UNIVERSITY of OTAGO

Te Whare Wānanga o Otāgo

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Mariusz Nowostawski
Noria Foukia

The Information Science Discussion Paper Series

Number 2007/05
August 2007
ISSN 1177-455X

University of Otago

Department of Information Science

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Department of Information Science
University of Otago
P O Box 56
Dunedin
NEW ZEALAND

Fax: +64 3 479 8311
email: dps@infoscience.otago.ac.nz
www: http://www.otago.ac.nz/informationscience/

Social collaboration, stochastic strategies and information referrals

Mariusz Nowostawski
Noria Foukia
Information Science Department
The University of Otago
PO BOX 56, Dunedin, New Zealand
MNowostawski,NFoukia@infoscience.otago.ac.nz

Abstract

Referrals are used in multi-agent systems, network agents and peer-to-peer systems for the purpose of global or local information spreading to facilitate trust relationships and reciprocal interactions. Based on referral local interactions can be altered with a purpose to maximise the utility function of each of the participants, which in many cases requires mutual co-operation of participants. The referral system is often based on the global detailed or statistical behaviour of the overall society. Traditionally, referrals are collected by referring agents and the information is provided upon request to individuals. In this article, we provide a simple taxonomy of referral systems and on that basis we discuss three distinct ways information can be collected and aggregated. We analyse the effects of global vs. local information spreading, in terms of individual and global performance of a population based on the maximisation of a utility function of each of the agents. Our studies show that under certain conditions such as large number of non uniformly acting autonomous agents the spread of global information is undesirable. Collecting and providing local information only yields better overall results. In some experimental setups however, it might be necessary for global information to be available otherwise global stable optimal behaviour cannot be achieved. We analyse both of these extreme cases based on simple game-theoretic setup. We analyse and relate our results in the context of e-mail relying and spam filtering.

1. Motivation

This study concentrates on benefits of localisation for the purpose of information distribution, storage and referrals. We focus here on the notion of locality in the context of trust and trust referrals.

Trust is a numerical or symbolic prediction of agent's behaviour (or behavioural pattern) as perceived by a single agent. We may talk about trust relationship between two agents, if both agents have accurate representation of each other behavioural patterns. *Reputation* is a perceived collective trust value. In other words, aggregated individual trust provides the notion of a reputation of a given agent. *Referral* is an act of referring or recommending. In other words, referral is the act of communicating trust or reputation information. Each individual agent can accumulate its own trust information based on historical interactions. Each agent can built a reputation information through exchange of trust information with other agents. In our system, each agent is responsible for collecting storing and propagating both trust and reputation information.

Recently, many multi-agent systems (or systems that can be modelled as such) are characterised by a large number of locally interacting components distributed in spatio-temporal space[1]. This is typical for example for sensory networks, peer-to-peer systems, Internet nodes, mail server relays, etc. The size of the spatio-temporal space and the number of interacting elements create a number of challenges in the context of information spreading and referrals.

In this article we take into account two main metrics of information spreading in the context of referral systems: a) speed of information spread, b) cost of information spread.

Referral systems, based on local information spreading only, will be typically characterised by a faster system response to local variations and will require less information propagation within the system itself. Modelling, analysing and predicting the effects of these tendencies on the overall utility function of the individual participant and population as a whole are the main objectives of this study.

In the following Section 2 we present our abstract notion of locality. Then in Section 3 we introduce basic concepts related to game analysis, such as reward matrix, Nash equilibrium, and Pareto optimality. In Section 4, we expand tra-

1 By the term *spatio-temporal* we mean distribution in space and time. Space can be a physical 3-dimensional euclidean space as in the context of sensory networks physically deployed in a real physical environments. Or it can be an abstract space with a distance function based on the number of hops between the nodes.

ditional concepts with our own model of behaviour emerging from selfish interests. We discuss various equilibrium concepts and provide notions of stable, and optimal strategies. In Section 5 we present the details of the games that we have used in our experiments. Section 6 contains the experimental results of the abstract game analysis. Section 7 contain a discussion of applicability of our findings in the context of spam and mail relying. The article is summarised in Section 8.

