Locating Supernovae via Artificial Neural Networks

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Introduction

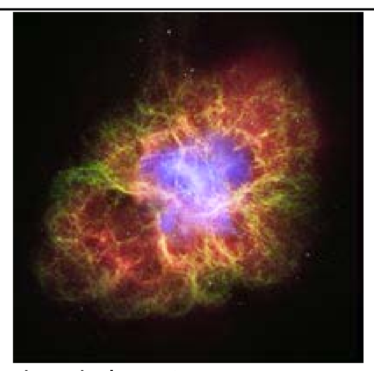
The rate at which supernova occur at large distances with high redshifts is hard to obtain. New data collection would require several hundred orbits on the Hubble Space Telescope (HST). However, there are enough HST images of sufficiently deep, extragalactic fields available in archives and the only challenge is locating and identifying the supernovae within them to add the statistical rate analysis. There is a wealth of information on the appearance of high redshift events in relation to their host galaxies that can be used to train artificial neural networks (ANNs) to identify unique magnitude, color, and separation parameter spaces.

Why Hunt Supernovae

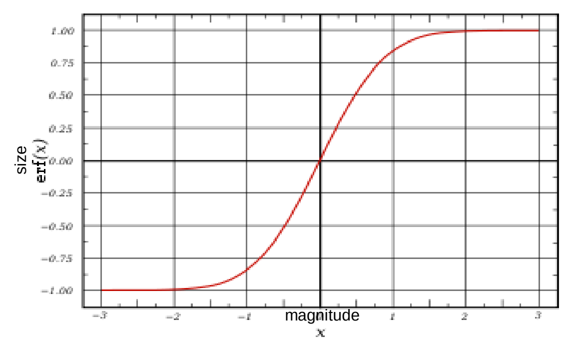
The rate at which supernovae occur in the early universe puts important constraints on the nature of their progenitors, and systematic uncertainty on the nature of *dark energy*.

What are Supernovae?

Star explosions! A star much larger than our sun will die by exploding with so much energy that it can be brighter than an entire galaxy. This project uses **type Ia supernovae** since they always ignite once they reach a specific mass known as the Chandrasekhar limit. This is helpful in cosmology since they explode with the same energy, making them "standard candles" for measuring the history of cosmic expansion.



