Network Science @ Recommender Systems

László Grad-Gyenge

Electronic Commerce Group
Vienna University of Technology, Vienna, Austria
laszlo.grad-gyenge@ec.tuwien.ac.at

Abstract. We present a conceptual approach in the field of recommender systems, which is intended to model human consumption by maintaining a network of heterogeneous nodes and relationships. We think of this model as the reflection of the corresponding cognitive functionality of human thinking, as we maintain a structure which is similar to the structures established by neural networks. To explain our motivation and the proposed structure we are combining the results of recommender systems and network science. We propose a generalized approach that intends to involve concepts from social networks, semantic distance, association rule mining, ontological modeling and expert systems. Our approach will access and integrate different information sources, modeling also additional information types. We expect that our approach will find the importance factors of the aforementioned information sources for the generation of high quality recommendations.

Keywords: Network Science, Recommender Systems, Spreading Activation, Error Back-propagation, Recommendation Spreading.

1 Introduction

What are the mechanisms and what is the structure of the motivations behind consumption? This question could be reconstructed into a form that brings us closer to a methodology that helps us to measure the mechanisms of human consumerism through the lens of recommender systems. Recommender systems basically build a model or provide a methodology that provides a personalized and prioritized list of consumer goods and services that could be relevant for a particular customer. In other words recommender systems model human behavior from the aspect of consumption.

The origin of recommender systems can be dated back to 1966 [15] and were popularized in 1993 [1]. Since then, in the last 20 years the strong pressure from electronic commerce and the content industry have catalyzed the evolution of recommender systems and have led to a considerable progress in this area. This development can be measured either in the increasing amount of information sources involved and also in the ascending number of the methods and models that are processing the data. Researchers developed several models and found many sources of information to produce personalized recommendations. By utilizing these models and methods recommender systems are implicitly modeling the incentives of

consumption by maintaining a personalized, reflective model of human consumer motivation, with rather good results.

Our goal is to build an appropriate framework that is suitable for modeling human consumption by working with a methodology that generalizes the concept of information source type and the relation between the aforementioned types. We present a conceptual contribution of our novel framework in the area of recommender systems that will act as the basis of the analysis of heterogeneous information sources personalized recommendations can be supported by. The framework helps us to find the importance factor of each information source type. The approach is strongly based on the achievements of network science and maintains a knowledge base with a structure of a labeled, directed, weighted non-acyclic graph, namely a network.

The related work in the area of recommender systems will be discussed in more details in Section 2. Section 3 contains a detailed description of our motivation. In Section 4 we present our conceptual framework, we also propose novel sources of information we expect to benefit from. To summarize our contribution, the paper is to be concluded with Section 5.

2 Related Work

The first algorithm providing personalized recommendations to end-users that was developed in the area of recommender systems was mining association rules between products based on purchased-together events. The goal of Association Rule Mining (ARM) [21] is to find the articles that customers tend to purchase together. The first association rule method appeared in 1966 [15] and was popularized in 1993 [1].

The need for better recommendations involved additional sources of information to make personalized recommendations more precise. A possible categorization of recommender systems: collaborative recommendations, content-based recommendations and knowledge-based recommendations [17]. The aforementioned approaches are often combined to improve recommendation quality by various hybridization techniques [7].

Collaborative recommendation – often referred to as Collaborative Filtering (CF) – is basically a prediction of user rating supported by a historical rating database which is in most cases represented as a huge and sparse matrix. Probabilistic methods treat the rating matrix as a sample of a distribution and try to model it by applying various probabilistic methods. Examples are naïve Bayes classifier [30], matrix factorization (SVD) [20] and tensor factorization (HOSVD) [26].

Advanced CF methods for instance involve sampling [23], Bayesian belief networks [31] or apply clustering [32]. In the clustering case, CF can be treated as the refinement of the ARM technique. The most conspicuous problem of group or cluster based CF is the cold start effect, which means that the recommender system cannot provide reliable recommendations until the necessary information is collected on the user. There are various techniques developed to avoid the cold start effect, for example by defaulting ratings [5], or by involving social network [12]. The basic idea behind group based CF is that people with similar friends or interests tend to buy items similar to those a particular person would purchase [13].