2. The concept of locality

Locality is in other words a measure of distance within a particular topology. Locality captures the notion of how close elements are. In our studies we use the concept in a dual meaning: a) derived from the notion of connectivity and distance in graphs, and b) derived from the notion of distance in time. Informally, elements that require less hops (a number of nodes in a path in a graph) are said to be close, or local. Same, elements that occur one after another in time, are said to be close, or local.

To define such a distance measure in the abstract spatio-temporal space, we use the notion of connected graphs (networks) and the traffic passing through such a network. The nodes represent the processing units (computers, e-mail servers, agents, etc) and the vertices are the communication channels which allow the information flow between the nodes. The information can be of any form, e-mail messages, agent communication messages, etc.

We say that the given set of nodes is local, or close, if they are directly connected with one another (1 hop). We say that nodes are non-local if there is another node on the path between them.

3. Cooperation through game analysis

Some authors argue that incentive based control of emerging behaviour of agent societies may not be sufficient [3] and explicit normative prescriptions and rules on the behaviour must be employed and enforced. There is much merit to such views, however, their applicability in open multi-agent systems is limited or not applicable without fixed and centralised services, such as specialised middleware. For open multi-agent systems a different approach needs to be taken. In our work we assume that decisions made by individual agents are the sole cause of any global patterns of the behaviour within a multi-agent society. We do not assume any other institutional or normative regulatory mechanisms. In particular, in case of spam filtering no such regulatory mechanism are in place at the time of writing this article, therefore the only way to remedy the situation is through specially engineered bottom-up mechanisms and related investigations.

For our analysis and abstract experiments we have chosen the game theoretic approach [5]. Game theoretic analysis is one of the popular ways of conducting studies about trust and cooperation. The setup usually involves 2- or more players (agents, participants). Each of the participants makes a decision at the same time without knowing others decisions. Each player is then given a payoff (reward) based on its and all others decision. If we consider each decision as a row and column index and each cell of such a matrix a vector of payoffs given to each of the players accordingly, then such a matrix is called a payoff (or reward) matrix. Note, the dimension of the matrix is equal to the number of choices each player can make, and the dimension of the vector equals to the number of players. *Strategy* is the way a given player makes its decision. We distinguish two basic types of strategies. *Fixed strategies*, such that players decision is invariant in time. *Adaptive strategies* change in time subject to external and internal influences. Strategies are also characterised by the history horizon, that is, how many previous iterations are being taken into account. Games are often called dilemmas (such as Prisoner Dilemma), and played iteratively many times with various initial conditions, strategies and other parameters.

Various dilemmas developed for experiments show the intrinsic complexity of agent's choices regarding trust and cooperation. Software simulations allow modelling different forms of matrix games with number of variables, various fixed and adaptive strategies with large number iterations. Some of these studies can only be conducted through experimentation and simulation due to the large number mutually dependent variables and adaptive character of some strategies.

There is a number of existing concepts [6] that are useful in the context of analysis of behaviour and establishing trust relationships, and others have proposed various models for modelling mutual trust relationships (e.g. [1, 6]). We will follow game-theoretic approach, similarly to [5] and we will briefly discuss here two mostly used notions: Pareto and Nash equilibrium.

Pareto optimality[2] is a situation which exists when rewards have been allocated in such a way that no-one can be made better off without sacrificing the well-being of at least one other player. In other words, movement in the reward matrix along any of the rows or columns is not possible without at least one player being worst off. That means that a current strategy cannot be improved without a sacrifice of at least one of the players. The concept of Pareto optimality is useful in establishing local optima and stable game strategies. However, Pareto optimality says nothing about global optima and globally stable strategies. By requiring that no participants be worse off, Pareto optimality protects the status quo and therefore any inequity or suboptimality of the strategy distribution already existing or established.

