Wisdom of Crowds in the Prisoner's Dilemma Context

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Abstract

This paper provides a new way of making decisions– using the wisdom of crowds (collective wisdom) to handle continuous decision making problems, especially in a complex and rapidly changing world. By simulating the Prisoner's Dilemma as a Complex Adaptive System, the key criteria that separate a wise crowd from an irrational one are investigated, and different aggregation strategies are suggested based on different environments.

1. Introduction and Background

Decision-making has been the subject of research from several perspectives. From a cognitive perspective, the decision making process is regarded as a continuous process characterized by the interaction with the environment. From a normative perspective, the analysis of individual decisions is concerned with the logic of decision making and rationality and the invariant choice it leads to [2]. Generally speaking, decision making is the process of selecting one course of action from several alternative actions. It involves using what you know (or can learn) to get what you want [3]. The decision making techniques used in everyday life include 1) flipping a coin, 2) asking friends or experts, 3) evaluating the disadvantages and advantages, 4) performing the cost-benefit analysis, etc. Since decision-making involves expertise, information, experience, emotions, relationships, and goals, many computer-based Decision Support Systems are promoted to help people make decisions in complicated situations for either individual or business purposes. Although knowledge-based decision support systems have been widely used, managers sometimes feel disappointed with their performance because of: 1) difficulties in collecting useful information in a specific field; 2) the cost of setting up and updating knowledge databases; 3) inherent inadequacies in dealing with complex and rapidly changing environments; and 4) difficulties in determining the proper decision-making model/strategy, especially for problems in social sciences or economics which involve numerous human interactions and uncertain personal feelings. With these concerns in mind, a new concept for making decisions is introduced-- the (modified) wisdom of crowds.

The idea of using the wisdom of crowds for decision-making is originally introduced by J. Surowiecki [1]. In the book, he argues that under certain circumstances the performance of a crowd is often better than that of any single member of the group. This idea appears to be appropriate for explaining the behavior of financial markets as expressed by the Nobel-winning economist William Sharpe [5]. Similarly, the concept of "wise crowds" might be useful to decision makers to solve complex problems. For example, collective voting has already been successfully used by some search engines, including Google [6]. Even though there are many case studies and anecdotes which demonstrate the importance of collective wisdom, there are also authors supporting the opposite conclusion, some of them cited in the text “Extraordinary Popular Delusions and the Madness of Crowds,” by Charles MacKay [7]. Since Surowiecki dealt with these concerns in his book, we will not repeat those arguments here.

In the following sections, Surowiecki’s theory is extended to address a continuous decision-making problem, one that deals with a complex and rapidly changing world with interactions. The key criteria separating the wise crowd from the irrational one are investigated using a computer-based simulation. Also, the ability to learn is added to make both individuals and crowds “smarter” over time. Finally, a relationship between the size of crowds and their performance (aggregation strategies) is suggested for varying environments.

2. Methodology

In this paper, a simulation using the framework of Complex Adaptive Systems is designed and implemented to demonstrate the wisdom of crowds in the context of the Prisoner’s Dilemma problem. The Prisoner’s Dilemma is a type of non-zero-sum game developed in the game theory. The basic idea is for two suspects who committed a crime to decide whether to “cooperate” with each other or to “defect.” Cooperating is the best outcome for both--they go free as there is no proof that they committed the crime. However, as they do not trust each other, they are enticed to defect from the agreement and confess the crime, thus getting a lighter sentence than their partner in crime. Of course, the worst-case scenario is if they both defect, thus securing a lengthy prison sentence for both.

In order to establish a crowd, we extended the two-player game into a many-players situation. Our Prisoner's Dilemma game involves hundreds of players (crowd) playing against each other pair-wise, which allows for exploration of various aggregation strategies. The details describing the Prisoner's Dilemma in this context are introduced in Section 3.

The Complex Adaptive System (CAS) framework represents a dynamic network of agents (representing cells, species, individuals, firms, nations, etc.) acting in parallel, while constantly reacting to what the other agents are doing [8, 9]. A system is considered complex if it is agent-based and exhibits non-linear behavior, feedback loops, self-organization, and emergence [10]. Such a system is considered adaptive if it has the capacity to change and learn from experience.

The control in a CAS is distributed. Any coherent behavior of the system has to arise from the competition and cooperation among the agents (constituent parts) themselves. The overall behavior of the system is a result of the decisions made by individual agents in each cycle [8]. The system often exhibits the property of self-organization. Self-organization is a process in which the internal organization of the system increases in complexity without being guided or managed by an outside source. Self-organizing systems frequently demonstrate emergent properties [9].

Examples of CAS include the stock market, social insect and ant colonies, the biosphere and the ecosystem, the brain, the immune system, and any human social group-based endeavor [11-13]. Hence, it is natural to describe the Prisoner's Dilemma as a complex adaptive system in order to reveal spontaneous reactions among individual players, as well as the wisdom hidden inside the group as a whole.

3. Wisdom of Crowds in the context of Prisoners' Dilemma

3.1 Theories of Wisdom of Crowds

A "crowd" in Surowiecki's book [1] is any group of people who can act collectively to make decisions and solve problems. The wisdom of crowds theory simply suggests that a collective can solve a problem better than most of the members in the group can by acting alone. As MacKay [7] pointed out, not all crowds (groups) are wise. One needs to look no further than the stock market and its many examples of fads and market bubbles. Consequently, efforts have been made to understand under what circumstances the wisdom of crowds may take effect. Surowiecki suggests the following key criteria to separate wise crowds from irrational ones [1]:

- *Diversity of opinion* - Each person should have private information even if it's just an eccentric interpretation of the known facts.
- *Independence* - People's opinions aren't determined by the opinions of those around them.
- *Decentralization* - People are able to specialize and draw on local knowledge.
- *Aggregation* - Some mechanism exists for turning private judgments into a collective decision.

