Information Processing and Management 57 (2020) 102078

Contents lists available at ScienceDirect

Information Processing and Management

journal homepage: www.elsevier.com/locate/infoproman

An extensive study on the evolution of context-aware personalized travel recommender systems

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ARTICLE INFO

Keywords:
Recommender system
Personalization
Context aware
Big data
Travel and tourism

ABSTRACT

Ever since the beginning of civilization, travel for various causes exists as an essential part of human life so as travel recommendations, though the early form of recommendations were the accrued experiences shared by the community. Modern recommender systems evolved along with the growth of Information Technology and are contributing to all industry and service segments inclusive of travel and tourism. The journey started with generic recommender engines which gave way to personalized recommender systems and further advanced to contextualized personalization with advent of artificial intelligence. Current era is also witnessing a boom in social media usage and the social media big data is acting as a critical input for various analytics with no exception for recommender systems. This paper details about the study conducted on the evolution of travel recommender systems, their features and current set of limitations. We also discuss on the key algorithms being used for classification and recommendation processes and metrics that can be used to evaluate the performance of the algorithms and thereby the recommenders.

1. Introduction

The travel and tourism industry is witnessing an amazing growth in recent years and it has become one of the largest service industries in fast developing nations like India. As per World Travel & Tourism Council (WTTC), Travel and Tourism is one of the largest economic sectors of the world, providing 292 million jobs and contributing 10.2% of the global GDP (Gross Domestic Product) valuing $7.6 trillion in 2016. As per the 2017 Edition of UNWTO (United Nations World Tourism Organization) Tourism Highlights, tourism ranks third among the worldwide export categories with a share of 7% of the total exports of goods and services.

A recommender system can be treated as an algorithm or a software that could predict what a user may or may not do or like among a list of available options. Researchers have come up with real world recommender systems in almost every domain like e-commerce, tourism, content-based portals, entertainment, match making, etc. Tapestry (Goldberg, Nichols, Oki, & Douglas, 1992) is considered as the first known recommender system and was developed as an experimental mail filtering system to recommend artefacts from newsgroups to a group of users. From this stage, the recommender system concept has further evolved as an important tool to deal with the information overload problem of the modern era. The drastic developments in the areas of artificial intelligence and big data enabled recommender systems to become more intelligent, personalized and contextual.

Travel and Tourism is an important business domain that can leverage the power of recommender systems in various stages starting from trip planning to execution. Internet has a huge volume of information on tourism/leisure spots and activities. It is a

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https://doi.org/10.1016/j.ipm.2019.102078
Received 4 January 2019; Received in revised form 27 April 2019; Accepted 4 July 2019
Available online 11 July 2019

really challenging task for travelers to read through all such information in order to plan their trip/leisure time. A travel recommender can help in this scenario by supporting the decision-making process in the areas like choice of destinations, selection of attractions, finalization of routes, mode of transport, identification of appropriate accommodations and restaurants, etc. Modern recommender systems can add the personalization aspects like learned user preferences from past user traits to arrive at recommendations. It can also recommend traits observed in other travelers who belong to similar demographic groups of the user in consideration. A simple contextualization may include proposing options to traveler based on the forecasted weather at the locations in consideration on any proposed period.

This paper is organized as follows - Section 1 introduces the importance of travel and tourism domain and the significance of recommender system in the area, Section 2 explains various recommender system paradigms, important algorithms and performance metrics, Section 3 briefs on various researches and developments on travel recommenders over the last two decades, Section 4 discusses the observations from the study and Section 5 concludes with the inferences and future directions.

2. Antecedents

2.1. Recommender system paradigms

The key expectation from a recommender system is to minimize the information overload by providing only relevant suggestions to the end user. There are various information filtering strategies being adopted for this purpose. This section provides a quick summary of these approaches in order to enable the readers to relate them to the study covered in this paper while more elaborative details can be found in existing literatures like (Adomavicius & Tuzhilin, 2005; Ricci, Rokach, & Shapira, 2010; Bobadilla, Ortega, Hernando, & Gutiérrez, 2013). In real time recommender systems, it can be always observed that a combination of these paradigms is in use.

2.1.1. Content-based systems

The concept behind content-based filtering (Van Meteren & Van Someren, 2000) is to recommend items to a user, which are similar to the ones that the particular user has already liked in the past (Fig. 1). The similarity of items is calculated based on their similarity with respect to features. In content-based recommender systems, items are represented as multi-dimensional vectors using vector space model where each feature is represented in a dimension. Common learning techniques used in content-based systems include Bayesian Classifier, Relevance Feedback, Neural Networks and Genetic Algorithms.

2.1.2. Collaborative systems

The underlying concept of collaborative filtering (Schafer, Frankowski, Herlocker, & Sen, 2007) is that multiple individuals sharing similar interests in an area tend to have inclination towards similar items from other areas as well (Fig. 2). The similarity between users are figured out based on their past behavior. Collaborative filtering systems uses neighborhood-based approach to select a group of users who are similar to the active user for whom recommendations need to be given. The prediction or

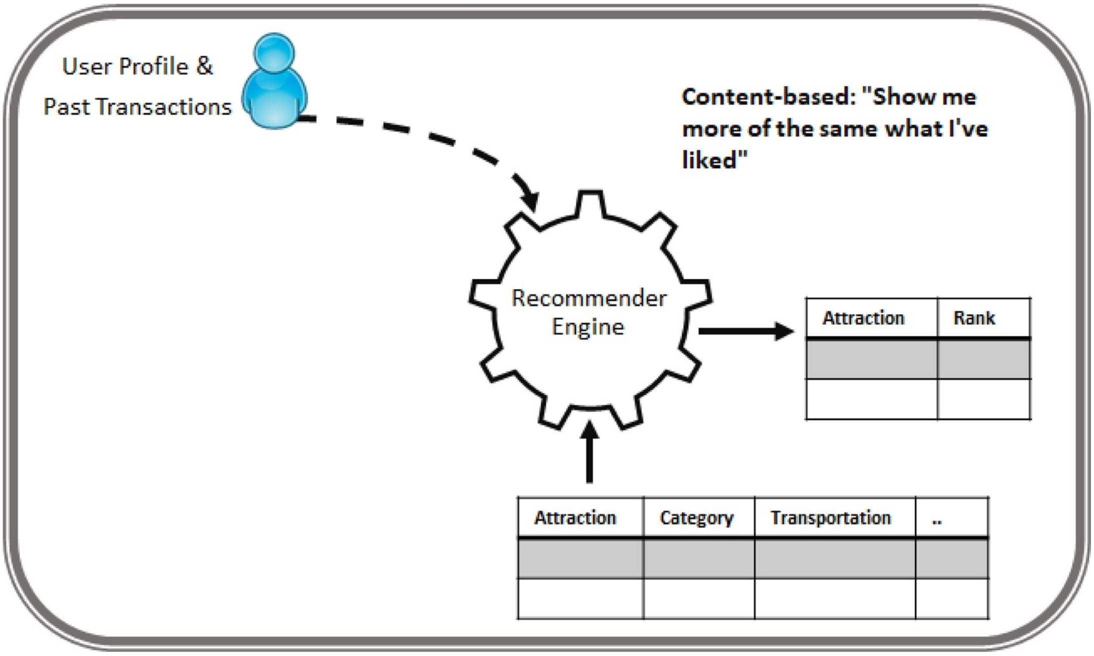

Fig. 1. Content-based Systems.

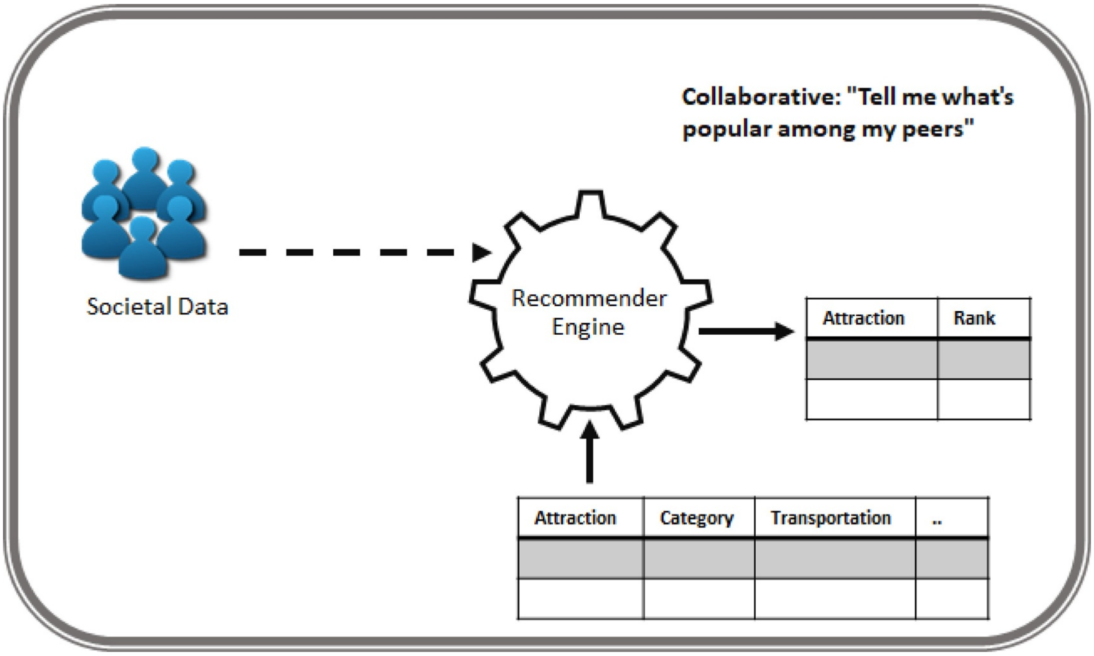

Fig. 2. Collaborative Systems.

