USE: a Multi-Agent User-Driven Recommendation System for Semantic Knowledge Extraction

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ABSTRACT

Semiotics is a field where research on Computer Science methodologies has focused, mainly concerning Syntax and Semantics. These methodologies, however, are lacking of some flexibility for the continuously evolving web community, in which the knowledge is classified with tags rather than with ontologies. In this paper we propose a multi-agent system for the recommendation of tagged pictures obtained from mainstream Web applications. The agents in this system execute a hybrid reasoning based on *WordNet* and Markov chains that is able, driven by user feedback, to iteratively disambiguate the semantics of the picture tags and thus to generate knowledge from the, a priori arbitrary, information available in the Internet..

Keywords: semiotic, ambiguity and disambiguation, multi-agent based recommendation systems, Markov chains, knowledge generation.

1. INTRODUCTION

Nowadays the communication professionals, particularly those who work on visual communication and branding design, do not have any specialized tool to work on an individual brainstorming, and the creative research is based on a relationship between concepts and depends on their distance to the knowledge. The search for inspiration is commonly based on a free navigation over the Internet, relating concepts and matching associations on a non-cooperative method.

In this context, recommendation systems [32] can be useful in building innovative tools that lead those professionals in their creative searches. The emergence of recommendation systems was fostered by the user need to deal with internet information overload. Such systems are a means to provide personalized recommendations, content, and services to them. They have been studied and applied in several domains such as Web content, music, movies recommendation. In recommender systems users *rate* items they like and such ratings are stored and used by the systems to make further recommendation.

In literature, recommendation systems have been classified into *content-based*, *collaborative filtering* and *hybrid* systems [8]. Content-based systems recommend the user by means of an utility function which computes the degree of similarity of new items w.r.t. the previously user rated and especially deal with text-based recommendation (Web pages). The recommendation process is based on keywords and some heuristics or Bayesian classifiers [12,13]. Collaborative recommendation systems are based on ratings computed by the utility function taking into account the rate of other users to the same items [15]. Both approaches deal moreover with *absolute* value prediction of non rated items. The prediction is estimated in many different ways using methods from machine learning such as clustering, decision trees and artificial neural networks, approximation theory, and various heuristics. Several problems have been identified for such approaches, such as limited content analysis, new user, new items, overspecialization, and sparsity [9]. Though some of these problems can be overcome by hybrid approaches [10,11], still some problems remain unsolved such as the comprehensive understanding/building of the users profiles/behaviors and items and non-intrusiveness [9].

In the following we propose an hybrid approach where we address these limitations focusing on the creation of a user behavior, world behavior model and on the human computer interaction design which makes the rating process more natural to the user.

The paper is organized as follows. In the next section we present the theoretical background based on the semantic and semiotics study and we introduce the meta-agent concept as the algorithm we use to find common paths on knowledge discovery and semantic association. In Section 2 the main motivations and objectives of the *USE* system are summarized. Section 3 describes the technology background we have chosen to fulfill the *USE* requirements. In Section 4 we explain the ambiguity and disambiguation processes by means of an example. Section 5 outlines the system deployment. Finally, Section 6 and 7 cover the related works and present some conclusions.

2. THE *USE* SYSTEM

Because the text search in Internet is always bound to objects, images can be used as the signs on a specific semiosis process.

In this context, we introduce *USE* ('Uplift Seek Engine'), a tool for the improvement of the individual brainstorm process for the search of images. This is accomplished by receiving the user inputs on how accurately the tags assigned to an image semantically describe it, and continuously using the generated history of the semantic relationships established between the concepts and the tags.

By its conception, *USE* is a self-brainstorming engine that pursuits the attempt to establish a systems-semiotic framework to explain creativity in the design process, where the design process is considered to have as its basis the cognitive process, identified as a dynamic relationship between abstract concepts mapped over a sequence of selected signs.

Concept navigation, represented as a flow, allows the users for some different approaches whether the state of the work is on the problem definition, including problem analysis, redefinition, and all aspects associated with clearly defining the problem; on the idea generation, related to the divergent process of coming up with ideas; or on the idea selection, as the convergent process of reducing all the many ideas into realistic solutions. The identification of the exact conjuncture is based on two distinct aspects: the ambiguity or disambiguation of a certain sign.

Therefore, our system is also, in a way, a process of knowledge generation. This generation is based on the optimization of the semantical disambiguation process by analyzing the decision paths taken by the user, and the dissociation of pre-established misconceptions on the ambiguity process.

