Week 8: Knowledge Based RSs – Part II

CSX4207/ITX4207: 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

Outlines

- Conjoint Analysis
- Knowledge based recommendation algorithm
  - Critiquing
- Pros and Cons of Knowledge based RS
- Articles' Presentation and Discussion

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

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		
		54 holes **50**	**36 holes** **25**	**18 holes** **0**
Average Driving Distance	**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

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

Buyer 1

		Average Ball Life		
		54 holes **50**	**36 holes** **25**	**18 holes** **0**
Price	**$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

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

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

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

Buyer 1 prefers choice 2 more than choice 1.

*: 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)

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

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

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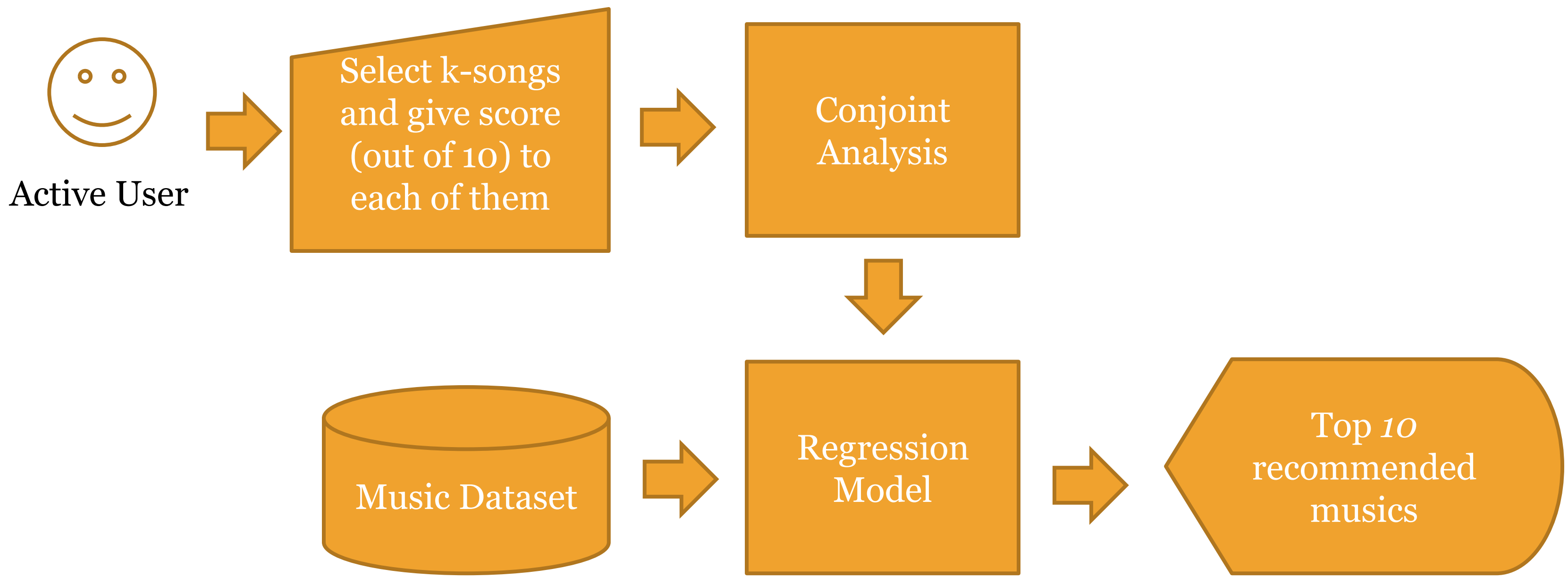
Applying Conjoint Analysis in RS – 1/3

