

Recommendation of Multimedia Objects for Social Network Applications

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ABSTRACT

Recommender systems help people in retrieving information that match their preferences by recommending products or services from a large number of candidates, and support people in making decisions in various contexts: what items to buy, which movie to watch or even who they can invite to their social network. They are especially useful in environments characterized by a vast amount of information, since they can effectively select a small subset of items that appear to fit the user's needs.

We present the main points related to recommender systems using multimedia data, especially for social networks applications. We also describe, as an example, a framework developed at the University of Naples "Federico II". It provides customized recommendations by originally combining intrinsic features of multimedia objects (low-level and semantic similarity), past behavior of individual users and overall behavior of the entire community of users, and eventually considering users' preferences and social interests.

Categories and Subject Descriptors

H.4 [Information Systems Applications]: Miscellaneous;
H.5.1 [Information Interfaces And Presentation]: Multimedia Information Systems

General Terms

Multimedia Recommender System, Social Networks

1. INTRODUCTION

Images, Audios and Videos are the kind of data most involved in Social Networks applications, due to the extraordinary technological progress that makes possible the generation and exchange of multimedia content at low cost and in a very easy way: just to make an example, tons of short messages, images and video are produced and exchanged using smart phone, pads and laptop, and are posted every day over popular social networks (e.g. Facebook, Twitter etc.).

As a consequence, massive collections of multimedia objects are now widely available to a large population of users and to the appealing and sophisticated tools and applications used for social networks. However, the retrieval of such objects and, in particular, of the "right" multimedia component that can be suitable for a certain application, still remains a challenging problem. To this aim, a number of algorithms and tools – generally referred to as *Recommender Systems* – are being proposed to facilitate browsing of these large data repositories.

We note that the use of recommender systems is one of the steps for realizing the transition from the *era of search* to the *era of discovery*: that is, according to *Fortune* magazine writer Jeffrey M. O'Brien, *search is what you do when you are looking for something while discovery is when something wonderful that you didn't know existed, or didn't know how to ask for, finds you*.

Recommender systems help people in retrieving information that match their preferences by recommending products or services from a large number of candidates, and support people in making decisions in various contexts: what items to buy [1], which movie to watch [2] or even who they can invite to their social network [3]. They are especially useful in environments characterized by a vast amount of information, helping people to effectively select a small subset of items that fit the user's needs [4, 5]. This kind of systems can be used in many contexts, as example in Cultural Heritage, for guiding the tourists in their browsing activities or, in e-Commerce, for suggesting items that the users are likely to buy.

Here, we present the main points related to recommender systems using multimedia data, especially for social networks applications. We also describe, as an example, a framework developed at the University of Naples "Federico II". It provides customized recommendations by originally combining intrinsic features of multimedia objects (low-level and semantic similarity), past behavior of individual users and overall behavior of the entire community of users, and eventually considering users' preferences and social interests.

2. THEORETICAL BACKGROUND

Wikipedia defines Recommender Systems as "a specific type of information filtering technique that attempts to present information items (movies, music, books, news, images, web pages, etc.) that are likely of interest to the user".

However, this definition shows only one basic idea of the number of features and aspects of modern recommender systems.

From a general point of view, recommenders are a class of applications that try to predict users choices [6]. Just to bring the problem into focus, some good examples of recommendation systems are described in the following.

Product Recommendations - perhaps the most important use of recommendation systems; on-line vendors present each returning user with some suggestions of products that they might like to buy on the base of the purchasing decisions made by similar customers. *Movie Recommendations* - in MovieLens.org, for example, users initially rate some subset of movies that they have already seen, with ratings specified on a scale from 1 to 6 stars, where 1 is “Awful” and 6 is “Must See”; MovieLens then uses the ratings of the community to recommend other movies that user might be interested in or to predict how that user might rate a movie; therefore, the recommendation engine should be able to estimate (predict) the ratings of non-rated movie/user combinations and generate appropriate recommendations based on these predictions. *News Articles* - news services have attempted to identify articles of interest to readers, based on the articles that they have read in the past. *Social Recommendations* - recommending new friends in social nets, such as Facebook, Twitter, and so on based on common interests retrieved from the analysis of the published posts.

In these examples we recognize different kinds of recommendation, such as *personalized recommendation* - based on the individual’s past behavior, *social recommendation* - based on the past behavior of similar users, *item recommendation* - based on features related to the item itself and any *combination* of the approaches above.

