Helping to Improve the Analysis of SNO+ Data with Machine Learning

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on behalf of the SNO+ collaboration

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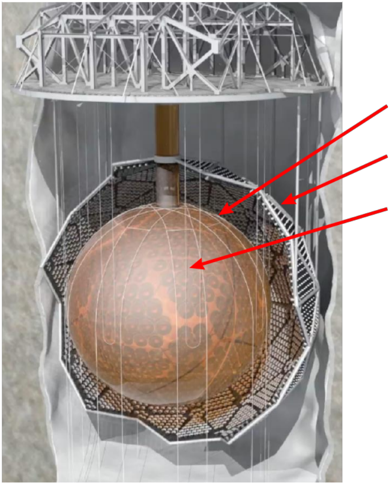
Overview

- SNO+ detector and physics goals
- Machine learning basics
- Applications of machine learning to SNO+
    - Antineutrinos
    - Reconstruction

The SNO+ Detector

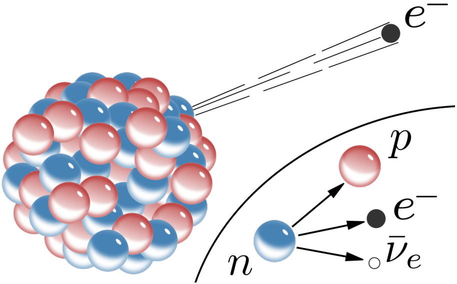


- Multipurpose neutrino experiment
- 2km underground
- 12m diameter acrylic vessel
- ∼10,000 PMTs
- 900Mg water / 780Mg scintillator
- Physics goals include
  - Neutrinoless double beta decay
  - Low energy solar neutrinos
  - **Antineutrinos**

SNO+ Antineutrinos

- Antineutrinos originate from several sources
  - β-decay in nuclear reactors (reactor neutrinos)
  - β-decay of radioactive isotopes in the Earth (geo-neutrinos)

$$\mathrm{n} \longrightarrow \mathrm{p} + \mathrm{e}^{-} + \bar{\nu}_e$$



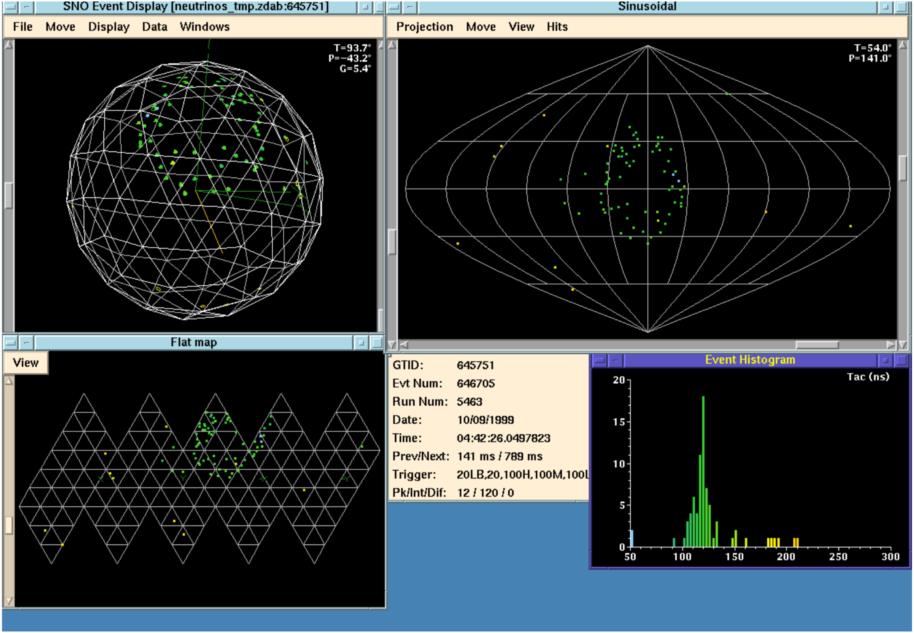
[1]

