Behavioral Analysis of Agent Based Service Channel Design using Neural Networks

University of Ontario Institute of Technology— Faculty of Business and Information Technology

Researchers: Ralph Laite & Dr. Nataliya Portman | Supervisor: Dr. Karthik Sankaranarayanan

Abstract

Integrating neural networks into agent based models could potentially provide a better understanding of dynamic agent responses when modelling complex systems. Additionally, due to the nature of agent based models and the networks that exist in them, individual neural networks can be trained in a supervised learning environment and assigned to individual agents. The potential advantage of using this approach is that individual agents become more unique and make decisions based on what the neural network has learned during the training phase.

Agent Based Modelling and Simulation

Agent based modelling and simulation (ABMS) has been applied to many fields, including but not limited to: biology, economics, marketing & communication. Using ABMS to simulate and predict complex systems is especially advantageous when systems consist of nonlinear interactions and individual agents have different properties. One notable drawback of ABMS is the irrational behaviors that humans exhibit may not be represented in the simulation.

The following model differs from the majority, as current models have done very little to incorporate the impact of individual decision making; that is, how individuals form expectations from information and experiences. The model considers a network of agents, each of whom must choose a queue each period to wait at (see figure 1). Agents make there decisions based on what queue they expect to have the shortest sojourn time. Once all agents have made a choice for that time period, there waiting times are calculated, agents then update expected sojourn times for each queue for the next period. Agents update there expectations based on there own sojourn time and there best neighbor's sojourn time. An agents neighborhood consists of two agents, one on each side. Each agent receives the chosen queue of the neighbor with the shortest sojourn time, as well as that neighbor's experienced sojourn time at the chosen queue.

For the experimental simulation (no students), 120 agents were given a choice of 3 queues (facilities), each having the same service rate. The simulation was run for only 50 periods, as this was the optimal length to see most stable patterns form; results can be seen in figure 2.

Student Simulation

It is often believed that humans make rational decisions; however, in reality humans have a limited capability to make rational decisions. Due to this, agent based models often struggle to capture all the irrational decisions that take place. Additionally, since humans are inherently irrational it is important to test the reliability of agent based models by running human experiments. To test the current model a student experiment was conducted; where one student assumed the role of one agent and selected a facility for 45 periods. Students were provided with all the same information the as the agents, and were asked to enter there expectations for each of the 3 queues every period. Additionally, each student was asked to fill out a questionnaire about what strategy they adopted at first and if they changed there strategy. These questionnaires were reviewed and from 60 student responses 12 identifiable strategies were found.

The most common strategy used was number one; the student used the given service capacity and the lowest neighbours experience to make their decision for the following day. The second most prompt strategy was number 4; the student would switch to their neighbours queue if there experienced wait time was less. The students predicted that the agents within the model would see the lowest sojourn time and then choose that queue the following day. Lastly, strategy 5 involved repetitive selection of queues, regardless of information provided. The top three strategies can be viewed in figure 3.

On the far right, clustering plots for the student simulation can be seen for 3 different sensitivities. The clustering plots clearly show that the majority of clusters are centered close to one another, with a couple outliers. Even though there are a number of clusters grouped together, there is still enough variance between them to consider them as unique. The clustering plots make it clear that each student is unique even if they are in the same cluster, and thus to simulate this unique behaviour accurately our model must also have the same level of uniqueness. One potential solution is to create a artificial neural network to copy these unique behaviours.

Artificial Neural Networks

A complex system may be divided into smaller parts in order to reduce the complexity of forming a solution. Additionally, these smaller parts can be put together to produce a more complex system. An artificial neural network (ANN) is constructed from a series of nodes organized in to separate layers; furthermore, nodes communicate between layers from the input layer to the output layer. Layers between the input and output layers are called hidden layers. Each node is considered a computational unit ,where information is passed through and manipulated. The current ANN used for this research is known as a Multi-layer perceptron (MLP), where the ANN is trained in a supervised learning environment by an algorithm.

A MLP networks learn through a process called back propagation; random weights are assigned to connections between nodes in hidden layers, and are updated by regression using stochastic gradient descent (SGD). Additionally, SGD , updates weights using the gradient of the loss function. The loss function is determined as measure of how close to the "true" value the network predicts. The process of back propagation is used to minimize the value of the loss function, and this is completed using SGD to update the network's weights. This is why data is a key aspect of training a neural network. The neural network's training data is the predicted expectations of the queues (input) and the selected queue (output); it is the neural networks job to predict the selected queue based on the given expectations. A general layout of the MLP network can be seen in figure 4.

