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An Overview on Related Searches Recommendation

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ABSTRACT

Modern search engines have enriched their regular web search results by providing new kinds of recommendations to users' queries. These recommendations are suggestions in the form of named entities related to the main query. This new trend bridges the gap between two important domains: search engines and recommender systems. Studies and research on bridging these two popular systems vastly improve user experience when using such hybrid system. Indeed, it is very intuitive to a user to get related searches in the form of entities to the entity appearing in its search query. This new task has attracted considerable interest. In this paper, we conduct a survey of related searches recommender systems. We collected recently published papers in this area to summarize them from various perspectives. We investigate the proposed approaches by focusing on how they get benefit from contextual data and user's feedback and how they utilize the knowledge graph for accurate recommendations.

1. INTRODUCTION

Search engines are everywhere and are used by billions of people. They have become very commonplace this last decade, some argue we no longer even notice that search engines exist as a service [1]. Modern search engines have changed from being systems for document retrieval to being platforms for helping people find new information [2]. In fact, current web search engines provide recommendations to a user's query and offer a list of ranked related entities in an entity pane. This improves the quality of standard web search results and user' experience. Web search engines may be used in connecting search queries with knowledge base entities as a result of the growth of knowledge bases like DBpedia, YAGO, and Freebase [3]. Indeed, knowledge graphs are visual databases that show relationships between different types of entities and can be used to enhance user's search and to retrieve entities related to that search [4]. Graph embedding learning and recommendation methods can now be integrated for better suggestions thanks to knowledge graphs development [5]. Other methods of related searches suggestion incorporate entity recommendations for a query based on users' interaction with the search engines.

This review's motivation is to present an overview of related searches and recommendations for users' queries. This new trend connected two important domains: web search engines and recommendation systems. This new combination has attracted considerable interest this last decade. Numerous researches have been conducted. We divided recent studies into two classes: recommending related entities according to an entity/query and recommending related entities according to a user. We presented different strategies and approaches proposed in the context of related searches recommendation and more precisely in the context of related entities recommendation. We conclude according to several studies that knowledge graph-based recommendation systems perform better when combined to users' behavior analysis. Furthermore, the ranking methodology is decisive to choose the most relevant related entities to a query.

1.1 Methodology

Although there has been a lot of work done in the fields of recommender systems, web search, and information retrieval, entity recommendation and search techniques are distinct from these fields. In order to establish this new trend of recommending related entities to users' queries, numerous works and studies have been conducted. We followed PRISMA guidelines when conducting the review [6]. We searched papers related to searches and entities recommendations and related entities recommendation using Google Scholar (Springer link library, ACM library, Science Direct library, IEEE library, etc.) starting in 2013 (emergence of the first recommendation system of related entities to queries [7]). Additionally, we looked for publications that used knowledge graphs, user interactions and the context of user to recommend entities. Although there isn't much research on recommending related entities, we did notice that knowledge-based recommendation is widely used in general. The PRISMA flowchart is used in Figure 1 to depict the entire paper selection process [6]. As shown in Figure 1, Search terms "Entity recommendation", "Related entities recommendation", "Context-aware entity", "Knowledge graph entity recommendation", "Time aware entity recommendation," "Search log entity recommendation", "User interest entity recommendation" were used. We also kept the search results limited to papers after 2013. From the resulting articles, we categorized them to papers that recommend entities given an entity and papers that recommend entities given a query and papers that recommend entities given a user [8] as shown in Figure 2.

Overall, for related entities recommendation, we selected around 25 papers out of which 12 articles recommend entities given an entity or a query and 10 articles recommend entities given a user, while 3 articles defined a new context task used for recommendation.

