



Recommender Systems & Collective Intelligence

COMP47580

Dr. Michael O'Mahony

michael.omahony@ucd.ie



Overview

- Recommender Systems
 - Non-personalised vs. personalised approaches
- Content-based recommendation:
 - Traditional content-based (unstructured) vs. case-based (structured) recommendation
 - Recommendations are based on product/content similarity.
- Collaborative filtering:
 - *Content-free* recommendation
 - Recommendations are based on user preference data – no information about product content is required.



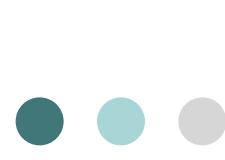
“Single-Shot” Recommendation

- Single-shot recommendation model:
 - Limited to single interaction between user and recommender system
 - What happens if the user is not satisfied? Rate additional items to obtain new recommendations...
 - Consider e-commerce domains:
 - User may not know exactly what s/he wants (e.g. purchasing a digital camera – different cameras have different features/specifications, prices...).
 - Single shot models do not readily facilitate an exploration of the product space
 - Move towards a different model – as the user learns more about available options and features, facilitate her to navigate through the product space (e.g. *“this camera is expensive! – show me some cheaper options”*, *“show me similar cameras but with better resolution”*)



This lecture...

- Conversational Recommender Systems:
 - Engage users in extended dialogue
 - Engagement begins with a query (specified by the user or inferred from the user's profile)
 - Have multiple interactions (recommendation cycles) with users
 - Small number of recommendations displayed during each cycle (in some instances, just one)
 - Elicit user feedback on displayed recommendations – leverage feedback to eliminate some items in the product space and to identify suitable recommendations for the next cycle...
 - Help users to more effectively navigate complex product spaces
 - Think online “sales assistant”



Case-based Recommendation

- **Item representation:** items are represented in a structured manner using a well-defined set of features and feature values
- **Similarity assessment:** case-based representation allows for sophisticated and fine-grained judgements about the similarity between items and other items (or user queries):
 - Case-level similarity – based on explicit mappings between case features, weights encode the relative importance of features:

$$\text{Sim}(T, C) = \frac{\sum_{i=1}^n w_i \times \text{Sim}(v_{C,i}, v_{T,i})}{\sum_{i=1}^n w_i}$$

- Feature-level similarity – numeric (symmetric, asymmetric similarity functions) and non-numeric (set-based, ontology-based approaches)
- This approach to item representation and similarity assessment facilitates:
 - Search and navigation of complex information spaces
 - Flexible user-feedback options



Example Cases...

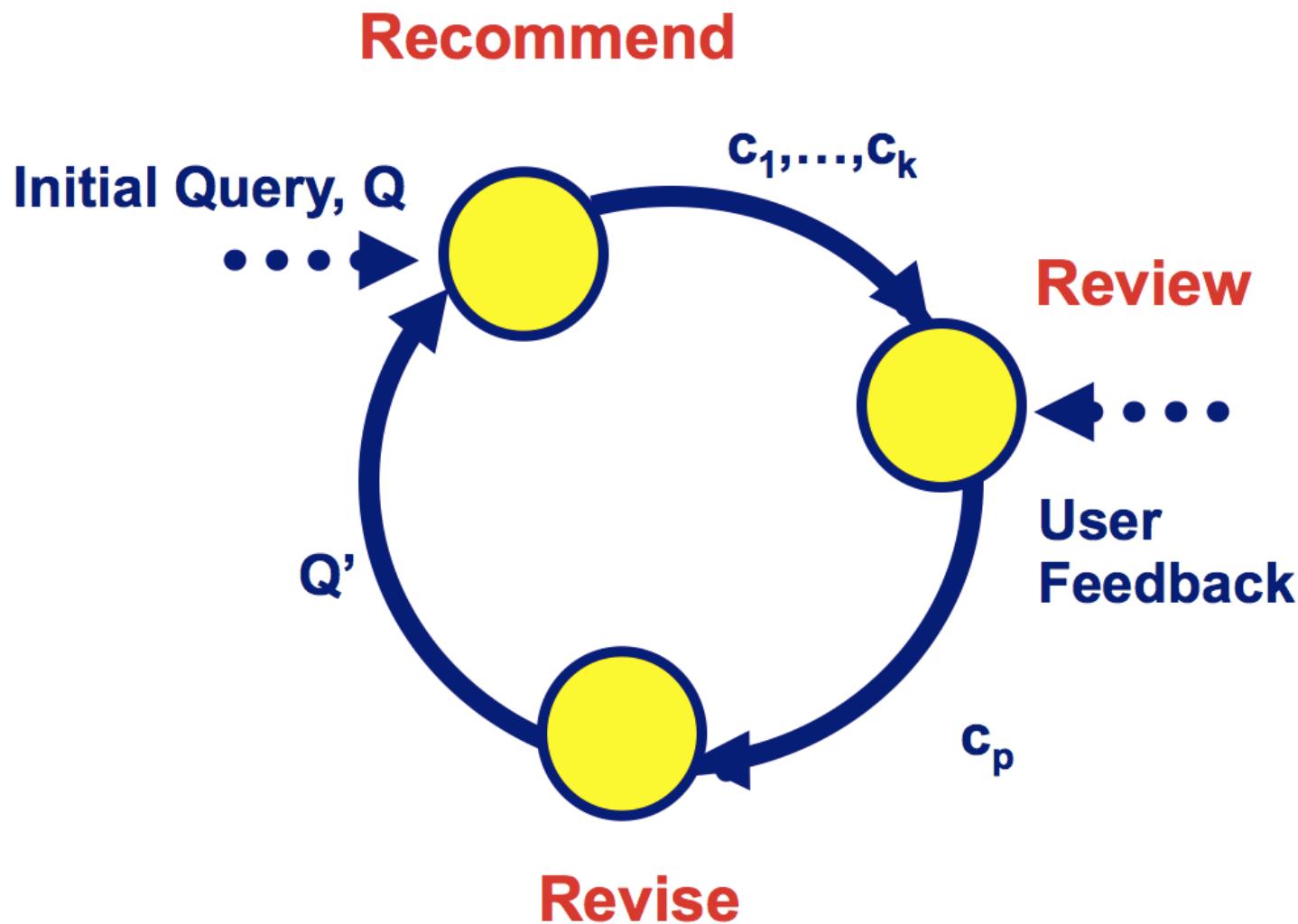
Epson Expression Home XP-235 All-in-One Inkjet Printer
£44.00 & FREE Delivery in the UK. [Details](#) | In stock. Dispatched from and sold by Amazon. Gift-wrap available.

	Epson Expression Home XP-235 All-in-One Inkjet Printer		Epson Home XP-335 Expression All-in-One Inkjet Printer
Customer Rating			
Price	£44.00	£44.99	
Delivery	FREE Delivery	FREE Delivery	
Sold by	Amazon.co.uk	Amazon.co.uk	
Connectivity Technology	WiFi	USB 2.0, Wireless LAN	
Resolution	1200 Dots Per Inch	1200 Dots Per Inch	
Ink Colour	Multicoloured	Multicoloured	
Dimensions	14.5 cm x 30 cm x 39 cm	14.5 cm x 39 cm x 30 cm	
Item Weight	Information not provided	4.2 kg	
Maximum Printspeed Black White	26 ppm	33 ppm	
Model Year	Information not provided	2015	
Scanner Type	Flatbed	Flatbed	

[Add to Basket](#) [Add to Basket](#)



Conversational Recommender System Cycle





Considerations

- Initial query formation (user specifies initial query with some feature values or feature values can be inferred from the user's profile)
- Recommendation generation
- Presentation of candidates
- Feedback mechanism
- Recommendation explanation
- Cognitive load



Navigation & Feedback

- Conversational recommenders are distinguished by the kind of *navigation* considered and how *feedback* is elicited
- **Navigation by Asking:**
 - Users are asked a series of questions about their requirements...
 - E.g., “*What style of camera do you want - Compact or SLR?*” or “*How much optical zoom do you need?*”
 - Such feedback is referred to as *value elicitation*
- **Navigation by Proposing:**
 - Avoid posing direct questions to users
 - System engages users in recommendation cycles – during each cycle:
 - Present users with interim recommendation(s)
 - Users are asked for feedback in the form of e.g. a rating or simple preference (e.g. none of the current recommendations are ideal, but this one best meets my needs...)
 - System uses feedback to select the recommendations for the next cycle



Types of Feedback

- Value Elicitation
- Ratings-based Feedback
- Preference-based Feedback
- Critiquing-based Feedback



Value Elicitation

- Navigation by asking
- User are requested to provide specific values for features:
 - E.g., in the laptop domain, the price they are prepared to pay, memory and hard disk requirements, preferred manufacturer...
 - **Before** presentation of recommendations
- Feature-level interaction
- Provides very rich feedback:
 - Most direct approach to elicit user requirements
- High cost:
 - Requires very precise feature-level interaction
 - Users must possess a high level of domain knowledge
 - Users must be willing to answer direct/specialised questions

| Value Elicitation – Example

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.*

- Adaptive Place Advisor Recommender System:
 - Dialogue between user (inquirer) and system (advisor) to recommend restaurants
 - System asks free-form questions; user may also ask questions of system
 - System selects questions to narrow down the range of possible recommendations
 - Recommendations are made when only a few items remain



Ratings-based Feedback

- Navigation by proposing
- Users are requested to provide explicit ratings for recommendation candidates:
 - Positive/negative, 1-5 stars...
 - Post presentation of recommendations
- Case-level interaction
- Cost:
 - Users express qualitative indication of interest at the level of an individual case(s)
 - But may need to rate many cases...
 - Detailed domain knowledge not necessary but user must consider the case as a whole

http://serendipity.ucd.ie:8080/store/index.jsp

Serendipity

[View Basket](#) | [Checkout](#) | [About Us](#) | [Contact Us](#)

[Home](#) [Jewellery](#) [Phones](#) [Weddings](#) [Electronics](#) [Computers](#)

Serendipity - Your Wedding Dress Destination

Browse: Weddings

- [Wedding Dresses](#)
- [Bridesmaid Dresses](#)
- [Mother of the Bride Dresses](#)
- [Wedding Accessories](#)
- [Bridal Veils and Wedding Veils](#)
- [Prom Dresses](#)

Your Basket

Items in your basket:

There are no items in your basket.