Three distinct problems have been specified in which crowds may be smarter than individuals [1]. The first is a *needle-in-the haystack* problem where some people in the crowd may know the answer while many, if not most, do not. The second is a *state estimation* problem, where some person may get lucky to hit the precise answer (while not being aware of their "accuracy" in advance), but the group does not. Finally, there is a *prediction* problem, where the answer has yet to be revealed [14, 15]. For the prediction problem, the unrevealed answer can be either fixed (e.g., the prediction of the next Oscar winner does not change the answer itself) or it can be "fluid" (e.g., the return on your next investment where your action might affect the answer).

The well-known example for the "needle in the haystack" problem is the show "Who Wants to Be a Millionaire." In this show, a contestant is asked a series of multiple-choice questions leading to the ultimate prize of $1M. The contestant can choose from one of three options for getting help to answer the question she does not know: (1) eliminate two of the four possible answers, (2) call a predetermined "expert" for counsel, or (3) poll the studio audience. The results show that the experts provide the correct answer a respectable two-thirds of the time, while the audience – a group of folks with nothing better to do on a weekday afternoon – return the correct answer over 90 percent of the time. The success of polling lies in the fact that, assuming randomness in the answers provided, even a small percentage of the people in the crowd who know the correct answer can add a noticeable advantage to that answer, which helps it stand out using the majority rule.

The "stated estimation" problem normally defines the "guess a quantity number" situations. An interesting characteristic of this type of problem is that although one or several of the crowd members may come close to predicting the correct value/quantity of the target variable, none of them know it for sure when they offer the guess. The well-known example is the "Francis Galton's surprise." The crowd at a county fair was asked to guess the weight of an ox that was exhibited at the fair. The person with the most accurate answer was promised a prize. Everyone tried his or her best to provide the right answer, while maintaining the secrecy of the guess. The participants included some experts (e.g., butchers) and many non-experts. It was obvious that the experts stood a better chance of wining the prize than the non-experts. However, since the target number was a continuous/real number, the non-experts still had a small chance of hitting the most precise number by luck and win the competition. To his surprise, Galton discovered that the average of all the responses was, in fact, closer to the ox's true butchered weight than the individual estimates of most crowd members, including those made by the cattle experts.

Let's look closer into this stated estimation problem. The collective error can be described as [14]:

Collective error = Average individual error – Prediction diversity

The average individual error combines the squared errors of all of the participants, while the prediction diversity combines the squared difference between the individuals and the average guess. This equation tells us [14]:

1. The crowd's aggregate prediction is always better than those of most individuals in it, regardless of whether the crowd has a normal or skewed distribution of answers. Sometimes it can even be better than the best individual, given enough diversity in the right direction.
2. We can reduce the collective error by either increasing the accuracy or increasing the diversity of the crowds.

Other types of problems have been grouped into the third category: the prediction problems. An interesting story is told in Surowiecki's book [1], regarding a submarine lost at sea. The task was to locate the submarine with a very limited knowledge of when and under what weather conditions the submarine went down. A group of specialists with a wide range of expertise was asked to offer their best independent/individual guesses regarding the various scenarios for submarine's trajectory in the last moments. Although no one knew exactly what happened, by building a composite picture of the projected submarines movements a remarkably accurate guess was formed and the submarine was found. In this case, even though no single individual in the group knew any of the exact answers, the group as a whole produced them all. This story suggests that even if the crowd is not aware of how much useful information each individual has, the appropriate aggregation of partially available information can provide the best answer.

In order to test this idea, we designed and implemented a simulation that can aggregate information from a “crowd” in the context of the Prisoner’s Dilemma problem. Furthermore, this simulation is used to explore the effectiveness of the wisdom of crowds when the right answer is not fixed, but rather a continuous decision-making is called for. The following sections provide the details of the simulation.

3.2 Wisdom of Crowds in the Prisoner’s Dilemma Game

Since it was first raised by Merrill Flood and Melvin Dresher in the 1950’s [16], a lot of research has been done on the Prisoner's Dilemma (PD) problem, especially after Robert Axelrod introduced the concept of the iterated prisoner’s dilemma in his book “The Evolution of Cooperation” [17]. The PD is a typical type of non-zero-sum game explored in the game theory, based on the well-known expression of PD, the Canonical PD payoff matrix [17], which shows the non-zero net results for the players.

	Player B		
Player A		Cooperate	Defect
	Cooperate	3,3	0,5
	Defect	5,0	1,1

Some of the best-known strategies for solving this game are listed below [17,25]:

- *Tit-For-Tat* -- Repeat opponent's last choice
- *Tit-For-Two-Tats* – Similar to Tit-For-Tat, except that the opponent must make the same choice twice in a row before it is reciprocated
- *Grudger* -- Co-operate until the opponent defects. Then, always defect (unforgiving)
- *Pavlov* - Repeat the last choice if it led to a good outcome
- *Adaptive* - Start with the set of pre-selected choices (c, c, c, c, c, c, d, d, d, d, d) , then after the initial 11 moves, select actions which give the best average score; re-calculated after each move

Finding the strategy to gain the highest number of points is the ultimate problem for the Iterated Prisoner's Dilemma game. Every year, the IPD tournament [18] is held to evaluate strategies from different competitors. Also, the genetic algorithms have been widely used [19, 20] to discover the best strategy. Currently, memory- and outcome-based strategies such as Tit-For-Tat [21] and Pavlov [21] are regarded as the most effective ones [22-25].