Once the network has been trained, it can be tested for accuracy. Testing the trained network uses the same process as the back propagation process, accept the network weights are not adjusted. For our network, the testing data was run 5 times, each time using a different and random 20% of the total data set for a single student (the other 80% was used for training). Over a total of 60 students the average accuracy achieved using this method was 71%. An accuracy of 71%, means that the network can effectively learn from student data and make choices in a similar manner; furthermore, this means that the network can capture the majority of student behaviour and this behaviour can be mimicked by the network. The network's ability to copy student behaviour shows promise for implementation into ABMS.

Conclusion

Achieving an average accuracy of 71% with an un-tuned MLP network, shows that neural network agent based models could provide more realistic simulations. Additionally, the integration of neural networks into agent based models can create a more dynamic agent response by effectively translating individual human behaviour into agents.

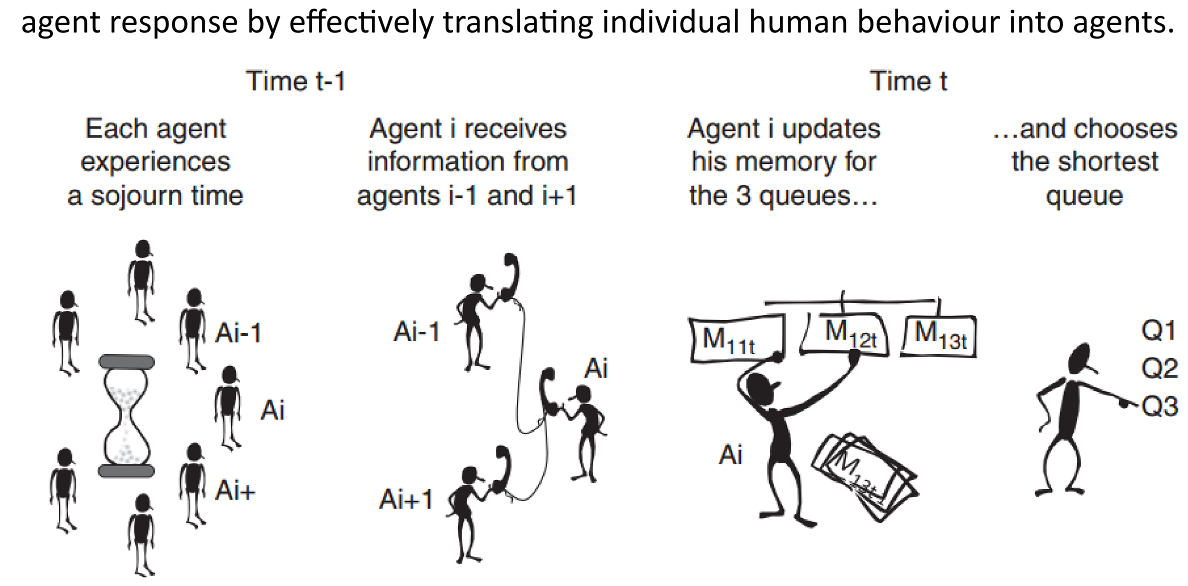
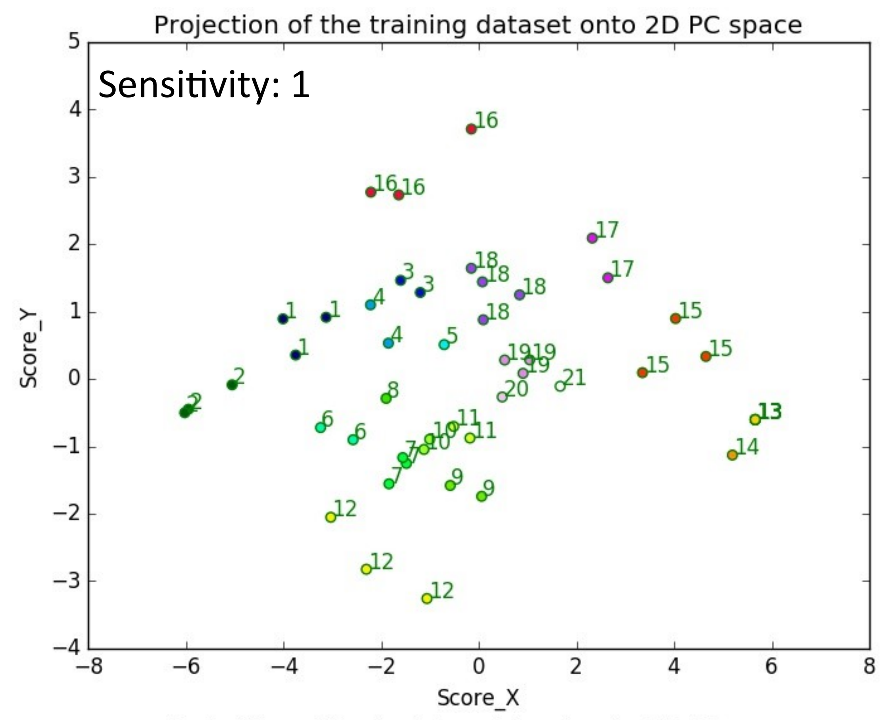
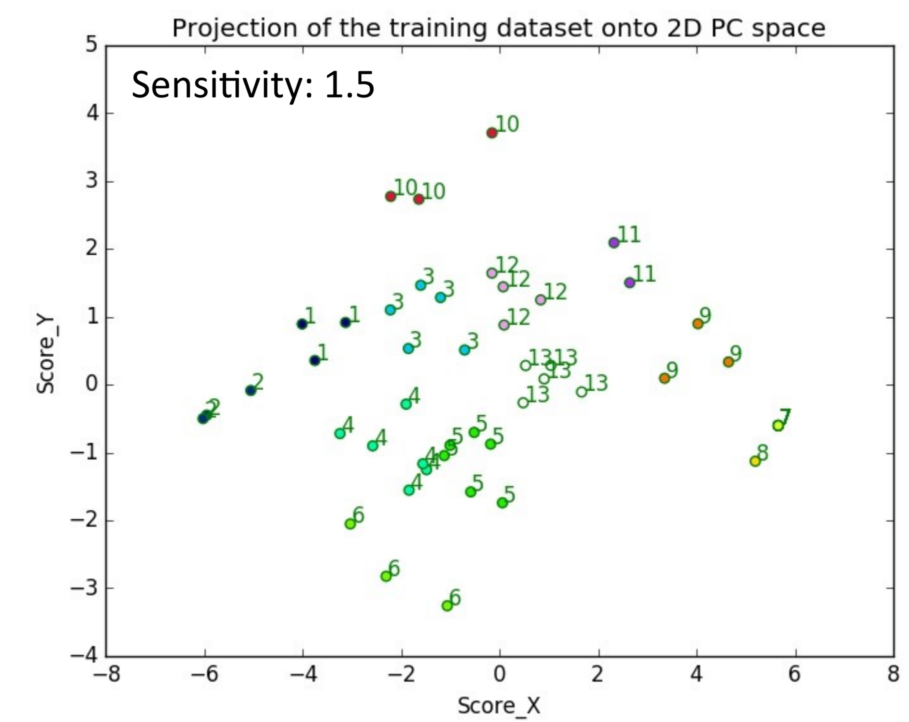
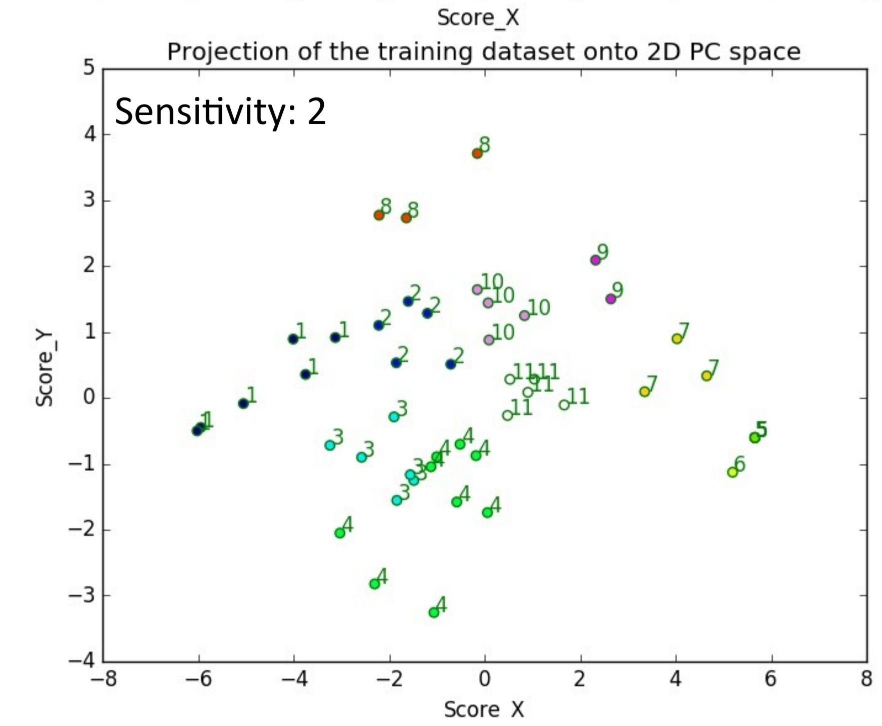


Figure 1: An illustration of the sequence of decisions an agent makes in order to decide which service facility to use in a given time period.







