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JOINT OPTIMIZATION STRATEGY FOR BIDDING AND PRICING OF ONLINE FASHION RETAILER UNDER BIDDING RANKING

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Abstract

With the development of Internet economy, bidding rank marketing were brought into focus, especially in the clothing industry. Decent bidding rank not only has positive influence on online retailers' click rates and conversion rates, but also improves customer's reservation price. Based on online fast fashion retailers, we have established a click rate model, a conversion rate model and a profit model by commercial mode to discuss joint optimization model of bidding and pricing. We analyzed how bidding and pricing affect link click rates and conversion rates through numerical simulation. Simulation results conform to the value law of fashion, joint optimization strategy is that cut price and increase bidding costs with fashion degree. Compared to static decision, dynamic decision can better match demand with supply and increase profit significantly.

Keywords: Bidding rank, click rate, fast fashion, reservation price, dynamic pricing

INTRODUCTION

With the rapid popularization of Internet, online shopping has gradually become a consumption fashion. According to the statistics of China network economy market in 2015 released by Iresearch, the revenue of online economy reached 1.12187 trillion RMB, an increase of 45% compared to that of the previous year. Meanwhile, the fast fashion brands with online sales channel pay more attention to network marketing than ever. Online retailers get more profit through various online marketing activities, such as keyword auction which includes Google, Baidu and other famous search engines. Sponsored searching maximizes the financial gains through competitive bidding: good ranking position brings the product link more clicks, especially for those on the top positions. Ghose and Yang (2009) tracked Google bidding data of hundreds of keywords in six months to verify the positive influence of bidding on click rate. High position gives consumers positive psychological influence that they tend to believe in these searching results. Thus, it improves consumers' reserve price and increases conversion rate accordingly.

As the earliest E-commerce commodity, clothing industry has long been the largest online commerce category, accounting for 20% of online shopping. Fast fashion is a typical seasonal product, as the sales period is short with wide varieties. Its product value decreases with time and its residual value is very low. In order to quickly response to the change of market demands, fast fashion brands use network marketing to expand their online sales channels. The most representative fast fashion brand, Zara succeed in online marketing strategy and helped its parent firm Inditex gain 20.9 billion euros in 2016, an 15.4% increase compared to 2015 when the global economic faced a downturn. More than 90% of top fast fashion brands have their own T-mall online shops, including ZARA, uniqlo, GU, GAP, FOREVER 21, C&A, TOPSHOP, SPAO and so on.

In addition to bidding rank marketing, dynamic pricing is also an important way to adjust the supply and demand for clothing enterprises. Dynamic pricing means online retailers should determine the price of the product according to the trade status. Since network is more transparent than physical channels, information is faster to spread. In the process of online dynamic pricing, high profit coexists with high risk. Therefore, how to optimize network bidding and pricing decision becomes a hot pot in online commerce industry and academic research.

Domestic and foreign scholars have done many contributive research of bidding rank and dynamic pricing problem from different perspectives. Bidding rank study can be divided into three types relatively based on search engine, advertisers and utility of the keywords. Zhang E and Wang Yingluo (2006) analyzed keyword auction under public or private bidding information, then came to a conclusion that single item and homogeneous goods auction revenues are equivalent under both winner-pay and all-pay payment rules. Chen Ligang and Li Yijun (2010) studied quality-based GSP which takes the click rate, website quality, relevance of keywords and web pages into consideration, then found that under the auction rules, appropriate keywords obtained better advertising effect while more clicks gave advertisers an operation of bidding equilibrium and multi-stage minimum mark-up strategy. Xiang-hua Lu (2013) empirically analyzed Taobao bidding marketing and found that mark-up average bid can get three times more clicks than simply increase keywords number. The keywords exert high influence on click-through rates and conversion rates, so the keywords should be selected based on the characteristics of goods. Kitts B and Leblanc (2004) established a multi-stage bidding model to maximize advertiser's profits. Standardized method can solve the model, but the difficulty lies in the estimation of unknown parameters. Pricing is the key factor on the demand of clothes, optimizing the joint decision-making can effectively increase the retailers' profits.

Traditional pricing method failed to take the value law and practical factors of perishable goods into account. The fast fashion pricing is influenced by discounts, money off, coupons and gifts with purchase. Xu Qi and Wang Xiaofeng (2008) used principal component analysis to choose fashion-related factors based on fashionable index build pricing model. The simulation results proved that consider fashion can help reduce unsalable clothes. Li Gendao (2009) researched dynamic pricing of fast fashion whose demand affected by the inventory. He used Monte-Carlo simulation with stochastic programming demand to prove that take inventory into consideration can increase profits. Lu Chen (2013) found that customers develop their own reservation price according to historical pricing. He defined a discount factor in two period dynamic pricing researches and obtained the optimum price path by inverse method. Bitran and Mondschein (1997) established dynamic programming model that consumers arrived at the weibull distribution. He concluded that the uncertainty of new products' demand can lead to high price, high discount and high inventories. Xu and Whinston (2011) studied two online retailers competition in bidding ranking and pricing behaviors to seek balanced decisions. Existing dynamic pricing researches focused on the related influence factors, such as inventory, consumers' strategic behavior, operation strategy. Xiong Zhongkai (2008) hypothesized that customers can learn from historical prices and defined need function. He found that the optimal dynamic pricing keep vibrate, but this paper is not online bidding case. In existing literature, there are not sufficient joint decision study of dynamic pricing and bidding, especially in fashion industry.

