Forecasting Evolution of Clusters in StarCraft II with Hebbian Learning

Beomseok Kang, Graduate Student Member, IEEE, and Saibal Mukhopadhyay, Fellow, IEEE

Abstract—Tactics in StarCraft II are closely related to group behavior of the game agents. In other words, human players in the game often group spatially near agents into a team and control the team to defeat opponents. In this light, clustering the agents in StarCraft II has been studied for various purposes such as the efficient control of the agents in multi-agent reinforcement learning and game analytic tools for the game users. However, these works do not aim to learn and predict dynamics of the clusters, limiting the applications to currently observed game status. In this paper, we present a hybrid AI model that couples unsupervised and self-supervised learning to forecast evolution of the clusters in StarCraft II. We develop an unsupervised Hebbian learning method in a set-to-cluster module to efficiently create a variable number of the clusters, and it also features lower inference time complexity than conventional k-means clustering. For the prediction task, a long short-term memory based prediction module is designed to recursively forecast state vectors generated by the set-to-cluster module. We observe the proposed model successfully predicts complex evolution of the clusters with regard to cluster centroids and their radii.

Impact Statement—While there have been many efforts for AI models in StarCraft II to efficiently control or display the game agents by clustering, how the clusters evolve across both space and time is rarely studied. As dynamics in the game is difficult to mathematically design, forecasting evolution of such complex dynamical system by data-driven approach is an important task in recent AI research. In this work, we present a hybrid AI model to forecast evolution of the agents in a cluster level. The proposed model efficiently predicts the complex configurations of the clusters such as where new clusters will appear and how large they will be. In the future, we expect that our model can be also applied to other multi-agent systems where agents often behave as a team.

Index Terms—Artificial intelligence in games, Clustering, Hebbian learning, Multiagent systems, Unsupervised learning.

I. INTRODUCTION

Advances in real-time strategy (RTS) games have provided various challenging problems to artificial intelligence (AI) research [1], [2], [3]. StarCraft II is a representative example where multi players control hundreds of the game agents and build several strategies to defeat opponents. It particularly features vast action space due to the numerous game agents, and consequently, uncertainty in intractable future strategies makes learning dynamics of the agents difficult [4]. With growing interests on AI models that is able to learn and predict complex dynamical systems, forecasting evolution of the agents in StarCraft II has been an excellent testbed.

Dynamics of the agents in StarCraft II is often defined on groups of the agents. In other words, players frequently group the spatially near agents as a team, and judiciously determine how to arrange and control the team to survive from complex battles. Fig. 1 shows a crop of the game map in which the agent clusters are marked with different colors. As the figure displays groups of the agents in a combat scenario, several strategies are used to be described by spatio-temporal changes in the agent clusters [5]. A general strategy used in combats is to first gather soldier agents into a cluster and then kill enemies one by one instead of attacking multi enemies [6]. In this light, tactics in StarCraft II are closely related to dynamics of the agent clusters [1], and learning dynamics of the clusters will enable the models to efficiently understand underlying tactics.

Apart from the strategic understanding, other usefulness of clustering the agents has been also reported. Recent studies on multi-agent reinforcement learning in StarCraft II have exploited clustering to assign the same action to a group of near agents so that the large action space is reduced [7], [8], [9]. The motivation behind the clustering is that the spatially close agents are likely to perform similar actions [10]. Furthermore, clustering groups of the agents has been utilized in visualization instruments for game analytic purposes [11], [5]. It helps game users to easily discover the motion of many units and quickly identify important events such as a large number of dead. However, these works do not aim to learn and predict dynamics of the agent clusters, limiting the applications of clustering the agents to currently observed game status.

In this paper, we propose a hybrid AI model that couples
unsupervised (Hebbian) and self-supervised (Gradient based) learning to forecast evolution of the agent clusters in StarCraft II. The evolution here refers to movement, appearance, and disappearance of the clusters. Our model is designed with a set-to-cluster module and prediction module. The set-to-cluster module represents a set of the agents with regard to cluster centroids and radii into a state vector. We develop an unsupervised Hebbian learning method for the set-to-cluster module to efficiently create a variable number of the clusters. In particular, a modified Hebbian learning rule and Winner-take-all algorithm enable to activate a different number of cluster centroids with their radii. It is important as the number of the clusters frequently changes in the heat of battles while there are few clusters in the early stage of the game. A long-short term memory (LSTM) based prediction module recursively forecasts the state vectors generated by the set-to-cluster module in the next time steps. LSTM is trained in a self-supervised setting using gradient based learning.

