Whether Human All Social Activities Can Be Considered As A Huge Neural Network

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***Abstract*—In this paper, author investigate the similarity between social activities and neural networks and demonstrate mathematically that social activities can be considered mathematically as neural networks.**

***Index Terms*—Neural Network, Social Network**

I. Introduction

In real social activities, people are often influenced by the outside world when making decisions and behaviors, which can then further influence the behaviors and decisions of others [2]. Thus, when social activities are associated with neural networks, we can find many similarities between the two. However, it is also obvious that social activities and common neural networks are not entirely consistent. Therefore, the purpose of this paper is to try to mathematically prove that social activities and neural networks are similar and to identify in which areas they are similar to neural networks. Through the mathematical modeling and proofs presented in this paper, we can conclude that social activities are somewhat similar to neural networks, and graph neural networks can effectively simulate some social activities.

II. Interviews and Opinions of Experts

To ensure that the topic of this paper is meaningful and to identify the appropriate research direction, I interviewed two experts in the field of neural networks: doctor Irene Jiang who is the VP of L'Oreal ModiFace, and doctor Harris Chan who is the PhD in the Department of Computer Science at the University of Toronto. Both experts agree that social activities can be considered as neural networks. Both have similarities in signaling and information transfer and can exhibit complex behaviors and patterns from simple interactions. By using graph theory and graph neural networks we can model social activity mathematically. However, social activity is also often more complex than common neural networks because social nodes tend to update frequently and have more complex connection directions.

III. Induction of Examples

Based on the views and suggestions of the aforementioned experts regarding the topic of this paper, I have decided to employ mathematical modeling of several examples of social activities and use induction to demonstrate that social activities are similar to neural networks. I will begin by using examples to illustrate that neural networks with complex connections should be considered as neural networks.

A. Stock Market Example

The first example concerns simpler social activities with a single connection direction. Investing in the stock market is a very common social activity today. Individuals who invest in stocks make decisions to buy or sell according to the information they receive, and the stock market price is influenced by the volume of such actions, resulting in higher or lower performance. From the example, it is clear that the logic of stockholders' behavior is straightforward: they receive the relevant news and then decide whether to buy and sell the stock or do nothing. They also tend not to repeat as nodes in each round of information input, because no rational person would hold onto stocks that are plummeting, but would sell them short in one breath.

Therefore, at this point, we can extract and model the behavior of certain stockholders regarding a particular stock as a typical multilayer neural network. In this neural network, each shareholder will act as a node, X is their decision on the input information, and the weight of their influence on subsequent nodes, W, represents the number of shares they hold, with larger shareholders typically having more influence than retail investors. When information is passed, each node receives and aggregates the information from the previous level, and applies it to its own activation function F to make decisions and influence the next level. When information about a stock is fed to these stockholders, they make decisions about whether to buy, hold, or sell and ultimately output the impact on the stock price, i.e., whether the stock price is rising or falling. After numerous iterations, the stock price will stabilize in a range where the loss function of the stock price adjustment is minimal. As a result, a common simple multilayer neural network is formed.

Meanwhile, the entire stock market is composed of numerous such operations on stocks, so we view the entire stock market as a more extensive and complicated neural network composed of several comparatively smaller neural networks.

In this more intricate neural network the nodes represent each stock, the adjustment of the stock price is represented by x for each node, and the volume of this stock in the market is its weight w. The final output of this neural network under the influence of all stocks is the trend of the stock market such as bull market or financial crisis. In summary we demonstrate that social activities with a simple single connection direction can be considered as common multilayer neural networks.

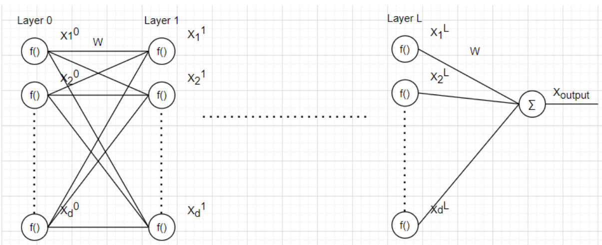

Fig. 1. stock market neural network

In the above example we demonstrated that social activities with a single connection direction can be considered as a neural network, but in real life more social activities tend to have more connections in more directions and a social node often appears multiple times in a social network. In this case, using common neural networks is not a good way to model this type of social activity. Therefore, we need to use graph theory and graph neural networks to simulate them in a more suitable way. We also demonstrate from an example how graph neural networks can model such social activities.

