Query Clustering based on Bid Landscape for Sponsored Search Auction Optimization

Ye Chen, Weiguo Liu, Jeonghee Yi, Anton Schwaighofer, Tak Yan
Summary

• Problem:
  – Cluster queries into smaller yet more effective micro-markets, defined by cluster-based auction parameters.

• Methodology:
  – Query is represented as a two-component Gaussian mixture (mainline and sidebar) of values.
  – A novel clustering algorithm that clusters GMMs.

• Results: deployed to Bing Search Ads!
  – Offline 22% CTR gain over $k$-means.
  – Online 5% improvement in revenue.
Introduction: Sponsored Search

• Sponsor search:
  – In search advertising, advertisers bid on keywords for advertising opportunities alongside algorithmic search results, through a generalized second-price auction (GSP).
Introduction: Example and Notations

**Mainline**

- **query**
  
  - **WEB**
  - **IMAGES**
  - **VIDEOS**
  - **MAPS**
  - **NEWS**
  - **MORE**

  - **chicago souvenirs**

  - **ALSO TRY:** Chicago Souvenirs Online · Chicago Souvenirs Ideas · Chicago Souvenir ...

  - **21,400,000 RESULTS**

  - **Any time**

**Sidebar**

- **Chicago Souvenirs - 1000+ Chicago Illinois Designs.**
  
  - www.cafepress.com
  - Shop Now!
  - Chicago · Texas · New Jersey · New Mexico

- **Chicago Gifts: Chicago Souvenirs, Chicago T-shirts, Chicago ...**
  
  - www.greatchicagogifts.com
  - Great Chicago Gifts - Chicago souvenirs, t-shirts, Bears, Cubs, Bulls, snow globes and other gifts.

- **Welcome to Chicago Souvenirs**
  
  - chicasouvenirs.net
  - Chicago Souvenirs is the home for high quality and unique, laser etched and sculpted landmarks of the Windy City.

- **Blackhawks NHL Souvenirs**
  
  - Blackhawks.Fanatics.com
  - Buy Chicago Blackhawks Souvenirs!
  - The Chicago Blackhawks Fan Shop.

  - fanatics.com is rated ★★★★★ on PriceGrabber (140 reviews)

- **Chicago Experience Gifts**
  
  - www.Cloud9Living.com/Chicago
  - Shop for Unique Chicago Experiences Racing, Adventure, Relaxation, More

- **Chicago Cubs Souvenirs**
  
  - www.WrigleyvilleSports.com
  - Find Chicago Cubs Souvenirs at the Wrigleyville Sports Store!
Introduction: GSP Auction

- Ranking
  - Given a keyword-ad pair, the estimated position-unbiased CTR $\rho$, the CPC bid $b$, the rank score is defined as $s = b\rho^\alpha$, where $\alpha$ is called click investment power.

- Pricing
  - In a GSP, if ad $i$ is clicked, the payment or price per click depends on the next highest bidder $i + 1$, i.e., $c_i = b_{i+1}\rho_{i+1}/\rho_i^\alpha$.

- Allocation
  - Ads are allocated, in the descending order of their rank scores, from top to bottom positions.
  - Ad positions are primarily from two page sections: mainline (ML) and sidebar (SB).
  - There are two reserve prices in the unit of rank score controlling the sectional allocation: mainline reserve $R$ and sidebar reserve $r$. 
Introduction: Auction Optimization

• For auction optimization, one maximizes revenue $y$ or clicks $w$, w.r.t. auction parameters, e.g., $R$ and $\alpha$, constrained on the number of ads shown.

$$\max_x \sum_{p,j} w_{pj} x_{pj}$$

s.t. $$\sum_{p,j} y_{pj} x_{pj} \geq g_1;$$

$$\sum_{p,j} (a_{pj} v_p x_{pj}) / \sum_p v_p \leq g_2;$$

$$\sum_j x_{pj} = 1, \forall p;$$

$$x_{pj} \in \{0, 1\}, \forall p, j.$$
Motivation

• For auction optimization, cluster queries for
  – dimensionality reduction (of the LP),
  – a parsimonious model, and hence
  – generalizes well.

• For auction design, queries are
  interchangeable commodities.