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

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 **<u>has a higher effect</u>** 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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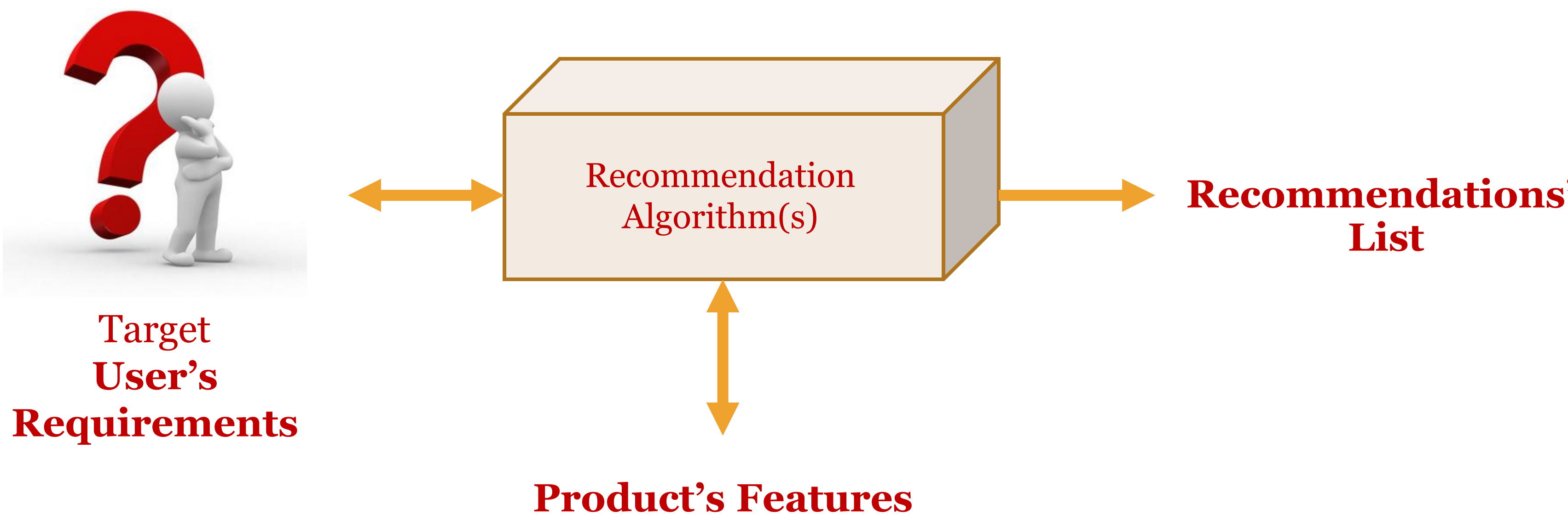
How to Generate Recommendation Using Knowledge Based Filtering Approach



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

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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 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

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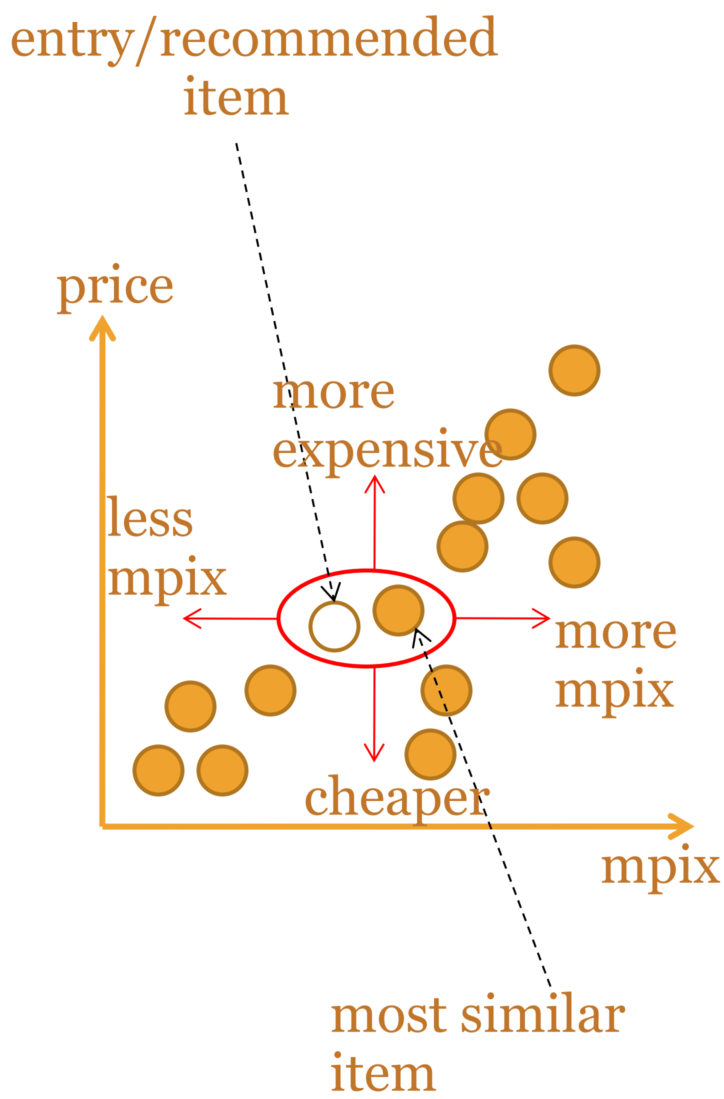
Critiquing