Impression - 2663	Impression - 2624	Impression - 2648
Recommended Price \$690	Recommended Price \$730	Recommended Price \$550
Our Price \$495	Our Price \$515	Our Price \$425
Add To Basket	Add To Basket	Add To Basket



◀ Pic 1/4 ▶



◀ Pic 1/3 ▶



◀ Pic 1/4 ▶

Preference	Preference	Preference	
Designer	Impression	Impression	
Colors	Ivory/Champagne	Ivory	Ivory
Sizes	2	2	2
Neckline	Strapless	Strapless	Strapless
Waist/Silhouette	Mermaid	Mermaid	Mermaid
Pieces/Separates	One-piece	One-piece	One-piece
Train Length	Sweep	Sweep	Sweep
Fabric	Lace	Lace	Chiffon
Formality	Formal	Formal	Formal
Sleeve length	Strapless	Strapless	Strapless
Hem Line	Floor Length	Floor Length	Floor Length
Lace	cn.....cn..	cn.....cn..	cn.....cn..

Filters

Size	<input type="text" value="PleaseSelect"/>
Neckline	<input type="text" value="Bateau"/> <input type="text" value="Bateau, Scalloped"/> <input type="text" value="Drape"/>
Designer	<input type="text" value="Alfred Angelo"/> <input type="text" value="Bonny"/> <input type="text" value="DeVinci"/>
Waist / Silhouette	<input type="text" value="A-Line"/> <input type="text" value="A-Line, Empire"/> <input type="text" value="Ballgown"/>
Colour	<input type="text" value="Antique"/> <input type="text" value="Black"/> <input type="text" value="Blue"/>
Price	Min: <input type="text" value="No Limit"/> Max: <input type="text" value="No Limit"/>
more... Update	



Preference-based Feedback

- Navigation by proposing
- Users are requested to indicate a preference (usually positive, but can be negative) for one candidate recommendation from those presented:
 - Post presentation of recommendations
- Case-level interaction
- Cost:
 - Users consider and choose one preferred case out of k presented cases – simpler than ratings-based
 - Must consider and compare cases as a whole
 - Relatively low domain expertise required
- Limited in its ability to guide the navigation process
 - Not always clear why user has selected one case over alternatives



Critique-based Feedback

- Navigating by proposing
- Typically users are presented with a single recommendation during each cycle
- Users are requested to provide a directional preference on a feature-value (e.g. price less than €1000)
 - Post presentation of recommendations
- Feature-level interaction
- Powerful form of feedback
 - Individual critiques act as a filter over the remaining cases (items)
- Low cost:
 - Does not require detailed domain knowledge
 - Provide feedback at feature-level rather than considering entire case

Case Study 1

Critique-based Feedback



Critique-based Feedback

- Feedback is in the form of a directional feature constraint:
 - E.g., a user may ask for a camera that is *cheaper* than the current recommendation – example of *unit* critique
- Each critique acts as a filter over the item space:
 - In the next recommendation cycle, items (e.g. restaurants, cameras etc.) that do not satisfy the critique are eliminated from consideration
- Compound critiques:
 - Designed to cover *multiple* features
 - E.g. show me a *sportier* car than the current recommendation, i.e. a car with a larger *engine size* and with better *acceleration*
 - Allows the recommender to take larger steps through the item-space and eliminate more items during each recommendation cycle



“Find Me” Systems

The screenshot shows a web-based application with a purple header featuring the logo "Entrée Chicago" with a stylized dome icon. Below the header, there are two sections of text input fields:

I would like to eat at a restaurant that has:

Cuisine	Price	
Style	Atmosphere	Occasion

I would like to eat at a restaurant just like:

Chinois on Main	Los Angeles
-----------------	-------------

At the bottom are two buttons: "New Query" and "Submit".

Figure 1: Entry point for the Entrée system

Entrée – A Restaurant Recommender System

- Users start off by indicating what kind of a restaurant they are looking for

Two modes of interaction:

- Term-based selection
- Similarity-based selection

See reading (Burke 2000)

Retrieval and User Feedback in Entrée

Retrieval and Recommendation

- The system retrieves restaurants that are considered to be similar to the user's current requirements

User Feedback

- The user indicates a feature critique or 'tweak' to constrain the value range of that feature

{cheaper, quieter, livelier...}

Unit Critique

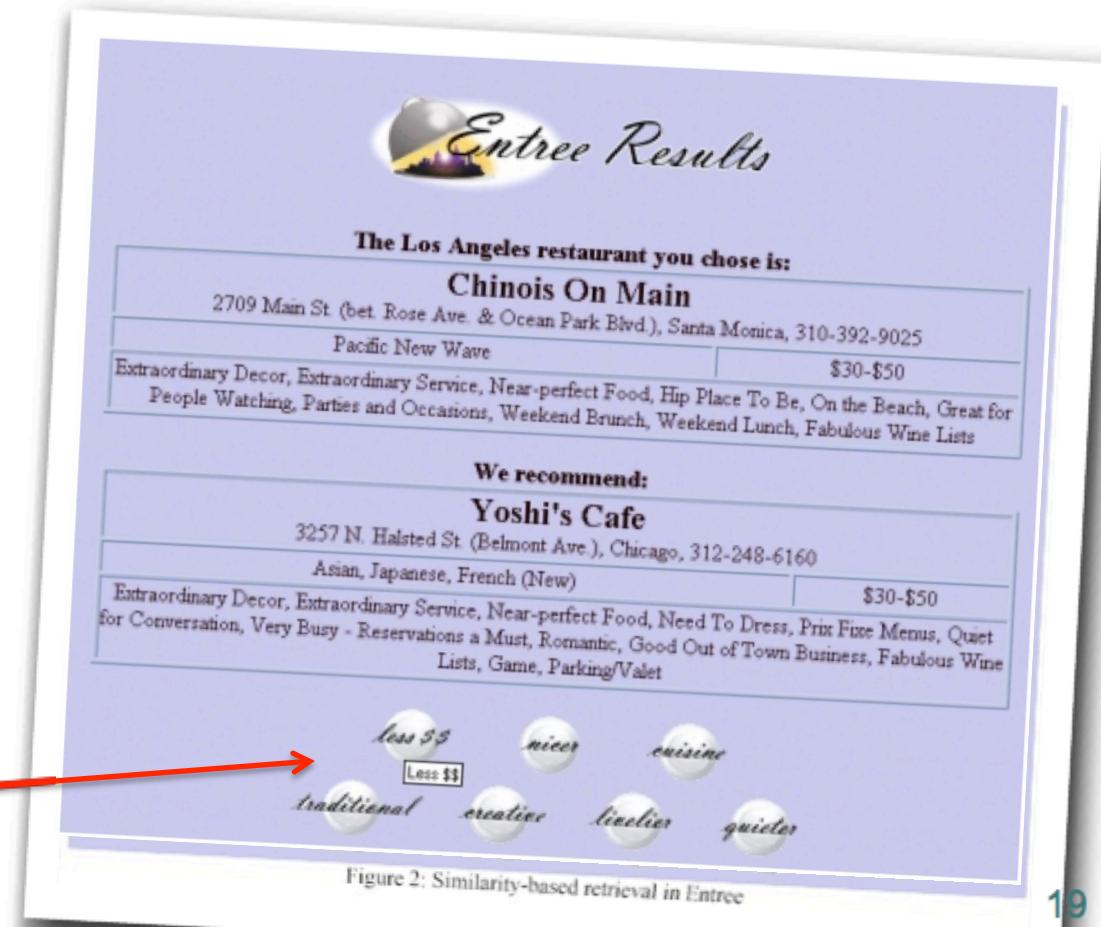


Figure 2: Similarity-based retrieval in Entrée



Compound Critiques

“Find-Me” systems

- [Burke et al.]
- Car Navigator
- Critique allows user to manipulate multiple features
- Hard-coded, static and fixed

The image illustrates a compound critique interface. On the left, a grid of car images includes the Nissan Altima, Honda Accord, Chrysler LeBaron, Mazda 626, and Pontiac Sunbird, each labeled 'New!'. In the center, four cards list qualities: 'CLASSIER!', 'ROOMIER!', 'CHEAPER!', and 'SPORTIER!'. A red arrow points from the 'SPORTIER!' card to the right side of the interface. The right side shows a detailed critique interface comparing the Nissan Altima to another car. It lists various car features with up and down arrows for adjustment:

Feature	Current Value	Adjustment	Comparison Value
\$	\$15600	↑ ↓	\$15000
Horsepower	150 Horsepower	↑ ↓	190 Horsepower
0-60	0-60 in 9.4 sec.	↑ ↓	0-60 in 8.8 sec.
City MPG	21 City MPG	↑ ↓	20 City MPG
Highway MPG	29 Highway MPG	↑ ↓	36 Highway MPG
Width	2.4 Width	↑ ↓	3.7 Width
Passenger Capacity	5 people	↑ ↓	5 people
Headroom	39.3 inches	↑ ↓	38.1 inches
Legroom	42.6 inches	↑ ↓	45.4 inches
Cargo Space	14.0 cubic feet	↑ ↓	13.4 cubic feet

Compound Critique



Dynamic Critiquing

Dynamic Critiquing

- Flexible Approach
- Unit critique
- Compound critique
- Generate compound critiques on the fly

See reading:
- McCarthy 2005a

The screenshot shows a web page from QwikShop.com. At the top, there's a navigation bar with links for HOME, ABOUT THIS PROJECT, and CONTACT. Below that is a search bar with the placeholder text "Shop for: Digital Cameras, Holidays, PCs". The main content area features a large image of a Canon EOS 300D digital SLR camera. To the right of the camera, a message says "Adjust your preferences in real time and let us find the right product for you!". Below this are several filter options with dropdown menus and checkboxes:

Filter Type	Value	Action
Manufacturer	Canon	X
Model	EOS-300D	X
Price (\$)	871.0	↑ ↓
Format	SLR	X
Resolution (M Pixels)	6.29	↑ ↓
Optical Zoom (X)	10.0	↑ ↓
Digital Zoom (X)	0.0	↑ ↓
Weight (grams)	645.0	↑ ↓
Storage Type	Compact Flash	X
Storage Included (MB)	0.0	↑ ↓

Below the filters, a section titled "Item Found: CASE2" displays the following specifications:

Specifications
6.3 Megapixel CMOS sensor
7-point wide-area AF
High-performance DIGIC processor
100-1600 ISO speed range
Compatible with all Canon EF lenses and EX Speedlites
PictBridge, Canon Direct Print and Bubble Jet Direct compatible - no PC required

At the bottom left are two buttons: "ADD TO BASKET" and "START OVER". On the right, there's a list of "We have more matching products with the following.." with three items, each with "PICK" and "EXPLAIN" buttons:

1. Less Optical Zoom & More Digital Zoom & A Different Storage Type (139) PICK EXPLAIN
2. A Lower Resolution & A Different Format & Cheaper (169) PICK EXPLAIN
3. A Different Manufacturer & Less Optical Zoom & More Storage (167) PICK EXPLAIN

At the very bottom, it says "COPYRIGHT 2004 ©".



Mining Dynamic Critiques

Generate Critique Patterns

- Re-describe every other case in relation to current case

Mine Compound Critiques

- Identify recurring patterns within set of critique patterns – Apriori [Agrawal et al.]

Select & Present

- Choose *Compound Critiques* to present to user



Generate Critique Patterns

	Current Case	Case c from CB	Critique Pattern
HolidayType	Education	Language	\neq
Price (Euro)	3738	2039	<
NumberOfPersons	2	1	<
Region	Egypt	Malta	\neq
Transportation	Plane	Plane	=
Duration (Days)	14	21	>
Season (Month)	October	September	\neq
Accommodation	FourStars	TwoStars	\neq
Hotel	Anlage Arabia	Sprachkurs Malta	\neq

Feature “Price” is assigned a “<” critique since case c is cheaper than the current case

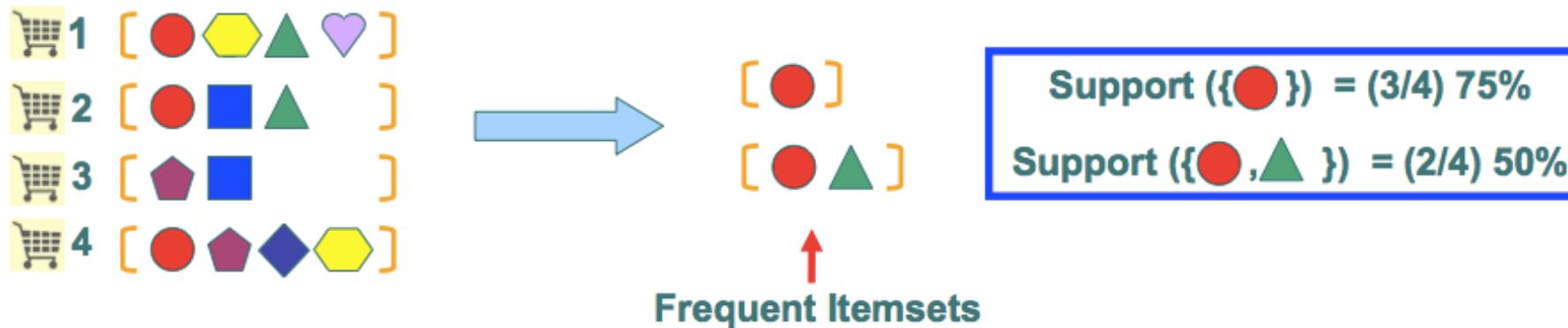
Feature “Duration” is assigned a “>” critique since case c is longer than the current case



Mining Compound Critiques

- Key Idea

- Identify recurring subsets of patterns within the pattern base
- E.g. *Market-Basket Analysis*



- Apriori

- [Agrawal et al.]
- Use to find frequent itemsets
- Rank itemsets by 'support' value



Mining Compound Critiques

	Price	Holiday Type	Duration	No. of Persons
Case 1	>	!=	<	>
Case 2	>	!=	>	<
Case 3	>	=	>	>
Case 4	>	!=	<	>
Case 5	<	=	>	<
Case 6	>	!=	<	<

- Candidate Compound Critiques
 - { [Price '>'], [Holiday Type '!='] }
 - { [Holiday Type '='], [Duration '>'] }

Support value of (4/6) 67%

Support value of (2/6) 33%



Select and Present

Three Selection Strategies

- Low-Support (LS) – Pick compound critiques with lowest support
- High-Support (HS) – Pick compound critiques with highest support
- Random (RAND) – Pick a set of random compound critiques

Present to User

- { [Price '>'], [Holiday Type '!='] }
- “A Different Type of Holiday which is More Expensive”



QWIKSHOP Application

QWIKSHOP.COM

HOME : ABOUT THIS PROJECT : CONTACT

Digital Cameras

Shop for: Digital Cameras, Holidays, PCs



Item Found: CASE2

Specifications

6.3 Megapixel CMOS sensor
7-point wide-area AF
High-performance DIGIC processor
100-1600 ISO speed range
Compatible with all Canon EF lenses and EX Speedlites
PictBridge, Canon Direct Print and Bubble Jet Direct compatible - no PC required

Adjust your preferences in real time and let us find the right product for you!

Manufacturer	<input checked="" type="checkbox"/> Canon	<input type="checkbox"/>
Model	<input checked="" type="checkbox"/> EOS-300D	<input type="checkbox"/>
Price (\$)	<input type="button" value="▼"/> 871.0	<input type="button" value="▲"/>
Format	<input checked="" type="checkbox"/> SLR	<input type="checkbox"/>
Resolution (M Pixels)	<input type="button" value="▼"/> 6.29	<input type="button" value="▲"/>
Optical Zoom (X)	<input type="button" value="▼"/> 10.0	<input type="button" value="▲"/>
Digital Zoom (X)	<input type="checkbox"/> 0.0	<input type="button" value="▲"/>
Weight (grams)	<input type="button" value="▼"/> 645.0	<input type="button" value="▲"/>
Storage Type	<input checked="" type="checkbox"/> Compact Flash	<input type="checkbox"/>
Storage Included (MB)	<input type="checkbox"/> 0.0	<input type="button" value="▲"/>

We have more matching products with the following..

1. Less Optical Zoom & More Digital Zoom & A Different Storage Type (139)
2. A Lower Resolution & A Different Format & Cheaper (169)
3. A Different Manufacturer & Less Optical Zoom & More Storage (167)

COPYRIGHT 2004 ©

Explanatory Benefits

● ● ● |

QWIKSHOP.COM

HOME : ABOUT THIS PROJECT : CONTACT

Digital Cameras

Shop for: Digital Cameras, Holidays, PCs



Adjust your preferences in real time and let us find the right product for you!

Manufacturer: Sony

Model: DSC-V1

Price (\$): 455.0

Format: Ultra Compact

Resolution (M Pixels): 5.0

Optical Zoom (X): 4.0

Digital Zoom (X): 4.0

Weight (grams): 298.0

Storage Type: Memory Stick

Storage Included (MB): 32.0

Item Found: CASE40

Specifications

1/1.8" 5.0 Megapixel
Memory Stick Media
5 Megapixel (2592 x 1944) Image Size
Traditional, Yet Compact Design
NightShot Infrared System
Carl Zeiss Vario-Sonnar Lens
1.5" LCD Monitor
MPEG Movie VX Mode
Continuous Auto Focus

ADD TO BASKET

START OVER

We have more matching products with the following..

