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A Survey on Decision Support Systems in Social Media

M. Thangaraj
Madurai Kamaraj University
Madurai, India

R. Indra
Alagappa University
Government Arts College For Women
Sivagangai, India

Abstract: Web 3.0 is the upcoming phase in web evolution. Web 3.0 will be about "feeding you the information that you want, when you want it" i.e. personalization of the web. In web 3.0 the basic principle is linking, integrating and analyzing data from various data sources into new information streams by means of semantic technology. So, we can say that Web 3.0 comprises of two platforms semantic technologies and social computing environment. Recommender system is a subclass of decision support system. Recommendations in social web are used to personalize the web [20]. Social Tagging System is one type of social media. In this paper we present the survey of various recommendations in Social Tagging Systems (STSs) like tag, item, user and unified recommendations along with semantic web and also discussed about major thrust areas of research in each category.

Keywords: Social Tagging System, Recommendation, Semantic web**,** Tag Recommendation, Item Recommendation, User Recommendation, Unified Recommendation.

1. INTRODUCTION

Social tagging systems allow users to annotate web resources using tags. While not restricted to controlled vocabulary, tags are freeform keywords that convey meaning and interpretation from the user about the resource being annotated. It facilitates navigation and improves searching without dependence on pre-configured categories. It provides one way of organizing resources resulting in Folksonomy. Folksonomy is different from taxonomy which is hierarchical and exclusive whereas Folksonomy is nonhierarchical and inclusive. According to what kind of resources are supported, there are different systems like Flickr, citeUlike, Connotea, last.fm, Bibsonomy, BIBTEX and Technorati. Advantages of Folksonomies are their flexibility, rapid adaptability, free-for-all collaborative customisation and their serendipity. Formally a folksonomy is a tuple F := (U, T, R, Y) where

- U, T and R are finite sets, whose elements are called users, tags and resources respectively and
- Y is a ternary relation between them, i.e. $Y \in U \times T \times R$, whose elements are called tag assignments

Recommender systems can alleviate information overload and combat noise by personalizing the user's view of the system. Such a system provides information with three decisive factors of "customized", "interested" and "useful" for any individual user by analyzing his/her preferences and the content of the items. These factors distinguish the recommender systems from traditional information retrieval systems and search engines. Recommender algorithms should favor items bookmarked by more users. But recommender algorithms without tags do not take into account the number of raters and neighborhood calculation may not be the most efficient because due to the large volume of items and low overlap between user bookmarks, two users who are very similar in their interests may still have too few common items bookmarked. In this context, tags can provide a more reliable approach to find similar users and this can be used to get better recommendation.

First based on what is recommended we have categorized Recommendations in STSs into three types as tag, item and user recommendations. All three recommendations combined together referred to as unified recommendation. Then in each type of recommendation based on the methods used for recommendations we have classified as shown in Figure 1. This paper is organized as follows. Tag, item, user and unified recommendations are specified successively from Section 2 through Section 5 and Section 6 deals with semantic web. Advantages and limitations of these recommendations are given as findings in Section 7 and we conclude in Section 8.

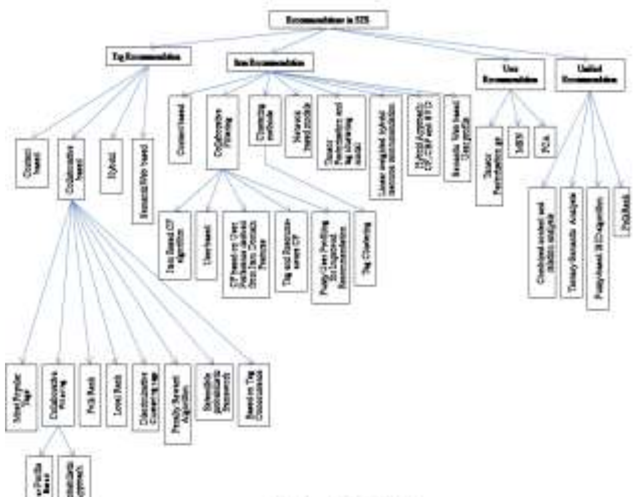

Fig. 1 Recommendations in Social Tagging Systems

2. TAG RECOMMENDATION

Tags are recommended at the time when a user wants to annotate a resource. As most tags in the STSs are uncontrolled, redundant and ambiguous the tag recommenders are useful in simplifying the tagging process for users to find good tags and consolidate the tag vocabulary across users as well. There are two types of tag recommendation such as prediction or Collective tag recommendation which does not assume a query user for recommendation and Personalized tag recommendation recommends tags for a query user. Tag recommendation techniques can be classified into four categories: content based, collaborative, hybrid approaches and semantic approaches.

2.1 Content based

It focuses on the suggestion of keywords (tags) extracted from resource contents and meta-data. It exploits the technology of the automatically textual extracting keywords. One method used in content-based tag recommendation is Discriminative clustering approach [22]. In this approach two clustering models of the posts are created: one based on the tags assigned to the posts and second based on the content terms of the posts. From the clustering model ranked lists of tags and terms for each cluster is generated. The final recommendation is done by using both lists, together with the user's tagging history if available. Prediction results of, tag based clustering model is more accurate than term based clustering model.

Another method used in content based tag recommendation is three-step tag recommendation system [18]. In this system basic tags are extracted from the resource title. In the next step, the set of potential recommendations is extended by related tags proposed by a lexicon based on co-occurrences of tags within resource's posts. Finally, tags are filtered by the user's personomy – a set of tags previously used by the user.

Yet another method compiles a set of resource specific tags, which includes tags related to the title and tags previously used to describe the same resource (resource profile). These tags are checked against user profile tags – a rich, but imprecise source of information about user interests. The result is a set of tags related both to the resource and user [17].

