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Entities recommendations using contextual information

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ABSTRACT

Generating entities recommendations has attracted considerable interest in recent years. Most recently published works mainly focus on providing a user with the most relevant and/or personalized entity recommendations that score highly against the query and/or the user's preference. Some works consider user side information, such as the user network, user relations, and user's demographic information, and propose to integrate them into the framework of recommender systems. These approaches have been shown to increase the users' satisfaction and engagement with the system. In this paper, we investigate entities recommender systems and summarize the recent efforts in this domain by categorizing approaches. The first category presents different approaches that utilize knowledge graph as side information. The second category gathers work that consider both the current query, and the users' previous interactions with the system. These latter works have considered the full user history to personalize the ranking of recommended entities related to the query. In this review paper, we emphasize contextual information-based approaches that utilize user's context and feedback to improve the recommendations. We accomplished a summary of the literature and synthesized the papers according to different perceptions. Finally, a comparison between approaches is provided and some drawbacks are identified.

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1. INTRODUCTION

The task of entity recommendation in the context of web search can be defined as finding the entities related to the entity appearing in a web search query. With the emergence of large knowledge bases like DBpedia, YAGO and Freebase, search queries can be linked to an entity in the knowledge bases [1]. Indeed, knowledge graph (KG) is graphical databases of relationship information between entities and can be used as a convenient way to enrich users and items information [2], [3]. Some approaches of entity recommender systems rely on the users' interactions with the search engine to involve entity recommendations. Furthermore, related entities require a ranking method to select the most relevant ones. Most studies have considered this point.

In this review paper we present an analysis on related entities recommender systems. We illustrate related entity recommendation studies by categorizing them into two classes: recommendation of related entities given an entity/query and recommendation of related entities given a user. Although many works have been done in the field of information retrieval and web search and in the field of recommender systems, entity recommendation and search techniques differ from them. Numerous works have been done to present this new concept of related entities recommendation.

We used Google Scholar (ACM library, IEEE library, Science Direct library, and Springer link library) from 2013 (emergence of the first entity recommender system [4]) to search for articles related to entity recommendation and related entities recommendation. We also checked for publications where the interactions and the context of the user are exploited to recommend entities. We discovered that there is limited work on recommending related entities; however, we did notice that there is a large use of knowledge based in recommendation in general [4], [5]. First, we focused on creating a framework for this assessment. We analyzed the applied methods, the way the outcomes were presented, and the data utilized in the experiments.

This review is organized according to the following: section 2 is an overview on the two domains: recommender systems and web search engines. Section 3 delves into the idea of proposing relevant entities. Section 4 offers a review of the literature, emphasizing research on recommender systems for related entities. Section 5 critically examines and contrasts earlier works. The final section, Section 6, summarizes the findings.

2. A COMPARISON BETWEEN RECOMMENDER SYSTEMS AND SEARCH ENGINES

Recommender systems are a core technology in many applications. They provide users with ranked lists of recommendations (suggestions). These suggestions are made for items that are most likely to be of interest to the user. Recommender systems are generally categorized into three classical approaches [6]. The first approach is content-based filtering. It consists of analyzing the content or the descriptions of the candidate items for recommendation. In content-based recommender systems, the recommendation results depend upon the content in the query. These recommender systems create a profile for each item/product to define its nature. The second approach is collaborative filtering. In this case ratings from other users are used for recommendation. Users having similar taste as you are considered for recommendation [1]. Hybrid approach is the third approach which combines content-based recommendation and collaborative filtering.

Web search engines search for keywords to answer users' queries. The main focus of search engines is solving queries with close to precise results in small period of time using advanced algorithms [7]. The semantic web intelligently understands the user's query and search for those results that match keywords and also the meaning of the query [7]. The primary goal of a search engine is to provide high quality search results over a rapidly growing world wide web. As instance, Google employs a number of techniques to improve search quality including page rank, anchor text, and proximity information. Google is a complete architecture for gathering web pages, indexing them, and performing search queries over them [8]. In Table 1, we define and summarize differences between traditional recommender systems and traditional web search engines.