1. A Different Manufacturer & A Lower Resolution & Cheaper (67) **PICK** **EXPLAIN**
2. A Different Format & Less Digital Zoom & Less Optical Zoom (60) **PICK** **EXPLAIN**
3. A Different Model & Heavier & More Expensive (54) **PICK** **EXPLAIN**

COPYRIGHT 2004 ©



Explanatory Benefits

The explanatory power of compound critiques is evident in the information they convey to the user;

- They highlight the common interactions that occur between features of the remaining cases, e.g. more expensive and greater resolution tells the user that if they want a camera with greater resolution they should expect to pay more.
- They map out the product space by highlighting the recommendation opportunities that exist, e.g. cheaper and less resolution tells the user there exists products in the product space that satisfy that critique.



Explanatory Benefits

The screenshot shows a user interface for filtering products based on storage capacity. A dropdown menu is open, showing 'Storage Included (MB)' with a value of '32.0' selected. Below this, a message says 'We have more matching products with the following..'. Three items are listed:

1. A Different Manufacturer & A Lower Resolution & Cheaper (67) [PICK](#)
2. A Different Format & Less Digital Zoom & Less Optical Zoom (60) [PICK](#)
3. A Different Model & Heavier & More Expensive (54) [PICK](#)

To the right, a window titled 'http://burnout.ucd.ie:8080 - Explain.. - Microsoft Internet Explorer' displays an explanatory critique. The critique is for a compound criterion: 'A Different Manufacturer & A Lower Resolution & Cheaper'. It covers 67 cases in the casebase.

Explanation:

Manufacturer

- Value = Sony,
- Critique = Not Equal To Nominal ('<>')
- Range Remaining = (Nikon, Kodak, Canon, Ricoh, Fuji, Pentax, Toshiba, Samsung, Olympus, Konica Minolta, Casio, Contax, Hewlett-Packard, Kyocera)

Resolution

- Value = 5.0
- Critique = Less Than Ordinal ('<')
- Range Remaining = (1.9 to 4.92)

Price (\$)

- Value = 289.0
- Critique = Less Than Ordinal ('<')
- Range Remaining = (114.0 to 289.0)

At the bottom of the critique window are 'BACK' and 'PICK' buttons. The status bar at the bottom of the browser window shows 'Done' and 'Internet'.



Diversity

Problem

- Compound critiques presented, critique some of the features in the same way

Implications

- Limits the scope of feedback options
- Limits the applicability of the compound critiques offered
- Off-putting and contrary to user expectations

Solution

- Present compound critiques which cover a wider range of feature critique combinations

Manufacturer	<input type="text"/> Cannon	<input type="button"/>
Model	<input type="text"/> EOS D60	<input type="button"/>
Pixel	<input type="button"/> ↓ 6.3 <input type="button"/>	
Memory Size(MB)	<input type="button"/> ↓ 8.0 <input type="button"/>	
Memory Type	<input type="text"/> CompactFlash Card	<input type="button"/>
Num of Batteries	<input type="text"/> 1.0	<input type="button"/>
Battery Type	<input type="text"/> BP-511	<input type="button"/>
Strap	<input type="text"/> Neck	<input type="button"/>
Cable	<input type="text"/> USB and Video	<input type="button"/>
Software	<input type="text"/> CD- Rom featuring Adobe Photoshop LE	<input type="button"/>
Price	<input type="button"/> ↓ 869.0 <input type="button"/>	

Compound Critiques

1. A Different Manufacturer & Less Pixels & Cheaper (72)	<input type="button"/> PICK
2. Less Pixels & Less Memory & Cheaper (84)	<input type="button"/> PICK
3. A Different Type of Memory & Different Software & Cheaper (80)	<input type="button"/> PICK

“Less Pixels” occurs in
2 compound critiques

“Cheaper” is common
to all 3 compound critiques



Diversity Enhancement

- 1. A Different Manufacturer & Less Pixels & Cheaper (72)
- 2. Less Pixels & Less Memory & Cheaper (84)
- 3. A Different Type of Memory & ...

PICK

- 1. A Different Manufacturer & Less Pixels & Cheaper (72)
- 2. A Different Model & More Memory & More Expensive (79)
- 3. A Different Type of Memory & Different Cable & Less Memory (83)

PICK

PICK

- Use the Bounded Greedy Approach
- Produces compound critiques with fewer overlapping unit critiques
- Diverse critiques more likely to satisfy user as they cover more options
- Reduce session lengths



Cognitive Load

Level of effort associated with thinking and reasoning.

Important for us to understand the level of effort required by the user during system interactions.

Measured by interaction/response time.



Cognitive Load in Conversational Recommenders

Recommender systems make cognitive demands on users in some way.

Limiting factors:

- Users rarely have a clear understanding of what product they are looking for.
- Users may not be proficient in the required product description knowledge.
- Users may be unable to compare presented suggestions.
- Users are often incapable of retaining learned information in short-term memory.



Cognitive Load in Conversational Recommenders

Case Evaluation Level

- Cognitive load experienced at case level.
- Comparative cognitive cost.
- i.e. Preference based feedback.

			
<u>Air Durham (men)</u>	\$100	\$90	\$85
<u>Buy It!</u>	<u>Buy It!</u>	<u>Buy It!</u>	<u>Buy It!</u>
<u>Surface</u>	Road Shoe	Road Shoe	Road Shoe
<u>Midsole</u>	PU midsole	Phylon midsole	Phylon midsole
<u>Width</u>	Standard	Standard	Standard
<u>Motion Control</u>	★★★	★★★	★★★
<u>Feel: Impact Protection</u>	★★★	★★★	★★★
<u>Feel: Responsiveness</u>	★★★	★★★	★★★
<u>Breathability</u>	★★★	★★★	★★★
<u>Water Resistance</u>	No	No	No
<u>Weight</u>	14.5 ounces	12.6 ounces	12 ounces



Cognitive Load in Conversational Recommenders

Feature Interaction Level

- Cognitive load experienced at feature level
- Users must breakdown and understand critique options offered.
- Unit critiques .
- Compound critiques.

The screenshot shows a user interface for a conversational recommender system. At the top, there is a navigation bar with icons for back, forward, search, and help. Below the navigation is a header with the text 'Cognitive Load in Conversational Recommenders' and a subtitle 'Feature Interaction Level'.

The main content area displays a product's technical specifications in a table format:

Attribute	Value	Action
Manufacturer	Cannon	X
Model	EOS D60	X
Pixel	6.3	↓ ↑
Memory Size(MB)	8.0	↓ ↑
Memory Type	CompactFlash Card	X
Num of Batteries	1.0	↑
Battery Type	BP-511	X
Strap	Neck	X
Cable	USB and Video	X
Software	CD- Rom featuring Adobe Photoshop LE	X
Price	869.0	↓ ↑

Below the table, there is a section titled 'Compound Critiques' listing three suggestions:

1. A Different Manufacturer & Less Pixels & Cheaper (72) PICK
2. A Different Model & More Memory & More Expensive (79) PICK
3. A Different Type of Memory & Different Cable & Less Memory (83) PICK



Cognitive Load – Unit Critiques

The screenshot shows a software interface for critiquing camera specifications. On the left is a list of features with dropdown menus and critique icons. On the right is a list of feature values with critique icons. A red box highlights the critique icons for the first three features. Below the list is a section titled "Compound Critiques" with three numbered items and a "PICK" button.

Manufacturer	Cannon
Model	EOS D60
Pixel	6.3
Memory Size(MB)	8.0
Memory Type	CompactFlash Card
Num of Batteries	1.0
Battery Type	BP-511
Strap	Neck
Cable	USB and Video
Software	CD- Rom featuring Adobe Photoshop LE
Price	869.0

Compound Critiques

1. A Different Manufacturer & Less Pixels & Cheaper (72) **PICK**
2. A Different Model & More Memory & More Expensive (79) **PICK**
3. A Different Type of Memory & Different Cable & Less Memory (83) **PICK**

Unit Critiques

- Icons fixed.
- Do not change position from cycle to cycle.
- Feature values displayed.
- Easy to understand.



Cognitive Load – Dynamic Compound Critiquing

The screenshot shows a user interface for configuring a camera. On the left, there is a list of product specifications with input fields and control buttons:

Manufacturer	<input type="text"/> Cannon	<input type="button"/>
Model	<input type="text"/> EOS D60	<input type="button"/>
Pixel	<input type="text"/> 6.3	<input type="button"/> <input type="button"/>
Memory Size(MB)	<input type="text"/> 8.0	<input type="button"/> <input type="button"/>
Memory Type	<input type="text"/> CompactFlash Card	<input type="button"/>
Num of Batteries	<input type="text"/> 1.0	<input type="button"/> <input type="button"/>
Battery Type	<input type="text"/> BP-511	<input type="button"/>
Strap	<input type="text"/> Neck	<input type="button"/>
Cable	<input type="text"/> USB and Video	<input type="button"/>
Software	<input type="text"/> CD- Rom featuring Adobe Photoshop LE	<input type="button"/>
Price	<input type="text"/> 869.0	<input type="button"/> <input type="button"/>

Below the specification table, there is a section titled "Compound Critiques" containing three numbered items:

1. A Different Manufacturer & Less Pixels & Cheaper (72) PICK
2. A Different Model & More Memory & More Expensive (79) PICK
3. A Different Type of Memory & Different Cable & Less Memory (83) PICK

Compound Critiques

- 3 presented to user.
- Change on each cycle.
- Each compound critique made up of 3 unit critiques.
- No value information.



