SCUOLA DI DOTTORATO
UNIVERSITÀ DEGLI STUDI DI MILANO-BICOCCA

Dipartimento di Informatica, Sistemistica e Comunicazione (DISCo)

Dottorato di Ricerca in Informatica

Ciclo XXX

Context-Aware Approaches to Mobile Search

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ANNO ACCADEMICO / ACADEMIC YEAR 2017/2018

Abstract

In the *'mobile tourism'* domain, travel recommendation is a crucial task that aims to assist tourists in finding relevant Travel-Related services based on their specific contextual situation. In this thesis, in particular, we focus on two main dimensions of the user's current context: (i) the spatio-temporal context, and (ii) the cognitive context, i.e., represented by the user's topical interests.

With the improvement of context-aware technologies, a big amount of contextual factors (e.g., weather, season, location, time, mood, or companion) can be automatically gathered. However, not all of them are equally important for providing effective recommendations. Hence, it is imperative to identify and collect only those factors that truly affect the user's preferences and improve the system effectiveness. For this reason, as a first aim of this thesis, we proposed an effective method for gathering and modeling relevant contextual factors. Our method, based on a selective context acquisition procedure, deems a contextual factor as relevant if it improves the system accuracy. We extensively explored the proposed method in the context of mobile Web search.

Another issue that has been considered in this thesis concerns the fact that traditional approaches for personalized recommendation make use of a variety of the user's historical behaviors on the Web (e.g., search logs, click-through data, etc.) to define the user's interests. This kind of information may be affected by noise, while reliable sources to model the user's topical interests are absolutely necessary to have accurate recommendations. For this reason, in this thesis we focused on the extraction of the user's topical interests from on-line *User-Generated Content* (UGC). More specifically, we proposed a multi-layer user profile, where each layer represents the user's preferences (i.e., her/his likes) with respect to a distinct Travel-Related service category. We used statistical language models to model the different layers. This model enables us to depict the probability distribution of words within a user's language that s/he employs over social media in form of textual reviews. The expressive nature of the user profile modeled this way has been investigated for Travel-Related services recommendation in a restricted geographical area.

Furthermore, based on the considered contextual factors, we proposed a context-aware and content-based approach for travel recommendation. This approach jointly leverages the spatio-temporal context and the user's topical interests represented by her/his user profile to recommend Travel-Related services. First, a contextual pre-filtering is applied to estimate the relevance of Travel-Related services with respect to the user's spatio-temporal context. Then, a novel *Content-Based Filtering* (CBF) approach is performed on top of the selected Travel-Related services. The CBF approach considers both the user's profile – as modeled in this thesis – and the Travel-Related services' profile, and compare them by means of suitable similarity measures in order to recommend to the user the top-k services that are more similar to the user's interests. The proposed approach has been evaluated by using a real-world dataset, and precision-oriented measures. The experimental results demonstrated that the incorporation of both the user's spatio-temporal context and her/his topical interests into the recommendation algorithm enhance the system accuracy.

The user profile and the context-aware and content-based recommendation approach proposed in this thesis have been employed in a mobile application that has been developed as a further contribution of this thesis. In particular, we designed a mobile user-friendly recommender system, namely LOOKER, which leverages travel recommendations to a mobile user who is visiting a new city. Moreover, LOOKER addresses the improvement of the user experience through an active learning of users preferences and interactive recommendation. The application was implemented as a *Rich Mobile Application* (RMA), within the PASRI project[1] funded by European Union.

We conducted a user study that allowed to measure both the user's satisfaction and attitude towards the proposed system. The results demonstrated that our context-aware and content-based approach can increase the recommendation accuracy while improving the user's experience.

Keywords: Travel-Related Services Recommendation, Mobile Recommender Systems, Context-Awareness, Content-Based Filtering, Personalization, Language Models, User-Generated Content.

[1] http://www.pasri.tn/

Acknowledgements

This manuscript is the result of several years of work. In all this time I have received the support of my family and my friends, to whom I am very grateful.

First of all, I wish to express immense amount of gratitude to my supervisor Prof. Gabriella Pasi for her guidance and feedback that helped in uplifting my spirit and motivated me strongly for research. I am glad that I had the privilege to join her research group and to work with such an encouraging professor.

I am also grateful to my supervisor Prof. Rim Faiz for her constant motivation and encouragement. She guided me through the interesting path of the research and also taught me important life lessons.

I am also thankful to my co-supervisor Marco Viviani for providing me with valuable feedback and giving final shape to this thesis.

My sincere appreciation goes to my parents Cherifa and Ezzeddine for always believing in me. To my brother, my sisters and my lovely niece Aicha: no words can express the depth of gratitude I feel for a lifetime love and support.

