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"GPT" Task Pricing Model

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Abstract. "Get Paid To (GPT)" is a self-service model under the mobile Internet. The user downloads the APP, registers as an APP member, and then takes the task (such as going to the supermarkets to check the availability of a certain product) from the APP to earn the nominal fee of the APP for the task. Based on the pricing data given by an APP in Guangdong, this paper designs a new task scheme to make the pricing more reasonable. I used task pricing data, including the location, pricing and fulfillment of each task; and member information data, including the location of members, the credit and the booking time and booking limit referred to the member's credit. In principle, members of the higher credit, the more priority to start selecting tasks, the greater its limit.

1. Introduction

In order to make a more rational pricing scheme, I set up a pricing model based on random threshold algorithm, and got an optimized pricing scheme. The model takes into account the latitude and longitude position, pricing and members' location of the task, its credit rating, the scheduled time and the task limit. An appropriate task pricing scope is given after the correlation analysis of the completed task pricing, aims to traverse the price in order to determine the optimal allocation set M for the task under the constraints of the established distance efficiency function U. On this basis, I maximize the credit function P as a constraint condition, and select the most suitable member in the distribution center, so that we can deduce the optimal pricing relative to this task. Compared with the original proposal, the pricing scheme improved the completion rate of the task by 10.659% and its pricing is generally lower.

2. Pricing Model Based on Random Threshold Algorithm

2.1 Data Analysis

Before starting to build models and algorithms, we first analyze the members' information. The red dot on the left shows the high and finished distribution of the task, and the red dot on the right shows the distribution of the high and unfinished task.

As can be seen from the figure below: Reputable members did not fully choose the pay-high work, at the same time found the right figure, reputable members may not be able to complete the task. The reason may be: The high pay for the project is because of the difficulties, so most of the members with high credibility will choose convenient, concentrated workload of the project to do. In addition, reputable members get higher profits in the same task, so there is no need to find other tasks. At the same time, due to the relatively small quota of ordinary members, so they will choose the task of high pay to get greater profits.

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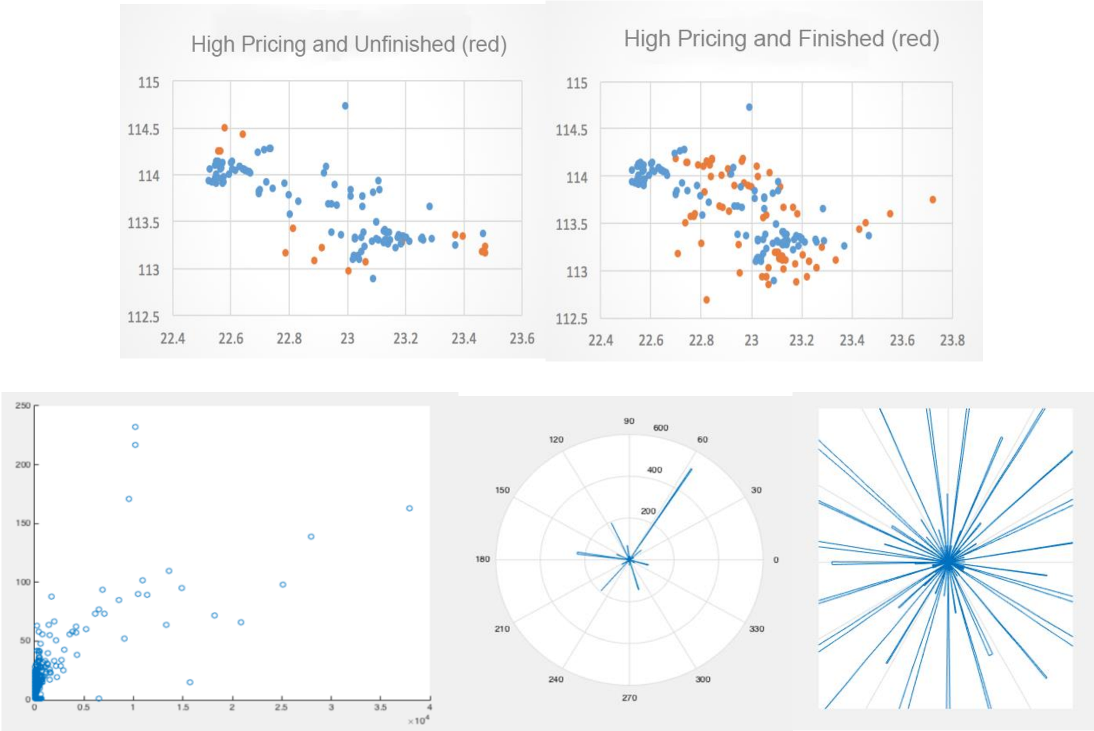

Fig. 1 Relationship between Credit and Task Quota

Fig. 1 is the relationship between the user's credit rating and the task quota. As can be seen from the scatter chart, when the credit rating is greater than 0.3*104, the corresponding task quota will randomly multiply. That is, if the user's reputation reaches a certain height, the task quota will reach a satisfactory state. By analyzing the wind map and its partial enlargement graph, it can also be found that when the credit is greater than a certain value, the task quota issued is highly concentrated (about 1,700), and once this value range is exceeded, the task quota is distributed randomly.

