



# Targeting Converters in Display Advertising

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# Agenda

- Background on Advertising
- Display Advertising
  - Futures Market
  - Spot Market --- Ad-exchange, Real-time bidder (RTB)
- User Targeting Problem in Display Advertising
  - Current practice, state-of-the-art
- Our approach
  - Using historic campaign data to target new campaigns
- Modeling Details
  - Factor Model
- Experiments



# The two basic forms of advertising

## 1. Brand advertising

- creates a distinct favorable image

## 2. Direct-marketing

- Advertising that strives to solicit a "direct response":

buy, subscribe, vote, donate, etc, now or

soon

# Brand advertising ...



# Sometimes both Brand and Performance



**PALO ALTO/EAST PALO ALTO**  
263 University Avenue  
(Downtown/Delivery to Stanford)  
**650-322-2893**



**Round Table PIZZA**

*We Deliver*

<p><b>E-01</b> <b>20% OFF</b> <b>Any Order</b></p> <p>Offer excludes beverages, Manager's Specials, Kids Meal or any promotional items.</p> <p><small>Offer valid on Drive-In, Carry-out, or Delivery. Limited delivery area &amp; hours. Minimum delivery fee may apply. Not valid with any other offer or discounts. Expires 7/15/06.</small></p>	<p><b>E-02</b> <b>\$15.99</b> <small>REG. \$18</small></p> <p><b>Any Large Specialty Pizza</b> Original or Skinny Crust only.</p> <p><small>Offer valid on Drive-In, Carry-out, or Delivery. Limited delivery area &amp; hours. Minimum delivery fee may apply. Not valid with any other offer or discounts. Expires 7/15/06.</small></p>
<p><b>E-03</b> <b>\$11.99</b> <small>REG. \$14</small></p> <p><b>Any Large 1-Topping Pizza</b> Original or Skinny Crust only.</p> <p><small>Offer valid on Drive-In, Carry-out, or Delivery. Limited delivery area &amp; hours. Minimum delivery fee may apply. Not valid with any other offer or discounts. Expires 7/15/06.</small></p>	<p><b>E-04</b> <b>\$12.99</b> <small>REG. \$15</small></p> <p><b>Any Large 2-Topping Pizza</b> Original or Skinny Crust only.</p> <p><small>Offer valid on Drive-In, Carry-out, or Delivery. Limited delivery area &amp; hours. Minimum delivery fee may apply. Not valid with any other offer or discounts. Expires 7/15/06.</small></p>
<p><b>E-05</b> <b>\$5.00 OFF</b> <small>ANY X-LARGE PIZZA</small></p> <p><b>\$4.00 OFF</b> <small>ANY LARGE PIZZA</small></p> <p><b>\$2.00 OFF</b> <small>ANY MEDIUM PIZZA</small></p> <p><small>Offer valid on Drive-In, Carry-out, or Delivery. Limited delivery area &amp; hours. Minimum delivery fee may apply. Not valid with any other offer or discounts. Expires 7/15/06.</small></p>	<p><b>E-06</b> <b>FREE</b> <b>Medium 1 Topping Pizza</b> with the purchase of any Large or X-Large Specialty at regular menu price.</p> <p><small>Offer valid on Drive-In, Carry-out, or Delivery. Limited delivery area &amp; hours. Minimum delivery fee may apply. Not valid with any other offer or discounts. Expires 7/15/06.</small></p>

ADVERTISE WITH MONEY MAILER OF PALO ALTO/LOS ALTOS WITH VIEW (850) 960-1238  
2226-07-0080 2226-07-0082

 H.O.T! Coupons Web Ad • 226-07-0082F  
Deepak Agarwal @UTAustin'11

©2006 Money Mailer LLC  
<http://www.hotcoupons.com>

3 5



# Web Advertising

There are lots of ads on the web ...  
100s of billions of advertising dollars  
spent online per year (e-marketer)

# Web Advertising: Comes in different flavors

- Sponsored (“Paid” ) Search
  - Small text links in response to query to a search engine
- Display Advertising
  - Graphical, banner, rich media; appears in several contexts like when visiting a webpage, checking e-mails, facebook,....
    - Brand Awareness campaign
    - Performance campaign
      - More like direct marketing in offline world, target users for some favorable response in the near-term (buy, vote, etc)





# Paid Search: Advertise Text Links

Firefox | hotels near disneyland - Google Search | www.google.com/search?q=hotels+near+disneyland&ie=utf-8&oe=utf-8&aq=t&rls=org.mozilla:en-US:official&client=firefox-a | hotels near disneyland

Search **hotels near disneyland** About 949,000 results (0.27 seconds)

Everything  
Images  
Maps  
Videos  
News  
Shopping  
More

Palo Alto, CA  
Change location

Any time  
Past hour  
Past 24 hours  
Past week  
Past month  
Past 2 months  
Past year  
Custom range...  
More search tools

**Hotels Near Disneyland | Marriott.com**  
www.marriott.com/Anaheim  
Enjoy **Hotels Near Disneyland**. Get Marriott's Best Rate Guarantee

**Hotels Near Disneyland | HolidayInn.com**  
www.holidayinn.com  
Stay You™ & Experience the new look and feel of Holiday Inn. Book Now!

**Hotels near Disneyland | Booking.com**  
www.booking.com/Disneyland-Hotels  
booking.com is rated ★★★★★ 959 reviews  
50 **Hotels near Disneyland**. No reservation costs. Great rates

**Good Neighbor Hotels near Disneyland® Resort | Expedia.com**  
www.expedia.com > ... > All Disney > Disneyland Resort  
It's easy to find and book your perfect **Disneyland® Anaheim hotel** on Expedia.

**Good Neighbor Hotels | Disneyland Resort**  
disneyland.disney.go.com/hotels/good-neighbor/  
42 Items – Good Neighbor **Hotels Near** the **Disneyland** Resort ... View on Map.  
Anabella Hotel Less than half a mile Microwave  
Anaheim Camelot Inn & Suites Across the Street Microwave ...

**Hotels near Disneyland Park - Map of Disneyland Park Area Hotels ...**  
www.tripadvisor.com/LocalMaps-g29092-d103346-Disneyland\_Par...  
Map of **hotels near Disneyland** Park, Anaheim: Locate Anaheim **hotels around Disneyland** Park based on popularity, price, or availability, and see TripAdvisor ...

**Affordable Anaheim Hotels Near Disney!** ...  
www.candycaneinn.net/  
Our complimentary amenities include wireless Internet access, a breakfast buffet and cable TV ...  
★★★★★ 13 Google reviews

1747 South Harbor Blvd.  
Anaheim, CA  
(800) 345-7057

**Map for hotels near disneyland**

Ads - Why these ads?  
**Hotels Near Disneyland**  
www.orbitz.com  
Save Up To 50% on **Hotels!** Great **Disneyland Hotel** Deals at ORBITZ.

**Hotels - Up to 70% Off**  
www.travelzoo.com  
travelzoo.com is rated ★★★★★  
Find the Cheapest **Hotel** Rooms Now  
Compare Rates up to 70% Off!

**Hotels Near Disneyland**  
www.expedia.com/Disney  
Research **Disney Hotel** Deals and Customer Reviews Online at Expedia

**145 Anaheim Great Hotels**  
www.hotels.com/AnaheimHotels  
hotels.com is rated ★★★★★  
Great **Hotels** in Anaheim.  
**Hotel** Deals to Call Home About!





# Display Advertising: Examples

The screenshot shows the Yahoo! Finance website interface. At the top, there's a navigation bar with 'HOME', 'INVESTING', 'NEWS', 'PERSONAL FINANCE', 'MY PORTFOLIOS', and 'EXCLUSIVES'. A search bar is prominently displayed. Below the navigation, a large banner for Scotttrade is circled in red, featuring the text 'Real-time streaming quotes. No fee research & education. Free mobile app. Open A New Account'. Underneath the banner is a market data table with columns for US, Europe, and Asia, and rows for Dow, Nasdaq, S&P 500, EUR/USD, Gold, Oil, and Russell 2000. Below the market data, there are several advertisement tiles: 'Is It Time to Buy Now? Let History Be Your Guide', 'Luxury Gifts for the Holidays', '12 Most Overrated Jobs', and 'Millions shocked at how bad their credit scores are...'. At the bottom, there's a 'MARKET DATA' section with a table for 'Currencies'.