What is an “item”? In real applications it is more than simple text: it includes images, audio and video streams, and it is not ensured the presence of and adequate metadata system. In this framework, the challenge is then how to exploit the information given by multimedia objects, and how to combine it with past behavior of the single user or of a community of users in order to provide easy and effective recommendations.

Let us give some formal description of the above described problem.

A recommendation system deals with a set of users $U = \{u_1, u_2, \dots, u_i, \dots, u_m\}$ and a set of objects $O = \{o_1, o_2, \dots, o_j, \dots, o_n\}$ ¹. For each pair (u_i, o_j) , a recommender can compute a score $r_{i,j}$ that measures the expected interest of user u_i in object o_j (or the expected utility of object o_j for user u_i), using a knowledge base and a *scoring* (or *ranking*) algorithm that should take into account that users preferences change with context. In other terms, for each user $u \in U$, the recommendation problem is to choose a set of items in O that maximize the user’s utility, given the current context.

In this formulation, the utility of an item is usually represented by a rating which can be an arbitrary function, including a profit function.

Depending on the application, utility can either be specified by the user, as it is often done for user-defined ratings, or computed by the application, as in profit-based utility functions. Each user in U can be associated with a profile that includes various characteristics, such as age, gender, income, marital status, and so on; similarly, each data item in O is associated with a set of features.

¹Both O and U can be very large, in the order of thousands or even millions of items, such as in book recommendations systems

For instance, in a movie recommendation application, O being a collection of movies, each movie can be represented by its title, genre, director, year of release, main actors, etc.

The utility is usually not defined on the whole $U \times O$ space, but only on some subset of it, and thus the central problem is to extrapolate r to the whole space $U \times O$.

Extrapolations from known to unknown ratings are usually done by: (i) specifying heuristics that define the utility function and empirically validating its performances and (ii) estimating the utility function that optimizes certain performance criterion, such as the mean square error. Once the unknown ratings are estimated, actual recommendations of an item to a user are made by selecting the highest rating among all the estimated ratings for that user. Alternatively, we can recommend the N best items to a user or a set of users to an item.

As an example of novel and effective recommendation techniques, in the following we show a system for recommendations of multimedia items, that originally combines intrinsic features of multimedia objects (low-level and semantic similarity), past behavior of individual users, and overall behavior of the entire community of users and eventually considering users’ preferences and social interests. Recommendations are ranked using an importance ranking algorithm that resembles the well known *PageRank* [7] ranking strategy.

In order to best understand the described system, let us consider a typical scenario, where an effective multimedia recommender system would be desirable in social networks applications. In particular, let us consider popular social networks (e.g. Facebook, Twitter, Flickr) that, supporting an intelligent browsing of images’ collection, allow users to quickly retrieve her or of her friends’ pictures with respect to a given category (e.g. landscapes, animals, vacation, etc.) in order to automatically create personalized photographic album. For example, if the user wants to create an album of *London* using photos of her last vacation and other images of her friends that have just visited the city, an image recommender systems should be able to suggest all the similar images with respect to that observed by the user considering: similarities among images, past behaviors of the users community, users social interests and preferences.

3. RELATED WORK

Literature about recommender systems is reported in different surveys[4, 8, 9], in which these systems are broadly classified into three major categories: *content based recommendation*, *collaborative filtering* and *hybrid approaches* (that combine collaborative and content-based methods), using the main results in cognitive sciences, approximation theory, information retrieval, and forecasting theories.

Recommendations based on content-based approach arise from research in information retrieval and information filtering [10]: in such frameworks, the suggested item is in some way “similar” to the previous ones; for example, if a user would like to have a recommendation about a good movie to watch, the system tries to understand the commonalities among the movies the user u has rated highly in the past (specific actors, directors, genres, subject matter, etc), and only the movies that have a high degree of similarity to the user’s preferences would be recommended. In recent times, the content-based approach has been applied to other types of multimedia data as in [11], [12].

Collaborative filtering techniques associate each user to a set of other users having *similar* profiles and recommending items based on the similarity between users, rather than on the similarity between data items themselves [13, 14]. In other terms, this process uses the opinions of other people, shares opinions with others, as in real life peoples discusses about fashion or places to visit [4], [9].