- 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*.



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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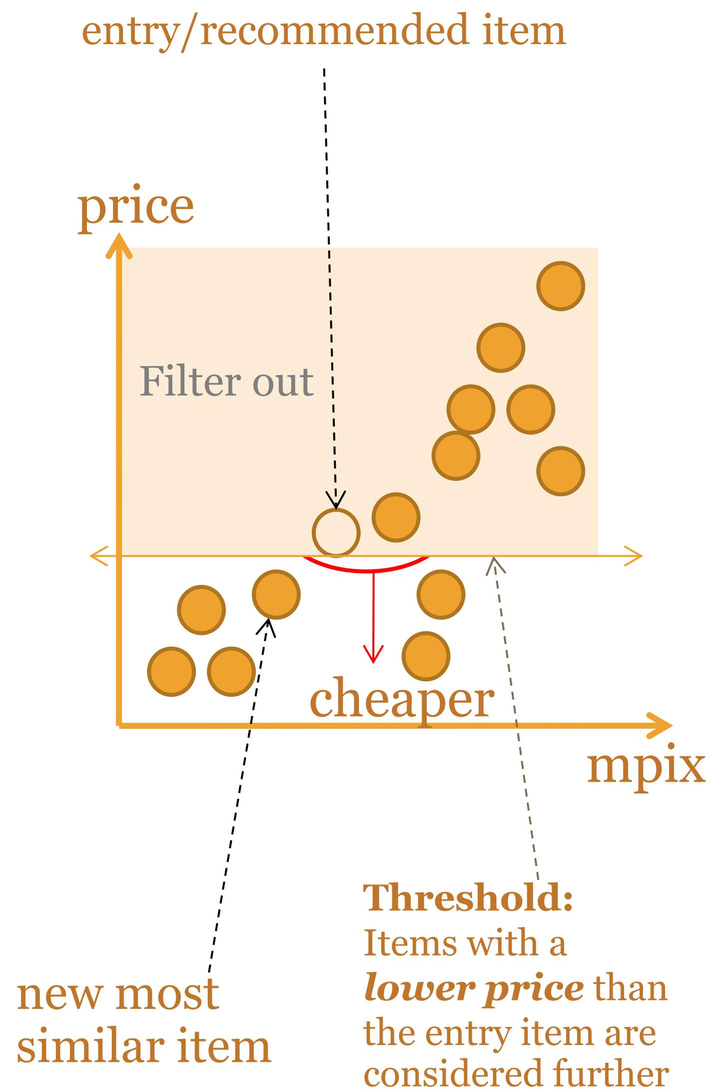
Item Recommendation

- 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).



