

Successful Contrastive Pretraining of Set Transformer

Divyashree Koti

Middle Tennessee State University

dsk2v@mtmail.mtsu.edu

Advisor:

Dr. Joshua Lee Phillips

August 19, 2023



Computational Finance

Presentation Overview

1 Introduction

Data

2 Background

3 Methods

Set Transformer

Contrastive Learning using Set Transformer

Fine Tuning

Generalization

Visualization

4 Results

Set Transformer

Contrastive Learning using Set Transformer

Fine Tuning

Generalization

Visualization

5 Conclusion

Introduction

- Transformer - Process sequence of data
- Vision Transformer - Process images
- Set Transformer - Process unordered sets
- Contrastive Learning
- Generalization
 - Weak generalization
 - Strong generalization
- Point cloud 3D Body scan



Computational Science

Data

- 75 Participants
- Collected by Dr. Frederick Steven Cottle
- KX-16 Body Scanner
- Point cloud count - 51000 to 63000

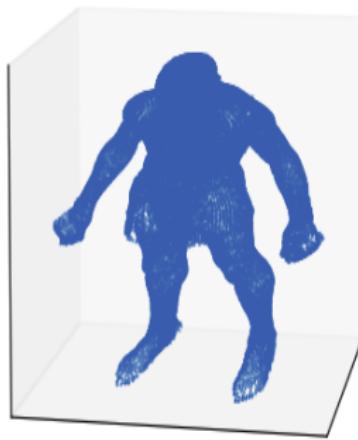


Figure: Original 3D Body Scan

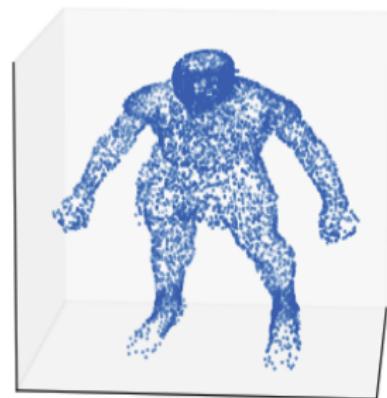


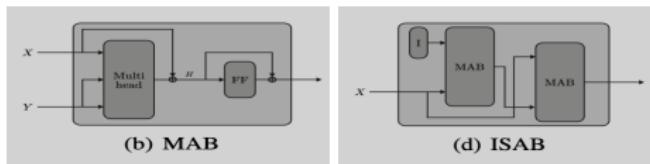
Figure: Subsampled 3D Body Scan



Background

- Set Transformer - Lee, J. et. al. (2018)
 - Induced Set Attention Block(ISAB) - speeds up computation and extracts meaningful features.
 - Pooling layer - parameterized aggregation function, helps to capture the varying contribution of the instances, for better aggregation.
- Simple framework for Contrastive Learning - Chen, T. et. al. (2020): ResNet-50 on ImageNet dataset, Positive pair/ Negative pair. Using SimCLR self-supervised method shows similar performance by Resnet-50 supervised learning.
- Generalization
 - Kullback–Leibler divergence(KL divergence)

$$D_{KL}(P||Q) = \sum_{x \in X} P(x) \log \left(\frac{P(x)}{Q(x)} \right) \quad (1)$$



Computational Science

Methods

- Experimental setup
- Data Loader
- Batch size - train:4, validation:4
- Sub sample size - train:8000, validation:2048
- Train : Validation = 80:20
- Monte Carlo Simulation - 10
- Loss - Sparse categorical cross entropy



Set Transformer

- Hyperparameters
 - Embedded dimension - 32, 64
 - Number of heads - 4, 16, 32
 - Induce points - 32, 64, 128
 - stack - 2 to 6
 - Dropout - 0.05, 0.2
 - Optimizer - Adam
 - Learning rate - 1e-02 to 1e-04
 - Number of epochs - 250

Set Transformer

Set Transformer architecture

- 1: $y = \text{Linear}(3, \text{embed_dim})$
- 2: **for** $j = 1$ to stack **do**
- 3: $y = \text{InducedSetAttentionBlock}(y)$
- 4: **end for**
- 5: $y = \text{Dropout}(0.05)(y)$
- 6: $y = \text{PoolingByMultiHeadAttention}(y)$
- 7: $y_{\text{embedding}} = \text{Dropout}(0.05)(y)$
- 8: $y = \text{FinalDense}(\text{numberofclasses})(y_{\text{embedding}})$
- 9: *return* $y, y_{\text{embedding}}$



