

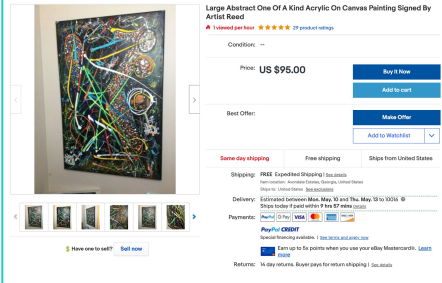
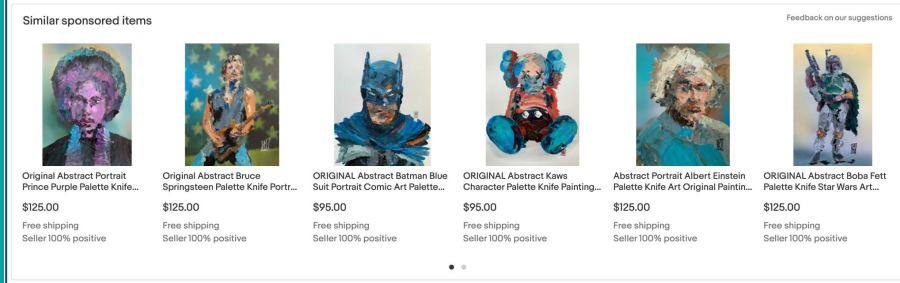
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Relevance Constrained Re-ranking in Sponsored Listing Recommendations

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Background

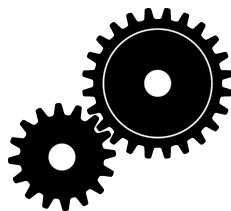


similar item recommendation

Seed item

Sponsored Listing

features (e.g. title, price, item attributes, user preference)



GBT model

purchase probability
 p

$$\text{score} = \overbrace{p \cdot c}^{\text{Organic revenue}} + \overbrace{w \cdot p \cdot b}^{\text{Ad revenue}}$$

p : Purchase probability

c : Selling Cost

w : Ad Revenue Weight

b : Ad Bid Rate

Background

Revenue Relevance Trade-off

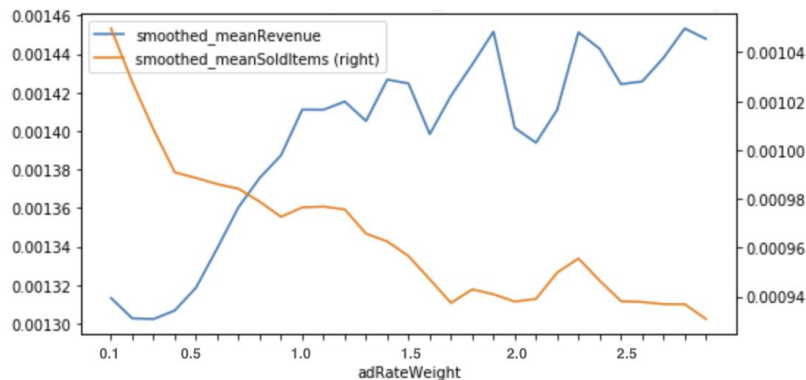


Figure 1. Average Ad revenue & Average Item Sold Count vs. Ad Revenue Weight



Many similar ones



Few similar ones

$$score = p \cdot c + \underline{w} \cdot p \cdot b \quad \rightarrow \quad score = p \cdot c + \underline{f(\delta)} \cdot p \cdot b$$

Purchase probability ranking

$$P \quad item_ranking = \{r_1 = 0.5, r_2 = 0.45, r_3 = 0.4, r_4 = 0.3, r_5 = 0.2, r_6 = 0.15\}$$

r_i is the i th ranking position

Final ranking given different w

$$score = p \cdot c + \underline{f(\delta)} \cdot p \cdot b$$

$$Q_{w1} \quad item_ranking_{w1} = \{r_1 = 0.45, r_2 = 0.5, r_3 = 0.3, r_4 = 0.4, r_5 = 0.15, r_6 = 0.1\}$$

$$Q_{w2} \quad item_ranking_{w2} = \{r_1 = 0.1, r_2 = 0.5, r_3 = 0.45, r_4 = 0.3, r_5 = 0.4, r_6 = 0.2\}$$

$$D_{kl}(P||Q_{w1}) = 0.021 \quad \star$$

$$D_{kl}(P||Q_{w2}) = 0.258$$

$$Q^* = \arg \max_{w \in W} f_{rev}(Q_w)$$

$$\text{s.t. } D_{kl}(P || Q_w) \leq \theta_{KL}$$

θ_{KL} is a constant. $f_{rev} : \mathbb{R}^k \rightarrow \mathbb{R}$ is the estimated ad revenue for ranking Q_w .

