INTRODUCTION

The Gemini Planet Imager is an instrument installed on the Gemini South Telescope in Cerro Parcho, Chile, designed to search for thermal emission from young hot exoplanet surfaces at wide angular separation. The GPI Exoplanet Survey is well under way, with many successful detections, but contrast remains limited by atmospheric aberrations and imperfections in the AO system. Notably, the presence of the so-called "t Trail Butterfly" (as called because of their figure-8 or lemon-slice shape) scatters significant light into the coronographic dark hole, causing the residual PSF to break azimuthal symmetry in the image plane, and reducing the final contrast ratio. This PSF pattern is consistent with wavefront errors from aero lag. A team of three micrometer error in positioning the deformable mirror in response to the wavefront sensor causes an effective displacement of the atmospheric turbulence relative to the applied correction. This effect produces a phase pattern on the detector whose Fourier transform has preferential direction. Classification of the survey dataset into categories which separate these images which contain this aberration from those who do not will be useful for doing various follow-up studies with the overall goal of improving survey sensitivity.

DATASET

The Dataset contains 20,561 Images, each of which is a (37,281,281) dataset of fits files, which contains thirty-seven different spectral images of the target taken over the course of a thirty-second exposure. Exposure sequences are blocked into hour-long chunks of particular targets. The data cubes contain 32-bit floating point numbers, as well as NaNs which arise from post-processing where no measurements were made. NaNs are converted to 0 to maintain analyzability during metric multiplication. Just over forty percent of the Dataset was labeled by hand over eight hours of playing a simple labeling game script, with an estimated self-consistency for human level performance of 80% from comparisons of duplicate labels. Then, the labeled dataset was separated in Training, Development, and Testing sets with a ratio of 60/20/20. The figure below shows an example of each class of labeled data, the difference between them is the presence of the lemnanate-shaped wave deformation which we would like to identify.

NETWORK ARCHITECTURE

The network architecture is a very simple model, consisting of four hidden layers of decreasing size, with Rectified Linear Unit (ReLU) activations and a final sigmoid output for binary classification. The total number of trainable parameters is 38,981,947. A cross entropy loss function is computed to optimize the parameters during backpropagation.

\[
C(y, \hat{y}) = \frac{1}{m} \sum_{i=1}^{m} y(i) \log(\hat{y}(i)) + (1 - y(i)) \log(1 - \hat{y}(i))
\]

PERFORMANCE

The network was trained over the course of multiple weeks on an Nvidia GTX 980 GPU, for a total of three thousand epochs, with a decaying learning rate of 10^-3, 10^-4, and 3 x 10^-5, transmitting at epochs 500 and 1000, respectively. The optimization algorithm used was an Adam Optimizer.

Convergence of training loss during training.

Figure: The network converges quickly to a local minimum during training.

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CONCLUSION

In Summary, we were able to demonstrate that a simple deep learning model was able to match (and perhaps exceed) human level performance in the categorization of astronomical data in the GPI Exoplanet Survey Dataset, with an unbiased estimate of performance on the Test Set of 80%, which is an improvement over our estimate of human accuracy of 81.8%. Previous setting algorithms designed with application-specific knowledge were even less superior, with performance accuracies of 71.7%. Use of this categorization algorithm will be useful for automatically classifying new image cubes from the telescope, which will in turn assist in developing reduction models and improve planet detection sensitivity.

REFERENCES


Stanford University

Exoplanet Survey