Extending the "two-player" game to the "many players" context brings about the situation where hundreds of players (a crowd) play together/against each other. With no central control, players begin to play "cooperate" or "defect" based on their own strategies. After each round, points are added up for each player. Consequently, a potential "smart" crowd is formed. This decentralization of strategies for playing is interpreted as a set of diverse opinions held in the crowd.

Then, a simple polling of playing strategies serves as the aggregation method for understanding the vote/wisdom of the crowd.

As opposed to the needle-in-the-haystack problem and stated estimation problem, Prisoner's Dilemma states a different type of problem -- dynamic prediction problem [14]. The term "dynamic" is used because the outcome is influenced not only by each play, but also by each player's history of previous predictions. The introduction of this "dynamic" process helps us evaluate performance of various strategies in different crowds over time, which is similar to the decision-making process or cognitive behavior of agents in the real life.

Although more complicated, the participating crowd in the context of Prisoner's Dilemma satisfies the four key criteria to get a smart crowd:

a. Diversity and Decentralization

Page [14] divides diversity into four frameworks:

- Perspective: ways of representing situations and problems
- Interpretations: ways of categorizing or partitioning perspectives
- Heuristics: ways of generating solutions to problem
- Predictive Models: ways of inferring causes and effects

Definition for decentralization is the dispersion or distribution of functions and powers, specifically the delegation of power from a central authority to regional and local authorities. As one of the key criteria forming a smart crowd, decentralization emphasizes that people are able to specialize and draw on local knowledge [14].

In the Prisoner's Dilemma setting, each agent is given a memory and a strategy. The memory serves to record and accumulate new knowledge, which represents diversity in two ways: the agent's game history with a certain player, and the accumulation of local knowledge. The agent's strategy is the ability to choose either to cooperate or to defect based on the information stored in the memory. The strategy also represents diversity in two ways: diversity in the ways of generating solutions to the problem, and diversity in the ability to draw conclusions from the local knowledge, since the agent does so without the preset upper-level/centralized guidance. This diversity and decentralization among the agents are guaranteed through the combination of interpretations and heuristic frameworks described above, as well as through the process of dispersed decision-making.

b. Independence

The Prisoner's Dilemma as played in our system (the Iterated Prisoner's Dilemma) allows communication between, and learning from other, agents. This aspect is fundamentally different from Surowiecki's approach. However, we still provide a "controller" for ensuring agent independence in the system, which enables us to experiment with both independence-securing and learning-enabling environments.

c. Aggregation

Aggregation means combining outputs/solutions from different entities into higher-level entities. In the Prisoner's Dilemma game, aggregation assumes deriving a group-level solution by combining the individual members' contributions (or solutions), regardless of whether these contributions are duplicate, contradictory, or incomplete. The most commonly used methods for this type of aggregation are sampling, polling, and voting.

3.3 Implementation

In order to design a CAS for the Prisoner's Dilemma game, first we need to create: 1) individual "player-agents" who can "cooperate" or "defect" when playing the game based on their own strategy, and 2) special "aggregator-agents" who represent the wisdom of crowds by acting as aggregators of various groups within the crowd of agents. These aggregators also participate in the game, but they have a different decision-making procedure. Since agents play against each other repeatedly without a central control (via random selection), we assign each agent a memory that is used to store information (knowledge) about their previous "matches." The player-agents initially "receive" a randomly allocated strategy that they use to select their actions, based on the information they have. The aggregator-agents are given the ability to make their decisions upon consulting with their "advisory group," formed from the set of player-agents selected by each aggregator-agent.

The question now becomes: what kind of strategies should be available to the agents? One way to approach this problem is to understand how humans perceive and approach problems. This is obviously related to human personality factors. Raymond Cattelle's suggests that there are 16 personality factors [26] that influence human perception of and approach to problems. To keep things manageable in this project, we selected three personality factors to describe the way people perceive problems: dominance, vigilance, and openness to change.

a. Dominance

Agents that are less dominant are: deferential, cooperative, adverse to conflict, submissive, humble, obedient, easily led, docile, and accommodating. An agent that is perceived as dominant is characterized as: forceful, assertive, aggressive, competitive, stubborn, and bossy.

b. Vigilance

Agents low in vigilance indicate behavior that is: trusting, unsuspecting, accepting, unconditional, and easy-going. A highly vigilant agent is characterized as suspicious, skeptical, distrustful, and oppositional.

c. Openness to change

Not-so-open-to-change agents are defined as: traditional, attached to the familiar, conservative, and respectful of traditional ideas. Highly open agents are defined as: analytical, critical, freethinking, and flexible.

