ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 2, February 2017

Literature Survey on Tourism Recommendation

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ABSTRACT: Recommender systems are information search and decision support tools used when there is an awesome set of option to judge or when the user lacks the domain-specific knowledge essential to take autonomous decisions. They provide users with personalized recommendations adapted to their needs and preferences in a particular usage context. Recommender systems are useful not only when users are overwhelmed by a large number of options to consider but also when they do not have adequate domain specific knowledge to take their decision. Different types of recommender systems and algorithms target on helping tourists from different perspectives. However,tourists need system maintain throughout stages of travel, beginning from pretravel planning through to the final stages of travel. Topic models are usually based upon the idea that documents (including messages, emails, etc.) are mixtures of latent topics, where a topic is a probability distribution over words. Topic models (especially LDA)-based methods perform well in the text-related or other recommendation tasks.

KEYWORDS: Recommender system, comparative description, mobile system,topic modelling.

I. INTRODUCTION

As a promising trend, more and more travel companies provide online services. However, the rapid growth of online travel information imposes an increase challenge for tourists who have to select from a large number of existing travel packages for satisfying their personalized needs. Moreover, to increase the profit, the travel companies have to understand the preferences from different tourists and serve more attractive packages. Therefore, the demand for intelligent travel services is expected to increase dramatically. Since recommender systems have been effectively applied to enhance the quality of service in a number of fields, it is natural choice to provide travel package recommendations. Actually, recommendations for tourists have been studied before and to the best of our knowledge, the first operative tourism recommender system was introduced by Delgado and Davidson.

When visiting cities as tourists, most users intend to explore the area and find interesting things to see or information about places, objects, events, and so on. Recommender systems are information search and decision support tools used when there is an overpowering set of options to consider or when the user lacks the domain-specific knowledge necessary to take autonomous decisions. They provide users with personalized recommendations modified to their needs and preferences in a particular usage context.

Recommender systems are useful not only when users are overwhelmed by a large number of options to consider but also when they do not have enough domain specific knowledge to take their decision. the above systems and algorithms target on helping tourists from different perspectives. However, tourists need system support throughout stages of travel, beginning from pretravel planning through to the final stages of travel.

II. RELATED WORK

The related work can be categorised into two groups:

The first group includes the research work associated to topic models and their applications on recommender systems. Topic models are usually based upon the idea that documents (including messages, emails, etc.) are mixtures

 DOI: 10.15680/IJIRCCE.2017. 0502155

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of latent topics, where a topic is a probability distribution over words.Many topic models have been proposed. Among them, the latent Dirichlet allocation (LDA) [6] model possesses totally generative semantics, and thus has been broadly studied and extended for many applications. Rosen-Zvi et al. [1] extended LDA to the author-topic (AT)model for computing similarity between authors and the entropy of author output. Based on LDA and AT models,McCallum et al. [2] provided the author-recipient-topic(ART) model for social network analysis.

The second group focuses on the people who aim on providing more context-aware travel information to the on-tour tourists with mobile devices. Averjanova et al. [4] developed a map-based mobile system that can provide users with some personalized recommendations. Carolis et al. [5] used a map for outlining the location and the information of landscapes in a town region. Finally, a more sophisticated on-tour support system, MobyRek, was developed by Ricci and Nguyen [3].

Author-topic model for authors and documents[1]describe a generative model for document collections, the author-topic model, that concurrently models the content of documents and the interests of authors. This generative model represents each document with a mixture of topics, as in state-of-the-art approaches like Latent Dirichlet Allocation and extends these approaches to author modeling by allowing the mixture weights for dissimilar topics to be determined by the authors of the document. By learning the parameters of the model, we find the set of topics that appear in a corpus and their relevance to different documents, as well as identifying which topics are used by which authors.This describes three generative models for documents: one that models documents as a mixture of topics , one that models authors with distributions over words, and one that models both authors and documents using topics. All three models use the same notation. A document d is a vector of N_d words, wd, where each w_{id} is chosen from a vocabulary of size V, and a vector of A_d authors a_d, chosen from a set of authors of size A. A collection of D documents is defined by

