What Makes Them Click: Empirical Analysis of Consumer Demand for Search Advertising

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Introduction:

- Objective: Understand the behavior or users in sponsored search advertising
- Existing Restrictive Models:
  - Edelman, Ostrovsky, and Schwarz (2007) (EOS) assumes CTR for a given ad in a given position is a product of an ad and position-specific effect, and it does not depend on other displayed ads.
  - Cascade Model: users consider the ads sequentially from top to bottom, deciding whether to click on the current ad and whether to continue clicking
- The paper presents a less restrictive model

Introduction: Why is the paper interesting?

- Test EOS separability assumption
- Measure elasticity of substitution for each query
- Measure how far we are from the welfare-optimal allocation
- Dynamic programming model to measure the impact of NFP lines on user behavior

Introduction:

- Empirical analysis contradicts existing theoretical models
- Against EOS: CTR on a given ad in a given position **DEPENDS** on other ads shown in other positions
- Against "Casacade Model":
  - 46% of users who click on ads do not click sequentially
  - CTR on a given ad and position depends on which ads are shown below it
  - CTR on a given ad and position depends on the order of shown ads in higher positions

Introduction: Model

- User chooses clicks sequentially under uncertainty about the quality of ads (prior)
- Ad-quality signals coming from ad descriptions, ratings,... are used to update the prior of quality ads (posterior - learning model)
- Model parametrizes the degree of substitutability (satiation) among ads
- Model endogenizes the drop in the CTR associated with lower positions:
  - scrolling costs (fixed effects)
  - users' expectations about the quality of ads at different positions
    - priors about the quality of ads on each position - user's specific
    - Users update priors with signals about the quality of an ad contained in an ad description

Introduction: Results

- The estimate of the mean substitutability parameter is statistically different from 0
- There exists heterogeneity across users and uncertainty regarding ads quality
- Counterfactuals
  - If substitutability were absent, clicks would have been 51% higher
  - If user's uncertainty regarding ads quality were resolved prior to clicking, consumer welfare would be 1% higher and CTR would increase 0.4%
  - Generate impressions that maximize the total CTR or the expected user welfare
    - In the EOS model, CTR is maximized by assortative matching of higher-quality ads to better positions $-->$ Improves welfare by 11% and CTR by 8%
    - Welfare-optimal $-->$ 33% welfare improvement and 23% CTR improvement

The data and industry

- Microsoft's Live Search Advertising Engine (2008)
- Search strings (exact match): "games", "weather", "white pages", "sex"

The data and industry: Existence of Externalities

- EOS assumption does not hold

Competitor	CTR Domain 1
Domain 2	0.0763 (0.0060)
Domain 3	0.1842 (0.0138)
Domain 4	0.1078 (0.0240)

Competitor	CTR Domain 1
Domain 2	0.0189 (0.0020)
Domain 3	0.0535 (0.0038)
Domain 4	no observations

Figure: White Pages Weather

- Domain 1's CTR if located in position 2 as a function of domains in position 1
- Users being satiated after clicking on good advertisements (negative externalities: Domain 2 good ad - Domain 3 bad ad)

The data and industry: Existence of Externalities

	Domain 1 present as a competitor in lower positions?	CTR of position 1	Difference in CTRs of position 1	No. obs.	Average no. of ads in the impression
Domain 2	Yes	0.11	0.074^{***}	5,061	6.1
in position 1	No	0.18	(0.009)	2,112	7.1
Domain 3	Yes	0.16	0.067^{***}	1,560	7.1
in position 1	No	0.22	(0.013)	2,022	7.6
Domain 4	Yes	0.16	0.019	304	7.3
in position 1	No	0.17	(0.032)	253	7.3

The data and industry

	Search string and domain at position 1			
	games Domain 1	weather Domain 1	white pages Domain 1	sex Domain 1
Clicking on pos. 1	0.051	0.046	0.17	0.037
Not clicking on pos. 1	0.034	0.043	0.116	0.045
Difference	0.017*** (0.005)	0.003 (0.006)	0.054*** (0.009)	0.008 (0.006)

Figure: Proba of clicking on ads in positions 2-8 conditional on clicking and not clicking in position 1

- Positive correlation between clicks on different positions in a given impression
- EOS model predicts correlation equals zero
- Satiation will create negative correlation among clicks
- Paper models vertical heterogeneity of user valuations of ads (δ_i): users may have higher utilities for all ads

Model

- The user's value of clicking on an ad "a"

$$v_{ai} = v_a + \epsilon_{ai} + \delta_i$$

  where
  - v_a mean quality of the link a common to all users
  - ϵ_{ai} idiosyncratic shock to quality of the link a
  - δ_i user specific shock to value of any sponsored links (ad independent)
  - v_{ai} is unobserved before clicking, but user has a prior that is updated after reading ad description (ratings, sitelinks, ...)

