Case-based Recommendation

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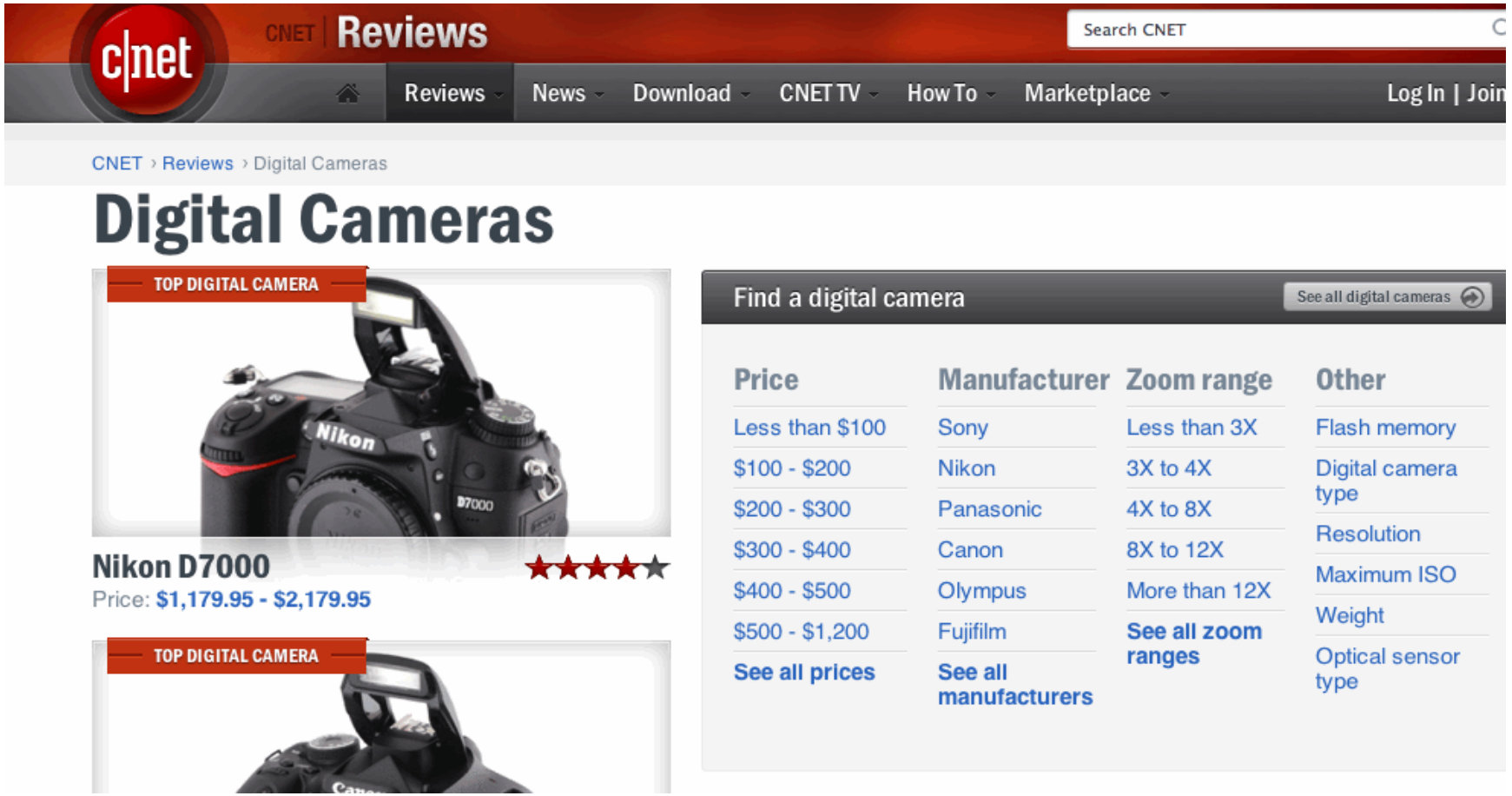
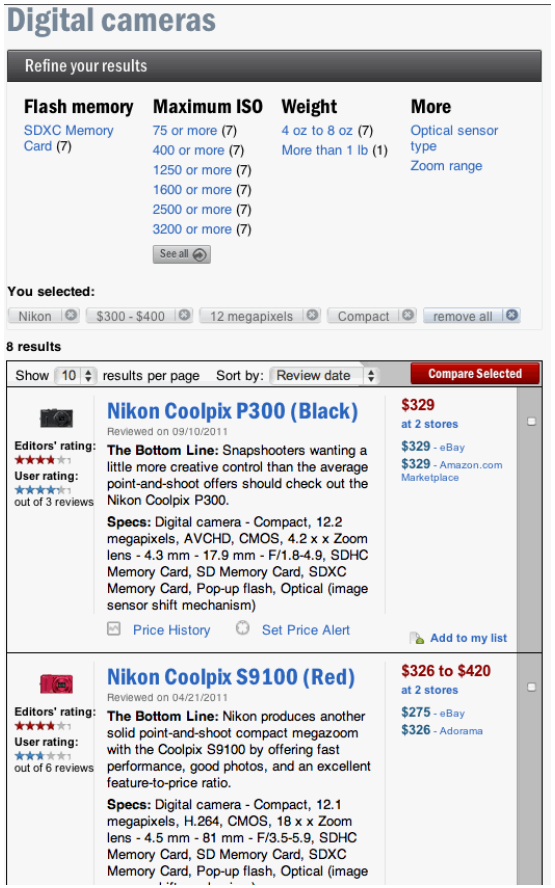
with slides of Danielle Lee

