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Tag Based Model for Knowledge Sharing in Agent Society

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ABSTRACT

In this paper we discuss a tag-based model that facilitates knowledge sharing in the context of agents playing the knowledge sharing game. Sharing the knowledge incurs a cost for the sharing agent, and thus non-sharing is the preferred option for selfish agents. Through agent-based simulations we show that knowledge sharing is possible even in the presence of non-sharing agents in the population. We also show that the performance of an agent society can be better when some agents bear the cost of sharing instead of the whole group sharing the cost.

General Terms

Algorithms, Design, Experimentation, and Human Factors.

Keywords

Cooperation, Altruism, Tags, Knowledge Sharing, Multi-agent Based Simulation and Artificial Society.

1. INTRODUCTION

Both human and animal societies have an innate ability to operate in groups. The baboons and the hunter gatherer societies had some well-known advantages for being a part of a group such as access to food and protection [14]. For human beings, the group mechanism has provided a social machinery that enables cooperation and collaboration easily possible. It has been observed in nature that animals that look similar form a group (e.g. schools of fish, herd of wild buffalos). Entities that belong to a group have certain characteristic (a tag) that brings them together. These tags can be differently interpreted by external observers. Our interest in this paper is to extend our work on tag-based models for group formation in artificial agent societies. For this purpose we employed a conversion-based mechanism.

Consider a scenario where there are different groups that use different techniques for cultivating a crop. The group with the best technique might have a higher yield hence this group can be considered as outperforming others. Eventually the other groups will follow the technique of the successful group. In other words, the other groups get converted to the best group (by following their technique). This is a simple example of the conversion process. This process can lead to the betterment of a society in many cases.

Another example of conversion is the adaptation of ideas. In the academic research domain, we may be influenced by ideas reported by different research groups and hence embrace valid ideas.

Thus, conversion is a powerful mechanism that has been present in human societies for a long time, such as converting people from a conquered land to adopt new customs, beliefs, skills and even religion. Traditionally, new members that are being inducted to a group take up the new skills in order to secure their survival and growth. Moreover, the strategies employed by the winning group tend to be the successful strategy (at least for the time being). In this work, we have adopted one such conversion mechanism in playing a knowledge sharing game for the betterment of the whole society.

In equitable societies, it is always best to share the cost of communal services (such as the cost of road works, setting up parks). But, in some cases, it is best for an individual to bear costs rather than dividing the whole cost to the entire society. In this work we demonstrate one such example where the whole society is better off when some individuals bear the cost.

1.1 Tags

Tagging is a group-forming technique. These tags are different from folksonomy [7] tags used in sites such as YouTube [2], CiteSeer [3]. That is collaborative tagging [7] where the user employs the tag according to his understanding of the content and the usage.

The tags we use here are different, in that they are not deposited by users with an implied meaning in a social context. The tags we use are simply markings that are "visible" to other agents and are used just for grouping purposes. Some real world tag examples are people of same culture, ethnicity, native tongue etc. Some natural tag examples are birds flocking together, animals forming herd and ants forming colony. They interact within their group; act together (pass information/instruction or whatever) and those small interactions among them lead to collective behavior/emergence. Thus the tagging mechanism that we use is inspired by nature, and it has been widely used to model the behaviour of artificial agent societies.

A simple way to think of these tags is to assume that they represent group names for sets of agents: agents having the same tags belong to the same group, and agents of the same group have some preference to interact with others within their group. Thus people are usually friendly to those who are similar to them (belong to the same group of interests, education, ethnicity, profession, culture, personality etc.). They choose their friends, partners based on certain similarities that are assumed to represent compatibility. We use this biologically inspired tagging model in our multi-agent based simulation of an artificial society.

Our concern in this paper is to experiment with tag-based mechanisms, where groups are formed using tags. Members that belong to a particular group share their skills with other members of the group. To start with, not all members in the society might be skilled in performing a task, and also not all members that possess the skill might want to share it with their group members let alone other group members. We investigate how to make knowledge sharing possible even in the presence of non-sharing selfish agents in the population.

1.1.1 Advantages of using Tags

Tags offer several advantages. Using tags is relatively simple when compared to other complicated techniques which are used to achieve cooperation/altruism. For example, other known techniques used are direct/indirect reciprocity [10], kin selection [11], centralized control systems and reputation mechanism [9].

In the reciprocity mechanism, keeping the memory of past interactions is needed. In kin selection, it is necessary to have a good recognition mechanism to identify the kin. Centralized controlling systems need a monitor to employ punishment or an incentive mechanism, which is not a good mechanism for decentralized systems, due to the explosion of state spaces. Reputation mechanisms need to record a history about peers' reputations.

