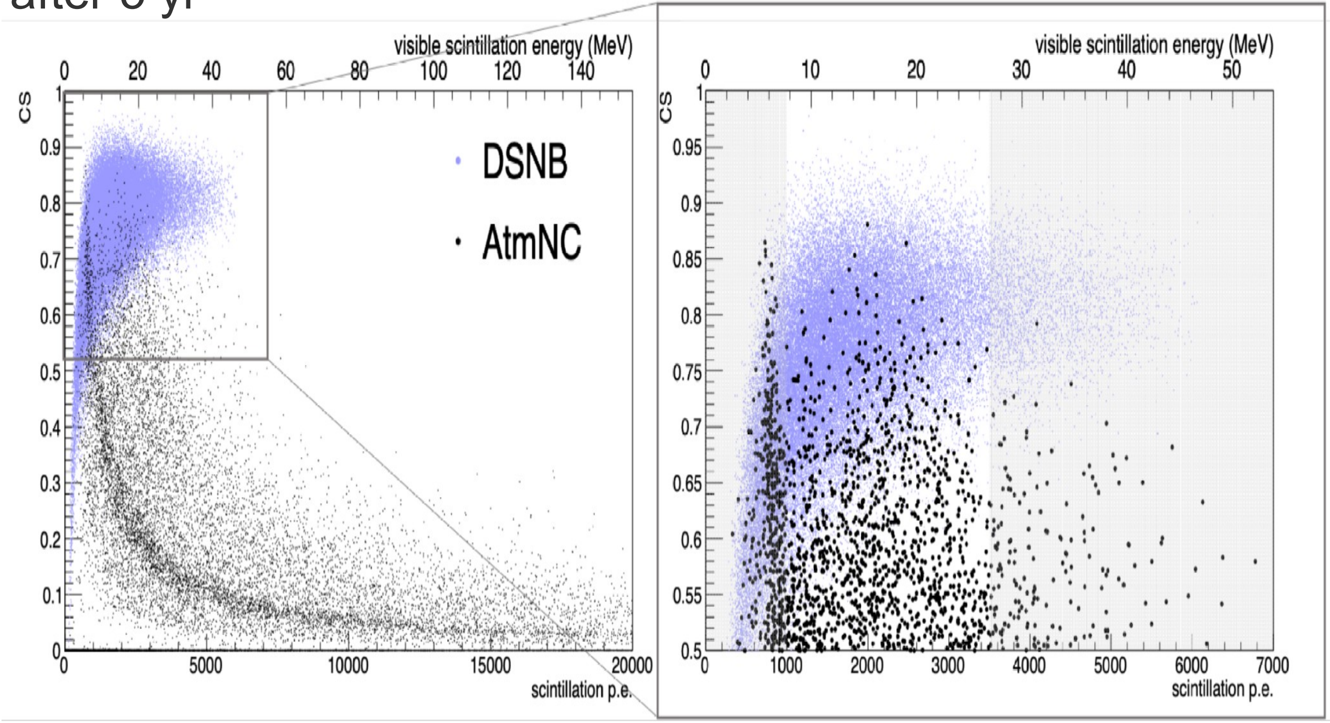
Theia White Paper

DSNB with Theia

- **Combines Neutrino signal of past SN**
- **Encoded information from:**
  - Star formation rate
  - Average core-collapse neutrino spectrum
- **Advantage Theia:**
  - Pulse-shape discrimination, Ring-Counting C/S-ratio

    → 5σ conceivable after 5 yr

Theia White Paper



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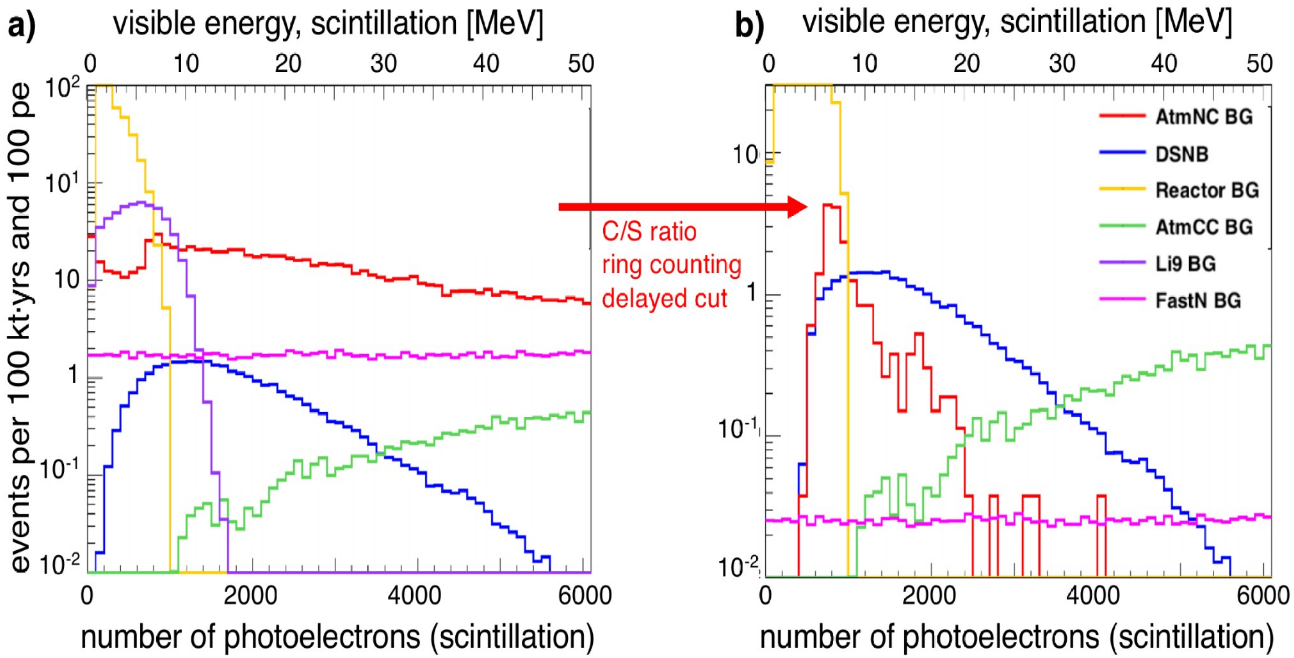
Theia White Paper

