Multi-Armed Bandits: Applications to Online Advertising

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*Based on joint work with Denis Saure



source: Interactive Advertisement Bureau Internet Advertisement Revenue Report (by PricewaterhouseCoopers)

Online Advertisement: Industry Overview

% of 2009 Second-Quarter Revenues



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Profit maximization

- ad pool
 - user information
- ad/user performance

pricing model...



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anonymity on the Internet



"On the Internet, nobody knows you're a dog."

July 1993, The New Yorker

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- common practice
 - internet cookies
 - list of categories of interest
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- user information
 - behavioral, geographical, demographical data ...



July 1993, The New Yorker

Advent of the Internet has transformed consumer experience of advertisements and media...

dynamic/customized advertisement display

- one-to-one interaction with users...
- contracts (CPC) are increasingly performance-based
- customization to individual users exploiting side information
- dynamic decision making to balance learning and profits

Focus: Publisher's display decision in dynamic environment

- I. Customization in online advertisement
 - publisher's problem definition
 - need for dynamic learning of ad performance
- II. Stylized model for display-based online advertisement
 - limit of achievable performance
 - policy construction and guarantees
- III. Insights and takeaway messages

- 1. direct revenue: cost per click (cpc)
- 2. click probability:

user profile + ad mix \rightarrow click probability

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additional considerations: display capacity...

maximize expected revenue from interaction with users

$$\max_{\text{ad mix}} \left\{ \sum_{\text{ad in mix}} cpc(ad) \cdot f(\text{ad, user profile, ad mix}, \beta) \right\}$$

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estimation accuracy vs profit maximization

Learning approach to interactive marketing

- Gooley and Lattin (2000)
 - message customization
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 - solve for each segment separately

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Multi Armed Bandit (MAB) Literature

- Slivkins (2009), Lu et al (2009)
 - side information: MAB in metric spaces

II. Stylized model for display-based online advertisement

III. Insights and takeaway messages

Stylized model for display-based online advertisement

- finite users (T) arrive sequentially
- finite pool of ads (\mathcal{N}) with given profit margins (w_i)
- ad-mix $(s \in \mathcal{S})$...








ad-slots are interchangeable, no budget constraints

- objective: maximize revenue by suitable ad display policy
- user clicks on at most one ad ...
- users are utility maximizers

$U(user profile, ad) + ad-mix \rightarrow click decision$

Logit model with user-specific mean utility



Logit model with user-specific mean utility

utility of ad i $U_i = \beta_i \cdot x + \epsilon_i$ ad factors $\int \int user profile (unobserved...)$

Logit model with user-specific mean utility



Logit model with user-specific mean utility

utility of ad i , for a i , we have $U_i = \beta_i \cdot x + \epsilon_i$ ad factors \mathcal{J} , user profile

user profile x is d-dimensional vector [observed]
ad factors β_i is d-dimensional vector [to be estimated]

 $\begin{array}{c} x \\ \left(\begin{array}{c} 0.4 \\ 0.9 \\ 35 \\ 1 \end{array} \right) & \begin{array}{c} \text{sport affinity} \\ \text{prob. male} \\ \text{exp. age} \\ \text{dummy} \end{array} \right.$

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- ad factors β_i is *d*-dimensional vector [to be estimated]

our approach: Logistic regression (profiles) $f_i(s, x, \beta) = \frac{\exp \{\beta_i \cdot x\}}{1 + \sum_{j \in s} \exp \{\beta_j \cdot x\}}$ ad mix • expected revenue from displaying ad mix s to user profile x:

$$r(s, x, \beta) = \sum_{i \in s} w_i \cdot \left(\frac{\exp\left\{\beta_i \cdot x\right\}}{1 + \sum_{j \in s} \exp\left\{\beta_j \cdot x\right\}} \right)$$

ad profit margin $\int \int \int \log t \operatorname{click} \operatorname{prob}$.

