

Recommender Problems for Content Optimization

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Stanford, CA

Main Collaborators in Research

- Bee-Chung Chen (Yahoo!)
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- Several others in Engineering, Product contributed to the ideas presented in this talk



Web Images Video Local Shopping More

Web Search

Make Y! your homepage

TODAY MODULE

Hi, Deepak | What are you do... | Sign Out | Page Options

- ORITES + Add
- Yahoo! Sites
- Yahoo! Mail
- Webbook
- Yahoo! Mail
- Yahoo! Photos
- Yahoo! News
- Yahoo! Finance (Dow Jones)
- Yahoo! Games
- Yahoo! Jobs
- Yahoo! Maps
- Yahoo! Messenger
- Yahoo! Movies
- Yahoo! Sports
- Yahoo! Dates
- 1 2 Add

TODAY - February 01, 2010



Pink makes a big splash at the Grammys

Pink is a high-flying, human sprinkler, while Beyoncé shows off her tougher side. [» Watch the best routines](#)

- Swift's Grammy glory
- Best and worst moments
- [Photos from the show](#)

Pink's big splash at Grammys	Best & worst Grammy looks	Student fired for hoops mistake	Obama unveils \$3.8 tril budget

1 - 4 of 14 1 2 3 4

NEWS WORLD LOCAL FINANCE

- Obama's budget would raise a host of taxes on businesses
- Haiti: American Baptists may be sent to U.S. for prosecution
- Toyota tells dealers parts to fix gas pedals are on the way
- FAA proposes \$2.5 million penalty against American Eagle

- TRENDING NOW
- | | |
|------------------------|-------------------|
| 1. Kristen Bell | 6. Roger Federer |
| 2. Rip Torn | 7. Toyota |
| 3. Black History Mo... | 8. Prince Harry |
| 4. Deadliest Catch | 9. Neil Young |
| 5. Kings Of Leon | 10. National Debt |

Download new Ovi Maps - Ad Feedback

Most emailed photos on Yahoo! News

	World's tiniest & tallest men hold hands		Comparison of da Vinci & 'Mona Lisa'
	Plane performs in desert show		Galaxy group snapped by Hubble

Routes Traffic to other Y! pages

4 slots exposed 1,2,3,4

First slot has Max exposure

Problem definition

- Display “best” articles for each user visit
- Best - Maximize User Satisfaction, Engagement
 - BUT Hard to obtain quick feedback to measure these
- Approximation
 - Maximize utility based on immediate feedback (click rate) subject to constraints (relevance, freshness, diversity)
- Inventory of articles?
 - Created by human editors
 - Small pool (30-50 articles) but refreshes periodically

Where are we today?

- Before this research : Articles created and selected for display by editors
- After this research : Article placement done through statistical models
- How successful ?

"Just look at our homepage, for example. Since we began pairing our content optimization technology with editorial expertise, we've seen click-through rates in the Today module more than double. And we're making additional improvements to this technology that will make the user experience ever more personally relevant."

----- Carol Bartz, CEO Yahoo! Inc (Q4, 2009)

We've always been focused on specific events like the Olympics – not just as short-term traffic drivers, but also as ways to draw users into the Yahoo! experience and more deeply engage with them over time. Yet we know we can't run a business just waiting for major sporting events, awards shows and natural disasters. In earlier quarters, you've heard me mention that we need to attract these types of audiences every day.

That's why we've been using our unique approach of combining human editors to choose great stories – and letting our content optimization engine determine the best content for our users. I want to talk about this content engine for a second, because it's an amazing technology that has been growing more and more advanced over the last several months.

In its first iteration, our content optimization engine recommended the most popular news items to our users. **The result was a 100% click-thru rate increase over time. In January, we introduced release 2 of the engine, which included some of our behavioral targeting technology. This capability – coupled with great content – led our Today Module to experience click-thru rates 160% over pre-engine implementation.**

----- Carol Bartz, CEO Yahoo! (Q1, 2010)

Main Goals

- Methods to select most popular articles
 - This was done by editors before
- Provide personalized article selection
 - Based on user covariates
 - Based on per user behavior
- Scalability: Methods to generalize in small traffic scenarios
 - Today module part of most Y! portals around the world
 - Also syndicated to sources like Y! Mail, Y! IM etc

Similar applications

- Goal: Use same methods for selecting most popular, personalization across different applications at Y!
- Good news! Methods generalize, already in use

The image shows two browser windows. The left window is Yahoo! Finance, displaying market data and a 'TOP STORIES' section. The right window is Yahoo! News, displaying a large article about firefighters in Los Angeles and a sidebar with other news items.

Yahoo! Finance - Business ...
http://finance.yahoo.com/
New User? Sign Up | Sign In | Help
YAHOO! FINANCE
HOME INVESTING NEWS & OPINION PERSONAL FINANCE MY PORTFOLIOS TECH TICKER
GET QUOTES Finance Search Tuesday, September 1, 2009, 1:41PM ET - U.S. M.
SCOTTRADE: \$7 Trades & Powerful Trading Tools
MARKET SUMMARY
US EUROPE ASIA
Dow 9,324.80 -171.48 -1.81%
Nasdaq 1,971.83 -37.23 -1.85%
S&P 500 1,000.98 -19.64 -1.92%
10 Yr Bond(%) 3.3570% -0.0440
Oil 69.16 -0.80 -1.14%
Gold 954.20 +2.50 +0.26%
Tue 1:30pm ET - Briefing.com
Broad-based weakness has taken the S&P 500 below the 1000 mark for the first time since August 20. Losses remain steepest among financial stocks, which are...
Brokers: E*TRADE TD AMERITRADE SCOTTRADE
CURRENCIES INVESTING

TOP STORIES
Wall Street Tumbles on Bank Failure Worries - AP
U.S. stocks sank on Tuesday on increasing worries that there could be more bank failures and concerns that equity prices may have run ahead of the economic recovery.
• Clunkers boosts Ford sales; Chrysler sales fall - AP
• Airline industry lost over \$6 billion in 1st half - AP
• July pending home sales rise to 2-year high - AP
• eBay to sell Skype stake for \$1.9B - Reuters
• Southwest Airlines reduces flights on 92 routes - AP
• Gulf Arab funds loosen purse strings - AP
• Will clunkers program kill good business? - IndieResearch
• Wall Street Chases Alternative Energy with Subsidies - Tech
Tickers
• Why Higher Oil Prices Haven't Saved the Solar Industry - Tech
Tickers
View more top stories

FOCUS ON LIFELONG INVESTING brought to you by Fidelity
The Biggest Mistake 401(k) Holders Are Making Now
The market's robust comeback has left many investors feeling overly confident about their top-performing assets.
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Yahoo! News
The top news headlines on ...
http://news.yahoo.com/...
Mexico evacuates thousands ahead of hurricane
AP - 30 mins ago
Slideshow: Tropical Storms and Hurricanes
Firefighters gain on blaze near Los Angeles
AP - 1 hr 32 mins ago
LOS ANGELES - Firefighters set backfires and removed brush with bulldozers across a huge swath of Southern California forest on Tuesday to try to contain a 190-square-mile wildfire that has destroyed 53 homes and threatened thousands more in foothill suburbs. Full Story »
Video: Fire surges toward LA, threatens thousands AP
Slideshow: Calif. Wildfires
Related: Raging wildfire menaces observatory, TV towers AP
Scotland faced no obstacles in Lockerbie decision
AP - 18 mins ago
Video: Scotland: Lockerbie decision based on 'Justice' AP
Slideshow: Dying Lockerbie bomber released from prison
World's oldest dog dies in NY at 21 - or 147
Swine flu: 10 things you need to know
Bonding with a Captor: Why Jaycee Dugard Didn't Flee
Coldest, Driest, Calmest Place on Earth Found
The AARP and Seniors: Clashing Views on Health Reform
More Most Emailed »
ADVERTISEMENT
dish NETWORK
GREAT TV AT A GREAT PRICE
LOCK IT UP.
LO... SAVINGS FOR A FULL YEAR
SPECIAL OFFER:
HBO® SHOWTIME
FREE
for 3 months
with Agreement
\$24.99/mo
Including local channels (where available) (with Agreement)
LEARN MORE »
Residential apply.
Featured
Video: 'He kept fighting'
Politico's David Rogers on Sen. Kennedy's life and legacy.
More from Politico
The Week in Photos
Candles light the words of Sen. Edward Kennedy during a vigil.

