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Personal Assistance: Helping the Users Find Their Way through the Information Space

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Abstract

Qualitatively enhanced access to data collections requires a more meaningful interface which endows the users with personal agents that are easily adaptable to the users' individual retrieval preferences. Tracking individual needs of users leads to personal digital assistance that appears in the system's interaction mode as the user's personal software agent. The main objective of personal assistance as envisaged here is enabling the system to give the users recommendations that are derived from best practice in searching for information. Best practice reflects the knowledge about how users perform successful retrieval activities and attempt to define the best ways of searching large document collections. Best practices are developed on an individual as well as on a community base.

The model presented here was developed for the information system IRAIA, a portal for economic information from huge data collections of Economic Research Institutes (ERI) and National Statistical Institutions (NSI). The personal agent draws on IRAIA's model of context-oriented retrieval and observe, record and analyse the users' search and navigation by applying concepts of the respective taxonomies.

1 The artefact of personal assistance

Personal assistance as discussed here is positioned within the framework of adaptable Web systems. These systems collect data for a user model from various sources that also include implicitly observing user interaction and enabling explicit user response. [Brusilovsky & Maybury 02] Instead of focusing on a user model we more concentrate on a use model. The model entails an adaptation effect that tailors retrieval interaction to different use types. Whereas a purely adaptive system bases solely on a user or a use model the adaptable system requires the user to specify major parts of its behaviour. In the context of our application area we concentrate on adaptable navigation support. Based on a number of successful approaches in adaptive hypermedia and web systems [see Billsus et al. 02, Yang et al. 99, for instance], our design of an adaptable system is intertwined with a strong linguistic layer that raises significantly the expressiveness of the interaction mode.

Personal agency endows an information system with an easy and highly user-oriented interaction mode. This is achieved by the installation of a personal agent that helps the user during navigation. It starts with observing the user's selections of entries from the concept hierarchies, i.e. with capturing query profiles. An actual profile then is compared with already stored ones and recommendations are derived if the agent can recognise a certain similarity between profiles. The recommendation refers to further selections of concepts suitable in an actual retrieval situation. Our design of a personal agent results from combining the approaches for agents as personalised companions [André & Rist 02, Billsus & Pazzani 99] and agents for automatic text analysis [Wermter 00, for an overview see Mladenic 99] and for developing interaction strategies [Durfee 01, Englmeier et al. 01].

2 Getting orientation in complex information spaces

Information arises from data when they are combined, arranged, and presented accordingly. Only a suitable combination of related time series and texts is in the position to convey the information that is contained in these separate and otherwise imperceptible components. An interface expressing the content of these components in a comprehensive and uniform way is of outstanding importance when it comes to proliferate information that has to be composed by distributed and heterogeneous data. This holds for most of the large-scale and complex data collections in general, but for those of ERIs and NSIs in particular. Our model for the construction of context-aware information spaces is derived from related models of retrieval environments for interacting with large data collections [Agosti et al. 92, Krause 96]. Interfaces presenting such a content overview help to construct a retrieval environment where the users explore data collections within a semantic coordinate system derived from taxonomies of the respective information domain. These taxonomies exist for a variety of application areas. They are a solid basis for a controlled and structured vocabulary and therefore and most appropriately for the content semantics defining a domain-related context.

A semantic coordinate system endows the users with a concise as well as comprehensive vocabulary. Hierarchically arranged and grouped along major content facets this vocabulary acts as a stable coordinate system easy to comprehend and memorise[1]. The users are thus much more in the position to localise themselves effortlessly. Successfully searching and navigating now means guided travelling from information to information just by changing the semantic coordinates, i.e. by pointing to relevant concepts. This structure on the other hand enables to pinpoint the semantic location of any kind of information. It also supports the correct identification of retrieval strategies which extends content searching and navigating towards context-assisted retrieval.