In contrast, a tagging mechanism does not involve any additional overheads, such as memory storage, maintaining reputation records, and monitoring logs. It is a straightforward approach that does not even require the agents to be rational to act. Neither decision-making nor complex learning is involved.

The primary benefit of having tags is to form groups, all other benefits of tags depend on the usage and design corresponding to the domain in which it is applied. Tags are good to provide micro to macro effect in the emergence of coordination/any kind of collective behavior. They are capable of achieving cooperation in P2P systems and very scalable to any decentralized open system.

Using tags in a multi-agent based simulation of artificial society offers a good test bed for experimenting with how collective behavior can possibly emerge in natural systems.

2. RELATED WORK

Tags have been used in modeling artificial societies ever since Holland used them [1]. By playing the donation game, agents employing tagging achieved altruism in the model described by Riolo et al. [4]. In this model, tag and tolerance values are used to form groups. An agent donates to another when the difference between their tag values is within the agent's tolerance level. Also an agent could be a member of more than one group. In that case, that agent may donate to the group members of all those groups and also receive donations correspondingly. This mechanism has been shown to achieve altruism among peers because of making use of tags. Riolo et al. [8], have showed how cooperation is achieved by using tags in playing the iterated Prisoner's Dilemma game.

In Hales' work [7], different types of tags used to achieve cooperation in different scenarios, like Prisoner's Dilemma, resource-sharing and load balancing. It was shown how tags can be used to achieve cooperation among agents in a single round of Prisoner's Dilemma. The resource-sharing model explain the behaviour of altruistic agents which donate resources that they don't require. The agent needs to have a matching skill in order to harvest the corresponding resource. The agents are offered a few resources. If they possess the matching skill, then they can use that resource. Otherwise they can donate it to some other agent that needs the resource, or they can discard the resource without donating. The agents have enough intelligence to find a suitable agent within their tag group that can utilize the resource, and searching is employed in this process. When a donation occurs, it incurs a cost. It was shown that the groups which are formed with a diversity of skills had better performance. In load balancing model, it was shown that when the agents made use of tags the idle time for the agents was reduced. For more details about tags, refer to Hales's PhD thesis [6] which is about tags achieving cooperation in artificial societies.

In the work presented in [12], it is shown that how altruism based on tags can be used to promote performances for distributed P2P systems of independent agents. In the context of the knowledge-sharing game, it is shown that tagging can help to increase sharing to some extent. The work presented in [15], describes the effect of tag-based mechanism for sustaining knowledge through sharing behavior. In the context of the knowledge-sharing game, it has explained the conditions under which sharing behavior spreads in the entire society and hence the knowledge is shared and sustained in the agent society.

The inspiration for our model comes from the work of Nemeth and Takacs [13]. In their work, sharing is based on proximity. Agents share their skill with their neighbors in their locality, and this leads to the evolutionary success in their model. But that work does not embrace usage of tags.

Most tag-related work improving cooperation are done on Prisoner's Dilemma game [4, 7]. We took a mere realistic model to investigate, which deals with knowledge sharing within a society composed of sharers and non-sharers. Some tag related work has been done on resource sharing [1, 7, 8]. But knowledge sharing is different from resource sharing since resources deplete by sharing but knowledge does not. Our work falls in the category of knowledge sharing, similar to the ones presented in [12, 15].

Our model and experimental setup are explained in Section 3 and 3.1. Results and comparison are presented in 3.2. In addition, experiment about cost sharing is presented in 4 with the result. Discussion and future work are presented in section 5.

3. EXPERIMENTAL MODEL

Our model presented here is a social interaction model, where the sharing of knowledge is preferred. Agents play a game called the knowledge-sharing game.

Having 'a piece of precious information' is considered to be knowledge in this work. For example, the information about the food source or possessing a particular skill can be considered to be the knowledge which directly relates to the fitness of an agent (or the wealth of the agent).

Non-sharing is the selfish option which benefits the individual but not the society. Sharing benefits the society by spreading the knowledge, which improves the overall wealth of the society. Sharing does cost the donor who shares but not the receiver who receives the benefit. As the donating agent spends some time and effort in the process of donating, it incurs this cost. The agent could have decided to be selfish and hence conserve that cost. Donation (sharing) costs the donor (not in terms of knowledge, but in terms of wealth), and the donor does not get anything in return (no reward or benefit). Donations reduce the score (wealth) of the donor, which reduces its survival and reproduction chances.

The parameters of the experiment are Knowledge (K), Sharing (S), Wealth (W) and Tag (T).