$$D = \{(w_1,a_1),\ldots, (w_D,a_D)\}$$

In LDA, the generation of a document collection is modeled as a three step process. First, for each document, a distribution over topics is sampled from a Dirichlet distribution. Second, for each word in the document, a single topic is chosen according to this distribution. Finally, each word is sampled from a multinomial distribution over words specific to the sampled topic.For modeling authors with words,there are topic models demonstrate how documents can be modeled as mixtures of probability distributions. This suggests a simple method for modeling the interests of authors. Assume that a group of authors, a_d, decide to write the document d. For each word in the document an author is selected uniformly at random, and a word is selected from a probability distribution over words that is exact to that author.The author-topic model draws upon the strengths of the two models defined above, using a topic-based representation to model both the content of documents and the interests of authors. As in the author model,a group of authors, a_d, decide to write the document d. For each word in the document an author is chosen uniformly at random. Then, as in the topic model, a topic is chosen from a distribution over topics specific to that author, and the word is generated from the selected topic.

The graphical model corresponding to this process is shown in Figure 1(c). As in the author model, x indicates the author responsible for a given word, chosen from ad. Each author is associated with a distribution over topics, θ, chosen from a symmetric Dirichlet(α) prior. The mixture weights corresponding to the chosen author are used to select a topic z, and a word is generated according to the distribution ∅ corresponding to that topic, drawn from a symmetric Dirichlet(β)earlier. The author-topic model subsumes the two models described above as special cases: topic models like LDA correspond to the case where each document has one unique author, and the author model corresponds to the case where each author has one unique topic. By estimating the parameters θ and ∅, we obtain information about which topics authors typically write about,as well as a representation of the content of each document in terms of these topics.

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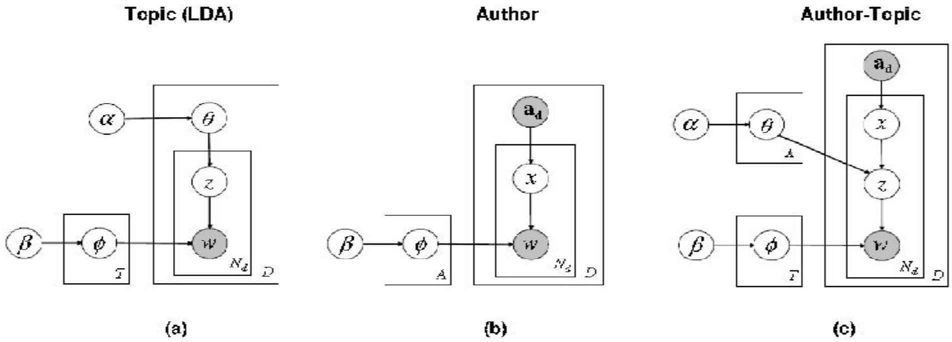

Figure 1: Generative models for documents. (a) Latent Dirichlet Allocation , a topic model. (b) An author model. (c) The author-topic model.

In [2],we propose an Author-Recipient-Topic (ART) model for email messages. The ART model captures topics and the directed social network of senders and recipients by conditioning the multinomial distribution over topics specifically on both the author and one recipient of a message.The ART model takes into consideration both author and recipients distinctly, in addition to modeling the email content as a mixture of topics.The ART model is a Bayesian network that simultaneously models message content,as well as the directed social network in which the messages are sent. In its generative process, for each message d, an author, a_d, and a set of recipients, r_d, are observed. To generate each word, a recipient, x, is chosen uniformly from r_d, and then a topic z is chosen from a multinomial topic distribution $\theta_{a_d x}$,where the distribution is specific to the author-recipient pair (a_d , x). This distribution over topics could also be smoothed against a distribution conditioned on the author only. Finally, the word w is generated by sampling from a topic-specific multinomial distribution $\emptyset_z$. The result is that the discovery of topics is guided by the social network in which the collection of message text was formed.

