Week 11:
Knowledge Based RSs – Part II

CSX4207/ITX4207: Decision Support and Recommender Systems

ITX4287: Selected Topic in Decision Support and Recommender Systems

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Objectives

- To be familiar with a widely used knowledge-based recommendation algorithms

- To present and discuss the applications of collaborative filtering approaches

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Outlines

- Conjoint Analysis

- Knowledge based recommendation algorithm

  ▫ Critiquing

- Pros and Cons of Knowledge based RS

- Articles' Presentation and Discussion

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Basic Conjoint Analysis

- A statistical technique that marketers usually apply to measure *customer satisfaction* on available products to determine *desirable* product's *features* and *price*

- Common steps:

    1. Marketers **prepare choices** of product **as a set of cards**

    2. User(s) **ranks** the cards **wrt their preferences**

    3. Based on the ranks in step 2, **calculate a utility function** (representing user's preference) and/or relative importance (of available features)

Ref: Joseph Curry, **Sawtooth Software *RESEARCH PAPER SERIES:*** Understanding Conjoint Analysis in 15 Minutes, Sawtooth Technologies, Inc., 1996
https://sawtoothsoftware.com/resources/technical-papers/understanding-conjoint-analysis-in-15-minutes

An Example

- To market a new golf ball with three important product *features*:

  ▫ Average driving distance

  ▫ Average ball life

  ▫ Price

- **Goal:** What is the desirable features' value for

  a new golf ball?

Ref: Joseph Curry, **Sawtooth Software** *RESEARCH PAPER SERIES:* Understanding Conjoint Analysis in 15 Minutes, Sawtooth Technologies, Inc., 1996

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An Example

1. Marketers **prepare choices** of product **as a set of cards**

    ▫ The no. of choices = 3 x 3 x 3 = 27. In this example will simplify the step.

Average Driving Distance	Average Ball Life	Price
275 yards	54 holes	$1.25
250 yards	36 holes	$1.50
225 yards	18 holes	$1.75

Ref: Joseph Curry, **Sawtooth Software _RESEARCH PAPER SERIES:_** Understanding Conjoint Analysis in 15 Minutes, Sawtooth Technologies, Inc., 1996

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An Example

2. User(s) **ranks** the choices (the cards) **wrt their preferences**

Figure 2a

Buyer 1	Average Ball Life		
	54 holes	**36 holes**	**18 holes**
Average Driving Distance **275 yards**	1	2	4
250 yards	3	5	6
225 yards	7	8	9

Figure 4a

Buyer 1	Average Ball Life		
	54 holes	**36 holes**	**18 holes**
Price **$1.25**	1	4	7
$1.50	2	5	8
$1.75	3	6	9

Ref: Joseph Curry, **Sawtooth Software RESEARCH PAPER SERIES:** Understanding Conjoint Analysis in 15 Minutes, Sawtooth Technologies, Inc., 1996

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An Example

3. Use user's ranks to generate the utility values of each attribute (could also be derived from a linear regress model)

From Figure 2a to **Figure 3**

Buyer 1

Average Ball Life

Average Driving Distance		54 holes 50	36 holes 25	18 holes 0
275 yards	100	sum (1) 150	(2) 125	(4) 100
250 yards	60	(3) 110	(5) 85	(6) 60
225 yards	0	(7) 50	(8) 25	(9) 0

Find a set of values for Average Driving Distance and a second set for Average Ball Life for Buyer 1 so that when adding these values together for each ball, they reproduce Buyer 1's rank orders

From Figure 4a to **Figure 4b**

Buyer 1

Average Ball Life

Price		54 holes 50	36 holes 25	18 holes 0
$1.25	20	(1) 70	(4) 45	(7) 20
$1.50	5	(2) 55	(5) 30	(8) 5
$1.75	0	(3) 50	(6) 25	(9) 0