Computational Science

Contrastive Learning using Set Transformer

- Base model - Set Transformer, to extract the feature embeddings
- For every batch a sample with its augmented self is a positive pair.
- For every batch a sample with the rest of the sample is negative pair.
- Experimented batch size - 4, 16, 32
- Point cloud - 8000, 2048, 1024
- Temperature - 0.5, 1.0, 2.0
- Optimizer - Adam with learning rate 1e-03



Contrastive Learning using Set Transformer

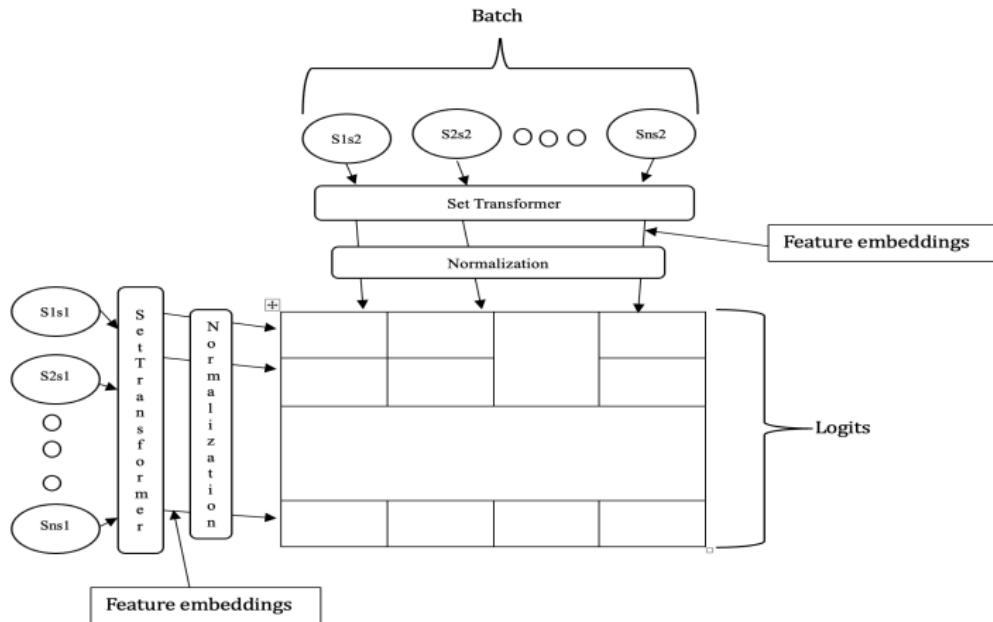


Figure: Contrastive Learning using Set Transformer architecture

Contrastive Learning using Set Transformer

Contrastive Learning architecture

- 1: $y1, y_embedding1 = \text{SetTransformer}(\text{batch1})$
 - 2: $y2, y_embedding2 = \text{SetTransformer}(\text{batch2})$
 - 3: $y_embedding1 = \text{Linear}(\text{embed_dim}, \text{projection_dim})(y_embedding1)$
 - 4: $y_embedding2 = \text{Linear}(\text{embed_dim}, \text{projection_dim})(y_embedding2)$
 - 5: $y_embedding1 = \text{Norm}(y_embedding1)$
 - 6: $y_embedding2 = \text{Norm}(y_embedding2)$
 - 7: $y = \text{Mul}(y_embedding1, y_embedding1.T) * \text{Temperature}$
-



Computational Finance

Fine Tuning

- Additional Layers:
 - Linear layer - 1024, 256, 128
 - Non-linear activation function - LeakyReLU
 - Dropout - 0.1
- Hyperparameters - same as that of standard Set transformer



Generalization

- Weak Generalization - Has knowledge about all the category data at the time of training.
- Strong Generalization(leave one out) - Is not aware of a particular class data at a given training period.
- Probability matrix - 75×75
- Reassign all diagonal elements in weak generalization 0.
- Normalize both of the matrices
- Apply KL Divergence



Computational Finance

Visualization

- Get feature embeddings for both standard Set transformer and Contrastive pre-trained model.
- 10 vectors for each sample.
- Applied PCA with 2 principal components to visualize in 2D.
- Applied t-SNE with a 2D component with the perplexity of 20.
- Evaluate along the 2D axis if, distribution is relatable to human distinguish.



