Networks Structure and Dynamics
10. Recommendation algorithms

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Outline

An information filtering problem

Main source: Mining Massive Datasets - *J.Leskovec, A.Rajaraman, J.D.Ullman*

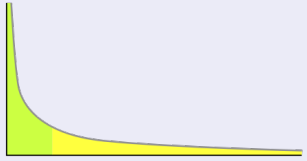
From "scarcity" to "abundance"

- Physical retailer (Leclerc, Lidl, Walmart, . . .):
  limited shelf space ⇒ limited number of products
- Web era (Amazon, Google news, Netflix, . . .):
  ⇒ commodities at dissemination cost ≃ 0
  ⇒ paradigm shift

An information filtering problem

Reaching the "long-tail"

Ordering items by preference:



- limited shelf space ⇒ cut-off in the distribution
- unlimited shelf space ⇒ access to items in the long-tail

example: "Touching the Void" (La mort suspendue) phenomenon
see https://www.wired.com/2004/10/tail/

An information filtering problem

Also new challenges and questions to solve:
how to guide users browsing large catalogs?

Functions

- primary: information filtering, bring more relevant information for less research time
- secondary: bring serendipity to users “happy discoveries”

Difference with search engines

- searching (with a query) is active
- being recommended is passive

but the frontier can be thin

Some historical elements

- First appearance of the term associated with Gerry Salton (80s) Salton and McGill - *Introduction to modern Information Retrieval System. 1980*
- First implementations (in today’s sense) in the 90s:
  - spam filter Tapestry (@Xerox, Palo Alto): uses annotations from other users to evaluate relevance Goldberg et al. - *1992*
  - document search by GroupLens (@University Minnesota): uses comments for news selection on UseNet Resnick et al. - *1994*
  - musical album search Ringo (@MIT): thresholding based on social similarity Shardanand and Maes - *1995*
- More recent interesting examples:
  - Amazon shopping collaborative filtering system
  - Pandora vs Last.fm (webradios in the 2000’s)

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Recommendation systems in machine learning

Recommendation systems are now deeply related to the machine learning field

Reformulating the recommendation task

- either to predict a score (eg., user rating)
- or to predict if a user clicks or buys, ...

From a machine learning perspective:

- a **regression** task (predicting a score)
- a **classification** task (predicting if an interaction happens)

Both are **supervised learning** tasks

Recommendation approaches

From basic

- *top-5 more popular products*, ...
  → typically on website frontpages
- but does not help reaching the long-tail, no personalization

To personalization: useful information

1. The user's tastes
2. User relatively to other users
   Very niche tastes more informative than very usual tastes
3. Knowledge of the items to recommend
   ex of a movie: director, actors, genre, year ...
4. Item relatively to other items
   Very niche genre more informative than very popular genre

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Two main recommendation families

Content-based filtering

- identify the features in an item that a user likes
- uses factors 1, 3 and 4 but not 2
- *example: Pandora and the Music Genome Project*

Collaborative filtering

- identify users who have similar tastes
- uses factors 1, 2 and 4 but not 3
- a lot of them...
  examples: Tapestry, Ringo, Amazon, Last.fm

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A baseline recommendation

Illustration on a rating problem, we want to predict $r(u, i)$

A standard baseline score:

$$r_B(u, i) = \overline{r} + (\overline{r(u)} - \overline{r}) + (\overline{r(i)} - \overline{r})$$

where

- $\overline{r}$ is the average rating of the dataset
- $\overline{r(u)}$ is the average rating of user u in the dataset
- $\overline{r(i)}$ is the average rating of item i in the dataset

minimal level of personalization, how can we improve that?

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Vectorial approach to content-based filtering (1)

First step: item as a vector of features

Listing relevant features → associate score to each item

Examples:

- movie → genre scores (given by expert)
  Back to the Future: 2 Sci-Fi, 3 Action, 2 Comedy, 0 Romance, 0 Drama
- document → set of words with a score of importance (tf-idf)

Limitations

- Assumes an expertise of the field
- Loss of information
  ex: set of words → no idea of context, of order

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Vectorial approach to content-based filtering (2)

Second step: user profiling

- Using formerly selected items

  item 1: [0 0 1 0 2 0]
  item 2: [1 3 0 0 0 0]
  item 3: [1 1 1 0 0 0]
  ⟶ profile: [2/3 2 2/3 0 2/3 0]

- Option: give weights according to feedbacks

  ex: item1 disliked (weight = -1); i2 liked (+1); i3 neutral (0)

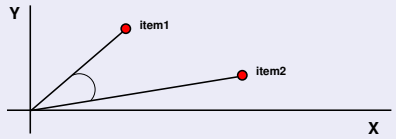
  ⟶ profile: [1/2 3/2 -1/2 0 -1 0]

Vectorial approach to content-based filtering (3)

one example of classic similarity measurement
but many others available . . .

