Week 7: Knowledge Based RSs – Part I

CSX4207/ITX4207: Decision Support and Recommender Systems

Asst. Prof. Dr. Rachsuda Setthawong

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Objectives

- To understand the concept of knowledge based filtering approach
- To understand the necessity for this recommendation approach.
- To understand main advantages of knowledge-based recommender systems
- To be familiar with a widely used knowledge-based recommendation algorithm

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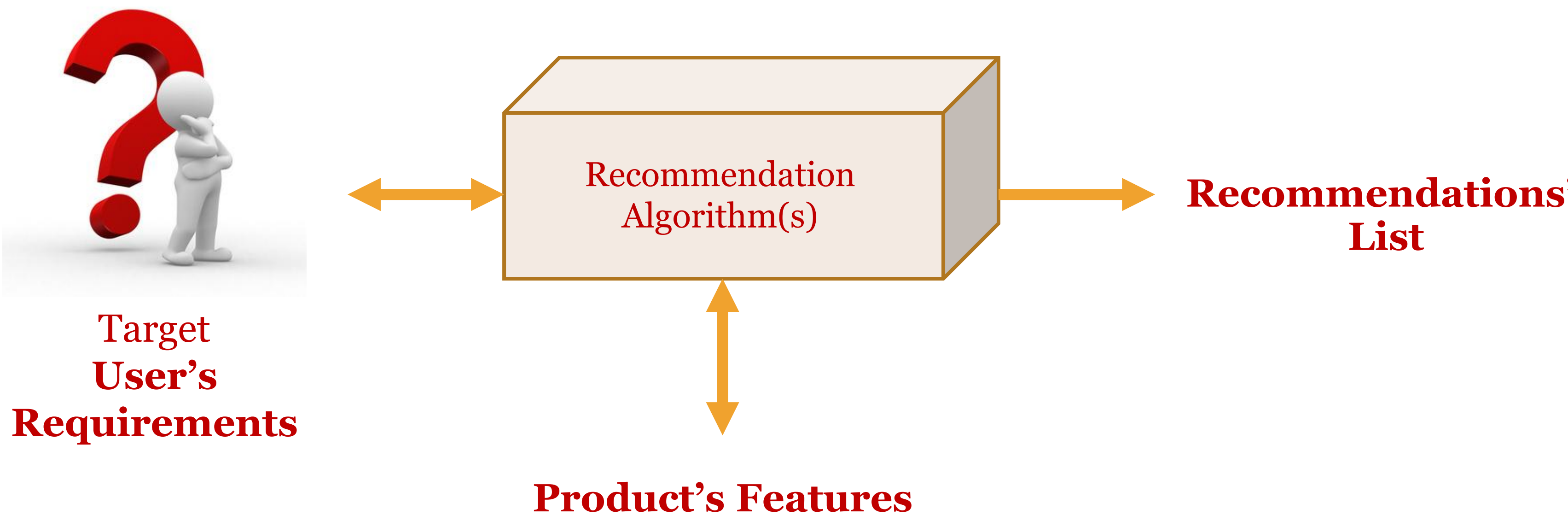
Outlines

- Main idea and definition of knowledge based filtering
- Motivation and main advantages of knowledge-based recommender systems
- A Constraint Satisfaction Problem (CSP)
- Using Defaults
- Knowledge-based recommendation algorithm
  - Constraint based

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.

How to Generate Recommendation Using Knowledge Based Filtering Approach



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

Definition

- "Recommenders that *rely on knowledge sources* NOT exploited by collaborative and content-based approaches are by default defined as knowledge-based recommenders" – *Burke (2000) and Felfernig and Burke (2008)*

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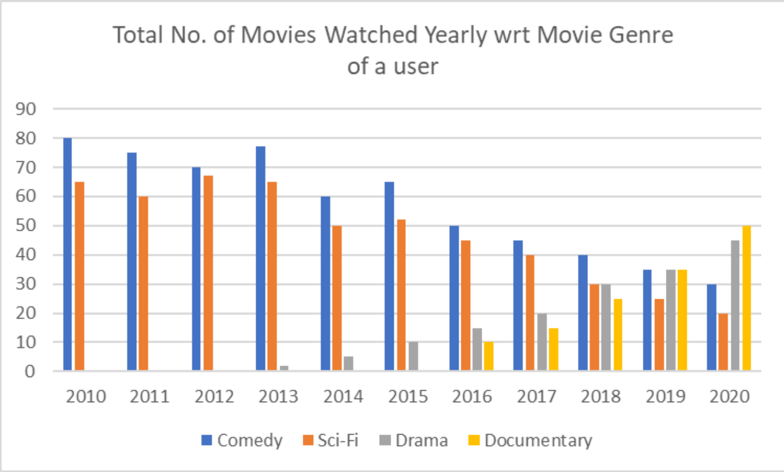
Motivations

- Situations that collaborative and content-based recommender algorithms do NOT work well:
  - Low number of available ratings (e.g., buying a house)
  - Time spans (e.g., outdate ratings of *technology-related* items)
  - Changes of user preferences over times (e.g., changes in lifestyles, family situations)

- Remark: *Explicit* requirements are needed.
  - E.g.,
    - The max. price of the car is x.
    - The color should be black.



Main Advantages of Knowledge-based Recommender Systems

Limitation in collaborative based RS →

- No ratings required
  - Recommendations are calculated independently of individual user ratings.

Limitation in content-based RS →

- No ramp-up problems
  - Exploit customer requirements and items' feature.
- Highly interactive to the user

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Goal

- Suggest items from a catalog that match the user's preferences or hard requirements.

Id	Price (€)	Mpix	Opt-zoom	LCD-size	Movies	Sound	Waterproof
p1	148	8	4x	2.5	no	no	yes
p2	182	8	5x	2.7	yes	yes	no
p3	189	8	10x	2.5	yes	yes	no
p4	196	10	12x	2.7	yes	no	yes
p5	151	7.1	3x	3.0	yes	yes	no
p6	199	9	3x	3.0	yes	yes	no
p7	259	10	3x	3.0	yes	yes	no
p8	278	9.1	10x	3.0	yes	yes	yes

Digital camera dataset

Knowledge Representation and Reasoning

- How to represent user's requirements and domain knowledge to build a knowledge-based RS
  - Representation of user's requirements:
    - *Desired values* or *value ranges* for an item's features.
    - E.g.,
      - The **price** should be *lower than 300€*.
      - The **usage** of camera is for *sports photography*.

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Basic Types of Knowledge-based Recommender Systems

- Constraint-based
- Case-based

A Constraint Satisfaction Problem (CSP)

- Given a-tuple (V, D, C) where
  - V is a set of *variables*
  - D is a set of finite *domains* for these variables
  - C is a set of *constraints* that describes the combinations of values the variables can simultaneously take.

- Goal: Assign a value to each variable in V in a way that *all constraints* are *satisfied*.