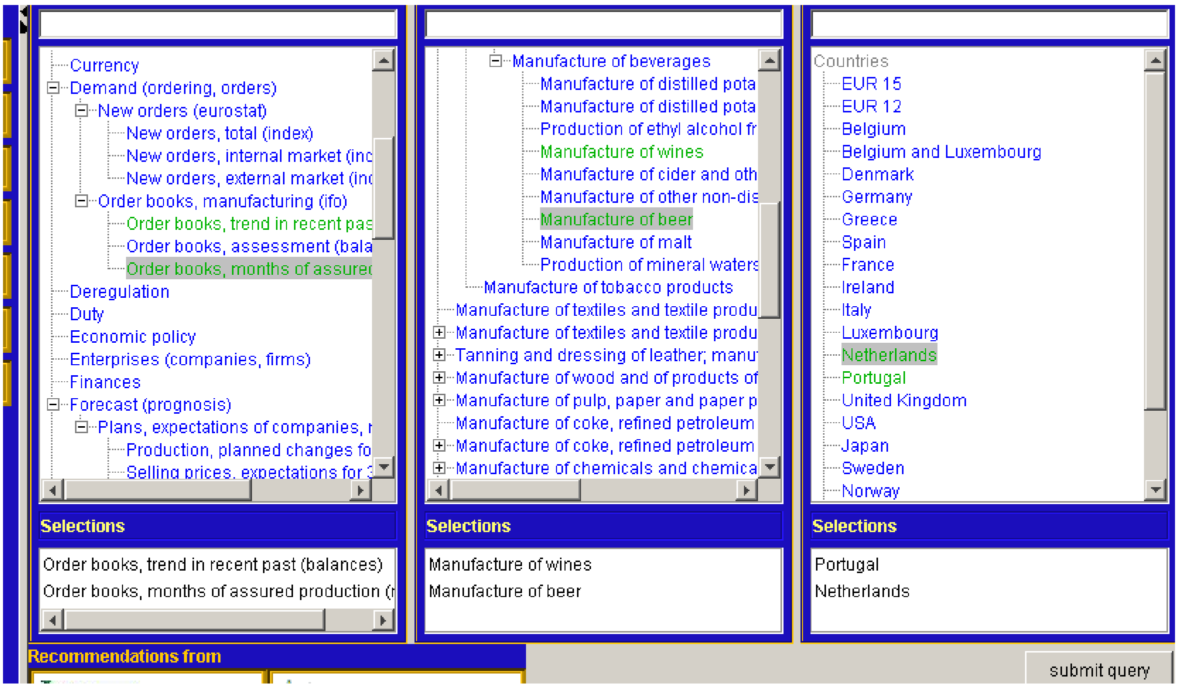

Figure 1. Searching and navigation in a semantic coordinate system. Selected concepts make up the initial query profile. While realising his retrieval strategy the user usually performs iterative steps of defining a query and analysing the retrieved results. In IRAIA, the documents are annotated solely with entries from the hierarchies. While viewing a document the interface shows also the annotated concepts (similar to the screen above) that are thus already familiar from the initial query formulation. Modifying the set of annotated concepts is thus tantamount with repetitive query formulation.

[1] The coordinate system itself can be presented simultaneously in different languages. This ensures that the domain model mentioned later features multilinguality.

Semantic coordinates can be rendered simply and efficiently by concept hierarchies displayed in adjacent windows. The user just pinpoints to the relevant concept (i.e. a phrase of terms). A group of selected concepts that is sent to the system reflects a query or query profile. In this context, a sequence of such profiles represents a navigation history. In addition to this, a particular best practice in retrieval is reflected by a set of individual navigation histories that appear quite frequently among all observed histories.

For IRAIA we produced a powerful taxonomy that merges two of the most important structures in this field: eurostat's NACE[2] nomenclature and the industry systematic of the IFO institute for economic research. The unified taxonomy creates a semantic coordinate system that enables exact and automatic positioning[3] of coherent documents even if they are of different types. It also provides users with the necessary orientation while exploring the information space. Like in using languages it helps users as a passive vocabulary to identify the topics of their information problem.