MODEL DESCRIPTION AND SYMBOLS

Consider a fast fashion online retailer with no replenishment in the sales season and no discount on his remaining clothing product clearance sales at the end of season. Due to frequent demand change of the fast fashion, clothing will get outdated quickly over time. Thus, online retailers take a sales strategy called 'more designs less inventory'. Assuming consumers visit web continuously and sales period could be divided into few cycles with only one customer search keyword during each cycle. Customers click on the link at a certain ratio that determine by bidding advertising. The click rates reflect the clicks volume divide web page showing amount. After consumers searching for keywords, they click on link and access to product information. Conversion rate reflects the possibility of visitors buy goods after visiting web page, it is influenced by the consumer psychological price and actual price.

Table 1. The Symbols

Symbol	Description	Symbol	Description
t	Sale cycle	p	Price of commodity
b	Bidding price	y	Inventory level
λ	Click rate	c	Manufacturing cost
X	Reservation price (no bidding rank)	Y	Reservation price
g	probability density of X	G	Cumulative of X
μ	Mean value factors	σ	Standard deviation factors
$\prod$	Expected profit	Δ	Opportunity cost
π	Marginal profit	$\bar{F}$	Conversion rate

Online retailers bidding rank marketing process include setting the price and bidding, advertise expense depends on consumer click amount. If there is no click at all, online retailers do not need to pay bidding fee, but retailer need to pay bidding cost even though consumer didn't buy it. Only conversion could bring profit to advertising clients. Assume online retailers set keyword bidding price b_t and commodity pricing p_t at the beginning of each cycle t. As for every valid click, online retailers need to pay the auction fee b_t, the total bidding cost is marketing expenses. If the consumer's reservation price is higher than commodity price, the consumers purchase it anyway. The symbols mentioned in this paper are shown in table 1 above.

MATHEMATIC MODEL

Click rate model

Click rate decides by mass factors such as click through rate, price, bid, reservation price, the quality of web content and bidding rank. We define CTR as the click rate when link rank at top position and web content is attractive. We obtain CTR when divide showing amount by click volume. The quality of web content relates to correlation of keyword, creativity, history click rate. We assume that click rate is CTR minors link rank and pricing passive effect.

Assumption 1. The click rate $\lambda(b_t, p_t)$ in t cycle is a strictly positive function, which is increasing with bidding b_t and dropping by pricing p_t. We may define the click rate model as below.

$$\lambda(b_t, p_t) = \max(0, CTR - \chi \times e^{-\eta b_t} - \alpha \times \max(0, p_t - EY_t) - \beta \times \min(0, p_t - EY_t))$$
$$= \begin{cases} \max(0, CTR - \chi \times e^{-\eta b_t} - \alpha \times (p_t - EY_t)), if\ p_t > EY_t \\ \max(0, CTR - \chi \times e^{-\eta b_t}), if\ p_t = EY_t \\ \max(0, CTR - \chi \times e^{-\eta b_t} - \beta \times (p_t - EY_t)), if\ p_t < EY_t \end{cases} \quad (1)$$

In function (1) , $-\chi \times e^{-\eta b_t}$ is the passive effect of unfavorable rank, χ is the keyword correlation coefficient. The higher relativity between keyword and product χ is relative bigger. Since the relativity and bidding price determine the rank, the search engine marketing effect is correlation coefficient χ times bidding effect function $-e^{-\eta b_t}$. η is the sensitive coefficient of bidding ranking, higher positions need more expenses accordingly. We can set sensitive coefficient by the characteristics of fast fashion products. The bid is not infinite: link's rank can only be improved to first position. Advertising effect no longer increases when link reach the first position. To conform the reality bidding advertising effect law, bidding effect is the negative exponential function.

The consumer's reservation price is the highest price customers willing to pay. The mean value EY_t of consumer's reservation price in t cycle and price are factors of click rate. α is the pricing sensitive coefficient when clothes price is higher than reservation price, while reservation price is higher than actual price is β. Since customers are resist mentally when the clothes is too expensive ($p_t > EY_t$), also people are unwilling to buy cheap clothes that quality might be poor ($p_t < EY_t$). The appropriate price is very important.

Reservation price distribution

From the discussion above, the online retailer's web content quality, bidding, pricing and other factors decide link ranking. The link rank impacts consumer reservation price. Fast fashion clothing is seasonal and fashion perishable, so fashion degree has important influence on reservation price. Therefore, the distribution of reservation price mainly depends on bidding, clothes' fashion degree. We assume that consumers make a deal without strategic behavior when reservation price is higher than the pricing. The conversion rate equal to the probability of the reservation price is higher than clothing pricing. Set Y as consumer's reservation price with search engine marketing and X is original reservation price. Follow the definition above, we define the reservation price model as follow.

$$Y(b_t,t)=\mu(b_t)+\sigma(b_t)\times(\rho(t)\times X) \quad (2)$$

In the reservation price model, b_t is bid of cycle t, $\rho(t)=e^{\theta(t-T)}$ ($\rho(t)\in(0,1]$) is fashion degree function that continuous decreases with t ($t<T$) and depict the attenuation law of reservation price. The negative exponential function satisfies the characteristics of fast fashion products that value decreases with the fashion degree.

The boundary conditions of reservation price is $Y(t)=\rho(t)\times X$ when mean and standard deviation is $\mu(0)=0$ and $\sigma(0)=1$. Set $G(\cdot)$ and $g(\cdot)$ as the cumulative distribution of reservation price and probability density respectively. For the convenience of calculation, define that cycle T as at the beginning of sale season and end as $t=1$. During the very beginning of sale cycle, fashion degree function $\rho(T)=1$ and reservation price is $Y(b_t)=\mu(b_t)+\sigma(b_t)\times X$.