Figure 5

Average Driving Distance		Average Ball Life		Price	
275 yards	100	54 holes	50	$1.25	20
250 yards	60	36 holes	25	$1.50	5
225 yards	0	18 holes	0	$1.75	0

utility values

Ref: Joseph Curry, **Sawtooth Software *RESEARCH PAPER SERIES:*** Understanding Conjoint Analysis in 15 Minutes, Sawtooth Technologies, Inc., 1996
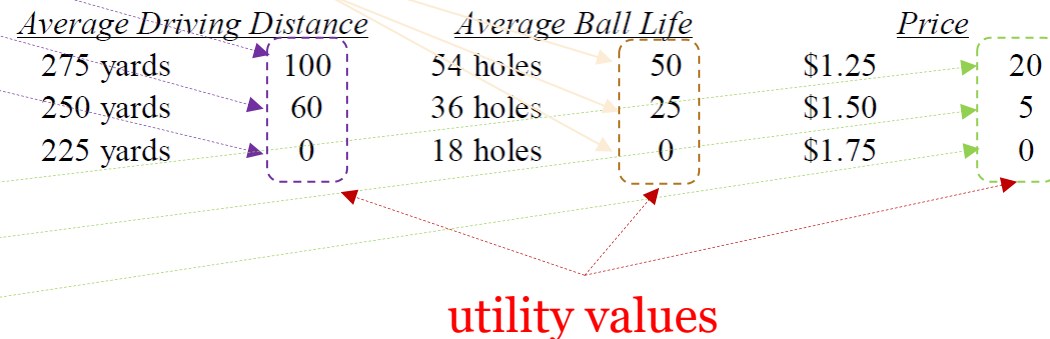
An Example

- Apply the obtained utility values* to calculate utility values for the user.

Figure 5*

| Average Driving Distance		Average Ball Life		Price	
275 yards	100	54 holes	50	$1.25	20
250 yards	60	36 holes	25	$1.50	5
225 yards	0	18 holes	0	$1.75	0

*: Could also be derived from a *linear regression model*

$$S = B0 + B11(AD1) + B12(AD2) + B13(AD3) + B21(AB1) + B22(AB2) + B23(AB3) + B31(P1) + B32(P2) + B33(P3)$$

Figure 7

Choice 1   Choice 2

Buyer 1	Distance Ball		Long-Life Ball	
Distance	275	100	250	60
Life	18	0	54	50
Price	$1.50	5	$1.75	0
Total Utility		105	<	110

$$S = 9.08 - 4.75(AB1) - 2.17(AB2) - 4.44(AD1) - 2.5(AD2) - 2.78(P1) - 1.78(P2)$$

Buyer 1 prefers choice 2 more than choice 1.

Ref: Joseph Curry, **Sawtooth Software RESEARCH PAPER SERIES:** Understanding Conjoint Analysis in 15 Minutes, Sawtooth Technologies, Inc., 1996

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Applying Conjoint Analysis in RS – 1/3
Example 1: Music Recommender System using Conjoint Analysis

Ref: https://medium.com/@pum.crab/music-recommender-system-using-conjoint-analysis-f20fdc9cd8ec

