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Linked Open Data in Location-Based Recommendation System on Tourism Domain: A Survey

PHATPICHA YOCHUM, LIANG CHANG, TIANLONG GU, AND MANLI ZHU

Guangxi Key Laboratory of Trusted Software, Guilin University of Electronic Technology, Guilin 541004, China

Corresponding author: Liang Chang (changl@guet.edu.cn)

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ABSTRACT Linked open data is a relatively new topic area with great potential in a wide range of fields. In the tourism domain, many studies are using linked open data to address the problem of location-based recommendation by integrating data with other linked open datasets to enrich data and tourism content for reacting to the needs of tourists. This work aims not only to present a systematic review and mapping of the linked open data in location-based recommendation system on tourism domain, but also to provide an overview of the current research status in the area. First, we classify journal papers in this area from 2001 to 2018 by the year of publication. Second, we analyze and categorize journal papers by the different recommendation applications including problem formulations, data collections, proposed algorithms/systems, and experimental results. Third, we group the linked open data sources used in location-based recommendation system on tourism. Next, we summarize the research achievements and present the distribution of the different categories of location-based recommendation applications via linked open data. Last, we also guide the possible future research direction for the linked open data in location-based recommendations on tourism.

INDEX TERMS Linked open data, open data, recommendation system, location recommendation, location-based service, tourism

I. INTRODUCTION

Linked Open Data (LOD) is a successful realization of connections between data on the Web. It integrates heterogeneous data from multiple sources in different organizations for creating novel knowledge and enabling powerful services and applications. The large volumes of semantic data are being generated to freely share and use the content. As a result, the use of LOD has brought enormous benefits including transparency, discoverability, accessibility, reusability, and interoperability for various application fields.

For instance, LOD has the potential for use in tourism due to the several forms of data related to tourism information, activities and services produced by online applications, such as TripAdvisor, Booking, Yelp, and Lonely Planet. It can be an alternative for connecting and sharing tourism data, enriching information content, and exploring large tourism datasets. For tourist destinations, there are significant opportunities to use LOD to further improve sightseeing, transportation, marketing, and the environment. People focus on the quality of the tourist experience, so the demand for LOD in tourism research has become extremely intense. Therefore, the linked open data is being used in tourism to respond to the needs of tourists and integrate data with other linked open datasets to enrich data and tourism content.

The huge amount of tourism-related LOD with the advantage of multi-resource and semantically interrelated data is thus a great opportunity for boosting recommendation systems in the tourism domain. Several works on tourism recommendation systems have been proposed in LOD [1]–[4]. More formally, Hsu *et al.* [1] implemented an intelligent tourist attractions recommendation system and applied the Bayesian networks approach to estimate a tourist's preferred attraction by considering user preferences. Google Maps API was merged into the system to interact user interface with the geographic data based on personal needs. While Lucas *et al.* [3] developed a recommended methodology for tourism by generating users' groups from the similar

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preferences and characteristics. These studies have shown that the integration of linked open tourism data into the recommendation process is one of the solutions to solve recommendation system problems. It can improve the accuracy and quality of recommendation systems, and overcome the limitations of traditional recommendation techniques, such as cold-start, data sparsity, and scalability problems.

With the increasing popularity of smartphones and the availability of online applications, such as Facebook, Twitter, and Foursquare, these play an important role in location-based services as well as trajectory-based information. Those services and contents also provide tourism information to user and enable a deeper understanding of user preferences and behavior. It has stimulated research into novel location-based recommendation system to bridge the gap between user travels and social interactions. Although tourism information can be obtained from these resources, but otherwise do not expose, share, and connect pieces of information. Another problem is lack of support in augmenting one data source with additional knowledge. To address these issues, many researchers have studied location-based tourism recommendation system problems by using LOD and proposed various algorithms for solving these limitations. The collected large volumes of data, such as profiles [5]–[7], ratings [8], [9], comments [10], [11], check-ins [12]–[14], and route patterns [15]–[17] on a daily basis have diverted the focus of researchers from the problem of information retrieval towards recommendation systems in the area of the tourism. In [18], the authors extracted the popularity of landmarks from geo-tagged photos and built location profiles from temporal and weather context. Wang *et al.* [14] exploited photos, user check-in patterns, and text description from the user generated content to find location semantic similarity. Fig. 1 illustrates a taxonomy of the general area of location-based recommendation research, which is further divided into the type of output recommendations.

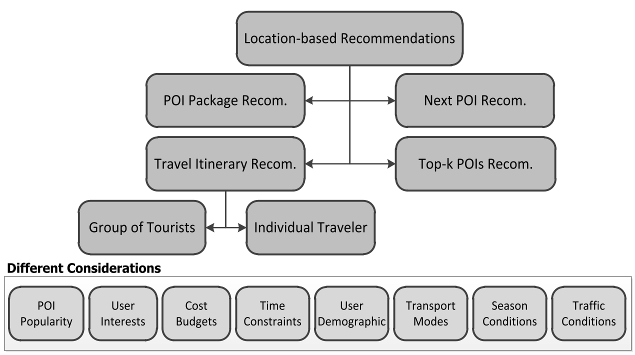

FIGURE 1. Taxonomy of location-based recommendation.

In recent years, various literature surveys have been presented a general overview and research challenges in the location-based recommendation systems [19], [20], [21], [22] and the tourism recommendation systems [23]–[26]. While these surveys offer interesting discussions into different aspects of recommendation systems, the novelty of our survey differs from the earlier articles, that is, we focus on the linked open data in location-based recommendation system on tourism. To the best of our knowledge, no review study has been conducted to investigate this area. In this research, we conduct a comprehensive literature review related to linked open data in location-based recommendation system on tourism. Our survey presents the publications in this area from 2001 to 2018. For each journal, we investigate three aspects: (1) the objective of integrating linked open data; (2) the linked open data source used in tourism; and (3) the methodology produced in recommendation. According to these three aspects, the key contributions of this research are summarized as follows:

1) We present a systematic review and mapping of the linked open data in location-based recommendation system on tourism domain.
2) We classify journal papers of the linked open data in location-based recommendation system on tourism from 2001 to 2018. Moreover, the distribution of the journal paper publications per year during the same period is presented.
3) We analyze and categorize the different recommendation applications in the linked open data in location-based recommendation system on tourism domain. We also explain and give the example of categorization by those applications, covering the whole process from problem formulations, data collections, proposed algorithms/systems, and experimental results.
4) We group the linked open data sources used in location-based recommendation system on tourism.
5) We summarize the research achievements in the linked open data in location-based recommendations on tourism. Additionally, we present the distribution of the different categories of location-based recommendation applications.
6) We outline the future research challenges in the linked open data in location-based recommendation systems on tourism fields.

The remainder of this paper is organized as follows. Section 2 introduces related work. Section 3 describes the systematic review and mapping. In Section 4, an overview of linked open data in location-based recommendation system on tourism domain is presented. The future directions are shown in Section 5. The last section provides conclusions.

II. RELATED WORK

Since the mid-1990s, recommendation systems have been becoming an important research area [27]. Researchers started concentrating on recommendation problems that explicitly rely on the rating structure. The most common techniques in recommendation systems are designed to predict ratings for the items that have not been seen before by a user. Generally, the prediction is often based on the ratings given by this user to other items and some other information.

TABLE 1. An example of a user-item rating matrix.

	Statue of Liberty	Central Park	Disneyland
Alexander	5	4	3
Benjamin	-	-	5
Carter	4	-	2
Diana	3	5	-

The recommendation problem can be easily found as well as online shopping. The item set can be extremely large, such as recommending books, movies, or news. Similarly, in some cases, the user set also can be very large. An example of a user-item rating matrix for a tourist attraction recommendation application is presented in Table 1, where ratings are specified on a scale of 1 to 5. The '-' symbol in Table 1 means that the users have not rated the corresponding tourist attractions. For example, Diana gave the tourist attraction 'Statue of Liberty' a rating of 3 (out of 5). The recommendation system will create the profile. Each element of the user can be defined with a profile that includes various characteristics of users, such as age, gender, country, etc. Similarly, each element of the item is defined with a set of item characteristics, such as name, category, location, year of build, etc. Therefore, the recommendation engine should be able to predict the ratings of the unrated tourist attraction/user combinations and issue appropriate recommendations based on these predictions.

Recommendation systems are usually classified according to their approach to rating prediction. In the next section, we will present the common recommendation techniques, linked open data for tourism, and location-based recommendation system.

A. COMMON RECOMMENDATION TECHNIQUES

An overview of recommendation techniques is illustrated in Fig. 2. The following are three groups of recommendation engines:

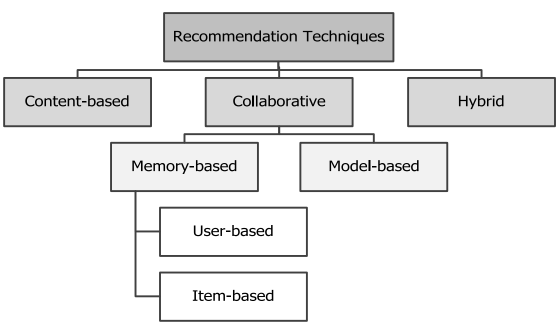

FIGURE 2. An overview of recommendation techniques.

- *Content-based recommendations* The user will be recommended items that are similar to the ones the user favored in the past.
- *Collaborative recommendations* The user will be recommended items that people who have similar tastes and preferences preferred in the past.
- *Hybrid approaches* These methods normally are composed of collaborative and content-based methods.

1) CONTENT-BASED METHODS

The content-based recommendation approach has its roots in information retrieval and information filtering research [28]. Most content-based recommendation methods focus on recommending items containing text that rely on textual information and keyword similarity.

To improve the traditional information retrieval approaches, content-based recommendation systems select the use of user profiles that contain data representative of the user interests, user tastes, preferences, and needs. The item profile is a set of features characterizing items and determines the appropriateness of the item for recommendation purposes. The recommendation process basically matches up between items based on the features of the item profile. The user profile is taken into account to find similar items. For example, Carter likes 'Statue of Liberty' attraction then the system can recommend him the attraction of 'Central Park' or attractions with the theme "Park". The result is a relevance judgment that represents the user's interest level in that item. If a profile reflects user preferences accurately, it has a great advantage for the effectiveness of an information access process.

In the past decades, many research works employed content-based recommendation methods widely. There are several works related in news [29], TV program [30], product [31], and tourism domain [1], [32]–[34]. For instance, Binucci *et al.* [32] designed the Content Analyzer and implemented the technique in a system called Cicero for recommending a travel destination. The Content Analyzer is a module that receives as input a set of point of interests and a set of topic of interests, and it computes the relevance of each point of interest with respect to each topic of interest.

A widely used algorithm in a content-based approach is TF-IDF [35], short for term frequency-inverse document frequency to evaluate term weighting scheme a word in a document. Besides, several machine learning methods also used to improve the performance of content-based recommendations, such as Fuzzy set [31], Classification [29], Clustering [36], Neural network [37], and Bayesian Network [38].

2) COLLABORATIVE METHODS

The underlying assumption of collaborative systems (or collaborative filtering systems) relies on the availability of user ratings that try to predict the items for a user based on the items rated by other users before.

According to [39], the collaborative approach can be divided into two methods: (1) memory-based and (2) model-based methods.

The memory-based algorithm depends on the whole rating that exists in the user-item matrix for calculating neighbors of the active user to generate recommendations tailored to user preferences. The memory-based recommendation method can be grouped into two general ways: (1) user-based and (2) item-based.

The user-based method predicts the rating that a user might assign to an item by calculating the ratings that the most similar users have similar ratings in the past. So, we can predict missing values in the rating matrix on the specific items according to similar users' ratings on given items. In contrast, item-based method focuses on the similarities among items. The items recommended to the user are ranked by calculating the similarities between items and the items that user given previously ratings.

A typically collaborative has four actions: (1) calculating the similarity between users or items by cosine similarity, correlation similarity, adjusted cosine similarity, or Euclidean distance; (2) acquiring neighbors by finding the most similar items based on a given distance metric; (3) producing a prediction for the user by taking the weighted average of ratings; and (4) generating the recommend list.

For instance, Spindler *et al.* [40] proposed user-based collaborative filtering in mobile tourist information systems based on spatio-temporal proximity in social contexts. They exploited mode of information sharing resulting from tourists and showed that users who share social contexts have similar interests. It can be used as a basis for collaborative recommendation.

In contrast, the model-based algorithm focuses on addressing training based on the whole rating that exists in the user-item matrix for learning a model to generate the final recommendation. The well-known machine-learning techniques used in this approach include matrix factorization [41], Singular Value Decomposition (SVD) [42], Support Vector Machine (SVM) [43], fuzzy systems [44], generic algorithms [45], clustering [46], Bayesian networks [47], latent features [48], neural networks [49], and especially Deep learning methods [50].

In [42], the authors employed opinion-mining in tourism destination recommender system to refine user emotional and integrated it into matrix factorization. Meanwhile, the temporal dynamics is used to represent user preference and destination popularity drifting over time. These elements are fused with the SVD++ approach by jointing user emotional and temporal influence.

3) HYBRID METHODS

To achieve higher performance and overcome the drawbacks of traditional recommendation techniques, a hybrid approach combines two or more recommendation techniques in an attempt to overcome the limitations of traditional approaches [25], [51]. In the situations that there is no information about users or their ratings, the content-based part of a hybrid recommendation system can be helpful to retrieve useful information to generate a recommendation. On the other hand, when information about the contents associated with the items is not sufficient, the collaborative part of the hybrid recommendation system can be supportive. Consequently, issues in terms of data sparsity, cold start, and scalability in recommendation systems will be resolved [52].

Many cases [2], [53]–[55] in recommendations are combined between content-based and collaborative filtering. One example in [55], a hybrid gallery recommendation is using a weighted coefficient with collaborative and content-based in wallpaper photos. First, the use of the nearest and furthest neighbors of users reduced the dataset and applied a Pearson correlation to get score means in a collaborative algorithm. Second, a content-based method is to find a rating based on the distance of an item to the decision boundary. Finally, a hybrid recommender is to predict the scores of both two algorithms. The compressed dataset improves scalability, alleviates sparsity, and reduces the computational time of the system.

Moreover, the researchers combine content-based with other technique(s) [56]–[58]. An example of this combination is [56], a hybrid approach used in a movie is to create a user profile by considering the user history. Then a fuzzy-based approach is employed to find the similarities and differences between the user profile and the items and to predict the ratings. The results showed that the performance of the system is further improved in movie domain.

There are many studies [4], [59]–[61] in which collaborative filtering is combined with other technique(s). Liu *et al.* [4] developed a tourist-area-season topic (TAST) model to represent travel packages and tourists by different topic distributions as well as locations and travel seasons of the landscapes and to capture the latent relationships among the tourists in each travel group. Then, a cocktail approach used a collaborative method to predict the possible price distribution of each tourist and reorder the packages. Finally, the final recommendation list is generated to users.

Several hybrid recommendation systems apply content-based, collaborative, and other technique(s) into recommendation [3], [62], [63]. Pessemier *et al.* [63] proposed a hybrid travel recommender system, which merged content-based, collaborative, knowledge-based solution for travel destinations to individuals and groups. These recommendations are based on the users' rating profile, personal interests, and specific demands for their next destination.

B. LINKED OPEN DATA FOR TOURISM

The Linked Open Data (LOD) is the new concept to fully benefit from a successful realization of Semantic Web, Linked Data, and Open Data. It can be interlinked and integrated the heterogeneous data on the web using the open standards like URI (Uniform Resource Identifier), HTTP (Hypertext Transfer Protocol), and RDF (Resource Description Framework) for creating new knowledge and enables powerful services and applications.

