Personalized Configuration

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Configuration Task

Definition (Configuration Task). A configuration task can be defined as a constraint satisfaction problem (V, D, C). V = {$v0$, $v1$, ..., vn} represents a set of finite domain variables and D = {$dom(v0)$, $dom(v1)$, . . . , $dom(vn)$} represents a set of domains, where *domi* is assigned to *vi*. C = *CKB* ∪ *CR* represents a set of constraints, where *CKB* = {$c0$, $c1$, . . . , cm} represents the configuration knowledge base that restricts the possible combinations of values assigned to the variables in V, and *CR* = {$r0$, $r1$, . . . , rq } represents user requirements.

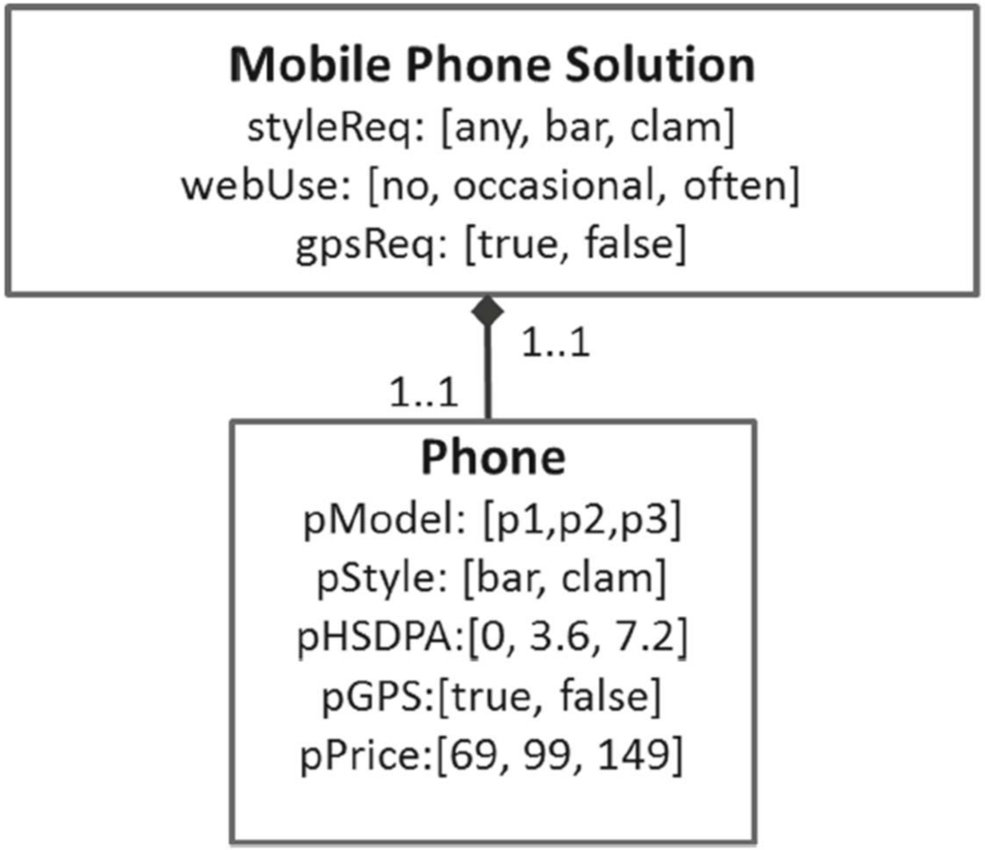
Example Knowledge Base

- V ={styleReq, webUse, GPSReq, pModel, pStyle, pHSDPA, pGPS, pPrice}

- dom(pModel) = {p1, p2, p3}, dom(pStyle) = {bar, clam}
- dom(pHSDPA) = {0, 3.6, 7.2}, dom(pGPS) = {false, true}
- dom(pPrice) = {69, 99, 149}.

- $c1$: webUse = no → pHSDPA = 0 true} /∗ web use requires a fast internet connection ∗/
- $c2$: styleReq = any ∨ styleReq = pStyle /∗ the phone should support the user's preferred style ∗/
- $c3$: GPSReq = true → pGPS = true /∗ if GPS navigation is required, the phone must support it ∗/

Example Knowledge Base



Example: Phone Models

Table 13.1 Phone models in the working example: `pModel` specifies the existing phone models, `pStyle` the phone styles, `pHSDPA` specifies the supported HSDPA data rate (a value of 0 indicates that the phone does not support HSDPA), `pGPS` whether the phone supports GPS navigation, and `pPrice` specifies the price of the phone.

pModel	**pStyle**	**pHSDPA**	**pGPS**	**pPrice**
p1	bar	0	false	69
p2	clam	7.2	true	149
p3	clam	3.6	false	99