SNO+ Antineutrinos

- Goal is to detect antineutrino signal in water
- Detected via inverse beta decay

$$\bar{\nu}_e + \mathrm{p} \longrightarrow \mathrm{e}^+ + \mathrm{n}$$

- Coincident signal
  - Positron deposits energy, annihilates (*prompt* event)
  - Neutron is captured later by a proton (*delayed* event)
    - Emits 2.2MeV γ
  - Signals present as rings on the detector
- Antineutrino signals are difficult to detect in water
  - Low energy deposited
  - Dominated by other backgrounds in the detector


SNO Event Display [neutrinos_tmp.zdab:645751]
File
Move
Display
Data
Windows
T=93.7°
P=−43.2°
G=5.4°
Sinusoidal
Projection
Move
View
Hits
T=54.0°
P=141.0°
Flat map
View
GTID: 645751
Evt Num: 646705
Run Num: 5463
Date: 10/09/1999
Time: 04:42:26.0497823
Prev/Next: 141 ms / 789 ms
Trigger: 20LB,20,100H,100M,100L
Pk/Int/Dif: 12 / 120 / 0
Event Histogram
Tac (ns)
20
15
10
5
0
50
100
150
200
250
300

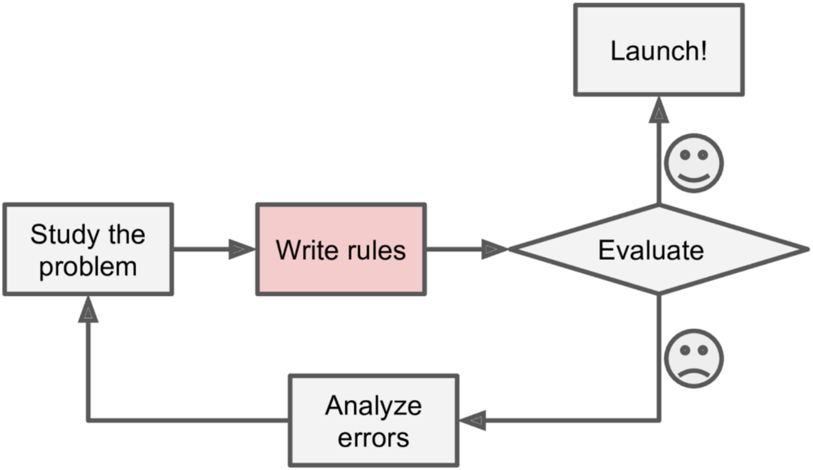
Machine Learning

- A prediction function, f, takes some input, $\boldsymbol{X}$, and produces a meaningful output, $\boldsymbol{Y}$
- Goal of machine learning is to *learn* the prediction function
    - Known inputs and outputs used to train the model
- Patterns in the data not obvious to us can be recognized in the learning process

$$\underbrace{\boldsymbol{Y}}_{\textit{Target}} = \underbrace{f}_{\textit{Prediction Function (Model)}}(\underbrace{\boldsymbol{X}}_{\textit{Input}}) + \underbrace{\varepsilon}_{\textit{Noise Term}}$$

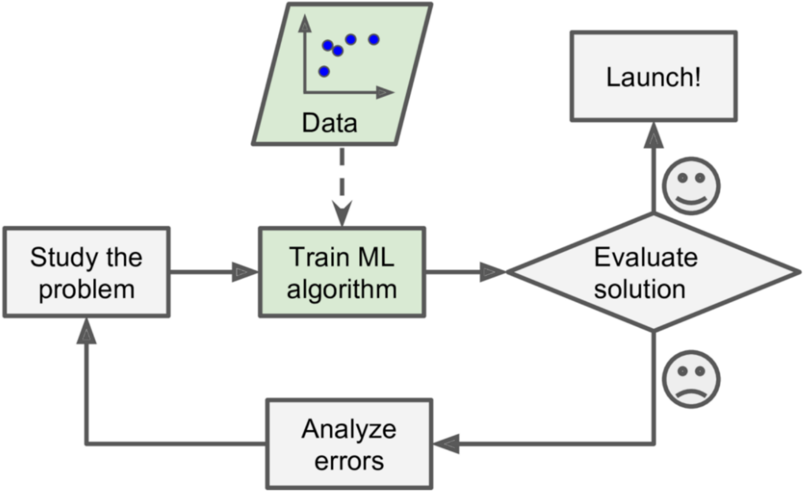
$$\underbrace{\hat{\boldsymbol{Y}}}_{\textit{Predicted Output}} = f(\boldsymbol{X})$$