In *USE*, the target user we want to arrive to is highly technology-dependent and with a particular sensibility for using applications that have no objectively defined purpose. Hence they prefer to spend much of their time in virtual playgrounds or on open-mind activities. The essence of the creative process is specifically the abstraction of the duty of finding distinctive ways to communicate the target values.

Because there is not so far enough research on concentrating and maximizing the efforts of these users, we consider *USE* a novel tool with an scalable architecture that can be applied in other domains that deal with cognitive processes and conceptual knowledge generation. *USE* is, in conclusion, a tool raised from the need of finding a new idea, within the minimum amount of time, on a intuitive and relaxing way. Opposed to the actual search tools, *USE* is used to find what has not been searched before.

3. TECHNICAL BACKGROUND

Semantic and tags. *WordNet*

A lot of potentially useful information available in the World Wide Web is associated with tags: pictures, texts, maps, video clips, music tracks are just a few examples. Tags are metadata pieces expressed in the form of keywords or terms which try to identify a single information item [2]. These tags are assigned by Internet users, either directly by the application this information is hosted in, or either by adding a link to the item in a Web aggregator like *del.icio.us*. This cognitive process has a wide degree of freedom, and only requires from the user to write down a list of related but potentially arbitrary keywords [3].

It can be argued that this "excessive" freedom required by the tagging process makes it difficult, if not impossible, to properly classify and give semantics[1] to the concepts and relationships defined by the tags. However, in the last years research on tagging has been growing and solutions to this problem are currently being addressed [4,5]. In this paper we will focus on human-driven disambiguation, using *WordNet* as a support tool for the retrieval of semantic knowledge associated to tags.

WordNet [6] is a large browseable lexical database, available in several languages, which groups synsets[2] that express a distinct concept. Semantic and lexical relationships between pairs of synsets are also expressed as links in the database.

Semiotics – Ambiguity and Disambiguation

The system front-end provides the user a simple and intuitive interface where he can navigate over different images, building his own conceptual map, and a text search field where he inputs the first string that unchains the semiotic catharsis or cooperative sign processing (semiosis). The semiotic machine anticipates the relationship between related concepts and consequently interprets the context of such exploratory search based on the previous relationships and the word links previous defined.

If we define *semiotics* as Peirce: "the doctrine of the essential nature and fundamental varieties of possible semiosis", *semiosis* as the "intelligent, or triadic action of a sign" which involves "a cooperation of three subjects, such as a sign, its object, and its interpretant", and if we accept Peirce's "provisional assumption that the interpretant is […] a sufficiently close analogue of a modification of consciousness" [20], the idea of a *semiotic machine* must appear a contradiction in terms. *Semiotic*, according to such premises, seems to presuppose living organisms as sign producers and sign interpreters. Whether the "action of the sign" can also develop in machines or whether semiosis does in fact presuppose life is the problem to be examined in the following on the basis of Peirce's semiotics.

Whereas the sign processes within machines are semiotic processes [21], processes in which machines serve as mediators in human semiosis are certainly processes of genuine semiosis. If a traffic sign is a genuine sign to a driver, an automatic traffic light is no less a genuine sign. In this sense, sign processing in the interface between humans and computers is genuine semiosis [22, 23]. Signs are produced by humans, mediated by machines, and interpreted by humans. In this classical communication chain, the computer pertains to the message [24].

However we propose a system that induces an automatic learning agent working like an interpretant that is one step forward on the semiosis process of the user it represents. [25] Therefore the implemented semiotic machine is a prediction entity of semiotic "artifacts:" signs, messages, and significations.

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[1] Semantics, in linguistics, is the study of the interpretation of signs [1].
[2] A synset is a set of cognitive synonyms.

