Transformer Model for Trajectory Prediction Using the Unitraj Framework

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Introduction

This poster aims to provide a succinct overview of the progress and improvements made in our transformer trajectory prediction deep learning model through various enhancements and hyperparameter tuning.

Objectives

Key objectives included defining temporal and social attention functions and implementing a positional encoder. Post-completion, the focus was on enhancing the model and conducting hyperparameter tuning to optimize performance and reach the defined baselines. The overarching goal was to understand the architecture of the transformer and the tuning parameters in order to develop a reliable and efficient tool for trajectory prediction.

Methodology

After implementing the positional encoder, temporal attention function, and social attention function, we proceeded by tuning all of the model's hyperparameters sequentially and using training and validation curves of MinADE6 seen in *Figure 1* to measure performance. The primary hyperparameters changed included the learning rate, learning scheduler, L2 regularization, model size in the form of hidden layer dimension and encoder and decoder dimensions, dropout rate, and the maximum number of samples to train on from the provided datasets.

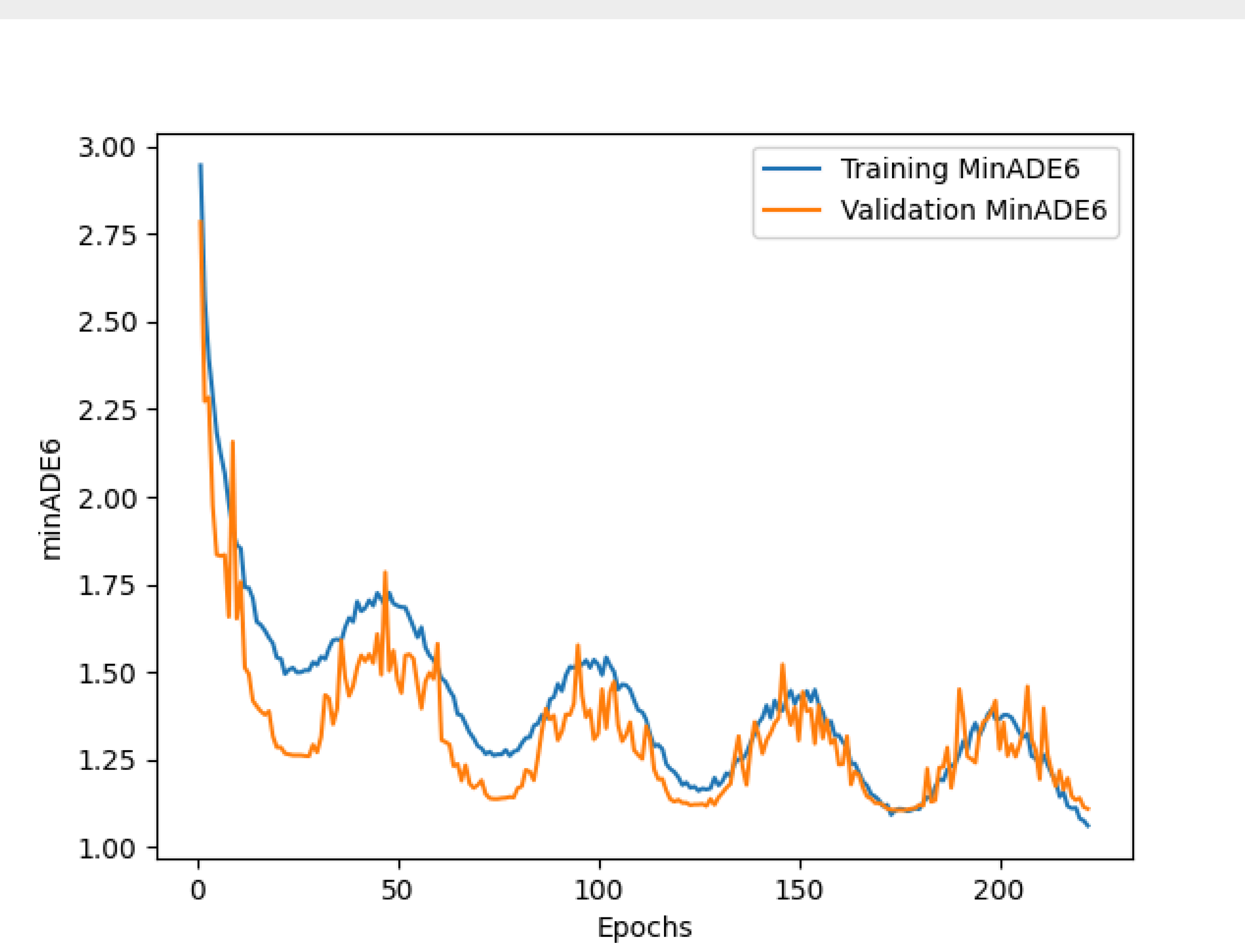

Figure 1: Training and Validation Curves for the best performing model.

Results

minAE6 of 0.988

Figure 1 shows the MinADE6 with respect to the epochs, ending at 225 epochs. The most important features of this model were the following:

- L2 regularization with Weight Decay of 0.00001
- Adam Optimization
- Cosine Scheduler Restarting Every 25 Epochs
- Dropout of 0.2
- Max Data Samples of 120.000
- Dimension of Hidden Layers of 64

Conclusions

For the trajectory prediction transformer model, the most important changes that were made that improved the model the most was the addition of L2 regularization due to the highly correlated nature of the data, and the addition of more data on which to train the model.

Key Findings

- L2 Regularization is incredibly important to include in trajectory prediction models due to high inter-datatype correlation.
- Increasing the number of unique data points does not always improve model performance if the dataset is improperly balanced or loaded.

Future Work

Based on our findings, aside from exploring new model architectures, the best way to improve model performance would be to generate and publish more varied datasets. We would also be interested in exploring data augmentation and more forms of regularization that can help the mode generalize highly correlated data.

The codebase can be found in the following GitHub repository: [https://github.com/Andrew123098/unitraj-DLAV]