Exploration of Self-Supervised Learning

PURDUE UNIVERSITY | The Data Mine

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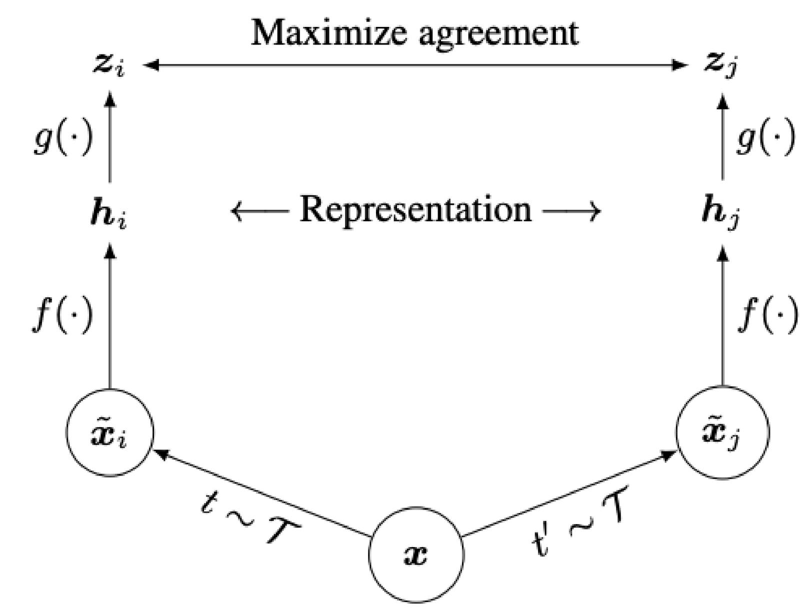
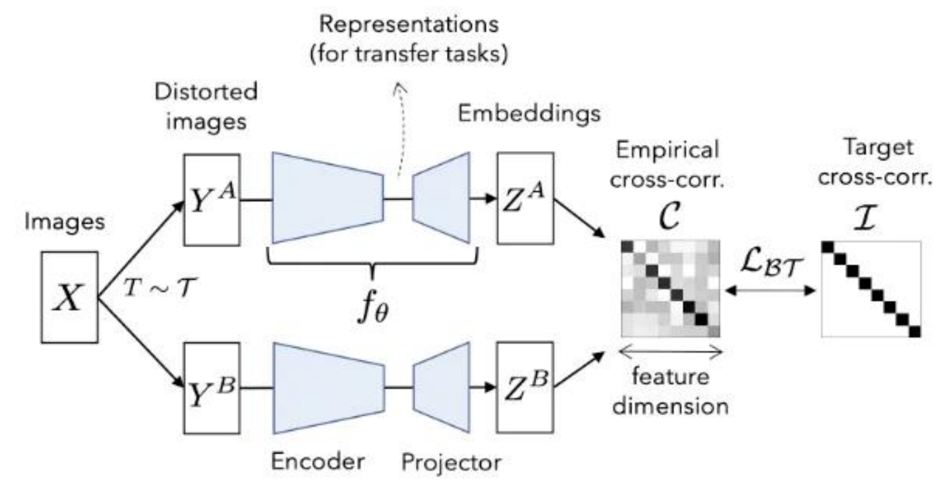
Introduction

Supervised learning is the most widely used method of machine learning, where a model is trained using labeled data. However, labeling data manually is a costly and time-consuming process, and with the increasing demand for data by neural networks, training them can be challenging. A new paradigm called self-supervised learning addresses this issue by utilizing unlabeled data to obtain meaningful representations that can be used for various learning tasks.

During the previous semester, we studied advanced self-supervised models like SimCLR (a Simple framework for Contrastive Learning) and Barlow Twins. The project this semester is an exploration into self-supervised learning and its applications.



Architecture of SimCLR



Architecture of Barlow Twins

BioCLR

Inspired by the neuroscience findings that the brain processes visual information in multiple segregated pathways, we designed a new self-supervised contrastive learning model based on SimCLR. Our model is called BioCLR (Biological Contrastive Learning) and is more biologically plausible than the original SimCLR model.

