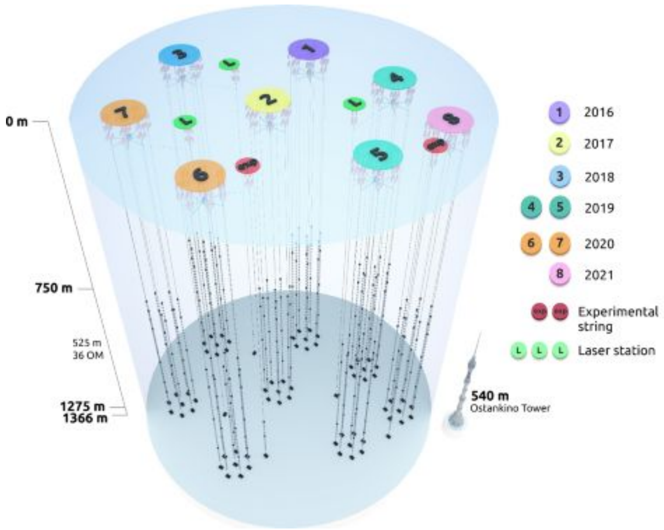
Machine learning in Baikal-GVD

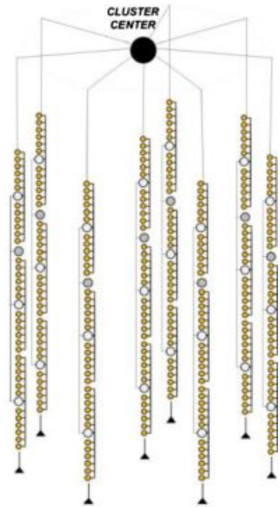
Workshop on ML for cosmic-ray air showers, 03.02.22

Plan of the talk

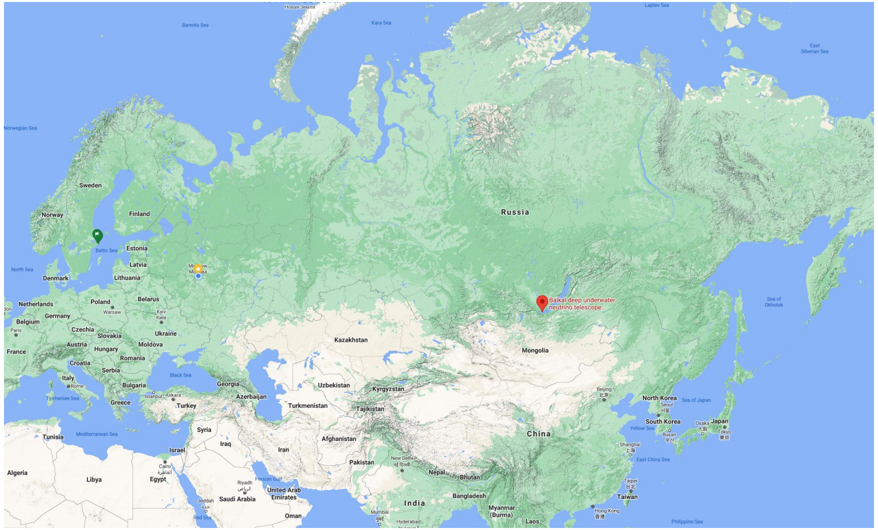
1. Baikal-GVD in general
2. ML tasks:
   a. Signal-noise separation for individual events
   b. Muons-neutrinos separation
   c. Arrival direction reconstruction
3. Conclusion and outlook

Baikal-GVD





- Studies neutrino astrophysics
- Collaboration: 6 countries, 10 institutions
- Deep underwater detector in lake Baikal
- 8 clusters →
  - 8 strings →
    - 36 optical modules
- Working volume ~ 1 km^3

