

UC Merced

Proceedings of the Annual Meeting of the Cognitive Science Society

Title

Fishing Free-Riders using Altruism: Zero-Sum Fitness Competition in Prey-Predator System

Permalink

<https://escholarship.org/uc/item/74t0m3xc>

Journal

Proceedings of the Annual Meeting of the Cognitive Science Society, 44(44)

Authors

Hong, Jehun
Gu, Jain
Lee, Yoon Kyung
et al.

Publication Date

2022

Peer reviewed

Fishing Free-Riders using Altruism: Zero-Sum Fitness Competition in Prey-Predator System

Jehun Hong (prxxzc@snu.ac.kr)

Human Factors Psychology Lab, Seoul National University, Seoul, Korea, Republic of
Sungkyunkwan University, Seoul, Korea, Republic of

Jain Gu (foend39@gmail.com)

Sungkyunkwan University, Suwon, Korea, Republic of

Yoon Kyung Lee (yoonlee78@snu.ac.kr)

Human Factors Psychology Lab, Seoul National University, Seoul, Korea, Republic of

Sowon Hahn (swhahn@snu.ac.kr)

Seoul National University, Seoul, Korea, Republic of

Abstract

How altruistic behavior evolves despite its evolutionary cost is still an intriguing question. Using Neural Network and Gradient descent algorithms, we proposed a mixed computational model of fitness competition among three artificial agents (predator, altruistic prey, recipient prey), in the zero-sum game environment. We found that altruism emerged without direct reciprocity when the predator invested in altruism aiming to use the prey's altruistic behavior as "bait" to fish for more prey. For the decisive factor of this mechanism, we demonstrated that the long-term decision-making of a predator enhanced its investment in the prey's altruistic behavior, which leads to a significant increase in altruism and fitness in altruistic prey. We interpreted our findings from economic, evolutionary, and psychological perspectives, connecting zero-sum economies, K-selection, and third-party emotional decision-making to the emergence and maintenance of altruistic behavior.

Keywords: altruism; long-term decision-making; cooperative hunting; Prey-Predator model; zero-sum game; evolution; Neural Network

Introduction

The evolution of altruism is a perplexing problem in biology, anthropology, psychology, and cognitive science; altruistic behavior enhances inclusive fitness by providing reproductive success to an organism's relatives (Hamilton, 1964). However, non-kin altruism directly leads to the loss of evolutionary fitness while increasing others' fitness, not genetically related to the donor of altruism (Trivers, 1971). Nevertheless, various prosocial and highly intelligent animal species such as humans, primates, and even some bird species have a high quality of non-kin altruistic nature; altruism even composes the fundamental principles of ethics in human culture.

To answer the complex question of altruism, reciprocal altruism theory (Trivers, 1971), competitive altruism (Alexander, 1987), and Costly Signaling Theory (Zahavi, 1975) were presented to explain the widespread altruistic nature regardless of its cost. Above all, reciprocal altruism

theory, combined with computational modeling research methods (Axelrod & Hamilton, 1981), has been the main hypothesis of altruism's universal evolutionary and cognitive mechanism. This theory represents altruism can be evolved since the recipient of altruism compensates the loss of altruism by giving altruistic behavior back at a later time, or

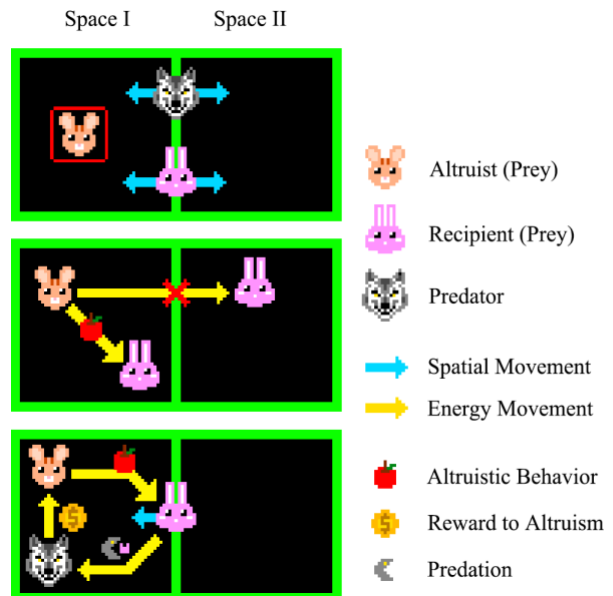


Figure 1: Description of model structure. The top and middle figures depict the agents' mobility and altruism. The bottom figure describes fitness score exchanges among agents.

