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Blending Semantic Web with Recommender Systems

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Abstract— Semantic web, since its inception is approved for providing contexts to the search strings applicable to a given domain. Various frameworks or models based on semantic technologies utilizing semantic enhanced annotations and reasoning are recognized to deliver more relevant outputs. Thus, Semantic Web based recommenders are required for enriched recommendations in this age of information overload on the web. Contextual data may be used not only to represent domain objects and the user preferences in a more precise and refined way but also to apply better matching procedures with the aid of semantic similarity measures. Also, the presently used content-based recommendation techniques and collaborative filtering ones may certainly benefit from the introduction of explicit domain knowledge to produce recommendations using logical inferences applicable in that domain. Both recommender systems and semantic web complement each other and may aid in their progress mutually. In the last decade, there has been some research work done utilizing the semantic web technologies for aiding recommender systems, which play a significant role towards the goal of semantic web. In this paper, first, recommender systems (RS) have been discussed along with key research concerns, benefits and issues being explored and revisited. Second, scope and literature survey has been presented in the track of how semantic web technologies have contributed to enhancements of RS. Third, the role of various semantic web technologies has been explored and discussed for enhancement of present recommender systems. Fourth, useful inferences of the work done are tabulated along with the key discussions.

Keywords— Semantic aided recommender systems, ontology, semantic web technologies, recommendation issues. Linked open dataset

I. INTRODUCTION

The ever-increasing emergence of social media sites and pervasive mobile devices has led to the publication of an enormous amount of data on the Web. Potentially, such huge collection of information allows users to discover anything as per requirement. However, humans cannot run through such massive information without the assistance of any automatic filtering tool. This situation also increases considerably redundant as well as substandard information, resulting in a dilution of the quality of information. Thus, the immense variety of results obtained may perplex the users to arrive at the aptest choices. All this has jointly produced a situation of paradox [1] for the information seekers on the web which is deteriorating as a result of constantly increasing data leading to an information crisis [2] in this information age due to inability to adequately value, govern, and trust the published information. Further, the published content is hardly machine-understandable, constraining the potentials of computing machines [3]. Size of web is growing at a huge pace and the number of internet users are increasing at tremendous rate as shown in the figure 1. It gives an idea for an approximate analysis of growth of global internet users annually. Poor structuring of contents on the web has aggravated this situation of information overload and is the measure concern.

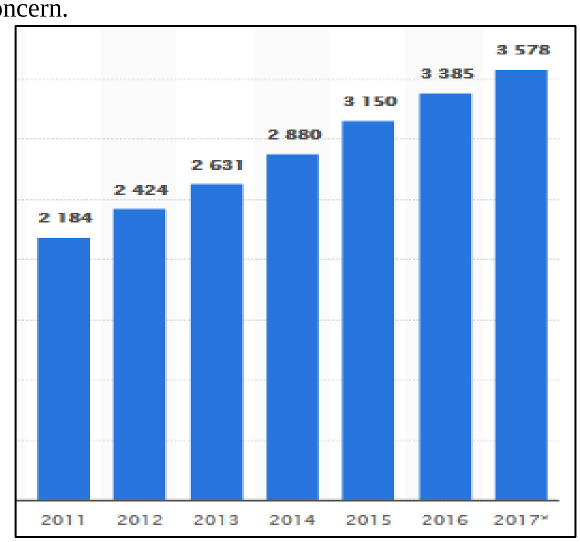

Fig. 1: Yearly distribution of the number of users on the internet (per million)