3 Task model of the personal agent

At each decision point that is again represented by a query profile the user can ask the agent to show recommendable concepts. These concepts are part of a profile in the sequence of an archived navigation that follows the profile corresponding to the decision point. This means there is a sequence of profiles having significant concepts in common and additionally at least one profile that reaches beyond the decision point. Again, the prerequisite for being a candidate for recommendation is that such a profile has a significant overlapping navigation history with the actual sequence in the recent past of the decision point. In the figure below this profile has the number 19 and contains concepts for recommendation. This means, these concepts are marked respectively in the corresponding hierarchies presented in the user interface.

An archived profile is suitable for recommendation if it contains similar query profiles up to the corresponding decision point and if there is a query profile that reaches beyond this point. In this context, it is not important if the pro-

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2 Nomenclature des Activités dans la Communauté européenne -systematic of the economic activities of the European Union

3 Automatic positioning means annotating a document with entries from the concept hierarchies. During the automatic process the terms of a document are matched with those of the hierarchies and their synonyms. The hierarchy entries which got the highest frequency of matches are chosen for the annotation.

files belong to the user's personal history lists or to the common collection of best practices.

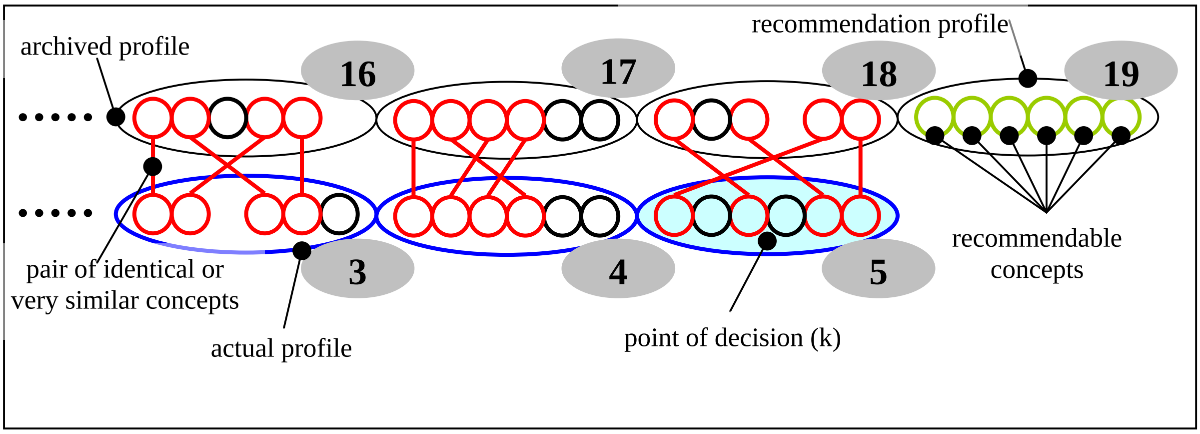

Figure 2. Schema of a recommendation situation. The upper profiles (16 through 19) are archived ones. Due to concept similarities up to the decision point (k) and the availability of a further profile (19) that reaches beyond k they are suitable for recommendation. The lower profiles reflect the actual navigation of the user. Pairs of similar concepts are marked by circles with links in between them. The order of the nodes within a query profile is not important. In this example, the users ask for recommendation while completing query no. 5 and gets concepts from profile 19.

3.1 Human-agent interaction

A profile can be regarded similar to another one if it covers at least 80% of its concepts. Taking into account that coverage varies among the profiles of an observed track the same threshold is applied to measure the overall similarity between two tracks. Among all tracks with similarity values above this threshold the one with the highest value is selected for recommendation.

