Equivariant Neural Networks for Dark Matter Morphology with Strong Gravitational Lensing

Google Summer of Code Program 2021 Project Proposal

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Project Abstract

The study of substructures in the dark matter has shown signs of promise to deliver on the open-ended and long-standing problem of the identity of dark matter. To probe these substructures, strong gravitational lensing has been used in the past and provided some interesting results. The approaches based on deep learning have the ability to identify and differentiate among these substructures using images from the simulation of strong gravitational lensing. This project explores the scope of use of equivariant neural networks that can benefit from inherent symmetry present in natural images. We will be implementing and benchmarking the results of equivariant neural networks on the available DeepLens simulated dataset. We will also integrate all these architectures with the DeepLens pipeline to provide a high-level interface for future work.

Project Description

Background

An open-ended search for the true identity of dark matter has been a major focus in the domain of physics ever since the dark matter was discovered. Even with all the advancements made in the field, the mystery associated with it still remains to be untangled. In the last half-century, a number of promising candidates have been proposed that could answer the question concerning the true identity of dark matter. Weakly Interacting Massive Particle (WIMP) is considered to be one of the major candidates that could prove insightful to this search. Another promising candidate in this search is condensate models of dark matter including Bose-Einstein condensate (BEC) and Bardeen-Copper-Schrieffer (BCS). The aforementioned condensate models have the property that they can form the *vortices*. If they exist, vortices compose a substructure component for dark matter halos. This enables us to **discriminate between different models of dark matter by exploring these substructures in dark matter halos**.

Strong Gravitational Lensing provides us with an effective way to study the substructure of dark matter which in turn allows us to better comprehend its underlying nature. To explain gravitational lensing in simple terms, as the light emitted by distant galaxies passes by massive objects in the universe, the gravitational pull from these objects can distort or bend the light. This is called gravitational lensing. In the past, **strong lensing has already been used as an effective tool to explore substructures in dark matter. In fact, it has also been used to distinguish between different types of dark matter substructures**.

Motivation

In the previous works, Convolutional Neural Network (CNN) and Autoencoder-based deep learning architectures have been used to identify images containing substructures and distinguish between different types of dark matter substructures. **CNN's, however, are only equivariant under translation which means a convolution with a translated image is the same as the translation of a convolved image.** This directly enables efficient detection of objects of the same shape and orientation. We can **use a smarter alternative in Equivariant Neural Network that is equivariant to symmetry transformations.** This means that they can learn the features that equivary under 90-degree rotations and mirror reflections besides being equivariant under translation only. It means that the network can identify differently oriented objects as the same in a smart manner. In previous works using CNN, data augmentation becomes a necessity to enable the architecture to capture the underlying patterns. **Equivariant networks, on the other hand, can increase learning efficiency by using natural symmetries and benefit greatly from hard-coded equivariance.** This ability of equivariant networks can be used in our application with great efficiency given the invariance we want our architecture to learn.

Key Tasks:

- Conducting a literature survey and finalising the variants of the equivariant neural networks to implement.
- Implementing the selected network architectures in PyTorch.
- Training and testing these networks on various datasets.
- Integrating the developed models with DeepLens pipeline.
- Documenting all the implementation, results, and analysis in detail.

Proposed Timeline:

- The main priority of the project is the implementation of an equivariant neural network for stable training of DeepLense simulation data.
- Following this, we will tune the hyperparameters of the network for all the available data and compare our results with standard baseline architectures.
- In the next step, my focus will be on the integration of the developed neural network architecture with the DeepLens pipeline to expand its functionality.

- Finally, we will work on documentation of our results and the code to make itt simpler to understand and use.

- **<u>June 7 (coding begins)</u>** - By this time, I will familiarize myself with the functioning of the DeepLens pipeline. Since DeepLens is based on PyAutoLens, I will **explore PyAutoLens**. I will **shortlist some variants of equivariant neural networks** through a comprehensive literature survey that I will be implementing and experimenting with. Also, I will install all the required dependencies and **set up the environment** that will be needed for the implementation of these equivariant neural networks.

- **<u>July 12-July 16 (First Evaluation)</u>** - By the end of phase 1, I plan to complete the following tasks:

    - Results of the data exploration (visualization and basic analysis).
    - The general data loader class in order to load the simulated data in a suitable format to feed into our neural networks.
    - Implementation of the selected equivariant neural network architectures.

- **<u>August 16-August 23 (Second Evaluation)</u>** - By the time of final evaluation, I plan on expanding the DeepLense functionality with equivariant networks suitable for computer vision tasks applicable to DeepLense data along with proper documentation.

    - It will comprise of 2-3 selected variants of equivariant neural networks that can be trained and validated on DeepLense simulated data.
    - To go with our results, we will add the option of using our pre-trained models in the DeepLense pipeline to use our networks without training them.

- **<u>August 31 (Final Results Announced)</u>** - Refine my already provided documentation (documentation of all my work will be done in parallel to its implementation) so that the users can easily train the equivariant networks on their simulated data.

