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Bipartite Graph Learning for Autonomous Task-to-Sensor Optimization

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BIPARTITE GRAPH LEARNING FOR AUTONOMOUS TASK-TO-SENSOR OPTIMIZATION

EXECUTIVE SUMMARY

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Project Summary

This study explores the question of how machine learning can be applied to identify the most appropriate 'sensor' for a task by optimizing task-to-sensor matching. The concept of a bipartite graph provides a mathematical framework for task-to-sensor mapping by establishing connectivity between various high-level tasks and the specific sensors and/or processes that must be invoked to fulfil those tasks and other mission requirements. The connectivity map embedded in the bipartite graph can change depending on the availability/unavailability of resources, the presence of constraints (physics, operational, sequencing), and the satisfaction of individual tasks. All these considerations may be encoded in the value matrix of the graph. Changes can also occur according to the valuation, re-assignment, and re-valuation of the perceived task benefit and how the completion of a specific task (or group of tasks) can contribute to the state of knowledge prompting the need to periodically re-solve the matching problem. The methodology for this project includes developing generic bipartite models to represent small- and large-scale task-to-sensor problems. A deep network architecture is used to understand how to solve bipartite matchings using neural networks. Network weight pruning is used to investigate strategies for accelerating learning towards online/real-time applications. The results of this study show that a deep neural network architecture can be used to solve the bipartite matching problem in an autonomous fashion. The scalability of the approach is demonstrated using an 800 by 800 graph to represent a problem scale relevant to joint targeting and fires. It is recommended that learning acceleration be further explored as part of future investigations.

Keywords: *bipartite graphs, matching problems, assignment problems, machine learning, deep learning, residual networks, large scale problems, accelerated learning*

Background

This study addresses aspects of Naval Special Warfare's question on how machine learning/artificial intelligence can enable optimization for Joint Targeting and Fires. Part or the targeting and fires problem involves the assignment or tasking of resources. This problem can be modeled using bipartite graphs. A bipartite graph has two disjoint and independent sets of vertices representing inputs and outputs (e.g., tasks [inputs] and sensors [outputs]). Each task can be connected (assigned) to a sensor by a link called an 'edge.' The bipartite graph provides an assignment when one task is be connected to one sensor by an edge. The goal is to determine the set of edges that maximizes the value of the assignment, or equivalently minimizes the cost of the assignment. This is an optimization problem. Machine learning can be advantageous over conventional algorithms for solving such problems, especially in online/real-time applications, because it is possible to transform the problem statement into a differential equation. The simplicity of the calculations is amenable to hardware implementation for solving large scale problems more quickly.

In this study, deep-learning networks, specifically weighted residual networks are explored for identifying solutions to the maximum matching problem of single-layer bipartite graphs. The methodology for this project is to develop bipartite models of generic mappings for both small- and large-scale scenarios to represent task-to-sensor problems and to understand how to solve the associated bipartite matchings using neural networks. These solutions can be used by the DoD to enable autonomous link prediction in a bipartite framework. The results support machine learning enabled decision making that can be applied to the joint targeting and fires problem set.

Findings and Conclusions

Several illustrative examples of the application of the deep neural network architecture were studied. Problem sizes ranging from 4x4 to 800x800 bipartite graphs illustrated the scalability of the results. The objective of the machine learning problem is to produce (as the network output) the optimal bipartite matching. There is one output neuron for each of the possible pairings. The evolution of the neural network outputs represents that activation or strength of the connection between the input (task) and output (assigned sensor). If an output neuron has activation close to 1, then there is a connection from task *i* to sensor *j*. If an output neuron has low activation close to 0, then there is no connection between task *i* to sensor *j*. By polling the output neurons of the converged network, the bipartite graph shown can be constructed. This approach provides an autonomous mechanism for decision making. For large scale problems, it was possible to obtain solutions having similar cost values to results presented elsewhere. The sponsor should apply the approach using their specific datasets to evaluate the overall suitability of the approach for DoD problem spaces.

Learning rates are influenced by the number of non-zero network weights, as these influence the connectivity of the network layers. By applying different weight pruning templates, the convergence of the network outputs can be altered. Using one pruning template, learning was found to become destabilized, and the network output showed significant oscillations. Using another pruning template, the network outputs converged more quickly to the correct output as compared to the baseline network. This is an example of learning acceleration that can be used to improve the performance of the approach in an on-line/time-critical instantiation. As part of a follow-on study, systematic investigation of this aspect is highly recommended.

Recommendations for Further Research

This study explored the question of how machine learning can be applied to identify the most appropriate ‘sensor’ for completing a ‘task’ by optimizing a task-to-sensor matching problem. The mathematical concept of a bipartite graph provides a framework for solving this problem. Using machine learning, it is possible to transform the problem statement into a differential equation, which can be implemented efficiently to support online/real-time decision making. It is demonstrated that bipartite matching problems can be solved by using a weighted residual neural network architecture. Moreover, the approach is scalable to large dimensional problems. Accelerating the machine learning process was also studied and it was found that different constructions of the neural network weight matrix can be used to speed up learning whereas others might destabilize the learning process. Further investigation into how learning can be accelerated for online/real-time applications is highly recommended. Future work that exercises the concepts in the context of DoD specific problem data should also be done.