There are several examples in linked open data, for instance, DBPedia is a Linked Open Data that extracting structured information from Wikipedia. It often acts as a data integration hub between data sources [64]. Flickr is an image and video service website. It is a photo-sharing web where users can share their images, which also can be reused by other users. Besides, an ontology is a description of the concepts and relationships that can exist in a specific knowledge area. The creation of an ontology for LOD has the goal to identify the context of linked data and share the same semantics made up of open standards and a common data structure [65].

In particular, the impact of semantic sites expands their capabilities by supporting user-generated content, such as reviews, comments, and past experiences, to recommend future purchases. The more the product online review features available to users, the higher the likelihood of sales of related items within the product category.

According to [66], tourism is the first industry concerned by open data, and mobility the main issue. The various kinds of data related to tourism activities and services are produced and utilized across a wide range of online applications. TripAdvisor and Yelp have an influence on travel decisions in many aspects, e.g. selection of a tourist destination, accommodation, and attractions. Tourists can access all of this information to make a decision. It is primarily the outcome of the increasing data, the development of open sources and open data policies. The challenge now is finding the use of information on the web and sharing information with everyone. Thus, Linked Open Data has played a great role in concept as the data is shared and built on by anyone, anywhere, and for any purpose.

Many researchers applied the concept of linked open data in tourism domain. Sabou *et al.* [64] observed the Linked Data platform for integrating data from TourMIS, World Bank, and Eurostat data sources. Besides, the ETIHQ Dashboard for data analytics was implemented to support cross-domain over tourism. They described that TourMIS was exposed as Linked Data and then combined different data sources, thus providing a technology basis for quick and automatic integration of tourism data with statistics from other domains. In [67], an online demo system is the personalized concept-based search for tourism domain. The authors used a tourism domain to create a benchmark dataset using LOD resources. The system has two main parts: 1) allow a user searches on LOD and categorizes the retrieved search results, and 2) the search results are personalized to individual users based on user interactions. Pantano *et al.* [68] explored the usage of open data to predict tourists' responses towards a certain destination, in terms of ratings. A large set of open data is freely available on tripadvisor.com. They also proposed the classification function for predicting the destination tourists. The CitySDK Tourism API was developed by [69] to access information about point of interests, events and itineraries of Amsterdam, Helsinki, Lamia, Lisbon and Rome cities. It has cooperation from municipalities, other government levels and other private or public organizations. Currently, several companies have developed mobile applications that use the API. While Wu *et al.* [70] developed a tourism service application by using open data in which released by relevant authorities. A user can access travel-related open data, including weather, location of a hospital or restaurant, public transit schedule and the address of a hotel in Taiwan. Sohn *et al.* [71] developed the ACARDS via the hybrid SPAQL query generation system to increase the degree of user satisfaction. The recommender system collected knowledge from LOD cloud and improved the quality of the context recommendation service using the augmented tag cloud.

In addition many researchers also incorporated linked open data into ontology concept for their purpose in tourism domain [72]–[75]. Arigi *et al.* [72] proposed a context recommender based on the ontology system to represent knowledge in the tourism domain. The system recommended tourist destinations by using user preferences of the categories of tourism and contextual information, such as user locations, the weather of tourist destinations, and destination's closing time. Corsar *et al.* [73] presented the GetThere system that is a semantic mobility travel information system to provide real-time passenger information. An ontology framework was developed to support the system, along with the Linked Data method used to integrate heterogeneous information from multiple sources including government, transport operators, and the public. Especially, the Open City Data Pipeline was presented by [74]. The framework, which is a platform for collecting, integrating, and enriching open city data from several data providers, contains a data crawler, ontology-based integration platform, and missing value prediction module. As the prediction of missing values is a crucial component then they used both basic regression methods and reasoning with equations. García *et al.* [75] implemented the SmartTourism, which is a touristic mobile application. They showed a possibility to generate knowledge using semantic ontology and learning from the collaboration among different data sources using linked open data.

C. LOCATION-BASED RECOMMENDATION SYSTEM

With the growth of smartphones and the availability of online applications, location-based recommendation systems have achieved great success in recent years. Location-based recommendations are developed from two lines of services: (1) location-based services and (2) recommendation services. Location-based services allow users to easily perform check-in actions that pin the geographical information of current locations and timestamps via online applications [76]. While the goal of recommendation services is to create some sort of utility, e.g., provide users with relevant information, improve customer retention, and increase revenue [77]. So, a location-based recommendation system aims to recommend the items, such as, venues, places, travel routes, activities, friends, or social media, to a user with the consideration of the geographical preferences (e.g., current location, historical locations, and spatio-temporal location), the user preferences (e.g., user profile and user friends), or the venue preferences (e.g., the category of venue).

According to [19] and [20], the categories of location-based recommendation systems can be divided into two groups: (1) stand-alone location recommendation systems, which recommend individual locations for users, such

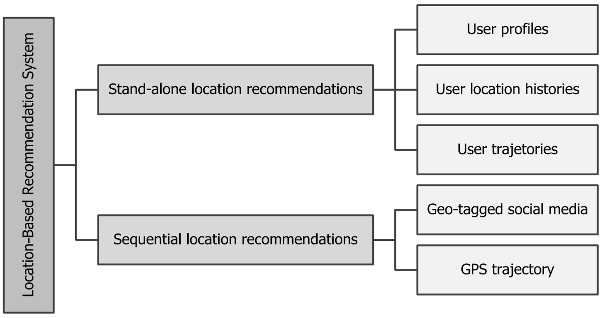

FIGURE 3. Location-based recommendation system techniques.

as restaurants or cities that match their preferences and (2) sequential location recommendation systems, which provide a series of locations (e.g., a popular travel route in a city) to users based on their preferences and their constraints, such as time budget and cost as shown in Fig. 3.

1) STAND-ALONE LOCATION RECOMMENDATIONS

Many recent studies have focused on the stand-alone location recommendation systems. There are three parts as follows:

- **User profiles** These location recommendation systems suggest locations by matching the user's profile against the location metadata, such as description, semantic text, and tags [78]–[80]. Ravi *et al.* [79] developed a recommendation model, named Hybrid Location-based Travel Recommender System (HLTRS) to generate the point of interest recommendations by considering user's needs and preferences. HLTRS constructed an individual user profile for predicting the locations based on the individual and group activity information of the target user.
- **User location histories** A user's location history includes a) the rating history (e.g., attractions, hotels, and restaurants) and b) the check-in history. The availability of online web services, e.g. TripAdvisor, Booking, and Yelp, allows users to express their satisfaction for locations by given ratings. Many researchers developed a location recommendation system based on user location history [81], [82]. Bao *et al.* [81] studied the problem of a new place recommendation. The method applied the user-based collaborative filtering to compute a similarity score between user and local experts. It provided a user with location recommendations around a specified geo-position based on the preferences of the user. Location history of users and social opinions from local experts could share similar interests.
- **User trajectories** Compared to the user profiles and user location histories, user trajectories contain a richer set of information, such as the travel sequences among locations and the duration of stay at each location. As a result, trajectory data can be used to more accurately estimate a user's preferences [83], [84]. For instance, Zheng and Xie [83] proposed a Hypertext Induced Topic Search (HITS) model to build a travel recommendation framework using GPS trajectory data. The HITS model was based on the assumption that the interesting places might be visited by travel experts, and the tourists might visit more interesting places.

2) SEQUENTIAL LOCATION RECOMMENDATIONS

There are more complex objectives in sequential location recommendations. A number of sequential location recommendation systems have been proposed based on geo-tagged social media data or GPS trajectories.

- **Geo-tagged social media** A user's geo-tagged social media content can be used as a knowledge base for making sequential location recommendations [18], [85]. Majid *et al.* [18] developed a trip-planning method for recommending tourist locations. They extracted the popularity of landmarks by uncovering the value of photos from geo-tagged photos by K-means and mean-shift clustering methods and built location profiles from temporal and weather context. The system acquired travel preferences of users for computing travel similarities between users from their travel histories in one location and recommending tourist locations in other cities.
- **GPS trajectory** GPS trajectories contain a rich set of information, including the duration a user spent at a location and the order of location visits that can improve sequential location recommendations [86]–[88]. Zheng *et al.* [86] studied the relationship between the locations of users and their social ties. A hierarchical similarity measurement is based on users' GPS trajectories to consider the importance of a location for creating a friend and location recommendation system.

III. SYSTEMATIC REVIEW AND SYSTEMATIC MAPPING

In this study, we selected papers reviewed using a systematic mapping process. According to [89], a systematic mapping should allow guiding the focus of future systematic literature reviews while also identifying areas for further primary studies to be conducted.

The strictly following the recommendations proposed by [89], our survey was conducted by using the following three steps: planning, conducting, and reporting.

A. PLANNING

In the planning phase, the research objectives are clearly identified, and the research questions are well formulated, thus a search string is generated.

We designed the present systematic mapping for answering the following three primary research questions:

- (RQ01) What are the objectives that Linked Open Data is being used to the location-based recommendation systems for Tourism Domain?
- (RQ02) What are the Linked Open Data datasets used for location-based recommendation systems for Tourism Domain?

- (RQ03) What are the methodologies used for location-based recommendation systems via linked open data on Tourism Domain?

Based on the above research questions, it was possible to extract the keywords (linked open data, location-based, tourism, recommendation) and their synonyms (linked data, open data, ontology, knowledge, location, attraction, travel, tourist, POI, point-of-interest, recommender). The combination of these terms resulted in the search string as follows:

("Linked Open Data" OR "Linked Data" OR "Open data" OR "Ontology" OR "Knowledge") AND ("Location-based" OR "Location") AND ("Tourism" OR "Attraction" OR "Travel" OR "Tourist" OR "POI" OR "Point-of-interest") AND ("Recommendation" OR "Recommender")

We selected the papers according to their relevance to the area under study as following inclusion criteria: (1) has a distinct location-based recommendation techniques; (2) uses linked open data as data source; (3) published in the top-level journal papers from 2001 to 2018 taking into account the impact factor of the journal; and (4) the application domain area is tourism.

The following are criteria for exclusion of articles:

- The techniques used for the recommendation system are not clearly indicated by the authors of the article.
- The domain of the location-based recommendation system is not tourism.
- The recommended items are neither attractions nor travel spots.
- The recommended target is an individual.
- The articles with only the abstract were published without the full paper.
- The survey papers whose main goals were to report the results of review studies.

B. CONDUCING

The systematic mapping was started by searching and downloading journal papers from 2001 to 2018 in which included six databases: ACM Digital Library, IEEE Xplore Digital Library, EI Compendex, ScienceDirect, Springer Link, and Web of Science.

As the survey of the area on Linked Open Data in Location-Based Recommendation System on Tourism Domain following the selection criteria, a total of 834 papers were retrieved to analyze.

In the first step of the article selection process, a total of 834 relevant papers were retrieved. After reading the titles and abstracts of the papers, resulting in 306 being discarded, and 528 is selected for the subsequent step of the more detailed analysis.

In the second stage, a closer analysis of the papers was performed, by reading the abstracts and the whole paper. 402 studies were rejected using the mentioned exclusion and inclusion criteria. Thus, 126 top-level journal papers published from 2001-2018 were selected for the data extraction step.

IV. OVERVIEW OF LINKED OPEN DATA IN LOCATION-BASED RECOMMENDATION SYSTEM ON TOURISM DOMAIN

In this section, we present an overview of selected publications on Linked Open Data in Location-Based Recommendation System for Tourism Domain.

Linked Open Data has the potential for use in Location-based Recommendation System due to the characteristic nature of the tourism data and resources produced by many universities and companies [66], [90]. It can make the content of different repositories more discoverable, accessible, connectable, and reusable.

The analysis of the examined 126 top-journal papers indicates that the use of Linked Open Data in Location-Based Recommendation System for Tourism Domain has the results in four sections as follows:

1) Classify the journal papers that were published from 2001 to 2018 in the field of linked open data in location-based recommendation system on tourism domain;
2) Categorize the different recommendation applications used by linked open data in location-based recommendation system on tourism;
3) Group the linked open data sources of location-based recommendation system on tourism;
4) Summarize the research achievements of the linked open data in location-based recommendation system on tourism.

A. CLASSIFICATION OF PUBLICATIONS ON LOCATION-BASED RECOMMENDATION SYSTEM ON TOURISM DOMAIN

In order to give a clear picture of the distribution of publications for the last 19 years, we summarize the achievements made in this area in terms of research output. Fig. 4 shows an overview of the studies by year of publication that started being researched with significant growth in 2001-2018. A total of 126 journal paper publications relevant to linked open data in location-based recommendation systems on tourism domain were analyzed and classified according to the year of publication. According to Fig. 4, the linked open data in location-based recommendation system on tourism domain has played a role since 2001. There were tiny numbers of journal papers between 2001 and 2010. The number of journal papers increased slightly from 2011 to 2014. After that, it gradually moved up year on year and reached a peak of 24 in 2018. It is expected that the linked open data in location-based recommendation system on tourism domain will continue to grow in the future.

B. CATEGORIZATION OF RECOMMENDATION APPLICATIONS FOR LOCATION-BASED RECOMMENDATION SYSTEM ON TOURISM DOMAIN

In selected journals, researchers developed several applications in the linked open data in location-based

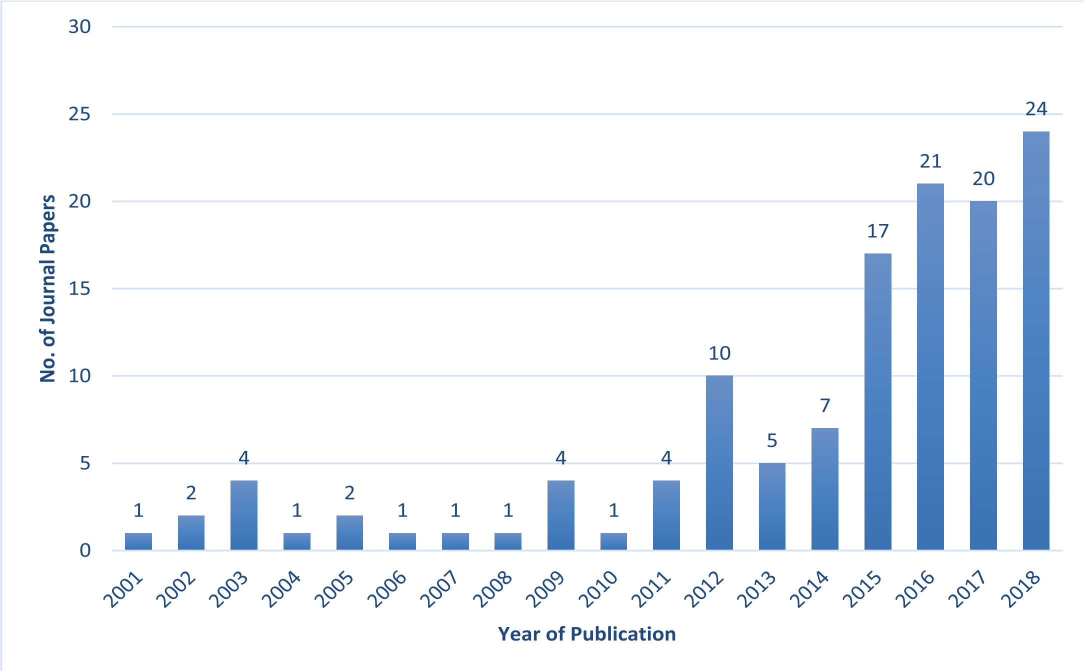

FIGURE 4. Number of publications over years.

recommendation system on tourism domain. Existing works can be categorized into six types as follows:

- *Stand-Alone Point Location Recommendations* are to recommend point of interest or popularity of place around user location to a user based on user preferences and user constraints.
- *Travel Route Recommendations* provide the output of the recommended travel route and travel itinerary.
- *GPS Trajectory-based Recommendations* are to use travel patterns and behavior from GPS trajectory records for the recommendation problems.
- *Geo-tagged-media-based Recommendations* have the key task to extract multimedia data from textual or photos to discover places, context information, and user profiles.
- *Ontology-based Recommendations* collect datasets and build tourism ontology for the different recommended targets, such as a list of point of interests, popularity of locations, travel itinerary, and route planning.
- *Location-based Friend Recommendations* aim at using user's social connections to recommend places based on friends' preferences.

