Interstellar knowledge dynamics

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Abstract. Knowledge has always been an important cornerstone of our civilization, and we believe this will continue to be true for our future interstellar society. In this study, we construct an interstellar knowledge dynamics model, which allows us to explore how innovations would look like in a social system subjected to special relativity. Our simulation results illustrate some interesting insights on how speed of light, distance-based cooperator selection strategies, and movement strategies, are going to affect the efficiencies and rewards of the social system. The implementation is available at https://github.com/Adriankhl/relativitization-model-knowledge-dynamics.

Keywords: agent based model, knowledge diffusion, interstellar society, special relativity

1 Introduction

Scientific development is a major driver of our society. There are many ways to study scientific development. On the more theoretical side, philosophers dive deep into the fundamental definition of "scientific progress" [11]. On the more practical side, one can study the sociological aspect of innovations, such as modeling and measuring innovation diffusion networks [2, 9, 15, 10, 13]. Recent developments have gone beyond simple diffusion processes to address the more fundamental nature of knowledge, introducing addition mechanisms such as self-learning [13], perception of knowledge value [8], and network representation of knowledge [12]. However, extending network models greatly complexifies the underlining mathematics, making it not easy to explore more complicated knowledge dynamics.

Alternatively, agent based modeling (ABM) can be used to model knowledge dynamics. ABM allows scholars to explore complicated knowledge dynamics models without dealing with mathematical subtleties. While it remains to be a challenge to calibrate and validate the model, many ABMs have been created to study innovation diffusion [14]. Particularly, we are interested in the family of *simulating knowledge dynamics in innovation networks* (SKIN) models [1]. Inspired by how neo-Schumpeterian economics theorizes innovations [5], SKIN models feature the *kene* representation of knowledge. Agents can research to update their *kenes*, form collaboration to exchange *kenes*, and produce outputs based on their *kenes*. Different SKIN models have been applied to study many hypothetical scenerios as well as real-world scenerios [3].

In this study, we extend the idea of SKIN models to create an agent based model to investigate the knowledge dynamics of our distant future - when human society become interstellar. The model is built on top of the *Relativitization* framework [7, 6], which helps to take care of the effects of relativistic physics in interstellar social simulation. The model allow us to explore how relativistic effects, such as time delay, time dilation, relativistic movement, affect the pattern of knowledge creation, cooperation, and diffusion in interstellar societies. Particularly, we will simulate the model to demonstrate the impact of speed of light, distance-based cooperator selection strategy, and agents movement, on the efficiency and reward of the innovation system.

2 Model

See [4] for the detail of the model.

3 Simulation result

There are 3 core variables in our studies: speed of light, cooperator selection strategies, and agent movement. If we set the speed of light to infinity, our model becomes a normal model in a normal world without relativistic effects. Therefore, in Sec. 3.2, we assume random cooperator selection and disable agent movement to explore the effect of speed of light. Then, in Sec. 3.3, we explore how distance preferences of cooperators affect the simulation results. In Sec. 3.4, we turn on agent movement to see the impact of distances between agents and time dilation. The implementation is available at https://github.com/Adriankhl/relativitization-model-knowledge-dynamics.

3.1 Parameters and initialization

Parameters in Table 1 determine how the simulated world is initialized. Additionally, when an agent is initialized, it receives 3 random *kenes* to its knowledge base, and the random *kenes* are added to its innovation hypothesis immediately. The capability C_{ik} of the random *kene* is an random integer between 0 and 30. Since 30 is smaller than $C_{\max}$, there are space reserved for improving qualities of agent outputs (see Eq. 5 of [4]). The ability A_{ik} of the *kene* is an integer between 0 and $A_{\max}$, and the expertise E_{ik} of the *kene* is 0.

3.2 Speed of light effects

We set $p_{\text{forget}} = 0.05$, $p_{\text{self-incremental}} = 0.1$, $p_{\text{self-radical}} = 0.4$, $t_{\text{cooperation}} = 5$, and $n_{\text{max-cooperation}} = \infty$. Furthermore, $v_i = 0$ and $\delta_i = 0$ for every agent i. Then, we run 4 sets of simulations with $c \in \{0.1, 1.0, 10.0, 200.0\}$, in each set of simulations there are 10 runs with different random seeds.