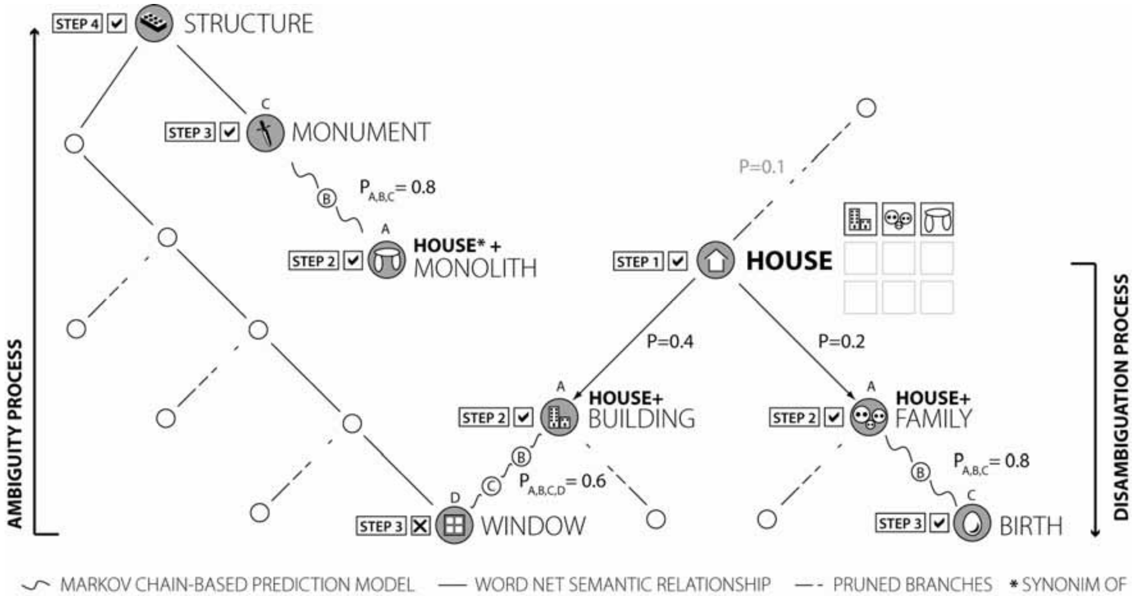

Figure 1: Ambiguity and Disambiguation processes

Another acknowledgment is if some sign entity were provided as input to the semiotic machine, the system would generate interpretations according to a given context [26]. We cannot escape the cultural understanding, or the more specific semiotic understanding, without ignoring interpretations based on how people conceive of and use machines, or become involved in particular sign processes [27]. For that reason the system is able to identify certain patterns on the different users' cognitive models, storing and reinforcing some of the relationships among concepts. The task of the system is to understand what types of signs exist, how they combine, how they yield simple or complex significations, and, eventually, how they refer to an object or to a thought [28].

The system's main criteria are to identify the scope of the significations, contextualizing them with new signs. As the system shows some images tagged with words following the path of the disambiguation process (or contextualization), the user could evaluate some of them as "non-valid". Therefore he identifies a wrong context, and the system finds new ambiguity concepts where new creative paths can be distilled [29, 30].

The ambiguity process is presented in three types: ambiguity of information, ambiguity of context and ambiguity of relationship. Ambiguity of information is inherent in how information is presented. This approach contributes to various interpretations (subjective understandings), and challenges the participants to apply their existing knowledge in different ways. On the concept map it means that we are considering that the miss-evaluated image is part of a bigger concept and the subjection of this concept give new ways to the user on how to exchange between significations. Ambiguity of context is manifested in different or unique situations in order to contribute/impact someone's interpretation. This approach uses juxtaposition and dualities to elicit multiple understandings. It means that the significations are seemed as correct but the signs are not well identified. The system presents new leaves over the same major concept when identify a strong correlation between the right-evaluated images and the ones the user chooses to be less accurate. Lastly, ambiguity of relationships draws upon one's personal or reactionary relationship to an object that is not necessarily ambiguous itself. This approach relies on the automatic learning process of the MindMap agent that tries to arrive at mostly affected meanings specific for each particular user cognitive process.

The exchange between the ambiguity and disambiguation process results on a highly effective way to reach to hidden concepts on the early design briefing.

Multi-Agent Systems

Multi-Agent Systems [17] are computing systems in which a set of autonomous intelligent agents interact in order to achieve shared or individual goals or fulfill tasks in a distributed fashion. This paradigm has been applied in many fields and is currently being integrated with other distributed technologies, such as Web Services [19] or the Grid [18].

Thus, in a multi-agent system, each agent is a piece of software that has a certain behavior with some level of intelligence, and can also create, receive, manage and communicate beliefs, intentions and goals.

Multi-agent systems provides us with a well defined communication specification composed of performatives an protocols, which allows us to integrate our system with already existing FIPA-compliant agents and integrate with other multi-agent systems, including Virtual Organizations and Electronic Institutions.

