# Maximizing the Revenue for Clients in Peer-assisted Storage Scheme

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***Abstract*—The pervasive in-network caching enables service provider to save storage expense by exploiting the spare caching resource of clients with reasonably low payment. In such peer-assisted storage scheme, the critical component is the economic catalyst to inspire clients to contribute their spare resource. Previous literature studies this problem from the view of service providers, and the goal is to pay less and get more resources. We are inspired to study the economic problem of leasing revenue from the view of clients, and propose optimal strategies for clients. In detail, we model this rewarding problem by Fixed Prize Reward Mechanism under reasonable assumptions, and propose a modified Markov Decision Process (MDP) method with doubly censored estimation to maximize revenue for the clients. Experimental results reveal the great performance advantage of the proposed method over other online strategies.**

## I. Introduction

The pervasive in-network caching (e.g. CDN, ICN) allows consumers to retrieve their desired contents from nearly caching nodes, which greatly improves the networking performance by reducing server load and consumer retrieval latency, as well as enhances service reliability. Moreover, caching could also save service provider's storage expense by fully utilization of the spare storage resources of other nodes in the network with reasonably low payment, which is named peer-assisted storage scheme. This scheme is applicable to not only CDN or ICN networking, but also cloud storage service like AmazingStore, FS2You, Xunlei, etc.

In such peer-assisted storage scheme, the economic issue between clients and providers is crucial, which may impact the widespread adoption of the peer-assistance. The economic issue between clients who provide resource and providers who accept the resource with payment consists of two components, i.e., minimizing the payment for providers and maximizing the revenue for clients.

Most of existing studies in the topic of peer-assisted storage scheme concentrate on the technical feasibility of peer-assisted scheme and its performance improvement. Only a few (e.g. [1]) examine the economic issue in this new paradigm or the incentive mechanisms to encourage clients to contribute the spare resource. Inspired by the above observation, we consider the problem from the client's part to maximize the revenue and encourage their contribution.

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In this paper, we try to maximize the revenue of clients when they can submit their resources to service providers with desired monetary returns. Considering that service providers may adopt different forms of payment, such as money, membership, service, etc. Such a rewarding problem is an online problem and clients make decision in each step whether to contribute resource and how much to contribute. We model this with Fixed Prize Reward Mechanism, employ the method of Markov Decision Process to solve this problem. The algorithm relies on the knowledge of threshold quantity distribution, which is not practical in reality. Thus we adopt Doubly Censored Estimation and propose offering strategy to maximize client's revenue. Experimental results reveal the above strategy gets much more reward compared with other online strategies under various settings.

The main contributions of this work are as follows.

1) Different from previous work which studies service provider oriented caching problems, we study the economic issue in peer-assisted storage scheme by maximizing client's revenue, by modeling this problem with Fixed Prize Reward Mechanism under reasonable assumptions.
2) We propose online algorithm to solve the Fixed Prize Reward Mechanism and offering strategy for clients to maximize their revenue, which performs reasonably well, compared with existing online strategies.

## II. Model and Strategy

### A. Fixed Prize Reward Model

We model the rewarding problem by *Fixed Prize Reward Mechanism*, assuming that fixed prize which could not be divided, such as membership or service, is used as payment. Under Fixed Prize Reward Mechanism, clients make decision about how many resources they want to provide, providers accept offers with larger quantity of resource until the expected resource pool is fulfilled. From the client's view, this mechanism is equivalent to the threshold mechanism [2] in which for each time slot there is a threshold for the quantity of resource which is unknown to clients. The offer would be accepted if it exceeds the standard. The problem could be formalized using the following model:

*Reward for each time slot is fixed as $P$. In slot $i$, client offers $s_i$ resource to provider. If $s_i$ exceeds the standard quantity $q_i$*

*that provider requires, resource of quantity $s_i$ is occupied and client gets reward $P$. Otherwise, client maintains resource and gets no reward. The goal for a client is to maximize the number of reward within $S$ time slots with resource of quantity $R$.*

### *B. Maximizing the Revenue*

Since the prize reward mechanism is equivalent to threshold mechanism, the decision making procedure of client can be formalized as a MDP (Markov Decision Process) problem. In this section, we design an algorithm to solve the MDP problem and construct the corresponding offering strategy.

