Low-energy reconstruction techniques at Super-Kamiokande

IRN Neutrino 2021

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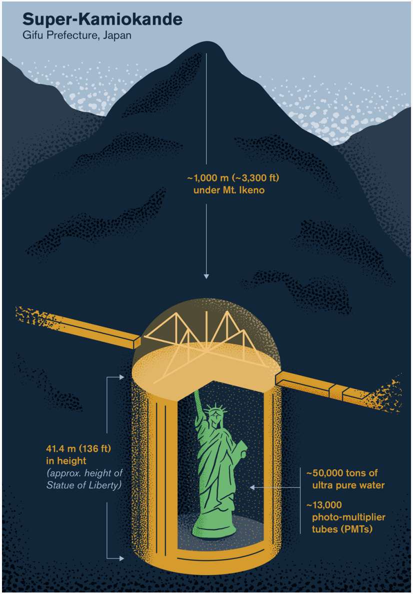
A 50-kton water Cherenkov detector in Japan's Kamioka mine



- Located under Mt. Ikeno in Gifu Prefecture, Japan
- Shielded from cosmic ray activity by $\sim$1 km of rock
- Inner Detector: 11129 PMTs
- Resolution: 50cm, 3 ns
- Energy coverage: 4 MeV $\leftrightarrow$ $\sim$TeV
- Water constantly recirculated and purified
- SK phases I-V: ultrapure water
- SK phases VI+ (starting summer 2020): water doped with Gadolinium sulfate, enhancing the signature of a neutron in the detector

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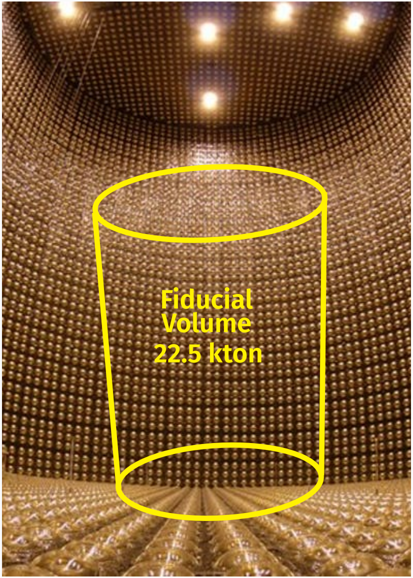

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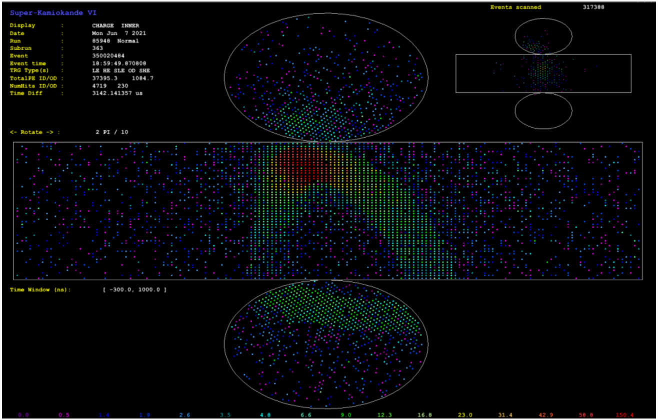
An example SK event

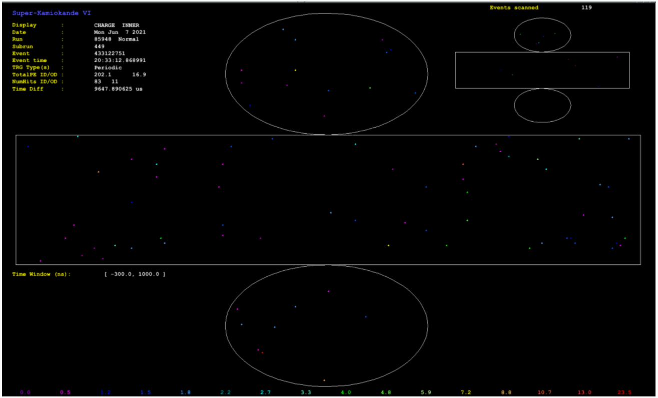
High Energy: GeV Scale



- Energy: $\sim$few GeV
- 1000s of PMTs lit up
- Several photoelectrons produced at each PMT
- Cherenkov cone pattern readily identifiable
- **Event vertex heavily constrained**

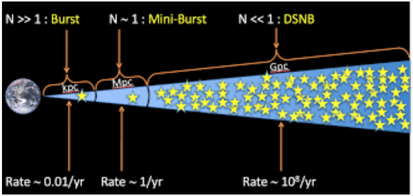
An example SK event

Low Energy: MeV Scale



- Energy: ∼few MeV
- 10s of PMTs lit up
- Typically a single photoelectron per PMT hit
- Cherenkov ring pattern easily lost among noise
- **Event vertex not readily constrained**