Markov chains

We use the same model, based in Markov chains, for estimating both current and foreseen patient behavior and location [31]. In Markov chains, the transition probability of moving from one state to another is dependent from the current perception of the state and a limited number of previous states. Our model is composed by:

- a state space S
- actions $A(s) \subseteq A$ applicable in each state $s \in S$

- transition probabilities $P_a\ (s' \mid s)$ for $s \in A$ and $a \in A(s)$
- action costs $c(a,s) > 0$
- a set $G \subseteq S$ of goal states

The state s_{i+1} that results from a state s_i and an action a_i are not predictable but are observable, and hence provide feedback for selecting the next action a_{i+1}. As a result, a solution of a Markov chain is not an action sequence, but a function π mapping states s into applicable actions $a \in A(s)$. Such a function is called a policy. A policy π assigns a probability to every state trajectory $s_0, s_1, s_2,\ldots$ starting in a state s_0, that is given by the product of all transition probabilities $P_{ai}\ (s_{i+1} \mid s_i)$ where $a_i = \pi\ (s_i)$. We assume that action in goal states have no costs and no effects (i.e., $c(a,s) = 0$ and $P_a(s \mid s) = 1$ if $s \in G$). The expected cost associated with a policy π starting in state s is the weighted average of the probability of such trajectories times their cost:

$$cost(\pi, s) = \sum_{i=0}^{\infty} c(\pi(s_i),s_i) \qquad \textbf{Eq. (1)}$$

An optimal solution is a control policy π^* that has a minimum expected cost for all states $s \in S$.

4. AMBIGUITY/DISAMBIGUITY AND REPERCUSION ON THE RECOMMENDATION

We will describe how and on which cases the system generates more ambiguous concepts and how it disambiguate other ones by using the example presented in Figure 1.

The user starts typing the word *House* (step 1). The system find nine images containing the imputed tag or any of the synonymous found on *WordNet* database (e.g. *Monolith*) and salvage the other tags associated to each image. The user is now involved in a selection procedure through which the system can identify which images are not within the abstract user's creativity process. Therefore, when the user evaluates positively one image, the system calculates global probabilistic model that connects the other tags of the image with other concepts the user may be interested in (e.g. *Building* with *Window*). This function is given by:

$$p(a,b) = k \cdot p_{wn}\,(a,b) + k' \cdot p_{mm}\,(a,b) + k'' \cdot p_{mm'}\,(a,b) + k''' \cdot p_s\,(a,b) \qquad \textbf{Eq. (2)}$$

Where p_{wn} is the probability based on the semantic relationships found on *WordNet*, p_{mm} the probability based on the user recorded mind map, $p_{mm'}$ the probability based on the collective mind map of all the users and p_s the probability based on the specific current session of work.

This relationship corresponds to the previous described disambiguation process. What we observe, for example, on the concept relation between *Building* and *Window* is a quick jump between a "global" concept *Building* and a more "concrete" concept *Window* using the above probabilistic model based on the Markov chains as explained further more on this paper. This short path saves the middle nodes because, observing the past steps and the past user(s) mind map(s), there is an high foreseen probability of reaching the *Window* concept.

However, when a concept is negatively evaluated, for example *Window* and *Monument*, both on the same step (step 3), the system proceeds with the ambiguity process, i.e. the system will find a common "global" concept on the *WordNet* semantic structure that subsumes the two denied tags under (in our example *Structure*).

The course of action of the simultaneous ambiguity/ disambiguation procedures opens the system to new free associations and dissociations. Each time a path is chosen, the probabilistic model of the relations is reinforced positively or negatively with different weights on his present session, on the personal atemporal mind map and on the collective mind map. The conjugation of reinforcements is the core of the dynamic semantic extraction that progressively makes the future creative processes more accurate.

5. MULTI-AGENT BASED RECOMMENDATION SYSTEM DESIGN

In the multi-agent system we have designed for our recommender system, there are four types of agents.

MindMap
It provides and executes the algorithms that implement the semantic analysis, the ambiguity/disambiguation resolution, and the path recommendation algorithms. Each user is represented by a MindMap agent in the system. These agents store the user profile and the Markov chain of the user being represented. Additionally, there is always a MindMap representing the community which is updated at each score given by any user at any moment.

Meta-Agent
An instance of the Meta-Agent is identified by the user and the word of the query. It maintains a continuous communication with the MindMap, sending the scores and updating the sets of words to search by. and manages the It also interacts with the *WordNet* database, the Crawlers and the Interface Provider.