3rd party's altruism compensates it (Roberts, 2008). The existence of reciprocity is attempted to be explained with 3rd party punishment (Fehr & Gächter, 2000): This model based on game theory suggested that altruism evolved when altruistic behavior leads to more efficient results (e.g., cooperative hunting), and free-riders of altruism or public goods must be punished by 3rd parties in the society.

However, there were numerous unsolved problems: 3rd party punishment is costly and risky (Barclay, 2006), and altruism can only evolve when public goods' efficiency is higher than 1. Furthermore, the existing mathematical and agent-based model does not explain the effect of cognitive abilities on the emergence of altruism.

Innate mental factors which affect altruistic behavior were also investigated with psychological and neurological research methods. Based on the somatic marker hypothesis (Damasio, 1985), Psychological theories have suggested that emotions based on physical factors including neural mechanisms have an important influence on decision-making rather than logical cost-benefit computations (Schwarz, 2000; Lerner et al., 2015). It has been found through neural and behavioral response experiments that emotion acts as an important factor not only in moral decision-making closely related to altruism (Naqvi et al., 2006), but also in economic decision-making that judges the expected material costs and benefits (Sanfey et al., 2003); These emotions were interpreted as empathy (Batson et al., 1991), or expectations for emotional rewards such as praise, gratitude, and intimacy returned by the recipient (Batson & Shaw, 1991; Barasch et al., 2014).

These psychological and neuroscientific findings provide the insight that altruistic behavior is not determined solely by the immediate cost-benefit given in the external environment, but is caused by innate and long-term cognitive strategies, such as the emotions of altruistic behavior actors. However, these theories of psychology and neuroscience do not sufficiently explain why evolutionary fitness remains stable due to intrinsic cognitive factors involved in altruism, such as emotions.

To solve these questions in computational biology and psychology, cognitive modeling using multi-agent artificial intelligence systems, which combines psychological insights about cognitive capacity into computational research methods, has been introduced as a new research methodology (Yong, 2001; Ueda, 2004). Recently, various machine learning algorithms are designed for imitating the human cognition structure; unsupervised reinforcement learning algorithms are actively used for structuralizing cognition and decision-making in social dilemmas (Leibo et al., 2017; Hughes et al., 2018).

In this manner, research methods using Neural Network and reinforcement learning are applied to the altruism problem to figure out the problem with the cognitive approach (Zhao, 2012; Wang, 2019; Hostallero et al., 2020). These machine learning-based research figured out the principles of altruistic decision-making facilitated when expecting the recipient's reciprocal behavior. This approach has a limitation of implementing reciprocal altruism and 3rd party punishment to cognitive abilities such as complex decision-making; this did not present a new solution to the altruism problem with cognitive factors or the model other than reciprocal altruism.

In this study, we suggest a new model for investigating how altruism evolves, replacing the 3rd party punishment with

the 3rd party investment from predator to a prey species, postulating the ecological resource as zero-sum. Furthermore, we applied the mixed methodology with Neural Network and gradient descent algorithm, to optimize the fitness of agents. Neural Network is used to model the long-term decision-making cognitive factor inversely proportional to the sensitivity to environmental change. The gradient descent algorithm is used to model the instantaneous modification of behavioral strategies, aiming to optimize agents' fitness.