B. Facebook Example

Facebook is one of the most popular online social media outlets today. Users will share their views on current popular issues with their friends or followers on Facebook and in the process influence others or be influenced by others' views based on their social influence and then eventually generate mainstream opinions or trends on the issue. From Figure 2 we can roughly see how the user nodes are connected together on social media, but it doesn't look like a neural network.

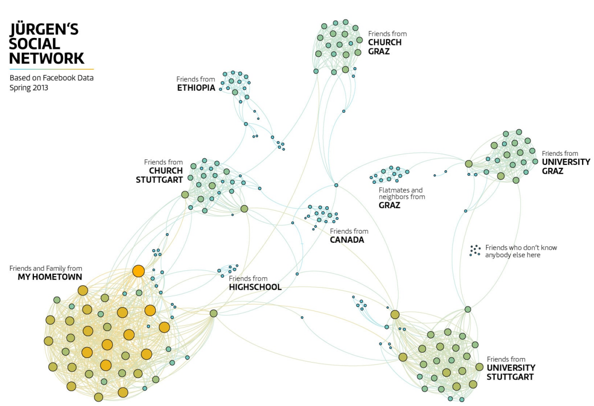

Fig. 2. Social media network Source: [5]

We can start with the basic problem at first, and extract a group of very small users from this picture to see how it forms a neural network. Figure 3 shows our extracted users, which represent a very small group of users G = (V, E) who follow each other and often discuss problems and exchange ideas together. Since they communicate together frequently, their opinions will spread and influence each other in the process. Now we can translate the process of exchanging ideas in the user group discussing issues in Figure 3 into a subtree in Figure 4 based on graph theory, where the same node can appear multiple times in the subtree since different nodes can have the same feature vector [1]. This is a good simulation of a person who repeatedly participates in a certain social activity and leaves an impact in a social activity. In the figure 4 they repeatedly discuss this one event and propagate their views layer by layer, then iteratively change their views in the process, eventually outputting a view that is dominant in the group. This forms a simple graph neural network, and we can add more details to this subtree to see how it works.

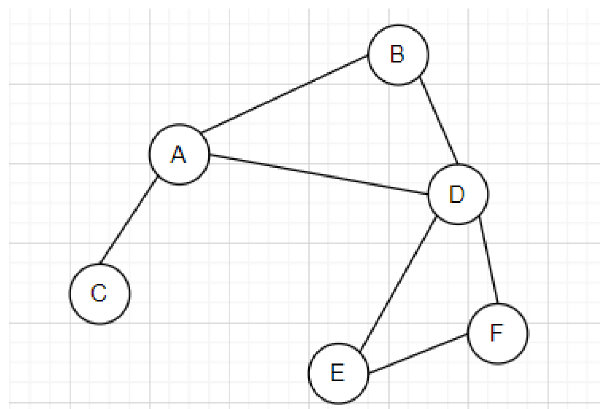

Fig. 3. User group graph

In the figure 5, We can divide this graph neural network into three layers, in which X is the feature vector of each node, which represents their current opinion on an issue. W represents their influence in the social network, which may consist of many factors for example the opinion of university professors tends to be more convincing. S is the sum of the multipliers of X and W, and F represents the activation function used. This process represents the user's attempt to persuade others with their viewpoint, and each user will also decide whether to change their opinion under the influence of many others' opinions. In the graph of this group of users, their discussion of the problem will consist of many such neural networks and form a complex multilayer graph neural network. After a certain number of iterations, this graph neural network will output a feature vector representing the graph which is their mainstream opinion of the problem. Thus, a graph neural network with a complete structure is formed.