Rest of the talk

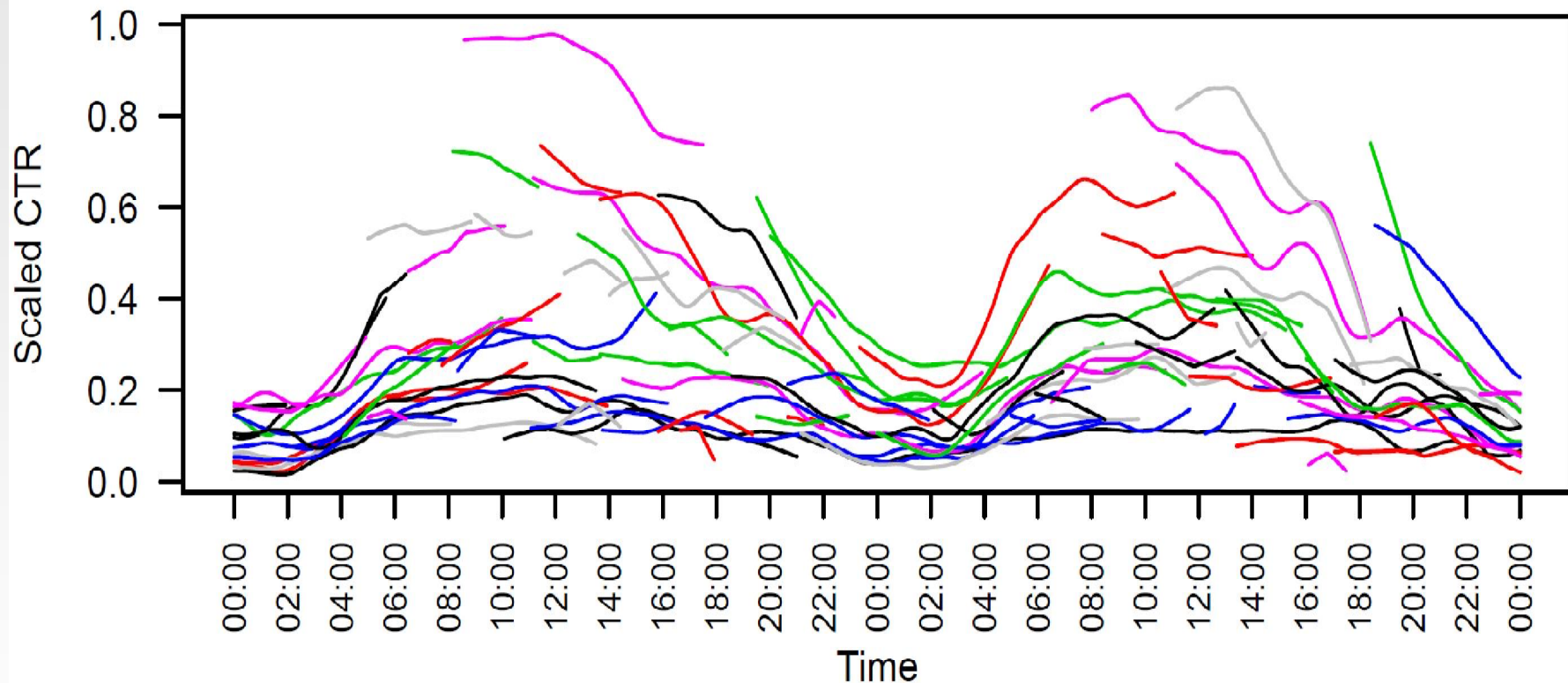
- Selecting most popular with dynamic content pool
 - Time series, multi-armed bandits
- Personalization using user covariates
 - Online logistic regression, reduced rank regression
- Personalization based on covariates and past activity
 - Matrix factorization (bilinear random-effects model)

Assumptions made in this talk

- Single slot optimization (Slot 1 with maximum exposure)
 - Multi-slot optimization with differential exposure future work
- Inventory creation and statistical models decoupled
 - Ideally, there should be a feedback loop
- Effects like user-fatigue, diversity in recommendations, multi-objective optimization not considered
 - These are important

Selecting Most Popular with Dynamic Content Pool

Article click rates over 2 days on Today module



No confounding, traffic obtained from a controlled randomized experiment

Things to note:

a) Short lifetimes b) temporal effects c) often breaking news story

Statistical Issues

- Temporal variations in article click-rates
- Short article lifetimes → quick reaction important
 - Cannot miss out on a breaking news story
 - Cold-start : rapidly learning click-rates of new articles
- Monitoring a set of curves and picking the best
 - **Set is not static**
- Approach
 - Temporal - Standard time-series model coupled with
 - Bayesian sequential design (multi-armed bandits)
 - To handle cold-start