According to the definition above, we define the cumulative distribution function of reservation price $Y(b_t,t)$ as $F(\cdot\,|\,(b_t,t))$. We conclude the function as below.

$$F(p_t\,|\,(b_t,t))=G\left(\frac{p_t-\mu(b_t)}{\sigma(b_t)\times\rho(t)}\right) \quad (3)$$

The function describes the reservation distribution affect by bidding, pricing and fashion.

Assumption 2. The reservation price under bidding ranking possesses properties as below.

(a) The standard deviation $\sigma(b_t)$ is decreasing with bidding price;

(b) The variable coefficient $\sigma(b_t)/\mu(b_t)$ is increasing with bidding price.

According to assumption 2, the standard deviation and mean value are increasing with bidding. It also assures that the increasing step of mean value bigger than standard deviation and we get the proposition 1.

Proposition 1. The reservation price is increasing with bidding price and decreasing with time.

Prove: First defines $x=\xi(b_t,p_t)=\dfrac{p_t-\mu(b_t)}{\sigma(b_t)}$ and it deficits the joint decision of bidding and pricing. From the definition we know that x is increasing with p and decreasing with b_t. We know that $\mu(b_t)/\sigma(b_t)$ is increasing with b_t and $p_t/\sigma(b_t)$ is decreasing with b_t from assumption2 (b). So $\xi(b_t,p_t)$ is decreasing with b_t and we conclude that $F(p_t\,|\,b_t)=G(\xi(b_t,p_t))$ is decreasing with b_t when $p_t\geq 0$ according to the definition of distribution $F(p_t\,|\,b_t)=G(\xi(b_t,p_t))$.

$\bar{F}(p_t \mid b_t) = 1 - F(p_t \mid b_t)$ is increasing with b_t when $p_t \geq 0$. So we proved $Y(b_t, t)$ is increasing with b_t. From the definition of reservation price and the fashion degree function $\rho(t) = e^{\theta(t-T)}$, we conclude that reservation price is decreasing over time.

Different positions of search engine marketing usually lead to different psychological feelings, they indeed shake customer's reservation price. Ghose and Yang (2009) put forward that high rankings attract two types of consumers. On the one hand, top rank positions could attract high-end customers whose reservation price is higher than others, on the other hand, low-end customers are also more likely to click top rank link for information and this could lead to profits loss. High rank could increase uncertainty of customer's reservation price. They found the profit from high-end customer dominates the loss cause by low-end customer in their case.

The assumption 2(a) divides costumes into two types, high-end customer attracted by high-rank and low-end customer. The assumption 2(b) considers profit from high-end customer and the loss caused by low-end customer. The conversion rate will increase with higher rank according to the relationship between rank and reservation price. To reach the optimal decision, we present assumption 3 and assumption 4. The assumption 3 ensures Cauchy convex of profit function. Regularity conditions in assumption 4 are to ensure the reservation price distribution in accordance with the reality.

Assumption 3. Consumers' cumulative distribution function $G(x)$ has an increasing failure rate(IFR), i.e, $g(x)/\bar{G}(x)$ is increasing.

Assumption 4. The distribution of reservation price has the following regularity conditions.

(a) The probability density of distribution's lower bound is zero, i.e, $g(\underline{x}) = 0$.

(b) Consumers' cumulative distribution function $G(x)$ has a continuous first derivative;

(c) $\mu(b)$ and $\sigma(b)$ has a continuous first derivative.

The Gamma distribution and Weibull distribution meet the assumption 3 and 4, both satisfy with requirement of the numerical simulation.

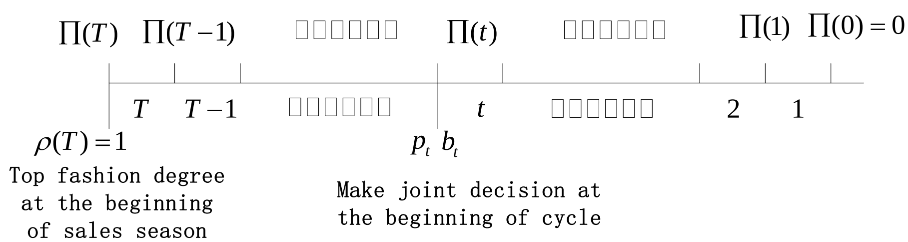
Conversion rate model

The bidding rank marketing can achieve higher conversion rate. Online retailers can adjust the bid and price in each cycle. As mentioned, the conversion rate is the possibility that consumers purchase after visiting web, it's determined by bidding, pricing and the reservation price. We consider the conversion as possibility that the reservation price higher than price. When consumers develop their reserve price $F(\cdot|(b_t,t))$, the conversion rate should be $\overline{F}(p_t|(b_t,t))=1-F(p_t|(b_t,t))$.

Online retailer's profit model and the optimal joint decision model

According to click rate model and conversion rate model, online retailer's profit equals to sales income minus the advertising cost. Online retailers sales season could be divided into T cycle, only one visitor each cycle, cycle T is the beginning of the sales season and cycle 1 is the end and online retailers selling time line as shown in figure 1.

