General course info

- Course Website: [http://www.stanford.edu/class/msande239/](http://www.stanford.edu/class/msande239/)
- Instructors
  - [Dr. Andrei Broder](mailto:broder@yahoo-inc.com), Yahoo! Research
  - [Dr. Vanja Josifovski](mailto:vanjaj@yahoo-inc.com), Yahoo! Research
- TA: [Krishnamurthy Iyer](mailto:)
  - Office hours: Tuesdays 6:00pm-7:30pm, Huang
- Course email lists
  - Staff: [msande239-aut1112-staff](mailto:)
  - All: [msande239-aut1112-students](mailto:)
  - Please use the staff list to communicate with the staff
- Lectures: 10am ~ 12:30pm Fridays in HP
- Office Hours:
  - After class and by appointment
  - Andrei and Vanja will be on campus for 2 times each to meet and discuss with students. Feel free to come and chat about even issues that go beyond the class.
Course Overview (subject to change)

1. 09/30 Overview and Introduction
2. 10/07 Marketplace and Economics
3. 10/14 Textual Advertising 1: Sponsored Search
4. 10/21 Textual Advertising 2: Contextual Advertising
5. 10/28 Display Advertising 1
6. 11/04 Display Advertising 2
7. 11/11 Targeting
8. 11/18 Recommender Systems
9. 12/02 Mobile, Video and other Emerging Formats
10. 12/09 Project Presentations
Based on

A. David Hallerman, Buying Display Ad Inventory, E-Marketeer Webinar, Aug 25, 201

B. Agarwal, Kota, Agrawal, Khanna: *Estimating Rates of Rare Events with Multiple Hierarchies through Scalable Log-linear Models, KDD 2010*

C. Slideware from many sources

D. Help from many colleagues in particular, Jai Shanmugasundaram
Disclaimers

- This talk presents the opinions of the authors. It does not necessarily reflect the views of Yahoo! Inc or any other entity.
- Algorithms, techniques, features, etc mentioned here might or might not be in use by Yahoo! or any other company.
- These lectures benefitted from the contributions of many colleagues and co-authors at Yahoo! and elsewhere. Their help is gratefully acknowledged.
Lecture plan for today

- Review of last lecture
- Non guaranteed display advertising
- Presentation on Mobile advertising [15 min incl discussion]
- Prediction technology
Guaranteed vs. Non-Guaranteed

- Advertiser can buy the ad space
  1. in advance (1-24 months) as GD
     - Pay a premium
     - Get premium inventory
     - Many targeting attributes
  2. on the spot market (at the time of page view) as NGD
Why GD?

- Currently, GD commands premium prices and is also known as “premium inventory” or “direct buy”
- Bought directly from publisher, via a sales team rather than automated methods
- Advertisers get maximum control over timing, position, property, etc
  - E.g. GM knows will launch a new model targeted to single, young, irresponsible males in Nov 2011…
  - Can buy an exclusive (no competing ads)
- In general: quality of inventory (page views) given to GD contracts > non-guaranteed
  - We have seen how to trade-off quality given to GD vs. revenue
Key points of last lecture

Display advertising

- Complex optimization problem – a lot more math than you might suspect
- Interplay of forecasting, optimization, economics
- Need to have solutions for:
  1. Forecast supply, demand, NGD pricing
  2. Admission control
  3. Pricing
  4. Optimal allocation of impressions to contracts
  5. Ad serving
GD is considered the most desirable inventory

<table>
<thead>
<tr>
<th>Method</th>
<th>% of Respondents</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pre-negotiated/reservation-based buying from sites</td>
<td>67%</td>
</tr>
<tr>
<td>Real-time buying via demand-side platforms</td>
<td>47%</td>
</tr>
<tr>
<td>Real-time buying from ad networks or exchanges</td>
<td>47%</td>
</tr>
<tr>
<td>Pre-negotiated/reservation-based buying from ad networks</td>
<td>41%</td>
</tr>
</tbody>
</table>

Note: n=50 media buyers from advertisers and agencies; "high" or "highest" satisfaction on a 4-point scale
The NGD Marketplace
The three actors: Publishers, Advertisers, Users, & “Match maker”

Note: The intermediaries in the display market are quite complex.
Advertisers: basic principles

• Display advertisers aim to
  • **Reach** audiences of interest with certain frequency
  • Achieve certain **performance** of the campaign

• In marketing terms, display advertising aims for both
  • Brand marketing that raises the awareness for a brand
  • Direct marketing

• For both reach and performance campaigns, the key challenge is to select the right audience, i.e. to **target** the right users
  • Many advertisers have multiple simultaneous campaigns with different goals

• In all cases, ultimate goal is to maximize **ROI (Return on Investment)** or **ROAS (Return On Advertising Spend)**
Advertiser Process

1. Pick a Marketing Objective
2. Define Audience: Demos, Geo, Behaviors, Interests, Purchasing
3. Develop Creative: Video, Rich Media, Large Canvas, Banners
4. Reach Audience: Guaranteed (GD) or Opportunistic (NGD)
5. Measure Results

Key Focus: Maximize Return on Ad Spend
Publisher Process

Develop Content

Attract, Retain Audience

Package Content and Audience

Monetize: Direct Sale
Exclusives, Sponsorships, Guarantees, Price

Monetize: Indirect Sale
Ad Networks, Exchanges

Key Focus: Yield while controlling the user experience
Publishers

- Own and operate the site
- Some impressions more valuable than others – price determined by supply and demand:
  - More competition for “females, 30-50, high income” than for “teenager drop-outs”
  - Also reflected in property “Yahoo horoscopes” less valuable than “Yahoo finance”
- Sell a portion of the impressions as premium e.g. $15 CPM
  - Usually sold on a “guaranteed” base by a publisher’s direct sales force
- Rest sold as “remnant”, “network”, etc e.g. <$2 CPM
  - Non-guaranteed inventory usually sold via intermediaries
- Maximizing long term revenue is the primary goal
- Want control of:
  - Pricing
  - Targeting information
  - Supply
  - User experience
- Some big publishers: Yahoo!, Facebook, MSN, AOL, etc
Challenge: display advertising is not perceived very trustworthy

