**BIC Coursework:**

**Introduction :**

Machine learning is now an established tool when it comes to solving classification problems. Recent developments are evolution of the perceptron; a linear classifier and as such has limited effectiveness with real world problems with multiple dimensions. They work by applying weights and biases to the input layer and, through the use of an activation function such as the sigmoid function, make predictions on the class of a given input. Artificial Neural Networks (ANNs) are, in essence, a collection of perceptrons (‘neurons’) working in discrete layers to achieve their predictions and is based off the human brains and its synapses. They consist of 3 main features, an input layer, a hidden layer and an output layer. There can be many hidden layers, which is where the term ‘deep learning’ originates. These neurons are connected by to one another by synaptic weights that, during the networks training process, the ANN updates based off user defined process, classically gradient decent. Once trained it is essential to test the network on separate data to the training set, to assess the models generalisation ability and further assess its predictive accuracy.

Many classic ANNs are limited by their inability to provide adequate accuracy rates out with training but also cannot explore multimodal and noncontinuous surfaces. Evolution of such ANNs is therefore necessary if real world application is to be achieved successfully. The main features of an ANN that limit its effectiveness are its topology, its transfer functions and it set of synaptic weights and biases. Efforts to improve ANNs therefore predominantly focus optimising these areas.1 Biologically Inspired Algorithms (BIA) aim to optimise such features to make ANNs more generalisable.2 They allow for exploration of multimodal and non-continuous search spaces, thus rectifying some limitations of ANNs. There are two main fields in which solutions are proposed, namely evolutionary optimisation and swarm optimisation.3 In this paper we will focus on Swarm intelligence. Swarm intelligence is a BIA development composed of naïve units that, when working in unison, produce intelligent behaviour, likened to bird flocking or fish schooling in nature.4 These metaheuristic methods of training utilise different techniques such as population methods and co-operative evolutionary models.5 PSO is an ANN optimisation technique using information on the position of its best particle in the population and memory of prior experiences of its members. 6 A particles multidimensional location within the search space is evaluated using an optimisation function, its current position and population best position are tracked. In each iteration a particles position is updated in an attempt to find a new optimum and compared against the best previously found across all particles in the population.

* Unsure if useful in intro but here for later use

PSO Velocity Update Formula

V*i*(*t*+1) = ωV*i*(t) + *c1r1*(**P**i(*t*)-X*i*(*t*)) + c2r2(Pg(*t*)-Xi(*t*))

**References :**

1. Yao, X. Evolving artificial neural networks. *Proc. IEEE* **87**, 1423–1447 (1999).

2. Rivero, D. & Periscal, D. Evolving Graphs for ANN Development and Simplification. *Encycl. Artif. Intell.* 618–620 (2011). doi:10.4018/9781599048499.ch094

3. Angeline, P. J. Evolutionary optimization versus particle swarm optimization: Philosophy and performance differences BT - Evolutionary Programming VII. in (eds. Porto, V. W., Saravanan, N., Waagen, D. & Eiben, A. E.) 601–610 (Springer Berlin Heidelberg, 1998).

4. Eberhart, R. & James Kennedy. A New Optimizer Using Particle Swarm Theory. *Sixth Int. Symp. Micro Mach. Hum. Sci.* **0**-**7803**–**267**, 39–43 (1999).

5. Alba, E. & Martí, R. Metaheuristic Procedures for Training Neural Networks Operations Research / Computer Science. *Computer (Long. Beach. Calif).* 252 (2006).

6. Kennedy, J. Swarm Intelligence BT - Handbook of Nature-Inspired and Innovative Computing: Integrating Classical Models with Emerging Technologies. in (ed. Zomaya, A. Y.) 187–219 (Springer US, 2006). doi:10.1007/0-387-27705-6\_6