Methods

Models

We constructed a simplified ecological model which imitates the real-world situation that one predator must decide whether to prefer prey as altruists or prey who only receives the benefits from other prey's altruistic behavior; gathers around altruists but returns nothing. The model contains three agents, corresponding to one predator, and two prey (altruistic prey and recipient prey).

Each agent aims to maximize its fitness score; the agent spontaneously modulates behavioral factor values (e.g., investment ratio to altruism) to enhance the score corresponding to the environmental conditions given by other agents. We constructed a predator agent as a Neural Network agent with a Stochastic Gradient Descent algorithm to examine the effect of long-term decision-making capacity on the emergence of altruistic behavior. Prey agents were designed as computational equations with Gradient Descent Algorithm.

Predator System Structure We designed the zero-sum prey-predator system model which represents the ecological situation where one species of predator and two species of prey are competing to maximize their fitness, in the closed energy system. Two virtual spaces (I, II) are given: altruistic prey ("Altruist") is fixed to space I, and can give benefit to recipient prey ("Recipient") only when the Recipient is in the same space. The recipient can decide its location with the probability of being in space I. The predator ("Predator") also can modulate its probability of being in space I and reward Altruist proportional to the quantity of altruistic behavior.

Fitness Score Calculation Each agent aims to maximize the value of the fitness score equivalent to its survival and evolutionary success. The fitness score of Altruist, Recipient, and Predator is described as follows:

$$\begin{aligned}
 F(A) &= qw l_P - q l_R - l_P \\
 F(R) &= q l_R - l_R l_P - (1 - l_R)(1 - l_P) \\
 F(P) &= -qw l_P + l_P + l_R l_P + (1 - l_R)(1 - l_P)
 \end{aligned}$$

Table 1: Variables of fitness score equations

Variable ¹	Meaning
$F(\text{Agent})$	Fitness Score of agent.
q	Quantity of altruism from Altruist to Recipient.
l_{Agent}	The probability that the agent is in space I.
w	Quantity of reward from Predator to Altruist.

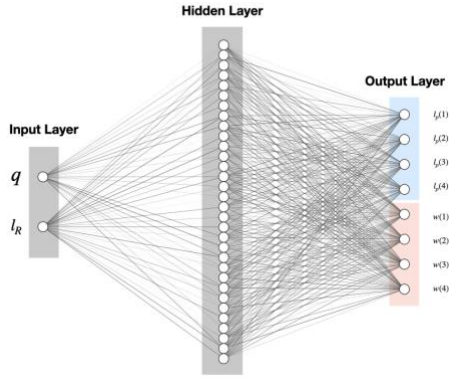


Figure 2: Sample architecture of fully-connected Neural Network of the Predator agent. This sample Neural Network has a pair of 4 output neurons; for instance, the 8th output neuron’s value represents Predator’s w value after 3-time steps from the input.

Neural Network To investigate whether a Predator’s long-term decision-making enhances the emergence of Altruist’s altruistic behavior, we used a fully connected Neural Network as a Predator agent. This Neural Network has an input layer with two inputs (q , l_R), one hidden layer with 32 neurons with activation function as ReLu, and an output layer, with activation function as sigmoid function. The output layer has the number of neurons equivalent to the doubled value of the series of future actions, ranging from 23 to 210. Half of the output neurons decide the l_p value of the Predator, and the other half decide the w value of Predator. Each output value from the neurons, at respective time steps, designates the l_p value or w value. The number of output neurons is equivalent to the time-length of future actions (behavioral strategies) from given inputs.

We used the Stochastic Gradient Descent optimizer provided by Keras open-source library (Chollet et al., 2021)², postulating maximizing Predator’s fitness score as the goal of Neural Network optimization. In the optimizer, Predator’s Neural Network was updated 10 times through the following process: the weight values of the Neural Network were

¹ All values of variables are greater than or equal to 0, and smaller than or equal to 1.

designated as variables. In addition, setting the initial q value and l_R value to 0, the average of the predator’s fitness score during 512-time steps of the simulation in which the three agents interacted together was designated as a target function. Among the 10 updates, the weight value of the neural network that generated the highest average fitness score was extracted; the output values calculated in the state of the Neural Network at this time were collected as samples of output values corresponding to the experiment results.