Time series Model for a single article

- Dynamic Gamma-Poisson with multiplicative state evolution

$$c_t \mid n_t, p_t \sim \text{Poisson}(n_t p_t)$$

$$p_{t+1} = p_t \epsilon_{t+1}$$

$$\epsilon_{t+1} \sim \mathcal{D}(\text{mean} = 1, \text{var} = \eta)$$

- Click-rate distribution at time t+1

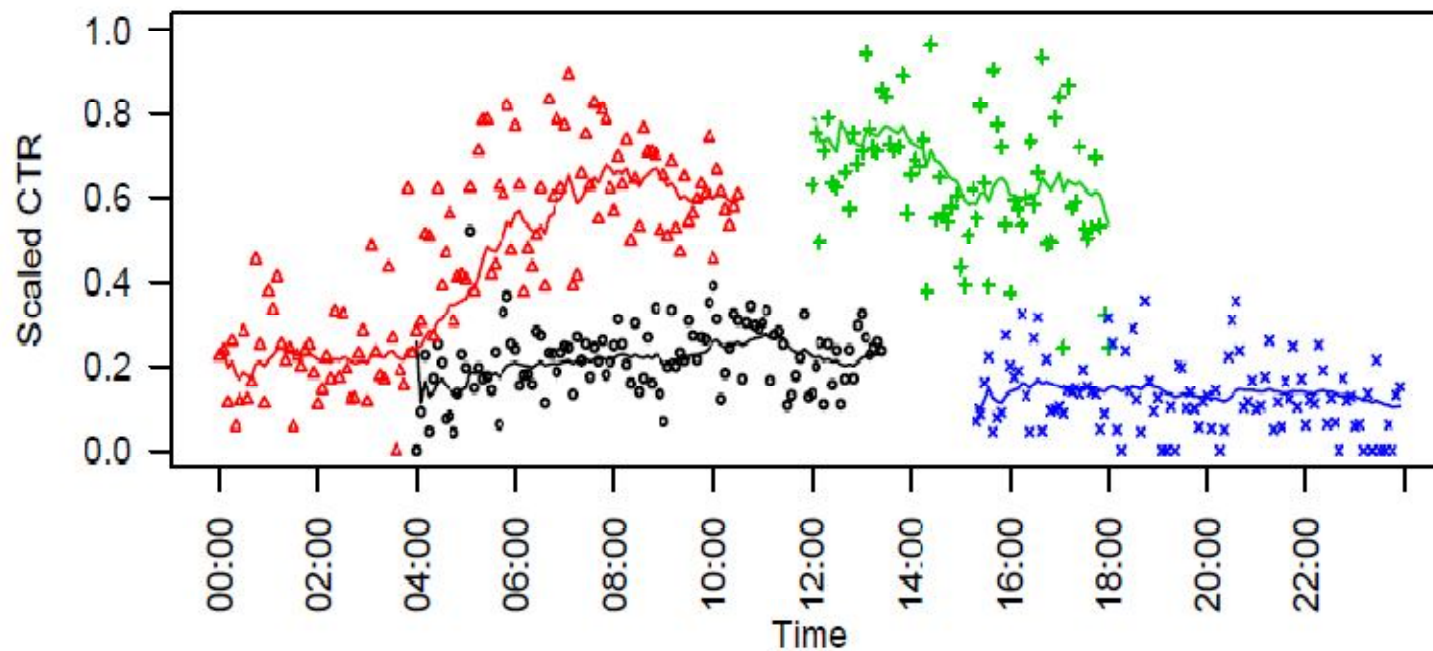
- Prior mean: $E(p_{t+1} \mid D_t) = \hat{p}_{t|t}$

- Prior variance: $Var(p_{t+1} \mid D_t) = \hat{\sigma}_{t|t}^2 + \eta(\hat{p}_{t|t}^2 + \hat{\sigma}_{t|t}^2)$

High CTR items more adaptive

Tracking behavior of Gamma-Poisson model

- Low click rate articles – More temporal smoothing



Explore/exploit for cold-start

- New articles (or articles with high variance) with low mean
- How to learn without incurring high cost
- Slow reaction:
 - can be bad if article is good
- Too aggressive:
 - may end up showing bad articles for a lot of visits
- What is the optimal trade-off?
 - Article 1: CTR = 2/100; Article 2: CTR = 25/1000
 - Best explore/exploit strategy
 - Look ahead in the future before making a decision
 - Bandit problem

Cold-start: Bayesian scheme, 2 intervals, 2 articles

- 2 interval look-ahead : # visits N_0, N_1
- Article 1 prior CTR $p_0 \sim \text{Gamma}(\alpha, \gamma)$
 - Article 2: CTR q_0 and q_1 , $\text{Var}(q_0) = \text{Var}(q_1) = 0$
- Design parameter: x (fraction of visits allocated to article 1)
- Let $c | p_0 \sim \text{Poisson}(p_0(xN_0))$: clicks on article 1, interval 0.
- Prior gets updated to posterior: $\text{Gamma}(\alpha+c, \gamma+xN_0)$
- Allocate visits to better article in interval 2
 - i.e. to item 1 iff post mean item 1 = $E[p_1 | c, x] > q_1$

Optimization

- Expected total number of clicks

$$N_0(x\hat{p}_0 + (1-x)q_0) + N_1E_{c|x}[\max\{\hat{p}_1(x,c), q_1\}]$$
$$= N_0q_0 + N_1q_1 + N_0x(\hat{p}_0 - q_0) + N_1E_{c|x}[\max\{\hat{p}_1(x,c) - q_1, 0\}]$$

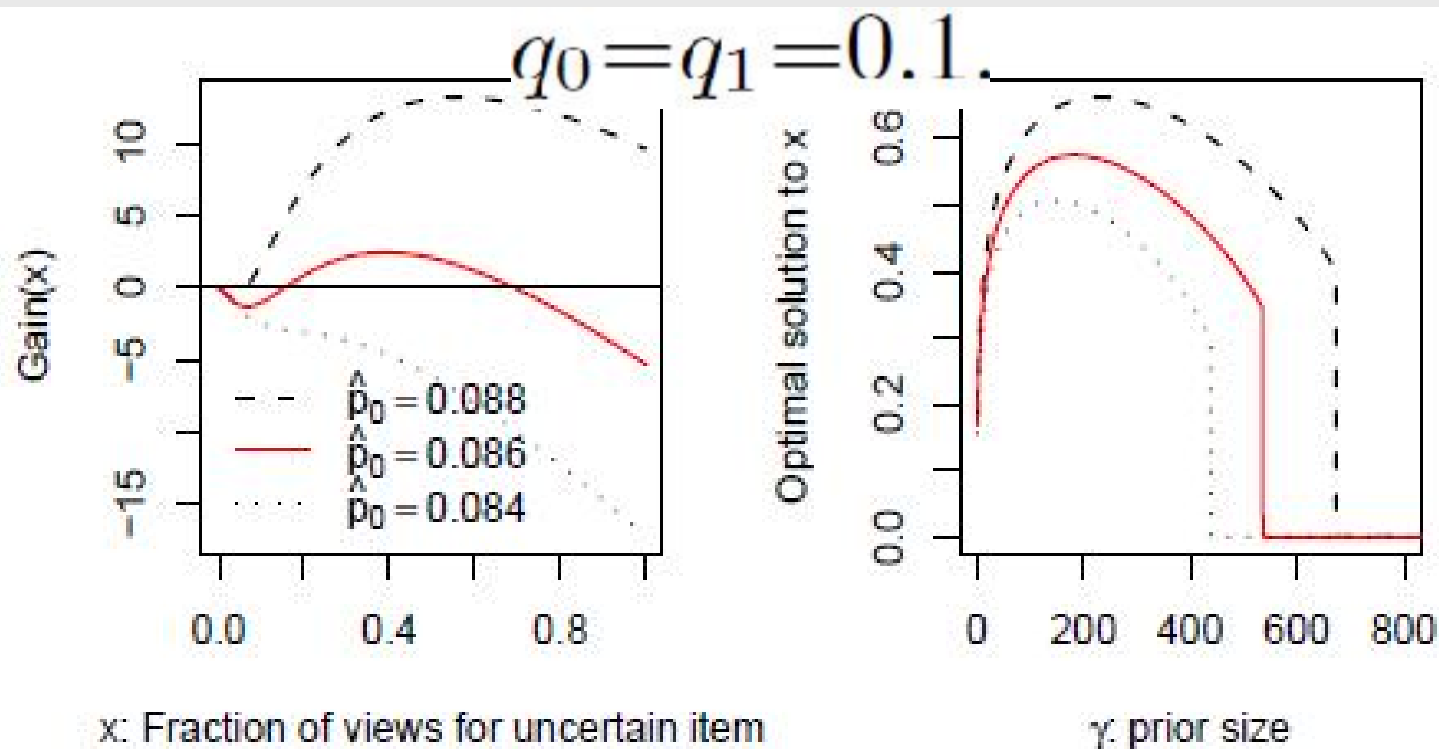
The diagram shows two curly braces under the equation above. The first brace is under the first two terms of the second equation, $N_0q_0 + N_1q_1$. The second brace is under the last two terms, $N_0x(\hat{p}_0 - q_0) + N_1E_{c|x}[\max\{\hat{p}_1(x,c) - q_1, 0\}]$.