Market	Index	Price	Change	% Chg
US	Dow	12,153.68	+2.19%	
	Nasdaq	2,678.75	+2.04%	
	S&P 500	1,263.85	+1.95%	
Europe	EUR/USD	1.3750	+0.0143	+1.05%
	Gold	1,789.10	+1.72%	
Asia	Oil	96.80	-1.00%	
	Russell 2000	744.64	+19.14	+2.64%

MARKET DATA			
Currencies			
Name	Price	Change	% Chg
EUR/USD	1.3750	+0.0143	+1.05%
USD/JPY	77.3835	-0.2680	-0.35%
GBP/USD	1.6641	-0.0214	-0.82%



# Display Advertising: Examples

The screenshot shows a Firefox browser window displaying the Yahoo! Mail interface. The address bar shows the URL `us.mg6.mail.yahoo.com/neo/launch?.rand=a4ml6nd3np75`. The page header includes the user's name "Hi, Deepak", navigation links like "Sign Out", "Options", and "Help", and a search bar. The main navigation area shows "WHAT'S NEW", "INBOX (3325)", "CONTACTS", and "UPDATES". A "Compose Message" button is visible. On the left, there's a sidebar with "View your 2011 Credit Report" (598), "Inbox (1947)", "Conversations", "Drafts (37)", "Sent", "Spam (12)", "Trash", "Folders", and "Top Contacts" (pandey9us, Vanh Soyinthisane, shri\_naidu, nagarajk66, ravi\_k53, tamas.sarfos, mmarschall, John Tomlin, Todd Beaupre). The main content area features a "Welcome to your brand new Inbox!" message, "1948 UNREAD EMAILS" with a "GO TO INBOX" link, and a "TODAY" section. A prominent advertisement for "Smartphone Sale" is circled in red. The ad shows two smartphones, one with a woman's face on the screen, and a price tag of "\$49.99 or less". A blue button says "Shop Smartphones". A small banner in the top right of the ad says "\$25 off Online Orders". Below the ad, there's a "TRENDING NOW" section with a list of 10 items: Ashley Greene, Demi Moore, Ozzy and Blac..., Lisa Irwin, Electric vehi..., Shania Twain, Tiger Woods, Floyd Mayweat..., Nixon secret ..., and Stocks. At the bottom, there's a "PHOTO SLIDESHOWS RIGHT IN YOUR EMAIL" section with a "See how >" link and a Yahoo! logo icon.



# Display Advertising: Examples

The screenshot shows a Firefox browser window displaying a Facebook message conversation. The browser's address bar shows the URL `www.facebook.com/messages/other/?action=read&tid=id.232113880153102`. The Facebook interface includes a search bar, navigation links for 'Deepak Agarwal', 'Find Friends', and 'Home', and a left-hand sidebar with sections for 'FAVORITES', 'LISTS', 'GROUPS', and 'APPS'. The message conversation is with 'Liz Morgan', dated July 18. The message content includes a profile picture, a text introduction, a link to a Microsoft careers page, and a section for 'Attachment Unavailable'. A 'Write a reply...' input field with a 'Reply' button is visible at the bottom of the message. On the right side of the conversation, there are sections for 'People You May Know', 'Friend Requests', and 'Sponsored'. The sponsored advertisement, titled 'Alien Caught on Video!', is circled in red. It features a video thumbnail and the text 'An alien in Brazil? See the video!'. Below the video is another sponsored advertisement for 'Pickle Addicts' with a picture of pickles and the text 'PICKLES! You know you want them! Visit our FB page for all things pickle! Like us for special FB only pickle offers!'. The bottom of the page shows the footer with 'Facebook © 2011 · English (US)' and various utility links.



# Paid Search versus Display Advertising

## Paid Search

- Context (Query) important to match
- Small text links
- Performance based
  - Clicks, conversions
- Advertisers can cherry-pick *instances*

## Display

- Reaching desired audience main goal
- Graphical, banner, Rich media
  - Text, logos, videos,..
- Hybrid
  - Brand, performance
- Bulk buy
  - But things evolving
    - Ad exchanges, Real-time bidder (RTB)

# Display Advertising Models

- Futures Market (Guaranteed Delivery)
  - Brand Awareness (e.g. Coke, MacDonald's,..)
  
- Spot Market (Non-guaranteed)
  - Marketers create campaigns targeted to user segments
    - Ad-exchanges have made this process efficient
      - Connects buyers and sellers in a stock-market style market

# Guaranteed Delivery (Futures Market)

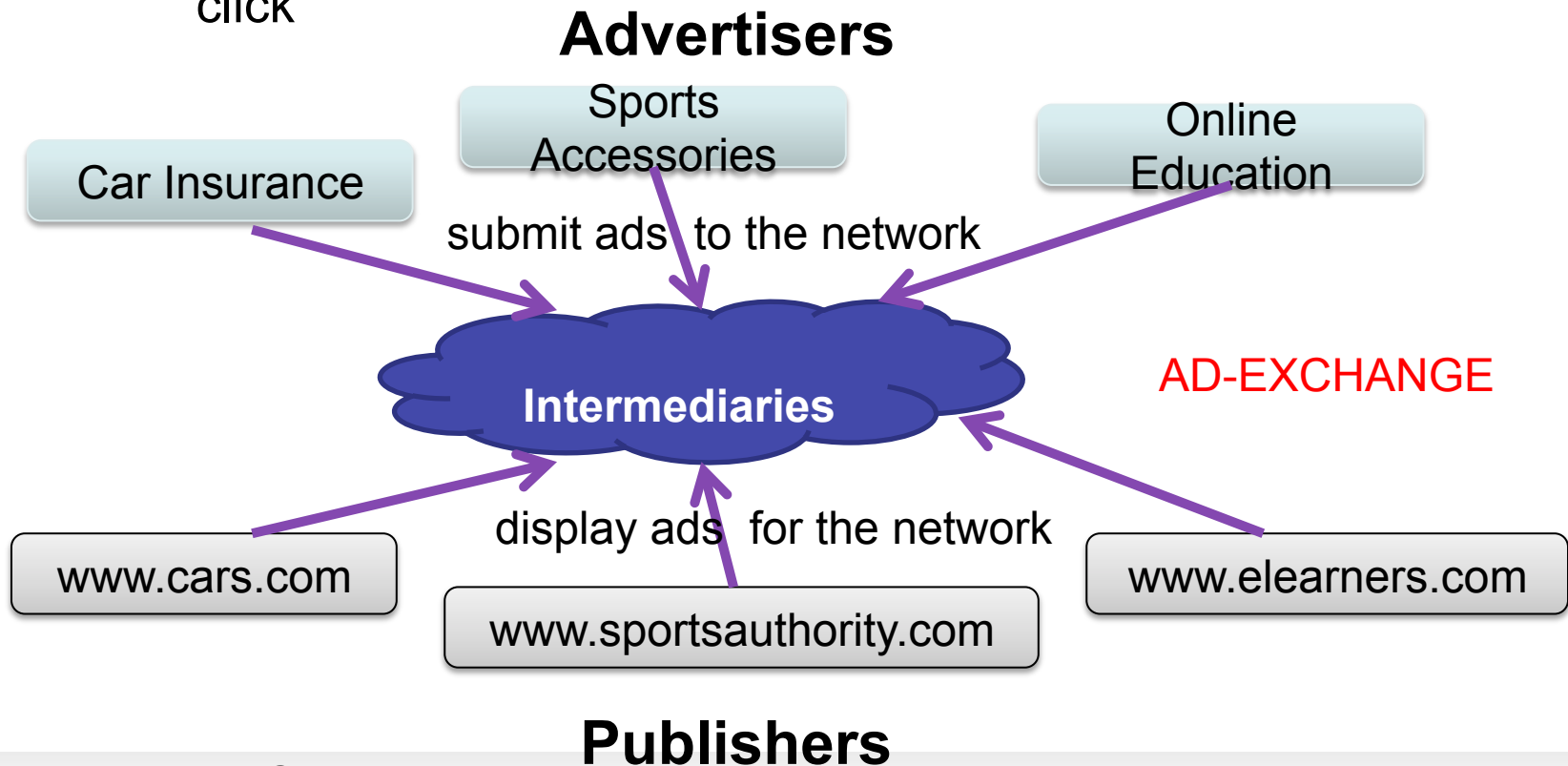
- Revenue Model: Cost per eyeball (CPM)
  - Traditional Advertising Model:
    - Ads are bought in bulk targeted to users based on demographics and other behavioral features
      - GM ads in Y! autos shown to *“males above 55”*
      - Mortgage ad shown to *“everybody on Y! Front page”*
- Book a slot well in advance
- *“2M impressions in Jan next year”*
  - Future impressions must be **guaranteed** by the ad network
  - Prices are significantly higher than in Spot market
    - Publishers ensure higher quality inventory