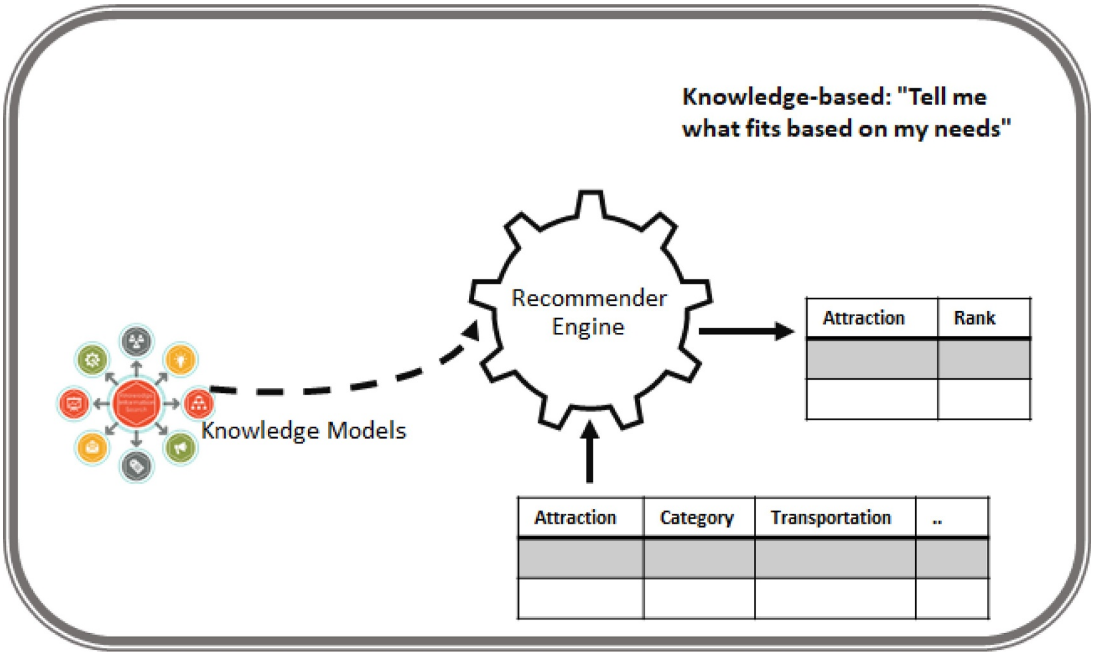

Fig. 3. Knowledge-based Systems.

recommendation is provided as a weighted average of the ratings or actions of this group. The weight is determined by the correlation between the group member and the active user.

Common similarity measures being used by collaborative recommender systems include Cosine Coefficient, Dice Coefficient, Euclidean Distance, Jaccard Coefficient, Manhattan Distance and Minkowski Distance.

2.1.3. Knowledge-based systems

Knowledge-based systems (Burke, Hammond, & Young, 1996) completely rely on domain knowledge (Fig. 3). It understands needs and preferences of the user and produce suitable recommendations based on the details available with its knowledge models.

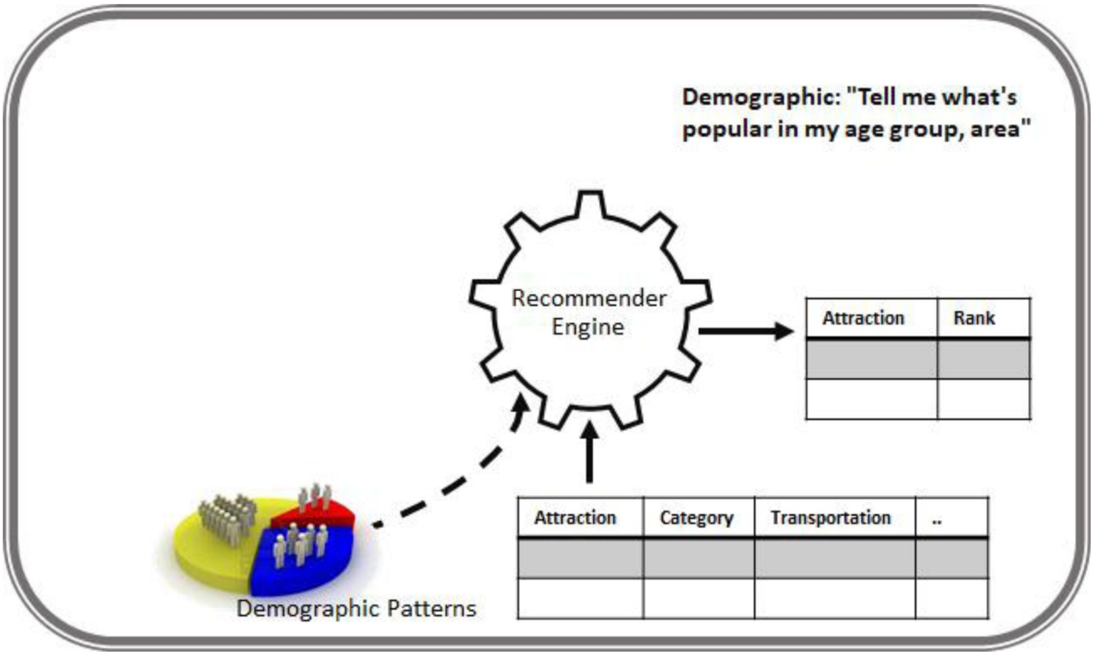

Fig. 4. Demographic Systems.

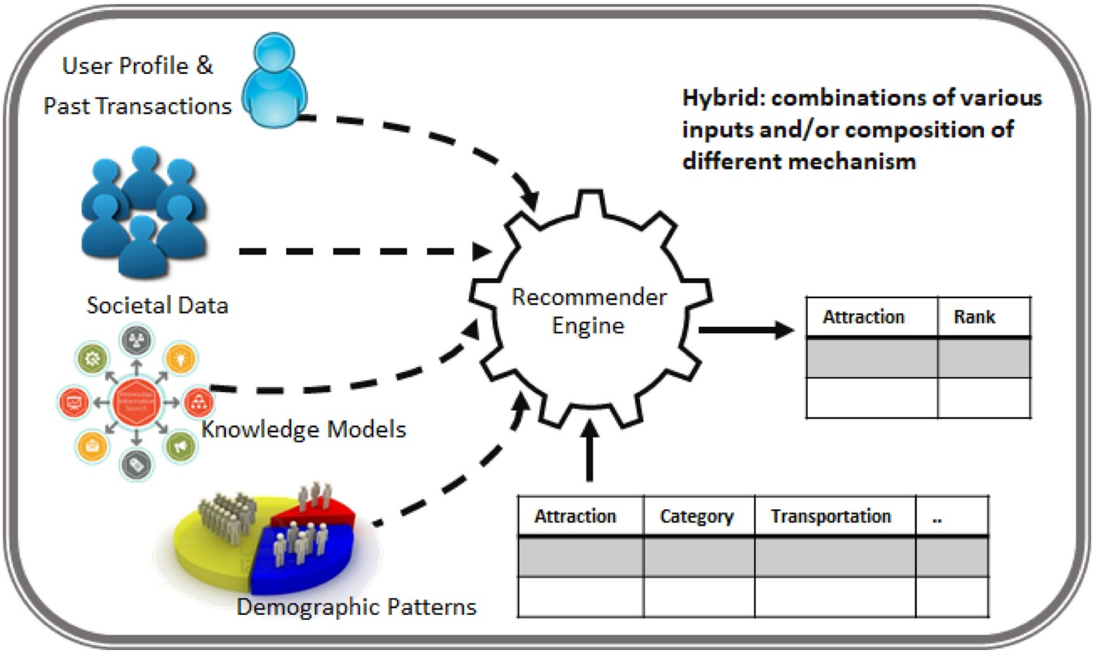

Fig. 5. Hybrid Systems.

The knowledge models store information on how an item can address a particular user need.

Knowledge-based systems are often considered as an alternative to content-based and collaborative systems to deal with the cold-start problem. However, this approach is highly computational-intensive as it need to deal with knowledge acquisition and representation for all items in the recommender systems.