The combination of collaborative and content based methods is at the basis of hybrid approaches; as reported in [4], they are usually classified into different techniques: (i) implementation of collaborative and content-based methods separately and combination their predictions [15], (ii) incorporation of some content-based characteristics into a collaborative approach [16, 17], (iii) incorporation of some collaborative characteristics into a content-based approach [18], and (iv) construction of a general unifying model that incorporates both content-based and collaborative characteristics [19].

Hybrid recommendation systems can also use knowledge-based techniques, such as case-based reasoning, in order to improve recommendation accuracy and to address some of the limitations (e.g., new user, new item problems) of traditional recommender systems [20, 21]. Some authors [16, 17, 18] empirically compare the performance of the hybrid with the single ones and demonstrate that the hybrid methods can provide more accurate recommendations than pure approaches [22].

In the last years approaches based on the use of knowledge representation techniques and semantic relationships among recommended objects have been proposed. For example, in [23] the authors propose an approach that combines the on-line user's personal preferences, general user's common preference from users' most recent experiences, and experts knowledge for personalized recommendations.

Moreover, a recommending approach that shows ranked news to users, considering previous visits, the terms contained in articles and the category they are assigned to is presented in [24] and [25]. The authors designed two probabilistic models based on the aspect model to identify semantic relationships [26] in user access to classified news.

4. THE RECOMMENDATION STRATEGY

So far we have discussed that a multimedia recommender system for multimedia collections in a social network context has to provide the capability of reliably identifying those objects that are most likely to match the interests of a user at any given point of her exploration.

Generally, we have to address four fundamental questions: (i) How can we select a set of objects from the collection that are good candidates for recommendation? (ii) How can we rank the set of candidates? (iii) How can we capture, represent and manage semantics related to multimedia objects to reduce the semantic gap between what user is watching and what she is looking for? (iv) How can we arrange the recommended objects considering users' preferences and social interests?

To give an answer to the first two questions, we adopt a recommendation strategy based on an importance ranking method that strongly resembles the *PageRank* ranking system and that the authors proposed in [7, 27].

Our basic idea is to assume that when an object o_i is chosen after an object o_j during the same browsing session, this event means that o_j "is voting" for o_i .

Similarly, the fact that an object o_i is very similar to o_j can also be interpreted as o_j "recommending" o_i (and vice-versa). Thus, we model a browsing system for a set of objects O as a labeled graph (G, l) , where $G=(O, E)$ is a directed graph and $l: E \rightarrow \{pattern, sim\} \times R^+$ is a function that associates each edge in $E \subseteq O \times O$ with a pair (t, w) , where t is the type of the edge which can assume two enumerative values (*pattern* and *similarity*) and w is the weight of the edge. According to this model, we list two different cases: (i) a *pattern label* for an edge (o_j, o_i) denotes the fact that an object o_i was accessed immediately after an object o_j and, in this case, the weight w_{ij} is the number of times o_i was accessed immediately after o_j ; (ii) a *similarity label* for an edge (o_j, o_i) denotes the fact that an object o_i is similar to o_j and, in this case, the weight w_{ij} is the similarity between o_j and o_i . In other terms, a link from o_j to o_i indicates that part of the importance of o_j is transferred to o_i .

Given a labeled graph (G, l) , we can formulate the definition of *preference grade* of an object o_i as follows:

$$\rho(o_i) = \sum_{o_j \in P_G(o_i)} w_{ij} \cdot \rho(o_j) \quad (1)$$

where $P_G(o_i) = \{o_j \in O | (o_j, o_i) \in E\}$ is the set of predecessors of o_i in G , and w_{ij} is the normalized weight of the edge from o_j to o_i . For each $o_j \in O$ $\sum_{o_i \in S_G(o_j)} w_{ij} = 1$ must hold, where $S_G(o_j) = \{o_i \in O | (o_j, o_i) \in E\}$ is the set of successors of o_j in G .

It is easy to see that the vector $R = [\rho(o_1) \dots \rho(o_n)]^T$ can be computed as the solution to the equation $R = C \cdot R$, where $C = \{w_{ij}\}$ is an ad-hoc matrix that defines how the importance of each object is transferred to other objects and can be seen as a linear combination of the following elements [7].

