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Optimal Price Discount Schedule for Digital Music Downloads

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INTRODUCTION

It is now commonly believed that the potential demand for music downloads is huge. Researchers at Webnoize found that in August 2001, music-lovers transferred more than three billion music files using websites like FastTrack, Audiogalaxi, and Gnutella. In September 2001, an estimated of one million users were logged on to the networks of music-sharing services at a given time. The music industry tapped into this huge potential demand. Bestbuy.com, pressplay.com, musicnet.com, and cdnow.com, to name a few, have already offered digital music downloads. It is still unclear, however, what revenue model should be used in this new paradigm.

Adams and Yellen (1976) identify three bundling strategies: pure bundling, mixed bundling, and pure unbundling. In pure bundling, consumers are required to purchase either the entire bundle or nothing at all. This strategy is functionally similar to a subscription-based service, where music-lovers pay a subscription fee in order to download a limited number of songs per period. In pure unbundling, consumers buy individual components and put together their own bundle. The price of the bundle is the total price of the individual components. This strategy is similar to a pay-per-song service without any price discount, where music-lovers do not pay any subscription fee. In mixed bundling, consumers are offered a menu of different bundles, including individual components, at different prices. The price of a bundle is no more than the total price of its individual components. This strategy is similar to a pay-per-song service with price discounts.

Chuang and Sirbu (2000) show that of those three bundling strategies, mixed bundling is the dominant (i.e., profit maximizing) strategy. By offering a menu of different bundles at different prices, the seller creates an incentive-compatible condition, inducing customers to reveal their preferences by self-selecting into the appropriate consumption groups. Thus, the seller can extract consumer surplus more completely via consumer self-selection. Bakos and Brynjolfsson (2000) argue that pure bundling reduces the effective heterogeneity of the consumers' demands so that a single price can effectively and efficiently allocate goods to the consumers. If consumers' demands remain heterogeneous even after pure bundling, then a mixed bundling strategy will dominate pure bundling. It seems that consumers' demands for music fit the later case. Thus, there seems to be a case to favor pay-per-song strategy with price discounts in selling digital music downloads. In this work, we operationally analyze an optimal (i.e., profit maximizing) price discount model for digital music downloads, which could be generalized to other information goods such as software, research reports, video clips, etc.

THE MODEL

We consider a record company that offers digital music downloads, which adopts a pay-per-song strategy to sell its music. Via the Internet, customers self-select the songs they want and pay only for those songs they selected. To stimulate demand, the company offers a progressively increasing price discount schedule. For example, if the total amount of purchase is \$6.00, the customer receives 10% discount for the first two dollars of purchase, 25% for the second two dollars, and 50% for the last two dollars. The customer pays only \$4.30 (=\$1.80+\$1.50+\$1.00). Based on the demands of increments of total purchase amount, the company establishes an optimal incremental price discount schedule. We assume the followings:

1. Customers' demands for music are heterogeneous.

2. The available demand data provide estimates of demand for each of several discounts and several levels of total purchase amounts.

- The price elasticity of the demand is everywhere an increasing function of the price. Thus, at higher prices or smaller discounts, customers are less willing to buy songs because they have more opportunities to substitute songs with other competing products and services.
 Nominal unit price of each song is given. The cutoff points to
- determine levels of purchase are also given.
- 5. Each customer buys at most one copy of a particular song per transaction and customers are prohibited to resale the songs.

To illustrate the model, we will use an example. Consider the raw data in Table 1, which can be easily obtained from the records of customers' purchases at different price discounts. As we can see from Table 1, customer C3 purchased two songs, songs 1 at \$0.75 and song 4 at \$1.25, for a total of \$2.00 before a 10% discount. Similarly, customer C7 bought four songs for a total of \$3.90 before a 25% discount.