Nash equilibrium[3] is a kind of solution concept of a

2 Named after Italian sociologist and economist Vilfredo Pareto (1848-1923).

3 named after John Forbes Nash (born 1928).

game involving two or more players, where no player has anything to gain by changing only his or her own strategy unilaterally. If each player has chosen a strategy and no player can benefit by changing his or her strategy while the other players keep theirs unchanged, then the current set of strategy choices and the corresponding payoffs constitute a Nash equilibrium.

In most multi-agent systems composed of selfish agents a typical stable uniform strategy lies on the Nash equilibrium. Nash equilibrium configuration implies that there is no benefit for one player to change its strategy if the other agent's strategy does not change. However, in the context of non-zero sum games this is rarely the optimal strategy for players to adapt. Economists use the game analysis for predicting various social behaviour in market situations, and there is usually a consensus that societies in the models settle for Nash equilibrium. There are some studies that challenge this typical game-theoretic approach. For example, the work of Banerjee et al [1] considers 1-level agents who select actions based on expected utility considering probability distributions over the actions of the opponent(s). In certain situations, such stochastically-greedy agents can perform better (by developing mutually trusting behaviour) that those that explicitly attempt to converge to Nash equilibrium.

4. Cooperative behaviour: reputation and trust

In [6] authors developed a trust mechanism that selects the number of agents to query for referrals. The proposed mechanism works effectively if the knowledge of the agents behaviour distribution is known in advance. An agent can make an informed decision, given the expected probability distribution and the referral information. In the case of unknown probability distribution, given a referral, agent is unable to establish how far from expected behaviour that referral is. For an unknown adaptive mechanism we propose the modification based on the new Selfish Stochastic Strategy and dynamic referral information spreading. These concepts will be described with more details later.

For the purpose of our initial abstract experiments, we will consider only stochastic environments, where exact information about players is not available. That means players cannot distinguish with whom they played in the past. Only the average local and global score information is propagated through the referral system.

We will formally introduce here three concepts related to game equilibrium. These concepts are discussed as optimal strategies, in the context of trust/reputation and optimisation of agent's utility function. These are Best Cumulative Strategy, Greedy Stochastic Strategy and Selfish Stochastic Strategy.

Note, the utility function can be defined in various forms and ways and for a different purpose. In the context of e-mail filtering, the utility function is directly related to the traffic granted (reward) by other email servers and/or the spam that is at the end not received by an email server. This notion will be used later when the e-mail filtering system is analysed and discussed with more details.

4.1. Greedy Stochastic Strategy

Greedy Stochastic Strategy (GSS) is a strategy that a single player would play, exclusively to maximise its own payoff intake, given a static snapshot of probability distribution of all strategies of other players, The GSS strategy assumes that one's decision is insignificant for the overall probability distribution of population strategies. That is, GSS disregards its own impact on the probability distribution change. That means that each player makes its own choice as if its own strategy would not influence anybody else decisions. As if a given agent was outside of the population pool. This is obviously a simplified model for rational decision making, as each individual player is almost always influential in other players decision making. In some large systems, where interactions are random between players, there is quite a substantial *inertia* between individual player decision and the influence on he global strategies probability distribution. In other systems, where interactions are frequently with the same group of players, such as in our anti-spam relay model, the influence is substantial and immediate.

In terms of strategies probability distribution of a given population, GSS strategy tries to achieve the maximum individual reward intake, disregarding the future shape of the probability distribution of strategies. This usually renders the GSS strategy to drive the probability distribution of strategies towards GSS steady state. One can interpret this as the state where players do not exhibit trust in other players good will and cooperation.

4.2. Selfish Stochastic Strategy

Selfish Stochastic Strategy (SSS) is similar to GSS. SSS is the universally optimal strategy in the context of maximising one's utility function based on a given probability distribution of other players' strategies. SSS works under the assumption that one's decision influences the probability distribution significantly. This assumption may seem strange, in the context of games played by large number of players, where individual decision may seem significant. However, in most cases in the long run, in particular, when the game is played indefinitely, the actual population size does not matter. Each decision is statistically significant for the overall probability distributions, even for large populations. In the context of interactions with small closed group of players (such as federated servers that rely traffic to one another) the influence is substantial.