# Spot Market

- Different advertiser objectives
  - Brand awareness to target future sales: CPM
  - Performance based (auto, washing machine, pizza, donation,...)
    - Pay by conversion (favorable action on landing page) or/and click



# Advertising Eco-System

- Ad exchange (like a stock-market)
  - Winner decided through an auction process
    - Several intermediaries (ad-networks, pub-networks,...)
  - Still bulk buy, advertisers specify targets and a bid
- New technologies
  - Real-time bidder: change bid dynamically
    - Based on user cookie and other information passed by publishers to the broker
      - New intermediaries: sell user data (BlueKai,...)
  - Demand side platforms: single unified platform to buy inventories on multiple ad-exchanges



*"Half the money I spend on advertising is wasted; the trouble is, I don't know which half." - [John Wanamaker](#)*

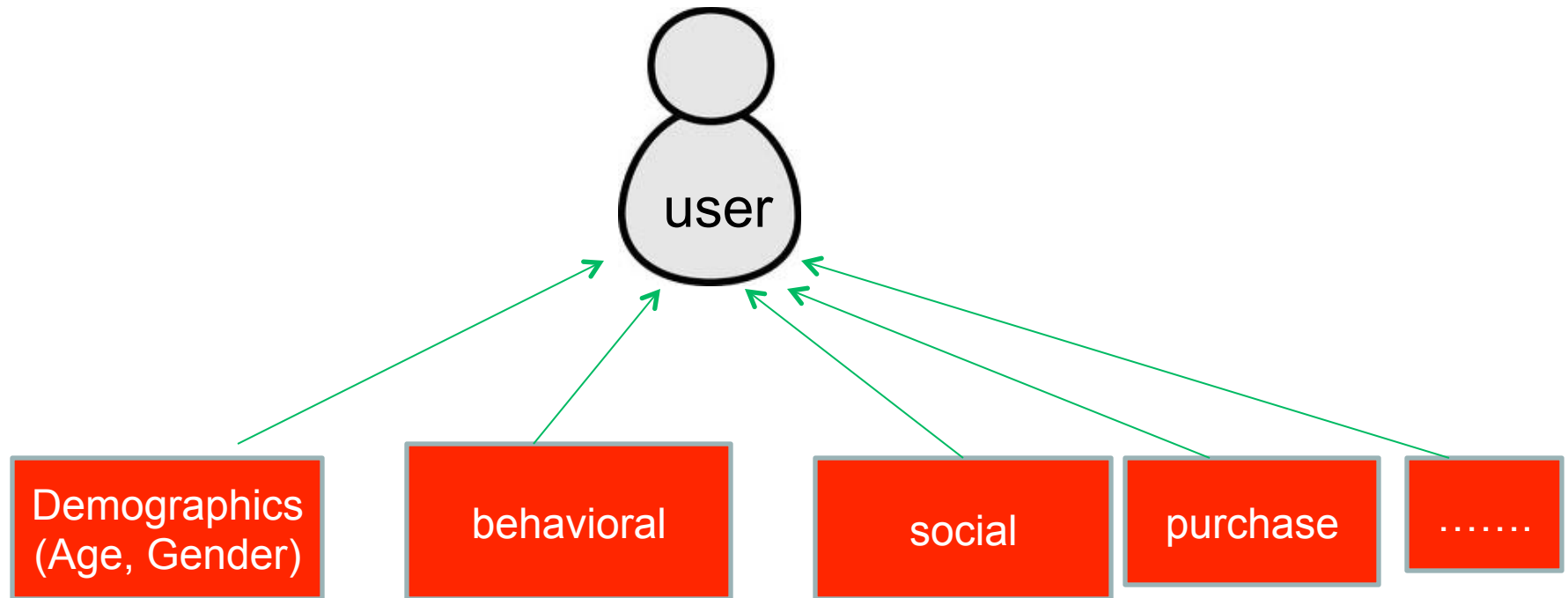
# PROBLEM: BETTER USER TARGETING



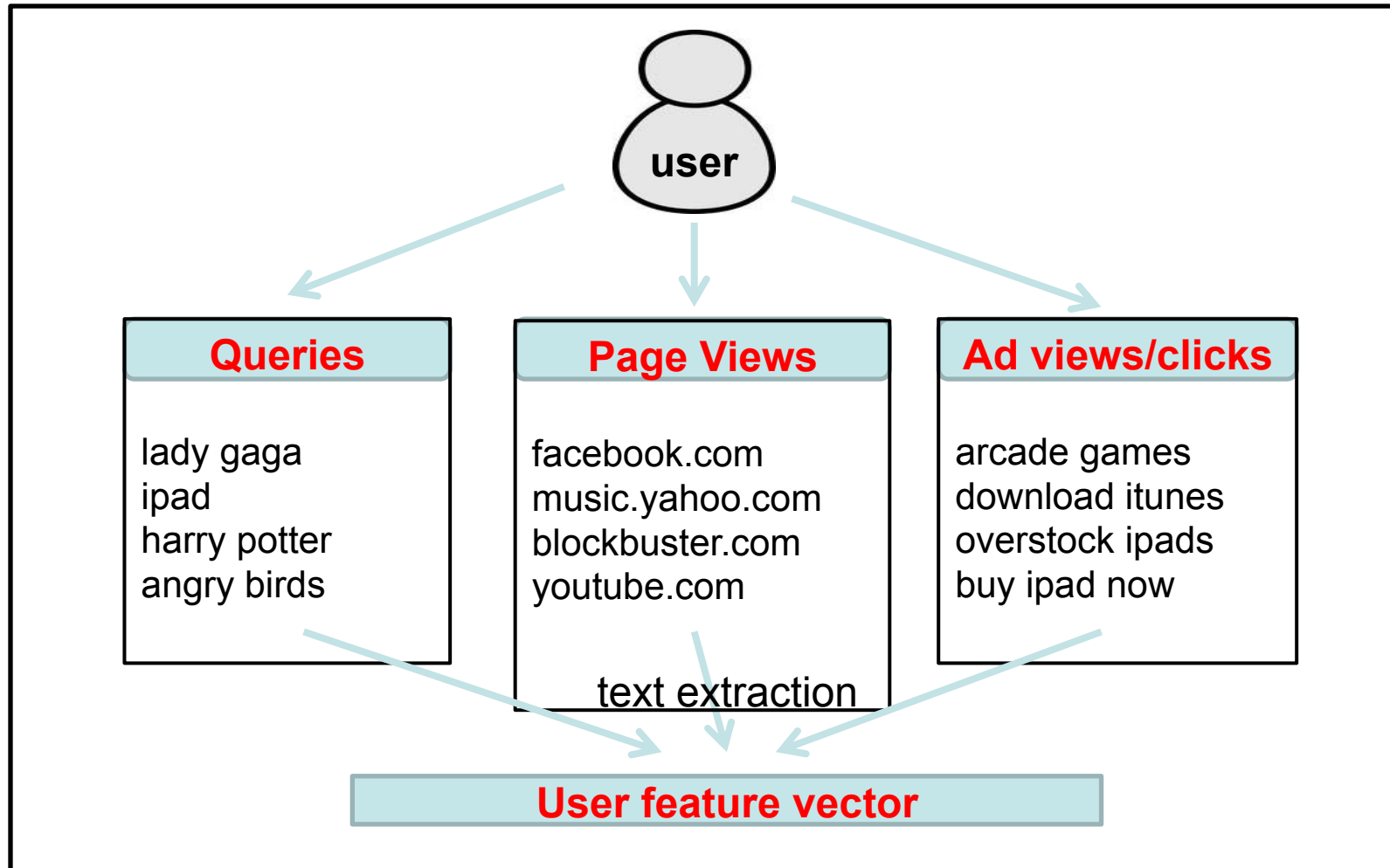
# Our problem: User Targeting for Performance

