智能系统原理与开发
第09章 智能推荐系统

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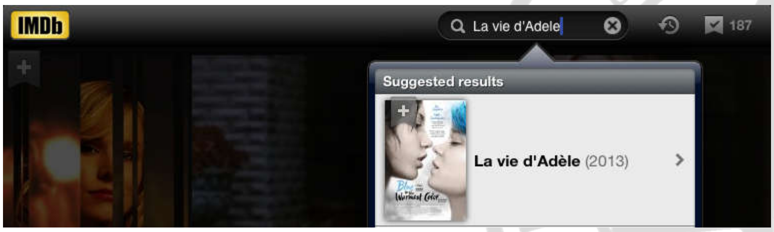
Search vs Recommendation

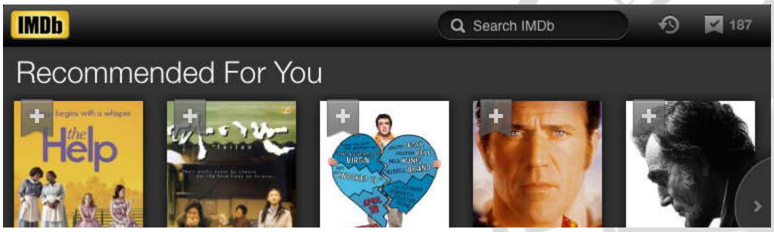
- Search – Information Retrieval



  - Know what you want
  - Query using key words
  - Return expected results
  - You find something!

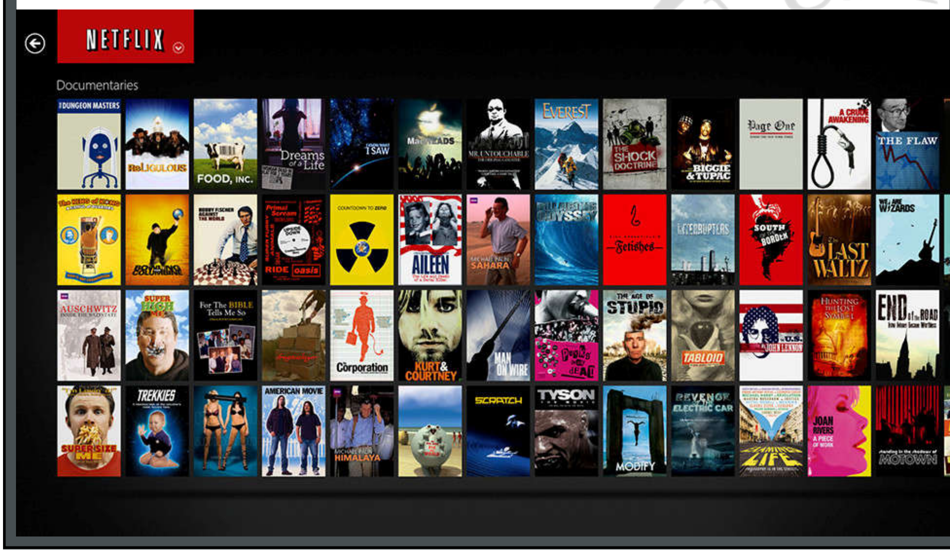
Search vs Recommendation

- Recommendation – Information Discovery



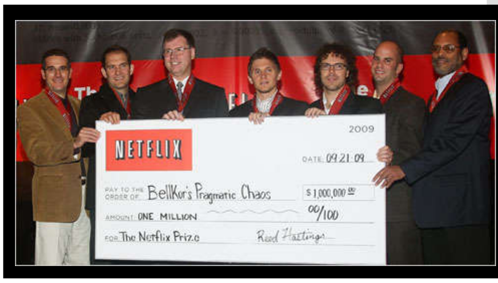
  - Do not know its existence
  - Do not know how to find
  - Return serendipitous results
  - Something finds you!