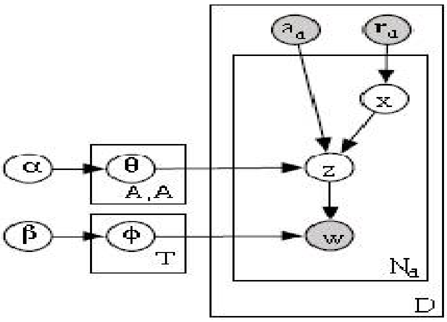

Figure2: Author-recipient-topic model

In [3],MobyRek, deals with the on-tour stage. On-tour support is required by travellers when they are on the move to, or during the stay in, their selected destination. In the on-tour stage, travellers normally use mobile devices to search for desired travel products, or to harmonize their pre-travel plan.MobyRek is based on the supposition that the complementary products should conform to what have already been selected in the pre-travel stage. In addition, we hypothesize that when a traveller is on the move the time span and cognitive effort spent to discover his or her desired products should be minimized using appropriate methodologies.In the MobyRek system the decision support is provided to travellers through personalized recommendations. Given a traveller's request, MobyRek makes those travel product recommendations that are personalized to the traveller in that particular situation. To reduce the user's effort, MobyRek does not need the user to formulate a precise and complete query at the time of the request, but involves the user in a dialogue (i.e. a conversation), which interleaves system's recommendation with user's critique.The fundamental initiative is that critique-based elicitation of user preferences (i.e. by inter leaving elicitation with recommendation) seems to be more effective in pushing the users to the elicitation of their requirements while keeping the interaction alive. Usually, users communicate their needs and preferences when they are convinced that they will

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benefit from that.The request of formulating a precise and complete query right from the beginning of the interaction may not be useful, especially for mobile users.

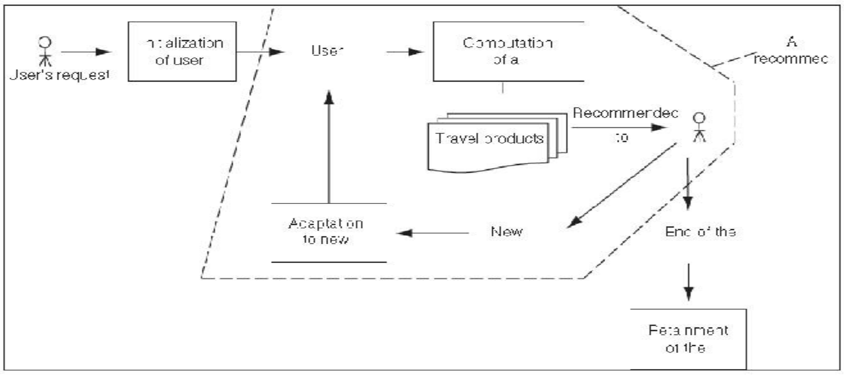

Figure 3: The on-tour recommendation process

In [4], Mapmobyrek,we present an extended and improved version of the system called MapMobyRek.It uses maps as the main interface for items access and information display and provides new decision-support functions based on the map. The design of the map-based interface of MapMobyRek focused on the following user functions:

- to enter the search query by specifying preferences for item features,
- to see the system’s recommendations on the map,
- to recognize immediately the differences between good and weak recommendations,
- to compare two selected recommendations,
- to input critiques to the recommended items,
- to see on the map how the expressed critique influences the system’s recommendations, and
- to select the best items

MapMobyRek provides the following new features.

(1)Map-based, instead of list-based, visualization. In MapMobyRek, the recommended items are revealed as objects on the map (see Figure 4a). The map interface supports typical electronic map features, such as zooming in/out or panning up/down/left/right. On the map, a user can easily perceive the recommended items’ relative distance to her position and directly access any of the recommended items.