Computational Science

Results



Computational Science

Standard Set Transformer

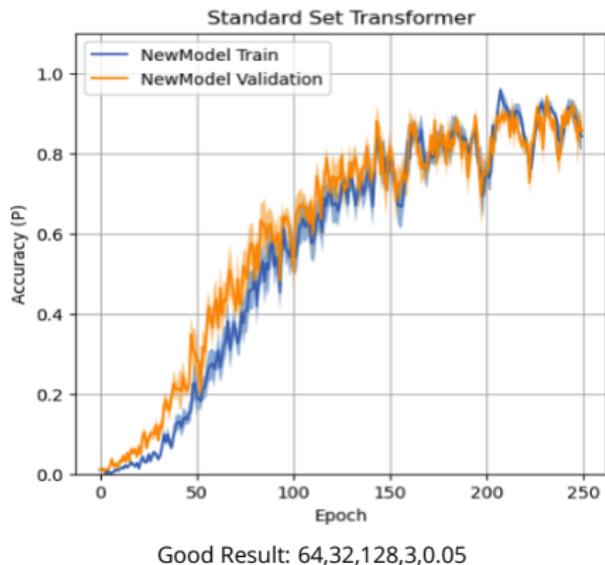
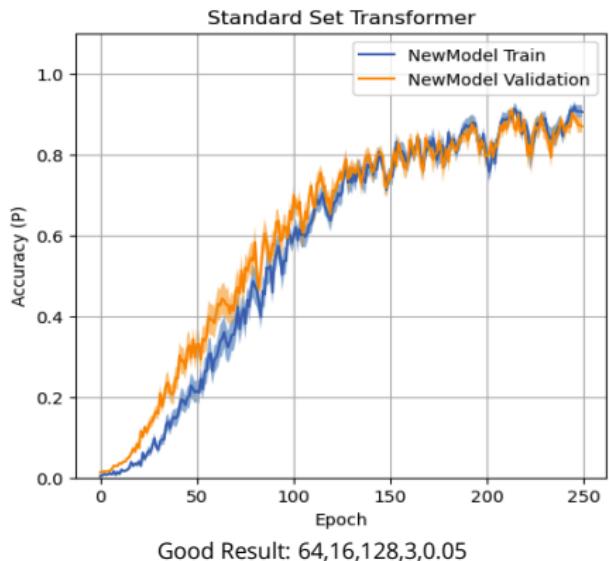
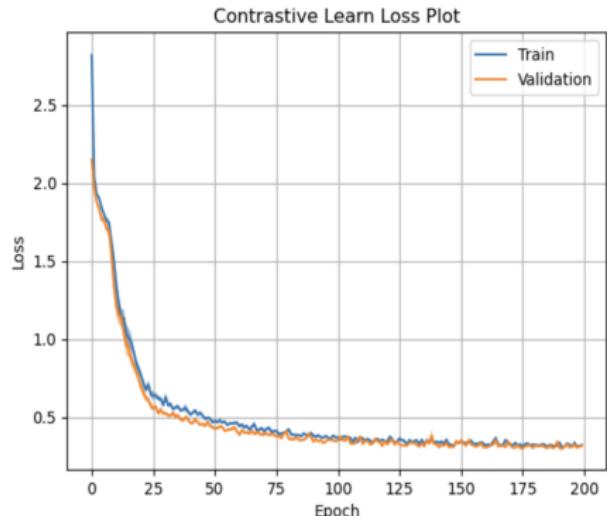
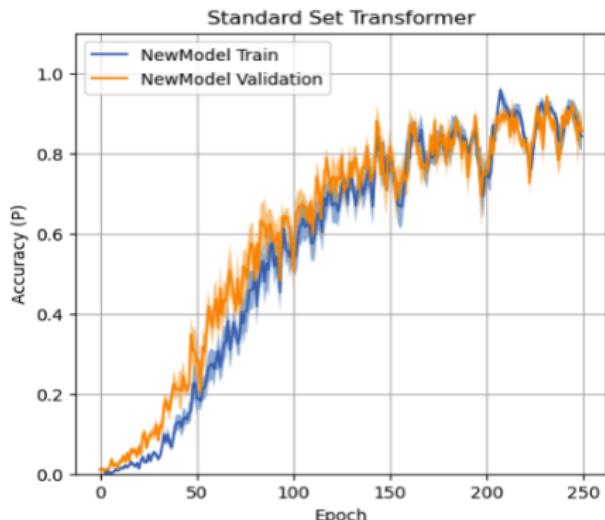