RSDC'08 Tag Recommendation [19] comes under content based recommendation. In this method document (web pages and publications) model is constructed using the textual content associated with bookmarks, user model is constructed based on their tagging and based on these models tags are suggested for new bookmarks. A combination of statistical and semantic features are used to build document and user models.

2.2 Collaborative based

It exploits the relations between users, resources and tags of the folksonomy graph to select the set of recommended tags. Following methods come under this approach.

2.2.1 Most Popular Tags [14]

Tags are recommended based on tag counts. Some variants of this approach are as follows.

For any user u and any resource r, recommending the most popular tags of the folksonomy is the most simplistic approach.

$$\tilde{T}(u,r) := argmax^{n}_{t\in T}(\,|Y_t|\,)$$

Tags that are most specific to the resource globally will be recommended when using the most popular tags by resource.

$$\tilde{T}(u,r) := argmax^{n}_{t\in T}(\,|Y_{t,r}|)$$

Since users might have specific interests for which they already tagged several resources, using the most popular tags by user is another option.

$$\tilde{T}(u,r) := argmax^{n}_{t\in T}(|Y_{t,u}|)$$

Another approach is to recommend a mix of the most popular tags of the user with the most popular tags of the resource. The simplest way to mix the tags is to add their counts and then sort them by their count

$$\tilde{T}(u,r) := argmax^{n}_{t\in T}(|Y_{t,r}| + |Y_{t,u}|)$$

2.2.2 Collaborative Filtering (CF) [14]

Because of the relational nature of folksonomies, traditional CF cannot be applied directly. Reduce the ternary relation Y into two 2-dimensional projections i.e. user's resources and user's tags. Either can be used to find user's neighborhood as follows.

$$N_u^k \;:=\; argmax^{k}_{v\in U\setminus\{u\}}\, \mathrm{sim}\,(\vec{x}_u, \vec{x}_v)$$

For determining, for a given user u, a given resource r, and some $n \in \mathbb{N}$, the set $\tilde{T}(u,r)$ of n recommended tags we use

$$\tilde{T}(u,r) := argmax^{n}_{t\in T} \sum_{v\in N_u^k} \mathrm{sim}\,(\vec{x}_u, \vec{x}_v)\, \delta(v,t,r)$$

where $\delta(v,t,r) := 1$ if $(v,t,r) \in Y$ and 0 else.

Some variations of CF approaches are as follows.

User profile based tag recommendation [32]

Tag based user profile : profile (u) = $\{(w_1,t_1), (w_2,t_2)..(w_n,t_n)\}$ where $t_i \in T$, w_i is the weight of the t_i, represents the importance of this tag to the user. Items are selected using balanced strategy, item tag matrix is constructed, for user u the preference relation between t_i and t_j for item k is calculated and ranking is done using voting, a vector is formed by the ranking tags, the profile of user u for item k is presented, ITW – Itemtagweight matrix is constructed, user similarity using Pearson correlation coefficient is calculated and most frequently used tags from the k similar user are recommended.

Probabilistic Approach [13]

For personalized tag recommendation, a probabilistic framework that is based on personomy translation which translates from the resource tags to personomy tags is used. It is used for translation from similar users for expanding the candidate tags for recommendation. To compute the relevance score for a candidate tag the likelihood of the tag is estimated.

The overall likelihood of a candidate tag is the weighted average of the likelihoods estimated from users. Here weight is the similarity between the neighbor and the query user. Personomy translation method can be used for estimating the likelihood. Users are profiled by a set of translation probabilities one for each t_r and similarity between users can be measured by using distributional divergence metric.

2.2.3 Graph-based Approach - Folksonomy-Adapted PageRank – FolkRank[14]

Folksonomy is converted into an undirected Graph with V set of nodes consisting of the disjoint union of the sets of tags, users and resources. Each triple (u,t,r) in Y gives rise to the three undirected edges {u, t}, {u, r} and {t, r} in E. The rank of the vertices of the graph is computed with the weight spreading computation

$$\vec{w}_{t+1} \leftarrow dA^T\vec{w}_t+(1-d)\,\vec{p}$$

where $\vec{w}$ is the weight vector with one entry for each node in V. A is the row-stochastic version of the adjacency matrix ($a_{ij} := \frac{1}{\deg(i)}$ if $\{i,j\} \in E$ and 0 else) of the graph G, $\vec{p}$ is the random surfer vector – which is the preference vector and $d \in [0,1]$ is determining the strength of the influence of $\vec{p}$. The rank of each node is its value in the limit $\vec{w} := \lim_{t\in\infty} \vec{w}_t$ of the iteration process. For a global ranking, one will choose $\vec{p} = 1$, i.e., the vector composed by 1's. In order to generate recommendations, however $\vec{p}$ can be tuned by giving a higher weight to the user node and to the resource node for which one currently wants to generate a recommendation (i.e. $\vec{p}[u] = 1+|U|$ and $\vec{p}[r] = 1+|R|$). The recommendation $\tilde{T}(u,r)$ is then the set of the top n nodes in the ranking, restricted to tag nodes

2.2.4 LocalRank [21]

In Folk rank scalability and update are the main issues. To avoid these issues new tag recommendation LocalRank has been proposed in which the rank weights are calculated only based on the local "neighborhood" of a given user and resource. Instead of considering all elements in the folksonomy, local rank focuses on the relevant ones only. The rank computation in LocalRank takes into account, how often certain tag was used by a user and how often a tag was attached to a resource. Rank computation and weight propagation in LocalRank is done similar to FolkRank but without iteration.

$Y_u \subseteq Y$ is the set of all (u, t, r)-assignments of Y where u is the given user.

$Y_r \subseteq Y$ is the set of all (u, t, r)-assignments of Y where r is the given resource.

