SOCIAL NETWORK INTERACTION QUANTIFICATION AND RELATIONSHIP TREND ANALYSIS WITH MULTI-AGENT SYSTEMS

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ABSTRACT

Multi-agent systems (MAS) have been used to simulate interpersonal relationships and communication in a variety of studies. Using MAS, we propose the NCRAE (Neighborhood Cumulative Reward Average Evaluation) method to model interactions between individuals in a social network and interpret changes in their relationships over time. By quantifying the effects of call and SMS interactions in a given dataset among our simulation environment, we identify influences that may cause shifts in relationship closeness. Our results show a successful differentiation of close and distant relationships through their respective communication patterns and characteristics. We find that close relationships maintain a high level of interaction frequency and duration with no significant increase in closeness, whereas more distant relationships engage in little to no communication but engage in proximity interaction that defines its changes in relationship closeness.

Keywords: Social Simulation, Social Interaction Rules.

1 INTRODUCTION

Social networks are comprised of complex interaction patterns that are dependent upon an individual's personality and communication tendencies. These communication tendencies makes each agent in a social network unique, and makes simulating MAS intricate and a conglomerate of the different effects of social interactions. Past social network research engage in behavioral modeling of static networks, meaning the effects of time are relatively insignificant when examining individual actions given a certain social environment at a given time (Shoham and Tennenholtz 1997). By incorporating the effects of time into a social network reveals a new set of possible observations in the simulation and is referred to as dynamic social networks.

Similar studies made previously provide mathematical quantification of interaction effects on certain social relationships between individuals (Joseph, Wei, & Carley 2013). These quantifications take into consideration the impact of the length and frequencies of different communication methods, as well as the distribution of these interactions over time. With the help of MAS, our method of interaction reward quantifier is incorporated in a dynamic social network to identify associations between patterns of communication and shifts in relationship closeness.

The MAS used in this research represents individuals as agents, where each agent interacts with one another and gains certain social benefits through each unique interaction over time. The amount of social benefits gained through these interaction are dependent upon the social characteristics of its initiator and recipient, thus giving each interaction a unique effect within the social network. Along with each unique interaction, each agent will demonstrate different behaviors which will then be recorded in a state-action

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dynamic programming lookup table for prediction once the system has gained enough knowledge of each agent.

While previous work also observes the creation and dissolution of relationships, our research will overlook such phenomena in that we will only observe the shifts in the magnitude of closeness between individuals over time. Using multi-agent systems, we will model each individual's interaction with its social neighborhood, and evaluate the associated interaction reward while taking into consideration the network's communication pattern as a whole. These evaluations, which we call Neighborhood Cumulative Reward Average Evaluation (NCRAE), is then used to measure the significance a method of interaction has between two agents while considering time-discounted rewards in past. The NCRAE is made on two methods of interaction, namely call and SMS. By integrating an appropriate dataset for evaluation, we will analyze the correlation between these communication reward evaluations and the changes in perceived relationship closeness.

Our results shows that our method of interaction reward quantification differentiates relationships that are close from those that are distant. And by using the NCRAE method described in this study, we were able to identify the effects of social interactions on relationships with different levels of familiarity. More specifically, that close relationships experience greater rewards in communication patterns but show no significant changes in its familiarity; and that distant relationships, while lacking call or SMS communication, are greatly affected by proximity interactions.

2 RELATED WORK

In our model, each agent will interact with one another in a way that is affected by a variety of factors. We have presented a set of interaction rules described by other social network researches and studies, and will discuss the differences our model has with these definitions.

- Simple Majority (SM): This rule is the simplest form of an update function, in that an agent will change to an alternate strategy if more instances of another strategy has been observed in the neighborhood of said agent. Moreover, if one or more strategies have been observed to have higher occurrence than the present, the agent will adopt the one that is observed the most often (Walker and Wooldridge 1995). The main difference between our utilization of a population decision evaluation is not in the context of an agent's choice, instead it is that the interaction rewards received by an agent can be affected by the communication tendencies of its neighborhood.
- Generalized Simple Majority (GSM): As a generalized version of the Simple Majority rule, the GSM notes that an agent will adopt an alternate strategy if this other strategy has been adopted by more than half of its neighboring agents in a two-state system (Delgado 2002). Similar to the rationale for Simple Majority, it is not a matter of strategy choice, but an effect on the rewards received by an agent.
- Pay-and-Call (PaC): Developed to qualify mobile communication interactions between agents, this method notes that each agent will attempt to maximize some "emotional capital" or payoff. This payoff value will be expended and gained depending upon length of interaction, cost associated to interaction initialization, and cost for interaction per unit of time. The payoff would then contribute to a friendliness value with another individual; this in turn affects the likelihood an agent will initiate a replacement connection if such value falls below a defined threshold (Joseph, Wei, & Carley 2013). This notion is important in our simulation in that it differentiates interactions in its duration, so that longer interactions have a more significant impact on a relationship. Moreover, the idea of interaction initiation cost and cost associated with interaction length distinguishes each communication to have different effects on the initializer and the receiver. Instead of initiating replacement connections, as the relationships in our model is weighted, the emotional capital used in an interaction can affect the perceived closeness between agents, i.e. from close to distant.