Lastly, and most importantly, all praises are due to ALLAH swt for His Blessings and Mercy that with which I am humbled.

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CHAPTER 1

INTRODUCTION

“*A wealth of information creates a poverty of attention.*”

— Douglas Adams

In this chapter we present a general overview of the thesis. We discuss the limitations in the considered domain that motivated this research work, and we describe the main research issues addressed. In particular, we give an outline of the conducted research, and we report and discuss our main contributions.

1.1 Motivations and Problem Statement

Recently, mobile devices have become the primary platform to access information on the Web [157]. They offer an environment that provides a multitude of services to users, giving rise to the so called *information overload* problem [161]. In fact, mobile users receive an endless flow of information from multi-channel devices, often at a rate that is well above their filtering capacities. A fundamental solution to this problem has been the use of Recommender Systems (RS)s. RSs make use of different sources of information (e.g., users' interests, ratings, behavior) to provide users with suggestions for items likely to be of their interest [161]. Since their introduction as an independent research area in the 1990s, Recommender Systems have demonstrated to be useful for recommending items according to users' preferences in many domains, including health [10], cinema [121, 164], music [12, 42], tourism [13, 156], and news [66].

According to Kenteris et al. [107], the concept of *mobile tourism* has recently emerged wherein users access tourist content through mobile devices. Mobile tourism, recently referred as *m-Touism*, constitutes nowadays a steadily growing economy [183]. In fact, according to the

World Travel & Tourism Council (WTTC),[1] the on-line travel sales in 2016 have reached 40% of the global travel sales (see Figure 1.1).

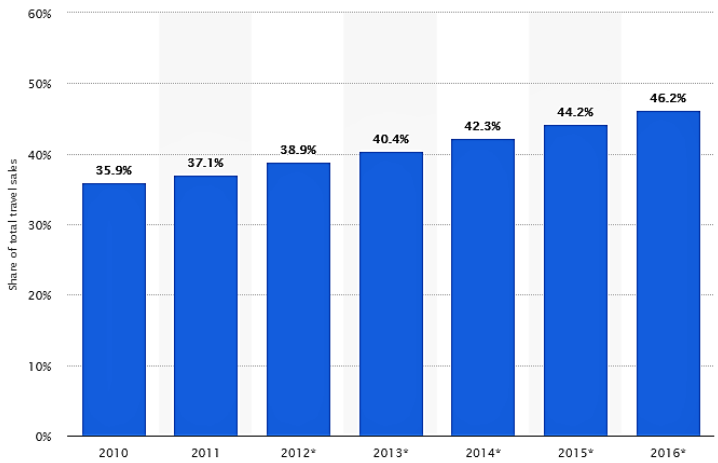


Figure 1.1: Worldwide digital travel sales growth from 2010 to 2016 (Source Statista 2017).

In this context, the task of providing tourists with relevant content becomes challenging since there is a data deluge in *m-tourism* domain. Consequently, mobile Recommender Systems have become widely used to support tourists in accomplishing various tasks [34, 74, 116]:

(i) planning their trips [156];

(ii) obtaining relevant information 'anytime and anywhere';

(iii) taking travel-related decisions based on information they obtain from the social media [208].

Furthermore, there has been a growing interest in providing travel recommendations in popular Web sites. For example, several e-tourism portals such as TripAdvisor,[2] Trippy,[3] Expedia,[4] and Yelp,[5] implemented recommendation services for *points of interest* (POI)s (e.g., hotels, restaurants, museums, etc.).

The challenge in the so called *Travel Recommender Systems* is to produce accurate suggestions to a specific user by taking into account the user's *context*. The key notion of context has different interpretations, depending on the considered domain; it may be related either to the topical preferences of a specific user, or to spatio-temporal factors [147]. Ultimately, an effective Travel Recommender System mainly depends on:

- The 'context model' which formally represents the spatio-temporal contextual knowledge [5, 96].

[1] https://www.wttc.org/
[2] http://www.tripadvisor.com/
[3] http://www.trippy.com/
[4] http://www.expedia.com
[5] https://www.yelp.com/

- The 'user model' (also called user profile) which represents the user's topical interests (in this case contextualization is referred as personalization) [77, 146].

1.1.1 Context-Aware Approaches for Recommendation

Traditional approaches to travel recommendation [156] have been developed to recommend points of interest by exploiting historical data related to the user's on-line behavior [4]. These approaches assume that the user's behavior does not change quickly. They consider the user's interests to be relatively stable, which helps in predicting the user's preference for an item conveniently. This assumption is no more valid in the *mobile tourism* domain, where the preferences of tourists can be truly affected by the changing context of the user. The user's interests can be influenced by many varying contextual factors such as current location, time and weather. However, the majority of traditional Travel Recommender Systems fail to adapt the user's preferences to the changing context.

