Evaluation Methods and Challenges

Evaluation Methods

- Ideal method
  - Experimental Design: Run side-by-side experiments on a small fraction of **randomly** selected traffic with new method (treatment) and status quo (control)
  - Limitation
    - Often expensive and difficult to test large number of methods

- Problem: How do we evaluate methods offline on logged data?
  - Goal: To maximize clicks/revenue and not prediction accuracy on the entire system. Cost of predictive inaccuracy for different instances vary.
    - E.g. 100% error on a low CTR article may not matter much because it always co-occurs with a high CTR article that is predicted accurately

Usual Metrics

- Predictive accuracy
  - Root Mean Squared Error (RMSE)
  - Mean Absolute Error (MAE)
  - Area under the Curve, ROC
- Other rank based measures based on retrieval accuracy for top-k
  - Recall in test data
    - What Fraction of items that user actually liked in the test data were among the top-k recommended by the algorithm (fraction of hits, e.g. Karypsis, CIKM 2001)
- One flaw in several papers
  - Training and test split are not based on time.
    - Information leakage
    - Even in Netflix, this is the case to some extent
      - Time split per user, not per event. For instance, information may leak if models are based on user-user similarity.

Metrics continued..

- Recall per event based on Replay-Match method
  – Fraction of clicked events where the top recommended item matches the clicked one.

- This is good if logged data collected from a randomized serving scheme, with biased data this could be a problem
  – We will be inventing algorithms that provide recommendations that are similar to the current one
    - No reward for novel recommendations

Details on Replay-Match method (Li, Langford, et al)

- x: feature vector for a visit
- **r** $= [r_1, r_2, \ldots, r_K]$: reward vector for the K items in inventory
- h(x): recommendation algorithm to be evaluated
- Goal: Estimate expected reward for h(x)

$$E_{(x,r)\sim\mathcal{P}}\left[\sum_i \Pr(h(x)=i)\cdot r_i\right]$$

- s(x): recommendation scheme that generated logged-data
- $x_1,..,x_T$: visits in the logged data
- r_{ti}: reward for visit t, where i = $s(x_t)$

Replay-Match continued

- Estimator

$$\frac{1}{T}\sum_t \sum_i I(h(x_t) = i \text{ and } s(x_t) = i) \cdot r_{ti} \cdot \alpha_t$$

- If importance weights $\alpha_t = \frac{1}{\Pr(s(x_t) = i \mid h(x_t) = i)}$ and (x_t, r_t) iid $\sim \mathcal{P}$.
  - It can be shown estimator is unbiased

- E.g. if s(x) is random serving scheme, importance weights are uniform over the item set
- If s(x) is not random, importance weights have to be estimated through a model

Back to Multi-Objective Optimization

Recommender + EDITORIAL

content

- Clicks on FP links influence downstream supply distribution

SPORTS

NEWS

OMG

FINANCE

AD SERVER

PREMIUM display (GUARANTEED)

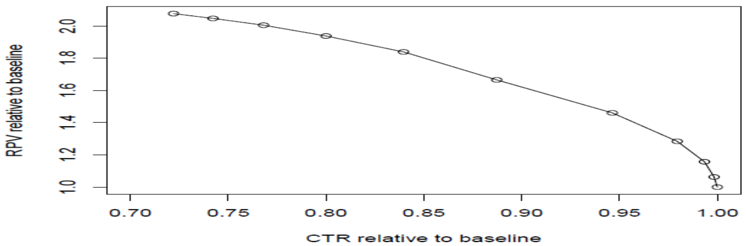
Spot Market (Cheaper)

Downstream engagement

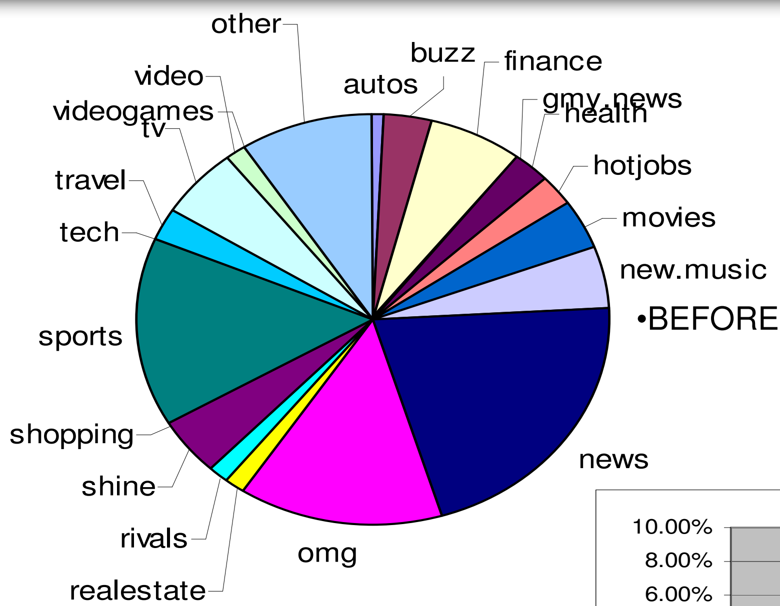
(Time spent)