Cognitive Load – Results

Elapsed response time as a measure of cognitive load.

Increased cognitive load associated with compound critiques.

Additional cognitive effort is worthwhile

- Less elapsed time (28% reduction).
- Less recommendation cycles (71% reduction).

User behaviour differs

Cognitive load increase outweighed by recommendation efficiency improvements



Evaluating Dynamic Critiquing

Preformed both simulations and real user experiments to evaluate and validate our approach

Off-line simulations

- Reductions in session lengths of 36% - 66%

Live user studies

- Reductions in session lengths of 70% - 80%
- Number of cycles falls from 34 to 10
- Users apply compound critiques 25% of time

Case Study 2

Preference-based Feedback

http://serendipity.ucd.ie:8080/store/index.jsp

Serendipity

[View Basket](#) | [Checkout](#) | [About Us](#) | [Contact Us](#)

[Home](#) [Jewellery](#) [Phones](#) [Weddings](#) [Electronics](#) [Computers](#)

Serendipity - Your Wedding Dress Destination

Browse: Weddings

- [Wedding Dresses](#)
- [Bridesmaid Dresses](#)
- [Mother of the Bride Dresses](#)
- [Wedding Accessories](#)
- [Bridal Veils and Wedding Veils](#)
- [Prom Dresses](#)

Your Basket

Items in your basket:

There are no items in your basket.

Impression - 2663	Impression - 2624	Impression - 2648
Recommended Price \$690	Recommended Price \$730	Recommended Price \$550
Our Price \$495	Our Price \$515	Our Price \$425
Add To Basket	Add To Basket	Add To Basket



◀ Pic 1/4 ▶



◀ Pic 1/3 ▶



◀ Pic 1/4 ▶

Preference	Preference	Preference	
Designer	Impression	Impression	
Colors	Ivory/Champagne	Ivory	Ivory
Sizes	2	2	2
Neckline	Strapless	Strapless	Strapless
Waist/Silhouette	Mermaid	Mermaid	Mermaid
Pieces/Separates	One-piece	One-piece	One-piece
Train Length	Sweep	Sweep	Sweep
Fabric	Lace	Lace	Chiffon
Formality	Formal	Formal	Formal
Sleeve length	Strapless	Strapless	Strapless
Hem Line	Floor Length	Floor Length	Floor Length
Lace

Filters

Size	<input type="text" value="PleaseSelect"/>
Neckline	<input type="text" value="Bateau"/> <input type="text" value="Bateau, Scalloped"/> <input type="text" value="Drape"/>
Designer	<input type="text" value="Alfred Angelo"/> <input type="text" value="Bonny"/> <input type="text" value="DeVinci"/>
Waist / Silhouette	<input type="text" value="A-Line"/> <input type="text" value="A-Line, Empire"/> <input type="text" value="Ballgown"/>
Colour	<input type="text" value="Antique"/> <input type="text" value="Black"/> <input type="text" value="Blue"/>
Price	Min: <input type="text" value="No Limit"/> Max: <input type="text" value="No Limit"/>
more... Update	



Preference-based Feedback

- Assumptions:

- The user has some product requirement
- The requirement is sufficiently vague (the user cannot simply specify all feature values)
- The user provides an initial query (e.g. some initial feature values are specified or query is based on user profile) – small set of recommendations returned
- The user is facilitated to find a good product by providing preference-based feedback on items displayed during each recommendation cycle (i.e. I prefer this item)
- User feedback is leveraged to select the set of products to be displayed during subsequent recommendation cycles

- Practical Applications

- Recommending restaurants, cars, cameras, property etc.



Limitations

- During each recommendation cycle, users simply indicate a preference for one item over the others:
 - Well suited to domains where users have limited domain knowledge
- Simple and relatively low cost form of feedback, but has limitations:
 - May not be clear why the user picked one item over the alternatives presented
 - Items presented may have some features in common and some which distinguish them
- One approach: *comparison-based recommendation* (**McGinty 2002**):
 - Proposes a variety of query revision strategies that are designed to update the current query as a result of preference-based feedback

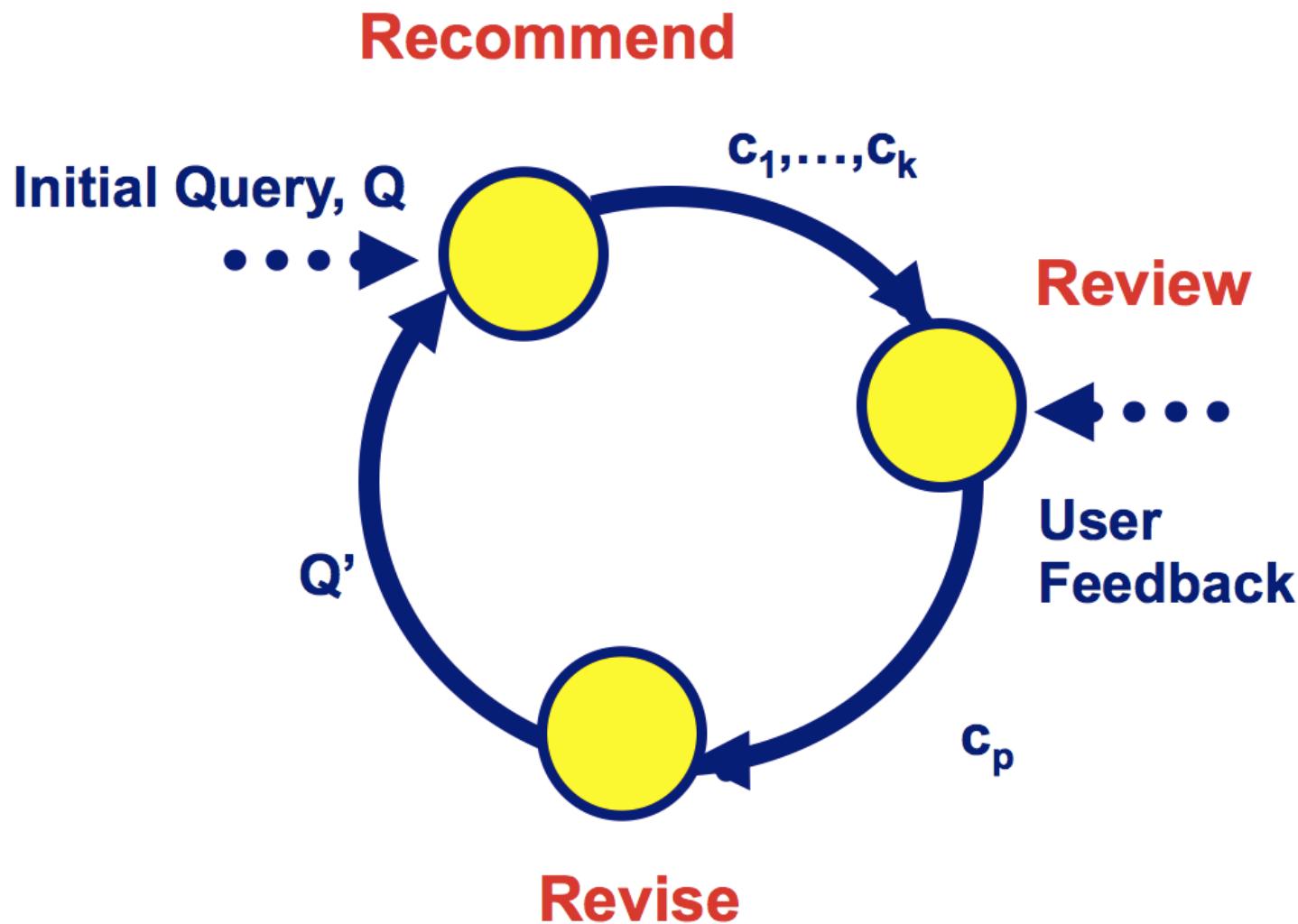


User Feedback

- The review process is conceptually simple...
- The user is simply asked to select the item that best matches their needs – form of *positive feedback*.
- Alternatively the user can provide *negative feedback* by selecting the item which best corresponds to items that the user is not interested in.
- Here, focus on positive feedback.