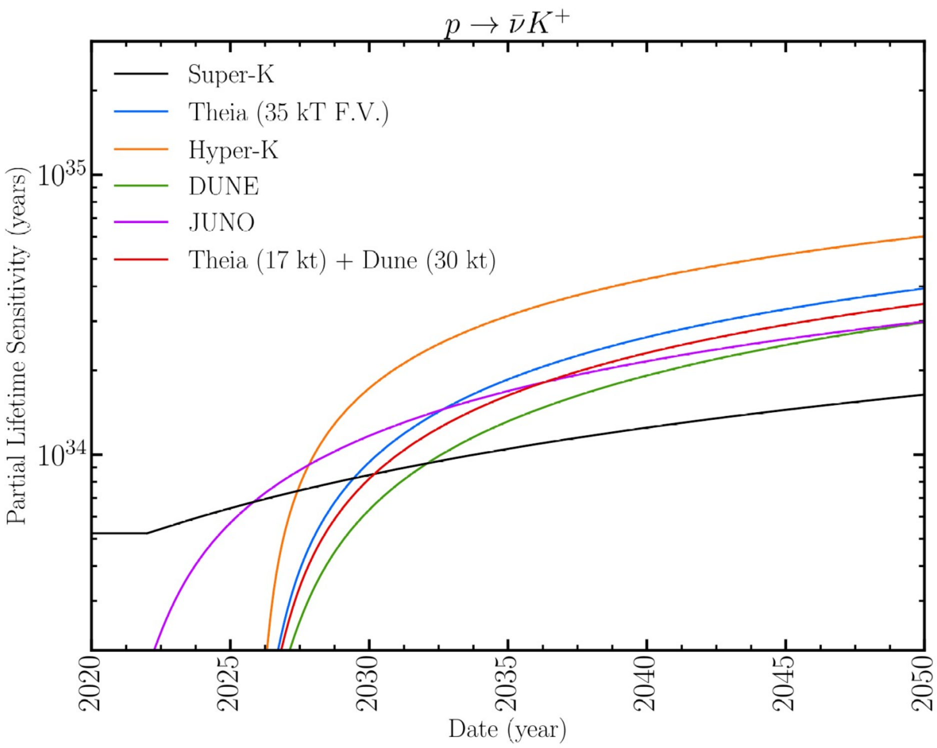


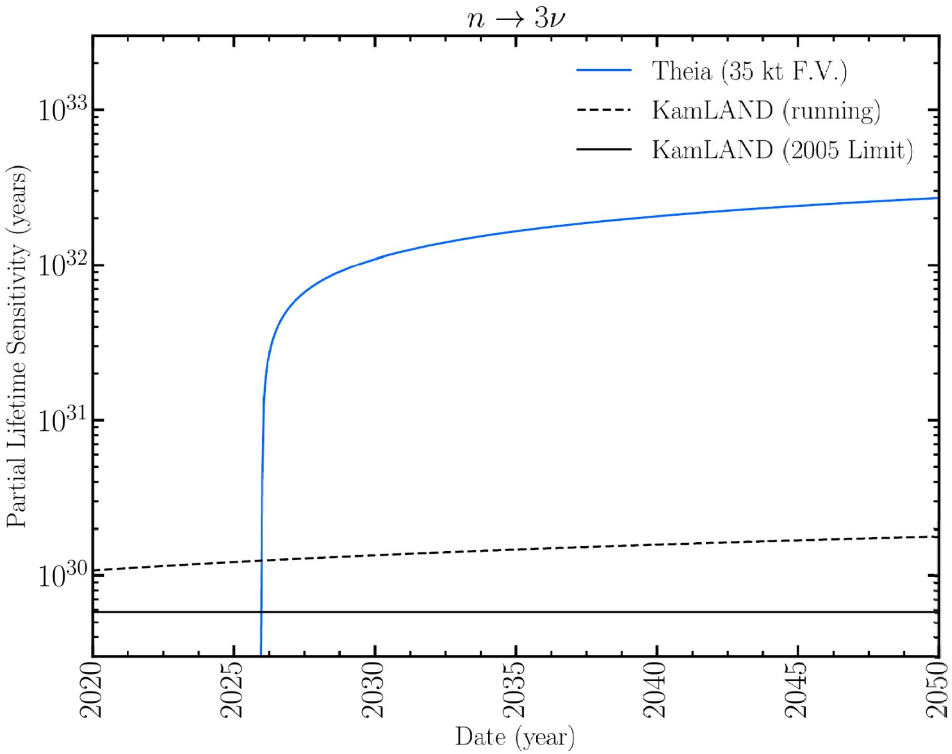
17kt fiducial mass

Nucleon Decay with Theia

- **Triple coincidence:** $p \rightarrow \bar{\nu} K^{+} \rightarrow$ Kaon decay $\rightarrow$ decay of decay product
- **Invisible decay of oxygen nucleus:**