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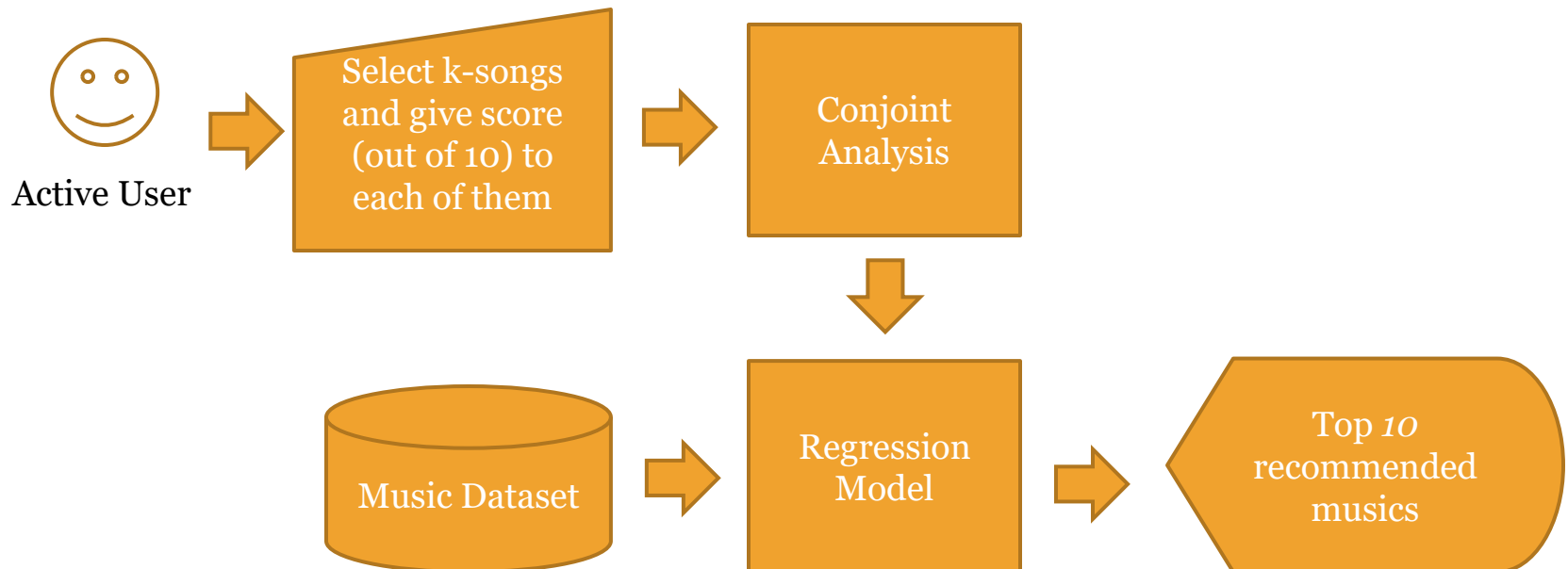
Applying Conjoint Analysis in RS – ½
Example 2: analyze **ranks** of variables that affects user's decision

- Given

  - Ranges of **price**: $price_1$[100-159], $price_2$[160-199], $price_3$[200-300]

  - Ranges of **mpix**: $mpix_1$[5.0-8.0], $mpix_2$[8.1-11.0]

- Then, a target user **ranks** of all possible combination of price's and mpix's choices

	$price_1$ [100-159]	$price_2$ [160-199]	$price_3$ [200-300]
$mpix_1$ [5.0-8.0]	4	5	6
$mpix_2$ [8.1-11.0]	2	1	3

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Applying Conjoint Analysis in RS – 2/2

Table1	price$_1$ [100-159]	price$_2$ [160-199]	price$_3$ [200-300]	avg_rank(mpix$_x$)
mpix$_1$ [5.0-8.0]	4	5	6	5
mpix$_2$ [8.1-11.0]	2	1	3	2
avg_rank(price$_x$)	3	3	4.5	**3.5**

Table2	d = avg(ranking) − avg_rank(attr$_x$)
avg(ranking) – avg_ranking(mpix$_1$) (**3.5** - 5)	-1.5
avg(ranking) – avg_ranking (mpix$_2$) (**3.5** - 2)	1.5
avg(ranking) – avg_ranking (price$_1$) (**3.5** - 3)	0.5
avg(ranking) – avg_ranking (price$_2$) (**3.5** - 3)	0.5
avg(ranking) – avg_ranking (price$_3$) (**3.5** − 4.5)	-1.0

The **relative importance** of each attribute is calculated by considering *how much difference* each attribute could make in the total utility of a product (the **range** in the **attribute's utility values**.)

