Introduction to the Social Web

Recommendation and Mining

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Yesterday’s 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

Collaborative rating systems

- **Places where users express their opinion on a content item in the form of a rating**
- **Of great interest to:**
  - Analysts who seek to explore users' opinion on items
  - End-users who seek to make choices, find similar/dissimilar users

User data on collaborative rating systems

a set of rating records:

<item attributes, user attributes, rating>

ID	Movie	Name	Gender	Age	Occup.	Rating
r_1	Toy Story	John	M	young	teacher	4
r_2	Toy Story	Jennifer	F	old	teacher	3
r_3	Toy Story	Mary	F	old	teacher	2
r_4	Titanic	Carine	F	old	other	4
r_5	Toy Story	Sara	F	young	student	3
r_6	Toy Story	Martin	M	young	student	5
r_7	Titanic	Peter	M	young	student	1

Data from MovieLens

MovieLens and IMDb

ID		Title	Genre	Director		Name	Gender	Location		Rating
1		Titanic	Drama	James Cameron		Amy	Female	New York		8.5
2		Schindler's List	Drama	Steven Speilberg		John	Male	New York		7.0

	MovieLens (+IMDb)	BookCrossing
#Users	6,040	38,511
#Items	3,900	260
#Ratings	1,000,209 (million)	196,842
Rating Scale	1 to 5	1 to 10

MovieLens
http://grouplens.org/datasets/movielens/

MovieLens 100k

100,000 ratings from 1000 users on 1700 movies.

- README.txt
- ml-100k.zip
- Index of unzipped files

MovieLens 1M

1 million ratings from 6000 users on 4000 movies.

- README.txt
- ml-1m.zip

MovieLens 10M

10 million ratings and 100,000 tag applications applied to 10,000 movies by 72,000 users.

- README.html
- ml-10m.zip

Social data mining: definition

- **Define social data mining as mining user groups**
  –because labeled user groups exhibit less sparsity and less noise than individual records
  –because labeled groups provide new insights

- **Group: set of rating records describable by a set of attribute values**

Example user groups

- *Young people who rated Woody Allen movies*
- *Middle-aged females in California*
- *People who rated movies starring Scarlett Johannson*
- *Female engineers who rated Star Wars*
- *[25-35] year-old professionals who live in Grenoble and who rated movies starring Sean Penn*

Social data mining problem

Given a rating dataset, discover *good* groups

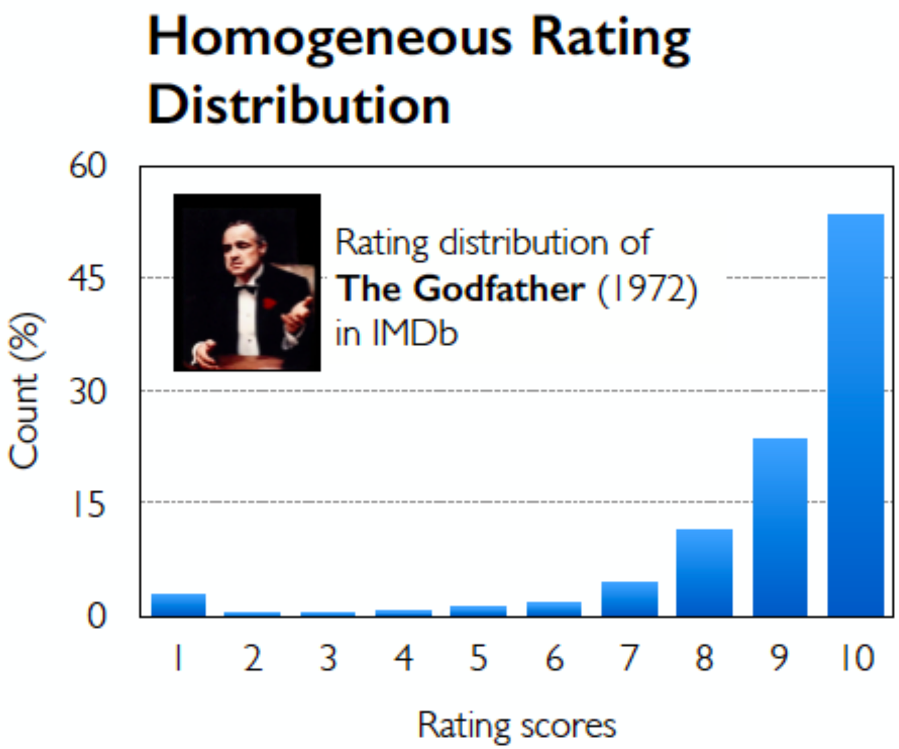
Challenges and outline

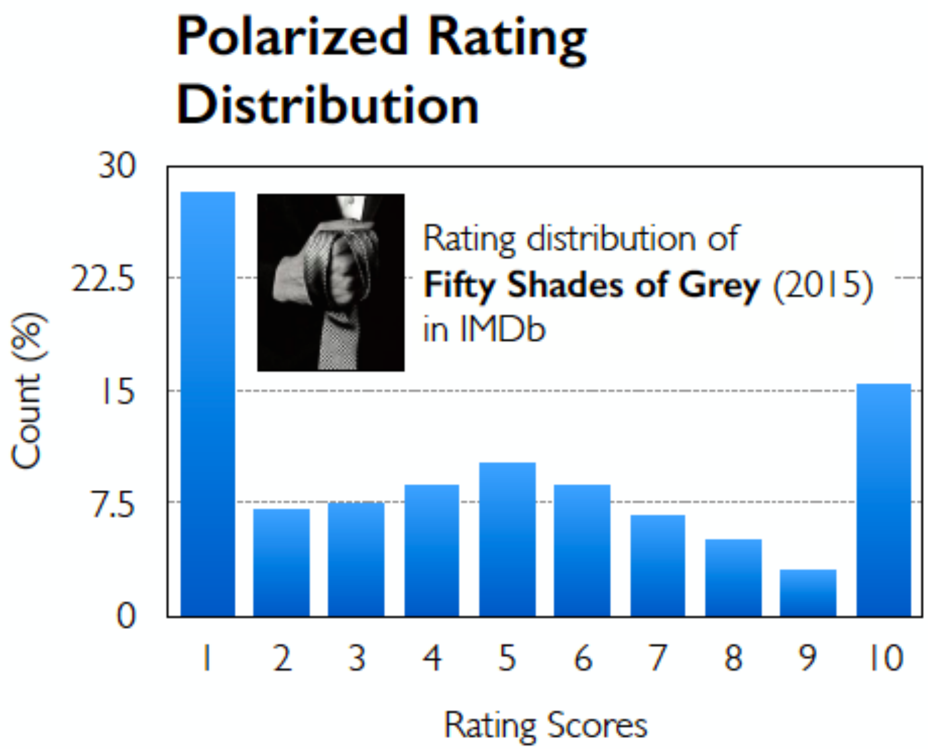
- **Challenges**
  - How to express group quality?
  - How to find groups quickly?

- **Outline**
  1. Social data mining
  2. Multi-objective mining
  3. Open questions
     1. Tag-based mining
     2. Interactive mining

Pre-defined user groups on IMDb

What is a good group, locally speaking?





What is a good group, globally speaking?

IMDb

Ratings for romance genre movies.

young females
average rating:
3.7
variance:
2

females in DC
average rating:
4.6
variance:
1.5

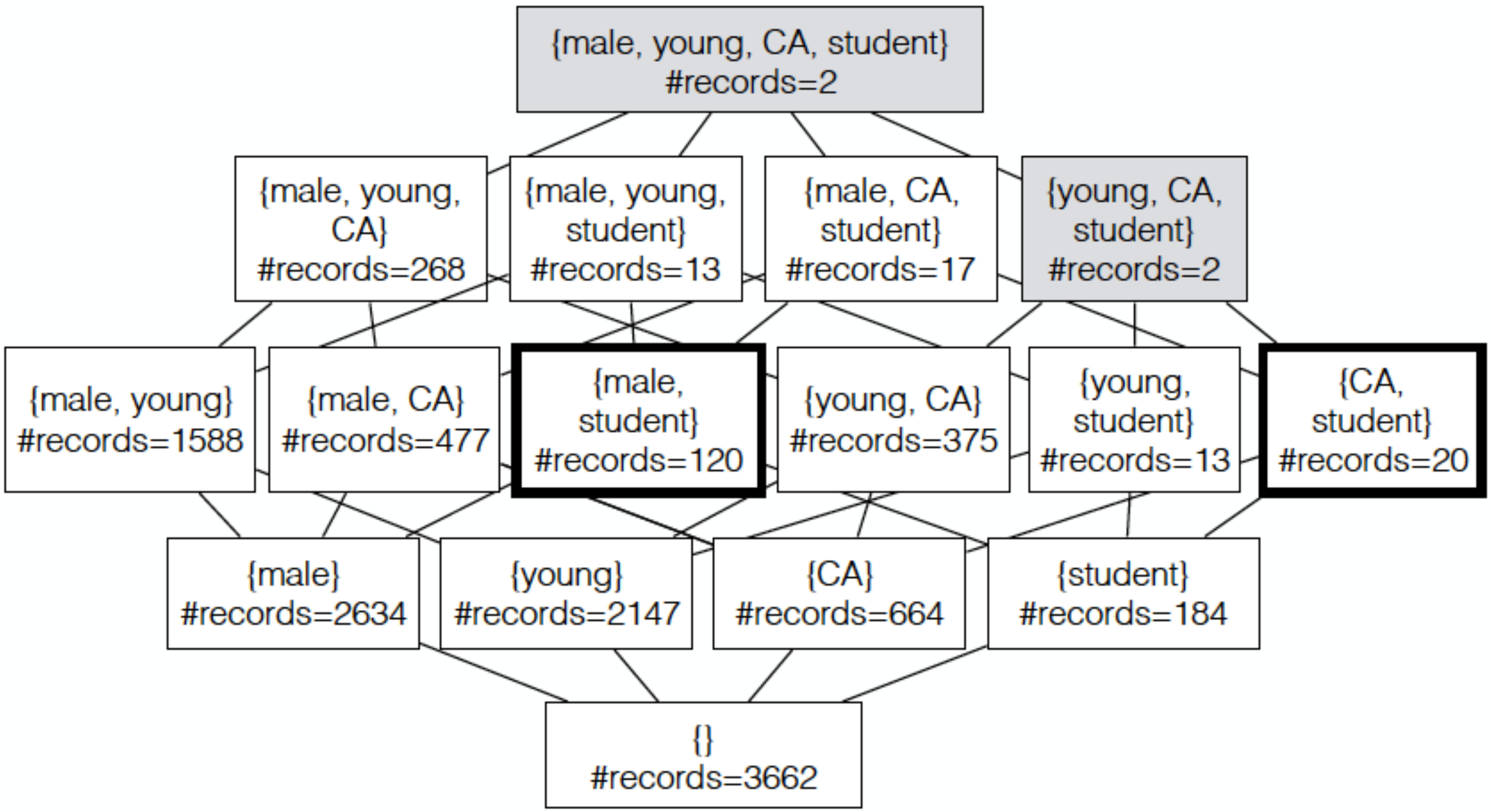
male teenagers
average rating:
3.1
variance:
3.4

— user groups that cover most ratings

I believe romantic movies are mostly watched by females.