Hebbian learning is a biologically inspired unsupervised algorithm that updates a synaptic weight where two adjacent neurons fire together. There have been several applications with Hebbian learning in image processing, reinforcement learning, and clustering [12], [13], [14], [15], [16], [17]. However, these methods have been evaluated by simple dataset such as MNIST or dealt with a single agent [18], [14]. More importantly, most of the prior works on Hebbian learning have not been considered in prediction models for complex and dynamic multi-agent systems. We mainly describe our Hebbian learning approach for clustering in section II. The prediction model and training procedure for it are explained there as well. Dataset and cluster prediction results are described in section III, and there the details in the performance such as failure analysis and comparison with other method are also considered.

II. PROPOSED APPROACH

A. Set to cluster module

The number of the agents in StarCraft II is an actively changing variable. Our first step to learn dynamics of the agent clusters is to encode the sets to vectors so that LSTM is trained in fixed dimension latent space. We design a set-to-cluster module based on PointNet formed with MLP and a MaxPooling layer [19]. Fig. 2 shows the module design where input is a set of agent positions in a frame. We apply Hebbian learning on a fully-connected (FC) layer in the module, and the other modules are trained by supervised learning. It is important to note that the set-to-cluster module incorporates Winner-take-all (WTA) network. Fig. 2(a) describes the output of the module, showing that each positional vector is transformed to a state vector (s). Then, a MaxPooling layer aggregates state vectors to find the maximum state value of each neuron. With a pooled state vector and corresponding weight vectors, we can create a variable number and size of the clusters. From here, we simply call the pooled vector as a state vector.

B. Hebbian learning for clustering

There are different types of Hebbian learning rules. A variant, Grossberg’s instar rule, additionally includes the multiplication of output and a weight vector in a basic Hebbian learning rule as in (1) [20].

$$\Delta w \propto y(x - w)$$ (1)

It updates a weight vector (w) to be close to an input vector (x) if output (y) is activated. We apply the modified Hebbian learning algorithm on the fully-connected (FC) layer where input is a position of the agent and output is a state vector to represent which centroid is closest from the agent and the distance between them.

Hu et al. have shown that k-means clustering can be realized by competitive Hebbian learning [17]. However, the prior work attempts to hierarchically cluster natural images with deep belief networks. While we take advantage of the basic concept in [17], we aim to process a set of the agents which dimension actively changes and create a variable number of the clusters. Fig. 2(a) shows that WTA algorithm is applied to an output vector (y) to competitively fire a single output neuron where $||x - w||_2$ is the minimum. It implies that the weight vector of a winner neuron can be considered as the position of a corresponding cluster centroid. Hence, the output from WTA network has a single winner neuron which weight vector corresponds to the position of a cluster centroid. We refine (1) to (3) by introducing a function $f(|x - w|)$:

$$f(|x_i - w_j|) = \begin{cases} 1 & \text{if } i = \arg \min_k |x_k - w_j| \\ 0 & \text{otherwise} \end{cases}$$ (2)

$$\Delta w_j = \eta \frac{1}{N} \sum_i f(|x_i - w_j|)(x_i - w_j)$$ (3)

where $\eta$ is the learning rate, and $N$ is the number of the agents being processed. The function determines whether a weight vector ($w_j$) is to be updated depending on the Euclidean distance from an input position ($x_i$).

We also introduce a state value for a winner neuron to incorporate a cluster radius into the representation. The state value is simply defined by $||x - w||_2$. For loser neurons, the output values are forces to be zero, indicating the radii of these clusters are zero. We restrict the minimum radius of winner neurons to 1e-2 to avoid the zero radii when the agent is exactly on a cluster centroid. We differentiate an output vector (y) and state vector (s) in the sense that a cluster radius
Fig. 3. Schematic of entire model design for cluster prediction. The set-to-cluster module generates state vectors from observed agent sets, and the prediction module recursively predicts state vectors in the next time steps.