avg(mpix$_x$) **span**
= |max_d$_{mpix}$ − min_d$_{mpix}$|
= |1.5 −(-1.5)| = 3
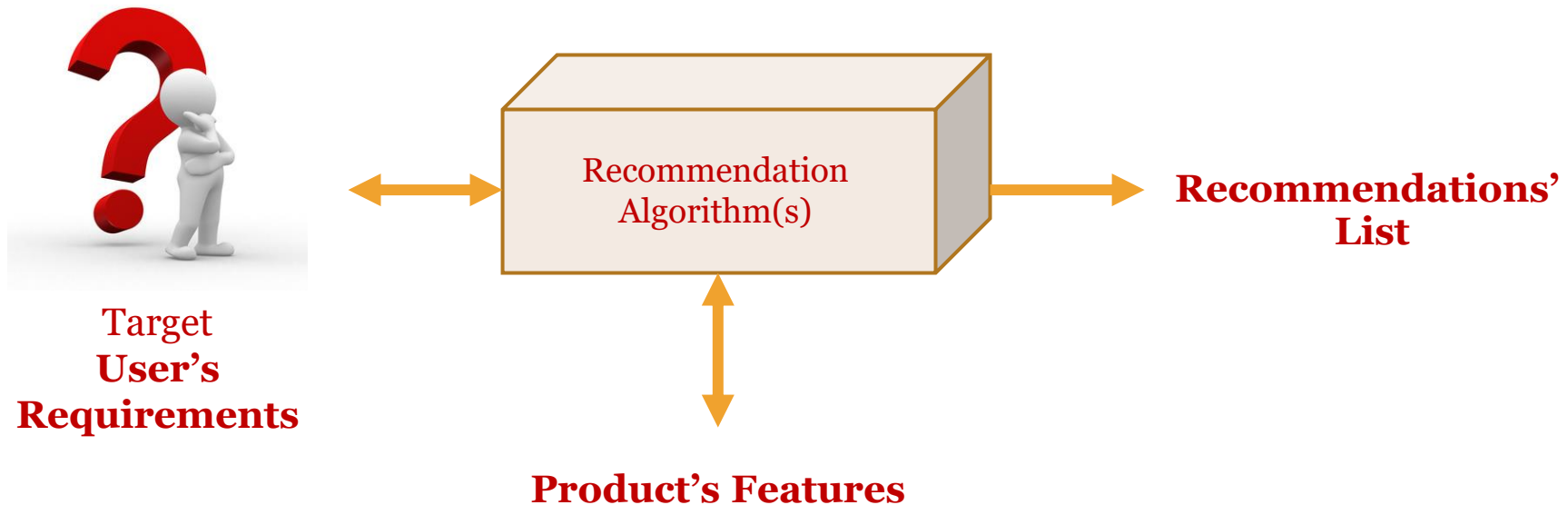
avg(price$_x$) **span**
= |max_d$_{price}$ − min_d$_{price}$|
= |0.5 − (-1.0)| = 1.5

Conclusion: Mpix changes **has a higher effect** on the overall utility (for this customer) than price changes.

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Revising Knowledge-based Recommendation
Main Idea

- To match *user requirements* with item's features.

- To use *user interaction* to refine recommendations.

- To predict which items the current user will most probably like.

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How to Generate Recommendation Using Knowledge Based Filtering Approach

Recommendation Algorithm(s)

Recommendations' List

Target **User's Requirements**

Product's Features

Knowledge based: "Tell me what fits based on my needs."

Outlines

- Conjoint Analysis

- Knowledge-based recommendation algorithm

  - Critiquing

- Pros and Cons of Knowledge based RS

- Articles' Presentation and Discussion

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Basic Types of Knowledge-based Recommender Systems

- Constraint-based

- Case-based

Interacting with Case-based Recommenders

- Motivation: a pure query-based approach requires

  ▫ Respecifying user's requirements until a target item has been identified

  ▫ A substantial domain knowledge to perform well

- Alternatives: browsing-based approaches to item retrieval

  ▫ By *navigating* in the item space with the goal to *find useful alternatives* (initially unknown)

  ▫ E.g., Critequing

Critiquing

- Idea: users specify their ***changes*** requests in the form of goals (critiques) for the currently unsatisfied items recommended.

  ▫ E.g. of critiques (in the level of *technical properties*)

  • *cheaper* (on *price* feature)

  • *more mpix* (on *mpix* feature)

  ▫ E.g. of critiques (in the level of *abstract dimensions*)

