Optimal versioning strategy for information products with behavior-based utility function of heterogeneous customers

Minqiang Li *, Haiyang Feng, Fuzan Chen, Jisong Kou

College of Management and Economics, Tianjin University, Tianjin 300072, PR China

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A B S T R A C T
This paper reconsiders two fundamental assumptions (i.e., on the quality of information product and the self-selection behavior of customers) that decide the optimality of versioning strategy (or vertically differentiated product line) for information products. The quality of an information product is clarified in terms of functional and nonfunctional features. The customers’ behavior of self-selection among multiple versions of an information product is examined, and the disability of linear valuation function for exactly capturing customers’ valuation on information products is clarified. The required quality is introduced to depict a customer’s requirement on the quality of an information product, and a behavior-based utility function is thus defined, where a customer has a marginal decrease (different from the constant marginal in linear valuation function) on the valuation of versions with quality levels higher than the required, but the valuation of a customer diminishes quickly on versions with quality levels lower than the required. Then, a bilevel programming model is built to represent the task for optimizing the strategy of versioning an information product, with the monopolist as the leader and all customers as followers. Optimal quality levels and prices for multiple versions are obtained for a given number of versions. To deal with the nonlinearity and multimodality of this model due to correlated decision variables, a steady-state evolutionary algorithm, hybridized with the local search method (called the hybrid steady-state evolutionary algorithms), is developed to improve the global optimality of versioning schemes. Numerical experiments are conducted on the bilevel programming model with specific parameterization by using the hybrid algorithm. Experimental results verify the optimality of multi-version strategy and reveal various facets of its property. With the behavior-based valuation function of heterogeneous customers, the multi-version strategy is superior to the one-version scheme. The total profit increases logarithmically with the maximal number of versions, which means that the introduction of a new lower-quality version contributes less to the total profit of a monopolist. Furthermore, when a lower quality level version is offered to the market, higher quality versions are priced higher than they were in previous versioning schemes, indicating that a multi-version scheme can make more detailed segmentation of the market. Therefore, a monopolist is able to gain greater revenue via price discrimination on heterogeneous customers through vertically differentiating information products.

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1. Introduction

Although Shapiro and Varian [20] presented the clear-cut advantage of the versioning strategy for information products through profound qualitative analyses and successful industrial instances, there have been controversial conclusions on the optimality for vertically differentiating an information product [14,4,5,8].

For instance, the versioning was proved to be suboptimal [4,11,6,25] when customers’ valuation or willingness to pay (WTP) for an information product was defined as a linearly multiplicative function of customer type and product quality, e.g., customer WTP function: \( W(v,q) = vq \), customer utility function: \( U(v,q,p) = vq - p \), where \( v \) indicates customer type or preference (marginal valuation), \( p \) is the price of version with quality \( q \), \( v \in [0, q_{\text{max}}] \), \( q_{\text{max}} \) is the maximal marginal valuation, \( q_{\text{max}} \) is the maximal quality. All potential customers were usually assumed to be uniformly distributed with regard to their types or preferences. Based on this linear valuation function of customers, the introduction of a low-quality version of an information product will not surely lead to greater revenue for a monopolist when there has been a high-quality version in the current market. Customers with lower preference usually buy the low-quality

*Corresponding author. Tel./fax: +86 22 27404796.
E-mail addresses: mlq@tju.edu.cn, mlq2@hotmail.com (M. Li), hyfeng@tju.edu.cn (H. Feng), fzchen@tju.edu.cn (F. Chen), jskou@tju.edu.cn (J. Kou).
1 Information products mean anything that can be digitized and transmitted based information and communication technologies (ICT), including various softwares, digitized contents on the Internet, and information services, etc.
version. Meanwhile, some customers with higher preference will probably shift to purchase the low-quality version. This strategy induces customers’ self-selection between two versions based on their utilities. The income brought by the low-quality version may be offset by the profit loss of high-quality version when the low-quality version cannibalizes a large market share of the high-quality version. There exist many factors that determine the optimality of two-version scheme (or multi-version schemes with more than two versions of different quality levels), including customer distribution, marginal cost of an information product, position of quality levels, and prices of different versions. Bhargava and Choudhary [4,5] proved that versioning became optimal for a monopolist only when the highest-quality version of an information product had the best benefit-to-cost ratio or if the relative valuation decreased with customer preference. Jing [11] pointed out that positive network effect would make the versioning optimal.

There are two fundamental assumptions (explicitly or implicitly assumed) in previous researches on the optimality of versioning information product. The first one is about the self-selection behavior of customers when multiple versions are available in the market. A customer with marginal valuation \( v \) selects the version that brings him/her the greatest utility, \( q^* = \max\{U(v, q_H, p_H), U(v, q_L, p_L)\} \), where \( \{q_H, q_L\} \) denote the high-quality version and the low-quality version respectively, \( (p_H, p_L) \) indicate prices of high-quality version and low-quality version respectively, and \( U(v, q_H, p_H) = vq_H - p_H \), \( U(v, q_L, p_L) = vq_L - p_L \). Suppose that a monopolist offers two versions \( q_H = 1, q_L = 0.2 \) at prices \( p_H = 0.95, p_L = 0.1 \), and then a customer with \( v = v_{\text{max}} = 1.0 \) selects the low-quality version instead of the high-quality version by \( U(v, q_H, p_H) = 0.05 < U(v, q_L, p_L) = 0.1 \). However, the exact situation is that a customer chooses either the low-quality version or the high-quality one just based on his/her need for quality.