Involving social networks into recommender systems is a novel and promising trend to improve the quality of recommendations. Guy et al. [12] improve CF by replacing the implicit weights with explicit weights derived from social ties to generate recommendations. He et al. [13] define a naive Bayes approach, which generates recommendations based on item attribute values, user attribute values and social ties. Defining their model they distinguish between immediate and distant friends. Yang et al. [33] define a distributable querying approach based on social networks and Bayesian inference. Konstas et al. [19] compute the recommendations utilizing random walks with the help of an adjacency matrix on a network containing users, tags and recommendable items. They introduce different weights for user-user, user-tag and user-item relationships. Kazienko et al. [18] define a layered representation of social networks where each layer represents a different aspect of the social relationships between users. These approaches show that involving social networks into recommendations is a promising source of information and also describe various methods for the technical implementation of gathering this information.

Content-based approaches – often referred to as Content-Based Filtering (CBF) – are based on a similarity measure between the recommendable items. The similarity measure is usually defined over a vector based representation of text documents. The representation can be prepared for example with a variant of the bag of words method [24] or with term frequency/inverse document frequency (TF-IDF) [27]. A common practice in text representation is to use manually defined features, like title keyword frequency related to the content [4] or genre [35]. After the document is transformed into the vector space, similarity measures (binary cosine, Jaccard [16] or cosine similarity [23]), clustering [2], linear algebra methods, linear classifiers [34], similarity trees [4] can be applied to item recommendations. The recommendations of CBF methods are the items that in the meaning of the applied distance method are similar to the items the particular customer implicitly or explicitly already expressed interest.

Knowledge-based approaches are useful in scenarios where the items have a well-structured attribute set. The philosophy of these methods is to help the user to explore the item space by following different strategies. The two most important classes of knowledge-based approaches are constraint based [10] and case based [29] recommendation techniques. Constraint based techniques are narrowing the set of possible items by asking the user for limiting constraints. Constraint based methods are also describing various strategies to resolve conflicting condition sets. Case based methods define strategies to aid the user explore the items in the high dimensional space of attributes.

The basic idea behind **hybridization** is to combine the strengths of different techniques. Parallelized hybridization design combines the results of self-contained methods by various techniques, for example the mixed, weighted or switching method [7]. Pipelined hybridization design follows a cascading rule, where recommender systems in the pipeline act as filters on the list of the recommendable items [7].

3 Motivation

The basic motivation behind hybridization techniques is to combine different recommender systems as subsystems while usually treating them as autonomous units. This technique is excellent from the point of view of system architecture and modularity, but unfortunately has the potential to lose important information that can be found in small information chunks which might be present at the level of the model, but is inherently filtered out by the hybridization technique.

Next to the information sources presented in Section 2, additional information sources can also be involved to produce recommendations. These sources are for example user tagging, rating, commenting (user-item relation with textual data); visiting patterns as transitions (item similarity with direction); sophisticated social network features (user blocks another user, user influence on another user, SNA group membership); person or item clustering on attributes or on dimension reduced attributes (PCA); calculating with antonyms in textual description or the exclusion of a manufacturer by personal taste.

We think that it is important to build a system that has the potential to involve even the smallest information chunks that can be found between the different actors because after a possible accumulation these chunks can have the influence on the final relevance order. In Section 4 we present a hybridization technique that has the capability to combine multiple information sources with the possible highest integration and lowest possibility of information loss.