![Diagram of model design](image)

Fig. 4. Data flow in cluster prediction module. Output vectors in previous predictions are used for input to the next predictions.

is not considered in the output vector. The output and state vectors are mathematically described as:

\[
y_i = \begin{cases} 
1 & \text{if } i = \arg \min_j \| x - w_j \|_2 \\
0 & \text{otherwise}
\end{cases} 
\]  

\[
s_i = \begin{cases} 
\max(0.01, \| x - w_i \|_2) & \text{if } i = \arg \min_j \| x - w_j \|_2 \\
0 & \text{otherwise}
\end{cases} 
\]  

where \( i \) indicates the \( i \)-th element of vectors.

Fig. 2(b) shows a scenario where two game agents are being processed by the FC layer. As each agent is individually processed, two state vectors are created with different winner neurons. For example, \( w_i \) is the weight vector of a winner neuron for the agent \( 1 \) and \( w_j \) is for the agent \( 2 \). The weight updates in the figure are only defined at the two activated clusters while other weight vectors remain at the same positions. During the training, weight vectors gradually move to the average positions of the agents.

C. Cluster prediction model

Fig. 3 shows a schematic of our cluster prediction model. There are mainly two modules, the set-to-cluster module and prediction module. The set-to-cluster module transforms the positions of the observed agent sets to the state vectors, which allows LSTM to learn temporal dynamics of the agent groups in fixed dimension space. The prediction module includes LSTM and FC Layers, and predicts the state vectors of the next time steps. LSTM learns temporal dynamics in the latent space, and a following FC layer predict cluster radii from the latent space. Another FC layer and LayerNorm layer are included between the set-to-cluster module and LSTM to normalize the distribution of elements in each state vector. We observe that the model performs better when LayerNorm is applied only in the observation stage.

D. Training cluster prediction model

It is important to note that the set-to-cluster module is trained by unsupervised Hebbian learning that does not require a loss function. However, the prediction module is trained by supervised learning which ground truth should be prepared in advance. For the reason, the clustering module is first trained so that the ground truth is defined as output state vectors of the pre trained module. The weights of the module are initialized by uniform distribution \( U[0, 1] \). As positions of the agents are normalized from 0 to 1, such initialization enables the more weight vectors to be effectively used as cluster centroids. Once the training is finished, cluster centroids are fixed and cluster radii are the only variable in the cluster representation. We save the state vectors of game frames before training the prediction module to reduce the running time of the clustering module.

Fig. 4 shows the data flow in the prediction module during repeated prediction. The module observes the first 25 state vectors, and then repeatedly predicts the next 25 state vectors by using previously predicted state vectors as the next input. Mean square error (MSE) loss is used for the optimization, and the loss is calculated every time step. Hence, we optimize the loss from the total 49 state vectors. We set the learning rate 1e-3, batch size 16, and use Adam optimizer. The loss function is written by:

\[
L_{mse}(s, \hat{s}) = \frac{1}{N} \sum_i^N (s_i - \alpha \hat{s}_i)^2
\]  

where \( N \) is the number of the elements in \( s \) and \( y \), and \( \alpha \) is an additional parameter to adjust the scale of cluster radii. While the map coordinate is normalized from 0 to 1, most of the cluster radii are smaller than 1e-1. It results in the linear
approximation of MSE loss, decreasing the misprediction error for the large clusters. We heuristically set $\alpha$ to be 10 to avoid the linear approximation.

### III. Experimental Results

#### A. Dataset

PySC2 is a Python-based machine learning environment for StarCraft II [21]. It supports to extract the useful properties of units in replay videos such as position and health. We are only interested in the position of units in this paper. Replay videos are uploaded on GitHub by Blizzard (https://github.com/Blizzard/s2client-proto). We randomly choose a Terran versus Terran game from the replay pack1 in the source. It has 11,000 frames that are captured every 0.2 seconds, and the resolution is set to (256, 256). We use 8,800 frames for training data, and 1,100 frames are used for validation and test data. For the temporal learning purpose, the frames are divided into 220 chunks where each chunk has successive 50 frames (i.e. 10 seconds). 176 chunks are used as training data, and rest two 22 chunks are used as validation and test data.