Currently, the advances in mobile technology allow to capture the user's context easily and effectively [157]. The importance of context in Recommender System is more and more recognized, and *Context-Aware Recommender System* (CARS) have been proposed [3]. Context-Aware approaches to Recommender Systems [3] can leverage the knowledge of the contextual factors to predict how the user would rate an item while experiencing it in a specific situation [34, 36, 74]. For example, using the temporal context, a Travel Recommender System would provide vacation destinations in summer that would be very different from the ones suggested for winter. In summary, Table 1.1 lists the significant differences between use of traditional methods and those that rely on the user's context for travel recommendation.

Table 1.1: Difference between traditional approaches and Context-Aware approaches for travel recommendation.

Traditional approaches	Context-Aware approaches to travel recommendation
Historical data of the user's online behavior.	New sources of dynamically changing data (i.e., contextual factors and social media streams).
Explicit interaction of the user with the system.	Implicit identification of useful contextual information (the user unaware of this).
Limited consideration of the social influence on travel-related decision.	Important consideration of the role of social media in tourism.
Consider the user's general interests to be relatively stable.	Support the user's mobility and her/his associated evolving preferences.

1.1.2 Modeling User Profiles through the Social Web

The main issue of Recommender Systems is to provide useful information to the user by considering her/his interests. The user's interests can be represented in a user profile, and traditional approaches for user profile modeling make use of a variety of information sources (e.g., Web pages, e-mails, calendar items, etc.) [77]. Approaches to user modeling usually exploit the user's interaction history (e.g., search logs, click-through data) that is collected automatically (i.e., via search engines). However, traditional methods for modeling user profiles suffer from many issues, among them the possible presence of noise within the collected data or the uncertainty connected with them. For example, the user's queries can be too short and often ambiguous, which causes uncertainty about the user's information needs [130].

Nowadays, the growing popularity of social media has resulted in a massive source of information for user profile construction. As illustrated in Table 1.2, users have become active data producers in many different social platforms. They create and share multiple contents, which allows to dispose of a big amount of on-line *User-Generated Content* (UGC), which in the tourism domain can refer to many different items (e.g., hotels, travel destinations, cultural points of interest, etc.). The growing availability of UGC (e.g., folksonomies, tags, posts, comments, reviews and multimedia information) has suggested to consider it as a source of evidence for developing personalized content-based Recommender Systems [124]. The real-time nature of UGC allows (i) to represent the user's dynamic interests and to build the user's profile [175], (ii) to infer the user's opinions (like and dislike for an item) for travel recommendation [47].

Table 1.2: Massive amount of UGC in an Internet day as of July 2017. (Source Statista 2017).

	Amount per day
Tweets sent by Twitter users	656 million tweets
Videos watched by YouTube users	4 million hours
Photos shared on Snapchat	527,760
Posts by Instagram users	67,305,600
Facebook messages	4.3 billion

1.2 Open Issues

Common characteristics of existing travel recommendation approaches are the following:

- Relying solely on contextual factors to predict the user's preferences for an item [13, 34, 213, 215], assuming that all factors are equally important for improving recommendation.
- Making use of social media data for user profile construction, in particular tag-based profiling models [45, 69, 175] for improved recommendation.
- Making use of context-aware approaches under Collaborative Filtering techniques [14, 106, 212, 214].
- Focusing on the algorithmic aspect of recommendations and taking into limited consideration the visualization and related issues for the user interface design [129, 151, 189].

However, there are a number of open issues that need to be further explored:

- The user's ratings/preferences are not always influenced by all contextual factors. Consequently, the contextual information will not help in improving the Recommender System effectiveness and can become noise [14, 100]. Hence, a first issue to be addressed is the assessment of contextual factors relevance in the recommendation process.

- Tag-based profiling models help to get more insights about users interests. However, they provide several difficulties such as polysemy and synonymy of tags, that may result in chaotic proliferation of tags [95]. Moreover, the exploitation of users' tags tend to be too ambiguous to describe personal opinions, and the user's profiles tend to loose specificity [124].

- Collaborative Filtering techniques rely on a user-item matrix of pre-collected ratings about items. This matrix is typically sparse because users rate few items [138]. Moreover, the data sparsity can increase with the integration of context-aware approaches [5]. Data-sparsity in Context-Aware Recommender Systems is related to the need of a large amount of contextually-related ratings to provide accurate recommendation [13]. However, even the most active users can only rate a small subset of the overall data under different contextual situations. Therefore, recommender systems may not have enough data (i.e., contextually-related ratings) for accurate recommendation [5]. Additional information such as the user's topical preferences gathered from the user's feedbacks gathered from social media could partially solve this issue.