Movie Recommendation



Netflix Prize

- October 2006, Netflix offered a $1,000,000 Grand Prize
- The grand prize accelerated the research of recommendation
- The winning team uses machine learning techniques

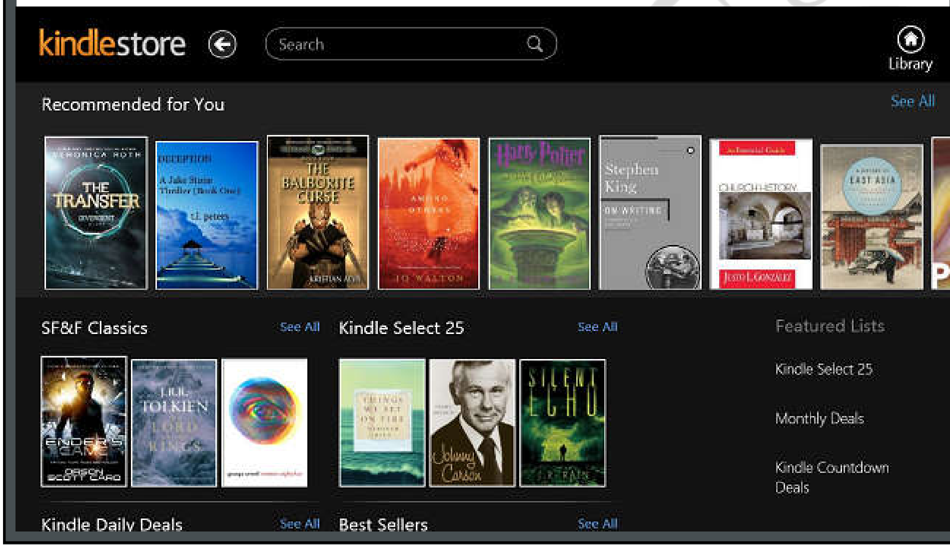


Outperforms

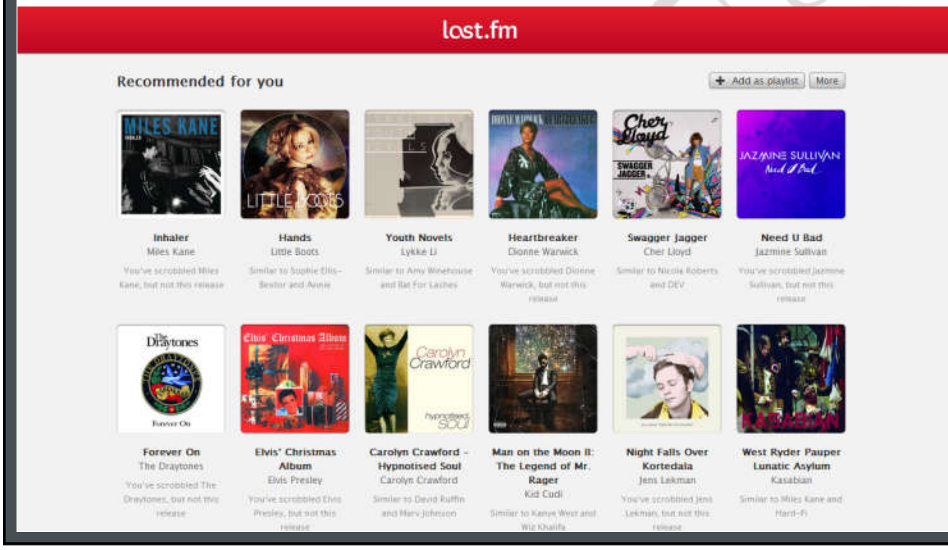
"Cinematch"