Serving Content on Front Page: Click Shaping

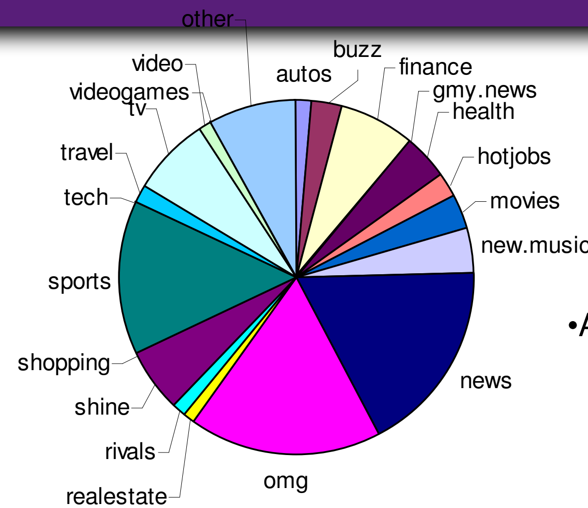
- What do we want to optimize?
- Current: Maximize clicks (maximize downstream supply from FP)
- But consider the following
  - Article 1: CTR=5%, utility per click = 5
  - Article 2: CTR=4.9%, utility per click=10
    - By promoting 2, we lose 1 click/100 visits, gain 5 utils
- If we do this for a large number of visits --- lose some clicks but obtain significant gains in utility?
  - E.g. lose 5% relative CTR, gain 40% in utility (revenue, engagement, etc)



Why call it Click Shaping?

