Countering Free Riding in Utility Sharing with Sequential Contests

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Abstract

Free riding is a common problem that arises in many online communities such as peer-to-peer file sharing systems, user-generated content platforms, and open-source software development. Agents' free riding behaviors severely reduce the production of society and can often lead to the tragedy of the commons. In this paper, we introduce a sequential contest mechanism to counter agents' freeriding behavior. The mechanism allocates a number of tokens to each agent that has made contributions to the utility production before a private deadline, and then conducts a ratio-form contest among the qualified agents. The sequential contest mechanism is resistant to free riding and also satisfies the budget constraints. We conducted experiments with real-world dataset to evaluate its performance and robustness. Experimental results demonstrate that stakeholders can achieve optimal results by tuning the parameters of the sequential contest mechanism. Our method brings new insights into how to design free riding resistant mechanisms for utility sharing.

1 Introduction

The free rider problem arises in many real-world scenarios, including crowdfunding [Agrawal et al., 2014], open-source software development [Baldwin and Clark, 2006], user-generated content platforms [Lao, 2010], strategic network diffusion [Shen et al., 2019], and peer-to-peer file sharing systems [Ramaswamy and Liu, 2003]. A free rider usually gain benefits from the contributions made by others without contributing to the development of public resources. For instance, millions of people use Wikipedia — a free encyclopedia every day but only a small fraction of the users pay to support its operation or put efforts into increasing its contents or improving its quality. Most of the users receive benefits from Wikipedia without contributing to its development [Antin and Cheshire, 2010]. These users are often referred as the *free riders*.

Free riding is a key challenge in cooperation among organizations [Hogg and Huberman, 2008]. Agents' free riding behavior is usually harmful to the growth of the pub-

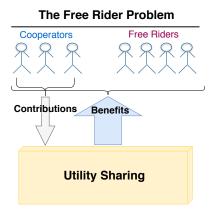


Figure 1: An illustration of the free rider problem.

lic resources. It often makes the public goods unsustainable [Grossman and Hart, 1980]. For example, the Wikipedia would not be able to sustain its operation if no one donates or no one spend time helping improve it. A main reason for the free rider problem is that there is a lack of mechanisms that exclude non-cooperators (e.g., Wikipedia do not prevent users from having access to it) [Antin and Cheshire, 2010].

Another problem in utility sharing is that even some agents choose to contribute, they may not be willing to contribute early [Shen *et al.*, 2018]. The agents usually have uncertainty about the prospect of the public goods. For instance, if users believe that the Wikipedia would not sustain in the near future, they are unlikely to contribute to its operation. Therefore, stakeholders of the public goods must not only provide incentives to agents that have contributed but also need to incentivize those who have contributed early.

To counter the free riding behavior in utility sharing, we introduce a novel mechanism called the *Sequential Contest Mechanism* (SCM). The sequential contest mechanism initially assign the same number of tokens to each of the newly joined agents. It updates the tokens according to normalized weight of the agent's contributions to the utility sharing. If an agent chooses not to contribute, his weight of contributions will be diluted to a small amount that disqualify him from gaining the benefits. In this way, the mechanism encourages agents to contribute. Another benefits of using sequential contests is that agents have extra incentives to con-

tribute early because early movers have an advantage in the final outcomes in sequential contests. The efforts and payoffs of earlier movers are strictly higher than later players. The earlier players may impact the followers and they do not have direct competitors.

We conducted numerical simulations with real-world data to evaluate the performance of the sequential contest mechanism. Results show that the proposed mechanism can achieve optimal performance through parameter tuning and is resistant to free riding. Our work demonstrates the promising prospective of proper competition in countering free riding in utility sharing.

2 The Free Rider Problem in Utility Sharing

This section introduces the free rider problem in utility sharing and formulates the mechanism design problem. Before describing the agents' decision models, we first introduce the notations used.