Table 1. Regular search engines vs regular recommender systems

	Regular search engines	Regular recommender systems
Purpose	Information retrieval tools.	Information filtering tools.
Use	Large repositories of unstructured content about a large variety of topics.	Collections of information that are centered around a specific theme or subject, containing less extensive material than what is typically found in conventional search engines.
Results	Documents/web pages.	Items (products/services/information).
Query	Free text query.	The recommendation systems do not create queries from the start. Instead, they analyze user behavior and build queries based on the user's interests in certain cases.
Principle	Searching within a document collection for a particular information need (a query).	Predict users' interests and recommend product items that quite likely are interesting for them [9].
Domain	Web.	Different domain: books, movies, products, services and scientific papers.
Techniques	Representation, storage, organization of unstructured data, matching, scoring then ranking results.	Predicting, ranking, selecting the most relevant items.
Examples	Google/Yahoo! /Baidu.	Amazon/MovieLens.

As shown in Table 1, search engines are not recommender systems but have many similarities. They both rank items and rely on users to create, generate and update content. The study of recommender systems has adopted approaches and methods from the field of information retrieval. This indicates that the research in recommender systems is heavily influenced by the principles and techniques used in information retrieval to deliver personalized recommendations to users (e.g. content-based filtering) while search engines have used ideas coming from recommender systems, ex, when a page receives validation from peers, it gains significance through their support [10]. These two communities are increasingly coming back together as advances in search engines include lessons learned from information filtering techniques (e.g. collaborative search) and recommender systems start exploiting well established information retrieval techniques (e.g. learning to rank).

3. ENTITY RECOMMENDER SYSTEMS

Entity recommendation bridges the gap between the two important domains: recommender systems and search engines. Entity recommendation is the concept of providing entity suggestions to assist users in discovering interesting information [11]. Related entities are then presented/recommended given a main entity of the user's query. They are generally ranked by similarity, relevance and popularity. Table 2, summarizes some properties of entity recommender systems [5].

Table 2. Properties of entity recommender systems

	Entity recommender systems (ERS)
Use	Repositories of unstructured content + knowledge base/user logs.
Result	Related entities to a main entity of the user's query.
Query	Entities/Extracted entities from keyword queries.
Purpose	Recommending relevant entities related to the main entity of the query.
Domain	Different domain: movies, and products/Web
Techniques	Merge techniques from recommender systems and search engines areas.
Examples	Google and modern search engine/Platforms like: Alibaba [12].

As shown in Table 2, entity recommendation is a new task of retrieving a ranked list of related entities. In this survey, we will present the most important approaches of this field: some of them introduce the use of knowledge bases, others rely also on user' behavior. Different searching and ranking techniques were redefined for this new field. Two categories of recommendations could be cited [12], [13]:

– Recommendation of entities given an entity: this supposes to exploit different features to recommend entities given a main entity such as: co-occurrence or similarity. In these types of approaches, related entities are recommended based on similarities to the main entity that the user searched for. Various measures of similarity could be used between the main entity and the entity to recommend. A common measure is the frequency of the two entities being co-clicked in the same session across all search users [14]. A related entity is then recommended if and only if it is frequently co-clicked with the main entity [14].
– Recommendation of entities given a query: this supposes retrieving and search entities in response to a query. Entity recommendation can consider the query being issued at each time step independently, while ignoring the in-session context queries [4], [15], [16]. This approach considers the most frequent meaning for a query. It uses the query it- self for disambiguating the meaning of entities with the same surface form [17].

4. RELATED ENTITES RECOMMENDATION USING CONTEXTUAL INFORMATIONS

Entity recommendation has been proposed as new concept that provides users with an improved experience via assisting them in finding related entities for a given query [18]. Related entity recommendations have thus become a standard feature of the interfaces of modern search engines. These systems typically combine a large number of individual signals (features) extracted from the content and interaction logs of a variety of sources [4]. In several models of recommendation, knowledge graphs have been integrated to augment the informational value of an item by means of its related entities in the graph [19].

The principle when using knowledge bases like DBpedia or YAGO is that to retrieve a ranked list of related entities found in response to a main entity of the query, the system requires potential entities that can be considered as related and relevant to the main entity. These potential candidates can be obtained from the knowledge base. Knowledge base provides heterogeneous information including both structured and unstructured data with different semantics [16]. Knowledge graphs enable hybrid graph-based recommendation models encompassing both collaborative and content information [20]. Knowledge-based filtering has no strict border with content-based filtering. Content-based techniques can be referred as a subset of knowledge-based approaches [21]. Indeed, the item characteristics can be interpreted as a knowledge about the items. However, content-based filtering technique focuses more on exploiting the item's description or the item's content for finding similarity between the items. Most of the recent works consider the problem of ranking entities related to the user's current query, or focus on specific recommendation domains requiring supervised selection and extraction of features from knowledge bases [1]. Some works consider the current query, and typically disregard the users' previous interactions with the system. Approaches that consider the full user history to personalize the ranking of recommended entities related to the query are summarized in Table 3.