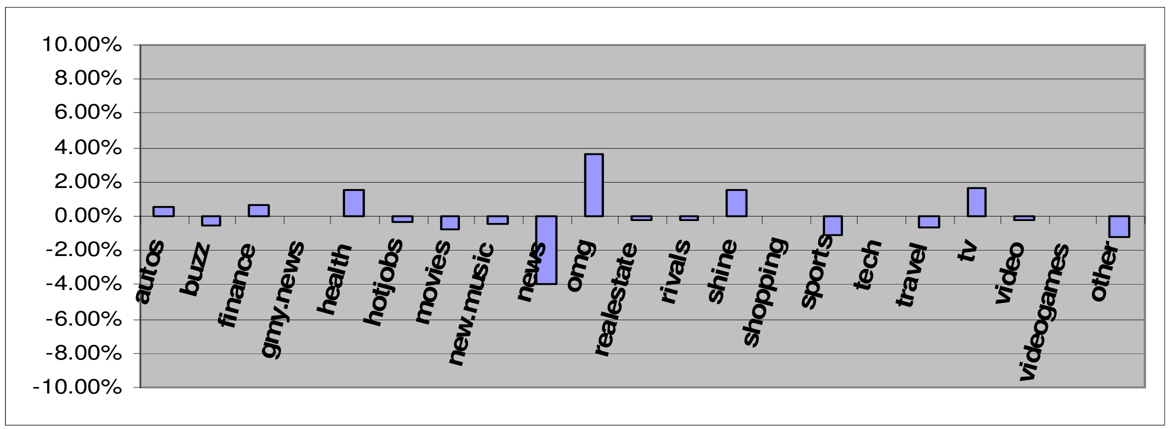


•BEFORE



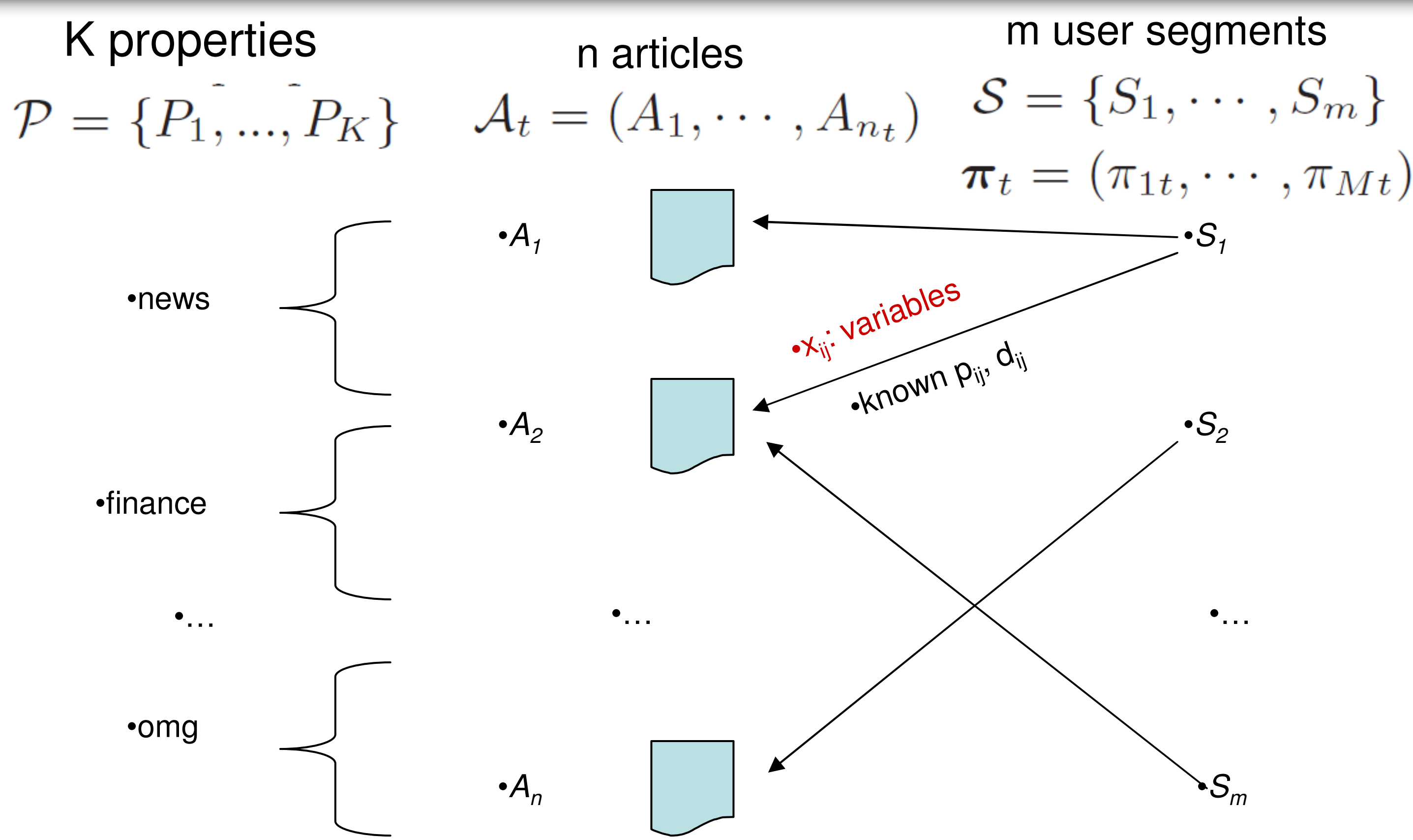
•AFTER

•Supply distribution
•Changes



•SHAPING can happen with respect to any downstream metrics (like engagement)

Multi-Objective Optimization



- CTR of user segment *i* on article *j*: p_{ij}
- Time duration of *i* on *j*: d_{ij}

Multi-Objective Program

- Scalarization

$$\lambda \cdot TotalClicks(\mathbf{x}) + (1-\lambda) \cdot Downstream(\mathbf{x})$$

$$x_{ij} = \begin{cases} 1, & \text{if } j = \arg\max_J \lambda \cdot p_{iJ} + (1-\lambda) \cdot p_{iJ} d_{iJ} \\ 0, & \text{otherwise} \end{cases}$$

Goal Programming

$$\begin{aligned} \text{maximize } & Downstream(\mathbf{x}) \\ \text{s.t. } & TotalClicks(\mathbf{x}) \geq \alpha \cdot TotalClicks^* \end{aligned}$$

