Introduction to the Social Web

Recommendation and Mining

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Apr 30th, 2019

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- Research Scientist, at&t labs: 1999-2006
- Senior Research Scientist, Yahoo! Research: 2006-2011
- Principal Research Scientist, QCRI: 2011-12
- Since Dec 2011: DR1 CNRS@LIG
  - Big Data Management and Query Processing for Search and Recommendation and their application to Social Computing, Large-scale information exploration algorithms
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Social Content Sites

- **Web destinations that let users:**
  - Consume and produce content
    - Videos / photos / articles /…
    - tags / ratings / reviews /…
  - Engage in social activities with
    - friends / family / colleagues / acquaintances /…
    - people with similar interests / located in the same area /…
- **Two major driving factors:**
  - Social activities improve the attractiveness of traditional content sites
    - the “similar traveler” feature improves user engagement
  - Content is critical to the value of social networking sites
    - a significant amount of user time is spent browsing other people’s photos, posts, etc.

Social Content Sites

- **Users engage the system**
  - Contribute content
  - Disclose information about themselves
  - Need help navigating the ever-growing cyber-city maze

- **Ultimate goal**
  - Personalize search and information discovery
  - Predict what a user's interests will be in the future
  - Understand user behavior

- **Many social content sites, collaborative tagging sites are one particular kind**
  - *Flickr*, *YouTube*, *Delicious*, *Instagram*

Course Outline

- Apr 29th: Recommendations
- Apr 30th: Social data mining

Recommendation Outline

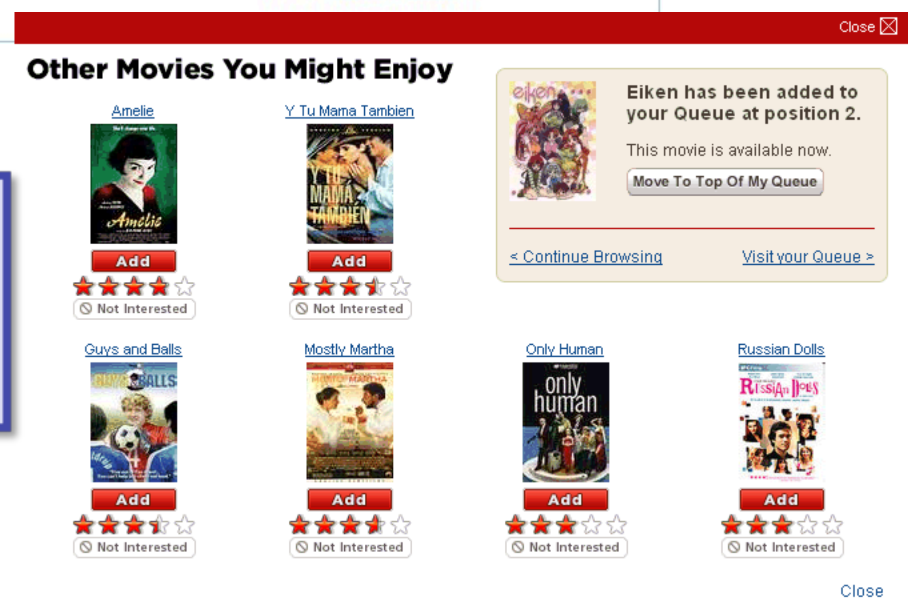
- Recommender Systems
  - **What are recommender systems** and how do they work?
  - How are recommender systems evaluated?

- Recommendation challenges
  - Well-known challenges
  - Recommendation diversity
  - Group recommendation
  - Contextual recommendation

Recommender Systems

All are social content sites that thrive on
User Generated Content (UGC)!