<table>
<thead>
<tr>
<th>Types of Ads/Recommendations Trusted by US Consumers, Q1 2011</th>
<th>% of respondents</th>
</tr>
</thead>
<tbody>
<tr>
<td>Personal recommendations</td>
<td>76%</td>
</tr>
<tr>
<td>Online consumer opinions</td>
<td>49%</td>
</tr>
<tr>
<td>Opt-in emails</td>
<td>40%</td>
</tr>
<tr>
<td>Brand websites</td>
<td>35%</td>
</tr>
<tr>
<td>Search ads</td>
<td>21%</td>
</tr>
<tr>
<td>Online video ads</td>
<td>19%</td>
</tr>
<tr>
<td>Online banner ads</td>
<td>16%</td>
</tr>
<tr>
<td>Social network ads</td>
<td>15%</td>
</tr>
<tr>
<td>Mobile ads</td>
<td>13%</td>
</tr>
</tbody>
</table>

Note: respondents who chose "trust completely" or "trust somewhat"  
**Very low CTR**

<table>
<thead>
<tr>
<th>Mobile banner</th>
<th>Online banner</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.07%</td>
<td>0.61%</td>
</tr>
</tbody>
</table>

Note: on the MediaMind network; includes campaigns with at least one active mobile ad


www.emarketer.com
On the other hand online ads have a considerable off-line effect!

• See:
  “Does Retail Advertising Work? Measuring the Effects of Advertising on Sales via a Controlled Experiment on Yahoo!” by Randall A. Lewis and David H. Reiley

Intermediaries

• Dozens of different companies with different business models
  • Connect the advertisers and the publishers
  • Optimize the connections
  • Package impressions into audiences
  • Match the ads with the users and the context
  • Increase the fluidity of the market
  • Charge for the added value

• Etc
Intermediation & disintermediation

- **Intermediation**
  - Reduces friction
  - Ads value
  - Decreases transparency – what exactly are you buying?
  - E.g. Buy a house using a real estate agent – you pay but get advice, selection

- **Disintermediation**
  - Reduces costs
  - Increases transparency
  - E.g. Buy a house on your own
## Methods Used by US Ad Agencies to Buy Online Advertising, Q1 & Q2 2011

<table>
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<td>69.1%</td>
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<td>Direct from the publisher (Expedia, OpenTable, NCAA, etc.)</td>
<td>41.5%</td>
<td>43.5%</td>
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<tr>
<td>Through a DSP or exchange (Invite Media, Right Media, Acxiom, etc.)</td>
<td>10.6%</td>
<td>19.4%</td>
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<tr>
<td>Through self-services (FatTail's PageGage, Adap.tv's Marketplace, etc.)</td>
<td>2.1%</td>
<td>3.7%</td>
</tr>
<tr>
<td>Other</td>
<td>6.4%</td>
<td>8.3%</td>
</tr>
</tbody>
</table>

*Source: STRATA, "2nd Quarter 2011 Survey Results," July 26, 2011*
Display advertising ecosystem (Luma Partners, 2011)
Principal components
Principal components

- Publishers
- Yield optimization & supply side platforms (SSP)
- Ad networks
- Exchanges
- Demand side platforms (DSP) & Trading Desks
- Advertisers
Ad networks defined

- Companies that aggregate supply from multiple publishers or other intermediaries and matches it with advertiser demand
- Often sells inventory not sold as GD (“remnant”) or from small publishers
- Predate the exchanges
- Translate from **publisher audience** (people that visit section X) to **advertiser audience** (people interested in Y)
  - Typically groups ad inventory by categories or demographics
  - Create segments of users that cut across multiple sites
  - **Key proposition that justifies the existence of many of the intermediaries**
- Margin revenue model: a percentage of transactions
- Horizontal, vertical, targeted, international,…
- Estimated > 300 ad networks!!
### Top 20 US Ad Networks, Ranked by Unique Visitors, Dec 2010

<table>
<thead>
<tr>
<th>Rank</th>
<th>Network</th>
<th>Visitors (Millions)</th>
<th>Reach (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Google Ad Network</td>
<td>197.7 (93.3%)</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>Yahoo! Network Plus</td>
<td>183.5 (86.6%)</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>AOL Advertising</td>
<td>180.0 (85.0%)</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Turn Media Platform</td>
<td>168.8 (79.7%)</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>ValueClick Media</td>
<td>167.8 (79.2%)</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>24/7 Real Media</td>
<td>165.2 (78.0%)</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>Collective Display</td>
<td>159.4 (75.2%)</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>adBrite</td>
<td>155.5 (73.4%)</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>Specific Media</td>
<td>151.4 (71.4%)</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>Microsoft Media Network US</td>
<td>147.5 (69.6%)</td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>Vibrant Media</td>
<td>146.0 (68.9%)</td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>Traffic Marketplace</td>
<td>143.4 (67.7%)</td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>Tribal Fusion</td>
<td>143.1 (67.6%)</td>
<td></td>
</tr>
<tr>
<td>14</td>
<td>FOX Audience Network</td>
<td>142.0 (67.0%)</td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>AudienceScience</td>
<td>141.8 (66.9%)</td>
<td></td>
</tr>
<tr>
<td>16</td>
<td>interclick</td>
<td>140.2 (66.2%)</td>
<td></td>
</tr>
<tr>
<td>17</td>
<td>Burst Media</td>
<td>139.0 (65.6%)</td>
<td></td>
</tr>
<tr>
<td>18</td>
<td>Adconion Media Group</td>
<td>133.4 (63.0%)</td>
<td></td>
</tr>
<tr>
<td>19</td>
<td>Casale Media—MediaNet</td>
<td>128.4 (60.6%)</td>
<td></td>
</tr>
<tr>
<td>20</td>
<td>Undertone</td>
<td>119.4 (56.3%)</td>
<td></td>
</tr>
</tbody>
</table>

Source: comScore Networks cited as by Barclays Capital, "Internet Data Book January 2011," provided to eMarketer, Jan 13, 2011
Exchanges defined

- Marketplace for trading impressions between ad networks and some large advertisers or agencies
  - Similar to stock exchanges
  - Increase the liquidity of the marketplace by aggregating supply and demand
  - Use auction models to sell and charge for impressions
- Charge per transaction (not percentage)
- Buying possibilities:
  - Bulk buying – conditionally buy multiple impressions at once (e.g. offer $10 CPM for any mid age female on an entertainment page, total budget $1000/day)
  - Real time bidding (RTB) -- buy single impression (spot market) – e.g. offer 1c for a particular impression and a particular user
- Not every exchange allows RTB
Exchanges provide value to publishers