- Knowledge (K bit) could be 0 or 1. If K=1, the agent possesses the knowledge, otherwise it does not.
- Sharing (S bit) could be 0 or 1. If S=1, the agent is willing to share, otherwise it does not.
- Wealth (W) could be 1 or below. When the agent initially possesses the knowledge, has its Wealth set to 1. But each time it shares the knowledge, it losses 0.1from its Wealth.
- Tag (T) is a string of binary bits. Agents having the same tag belong to the same group.

3.1 Experimental Setup

Among 100 individuals at the outset, half are sharers (S=1), and half are not (S=0). Every player is randomly assigned a tag which is a 3-bit string (000, 001, 010, 011, 100, 101, 110 and 111). The population has 8 (2^3) different tag groups. Out of 100 individuals initially 20 have knowledge (K=1) to start with, hence they have the wealth score of 1 for possessing knowledge. The agents in the experimental setup are of 4 different types.

- **Type K+S+:** agents with knowledge, do share (K=1, S=1)
- **Type K-S+:** agents without knowledge, do share (K=0, S=1)
- **Type K+S-:** agents with knowledge, do not share (K=1, S=0)
- **Type K-S-:** agents without knowledge, do not share (K=0, S=0)

Figure 1 shows the initial set up of the population composed of 4 types of agents. All the 8 groups get random distributions of these 4 types of players. In this game, players are randomly paired and are made to interact. When they interact, they either share or do not share. After the interaction there is conversion. For the conversion process, 10% are randomly selected and paired. In each pair stronger 5% convert the weaker 5%. This process continues in every iteration. More details about how they interact and convert are discussed later.

Sharing happens only if their tags match (they only share with their fellow group members) and when one player (player1) has the knowledge and the tendency to share (K=1, S=1) and the paired player (player 2) is without knowledge (K=0). The player who acquires the knowledge gains the wealth score 1. 1 is the maximum value of wealth that a player can have at any time in this game. Thus, if a player received the knowledge once, its wealth value can never surpass 1. When it comes to conversion, the agent with a higher wealth score is chosen when these two agents are compared on their strengths. Sharing the knowledge does cost the donor (0.1) in terms of wealth. Each time it shares, it loses 0.1 from its wealth. The receiver gets the wealth benefit of 1 without incurring cost.

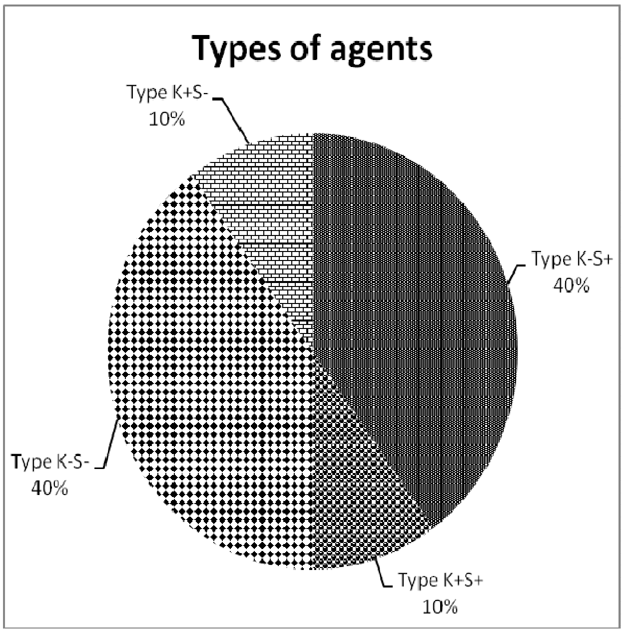

Figure 1: Initial population with 4 types of agents.

In our mechanism the behavior of the agent is independent of the tag, which means that even though the tags match, they do not have to cooperate/share. Behavior is based on the strategy bit (tag and behavior are not correlated). From the individual agent's perspective, it is better not to share, so that it can keep its score high and increase its survival chances. But for the overall society's welfare, it is good to share. The game is played with 100 players over duration of 1000 iterations. In each iteration, every player gets to play the game once as a donor (player1) and once as a receiver (player2). The conversion process at the end of each iteration works in the following way. 10% of the population is picked randomly, paired and compared by wealth score. With every pair the high scorer in wealth gets the chance to convert the low scorer to its tag group. If both players are of same wealth in a pair, one of them gets to convert by random selection. Up to this part it is the same mechanism as explained in the work [15]. The current work differs in the following steps where conversion takes place.

The winning agent converts the losing agent by adding the agent to its group (i.e the low scorer joins the tag group of the high scorer). The converted agent does not have the knowledge (K=0) when joining the new group. The converted agent retains its original behavior (S bit). Since it loses the tournament to another agent (n-tournament selection, n=2)[1], it joins the winner's group with no knowledge but retains the behaviour.

