

# A Dynamic Pricing Mechanism for P2P Referral Systems

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## Abstract

*Most existing research on peer-to-peer systems focuses on protocol design. In this paper, we consider the issue of free riding in peer-to-peer referral systems. Free riders are agents that refuse either to answer a query or to give referrals. Free riding is detrimental to the system, since it may prevent requesters from finding high quality providers efficiently. To mitigate the issue of free riding, we propose a dynamic pricing mechanism to motivate the agents to behave rationally. Service providers learn appropriate prices of referrals and answers in order to maximize their payoffs through stochastic iterative learning algorithms.*

## 1. Introduction

This paper presents a P2P referral system, in which peers cooperate to search the relevant information in the system through referrals. Referral systems have been studied by [4, 5, 7], but the problem of *free riding* remains to be addressed [1]. A natural approach to control free riding is to introduce a micropayment protocol into referral systems, in which each peer has to pay for the services it receives from others, e.g., [3]. The prices in a micropayment protocol could be static (fixed) or dynamic. Fixed pricings in micropayment protocols can reduce free riding in P2P systems, but they don't consider quality of services provided by different peers and the supply-demand relationship in the system. In this paper we propose a dynamic pricing mechanism to motivate each peer to behave rationally in peer-to-peer search processes [6]. The requesting peer can decide which referral or answer it wants to pay in the micropayment protocol, but the prices from the same peer are dynamic for different search processes. The prices of referrals and answers are chosen from a discrete space of prices and determined by qualities of services and the supply-demand relationship in the system [2].

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## 2. Dynamic Pricing Mechanism

We consider two research challenges in the design of the dynamic pricing mechanism: (1) how to choose the intermediate peers  $P_k$  so the requesting peer knows the service  $P_k$  provides deserve the price it declares; (2) what are the best pricing strategies for the intermediate peers and service providers to maximize their profits.

### 2.1. Micropayment Protocol

Suppose  $P_r$  is the requesting peer, and  $\{P_1, P_2, \dots, P_n\}$  are a set of acquaintances of  $P_r$ .  $P_r$  has two *selling prices* in its profile:  $Y_r'$  for a referral and  $X_r'$  for an answer.  $X_r'$  and  $Y_r'$  are chosen from a discrete space of prices, respectively. For any peer  $P_i$ ,  $1 \leq i \leq n$ ,  $P_r$  has two *reserve prices* he is willing to pay:  $Y_i$  for a referral and  $X_i$  for an answer. Given a peer  $P_r$  and any of its acquaintances  $P_i$ , the reserve prices for  $P_i$  are initialized as:  $X_i = X_0$ ,  $Y_i = Y_0$ , where  $X_0$  and  $Y_0$  are constants in the system.

The reserve prices are used to estimate if the selling prices from other peers are reasonable. For example, at time  $t$ , peer  $P_r$  receives a set of prices for answers from sellers  $\{P_l, P_{l+1}, \dots, P_m\}$ . For any seller  $P_j$ , the estimated margin of the reward for choosing peer  $P_j$  is  $X_j - X_j'$ , where  $X_j$  is the reserve price of an answer in the acquaintance model for  $P_j$  at time  $t$  ( $X_j = X_0$  if there is no acquaintance model for  $P_j$ ) and  $X_j'$  is the selling price of an answer in the profile of peer  $P_j$ . Similarly, for referring services, the requesting peer  $P_r$  computes the estimated margin for a referral from  $P_j$  as  $Y_j - Y_j'$ .

Given a set of referring services, the requesting peer will choose referrals from the highest to the lowest estimated margins for a single referral. For a given referral graph  $G$ , the requesting peer will choose the referral with the highest estimated margin to expand the graph, where the requesting peer pays all referrals  $P_j$  has. After the requesting peer receives an answer, it or its user will evaluate the quality of the answer and revise the reserve price for the service from the answering peer. On the other hand service providers adjust the estimated values for prices of referrals and answers.

## 2.2. Pricing Strategies

In this section we present a stochastic iterative algorithm as an effective dynamic pricing strategy for a peer. In this algorithm a peer estimates the value of each price, and most of the time chooses the price with the higher value estimation. The algorithm is composed of two parts: the first is *value estimation* and the second is *price selection*.

**Value estimation** The estimated value of price  $a$  for a referral or an answer after  $t$  plays is denote by  $Q_t(a)$  and  $r_{k_a}$  is the reward from choosing price  $a$  at the  $k_a$ -th time. A peer updates the estimated value of a price, if the price is chosen, based on the current reward and the previous estimated value. The update of the estimated value is based on the following rule:

$$Q_{k_a+1}(a) = Q_{k_a}(a) + \alpha(r_{k_a+1} - Q_{k_a}(a)) \quad (1)$$

where step size  $\alpha$  is a constant,  $0 < \alpha \leq 1$ . Based on this rule the recent rewards are weighted more heavily than long past ones. This is necessary in a non-stationary environment in which the mean reward of a price changes over time. The recent environment, e.g., acquaintances of each peer, is more similar to the environment today and therefore gives more information, than the environment of long past. With a constant step size  $\alpha$ , the estimates never completely converge but continue to vary in response to the most recently received rewards [2].

**Price selection** Although a peer can exploit the estimated values of prices for price selection, exploring other prices is necessary to gain information on the prices that have been rarely chosen in the past. We suggest the  $\epsilon$ -greedy method to choose an appropriate price. In this method a peer behaves greedily, i.e., chooses the price with the highest estimated value, most of the time, but every once a while, say with probability  $\epsilon$ , select a price at random. A peer will not select among the other prices equally. The selection among other prices is directed by the uncertainty level of the value estimation to encourage exploration. One way to estimate the uncertainty of the price is to compare the number of times that the price has been chosen and the number of time that the price offered rewards. Suppose  $n_a$  is the number of price  $a$  being chosen and  $n'_a$  is the number of price  $a$  being offered reward, then the uncertainty for this price can be estimated as  $(n_a - n'_a)/n_a$ , where  $n'_a \leq n_a$ .<sup>1</sup> The potential rewards for price  $a$  is  $Q(a) * n_a / (n_a - n'_a)$ , where  $Q(a)$  is the average rewards received at price  $a$ .

Another consideration in the design of pricing mechanisms is the initial value for the average reward  $Q(a)$  of each price  $a$ . The algorithms we discussed so far are dependent on the initial price-value estimates,  $Q_0(a)$ . For ex-

ample, for any price  $a$ , initially  $Q_0(a) = 0$ . The kind of design is problematic when we estimate the uncertainty of each price during exploration. In such cases, some prices could be never explored since the potential reward is zero. One solution is to use an optimistic estimate for any price  $a$ , e.g.,  $Q_0(a) = Y_0$  for any referring services. This optimistic estimate encourages the exploration of each price at least once.

## 3. Conclusion

This paper proposes a dynamic pricing mechanism to motivate each peer to behave rationally in referral systems. Our paper only provides a preliminary study of pricing mechanism design in referral systems. For example, we simply assume that the qualities of services are consistent for each peer. Also, we don't consider how to effectively determine the upper bounds of selling prices for referrals and answers during exploration. In future work, we plan to focus on these problems and develop more efficient and incentive compatible mechanisms for referral systems and peer-to-peer systems in general.

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<sup>1</sup>  $n_a = 1$  when price  $a$  is never chosen or is chosen once.