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A Recommender's Knowledge Base (V)

- $V = V_c \cup V_{PROD}$
  - Requirements of potential customer (V_c)
  - Product properties (V_{PROD})
  - Example,

	Requirement / product property	Domain (D)
V_c	{max-price, usage, photography}	(0…1000) (digital, small-print, large-print) (sports, landscape, portrait, macro)
V_{PROD}	{price, mpix, opt-zoom, lcd-size, movies, sound, waterproof}	(0…1000) (3.0…12.0) (4x…12x) (2.5…3.0) (yes, no) (yes, no) (yes, no)

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A Recommender's Knowledge Base (V) – *Cont.*

- $V = V_c \cup V_{PROD}$
  - Requirements of potential customer (V_c)
  - Product properties (V_{PROD})
  - Example,

- May NOT be the SAME variables
- May need Compatibility/Filter constraints for mapping V_c to V_c or V_c to V_{PROD}

	Requirement / product property	Domain (D)
V_c	{max-price, usage, photography}	(0...1000) (digital, small-print, large-print) (sports, landscape, portrait, macro)
V_{PROD}	{price, mpix, opt-zoom, lcd-size, movies, sound, waterproof}	(0...1000) (3.0...12.0) (4x...12x) (2.5...3.0) (yes, no) (yes, no) (yes, no)

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Three Sets of Constraints (C)

- $(C = C_R \cup C_F \cup C_{PROD})$
  - Compatibility constraints (C_R)
    - **Derive customer properties** from existing ones
  - Filter constraints (C_F)
    - **Derive product properties** from customer properties
  - Product constraints (C_{PROD})
    - **Currently available products** in form of constraints

- Example,

C_R	{usage=large-print → **max-price** > **200**} *customer* property → *customer* property
C_F	{usage=large-print → **mpix** > **5.0**} *customer* property → *product* property
C_{PROD}	{ (id=p1∧ price=148∧ mpix=8.0 ∧ opt-zoom=4 ∧ lcd-size=2.5 ∧ Movies=no ∧ sound=no ∧ waterproof=yes) ∨...∨ (id=p8∧ price=278∧ mpix=9.1 ∧ opt-zoom=10 ∧ lcd-size=3.0 ∧ Movies=yes ∧ sound=yes ∧ waterproof=yes) }

The Customer Requirements (REQ)

- Encoded as unary constraints over the variables in V_c and V_{PROD}

- Example,

REQ	{ max-price=300, usage=large-print, photography=sports }

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Defining Knowledge Based Recommendation Problem as a CSP Problem

- **Given:** CSP ($V = V_c \cup V_{PROD}$, D, $C = C_R \cup C_F \cup C_{PROD} \cup REQ$)
- **Find:** A consistent recommendation (RES) wrt CSP
- Example,

RES	{max-price=300, Usage=large-print, photography =sports,	REQ
	id=p8, price=278, mpix=9.1, opt-zoom=10, lcd-size=3.0, Movies=yes, sound=yes, waterproof=yes}	C_{PROD}

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A Simple Approach - **Conjunctive Queries**

- View the item selection (σ) problem as a data filtering task.
  - Construct a conjunctive query (a database query with a set of selection criteria connected *conjunctively*.)
  - E.g., **REQ** **{***usage=large-print, waterproof=yes***}**
    - Apply also constraints (C_R, C_F) if provided:

{usage=large-print → **max-price > 200**}

{usage=large-print → **mpix > 5.0**}

$\sigma_{[\text{mpix} > 5.0,\ \text{price}>200,\ \text{waterproof}=\text{'yes'}]}(P) = \{p8\}$

Id	Price (€)	M-pix	Opt-zoom	LCD-size	Movies	Sound	Waterproof
p1	148	8	4x	2.5	no	no	yes
p2	182	8	5x	2.7	yes	yes	no
p3	189	8	10x	2.5	yes	yes	no
p4	196	10	12x	2.7	yes	no	yes
p5	151	7.1	3x	3.0	yes	yes	no
p6	199	9	3x	3.0	yes	yes	no
p7	259	10	3x	3.0	yes	yes	no
p8	278	9.1	10x	3.0	yes	yes	yes

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Ranking Recommended Items

- What if multiple items are retrieved wrt potential user's requirements?
  - E.g., REQ {max-price<200}
    - How to rank them?
      - using similarity measure

Id	Price (€)	Mpix	Opt-zoom	LCD-size	Movies	Sound	Waterproof
p1	148	8	4x	2.5	no	no	yes
p2	182	8	5x	2.7	yes	yes	no
p3	189	8	10x	2.5	yes	yes	no
p4	196	10	12x	2.7	yes	no	yes
P5	151	7.1	3x	3.0	yes	yes	no
p6	199	9	3x	3.0	yes	yes	no
p7	259	10	3x	3.0	yes	yes	no
p8	278	9.1	10x	3.0	yes	yes	yes

Case-based Recommendation Approach

- Similarity measure used to retrieve and rank items wrt user's requirements:

$$similarity(p, REQ) = \frac{\sum_{r \in REQ} w_r * sim(p, r)}{\sum_{r \in REQ} w_r}$$

- where,
  - p : a product (item)
  - r : the requirement ($r \in REQ$)
  - sim(p, r) : the similarity between an *item attribute value* $\phi_r(p)$ to *the customer requirement* $r \in REQ$
  - w_r : the important *weight for requirement* r

sim(p, r)

Note: user's requirement may be represented as value's range.

- More-is-better (MIB) properties

$$sim(p,r) = \frac{\phi_r(p) - \min(r)}{\max(r) - \min(r)}$$

- Less-is-better (LIB) properties

$$sim(p,r) = \frac{\max(r) - \phi_r(p)}{\max(r) - \min(r)}$$

- Alternative similarity measure

$$sim(p,r) = 1 - \frac{|\phi_r(p) - r|}{\max(r) - \min(r)}$$

Certain attr. value from the user

p : a product (item)

r : the requirement (attribute value) ($r \in REQ$)

$\phi_r(p)$: an *item attribute value* for $r \in REQ$

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Attribute Examples for sim(p, r)

- More-is-better (MIB) properties

$$sim(p,r) = \frac{\phi_r(p) - \min(r)}{\max(r) - \min(r)}$$

Mega-pixel of a digital camera

- Less-is-better (LIB) properties

$$sim(p,r) = \frac{\max(r) - \phi_r(p)}{\max(r) - \min(r)}$$

Price of an item

- Alternative similarity measure

$$sim(p,r) = 1 - \frac{|\phi_r(p) - r|}{\max(r) - \min(r)}$$

Released year of a movie

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An Example of Cases and Similarities

- REQ = {mpix≥9, 150≤price≤300}
- Calculate
  - $sim_{MIB}(p4, r_{mpix})$ = (10-9)/(10-9) = 1
  - $sim_{LIB}(p4, r_{price})$ = (300-196)/(300-150) = 0.693
  - Suppose that *mpix* and *price have* equal weight,

    similarity(p4, REQ)

    $$= \frac{(w_{mpix} * sim(p4, r_{mpix}) + (wprice * sim(p4, rprice)))}{w_{mpix} + w_{price}}$$

