UFMG UNIVERSIDADE FEDERAL DE MINAS GERAIS

Recommender Systems

Case-based Recommendation

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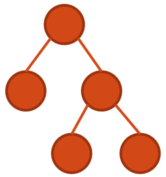
How to recommend this?

Users may have their own ***explicit requirements***

- 25m+ swimming pool
- 10+ bedrooms
- 8+ parking spaces

How to recommend?

user profile



knowledge models

Recommender

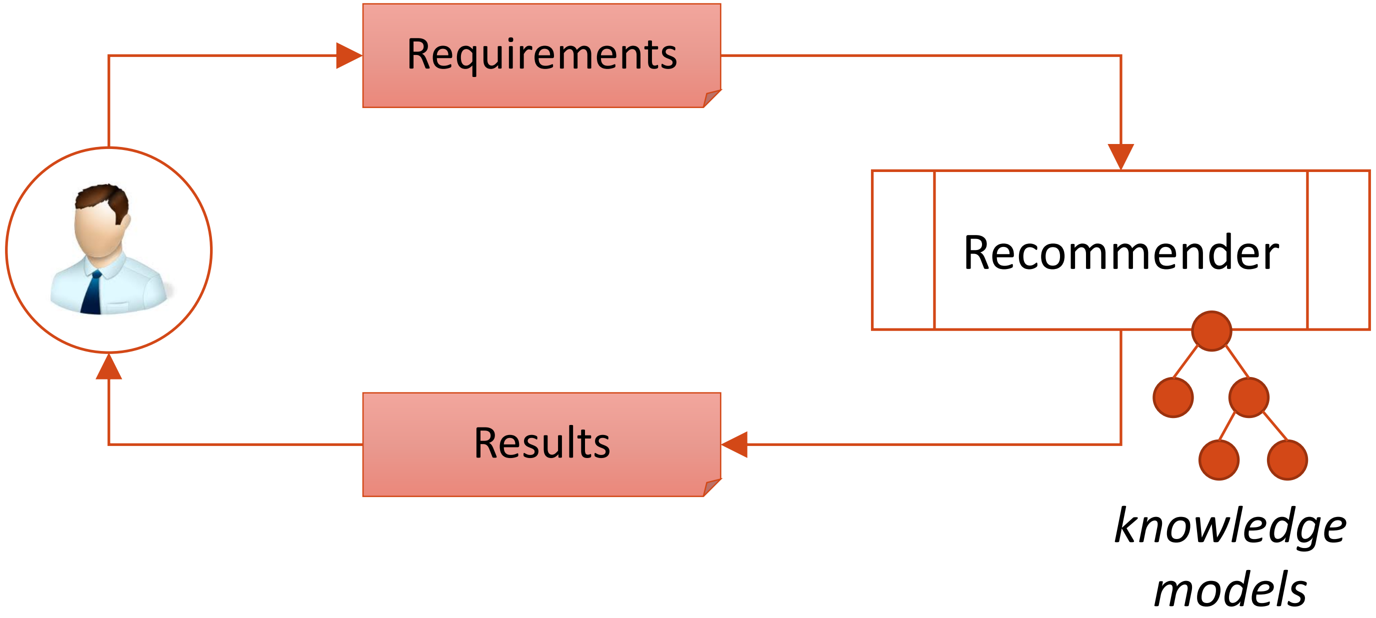
Knowledge-based

"tell me what fits based on my needs"

item	score
1	0.7
2	0.3
…	…

Knowledge-based recommendation

Conversational recommendation process



Knowledge about items

Example for digital cameras

id	price	mpixel	zoom	LCD	video	sound	wproof
i_1	148	8.0	4×	2.5	no	no	yes
i_2	182	8.0	5×	2.7	yes	yes	no
i_3	189	8.0	10×	2.5	yes	yes	no
i_4	196	10.0	12×	2.7	yes	no	yes
i_5	151	7.1	3×	3.0	yes	yes	no
i_6	199	9.0	3×	3.0	yes	yes	no
i_7	259	10.0	3×	3.0	yes	yes	no
i_8	278	9.1	10×	3.0	yes	yes	yes

Knowledge about users

Absolute requirements

- *Price lower than US$ 300*
- *Suited for sports*

Constraint-based recommendation

What if I have no knowledge about digital cameras?

- Which camera features should I care about?
- What is a good setting for each considered feature?
- What is a reasonable price for the chosen settings?