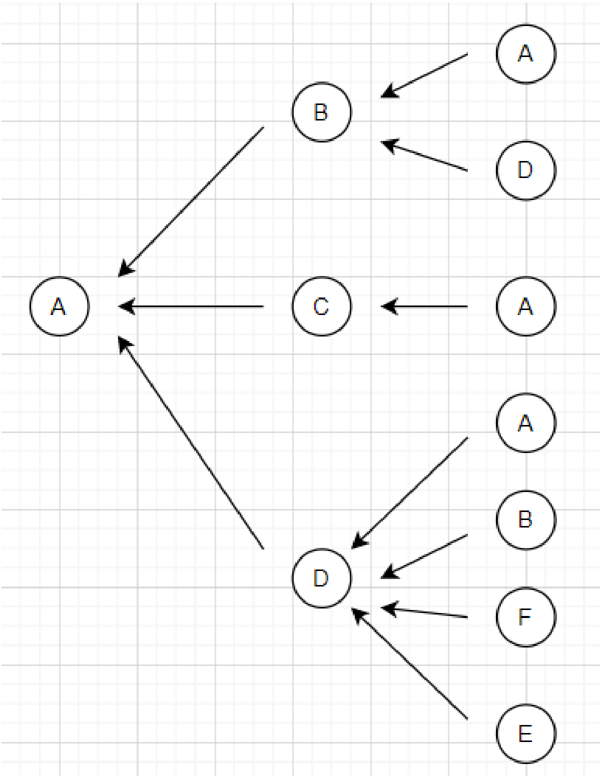

Fig. 4. User group graph subtree

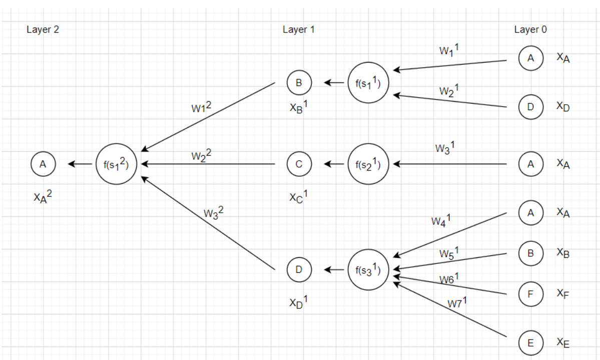

Fig. 5. Graph neural network of user group

Now that we have shown that we can treat a small group of users as a graph and model the process by which they discuss issues and exchange ideas as a graph neural network, then when we return to the original big question, we find that the entire Facebook social media in figure 6 is made up of graphs of many such groups of users. At this point we can consider each graph as a node, and the feature vector X of each graph is the mainstream opinion of their group. And the W of each node is the social influence of this user group e.g. the view of a group of professors is always more influential than the view of a group of students. Thus we can consider the combination of these graphs as a big graph and simplify it to look like the graph in figure 3, where the opinions of user groups communicate with each other and form a larger and more complex graph neural network. After many iterations eventually output a mainstream opinion for a certain problem of the whole Facebook. In summary we demonstrate that people's activities on social media can be considered as graph neural networks, which means that social activities with more complex directions and more connections can be considered as graph neural networks.

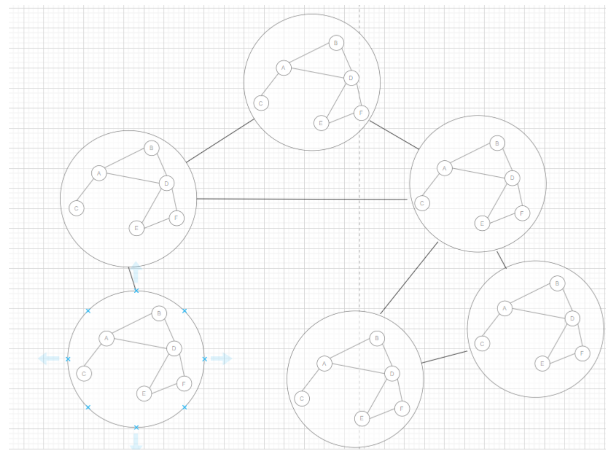

Fig. 6. big graph of user groups

The above example has shown that even in complex connected social activities, we can still model them as neural networks even if the nodes appear repeatedly. However, there is an opposite situation in real-life social activities, where a social node may not appear in the social network every time. Therefore, we can use the mathematical concept of dropout to help graph neural networks to simulate this situation.

C. Netflix Example

Netflix is one of the most common video viewing platforms nowadays. Netflix users can freely choose the movies they want to watch and rate the movies based on their viewing experience, and the user ratings of the movies will attract more users to watch the movies or watch the movies again. Unlike the Facebook example above, users tend to watch and rate movies on Netflix in parallel, and they do not watch each movie but choose movies based on their own preferences or on the promotion of others, and each user is given the same weight when performing this behavior.

