Strategic Trading in Credit Networks

Samantha Luber
University of Michigan

Introduction

In order to gain more exposure to the financial market analysis aspect of artificial intelligence, I worked on a credit networks project under the supervision of Dr. Michael Wellman. My semester-long work consisted of familiarizing myself with the EGTA Credit Network system and Dr. Wellman's associated publications on credit market analysis, generating simulation in the credit network with agents of various strategies and analyzing strategy performance, and introducing a bank to the existing EGTA Credit Network system and analyzing strategy performance in this modified credit network. This project write-up contains a detailed summary of my work on each of the aforementioned tasks.

Understanding the EGTA Credit Network System

As described in *Strategic Formation of Credit Networks*, the simulation of agents in a credit network for analysis is based on the idea that nodes can represent agents, each node assigned with a particular credit-issuing strategy. When an agent A issues credit to another agent B, a link is created between the two nodes to represent an IOU from agent B to agent A equal to the amount of credit issued from agent A plus the cost of borrowing this cost in agent A's currency. With its newly acquired credit, agent B may then in turn issue credit to other nodes. If an agent pays its IOU's, the lending agents incur a positive payoff from this transaction. However, if an agent defaults, the lending agents incur a negative payoff.

At the initialization of the credit network simulation, nodes are randomly assigned several player characteristics, including a default probability, a credit-issuing strategy, and an initial credit amount, based on a specified probability distribution function. Depending on the parameters of the simulated credit network, nodes may know nothing about the default probabilities of the other nodes, the default probability of its neighboring nodes only, or the default probability of all of the nodes in the credit network. Based on this information, each node uses its assigned strategy to determine how much credit it will issues to each of the other nodes in the credit network during this simulation round.

After the simulation, the payoff of each node and, more importantly, the average payoff of each strategy is calculated. When a credit network is in equilibrium, there is no payoff gain for a node to change its strategy to another strategy. In this equilibrium, the overall average payoff of all nodes in the network is maximized.

Analyzing Strategy Payoff in the Credit Network System

In order to automate testing the performance of many player strategy combinations, the EGTA online system allows users to create a Game Scheduler on a particular credit network simulator. Various Game Scheduler parameters allow the user to set various simulation settings, such as the number of agents, the number of nodes in the credit network simulation, and the knowledge each node has about the existence of other agents in the network and their respective default probabilities. Based on the selected strategies to be tested, the Game Scheduler generated a series of simulations, one for each possible combination of agent strategy assignments. Upon completion of the simulations, the user can run an analysis scipt on the game of simulations to determine which strategy combinations create an equilibrium in the credit network and result in the highest average player payoff.

Based on the simulation results of the Game Scheduler, a Deviation Scheduler can be used to analyze the performance of additional strategies that weren't included in the previous simulations in comparison to the previously simulated strategies with the ultimate goal of determining the optimal strategies for a given credit network.

Searching For Optimal Strategies in Specific Credit Networks

Strategic Formation of Credit Networks concludes that in certain credit networks, specifically a credit network with complete information about node default probabilities and relatively low default probability values, optimal strategies can be determined. After simulating a variety of strategies, including issue no credit, issue one unit of credit to all nodes, issue credit to the nodes producing the highest trade profit, and issue credit to the nodes with the lowest default probabilities, it was determined that issuing credit to the 5 nodes with the lowest default probability, a strategy named DefProb_best5_get5, is the optimal strategy for the credit network.

After getting up-to-speed on the project, I was asked to experiment with various strategies issuing credit to K of the N nodes with the lowest default rate, a strategy called DefProb_bestN_getK, to see if a more optimal solution than N = 5, K = 5 existed. From test simulations, I determined than N, K values greater than 10 begin performing poorly as many defaulting nodes are issued credit under the strategy. For all N, K combinations running from N = 1 to N = 10 with all K values from K=1 to K = N, I ran 100 simulations and averaged the payoff of each strategy with one third of the nodes playing the DefProb_bestN_getK strategy, one third of the nodes playing the DefProb_best5_get5 strategy, and one third of the nodes playing the all_0 strategy to serve as a benchmark. Table 1 shows the average payoffs of the best strategies from these simulations.

N, K	DefProb_best5_get5:	DefProb_best5_get5:	All_0
2, 2	34.4516429	31.0535129	6.76648527
3, 2	36.6758448	32.566598	11.4957895
4, 2	36.6729169	32.3362241	4.53951829
4, 3	35.3630053	31.8347723	6.6374509
5, 5	34.908	34.96021	8.87097
6, 5	35.5988121	32.8019151	10.7937194

Table 1. Average Strategy Payoffs on the Credit Network. This table shows the average payoff for DefProb_bestN_getK with various N, K values in comparison to the average payoff of the DefProb_best5_get5 and all_0 strategies.