  • The apartment should be *more modern-looking.*
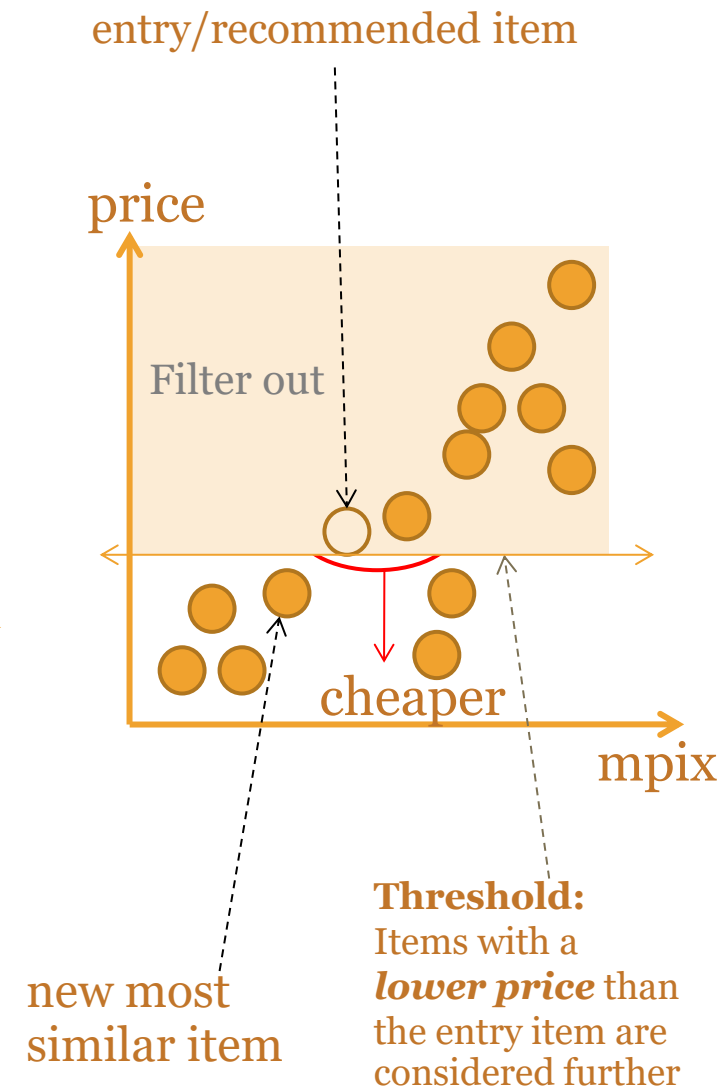
  • The hotel location should be *nearer to the sea.*

entry/recommended item

price

more expensive

less mpix

more mpix

cheaper

mpix

most similar item

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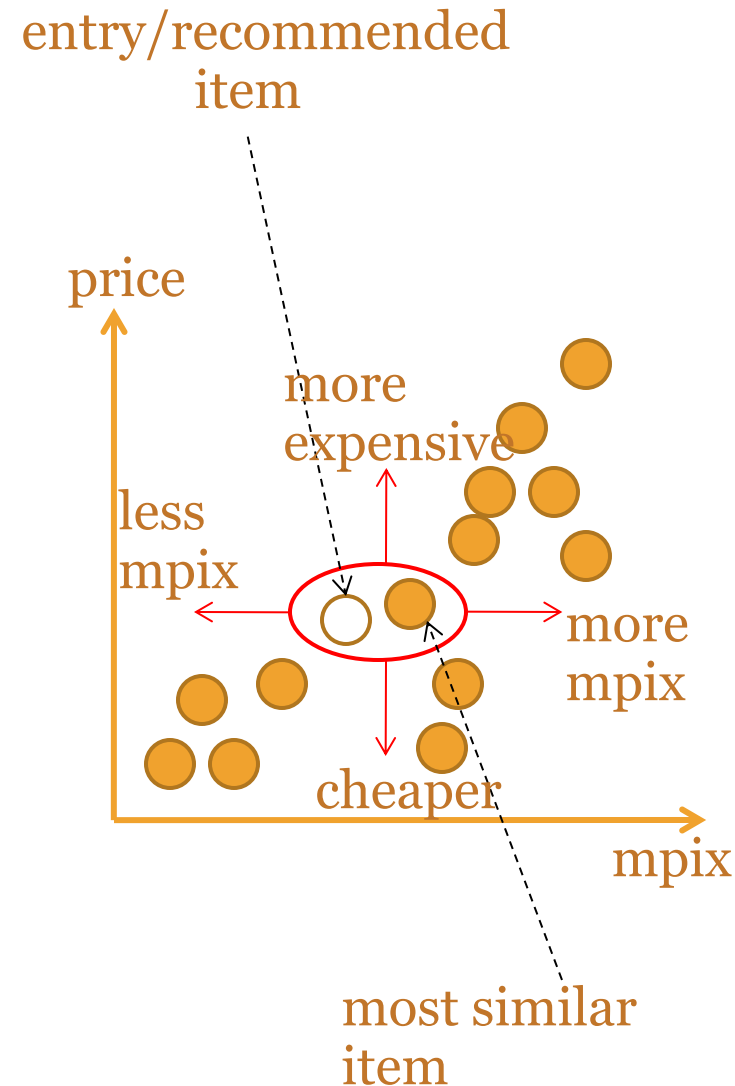
Benefit and Major Goals of Critiquing based Recommender Systems