The hyperparameters of this Neural Network and optimizer are as follows:

Table 2: Hyperparameters

Hyperparameter	Value
Learning rate	0.001
Momentum	0
Decay	0
Nesterov momentum	false
Input domain	float between 0 and 1
Weight Initialization	0 for all weights

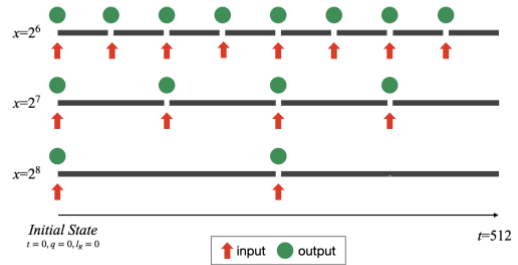
Prey Models Models of Altruist and Recipient are constructed with a gradient descent algorithm. Each model computes the differential value of fitness by its score variables. Then, the agent adds the differential value multiplied by the learning rate ($\eta = 0.2$) to the score variable. This computation updates the latest fitness score. The model formula is constructed as follows:

$$q \leftarrow q + \eta(wl_p - l_R)$$

$$l_R \leftarrow l_R + \eta(q - 2l_p + 1),$$

Experiment Procedure

We computed the simulation experiment with 8-level long-term decision-making conditions, 512-time steps, and 500 trials to measure changes in agents’ fitness scores, location, altruism, and reward to altruistic behavior by the degree of the long-term behavioral strategy of Predator.



²<https://github.com/keras-team/keras/blob/master/keras/optimizers.py#L157>

Figure 3: Examples of Neural Network decision-making that vary depending on the degree of future actions time-length (x). The red arrow represents the time that the Neural Network takes the input value, and the green dot represents the time that the neural network decides the future behavioral strategies (l_p, w) within the time-length (x). Time step (t) is limited to 512; the number of changes in behavioral strategies is inversely proportional to x .

Agents changed their behavior in 512-time steps. Levels of long-term decision-making conditions were divided into 8 conditions, from 2^2 (with 2^7 strategies) to 2^9 (with a single behavioral strategy) with a geometric progression of 2.

We optimized the Predator's neural network 10 times, selected the most optimized neural network, and measured the result that the network finally adjusted the six variables of three agents: $F(A)$, $F(R)$, $F(P)$, l_R , q , and w . We repeated the computation 500 times and obtained the average values.

Results

Effect of long-term decision-making level (time-length of future actions, x) and six variables ($F(A)$, $F(R)$, $F(P)$, l_R , q , and w) was computed in the zero-sum condition. First, we examined the Altruist's quantity of altruistic behavior (q) by the time-length conditions of the Predator's decision-making. There was no significant altruistic behavior in the conditions of Predator's "short-term" decision-making ($q=5.93E-05$ when $x=2^2$; $q=0.0002$ when $x=2^3$; $q=0.008$ when $x=2^4$). However, after the transition period ($x=2^5$; $q=0.227$, $std = 0.198$), the q value significantly increased and the maximum q value recorded $q=0.352$ ($std = 0.071$) when $x=2^6$. There was a significant decrease in altruism value when $x=2^9$ ($q=0.145$, $std = 1.49E-08$), which is an extreme condition that the Predator agent only can take a single behavioral strategy.

Altruistic behavior instantaneously reduces an Altruist's fitness score; Predator's long-term decision-making made altruistic behavior adaptive to Altruist, even compared to Recipient. $F(A)$ significantly increased from -1 ($std = 0.006$, $x=2^2$) to -0.691 ($std = 0.043$, $x=2^8$), while $F(R)$ decreased from 0 ($std = 0.002$, $x=2^2$) to -0.32 (both except when $x=2^9$). Furthermore, in the extreme condition when $x=2^9$, $F(A)$ increased to -0.573 ($std = 5.96E-08$) and $F(R)$ decreased to -0.43 ($std = 2.98E-08$).