Traditional (Human-Based) Analysis Approach



[2]

Machine Learning Analysis Approach



[2]

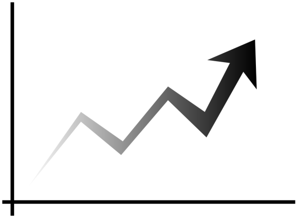
Machine Learning

- Two broad categories of machine learning
  - Supervised learning
    - Provide training data with explicitly labelled inputs and outputs
  - Unsupervised learning
    - Provide unlabelled data and try to infer patterns from it
- Divide supervised learning into two categories based on the target(s)

Classification (binary/multiclass)

[3]

Regression (continuous)



[4]

Machine Learning for SNO+

- Machine learning can help in SNO+ data analysis
    - Antineutrino Search
        - *Classification* problem
        - Lots of data
        - Identify patterns / detect anomalies
    - Reconstruction of event positions in the detector
        - *Regression* problem
        - Lots of data
- Primary focus on neural networks
    - Found to perform faster and better than other approaches
    - Existing efficient implementations of matrix multiplication
    - Easy implementation of algorithms that utilize GPUs for training and inference

Identifying Antineutrino Events

AmBe Calibration Source

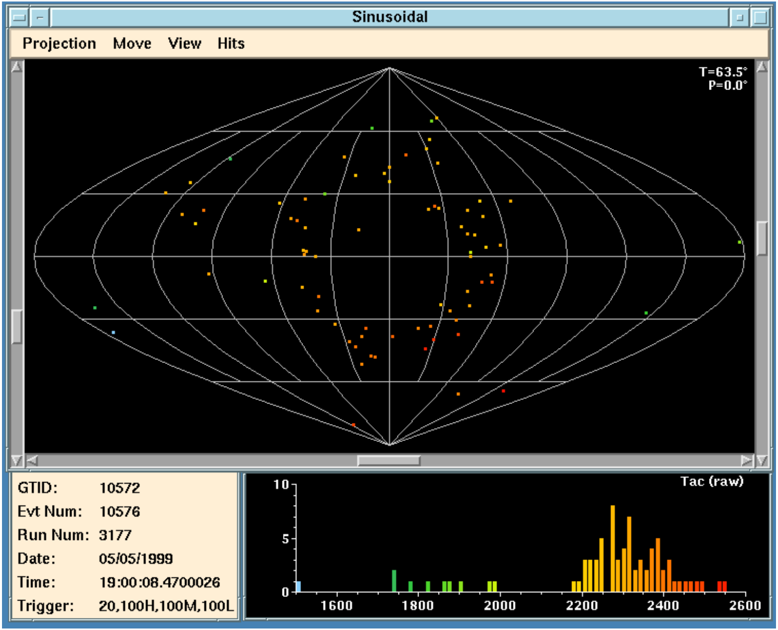
- Need a large training set of data for machine learning
- Americium-241 Beryllium-9, "*AmBe*", calibration source
  - Provides two energy calibration measurements
  - **Mimics the antineutrino signal** $(\bar{\nu}_e + \mathrm{p} \longrightarrow \mathrm{e}^+ + \mathrm{n})$

$$\alpha + {}^{9}\mathrm{Be} \longrightarrow {}^{12}\mathrm{C} \;\; + \mathrm{n} \qquad \text{(40\%)}$$
$$\alpha + {}^{9}\mathrm{Be} \longrightarrow {}^{12}\mathrm{C}^* + \mathrm{n} \qquad \text{(60\%)}$$
$${}^{12}\mathrm{C}^* \longrightarrow {}^{12}\mathrm{C} + \gamma \text{ (4.4MeV)}$$

- 4.4MeV γ is basically instant (*prompt* event, like the e^+)
- n is captured in water some time later (*delayed* event)
  - Emits 2.2MeV γ
  - Fitted neutron capture time in water: $202.6 \pm 3.7\mu$s [5], $204.8 \pm 0.4\mu$s [6], $208.2 \pm 2.1\mu$s [7]