A *local browsing matrix* $A_l = \{a'_{ij}\}$ for each user $u_i \in U$. Its generic element a'_{ij} is defined as the ratio of the number of times object o_i has been accessed by user u_i immediately after o_j to the number of times any object in O has been accessed by u_i immediately after o_j . A *global browsing matrix* $A = \{a_{ij}\}$. Its generic element a_{ij} is defined as the ratio of the number of times object o_i has been accessed by any user immediately after o_j to the number of times any object in O has been accessed immediately after o_j . A *multimedia similarity matrix* $B = \{b_{ij}\}$ such that $b_{ij} = \sigma(o_i, o_j) / \Gamma$ if $\sigma(o_i, o_j) \geq \tau \forall i \neq j$, 0 otherwise. σ is any similarity function defined over O which calculates for each couple of objects their multimedia relatedness in terms of low (features) and high level (semantics) descriptors; τ is a threshold and Γ is a normalization factors which guarantees that $i b_{ij} = 1$.

Matrix B allows to address the third question that we introduced at the beginning of the section and thus to introduce a sort of content-based retrieval in the recommendation process.

In particular, to compute B matrix in the image realm, we can adopt the most diffused multimedia features (Tamura descriptors, MPEG-7 color-based descriptors, MPEG-7 edge-based descriptors, MPEG-7 color layout-based descriptors and all MPEG7 descriptors) and the related similarity metrics. In addition, we can exploit specific image metadata – depending on the considered domain – and the semantic similarity can be computed using the most diffused metrics for semantic relatedness of concepts based on a vocabulary (Li-Bandar-McLean, Wu-Palmer, Rada, Leacock-Chodorow, Budanitsky).

As an example, in [27], we consider the set of digital paintings belonging to a social network related to Cultural Institutions and the semantic similarity combines similarities among *artists*, *genres* and *subjects* metadata obtained by using a fixed taxonomy produced by domain experts with image features. The combination between high and low level descriptors is based on Sugeno fuzzy integral of Li and MPEG-7 color layout- based similarities, and Sugeno fuzzy integral of Wu-Palmer and MPEG-7 color based similarities, in order to have more high level values of precision and recall; thus we used this last combination for matrix B computation.

Still remains to discuss how to compute customized rankings for each individual user considering user context information. In this case, we can then rewrite previous equation considering the ranking for each user as $R_i = C \cdot R_i$, where $R_i = [\rho(o_i) \dots \rho(o_n)]^T$ is the vector of preference grades, customized for a user u_i .

We note that solving equation $R = C \cdot R$ corresponds to find the stationary vector of C , i.e., the eigenvector with eigenvalue equal to 1. In [7], it has been demonstrated that C , under certain assumptions and transformations, is a real square matrix having positive elements, with a unique largest real eigenvalue and the corresponding eigenvector has strictly positive components. In such conditions, the equation can be solved using the *Power Method* algorithm.

It is important to note that C takes into account the user's context and does not have to be computed for all the database objects, but it needs to be computed only for those objects that are good candidates, i.e. the most *similar* objects to that a user is currently watching (*pre-filtering strategy*).

Finally, to met the last question, the set of suggested items is organized in apposite recommendation lists: they are not fixed and are arranged on the base of *social* user interests and preferences in terms of *taxonomic attributes* – e.g. favorite artists, genres and subjects –, which values can either retrieved using proper questionnaires or gathered by means of apposite API from the most diffused social networks. The preference degree of objects, which do not reflect user needs in terms of semantic similarities, are penalized and such objects could be excluded from recommendation (*post-filtering strategy*).

5. SYSTEM DESCRIPTION

Figure 1 shows an overview of our multimedia recommender system, which takes as input the current context in terms of observed objects (e.g. an image) and generates a list of items. We distinguish the following components.

Items Manager - It is a repository manager that stores the items to be suggested with the related descriptions. In the case of images, it consists of an image DBMS, storing raw data with the related low level features and metadata. *Users Log Tracker* - It is a module devoted to capture and store - in an appropriate format - all the users' browsing sessions in terms of accessed items during their explorations. *User Preferences Manager* - It is a module devoted to gather from social networks and manage all the user social interests and preferences in terms of taxonomic attributes values. *Items Deliverer* - It aims at delivering recommended objects to each user in a format that will depend on the user profile and device. *Recommendation Engine* - It is the system core that for each user and on the base of current context dynam-

ically proposes a set of recommended objects ordered on the base of their utility. In particular, it is composed by: (i) a *Browsing Matrices Computation* Module - able to transform the collected browsing sessions into two matrices: a global matrix which takes into account the overall browsing behavior of the users, and a local matrix which considers the behavior of a single user; (ii) a *Similarity Matrix Computation* Module - capable of computing a similarity degree for each couple of objects and storing such degrees into a matrix; (iii) a *Candidate Set Building* Module - computes the subset of items that are more suitable for users needs; (iv) a *Items Ranks Computation* Module - performs the ranking and post-filtering of the selected candidates for recommendation.