The new agents acquire knowledge when they interact with other agents in the population that have knowledge and the same tag and also have the tendency to share their knowledge. By this process, after each iteration 5% of the population gets converted. The population thus has a steady state with a value fixed at 100. The generational algorithm is given in figure 2.

```
FOR each generation
    FOR each player
        Play with a random player
        IF tags match
            Interact
            Collect payoff
        END IF
    END FOR
    Select 10% of the population
    Pair them for comparison of wealth (payoff)
    FOR each pair
        Stronger converts Weaker
        Converted one gets the tag (T) of Stronger
    END FOR
END FOR
```

Figure 2: Pseudocode of the generational algorithm.

In our algorithm, conversion does not apply for all individuals (the whole population) at the same time. In many other works the whole population converts at the same time. In nature it does not work that way. Letting the whole society convert at the same time will result in unrealistic results. In reality, conversion takes place gradually in the population. In our algorithm 10% of the population is selected randomly in every iteration for conversion.

3.2 Results and Comparison

In our results, when we say 'knowledge is sustained' it refers to the agent population where more than 85% of the agents having the knowledge and also the knowledge is passed on to the newcomers which are being converted in every iteration.

Both works [15 and the current work] have the same initial setup with 4 types of agents as shown in Figure 1. In both works, the final population (at the end of iterations) belongs to single tag group which is the strongest and all other group members have been converted to the winning group. This is the emergent behaviour observed. In the evolutionary sense, it is called as the survival of the fittest or in other words the genocide of the rest of the tag groups. Figure 3 shows the resultant behavior.

Our current results (Figure 4 and 5) show that the knowledge could be sustained in the population even with the presence of selfish agents. It is an interesting result since the society sustained knowledge all the time (100% as opposed to 16%in the previous mechanism [15]).

[1] We found tournament selection better over the roulette wheel in this setup for faster convergence.

Result from a sample run is presented in figure 4. It is shown that the number of sharers is always 50 (see the S line) and the knowledge is sustained (see the K line) in the society. Remember the experiment started with 50 sharers and 50 non-sharers. They remain the same throughout the experiments. Just that they get converted to different tag group. The Figure 5 shows the distribution of 4 types of players at the end.

The result from the previous work [15] needs to be explained here for better understanding. Previous mechanism presented in [15], has sustained knowledge at the end of iterations, only when the population gets rid of all the selfish non-sharers (S-) and composed only of sharers (S+). Whenever the population ends up with non-sharers the society could not sustain their knowledge and they become almost knowledge less society. The probability for getting knowledge-shared result is approximately 0.16. It means, not all the time, the society ended up with knowledge at the end of the iterations, but only 16 out of 100 times approximately. It was observed in [15], that the knowledge sharing is achievable only with the absence of non-sharers. A sample result is taken and shown in Figure 6 where the number of sharers increased and the whole population is full of sharers, hence the knowledge is sustained.

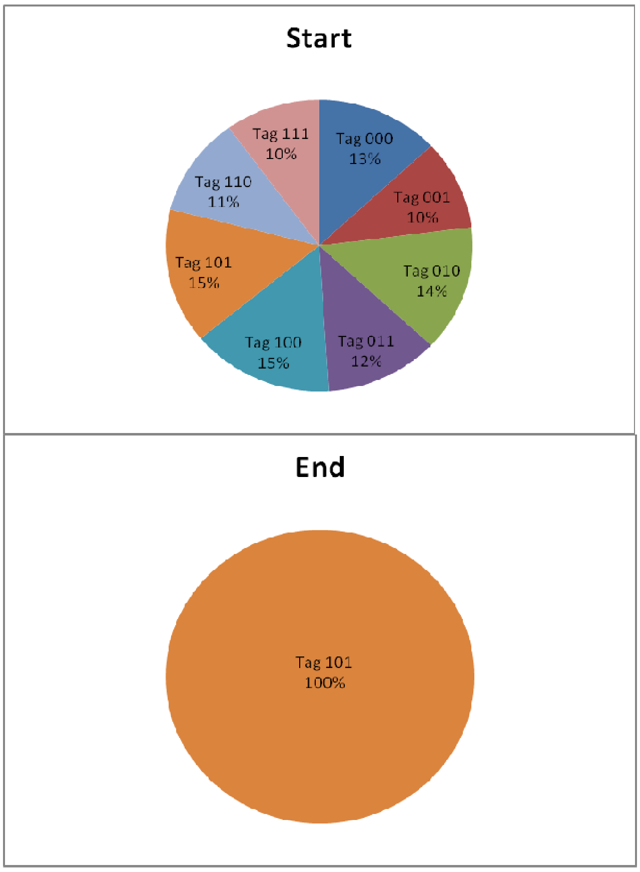

Figure 3: Initial tag groups stated with (shown in the top graph), and the final group ended with (shown in bottom graph).