Knowledge bottleneck

Requirements elicitation may be tricky

- Items may have too many features
  - *Resolution, sensor type, focal length, aperture, ...*
- Features may be too complex for non-experts
  - *Exposure compensation?!?*
- Features may be interdependent
  - *Stabilization depends on the lens*

Knowledge about users

Absolute requirements

- *Price lower than US$ 300*
- *Suited for sports*

Relative requirements

- *Price lower than the current*
- *More sporty than the current*

Constraint-based recommendation

Case-based recommendation

Case-based reasoning

“

A case-based reasoner solves new problems by adapting solutions that were used to solve old problems

◦ Riesbeck and Shank, 1989

Case-based reasoning

Four steps

- **Retrieve** an initial case from memory
- **Reuse** the retrieved case as a first guess
- **Revise** the current case if wrong
- **Retain** the current case if correct

Case-based recommendation

Given

- An input case (i.e., an item)
- (Potential) critiques (e.g., “cheaper”)

Return

- Matching cases (i.e., items) similar to the input case and that satisfy the critiques made thus far

Critiquing [Burke et al., Expert 1997]

Users may change requests not met by current case

- Change request = ***critique***

Examples

- *“the camera should be cheaper”*
- *“the hotel should be nearer the sea”*
- *“the flat should be more modern-looking”*

Static critiquing

Input:

- Initial user query *q*
- Candidate items *I*

```
StaticCritiquing(q, I)
  repeat
    r ← Recommend(q, I);
    q ← Review(r, I);
  until empty(q);
```

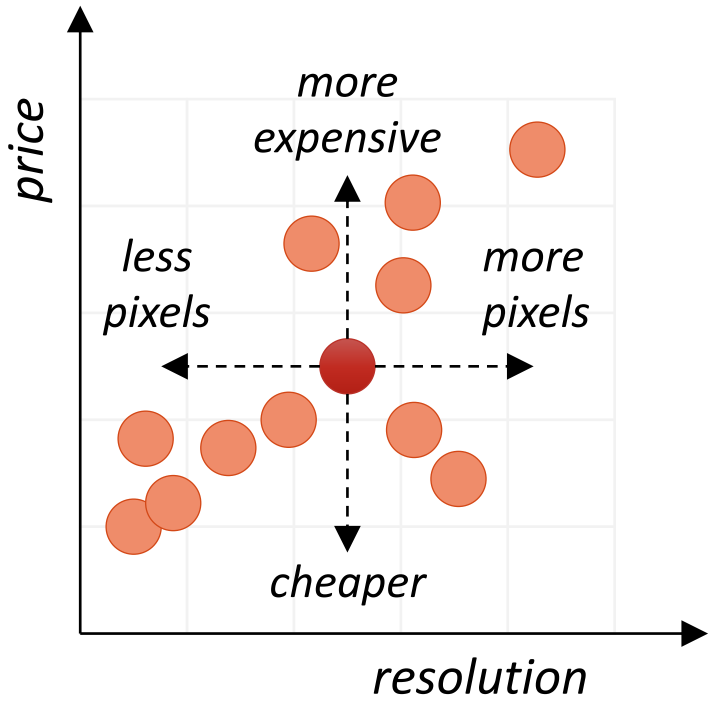
```
Recommend(q, I)
  I ← {i∈I : sat(i,q)};
  r ← 1-NN(I, q);
  return r;
```

```
Review(r, I)
  q ← critique(r);
  I ← I – r;
  return q;
```

Simple vs. compound

Simple critiquing

- "cheaper"