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profile X_t drawn from a finite set \mathcal{X} according to distribution G

- finite number of user segments...
- G reflects histogram of population

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ad *i* factors β_i initially unknown for all ads

Suppose publisher knows β a priori

formulate and solve an optimization problem

$$J^{*}(T|\beta) := \sup_{s(\cdot)} \mathbb{E} \left[\sum_{t=1}^{T} r(s(t), X_{t}, \beta) \right]$$
known parameters f (expected revenue expected revenue)

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Oracle policy: offer $s^*(X_t, \beta)$ to user t

$$s^*(x,\beta) \in \operatorname{argmax} \left\{ r(s,x,\beta) : s \in \mathcal{S} \right\}$$
expected revenue \int

- ad mix decision for feasible policies based on history of past interaction and current user profile
- performance of ad mix policy π :

revenue loss relative to oracle policy

$$\mathcal{R}(\pi, T) := J^*(T|\boldsymbol{\beta}) - \mathbb{E}\left[\sum_{t=1}^T r(s^{\pi}(t), X_t, \boldsymbol{\beta})\right]$$
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expected revenue

Main Q: how small can we make this revenue loss? structure of an optimal policy? Theorem [Saure and Z (2012)] Any *good* policy π must incur revenue loss

$$\mathcal{R}(\pi, T) \ge \sum_{i \in \mathcal{N}} K_i \log T$$





























i is "Interesting"





Theorem [Saure and Z (2012)] Any good policy π must incur revenue loss $\mathcal{R}(\pi, T) \ge \sum_{i \in \mathcal{N}} K_i \log T$



Theorem [Saure and Z (2012)]
$$K_i \sim rank(\mathcal{X}_i) - rank(O_i)$$

Any good policy π must incur revenue loss
 $\mathcal{R}(\pi, T) \geq \sum_{i \in \mathcal{N}} K_i \log T$

• Fix ad
$$i \in \mathcal{N}$$
 :



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 - need to assess performance only on some profiles (\mathcal{X}_i)
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- use information that does not contribute to revenue loss
 - use profiles for which an ad is optimal
- information contributing to revenue loss must be capped
 - performed on order $\log T$ users...

Intuition: force right frequency of ad *i* experimentation on suitable estimation-set $(E_i \in \mathcal{X})$
Construction:

 \blacksquare estimate model parameter for ad i using only information on profiles in E_i

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for user t force order- $(\log t)$ exploration on E_i

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 - otherwise, EXPLOIT approximate oracle solution $s^*(X_t, \hat{\beta})$

Theorem [Saure and Z (2012)]

For suitable chosen tuning parameter κ ,

$$\mathcal{R}(\pi^*, T) \leq \overline{K} \sum_{i \in \mathcal{N}} (rank(\mathcal{X}_i) - rank(O_i)) \log T + K,$$

where \overline{K} , K > 0 are finite constants

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Key results: for each profile

- uninteresting ads displayed to finite (independent of T) number of users
- ads in the optimal mix displayed outside that mix finitely many times

discrete nature of optimization problem



discrete nature of optimization problem

min optimality gap across profiles + $\begin{array}{c} \text{continuity of expected} \\ \text{revenue w.r.t } \beta \end{array}$ + $\begin{array}{c} \text{threshold on} \\ \text{estimation error} \end{array}$

discrete nature of optimization problem

■ parameter estimation with
$$O(\log t)$$
 tests
threshold error $finite{} finite{} fin$

balance exploration and exploitation error $(\kappa > c^{-1})$

5

$$\mathcal{R}(\pi^*, T) \le O\left(\kappa \log T + \sum_{t=1}^T \frac{1}{t^{c\kappa}}\right)$$

4 products, 3 two-dimensional profiles
feasible set S := {s ⊂ N : |s| ≤ 2}, κ = 40

$$\beta = \begin{pmatrix} -1.30 & 2.00 & 2.75 & 3.00 \\ 3.00 & 2.00 & 2.75 & -1.30 \end{pmatrix} \qquad \mathcal{X} = \begin{pmatrix} 0.1 & 0.5 & 0.9 \\ 0.9 & 0.5 & 0.1 \end{pmatrix}$$

profile	x_1	x_2	x_3
opt. mix	$\{1, 2\}$	$\{2, 3\}$	$\{2,4\}$
opt. revenue	0.587	0.546	0.578
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anon. mix	$\{1, 2\}$	$\{1, 2\}$	$\{1, 2\}$
anon. revenue	0.587	0.543	0.525



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III. Insights and takeaway messages

- value of customization
 - speed of learning
 - misspecification risk



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Final Thoughts

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 - minimal exploration needed
 - significant gains from customizing policies to application
- analysis tools / machinery
 - information theoretic inequalities [lower bounds]
 - martingale methods, large deviation bounds [analysis of policies]
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- related recent applications of MAB
 - dynamic content referral [Besbes, Gur and Z (2012a)]
 - temperature tracking and restless bandits [Besbes and Z (2012b)]
 - personalization (Pandora, various recommendation systems etc)
 - dynamic design of experiments / screening
 - cognitive radio [Lai et al (2011)]
 - mechanism design formulation [Kakade et al (2012)]