Neural Network Classifier: Approach

- Machine learning allows for the identification of the neutron capture signal
  - Supervised learning problem
  - Trained on AmBe Monte Carlo data
    - Salted with background data from the detector
  - Inputs: PMT positional coordinates and PMT time
    - PMT coordinates relative to the median of all hit PMTs in an event
    - Total size is $4 \cdot \text{nhits}$ $(x - x_m, y - y_m, z - z_m, t)$
  - Output: a classification
    - Neutron capture or background

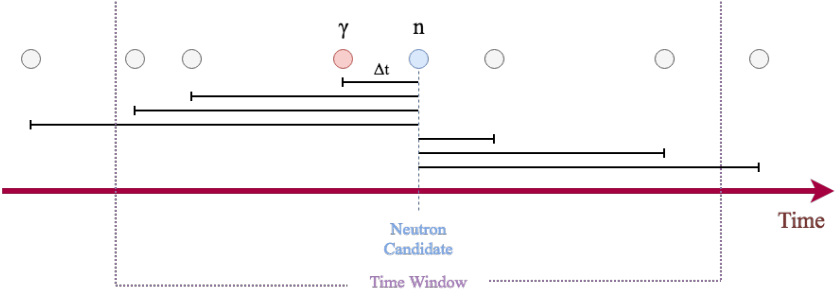

Sinusoidal
Projection Move View Hits
T=63.5°
P=0.0°
GTID: 10572
Evt Num: 10576
Run Num: 3177
Date: 05/05/1999
Time: 19:00:08.4700026
Trigger: 20,100H,100M,100L
Tac (raw)
10
5
0
1600
1800
2000
2200
2400
2600

Neural Network Classifier: Results

- Accuracy on test set $>$90% for identification of both background and neutron capture
  - The test set is completely separated from the training set
- More importantly, predictions are consistent with real AmBe calibration data from the detector
  - Coincident signal is used to test the model
  - The time difference between delayed events predicted by the neural network (neutron candidates) and the event directly before (prompt event) should produce a specific timing distribution
  - Timing distribution fit will produce the neutron capture constant in water

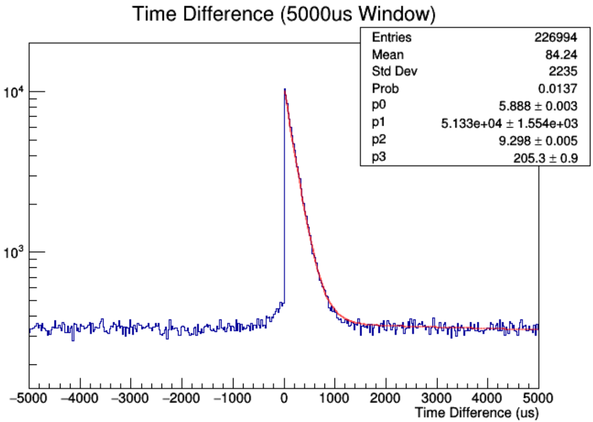
Neural Network Classifier: Results

- Time difference between events within a 5000μs before/after the candidate are binned
- Negative time difference (i.e., events *after* the candidate) are Poisson distributed similarly to data
  - Consists of backgrounds
- Positive time difference (i.e., events *before* the candidate) are Poisson distributed with a parameter of neutron capture constant
  - Consists of prompt events and backgrounds



Neural Network Classifier Performance

- Fit sum of two exponentials, $\exp\left([0] - \frac{1}{[1]}\Delta t\right) + \exp\left([2] - \frac{1}{[3]}\Delta t\right)$
  - $p0$ and $p1$ are constrained by negative fit and thus fixed
  - $p3$ is the neutron capture constant!



