# Self-Organizing Maps (SOM) and their applications in motor validation

Nicholas Parise 7242530

***Abstract*—This project implements a Self-Organizing Map (SOM) to visualize the distribution of good and bad motors in the provided motor dataset. The SOM organises the motor data into a 2D topology, and places similar vectors closer together. A neighborhood function using toroidal (wrap around) distance along with a time decaying learning rate is used to generate the weight matrix. Then after the vectors are all set, an activation map (which acts as a heat map) is created to properly visualize the good and bad motors. The effectiveness of SOM's in differentiating good and bad motors is tested with testing three topologies: 5x5, 6x6, 7x7 and two input vector sizes (16 and 32 samples).**

## I. Introduction

TRADITIONAL feed-forward neural networks are great at learning trends and patterns, but they do not create a direct visual representation of the data. This is where a Self-Organizing Map (SOMs) comes in. They allow for an unsupervised way of clustering high dimensional data into an easy to visualize 2D grid. In this project that 2D grid allows us to determine if a motor is good or bad based on its input data. It also allows for a deeper understanding of how a 'good' and 'bad' motor differ. Through experimentation, different hyper parameters will be tested to determine which has the best clustering and differentiation.

## II. Experimental Setup

The project is written in Python and uses numpy to help with matrix calculations. The dataset consists of motor voltage readings over time which are classified as good or bad. There are two input sizes used, 16 and 32 vector length. The three SOM topologies chosen were: 5x5, 6x6, and 7x7 grid sizes.

- Each neuron's weight vector was initialised randomly in a range of [-0.25, 0.25].
- The training process used a decaying learning rate and a toroidal neighbourhood function with a decaying radius.
- The training process used a decaying learning rate and a toroidal neighbourhood function with a decaying radius.
- In each epoch every input was randomly chosen until all went through the distance function.
- The SOM was run with a starting learning rate of 1.0, and was given 2000 epochs

After training concluded, the activation graph was generated by running the SOM in a supervised mode where the reaction from the good and bad motors gave each index in the graph a value. This value was then used to color the square, where a value closer to positive 1 means the motor is good and a value closer to -1 means the motor is bad.

## III. Findings

The following heat maps are used to visualize the high dimensional motor data. Here Red means a good motor, and Blue means a bad motor

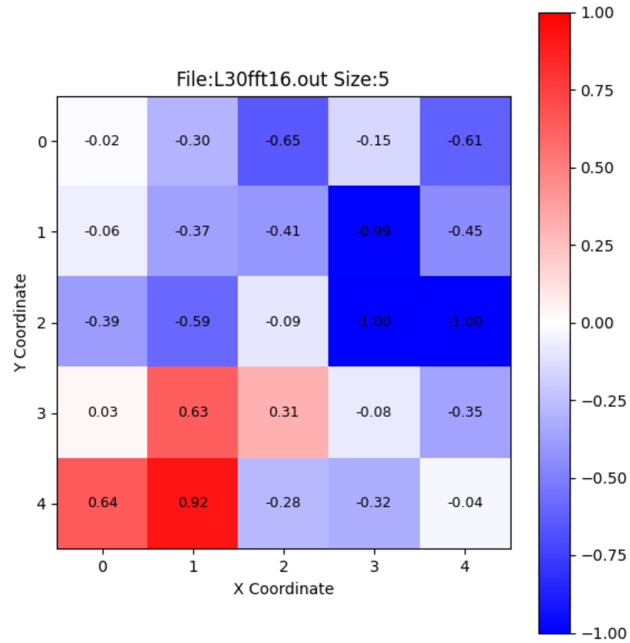


Fig. 1. Depth:16 Size:5

## IV. Discussion

After training, the SOM was successfully able to organize the inputs into coherent distinct clusters corresponding to good and bad motors. Elements close together tended to have similar numbers, and there tends to be neutral values between the clusters as well. Some randomness in initialization caused slight differences between runs, but overall patterns remained consistent. The heat map highlights regions of high activation for each class, confirming the SOM's ability to distinguish between the two input categories. Overall the SOM performed best in clustering the bad motors, this is evident in the fact that every figure had at least four sometimes more regions within the range [-0.8,-1].