Methodology:

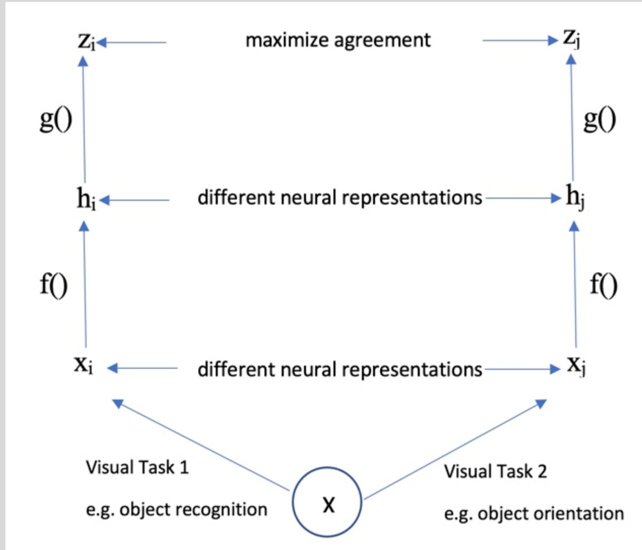
•Used supervised learning to train ventral and dorsal visual pathways in Google Colab with Cifar 10 dataset
•Produced different neural representations of the same images using two artificial pathways
•Replaced the data augmentation part in SimCLR with the neural representations produced by the two pathways
•Provided extracted neural activities from the two pathways as inputs to BioCLR

Results:

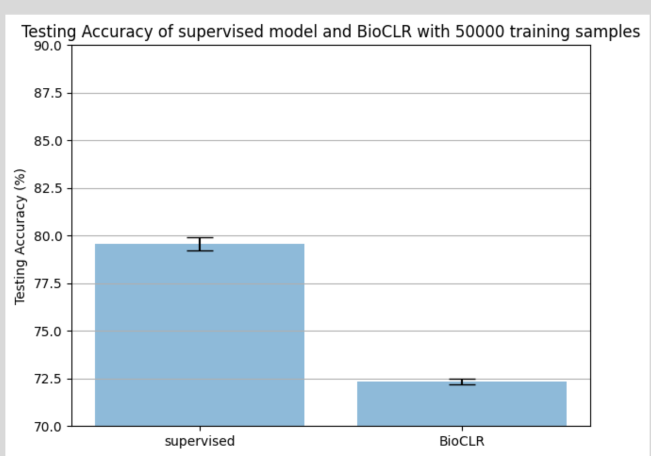
•BioCLR achieved 72% testing accuracy with 50000 training samples and 55% testing accuracy with 2000 training samples
•Supervised model achieved 79% testing accuracy with 50000 training samples and 49% testing accuracy with 2000 training samples
•However, the testing accuracy of BioCLR was the same with or without contrastive learning. It indicates that contrastive learning was not contributing to the performance of BioCLR. BioCLR performed better with smaller dataset might be because its pathways were pretrained.

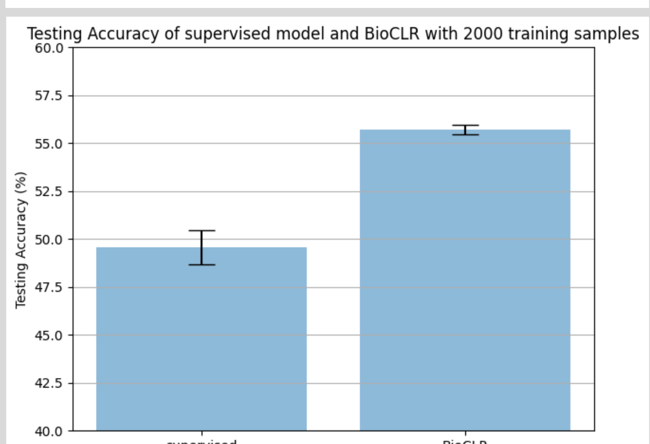
Possible ways to improve BioCLR:

1. Change upstream tasks or the downstream task.
2. Increase the size of the two artificial pathways and reduce the size of the contrastive learning network in BioCLR.