Figure 1. Online retailer selling time line



During selling season, there are three possible circumstances of search engine marketing: customers who click on the links and purchase, customers who click but don't buy and those who don't click the link at all. Set $\prod(y,t)$ as online retailers' expect profits when remains t cycles and y inventory level. It can be represented as below.

$$\prod(y,t)=\max_{b\geq 0,p\geq 0}\left\{\begin{array}{l}(1-\lambda(b_t,p_t))\prod(y,t-1)\\ +\lambda(b_t,p_t)F(p_t|(b_t,t))(\prod(y,t-1)-\varepsilon_{b_t})\\ +\lambda(b_t,p_t)\overline{F}(p_t|(b_t,t))(\prod(y-1,t-1)+p_t-c-\varepsilon_{b_t})\end{array}\right\}, for: y>0;$$
$$\prod(0,t)=0. for\ t=1,...,T,$$
$$\prod(y,0)=0. for: y>0. \qquad (4)$$

The right part of function (4) is profit of t cycle remained, in the first part of profits function is the situation that consumers do not click on the links, the second part profits function is the situation that consumers click on link but didn't buy, the third part of profits function is that consumers click on the links and buy goods. In order to obtain maximum profits, online retailers set price p_t and bidding b_t at the beginning of each cycle. We assume there is no replenishment and commodity salvage value is zero in sale season. Function (4) can be further algebraic substitution.

$$\prod(b(y,t),p(y,t)) = \prod(y,t-1) + \max_{b_t\geq 0,p_t\geq 0}\begin{Bmatrix}\lambda(b_t)F(p_t\mid b_t)\prod(y,t-1)-\lambda(b_t)\prod(y,t-1)\\ -\lambda(b_t)F(p_t\mid b_t)\varepsilon_b-\lambda(b_t)\bar{F}(p_t\mid b_t)\varepsilon_{b_t}\\ +\lambda(b_t)\bar{F}(p_t\mid b_t)(p_t-c+\prod(y-1,t-1))\end{Bmatrix}$$

$$= \prod(y,t-1) + \max_{b_t\geq 0,p_t\geq 0}\begin{Bmatrix}\lambda(b_t)\bar{F}(p_t\mid b_t)(p_t-c+\prod(y-1,t-1))\\ -\lambda(b_t)\bar{F}(p_t\mid b_t)\prod(y,t-1)-\lambda(b_t)\varepsilon_{b_t}\end{Bmatrix}$$

$$= \prod(y,t-1) + \max_{b_t\geq 0,p_t\geq 0}\left\{\lambda(b_t)[\bar{F}(p_t\mid b_t)(p_t-c-\Delta(y,t))-\varepsilon_{b_t}]\right\}$$

The function (4) can be rewritten as:

$$\prod(b(y,t),p(y,t)) = \prod(y,t-1) + \max_{b_t\geq 0,p_t\geq 0}\left\{\lambda(b_t)[\bar{F}(p_t\mid b_t)(p_t-c-\Delta(y,t))-\varepsilon_{b_t}]\right\} \quad (5)$$

Set production cost of clothes as c and define $\Delta(y,t)=\prod(y,t-1)-\prod(y-1,t-1)$ as the opportunity cost of retailer sales, namely, in order to sell products in this cycle and give up profits in the next cycle. The opportunity cost is the value been abandoned of this decision. Since clothes have limited shelf time and fashion trend is constantly changing, opportunity cost is also reduced gradually along with time. The margin profit of t cycle can be represented as:

$$\pi(b_t,p_t,\Delta)=\lambda(b_t)[\bar{F}(p_t\mid b_t)(p_t-c-\Delta)-b_t] \quad (6)$$

Combine function (5) with function (6), the online retailer profits function could be transfer into optimization problem.

$$\prod(y,t)=\prod(y,t-1)+\max_{b\geq 0,p\geq 0}\pi(b_t,p_t,\Delta(y,t)) \quad (7)$$

According to the optimal decision mechanism of online retailers, we can define the optimal joint decision as below.

$$\left\langle b^*(\Delta),p^*(\Delta)\right\rangle := \operatorname*{arg\,max}_{b\geq 0,p\geq 0}\pi(b_t,p_t,\Delta),$$

$$\left\langle b^*(y,t),p^*(y,t)\right\rangle := \left\langle b^*(\Delta(y,t)),p^*(\Delta(y,t))\right\rangle$$

Known $\pi(b_t,p_t,\Delta)$ is marginal profit of online retailers and the opportunity cost of rest inventory is $\Delta(y,t)$. The production cost is c, the corresponding optimal bidding and optimal pricing is $\left\langle b^*(\Delta),p^*(\Delta)\right\rangle$. The optimal joint decision-making mechanism is to achieve biggest profit by determining the optimal pricing and bidding, which is based on continuous variables $\Delta\in[0,\Delta(1,T)]$. Next section will solve the optimal decision through the numerical simulation.