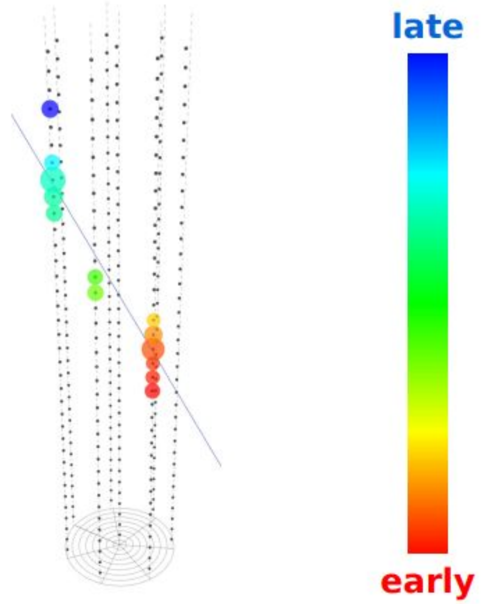


Tasks for ML

Working with only one cluster (3rd).

Triggering condition: 4.5 and 1.5 p.e. signal on adjacent OMs within 100 ns window

Problem 1: Signal-noise separation for individual events
Low threshold for writing signals from OMs →
need to suppress noise due to water luminescence



Problem 2: Muons-neutrinos separation
Was it a muon-induced or neutrino-induced event?

Problem 3: Arrival direction reconstruction
Where did the neutrino come from?

