Benchmarking Simulated Gravitational Lensing Classification with Neural Nets

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Background

When a massive object curves space time, the path of light passing through it is bent, causing gravitational lensing. In strong lensing (SL), galaxies are the massive foreground object.

We lack good, non-manual ways to find galaxy-galaxy SL. Machine learning, particularly deep learning, can help solve this problem.

Large galaxy acts as **gravitational lens**:

Figure 1. "This diagram illustrates a cosmic phenomenon

Results and future steps

The trained model with best results would have a higher true and lower false positive rate as shown in the Receiver Operating Characteristic (ROC) curve (Fig. 4), and decreasing and close to zero training and validation in the loss curve (Fig. 3).

FERMILAB-POSTER-23-212-STUDENT





gravitational known as Representation lensing." due to a galaxy. Credit to Zina Deretsky, NSF (2010)

First

simulated lenses

row

sources



Figure 3. Training and validation loss curve for datasets run with the chosen three architecture.

Table 1. Information on the simulation data used to run the architecture chosen

We want to test and compare many deep learning model architectures with simulated and real data. We intend to build a pipeline to quickly test architectures on benchmark datasets combinations and to identify galaxy-galaxy SL.

Here, we compare the performance of three simulated datasets used for training of one architecture, Lens Challenge CNN. A CNN is a deep learning architecture with convolutional and pooling layers for abstraction to learn from visual data.

Based on this, Sim Jacobs (2018) gave the best results, perhaps due to its lack of noise. Zaborowski (2022) did well too despite its noisy background and small image size (concerning as images are scaled down and pooled), probably due to being a large dataset. Noisy but with fewer images than Zaborowski, **DES-like Jacobs (2018) understandably did worse.**



Methods and data

We gathered three simulation types (Table 1). Jacobs (2018) has a dataset where both the lens and galaxy are simulated and the background are DES-like simulations, and a dataset with clean simulations without background. Zaborowski (2022) contains simulated lenses over real DELVE imaging.

In the future, we will account for **domain shifts** — i.e., when training and application data have different probability distributions (Sim Jacobs looks unrealistic, so domain shifts should be considered when used) — and test for the best dataarchitecture combinations for SL detection.



False Positive Rate

Figure 4. ROC curves, graph with the true rate (positives positive classified as correctly positives) adainst the false rate positive incorrectly (negatives classified as positives), three datasets used to train the chosen Lens Challenge CNN architecture.

Collected data was formatted to hdf5 format and plotted as RGB images for visualization purposes (Fig. 2). We then trained the Lens Challenge CNN on all datasets.



References

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This manuscript has been authored by Fermi Research Alliance, LLC under Contract No. DE-AC02-07CH11359 with the U.S. Department of Energy, Office of Science, Office of High **Energy Physics.**

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