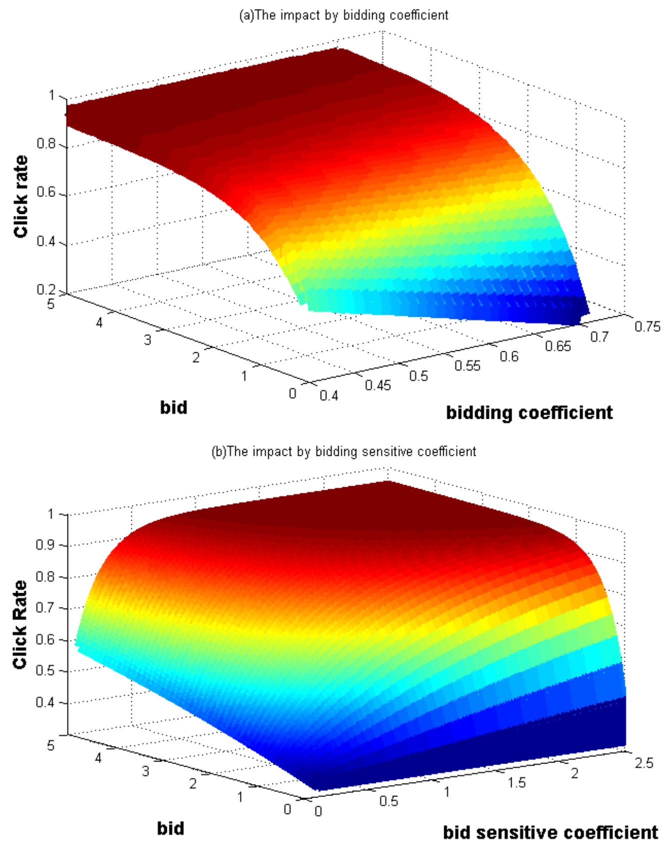
THE NUMERICAL SIMULATION AND ANALYSIS OF BIDDING AND PRICING JOINT DECISION

Sensitivity analysis of parameter

Click rate model function (1) have two parameters related to the advertising effect of bidding ranking. χ is the bidding coefficient reflects the biggest impact on the click rate and η is bidding sensitive coefficient reflects the sensitivity of bid. Figure 2 (b) is the click rate affect by the bidding sensitive coefficient and bid when $\chi = 0.6$. There is no impact from bidding, when bidding sensitive coefficient $\eta = 0$, only price and reservation price change the click rate. Click rate reached the highest level when bidding price over 2. Figure 2 (a) is the click rate affect by the bidding coefficient and bid when $\eta = 1$. The bidding coefficient determines the range of click rates. The result of numerical simulation well illustrates the click rate of link.

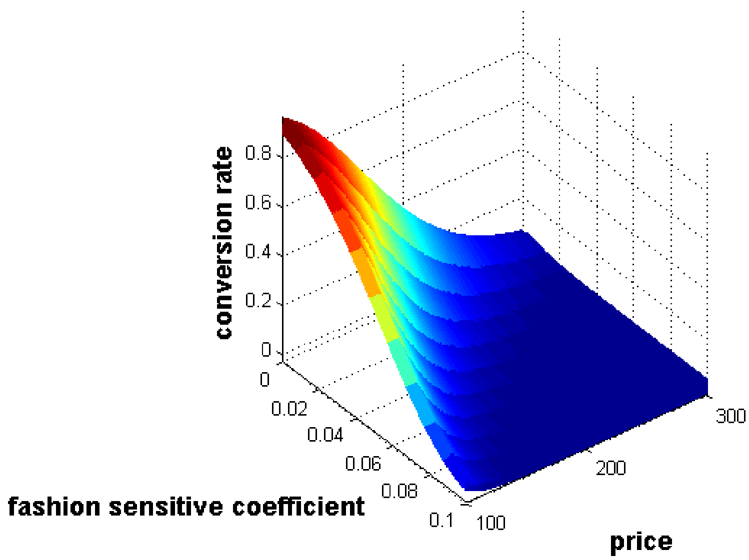
Parameter sensitivity analysis shows that we could make optimal joint decision according to the competitive ranking advertising effect. According to certain Taobao online retailer that sell short-sleeved blouse online, we set $\chi = 0.6$ $\eta = 1$.

Figure 2. The impact on click rate by χ and η



We have set up a fashion index function $\rho(t)=e^{\theta(t-T)}$, the fashion sensitive coefficient θ reflects consumers' sensitivity of fashion and it determines how the consumer reservation price changes with time. Clothing is very sensitive to fashion degree. As shown in figure 3, we analyzed how the fashion sensitive coefficient influence conversion rate by numerical simulation when $t=14, b_t=5$. The higher the fashion sensitive coefficient, the lower the conversion rate in equivalent situation. The conversion rate change in a reasonable range with different price when fashion sensitive coefficient $\theta \in [0, 0.04]$. We take $\theta=0.01$ and the conversion gradually reduces with price. Therefore, the higher fashion sensitivity is, the greater impact exerts on conversion rates. Companies should grasp the beginning of sales period and fully optimize the bidding and pricing strategy to get more profits.

Figure 3. The conversion rate's influence by fashion sensitive coefficient



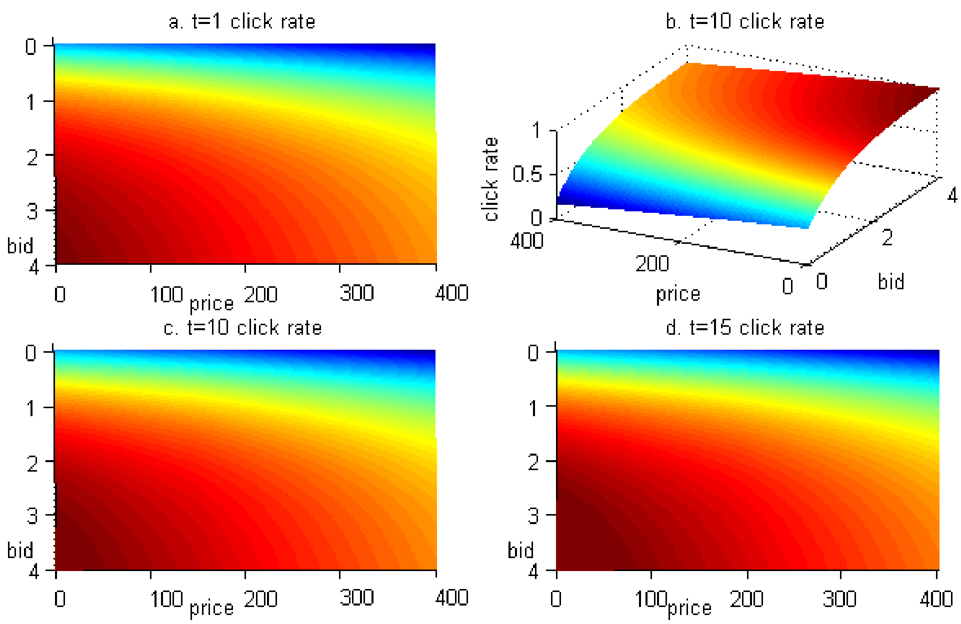
How bid and price affect click rate

An online retailer that sell short-sleeved blouse get $CTR=0.95$ when rank at the first position and reasonably priced. Based on the case, we set parameters as below.