2.1 Notations

We consider discrete time $T = \{1, 2, ...\}$ with a set of players $I = \{1, 2, ...\}$ arrive sequentially in a utility sharing scenario. At each time $t \in T$, a player $i \in I$ that has not exerted his effort previously decides whether to exert his effort $e_{i,t} \in \mathbb{R}_{\geq 0}$ or not. Without loss of generality, we assume that $e_{i,t} \in [0,1]$ for all $i \in I, t \in T$. For simplicity's sake, we further assume that the total efforts that a player has invested in the utility sharing should be less than or equal to 1. That is, $\sum_{i=1}^{|T|} e_{i,t} \in [0,1]$. Let i=1, and i=1.

is, $\sum_{t=1}^{|T|} e_{i,t} \in [0,1]$. Let n=|T|, and m=|I|. The effort investment of player i during the n periods is represented by a vector $\mathbf{e}_i=(e_{i,1},e_{i,2},...,e_{i,n})$. For all $i\in I,t\in T$, we have $e_{i,t}\in [0,1]$. Thus, $\mathbf{e}_i\in \Theta_i=\{(x_1,x_2,...,x_n)\in [0,1]^n|\sum_{t=1}^n x_t\leq 1\}$. Therefore, the space for all players' invested efforts $\mathbf{e}\in Theta$ where $\Theta=(\Theta_i)_{i\in I}$. Without loss of generality, we assume that a player only invests his effort in one of the time $t\in T$. That is, if player i invests a total effort of i in the time periods of i, then we can assume that player i only invests his efforts at time i (i.e., i, i, i), and invests no effort in other times (i.e., i, i), and i0 for other times). Let i1 denote the set of players that invest their efforts in time i2 (i.e., i3 denote the total effort invested from time 1 to i4, we have

$$e_t = \sum_{i \in I} \sum_{j \le t} e_{i,j} . \tag{1}$$

In utility sharing, the principal is interested in solicits as many efforts as possible. The minimum total invested efforts is 0, while the maximum total invested efforts possible is $m \cdot 1 = m$. Thus, the total invested efforts to the principal $e_t \in [0, m]$. Without loss of generality, the utility of total invested efforts to the principal can be presented as a function $g(b_t)$ where $g: \{0, m\} \rightarrow [0, 1]$ such that g(0) = 0 and g(m) = 1.

In practice, it is often difficult or even unfeasible to solicit the maximum amount of efforts (i.e., $b_t = m$). The principal often has a private threshold $\theta \in (0,1]$ for her utility. That is, the principal will be interested in soliciting the efforts such that her utility reaches her threshold θ . Assume that the principal's utility g reaches the threshold θ at time $t(\theta, \mathbf{e})$. We

have

$$t(\theta, \mathbf{e}) = \begin{cases} \min\{t \in I | g(e_t) \ge \theta\} & \text{if } u(e_t) \ge \theta \text{ for some } 1 \le t \le n; \\ -+\infty & \text{otherwise.} \end{cases}$$
(2)

2.2 The Free Rider Problem

In utility sharing, players typically want to maximize their payoffs. At time t, player i receives a utility u_t that is determined by the principal. Note that, the utility u_t is the same for all the players $i \in I$ at time t. Let $t' = t(\theta, \mathbf{e})$, player i's utility at time t is calculated by

$$u(i,t') = u_{t'} \cdot s_{i,t'} - \sum_{t=0}^{t'} e_{i,t} , \qquad (3)$$

where $s_{i,t'} \in [0,1]$ is player *i*'s estimate of the probability that the principal's utility exceeds her private threshold θ at time t'. In large-scale utility sharing that consists of thousands of players, it is without loss of generality to assume that player *i*'s estimate of the probability $s_{i,t'}$ are independent and identically distributed according to the normal distribution $\mathcal{N}(0,1)$. Thus, the expected value for $s_{i,t'}$ is $\mathbb{E}(s_{i,t'}) = 0.5$.