T_u is the set of all tags appearing in the (u, t, r)-assignments of Y_u.

T_r is the set of all tags appearing in the (u, t, r)-assignments of Y_r.

The overall set of relevant tags to be ranked by the algorithm is $T_u \cup T_r$

The rank of each $t \in T_u$ is calculated as

$$\text{rank}(t) = |Y_{u,t}| \times \frac{1/N}{|Y_u|}$$

The rank of each $t \in T_r$ is calculated as

$$\text{rank}(t) = |Y_{r,t}| \times \frac{1/N}{|Y_r|}$$

Tags that appear in both sets ($t \in T_u \cap T_r$) are on principle more important than the others and should receive a higher weight. Therefore we sum up the individual rank weights obtained from the two calculations.

LocalRank propagates the weight of the given user and the resource nodes to all their adjacent tags. Therefore, it computes rankings for user and resource relevant tags and returns a list of tags and their ranks. The recommendation of tags can then be done by picking the top n elements with the highest rank values.

2.2.5 Discriminating Clustering [11]

Tag recommendation based on discriminative clustering recommends the top tags of the most similar clusters for a post. A discriminative method is used to cluster the historical data of posts based on the posts' tags. This method maximizes the sum of the discrimination information provided by posts and outputs a weighted list of discriminating tags for each cluster. Given a new post, and based on the post's contents, the top 5 tags of the most relevant cluster for the post are recommended.

2.2.6 Extendible Probabilistic Framework [25]

It aggregates and exploits the knowledge that exists at four different contextual layer ie. Personal Context, Social Contact Context, Social Group Context and Collective Context. For each context weighted network of tags has to be derived, with nodes representing unique tags t_i and edges occurring when two tags have been used to annotate the same photo. Weights are defined by the number of times this happens in our data set. For all the tags of all the photos in the collection, we calculate the occurrence tally $o(t_i)$ and the co-occurrence tally $c(t_i,t_j)$. The probability of a tag occurring and the conditional probability of two tags co-occurring are formulated as:

$$p(t_i) = \frac{o(t_i)}{\sum_{t\in T} o(t)}$$

$$p(t_i,t_j) = \frac{c(t_i,t_j)}{o(t_j)}$$

To produce a set of recommendations for a given set of input query tags, each query tag is first used to generate a intermediate set of recommendations and these sets are then combined. The set of recommendations for a given query tag for a given context is the complete set of tags that co-occur with that tag in that context's network. Probability of an intermediate suggestion given a query set of tags is calculated. Each resultant probability is then used to produce an ordered list of tags in descending order of probability. The top N tags are then the final recommendations as given by that context's network of tags for a given query tag set. The four individual ranks produced from the tag networks of four different contexts are then combined using Borda Count method.

2.2.7 Penalty-Reward Algorithm[37]

First, it favors tags that are used by a large number of people (with good reputation). Then it aims to minimize the overlap of concepts among the suggested tags to allow for high coverage of multiple facets. It also honors the high correlation among tags for example if two tags are used together by most users for a given object, they will co-occur in the suggested tags. All these things are done using Penalty-reward algorithm. It rewards good tags (i.e. high coverage of multiple facets, high popularity, uniformity and least effort) and penalizes redundant information yielding best output.

2.2.8 Tag Recommendation based on Tag Co-occurrence [29]

Users not only tag the visual contents of the photo, but also provide a broader context in which the photo was taken, such as, location, time, and actions. Given a photo with user-defined tags, an ordered list of m candidate tags is derived for each of the user-defined tags, based on tag co-occurrence. The lists of candidate tags are then used as input for tag aggregation and ranking, which ultimately produces the ranked list of n recommended tags. We define the co-occurrence between two tags to be the number of photos [in our collection] where both tags are used in the same annotation. It is common to normalize the co-occurrence count with the overall frequency of the tags. There are essentially two different normalization methods: symmetric and asymmetric.

Symmetric measures.: According to the Jaccard coefficient we can normalize the co-occurrence of two tags t_i and t_j by calculating:

$$J(t_i,t_j) := \frac{|t_i \cap t_j|}{|t_i \cup t_j|}$$

Alternatively, tag co-occurrence can be normalized using the frequency of one of the tags. For instance, using the equation:

$$P(t_j|t_i) := \frac{t_i \cap t_j}{t_i}$$

it captures how often the tag t_i co-occurs with tag t_j normalized by the total frequency of tag t_i. Two aggregation strategies exist. One strategy is based on voting, and does not take the co-occurrence values of the candidate tags into account, while another strategy ie. the summing strategy uses the co-occurrence values to produce the final ranking. In both cases, we apply the strategy to the top m co-occurring tags in the list.

2.3 Hybrid

The hybrid approaches combine two or more approaches and outperforms well in precision and recall. But have higher computational complexity.

2.4 Semantic Web based [1]

Title Recommender Model

It extracts words i.e. adjectives, nouns and Non-WordNet words from the resource's attribute (title or URL) and suggests them as tags.

Tag to tag recommendation

It may be useful to recommend tags based on other recommended tags. Given a tag, other tags can be produced from its related terms like synonyms and hypernyms. This type of meta-recommenders improves the quality and quantity of the recommendation, when the main recommender fails to provide a sufficient number of tags.

3. ITEM RECOMMENDATION

Recommender systems apply knowledge discovery techniques to the problem of making personalized recommendations for information, products or services during a live interaction. Item recommender systems helps users to find the items that they would like to purchase at E-commerce sites by producing predicted likeliness score or a list of top-N recommended items for a given user, using data analysis techniques. Recommendations can be based on demographics of the users, overall top selling items or past buying habit of users as a future predictor of future items.[27] Various methods available for item recommendation are Content based, Collaborative based, Hybrid, Network based, Clustering based and Semantic based. In hybrid approaches two or more above mentioned methods are combined.