- What makes a Recommender System successful are both its recommendation algorithm and its interaction design, i.e., the graphical user interface [189]. However, most of the research efforts have focused on the algorithmic aspect. Martin in [129] claims that the graphical interface is the most effective component in a Recommender Systems that has 50% relevance in industrial application (i.e., according to its ability to enhance users' satisfaction). In particular, the development of user-friendly and intuitive interfaces improves the user experience in using mobile Recommender Systems. Therefore, the design of a suitable graphical user interface and related issues are particularly challenging in travel recommendation, since they increase the user's satisfaction [90]. Travel Recommender System must adapt their outcomes by considering this aspect and provide an effective visualization of the recommendations, including item descriptions [151].

1.3 Research Questions

By considering the aforementioned open issues, in this thesis we address the following core research question:

> **How can we effectively utilize the user's current context along with User-Generated Content in social media to reflect the user's interests and preferences for improving mobile recommendations in the tourism domain?**

Consequently, the following research questions are raised and answered:

1. **Which contextual factors should be considered to improve the system accuracy?**

   Despite the successful exploitation of the contextual knowledge to enhance a system accuracy [5], the availability of multiple contextual factors (e.g., spatio-temporal context, personal context, social context) may effect the user's experience negatively. Baltrunas et al. [14] studied the effect of contextual factors on recommendation effectiveness at different granularities. Baltrunas et al.'s findings revealed that when a contextual factor has no influence on the user's preferences, it plays the role of noise.

   In this thesis, we pursue this challenge and we provide a method that determines relevant contextual factors that truly affect the user's preferences. Then, we evaluated their relevance in the scenario of mobile search.

2. **Is it possible to utilize social information (for example textual UGC) in order to create a richer and multi-domain user profile?**

   As discussed in Section 1.2, the tag-based user modeling techniques attracted significant attention over the years [68, 75, 98, 155, 175]. However, Huberman et al. [95] discussed their main limitation for user profiling. Their findings revealed that social tags can be ambiguous, and this can results on a lack of specificity of user profiles. Instead, User-Generated Content in social media allows to follow the evolution of the user's opinions across time and different domains. Hence, we explore UGC and in particular textual reviews as an alternate source for the user profile creation.

3. **How to handle natural language in UGC to identify the user's opinions and interests?**

   In this thesis, we explore textual User-Generated Content as a written evidence explicitly provided by the user [140]. The short-text and the real-time nature of UGC have introduced new challenges such as the dynamically changing vocabulary [133]. Language models [148], allow to take these issues into consideration. In this thesis, we propose a language modeling approach to model the probability distribution of words within a user's language that s/he employs over social media in form of textual reviews.

4. **How to exploit the user's context accurately in the recommendation process while dealing with the context-data sparsity issue?**

   As discussed above, most existing context-aware recommendation approaches draw on Matrix Factorization (MF) models [106, 112, 178]. However, MF are challenging because the ratings' matrix is sparse. In fact, the number of contextually-tagged ratings is very low, as users rate a small proportion of the available items in different contextual situation [5, 14, 52]. To tackle this issue, we explore Content-Based Filtering approaches to overcome the data sparsity problem. Content-based approaches are useful when data sparsity is very high due to their ability to recommend items that have no rating assigned [124]. Hence, we proposed a contextual pre-filtering strategy to select a subset of contextually relevant items. Then, we employed a Content-Based Filtering approach to discriminate items the user likes from others she/he does not like.

5. **How can the user satisfaction increase toward mobile recommendation systems while maintaining accuracy?**

   In the *m-tourism* domain, Recommender Systems are running in a mobile environment [32, 46]. Hence, it is important to explore the *ubiquity* property, i.e., the ability to deliver the information and services to mobile users wherever they are [157]. However, most existing approaches focus on the recommendation accuracy without considering the user experience [111]. In this thesis, we explore mobile recommendation techniques to achieve accurate recommendation and enhance the users experience [87].

1.4 Contributions

This section describes the main contributions of this thesis. We focus on the personalized recommendations of Travel-Related services presenting a novel approach that addresses the open issues detailed in Section 1.2.

Thesis Statement: To build an effective mobile Recommender System for Travel-Related services, we consider both: (i) contextual factors, and (ii) the user's topical interests. We jointly utilize User-Generated Content gathered from social media and contextual factors to provide a personalized recommendation approach.