Without extra incentives, players tend to exert no efforts at all, which results in free riding (e.g., $\sum_{t=0}^{t'} e_{i,t} = 0$). The players receive positive utilities, but contribute nothing to the utility sharing. Eq 3 can be simplified as

$$u(i,t') = u_{t'} \cdot s_{i,t'} . \tag{4}$$

In order to counter the free riding behavior, the principal may provide rewards to the players that have invested efforts into the utility sharing. Let $\pi(i) \in \mathbb{R}_{\geq 0}$ denote the rewards that player i receives in the utility sharing. When the principal receives the rewards, player i's utility is

$$u(i,t') = (u_{t'} + \mathbb{E}(\pi(i))) \cdot s_{i,t'} - \sum_{t=0}^{t'} e_{i,t} .$$
 (5)

By Eq. 4 and Eq. 5, the relative utility for player i not performing free riding is

$$\Delta u(i, t') = (u_{t'} + \mathbb{E}(\pi(i))) \cdot s_{i, t'} - \sum_{t=0}^{t'} e_{i, t} - u_{t'} \cdot s_{i, t'}$$
(6)

$$= \mathbb{E}(\pi(i)) \cdot s_{i,t'} - \sum_{t=0}^{t'} e_{i,t} . \tag{7}$$

In our model, we assume that player i's utility is his relative utility $\Delta u(i, t')$. Thus, we have player i's utility in the utility sharing for contributing a effort in one of the time periods is

$$\mathbb{E}(u(i)) = \mathbb{E}(\pi(i)) \cdot s_{i,t'} - \sum_{t=0}^{t'} e_{i,t} . \tag{8}$$

In order to counter players' free riding behavior, the principal must provide incentives that is increasing in terms players' efforts before the terminating time $t' = t(\theta, \mathbf{e})$.

2.3 Mechanism Design in Utility Sharing

In utility sharing, a principal is interested in obtaining the desirable utility production as early as possible by providing incentives to some players that have exerted positive contributions to the utility production. That is, the principal is interested in a utility sharing mechanism π that determines the rewards for each agent that has exert efforts.

Definition 1. A utility sharing mechanism π is a tuple of payments for each agent $i \in I$. That is, $\pi = (\pi(i)_{i \in I})$, where $\pi(i) : \Theta \to \mathbb{R}$.

The utility sharing mechanism should be able to counter the free riding behavior. In other words, players would be better off to participate in the investment of their efforts than exerting no efforts at all.

Definition 2 (Free-Riding-Proofness). A utility sharing mechanism π is free-riding-proof if for all the players it is better off to participate in the sequential production than not participating. That is, $u(i) \geq 0$ for all $i \in I$ that has invested efforts before $t' = t(\theta, \mathbf{e})$.

To be economically feasible, a utility sharing mechanism should be budget constrained. That is, the total amount of the rewards should not exceed a fixed portion $\vartheta \in \mathbb{R}_{>0}$ of the total aggregated efforts.

Definition 3 (Budget Constraint). A utility sharing mechanism π is budget constrained if

$$\sum_{i \in I} \pi(i) \le \vartheta \cdot e_{t'} .$$

3 Sequential Contest Mechanism

We introduce the *sequential contest mechanism* (SCM) to encourage agents to contribute to the utility production. The intuition of the SCM is that it performs a sequential contest among the players that have exerted positive efforts before the terminating time $t'=t(\theta,\mathbf{e})$.

At time t, the mechanism first assign the tokens $c_{i,t}$ to a player i that exerts an effort of $e_{i,t}>0$. At time t+1, the mechanism first checks if $t+1\geq t(\theta,\mathbf{e})$. If it is not, the mechanism updates the tokens for all players by $c_{i,t+1}=\lambda\cdot c_{i,t}$ where $\lambda\in\mathbb{R}_{\geq 1}$. Here λ serves as a discounting factor, it encourages the players to exert efforts as early as possible because early contributions weigh more. If $t+1\geq t(\theta,\mathbf{e})$, the mechanism conduct a ratio-form contest among all the players that have positive number of tokens. Player i's probability of winning is

$$Pr(c_{i,t'}) = \frac{(c_{i,t'})^{\rho}}{\sum_{j \in I} (c_{j,t'})^{\rho}} , \qquad (9)$$

where $\rho \in (0,1]$ is the noise factor of the contest, and $t' = t(\theta,)$. Here, $Pr(c_{i,t'}) \in [\beta,1]$, where $\beta \in (0,1]$ is the minimum possibility that the principal set for a player to receive the rewards.

