TSINGHUA UNIVERSITY

Rating based Recommendation: From Practice to Theory

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Outline

- What is recommender system?
  - Mission
  - History
  - Problems
- What is good recommender system?
  - Experiment Methods
  - Evaluation Metric
- Rating based recommender algorithms
- Two instances
  - YouTube Video Recommendation
  - Rating Frequency based Recommendation
- Conclusions & Future work

What is recommender system?

Information Overload

How to solve information overload?

Search Engine VS. Recommender System

- User will try search engine if
  - they have specific needs
  - they can use keywords to describe needs
- User will try recommender system if
  - they do not know what they want now
  - they can not use keywords to describe needs

Mission

- Help user find item of their interest
- Help item provider deliver their item to right user
- Help website improve user's loyalty

History I

- Content Filtering
  - An architecture for large scale information systems [1985] (Gifford, D.K)
- Tapestry
  - First collaborative filtering system [1992] (Xerox Palo Alto)

History II

- Grouplens
  - First rating based collaborative filtering system [1992]
- Movielens
  - First movie recommender system [1997]
  - Provide well-know dataset for researchers
  - MovieLens 100K, MovieLens 1M, MovieLens 10M

ACM Software System Award

- Awarded to an institution or individual(s) recognized for developing a software system that has had a lasting influence, reflected in contributions to concepts, in commercial acceptance, or both. The Software System Award carries a prize of $35,000. Financial support for the Software System Award is provided by IBM.

2010 – GroupLens Collaborative Filtering Recommender Systems

Bergstrom, Peter
Gordon, Lee R
Herlocker, Jonathan L
Iacovou, Neophytos
Konstan, Joseph A
Lam, Shyong (Tony) K.
Maltz, David
McNee, Sean
Miller, Bradley N
Resnick, Paul J
Riedl, John T
Suchak, Mitesh

History III

- Amazon proposed item-based collaborative filtering (Patent is filed in 1998 and issued in 2001)
- Netflix Prize (2006-2009)
  - 1M $ improve accuracy by 10% in term of RMSE
  - Yehuda Koren's team get prize
- ACM Conference on Recommender System
  - Minneapolis, Minnesota, USA [2007]

Problems

- Top-N Recommendation
- Rating Prediction

Top-N Recommendation

- Input

user	item
A	a
B	a
B	b
…	…

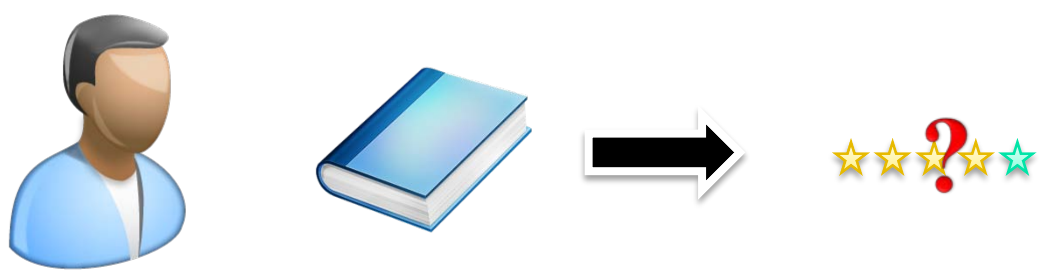
- Output

Rating Prediction

- Input

user	item	rating
A	a	★★★★☆
B	a	★★★★★
B	b	★☆☆☆☆
…	…	…

- Output



What is good recommender system?

Experiment Methods

- Offline Experiment
  - Train/Test
- User Survey
- Online Experiment
  - AB Testing

Experiment Metrics

- Prediction Accuracy
  - Top-N Recommendation: Precision, Recall
  - Rating Prediction: MAE, RMSE
- Coverage
- Diversity
  - The ability to cover users' different interests
- Real-time
  - Generate new recommendations when users have new behaviors immediately
- ……

Rating based Recommender Algorithms

The Process

- Input
  - List of m users and a list of n Items
  - Each user has a list of items he/she expressed their opinion about (can be a null set)
    - Explicit opinion: a rating score (numerical scale)
    - Implicitly: purchase records
- Output
  - Prediction: a numerical value, expressing the predicted likeliness of an item the user hasn’t expressed his/her opinion about
  - Recommendation: a list of N items the active user will like the most (Top-N recommendations)