Table 3. Approaches of entities recommendation

Papers	Data sources	Technique	Dataset
Yu *et al*. (2014) [22]	Movie and local business.	Combining heterogeneous relationship information for each user and providing personalized recommendation using user implicit feedback data.	Two real-world datasets: IM100K (MovieLens-100K dataset + IMDb dataset) and Yelp Dataset.
Reinanda *et al*. (2015) [23]	Users' search sessions from query logs.	Proposing two approaches based on semantic relatedness and aspect transitions within user sessions by computing click similarity for the context terms Recommending other aspects related to the aspect currently being queried.	"Dev-contexts" (1-year query log sample) and queries "Dev-clicks" (1-month sample) from Yahoo search engine and AOL dataset.
Duan and Zhai (2015) [24]	Entity searches logs in the domain of product search.	A language model to capture query terms used for search and a series of probabilistic distributions on entity attributes. Learning query intent representation for entity search task.	An evaluation set created randomly from real-world search logs.
Tobías and Blanco (2016) [1]	User's full search session (US Market).	Generating entity suggestions using nearest neighbors collaborative filtering. Exploiting query log data.	A large dataset from a commercial search engine.
Tran *et al*. (2017) [25]	Different domains: people and locations.	Introducing the notion of contextual entity relatedness. Computing contextual relatedness with time and topic model by exploiting entity graph.	Real-world data set from Wikipedia.
Huang *et al*. (2018) [26]	In-session preceding context queries.	Using a multi-task learning framework based on neural networks, which maps both queries and candidate entities to be recommended in vector space. Using the preceding queries as contexts to improve the recommendation quality.	Real-world search logs of commercial web search engine.
Tuker *et al.* (2019) [27]	Sports, Entertainment, Business, Emergencies, Science and Politics. DBpedia as knowledge base.	Considering time-awareness for entity recommendation by leveraging heterogeneous knowledge of entities to allow users restrict their interests of entities to a customized time range.	A new evaluation set was created.
Huang *et al*. (2020) [28]	In-session and historical user search behavior across all sessions (short and long-term history).	Multi-task learning framework with deep neural networks (DNNs) to learn and optimize recommendation. Understanding the user's search intent by introducing long-term search history.	Real-world search logs of a commercial web search engine.
X. Wang *et al*. (2021) [29]	Book, music, and fashion domain.	Exploring intents behind a user-item interaction. Modeling each intent as an attentive combination of KG relations and a new information aggregation scheme.	Amazon-Book and Last-FM datasets and Alibaba-iFashion dataset [28].
Jacucci *et al*. (2023) [30]	Movie and music domains.	Modeling user's dynamic interest. Provide semantic understanding of each item in user's historical interest sequence.	Two public datasets and two industrial datasets of Alipay.

The previous works of entities recommendation supposed to exploit information about users such as user log (correspondence between user and items or user and query) and to use them to recommend entities. Users' interactions are collected in the search click log and the entity pane log. The search click log stores history of user clicks on URLs, while the entity pane log stores click on the entity pane. Entities, which are related to a given main entity are suggested based on the user's past history stored in the usage logs. In Table 4, we summarize limitations of some approaches presented previously. In the following part, we will examine and offer our interpretation of the works that have been previously introduced.

Table 4. Advantages/disadvantages of the approaches

Approaches	Advantage	Disadvantage
Blanco *et al*. [4], Yu *et al*. [20], [22].	Query at each time step is considered independently from history.	Can not handle well the ambiguous queries.
Tobías and Blanco [1], Huang *et al*. [26], [28].	Users' past behaviors that have been observed in search logs are used.	Data sparsity and cold start problems.
Existing datasets Brams *et al*. [14]	Explicit ratings on items are provided.	No information is provided about users' opinions of other (non-recommendable) entities.
Blanco *et al*. [4], Aggarwal *et al*. [9], Huang *et al*. [28].	Queries with explicit entities are considered.	Fail to handle complex queries (without entities).
Blanco *et al*. [4], Yu *et al*. [20], [22].	Require a rich set of domain-dependent entity features derived from a knowledge graph.	Can be applied only when the target domain is known.