Given the the budget constraint, the mechanism distributes a total amount of $\alpha \cdot e_{t'}$. Therefore, the expected rewards for player i that has exerted efforts before the terminating time t' are

$$\mathbb{E}(\pi(i)) = Pr(c_{i,t'}) \cdot \alpha \cdot e_{t'} , \qquad (10)$$

where $Pr(c_{i,t'})$ and $e_{t'}$ are determined by Eq. 10 and Eq. 1, respectively.

To satisfy the free-riding-proofness, player i's expected utility should be always non-negative. To achieve this requirement, the parameter α should be carefully chosen. Since $\mathbb{E}(s_{i,t'})=0.5$, by Eq. 8 Eq. 1 and Eq. 10, we have

$$\mathbb{E}(u(i)) = \frac{1}{2}\mathbb{E}(\pi) - \sum_{t=0}^{t'} e_{i,t}$$

$$= \frac{1}{2}\alpha \cdot Pr(c_{i,t'}) \cdot e_{t'} - \sum_{t=0}^{t'} e_{i,t}$$

$$= \frac{1}{2}\alpha \cdot Pr(c_{i,t'}) \cdot (\sum_{k \in I} \sum_{j \le t'} e_{k,j}) - \sum_{t=0}^{t'} e_{i,t}$$

$$= \frac{1}{2}\alpha \cdot Pr(c_{i,t'}) \cdot (\sum_{t=0}^{t'} e_{i,t} + \sum_{k \in I/\{i\}} \sum_{j \le t'} e_{k,j}) - \sum_{t=0}^{t'} e_{i,t}$$

$$= (\frac{1}{2}\alpha \cdot Pr(c_{i,t'}) - 1) \sum_{t=0}^{t'} e_{i,t} + \frac{1}{2}\alpha \cdot Pr(c_{i,t'}) \sum_{k \in I/\{i\}} \sum_{j \le t'} e_{k,j}$$

$$\geq (\frac{1}{2}\alpha\beta - 1) \sum_{t=0}^{t'} e_{i,t} + \frac{1}{2}\alpha \cdot Pr(c_{i,t'}) \sum_{k \in I/\{i\}} \sum_{j \le t'} e_{k,j}$$

$$> (\frac{1}{2}\alpha\beta - 1) \sum_{t=0}^{t'} e_{i,t}$$

$$(11)$$

Let $\alpha=\frac{2}{\beta}$, we have $\frac{1}{2}\alpha\beta-1\geq 0$. Thus, we have $(\frac{1}{2}\alpha\beta-1)\sum_{t=0}^{t'}e_{i,t}\geq 0$. Therefore, we have $\mathbb{E}(u(i))>0$.

The mechanism π only reward the agents that have made positive contributions before the terminating time t' and have a probability of winning that is no less than the minimum value β . The SCM thus satisfies the free-riding-proofness.

Algorithm 1 Sequential Contest Mechanism

```
Input: \theta-the threshold of the utility production.
     Output: \pi-payment for each player i \in I
     Initialize: \pi(i) = 0, c_{i,0} = 0 for all i \in I
     while time t is less than t(\theta, \mathbf{e}) do
          for existing player i \in I and c_{i,t} > 0 do
 2:
 3:
               Update tokens c_{i,t+1} \leftarrow \lambda \cdot c_{i,t}
 4:
          end for
          for each newly joined player i \in I and e_{i,t} > 0 do
 5:
 6:
               Assign tokens c_{i,t} \leftarrow e_{i,t}
 7:
          end for
 8: end while
     for each player i \in I and c_{i,t'} > 0 do
 9:
          Calculate player i's Pr(c_{i,t'}) by Eq. 9.
10:
          if Player i's Pr(c_{i,t'}) \geq \beta then
Update rewards \pi(i) \leftarrow \pi(i) + Pr(c_{i,t'}) \cdot \alpha \cdot e_{t'}
11:
12:
          end if
13:
14: end for
15: return \pi
```

The sequential contest mechanism (See Algo. 1) operates in a online fashion. Each time, the mechanism checks if the principal's utility of the aggregated efforts exceed the threshold value θ (See line 1, Algo. 1). If so, it first updates the tokens of the players that have invested efforts in previous times by multiplying a discounting factor λ (See lines 2–4, Algo. 1). It then assign tokens to the newly joined players that have exerted positive efforts (See lines 5–7, Algo. 1).