In the Prisoner's Dilemma simulation, the action of each agent includes methods for perceiving and solving problems. The methods for perceiving problems can be described by considering the questions described in Figure 1:

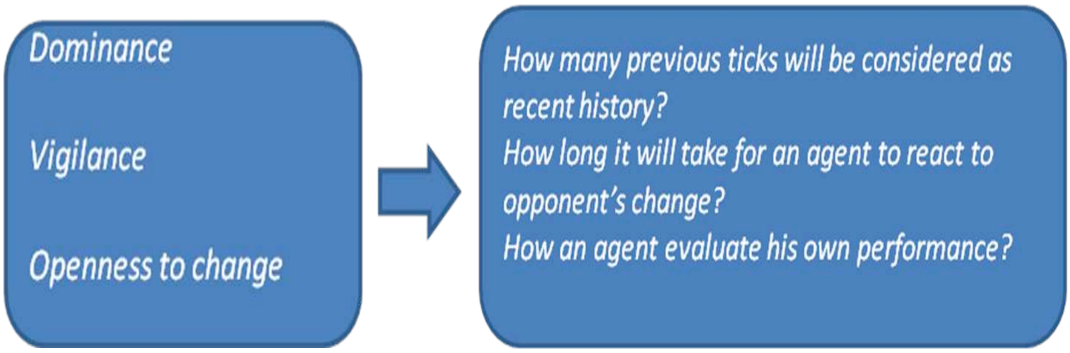


Figure 1: Personality vs. Action Mode

a. How many previous ticks will be considered as a recent history?

Agents with a "conservative personality" prefer consulting a longer history; otherwise they are open to change and only care about the most recent history.

b. How long will it take for an agent to react to an opponent's change in behavior?

Agents with a "vigilant personality" are more suspicious of negative behavior. They are also easier to make hostile. Otherwise, they are less sensitive to betrayal.

c. How does an agent evaluate his own performance?

Agents with a "domineering personality" are more aggressive and competitive, thinking of their opponents relative to their own gain or loss. Otherwise, they care only about their own absolute gain.

The methods for solving problems can be described with the following rules[4]:

a. Repeat the opponent's last action

b. Assume an action opposite to the opponent's last action

c. Co-operate

d. Defect

e. Repeat own last action

f. Assume an action opposite to your own last action

Consequently, in the system each player-agent is described using a chromosome-like structure: [4]

Agent Number	Basic Strategy	Limitation	Reaction1	Reaction2

Where:

- *Agent Number* identifies each player.
- *Basic Strategy* indicates the strategy an agent chooses to guide its behavior.
- *Limitation* modifies the Basic Strategy as described below. Taken together, these two numbers define the judgment of the situation the agent is facing.
- *Reaction1* defines the behavior of the agent if the situation described by Basic Strategy + Limitation applies in the current case/match.
- *Reaction2* defines the behavior of the agent if the situation described by Basic Strategy + Limitation does not apply in the current case/match.

There are five basic strategies:

0. The agent does not care what happened before.
1. The agent takes into consideration the total number of times the opponent cooperated or defected in the past.
2. The agent takes into consideration whether during the previous X number of matches/time (X defined by Limitation) the opponent cooperated or defected (X

times in a row).

3. The agent takes into consideration the average number of points it got previously by cooperating/defecting when playing against the same opponent.
4. The agent takes into consideration whether the number of points it got from the last play is less than three points.

Reaction1 and Reaction2 can assume one of the following values:

0. Repeat opponent's last action
1. Assume an action opposite to opponent's last action
2. Co-operate
3. Defect
4. Repeat own last action
5. Assume an action opposite to its own last action

For example, Competitor 001 shown below simply repeats the opponent's last action. This is a typical Tit-for-Tat.

001	0	0	0	0

Competitor 101 repeats the opponent's last action if its' opponent cooperated the last two times/matches; otherwise it chooses an action opposite to its own last action.

101	2	2	0	5

As can be seen from the above, our agents do not simply "cooperate" or "defect." They choose to "repeat" or "reverse" an action performed earlier either by their opponents or by themselves. This may be more similar to the way people behave in real life. This process also aggregates redundant strategies often present in evolutionary algorithms.

Another parameter, "forgiveness," could be added to the chromosome to represent the random or predefined chance to cooperate (when defecting for a long time) or to defect (to test the opponent after cooperating for a long time). Using "forgiveness" the chromosome could represent even a greater variety of strategies.

Also, the parameter called "history-weight" is added to the chromosome to represent the different attitudes that agents could have regarding their own history. They may choose to regard every match in their entire history equally, or they may adjust how much emphasis they want to put on either their earlier matches or their most recent ones.

Aggregator-agents represent special participants (competitors) in the game. On each turn, aggregator-agents choose to cooperate or to defect according to the opinions from their chosen player-agent group. Unlike the regular player-agents, aggregator-agents have no strategy that can give them guidance regarding cooperation or defection; their only strategy is to decide (a) which player-agent group they want to listen to, and (b) the manner in which they plan to aggregate the group's advice.

Each Aggregator-agent is described using a chromosome-like structure:

Agent Number	Selection Strategy	Select_Number	Aggregation Strategy

Where:

- *Agent Number* identifies each aggregator-agent.

- *Selection Strategy* indicates the strategy used to select a player-agent group.
- *Select_Number* indicates how many player-agents are chosen to form the group; it can be any number between 1 and the total number of player-agents.
- *Aggregation Strategy* indicates the strategy used for aggregation.

There are 4 selection strategies:

1. The agent chooses the top Select_Number player-agents ranked by points.
2. The agent chooses the bottom Select_Number player-agents ranked by points.
3. The agent chooses the top N and bottom (Select_Number–N) player-agents ranked by points.
4. The agent chooses Select_Number player-agents randomly.