We did not postulate the initial value of fitness scores as $F(A)=-1$ and $F(R)=0$; $F(A)$ is computed as -1 when $q=0$ because all portion of Altruist is hunted by Predator since $F(A)$ is equivalent to $qw l_p - q l_R - l_p$, $q=0$ and $l_p=1$. In the same condition, $F(R)=0$ since $F(R) = q l_R - l_R l_p - (1 - l_R)(1 - l_p)$, $q=0$, and $l_R=0$. The difference in baseline between $F(A)$ and $F(R)$ is occurred by initial environmental inequity between the two agents; Altruist cannot avoid predation since the location of Altruist is constantly fixed to space I ($l_A = 1$), however, Recipient can modulate the value of l_R to maximize its fitness score, regarding avoiding predation and taking altruistic benefits from Altruist.

There was a clear loss of fitness score of Altruist caused by the expense from altruistic behavior, however, altruism was

adaptive because Predator gave rewards to altruistic behavior, which is represented as w . There was no significant compensation of altruistic behavior to Altruist in the condition of the lower level of long-term decision making ($w=1.158E-06$ when $x=2^2$, $w=3.879E-06$ when $x=2^3$, $w=0.001$ when $x=2^4$). However, after the $x=2^5$ transition period ($w=0.202$, $std = 0.243$), the w value significantly increased and remained approximately 0.5, even in the extreme condition when $x=2^9$ ($w=0.495$, $std = 5.96E-08$).

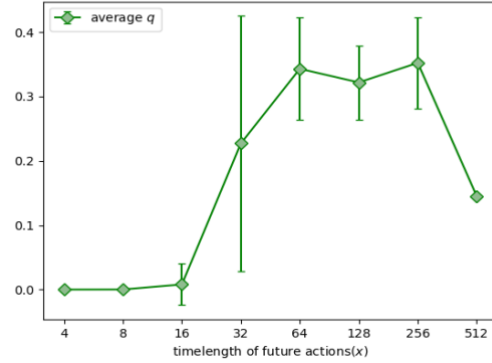


Figure 4: Altruism(q) significantly enhanced when the time-length of future actions(x) was over 2^5 .

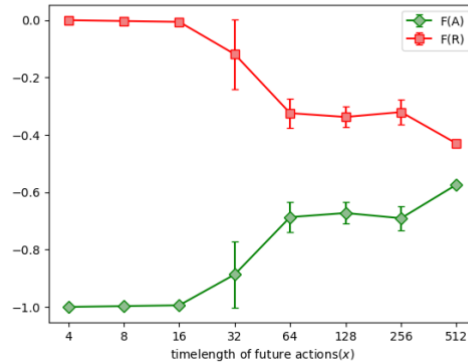


Figure 5: Fitness score of Altruist ($F(A)$) significantly enhanced when time-length of future actions (x) was over 2^5 , while fitness score of Recipient ($F(R)$) significantly decreased at the same condition, despite the enhancement of altruistic behavior (q).

Like the altruistic behavior of Altruist, the reward from Predator to Altruist also was a significant factor that reduces Predator's fitness score. $F(P)$ increased when x was higher than 2^5 , which were the conditions that Predator invested w value of approximately 0.5. Maximum $F(P)$ was 1.011 when $x=2^8$, though the score remains $F(P)=1$ when x was under the transition period ($x < 2^5$). However, there was a significant decrease in $F(P)$ when $x=2^9$ ($w=0.145$, $std = 1.49E-08$).

