Case-based Recommendation

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with slides of Danielle Lee

Modern E-Commerce Site

Digital Cameras

Find a digital camera

<table>
<thead>
<tr>
<th>Price</th>
<th>Manufacturer</th>
<th>Zoom range</th>
<th>Other</th>
</tr>
</thead>
<tbody>
<tr>
<td>Less than $100</td>
<td>Sony</td>
<td>Less than 3X</td>
<td>Flash memory</td>
</tr>
<tr>
<td>$100 - $200</td>
<td>Nikon</td>
<td>3X to 4X</td>
<td>Digital camera type</td>
</tr>
<tr>
<td>$200 - $400</td>
<td>Panasonic</td>
<td>4X to 8X</td>
<td>Resolution</td>
</tr>
<tr>
<td>$400 - $600</td>
<td>Canon</td>
<td>8X to 12X</td>
<td>Maximum ISO</td>
</tr>
<tr>
<td>$600 - $1,000</td>
<td>Olympus</td>
<td>More than 12X</td>
<td>Weight</td>
</tr>
<tr>
<td>$500 - $1,200</td>
<td>Fujifilm</td>
<td>See all zoom ranges</td>
<td>Optical sensor type</td>
</tr>
</tbody>
</table>

See all prices

Nikon D7000
Price: $1,179.95 - $2,179.95

TOP DIGITAL CAMERA
The Power of Metadata

• Modern e-commerce sites have a range of metadata for each item
  ▫ Travel information presented in its price, duration, accommodation, location, mode of transport, etc.
  ▫ Job information presented in the job kinds, salary, business category of each company, educational level, experience, location etc.
• This data is used in modern Faceted Search, more powerful than keyword search
• The power of metadata can be also used for better recommendation this is the essence of case-based way

Metadata Could be Used in a Smarter Way

• “6 mega-pixel digital SLR for under $200”
  ▫ No result is returned → System slavishly respects customers’ queries (“stonewalling”)
• “Another camera like this one but with more optical zoom and a lower price”
  ▫ Too complex for customers to provide this form of feedback directly to the system.
• “I never accepted the cameras above $1000”
  ▫ Few commercial system to remember customers’ preferences over time.
  ▫ Customers start their search from scratch in every visit.
Case-Based Recommendation?

- A special form of *content-based* recommendation
- Assumes structured item information with a well defined set of features and feature values.
- Information are represented as a *case* and the system recommends the cases that are *most similar* to a user’s preference
- Case-based representation also supports more advanced recommendation dialogues and explanations

Case-based Reasoning

- Case-based recommendation origins in Case-Based Reasoning (CBR).
  - It is to solve new problems by reusing the solutions to problems that have been previously solved and stored as cases in a case-base.
  - Each case consists of a specification part, which describes the problem and a solution part, which describes the solution of the problem.
    - Solutions to similar prior problems are a useful starting point for new problem solving.
- “The users would like the similar one that they liked before.”
Simple Example of Case-based Recommendation

I want a laptop having 250GB HDD, 1GB memory, and 14 inch screen for $400.

<table>
<thead>
<tr>
<th>Product #1</th>
<th>HDD: 250 GB</th>
<th>Memory: 2 GB</th>
<th>Screen Size: 15 inch</th>
<th>Price: $550</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product #2</td>
<td>HDD: 150 GB</td>
<td>Memory: 1 GB</td>
<td>Screen Size: 15 inch</td>
<td>Price: $450</td>
</tr>
<tr>
<td>Product #3</td>
<td>HDD: 250 GB</td>
<td>Memory: 1 GB</td>
<td>Screen Size: 14.2 inch</td>
<td>Price: $420</td>
</tr>
</tbody>
</table>

Case-based Recommendation

Target Query, t
- Price: 1000
- Pixel: 6

Product Case Base

<table>
<thead>
<tr>
<th>Feature</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price</td>
<td>1000</td>
</tr>
<tr>
<td>Pixel</td>
<td>6</td>
</tr>
<tr>
<td>Memory</td>
<td>1 GB</td>
</tr>
<tr>
<td>HDD</td>
<td>250 GB</td>
</tr>
<tr>
<td>Screen Size</td>
<td>14 inch</td>
</tr>
<tr>
<td>Price</td>
<td>$550</td>
</tr>
</tbody>
</table>

Case Retrieval

Product Recommendations
- $c_1 \ sim(t, c_1)$
- $c_n \ sim(t, c_n)$
Case Representation