Figure: Monte Carlo simulated Standard Set Transformer Accuracy

Contrastive Learning using Set Transformer



Good Result: 64,16,128,3,0.05



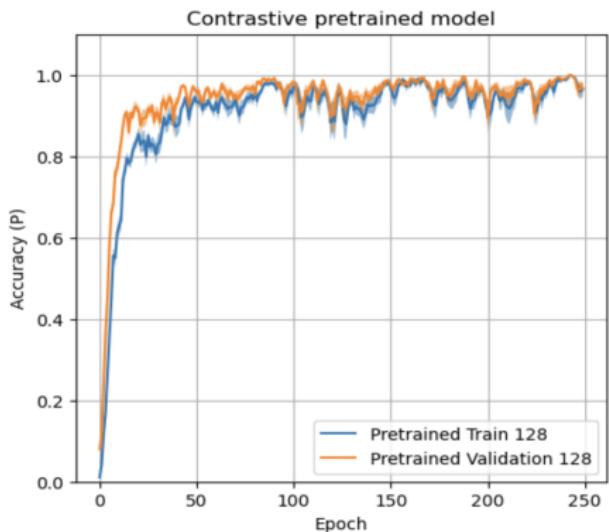
Good Result: 64,32,128,3,0.05

Figure: Monte Carlo simulated Contrastive Learning using Set Transformer Loss

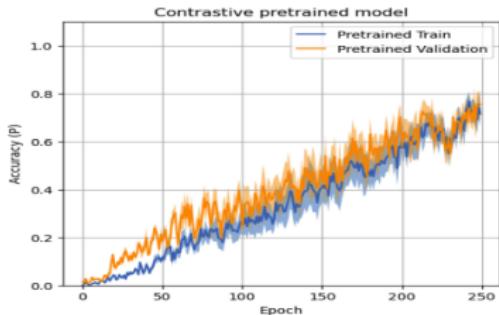


Computational Science

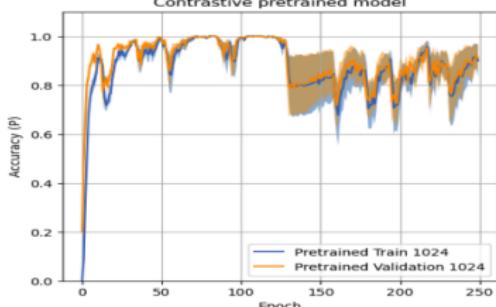
Fine Tuning



Good Result: 64,16,128,3,0.05, 128, 0.1



Good Result: 64,32,128,3,0.05, 128, 0.1



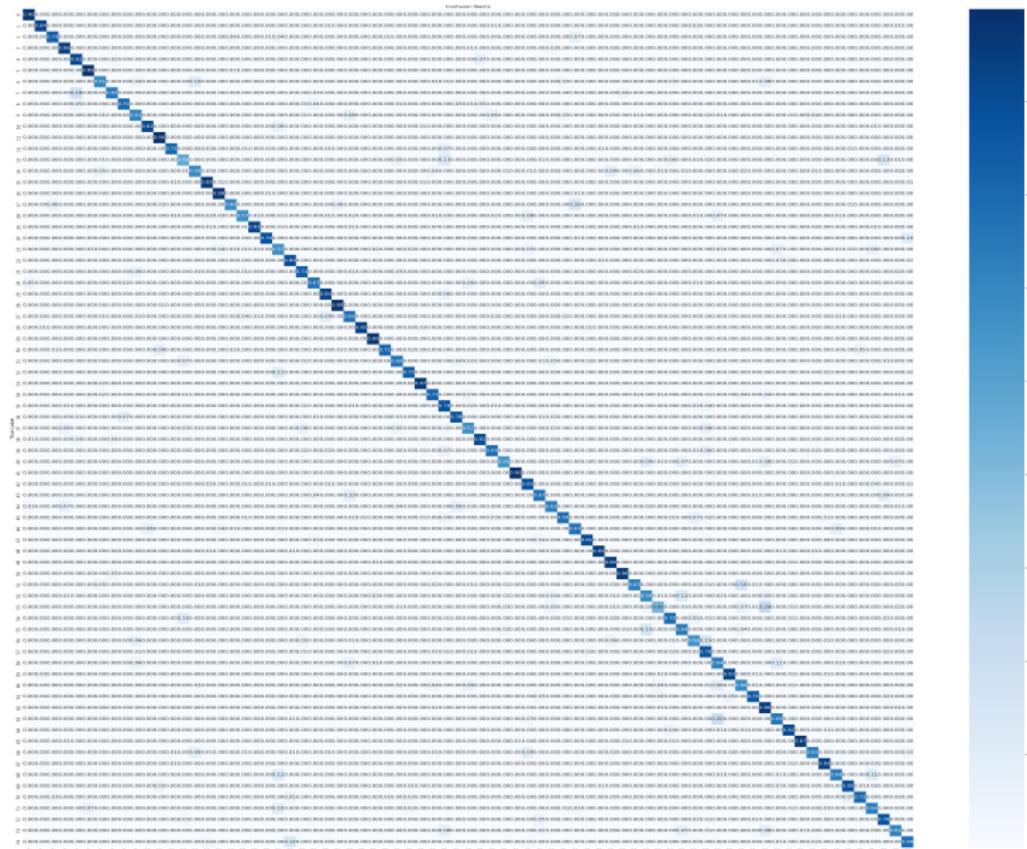
Good Result: 64,16,128,3,0.05, 1024, 0.1