<table>
<thead>
<tr>
<th>Advantage</th>
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<tbody>
<tr>
<td>Higher sell-through</td>
<td>48%</td>
</tr>
<tr>
<td>Ability to tap bigger budgets</td>
<td>47%</td>
</tr>
<tr>
<td>Access to more/undiscovered buyers</td>
<td>41%</td>
</tr>
<tr>
<td>Access to better targeting technology</td>
<td>28%</td>
</tr>
<tr>
<td>Ease of use/efficiency</td>
<td>21%</td>
</tr>
<tr>
<td>Better price for our audience quality/characteristics</td>
<td>11%</td>
</tr>
</tbody>
</table>

Note: n=33; "most" or "very" important on a 6-point scale
Demand Side Platforms (DSP) defined

- Ad exchanges complicated to use:
  - Which exchange?
  - When to bid?
  - What to bid?
- DSP: technology driven optimization for the demand providers
  - Unified access to multiple exchange
  - Integration with the data providers to allow Real Time Bidding (RTB)
  - Bid & budget management and optimization
  - Analysis of results
- Trading desks are essentially DSPs but serve a single agency → no competitive pressures/data leaks

- Audience Science, MediaMath, AdChemy, [x+1], Turn,…
# Use of DSP

## Methods Used by US Ad Agencies to Buy Online Advertising, Q1 & Q2 2011

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*Source: STRATA, "2nd Quarter 2011 Survey Results," July 26, 2011*
Real time bidding defined

- Component of an exchange protocol that allows buyers to bid for each ad impression (context + user) separately in real time.
- The buyers use their own data and targeting options + purchased data to decide how much to bid.
  - Profiles, location, recent activity, etc. More in the targeting lecture.
- RTB bid is usually CPM + first price.
RTB usage: small but growing faster than non RTB exchange

US Online Display Ad Spending, by Type, 2010 & 2011

<table>
<thead>
<tr>
<th>Type</th>
<th>2010</th>
<th>2011</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-RTB exchange</td>
<td>4.3%</td>
<td>5.7%</td>
</tr>
<tr>
<td>Real-time bidding (RTB)</td>
<td>4.0%</td>
<td>7.9%</td>
</tr>
<tr>
<td>Other</td>
<td>91.7%</td>
<td>86.4%</td>
</tr>
</tbody>
</table>

Source: Forrester Consulting, "RTB Hits the Mainstream" commissioned by Admeld, Feb 10, 2011
Ad Agencies

- Present in traditional and online advertising
- Define campaigns, and formats of advertising
- Manage budgets for the advertisers and split it between different online and offline formats
- Buy media in bulk from
  - Networks
  - Publishers
  - Exchanges
- Omnicom, WPP, IPG, Aegis,…
Data supply trade and aggregation

- Most publishers have multiple pixels on their pages (cookies or beacons)
- Benefit from this data by improved ad targeting
- Can the data also be a revenue source of its self?
- Data sale is a upcoming industry:
  - Mobile, location, social network
  - Auction based model or direct sale
- Still not regulated, but FTC is starting to note
- A mixture of new and old players:
  - BlueKai, eXelate, Experian, Comscore, Nielsen
- See: http://adage.com/adnetworkexchangeguide09/article?article_id=136003
- Key Quote: Aggregators and Exchanges Aim to Create 'Liquid Market' Based on Users' Activities, Not Their Locations - but Can They Get Past Privacy Concerns?
Putting everything together: Re-targeting
Re-targeting idea

- Use immediate search or browse to target/create ads

- Examples:
  1. User that has searched for “Prius” sees ads for Prius or Toyota dealer for the next few days on non-search context, e.g. when browsing a complete different site
  2. User that has browsed a fashion site sees ads for shoes when browsing a complete different site or using e-mail, etc
  3. User that has browsed BuyAGizmo.com but did not convert, sees “get back” ads for BuyAGizmo.com on many other sites, maybe + coupon, special discount

- Mostly search re-targeting due to higher intentionality
- Special case of BT (more recent, more specific)
- Companies: Advertising.com, FetchBack, Real Media, Dapper, Microsoft DrivePM, Audience Science, BlueLithium (Yahoo!),
Detour
Cookies
Cookies

Browser request a web page from a never-seen server

Server sends web page + cookie

Hello New User
27352

Browser requests another page from same server + sends cookie back

Hello New User
27352
Third party cookies

- First party cookie: cookies associated to the domain shown in the browser's address bar
- Third party cookies: cookies associated to different domains than shown in the browser's address bar.
  - Created because parts of the page are created by http requests to other domains, not the domain in the bar, e.g. an image stored on a different server
  - Extreme case: a beacon = 1 pixel invisible image used to track a user visit
- More in the targeting lecture
Basic search retargeting scheme

- User searches for shoes on the XYZ engine

Site ABC sends ad request + XYZ cookie to XYZ

XYZ creates shoes ad based on XYZ cookie that remembers “shoes”
Basic browse retargeting scheme

- User Joe views skiing site ABC that contains some XYZ produced ad or just “beacon”
- Joe’s XYZ cookie captures visit to ABC
- Now on site DEF Joe sees ski ads

Sends ad request + XYZ cookie to XYZ

- XYZ creates skiing ad based on XYZ cookie that remembers “skiing”
- Alternative: XYZ puts ad for ABC
AOL explanation

Did you know that many ads you see on the web are based on other websites you visit?

An ad company sends a cookie to Mr. Penguin’s computer, recording his visit.

Penguin’s Cookie File
COOKIE ID 123 = ANCHOVY


The ad company reads the cookie to display a relevant ad.

For more information from AOL about online advertising and your privacy choices:

Click Here.

AOL
Estimating Response Rates in Display Advertising through Multi-Hierarchy Smoothing

Deepak Agarwal & Nagaraj Kota, Yahoo!