Browsing-based retrieval

- Must navigate the item space to retrieve candidates

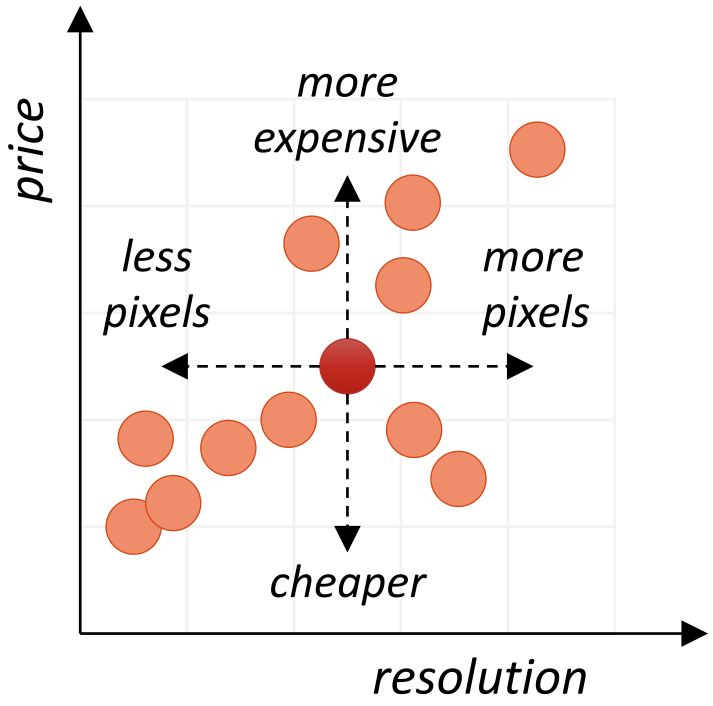
Query-based retrieval

- Must find similar cases

Simple vs. compound

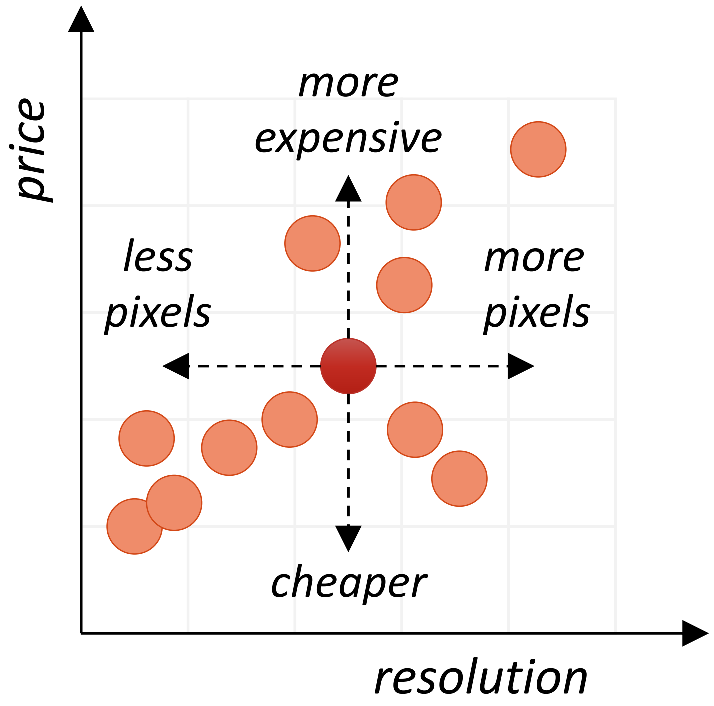
Simple critiquing

- “cheaper”



Compound critiquing

- “cheaper” + “more pixels”



Dynamic critiquing

Static critiquing may overwhelm the user

- All critiques displayed in every cycle

Dynamic critiques may be derived on-the-fly

- One critique per cycle

Dynamic critiquing

Critiques inferred from the remaining items

- e.g., *“42.9% of the remaining digital cameras have a higher zoom and a lower price”*

Compound critiques from association rules

- e.g., Apriori [Agrawal and Srikant, VLDB 1994]

Critique patterns

	id	price	mpixel	zoom	LCD	video
Entry item	e	278	9.1	9×	3.0	yes
Candidate items	i_1	148	8.0	4×	2.5	no
	i_2	182	8.0	5×	2.7	yes
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Critique patterns	p_1	<	<	<	<	≠

Critique patterns

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Critique patterns	p_1	<	<	<	<	≠
	p_2	<	<	<	<	=

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	p_3	<	<	>	<	=
Critique patterns	p_4	<	>	>	<	=
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	p_6	<	<	<	=	=
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	p_4	<	>	>	<	=
	p_5	<	<	<	=	=
	p_6	<	<	<	=	=
	p_7	<	>	>	=	=

Association rules (AR)	Compound critiques (CC)	Support	Conf.
ar1: >mpixel → >zoom	cc1: >mpixel(9.1), >zoom(9×)	28.6	100.0

Critique patterns

	id	price	mpixel	zoom	LCD	video
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Critique patterns	p_1	<	<	<	<	≠
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	p_3	<	<	>	<	=
	p_4	<	>	>	<	=
	p_5	<	<	<	=	=
	p_6	<	<	<	=	=
	p_7	<	>	>	=	=

Association rules (AR)	Compound critiques (CC)	Support	Conf.
ar1: >mpixel → >zoom	cc1: >mpixel(9.1), >zoom(9×)	28.6	100.0
ar2: >zoom → <price	cc2: >zoom(9×), <price(278)	42.9	100.0

Critique patterns

	id	price	mpixel	zoom	LCD	video
Entry item	*e*	278	9.1	9×	3.0	yes
Critique patterns	p_1	<	<	<	<	≠
	p_2	<	<	<	<	=
	p_3	<	<	>	<	=
	p_4	<	>	>	<	=
	p_5	<	<	<	=	=
	p_6	<	<	<	=	=
	p_7	<	>	>	=	=

Association rules (AR)	Compound critiques (CC)	Support	Conf.
ar1: >mpixel → >zoom	cc1: >mpixel(9.1), >zoom(9×)	28.6	100.0
ar2: >zoom → <price	cc2: >zoom(9×), <price(278)	42.9	100.0
ar3: =video → <price	cc3: =video(yes), <price(278)	85.7	100.0

Ranking critiques

Mining may result in too many critiques

- We must present the user with the most relevant

Critiques with high support

- Eliminate a low number of candidate items
- Increase the chance of finding the desired item