- Highest Rewarding Neighborhood (HRN): This rule allows each agent in the network to act upon their own interests, which is to maximize the utility received from neighboring agents. Each agent will dissolve a relationship with another if the received reward is less than the average reward received in its respective neighborhood (Zhang and Leezer 2009); here, previous interactions are not discounted due to time, which differs from our model as we consider past interactions to have less impact than more recent ones.
- Highest Cumulative Reward (HCR): Through an agent's interaction with others, the agent is able to gather information over time on its respective network. The HCR rule indicates that the information gathered over a specified timeframe will contribute to a reward value, in which the agent will evaluate other strategies in the same elapsed time and switch if the cumulative reward of some other strategy is higher than the current (Shoham and Tennenholtz 1997). In Shoham and Tennenholtz study, their approach is applied upon a static social network. As mentioned previously, it is important that we account for time as our model is dynamic.
- Highest Weighted Reward (HWR): Similar to HRN, HWR is a rule where previous interactions are discounted with a time discount factor that is a value between 0 and 1. This is so that more recent interactions will have greater effects to a person's reward than interactions that occurred in the past (Wu and Zhang 2010). The Wu and Zhang study perceives relationships between agents to be binary, which is either connected or disconnected. Our research will interpret bonds between individuals as a weighted value to determine the magnitude of closeness instead.

3 NEIGHBORHOOD CUMULATIVE REWARD AVERAGE

The Neighborhood Cumulative Reward Average Evaluation (NCRAE) Rule referred to in this study is an extension of a previous study where the notion is based off the Highest Weight Reward (HWR) rule. Similar to the definition from the previous study, the NCRAE rule provides each agent in the network an indicator for certain relationship affecting actions in our simulation. Combining the ideas from PaC, HRN, HCR, and HWR, we devise a different definition than what was defined in Luby (2014).

Here, instead of having each agent break and create relationships depending on the average reward and its relationship to an upper and lower threshold value, we use the average reward of each agent's neighborhood as an indicator to whether to increase or decrease its closeness towards another agent in the network. In other words, the cumulative reward received from an agent is directly compared to that of its neighborhood cumulative reward average, where our simulation will then examine this ratio and react per the surveyed information in the dataset. It is evident that by adopting this new definition, we are now assuming a fully connected network where each connection holds a weight that indicates the magnitude of perceived closeness between individuals.

3.1 Interaction Payoff Functions

To measure the amount of reward received in each interaction, we must define a payoff function which will properly quantify the payoff while taking each agent's behavior and friendship perception into account. As we are examining two different methods of interaction and its associated effects, we devised two payoff quantifying formulas to determine the impact of each call and SMS interaction.

Definition 1. Benefits Function for Call Interactions, $BenefitsCall_{ij}(t)$, is defined as the benefits of a given call interaction between agents i and j at time t. The function is formulated as follows:

$$BenefitsCall_{ij}(t) = \frac{FriendshipWeight_{ji}(t)}{\sqrt{FriendshipWeight_{ij}(t) \times FriendshipWeight_{ji}(t)}} \times \frac{NumCalls_{ji}(t)}{NumCalls_{ij}(t)} \times IntLen_{ij}(t) \tag{1}$$

The $FriendshipWeight_{ij}(t)$ variable in the formula above denotes the perceived friendship or closeness value between agents i and j at time t. The $NumCalls_{ij}(t)$ represents the number of calls initiated by agents i to j at time t. And the $IntLen_{ij}(t)$ variable represents the length of interaction (in minutes) agent i and agent j engaged in at some timestep t. It is important to note that in this formula, the variables indicating friendship weight and number of initiated calls are directed interactions in the network, whereas interaction length is undirected in that both $BenefitsCall_{ij}(t)$ and $BenefitsCall_{ji}(t)$ share the same value.

A study that examines the effects of self-rated and other-rated perspective taking on communication satisfaction shows that individuals in a workplace gain communication satisfaction through certain behavioral cues that indicates the other person's perspective. More importantly, a person's perspective is directly related to communicative responsiveness, which means an agent's emotional perception of a relationship reflects how he/she interacts with others (Park and Raile 2010). Hence, the rationale behind the use of a geometric mean for the first part of the equation is that the perceived friendship weight from agent *j* will be compared with a value that is more affected by the agent that perceives the friendship as more inferior. Simply put, the payoff received through a call interaction should depend more upon the person who is less proactive with the relationship. By doing so, we account for the fact that the more engaged member of the relationship would gain slightly more in interaction reward, whereas the less engaged member would gain a significant increase in reward for interacting with a more eager partner when compared to that of an arithmetic mean.

As for the ratio of number of initiated calls from *j* to *i* versus that of *i* to *j*, the rationale is similar to the friendship weight comparison. If agent *i* initiates more calls to *j* than *j* has to *i*, the benefits *i* received would be negatively impacted as its enthusiasm is not responded with the same interest. Conversely, in the same situation, agent *j* would gain a benefit that is greater in magnitude as each initiated call interaction is met with greater enthusiasm. Finally, the length of interaction linearizes the function so that the longer the call interaction, the more benefits one would gain from it.