2.1.4. Demographic systems

In demographic filtering (Safoury & Salah, 2013) users are categorized based on demographic attributes and recommendations are generated for these demographic classes (Fig. 4). Geographic region, age group, gender, seasonality, etc. are common demographic

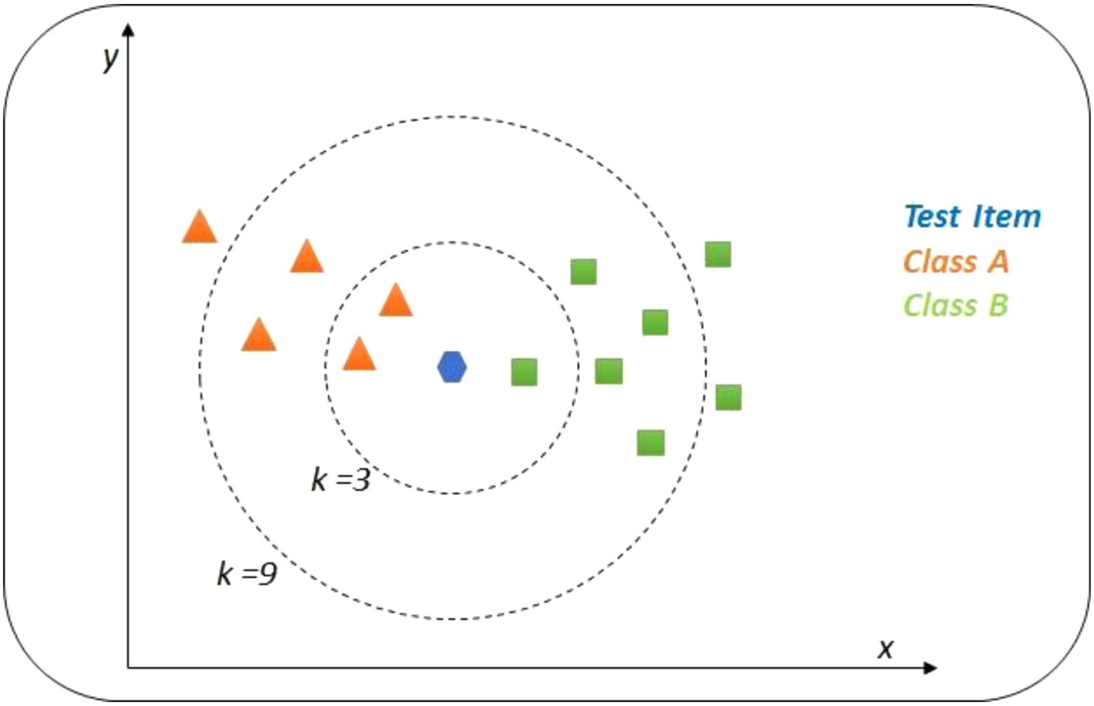

Fig. 6. kNN Algorithm.

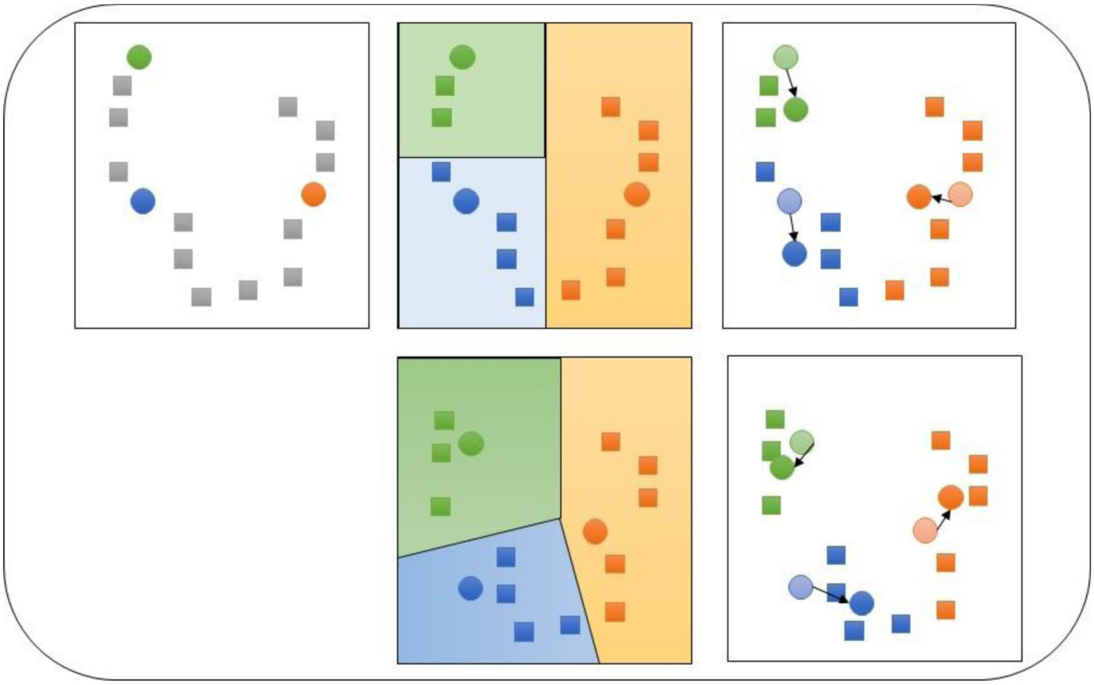

Fig. 7. k-means Algorithm.

classifiers being adopted by applications which use this approach. Lot of firms who attempts to provide recommendation services to its customers starts with this approach as it is quite simple, easy to implement and less computationally intensive.

This approach requires a market analysis to identify demographic correlations among the user groups. Analysis is normally performed by analyzing user profiles either from the organization database or by carrying out an explicit survey among users. The advantage of this approach is that it does not require historical data of user transactions unlike in the case of content-based or collaborative systems.

1. *Let k = 1*
2. *Generate all **Frequent Items Sets** of length 1*
3. *Repeat until no new **Frequent Items Sets** are identified*
    a. ***Generate** candidate item sets of length (k+1) from frequent items sets of length k*
    b. ***Prune candidate** item sets containing subsets of length k that are infrequent*
    c. ***Check the support** of each candidate in the training data*
    d. ***Eliminate** candidates that are infrequent*

Fig. 8. Apriori Algorithm.

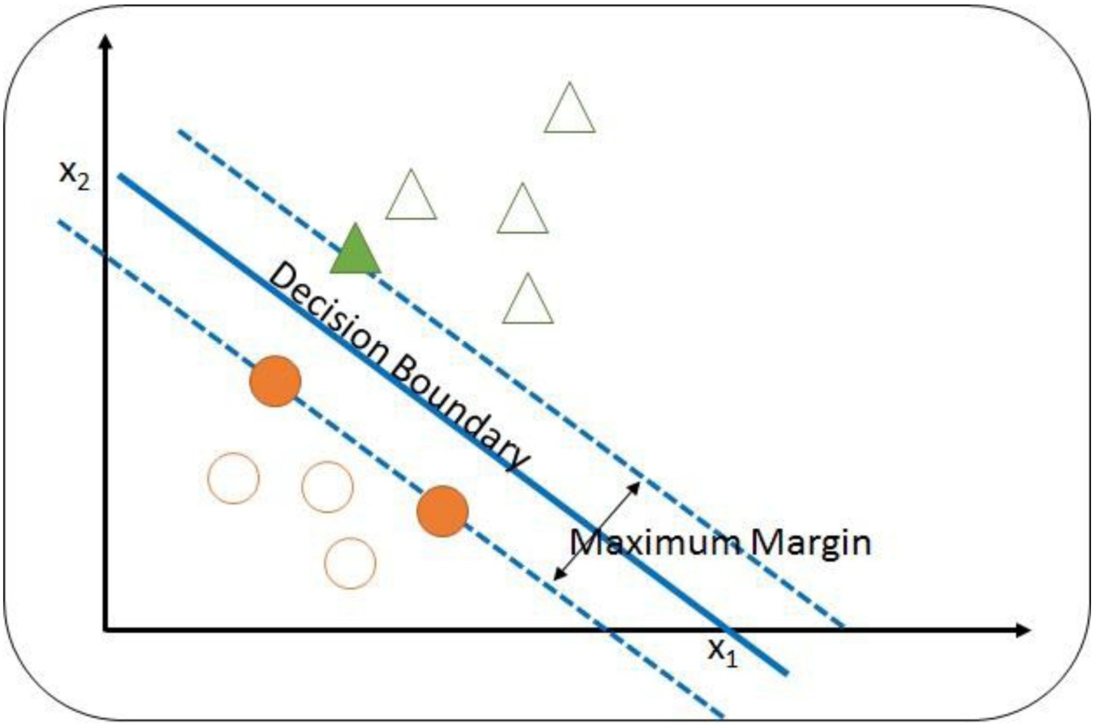

Fig. 9. Decision Boundary of an SVM.