Elena
social scientist

Partial lattice for the movie Toy Story An exponential search space



1. An example of user group mining *[1]*

For an input item covering R_I ratings, return a set C of k groups, s.t.

description error $\boxed{\mathtt{error}(C, R_I)}$ **is minimized, subject to:**

coverage $\boxed{\mathtt{coverage}(C, R_I)}$ $\geq \alpha$

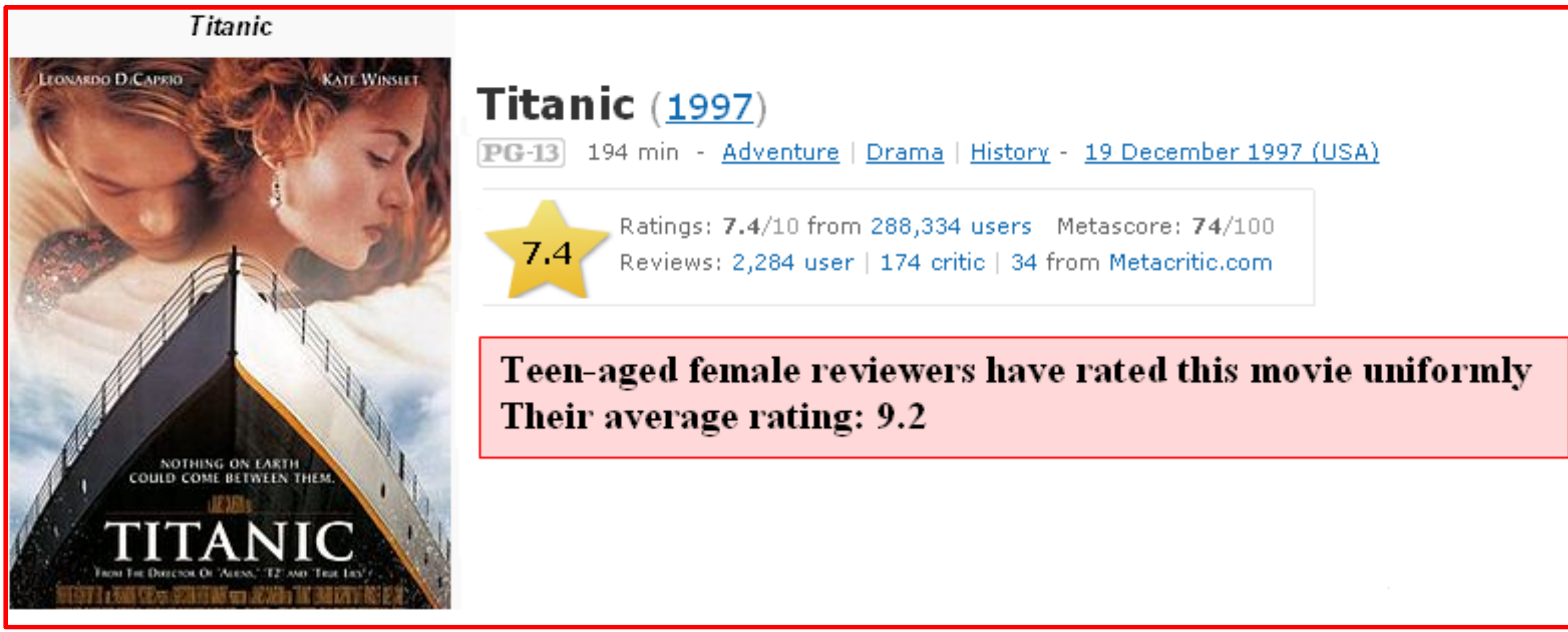
$$\boxed{\begin{aligned} \mathtt{error}(C, R_I) &= \Sigma_{r \in R_I}(E_r) \\ &= \Sigma_{r \in R_I} \mathtt{avg}(|r.s - \mathtt{avg}_{c \in C \wedge r \lessdot c}(c)|) \end{aligned}}$$

[1] MRI: Meaningful Interpretations of Collaborative Ratings, S. Amer-Yahia, Mahashweta Das, Gautam Das and Cong Yu. In PVLDB 2011.

Mining one group

k=1

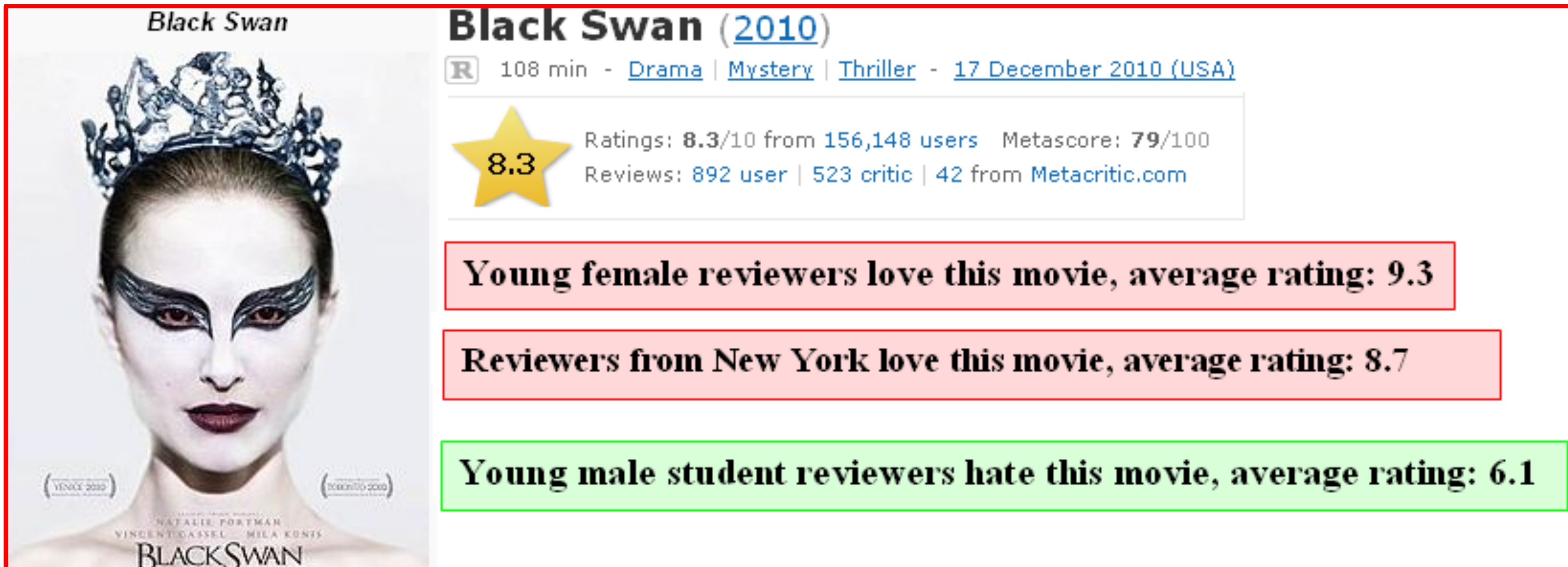
Identify groups of reviewers who consistently share similar ratings on items



Mining three groups

k=3

Identify groups of reviewers who consistently share similar ratings on items



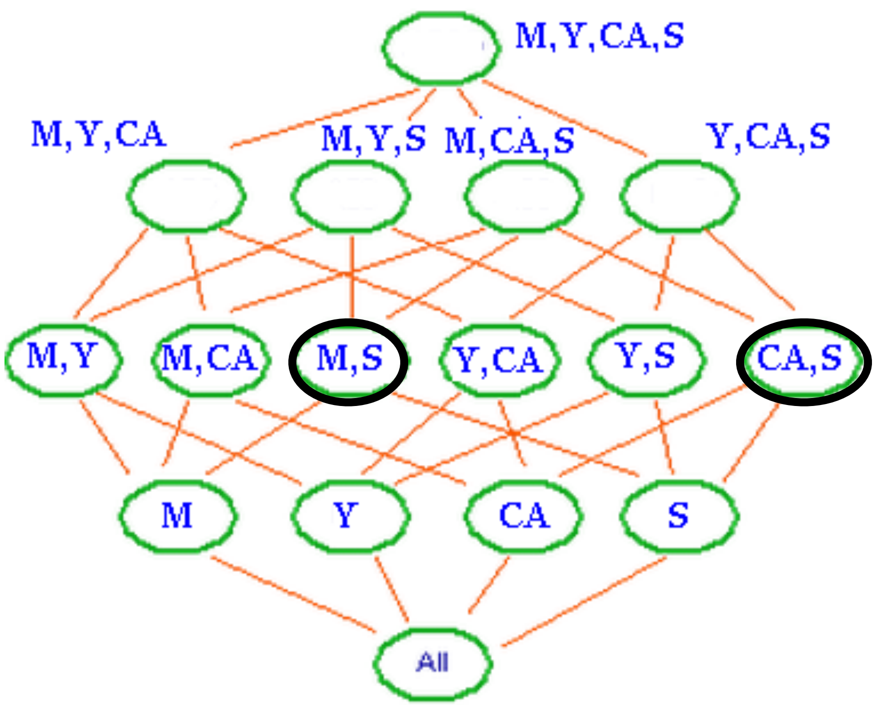
User group mining problem

THEOREM 1. *The decision version of the problem of meaningful description mining (DEM) is NP-Complete even for boolean databases, where each attribute ia_j in $\mathcal{I}_A$ and each attribute ua_j in $\mathcal{U}_A$ takes either 0 or 1.*

To verify NP-completeness, we reduce the Exact 3-Set Cover problem (EC3) to the decision version of our problem. EC3 is the problem of finding an exact cover for a finite set U, where each of the subsets available for use contain exactly 3 elements. The EC3 problem is proved to be NP-Complete by a reduction from the Three Dimensional Matching problem in computational complexity theory