Definition 2. Benefits Function for SMS Interactions, $BenefitsSMS_{ij}(t)$, is defined as the benefits of a given SMS interaction between agents *i* and *j* at time *t*. The function is formulated as follows:

$$BenefitsSMS_{ij}(t) = \frac{FriendshipWeight_{ji}(t)}{\sqrt{FriendshipWeight_{ij}(t) \times FriendshipWeight_{ji}(t)}} \times \frac{NumMsg_{ji}(t)}{NumMsgAvg_{j}(t)} \times NumMsg_{ij}(t) \tag{2}$$

With the first part of the function identical to that of *BenefitsCall*, we still adjust the amount of benefits received through SMS interactions based on the perceived closeness between two agents. Here, the $NumMsg_{ij}(t)$ variable denotes the number of messages sent by agent *i* to agent *j* at time *t*. The second part of function above rates the number of messages sent from *j* to *i* by comparing it to the average number of messages agent *j* sends to each connection. Thus this fraction discounts the amount of benefits agent *i* receives if agent *j* sends *i* a number of messages that is less than that the average number sent to the rest of *j*'s neighbors. On the other hand, if *j* sends *i* a higher number of messages than *j*'s average, this indicates an above-average engagement towards *i*, and therefore each message *i* sends to *j* will provide more reward to *i* itself.

Definition 3. Payoff Function for Call Interaction, $PayoffCall_{ij}(t)$, is defined as the net payoff in call interactions agent *i* receives through interacting with *j* at time step *t*. The function is formulated as follows:

$$PayoffCall_{ij}(t) = BenefitsCall_{ij}(t) - CPM \times IntLen_{ij} \tag{3}$$

Definition 4. Payoff Function for SMS Interaction, $PayoffSMS_{ij}(t)$, is defined as the net payoff in SMS interactions agent *i* receives through interacting with *j* at time step *t*. The function is formulated as follows:

$$PayoffSMS_{ij}(t) = BenefitsSMS_{ij}(t) - CPMs \times NumMsg_{ij} \tag{4}$$

In the equations above, CPM is the cost associated per minute of interaction, whereas *CPMs* is the cost associated per sent SMS message. In both equations we employ a cost-benefit relationship for every interaction in the network as proposed in a previous study, so that inter-agent interactions are affected by an associated cost in order to model an individual's analysis on the worth of some interaction. This affects each agent in that every interaction also involves the expense of some emotional capital.

3.2 Cumulative Reward Function

Using the notion of a time discount for payoff gained in history as described in HWR, past interactions affect the relationship between two agents less as time progresses. Here, we define a similar reward function proposed in Luby, 2014.

Definition 5. Cumulative Reward Function for Call Interactions, $rC_{ij}(t)$, is the cumulative payoff of all past call interactions from agent i to agent j incorporating a time discount factor ω, that is a proportion greater than 0 but less than 1 (Luby 2014). The function is formulated as follows:

$$rC_{ij}(t) = rC_{ij}(t-1) \times \omega + PayoffCall_{ij}(t) \tag{5}$$

Which we claim

$$rC_{ij}(t) = \sum_{k=1}^{t} PayoffCall_{ij}(k) \times \omega^{t-k} \tag{6}$$

Proof.

$$\begin{aligned}
rC_{ij}(t) \quad &= rC_{ij}(t-1) \times \omega + PayoffCall_{ij}(t) \\
&= [rC_{ij}(t-2) \times \omega + PayoffCall_{ij}(t-1)] \times \omega + PayoffCall_{ij}(t) \\
&= rC_{ij}(t-2) \times \omega^2 + PayoffCall_{ij}(t-1) \times \omega + PayoffCall_{ij}(t) \\
&= [rC_{ij}(t-3) \times \omega + PayoffCall_{ij}(t-2)] \times \omega^2 + PayoffCall_{ij}(t-1) \times \omega + PayoffCall_{ij}(t) \\
&= rC_{ij}(t-3) \times \omega^3 + PayoffCall_{ij}(t-2) \times \omega^2 + PayoffCall_{ij}(t-1) \times \omega + PayoffCall_{ij}(t) \\
&\dots \\
&= PayoffCall_{ij}(1) \times \omega^{t-1} + PayoffCall_{ij}(2) \times \omega^{t-2} + \dots + PayoffCall_{ij}(t) \\
&= \sum_{k=1}^{t} \boldsymbol{PayoffCall_{ij}(k)} \times \boldsymbol{\omega^{t-k}}
\end{aligned} \tag{7}$$

Definition 6. Cumulative Reward Function for SMS Interactions, $rS_{ij}(t)$, is the cumulative payoff of all past SMS interactions from agent i to agent j incorporating a time discount factor ω, that is a proportion greater than 0 but less than 1 (Luby 2014). The function is formulated as follows:

$$\boldsymbol{rS_{ij}(t) = rS_{ij}(t-1) \times \omega + PayoffSMS_{ij}(t)} \tag{8}$$