- Given a campaign that is focused on conversions, how do we target the best users to maximize advertiser ROI and publisher revenue?
- Why conversions? Why not clicks?
  - Conversions better and direct measure of user intent to buy
  - Clicks subject to problems: Fraud, bounce
  - Advertiser measure performance via conversions
- One important aspect of conversions
  - Definition varies across campaigns
    - Buying, filling-up a survey, subscription, and so on.

# Different kinds of user information



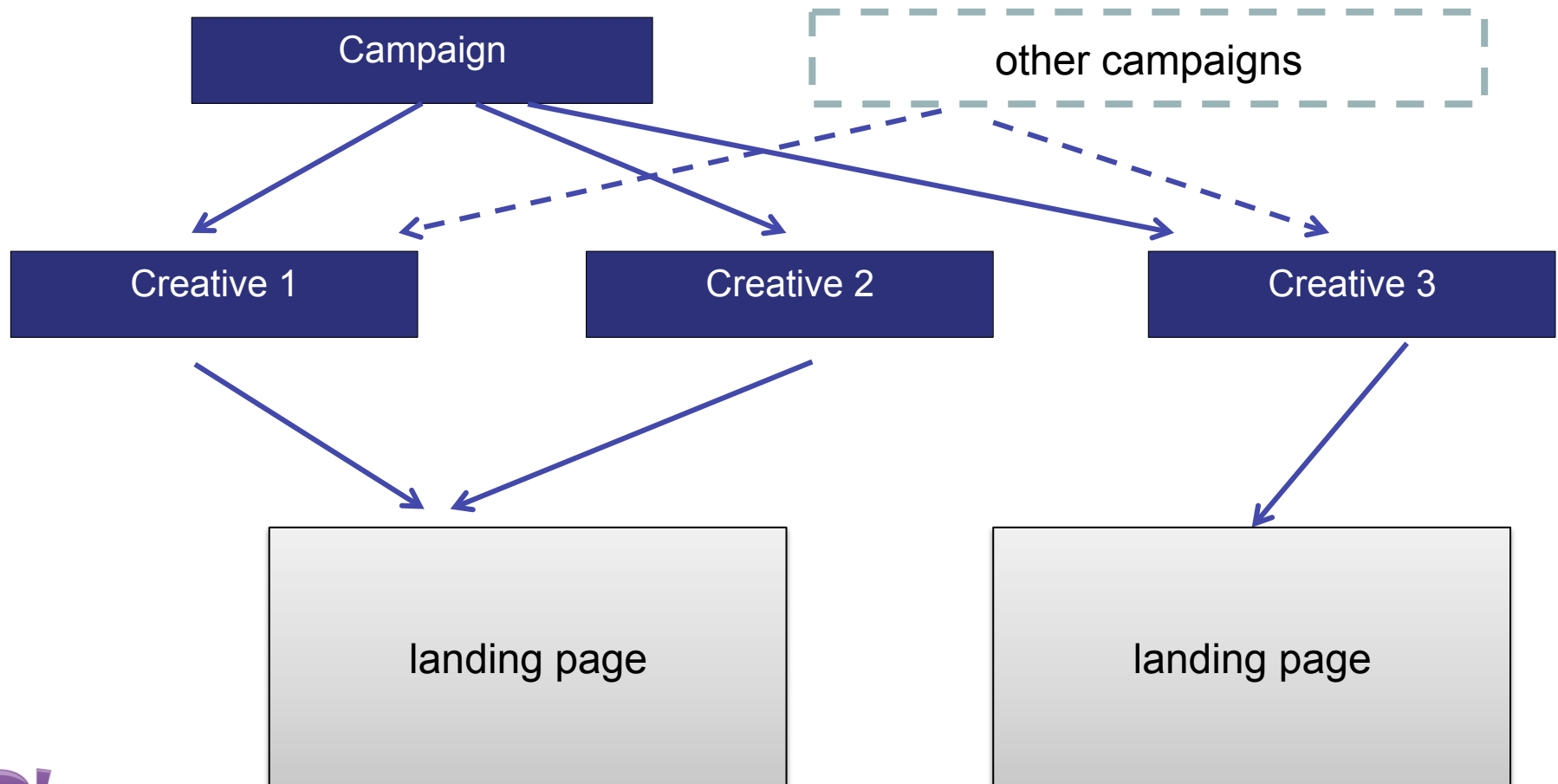
# Behavioral User profile: Main focus in this work





# Campaign information

## Campaign metadata



# Typical targeting

- Based on campaign information, look at different user dimensions and create a few targeting segments
  - E.g. campaign to sell Halloween costumes in Austin
  - Targeting attributes:
    - Users 25-50 living around Austin who searched for Halloween
  - Subjective, depends on the marketer
- Experimentation
  - Run the campaign for a while, collect conversion data and build a model to target users in a better way
    - Conversion rates low, experiment is expensive
    - Advertisers often lose patience and shut-off poor performing campaigns