$$\lambda(b,p)=0.95-0.6\exp(-b)-0.0005\times\max(0,p-EY)-0.0007\times\min(0,p-EY)$$

We use Matlab to simulate and get to know how bidding and pricing affect click rates as shown in figure 4. If the bid is too low, the link show in a bad position, click rates will decline. If the price is too high, click rate will drop (as shown in figure 4 b). Thus, reasonable pricing and bidding can reduce click rate's weaken influence of price. In addition, time have an impact to click rate since fashion value decline with time. As shown in figure 4d ($t=15$),deep red area bigger than other ones(click rate is higher), so at the beginning of the season clothing fashion the highest degree.

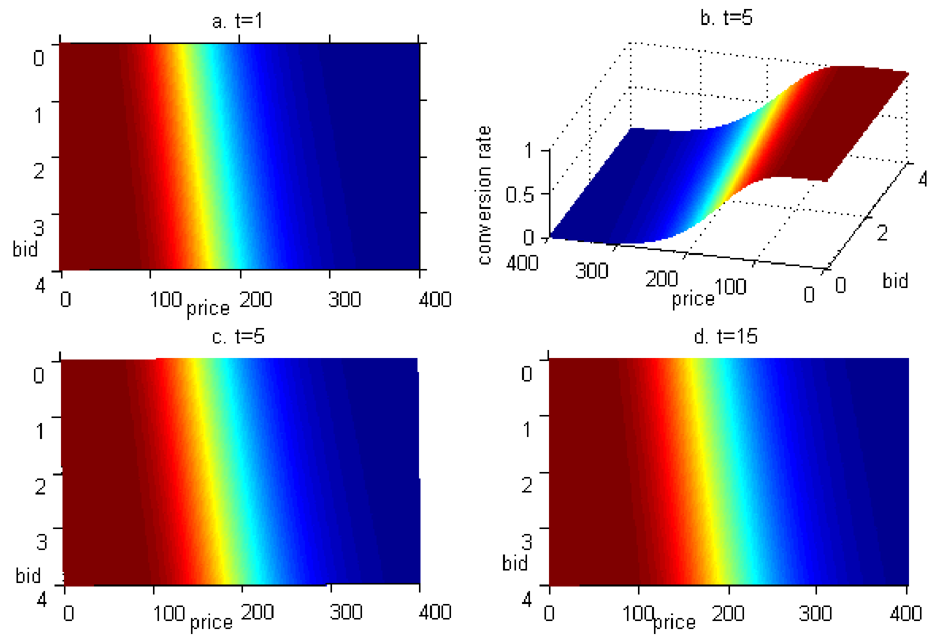
Figure 4. The click rate influence by bidding and pricing



How bid, price and fashion degree affect conversion rates

The conversion rate of bidding ranking depends on the pricing and consumers' reservation price. The reservation price distribution affect by the factors such as brand, fashion, bid and so on. Consumers' reservation price of the short-sleeved blouse in accordance with $Gamma(9,20)$, influence function of mean is $\mu(b_t)=0.5*b_t$ and influence function of standard deviation is $\sigma(b_t)=1+0.002*b_t$. The relationship between bid and price is shown in figure 5. The conversion rate increased with bidding, decreased with the pricing (as shown in figure 5b). The conversion rate is 0 when the price is more than 300. The appropriate price ranged from 100 to 250 since high prices frighten consumers away and low prices make retailers loss money. In addition, the decreasing of fashion value makes reservation price decrease with time. Red area in figure 4 represents the high conversion rate. At the beginning of season (t = 15) is the most fashionable period, we should keep high prices to correspond highest conversion rate. The overall conversion rate is reducing with decreasing fashion degree.

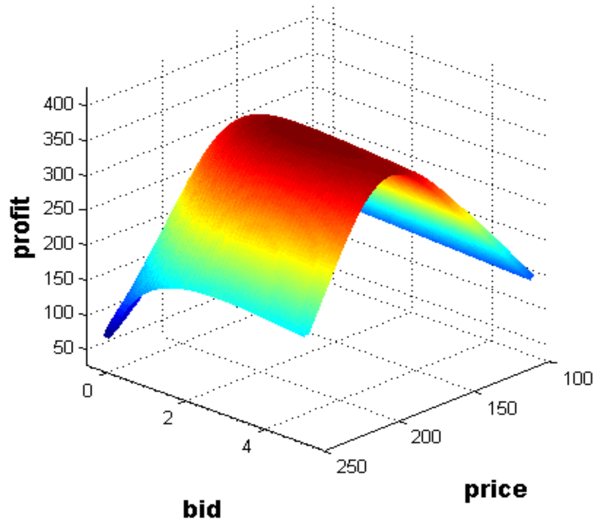
Figure 5. The conversion rate influence by bidding and pricing