The second assumption is that information products share identical quality concept with physical products. According to the Mussa and Rosen [19], the quality of physical products refers to performance measures [15]. Customers prefer high-quality products, as indicated by the linear valuation function. For instance, a notebook PC becomes more attractive when it has a faster CPU, a bigger memory size, a larger hard-disk capacity, and a higher maximum resolution for LCD screen. A computer firm usually offers simultaneously a basic model with fundamental specifications and more advanced models with extended specifications. The basic model meets the fundamental requirements of all customers, and advanced models accommodate the preference of customers with higher quality requirements. Previous researches also adopted the linear utility function to investigate the optimal versioning strategy of information products. However, information products have a concept of quality different from that of physical products.

The definition of software quality is referred to the ISO 9126-1. Software quality consists of six main features: functionality; reliability; usability; efficiency; maintainability; and portability. With commercial softwares, customers are most concerned about functionality, reliability, usability, and efficiency. These qualities meet customers’ functional or nonfunctional requirements. Customers in need of the high-quality software version rarely install low-quality versions. The software version that does not provide functions and nonfunctional performance that a customer requires is unacceptable in the real world. Otherwise, users would have their work efficiency negatively affected in application. For instance, the IBM DB2 is an object-relational database software for multiple platforms of operating systems.\(^2\) It has many versions developed for Linux, UNIX, and Windows, including enterprise server edition, workgroup server edition, expression edition, and Express-C (for free). Suppose that a firm needs the enterprise server edition for high-performing, robust, on-demand enterprise solution on parallel servers, it will definitely not choose the express edition even if it is much cheaper (entry-level price for small and medium businesses). Similarly, if the express edition meets the requirements of a small firm, this firm will not valuate the enterprise server edition much more than the express edition because it does not use the extra functions in the enterprise server edition. Customers choose “just right” versions as indicated by the Goldilocks selection [20,9].

Therefore, the customer self-selection behavior on multi-version information products is different from that on physical products in the real world. Hence, this feature requires reconsideration on customers’ valuation or utility function of information products. Some studies have been conducted in this stream of research.

Sundararajan [21] considered the nonlinear usage-based pricing for information products to make customer discrimination. Customers were charged according to their expected usage of the software through a usage-based contract, in which the expected usage of the software indicated that there was a continuum of customer types and a continuum of version quality in the vertical differentiation strategy. The quality was proportionate to the feature number of an information product.

Krishnan and Zhu [14] investigated the differentiation of development-intensive products (DIPs, including information products) for heterogeneous customers, in which the fixed cost of product development was much greater than variable cost. They introduced the concept of reservation quality and saturation quality to model customer utility as a piecewise linear function. Reservation quality was defined as the minimal quality level below which a customer would not value corresponding versions positively. Saturation quality was the quality level above which a customer had a zero marginal WTP; or the customer did not value the version with higher quality more than the version with saturation quality. A customer had a linearly increasing WTP from the reservation quality to the saturation quality. This piecewise linear utility function provided a different way to deal with managerial challenges on customers’ self-selection of information products.

Hui et al. [9] analyzed the discrepancy between research suggestions for offering only one or two versions of an information product to customers and firms’ actual practice of vertical differentiation with more than two versions. By considering versioning as a type of customized bundling of information product attributes, different versions form a menu of different-sized bundles serving as a self-select device. In their study, \( W(v, q) = v_0(q-q^2/2\theta) \) for \( q \leq \theta \), and \( W(v, q) = v_0\theta/2 \) for \( \theta < q \leq Q \), where \( q \in [0, Q] \) indicates the number of attributes (or quality level), \( \theta \in [0, Q] \) defines a customer’s consumption level (or customer type), \( v_0 \) is fixed and represents the common valuation of all customers on the basic quality level of an information product. This function indicated that customers did not have a continuously increasing marginal valuation for an information product when its quality was higher than what was required. Hence, a lower-type customer does not have a marginal valuation that increases monotonically with quality due to redundant attributes of high-quality versions.

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Hence, total profit increases with more versions, but the marginal benefit of an additional version decreases with the total number of versions.

This paper attempts to define a nonlinear function of customers’ WTP and utility based on the customer self-selection behavior by assuming that each customer has a specific quality requirement. A lower quality version will lead to a greater drop in the customer's WTP, but a higher quality version will not yield a linear growth in the customer's WTP. This is the first contribution of this paper to the optimal versioning strategy of information products in the market of heterogeneous customers.