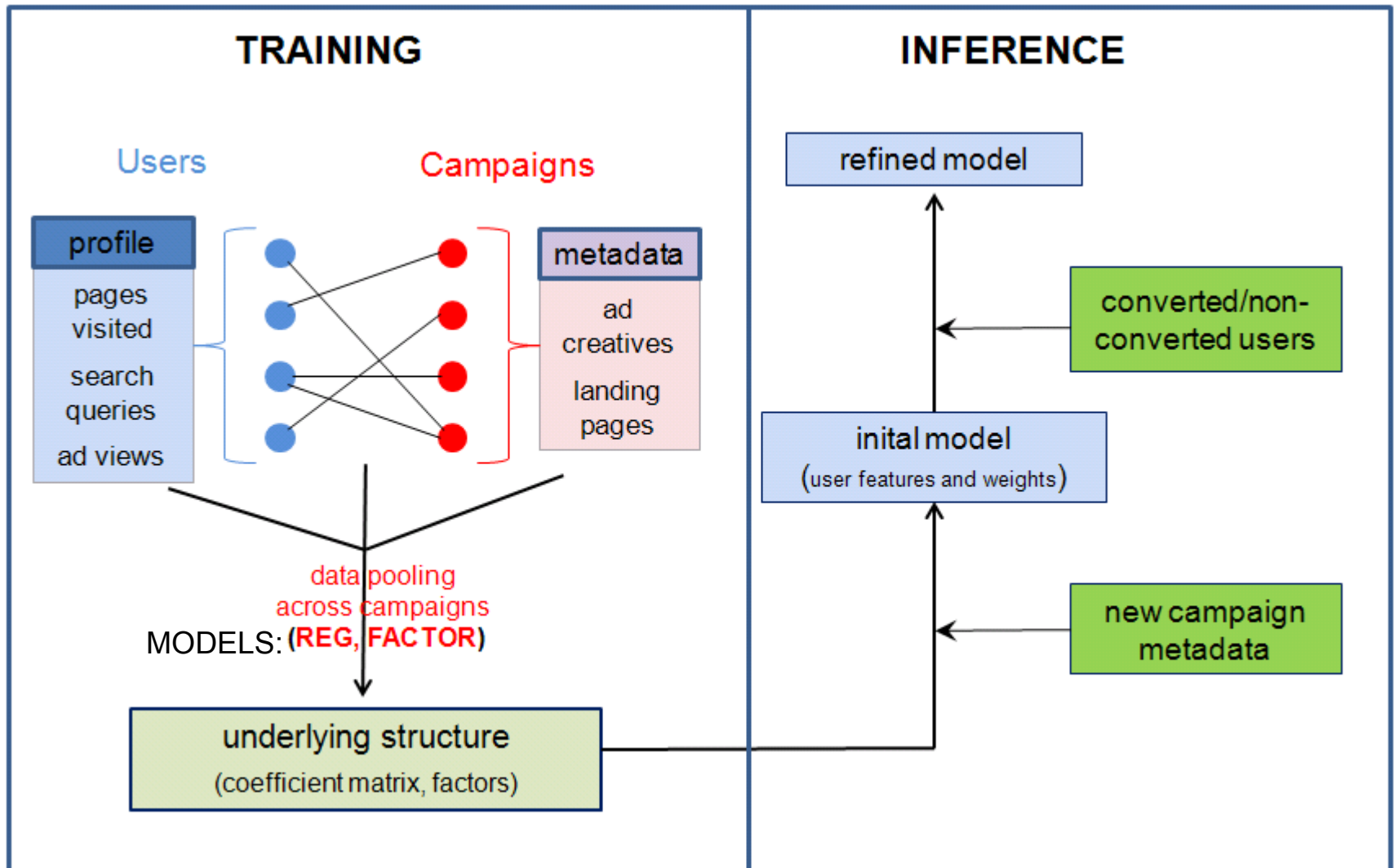


# Our Approach

- We take a fundamentally different approach
- Lots of campaigns run everyday in ad-exchanges, can we leverage this data and perform better user targeting for future campaigns?
  - Such data can also be constructed by other intermediaries in the advertising eco-system
- Intuitively, this seems plausible
  - Create clusters of campaigns, figure out where a new campaign fits
- Statistically, this is a challenging task



# Our Approach: Use past campaign performance



# MODELING



# Per campaign model

- $y_{kj}$   $k^{\text{th}}$  targeted user on campaign  $j$  (convert/non-convert)
- $\mathbf{X}_{kj}$  user feature vector (high dimensional)
- Model: Logistic regression

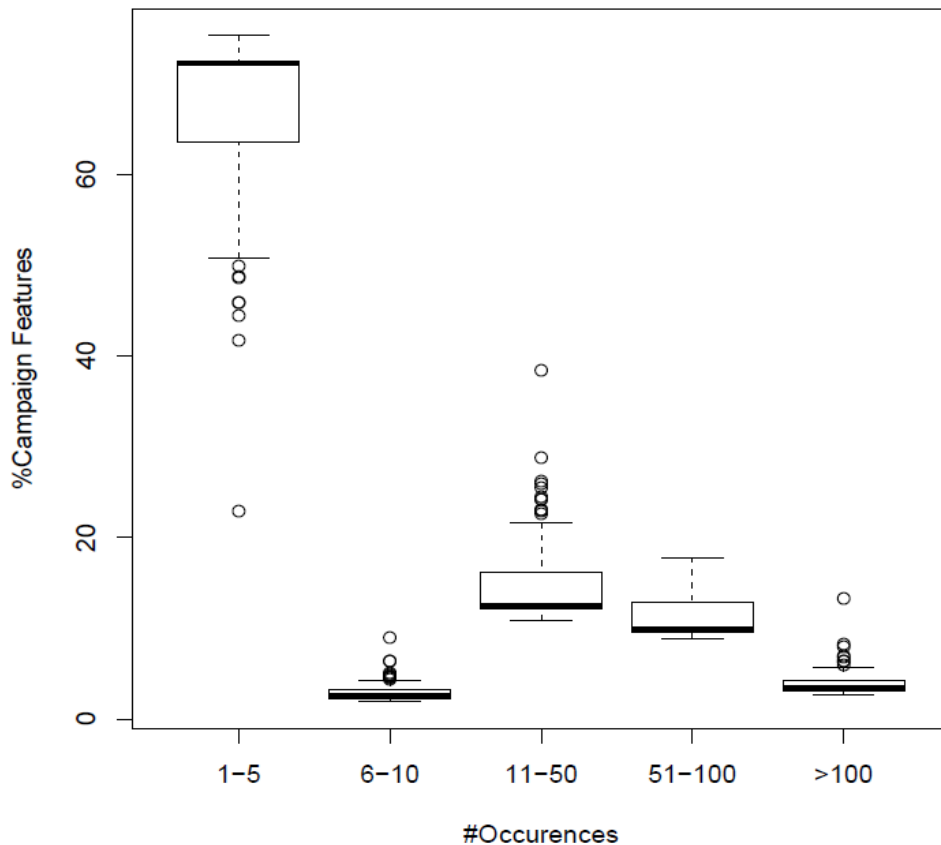
$$y_{kj} \sim \text{Bernoulli}(p_{kj}); k \in \mathcal{U}_j$$

$$\log \frac{p_{kj}}{1-p_{kj}} = \mathbf{X}'_{k,j} \boldsymbol{\beta}_j$$

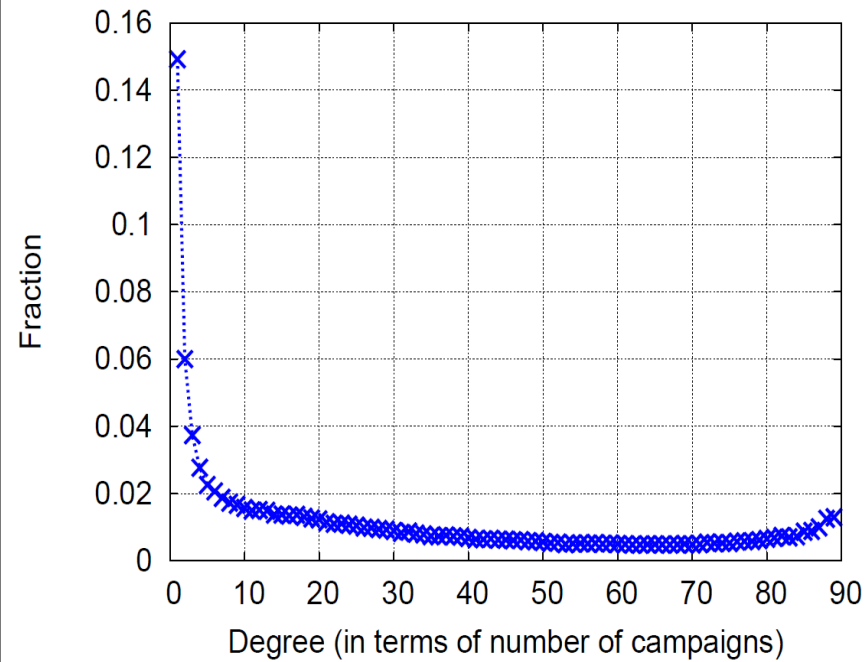
- Difficulties
  - Sparseness & rareness of conversions
    - Hundreds of thousands of user features, few hundred to few thousand conversions per campaign



# User Feature distributions: all features are binary (~100k)



Feature sparsity within campaign



Feature occurrence across campaigns

# Logistic regression ill-conditioned

- Need: Feature cones of converters and non-converters to *overlap* (Silvapulle, 1981)
- Difficult to achieve
  - Hundreds of thousands of features, most of them sparse
  - Few hundred to few thousand conversions
- Approach: Multi-level Hierarchical models
  - Assume the coefficients are drawn from some prior distribution

$$\beta_{ij} \sim N(\beta_{ij0}, \sigma^2)$$



PRIOR MEAN

	Campaign id							
User Feature id	X	?	X	?	....	?	?	X
	.....	.....	.....	.....	.....	.....	.....	.....
	.....	.....	.....	.....	.....	.....	.....	.....
	?	X	?	X	....	?	?	
	X	X	X	X	X	?	?	X
.....	.....	.....	.....	.....	.....	.....	.....	