Random Restart Hill Climbing Algorithm
k = 2

Satisfy Coverage	☐
Minimize Error	☐

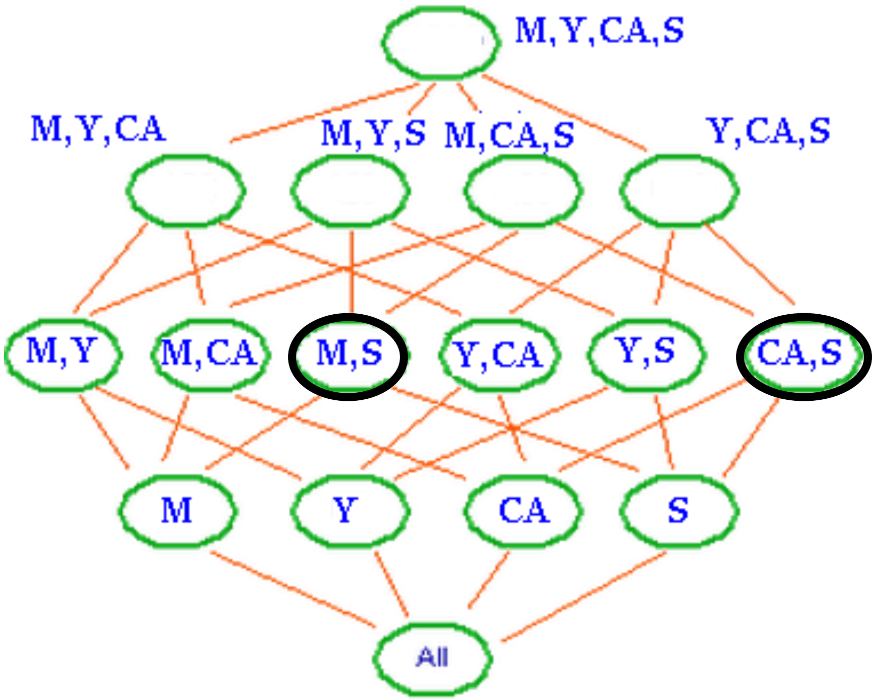


C= {Male, Student}
{California, Student}

Random Restart Hill Climbing Algorithm

k = 2

Satisfy Coverage	☐
Minimize Error	☐



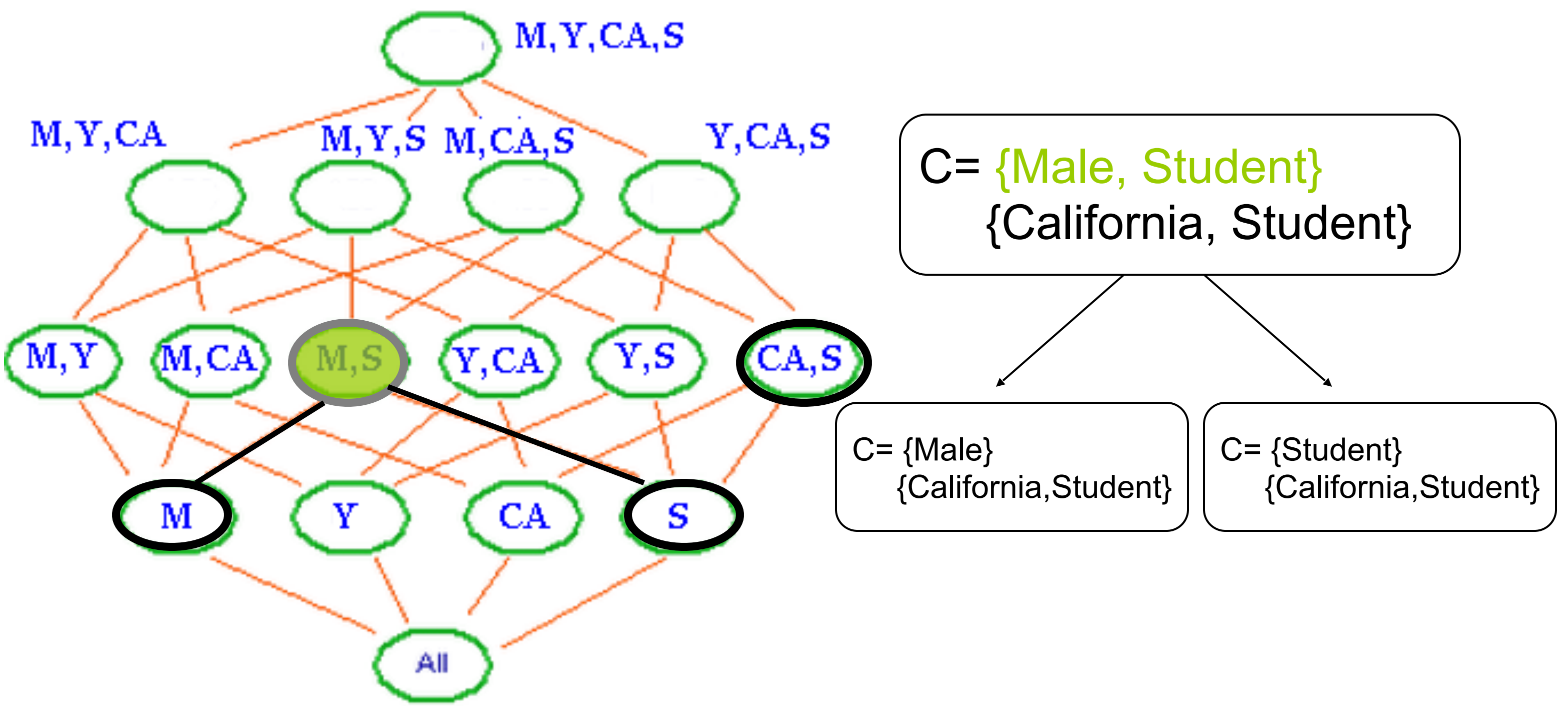
C= {Male, Student}
{California, Student}