Which we claim

$$\boldsymbol{rS_{ij}(t)} = \sum_{\boldsymbol{k=1}}^{\boldsymbol{t}} \boldsymbol{PayoffSMS_{ij}(k)} \times \boldsymbol{\omega^{t-k}} \tag{9}$$

Proof.

$$\begin{aligned}
rS_{ij}(t) \quad &= rS_{ij}(t-1) \times \omega + PayoffSMS_{ij}(t) \\
&= [rS_{ij}(t-2) \times \omega + PayoffSMS_{ij}(t-1)] \times \omega + PayoffSMS_{ij}(t) \\
&= rS_{ij}(t-2) \times \omega^2 + PayoffSMS_{ij}(t-1) \times \omega + PayoffSMS_{ij}(t) \\
&= [rS_{ij}(t-3) \times \omega + PayoffSMS_{ij}(t-2)] \times \omega^2 + PayoffSMS_{ij}(t-1) \times \omega + PayoffSMS_{ij}(t) \\
&= rS_{ij}(t-3) \times \omega^3 + PayoffSMS_{ij}(t-2) \times \omega^2 + PayoffSMS_{ij}(t-1) \times \omega + PayoffSMS_{ij}(t) \\
&\dots \\
&= PayoffSMS_{ij}(1) \times \omega^{t-1} + PayoffSMS_{ij}(2) \times \omega^{t-2} + \dots + PayoffSMS_{ij}(t) \\
&= \sum_{k=1}^{t} \boldsymbol{PayoffSMS_{ij}(k)} \times \boldsymbol{\omega^{t-k}}
\end{aligned} \tag{10}$$

3.3 Cumulative Rewards Neighborhood Evaluation

With each agent's payoff from both call and SMS described in the previous sections, we are now able to examine some received payoff between two agents relative to what he/she receives from each neighbor. Using this information, we will observe the shifts in friendship weight in accordance to different ratios of received payoff versus average received payoff. We, again, make use of a previously defined equation from Luby (2014).

Definition 7. Cumulative Rewards Average Function, $RC_i(t)$ & $RS_i(t)$, is the mean of all time discounted cumulative reward average agent *i* received from every one of its neighbors for Call and SMS interactions. The function is formulated as follows:

$$\boldsymbol{RC_i(t) = \frac{1}{n}\sum_{j=1}^{n} rC_{ij}(t)} \tag{11}$$

$$\boldsymbol{RS_i(t) = \frac{1}{n}\sum_{j=1}^{n} rS_{ij}(t)} \tag{12}$$

Where n is the number of agents in agent *i*'s neighborhood. For any given agent to determine the impact of some received reward from some neighboring agent, the received cumulative reward is then divided by the cumulative rewards average of the call or SMS interaction. Finally, two threshold values α and β are chosen in the attempt to find trends in the changes of perceived friendship weights based on the resulting ratios. We hope to see the following trends upon evaluating every agent in the network:

$$\begin{cases} \frac{rS_{ij}(t)}{RS_i(t)} > \alpha & \text{Positive trend in perceived friendship} \\ \alpha > \frac{rS_{ij}(t)}{RS_i(t)} > \beta & \text{Relatively static trend in perceived friendship} \\ \frac{rS_{ij}(t)}{RS_i(t)} < \beta & \text{Negative trend in perceived friendship} \end{cases} \tag{13}$$

4 DATASET

The Friends and Family dataset used in this study is provided by the MIT Human Dynamics Lab, and is used by many social network and related research for simulation and modeling (Aharony, Pan, Ip, Khayal, and Pentland 2011). This dataset involves members of a young family residential living community that is adjacent to a major research university in North America. These individuals participated in a mobile phone data collection experiment where their location, SMS information, call information, and friendship and relationship surveys are collected over a period of 15 months. The three set of data used are the call log, SMS log, and friendship survey data.

For the Call Log file in the dataset, the format of each line is as follows:

```
"participantID.A","participantID.B","local_time","type","duration","number.hash"
```

Where each of the `participantID.A` and `participantID.B` fields hold unique alpha-numeric ID values to represent the source and target of some call interaction. The `local_time` parameter indicates the date and time of some interaction. The `type` parameter indicates whether the call is outgoing, incoming, or missed. The duration represents the length of the call interaction in seconds. And finally, the hashed phone number of the data collecting phone.