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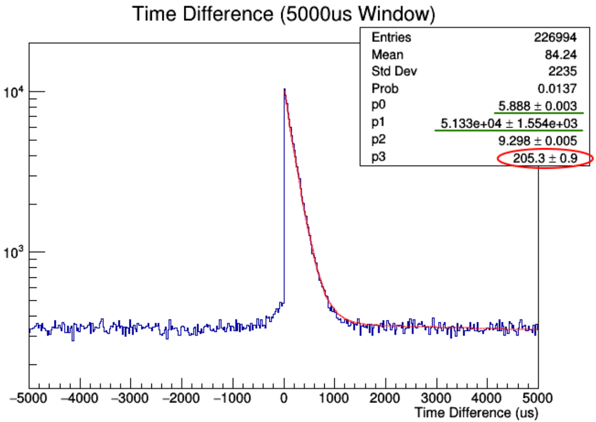
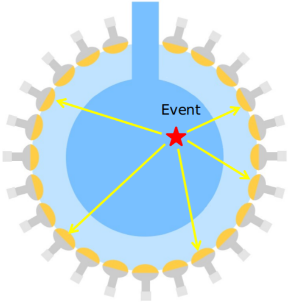


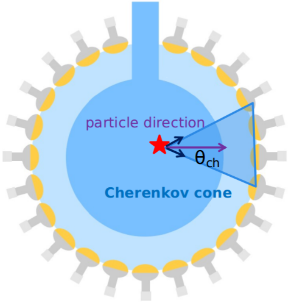
Reconstruction of Event Position in the Detector

Position Reconstruction

- Position reconstruction also suitable for machine learning
- Want to figure out where in the detector an event occurs
- Use relative PMT timing information
- Current approach involves a cascading of likelihood algorithms that account for complex physics processes



[8]

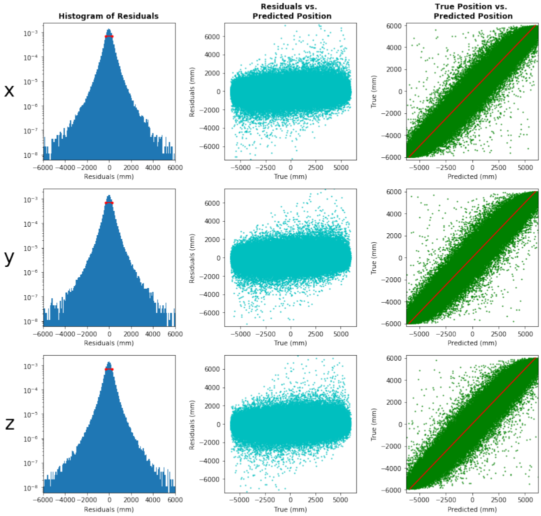


[8]

Position Reconstruction

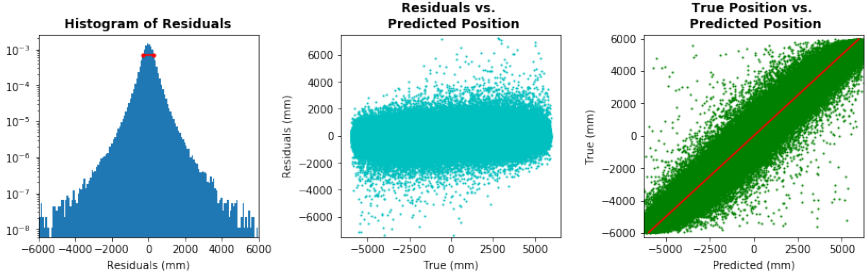
- With neural networks, a computational investment initially allows for fast inference later
  - Existing efficient implementations of matrix multiplication
  - Easy implementation of algorithms that take advantage of GPUs
  - A trained network is much quicker
- Supervised learning, regression problem
  - Train on Monte Carlo electrons
    - Uniformly distributed throughout the detector volume
  - Test on Monte Carlo and calibration data (tagged sources)

Position Reconstruction: **SNO+**



Position Reconstruction: **SNO+**

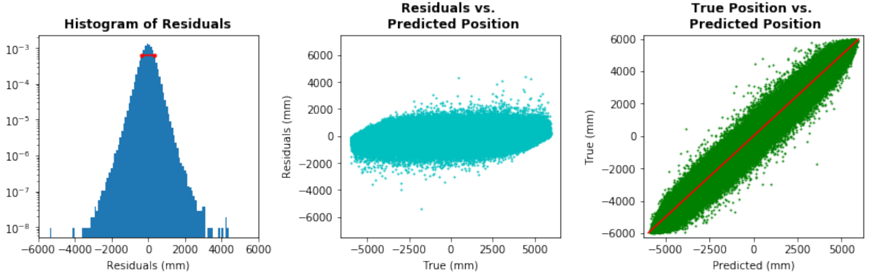
X



$$\mu_{\text{data}} = -0.261$$
$$\sigma_{\text{data}} = 399.312$$
$$\text{FWHM} = 586.344$$