#### B. Cluster representation

Fig. 5(a) shows the cluster centroids before and after Hebbian learning. As our Hebbian learning updates weights to reduce average Euclidean distance between the cluster centroids and agents, the trained centroids imply that the agents are more likely to be on them than the untrained centroids. The average distance is investigated to verify whether Hebbian learning actually reduces the distance. As the learning rule given in (1) is to minimize the distance, the cluster representation with smaller cluster radii is preferred. Fig. 5(b) shows the distance during training epochs with different learning rates. Here, the distance $d$ in a frame is defined by:

$$d = \frac{1}{N} \sum_{x \in S} \min_j \|x - w_j\|_2$$  \hspace{1cm} (7)

where $N$ is the number of agents and $S$ is an agent set in a frame. It means the average distance from agents to their closest cluster centroids. y-axis in Fig. 5(b) is calculated by accumulating the distance $d$ over all frames in validation data and dividing by the number of the frames. We observe the average distance 5.0e-3 in the untrained model while the trained models achieve minimum 0.8e-3. Hence, Hebbian learning decreases the average cluster radii required to represent the agent groups. However, there is no noticeable difference between trained and untrained centroids near edges and corners. We expect that these centroids are not often selected as winner neurons because they are too far from the frequently used paths of the agents. The learning rates higher than 1e-0 are not included in the figure as the average distance diverges in those settings. We set the learning rate 1e-0 and batch size 16 for the following experiments.

Fig. 6(a) is an example to show how the state vector temporally changes in successive frames. There are 19 neurons activated in the observed frames, so the other state values of loser neurons are omitted in the figure. The red boxes in the figure indicate sudden changes in the state values that imply the appearance or disappearance of clusters. As the state vector and weight vectors in the clustering module provide the information of cluster centroids and their radii, no additional decoding process is required. Fig. 6(b) shows agent level and cluster level representation at the frame number 7010 and 7040. There are initially two clusters near $(x, y) = (0.2, 0.2)$ in the figure, and the new cluster appears above them in the later frame. It is because some agents in the initial cluster move upwards and the new cluster centroid is activated as they get closer to it. We observe the corresponding state value $s_{51}$ clearly shows a sudden change during the two frame numbers in Fig. 6(a). This example only shows cluster division, but there happens similar scenarios in cluster merger as well.
C. Cluster prediction

Our main task is to forecast complex evolution of the clusters. Fig. 7 displays predicted configurations of the clusters and corresponding ground truth. Agent level representations are also incorporated in the figure to illuminate how individual agent is clustered. As the duration of each chunk data is 10 seconds, the predicted results are made for 5 seconds after observing the movement of the clusters for the first 5 seconds. We observe our prediction module is able to forecast complex evolution of the clusters during the prediction window. For example, there are the few cluster at the center of the map in early time steps. At "T+5", more clusters appear near the center, horizontally connecting the left and right areas in the map. The predicted clusters show that the corresponding cluster centroids are successfully activated at "T+5". Also, most of the clusters at other areas are reasonably predicted though few clusters are not activated or remained. The predicted results are made after training the model for 300 epochs with the learning rate 1e-3 and batch size 16.

Fig. 8(a) shows the average validation loss in each time step with different $\alpha$ values. The models are trained in the same configuration except $\alpha$ in the loss function. However, the loss in the figure is calculated without the $\alpha$ so that the values are compared in the same metric. We observe that the model performance clearly degrades without the consideration of $\alpha$ (i.e. $\alpha = 1$) while the validation loss is similar in other values. Given the maximum radius of the clusters in the training data is 0.112, negligible changes in cluster radii would make learning dynamics of the clusters difficult. Our experimental results are based on the model trained with $\alpha = 10$. Fig. 8(b) shows the training and validation loss for 300 epochs in $\alpha = 10$ setting, and the model starts to overfit to the training data after 100 epochs.