<table>
<thead>
<tr>
<th>Nominal Feature</th>
<th>Numeric Feature</th>
</tr>
</thead>
<tbody>
<tr>
<td>Manufacturer</td>
<td>Cannon</td>
</tr>
<tr>
<td>Model</td>
<td>EOS D60</td>
</tr>
<tr>
<td>Pixel</td>
<td>6.3</td>
</tr>
<tr>
<td>Memory Size (MB)</td>
<td>8.0</td>
</tr>
<tr>
<td>Memory Type</td>
<td>CompactFlash Card</td>
</tr>
<tr>
<td>Num of Batteries</td>
<td>1.0</td>
</tr>
<tr>
<td>Battery Type</td>
<td>BP-511</td>
</tr>
<tr>
<td>Strap</td>
<td>Neck</td>
</tr>
<tr>
<td>Cable</td>
<td>USB and Video</td>
</tr>
<tr>
<td>Software</td>
<td>CD-Rom featuring Adobe Photoshop LE</td>
</tr>
<tr>
<td>Price</td>
<td>869.0</td>
</tr>
</tbody>
</table>

Similarity Assessment (1)

- Similarity metrics that are based on an explicit mapping of case features and the availability of specialized feature level similarity knowledge.

\[
\text{Similarity}(t, c) = \frac{\sum_{i=1..n} w_i \cdot sim(t_i, c_i)}{\sum_{i=1..n} w_i}
\]
Similarity Assessment (2)

• In symmetric similarity, maximum similarity is achieved when a feature of a candidate case matches that of the target query. No bias in favor of either higher or lower values of the corresponding feature.

Similarity Assessment (3)

• In asymmetric similarity, there is a bias to either higher or lower values (i.e. a product that is $50 cheaper is better than $50 more expensive)
Similarity Assessment of Nominal Values

Partial Ontology of Vacation types

Acquiring Similarity Knowledge

- Based on knowledge made by a domain knowledge expert.
  - Normally it is hand-coded and expensive.
- Machine learning techniques.
  - Using several weight-learning algorithm, even knowledge-poor techniques can result in significant improvements in case-based classification tasks.
- Similarity assessment by users
  - A ‘similarity teacher’ evaluates the ordering for the given set of retrieval results.
  - The selections could be used not only for assessing the similarity but for acquiring users preference.
Case-based Job Recommendation

Database Developer job for a finance-related company in Boston

Job #1
Database Analyst job for Company A

Job #2
Database Administrator job for Company B

Job #3
Technical Support Engineer for Company C

Job Related Knowledge (1)

- Partial Ontology about job category.
Job Related Knowledge (2)

- Taxonomy about Company
  - Company A: Insurance company, downtown in Boston.
  - Company B: Pharmaceutical company, 5 miles distance from Boston.
  - Company C: Computer manufacturing domain, 1.5 miles distance from Boston.
“I want a 2-week vacation for two in the sun, costing less than $750, within 3 hours flying time of Ireland. I expect good night-life and recreation facilities on-site”

System suggests ...

1. Hercules Complex in the Costa Del Sol, Spain on the first two weeks of July
2. Hercules Complex in the Costa Del Sol, Spain on the first two weeks of August
3. Pleasure Complex in the Costa Del Sol, Spain on the last two weeks of July
4. Hercules Complex in the Costa Del Sol, Spain on the last two weeks of July
5. ...

Similarity vs. Diversity (1)
Similarity vs. Diversity (2)

- Bounded Random Selection: from the top $bk$ most similar cases to the target query, select $k$ random cases.
  - The diversity could increase but the similarity could also decrease.
- Bounded Greedy Selection: define the diversity of a set of retrieved cases to be the average dissimilarity between all pairs of these cases.
  - 50% improvement in relative diversity with a minor loss of less than 10% in similarity to the target query.
  - A unit drop in similarity can be traded for almost 3 units of diversity using this method.
  - Increased computational efficiency.

Bounded Greedy Selection

- The key idea is the quality metric that combines diversity and similarity.
  1. Select the best $bk$ cases according to the similarity.
  2. Pick up the one with the highest similarity.
  3. During each subsequent iteration, the case with the highest combination of similarity and diversity with respect to the set of cases selected during the previous iteration.

$$Quality(t, c, R) = Similarity(t, c) \times RelDiversity(c, R) \quad (11.4)$$

$$RelDiversity(c, R) = \begin{cases} 1 & \text{if } R = \{c\}; \\ \frac{\sum_{i=1}^{m}(1 - Similarity(c, r_i))}{m} & \text{otherwise} \end{cases} \quad (11.5)$$
Other approaches for diversity