The work of the agent now is

- to identify significantly similar queries,
- to decide if there is a significantly common navigation history,
- to present recommendable concepts,
- to show the user the way of their decision,
- to adapt its way of deciding by asking the user whether the recommendation was useful, potentially useful or not useful, and
- to accept new decision rules.

It is important to note that the archived sequences may reflect the user's individual navigation history or best practices from the user community. Tasks and decisions outlined above are the same for both cases even if different kinds of agents are in charge with. During navigation, recommendable concepts are marked respectively.

Figure 3. The user can ask the personal agent to look for recommendations in its local archive of personal navigation data or to ask remote agent for a suggestion derived from best practices.

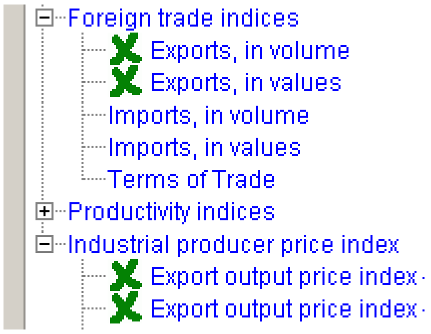

Figure 4. Nodes are marked according to the concepts of recommendation profile.

3.2 A decision model for the personal agent

Architecture of the agent system

The multi-agent environment in IRAIA addresses agents interacting in order to produce suggestions to the users navigating information spaces that are presented by theme specific taxonomies.

The evaluation criteria of recommendations

Let us define $O=\{o_1,o_2,\ldots,o_n\}$ as the user's (observed) navigation track and $T_j=\{t_{j1},t_{j2},\ldots,t_{jm_j},\ldots,t_{jn_j}\}$[4] as a recommendation from the archived sequence j of all available best practices or private navigation histories. Remember that track elements correspond to profiles containing nodes of the concept hierarchies. At each navigation step – i.e. at each query – the users select a number of concepts that constitutes a query profile.

An important role has the recommendation profile, when after a number of navigation steps the users need support for the decision which concepts to choose next. At this decision point k the user ask for recommendations that should be based on representative and helpful navigation examples from their own or the community's navigation histories.

We assume that a (community or individual) navigation history T_j is adequate for a user's retrieval if it contains in its first part (up to the point m_j that corresponds to the decision point k) as many profiles as possible similar to those of

[4] o_k and t_{jm_i} are query profiles; O and T_j contain n and n_j profiles respectively.

O and, at the same time, only a few different ones. Additionally, if there is a profile beyond t_{jm_j}, we may consider it as interesting to the user. Thus a recommendation for further navigation comprises all the nodes of the first profile of T_j beyond the point t_{jm_j}, that is t_{jm_j+1}. In general, it can be assumed that as closer the profile comes to the decision point the more useful it is for recommendation.

We assume that an information problem triggering and steering the user's navigation can be divided into a smaller number of sub-problems that can be observed frequently over a number of more complex problems. Even if two users have the same information problem they satisfy their need in a different way resulting in different sequences of profiles. Certain clusters among these sequences, however, are very similar. We therefore apply our analysis to these "atomic" problems. At the same time it can be assumed that the user needs decision support that addresses the most recent navigation history that usually coincides more with such an "atomic" problem rather than a larger sequence of past navigation steps. Let $O_c = \{o_{k-L}, \cdots, o_{k-1}, o_k\} \in O$ be a sequence of profiles in the actual navigation and $T_{jc} = \{t_{jm_j-L}, \cdots, t_{jm_j-1}, t_{jm_j}\} \in T_j$ the part to be compared from an archived navigation (of best practices or personal history).

Then the agent resorts to a certain archived track if it complies the following conditions[5].

1. Sufficient similarity between pairs of profiles.

Let us assume that I_{O_c} and $I_{T_{jc}}$ are the indexes of concepts in O_c and T_{jc} respectively, w_i the weight of a concept i, C the set of indexes of O_c also contained in T_{jc}, and D the set of indexes of O_c not contained in T_{jc}.