IISA 2011
Ad selection via bidding

Advertisers

Ad Network

Ads

Page

Publisher

User

Bids

Response rates (click, conversion, ad-view)

Statistical model

Click

Auction

Select argmax f(bid, rate)

Pick best ads
Exchanges

- Advertisers participate (bid) in different ways
  - CPM (pay by ad-view)
  - CPC (pay per click)
  - CPA (pay per conversion)
  - DCPM (Exchange bids CPM but based on conversion goals. Like CPA/CPC but advertiser takes the risk)

- To conduct an auction, normalize across pricing types
  - Compute eCPM (expected CPM)
    - Click-based ---- eCPM = click-rate*CPC
    - Conversion-based ---- eCPM = conv-rate*CPA
Pricing Types

- RevShare
- CPM
- CPM w CPC goal
- CPM w CPA goal
- CPC
- CPC w CPA goal
- CPA
- dCPM (dynamic CPM)
- dCPM w CPC goal
- dCPM w CPA goal
Statistical Issues

- Need to estimate the click or conversion probability
  \[ f(\text{context, user, ad}) \]
- High dimensional density estimation

\[ F(y \mid i, j) \]

- Response obtained through interaction among few heavy-tailed categorical variables (opportunity and ad)
Problem Definition

Example applications
Content, Movie, Advertising, Shopping, …

USER

Context
page, previous item viewed, …

Item Inventory
Articles, web page, ads, …

Construct an **automated** algorithm to select item(s) to show

Get feedback
(click, time-spent, rating, buy, …)
Refine parameters of the algorithm

Repeat (large number of times)
Optimize metric(s) of interest
(Total clicks, Total revenue, …)

Low Marginal cost per serve,
Efficient and intelligent systems can provide significant improvements
Structure in the Data

- Covariates available for both opportunity and ad
  - Opportunity: Publisher content type, user demographics,…
  - Ad: Industry, text/video, text (if any)

- Hierarchically organized
  - Publisher hierarchy: URL → Domain → Publisher type
  - Geo hierarchy for users
  - Ad hierarchy: Ad → Campaign → Advertiser
Statistical Issues

- Key: Modeling residual correlations in residual response rates when interacting variables are organized hierarchically
  - (Actually a DAG is fine, tree not needed)
- High dimensional
  - 100M “cells” from ~ hundred billion auctions
- Data sparsity
  - Large number of zeroes, extreme variation in #Tries
    - Small sample size corrections essential
- Model parsimony
  - Cannot store a large model in our ad-servers, parsimony along with accuracy important
- Temporal smoothing
Hierarchical Smoothing of residuals

- Assuming two hierarchies (Publisher and advertiser)

\[ \text{cell } z = (i, j) \]

- Use the well represented interactions for smoothing
Modeling data at granular resolutions

• Pros of learning things at granular resolutions
  • Better estimates of affinities at event level
    • (ad 77 has high CTR on publisher 88, instead of ad 77 has good CTR on sports publisher)
  • Bias becomes less problematic
    • The more we chop, less prone we are to aggregating dissimilar things, less biased our estimates from non-randomized data

• Challenges
  • Too much sparsity to learn everything at granular resolutions
    • We don’t have that much traffic
    • E.g. many ads are not even shown on many publishers
  • Explore/exploit helps but cannot do so much experimentation
  • In advertising, response rates (conversion, click) are too low, further exacerbates the problem
Solution: Go granular but with back-off

- Too little data at granular level, need to borrow from coarse resolutions with abundant data (smoothing, shrinkage)

\[ CTR(1) = w_1(0/5) + w_{11}(2/200) + w_{12}(40/1000) + w_{121}(200/5000) + w_{111}(400/10000) \]
Sometimes enough data at granular level

No need to back-off

\[ \text{CTR}(1) = \frac{100}{50000} \]

1. Pub-id=88, ad-id=80, zip=Arizona

11. Arizona

12. Pub-id=88, adv-id=8
How much to borrow from ancestors?

- Learning the weights when there is little data
- Depends on variance in CTRs of small cells
  - Ancestors with similar CTR child nodes are more credible
- E.g. if all zip-codes in Bay Area have similar CTRs, more weights given to Bay Area node
  - Pool similar cells, separate dissimilar ones
Common misconception

- If a parent has large amounts of data, the variance is small and hence it is a good back-off candidate
  - WRONG!

- The back-off depends on the variance in true CTRs of small cells nested in a parent node
  - This variance does not go to zero even with infinite data!

- But how do we estimate variance in true CTRs when the goal is to estimate the CTRs themselves?
  - Statistical modeling assumptions can help
Data

- Two kinds of conversion rates
  - Post-Click conv-rate = click-rate*conv/click
  - Post-View conv-rate = conv/ad-view

- Three response rate models
  - Click-rate (CLICK), conv/click (PCC),
  - post-view conv/view (PVC)
Datasets : Right-Media

- CLICK  [~90B training events, ~100M parameters]
- Post Click Conversion (PCC) (~.5B training events, ~81M parameters)
- PVC – Post-View conversions (~7B events, ~6M parameters)
  - Cookie gets augmented with pixel, trigger conversion when user visits the landing page
- Features
  - Age, gender, ad-size, pub-class, user fatigue
  - 2 hierarchies (publisher and advertiser)
- Two baselines
  - Pubid x adid [FINE] (no hierarchical information)
  - Pubid x advertiser [COARSE] (collapse cells)
Accuracy: Average test log-likelihood

(a) PCC

(b) PVC

(c) CLICK
More Details

- Agarwal, Kota, Agrawal, Khanna: *Estimating Rates of Rare Events with Multiple Hierarchies through Scalable Log-linear Models*, KDD 2010
Summary

- Scalable map-reduce log-linear models to precisely estimate rare response rates by exploiting correlation structures with cross-product of hierarchies

- Significantly better than state-of-the-art logistic regression methods widely used in computational advertising
Recent Work

- Mixture of Multi-Hierarchy Models
  - Baseline model using Decision Trees, one Multi-Hierarchy Model per node that are shrunk towards each other

- Hierarchical-Temporal Smoothing through Kalman filters
Key points

- Structure of the NGD marketplace
- Prediction should take advantage of hierarchical structure of the data
Questions?