Figure: Monte Carlo simulated Contrastive pre-trained model Accuracy

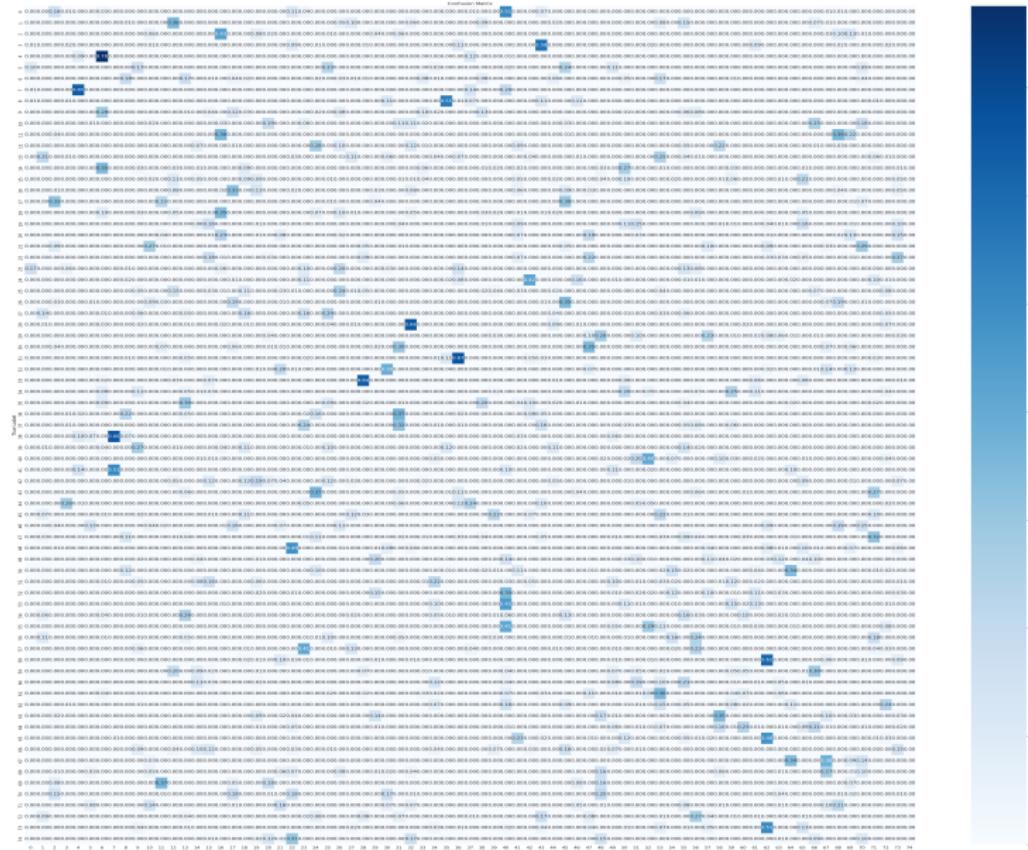


Computational Science

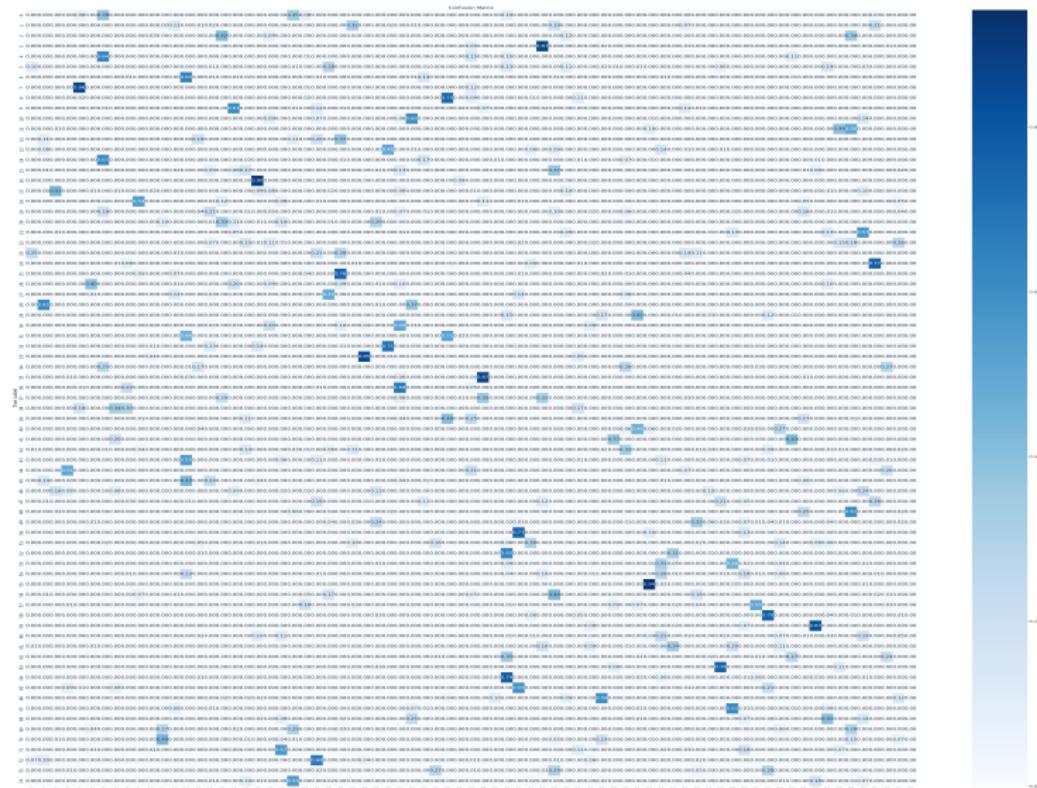
Weak Generalization: Standard Set Transformer



Strong Generalization: Standard Set Transformer



Strong Generalization: Contrastive pre-trained model



Generalization

Table: Results for Generalization using KL Divergence

Method	KL Divergence
Standard Set Transformer	6.60
Contrastive Pre-trained model	6.25



Visualization

PCA Visualization for Standard Set Transformer



Figure: PCA Visualization for Standard Set Transformer

- Principal Component 1: 30.26%
- Principal Component 2: 24.38%
- Total Principal Component: 54.64%

