GANs with Simultaneous Encoder Training for detecting substructures with anomaly contaminations

Mentors:

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Overview

Gravitational Lensing is the phenomenon of bending of path of light from distant sources due to presence of massive objects like galaxies or clusters of galaxies, which alter its course via strong gravitational forces. This phenomena can be used to estimate the amount and distribution of dark matter, which is thought to account for approximately 85% of the matter in the universe. Strong gravitational lensing is a promising probe of the substructure of dark matter to better understand its underlying nature. The successful application of deep learning methods to identify substructures, and to differentiate WIMP particle dark matter from other well motivated models, including cortex substructure of dark matter condensates superfluids, makes them a viable tool in the identification of dark matter and its components.

With the introduction of telescopes like the Euclid, the amount of strong lensing data for gravitational lensing is expected to increase phenomenally. So it becomes an increasingly time consuming task to label the real world gravitational lensing data making the need for unsupervised methods ever increasing. But unsupervised anomaly detection in high-dimensional data, like images, is a challenging task.

Generative Adversarial Networks are capable of modelling the highly complex, high-dimensional data distribution of normal image samples, and have shown to be a suitable approach to the problem. Previously published GAN-based anomaly detection methods often assume that anomaly-free data is available for training. However, this assumption is not valid in most real-life scenarios.

The goal of this project is to perform unsupervised anomaly detection using state-of-the-art GAN based architectures on both real and simulated strong lensing data, and evaluating the effect of contaminations in the image data.

Contents

Aim

The aim of this project is to develop state-of-the-art GAN-based image anomaly detection methods for detecting different dark matter substructures, and evaluating the effect of different contaminations in the data.

Goals/Deliverables

The final deliverables include:

- Pre-trained models
- Proper documentation
- Final Report of the project

Specifications

This project proposes anomaly detection using GAN-based methods on simulated strong lensing data, and comparing their performance.

Supervised anomaly detection techniques demand a data set with a complete set of “normal” and “abnormal” labels for a classification algorithm to work with. This kind of technique also involves training the classifier. Unsupervised anomaly detection, on the other hand, detects anomalies in an unlabeled data set based solely on the intrinsic properties of that data.

Models so far:

If we train an unsupervised machine learning algorithm on simulated strong lensing images without substructure, it is possible to identify data with substructure as an anomaly. We can further send the anomaly-marked data for Bayesian Likelihood Analysis or a supervised anomaly detection algorithm to further find the type of substructure observed.

In the paper “Decoding Dark Matter Substructure without supervision” by Stephon Alexander and Michael W. Toomey (also a mentor in this project), four separate unsupervised anomaly detection algorithms have been used for identifying dark matter substructures. The performance of these models have been given on simulated strong lensing image data consisting of images without substructure, and with substructures from two disparate types of dark matter - subhalos of CDM and vortices of superfluid dark matter. All the models have been tested for data with fixed redshift values and varying redshift values.

The performance of these models has been summarized in the table below:

Model	**Model ROC-AUC Scores for fixed redshifts**	**Model ROC-AUC Scores for varying redshifts**
Restricted Boltzmann Machine (RBM)	0.51540	0.50870
Deep Convolutional Autoencoder (DCAE)	0.73034	0.66992
Convolutional Variational Autoencoder (CVAE)	0.89910	0.73545
Adversarial Autoencoder (AAE)	0.93207	0.76943

The RBM architecture achieves the poorest AUC scores (around 0.5) and therefore seems to have failed to learn anything significant from the data for both fixed and varying redshift values. This happens because the model neglects any spatial information while reducing the input dimensions to a 1-dimensional vector.

The DCAE architecture showed an AUC of 0.73 for fixed redshift values, thereby performing decently at distinguishing images with and without substructures. The performance of this model reduces significantly to 0.67 for varying redshift values, thereby telling us that the models are unable to hold equally well due to added complexity in the dataset.

The VAE model contains 2 separate losses to minimize simultaneously, the Mean-squared error loss between input and reconstructed images, and the KL divergence for latent features. For the first 100 epochs of training, the reconstruction loss is minimized and after that the weight of KL divergence is increased from 0 to 1 gradually. The VAE achieves the AUC-ROC value of 0.899 for fixed redshift and 0.769 for varying redshifts, again showing the incapability of the model to capture the added complexity well enough.

