From the Clouds to the Trenches
Learning to Manage the Marketplace

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From the Clouds to the Trenches
Or How I Learned to Stop Worrying and Love Counterfactuals

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Overview

Very Brief Intro to Search Advertising
Marketplace Objective
Marketplace Optimization
Understanding the Marketplace
Very Brief Intro to Search Advertising

Marketplace Objective

Marketplace Optimization

Understanding the Marketplace
Search Advertising

- Advertisers are charged per click
  - Ad platforms typically provide features to optimize for other targets
- Ads can have “decorations”, making slot sizes variable
  - Decorations can be advertiser provided or generated by the platform
- Different ad products coexist on the same page
  - E.g. Text Ads and Product Ads can compete for the same slots
Beyond Web Search

Shopping Vertical

Visually Similar Products

Hotel Ads
Very Brief Intro to Search Advertising

Marketplace Objective

Marketplace Optimization

Understanding the Marketplace
• Ultimate objective is to maximize *Long-Term Revenue*

\[ \text{Revenue} = \#\text{Users} \times \text{Queries per User} \times \text{Ads per Query} \times \text{Clicks per Ad} \times \text{Cost Per Click} \]

• Can we compute the long-term Revenue \([\text{think years}]\)?
  • Need to estimate how our decisions would impact user activity and advertiser spend, over a long horizon.
    • E.g. how would showing more ads affect the user’s search activity?
  • Not trivial to model the dependencies accurately
    • Reinforcement Learning provides a framework for a path forward
History

• Assumption 1: satisfied users will engage more with the product
  • Short-term user satisfaction can be a proxy for long-term user activity

• **Assumption 2:** satisfied advertisers will increase spend
  • Short-term advertiser satisfaction can be a proxy for long-term advertiser spend

• Maximize all three short term metrics: Revenue, User Satisfaction and Advertiser Satisfaction

• Frequently formulated as:

\[
\begin{align*}
\text{maximize} & \quad (\text{Short Term}) \text{ Revenue} \\
\text{s. t.} & \quad (\text{Short Term}) \text{ User Satisfaction} \geq K_u \\
& \quad (\text{Short Term}) \text{ Advertiser Satisfaction} \geq K_a
\end{align*}
\]
Trenches

• How do we measure user satisfaction?
  • User agnostic relevance metrics
  • or implicit user feedback (e.g. click through rate, short dwelltime click rate)
  • or a combination?
How (not) to Pick your Metrics

Adding whitespace does not change the relevance of ads.

Pushing down all the other content typically improves click-through rates.

Is the page with only ads visible better for the user?
Trenches

• How do we measure user satisfaction?
  • User agnostic relevance metrics
  • or implicit user feedback (e.g. click through rate, short dwelltime click rate, space taken)
  • or a combination?

• How do we measure advertiser satisfaction?
  • Long Dwelltime Click Through Rate, Conversion Rate, Quality of Match?
One Size Does Not Always Fit All

• User query: “a z office supplies”

• Ad keyword: “office supplies”

• Click and Dwelltime metrics are reasonable
  • No advertiser concern on performance as they measure it

• However Advertiser complains about the brand mismatch
  • Not a concern shared by other advertisers given the ads are performing
Trenches

• How do we measure user satisfaction?
  • User agnostic relevance metrics
  • or implicit user feedback (e.g. click through rate, short dwelltime click rate, *space taken*)
  • or a combination?

• How do we measure advertiser satisfaction?
  • Long Dwelltime Click Through Rate, Conversion Rate, Quality of Match?

• Single metric rarely captures all information
  • No need to artificially limit ourselves to using one metric alone
Trenches

• How do we evaluate our choice of metrics?
  • Run long-term experiments to measure the relation between the proposed proxies and long-term metrics?
    • Challenges:
      • Treatment dilution due to limitations in identifying users
      • Geo-based experiments can be tricky to analyze even with synthetic controls
        • Unexpected events can impact only one region
        • Advertisers target locations, may be tricky to separate advertiser and user response
    • Use user/advertiser complaints to verify your metric choices?
How to Allocate Ads

• Rank and allocate ads to optimize the objective:

\[
\begin{align*}
\text{maximize} & \quad \text{(Short Term) Revenue} \\
\text{s.t.} & \quad \text{(Short Term) User Satisfaction} \geq K_u \\
& \quad \text{(Short Term) Advertiser Satisfaction} \geq K_a
\end{align*}
\]

• Can be solved via the Lagrangian Relaxation:

\[
\begin{align*}
\text{maximize} & \quad \text{Revenue} + \lambda_u \text{User Satisfaction} + \lambda_a \text{Advertiser Satisfaction}
\end{align*}
\]