Increased $F(P)$ in Predator's long-term decision-making conditions indicated that giving a reward to Altruist is adaptive to Predator despite the loss of fitness score driven

by the expense of w . The fitness of the Predator appears to be compensated by the increase of l_R while the x value increased;

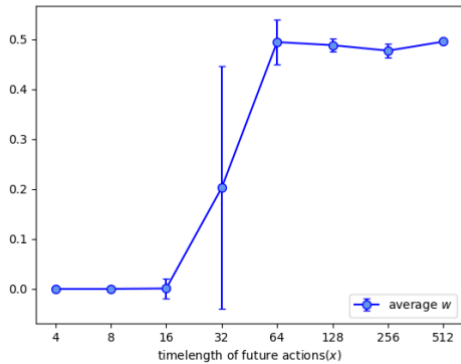


Figure 6: Predator’s reward to Altruist (w) significantly enhanced when the time-length of future actions (x) was over 2^5 , coinciding with the period of a significant increase in altruistic behavior (q).

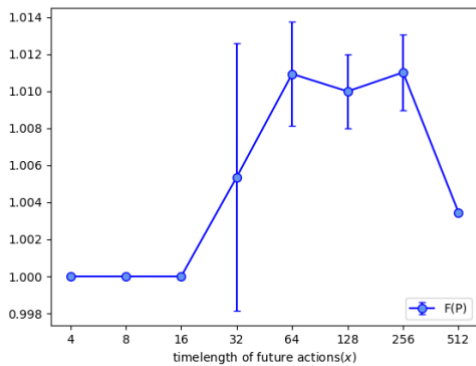


Figure 7: Fitness score of Predator ($F(P)$) significantly enhanced when time-length of future actions (x) was over 2^5 , despite the increase of reward to Altruist (w).

an increase in l_R makes prey gather in the same space and gives more amount and certainty of predation.

Recipient did not share location with Altruist when x was under the transition period ($l_R = 0$ when $x=2^2$ or $x=2^3$; $l_R = 0.001$, $std=0.016$ when $x=2^4$); Maximum l_R recorded 0.362 ($std=0.034$) when $x=2^6$, right after the transition period.

Discussion

We found long-term decision-making of the Predator affects the significant increase of altruistic behavior of prey agents (Altruist), by encouraging Predator to invest in altruism. From the experiment results, we figured out altruism (q), investment to Altruist (w), and the fitness of Altruist and Predator ($F(A)$, $F(P)$) significantly increased only when the Predator had cognitive ability to make decisions in the long-term time-length ($x > 2^5$).

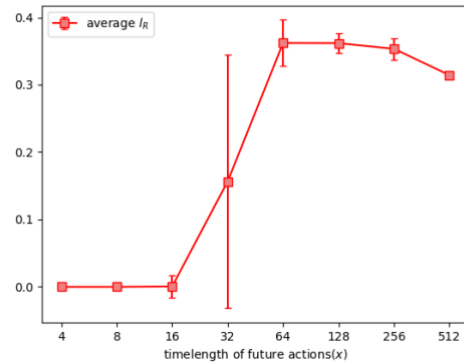


Figure 8: Recipient’s probability to be in space I (l_R) significantly enhanced when the time-length of future actions(x) was over 2^5 , which coincides with the period of the significant increase in altruistic behavior (q), and the period of the significant increase in Predator’s investment to altruism (w).

The result is interpreted as the mechanism as follows: Predator invests in altruistic prey’s altruistic behavior, then altruistic prey enhances altruistic behavior to get the reward from the predator; the reward can be interpreted as a direct reward or lower probability of being preyed. recipient prey is gathered to the surrounding location of Altruist to get the incentives of altruistic behavior of other prey. Therefore, the predator gets the benefit because prey is gathered at one location, which can be interpreted as lowered uncertainty of the hunting task.

This mechanism indicates that altruism is used as “bait” to reduce the spatial uncertainty of prey in hunting. Also, in the perspective of altruists, altruism is used as a behavioral strategy that seduces the free-rider to be exposed to higher predation risk and reduces the risk of predation pressure. Because this model environment is a zero-sum closed energy system, the Recipient’s fitness score decreased when Altruist and Predator increased their benefit from the bait-altruism strategy. This can be interpreted as cooperative hunting between Predator and Altruist: “fishing free-rider”, using altruism as bait. Therefore, unlike the existing theory of reciprocal altruism, our model suggests an evolutionary mechanism of altruism that is indirectly disadvantageous to free-riders and gives reward to altruism through 3rd party investors.