- **Shimazu (2001, 2002)**
  - It is suitable to the situations where the set of recommended cases is drawn from a set of sufficiently similar cases.
- **Similarity layers**
  - A set of cases are ranked by their similarity to the target query and partitioned into similarity layers.
  - The lowest similarity layer is selected using an optimal diversity maximizing algorithm.
- **Similarity intervals**
- **Order-based Retrieval**
- **Compromise-driven approach**
Conversational Recommendation

- Many case-based recommenders operate in a reactive and **single-shot fashion**.
  - If users don’t find what they want, the only option is to revise their query and start again.
  - User’s initial query could be adapted and refine as they learn more about a particular product-space.
- Conversational recommender is to engage users in an extended, interactive recommendation dialog during the query elicitation.
  - Navigation by asking
  - Navigation by proposing

Navigation by asking (1) - *Adaptive Place Advisor*

| 1. Inquirer: Where do you think I should eat tonight? |
| 2. Advisor: What type of food would you like? |
| 3. Inquirer: What types are there? |
| 5. Inquirer: Oh, maybe a cheap Indian place. |
| 6. Advisor: What kind of parking would you like? |
| 7. Inquirer: I don’t care, as long as it’s in Palo Alto. |
| 8. Advisor: I’m sorry, I don’t know of any restaurants like that, would you like to search for any price? |
| 10. Advisor: How does Mandarin Gourmet on 420 Ramona sound? |
| 11. Inquirer: No, what else do you have? |
| 12. Advisor: How about Jing-Jing Szechwan Hunan Gourmet on 443 Emerson Street? |
| 13. Inquirer: Sure, that sounds fine. |
Navigation by asking (2)

- The selection of questions does matter.
  - Entropy - Dolye & Cunningham (2000)
  - Information gain - Quinlan (1986); Quinlan (1993) and Shimazu (2001); Shimazu (2003)

- However, directly asking questions to users can be burden to them.
  - A long list of questions, uncertain answers or rejected questions.
  - Significant interfacing burden

Navigation by proposing (1)

- The users are presented with one of more recommendation alternatives, rather than a question, during each recommendation cycle.
  - Rating based feedback
  - Critique based feedback: Constraints over certain features of recommendations
  - Preference based feedback: Expressed preference for one alternative over the others
Critique based feedback

This apartment is OK, but make it...

bigger cheaper nicer safer

This neighborhood could be more...

convenient conservative dynamic

Compound Critiques

We have more matching cameras with the following:

1. Less Memory and Lower Resolution and Cheaper
2. Smaller and Less Zoom and Lighter
3. Lighter and Smaller and Different Case
### Case-based User Profiling (1)

- Conversational recommenders can react to the feedback provided by users within each session.
  - In-session personalization only and two users who respond in the same way within a session will receive the same recommendations.
  - How can the systems adapt to the users’ persistent preference?
- It is important for the recommenders to learn and maintain a long-term model of a user’s recommendation preferences.

#### Table: The top candidate according to your preferences

<table>
<thead>
<tr>
<th>Manufacturer</th>
<th>Price</th>
<th>Memory Type</th>
<th>Optical Zoom</th>
<th>Flash Memory</th>
<th>Screen Size</th>
<th>Depth</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Canon</td>
<td>$242.00</td>
<td>CompactFlash Card</td>
<td>3x</td>
<td>10 MB</td>
<td>1.8 in</td>
<td>1.27 in</td>
<td>8.3 oz</td>
</tr>
</tbody>
</table>

#### Table: We have more products with the following

- They are cheaper and lighter, but have fewer megapixels

<table>
<thead>
<tr>
<th>Manufacturer</th>
<th>Price</th>
<th>Memory Type</th>
<th>Optical Zoom</th>
<th>Flash Memory</th>
<th>Screen Size</th>
<th>Depth</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nikon</td>
<td>$88.95</td>
<td>SD Memory Card</td>
<td>3x</td>
<td>8 MB</td>
<td>2.9 in</td>
<td>1.8 in</td>
<td>6.9 oz</td>
</tr>
<tr>
<td>Canon</td>
<td>$130.00</td>
<td>CompactFlash Card</td>
<td>3x</td>
<td>10 MB</td>
<td>1.8 in</td>
<td>1.27 in</td>
<td>8.3 oz</td>
</tr>
<tr>
<td>Pentax</td>
<td>$109.99</td>
<td>SD Memory Card</td>
<td>3x</td>
<td>8 MB</td>
<td>2.9 in</td>
<td>1.8 in</td>
<td>6.9 oz</td>
</tr>
</tbody>
</table>