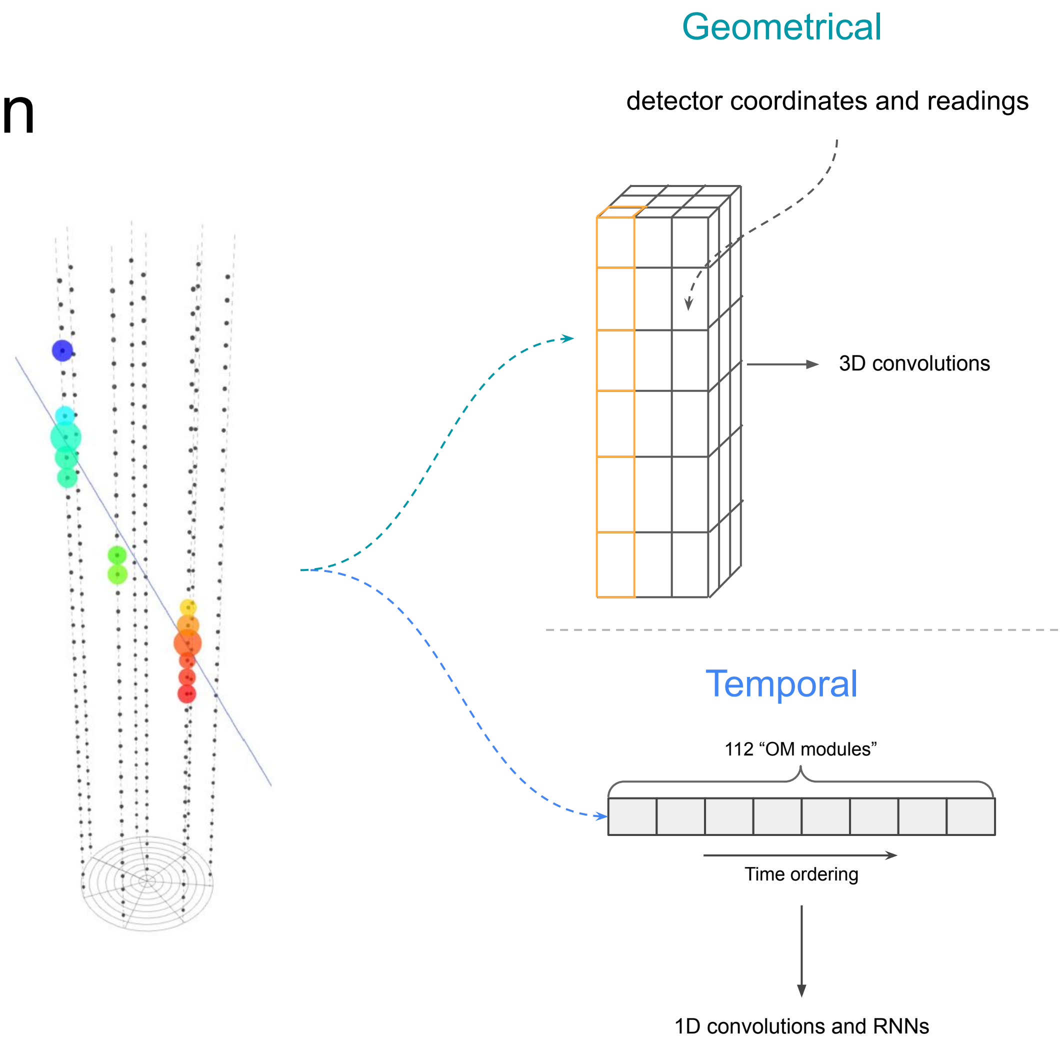
Data and its representation

MC simulations for μ (from cosmic rays) and ν_μ

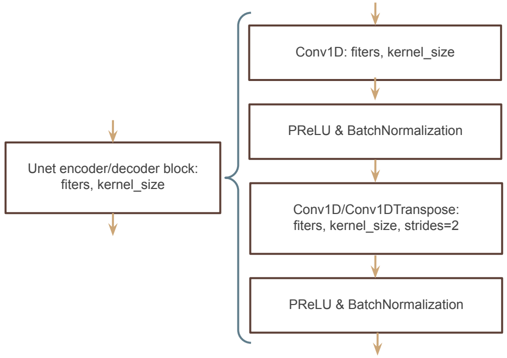
Waveforms → discrete impulses

Data includes:

1. Registered charge
2. Time of activation
3. Detectors coordinates
4. Hit labels (cascade/track/noise)



Signal-noise separation for individual events



Temporal NN is better (and faster)

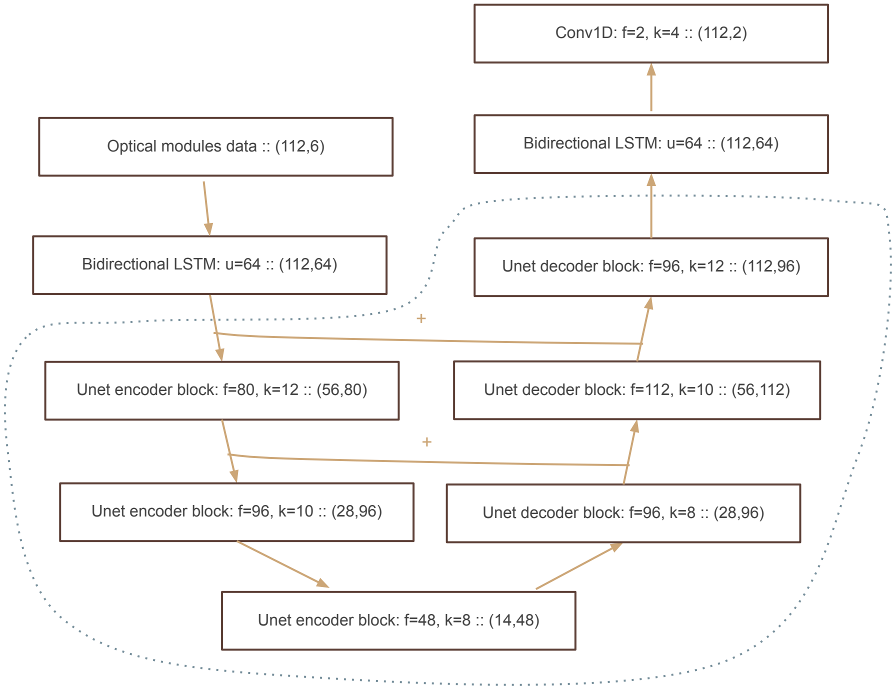
U-net-like architecture

Input data:

1-3) coordinates: x, y, z
4) integral signal
5) time of the activation
6) mask (auxiliary/true hit)