After the production utility reaches the threshold θ , the mechanism conduct a contest among the players that have positive number of tokens (See Lines 9–14, Algo. 1). In doing so, the mechanism first calculates the probability of winning according to a ratio-form contest function that is defined by 9 (See Line 10, Algo. 1). It then updates the rewards for each player pi that has a probability of winning no less than the minimum possibility β by adding the rewards $Pr(c_{i,t'}) \cdot \alpha \cdot e_{t'}$ (See line 12, Algo. 1).

The SCM π is computationally efficient. It takes O(|T||I|) time to compute the tokens for all the players (See Lines 1–8, Algo. 1). Calculating the rewards takes O(|I|) time (See Lines 9–14, Algo. 1). Therefore, the time complexity for the SCM is O(|T||I|).

Theorem 1 (Free-Riding-Proofness). *The utility sharing mechanism* π *is free-riding-proof.*

Proof. Let
$$\beta = \min\{Pr(c_{i,t'})\}$$
, and $\alpha = \frac{2}{\beta}$. By Eq. 11, it follows that $\mathbb{E}(u(i)) > 0$ for all $i \in I$.

The utility sharing mechanism π satisfies the budget constraint by construction.

Theorem 2 (Budget Constraint). *The utility sharing mechanism* π *is budget constrained.*

Proof. The mechanism π satisfies the budget constraint by construction because the total rewards are $\alpha \cdot e^{t'}$. Let $\vartheta \leq alpha$, we have the total rewards $\sum_{i \in I} \pi(i) = \alpha \cdot e^{t'} \leq \vartheta$. This completes the proof.

The SCM depends on several parameters such as the noise factor ρ , the discounting factor λ , and the principal's threshold θ . Thus, it is desirable to understand how its performance is influenced by these parameters in practice.

4 Experiments

This section describes the numerical experiments we conducted to evaluate the performance and the robustness of the sequential contest mechanism. Before presenting the results, we first introduce the dataset and the method.

4.1 Experimental Settings

Dataset In our experiments, we used the Kaggle ranked user data [Felipe Salvatore, 2018] as the initial dataset. The dataset reflects 4,767 individual users' efforts in Kaggle competitions. The dataset contains 4,767 rows with each row representing a ranked player. In each row, there are six data fields: the register date of the user, the current points earned by the user, the current ranking of the user, the highest ranking of the user, the country that the user is located at, and the

continent that the user belongs to. In our work, we removed two irrelevant data fields: the country and the continent.

The original dataset does not contains all the necessary data fields for the experiments. Before conducting the experiments, we performed data processing. We first normalized the players' data points by dividing each value by the maximum value observed in the data samples. We then selected the normalized data points as lower bound of the efforts that minimum efforts that the players would receive non-negative expected utilities (i.e., $E(u(i)) \geq 0$). Let e_i' denote player i's lower bound of the effort, we estimated the maximum efforts that player i could invest by

$$\hat{e_i} = e_i' \cdot \frac{\hat{r_i}}{r_i} \,, \tag{12}$$

where r_i , and $\hat{r_i}$ denote the current ranking and the highest ranking of player i, respectively.

To estimate the expected utility, an agent needs to have her cost coefficient. Unfortunately, the original dataset does not include this information. We estimated each agent's cost efficient δ_i by assuming her utility was zero. This is without of loss generality because agent i's utility is positively correlated to the cost coefficient according to Eq. 10. Thus, we have

$$\delta_i = \frac{R - r_i}{R \cdot e_i} \,, \tag{13}$$

where R=4767, and e_i is player i's normalized points number.

Method We selected the total efforts and the total utilities as the main metrics. The principal was interested in the total efforts while the players are interested in the total utilities. We also compared the average efforts, standard deviation of the efforts, the average utilities, and the standard deviation of the utilities for the first group of experiments. We performed four groups of experiments. In the first group of experiments, we compared the performance of the sequential contest mechanisms with different noise factors. In the second group, we varied the discounting factor to study how different discounting factors influenced the performance of the sequential contest mechanism. In the third one, we evaluated the performance of the sequential contest mechanism when we changed the threshold of the utility production. In the last group, we measured the robustness of the mechanism as the percentage of free riders increased.

