Enhancing the Compton Spectrometer & Imager's event reconstruction capabilities with machine learning

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Compton telescopes utilize a gamma-ray Compton scattering one or more times in their detector volume to reconstruct the photon's path and determine its initial scatter angle. For compact Compton telescopes this task is complicated by the fact that the time between successive interactions is shorter than the readout time of the detector. As a result, the correct path of the gamma-ray must be extracted from the raw data by determining the most likely scattering sequence. Here we consider the Compton Spectrometer and Imager (COSI) and the implications of using machine learning for COSI's event reconstruction. We have tested four different approaches to Compton event reconstruction for COSI: the classical Compton sequence reconstruction, a naive Bayesian, a random forest, and a neural network. These approaches were implemented in the Medium-Energy Gamma-ray Astronomy library (MEGAlib) software toolkit, which is also where we simulated the data, trained the approaches, and evaluated the results. Our findings show that these new methods outperform the classical event reconstruction approach and result in the lowest rates for wrongly reconstructed event paths.

Compton event reconstruction & *goodness* metric (ARM)

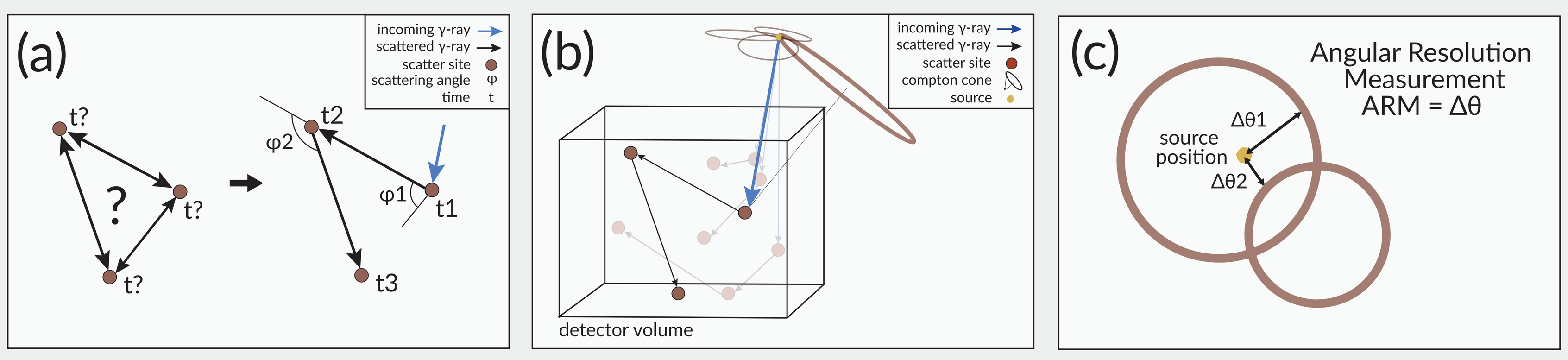


Figure 1. (a) Consider an incoming gamma-ray which Compton scatters twice within a detector volume and then gets absorbed. We can readout the position and energy information of each interaction, however the order of the interactions is not explicit in the raw data and must be extracted in the analysis pipeline. (b) Once the sequence of interactions is determined, the initial Compton scatter angle is determined and the gamma-rays origin is confined to an annulus (Compton cone) in the sky. Using overlapping Compton cones, the point of origin can be determined. (c) The key performance parameter of a Compton telescope is the Angular Resolution Measure (ARM). The ARM is defined by the shortest distance (in degrees) between the known photon's origin and the Compton cone.

Event reconstruction algorithms

Classical Compton sequence reconstruction

Benefits
- Computationally fast

Shortcomings
- Compton scattering is the only physical effect accounted for
- Only considers events with N>1 Compton scatters

