

Computational Advertising

UW CSE454

Thanks To:



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Thanks To:



Dr. Andrei Broder



Dr. Evgeniy Gabrilovich



Dr. Vanja Josifovska



2012 Global Ad Spend

\$530 Billion

“Half the money I spend on advertising is wasted; the trouble is I don't know which half.”

-- John Wanamaker (attributed) [1838-1922]



US online advertising spending

(source: eMarketer.com, November 2010)

Year	Online	Online % of total media
2009	\$22.7B	13.9%
2010	\$25.8B	15.3%
2011	\$28.5B	16.7%
2012	\$32.6B	18.3%
2013	\$36.0B	19.8%
2014	\$40.5B	21.5%

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What changed in 100 years? measurability and reach





- No more coupon codes
- Flexible ad targeting + conversion tracking
- Experimentation rules!

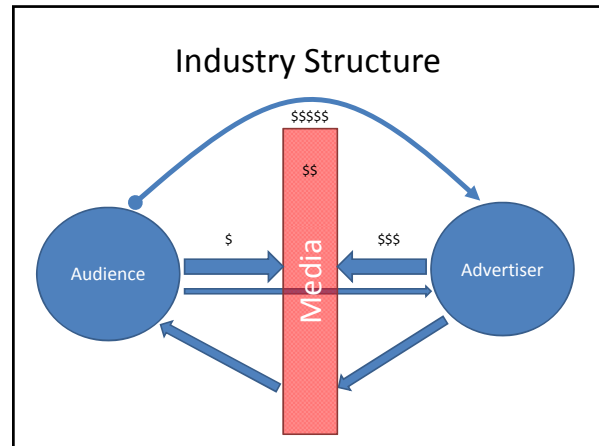
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Y! What is "Computational Advertising"?

A new scientific sub-discipline that provides the foundation for building online ad *retrieval* platforms
 Find the optimal ad for a given user in a specific context

Information retrieval, Microeconomics, Statistical modeling & machine learning, Large-scale text analysis, Computational Advertising

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The Great Divide

Brand

Direct Response

- Emotions
- Transactions
- Indirect benefits
- Gross profits
- Banners, TV, stadiums
- Search, coupons, 1-800, radio, mail

The New York Times

msn

Y! Anatomy of an ad

Tutorial at SIGIR 2010
 Information Retrieval Challenges in Computational Advertising
research.yahoo.com/tutorials/sigir

← Title
 ← Creative
 ← Display URL
 ← Landing URL

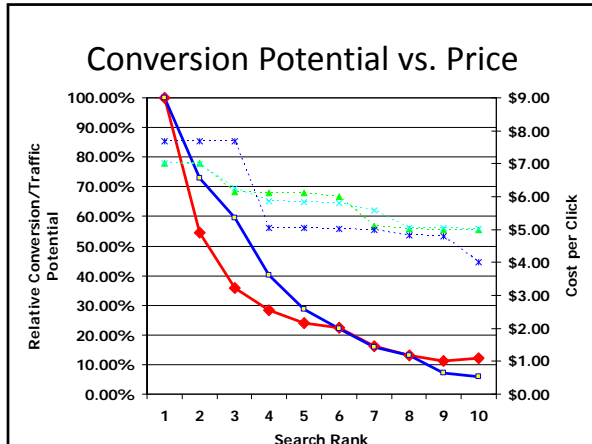
http://research.yahoo.com/sigir10_compadv

Bid phrases: {SIGIR 2010, computational advertising, Evgeniy Gabrilovich, ...}
Bid: \$0.10

Landing page

SIGIR 2010 Tutorial
 Information Retrieval Challenges in Computational Advertising

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Real World Example

Real World Example

- RefSrc on URL
- Drop cookie
- Pass RefSrc upon conversion
- Match with ad spend
- Calculate CPA