As discussed in [27], the system performances in terms of user's satisfaction are encouraging, providing a better (less frustrating) user experience during assigned browsing tasks with respect to classical image retrieval systems.

5.1 Application examples in Social Networks

The system is a platform that can provide services for many social network applications. Just to make few examples, in the case of image collection, we use recommendation services to assist users during browsing of image gallery containing objects with the same subject (e.g. landscape, animal) or to suggest the most effective tags for image indexing or to automatically create personalized photographic album. For audio and video data, we can exploit recommendation services to create personalized play-lists using, for example, *Youtube* linked data.

6. PRELIMINARY EXPERIMENTS

Recommender systems are generally complex applications that are based on a combination of several models, algorithms and heuristics. Recently, researchers began examining issues related to users' subjective opinions and developing additional criteria to evaluate recommender systems. In particular, they suggest that user's satisfaction does not always (or, at least, not only) correlate with the overall recommender's accuracy and evaluation frameworks for measuring the perceived qualities of a recommender and for predicting user's behavioral intentions as a result of these qualities should be taken into account.

Starting from these considerations and based on current trends in the literature, in [28] we decided to perform both a user-centric evaluation and a more traditional evaluation based on well-established accuracy metrics.

In particular, the proposed evaluation strategy aimed at measuring (i) user satisfaction with respect to assigned browsing tasks, and (ii) effectiveness of the system in terms of accuracy.

In this work, we in turn evaluated the improvement of accuracy performances due to the post-filtering strategy based on users' social preferences. We used the dataset provided by the <http://www.grouplens.org> website, which makes available data collected by the *MovieLens* recommender system. Through its website, MovieLens collects the preferences expressed by a community of registered users on a huge set of movie titles. The dataset contains (i) explicit ratings about 1682 movies made by 943 users (only users who have rated at least 20 movies are considered), (ii) demographic information about users (age, gender, occupation, zip code), and (iii) a brief description of the movies (title, year, genres).

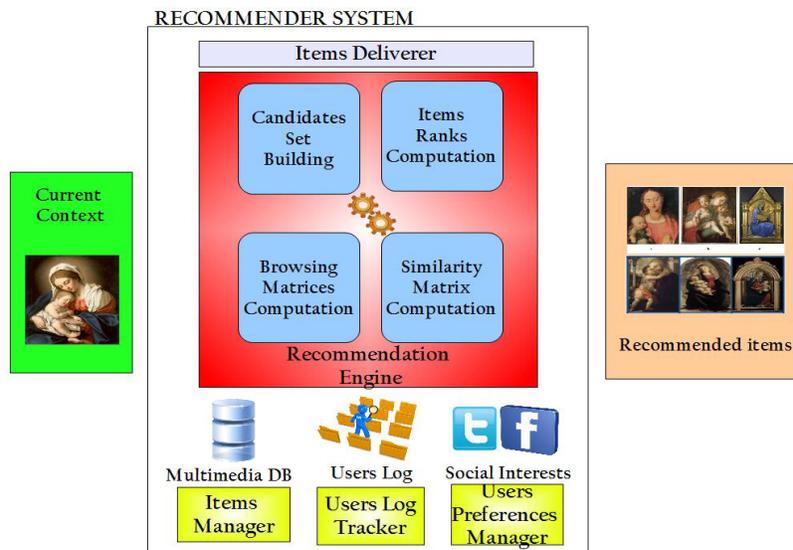


Figure 1: System Overview

Sparsity	Strategy	$RMSE$
0.7	Without post-filtering	0.95
0.7	Users' preferences post-filtering	0.87
0.75	Without post-filtering	0.95
0.75	Users' preferences post-filtering	0.95
0.8	Without post-filtering	1.02
0.8	Users' preferences post-filtering	0.97
0.85	Without post-filtering	1.07
0.85	Users' preferences post-filtering	0.99
0.90	Without post-filtering	1.15
0.90	Users' preferences post-filtering	1.04
0.95	Without post-filtering	1.32
0.95	Users' preferences post-filtering	1.16

Table 1: Accuracy Improvement using the post-filtering strategy

The experiments have been conducted on a collection of about 1,000 movies, rated by a subset of 100 users: each of them had rated at least 150 movies and at most 300, assigning each movie a score between 1 (“Awful”) and 5 (“Must to see”). Additionally, using the timestamp information, we were able to reconstruct usage patterns for each user and consequently the browsing matrices.