For the SMS Log file in the dataset, the format of each line is as follows:

```
"participantID.A","participantID.B","local_time","type","number.hash"
```

Here, the `participantID.A` and `participantID.B` fields are the same as in the Call Log file in that they indicate the source and target of some SMS interaction. The `local_time` is also formatted similarly to that of the Call Log file. Unlike the type information in Call Log however, the SMS Log file evidently does not include a missed variation as each message is either sent or received. And finally, the hashed phone number of the data collecting phone.For the Friendship Survey file, the format of each line is as follows: `"","source","target","weight","date"`

The first blank double quote is the index of the record within the file. The `source` and `target` of the record denote the agents in the relationship using the same alpha-numeric ID value. The `weight` is a number that ranges from 0 to 9, where 0 means the source perceives its friendship with the target agent as the most unfamiliar, and 9 indicates the maximum level of obtainable closeness between individuals. And finally, the `date` which, unlike the Call and SMS Log files, only contain the year, month and date of the survey. Through observation, the survey conducted in the experiment were only done in 4 dates: September 1st of 2010, December 1st of 2010, March 1st of 2011, and May 1st of 2011. Due to the limited amount of usable survey information, we assume all dates after a specific survey date to retain the same friendship weight values up until a new survey date is reached. We also assume that dates prior to the first survey date have all friendship weight data listed as 0.

5 RESULTS

The total number of adjustable parameters for the simulation can be found in Table 1. The lower and upper bounds for CRAR are variables that are dependent from the values for cost and time discount for both call and SMS, since changing latter will result in changes in resulting values produced by the simulation. Whereas changing the threshold values will only partition produced final CRAR with its corresponding friendship weight trends.

Table 1: Parameter value table describes all variations of values used in our simulation.

Variable	Description	Range	Value used in experiment	Unit	Rationale
t	Time variable	[0, 335]	[0, 335]	Day	The dataset contains 389 24 hour periods, separating each day into morning, afternoon and evening yields us 1467 time steps of 8 hour periods.
ω	Time discount factor	[0.2, 0.8]	{0.2, 0.4, 0.6, 0.8}	Constant	Discounts reward with the power value to be the total time steps elapsed since the occurrence of said payoff.
n	Total number of agents	[0, +∞]	125	Agent	Total number of participants in the dataset.
β	Lower threshold value	[0, +∞]	{0, 0.1}	Constant	Evaluates a target agent and its corresponding cumulative reward with the average cumulative reward among all its neighbors to achieve a ratio.
α	Upper threshold value	[0, +∞]	1	Constant	Evaluates a target agent and its corresponding cumulative reward with the average cumulative reward among all its neighbors to achieve a ratio. If the ratio is more than this value the bond is maintained. Within the lower and upper threshold means that the agent is tolerant.
$intLen_{ij}$	Interaction Length	[0, +∞]	Data	Minutes	The length of a calling interaction between two agents i & j. Where agent i is the sender and agent j is the receiver.
$numCalls_{ij}$	Number of Calls between two individuals within time step	[0, +∞]	Data	Count	The number of Calls initiated by agent i to agent j within a defined time step.
$numMsg_{ij}$	Number of SMS between two individuals within time step	[0, +∞]	Data	Count	The number of SMS interactions sent by agent i to agent j within a defined time step.
CPM	Cost in payoff per minute of interaction	[0, +∞]	{0, 0.02, 0.04, 0.06, 0.08, 0.1}	Constant	Cost associated to per minute of calling interaction.
$CPMs$	Cost in Payoff per SMS interaction	[0, +∞]	{0, 0.02, 0.04, 0.06, 0.08, 0.1}	Constant	Cost associated to per SMS interaction.

5.1 Friendship Weight Trend Analysis

For this portion of our study, we take all calculated CRAR between every ordered pair of agents and examine the effects of certain ratio values on the trends of friendship weight. With four survey periods, we extract all four values for each relationship to study patterns and inclinations. Our first set of tested parameter values were taken from a similar study made previously, which recommended a time discount factor of 0.8 for call interactions and 0.6 for SMS interactions, and about 0.02 for both CPM and CPMs. Initially, we set α_c and α_s to be 1 and β_c and β_s to be 0.

Our initial expectations for the trends of all 3 partitions of the trend lines were, however, different that the results we received. While CRAR of 0 resulted in a gradual rise in friendship weight over time, the trends of CRAR of less than 1 and greater than 1 showed similar but more noticeable increasing trends. In fact, the relationships with below average patterns of interaction tend to increase more in friendship weight over time than that of an above average interaction. Upon adjusting the upper threshold value, the trends did not reflect any significantly distinct results. We did notice that, however, the earliest call interaction record in the extracted data occurred on October 27th of 2010. This means that the first 4 months of the simulation period had no cumulative rewards for call interactions, making the effective observation period the last two survey dates. With the minimal noticeable difference in friendship weight growth between the middle and upper trend lines for call interactions, we report no significant findings in the effects of the threshold values. Although SMS interaction trend lines show an even greater difference in average friendship weights, the trends also show no significant difference in growth rate when adjusting the threshold values.

Parameter adjustments were made for cost from 0 to 0.1 in intervals of 0.02 for both methods of interaction. And the adjustments for time discount factors were made from 0.2 to 0.8 in intervals for 0.2. The trend lines are grouped in their respective partitions of the upper and lower thresholds for the evaluation of the effects of different parameter values. Since setting the lower threshold to 0 will consistently show the trend lines with no interaction, it is difficult to examine any noticeable difference in trends in upper and middle trend lines. Thus, the lower threshold value is set to 0.1 while the upper threshold remains to be 1 for all variations of parameter adjustments.