Practical Prediction Methods

- Baseline Algorithms
  - Per User Average
    - A rating prediction is to take the average of the previous ratings of the target user
  - Per Item Average
    - A rating prediction is to take the average of the previous ratings of all users on the target item
- Shortcoming
  - The former lacks diversity
  - The latter suffers from non-personalization

Collaborative Filtering

- User based
  - Users with similar history selections will share same future interest
- Item based
  - Users will like items similar to what they consumed before

The Process

- Similarity Measure
  - Cosine
  - Pearson Correlation
- Rating Prediction

$$p_{u,i} = \overline{r}_u + \frac{\sum_{v \in U(u)} s(v,u)(r_{v,i} - \overline{r}_v)}{\sum_{v \in U(u)} \left| s(v,u) \right|}$$

$$p_{u,i} = \overline{r}_i + \frac{\sum_{j \in I(i)} s(j,i)(r_{u,j} - \overline{r}_j)}{\sum_{j \in I(i)} \left| s(j,i) \right|}$$

Existing Problems

- Data Sparsity
  - Difficult to compute similarities
  - RBRA, Grey Forecast model
- Data Correlation
  - Inaccurate similarity measure
  - Orthogonalization, Grey Forecast model
- Rating Prediction
  - Grey Forecast model
  - RBRA
  - Rating Frequency (RF)

Two instances

=YouTube + Rating Frequency

Video Recommendation I

- Video Website Classification
  - User Generated Content (UGC)
    - YouTube, YouKu, TuDou
  - Specialized Video Content (SVC)
    - Hulu, Netflix, QiYi, SOHU

Video Recommendation II

	UGC	**SVC**
Video Number	More than 100M	Less than 1M
Video Length	Short	Long
Content Metadata	Tag only	Structured
Lifespan	Short	Long
Video Quality	Mixed, Substantially duplicate content	Good
Video Diversity	Variety	Not enough

YouTube Video Recommendation

- Video Suggestion and Discovery for YouTube: Taking Random Walks Through the View Graph (WWW'08)
- The YouTube Video Recommendation System (RecSys'10)

YouTube (WWW'08)

- User-Video Graph
  - Find video *v* for user *u*
    - *u* and *v* have a short path between them
    - *u* and *v* have several paths between them
    - *u* and *v* have paths that avoid high-degree nodes
  - Solution
    - Adsorption Averaging
    - Adsorption Random Walk
    - Adsorption Linear System

YouTube (RecSys'10)

- User Needs
  - To watch a single video that they found elsewhere
  - To find specific videos around a topic
  - To just be entertained by content that they find interesting