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- "Constant Elasticity of Substitution" utility function: The user can click a subset C of ad slots and obtain a gross utility of

$$U_i(C) = \left(\sum_{n \in C} v_{a(n)i}^{1+R_i} \right)^{1/(1+R_i)} - \sum_{n \in C} f_n$$

  where
  - f_n is the cost of clicking on an ad in position n (e.g. scrolling effort)
  - R_i (Satiation Parameter) captures the substitutability of different ads to the user.
- **Unobserved parameters**

Model

$$v_{ai} = v_a + \epsilon_{ai} + \delta_i$$

$$U_i(C) = \left(\sum_{n \in C} v_{a(n)i}^{1+R_i}\right)^{1/(1+R_i)} - \sum_{n \in C} f_n$$

where

- Additively separable utility ($R_i = 0$): User's clicking decisions on different ads are independent, no externalities are present across data
- $R_i = 0$ and "No user random effects": Model nests Edelman, Ostrovsky, and Schwarz (2007) (EOS) model.

$$CTR = \underbrace{(e^{v_a})}_{\text{Ad Fixed Effect}} \times \underbrace{(e^{-f_n})}_{\text{Position Fixed Effect}}$$

- Perfect Substitutability ($R_i = \infty$): user derives utility from at most one ad (e.g. no benefit from a second weather forecast)
- **R_i, v_a and f_n unobserved for the researcher**

Model: Decision Problem

1. user searches for a keyword and forms priors about the quality of ads at each position
2. User observes the impression and reads descriptions of all ads in the impression
3. User either clicks on an ad in a chosen position or stops clicking
4. User observes the true quality v_a of a clicked ad $a(c)$
5. Go to (3)

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Dynamic Programming Problem

- Let $C \subset \{1, ...N\}$ the set of clicked positions (decision variable)
- Let S the state variable that captures the utility of C, $S = \sum_{n \in C} v_{a(n)i}^{1+R_i}$

$$V_i(C, S) = max\{S^{1/(1+R_i)} - \sum_{n \in C} f_n, \max_{q \in \{1,\ldots,N\} \setminus C} EV_i \left(C \cup q, S + v_{a(q)i}^{1+R_i} \right)\}$$

Expectation taken with respect to the posterior of $v_{a(q)i}$

Estimation: Identification

- We observe the CTR of same domains placed in different positions: position fixed effect identification
- We observe CTRs of different ads in the same position: identification of ad quality v_a

Results: Clicking Costs Estimates (f_n)

	Search string			
	games	weather	white pages	sex
Position 1	-1.66 (0.031)	-1.10 (0.028)	-1.94 (0.025)	-2.01 (0.053)
Position 2	-1.64 (0.023)	-1.71 (0.032)	-2.59 (0.024)	-2.20 (0.051)
Position 3	-2.07 (0.020)	-2.12 (0.030)	-3.25 (0.031)	-2.54 (0.065)
Position 4	-3.68 (0.075)	-3.84 (0.048)	-5.30 (0.091)	-3.18 (0.206)
Position 5	-3.98 (0.140)	-4.28 (0.104)	-5.52 (0.201)	-4.38 (0.611)

Table 4: Estimates of clicking cost in the baseline model.

- Utility of not clicking is normalized to 0
- EOS world $R_i = 0$: Exponentiating the cost differences, we obtain the ratios of CTRs on different positions.

$$\frac{CTR_{1,games}}{CTR_{5,games}} = \frac{(e^{v_a}) \times (e^{-f_{1,games}})}{(e^{v_a}) \times (e^{-f_{5,games}})} = \frac{e^{-1.66}}{e^{-3.98}} \approx 10$$

Results: Mean Qualities v_a Estimates for Each Keyword

	Search string			
	games	weather	white pages	sex
Domain 1	-2.04 (0.054)	-2.70 (0.040)	-0.35 (0.057)	-0.38 (0.038)
Domain 2	-2.06 (0.051)	-3.66 (0.021)	-1.08 (0.040)	-2.11 (0.046)
Domain 3	-1.27 (0.055)	-3.82 (0.046)	-1.26 (0.033)	-2.70 (0.051)
Domain 4	-2.21 (0.058)	-2.70 (0.040)	-0.80 (0.081)	-1.36 (0.097)
Domain 5	-2.83 (0.036)	-4.53 (0.034)	-2.71 (0.044)	-3.13 (0.073)

Table 6: Estimates of domain quality and probabilities of relevance.

- The higher the estimate v_a, the higher is the relevance of the ad for a particular query.
- The estimates matches the visual inspection of ads

Results: Satiation Parameter (R_i) and Preference Shocks

Satiation parameter		Preference shock
Mean (R)	Std. dev. (σ_R)	Std. dev. (σ_δ)
0.57 (0.026)	0.18 (0.028)	2.15 (0.027)

- $R \neq 0$: Substitution across ads. Edelman, Ostrovsky, and Schwarz (2007) (EOS) assumption does not hold. Click decision on different ads **ARE NOT INDEPENDENT**