In terms of strategies probability distribution of a given population, SSS strategy tries to maintain the current status quo. This strategy does not drive the current state of affairs up or down, it just tries to conform to the current strategies distribution. In terms of trust the strategy follows the established track record of a given player (from self-knowledge and from the referral system).

4.3. Best Cumulative Strategy

Best Cumulative Strategy (BCS) is a strategy that when played by all players would yield the highest overall sum of their individual payoffs. This is a modified SSS in which an agent takes a pro-active role of driving the probability distribution of strategies towards the common global optimal state. In most game theoretic situations, such a global optimal state is highly unstable. The BCS is a theoretical model capturing the tendency of the population to reach that state.

In terms of probability distribution, BCS drives the strategies distribution towards a global optima. Players can be interpreted as exhibiting a pro-active and pro-trust activities. This can be implemented indirectly as shorter memory span for keeping negative players' information and having generally more positive outlook on other players. In highly competitive environments, BCS strategy usually would perform extremely poorly in some of the games.

We will look more into detailed abstract game models in the next section.

5. Abstract game models

To present details of the strategies described in the previous Section 4 we will use three simple variants of a popular Prisoner's Dilemma (PD). The first one is a classic PD, the second one is a modified PD with three choices, and the third variant is the Traveller's Dilemma (that can be seen as generalisation of PD to 99 choice variant).

5.1. Prisoner's Dilemma

Two suspects, A and B, are arrested by the police. The police have insufficient evidence for a conviction, and, having separated both prisoners, visit each of them to offer the same deal: if one testifies for the prosecution against the other and the other remains silent, the betrayer goes free and the silent accomplice receives the full 10-year sentence. If both stay silent, both prisoners are sentenced to only six months in jail for a minor charge. If each betrays the other, each receives a five-year sentence. Each prisoner must make the choice of whether to betray the other or to remain silent. However, neither prisoner knows for sure what choice the other prisoner will make. So this dilemma poses the question: How should the prisoners act?

Nash equilibrium for the above game is $< D, D >$. All allocations are Pareto optimal. BCS is C. GSS and SSS by definition depend on the actual or perceived probability distributions. However, in the case of PD game, the GSS D is independent of the current probability of playing C, which we denote as C_p. Assuming that the probability distribution of opponent choices $< C, D >$ in the population is vector $< C_p, D_{1-p} >$ the SSS will follow the exact strategy vector $< C_p, D_{1-p} >$. To understand SSS, note that it is in players interest to have C players around. With only D players around any strategy would be doing poorly. The only choice that would not destroy the existing balance is SSS $< C_p, D_{1-p} >$.

	Cooperate (C)	**Defect (D)**
Cooperate (C)	$< 3, 3 >$	$< 0, 5 >$
Defect (D)	$< 5, 0 >$	$< 1, 1 >$

Table 1. Classic Prisoner's Dilemma

5.2. 3-way Prisoner's Dilemma

Consider a generalised to 3 choices PD game below.

	C	**M**	**D**
C	$< 3, 3 >$	$< 1, 3 >$	$< 0, 5 >$
M	$< 3, 1 >$	$< 2, 2 >$	$< 1, 3 >$
D	$< 5, 0 >$	$< 3, 1 >$	$< 1, 1 >$

Table 2. 3-way Prisoner's Dilemma

Nash equilibrium for the above game is again $< D, D >$. All allocations but $< D, D >$ are Pareto optimal. BCS is again C. GSS is again D (which is not Pareto optimal this time). And SSS would be accordingly a vector of probability distributions $< C_p, M_{pp}, D_{1-p-pp} >$.