Simplex constraints on x_{iJ} is always applied

Constraints are linear

Every 10 mins, solve x

Use this x as the serving scheme in the next 10 mins

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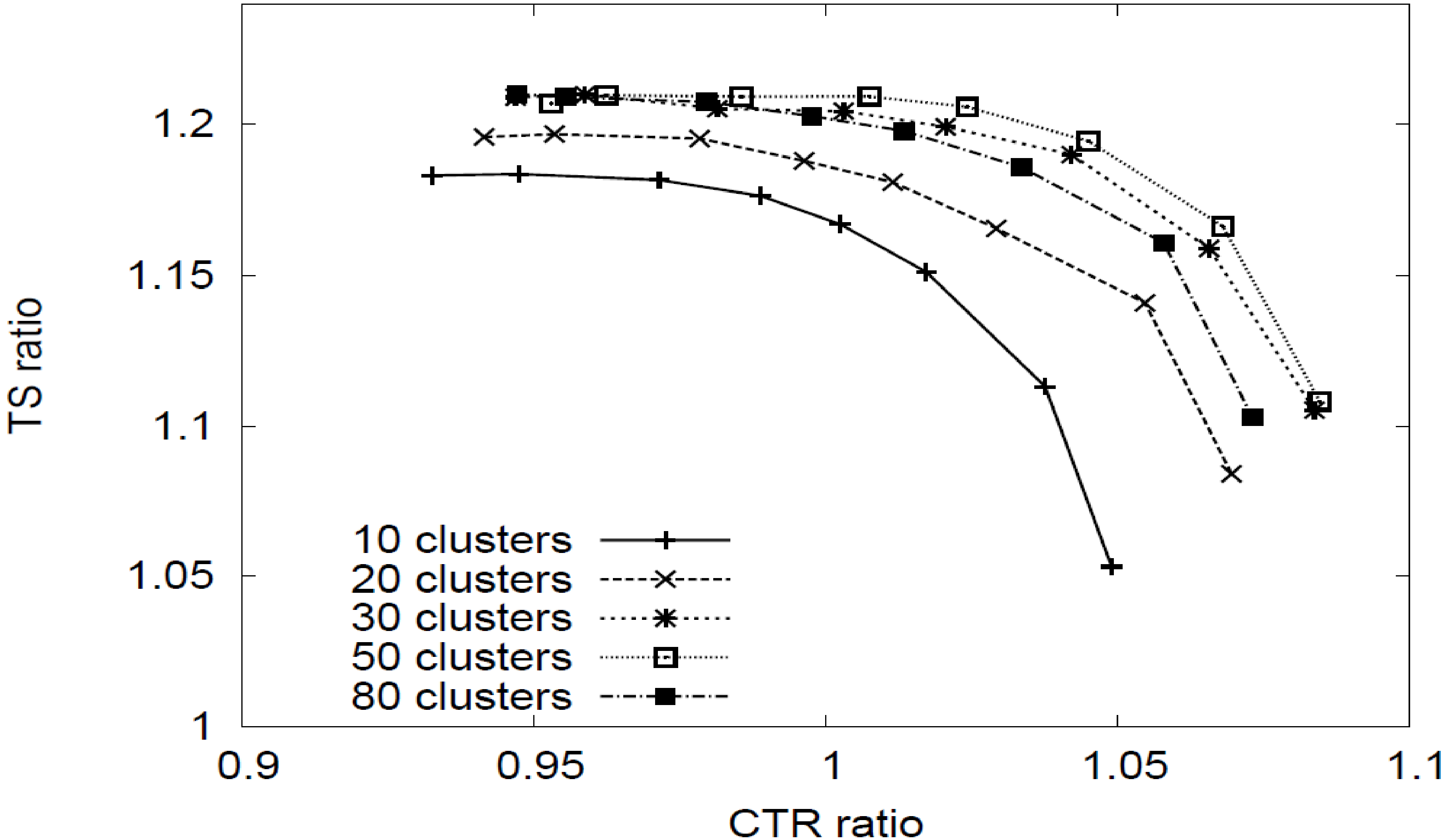
Pareto-optimal solution (more in KDD 2011)



Summary

- Modern recommendation systems on the web crucially depend on extracting intelligence from massive amounts of data collected on a routine basis
- Lots of data and processing power not enough, the number of things we need to learn grows with data size
- Extracting grouping structures at coarser resolutions based on similarity (correlations) is important
  - ML has a big role to play here
- Continuous and adaptive experimentation in a judicious manner crucial to maximize performance
  - Again, ML has a big role to play
- Multi-objective optimization is often required, the objectives are application dependent.
  - ML has to work in close collaboration with engineering, product & business execs

Challenges

Recall: Some examples

- Simple version
  - I have an important module on my page, content inventory is obtained from a third party source which is further refined through editorial oversight. Can I algorithmically recommend content on this module? I want to drive up total CTR on this module
- More advanced
  - I got X% lift in CTR. But I have additional information on other downstream utilities (e.g. dwell time). Can I increase downstream utility without losing too many clicks?
- Highly advanced
  - There are multiple modules running on my website. How do I take a holistic approach and perform a simultaneous optimization?

For the simple version

- Multi-position optimization
  - Explore/exploit, optimal subset selection
- Explore/Exploit strategies for large content pool and high dimensional problems
  - Some work on hierarchical bandits but more needs to be done
- Constructing user profiles from multiple sources with less than full coverage
  - Couple of papers at KDD 2011
- Content understanding
- Metrics to measure user engagement (other than CTR)

Other problems

- Whole page optimization
  - Incorporating correlations
- Incentivizing User generated content
- Incorporating Social information for better recommendation
- Multi-context Learning