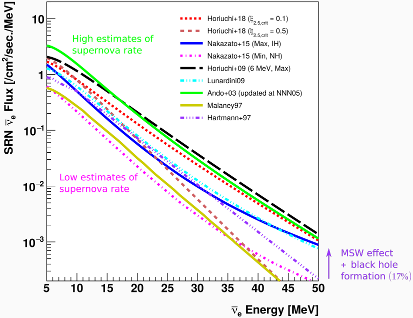
Neutrino flux from all distant core-collapse supernovae



J. Beacom

2-3 galactic supernovae/century

1 SN/s in the observable Universe

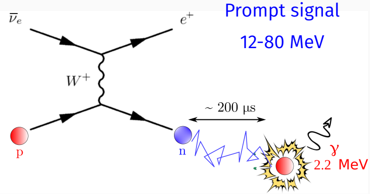


Y. Ashida

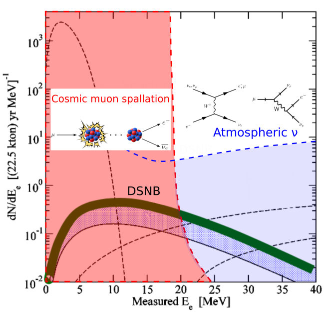
- Detection and characterization would allow for the study of aggregate properties of core-collapse supernovae, while probing the history of the universe and neutrino properties
- All flavors of neutrinos produced during CC SN, reaching Earth redshifted
- Expected signal is $\sim$10s of MeVs and has so far proved elusive

Detection of DSNB $\overline{\nu}_e$ via Inverse Beta Decay (IBD) in water

- 5-20 events/year
  Energy range: 12-80 MeV
- Need extremely powerful algorithms to characterize spallation and atmospheric backgrounds and **identify the neutrons**
- Current analysis: uses runs from the **SK-IV** data-taking era (Sep 2008-May 2018)
- Reconstruction separates into:
  1. Prompt event (e^+) vertex reconstruction
  2. Delayed event (n) tagging



Weak delayed signal



[Beacom and Vagins, Phys. Rev. Lett., 93:171101, 2004]

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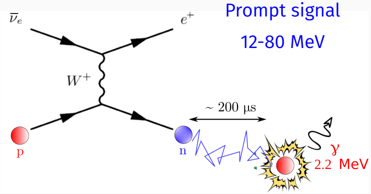

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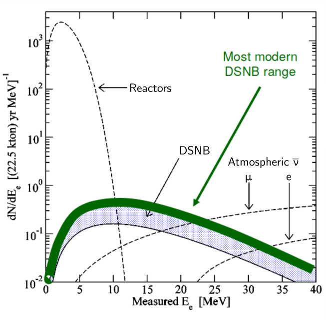

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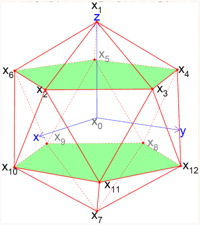
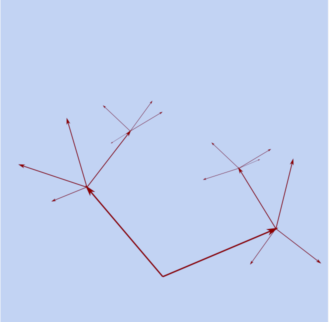
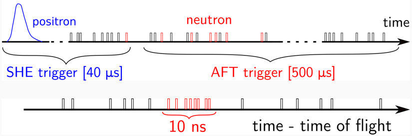
Prompt event reconstruction: the BONSAI algorithm

- **B**ranch **O**ptimization **N**avigating **S**uccessive **A**nneal**I**ng operations
- Need to scan possible vertex across the entire fiducial volume, correlating hits scattered across the detector
- Maximize vertex likelihood based on PMT hit timing
- Cherenkov cone opening angle θ_C constrains fitted event direction
- Naive approaches computationally intensize and prohibitively slow
- Trace many branches of a search tree, efficiently pruning for optimal performance
- **Highly effective for events within 10-100 MeV**
- **Not reliable for <4 MeV**