Finally, the AAE model reaches top performance among given architectures achieving the AUC scores of 0.903 and 0.769 for fixed and varying redshifts respectively.

Proposed Model and its architecture

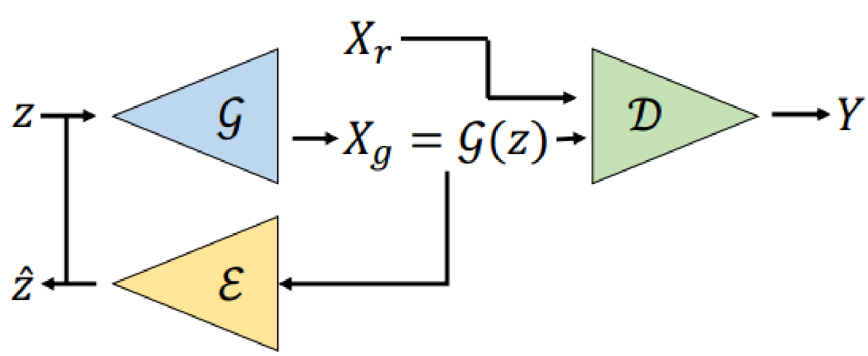
Previously used GAN-based architectures for outlier detection make the strong assumption that there are no anomalies in the training data and that it is completely normal. But this is often not the case in real world situations. So often the network performance deteriorates whenever any contaminations are introducted. In order to deal with this situation, we take inspiration from the paper "Unsupervised Learning of Anomaly Detection from Contaminated Image Data using Simultaneous Encoder Training" and add an additional encoder layer already at training time, further showing that joint generator-encoder training stratifies the latent space, thereby greatly reducing the effect of anomaly contaminations to training data.

In this project, I propose to effectuate a model that is a combination of progressive growing GAN (pGAN) and ClusterGAN. The pGAN model uses WGAN-GP loss and adds new layers to the generator and discriminator while training. This approach increases the stability and robustness of a GAN, especially while dealing with high-dimensional data. The generator and discriminator are inspired from the pGAN architecture while the additional encoder that we introduced for simultaneous training is inspired from the ClusterGAN architecture.

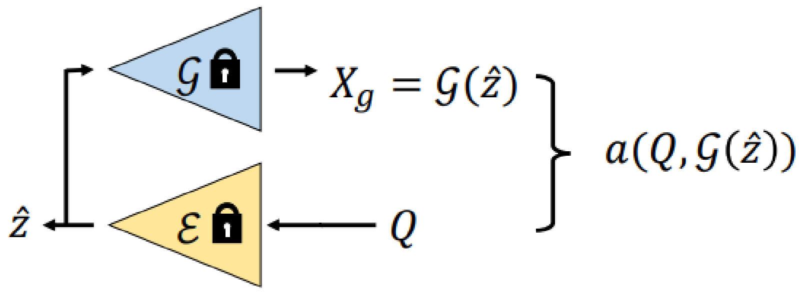
The GAN objective for the proposed methods finally takes the following form:

$$\min_{\theta_G, \theta_E} \max_{\theta_D} \mathop{\mathbb{E}}_{X \sim p_{\text{data}}} q(\mathcal{D}(X)) + \mathop{\mathbb{E}}_{z \sim p_z} q(1 - \mathcal{D}(\mathcal{G}(z))) + \mathop{\mathbb{E}}_{z \sim p_z} \|(\mathcal{G}(z) - \mathcal{G}(\mathcal{E}(\mathcal{G}(z)))\|_1$$

The architecture of the proposed model at the time of training finally looks like:



And at the time of testing looks like shown below:



Target Audience:

Through this package, we aim to target both researchers and amateurs alike who are willing to learn and make a mark in this field.