Say, C does not satisfy Coverage Constraint

Random Restart Hill Climbing Algorithm

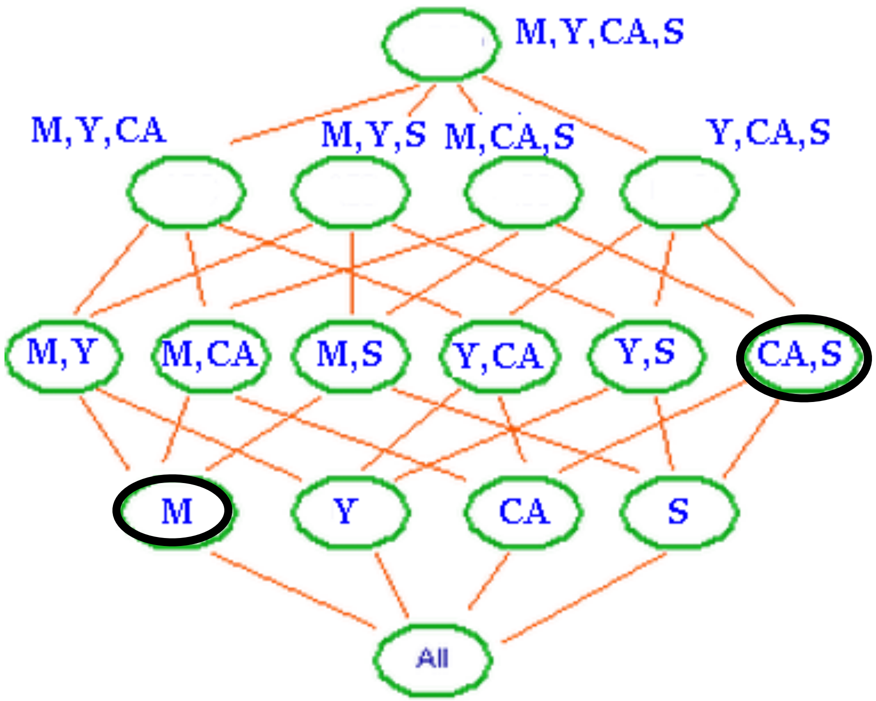
k = 2

Satisfy Coverage	☐
Minimize Error	☐



Random Restart Hill Climbing Algorithm
k = 2

Satisfy Coverage	√
Minimize Error	

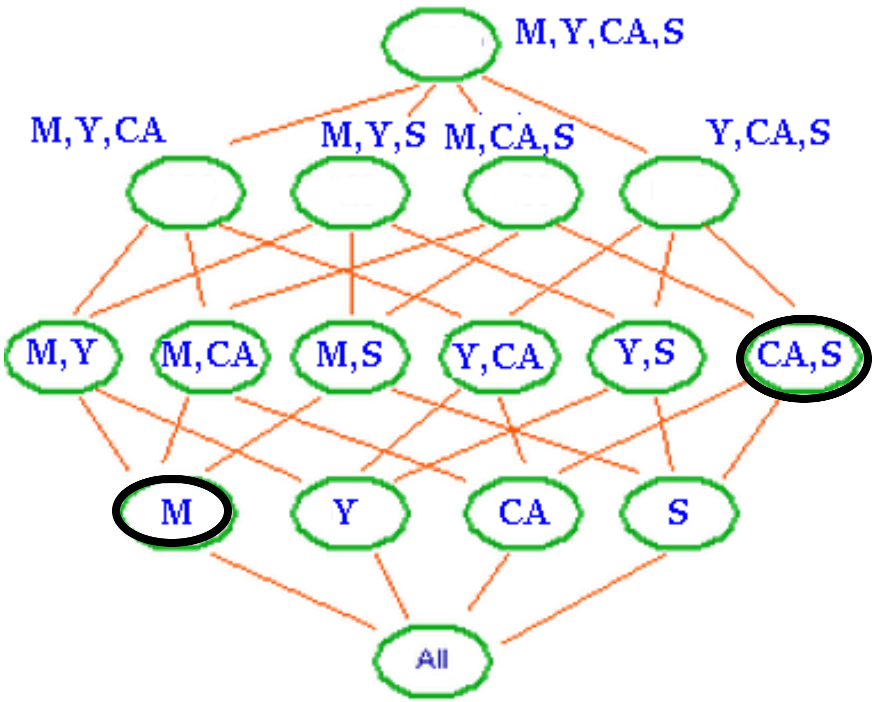


C= {Male}
{California, Student}

Say, C satisfies
Coverage Constraint

Random Restart Hill Climbing Algorithm
k = 2

Satisfy Coverage	√
Minimize Error	



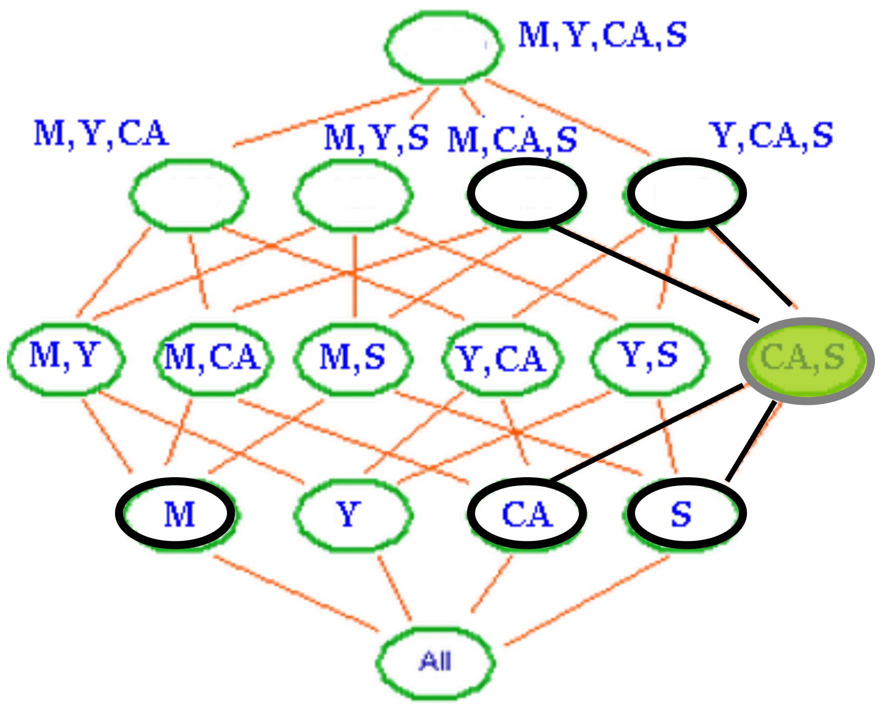
C= {Male}
{California, Student}

Random Restart Hill Climbing Algorithm

k = 2

Satisfy Coverage √

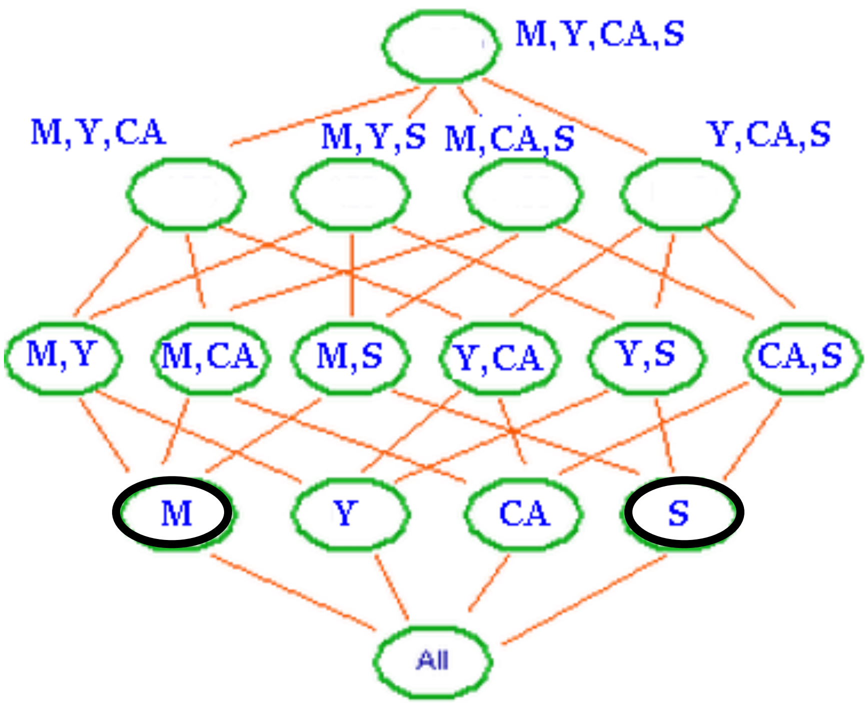
Minimize Error ☐



C= {Male}
{California, Student}

Random Restart Hill Climbing Algorithm
k = 2

Satisfy Coverage	√
Minimize Error	√

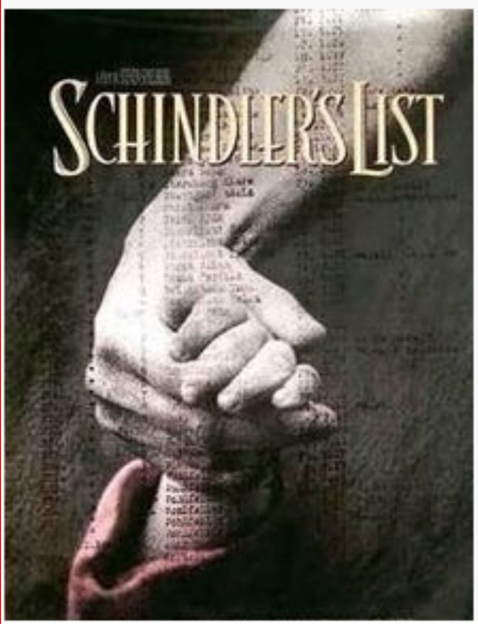


C= {Male}
{Student}

2. Another example of user group mining

Identify groups of reviewers who consistently disagree on item ratings

Schindler's List



Schindler's List (1993)

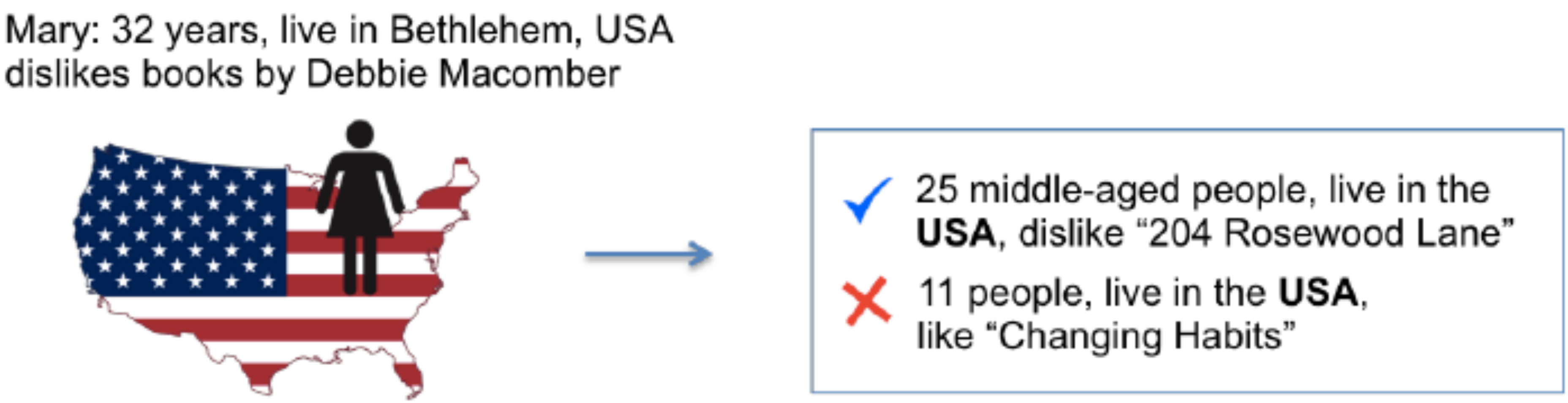
R 195 min - Biography | Drama | History - 15 December 1993 (USA)

8.9 Ratings: **8.9**/10 from 329,773 users Metascore: **93**/100
Reviews: 959 user | 95 critic | 23 from Metacritic.com

Teen-aged female reviewers and male middle-aged reviewers have rated this movie inconsistently; their average rating: 7.5

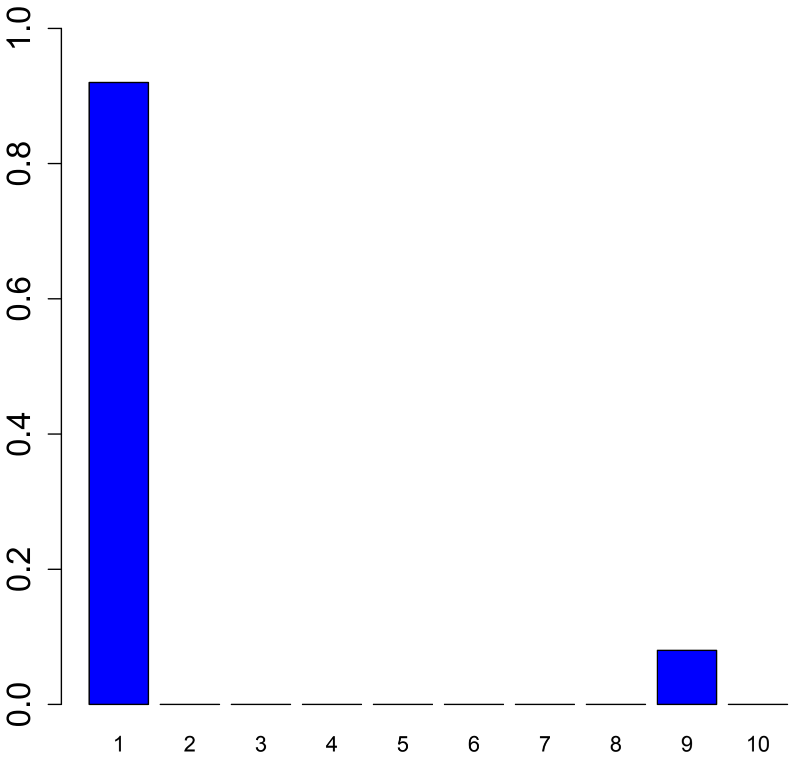
- **Middle-aged male reviewers love this movie, their average rating: 9.1**
- **Teen-aged female reviewers hate this movie, their average rating: 6.2**

3. A third example of user group mining People like/unlike me



We call this a rating map.

