Finding Optimal Product Price and Combination Promotions Through Customer Intervention

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***Abstract*— Online shopping is rapidly growing sector were all customers searching for the latest and the best products with unbelievable offers worldwide. Digital marketing is dynamic optimization model for a wholesaler's mart price promotions of various brands in products categories. In current online shopping a customer can meet thousands of suppliers with different price brands. There is no general consensus in online digital marketing, various literatures show the impacts of price promotions on bargain of consumer behavior activity. In this current system of e-commerce, a growing number of customers choose to go shopping online because it saves time and effort. Here the skyline query, a product which is not dominated by any other product is said to be a skyline product or it is in the skyline. The products in the skyline are the best possible trade-offs between all the factors that customers care about. The systems are not able to provide product skyline query attractive products. Now a days considering the requirements of customers for practical application scenario, I concerned about product selection under price promotion. I formulated a Constrained Optimal Product Combination(COPC) problem. I propose three effects like immediate, and positive impact of price deal on the sales of promoted brand with bargain products and provide combinations which both meet a customer's desires and bring the maximum discount rate. Secondly brand substitution where some consumers are provided with branded combination substitution with lower priced promoted from various vendors. Finally, consumers are promoted with good combinations, best discounted price from vendors and they post upcoming products. This project is characterizing the magnitude of discounts as well as the combinations of promotions. It is also providing various comparative statics that identify the depended of discounts and combinations upon key model parameters.**

***Keywords*— Digital marketing, Online shopping, skyline product and price promotion.**

I. Introduction

With the development of e-commerce, a growing number of customers choose to go shopping online because it saves time and effort. However, it always contraries to expectations of customers. This is because they may need to pickup one choice among thousands of products. To help customers identify attractive products, a skyline query is admittedly a common and effective methodology. According to the definition of the skyline query, a product which is not dominated by any other product is said to be a skyline product or it is in the skyline. The products in the skyline are the best possible trade-offs between all the factors that customers care about. The skyline query is useful in identifying attractive products. In Jing dong and Alibaba's Taobao Mall which are the most famous online shopping malls in China, there are many online stores that specialize in one category of products such as red wine, watches, television, laptop, to name just a few. During the weekends or holidays, these stores usually hold some price promotion campaigns to boost consumption. Under the price promotion campaigns of these stores, a customer could select an optimal product combination by himself. Besides, the customer is common to participate in cooperation with his families or friends for group buying. The present price promotion campaigns can be classified into two categories due to whether products can be chosen independently. The first category, namely, independent product selection, includes the campaigns such as "buy one product and get another product for free" and "25% discount for two pics" etc.

II. RELATED WORK

Current e-commerce, a growing number of customers choose to go shopping online because it saves time and effort. Skyline query, a product which is not dominated by any other product is said to be a skyline product or it is in the skyline. The products in the skyline are the best possible trade-offs between all the factors that customers care about. As the systems are not able to provide skyline query attractive products. Considering the requirements of customers in this practical application scenario, we are concerned about product selection under the price promotion.

III. PROPOSED WORK

Immediate and positive impact of price deal on the sales of promoted brand. Brand Substitution and Brand Combination with lowered price from various suppliers. Consumer stockpile a promoted brand during a deal period with asked price. Impact of discount on the demand for brand increase, the depth of a discount should be increased. The COPC problem aims to find skyline product combinations whose actual payments are not beyond the customer's willingness to pay. These skyline product combinations could bring the maximum discount rate.

Algorithm 1 Two_List_Exact(TLE) Algorithm
Input: The skyline product set SP, a price promotion campaign "get \$β off every \$α purchase", and a customer's payment willingness WTP
Output: A result set SP⋆ of the COPC problem
1: Divide SP into two parts: SP1={sp1,sp2,...,spNS/2} and SP2={spNS/2+1,spNS/2+2,...,spNS}
2: Generate all the product combinations SP'⊆SP1 with ActPay(SP')≤WTP, sort them in an increasing order of OriPri(SP'), and store OriPri(SP') as the list A={a1,a2,...,aN1}
3: Compute a⋆∈A which is with the maximum discount rate
4: Generate all the product combinations SP'⊆SP2 with ActPay(SP')≤WTP, sort them in a decending order of OriPri(SP'), and store OriPri(SP') as the list B={b1,b2,...,bN2}
5: Compute b⋆∈B which is with the maximum discount rate
6: SP⋆=argmaxOriPri(SP')∈{a⋆,b⋆}DisRate(SP')
7: Set the maximum discount number MaxDisNum=⌊WTP α−β⌋due to Lemma 3.1
8: for k=1 to MaxDisNum do
9: Initialize i=1, flag=0 and y⋆ k=(k+1)×α
10: for ai∈A do
11: j=flag+1
12: for bj∈B do
13: if ai+bj is equal to k×α then
14: y⋆ k=k×α and Break
15: else
16: if ai+bj>k×α then
17: j=j+1
18: y⋆ k=min{y⋆ k,ai+bj}
19: else
20: i=i+1
21: flag=j
22: Add SP''=argmaxOriPri(SP')=y⋆ j DisRate(SP') for 1≤ j≤MaxDisNum to SP⋆ and refresh SP⋆ by removing the combinations whose discount rates are less than that of SP''
23: Return SP⋆