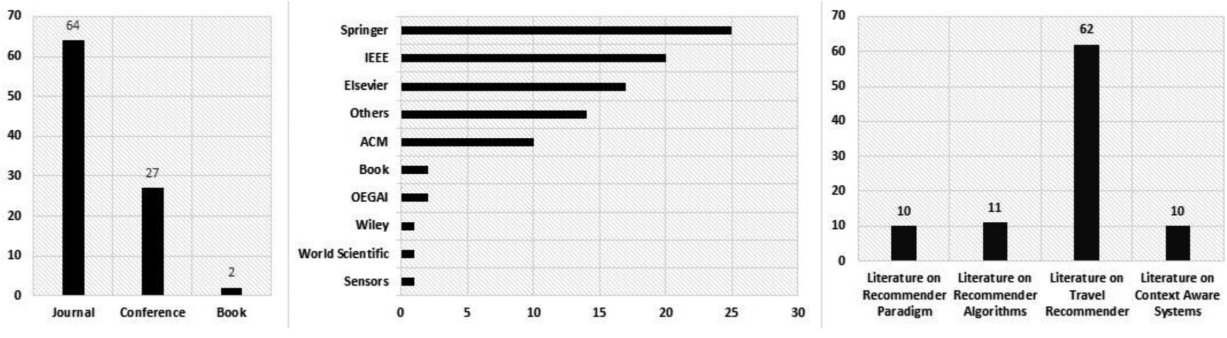

Fig. 10. Summary of Literature considered in this study.

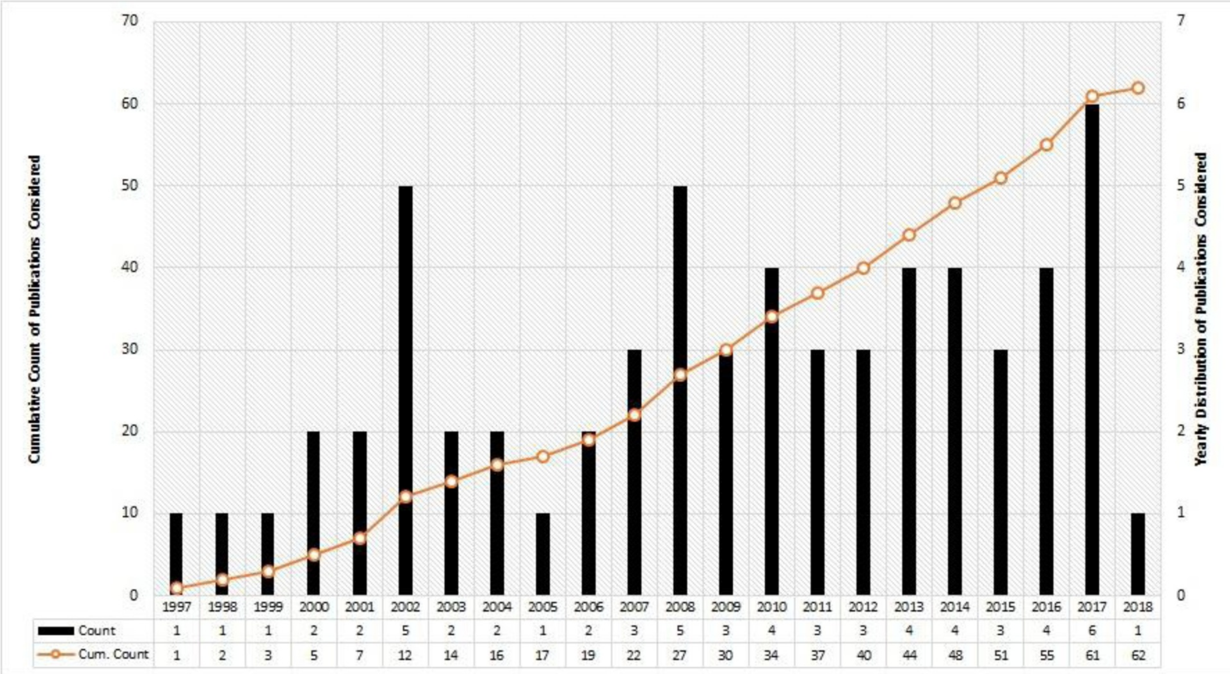

Fig. 11. Summary of Literature considered in this study.

Fig. 12. Domain-wise Summary of Literature considered in this study.

2.1.5. Hybrid systems

Hybrid systems (Burke, 2002) combine the features of content-based, collaborative and demographic filtering (Fig. 5). This way the shortcomings of one approach is overcome by the other. In this case algorithms for each of these approaches are run independently and the results are then aggregated to formulate the final set of recommendations.

There are different strategies (Isinkaye, Folajimi, & Ojokoh, 2015) being practiced for achieving aggregation in hybrid recommender systems. In weighted approach, results from all recommendation techniques are combined together to produce a single result. Switching approach adopts recommendations from the best suitable technique for the given situation whereas mixed approach presents all the recommendations together. In cascade approach one technique is used to refine the output of other technique based on certain priority. Output from one technique will act as input for another in feature augmentation approach. Feature combination

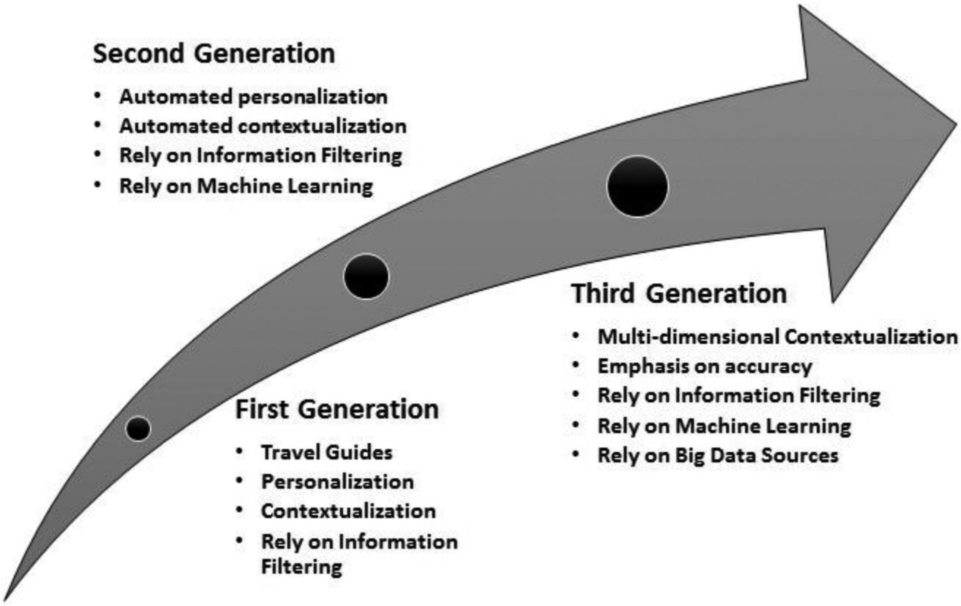

Fig. 13. Generations of Travel Recommender Systems.

model combines features from multiple knowledge sources and input to another recommendation algorithm. The strategy of using a model produced by one recommendation technique as input to another technique is called meta-level.

2.2. Key algorithms for recommender systems

2.2.1. K-Nearest neighbors (kNN) algorithm

K-nearest neighbors (kNN) (Wu et al., 2007; Fix & Hodges, 1989; Zhang & Zhou, 2005) is one of the most widely used algorithms in machine learning domain. Though kNN has capability to address both classification and regression problems, most of the industrial applications are for classification purpose. The algorithm relies on three key considerations – the training set, a similarity measure to measure distance and the number of neighbors, k. The algorithm computes distance of the test item with each labeled item in the training set, identify k number of nearest neighbors and then the most common class label among these nearest neighbors is assigned to the test item (Fig. 6).

The popular similarity or distance measures Renjith and Anjali (2013a,b) used with kNN algorithm include Euclidean Distance, Hamming Distance, Manhattan Distance, Minkowski Distance, Tanimoto Distance, Jaccard Distance, Mahalanobis Distance and Cosine Distance. The key challenges with this algorithm include selection of k, combining class labels and choice of distance measure.

2.2.2. The k-means algorithm

k-means (Wu et al., 2007; Lloyd, 1982; Nazeer & Sebastian, 2009) is a popular clustering algorithm where a given training set is partitioned into k number of clusters through an iterative process. The algorithm identifies k different groups from a given training set with maximum dissimilarity among each other. The first step of the algorithm is to identify k initial centroids to start the iteration with. Normally a random sampling is performed within the test data to identify the initial points. The algorithm further iterates between the 2 steps mentioned below until the centroids do not change (Fig. 7).

Step 1: Populate k clusters by assigning each item in test data to its closest centroid

Step 2: Re-calculate the centroid for each cluster

A simple and easiest measure for closeness of an item with a centroid is Euclidean distance. The advantages of the algorithm include easy to understand, flexibility, performance with large number of input attributes. The key challenges include initialization of centroids, selection of k, low computational efficiency and high need of memory to process due to more number of iterations required and high sensitivity to the presence of outliers in test data set.

2.2.3. The apriori algorithm

Apriori algorithm (Wu et al., 2007; Agarwal, Srikant, & others, 1994; Perego, Orlando, & Palmerini, 2001) is the most popular approach used in data mining scenarios to identify frequent item sets and derive association rules from a transaction database. The algorithm has a bottom up approach and perform as a two-step process:

Step 1: Generation of frequent item set – identify all items sets having support greater than the threshold using the algorithm depicted in Fig. 8.

