International Journal of Scientific Research in Computer Science, Engineering and Information Technology
© 2019 IJSRCSEIT | Volume 5 | Issue 2 | ISSN : 2456-3307
DOI : https://doi.org/10.32628/CSEIT1952259

Using Transfer Learning in an Ad Hoc Team

Sannidhya Sandheer[1], Tanya Sangtiani[1], Aditya Singh[1], Niharika Varshney[1], Piyush Soni[2]
[1]NMIMS, Shirpur, Maharashtra, India
[2]Assistant Professor, NMIMS, Shirpur, Maharashtra, India

ABSTRACT

In a practical scenario, we have a myriad of robotic systems; single and multi agent, not operating under any standard communication protocols. This is eminent from a point of view where independent robots can come together to achieve goals as a team. This problem is well defined in the domain of Ad Hoc Teamwork(AHT) which strives for a MAS wherein agents are heterogeneous, independent in their own respect and, as a whole accomplish goals that may be above any individual's capability. A key aspect is transfer learning which allows on the fly addition of team members. This paper shares development in transfer learning in the field of Ad Hoc Teamwork.
Keywords: Ad Hoc Teamwork, Transfer Learning, Multi Agent Systems

I. INTRODUCTION

The ideology to mimic intelligent choices in a non-organic entity has always been enticing to all fields of science. While we pride ourselves on advances in the domain of single agent tasks, such as strategy games [1], or unmanned vehicle manoeuvres [2]; we are yet to completely reproduce group behaviour in computers. This problem is in the area of Multi Agent Systems(MAS). The tasks undertook by multiple agents have witnessed specialized entities tailored to this one particular application.

Ad Hoc Teamwork is an attempt to make MAS agent-agnostic. [3] define the problem as agent cooperating within a team, wherein, it knows little about its teammates. For the purpose of this article, we consider an agent to be an entity, like a robot, with actions, goals and domain knowledge. It's behaviour is the way it acts within the environment.

MAS has existed as a subfield for more than a decade. In recent times, work is being undertaken in swarm robotics, a multi-robot system, in general. Amazon[4] is working towards using a multi drone system for its deliveries. Work in Ad Hoc Teamwork allows for real time team formation, planning and joint task completion. This can allow for region based sub teams within a large systems. Also, outside robots, the application only increase. In grid optimization, works in this field can applied directly, treating each node as an entity. This only goes on to say that the work outlining Ad Hoc Teamwork at large, is itself an amalgamation of team formation logic, communication protocols, and single agent goal setting for joint task achievement.

A key aspect of an ad hoc setting is the dynamic team formation as discussed above. This is often achieved through transfer learning by learning from similar teammates in a similar environment performing a similar task. Transfer learning, hence, is used to accelerate the learning process.

II. RELATED WORK

[5] share a Transfer Metric Learning which transfers metrics of all source tasks to the target task based on the task relatedness. Based on experimental results, an increase in accuracy is observed. [6] highlight the issue of ineffective transfer learning in Same Transition Model(STM) since the agents are unable to opt for effective policies. Their proposed solution works for agents with the same state transitions yet, different goals. The two-fold solution either transfer the source goal or explores states around it preferentially.

Another caveat is the assumption of same distribution for all of the data. Real world scenario might not be forgiving enough. This is addressed by transferring parameters through a projection matrix[7]. The parameter projection matrix is further learned, along with the classifier parameters. The results reported show significant advantages of this method.

[8] explore transfer learning in reinforcement learning paradigm for example problems of spatial navigation and network routing. This allows robots in the same environment to learn spatial information from previous teammates. This approach can be used for creating a global map of the environment for a rather distributed team without the need for each agent to explore individually. The approach incorporates environmental consequences of the agent's actions using agent-centred information.

For the online system to work collectively, [9] propose an algorithm, Heterogeneous Ensembled Online Transfer Learning (HetEOTL), heterogenous online transfer learning wherein the feature space of the target domain varies from that of the source domain. The algorithm, first, constructs classifiers from the source domain. Upon encountering a new instance in the target domain, the classifiers from the previous stage are amalgamated with the new classifier trained on the new instance. Finally, based on the results, an update is performed online. This algorithm outperforms other techniques considered during experimentation. An area for further study is the multi-class classification using HetEOTL.

III. METHODOLOGY

This project epitomizes the spirit of ad hoc teamwork. In ad hoc teamwork settings, agents encounter a variety of teammates and try to cooperate in order to accomplish a shared goal. In ad hoc teamwork research, researchers focus on designing a single agent or subset of agents that can cooperate with a variety of teammates. The desire is for agents designed for ad hoc teamwork to quickly learn about these teammates and determine how they should act on this new team to achieve their shared goals. Agents that reason about ad hoc teamwork will be robust to changes in teammates in addition to changes in the environment.

The UI will be built using Qt Creator in C++. This is a GUI library in C++ that leverages Qt Framework. The GUI will be linked to a graphical database that is used to represent the team of robots, as well. This database will be developed in Neo4j using it’s Python interface. The robots will communicate with the Supervising Agent using a network developed using Network Simulator 3. This network will be akin to a wireless network found in any modern home with an Internet connection. This will be built using Pyro, a Python library for distributed communication using TCP/IP and 802.11 wireless Ethernet. Each robot in the team will be running a Debian environment for embedded systems. This environment will be running a Python codebase that implements swarm intelligence using TensorSwarm. Since we can’t construct so many robots, we will be simulating the swarm using Argos3.