Modern E-Commerce Site



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

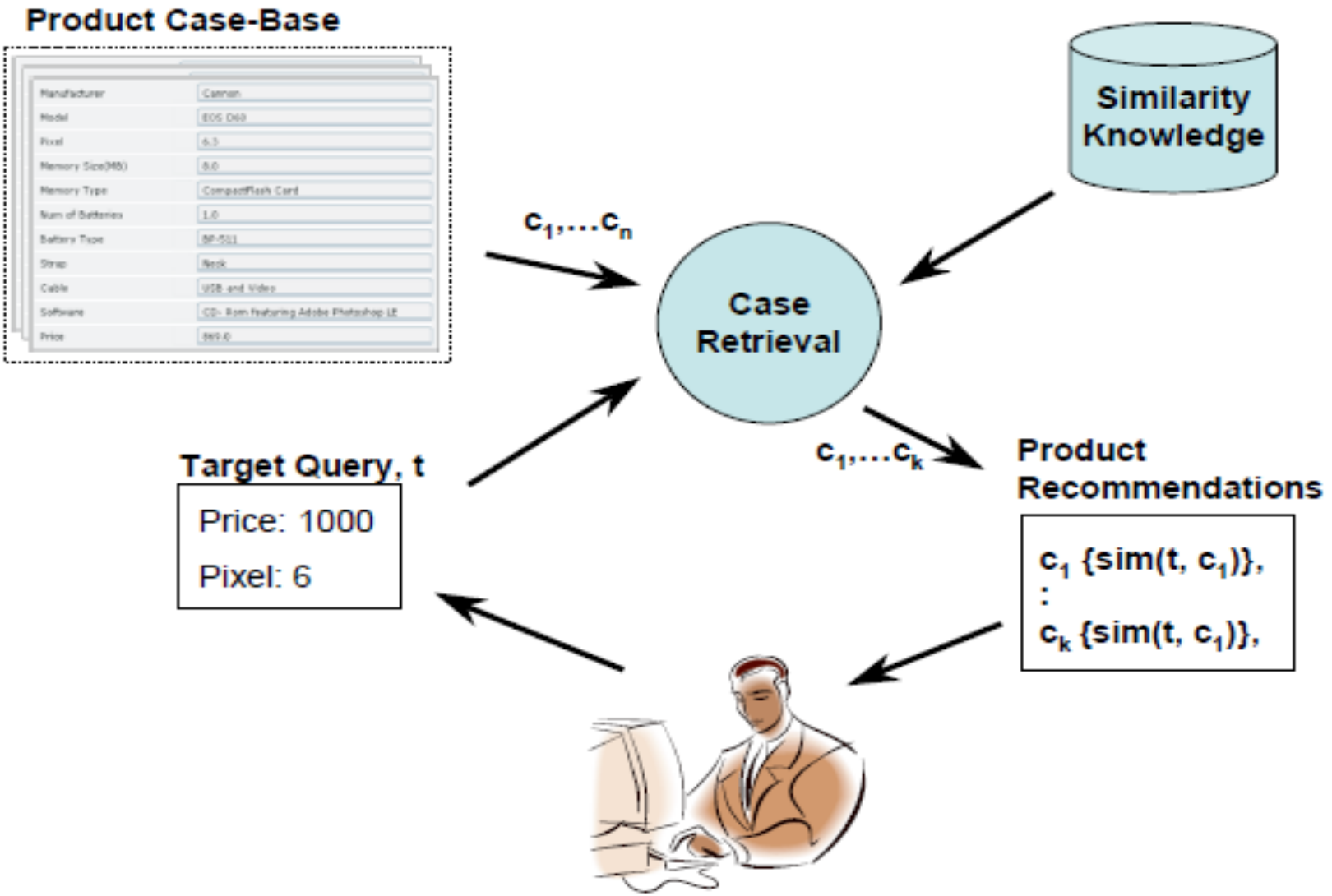
I want laptop having 250GB HDD, 1GB memory and 14 inch screen for $400

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

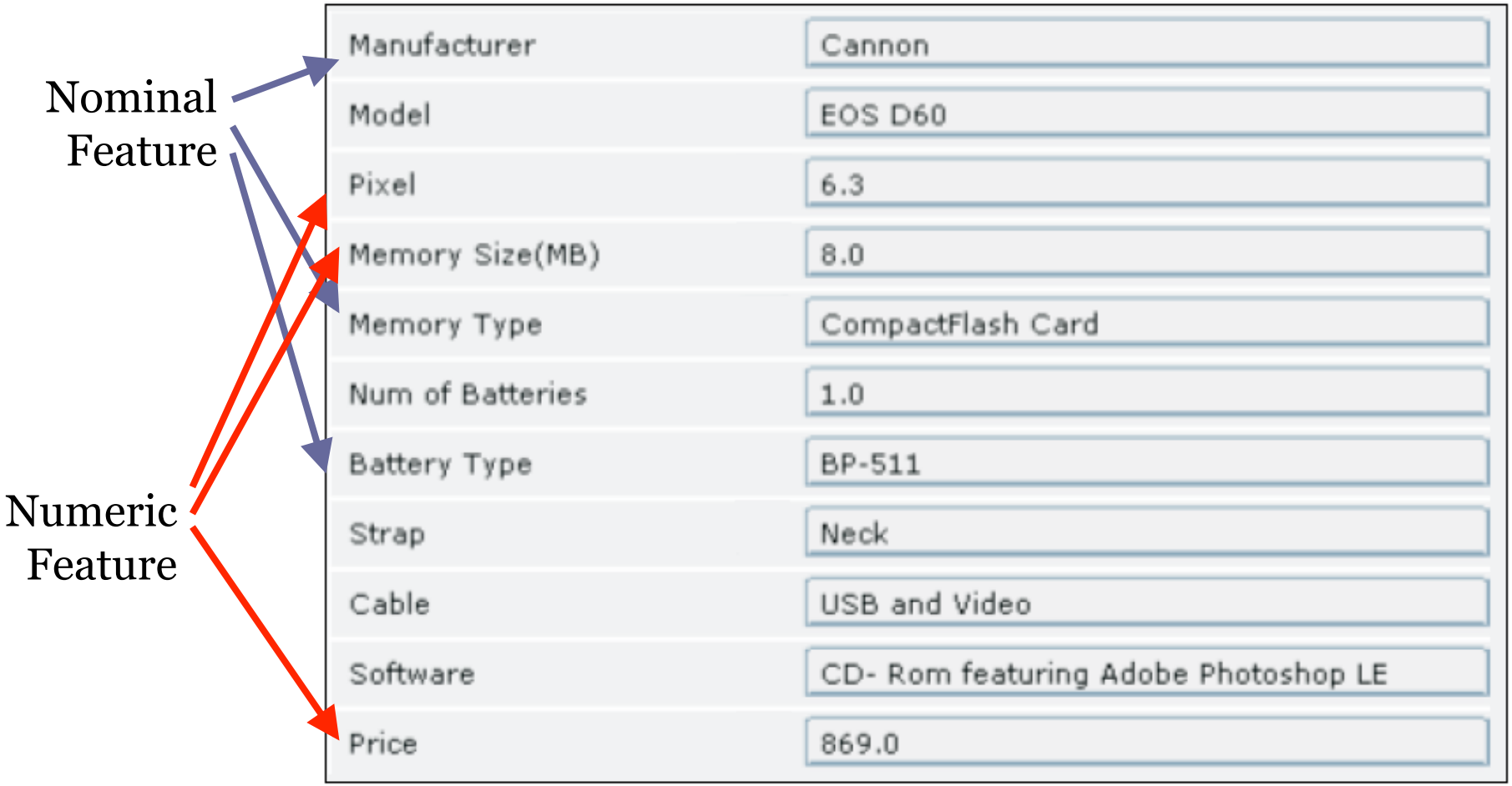
Product #2
- HDD : 150 GB
- Memory : 1 GB
- Screen Size : 15 inch
- Price : $450