Fig. 1 summarizes the simulated output qualities and rewards. Interestingly, while the output quality improves slower in a world with a slower speed of light

Parameter	value	Parameter	value
X_{max}	10	$n_{\text{hypothesis}}$	3
Y_{max}	10	C_{max}	100
Z_{max}	10	A_{max}	10
X_{target}	10	E_{max}	20
Y_{target}	10	c	?
Z_{target}	10	p_{forget}	?
n_{agent}	100	$p_{\text{self-incremental}}$	?
n_{type}	50	$p_{\text{self-radical}}$	?
n_{quality}	50	$t_{\text{cooperation}}$	?
n_{reward}	10	$n_{\text{max-cooperation}}$	?
$n_{\text{incremental}}$	8	v_i	?
n_{radical}	6	δ_i	?

Table 1: Simulation parameters. Some parameters are fixed throughout this study, parameters with ? value depend the specific simulation.

initially, the output quality will surpass other worlds with faster speeds of light eventually. The initial quality difference is driven by the knowledge diffusion, the faster the speed of light, the faster the knowledge diffusion rate, so the quality improves faster. However, because the reward is calculated by "comparison" (see Sec. 3.4 of [4]), a faster information travel speed means an agent is comparing itself with latest state of other agents, it is more competitive and receives a lower reward in average. Therefore, a faster speed of light also causes agents to become less likely to develop the expertise in their *kenes*. This is illustrated in Fig. 2, the capability factor is higher if the speed of light is higher, but the expertise factor is lower. Because the amount of knowledge (number of possible *kenes*) is limited in our model, as long as the rate of new knowledge discovery slows down, reflected in the slower increase of capability factor, the expertise factor is the deterministic factor of the overall quality and a slower speed of light is beneficial to the output quality.

3.3 Cooperator distance preference effects

In this section, we fix $c = 0.5$, $v_i = 0$ and vary δ_i to investigate the impact of distance preferences of new cooperators. To focus on the effect of cooperation, we increase p_{forget} to 0.5 to reduce the impact of old knowledge base, decrease $p_{\text{self-incremental}}$ to 0.1 and $p_{\text{self-radical}}$ to 0.02 to reduce the impact of self innovation. We also reduce $t_{\text{cooperation}}$ to 1 and $n_{\text{max-cooperation}}$ to 1 so that the choice of the only cooperator is important.

Fig. 3 shows the output qualities and rewards of 3 sets of simulation with $\delta_i \in \{0.0, 10.0\}$, where each set consists of 10 simulations with different random seeds. Since larger δ_i implies that the cooperation distances are smaller in average, there are more knowledge diffusions so the output qualities improve faster. Unlike Sec. 3.2, this does not signifiantly change the competition pressure so we always

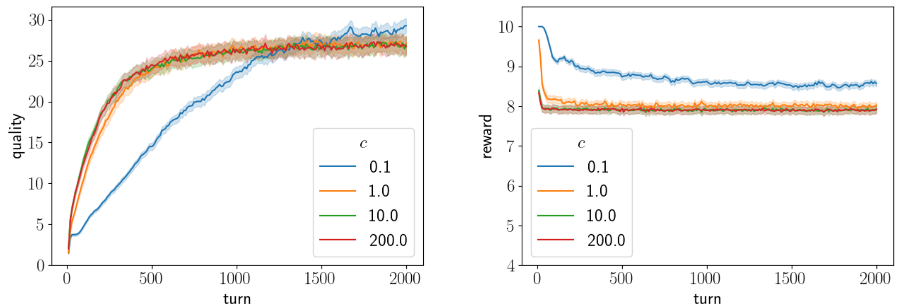

Fig. 1: (left) Output qualities improve with time, simulated worlds with slower speed of light start with slower quality improvement rates but catch up and surpass later on. (right) Rewards are higher for simulated worlds with slower speed of light.

