F20BC - Coursework Report

# Implementation

The approach we took was to create classes for the following: Artificial Neural Network, Particle Swarm Optimisation, Particle, and Hyperparameters.

## Hyperparameters Profile

We created hyperparameter profiles to store all the hyperparameters we plan to adjust. These include the number of layers and number of neurons per layer, activation functions for each layer, and the adjustable parameters for the PSO, which are the inertia, cognitive, social, and global component as well as the number of iterations and the number of particles. All of this helped us to make the testing of different configurations of the PSO and ANN easier.

## Artificial Neural Network

The ANN class stores layers sizes, activation functions, weights and biases. The weights and biases matrices are just filled with 0’s as we do not work with the ANN directly as the weights and biases come from the particles. Activation functions and layers sizes come from the Hyperparameter profiles. As we are using PSO to optimise the weights and biases we only need the ANN class to have forward propagation method to get the output. The forward propagation works by; for each hidden layer, multiplying the input matrix and the weight matrix together, then adding the resultant matrix with the bias matrix then finally applying the activation function of the layer to the output. After getting the outputs for each hidden layer we then do the same on the output layer consisting of 1 neuron as this is a binary classification problem, applying our activation function for the output layer we get the prediction.

## Particle

The particle class stores the velocity and position of the particle and handles the position update of the particle. It also stores the particles best position and best fitness value. The method that calculates the new position has been completed with boundaries of the min and max values (Xiaogang Gao, 2011) found in the dataset, which turned out to be min: -13 & max: 18. The update of position is simply adding the current position and the velocity matrices together, if the new position falls outside the boundary we randomly reset the particles position within the boundary.

## Particle Conversion

In order to discuss how to convert a Particle into a Neural Network, we need to, conceptually, understand how a Neural Network could be converted into a Particle (which wasn’t necessary in the implementation, but provided an understanding of how to convert a Particle to an ANN). It would be done in 5 steps:

1. Go through every layer (except the input layer)
2. Get the weight matrix from the previous layer to this layer
3. Flatten the weight matrix into a vector
4. Append the biases of this layer onto the end of this vector
5. The concatenation of all of these layers’ vectors in order produces a Particle’s Position

With that understood, the conversion of a Particle into a Neural Network works as follows:

1. Firstly, there exists a helper function “get\_particle\_layer\_counts”, which, based on an architecture of a Neural Network (an array of numbers representing number of neurons in each layer – the first number is no. neurons in the input layer, the last is no. neurons in the output layer).
2. This function allows us to get the number of weights and biases in each layer, based on the architecture of the Neural Network.
3. Secondly, there exists a helper function “get\_layer\_vectors”, which, given a Particle, converts its position into an array of vectors. Each vector in this array represents all the weights *and* biases for that layer, as described in the ANN-to-Particle conversion.
4. With that, the conversion of a Particle to a Neural Network works as follows:
   1. We take in a Particle, and, using “get\_layer\_vectors”, get the arrangement of weights *and* biases in each layer, based on its position
   2. Since we know, conceptually, that biases would be at the end of each layer’s vector, and that the number of biases would equal the number of Neurons in that layer, we extract them using a slicing operation.
   3. This leaves us with a flattened vector of weights
   4. Based on the number of neurons of the previous layer, m, and the no. neurons of this layer, n, we use NumPy’s “reshape” method to convert the flattened weight vector into a Weight matrix
   5. This is done for every layer except the input, producing weights and biases
   6. The resulting Neural Network is returned

## Particle Swarm Optimisation

Particle swarm optimisation has 4 functions, the PSO algorithm itself, finding informants of a particle, accessing the fitness of the particle and updating the velocity of the particle. All these functions are explained in more detail in the sections below. Initialising the PSO is done by first extracting all the relevant hyperparameters from the profile that has been chosen, as well as the data to be used and the labels from the data.

### PSO algorithm

The algorithm consists of first updating the particles position as described in the Particle section, then checking the fitness of the particle, replace the global and personal best positions accordingly if the fitness of the particle is higher than previously set positions, lastly we update the velocity. We do all of this for a set amount of iterations, in the end getting the global best fitness.

### Getting informants

Before Informants are acquired, the array of all particles is copied, and the particle looking for its informants is removed from this copy, producing just a list of possible informants.

Note – in our implementation, the minimum number of informants is 1. Therefore, it was chosen to enforce the minimum number of Particles in PSO to be 2, since, if there is only 1, the particle will remove itself from the list of possible informants, and there would be no informants to choose from.

Using NumPy’s “random.choice” method, N particles, where N is number of informants, are selected randomly, without replacement.

As one can see, it was chosen to randomly select informants at each time step, instead of pre-selecting informants for each particle at the beginning and retaining them.