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

Case-based Recommendation

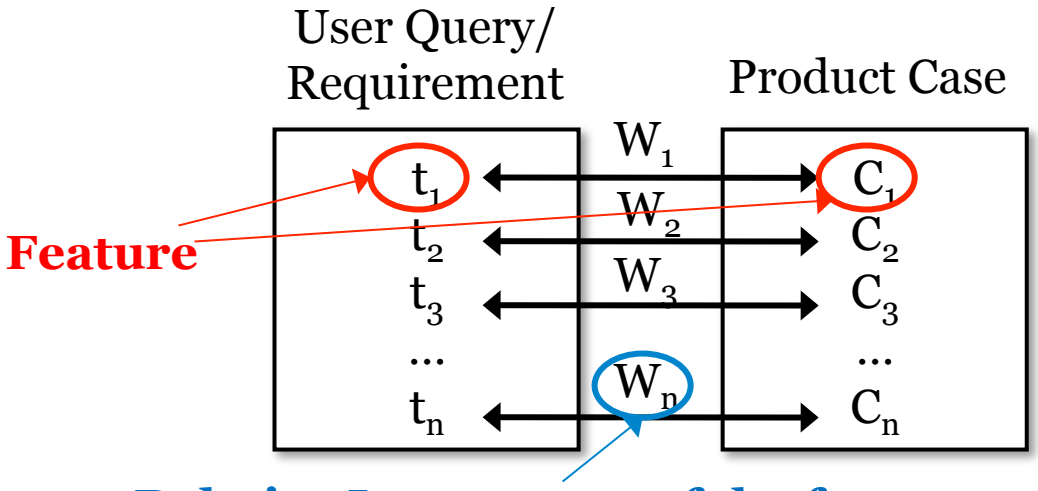


Case Representation



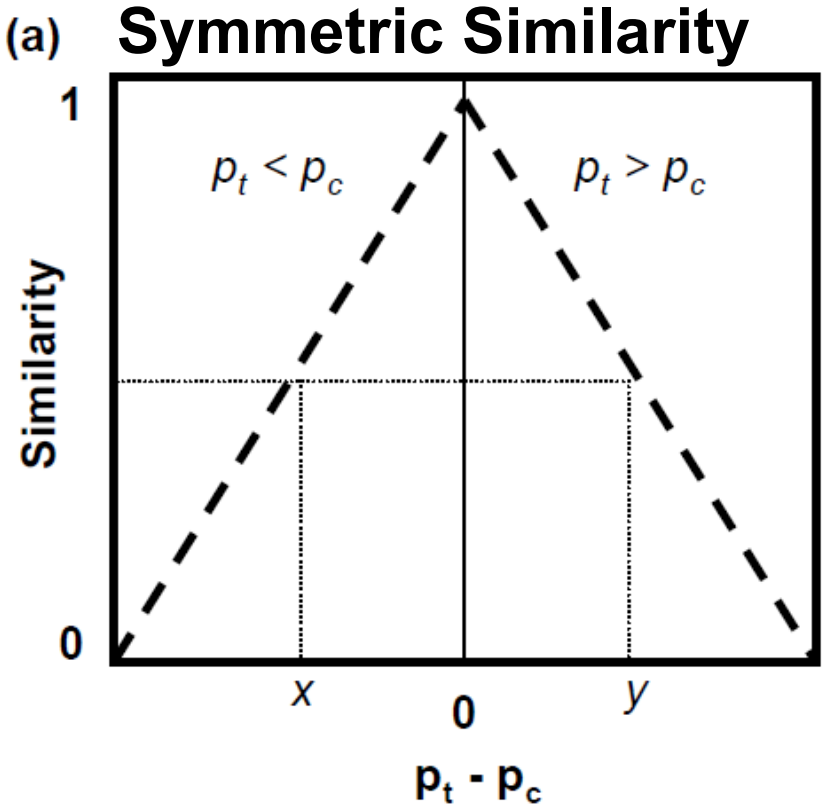
Similarity Assessment (1)

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



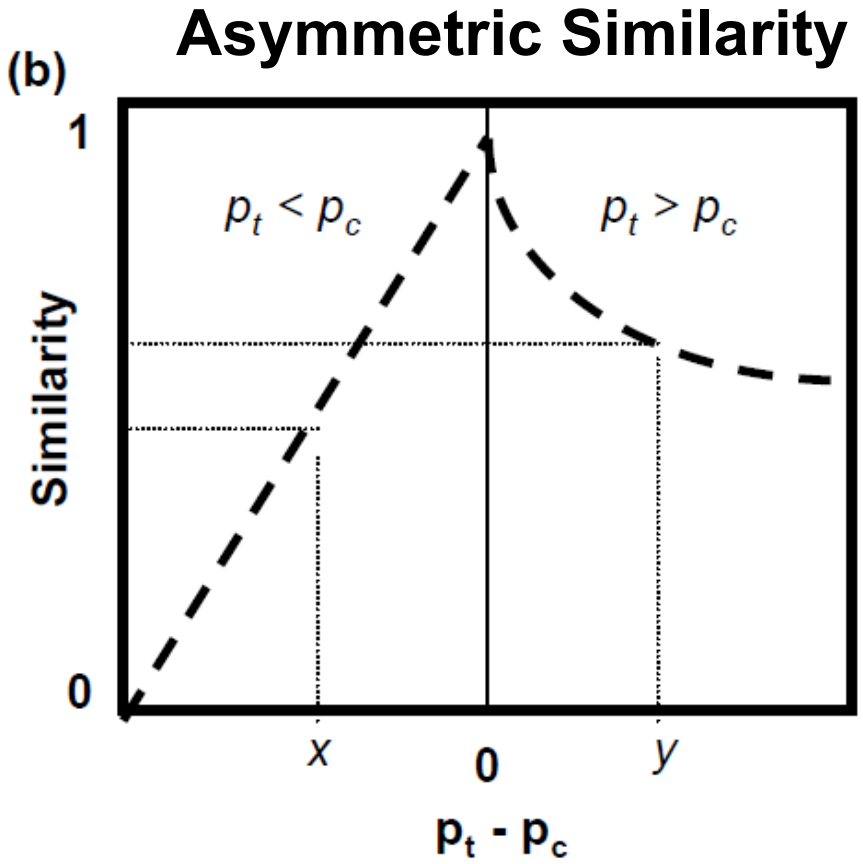
$$Similarity(t,c) = \frac{\sum_{i=1..n} w_i * sim_i(t_i, c_i)}{\sum_{i=1..n} w_i}$$

Similarity Assessment (2)