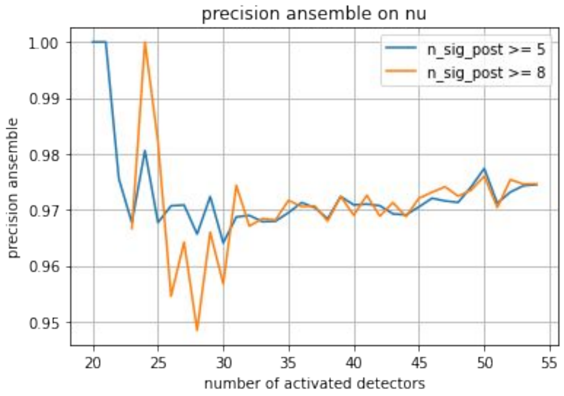
Output:

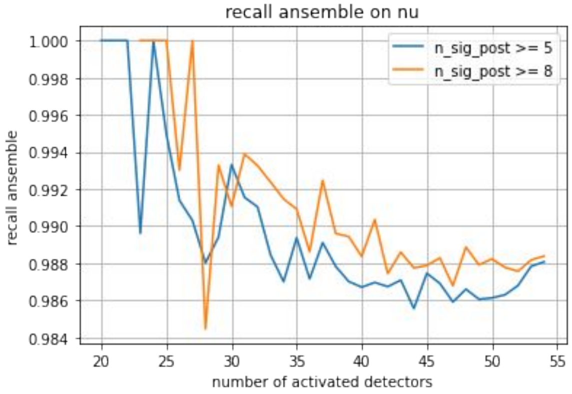
For each hit, the probability that it is due to signal or noise.

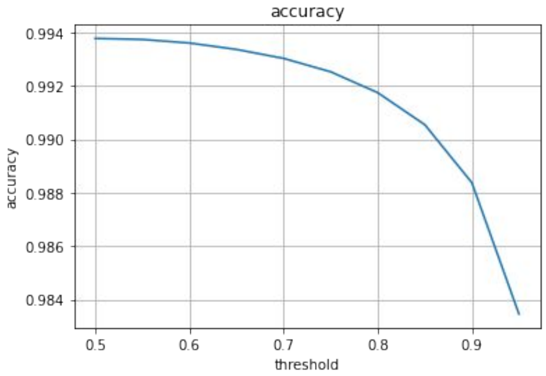


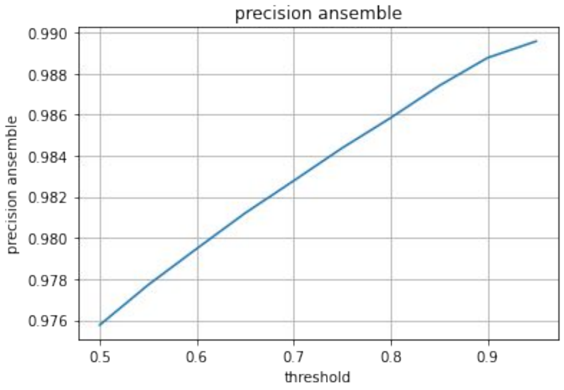
Results

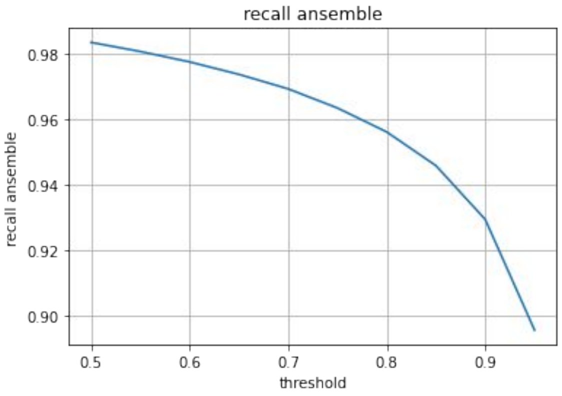
precision = t_s/(t_s+f_s), recall = t_s/(t_s+f_n)
(t_s - true signal,f_s - false signal, f_n - false noise)