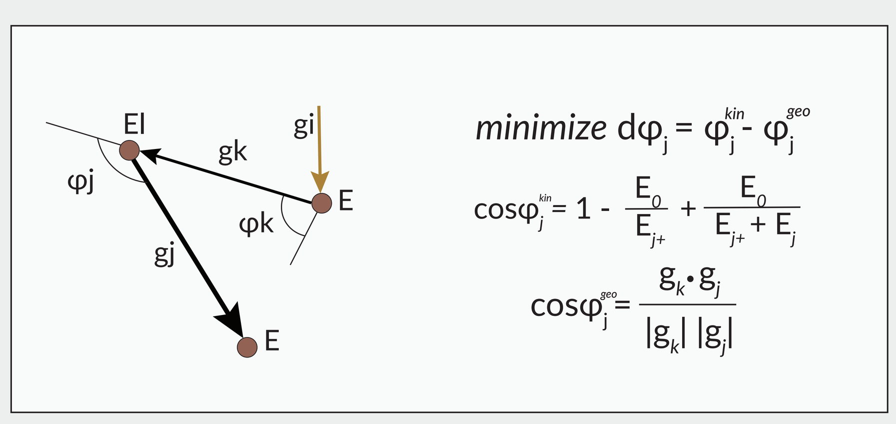


Figure 2. When a photon Compton scatters N times (N > 1), the second φk scattered angle can be determined both kinematically and geometrically. The classical approach pickes the sequence that minimizes this difference. While computationally fast, the classical approach only considers Compton scattering, excluding all other detector effects.

Naive Bayesian

Benefits
- (In theory) can account for all physical effects

Shortcomings
- Computationally demanding
- Data space is too large to compute

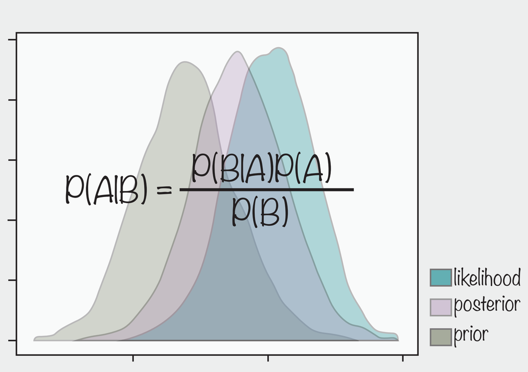


Figure 3. The Bayesian approach utilizes Baye's theorem to determine the probability of an original input given some obtained result. This approach works well for Compton event reconstruction because we can create an extensive set of simulation files for the Bayesian algorithm from which it can generate a probability graph to analyze all possible interaction sequences and determine the most likely reconstructed path. Unfortunately, the data space required to consider all relevant physical effects is too large to compute, causing important information to be left out of the calculations.

Random forest decision tree

Benefits
- Can account for all physical effects

Shortcomings
- To be quantified during bench marking process

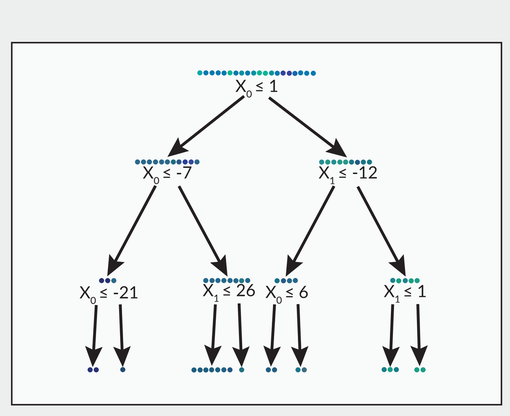


Figure 4. A random forest is a type of decision tree algorithm. Inputs are represented by nodes in the tree, output values are given by leaves, and the paths connecting a node to a leaf are represented by weighted branches. These weights are determined using simulation data.

Neural network

Benefits
- Can account for all physical effects
- Good at handling non-linearities
- Better performance than the other approaches