# Modeling Prior Mean

- ZEROMEAN: Usual L2 regularization

$$\beta_{ij0} = 0$$

- State-of-the-art in Display Targeting
- Limitation: Does not work with little or no data (Cold Start)

- REG 
$$\beta_{ij0} = \mathbf{g}_i' \mathbf{z}_j = \sum_k g_{ik} z_{jk}$$

$$G = (\mathbf{g}_1, \mathbf{g}_2, \dots)$$

- Too many parameters: e.g. 100k x 30 = 3M
  - Use L2 regularization on G

# New Approach: FACTOR

- Factorize the incomplete feature-id x campaign matrix
- Idea borrowed from collaborative filtering
  - Factorize User x Item matrix
  - Here factorization one level up in the multi-hierarchy model

$$\beta_{ij0} = \mathbf{u}_i' \mathbf{v}_j$$
$$\mathbf{u}_i \sim MVN(\mathbf{0}, a_u)$$
$$\mathbf{v}_j \sim MVN(\mathbf{D}\mathbf{z}_j, a_v)$$

- $r = \#$  factors (small, e.g. 4-5)
- $\mathbf{D}$  : ( $r + \#$ campaign features) (small compared to REG)

# Advantages of FACTOR

- Factorizing coefficient matrix reduces dimension
- Alternate parameterization of **FACTOR**

$$\begin{aligned}\beta_{ij0} &= \mathbf{u}'_i (\mathbf{D}z_j + \eta_j^{rx1}) + \varepsilon_{ij} \\ &= \mathbf{u}'_i \mathbf{D}z_j + \underbrace{\mathbf{u}'_i \eta_j^{rx1}}_{\text{Sharing parameters}} + \varepsilon_{ij}\end{aligned}$$

- Recall **REG**

$$\beta_{ij0} = \mathbf{g}'_i z_j + \varepsilon_{ij}$$

# Other related approaches

- Seemingly Unrelated Regressions (SUR) [Zellner, 1962]
  - We deal with logistic + model covariance in residuals through campaign features and low-rank matrix structure
- Multi-tasking
  - Assumes complete feature-id x campaign matrix (not the case)
  - Does not incorporate campaign feature information
  - Usual approach assumes

$$\beta_{ij0} = \mathbf{u}_i' \boldsymbol{\eta}_j \text{ (Low Rank)}$$

- low-rank + sparse (we assume low-rank + white-noise)
  - Provides robust estimates after adjusting for heterogeneity
- Relaxation important to adapt estimates with online data for new campaign, robustness is not the only issue here





# Model Fitting

# EM for our models (REG and FACTOR)

$Y$  : Data

$\Delta$  : Latent variables

$\Theta$  : hyper-parameters

Model:  $p(\mathbf{Y}|\Delta, \Theta)p(\Delta|\Theta)$

Output needed: Mode:  $\max_{\Theta} p(\Theta|Y)$

$p(\Delta|Y) \approx p(\Delta|Y, \hat{\Theta})$

# Computing the mode

$$\log(p(\Theta|Y)) = \log(p(\Theta, \Delta|Y)) - \log(p(\Delta|\Theta, Y))$$

$$\log(p(\Theta|Y)) = E_{old}(\log(p(\Theta, \Delta|Y))) - E_{old}(\log(p(\Delta|\Theta, Y)))$$

$E_{old}$  : Expectation w.r.t.  $p(\Delta|\Theta_{old}, Y)$

Second term: Maximized at  $\Theta_{old}$

Find new value of  $\Theta$  that increases first term

# The EM algorithm

Initialize  $\Theta$

Iterate

E-step :  $E_{old}(\log(p(\Theta, \Delta | Y)))$

M-step :  $\operatorname{argmax}_{\Theta} E_{old}(\log(p(\Theta, \Delta | Y)))$

Improving the log-likelihood in M-step is enough, no need to perform complete optimization (Generalized EM)

# EM algorithm to fit REG

$$\Delta = \{\beta_{ij}\}_{\forall(i,j)}; \Theta = (\mathbf{G}, \sigma^2)$$

Posterior independence across campaigns in E-step

$$[\beta_{.1}, \dots, \beta_{.j}, \dots | \mathbf{Y}_{.1}, \dots, \mathbf{Y}_{.j}, \dots, \Theta] = \prod_j [\beta_{.j} | \mathbf{Y}_{.j}, \Theta]$$

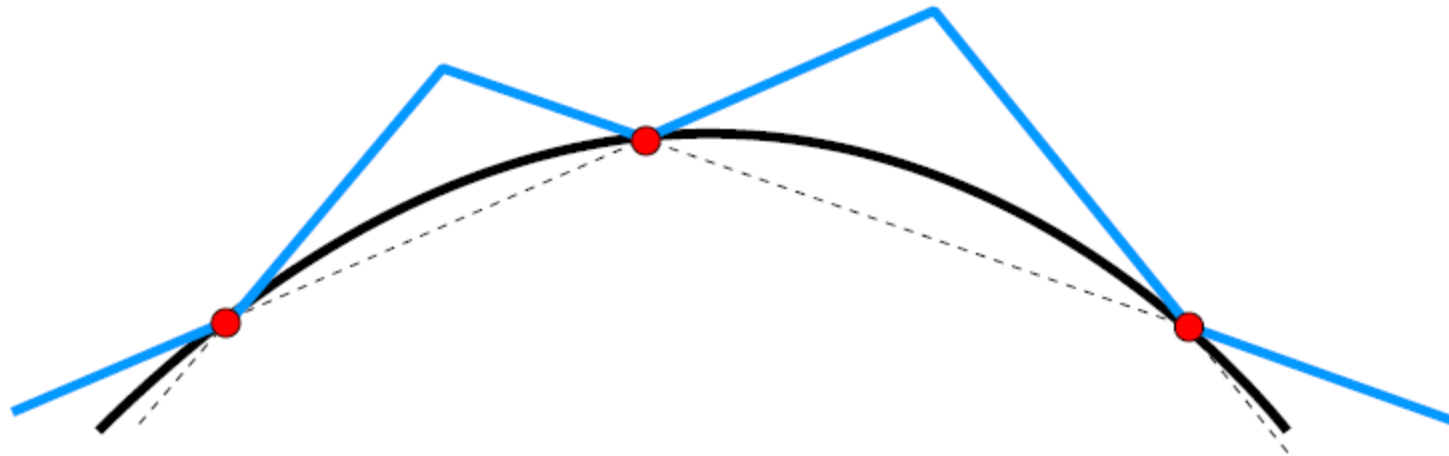
Posterior not in closed form

$$2 \ln[\beta_{.j} | \mathbf{Y}_{.j}, \Theta] = 2 \sum_k (y_{kj} \mathbf{X}'_{k,j} \beta_{.j} - l \exp(\mathbf{X}'_{k,j} \beta_{.j})) - \sum_i (\beta_{ij} - \mathbf{g}'_i z_j)^2 / \sigma^2 - C \log \sigma^2$$

We can sample through Gibbs sampling, each conditional log-concave  
Adaptive Rejection Sampling (ARS) (Gilks and Wild, '92)

# Adaptive Rejection Sampling (Gilks and Wild)

- Create upper (and lower bounds) to the density
- Perform rejection sampling, refine the envelope with each rejection (adaptive)



# EM algorithm for REG

- E-step: Sample using MCMC, parallelize on Hadoop
  - Mapper: split data by campaign
  - Reducer: run MCMC for each campaign

$$-2E \log p(\Delta, \mathbf{Y} | \Theta) = \sum_{(i,j)} ((\hat{\beta}_{ij} - \mathbf{g}'_i z_j)^2 + \tau_{ij}^2) / \sigma^2 + C \log \sigma^2$$