We ran each group of experiments for 30 times and reported the average numbers of each metrics. All the simulations were conducted on the same 3.7 GHz 6-core linux machine.

4.2 Results

Noise Factor We varied the noise factor from 0.0 to 1.0 with an increment of 0.02. Fig. 2 shows that all the four effort metrics – the total efforts, the average efforts, the maximum efforts, and the standard deviation of individual efforts initially increased to the peaks and then fall gradually as the noise factor increased. The trends indicated that the generated contest mechanism performed the best when the noise factor is low (e.g., noise factor $\rho = 0.06$). Fig. 3 demonstrates

that the players' utilities first increased when the noise factors were low (e.g., noise factor $\rho \leq 0.1$) and then decreased with fluctuations as the noise factor increased. From Figs. 2 and 3, we can see that a low noise factor (e.g., $\rho = 0.06$) is the most beneficial to both the principal and the players. Two factors contributed to this phenomenon: a majority of the agents were players with common or low ability (i.e., they had high cost coefficients); contests with a low noise factor favor players with average abilities [Jia *et al.*, 2013; Shen *et al.*, 2019]. Thus, a low noise factor is typically optimal for the principal to solicit efforts while also providing incentives for agents to contribute.

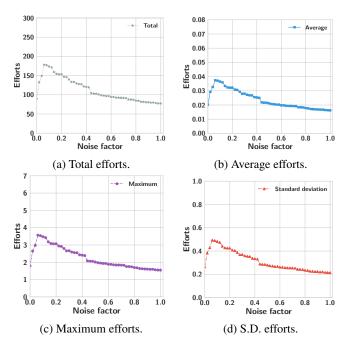


Figure 2: A comparison of four effort metrics by varying the noise factor from 0.0 to 1.0.

Discounting Factor We evaluated the total efforts and the total utility when we changed the discounting factor λ from 1.00 to 1.10 with an increment of 0.0005. Fig. ?? demonstrates that both the total efforts and the total utility increased gradually to the peaks when the discounting factor was ranging from 1.05 to 1.07. They then dropped slightly. The sequential contest mechanism received the highest performance for both metrics when the discounting factor was moderately high (e.g., discounting factor $\lambda = 1.06$). An explanation for this trend was that a relatively high discounting factor encouraged players to contribute early. This would enable to receive more efforts before the deadline (i.e., the time when the utility production exceeded the threshold).

Threshold of Production We measured the performance of the sequential contest mechanism when we changed the threshold of utility production from 0.0 to 1.0 with an increment of 0.005. As the threshold increased, the total efforts and the total utility first increased significantly until $\theta=0.05$ and then fluctuated around the same level. The reason is that

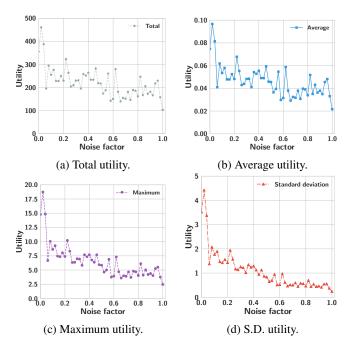


Figure 3: A comparison of four utility metrics by varying the noise factor from 0.0 to 1.0.

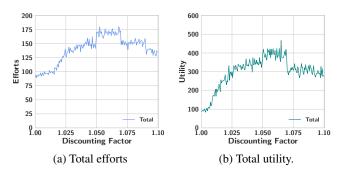


Figure 4: A comparison of total efforts and total utility by varying the discounting factor from 1.00 to 1.10 with threshold $\theta=0.50$, noise factor $\rho=0.06$.

initially the players needed to exert more efforts to receive a higher utility as the threshold of utility production increased. When the threshold reached a level, the players did not exert more efforts because otherwise they would receive fewer utilities or the required efforts were beyond their capacities.