Recommender System



- *Predict ratings for unrated items*
- *Recommend top-k items*

Motivation

- from http://blog.kiwitobes.com/?p=58
- Amazon makes 20-30% of its sales from recommendations. Only 16% of people go to Amazon with an explicit intent to buy something
- Collected data matters more than the algorithm.
  - Amazon's algorithm is essentially a large product-product correlation matrix for the past hour, but it works for them because they collect so much data through user actions
- A lot of types of data can be used: votes, ratings, clicks, page-view time, purchases, tagging…

Academia: An Overview

- **3 papers by HCI researchers (1995)**
- **12 years later**
  - ACM RecSys 2007
    - 203 submissions, thereof 140 long and 63 short papers
    - acceptance rate for long papers of 17% and of 34% overall
  - Fields: CS/IS, marketing, DM/statistics, MS/OR
- **Netflix $1M Prize Competition**
  - Data: ≈18K movies, ≈500K customers, 100M ratings
  - $1M Prize: improve Netflix RMSE rates by 10%
  - ≈ 40K contestants from 179 countries
  - Winners in June 2009: a coalition of four: BellKor's Pragmatic Chaos with statisticians, machine learning experts and computer engineers from America, Austria, Canada and Israel — declared that it had produced a program that improves the accuracy of the predictions by 10.05 percent.
- **2nd Netflix Workshop was at KDD in August 2008.**

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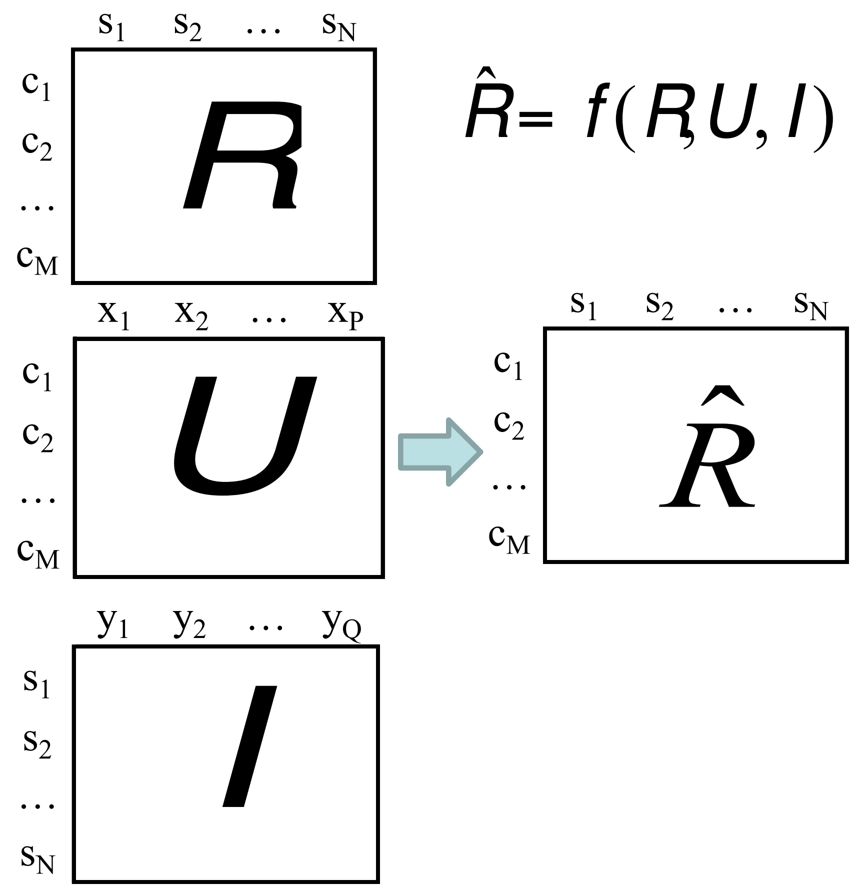
Recommendation Model

- **Input**
  - Rating matrix *R:* r_{ij} – rating user c_i assigns to item s_j
  - User attribute matrix *U:* x_{ij} – *attribute* x_j *of user* c_i
  - Item attribute matrix *I:* y_{ij} – *attribute* y_j *of item* s_i

- **Output**
  - Predicted new matrix $\hat{R}$

$$\hat{R} = f(R, U, I)$$



Types of Recommendations

- **Content-based**
  - How similar is an item *i* to items *u* has liked in the past?
  - Uses metadata for measuring similarity
  - Works even when no ratings are available on items
  - Requires metadata!