5.3. Traveller's Dilemma

The original formulation of TD [2]: An airline loses the suitcases of two travelers. Both suitcases happen to be identical and contain identical pieces of antique. An airline manager tasked to settle the claims of both travelers explains that the airline is liable for a maximum of $100 per suitcase, and in order to avoid inflated claims he separates both travelers and asks them to write down a number no less than 2 and no larger than 100. He also tells them that if both write down the same number, he will treat this number as the true dollar value of both suitcases and reimburse both travelers that amount in dollars. However, if one writes down a smaller number than the other, this smaller number will be taken as the true dollar value, and both travelers will receive that amount plus a bonus/malus: a $2 extra amount for the traveler who wrote down the lower value and a $2 deduction for the person who wrote down the higher amount. The question is: what strategy should both travelers follow to decide which number to write down?

	2)	3	4	...	99	100
2	$< 2, 2 >$	$< 4, 0 >$	$< 4, 0 >$		$< 4, 0 >$	$< 4, 0 >$
3	$< 0, 4 >$	$< 3, 3 >$	$< 4, 0 >$		$< 5, 1 >$	$< 5, 1 >$
4	$< 0, 4 >$	$< 2, 5 >$	$< 4, 4 >$		$< 6, 2 >$	$< 6, 2 >$
...						
99	$< 0, 4 >$	$< 1, 5 >$	$< 2, 6 >$		$< 99, 99 >$	$< 101, 97 >$
100	$< 0, 4 >$	$< 1, 5 >$	$< 2, 6 >$		$< 97, 101 >$	$< 100, 100 >$

Table 3. Traveller's Dilemma

Nash equilibrium for this game is $< 2, 2 >$. All allocations are Pareto optimal. The BCS is to play 100. Let us consider a GSS and SSS in a randomly distributed population of players, where $P_2 = P_3 = P_4 = \dots P_{100}$ in a choice vector $< 2, 3, 4, \dots, 100 >$. Let us assume this distribution as ω. In such ω environment, there are two GSS_ω: 96 and 97. And one global SSS 97. This notion of SSS and GSS can be generalised for Traveller's Dilemma with arbitrary probability distributions.

6. Experimental studies

Each individual player keeps track of its performed interactions. In other words, each individual keeps track of the history of its interactions. Based on the history, each individual agent creates its own internal trust model about other agents (individually, or as a probability distribution for the entire population). The simplest mechanism of referral is to ask other agents about their trust values. Based on that information, an internal reputation model can be established. The local trust value and the collective reputation are then used for a given agent to make a decision. The trust value is gained through direct interactions. However, for unknown players, or players with whom a given player played only few times, the trust value may be unreliable. Note also, that players can change their strategy dynamically, and the trust value a given agent holds about the opponent may become obsolete. This is why using referrals is beneficial. Referrals may increase the information propagation speed about players through indirect information spreading. On the other hand, indirect information may be inaccurate, and it also increases the overall communication costs.

In our experimental setup we used the three levels of information propagation:

1. personal knowledge, this is the base level, where agents rely exclusively on their own personal experiences
2. first-degree referrals, this is the base level where agents refer to their own personal knowledge, and share the information between each other.
3. second-degree referrals, this is the most advanced level, in which agents propagate not only personal knowledge, but also referral information obtained from other agents.

We have conducted experimental studies for establishing trust relationships in systems with reliable referrals, that is, agents always communicate the true information about their experiences. More complex models would need to be employed for situations were this is not the case and agents can provide unreliable information. Our working assumption is that through averaging large enough sample we can neglect the small probability of individual agents to provide inaccurate or wrong information. More detailed studies into that area are part of future work.

We have used simple game scenarios as discussed earlier. For experiments we used population of 5000 agents (players) with various strategies, playing with each other 1000 games per round, in 100 round settings. Agents employ various strategies and can vary them during the games. Agents can communicate their personal preference for adjusting their strategy locally or globally. Thus other agents can use the information and follow the success of others. In our experimental studies we have assumed all interactions to be unanimous, and agents make their decisions purely based on their perceived probability distribution of other players' strategies[4] and the referral system[5]. On Figure 1 we present the runs for the classic two-way PD game, with the payoff matrix as in Table 1. The two middle lines represent the completely random baseline, and the population in which agents adapt SSS strategy. In both of these cases, the average score per player is close to 2.25. As expected, the SSS strategy does not affect the overall probability distribution of other players strategies, therefore the average score per player in the entire population remains the same.