Distribution Q_w represents the ranked list X_w

$$X^w = [x_1^w, x_2^w, \dots, x_k^w]$$

$$\begin{aligned} f_{rev}(Q_w) &= f_{rev}(X^w) \\ &= \sum_{r=1}^k a_r^w \cdot v_r \end{aligned}$$

a_{rw} is the ad revenue for the item at slot r . v_r is the unbiased click through rate for slot r .

What if we don't want to search for the w , can we estimate it?

$$D_{kl}(w) = f(\text{recall set statistics, context, } w)$$


Recall set statistics: recall set size, and the maximum, minimum, mean, median, and standard deviation of all recall set item's price, PTR score, and bid rate

Regression

Ordinary Least Squares Regression (OLS)

$$R^2 = 0.43$$

GBT Regression

$$\underline{D_{kl}(w)} = f(\text{recall set statistics, context, } \underline{w})$$


Experiments

DESIGN

- Control (production): Fixed ad revenue weight at 0.25 for all impressions.
- Treatment 1: OLS based dynamic ad revenue weight (DARWO) variant.
- Treatment 2: Fixed ad revenue weight at 1.75. 1.75 is selected because it's the median value of predicted ad revenue weight from the OLS DARWO variant.

RESULT

Table 1: OLS DARWO vs. Fixed ad revenue weight by marketplace

		Ad Revenue	Purchase Count
US	treatment 1	+3.81% ¹	-4.05%
	treatment 2	+5.33%	-5.07%
UK	treatment 1	+6.89%	-4.11%
	treatment 2	+5.81%	-6.55%
AU	treatment 1	+7.10%	-1.97%
	treatment 2	+8.30%	-3.11%
DE	treatment 1	+6.44%	-3.44%
	treatment 2	+5.38%	-4.68%

¹:bold numbers are significant with $p < 0.1$

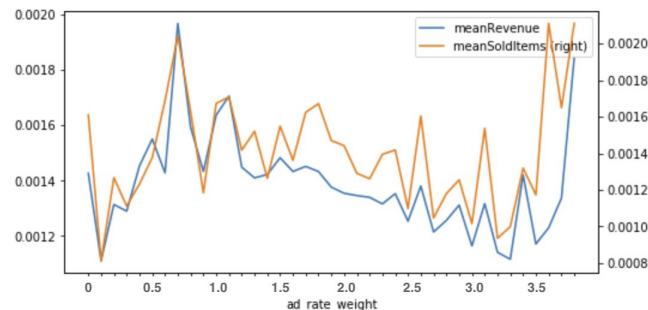


Figure 2. Average Ad revenue & Average Item Sold Count vs. Ad Revenue Weight (DARWO)

Ad revenue and purchase count have a pearson correlation of 0.724 ($p < 10^{-6}$)

DESIGN

- Control: OLS DARWO variant
- Treatment 1: GBT DARWO variant
- Treatment 2: Greedy optimization DARWO variant

RESULT

Table 2: GBT DARWO vs. Greedy DARWO by marketplace

		Ad Revenue	Purchase Count
US	treatment 1	+7.72%	+5.45%
	treatment 2	+8.70%	+8.53%
UK	treatment 1	+7.00%	0.90%
	treatment 2	+4.13%	+4.91%
AU	treatment 1	+7.45%	+2.49%
	treatment 2	+8.50%	+6.78%
DE	treatment 1	+4.67%	+1.33%
	treatment 2	+2.40%	+3.57%

Experiments

Compounded revenue and purchase changes ($p < 0.1$):

GBT: Revenue lift: **12.6%**

Purchase lift: **-1.8%**

Greedy: Revenue lift: **11.0%**

Purchase lift: **2.5%**

Summary

Table 3: Offline Purchase Ranking Comparison: Production, GBT DARWO and Greedy DARWO

	Mean Reciprocal Rank	NDCG@6	NDCG@12
Production	0.508	0.567	0.615
GBT DARWO	0.480	0.544	0.593
Greedy DARWO	0.516	0.576	0.620

Conclusion

Effective

- KL divergence can be used as a quality measurement for a re-ranked list;
- Controlling global standard by adjusting local ranked list's relevance individually


Can be estimated

KL divergence can be estimated through local inventory based features.

Easy to implement

This ad hoc re-ranking stage is completely independent of the previous ranking or conversion stages.

Thank you!

Questions?  zhge@ebay.com

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