There are 2 aggregation strategies:

1. The agent chooses the majority opinion
2. The agent chooses the minority opinion

As shown in Figure 2, all agents are scattered randomly in the display area (90*90 grid in the NetLogo environment) with player-agents represented by red dots and aggregator-agents represented by yellow person-shaped images. A set of basic strategies are assigned randomly to each agent. Agents move randomly in the display area (the speed of agents can be changed via the control panel). If two agents happen to be in the same neighborhood (8-neighbor grid) a meeting is initiated. Agents play a match based on the strategy they follow and the information they have about each other. After each play, the points are added and the agents move on to the next match [4].

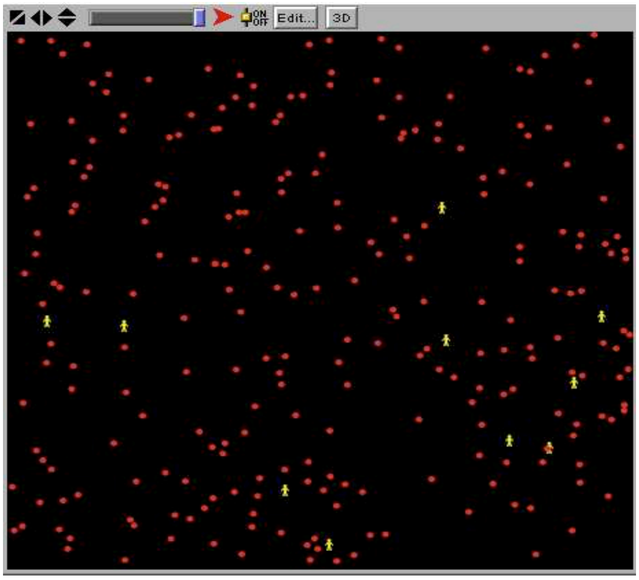


Figure 2. Application

4. Experiments

We have conducted numerous experiments to demonstrate the power of the (expanded) wisdom of crowd concept. This section provides a summary of the four major groups of experiments.

4.1 Experiment 1: Player-agents' performance in fixed crowds

In this experiment, we focus on the player-agents' performance in fixed crowds, where "fixed" denotes the same group of players playing the whole time, and no evolution or learning takes place. These settings satisfy all four of Surowiecki's criteria.

The performance of the player-agents is summarized in Figure 3. The jagged blue line shows the highest average-score (the winner's score). For each player-agent, the average-score is calculated as the total number of points gained from all the plays, divided by the total number of plays. The purple line shows the average of player-agent average-scores. It is computed as the sum of average-scores divided by the number of all player-agents, thus outlining the average performance of the whole society of agents. Finally, the black line shows the basic strategy, denoted by its numerical representation, chosen by the player-agent winner [4].

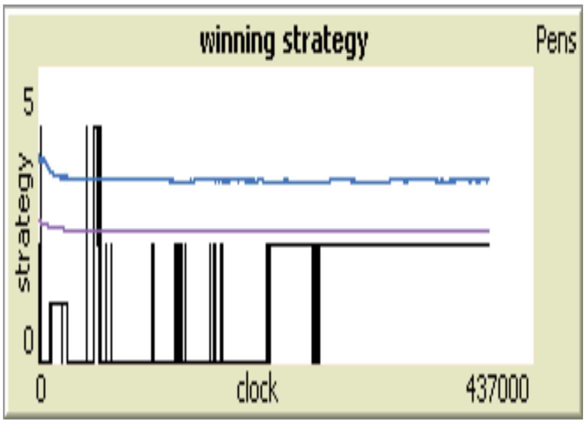


Figure 3: Player-agents' performance in fixed crowds

The chart in Figure 3 shows a smooth line for the best performance with a score slightly above 3, while the average performance records a score of slightly below 3. In this fixed society, the best performer is a greedy player who takes advantage of the "naïve" cooperating players by defecting all the time. The best recommendation for the aggregator-agent, therefore, is simply to listen to the best player-agent; i.e., always defect [4].

The reason that this society remains stable is because neither the player-agents nor the whole crowd has a goal (fitness function), which in the real life rarely happens.

So we introduce such a goal in the later experiments.

4.2 Experiment 2: Player-agents' performance in evolutionary crowds

In this experiment, we focus on the player-agents' performance in evolutionary crowds, where "evolutionary" means every certain number of steps/plays some of the players are replaced with preferred (higher scoring) player-agents. The whole society/crowds try to reach the goal--obtaining higher scores by eliminating the less competitive player-agents. These setting also satisfy all four of Surowiecki's criteria.

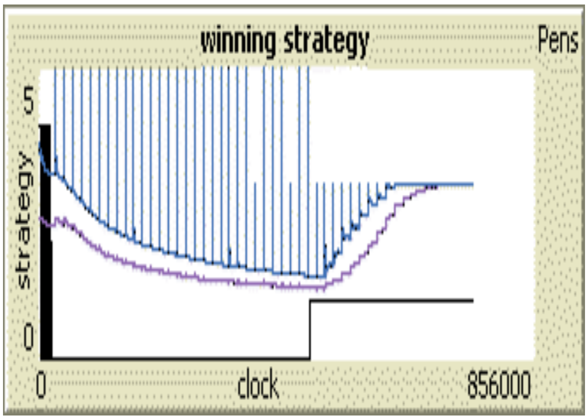


Figure 4: Player-agents' performance in evolutionary crowds

The chart in Figure 4 shows more volatility as the crowd is changing over time. The player-agents with the highest score gradually replace the lowest scoring agents. In the beginning, evolution shows preference for the greedy players and eliminates the naïve ones. This causes the score of the best performers to decrease and the average score to increase, thus making the crowd "smarter." Later on, after retaining too many greedy players and no naïve ones, the greedy ones die out and are replaced by those who are "smart" enough to both cooperate and defect according to a specific situation. The crowd thus ends up with the score of 3, which suggests that the final outcome/strategy is to "cooperate," and the best decision recommended for the aggregator-agent is simply to cooperate [4].