    = [(0.5 * 1) + (0.5 * 0.693)] / 1 = 0.8465
  - similarity(p7, REQ) = ?
  - Rank the suggested items?

$$similarity(p, REQ) = \frac{\sum_{r \in REQ} w_r * sim(p, r)}{\sum_{r \in REQ} w_r}$$

Id	Price (€)	Mpix	Opt-zoom	LCD-size	Movies	Sound	Waterproof
p4	196	10	12x	2.7	yes	no	yes
p7	259	10	3x	3.0	yes	yes	no

MIB: $sim(p, r) = \dfrac{\phi_r(p) - \min(r)}{\max(r) - \min(r)}$

LIB: $sim(p, r) = \dfrac{\max(r) - \phi_r(p)}{\max(r) - \min(r)}$

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Interacting with Constraint-based Recommenders (Steps)

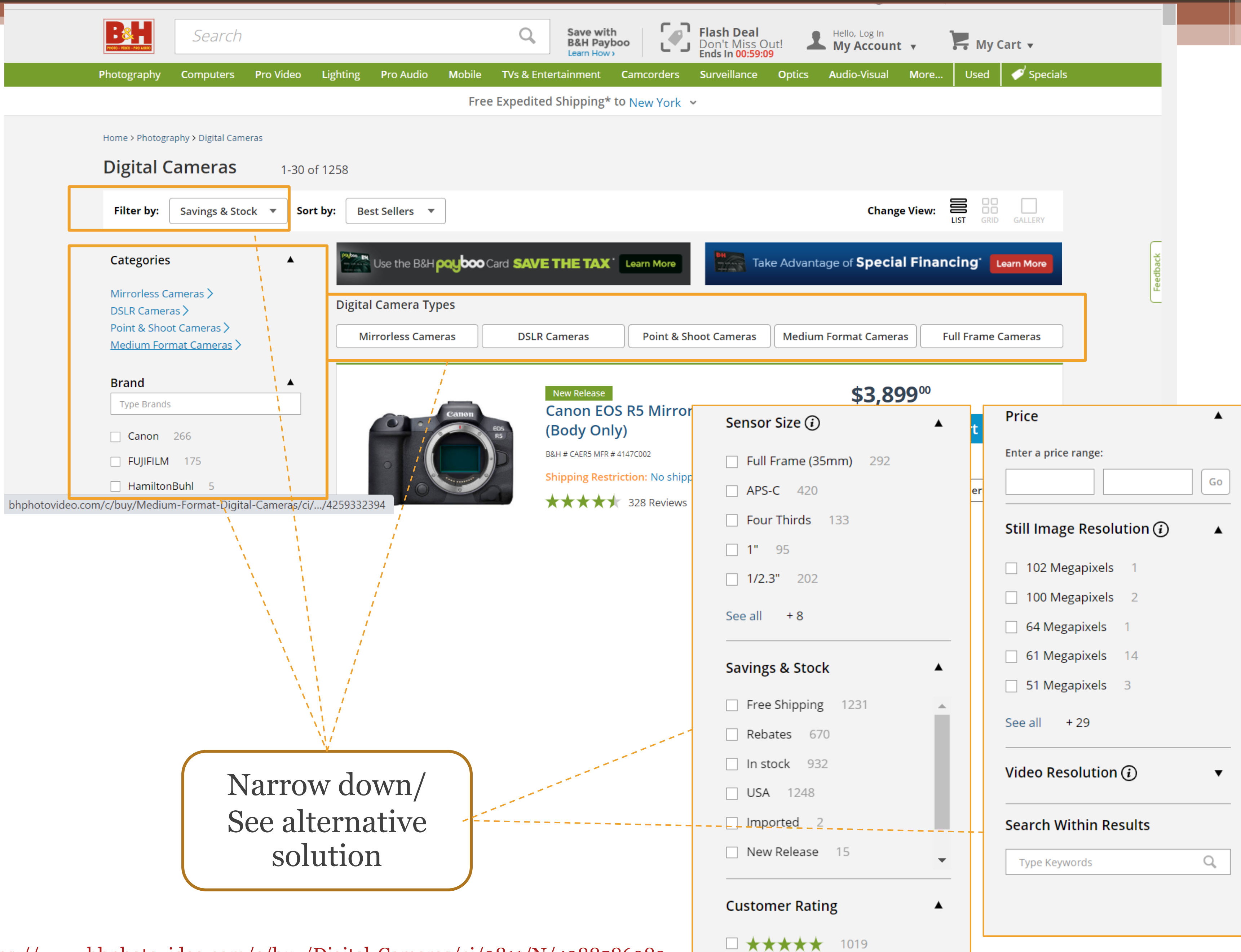
The user specifies his/her *initial* preferences

Form and question/answer

A set of *matching* items and explanation (optional) are presented to the user

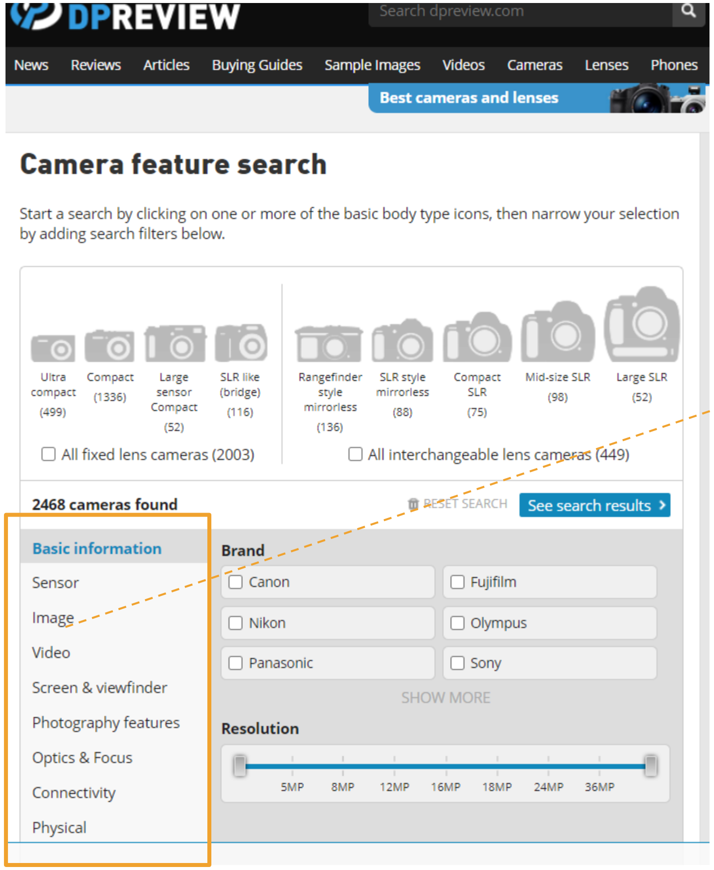
The user may *revise* his/her *requirements*.