Table 1
Travel Recommender Systems covered in this study – Mapping to recommender system paradigms and classification based on domain area as well as aspects of personalization and context-awareness.

Year	Proposed by	Domain area	Recommender system paradigms						
			Content-based	Collaborative	Knowledge-based	Demographic	Hybrid	Personalized	Context-aware
1997	G.D. Abowd et al.	Virtual Travel Guides	✗	✗	✗	✓	✗	✗	✓
1998	S. Rogers et al.	Virtual Travel Guides	✗	✗	✓	✗	✗	✓	✗
1999	N. Davies et al.	Virtual Travel Guides	✗	✗	✗	✓	✗	✓	✓
2000	K. Cheverst et al.	Virtual Travel Guides	✗	✗	✗	✓	✗	✓	✓
2000	R. Malaka et al	Virtual Travel Guides	✗	✗	✗	✓	✗	✓	✓
2001	V. Soo et al.	Software Travel Agents	✗	✓	✓	✗	✓	✓	✗
2001	D. Camacho et al.	Software Travel Agents	✗	✗	✓	✗	✗	✓	✗
2002	J.A. Delgado et al.	Travel Recommenders	✗	✓	✗	✗	✗	✓	✓
2002	F. Ricci et al.	Travel Recommenders	✗	✓	✗	✗	✗	✓	✓
2003	D.R. Fesenmaier et al.	Travel Recommenders	✗	✓	✗	✗	✗	✓	✗
2003	S. Loh et al.	Travel Recommenders	✗	✓	✗	✗	✗	✓	✗
2004	Q.N. Nguyen et al.	Travel Recommenders	✓	✓	✗	✓	✗	✓	✓
2004	M.V. Setten et al.	Travel Recommenders	✗	✓	✗	✗	✗	✓	✓
2005	F. Ricci et al.	Tourism Recommender Framework	✓	✗	✗	✗	✗	✓	✓
2006	W. Höpken et al.	Trip Recommenders	✗	✗	✓	✗	✗	✓	✓
2006	A. Venturini et al.	Travel Recommenders	✗	✗	✗	✗	✓	✓	✗
2007	U. Schiel et al.	Trip Recommenders	✗	✗	✓	✗	✗	✓	✗
2008	L. Castillo et al.	Travel Recommenders	✗	✗	✓	✗	✗	✓	✓
2008	T. Mahmood et al.	Travel Recommenders	✗	✗	✗	✓	✗	✓	✓
2008	O. Averjaûva et al.	Travel Recommenders	✓	✗	✗	✗	✗	✓	✗
2008	P. Srisuwan et al.	Travel Recommenders	✓	✗	✗	✗	✗	✓	✗
2008	L. Sebastia et al.	Group Travel Recommenders	✓	✗	✗	✓	✓	✓	✓
2009	A. Garcia-Crespo et al	Tourism Recommender Framework	✗	✓	✓	✗	✓	✓	✓
2009	I. Garcia et al.	Group Travel Recommenders	✓	✗	✗	✓	✓	✓	✗
2009	S. Schiaffiû et al.	Software Travel Agents	✓	✓	✗	✓	✓	✓	✗
2010	R. Anacleto et al.	Trip Recommenders	✗	✓	✓	✗	✓	✓	✓
2010	M. Clements et al.	Travel Recommenders using Community Tags	✓	✗	✗	✗	✗	✓	✗
2011	R. Anacleto et al.	Trip Recommenders	✓	✗	✗	✓	✓	✓	✓
2011	A. Garcia-Crespo et al.	Travel Recommenders	✓	✗	✓	✓	✓	✓	✗
2011	A. Cheng et al.	Travel Recommenders using Community Tags	✓	✗	✗	✗	✗	✓	✓
2012	F. Hsu et al.	Tourism Recommender Framework	✗	✗	✓	✗	✗	✓	✗
2012	M. Batet et al.	Software Travel Agents	✓	✓	✗	✗	✓	✓	✗
2012	C. Lamsfus et al	Tourism Recommender Framework	✗	✗	✗	✓	✗	✓	✓
2013	J.P. Lucas et al.	Tourism Recommender Framework	✓	✓	✗	✗	✓	✓	✗
2013	A. Moreû et al.	Travel Recommenders	✓	✓	✗	✗	✓	✓	✗
2013	W. Yang et al.	Travel Recommenders	✗	✓	✗	✗	✗	✓	✗
2013	S. Renjith et al.	Tourism Recommender Framework	✓	✓	✗	✗	✓	✓	✗
2014	S. Renjith et al.	Travel Recommenders	✓	✓	✗	✓	✓	✓	✗
2014	R. Anacleto et al.	Trip Recommenders	✗	✗	✓	✗	✗	✓	✓
2014	A.H. Celdran et al.	Travel Recommenders	✗	✗	✗	✓	✗	✓	✓
2015	D. Gavalas et al.	Trip Recommenders	✗	✗	✓	✗	✗	✓	✓
2015	M. Nilashi et al.	Travel Recommenders	✗	✓	✗	✗	✗	✓	✗
2016	I. Beûuaret et al.	Trip Recommenders	✗	✗	✓	✗	✗	✓	✓
2016	S. Jiang et al.	Trip Recommenders	✗	✓	✗	✗	✗	✓	✓
2016	H. Alghamdi et al.	Trip Recommenders	✓	✗	✗	✗	✗	✓	✓
2016	A. Anagûstopoulos et al.	Group Travel Recommenders	✓	✗	✓	✗	✓	✓	✗
2017	D. Chen et al.	Trip Recommenders	✓	✗	✗	✗	✗	✓	✗
2017	Y. Wen et al.	Trip Recommenders	✓	✓	✗	✗	✓	✓	✗
2017	P. Zhao et al.	Travel Recommenders using Community Tags	✓	✗	✗	✗	✗	✓	✗
2017	K.H. Lim et al.	Travel Recommenders using Community Tags	✓	✓	✗	✗	✓	✓	✗

(*continued on next page*)

Table 1 (*continued*)

Year	Proposed by	Domain area	Recommender system paradigms						
			Content-based	Collaborative	Knowledge-based	Demographic	Hybrid	Personalized	Context-aware
2017	C. Li et al.	Trip Recommenders	✗	✓	✓	✓	✓	✓	✓
2018	Y. Hsueh et al.	Trip Recommenders	✗	✓	✗	✗	✗	✓	✓
1997	G.D. Abowd et al.	Virtual Travel Guides	✗	✗	✗	✓	✗	✗	✓
1998	S. Rogers et al.	Virtual Travel Guides	✗	✗	✓	✗	✗	✓	✗

Step 2: Extraction of association rules – find association rules having support and confidence values greater than threshold support and threshold confidence respectively.

The advantages of the Apriori algorithm include ease of implementation and its support for large item sets. The key drawback is that it becomes computationally expensive when dealing with large number of candidate rules and while calculating the support as it has to go through the complete transaction database.

2.2.4. Naive Bayes algorithm

Naive Bayes classifier (Wu et al., 2007; Zhang, 2005) is considered as a powerful algorithm to perform classification task in data mining world. It is based on Bayes' theorem which deals with conditional probability. As per the conditional probability concept, the probability of an event can be calculated based on the prior knowledge about it.

Mathematically this can be represented as:

$$P(H|E) = \frac{P(E|H)}{P(E)}P(H) \tag{1}$$

where

H - Hypothesis
E - Evidence
P(H) - Probability of the hypothesis H
P(H|E)- Probability of the hypothesis H after getting the evidence E

Alternatively

$$Posterior = \frac{prior \times likelihood}{\text{evidence}} \tag{2}$$

Naive Bayes algorithm calculates the membership probability for a given item against each available class and the class having highest probability is selected as the most likely class. The advantage of this algorithm includes its simplicity, ease to construct, no need for iterations and applicability for huge data sets.

2.2.5. Support vector machines (SVM)

Support vector machines (Wu et al., 2007; Cortes & Vapnik, 1995) are considered as one of the most accurate approaches in the current machine learning space for both classification and regression needs. It is capable of handling multiple dimensions enabling it to deal with multiple attributes of an item in consideration. SVM can be treated as a non-probabilistic binary linear classifier due to its ability classify a candidate item into one of the two categories by learning from a given training set. SVM algorithmically defines a decision boundary or hyper-plane (Fig. 9) in the feature space which will act as a formal separator for the classification problem. SVM uses an approach called kernel trick to deal with non-linear classification problems. Kernel trick maps inputs to a high dimensional feature space to derive the decision boundary.

The advantages of SVM include its capability to work well with fewer training samples, avoidance of over-fitting, multi-dimensionality, absence of local minima, etc. Key challenges include the need to formulate problem as a 2-class classification, longer learning time and being a black box model making it difficult to interpret

2.2.6. Classification and Regression Tree (CART)

Classification and Regression Tree (CART) algorithm (Wu et al., 2007; Breiman, 2017) is a predictive machine learning model based on decision tree concept. It is organized as a series of questions and each response will lead to the next question or a terminal state. The resulting depiction is a tree like structure where each fork represents a question or predictor variable and terminal nodes represent a target or prediction.