Stage	Count
Impressions	4.4M
Clicks	2078
RegClick	69
Registrations	29

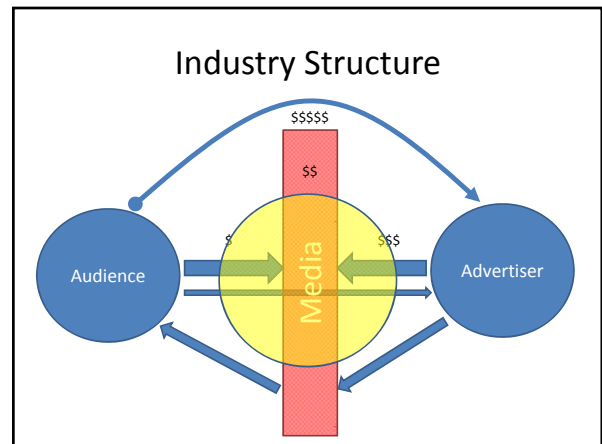
CTR=0.0469%
 CPC=\$0.65
 eCPM=\$0.31
 CPreClick=\$19.69
 CPReg=\$46.76

Bid Management



Term	Clicks	CPC	Pos	CR	Leads	CPA	AvgPrice	Revenue	Spend	GM
Nursing School	5,000	\$1.00	1	5%	250	\$20.00	\$7.50	\$1,875	\$5,000	-63%
Nursing Schools	5,000	\$2.00	3	20%	1,000	\$10.00	\$30.00	\$30,000	\$10,000	200%
Total	10,000	\$1.50	2	12.5%	1,250	\$12.00	\$25.50	\$31,875	\$15,000	113%

Bid Management

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Nursing Schools	5,000	\$2.00	3	20%	1,000	\$10.00	\$30.00	\$30,000	\$10,000	200%
Total	10,000	\$1.50	2	12.5%	1,250	\$12.00	\$25.50	\$31,875	\$15,000	113%
Optimized	8,000	\$2.43	1	22%	1,760	\$11.05	\$30.00	\$52,800	\$19,440	172%

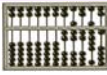


Y! Beyond keyword matching

- Matching ads is relatively simple for explicitly bid keywords
 - Exact match
- Covering only those is not enough – advertisers need volume !
 - Broad match (or advanced match)
- Suppose your ad is "Low prices on Seattle hotels"
- Naïve approach: bid on all queries that contain the word "Seattle"
- Problems
 - 'Seattle's Best Coffee Chicago' 
 - 'Alaska cruises start point' 
- Ideally: bid on queries related to Seattle as a travel destination
 - The system should facilitate concept-level ad matching


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Y! An ultra-brief history of approaches to Web advertising

 **The old school: database-style ad matching**

- Exact match (query = bid phrase)
- Broad match via query rewrites
- Content match: reduce the problem to exact match (extract bid phrases from pages)

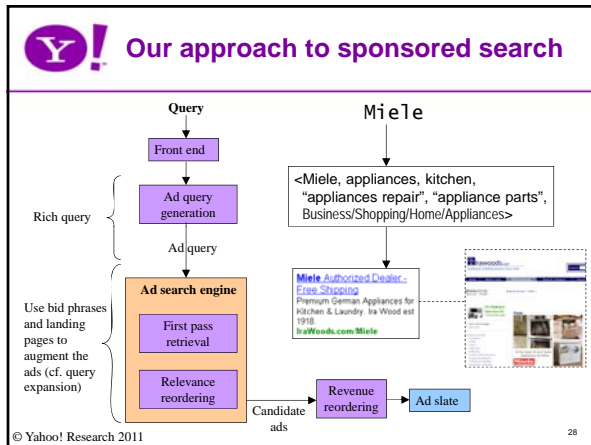
→ Essentially record lookup

 **The new approach: knowledge-based ad retrieval**

- Elaborate query expansion
- Ad indexing and scoring using all the info available
 - Bid phrases, title, creative, URL, landing page, etc.
 - Akin to document indexing in IR
- 2nd pass relevance reordering (re-ranking)
 - Using features not available to the 1st pass model (e.g., set-level features, click history)

Learning to rank

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Y! Ads vs. Web pages

Ads

- Very short
- Optimized for presentation, not for indexing
 - creatives have low SNR
- Legacy bid-phrase-centric definition dictated by the exact match scenario
 - very limiting today
- Complex structure

Web pages

- Not overly short (at least more often than not ☺)
- Simple structure: sections/subsections and (optional) HTML markup

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Y! Ad retrieval vs. Web search

Ad retrieval

- Smaller corpus
- Much broader notion of relevance (relatedness)
- Different (but rich) information is available
 - bids, budgets, landing pages, conversion rates, elaborate nested structure of campaigns, ...