At this point, we conducted a comprehensive analysis of the position, pricing and completion of the task, the credit of the members and the scheduled time. Through the analysis of the vertical task pricing and the member's completion of the task, we get the rule that the member should complete the task: Higher credibility, on the one hand, members will choose to do more to earn, while accepting the pricing is moderate or slightly lower task,on the other hand, members will choose to do less to earn more, that is, only select a small number of higher-priced tasks to obtain the efficiency. In addition, through horizontal analysis of the internal factors of members, we conclude the relationship between the member's credit and the scheduled quota and the scheduled time: High-credit members have higher quotas and higher-priority tasks. Meanwhile, members with high credit will also have a more centralized distribution of tasks distributed. Some of the above analysis will be considered in the new pricing model and the appropriate optimization.

2.2 Model Establishment

2.2.1 Some Definitions That Need to Be Used in the Model

(1) Task a: A camera task is defined as $a=(l_a,r_a,u_a)$. l_a represents the location of the task in space, choice l_a as the center of the circle, r_a as the radius of the area members to complete the task, u_a as the task pricing.

(2) Member w: A member is defined as $w=(l_w,r_w,c_w,q_w,t_w)$. l_w represents the location of the members in space. You can choose from within the radius of its movement r_w area of the task, the maximum number of tasks it can accept is a positive integer c_w. Each member has a reputation assessment $q_w \in (0,1]$, the higher the credit value, the more priority to start picking tasks, the greater its quota. The scheduled time t_w for a member's scheduled task affects its priority.

(3) Distance benefit function U: Member w and camera task t distance function is defined as $U(t,w)=u_t \times l_{aw} \times q_w$, the product of task pricing, distance, and member credit.

(4) Credit function P :It is a comprehensive evaluation index of the member, based on its credit q_w, scheduled task time t_w and the maximum number of tasks that can be accepted c_w : $P = xc_w + yt_w + zq_w$,x, y, z are the weights of each index.

(5) If a camera task requires N members to complete, it will be equivalent to N capacity of 1 task.

2.2.2 Stochastic Threshold Algorithm

Through the members' credit, and distribution in the geographical location. I given a camera task set T, membership set W and a distance benefit function U. The goal of the algorithm is to find the distribution of tasks and members.

First corresponds to a task, to determine a task pricing range, traversing the price within this range. Each given a task pricing, through a random threshold algorithm to determine a distribution plan, the specific process is as follows:

(1) Select a benefit threshold $\theta = \ln(U_{\max} + 1)$.

(2) A random value k is selected from 0, 1, ... θ-1 with the probabilities p0 ,p1 …, pθ-1 ($p_i > 0, \sum_{i=1}^{\theta-1} p_i = 1$)to determine the threshold value e^k.

(3) For a task, analyze whether the distance between the member and the surrounding members satisfies $|O_a O_w| \le |r_a + r_w|$, and set up members set M (contains m elements).

(4) If M is not an empty set, the m elements are traversed and their corresponding distance utility function is compared with the threshold value e^k. If U(t1, wi)< e^k, then no assignment is made. If U(t1, wi)⩾ e^k, then algorithm makes the assignment (ti,wj), adds it to the result set, and the member no longer participates in the traversal.

At this point, the distribution plan that determines the best benefit for each price is shown in the result set. And then find the best credit assignment candidate corresponding to the task according to the credit function P of the member so as to reversely deduce the optimal price corresponding to the task.

2.3 Algorithm Calculation Results

Through the above algorithm, re-assign the pricing plan for the tasks in App. The algorithm obtains the distribution of each task corresponding to different pricing. Due to space constraints, I selected 12 tasks and their distribution for further analysis. Corresponding to a task, I calculate the credit utility function value P corresponding to each distribution (assigned to different members), and take the maximum, so as to get the best pricing of the task. The 12 tasks are priced in Table 1 below:

Table 1. Part of the task of the new pricing

	Task Number	Member ID	Credit	Task Pricing
1	A002	B0388	0.324	62.5
2	A037	B0889	0.207	61.5
3	A044	B0125	0.326	60.5
4	A071	B0767	0.314	60
5	A114	B0430	0.177	63.5
6	A117	B1486	0.084	60
7	A118	B1529	0.054	63.5
8	A125	B0977	0.076	61.5
9	A130	B0378	0.268	70.5
10	A236	B0268	0.294	61
11	A237	B0399	0.314	82.5
12	A553	B1255	0.266	60.5

The following specific calculation of the task completion rate before and after the pricing program in Table 2 below:

Table 2. Comparison of old and new pricing situation task completion

	Original Pricing	New Pricing	Optimization Ratio
Task Completion Rate	62.515%	73.174%	17.050%

Consistent with the above analysis of the scatter plot, by the specific task completion rate data we can more specific analysis, the new pricing scheme has a 10.659% improvement over the original pricing scheme in the degree of task completion and the optimization ratio is 17.05%, largely optimized the old pricing scheme.

3. Summary

To sum up, the pricing scheme based on the stochastic threshold algorithm is more optimized than the original scheme in pricing and task completion rates. For task publishers, they can lower the cost of attracting high-quality, close to the members of the task, which is a win-win business and members.

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