(2)Color encoding to represent the recommendation level. MapMobyRek uses a range of colors to show the predicted degree of the suitability of the recommended items. The colors range is red-orangeyellow- green, where the best recommendations are shown in green and the worst in red or the ranked list produced by the recommendation algorithm is divided into four parts, where the items in the highest part of the list are encoded as green, those in the second part yellow, and so on. Smiley icons, shown on the top of the mobile screen, help the user understand the meaning of these colors (see Figure 4a).

(3)Visualization of the user critique’s influence on the recommendations. In our recommendation methodology, a critique stated as a must condition changes the recommendation list, i.e., some new items are recommended, and some formerly recommended items are removed. On the opposite, a critique stated as a wish condition only changes the ranking of the recommended items. In MapMobyRek, the influence of the user critique is visualized immediately and intuitively on the map. After the user has made a wish critique, MapMobyRek changes gradually the colors of the icons on the map (from red to green, or from green to red) and draws an arrow (upward or downward) on each recommended item to display the change (increase or decrease) of its recommendation level (see Figure 4b).After the user has expressed a must critique, some formerly recommended items may not satisfy the new condition, and hence they should be removed from the map. MapMobyRek shows this removal by gradually decreasing the icon size of those

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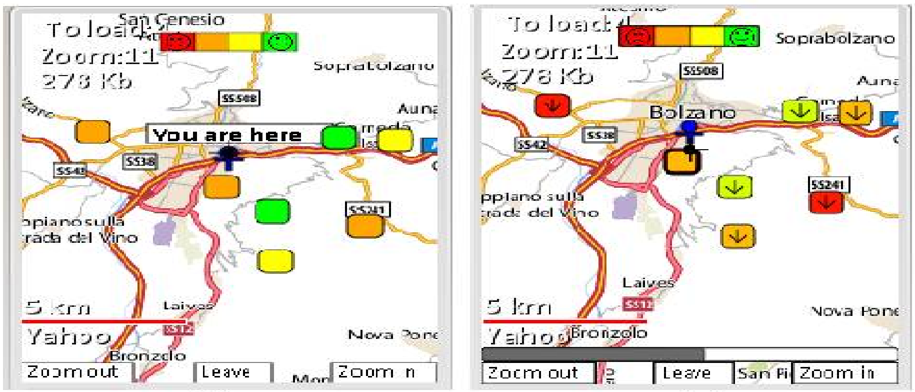
Vol. 5, Issue 2, February 2017

removed items until they vanish. Besides, MapMobyRek shows the new recommended items by gradually increasing their icon size until the final fixed size.



(a) (b)

Figure 4: MapMobyRek user interface(a) Visualization of the recommendations; (b)Recommendation-level change after a critique

(4)Items comparison functionality. During the interaction with MapMobyRek a user can compare two interested items. After choosing the two items, their characteristics are displayed side-by-side on the screen; so their prons and cons can be easily found out (Figure 5).

Figure 5: Items comparison functionality

To support map visualization in MapMobyRek, we used J2meMap (a freeware library for Java MIDP applications) that allows management and display of map-related content. For displaying objects as an overlay of the map, we used the J2ME SVG (Scalable Vector Graphics) library to draw various geometrical shapes and text objects.

In [5], MyMap, a mobile system that provides personalized recommendations of places of interest and delivers tailored information to tourists *when* and *where* they need them and according to their *situational interests*. Using a context-aware approach allows adapting and filtering items by exploiting the available knowledge about the situation of the user in order to produce more focused and useful recommendations.MyMap generates personalized suggestions and descriptions about what to see, by using an XML annotation for map-related knowledge representation, a ***Mobile User***

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Profiles (MUP) for managing contextualized user preferences, a media-independent content planner and a context sensitive surface generator and present how extended MyMap functionalities with the possibility of asking for comparative descriptions in order to support the user in selecting what to see among the places of potential interest chosen by the recommender system.