We welcome suggestions about all aspects of the course: msande239-aut0910-staff
Thank you!

broder@yahoo-inc.com
vanjaj@yahoo-inc.com

http://research.yahoo.com
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Targeting
Scientific perspective on targeting

Targeting from the matchmaker point of view
Targeting as a dual problem of ad selection

- Targeting is **audience selection**
- Traditionally not understood as such
- Duality not easy to explain to media buyers! 😊

**Ad Selection** <-> **duality** <-> **Targeting**

Find optimum ad given (context, user)  
Find optimum users given (context, ad)
Targeting specification

- “Classic” \(\rightarrow\) Rule based
  - Males in California, 25-35 age
  - Focus on a few dimensions in the user profile
  - Boolean selection (database query): the user is either qualified or not

- “Modern” \(\rightarrow\) Model based
  - Determine the weight for all dimensions/features
    - Market research – identify the characteristics of the most responsive users
  - Supervised approach: based on a given set of positive users
    - Users that have already interacted with the advertiser
    - Market research – identify the users that appear most likely to be responsive
Audience selection vs. traditional targeting

Implementation

Model-Based Similarity Search

\[ \text{users}(t) = \text{top}_K(\frac{u^T}{\|u\|} \cdot t) \]

Traditional targeting:
Database selection

- select user from users
- where user.state = "ca" and user.gender = "male";
Aim of targeting: move the curve up
Current trends in targeting

The world from the standpoint of the advertiser
Market Trend: Growing need for deeper targeting

- **Context was proxy for audience**
  Historically advertisers have bought inventory based on Context (e.g. Gillette advertises on Sports sites) or publisher defined segments.

- **Supply has fragmented**
  Increasing fragmentation of digital media consumption challenges advertisers to find audiences at scale.

- **Marketers are looking for highly targeted reach** as reach per unit of buy is going down.
Market needs: Advertisers want to target ‘personas’

**Targeting Personas:** Advertisers want to target a specific persona – that may not be available through a standard Demo or a publisher defined category

For cosmetics company, XYZ, the segments “**Women between 35-54**” or “**Interest Beauty-Cosmetics**” are not narrow enough as they don’t capture the unique beauty needs of women with different persona in the same age group.

- “Frazzled Mom”
- “High Flying career woman”
- “School Teacher”
More on personas

- Online users perform a sequence of (overlapping) tasks
- Personas share interests and behavior
- Usually pre-defined segments based on real world behavior
- Same user can have multiple personas: **personas are facets of personality**
  - Andrei is a computer geek
  - Andrei is also
    - An eclectic reader
    - An expert cook
    - A non-expert skier
    - Etc
- NB: “is” here means “behaves like”
Market needs: Campaign objectives are varied

**Objectives:** Every campaign is unique in what it’s looking to achieve – based on type of segment, product, purchase funnel, etc.

- **Large department store**
  - Goal: Drive weekend traffic
  - **Objective:** In-store traffic, weekend sales

- **Credit card company**
  - Goal: Promote new low introductory rate
  - **Objective:** Qualified credit card applications

- **Cosmetics company**
  - Goal: Raise awareness of new products
  - **Objective:** Reach / Unique users
Custom ads (dynamic ads, smart ads)

- Use targeting attributes to create custom ads
- Ads are modified at run-time (under the control of the advertiser)
- Contrast with the situation where ads are chosen by the intermediary
Sampler of targeting techniques
Demographic targeting

- Important indicator of people’s interest and potential of a conversion
  - Imagine you want to sell a $50K sports car. Who do you target?
- Used widely in traditional advertising:
  - TV, magazines, etc. maintain very detailed statistics of their audience
- Common classic dimensions:
  - Age
  - Gender
  - Income bracket
  - Location
  - Interests (“Golf enthusiast”)
  - …. 
- Each dimension has multiple values
Geo targeting

- Goal: determine user location
  - Home
  - Current
  - Often wrong 😞
- Inputs
  - Registration data
  - IP (Main source!)
  - Browser default language
  - Search language
  - Etc …
- Lots of papers/results, but no time to discuss …
Example: hostip.info

- **IP Address:** 209.131.62.115
- **Host Name:** nat-dip6.cfw-a-gci.corp.yahoo.com
- **Location:** Sunnyvale, CA, UNITED STATES (change)

Are you an ISP / host? **Update an entire block**

[Google Map of Sunnyvale]
Live demos

- Message selection based on location and weather data in a demo from Teracent (bought by Google) for Dunkin’ Donuts:
  http://adserver.teracent.net/tase/demo/DunkinDonuts.jsp
- Yahoo! Smart ads simulator
  http://advertisingcentral.yahoo.com/publisher/sa_simulator
- Visit www.overstock.com. The items you are examining are shown later on ads from overstock.com e.g. on http://dailycaller.com/
Behavioral Targeting (BT) aka “interest-based advertising”

- A technique used by publishers and advertisers to increase campaign effectiveness based on a given user’s historical behavior:
  - Previous searches/search sessions
  - Previous browsing activity
  - Previous ad-clicks
  - Previous conversions
  - Declared demographics data
  - Etc.

- Utility – everyone wins! (at least in theory 😊)
  - Advertisers: get a more appropriate/receptive audience, increased conversion rate, better ROI
  - Publishers: can ask for a premium
  - Users: see more interesting ads
How popular is BT?

Do you currently use or plan to use display advertising?
- yes: 59.7%
- no: 26.2%
- unsure: 14.1%

Do you currently use or plan to use behavioral targeting?
- yes: 65.0%
- no: 23.2%
- unsure: 11.8%

Do you believe behavioral targeting is effective?
- yes: 74.9%
- no: 6.1%
- unsure: 19.0%

Source: Datran Media survey of 3,000 execs from Fortune 1000 companies December 2008
Privacy concerns

- BT mostly based on cookies
- Users do not understand the cookie mechanisms
- Difficult to turn off – many sites stop being functional without cookies
- If you accept cookies from XYZ, XYZ can become aware of your visits to any site where XYZ has a visible or invisible presence on the page.
- Many proposals / regulations / “trust-me” solutions
  - E.g. Phorm (http://www.phorm.com/) promises to collect only category data and keep cookies anonymous (not linked to IP, name, etc)
  - Most companies have data retention policies (90 days for Yahoo!)
  - Most companies allow user control over stored data
  - Opt-out BT
  - Etc
Hot off the press: Network advertising initiative

- Signed on by all major players + trade groups
- Icon on all ads:

- Users click on it and get general “opt out” page
Opt out status

<table>
<thead>
<tr>
<th>Member Company</th>
<th>Status</th>
<th>Opt-Out</th>
</tr>
</thead>
<tbody>
<tr>
<td>aCerno</td>
<td>Active Cookie</td>
<td></td>
</tr>
<tr>
<td></td>
<td>You have not opted out and you have an active cookie from this network.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Opt-Out</td>
<td></td>
</tr>
<tr>
<td>AdBrite</td>
<td>Active Cookie</td>
<td></td>
</tr>
<tr>
<td></td>
<td>You have not opted out and you have an active cookie from this network.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Opt-Out</td>
<td></td>
</tr>
<tr>
<td>AdChemcy</td>
<td>No Cookie</td>
<td></td>
</tr>
<tr>
<td></td>
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<td></td>
</tr>
<tr>
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</tr>
<tr>
<td></td>
<td>Opt-Out</td>
<td></td>
</tr>
<tr>
<td>Adara Media</td>
<td>No Cookie</td>
<td></td>
</tr>
<tr>
<td></td>
<td>You have not opted out and you have no cookie from this network.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Opt-Out</td>
<td></td>
</tr>
<tr>
<td>Adify Media</td>
<td>Active Cookie</td>
<td></td>
</tr>
<tr>
<td></td>
<td>You have not opted out and you have an active cookie from this network.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Opt-Out</td>
<td></td>
</tr>
</tbody>
</table>
Summary
Key points

- Targeting is emerging as a key component of on-line advertising
- Demographic targeting mimics classic advertising, but it can be both declared and inferred
- Behavioral Targeting based on recent search and query behavior appears effective, quantitative aspects still TBD
- Re-targeting is becoming very popular, with new players mushrooming
- Privacy and regulatory concerns
30% of marketers or less cite content targeting as most important vs. at least 70% who favor audience targeting.

<table>
<thead>
<tr>
<th>Most Important Type of Targeting According to Advertisers and Agencies in North America, March 2011</th>
<th>% of respondents</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agency trading desk</td>
<td>90% 10%</td>
</tr>
<tr>
<td>Agency</td>
<td>72% 28%</td>
</tr>
<tr>
<td>Advertiser—brand</td>
<td>71% 29%</td>
</tr>
<tr>
<td>Advertiser—performance</td>
<td>70% 30%</td>
</tr>
<tr>
<td>Advertiser—mix</td>
<td>70% 30%</td>
</tr>
</tbody>
</table>

Limits of audience data—and therefore targeting—will be shaped increasingly by the types of info that users will NOT share.

<table>
<thead>
<tr>
<th>Types of Information that US Internet Users Would Not Share with Advertisers, July 2011</th>
<th>% of respondents</th>
</tr>
</thead>
<tbody>
<tr>
<td>Financial information</td>
<td>66%</td>
</tr>
<tr>
<td>Contact information (email, phone, physical address)</td>
<td>49%</td>
</tr>
<tr>
<td>Health-related information</td>
<td>52%</td>
</tr>
<tr>
<td>Current location</td>
<td>46%</td>
</tr>
<tr>
<td>Name</td>
<td>45%</td>
</tr>
<tr>
<td>Online browsing behavior</td>
<td>34%</td>
</tr>
<tr>
<td>Profession</td>
<td>32%</td>
</tr>
<tr>
<td>Demographic information (not PII)</td>
<td>27%</td>
</tr>
<tr>
<td>Hobbies/interests</td>
<td>26%</td>
</tr>
</tbody>
</table>

- Definitely would not consent
- Probably would not consent

Note: n=1,004
Source: Harris Interactive, "Behavioral Advertising and Privacy: What Consumers Think They Know...And What Advertisers Need to Do About It" commissioned by TRUSTe, July 25, 2011
Ad inventory options, sources and methods

- Publisher direct (premium)
- Ad networks
- Ad exchanges
- Private exchanges
- Demand-side platforms (DSPs)
- Agency trading desks
- Real-time bidding (RTB)
Ad inventory options, sources and methods

- Publisher direct (premium)
- Ad networks
- Ad exchanges
- Private exchanges
- Demand-side platforms (DSPs)
- Agency trading desks
- Real-time bidding (RTB)
### Publishers and networks (branding) vs. exchanges, DSPs, RTB (direct response)

#### Best Use of Select Display Inventory Sources/Buying Methods According to US Agencies, Dec 2010

<table>
<thead>
<tr>
<th>% of respondents</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Fostering engagement</td>
</tr>
<tr>
<td>2 Generating awareness</td>
</tr>
<tr>
<td>3 Prospecting</td>
</tr>
<tr>
<td>4 Direct response</td>
</tr>
<tr>
<td>5 Cost-effective</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Source</th>
<th>Premium publishers</th>
<th>General ad networks</th>
<th>Exchanges, DSPs, RTB</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Fostering engagement</td>
<td>22%</td>
<td>6%</td>
<td>5%</td>
</tr>
<tr>
<td>2 Generating awareness</td>
<td>54%</td>
<td>33%</td>
<td>13%</td>
</tr>
<tr>
<td>3 Prospecting</td>
<td>4%</td>
<td>14%</td>
<td>13%</td>
</tr>
<tr>
<td>4 Direct response</td>
<td>7%</td>
<td>13%</td>
<td>24%</td>
</tr>
<tr>
<td>5 Cost-effective</td>
<td>6%</td>
<td>33%</td>
<td>40%</td>
</tr>
</tbody>
</table>

*Note: n=109*

*Source: DataXu and Digiday, "Digital Advertising State of the Industry Survey," Dec 9, 2010*
How a DAA Compliance Solution Works

Advertising User Experience

1. A simple ad tag inserts the DAA icon

2. If clicked the icon launches privacy notice inside the ad

3. Consumers have option to click to Preference Manager and opt out of selected tracking networks
Consumers are Aware and Skeptical of Behavioral Advertising

**Awareness of OBA Concept**
- **Aware**: 70%
- **Not aware**: 30%

**Favorability Towards OBA Concept**
- **Do Not Like It**: 8%
- **Neutral**: 38%
- **Like It**: 54%

**BASE: Total Qualified Respondents (n=1004)**
Q710  Are you aware that some advertisers and websites track your browsing activities and show you ads deemed relevant based on your browsing history? This is commonly referred to as Online Behavioral Advertising.

Q715  How do you feel about Online Behavioral Advertising as described above?
Very few marketers believe they’ve effectively integrated data across their company or channels.