- M-step:
  - Estimate the  $\mathbf{g}$ 's per feature-id through regression
  - Variance estimate is closed-form

$$C \hat{\sigma}^2 = \sum_{(i,j)} (\hat{\beta}_{ij} - \hat{\mathbf{g}}'_i z_j)^2 + \tau_{ij}^2$$

# EM for FACTOR

- Parameters  $\Delta = (\{\beta_{ij}\}_{\forall(i,j)}, \{\mathbf{u}_i\}_{\forall i}, \{\mathbf{v}_j\}_{\forall j}); \Theta = (\mathbf{D}, \sigma^2, a_u, a_v)$
- Gibbs sampling for approximating posterior

$$[\{\beta_{ij}\}_{\forall(i,j)} | \{\mathbf{u}_i\}, \{\mathbf{v}_j\}, REST] \text{ ARS (parallelize)}$$

$$[\mathbf{u}_I | \{\mathbf{u}_i\}_{-I}, REST] = [\mathbf{u}_I | REST] \text{ (parallel)}$$

$$[\mathbf{v}_J | \{\mathbf{v}_j\}_{-J}, REST] = [\mathbf{v}_J | REST] \text{ (parallel)}$$

- Not amenable to Hadoop
  - One map-reduce job per MCMC iteration, infeasible



# Approximate EM for FACTOR

- E-step: Assume the factors to be fixed and sample the logistic coefficients using per campaign Gibbs sampler
- M-step: Fit the following model to obtain estimates of  $(\{\mathbf{u}_i\}, \{\mathbf{v}_j\}, \mathbf{D})$

$$\hat{\beta}_{ij} \sim N(\mathbf{u}_i' \mathbf{v}_j, \sigma^2)$$

$$\mathbf{u}_i \sim MVN(\mathbf{0}, a_u I); \mathbf{v}_j \sim MVN(\mathbf{Dz}_j, a_v I)$$

- $\sigma^2$  estimated as in REG with change in prior mean to  $\mathbf{u}_i' \mathbf{v}_j$



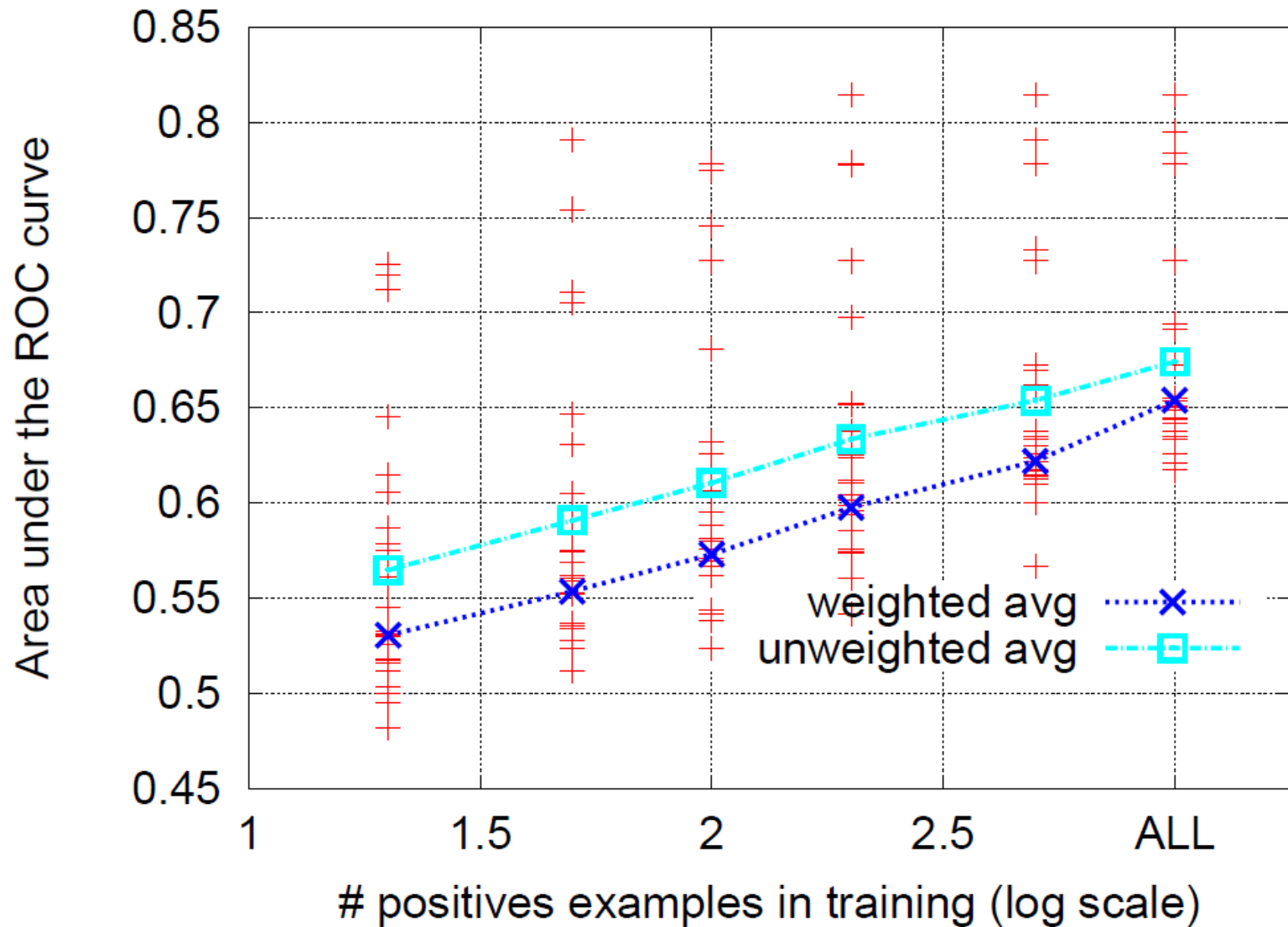
# Experiments

# Data example

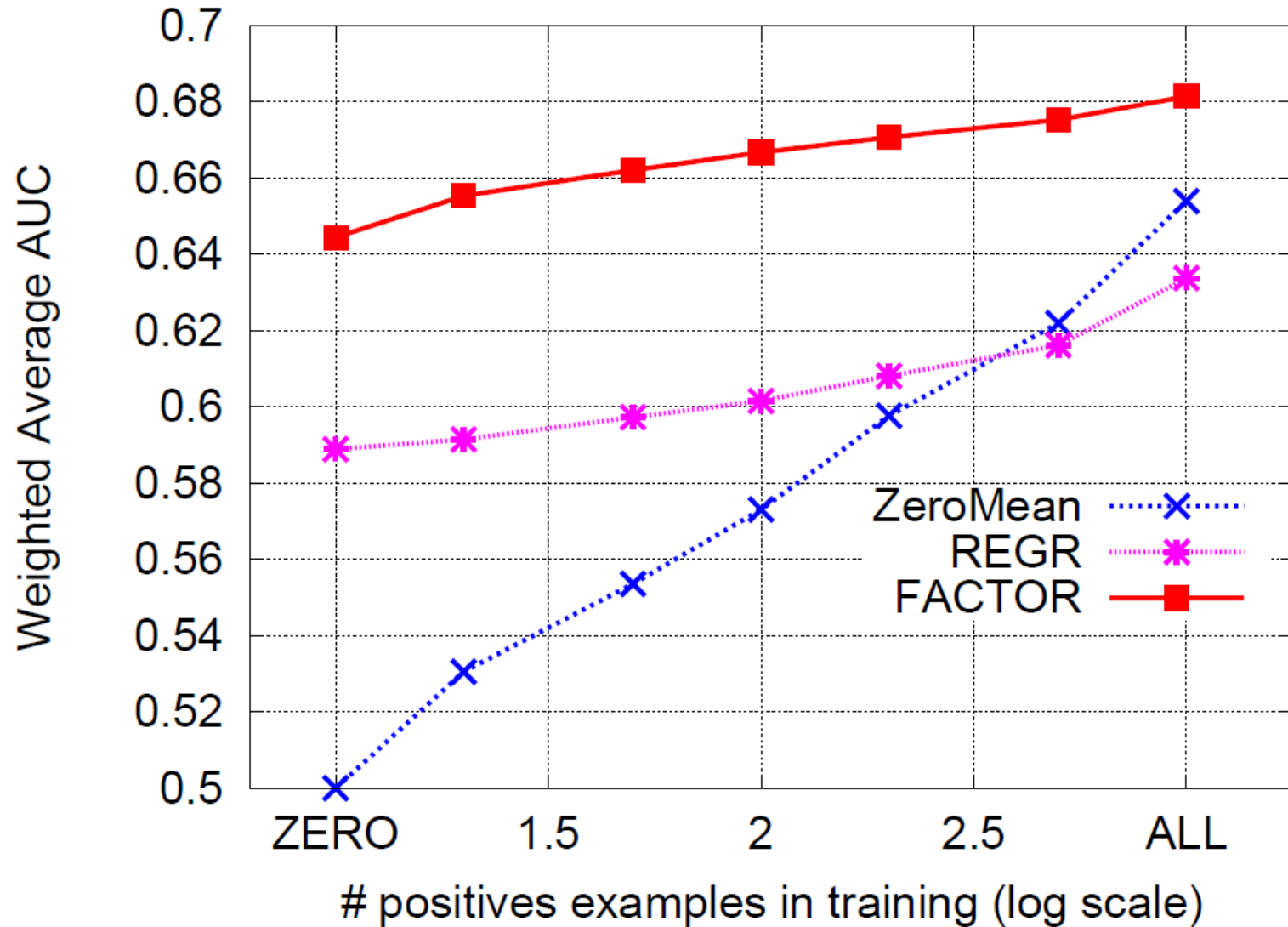
- 115 conversion based campaigns from Y! RightMedia
- 90 used for training, rest for testing
- TEST: simulate performance during different stages of a campaign's lifetime
- Evaluation metric
  - AUC (Area under the ROC curve)
    - $\Pr(\text{converter score} > \text{non-converter score})$