$E[\#\text{clicks}]$ if we always show the certain item

$\text{Gain}(x, q_0, q_1)$
Gain from experimentation

$$x_{\text{opt}} = \operatorname{argmax}_x \text{Gain}(x, q_0, q_1)$$

Example for Gain function



(a) Gain function

(b) Optimal solution

Generalization to K articles

- Objective function

$$R(\mathbf{x}, \boldsymbol{\theta}_0, N_0, N_1) = N_0 \sum_i x_{i0} \mu(\boldsymbol{\theta}_{i0}) + N_1 \sum_i E_{\boldsymbol{\theta}_1} [x_{i1}(\boldsymbol{\theta}_1) \mu(\boldsymbol{\theta}_{i1})].$$

Our goal is to find

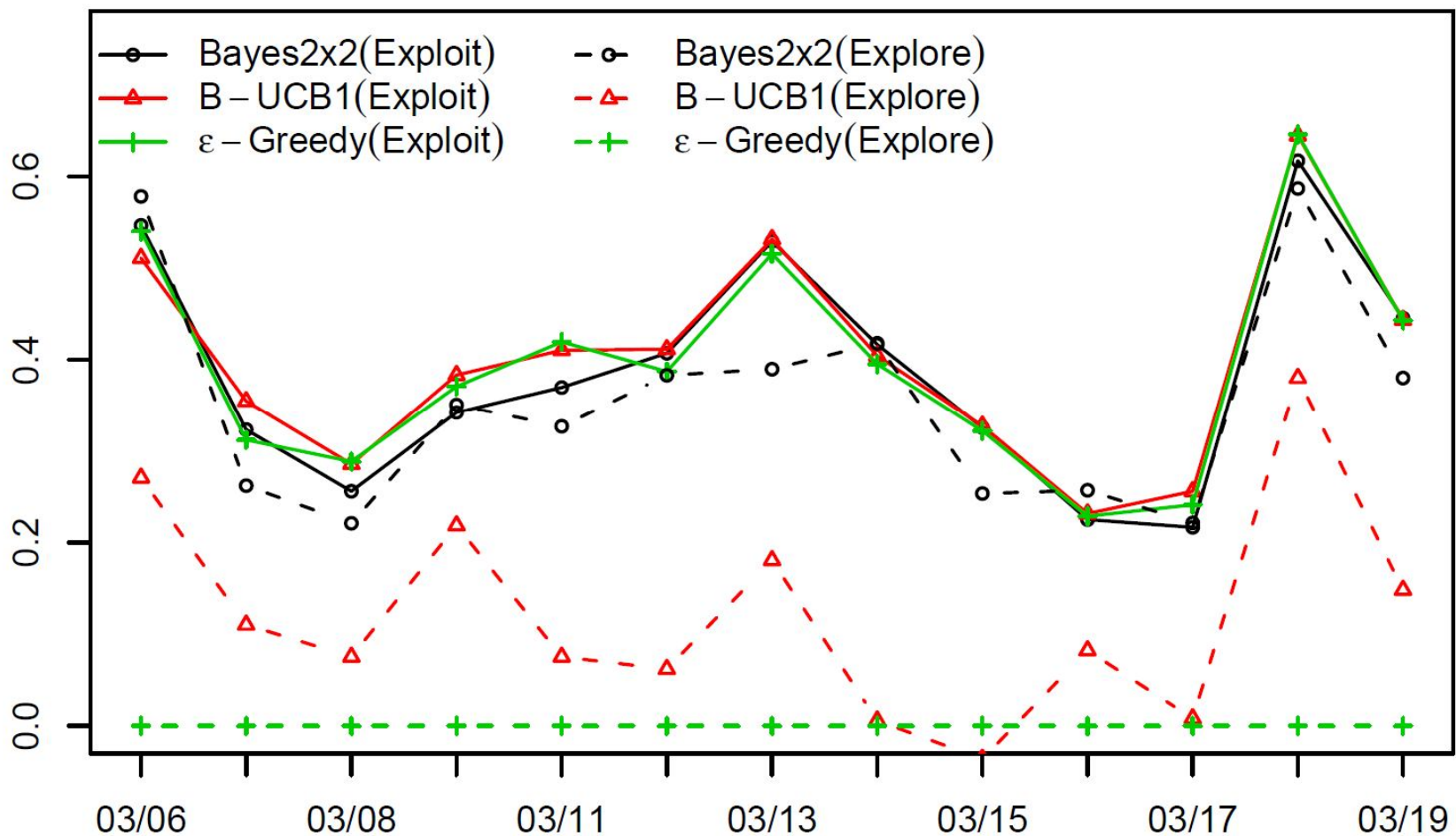
$$R^*(\boldsymbol{\theta}_0, N_0, N_1) = \max_{0 \leq \mathbf{x} \leq 1} R(\mathbf{x}, \boldsymbol{\theta}_0, N_0, N_1), \text{ subject to } \sum_i x_{i0} = 1 \text{ and } \sum_i x_{i1}(\boldsymbol{\theta}_1) = 1, \text{ for all possible } \boldsymbol{\theta}_1.$$

- Lagrange relaxation (Whittle)

$$R^+(\boldsymbol{\theta}_0, N_0, N_1) = \max_{0 \leq \mathbf{x} \leq 1} R(\mathbf{x}, \boldsymbol{\theta}_0, N_0, N_1),$$
$$\sum_i x_{i0} = 1 \text{ and } E_{\boldsymbol{\theta}_1} [\sum_i x_{i1}(\boldsymbol{\theta}_1)] = 1.$$