Robustness to Free Riding To evaluate the robustness of the sequential contest mechanism, we evaluated the performance of the mechanism by varying the percentage of the free riders from 0% to 100% with an increment of 0.5%. Fig. ?? demonstrates that both the total efforts and the total utility first dropped sharply and then decreased gradually as the percentage of free riders increased. This results further indicate that the sequential contest mechanism is free-riding-proof.

Discussion Via extensive experiments, we demonstrate that stakeholders can both optimize the total efforts and counter agents' free riding behavior when they use the sequential contest mechanisms with proper (optimal) configurations (e.g.,

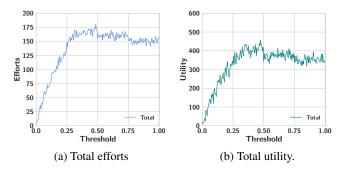


Figure 5: A comparison of total efforts and total utility by varying the threshold from 0.0 to 1.0 with noise factor $\rho=0.06$ and discounting factor $\lambda=1.06$.

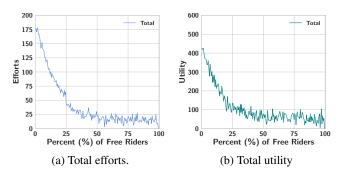


Figure 6: A comparison of total efforts and total utility by percentage of free riders from 0% to 100% with threshold $\theta=0.50$, noise factor $\rho=0.06$ and discounting factor $\lambda=1.06$.

noise factor $\rho=0.06$, threshold $\theta=0.05$, and discounting factor $\lambda=1.06$ in our experiments).

5 Related Work

Free riding reduces the efficiency of the utility sharing in the sense that it results in the under-production or overconsumption of the utility (or the good). It is harmful to both the stakeholders and the individuals that have made contributions [Grossman and Hart, 1980; Kim and Walker, 1984].

Because of its significance, many attempts have been made to address the free rider problem. For instance, Groves et al. (1977) introduced government provision or taxation to achieve the Pareto-optimal allocation of public goods. This methods imposed taxes on individuals that receive benefits from the utility sharing. It is convenient the the stakeholders have the authority but not feasible for non-government entities or individuals. Another method to counter the free riding behavior is through assurance contracts [Runge, 1984; Tabarrok, 1998]. This approach is suitable to the scenarios (e.g., crowdfunding) when the stakeholders can provide guarantees or refunds when the utility production fails to be delivered as promised. When the stakeholders cannot provide such assurance, however, this method is not implementable in practice. If the stakeholders can exclude individual players, they can established privileged groups such as clubs [Hampton, 1987]. Alternatively, the stakeholders may use the Coasian solution to pool the resources until a goal of production has been met [Coase, 1960]. Despite the insight-fulness of these methods, they require strong assumption on the rationality of the agents usually does not hold in practice. This is particularly true in scenarios that consist of a large number of agents.

Our work distinguishes itself from previous work in three aspects. First, it does not impose strong rationality assumption on agents. The agents have private thresholds (i.e., cost coefficient) to trigger their actions. Second, we take a different approach to counter agents' free riding behavior: introducing a sequential contest to increase the competitions among the agents. In order to receive rewards, the agents needs to compete with each other by investing efforts in utility production. This practice enables the stakeholders to attract contributions from the players that otherwise would not exert their efforts. Third, with appropriate configurations of the sequential contest mechanism, both the stakeholders and the players can receive the reasonably good utilities.

6 Conclusion

To counter agents' free riding behavior in utility sharing, we introduce a sequential contest mechanism. The mechanism rewards players that have made contributions before the realization of the utility production. It distributes the rewards through a ratio-form contest among the qualified players. We demonstrates that the mechanism is resistant to free riding and also satisfies the budget constraints. Through expensive experiments on real-world data, we demonstrate that the sequential contest mechanism can produce good performance when the parameters (e.g., the noise factor, the threshold, and the discounting factor) of contest are selected appropriately. The experimental results also confirmed the mechanism's robustness to free riders. Our work advances the state-of-the-art by offering a new approach to countering agents' free riding behavior in utility sharing.