Conversational Recommender System Cycle



Comparison-based Recommendation Algorithm

```

1. define Comparison-Based-Recommend(Q, CB, k)
2. begin
3.   Do
4.     R ← ItemRecommend(Q, CB, k)
5.     cp ← UserReview(R, CB)
6.     Q ← QueryRevise(Q, cp, R)
7.   until UserAccepts(cp)
8. end

9. define ItemRecommend(Q, CB, k)
10. begin
11.   CB' ← sort cases in CB in decreasing order of their sim to Q
12.   R ← top k cases in CB'
13.   return R
14. end

15. define UserReview(R, CB)
16. begin
17.   cp ← user selects best case from R
18.   CB ← CB - R
19.   return cp

20. define QueryRevise(Q, cp, R)
21. begin
22.   R' ← R - {cp}
23.   For each fi ∈ cp
24.     Q ← update(Q, fi, R')
25.   end For
26.   return Q
27. end

```



Query Revision

- The main idea is how the user's preference feedback can be leveraged to inform the subsequent recommendation cycle.
- The goal is to revise the current query based on what can be learned from the user's feedback.
- In the case of positive feedback – where the user selects a preferred case (item), c_p – the goal is to update query features with features from the preferred case that best reflect the user's implicit preferences.
- Query revision strategies:
 - MLT – More Like This
 - pMLT – Partial More Like This
 - wMLT – Weighted More Like This
 - LLT – Less Like This
 - MLT+LLT – More Like This + Less Like This



MLT – More Like This

- Simplest form of query revision
- Query features are assigned the feature values of the preferred case
- Advantage:
 - A partial user query (one in which only a few feature values are specified) can be instantly extended to include all features from the preferred case
- Disadvantages:
 - Not every feature of the preferred case may be preferred by the user
 - MLT may suffer from *overfitting* to user feedback, user may be guided to irrelevant parts of the item space
 - May result in an increased number of recommendation cycles where the user has to examine more cases than necessary

MLT RULE: `update(Q, f_i, R') : $Q.f_i := f_i$`



pMLT – Partial More Like This

- A revised form of MLT.
- Motivation is to reduce overfitting.
- A feature value from the preferred case is only assigned to the query if none of the rejected cases have the same feature value.
- Allows the recommender to focus on the those aspects of the preferred case that are unique in the current cycle.

pMLT RULE: $\text{update}(Q, f_i, R') : Q.f_i := f_i \text{ if } (\neg \exists c_j \in R' : c_j.f_i = f_i)$

wMLT – Weighted More Like This

- wMLT attempts to weight updated query features based on the degree of confidence that we can attribute to them as genuine user preferences.
- The main idea is that, for each feature, the more feature alternatives that have been presented to the user, the more confident we can be about learning their preference for that feature.
- Based on MLT – the wMLT strategy transfers all features from the preferred case to the query but weights them according to how diverse the feature is among recommendations in the current cycle.

wMLT RULE: $\text{update}(Q, f_i, R') : Q.f_i := \langle f_i, \text{weight}(f_i, R') \rangle$

$$\text{weight}(f_i, R') = \frac{\# \text{ of alternatives to } f_i \text{ in } R'}{|R'|}$$



LLT – Less Like This

- In addition to learning about features that the user is likely to prefer, it may also possible to infer features that the user tends to dislike
- The LLT strategy treats the query as a set of negative preferences and ordering cases during future recommendation cycles by prioritising cases that are most dissimilar to the negative query.
- LLT strategy – if rejected cases all have the same value for a given feature (which is different to the preferred case), then this feature value is added to the negative query.

LLT RULE: $\text{update}(Q, f_i, R') : Q_{neg}.f_i := f'_i \text{ if } (\forall c_j \in R', c_j.f_i = f'_i) \wedge (f'_i \neq f_i)$



pMLT + LLT – Partial More Like This + Less Like This

- Combines pMLT and LLT to learn both positive and negative preferences in a single recommendation cycle.
- The query has two components – a positive and negative component.
- To compute the relevance between this query and a candidate case, compute the similarity between the positive query component and the case and subtract the similarity between the negative component and the case.

pMLT+LLT RULE: = **update**(Q, f_i, R') :
$$\begin{aligned} Q_{pos}.f_i &:= f_i \text{ if } (\neg \exists c_j \in R' : c_j.f_i = f_i) \\ &\wedge \\ Q_{neg}.f_i &:= f'_i \text{ if } (\forall c_j \in R', c_j.f_i = f'_i) \wedge (f'_i \neq f_i) \end{aligned}$$



Evaluation Methodology

- Compare performance of the five query revision strategies against a benchmark (single shot) similarity-based approach
- PC dataset, containing 120 cases, each describing a unique PC
- Feature set: (1) *PC type*, (2) *processor type*, (3) *processor speed*, (4) *memory*, (5) *disk size*, (6) *display size* and (7) *price*.
- Adopt a leave-one-out evaluation methodology – each case (current) in turn in the dataset is temporarily removed and used in two ways:
 - First the case in the dataset which is the most similar to the current case is used as the *target case*
 - Second the current case serves as the basis for a set of random queries of varying sizes
 - Vary values of q (the number of initial features per query) from 1 to 5
 - Vary values of k (the number of cases returned during each recommendation cycle) from 2 to 5
 - 1200 separate queries generated

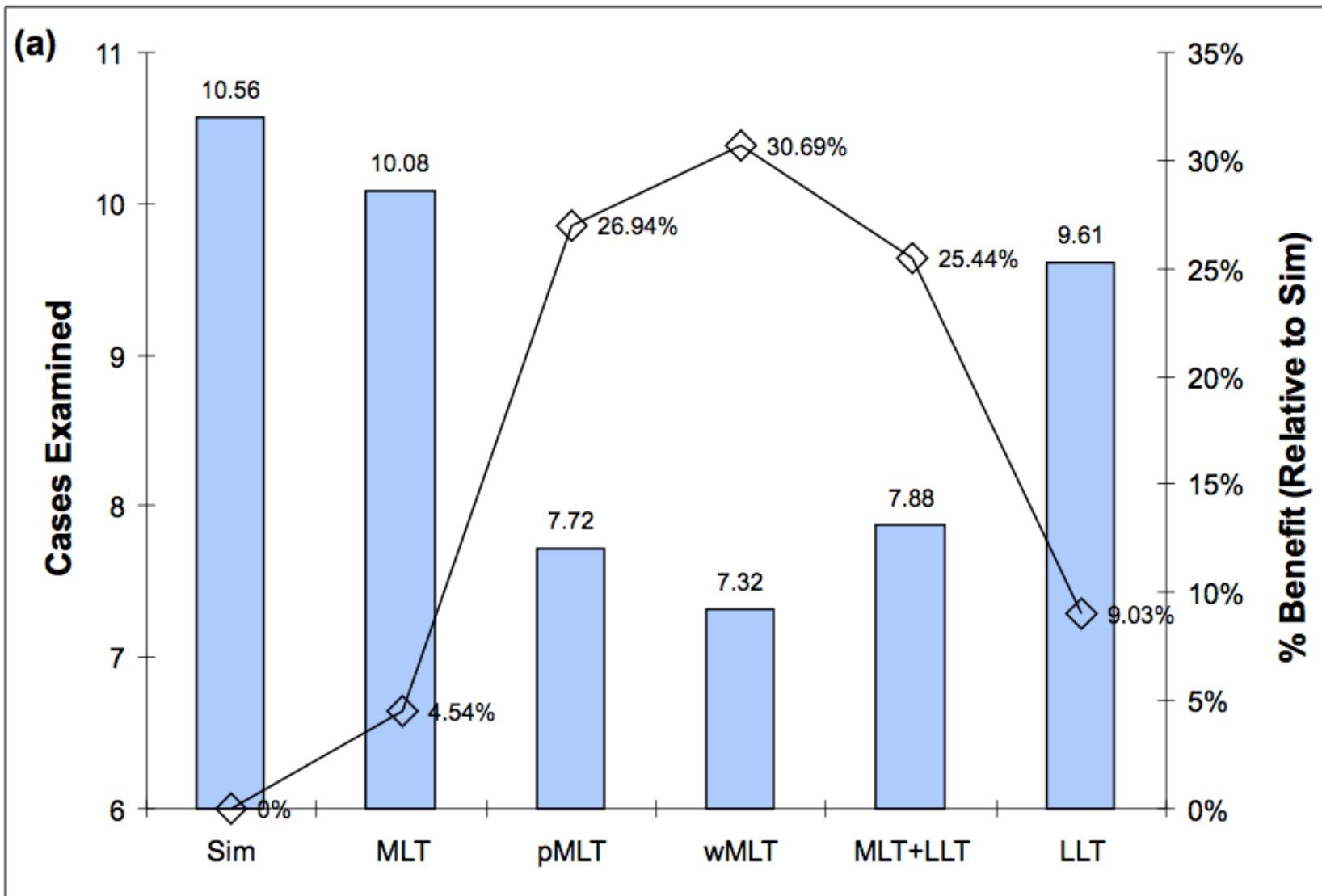


Evaluation Metrics

- Benchmark – standard single-shot similarity-based retrieval approach, rank all cases by decreasing similarity. Compute the average rank (over all queries) of the target case.
- Count the average (over all queries) number of cases the user needs to examine before the target case is presented for each query revision strategy and compare to the benchmark.
- The number of “wins” for each query revision strategy compared to the benchmark:
 - Count the number of trials where a strategy results in fewer cases being examined before the target case is presented