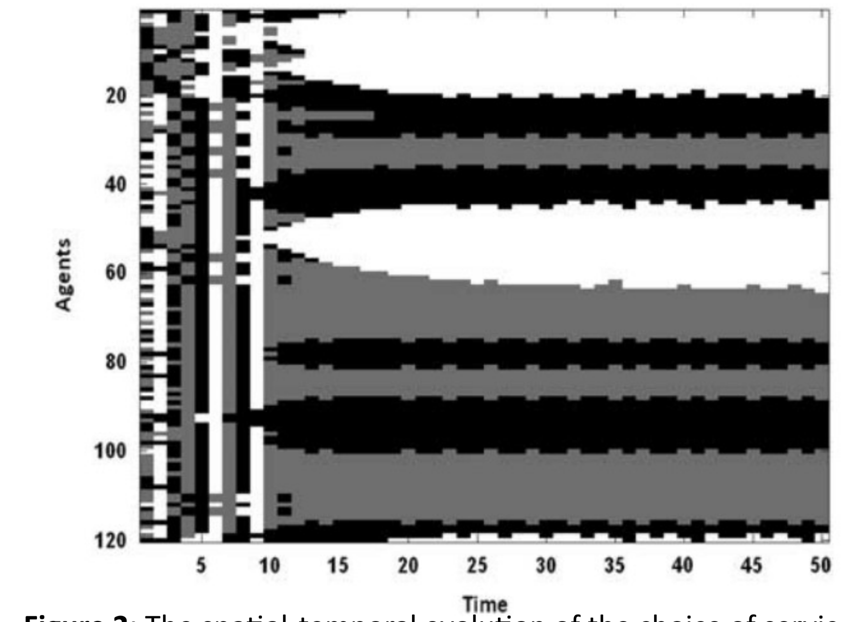


Figure 2: The spatial-temporal evolution of the choice of service facility over 50 periods. Each colour represents a facility (black=facility 1, grey=facility 2, white=facility 3) .

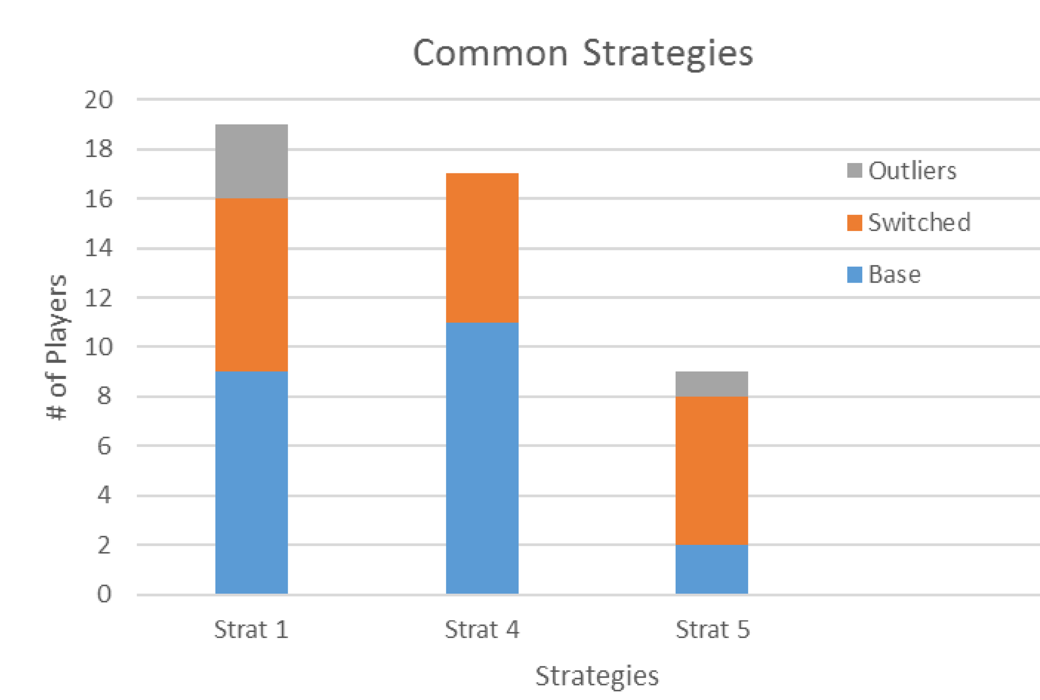


Figure 3: Graphical representation of the top three strategies declared by individuals from student simulation