With the time discount factor adjustments for call interactions, we see that a factor of 0.2 offsets the trend line distinctions of upper and middle partitions by a significant amount. For call CRAR between 0.1 and 1, a noticeably lower friendship weight average can be seen and a much higher average is shown for ratios greater than 1 as shown in Figure 1. This indicates that using 0.2 as a time discount value differentiates close relationships to those that are more distant, implying relationships where past interactions rewards are less significant than current interactions demonstrate significantly distinguishes close and distant friendships when comparing interaction patterns. Since more distant relationships with a less frequent interaction pattern will have each previous communication weigh more towards cumulative interaction rewards, the offset in close and distant friendship weight rewards is less significant with a higher time discount factor when compared that of a lower time discount factor. This result points out the difference between favoring past interactions versus more recent interactions specifically for call interactions; in that by favoring immediate rewards, closer relationships with higher rates of call interactions will have a significantly higher CRAR value than that of a lower interaction frequency. For the lower partition, however, we see a gradual increase in friendship weight average over time. This is an unexpected result as lower partition relationships involve close to no call interactions.

To properly interpret the trends, we performed a paired T-Test to examine the significance of the trend in each of the three partitions and their respective time discount adjustments. We find that the upper and middle partition friendship weight average trend are insignificantly fluctuating; this implies that high levels of interaction indeed indicates generally higher magnitudes of closeness, but in the upper partition's case, frequent interactions does not necessarily increase or decrease the friendship weight over time. Moreover, what is interesting to point out is that the lower partition T-Test results show a significant increase through the four time steps. The lower partition signifies relationships where call interactions are not present or insignificant compared to others. This brings us to question whether there is an external influence that encourages friendship weight growth for relationships where call interactions are non-existent.

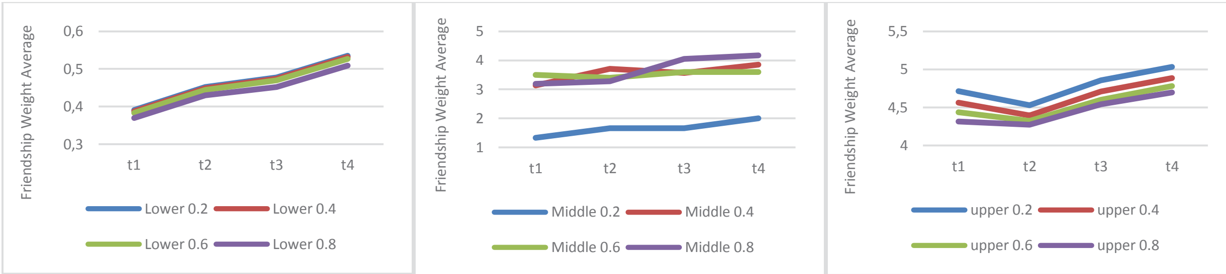

Figure 1: Call Interaction CRAR partitions with time discount adjustments and cost at 0.02; Lower indicates CRAR less than 0.1, middle indicates CRAR between 0.1 and 1, upper indicates CRAR above 1. T-Test results show lower partition friendship weight increases to be significant, whereas middle and upper partitions show no statistically significant fluctuations over the four survey periods.

Our approach in identifying this external influence is by examining the Location.csv data file presented in our dataset. Within this location file, we find logs of each agent's estimated location affine-transformed. Incorporating this dataset into our simulation, we find the amount of time in minutes where two agents are within 20 meters of each other by using the affine-transformed coordinates. Using this information, we gather the total of these proximity time values over the four survey dates and normalize these values to 0 to 10 to observe correlation between agent to agent proximity and friendship weight trends. As seen in Figure 2, there is indeed a noticeable increase in proximity times in relationships of the lower partition, and that all lower partition proximity trend lines overlap each other among the four time-discount variations. It is then reasonable to assume that although there are no call interactions the agents are possibly spending more time in proximity of one another over the course of the simulation period, thus explaining the significant increase in average friendship weight over time in the lower partition as shown in our T-Test results. It is important to note that the earliest relevant location log data was in mid-July, this affected the normalized value for proximity minutes in the first survey date in that it only involved one month of location data. Therefore, it is no surprise that the proximity information on survey date 1 is significantly lower than that of the remaining three.