Cosine similarity

$$cos(\vec{u}, \vec{i}) = \frac{\vec{u} \cdot \vec{i}}{||u|| \cdot ||i||} = \frac{\sum_k u_k . i_k}{\sqrt{\sum_k u_k^2} \sqrt{\sum_k i_k^2}}$$



Recommend items most similar to the user

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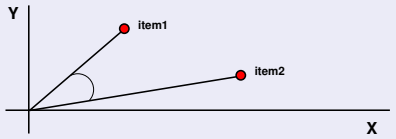

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Further analysis of content-based filtering

Advantages

- Personalized
- Explanatory: we know why an item is recommended
- Independent of other users tastes
- Allows to make recommendation of new or unpopular items

Drawbacks

- Expert knowledge needed → manual feature definition and processing (*ex: how to define a film plot?*)
- Do not use feedback from other users
- Overspecialization: tends to recommend specific items similar to those already selected by a user

Content-based filtering tends to disappear

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Neighborhood approach to collaborative filtering (1)

Case-study: users give explicit feedback on items via rating

	A	B	C	D	E
Blade Runner	5	3	4	1	2
Back to the Future	4	3	5	1	-
Pride & Prejudice	1	3	2	4	-
Inception	-	4	2	5	4
Shrek	-	4	-	-	-

First step: find neighborhood

- neighborhood = group of users with similar tastes

How to find neighborhood?

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Here, $\vec{X}$ is the vector of ratings of user X

But two major limitations in this context:

- unrated items seen as 0
- humans have idiosyncrasies in their rating behavior:

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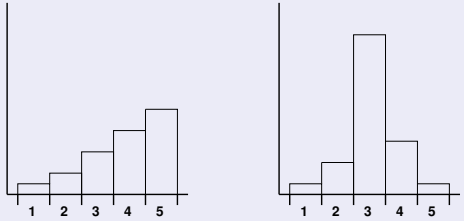

Neighborhood approach to collaborative filtering (1)

Centered cosine similarity

- compute *rating - average rating* (centering)

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average	10/3	17/5	13/4	11/4	6/2

- missing rating → average rating
- $sim(A, B) = cos(\vec{A'}, \vec{B'}) = \frac{\sum_i (A_i - \overline{A}).(B_i - \overline{B})}{\sqrt{\sum_i (A_i - \overline{A})^2}\sqrt{\sum_i (B_i - \overline{B})^2}}$
  = Pearson coefficient (A, B)

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Back to the Future	+2/3	-2/5	+7/4	-7/4	-
Pride & Prejudice	-7/3	-2/5	-5/4	+5/4	-
Inception	-	+3/5	-5/4	+9/4	+2/2
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cent. average	0	0	0	0	0

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Neighborhood approach to collaborative filtering (2)

Score prediction

Predict score between user u and item i:

- select N_u: k users most similar to u who have selected i
- prediction of $r(u,i)$ is the average score over N_u:

$$r(u,i) = \frac{1}{k} \sum_{x \in N_u} r(x,i)$$

- (more elaborate) weighted average score over N_u:

$$r(u,i) = \frac{\sum_{x \in N_u} sim(u,x).r(x,i)}{\sum_{x \in N_u} sim(u,x)}$$

User-based collaborative filtering

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Neighborhood approach to collaborative filtering: Item-based CF (1)

Similar principle, but based on item similarity

Centered cosine similarity

- User-item rating matrix

	A	B	C	D	E	avg
B. R.	5	3	4	1	2	15/5
B. to the F.	4	3	5	1	-	13/4
P. & P.	1	3	2	4	-	10/4
Inc.	-	4	2	5	4	15/4
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Item-based CF is more efficient than User-based CF in many practical applications

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- Personalized
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  $\Rightarrow$ very popular because feature selection is hard
- Use feedback from other users

Drawbacks

- Not explanatory (no other information than users tastes)
- Does not allow to recommend new or unpopular items
- Need a lot of users (the *critical mass*)
- Tendency to popularity bias: popular items are often in a neighborhood: *the Harry Potter effect*

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How to set the method parameters?

Prediction methods have many parameters:

- Content-based: what are the significant features? ...
- Collaborative: neighborhood size? similarity measure? ...

How to set these parameters in the "best" way?

Need an evaluation methodology:

- **score** to measure efficiency
- **measure** efficiency on known data
- **compare scores** $\rightarrow$ best parameters for predictions

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Evaluation scores

Depending on the problem (classification, regression)
a lot of evaluation scores are available

Regression problems (our example)

Comparing the actual rating (r_i^*) to the predicted rating (r_i):

- Root Mean Square Error

$$RMSE = \sqrt{\frac{\sum_{i=1}^{K}(r_i^* - r_i)^2}{K}}$$

Relevant to give the same importance to all scores?
$\rightarrow$ e.g. just focus on top-5,...