  $n \rightarrow 3\nu \rightarrow$ One 6.18 MeV γ from excited nucleus

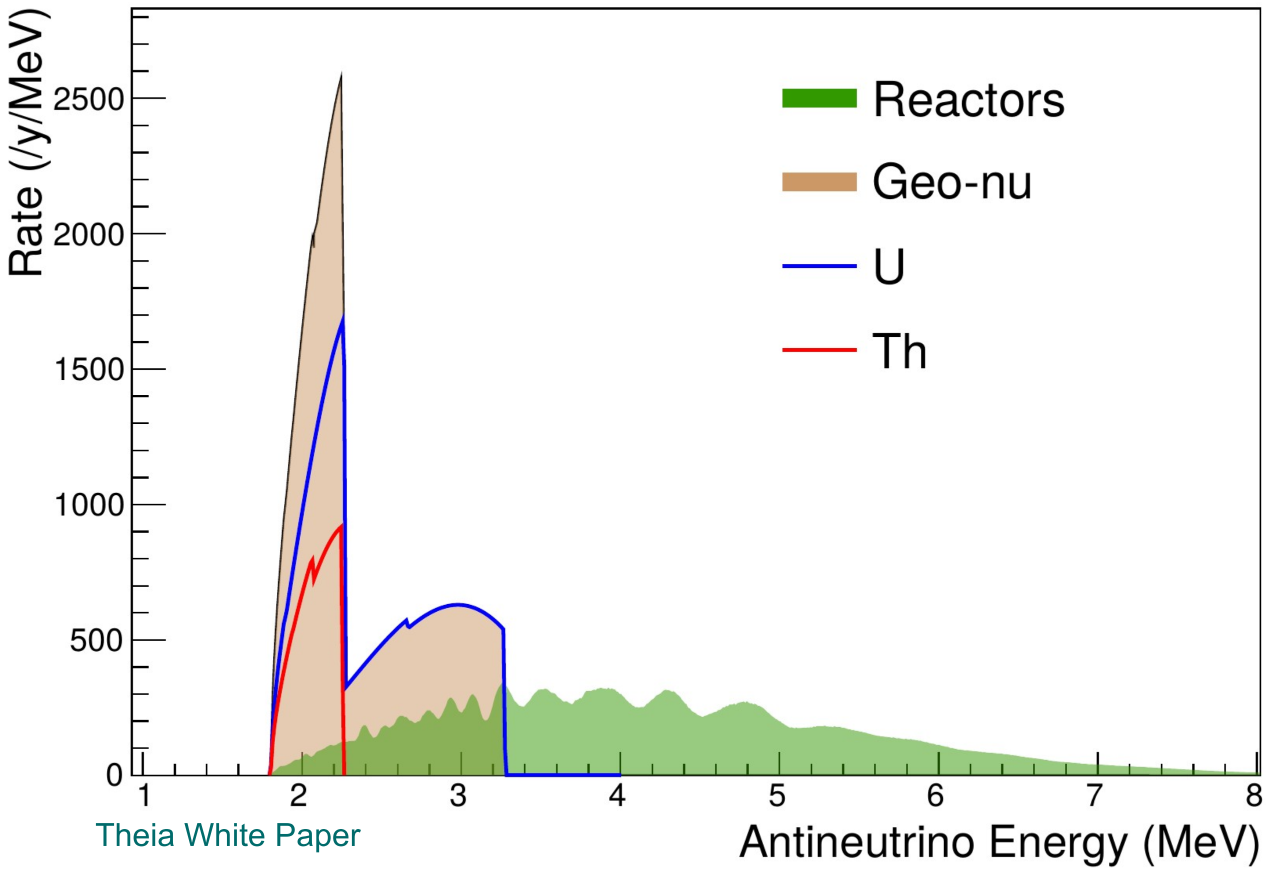




Theia White Paper

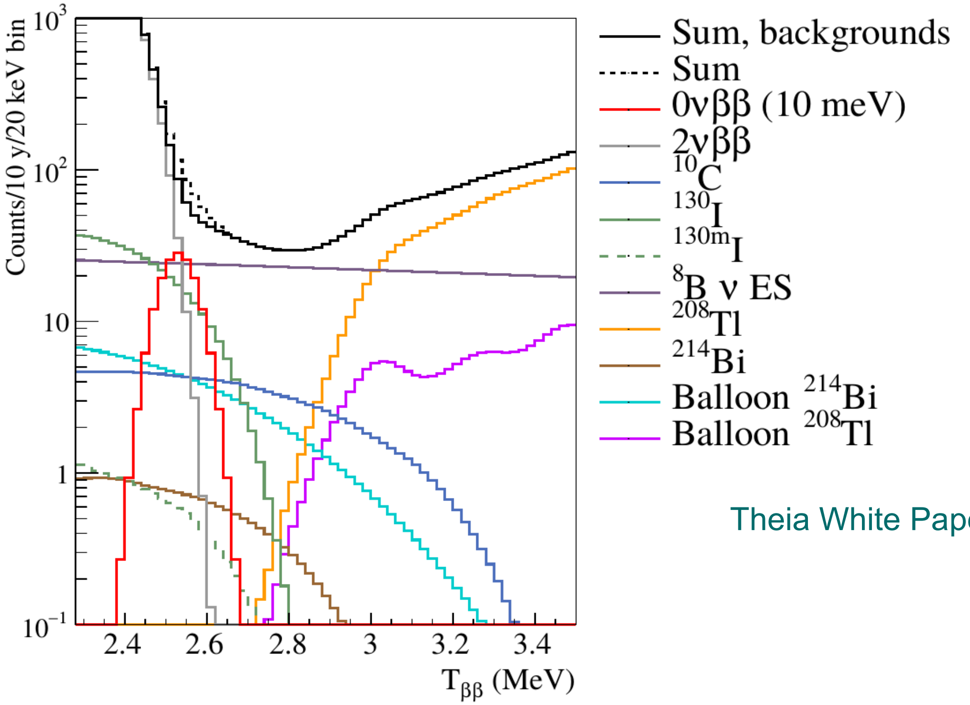
Geo-Neutrinos with Theia

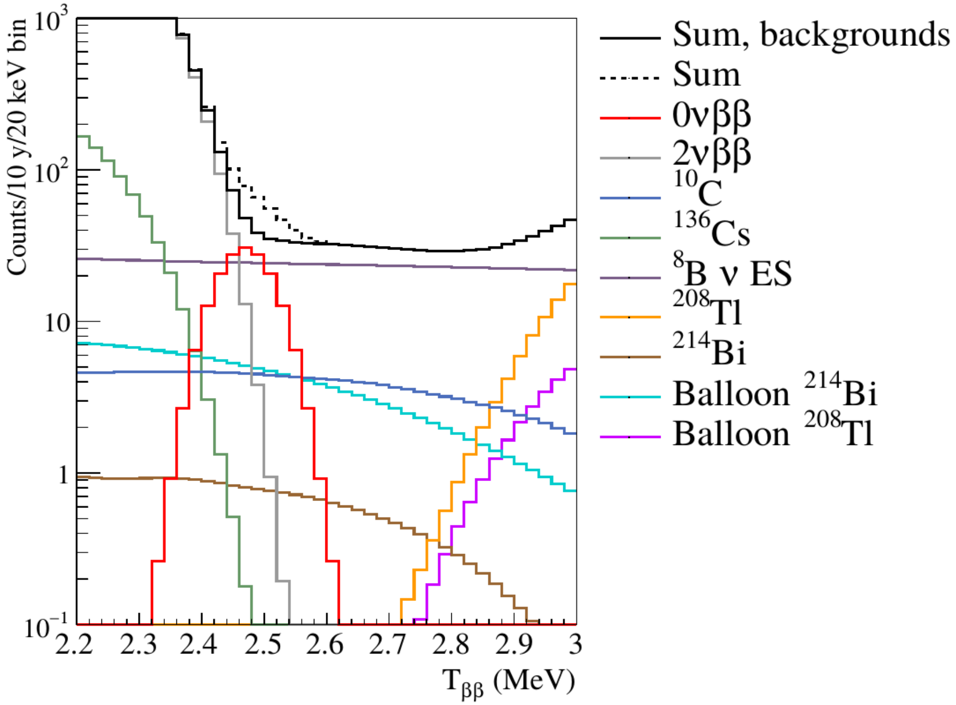
- Thousands of Geo-neutrino events per year
  → Precise measurement of Th & U components in spectrum
- Expected rate would be 2s greater than the KamLAND rate after 1 year (at SURF)
  → First evidence for surface variation of flux possible



Theia White Paper

0νββ in Theia: Expected Endpoint Spectra





Theia White Paper

- **Resulting Sensitivity** (90% C.L.):

$$\textbf{Te}: \ T_{1/2}^{0\nu\beta\beta} > 1.5 \times 10^{28} \text{ y}, \ m_{\beta\beta} < 5.4 \text{ meV}$$

$$\textbf{Xe}: \ T_{1/2}^{0\nu\beta\beta} > 2.7 \times 10^{28} \text{ y}, \ m_{\beta\beta} < 4.8 \text{ meV}$$

After 10 years

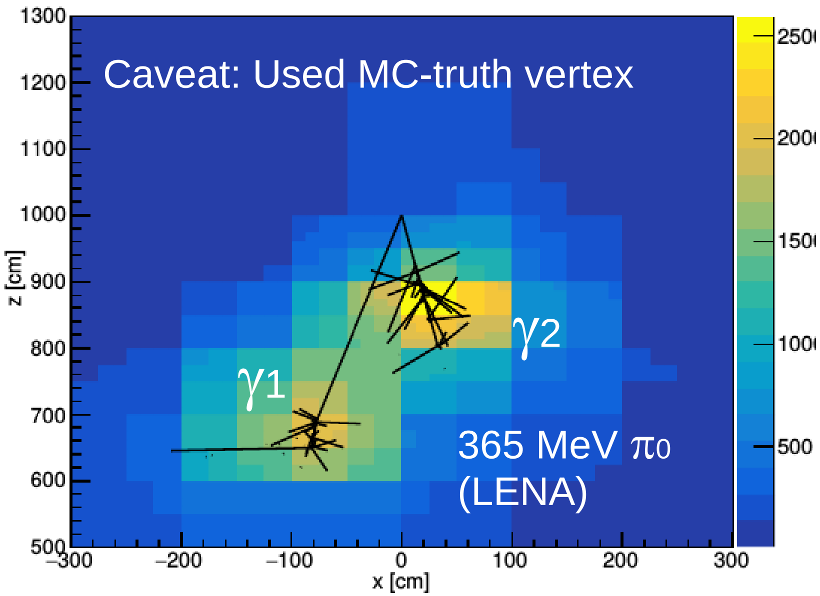
(Signal loss due to B-8 rejection not included yet)