- **Benefit:** Allow users to ***easily articulate*** preferences instead of *specifying concrete* values for item properties.

- Major Goals:

  - Saving item selection time

  - Obtaining the same recommendation quality as standard query-based approaches

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Item Recommendation

- Apply the algorithm SIMPLECRITIQUING (slide 21) to obtain entry item (recommended items)

- **Idea:** Iterate the two tasks until Critique is null.

  - ITEMRECOMMENDED()

    - Select an item r to be presented to the user
      - First round: entry item r = the ***most similar*** item between the **user's query q** and the candidate items
      - Next rounds: recommended item r = the ***most similar*** item between **currently recommended item** and the candidate items

  - USERREVIEW()

    - ***Review*** the recommended (entry) item and ***either accept it or selects another critique*** (modify q).

entry/recommended item

price

Filter out

cheaper

mpix

new most similar item

Threshold: Items with a ***lower price*** than the entry item are considered further

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SimpleCritiquing(q, CI)

Input: Initial user query q; Candidate items CI
procedure SimpleCriquing(q, CI)
 repeat
  r ← ItemRecommend(q, CI);
  q ← UserReview(r, CI);
 until empty(q)
end procedure

procedure ItemRecommend(q, CI)
 CI ← {ci ∈CI: satisfies(ci, q)};
 r ← mostsimilar(CI, q);
 return r;
end procedure

procedure UserReview(r, CI)
 q ← critique(r);
 CI ← CI − r;
 return q;
end procedure

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Unit Critiques vs Compound Critiques

- Unit critiques allows the definition of change requests that are related to **a single item property.**

- Compound critiques allows the definition of change requests that are related to **multiple item properties.**

  - E.g., *cheaper* and *more mpix*

entry/
recommended
item

Threshold:
Items with a **higher mpix** than
the entry item are
considered further

price

Filter out

mpix

new most
similar item

Threshold:
Items with a **lower price** than
The entry item are
considered further