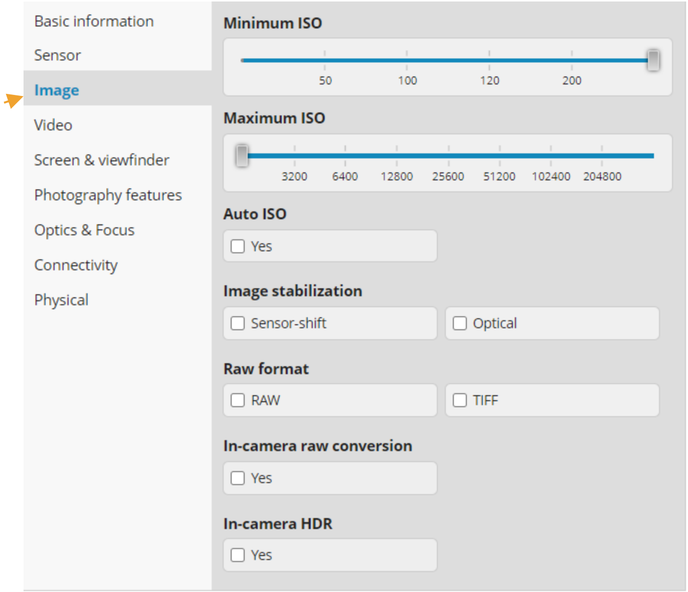
Narrow down/ See alternative solution



Narrow down/
See alternative
solution

Ref: https://www.bhphotovideo.com/c/buy/Digital-Cameras/ci/9811/N/4288586282





Ref: https://www.dpreview.com/products/search/cameras#!

Using Defaults During Recommendation Process

- For naïve user who doesn’t know about features of items, using defaults will give him/her a reasonable suggestion

- Side effect: Ethical issue since it may lead the user to choose certain options. (e.g., select items with over specification)

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Ways to Generate Defaults

- Static defaults
  - One default per customer property
  - E.g., default(usage) = large-print
- Dependent defaults
  - One default per different combinations of potential customer requirements
  - E.g., default(max-price $_{\text{(usage=small-print)}}$) = 300
- Derived defaults
  - Exploit existing *interaction logs* for the automated derivation of default values

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An Example of Derived Defaults

Customer Interaction Log

customer (user)	price	opt-zoom	lcd-size
cu_1	400	10x	3.0
cu_2	300	10x	3.0
cu_3	150	4x	2.5
cu_4	200	5x	2.7
cu_5	200	5x	2.7

price=400

opt-zoom$_{default}$=?

A new user

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Alternatives for Derived Defaults: 1-Nearest neighbor

- Most similar entry in the *interactive log* to the user's REQ

$$similarity(p, REQ) = \frac{\sum_{r \in REQ} w_r * sim(p, r)}{\sum_{r \in REQ} w_r}$$

- E.g., REQ = {r1: price=150, r2: opt-zoom=4x};

Lcd-size$_{default}$=?

customer (user)	price	opt-zoom	lcd-size
cu_1	400	10x	3.0
cu_2	300	10x	3.0
cu_3	150	4x	2.5
cu_4	200	5x	2.7
cu_5	200	5x	2.7

Lcd-size$_{default}$=?

A user

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Alternatives for Derived Defaults: Weighted Majority Voter

- The default value is based on the **majority voting** of neighbor items (k-NN).

$$similarity(p, REQ) = \frac{\sum_{r \in REQ} w_r * sim(p, r)}{\sum_{r \in REQ} w_r}$$

- E.g., REQ = {r1:price=400};
- opt-zoom$_{default}$ = ?

customer (user)	price	opt-zoom	lcd-size
cu_1	400	**10x**	3.0
cu_2	300	**10x**	3.0
cu_3	150	4x	2.5
cu_4	200	5x	2.7
cu_5	200	5x	2.7

opt-zoom$_{default}$=?

A user

For n=3,

3-NN(REQ)={cu_1, cu_2, cu_4}
Majority Voting = Max(10x, 10x, 5x)
opt-zoom$_{default}$=10x

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A Major Problem with Using 1-NN and Weighted Majority Voters for Derived Defaults

- CANNOT guarantee that the result is a *non-empty* set.

customer (user)	price	opt-zoom	lcd-size
cu_1	400	10x	3.0
cu_2	300	10x	3.0
cu_3	150	4x	2.5
cu_4	200	5x	2.7
cu_5	200	5x	2.7

REQ = {r1:opt-zoom=3x}; $\text{lcd-size}_{default}$ = ?

For n=3,
3-NN(REQ)={cu_3, cu_4, cu_5}

$\text{lcd-size}_{default}$=2.7

Id	Price (€)	Mpix	Opt-zoom	LCD-size	Movies	Sound	Waterproof
p1	148	8	4x	2.5	no	no	yes
p2	182	8	5x	**2.7**	yes	yes	no
p3	189	8	10x	2.5	yes	yes	no
p4	196	10	12x	**2.7**	yes	no	yes
p5	151	7.1	**3x**	3.0	yes	yes	no
p6	199	9	**3x**	3.0	yes	yes	no
p7	259	10	**3x**	3.0	yes	yes	no
p8	278	9.1	10x	3.0	yes	yes	yes

$\sigma_{[\text{opt-zoom}=3x,\ \text{lcd-size}=2.7]}(P)$
$= \varnothing$

Soln. slide 35

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Selecting the Next Questions
(Propose *Default* for Next Property) – Approach 1

- E.g., what is the **first** recommended PROPERTY interested by the user?
- Pre-condition: user interaction log is available.
- Approach 1: using the principle of frequent usage (popularity)

$$popularity(attribute, pos) = \frac{\#selections(attr, pos)}{\#sessions}$$

Sess-ion-id	pos:1	pos:2	pos:3	pos:4	pos:5	pos:6	…
1	**price**	opt-zoom	mpix	movies	lcd-size	sound	
2	**price**	opt-zoom	mpix	movies	lcd-size	-	
3	**price**	Mpix	opt-zoom	lcd-size	movies	sound	
4	**mpix**	price	opt-zoom	lcd-size	movies	-	
5	**mpix**	price	lcd-size	opt-zoom	movies	sound	

popularity(price, pos:1)=3/5
=0.6

popularity(mpix, pos:1)=2/5
=0.4

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Selecting the Next Questions
(Propose *Default* for Next Property) – Approach 2

- E.g., *Given current REQ* contains properties {price, opt-zoom},

  what is the **next** recommended PROPERTY interested by the user?
- Pre-condition: user interaction log is available.
- Approach 2: using the **weighted majority voters**

