Trading Discount for Reputation? – On the Design and Analysis of E-Commerce Discount Mechanisms

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ABSTRACT

We develop an optimization framework to trade short-term profits for reputation (i.e., reducing *ramp-up time*). We apply the stochastic bandits framework to design an online discounting mechanism which infers the optimal discount from a seller's historical transaction data. We conduct experiments on an eBay's dataset and show that our online discounting mechanism can trade 60% of the short-term profits for reducing the ramp-up time by 40%.

Categories and Subject Descriptors

H.4 [**World Wide Web**]: Web applications – Electronic commerce

Keywords

Reputation; Discount; E-commerce

1. INTRODUCTION

Reputation system has become an indispensable component of modern E-commerce systems (e.g., Alibaba, Amazon, eBay, etc), as it helps buyers make informed decisions in choosing trustworthy sellers [3]. Because it is quite common for a buyer to purchase products from a seller whom he has never transacted with before in an E-commerce system, it is critical for buyers to know whether a seller is trustworthy or not [3]. One inefficiency of the reputation system is that new sellers may need to spend substantial amount of time to attain a trustworthy reputation [4], and we call this the "*ramp-up time*". It was found out in [4] that sellers in eBay need to spend around eight hundred days to get ramped up. Reducing the ramp-up time is highly desirable for sellers in real world E-commerce systems. To reduce the ramp-up time, more than 11,000 sellers in Taobao have been identified to accelerate the reputation accumulating process even via illegitimate methods, i.e., fake transactions [5]. Another evidence is the emergence of professional fake-transaction services [5]. Typical companies providing such services include Lantian [1] with 6,700,000 fake-transactions (estimated) per year [5].

In this work, we propose a legitimate way to accelerate the reputation accumulating process through price discounts. The idea is that by providing some price discounts, a new seller can attract more buyers even when the seller has a low reputation score. The challenge is to determine the appropriate price discount. The larger the discounts, the more buyers a new seller can attract. However, it also reduces his profits, which is critical to a new seller to survive in a competitive E-commerce system. So, the first challenge we need to address is to *quantify the tradeoffs in selecting the appropriate price discounts*. Secondly, sellers usually have no prior knowledge on buyers' preferences over price discounts, i.e., for some buyers, a small discount is sufficient to attract them to purchase a product, while other buyers may need to have a higher price discount to lure them for a transaction. The second challenge we want to address is *to learn (or infer) the buyers' preferences and set the appropriate price discounts simultaneously.*

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2. SYSTEM MODEL

A buyer pays the seller $p \in [0,1]$ to purchase a product. We consider a normalized manufacturing cost $c \in [0,1]$. After selling a product, the E-commerce system charges a transaction fee $\tau \in [0,1)$ from the seller. Let u be the unit profit of a seller after selling one product, we have $u = p - c - \tau$.

• **Reputation System Model:** We consider an eBay-like reputation system. After receiving a product, a buyer provides a rating to indicate the quality of the transaction, such as the product quality, the shopping experience, etc. The feedback rating can be one of three levels, i.e., $\{1\,(\text{positive}), 0\,(\text{neutral}), -1\,(\text{negative})\}$. We use a probabilistic model to capture human factors such as personal preferences, biases in ratings. Denote P^+, P^0, P^- as the probability that a seller receives a positive, neutral and negative rating respectively. Note that $P^+ + P^0 + P^- = 1$. One can vary the values of P^+, P^0, P^- to reflect different levels of personal biases. A seller's reputation is quantified by the total sum of all his feedback ratings. Denote $r \in \mathbb{Z}$ be the reputation score of a seller. A new seller who just joins an E-commerce system is initialized with $r = 0$. We use a continuous time system to characterize the reputation update dynamics. Let $r(t)$ denote a seller's reputation score at time $t \in [0, \infty)$. When a seller joins an E-commerce system (at time $t = 0$), his reputation is initialized as $r(0) = 0$.