Mary's distribution for Debbie Macomber's books



EMD as a rating comparison measure

ρ_1 = [0.9, 0.025, 0.025, 0.025, 0.025]
ρ_2 = [0.025, 0.9, 0.025, 0.025, 0.025]
ρ_3 = [0.025, 0.025, 0.025, 0.025, 0.9]

Measure	(ρ_1, ρ_2)	(ρ_1, ρ_3)
Cosine	0.058	0.058
KL-Divergence	3.13	3.13
JS-Divergence	0.53	0.53
Euclidean distance	1.24	1.24
Hellinger Distance	0.791	0.791
Total Variation Distance	0.875	0.875
Renyi Entropy Distance (0.5 order)	1.962	1.962
Battacharya Distance	0.981	0.981
Distance correlation	0.2500	0.2500
Signal Noise Ratio	2.0372	4.221
Lukaszyk-Karmowski Metric	1.1625	3.525
EMD	0.875	3.5

People like me/unlike me problem *[2]*

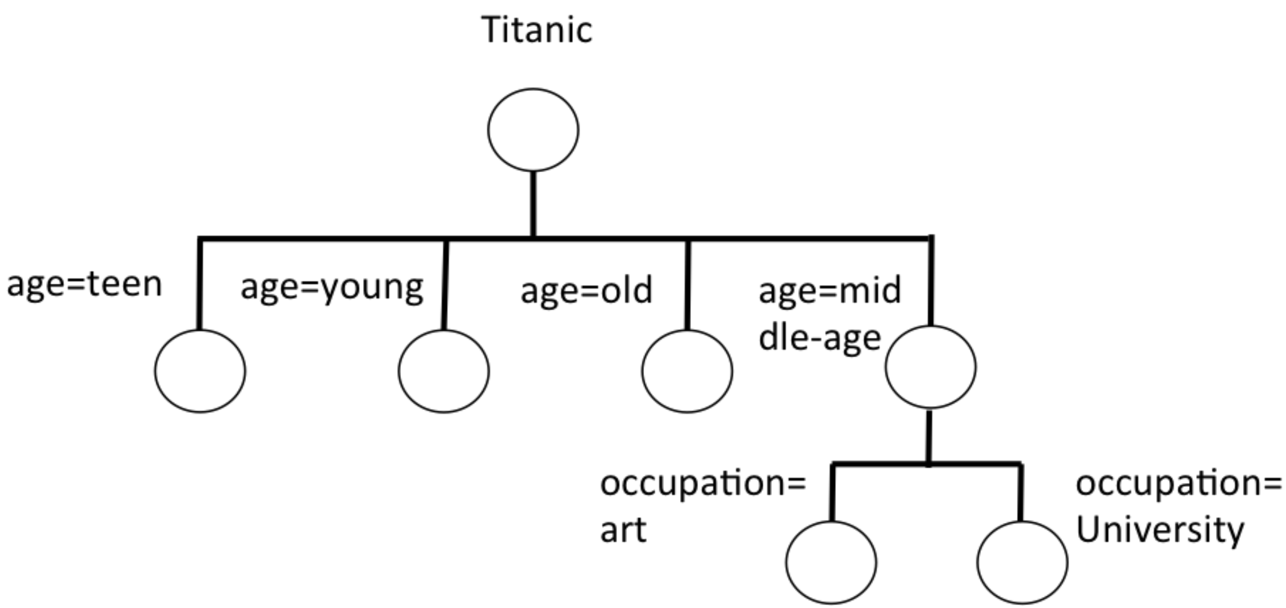
Given a set of input distributions *{$\rho_1,\ldots,\rho_k$}*, find the *largest distinct user groups* whose distribution is the closest to one of *{$\rho_1,\ldots,\rho_k$}* *(using an EMD threshold θ)*

- *Groups with a shorter description are preferred*
- *Large groups are preferred*
- *Groups with different descriptions are preferred*

[2] Exploring Rated Datasets with Rating Maps Sihem Amer-Yahia, Sofia Kleisarchaki, Naresh Kumar Kolloju, Laks V.S. Laskhmanan, Ruben H. Zamar WWW 2017

Partition Decision Tree (PDT)

- The set of rating records can be organized in a PDT
- Each node is a user group with a description



Brief sketch of algorithms

- **DTAlg**
  - minimizes description length by finding a minimum height partition decision tree
  - classic decision trees driven by gain functions like entropy and gini-index.

$$\mathtt{Gain}(\mathtt{Attr}_i) = \frac{n}{\sum_{j=1}^{n} min_{\rho \in \{\rho_1, \cdots, \rho_k\}} \mathrm{EMD}(c_j^i, \rho)}$$

- **Random Forests**
  - splitting input dataset hurts coverage
  - runs multiple iterations of DTAlg with different splitting attributes and combines trees with RF-Cluster, RF-Desc, RF-Random, RF-Size, and RF-EMD

Summary and outline

1. **Social data mining**
   - formulated as mining user groups
   - a constrained optimization problem with a single objective:
     - groups whose ratings are uniform/polarized, and that satisfy a coverage constraint
     - largest groups whose ratings are close to an input distribution
   - hard problems that necessitate appropriate heuristics

2. **Multi-objective mining**
3. **Open questions**

Summary and outline

1. **Social data mining**
   – formulated as mining user groups
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      – groups whose ratings are uniform/polarized, and that satisfy a coverage constraint
      – largest groups whose ratings are close to an input distribution
   – hard problems that necessitate appropriate heuristics

2. **Multi-objective mining [3]**
3. **Open questions**

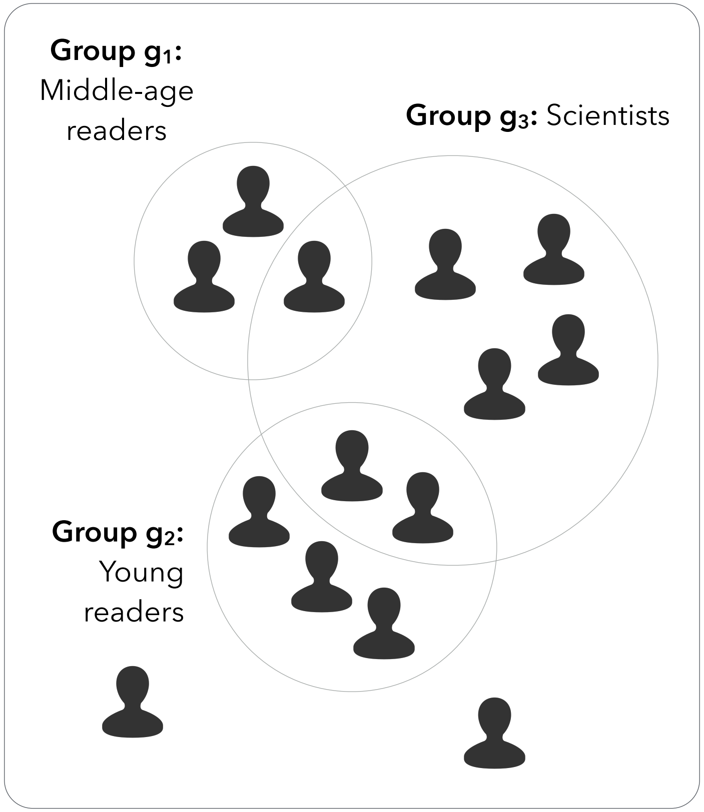
[3] Multi-Objective Group Discovery on the Social Web. B. Omidvar-Tehrani, S. Amer-Yahia, P. F. Dutot, and D. Trystram. ECML/PKDD 2016

User Group Quality Dimensions

For a group-set G and set of rating records R

- Coverage. The percentage of ratings in R contained in groups in G.
  - coverage(G,R) = $|U_{g \in G} (r \in G, u \in R)| / |R|$
- Diversity. Measures how distinct groups in group-set G are from each other.
  - diversity(G,R) = $1 / (1 + \Sigma_{g,g' \in G}|r \in R, r \in g, r \in g')$
- Variance. Average diameter of rating scores.
  - diameter(G) = $avg_{g \in G} (max_{r \in g} (r.s) - min_{r' \in g} (r'.s))$

R: Rating records



$G = \{g_1, g_2, g_3\}$

Problem Definition

- A multi-objective optimization problem
- Given set of ratings R, identify all group-sets where each group-set G satisfies:
- Objectives
  - coverage(G, R) is maximized;
  - diversity(G, R) is maximized;
  - diameter(G, R) is minimized;
- Constraints
  - $|G| \leq k$;
  - $\forall g \in G: |g| \geq \sigma$.
- Proved to be NP-Complete by a reduction from the Exact 3-Set Cover problem (EC3)

Multi-Objective Optimization Principles

Definition 2 (Plan). *Plan p_i, associated to a group-set G_i for a set of rating records $R \subseteq \mathcal{R}$, is a tuple* $\langle |G_i|, coverage(G_i, R), diversity(G_i, R), diameter(G_i) \rangle$.

Definition 3 (Sub-plan). *Plan p_i is the sub-plan of another plan p_j if their associated group-sets satisfy $G_i \subseteq G_j$.*

Definition 4 (Dominance). *Plan p_1 dominates p_2 if p_1 has* better *or equivalent values than p_2 in every objective. The term* "better" *is equivalent to* "greater" *for* maximization *objectives (e.g., diversity, coverage and polarization), and* "lower" *for* minimization *ones (e.g., homogeneity). Furthermore, plan p_1 strictly dominates p_2 if p_1 dominates p_2 and the values of objectives for p_1 and p_2 are not equal.*

Definition 5 (Pareto Plan). *Plan p is Pareto if no other plan strictly dominates p. The set of all Pareto plans is denoted as $\mathcal{P}$.*

NP-Completeness

Theorem 1. *The decision version of our problem is NP-Complete.*

Proof. (sketch) It is shown in [4] that a single-objective optimization problem for user group discovery is NP-Complete by a reduction from the Exact 3-Set Cover problem (EC3). There, homogeneity is maximized and a threshold on coverage is satisfied. In our case, two new conflicting dimensions (diversity and coverage) are added. This means that the problem in [4] is a *special case* of ours, hence our problem is obviously harder. □

Optimality Principles

- Optimality Principle (POO). In case of maximization, if the objective value(s) of sub-plans of a plan p increases, then the objective value(s) of p cannot decrease.

- Near-optimality Principle (PONO). Given an objective f and $\alpha \geq 1$, derive G' from G by replacing G_1 by G'_1 and G_2 by G'_2. Then $f(G'_1) \geq f(G_1) \times \alpha$ and $f(G'_2) \geq f(G_2) \times \alpha$ together imply $f(G') \geq f(G) \times \alpha$.