There are three main elements for a CART algorithm – rules for splitting, rules for stopping and the prediction in terminal node. Advantages of CART include not relying on any type of distributions, ability to produce quick and valuable insights from massive data and ability to handle missing values. CART has the limitations like being nonparametric it lacks the ability to create generalizations from observed results and the resultant tree being relatively complex after seven levels.

2.3. Recommender system performance metrics

As like in any other scenario, performance evaluation is important in the context of recommender systems as well. Performance evaluation helps us to compare multiple recommender systems and thereby help us to identify improvement areas for any particular system. This section explains three key evaluation areas for a recommender system and the various techniques that can be adopted for the same.

2.3.1. Prediction quality metrics

The prediction quality of a recommender system is measured in terms of accuracy and coverage.

Accuracy: Accuracy of a recommender system is the measure of its ability to predict the items that are already rated or interacted with. Accuracy gives an indication on how closely the predicted ratings are to the actual ratings. Two key metrics in this area are Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). MAE is used to calculate the deviation between predicted ratings and actual ratings. RMSE is also similar to MAE but gives more weightage to larger deviations.

$$MAE = \frac{1}{n}\sum_{u,i} |P_{u,i} - r_{u,i}| \tag{3}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{u,i} (P_{u,i} - r_{u,i})^2} \tag{4}$$

where

n – Number of ratings
$P_{u,\ i}$ – Predicted user rating for item i
$r_{u,\ i}$ – Actual rating for item i

Coverage: Coverage of a recommender system measures the percentage of objects that it could recommend to users in the system. The expectation on a recommender system is to have a higher coverage in terms of item space or user space.

$$Coverage = \frac{N_d}{N} \tag{5}$$

where

N_d – Number of distinct objects
N – Total number of objects

2.3.2. Recommendation quality metrics

Quality of recommendation indicates whether the recommendations generated by the recommender systems are relevant to its users or not. The acceptance for a recommender system by user community is based on its quality of recommendations and accuracy. Recommendation quality is normally evaluated in terms of precision, recall and F1-measure.

Precision: Precision of a recommender system is a measure of its exactness. It is determined as the ratio of relevant recommendations to all recommendations made.

$$\text{Precision} = \frac{t_p}{t_p + f_p} \tag{6}$$

where

t_p– Number of true positives
f_p– Number of false positives

Recall: Recall of a recommender system is a measure of its completeness. It is determined as the ratio of relevant recommendations to all relevant items.

$$Recall = \frac{t_p}{t_p + f_n} \tag{7}$$

where

t_p– Number of true positives
f_n– Number of false negatives

F1-Measure: Typically, a recommender system can increase its precision at the cost of its recall. So, in order to compare recommender systems precision and recall parameters can be combined together to form a new metric called F1-Measure which can provide a more balanced view to a recommender system performance.

$$F1 - Measure = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{8}$$

2.3.3. Recommendation ranking metrics

It can be observed that users mostly tend to consider only first few items in the list of recommendations offered to them. So, any errors in the ranking of recommendations can make the recommender system less trust worthy for end users. The recommendation ranking metrics are formulated in consideration of this scenario. Two important ranking metrics in consideration are Half Life (HL) Utility and Discounted Cumulative Gain (DCG).

Half Life Utility: Half Life specifies that the interest of a recommender system user decreases exponentially when he moves down in the list of recommendations received. The half-life can be explained as the rank of an item on the recommendation list, such that there is a 50% probability that the user may view the item.

$$HL = \sum_j \frac{\max(R_{u,sj} - d, 0)}{2^{\frac{(j-1)}{(\alpha-1)}}} \tag{9}$$

where

s_j - j th item on the recommendation list
$R_{u,sj}$ - User u's rating of item s_j
d- Default rating
α - Half-life decay parameter

Discounted Cumulative Gain: Discounted Cumulative Gain specifies that the interest of recommender system user decreases logarithmically when he moves down in the list of recommendations received.

$$DCG = \text{rel}_1 + \sum_{i=2}^{\text{pos}} \frac{\text{rel}_i}{\log_2 i} \tag{10}$$

where

pos - Position up to which relevance is accumulated
rel_i- Recommendation relevance at position i

3. Literature survey

There are a lot of researches being conducted in the area of recommender systems based on various machine learning techniques. The volume of these studies is enormous, and they span across multiple business domains. This study is focused on the journal and conference papers published since 1997 to early 2018 in the areas of travel recommender systems and context aware systems. The aim of this study was to understand different input data sources, travel contexts, approaches and/or algorithms being adopted and their limitations. In addition, we have also referred to key literature on recommender system paradigms and algorithms [Fig. 10].

3.1. Evolution of travel recommender systems

The study on evolution of travel recommender systems covered 62 articles/researches in the area of travel recommender systems published in reputed journals or major conferences during the period from 1997 to early 2018. Fig. 10 depicts the periodic distribution of artefacts taken as input for the study.

Fig. 11 represents the distribution of the literature under different domain areas covered as part of the study. More details on each of the focus areas are explained in subsequent sections (Fig. 12).

3.1.1. Virtual travel guides

One of the first noted research in the area of travel recommender was published by Abowd et al. (1997). They proposed the prototype for a mobile context-aware tour guide namely Cyberguide. The attempt was to create a virtual tour guide leveraging the knowledge of user location and history of locations. (Rogers & Langley, 1998) proposed an interactive planning system which recommends personalized driving routes. The initial recommendations are refined based on inferences drawn from the actions of the driver. Personalization is achieved in terms of deciding the routes, defining the cost function and in the presentation of routes.

Davies, Cheverst, Mitchell and Friday (1999) proposed a context-sensitive tourist guide, called GUIDE for the city of Lancaster. In this approach dynamically tailored information and interactive services are provided to the visitors of the city based on their preferences and environmental context downloaded to a portable unit via a city-wide high bandwidth wireless network. Cheverst, Davies, Mitchell, Friday and Efstratiou (2000) presented an enhancement to GUIDE by replacing high bandwidth wireless network with cell-based wireless communication. It also tried to address two aspects of contexts for a tourist – personal and environmental. Malaka and Zipf (2000) proposed a mobile system called Deep Map to generate personalized guided walks for tourists. This was built in the context of the city of Heidelberg in Germany and attempted to address personal interests and needs of the tourists based on the demographic and contextual information with the help of a geographical information system.

3.1.2. Software travel agents

Soo and Liang (2001) presented the architecture and design of a software travel agent which could negotiate with human travelers to achieve a tradeoff between preferences and constraints of the traveler before recommending a trip plan for them. The negotiation process is driven by the mechanisms of resolution of constraint violation. Camacho, Borrajo and Molina (2001) presented Intelligent Travel Planning (I.T.P.) as an example of multi-agent planning system having the goal to search for better solutions in the electronic-tourism domain. ITP adopts problem solving using cooperative techniques with information sources spanning across the Web and in the agent knowledge bases.

Schiaffino and Amandi (2009) proposed an expert software agent called Traveller to assist users in the travel and tourism domain. This was a hybrid approach combining the capabilities of collaborative filtering and content-based recommendations. It also used customer's demographic information to suggest tour packages. Batet, Moreno, Sánchez, Isern and Valls (2012) proposed Turist@, an agent-based travel recommendation system combining content-based and collaborative recommendation strategies. Turist@ is implemented as a multi-agent system having user, activity, broker and recommender agents.

3.1.3. Travel recommenders

Delgado and Davidson (2002) proposed a new system called Trip Matcher using a hybrid strategy for information filtering and matching. It could identify and recommend attractions, events and activities matching to user profile without human intervention by achieving an automatic rating of items against a search taxonomy in the knowledge base which is represented as a vector space model. Ricci, Arslan, Mirzadeh and Venturini (2002) proposed a case-based travel advisory system called ITR (Intelligent Travel Recommender). ITR is a web-based recommender system that supports user information filtering and bundling of personalized travel plans based on collaborative approach where users' travel plan similarity is considered instead of past behavior similarity.

Fesenmaier, Ricci, Erwin, Karl and Cristiano (2003) proposed a new case-based travel planning recommender system called DieToRecs. It tried to incorporate a human decision model to take care of individual differences and decision styles and leveraged collaboration filtering technique through case similarity for personalizing the recommendations. Loh, Lorenzi, Saldaña and Licthnow (2003) proposed a recommender system based on collaborative algorithm and text analysis to assist travel agents in identifying tourist options for their customers. The system analyses private chat messages between the customer and the agent using text mining algorithms and a tourism ontology to discover suitable options for each customer.

Nguyen, Cavada and Ricci (2004) presented mITR, a restaurant recommender system for travelers on the move. mITR leverages the traits of past user transactions and implicit preferences set by the user to initialize the recommendation process. Initial options are then iterated using user feedbacks to arrive at final recommendations. Van Setten, Pokraev and Koolwaaij (2004) presented the context-aware mobile tourist application called COMPASS which could generate recommendations based on user's interest and contextual factors. It is built upon WASP platform and user prediction is achieved using social filtering, case-based reasoning, item-item filtering and category learning.