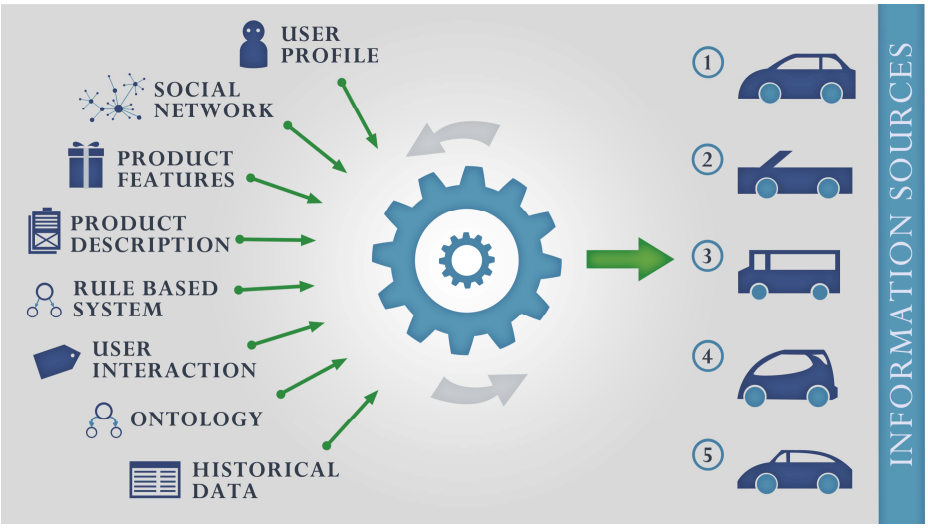

Fig. 1. The different kinds of information sources recommendations can be calculated from.

Figure 1 presents a summary of the possible information sources recommender systems can derive the recommendations from. As Figure 1 shows the scenario is very heterogeneous. Our intention is to create a generalized representation of information

that is able to unite all the already existing information sources and has the potential to provide space also for additional types as newcomers. Once the system sits on top of a huge and heterogeneous collection, then it should have the ability to learn the importance factor of each information source.

By estimating probability utilizing naive Bayes, Bayesian inference methods, applying clustering, grouping the persons and items or creating weighted sums of data, most CF and CBF methods aggregate the information. The motivation behind applying these methods is to avoid overfitting and overlearning the represented model as well as to avoid computational burdens. Our goal is to produce personalized and high quality recommendations. Our proposed method keeps the data in a higher fidelity by applying an appropriate representation method.

The social ties between human entities and the structure of the social network play an important role in the life of human individuals. People strongly rely on their social relationships even when looking for a job [11] or gathering information on the Internet [8]. The principle that individuals tend to be similar to their friends [9] is reflected also in their consumption behavior. Human entities often receive recommendations from their friends either implicitly (by experiencing new consumer behavior among acquaintance) or explicitly (by asking individuals in their social network). Modeling the cascading behavior [9] in social networks is another aspect showing that the information – which in our case is a recommendation – spread in social networks is a general property of human communication. Our intention is to utilize this mechanism of homophily in its living context, in the network, to produce more human-like recommendations.

CBF methods often involve shallow text processing methods to measure item similarity. Shallow text processing methods operate with statistical text representation and miss the semantical interpretation of the descriptions of the recommendable items or – in the case of a news recommender system – of the item itself. Although the accuracy of statistical text processing is often inadequate, it is more widely used than semantical text processing. The reason why semantic analysis is not popularized in this area could be traced back to historical reasons and its high resource requirements. Our concept gives a method for the implicit calculation of semantic distance utilizing the background information that exists in the relationships between ontology items, which calculates semantic distance with similar resource requirements than processing the other information sources.

Explanations play an important role in the life of recommender systems. Presenting reasonable explanations to the users next to the recommendations significantly increases the effectiveness of the recommendation process [17]. In order to provide explanations, nodes or paths with the highest activation values will be presented to the user. We expect that our proposed method produces effective explanations, because the method of their generation is similar to human thinking.

3.1 A Sample Scenario

Before we introduce the system, we illustrate our motivation with an imaginary scenario, which can help us to explain the proposed mechanism behind the generation of recommendations.

Eve wants to buy a new perfume to replace her current one, Orienta. There are two possible candidates, Pinky and Fracca. She asks her boyfriend, Peter, and he suggests Pinky. Eve also asks her friend, Irene, who is not interested in perfumes but asks her friends, Petra and Sarah. Petra votes for Pinky and Sarah votes for Fracca. Reading the product descriptions Eve finds out that Fracca is produced in Paris and Orienta is produced in Angers. Both cities are located in France. Besides other components, Orienta contains Musk and Amber. Eve likes Musk, but dislikes Amber. Musk is also the component of Pinky and Amber is also the component of Fracca.

