Inventory Based Recommendation Algorithms

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Outline

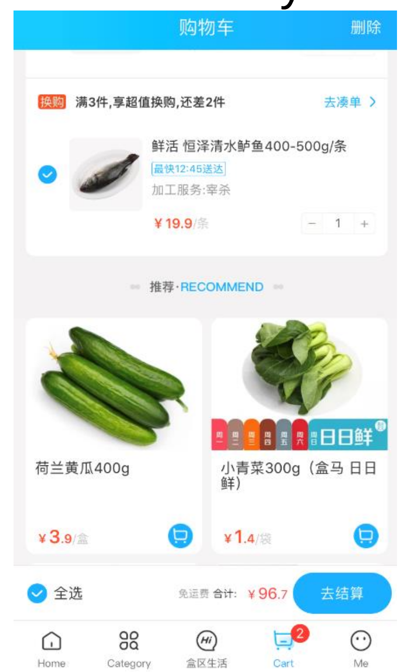
Background

- Freshippo is a supermarket owned by Alibaba Group
- Both online and offline channels, but a large portion of the revenue is from its online channel
- 3000+ SKUs
- Get replenished every morning; Dispose; Limited inventory

Freshippo

Alibaba Group

- Home Page



- Cart Page

Background

- Alibaba Recommendation Workflow

Customer arrival → Recall → CTR&CVR estimation → Top-K recommendation

Recall: 3k+ SKUs → about 300 SKUs

CTR&CVR estimation: Alibaba in-house system

Top-K recommendation: Maximum expected revenue

- Greedy Algorithm (maximum expected revenue recommended first) causes 50% loss of optimal revenue

- Research Question:
  - **How does Freshippo make real-time Top-K recommendation to arrived customers so that revenue is maximized in a single day, especially when products are perishable and have limited inventories**

Notations

- n: the online retailer sells n products
- r_i: price of product i
- w_i: salvage value of product i
- T: total periods, one customer arrives in each period.
- S: total segments.
- $\widehat{ctr}_{it}^{s}$, $\widehat{cvr}_{it}^{s}$: historical click through rate (ctr) and conversion rate (cvr)
- C_i: initial inventory of product i
- $\hat{b}_i^s$: initial inventory of product i at the beginning of segment s
- K: assortment cardinality. $K = 20$

Linear Programming Based Algorithm

- LP model is based on history data: maximizing revenue in segment s

$$[\text{P1}]\quad \max \quad \sum_{i=1}^{n}\sum_{t=1}^{\hat{T}_s} \hat{cvr}_{it}^{s}\hat{ctr}_{it}^{s} r_i x_{it} + \sum_{i=1}^{n} w_i I_i$$

$$\text{s.t.}\quad \sum_{t=1}^{\hat{T}_s} \hat{cvr}_{it}^{s}\hat{ctr}_{it}^{s} x_{it} + I_i = \hat{b}_i^s,\ \forall i = 1,2\ldots n(1)$$

Inventory Constraint

$$\sum_{i=1}^{n} x_{it} \le K,\ \forall t = 1,2,\ldots \hat{T}_s$$

Cardinality Constraint

$$\boxed{\begin{aligned} & I_i \ge 0,\ \forall i = 1,2,\ldots,n \\ & 0 \le x_{it} \le 1, \forall i,t \end{aligned}}$$

Standard Constraint

Linear Programming Based Algorithm

- Shadow Price α_i^s: opportunity cost of recommending product i during segment s

$$
\begin{aligned}
\text{[P1]}\quad \max \quad & \sum_{i=1}^{n}\sum_{t=1}^{\hat{T}_s} c\hat{v}r_{it}^{s} c\hat{t}r_{it}^{s} r_i x_{it} + \sum_{i=1}^{n} w_i I_i \\
\text{s.t.} \quad & \sum_{t=1}^{\hat{T}_s} c\hat{v}r_{it}^{s} c\hat{t}r_{it}^{s} x_{it} + I_i = \hat{b}_i^s, \ \forall i = 1,2\ldots n (1) \\
& \sum_{i=1}^{n} x_{it} \le K, \ \forall t = 1,2,\ldots \hat{T}_s \\
& I_i \ge 0, \ \forall i = 1,2,\ldots,n \\
& 0 \le x_{it} \le 1, \forall i,t
\end{aligned}
$$

Shadow Price / Dual Price

α_i^s

Linear Programming Based Algorithm

- Instruct real-time recommendation by modifying ranking scores with α_i^s

Algorithm 1 LP-based Algorithm

for s=1,2,...,S **do**
    Prepare parameters $(\hat{cvr}^s_{it}\hat{ctr}^s_{it}, \hat{b}^s_i)$ ▷ Segment-specified parameters
    Solve [P1] with above parameters
    Get the shadow price α_i^s of constraint (1)
    for Customer t in Period T_s **do**
        Remove products with zero inventory value
        Get the estimation of $cvr^s_{it}ctr^s_{it}$
        $score_{it} \leftarrow (r_i - \alpha_i^s)cvr^s_{it}ctr^s_{it}$
        Sort $\{score_{it}\}_{i=1}^n$ in descending order, obtain sorted rank $[i]$
        $S^t = \{i : [i] \leq K\}$
    end for
end for