Based on this statement, this thesis brings the following contributions:

1. **An effective method to model and acquire the relevant contextual factors**

   This thesis proposes a novel approach utilizing a context-aware technology that helps in modeling and acquiring relevant contextual factors. In particular:

   - First, we provide a formal model that allows to capture and present contextual factors with respect to a mobile user's situation. We explore the use of *Context Modeling Language* (CML) to: (i) model contextual factors and their metadata, and (ii) define dynamic mappings between users and entities implied in their context (Chapter 4; Missaoui et al. [132]).
   - Second, we propose a selective context acquisition method that helps in selecting relevant contextual factors. The proposed method estimates the relevance of a contextual factor with respect to its ability to improve the system accuracy. We consider mobile Web search as an example of application. Thereby, the relevance of a contextual factor is seen as the probability of generating a query from the document language model while responding to the user's preferences (Chapter 4; Missaoui et al. [131]).

2. **A dynamic user profile based on the content generated by the user**

   This thesis explores the use of on-line User-Generated Content to infer the user's topical interests. The proposed model enables to infer the user's opinions (i.e., her/his likes and dislikes) to provide personalized recommendation in a restricted geographical area (Chapter 5; [181]). The user model has been also enriched and a *multi-layer user profile* has been proposed (Chapter 6). The idea is that each layer represents the user's preferences with respect to a distinct Travel-Related service category. To model each layer, the proposed approach adopts a statistical language model on the textual reviews. More specifically, statistical language models are proposed to model the probability distribution of words within a user's language that s/he employs over social media in form of textual reviews.

3. **A context-aware and content-based approach for recommendation in the tourism domain**

   This thesis proposes a context-aware and content-based approach for Travel-Related services recommendation. The proposed approach jointly leverages contextual factors and the user's topical interests represented by her/his user profile to recommend Travel-Related services in the mobile context (Missaoui et al. [181]). This approach applies a contextual pre-filtering strategy that estimates the relevance of items with respect to the user's current context (i.e., the set of contextual factors). Then, the results of this pre-filtering are used by a novel Content-Based Filtering (CBF) strategy. The CBF approach explores on-line UGC to learn hidden aspects of candidate items. Then, it compares the user profile to the items profile represented via language models to provide personalized recommendation. The proposed approach has been evaluated by using the Yelp challenge dataset, and precision-oriented measures. Experimental results demonstrate that the incorporation of both the user's topical interests and contextual information into the recommendation approach improve recommendation accuracy. The proposed approach alleviated the sparsity problem and served as a significant basis towards the incorporation of UGC in the recommendation methodology.

4. **A rich mobile application for travel recommendation**

   The above discussed contributions have been used, implemented and incorporated in a concrete prototype of a mobile Recommender System. LOOKER – this is the name of the developed mobile application – is a Context-Aware system that recommends Travel-Related services in Tunisia. It has been implemented as a *Rich Mobile Application* (RMA) that has been developed within a research project funded by European Union: the PASRI project.[6]

   LOOKER generates personalized recommendations of Travel-Related services to a mobile user visiting new destinations. We made a user study that allows to investigate the system usability and the user's satisfaction toward the system. The conducted user study gives a more practical insight into context-aware recommendation and the travel-related

[6] http://www.pasri.tn/

decisions of tourists under changing contexts. Using data gathered in the user study, we evaluate the correlation between the users' satisfaction and recommendations accuracy in a real-world dataset (Chapter 6).

1.5 Thesis Structure

This thesis is organized as follows:

- In the Introduction, we introduced the research motivations and the problem statement along with the main research question and goals, as well as the contributions of this work.
- Chapter 2 presents some background concepts about Recommender Systems and context-awareness.
- In Chapter 3, we present a description of the state-of-the-art related to the core research areas of the thesis. We provide an overview of Travel Recommender Systems. We overview most popular travel recommendation techniques and discuss their most common shortcomings. Then, we presents a brief overview of language modeling.
- Chapter 4 motivates the problem of context modeling and acquisition. It presents our proposal for modeling and acquiring relevant contextual data in a mobile context.
- Chapter 5 motivates the problem of user profiling for personalized recommendation. It discusses our proposed user model that leverages user generated content to infer the user's topical interests. Then, it presents a content-based approach that employs the user profile to recommend Travel-Related services in a restricted geographical area.
- Chapter 6 presents a context-aware and content-based Recommender System that employs both contextual factors and the multi-layer user profile model to personalize the travel recommendation in the mobile context. The chapter discusses the implementation of a mobile travel recommender system namely LOOKER. It presents the system architecture and describes the user interface. Through a user study, we demonstrate that LOOKER enables to improve the user experience while maintaining the recommendation accuracy.
- Chapter 7 concludes this thesis with a discussion on the main contributions and an outline of future work.