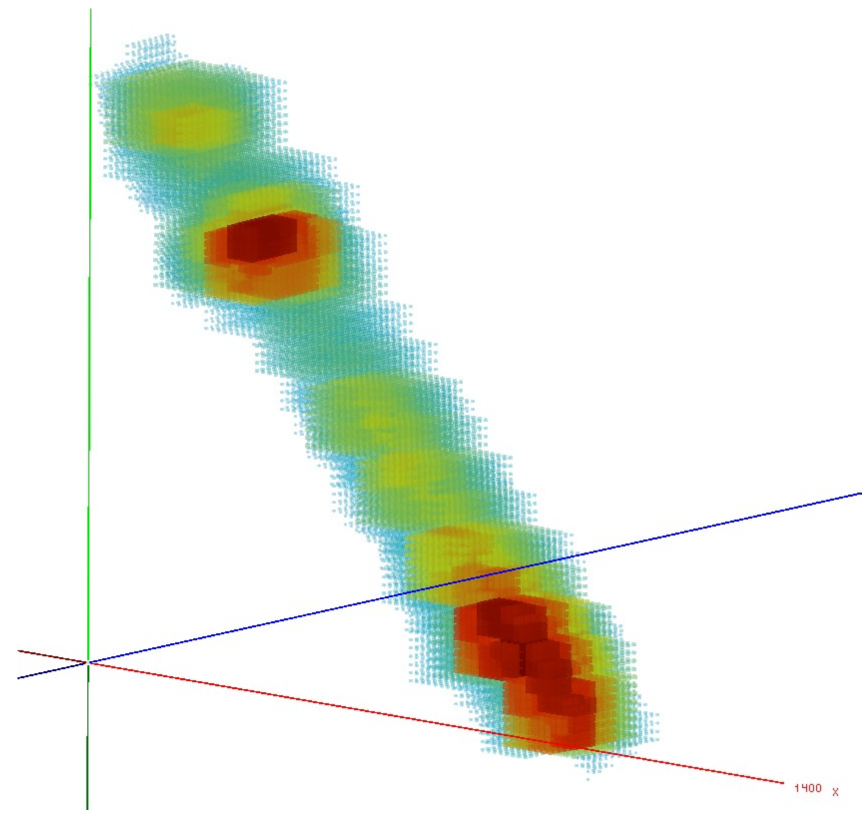
Topological Reconstruction at High Energies

Topological Reconstruction

In unsegmented large-volume liquid scintillator detectors

- Can make dE/dx and complex event structure visible (even in pure LS)
- Needs fast timing & good time resolution





See B.W. et al., arXiv:1803.08802

My Basic Idea

Assumption:

- One known reference-point (in space & time)
- Almost straight tracks
- Particle has speed of light
- Single hit times available

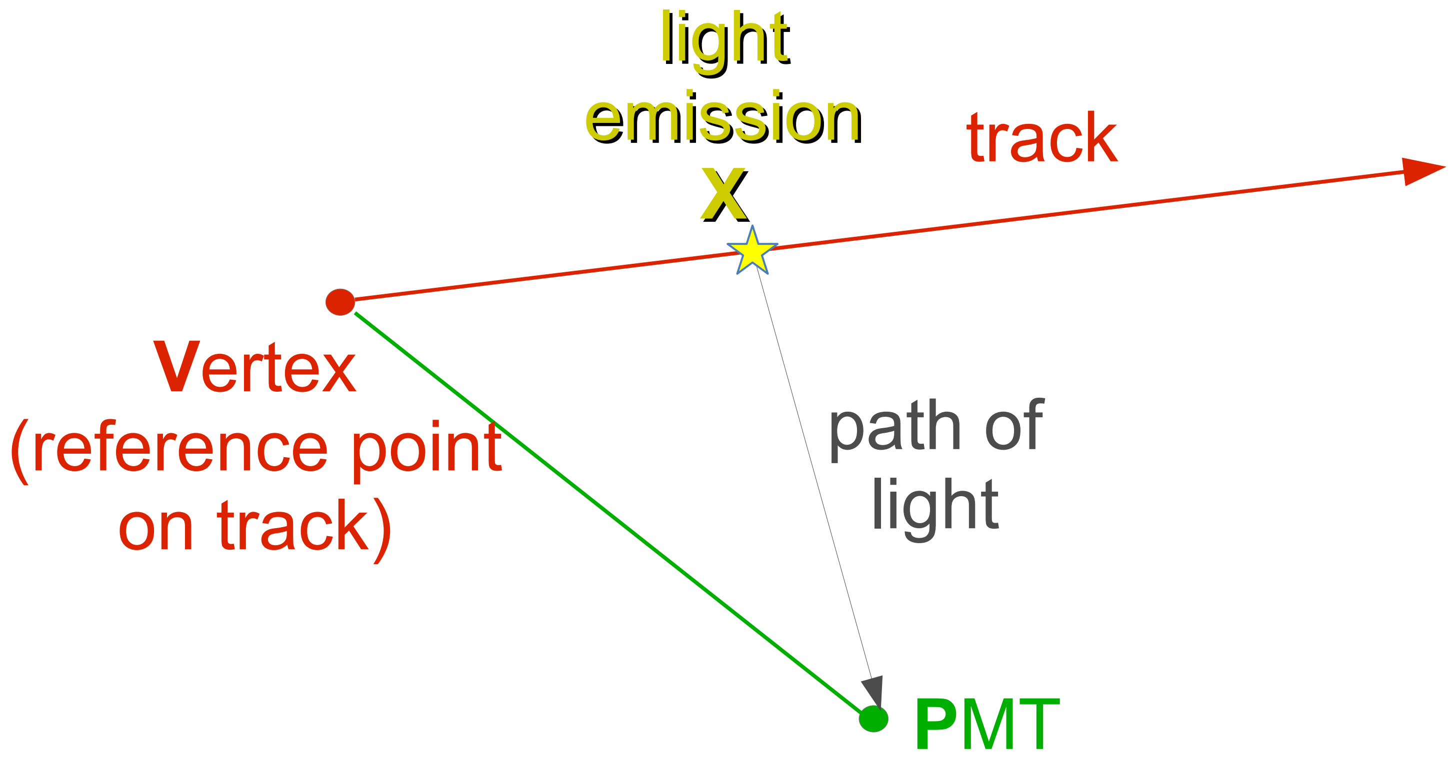
Concept:

- Take this point as reference for all signal times

The Drop-like Shape

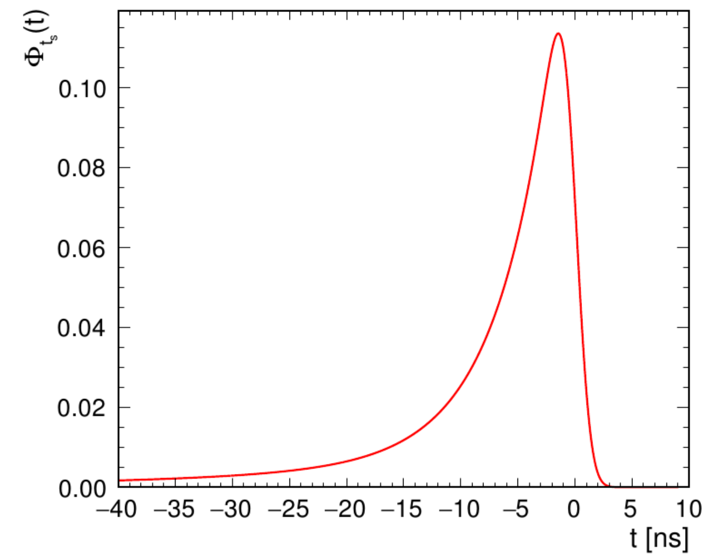
Signal time = particle tof + photon tof

→ ct = |VX| + n*|XP|

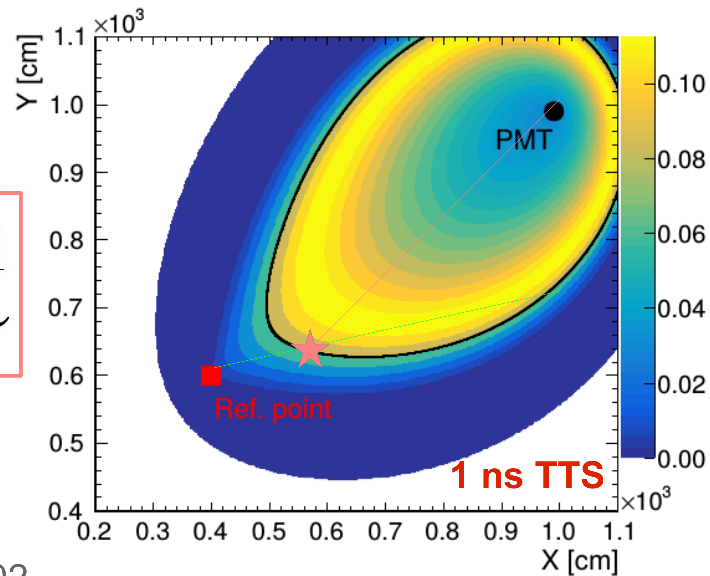


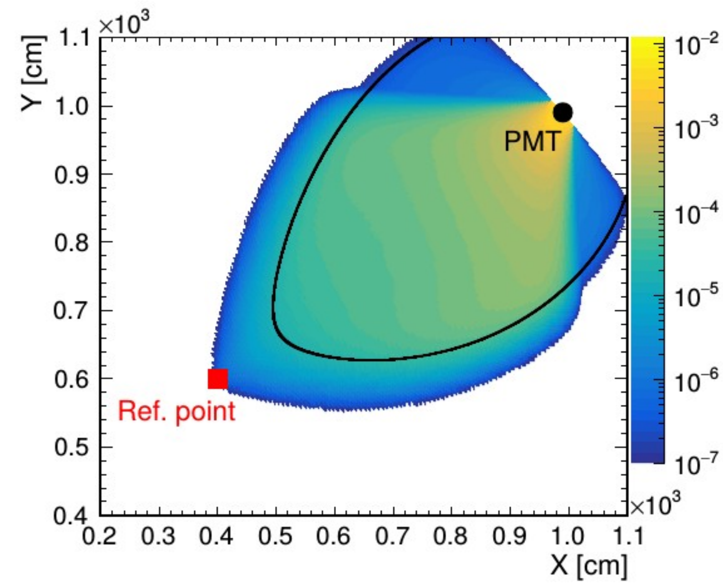
Working Principle Part I Summary

- For each signal:
  - Time defines drop-like surface
  - Gets smeared with time profile
    (scintillation & PMT-timing)
  - Weighted due to spatial constraints
    (acceptance, optical properties, light concentrator, …)
- → Spatial p.d.f. for photon emission points



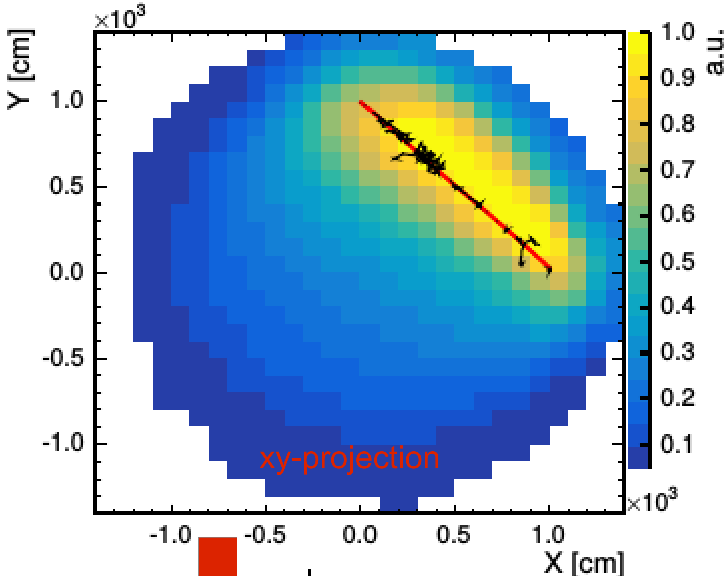
$$t(\mathbf{x}) = t_{\mathrm{ref}} \pm \boxed{\underbrace{\frac{|\mathbf{x}-\mathbf{r}_{\mathrm{ref}}|}{c_0}}_{\text{particle}}} + \boxed{\underbrace{\frac{|\mathbf{r}_j-\mathbf{x}|}{v_g(\epsilon)}}_{\text{photon}}}$$