4.3 Experiment 3: Player-agents' and Aggregator-agents' performance with the learning ability in evolutionary crowds

Adding the learning ability to the player-agents enables them to learn individually and to improve their decisions. Although this violates one of Surowiecki's criteria –independence – it is crucial for success in real life. Experiments show that by keeping enough diversity of opinion in the crowd, the aggregate wisdom of the crowd can still perform better than most individual members, even better than the best individual. Consequently, in this experiment we focus on the player-agents' performance with learning ability in evolutionary crowds.

Each experiment was run ten times with a different random seed. During each round, 250 player-agents were placed on the grid. After player-agents had had a chance to play against and learn from each other for a certain learning period, the aggregator-agents with different strategies were introduced into this game. Aggre1, 5, 9.., 250 represent the aggregator-agents with different aggregation strategies. For example, an aggregator-agent whose strategy is to consult player-agents with the highest scores may choose to follow the advice of the group of player-agents having the current highest score, and we call it aggre1. This is likely a wise strategy for the aggregator-agents. Similar strategies include the best players, median players, and average players.

The charts in Figure 5 show the performance of player-agents and aggregator-agents, after certain duration of learning, using ten different seeds (formation of crowds).

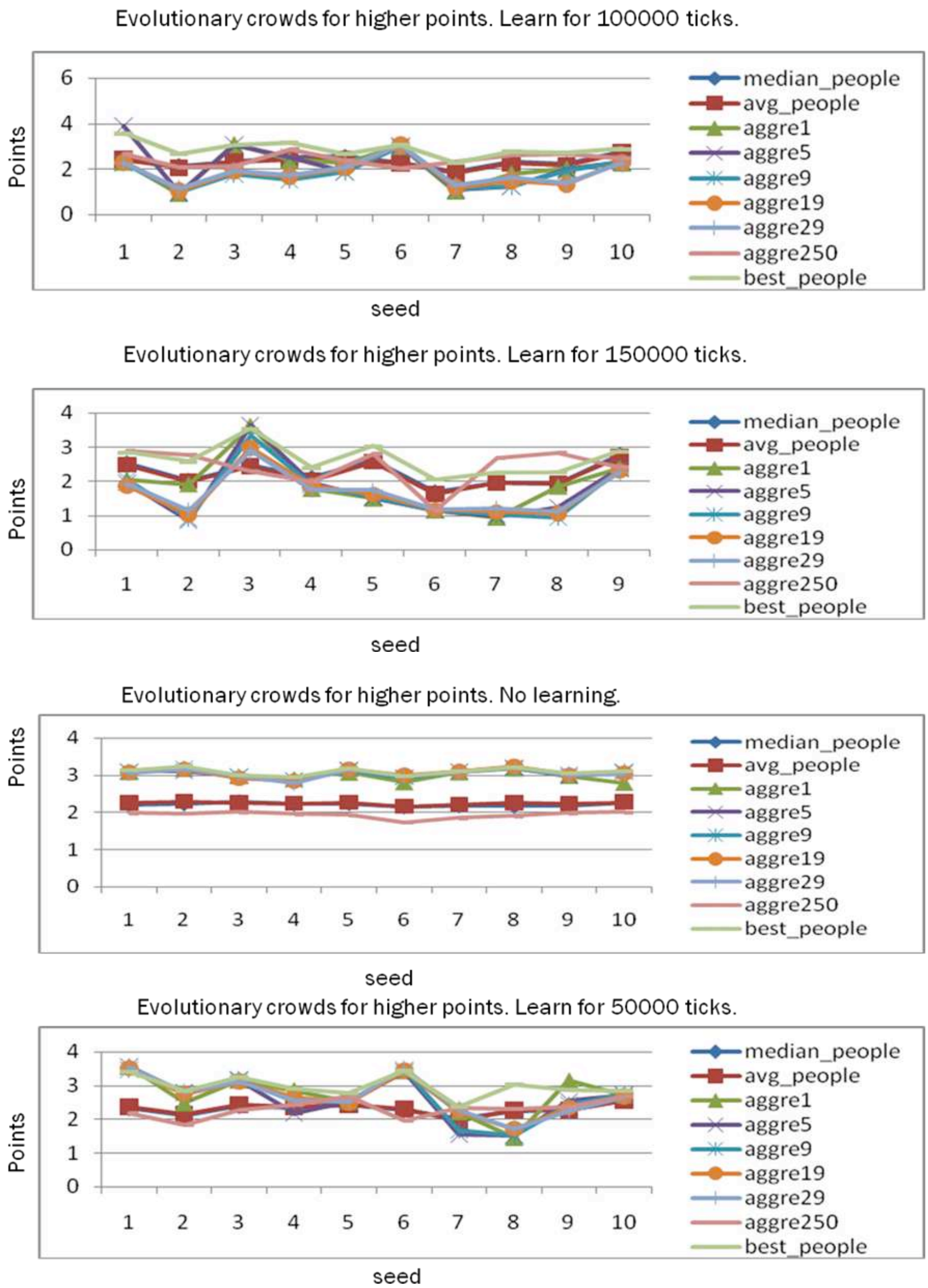


Figure 5: performance of Player-agent and Aggregator-agent in different seeds varying in duration of learning

