Case-based Recommendation

Peter Brusilovsky
with slides of Danielle Lee
## Where we are?

<table>
<thead>
<tr>
<th></th>
<th>Search</th>
<th>Navigation</th>
<th>Recommendation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Content-based</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Semantics / Metadata</td>
<td></td>
<td></td>
<td>![Red square]</td>
</tr>
<tr>
<td>Social</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
# Modern E-Commerce Site

## Digital Cameras

### Nikon D7000

**Price:** $1,179.95 - $2,179.95

<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 - $300</td>
<td>Panasonic</td>
<td>4X to 8X</td>
<td>Resolution</td>
</tr>
<tr>
<td>$300 - $400</td>
<td>Canon</td>
<td>8X to 12X</td>
<td>Maximum ISO</td>
</tr>
<tr>
<td>$400 - $500</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

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

**Product #1**
- HDD : 250 GB
- Memory : 2 GB
- Screen Size : 15 inch
- Price : $550

**Product #2**
- HDD : 150 GB
- Memory : 1 GB
- Screen Size : 15 inch
- Price : $450

**Product #3**
- HDD : 250 GB
- Memory : 1 GB
- Screen Size : 14.2 inch
- Price : $420
Case-based Recommendation

**Product Case-Base**

- Manufacturer: Canon
- Model: EOS 60D
- Pixel: 18.0
- Memory Size (MB): 8.0
- Memory Type: CompactFlash Card
- Num of Batteries: 1.0
- Battery Type: BP-511
- Strap: Black
- Cable: USB and Video
- Software: CD: Raw Processing Adobe Photoshop LE
- Price: ¥112,800

**Target Query, t**

- Price: 1000
- Pixel: 6

**Case Retrieval**

- \( c_1, \ldots, c_n \)

**Product Recommendations**

- \( c_1 \{ \text{sim}(t, c_1) \}, \ldots, c_k \{ \text{sim}(t, c_k) \} \)
## Case Representation

<table>
<thead>
<tr>
<th>Feature</th>
<th>Value</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>

- **Nominal Feature**: Manufacturer, Model, Memory Type, Num of Batteries, Battery Type, Strap, Software
- **Numeric Feature**: Pixel, Memory Size, Price
Simularity Assessment (1)

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

\[
\text{Similarity}(t, c) = \frac{\sum_{i=1..n} w_i \times sim_i(t_i, c_i)}{\sum_{i=1..n} w_i}
\]
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.
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

Diagram showing the relationship between vacation types and activities with similarity assessments.
Representing Similarity Knowledge

<table>
<thead>
<tr>
<th></th>
<th>Small Car</th>
<th>Medium Car</th>
<th>Large Car</th>
<th>SUV</th>
<th>Mini Van</th>
</tr>
</thead>
<tbody>
<tr>
<td>SmCar</td>
<td>1</td>
<td>???</td>
<td>???</td>
<td>???</td>
<td>???</td>
</tr>
<tr>
<td>MdCar</td>
<td>???</td>
<td>1</td>
<td>???</td>
<td>???</td>
<td>???</td>
</tr>
<tr>
<td>LgCar</td>
<td>???</td>
<td>???</td>
<td>1</td>
<td>???</td>
<td>???</td>
</tr>
<tr>
<td>SUV</td>
<td>???</td>
<td>???</td>
<td>???</td>
<td>1</td>
<td>???</td>
</tr>
<tr>
<td>Minivan</td>
<td>???</td>
<td>???</td>
<td>???</td>
<td>???</td>
<td>1</td>
</tr>
</tbody>
</table>
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 algorithms, 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

<table>
<thead>
<tr>
<th>Job #1</th>
<th>Job #2</th>
<th>Job #3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Database Analyst job for Company A</td>
<td>Database Administrator job for Company B</td>
<td>Technical Support Engineer for Company C</td>
</tr>
</tbody>
</table>

![Image](image.jpg)
Job Related Knowledge (1)

- Partial Ontology about job category.

```
Job Category

- Technical Support
  - Technical Support Represen.
  - Database Developer
- Database Engineer
- Database Admin
- Database Admin. Engineer
  ...
```
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.
### Proactive - Job Recommendation System

