ML challenges in Theia and WBLS

Presented by

Björn Wonsak
on behalf of the THEIA collaboration

NPML, 17\textsuperscript{th} July 2020
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-characteristics
  - **Combined:** C/S-ratio
    → Improved particle discrimination

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

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
Theia Physics Program

Long-baseline physics

Solar neutrinos

Supernova burst neutrinos & DSNB

Neutralinoless double beta decay

Geo-neutrinos

Nucleon decay

and more ...
Using Other Experiments as R&D Testbeds

- **EGADS**: Gd loading and purification (200t)
- **BNL 1-t**: Water-based liquid scintillator
- **SNQ**: Te loading (780t)
- **WBLS in phase III**: Neutron yield, LAPPD deployment (30t)
- **Infrastructure, underwater integration**: 10kt
- **WbLS, Gd, LAPPD, HQE PMT, full integration prototype**: 1kt

**Note: not an exhaustive list!**

**Broad community interest!**

Courtesy to G.D. Orebi Gann
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)

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

- **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!

---

**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)
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 ($\sigma_{TTS} = 1.27$ ns)
    ~12000 MCP PMTs ($\sigma_{TTS} = 5.1$ 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 $\alpha$ and proton time spectrum

$\alpha/\beta$ discrimination at 90 % efficiency

$\alpha/\beta$ discrimination at 90 % efficiency

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

Results Particle Identification II

- Discrimination based on topological differences
  (additional $\gamma$, several Compton scattering points, etc.)

  e+/e- discrimination at 50% efficiency

  e-/\gamma discrimination at 50% efficiency

- ML best for e+/e- but TR best for e-/\gamma
- 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)


The 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

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

Choice of ML-Tool: DGCNN

- **Dynamic Graph CNN (DGCNN):**
  - 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

<table>
<thead>
<tr>
<th>set</th>
<th>count</th>
<th>energy</th>
<th>position</th>
</tr>
</thead>
<tbody>
<tr>
<td>training</td>
<td>210,000</td>
<td>3 MeV</td>
<td>center and z-axis *</td>
</tr>
<tr>
<td>validation</td>
<td>5,200</td>
<td>4 MeV</td>
<td>center</td>
</tr>
<tr>
<td>energy evaluation</td>
<td>8 x 5,200</td>
<td>1 - 8 MeV</td>
<td>center</td>
</tr>
<tr>
<td>vertex evaluation</td>
<td>5 x 5,200</td>
<td>4 MeV</td>
<td>z-axis: 0 to 10 meters</td>
</tr>
</tbody>
</table>

* 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)

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/$\sqrt{E}$ vertex resolution
- 0.1 ns vertex time resolution

**Blue & red line:**
The same as before

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

**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

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

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
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?

Caveat: Used MC-truth vertex
How to do Something Similar 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:

<table>
<thead>
<tr>
<th>Position</th>
<th>Mean distance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Entrance</td>
<td>0.16 ± 0.09 m</td>
</tr>
<tr>
<td>Peak</td>
<td>0.22 ± 0.14 m</td>
</tr>
<tr>
<td>Exit</td>
<td>0.20 ± 0.12 m</td>
</tr>
</tbody>
</table>

Next steps:
- Go to more realistic detector/simulation
- Look at more complicated events
Outlook: First Results Voxel Reconstruction

**Red:** MC Truth

**Blue:** Network output

- Result of homogeneous network
- Result after propagation layers
- Result heterogeneous network (after training)

Using L1-regularization in loss function
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
Identifying CCQE-$0\pi$ Events

- Two classification tasks:
  
  Electron vs. muon

  20k Test Set

  Normalized confusion matrix
  CNN model with 94.3% accuracy
  PMT+LAPPD (5x5 res) tf

  Preliminary

  Predicted label
  NN Prediction Distribution
  Error=20

  Counts
  Probability for Muons

  Result: Up to 5% increases of accuracy compared to classical methods

  → Efficiency > 92% for each task (impurity <0.3%)

  CCQE-$0\pi$ candidates

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

  10k Test Set

  Ring Counting 83% acc on testset
  PMT+LAPPD 5x5

  Preliminary

  Predicted label
  NN Prediction Distribution
Summary/Conclusion

- **Theia is a proposed detector**
  - Large community interest, collaboration has been formed

- **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-ration and ring-counting

A. Elagin et al., arXiv:1609.09865
Backup slides
Theia Interest Group

Picture from FROST-Workshop 2016 in Mainz

Concept paper - arXiv:1409.5864

Most of these institutes joint the Theia proto-collaboration!