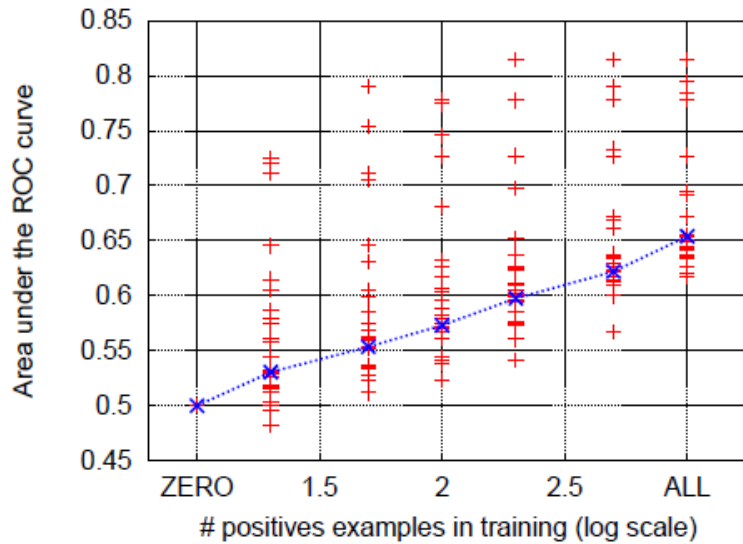
# ZEROMEAN performance



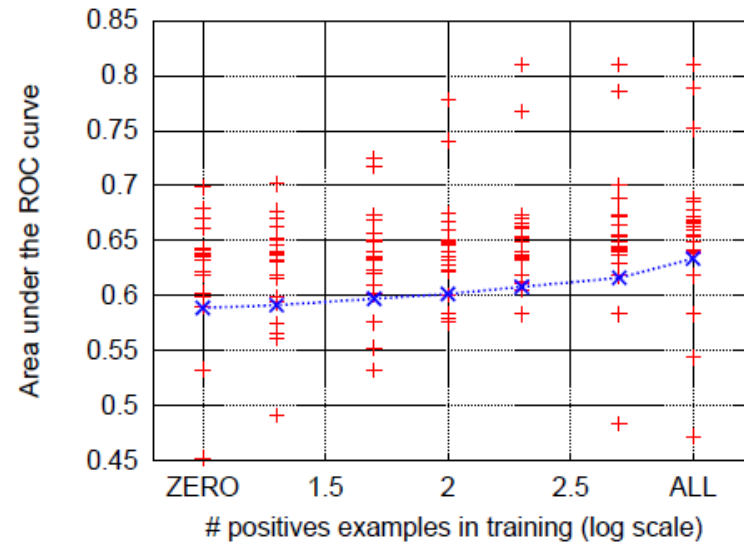
# Comparing all methods



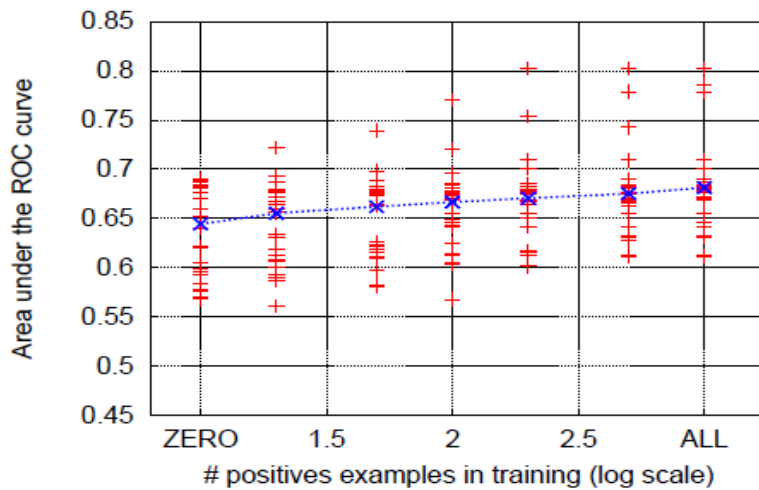
# Variation across campaigns



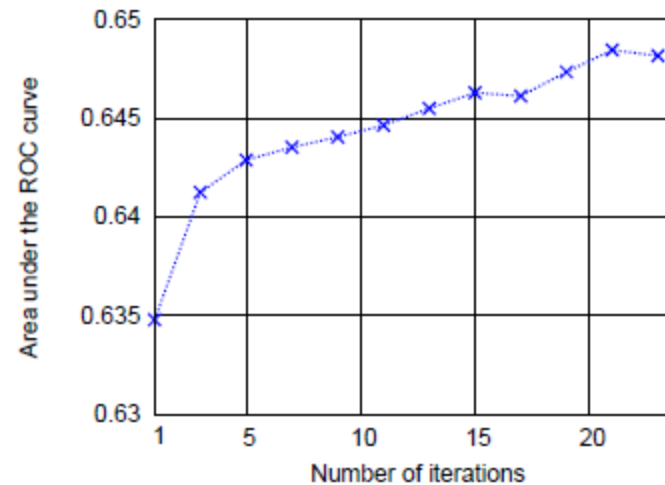
(a) ZEROMEAN



(b) REG



(c) FACTOR



# Discussion

- Using previous campaign data via FACTOR helps provide better performance at the beginning of the campaign itself, encouraging for advertiser ROI
- FACTOR adapts as more conversions *trickle in* and improves model performance for a campaign
- Fitting algorithm scales in a map-reduce framework



# To Conclude

- Targeting users is at the heart of Display Advertising that involves ingesting user information from disparate sources
  - e-marketer estimates this to be an 80B industry growing at 17% p.a
- Current techniques are subjective and involves marketers inspecting few dimensions based on domain knowledge
- We showed using past conversion data can be a useful source to build effective targeting strategy for new campaigns, such data available to multiple entities in the advertising eco-system
- We achieved this through a new multi-tasking approach called FACTOR that handles sparsity, heterogeneity, and scales in a map-reduce framework