• Price is determined only after allocation. Replace Revenue \(p(\text{click}) \times \text{price}\) with Welfare \(p(\text{click}) \times \text{bid}\)

\[
\text{objective function} = \text{Welfare} + \lambda_u \text{User Satisfaction} + \lambda_a \text{Advertiser Satisfaction}
\]
How to Allocate Ads

A Per Slot Greedy Allocation Algorithm

\[ \text{objective function (rankscore, } rs) = \text{Welfare} + \lambda_u \text{User Satisfaction} + \lambda_a \text{Advertiser Satisfaction} \]

Generalized Second Price

- Need probability of click, user satisfaction and advertiser satisfaction for that slot. E.g. \( p(\text{click}|\text{slot} = i) \)

Pricing

smallest bid \( b' \) such that \( rs_1(b') \geq rs_2 \)
How to Allocate Ads

A Per Slot Greedy Allocation Algorithm

objective function \((\text{rankscore, rs}) = \text{Welfare} + \lambda_u \text{User Satisfaction} + \lambda_a \text{Advertiser Satisfaction}\)

Generalized Second Price

- \(rs_1\)
- \(rs_2\)
- \(rs_3\)

Need probability of click, user satisfaction and advertiser satisfaction for that slot. E.g. \(p(\text{click}|\text{slot} = i)\)

What if slot size is variable?

- \(rs_1\)
- \(rs_2\)
- \(rs_3\)

Condition on size too?

\(p(\text{click}|\text{slot} = i, \text{size} = x)\)

or

Pricing

smallest bid \(b'\) such that \(rs_1(b') \geq rs_2\)
How to Allocate Ads

A Per Slot Greedy Allocation Algorithm

*objective function* \((rankscore, rs) = Welfare + \lambda_u User Satisfaction + \lambda_a Advertiser Satisfaction\)

Generalized Second Price

- \(rs_1\)
- \(rs_2\)
- \(rs_3\)

Need probability of click, user satisfaction and advertiser satisfaction for that slot. E.g. \(p\text{(click|slot = i)}\)

What if slot size is variable?

- \(rs_1\)
- \(rs_2\)
- \(rs_3\)

Use a coalition of ads to compete with larger ads

Pricing

smallest bid \(b'\) such that \(rs_1(b') \geq rs_2\)
Back to the Objective Function

• Need to compute the $\lambda'$s

\[
\text{Welfare} + \lambda_u \text{User Satisfaction} + \lambda_a \text{Advertiser Satisfaction}
\]

• $\lambda_u$ and $\lambda_a$ can be interpreted as shadow prices:
  • $\lambda_u$ is the cost of degrading user satisfaction by one unit
  • $\lambda_a$ is the cost of degrading advertiser satisfaction by one unit

• Estimate using long-term experiments
  • Requires high accuracy. Small differences in the estimate may result in large differences in the outcome.

• Tune $\lambda'$s to meet business constraints and maximize the objective
How to Tune $\lambda$’s

- If we could estimate the outcome of setting $\lambda$’s to any value, we could find the values that maximize the objective

<table>
<thead>
<tr>
<th>$\lambda_u$</th>
<th>$\lambda_a$</th>
<th>Revenue</th>
<th>Long Dwelltime Click Yield</th>
<th>Conversion Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>120</td>
<td>0.080</td>
<td>0.010</td>
</tr>
<tr>
<td>1</td>
<td>10</td>
<td>118</td>
<td>0.080</td>
<td>0.020</td>
</tr>
<tr>
<td>1</td>
<td>20</td>
<td>116</td>
<td>0.090</td>
<td>0.030</td>
</tr>
<tr>
<td>...</td>
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<td>...</td>
<td>...</td>
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<td>100</td>
<td>50</td>
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<td>0.120</td>
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</tr>
<tr>
<td>100</td>
<td>100</td>
<td>105</td>
<td>0.130</td>
<td>0.027</td>
</tr>
</tbody>
</table>

Maximum Revenue
s.t.
Long Dwelltime Click Yield > 0.11
Conversion Rate > 0.022
How to Tune $\lambda'$s

• If we could estimate the outcome of setting $\lambda'$s to any value, we could find the values that maximize the objective.

• How to estimate the outcome of different $\lambda'$s?

Output of $\lambda_u, \lambda_a$ values that were used to serve the request online

Output of new $\lambda_u, \lambda_a$ values that were not observed online

User Click

How would the user respond?
How to Tune $\lambda$’s

• If we could estimate the outcome of setting $\lambda$’s to any value, we could find the values that maximize the objective.

• How to estimate the outcome of different $\lambda$’s?
  