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Splitting data

A general framework for learning problems:

	u_1	u_2	u_3	u_4	u_5	u_6	u_7	u_8	u_9	u_{10}
i_1	2	4	-	-	-	4	1	3	2	-
i_2	2	5	5	-	-	-	4	5	2	1
i_3	-	-	2	-	-	-	3	3	-	1
i_4	-	5	5	5	-	5	-	2	-	-
i_5	-	-	1	2	4	4	-	-	1	-
i_6	-	-	-	1	4	5	-	-	-	-
i_7	-	5	4	5	-	-	4	4	3	5
i_8	-	-	1	2	-	-	-	-	1	5

Splitting matrix: learning set vs test set (blue cells)
→ best prediction on the test set using the learning set

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i_3	-	-	2	-	-	-	3	3	-	1
i_4	-	5	5	5	-	5	-	2	-	-
i_5	-	-	1	2	4	4	-	-	1	-
i_6	-	-	-	1	4	5	-	-	-	-
i_7	-	5	4	5	-	-	4	4	3	5
i_8	-	-	1	2	-	-	-	-	1	5

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Collaborative Filtering in practice

A simple implementation of a user-based CF

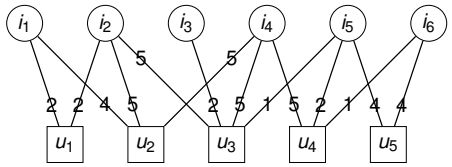
- select x% of ratings randomly ($\equiv$ test set), remaining $(100 - x\%)$ ratings $\equiv$ learning set
- for each rating $r(u, i)$ of the test set:
  - find users in the learning set who have rated the item i
  - compute their similarities to user u (in the learning set)
  - select the k most similar
  - compute predicted score and compare to the actual score

Outline

Recommendation seen as a graph

Recommendation based on user-item matrix
and a matrix can be seen as a bipartite graph...

	u_1	u_2	u_3	u_4	u_5
i_1	2	4	-	-	-
i_2	2	5	5	-	-
i_3	-	-	2	-	-
i_4	-	5	5	5	-
i_5	-	-	1	2	4
i_6	-	-	-	1	4



Recommendation seen as a graph

Notion of neighborhood:
cluster of users around a user

	u_1	u_2	u_3	u_4	u_5
i_1	2	4	-	-	-
i_2	2	5	5	-	-
i_3	-	-	2	-	-
i_4	-	5	5	5	-
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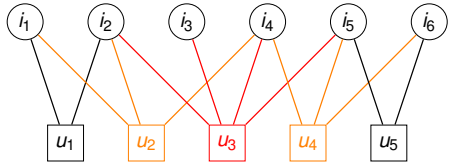

Recommendation seen as a graph

How to represent content information?
ex: t_1 is SF, t2 is comedy, t_3 is drama

	u_1	u_2	u_3	u_4	u_5
i_1	2	4	-	-	-
i_2	2	5	5	-	-
i_3	-	-	2	-	-
i_4	-	5	5	5	-
i_5	-	-	1	2	4
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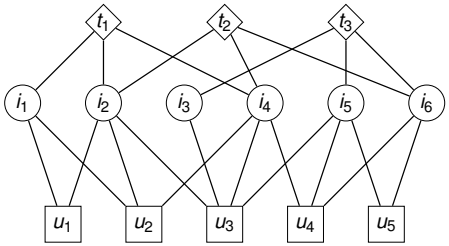

Heterogeneous Information Networks

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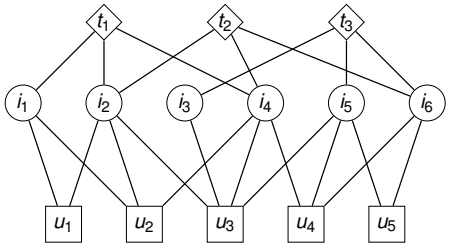

Heterogeneous Information Networks

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Reliance on data

Both content-based and collab. methods need data to work

When is recommendation hard?

- Cold start (both):
  - user is new to the platform (no user profile)
- Content-based filtering:
  - user never selected/rated an item of a given type
  - item profile not expert-evaluated yet
- Collaborative filtering:
  - item is new to the platform (first rater problem)
  - no critical mass of ratings for a user and for an item
    → need enough users rating a product (sparsity problem)

data available is a severely limiting factor
⇒ importance of the data market. . .

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Reliance on data (2)

How to temper these problems?

- User: look for any information available to get a profile
  ex: self-reported info, language, IP address, browser, OS, incoming website, . . .
- Item: look for content information about new items

Combine content to collaborative information
→ leads to hybrid recommender systems

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Do we answer the actual problem?

What is satisfaction?

Replace *satisfaction* with *a score prediction*
But is it legitimate?

- Depending on the context a recommendation does not have the same value
- User *u* rated high *Harry Potter 3* and *4* ⇒ predicting high score for *Harry Potter 5* is easy but useless
  → there is no serendipity here

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Do we answer the actual problem?

Humans are unreliable raters

- Depending on the moment, evaluations fluctuate
- Human have biases in their evaluation
  ex: aspiration bias
- In anyway few ratings even for very active users

From active to passive data collection

- More info from **activity** than from **rating**
  → measure clicks, watch time, time spent on the platform
- . . . but harder to get dislike information

⇒ Combine active and passive feedbacks

Covington et al. - *Deep Neural Networks for YouTube Recommendations, 2016*

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