Firstly, we can convert the act of watching and scoring a movie into a simple graph as shown in Figure 7. The nodes in the outer circle represent the users, and the edges represent the act of watching and rating the movie while the nodes in the center represent the total rating of the movie. Next we can model this graph into the form of a neural network in Figure 8. We can find that this is a single layer neural network, all users registered on Netflix represent a node, X is the feature vector of the node, it represents the user's preference and rating. At the same time, each edge has the same weight, and the final output of the whole neural network is averaged from the ratings of all users. The most important point is that each node has an attribute B, which represents the attractiveness to the user, i.e. whether the user will choose to participate in the process of watching and scoring a movie, and in the neural network represents whether the node will be used in this iteration. By using the dropout method we can input B into the Bernoulli function or Gaussian distribution [3] to determine the current B, i.e. the current attractiveness of a movie to the user. Therefore, the nodes will appear in the neural network with a certain probability [4], which is expressed in the social activity whether the user is successfully attracted to watch the movie or not or to watch again. In each iteration, the movie will attract users to watch and rate it to further attract more users. After a certain number of iterations, the movie will not attract more users e.g. some users are always not interested in romance movies, and the neural network outputs a feature vector that represents the final rating of the movie. In summary, we show that even if the social nodes in a social activity do not always appear in the social network, we can still simulate and model them using neural networks with dropout methods.

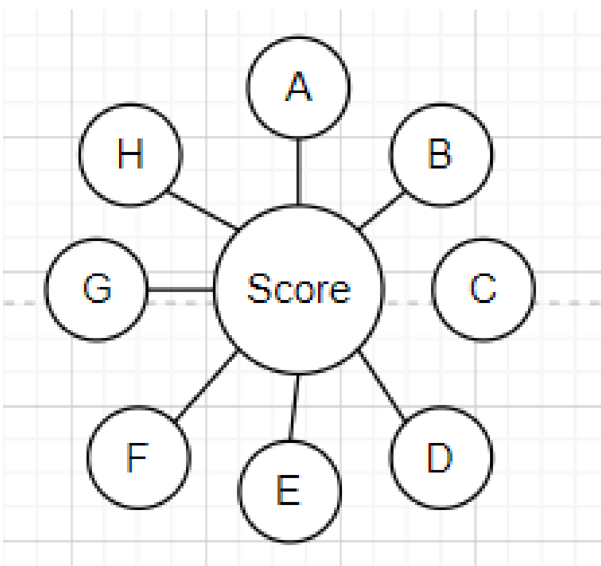

Fig. 7. User scoring movies behavior

IV. Discussion

Taking the examples demonstrated above together into consideration, we have demonstrated through mathematical modeling that most types of social activities can be simulated by neural networks, especially graph neural networks, to a certain extent. Thus, we can consider social activities as neural networks from a mathematical perspective. However, at the same time, we still have doubts about the complete equivalence of the two, because social activities are often more dynamic and are also susceptible to factors that are difficult to model, such as history and culture. Therefore, in the future, it will be interesting and worthwhile to explore further whether social

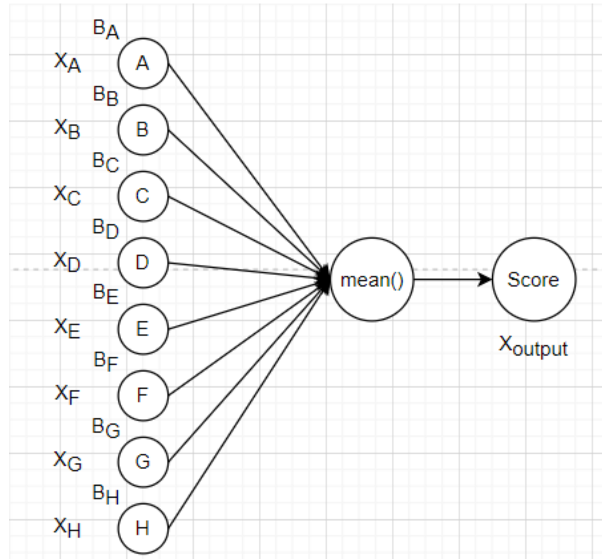

Fig. 8. Neural network of user scoring movies behavior

activities can be considered as neural networks. Beyond that, I think most human social activities can be considered as a huge neural network in mathematical terms.

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