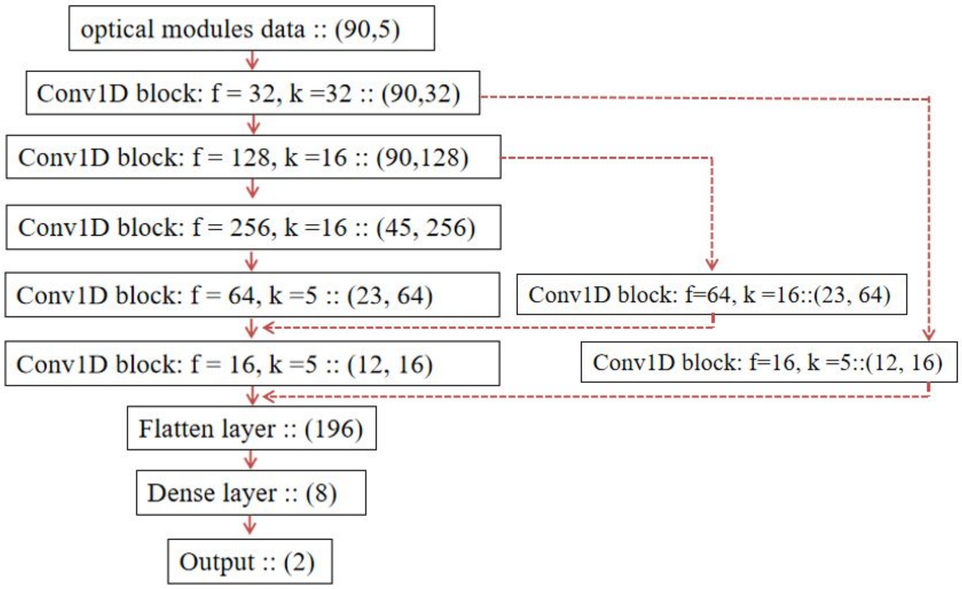




Muons-neutrinos separation: NN architecture

Temporal NN is better (and faster)

U-net architecture



Input data:

Purified (only signal hits)

1-3) coordinates: x, y, z

4) integral signal

5) time of the activation

Output:

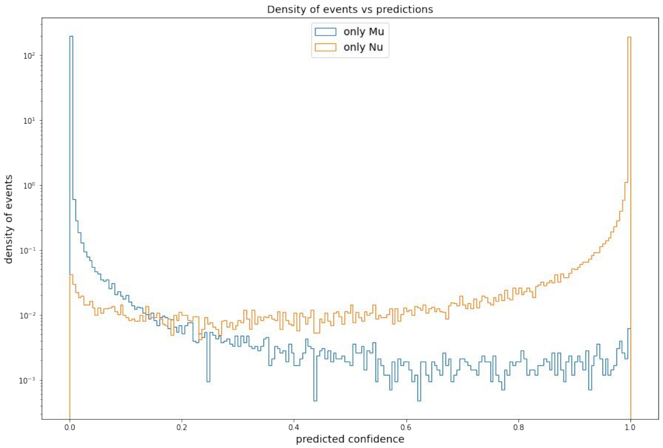
For each event, the probability that it is neutrino- or muon-induced.

Optimization in progress

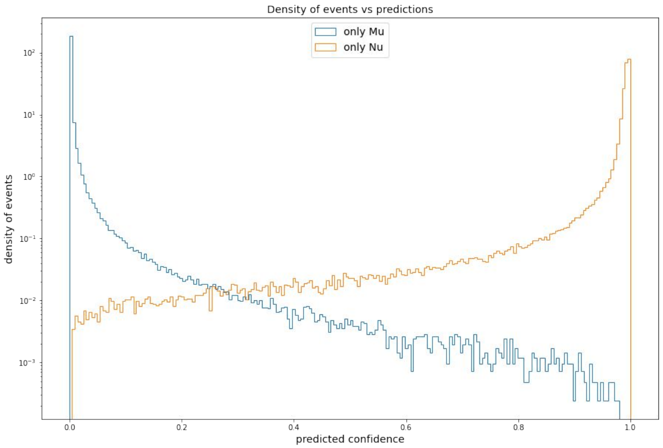
Muons-neutrinos separation: loss function