Similarity Metrics

$$Q = \{pPrice = 69;\ pHSDPA = 7.2;\ pGPS = true\}$$

The similarity of item I to the default query Q is determined with respect to each attribute a in Q. Formula 13.1 is used for MIB attributes, Formula 13.2 for LIB attributes, and Formula 13.3 for NIB attributes (McSherry, 2005). In these formulae, *max(a)* and *min(a)* refer to the maximum and minimum values of the attribute a in the case base. $\phi_a(Q)$ is the value of a in the (default) query Q and $\phi_a(I)$ is the value of a for the item I. In these formulae, Boolean attributes values `false` and `true` are interpreted as `0` and `1`, respectively. The union of all attributes in the case base is V (the set of variables).

$$sim_{(MIB)}(a, I, Q) = 1 - \frac{|\phi_a(I) - \phi_a(Q)|}{max(a) - min(a)} = \frac{\phi_a(I) - min(a)}{max(a) - min(a)} \quad (13.1)$$

$$sim_{(LIB)}(a, I, Q) = 1 - \frac{|\phi_a(I) - \phi_a(Q)|}{max(a) - min(a)} = \frac{max(a) - \phi_a(I)}{max(a) - min(a)} \quad (13.2)$$

$$sim_{(NIB)}(a, I, Q) = 1 - \frac{|\phi_a(I) - \phi_a(Q)|}{max(a) - min(a)} \quad (13.3)$$

Static Default Recommendation

Table 13.2 Static default recommendation for phone models of the working example. `pModel` is the phone model, `pHSDPA` is the supported HSDPA data rate, and $\boxed{sim_{\texttt{pHSDPA}}}$ is similarity value of the MIB attribute `pHSDPA` (Formula 13.1). `pPrice` is the price of the phone, $\boxed{sim_{\texttt{pPrice}}}$ is the similarity value of the LIB attribute `pPrice` (Formula 13.2). `pGPS` specifies if the phone supports GPS, and $\boxed{sim_{\texttt{pGPS}}}$ is the similarity value of the Boolean NIB attribute `pGPS` (Formula 13.3). Finally $\sum$ represents $\boxed{\sum_{a \in V} sim(a, \texttt{pModel}, Q)\text{—the total similarity of } \texttt{pModel}}$ with regard to best values Q.

pModel	pHSDPA	$sim_{\texttt{pHSDPA}}$	pPrice	$sim_{\texttt{pPrice}}$	pGPS	$sim_{\texttt{pGPS}}$	$\sum$
p1	0	0.000	69	1.000	false	0.000	1.000
p2	7.2	1.000	149	0.000	true	1.000	2.000
p3	3.6	0.500	99	0.625	false	0.000	1.125

Rule-based Default Recommendation

Rule-based default recommendation. The rule-based approach calculates defaults based on already specified user requirements and explicitly defined rules that embody domain knowledge for determining recommendations (Falkner et al., 2011). In our example of the mobile phone domain for example, we can specify the rule that if the user indicates that he/she often wants to use the mobile phone for browsing the web, the value for `HSDPA` is recommended to be set to the highest value.

/∗ rule: frequent web use requires a fast internet connection ∗/

$$webUse = often \rightarrow pHSDPA = 7.2$$

Collaborative Recommendation

The distance between the already specified user requirements $conf_u$ and a neighbor configuration $conf_a$ is the sum of individual distances (McSherry, 2003) between corresponding feature values $f_{i,u}$, and $f_{i,a}$, weighted by feature importance weights $w(f_i)$ (see Formula 13.4).

$$\boxed{dist(conf_u, conf_a) = \sum_{f_i \in F_u} d_{f_i}(f_{i,u}, f_{i,a}) * w(f_i)} \quad (13.4)$$

To provide an example of the Nearest Neighbor based approach, Table 13.3 contains three valid configurations $conf_1$, $conf_2$, and $conf_3$ from previous configuration sessions. Let us assume that the current user has already specified the requirements $\boxed{C_R = \{r_0 : \texttt{styleReq=clam}, r_1 : \texttt{webUse=often}\}}$ Intuitively, the nearest neighbor for this combination of requirements is $conf_2$ since the feature values of `styleReq` and `webUse` are identical with the values specified in C_R. To predict a value for the feature `GPSReq`, we use the value specified in $conf_2$, i.e., `GPSReq = true`.

