Content

- Paradox of choice and information overload
- Personalization
- Recommender system
- Step 1: Preference elicitation
- Step 2: Preference prediction - rating estimation techniques
  - Contextualization
- Step 3: Recommendations' presentation
- Issues and problems
- Questions
Explosion of Choice

- A trip to a **local supermarket:**
  - 85 different varieties and brands of crackers.
  - 285 varieties of cookies.
  - 165 varieties of “juice drinks”
  - 75 iced teas
  - 275 varieties of cereal
  - 120 different pasta sauces
  - 80 different pain relievers
  - 40 options for toothpaste
  - 95 varieties of snacks (chips, pretzels, etc.)
  - 61 varieties of sun tan oil and sunblock
  - 360 types of shampoo, conditioner, gel, and mousse.
  - 90 different cold remedies and decongestants.
  - 230 soups, including 29 different chicken soups
  - 175 different salad dressings and if none of them suited, 15 extra-virgin olive oils and 42 vinegars and make one’s own
New Domains for Choice

- Telephone Services
- Retirement Pensions
- Medical Care
- News
- Choosing how to work
- Choosing how to love
- Choosing how to be
Choice and Well-Being

- We have **more choice**, more freedom, autonomy, and self determination.
- It **seems** that increased choice **improves well-being**:
  - *added options can only make us better off: those who care will benefit, and those who do not care can always ignore the added options.*
- Various assessment of well-being have shown that **increased affluence** have accompanied by **decreased well-being**.
Neuroscience and Information Overload

- Neuroscientists have discovered that unproductivity and loss of drive can result from decision overload
- Our brains (120 bits per second) are configured to make a certain number of decisions per day and once we reach that limit, we can’t make any more
- Information processing has a cost: we can have trouble separating the trivial from the important – this inf. processing makes us tired.
Information Overload

- **Internet = information overload =** having too much information to **make a decision** or **remain informed** about a topic

- To make a decision or remain informed about a topic you must perform **exploratory search** (e.g., comparison, knowledge acquisition, product selection, etc.)
  - not aware of the range of available options
  - may not know what to search
  - if presented with some results may not be able to choose.
Personalization

“If I have 3 million customers on the Web, I should have 3 million stores on the Web”

- Jeff Bezos, CEO and founder, Amazon.com
- Degree in Computer Science
- $34.2 billion (net worth), ranked no. 15 in the Forbes list of the America's Wealthiest People
Amazon.it

Ciao Ricci (Se non sei Ricci Francesco, clicca qui)

I suggerimenti di oggi

Ecco una selezione giornaliera degli articoli suggeriti. Clicca qui per visualizzare tutti i suggerimenti.

1Q84. Libro 3. Ottobre-dicembre (Rilegato) di Haruki Murakami
⭐⭐⭐⭐⭐ (66) EUR 15,73
Migliora questo suggerimento

Martha Argerich & Friends - Li... (Audio CD) ~ Martha Argerich
⭐⭐⭐⭐⭐ (1) EUR 13,71
Migliora questo suggerimento

L'uccello che girava le viti... (Brossura) di Haruki Murakami
⭐⭐⭐⭐⭐ (8) EUR 13,13
Migliora questo suggerimento

A sud del confine, a ovest de...
(Rilegato) di Haruki Murakami
⭐⭐⭐⭐⭐ (2) EUR 17,00
Migliora questo suggerimento
Recommendations account for about 60% of all video clicks from the home page.
## Consumer Attitudes to Personalized Shopping Experiences

% of respondents  
**January 2014**

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<tr>
<th>Percentage</th>
<th>Description</th>
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<tr>
<td>20%</td>
<td>20% of respondents have encountered personalized offers/promotions in-store, while 27% have seen them online</td>
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<td>32%</td>
<td>32% have experienced product recommendations based on previous purchases online, compared to 18% in-store</td>
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<td>86%</td>
<td>Of those who have experienced personalization believe it has influenced what they purchase to some extent, including 25% who believe it has significantly influenced what they purchase</td>
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<td>67%</td>
<td>Of those who have experienced personalization are in favor of personalized coupons; personalized offers/promotions based on previous experiences (62%) and product recommendations based on previous purchases (58%) are also favored</td>
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<td>31%</td>
<td>31% of consumers wish their shopping experience was more personalized than it currently is</td>
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<td>20%</td>
<td>20% have never experienced any kind of personalized offers/promotions based on previous purchases, and 19% have never received product recommendations based on previous purchases</td>
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Source: Infosys
The Long Tail

