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Transformers for Dark Matter Morphology with Strong Gravitational Lensing

MENTORS

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SYNOPSIS

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.

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 using transformers (e.g. vision transformers) to augment the performance of DeepLense algorithms (e.g. classification and regression).

TECHNICAL DETAILS

Gravitational Lensing: The gravity from planets bends the path of light. Galaxies, and galaxy clusters, can magnify the light from more distant objects, allowing researchers to detect worlds in orbit around other stars. This effect is called "gravitational lensing"

DELIVERABLES

- Implement classification of Dark Matter Substructure based on simulated strong lensing images with different substructures using Vision Transformers (ViT)
- Design a Deep Learning Framework to enable domain adaptation for dark matter searches in strong gravitational lensing using Vision Transformers as the base architecture.
- Use masked autoencoders (MAE) to infer the presence of substructure in dark matter halos without any supervision.
- Deep Learning Frameworks: PyTorch, Tensorflow/Keras
- Scientific Libraries: NumPy, SciPy, Matplotlib
- Cloud Platform for training and Storage: AWS Sagemaker

TIMELINE

Community Bonding Period

- Read the given and all other relevant literature.
- Interaction with the mentors to get a better grip on the development procedure and refine my understanding of the topic.
- Perform hyperparameter tuning and transformations on the evaluatory notebook to better understand the idiosyncrasies and evaluate the performance of the model accordingly.

Week 1

- Start working on the classification task. Understand the dataset, apply transformations, create DataLoaders and work on a baseline model as constructed in the evaluatory notebook with default hyperparameters.

Week 2

- Tune hyperparameters to extract increased performance. Evaluate performance from AUC score, ROC curve, and confusion matrices and repeat the cycle.

Week 3

- Extensively read literature related to Adversarial Discriminative Domain Adaptation (ADDA).
- Leverage the supervised classification model (C) trained during the evaluatory period, and tuned during the community bonding period. Code the discriminator (D) for the ADDA which takes the feature vector from the embeddings of the transformer as input.

Week 4

- Continue with coding the discriminator for the ADDA to train it to output into domain label d (i.e. 0 for source domain, 1 for target domain). Perform hyperparameter tuning for accuracy taking AUC score and ROC curve as metrics

Week 5

- Keep this week as a buffer period to finish up with any backlogs. Take this time to document my progress and discuss further steps with the mentors.
- Evaluation phase 1 begins.

Week 6

- Read literature on Masked Autoencoders. The MAE consists of an encoder and decoder.

- Coding the encoder requires patches from the image matrix which are added with positional embeddings. These patches are randomly deleted (masked) and fed into the encoder as tokens.

Week 7

- Code the decoder which reconstructs the original image, by reattaching the masked tokens with the encoded token as input. The decoder is also a transformer that outputs a vector for each token. The linear vectors are then projected into an image representation for calculating the MSE to identify anomalies (classes other than the input class).

Week 8

- Perform hyperparameter tuning (mask ratio, etc.) to extract maximum performance. Evaluate AUC and ROC metrics from anomaly detection.
- Document findings, results, and model architectures and fix bugs.

Week 9-10

- Buffer period to complete documentation of the models and refactor code, complete other pending tasks, and make further modifications.

Post GSoC and Future Work:

- Implement additional features and contribute further to ML4SCI. I also wish to be a part of the research community in the ML4SCI organisation.

OTHER INFORMATION

Benefits to The Community

Machine Learning is a field that has found its applications far and wide. Researchers from different backgrounds, developers, and manufacturers have employed it in ground-breaking ways. This project aims to create new state-of-the-art deep learning models in gravitational lensing to aid researchers in accurately identifying images containing substructure, and differentiate WIMP particle dark matter from other well-motivated models, including vortex substructure of dark matter condensates and superfluids.

Why ML4SCI

I'm passionate about Machine Learning and Deep Learning, and its applications. It is particularly fascinating to implement state-of-the-art computer vision architectures to decipher the morphologies of dark matter. Moreover, my interests align with the ML4SCI organization, since I want to perform research in-depth on different computer vision models for tasks such as segmentation, classification, detection, etc.

Related Work

I have created several mini-projects that entail building models from scratch, training them, and performing transfer learning using various frameworks. All of which can be found here.

Past Experience

I have contributed to Open Source Project (wink-nlp) an NLP library for JavaScript developers. I have learned a lot from my mentors and fellow contributors, maintaining, packaging, refactoring, testing, etc. One thing I've imbibed within myself is to strive for the best results through multiple iterations with consistency and I think that will play a big hand as our target is to achieve state-of-the-art performance.

Familiarity with Tech Stack

I have extensively worked with DL Frameworks such as PyTorch and Tensorflow/Keras to create computer vision models. I have the versatility to code efficiently using both frameworks, and I'm endowed with the skill to code cleanly in a Pythonic manner. Besides, I have taken up courses on Deep Learning and Machine Learning to aid me in this journey. I have instilled in myself the habit of reading papers and gaining intuition from the work of others.

References

- Deep Learning the Morphology of Dark Matter Substructure
- Domain Adaptation for Simulation-Based Dark Matter Searches Using Strong Gravitational Lensing
- Decoding Dark Matter Substructure without Supervision
- Masked Autoencoders Are Scalable Vision Learners