by 10%

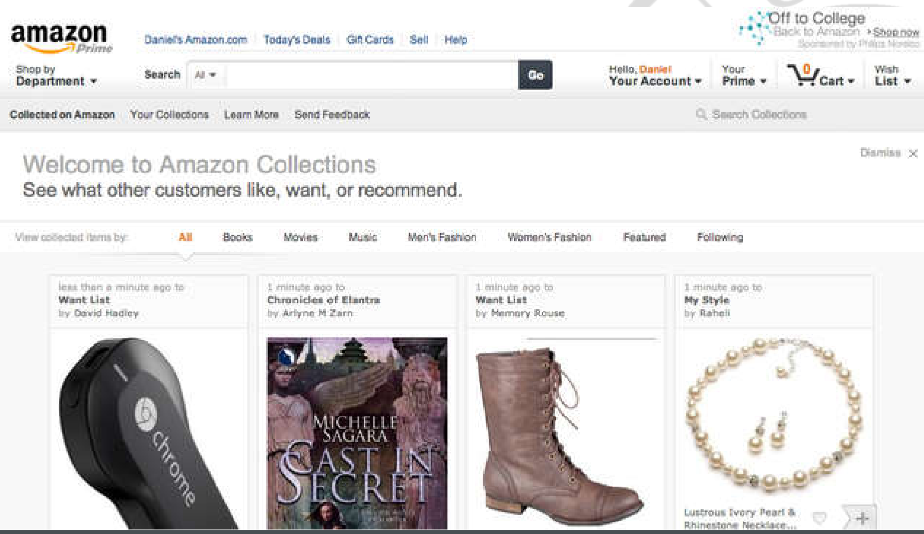
Book Recommendation



Music Recommendation



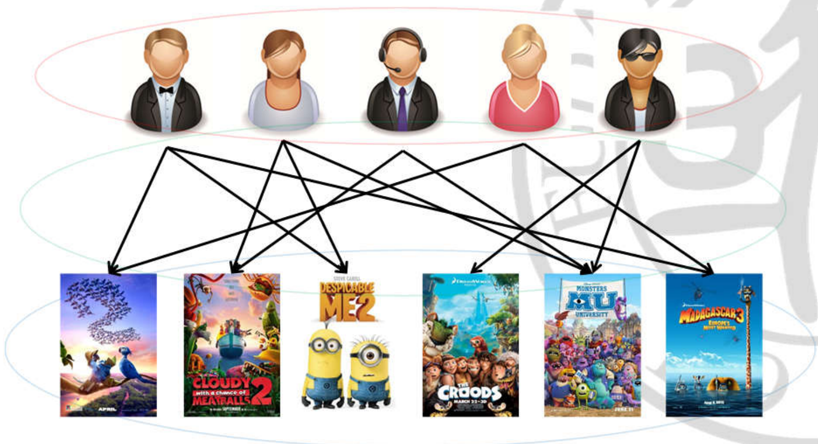
Product Recommendation



Omnipresent Recommendations

Recommendation Problem

- Three key elements



Recommendation Problem

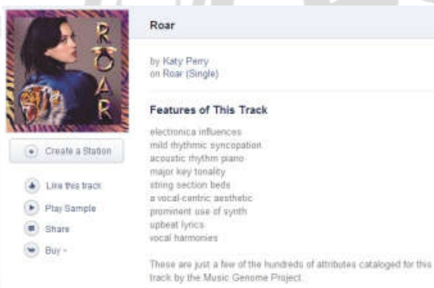
- User profiles用户画像
  - Basic: Genders, Ages, Occupations, Regions, etc.
  - Extra: Social relationships, User Tags, etc.

Male; Age 28; IT Engineer; US CA94035
[Tags] Travel, Steve Jobs, Photography, “TBBT”, …

Female; Age 20; Accounting; AU NSW2007
[Tags] Music, Taylor Swift, Katy Perry, “Gossip Girl”, …

Recommendation Problem

- Item attributes
  - Basic: Any form of descriptive data (e.g., movie metadata)
  - Extra: Item taxonomy分类法, knowledge base (e.g., Wikipedia)



Recommendation Problem

- Preference (explicit)
  - Ratings
  - Likes
- Preference (implicit)
  - Click-through
  - Purchased records