We can summarize these raw data in a tabular array (see Table 2) in which the rows correspond to different discounts and the columns correspond to the different ranges of purchase amounts. An entry in the table shows the number $n(d, P_i < P \pounds P_i + r)$ of customers who at the price discount *d* spent a purchase amount before discount *P*, which is greater than P_i but less than or equals to $(P_i + r)$. The width of a level of purchase amount is *r*. In our example, we set r = 2 exogenously. For example, an entry of 2 in the first row and first column of Table 2 means that when the discount *d* is 50%, there are two customers each has a total purchase amount, before discount, that is greater than zero but less than or equals to \$2.00.

Table 1: Customers' purchases for different discounts

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	Custid S	ongio	d Price O	rderTotal	Discount	Custid	Songi	d Price C	orderTota	Discount
	C1	4	\$1.25	\$2.75	0.00%	C9	1	\$0.75	\$1.65	25.00%
		5	\$1.50				2	\$0.90		
	C2	1	\$0.75	\$2.00		C10	2	\$0.90	\$4.65	
		4	\$1.25				3	\$1.00		
	C3	1	\$0.75	\$2.00	10.00%		4	\$1.25		
		4	\$1.25				5	\$1.50		
	C4	1	\$0.75	\$1.65		C11	2	\$0.90	\$0.90	
		2	\$0.90			C12	1	\$0.75	\$5.40	50.00%
	C5	3	\$1.00	\$3.75			2	\$0.90		
	1.0	4	\$1.25				3	\$1.00		
		5	\$1.50				4	\$1.25		
)	C6	2	\$0.90	\$4.65			5	\$1.50		
		3	\$1.00			C13	2	\$0.90	\$3.90	
		4	\$1.25				3	\$1.00		
		5	\$1.50				4	\$1.25		
	C7	1	\$0.75	\$3.90	25.00%		1	\$0.75		
		2	\$0.90			C14	1	\$0.75	\$3.90	
		3	\$1.00				2	\$0.90		
		4	\$1.25				3	\$1.00		
	C8	1	\$0.75	\$3.90			4	\$1.25		
		2	\$0.90			C15	1	\$0.75	\$2.00	
		3	\$1.00				4	\$1.25		
		4	\$1.25			C16	5	\$1.50	\$1.50	

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0 <p≤2< th=""><th>2<p≤4< th=""><th>4<p≤6< th=""></p≤6<></th></p≤4<></th></p≤2<>	2 <p≤4< th=""><th>4<p≤6< th=""></p≤6<></th></p≤4<>	4 <p≤6< th=""></p≤6<>
2	2	1
2	2	1
2	1	1
1	1	0
	2 2 2	2 2 2 2 2 1

Table 3: $N(d, (P_i, P_i+r])$

(1-d)	(0, 2]	(2, 4]	(4, 6]	
0.50	5	3	1	
0.75	5	3	1	CON
0.90	4	2	1	
1.00	2	1	0	

Let us denote the i^{th} level of purchase amount that is greater than P_i but less than or equals to $(P_i + r)$ as level $(P_i, P_i + r]$. The demand for purchase amount level $(P_i, P_i + r]$ is the number of customers whose total purchase amounts are at least as high as level $(P_i, P_i + r]$. From Table 2, we can construct Table 3, where each entry in Table 3 is the demand at discount *d* for level $(P_i, P_i + r]$. This demand is calculated as follows:

$$N(d, (P_i, P_i + r]) = \sum_{j=i}^{k} n(d, (P_j, P_j + r])$$
(1)