Another stream of researches, that is still in its infant on information products but has been systematically studied on physical products [13,13,10], is the product line design or design of a product family. Because the differentiation of information products has been investigated mainly under the linear valuation function, only the suboptimality of two versions in vertical differentiation of an information product has been verified analytically. There has been no effort on the design and pricing of an information product line consisting of multiple versions that are vertically compatible in quality. As for the physical product, Alexouda [1] solved the share of choices problem in designing a product family. Because the differentiation of information products but has been systematically studied on the market of heterogeneous customers.

This section presents basic concepts of and assumptions on designing optimal versioning schemes with regard to quality levels and prices under three customer type distributions and three marginal cost functions. Discussions are also made on properties of optimal versioning strategies for segmenting the market. Section 7 summarizes main contributions of this paper and discusses directions for future research.

2. Features of multiple version strategy

This section presents basic concepts of and assumptions on information products from the firm’s point of view. Suppose that the available highest quality of an information product is determined exogenously through various market investigation channels, and that a monopolist has developed the highest quality product, denoted as \( q_H \). As the fixed cost is sunk in the design and development of the highest quality version of an information product, the investment for developing a lower quality version with fewer functional features and degraded nonfunctional performance is usually very small. No challenging technical tasks exist in developing lower-quality versions, which also does not constitute a hard demand on the firm’s budget.

A firm offers a group of compatible information products with different quality levels in the multi-version strategy: \( Q = q_1, q_2, ..., q_K \), where \( q_1 > q_2 > ... > q_K \). \( q_H = q_1 \) denotes the lowest quality level that has the least subset of product features to meet the basic requirements of all customers. \( q_H \) and \( q_L \) denote versions of the highest-quality level and the lowest-quality level respectively. \( K \) is the maximal number of versions that a monopolist provides to market. All versions are vertically compatible, which means that a higher-quality version contains all features that a lower-quality version has, and the latter can be upgraded to a higher-quality version by updating its existing modules or adding new ones.

As many information products can be digitally stored in large-capacity compact discs or transmitted on the Internet [20,23], the marginal costs \( MC = [c_1, c_2, ..., c_K] \) of different versions are usually treated as equal (and often as 0 in literatures). But large-scale business-oriented softwares (such as the ERP, data warehouse tools, and data mining tools) usually require more before-sale and after-sale service for sophisticated customers. For the sake of generality, three types of marginal cost are considered for versions of different quality levels: (1) constant marginal cost: \( c_1 = c_2 = ... = c_K = c \); (2) linearly increasing marginal cost function: \( c_k = c_0 + aq_k \), \( c_k \in MC, a > 0, k = 1, 2, ..., K \); (3) quadratically increasing marginal cost function: \( c_k = c_0 + aq_k + bq_k^2 \), \( c_k \in MC, a > 0, b > 0, k = 1, 2, ..., K \).

For an information product, the monopolist charges a price \( p_k \) for version \( q_k \). \( P = \{p_1, p_2, ..., p_K\} \) represents the price decision variable set of all versions, and generally there exists \( p_1 > p_2 > ... > p_K \).

3. Features of customers’ self-selection behavior

This section characterizes customers’ valuation and self-selection for information products and defines the behavior-based utility function. A customer \( v \in [0, v_{max}] \) potentially buys a version of quality level \( q_k \) with \( U(v, q_k, p_k) \geq 0 \) or not with \( U(v, q_k, p_k) < 0 \), \( k = 1, 2, ..., K \). Among all versions \( Q = \{q_1, q_2, ..., q_K\} \) of an information product, a
customer buys only one version with $q^* = \arg\max_k \{U(v, q_k, p_k)\}$, $k = 1, 2, \ldots, K$ when more than one version satisfies $U(v, q_k, p_k) > 0$, where version $q^*$ is priced as $p^*$. The firm obtains marginal profit $\pi(v, q^*, p^*) = p^* - c^*$ from this customer, where $c^*$ is the marginal cost of version $q^*$.

Let us consider the valuation of heterogeneous customers on information products discussed in Section 1. The intrinsic characteristics of information products induce a specific mechanism of customer self-selection among multiple versions of different qualities. As a linear valuation function cannot exactly capture the real valuation and self-selection behavior of customers, a new WTP function is proposed for versioning information products.

Suppose that a customer $v \in [0, v_{\text{max}}]$ has the specific quality requirement $q_v = g(v)$, $g(v) \geq 0$, $g'(v) > 0$, indicating that a higher type customer has a higher requirement for quality than a lower type customer. In experiments, we take $q_v = (V/v_{\text{max}})q_{\text{min}}$, which means that a customer’s required quality is corresponding to its type. Suppose that $q_v$ is the required quality for customers $v$, the valuation function is defined as:

$$W(v, q) = \begin{cases} vq - [1 + \gamma v (\frac{q - q_v}{\gamma q_v})^\alpha] & q \geq q_v, \\ vq - [1 - (\frac{q - q_v}{\gamma q_v})^\alpha] & q < q_v, \end{cases}$$