How the bid and price decisions impact on the profits

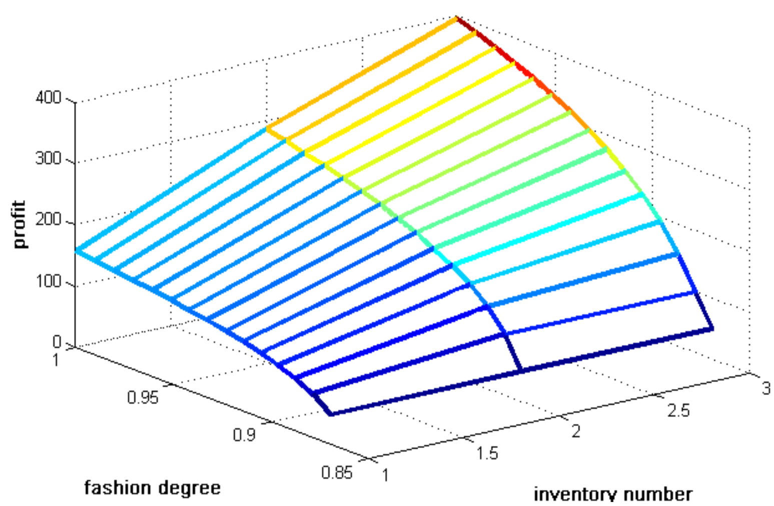
We divided online retailers' bid and price decisions into static and dynamic, the static joint decision was made at the beginning of the sales period, once the price and bid were made and it won't change during the whole period. Dynamic decision was made at the beginning of each cycle; consumers may see different price and website rankings each cycle. As for the simulation of static joint decision, we assumed the sales period have 15 cycle (T = 15) and inventory is 3 at the beginning (I = 3). We used the local search algorithm to find the optimal decision of the retailer profit model, as shown in figure 6. Bid of static simulation was ranging from 0 to 5; the price was ranging from 100 to 300. Online retailers gain maximum profit of 375.905, when the bid is 2.7 and priced at 193. Pricing between 150 and 230 can obtain ideal profit, due to click rate and conversion rate maintain a higher level. In this case, online fashion retailers should price slightly on the high side and bid to maintain moderate levels. Bidding increasing from 0 to 3 has a significant positive influence on profits, but it won't change obviously when bidding more than 3, since the largest advertising effect already been achieved. The advertising effects have little impact on profit when bidding reached a certain point, so we need to optimize the bidding decisions.

Figure 6. The profits under static joint decision



Static joint decision can meet the needs of most of the online retailer. But for seasonal and fashion goods, static decision lack of flexibility and might loss profit. Therefore, we further discuss the impact of the combination of bidding and pricing on the profits. Dynamic decision was conducted at the beginning of each cycle, it was based on current inventory levels and consumer reservation price, the simulation discusses the relationship between profits and inventory levels by time. The simulation results of the search algorithm under dynamic decision is shown in figure 7, the profit and inventory levels are in direct proportion to the remaining sales cycle. In the remaining 15 sales cycle and 3 units of inventory, optimal dynamic joint decision obtain profit at 397.7355(as shown in table 2) and it nearly 6% higher than that of static profits. Thus, it can be seen that the profits obtained under the dynamic decision are higher in the online retailer's sales cycle.

Figure 7. The profits under dynamic joint decision



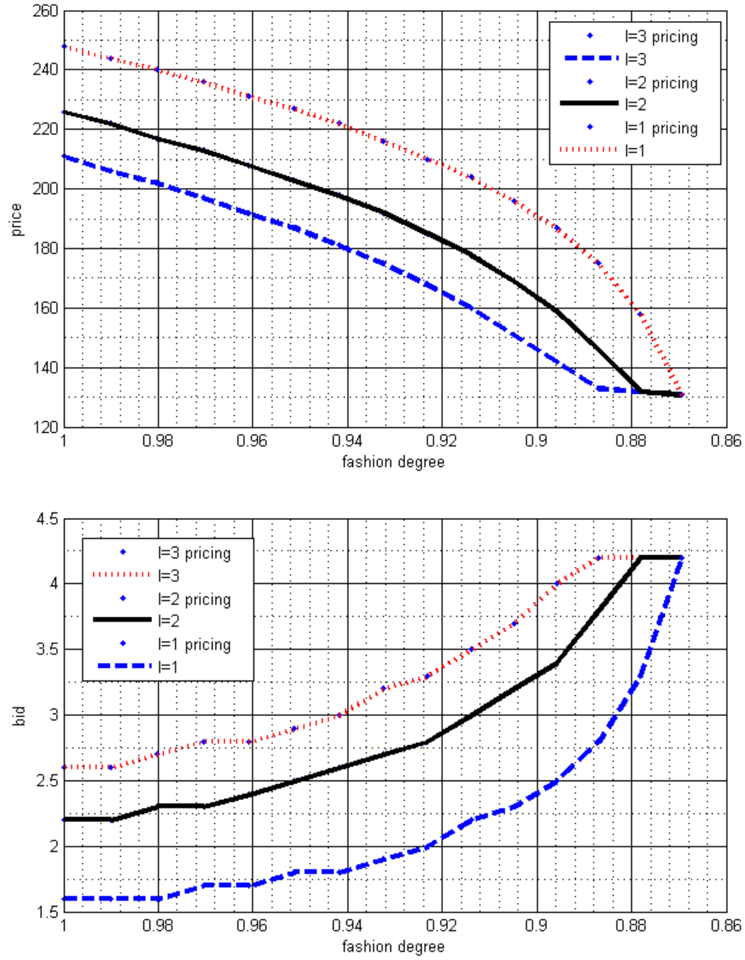
The simulation results show that reasonable pricing and bidding advertising can effectively improve the click rate and conversion rate, dynamic decision can improve the online retailer's profit by adjusting the relationship between supply and demand of online retailers. The joint decisions conform to the law of the value law of fashion products and alleviate the inventory pressure at the end of the sales season. The price of fashion products changes with the remaining sales cycle and inventory levels, and the optimized joint decision makes the online retailer more profitable.