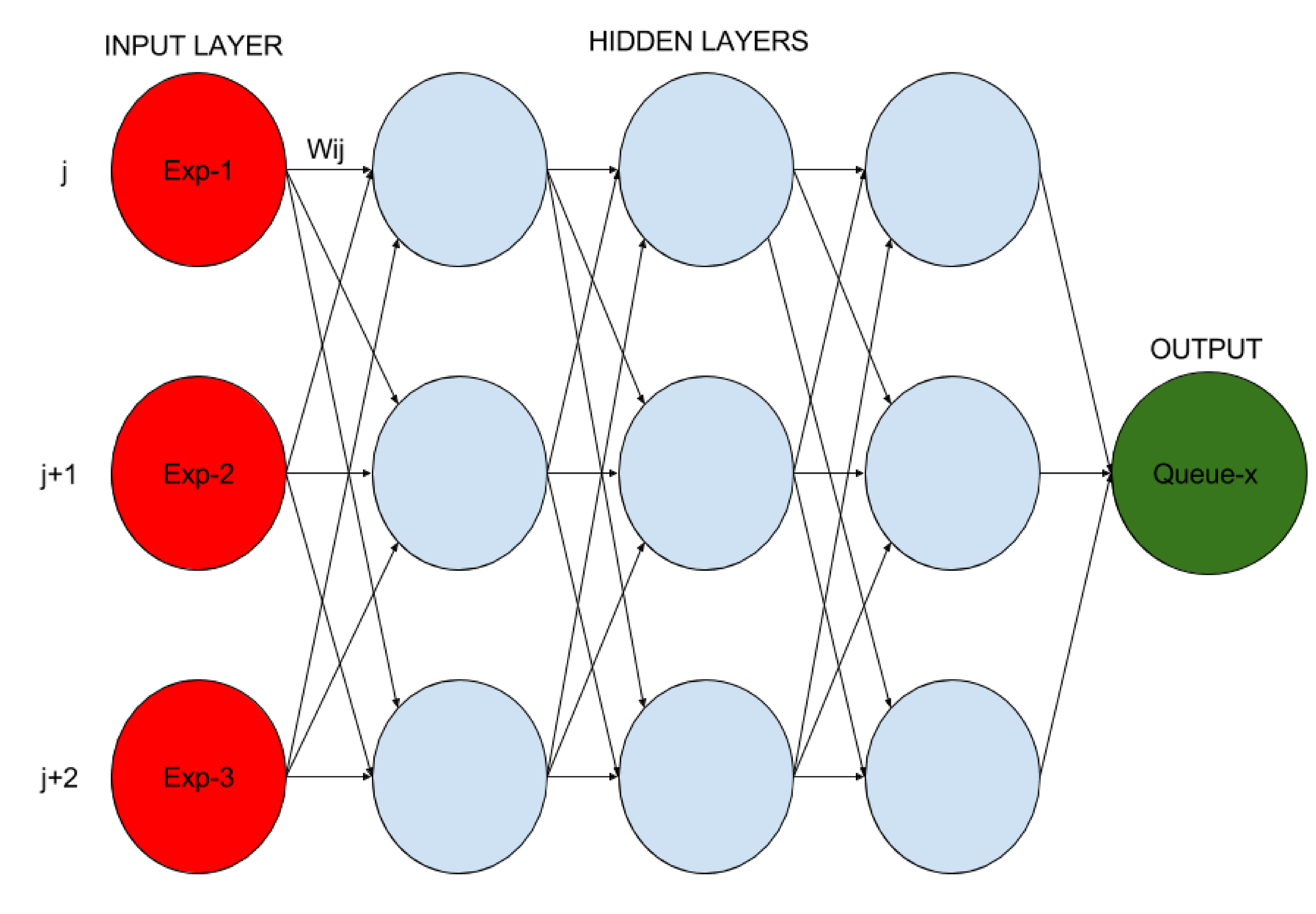


Figure 4: Breakdown of the ANN used for experimentation.