MyMap uses a map1 for outlining places of interest in a town region.During its use, MyMap may provide suggestions and information about places either proactively, according to context parameters such as the user position and time, or on-request when the user requests an explanation about either a single place or a category of places (i.e.eating facilities, monuments, etc.). In this context, for supporting users in making decisions about what to see among relevant places, it could be useful for the user to understand why they were recommended and also to have a comparative description of the suggested places rather than a set of individual ones. Comparative descriptions may help users in making decision about places to visit without losing time looking at the description of each place and avoiding the cognitive effort of keeping in mind and comparing all their relevant features.The knowledge sources of our system are exploited for grouping objects of interest belonging to the same category and for generating comparative descriptions according to a simple Natural Language Generation (NLG) approach based on the use of a discourse plan which outlines the 'commonalities' and the 'alignable' and 'non alignable' differences among described objects.*Commonalities are* common attributes with the same values, *Alignable_Differences are* common attributes with different values *and Non-Alignable Differences are* peculiar attributes. In the comparative description only features that are appropriate to the user, according to the content of his/her profile, will be emphasized: commonalities are presented first, alignable differences second and non-alignable differences at the end. MyMap executes the following steps:

i) Selection of relevant content to be presented: this is done by matching user preferences, situation and context features with the metadata describing the region of the map where the user is located. Then, given the description of the situation *S* of a user *u* as a set of features ($S(u)=[sf_1, \ldots, sf_n]$), according to the dynamic context features represented by the time *t*, user's position *p* and weather condition *w*, the system selects a set of relevant situational statements (SSt(u)=Select(MUP(u),S(u),t,p,w,all)) in the *MUP* of the user *u* and regarding *all* categories of objects of interest in MyMap. The resulting statements are grouped according to their categories. For each situational statement in a category c_j the list of attributes against which perform the matching of the attributes a_i of items of interest is extracted and then the list of preferred items i_k is formed by ordering them according to the number of matched user interests and to their confidence value. This rank is calculated according as follows: for each matching attribute ma of objects present in the area a around the user: $rank(i_k)=\Sigma\ confidence\ (ma(i_k,a))/nr(ma)$. Items whose value is above a certain threshold (0.5) are presented to the user on the map to be used for generating both individual and comparative descriptions. If none of them goes above the threshold, then the system presents all items and indicates to the user that none of them is close to her preferences or interests. Information about the matched user preferences are exploited to generate an explanation about why the items were recommended. In case the user explicitly asks for recommendations about a category c_j, MyMap applies the same procedure by specifying it in the selection query:

SSt(u)=Select(MUP(u),S(u),h,p,j)).

ii) Selection of the presentation plan that best suits the ***user request***. In MyMap we use plans formalized in DPML corresponding to the following communicative goals: **Describe(single_object),** as a consequence of the user click on the map spot, **DescribeArea(list_of_objects)**, allows describing objects of interest belonging to different categories and **Compare(list_of_objects)** allows describing by comparison a set of objects of interest of the same type.

iii) Instantiation the generic plan with selected data.

iv) Rendering the result as a web page structured as follow:
a) on the **left side** the portion of the **map** of the town area where the user is located and the graphical indications about places of interest are displayed
b) on the **right side** a compact **description** of those places is provided
c) if more than one object of the same type is present in the list, the ***Compare* link** is displayed and the user may ask for a comparative description by clicking on it

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d) on the bottom part, when the user selects one of the places in the list or asks for comparison, the correspondent message is displayed. The user may also access information about an individual place directly clicking on the icons on the map.

The user may always ask for the visualization of all the items present on the map without any personalization and may deactivate the comparison functionality in her setting page.

III. CONCLUSION

In this paper,we made a widespread review about various tourism recommendation systems and topic models and their applications on recommender systems. This paper also covers more context-aware travel information to the on-tour tourists with mobile devices. The above systems and algorithms target on helping tourists from different perspectives. However,tourists need system support throughout stages of travel, beginning from pretravel planning through to the final stages of travel. Topic models (especially LDA)-based methods perform well in the text-related or other recommendation tasks. Furthermore, we can easily integrate heterogeneous data sources into a unified framework by extending current models.

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