Crawler
Agents of this type are basically information gatherers. When becoming active, they assign themselves an Internet site where the rest of the Crawlers are not working on. In our use case, each Crawler retrieves links to pictures identified by tags that expresses a mega-concept of *WordNet*. The links are stored in a database, along with all the tags that are bound to each of them.

Interface Provider
An agent responsible for interacting with the user, receiving the queries and scores, as well as showing the results. When a query is received, a new project context is created and an available meta-agent is assigned for handling the task. The Interface Provider also interacts with the MindMap agent in order to dynamically create interfaces adapted to the user.

As expressed in the Figure 2, the actors of the system interact as follows:

1. Users connect to the web server though a browser. They send one or more queries, each composed of one word that tries to define the concept of the image they aim to find.

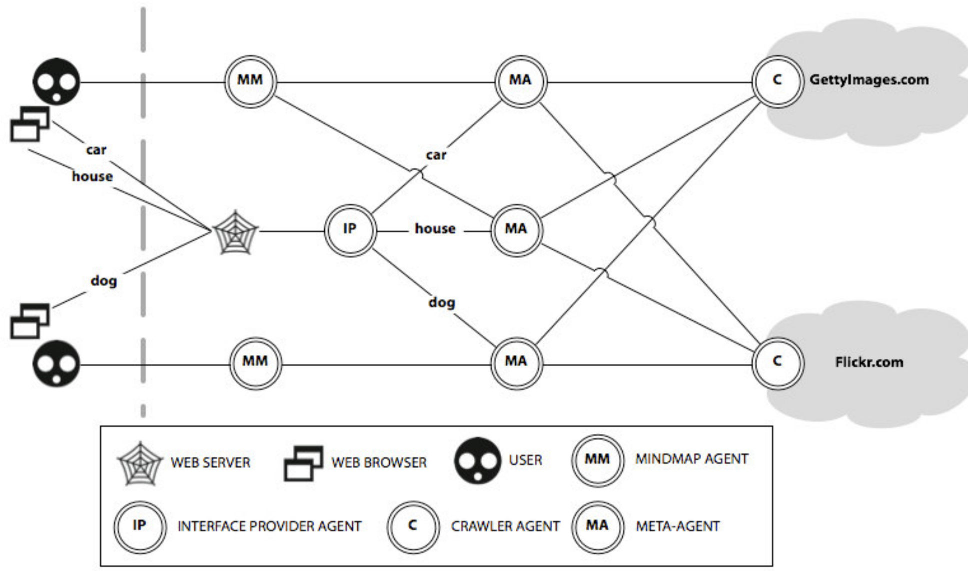

Figure 2: Deployment of the *USE* system

2. The web server redirects the query to the InterfaceProvider agent, which creates a Meta-Agent indicating the user that made the query and the word objective.
3. The Meta-Agent creates a set of sets of words with only one set, containing only one word, the one provided by the query.
4. For each set of sets of words, the Meta-Agent sends a query to the Crawlers available, treating the words of each set as the picture tags to be identified.
5. As the pictures arrive, N[3] of them are randomly selected and given back to the InterfaceProvider.
6. Through the web server, the InterfaceProvider receives the scores of each one of the N pictures and redirects them to the Meta-Agent.
7. The Meta-Agent communicates the results to the MindMap of the user.
8. The MindMap of the user updates the Markov chain, and asks the MindMap of the community to update its chain as well.
9. The Meta-Agent retrieves from the MindMap of the user the recommended next set of sets of words to search by.
10. Repeat from Step 4 until the user desires to stop the process.

The components of this multi-agent system can be deployed in distributed heterogeneous environments. For example, it is not necessary that the web server or the Meta-Agent share computer with a Crawler.

6. RELATED WORK

Many recommender systems based on software agents have been proposed in the last years. For instance, *SUGGEST* [33] and *C-Graph* [34] support user Web navigation dynamically generating links to pages that are unvisited by a user, and respectively monitoring user behavior and learning user preferences, to provide him with a set of recommendations. In the former historical information about the user behavior is maintained by means of an incremental graph partitioning algorithm, and in the latter the user knowledge is modeled into an ontology as a rooted labeled direct graph. *CBCF* [36] uses a content-based predictor to enhance existing user data, to exploit collaborative filtering to generate personalized suggestions. *X-Compass* [35] is an XML-based agent model that supports a user in his Web activities by monitoring the behavior in the Web pages access to automatically construct and manage his profile. *X-Compass* exploits such profiles to provide content-based and collaborative filtering recommendations.

