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Proposal

Transformers for Dark Matter Morphology with Strong Gravitational Lensing

By
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1. Introduction and Student Information

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2. Abstract

Strong gravitational lensing is a promising probe of the substructure of dark matter to better understand its underlying nature. Deep learning methods have the potential to accurately identify images containing substructure, and differentiate WIMP particle dark matter from other well-motivated models, including vortex substructure of dark matter condensates and superfluids.

This project will focus on the further development of the DeepLense pipeline that combines state-of-the-art of deep learning models with strong lensing simulations based on lenstronomy. The focus of this project is to use transformers to augment the performance of DeepLense algorithms.

3. Evaluation Tasks

3.1 Approach

ResNet-18 is a deep convolutional neural network that has been proven to work well for image classification tasks. Its unique architecture, which includes skip connections between layers, allows it to better capture and propagate information through the network, resulting in better accuracy and faster training times. Additionally, ResNet-18 is a relatively small network compared to other deep learning architectures, making it more convenient to train and test models for evaluation. And sure enough, it was able to produce reasonable results considering the size and complexity of the datasets.

ViT (Vision Transformer) is a neural network architecture that uses transformers, which are typically used in natural language processing, for image classification tasks. ViT's use of transformers allows it to capture global spatial relationships between different parts of the image, which can be beneficial for tasks that require understanding of the image as a whole. However, there are also some limitations to ViT. One issue finding the optimal patch size can be a challenging task. Additionally, ViT is computationally expensive.

CoAtNet (Convolutional Attention Network) is a neural network that combines convolutional layers with self-attention layers which results in an architecture that is able to capture both local and global spatial relationships in the image, while also being computationally efficient.

With regard to this project, I have completed two evaluation tasks - one is the common task where I trained a RestNet-18 model for classifying the lensing images into no substructure, spherical substructure, and vortex substructure. Second is the specific task of this project where I trained a pure ViT model with and without pretrained weights to classify lensing images with and without substructure which did not perform so well. The rate of improvement was slow even after changing parameters like learning rate and batch size. Then I used CoAtNet which showed excellent results.

3.2 Results

In the common task, the model achieved more than 0.99 of AUC for both validation and testing datasets. And the ROC curves for the same can be browsed here. The training progress can be tracked here on the Weights and Bias platform which shows that the model reached 0.99 AUC within 30 iterations. The accuracy on the test set also reached around 95%.

In the specific task, the model achieved around 1 AUC for validation dataset and 0.9997 AUC for testing dataset. And the ROC curves for the same can be browsed here. The training progress can be tracked here on the Weights and Bias platform which shows that the model reached 0.992 AUC within 10 iterations. The accuracy on the test set also reached around 99%.

4. Proposed Deliverables

My key tasks in this project will be exploring and implementing state-of-the-art transformer architectures like EfficientNet, ViT variants - DeiT, ConViT, CoAtNet, VOLO, MogaNet on DeepLense data.

In addition to these, I can explore Reinforcement Learning and Genetic Algorithms based Neural Architecture Searches (NAS) to create custom transformer architectures. This can be used for finding and tuning the model architectures.

4.1 Schedule of Deliverables

Community Bonding Period (May 4th - May 28th)

I will get feedback from mentors about the proposal and discuss goals, priorities, deliverables, and meeting schedules. Based on this I will update the schedule. Once the logistics part is done, I will start discussing the key details like what datasets to use, what models to implement, and what metrics to choose. I will look into the relevant literature useful for the project and start learning relevant physics-based concepts since I am from a Computer Science background. I would also like to know more about organizations' work on a broader scale and potentially find a thesis topic for my Masters.

Week 1 (May 29th - June 5th)

Look more closely at the previous related work and start playing around with it. Start implementing a model on a dataset. Document the approach and results of the model.

Week 2 (June 5th - June 12th)

After the initial model development, make it more robust and implement relevant augmentation techniques. Look for methods to improve the model performance if possible. Document the approach and results of the model after all the modifications.

Week 3 (June 12th - June 19th)

If there are multiple datasets to the benchmark then apply the relevant preprocessing based on the previous week's work. Adapt the implemented model to the rest of the datasets. Document the approach and results of the model on multiple datasets.

Week 4 (June 19th - June 26th)

Train the 2-3 decided models on the datasets and document them. This process will be easier since preprocessed datasets and a model implementation is available. Document the methods and results of the models on multiple datasets.

Week 5 (June 26th - July 3rd)

It is hard to plan for certain every step in the model development since there are many moving parts in it. So based on the performance of the models work on optimizing and tuning the models or implementing more models. Visualize the comparisons of implemented models so far and write an analysis on them.

Week 6 (July 3rd - July 10th)

Complete all previous tasks. This is a buffer week for any unprecedented delays. Publish a blog post and prepare for Phase 1 Evaluation.

Week 7 and Week 8 (July 17th - July 31st)

If chosen to implement NAS (Neural Architecture Search) based approaches on Vision Transformers then review the existing literature. Or else proceed with implementing more models in the CNN and transformers space.

Week 9 and Week 10 (July 31st - August 10th)

If chosen to implement NAS then implement one or two architectures based on it. Note that this is a high-level explanation since I have not implemented NAS yet. Or else proceed with implementing more transformer-based models and document them.

Week 10 and Week 11 (August 10th - August 21st)

Write a final report about the project, publish a blog post and prepare for submission.

Post GSoC and Future Work

After the proposed 11-week timeline, I would love to start implementing any additional features and contribute to ML4SCI even after GSoC and given an opportunity I would love to collaborate with the mentors for my Master's thesis. Or even better collaborate on a research paper together with the mentors.

5. Other Information

5.1 Why ML4SCI

I believe that my interests in the fields of machine learning, deep learning and its applications are well aligned with ML4SCI goals. I strongly believe interdisciplinary research is the key to scientific advances and what more can I ask for when I get to do this myself. I believe that the broader impact of my deep learning work will greatly help researchers and practitioners to explore a plethora of other phenomena and moreover significantly simplify their work.

5.2 Relevant Background and Past Experience

I did a Neural Networks and Essentials of AI course as a part of my coursework at the University. This semester I’m doing Machine Learning and Deep Learning courses where I’m learning about the various architectures and implementing them in

PyTorch. As a part of the course, I'm currently working on Astronomical Images Super Resolution Project using R-UNets. I will put in extra effort during the project to learn about the physics part if the project demands me to.

Besides my coursework, I also did a summer internship involving deep learning and distributed computing where I had to implement an optimizer in a distributed training environment. And the last winter internship I implemented classical ML algorithms in eBPF (kernel space) for packet filtering.

As for my familiarity with technology stacks, I have used Tensorflow as part of some workshops and I'm learning PyTorch as a part of this semester's coursework. I have used scikit-learn for many Machine Learning projects. I'm familiar with other related libraries such as Numpy, Pandas, Matplotlib, Seaborn, and Plotly to name a few. I am fluent and very comfortable with Python.

5.3 Other commitments

My semester exams will begin in the second week of May and wrap up by the end of May. Post that, I will be able to spend 30-35 hours per week throughout the summer on this project. I will be travelling during August 15th - August 19th and will not be available during that duration. Besides this, if anything comes up I will be sure to inform my mentors immediately.