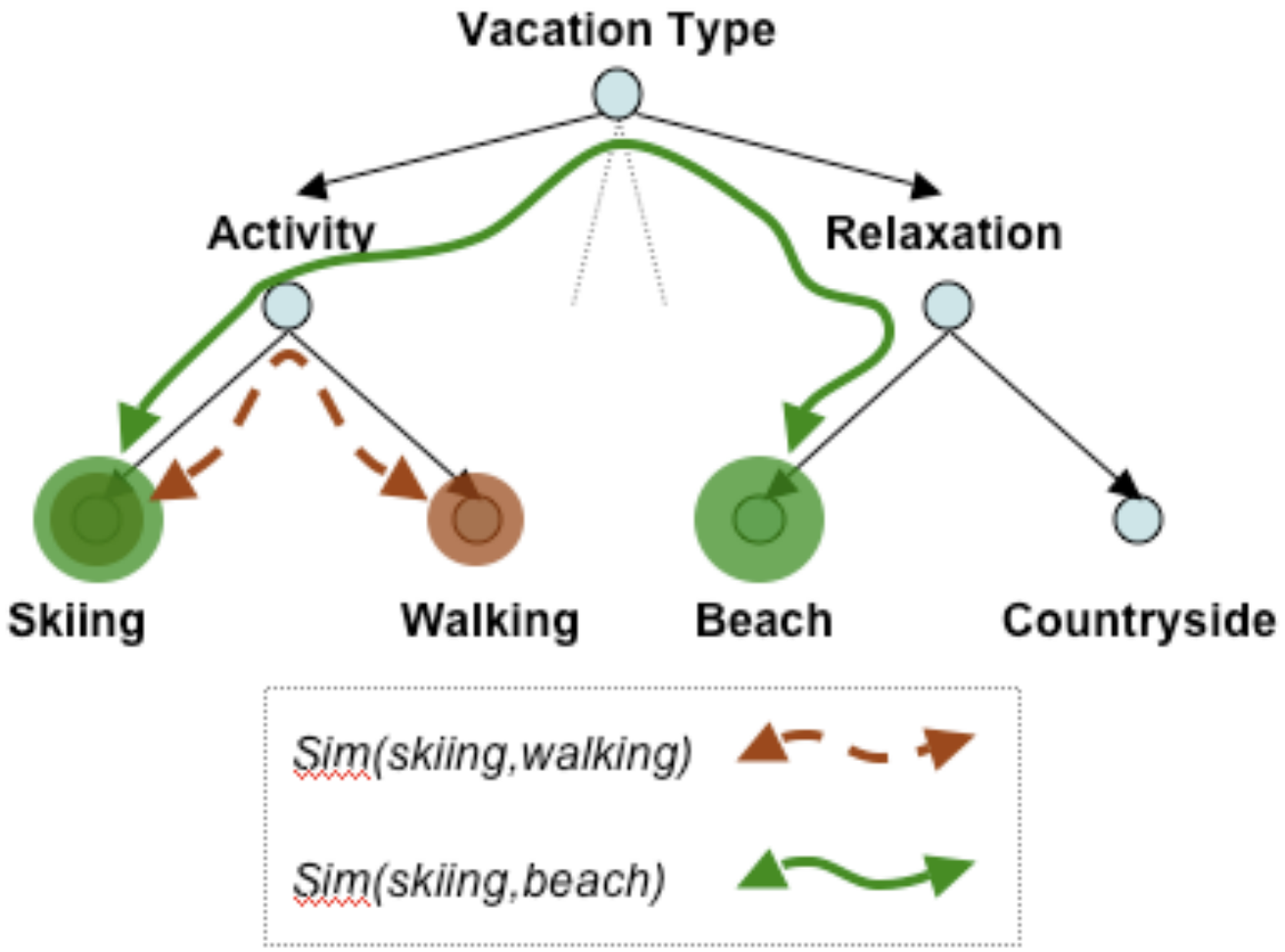
- In symmetric similarity, maximum similarity is achieved when a feature of a candidate case matches that of the target query. **No bias in favor** of either higher or lower values of the corresponding feature.

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

Danielle Lee

Representing Similarity Knowledge

	Small Car	Medium Car	Large Car	SUV	Mini Van
SmCar	1	???	???	???	???
MdCar	???	1	???	???	???
LgCar	???	???	1	???	???
SUV	???	???	???	1	???
Minivan	???	???	???	???	1

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

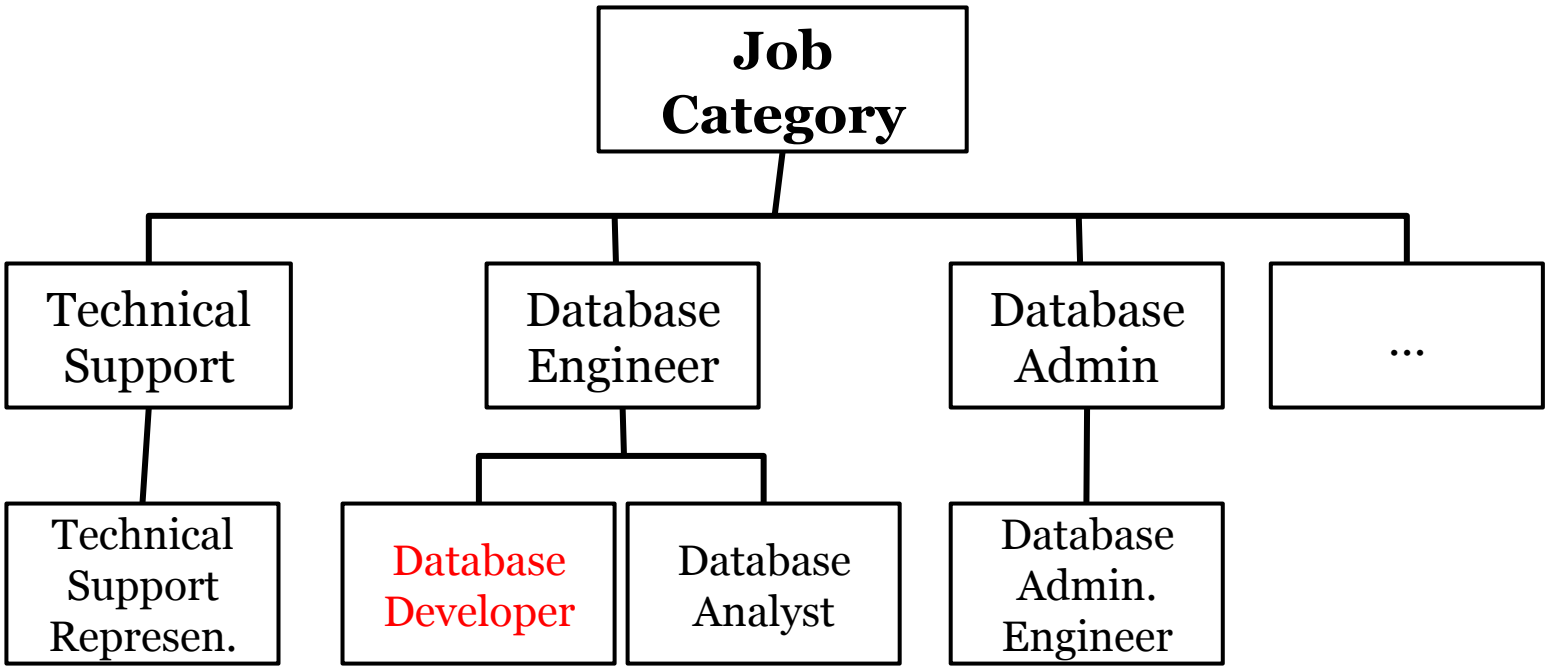
Job #1
Database Analyst job for Company A

Job #2
Database Administrator job for Company B

Job #3
Technical Support Engineer for Company C

Job Related Knowledge (1)