— Proofs are available in our technical report

Near-Optimality Principle

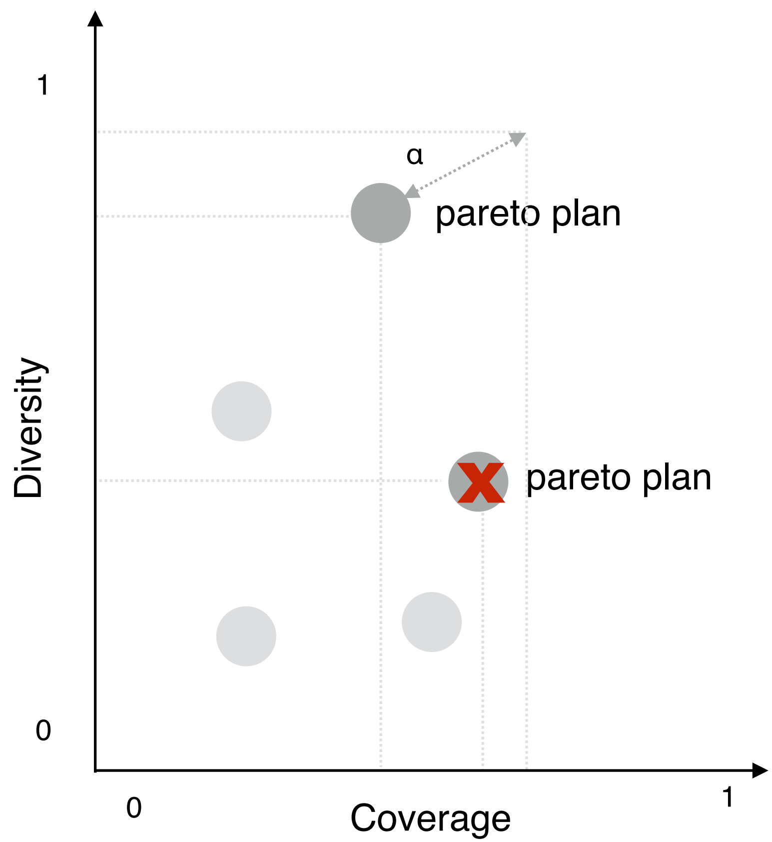
Definition 6 (PONO). *Given a maximization objective f (e.g., diversity, coverage, polarization) and $\alpha \geq 1$, let p_1 be a plan with sub-plans p_{11} and p_{12}. Derive p_2 from p_1 by replacing p_{11} by p_{21} and p_{12} by p_{22} where p_{21} and p_{22} are sub-plans of p_2. Then $f(G_{21}) \geq f(G_{11}) \times \alpha$ and $f(G_{22}) \geq f(G_{12}) \times \alpha$ together imply $f(G_2) \geq f(G_1) \times \alpha$. The extension for a minimization objective is straightforward.*

Definition 7 (Approximated Dominance). *Let $\alpha \geq 1$ be the precision value, a plan p_1 α-dominates p_2 if for every maximization objective f (e.g., diversity, coverage, polarization), $f(G_1) \geq f(G_2) \times \alpha$. The extension for a minimization objective is straightforward.*

Definition 8 (Approximated Pareto Plan). *For a precision value α, plan p is an α-approximated Pareto plan if no other plan α-dominates p.*

Multi-Objective Group Discovery

- Set of optimal solutions as Pareto plans.
- Exhaustive execution to verify all group-sets of size 1 to k.
- Generating fewer plans makes a Multi-Objective optimization algorithm run faster.



Approximation Algorithm

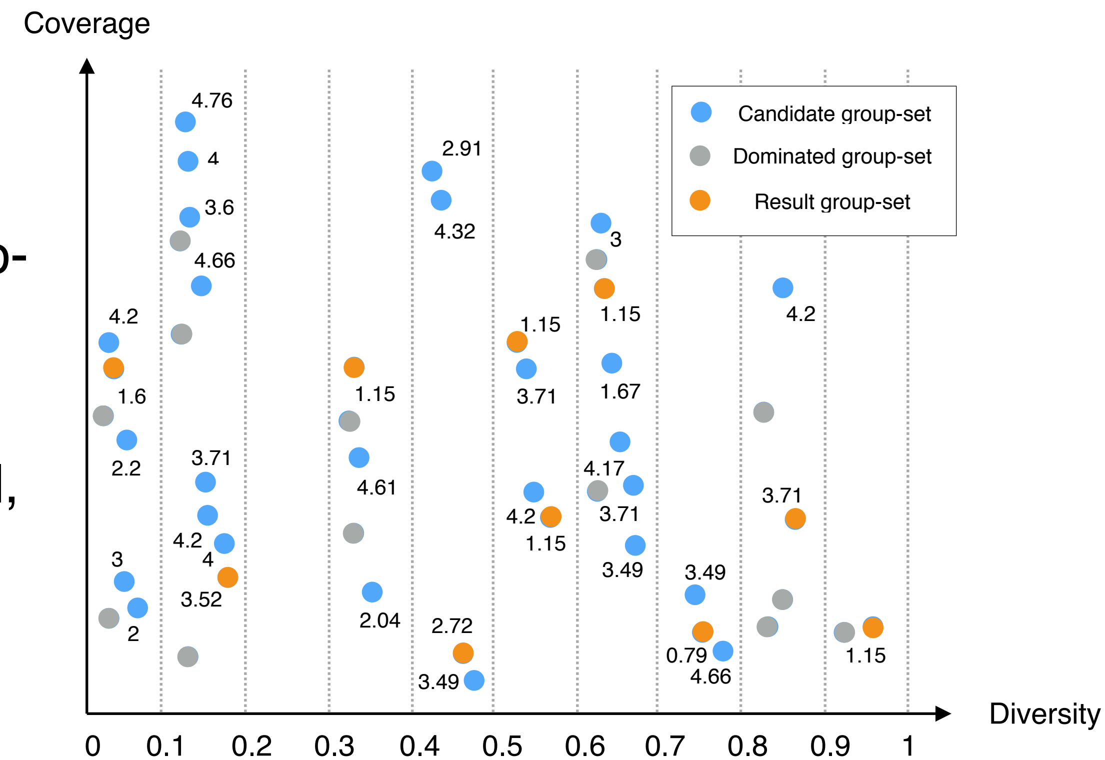
- Input. k, $\alpha > 1$, R
- Output. Pareto result set P

1. $P \leftarrow \varnothing$
2. For all user groups g do
3. G ← Singleton group-set containing g
4. If G is not α-dominated by any other group-set $\in$ P, then add G to P
5. end
6. For $n \in [2,k]$ do
7. For each possible group-set G of size n do
8. If G is not α-dominated by any other group-set $\in$ P, then add G to P
9. End
10. End
11. Return P

— Based on: Trummer, I., Koch, C.: Approximation schemes for many-objective query optimization. In SIGMOD 2014

Heuristic Algorithm

1. Find n group-sets with maximized coverage
2. Remove dominated group-sets in each diversity interval.
3. For each diversity interval, report the group-set with the optimal value of diameter.



Approximation vs Heuristic

Solutions

Approximation beats heuristic in at least 62% of solutions.

Approximation algorithm generates much more solutions than heuristic.

Objectives

Heuristic achieves around 50% of supremacy.

Heuristic can return an acceptable representative subset of results.

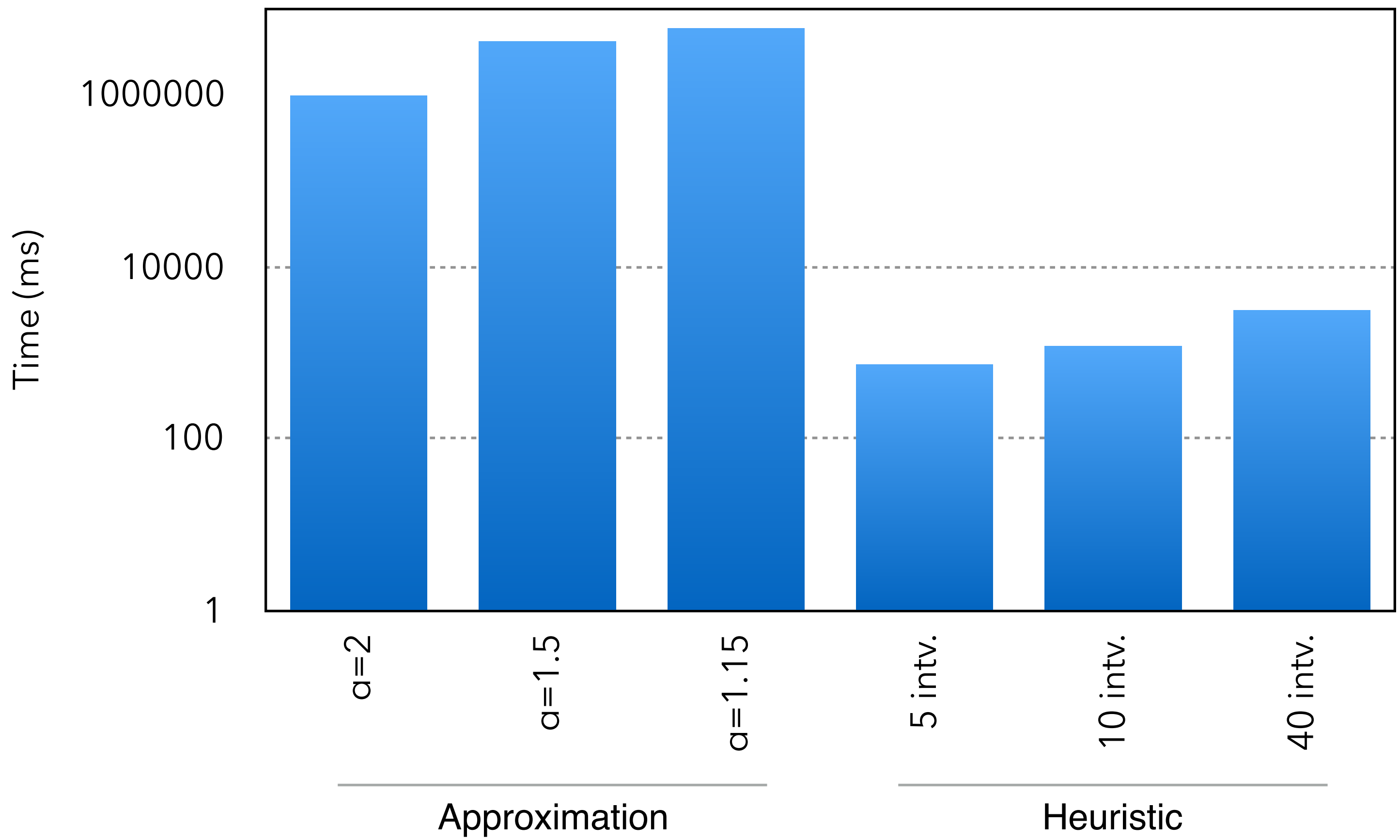
Choosing between Algorithms

- Approximation algorithm in an offline context to produce an exhaustive set of user groups with a precision defined by α for further analysis.