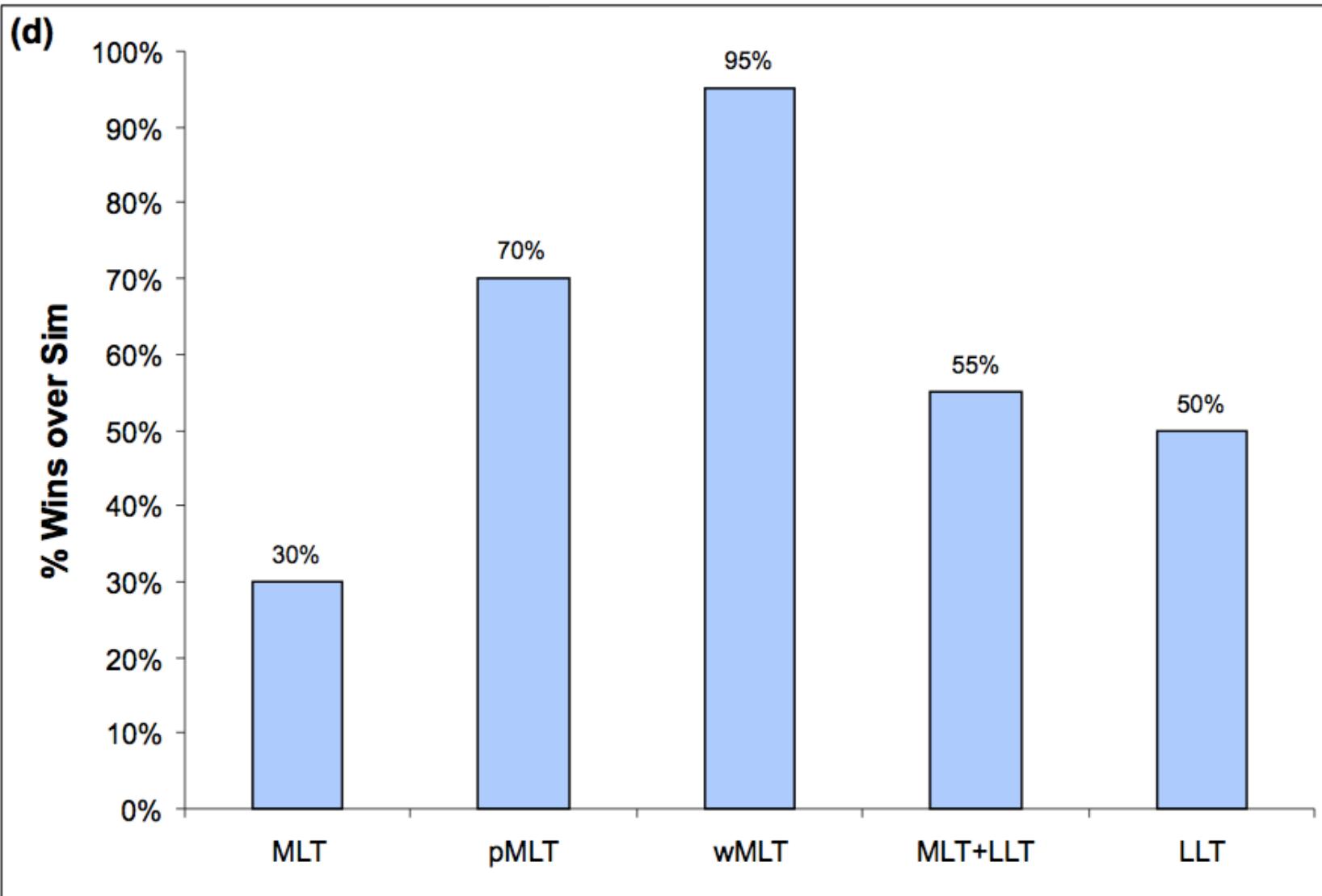
Results





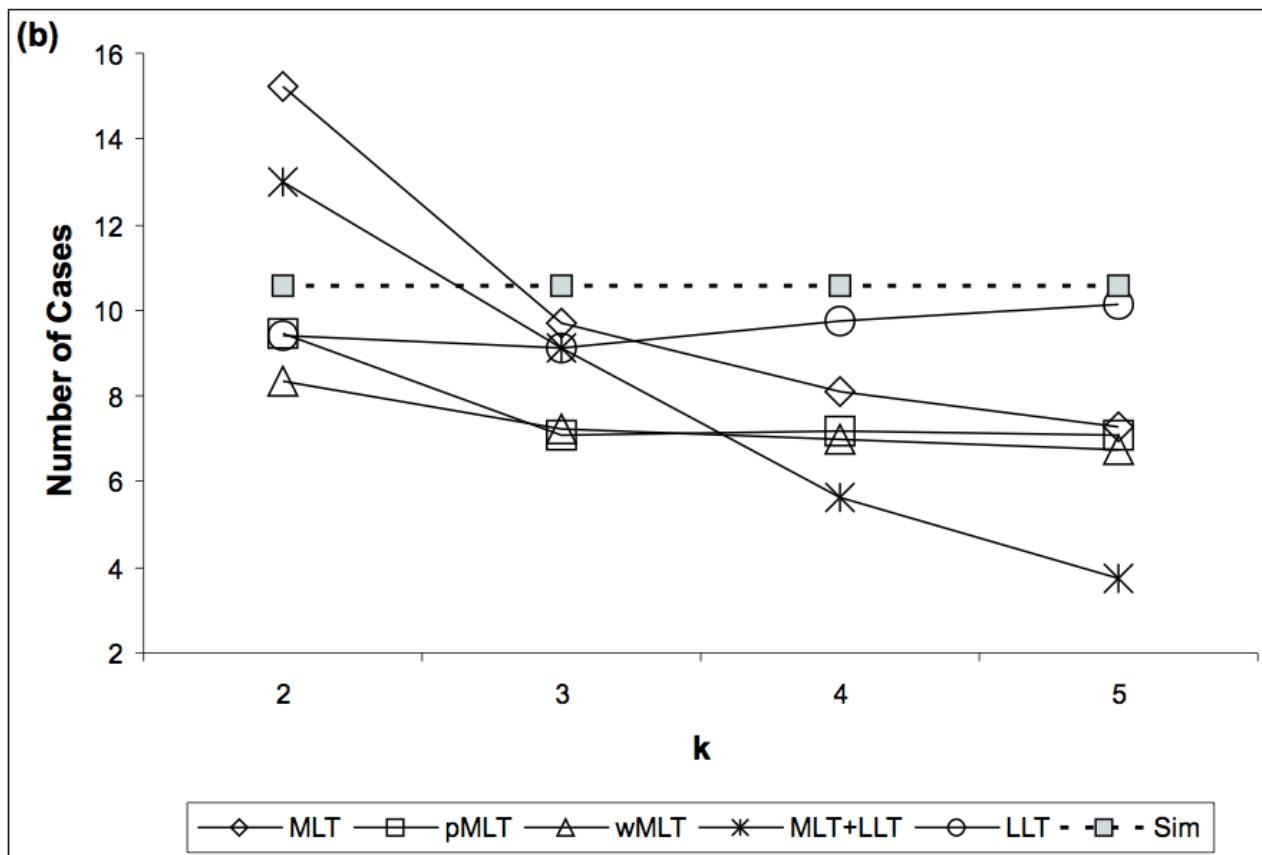
Results

trials where a strategy results in fewer cases being examined before the target case is presented





Results

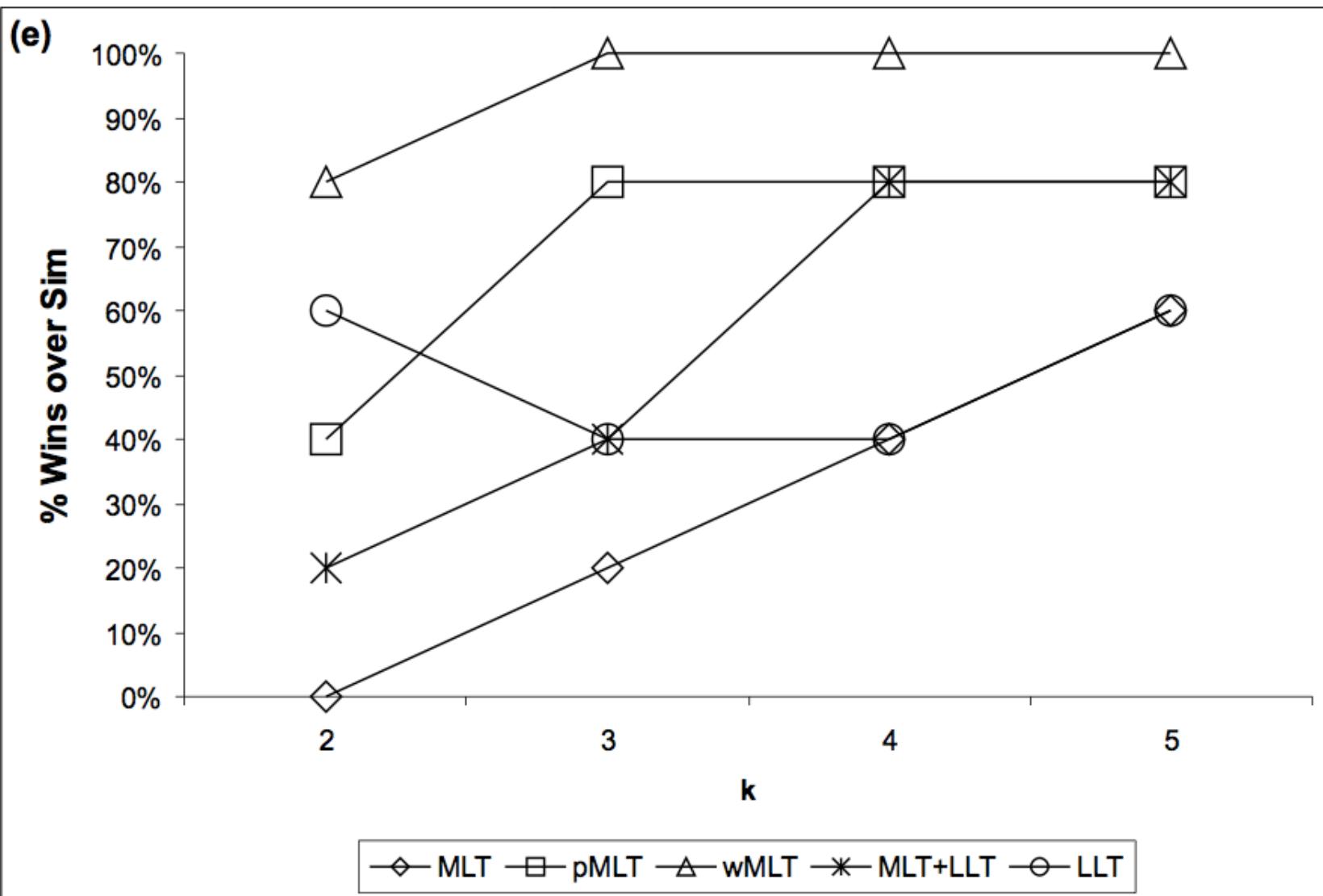


- As k increases the average number of cases examined by the user decreases
- MLT and MLT+LLT lose to Sim (benchmark) for $k=2$
- MLT+LLT – LLT on its own performs well at $k=2$, indicating poor performance is due to MLT
- Results indicate that simple MLT is not an effective strategy