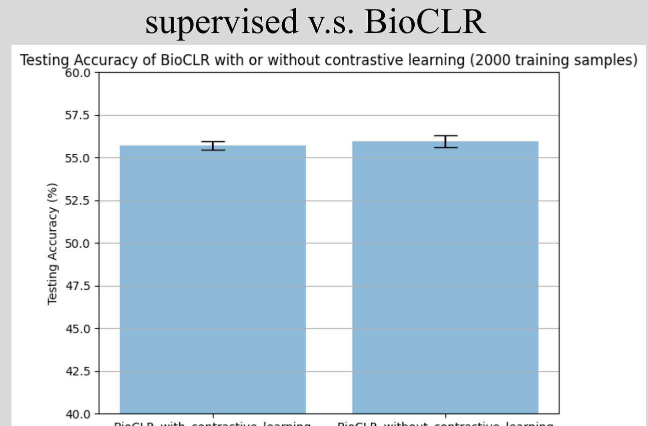


Above: Architecture of BioCLR model





Above: Comparison of results of supervised v.s. BioCLR

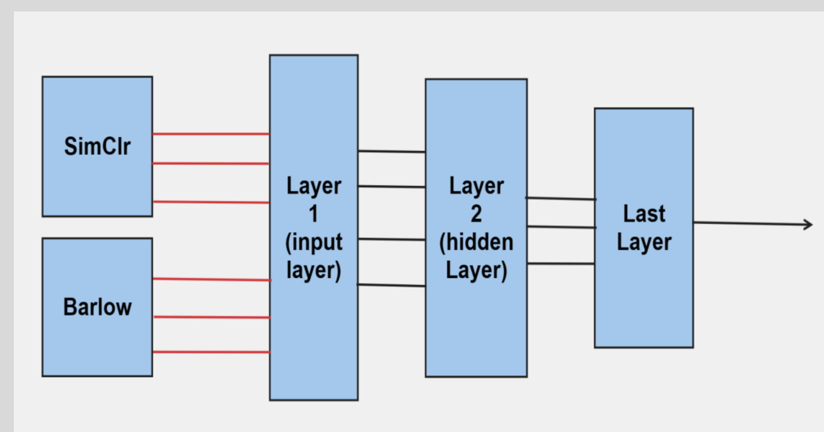


Above: Comparison of results of BioCLR with/without contrastive learning

Ensembling Machine Learning Models for Improved Predictive Performance

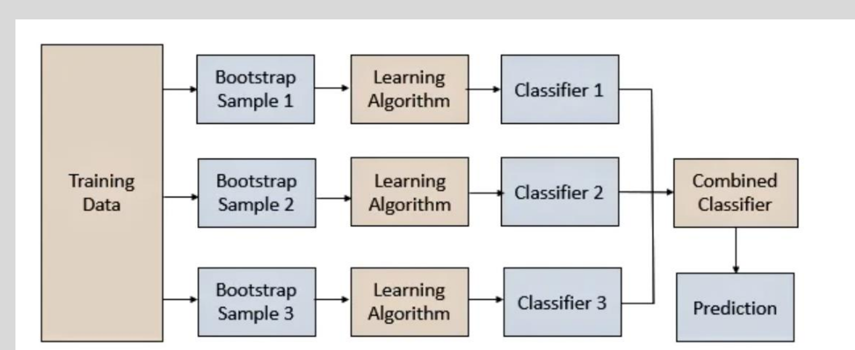
This project aims to create a new model by ensembling two self-supervised learning models together. This new model would have a better Top 5% accuracy than either of its base models and be better than the top 5% accuracy of some supervised learning models.

Methodology:



Above: Stacking Model representation

- We generate an input tensor for the connected layers by appending the penultimate representation of each model, SimCLR and Barlow Twins.
- He connected Layer uses a cross-entropy loss function to train.
- The connected Layer is also modular to the number of nodes in each Layer, to allow adapting to different datasets and input models.



Above: Bagging Model Representation

- We combined the results of multiple models into a generalized result by decreasing the model's variance
- Used bootstrapped datasets to train the SimCLR and Barlow Twins models and then combined the probability distribution given by them using soft-voting to compute our final result.

Results:

- Focused on the top 5% accuracy when applying each of the ensemble methods
- Combined a TensorFlow based model and Py-torch based model successfully.

Conclusion

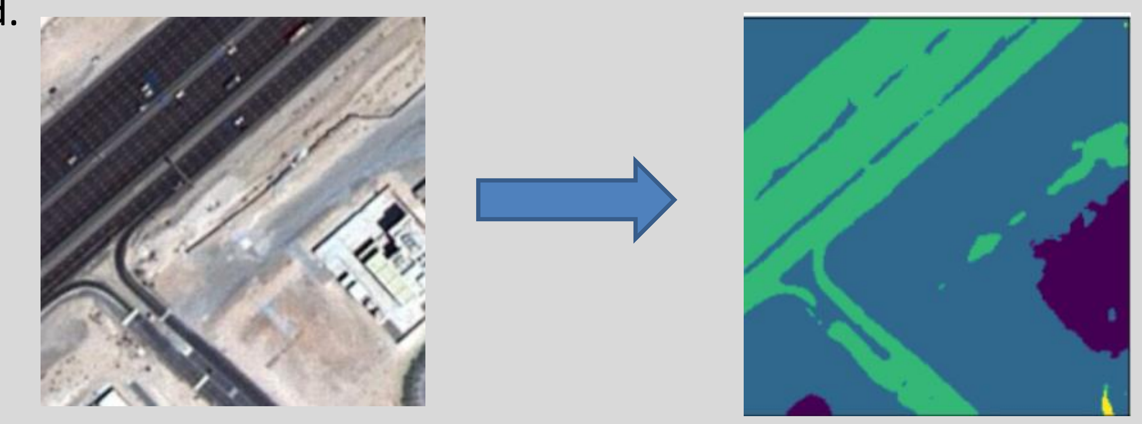
Self-supervised learning offers many benefits as opposed to conventional supervised and unsupervised learning methods. Self-supervised learning features reduced time and energy intensive practices commonly found in supervised training while having a better accuracy than unsupervised learning. Through these methods and despite some initial challenges, the teams have been able to experiment, combine, and apply such models to achieve their results.