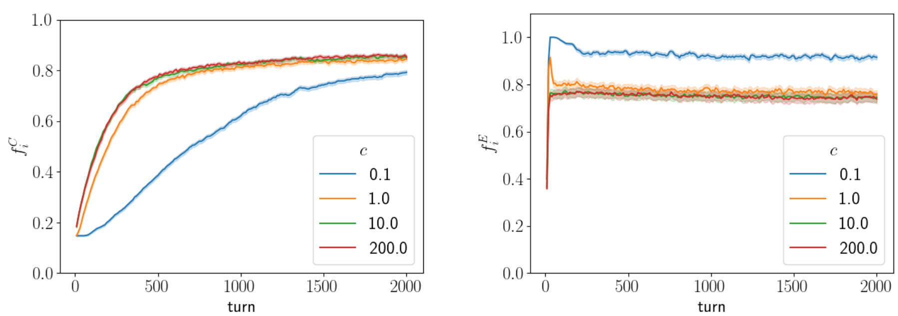

Fig. 2: (left) worlds with faster speed of light have higher capability factors. (right) worlds with slower speed of light have higher expertise factors.

see larger higher qualities for larger δ_i. The reward pattern is not too interesting in these simulations. To see the impact of δ_i on rewards, we run another 50 simulations with different random seeds where 34 agents with $\delta_i = 0.0$, 34 agents with $\delta_i = 0.5$, and 32 agents with $\delta_i = 10.0$ compete with each other in the same simulated world, as illustrated in Fig. 4. Agents with larger δ_i outperform agents with smaller δ_i in both output qualities and rewards because they undergo more knowledge diffusions.

3.4 Agent movement effects

For the simulation in this section, we are interested in the effects of agent movement. Movement introduces two effects: (1) because of how we design the movement (see Sec. 3.1 of [4]), moving agents keep getting closer to each other, (2) moving agents experience time dilation, so everything, e.g., production, receiving

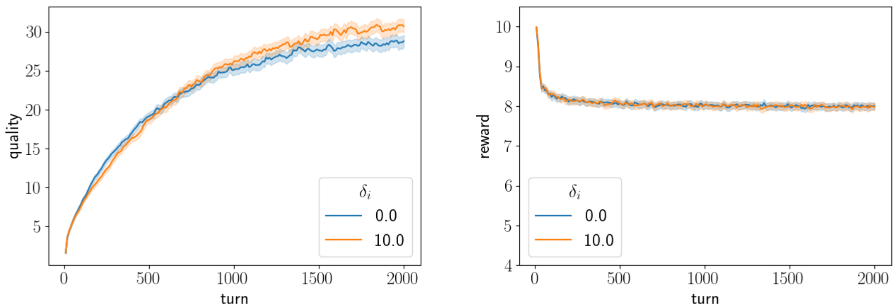

Fig. 3: (left) Output qualities improve with time, closer cooperations (larger δ_i) improve the qualities faster. (right) Rewards remain similar regardless of the cooperation distance preference.

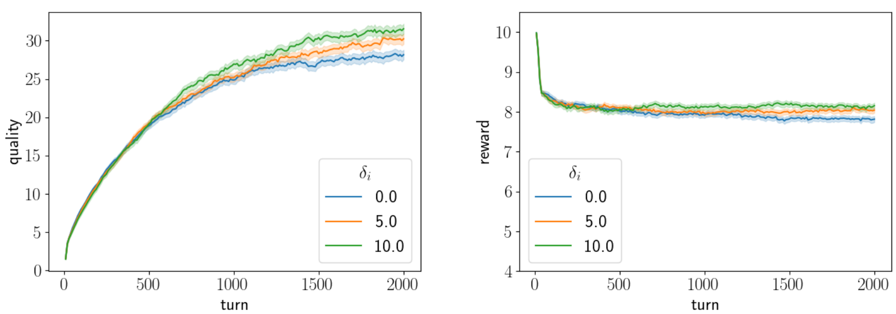

Fig. 4: (left) Agents who prefer closer cooperators (larger δ_i) improve the qualities faster. (right) Agents who prefer closer cooperators (larger δ_i) outcomplete agents who prefer farther cooperators (smaller δ_i).