We will explain in detail including the concept of categorization and the whole process of those applications from problem formulations, data collections, proposed algorithms/systems, and experimental results.

1) STAND-ALONE POINT LOCATION RECOMMENDATIONS

Stand-alone point location recommendation systems are the one type of application that suggests individual venues and attractions for the user to visit.

The main important is to improve recommendation performances. For example, Li et al. [8] believed the rating a place does not express real user preferences. They assumed that ratings of a certain user can be ranged according to the time when the user gives the rating. So they addressed the problems based on the assumptions by proposing a new model to learn user preference from user ratings and time stamps. They counted in a number of the previous point of interests to form a collection for each user and supposed a higher score to the newly visited locations. User behavior was used to model through a latent factor and used a matrix factorization technique to personalize point of interest recommendations. The results reported that certain time stamps can significantly improve recommendation performances. Tuan *et al.* [91] studied a location-based collaborative filtering system with dynamic time periods for recommending point of interests. They calculated the similarity between point of interests and recommended items based on user current location and time conditions. The model can solve the calculation time and the transmission of the user-required information problem. The results implied that it improved point of interest recommendation quality by applying location-based services and enhancing user satisfaction. Lu *et al.* [12] argued that the decisions of users to visit place depend on multiple factors. They developed a dynamic personalized recommendation framework using collaborative filtering methods for a location recommendation based on user preferences and check-ins during the period. They modeled user preferences by designing weighting strategies and aggregating the results of different recommendation functions. The framework was flexible and dynamic because it can combine location recommenders and track user preferences. The results indicated that it achieved the robustness of recommendation performances. While Rios *et al.* [92] studied how to select neighbors in the context of a collaborative filtering method for point of interest recommendation. They used the different elements available in location-based social networks to select users in recommendation process. There are four strategies; two based on the geo-location information, such as the place where users live and walk around, and two based on the relationships, such as friendship and co-located visits. The results mentioned that the best strategy for selecting neighbors was the one that chose users who visited at least a place that has been visited by the target user. This strategy reduced the error in the prediction step of the collaborative filtering approach.

Liu *et al.* [93] solved a personalized point of interest recommendation problems by analyzing geographical influence and user mobility factors. They proposed a general geographical probabilistic factor framework using the geographical information of point of interests, user mobility patterns, and the latent regions with these sources of information. There are three advantages to this recommendation method. First, the model captured the geographical influences on a user's check-in behavior. It meant user mobility behaviors can be effectively leveraged in the recommendation model. Second, they extended the latent factors as well as the skewed user check-in count data to implicit feedback recommendation. Last, it was flexible and could be merged with different latent factor models for recommendations. The experimental results implied that the proposed method improved latent factor models by a significant margin. Zhao *et al.* [13] showed that the contextual check-in information can compose an individual's daily check-in sequence for improving the recommendation process. They exploited the embedding learning techniques to capture the contextual check-in information and proposed the GT-SEER model for point of interest recommendation. First, they presented point of interests' contextual relations from user check-in sequences based on word2vec framework. It captured sequential patterns both the consecutive check-ins' transitive probability and point of interests' intrinsic relations represented in sequences. Next, they captured temporal features in sequences on different days and then learned user preferences and sequence patterns into temporal influences. Last, they merged user preference, sequence patterns, temporal influences, and geographical influences to improve recommendation performances. Experimental results demonstrated that the GT-SEER model improved at least 28% on datasets for precision and recall metrics. Dao *et al.* [94] proposed the CACF-GA model for location-based advertising based on user's preferences and interaction's context. They presented personal context information in three dimensions; location, time, and needs type. First, they applied a genetic algorithm to optimize a set of values in the context-similarity matrix. Second, user information was inputted into the CACF-GA model including visiting a location, visiting date, visiting time, and needs type. The located areas far from the user's current location were filtered out by the model. Next, the collaborative filtering was used to find neighbors to the user, and calculated similarity for the items that the user has not visited. Finally, the recommendation system provided a list of items to the user. The results indicated that the concept of context similarity can improve the relevancy of the recommendation process.

The geographical influences have been intensively used in location recommendations. However, these cannot fully capture human movement sequential patterns, so the spatio-temporal sequential influence is applied in location recommendation. Zhao *et al.* [95] studied the temporal characteristics problems, such as periodicity, consecutiveness, and non-uniformness. They proposed the ATTF model for point of interest recommendation to capture the temporal influence in three features; user, time, and location at different time scales. They used a tensor factorization method to construct a user-time-point of interest for representing the check-in pattern. The ATTF model outperformed a single temporal factor model and improved in the recommendation task. To take into account the multi-dimensional contextual information in the check-in data, Yao *et al.* [96] proposed a collaborative filtering with tensor factorization algorithm for point of interest recommendation. The framework composed of dimensions of users, locations, and time in contextual information of check-in data. They analyzed users' social, temporal patterns and spatial visited locations by using check-in information and employed tensor factorization algorithm to enable point of interest recommendations in a higher-dimensional space. The proposed framework improved the recommendation accuracy by applying the internal relations of users and locations to generate latent factors. Si *et al.* [97] considered the effect of various features in check-in data by presenting a point of interest recommendation approach combining check-in and temporal features. First, they mined features of user activity and check-in behavior by the probability statistical analysis method. Then K-means algorithm was used to classify the users into active users and inactive users. Finally, they listed point of interests by calculating the similarity of a different time with active users. The proposed method can improve precision and recall metrics in point of interest recommendation methods. Zhou *et al.* [98] focused on the integration-based perspective of the category information to represent the temporal patterns in check-in data for location recommendation. They extracted the category of locations from temporal patterns and applied a collaborative filtering method to calculate the similarity of temporal patterns in users' check-in behavior. While the spatial used the geographical to filter out not interested locations. The results mentioned that it improved the time efficiency of the recommendation process. Zhao *et al.* [99] studied a new problem of personalized locally interesting venue recommendations to users. They provided a solution by adopting the user-generated location contents in social networks. First, they proposed a Bayesian method to extract the social dimensions of people in different regions to capture latent local interests. Next, they mined the local interest communities in each region and used users' temporal visiting behaviors to represent each local community. Finally, they matched communities in different regions and generated venue recommendations to users. The framework showed that the effectiveness of cross-region recommendations can be gained.

Existing works have distinct differences in terms of the recommendation problems, such as cold-start, data sparsity, scalability. Yin *et al.* [9] solved the cold start recommendation problem by adopting a location-aware probabilistic generative algorithm based on user ratings. The framework considered user location and users' preferences and then recommended items were close in taste and travel distance by capturing item location co-occurrence patterns. The results showed that they deployed the model to user profiles and achieved more accurately. In [100], the authors added semantic information to a content-aware collaborative filtering framework for the location recommendation system. They extracted semantic contents from implicit feedback and incorporated them into content-aware matrix factorization. The results implied that the framework improved the accuracy of the recommendation and solved the cold-start problem of new users. Wang *et al.* [101] proposed location recommendation framework by using ratings, geo-locations, and tags to generate a recommendation. First, all users were clustered by a memetic algorithm based clustering method. Next, they applied a latent dirichlet allocation method to mine interests of users and the geographical information based on ratings and tags for recommending a list of items. Finally, the recommendation list was recommended to all users in a cluster. The proposed algorithm improved the performance of solving the cold-start problems.

Aliannejadi and Crestani [102] solved the data sparsity problem by boosting personalized location keywords in a user's history. They presented a probabilistic model to map taste keywords and user tags for a new location. Location's content and reviews were used to find relevance of scores and calculated the similarity between a user's history and a location for ranking locations. They claimed that the proposed approach captured user preferences accurately and addressed the data sparsity problem. Ren *et al.* [103] studied the sparsity problems of user-point of interest matrix by presenting a context-based probabilistic matrix factorization method to recommend point of interest to the users by adding more information. First, they exploited the interest topics of users by latent dirichlet allocation and text mining techniques and generated interest relevance scores. Second, they proposed a kernel estimation method to model the geographical correlations and generated a geographical relevance score. Next, they generated social relevance from the distribution of user social relations. Then, they combined the category of users and the popularity of point of interests to get a categorical relevance score. Finally, they integrated the topic model, geographical, social and categorical relevance scores into probabilistic matrix factorization model for point of interest recommendation. This model achieved a significant improvement in point of interest recommendation quality. Yin *et al.* [80] focused on alleviating the issue of data sparsity using social-spatial information. They proposed the decision-making process of user's check-in behaviors in urban and non-urban. The temporal pattern, social-spatial, and geographical were extracted from check-in records to find the topic user's interest. They designed an attribute pruning algorithm to merge different dimensions and support a fast online recommendation for large-scale social data. The results mentioned that distinguishing user interests improved the recommendation process. Shen *et al.* [104] focused on the low frequency of tourism and the styles of attractions in different cities. They developed a personalized travel recommendation consisting of collective intelligence collection, knowledge extraction, PAS-model, and user interaction modules. In the first module, they collected heterogeneous data from Flick, TripAdvisor and Wikitravel websites. Then, knowledge was extracted aspects of attractions, such as content, semantic and social terms. Next, the personalized attraction similarity model (PAS-model) was constructed graph-links with the three knowledge aspects and computed the weight of features. Finally, they recommended a list of attractions based on positive and negative labels. The results showed that PAS-model can solve data sparsity and cold-start problems.

Besides, several works are specific to the main proposed, for example, the ranking prediction, the next point of interest, and the next city. Cheng *et al.* [105] found that users tend to check in several attractions and users have different numbers of attractions. The users are often interested in the top 10 recommended point of interests. So, a personalized ranking is important in this work. They first studied personalized users' moving patterns to capture the geographical influence on user's check-ins. For each user, they extracted attractions based on user check-ins. For a new location, they defined the probability based on the user's interests. Next, a fused matrix factorization model was proposed to merge the geographical influence of users' check-in locations. Finally, they presented the ranking-oriented collaborative filtering with all information by leveraging Bayesian personalized ranking loss to learn a point of interest recommendation model. The results indicated that the proposed framework can produce better performance in recommendation system. Xing *et al.* [106] proposed the ReGS model by integrating heterogeneous data from different areas and structures to learn users' preferences for point of interest recommendation. First, they captured point of interest topics in textual review using the convolutional neural network technique. Second, users' check-in records in geographical influences were used to build geographical neighbor weight. Next, they computed user similarity by using user social relations like user characteristics. Finally, they integrated point of interest topics, geographical, and social relations for predicting ratings. The model improved predictions of users' preferences. Both [5] and [107] learned user preferences through implicit feedback from user check-in behaviors. They captured the correlation between users and optimized pair order by the Bayesian personalized ranking method for point of interest recommendation. The algorithms with the neighborhood and geographical information were achieved better results and a great ranking-based method. Existing works are unable to address time intervals between nearby check-in behaviors properly in modeling sequential data. So Gao *et al.* [108] focused on the impact of time, spatial-temporal sequential, and social influence from users' check-in. The framework was built based on tensor factorization, such as user-location, user-friend, friend-location, location-time, and location-location. Besides, the Bayesian personalized ranking technique was applied to optimize tensor factorization and ranked the location list. It improved a ranking-based estimator for recommendation performances. Xia *et al.* [109] studied the venue recommendation as a ranking problem. A framework was proposed using check-in data to capture the user's preferences. They combined the temporal influence and the category of locations from users' check-in records to improve location-based recommendations. The embedded space ranking SVM was used to learn function to reduce time in a ranking recommendation model. The experiment results proofed that the proposed strategy had better performances in precision while maintaining high location coverage.

Liu and Wang [110] studied the problems of the prediction in the next point of interest recommendations by considering the current location and previous location. They applied the Markov model to combine the geographical influence and temporal popularity of users' checked-ins in the recommendation algorithm. The results demonstrated that the proposed algorithm improved effectiveness in recommendation process. Chen *et al.* [111] adopted spatial information to recommend places to a user. They applied a user-based collaborative filtering technique based on the user's location and user's semantics of the check-in information. First, they made clusters of the check-in information. Second, they calculated the gravity center of each cluster to represent the cluster position. Next, they used a semantic analysis of the users' interests and calculated the similarity score among the users. Finally, the recommendation list was ranked by top similar users. The proposed method showed that semantic information improved more accurate location-based recommendations. Chen *et al.* [112] focused on the problem of spatio-temporal point of interest recommendation. They aimed to use temporal and spatial information for predicting next place at a certain time. First, they analyzed the weights of visited point of interest and presented a probabilistic method to detect users' spatial. Second, they applied a collaborative filtering method to exploit users' temporal preferences. Then, they integrated the spatial and temporal influences to build a unified framework for the recommendation. Social network information was explored to improve location recommendation performances. In [90], the user's social information was added to the algorithm in this work for solving one-dimensional geographic distance influence and non-personalized geographical influence. They proposed the CoRe framework, which was a location recommendation framework by integrating the geographical influence and social influence to enhance user preference. They employed a kernel density estimation technique to get the personalized check-in probability density over the two-dimensional geographic. The geographical and social were integrated into the recommendation phase. It predicted the probability of a user visiting new locations using a personalized check-in probability density. The results reported that it achieved a better quality of location recommendations. While Gao *et al.* [113] improved the quality of location recommendations from the CoRe baseline. They applied a kernel density estimation method to model geographic influence from users' personalized check-in behaviors. Then they incorporated trust social information based on SVD++ method, which was a trust relationship of user and ratings. Finally, the social information and geographical influence were integrated by matrix factorization to calculate a preference score for user to the unvisited point of interest. It provided significantly superior performances compared to previous work.

Zhang and Wang [114] proposed a cross-region collaborative filtering (CRCF) model to recommend point of interests for users who travel to a new city. First, they used a feature of point of interest to build the content recommender for predicting the user's rating by a collaborative filtering method. Second, the location recommender was constructed to predict the user's preference on point of interest by the location of the user and the location of the place. Last, the list of point of interests was ranked by matching user interests in content recommender and filtering out by location in location recommender. The framework solved the new city problem and it was independent of a user's preference and location. Chen *et al.* [115] focused on the problem of a new place recommendation by considering the relevance and diversity. The relevance means users' preference while diversity means location categories. They assumed that the needs of users who want to visit a new category place will decrease over time. So, they studied users' check-in data on visiting location categories and formulated the weighting of two factors to represent user preference. First, they analyzed the check-in data and clustered the similarity of users from the history of travel. Next, they applied the Chebyshev polynomial method to build a function between the number of location categories and a weight value for each user. Finally, the parameter value was adjusted according to each user's preference. The proposed approach showed that it made a good balance of weighting the two factors and provided a better recommendation. Zhang *et al.* [116] claimed that the geographical influence on users' check-in data should be personalized. So, a personalized geographical influence on users' check-in data was presented for location recommendation. They used geographic information by a kernel density estimation method to find one-dimensional distance probability distribution. This approach can predict the probability of a new visiting location. In [117], they proposed the LORE model to exploit the spatio-temporal sequential pattern for revising the order sequence location recommendations. First, the check-in sequences of all users were extracted sequential patterns by the LORE. Next, they calculated the weight between the visited location and the new location by the Markov chain method and predicted the probability of a user visiting a new location. The framework integrated spatio-temporal, social friends, and popularity to rank places. LORE achieved significantly better recommendation performances. Zhang and Chow [118] extended LORE by adding time feature in temporal influence to recommend time to visit the location. They constructed user-based and location-based with the check-in behaviors and used the kernel density estimation method to forecast the time probability density of users. The model improved the quality of location recommendations.