Semantic Web (SW), as anticipated by Sir Tim Berners Lee, is an advanced web to tackle the limits of the current web [4]. SW was proposed for providing enhanced structure and linking capabilities to online published data [5]. It will significantly increase the relevance of results produced, by providing a context to the search domain, producing user personalized results. For e.g. an apple employee searching “Apple” on the web will find Apple Inc. more relevant as compared to a fruit named Apple. The transition of ‘keyword-based’ search to ‘contextual search’ can be obtained by embedding meaning to online published content using ontologies [6]. This leads to machine interpretable content on the web that can be used by agents to make inference on the web content automatically. Likewise, the Linked open data (LOD) cloud [7] containing formal semantically annotated data can be utilized to present cross-domain linkages for entities. URIs are designated for global recognition of resources (like users and items) making it easier to link the resources worldwide in the information space. These innovative standards [8] of Semantic Web are being extended to offline projects to incorporate machine intelligence in business and commercial domains by providing context to these systems. SW technologies when utilized in Information extraction, along with Natural language processing (NLP) have been ascertained to significantly increase the system’s productivity. In recent times, technologies like RDF and SPARQL along with LOD clouds are being applied for innovating exploratory search and recommender systems [9]. While present Web search engines are capable to determine potentially related documents, users are still required to scrutinize through a long list of URLs, scan each document to identify any relevant bits of information, and gather the extracted findings prior to solve the problem. The RS is a family of information filtering tools, established in assisting users to explore and consume, in a personalized manner, what is relevant for them in such overflowing complex information spaces. For users, it is easier to recognize than to articulate what they are seeking. Various Product-based as well as Service-based companies such as search engines, e-Commerce, e-Learning, e-Placement platforms etc. are researching and incorporating recommender systems in their services to overcome the problems of seeking results by offering personalized information based on user’s preferences. Therefore RS are quite significant in present scenario of search on web.

Even though RS have been established for the past two decades, present systems are still insufficient to attain their goals, hence improvements are required to generate appealing personalized recommendations effectively. Present recommender systems utilize machine learning techniques, where selection criteria are primarily based on domain keywords rather than entities in a domain. This leads to utilization of computing power of machines for indexing and ranking of keywords (and their aliases), without recognizing the semantics of the objects being searched. Oftentimes this keyword based recommendation criteria produces irrelevant results leading to very low precision-recall values for search leading to increased transaction costs of user interaction with the system. By embedding semantics and providing context using SW, a new breed of RS can be generated which may tackle the limitations of current RS like efficiency, novelty, diversity and cross recommendations etc. Reasoning can be used to check for inconsistencies in recommendations. Further, sources of data generation can be analyzed to prove the authenticity of content (called “items” in RS). Besides, the advancements in RS can complement the progress of Semantic Web as projected. Multilingual support can be incorporated as an additional but comprehensive functionality.

In former decade, a substantial research work has been done which combine methodologies from Semantic Web to enhance RS. The goal of those approaches is to realize the enhancements in recommender systems leading to improvements in the Semantic Web itself. In this paper, the major concern with the use of Semantic Web to support the mechanism of recommendation in the big data era.

This paper is further organized as follows:
Section 2 describes the concept of RS in detail including its various research concerns along with a discussion of its methodologies, types and key issues. In section 3, a literature survey on how Semantic web Technologies have contributed to enhancements of RS have been provided. Section 4 describes the key features of using Semantic web technologies in realisation of RS. Application areas and present challenges have also been elaborated. In Section 5, inferences of the research work are tabulated along with discussions.

II. RECOMMENDER SYSTEMS

Introduction:

Recommender Systems are a subset of information filtering systems [9] which were introduced to cope up with the problems of information explosion [10, 11] as well as pseudo-information content [12] leading to redundant or unwanted or substandard results in this age of big data. RS are models and software tools that provide recommendations for items that are most likely of interest to a particular user [13]. Searching and selection of various items such as web pages, documents, groups, books and other commercial products etc. are done using RS. Fundamentally, these recommendations are result of interaction of users with search/exploratory systems on content-based websites such as google.com, amazon.com [14] etc., that provides outputs on basis of the features of items viz. product or services (the content-based method), or the user's social environment viz. age, gender, location, profession etc. (collaborative filtering method).

The following figure is an attempt to layout the research concerns of the recommender systems.

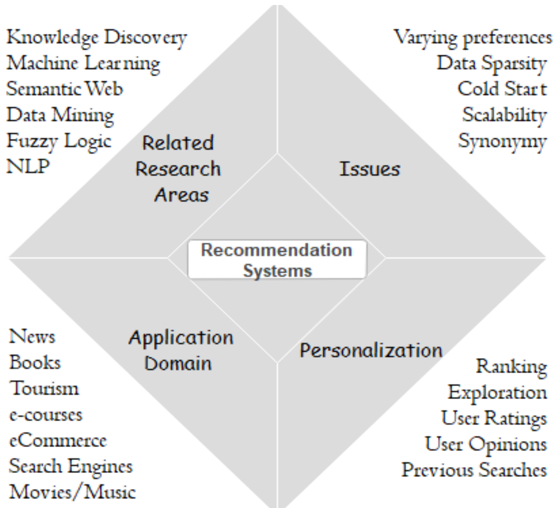

Fig. 2: Research concerns of the recommender systems

The related research areas are elaborated as below:

Knowledge discovery provides a means to discover and infer diverse items based on the links (relationships). *Machine learning* approaches are readily used for enhancing the accuracy and efficiency of the RS. The role semantic web technologies is elaborated further in section IV. Fuzzy logic (clustering and classification) is used to categorize products in diverse ways using explorations. NLP is used in opinion mining as well as interest identification of the user from reviews or posts of the user. Also, enhancements in RS can lead to mutual enhancements in these research areas.