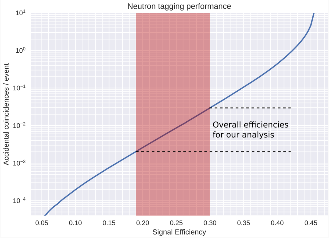




A faint neutron capture signal amid a sea of low-energy background



- **2.2 MeV neutron capture** signal extremely weak; easily lost among abundant low-energy backgrounds (4 kHz PMT noise, radioactivity, flasher events...): BONSAI not powerful enough
- **Wide trigger scheme** (540 μs time window), makes detection of neutron captures in water ($\tau_{\text{CAP}} \sim 200\mu$s) feasible.
- Up to $\mathcal{O}(10^4)$ reduction required after candidate selection



- Maximally exploit correlations with well-reconstructed primary vertex
- Use a BDT (a Machine Learning method) to classify neutron candidates, achieving ∼20%-30% overall efficiency

⋆ Gd has recently been dissolved inside the tank, producing **brighter, 8 MeV capture signals**. Efficiency is expected to increase to >80% for future analyses.

Limitations of current strategy

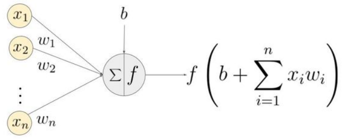
- Current algorithms treat prompt and delayed signals independently, with **no unified reconstruction**
- Every new analysis potentially **requires the development and tuning of new discriminating observables** for neutron tagging, despite the task being conceptually similar across analyses
  - → Tagging neutrons in pure vs. Gd-Doped water
  - → Tagging neutrons produced at higher energies
  - → Tagging neutrons at Hyper-Kamiokande (near future!)
  - → etc...
- Signal rarity means we need extremely powerful background rejection.. Could we be missing some correlations?

→ Would like an algorithm able to be applied more generically to a **variety of low-E reconstruction tasks**

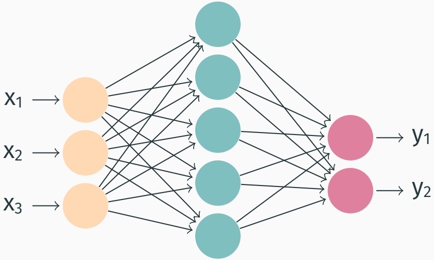
→ A possibility: using **Deep Learning**

Aside: Neural Networks

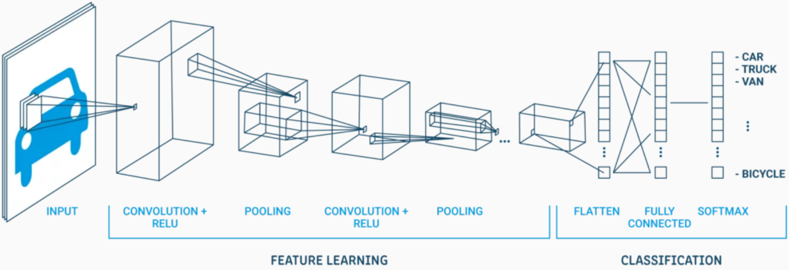
- Broadly, neural networks work to approximate any generic function from input x_i to output y_i
- Inputs are connected to outputs via intermediate ”neurons”
- Each neuron associated with a set of parameters: a weight for each input and overall bias
- During training all the parameters in the network are tuned to fit the desired function
- Deep Learning: neural network with many intermediate layers and more complex architecture



An example of a neuron showing the input (x_1 - x_n), their corresponding weights (w_1 - w_n), a bias (b) and the activation function f applied to the weighted sum of the inputs.



Aside: Convolutional Neural Networks



- CNNs: deep learning applied to image analysis
- Each pixel is a single input for the function
- Look for spatial correlations between neighboring pixels
- The networks learn to recognize abstract patterns from raw pixel data

Problem: an SK event is not at all a 2D image

2D image

Simple euclidean geometry

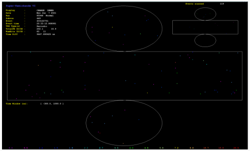
Translational invariance

Well-defined image edge

Pixels correlate to immediate neighbors

All pixels relevant

low-E SK event



Non-trivial detector geometry

No translational invariance

Non-trivial region boundaries

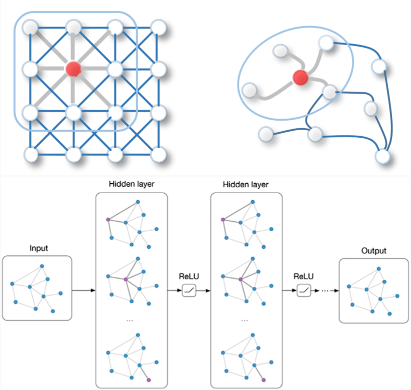
Pixels correlate across the detector

Most pixels off (sparseness)