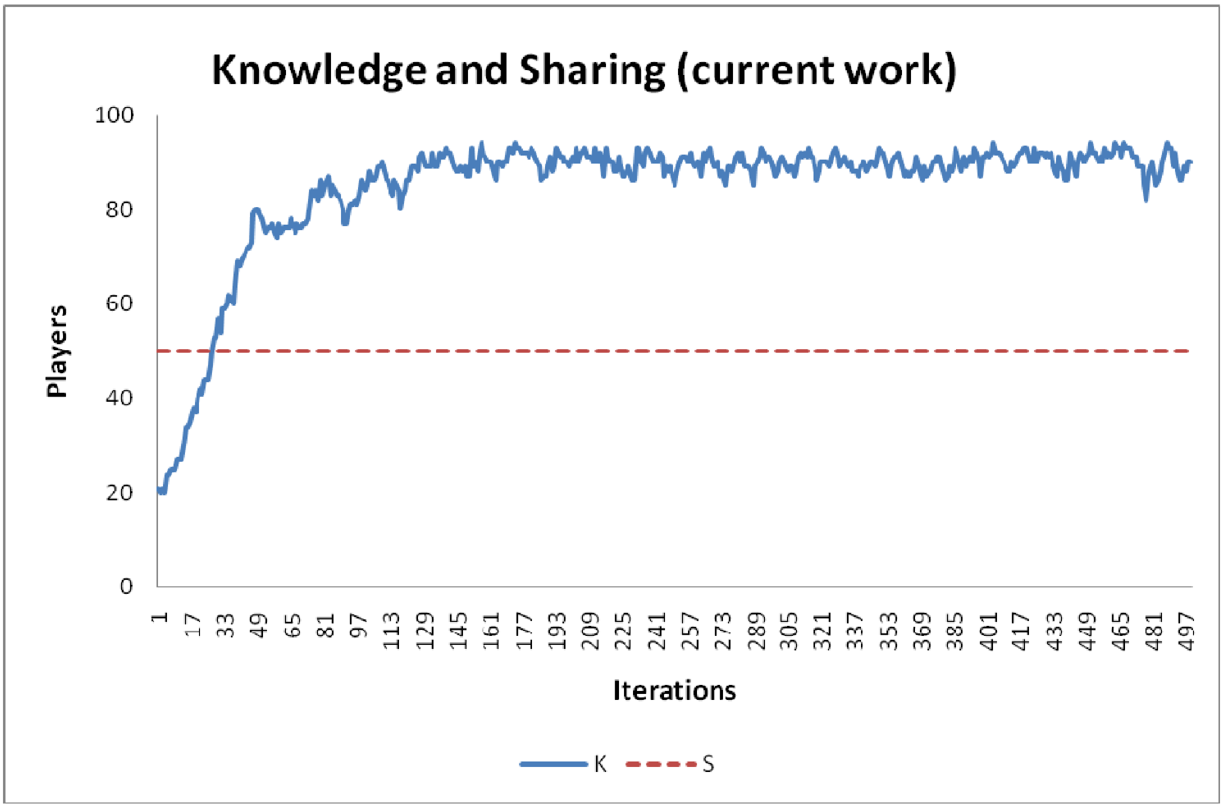

Figure 4: The K line shows the knowledge and the S line shows the sharing.

The change in the algorithm is made in the conversion phase where the new member agents retained their behavior and inherited the tag, instead of inheriting the behavior of the high scorer with tag as presented in the previous mechanism [15].

Having said that the current mechanism works better, we explain the important feature that lies in the conversion process. It is known that, in a group, K+S- players are likely to have higher score than any others in the population as they never share.

In the previous work [15], the K+S- player converts the other player to his tag group and to his behavior as a non-sharer. As a result this will lead to produce more K-S- players. The sharer from another group will be converted as a non-sharer because of his low score by incurring cost. So, the group will end up with most K-S- players and few K+S- players. As a result, the population will end up with non-sharing behavior most of the times and would not sustain the knowledge. This happens almost 84% of the times approximately.

The population will end up with sharing and knowledge only when certain conditions are met. When there is a group which could get rid of all its non-sharers and also have at least one K+S+ player who would share the knowledge with others in the group, then that group is likely to become stronger and take over others. That group will grow more and have all the players in it and also sustain the knowledge. This happens only 16% of the times approximately.