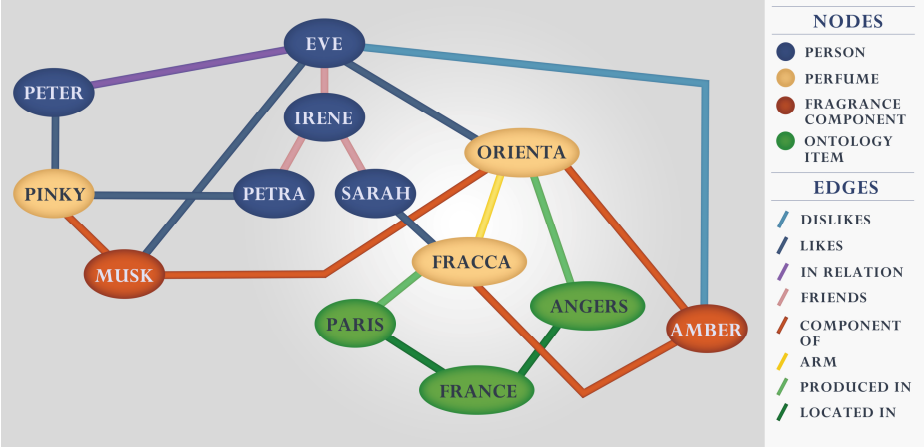

Fig. 2. A sample scenario for a recommendation case. The nodes of the network show the entities and the edges show the relationships between the entities.

Figure 2 visualizes the described scenario, illustrating the different node and relationship types with their respective colors. For this imaginary recommendation case various information sources present for the estimation of the most adequate perfume for Eve. Eve, Peter, Irene, Petra, Sarah and the relationships "in relation" and "friends" between them illustrate a social network. The edge "likes" between persons and perfumes show their relationship to the perfumes. Musk, Amber, their relationships "component of" to the perfumes and the edges "likes" and "dislikes" from Eve to Amber and Musk can be processed involving an expert system. The relation "located in" between Angers and Paris can be perceived with the help of an ontology, while the edges "produced in" between perfumes and ontology items illustrate the result of text processing. The edge "ARM" between Orienta and Fracca illustrates that association rule mining can also aid recommendations.

This example illustrates that this scenario combines (i) social networks – as a special case of CF; (ii) expert systems – as an illustration of knowledge-based recommendation; (iii) ARM – a similarity measure for CF and (iv) ontology as a semantic distance, which can be treated as a CBF approach.

Analyzing Figure 2 we may ask the following questions: Which perfumes are suggested to Eve? Are the social relationships or perfume components (expert system) more important than the geographical locations (ontology relations) for producing

recommendations? How do recommendations depend on the distance in the graph of the social network? Is it enough to define a weight for each relationship type or is it necessary to involve the weights inherently presenting in a social network, thus it can lead to higher quality recommendations?

4 Description of the Method

In Section 3 we expressed in detail that we would like to define a sophisticated recommender system which involves social networks; integrates the information sources instead of working with autonomous units; aggregates multiple kinds of information sources; works with semantic distance instead of shallow text processing; generates human-like recommendations; provides explanations which fit to human thinking and is as sophisticated as possible by the availability of avoiding the creation of user groups or clusters.

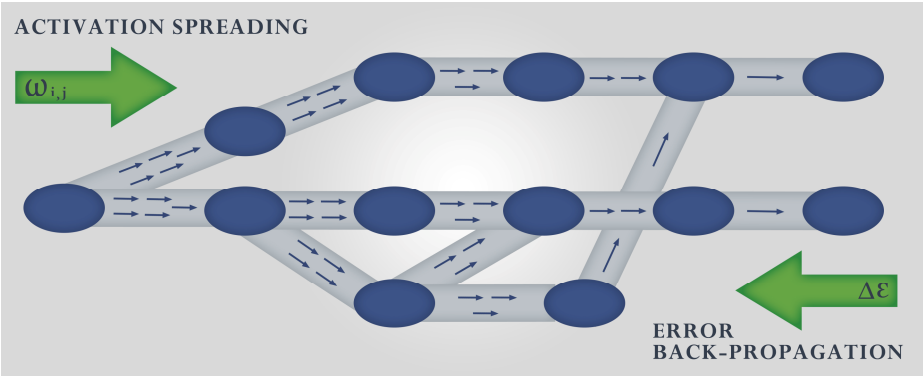

Fig. 3. Recommendations are generated by applying spreading activation, the relationship type weights are maintained by error back-propagation.