Furthermore, using the zero-sum energy environment model, we showed that altruism emerges even in the social or ecological environment where the additional energy or economic income is not continuously supplied from the external system. Our findings imply that altruism can emerge even when there is no economic growth or an isolated environment.

We also found that long-term decision-making is the key factor in altruistic behavior. This provides insights into both the evolutionary origins and psychological basis of altruism. First, we can interpret long-term decision-making as the long

generation time of a species, and modification of behavioral strategy as changes in gene pool composition of behavioral traits by natural selection. In this perspective, species that have longer generation time to reproduce offspring, and consequently have slower genetic adaptation to the environment would lead to the evolution of altruistic behavioral traits. According to r/K selection theory (Pianka, 1970), at K-selection with less quantity and more quality of offspring, which the survival and reproduction strategy adaptive when higher stability of the environment, animal species have linked attributes containing longer life expectancy and generation time, longer growth period and parental care and consequential higher intelligence (Rushton, 2004). In this manner, altruism might not be the consequence of higher intelligence (Millet & Dewitte, 2007); altruism and higher intelligence would have occurred from a longer lifespan and originated from a stable environment.

Second, our findings investigated that altruists do not need long-term decision-making, but rather their sponsor's (Predator in our model) long-term decision-making capacity supports altruism and acts as an important factor in generating altruistic behavior. In our model, Altruist instantaneously decided whether to perform altruistic behaviors regarding external information such as cost and benefit; for altruism to evolve, the motivation of sponsors who support the altruists would be based on intrinsic and long-term emotions rather than spontaneous reactions to external stimuli. This suggests that, in addition to the cognitive factors of altruists, the cognitive factors of 3rd parties involved in altruism play an important role in the conditions of the emergence of altruism. For instance, the emotional and cognitive attributes of laities who feel religious awe of the clergies (Prade & Saroglou, 2016), can be a crucial factor in maintaining the altruistic behavior of clergies.

However, our experiment results also showed that if these sponsors' trust is overly consistent such as not changing at all once determined, another "free-riding" in which altruists deceive and exploit sponsors by performing less altruistic behavior while taking continuous benefit from sponsors. Under the condition of $x=2^9$ where the Predator minimized the modifications of the behavioral strategy in the Neural Network, the predator maintained a high value that gives a reward for Altruist's altruistic behavior. At this time, Altruist maximized its fitness score by reducing altruistic behavior according to the instantaneous cost and benefit calculation. As a result, the fitness score of the Predator decreased to a lower level than the transition period. This suggests that appropriate time intervals of updating reward policy for altruistic behavior, as well as long-term decision-making, are required to maintain altruism.

The current study leaves collateral parametric effects and comparison among technical conditions unexplored; in future research, we suggest the reward from Predator to Altruist to expand to Neural Network, to precisely figure out the correlation and causality between reward policy and altruistic behavior. In the current research, the learning rate of prey

agents was fixed at 0.2; the effect of the learning rate on altruism should be examined. Furthermore, future studies may expand our model simulations to a wider range of various machine learning techniques such as DNN, Genetic Algorithm, and Reinforcement Learning to explore how the evolution of altruism differs by algorithmic attributes of artificial intelligence agents.