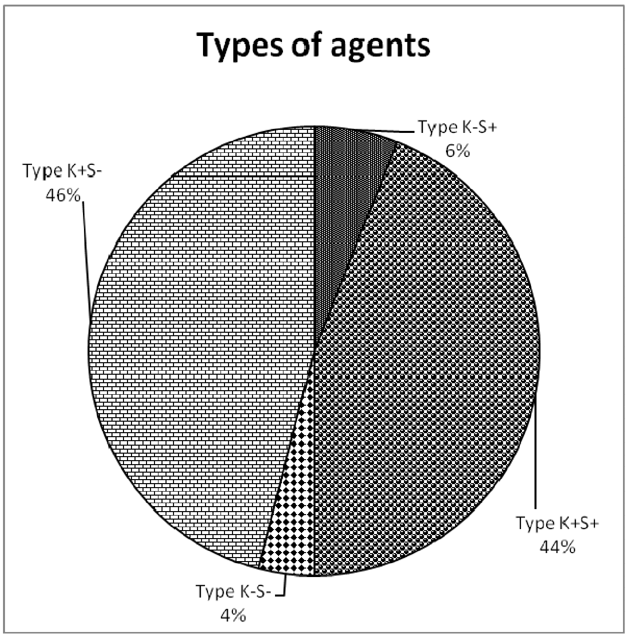

Figure 5: 4 types of agents at the end of the iterations.

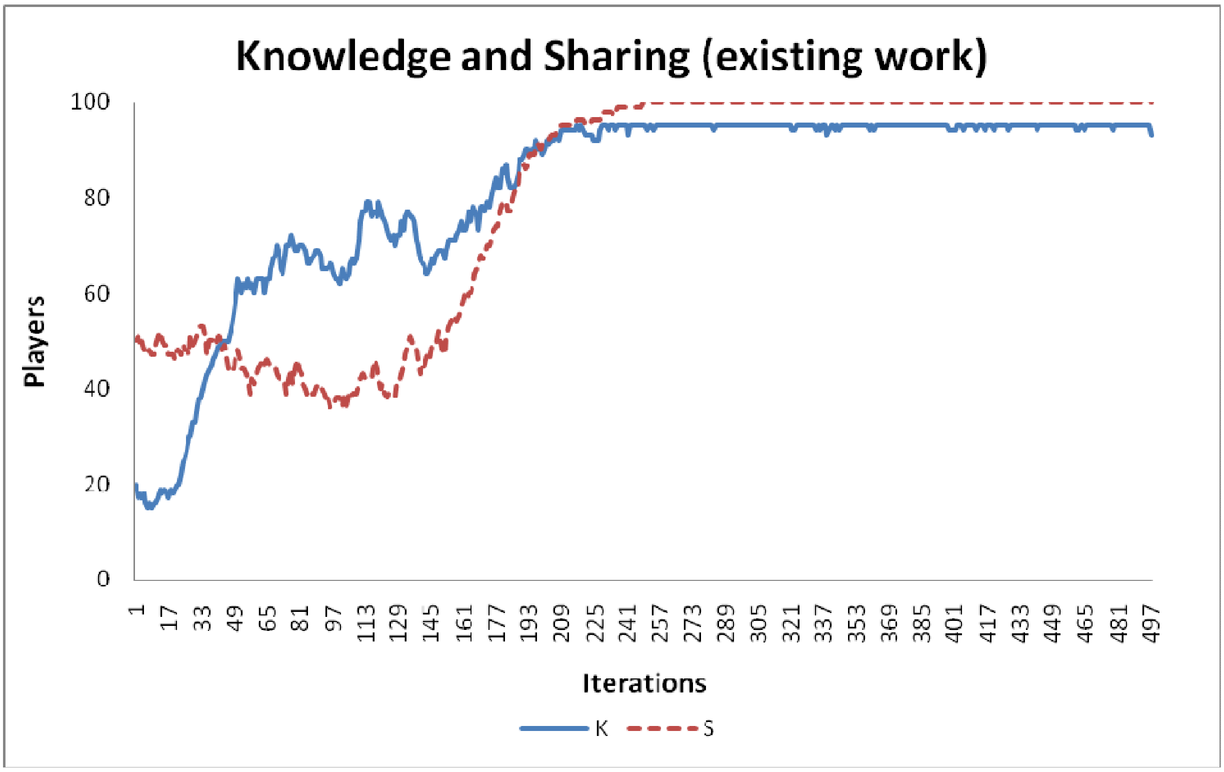

Figure 6: The K line shows the knowledge and the S line shows the sharing.

In the current work, that employs the conversion process the newcomer retains its own behavior and inherits the tag. If the newcomer is a non-sharer it comes to the new group as a non-sharer without knowledge. If it is a sharer it comes as a sharer, but does not possess the knowledge. These both cases are advantages in the current mechanism.

- If a sharer comes to the group and receives knowledge from an existing sharer in this group, he starts sharing within the group as well (K-S+ becomes K+S+).