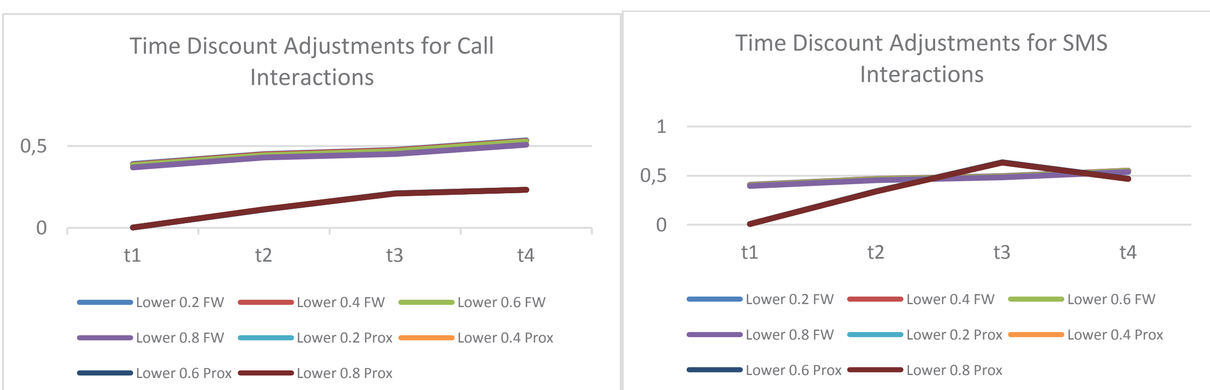

Figure 2: Lower friendship weight trend values and the normalized proximity information over the four survey dates for call and SMS interactions; The legend shows labels with FW (Friendship Weight Average) and Prox (Normalized number of minutes that two agents are within 20 meters of each other)

For SMS interactions, increasing the time discount factor would lower the average friendship weights of agents for upper partitions in Figure 3. This implies a greater overall CRAR for all relationships, thus causing trends with CRAR above the upper threshold to consequently include a wider range of relationships and thus bring down the average friendship weight in the upper partition. For SMS interactions, we see a noticeably low number of relationships with CRAR values ranging from 0.1 to 1, this shows that only relationships with a certain degree of closeness will involve SMS interactions. Due to the low number of relationships in the middle partition, its friendship weight trends are noisy and is therefore not suitable for trend interpretations as seen in Figure 3. Similar to time discount adjustments for call interactions, Figure 3 shows relationships with a CRAR value of less than 0.1 are insignificantly affected by the time discount variations.

Upon doing similar paired T-Tests described previously, we obtain comparable results for SMS interactions in that the lower partition trends are significantly increasing whereas the remaining two partitions show no significant trends among the four time-discount variations. Similar to call interactions, we see a relatively higher rate of interactions but no significant rise in perceived closeness in the relationships of the upper partition, possibly implying that it's reached a state of relationship maturity. Again, we did the same agent-to-agent proximity analysis to determine correlation between close range contact and the gradual increase in friendship weight in the lower partition. As expected, there is indeed an increase in contact time over the four survey periods as shown in Figure 2.

Figure 3: SMS Interaction CRAR partitions with time discount adjustments and cost at 0.02; Lower indicates CRAR less than 0.1, middle indicates CRAR between 0.1 and 1, upper indicates CRAR above 1. T-Test results show lower partition friendship weight increases to be significant, whereas middle and upper partitions show no statistically significant fluctuations over the four survey periods.

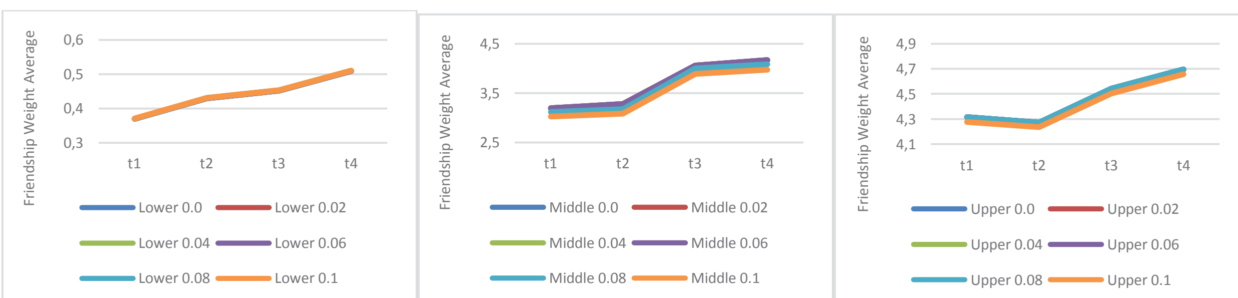

Figure 4: Call Interaction CRAR partitions with cost adjustments and time discount at 0.8; Lower indicates CRAR less than 0.1, middle indicates CRAR between 0.1 and 1, upper indicates CRAR above 1.

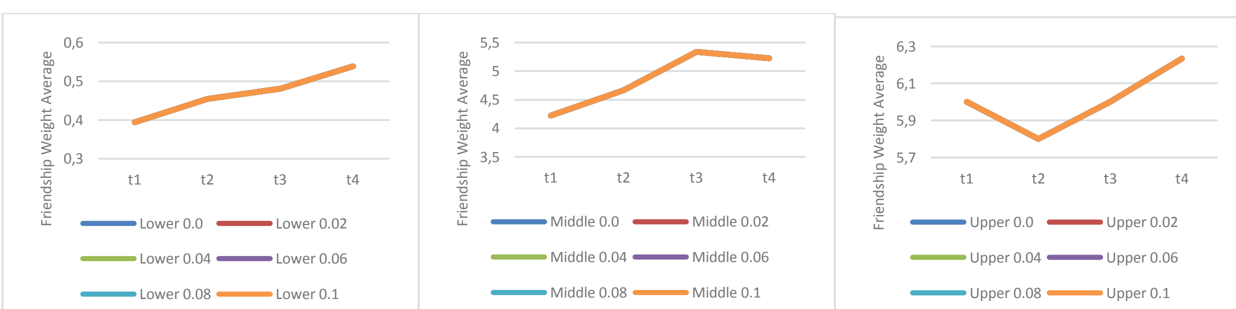

Figure 5: SMS Interaction CRAR partitions with cost adjustments and time discount at 0.8; Lower indicates CRAR less than 0.1, middle indicates CRAR between 0.1 and 1, upper indicates CRAR above 1.