• For one player (Pin & Key, 2011)

\[
E[U(v, b)] = \sum_{k=0}^{n} \binom{n}{k} s_k \int_r^v (1 - F(b))^k F(\min(t, b))^{n-k} dt,
\]

where \( r \) is reserve and \( F(b) \) is the CDF of CTR-weighted bid (rank score).
Clustering Gaussian Densities
(a reality check)

• KL for Gaussian (closed-form!)

\[ D_{KL}(p||q) = \frac{1}{2} \left( \frac{\sigma_p^2}{\sigma_q^2} + \frac{(\mu_p - \mu_q)^2}{\sigma_q^2} - \log \left( \frac{\sigma_p^2}{\sigma_q^2} \right) - 1 \right) \]

• To derive a \( k \)-means variant

\[
\min_{\mu_p, \sigma_p^2, \forall p} \ L = \sum_p \sum_{q \in p} D_{KL}(p||q)
\]

\(-\ L\ is\ convex\ function,\ there\ is\ unique\ global\ minimum,\ solved\ using\ coordinate\ descent.\)
Clustering Results (Gaussian)
Model Assumption: Gaussian?
A Better Assumption: GMM

• Hypothesis:
  – There are two reserves, bidders know and react to one at a time, RSR or MLR.

• Clustering GMM densities
  – More realistic.
  – May expose opportunities to LP, two peaks per query.
  – But, much harder to solve.
Hypothesis Test (”lottery results”)
Hypothesis Test ("online shopping")
Clustering GMM Densities

• KL no longer has closed form.

• Solution: variational EM
  – Derive an easy-to-optimize upper bound,
  – Use EM to minimize the upper bound.

• Each query is represented as a GMM
  – A fast EM to learn GMM’s for millions queries.
  – Can be trivially parallelized.
Learning GMM (per-query)

- Gaussian mixture model (GMM):
  \[ p(x|\theta) = \sum_{z=1}^{Z} p(z) \left( \frac{1}{\sigma_z \sqrt{2\pi}} e^{-\frac{(x-\mu_z)^2}{2\sigma_z^2}} \right) \]

- Given the two-reserve bidding mechanism.
  - The hidden variable or the membership of Gaussian component for each bid are known (think of the generative process).
  - The mixture weights of GMM are known.

- Good news! No iterative EM needed.
Learning GMM (empirical evidence)
Learning GMM (more evidence)
Deriving the EM Algorithm (GMM)

• Gaussian mixtures for centroids and queries:
  \[ p(x) = \sum_z \pi_z p_z(x), \sum_z \pi_z = 1, p_z(x) \sim N(\mu_{pz}, \sigma_{pz}^2); \]
  \[ q(x) = \sum_z \omega_z q_z(x), \sum_z \omega_z = 1, q_z(x) \sim N(\mu_{qz}, \sigma_{qz}^2); \]

• KL divergence has no closed form, but has an upper bound:
  \[ D_{KL}(p \| q) \leq D_{KL}(\pi \| \omega) + \sum_z \pi_z D_{KL}(p_z \| q_z) \]

• To derive an variational EM:
  \[ \min_{\pi_p, \mu_p, \sigma_p^2, \forall p} L = \sum_p \sum_{q \in p} \left( D_{KL}(\pi_p \| \omega_q) + \sum_z \pi_{pz} D_{KL}(p_z \| q_z) \right) \]
The EM Algorithm (GMM)

• E-step:

\[ \pi_{pz} \propto \exp\left(\sum_{q \in p} (\log \omega_{qz} - D_{KL}(p_z || q_z) - 1) / \sum_{q \in p} 1\right), \forall p, z; \]

• M-step:

\[ \mu_{pz} = \left(\sum_{q \in p} \frac{1}{\sigma_{qz}^2} \mu_{qz}\right) / \sum_{q \in p} \frac{1}{\sigma_{qz}^2}, \forall p, z; \]

\[ \sigma_{pz}^2 = \sum_{q \in p} 1 / \sum_{q \in p} \frac{1}{\sigma_{qz}^2}, \forall p, z. \]
Clustering Results (GMM)
## Results

**Table 1: Auction optimization results with different clustering methods**

<table>
<thead>
<tr>
<th>Model</th>
<th>Lift in clicks@5% MLIY</th>
</tr>
</thead>
<tbody>
<tr>
<td>$k$-GMM</td>
<td>13.01%</td>
</tr>
<tr>
<td>$k$-Gauss</td>
<td>8.78%</td>
</tr>
<tr>
<td>$k$-means</td>
<td>10.66%</td>
</tr>
<tr>
<td>$k$-bins</td>
<td>2.46%</td>
</tr>
</tbody>
</table>

**Table 2: Online A/B testing results**

<table>
<thead>
<tr>
<th>Metric</th>
<th>Lift of $k$-GMM over $k$-bins</th>
</tr>
</thead>
<tbody>
<tr>
<td>Revenue</td>
<td>5.60%</td>
</tr>
<tr>
<td>Clicks</td>
<td>5.79%</td>
</tr>
<tr>
<td>CPC</td>
<td>$-0.27%$</td>
</tr>
<tr>
<td>MLIY</td>
<td>0.80%</td>
</tr>
</tbody>
</table>
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