Where k is the number of purchase amount levels. An entry of 3 in the first row and second column of Table 3 means that when the discount d is 50%, there are three customers; each of these customers has a total purchase amount, before discount, at least as high as purchase amount level (2, 4]. To calculate profit (p) from offering price discount d and from purchase amount level (P_i, P_i+rJ , let us define $f(P_i > P_i + r)$ as an indicator function, which is equal to one if $P_j > P_i + r$ and zero otherwise. P_j is the total purchase amount of customer j. Note that $P_i > P_i$ since we are interested in the purchase amount level ($P_i, P_i + rJ$). Since we are dealing with digital goods, it is reasonable to assume that the marginal cost of digitized music is zero. Thus, the profit is as follows:

$$\pi(d, (P_i, P_i + r]) = (1 - d) * \left\{ \sum_{j=1}^{N(d, (P_i, P_i + rj))} f(P_j > P_i + r)^{\frac{1}{2}} \right\}$$

$$*r + (1 - f(P_j > P_i + r)) * (P_j - P_i) \right\}$$
(2)

where $P_j = \sum_{i=1}^{m} p_{ji} x_{ji}$, and p_{ji} is the price of song *i* charged to a customer

j, x_{ji} is an indicator variable, which is equal to one if customer *j* buys song *i*, and zero otherwise, and *m* is the number of available songs.

The optimal price discount for purchase amount level $(P_{\mu}, P_{i}+r)$ is the one that maximizes equation (2). Based on data in Table 1 and Table 3, we can determine the profits at different discounts for each purchase amount level, as shown in Table 4.

To calculate the profit amount of \$4.75 as shown in the first row and first column entry in Table 4, we proceed as follows. In Table 3, when discount is 50%, there are five customers. Each of these customers has a total purchase amount, before discount, at least as high as purchase amount level (0, 2]. They are C12 through C16 (see Table 1). Although each of customers C12, C13, and C14 has a total purchase

Table	4: P	rofit	after	discount
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(1-d)	(0, 2]	(2, 4]	(4, 6]	Profit with <u>Uniform</u> Discount
0.50	\$4.75	\$2.90	\$0.70	\$8.35
0.75	\$6.41	\$4.35	\$0.49	\$11.25
0.90	\$6.89	\$3.38	\$0.59	\$10.85
1.00	\$4.00	\$0.75	0	\$4.75
Profit with In	ncremental E	\$11.94		

amount that is greater than \$2.00, we apply the 50% discount only on the first \$2.00 of their purchase amounts. For C15 and C16, each of their total purchase amounts is less than or equals to \$2.00. Thus, we apply 50% discount on all of their purchase amounts. Therefore, the profit at 50% discount from the purchase amounts of up to \$2.00 is (1-0.5) * (2+2+2+2+1.50), which is \$4.75. Using the same method, we can calculate the profits from the purchase amounts of up to \$2.00 when the discounts are 25%, 10%, and 0%. These are \$6.41, \$6.89, and \$4.00, respectively. Consequently, 10% is the amount of discount that produces the highest profit (\$6.89) for purchase amounts of up to \$2.00. Using the same method, we can calculate other entries in Table 4. Thus, the record company should offer the following progressive price discount schedule:

Range of Total Purchase Amount (P)	Applicable Discount (d)
0.0 < P £2.0	10%
2.0 <p td="" £4.0<=""><td>25%</td></p>	25%
4.0 <p td="" £6.0<=""><td>50%</td></p>	50%

Note that as we can see from Table 4, the total profit obtains from the incremental discount schedule is 11.94 (=8.89+, 4.35+, 0.70). We can also see the highest total profit (11.25) that can be attained by using a uniform discount, which is at a discount of 25%. This profit is smaller than the total profit obtains using incremental discounts. The gain from incremental price discounts shown in this example is due to the heterogeneity among customers. Segmenting the market into levels of purchase amounts enables the seller to induce demand by offering higher discounts for the larger total purchase amounts.

CONCLUSION

In this work, we show by an example how to develop an optimal price discount schedule for digital music downloads based on raw data that can be easily obtained from the records of customers' purchases. In Table 1, the seller arbitrarily chooses the discount amounts of 10%, 25%, and 50%. A better model would be to make the number of purchase amount categories and the discount amount for each category as the decision variables to optimize. We are working on an empirical study of this model and also on its extensions.

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