Table 2. The comparison of profits between static and dynamic joint decisions

Inventory	Decision type	$X \sim gamma(9,20)$			
		price	bid	profit	Growth rate
1	static	218	2.1	147.4107	6.6454%
	dynamic	248 244 240 236 231	1.6 1.6 1.6 1.7 1.7	157.2068	
		227 222 216 210 204	1.8 1.8 1.9 2.0 2.2		
		196 187 175 158 131	2.3 2.5 2.8 3.3 4.2		
2	static	204	2.4	270.1707	6.5013%
	Dynamic	226 244 240 236 231	2.2 2.2 2.3 2.3 2.4	287.7355	
		227 198 192 185 178	2.5 2.6 2.7 2.8 3.0		
		169 159 146 132 131	3.2 3.4 3.8 4.2 4.2		
3	Static	193	2.7	375.9050	5.8074%
	Dynamic	211 206 202 197 192	2.6 2.6 2.7 2.8 2.8	397.7355	
		187 181 175 168 160	2.9 3.0 3.2 3.3 3.5		
		151 142 133 132 131	3.7 4.0 4.2 4.2 4.2		

* The dynamic decision values in the table are arranged in chronological order.

Figure 8. The profits under dynamic joint decision



How bid and price change with fashion degree

In view of the fast fashion product seasonal characteristics, dynamic decision will pricing, and bidding with the changing fashion degree, the trends reflect the online retailer's strategy. Setting T = 15 and I = 3, the trend of pricing and bidding by fashion degree is shown in figure 8. The price of online retailers gradually decreases as the remaining sales cycle decreases, while bidding increases gradually.

Obviously, since fashion degree is decreasing with time, and the reservation price of consumers is reducing. To ensure the sales volume, the price of the product will be reduced and the bidding will be raised. In addition, the price is lower and the bid is higher when the inventory is getting higher. The joint decision can improve the click rate and conversion rate, reduce inventory, ensure that online retailers maximize profits.

The numerical simulation conclusion

According to the modeling and numerical simulation, we get the following conclusions:

(1) The relationship between bid and pricing, click rate and conversion rate: Bid ranking advertisement obtain more viewers and attract more clicks by better link position, it also promote the reservation price. When the price is in the right range, the conversion rate increases with the bid and decreases with the price. Meanwhile, inappropriate prices could leading to a waste of bidding costs.

(2) The relationship between fashion degree and reservation price: the fashion degree of clothing products decreases with time, while consumers reservation price influenced by fashion and bidding. In order to improve conversion rates, optimizing the bidding and pricing can effectively guarantee the click conversion at a certain level and can balance the reservation price and bid cost. Thus, improve the fashion online retailers' profits.

(3) The profit under static and dynamic joint decision: The profit of optimal joint decision is decreasing with bidding, and the monotonically increasing of the inventory opportunity cost. In any inventory level and any cycle, the optimal joint strategy of online retailer follow $x^*(\Delta(y,t)) < \bar{x}$ and $\Delta(y,t) < \mu(b^*(y,t)) + \sigma(b^*(y,t))\bar{x}$. Static or dynamic joint decisions have important influence on profits. As for fast fashion products, dynamic joint decisions can improve conversion rate by fashion degree, inventory levels and reservation prices. Compared with the static joint decision, dynamic decision can improve the revenue of online retailers.

CONCLUSIONS

Bidding ranking integrate network advertising, auction and online resources, its widely apply on the internet and it connect the buyers and the sellers, improve the online traffic and conversion rate. Especially for fast fashion, because of its fashion degree and market value will reduce with time. Fast fashion online retailers optimizing bidding and dynamic pricing decisions has a realistic significance. This paper constructs the click rate and conversion rate model under bidding rank and analyzes the link rank and click rate of online retailer influence by bidding. The reservation price distribution base on bidding and fashion degree. On this basis, we study the profit model of online retailer by considering the cost of production, the cost of bidding and the cost of sales opportunity. This paper analyzes the bidding, pricing and fashion degree effect on the click rate and conversion rate by the simulation, static and dynamic joint decision influence on online retailer profits, the relationship between the bidding and pricing with time and fashion sensitive coefficient effect on the conversion rate. Based on our findings, we recommend that online retailers cut price and increase SEM cost with time according the fashion value law and opportunity cost law.

The fashion value of clothing and the cost of sales opportunity is gradually reduced with time. The conclusions of this study are in line with the fast fashion products' characteristic of "more style less inventory". The numerical simulation verifies the correctness of the click rate and conversion rate model, which conform to online bidding rankings websites such as Taobao. Meanwhile, it also prove that dynamic joint decision can make higher profit than the static joint decision. According to the simulation, we suggest that retailer should be flexible when make price and marketing decisions. To maximum profit, mark down clothes price with time and adjust web visiting amount by bidding. As we know that bid and price can affect demand and supply, it's very important to forecast the demand and using joint decision to readjust it.

Due to time limitation, this study still insufficient. Reservation price distribution haven't reflect fast fashion clothing value law and the profit model limit inventory levels during each sales cycle. We can take inventory into consideration to improve the joint decisions-making.

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