Web search

- Huge corpus
- Mainly aiming at pages that subsume all the query terms
 - Strict notion of relevance
- Anchor text and other valuable signals are available

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RPV Optimization: Problems with Sort by CPC


Example Term: "mba"		
Ad Title	Univ. of Phx: Online MBA	Univ. of Washington MBA
Ad Body	100% online university. Fully accredited.	Foster School of business. Top 30 ranked.
CPC	\$10.00	\$0.50

RPV Optimization: Problems with Sort by CPC

Example Term: "mba"		
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Ad Body	100% online university. Fully accredited.	Foster School of business. Top 30 ranked.
CPC	\$10.00	\$0.50
CTR	0.01%	4%
Position	#1	#10
RPV	\$0.0010	\$0.0200

Should we show ads at all Learning when (not) to advertise (CIKM 2008, Broder et al.)

- **One does not have to show ads!**
 - Roughly **half** of the queries have no ads
- Repeatedly showing non-relevant ads can have detrimental long-term effects
 - Modeling actual (short- and long-term) costs of showing non-relevant ads is very difficult
- **Goal: predict when (not) to show ads**



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Should we show ads at all Two approaches: Thresholding vs. Machine Learning

- **Global threshold** on relevance scores of **individual ads**
 - Only show ads with scores above the threshold
- **Problem:** Scores are not necessarily comparable across queries!
- **Learn** a binary prediction model for **sets of ads**
- Features defined over **sets of ads** rather than individual ads
 - **Relevance** (word overlap, cosine similarity between ad and query/page etc.)
 - **Result set cohesiveness** (coefficient of variation of ad scores, result set clarity, entropy)

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Should we show ads at all Features

- Relevance features
 - Word overlap, cosine similarity between ad and query/page
- Vocabulary mismatch features
 - Translation models
 - PMI between query/page terms and bid terms
- Ad-based features
 - Bid price (higher bids often indicate better ads)
- Result-set cohesiveness features
 - Coefficient of variation of ad scores (std/mean)
 - Result set clarity
 - If the set of ads is very cohesive and focused on 1-2 topics, the relevance language model is very different from the collection model
 - Entropy

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Should we show ads at all Incorporating click history (WSDM 2010, Hillard et al.)

- Binary classifier (relevant / non-relevant ads)
 - Baseline: text overlap features (query/ad)
- Click history (query/ad) with back-off
- Click propensity in query/ad translation

*p(D | Q) = p(D | Q) * p(Q)*

Bayes' rule

IBM Model 1

$$trans(q_j | d_i) = \frac{\sum_{j=1}^{log_2} count(q_j | d_i)}{\sum_{q=1}^{log_2} \sum_{d=1}^{log_2} count(q | d)}$$

Counting clicks for query/ad word pairs

- Cold start (i.e., no click history) is OK
- Using click data to overcome synonymy
 - Query = "running gear"
 - Ad = "Best jogging shoes"

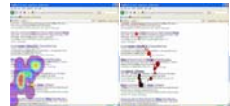
Results

Query coverage ↓ **9%**
 Ads per query ↓ **12%**
 CTR ↑ **10%**
Same # clicks on fewer ads

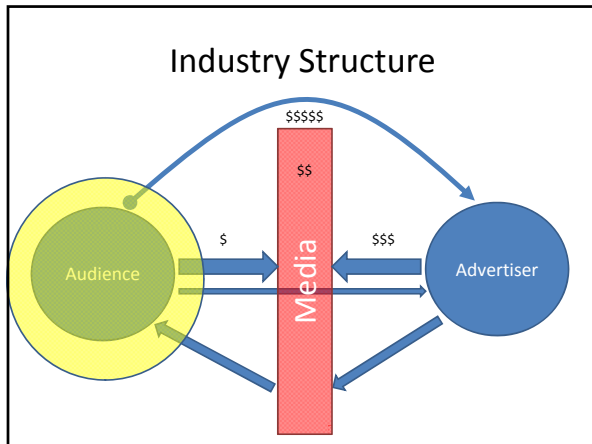
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Should we show ads at all Incorporating multi-modal interaction data (SIGIR 2010, Guo & Agichtein)