**US Marketers Who Believe They Have Effectively Integrated Multiple Marketing Channels, April 2011**

<table>
<thead>
<tr>
<th>Category</th>
<th>Effective integration</th>
<th>Moderately effective integration</th>
<th>Ineffective integration</th>
</tr>
</thead>
<tbody>
<tr>
<td>Messaging across channels</td>
<td>27.4%</td>
<td>55.4%</td>
<td>17.2%</td>
</tr>
<tr>
<td>Timing of deployments across channels</td>
<td>16.7%</td>
<td>62.3%</td>
<td>21.0%</td>
</tr>
<tr>
<td>Customer and prospect data across the enterprise</td>
<td>14.8%</td>
<td>53.9%</td>
<td>31.4%</td>
</tr>
<tr>
<td>Data analytics across channels</td>
<td>14.3%</td>
<td>41.0%</td>
<td>44.7%</td>
</tr>
<tr>
<td>Sequencing of channels</td>
<td>14.0%</td>
<td>61.2%</td>
<td>24.8%</td>
</tr>
<tr>
<td>Digital asset management</td>
<td>10.4%</td>
<td>47.4%</td>
<td>42.2%</td>
</tr>
</tbody>
</table>

*Note: numbers may not add up to 100% due to rounding*

*Source: Direct Marketing Association (DMA), "Rowing as One: Integrated Marketing Today," May 11, 2011*
RTB’s audience targeting raises hackles of privacy advocates, and users are ever more aware of being tracked.

### Awareness of Select Online Ad Terms Among US Internet Users, July 2011

<table>
<thead>
<tr>
<th>Term</th>
<th>% of respondents</th>
</tr>
</thead>
<tbody>
<tr>
<td>Internet cookies</td>
<td>84%</td>
</tr>
<tr>
<td>Interest-based advertising</td>
<td>66%</td>
</tr>
<tr>
<td>Online tracking</td>
<td>65%</td>
</tr>
<tr>
<td>Behavioral targeting</td>
<td>42%</td>
</tr>
<tr>
<td>Location-based tracking and advertising</td>
<td>41%</td>
</tr>
<tr>
<td>Online advertising networks</td>
<td>40%</td>
</tr>
<tr>
<td>Online behavioral advertising</td>
<td>35%</td>
</tr>
<tr>
<td>Do not track</td>
<td>30%</td>
</tr>
</tbody>
</table>

Note: n=1,004; number shown is percent of respondents who answered "yes" to each of the items when asked "Are you familiar with each of the following terms?"

Source: Harris Interactive, "Behavioral Advertising and Privacy: What Consumers Think They Know...And What Advertisers Need to Do About It" commissioned by TRUSTe, July 25, 2011
Estimating Response Rates in Display Advertising through Multi-Hierarchy Smoothing

Deepak Agarwal* Y! Research, Santa Clara, USA

Nagaraj Kota
Y! Labs, Bangalore, India

IISA conference 2011, Raleigh, 23rd April, 2011
Agenda

- Motivating Example: Computational Advertising

- Problem Definition: Predicting response rates of rare events by exploiting multiple hierarchies

- Our Log-linear model for multiple hierarchies (LMMH)

- Scalable model fitting in a map-reduce framework

- Experiments: Data from Right Media Ad Exchange

- Summary
Computational Advertising: Matching ads to opportunities

Advertisers

Examples: Yahoo, Google, MSN, Ad exchanges (network of "networks") ...

Opportunity

User

Page

Picks best ads

Publisher

Ads
How to Select “Best” ads

Advertisements

Response rates (click, conversion, ad-view)

Statistical model

Click

Pick best ads

Auction

Select argmax f(bid, rate)

Bids

Advertisements

User

Page

Publisher

Ad Network

Conversion
Statistical Issues in Conducting Auctions

- \( f(\text{bid, rate}) \) ---- rate is unknown, needs to be estimated
- Goal: maximize revenue, advertiser ROI
- High dimensional density estimation
  \[ F(y | i, j) \]

- Response obtained through interaction among few heavy-tailed categorical variables (opportunity and ad)
  - \#levels : could be millions and changes over time
Other Structure in our Data

- Covariates available for both opportunity and ad
  - Opportunity: Publisher content type, user demographics,…
  - Ad: Industry, text/video, text (if any)

- Hierarchically organized
  - Publisher hierarchy: URL → Domain → Publisher type
  - Geo hierarchy for users
  - Ad hierarchy: Ad → Campaign → Advertiser

- Past empirical analysis (Agarwal et al 2007)
  - Hierarchies: Induces residual correlations
    - E.g. Residual rates of sporty ads shown to Palo Alto users
Statistical Issues

- Key: Modeling residual correlations in residual response rates when interacting variables are organized hierarchically (DAG is fine, Tree not needed)

- High dimensional
  - Data shown here: 100M “cells” from ~ hundered billion auctions

- Data sparsity
  - Large number of zeroes, extreme variation in #Tries
    - Small sample size corrections essential

- Model parsimony
  - Cannot store a large model in our ad-servers, parsimony along with accuracy important

- Temporal smoothing
Model Setup

\[ p_{ijc} = B(x_i, x_c, x_j) \lambda_{ij} \]

\[ E_{ij} = \sum_c B(x_i, x_c, x_j) \text{ (Expected Success)} \]

\[ S_{ij} \sim \text{Poisson}(E_{ij} \lambda_{ij}) \]

Obviously, MLE does not work
Hierarchical Smoothing of residuals

- Assuming two hierarchies (Publisher and advertiser)

Pub-class

Pub-id

cell $z = (i,j)$

$(S_z, E_z, \lambda_z)$

Cross-product of paths

$\lambda_z = \prod_{s=1}^{m} \prod_{t=1}^{n} \phi_{i_s, j_t}$
Spike and Slab prior on node States

- Prior on node states: IID Spike and Slab prior

\[ \pi(\phi; a, P) = P \mathbb{1}(\phi = 1) + (1 - P) \text{Gamma}(\phi; 1, 1/a) \]

- Encourage parsimonious solutions
  - Several cell states have residual of 1

- We choose \( P = .5 \) (and choose “a” by cross-validation)
  - a – psuedo number of success
Model Fitting to find posterior mode

- Find a solution that maximizes

\[ l(\phi) + \sum_{ij} \log(\pi(\phi_{ij}; a, P)) \]

\[ [\phi_k | \phi^1, \ldots, \phi^t_{k-1}, \phi^t_{k+1}, \ldots, \phi^t_{M-1}, \text{Data}] \]
Conditional mode – closed form

- Reduces to computing 1-d conditional modes

\[ [S | E^*, \phi] \sim \text{Poisson}(E^* \phi) \]
\[ [\phi] \sim \pi(\phi; a, P) \]