D. Failure case

We observe the reasonable prediction of the dynamically moving clusters in Fig. 7. However, there also exist few clusters failed to be predicted. Fig. 9 shows an example in which the model fails to correctly predict the newly appeared clusters in the early stage of the game. Given active battles are not likely to be happened early, most of the clusters are not actively moving, rather remain to motionless. For example, in the ground truth, there is the one cluster at the left middle area until "T+4", and the new cluster suddenly appears at "T+5". As there is no noticeable change in the single cluster with regard to its radius before "T+4", it seems the agent in the
cluster suddenly starts to move creating the new cluster. Such discontinuous and uncertain dynamics in the clusters are failed to be predicted by the model. However, the figure shows that the new cluster is predicted in advance with a small radius, and similar result is also observed in the right bottom area. While the radii are not accurate, the model makes the prediction with the non zero radii at the probable cluster centroids.

### E. Comparison with other method

Our clustering method is similar with k-means clustering in terms of minimizing the distance $\|x - w\|_2$. A difference in our method is lower inference time complexity. As there is no difference between training and inference in k-means clustering, the time complexity of approximated k-means clustering is given by $O(n \times k \times i)$ where $n$ is the number of points, $k$ is the number of clusters, and $i$ is the number of iterations. Our method also has the same time complexity $O(n \times k \times i)$ for training, but it becomes $O(n \times k)$ for inference. It is because the FC layer in the set-to-cluster module stores the cluster centroids as the weight vectors in advance, hence we do not need to repeatedly optimize the centroids again during the inference. Also, the set-to-cluster module enables to create a variable number of clusters while k-means clustering creates $k$ clusters regardless of the configuration in the agents. However, k-means clustering is a non-parametric method while our method requires the FC layer to store the pre-trained centroids. Table I shows the computational complexity of the modules per prediction for a frame. The single FC layer does not incorporate the large number of weight parameters, so the overhead of the clustering module is negligible compared to the parameters of the prediction module.

### IV. Conclusions

This paper proposes a Hebbian learning based spatial clustering method for game agents in StarCraft II and a prediction module to forecast complex evolution of the clusters. Our clustering method deals with a variable number of the clusters using cluster radii as a state variable and shows lower time complexity compared to k-means clustering. With the cluster representations, the prediction module learns dynamics of the clusters and predict the cluster radii in the future. The proposed model aims to forecast the dynamic agent clusters in StarCraft II, but extending the application to other multi-agent systems where agents frequently create a group will be an interesting future work.

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Beomseok Kang (Graduate Student Member, IEEE) received the B.S. degree in electronic and electrical engineering from Sungkyunkwan University, Suwon, South Korea, in 2020. He is currently pursuing the Ph.D. degree in electrical and computer engineering with the Georgia Institute of Technology, Atlanta, GA, USA, under the supervision of Prof. S. Mukhopadhyay. His current research interests include unsupervised learning, machine learning for dynamical system and multi-agent system.

Saibal Mukhopadhyay (Fellow, IEEE) received the B.E. degree in electronics and telecommunication engineering from Jadavpur University, Kolkata, India, in 2000, and the Ph.D. degree in electrical and computer engineering from Purdue University, West Lafayette, IN, USA, in 2006. He was a Research Staff Member with the IBM Thomas J. Watson Research Center, Yorktown Heights, NY, USA, from August 2007 to September 2007. He is currently a Joseph M. Pettit Professor with the School of Electrical and Computer Engineering, Georgia Institute of Technology, Atlanta, GA, USA. He has authored or coauthored more than 200 papers in referred journals and conferences, and holds five U.S. patents. His research interests include design of energy-efficient, intelligent, and secure systems in nanometer technologies. He was a recipient of the Office of Naval Research Young Investigator Award in 2012, the National Science Foundation CAREER Award in 2011, the IBM Faculty Partnership Award in 2009 and 2010, the SRC Inventor Recognition Award in 2008, the SRC Technical Excellence Award in 2005, and the IBM PhD Fellowship Award for years 2004 to 2005.