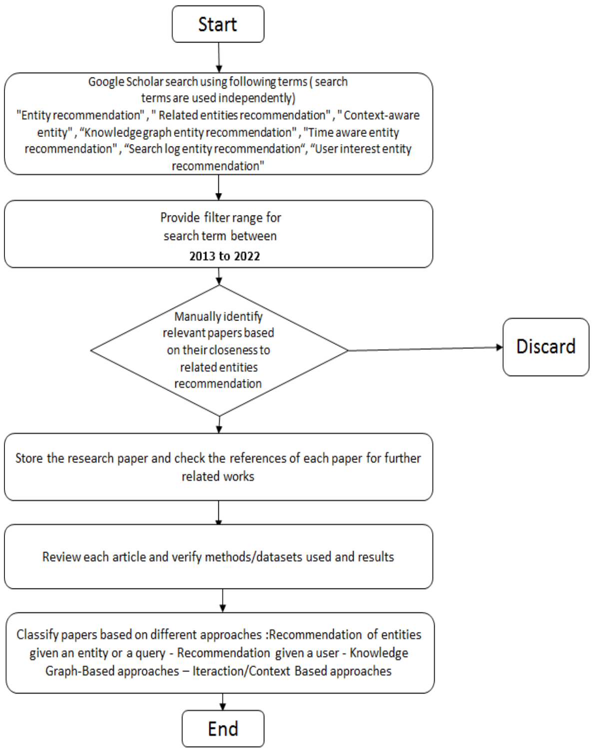

Figure 1. Methodology flowchart used to select articles

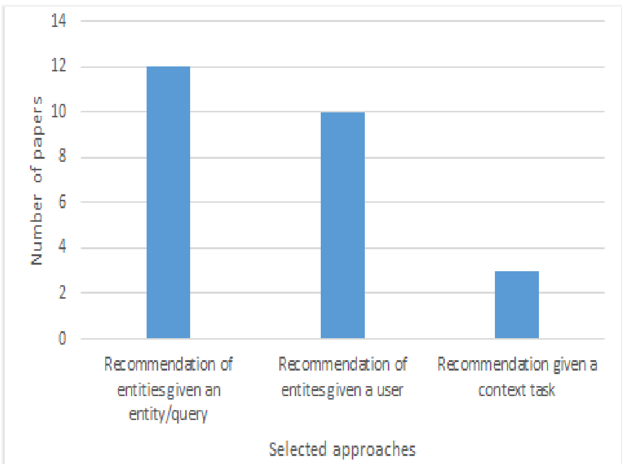

Figure 2. Representation of related entities recommendation papers used, based on the variety of the approaches

Figure 2 presents the distribution of the selected research articles on the basis of the categories using a bar chart. The next step was to prepare an outline for this review. We evaluated the techniques used, how the results were reported, and the data used in the experiments.

This review paper is organized as follows: Section 2 is an overview on the two domains: web search engines and recommender systems. Section 3, illustrates the concept of entity recommendation. Section 4, presents a literature review and highlights the works on related entities recommender systems. Section 5 discusses and compares the different works. Finally, a conclusion is discussed in Section 6.

2. A COMPARISON BETWEEN RECOMMENDER SYSTEMS AND WEB SEARCH ENGINES

In many applications, recommender systems are a key technology. They offer users ranked lists of suggestions (recommendations). These recommendations are made for products that the user is most likely to find interesting. Three classical approaches are typically used to classify recommender systems [9, 10]. The first method, known as content-based filtering, involves reading through the descriptions or content of potential recommendation candidates. The recommendation outcomes in content-based recommender systems depend on the content of the query. To describe each item or product, these recommender systems build a profile. Collaborative filtering is the second strategy. In this instance, recommendations are based on user ratings. Users who share your taste are taken into consideration for recommendations [2]. The third strategy is a hybrid one. It combines content-based and collaborative filtering recommendations.

Search engines on the web look for keywords to respond to user queries. The primary goal of search engines is to quickly and accurately answer user queries using cutting-edge algorithms [11]. The user's query is intelligently understood by the semantic web, which then looks for results that match the query's meaning and keywords [11]. A search engine's main objective is to provide excellent search results across the rapidly expanding World Wide Web. For instance, Google uses a variety of strategies, including page rank, anchor text, and proximity data, to enhance the quality of its search results. Google is an integrated web page collection, indexing, and search engine [12]. Table 1 lists the distinctions between conventional recommender systems and conventional search engines.