Sess-ion-id	pos:1	pos:2	pos:3	pos:4	pos:5	pos:6	…
1	price	opt-zoom	**mpix**	movies	lcd-size	sound	
2	price	opt-zoom	**mpix**	movies	lcd-size	-	
3	price	Mpix	opt-zoom	lcd-size	movies	sound	
4	mpix	price	opt-zoom	lcd-size	movies	-	
5	mpix	price	lcd-size	opt-zoom	movies	sound	

Previous selection of the current user =
{price, opt-zoom}

2-NN={1,2}

Next property (*pos:3*) =*mpix*

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Dealing with Unsatisfiable Requirements and Empty Result Sets – 1/2

- E.g., Given
  - REQ = {
    - r1: price <= 150,
    - r2: opt-zoom = 5x,
    - r3: sound = yes,
    - r4: waterproof = yes}
  - $P = \{p_1, p_2, p_3, p_4, p_5, p_6, p_7, p_8\}$

Id	Price (€)	Mpix	Opt-zoom	LCD-size	Movies	Sound	Waterproof
p1	148	8	4x	2.5	no	no	yes
p2	182	8	5x	2.7	yes	yes	no
p3	189	8	10x	2.5	yes	yes	no
p4	196	10	12x	2.7	yes	no	yes
p5	151	7.1	3x	3.0	yes	yes	no
p6	199	9	3x	3.0	yes	yes	no
p7	259	10	3x	3.0	yes	yes	no
p8	278	9.1	10x	3.0	yes	yes	yes

- IF: $\sigma_{[\text{price} <= 150,\ \text{opt-zoom} = 5x,\ \text{sound} = \text{yes},\ \text{waterproof} = \text{yes}]}(P) = \emptyset$

- Solution: *Relax constraints until* the recommended product is met.

Dealing with Unsatisfiable Requirements and Empty Result Sets – 2/2

- **Assumption**: user's requirements V_C are *directly related* to item properties V_{PROD}.

- Basic idea: identifying and resolving requirements-immanent conflicts induced by the set of product P.
  - Step 1: provide the user *a minimal set of requirements*, once *changed*, leading to a solution.
  - Step 2: propose the adaptations of the initial requirements that guarantee a solution.

Step 1: Model-based Diagnosis (MBD) – 1/2

- The basis for automatically identification and repair of ***minimal*** *sets of* ***faulty*** *requirements*
  - The diagnosis task is to *identify* $r \in REQ$ that may cause ***solution-not-found***.
  - **Output**: A diagnosis (d) is a minimal set of users requirements whose repair (adaptation) will allow the retrieval of a recommendation.
    - So that, once repair, at least one solution is found: $\sigma[_{REQ-d}](P) \neq \emptyset$

Step 1: Model-based Diagnosis (MBD) – 2/2

- Given
  - $P = \{p_1, p_2, \ldots, p_n\}$
  - $REQ = \{r_1, r_2, \ldots, r_m\}$
- Goal: Calculate a set of diagnoses $\Delta = \{d_1, d_2, \ldots, d_k\}$,

  where $\sigma[_{REQ - d_i}](P) \neq \emptyset \; \forall d_i \in \Delta$

- Finding diagnoses $d_i \in \Delta$ is based on the determination and resolution of conflict sets.

Conflict Set (CS)

- A subset $\{r_1, r_2, \ldots, r_l\} \subseteq$ REQ, s.t. $\sigma_{[CS]}(P)=\varnothing$
- Is *Minimal* **iff** there does NOT exist a CS′ with CS′ $\subset$ CS.

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Revisiting the Problem:
Dealing with unsatisfiable requirements and empty result sets

- E.g., Given
  - REQ = {
    - r1: price <= 150,
    - r2: opt-zoom = 5x,
    - r3: sound = yes,
    - r4: waterproof = yes}
  - P = {p_1, p_2, p_3, p_4, p_5, p_6, p_7, p_8}

Id	Price (€)	Mpix	Opt-zoom	LCD-size	Movies	Sound	Waterproof
p1	148	8	4x	2.5	no	no	yes
p2	182	8	5x	2.7	yes	yes	no
p3	189	8	10x	2.5	yes	yes	no
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p7	259	10	3x	3.0	yes	yes	no
p8	278	9.1	10x	3.0	yes	yes	yes

- IF: $\sigma_{[\text{price} <= 150,\ \text{opt-zoom} = 5x,\ \text{sound} = \text{yes},\ \text{waterproof} = \text{yes}]}(P) = \emptyset$
- Solution: Finding 1.1) the Minimal Conflict Set (CS), then used it to find 1.2) Diagnoses $d_i \in \Delta$ and propose them to the user (for *relaxing* user *requirements*)

Step 1.1: Finding the Minimal Conflict Set (CS)

Id	Price (€)	Mpix	Opt-zoom	LCD-size	Movies	Sound	Water proof
p1	148	8	4x	2.5	no	no	yes
p2	182	8	5x	2.7	yes	yes	no
p3	189	8	10x	2.5	yes	yes	no
p4	196	10	12x	2.7	yes	no	yes
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p7	259	10	3x	3.0	yes	yes	no
p8	278	9.1	10x	3.0	yes	yes	yes

- Given
  - REQ = {
    - r1: price <= 150,
    - r2: opt-zoom = 5x,
    - r3: sound = yes,
    - r4: waterproof = yes}

- CS1 = $\{r_1, r_2\}$, $\sigma_{[CS1]}(P) = \varnothing$
- CS2 = $\{r_2, r_4\}$, $\sigma_{[CS2]}(P) = \varnothing$
- CS3 = $\{r_1, r_3\}$, $\sigma_{[CS3]}(P) = \varnothing$

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QuickXPlain (P, REQ)

- Find the conflict set (CS).

Input: trusted knowledge (items) P; Set of requirements REQ

Output: minimal conflict set CS

if $\sigma_{[REQ]}(P) \neq \varnothing$ or REQ = $\varnothing$ **then** return $\varnothing$

else return QX'(P, $\varnothing$, $\varnothing$, REQ);

Function QX'(P, B, Δ, REQ)

if $\Delta \neq \varnothing$ and $\sigma_{[B]}(P) = \varnothing$ **then** return $\varnothing$;

if REQ = {r} **then** return {r};

let $\{r_1, \ldots, r_n\}$ = REQ;

let k be n/2;

$REQ_1 \leftarrow r_1, \ldots, r_k$ and $REQ_2 \leftarrow r_{k+1}, \ldots, r_n$;

$\Delta_2 \leftarrow$ QX'(P, $B \cup REQ_1$, REQ_1, REQ_2);

$\Delta_1 \leftarrow$ QX'(P, $B \cup \Delta_2$, Δ_2, REQ_2);

return $\Delta_1 \cup \Delta_2$;

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Step 1.2: Calculating Diagnoses d_i