Welcome to Proactive, Danielle

---

<table>
<thead>
<tr>
<th>Job Category</th>
<th>Title</th>
<th>Company</th>
<th>City</th>
<th>State</th>
<th>Position Type</th>
<th>Salary</th>
<th>Experience</th>
<th>Education</th>
<th>Post Date</th>
<th>Relevance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Database Manager</td>
<td>Marketing Database Manager</td>
<td>Info Technologies, Inc.</td>
<td>New York</td>
<td>NY</td>
<td>Full-Time, Contract</td>
<td>unspecified</td>
<td>5-10 Years Experience</td>
<td>unspecified</td>
<td>01-23-08</td>
<td>****</td>
</tr>
<tr>
<td>Database Architect</td>
<td>.NET Developer (.C#, .C#)</td>
<td>Concepts in Staffing</td>
<td>New York</td>
<td>NY</td>
<td>Full-Time, Employee</td>
<td>unspecified</td>
<td>5-10 Years Experience</td>
<td>Bachelor's degree</td>
<td>01-23-08</td>
<td>****</td>
</tr>
<tr>
<td>Database Architect</td>
<td>Database Architect [SAVE]</td>
<td>Spot Runner</td>
<td>Los Angeles</td>
<td>CA</td>
<td>Full-Time, Employee</td>
<td>unspecified</td>
<td>10-15 Years Experience</td>
<td>Bachelor's degree</td>
<td>01-23-08</td>
<td>****</td>
</tr>
<tr>
<td>Database Architect</td>
<td>Solutions Architect [SAVE]</td>
<td>Silver Key</td>
<td>San Francisco</td>
<td>CA</td>
<td>Full-Time, Employee</td>
<td>unspecified</td>
<td>2-5 Years Experience</td>
<td>Bachelor of Science</td>
<td>01-23-08</td>
<td>****</td>
</tr>
<tr>
<td>Database Architect</td>
<td>ETL Architect [SAVE]</td>
<td>Kinetic Networks, Inc.</td>
<td>San Francisco</td>
<td>CA</td>
<td>Full-Time, Employee</td>
<td>unspecified</td>
<td>2-5 Years Experience</td>
<td>unspecified</td>
<td>01-23-08</td>
<td>****</td>
</tr>
<tr>
<td>Database Specialist</td>
<td>EDUCATIONAL SALES SPECIALIST - EAST [SAVE]</td>
<td>Sika Samall, Inc.</td>
<td>New York</td>
<td>NY</td>
<td>Full-Time, Employee</td>
<td>unspecified</td>
<td>5-10 Years Experience</td>
<td>Bachelor of Science</td>
<td>01-23-08</td>
<td>****</td>
</tr>
<tr>
<td>Database Architect</td>
<td>MySQL DBA / Architect [SAVE]</td>
<td>Slide, Inc.</td>
<td>San Francisco</td>
<td>CA</td>
<td>Full-Time, Employee</td>
<td>unspecified</td>
<td>2-5 Years Experience</td>
<td>unspecified</td>
<td>01-23-08</td>
<td>****</td>
</tr>
<tr>
<td>Database Architect</td>
<td>SQL Database Architect [SAVE]</td>
<td>Global Technical Talent</td>
<td>New York City</td>
<td>NYC</td>
<td>Full-Time, Contract</td>
<td>unspecified</td>
<td>2-5 Years Experience</td>
<td>unspecified</td>
<td>01-23-08</td>
<td>****</td>
</tr>
<tr>
<td>Database Manager</td>
<td>Release Manager [SAVE]</td>
<td>Kaiser Permanente</td>
<td>Oakland</td>
<td>CA</td>
<td>Full-Time, Employee</td>
<td>unspecified</td>
<td>5-10 Years Experience</td>
<td>unspecified</td>
<td>01-23-08</td>
<td>***</td>
</tr>
<tr>
<td>Database Architect</td>
<td>Sr. Database Architect [SAVE]</td>
<td>Careers on the Move</td>
<td>New York</td>
<td>NY</td>
<td>Full-Time, Employee</td>
<td>$120,000 to $150,000 per year</td>
<td>10-15 Years Experience</td>
<td>Master of Science</td>
<td>01-23-08</td>
<td>***</td>
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<tr>
<td>Database Developer</td>
<td>Java Developer - Database Developer [SAVE]</td>
<td>Adobe Systems</td>
<td>San Francisco</td>
<td>CA</td>
<td>Full-Time, Employee</td>
<td>unspecified</td>
<td>5-10 Years Experience</td>
<td>Bachelor of Science</td>
<td>01-21-08</td>
<td>***</td>
</tr>
<tr>
<td>Technical Support Consultant</td>
<td>Patient Monitoring Technical Consultant [SAVE]</td>
<td>Philips North America</td>
<td>New York</td>
<td>NY</td>
<td>Full-Time, Employee</td>
<td>unspecified</td>
<td>2-5 Years Experience</td>
<td>Bachelor's degree</td>
<td>01-20-08</td>
<td>***</td>
</tr>
<tr>
<td>Technical Support Consultant</td>
<td>Summit System Support Consultant [SAVE]</td>
<td>Solomon-Page Group</td>
<td>New York</td>
<td>NY</td>
<td>Full-Time, Contract</td>
<td>$450 to $650 per year</td>
<td>5-10 Years Experience</td>
<td>Bachelor of Science</td>
<td>01-20-08</td>
<td>***</td>
</tr>
<tr>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
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)