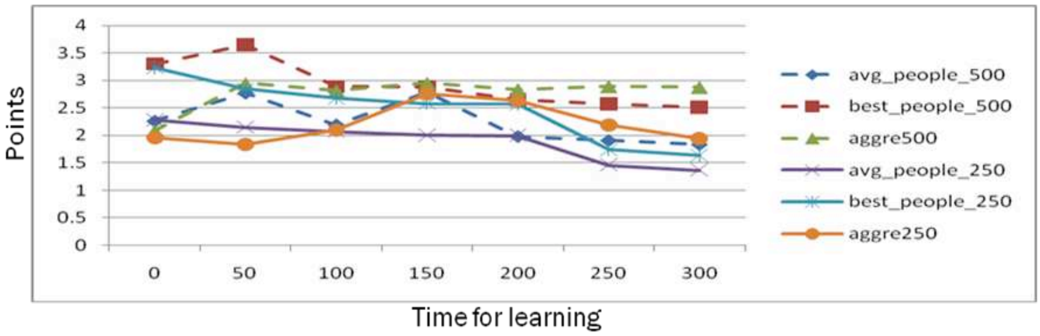
By introducing the ability to learn, the performance of player-agents and aggregator-agents show increasing volatility reflected in their scores for different seeds (crowds). When no learning happens, the performance of player-agents and aggregator-agent keeps relatively stable no matter what seed (formation of crowds) is used. Although the performance line for best-players is always on the top of the chart, depicting their superiority, we observe that the lines for Aggre19 and Aggre29 are close to the one for the best players (best_people), which suggests that the best way to make the decision by using the wisdom of the crowd in this situation is to listen to the top 10% performers in the crowd, so that the aggregators' performance will be similar (yet more stable) to the performance of the best individual in the crowd (though slightly lower). The best individual might change at each tick, while the performance of the aggregators remains high all the time.

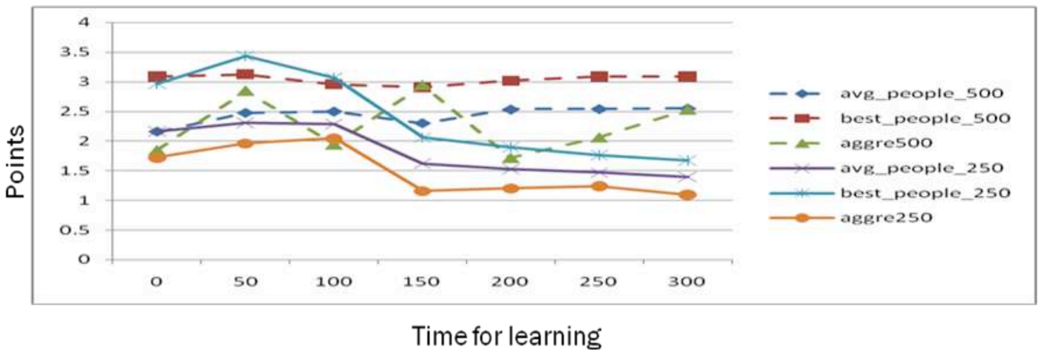
As we introduced learning, more volatility occurred and the best player is not necessarily the all-time winner. In the chart in Figure 5, which shows the situation after learning for 150,000 ticks, the aggregator player performs better than the best player six times out of ten. This suggests that more than half the time making a decision using the wisdom of the crowd is even better than using the advice of the best individual in the crowd.

4.4 Experiment 4: Player-agents' and Aggregator-agents' performance varying with the size of crowds

The size of crowds, which is related to the diversity of opinions in the crowd, is another factor of agents' performance. In this final experiment, we focused on the player-agents' and aggregator-agents' performance while varying the size of the crowds. Two sets of experiments were run using different random seeds: 250 player-agents and 500 player-agents (Figure 6).

Number of people-agent Factor in different seed (x-axis – time for learning)





Wisdom of Crowds(C) VS Best People-agent (B)VS Average People-agent (A)

# out of 10	C > B > A	B > C > A	B > A > C
250 agents	6	2	2
500 agents	6	3	1

Figure 6: performance of Player-agent and Aggregator-agent varying in size of crowds

In Figure 6, avg_people_250 and best_people_250 represent the average player-agent and the player-agent with the current high score in a crowd of 250 player-agents, while aggre250 represents the aggregator-agent who chooses the strategy to listen to all 250 player-agents in the crowd. Similar explanation holds for avg_people_500, best_people_500 and aggre500.

The charts in Figure 6 show that despite the choice of different random seeds, the increased size of the crowd (which increases the diversity of opinion) results in a better performance for both player-agents and aggregator-agents. The aggregator-agent using the wisdom of the crowd performs better, most of the time, than the best player-agents in those crowds.