3.1 Content based Recommendation [27]

The Content Based Filtering (CBF) approach creates a profile for each user or product to characterize its nature. For example, a movie profile could include attributes regarding its genre, the participating actors, its box office popularity, and so forth. User profiles might include demographic information or answers provided on a suitable questionnaire. The profiles allow programs to associate users with matching products. A known successful realization of content filtering is the Music Genome Project, which is used for the Internet radio service Pandora.com.

The system can build a profile based on the attributes present in the items that user has rated highly. The interest a user will have in an unrated item can then be deduced by calculating its similarity to their profile based on the attributes assigned to the item.

3.2 Collaborative Filtering (CF) [27]

The main aim of this algorithm is to suggest new items or to predict the utility of a certain item for a particular user based on the user's previous likings and the opinions of other like-minded users. In this algorithm

$U = \{u_1, u_2, \ldots u_m\}$ → List of m users

$I = \{ i_1, i_2 \ldots i_n\}$ → List of n items

Each user u_i has a list of items I_{ui} which the user has expressed his opinions about.

There are two types of collaborative filtering algorithms namely Memory-based and Model-based algorithms. Memory based approaches which include user-based and item-based algorithms, employ statistical techniques (correlation or vector similarity) to find a set of users, known as neighbors that have a history of agreeing with the target user (i.e. they either rate different items similarly or they tend to buy similar set of items). Once a neighborhood of users is formed, these systems use different algorithms to combine the preferences of neighbors to produce a prediction or top-N recommendation for the active user. It is also known as nearest-neighbor. Correlation can be extended using default voting and vector similarity can be extended using Inverse user frequency. Later algorithm, provide item recommendation by first developing a model of user ratings. It computes the expected value of a user prediction, given his/her ratings on other items using probabilistic approach. The model building process is by different machine learning algorithms such as Bayesian network, Clustering and rule-based approaches. Matrix factorization approaches, such as SVD and NMF have been proved useful in model-based CF, which predict unobserved user-matrix.

3.2.1 Item based Collaborative Filtering Algorithm [27]

Item-based approach looks into the set of items the target user has rated and computes how similar they are to the target item and then selects k most similar items. At the same time their corresponding similarities are also computed. Once the most similar items are found, the prediction is then computed by taking a weighted average of the target user's ratings on these similar items. The basic idea in similarity computation between two items is to first isolate the users who rated both of these items and then to apply similarity computation technique to determine the similarity. There are different similarity computation techniques like Cosine-based Similarity, Correlation-based similarity etc. Once we isolate the set of most similar items based on the similarity measures, the next step is to look into the target users' ratings and use a technique such as weighted sum or regression to obtain predictions.

Obviously, the users' opinions and interests can be driven implicitly or explicitly. Examples of explicit data include the following:

_ Rating score to the items based on a defined scale

_ User's interests and preferences

_ Information of any questionnaire being filled out by a user

Discovering implicit information is a difficult task because they are usually hidden. Depending on the domain of the application, there are different methods for extracting implicit information from available data. Examples of implicit data include the followings:

_ User's behaviors and activities

_ User's social and relational behaviors in a group

_ Items being visited by users

_ Expended observation time for the items

_Web usage data mining regarding user's navigation

3.2.2 User-based Collaborative Filtering [5]

Classic Collaborative Filtering(CCF) uses Pearson Correlation to calculate similarity between users and a classic adjusted ratings formula to rank the recommendations. Neighbor-weighted Collaborative Filtering, takes into account the number of raters in the ranking formula of the recommendations. Another approach explores an innovative way to form the user neighborhood based on a modified version of the Okapi BM25 model over users' tags. In the said three approaches, users are collected and for each user, the neighborhood of users who posted her same articles and the neighborhood of users who share the same tags are included in this collection.

3.2.3 CF based on User Preference Derived from Item Domain Features [33]

In Social tagging system, user-created tags are utilized to depict user preferences for personalized recommendation but it is difficult to identify users with similar interests due to the difference between users' descriptive habits and the diversity of language expression. So item domain features are utilized to construct user preference models and combined with CF for personalized recommendation. Because of the diversity of domain characteristics, traditional personalized recommendations do not adapt well to all domains. Hence, it is required to combine domain characteristics and personalized recommendation. It could make recommendations to users who have not selected any common items with others. Here first item domain features are used to model user preference matrix then the user preferences vector is derived from user preference matrix and user preference models are combined with CF to provide personalized recommendations.

3.2.4 Tag and Resource-Aware Collaborative Filtering Algorithms for Resource Recommendation [7]

Sparsity is a problem which occurs in a Social Recommender system, when the number of tags and resources to profile a user are inadequate, to provide quality recommendations. To address this problem Tripartite Nearest Neighbor Algorithm (TRNNA) which combines the similarity based on the Tag Vector Model, the Resource Vector Model and the Resource Vector of tags with weights is used.

3.2.5 Fuzzy User Profiling for Improved Recommendation [4]

Recommender systems, generally have, at their disposal, information regarding genres/categories that a movie/ book belongs to. However, the degree of membership of the objects in these categories is typically unavailable. Such information, if available, would provide a better description of items and consequently lead to quality recommendations. Fuzzy item profile is formed by first identifying the set of tags representative of each genre and then measuring the genre content of each movie. Information about actors and directors are also included in this profile. This item profile is combined with user preference data, which is also represented as a fuzzy set membership value to automatically derive a fuzzy user preference profile. These profiles are then used in multiple ways for both CF and CB systems to derive recommendation. Fuzzy user profile formed here contains user preference information, content information and tag information.