where $0 < \alpha < 1, 0 < \gamma_1, \gamma_2 < 1$; and $\alpha = 0.5, \gamma_1 = 0.1, \gamma_2 = 0.5$ are set as default in experiments. Thus, there is $0W(v, q) > q_0$, (4) $\frac{\partial^2 W(v, q)}{\partial q^2} > 0$ for $q > q_v$, and $\frac{\partial^2 W(v, q)}{\partial q^2} > 0 > \frac{\partial W(v, q)}{\partial q}$ when $q_2 q_v \leq q < q_v$. $\gamma_1$ indicates the increment scope of quality on the required quality that a customer has a larger marginal valuation than that with the linear function, $W(v, q) > vq$ for $q_v \leq q \leq q_1(1 + \gamma)$. When the increment of quality becomes larger, as $q > q_v(1 + \gamma)$, then there is $W(v, q) < vq$. Hence, customers’ preference for versions with the quality that is higher than the required decreases marginally. For $q_2 q_v \leq q < q_v$, there is always $0 < W(v, q) < vq$, indicating that a customer drastically diminishes valuation on versions with lower quality than the required. There is an infimum point $(q_2 q_v)$, indicating that a version with a further lower quality is valued zero by the customer. This valuation function is schematically drawn in Fig. 1.

This behavioral valuation function on information products is similar to what was defined by Kahneman and Tversky [12] in the Prospect Theory for decisions between alternatives involving risk (especially in financial decisions). When the expected outcome of a customer is fixed as the reference point, the value function is concave for gain (larger outcomes) and convex for loss (lower outcomes). For identical deviations from the reference point, the valuation decreases larger on losses than the valuation increases on gains, indicating that customers are of loss aversion. Actually, customer behavior was once considered in the design of dynamic valuation function for characterizing customer impatience in consumption (immediate gratification or expedite consumption) of information products [23], which was also an inspiration to the proposal of the new valuation function in this research.

\begin{enumerate}
\item First level: monopolist’s decision
\begin{align}
\max_{\{q, p\}} \pi(q, p, x) &= \sum_{j=1}^{M} \{ \sum_{i=1}^{K} (p_i - c_i) x_{ij} \} \\
\text{s.t.} & & p_1 > c_1, \quad i = 1, 2, \ldots, K, \\
& & p_i > p_{i+1}, \quad i = 1, 2, \ldots, K - 1, \\
& & q > q_{i+1}, \quad i = 1, 2, \ldots, K - 1, \\
& & \text{where, quality levels and prices of all versions \{q_i, p_i\} (i = 1, 2, \ldots, K) are decision variables of the monopolist, } \pi(q, p, x) \text{ denotes the total marginal profit of a multi-version strategy. The price for a version of a certain quality level should be larger than its marginal cost, as indicated by constraint (3). By constraint (4), a higher quality version is priced higher than a lower quality version. The decision of customer } U_j \text{ for purchasing version } q_i \text{ or not is represented by } x_{ij}, \text{ which is decided in the second level.}
\end{align}
\item Second level: self-selection decision of every customer \(j = 1, 2, \ldots, M\)
\begin{align}
\max_{x_j} \pi(x_j) &= \sum_{i=1}^{K} \{ \sum_{j=1}^{M} (p_j - c_j) x_{ij} \} \\
\text{s.t.} & & x_{ij} x_{ij} = 0, \\
& & x_{ij} U_j(v, q_i, p_i) \geq 0.
\end{align}
\end{enumerate}
$x_{ij} = 0$ or 1, \hspace{1cm} (9)

$(i_1 \neq i_2, \{i_1, i_2\} = 1, 2, \ldots, K : i = 1, 2, \ldots, K)$

where $x_{ij}$ is the decision variable of customer $j$, $p_i$($k$) stands for the utility of customer $j$ by purchasing a version of a certain quality level. It is computed by $U(v_j, q_i, p) = V(v_j, q_i) - p_i$ based on formula (1). A customer buys only one version of an information product at most or buys nothing, which is represented by constraint (7). A customer does not buy the version if he/she has a negative utility on it, as indicated by the constraint (8).

The bilevel programming model has a good generality in that it considers both quality levels and prices in the market with a finite number of potential customers. We need not concern about the number of potential customers. We need not concern about the utility of customer $j$ by purchasing a version of a certain quality level. It is computed by $U(v_j, q_i, p) = V(v_j, q_i) - p_i$ based on formula (1). A customer buys only one version of an information product at most or buys nothing, which is represented by constraint (7). A customer does not buy the version if he/she has a negative utility on it, as indicated by the constraint (8).

5. Hybrid EAs for obtaining optimal solutions

The optimal versioning strategy involves finding quality levels and prices of multiple versions for gaining maximal profit when the maximal version number is fixed a priori. As decision variables (e.g., quality levels and prices of versions) are highly correlated, strong epistasis exists among real-valued genes in chromosomes when all decision variables are encoded as a vector in the EAs. This feature incurs a difficulty for coadapting real-valued genes in the population of EAs [16], which usually causes the stagnation of the EAs evolution process in solving the bilevel programming model. Therefore, a hybrid scheme is designed by combining the niching steady-state EAs (SSEAs, previously proposed by Li et al. [17]) with an efficient local search algorithm, which is able to maintain population diversity for obtaining better near-optimal solutions. Many ideas were proposed to enhance the population diversity for enforcing the exploitation capability of algorithms, for instance, the “Emigration” and “Malthusian” selection strategies and heterogeneous mating approach [3], the multi-population pattern for genetic algorithm [22], the coevolution of population diversity and solution quality [24]. With the SSEAs, to maintain population diversity, we employ the nearest neighbors replacement crowding (NNRC) to ensure that the algorithm has a good niching capability on multimodal landscape [17]. This scheme resorts to the bottom-up automatic niching mechanism, different from the conventional top-down approach to maintain population diversity through confining global competition of individuals in population via multiple subpopulations or specific genetic operators.