5. Lessons Learned and Future Work

In this paper, we extend the concept of wisdom of crowds to a continuous decision making problem – The Prisoner's Dilemma. A simulation using the concept of Complex Adaptive Systems is built to demonstrate the wisdom of crowds, thus testing Surowiecki's four criteria to form a smart crowd. However, it is hard to imagine a continuous decision-making example from the real world where members of the crowd are truly independent from each other. Therefore, by partially violating the independence criteria, we added the learning ability to the agents. Our experiments show that this addition makes both individual players and the aggregate-players smarter, while still guaranteeing the diversity of opinion. Furthermore, these experiments show that in a crowd where the "membership" can be defined dynamically, and where members of the crowd can communicate with each other and learn from each other, the wisdom of crowds approach is superior to the best performing members of the crowd.

Future work will focus on:

1. Characterizing the structure of crowds more precisely, using variables such as size, density, and diversity.
2. Identifying the behavior of the crowds with different agent settings: heuristic problem solving, differing behavior patterns, degrees of social influence, and varying speed of learning speed.
3. Quantifying and qualifying the characteristics of aggregators.

6. Summary

The research on the wisdom of crowds reported in this paper provides us with a new way of decision-making. Unlike the widely used knowledge-based decision strategies which rely on collecting and analyzing specific knowledge for specific problems, the method proposed in this paper helps practitioners to better handle social science or economics problems that involve numerous human interactions, uncertain personal feelings, and dynamic changes.

By simulating the Prisoner's Dilemma game in a Complex Adaptive System, we investigated the key criteria that separate wise crowds from the irrational ones. We suggested different aggregation strategies for different environments. The further research on the collective wisdom will provide deeper insights along many of the dimensions only touched upon in this paper.

References

[1] James Surowiecki, 2004, *"The Wisdom of Crowds: Why the Many Are Smarter Than the Few and How Collective Wisdom Shapes Business, Economies, Societies and Nations"* ISBN 0-385-50386-5

[2] Daniel Kahneman, Amos Tversky, 2000, *"Choice, Values, Frames"* The Cambridge University Press, ISBN 0521621720

[3] Walker, Doris Katey, 1987, *"Improving Decision-Making Skills"* Manhattan, KS: Kansas State University Cooperative Extension Service, MF-873

[4] Mirsad Hadzikadic and Min Sun, 2007, "*A CAS for Finding the Best Strategy for Prisoner's Dilemma", ICCS* 2007, Boston, 2007.

[5] Ayse Ferliel, 2004, *Inteview with William Sharpe*, Investment Adviser

[6] David Austin, 2006, "*How Google Finds Your Needle in the Web's Haystack"*, American Mathematical Society Feature Column

[7] Charles MacKay, 1841, "*Extraordinary Popular Delusion and the Madness of Crowds",* ISBN 1853263494, 9781853263491

[8] M. Mitchell Waldrop, 1992, "*Complexity: The Emerging Science at the Edge of Order and Chaos"*

[9] http://en.wikipedia.org/wiki/Complex_adaptive_system

[10] http://www.cscs.umich.edu/old/complexity.html

[11] Johnson S., 2001, *Emergence:" The connected lives of ants, brains, cities and software"*, ISBN-10: 068486875X

[12] Kelso, J.A.S, 1995, "*Dynamic patterns: The self-organization of brain and behavior"* ISBN-10: 0262611317

[13] John H. Miller and Scott E. Page, 2007, "*Complex Adaptive Systems: An Introduction to Computational Models of Social Life"* ISBN-10: 0691127026

[14] Scott Page, 2007, "*The Difference: How the Power of Diversity Creates Better Groups, Firms, Schools, and Societies"* ISBN13: 978-0-691-12838-2

[15] Michael Mauboussin, 2007, "*Explaining the Wisdom of crowds"*, Legg Mason Capital Management

[16] Flood, M.M., 1958, "*Some Experimental Games, Research Memorandum" RM-789,RAND Corporation*

[17] Robert Axelrod, 1984, "*The Evolution of Cooperation"* New York: Basic Books ISBN 0-465-02121-2

[18] http://www.prisoners- dilemma.com/results/cec04/ipd_cec04_full_run.html

[19] Axelrod, R, 1987, "*Evolving New Strategies"*, Genetic Algorithm and Simulated Annealing, ISBN-10: 0934613443

[20] Jennifer Golbeck, 2002, "*Evolving Strategies for the Prisoner's Dilemma"*, Advances in Intelligent Systems, Fuzzy System, and Evolutionary Computation

[21] http://www.iterated-prisoners-dilemma.net/prisoners-dilemma-strategies.shtml

[22] Fogel D., 1993, "*Evolving Behaviors in the Iterated Prisoner's Dilemma"*, Evolutionary Computation 1(1)

[23] Darwen, P. and X, Yao, 1994, "*On Evolving Robust Strategies for Iterated Prisoner's Dilemma"*, Lecture Notes in Artificial Intelligence, AI '93 and AI '94 Workshops on Evolutionary Computations, Melbourne, Australia

[24] Kraines D and Kraines V, 1993, "*Learning to Cooperate with Pavlov – an adaptive strategy for the Iterated Prisoner's Dilemma with Noise"*, Theory and Decision

[25] Kraines D and Kraines V, 1995, "*Evolution of Learning among Pavlov Strategies in a Competitive Environment with Noise",* Journal of Conflict Resolution

[26] Cattell, R. B,1966, *"The Scree Test for the Number of Factors"* Multivariate Behavioral Research