3.3 Clustering Methods [27]

Clustering techniques work by identifying groups of users who appear to have similar preferences. Once the clusters are created, predictions for an individual can be made by averaging the opinions of the other users in that cluster. Each user may be represented with partial participation in several clusters in some clustering techniques. The prediction is then an average across the clusters, weighted by degree of participation.

3.3.1 Tag Clustering [28]

Clustering Algorithm is able to aggregate tags into topic domains. Hierarchical clustering is proposed to generate a taxonomy from a folksonomy. Tag clusters are presumed to be representative of the resource content. Thus, a folksonomy of Web resources is used to move the Internet closer to the Semantic Web. Tag clustering can support tag recommendation, reducing annotation to a mouse click rather than a text entry. Well-chosen tags make the recovery process simple and offer some control over the tag-space diminishing tag redundancy and ambiguity to some degree.

Each user, u, is modeled as a vector over the set of tags, where each weight, $w(t_i)$, in each dimension corresponds to the importance of a particular tag, t_i.

$$\vec{u} = (w(t_1), w(t_2) \ldots w(t_{|T|}))$$

Resources can also be modeled as a vector over the set of tags. In calculating the vector weights, a variety of measures can be used. The tag frequency, tf, for a tag, t, and a resource, r, is the number of times the resource has been annotated with the tag. We define tf as:

$$tf(t,r) = |\{a = (u, r, t_i) \in A : u \in U\}|$$

Likewise, the well known term frequency * inverse document frequency can be modified for folksonomies. The tf*idf multiplies the aforementioned frequency by the relative distinctiveness of the tag. The distinctiveness is measured by the log of the total number of resources, N, divided by the number of resources to which the tag was applied, n_t . We define tf*idf as:

$$tf{*}idf(t,r) = tf(t,r) * \log(N/n_t)$$

With either term weighting approach, a similarity measure between a query, q, represented as a vector over the set of tags, and a resource, r, also modeled as a vector over the set of tags, can be calculated. The user interacts with the system by selecting a query tag and expects to receive resource recommendations. A query is a unit vector consisting of a single tag and Cosine Similarity can be calculated as follows:

$$\cos(q,r) = \frac{tf(q,r)}{\sqrt{\sum_{t \in T} tf(t,r)^2}}$$

To recommend resources, we can calculate the similarity of the selected tag to each resource and recommend the top n. Let it be R' subset of resources R.

The Personalized recommendation process proceeds in two stages. First, given a user's click on a tag, the standard non-personalized recommendation algorithm is applied to produce a set of recommended resources R'. This set is then personalized by taking the user profile and tag clusters into account and re-ranking the results accordingly.

3.4 Network-based Models [35]

A tag-based network can be viewed as a tripartite graph which consists of three integrated bipartite graph or a hypergraph. Therefore, network-based methods are widely used to describe the tag-based graph. In a typical bipartite graph, there are two mutually connected communities, which contrastively have no link within each community. Probability Spreading(random walk), Heat Spreading, tag-aware diffusion-based method, user-centric diffusion-based similarity are the network based methods for item recommendation.

3.5 Tensor Factorization and Tag Clustering Model [26]

Tensor Factorization and tag clustering model consist of three steps. The first step involves of tag propagation by exploiting content, so as to face the issues of sparsity, "cold start" and "learning tag relevance". It is based on a relevance feedback mechanism, in order to perform tag (less noisy tags) propagation between similar items only if they belong to the same concept. The second step of the TFC model is tag clustering in order to reveal topics and identify the taste of users in these topics. Here the sparsity problem is solved. After producing tag clusters, an innovative tf-idf weighting scheme is followed to calculate users' interests. The third step is using High Order Singular Value Decomposition (HOSVD) which is used to reveal the latent association among users, topics and images. Finally for making recommendation the elements of the reconstructed tensor is used.

3.6 Linear Weighted Hybrid Resource Recommendation[15]

It composed of KNN user-based collaborative filtering algorithm, tag-specific user-based collaborative filtering algorithm, item-based collaborative filtering, tag-specific item-based collaborative filtering, tag model similarity and popularity model. It provides a flexible, general and effective approach to capitalize on strong relationships across different dimensions of the data and to incorporate the most effective components into a single recommendation framework.

3.7 Hybrid Approach : CF, CBF and SVD[2]

This approach is used in queveo.tv, a system for highly customized TV content recommendation. The gray-sheep problem, cold-start problem and first-rater problem in CF recommender system can be eliminated using CBF. The problem with the CBF is its tendency to overspecialize item selection because it only recommend items similar to those the user has previously liked. So both CF and CBF are combined. Again there will be a problem of sparsity and scalability. So SVD is used to reduce the dimensionality of the recommender system database.

3.8 Semantic Web based User profile [30]

Amazon.com provides a recommendation service that is based on collaborative filtering: if a user buys an item that has been bought by a number of other users in combination with some other items, then those other items will be recommended by Amazon.com to the user. These recommendations are entirely based on what goes on inside the system ignorant of any external knowledge about the items or the users themselves. To improve such recommendation techniques, we think it might be useful to incorporate data from as many sources as possible to build richer profiles that model many facets of interest that might be difficult and impractical to capture by a single system or service. Users information can be obtained by analyzing their shared profile in MySpace, bookmarks in del.icio.us, photos in Flickr, references in Connotea and any other popular Web 2.0 applications.

This approach is used in movie recommendation. Data representation is done by importing both IMDB database and Netflix rating data into a relational database. String matching is then used to correlate the movie titles in the Netflix with their counterparts in the IMDB data set. To provide a homogeneous view over both data sources, an ontology is used in conjunction with the D2RQ mapping technology, supplying a SPARQL end-point which can be queried to find extensive amounts of information on movies.

For making recommendation, first tag clouds are formed based on the keywords and ratings assigned to the movies by the users. Then three methods are used to make recommendation. 1. Average-based rating 2. Simple Tag-Cloud comparison 3. Weighted tag cloud comparison.