4		5			3
	3	4		3	
	3			4	
4					4
			2	5	

Recommendation Problem

- Given user set
  - User profiles – optional
- Given item set
  - Item attributes – optional
- Given preference
  - Explicit/Implicit preference data – mandatory强制的

- Real-world RSs tend to make full use of available data
- The most basic RS problem only use preference data – focus of the ML research for RS

Recommendation Problem

- Goal
  - Predict ratings
  - Rank items

4					3
	3	4		3	
?	3	?	?	4	?
4		5			4
			2	5	

RS Problem Example: MovieLens

- UserID::Gender::Age::Occupation::Zip (user info file format)
  - Age is chosen from 7 ranges: * 1: "Under 18" * 18: "18-24" * 25: "25-34" * 35: "35-44" * 45: "45-49" * 50: "50-55" * 56: "56+"
  - Occupation is chosen from 20 choices: * 0: "other" or not specified * 1: "academic/educator" * 2: "artist" * 3: "clerical/admin" * 4: "college/grad student" * 5: "customer service" * 6: "doctor/health care" * 7: "executive/managerial" * 8: "farmer" * 9: "homemaker" * 10: "K-12 student" * 11: "lawyer" * 12: "programmer" * 13: "retired" * 14: "sales/marketing" * 15: "scientist" * 16: "self-employed" * 17: "technician/engineer" * 18: "tradesman/craftsman" * 19: "unemployed" * 20: "writer"
- MovieID::Title::Genres (movie info file format)
  - Titles are provided by the IMDB (including year of release)
  - Genres are selected from 18 genres: * Action * Adventure * Animation * Children's * Comedy * Crime * Documentary * Drama * Fantasy * Film-Noir * Horror * Musical * Mystery * Romance * Sci-Fi * Thriller * War * Western

[1] Download at http://grouplens.org/datasets/movielens/

RS Problem Example: MovieLens

- UserID::MovieID::Rating::Timestamp
  - Ratings in 5-star scale {1,2,3,4,5}
  - Timestamp is represented in seconds (can be transformed into dd-mm-yyyy)

Training Data

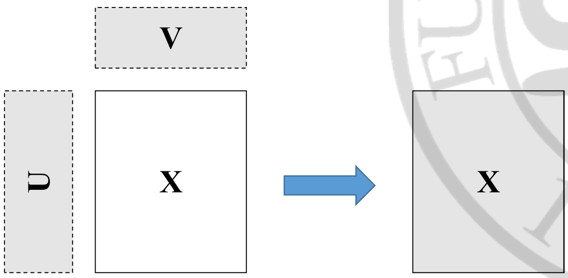
user	movie	date	rate
1	34	11-04-02	3
1	296	09-05-02	4
2	11	18-01-02	5
2	59	23-02-02	4
2	124	03-04-02	2
3	58	05-07-02	3

Test Data

user	movie	date	rate
1	75	21-02-03	?
1	126	09-03-03	?
2	92	18-01-03	?
2	257	29-05-03	?
3	66	22-03-03	?
3	394	02-06-03	?

RS Problem Formalization

- Given a User-Info Matrix (optional): **U**
- Given an Item-Info Matrix (optional): **V**
- Given a User×Item partially observed Preference Matrix: **X**
- Complete the missing entries in **X**



RS Categorization

- Data Perspective
  - Demography-based-基于人口统计的 (rely on user profiles) ☆
  - Content-based-基于内容的 (rely on item attributes) ☆
  - **Collaborative Filtering based (rely on preference) ★ 基于协同滤波**
  - Hybrid

- Method Perspective
  - Rule-based (database approach)
  - **Memory-based (information retrieval approach) ★**
  - **Model-based (machine learning approach) ★**
  - Hybrid