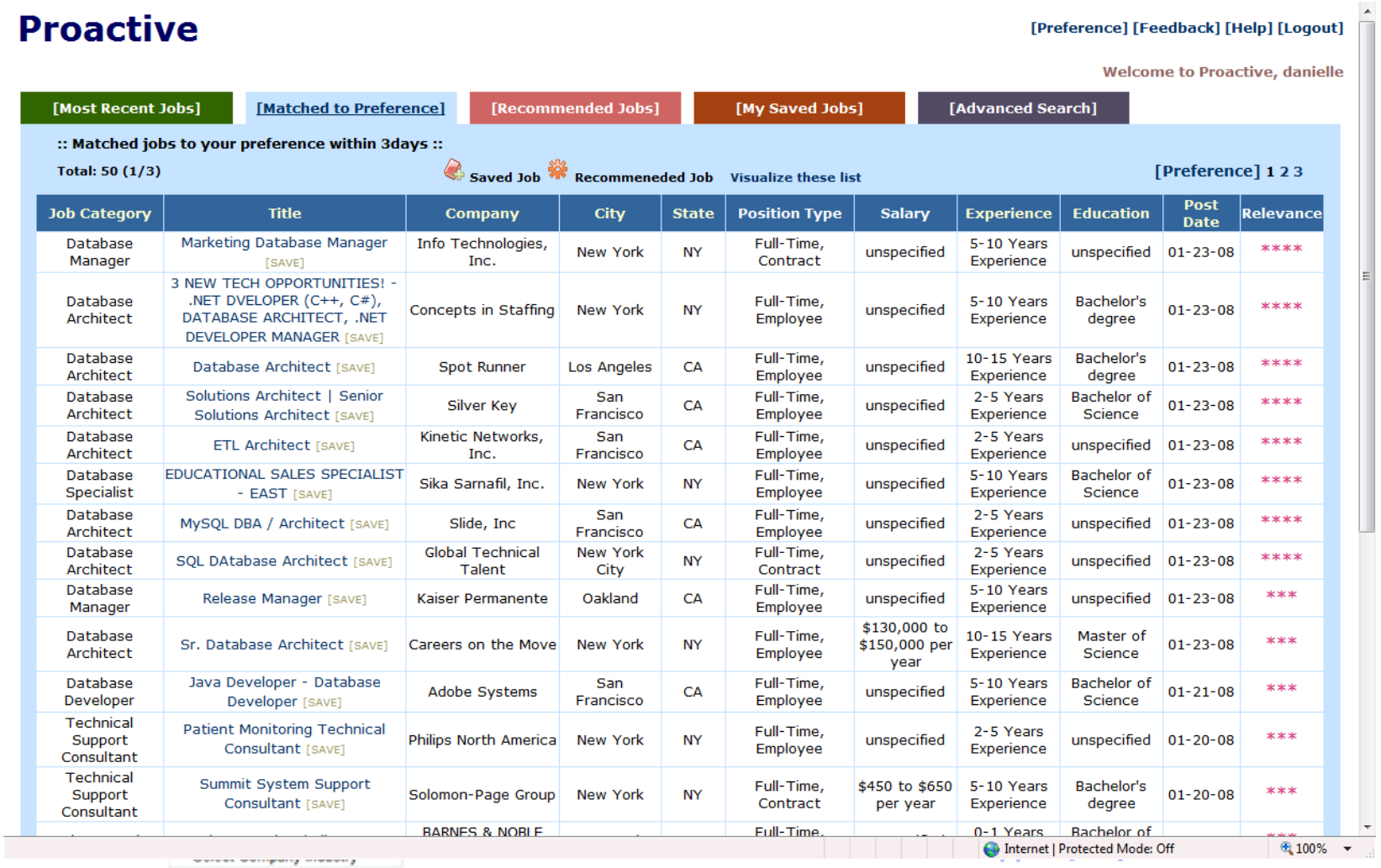
- Partial Ontology about job category.



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.

Proactive – Job Recommendation System



Proactive

[Preference] [Feedback] [Help] [Logout]

Welcome to Proactive, danielle

[Most Recent Jobs] [Matched to Preference] [Recommended Jobs] [My Saved Jobs] [Advanced Search]

:: Matched jobs to your preference within 3days ::

Total: 50 (1/3) Saved Job Recommeneded Job Visualize these list [Preference] 1 2 3

Job Category	Title	Company	City	State	Position Type	Salary	Experience	Education	Post Date	Relevance
Database Manager	Marketing Database Manager [SAVE]	Info Technologies, Inc.	New York	NY	Full-Time, Contract	unspecified	5-10 Years Experience	unspecified	01-23-08	****
Database Architect	3 NEW TECH OPPORTUNITIES! - .NET DVELOPER (C++, C#), DATABASE ARCHITECT, .NET DEVELOPER MANAGER [SAVE]	Concepts in Staffing	New York	NY	Full-Time, Employee	unspecified	5-10 Years Experience	Bachelor's degree	01-23-08	****
Database Architect	Database Architect [SAVE]	Spot Runner	Los Angeles	CA	Full-Time, Employee	unspecified	10-15 Years Experience	Bachelor's degree	01-23-08	****
Database Architect	Solutions Architect | Senior Solutions Architect [SAVE]	Silver Key	San Francisco	CA	Full-Time, Employee	unspecified	2-5 Years Experience	Bachelor of Science	01-23-08	****
Database Architect	ETL Architect [SAVE]	Kinetic Networks, Inc.	San Francisco	CA	Full-Time, Employee	unspecified	2-5 Years Experience	unspecified	01-23-08	****
Database Specialist	EDUCATIONAL SALES SPECIALIST - EAST [SAVE]	Sika Sarnafil, Inc.	New York	NY	Full-Time, Employee	unspecified	5-10 Years Experience	Bachelor of Science	01-23-08	****
Database Architect	MySQL DBA / Architect [SAVE]	Slide, Inc	San Francisco	CA	Full-Time, Employee	unspecified	2-5 Years Experience	unspecified	01-23-08	****
Database Architect	SQL DAtabase Architect [SAVE]	Global Technical Talent	New York City	NY	Full-Time, Contract	unspecified	2-5 Years Experience	unspecified	01-23-08	****
Database Manager	Release Manager [SAVE]	Kaiser Permanente	Oakland	CA	Full-Time, Employee	unspecified	5-10 Years Experience	unspecified	01-23-08	***
Database Architect	Sr. Database Architect [SAVE]	Careers on the Move	New York	NY	Full-Time, Employee	$130,000 to $150,000 per year	10-15 Years Experience	Master of Science	01-23-08	***
Database Developer	Java Developer - Database Developer [SAVE]	Adobe Systems	San Francisco	CA	Full-Time, Employee	unspecified	5-10 Years Experience	Bachelor of Science	01-21-08	***
Technical Support Consultant	Patient Monitoring Technical Consultant [SAVE]	Philips North America	New York	NY	Full-Time, Employee	unspecified	2-5 Years Experience	unspecified	01-20-08	***
Technical Support Consultant	Summit System Support Consultant [SAVE]	Solomon-Page Group	New York	NY	Full-Time, Contract	$450 to $650 per year	5-10 Years Experience	Bachelor's degree	01-20-08	***
		BARNES & NOBLE			Full-Time,		0-1 Years	Bachelor of		