- **Collaborative filtering**
  - Treat items and users as vectors, compute vector distances

Taxonomy of Traditional Recommendation Methods

- Recommendation approach [Balabanovic & Shoham 1997]
  - Content-based, collaborative filtering
- Nature of the prediction technique
  - Heuristic-based (uses matrix as is), model-based
- Support for rating/transaction data
  - Both, rating-only [R], transaction-only [T]

	Heuristic-based	Model-based
Content-based		
Collaborative filtering		

Content-based, Heuristic-based

- Item similarity methods [Lang 1995; Pazzani & Billsus, 1997; Zhang et al. 2002]
  - Information Retrieval (IR) Techniques
  - Treat each item as a document
  - Item similarity computed as document similarity
- Instance-based learning [Schwab et al. 2000]
- Case-based reasoning [Smyth 2007]

	Heuristic-based	Model-based
Content-based		
Collaborative filtering		

Term Frequency

Variants of TF weight

weighting scheme	TF weight
binary	$0, 1$
raw frequency	$f_{t,d}$
log normalization	$1 + \log(f_{t,d})$
double normalization 0.5	$0.5 + 0.5 \cdot \frac{f_{t,d}}{\max_{\{t' \in d\}} f_{t',d}}$
double normalization K	$K + (1 - K)\frac{f_{t,d}}{\max_{\{t' \in d\}} f_{t',d}}$

Inverse Document Frequency

Variants of IDF weight

weighting scheme	IDF weight ($n_t = \lvert\{d \in D : t \in d\}\rvert$)
unary	1
inverse document frequency	$\log \frac{N}{n_t}$
inverse document frequency smooth	$\log(1 + \frac{N}{n_t})$
inverse document frequency max	$\log\left(1 + \frac{\max_{\{t' \in d\}} n_{t'}}{n_t}\right)$
probabilistic inverse document frequency	$\log \frac{N - n_t}{n_t}$

Item Similarity based on IR

- Item attributes are word occurrences in each document

$$y_{ij} = TF_{ij} \cdot IDF_j$$

- TF_{ij} – term frequency: frequency of word y_j occurring in the description of item s_i;
- IDF_j – inverse document frequency: inverse of the frequency of word y_j occurring in descriptions of all items

- Each item becomes a vector of y_{ij}

Item Similarity

Content-based profile v_i of user c_i constructed by aggregating profiles of items c_i has experienced

$$\hat{r}_{ij} = score(\mathbf{v}_i, \mathbf{y}_j)$$

$$\hat{r}_{ij} = \cos(\mathbf{v}_i, \mathbf{y}_j) = \frac{\mathbf{v}_i \bullet \mathbf{y}_j}{\| \mathbf{v}_i \|_2 \cdot \| \mathbf{y}_j \|_2}$$

Content-based, Model-based

- Classification models [Pazzani & Billsus 1997; Mooney & Roy 1998]
- One-class Naïve Bayes classifier [Schwab et al. 2000]
- Latent-class generative models [Zhang et al. 2002]

	Heuristic-based	Model-based
Content-based		
Collaborative filtering		

Collaborative Filtering, Heuristic-based

- **Neighborhood methods (assignment)**
  - User-based algorithm [Breese et al. 1998; Resnick et al. 1994; Sarwar et al. 1998]
  - Item-based algorithm [Deshpande & Karypis 2004; Linden et al. 2003; Sarwar et al. 2001]
  - Similarity fusion [Wang et al. 2006]
  - Weighted-majority [Delgado and Ishii 1999]
  - Matrix reduction methods (SVD, PCA processing) [Goldberg et al. 2001; Sarwar et al. 2000]
- **Association rule mining [Lin et al. 2002]**
- **Graph-based methods [Aggarwal et al. 1999; Huang et al. 2004, 2007]**

	Heuristic-based	Model-based
Content-based		
Collaborative filtering		
Hybrid		

Collaborative Filtering, Heuristic-based

	HP1	HP2	HP3	TW	SW1	SW2	SW3
A	4			5	1		
B	5	5	4				
C				2	4	5	
D		3					3

Jaccard

	HP1	HP2	HP3	TW	SW1	SW2	SW3
A	4			5	1		
B	5	5	4				
C				2	4	5	
D		3					3

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|}$$

Jaccard(A,B) = 1/5 < 2/4 = Jaccard(A,C)

Cosine

	HP1	HP2	HP3	TW	SW1	SW2	SW3
A	4			5	1		
B	5	5	4				
C				2	4	5	
D		3					3

$$\text{similarity} = \cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\| \|\mathbf{B}\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \sqrt{\sum_{i=1}^{n} B_i^2}}$$