Ranking critiques

Mining may result in too many critiques

- We must present the user with the most relevant

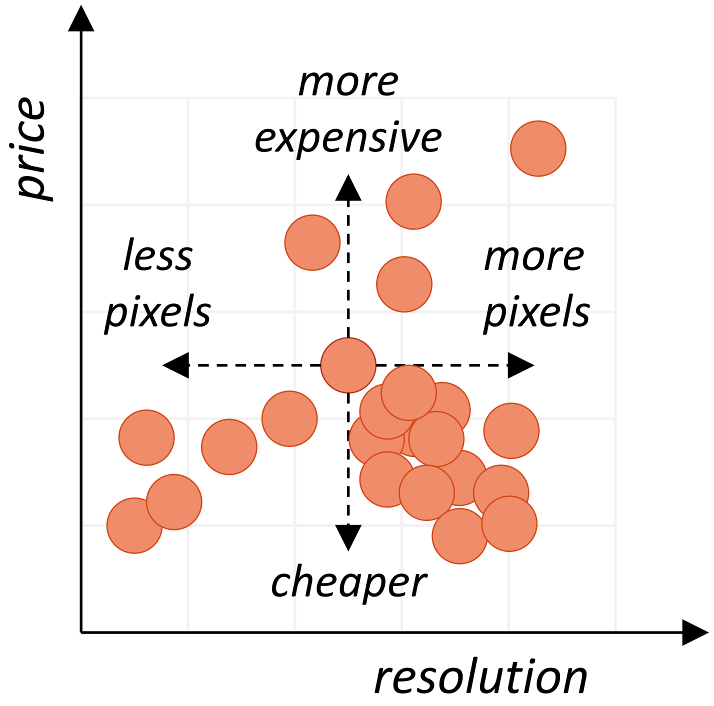
Critiques with low support

- Significantly reduce the set of candidate items
- Risk not identifying the desired item

Critique diversity

Critiquing in “hot spot” areas

- Slow convergence



Diversified critiques

- $score(c, C) = \left(support(c)\ overlap(c, C)\right)^{-1}$
  - c: candidate critique
  - C: currently selected critiques

Critique overlap

- $overlap(c, C) = \frac{|I_c \cap I_C|}{|I_c \cup I_C|}$

Item recommendation

Item quality score

- $score(e, C, i) = sat(C, i)\ sim(e, i)$
  - e: entry item; C: critique set; i: candidate item

Item compatibility

- $sat(C, i) = \frac{|\{c \in C \,:\, sat(c,i)\}|}{|C|}$

Example

Entree case-based recommender [Burke et al., Expert 1997]

- Initial goal as a restaurant guide for the 1996 Democratic Convention, prolonged use afterwards

Entry point

- Explicit requirements (***constraint-based***)
- Reference restaurant (***case-based***)


Entree
Chicago
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
New Query
Submit

Entree Results

The Los Angeles restaurant you chose is:

Chinois On Main 2709 Main St. (bet. Rose Ave. & Ocean Park Blvd.), Santa Monica, 310-392-9025	
Pacific New Wave	$30-$50
Extraordinary Decor, Extraordinary Service, Near-perfect Food, Hip Place To Be, On the Beach, Great for People Watching, Parties and Occasions, Weekend Brunch, Weekend Lunch, Fabulous Wine Lists	

We recommend:

Yoshi's Cafe 3257 N. Halsted St. (Belmont Ave.), Chicago, 312-248-6160	
Asian, Japanese, French (New)	$30-$50
Extraordinary Decor, Extraordinary Service, Near-perfect Food, Need To Dress, Prix Fixe Menus, Quiet for Conversation, Very Busy - Reservations a Must, Romantic, Good Out of Town Business, Fabulous Wine Lists, Game, Parking/Valet	

less $$ nicer cuisine

Less $$

traditional creative livelier quieter

Entree Results

For a cheaper restaurant than:

Yoshi's Cafe 3257 N. Halsted St. (Belmont Ave.), Chicago, 312-248-6160	
Asian, Japanese, French (New)	$30-$50

We recommend:

Lulu's (map) 626 Davis St. (bet. Chicago & Orrington Aves.), Evanston, 708-869-4343	
Japanese, Asian	below $15
Good Decor, Excellent Service, Excellent Food, Creative, No Reservations, Weekend Brunch, Wheelchair Access, Long Drive	

less $$ nicer cuisine

traditional creative livelier quieter

Summary

Case-based recommendation

- Similarity-based navigation in item space
- Critiques guide navigation direction

Efficient critiquing

- Compound critiques for faster navigation
- Dynamic critiques for relevant navigation

References

Recommender Systems: An Introduction (Sec. 4.4)

Recommender Systems: The Textbook (Sec. 5.3)