4. USER RECOMMENDATION

This recommendation service helps users to discover new interesting multimedia resources, encourages interaction between users with similar interests and improve users' satisfaction (which means more advertising revenue for web sites). There are three techniques for making user recommendation namely Tensor Factorization, Formal Concept Analysis (FCA) and Multidimensional Social Network (MSN).

4.1 Tensor Factorization in Social Networks [36]

First, new model is proposed with tensor factorization to capture the potential association among user, user's interests and friends. Second a novel approach is proposed to recommend new friends with similar interests for users. This method considers both link structure and user's tagging content. User's tags indicate user's interests. User makes friends with others based on similar interests. Given a user u, the user recommender system is set to predict a personalized ranking list of Top-N users whom u wants to make friends with.

4.2 Mining and Representing User Interests using FCA [10]

Tags are used to depict people's interest in online resources, and tags in most social Web sites have become an available feature. Since tags are used to organize individuals' ideas and thoughts as well as to encourage their social interactions, tagging activities on social web sites can be considered a new way of collective authorship. Once a set of tags is assigned to a resource, a network structure can be constructed given a number of users and the tags that they assign to a set of shared resources. An interest group based on tagging data is extracted from tagging behaviors; sets of tags can be used to build social networks and promote their use by other people in online communities. Formal Concept Analysis (FCA) is a mathematical theory used for conceptual data analysis and unsupervised machine learning. FCA models the world of data through the use of objects and attributes. The relations between objects and attributes in a data set form the formal context. A formal concept refers to the relationship between a set of formal objects and a set of attributes. Based on FCA, given a set of users U and considering the tags that they have in common, the interest group of U is the set of users who are using these tags. The intent of a set of users U is the set of tags which are used by every user in U. The extent of a set of tags T is the set of users using every tag in T. Thus an interest group would be a set of users that use a significantly similar collection of tags to identify their resources. Folksonomy represents a formal context. List of concepts can be extracted from a formal context using the algorithm by Ganter and Kuznetsov and the significance score of each concept is also calculated.

4.3 Social Recommender System using MSN [24]

All online sharing systems gather data that reflects users' collective behavior and their shared activities. We can use this data to extract different kinds of relationships which are grouped into layers and forms the basic components of the multidimensional social network (MSN). The layers created are based on the two types of relations between humans such as direct social links between individuals and object based semantic links between individuals. This MSN is used in recommender system to suggest one human being to another so as to expand the human community. It mainly makes use of relationships come from indirect connections via Multimedia Objects (MOs) rather than from direct links. The system and personal weights that are assigned independently to each layer make the recommendation process personalized. Also the system is adaptive due to personal weights that are adaptively recalculated when the user utilizes the recommendations.

5. UNIFIED RECOMMENDATIONS

It provides all three types of recommendation i.e. user, tag and item. There are four ways of providing all recommendations namely combining content and relation analysis, Ternary Semantic Analysis, Internet Social Interest Discovery algorithm (ISID) and FolkRank.

5.1 Combining Content and Relation Analysis for Recommendation [34]

One recommendation system for social tagging system combines content and relation analysis in a single model. By modeling the generative process of social tagging systems in a latent Dirichlet allocation approach, we can build a fully generative process of social tagging. By leveraging it to estimate the relation between users, tags and resources we can achieve tag, item and user recommendation tasks.

5.2 FolkRank [12]

FolkRank takes into account the folksonomy structure for ranking search requests in folksonomy based systems. It is used for two purposes : determining an overall ranking and specific topic-related rankings. FolkRank is already discussed in Tag Recommendation. The preference vector p is used to determine the topic. We can define a topic by assigning a high value to either one or more tags and/or one or more user and/or one or more resources. FolkRank provides one topic-specific ranking for each given preference vector. FolkRank yields a set of related users and resources for a given tag and vice versa. Thus FolkRank can be used to generate recommendations within folksonomy systems. These recommendations can be presented to the user at different point in the usage of a folksonomy system.

5.3 Fuzzy-based Internet Social Interest Discovery Algorithm (ISID) [16]

Fuzzy-based ISID algorithm consists of the component called Syntactic variation which avoids the syntactic variations of the posts. And also provides functions such as finding topics of interests, resource clustering and topics of interest indexing. In the function finding topics of interest, for a given set of bookmark post find all topics of interest. Each topic of interests is a set of tags with the number of their co-occurrences exceeding a given threshold. In the function Clustering, for each topics of interests, find the URLs and the users such that those users have labeled each of the URLs with all the tags in the topic. In the function Indexing, import the topics of interests and their user and URL clusters into an indexing system for application queries.

5.4 Ternary Semantic Analysis [23]

The three types of entities (user, item, tag) that exist in STS are modeled using 3-order tensor. Dimensionality reduction technique Higher Order Singular Value Decomposition (HOSVD) is applied in 3-order tensor to reveal latent semantic associations between users, items and tags. Smoothing technique based on Kernel-SVD is also applied to address the sparseness of data. HOSVD uses the taxonomy and outputs the reconstructed tensor Â. Â measures the associations among the users, items and tags. Each element of Â can be represented by a quadruplet {u, i, t, p}, where p measures the likeliness that user u will tag item i with tag t. Therefore items can be recommended to u according to their weights associated with {u, t} pair. A similar approach is followed for user and tag recommendation

6. SEMANTIC WEB

In general, tag ontologies in STSs can contribute in the following three areas:

• *Knowledge Representation Sophistication*: A tag ontology can robustly represent entities and relationships that shape tagging activities. It could make the knowledge structure of tagging data explicit and facilitate the Linked Data (Berners-Lee, 2006) of tagging data on the Web.