While several works used machine learning and deep learning methods to learn latent features for location recommendation systems. As shown in [119], they studied human mobility behaviors in a new city. An exploratory study on cross-urban human mobility patterns was learned based on check-in data. A machine learning model was applied in this work to recommend a possible point of interests for users visiting a new city. The different types of users and check-in patterns were also used for predicting human mobility behavior. The results of work found that the change in the categories of places visited by visitors within 24 hours a day is effected to cross-urban human mobility. Zhao *et al.* [120] studied the problem of learning effective for location recommendation and link prediction. They proposed a representation learning method, named Joint Representation Learning Model (JRLM) to model check-in sequences with social connections, and produced a latent representation for user and location. The characteristics of JRLM were check-in sequences using a similar way to design word sequences while social connections using current user to generate user friends. It showed the effectiveness of the proposed model for location recommendation can be achieved. Ying *et al.* [121] proposed the UPOI-Walk for recommending point of interests in urban. First, they extracted user's social intentions, preference intentions, and popularity intentions from check-in behavior. Second, they constructed user-point of interest as a graph network then applied the dynamic HITS-based random walk method to calculate the relevance score of user and point of interest. After getting the user-point of interest matrix, UPOI-Walk ranked the point of interest recommendation list. The framework can deal with heterogeneous data problems and it was very effective in recommendation system. Ravi and Vairavasundaram [122] proposed a social pertinent trust walker model based on a random walk method for an efficient category of location recommendations. They used ratings and location categories for predicting trust pertinence. The rating score of the locations was computed by the social pertinent trust walker algorithm based on the existing score for the similar location categories. So, the list of locations was ranked to a user. The proposed model can solved the issue of traditional recommendation problems.

Chen *et al.* [123] believed that point of interest recommendation is even harder to be accurate because check-in data per user is more sparse, and sometimes check-in time stamps span a long period of time. So, they considered three factors; successive behavior, locality behavior, and group preference to boost recommendation performances. First, users' successive locations from check-in data were used to predict the location category and ranked the locations. Second, users' demographics and frequently visited locations were used to simulate group preference. Then, a bipartite graph was constructed based on the recommended categories for each user by applying a weighted HITS algorithm. Finally, the list of next locations was ranked to the user. The experimental results demonstrated that the proposed approach obtained improvement by a large margin. [124] and [125] proposed novel spatio-temporal aware models, which were used geographic and temporal information as a relationship connecting users and point of interests. The proposed model adopted knowledge graph representation learning-TransR method to embed a spatio-temporal pair of time and location of users to point of interests by considering visiting at the same time. The point of interest embedding closed to the user embedding, the recommendation selected the top-k point of interests similar to the translated point of interest by the same type of objects. The results of two works proofed that there were very effective in solving the problem of data sparsity for recommendation system.

As traditional recommendation techniques, the textual information associated with point of interests is usually incomplete and unclear. So, the semantic analysis plays a role in the meaning of words and understands user expression. Yin *et al.* [126] claimed that users have the same preferences both visiting urban and non-urban areas. The use of spatial attributes of point of interests was applied to alleviate data sparsity and cold-start problems by deep representation learning method, which integrated matrix factorization and semantic representation. The results mentioned that the proposed models solved cold-start recommendation scenarios. Xu *et al.* [10] would like to help users accurately locate point of interests with overall positive reviews. They presented a sentiment supervised random walk approach for point of interest recommendation. First, they built each graph of user check-ins, point of interests, and reviews. Second, they merged each graph into one graph network to distribute user and point of interest. Next, computing relationships between users and point of interests were calculated for selecting the favorite point of interests. A random walk algorithm was used to define the most preferred point of interest for user and computed top-N scores in recommendation system. From the proposed method, they can differentiate the polarity of user reviews on point of interests and supervise the random walk over a multi-relational graph of users, point of interests, and reviews. A deep neural network for personalized point of interest recommendation, named RecNet, was presented by [127]. First, they leveraged users' check-in data to generate the co-visiting matrix. Then, matrix factorization method was adopted to embed co-visiting patterns into latent vector representations. Second, geographical influence was used to construct latent vector representations, and categorical correlation matrix also adopted to obtain latent vector representation by matrix factorization method respectively. Next, they used a deep neural network to incorporated three features and ranked high-order interactions. The similarity between latent vectors was exploited to a similar point of interests and users who share common interests. The framework solved the data sparsity problem and improved recommendation accuracy.

Previous adaptive hypermedia research places very little emphasis on end-user. For example, Cheverst *et al.* [6] presented the GUIDE, which was an example of a visible application stream. They used context information, such as the user's current location, user's interest, user's preferences, and the landmarks user visited. The system filtered out the order in which items of information and achieved interaction between the visualization models. The system can be used as hand-held units as tools for navigation and displayed an adaptive tourist guide. INTRIGUE was developed by [128], a tourist information system that assisted the user in the organization of a tour around Torino city, provided personalized information that can be displayed on WAP phones. The system recommended sightseeing destinations and itineraries based on the user's preferences, such as day of the visit, arrival/departure time, and location. It can solve the problem in tour scheduling recommendations. Ardissono *et al.* [129] extended the INTRIGUE by the integration of heterogeneous software and the development of agents to offer specialized facilities within a recommender system. The system designed a personalized suggestion recommender system based on Multi-Agent System architecture by considering the user's interests and the user's preferences. Franke [130] introduced the TourBO system to present possible approaches, such as fuzzy stereotyping, group support tools, and location-based services. The integration of personality types and the user model have developed a personalized system for tourism services.

Gavalas and Kenteris [131], [132] proposed mobile tourism recommendation systems to recommend the next point of interest, which employed collaborative filtering methods to use both ratings and contextual information. First, the K-means clustering algorithm was adopted to classify tourists from similar features. Next, they computed similar interests from contextual information, such as user's current location, time, weather conditions and historical context of other tourists. The weighting of user ratings was calculated by the distance from the current location to the next point of interest, and then the recommendation list was built. The results showed that the system selected best places to visit, and reduced the information overload for the user. Noguera *et al.* [133] presented a novel location-aware hybrid recommender system that included a mobile 3D GIS architecture. They applied user's location and preferences to generate a hybrid recommendation system. Collaborative filtering method used for grouping users and knowledge-based filtering method used for setting preferences. First, they reduced the number of items according to the user's location by a contextual filtering process. Next, these items were used to generate a list of items. Last, they ranked the previous items again by the physical distance from the user to each item. Also, they designed an interface of a recommendation system with actual imagery and landmarks on a mobile 3D GIS. The system can efficiently provide information in location recommendations on mobile devices.

2) TRAVEL ROUTE RECOMMENDATIONS

Based on the sequential associations with others' traveling patterns, the location-based recommendation systems can help a user to plan routes or trips based on user preferences. The best planning path enables people to enjoy life with less time and energy costs. Besides, with the popularity of smartphones, location sensing, and Web technologies, location-based social networks allow users to share their visited locations and other information, which generate user check-in records. These data can be used to determine user preferences and related information for recommending routes.

The historical data and check-in records are usually observed in the travel route recommendations. Hang *et al.* [134] studied the problem of personalized users' preferences to recommend a travel route by using the linked open travel data. They used an association rule mining-based method to get users' preferences with contextual information, such as date, season and places visited. Besides, a genetic algorithm was applied to find the optimal travel route in the recommendation system. They implemented the prototype application by embedding a map to plot the travel route and give information on travel spots. The results of the work indicated that the proposed system had great potential for linked open data in travel planning. Wallace *et al.* [135] applied a collaborative approach for solving the problems of user interaction by an intelligent recommendation system with different types of tourist services. They clustered the usage history by an agglomerative clustering algorithm to extracted tourist behaviors and travel plans. Then, these information and user feedbacks were mapped into a neural network for the recommendation process. The framework improved efficient recommendations.

Mocholí *et al.* [136] studied the routing problems by presenting a semantic multi-criteria ant colony algorithm to recommend the travel route. The proposed approach collected contextual data and learned the sequences of contextual information. The route database was applied to search and learn via conceptual distance measures, then the next point of interests based on user location and context data were ranked. Finally, they used the spatial and semantic to recommend a route by an ant colony optimization algorithm. The results mentioned that the proposed method obtained high-quality solutions when a semantic distance to the restriction. Zhang *et al.* [137] solved the trip recommendation problem by using constraints in user's personalized preferences, user's traveling and visiting time, uncertain traveling time between point of interests, and diversity various point of interests in categories. First, they applied a collaborative filtering method with check-in records to estimate user's preferences on the unvisited point of interests. Then, they adopted a prefix-based depth-first search method and heuristic algorithm to get point of interests with all constraints and recommend route trips. The results reported that it was superiority over previous trip recommendation algorithms. Tsai and Lo [138] studied in museum service quality by developing visitors a customized museum visiting itinerary. They took previous popular visiting behaviors and developed a sequential pattern route system to recommend personalized visiting routes. First, they collected data histories in the database. Next, the I-PrefixSpan algorithm was applied to determine time-interval sequential patterns. When the time-interval sequential patterns meet users' intended visiting time and must-see point of interests, the system will suggest candidate routes. Then, the candidate routes with higher rankings were recommended to users. The results implied that the proposed system succeeded in museum visitor satisfaction. Zhu *et al.* [139] proposed the FineRoute model, which was a personalized and time-sensitive route recommendation system by considering user's preferences, proper visiting time, and transition time. First, they constructed user's preferences from users, locations, and time information. Next, they applied the Kullback-Leibler divergence algorithm to get the proper visiting time between two locations. They also used an origin location and length of route to generate routes. Finally, the route trip was recommended by the classic longest path algorithm. The results demonstrated that the proposed model was better than other existing route recommendation methods. Wörndl *et al.* [16] studied tourist trip problems by comprising different point of interests with a reasonable routing for a short city trip. They calculated the scoring of the level of interest of place by a number of places per category. Then user preferences and discovered places were combined to recommend the shortest path route. They applied the Dijkstra's algorithm with user constraints, such as user-provided time and budget, to find the shortest path. Finally, the proposed solution was implemented in the web application. The results proofed that the application was accepted by the test user and improved the accuracy of the recommendation.

Liu *et al.* [88] studied traffic jams and long queuing problems in attractions by adopting real-time traffic. They designed a personalized route recommendation system for self-drive tourists. The user interests, user preferences, road conditions, and traffic conditions were considered in this work. Besides, a fuzzy algorithm was applied to calculate the route score and recommend the best route. The proposed approach reduced traffic jams and queuing time in attractions, and provided a personalize visiting routes based on the user's preferences. The results demonstrated that it saved visiting time and met users' specific visiting preferences. Socharoentum and Karimi [140] studies on the gap the wayfinding and navigation services in the task of multi-modal transportation with walking for trip planning. They proposed multi-modal transportation with multi-criteria walking, named MMT-MCW, to build a personalized route recommender. The contain walking mode of transportation considered multiple criteria, such as destinations, tourist's behavior, physical to optimal route choices, location, and environment. They computed MMT-MCW routes using their algorithm, and the context-aware and walking routes were calculated by scores. The proposed method recommended candidate routes with routing options. The results showed that it can use to perform the suitability of walking routes with respect to tourist preferences.

Several researchers focused on other additional information, such as spatial and temporal and context information. Yu *et al.* [87] solved the location-based recommendation of point of interests by leveraging crowdsourced data. They first collected data from the Jiepang website to extract user preferences, determine points of interest, and verify a location from check-in data. Next, they generated a personalized travel route by considering user preferences, point of interest characteristics, and temporal-spatial constraints. The popularity of point of interest was calculated from the peak of point of interest based on the impact of time. The user check-in data was mapped to temporal-spatial trajectories to find frequent travel routes visited. Finally, the system generated a travel route sequence. The results indicated that the system can provide the number of destinations related to time slots. To enhance previous work, Yu et al. [84] added more user constraints, such as user preference to point of interests, distance between point of interests, traveling time, and start location. They proposed a recommending personalized travel route from Jiepang open data. First, they constructed user profile and location detail based on check-in records. Second, the collaborative method was used to discover and rank the point of interests based on travel packages and visiting sequences. Then, they recommended route sequence by adopted route planning algorithm to select point of interests from the candidate point of interest list with spatio-temporal constraints. Last, they implemented a prototype recommendation system via mobile service. The results mentioned that the proposed approach improved the accuracy of recommendation with moderate computational complexity. In [141], they focused on frequent sequential patterns to describe user's spatial and temporal behavior. First, they used location, item, and time factors to make a trip sequence. Next, they applied data mining algorithms to discover frequent sequential patterns based on location-item-time. The constraints of users in visiting time, regions, recreation facilities were used in their proposed. Finally, the recommended route retrieved suitable sequential patterns. The results proofed that the proposed method provided appropriate visiting experiences for users.

The prototype of travel route recommendation systems was built and launched in many works, for instance, The PAT-Planner was developed by [142] to merge tourist attractions and tour packages for personalized trip planning satisfying user's travel constraints. First, tourist packages, tourist attractions, check-in records, and social link relations were collected from linked open data. Then, they applied user-based and temporal-based collaborative methods to calculate the score of tourist attraction or package. Finally, the user's travel constraints were used to plan a trip in a personalized recommendation. The results demonstrated that the system achieved excellent planning effects. Gavalas *et al.* [143] solved the problem of personalized recommendation system in daily tourist itineraries for tourists. They developed the DailyTRIP, which was a heuristic approach considering user preferences, current location, time visiting and opening days. The algorithm filtered point of interests out from the problem's space and traveling time. Then, the construction of itinerary trees was proposed to recommend route trip. The DailyTRIP improved results in the last phase ensuring a near-optimal itinerary for each day in terms of length. In [144], the e-Tourism was a tourist planning recommendation system to help users organizing their trips. It applied a hybrid recommendation technique by using user's tastes, demographics, history trips to consider the current visit preferences. Then it recommended a list of places and schedule plans based on temporal characteristics, such as the user visit date, the user available time, and the user's current location. The results mentioned the user can get an agenda of recommended activities and the system can calculate the distance between places or the place's opening time.

Ricci and Werthner [145] presented an intelligent recommendation system to support traveler selecting a destination and making travel plan. The system considered user interest, locations, services and activities following past travels. It integrated data from several open data and built to XML-based. Case-Based Reasoning techniques were applied to recommend and ranked point of interests. The results of the proposed approach were a middleware for providing personalized recommendations to users. In [15], CrowdPlanner, which was a novel crowd-based route recommendation system was developed by leveraging crowds' knowledge with large-scale real trajectory dataset. The system provided travel routes with the best traveling experience for users based on traveling time, traveling distance, traffic conditions, etc. The evaluation results showed that the proposed system can recommend the best route based on user feedbacks. Zheng *et al.* [146] extended the CrowdPlanner system by proposing some strategies to verify truths and know the best routes near the locations and dealing with text queries more efficiently. Besides, it evaluated route trip by mapping services with popular route-mining algorithms. The results implied that the system can recommend the most satisfactory routes to users. The BerlinTainment system was developed by [147] to provide a personalized location-based recommendation system based on feature-based filtering methods. The framework ranked point of interest to users based on the route between different locations. The system can provide an easy and effective way of user interface generation.

