Synthetic AI Network Analysis: Socially Aware AI Agents

EECS 5414 Information Networks
Project Proposal

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Abstract

There have been numerous studies on the construction, online analytical processing, and mining of information networks in multiple fields, including social network analysis, data mining, and communication networks given the prevalence of information networks and their broad applications. Also, there has been a growing interest in analyzing information framed as graphs in recent years, owing to their rich expressiveness and natural ability to depict complex relationships. There are many techniques for analyzing and creating static graphs, that cannot evolve and are capable of representing only a single data snapshot. However, in the real world, networks are repetitively altering. The goal of this project is to develop a method for analyzing synthetic weighted, directed, dynamic graphs generated from AI simulations.

Keywords: Machine Learning and AI, Synthetic Information Networks, AI communities, Machine Learning

1 Introduction

Graphs indeed signify the inter-dependencies by edges or links between the related objects. As a result, a graph network is a strong way to represent a set of objects and their relationships. Most recent research have concentrated on evaluating the relational structure of data employing graphs as a powerful data representation. The significance of these studies can be seen in a variety of applications, including social networks that connect users through relationships such as transactional communications which is an example of a dynamic network which is constantly changing its structure or characteristics.

In this project, we aim to use the advantage of artificial networks for creating a comprehensive information network that can be modeled as graphs. More specifically, each agent (node) has a neural network that controls aspects of their behaviour and awareness of other agents around them which will be analyzed as an Information Network.

1.1 Artificial Neural Networks

In recent years, artificial neural networks (ANNs) have been extensively employed in a variety of applications. Artificial neural networks are being developed by researchers from a range of scientific fields to tackle a variety of issues in pattern recognition, prediction, optimization, and associative memory.

Artificial neural networks are computational networks that aim to replicate the decision process in networks of nerve cells (neurons) in the biological (human or animal) central nervous system, as their name implies. This is a general cell-by-cell (neurons-by-neurons, element-by-element) simulation [1]. It is based on neuroyeasphysiological understanding of biological neurons and biological neuron networks. It therefore varies from traditional (digital or analogue) computing devices, which aim to replace or accelerate human brain processing without concern for the arrangement of computing parts or their networking [7], [11].

1.2 Dynamic Graphs

A dynamic graph can be represented as an ordered list or an asynchronous stream of timed events, such as additions or deletions of nodes and edges. Dynamic graphs generation, analysis and extracting embedding from such graphs have attracted great attention.

A conversational dynamics influence in communication network graphs has been studied in [8] by Khrabrov et al. on Twitter as the reference network and data source. They focused on building a replier graph from each user A's messages mentioning another user B , and studying how this graph evolves by computing a pagerank-type score.

A novel class of evolving range-dependent random graphs providing a tractable framework for modelling and simulation has been introduced in [6] by Grindrod et al. In their study, a spectrum technique for calibrating a set of edge ranges from a succession of network images and demonstrate it on some neuroscience data has been designed.

In the research study [9] by Leskovec et al., a wide range of real graphs has been investigated. They found out that most of these graphs densify with time, with the number of edges increasing super-linearly in proportion to the number of nodes. Based on their investigation it can be also observed that the average distance between nodes frequently reduces with time, despite the fact that such distance parameters (such as O (log n)) should rise slowly as a function of the number of nodes.

2 Problem definition

We are creating an artificial network of AI "Agents", that will be analyzed by our analysis software which will be comprised of both preexisting algorithms and our own additions.

Each Agent has:

A genetic code that makes up it's unique Neural Network. The Agent's Neural Network will dictate its behaviour, which includes: motion, spacial awareness (the Agent's ability to locate itself in the world as well as locating the world's boundaries) , as well as social awareness (the Agent's ability to locate other Agents around it, the 'Neighbours').

When an Agent, Agent A, comes 'in contact' or is within range of another Agent, Agent B, a random piece of each Agent's Genetic code will be copied, transferred to the other Agent, and placed in a random position in the other Agent's Genetic Code.

Meaning that if Agent A and Agent B come in contact or are within a specific range of the other (will be specified based on the genetic code of each agent, this is their Social Awareness parameter), Agent A will take a random piece of its own Genetic Code and will copy it and give it to Agent B to be placed randomly in its Genetic Code. All the while, Agent B is doing the exact same thing (if Agent A is within its awareness range), Agent B will take a random piece of its own Genetic Code, copy it, and place it randomly in Agent A's Genetic Code.

The analysis run on this Network can tell us a lot of things about the Network and the Agents and how everything changes over time. How the Agents are evolving? What is the rate of this evolution? Is the Agent's evolution making them smarter, dumber, more or less alike? Is the evolution making the Agents more or less connected to the rest of the Network as a whole? Can we predict the potential evolution of the Agents? of the Network as a whole? and many more questions.

2.1 Potential applications

This work helps us understand how AI Agents learn and what they can learn from each other when put in a limited environment, will they over come any deficits and evolve to better things and continue to evolve or will they reach a point of stagnation where nothing new happens? This work will be very helpful in pushing things forward in the ever developing Machine Learning field. Here are some examples of relevant studies in this field: Braitenberg's Vehicles [4], Papert's Mindstorms [10], the Infranet installation [2], and the Evolving Soft Robots article [5] and video [3].

3 Methodology

It can be seen that creating and evaluating dynamic networks depicted as graphs, as well as their functionality for extracting relevant information, has attracted a lot of attention, particularly in machine learning and data mining tasks. In this respect, the goal of this project is to present an approach for creating a dynamic network and apply DyNetx and perform clustering methods for analyzing node behaviours and providing embedding recommendations. Our primary challenge is divided into two subtasks: constructing a graph and extracting important information for general machine learning tasks, which are discussed further below.

3.1 Agent Creation Steps Overview

In this step, we aim to create a dynamic network modeled as a graph in NodeJs as follows:

- Creating agents with a simple genetic code and simple neural network that controls behaviour and spatial awareness (of environment and other agents).
- Building a community of 300-500 agents
- Keeping track of all the agents (and their properties) in the system
- Having all the information being outputted at regular intervals to be read and analyzed by the analysis software

3.2 Network Analysis Steps Overview

Based on the dataset obtained in 3.1, we may apply graph-based techniques such as DeepWalk for embedding recommendations. Graph embedding is a method for transforming nodes, edges, and their characteristics into vector space (a lower dimension) while maintaining as many properties as possible, such as graph structure and information. Deepwalk is a graph embedding approach that employs walks, which are a graph theory concept that allows traversal of a network by travelling from one node to another as long as they are connected by a common edge. We also, intend to analyze the behaviour of nodes (agents) in our generated network utilizing clustering techniques.

4 Evaluation

We plan on running the simulation of the Agents and the analysis many times to see if there is some kind of trend in the changes. Will the Network 'Stabilize', work towards reaching a certain state, every time the simulation is run? Will the Agents reach the same 'prime' state every time? What are the different dominant Neural Networks in each simulation is there any similarity between the different simulations? We aim to use JavaScript for graph generation and Python for clustering and studying graph embedding. The first task (graph generation) will be implemented in NodeJS and the second task (graph analysis) will be performed in google colab environment.

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