Then, we define the rate of common concepts as $\phi = \frac{\sum_{i \in C} w_i}{\sum_{I_{o_c}} w_i}$.

In the same way we define the rate of distinct concepts as $\delta = \frac{\sum_{i \in D} w_i}{\sum_{I_{T_{jc}}} w_i}$.

Therefore, a sufficient similarity is expressed here by ϕ >= 0.5.

5 All the values mentioned here are just initial ones. They all have to be approved by later tests.

If two profiles $t_v \in T_{jc}$ and $o_u \in O_c$ fulfil this criteria, we say both are similar or $t_v \approx o_u$.

Thus, we can define the following similarity function $\sigma = \phi(1-\delta)$
If O_c and T_{jc} contain exactly the same concepts holds $\sigma = 1$, whereas it holds $\sigma = 0$ if they are completely different. According to our model we may put $|O_c| = |T_{ic}|$, $w_i = 1/|O_c|$ $\forall i \in I_o$ and additionally the half of concepts are common, then we have $\sigma = 1/4$. In other words, the existence of distinct concepts impose a penalty to the similarity aggregated function. The more the distinct concepts in T_{jc} are important, the bigger this penalty.

These criteria are evaluated independently of profiles, that is, we use all concepts in O_c and T_{jc}. It can be clearly a problem, but it permits to do a first evaluation of tracks T_{jc}.

Thus, the decision processes of the agents are single filtering processes. In such case, we think the user have no deal with this filtering and they must remain ignorant about the agent's logic. Only the experts may set the values of these parameters.

2. Sufficient similar history among both sequences of profiles O_c and T_{jc}.
O_c and T_{jc} are similar if:
$\forall o_u \in O_c \wedge \forall t_v \in T_{jc} : o_u \approx t_v$ with $k - L \le u \le k$ and $m_j - L \le v \le m_j$. For the time being we put $L \ge 2$.

3. The **ordering** of concepts within a profile o_u or t_v, as well as the ordering of profiles within O_c or T_{jc} is irrelevant.

4. Availability of recommendation profiles.
$o_k \approx t_{jm_j}$ and $\exists t_{jm_j+1}$. This means that the decision point may lay anywhere in O as long as there is a corresponding point m_j in T_{jc} that has a profile in $m_j + 1$.
Let l_{uv}^j be the shortest path from $o_u \in O_c$ to $t_v \in T_{jc}$ $(t_v \notin O_c)$. Then, total distance to non common concepts is expressed by $\theta = \sum_v \min_u \{l_{uv}^j\}$. Thus we have three criteria used for evaluate the recommendation quality: $g_1(T_{jc}) = \phi$, $g_2(T_{jc}) = \delta$ and $g_3(T_{jc}) = \theta$.

Note that the similarity and dissimilarity functions permit to establish what a practices are recommendable or not:

- $g_1(T_{jc}) \geq \xi_1 \quad and \quad g_2(T_{jc}) < \xi_2$, T_{jc} is a recommendable practice.
- $g_1(T_{jc}) \geq \xi_1 \quad and \quad g_2(T_{jc}) \geq \xi_2$, T_{jc} is not a recommendable practice.
- $g_1(T_{jc}) < \xi_1 \quad and \quad g_2(T_{jc}) < \xi_2$, T_{jc} is not a recommendable practice.
- $g_1(T_{jc}) < \xi_1 \quad and \quad g_2(T_{jc}) \geq \xi_2$, T_{jc} is not a recommendable practice.

Here, $\xi_1 \in [0.5,1), \xi_2 \in (0,0.5]$ are thresholds representing the expected similarity and dissimilarity bounds, respectively, for the recommended practices (or archived sequences).