Internet | Protected Mode: Off 100%

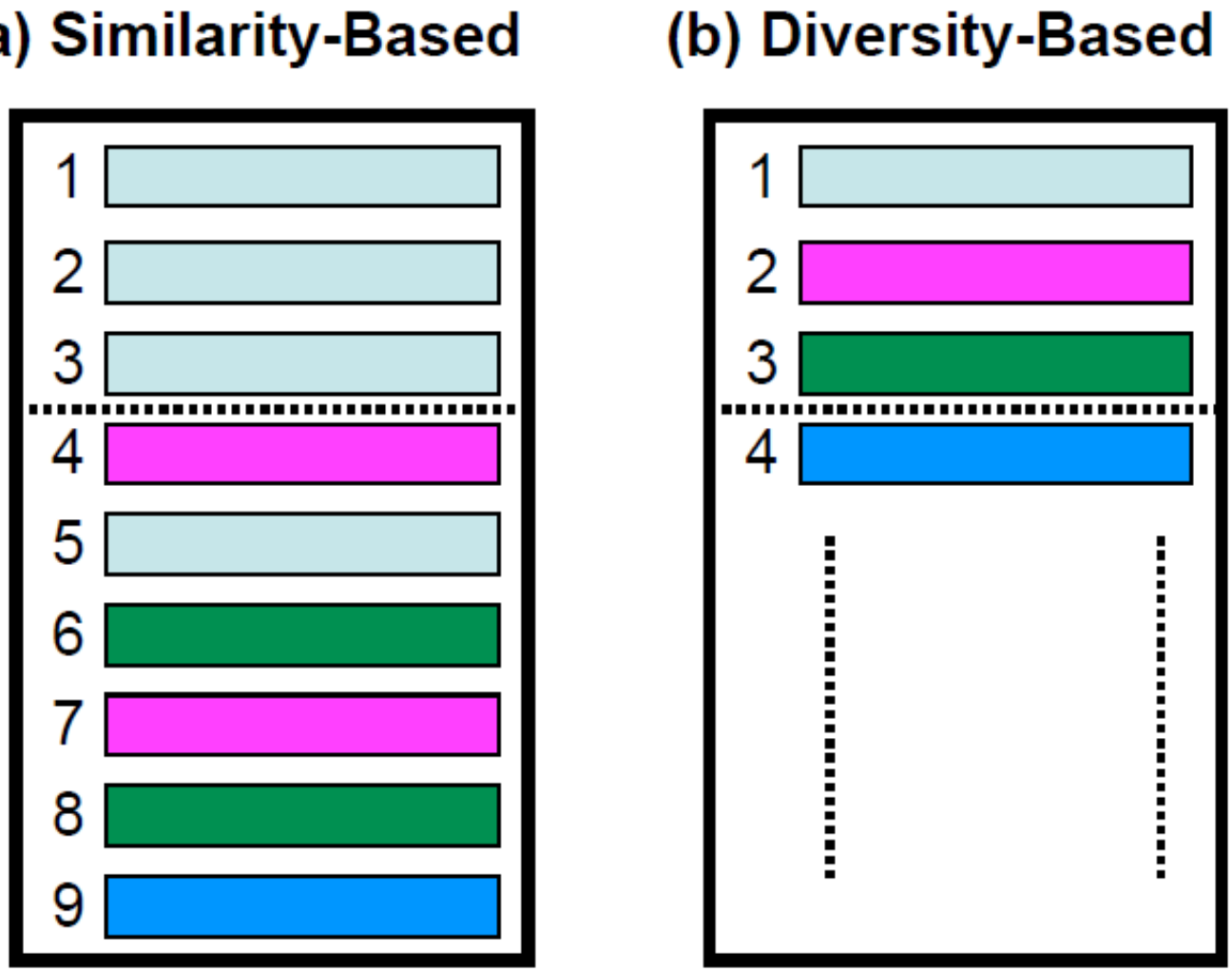
Diversity

"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.