We compared in Table 1 the accuracy in terms of Root Mean Square Error of the predictions computed by our recommender system without and with the post-filtering strategy. In particular, we selected 50 test users (whose social preferences are captured by proper questionnaires) and computed the average accuracy for 50 predictions on a subset of the most recently observed items, increasing data sparsity for the same users.

7. FUTURE WORK

Recommender systems made a significant progress over

the last decade when numerous methods and several systems have been proposed. However, despite all these advances, the current generation of recommender systems still requires further improvements. These extensions include the improved modeling of users and multimedia large items' collections, generally depending on the considered application, incorporation of the contextual information into the recommendation process, support for multi-criteria ratings, and provision of a more flexible and less intrusive recommendation process [4].

Our proposal represents an extension of a hybrid recommender system supporting intelligent browsing of multimedia collections in social networks domain. We have shown that the customized recommendations may be computed combining several features of multimedia objects, past behavior of individual users and overall behavior of the entire community of users and users' social preferences. These techniques, described into details for images, can be easily adapted and extended to several kinds of multimedia data such as video, audio and texts.

In according to the research future directions, the system could be improved: (i) introducing explicit user profiling mechanism based on the creation of users categories, (ii) scaling the systems for large multimedia data collections, (iii) integrating the several strategies using SOAP as a built-in service for popular social networks.

8. REFERENCES

- [1] Xinrui Zhang and Hengshan Wang. Study on recommender systems for business-to-business electronic commerce. *Communications of the IIMA*, 5:53–61, 2005.
- [2] Song Qin, Ronaldo Menezes, and Marius Silaghi. A recommender system for youtube based on its network of reviewers. In Ahmed K. Elmagarmid and Divyakant Agrawal, editors, *SocialCom/PASSAT*, pages 323–328. IEEE Computer Society, 2010.