1.6 Publications

International Journals

- Missaoui, Sondess, and Rim Faiz. "A Preferences Based Approach for Better Comprehension of User Information Needs." Transactions on Computational Collective Intelligence XVIII. Springer, Berlin, Heidelberg, 2015. 67-85.

International Conferences

- Missaoui, S., Viviani, M., Faiz, R., and Pasi, G. (2017, April). A language modeling approach for the recommendation of tourism-related services. In Proceedings of the Symposium on Applied Computing (pp. 1697-1700). ACM.
- Missaoui, Sondess, and Rim Faiz. "A new preference based model for relevant dimension identification in contextual mobile search." Networked Systems. Springer, Cham, 2014. 215-229.
- Missaoui, Sondess, and Rim Faiz. "Context filtering process for mobile web search." Computer Systems and Applications (AICCSA), 2013 ACS International Conference on. IEEE, 2013.

National Conferences

- Missaoui, S., and Faiz, R. (2014). Identifying Relevant Contextual Parameters to Enhance Mobile Search Query. In proceedings 8ème édition de la Conférence nationale sur les Avancées des Systèmes Décisionnels(ASD).

CHAPTER 2

Background

As described in Chapter 1, in this thesis we address the issue of providing accurate recommendations to mobile users by considering both their spatio-temporal and cognitive context. For this reason, in this chapter we provide an overview of Recommender Systems in general, the main techniques that have been proposed for implementing them over the years, and the main evaluation methodologies that have been applied to Recommender Systems. Furthermore, we present the concept of context, we highlight the challenges that context-awareness raises for Recommender Systems, and we present context modeling and acquisition approaches for personalization tasks.

2.1 Recommender Systems

Recommender Systems (or *Recommendation Systems*) (RS)s rely on *Information Filtering* (IF) [22, 86]. An Information Filtering is a process that allows to reduce the *information overload problem*. It handles large amount of data in order to push to the user the subset of information likely to be of her/his interest [109]. Recommender Systems are IF tools that recommend to the user items to be of use based on her/his preferences [158].

2.1.1 Formulation of the Recommendation Model

The most common model for Recommender Systems was defined by Adomavicius and Tuzhilin in 2005 [4] and revised by Ricci in [158]. Formally, given a set of users U and a set of items I, a RS model implements an evaluation function r^* defined on the product space of U and I, formally:

$$r^* : U \times I \longrightarrow R$$

where R is the evaluation scale containing the ordered evaluation values. This model predicts how a pair of a user $u \in U$ and an item $i \in I$ is mapped to the evaluation $r^*(u,i)$ of the user u for the item i. Therefore, the evaluation $r^*(u,i)$ is defined as the *predicted evaluation* [158]. A RS recommends to a user u the set of items with the largest *predicted evaluations*.

2.1.2 Recommendation Techniques

Recommendation approaches differ according to the exploited source of the user's preferences, and to the way in which the *evaluation function* is estimated [158]. Three main categories of RSs are commonly identified, depending on which Information Filtering algorithm they are based on: (i) *Collaborative Filtering* (CF), (ii) *Content-Based Filtering* (CBF), and (iii) *hybrid approaches* [28] (see Figure 2.1).

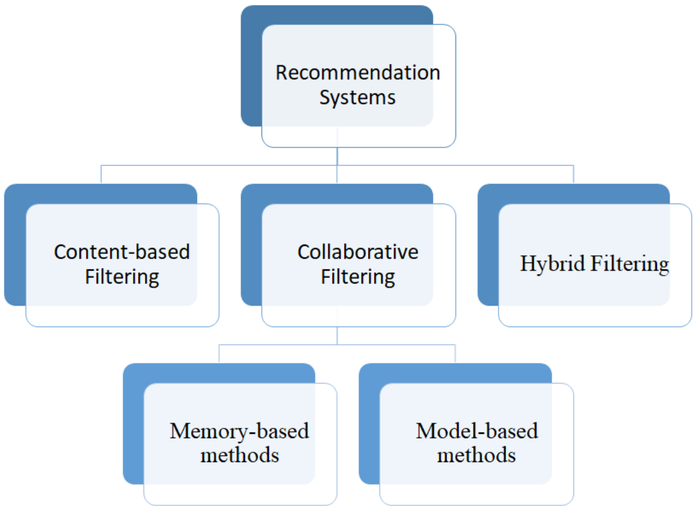


Figure 2.1: Recommendation techniques.