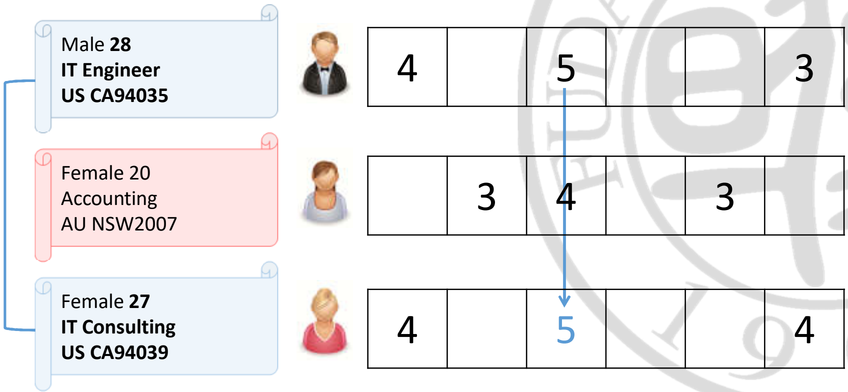
Real-world RSs

- Real-world RSs are usually Hybrid
  - Combine multiple recommendation strategies in different scenarios
  - Mainly based on CF（协同过滤） techniques with rule-based and content-based as complementary strategies

- Amazon combines demography-based, Content-based, and CF-based strategies
  - User demographic info
  - User purchased records, click-through histories, etc.
  - Item attributes, item taxonomy
  - Item popularities

Demography-based (Brief Intro)

- User correlation by comparing demographic info
- Recommend items from highly correlated users



Demography-based (Brief Intro)

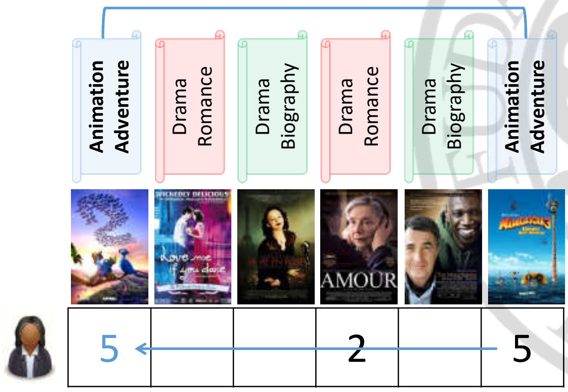
- Require User-Info Matrix and Preference Matrix
- Advantages
  - Domain-independent (cross item-domain recommendations)
  - No cold-start problem (not rely on historical preference data)
- Disadvantages
  - Coarse and inaccurate to model preference
  - Demographic data may be incomplete

Female 27
IT Consulting
US CA94039

I'm not an IT nerd …

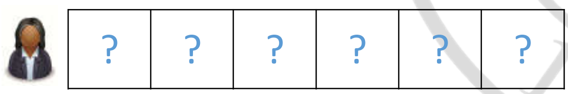
Content-based (Brief Intro)

- Item correlation by comparing item content
- Recommend items highly correlated to historical preference



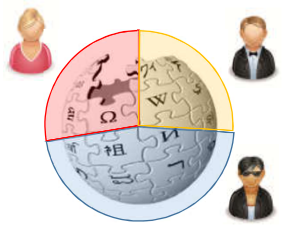
Content-based (Brief Intro)

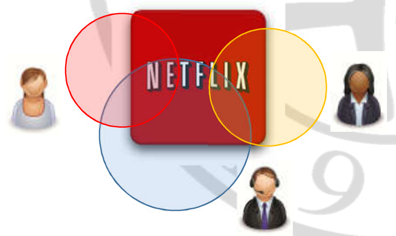
- Require Item-Info Matrix and Preference Matrix
- Advantages
  - Fine and accurate to model preference
  - Tags are effective if provided
- Disadvantages
  - Rely on item attributes (complete and comprehensive)
  - Cold-start problem (new users have no historical data)



Collaborative Filtering (Overview)

- Web 2.0 emphasizes user participation and contributions
  - Tags (Flickr), Articles (Wikipedia), Reviews (Amazon), etc.
- Collective Intelligence (CI)
  - Making use of the union of individual contributions
- Collaborative Filtering (CF) is CI
  - But focus on discovering intersected individual contributions



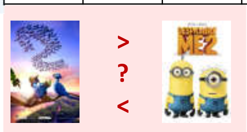


Collaborative Filtering (Overview)

- Main idea of CF
  - Find neighbors based on historical preference – How to decide?
  - Recommend items highly rated by neighbors – How to rank?