, where A_i and B_i are components of vector A and B respectively.

cos(A,B) = 0.380 > 0.322 = cos(A,C)

Rounding the data

	HP1	HP2	HP3	TW	SW1	SW2	SW3
A	4			5	1		
B	5	5	4				
C				2	4	5	
D		3					3

Replace ratings 3, 4, 5, with 1
And ratings 1, 2, with 0

Compute Jaccard and Cosine

Shows that C is further from A than B is

Normalizing ratings

	HP1	HP2	HP3	TW	SW1	SW2	SW3
A	$2/3$			$5/3$	$-7/3$		
B	$1/3$	$1/3$	$-2/3$				
C				$-5/3$	$1/3$	$4/3$	
D		0					0

Replace each rating with its difference with the mean (average) for that user
Low ratings become negative
High ratings are positive

Cosine: users with opposite views on common movies will have vectors in opposite directions and users with similar opinions aboutmovies rated in common will have a small angle.

cos(A,B) = 0.092 > -0.559 = cos(A,C)

Collaborative Filtering, Model-based

- Matrix reduction methods [Takacs et al. 2008; Toscher et al. 2008] - assignment
- Latent-class generative model [Hofmann 2004; Kumar et al. 2001; Jin et al. 2006]
- User-profile generative model [Pennock et al. 2000; Yu et al. 2004]
- User-based classifiers [Billsus & Pazzani 1999; Pazzani & Billsus 1997]
- Item dependency (Bayesian) networks [Breese et al. 1998; Heckerman et al. 2000]

	Heuristic-based	Model-based
Content-based		
Collaborative filtering		
Hybrid		

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Evaluation Approaches

- **Industry outcome**
  - Add-on sales
  - Click-through rates
- **In research**
  - Offline: To anticipate the above beforehand
- No actual users are involved and an existing dataset is split into a test and a training set
- Using the ratings in the training set, predict the ratings in the test set
- Predicted ratings are compared with ratings in the test set using different measures
- In K-fold cross validation (a common cross validation technique), the data set is partitioned into K equal-sized subsets: one is retained and used as the test set, the other subsets are used as training set. This process is repeated K times, each time with a different test set.
  - Online: User satisfaction

Evaluation Metrics

- Accuracy Metrics
  - measure how well a user's ratings can be reproduced by the recommender system, and also how well a user's ranked list is predicted
  - 3 kinds of accuracy metrics
    - Predictive
    - Classification
    - Rank
- Other metrics:
  - Coverage, Confidence, Diversity, Novelty and Serendipity

Predictive Metrics

- measure to what extent a recommender system can predict ratings of users.
- useful for systems that display the predicted ratings to their users.
- MAE = (|0|+|1|+|3|+|0|+|− 2| + |0| + |2|)/7 = 1.143

$$MAE = \frac{1}{|B_i|} \sum_{b_k \in B_i} |r_i(b_k) - p_i(b_k)|$$

	Ranking		Rating	
Item	**User**	**RS**	**User**	**RS**
A	1	1	5	5
B	2	5	4	3
D	3	4	4	4
G	4	6	4	2
E	5	3	3	5
C	6	2	2	5
F	7	7	2	2

Classification Metrics

- measure to what extent a RS is able to correctly classify items as interesting or not.
- Ignores rating difference

- *Precision: #good items recommended/#recommendations*
  - measures proportion of recommended items that are good

- *Recall: #good items/#all good items*
  - measures proportion of all good items recommended

Rank Metrics
DCG, nDCG for list comparison

- A measure of effectiveness of a web search engine algorithm or related applications
- DCG measures the usefulness, or *gain*, of a document based on its position in the result list
- Two assumptions are made in using DCG:
  - Highly relevant documents are more useful when appearing earlier in a search engine result list (have higher ranks)
  - Highly relevant documents are more useful than marginally relevant documents, which are in turn more useful than irrelevant documents.
- DCG originates from an earlier, more primitive, measure called Cumulative Gain.

Cumulative Gain: CG

It is the sum of the graded relevance values of all results in a search result list.