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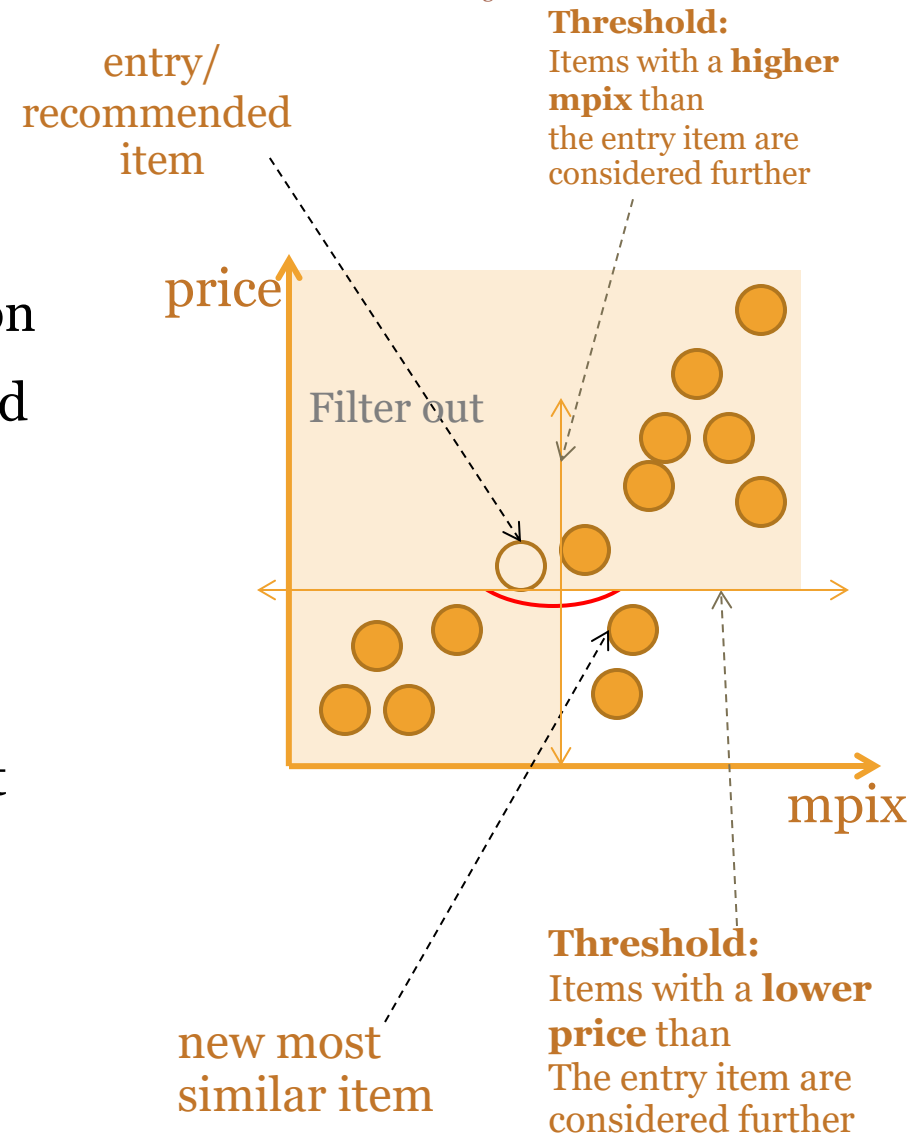
An Advantage and a Disadvantage of Compound Critiques

- **Advantage**: provide a faster progression through the item space.

- **Disadvantage**: must formulate critiques statistically.
  - All critique alternatives are available beforehand.
  - E.g.,

User requirements	(Static) critiques
fastest CPU available on the market and *maximum available storage capacity*	*faster CPU* and *more storage capacity (more efficient)*

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Dynamic Critiquing

- Exploits patterns.

> **Pattern** = *Generic descriptions* of differences between the recommended (entry) item and the candidate items

- Use the patterns in deriving compound critiques on the fly (in each critiquing cycle).

  - Use the concept of association rule mining in calculating dynamic critiques

- Apply the algorithm DYNAMICCRITIQUING (slide 26) to obtain entry item (recommended items).

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Item Recommendation (DYNAMICCRITIQUING())

□ ITEMRECOMMEND()

  □ Select an item r to be presented to the user

□ COMPOUNDCRITIQUES()

  □ Based on r, identify critique patterns (CRITIQUEPATTERNS())

  □ Calculate and select compound critiques $cc_i \in CC$ (APRIORI() and SELECTCRITIQUES())

• USERREVIEW()

  ▫ Display the identified compound critiques in CC to the user.

    • The critiquing will stop if the user does not select any critique.

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DynamicCritiquing(q, CI)

Input: Initial user query q; Candidate items CI;

number of compound critiques per cycle k;

minimum support for identified association rules σ_{min}

procedure DynamicCriquing(q, CI, k, σ_{min})
 repeat
  r ← ItemRecommend(q, CI);
  CC ← CompoundCritiques(r, CI, k, σ_{min});
  q ← UserReview(r, CI, CC);
 until empty(q)
end procedure

procedure ItemRecommend(q, CI)
 CI ← {ci ∈CI: satisfies(ci, q)};
 r ← mostsimilar(CI, q);
 return r;
end procedure

procedure UserReview(r, CI, CC)
 q ← critique(r, CC);
 CI ← CI − r;
 return q;
end procedure

procedure CompoundCritiques(r, CI, k, σ_{min})
 CP ← CritiquePatterns(r, CI); //slide 27
 CC ← Apriori(CP, σ_{min}); //slide 28
 SC ← SelectCritiques(CC, k); //slide 29
 return SC;
end procedure