Conflict set:
$CS1 = \{r_1, r_2\}$,
$CS2 = \{r_2, r_4\}$,
$CS3 = \{r_1, r_3\}$

- Calculated by resolving conflicts in the given set of requirements.
  - By deleting one of the elements from CS.
  - Obtaining a corresponding diagnosis (an outcome)

1st conflict set

(1) $CS1 = \{r_1, r_2\}$

delete $\{r_1\}$ → Next conflict set (2) $CS2 = \{r_2, r_4\}$

delete $\{r_2\}$ → (3) $CS3 = \{r_1, r_3\}$ Next conflict set

(2) delete $\{r_2\}$ → $d_1 = \{r_1, r_2\}$

(2) delete $\{r_4\}$ → $d_2 = \{r_1, r_4\}$

(3) delete $\{r_1\}$ → $\neq$

(3) delete $\{r_3\}$ → $d_3 = \{r_2, r_3\}$

- From the example,
  - $\Delta = \{ d_1:\{r_1,r_2\},$
    $d_2:\{r_1,r_4\},$
    $d_3:\{r_2,r_3\} \}$

REQ = {
r1: price <= 150,
r2: opt-zoom = 5x,
r3: sound = yes,
r4: waterproof = yes}

Id	Price (€)	Mpix	Opt-zoom	LCD-size	Movies	Sound	Water proof
p1	148	8	4x	2.5	no	no	yes
p2	182	8	5x	2.7	yes	yes	no
p3	189	8	10x	2.5	yes	yes	no
p4	196	10	12x	2.7	yes	no	yes
p5	151	7.1	3x	3.0	yes	yes	no
p6	199	9	3x	3.0	yes	yes	no
p7	259	10	3x	3.0	yes	yes	no
p8	278	9.1	10x	3.0	yes	yes	yes

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Step 2: Proposing Repairs for Unsatisfiable Requirements

- Derive alternative repair action by *querying the product* table P *with*

  $\Pi_{[attributes(d)]}\sigma_{[\mathbf{REQ\text{-}d}]}(P)$.

  - Example: *repair alternatives* for the requirements in

    REQ: {r1: price <= 150, r2: opt-zoom = 5x, r3: sound = yes, r4: waterproof = yes}

	r1	r2	r3	r4
repair	**price**	**opt-zoom**	**sound**	**waterproof**
repair1	278	10x	√	√
repair2	182	√	√	no
repair3	√	4x	no	√

$\Delta = \{ d_1:\{r_1, r_2\}, d_2:\{r_1, r_4\}, d_3:\{r_2, r_3\} \}$

Atfer repair	Recom-mended ID	Price (€)	Mpix	Opt-zoom	LCD -size	Movies	Sound	Waterproof
repair1	p8	278	9.1	10x	3.0	yes	yes	yes
repair2	p2	182	8	5x	2.7	yes	yes	no
repair3	p1	148	8	4x	2.5	no	no	yes

Relaxed constraints

√: matched constraints

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Better Solution: MINRELAX(P, REQ)

- Find a complete set of diagnoses (integrating the steps 1.1 and 1.2)
  - NO *explicit conflict sets* extraction is required.

ALGORITHM: *MinRelax*
In: A query Q, a product catalog P
Out: Set of minimal relaxations $minRS$ for Q

```
MinRS = ∅
forall p_i ∈ P do
    PSX = Compute the product-specific relaxation PSX(Q, p_i)
    % Check relaxations that were already found
    SUB = {r ∈ MinRS | r ⊂ PSX}
    if SUB ≠ ∅
        % Current relaxation is superset of existing relaxation
        continue with next p_i
    endif
    SUPER = {r ∈ MinRS | PSX ⊂ r}
    if SUPER ≠ ∅
        % Remove supersets
        MinRS = MinRS \ SUPER
    endif
    % Store the new relaxation
    MinRS = MinRS ∪ {PSX}
endfor
return MinRS
```

Fig. 4. Algorithm for determining all minimal relaxations.

Reference: https://web-ainf.aau.at/pub/jannach/files/Journal_AICOM09.pdf

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Product-Specific-Relaxation (PSXs)'s Idea

ID	USB	Firewire	Price	Resolution	Make
p1	true	false	400	5 MP	Canon
p2	false	true	500	5 MP	Canon
p3	true	false	200	4 MP	Fuji
p4	false	true	400	5 MP	HP

Fig. 2. Product database of digital cameras.

ID	p1	p2	p3	p4
Q1	1	0	1	0
Q2	0	1	0	1
Q3	0	0	1	0
Q4	1	1	0	1

Product-specific relaxation for p1

Fig. 3. Evaluating the subqueries individually.

Let the user's query consist of the following requirements (atoms) which results in a theoretical search space of $2^4 = 16$ combinations of atoms.

$Q = \{$ usb = true (Q1), firewire = true (Q2), price $<$ 300 (Q3), resolution $>=$ 5 MP (Q4)$\}$

The list of product-specific-relaxation (PSXs) = <{Q2,Q3},{Q1,Q3},{Q2,Q4},{Q1,Q3}>
The set of ***minimal*** relaxation is {{Q1,Q3},{Q2,Q3},{Q2,Q4}}

(Duplicated PSX)

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Example - MINRELAX(P, REQ) 1/9

REQ: {
r1: price <= 150,
r2: opt-zoom = 5x,
r3: sound = yes,
r4: waterproof = yes}

Id	Price (€)	Opt-zoom	Sound	Waterproof	product-specific-relaxation (PSXs)
p1	148	4x	no	yes	{r2, r3}
p2	182	5x	yes	no	{r1, r4}
p3	189	10x	yes	no	{r1, r2, r4}
p4	196	12x	no	yes	{r1, r2, r3}
p5	151	3x	yes	no	{r1, r2, r4}
p6	199	3x	yes	no	{r1, r2, r4}
p7	259	3x	yes	no	{r1, r2, r4}
p8	278	10x	yes	yes	{r1, r2}

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Example – MINRELAX(P, REQ) 2/9

ALGORITHM: *MinRelax*
In: A query Q, a product catalog P
Out: Set of minimal relaxations $minRS$ for Q

```
MinRS = ∅
forall p_i ∈ P do
    PSX = Compute the product-specific relaxation PSX(Q, p_i)
    % Check relaxations that were already found
    SUB = {r ∈ MinRS | r ⊂ PSX}
    if SUB ≠ ∅
        % Current relaxation is superset of existing relaxation
        continue with next p_i
    endif
    SUPER = {r ∈ MinRS | PSX ⊂ r}
    if SUPER ≠ ∅
        % Remove supersets
        MinRS = MinRS \ SUPER
    endif
    % Store the new relaxation
    MinRS = MinRS ∪ {PSX}
endfor
return MinRS
```

Fig. 4. Algorithm for determining all minimal relaxations.