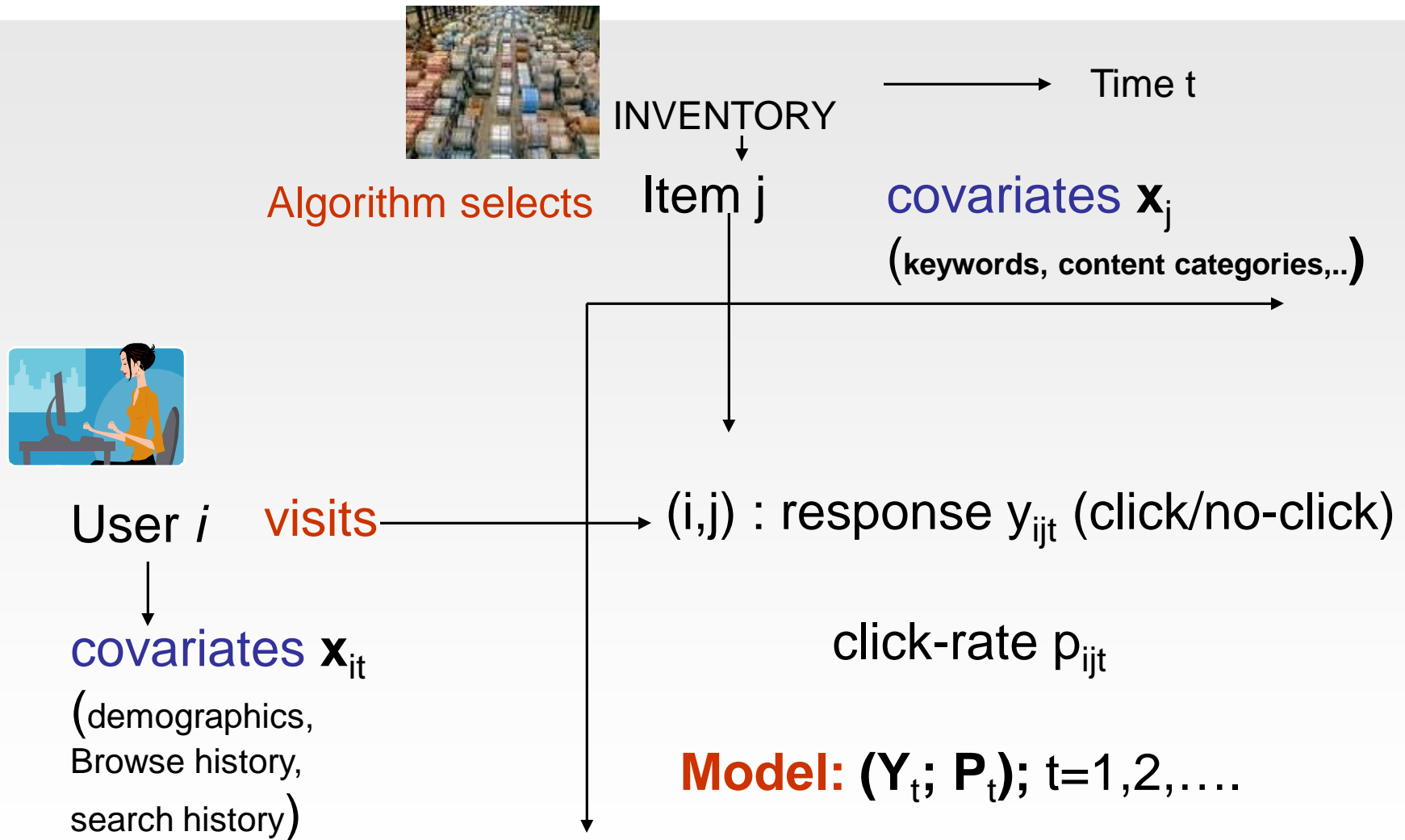
Test on Live Traffic

15% explore (samples to find the best article);
85% serve the “estimated” best (false convergence)



Covariate based personalization

DATA



Natural model: Logistic regression

- Estimating (user, item) interactions for a large, unbalanced and massively incomplete 2-way binary response matrix
- Natural (simple) statistical model

$$y_{ijt} \sim \text{Bernoulli}(p_{ijt})$$

$$s_{ijt} = \log \frac{p_{ijt}}{1-p_{ijt}}$$

$$s_{ijt} = \mathbf{x}'_{it} \mathbf{A} \mathbf{x}_j + \mathbf{x}'_{it} \mathbf{v}_{jt}$$

Item coefficients

High dimensional random-effects
In our examples, dimension ~ 1000

- Per-item online model
 - **must estimate quickly for new items**

Connection to Reduced Rank Regression (Anderson, 1951)

- $N \times p$ response matrix ($p = \text{\#items}$, $N = \text{\#users}$)
- Each row has a covariate vector \mathbf{x}_i (user covariates)
- p regressions, each of dim q : $(\mathbf{x}_i' \mathbf{v}_1, \mathbf{x}_i' \mathbf{v}_2, \dots, \mathbf{x}_i' \mathbf{v}_p)$
 - $\mathbf{V}_{q \times p}$: too many parameters
 - Reduced rank: $\mathbf{V}^T = \mathbf{B}_{p \times r} \mathbf{\Theta}_{r \times q}$ ($r \ll q$; rank reduction)
- Generalization to categorical data
 - Took some time, happened in around '00 (Hastie et al)
- Difference
 - Response matrix highly incomplete
 - Goal to expedite sequential learning for new items

Reduced Rank for our new article problem

- Generalize reduced rank for large incomplete matrix

$$s_{ijt} = \mathbf{x}'_{it} \mathbf{A} \mathbf{x}_j + \mathbf{x}'_{it} \mathbf{B} \boldsymbol{\theta}_j$$

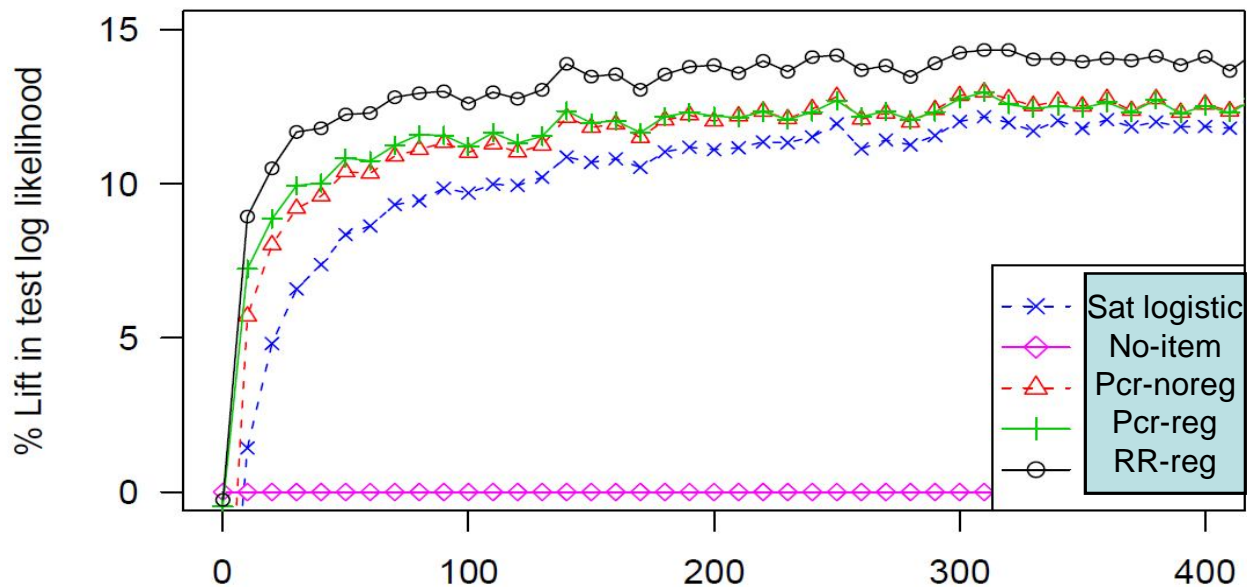
Low dimension (5-10),
 \mathbf{B} estimated retrospective data

- Application different than in classical reduced rank literature
 - Cold-start problem in recommender problems

Experiment

- Front Page Today module data ~ 1000 user covariates (age, gender, geo, browse behavior)
- Reduced rank trained on historic data to get B of ranks 1,2,...,10
- For out-of-sample predictions, items all new
- Model selection for each item done based on predictive log-likelihood
- We report performance in terms of out-of-sample log-likelihood
- Baseline methods we compare against
 - *Sat-logistic* : online logistic per item with ~1000 parameters
 - *No-item*: regression based only on item features
 - *Pcr-reg*; *Pcr-noreg*: principal components used to estimate B
 - *RR-reg*: reduced rank procedure

Results for Online Reduced Rank regression



- Summary:

- Reduced rank regression significantly improves performance compared to other baseline methods

- *Sat-logistic* : online logistic per item with ~1000 parameters
- *No-item*: regression based only on item features
- *Pcr-reg*; *Pcr-noreg*: principal components used to estimate B
- *RR-reg*: reduced rank procedure