See B.W. et al., arXiv:1803.08802

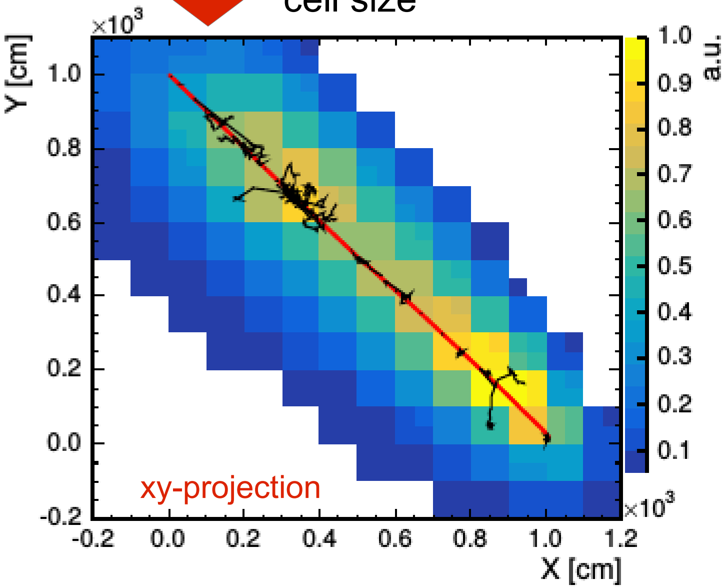
Working Principle Part II



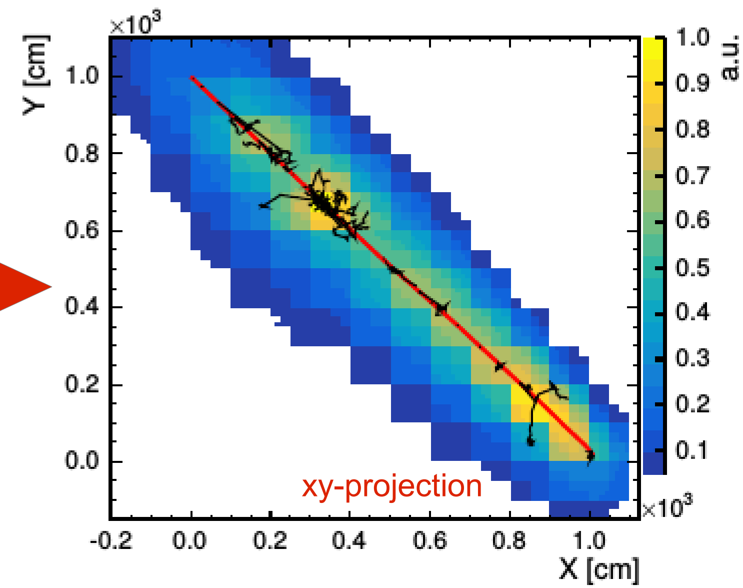
- Add up all signals (Need arrival time for every photon)
- Divide result by local detection efficiency
  → Number density of emitted photons
- Use knowledge that all signals belong to same topology to 'connect' their information
  → Use prior results to re-evaluate p.d.f. of each signal

That is what I call probability mask (PM)

decrease cell size



decrease cell size



dE/dx accessible

See B.W. et al., arXiv:1803.08802

Loss Function

- **Loss-function:** TF.Losses.Cosine_Distance

  (Tensor-standart-Loss-Function)

- **Minimizes:** $L = \sqrt{\left(\cos\left(\theta - 1\right)\right)^2}$

  θ = angle between reconstructed and true direction

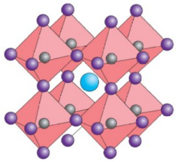
- **True direction:**
  - Used start direction of event
  - Not average flight direction of electrons

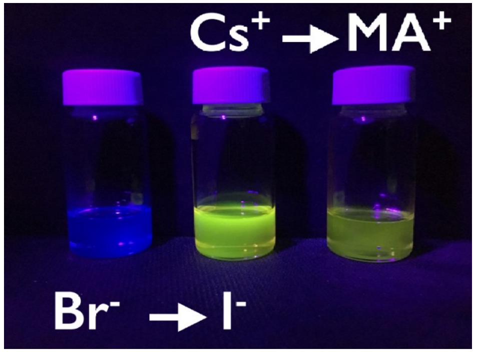
Remark: Resolution for the later could be better, but at least for background reduction we are interested in the former. For correction of energy reconstruction it would be better to take average direction.

Improving Liquid Properties

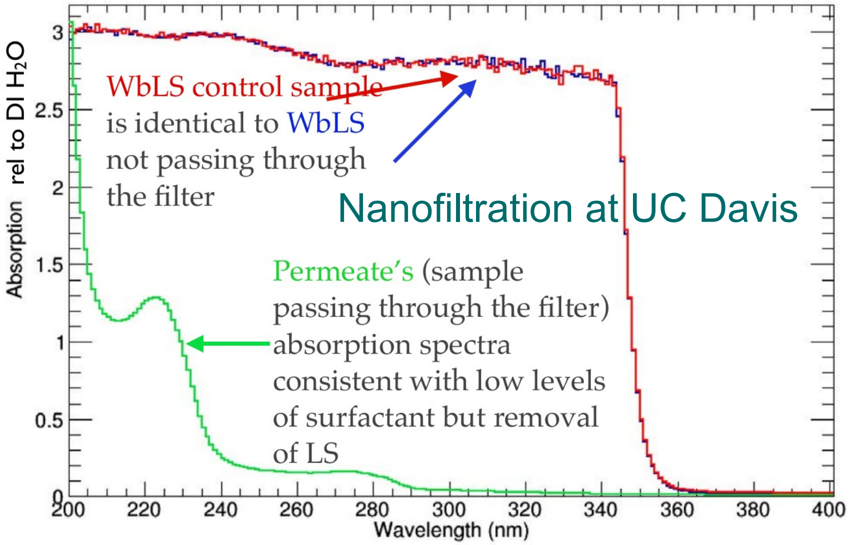
- **Development of scintillating liquids**
  - WBLS (Brookhaven NL, JGU Mainz, TU Munich)
  - Isotope loading (BNL, MIT) (Li,B,Ca,Zr,In,Te,Xe,Pb,Nd,Sm,Ge,Yb)
  - Oil-diluted LS (JGU Mainz)
- **Characterization** (Brookhaven NL, JGU Mainz, TU Munich, ...)
  - Optical properties (Emission, attenuation, ..)
  - Timing properties (Time spectrum, ortho-positronium, ...)
- **Filtering methods** (Attenuation, radiopurity)
  - Nanofiltration (UC Davis)
  - JUNO-test facility achieved A.L > 23 m (LAB + PPO + bis-MSB)