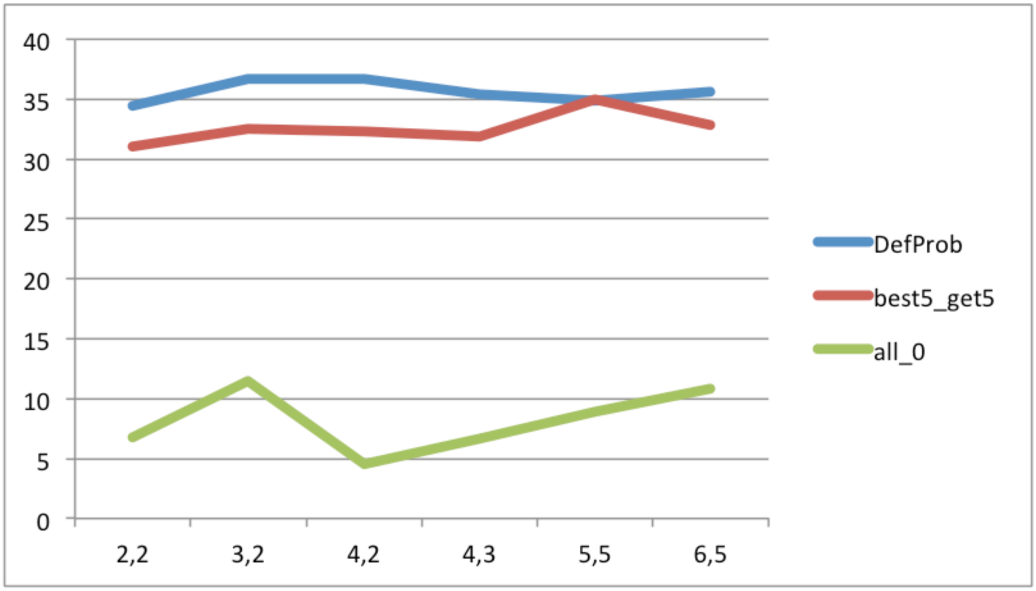

Figure 1. Plot of Average Strategy Payoffs for DefProb_bestN_getK strategy. This plot shows the average payoff for the DefProb_bestN_getK strategy with various values of N, K averaged over 100 simulations.

From Figure 1, we can see that lower N and K values tend to perform better than DefProb_best5_get5 in these simulations. In order to confirm the existence of a more optimal strategy, the best strategy from these simulations, DefProb_best4_get2, was run against the current optimal strategy, DefProb_best5_get5 on a Game Scheduler on EGTA. The analysis of the results of the scheduler's simulations shows that DefProb_best4_get2 is an exact pure strategy Nash Equilibria; thus, DefProb_best4_get2 is a more optimal strategy than the existing best strategy, DefProb_best5_get5.

Introducing a Bank to the Credit Network

After searching for optimal strategies in the existing credit network of interest, I introduced a bank to the credit network to interact with nodes and analyze its effect on strategy performance. The bank is represented as a special node in the credit network with a zero default probability rate and a zero transaction value. The bank issues a user-specified amount of credit to every node in the network and every node in the network issues a user-specified amount of credit to the bank. The introduction of a bank node is particularly interesting because it creates credit network links between nodes that, due to the nodes' strategies of credit issuing, would have never been connected. Consequently, more transactions occur in the credit network with a bank. In order to find optimal strategies in the Bank Credit Network, I created a Game Scheduler to test four preliminary strategies. Upon analysis of the optimal strategy from these simulations, I created two Deviation Schedulers to compare the optimal strategy's performance with other strategies.

Strategy:	Average Payoff:
BuyValue_best5_get5	53.6599
DefProb_best4_get2	64.1247
DefProb_best5_get5	59.6102
EU_best5_get5	54.701
Index_best5_get5	55.325
OneSD_best5_get5	55.0724
TradeProfit_best5_get5	56.8174
TradeValue_best5_get5	56.5332
TradeDef_best5_get5	60.798
WghtTrade_best5_get5	58.6023
All_0	64.8415
All_1	43.0027

Table 2. Average Strategy Payoff. This table includes the average payoff of various strategies simulated together on the bank credit network with the payoff averaged over 100 simulations.

In Table 2, we can see that the average payoff for all strategies is considerably higher with the presence of a bank node. Because more nodes are connected through the bank, more transactions occur, resulting in a higher payoff for all nodes.