- Economic model in which the market for non-hits (typically large numbers of low-volume items) could be significant and sometimes even greater than the market for big hits (typically small numbers of high-volume items).
Goal

- Recommend items that are good for you!
  - relevant
  - improve well being
  - rational choices
  - optimal
Step 1: Preference Elicitation
Tell us about your music taste

To give you great recommendations we need to know about your current music taste. Get started by adding your favourite artists to your music library.

Add your favourite artists to your music library

Search for an artist... Refresh artists

Wolfgang Amadeus Mozart
Johann Sebastian Bach
Johannes Brahms
Ludwig van Beethoven
The Beatles
Rating Recommendations

Recommended for You

Introduction to Graph Theory (Dover Books on Mathematics)
by Richard J. Trudeau (February 9, 1994)
In Stock
List Price: $44.95
Price: $3.99
59 used & new from $3.26

Because you purchased...

Patterns of Software: Tales from the Software Community (Hardcover)
by Richard P. Gabriel (Author)

Machine Learning (Hardcover)
by Tom M. Mitchell (Author)

Reinforcement Learning: An Introduction (Adaptive Computation and Machine Learning) (Hardcover)
by Richard S. Sutton (Author), Andrew G. Barto (Author)
Alternative Methods

**Independence Day (ID4) (1996)**
145 Min
IMDb
Watch trailer

The aliens are coming and their goal is to invade and destroy. Fighting superior technology, man's best weapon is the will to survive.

**A Clockwork Orange, A (1971)**
136 Min
IMDb
Watch trailer

In future Britain, charismatic delinquent Alex DeLarge is jailed and volunteers for an experimental aversion therapy developed by the government in an effort to solve society's crime problem... but not all goes to plan.
Remembering

- D. Kahneman (nobel prize): what we remember about an experience is determined by *(peak-end rule)*
  - *How the experience felt when it was at its peak (best or worst)*
  - *How it felt when it ended*

- We rely on this summary later to remind how the experience felt and decide whether to have that experience again.

- *So how well do we know what we want?*
  - It is doubtful that we prefer an experience to another very similar just because the first ended better.

Bias of Remembered Utility
Step 2: Model Building
# Movie rating data

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</table>
**Item-to-Item Collaborative Filtering**

Suppose the prediction is made using two nearest-neighbors, and that the items most similar to “Titanic” are “Forrest Gump” and “Wall-E”

- $w_{titanic, forrest} = 0.85$
- $w_{titanic, wall-e} = 0.75$
- $r^*_{eric, titanic} = \frac{(0.85 \times 5 + 0.75 \times 4)}{(0.85 + 0.75)} = 4.53$

<table>
<thead>
<tr>
<th></th>
<th>The Matrix</th>
<th></th>
<th></th>
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<th></th>
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</thead>
<tbody>
<tr>
<td>John</td>
<td>5</td>
<td>1</td>
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<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Lucy</td>
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<td>2</td>
<td>5</td>
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<td>Eric</td>
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<td></td>
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<td>5</td>
<td>4</td>
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<tr>
<td>Diane</td>
<td>4</td>
<td>3</td>
<td>5</td>
<td>3</td>
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</tbody>
</table>
Collaborative-Based Filtering