Timeline

Pre-GSoC Period	
Today - May 4, 2023	• Learn about Dark Matter and its substructures. Also familiarize with Gravitational Lensing theory and models that might be helpful for given aim
Community Bonding Period **May 4, 2023 - May 28, 2023**	
Weeks 1, 2 and 3	• Interact with the community and find out about Lenstronomy and PyAutoLens module, their needs and exciting applications • Interact more with mentors. Get comfortable with the Deeplense pipeline • Learn about the best architectures so far for the purpose and get decent idea on what works and what doesn’t
Coding Period **(May 29, 2023 onwards)**	

Weeks 4 and 5	• Simulate strong lensing images using the PyAutoLens package for the different substructures.
Weeks 6 and 7	• Implement the already existing Autoencoder based methods (DCAE, CVAE and AAE) on simulated data
Week 8	• Evaluate the performance of above AE-based algorithms on data contaminated with anomalies
Weeks 9 and 10	• Program and implement the proposed GAN-based algorithm • Evaluate the performance of the GAN on anomaly contaminated data
Weeks 11 and 12	• Debugging the code for final submission, as required, as advised by the mentor. (can be used as buffer period too) • Final touches
Midterm Evaluations (July 10, 2023 - July 14, 2023)	
July 10, 2023 - July 14, 2023	• Midterm Evaluations
Students Submit Code and Final Evaluations (Aug 21, 2023 - Aug 28, 2023)	
Aug 21, 2023 - Aug 28, 2023	• Final code submission

[Note: My Fall semester begins on Aug 2. Hence, I'm trying to keep most of the work before that. I can still work in that period if required. I can make up for this period by giving more time in the previous weeks. Also, I plan to follow this timeline but if there are any deviations, I will surely convey that information to my mentors.]

Related Work

Papers quoted in this text:

1. Decoding Dark Matter Substructure without Supervision
2. Deep Learning the Morphology of Dark Matter Substructure

3. Unsupervised Learning of Anomaly Detection from Contaminated Image Data using Simultaneous Encoder Training
4. Domain Adaptation for Simulation-Based Dark Matter Searches Using Strong Gravitational Lensing

Motivation for GSoC

I was not directly associated or acquainted with GSoC, but I happened to use various libraries such as PyTorch and Tensorflow and various other data analysis libraries for my research projects that I have worked on so far. Though I still continue to use the Tensorflow machine learning stack for my research, I realized that all these state-of-the-art libraries had been used for conducting ground-breaking research across the world, and they were completely open-source!

This really made me wonder and eventually prompted me to support open-source development. The community involved in open source development is very helpful if we are stuck on a problem, and really helps in building something new.

About Me

Background

I am a fourth year dual degree student at the Indian Institute of Technology, Kanpur (IIT Kanpur), majoring in Civil Engineering. I am broadly interested in the areas of Machine Learning and Deep Learning.

My last year's research mainly lies in anomaly detection. Last semester, I worked under Prof. Pranamesh Chakraborty, IITK to build models for traffic accident detection on US roads and highways. Last summer, I also worked as a research intern at Siemens Technologies to effectuate Autoencoder-based Anomaly Detection models and further carried out fault identification. I also built a streamlit-based web application to run the entire pipeline effectively.

Apart from formal research, I have worked on several projects during my stay at IIT Kanpur. I have also mentored 25 students for a 6-week long project titled 'Computer Vision applications in Transportation Engineering'. I have also worked as a secretary at Startup development, Entrepreneurship Cell, IIT Kanpur. I also like development and have built several android applications using Flutter and Dart.

I am very enthusiastic to contribute to the open-source community and be a part of the Deeplense Project for GSoC 2023.

Experience

A lot of my projects are available at my github. A selected few are listed here:

- I worked as research intern at Siemens to implement Anomaly Detection and Identification using multiple statistical and deep learning methods on machine data
- I worked with Prof. Pranamesh Chakraborty, IITK to build pipeline for traffic anomaly detection on US highways data and evaluated on Indian conditions, using YOLOv3, Nearest Neighbor and K-means clustering in the process
- I worked on state-of-the-art Neural Network architectures for tasks such as Sentiment Analysis and Language Translation as part of Summer Project
- I forecasted mode of transportation on accelerometer data by training various shallow Machine Learning models

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