- \( E^* = \text{Adjusted eSucc aggregating statistics on all paths that include the node being updated} \)

\[
\text{Poisson}(S_1, E_1^* \phi_1) \pi(\phi_1) \text{ where } E_1^* = \phi_{11} E_{11} + \phi_{12} E_{12}
\]
Conditional model — closed form

\[ \tilde{\phi} = 1 \text{ if } Q = \log(g(\phi_m; S + a, E^* + a) - g(1; S + a, E^* + a)) = \phi_m \text{ otherwise} \]

where

\[ Q = \log \frac{\text{Poisson}(S, E^*)}{\text{NB}(S; 1, E^*, a)} + \log \left( \frac{P}{1 - P} \right) \]

\[ \tilde{\phi}_m = \frac{(S + a - 1)}{(E^* + a)} \]
Algorithm 1 Psuedocode for map-reduce implementation

Initialize the global constant $a$, the state variables $\phi_0^0 = 1$.
Iterate until convergence,
Iterate $t$ over the conjunction of paths $z = (i, j)$ in the data,
Iterate over all node pairs $(i_s, j_t)$, indexed by $k = 1, \ldots, M$. Note
that $(k - 1)$ is $M$ from $(t - 1)'th$ iteration, when $k = 1$ and $t > 1$.
For 1'st iteration with $k=1$, $(k - 1)$ would be treated as record id
and the corresponding parent node state variable as 1.

$$\text{Map} : (k - 1, \text{data}, S_z, E_z^*) \bowtie (k - 1, \phi_{k-1}^t)$$
$$\quad \rightarrow (k, \{\text{data}, S_z, E_z^*\phi_{k-1}^t\})$$

$$\text{Reduce} : (k, \{\text{data}, S_z, E_z^*\phi_{k-1}^t\}) \bowtie (k, \phi_{k}^{t-1})$$
$$\quad \rightarrow \left\{ \begin{array}{l}
 (k, \{\text{data}, S_z, E_z^*\phi_{k-1}^t/\phi_{k}^{t-1}\}) \\
 (k, \phi_{k}^{t})
 \end{array} \right\}$$

where, $\phi_{k}^{t}$ is computed for key $k$ using $\sum S_z$, $\sum E_z^*\phi_{k-1}^t/\phi_{k}^{t-1}$,
using mode formula described in Theorem 1.
Our data --- Ad- exchange (RightMedia)

- Advertisers participate in different ways
  - CPM (pay by ad-view)
  - CPC (pay per click)
  - CPA (pay per conversion)

- To conduct an auction, normalize across pricing types
  - Compute eCPM (expected CPM)
    - Click-based ---- eCPM = click-rate*CPC
    - Conversion-based ---- eCPM = conv-rate*CPA
Data (2)

- Two kinds of conversion rates
  - Post-Click --- conv-rate = click-rate*conv/click
  - Post-View --- conv-rate = conv/ad-view
    - Not important for this talk

- Three response rate models
  - Click-rate (CLICK), conv/click (PCC),
  - post-view conv/view (PVC)
Multiple (K) hierarchies

- Product of $^K C_2$ pair wise hierarchies
- Primarily done to deal with data sparseness
- Ongoing research

- Find small subset of 3-way, 4-way combinations that are important

- Main idea is to adjust for multiple tests by “shrinking” Observed/expected from all 2-factor models to detect significant higher order interactions
Datasets: RightMedia

- **CLICK**  (~90B training events)
- Post Click Conversion (PCC) (~.5B training events)
  - Conversion only through click
- PVC – Post-View conversions (~7B events)
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- Covariates
  - Age, gender, ad-size, pub-class, user fatigue
  - 2 hierarchies (publisher and advertiser)
- Two baselines
  - Pubid x adid [FINE] (no hierarchical information)
  - Pubid x advertiser [COARSE] (collapse cells)
Other baselines: variations of logistic regression

- Log I
  - Main effects using leaf nodes as covariates (size ~ 200-300k)

- Log II
  - Main effects but using both leaf and non-leaf (size ~ 300-700k)

- Log III
  - Interactions added by using large number of sparse random projections of original interaction covariates
    - Added roughly 500K projections
  - All three variations run on Map-Reduce using Y! code
Accuracy: Average test log-likelihood

(a) PCC

(b) PVC

(c) CLICK
Model Parsimony

- With spike and slab prior
- Parsimony

<table>
<thead>
<tr>
<th></th>
<th>#cells</th>
<th>#retained</th>
</tr>
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<tbody>
<tr>
<td>PCC</td>
<td>~81M</td>
<td>4.4M</td>
</tr>
<tr>
<td>PVC</td>
<td>~6M</td>
<td>35K</td>
</tr>
<tr>
<td>CLICK</td>
<td>~16.5M</td>
<td>150K</td>
</tr>
</tbody>
</table>
Some rough computation time

- CLICK : 135 mins, 50 reducers
- PVC : 123 minutes, 25 reducers
- PCC: 109 minutes, 20 reducers

- LogI, II, III (CLICK) : 4, 6, 7 hours; 80 reducers
  - PVC: 3, 4.5, 5 hours with 40 reducers
  - PCC: 4.5, 8, 9 hours with 80 reducers
How do we estimate variance for a parent?

- Simple example: CTR of an ad in different zip-codes
  - \((si, ti): i=1, \ldots, K\); \(\text{emCTR}_i = si / ti\)
  
  \[ E(s_i / t_i) = p_i \]

  \textbf{Backoff depends on } \text{Var}(p_i)\]

- \text{Var(\text{emCTR}_i)} good measure of \text{Var}(\text{pi})?
  - Not quite, empirical estimates not good for small \(t_i\) and(or) \(s_i\)

\[
\text{Var}(s / t) = \text{Var}(E(s / t) \mid p) + E(\text{Var}(s / t) \mid p) \\
= \text{Var}(p) + E(p(1 - p) / t) \\
\xrightarrow{t \to \infty} \text{Var}(p)
\]

- Hence, using variance in empirical CTRs can lead to overestimates in variance, will reduce the amount of back-off
How do we estimate variance in unbiased way?

- Simple example: CTR of an ad in different zip-codes 
  \((s_i, t_i): i=1,\ldots,K; \text{emCTR}_i = \frac{s_i}{t_i}\)

- Use a model 
  \(s_i \sim \text{Binomial}(t_i, p_i)\)
  \[E(p_i) = \mu; \text{Var}(p_i) = \sigma^2\]

- Variance among true CTRs can be estimated in an unbiased way using MLE/MOM 
  (Agarwal & Chen, *Latent OLAP, SIGMOD 2011*)

- For more complex data at multiple resolutions, better statistical models needed