3) GPS TRAJECTORY-BASED RECOMMENDATIONS

GPS Trajectory-based is increasingly common in smartphones or dedicated GPS trackers. The location-based recommendation systems can use information from GPS trajectory records traveling pattern or locating a current location.

GPS trajectory information was used to the purpose of the work in the form of the research problem, such as rating and route problems. Zheng *et al.* [148] solved the sparse rating in the recommendation problem by modeling user-location-activity rating. They merged user preferences, location features and activity correlations from the GPS histories into the tensor factorization method to predict the missing rating values. It focused on optimizing the ranking in user preferences on locations and activities. The results implied that user similarities of three factors can adopt in collaborative filtering recommendation tasks. Zhu *et al.* [149] focused on the data sparsity problem in location information. First, they translated the geographical information into semantic information from GPS trajectories. Then, they classified the locations in different types and computed the similarity between users. Next, they constructed a location sequence pattern based on user familiarity and popularity of location. The results demonstrated that the proposed method provided a better recommendation performances than the other related approaches.

Cui *et al.* [150] studied on users' travel behavior in a single transportation mode from historical GPS trajectories for location-based travel route recommendation. First, they extracted the travel behavior to sub-trajectories and computed the travel behavior frequencies by matrix factorization method. Next, the naïve Bayes model was applied to travel route recommendation to calculate a probability of a user's travel behavior and generated route trip. They also used the distance with the user travel behavior probability to improve the performance of route recommendation. The performance of the method showed that it outperformed the shortest distance path method. Chen *et al.* [151] solved the problem of recommending tours to travelers in the task of recommending a sequence of point of interests. They considered various sources of information about location, point of interests, categories and past behavior. Information about point of interests was used to learn a point of interest preference from the start to end of the trip. Previous trajectory records were used to learn location transition patterns. A probabilistic model was proposed to combine a list of point of interests and location transitions for recommending a route trip. The results showed that research should consider places and routes for trajectory recommendation. While Console *et al.* [152] studied the problems of applications on board vehicles. They presented an architecture for providing personalized tourist information on board a vehicle based on user preferences, user interests, and context of interaction. The system designed user modeling and adaptation techniques concerning the location of the car, GPS coordinates, and the current driving conditions.

Hsieh *et al.* [153] developed the TripRouter system with the concept of the goodness of a route. They extracted interesting locations and activities from trajectory data and considered many features, such as popularity, visiting queue, visiting time, and transit time. Besides, they developed a route search algorithm, named Guidance Search to model the most popular location sequence patterns with the best time. The prototype system showed that GPS trajectory data can solve the drawbacks of check-in data and perform some preprocessing in advance to identify the main locations. Chen *et al.* [17] focused on location-based personal route prediction system by the strategy of different modes of transportation. First, they collected and filtered the personal trajectory data from a GPS device. Next, Continuous Route Pattern Mining (CRPM) was developed to extract route pattern mining from route patterns of users. Last, they presented two decision tree algorithms: basic algorithm and heuristic algorithm to provide offline and online route predictions. With offline prediction, the next position and the route were predicted before the trip begins. With online prediction, the next position and the route were predicted during the journey. The results mentioned that CRPM can extract more routes and longer route patterns. Duan *et al.* [154] boosted location route recommendation by adding spatio-temporal information from GPS trajectories to improve service recommendations. They used the two-dimensional correlations between services and trajectories to provide users with nearby recommendations in traffic environments by considering real-time current location, service-visiting behaviors, and preferences. A spatio-temporal was used for clustering trajectories at each spot where travelers stayed at a certain point in time. So, the proposed method recommended route trip. The results demonstrated that it reduced the deviation of the trajectory and enhanced the success ratio of the recommendation.

Liu and Seah [155] defined a time point of interest recommendation problem to recommend point of interests for users from GPS trajectories based on popularity-temporal-geographical features. First, they extracted point sequences and semantic of point of interests by using a clustering algorithm. Then, they computed each type of scores from popularity, temporal and geographical. Finally, a linear interpolation was applied to weight the three scores and calculated the final recommendation score for point of interest. Zheng and Xie [83] proposed generic and personalized recommendations during a journey by mining multiple users' GPS traces. In the first model, they used users' histories with a tree-based hierarchical graph method to recommend a user with high interesting locations and travel sequences in the region. In the other model, they predicted a user's interests in an unvisited location by using a collaborative filtering method to make a personalized recommendation. The proposed methods achieved better performance in recommendation system. A GPS receiver is also used in the MobiDENK system, which developed by [156]. The application provided location-based multimedia information at sightseeing spots including historical information and images. It recommended attractions nearby located in the neighborhood of the user positions and displayed a user's current location on a map. The results demonstrated that the system got feedback in a positive. Santiago *et al.* [157] developed the GeOasis recommender system in a semi-automatic way by using web mining techniques. The objective was to help tourist information as a guide while they take a journey. The system provided information relative to the point of interest of the region. It was an integrated GPS navigator to locate user position and speed to estimate the time and place. The relevance of each pre-selected point of interest, user preferences, and user histories were considered for making route planning. The results showed that it can generate the list of point of interests and build the schedules according to real-time constraints.

4) GEO-TAGGED-MEDIA-BASED RECOMMENDATIONS

A vast amount of information available on the Web is great opportunities and challenges for new researches and applications. For example, the geo-tagged-media-based recommendation systems are usually used multimedia data, such as user-generated and geo-tagged media, such as photos, news, and messages to provide recommendations. These multimedia data not only contain textual information, such as tags, titles, notes, and descriptions but also are tagged with temporal context and spatial context where the photo was taken.

Many researchers used clustering algorithms to discover popular tourist attractions from geo-tagged media. Chen and Wang [158] studied the photo classification problem for a location-based recommendation. First, they calculated the similarities with photos in each city by classifying photos and evaluated the hottest place for each city. They combined the similarity and the hottest place according to the user's preference and ranked the highest combination score to recommend the first city. Then, they mined information between cities pairwise with proximity and co-visit factors to suggest the second city. Finally, they applied the greedy algorithm to recommend one city at a time and generated a tour route consisting of all the recommended cities. The result proofed that the proposed method achieved the effectiveness and reliability of the recommendation system. Peng and Huang [159] proposed a method for discovering popular tourist attractions by combining spatial clustering and text mining approaches. First, they used a spatial clustering method from the concept of fast search and find of density peaks. Second, TF-IDF was applied to build a tag vector and calculate text vector similarity. A set of point of interests with TF-IDF weights was assigned to each cluster. Finally, they recommended popular tourist attractions. The result showed that the proposed approach was higher in classification accuracy compared with the traditional method.

Majid *et al.* [18] presented semantically meaningful to build personalized tourist location recommendations using geo-tagged social media. First, the clustering algorithm was applied to extract tourist locations using spatial and temporal photos. Next, they used semantic tags annotated to generate textual descriptions for location. The location profiles were built to present the contexts including geo-tags, time-stamps, temporal and weather contexts. Finally, they created the relationship between users and locations and calculated the similarities among users based on users' preferences using a collaborative filtering method to build a personalized tourist location recommendation. The proposed method result demonstrated that it can predict users' preferences in a new city and improved the performance of recommendation compared to other approaches. Huang [160] explored context-aware methods to build location recommendations matching a user preference and visiting context. They applied clustering methods to determine tourist locations and extracted travel histories from geo-tagged photos. The weather data was collected and integrated to build user profiles. Then, user and context similarity were computed top-k ranked locations by a collaborative method. The proposed method implied that the context similarity measure can adopt in location recommendations with significantly better performances.

Sun *et al.* [161] presented a new idea of routing by separating the road segment. They built a recommendation system by choosing the most popular landmarks with the best travel routings. First, a spatial clustering method used to extract geo-tagged images and ranked the main landmarks. Then, they calculated the popularity of the road by using a number of point of interests and a number of users. The route recommendation system was built based on the popularity of point of interest and length of the road. Finally, the best travel routing suggested route by reducing distance and covering top landmarks. The proposed method showed that the system can suggest travel planning with top-ranking attractions and suitable routings. Kurashima *et al.* [162] designed a travel route recommendation framework using the large-scale collection of geo-tagged and time-stamped photographs from linked open data sites. First, they collected photos, which were a sequence of visited locations, so they estimated the probability of visiting a landmark. Next, the probabilistic behavior model was proposed by combining topic models and Markov models. Finally, the route recommendation method suggested a set of personalized travel plans matching user's preferences, current location, visiting time and transportation means. The result reported the effectiveness of the proposed method can predict the accuracy of travel behavior. Jiang *et al.* [163] solved a gap between user preference and travel routes recommendation by presenting a personalized travel sequence recommendation from travelogues and photo collections. The advantages of this work are that the system determined user's and routes' travel topic preferences including topic interest, cost, time and season. Besides, the system recommended point of interests and travel sequence by considering the popularity of places and user's preferences. They ranked famous routes based on the similarity between user package and route package and optimized the top famous routes according to social similar users' travel records.

Lim *et al.* [164] proposed the PERSTOUR method for a personalized trip recommendation by focusing on levels of user interest and visit duration. The algorithm used point of interest popularity and user preferences from geo-tagged photos to recommend personalized tours. They first extracted geo-tagged photos from Flickr to the Wiki point of interest database and identified the popularity of point of interests by user interests. Then, the concept of time-based user interest was presented in which sorted point of interest visiting time, and used the first and last photo taken at each point of interest to construct user travel sequence. Last, they used user preferences with visit duration, point of interest popularity, and trip constraints, such as time limits and specific point of interests from start and end points to recommend personalized trip itineraries. The approach demonstrated that it can recommend a suitable point of interests visit duration and the time to spend at each point of interest. Han and Lee [165] were also focused on user constrains problems in landmark recommendation system problems using location-based social media. They extracted landmarks from geo-tagged social media to get spatial and temporal properties on places visited. Next, explicit information was used to calculate the similarities between a landmark and a user. Finally, they clustered the probability of landmarks to the landmark recommendation system. The evaluation mentioned that the proposed method improved the accuracy and user satisfaction of the recommended landmarks. Kaushik *et al.* [166] presented how crowdsourcing can be used to generate a list of recommended locations to assist tourists to make the decision about visiting places. They developed the recommendation system by collecting images, audio, and feedback from a crowdsourcing approach. Fuzzy technique was applied to generate a popularity score of each place near the tourist's current location. Then, the system sorted the scores of each place and sent the recommended list to the tourist. The results showed that the proposed system can use location-aware crowdsourcing to recommend places to the user.

Xu *et al.* [167] studied the problem of travel recommender based on topic distribution by mining user preference. Clustering algorithm was applied to cluster photos from the geo-tagged of photos for identifying tourist locations. Then, they built location profiles to present the context, such as season and weather information. They explored user interests from the topic model, constructed a user-user matrix similarity, and calculated the similarities among users by using a collaborative filtering method for ranking location lists. The results presented that geo-tagged photos can able to generate better location recommendation. Xu *et al.* [168] extended previous work by considering dynamic topics and travel preferences for travel recommendation system. They extracted implicit information, such as topic of users and locations and explicit information, such as contents, check-ins, and point of interest categories from geo-tagged photos. The user-user and location-location matrixes were computed similarity in the matrix factorization method. Then travel location recommendation method was ranked location lists based on a user-location matrix. The results implied that the proposed method can provide effective recommendations and can solve the sparsity problems of user-location interactions. Memon *et al.* [169] studied new city recommendation problems by extracting semantically meaningful for tourist locations from the community contributed collections of geo-tagged photos. They presented a method by considering the context of temporal, spatial and weather. The collaborative filtering and context rank methods were used to fetch tourist preferences and the context of a user, and calculated similarities between user and location profiles for location recommendation system. They also showed how to cluster photos using geo-tags to define tourist locations. The results showed that the proposed method can predict famous places or new places. Yu *et al.* [170] focused on an interesting group-like travel trajectory from Instagram photos taken by different tourists. First, they built a trajectory database from Instagram photos, and then clustered trajectories to find tourist density. Next, the spatio-temporal trajectories were transformed into a sequence of clusters to find point of interest patterns. Finally, distance and conformity information were applied to recommend popular tour routes. The results implied the proposed method improved the effectiveness and efficiency of the recommendation tasks.

Besides, the check-in patterns and user contents are pulled out of user-generated on linked open data. Wang *et al.* [14] studied on venue semantics about text descriptions, photos, check-in patterns, and context from user-generated content in different social networks for location semantic similarity measurement. They proposed a venue semantics recommendation algorithm to mine the user's interest based on check-in records. Location semantic similarity was computed to rank location recommendation. The research work showed that the user-generated contents can describe the venue semantics and improve recommendation performances. Pálovics *et al.* [171] addressed the problem of highly volatile items for users by recommending top-k location based on Twitter messages, hashtags, and locations. They learned the personalized importance of hierarchical geo-location, and then they combined the personalized data with the popularity of hashtag by using matrix factorization and machine learning techniques to recommend new hashtags. The method was based on measuring the popularity and learned the importance of the locations. It can solve cold-start problems in recommendation. Hosseini *et al.* [172] focused on the problem of location recommendation tasks in social networks by using temporal influence and in-depth performance analysis from check-in data. The proposed model predicted user's time-oriented mobility patterns based on all temporal aspects in user-item and recommended a list of new point of interests. The result showed that it can use many types of recommendations and can work efficiently in multiple time-scales. Albanna *et al.* [173] studied the problems of user interest awareness on user history by using location-based social networks for location recommender. They extracted the geo-content and calculated a recommended list based on a scoring method. The model showed that it can reduce the cold start problems for new users of recommendation system.

5) ONTOLOGY-BASED RECOMMENDATIONS

The concept of ontology-based recommendation systems in the tourism domain is to collect tourism datasets from linked open data and build tourism ontology on location-based according to the researchers' study purpose, such as a list of point of interests, popularity locations, travel itinerary, and route planning.

Smirnov *et al.* [174] presented a recommender application to solve the infomobility concept. They built the tourist cultural heritage ontology by collecting cultural heritage information, such as text, images, and videos from open data. The user preferences and current situation in the region were analyzed based on cultural heritage ontology and used collaborative filtering techniques to rank the list of cultural heritage. The application is available on the Google Play Store for Android OS. The evaluation results mentioned that the application can suggest cultural heritage during the trip. Hinze *et al.* [175] designed the model of a personalized tourist recommendation system to solve issues of the personalized tourist information provider by considering timeline and rich information factors. The model aimed at taking the history of the user into account and linking between sight-related information. They filtered out ontology tourist information based on an event-based system and location-based service. The user preferences were built from user requirements and current location. The system selected tourism ontology based on the level of user interests and used cluster method to rank point of interests based on user histories. It can completely fulfill requirements on modeling techniques.