2.1.2.1 Collaborative Filtering

Collaborative Filtering (CF) is considered to be the first technique developed for recommendation, and it has been developed in the mid 90's to automatically filter electronic mails [81]. CF methods predict the evaluation of a user for an item according to the ratings provided by other users, i.e., users considered to have similar preferences with the active user [62]. CF methods simply exploit the users' past ratings, stored in *user-item rating matrix* (see Figure 2.2), to generate new recommendations [62]. CF techniques were classified into two categories: *Model-based approaches* and *Memory-based approaches*.

Model-based approaches *Model-based approaches* use the ratings in the user-item matrix as a training set to learn a predictive model. Commonly, the predictive model is a statistical model that will be applied to predict ratings of users for new items [62]. In model-based approaches ratings are carefully selected using several techniques that exclude noise and redundancy, which leads to an important increase in accuracy and efficiency of the recommendation [4]. For model-based approaches, a wide range of methods have been developed under the machine learning framework, such as the probabilistic relational model [76], Bayesian networks

[50], linear regression [167], and latent factor models [113]. In particular, approaches based on *Matrix Factorization* (MF) [113] have gained a huge popularity do to their effectiveness. MF techniques such as *Singular Value Decomposition* (SVD) [113] learn latent features to determine how user rates an item. Through the latent features, MF gives the opportunity to incorporate several information such as temporal information [122], contextual information [11] and social information [126].

Memory-based approaches Memory-based approaches provide rating predictions based on the entire ratings collection stored in the user-item matrix (see Figure 2.2). They can be based either on *user-based* or on *item-based* model. The most popular user-based model is the

	K-PAX	Life of Brian	Memento	Notorious
Alice	4	3	2	4
Bob	∅	4	5	5
Cindy	2	2	4	∅
David	3	∅	5	2

Figure 2.2: Schematic view of a fragment of rating matrix in movie recommender system [4].

Neighborhood-based model that aggregates ratings from similar users to make recommendations [62]. More specifically, this model predicts the evaluation of a user u for an item i using the ratings for this item provided by users similar to u, called *neighbors*. Formally, the evaluation function, that allows to generate *predicted ratings*, is estimated as follows:

$$r^*(u,i) = C \sum_{v \in N_k(u,i)} sim(u,v) r(v,i) \tag{2.1}$$

where N_k denotes the user neighborhood of size k, $sim(u,v)$ is the similarity between the target user u and her/his neighbor v based on their past ratings. $r(v,i)$ denotes the rating of v for an item i, C is a normalization factor (defined differently from one model to another).

In [4], different techniques have been presented to aggregate the ratings from the neighborhood model. The similarity between two users is mainly computed by means of different metrics such as the *Pearsons Correlation Coefficient* (PCC) (Equation 2.2) and the *Cosine similarity* (Equation 2.3). The Pearson Correlation Coefficient computes the statistical correlation between two user's common ratings to determine whether they are neighbors or not.

Formally, let r_{ui} denotes the rating given by a user u to an item i. In the same manner r_{vj} is the rating given by a user v to same item i. The PCC is computed as following:

$$sim(u,v)^{PCC} = \frac{\sum_i (r_{ui} - \overline{r}_u)(r_{vi} - \overline{r}_v)}{\sqrt{\sum_i (r_{ui} - \overline{r}_i)^2} \sqrt{\sum_i (r_{vi} - \overline{r}_v)^2}} \tag{2.2}$$

where $\sum_i$ represents the set of common rated items by users u and v. $\overline{r}_u$ and $\overline{r}_v$ represent the average rating values of users u and v respectively.

The cosine similarity, also known as vector-based similarity, views two users and their ratings as vectors, and defines the similarity between them as the angle between these vectors:

$$sim(u,v)^{cos} \frac{\sum_i r_{ui} r_{vi}}{\sqrt{\sum_i r_{ui}^2}\sqrt{\sum_i r_{vi}^2}} \tag{2.3}$$

For the *item-based* model, the similarity is computed between the item ratings. The set of items previously rated by the target user are used to find other items that are "similar" to them [167]. The Amazon.com Recommender System represents one of the most famous item-based CF models. It considers that users who view or buy the product x may also buy the product y, that is similar to x.

CF advantages and limitations CF have been recognized as a successful recommendation technique in the sense that it makes recommendations based solely on the user-item ratings matrix. CF techniques do not incorporate any meta-data on users and items to produce accurate recommendations. Hence, CF can be generalized and applied to many domains, including products recommendation for Amazon.com[1], music recommendation in Last.fm[2], new friends, communities or even jobs recommendations in Facebook[3], LinkedIn[4] and MySpace[5] respectively. Despite the advances achieved by CF in Recommender Systems, the recommendation accuracy may be affected by some important drawbacks such as the cold-start and sparsity problems [28, 65, 169]. The cold start problem is related to the situation when the system has not enough ratings to compute personalized recommendations to a new user (the *new user problem*) or to recommend a new item to the existing users (the *new item problem*) [4]. The second limitation of CF is the sparsity of data. This problem is due to the insufficient number of the rating data, which limits the usability of the CF.