- A collection of $n$ users $U$ and a collection of $m$ items $I$
- A $n \times m$ matrix of ratings $r_{ui}$, with $r_{ui} = ?$ if user $u$ did not rate item $i$
- Prediction for user $u$ and item $j$ is computed as

$$r_{uj}^* = r_u + K \sum_{v \in N_j(u)} w_{uv} (r_{vj} - r_v)$$

A set of neighbours of $u$ that have rated $j$

- Where, $r_u$ is the average rating of user $u$, $K$ is a normalization factor such that the absolute values of $w_{uv}$ sum to 1, and

$$w_{uv} = \frac{\sum_{j \in I_{uv}} (r_{uj} - r_u)(r_{vj} - r_v)}{\sqrt{\sum_{j \in I_{uv}} (r_{uj} - r_u)^2} \sqrt{\sum_{j \in I_{uv}} (r_{vj} - r_v)^2}}$$

Pearson Correlation of users $u$ and $v$
Latent Factor Models

- Geared towards females: The Princess Diaries
  - Geared towards males: The Lion King
- Escapist: Sense and Sensibility
  - Serious: Amadeus
Basic Matrix Factorization Model

A rank-3 approximation

12 x 3 entries
6 x 3 entries
54 total entries
Estimate Unknown Ratings

A rank-3 approximation
Estimate Unknown Ratings

\[-0.5(-2) + 0.6(0.3) + 0.5(2.4) = 2.4\]

A rank-3 approximation
Matrix factorization as a cost function

\[
\text{Min}_{p^{*}, q^{*}} \sum_{\text{known } r_{ui}} \left[ (r_{ui} - p_u^T q_i)^2 + \lambda \left( \|p_u\|^2 + \|q_i\|^2 \right) \right]
\]

- \(p_u\) - user-factors of \(u\)
- \(q_i\) - item-factors of \(i\)
- \(r_{ui}\) - rating by \(u\) for \(i\)

- Optimize by either stochastic gradient-descent or alternating least squares
### “Core” Recommendation Techniques

<table>
<thead>
<tr>
<th>Technique</th>
<th>Background</th>
<th>Input</th>
<th>Process</th>
</tr>
</thead>
<tbody>
<tr>
<td>Collaborative</td>
<td>Ratings from $U$ of items in $I$.</td>
<td>Ratings from $u$ of items in $I$.</td>
<td>Identify users in $U$ similar to $u$, and extrapolate from their ratings of $i$.</td>
</tr>
<tr>
<td>Content-based</td>
<td>Features of items in $I$</td>
<td>$u$’s ratings of items in $I$</td>
<td>Generate a classifier that fits $u$’s rating behavior and use it on $i$.</td>
</tr>
<tr>
<td>Demographic</td>
<td>Demographic information about $U$ and their ratings of items in $I$.</td>
<td>Demographic information about $u$.</td>
<td>Identify users that are demographically similar to $u$, and extrapolate from their ratings of $i$.</td>
</tr>
<tr>
<td>Utility-based</td>
<td>Features of items in $I$.</td>
<td>A utility function over items in $I$ that describes $u$’s preferences.</td>
<td>Apply the function to the items and determine $i$’s rank.</td>
</tr>
<tr>
<td>Knowledge-based</td>
<td>Features of items in $I$. Knowledge of how these items meet a user’s needs.</td>
<td>A description of $u$’s needs or interests.</td>
<td>Infer a match between $i$ and $u$’s need.</td>
</tr>
</tbody>
</table>

[Burke, 2007]
Content-Based Recommender with Centroid

Centroid

Not interesting Documents

Interesting Documents

Doc1 is estimated more interesting than Doc2
Recommendations can be wrong

- Recommenders tend to recommend items similar to those browsed or purchased in the past.
Context-Aware Computing

- Gartner Top 10 strategic technology trends for IT

- Context-aware computing is a style of computing in which situational and environmental information about people, places and things is used to anticipate immediate needs and proactively offer enriched, situation-aware and usable content, functions and experiences.

Google Now

https://www.google.com/landing/now/
Types of Context - Mobile

- **Physical context**
  - time, position, and activity of the user, weather, light, and temperature ...

- **Social context**
  - the presence and role of other people around the user

- **Interaction media context**
  - the device used to access the system and the type of media that are browsed and personalized (text, music, images, movies, ...)

