Background

Sponsored Listing

Similar sponsored items

Original Abstract Portrait Prince Purple Palette Knife Art $125.00
-free shipping better 100% positive

Original Abstract Bruce Springsteen Palette Knife Art $125.00
-free shipping better 100% positive

original Abstract Black Super Hero Palette Knife Art $195.00
-free shipping better 100% positive

Original Abstract Kwon Chef Knife Palette Knife Art $195.00
-free shipping better 100% positive

Abstract Portrait Alien Skin Palette Knife Art Original Paint $205.00
-free shipping better 100% positive

Original Abstract Star Trek Palette Knife Star Wars Art $205.00
-free shipping better 100% positive

similar item recommendation

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

GBT model

purchase probability $p$

Seed item

score $= p \cdot c + w \cdot p \cdot b$

$\mathbf{p}$: Purchase probability

$\mathbf{c}$: Selling Cost

$\mathbf{w}$: Ad Revenue Weight

$\mathbf{b}$: Ad Bid Rate

Organic revenue

Ad revenue

ADKDD Aug 2021
Background

Revenue

Relevance

Trade-off

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

\[ \text{score} = p \cdot c + w \cdot p \cdot b \quad \Rightarrow \quad \text{score} = p \cdot c + f(\delta) \cdot p \cdot b \]
Dynamic Ad Revenue Weight Optimization (DARWO)

Kullback–Leibler divergence constraint

Purchase probability ranking

\[
P \quad \text{item\_ranking} = \{r_1 = 0.5, r_2 = 0.45, r_3 = 0.4, r_4 = 0.3, r_5 = 0.2, r_6 = 0.15\}
\]

\( r_i \) is the \( i \)th ranking position

Final ranking given different \( w \)

\[
\text{score} = p \cdot c + f(\delta) \cdot p \cdot b
\]

\[
\begin{align*}
P_{w_1} \quad \text{item\_ranking}_{w_1} &= \{r_1 = 0.45, r_2 = 0.5, r_3 = 0.3, r_4 = 0.4, r_5 = 0.15, r_6 = 0.1\} \\
P_{w_2} \quad \text{item\_ranking}_{w_2} &= \{r_1 = 0.1, r_2 = 0.5, r_3 = 0.45, r_4 = 0.3, r_5 = 0.4, r_6 = 0.2\}
\end{align*}
\]

\[
D_{kl}(P||Q_{w_1}) = 0.021 \quad ★
\]

\[
D_{kl}(P||Q_{w_2}) = 0.258
\]
\[ Q^* = \arg \max_{w \in W} f_{\text{rev}}(Q_w) \]
\[ \text{s.t.} D_{\text{KL}}(P || Q_w) \leq \theta_{KL} \]
\[
\theta_{KL} \text{ is a constant. } f_{\text{rev}} : \mathbb{R}^k \rightarrow \mathbb{R} \text{ is the estimated ad revenue for ranking } Q_w. \\
\text{Distribution } Q_w \text{ represents the ranked list } X_w \\
X_w = [x_1^w, x_2^w, \ldots, x_k^w] \\
f_{\text{rev}}(Q_w) = f_{\text{rev}}(X_w) \\
= \sum_{r=1}^{k} a_r^w \cdot v_r \\
\]
\(a_w\) is the ad revenue for the item at slot \(r\). \(v_r\) is the unbiased click through rate for slot \(r\).
Dynamic Ad Revenue Weight Optimization (DARWO)

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

Ordinary Least Squares Regression (OLS)

$$R^2 = 0.43$$

GBT Regression

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

Part - 1

**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

<table>
<thead>
<tr>
<th></th>
<th>Ad Revenue</th>
<th>Purchase Count</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>US</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>treatment 1</td>
<td>+3.81%¹</td>
<td>-4.05%</td>
</tr>
<tr>
<td>treatment 2</td>
<td>+5.33%</td>
<td>-5.07%</td>
</tr>
<tr>
<td><strong>UK</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>treatment 1</td>
<td>+6.89%</td>
<td>-4.11%</td>
</tr>
<tr>
<td>treatment 2</td>
<td>+5.81%</td>
<td>-6.55%</td>
</tr>
<tr>
<td><strong>AU</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>treatment 1</td>
<td>+7.10%</td>
<td>-1.97%</td>
</tr>
<tr>
<td>treatment 2</td>
<td>+8.30%</td>
<td>-3.11%</td>
</tr>
<tr>
<td><strong>DE</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>treatment 1</td>
<td>+6.44%</td>
<td>-3.44%</td>
</tr>
<tr>
<td>treatment 2</td>
<td>+5.38%</td>
<td>-4.68%</td>
</tr>
</tbody>
</table>

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 \( (p < 10^{-4}) \)
Part - 2

Experiments

- 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

<table>
<thead>
<tr>
<th></th>
<th>Ad Revenue</th>
<th>Purchase Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>US</td>
<td></td>
<td></td>
</tr>
<tr>
<td>treatment 1</td>
<td>+7.72%</td>
<td>+5.45%</td>
</tr>
<tr>
<td>treatment 2</td>
<td>+8.70%</td>
<td>+8.53%</td>
</tr>
<tr>
<td>UK</td>
<td></td>
<td></td>
</tr>
<tr>
<td>treatment 1</td>
<td>+7.00%</td>
<td>0.90%</td>
</tr>
<tr>
<td>treatment 2</td>
<td>+4.13%</td>
<td>+4.91%</td>
</tr>
<tr>
<td>AU</td>
<td></td>
<td></td>
</tr>
<tr>
<td>treatment 1</td>
<td>+7.45%</td>
<td>+2.49%</td>
</tr>
<tr>
<td>treatment 2</td>
<td>+8.50%</td>
<td>+6.78%</td>
</tr>
<tr>
<td>DE</td>
<td></td>
<td></td>
</tr>
<tr>
<td>treatment 1</td>
<td>+4.67%</td>
<td>+1.33%</td>
</tr>
<tr>
<td>treatment 2</td>
<td>+2.40%</td>
<td>+3.57%</td>
</tr>
</tbody>
</table>
Experiments

Summary

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%**

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

<table>
<thead>
<tr>
<th></th>
<th>Mean Reciprocal Rank</th>
<th>NDCG@6</th>
<th>NDCG@12</th>
</tr>
</thead>
<tbody>
<tr>
<td>Production</td>
<td>0.508</td>
<td>0.567</td>
<td>0.615</td>
</tr>
<tr>
<td>GBT DARWO</td>
<td>0.480</td>
<td>0.544</td>
<td>0.593</td>
</tr>
<tr>
<td>Greedy DARWO</td>
<td>0.516</td>
<td>0.576</td>
<td>0.620</td>
</tr>
</tbody>
</table>
Conclusion

- 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

KL divergence can be estimated through local inventory based features.

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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