For the knowledge base of our approach we choose a directed weighted labeled graph. The nodes represent the entities. An entity is for example a user, a recommendable item, an ontology item, a tag, a group of items or a customer group. The weighted edges represent the relationships between the entities. A relationship is for example a friendship, a like, an is-a relation between ontology items or a tag presence on an item or group membership. Each edge has a type and a weight is assigned to each edge type. The recommendations are produced applying a spreading activation algorithm [3]. The type weights are tuned applying error back-propagation [6], as illustrated on Figure 3.

The model distinguishes between the weights belonging to the relationships and the weights belonging to the relationship types. A relationship type weight may represent the strength of a social tie between two persons or the confidence of an ARM rule between two items. The relationship type weights are introduced to distinguish the importance of different kinds of relationships which exist among the

nodes. It is important to let the model adapt for example to the difference between the importance of social ties and the is-a relationship in the ontology. These weights are then fine-tuned by the error back-propagation algorithm based on the feedbacks provided by the users and after a long time application on a specific domain we expect these weights to converge and let us reveal the structure behind the importance of these factors.

The model enables assigning attributes to the nodes of the network, which we treat as the content of the nodes. Deriving relationships from the content of the nodes is important because these relationships can help us provide better recommendations. A possibility that is inherently supported by our model is to create grouping nodes based on the attributes of the persons or items. Figure 2 illustrates how these relations can be represented in the case of perfumes and perfume fragrance compounds. These attributes can be processed by various clustering algorithms or expert systems and can bind the person or item nodes to clustering or grouping nodes. By involving clustering methods and examining how their relationship type weight is related to the weights of explicit relationship types the usefulness of aggregated information versus high fidelity information can be revealed.

In Section 3 we mentioned that one of our goals is to introduce a distance measure that is a possible alternative to shallow text parsing. IJntema et al. [16] define a measure over textual content involving an ontology by examining how the direct contexts (one step away in the ontology) of the two words overlap. In our approach we will extend this one-step context of words inherently by spreading activation. The ontology will be stored in our knowledge base as a subnetwork with the distinguishing node type: “ontology”. To preserve the ontology relationships we introduce the following relationship types: “hypernym”, “hyponym”, “synonym”, “acronym” and “meronym” and will assign these types to the corresponding relationships. We will bind the item nodes to ontology nodes based on the result of text processing (for instance: TF-IDF). We expect that our spreading method will reveal hidden relationships between nodes, provides a more appropriate measure of textual items, and will act as a proper semantic similarity.

A frequently used relationship between recommendable items is provided by ARM. As our model is flexible, it can represent an association rule between two items as a relationship between the nodes representing the particular items. The attributes of this derived relationship represent the confidence and support of the association rule, and similarly to Lin et al. [22] its weight can be derived from these measures.

4.1 Spreading Activation

Web science has a strong influence on our approach. An often mentioned and illustrative method for the calculation of the importance of nodes in networks is PageRank algorithm [25]. PageRank is an iterative algorithm that can be explained by circulating a "fluid" in the network, which fluid represents importance (in its specific meaning) and will be accumulated at the influential nodes. The PageRank algorithm can be treated as a spreading activation algorithm.

Spreading activation is applied on networked data. Its goal is to define a similarity or distance measure among the nodes in a network. The interpretation of the distance

depends on the information stored in the knowledge base, to which it is applied. Spreading activation was introduced in 1983 [3] and has several applications, for example Sieg et al. [28] involve this technique to generate personalized web search results, Hochmeister [14] spreads expertise scores among topics in learners' models.

Our spreading activation algorithm starts with initial spreading values in the nodes. In the recommendation case for a particular person we will set its activation value to an initial constant value. The activation value of other nodes will be set to zero. Each iteration step a percentage of the activation value spreads out from each node to its neighboring nodes weaken by the weight values of relationships and relationship types. The activation of each node will be decreased by a factor, with the intention to reduce the static activation towards zero in time. Thresholding is applied to the activation scores and to the length of the activation path. The spreading continues until a termination condition occurs.

4 Conclusion

We presented a conceptual recommendation technique in the field of recommender systems with the involvement of network science. We introduced an approach that (i) aggregates multiple information sources, (ii) shows a refined hybridization technique, (iii) works at a higher level of fidelity, (iv) suggests an enhancement to shallow text analysis by integrating an ontology, (v) involves social networks and (vi) provides explanations that are close to human thinking.