Crab Nebula, a Supernova Remnant

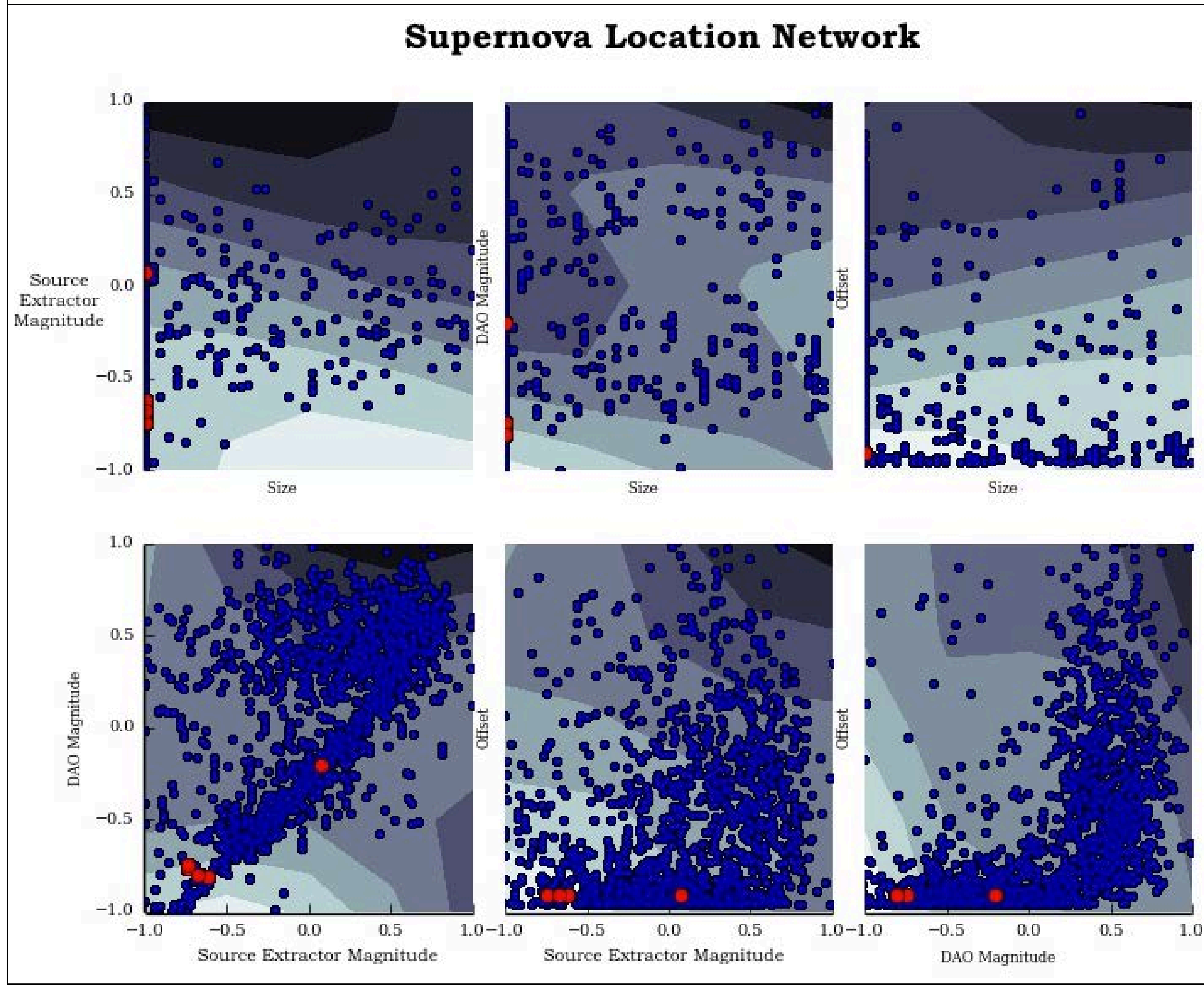


Sigmoid function

Artificial Neural Networks

The python package PyBrain was used to create the SN-ANN. The network first trains a data set by repeatedly weighting input data to fit to a sigmoid function to predict the output: probability of being a supernova. The network fits the data to a sigmoid function with the lowest error. Then the network applies a separate testing data set (with the same input characteristics) to the fitted function.

Example of Network Results:



This SN-ANN is a preliminary test on a selected region where there are known supernovae. 2510 point sources were used for training from one region of and 4006 samples were used for testing from a different region. Each contour was created from the training data set. Lighter contours represent higher probability of being a supernova event. The data points are the testing data set with red representing known supernova events and blue representing other objects. **This network accurately located 3 out of 4 known supernova events.** The network identified 22 events as supernovae with 3 being correct. These false positives prove more investigation in the archives is required.

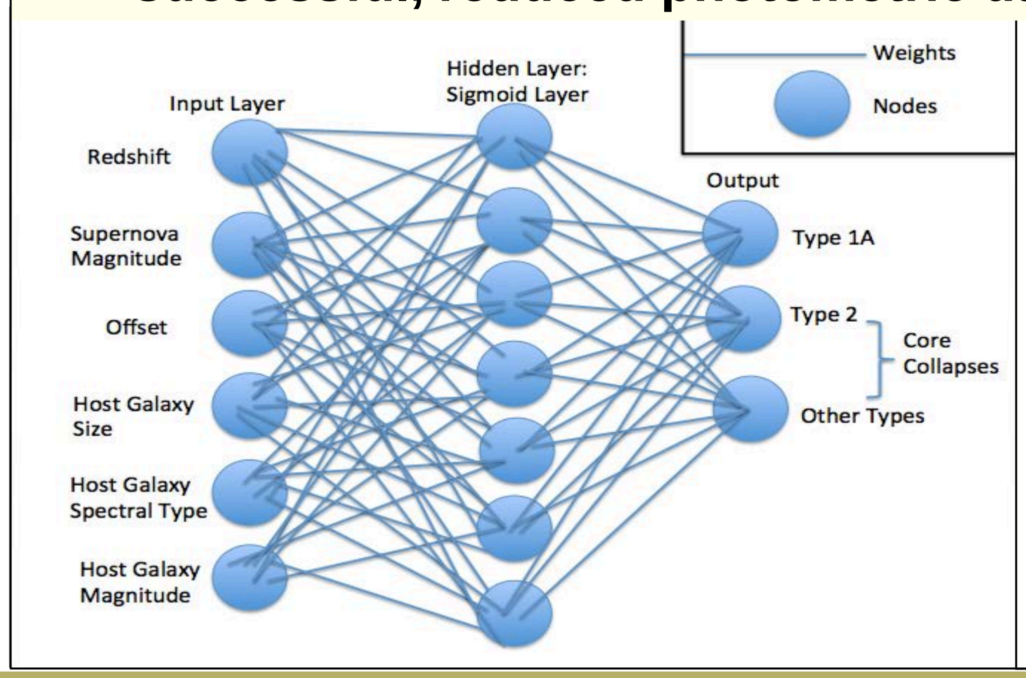
Verification after the network identifies an object is more time efficient than current methods of finding the correct events individually.

Supernova Type Classifying Network

The other network not shown is a network that identifies the type of supernova. From this network, the following results were found:

- There is bias towards more luminous type Ia supernova events with smaller, fainter, brighter host galaxies at a smaller redshift and a higher offset from the host galaxy.

- The type classification ANN does not succeed with observable properties as an input. It deems all point sources to be supernova. To make this network successful, reduced photometric data is needed.



The ANN shown in the figure uses observed characteristics of SNe Ia and their host galaxies at redshift > 1 for the machine's input.

Conclusion

Preliminary test results are encouraging. In regions with known supernovae, the location network adequately recovered 75% of these events. The identification network's precision was lower with a net 31% accuracy. These tests also recover trends anecdotally noted about these scientific surveys and whether or not this represents an unresolved selection bias will be further explored. It is expected that both networks will greatly improve with larger training sets. The supernova type classifier network was created based off of observable properties, but was unable to differentiate between classes. Refining the classifier network by adding reduced data of events at high redshift may allow such differentiation. It is expected the orders of magnitude increase in survey area will compensate for the increased standard error budget from the classification error, leading to a reduced population mean rate in the desired redshift range.