Signal to noise ratio: 10^{-6}-10^{-5} , expected ν_μ events ~ $5*10^3$ year^{-1}

- Introduce weights (~10) for muon-induced events;
- Use focal loss (arXiv:1708.02002): Loss = $(1-p_{correct})^2$*bce.



focal loss

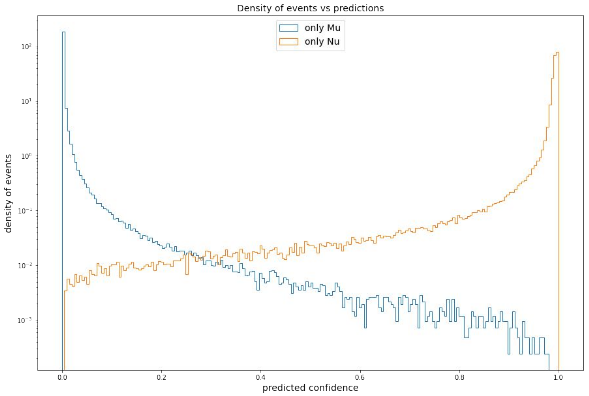


Muons-neutrinos separation: optimal threshold

$P(\mu \mid \text{det-}\nu) \sim N_{false\_\nu}(cut) / N_{true\_\nu}(cut)$ → minimize by optimising threshold

Best values: P=0, cut=0.9875, exposure=82%

(P(cut=0.98) = $2.1 \cdot 10^{-6}$)



Important:

- Use ensemble of NNs to suppress fluctuations
- Independent sets for EarlyStopping and cut optimization

Arrival direction reconstruction

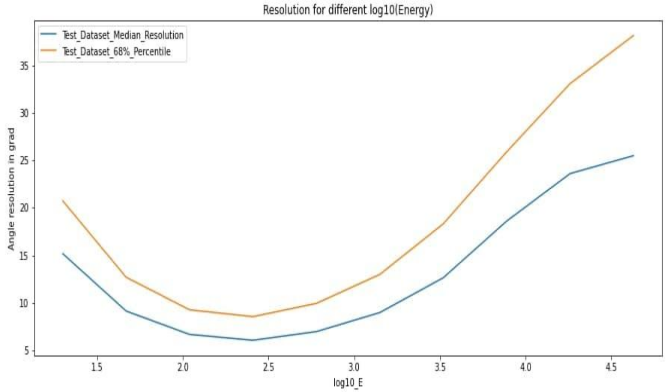
Neutrino events: arrive from under the earth

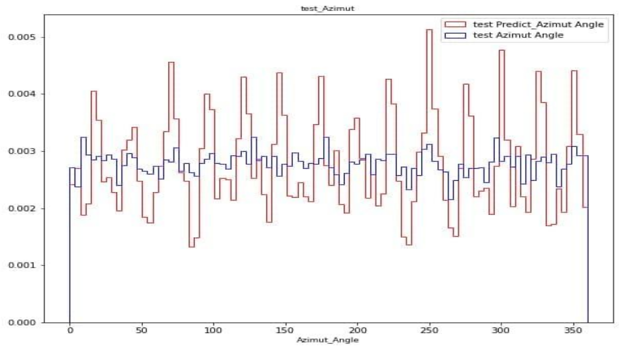
Work at early stages…

Geometrical NN is better

Problems:

- Clear peaks in azimuth angle reconstruction
- Low angle resolution





Conclusions

1. Temporal NNs are great, except for geometrical questions
2. For extreme purity, employ focal loss

Outlook

- Try graph neural networks
- Go to multicluster regime
- Optimize NNs further