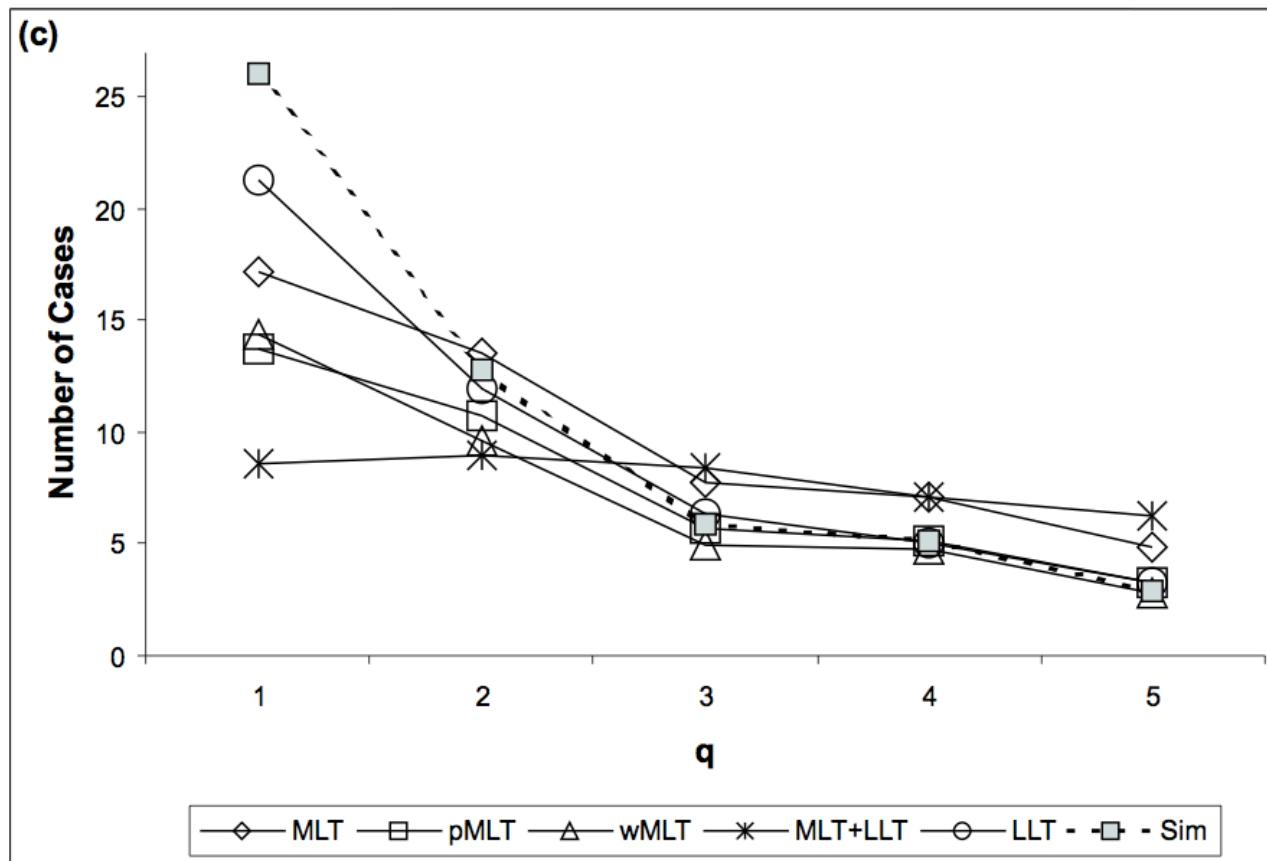
Results

trials where a strategy results in fewer cases being examined before the target case is presented





Results

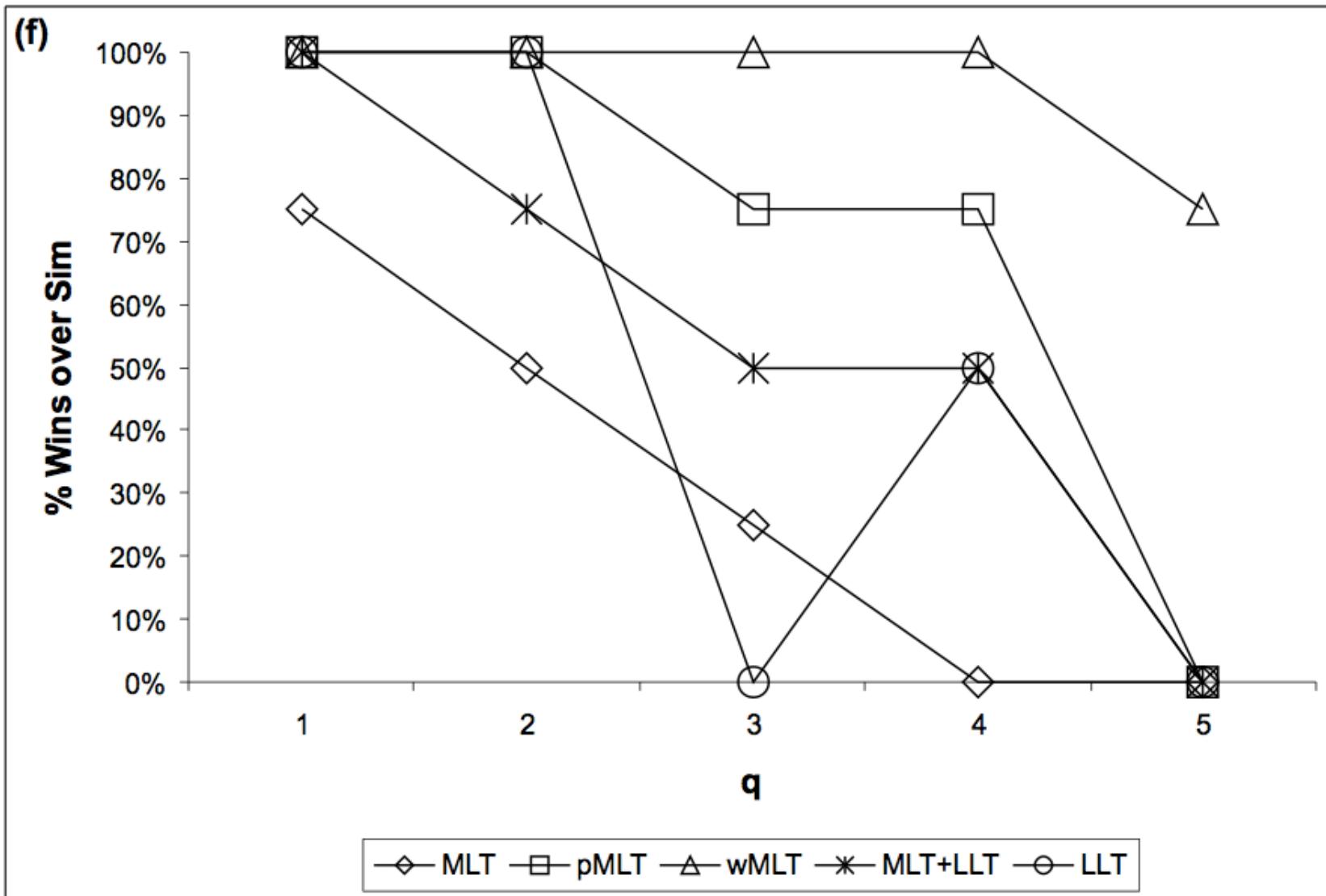


- Significant reductions in number of cases examined as q increases (as expected)
- MLT again performs poorly, losing to Sim for values of $q > 2$
- pMLT and wMLT - best overall performance, winning outright for $q > 2$
- wMLT outperforms pMLT indicating value conferred by its weighting technique



Results

trials where a strategy results in fewer cases being examined before the target case is presented





Summary

- Recommender systems:
 - Non-personalised vs. personalised
 - Content/case-based vs. content-free (CF)
 - Single-shot vs. conversational:
 - Conversational – feedback, presentation, explanation, cognitive load...
- No “silver bullet” solution:
 - Dependancies: domain, available data, user base ...