- **<u>Post GSoC</u>** - Work with the community to get my code merged with the DeepLens pipeline.

<u>Proposed Schedule:</u>

<u>March 29 - April 13 (Application Period)</u>

Present a detailed proposal that comprises of key tasks and background of the project along with the proposed timeline and gets frequent feedback from the community to refine my proposal.

April 13 - May 17 (Acceptance Waiting Period)

- Make sure a proper development environment is set up properly.
- Conduct an extensive literature survey of the equivariant neural networks.
- Understanding the working of PyAutoLens library and DeepLens pipeline.
- Make a to-do list of tasks to be done in each phase.

May 17 - June 7 (Community Bonding Period)

- Discuss with the mentors about the project.
- Finalisation of the variants of an equivariant neural network to be implemented after discussion with the mentors.
- Discuss with the mentor about foreseen challenges and try to resolve them.

June 7 - July 16 (First Half)

- Analysing the dataset to **identify any class imbalance, biases, or any other predictive modelling issues.** This will help us in identifying the steps needed for dataset preprocessing.
- Implementation of a **general data loader class for simulated data**. Users can directly use this class for some defined problem and can inherit this class to make modifications for their own data.
- **Implementing the architecture of equivariant neural networks** selected after discussion with mentors.

July 16 - August 16 (Second Half)

- Writing the code for training and testing all the developed equivariant neural network.
- Training and testing all the developed equivariant neural network architectures with different hyperparameters and comparing their results with current state-of-the-art architectures.
- Integrating the developed architecture with the DeepLens pipeline.
- Adding tutorial notebooks/scripts for using the code and documenting the whole work done.

Deliverables

- **2-3 equivariant neural network models** integrated into DeepLense pipeline.
- Several **general data loaders** to simplify the task of feeding the simulated data into the neural networks.
- **Pre-trained models** for all the networks for the available data that can be directly downloaded and used without training.
- **Tutorial notebooks** for using the code for training the model and using pre-trained models.
- The **benchmarking result**s will include publication-ready graphical material (such as

plots, trends, graphics, tables) to present and show the test results on the simulated data.

Conflict of Interests or Commitment

I am in my final year of undergraduate studies and my final examination will end in the first week of May. There will be a gap of 3 months between the completion of my undergraduate degree and the start of my masters so I will be completely free during that time. Thus I can fully commit to the project.

Major Challenges foreseen

- Prior to this, equivariant neural networks have not been tested on real-world datasets extensively especially for any astronomical datasets. This might pose some issues that have to be dealt with via extensive preprocessing.
- The final code to be published will need to be compatible with parallel GPU usage and compatible for different versions of python and other dependencies.

References

- Alexander, Stephon, Sergei Gleyzer, Evan McDonough, Michael W. Toomey, and Emanuele Usai. "Deep Learning the Morphology of Dark Matter Substructure." The Astrophysical Journal 893, no. 1 (2020): 15.
- Alexander, Stephon, Sergei Gleyzer, Hanna Parul, Pranath Reddy, Michael W. Toomey, Emanuele Usai, and Ryker Von Klar. "Decoding Dark Matter Substructure without Supervision." *arXiv preprint arXiv:2008.12731* (2020).
- Olah, Chris, Nick Cammarata, Chelsea Voss, Ludwig Schubert, and Gabriel Goh. "Naturally Occurring Equivariance in Neural Networks." Distill 5, no. 12 (2020): e00024-004.

Relevant Background Experience

- I have had a decent exposure to writing and debugging **Python and C++** code for medium-sized projects using the **PyTorch** framework.
- I have a lot of experience in training and building deep learning models as I have been part of a number of deep learning-based projects in the past. I have also successfully published 4 research papers in the various applications of deep learning. I am currently working in the **CRUNCH group under Prof. George Karniadakis at Brown University** and in the past at **Max Planck Institute for Dynamics of Complex Technical Systems under Prof. Peter Benner**.
- I was also a finalist in the Smart India Hackathon organised by the Ministry of Education, India.

Personal

I am a fourth-year Electrical Engineering student at NIT Silchar, Assam, India. I have good research experience in working on deep learning research as well as applied deep learning. I have been part of several projects in this domain with some of them turning into publications for the past 3 years. Currently, I am an intern under Prof. George Karniadakis' Lab at Brown University where I am working on developing an unsupervised stochastic dynamic graph embedding model. In future, **I want to work on the generalization of deep learning models in applications of computer vision. This project will help me in learning a new dimension of neural networks models in that application.**

Experience

Here is a link to my Personal Website - http://apoorvavsingh.github.io/
Here is a link to my CV - Link to CV

My relevant experience involve -

- Text classification using LDA and GCN - Link to the research paper
- UNIX Command Line Prediction - Link to the research paper
- Towards Better Drug Repositioning Using Joint Learning - Link to the research paper
- Patient Case Similarity, Smart India Hackathon - Link to the project

Technical Strengths

Computer Languages: Python, MATLAB, C/C++
Data Analysis, ML, DL: Pytorch, Keras, scikit-learn, NLTK, OpenCV