Inventory-Balancing (IB) Algorithm

- Modify ranking scores with an inventory-based penalty function Ψ
- An increasing penalty function $\Psi : [0,1] \rightarrow [0,1]$ with $\Psi(0) = 0, \Psi(1) = 1$
- In our study, $\Psi(x) = \frac{e}{e-1}(1 - e^{-x})^{*}$

$$Score_{it} = \Psi\left(\frac{I_i^{t-1}}{C_i}\right)(r_i - w_i)ctr_{it}cvr_{it}$$

Algorithm 2 Inventory Balancing Algorithm

for period t=1,2,...,T **do**
  $\boxed{score_{it} \leftarrow \Psi(I_i^{t-1}/C_i)(r_i - w_i)cvr_{it}ctr_{it}}$
  $\boxed{\text{Sort } \{score_{it}\}_{i=1}^{n} \text{ in descending order, obtain sorted rank } [i]}$
  $x_{it} = 1$ if $[i] \leq K$, $x_{it} = 0$ otherwise
end for

* Golrezaei N, Nazerzadeh H, Rusmevichientong P. Real-time optimization of personalized assortments[J]. Management Science, 2014, 60(6): 1532-1551.

Dataset

- Two-day page view data from 5:55 AM to 22:55 PM in a store, which includes approximately 27 millions records for each day
- Each record contains ***SKUID***, predicted ***CTR***, predicted ***CVR***, ***pvtimestamp***, and ***pvid***
- **Price**, product **category** (nonperishable or perishable), **salvage value**, and **initial inventory level** at the beginning of the day

TABLE I
DESCRIPTIVE STATISTICS ABOUT SKUS

		Mean	Std	Min	25%	50%	75%	Max
Non-perishable Product	Price	2.54	2.58	0.48	1.75	2.11	2.57	4.79
	Salvage	2.49	2.53	0.43	1.70	2.06	2.52	4.74
	Initial Inventory	3.55	3.99	1.00	2.40	3.00	3.64	6.79
Perishable Product	Price	2.46	2.80	0.01	1.77	2.11	2.55	5.80
	Salvage	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Initial Inventory	4.76	5.52	1.00	2.89	3.69	4.61	6.91

Simulation Results

- We compared four algorithms

Algorithms	Scores	Meanings
GREEDY	$ctr_{it} * cvr_{it} * r_i$	Expected Revenue (ER)
LP-based Algorithm	$ctr_{it} * cvr_{it}(r_i - \alpha_i^s)$	Adjusted ER rule out opportunity cost
IB Algorithm	$\Psi\left(\frac{I_i^{t-1}}{c_i}\right) * ctr_{it} * cvr_{it} * r_i$	Adjusted ER modified by penalty function
REAL	$ctr_{it} * cvr_{it} + ctr_{it}$	Click + Conversion

Simulation Results

Table 2. Numerical Study Results

	Without Salvage					With Salvage		
	GREEDY	LP-based		IB	REAL	LP-based	IB	REAL
Revenue-Related		-1day	-1seg			-1seg		
Sales Volume	-	-2.84%	+2.33%	+4.29%	+4.56%	-1.00%	-2.71%	+4.56%
Revenue	-	+0.12%	+0.70%	+1.97%	-11.11%	-4.50%	-3.98%	-11.11%
Peri.Ratio	-	-14.18%	-7.22%	-3.78%	-0.64%	+13.95%	+18.54%	-0.64%
Revenue+Salvage	-	-0.84%	-0.06%	+0.16%	-1.53%	+0.85%	+1.24%	-1.53%
RevenuePerPv	-	+0.11%	+0.67%	+2.01%	-11.06%	-4.46%	-4.02%	-11.06%
RevenuePerOrder	-	+2.89%	-1.31%	-2.54%	-14.11%	-3.85%	-1.40%	-14.11%
Inventory-Related								
Sold-out Rate	-	-3.06%	+0.33%	+3.29%	+2.02%	+0.22%	-5.32%	+2.02%
Leftover Rate	-	+0.00%	-2.62%	-6.63%	-2.61%	-3.11%	+0.16%	-2.61%

- Sales Volume: IB+4.29%, LP+2.33%; REAL+4.56%
- Revenue: IB+1.97%
- Sales Volume & Revenue : decreasing
- Peri.Ratio: LP+13.95, IB+18.54

Conclusion

- Both LP-based algorithm and inventory-balancing algorithm can achieve higher revenue compared to prevailing greedy algorithms.

- Incorporating salvage values can boost sales volume of perishable products.

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Q&A