All the aforementioned systems exploit an internal profile to store information relative to the user. In that sense our approach is different because we do not need to define a model of the user as we exploited Markov chains, to create a stochastic model based on the user decision paths.

Similarly, in [37] the recommendation process is viewed as a sequential decision problem and thus tackled using Markov for generating recommendations but it lack of a semantic ambiguity and disambiguation recommendation process.

7. CONCLUSIONS AND FUTURE WORKS

This project is quite challenging in terms of research, not only because of the previously defined objectives of the *USE* system, but because there are quite a few tasks to be fulfilled in the next few months.

First, we will fully formalize the user model, the recommendation process and the similarity function between users, using Graph Theory and stochastic models. Our plan is to abstract our methodology and architecture from the image recommendation domain, to make it usable in other contexts where recommendation can be useful.

We also plan to adapt this multi-agent system to its use in Virtual Organizations. Also, we will study the option of replacing Markov chains by the agent ant farm paradigm.

[3] *N* is an arbitrary number that can be changed by the user.

Finally, note that we are currently under the development of the system prototype. We will disseminate the results of the experimentations and the analysis of the validity of our model.

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REFERENCES

[1] John Lyons, **Semantics**, Cambridge University Press, ISBN:0521291860, 1977.

[2] E. Speller, "Collaborative tagging, folksonomies, distributed classification or ethno classification: a literature review", **Library Student Journal**, 2007.

[3] R. Sinha, "A cognitive analysis of tagging (or how the lower cognitive cost of tagging makes it popular)", http://www.rashmisinha.com/archives/05_09/tagging-cognitive.html, 2005.

[4] S.A. Golder and B.A. Huberman, "The Structure of Collaborative Tagging Systems", Information Dynamics Lab, HP Labs, 2005.

[5] A. Mathes, "Folksonomies – Cooperative Classification and Communication Through Shared Metadata", http://www.adammathes.com/academic/computer-mediated-communication/folksonomies.html, 2004.

[6] C. Fellbaum, ***WordNet*: An Electronic Lexical Database | Christiane Fellbaum**, MIT Press, ISBN:026206197X, 1998.

[8] M. Balabanovic and Y. Shoham, "Fab: Content-Based, Collaborative Recommendation," **Comm. ACM**, vol. 40, no. 3, 1997, pp. 66-72.

[9] G. Adomavicius, A. Tuzhilin, "Toward the Next Generation of Recommender Systems: A Survey of the State-of-the-Art and Possible Extensions", **IEEE Transactions on Knowledge and Data Engineering**, Vol. 17, No. 6., 2005, pp. 734-749.

[10] C. Basu, H. Hirsh, and W. Cohen, "Recommendation as Classification: Using Social and Content-Based Information in Recommendation," **Recommender Systems. Papers from 1998 Workshop, Technical Report WS-98-08**, AAAI Press, 1998.

[11] I. Soboroff and C. Nicholas, "Combining Content and Collaboration in Text Filtering," **Proc. Int'l Joint Conf. Artificial Intelligence Workshop: Machine Learning for Information Filtering**, 1999.

[12] R. Baeza-Yates and B. Ribeiro-Neto, **Modern Information Retrieval**, Addison-Wesley, 1999.

[13] G. Salton, **Automatic Text Processing**, Addison-Wesley, 1989.

[14] D. Billsus and M. Pazzani, "Learning Collaborative Information Filters," **Proc. Int'l Conf. Machine Learning**, 1998.

[15] J.S. Breese, D. Heckerman, and C. Kadie, "Empirical Analysis of Predictive Algorithms for Collaborative Filtering", **Proc. 14th Conf. Uncertainty in Artificial Intelligence**, 1998.

[16] G. Shani, R. Brafman, and D. Heckerman, "An MDP-Based Recommender System", **Proc. 18th Conf. Uncertainty in Artificial Intelligence**, 2002.

[17] G. Weiss, **Multiagent Systems: A Modern Approach to Distributed Artificial**, MIT Press, ISBN:0262731312, 1999.

[18] I. Foster, N.R. Jennings and C.Kesselman, "Brain meets brawn: why grid and agents need each other", **3rd International Conference on Autonomous Agents and Multi-Agent Systems**, 2004.