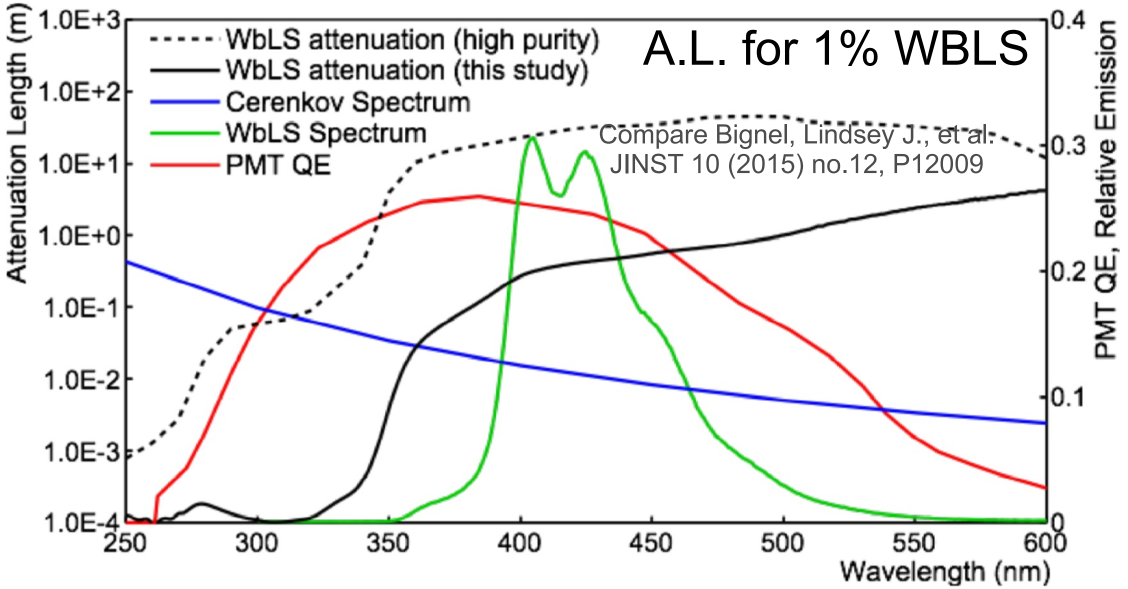
New WBLS: JHU Mainz & TU Munich





Nanocrystal-Doped Liquid Scintillator arXiv:1908.03564





Finding the Right Cocktail

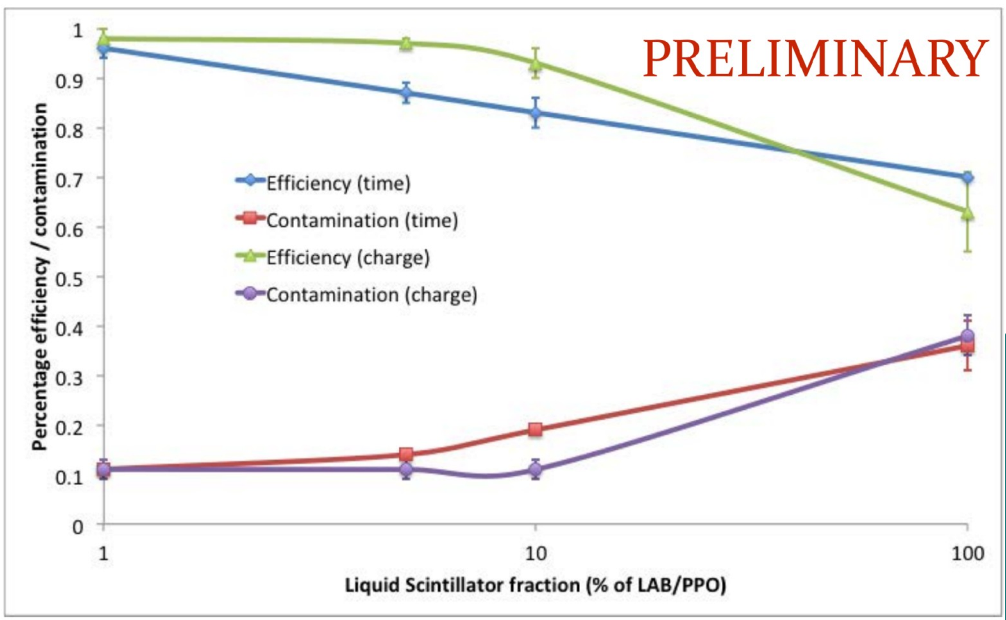
- **CHE**renkov **S**cintillation **S**eparation
  - Cosmic muon ring-imaging experiment
  - Select vertical cosmic muon events
  - Image Cherenkov ring in Q and T on fast PMT-array
  - Allows charge- and time-based separation

Work at UC Berkeley

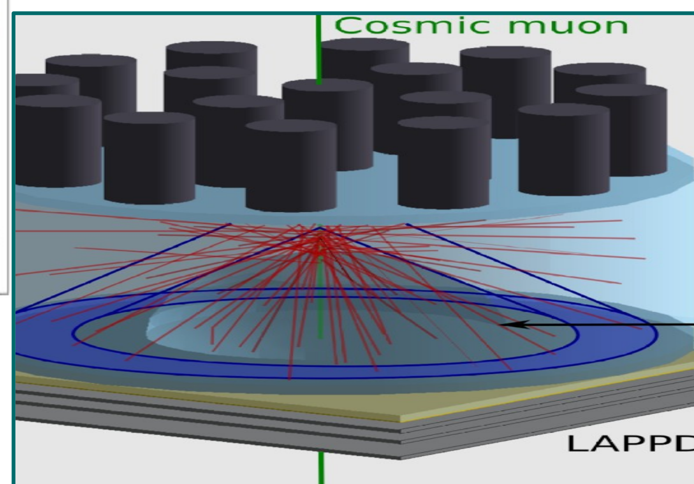
PRC 95 055801 (2017)

CHESS

See also Eur. Phys. J. C (2017) 77: 811



First demonstration of Cherenkov-light separation in LAB-PPO

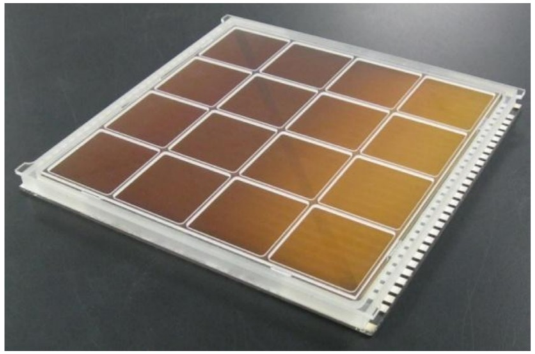


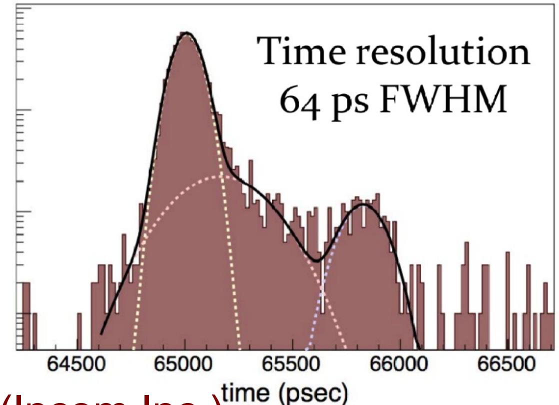
Development of similiar cell with LAPPDs at JGU Mainz

Larger light path in liquid to study propagation effects

Photo Sensor Development
(Fast & Efficient & Affordable & High Granularity)

- LAPPDs (Fast timing & high granularity)

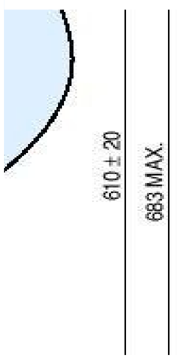




Commercially available now (Incom Inc.)
Used in ANNIE + R&D at U Chicago

- HQE 20” PMTs (Efficient & affordable)