The SSEAs yield one or two offspring by recombination and mutation in one iteration, and new offspring replace similar individuals in the current population. To enhance the efficiency of total evolutionary process, a local search algorithm based on real-valued genes (LRSR) is developed to fine-tune solutions represented by new offspring. Suppose that a real-valued optimization problem is represented as $x^* = \arg \max \{f(x) | x \in \mathbb{R}^n\}$, a real-coded chromosome is represented as a vector of continuous decision variables $\mathbf{a} = (a_1, a_2, \ldots, a_n)$, $a \in \mathbb{R}^n$. The population is denoted as $\mathbf{P}$, and all offspring produced by genetic operations and the local search algorithm are represented as $\mathbf{P}_{offspring}$. The hybrid algorithm (called the hybrid-SSEAs) is then constructed as shown in Fig. 2.

In the bilevel programming model, a feasible solution consists of quality levels and prices of $K$ versions that satisfy all constraints. It is encoded as a real-valued vector $(q_1, p_1, q_2, p_2, \ldots, q_K, p_K)$ used as the chromosome to randomly produce the initial population of the hybrid-SSEAs. The fitness of an individual is the total profit computed at the first level. The subprocedure $P_{offspring}(t) = S-C(M)(P(t))$ indicates the reproduction of offspring by selection, crossover, and mutation operations ($S, C, M$) exerted on $P(t)$ in $(t + 1)$-th iteration. To make an explorative search in the feasible solution space, random selection, BLX-alpha crossover [2], and the Gaussian mutation operation are recommended. Two individuals are randomly selected in the current population as parents to produce offspring. The BLX-alpha crossover recombines two parents to output two offspring by drawing uniformly $a'_{i}$ in $[a_{i} - \alpha(a_{i+1} - a_{i}), a_{i+1} + \alpha(a_{i+1} - a_{i})]$, where $a_{i} < a_{i+1}$ is assumed, and $\alpha > 0$ is a constant ($\alpha = 0.5$ as default). $\mathbf{a}' = (a'_1, a'_2, \ldots, a'_n)$ is an offspring, $\mathbf{a}_1 = (a_1, a_1, a_1, \ldots, a_n)$ and $\mathbf{a}_2 = (a_2, a_2, \ldots, a_2, a_2)$ are the two parents. Thus, the BLX-alpha crossover can explore a larger region than other real-valued arithmetic operations. The Gaussian mutation changes real genes in an offspring by adding small real values generated by the Gaussian probability function $G(0, \sigma^2)$, where $\sigma$ is the deviation. The LSRG makes a gene-wise based local search on an offspring and yields a fine-tuned solution. The NNRC carries out the replacement of the fine-tuned offspring in the current population to maintain a diverse population. These two subprocedures are defined as follows.

The LRSR is especially designed to enhance the exploitation capability of the SSEAs on real-valued optimization problems. For an offspring $\mathbf{a} = (a_1, a_2, \ldots, a_n)$ with fitness $f(\mathbf{a})$, $\mathbf{a} \in \mathbf{P}_{offspring}(t)$ in the $(t + 1)$-th iteration, the LSRG makes a gene-wise scan from left to right and changes each real-valued gene sequentially. For instance, suppose that $a_i$ ($i = 1, 2, \ldots, n$) is focused in the scan process, a small real value $\Delta_i$ is drawn from $G(0, \sigma^2)$, and two

```plaintext
procedure Hybrid_SSEAs
set: t := 0;
initialize: $P(0)$;
compute individual fitness: $f_1(0), f_2(0), \ldots, f_n(0)$;
while stopping_criteria not met do
produce offspring by performing selection, crossover, mutation:
$P_{offspring}(t) := S-C(M)P(t)$;
compute individual fitness: $f_1(t), f_2(t), \ldots, f_{P_{offspring}(t)}(t)$;
Local search to fine-tune offspring: $P_{offspring, for tune}(t) := LRSR P_{offspring}(t)$;
produce new population by NNRC:
$P(t + 1) := NNRC P(t), P_{offspring, for tue}(t)$;
set: $t := t + 1$;
return: $P(t)$;
end procedure
```

Fig. 2. Basic procedure of hybrid-SSEAs.
variants of \( a \) are produced as \( a_i = (a_1, \ldots, a_i + \Delta_i, \ldots, a_n) \), \( a'_i = (a_1, \ldots, a_i - \Delta_i, \ldots, a_n) \). The fitness \( \{ f(a_i), f(a'_i) \} \) are computed, and the variant with the largest fitness \( a^* = \arg \max \{ f(a_i), f(a'_i) \} \) is selected to update the current offspring by \( a' = a^* \). Then, the focus moves from gene \( a_i \) to \( a'_i \). After completing a scan process from \( a_i \) to \( a'_i \), the current offspring is probably improved regarding its fitness. As an offspring is randomly perturbed in sequence, it is usually very difficult to obtain an increment of fitness when decision variables are correlated in the optimization of version quality levels and prices. Thus, the scanning-based sequential perturbation is repeated many times, such that an offspring is fine-tuned with a potentially larger increment of fitness. The maximal scanning loop number is fixed a priori. This subprocedure is described in Fig. 3.