Algorithm 2 Lower_Bound_Approximate Algorithm
Input: The skyline product set SP with |SP|=NS, a price promotion campaign "get \$β off every \$α purchase", a customer's payment willingness WTP, and a trimming parameter ϵ for 0<ϵ<1
Output: A result set SP⋆ of the COPC problem
1: Remove each product p'∈SP with ActPri(p')>WTP
2: Initialize L={0}
3: Set the maximum discount number MaxDisNum=⌊WTP α−β⌋due to Lemma 3.1
4: Initialize y⋆ j =∞for 1≤j≤MaxDisNum
5: while SP is not empty do
6: L=L∪{y+Ori(p) : y∈L}for p∈SP
7: Sort all the elements in L in an increasing order and remove each element y from L if y−⌊y α⌋×β>WTP
8: Compute y⋆ j∈L where @y'∈L−{y⋆ j},y'<y⋆ j with y',y⋆ j∈[j×α,(j+1)×α) for 1≤j≤MaxDisNum and j is an integer
9: Remove each element y from L which is larger than y⋆MaxDisNum
10: L=Trim(L−y⋆ j, ϵ 2NS) for 1≤j≤MaxDisNum
11: Return SP⋆=argmaxOriPri(SP')=y⋆ j DisRate(SP') for j is an integer and 1≤j≤MaxDisNum
12: Function: Trim(L, δ)

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Initialize L'={y1}
last=y1
for i=2 to|L|do
if yi>last×(1+δ) then
Append yi onto the end of L'
last=yi
Return L'
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IV. COMPARITIVE RESULTS

In Fig 1: In this admin page admin can add the new products or delete the existing products and also replace old products with new products.

In Fig 2: Admin can see the user ordered list. Which type of products are more demand and which products are purchased by the customer's.

In Fig 3: This Catalogue page can see the admin as well as user. Admin can update the Catalogue page and customer can buy or select the product frim catalogue page.

In Fig 4: The Customer can select the product and buy the product and also bargain on particular selected product. This bargain is done with the Admin of the Products.

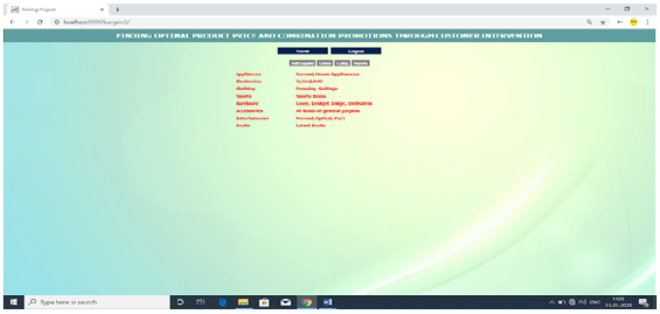

Fig 1: Admin Menu

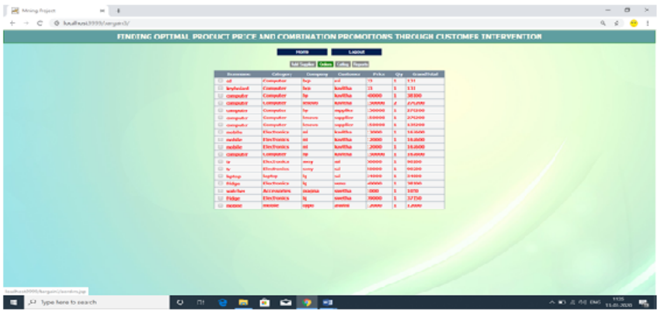

Fig 2: User Ordered List

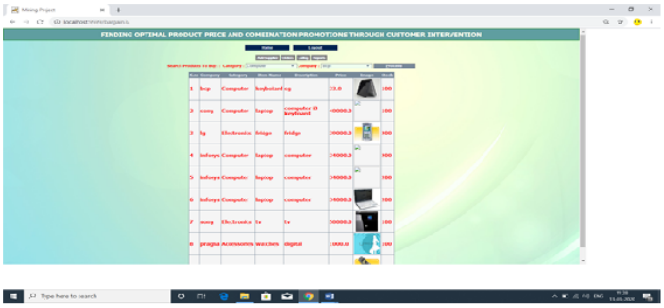

Fig 3: Catalogue Page

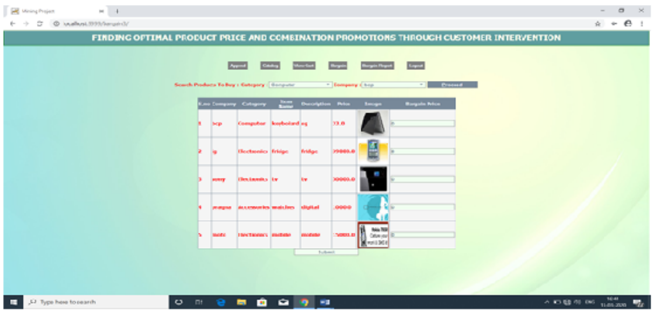

Fig 4: User Bargain Page

V. CONCLUSION

In this paper, we formulate the COPC problem to retrieve optimal skyline product combinations that satisfy the customer's payment constraint and bring the maximum discount rate. To tackle the COPC problem, we propose an Exact Algorithm(EA), design an Lower Bound Approximate Algorithm(LBAA) with an approximate bound, and develop an incremental greedy algorithm(GA) to boost the performance. We conduct a customer study to verify the significant of our COPC problem. Additionally, the experimental results on both real and synthetic datasets illustrate the effectiveness and efficiency of the proposed algorithms.

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