The GSS strategy adapted by a some players at early rounds, when advertised through the referral system globally caused more players to switch to GSS. Although for those individual players (up to 5% at the end of round 100) their score went substantially up due to adaptation of GSS, the overall score of the population went down. This is represented on a graph by a decrease of an average score per player per game. Same with the average score per player. In

4 For experiments the actual statistical probability distribution was given to agents globally.

5 The referral in that case does not relate to individual players but to the general trend of the population.

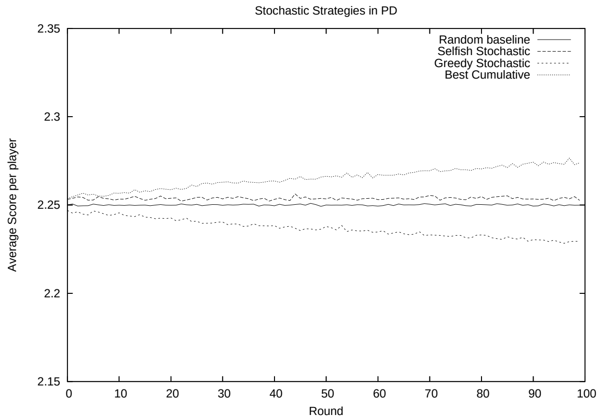

Figure 1. Comparison of various strategies in Prisoner's Dilemma settings.

the longer run, GSS would dominate the population. Simple individual mechanism to advertise successful local strategies would lead for this population to achieve Nash equilibrium.

Adaptation of BCS strategy is not in agent's selfish interest and therefore was not a popular in a global referral setting. We have adapted additional voting mechanism, in which players can express their approval or disapproval for recent changes to the probability distribution caused by agents' strategies change. That means, agents would not advertise their own strategies, but, will vote for the current probability distribution. Initial change of few players to BCS in early rounds caused the common consensus on benefits of BCS, and more and more players were locked in BCS through the majority voting. This is shown by the rising line of BCS strategy.

Similar experiments have been conducted for 3-way PD and Traveller's Dilemma games, with similar outcomes.

7. Applications: anti-spam rely

In the anti-spam relay scenario we consider a collaboration of email servers that belong to a federation or collaboration **C** of servers which will cooperate in order to decrease the local spam traffic that each email server is receiving or the global spam traffic that the federation of servers is receiving based on the three strategies mentioned in section 4. The explanation of the parameters that are used are taken from a previous work done by Foukia et al. in [4]. Following the setup described in section 3, the anti-spam relay scenario is composed of at least 2 players (or email servers). Each email server can decide or not to filter its outgoing spam. Its decision can be made at the same time as another email server without knowing the other email server's decision. Each server is then given a payoff (reward) based on its decision and all others email server's decision. The reward is expressed in terms of email traffic accepted by other servers in the federation of servers.

7.1. Greedy Stochastic Strategy

In the GSS, the server X will only try to decrease the effect of spam coming from Y on its local users by controlling the local spam rate ($AS_{XY}(K)$) in its local traffic LT_{XY}. LT_{XY} is given by equation (8) in [4]:

$$LT_{XY}\text{=sizeof}\{e|e \in E_{XY}, now - t < T(e) < now\}$$

See [4], for more explanation about how LT_{XY} is computed.

In this strategy, X disregards its own impact on other servers. It does not try to benefit the collaboration by also controlling the spam coming from Y and passed to the collaborators. Following the explanation of section 4.1, server X tries to achieve the maximum individual intake by only controlling the impact of spam on its local traffic. Consequently, in this case, there is a chance that X may be quickly blacklisted by its collaborators and be excluded from the collaboration. This is what we interpreted as the state where servers in the collaboration **C** do not exhibit trust in X's good will and cooperation.