Generally, the users know what they want, but sometimes the users do not know what kind of information they need. The current works skip the user's demand. So, Shi *et al.* [176] focused on the strategies in an ontology-driven recommendation for tourism in the user demand and context-based recommendation methods. They integrated tourism resources and used ontology to get user's needs and user preferences based on semantic text analysis, and ranked the next location in a recommendation process. The experiments showed that the proposed approach was feasible. Balduini *et al.* [177] developed the BOTTARI ontology model, which was a personalized point of interests recommendation system collected from the opinions of the social media community. The various data sources and services were integrated into ontology and the model recommended a list of point of interests to the user. The prototype showed that it can be more effective than guide books and travel review websites. In [178], the semantic information was exploited in a recommender system by considering user opinions, place contexts, and geographic aspects. First, tourism ontology was built from linked data sources. Second, the system selected tourism information based on user current location, user preferences, point of interests, distances, and opinions. Finally, they applied the analytic hierarchy process method to rank tourist attractions in recommendation process. The results can compose of recommended point of interests for the user and related to the user profile. Missaoui *et al.* [179] assumed that an explicit representation of knowledge as well as uses click-stream analysis can improve a recommender system. So, the metadata about the content in domain ontology was applied for the location recommendation system. They used ontology and relationships at different levels of the location to determine the user's profiles. The mining methods and recommendation techniques were used to recommend the set of point of interests. Loh *et al.* [180] presented a recommender system to support the travel agent for discovering interesting areas. The system was a Web chat between the travel agent and tourists by using text mining techniques to discover interesting areas, such as goals of the travel, kinds of attractions interesting, seasons of interest, etc. A collaboration filtering method was applied to the system. Then it matched user preferences and locations from tourism ontology and finally recommended cities and attractions to users. The benefit of the system is to free agents from knowing a lot of tourist options and remembering at the moment when to recommend a good option to the customer.

Besides, Castillo *et al.* [181] designed a prototype recommendation system which the goal was to help different people visit different cities. First, they built ontology consisting of users, activities, and city information. Next, the system requires current location, user interests, and user histories from the user. The list of point of interests was generated following user preferences. Finally, the system recommended a tourist plan based on the computed list of point of interests. They showed that the ontology collected information about user and activities can perform in a recommendation system in a city and the city itself. Kumar *et al.* [182] developed the multi-ontology model based on point of interests for the travel recommendation system. The semantic information was used to descript a route textual. The popular travel locations were clustered based on the level of equableness and ordered travel locations based on the user's histories. Then they merged multi-ontology, route semantic, and popularity to recommend a personalized route sequence. The results concluded that the proposed algorithm can get better performances by investigating from travel logs. Cao and Nguyen [183] presented a novel semantic algorithm for a travel itinerary recommendation system. Ontology was collected from linked data for filtering semantic of the user interests. Ant colony optimization technique was applied to optimize the length and match user interests. Finally, the proposed system recommended the interesting places and the best itinerary from a starting point, user interests, and location distances. The results confirmed that the power of semantic web technologies can be successful, such as accessing data from various sources and provide information in a smart way. Lee *et al.* [184] developed an ontological recommendation multi-agent for supporting travel in Tainan City in Taiwan. The proposed system collected data and built an ontology for Tainan city to match the tourist's requirements. The recommender system used fuzzy logic techniques to the rank point of interests and used an ant colony optimization algorithm to construct a travel route. Finally, the system can find a personalized tour and plot a route on the Google Map. The results mentioned that the system can recommend a travel route that matched the tourist's requirements and tourists can follow the personalized travel route to enjoy places and local foods. A system for personalized recommendations of tourist attractions in a travel destination was presented by [185]. First, a tourism ontology collected information about tourist attractions in the destination. Second, they used the Bayesian network technique to define the user preferred activities and computed the similar taste between user and other behaviors. Next, they applied the analytic hierarchy process algorithm to rank the tourist attractions based on current location and user profiles. Finally, route planning was generated on spatial web services. The experiments showed that the system can recommend and satisfy user needs perfectly. Zipf and Jöst [186] studied issues related to personalize and context-aware GI services. They developed a route recommendation system that focused on ontology in pedestrian navigation and tourist information for users through a city. The ontologies can be used for representing user and context information needed for adaptation purposes explicitly, for example, spatial ontologies for semantic interoperability. Volkova *et al.* [11] proposed a travel itinerary recommender system based on a set of venue categories of user's interests. The system focused on user preferences in venue aspects from reviews in open data. User preferences were used to weight aspects in point of interest and time restriction. The ontology of sightseeing used to enhance the search for relevant venues. Travel itinerary recommender was designed to rank point of interests from venue aspects. The results proofed that the system was effective and flexible in planning a trip. Ferraro and Re [187] developed an ontology-driven adaptive recommender system. They used semantic information to assist users in travel planning. Data mining techniques were applied to find users' interests and preferences and improve the quality of the suggestions to users. The proposed architecture improved the quality of the suggestions made to users and included a capability designed to infer users' needs. Moreover, the SigTur/E-Destination was developed by [188]. It was a web-based personalized recommendation system of touristic activities. GIS stored geospatial information to generate semantic information for the ontology. The system used user profiles based on demographic information, user behavior, and rating of point of interests. Then the similarities of point of interests were calculated to rank a list of point of interests. Finally, travel planning was generated a route with point of interests. The results demonstrated that the recommender system was useful for tourists.

6) LOCATION-BASED FRIEND RECOMMENDATIONS

The location-based friend recommendation systems aim at using user's social connections from social network information to recommend places. Several studies have shown that they recommend friends based on their preferences, traveling patterns, and visiting locations.

Gao *et al.* [189] studied the problems of prediction of friendship for friend recommendations on location-based. First, they used the word 'check-in' based on time and the location to define different features, such as social relationships, check-in distances, and check-in types. Next, a support vector machine classification algorithm was applied to construct a model. They calculated the distance between friends and observed that the probability of friendship decreases with the increasing of their distances. The experiment results showed that three key features were higher than one feature and improved the prediction accuracy. Kosmides *et al.* [190] focused on the prediction problems to enhance the recommender system. A novel method was presented to predict a user's location by considering user's preferences and their social friend connections. They collected data from location-based social networks and applied the K-means clustering algorithm to cluster dataset. In the prediction process, they applied a probabilistic neural network technique to enhance the recommender system. The prediction results indicated that it can use to make suggestions for points of interests. Kesorn *et al.* [7] studied the problems of data overload and user profiles for the recommender. They developed a personalized attraction recommendation system by using user check-in data and user friends' check-ins data to analyze user interests and activities for user profiles. The system used close friends' information, such as affinity score, edge weight, and time decay, to recommend attractions to user. The results implied that attraction recommendations resolved the cold-start problem, and improved recommendation quality in the tourism domain.

While the relation between location and interest interaction among social media users is inconspicuous, there are many works try to solve these problems [86], [191]. Zhu *et al.* [191] presented the neighbor-based friend recommendation system to improve these problems. They mined user interest from short tweets and used the hypercube method to explore multiple topics. A topic matching shortcut algorithm was built for friend-finding based on users' interest and users' location similarity between two users. The experimental results reported that the proposed approach achieved high performances in recommendation. Zheng *et al.* [86] studied the relationship between locations of users and social information to exploit a personalized friend and location recommendation system. First, they considered three factors; check-in sequence, visited popularity, and hierarchical of place. Next, the hierarchical-graph based similarity measurement was used to find the similarity among users in location histories. A user interest was related to location history and other users. Last, they merged a content-based method and a user-based collaborative filtering method to calculate the rating of a user on an item and created friendships and attractions in recommendation system. The proposed system showed that users can get more locations.

Previous models were failed to adequately capture user time-varying preferences, so Kefalas *et al.* [192] focused on the time dimension for the friend recommendation system. They constructed a hybrid tripartite graph with the heterogeneous spatio-temporal method consisting of sessions, users, and locations to capture the similarity between users and user location. The results implied that the time dimension can improve the accuracy of the final recommendations. The time complexity and memory overhead of these existing algorithms have not been thoroughly solved, then Zhao *et al.* [193] proposed a generic location recommendation system by mining the correlations of users and point of interests. They extracted neighborhood-based feature and path-based feature to express the characteristics of link formation of user-user pairs and user-point of interest pairs from a number of common friends and overall path structure in network relationships. An ELM algorithm was applied in recommending a process to recommend friends to users. The results demonstrated that the model can learn massive data more effective and the recommendation results more accurate.

However, the distances between users' places of residence are a challenge for recommendation methods. Huang *et al.* [194] presented a semi-supervised probabilistic model based on a factor graph model. They assumed that less than 10% of user's check-ins data is visited by his friends, the probability of checking in the same point of interest for two friends is higher than that for two strangers. So, they integrated geographical influence and social influence to predict the next place. The approach achieved high accuracy and scalability in recommendation process. Gao *et al.* [195] studied the cold-start problem of recommending new check-ins by capturing geo-social correlations on location-based. They used user friends' check-in behavior and the correlations between geographical distances and social networks. The geo-social correlation measures, such as user frequency and location frequency, were proposed to calculate similarities of users and recommend locations to users. The results showed that social network information can solved the cold-start problem in a recommendation.

A general discussion presents objectives and examples of using Linked Open Data. In addition, this section provides an overview of ''What are the objectives that Linked Open Data is being used to the location-based recommendation systems for Tourism Domain?'' (RQ01).

C. GROUP OF LINKED OPEN DATASETS IN CATEGORIES OF LOCATION-BASED RECOMMENDATION APPLICATIONS ON TOURISM

In this section, we show datasets, which are data sources used in location-based recommendation systems on tourism domain by grouping following the categories of recommendation applications.

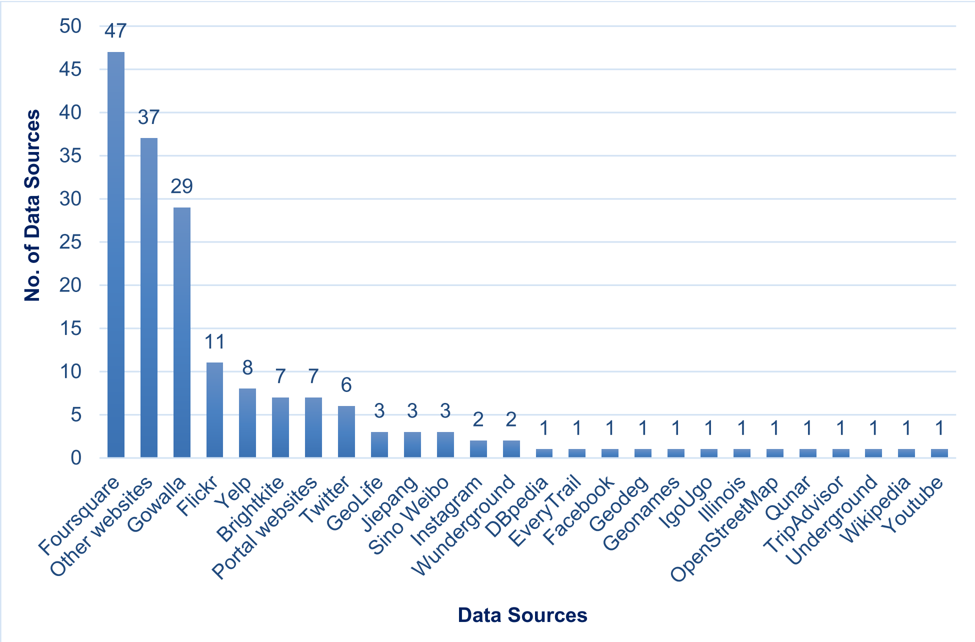

FIGURE 5. Distribution of the different data sources.

1) *Stand-Alone Point Location* Researchers collected data from open data sources, for example, user demographics, user rating, user check-in, and other information. Several websites, such as, TripAdvisor, Yelp, Foursquare, Gowalla, Brightkite, and Twitter, support travelers to share locations, events, and feelings with others. It further boosts the advantage for stand-alone point location recommendation system as well as these contents refine categories to point of interests and using these point of interest categories to determine the interests of tourists.
2) *Travel Route* The data collection method is the same as the Stand-Alone Point Location group but the recommended output is different. Hence, exploiting check-in to venues or locations that tourists have visited is the key point. These check-in locations, such as point of interests and restaurants, which can be further divided into sub-categories and consider the popularity of places or visiting time to construct the route trip and path planning.
3) *GPS Trajectory-based* Another largest source for obtaining GPS trajectories is Geolife website. Although GPS trajectory-based traces are the popular data sources for location-based recommendation. These trajectories are traced based on GPS-enabled devices, such as smartphones and GPS navigators, but not many people are likely to share their activities on the public sources in order to prevent privacy risks. Hence, some researchers gained the trajectory record of a user's movement by personal permission.
4) *Geo-tagged-media-based* Using geo-tagged media and user-generated, researchers get the popularity of point of interests or locations by extracting from photos, news, and messages. The most prevalent data sources are Flickr or Instagram photographs and Twitter texts. There are three common steps: 1) Constructing an ordered sequence of relevant photographs or text; 2) Mapping its to popular point of interests, hence, the location of place compose latitude and longitude; and 3) Generating times sequences of point of interest visits.
5) *Ontology-based* With the growing value of linked open data, many authors, universities, and companies produce tourism data and resources. These linked open data are built by gathering tourism ontologies to study following researchers' purposes, such as point of interests, popularity of places, travel itinerary, and route planning. In our work, the tourism ontologies were collected from various sources, such as Youtube, Qunar, IgoUgo, Weather Underground, and official websites of government. Researchers used tourism ontology to integrate the linked open data and browse through complex data become easier and much more efficient for location-based recommendation systems.
6) *Location-based Friend* As shown above, social networking sites, such as Sina Weibo, Facebook, Foursquare, and JiePang, are able to follow one another to another like a friendship links. These websites are also popular open data sources to crawl data for location-based friend recommendation topic.

The distribution of the different data sources of location-based recommendation applications as shown in Fig. 5. The linked open datasets used in the location-based recommendation systems provide an answer to the second

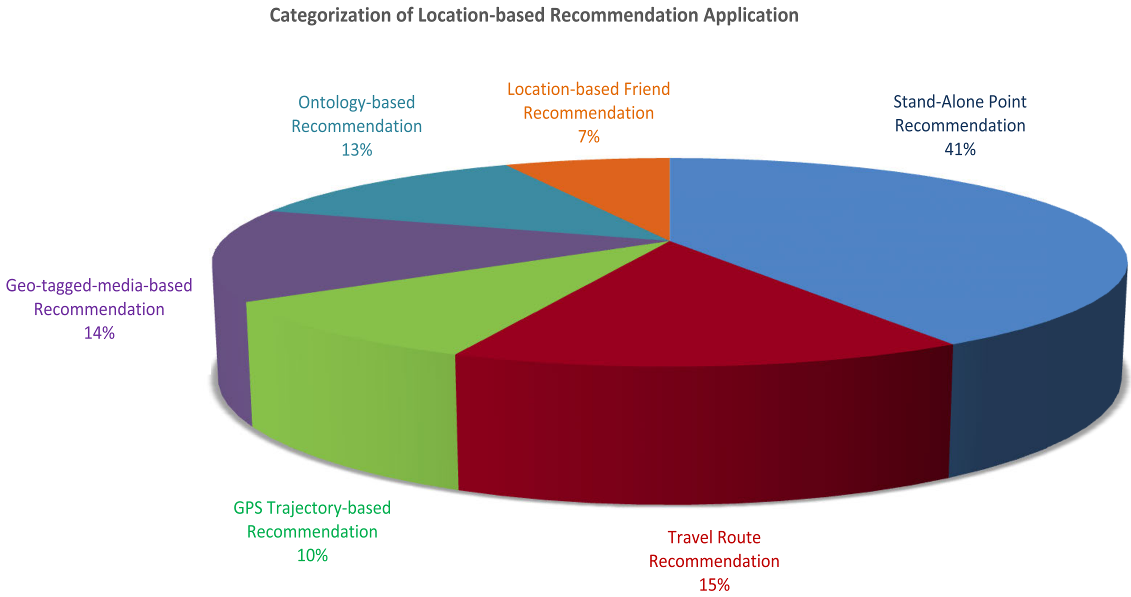

FIGURE 6. **Distribution of publications by the different categories.**

question: ''What are the Linked Open Data datasets used for location-based recommendation systems for Tourism Domain?'' (RQ02).