As the technology develops, self-supervised learning may rival supervised learning in accuracy at a fraction of the cost, thus becoming the new gold standard for future machine learning models.

Using Self-Supervised Learning to Classify Land Use in Satellite Imagery

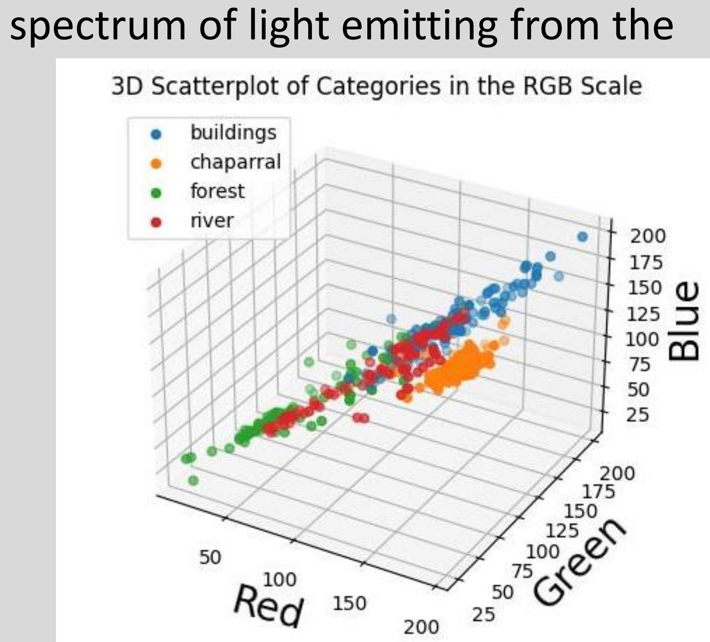
In this semester-long project, the team has analyzed data input from maps and from satellite imagery to classify the land use in the image using self-supervised learning. The main goal is to input an entirely blank map and run it through a model to classify the land use of the images into separate categories, of which could include urban landscapes, forest, oceans, desert, and farmland.

Right: The goal of the model is to accept the input image such as the image on the left And return the map such as The one on the right with the Separate regions classified

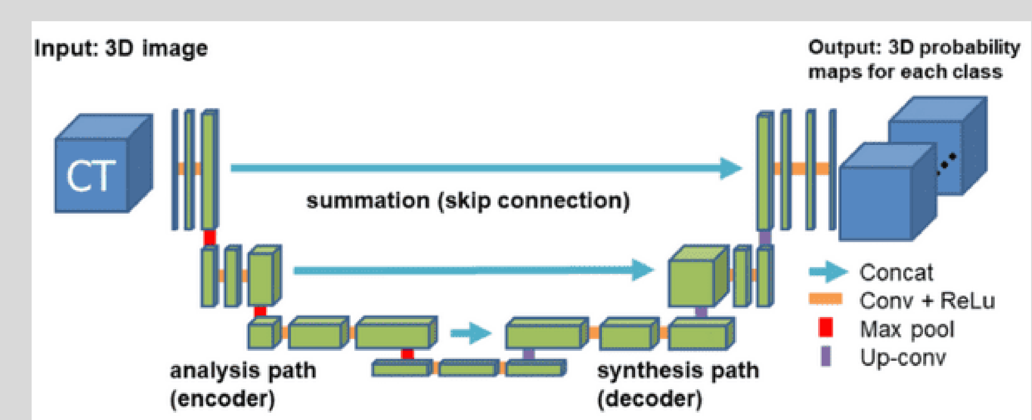


Methodology:

•The model will comprise mostly of image segmentation of the map, which will break down the image into separate regions of which the properties are the same.
•These regions will be identified using the ultraviolet spectrum of light emitting from the ground.
•As part of pretraining process, a dictionary of categories and their respective cluster centers will be accessed by a U-Net Model to then cross-reference any input images with those categories
•Will be trained on the classifiers using a dataset provided by a study conducted by the UC Merced Research Laboratory.



Above: 3D scatterplot of categories found in the RGB spectrum



Left: Model Architecture of U-Net, which involves a series of convolution , ReLU, and max pooling layers for down-sampling followed by up-convolution to output a segmented image

Results:

•The changing of the final output from having a model with different scales and labels to a simpler image segmentation model that classifies the land use with self-supervised learning
•Pretrained data of the Satellite Bands and their respective vector classifications

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