Canada
Alberta
Laurentian
Queens
Toronto

Finland
Jyvaskyla
Oulu

Germany
Aachen
Dresden

Juelich
Mainz
TU Munich
U. Hamburg

UK
Sheffield

US
Brookhaven NL
Boston U.
U. Chicago

Cornell U.
U. Hawaii
Iowa State
Lawrence
Berkeley NL
LSU
MIT

U. Penn
Stony Brook
SURF
Temple
UC Berkeley
UC Davis

China
Tsinghua
Bringing everything together

- **EGADS**
  - 200t
  - Gd loading and purification

- **BNL 1-t**
  - Water-based liquid scintillator

- **SNQ**
  - Te loading
  - 780t

- **WBLS in phase III**
  - Neutron yield, 30t
  - LAPPD deployment

- **Infrastructure, underwater integration**
  - 10kt

- **WBLS, Gd, LAPPD, HQE PMT, full integration prototype**
  - 1kt

- **Note: not an exhaustive list!**

- **CHIPS**

- **WATCHMAN**

- **Broad community interest!**

Courtesy to G.D. Orebi Gann

WbLS R&D, G. D. Orebi Gann
## Community Interest

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

Schematic for best PID- and RC-model:
- Kernels per conv. layer: 400
- Kernel size: (3x3)
- Double conv. layers: 3
- Dense layers: 2

Batch normalisation + Dropout 20%

Flattening

Width = 500

Output layer

# of kernels

Feature Maps

Feature Maps

Max-pooled Maps

Feature Maps

Feature Maps

Max-pooled Maps

# of double convolutional layers

Kernel size

# of dense layers
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?

$\alpha/\beta$:
- $\alpha$-background from natural radioactivity

$p/\beta$:
- supernova: e.g. elastic scattering channel with protons (signal) vs $\beta^-$ 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($\alpha,n)^{16}$O interactions, which can result in elastic scattering on proton

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

$e^-/\gamma$:
- 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, 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
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 \( ^7Li + \nu_e \rightarrow ^7Be + e^- \) \( (Q = 862 \text{ keV}) \)

**Dependence of CNO-Sensitivity on angular resolution**

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

<table>
<thead>
<tr>
<th>Reaction</th>
<th>Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\bar{\nu}_e + p \rightarrow n + e^+$</td>
<td>$19,800$</td>
</tr>
<tr>
<td>$\nu + e \rightarrow e + \nu$</td>
<td>$960$</td>
</tr>
<tr>
<td>$^{16}\text{O}(\nu_e, e^-)^{16}\text{F}$</td>
<td>$340$</td>
</tr>
<tr>
<td>$^{16}\text{O}(\bar{\nu}_e, e^+)^{16}\text{N}$</td>
<td>$440$</td>
</tr>
<tr>
<td>$^{16}\text{O}(\nu, \nu)^{16}\text{O}^*$</td>
<td>$1,100$</td>
</tr>
</tbody>
</table>

![Energy spectrum](image)

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
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
  
  \[ 5\sigma \text{ conceivable after } 5 \text{ yr} \]

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:** 
  \[ n \rightarrow 3\nu \rightarrow \text{One 6.18 MeV } \gamma \text{ from excited nucleus} \]
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

![Graph showing antineutrino energy distribution with Theia White Paper and Reactors, Geo-nu, U, and Th rates.]

09/07/20
0νββ in Theia: Expected Endpoint Spectra

- **Resulting Sensitivity (90% C.L.):**
  
  \[
  \text{Te: } T_{1/2}^{0νββ} > 1.5 \times 10^{28} \text{ y}, \quad m_{ββ} < 5.4 \text{ meV}
  \]
  
  \[
  \text{Xe: } T_{1/2}^{0νββ} > 2.7 \times 10^{28} \text{ y}, \quad m_{ββ} < 4.8 \text{ meV}
  \]

  (Signal loss due to B-8 rejection not included yet)
Topological Reconstruction at High Energies

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

Caveat: Used MC-truth vertex

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

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)

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

- **Loss-function**: TF.Losses.Cosine_Distance
  (Tensor-standart-Loss-Function)

- **Minimizes**: 
  \[ L = \sqrt{\cos(\theta - 1)^2} \]

  \( \theta = \) 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)

- Compare Bignel, Lindsey J., et al. JINST 10 (2015) no.12, P12009

- New WBLS: JHU Mainz & TU Munich

- Nanocrystal-Doped Liquid Scintillator arXiv:1908.03564
Finding the Right Cocktail

- **CHE**renkov **Scintillation** Separation

  - 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

First demonstration of Cherenkov-light separation in LAB-PPO

Development of similar cell with LAPPDs at JGU Mainz

Larger light path in liquid to study propagation effects


Work at UC Berkeley

**PRELIMINARY**

PRC 95 055801 (2017)

CHESS
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)
  - QE ~28%: Used in JUNO
  - Dynamic-PMT (Hamamatsu)
  - MCP-PMT (NNVT)

- **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

---

*09/07/20*
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.)

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

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