5. DISCUSSION

This study centers on enhancing search recommendations, a crucial element in contemporary search engines. It explores the fusion of recommendation systems with search engines, emphasizing the importance of integrating knowledge graphs, user context, and feedback to improve search outcomes. The aim is to refine search recommendations by leveraging user behavior and context effectively.

Major web search engines (Google [31], Yahoo! [32], and Microsoft [20]) are providing now a ranked list of related entities on the entity pane next to regular search results in addition to information about the entity searched by the user. This was called related entities recommendation [16], [33], [34]. In this survey, several publications on related entities recommendation are collected from journals and conferences from Google Scholar library such that the library is searched from 2013 till 2023. The number of publications decreased from 2016 to 2019 then begun to increase in 2020. This is due to the publication (from 2020) of the recent tasks that consider user side information in the knowledge graph. Most works of this survey mainly focus on providing a user with the most relevant [4] and/or personalized [35]–[37] entity recommendations that score highly against the query and/or the user's preference. We selected around 25 papers, out of which 12 papers used knowledge graph approaches as a principal technique and 10 papers used interactions of the user (user history) while 3 papers used the context of user. We noticed that papers of this latter category are also knowledge graph approaches. Most of the experiments were conducted on real-world datasets collected from different search engines. This study centers on enhancing search recommendations, a crucial element in contemporary search engines. It explores the fusion of recommendation systems with search engines, emphasizing the importance of integrating knowledge graphs, user context, and feedback to improve search outcomes. The aim is to refine search recommendations by leveraging user behavior and context effectively.

When studying papers recommending related entities; we found that a majority of them used knowledge graph approaches. Indeed, knowledge graphs play an increasingly important role in recommender systems. Currently, the advancement of knowledge graphs has made it possible to integrate graph embedding learning and recommendation techniques for improving the explanation of recommendations [24], [30], [38]. Some studies on explainable recommendations [20], [27], [39] have demonstrated that explaining recommendations increase trust, transparency, and user acceptance in KG-based recommender system responses. Research on knowledge graph-based models for explainable recommendation represents one of the future directions for intelligent systems research since they can provide personalized recommendations in many research areas [25], [29], [40].

6. CONCLUSION

In actual web search engines, entity recommendation tries to improve the experience of users by helping them to find related entities for a given query. This concept has become an important feature. Indeed, when manipulating web search engines, some users know what they are looking for, but others are looking to explore information related to an initial interest. Most approaches explored the fact that user's initial interest is often linked to an entity in a knowledge base. In this case, it is natural to recommend the explicitly linked entities for further exploration. This was called entity recommendation. This survey accomplished a summary of the literature and categorized and synthesized the papers according to different perceptions. Several publications are found and collected in the field of related entities recommender systems from 2013 to 2023, and then classified according to two types: recommendation given a user (interactions-based recommender systems) and recommendation given an entity or a query. In this survey paper, we investigate related entities recommender systems and summarize the recent efforts in this domain. This paper presents different approaches that utilize the knowledge graph as side information as well as approaches that utilize user's context and feedback to improve the recommendation. Finally, a discussion and a comparison between different approaches and suggests potential areas for future exploration. We hope this survey paper can help readers better understand work in this area.

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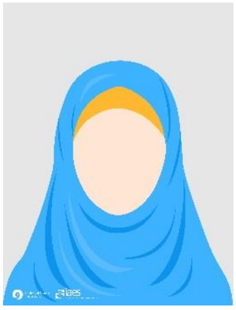

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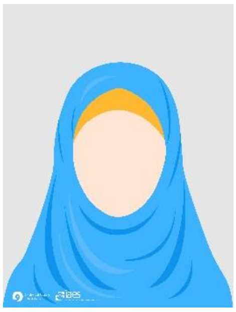

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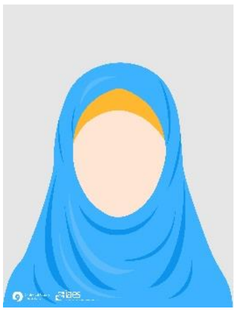

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