References

- Alexander, R. D. (1987). *The biology of moral systems*. New York: Aldine de Gruyter.
- Axelrod, R., & Hamilton, W. D. (1981). The evolution of cooperation. *science*, 211(4489), 1390-1396.
- Barasch, A., Levine, E. E., Berman, J. Z., & Small, D. A. (2014). Selfish or selfless? On the signal value of emotion in altruistic behavior. *Journal of Personality and Social Psychology*, 107(3), 393.
- Barclay, P. (2006). Reputational benefits for altruistic punishment. *Evolution and Human Behavior*, 27(5), 325-344.
- Batson, C. D., & Shaw, L. L. (1991). Evidence for altruism: Toward a pluralism of prosocial motives. *Psychological Inquiry*, 2(2), 107-122.
- Batson, C. D., Batson, J. G., Slingsby, J. K., Harrell, K. L., Peekna, H. M., & Todd, R. M. (1991). Empathic joy and the empathy-altruism hypothesis. *Journal of Personality and Social Psychology*, 61(3), 413.
- Fehr, E., & Gächter, S. (2000). Cooperation and punishment in public goods experiments. *American Economic Review*, 90(4), 980-994.
- Hamilton, W. D. (1964). The genetical evolution of social behaviour. II. *Journal of Theoretical Biology*, 7(1), 17-52.
- Hostallero, D. E., Kim, D., Moon, S., Son, K., Kang, W. J., & Yi, Y. (2020). Inducing cooperation through reward reshaping based on peer evaluations in deep multi-agent reinforcement learning. In *Proceedings of the 19th International Conference on Autonomous Agents and MultiAgent Systems*. (pp.520-528).
- Hughes, E., Leibo, J. Z., Phillips, M. G., Tuyls, K., Duéñez-Guzmán, E. A., Castañeda, A. G., & Graepel, T. (2018). Inequity aversion improves cooperation in intertemporal social dilemmas. *arXiv preprint arXiv:1803.08884*.
- Leibo, J. Z., Zambaldi, V., Lanctot, M., Marecki, J., & Graepel, T. (2017). Multi-agent reinforcement learning in sequential social dilemmas. *arXiv preprint arXiv:1702.03037*.
- Lerner, J. S., Li, Y., Valdesolo, P., & Kassam, K. S. (2015). Emotion and decision making. *Annual Review of Psychology*, 66, 799-823.
- Millet, K., & Dewitte, S. (2007). Altruistic behavior as a costly signal of general intelligence. *Journal of Research in Personality*, 41(2), 316-326.
- Naqvi, N., Shiv, B., & Bechara, A. (2006). The role of emotion in decision making: A cognitive neuroscience perspective. *Current Directions in Psychological Science*, 15(5), 260-264.

- Pianka, E. R. (1970). On r-and K-selection. *The American Naturalist*, 104(940), 592-597.
- Prade, C., & Saroglou, V. (2016). Awe's effects on generosity and helping. *The Journal of Positive Psychology*, 11(5), 522-530.
- Roberts, G. (2008). Evolution of direct and indirect reciprocity. *Proceedings of the Royal Society B: Biological Sciences*, 275(1631), 173-179.
- Rushton, J. P. (2004). Placing intelligence into an evolutionary framework or how g fits into the r-K matrix of life-history traits including longevity. *Intelligence*, 32(4), 321-328.
- Sanfey, A. G., Rilling, J. K., Aronson, J. A., Nystrom, L. E., & Cohen, J. D. (2003). The neural basis of economic decision-making in the ultimatum game. *Science*, 300(5626), 1755-1758.
- Schwarz, N. (2000). Emotion, cognition, and decision making. *Cognition & Emotion*, 14(4), 433-440.
- Trivers, R. L. (1971). The evolution of reciprocal altruism. *The Quarterly Review of Biology*, 46(1), 35-57.
- Ueda, H., Tanizawa, T., Takahashi, K., & Miyahara, T. (2004). Acquisition of reciprocal altruism in a multiagent system. In *2004 IEEE Region 10 Conference TENCN 2004*. (pp. 334-337). IEEE.
- Yong, C. H., & Miikkulainen, R. (2001). *Cooperative coevolution of multi-agent systems* (pp. Ai01-287). Technical Report AI01-287, The University of Texas at Austin Department of Computer Sciences.
- Zahavi, A. (1975). Mate selection—A selection for a handicap. *Journal of Theoretical Biology*, 53(1), 205-214.
- Zhao, X., Xia, H., Yu, H., & Tian, L. (2012). Agents' cooperation based on long-term reciprocal altruism. In *International Conference on Industrial, Engineering and Other Applications of Applied Intelligent Systems* (pp. 689-698). Springer, Berlin, Heidelberg.