We propose a novel hybridization technique and a possible alternative to collaborative filtering (in case of involving a social network), content based filtering (utilizing the network to measure item similarity) and knowledge based recommendations (a reasoning technique based on spreading). Deduced from its architecture our approach is not intended to be used as a constraint based recommender system. As mentioned in Section 4, in case a social network is not available, clustering methods can be applied to create clustering nodes of persons. By spreading through these clustering nodes our method can be treated as a CF approach. Similar to clustering nodes on persons, grouping nodes of items based on item properties can also be created. Starting the spreading from these grouping nodes leads to a case based recommendation technique.

In case of a huge network, activation spreading can be resource consuming. To avoid the resource burden we apply constraints to the spreading, which may lead to a decrease in the recommendation quality. Another possibility is to involve distributed computing, in which case the computations can be evaluated over the network in parallel.

To evaluate our approach we are primarily interested in its accuracy (precision, recall, root mean squared error) as also described by Jannach et al. [17] as a pure measurement of recommendation quality. Based on measures of precision and recall ROC curves of different relationship type weight configurations will also be examined as high level indicators.

Future work focuses on implementation. In the meantime we will be continuously looking for possible applications. As our method is strongly based on a social

network, we intend to introduce our method as a background service in an online environment. This is also a weakness of our approach, that in order to be able to test or utilize its capabilities a very heterogeneous database is necessary, which is probably not present at the moment.

Recommendation spreading in a heterogeneous network described in this paper and then back-propagating the error will help us finding the optimal weights for different relationship types. We expect that with the help of this technique we will reveal the importance factors of each information source types recommendations can be generated from.

Our approach maintains its knowledge base at a finer level of fidelity, while making it possible to aggregate the information. We expect that the forthcoming research with this technique will provide us with information about the optimal level of fidelity to maintain information at, for the generation of high quality, personalized recommendations.

References

1. Agrawal, R., Imielinski, T., Swami, A.: Mining Association Rules between Sets of Items in Large Databases. In: SIGMOD '93, pp. 207--216. ACM, New York, NY, USA (1993)
2. Allan, J., Carbonell, J., Doddington, G., Yamron, J., Yang, Y.: Topic Detection and Tracking Pilot Study: Final Report. In: Proceedings of the DARPA Broadcast News Transcription and Understanding Workshop, pp. 194--218. Lansdowne, VA, USA (February 1998)
3. Anderson, J.: A spreading activation theory of memory. Journal of Verbal Leaning and Verbal Behaviour 22, 261--295 (1983)
4. Bieliková, M., Kompan, M., Zeleník, D.: Effective hierarchical vector-based news representation for personalized recommendation. Comput. Sci. Inf. Syst. 9(1), 303--322 (2012)
5. Breese, J., Heckerman, D., Kadie, C.: Empirical analysis of predictive algorithms for collaborative filtering. In: UAI'98, pp. 43--52. Morgan Kaufmann Publishers Inc., San Francisco, CA, USA (1998)
6. Bryson, A., Ho, Y.: Applied Optimal Control. Blaisdell, New York (1969)
7. Burke, R.: Hybrid web recommender systems. In: Brusilovsky, P., Kobsa, A., Nejdl, W. (eds.) The adaptive web. LNCS, vol. 4321, pp. 377--408. Springer-Verlag, Berlin, Heidelberg (2007)
8. Chi, E.: Information Seeking Can Be Social. Computer 42(3), 42--46 (March 2009)
9. Easley, D., Kleinberg, J.: Networks, Crowds, and Markets: Reasoning About a Highly Connected World. Cambridge University Press, New York, NY, USA (2010)
10. Felfernig, A., Burke, R.: Constraint-based recommender systems: technologies and research issues. In: ICEC '08, pp. 3:1--8. ACM, New York, NY, USA (2008)
11. Granovetter, M.: The Strength of Weak Ties. The American Journal of Sociology 78(6), 1360--1380 (1973)
12. Guy, I., Zwerdling, N., Carmel, D., Ronen, I., Uziel, E., Yogev, S., Ofek-Koifman, S.: Personalized recommendation of social software items based on social relations. In: RecSys '09, pp. 53--60. ACM, New York, NY, USA (2009)
13. He, J., Chu, W.: A Social Network-Based Recommender System (SNRS). In: Memon, N., Xu, J., Hicks, D., Chen, H. (eds.) Data Mining for Social Network Data. Annals of Information Systems, vol. 12, pp. 47--74. Springer US, Boston, MA (2010)