- If a non-sharer comes to the group and receives knowledge from an existing sharer in this group, his wealth becomes 1 (K-S- becomes K+S-). As he never shares his wealth is high and he converts other players and brings new members to this group.

That is the reason that the number of sharers and non-sharers remained the same but still the knowledge sharing was made possible and was sustained and passed on for future generations. In summary, in the previous work knowledge is sustained only 16% of the runs approximately. The current experiment knowledge is sustained in all the runs.

4. EXPERIMENT ON COST SHARING

We have also experimented on individual vs. group cost bearing. In the setup explained in 3.1, the sharer who shares always pays the cost for donation which reduces its wealth. So we have used a different mechanism where the cost should not be incurred individually by the sharer alone but by everyone in the group. Everyone's wealth is reduced by *cost/n* where *n* is the number of members. We experimented with both of these cost bearing mechanisms (Individual vs. Group cost sharing) to find which is better.

We tested 2 types of cost bearing with 2 sets in a population. Each set has 4 groups. They play the knowledge sharing game within their group. In the setup explained in 3.1, the game is played with 8 tag groups with individual cost sharing. In the current experiment out of 8 groups, 4 play with individual cost sharing and 4 play with group cost sharing. We wanted to know which one is better. Figure 6 shows the pseudocode of the comparison algorithm. Except having 2 sets having different cost bearing mechanisms, everything else is the same and played in the same manner as explained in 3.1.

Set 1: Individual cost bearing
Set 2: Group cost bearing

```
IF Group belongs to Set 1
        Sharer bears the cost
        Receiver receives the benefit
END IF

IF Group belongs to Set 2
        Group members bear the cost
        Receiver receives the benefit
END IF
```

Figure 7: Cost bearing in 2 different sets (in pseudocode).

Our results showed that groups from set 1 become the winner every time. It is because when the cost is shared just by a sharer during a game, only one person's wealth is reduced, hence its survival chance is low. It could be converted to other group if it gets picked against a wealthier player.

In the other case where the cost is shared by everyone in the group, everyone loses a little of their wealth when every time there is a sharing in the group. It makes the whole group weaker and the members are prone to be converted when playing against the wealthier player.

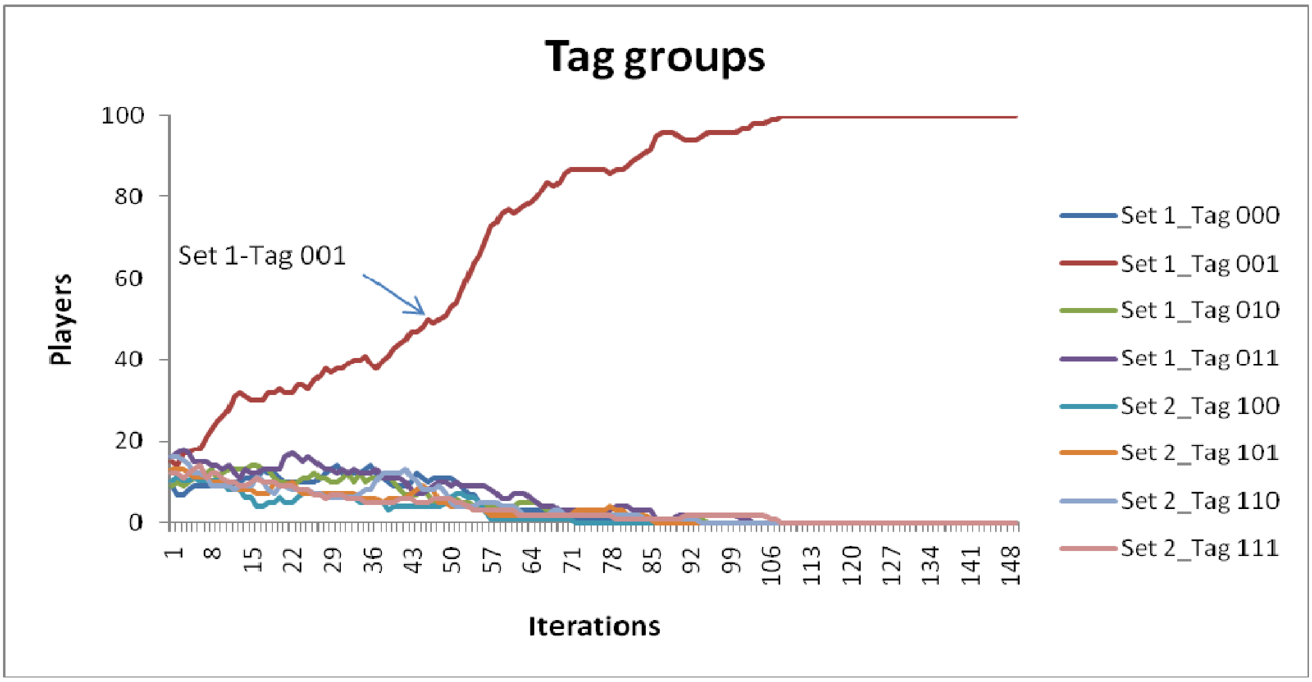

Figure 8: Tag groups from 2 sets.