reward, is slower. We fix $c = 1.0$. We keep $p_{\text{forget}} = 0.5$, $p_{\text{self-incremental}} = 0.1$ and $p_{\text{self-radical}} = 0.02$. To give agents who move closer to each other an advantage we set $\delta_i = 10$, $t_{\text{cooperation}} = 10$ and $n_{\text{max-cooperation}} = 10$ so those agents can find closer cooperators.

We run a set of 20 simulation with different random seeds, in each simulation, half of the agent (50) moves at $v_i = 0.9c$ and the other half (50) stand still ($v_i = 0$). The simulation result is show in Fig. 5. Initially, moving agents receive fewer rewards because they experience time dilation. After the moving agents arrive coordinate $(0, 0, 0)$ and stop there, they can set up close by cooperations so they undergo more knowledge diffusions and start to outperform non-moving agents.

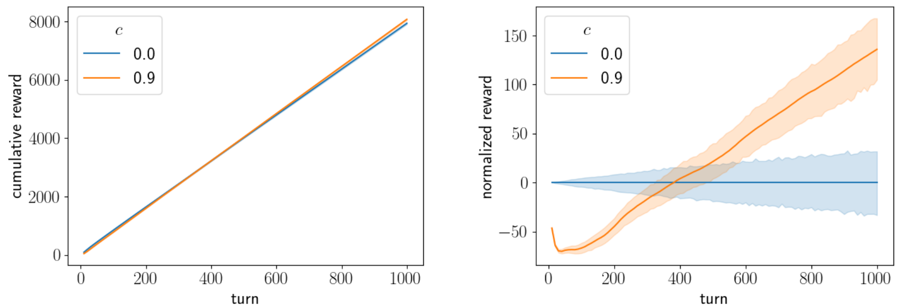

Fig. 5: (left) Moving agents lack behind initially in cumulative rewards but it pays off later on. (right) the same plot as the (left) plot but the trend is clearer by subtracting the average reward of agents with $v_i = 0$.

4 Discussion

We have constructed a interstellar knowledge dynamics model based on the SKIN framework. The simulations illustrated some interesting results: a world with slower speed of light starts worse but reaches a higher average product quality eventually, agents who prefer closer cooperator have a better performance, and agents who move closer to each other performs worst but outcompete other agents later on. These results give us some insights on how knowledge dynamics work in interstellar societies.

While this is a hypothetical scenario where realism cannot be judged easily, we can still critize our model sensibly. One of the biggest issue of the model is how the reward is calculated. As described in Sec. 3.4 of [4], the reward is computed by "comparison". This makes sense in a market with no time delay, since one can argue that if you have a product with better quality, you can expect a higher profit. However, since we have introduced time delay in our simulation, the total reward is no longer a fixed number as it can depend on the time delay, as what we have found in Sec. 3.2. While we can interpret this reward as the overall welfare of the people, a more realistic reward system may help to unveil how an interstellar market actually work.

The relativistic effect we considered in this study - time delay and time dilation, might find their relevance in the "real world" which is not (yet) interstellar. For example, there is always a delay when information diffuses in network, so our results related to time-delay in Sec. 3.2 and Sec. 3.3 may also give some insight to "real world" problems, i.e., slower information diffusion rate may benefit the society in the long term, and people in the real world may want to prioritize closer cooperators. The time dilation in this model essentially associates a cost to agent movement, which is also not uncommon in the "real world", where people might have to make the decision between taking efforts to move to a better city (with closer cooperators) and staying at the current place. Sec. 3.4 might teach us something about these “real world” mobility problems, where moving to a better place pays off in the long term.

While the model is not fully realistic and it cannot be verified in the near future, this study shows that simulations can be used to explore our interstellar future scientifically.

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