Our work opens several exciting revenues for further research. In our model, we assumed that the agents have fixed cost coefficient. It would be interesting to study how to counter agents' free riding behavior when they have adaptive cost coefficient. A possible solution is through online learning of agents' preferences [Fürnkranz and Hüllermeier, 2010]. Another fruitful area is to develop novel methods to automatically select optimal parameters of the sequential contest mechanism. To do so, the stakeholders need to conduct inference and perform realistic simulations with real-world data. We also find it very rewarding to bring contests into other domains such as cybersecurity and disaster response.

References

[Agrawal *et al.*, 2014] Ajay Agrawal, Christian Catalini, and Avi Goldfarb. Some simple economics of crowdfunding. *Innovation Policy and the Economy*, 14(1):63–97, 2014.

[Antin and Cheshire, 2010] Judd Antin and Coye Cheshire. Readers are not free-riders: reading as a form of participation on wikipedia. In *Proceedings of the 2010 ACM conference on Computer supported cooperative work*, pages 127–130. ACM, 2010.

- [Baldwin and Clark, 2006] Carliss Y Baldwin and Kim B Clark. The architecture of participation: Does code architecture mitigate free riding in the open source development model? *Management Science*, 52(7):1116–1127, 2006.
- [Coase, 1960] Ronald H Coase. The problem of social cost. In *Classic papers in natural resource economics*, pages 87–137. Springer, 1960.
- [Felipe Salvatore, 2018] Felipe Salvatore. Ranked users kaggle data. https://www.kaggle.com/felsal/ranked-users-kaggle-data/, 2018. accessed 03rd January 2019
- [Fürnkranz and Hüllermeier, 2010] Johannes Fürnkranz and Eyke Hüllermeier. *Preference learning*. Springer, 2010.
- [Grossman and Hart, 1980] Sanford J Grossman and Oliver D Hart. Takeover bids, the free-rider problem, and the theory of the corporation. *The Bell Journal of Economics*, pages 42–64, 1980.
- [Groves *et al.*, 1977] Theodore Groves, John Ledyard, et al. Optimal allocation of public goods: A solution to the free rider problem. *Econometrica*, 45(4):783–809, 1977.
- [Hampton, 1987] Jean Hampton. Free-rider problems in the production of collective goods. *Economics & Philosophy*, 3(2):245–273, 1987.
- [Hogg and Huberman, 2008] Tad Hogg and Bernardo A Huberman. Solving the organizational free riding problem with social networks. In *AAAI Spring Symposium: Social Information Processing*, pages 24–29, 2008.
- [Jia et al., 2013] Hao Jia, Stergios Skaperdas, and Samarth Vaidya. Contest functions: Theoretical foundations and issues in estimation. *International Journal of Industrial Organization*, 31(3):211–222, 2013.
- [Kim and Walker, 1984] Oliver Kim and Mark Walker. The free rider problem: Experimental evidence. *Public Choice*, 43(1):3–24, 1984.
- [Lao, 2010] Marina Lao. Resale price maintenance: The internet phenomenon and free rider issues. *The Antitrust Bulletin*, 55(2):473–512, 2010.
- [Ramaswamy and Liu, 2003] Lakshmish Ramaswamy and Ling Liu. Free riding: A new challenge to peer-to-peer file sharing systems. In *36th Annual Hawaii International Conference on System Sciences*, 2003. Proceedings of the, pages 10–pp. IEEE, 2003.
- [Runge, 1984] Carlisle Ford Runge. Institutions and the free rider: The assurance problem in collective action. *The Journal of Politics*, 46(1):154–181, 1984.
- [Shen et al., 2018] Wen Shen, Jacob W Crandall, Ke Yan, and Cristina V Lopes. Information design in crowdfunding under thresholding policies. In *Proceedings of the 17th International Conference on Autonomous Agents and MultiAgent Systems*, pages 632–640. International Foundation for Autonomous Agents and Multiagent Systems, 2018.
- [Shen et al., 2019] Wen Shen, Yang Feng, and Cristina V. Lopes. Multi-winner contests for strategic diffusion in

- social networks. In *Proceedings of the 33rd AAAI Conference on Artificial Intelligence (AAAI-19)*. AAAI Press, 2019
- [Tabarrok, 1998] Alexander Tabarrok. The private provision of public goods via dominant assurance contracts. *Public Choice*, 96(3-4):345–362, 1998.