While all outputs have very good classification, those with more data tended to have better separability. For instance Fig. 6 has 2 distinct large clusters, taking into account the edge wrapping all the bad motors are part of one distinct blue area, and all the good motors are all connected directly into one large good area. While this same separability can be seen

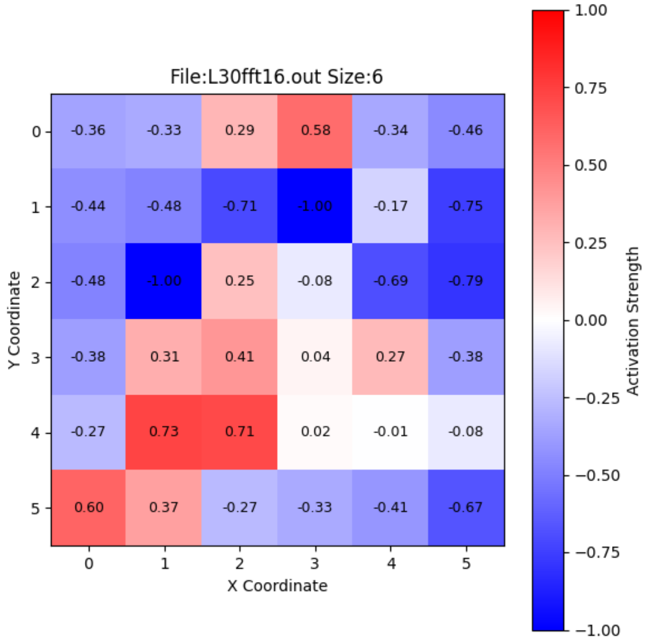


Fig. 2. Depth:16 Size:6

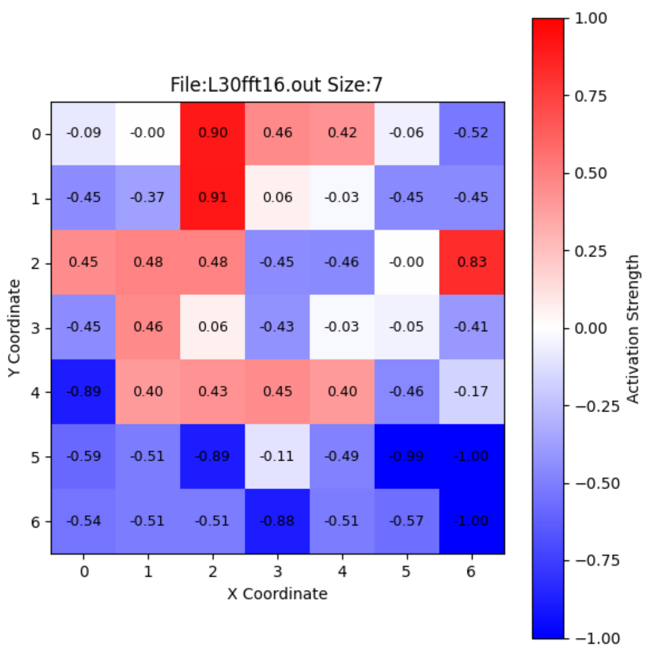


Fig. 3. Depth:16 Size:7

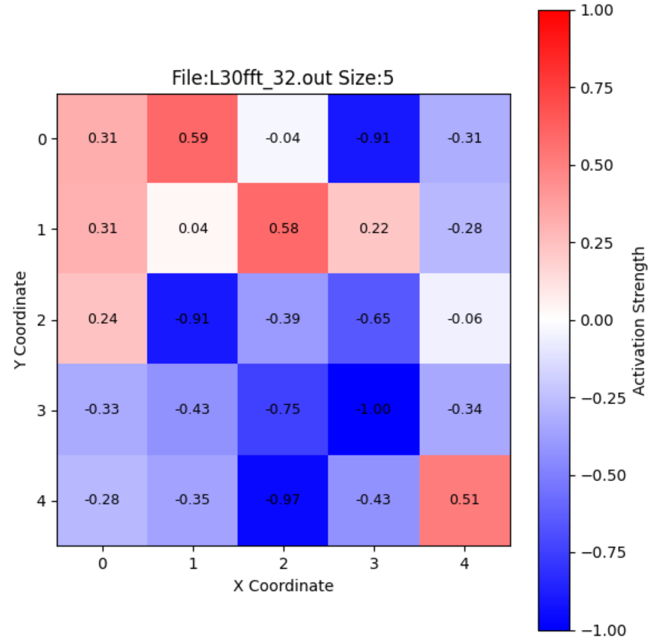


Fig. 4. Depth:32 Size:5

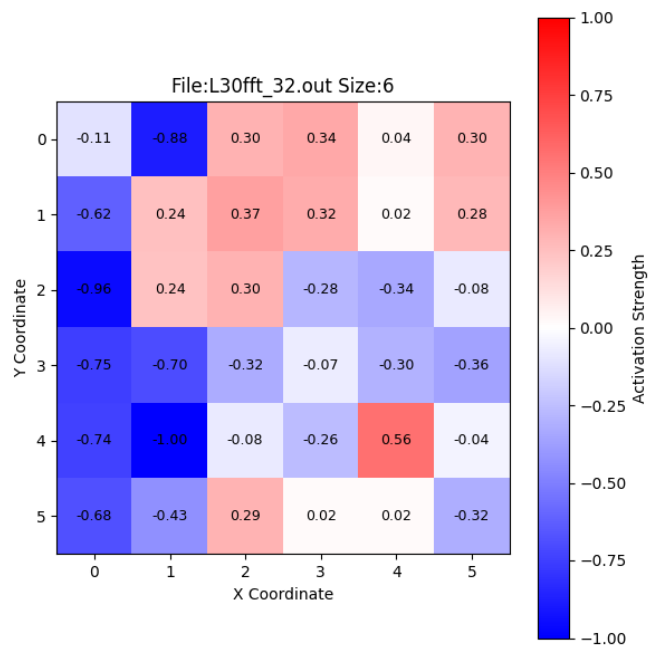


Fig. 5. Depth:32 Size:6

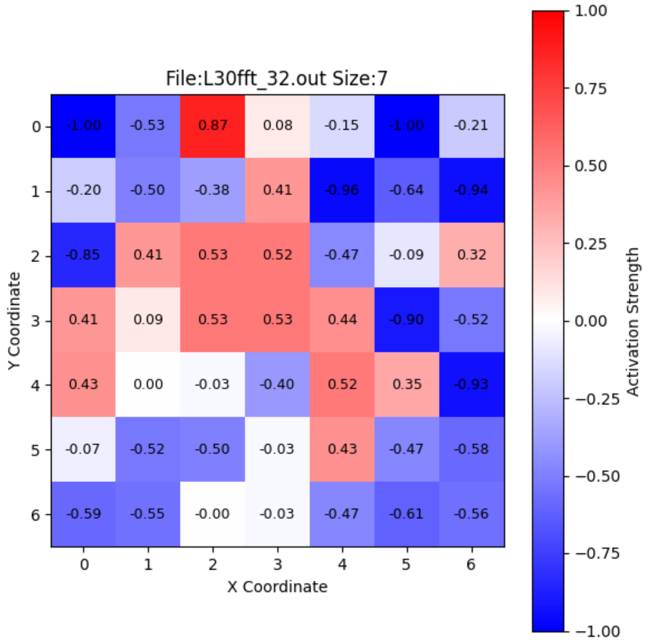


Fig. 6. Depth:32 Size:7

across all figures it is more evident in the ones with larger sizes except for Fig. 1 . Figure 1 has very easily seen separability where the bottom left corner is pure red with positive motors and everywhere else is deep blue with bad motors.

## V. Conclusion

This project demonstrates the utility and effectiveness of a self organizing map (SOM). The ability to effectively cluster and visualize the high dimensional motor data is very useful in being able to debug Neural networks along with using the SOM as is to determine if a motor is good or bad. The heat maps this SOM creates clearly identify regions of good and bad motor readings. Another reason to use SOM's is their incredibly fast training time, needing only a fraction of a feed forward neural networks time and memory to get similar results. Future experiments could be done to determine the best size of map along with input vector sizes.