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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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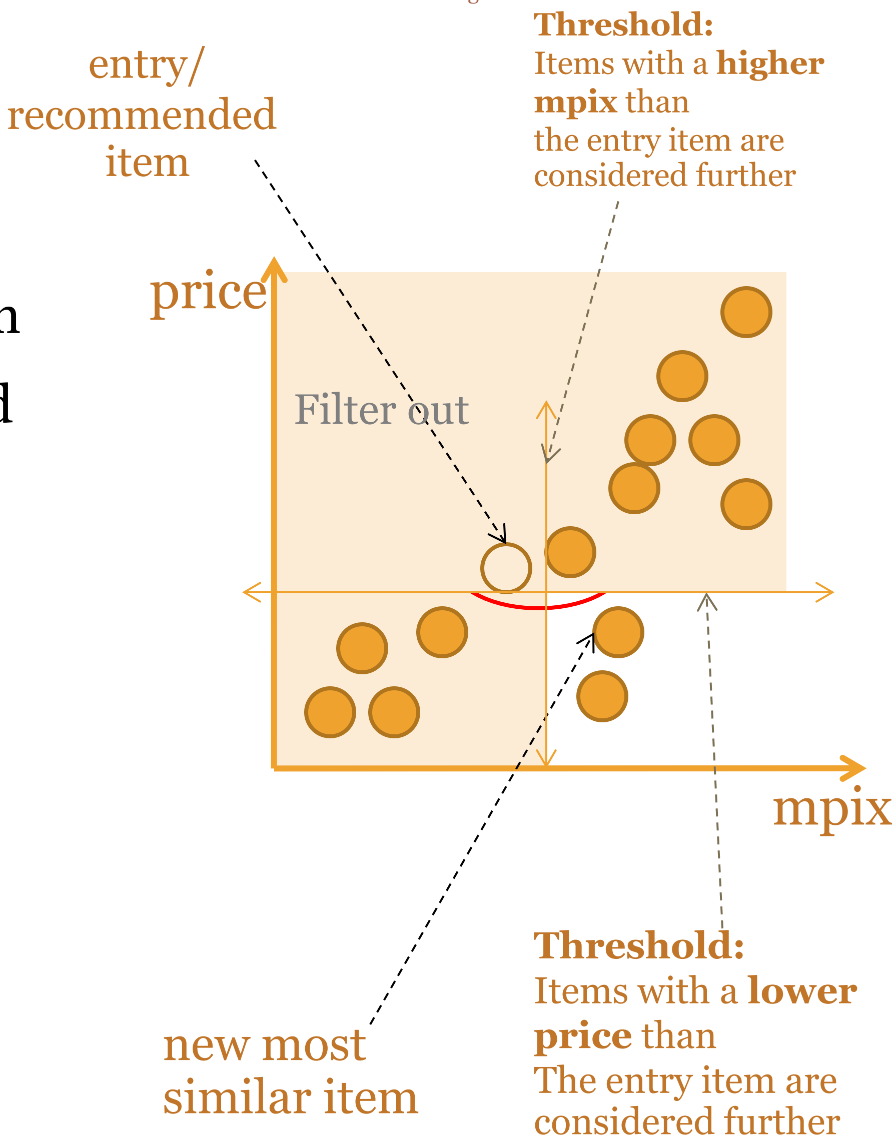
Unit Critiques vs Compound Critiques

- 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`



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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 statically.
  - 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

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

- Exploits patterns.
- 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).

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 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

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
```

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
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	$<$	$<$	$<$	$<$	$\neq$
	cp_2	$<$	$<$	$<$	$<$	$=$
	cp_3	$<$	$<$	$>$	$<$	$=$
	cp_4	$<$	$>$	$>$	$<$	$=$
	cp_5	$<$	$<$	$<$	$=$	$=$
	cp_6	$<$	$<$	$<$	$=$	$=$
	cp_7	$<$	$>$	$>$	$=$	$=$

compare

to generate

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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: $>_{mpix} \rightarrow >_{zoom}$	cc_1: $>_{mpix(9.1)}, >_{zoom(9x)}$	2/7 = 28.6	2/2 = 100.0
ar_2: $>_{zoom} \rightarrow <_{price}$	cc_2: $>_{zoom(9x)}, <_{price(278)}$	3/7 = 42.9	3/3 = 100.0
ar_3: $=_{movies} \rightarrow <_{price}$	cc_3: $=_{movies(yes)}, <_{price(278)}$	6/7 = 85.7	6/6 = 100.0

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

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- Articles' Presentation and Discussion

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Pros and Cons of Knowledge based RS

Pros	Cons

• 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.
	• 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