Task-3

★ Write a thorough critical analysis (review) of the paper, discussing the pros and cons of the paper, any technical error in the paper related to method or experimentation, technical suggestions for improving some component of the technique or experimental analysis, directions for future research, etc. in around 900-1000 words.

➔Critical analysis of the paper:

The problem we generally face is difficulty modeling human behaviour in economic games therefore by investigating the role of finite levels of iterated reasoning and non-selfish utility functions in a Partially Observable Markov Decision Process model that incorporates game theoretic notions of interactivity. Here, the generative model captures a broad class of characteristic behaviours in a multi-round Investor-Trustee game.

In a Multi-Round-Investor-Trustee game there are a class of sequential decision-making problems under uncertainty, this includes problems with partially observable states and uncertain action effects, so the best suitable machine learning component is partially observable markov decision process(POMDP)

In brief, it provide a formalization in terms of partially observable Markov decision processes, approximating type-theoretic Bayes-Nash equilibria using finite hierarchies of belief, where subjects' private types are construed as parameters of their inequity averse utility functions.

➔Pros:

➔ This paper has shown various benefits of using POMDP in modeling human behaviour in economic games: (1) The abilities of reasoning human internal state(belief and action); (2) Handling the error from observations; and (3) Balancing the trade-off between the feedback to the human and the feedback to the opponent.

➔ Inclusion of social factors, which are crucial in prediction of human behaviour like (crudely envy, parameterized by α) and (guilt, parameterized by β)

➔ Algorithms to compute BNE(Bayes-Nash Equilibrium) solutions have been developed but, in the general case, are NP-hard and thus infeasible for complex multi-round games. (infinite hierarchy of beliefs)

- This paper has utilized one obvious approach to this complexity i.e to consider finite rather than infinite belief hierarchies. Which consists of both theoretical and empirical support. Here, finite hierarchy of beliefs has probably approximated the equilibrium solution that arises in an infinite belief hierarchy arbitrarily closely. (Which increases prediction accuracy)
- This paper consists of multiple players(technically: multiple classes) so the suitable activation function is Softmax which indeed used in the paper, so the advantages of using softmax activation function are it is able to handle multiple classes only one class in other activation functions—normalizes the outputs for each class between 0 and 1, and divides by their sum, giving the probability of the input value being in a specific class.
- To avoid infinite recursion the authors assumed that each player has k levels of strategic thinking as in the Cognitive Hierarchy framework which probably helps in reducing dimension of computational time complexity.
- The probability distributions are continuous-valued rather than discrete. To make this computationally reasonable, the paper discretized the values of the types. For example, if there are only two types for a player the belief state, which is a continuous probability distribution over the interval [0, 1] is discretized to take K values $b_{i1} = 0, \dots, b_{iK} = 1$.

➔ Cons:

- In the paper we observe that the recognition model tends to misclassify Trustees with low β_T as having $k_T = 2$. This is because the Trustees with those characteristics will offer high amounts to coax the Investor. Investors are shown to be correctly classified in most cases. Overall the recognition model has a tendency to assign higher k_T to the Trustees than their true type, though the model correctly assigns the right cooperative/uncooperative type to the Trustee.
- K-level reasoning in the paper is limited to 0,1 and 2 but this is not the case in real life situation people with better logic can also have higher values of K. This might have a significant impact on accuracy of prediction. In general we know that each player has k levels of strategic thinking as in the Cognitive Hierarchy framework. There was an assumption in the paper that each k-level player assumes that his opponent is a k−1 level player, But this may not yield better predictions because players are randomly matched and we have to consider that opponent can also be a k-2 level player.
- Values of parameters(like β) are discretized although they are continuous, In this case we can increase randomness by considering a large set of values.

➔ Technical errors and Technical suggestions:

➔ A very wide range of patterns of dyadic interaction can thus be captured by varying just the limited collection of parameters of the model. There are few specific values in the paper like $\beta_T^{low} = 0.3$ and $\beta_T^{high} = 0.7$, To test the robustness of the recognition model authors also generated behaviours with different values of β_T (β_T^{low} = [0, 0.1, 0.2, 0.3, 0.4] and β_T^{high} = [0.6, 0.7, 0.8, 0.9, 1.0]). But what we need to know is that in practice we can't discretize a parameter like β, so we can consider a large number of values lying between 0 to 1 like around 100 or 1000 to approximate practicality.

➔ We should also consider K-level reasoning to be practical, because in paper there are few assumptions related to it which can be approximated by considering broader values of K in the required specific cases.

➔ Directions for future research:

➔ Unlike our Naive players still build models in the paper, albeit unsophisticated ones, of the other player (in contrast to level 0 players who assume the opponent to play a random strategy). So this might lead to an investigation of how sophisticated and naive theory of mind models are built by subjects in the game.

➔ We need to incorporate some of the other parameters of our model, such as the Investor's envy and the temperature parameter of the softmax distribution in order to capture the nuances in the interactions. Further it would be interesting to use the recognition model in pathological populations, looking at such conditions as autism and borderline personality disorder. Which will have a significant contribution to the society.

➔ This computational model provides a guide for designing experiments to probe aspects of social utility, strategic thinking levels and prior beliefs, as well as inviting ready extensions to related tasks such as Public Goods games. The inference method may also have wider application, for instance to identifying which of a collection of Bayes-Nash equilibria is most likely to arise, given psychological factors about human utilities.