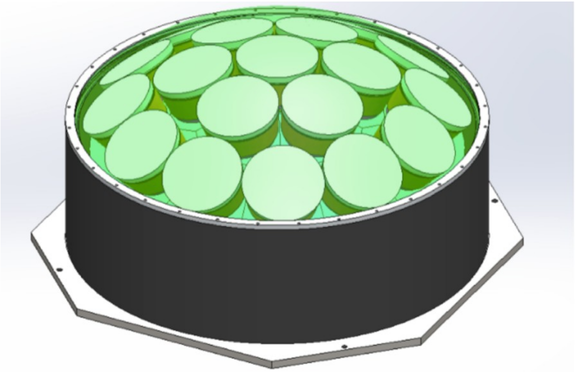
Dynode-PMT (Hamamatsu)



MCP-PMT (NNVT)

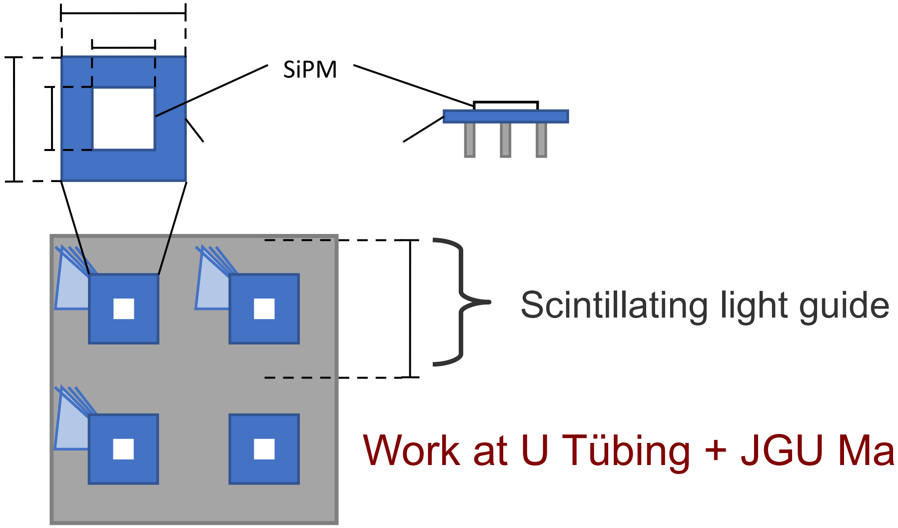
QE ~28%: Used in JUNO

- Modular PMTs
  (Good compromise of everything)



Water-Cherenkov Test Beam Experiment

- SiPM + active light guide
  (Very efficient + increasing affordability)



Work at U Tübing + JGU Mainz

Cherenkov-Light Separation by Wavelength

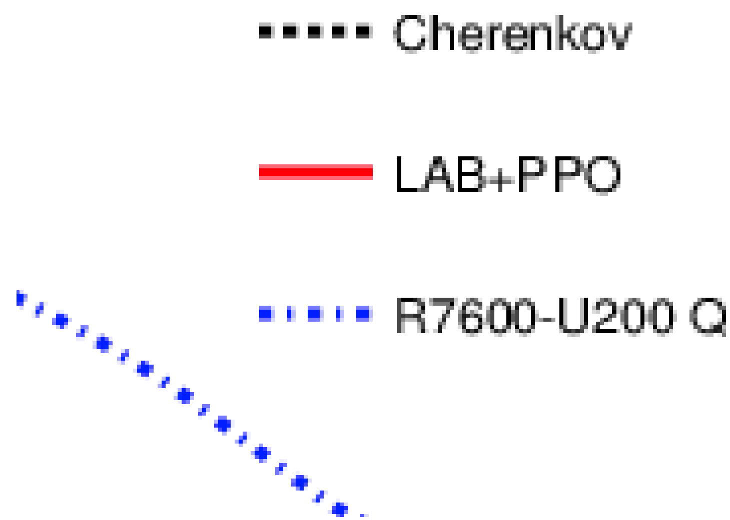
- Using dichroic filter

  (transmitting above or below a certain threshold, reflecting the rest)

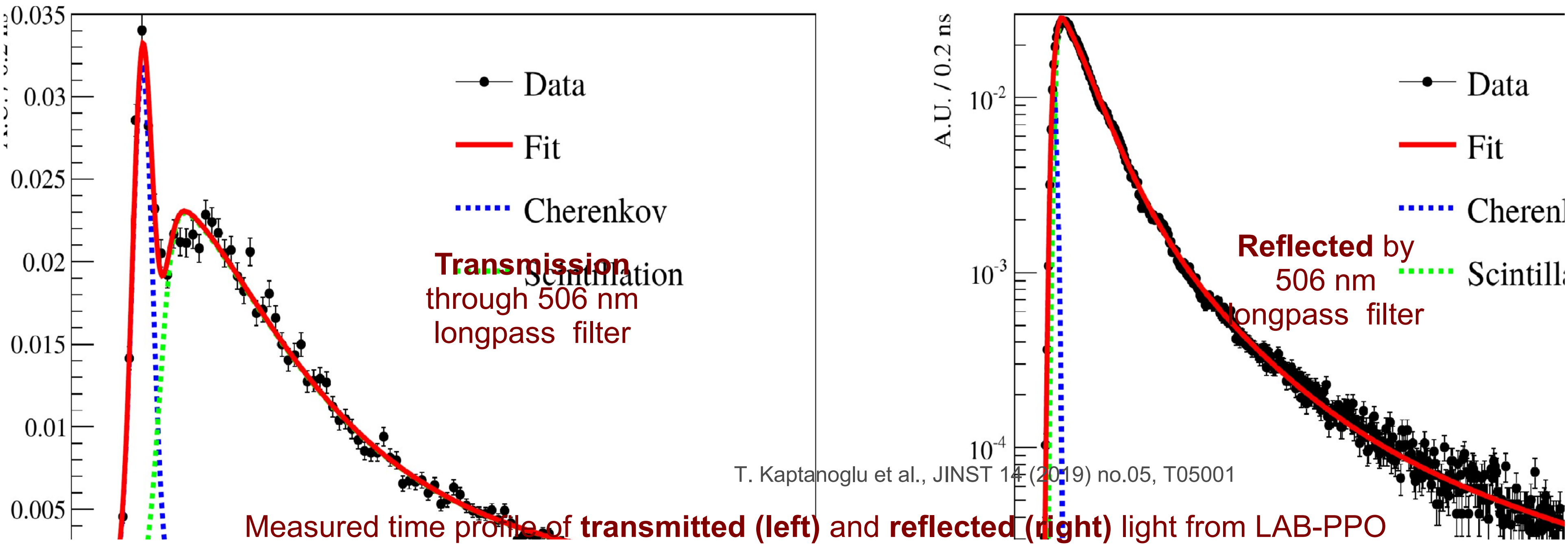
- Optimal cut for LAB-PPO (2g/l): 450 nm

  Full description in T. Kaptanoglu et al., JINST 14 (2019) no.05, T05001

- Studying application as light concentrator (U. Penn.)



T. Kaptanoglu et al., JINST 14 (2019) no.05, T05001



T. Kaptanoglu et al., JINST 14 (2019) no.05, T05001

Measured time profile of **transmitted (left)** and **reflected (right)** light from LAB-PPO