**Per user, per item models
via bilinear random-effects model**

Factorization – Brief Overview

- Latent user factors: $(\alpha_i, \mathbf{u}_i = (u_{i1}, \dots, u_{ir}))$
- Latent movie factors: $(\beta_j, \mathbf{v}_j = (v_{j1}, \dots, v_{jr}))$

Interaction

$$\alpha_i + \beta_j + u'_i v_j$$

- $(N + M)(r+1)$ parameters \longrightarrow will overfit for moderate values of r
- Key technical issue: \longrightarrow *Regularization*
- Usual approach: \longrightarrow Gaussian ZeroMean prior

Existing Zero-Mean Factorization Model

Observation
Equation

$$y_{ij} \sim N(m_{ij}, \sigma^2)$$



$$x'_{ij} \mathbf{b} + \alpha_i + \beta_j + u'_i v_j$$

State
Equation

$$\alpha_i \sim N(0, a_\alpha)$$

$$\beta_j \sim N(0, a_\beta)$$

$$u_i \sim MVN(\mathbf{0}, A_u)$$

$$v_j \sim MVN(\mathbf{0}, A_v)$$

Predict for new dyad: $(x_{ij}^{new})' \hat{\mathbf{b}} + \hat{\alpha}_i + \hat{\beta}_j + \hat{u}'_i \hat{v}_j$

Regression-based Factorization Model (RLFM)

- Main idea: Flexible prior, predict factors through regressions
- Seamlessly handles cold-start and warm-start
- Modified state equation to incorporate covariates

$$\begin{aligned}\alpha_i &= g'_0 w_i + \epsilon_i^\alpha, & \epsilon_i^\alpha &\sim N(\mathbf{0}, a_\alpha) \\ \beta_j &= d'_0 z_j + \epsilon_j^\beta, & \epsilon_j^\beta &\sim N(\mathbf{0}, a_\beta) \\ u_i &= G w_i + \epsilon_i^u, & \epsilon_i^u &\sim MVN(\mathbf{0}, A_u) \\ v_j &= D z_j + \epsilon_j^v, & \epsilon_j^v &\sim MVN(\mathbf{0}, A_v)\end{aligned}$$

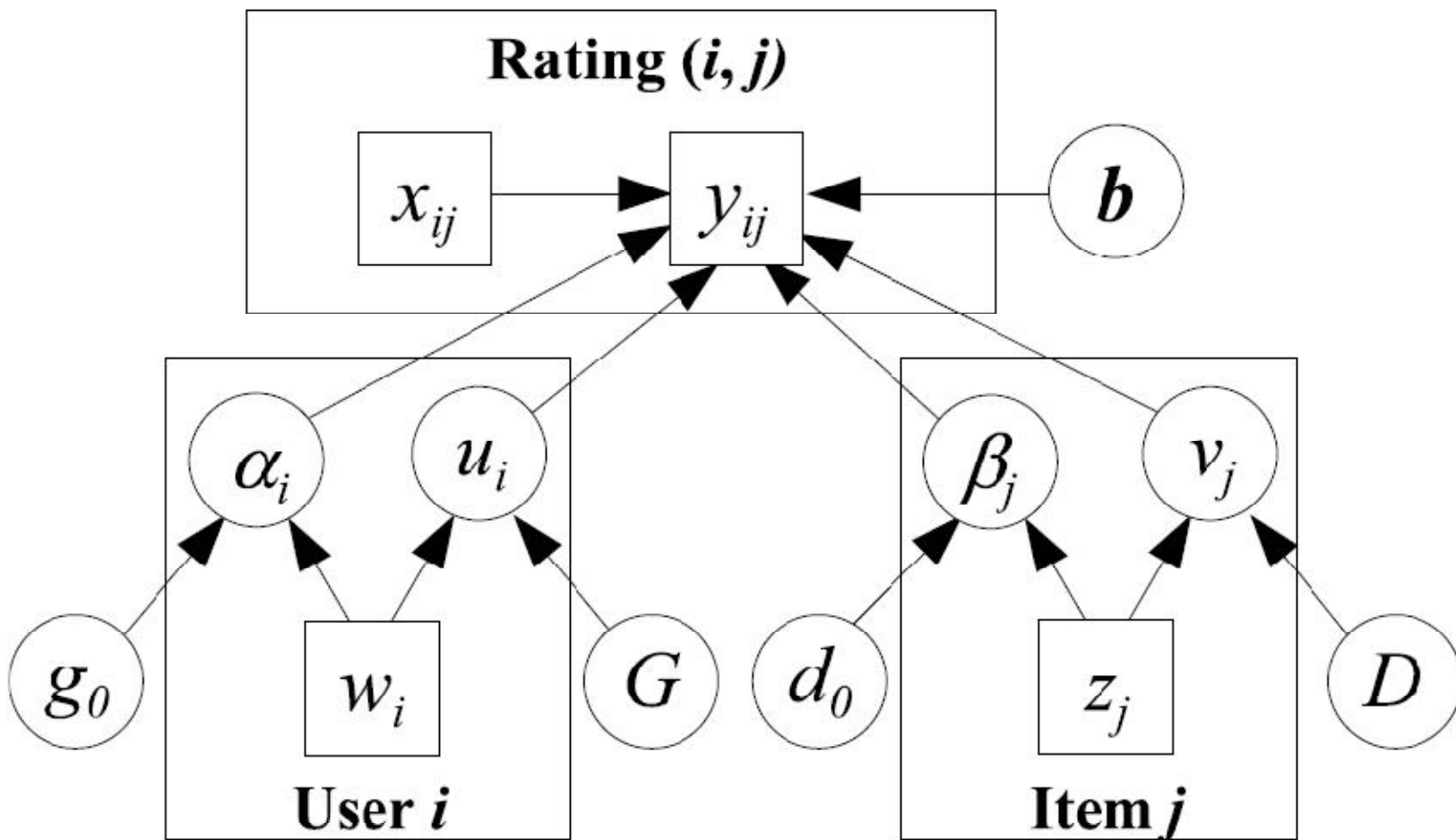
Advantages of RLFM

- Better regularization of factors
 - Covariates “shrink” towards a better centroid
- Cold-start: Fallback regression model (**Covariate Only**)

$$y_{ij} \sim N(m_{ij}, \sigma^2)$$

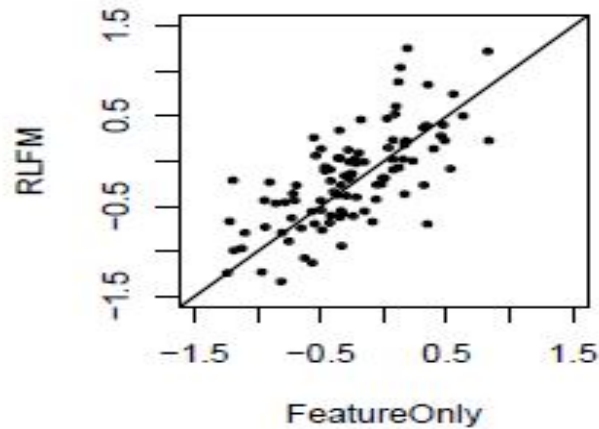
$$m_{ij} = x'_{ij} \mathbf{b} + g'_0 w_i + d'_0 z_j + w'_i G' D z_j$$