Table 1. Traditional search engine vs. traditional recommender systems

	Traditional search engines	Tradition recommender systems
Nature	Information retrieval tools	Information filtering tools
Input	Large unstructured content repositories. A wide variety of topics	Repositories on a single topic. Smaller content than in traditional search engines
Output	Documents/ web pages	Items (products / services / information, etc.)
Query	Free text query	Query isn't built. Recommendations engines observe actions and construct queries for user / Entering interest
Principle	Searching within a document for a particular information need	Predict users' interests and recommend product items that may be of interest
Domain	Web	Different domain: books, movies, products, services, scientific papers, etc.
Techniques	Representation, storage, organizing unstructured data, matching, scoring, ranking results	Predicting, ranking, selecting the most relevant items
Examples	Google/ Yahoo!	Amazon/ MovieLens

Despite having many similarities to recommender systems, as Table 1 demonstrates, search engines are not them. Both of them use user-generated content to create, generate, and update rankings of items. While search engines have used concepts from recommender systems (ex., a page is important is linked/endorsed by another) using the support provided by peers [13], research in recommender systems has taken techniques from information retrieval (e.g., content-based filtering). As search engine innovations incorporate lessons learned from information filtering techniques (e.g., collaborative search) and recommendation systems begin utilizing tried-and-true information retrieval methods (such as learning to rank), these two communities are increasingly coming back together.

3. ENTITY RECOMMENDER SYSTEMS

The gap between search engines and recommendation systems is filled by entity recommendation. To assist users in finding information of interest, entity recommendation offers entity suggestions [14]. Following that, given the main entity of the user's query, related entities are suggested. Utilizing factors like similarity, popularity, relevance, etc., one can rank them. The characteristics of entity recommendation systems are summarized in Table 2 [13].

Table 2. Entity recommender systems

	Entity Recommender Systems (ERS)
Input	Unstructured content repositories + knowledge base / user logs
Output	Related searches: entities relevant to the query's main entity
Query	Entities' query / extracted entities from a keyword query
Principle	Recommendation of relevant entities which are related to a query's main entity
Domain	Web / Different domain: Products, movies, etc.
Techniques	Blending techniques coming from the domains of search engines and recommendation systems
Examples	Current search engine like Google / Platforms like: Alibaba

Entity recommendation is the task of returning a ranked list of related searches in the form of entities, as shown in Table 2. In this review, we highlight the most significant methods in this field; some of them make use of knowledge bases, while others also take user behavior into account. For this new field, various searching and ranking techniques were redefined. In the next sections we will summarize works on related entities recommender by dividing them into two classes: recommending related entities according to an entity/query and recommending related entities according to a user. We will then compare them. In the discussion section, we will present our findings and some future directions.

4. LITERATURE REVIEW ON RELATED ENTITIES RECOMMENDATION

Entity recommendations have been put forth as a novel idea that offers users an engaging experience by assisting them in locating entities relevant to a given query [15]. As a result, the recommendation of related entities has become a common feature of modern search engine interfaces. These systems combine many different signals (features) that were extracted from content and interaction logs from different sources [7]. Knowledge graph has been incorporated into a number of recommendation models to enhance item information through related entities on the graph [16, 17]. In order to obtain a list of ranked related entities found in response to the main entity of a query, the system typically needs potential entities that can be thought of as relevant and related when using knowledge bases such as YAGO or DBpedia.

One subset of knowledge-based approaches is content-based techniques [18, 19]. In fact, an understanding of the items can be inferred from the item characteristics. However, the content-based filtering techniques are more concerned with utilizing the description of the item or the content to compare different items.

4.1 Related entities recommendation approaches

Recommendation of entities given an entity [13] and Recommendation of entities given a query [20, 8] are two approaches to recommending related.

(1) Recommendation of entities given an entity: this method entails using various features, such as co-occurrence or similarity, to suggest entities given a primary entity. These kinds of approaches suggest related entities based on how closely they resemble the main entity the user is looking for. A recommendation entity and the main entity could be compared using a variety of similarity metrics. Calculating how often two entities are clicked on simultaneously across all search users is a useful measurement [21]. If a related entity frequently co-clicks with the primary entity, it is then suggested [22, 23].

(2) Recommendation of entities given a query: this is supposed to search and retrieve entities. While ignoring in-session contextual queries, entity recommendation can take into account queries issued at each time step separately [24, 25]. This method takes into account a query's most common meaning. To clarify the meanings of entities with the same surface form, it uses the query itself [26, 27]. Table 3 provides an overview of methods for suggesting related entities given an entity or a query.