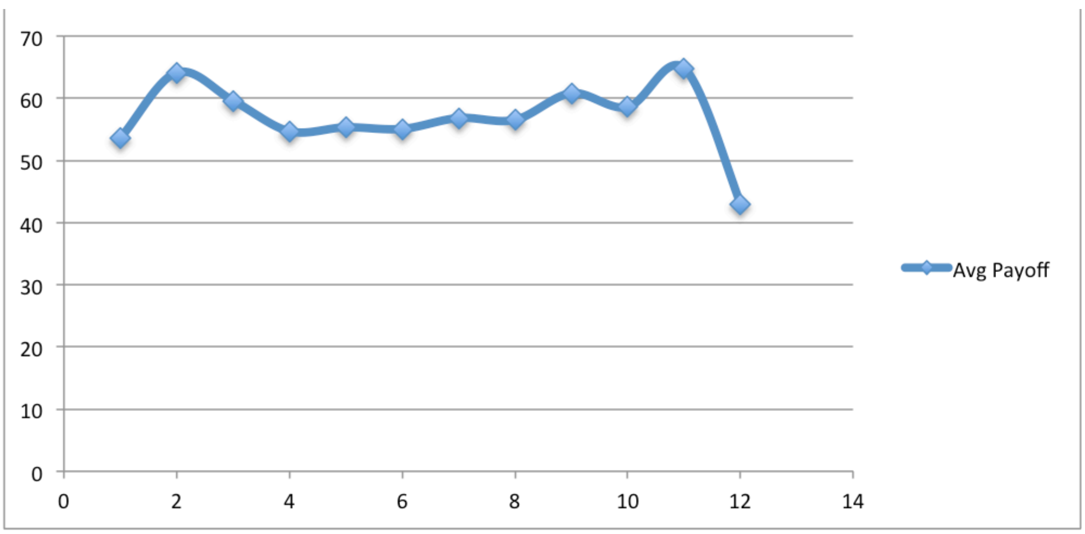

Figure 2. Average Strategy Payoffs on the Bank Credit Network. This plot shows the average payoff for each of the above strategies in the following order (left to right): BuyValue_best5_get5, DefProb_best4_get2, DefProb_best5_get5, EU_best5_get5, Index_best5_get5, OneSD_best5_get5, TradeProfit_best5_get5, TradeValue_best5_get5, TradeDef_best5_get5, WghtTrade_best5_get5, all_0, all_1.

Based on the average payoffs from these simulations, seen in Figure 2, the apparent optimal strategies, including DefProb_best4_get2, DefProb_best5_get5, and all_0, are simulated in the initial Game Scheduler on EGTA. The analysis of the resulting game simulation concludes that both DefProb_best4_get2 and DefProb_best5_get5 are pure strategy Nash equilibrium; thus both of these default rate-based strategies are the apparent best strategy in a Bank Credit Network.

The other strategies are simulated in comparison to the performance of the apparent best strategies, DefProb_best4_get2 and DefProb_best5_get5, via a Deviation Scheduler. The analysis of the simulated game from the deviation scheduler shows that, in addition to the DefProb_best4_get2 and DefProb_best5_get5 strategies, Trade_Def_best5_get5 and Wght_Trade_Def_best5_get5 are also maximal sub games and potential more optimal strategies with Trade_Def_best5_get5 being the best deviation strategy from the default rate probability-based strategies.

A final Game Scheduler was created to analyze all possible combinations of DefProb_best4_get2, DefProb_best5_get5 strategies, Trade_Def_best5_get5, and Wght_Trade_Def_best5_get5 to determine the optimal strategy for the Bank Credit Network. The analysis of the simulated games confirms that DefProb_best4_get2 and Trade_Def_best5_get5 are the pure strategy Nash equilibrium and optimal strategies in the Bank Credit Network.

Conclusions

From my simulations on the Credit Network system, I have determined DefProb_Best4_Get2 to be a more optimal strategy than the current optimal strategy, DefProb_Best5_get5, as described in *Strategic Formation of Credit Networks* Furthermore, from establishing a bank node in the existing Credit Network system, I have observed, higher average payoffs for all strategies and determined DefProb_best4_get2 and Trade_Def_best5_get5 to be the optimal strategies in this Bank Credit Network system.

Future Work

Bryce Wiedenbeck, one of Dr. Wellman's graduate students, has re-implemented the Credit Network system to make it a cleaner implementation and more compatible with the Bank Credit Network system. To confirm the accuracy of the new implementation, the strategy payoffs simulated in this Bank Credit Network system and Bryce's new Credit Network system will be compared. Another potential area for work on this project is grounding the credit network simulation environment by applying it to a specific-real world problem, an open-ended task that would involve tailoring the simulation to make it more real-world applicable.

References

Pranav Dandekar, Ashish Goel, Michael P. Wellman, and Bryce Wiedenbeck. Strategic Formation of Credit Networks. 13 November 2011.