*1) Markov Decision Process:* In our case, the MDP state space is given as $S = [R, T]$, where $R$ is the quantity of available resources and $T$ is the number of remaining time slots. Taking action $a$ in state $(r, t)$ may result in two types of transition. The next state could be $(r, t-1)$ or $(r-a, t-1)$. In the former case, the client's offer is not accepted by service provider. Therefore, we have $P = 1 - \sum_{i=1}^{a} p(ths = i)$. Since the client would not get the prize, $r(a, (r, t), (r, t-1)) = 0$. In the latter case, client's offer is accepted and resource of size $s$ gets occupied by the service provider. The transition probability is $P = \sum_{i=1}^{a} p(ths = i)$.

*2) Algorithm:* Here we adopt dynamic programming to solve the MDP problem. We assume that the transition probability distribution $P$ is known. Let $W(b, t)$ (the reward function) denote the expected number of prize a client could get using the optimal strategy from state $(b, t)$. Let $V(a, b, t)$ donate the reward by taking action $a$ at state $(b, t)$ and then following the optimal strategy. $V(a, b, t)$ could be written in the following form:

$$V(a,b,t) = P(a < ths)W(b, t-1) + P(a \geq ths)W(b-a, t-1),$$

where $P(a \geq ths)$ is the probability that client's offer exceeds the threshold quantity in which case the resource offered in this slot is occupied and client gets rewarded. Therefore, the state would transit to state $(b-a, t-1)$ with reward 1. Furthermore, the optimal strategy would take actions that maximize the expected reward:

$$optimal = \arg\max\{V(a, b, t)\}.$$

*3) Offering Strategy:* Here we propose client's offering strategy, by maintaining an estimation of $P$. With budget $b$ and $t$ time slots remaining, the algorithm will greedily use its current estimate of $p$, and offer $a(b, t)$ calculated by the algorithm above. In the strategy, client offers resource greedily, and updates his resource utilization and an estimation of $P$ using doubly censored estimation [3]. The detail of the offering strategy is omitted due to space limit.

## III. Evaluation and Outlook

In this section, we evaluate the performance of the offering strategy (namely MDP) under various settings. Other feasible strategies include: *Fixed*, *Random* and *Online Knapsack*.

Figure 1 plots client benefits when varying the quantity of resource under different offering strategies. It is obvious that when there are more resource, all strategies get more reward.

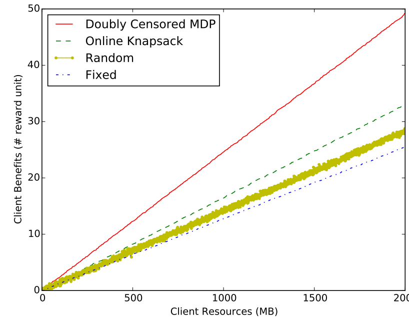


Fig. 1: Client benefits when varying resources under different strategies

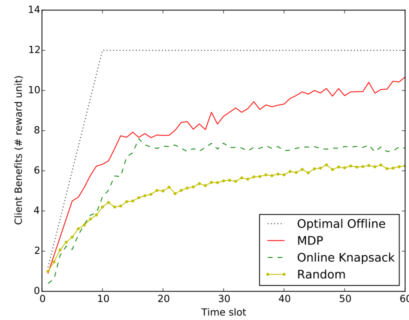


Fig. 2: Client benefits when varying #(slots) under different strategies.

*Fixed* and *Random* get nearly the same and least reward, due to their failure of capturing the variation of quantity threshold in different time slots. Nevertheless, *MDP* always gets the highest reward amongst the considered strategies.

The reward each strategy obtains when varying the number of time slots is shown in Figure 2. From the figure, as the number of slots increases, the gap of reward between each online strategy and the optimal strategy narrows and becomes stable when the number of slots is sufficiently large (e.g. 16 for *online Knapsack*). Amongst these online strategies, *MDP* always gets the highest reward. When the number of slots increases, this performance advantage by *MDP* becomes larger, as it could better estimate the distribution of quantity threshold if more history is available.

In summary, we could show that the proposed offering strategy achieves the best performance among the considered online strategies by combining the power of Markov Decision Process and doubly censored estimation. Our future work will concentrate on to elaborate the missing details of the proposed strategy, and evaluate its feasibility and advantage under multi-client scenario and with other distribution of quantity threshold.

## References


[1] Zhao J, et al. "Online procurement auctions for resource pooling in client-assisted cloud storage systems", IEEE Comp. Comm., 2015

[2] Chakrabarty D, et al. "Budget constrained bidding in keyword auctions and online knapsack problems", WWW, 2007

[3] Turnbull B W. "Nonparametric estimation of a survivorship function with doubly censored data", Journal of the American Statistical Association, 1974