Elaborating suggestions to user

Evaluating and selecting recommendations for the user means assigning best practices selected by the personal agent according to one of three classes: interesting (C_3), potentially interesting (C_2) or non interesting (C_1) suggestions. A category is explained by one (or two) bounder profile, i.e. a vector where each component indicates the evaluation on a criterion for a particular recommendation situation (see Fig. 7). Let b_h $(h = 1,2)$ a category bounder profile; then, it is perfectly defined, in terms of criteria, by the vector $(g_1(b_h), g_2(b_h), g_3(b_h))$.

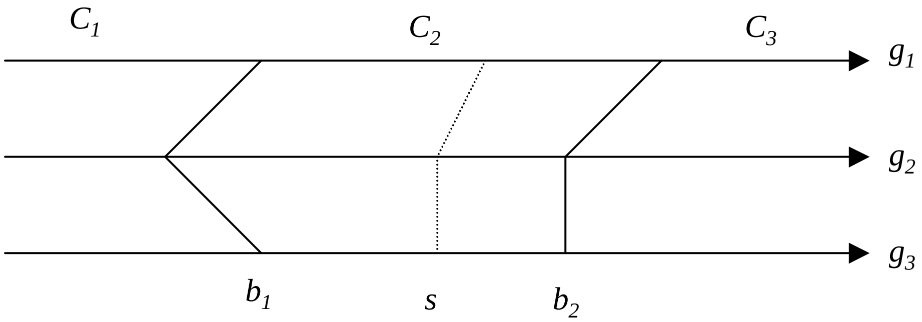

Figure 7. Criteria, categories and bounders of category profiles

Thus, let $s \in S$ be a suggested best practice and S a binary preference relation, nominated an *outranking relation,* such that the expression $s \geq b_h$ means that s is "at least as good as" b_h, i.e. $(g_1(s), g_2(s), g_3(s))$ is globally evaluated, in terms of preferences, as similar or right-side from $(g_1(b_h), g_2(b_h), g_3(b_h))$. For instance, we have $s \geq b_1$, but *not*($s \geq b_2$).

At this point, we propose to use the pessimistic ELECTRE TRI method [Mousseau et al. 01] to assign best practices. This method bases on a paired comparison between suggested best practices and the category bounder profiles. Therefore, in the pessimistic assignment procedure $s \in S$ is assigned to C_{h+1} if b_h $(h = 2,1)$ is the first profile where $s \geq b_h$. Actually, in ELECTRE TRI, one must set an index $\sigma(s,b_h)$ reflecting the credibility of statement $s \geq b_h$. A cutting level λ is also set to found the minimal credibility which permits to validate the statement. The next relations describe the global comparison among a suggested best practice and a bounder profile:

$$
\begin{array}{llllllll}
\sigma(s,b_h) \geq \lambda & \textit{and} & \sigma(b_h,s) \geq \lambda & \Rightarrow & s \geq b_h & \textit{and} & b_h \geq s & ;s \ \textit{assigned to } C_{h+1} \\
\sigma(s,b_h) \geq \lambda & \textit{and} & \sigma(b_h,s) < \lambda & \Rightarrow & s \geq b_h & \textit{and} & \textit{not}(b_h \geq s) & ;s \ \textit{assigned to } C_{h+1} \\
\sigma(s,b_h) < \lambda & \textit{and} & \sigma(b_h,s) \geq \lambda & \Rightarrow & \textit{not}(s \geq b_h) & \textit{and} & b_h \geq s & ;s \ \textit{not assigned to } C_{h+1} \\
\sigma(s,b_h) < \lambda & \textit{and} & \sigma(b_h,s) < \lambda & \Rightarrow & \textit{not}(s \geq b_h) & \textit{and} & \textit{not}(b_h \geq s) & ;s \ \textit{not assigned to } C_{h+1}.
\end{array}
$$

4 Conclusion

In this paper, we presented a model of user involvement that goes beyond the scope of the methods of usability engineering. It means placing the users in the control loop by enabling them to manipulate retrieval protocols that otherwise would be compiled and applied automatically. This outstanding trait requires the use of personal assistance that is made possible by adaptable software agents. These personal software companions are available to the users just-in-time, on-demand and help users, for instance, with refinement of retrieval strategies. The assistance is derived from best practice with individual or community-wide information search strategies without loosing the view on privacy issues. Software companions facilitating this assistance are adaptable to the users' individual retrieval needs and preferences. This kind of personalisation will be more and more an issue for future emerging systems.