- Heuristic algorithm in an online or streaming context, to immediately produce a representative subset of results.

Experiments: Performance

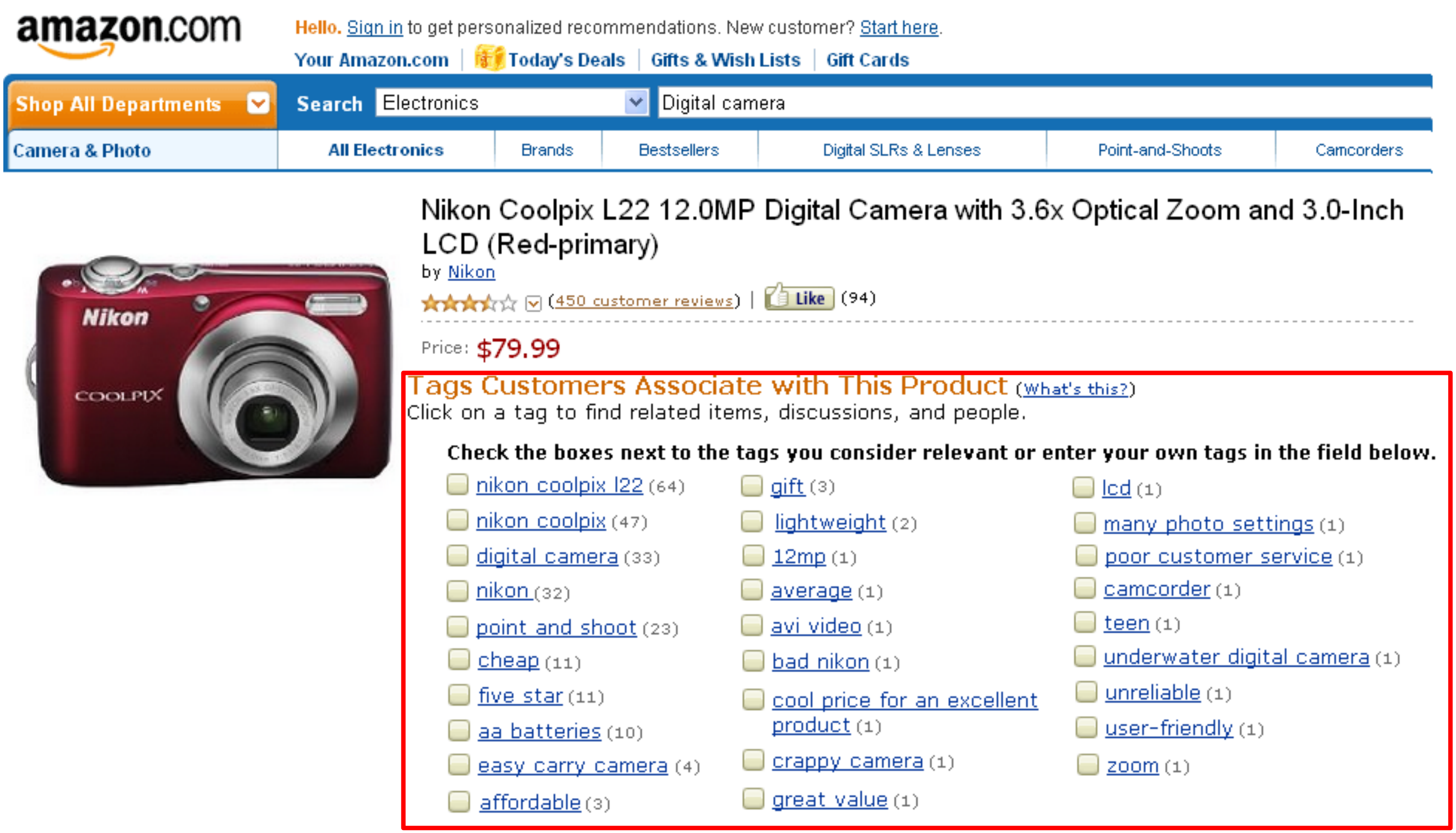
- MovieLens dataset for the movie American Beauty



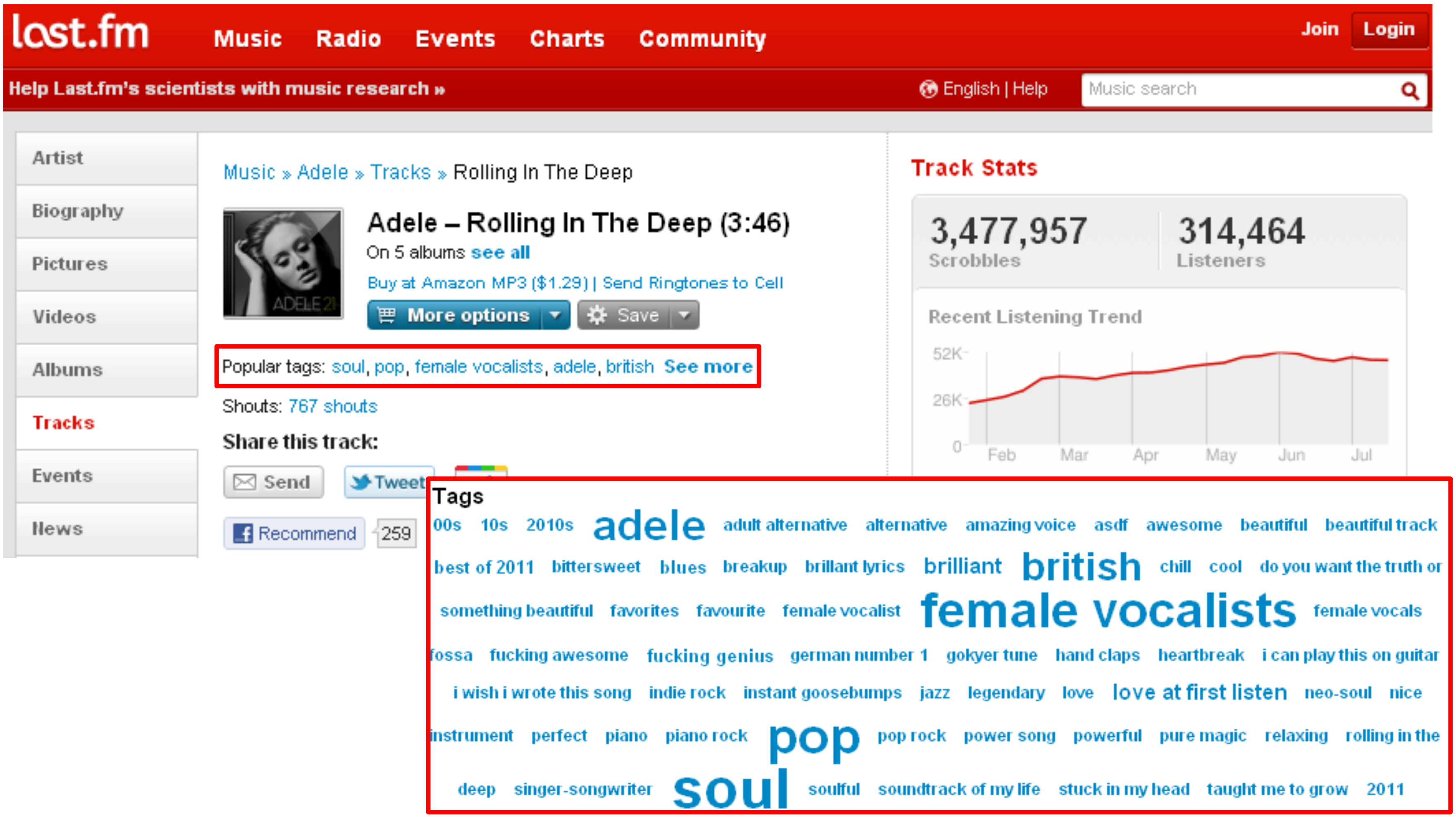
Outline

1. Social data mining
2. Multi-objective mining
3. Open questions
    1. **Tag-based mining**
    2. Interactive mining

Collaborative tagging system (Amazon)



Collaborative tagging system (LastFM)



MovieLens instances (with tags) *[4]*

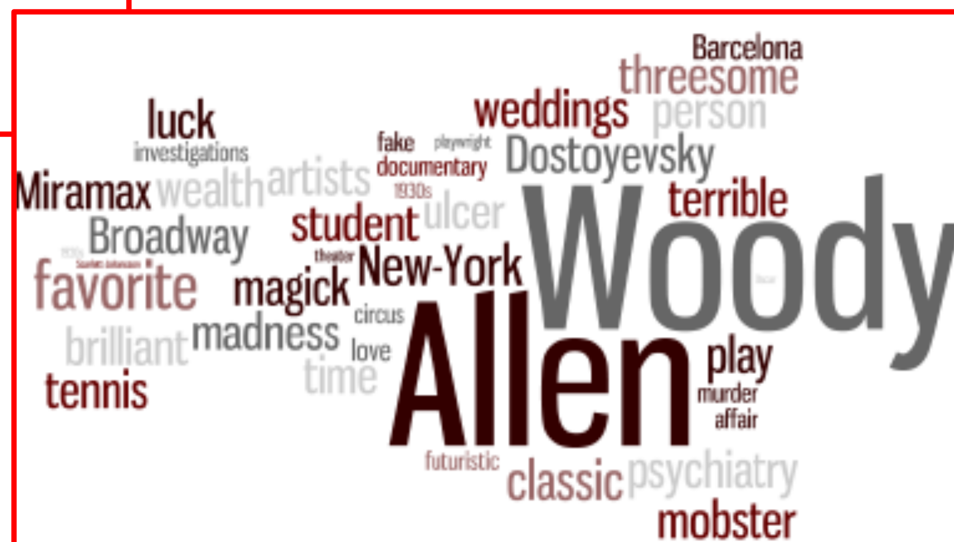
ID		Title	Genre	Director		Name	Gender	Location		Tags
1		Titanic	Drama	James Cameron		Amy	Female	New York		love, Oscar
2		Schindler's List	Drama	Steven Speilberg		John	Male	New York		history, Oscar

[4] Mahashweta Das, Saravanan Thirumuruganathan, Sihem Amer-Yahia, Gautam Das, Cong Yu. Who Tags What? An Analysis Framework. Proceedings of the VLDB Endowment (PVLDB), VLDB Endowment, 2012, 5 (11), pp.1567-1578.

