Agenda

• Focus:
  – Recommender problems for dynamic, time-sensitive applications
  • Content Optimization

• Introduction (20 min, Deepak)
  – Content optimization, match-making, example applications

• Offline components (40 min, Deepak)
  – Collaborative filtering (CF), methods for cold-start

• Online components + initialization (70 min, Bee-Chung)
  – Time-series, online/incremental methods, explore/exploit (bandit)

• Evaluation methods (15 min, Deepak)

• Challenges (5 min, Deepak)
Content Optimization

• Goal
  – Effectively and “pro-actively” learn from user interactions with content that are displayed to maximize our objectives.

• A new scientific discipline at the interface of
  – Large scale Machine Learning & Statistics
    • Offline Models
    • Online Models
    • Collaborative Filtering
    • Explore/Exploit
  – Multi-Objective Optimization in the presence of Uncertainty
    • Click-rates (CTR), Engagement,….
  – User Understanding
    • Profile construction
  – Content Understanding
    • Topics, “aboutness”, entities, follow-up of something, breaking news,…
Content Optimization: High level flowchart

• Flow
  – Understand content (Offline)
  – Serve content to optimize our objectives (Online)
  – quickly learn from feedback obtained using ML/Statistics (Offline + Online)
  – Constantly enhance our content inventory to improve future performance (Offline)
  – Constantly enhance our user understanding to improve future performance (Offline + Online)
  – Iterate
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?
Recommend applications

Recommend search queries

Recommend packages:
Image
Title, summary
Links to other pages

Pick 4 out of a pool of $K$
$K = 20 \sim 40$
Dynamic

Routes traffic other pages

Recommend news article
Problems in this example

• Optimize CTR on different modules together in a holistic way
  – Today Module, Trending Now, Personal Assistant, News, Ads
  – Treat them as independent?

• For a given module
  – Optimize some combination of CTR, downstream engagement and perhaps revenue.
Single module CTR optimization problem

• 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
Recommendation: A Match-making Problem

- Recommendation problems
- Search: Web, Vertical
- Online advertising
- ...

Opportunity
Users, queries, pages, ...

Item Inventory
Articles, web page, ads, ...

Use an automated algorithm to select item(s) to show

Get feedback (click, time spent,..)
Refine the models

Repeat (large number of times)
Measure metric(s) of interest
(Total clicks, Total revenue,..)
Important Factors affecting solution in Match-making Problems

- **Items**: Articles, web pages, ads, modules, queries, users, updates, etc.

- **Opportunities**: Users, query keywords, pages, etc.

- **Metric** (e.g., editorial score, CTR, revenue, engagement)
  - Currently, most applications are single-objective
  - May be multi-objective optimization (maximize $X$ subject to $Y$, $Z$,..)

- **Properties of the item pool**
  - Size (e.g., all web pages vs. 40 stories)
  - Quality of the pool (e.g., anything vs. editorially selected)
  - Lifetime (e.g., mostly old items vs. mostly new items)
Factors affecting Solution continued

- **Properties of the opportunities**
  - **Pull**: Specified by explicit, user-driven query (e.g., keywords, a form)
  - **Push**: Specified by implicit context (e.g., a page, a user, a session)
  - **Size** (e.g., user base); **continuity** (e.g., session vs. single event)

- **Properties of the feedback on the matches made**
  - **Types and semantics of feedback** (e.g., click, vote)
  - **Latency** (e.g., available in 5 minutes vs. 1 day)
  - **Volume** (e.g., 100K per day vs. 300M per day)

- **Constraints specifying legitimate matches** (e.g., business rules)

- **Available Metadata** (e.g., link graph, various user/item attributes)
## Recommendation vs. Other Match-Making Problems

<table>
<thead>
<tr>
<th>Main Metric</th>
<th>Recommendation</th>
<th>Search</th>
<th>Advertising</th>
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<tbody>
<tr>
<td><strong>Main Metric</strong></td>
<td>User engagement</td>
<td>Relevance to the query</td>
<td>Revenue</td>
</tr>
<tr>
<td><strong>Items</strong></td>
<td>Anything (except for ads)</td>
<td>Anything (except for ads)</td>
<td>Ads</td>
</tr>
<tr>
<td><strong>Opportunities</strong></td>
<td>Push (implicit)</td>
<td>Pull (explicit)</td>
<td>Push</td>
</tr>
<tr>
<td></td>
<td>The system guesses users info needs</td>
<td>Users specify their info needs</td>
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<tr>
<td><strong>Examples</strong></td>
<td>Recommend articles, friends, feeds to users</td>
<td>Web search Vertical search</td>
<td>Sponsored search Content match Behavior targeting Display advertising (non-guaranteed)</td>
</tr>
</tbody>
</table>
More on Recommendation vs. Search

• Recommendation
  – User intent: See something “interesting” (browse mode, implicit)
    • The system tries to guess what a user likes on an entity/topic page
  – No query reformulation (unless we suggest related topics/entities)
  – False +ve more costly than false –ve
    • Showing a bad article is a worse than missing a good one

• Search
  – User intent: Explicit, users express what they want
  – Users can reformulate queries
  – False –ve more costly (but depends on the query)
    • Users want to get the results they are looking for
Modeling: Key components

Feature construction
Content: IR, clustering, taxonomy, entity, ..
User profiles: clicks, views, social, community, ..

Offline
(Logistic, GBDT, ..)

Initialize

Online
(Fine resolution Corrections) (item, user level) (Quick updates)

Explore/Exploit
(Adaptive sampling)
Modeling Problems that has received attention

• Univariate response (e.g. click); single objective (e.g. maximize CTR)

• Our solution
  – Initialize online through offline models
  – Learn “corrections” to offline models at very granular levels (user, item) and learn rapidly in an online fashion
  – Online correction models have reduced dimension through clever representations of parameters and by exploiting the fallback mechanism to coarser models
  – The models are tightly coupled with Explore-exploit to ensure fast convergence to areas of high valued response
Example Application:
Today Module on Yahoo! Homepage

Currently in production powered by some methods discussed in this tutorial.
Recommend packages:
- Image
- Title, summary
- Links to other pages

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Problem definition

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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. ----- Carol Bartz, CEO Yahoo! Inc (Q4, 2009)
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
Next few hours

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<th>Most Popular Recommendation</th>
<th>Personalized Recommendation</th>
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<td>Time-series models</td>
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<td>(cold-start problem)</td>
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<td>Intelligent Initialization</td>
<td>Prior estimation</td>
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<td>Explore/Exploit</td>
<td>Multi-armed bandits</td>
<td>Bandits with covariates</td>
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