The personalization section is elaborated as below:

User r*atings and opinions* can be used to track the interest and favourability (*ranking*) of the items being recommended to the user. The user may use the site for *exploration*, which may also be used to gather the user's interest which may be accounted along with *previous interactions* of the user.

Benefits of Recommender system

Classes of RS are being utilized by several sites and apps as these provide multi-fold benefits when used as mentioned below:

1. Customization for customers leading to relevant results such as recommending items based on user demographics.
2. From Visitors to Customers: from surfing websites to bringing them to regular customers with help of effective recommendations [15].
3. Cross recommendations and up recommendations: sell what is not directly expected by the visitor which is technically termed as serendipity. RS must be able to persuade user for product consumption [16].
4. Loyalty: the site makes users feel home so that they prefer that site. The more the user interacts with the system, the more the system knows about that particular user, making efficient recommendations specific to that user [15].
5. Bringing down transaction cost: of searching and selecting items on the web, thus profiting both users and the serving companies [16].
6. Energy efficient as in UBER and OLA for recommending best routes for drivers [17].

Recommender systems Types

On basis of user interaction, RS can be categorized as follows:

1. Active interaction: these are referred as onsite interactions, where users are live on the system. These are more effective for the RS to learn user behavior as the user is in its boundary.
2. Passive interaction: these are offsite interaction, used to bring users back to onsite systems by sending recommendations through emails, texts, notifications on mobile etc. These are used as a follow-up for the user where a series of suggested items are sent to consumers. The responses are the fed to the recommender systems. It is liable to spoofing attacks, thus customers might not take them seriously.

Families of RS methodologies:

Following table showcase the brief description of traditional families of Recommendation methodologies.

Table 1: Recommender system methodologies

PARAMETERS	*TECHNIQUES*	
Type	*CONTENT-BASED FILTERING(CB) [19, 20]*	*COLLABORATIVE FILTERING(CF) [19, 21]*
Objective	Finding user's queried item based on item feature description.	Finding unspecified ratings of products based on available ratings by a set of Users and Items.
Outline	-Non-personalized -Recommends items with a similar	-Personalized -Produces user-specific recommendations.

	description to the queried item.	
Input	Content description and User preferences	Usage data
Types	• Information Retrieval and Filtering • Machine Learning	• Memory-based • Model-based
Benefits	Accurate while varying preferences of users. Can recommend items with rare features.	Minimal domain Knowledge required. Captures user's preferences.
Application	Pandora Radio, Rotten Tomatoes LIBRA, News Dude, CiteSeer	Facebook, LinkedIn Twitter, Myspace, Ringo, GroupLens
	Hybrid Approaches [19, 20, 21]	
Outline	Blends features of Content-based and Collaborative filtering methodologies.	
Input	User and Item features along with usage data	
Types	Weighted, Feature Combination, Meta level, Mixed	
Benefits	Frequently outperforms CB and CF alone	
Applications	Netflix, Amazon.com	

Concerns of Recommender systems

Despite the success of traditional filtering techniques, several concerns have been identified as in table 2:

Table 2: Recommender System Issues

ISSUE	ELABORATION
Cold start	Unavailability of previous usage data. [23]
Data sparsity and scarcity.	Large datasets leading to cold start problem affecting recommendation due to the introduction of new user or items which lacks ratings, only minute data available. [24]
Serendipity	Unexpected but fortunate recommendations.
Diversity	The dissimilarity of recommendations in a given list [25].
Popularity bias	Even if not user-specific, popular things are always recommended occupying the recommendation list. It compromised novelty-serendipity.
Synonymy	The same item may be referred by several names, lacking semantic association [26, 38].
Scalability	The volume of references users and items hampers the efficiency generating inadequate recommendations [38].
Novelty	An inverse measure of the popularity of products [25].
Varying preferences	The user may not be subjective to a single category for recommendations. Can wrongly view or search an item, incorrectly training the RS. [27]
Privacy	RS seeks Usage information that may predict the behavior of users leading to privacy concerns. [28]
Trust	Recommendations are based on trust factor between the connected users.
Domain dependence	High dependency on Taxonomy, limited to the vocabulary available for a specific domain (isolation of book, movie, tourism domain etc.)
Unique Name Assumption	Analogous to drawbacks of synonyms that occurs due to the isolated syntactic existence of the exactly same items. [29]
Gray/Black Sheep	The existence of opinions of groups doesn't qualify for generating recommendations for the user [41].
Shilling attacks	Biased ratings in competitive environments [39].
Coverage	Increasing sales by covering a range of items in recommendation space [40].

Recommender systems Evaluation

Evaluation for comparison of various recommender systems include a set of following parameters [23, 24]:

1. *Accuracy: a* measure that is defined oven the fraction of accurate recommendations over total recommendations.
2. *Validity:* if the RS gives explanations to allow users validate the recommendation. For example, "The bus having only one seat can't be recommended to a couple."
3. *Diversity:* for a given list of recommendations, the items must be as diverse (not similar) as possible.
4. *Novelty:* the recommendation list should also contain items that are not popular (novel).

5. *Serendipity:* the user should get unexpected but favorable recommendations with the notion that user may not know what he may be looking for.

The 3rd, 4th, and 5th above evaluation measures are very prevalent among the classes of semantic recommender systems.

III. LITERATURE SURVEY

One of the first efforts to generate the link between semantic web and RS by evaluating and comparing tools is done by Noia and Tommaso [18]. A total of 9 participants' approaches have been evaluated using RMSE for rating, F-Measure for ranking and Intra-list Diversity (ILD) for diversity on DBbook dataset. This comparison based study is concerned with a single domain (books) and only well-established tools have participated in the international challenge restricted to only three evaluation metrics.

A generic RS [21] has been proposed to compute global popularity score, average score and subjective importance score to a book using multiple linked datasets. RapidMiner LOD extension was used to mapping the books with features from LOD datasets. RapidMiner recommendation Extension was used for recommendation functionality and evaluated for rating, ranking and diversity purpose. NutElcare model [22] is proposed for nutrition recommendations where a combination of ontologies are merged as the knowledge base is utilized. The nutritional ontology stores the individual items such as diets/foods whereas user ontology stores user description and interests. The semantic similarity measure is used for providing appropriate recommendations about items present in a knowledge base using rule-based reasoning. Semantic RS has been proposed where the combination of User and Item-based Collaborative filtering method is used in e-commerce domain [23]. The items are selected based on the weighted similarity between item's rating and its semantic similarity. It then collaborates with user's demographic data for predicting the rating for the target item. A comprehensive evaluation is done using MovieLens dataset for verifying the performance of the RS. An adaptive attribute-based re-ranking approach [24] based on Entropy has been proposed for the analysis of diversity. The user's propensity is computed using user profile information. The approach is further evaluated in movie domain to showcase the accuracy-diversity measures. Semantic recommendation approach for learning management system [37] is proposed where semantic indexed based on domain ontology is used. The keywords are extracted from Learning objects (books, tutorials etc.) from the dataset and conceptualized - indexed in an E-learning domain ontology. Nutrition Recommendation framework [25] is proposed where semantic similarity (TF-IDF) between recipes and user profile attributes defined as concepts in ontology and health heuristics are computed. It is an extension of previously used Hermes framework for news recommendation. Evaluation includes Accuracy, Precision-Recall, F-measure, and Specificity using confusion matrix for each user. Semantic web mining aided recommendation framework [26] has been proposed that exploits Collaborative filtering technique. Historical data having semantic annotations (mapped using domain ontology) is used. The approach is applicable for both Off-line and Online recommendations processes and tackles cold start, first-rater, scalability as well as sparsity issues of the traditional RS systems by means of data associative classification algorithm. The evaluation of the approach is done using MovieLens dataset for data mining algorithms namely CBA, CMAR, FOIL, and CPAR with 10-cross-validation. Dzyabura and Haurse [27] have proposed an approach where LOD is utilized for the enrichment of four parameters namely items' description, users' interests, their relations, and social network. The domain of application is generic depending on input type (can be user or item alike) based on which set of people and items are recommended. Utility, Novelty and Accuracy metrics are computed for evaluation of the proposed technique. Though accuracy during evaluation seems promising the comparison is limited to traditional non-LOD based RS. Another LOD based approach [28] has been proposed which exploits LOD Cloud for automatically populating the RS using feature extraction techniques. Few guidelines are discussed for accuracy centric and diversity centric algorithm and a trade-off between these two. A comprehensive evaluation of these parameters is done over MovieLens (Principal Component Analysis having highest accuracy measure) and DBbook (Intimation groups having prevalent accuracy). GR and SVM scored highest diversity values over the two datasets respectively. In this work [34], Points of interest (POIs) in Tourism domain are suggested to the users via linked data principles and location-based services. This takes into account social, semantic and geographic aspects for user profiling to generate a weighted route for the users by applying a variant of K-function. An Ontology network comprising three ontologies (for WGS84, Tourism, and POI) is also presented. SEMWEX1 [35], a hybrid recommender approach populating features from DBpedia and semantic information from NLP features. It also uses a variation of content-boosted matrix factorization and represents a multilingual capability by using 7 DBpedia languages.