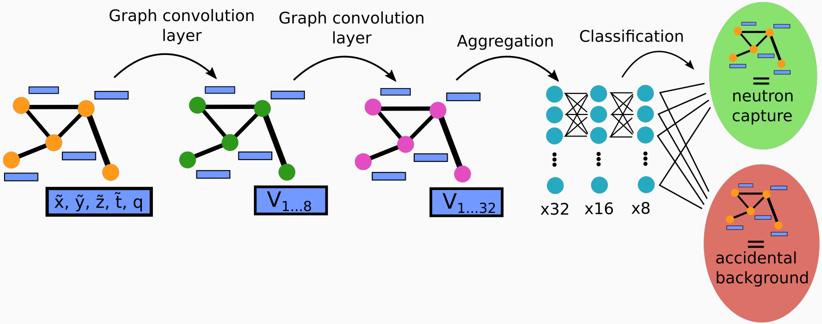
Graph Neural Networks

- Generalize CNN to analysis of graph data
- Each node in the graph is an input to the function
- Look for correlations between connected nodes
- Each layer in the GNN preserves the structure of the input graph and applies a transformation to the values of the nodes
- Have been sucessfully applied to neutrino detection (IceCube) and irregular detector geometries (CMS)

  ArXiv:1809.06166,
  ArXiv:1902.07987

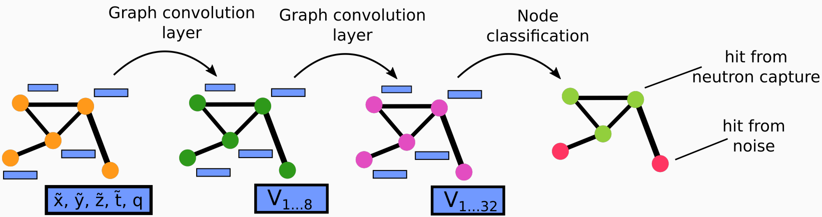


GNN architecture (simplified)



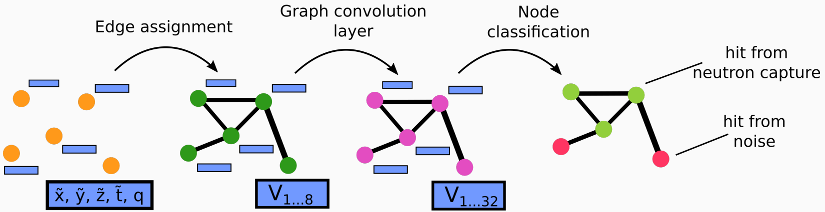
- Network structure assumes very little about original graph: **high-level features inferred** during training
- After graph convolution, high-level features are used in traditional neural net classification

GNN architecture: an alternative



- Teach GNN to distinguish neutron captures from background at the **PMT-hit level** (node classification) rather than at the event-level (graph classification)
- GNN is trained to distinguish signal from noise within the event, rather than learning on noisy signal.

GNN architecture: a further alternative

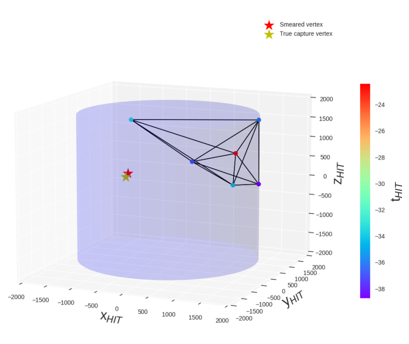


- Start from a **disconnected graph**
- The graph structure itself can be inferred and optimizes by the GNN
- Demands highest level of abstraction from GNN, starting from truly low-level hit information
- Most general tool with least prior assumptions

A first application: neutron tagging

- First goal: train a neutron tagging classifier that can compete with the current algorithm
- Classify a set of candidate hits associated with a primary vertex as a neutron capture instance or background

- Each PMT hit assigned to a node, with relative position, relative time, and charge information
- Two nodes share an edge if they could have originated from the same Cherenkov cone, given the primary vertex
- First implementation: simple graph classifier with no optimization attempted.
- Very preliminary results; encouraging for further study



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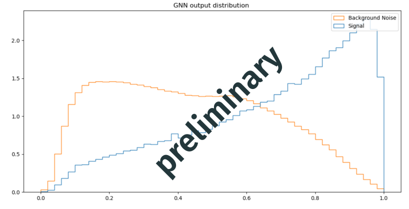

Summary

- Wide array of tools currently implemented for low-energy event reconstruction at SK, from traditional to ML-based
- Good performance is achieved but current algorithms are typically limited in their scope and not readily compatible with each other
- Graph Neural Nets could open the door for **more powerful and broadly-applicable particle reconstruction at SK and HK**
- Stay tuned for some early results in the near future!

Thanks for your time!