Id	product-specific-relaxation (PSXs)
p1	{r2, r3}
p2	{r1, r4}
p3	{r1, r2, r4}
p4	{r1, r2, r3}
p5	{r1, r2, r4}
p6	{r1, r2, r4}
p7	{r1, r2, r4}
p8	{r1, r2}

PSX(p1) = {r2, r3}
SUB = ∅, SUPER = ∅
MinRS = {{r2, r3}}

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Example – MINRELAX(P, REQ) 3/9

ALGORITHM: *MinRelax*
In: A query Q, a product catalog P
Out: Set of minimal relaxations *minRS* for Q

```
MinRS = ∅
forall p_i ∈ P do
    PSX = Compute the product-specific relaxation PSX(Q, p_i)
    % Check relaxations that were already found
    SUB = {r ∈ MinRS | r ⊂ PSX}
    if SUB ≠ ∅
        % Current relaxation is superset of existing relaxation
        continue with next p_i
    endif
    SUPER = {r ∈ MinRS | PSX ⊂ r}
    if SUPER ≠ ∅
        % Remove supersets
        MinRS = MinRS \ SUPER
    endif
    % Store the new relaxation
    MinRS = MinRS ∪ {PSX}
endfor
return MinRS
```

Fig. 4. Algorithm for determining all minimal relaxations.

Id	product-specific-relaxation (PSXs)
p1	{r2, r3}
p2	{r1, r4}
p3	{r1, r2, r4}
p4	{r1, r2, r3}
p5	{r1, r2, r4}
p6	{r1, r2, r4}
p7	{r1, r2, r4}
p8	{r1, r2}

PSX(p2) = {r1, r4}
SUB = ∅, SUPER = ∅
MinRS = { {r2, r3}, {r1, r4} }

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Example – MinRelax(P, REQ) 4/9

ALGORITHM: *MinRelax*

In: A query Q, a product catalog P

Out: Set of minimal relaxations *minRS* for Q

```
MinRS = ∅
forall p_i ∈ P do
    PSX = Compute the product-specific relaxation PSX(Q, p_i)
    % Check relaxations that were already found
    SUB = {r ∈ MinRS | r ⊂ PSX}
    if SUB ≠ ∅
        % Current relaxation is superset of existing relaxation
        continue with next p_i
    endif
    SUPER = {r ∈ MinRS | PSX ⊂ r}
    if SUPER ≠ ∅
        % Remove supersets
        MinRS = MinRS \ SUPER
    endif
    % Store the new relaxation
    MinRS = MinRS ∪ {PSX}
endfor
return MinRS
```

Fig. 4. Algorithm for determining all minimal relaxations.

Id	product-specific-relaxation (PSXs)
p1	{r2, r3}
p2	{r1, r4}
p3	{r1, r2, r4}
p4	{r1, r2, r3}
p5	{r1, r2, r4}
p6	{r1, r2, r4}
p7	{r1, r2, r4}
p8	{r1, r2}

PSX(p3) = {r1, r2, r4}

SUB = {r1, r4}

MinRS = { {r2, r3}, {r1, r4} }

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Example – MinRelax(P, REQ) 5/9

```
ALGORITHM: MinRelax
In: A query Q, a product catalog P
Out: Set of minimal relaxations minRS for Q
MinRS = ∅
forall p_i ∈ P do
    PSX = Compute the product-specific relaxation PSX(Q, p_i)
    % Check relaxations that were already found
    SUB = {r ∈ MinRS | r ⊂ PSX}
    if SUB ≠ ∅
        % Current relaxation is superset of existing relaxation
        continue with next p_i
    endif
    SUPER = {r ∈ MinRS | PSX ⊂ r}
    if SUPER ≠ ∅
        % Remove supersets
        MinRS = MinRS \ SUPER
    endif
    % Store the new relaxation
    MinRS = MinRS ∪ {PSX}
endfor
return MinRS
```

Fig. 4. Algorithm for determining all minimal relaxations.

Id	product-specific-relaxation (PSXs)
p1	{r2, r3}
p2	{r1, r4}
p3	{r1, r2, r4}
p4	{r1, r2, r3}
p5	{r1, r2, r4}
p6	{r1, r2, r4}
p7	{r1, r2, r4}
p8	{r1, r2}

PSX(p4) = {r1, r2, r3}

SUB = {r2, r3}

MinRS = { {r2, r3}, {r1, r4} }

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Example – MINRELAX(P, REQ) 6/9

ALGORITHM: *MinRelax*
In: A query Q, a product catalog P
Out: Set of minimal relaxations $minRS$ for Q

```
MinRS = ∅
forall p_i ∈ P do
    PSX = Compute the product-specific relaxation PSX(Q, p_i)
    % Check relaxations that were already found
    SUB = {r ∈ MinRS | r ⊂ PSX}
    if SUB ≠ ∅
        % Current relaxation is superset of existing relaxation
        continue with next p_i
    endif
    SUPER = {r ∈ MinRS | PSX ⊂ r}
    if SUPER ≠ ∅
        % Remove supersets
        MinRS = MinRS \ SUPER
    endif
    % Store the new relaxation
    MinRS = MinRS ∪ {PSX}
endfor
return MinRS
```

Fig. 4. Algorithm for determining all minimal relaxations.

Id	product-specific-relaxation (PSXs)
p1	{r2, r3}
p2	{r1, r4}
p3	{r1, r2, r4}
p4	{r1, r2, r3}
p5	{r1, r2, r4}
p6	{r1, r2, r4}
p7	{r1, r2, r4}
p8	{r1, r2}

PSX(p5) = {r1, r2, r4}
SUB = {r1, r4}
MinRS = { {r2, r3}, {r1, r4} }

Example – MINRELAX(P, REQ) 7/9

ALGORITHM: *MinRelax*
In: A query Q, a product catalog P
Out: Set of minimal relaxations *minRS* for Q

```
MinRS = ∅
forall p_i ∈ P do
   PSX = Compute the product-specific relaxation PSX(Q, p_i)
   % Check relaxations that were already found
   SUB = {r ∈ MinRS | r ⊂ PSX}
   if SUB ≠ ∅
      % Current relaxation is superset of existing relaxation
      continue with next p_i
   endif
   SUPER = {r ∈ MinRS | PSX ⊂ r}
   if SUPER ≠ ∅
      % Remove supersets
      MinRS = MinRS \ SUPER
   endif
   % Store the new relaxation
   MinRS = MinRS ∪ {PSX}
endfor
return MinRS
```

Fig. 4. Algorithm for determining all minimal relaxations.