- They have more megapixels and bigger screens, but are more expensive

<table>
<thead>
<tr>
<th>Manufacturer</th>
<th>Price</th>
<th>Memory Type</th>
<th>Optical Zoom</th>
<th>Flash Memory</th>
<th>Screen Size</th>
<th>Depth</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nikon</td>
<td>$285.00</td>
<td>Internal Memory</td>
<td>3x</td>
<td>16 MB</td>
<td>2.9 in</td>
<td>1.8 in</td>
<td>6.9 oz</td>
</tr>
<tr>
<td>Canon</td>
<td>$290.00</td>
<td>CompactFlash Card</td>
<td>3x</td>
<td>10 MB</td>
<td>1.8 in</td>
<td>1.27 in</td>
<td>8.3 oz</td>
</tr>
<tr>
<td>Pentax</td>
<td>$120.00</td>
<td>SD Memory Card</td>
<td>3x</td>
<td>8 MB</td>
<td>2.9 in</td>
<td>1.8 in</td>
<td>6.9 oz</td>
</tr>
</tbody>
</table>

- They are lighter and thinner, but have less flash memory

<table>
<thead>
<tr>
<th>Manufacturer</th>
<th>Price</th>
<th>Memory Type</th>
<th>Optical Zoom</th>
<th>Flash Memory</th>
<th>Screen Size</th>
<th>Depth</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pentax</td>
<td>$289.99</td>
<td>Internal Memory</td>
<td>3x</td>
<td>16 MB</td>
<td>2.9 in</td>
<td>1.1 in</td>
<td>5.9 oz</td>
</tr>
<tr>
<td>Canon</td>
<td>$275.00</td>
<td>CompactFlash Card</td>
<td>3x</td>
<td>10 MB</td>
<td>2.9 in</td>
<td>1.27 in</td>
<td>8.3 oz</td>
</tr>
<tr>
<td>Nikon</td>
<td>$220.95</td>
<td>Internal Memory</td>
<td>3x</td>
<td>12 MB</td>
<td>2.5 in</td>
<td>0.8 in</td>
<td>4.2 oz</td>
</tr>
<tr>
<td>Pentax</td>
<td>$189.99</td>
<td>SD Memory Card</td>
<td>3x</td>
<td>8 MB</td>
<td>2.9 in</td>
<td>1.1 in</td>
<td>5.9 oz</td>
</tr>
<tr>
<td>Canon</td>
<td>$165.18</td>
<td>Internal Memory</td>
<td>3x</td>
<td>12 MB</td>
<td>2.5 in</td>
<td>0.8 in</td>
<td>4.2 oz</td>
</tr>
<tr>
<td>Nikon</td>
<td>$195.00</td>
<td>Internal Memory</td>
<td>3x</td>
<td>12 MB</td>
<td>2.5 in</td>
<td>0.8 in</td>
<td>4.2 oz</td>
</tr>
<tr>
<td>Pentax</td>
<td>$125.99</td>
<td>SD Memory Card</td>
<td>3x</td>
<td>8 MB</td>
<td>2.9 in</td>
<td>1.1 in</td>
<td>5.9 oz</td>
</tr>
<tr>
<td>Canon</td>
<td>$129.99</td>
<td>Internal Memory</td>
<td>3x</td>
<td>12 MB</td>
<td>2.5 in</td>
<td>0.8 in</td>
<td>4.2 oz</td>
</tr>
</tbody>
</table>

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**Explanations and Clustering**

- Conversational recommenders can react to the feedback provided by users within each session.
- In-session personalization only and two users who respond in the same way within a session will receive the same recommendations.
- How can the systems adapt to the users’ persistent preference?
- It is important for the recommenders to learn and maintain a long-term model of a user’s recommendation preferences.
Case-based User Profiling (2)

- CB leverages available content descriptions of cases as a form of case-based user profile.
  - User profile is made of a set of cases and the preference (like or dislike)
- CASPER : Online recruitment system using implicit user profile (from positive and negative points of view) and this profile is used to re-order the recommendations.
  - The Personal Travel Assistant also has similar approach.

Feature Level User Profiling

- The preference related to features and their values such as preferred values for a particular features, the relative importance of a particular attributes, etc.
  - In restaurant recommendation, the kind of cuisine has an importance weight of 0.4 and parking facilities have a preference weight of 0.1. The user also prefers Italian cuisine with 0.35 weight to German food with 0.1 weight.
Hybridization of CB and CF - PTV

- To solve sparsity problem or latency problem in CF, case-based technology was used.
- By the derived similarity knowledge using data mining technology, the relationships between information items was extended.
- Increased recommendation coverage and recommendation accuracy.

Question?