E-commerce systems usually classify sellers into different types based on their reputation scores. For example in eBay, sellers are classified into thirteen types, i.e., {no star, 1 star, 2 stars, ..., 12 stars}. Formally, our model classifies sellers into $S + 1$ types, i.e., {0 star, 1 star, ..., S stars}. Denote $\mathcal{S} : \mathbb{Z} \rightarrow \{0, 1, \ldots, S\}$ as a map which prescribes a number of stars for each reputation score, $\mathcal{S}(r) = 0$, if $r < n_1$ and $\mathcal{S}(r) = S$ if $r \geq n_S$. For $i = 1, \ldots, S-1$, $\mathcal{S}(r) = i$ if $n_i \leq r < n_{i+1}$. We use a Poisson process to characterize the buyers' arrival process. One can vary the arrival rate of the Poisson process to differentiate sellers in terms of the reputation. More concretely, the larger the number of stars, the higher is the arrival rate. Denote λ_s, where $s \in \{0, 1, \ldots, S\}$, be the buyers' arrival rate when a seller has a number of s stars. We have $\lambda_i \leq \lambda_j$ for $0 \leq i \leq j \leq S$.

• **The Price Discount Model:** A seller can set one of $M + 1$ potential price discount levels $\{0, 1, \ldots, M\}$, where $M \in \mathbb{N}$. Here, level 0 corresponds to the case that a seller does *not* provide any discount. The higher the discount level, the larger the discount on the price. Denote $P_m, m = 0, 1, \ldots, M$, as the probability that a buyer who clicks into an online store will purchase a product if the seller sets a level m price discount. We require $P_0 < P_1 < \ldots < P_M$ to signify that the larger the price discount, the higher the probability that a buyer will purchase a product. The values of P_m, where $m = 0, 1, \ldots, M$ are unknown to sellers. Note that the transaction's arrival process is still a Poisson counting process (via Poisson thinning argument). Denote $\lambda(t, m)$ as the transaction's rate at time t when a seller sets a level m discount. we have $\lambda(t, m) = \lambda_s P_m$, if $\mathcal{S}(r(t)) = s$

• **Ramp-Up Time:** Recall that new sellers are initialized with 0 star, with which it is quite difficult to attract buyers. Hence, one critical metric for sellers is the minimum time it takes to earn enough credits. Let $T(s) \triangleq \arg\min_t\{\mathcal{S}(r(t)) \geq s\}$ denote the minimum time to earn a number of $s \in \{0, 1, \ldots, S\}$ stars. Note that sellers can set a target on the number of stars to be earned.

3. DESIGN OBJECTIVE

• **Metrics:** Denote $\mathcal{M}$ as a mechanism which prescribes a price discount level for each product sold in the ramp-up process. The ramp up process is defined as the process for a new seller to earn s stars. One benefit of the mechanism $\mathcal{M}$ is in reducing the ramp-up time since setting a price discount can attract more buyers.

Definition 3.1. *Denote $T(s, \mathcal{M})$ as the ramp-up time corresponds to the mechanism $\mathcal{M}$. Define $\mathcal{R}(s, \mathcal{M}) \triangleq \frac{E[T(s)] - E[T(s,\mathcal{M})]}{E[T(s)]}$, as the ramp-up time reduction achieved by the mechanism $\mathcal{M}$.*

Notice that the mechanism $\mathcal{M}$ achieves the ramp-up time reduction at the expense of losing some short-term profits. Denote $G(s)$ and $G(s, \mathcal{M})$ as the short-term profits, which are earned in the ramp-up process when a seller sets no discount at all and uses the discount mechanism $\mathcal{M}$ respectively.

Definition 3.2. *Define $\mathcal{L}(s, \mathcal{M}) \triangleq \frac{E[G(s)] - E[G(s,\mathcal{M})]}{E[G(s)]}$ as the short-term profit loss due to the mechanism $\mathcal{M}$.*

• **Design Tradeoffs:** Our objective is to design a mechanism $\mathcal{M}$ which trades price discounts for reputation subject to different tradeoffs between the *ramp-up time* and the *short-term profit loss*:

$$\max_{\mathcal{M}} \quad z(s, \mathcal{M}) \triangleq \alpha\mathcal{R}(s, \mathcal{M}) - (1 - \alpha)\mathcal{L}(s, \mathcal{M}) \tag{1}$$
$s.t. \mathcal{M}$ sets discounts for products sold in the ramp-up process,

where $\alpha \in [0, 1]$ denotes a balance factor which can be controlled by a seller. The value of α reflects the aggressiveness of a seller in reducing the ramp-up time.