7.2. Selfish Stochastic Strategy

In the SSS, the server X will try to decrease the effect of spam coming from Y on its local users by controlling the spam rate in its local traffic LT_{XY}. X will also avoid to be blacklisted by its collaborators. This supposes that X minimizes the spam rate in LT_{XY} and at the same time X controls the spam rate in GT_{XY} so that:

$$\max_{Z \in C}(FSS_{ZX}(K)) < BT_X$$

The federated spam suspicion that server X computes for server Y, $FSS_{XY}(K)$ is given by equation (6) in [4]. This parameter corresponds to the aggregation value of local suspicion rates about Y exchanged between other servers of the collaboration **C** and X, that X integrates in $FSS_{XY}(K)$ based on how much X trusts (TR_{XZ}) the other servers Z in the collaboration **C**. $FSS_{XY}(K)$ is given by:

$$FSS_{XY}(K) = \frac{\Sigma_{(Z \in C)} LSS_{ZY}(K).TR_{XZ}}{\Sigma_{(Z \in C)} TR_{XZ}}$$

The blacklist threshold BT_X, determines that when a server in the collaboration computes a federated spam suspicion $FSS_{ZX}(K)$ for the traffic coming from X beyond the threshold BT_X, all traffic from X should be rejected. We assume that the threshold BT_X chosen for X by each server in **C** is the same.
Compared to ($AS_{ZY}(K)$), $LSS_{ZY}(K)$ is the local spam suspicion rate after the time span K taking into account the digressive effect on older spam. See [4], for more explanation about how $LSS_{ZY}(K)$ is computed in equation (5).

Following, the explanation given in section 4.2, in terms of strategy, server X tries to maintain the current status quo by maximizing its local rate of legitimate email and avoiding to be blacklisted by the collaborators.

7.3. Best Cumulative Strategy

In the BCS, each email server X will try to benefit the whole community of collaborating email servers by decreasing the spam rate in the global email traffic (follwowing the global optimal state explained in section 4.3) passed to all the collaborators. From X's point of view, this strategy corresponds to minimizing the normalized spam rate $AS_{XY}(K)$ that comes from Y to X at the end of each time span K in the Global Traffic Rate GT_{XY}. These two parameters were given by equation (4) and (9) in [4]:

$$AS_{XY}(K) = \Sigma S_e / (\Sigma e)$$

such that $\{e \in E_{XY}, now - t < T(e) < now\}$, E_{XY} the repository of incoming email from Y to X and S_e the spam suspicion value on email e. t is the duration of each time span K.

$$GT_{XY} = \Sigma_{(Z \in C)} \min(LT_{ZY}, GQ_{XY}.TR_{XZ})$$

where GT_{XY} is the global traffic that X will actually accept from Y for all the servers in the collaboration. See [4], for more explanation about how GT_{XY} is computed.

8. Conclusions and future work

We have presented a taxonomy of various classes of agent behaviour based on abstract game theory analysis. We have proposed three distinct strategies that agents may employ in various trust-based multi-agent scenarios. These are Greedy Stochastic Strategy (GSS), Selfish Stochastic Strategy (SSS) and Best Cumulative Strategy (BCS). Although globally optimal, the BCS is usually not attainable due to its high instability in social collaboration. We have conducted studies comparing GSS and SSS. The mechanisms developed during the experimental studies on abstract game scenarios were then employed for a spam filtering scenario. The initial investigations [4] have been extended in the context of BCS, GSS and SSS. From the spam filtering perspective, BCS is not attainable because e-mail relays cannot work for local and global spam filtering at the same time. They must relay global traffic, even if it may contain, in their view, prohibited content. The GSS and SSS are similar in the selfish behavior of the sending server X which tries to maximize its own local payoff, but in SSS, X avoids to be blacklisted. Morever, the GSS would have a tendency for dramatic fluctuations in the network email traffic (throughput), causing substantial delays and email traffic rejections. This is because sending servers do not take any pro-active actions to prevent their own blacklisting, when relaying spam and various virus infected files. When employing SSS, the servers do not suffer any loss of service since it is not blacklisted, and, the overall stability of the email traffic (throughput) is maintained throughout the lifespan of a given email server.

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