(a) Similarity-Based

(b) Diversity-Based
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.

\[
\text{Quality}(t, c, R) = \text{Similarity}(t, c) \times \text{RelDiversity}(c, R)
\]  \hspace{1cm} (11.4)

\[
\text{RelDiversity}(c, R) = 1 \text{ if } R = \{\}; \\
= \frac{\sum_{i=1}^{m}(1 - \text{Similarity}(c, r_i))}{m}, \text{ otherwise}
\]  \hspace{1cm} (11.5)
Similarity vs. Diversity (3)

Graph 1: Similarity vs. Result Set Size (k)
Graph 2: Diversity vs. Result Set Size (k)

Legend:
- ♦ Standard
- ■ Random
- ▲ Greedy
- × Bounded
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 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?
4. **Advisor:** You can say things like Chinese, Indian, and Mediterranean.
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?
9. **Inquirer:** No, I think I’d like Chinese instead.
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)
  ▫ Influence - Schmitt (2002)

• 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

UKRAINIAN VILLAGE. TWO bedroom rehab garden apartment. Lr, Eurokitchen, hwfl, excellent security, forced air, lots of closets, laundry in building. Garage space included. Dogs OK. Available immediately. $600/mo. 312-489-1554.

| Phone: 312-489-1554 | 2-bedrooms | $600 | 60622 (West Town Bucktown) |

This apartment is OK, but make it...

bigger cheaper nicer safer

This neighborhood could be more...

convenient conservative dynamic
Compound Critiques

Adjust your preferences to find the right camera for you:

- **Manufacturer**: Canon
- **Optical Zoom**: 7x
- **Memory (MB)**: 512
- **Weight (Grains)**: 780
- **Resolution**: 6.2 M Pixels
- **Size**: Large
- **Case**: Magnesium
- **Price**: 995

We have more matching cameras with the following:

1. **Less Memory and Lower Resolution and Cheaper**
   - Current Value: 512 MB
   - Critique: Less Than
   - Remaining: (0 to 256 MB)

2. **Different Manufacturer and Less Zoom and Lighter**
   - Current Value: 6.2 M Pixels
   - Critique: Less Than
   - Remaining: (1.4 to 5.9 M Pixels)

3. **Lighter and Smaller and Different Case**
   - Current Value: 995 €
   - Critique: Less Than
   - Remaining: (25 to 360 €)

Unit Critiques
## Explanations and Clustering (Pu)