The CG at a particular rank position p is defined as:
where rel_i is the graded relevance of the result at position i.

$$\mathrm{CG_p} = \sum_{i=1}^{p} rel_i$$

CG Example

$$D_1, D_2, D_3, D_4, D_5, D_6$$

the user provides the following relevance scores:

$$3, 2, 3, 0, 1, 2$$

$$\mathrm{CG_p} = \sum_{i=1}^{p} rel_i = 3 + 2 + 3 + 0 + 1 + 2 = 11$$

does not account for document ordering.

Discounted Cumulative Gain: DCG

DCG is that highly relevant documents appearing lower in a search result list should be penalized as the graded relevance value is reduced logarithmically proportional to the position of the result.
The discounted CG accumulated at a particular rank position is defined as:

$$\mathrm{DCG_p} = rel_1 + \sum_{i=2}^{p} \frac{rel_i}{\log_2(i)}$$

No theoretical justification for using a logarithmic reduction factor other than it produces a smooth reduction.
An alternative formulation of DCG places stronger emphasis on retrieving relevant documents:

$$\mathrm{DCG_p} = \sum_{i=1}^{p} \frac{2^{rel_i} - 1}{\log_2(i+1)}$$

DCG Example

$D_1, D_2, D_3, D_4, D_5, D_6$

the user provides the following relevance scores:

$3, 2, 3, 0, 1, 2$

i	rel_i	$\log_2 i$	$\frac{rel_i}{\log_2 i}$
1	3	0	N/A
2	2	1	2
3	3	1.585	1.892
4	0	2.0	0
5	1	2.322	0.431
6	2	2.584	0.774

So the DCG_6 of this ranking is:

$$\mathrm{DCG_6} = rel_1 + \sum_{i=2}^{6} \frac{rel_i}{\log_2 i} = 3 + (2 + 1.892 + 0 + 0.431 + 0.774) = 8.10$$

Normalized DCG

$$\mathrm{nDCG_p} = \frac{DCG_p}{IDCG_p}$$

Search result lists vary in length depending on the query.

Comparing a search engine's performance from one query to the next cannot be consistently achieved using DCG alone.

The cumulative gain at each position for a chosen value should be normalized across queries.

Ideal DCG (IDCG) at position p is obtained by sorting documents of a result list by relevance, producing the maximum possible DCG till position p.

nDCG Example

$$D_1, D_2, D_3, D_4, D_5, D_6$$

the user provides the following relevance scores:

$$3, 2, 3, 0, 1, 2$$

$$3, 3, 2, 2, 1, 0$$

The DCG of this ideal ordering, or *IDCG*, is then:

$$\mathrm{IDCG}_6 = 8.69$$

And so the nDCG for this query is given as:

$$\mathrm{nDCG}_6 = \frac{DCG_6}{IDCG_6} = \frac{8.10}{8.69} = 0.932$$

Online Evaluation: User Studies

- Traditionally small-scale controlled experiments: at best 50 subjects
- Large-scale controlled experiments using crowdsourcing such as Amazon Mechanical Turk

Mechanical Turk Summary

- **Provide a “crowd-sourcing” marketplace where**
  - requesters (i.e., individuals or institutions who have tasks to be completed)
  - workers (i.e., individuals who can perform the tasks in exchange for monetary reward) can come together.
- **A platform where the tasks (i.e. HITs) are**
  - hosted and executed, money is transferred securely
  - the reputation of workers and requesters is tracked
- **The simplest HIT often presented as**
  - a web form, where the worker answers the questions on the form
  - AMT transmits the answers to the requester for further analysis
- **The requester can also specify certain criteria that a worker must satisfy in order to perform the task.**
- **A single user can be limited to perform at most x HITs from each group, ensuring user diversity**

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- Recommender Systems
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- **(some) Recommendation challenges**
  - Well-known challenges
  - Recommendation diversity
  - Group recommendation
  - Contextual recommendation

Well-Known Challenges

- The new user problem
- The recurring startup problem
- The sparse rating problem
- The scaling problem

The New User Problem

- To be able to make accurate predictions, the system must first learn the user's preferences from the input the user provides (e.g., movie ratings, URL tagging).
- If the system does not show quick progress, a user may lose patience and stop using the system

The Recurring Startup Problem

- New items are added regularly to recommender systems.
- A system that relies solely on users’ preferences to make predictions would not be able to make accurate predictions on these items.
- This problem is particularly severe with systems that receive new items regularly, such as an online news article recommendation system.