In the subprocedure LSRG, the decreasing deviation for gene-wise perturbation is generated using \( \sigma = \sigma_{\text{initial}} \times (1 - \lambda \cdot \text{max\_loop\_num})^2 \), which tends to explore contracting subspace around the currently found solutions in repetitions of local search. Thus, a larger initial deviation can be specified, and users are exempted from the burden of selecting right value for constant deviation. This scheme is more adaptable in real-world applications. Finally, the LSRG outputs a fine-tuned offspring.

The NNRC was originally proposed in the recombination replacement paradigm of the steady-state genetic algorithms, where this scheme was also called the q-NNR crowding strategy [16]. Since offspring only replace most genotypically similar individuals in the current population, the competition is conducted between offspring and nearest individuals are denoted as \( P_{\text{NN}} = \{ a_1, a_2, \ldots, a_q \} \), which consists of individuals with smaller distance to \( a' \) by \( d(a_i, a')_l = \| a_i - a' \|_2 = \sqrt{\sum_{k=1}^{n} (a_{ik} - a_{i'}k)^2} \), \( a_i \in P \). The q nearest individuals are denoted as \( P_{\text{NN}} = \{ a_1, a_2, \ldots, a_q \} \), which consists of individuals with smaller distance to \( a' \) by \( d(a_i, a')_l \). Then, \( a^* = \arg \min \{ f(a), a \in P_{\text{NN}} \} \). The subprocedure of the NNRC is shown in Fig. 4.

Parameter \( q \) decides the competition among individuals during replacement in the current population. If a larger \( q \) is taken, the replacement will cover a larger region in the solution space, and the current population will lose diversity more quickly. When \( q = N \) (the worst deletion scheme in the standard SREAs), there will emerge global competition among individuals during replacement, and all individuals will soon become homogeneous. As the LSRG is adopted to enhance the exploitation of the SREAs, a smaller value for \( q = [5\% \times |P|] \) in the experiments) is used to balance the exploration capability and efficiency of this algorithm.

6. Experiments and discussions

The proposed algorithm is used to solve the bilevel programming model for obtaining the optimal versioning strategy defined in the Section 4. As both the sunk cost for developing the highest quality version and the menu cost for managing multiple versions of different quality levels are not considered, quality levels and prices of multiple versions are optimized for the monopolist to maximize total marginal profit. This section consists of two subsections. The first subsection presents experimental settings for heterogeneous customers, an information product and its versions, and also for the hybrid-SSEAs. The second one reports experimental results and corresponding observations.

6.1. Experimental settings

Suppose that customer type follows one of the three distributions, namely, uniform distribution \( U(r_1, r_2) \), Gaussian distribution \( N(\mu, \sigma^2) \), and exponential distribution \( \text{Exp}(\lambda) \), and total number of customers is fixed as 10,000 in the potential market. These scenarios are presented in Table 1.

Table 2 shows features of information products in terms of the total number of versions and three marginal cost functions.

The hybrid-SSEAs are parameterized in Table 3. In all experiments, a constant population size is used as 50, and the maximal iteration is fixed as 1000. Two offspring are produced in each iteration and are then fine-tuned by the LSRG for a maximal number of scanning loops, fixed as 20. Thus, the total number of fitness evaluations is estimated as \( 1000 \times 2 \times 20 \times K = 40,000 \times K \), where \( K \) is the maximal number of versions. To improve the global optimality of the best solution found by the hybrid-SSEAs for an optimal multi-version scheme with a specific parameter setting, the hybrid-SSEAs is carried out 10 times with independently initialized populations. The best solution in all 10 executions is taken as the global optimum. Empirically, the executions that successfully yield the best solution take a proportion of 92% in average.

6.2. Experimental results and observations

This subsection is arranged into two parts. The first part reports optimal quality levels and prices with regard to different distributions of customer types. The maximal number of versions is assigned a priori as \( K \in \{1, 2, 3, 4, 5, 6, 7, 8, 9\} \), and constant marginal cost is assumed. This setting intends to illustrate the positioning of
multiple versions regarding quality levels and prices under a specific distribution of customer types. Moreover, optimal strategies are compared under three distributions of customer types with a specified maximal number of versions. The second part reports optimal versioning strategies when linear or quadratic marginal cost functions are assumed. It illustrates the impact of the monotonically increasing marginal cost on optimal quality levels and prices of multiple versions.