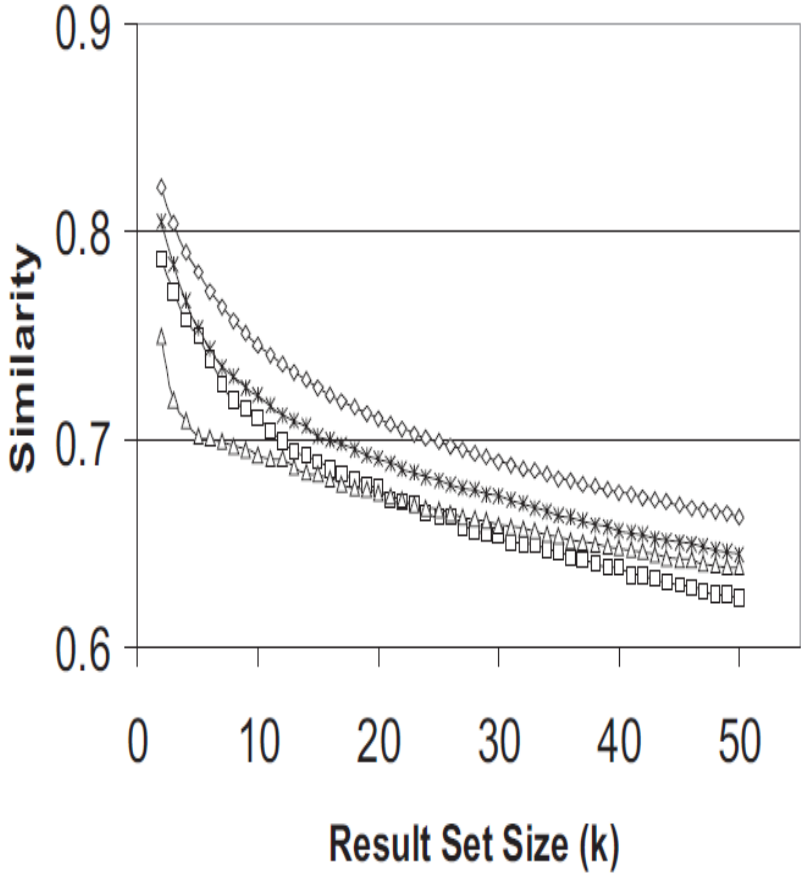
Bounded Greedy Selection

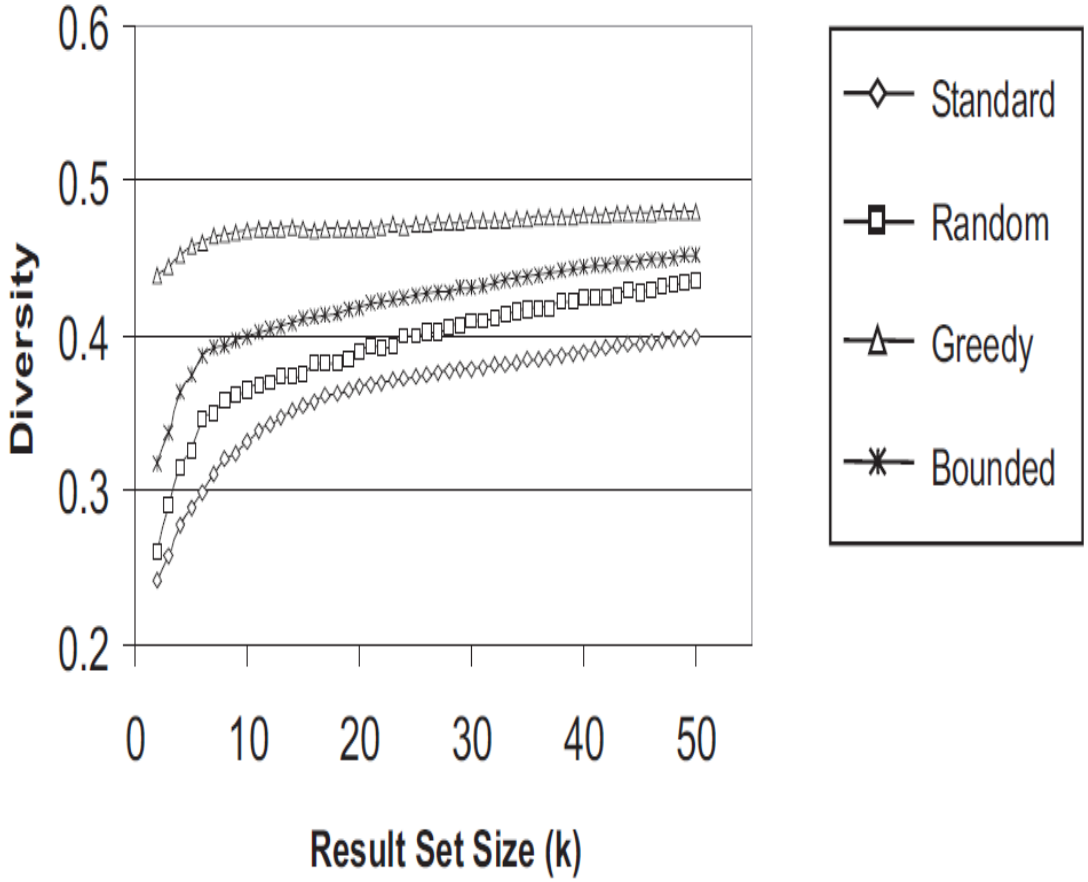
- Proposed in Smyth & McClave (2001).
- The key idea is the quality metric that combines diversity and similarity.
  1. Select the best *bk* cases according to the similarity.
  2. Pick up the one with the highest similarity.
  3. During each subsequent iteration, the case with the highest combination of similarity and diversity with respect to the set of cases selected during the previous iteration.

$$Quality(t,c,R) = Similarity(t,c) * RelDiversity(c,R) \qquad (11.4)$$

$$RelDiversity(c,R) = 1 \; if \; R = \{\};$$
$$= \frac{\sum_{i=1..m}(1 - Similarity(c,r_i))}{m}, otherwise \qquad (11.5)$$

Similarity vs. Diversity (3)





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?[1]
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.*

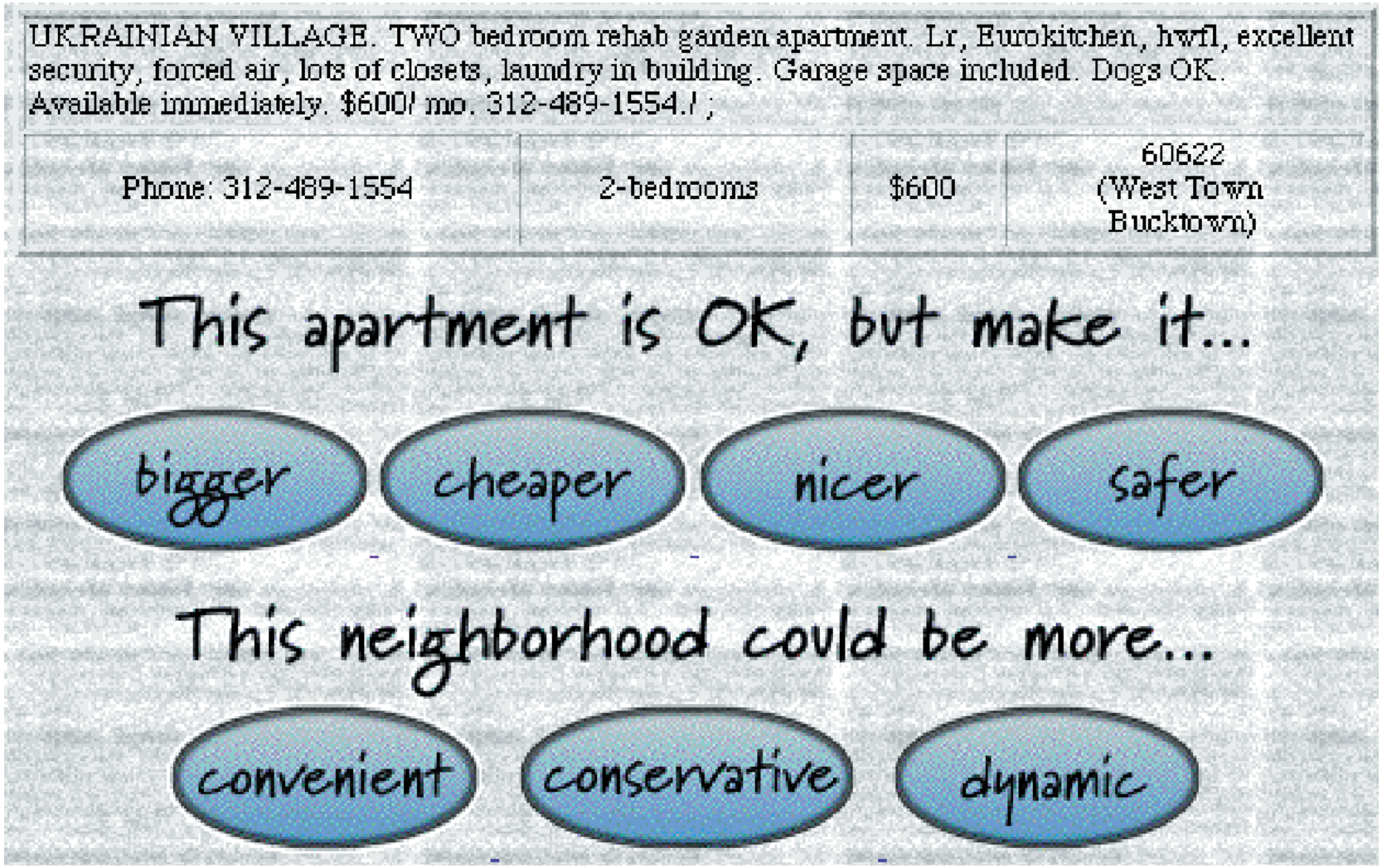
Navigation by asking (2)