Algorithm Design I

- Similarity Computation

$$r(v_i, v_j) = \frac{c_{ij}}{f(v_i, v_j)}$$

$$f(v_i, v_j) = c_i \cdot c_j$$

- Video Graph

Algorithm Design II

- Related Video Set

$$C_1(S) = \bigcup_{v_i \in S} R_i$$

$$C_n(S) = \bigcup_{v_i \in C_{n-1}} R_i$$

- Final Candidate

$$C_{final} = (\bigcup_{i=0}^{N} C_i) \setminus S$$

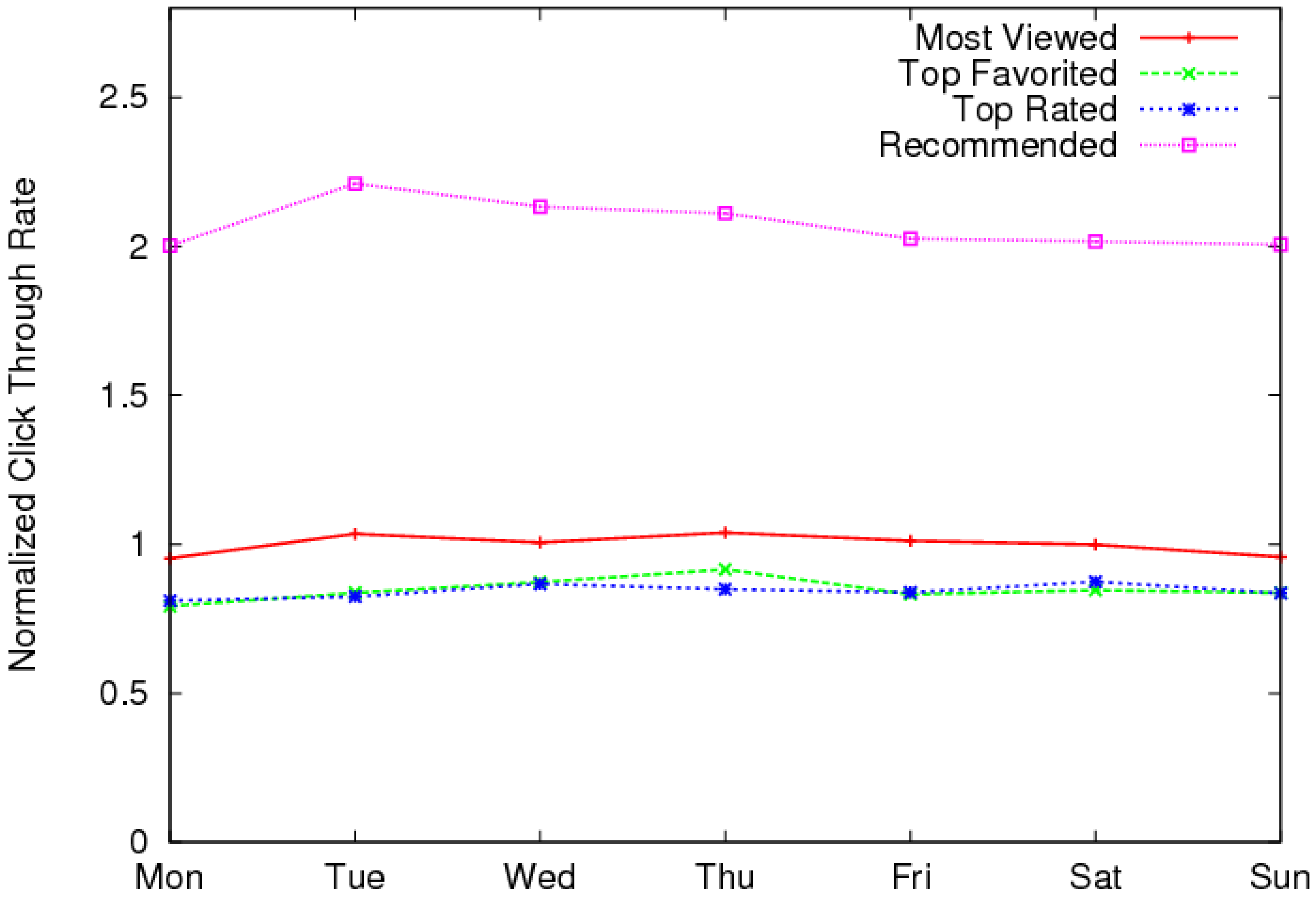
Algorithm Design III

- Ranking
  - Video quality
  - User specificity
  - Diversification
- Recommendation

Evaluation

- Comparison
  - Most viewed
  - Top Favorited
  - Top Rated
  - Recommended
- Evaluation Method
  - 21 days A/B online test
- Metric
  - Click Through Rate (CTR)

Result


Most Viewed
Top Favorited
Top Rated
Recommended
Normalized Click Through Rate
2.5
2
1.5
1
0.5
0
Mon
Tue
Wed
Thu
Fri
Sat
Sun

Conclusions

- Hundreds of recommender algorithms are useless in practice due to
  - Algorithm complexity
  - Dataset dependence
- Compromise between accuracy and efficiency
  - User/Item based collaborative filtering
  - Hybrid method
  - Amazon, YouTube, Hulu
- No demand, no product; no practice, no theory

Future Work

- Cross domain / transfer learning
- Social recommendation
- Friends recommendation
- Group recommendation (group discovery / clustering)
- Graph based recommendation
- Privacy preserving

Questions?

Thank you!