Visualization

PCA Visualization for Contrastive Pre-trained Model

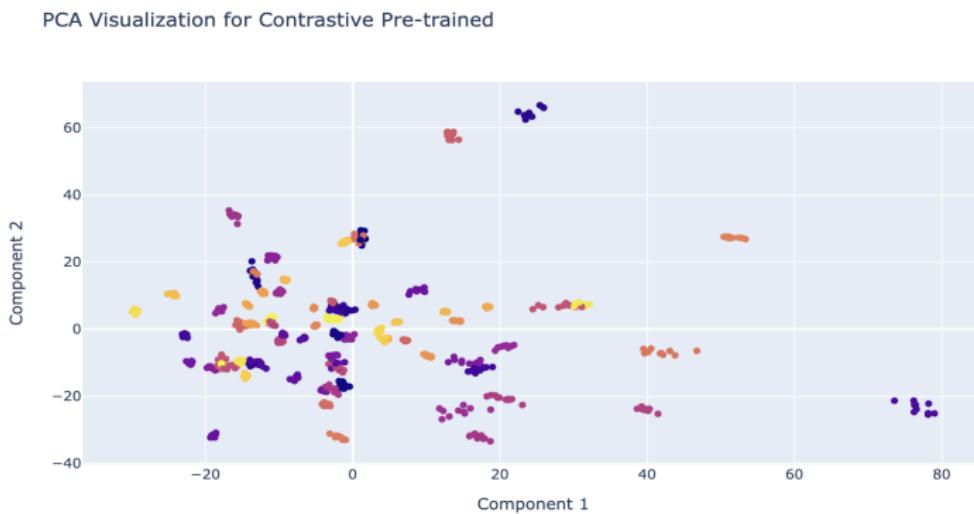


Figure: PCA Visualization for Contrastive Pre-trained

- Principal Component 1: 20.50%
- Principal Component 2: 18.35%
- Total Principal Component: 38.85%