The Sparse Rating Problem

- In any recommender system, the number of ratings already obtained is very small compared to the number of ratings that need to be predicted.
- Effective generalization from a small number of examples is thus important.
- This problem is particularly severe during the startup phase of the system when the number of users is small.

The Scaling Problem

- Recommender systems are normally implemented as a centralized algorithm and may be used by a very large number of users.
- Sometimes, predictions need to be made in real time and many predictions may potentially be requested at the same time.
- The computational complexity of the algorithms needs to scale well with the number of users and items in the system.

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Diversification

From the pool of relevant items, identify a list of items that are dissimilar to each other and maintain a high cumulative relevance, i.e., strike a good balance between relevance and diversity.

Existing Solutions for recommendation diversity

- **Attribute-based diversification in 3 steps:**
  - pair-wise item-to-item distance function on item attributes
  - Perform Diversification:
    - Optimize an overall score as a weighted combination of relevance and distance
    - Constrain either relevance or distance, maximizing the other
  - Overhead of retrieving item attributes

- **Explanation-Based Diversification**

Cong Yu, Laks V. S. Lakshmanan, Sihem Amer-Yahia: Recommendation Diversification Using Explanations. ICDE 2009: 1299-1302

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Group Recommendation (motivation)

- How do you decide where to go to dinner with friends?
  - email/text/phone
  - not optimal for reaching consensus
- What if there was a system that knew each user's preferred list?
- What is the best way to model consensus?
- How to *evaluate* that?
- How to *efficiently* compute *group recommendations*?

Group Recommendation by Example

- **Task: recommend a movie to group G ={u1, u2 ,u3}**
  - predictedRating(u1,"God Father") = 5
  - predictedRating(u2, "God Father") = 1
  - predictedRating(u3, "God Father") = 1

  - predictedRating(u1, "Roman Holiday") = 3
  - predictedRating(u2, "Roman Holiday") = 3
  - predictedRating(u3, "Roman Holiday") = 1

- ***Average Rating*** **and** ***Least Misery*** **fail to distinguish between "God Father" and "Roman Holiday"**

Group Reco Problem Definition

Consensus function combines **relevance** (average or least misery) and **disagreement** (average pair-wise or variance) in the score of a group recommendation

$$\mathcal{F}(\mathcal{G}, i) = w_1 \times \mathtt{rel}(\mathcal{G}, i) + w_2 \times (1 - \mathtt{dis}(\mathcal{G}, i)),$$ *where* $w_1 + w_2 = 1.0$ *and each specifies the relative importance of relevance and disagreement in the overall recommendation score.*

Problem: Given a user group G (formed on-the-fly) and a consensus function F, find the k best items according to F, such that each item is new to all users in G