5.2 Friendship Weight Prediction Results

As shown in Figure 6, the predicted number of occurrences are off by over 50 percent of the actual number. What this prediction method did not perform was reasonable predictions of friendship weights other than 0. One of the biggest contributing factors to this phenomenon is that upon evaluating each agent's learning table, a majority of the tables have only two or three seen CRAR inputs. In fact, CRAR of 0 was observed the most frequently with corresponding friendship weight values that range between 0 to 9. This implies that there are a significant number of agents who lack interaction with any of its neighbors, but are recording friendship weight values that fluctuate over time. This is possibly due to the proximity information that are associated with relationships with low call and SMS interactions, in that these low interacting relationships have a relatively low CRAR value. Previously, we noted that CRAR values below 0.1 indeed show an increase of time spent in proximity, so the fluctuation of CRAR may be associated with this information.

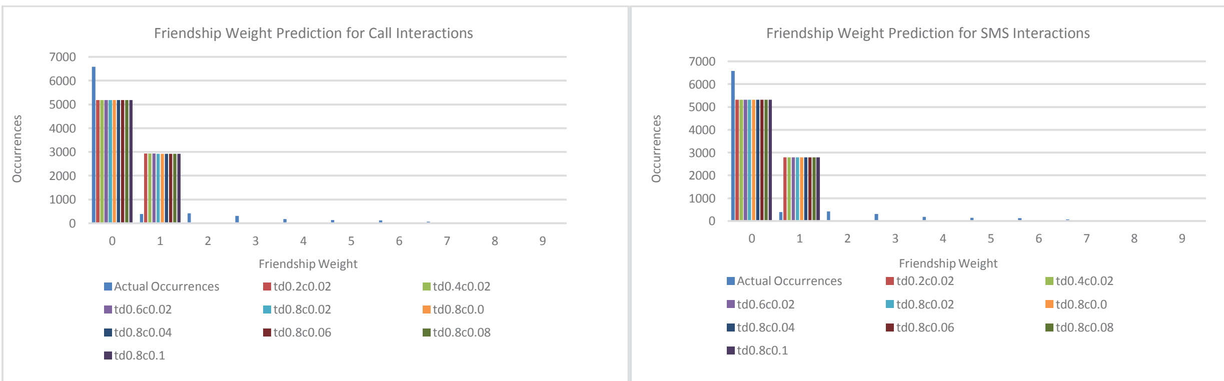

Figure 6: Friendship weight predictions with actual occurrence of friendship weight values vs. predicted number of occurrences with parameter adjustments for call and SMS interactions; The number following "td" is the time discount factor, and the number following "c" is cost per minute.

6 LIMITATIONS AND FUTURE WORK

It is evident that our method of interaction quantification is an effective way of reflecting differences in relationship closeness. We found that adjusting the time discount parameter had a more significant effect on identifying close and distant relationships, while interaction cost adjustments made little to no difference. Also, with our values for lower and upper thresholds, we could associate patterns of interactions between agents with relationships with varying magnitude of closeness. In addition, we see that lower partition relationships may rely on proximity interaction to cause a gradual rise in friendship weight, whereas upper partition relationships are maintained by frequent interactions but show no significant change in closeness. Through our method of friendship weight predictions with learning tables, we found that using a simple look up table with linear approximation is not a suitable strategy. However, we were able to identify certain phenomena that caused such discrepancy between actual and predicted friendship weight values.

The nature of the dataset caused several undesirable effects to our simulation. The inconsistency of interaction data led to very sparse instances of communication within our network. With the first call interaction beginning five months into our simulation time frame, and the inconsistent distribution of friendship survey data, it was difficult to produce meaningful analysis on the correlation between interactions and relationship changes. Furthermore, it is important to note that our simulation interprets face to face communication that may be inaccurate and less in depth than that of call and SMS, in that we are only considering phone communications in determining major relationship effects. Thus, it is imperative for future attempts on this topic to consider all types of interactions appropriately to produce accurate results that reflect reality.

Due to the large number of relationships evaluated in this study, results produced by different parameter settings are only demonstrated in a very general sense. A natural next step is to refine our methods of friendship weight prediction, and perhaps a more holistic approach to relationship analysis. Additionally, we have viewed all relationships as a complete network with no creation and dissolution of connections. In the future, this model can be easily revised by adding decision making and create a dynamic network.

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