D. SUMMARIZATION OF THE RESEARCH ACHIEVEMENTS OF THE LINKED OPEN DATA IN LOCATION-BASED RECOMMENDATION SYSTEM ON TOURISM

In this survey, we reviewed, classified and categorized high-quality journal papers with an impact factor. Fig. 6 summarizes the distribution of publications by the different categories of our review study. It is obvious from the results of this survey that the number of publications on linked open data in location-based recommendation systems on tourism domain from 2001 to 2018 saw a significant increase. This is an indication of increasing research interest in these fields of study. The distribution of the different categories of location-based recommendation applications as shown in Fig. 6. In terms of stand-alone point location recommendation, researchers have studied more than 50 papers on location-based recommendation area. The travel route recommendation was ranked in the second position with 19. Similarly, the numbers of GPS trajectory-based, geo-tagged-media-based, and ontology-based recommendations were 12, 18, and 16 respectively. While location-based friend recommendation was presented the least in this area, with just 9.

The results further reveal that linked open data in location-based recommendation techniques are widely used for tourism domain. Researchers use many techniques, such as ontology, content-based, collaborative filtering, hybrid, fuzzy, deep learning, etc. Moreover, it improves the recommendation system, such as accuracy, sparsity, cold start, scalability, and efficiency challenge.

In this work, the summarization of location-based recommendation applications is illustrated (see Appendix A - Table 2, summarization of linked open data in location-based recommendation system in tourism domain). Especially, it provides an explanation of ''What are the methodologies used for location-based recommendation systems via linked open data on Tourism Domain?'' (RQ03). We present the different types, methodologies, key focuses, functionalities, and challenges of each journal paper. Some researchers had studied multiple functionalities, for instance, Zheng *et al.* [86] studied the relationship between the locations of the user and social friends' histories for suggesting both friendships and destinations in recommendation system.

V. FUTURE DIRECTIONS

A number of studies on the linked open data in location-based recommendation systems on tourism domain have been steadily rising over the last few years. However, there are still challenges and issues that need to be addressed to further improve the performance of the linked open data in location-based recommendation system on tourism domain. In this section, we present the possible future research direction for this field.

1) *Multiple heterogeneous data sources* Most of the existing tourism domain in location-based recommendations via linked open data use only a single type of data source to develop recommendations. Cross domains, information fusions, and multimedia data can improve effective recommendations. Multiple heterogeneous data sources may include locations, friendships, user histories, and traffic and weather conditions.
2) *Transport modes* The various modes of transport can be considered for user preferences and route planning.

TABLE 2. Summarization of linked open data in location-based recommendation system in tourism domain.

Reference	Location Type	Methodology	Key Focus	Functionality	Data source	Challenge
Albanna et al. (2016)	Geo-tagged-media-based	Hypertext Induced Topic Search	Explore tag, venues, interests and check-ins	Suggest attractions/destinations	Foursquare, Instagram	Accuracy, Efficiency
Aliannejadi and Crestani (2018)	Stand-Alone Point	Content-based	Mapping tag and location by extracting location contextual	Suggest attractions/destinations	Foursquare, Yelp	Sparsity
Ardissono et al. (2003)	Stand-Alone Point	Hypermedia	Use the user preferences and tourist information	Suggest attractions/destinations	Not specific websites	Suitability
Ardissono et al. (2005)	Stand-Alone Point	Multi-Agent	Extend previous work by exploit the user interests and the user preferences	Suggest attractions/destinations	Not specific websites	Efficiency
Balduini et al. (2012)	Ontology-based	Stream Reasoning	Learn the opinions of the social media community	Suggest attractions/destinations	Twitter	Accuracy, Efficiency
Cao and Nguyen (2012)	Ontology-based	Ant colony optimization, Semantic	Adapt user profiles semantic matching the user interests location	Complete route trip	Flickr, DBpedia, Geonames, Youtube	Efficiency
Castillo et al. (2008)	Ontology-based	Case-based Reasoning	Use the user current location, user interests, user histories and preferences	Complete route trip	Not specific websites	Efficiency
Chen and Wang (2012)	Travel Route	Classification	Explored photo, textual, temporal, geographic information	Complete route trip	Flickr, Wikipedia	Accuracy, Efficiency
Chen et al. (2011a)	GPS Trajectory-based	Data Mining	Extract route pattern from user personal trajectory	Complete route trip	University open data	Accuracy, Efficiency
Chen et al. (2013)	Stand-Alone Point	User-based Collaborative	Focus on user check-in activities on location	Suggest attractions/destinations	Sina Weibo	Accuracy, Efficiency
Chen et al. (2016a)	GPS Trajectory-based	Heuristic	Focus on the ranking point of interests from the start and end points of users	Complete route trip	Flickr	Efficiency
Chen et al. (2016b)	Stand-Alone Point	Hypertext Induced Topic Search, Tensor Factorization	Find a distance weighted of location category and group user locations	Suggest attractions/destinations	Foursquare	Accuracy, Efficiency
Chen et al. (2017)	Stand-Alone Point	Chebyshev Polynomial Approximation	Focus on user check-in on visiting location categories	Suggest attractions/destinations	Foursquare, Gowalla	Accuracy, Efficiency
Chen et al. (2018)	Stand-Alone Point	Collaborative	Detect the spatial and temporal influences in locations	Suggest attractions/destinations	Foursquare, Gowalla	Accuracy
Cheng et al. (2016)	Stand-Alone Point	Matrix Factorization, Data mining	Compute the probability of user check-in	Suggest attractions/destinations	Foursquare, Gowalla	Accuracy, Sparsity
Cheverst et al. (2002)	Stand-Alone Point	Content-based	Investigate user interests, histories, preferences, and contexts	Give tourist information	Not specific websites	Suitability
Console et al. (2003)	GPS Trajectory-based	Adaption	Study the user preferences, user interests, and context of interaction based on current location, GPS coordinates, and driving conditions	Give tourist information	Not specific websites	Accuracy
Cui et al. (2018)	GPS Trajectory-based	Collaborative, Naïve Bayes	Defined user behaviors from historical GPS trajectories	Complete route trip	GeoLife	Cold start, Efficiency
Dao et al. (2012)	Stand-Alone Point	CF, Genetic Algorithm	Consider user preferences and context information	Suggest attractions/destinations	Korea websites	Accuracy
Ding and Chen (2018)	Stand-Alone Point	Hybrid, Content-based, Collaborative, Matrix Factorization, Deep Learning, Neural Network	Incorporate user behavior, co-visiting, geographical and categorical influences to embed in deep neural network	Suggest attractions/destinations	Foursquare, Gowalla	Accuracy
Duan et al. (2018)	GPS Trajectory-based	Collaborative, Clustering	Study real-time current location and visiting behaviors in the past	Suggest attractions/destinations	Province open data	Accuracy, Efficiency, Reduction
Ferraro and Re (2014)	Ontology-based	Data Mining, Semantic	Study semantic of user interests and user preference	Complete route trip	Not specific websites	Accuracy, Efficiency
Franke (2002)	Stand-Alone Point	Fuzzy	Integrate personality types and the user model for tourism services	Suggest attractions/destinations	Not specific websites	Efficiency
Gao et al. (2015)	Location-based Friend	Hybrid	Focus on friend check-in behaviors, context of social correlations and geographical distances	Suggest attractions/destinations	Foursquare, Twitter	Accuracy, Cold start, Efficiency
Gao et al. (2017)	Location-based Friend	Multi-criteria, Support Vector Machine	Learn user social relationship, check-in distance and check-in behavior	Suggest attractions/destinations	Brightkite, Gowalla	Accuracy
Gao et al. (2018a)	Stand-Alone Point	Bayesian Personalized Ranking	Capture the user preference, check-in behaviors and geographical influences	Suggest attractions/destinations	Foursquare, Yelp	Accuracy
Gao et al. (2018b)	Stand-Alone Point	Tensor Factorization, Bayesian Personalized Ranking	Explore the impact of time, spatial-temporal sequential influence and social influence.	Suggest attractions/destinations	Foursquare, Gowalla	Accuracy, Efficiency
Gao et al. (2018c)	Stand-Alone Point	Collaborative, Singular Value Decomposition, Matrix Factorization	Study the geographic influences and social information based on check-in behavior	Suggest attractions/destinations	Foursquare	Sparsity, Cold start
Gavalas and Kenteris (2011)	Stand-Alone Point	Collaborative, K-means Clustering	Consider the user current location, the visited places, user ratings, weather and time.	Suggest attractions/destinations	Not specific websites	Accuracy, Efficiency
Gavalas and Kenteris (2012)	Stand-Alone Point	Content-based	Consider user preferences, user location, current time, weather conditions and user histories to rank the similar context	Suggest attractions/destinations	Not specific websites	Efficiency
Gavalas et al. (2012)	Travel Route	Heuristic	Consider user preferences, current location, and time available	Complete route trip	Not specific websites	Scalability, Efficiency
Guo et al. (2018)	Stand-Alone Point	Bayesian Personalized Ranking	Extract implicit feedback to get the geographical characteristics and calculate nearest neighbor	Suggest attractions/destinations	Brightkite, Gowalla	Accuracy, Efficiency
Han and Lee (2015)	Geo-tagged-media-based	Clustering, Adaption	Focus on the spatial and temporal property in popular places	Complete route trip	Flickr	Accuracy
Hinze et al. (2009)	Ontology-based	Semantic	Explore event and location to filter out tourist information and develop user preferences based on user current location	Suggest attractions/destinations	Not specific websites	Efficiency, Scalability
Hosseini et al. (2017)	Geo-tagged-media-based	Hybrid	Detect the temporal correlations and the user check-in behaviors	Suggest attractions/destinations	Brightkite, Foursquare	Efficiency, Sparsity
Hsieh et al. (2014)	GPS Trajectory-based	Route Mining	Explore the popularity of places, the visiting order of places, the proper visiting time	Complete route trip	Gowalla	Accuracy, Efficiency
Huang (2016)	Geo-tagged-media-based	Hybrid	Learn user contexts, user histories, matching a user preference	Suggest attractions/destinations	Flickr	Efficiency
Huang and Bian (2009)	Ontology-based	Bayesian Network, Analytic Hierarchy Process	Estimate the user preferred activities based on information of tourist attractions and user behaviors	Complete route trip	Not specific websites	Efficiency

TABLE 2. ***(Continued.)*** **Summarization of linked open data in location-based recommendation system in tourism domain.**

Huang et al. (2015)	Location-based Friend	Graph Model	Assume the probability of check-in the same point of interest for two friends is higher than that for two strangers	Suggest attractions/destinations	Foursquare, Gowalla	Accuracy, Scalability
Jiang et al. (2016)	Geo-tagged-media-based	Route Mining	Consider user topical interest and preference of visiting time and season	Complete route trip	Not specific websites	Accuracy
Kaushik et al. (2016)	Geo-tagged-media-based	Fuzzy	Learn the crowd visiting places and collective knowledge	Suggest attractions/destinations	Not specific websites	Accuracy
Kefalas et al. (2018)	Location-based Friend	Graph Model	Study the relation among users, times, and locations	Recommend friends	Foursquare, Gowalla	Accuracy, Efficiency
Kesorn et al. (2017)	Location-based Friend	Collaborative	Study the close friends matching user interests and activities for user target profiles	Suggest attractions/destinations	Facebook	Accuracy, Cold start
Kosmides et al. (2016)	Location-based Friend	Neural Network, K-means Clustering	Learn user preferences and user friends' histories based on user check-ins and the ratings	Suggest attractions/destinations	Foursquare	Accuracy
Krosche et al. (2004)	GPS Trajectory-based	Adaption	Use the GPS satellite systems for locating the user location	Suggest attractions/destinations	Not specific websites	Efficiency
Kumar and Thangamani (2018)	Ontology-based	Ant Colony Optimization, Semantic, Fuzzy, Clustering	Exploit semantic information of the point of interest and routes textual description	Complete route trip	IgoUgo	Accuracy, Efficiency, Sparsity
Kurashima et al. (2013)	Geo-tagged-media-based	Markov chain	Exploit the user current location, user interests, spare time and means of transportation	Complete route trip	Flickr	Accuracy, Efficiency
Lee et al. (2009)	Ontology-based	Ant Colony Optimization, Semantic, Multi-Agent	Learn semantic and geographic to enrich travel data with user preferences and location distances	Complete route trip	Taiwan tourism websites	Efficiency
Lei Hang (2018)	Travel Route	Association Rule Mining	Analyze user histories and user preferences with date, season and places	Complete route trip	Open data portal	Efficiency
Li et al. (2015)	Stand-Alone Point	Collaborative	Model user rating behaviors from location and time stamp	Suggest attractions/destinations	Yelp, TripAdvisor	Accuracy, Sparsity
Lian et al. (2018)	Stand-Alone Point	Collaborative, Semantic	Incorporate semantic contents with implicit feedback	Suggest attractions/destinations	Jiepang	Efficiency
Lim et al. (2018b)	Geo-tagged-media-based	Orienteering Problem	Study the travel sequences, the popularity of point of interests, and user interest preferences	Complete route trip	Flickr	Accuracy
Liu and Seah (2015)	GPS Trajectory-based	Mining, Clustering	Learn the popularity of point of interests, temporal and geographical features	Suggest attractions/destinations	GeoLife, Illinois	Accuracy, Sparsity
Liu and Wang (2018)	Stand-Alone Point	Markov Chain	Use the user current location and previous locations to predict the user next favorite place	Suggest attractions/destinations	Brightkite, Gowalla	Efficiency, Scalability
Liu et al. (2014a)	Travel Route	Fuzzy, Genetic Algorithm	Consider the user interests and preferences and the route attributes including distance, fee, road conditions, and traffic conditions	Complete route trip	Not specific websites	Efficiency
Liu et al. (2015)	Stand-Alone Point	Collaborative, probabilistic matrix factorization	Study the geographical influence and user patterns of check-in	Suggest attractions/destinations	Brightkite, Foursquare, Gowalla	Sparsity
Liu et al. (2017)	Stand-Alone Point	Knowledge Graph Embedding	Capture the geographic and temporal effects by time and location	Suggest attractions/destinations	Foursquare, Gowalla	Accuracy, Sparsity, Cold start, Efficiency
Loh et al. (2003)	Ontology-based	Collaborative, Text Mining, Decision Support System	Focus on user needs like cities and attractions based on the interesting locations in ontology data	Suggest attractions/destinations	Not specific websites	Efficiency
Lu et al. (2016a)	Travel Route	Hybrid	Focus on score of attraction, check-in logs, and temporal constraints	Complete route trip	Gowalla	Accuracy, Efficiency
Lu et al. (2017)	Stand-Alone Point	Collaborative	Focus on the number of check-ins during the period with the temporal effects	Suggest attractions/destinations	Foursquare, Gowalla	Accuracy, Sparsity
Majid et al. (2013)	Geo-tagged-media-based	Collaborative	Find tourist locations and the popularity of locations from photo textual information	Suggest attractions/destinations	Foursquare, Wunderground	Accuracy
Memon et al. (2015)	Geo-tagged-media-based	Collaborative	Study the location, time, weather, tag, and title of attraction photo	Suggest attractions/destinations	Flickr, Underground	Efficiency, Scalability
Missaoui et al. (2017)	Ontology-based	Pattern Mining	Use metadata in the content matching location, proximity, and so on	Suggest attractions/destinations	Not specific websites	Efficiency
Mocholi et al. (2012)	Travel Route	Ant Colony Optimization	Learn semantic multi-criteria, such as user current location and user routes including associated context information	Complete route trip	Not specific websites	Scalability
Moreno et al. (2013)	Ontology-based	Collaborative	Study user profile based on demographic information, user behaviors, and user ratings	Suggest attractions/destinations	Not specific websites	Accuracy, Efficiency, Sparsity
Noguera et al. (2012)	Stand-Alone Point	Hybrid	Focus on user current location	Suggest attractions/destinations	Not specific websites	Accuracy, Efficiency
Palovics et al. (2017)	Geo-tagged-media-based	Matrix Factorization	Learn twitter hashtag for places with GPS location	Suggest attractions/destinations	Twitter	Accuracy, Cold start
Peng and Huang (2017)	Geo-tagged-media-based	Clustering, Text Mining	Focus on hotspots through spatial influence	Suggest attractions/destinations	Foursquare, Wunderground	Accuracy
Qian et al. (2018)	Stand-Alone Point	Knowledge Graph Embedding	Extend Liu et al. (2017) by capture the user interest in the spatial and temporal information.	Suggest attractions/destinations	Foursquare, Gowalla	Cold start, Sparsity
Ravi and Vairavasundaram (2016)	Stand-Alone Point	Trust walker algorithm	Exploit the rating score of locations with location categories	Suggest attractions/destinations	Foursquare	Accuracy, Efficiency
Ren et al. (2017)	Stand-Alone Point	Collaborative, Probabilistic Matrix Factorization	Focus on the popularity of places by exploiting the interest topics, geographical, social and categorical relevance scores	Suggest attractions/destinations	Foursquare, Twitter	Accuracy, Efficiency
Ricci and Werthner (2001)	Travel Route	Case-based Reasoning	Consider user interest, locations to visit, services and activities	Complete route trip	Not specific websites	Efficiency
Rios et al. (2018)	Stand-Alone Point	Collaborative	Exploit neighborhood and user preferences	Suggest attractions/destinations	Foursquare	Efficiency
Rivera et al. (2015)	Ontology-based	Semantic	Learn different opinions tourism context matching user current location, user preferences, point of interests, distances	Suggest attractions/destinations	Foursquare, French government, Maxican government	Accuracy
Santiago et al. (2012)	GPS Trajectory-based	Data Mining	Use the device GPS to locate the tourist and estimate time to reach a location	Complete route trip	Not specific websites	Accuracy, Efficiency