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Identification of Critique Patterns

- Critiques patterns are a ***generic representation of the differences*** between the currently recommended item (entry item) and the candidate items.

	id	price	mpix	opt-zoom	LCD-size	movies	
entry item (EI)	ei_8	278	9.1	9x	3.0	yes	compare
candidate item (CI)	ci_1	148	8.0	4x	2.5	no	
	ci_2	182	8.0	5x	2.7	yes	
	ci_3	189	8.0	10x	2.5	yes	
	ci_4	196	10.0	12x	2.7	yes	
	ci_5	151	7.1	3x	3.0	yes	
	ci_6	199	9.0	3x	3.0	yes	
	ci_7	259	10.0	10x	3.0	yes	
critique patterns (CP)	cp_1	<	<	<	<	≠	to generate
	cp_2	<	<	<	<	=	
	cp_3	<	<	>	<	=	
	cp_4	<	>	>	<	=	
	cp_5	<	<	<	=	=	
	cp_6	<	<	<	=	=	
	cp_7	<	>	>	=	=	

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Mining Compound Critiques from Critique Patterns

- Identify **compound** critiques that **frequently co-occur** in the set of critique patterns (CP) wrt. Confidence level.

  ▫ Apply APRIORI algorithm

    • Output: A set of association rules: p → q

	id	mpix	opt-zoom
critique patterns (CP)	cp_1	<	<
	cp_2	<	<
	cp_3	<	>
	cp_4	>	>
	cp_5	<	<
	cp_6	<	<
	cp_7	>	>

	id	price	mpix	opt-zoom	LCD-size	movies
entry item (EI)	ei_8	278	9.1	9x	3.0	yes

Examples of association rules (AR) -- *output*	compound critiques (CC)	SUPP	CONF
ar_1: $>_{mpix}$ → $>_{zoom}$	cc_1: $>_{mpix(9.1)}$, $>_{zoom(9x)}$	2/7 = 28.6	2/2 = 100.0
ar_2: $>_{zoom}$ → $<_{price}$	cc_2: $>_{zoom(9x)}$, $<_{price(278)}$	3/7 = 42.9	3/3 = 100.0
ar_3: $=_{movies}$ → $<_{price}$	cc_3: $=_{movies(yes)}$, $<_{price(278)}$	6/7 = 85.7	6/6 = 100.0

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Ranking Compound Critiques

- Rank compound critiques according to the ***support values*** of association rules.

  - E.g., Rank of CC: $\{cc_1, cc_2, cc_3\} = cc_3, cc_2, cc_1$

association rules (AR)	compound critiques (CC)	SUPP	CONF
ar_1: $>_{mpix} \rightarrow >_{zoom}$	cc_1: $>_{mpix(9.1)}$, $>_{zoom(9x)}$	28.6	100.0
ar_2: $>_{zoom} \rightarrow <_{price}$	cc_2: $>_{zoom(9x)}$, $<_{price(278)}$	42.9	100.0
ar_3: $=_{movies} \rightarrow <_{price}$	cc_3: $=_{movies(yes)}$, $<_{price(278)}$	85.7	100.0

Outlines

- Conjoint Analysis

- Knowledge-based recommendation algorithm

  ▫ Critiquing

- Pros and Cons of Knowledge based RS

- Articles' Presentation and Discussion

Pros and Cons of Knowledge based RS

Pros

- Address a cold start problem.
  - ▫ Capable of suggesting items to new users.
  - ▫ Capable of suggesting new items to users.
- Quick access and easy to manipulate data.
- Capable of refining suggestion.

Cons

- Require details of items to construct item profile.

Outlines

- Conjoint Analysis

- Knowledge-based recommendation algorithm

  - Critiquing

- Advanced item recommendation

- Critique Diversity

- Pros and Cons of Knowledge based RS

- Articles' Presentation and Discussion