[19] M.N. Huhns, "Agents as Web services", **Internet Computing, IEEE**, Volume: 6, Issue: 4, 2002, pp. 93-95.

[20] C.S. Peirce, **1931-1958. Collected Papers**, Vols. 1-6, eds. C. Hartshorne & P. Weiss, vols. 7-8, ed. A. W. Burks, Cambridge, Mass.: Harvard Univ. Press, 1931-1958.

[21] P.B. Andersen, (1986). "Semiotics and informatics: computers as media." In **Information Technology and Information Use. Towards a Unified View of Information and Information Technology** (P. Ingwersen, L. Kajberg, A. Mark Pejtersen, eds.), London:Taylor, Graham, 1986, pp. 64-97.

[22] P.B. Andersen, Peter Bogh, "The force dynamics of interactive systems. Towards a computer semiotics." In **Semiotica** 103, 1/2. Berlin:Walter de Gruyter, 1995, pp. 5-45.

[23] W. Nöth, Winfried, "Semiotic Machines." In: **Cybernetics and Human Knowing**, Vol. 9, Nr. 1. UK:Imprint Academic, 2002.

[24] R. Gudwin and J. Queiroz, "Towards an Introduction to Computational Semiotics", In: C. Thompson and H. Hexmoor, eds. **Proceedings of the International Conference on Integration of Knowledge Intensive Multi-Agent Systems. KIMAS '05: Modeling, Evolution, and Engineering. IEEE Systems, Man and Cybernetic Society**, Vol.1, 2005, pp. 393-398

[25] M. Nadin, "Sign and fuzzy automata." In: **Semiosis**, Heft 1, 5. Baden-Baden: Agis Verlag, 1977.

[26] M. Nadin, **Mind—Anticipation and Chaos. (Milestones in Thought and Research)**, Zurich/Stuttgart: Belser Presse, 1991.

[27] P. Sengers, T. Kulessa and W-D. Geng, "The influencing machine - Emotions in interaction", http://www.edutainment-robotics.com/Workshop-Papers/EDU_07.pdf, 2007.

[28] C.S. de Souza, "Semiotic engineering: bringing designers and users together at interaction time." In **Interacting with Computers**, 17(3), 2005, pp. 317-341.

[29] W.W. Gaver, J. Beaver and S. Benford, "Ambiguity as a resource for design", **Proc. of the Conference on Human Factors in Computing Systems**, Fort Lauderdale, FL, New York: ACM Press, 2003.

[30] G. Döben-Hensich, L. Erasmus, J. Hasebrook, "Knowledge Robots for Knowledge Workers: Self-Learning Agents Connecting Information and Skills", In: Jain, L.C., Zhengxin Chen, N. Ichalkaranje, eds. **Intelligent Agents and Their Applications (Studies in Fuzziness and Soft Computing)** Vol. 98. New York:Springer, 2002.

[31]Charniak, E., Hendrickson, C., Jacobson, N., and Perkowitz, M. Equations for part-of-speech tagging. In **Proceedings of the Eleventh National Conference on Artificial Intelligence**. AAAI Press/MIT Press, Menlo Park, 1993, 784-789.

[32]**Proceedings of the 2007 ACM Conference on Recommender Systems**. ISBN: 978-1-59593-730-8

[33]Silvestri, F., Baraglia, R., Palmerini, P., Serran`o, M.: On-line generation of suggestions for web users. J. of **Digital Information Management** 2(2), 104–108 (2004).

[34]Buccafurri, F., Lax, G., Rosaci, D., Ursino, D.: A user behavior-based agent for improving web usage. In: **CoopIS/DOA/ODBASE**, pp. 1168–1185 (2002).

[35]Garruzzo, S., Modafferi, S., Rosaci, D., Ursino, D.: X-Compass: An XML Agent for Supporting User Navigation on the Web. In: Andreasen, T., Motro, A., Christiansen, H., Larsen, H.L. (eds.) FQAS 2002. LNCS (LNAI), vol. 2522, pp. 197–211. Springer, Heidelberg (2002).

[36]Melville, P., Mooney, R.J., Nagarajan, R.: Content-boosted collaborative filtering for improved recommendations. In: **AAAI/IAAI**, pp. 187–192 (2002).

[37] G. Shani, R. Brafman, and D. Heckerman, "An MDP-Based Recommender System," Proc. **18th Conf. Uncertainty in Artificial Intelligence**, Aug. 2002.