Neighbors?

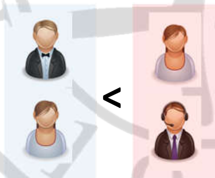
4		5			3
			2	5	



Collaborative Filtering (Overview)

- User-based Collaborative Filtering (similar users)
- User-based vs. Demography-based
  - Demography-based uses user-info to compute similarity
  - User-based uses historical preference data to compute similarity

4		5			3
	3	4		3	
	3			4	



Collaborative Filtering (Overview)

- Item-based Collaborative Filtering (similar items)
- Item-based vs. Content-based
  - Content-based uses item-info to compute similarity
  - Item-based uses associated preference data to compute similarity

		5
3	3	4
3	4	
	5	

Collaborative Filtering (Overview)

- Both user-based and item-based are "memory-based"
  - User-based has long history
  - Item-based was invented by Amazon as an improvement of user-based
- User-based vs Item-based – How to choose?
  - It depends …

User-based CF	Item-based CF
item # < user #	item # > user #
Items change rapidly	Items stay stable
News RS	Product RS (e.g., Amazon)

Collaborative Filtering (Overview)

- Model-based (compared to memory-based)
  - Using ML models for preference-matrix completion
  - Recommend items based on the estimated ratings
- Matrix Factorization Approach
  - Singular Value Decomposition (SVD)
  - SVD variants
  - Bayesian Probabilistic Matrix Factorization
- Mixture Model Approach
  - Flexible Mixture Models
  - Bi-LDA (variant of Latent Dirichlet Allocation)

Collaborative Filtering (Overview)

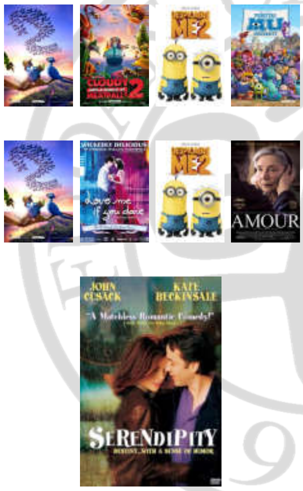
- CF is the most widely used recommendation mechanism
- Advantages
  - Only based on historical preference data
  - Domain independent (model not specific to certain item domains)
  - Well defined ML problem (numerous ML methods can be applied)
- Disadvantages – Challenges
  - Cold-start problem (new user has no preference data)
  - Sparsity problem (preference matrix is very sparse)
  - Noise problem (rely on the quality of preference data)

Hybrid Strategies

- Weighted Hybridization
  - Combine weighted results of multiple recommenders to generate a final recommendation
- Switching Hybridization
  - Switch between different recommenders depending on situations
- Mixed Hybridization
  - Show results of different recommenders at different locations on a webpage
- Cascade Hybridization
  - Refine the result of another recommender from coarse to fine

Recommendation Criteria

- Personalization
  - Relevance to user’ s tastes
- Diversity
  - Coverage of user’ s multi-aspect tastes
- Serendipity
  - Exploration of user’ s new tastes



Recommendation Performance

- Rating Prediction (regression problem)
  - Measure the difference between predictions and ground-truths
- Evaluation Metrics
  - Mean Absolute Error (MAE) , Root Mean Squared Error (RMSE)

$$\text{MAE} = \frac{1}{N}\sum_{n=1}^{N} | r_n - \hat{r}_n |$$

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{n=1}^{N} (r_n - \hat{r}_n)^2}$$

Thanks

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