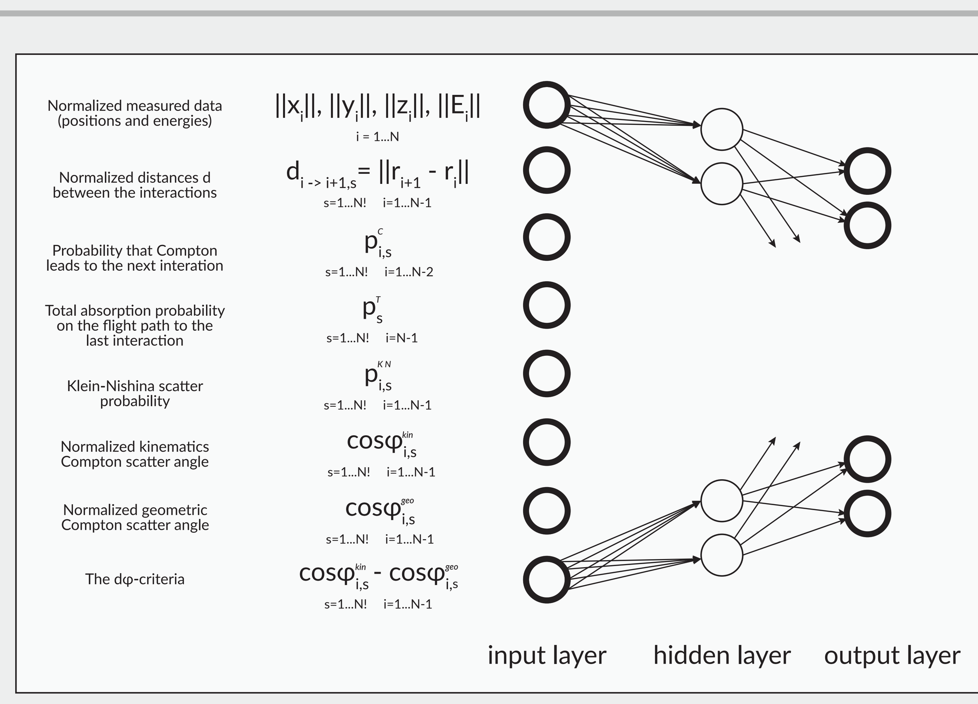
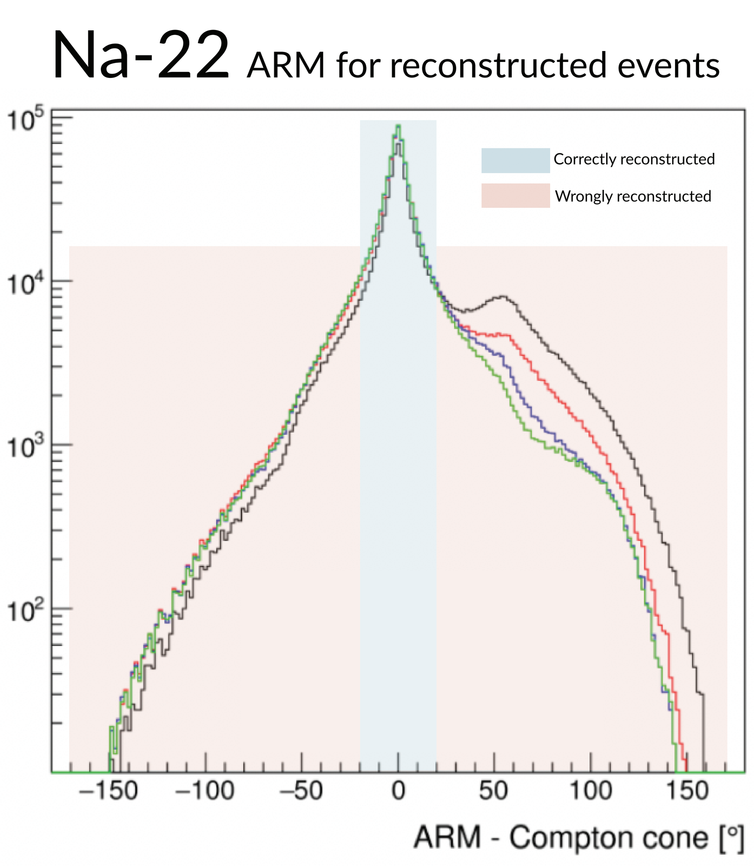


Figure 5. The neural network we used has a standard topology of a multi-layer perceptron with a single hidden layer and 8 different blocks of input nodes. The input layers accept input data, the output layers define possible outcomes, and the hidden layer transforms the data to match the outcome desired by the output layers by assigning weights between the different nodes of each layer (neurons) . The neural network is trained using simulations. As the network processes more and more data, the weights between the neurons are adjusted to minimize the difference between the network's results and the true results of the simulation.

Preliminary results



Method	RMS improvement
Classical	0%
Bayesian	17.0%
Random Forest	24.9%
Neural Network	27.4%

Figure 6. ARM plot demonstrating the performance of the four algorithms: classical, Bayesian, random forest, and neural network. Correctly reconstructed events appear in the central peak of the ARM distribution around 0°, and wrongly reconstructed events appear off-peak. For this plot, the algorithms were implement, trained, and evaluated in MEGAlib. 100,000,000 events were simulated using a Na-22 source in cosima and trained using the responsecreator. The trainings were then evaluated with ground-based Na-22 calibration data from the 2016 COSI balloon. The ARM plot shows clear improvement in performance for the machine learning approaches, with the neural network offering the most improvement.