Visualization

t-SNE Visualization for Standard Set Transformer

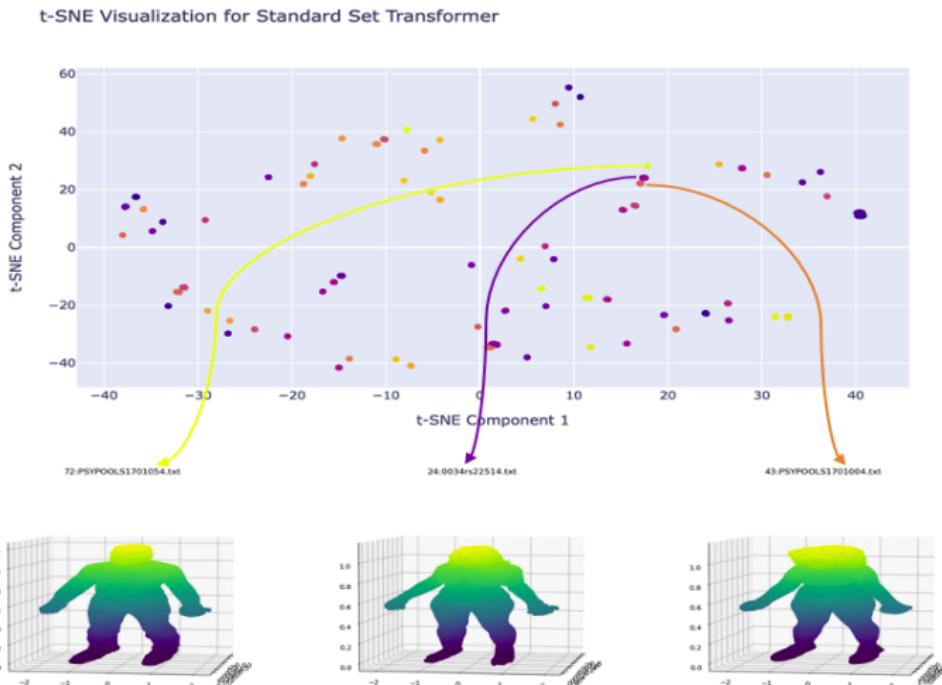


Figure: t-SNE Visualization for Standard Set Transformer



Computational Science

Visualization

t-SNE Visualization for Standard Set Transformer

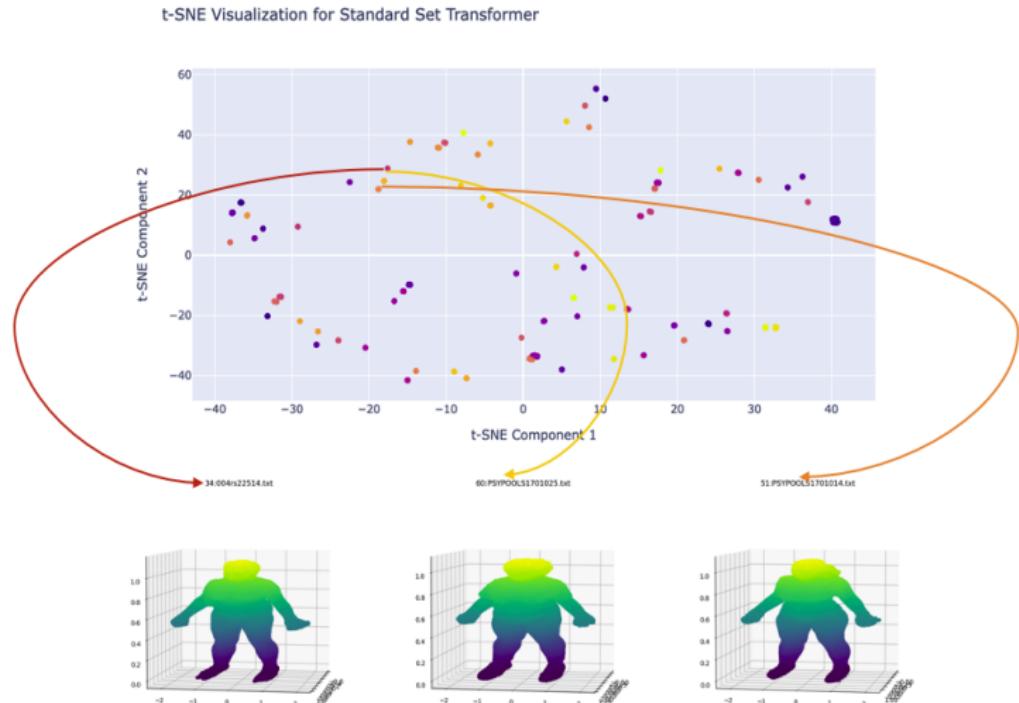


Figure: t-SNE Visualization for Standard Set Transformer



Computational Science

Visualization

t-SNE Visualization for Contrastive Pre-trained Model

t-SNE Visualization for Contrastive Pre-trained

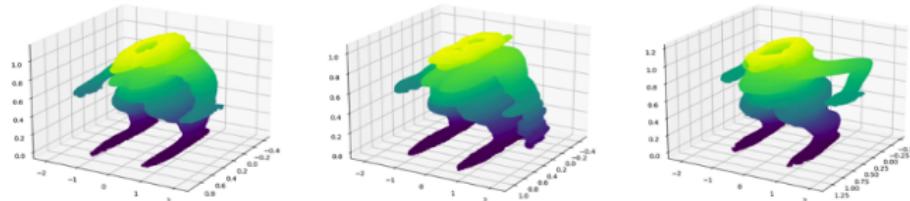
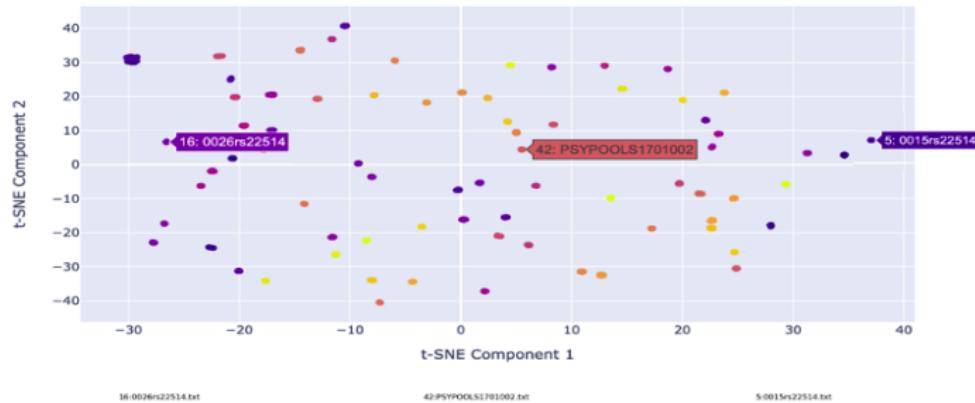


Figure: t-SNE Visualization for Contrastive Pre-trained Model.

Conclusion

- Standard Set transformer and Contrastive Pre-trained model for self-identification task.
- Weak and strong generalization for efficiency of the model.
- Contrastive Pre-trained model excelled Standard Set Transformer performance in terms of accuracy, speed, and stability.
- Contrastive pre-trained model showed improved generalization than the standard Set Transformer.



Conclusion

Future work

- Contrastive Pre-trained model can be used as a solid foundation for extended work like Generative Adversarial Set Transformer(GAST).
- GAST approach is to generate point cloud data to form a full or a partial 3D body scan.
- This approach is in the notion to provide support in case of missing scanned parts or lesser point cloud data that helps with increased precision.



Thank you