Id	product-specific-relaxation (PSXs)
p1	{r2, r3}
p2	{r1, r4}
p3	{r1, r2, r4}
p4	{r1, r2, r3}
p5	{r1, r2, r4}
p6	{r1, r2, r4}
p7	{r1, r2, r4}
p8	{r1, r2}

PSX(p6) = {r1, r2, r4}
SUB = {r1, r4}
MinRS = { {r2, r3}, {r1, r4} }

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Example – MINRELAX(P, REQ) 8/9

ALGORITHM: *MinRelax*
In: A query Q, a product catalog P
Out: Set of minimal relaxations $minRS$ for Q

```
MinRS = ∅
forall p_i ∈ P do
    PSX = Compute the product-specific relaxation PSX(Q, p_i)
    % Check relaxations that were already found
    SUB = {r ∈ MinRS | r ⊂ PSX}
    if SUB ≠ ∅
        % Current relaxation is superset of existing relaxation
        continue with next p_i
    endif
    SUPER = {r ∈ MinRS | PSX ⊂ r}
    if SUPER ≠ ∅
        % Remove supersets
        MinRS = MinRS \ SUPER
    endif
    % Store the new relaxation
    MinRS = MinRS ∪ {PSX}
endfor
return MinRS
```

Fig. 4. Algorithm for determining all minimal relaxations.

Id	product-specific-relaxation (PSXs)
p1	{r2, r3}
p2	{r1, r4}
p3	{r1, r2, r4}
p4	{r1, r2, r3}
p5	{r1, r2, r4}
p6	{r1, r2, r4}
p7	{r1, r2, r4}
p8	{r1, r2}

PSX(p7) = {r1, r2, r4}
SUB = {r1, r4}
MinRS = { {r2, r3}, {r1, r4} }

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Example – MINRELAX(P, REQ) 9/9

ALGORITHM: *MinRelax*
In: A query Q, a product catalog P
Out: Set of minimal relaxations $minRS$ for Q

```
MinRS = ∅
forall p_i ∈ P do
    PSX = Compute the product-specific relaxation PSX(Q, p_i)
    % Check relaxations that were already found
    SUB = {r ∈ MinRS | r ⊂ PSX}
    if SUB ≠ ∅
        % Current relaxation is superset of existing relaxation
        continue with next p_i
    endif
    SUPER = {r ∈ MinRS | PSX ⊂ r}
    if SUPER ≠ ∅
        % Remove supersets
        MinRS = MinRS \ SUPER
    endif
    % Store the new relaxation
    MinRS = MinRS ∪ {PSX}
endfor
return MinRS
```

Fig. 4. Algorithm for determining all minimal relaxations.

Id	product-specific-relaxation (PSXs)
p1	{r2, r3}
p2	{r1, r4}
p3	{r1, r2, r4}
p4	{r1, r2, r3}
p5	{r1, r2, r4}
p6	{r1, r2, r4}
p7	{r1, r2, r4}
p8	{r1, r2}

PSX(p8) = {r1, r2}
SUB = ∅, SUPER = ∅
MinRS =
{ {r2, r3}, {r1, r4}, {r1, r2} }

Then, can further apply "Step 2: Proposing Repairs for Unsatisfiable Requirements" (slide no. 44)

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Ranking the Items/Utility-based Recommendation – 1/3

- Rank recommendations before presenting them to the user.
- Based on the multi-attribute utility theory (MAUT),
  - Evaluates each item wrt its utility for the customer.
    - E.g.,

domain	**Evaluation measures (dimensions)**
Digital camera	Quality, economy
Financial services	Availability, risk, profit

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Ranking the Items/Utility-based Recommendation – 2/3

$$utility(p) = \sum_{j=1}^{\#(dimensions)} interest(j) * contribution(p,j)$$

Customer-specific preferences (***interest***)

User defined

customer (user)	quality	economy
cu_1	80%	20%
cu_2	40%	60%

Scoring rules (for calculating ***contribution***)

Knowledge base

	value	quality	economy
Price	≤250 >250	5 10	10 5
mpix	≤8 >8	4 10	10 6
opt-zoom	≤9 >9	6 10	9 6
lcd-size	≤2.7 >2.7	6 9	10 5
movies	yes no	10 3	7 10
sound	yes no	10 7	8 10
waterproof	yes no	10 8	6 10

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Example of Calculation *Contribution*(p_1, *j*)

Id	Price (€)	Mpix	Opt-zoom	LCD-size	Movies	Sound	Water proof
p1	148	8	4x	2.5	no	no	yes

	value	quality	economy
Price	**≤250** >250	**5** 10	**10** 5
mpix	**≤8** >8	**4** 10	**10** 6
opt-zoom	**≤9** >9	**6** 10	**9** 6
lcd-size	**≤2.7** >2.7	**6** 9	**10** 5
movies	yes **no**	10 **3**	7 **10**
sound	yes **no**	10 **7**	8 **10**
waterproof	**yes** no	**10** 8	**6** 10

contribution(p_1, quality)
= 5+4+6+6+3+7+10
= 41

contribution(p_1, economy)
= 10+10+9+10+10+10+6
= 65

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Ranking the Items/Utility-based Recommendation – 3/3

$$utility(p) = \sum_{j=1}^{\#(dimensions)} interest(j) * contribution(p,j)$$

Rank of Recommended Products

Customer-specific preferences (*interest*)

customer (user)	quality	economy
cu_1	80%	20%
cu_2	40%	60%

From previous slide's calculation:
contribution(p_1, quality) = 41
contribution(p_1, economy) = 65

Then,
utility(p_1) for cu_1 = (0.8*41) + (0.2*65) = 45.8
utility(p_1) for cu_2 = (0.4*41) + (0.6*65) = 55.4

Product utilities for customer cu_1 and cu_2

product	contribution(p_i, quality)	contribution(p_i, economy)	utility(p_i) for cu_1	utility(p_i) for cu_2
p_1	41	65	45.8 [8]	55.4 [6]
p_2	49	64	52.0 [7]	58.0 [1]
p_3	53	61	54.6 [5]	57.8 [2]
p_4	58	55	57.4 [4]	56.2 [4]
p_5	53	60	54.4 [6]	57.2 [3]
p_6	58	55	57.4 [3]	56.2 [5]
p_7	63	50	60.4 [2]	55.2 [7]
p_8	69	43	63.8 [1]	53.4 [8]

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Approaches for Determining a *Customer's* ***Degree of Interest***

- User-defined preferences
  - The user *explicitly specifies* his/her preferences beforehand.
- Utility-based preferences
  - *Apply the scoring rules* in the table.
  - E.g., REQ = {

    r_1: price <=200,

    r_2: mpix=8.0,

    r_3: opt-zoom=10x,

    r_4: lcd-size<=2.7 }
    - Interest(quality) = 5+4+10+6 = 25
    - Interest(economy) = 10+10+6+10 = 36
    - *Relative* Interest(quality) = 25/(25+36) = 0.41
    - *Relative* Interest(economy) = 36/(25+36) = 0.59

Example of *scoring rules*

	value	quality	economy
Price	**≤250** >250	**5** 10	**10** 5
mpix	**≤8** >8	**4** 10	**10** 6
opt-zoom	≤9 **>9**	6 **10**	9 **6**
lcd-size	**≤2.7** >2.7	**6** 9	**10** 5
movies	yes no	10 3	7 10
sound	yes no	10 7	8 10
waterproof	yes no	10 8	6 10