This was done for two reasons:

1. It would be less memory-intensive to pick random informants for particles rather than storing a Particle’s informants in memory.
2. If all of a Particle’s preselected informants converge on a Local Optimum, there would be no way for the Particle to do any better. However, if its informants are selected randomly, then there is a chance for the Particle to come across informants whose positions are close to the Global Optimum.

### Updating velocity

The velocity update function was implemented using this equation:

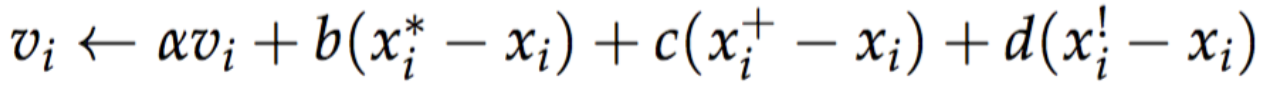


Figure 1 - Velocity Update Equation

First we take the velocity of each particle and multiply it by the inertia (the amount of the velocity we should keep, alpha), Then we will make sure the particle partially moves towards the best position previously discovered by itself (weight b in the equation), then towards the best position discovered by its informants(weight c in the equation), and finally previously discovered global best(weight d in the equation). This is done for each dimension in the velocity vector. The weights b,c, and d are all a random value between 0 and the value of hyperparameters β, γ, and δ this introduces non linearity into the algorithm allowing the particles to search more space without being influenced by the weights all the time, which could lead to a local maxima instead of the global one. The new velocity will then be used in the next iteration of PSO to update the position of the particle within the search space.

### Accessing fitness

For the fitness of the particle the specification mentioned to just use the accuracy of the artificial neural network for the given data and not worry about overfitting. The fitness function takes in the entire dataset, and the labels separately, then convers the particle into a neural network method for which is described in Particle Conversion section, then we run every datapoint in the dataset through the forward propagation method of our artificial neural network and get the predicted values, which then are converted into the classes by using a simple threshold where any values blow 0.5 are classed as 0 and values above 0.5 are class 1. We then compare the predicted labels against the actual labels and get the accuracy by this simple formula: (number of correctly predicted labels / total number of labels \* 100) giving us the percent accuracy of the network.

# Experimental investigation

## Experiment Aim

The chosen aim of this Experiment was to investigate how global best performance of Particles representing Artificial Neural Networks would change, by altering the Cognitive, Social or Global weights individually, and keeping all other hyperparameters the same.

## Experiment Variables

The following three Hyperparameters were changed – the Independent Variables:

1. Cognitive Weight – by how much a Particle’s Velocity should be updated to move towards its personal best position in the search space
2. Social Weight – by how much a Particle’s Velocity should be updated to move towards the best search space position of its randomly-picked informants
3. Global Weight – by how much a Particle’s Velocity should be updated to move towards the best position of *all* particles

The following Hyperparameters were unchanged – Control Variables:

1. PSO Hyperparameters:
   1. Inertia was set to 0.7 – when preparing the experiment, it was found early on that inertia did not do much to affect the performance of PSO
   2. Number of Iterations was set to 200 – we experimented with 100, 200, 250 and 300 iterations. Higher numbers of iterations led to higher performance, but considerably longer waiting times, so it was chosen to use 200 iterations as a balance of both good performance and decent speed
   3. Number of particles was set to 20, for similar reasons as b
   4. Number of informants was set to 4
2. Neural Network Hyperparameters:
   1. The Neural Network has 4 Input Neurons (corresponding to the size of the Dataset’s inputs)
   2. The Neural Network has 1 Output Neuron (corresponding to the classification in the Dataset)
   3. The Neural Network has 2 Hidden Layers – the first with 3 Neurons and the second with 2 Neurons
   4. The Activation function for the Hidden layers is ReLU, and for the output layer it is Sigmoid (since we have a binary classification problem and a value between 0 and 1 is needed)

The Variable we are measuring is the Global Best performance of all particles.