In this paper, we design a transfer learning framework for ad hoc teamwork. The strategy is

utilized to adjust the source data and target data, so that the useful data in the source domain and target domain are fully used to train a good learner.\par
In the field of machine learning, the topic of concept drift addresses distribution differences between the training and testing data. Concept drift assumes a single domain for both the training and testing data; however, the testing data changes distribution characteristics over time. A transfer learning environment assumes the training and testing data are originally drawn from different domains.

IV. EXPERIMENTAL RESULTS

A. DATASET

The data is being trained on the following data set which is being learned by the machine learning model. The complete model will be able to predict it's teammate's actions. The use of transfer learning is for allowing addition of new team members on the fly.

B. ANALYSIS

The domain adaptation strategy for the JDA algorithm attempts to simultaneously correct for the conditional and marginal distribution differences between the source and target data. A Principal Component Analysis (PCA) step is used for dimensionality reduction. The PCA algorithm is integrated with the Maximum Mean Discrepancy distance measure, which is used to correct the marginal distribution differences. The labelled source data is used to train a classifier that generates pseudo labels. These pseudo labels are used in the conditional distribution correction process. A base traditional learner is trained with the distribution aligned data.

V. CONCLUSION

This paper proposed a transfer learning framework for an Ad Hoc team. The authors can conclude that the proposed framework boosts the general goal of the Ad Hoc Teamwork domain. By using the proposed framework, we believe we can work towards something that provides a true ad hoc setting. The testing has been primarily been through simulations using ArGOS3 simulator. Machine learning is limited the time frame for learning. Transfer learning is, hence, best suited to overcome this.

VI.REFERENCES

[1] David Silver, Aja Huang, Christopher J. Maddison, Arthur Guez, Laurent Sifre, Georgevan den Driessche, Julian Schrittwieser, Ioannis Antonoglou, Veda Panneershelvam, MarcLanctot, Sander Dieleman, Dominik Grewe, John Nham, Nal Kalchbrenner, Ilya Sutskever,Timothy Lillicrap, Madeleine Leach, Koray Kavukcuoglu, Thore Graepel, and Demis Hass-abis. Mastering the game of go with deep neural networks and tree search. Nature, 529:484–503, 2016

[2] Vivek Wadhwa and Alex Salkever.The Driver in the Driverless Car: How Our Technol-ogy Choices Will Create the Future. Berrett-Koehler Publishers, 1st edition, 2017. ISBN1626569711, 9781626569713.

[3] Samuel Barrett and Peter Stone. Cooperating with unknown teammates in complex domains:A robot soccer case study of ad hoc teamwork. InProceedings of the Twenty-Ninth AAAIConference on Artificial Intelligence, AAAI'15, pages 2010–2016. AAAI Press, 2015. ISBN0-262-51129-0.

[4] Sunghun Jung and Hyunsu Kim. Analysis of amazon prime air uav delivery service.Journalof

Knowledge Information Technology and Systems, 12:253–266, 04 2017.

[5] S. Yue and S. Ozawa. A sequential multi-task learning neural network with metric-basedknowledge transfer. In2012 11th International Conference on Machine Learning and Appli-cations, volume 1, pages 671–674, Dec 2012. doi:10.1109/ICMLA.2012.125.

[6] T. Takano, H. Takase, H. Kawanaka, and S. Tsuruoka. Transfer method for reinforcementlearning in same transition model – quick approach and preferential exploration. In2011 10thInternational Conference on Machine Learning and Applications and Workshops, volume 1,pages 466–469, Dec 2011. doi:10.1109/ICMLA.2011.148.

[7] C. Chen, B. Jiang, and X. Jin. Parameter transfer extreme learning machine based on pro-jective model. In2018 International Joint Conference on Neural Networks (IJCNN), pages1–8, July 2018. doi:10.1109/IJCNN.2018.8489244.

[8] E. Chalmers, E. B. Contreras, B. Robertson, A. Luczak, and A. Gruber. Learning to predictconsequences as a method of knowledge transfer in reinforcement learning.IEEE Trans-actions on Neural Networks and Learning Systems, 29(6):2259–2270, June 2018. ISSN2162-237X. doi:10.1109/TNNLS.2017.2690910.

[9] Q. Chen, Y. Du, M. Xu, and C. Wang. Heteotl: An algorithm for heterogeneous online transferlearning. In2018 IEEE 30th International Conference on Tools with Artificial Intelligence(ICTAI), pages 350–357, Nov 2018. doi:10.1109/ICTAI.2018.00062.

Cite this article as :

Sannidhya Sandheer, Tanya Sangtiani, Aditya Singh, Niharika Varshney, Piyush Soni, "Using Transfer Learning in an Ad Hoc Team", International Journal of Scientific Research in Computer Science, Engineering and Information Technology (IJSRCSEIT), ISSN : 2456-3307, Volume 5 Issue 2, pp. 925-928, March-April 2019. Available at doi : https://doi.org/10.32628/CSEIT1952259

Journal URL : http://ijsrcseit.com/CSEIT1952259