IV. SEMANTIC WEB AIDED RECOMMENDER SYSTEMS

Introduction

SW was proposed for providing enhanced structure and linking capabilities to online published data that will significantly increase the relevance of results produced, by providing a context to the search domain, producing user personalized results [5]. As stated by James Hendler, semantic annotations are progressively incorporated by recommender organizations for improving the quality and precision of recommendations being produced [33]. Several research works have shown the great potential of linked data and especially DBpedia to compute semantic similarities. Such similarity measures are mainly used by recommenders.

Following are the key features of using Web semantic web technologies for the realization of RS:

- *Context and domain knowledge:* The domain knowledge is the knowledge of an area of a discipline, a human activity, etc. Domains such as Movie, Book, Nutrition, or Tourism has explicitly defined entities. All these entities can be traced and disambiguated when a user performs a query. [36]
- *Analysing Queries:* The queries by the user in the search can be to project what the user seeks. The entities can be examined and the relationship between them can be exploited to gain enough evidence for interpreting the query performed.
- *Tracing User Interests by entity extraction from posts of users using Social media platforms*: The entities in reviews/posts/comments can be extracted and disambiguated using contextual depictions in Knowledge Bases. Various tools based on LOD like TextRazor, Zemanta, AIDA, DBpedia Spotlight already exists for named entity recognition and linking.
- *Tracing User Preferences Opinion mining for the user using Social media platforms* – Buyers behavior leads to seller's opportunities. Likes and dislikes of users can be analyzed by analyzing the reviews/posts provided by the user on E-commerce/social media etc. Sentiment analysis of posts can provide ratings on binary as well as other scales. StanfordCoreNLP, NLTK, TextBlob, KNIME, and Rapidminer are some popular tools for mining sentiments. Eg: User u posts – "PM Narender Modi's government has not fulfilled his promises." in some social network.
- *Trust-aware RS:* provides authenticity of user's relationships. This is responsible for verification of the publisher of the content.
- *Personalization:* this remains a key aspect of recommendations in the diverse web by means contextual information about the queries placed by the user.
- *Taxonomic abstraction:* The generalization of the items using taxonomy in knowledge bases can be used to make overall opinions about a set of items. Thus prediction of missing ratings can be weighted using this property [006, 305].
- *Multilingual support:* around 50 percent global internet users are from non-English speaking countries. Multilingual annotated entities can increase the reach of users. LOD cloud already provides support for major languages used worldwide.

Ontology

In context of recommender systems, an ontology [30] can be well-defined as representation of the types of entities in a given domain where the entities comprises Users (people, friends) as well as Items (products, places, organisations etc.) in the domains such as tourism, health, education, commerce etc. Ontologies are abstract, hence representational standards [31] are not concerned.