- [3] Przemyslaw Kazienko and Katarzyna Musial. Recommendation framework for online social networks. In Mark Last, Piotr S. Szczepaniak, Zeev Volkovich, and Abraham Kandel, editors, *Advances in Web Intelligence and Data Mining*, volume 23 of *Studies in Computational Intelligence*, pages 111–120. Springer, 2006.
- [4] Gediminas Adomavicius and Alexander 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*, 17:734–749, 2005.
- [5] Saverio Perugini, Marcos André Gonçalves, and Edward A. Fox. Recommender systems research: A connection-centric survey. *J. Intell. Inf. Syst.*, 23:107–143, September 2004.
- [6] A.G. Parameswaran, H. Garcia-Molina, and J.D. Ullman. Evaluating, combining and generalizing recommendations with prerequisites. In *Proceedings of the 19th ACM international conference on Information and knowledge management*, pages 919–928. ACM, 2010.
- [7] Massimiliano Albanese, Antonio d’Acierno, Vincenzo Moscato, Fabio Persia, and Antonio Picariello. Modeling recommendation as a social choice problem. In *Proceedings of the fourth ACM conference on Recommender systems*, RecSys ’10, pages 329–332, New York, NY, USA, 2010. ACM.
- [8] Michael J. Pazzani and Daniel Billsus. *The Adaptive Web: Methods and Strategies of Web Personalization*, volume 4321 of *Lecture Notes in Computer Science*, chapter Content-Based Recommendation Systems, pages 325–342. Springer, 2007.
- [9] Xiaoyuan Su and Taghi M. Khoshgoftaar. A survey of collaborative filtering techniques. *Adv. in Artif. Intell.*, 2009:4:2–4:2, January 2009.
- [10] Nicholas J. Belkin and W. Bruce Croft. Information filtering and information retrieval: Two sides of the same coin. *COMMUNICATIONS OF THE ACM*, 35(12):29–38, 1992.
- [11] Veronica Maidel, Peretz Shoval, Bracha Shapira, and Meirav Taieb-Maimon. Evaluation of an ontology-content based filtering method for a personalized newspaper. In *Proceedings of the 2008 ACM conference on Recommender systems*, RecSys ’08, pages 91–98, New York, NY, USA, 2008. ACM.
- [12] Katarzyna Musial, Krzysztof Juszczyszyn, and Przemyslaw Kazienko. Ontology-based recommendation in multimedia sharing systems. *System Science*, 34:97–106, 2008.
- [13] Jae Kyeong Kim, Hyea Kyeong Kim, and Yoon Ho Cho. A user-oriented contents recommendation system in peer-to-peer architecture. *Expert Syst. Appl.*, 34(1):300–312, 2008.
- [14] Hyea Kyeong Kim, Jae Kyeong Kim, and Young U. Ryu. Personalized recommendation over a customer network for ubiquitous shopping. *IEEE Trans. Serv. Comput.*, 2(2):140–151, 2009.
- [15] Mark Claypool, Anuja Gokhale, Tim Miranda, Pavel Murnikov, Dmitry Netes, and Matthew Sartin. Combining content-based and collaborative filters in an online newspaper. In *Proceedings of ACM SIGIR Workshop on Recommender Systems*, 1999.
- [16] Marko Balabanović and Yoav Shoham. Fab: content-based, collaborative recommendation. *Commun. ACM*, 40(3):66–72, March 1997.
- [17] Prem Melville, Raymod J. Mooney, and Ramadass Nagarajan. Content-boosted collaborative filtering for improved recommendations. In *Proceedings of the Eighteenth national conference on Artificial intelligence*, pages 187–192, Menlo Park, CA, USA, 2002. American Association for Artificial Intelligence.
- [18] Ian Soboroff. Charles Nicholas and Charles K. Nicholas. Combining content and collaboration in text filtering. In *In Proceedings of the IJCAI’99 Workshop on Machine Learning for Information Filtering*, pages 86–91, 1999.
- [19] Andrew I. Schein, Alexandrin Popescul, Lyle H. Ungar, and David M. Pennock. Methods and metrics for cold-start recommendations. In *Proceedings of the ACM SIGIR ’02*, pages 253–260, New York, NY, USA, 2002. ACM.
- [20] Robin Burke. Knowledge-based Recommender Systems. In *Encyclopedia of Library and Information Systems*, volume 69, 2000.
- [21] Stuart E. Middleton, Nigel R. Shadbolt, and David C. De Roure. Ontological user profiling in recommender systems. *ACM Trans. Inf. Syst.*, 22:54–88, January 2004.
- [22] Flora Amato, Antonino Mazzeo, Vincenzo Moscato, and Antonio Picariello. Building and retrieval of 3d objects in cultural heritage domain. In *Complex, Intelligent and Software Intensive Systems (CISIS), 2012 Sixth International Conference on*, pages 816–821. IEEE, 2012.
- [23] Chunyan Miao, Qiang Yang, Haijing Fang, and Angela Goh. A cognitive approach for agent-based personalized recommendation. *Know.-Based Syst.*, 20(4):397–405, 2007.
- [24] Sergio Cleger-Tamayo, Juan M. Fernández-Luna, and Juan F. Huete. Top-n news recommendations in digital newspapers. *Know.-Based Syst.*, 27:180–189, 2012.
- [25] Flora Amato, Antonino Mazzeo, Vincenzo Moscato, and Antonio Picariello. Exploiting cloud technologies and context information for recommending touristic paths. In *Intelligent Distributed Computing VII*, pages 281–287. Springer, 2014.
- [26] Flora Amato, Antonino Mazzeo, Vincenzo Moscato, and Antonio Picariello. Semantic management of multimedia documents for e-government activity. In *Complex, Intelligent and Software Intensive Systems, 2009. CISIS’09. International Conference on*, pages 1193–1198. IEEE, 2009.
- [27] Massimiliano Albanese, Antonio d’Acierno, Vincenzo Moscato, Fabio Persia, and Antonio Picariello. A multimedia recommender system. *ACM Transactions on Internet Technology (TOIT)*, 13(1):3, 2013.
- [28] Massimiliano Albanese, Antonio d’Acierno, Vincenzo Moscato, Fabio Persia, and Antonio Picariello. A multimedia recommender system. *ACM Trans. Internet Techn.*, 13(1):3, 2013.