In this experiment we have noticed that the individual cost bearing is effective. This is because only few people lose their wealth by bearing the cost and others who are not sharing the cost are stronger and they convert weaker players from other groups. So always the winner is a group from the set 1. A sample result is shown in figure 7. Out of 8 groups from 2 sets, the tag group 001 from set 1 became the winner which ended up with all the players getting converted to its group and sustained the knowledge in the population.

In summary, it is good for the society to have some people who can sacrifice for the well being of the group instead of everyone in the society contributing to cost sharing.

5. DISCUSSION AND FUTURE WORK

In this paper we have presented our results about how a society could share and sustain knowledge even in the presence of selfish agents that are present in equal proportions. We have also showed that bearing the cost individually is a better option than bearing the cost across the whole group.

The results reported here are in the progressive stages of our more in-depth experimental investigations. There are several interesting research issues in this domain. In future work, we consider the following.

- In this paper we have considered effects of individual vs. group costs for sharing the knowledge. Another dimension that needs to be experimented with is the Wealth (W) of the agent. We would like to investigate whether group wealth or the individual wealth mechanism should be adopted for improving social welfare in multi-agent system.
- We are currently experimenting with an agent population having multiple knowledge bases. For example society A can have knowledge *x* and *y* while society B can possess knowledge *m* and *n*. It would be interesting to see how different types of knowledge or skills can be shared in an agent society. This might be useful in the context of P2P applications.
- In the current setup, agents interact only if the tags match. If the tags don't match, they do nothing. We are interested to see how agents act accordingly if the tags match/do not match. This is achieved by making agent do certain actions even if their tags do not match which does not directly contribute to the wealth.
- We are also currently investigating how a tag can be interpreted in different ways by different types of observers.

6. REFERENCES

[1] Holland, J.H.: The Effect of Labels (Tags) on Social interactions. Vol. SFI Working Paper 93-10-064, Santa Fe Institute, Santa Fe, NM (1993)

[2] YouTube, www.youtube.com

[3] CiteSeer, http://citeseer.ist.psu.edu

[4] Riolo, R.L., M.D. Cohen, and R. Axelrod.: Cooperation without Reciprocity. Nature 414, 2001: pp. 441--443 (2001).

[5] Hales, D.: Evolving Specialisation, Altruism and Group-Level Optimisation Using Tags. Multi-Agent-Based Simulation II: Third International Workshop, MABS 2002, Bologna, Italy, July 15-16, 2002, Vol. 2581, Lecture notes in computer science, pp. 26--35, Springer Berlin / Heidelberg (2003)

[6] Hales, D.: Tag Based Co-operation in Artificial Societies. Ph.D. Thesis, Department of Computer Science, University of Essex, UK, 2001.

[7] Folksonomy , http://en.wikipedia.org/wiki/Folksonomy

[8] Riolo, R.L.: The Effects of Tag-Mediated Selection of Partners in Evolving Populations Playing the Iterated Prisoner's Dilemma. 1997, Santa Fe Institute.

[9] Nowak, M.A. and K. Sigmund.: Evolution of indirect reciprocity by image scoring, Nature vol. 393, pp. 573--577 (1998)

[10] Trivers, R: The Evolution of Reciprocal Altruism, Quarterly Review of Biology 46 pp.35-57 (1971)

[11] Hamilton, W. D.: The genetical evolution of social behaviour. I, Journal of Theoretical Biology, 1964 Jul; 7(1):1-16.

[12] Savarimuthu, S., Purvis, M. A., Purvis, M. K., “Altruistic Sharing using Tags”, Proceedings of the 6th International Workshop on Agents and Peer-to-Peer Computing, Estoril, Portugal, May 2008 (in press).

[13] Németh, A. and K. Takács.: The Evolution of Proximity Based Altruism, Department of Sociology and Social Policy, 2006, Corvinus University of Budapest, Budapest.

[14] Clutten-Brock, T. H., and Parker, G. A.: Punishment in animal societies. Nature 373 (1995), 209 – 216.

[15] Savarimuthu, S., Purvis, M. A., Purvis, M. K., “Emergence of Sharing Behavior in a Multi-agent Society using Tags”, Proceedings of IEEE/WIC/ACM International Conference on Intelligent Agent Technology (IAT 2008), Sydney, Australia, December 2008 (in press).