Collaborative Recommendation

Table 13.3 Example: Valid configurations from previous sessions ($conf_1$, $conf_2$, $conf_3$).

feature f_i / configuration $conf_j$	$conf_1$	$conf_2$	$conf_3$	$conf_u$
f_1 = styleReq	bar	clam	clam	clam
f_2 = webUse	no	often	occasional	often
f_3 = GPSReq	false	true	false	
f_4 = pStyle	bar	clam	clam	
f_5 = pModel	p1	p2	p3	
f_6 = pHSDPA	0	7.2	3.6	
f_7 = pGPS	false	true	false	
f_8 = pPrice	69	149	99	

Utility-based Recommendation

Another approach to personalize item rankings was introduced in Felfernig et al. (2008). The approach utilizes Multi-Attribute Utility Theory (MAUT; Winterfeldt and Edwards, 1986) where products or, for example, individual attribute values are evaluated according to their performance on a predefined set of *interest dimensions* D and user preferences. Example dimensions in the mobile phone scenario could be *fashion (fa)*, *economy (eco)*, and *functionality (fu)*. Contribution of a product p to interest dimension d is predefined and expressed as *score* $sc_d(p)$. User preferences are expressed as interest with respect to each *dimension* in_d. The utility of a product $u(p)$ can be determined, for example, on the basis of Formula 13.5.

$$u(p) = \sum_{d \in D} sc_d(p) * in_d \qquad (13.5)$$

As a result, the order of products depends on the importance of the interest dimensions for the user. The importance of interest dimensions (in_d) can be determined via explicit assessment provided by the user or be derived from user requirements (see, e.g., Felfernig et al., 2013a). For simplicity, our example applies explicit interest dimension weights and assumes that values for $sc_d(p)$ are manually specified for each product when the product database is established.

Utility-based Recommendation

Table 13.4 Scores of phone models with respect to interest dimensions. pModel is the phone model; sc_{fa}, sc_{eco}, and sc_{fu} are scores for corresponding dimensions.

pModel	sc_{fa}	sc_{eco}	sc_{fu}
p1	2	5	1
p2	4	2	5
p3	3	3	2

Table 13.5 Interests of two users with respect to predefined interest dimensions.

dimension d	*user 1: in_d*	*user 2 : in_d*
fashion fa	3	1
economy eco	2	5
functionality fu	5	3

For user 1 utility of $p1$, $u(p1) = 2*3+5*2+1*5 = 21$, $u(p2) = 4*3+2*2+5*5 = 41$ and $u(p3) = 3*3+3*2+2*5 = 25$. For this user, who is mainly interested in *functionality* and less in *economy*, the most advanced phone $p2$ provides the highest utility and would be shown first, followed by $p3$ and $p1$. For user 2 the utilities are $u(p1) = 30$, $u(p2) = 29$, and $u(p3) = 24$. For this user, the cheapest phone $p1$ would be the first recommendation.

Recommendation of Repair Alternatives

$$C_R = \{r_0 : pStyle = clam, r_1 : pPrice < 70, r_2 : pGPS = true\}$$

Table 13.6 Preferences of example user regarding mobile phone parameter values (obviously, price has the highest priority, i.e., should not be part of a diagnosis).

$r_0 : pStyle = clam$	$r_1 : pPrice < 70$	$r_2 : pGPS = true$
10	80	10

$$CS_1 = \{r_0 : pStyle = clam, r_1 : pPrice < 70\}$$
$$CS_2 = \{r_1 : pPrice < 70, r_2 : pGPS = true\}$$

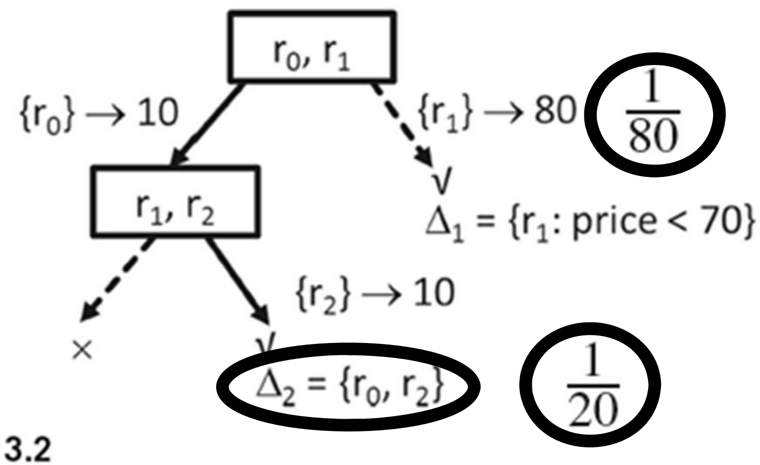


FIGURE 13.2

Preferred diagnosis for inconsistent requirements ($\{r_0, r_1, r_2\}$): Δ_2.

$$utility(\Delta) = \frac{1}{\sum_{r \in \Delta} preference(r)}$$

Exercises

1. For each of the three mentioned types of similarity metrics provide a corresponding example attribute.
2. Define two rule-based defaults for the product domain of digital cameras.
3. Define an example of collaborative filtering based default recommendation for a product domain not discussed in the lecture.

Thank You!

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