• *Facilitation of Knowledge Exchange*: Ontologies enable knowledge exchange among different users and applications by providing reusable constructs. Thus, a tag ontology can be shared and used for separate tagging activities on different platforms.

• *Machine-processable*: Ontologies and Semantic Web technologies in general (knowledge representation, processing and reasoning) expose human knowledge to machines in order to perform automatic data linking and integration of tagging data.

Various ontologies in STSs

An Ontology for tagging is not just a way to define meanings of certain tags, but it can also robustly represent the relationships among the entities that shape tagging activities, explicitly stating the knowledge structure of tagging data. Social Semantic Cloud of Tags (SCOT) aims to describe folksonomic characteristics and to offer social interoperability of semantic tag data across heterogeneous sources. This model can express the structure of, features of and relationships between tags and users, allows the exchange of semantic tag metadata for reuse in social applications, and enables interoperation among data sources, services or agents in a tag space. Typical social tagging systems do not provide explicit links between the involved entities, nor do they expose their data in a standard form. The design of the tag ontology was an attempt to provide a common conceptualization of 'what tagging means' by providing a standardized way to collect, interpret and use tagging data. One of the advantages of this ontology is that isolated tagging data can be easily made mobile and can be integrated across applications.

User information is represented using Semantically Interlinked Online Communities(SIOC). The Tag Cloud class in SCOT aggregates all tagging instances with their relevant information. At this level, tagging entities are represented with their collective feature underlying their relationships. The SCOT ontology can be utilized by SPARQL, the query language for Semantic Web data, to get minimal information to compute the significance of tagging data.

Newman's model describes the relationships between an agent, an arbitrary resource and one or more tags. MOAT(Meaning of a Tag) is intended for semantic annotation of content by providing meanings for free-text tagging. It provides the meaning class to represent customized, user-provided 'meanings' for tags. This class provides the meaning of tags to be unambiguous. The Nepomuk Annotation Ontology (NAO) is provided for annotating resources on the Social Semantic Desktop.

All earlier tag ontologies including Gruber and Newman's models do not provide a way of fully representing the meaning of a tag and the relationships between tags, since they focus on expressing individual tagging instances. On the other hand, SCOT offers various properties for representing tag semantics and collective characteristics of tagging entities.

As a subclass of tag:Tag from Newman's model, the class scot:Tag describes a natural-language concept, which is used to annotate a resource. The purpose of this class is to describe the semantics and collectiveness of tags that are aggregated from individual tagging activities.

The tag class has some properties for eliminating tags' ambiguity:

- scot:spellingVariant refers to variations in the way in which a word is spelt;
- scot:delimited is used to describe a multiple-word tag name where each word is separated by a certain character;
- scot:synonym defines synonymous terms

These properties can reduce tag ambiguity resulting from the use of different conventions and even recommend more common patterns for tag names. Furthermore, in order to represent tag frequencies, SCOT introduces two properties: scot:ownAFrequency and scot:ownRFrequency. The former is intended to describe the absolute value of popularity for a specific tag. The purpose of the latter is to represent the relative value in order to identify the significance of a tag proportional to all the tags.

A single tag can have both frequency formats. The popularity of a tag plays a key role in distinguishing its significance in folksonomies.

Collecting and sharing tag metadata [9]

Int.ere.st is a prototype of a tag-sharing platform conceived for reusing tagged resources across heterogeneous platforms. A major goal of int.ere.st is to create a Semantic Web-based tagging application capable of solving the common problems of tags and tagging systems. From a technical point of view, int.ere.st is built on a variety of technologies: Apache, PHP, and MySQL. These frameworks are used to implement most functions in typical social websites. The need to provide interoperability between tagging information has led to the use of Semantic Web technologies – RDF and SPARQL. The majority of social websites now provide APIs based on popular mechanisms (e.g. REST, SOAP, and XML RPC). These APIs provide community users and applications with easy and intuitive access to data from the sites. As the amount of aggregated sources may increase exponentially, it is difficult to generate and update semantic tag metadata synchronously. To solve this problem, we use the D2R Server, a tool that maps relational databases to RDF and that is accessible through SPARQL.

Converting tags into senses [31]

Tag Disambiguation algorithm allows easily to semantify the tags of the users of a tagging service : it automatically finds out for each tag the related concept of Wikipedia in order to describe web resources through senses. There are some services that analyze the tags of a specific user to detect tag usage inconsistencies like slightly different keywords : eg. Bookmark Cleaner and Del.icio.us tag cleaner. The systems and the procedures that use some sort of semantic information to better organize tags and understand their meaning can be divided into two groups. The first one comprises all the methods that introduce some sort of structure to the sets of tags taking into account only the information retrievable from tagging services, i.e. the collections of users, tags and tagged resources. They mainly try to group together similar tags on the basis of their relations with users and resources. In this way they identify sets of strictly related tags or understand the sense of ambiguous ones. The second group of semantic based approaches exploits external semantic resources to structure sets of tags. Some of them try to define the right meaning of each tag retrieving the semantic relations that occur between related tags so as to visualize tags on the basis of their sense and relevance. In order to achieve that, data extracted from different ontologies available over the web are collected and merged. The sense-based tagging is also a way to connect the social data collaboratively created through tagging and the Semantic Web.

Tagpedia is based on the model of term-concept networks; for each meaning of Wikipedia, Tagpedia groups together all the different words used to refer to it. Tagpedia is built to support the characterization of web contents through sense-based tagging and thus it easily disambiguate the meaning of a tag, is accessible over the web at the URL http://www.tagpedia.org/. It can also be queried by means of a dedicated Web API and it can be collaboratively edited. Tag Disambiguation Algorithm(TDA) relies upon Tagpedia. TDA collects the tags of a user from a tagging service and for each of them finds out the relative sense by linking it to the corresponding page of Wikipedia. In particular it identifies for each tag a list of candidate senses, referred to also as concepts or meanings and assigns them a number, called sense-rank SR; the higher the rank of a meaning, the better that meaning defines the sense intended by the user for that tag. First advantage of the adoption of sense-based tagging is represented by the possibility to group together user tags that refer to the same concept.