Position Reconstruction: **Neural Network**

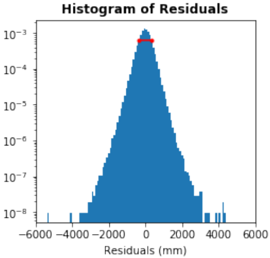
X

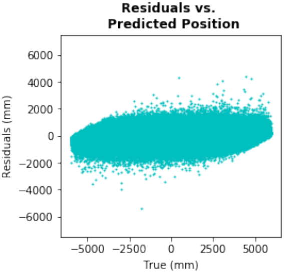


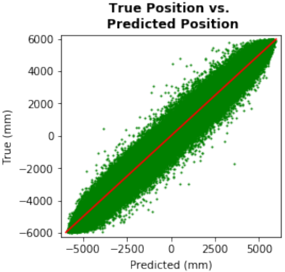
$$\mu_{\text{data}} = -9.796$$
$$\sigma_{\text{data}} = 350.687$$
$$\text{FWHM} = 675.440$$

Position Reconstruction: **Neural Network**

X







$$\mu_{\text{data}} = -9.796$$

$$\sigma_{\text{data}} = 350.687$$

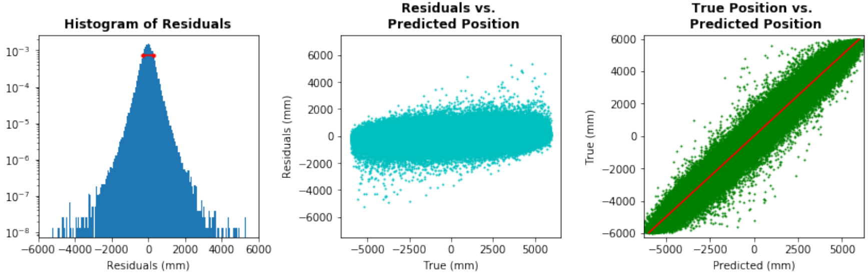
$$\text{FWHM} = 675.440$$

Position Reconstruction

- Resolution of neural network is slightly worse
- Spread of residuals has less outliers
- Neural network makes much faster predictions than SNO+ fitter
    - 100x - 1,000x quicker on CPU (Central Processing Unit)
    - 10,000x quicker on GPU (Graphics Processing Unit)
    - Conservative estimates
- Average results together to obtain better reconstruction

Position Reconstruction: **Neural Network and SNO+**

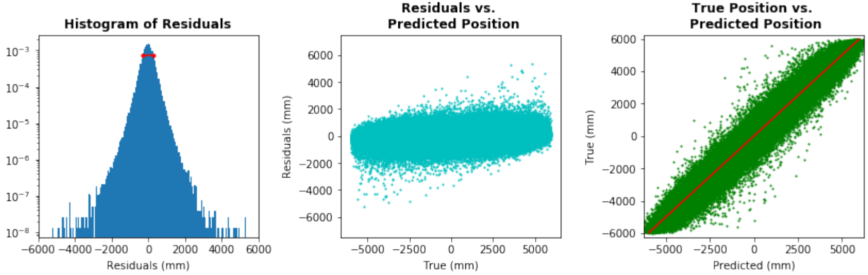
X



$$\mu_{\text{data}} = -5.028$$
$$\sigma_{\text{data}} = 326.874$$
$$\text{FWHM} = 580.510$$

Position Reconstruction: **Neural Network and SNO+**

X



$$\mu_{\text{data}} = -5.028$$

$$\sigma_{\text{data}} = 326.874$$

$$\text{FWHM} = 580.510$$

Conclusion

- Machine learning has proven successful on several analysis tasks
- Many more places where machine learning can be helpful
    - Monte Carlo simulations
    - Data cleaning and further background identification/reduction
- Results are promising entering the scintillator phase of the experiment

Thank You!

References

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