Exploring collaborative tagging in MovieLens

Tag Signature for all Users

Woody Allen



Tag Signature for all CA Users

Exploring collaborative tagging in MovieLens

Identify similar groups of reviewers who share similar tagging behavior for different items

Male Young

Jennifer Aniston

comedy,
drama,
friendship

Justin Timberlake

drama,
friendship

Exploring collaborative tagging in MovieLens

Identify diverse groups of reviewers who have different tagging behavior for the same items

Male Teen

gun, special effects

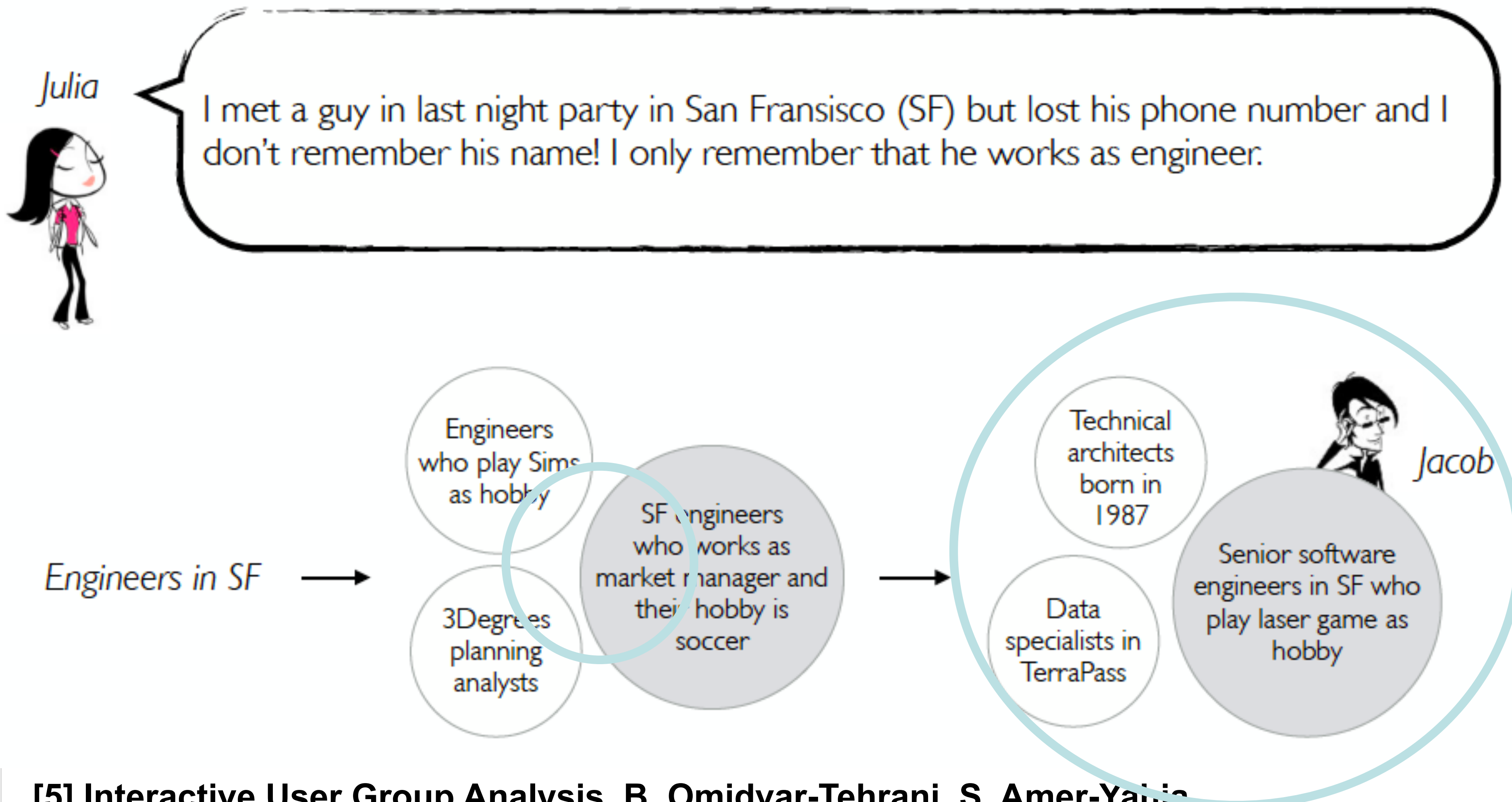
Female Teen

violence, gory

Outline

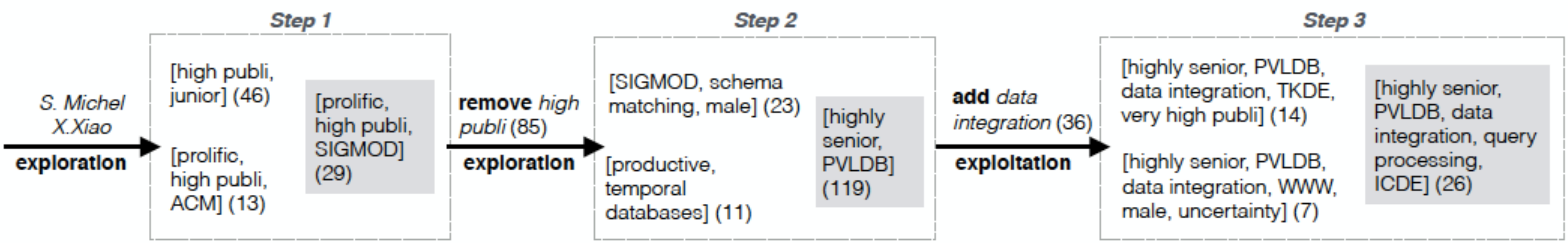
1. Social data mining
2. Multi-objective mining
3. Open questions
    1. Tag-based mining
    2. **Interactive mining**

Interactive mining [5]

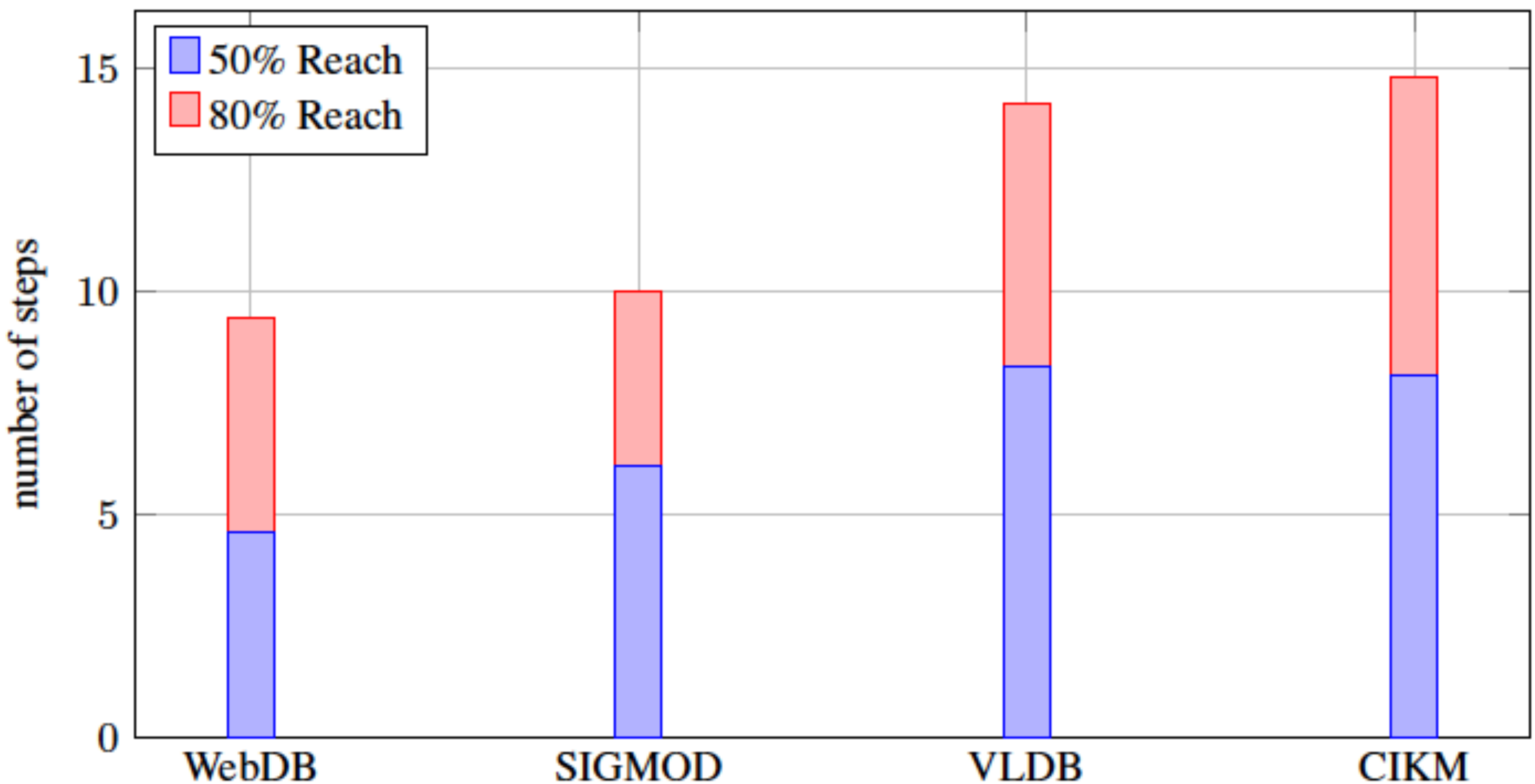


[5] **Interactive User Group Analysis. B. Omidvar-Tehrani, S. Amer-Yahia, A. Termier. CIKM 2015.**

Interactive mining



Interactive mining



Open questions with interactive mining

- **Personalized mining [6]**
  - learn a model and suggest mining operations

- **A benchmark for evaluating interactive exploration**
  - Generic: number of steps
  - Task-driven: offline and online qualitative studies

[6] One click mining: Interactive local pattern discovery through implicit preference and performance learning. M. Boley, B. Kang, P. Tokmakov, M. Mampaey, S. Wrobel. IDEAS (ACM SIGKDD Workshop), 2013.

References

[1] MRI: Meaningful Interpretations of Collaborative Ratings, S. Amer-Yahia, Mahashweta Das, Gautam Das and Cong Yu. In PVLDB 2011.

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[3] Multi-Objective Group Discovery on the Social Web. B. Omidvar-Tehrani, S. Amer-Yahia, P. F. Dutot, and D. Trystram. ECML/PKDD 2016.

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