The TDA manages automatically to convert each tag into the intended concept of Wikipedia and thus into the related URI of DBpedia. In this way we are able to generate for each user of a sense-based tagging service, a set of RDF triples describing his tagging profile; they include, for instance, a triple for each sense associated to a tagged resource. TDA is used to clean user tags grouping them by sense and also to classify the tagged resources on the basis of Wikipedia categories, YAGO classes and Wordnet synsets By characterizing web resources through Wikipedia concepts we can also connect the social data produced by tagging systems to the datasets of the Linked Data community.

Semantic Web Recommender Systems [3]

There are two novel approaches for recommender system in open decentralized scenarios, namely trust networks along with trust propagation mechanisms, and taxonomy-driven profile generation and filtering.

7. FINDINGS

Tag recommendation :

Content based approach is better to solve the cold start problem but it is difficult to apply in the field of multimedia data where as collaborative approach can be used here but has the problem of Sparsity, because users are not able to evaluate the items and they are not wishing to rank purchased items or viewed items, Reduced coverage due to sparsity, Acccuracy of the recommendation may be poor because of little ratings, Scalability and synonymy. In Collaborative approaches, user profile based tag recommendation provides better performance than Collaborative filtering, Probabilistic approach provide an ample improvement when adopting translation from neighbors, CF and most popular tags are Cheaper to compute than FolkRank and requires no iteration and both CF and most popular tags have similar costs but some advantage on the side of the mix of most popular tags. Compared to FolkRank, Local rank is easy to implement, simple, quicker, process large data sets and produce accurate result. Whereas extendible probabilistic framework has benefits for users who do not use English while interacting with Flickr, Penalty-reward algorithm rewards good tags (i.e. high coverage of multiple facets, high popularity, uniformity and least effort) and penalizes redundant information yielding best output, tag recommendation based on tag co-occurrence can be incrementally updated when new annotations become available and thus gracefully handle the evolution of the vocabulary. Hybrid approaches outperforms well in precision and recall, but have higher computational complexity. Semantic web based approaches improves the quality and quantity of the recommendation, when the main recommender fails to provide a sufficient number of tags but it's drawback is it cannot be used independently.

Item Recommendation :

Content-based strategies require gathering external information that might not be available or easy to collect. CBF may not be suitable for recommending products such as music, art, movie, audio, photograph, video, etc. which are sold in e-commerce sites since these products may not be easily analyzed for relevant attribute information. Both collaborative and content based recommendations have the problem when the new user or new items are added to the system because both depend on the user ratings. Hybrid recommender systems are used to alleviate these problems. Ontologies can also be used to represent user profiles. The benefits of this approach are more intuitive profile visualization and the discovery of interests through inferencing mechanisms. CF is domain free and it is used in application domains where it is difficult to profile using Content based filtering. Model based approaches generally perform better than memory-based approaches in terms of top-k recommendations metric. Second, models with tags perform better for dense data and are more efficient than the corresponding models without tags. Third, incorporating tags in the recommendation algorithms can help to obtain more accurate recommendation in the top 2% ranks.

In clustering methods the accuracy may be less compared to nearest neighbor algorithm but it may be used as the preprocessing step to reduce the candidate set. Clusters therefore provide an effect means to bridge the gap between users and resources. It works better on the denser dataset.

Network based methods and tensor based methods can overcome the sparsity of large-scale data but they only focus on the network structure without considering the relations among tags.

Linear-weighted hybrid resource recommendation provide a flexible, general and effective approach to capitalize on strong relationships across different dimensions of the data, and to incorporate the most effective components into a single recommendation framework.

The hybrid approaches works well because the algorithms complement each other.

Folksonomy-generated movie tag-clouds can be used to construct better user profiles that reflects a user's level of interest and provides a basis for prediction.

User Recommendation

User recommendation with Tensor Factorization outperforms well compared to Collaborative Filtering, Google Follower Finder and recommendation based on the KL-divergence between user interests.

In FCA, the disadvantage is the size of the concept lattice and the users and the tags in a lattice structure have a high degree of overlap among concepts. Therefore it is difficult to recommend the concepts when some queries are performed.

In STSs using MSN, as all the process is performed online, efficiency problem arises. So some tasks can be performed offline.

Unified Recommendation

When the relation between users, tags and resources becomes much sparser than usual, combining content and relation analysis for recommendation can extract knowledge required by the recommendation tasks from content information and reveal relation between different objects. By this characteristic, combining content and relation analysis for recommendation overcomes sparsity problem.

In Folk Rank, ranking is based on tags only, without regarding any inherent features of the resources at hand. This allows to apply FolkRank to search for pictures and other multimedia content, as well as for other items that are difficult to search in a content-based fashion.

Fuzzy-based ISID algorithm improves the performance of algorithms for interest discovery, through the clustering of syntactic variation in the data sources of social systems.

Ternary semantic analysis improves recommendations by capturing users multimodal perception of item, tag and user.

Semantic Web

SCOT, combined Gruber's conceptual model and Newman's vocabularies, is the ontology that must be suitable to represent collaborative tagging activities and it provides the most appropriate representations for the Folksonomy model. In addition linking between SCOT and MOAT is useful way to complement to define a meaning of tag. [8]

8. CONCLUSION

In this paper we have explored many possible recommendations in Social Tagging Systems. Research can be extended in any of the given recommendation technique by combining with other recommendation or semantic web. Since it explored two main building blocks of web 3.0 such as social web and semantic web, it will be more useful for future enhancement.

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