Graphical representation of the model

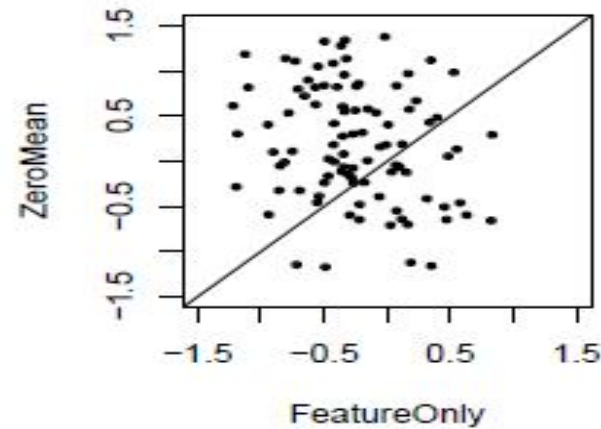


Advantages of RLFM illustrated on Yahoo! FP data

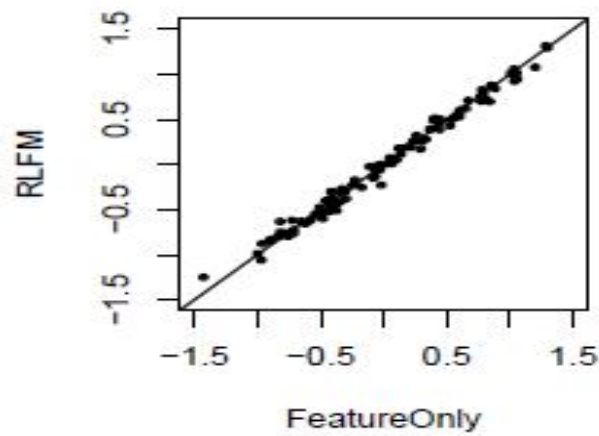
Only the first user factor plotted in the comparisons



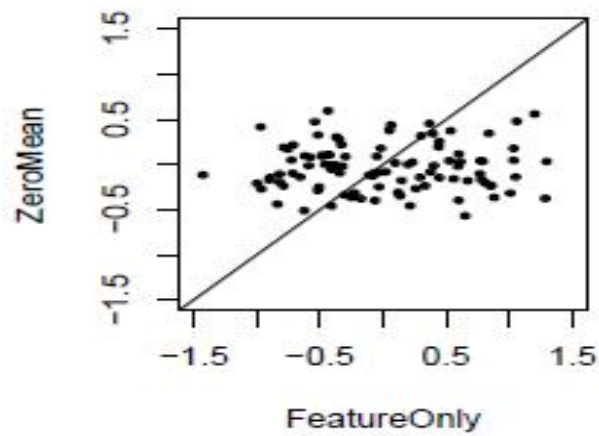
(a) RLFM for heavy users



(b) ZeroMean for heavy users



(c) RLFM for light users



(d) ZeroMean for light users

Closer look at induced marginal correlations for gaussian

$$E(y_{ij}) = x'_{ij} \mathbf{b} + g'_0 w_i + d'_0 z_j + w'_i G' D z_j$$

$$\begin{aligned} \text{Var}(y_{ij}) = \sigma^2 + a_\alpha + a_\beta + \text{tr}(A_u A_v) + \\ z'_j D' A_u D z_j + w'_i G' A_v G w_i \end{aligned}$$

$$\text{cov}(y_{ij}, y_{ij}^*) = a_\alpha + z'_j D' A_u D z_{j^*}$$

$$\text{cov}(y_{ij}, y_{i^*j}) = a_\beta + w'_i G' A_v G w_{i^*}$$

Model Fitting

- Challenging, multi-modal posterior
- Monte-Carlo EM (MCEM)
 - E-step: Sample factors through Gibbs sampling
 - M-step: Estimate regressions through off-the-shelf linear regression routines using sampled factors as response
 - We used t-regression, others like LASSO could be used
- Iterated Conditional Mode (ICM)
 - Replace E-step by CG : conditional modes of factors
 - M-step: Estimate regressions using the modes as response
- Incorporating uncertainty in factor estimates in MCEM helps

Latent dimension r	2	5	10	15
ICM	.9736	.9729	.9799	.9802
MCEM	.9728	.9722	.9714	.9715

Monte Carlo E-step

- Through a vanilla Gibbs sampler (conditionals closed form)

$$\text{Let } o_{ij} = y_{ij} - \alpha_i - \beta_j - x'_{ij} \mathbf{b}$$

$$\text{Var}[u_i | \text{Rest}] = (A_u^{-1} + \sum_{j \in \mathcal{J}_i} \frac{v_j v'_j}{\sigma_{ij}^2})^{-1}$$

$$E[u_i | \text{Rest}] = \text{Var}[u_i | \text{Rest}] (A_u^{-1} G w_i + \sum_{j \in \mathcal{J}_i} \frac{o_{ij} v_j}{\sigma_{ij}^2})$$

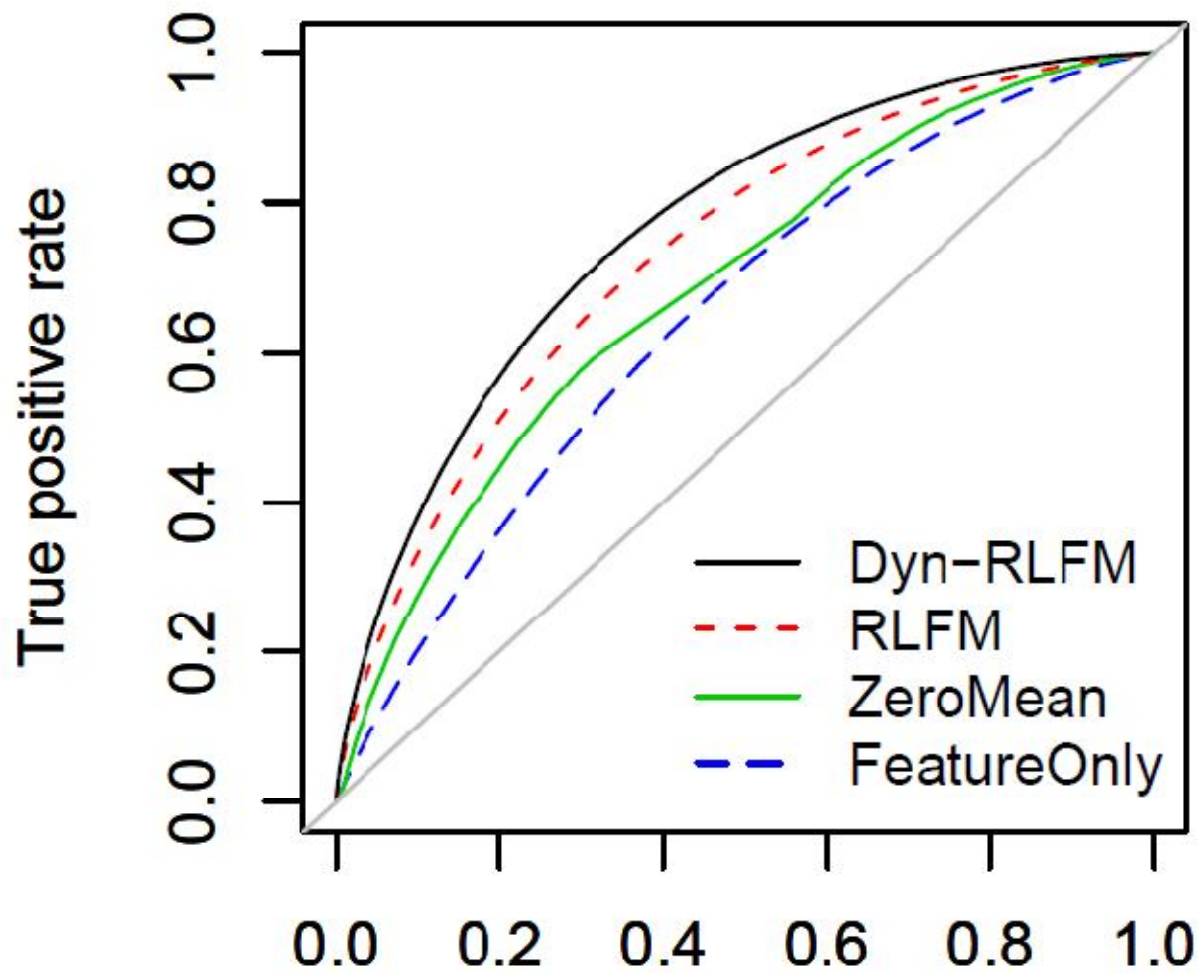
- Other conditionals also Gaussian and closed form
- Conditionals of users (movies) sampled simultaneously
- Small number of samples in early iterations, large numbers in later iterations