It specifies the entity types, their constraints, and relationships with other entities. Ontologies are majorly used in the areas of information retrieval, text processing, NLP and knowledge management. Contextual RS have popularised the idea of incorporation of domain Ontologies for representation of entities, making inferences. These are able to model all necessary information about a user such as their demographics, occupation, interests (books, movies, places), preferences (likes-dislikes, opinions) besides current activities etc. which are required to be timely updated. Further, the inferences in ontologies can be used to generalize these related entities for broader classification of the user. The reasoning can be used to check inconsistencies with the entities being populated in the ontologies using constraints. [32]

Table 4: Features of Ontology

• Similarity measure- Word sense disambiguation
• Data Integration via Mashup
• Interchange format
• Standard Open Vocabulary
• Semantic Heterogeneity
• Data Abstraction using an ontology for representation
• Inference and reasoning
• Trust network
• Semantic Search- context from queries
• Identity for each of Item and User
• Multilingual support

OTHER KEY TECHNOLOGIES

- *Linked open data cloud*: LOD cloud has been widely used in semantic aided recommender systems as Knowledge bases for entity disambiguation, feature extraction, and semantic annotations.
- *RDF* (Resource description framework) is a model for representing entities and their relationships in form of Triples (Entity1, Entity2, the relationship of both

entities). This provides the basic structure for embedding semantics in entities.

- *SPARQL* (SPARQL Protocol and RDF Query Language) for querying complex graph patterns on linked datasets can be used to extract interesting entities and the linked entities in a graph or relational data format. Extraction of Sub-graphs can be utilized for offline usage and can be updated based on the new arrival of entities. Federated queries can be exploited for querying over multiple LOD datasets (SPARQL Endpoints).
- *URI for the user and item identification*: The entities (Users/Items) are considered as resources in the ontology. Each resource is provided with a Universal Resource Identifier (URI) for tracing it in the graph-based representation. The Relationship by which two resources are linked also has a URI.
- *The proof layer* can be exploited for verifying the authenticity of the published content. It is a chain of assertions and reasoning rules with pointers to all supporting material.
- *Trust layer* can be used for user validation and also to seek past interaction and inconsistencies produced by users like shilling attacks etc. done for creating biased ratings. A link between the item and posted reviews is required such that the user posting negative opinions should have interacted with the item reviewed.
- *Cryptography:* preserving user's identity from unauthorized access. Data about user's interests/preferences should not be stolen by or sold to third-party vendors. Example - Various social media sites (majorly Facebook) in recent days are criticized for sharing the User's private data to silent [32,42] seekers for furthering engagements and advertisement, hence using data for commercial use. Privacy-invasive apps have thrived on this data without users being aware.

All the above-mentioned technologies of the semantic web are W3C standards incorporated at the industrial level.

V. RESULTS AND DISCUSSIONS

The key findings of this research work are presented in the following table:

Table 5: Key findings of the survey

PARAMETERS	DISCUSSION
Domain	Though the recommender systems have been applied to various application domains such as Health, Education, Movies, e-commerce, Books, Courses, research papers, the Movies domain was most popular for this category of RS.
Linked dataset	Various linked datasets have been explored out of which MovieLens by Grouplens is highly used as a standard dataset for evaluation of systems.
Evaluation	The evaluation metrics for Semantic Web aided RS was majorly concerned with measures of novelty and diversity besides accuracy.
Data mining approach	Data mining approach was not common among surveyed approaches but majorly used for feature extraction and selection from the LOD cloud.
Entity linking tool	The tools for named entity linking included DBpedia spotlight and AIDA.
Application of LOD cloud	LOD cloud was majorly utilized for exploring/enriching the interests and preferences of a user (or group).
behavior modeling	The interests and preferences are majorly extracted from social network sites (preferable twitter) or from user reviews at e-commerce platform (amazon.com).
RS methodology	Both content-based and collaborative filtering for RS has been exploited out of which collaborative filtering has been more widely used for user and modeling.
Others	A generic framework for domains is not that much observed in these recommender systems.
	The multilingual capability of DBpedia is also used in only one of the works discussed.
	Some Trust based systems are also exploited for proper prediction of user preferences.

VI. CONCLUSIONS AND FUTURE WORKS

In this paper, recommender systems have been discussed along with key research concerns, benefits and issues being explored and revisited. A survey has been presented in the track of how semantic web technologies have contributed to enhancements of RS. The role of various semantic web technologies has been explored and discussed for enhancement of present recommender systems. Useful inferences of the work done are tabulated along with the key discussions.

For future regards, the evaluation of the work can be done on a common domain to analyze the accuracy, diversity, and serendipity of the works under consideration. The inferences proposed can be utilized for enhancements in recommender systems.

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