  • Simulate the output of the system
    • Requires the ability to replay the end-to-end stack offline
    • Comprehensive logging is critical for high fidelity simulations

  • Simulate the user response
    • Requires estimating counterfactual probabilities
    • User model needs to be accurate for rarely seen ad slates as well
Counterfactual Click Modeling

• Goal: Estimate the $p(\text{click})$ for counterfactual allocations

• Model Inputs:
  • Query logs with click/no-click information
  • Post-allocation information
    • Ad position, ad size, other ads, page layout
    • Not available for the online models

• Model Output:
  $p(\text{click}|\text{query, user, ad, do(allocation)})$

• Need to handle biases that exist in observational data
  • E.g. Utilize Exploration and Propensity Scoring
Alternative to Simulation

• Disadvantages of simulation:
  • Requires replaying the end-to-end stack, can take time
  • Simulating the user response accurately may be challenging

• Idea: Explore different values of $\lambda$'s at run time
  • For some portion of real traffic, sample $\lambda$ values from a distribution
  • Use importance sampling to compute estimated metrics

\[
E_p[f(x)] = \int f(x) \frac{p(x)}{q(x)} q(x) dx = E_q \left[ f(x) \frac{p(x)}{q(x)} \right]
\]

• Disadvantages:
  • Randomization has short-term cost (can be reduced by joint sampling)
  • Confidence intervals widen as we increase the variance in exploration.
Very Brief Intro to Search Advertising

Marketplace Objective

Marketplace Optimization

Understanding the Marketplace
Explaining KPI Movements

What caused the KPI to diverge from the forecast?

- Did supply (user/query) change?
  - Unexpected news events can cause major changes in query distributions.

- Did demand (advertisers) change?
  - Advertisers unseasonably increasing or decreasing their budget can result in unexpected KPI movements.

- Did the system change?
  - Did we introduce a bug?

- Some factors like economy might cause both the supply and the demand to change.
Supply As A Case Study

- Can we quantify how supply changes impact KPIs?
  - E.g. what’s the contribution of supply differences in the analysis period vs the reference period on KPIs?
- Idea: Build a synthetic control for the reference period using only supply features

\[
\begin{align*}
KPI_{predicted} &= \sum_{q \in \text{Queries}} M_{KPI}(F(q)) \\
KPI_{Predicted} &\text{: Estimate of KPI on the supply observed in analysis period with the fixed system and demand from reference period.} \\
\Delta KPI_{Predicted} &= (KPI_{Predicted} - KPI_{Ref})/KPI_{Ref} \\
\Delta KPI_{Predicted} &\text{: Estimate for KPI change between reference and analysis period that is attributed to supply change.}
\end{align*}
\]
Measuring Advertiser Response

• Typical questions about advertiser response:
  • If we were to improve {Conversion Rate, ROI} would the advertisers increase spend?
  • Would the increase (if any) be sufficient to overcome the first order revenue drop?

• Challenges:
  • Number of active advertisers is small, and spend per advertiser is very skewed
  • Not all advertisers have the same objective
  • Advertisers may not respond, or even if they do response times might be variable and long (quarters instead of within session)
Advertiser Experiments

• Approach:
  • Experiment on advertisers who are likely to respond
    • Assume a simple a-priori model for advertiser response (e.g. the more the prices change the likelier the advertisers respond)
    • Estimate first order effect of the treatment per advertiser using simulations
    • Pick the set of advertisers with maximum predictive power
  • Randomly assign the selected advertisers to treatment and control
    • Pairwise stratified randomization works better than IID
  • Find the optimal policy (i.e. which advertisers should get the treatment)
    • Build a better model of advertiser response (using the experiment data)
    • Use the new model to pick the advertisers that would react positively to the experiment
Optimal Policy Identification

• Inputs:
  • \( \{x_j\}_{j \in J} \): Advertiser features, measured pre-experiment
  • \( \{t_j\}_{j \in J} \): Treatment indicators
  • \( \{y_{(t_j)}\}_{j \in J} \): Per sample reward, e.g. post-treatment spend per advertiser

• Task:
  • Find policy \( \pi: X \rightarrow \{0,1\} \) which maximizes \( R(\pi) = \frac{1}{n} \sum_{j \in J} y_{(\pi(x_j))} \)
  • I.e. characterise advertisers for which \( y_{(1)} > y_{(0)} \)

• Model: Honest Random Forests
  • Use control and treatment advertisers to build a forest per advertiser using leave-advertiser-out
  • Effect on sample \( j \) estimated as the difference between treatment and control samples in the same node (after excluding \( j \))

Effect on spend: -5.7% (-11.1% - -0.4%)

Effect on spend: 13.5% (8.1% - 18.8%)
3.9% (2.3% - 5.5%) increased spend
Looking Ahead

• Reinforcement Learning to directly optimize for the Long-Term
  • Already interesting work happening but under many assumptions

• Advertising Ecosystem is evolving
  • Advertisers are moving to AI/ML for everything: UX design, content generation, budget management and more
  • Modeling causal dependencies will be critical to react optimally

• User Interface is evolving
  • Definition of clicks or engagement needs to adapt