- Ready to buy or just browsing?
 - Classifying research- and purchase-oriented sessions
- **Inferring** eye gaze position from **observable** actions
 - Keystrokes, GUI (scroll/click), mouse movement, browser (new tab, close, back/forward)
- Research vs. purchase classification (in lab): F1 = 0.96
- **Ad clickthrough** in sessions classified as *Purchase* > 2X compared to sessions classified as *Research*
- Predicting future ad clicks: F1 = 0.07 → 0.17 (+141%)



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End Users

Don't bug me

Unless I like what you have to offer

Y! Ads as another source of content for enriching Web search results

"I do not regard advertising as entertainment or an art form, but as a medium of information...."

OGILVY ON ADVERTISING

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Better Matching

- Context detection
 - GPS, location
 - App vs. content
 - In-game
 - Info seeker vs. transactor
 - Calendars/schedules/events
 - Social networks/status
 - Twitter - now
 - Behavioral - esp. w/knowledge of specific site behaviors
 - Contextual
- Privacy
 - Google "AOL search data"

Y! Textual advertising

Sponsored Search

Ads driven by search keywords
a.k.a. "keyword driven ads" or "paid search"

Content Match

Ads driven by the content of a web page
a.k.a. "context driven ads" or "contextual ads"

Textual advertising on the Web is strongly related to NLP and information retrieval

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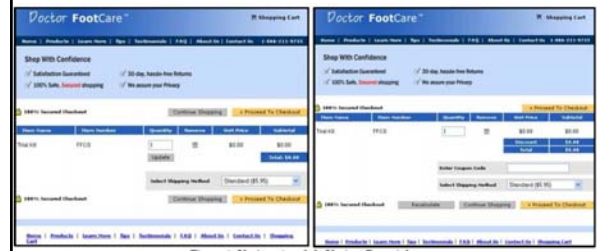
Context?

- Flowers
- Mentos gum
- Trial Prep
- Credit score
- Cosmetics
- Hampton Inns
- WeightWatchers
- Vacation Home Rentals
- Home Depot
- Web Hosting
- WebMD
- Colon Cleanse - Warning
- My Teeth Aren't Yellow
- Classmates.com

TESTING

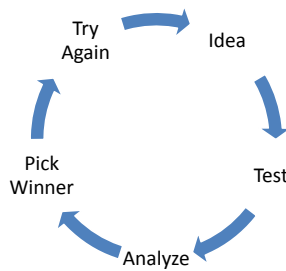
One accurate measurement is worth more than a thousand expert opinions
 — Admiral Grace Hopper

Nine Differences

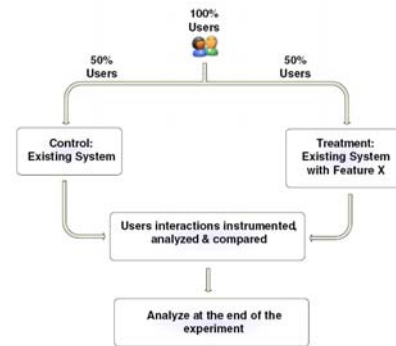


A → upgrade! → B
 Lost 90% revenue...
 Reverting coupon code increased CR 6.5%

Testing



A/B Split Test



Testing

Sample Size, margin of error, confidence

$$x = Z(c/100)^2 r(100-r)$$

$$n = N x / ((N-1)E^2 + x)$$

$$E = \text{Sqrt}[(N-n)x / n(N-1)]$$

Determine Sample Size

Confidence Level: 95% - 99%

Confidence Interval:

Population:

Calculate

Sample size needed:

Find Confidence Interval

Confidence Level: 95% - 99%

Sample Size:

Population:

Percentage:

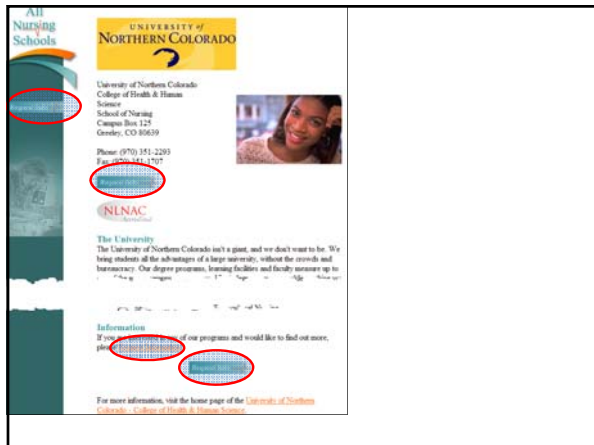
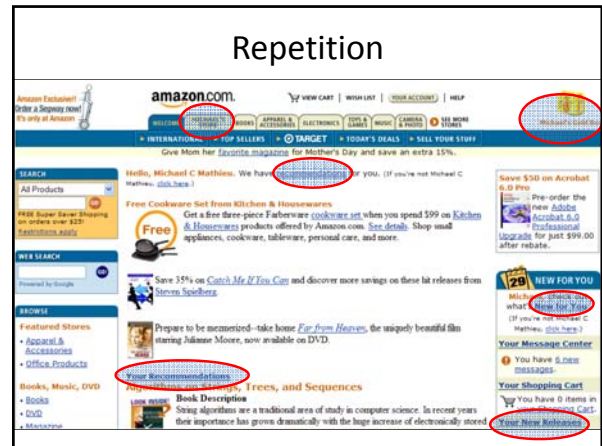
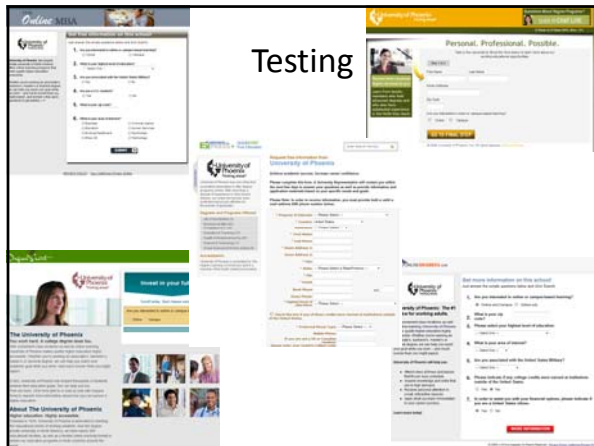
Calculate

Confidence Interval:

Sample Size Problems

- So many ideas, so little to sample...
 - Disproportionate advantage to scale
- Multivariate testing
 - Taguchi Method
 - Method for calculating signal-to-noise ratio of different parameters in an experimental design
 - Allows optimization with A/B test of each cross-product

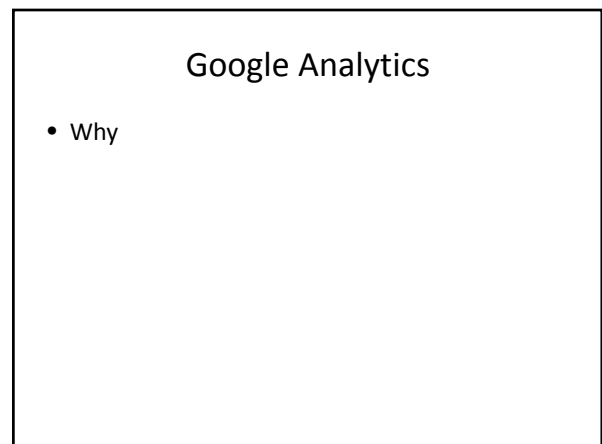




Fact Sheet Design

Existing Schools (n=1,428)	CR
Best	51.1%
Worst	0.4%
Average	11.6%

Test	# Schools	CR Lift
Professional photo	1	30%
More RFI buttons	3	21%
Marketing voice, more programs listed	1	28%
Photos + Marketing voice, more programs	1	50%



Opportunities Today

- Conversions
 - Low-RPV
 - Waste
 - Simplicity
- Risk
 - Scaling local, hyperlocal
 - Data exchanges
 - Under-monetized sites
- Context

Summary

- Conversions
- Risk
- Context
- Testing