TABLE 2. ***(Continued.)*** **Summarization of linked open data in location-based recommendation system in tourism domain.**

Sebastia et al. (2009)	Travel Route	Hybrid	Study the interest places, the user demographic, and history trips for the current visit.	Complete route trip	Not specific websites	Scalability, Efficiency
Shen et al. (2016)	Stand-Alone Point	Content-based	Match the explicit user interaction with user preferences	Suggest attractions/destinations	Not specific websites	Accuracy, Efficiency
Shi et al. (2014)	Ontology-based	Reasoning Rules	Study user direct needs and user preference	Suggest attractions/destinations	Qunar	Efficiency
Si et al. (2017)	Stand-Alone Point	User-based Collaborative	Focus on check-in behaviors and temporal features	Suggest attractions/destinations	Foursquare, Gowalla	Accuracy
Smirnov et al. (2017)	Ontology-based	Collaborative	Study tourist preferences and current situation in the location region	Suggest attractions/destinations	Not specific websites	Sparsity, Scalability
Socharoentum and Karimi (2016)	Travel Route	Multi-Criteria	Study the user behaviors and environment	Complete route trip	Not specific websites	Scalability
Su (2013)	Travel Route	Route Mining	Mining frequent path and landmarks	Complete route trip	Not specific websites	Accuracy, Efficiency
Sun et al. (2015)	Geo-tagged-media-based	Clustering, Data Mining	Identify the ranking landmarks and from the tourism popularity of the road	Complete route trip	Flickr, OpenStreetMap	Accuracy, Sparsity
Tsai and Lai (2015)	Travel Route	Sequence mining	Study the sequence of location based on user spatial and temporal behavior	Complete route trip	Not specific websites	Efficiency
Tsai and Lo (2010)	Travel Route	Data Mining	Study the previous popular visiting behaviors	Complete route trip	Not specific websites	Efficiency
Tuan et al. (2017)	Stand-Alone Point	Collaborative	Focus on time periods in place and current location	Suggest attractions/destinations	Geodeg	Accuracy, Sparsity
Volkova et al. (2017)	Ontology-based	Content-based, Natural Language Processing	Focus on user preferences in venue aspects from reviews	Complete route trip	Foursquare	Efficiency
Wallace et al. (2003)	Travel Route	Collaborative, Neural Network	Use the user histories and user behaviors	Complete route trip	Not specific websites	Efficiency, Sparsity
Wang et al. (2015b)	Geo-tagged-media-based	Semantic	Study the semantics of point of interest and user check-in patterns	Suggest attractions/destinations	Foursquare, Twitter	Accuracy
Wang et al. (2017)	Stand-Alone Point	Clustering, Latent Dirichlet Allocation	Focus on the user interests and the geographical information based on ratings and tags	Suggest attractions/destinations	Foursquare	Accuracy, Cold start
Wohltorf et al. (2005)	Travel Route	Collaborative	Use the location information, and route in different locations to suggest point of interest	Complete route trip	Not specific websites	Efficiency
Worndl et al. (2017)	Travel Route	Dijkstra	Focus on the start point, end point, and number of places	Complete route trip	Foursquare	Accuracy
Xia et al. (2017)	Stand-Alone Point	Support Vector Machine	Capture user preferences from the temporal influence and the category of locations with the check-in records	Suggest attractions/destinations	Foursquare	Accuracy, Scalability, Efficiency
Xing et al. (2018)	Stand-Alone Point	Neural Network, Matrix Factorization	Capture the geographical influences from user check-in behaviors and social relations	Suggest attractions/destinations	Foursquare	Efficiency
Xu et al. (2015)	Geo-tagged-media-based	User-based Collaborative, Data Mining	Focus on topic distribution by studying user interests and user travel histories	Suggest attractions/destinations	Flickr	Efficiency
Xu et al. (2016)	Stand-Alone Point	Random walk	Focus on user check-ins, point of interests, and sentiment reviews	Suggest attractions/destinations	Foursquare	Accuracy
Xu et al. (2017)	Geo-tagged-media-based	Dynamic Topic Model, Matrix Factorization	Learn metadata, check-in, point of interest categories, and content from photos	Suggest attractions/destinations	Flickr, Sina Weibo	Sparsity, Efficiency
Xu et al. (2018)	Stand-Alone Point	Case-Based Reasoning	Explore the non-native check-in data for new visitor and use different types of users and check-in patterns to predict human mobility behavior	Suggest attractions/destinations	Foursquare	Sparsity
Yao et al. (2018)	Stand-Alone Point	Tensor Factorization	Study the social constraints and spatial-temporal influence from check-in data	Suggest attractions/destinations	Brightkite, Gowalla	Accuracy, Efficiency
Yin et al. (2015)	Stand-Alone Point	Probabilistic generative	Use the user ratings to model user profiles by considering user home locations in both taste and travel distance	Suggest attractions/destinations	Gowalla	Cold start
Yin et al. (2016)	Stand-Alone Point	Latent Class Probabilistic Generative	Study user check-in behaviors and reviews both in hometown and out-of-town areas	Suggest attractions/destinations	Foursquare, Yelp	Efficiency, Sparsity
Yin et al. (2017)	Stand-Alone Point	Deep Learning	Use the geographical influence to correlate users in new locations	Suggest attractions/destinations	Foursquare, Yelp	Cold start
Ying et al. (2014)	Stand-Alone Point	Random Walk, Data Mining	Exploit social relations, place categories and popularity influences	Suggest attractions/destinations	EveryTrail, Gowalla	Sparsity
Yu et al. (2014)	Travel Route	User-based Collaborative	Focus on the popularity of point of interests based on check-in data records	Provide travel package	Jiepang	Accuracy
Yu et al. (2016)	Travel Route	Collaborative	Study the user check-in behavior and visiting sequence	Complete route trip	Jiepang	Accuracy, Diversity
Yu et al. (2017)	Geo-tagged-media-based	Data Mining	Study group-like travel locations and trajectory patterns	Complete route trip	Instagram	Efficiency
Zhang and Chow (2015a)	Stand-Alone Point	Collaborative	Focus on individual and integrate user preference, social influence, and geographical influence	Suggest attractions/destinations	Foursquare, Gowalla	Scalability
Zhang and Chow (2015c)	Stand-Alone Point	Markov chain	Focus on the location visited patterns	Suggest attractions/destinations	Foursquare, Gowalla, Yelp	Accuracy, Sparsity
Zhang and Chow (2016)	Stand-Alone Point	Kernel Density Estimation	Use the temporal influence both weekdays and weekends for recommending time-to-visit	Suggest attractions/destinations	Foursquare, Gowalla	Accuracy, Scalability
Zhang and Wang (2016)	Stand-Alone Point	Collaborative, K-means Clustering	Focus on users who travel to a new city or region that they have never visited before	Suggest attractions/destinations	Foursquare, Yelp	Sparsity
Zhang et al. (2015)	Stand-Alone Point	Probabilistic	Use user histories and check-in behaviors to compute the probability of users visiting new locations	Suggest attractions/destinations	Foursquare, Gowalla	Accuracy, Efficiency, Sparsity
Zhang et al. (2016)	Travel Route	Collaborative, Data Mining,	Focus on the popular attractions, user interests, and distance	Complete route trip	Foursquare, Yelp	Accuracy, Efficiency
Zhao et al. (2014)	Stand-Alone Point	User-based Collaborative	Cluster users based on the check-in counts	Suggest attractions/destinations	Foursquare, Twitter	Accuracy
Zhao et al. (2016)	Stand-Alone Point	Collaborative, Sequential Embedding Rank Model	Learn user preferences and geographical constraint	Suggest attractions/destinations	Foursquare, Gowalla	Scalability
Zhao et al. (2018a)	Stand-Alone Point	Tensor Factorization	Model check-in activity from the locations in different time	Suggest attractions/destinations	Foursquare, Gowalla	Sparsity
Zhao et al. (2018b)	Stand-Alone Point	Representation Learning	Incorporate user characteristics, social connections, and sequence data to produce a latent representation	Suggest attractions/destinations	Foursquare, Gowalla	Accuracy, Efficiency

TABLE 2. ***(Continued.)*** **Summarization of linked open data in location-based recommendation system in tourism domain.**

Zhao et al. (2018c)	Location-based Friend	Collaborative, Distributed ELM	Suppose the more similar users are, the more likely they will be friends in the future	Recommend friends	Brightkite, Gowalla	Accuracy, Cold start, Scalability, Efficiency
Zheng and Xie (2011)	GPS Trajectory-based	Collaborative, Hypertext Induced Topic Search	Focus on the level of user experiences and location interests	Suggest attractions/destinations	Not specific websites	Accuracy, Efficiency
Zheng et al. (2011)	Location-based Friend	Collaborative, Data Mining	Exploit the relationship between the locations of users and social interactions.	Recommend friends + Suggest attractions/destinations	Not specific websites	Accuracy, Cold start, Scalability, Efficiency
Zheng et al. (2012)	GPS Trajectory-based	Collaborative	Extract location and activity information from the GPS history data	Suggest attractions/destinations	Not specific websites	Accuracy, Sparsity
Zheng et al. (2016)	Travel Route	Route Mining	Study the popular route and places close to the current location	Complete route trip	Not specific websites	Accuracy, Efficiency
Zhou et al. (2016)	Stand-Alone Point	Curve Coupling	Study user check-in behaviors in different location and geographical influences for filtering out not interest places	Suggest attractions/destinations	Gowalla	Accuracy, Scalability
Zhu et al. (2015)	Location-based Friend	Hypercube Model	Mine user friend interests from short tweets to model the user interest with multiple topics	Recommend friends	Sina Weibo	Accuracy, Efficiency
Zhu et al. (2017a)	GPS Trajectory-based	Route Mining	Focus on the different location types in the geographical information	Suggest attractions/destinations	GeoLife	Accuracy, Efficiency, Sparsity
Zhu et al. (2017b)	Travel Route	Singular Value Decomposition, Tensor	Construct the user preferences and the proper visiting time for a certain location and time	Complete route trip	Foursquare	Accuracy, Sparsity
Zipf and Jost (2006)	Ontology-based	Adaption	Collect several tourism information for mobile service	Complete route trip	Not specific websites	Efficiency

There are many different in transport, such as walking, bus, train, taxi, and car. It may use during the tourist to visit a place by the transport constraints.

3) *Real-time factors* As the user preferences can be very active and may change during a short time in visiting places. The recommendation system needs to re-compute the user preferences, user interests, and the user similarities frequency. On the other hand, the current context of places and other conditions may update in the location recommendation process.
4) *Sentiments and contexts* Incorporating the textual descriptions and semantic information including user opinions and reviews, general contexts, environmental contexts, spatial-temporal, and social information, these sentiments need to be enabled to overcome the limitations of the existing recommendation systems.
5) *Methodologies* The hybrid techniques used to improve the drawbacks of traditional techniques. The social relation such as the distance between friends is to be considered in recommendation system. The network embedding method is a graph embedding in the network structure. It is also a challenge for recommendations.

VI. CONCLUSION

In this research, we presented a systematic review and mapping of the linked open data in location-based recommendation system on tourism domain. An overview of the current research status in the fields was provided. First, we classified journal papers in this area from 2001 to 2018 by the year of publication. Second, we analyzed and categorized journal papers by the different recommendation applications including problem formulations, data collections, proposed algorithms/systems, and experimental results. Third, we grouped the linked open data sources used in location-based recommendation system on tourism. Next, we summarized the research achievements and presented the distribution of the different categories of location-based recommendation applications via linked open data. Finally, we guided the possible future research direction for the linked open data in location-based recommendations on tourism.

The primary goal is to present the objective of integrating linked open data, the linked open data source used in tourism, and the methodology produced in location-based recommendation system. This survey showed that the linked open data in location-based recommendation system on tourism domain is a challenge for researchers. Furthermore, the integration of linked open data into the recommendation process can improve the accuracy and quality of recommendations and overcome the main drawbacks associated with the traditional recommendation techniques. Results further show that the linked open data is an effective resource to convey semantic information of knowledge in location-based recommendation systems for tourism. We hope that this review study can help researchers with state-of-the-art knowledge and provide useful guidelines for future development.

APPENDIX

See Table 2.

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PHATPICHA YOCHUM received the B.S. degree in software engineering from Mae Fah Luang University, Thailand, in 2009, and the M.S. degree in information technology from Rangsit University, Thailand, in 2017. She is currently pursuing the Ph.D. degree in information and communication engineering with the Guilin University of Electronic Technology, China. Her research interests include knowledge graphs, network embedding, and recommendation systems.

LIANG CHANG received the Ph.D. degree in computer science from the Institute of Computing Technology, Chinese Academy of Sciences, in 2008. He is currently a Professor with the School of Computer Science and Information Security, Guilin University of Electronic Technology, China. His research interests include data and knowledge engineering, formal methods, and intelligent planning.

TIANLONG GU received the Ph.D. degree from Zhejiang University, China, in 1996. From 1998 to 2002, he was a Research Fellow with the School of Electrical and Computer Engineering, Guilin University of Technology, and a Postdoctoral Fellow with the School of Engineering, Murdoch University, Australia. He is currently a Professor with the School of Computer Science and Information Security, Guilin University of Electronic Technology, China. His research interests include formal methods, data and knowledge engineering, and software engineering.

MANLI ZHU received the bachelor's degree in software engineering from Zhoukou Normal University, in 2013, the M.S. degree in computer science and technology from the Guilin University of Electronic Technology, China. Her research interests include knowledge graphs, knowledge graph representation, and recommendation systems.