The majority of the methods in Table 3 present ranking methods from entities relevant to the user's current query. Other works concentrate on particular fields that demand feature extraction and selection from supervised knowledge bases [2]. The majority of Table 3's works take the current query into account while typically ignoring the users' previous system interactions. Other methods have tailored the ranking of suggested related entities to a query by taking into account the complete user history. The following section features these methods.

Table 4 lists the drawbacks of some of the previously discussed approaches.

In the next section, we will discuss and provide our inference on the previously presented works.

5. DISCUSSION

Major search engines now offer a list of ranked related entities in an entity pane. Examples of these search engines are Google [30], Yahoo! [31], and Microsoft [32]. Along with standard search results, this entity pane displays information about the entity the user is looking for. Related entities recommendation is what this concept is known as [23]. In this study, a number of publications on related entities are gathered from journals and conferences in the Google Scholar library, with a search period of 2013–2022. The number of selected publications per year on related entity recommendations is shown in Figure 3.

Table 3. Recommendation given an entity/query

Papers	Purpose	Principle	Data sources / Domain	Dataset
Blanco et al. [7]	A final recommendation list of entities is produced by Learning to rank approach.	Extract several features from various data sources. Final scores are produced by combining features.	Yahoo!, Flickr, Twitter	4797 search queries collected from commercial search engines
Yu et al. [22]	A generic framework for entity recommendation is presented.	Using different pairwise similarity features and extract them from user log dataset and Freebase entity graph.	Recommendation to movie-related entities.	User click log obtained from search engines + Freebase dataset
Aggarwal et al. [24]	An entity recommendation system is built.	Learning to rank methods are used and combined with different extracted features from Wikipedia.	Textual content and Wikipedia hyperlinks collection	4.5 K search queries. Each query has about 10 entities labeled by human experts
Bi et al. [23]	Hidden structures are extracted and captured using correlation users, primary entities, related entities.	A probabilistic Three-way Entity Model (TEM) providing personalized related entities recommendations.	Knowledge bases, search click history, entity pane log	Two real world datasets: “movies” and“celebrity” collected from commercials web searches engines
Cheekula et al. [25]	Hierarchical knowledge is used for recommendation.	A content-based approach is described and adapted to spread activation algorithm over DBpedia category structure to identify entities.	Movie domain and DBpedia	Movielens dataset
Catherine et al. [26]	Recommendations and explanations are generated.	A Personalized PageRank procedure is used to generate recommendation and its explanations.	Knowledge base/ Movies	IMDb dataset
Huang et al. [14]	Entity recommendation’s performance is boosted in terms of serendipity.	Three sets of features (interesting, unexpected, relevant) are used to find related entities and to rank candidate entity.		Real world datasets collected from the web search engine Baidu
Jia et al. [15]	Using queries without explicit entities	Entities are derived for diverse and complex queries for search support.	Shen Ma Search Engine and Browser by Alibaba	Search logs extracted from commercial search engine in China
Ni et al. [27]	Wikipedia is organized into layers of graphs created on top of each other.	Entity representations is learned from their topology and content. They combined lightweight learning to rank algorithm for recommending related entities.	Yahoo! Knowledge-Graph, and its subset (Wikipedia)	
Brams et al. [16]	A new dataset is introduced and provides explicit ratings of users for knowledge graph entities and items.	The effect of including ratings on non-item knowledge graphs entities is presented as a comparative study.	The movie domain	102,000 ratings are collected from 1174 users on entities and items
Akase et al. [28]	The number of knowledge panels is increased to recommend related entities.	A production level system generating related entities from a massive knowledgebase and searches logs.		A new evaluation set was proposed
Jacucci et al. [29]	Entity-based computing and interaction is introduced.	An approach for comprehensive digital activity monitoring and entity-based interaction is proposed.		Realistic dataset

Table 4. Drawbacks of approaches

Approaches	Principle	Drawback
Blanco et al. [7], Yu et al. [22], Bi et al. [23]	Considering the query independently from history at each time step.	Do not handle the ambiguous queries.
Huang et al. [14], Fernández-Tob´ıas et al. [2]	Relying on past users behavior observed in searches logs.	Sparsity of data and cold start issues.
Existing datasets Brams et al. [16]	Providing only explicit ratings on items.	Do not provide information about users’ opinions of other entities. (non-recommendable).
Blanco et al. [7], Aggarwal et al. [24], Blanco et al. [7], Huang et al. [14]	Considering the queries with explicit entities	Fail to handle queries without entities (complex queries).
Bi et al. [23], Blanco et al. [7], Yu et al. [22]	Requiring a rich set of entity features which are dependent of the domain and derived from a knowledge graph.	Can be applied only if the target domain is known.