Venturini and Ricci (2006) presented the architecture and design of a decision support tool namely Trip@dvice used to support decision process of travelers on www.visiteurope.com. It integrates case base reasoning and cooperative query answering to generate travel recommendations. Castillo et al. (2008) came up with a user-oriented adaptive system, called SAMAP for planning tourist visits using a portable device. It uses case-based reasoning approach to predict the list of attractions with high probability to be interesting for the user. Mahmood, Ricci, Venturini and Höpken (2008) presented a conversational travel recommender system which leverages reinforcement learning techniques. Travel and tourism applications use conversational recommender systems to support their users to have interactive dialogues so as to acquire their goal of travel planning. Averjanova, Ricci and Nguyen (2008) presented an approach for integrating travel recommender system with electronic maps to achieve a map-based conversational mobile recommender system. The aim was to provide automatic and effective support to a traveler for gathering information on their desired services while on move. Srisuwan and Srivihok (2008) presented a personalized travel recommendation system called PRSET, which recommends trips to specific users by using statistic techniques based on Bayes Theorem to analyze user behaviors.

Garcia-Crespo, Lopez-Cuadrado, Colomo-Palacios, Gonzalez-Carrasco and Ruiz-Mezcua (2011) presented Sem-Fit, as a semantic based expert system to do hotel recommendations for tourism domain. Sem-Fit leverage on consumer experience and apply fuzzy logic techniques to relate customer and hotel characteristics. Moreno, Valls, Isern, Marin and Borràs (2013) proposed a novel ontology-based, personalized tourism and leisure activity recommendation system namely Sigtur/e-destination. A specific ontology is relied upon for classification and labeling of activities, which acts as the core of the system and is combined with content and collaborative filtering methods to achieve better results. Yang and Hwang (2013) came up with a cost-effective travel recommender system called iTravel, which generates on-tour attraction recommendation by analyzing the rating provided by other tourists on their visited attractions. It leverages on mobile peer-to-peer communication techniques to exchange ratings via their portable devices.

Renjith and Anjali (2014) demonstrated the implementation of Buddy@Move, a travel recommender based on hybrid algorithm combining the features of content-based, collaborative and demographic filtering paradigms. Celdran, Perez, Clemente and Perez (2014) proposed middleware named PRECISE, as a privacy-preserving context-aware recommender solution based on location in mobile cloud computing. Recommendations are generated based on users' context information, location, privacy policies and details of their past visits. Nilashi, Ibrahim, Ithnin and Sarmin (2015) developed a multi-criteria collaborative travel recommender system for generating hotel recommendations. The prediction accuracy is enhanced with the application of Gaussian Mixture Model along with Expectation Maximization (EM) algorithm, adaptive Neuro-Fuzzy Inference system (ANFIS) and Principal Component Analysis (PCA).

3.1.4. Trip recommenders

Höpken et al. (2006) proposed anIT framework called etPlanner as an innovation to existing technology by taking all trip phases into account making it a comprehensive travel guide. etPlanner was an attempt to personalize travel recommendations in terms of user, situational context and technical device involved with a complete trip perspective. Schiel, Baptista, Maia and Andrade (2007) presented a new travel recommender system namely SEI-Tur which is capable of creating trip plans in tourism and business contexts. It can create complete tours combining components like travel, lodging, food, local events, etc. based on user preferences using component level domain ontology and selection of best services.

Anacleto, Luz and Figueiredo (2010) proposed PSiS Mobile, a mobile recommender system which could leverage context-aware information to generate recommendations about places of interest based on tourist preferences. Anacleto, Figueiredo, Luz, Almeida and Novais (2011) presented the architecture and implementation of PSiS Mobile which could assist a tourist on move by updating the plan based on the current context. Anacleto, Figueiredo, Almeida and Novais (2014) extended their work on PSiS Mobile to a mobile application so that current user and sight context can be leveraged to suggest dynamic travel plans. Gavalas et al. (2015) introduced eCOMPASS as a context-aware application that works on web and mobile to design personalized multimodal tours. Benouaret and Lenne (2016) came up with a composite recommendation system to deal with the heterogeneous aspects of planning tourist visits. It recommends a set of attractions or points of interest (POI) as a package to the user to choose from where each package will constitute a tour. A scoring function and a ranking algorithm help the system to take care of user preferences as well as the diversity and popularity of the POI within an optimum cost and time that the user can afford to. Jiang, Qian, Mei ad Fu (2016) proposed a personalized travel sequence recommendation model which leverages heterogeneous data from big data sources like travelogues and community contributed photos. Personalized sequencing of attractions is formed by ranking popular routes based on similarity between user preferences and route packages and then optimizing them by checking similarity with travel traits of similar users. Alghamdi, Zhu and Saddik (2016) proposed a new algorithm called balanced orienteering problem to design trips for travelers. Combining this algorithm with a tourism recommender system they demonstrated a new mobile tourism guide called E-Tourism. Chen et al. (2017) presented PathRec, an interactive route analyzer cum route recommendation system which is capable of taking inputs from users before giving final route recommendations. It leverages machine learning algorithms and techniques for performing sequence recommendation tasks. Wen, Yeo, Peng and Hwang (2017) proposed Keyword-aware Representative Travel Route (KRTR) framework which uses the information from past transactions like travel and social interactions to solve travel route recommendation problem. The key contributions of this work include a new keyword extraction approach and a new route reconstruction algorithm.

Li, Chen, Chen and Hsieh (2017) presented Preferred Time-aware Route Planning (PTRP) problem to recommend routes with representative locations which satisfy user preference. In the four stage process, LocTimeInf inference method is used to predict visit time for locations, GST-Clus method is used to group travelers with similar location preferences, Time-aware Transit Pattern Mining (TTPM) algorithm is used to determine popular time-aware location-transition behaviors and Preferred Route Search (PR-Search) algorithm to decide the optimal time-aware routes. Hsueh and Huang (2018) proposed pirT, a personalized itinerary recommender framework with time constraints for location-based social network (LBSN). Information pertaining to geographical features and social relationships are extracted out of LBSN using a user-based collaborative filtering with time preference. These details are further leveraged by the framework to recommend personalized itineraries.

3.1.5. Group travel recommenders

Sebastia, Garcia, Onaindia and Guzman (2008) proposed another variation of e-Tourism, a tourist recommender cum planner to support users from an organization with personalized tour agenda. It could produce recommendations based on user tastes and static context information like distance between tourist spots and the opening hours of such attractions. Garcia, Sebastia, Onaindia and Guzman (2009) came up with an extension for e-Tourism, a web-based personalized tour recommender for a group of users. Recommendations were generated based on group tastes, demographic details and places visited in previous trips. Computation of group recommendations is performed by aggregation, intersection or incremental intersection of individual recommendations. Anagnostopoulos, Atassi, Becchetti, Fazzone and Silvestri (2016) attempted to provide the algorithmic implications in finding an optimal recommendation for the group considering the varying preferences of each group member.

3.1.6. Travel recommenders using community tags

Clements, Serdyukov, de Vries and Reinders (2010) proposed a process to predict the point of interests for a user in a city, based on the Flickr geotag he/she has in other cities. In it, similarity between geotag distributions of two users are defined using Gaussian kernel convolution and personalized recommendations are generated by re-ranking the most popular attractions after combining geotag of the most similar users. Cheng, Chen, Huang, Hsu and Mark Liao (2011) proposed the idea of mining for people attributes in community-contributed photos to generate personalized travel recommendations. They proved that good level of demographic information and travel trajectories can be gathered in this way. Further, contextual recommendations are generated by leveraging probabilistic Bayesian learning framework and user context in mobile devices.

Zhao et al. (2017) came up with Photo2Trip, a tour recommender system which utilizes visual contents from geo-tagged photos along with collaborative filtering technique. This system proposed to use Visual-enhanced Probabilistic Matrix Factorization (VPMF) to integrate the visual features extracted from photos taken by travelers with a collaborative filtering model so that user interests are learned from their past travel traits. Lim, Chan, Leckie and Karunasekera (2017) proposed PersTour, an algorithm to recommend personalized tours based on geo-tagged photographs. User preferences and POI popularity are derived out of historic travel sequences of users which are populated from geo-tagged photographs. The algorithm is also capable of accounting user level constraints for the trip like time and specific start and/or end POIs.

3.1.7. Tourism recommender framework

Ricci and Nguyen (2005) proposed an approach for generation of mobile recommendations based on interactive elicitation of user needs through critiques and demonstrated the implementation using a mobile travel recommender system which aimed to support travelers on move to select travel related services. In this approach, the recommender system proposes candidate recommendations and seek user feedback to iterate recommendations to form the final set of recommendations. García-Crespo et al. (2009) came up with the SPETA framework which combined the aspects of GIS systems, context-aware pervasive systems, social networks and semantics. SPETA uses a hybrid filtering approach combining sliding grid-window methodology, knowledge-based filtering and collaborative-based filtering.

