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## Project Description:

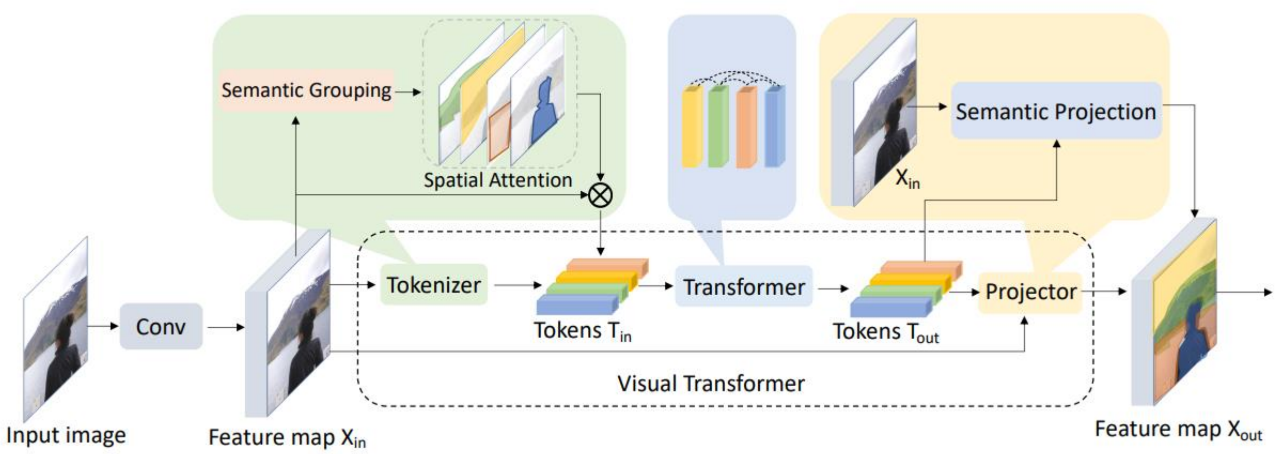
- Title: Transformers for Dark Matter Morphology with Strong Gravitational Lensing
- Goal: Further develop the DeepLense pipeline that combines state-of-the-art deep learning models with strong lensing simulations based on lenstronomy.

## Abstract:


The study of Dark Matter has been one of the most important research areas in modern physics. Recent studies have shown that using Machine Learning algorithms can help us better understand Dark Matter morphology with Strong Gravitational Lensing. This project aims to develop a deep learning-based framework using Transformers to study Dark Matter morphology and its effects on Strong Gravitational Lensing. The framework will be applied to simulated data from the Dark Energy Survey and Euclid surveys. The proposed work will contribute to the development of Machine Learning tools for analyzing large-scale astrophysical data.

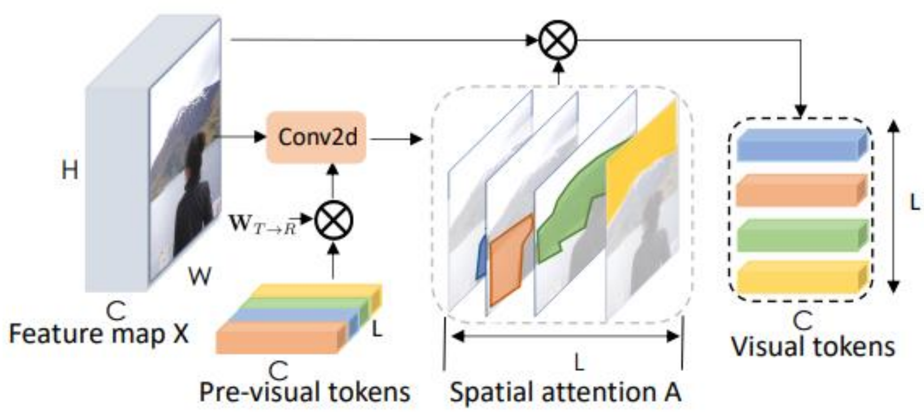

## Homework:

The proposed transformer model uses a similar architecture to ViT architecture, which was introduced in the paper "Visual Transformers: Token-based Image Representation and Processing for Computer Vision" by Dosovitskiy et al. (2020), but with some modifications to suit the specific task of predicting dark matter halo morphologies from gravitational lensing maps.



The architecture of the proposed transformer model can be broken down into the following stages:

- Input Encoding: The input to the transformer model consists of a set of two-dimensional (2D) gravitational lensing maps, where each map represents the distortion of light rays caused by a massive object such as a galaxy or a cluster of galaxies. Each 2D map is first encoded into a sequence of feature vectors using a convolutional neural network (CNN).
- Positional Encoding: To allow the transformer to capture the spatial relationships between the input features, the sequence of feature vectors is augmented with positional encodings. The positional encodings are added to each feature vector and encode the relative position of the vector within the sequence.
- Transformer Encoder: The transformer encoder is a stack of N identical layers, each consisting of a self-attention mechanism and a feed-forward neural network. The self-attention mechanism allows the model to attend to relevant parts of the input sequence and capture long-range dependencies. The feed-forward neural network applies a non-linear transformation to the output of the self-attention mechanism.
- Transformer Decoder: The transformer decoder is also a stack of N identical layers, each consisting of a self-attention mechanism, a cross-attention mechanism, and a feed-forward neural network. The self-attention mechanism allows the model to attend to relevant parts of the predicted sequence and capture long-range dependencies. The cross-attention mechanism allows the model to attend to relevant parts of the input sequence when predicting each output element.
- Output Decoding: The output of the transformer decoder is a sequence of predicted mass profiles, each represented as a set of pixels in a 2D map. The predicted mass profiles are decoded from the output sequence of the transformer decoder using a deconvolutional neural network (DeConvNet).




## Plan:

- Data Preparation:
    1. Collect and preprocess strong gravitational lensing data
    2. Generate Dark Matter morphology labels from simulations

- Transformer Model Development:
    3. Implement and fine-tune the transformer model
    4. Optimize the transformer model for large-scale training
- Model Evaluation:
    5. Evaluate the performance of the model using various metrics
    6. Compare the results with existing methods

## Deliverables:

1. A transformer-based model for predicting Dark Matter morphology from strong gravitational lensing data
2. A set of evaluation metrics and benchmarks for the model
3. A user-friendly software library and tools for Dark Matter researchers to use the model
4. Documentation and tutorials for using the software library and model

## Timeline:

- Week 1-2: Collect and preprocess strong gravitational lensing data
- Week 3-4: Generate Dark Matter morphology labels from simulations
- Week 5-7: Implement and fine-tune the transformer model
- Week 8-9: Optimize the transformer model for large-scale training
- Week 10-12: Evaluate the performance of the model using various metrics
- Week 13-14: Compare the results with existing methods
- Week 14-15: Integrating the model with software library for Dark Matter research
- Week 16-18: Develop user-friendly tools for Dark Matter researchers to use the model

## Conclusion:

The suggested work is to create a machine learning-based answer to predict the shape of Dark Matter from data on strong gravitational lensing. This project will have you implement a transformer-based model, optimizing that model, assessing how well it performs, and finally integrating that model with software library specifically designed for studying Dark Matter. Our knowledge of Dark Matter and its function in the universe could be vastly enhanced by the proposed solution.