14.Hochmeister, M.: Spreading Expertise Scores in Overlay Learner Models. In: CSEDU 1, pp. 175--180. SciTePress (2012)
15.Hájek, P., Havel, I., Chytil, M.: The GUHA method of automatic hypotheses determination. Computing, 1(4), 293--308. (1966)
16.IJntema, W., Goossen, F., Frasincar, F., Hogenboom, F.: Ontology-based news recommendation. In: EDBT '10, 16, pp. 16:1--6. ACM, New York, NY, USA (2010)
17.Jannach, D., Zanker, M., Felfernig, A., Friedrich, G.: Recommender Systems: An Introduction. Cambridge University Press (September 2010)
18.Kazienko, P., Musial, K., Kajdanowicz, T.: Multidimensional Social Network in the Social Recommender System. IEEE Transactions on Systems, Man, and Cybernetics, Part A, 41(4), 746--759 (2011)
19.Konstas, I., Stathopoulos, V., Jose, J.: On social networks and collaborative recommendation. In: SIGIR '09, pp. 195--202. ACM, New York, NY, USA (2009)
20.Koren, Y., Bell, R., Volinsky, C.: Matrix factorization techniques for recommender systems. Computer, 42(8), 30--37 (2009)
21.Kotsiantis, S., Kanellopoulos, D.: Association Rules Mining: A Recent Overview. International Transactions on Computer Science and Engineering 32(1), 71--82 (2006)
22.Lin, W., Alvarez, S., Ruiz, C.: Efficient Adaptive Support Association Rule Mining for Recommender Systems. Data Min. Knowl. Discov. 6(1), 83--105 (January 2002)
23.Linden, G., Smith, B., York, J.: Amazon.com Recommendations: Item-to-Item Collaborative Filtering. IEEE Internet Computing 7(1), 76--80 (2003)
24.Lorincz, A.: Innovation Engine for Blog Spaces. Technical report, DTIC Document (2011)
25.Page, L., Brin, S., Motwani, R., Winograd, T.: The PageRank Citation Ranking: Bringing Order to the Web. Technical Report 1999-66, Stanford InfoLab (November 1999)
26.Pilászy, I., Zibriczky, D., Tikk, D.: Fast als-based matrix factorization for explicit and implicit feedback datasets. In: RecSys '10, pp. 71--78. ACM, New York, NY, USA (2010)
27.Salton, G.: Automatic text processing: the transformation, analysis, and retrieval of information by computer. Addison-Wesley Longman Publishing Co., Inc., Boston, MA, USA (1989)
28.Sieg, A., Mobasher, B., Burke, R.: Web search personalization with ontological user profiles. In: CIKM '07, pp. 525--534. New York, NY, USA (2007)
29.Smyth, B.: Case-based recommendation. In: Brusilovsky, P., Kobsa, A., Nejdl, W. (eds.) The adaptive web. LNCS, pp. 342--376. Springer-Verlag, Berlin, Heidelberg (2007)
30.Wang, K., Tan, Y.: A new collaborative filtering recommendation approach based on naive Bayesian method. In: ICSI'11, pp. 218--227. Springer-Verlag, Berlin, Heidelberg (2011)
31.Weng, S., Liu, S., Wu, T.: Applying Bayesian Network and Association Rule Analysis for Product Recommendation. International Journal of Electronic Business, 9(2), 149--159 (2011)
32.Xu B., Bu J., Chen C., Cai D.: An exploration of improving collaborative recommender systems via user-item subgroups. In: WWW '12, pp. 21--30. ACM, New York, NY, USA (2012)
33.Yang X., Guo Y., Liu Y.: Bayesian-inference based recommendation in online social networks. In: INFOCOM, pp. 551--555. IEEE Press (2011)
34.Zhang T., Iyengar V., Kaelbling, P.: Recommender Systems Using Linear Classifiers. Journal of Machine Learning Research 2, 313--334 (2002)
35.Zibriczky, D., Hidasi, B., Petres, Z., Tikk, D.: Personalized recommendation of linear content on interactive TV platforms: beating the cold start and noisy implicit user feedback. In: UMAP Workshops. CEUR-WS.org (2012)