Figure 3 shows that from 2016 to 2019, the number of publications decreased before starting to rise in 2020. This is because recent works that take into account user-side information in the knowledge graph will be published (starting in 2020). The majority of works in this survey primarily concentrate on giving a user recommendation for the most pertinent [7] and/or personalized [2, 22, 23] entities that rank highly against the user's preference and/or the query. We chose about 25 papers, 12 of which used knowledge graph approaches as a primary technique, 10 of which used user interactions (user history), and 3 of which used user context. We discovered that papers falling under this latter category also employ knowledge graph techniques.

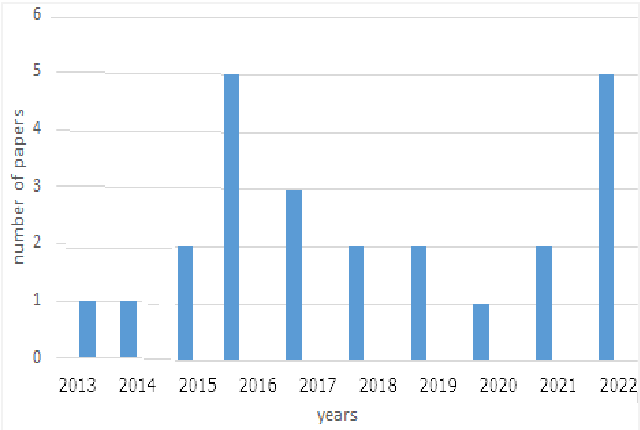

Figure 3. Number of publications on related entities recommendation per year

Figure 4 (a) shows that about 60% of the selected papers (15 out of 25 papers) has used the technique based on knowledge graph as a filtering algorithm. Most of the experiments were performed on real world datasets collected from various search engines. Figure 4 (b) shows the identified domains used in the selected works.

About 60% of the selected papers (Figure 4a) investigated how heterogeneous information in knowledge bases can be used to improve the quality of recommendations [17]. However, such existing knowledge bases may not cover all relationships that can be defined between related entities. Some studies have proposed extending the range of relationships defined by various mainstreams (ontologies, entity graphs extracted from various data sources) [7, 24, 32] while others suggested combining knowledge graph based recommendation to users' behavior analysis [22, 23]. On the other hand, most of the knowledge based approaches are combined to other methods (similarity features, user logs, learning to rank, etc.) to benefit from various strategies [33].

In about 40% of the selected papers (Figure 4a) There is growing interest in performing collaborative filtering using implicit user feedback [21, 24] which is much easier to collect. This type of approaches relies mainly on search click log and user behavior analysis.

Figure 4b shows that a recurrent domain was "movies" in 38% of works. Other domains are: product (in 19% of works), people, books, music, and some diverse domains tested together (sports, entertainment, business, emergencies, society, science and politics [28]. In Table 5, we present comparison in term of effectiveness of several approaches (presented in Section 4).