In addition, user involvement as envisaged here avoids having to design systems in which retrieval tasks are completely automated; some processes already observed are extremely difficult to automate. Although personalisation alleviates this, the result is an ad hoc compilation of the user's process descriptions.

We tested the outlined implementation of our model within the user evaluation phase of IRAIA, majorly to discuss privacy concerns of personalisation. Threshold values as presented here emerged from the estimation of the experts involved in the project. The assistance functionality was welcomed, in general. However, there were always privacy concerns raised that focused in our case on business critical information not being treated confidentially enough. This problem could be mitigated by realising personal assistance exclusively through locally installed software components with local storage of personal data. For the majority of users the current browser-based systems do not provide sufficiently for confidentiality.

5 References

[Agosti et al. 92]. Agosti, M.; Gradegnio, G.; Marchetti, P. "A hypertext environment for interacting with large databases." Information processing and management, 28 (1992), 371-387.

[André & Rist 02]. André, E.; Rist, T. "From adaptive hypertext to personalized web companions." Communications of the ACM, 45/5 (2002), 43-46.

[Billsus et al. 02]. Billsus, D.; Brunk, C.; Evans, C.; Gladish, B.; Pazzani, M. "Adaptive interfaces for ubiquitous web access." Communications of the ACM, 45/5 (2002), 34-38.

[Billsus & Pazzani 99]. Billsus, D.; Pazzani, M. "A personal news agent that talks, learns and explains." In: Etzioni, O. et al (eds), Proceedings of the third annual conference on autonomous agents. Seattle (USA). 1999. 268-275.

[Brusilovsky & Maybury 02]. Brusilovsky, P.; Maybury, M. "From adaptive hypermedia to the adaptive web." Communications of the ACM, 45/5 (2002), 31-33.

[Durfee 01]. Durfee, E. "Scaling up agent coordination strategies." Computer. 34/7 (2001) 39-45.

[Englmeier et al. 01]. Englmeier, K.; Mothe, J.; Pauer, B. "Users bootstrap searching the Web through interactive agents supporting best practice sharing." In: M.J. Smith; G. Salvendy; D. Harris; R.J. Koubek. Usability Evaluation and Interface Design: Cognitive Engineering, Intelligent Agents and Virtual Reality. Mahwah, USA (2001). 923-927.

[Krause 96]. Krause, J. "Informationserschließung und -bereitstellung zwischen Deregulation, Kommerzialisierung und weltweiter Vernetzung. ("Schalenmodell")." IZ-Arbeitsbericht Nr. 6. 19 (1996).

[Mladenic 99]. Mladenic, D. "Text-learning and related intelligent agents: a survey." IEEE INTELLIGENT SYSTEMS, 14/4 (1999), 44-54.

[Mousseau et al. 01]. Mousseau, V.; Figueira, J.; Naux, J. "Using assignment examples to infer weights for ELECTRE TRI method: some experimental results." European Journal of Operational Research 130 (2001) 263-275.

[Wermter 00]. Wermter, S. "Neural network agents for learning semantic text classification." Information Retrieval, 3/2 (2000), 87-103

[Yang et al. 99]. Yang, Y.; Carbonell, J.; Brown, R.; Pierce, T.; Archibald, B.; Liu, X. "Learning Approaches for Detecting and Tracking News Events." IEEE INTELLIGENT SYSTEMS, 14/4 (1999), 32-43.

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