### The top candidate according to your preferences

<table>
<thead>
<tr>
<th>Manufacturer</th>
<th>Price</th>
<th>Megapixels</th>
<th>Optical zoom</th>
<th>Memory type</th>
<th>Flash memory</th>
<th>LCD screen size</th>
<th>Depth</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Canon</td>
<td>$242.00</td>
<td>5.0 MP</td>
<td>3x</td>
<td>CompactFlash Card</td>
<td>32 MB</td>
<td>1.8 in</td>
<td>1.37 in</td>
<td>8.3 oz</td>
</tr>
</tbody>
</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>Megapixels</th>
<th>Optical zoom</th>
<th>Memory type</th>
<th>Flash memory</th>
<th>LCD screen size</th>
<th>Depth</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nikon</td>
<td>$167.95</td>
<td>4 MP</td>
<td>3x</td>
<td>SD Memory Card</td>
<td>14 MB</td>
<td>1.8 in</td>
<td>1.4 in</td>
<td>4.6 oz</td>
</tr>
<tr>
<td>Canon</td>
<td>$230.00</td>
<td>4.1 MP</td>
<td>3x</td>
<td>CompactFlash Card</td>
<td>32 MB</td>
<td>1.5 in</td>
<td>1.09 in</td>
<td>5.53 oz</td>
</tr>
<tr>
<td>Canon</td>
<td>$160.00</td>
<td>3.3 MP</td>
<td>3x</td>
<td>SD Memory Card</td>
<td>16 MB</td>
<td>2 in</td>
<td>0.93 in</td>
<td>4.06 oz</td>
</tr>
<tr>
<td>Canon</td>
<td>$219.18</td>
<td>4.2 MP</td>
<td>4x</td>
<td>MultiMedia Card</td>
<td>16 MB</td>
<td>1.8 in</td>
<td>1.51 in</td>
<td>5.35 oz</td>
</tr>
<tr>
<td>Canon</td>
<td>$163.50</td>
<td>3.2 MP</td>
<td>4x</td>
<td>MultiMedia Card</td>
<td>16 MB</td>
<td>1.8 in</td>
<td>1.5 in</td>
<td>6.3 oz</td>
</tr>
<tr>
<td>Canon</td>
<td>$199.40</td>
<td>3.2 MP</td>
<td>2.2x</td>
<td>SD Memory Card</td>
<td>16 MB</td>
<td>1.5 in</td>
<td>1.4 in</td>
<td>5.8 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>Megapixels</th>
<th>Optical zoom</th>
<th>Memory type</th>
<th>Flash memory</th>
<th>LCD screen size</th>
<th>Depth</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sony</td>
<td>$365.00</td>
<td>7.2 MP</td>
<td>3x</td>
<td>Internal Memory</td>
<td>32 MB</td>
<td>2.5 in</td>
<td>1.5 in</td>
<td>6.9 oz</td>
</tr>
<tr>
<td>Canon</td>
<td>$439.99</td>
<td>7.1 MP</td>
<td>3x</td>
<td>SD Memory Card</td>
<td>32 MB</td>
<td>2 in</td>
<td>1.04 in</td>
<td>6 oz</td>
</tr>
<tr>
<td>Fuji</td>
<td>$253.00</td>
<td>6.3 MP</td>
<td>4x</td>
<td>XD-Picture Card</td>
<td>16 MB</td>
<td>2 in</td>
<td>1.4 in</td>
<td>7.1 oz</td>
</tr>
<tr>
<td>Sony</td>
<td>$336.00</td>
<td>7.2 MP</td>
<td>3x</td>
<td>Internal Memory</td>
<td>32 MB</td>
<td>2 in</td>
<td>1 in</td>
<td>5 oz</td>
</tr>
<tr>
<td>Nikon</td>
<td>$304.18</td>
<td>7.1 MP</td>
<td>3x</td>
<td>Internal Memory</td>
<td>13.5 MB</td>
<td>2 in</td>
<td>1.4 in</td>
<td>5.3 oz</td>
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<tr>
<td>Olympus</td>
<td>$334.00</td>
<td>7.4 MP</td>
<td>5x</td>
<td>XD-Picture Card</td>
<td>32 MB</td>
<td>2.0 in</td>
<td>1.7 in</td>
<td>7.1 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>Megapixels</th>
<th>Optical zoom</th>
<th>Memory type</th>
<th>Flash memory</th>
<th>LCD screen size</th>
<th>Depth</th>
<th>Weight</th>
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</thead>
<tbody>
<tr>
<td>Pentax</td>
<td>$238.99</td>
<td>5.3 MP</td>
<td>3x</td>
<td>Internal Memory</td>
<td>10 MB</td>
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<td>0.8 in</td>
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<td>Canon</td>
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<td>4.0 MP</td>
<td>3x</td>
<td>SD Memory Card</td>
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<td>2 in</td>
<td>0.82 in</td>
<td>4.59 oz</td>
</tr>
<tr>
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<td>3x</td>
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<td>0.8 in</td>
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<tr>
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<td>3x</td>
<td>SD Memory Card</td>
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<td>2 in</td>
<td>0.81 in</td>
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<tr>
<td>Casio</td>
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<tr>
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<td>$309.10</td>
<td>6.3 MP</td>
<td>3x</td>
<td>XD-Picture Card</td>
<td>16 MB</td>
<td>2.5 in</td>
<td>1.1 in</td>
<td>5.5 oz</td>
</tr>
</tbody>
</table>
Case-based User Profiling (1)

• Conversational recommenders can react to the feedback provided by users within each session.
  ▫ In-session personalization only - 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 feature, 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?