In-progress work

Quantify the impact machine learning has on COSI's science capabilities
Does it improve COSI's sensitivity?

Benchmark and validate the approaches
Apply different data cuts to the reconstructed events and see how machine learning compares to the classical approach: Does it have improved reconstruction for events with shorter distances between Compton scatters? With smaller Compton scattering angles?

Na-22
511 keV
COSI SMEX geometry
cosima simulations
isotropic allsky
10^8 training events

Al-26
1.809 MeV
COSI SMEX geometry
cosima simulations
isotropic allsky
10^8 training events

Currently, we are working on generating sensitivity estimates for the full COSI SMEX geometry using these four different algorithms. For this calculation we have simulated 1×10^8 isotropic, monochromic, signal emission line events for the full COSI SMEX geometry using cosima — MEGAlib's particle simulation tool. Half of these simulation files are then passed into MEGAlib's reaponsecreator which generated training files for the Bayesian, random forest boosted decision tree, and neural network algorithms. These training files are then applied to reconstuct the events for the full continuum COSI will be observing, including point sources and backgrounds. Na-22 and Al-26 were considered because of their prevalence to COSI's science goals to image the 511 keV line and perform spectroscopy of radioactive decay lines. We are also working on benchmarking all the appoaches by considering how they fair for different parameter cuts on the data.

Next steps

Validate with ground based calibrations
COSI balloon data
Single SMEX detector

If benefits are evident: integrate machine learning event reconduction into MEGAlibs pipeline (Figure 7).

Identify other analyses within MEGAlib that could be improved with machine learning
Such as strip pairing

In tandem, determine if there are other algorithms could enhance results

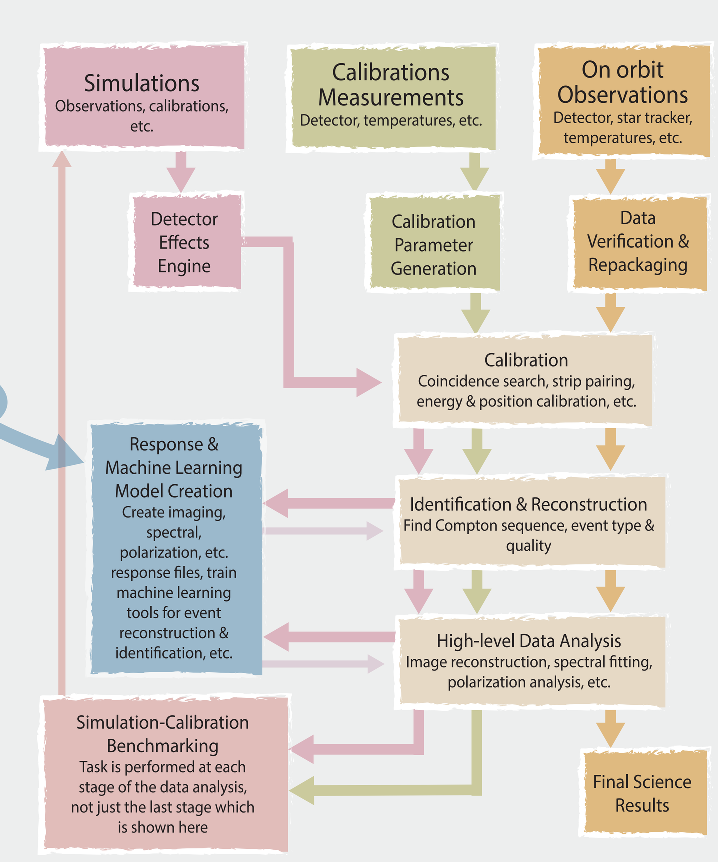


Figure 7. Overview of the COSI analysis pipeline.

Acknowledgements

The Compton Spectrometer and Imager is a NASA Explorer project led by the University of California, Berkeley with funding from NASA under contract 80GSFC21C0059.

Partial support for this work was provided by NASA under Astrophysics Research & Analysis grant 80NSSC21K1815.

Thank you to my advisors Dr. John Tomsick and Dr. Andreas Zoglauer

This work utilized the The Medium-Energy Gamma-ray Astronomy library (MEGAlib)

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