- The selection of questions does matter.
  - Enthropy -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

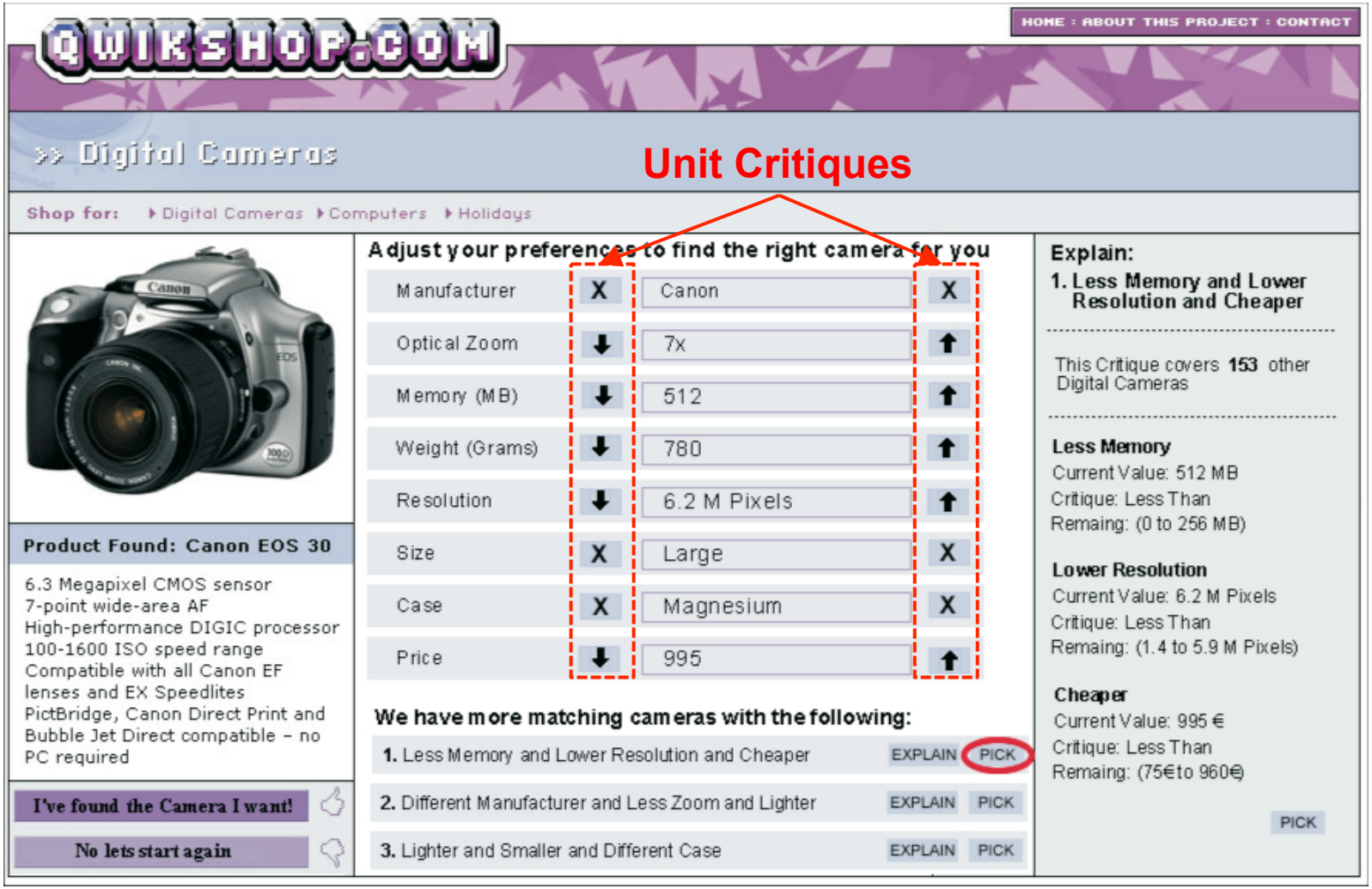
Navigation by proposing (1)

- 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



Compound Critiques



Explanations and Clustering (Pu)

The top candidate according to your preferences

Manufacturer	Price	MegaPixels	Optical zoom	Memory type	Flash memory	LCD screen size	Depth	Weight	
Canon	$242.00	5.0 MP	3x	CompactFlash Card	32 MB	1.8 in	1.37 in	8.3 oz	choose

We have more products with the following

they are cheaper and lighter, but have fewer megapixels

Nikon	$167.95	4 MP	3x	SD Memory Card	14 MB	1.8 in	1.4 in	4.6 oz	choose
Canon	$230.00	4.1 MP	3x	CompactFlash Card	32 MB	1.5 in	1.09 in	6.53 oz	choose
Canon	$180.00	3.3 MP	3x	SD Memory Card	16 MB	2 in	0.83 in	4.06 oz	choose
Canon	$219.18	4.2 MP	4x	MultiMedia Card	16 MB	1.8 in	1.51 in	6.35 oz	choose
Canon	$163.50	3.2 MP	4x	MultiMedia Card	16 MB	1.8 in	1.5 in	6.3 oz	choose
Canon	$199.40	3.2 MP	2.2x	SD Memory Card	16 MB	1.5 in	1.4 in	5.8 oz	choose

they have more megapixels and bigger screens, but are more expensive

Sony	$365.00	7.2 MP	3x	Internal Memory	32 MB	2.5 in	1.5 in	6.9 oz	choose
Canon	$439.99	7.1 MP	3x	SD Memory Card	32 MB	2 in	1.04 in	6 oz	choose
Fuji	$253.00	6.3 MP	4x	XD-Picture Card	16 MB	2 in	1.4 in	7.1 oz	choose
Sony	$336.00	7.2 MP	3x	Internal Memory	32 MB	2 in	1 in	5 oz	choose
Nikon	$304.18	7.1 MP	3x	Internal Memory	13.5 MB	2 in	1.4 in	5.3 oz	choose
Olympus	$334.00	7.4 MP	5x	XD-Picture Card	32 MB	2.0 in	1.7 in	7.1 oz	choose

they are lighter and thinner, but have less flash memory

Pentax	$238.99	5.3 MP	3x	Internal Memory	10 MB	1.8 in	0.8 in	3.7 oz	choose
Canon	$273.18	4.0 MP	3x	SD Memory Card	16 MB	2 in	0.82 in	4.59 oz	choose
Nikon	$329.95	5.1 MP	3x	Internal Memory	12 MB	2.5 in	0.8 in	4.2 oz	choose
Canon	$316.18	5.3 MP	3x	SD Memory Card	16 MB	2 in	0.81 in	4.59 oz	choose
Casio	$386.00	7.2 MP	3x	Internal Memory	8.3 MB	2.5 in	0.88 in	4.48 oz	choose
Fuji	$309.18	6.3 MP	3x	XD-Picture Card	16 MB	2.5 in	1.1 in	5.5 oz	choose

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.

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

- O' Sullivan, et al. (2002)
- 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?