6.2.1. Optimal quality levels and prices with a constant marginal cost

The hybrid-SSEAs are used to solve the bilevel programming model with specific parameter settings. Optimal multi-version schemes are obtained in terms of quality levels and prices under different maximal numbers of versions, and the maximal total profit is shown in Fig. 5.

When customer types obey any of the three distributions, more versions will surely bring greater profit to a monopolist. For instance, the one-version scheme of the highest quality level yields a total profit of 1826.07, 1648.64, and 889.50 with the uniform distribution, the Gaussian distribution, and the exponential distribution of customer types respectively. The optimal nine-version schemes produce the maximal total profit as 3208.14, 2862.67, and 1747.33 under identical distributions of customer types, which increase by 75.69%, 73.64%, and 96.45% respectively. Evidently, Fig. 5 shows that the total profit curves grow logarithmically with the maximal number of versions, indicating that the introduction of a new lower-quality version contributes less to the total profit of the versioning strategy.

When the total potential market is considered, the monopolist will realize larger market coverage by introducing more versions, as shown in Fig. 6. The market coverage rate\(^7\) of the one-version scheme (optimally priced) is 35.42%, 47.96%, and 23.72% with the uniform distribution, the Gaussian distribution, and the exponential distribution of customer types respectively. The optimal nine-version schemes cover 79.12%, 89.86%, and 62.14% of the total potential

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\(^7\) The market coverage rate is the proportion of customers having purchased versions of an information product among all potential customers.
market, which are 2.23, 1.87, and 2.62 times those of one-version schemes respectively. Because versioning schemes with more versions can make a greater coverage of the total market, a smaller portion of customers are left unserved.

With zero marginal cost, optimal version quality levels and prices depend on the maximal number of versions. When different maximal version numbers are considered, optimal quality levels and prices are obtained under three distributions of customer types, as shown in Figs. 7–9, where the highest quality version is always positioned at the highest quality level as \( q_1 = q_H = 1.0 \).

Because customers are quality sensitive in self-selection among versions based on the behavior-based valuation function, a new version is always positioned at a lower quality level to cover unserved customers when it is introduced in a multi-version scheme.

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**Fig. 7.** Optimal quality levels and prices: uniform distribution (horizontal axis: quality level, vertical axis: price).

**Fig. 8.** Optimal quality levels and prices: Gaussian distribution (horizontal axis: quality level, vertical axis: price).
so that the monopolist gains a greater profit. When a new version is added, both quality levels and prices of existing versions are raised in comparison with what they were in the previous scheme of an optimal strategy, which is clearly illustrated in Fig. 10.

Fig. 10 reports the ratio of optimal prices to quality levels when different maximal numbers of versions are assumed with three distributions of customer types respectively. The lower quality version always has a smaller optimal price, and the ratio decreases monotonically with the lowering of quality levels. When a lower-quality version is offered to the market, higher-quality versions are priced higher than they were in previous schemes, indicating that multi-version schemes can make a more detailed segmentation in the potential market. Hence, it becomes more profitable for the monopolist to charge higher prices to segmented customers.

Considering the contribution of every version to the total profit of an optimal multi-version scheme, we compute the proportion of profit by versions in the optimal four-version scheme, as shown in Fig. 11.
With whichever distribution of customer types, the highest-quality version takes the largest proportion in the total profit because of its higher price. Although there is a smaller-than-average proportion of high-valuation customers in both the Gaussian distribution and the exponential distribution of customer type, the highest quality version still contributes the largest proportion in the total profit in all optimal schemes. In a market with heterogeneous customers who are concerned about the required quality of an information product, the highest-quality version is capable of segmenting customers with higher valuation, so that the monopolist can gain greater profit when it is priced optimally. The three versions with qualities lower than the highest one in the optimal four-version scheme account for more than 50% of the total profit. Thus, multi-version schemes become very attractive to the monopolist when quality levels and prices are optimally positioned.

Because customer type is more dispersed with the uniform distribution than with both the Gaussian distribution and the exponential distribution, optimal quality levels and prices are featured differently, as shown in Fig. 12. For instance, versions except the highest quality one have higher optimal quality levels with the uniform distribution of customer type than those with the other two distributions (see Fig. 12(b)). These quality levels are positioned in the optimal strategy such that the monopolist is able to segment customers with higher heterogeneity in the uniform distribution. However, with the Gaussian distribution or the exponential distribution of customer types, customers’ requirements are centralized around the average quality or are mostly distributed on the lower quality. Hence, optimal quality levels and prices of multiple versions are smaller than those with the uniform distribution of customer types.

6.2.2. Optimal quality levels and prices with linear and quadratic marginal costs

This subsection presents experiment results on the optimization of versioning strategy when marginal cost is not constant with quality levels. The marginal cost is defined as a monotonically increasing function of quality levels in experiments, and a higher quality version will thus have a greater marginal cost, which will surely affect the optimal position of quality levels and prices in a multi-version scheme.