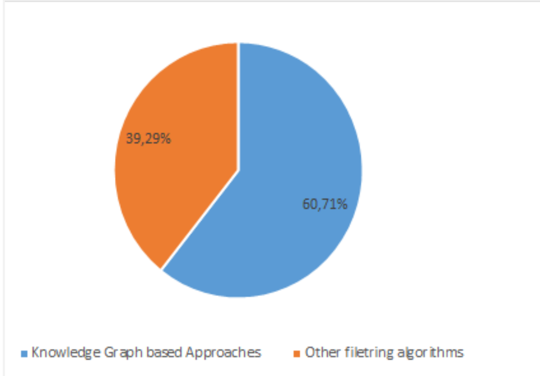

Figure 4. (a). Knowledge-based techniques VS other techniques

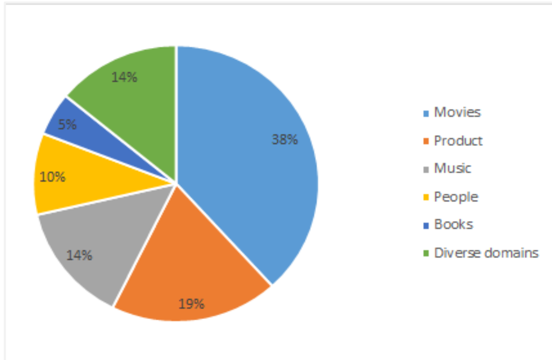

Figure 4. (b). Domains used in experiments of related entities recommender systems

Table 5. Comparison between approaches

Approach	Comparison	Compared to
Combining heterogeneous relationship information for user [22]	More effective	Implicit feedback recommendation techniques
Ranking by: Entropy-based methods [22]	Is better	Ranking by: Maximum likelihood and language modelling approaches
Recommending by: Behavioral Approach [22]	Is better	Recommending by: Semantic approach
Using Semantic Analysis [24]	Is better	Approach of Blanco et al. [7]
Inclusion of ratings on non-item knowledge-graph entities [16]	Improves recommendation quality.	Different state of the art recommendation models
Three-way Entity Model with a probabilistic framework [23]	More effective	State of the art baselines used by a web search engine
Interestingness is a strong feature set. Unexpectedness contributes to effectiveness [14]	Improves user engagement	Baseline methods: (co-click, Random, production, CTR model) and TEM [23]

Recommendations based on KGs appear to be accurate and will benefit from the valuable data they contain.

5.1 Future research directions

We discovered that the vast majority of papers on recommending related entities employed knowledge graph techniques. In fact, recommender systems increasingly depend on knowledge graphs. As knowledge graphs advance, graph embedding learning and recommendation techniques are being integrated to improve the explanation of recommendations [5]. The results of knowledge graph-based recommender systems perform better when they can be explained, according to several studies on explainable recommendations [26, 34]. Research on knowledge graphs-based explanatory recommendation models can provide tailored recommendations in a variety of research fields [5]. One of the areas in which research on intelligent systems will go in the future is this.

Other recent works [29, 35-38] take into account user side information, including the user network, user relation, and user's demographic data and suggest incorporating them into the structure of the present knowledge-based recommendation systems [39]. Another research direction might involve taking into account user-side data in the knowledge base and integrating it while recommending entities.

6. CONCLUSIONS

Entity recommendations in current web search engines aim to enhance the user experience by assisting users in retrieving entities that are relevant to a given query. Nowadays, this idea has become crucial. Some users of web search engines are aware of what they are looking for, while others are searching for content that is relevant to their initial interest [24]. The majority of strategies have looked into the fact that a user's initial interest is frequently connected to an item in the knowledge base [7]. It makes sense in this situation to suggest explicitly linked entities for additional research [7]. The term for this was entity recommendation. This survey summarized the literature and classified and synthesized the papers in accordance with various viewpoints. The literature on related entities recommender systems is searched, gathered, and divided into categories between 2013 and 2022: recommendations given users (interactions-based recommender systems) and recommendations given entities or queries. We examine related entities recommender systems and provided an overview of recent developments in this field in this survey paper. In addition to various approaches that use user's context and feedback to improve recommendations, this paper also presents various approaches that use the knowledge graph as side information. Finally, a discussion and comparison between approaches is provided and some future directions are identified. While conducting this review, we discovered that existing knowledge bases may not cover all the relations that can be defined between the related entities. We tried to identify strategies that extend coverage of defined relations by various mains (ontologies, entity-graph extracted from different data sources, etc.). We also present other strategies that suggested combining knowledge graph-based recommendation to users' behavior analysis. We conclude that knowledge graph-based recommendation systems perform better according to several studies. Furthermore, the ranking methodology is decisive to choose the most relevant related entities to a query. We hope that this review will help readers to better understand the researches in this area. As far as we know, this is the first review on related entity recommendation that considers strategies that combine knowledge graph-based recommendation along with user's context and user's history.

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