- **Modal context**
  - The state of mind of the user, the user’s goals, mood, experience, and cognitive capabilities.
Traditional contextual pre-filtering

- Only ratings acquired in exactly the same context are used

- **Hypothesis:** pre-filtering can be enhanced by exploiting semantic similarities between contexts
Distributional semantics of context

**Assumption:** two contexts are similar if their composing conditions influence ratings similarly

\[
\sum_{r_{uic} \in R_{ic}} (r_{uic} - \hat{r}_{ui}) \frac{1}{|R_{ic}|}
\]

<table>
<thead>
<tr>
<th>Condition</th>
<th>User1</th>
<th>User2</th>
<th>User3</th>
<th>User4</th>
<th>User5</th>
<th>User6</th>
<th>User7</th>
</tr>
</thead>
<tbody>
<tr>
<td>![Family]</td>
<td>1</td>
<td>-0.7</td>
<td>0</td>
<td>0.9</td>
<td>0.1</td>
<td>-0.6</td>
<td>0</td>
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<tr>
<td>![Sun]</td>
<td>0.7</td>
<td>-0.8</td>
<td>0.5</td>
<td>0.8</td>
<td>0.4</td>
<td>-0.2</td>
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<tr>
<td>![Sad]</td>
<td>-0.5</td>
<td>0.7</td>
<td>0.2</td>
<td>-1</td>
<td>0.9</td>
<td>0.8</td>
<td>0.5</td>
</tr>
</tbody>
</table>
Semantic contextual pre-filtering

- **Key idea:** reuse ratings acquired in similar contexts

![Diagram showing the process of semantic contextual pre-filtering]

- Ratings filtering
- "similar context" ratings
- Target context
- Semantic similarities
- Prediction model
- Predicted rating
Semantic Pre-Filtering vs. State of the art

% = MAE (mean absolute error) reduction with respect to a context-free Matrix Factorization model (the higher, the better)
South Tyrol Suggest (STS)

- A mobile Android context-aware RS that recommends places of interests (POIs) from a total of 27,000 POIs in South Tyrol region.
- STS computes rating predictions for all POIs using the personality of the users, the ratings, and 14 contextual factors, such as: weather forecast, mood, budget, and travel goal.

Big Five Personality Traits:
- Openness
- Agreeableness
- Neuroticism
- Conscientiousness
- Extraversion
Step 3: Recommendation Presentation
Anchoring

- How do we determine *what is reasonable to spend* for a race bicycle?
  - In an online shop that presents *only bicycles costing over 3.000€* we may believe that *1.500 is not enough*, or that a bicycle at that price will be a *bargain*
  - Even if nobody will select the highest-priced models, the shop can reap benefits from listing them – people is induced to buy the cheaper (but still expensive) ones.

Colnago Ferrari

Context *increases* Expected Utility
Dissatisfaction because of opportunity costs

- A study in which people were asked how much they would be willing to pay for subscriptions to magazines [Brenner, Rottenstreich, & Sood, 1999].
  - Some were asked about individual magazines or videos
  - Others were asked about these same items as part of a group with other magazines or videos
- Respondents placed a higher value on the magazine or the video when they were evaluating it in isolation
  - If evaluated as part of a group, opportunity costs associated with the other options reduce the value of each of them.

Context decreases Expected Utility
Context increases Expected Utility

Context used to differentiate options and decrease opportunity cost.

Near Castle Roncolo there is the cable car station San Genesio. The cable car "flight" from Bolzano to San Genesio (1087m)is about 9 minutes. The panoramic view of the Dolomites, the
Problems and Issues

- Cold Start (new user and new item) - old items are less interesting
- Learning to interact
- Measuring
- Filter Bubble
- How much to personalize
- When to contextualize
- How to deliver contextualized content?
- Multiple devices (synchronization)
Questions?

» Computer Science  » Artificial Intelligence

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Recommender Systems Handbook

Editors: Ricci, F., Rokach, L., Shapira, B., Kantor, P.B. (Eds.)

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