Hsu, Lin and Ho (2012) proposed a decision support system called Intelligent Tourist Attractions System (ITAS) by combining Engel–Blackwell–Miniard (EBM) model with Bayesian network. Lamsfus, Martín, Alzua-Sorzabal, López-de-Ipiña and Torres-Manzanera (2012) came up with the CONCERT framework which has capability to help travelers with context-aware information dissemination using a semantic rule engine. Lucas et al. (2013) proposed a new recommendation methodology for tourism domain based on associative classification methods where classification and association concepts are combined together to enable association rules to be applied in a prediction scenario. Renjith and Anjali (2013a,b) proposed a new travel recommender model with personalization aspect leveraging content-based prediction and collaborative recommendation techniques.

3.1.8. Literature on travel recommenders

There are many literatures on recommender systems in tourism domain. Some of the key articles are covered here as part of our analysis and study. Stabb et al. (2002) compiled together various articles regarding the challenges for intelligent systems in travel and tourism industry and proposed a list of technical and non-technical opportunities for further research. Ricci (2002) did a comparative analysis of two leading recommender system technologies of the period (TripMatcher from Triplehop and Me-Print from VacationCoach) and also brought up the need to come up with additional support functions to cater to new user demands. Werthner (2002) described on the structural changes happening in tourism industry and how intelligent systems like recommenders can contribute there.

(Modsching, Kramer, Hagen & Gretzel, 2007) presented a study on the usage of mobile tourism recommender systems. After analyzing various aspects of tourists using different recommendation techniques and tourists doing self-exploration using GPS services, they could identify that tourists equipped with a mobile travel recommender system could discover four times more attractions than the other category. (Felfernig, Gordea, Jannach, Teppan & Zanker, 2007) proposed the personalized recommendation aspect for tourism domain in mobile environments. They also suggested the need of various contextualization like space, time, social environment, mood, etc.

Luz, Anacleto and Almeida (2010) presented a comparative study on some of the existing travel recommenders and one of the key observations was that though there were several implementations, they were very basic and lacked solid implementation to use in a real world scenario. Kabassi (2010) proposed a personalized e-tourism service which is suitable for computers and mobile devices. It also covered theories for improved personalization in tourism recommender systems, application and evaluation of such theories. Borràs, Moreno and Valls (2014) published a comprehensive review of e-Tourism recommenders that were proposed in the preceding 6 years. The study covered details of functionalities, interfaces and algorithms used. They also came up with a set of guidelines for creation of tourism recommender systems. Kiseleva et al. (2015) reported their experiments with ranking models in travel destination recommendations. They tried three different methods to rank travel destinations – random, most popular and Naïve Bayes and compared those against existing techniques used in booking.com and observed that Naïve Bayes has an edge among the options with the significantly increased level of user engagement. Braunhofer and Ricci (2017) proposed acquisition of selective contextual information in travel recommender systems. Though there are many contextual factors that may affect the user experience in travel context, only a subset of them will really affect the user preferences and can help in improving the recommendation effectiveness. In this method a contextual factor is considered as useful when the user rates an item and the rating for that item was impacted by that particular contextual factor.

3.2. Evolution of context aware systems

Chen, Finin and Joshi (2003) proposed a new context-aware pervasive computing framework called Context Broker Architecture (CoBrA) and explained how to use Web Ontology Language, OWL for building an ontology foundation. It modeled the basic concepts of people, places, agents, events, etc. by providing a vocabulary that can be used to build practical systems in pervasive computing scenarios. It could also manage the privacy of users with the help of rules deducing whether they have the required rights to share and/or receive information. Wang, Zhang, Gu and Pung (2004) proposed an OWL encoded context ontology (CONON) to model context in pervasive computing scenarios and to support logic-based context reasoning. The upper context ontology in CONON captures basic context and provides extensibility to add more domain-specific ontology in hierarchical manner. Gu, Wang, Pung and Zhang (2004) proposed a formal context model based on ontology using OWL having the ability to reason about various contexts. Based on the model, they also proposed a Service-Oriented Context-Aware Middleware (SOCAM) architecture for building of context-aware services.

Sacramento, Endler and Nascimento (2005) proposed a privacy service, namely Context Privacy Service (CoPS) to impose the controlled access to context information. Baldauf, Dustdar and Rosenberg (2007) described various architecture principles and a layered conceptual design framework for context-aware systems. Ejigu, Scuturici and Brunie (2008) presented Enhanced CoCA, a collaborative context-aware service platform based on hybrid context management model (HCoM) and had the ability to perform reasoning and decisions. Stevenson, Ye, Dobson and Nixon (2010) proposed LOC8 as a location model and powerful programming framework which is capable of querying the location data of users. Jagtap, Joshi, Finin and Zavala (2011) presented a framework to manage information gathering in collaborative context aware applications so as to enable users with appropriate levels of privacy to protect their personal information. Dao, Jeong and Ahn (2012) proposed the new recommendation model called Context-Aware Collaborative Filtering using Genetic Algorithm (CACF-GA), mainly for the purpose of location-based advertising based on interaction context and user preferences. Genetic algorithm is used for optimizing the context aware recommendations generated through collaborative filtering on context similarity. Celdran, Garcia Clemente, Perez and Martinez Perez (2016) proposed the framework called Semantic Web-based Context Management (SeCoMan) for developing context-aware applications preserving users' privacy.

4. Discussion

The key focus of this analysis was to understand the evolution of travel recommender systems, usage of different data sources, approaches and algorithms being used, level of customization and the challenges or areas of improvements yet to be addressed. Based on our analysis the travel recommenders can be categorized to three generations based on the technology maturity they demonstrate, end user involvement necessitated, optimal results provided in traveler's perspective (Fig. 13).

As per our classification, the first generation travel recommender systems are mostly in the form of travel guides. These travel guides got further customized with personalization and contextual aspects attached to it with the aim of limiting available options in front of a traveler to only relevant items. The key constraint of being highly dependent on end user is remained as such making travel recommender systems primarily behaving like a knowledge repository providing filtered results based on user inputs.

The second generation of travel recommenders aimed at reducing the explicit user inputs required and thereby reducing the overhead for the traveler. In this stage, personalization is achieved through classification and prediction processes. For this, past behavioral traits of travelers are analyzed, and the future behavior is predicted using the same. Continuous developments and researches in the areas of information filtering and machine learning fueled the researches on travel recommenders as well. With mobile devices becoming more popular, automatic detection of contextual information also became very easy. Societal and/or demographic details are also considered critical in this stage since recommenders are built using collaborative algorithms.

The third generation travel recommender systems attempt to give multi-dimensional aspect for the recommendations. They attempt to provide solutions to all associated activities a traveler needs to consider in his tour plan. In addition to the choice of point of interests, it covers route plan, accommodation, food, budget, time, weather, mode of transport etc. Instead of attempting capture all these details as part of the recommender system logic, these recommenders leverage external sources to get required input on a case to case basis. With the advent of Big Data, it became easier to consume information available in external sources, mostly exposed as processed information which can be accessed via a web service or similar options. This can enable recommender systems to leverage distributed computing capabilities. With third generation recommender systems, accuracy of recommendations is expected to increase while dependency on end user is expected to decrease.

We also carried out a study on context aware frameworks that can be leveraged for travel recommender systems. We could observe multiple context aware frameworks that are build using Web Ontology Language, OWL like CoBra, CONON and SOCAM. Another key consideration in context aware frameworks is the privacy aspect and two attempts to address the same are CoPS and SeCoMan. Further the research focus shifted to collaborative context aware platforms and such attempts include Enhanced CoCA and CACF-GA.

Table 1 below chronologically summarizes the travel recommender systems and frameworks covered as part of this study along with the mapping to applicable recommender system paradigms. It also provides the details of the domain area where each of the system is covered under as well as information on whether it covers personalization and context-aware aspects.

5. Conclusion

From the study of literature available in the domain of travel recommender systems for a period of 22 years, we could observe that the travel recommender systems are also keeping its pace along with the technology changes. Compared to the early stage travel recommenders which provides static recommendations based on internal knowledge sources, the current systems are capable of generating highly personalized, real time, context aware recommendations. Collaborative algorithms play a crucial role in generating contextualized recommendations using societal data when the traveler undertakes an explorative journey.

We could observe that travel recommender systems are yet to leverage the Big Data resources to its full extent. With Big Data concepts and data available with online communities putting together, we believe that contextualization can be extended to multiple dimensions for any traveler covering various aspects of travel such as budget, commutation, food, accommodation, weather and any other specific preferences for a traveler. We also understand that there is a need for more privacy and security considerations while designing new recommender systems as the level of personalization and contextualization are getting expanded.

Acknowledgment

We acknowledge support from the Department of Computer Applications, Cochin University of Science and Technology for all guidance, reviews, valuable suggestions and very useful discussions. Shini Renjith also thanks Department of Computer Science and Engineering, Mar Baselios College of Engineering and Technology for all the support being extended to carry out this research work.

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