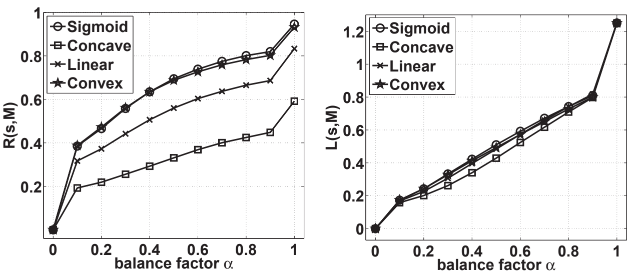
4. DISCOUNT MECHANISM

Mechanism: We apply the UCB algorithm [2] to set the appropriate discount. We outline the mechanism in Algorithm 1, where w_i denotes the waiting time of i-th transaction. In Algorithm 1, step one to step six correspond to initialization, where the seller tries each discount once. Step eight is the key step, which sets the appropriate discount based on historical transaction data.

Algorithm 1 : Online Discounting Mechanism

1: **for** $i = 1$ to $M + 1$ **do**
2: Set level $i - 1$ discount for i-th transaction, i.e., $m_i \leftarrow i - 1$.
3: Observe the waiting time w_i of i-th transaction
4: $R_{m_i} \leftarrow -\alpha\lambda_{\mathcal{S}(r_i)} P_0 w_i - (1 - \alpha)\frac{d_{m_i} p}{u}$, $N_{m_i} \leftarrow 1$
5: update reputation score r
6: **end for**
7: **while** $r < n_s$ **do**
8: $m_i \leftarrow \arg\max_m \left\{ \frac{R_m}{N_m} + \max\left\{ \frac{4\ln(i-1)}{N_m}, \sqrt{\frac{4\ln(i-1)}{N_m}} \right\} \right\}$
9: Observe the waiting time w_i of the i-th transaction
10: $R_{m_i} \leftarrow R_{m_i} - \alpha\lambda_{\mathcal{S}(r_i)} P_0 w_i - (1-\alpha)\frac{d_{m_i} p}{u}$, $N_{m_i} \leftarrow N_{m_i} + 1$
11: update reputation score r
12: **end while**

Experiments on eBay Data: We crawled a dataset from eBay in April 2013. It contains of 18,533,913 historical ratings which are received by 4,362 sellers from the first day that a seller joins the eBay till April 2013. We consider six levels of discounts and $d_m = m \times 5\%$. We synthesize $P_0, P_1, \ldots, P_5$ to reflect the real-world scenario as accurate as possible. We consider four representative types of buyers' preference to discounts: (1) **Sigmoid:** $P_m = 0.5/(1 + e^{-(m-3)})$; (2) **Concave:** $P_m = 0.0237(m + 1)^{0.5}$; (3) **Linear:** $P_m = 0.0237(m + 1)$; (4) **Convex:** $P_m = 0.0237(m + 1)^{1.5}$, where $m = 0, 1, \ldots, 5$ and the parameters 0.0237 and 0.5 are carefully selected to guarantee that the value of P_0 is the same for these four preference models. Without loss of generality, sellers aim to earn five stars in our experiments. Figure 1(a) shows that as the α increases, the ramp-up time reduction increases. However, as shown in Figure 1(b) that this is achieved at a price of losing more short-term profits. If a seller has a moderate investing budget (i.e., $\alpha = 0.6$) our mechanism can reduce the ramp-up time by at least 40% by trading 60% of the short-term profits.



(a) Ramp-up time reduction (b) Short-term profits loss

Figure 1: Ramp-up time and short-term profits.

5. REFERENCES

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