S. Amer-Yahia, S. B. Roy, A. Chawla, G. Das, C. Yu: Group Recommendation: Semantics and Efficiency. VLDB 2009.

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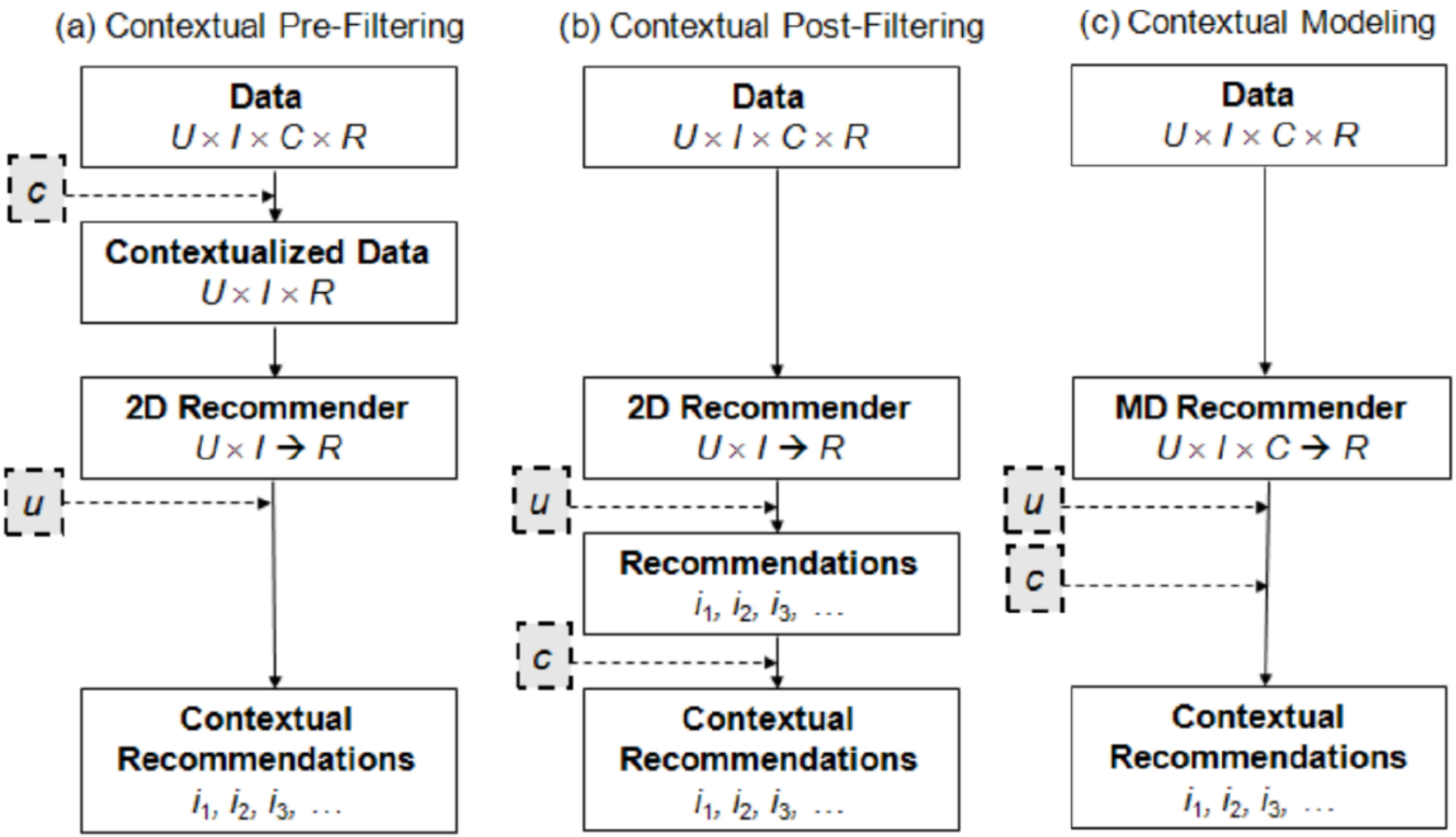
Contextual Recommendation

- Traditional recommendations
    - Users x Items → Ratings
- Contextual recommendations
    - Users x Items x Context → Ratings
- A multi-dimensional context dataset

User	Item	Rating	Time	Location	Companion
U1	T1	3	Weekend	Home	Kids
U1	T2	5	Weekday	Home	Partner
U2	T2	2	Weekend	Cinema	Partner
U2	T3	3	Weekday	Cinema	Family
U1	T3	?	Weekend	Cinema	Kids

Paradigms for incorporating context in recommendations



assignment

In practice

- Choose your similarity measure wisely, you will have to try more than one
- Define your goal early with the domain expert to determine how to evaluate your approach
- Build a prototype ASAP
- Use existing tools whenever possible

Main references

- Overview of Recommendation Systems

http://web.stanford.edu/class/ee378b/papers/adomavicius-recsys.pdf

- Collaborative Filtering: Chapter 9 of Mining Massive Datasets book

http://infolab.stanford.edu/~ullman/mmds/book.pdf

- Delicious recommendations

J. Stoyanovich, S. Amer-Yahia, C. Yu, C. Marlow: Leveraging Tagging Behavior to Model Users' Interest in del.icio.us (AAAI Workshop on Social Information Processing 2008)

- Diverse recommendations

Cong Yu, Laks V. S. Lakshmanan, Sihem Amer-Yahia: Recommendation Diversification Using Explanations. ICDE 2009: 1299-1302

- Group recommendations

S. Amer-Yahia, S. B. Roy, A. Chawla, G. Das, C. Yu: Group Recommendation: Semantics and Efficiency. VLDB 2009.

- Evaluating recommender systems

http://essay.utwente.nl/59711/1/MA_thesis_J_de_Wit.pdf