First, the total profit of multi-version schemes is computed with different types of marginal costs, as shown in Fig. 13. For a specific maximal number of versions, the monopolist receives less...
of the total profit when marginal cost is a linear function or a quadratic function of quality levels. As higher quality versions have greater marginal costs, they are priced higher than they are with a constant marginal cost. Fig. 14 reports quality levels and prices in the optimal four-version scheme with the uniform distribution of customer type.

When marginal cost function increases (either linearly or quadratically) with version quality, the optimal quality levels and prices increase more than those with constant marginal costs in multi-version schemes of the same maximal version number. Moreover, linearly or quadratically increasing marginal costs lead to a lower market coverage of an optimal multi-version strategy compared with the constant marginal cost, as highlighted in Fig. 15. Similar results are obtained with either the Gaussian distribution or the exponential distribution of customer type. These results indicate the evidence that increasing marginal cost engenders more detailed segmentations of customers when the monopolist intends to maximize its returns.

6.3. Discussions

The following observations are obtained from experimental results in Section 6.2.

(1) The behavior-based utility function characterizes more exactly the self-selection behavior of customers on information products, which is in line with the intrinsic property of information product quality. In contrast to the linear utility function that leads to the suboptimality of versioning strategies, this new utility function ensures that the multi-version strategy is optimal and more versions can bring greater returns to the monopolist. Thus, information product firms prefer multi-
version schemes in the market of quality-sensitive customers in reality. Aside from the example given in the Section 1 about the IBM DB2, another successful example is the Matlab software by MathWorks (http://www.mathworks.com/). It is composed of the basic platform module and numerous toolboxes that constitute a continuum of versions to meet the continuum quality requirement of customers, where the Matlab platform module is priced at a constant price. However, toolboxes (including mainly parallel computing toolbox, data acquisition toolbox, instrument control toolbox, math and optimization toolbox, statistics and data analysis toolbox, computational finance toolbox, and bioinformatics toolbox, etc.) and various application deployment modules are priced individually. A customer buys what is currently required; new toolboxes can be purchased in future when they are needed. This strategy is very effective to segment heterogeneous customers for a firm to obtain maximal revenue.

(2) The versioning optimality with linear utility function is conditioned on the nonlinear growth of versions’ marginal cost, or the quality/cost ratio is critically conditioned to make versioning strategy optimal [4,11,6]. Otherwise, a lower-quality version will cannibalize the market share of higher quality versions, and the total marginal profit of the multi-version strategy falls down [5,7]. In experiments with the behavioral-based utility function, non-constant marginal cost functions that increase with quality levels only contributes to a more detailed segmentation of heterogeneous customers. Higher quality versions with greater marginal costs are priced higher than those with constant marginal costs. Hence, the monopolist only gains less total profit. The definition of a nonlinearly increasing marginal cost with quality is not the precondition for the optimality of versioning strategies. Thus, the multi-version strategy is optimal with the behavior-based valuation function of heterogeneous customers. This result indicates that a monopolist can carry on price discrimination to heterogeneous customers through vertically differentiating an information product.

(3) The bilevel programming model provides a general approach to represent the decision making of the monopolist and customers at two layers. It offers a computational platform to optimize version quality levels and prices of multi-version schemes for maximizing total profit by a monopolist. Furthermore, it is adaptable to various distributions of customer types in the potential market based on numerical computation, and the computation precision can be ensured by increasing the number of customers sampled from specific distributions of customer types. This model can be easily expanded to contain network externality and dynamic demand in multiple periods [23] for optimizing various versioning schemes. These extensions are still under investigation.

(4) The hybrid-SSEAs were designed to deal with the complexity (i.e., nonlinearity and multimodality) of the bilevel programming model through properly coupling the capabilities of exploration and exploitation. This method has a good efficiency and robustness for finding optimal solutions with regard to quality levels and prices of multi-version schemes, which makes it feasible to model versioning strategies according to complex real-world situations without concerning about the impossibility of obtaining close-form solutions as in previous researches. It can also be used to address bilevel programming problems with various extensions in the versioning task of information products.

7. Conclusions

This paper proposed the behavior-based valuation function of heterogeneous customers on information products. This new valuation function represents the nonlinear variability of utility that a customer derives from the quality of an information product. The bilevel programming model was built to optimize the versioning strategy of an information product, with the monopolist as the leader and all customers as followers. For a maximal number of versions given a priori, this model yields an optimal versioning scheme, with quality levels and prices of multiple versions. As this model is nonlinear and multimodal due to interrelated decision variables, the hybrid-SSEAs were developed to improve the global optimality of obtained versioning schemes. Under specific parameters settings for the model and the algorithm, experimental results illustrated the properties of optimal multi-version schemes in terms of the total profit, quality levels, and prices of multiple versions. The monopolist was able to segment the potential market using optimal versioning strategies for gaining the maximal return. These corollaries were derived from the behavior-based utility function, which revealed that the optimality of versioning strategy depends on specific customer valuation functions of information products. Future research should focus on the properties of multi-version strategy by considering network externality, exogenously changeable demand, and dynamic upgrading from lower versions to higher versions in the information product market. These features depict more facets of customers’ behavior in valuating and purchasing information products in real-world situations, which definitely needs an in-depth investigation.

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