Experiment 2: Better handling of Cold-start

- MovieLens-1M; EachMovie
- Training-test split based on timestamp
- Covariates: age, gender, zip1, genre

Model	MovieLens-1M			EachMovie		
	30%	60%	75%	30%	60%	75%
<i>RLFM</i>	0.9742	0.9528	0.9363	1.281	1.214	1.193
<i>ZeroMean</i>	0.9862	0.9614	0.9422	1.260	1.217	1.197
<i>FeatureOnly</i>	1.0923	1.0914	1.0906	1.277	1.272	1.266
<i>FilterBot</i>	0.9821	0.9648	0.9517	1.300	1.225	1.199
<i>MostPopular</i>	0.9831	0.9744	0.9726	1.300	1.227	1.205
<i>Constant Model</i>	1.118	1.123	1.119	1.306	1.302	1.298

Results on Y! FP data



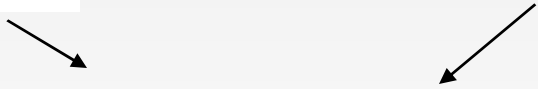
Online Updates through regression

- Update u 's and v 's through online regression
- Generalize reduced rank idea

$$s_{ijt} = (G_{p1 \times r1} \mathbf{x}_{it} + \epsilon_i^u)' B_{r1 \times r2} (D_{p2 \times r2} \mathbf{x}_j + \epsilon_{jt}^v)$$

$$u_{it} = G \mathbf{x}_{it} + \epsilon_i^u$$

$$v_{jt} = D \mathbf{x}_j + \epsilon_{jt}^v$$

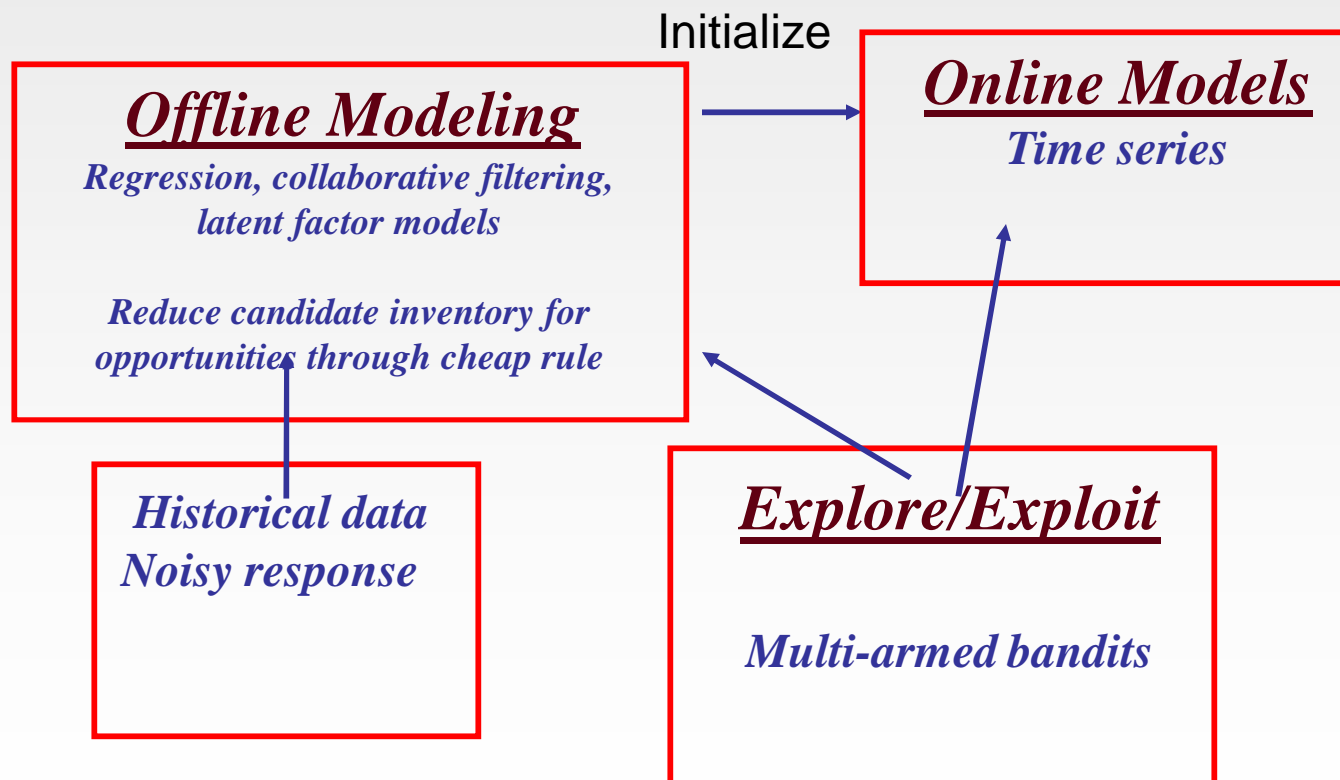

$$s_{ijt} = u_{it}' B v_{jt}$$

- Our observations so far : Reduced rank does not improve much if factor regressions are based on good covariates
- Online updates help significantly : (In movie-lens; reduced RMSE from .93 to .86)

Summary

- Simple statistical models coupled with fast sequential learning in near-real time effective for web applications
- Matrix factorization provides state-of-the-art recommendation algorithms with
 - Generalization to include covariates
 - Reduced dimension to facilitate fast sequential learning

Summary: Overall statistical methodology



What we did not cover today

- Multi-slot optimization (for a fixed slot design)
 - Correlated response
 - Differential exposure (how to adjust for these statistically?)
 - E.g. good articles shown on high exposure slots, how to adjust for this bias to obtain intrinsic quality score

To Conclude

- Rich set of statistical problems key to web recommender systems; require both mean and uncertainty estimates
- Scale, high dimensionality and noisy data challenges
- Good news:
 - Statisticians can design experiments to collect data
 - If these problems excite you, Y! one of the best places
 - Rich set of applications, large and global traffic.
 - (Y! front page is the most visited content page on the planet)