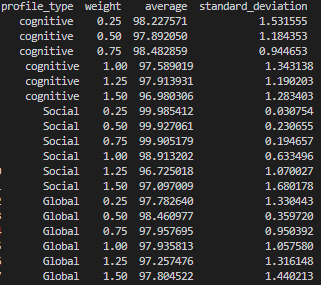
## Experiment Methodology

The Experiment will operate as follows:

1. We change each of the three independent variables in increments of 0.25, from 0.25 to 1.5
2. These values are looked at individually (first Cognitive Weight is changed in these increments and performance measured, then the Social Weight, and then the Global Weight)
3. The values that are not being changed have a default value of 1.25 as a control value
4. For each of these increments, the PSO Algorithm is run 10 times, and an average performance acquired – this is to mitigate the stochasticity of the PSO Algorithm
5. The experiment is carried out automatically, using a script “experimentation.py” (do note – experiments take a long time to run)

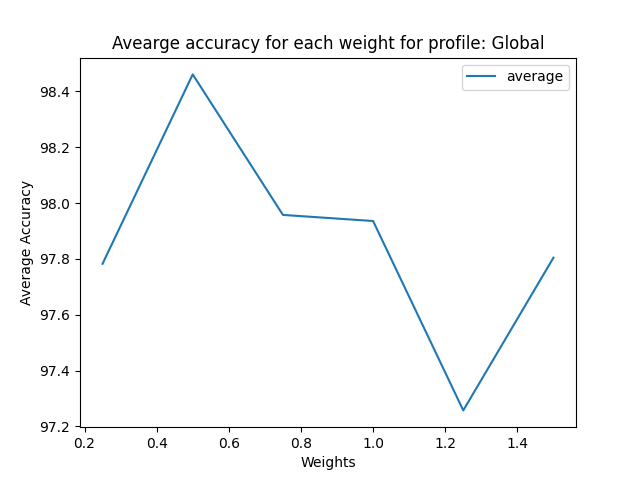
# Results

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*Figure 2 – Testing Results*

*Figure 4 – Average Accuracy graph 2*

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*Figure 5 – Average Accuracy graph 3*

*Figure 3 – Average Accuracy graph 1*

Graphs for standard deviation can be found in the appendices.

# Discussion and Conclusions

Figure 2 shows the results of the testing, with the profile and weight tested, the average over 10 runs and the standard deviation of those 10 runs.

There are a few notable results, if we look at the social tests, we can see that any social weight below 1 gives extremely accurate results with low standard deviation this is due to the particles being allowed to explore more rather than being influenced by the neighbouring particles.

The cognitive weight appears to be the least impactful of the test cases with the deviation being rather high across all tested weights.

The best global weight appears to be 0.5 and presumably for the same reason of allowing the particle to explore more of the search space to find the optimal solution.

Based on the data acquired and the graphs drawn, the following conclusions can be drawn:

1. As the Cognitive Weight increases, there is a downward trend in terms of accuracy. That being said, there are two “peaks” where the accuracy goes up again.
2. When the Social Weight is between 0.25 and 0.75, the PSO Algorithm performs reliably well, at an average accuracy of very close to 100%. After that, there is a sharp drop-off, and then a slight increase.
3. As the Global Weight increases, there doesn’t seem to be any particular trend – it goes up and down again. What’s interesting is that, at Global Weight = 0.25 and Global Weight = 1.5, similar accuracies were achieved. The best accuracy is reached when the Global Weight is at 0.5, but even that is below the Social Weight
4. The best-performing Configuration of a PSO’s Weights are 1.25 for Cognitive Weight, 0.25 for Social Weight, and 1.25 for the Global Weight, at an accuracy of 99.99% (2 decimal places)

What follows are some potential explanations for these conclusions:

1. The downward trend in accuracy with increasing Cognitive Weight can be explained by Particles reaching local optima and remaining at them, due to velocity update due to the Cognitive Weight overwhelming other parts of the velocity update.
2. All other things being equal, the small size of the Social Weight leading to such good performance could be explained by a Particle’s velocity not being too dependent on its informants, which could be stuck in local optima. Despite that, however, there is still that slight amount by which a Particle’s velocity *does* change based on informants, which would alter its course through the search space and allow for more exploration and better results.
3. At small global weights, Particles were not as swayed by the best position in the search space, so, even if their own or their informants’ bests were inferior, did not improve themselves that way. At large weights, Particles were so swayed by the best position of all particles that they ended up in a local optimum. At a value of 0.5, the Global Weight was small enough to not force Particles to conform to one best position, but also large enough to let Particles take into account a good general direction to move to.
4. At large values of the Social Weight, Particles were dependent on their informants’ positions, which potentially led to them reaching local optima in the search space. At a value of 0.25, the Particles were instead interdependent – they took into account informants’ best positions by a balanced amount, not too large to explore less of the search space due to being dependent on informants, but also not too small to become ignorant of how well other Particles are doing.

# References

Xiaogang Gao, S. S., 2011. Handling boundary constraints for particle swarm optimization in high-dimensional search space. Information Sciences, 181(20), pp. 4569-4581.

# A graph with a line Description automatically generatedAppendices

*Appendix 1 – Standard deviation for cognitive profile*

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Description automatically generated *Appendix 2 – Standard deviation for social profile*

*Appendix 3 – Standard deviation for global profile* A graph with a line

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