2.1.2.2 Content-Based Filtering

Content-Based Filtering (CBF) analyzes the descriptions/content (textual content) of items previously rated by the user and filter information according to them. More specifically, using the analyzed content, CBF builds a user model/profile, i.e., the filter that represents long-term interests of a user or a group of users. Then, the filtering process is achieved by matching up the content of the user profile against the content of the candidate item [124].

According to Belkin and Croft [22], CBF inherits *Information Retrieval* (IR) problems and methodologies. Commonly, CBF and IR techniques share the main goal of providing users with relevant information. However, they differ in many aspects that have been discussed by [22, 86] and reported in Table 2.1. Mainly, CBF is concerned with long-term changes over the user's interests and preferences. It requires gathering the user's feedbacks in order to build a user profile and accommodate the individual user's interests; in IR, the user's needs are generally represented in a query [86].

[1] https://www.amazon.com/
[2] https://www.last.fm/
[3] https://fr-fr.facebook.com/
[4] https://www.linkedin.com
[5] https://myspace.com/myspace/

Table 2.1: Comparison between Content-Based Filtering and Information Retrieval.

	Information Retrieval	Information Filtering
Goal	Selecting relevant data that match a user's query	Filtering out irrelevant data
Representation of information needs	Queries	Profiles
Frequency of use	Adhoc use for one-time information need	Repetitive use
Scope of the system	Relevance of the data	User modeling and privacy [86]

In summary, a CBF system comprises (see Figure 2.3):

- The *User Model Component*: it collects data representative of the user's interests and generalize it to model the user profile;
- The *Data Analyzer Component*: it analyses and represents the existing data in item models, that constitutes the input of the filtering component;
- The *Filtering Component*: it uses the user profile to determine the relevancy of the item. This component suggests relevant items by matching the user profile against the item profiles to be recommended;
- The *Learning Component*: it learns and modifies the user profile according to the user's evolving preferences.

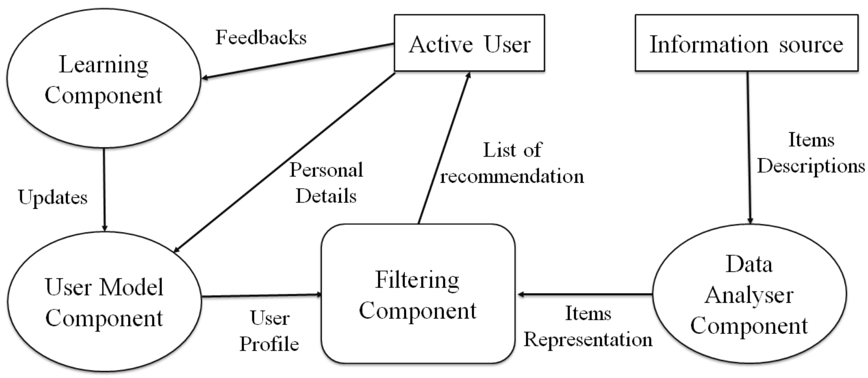


Figure 2.3: Architecture of a Content-Based Filtering system [86].

User Model The *user model* (also called *user profile*) is a fundamental component to the success of any CBF system. The CBF algorithm constructs a user profile based on the features/descriptions of the items rated by the user, which are assumed to reflect the user's topical interests. The user profile is then adopted to recommend new relevant items [124]. The problem of learning user profiles is an important although difficult task, which involves three main processes: acquisition, representation and updating [146].

- **Acquisition of User-Related Information** For the *acquisition process*, two main techniques are essentially employed to capture the user's topical interests. Gauch et al. (2007) in [71] discussed implicit and explicit approaches to information gathering. The explicit approach requires user intervention to provide the system with her/his interests. Users define their interests by providing relevance feedbacks about retrieved documents [77], adding ratings to recommended items [28] or fill in site-specific survey. Implicit approaches automatically capture the user's interests. Indeed, the implicit acquisition approach keeps track of the user-system interaction. A variety of information sources can be considered [187] such as recently browsed or tagged Web pages [70, 179], emails and desktop information [64], query logs and click-through data [130]. The collected information can be classified in either *user* or *usage information*. The user information includes personal and demographic information such as the user's name, age, language, job title, country, etc. The usage information refers to the user's behavior including her/his search history, search logs, click-through data, visited URLs and viewed documents. Recently, thanks to the diffusion of social media, user and usage information may have a richer information source. The growing availability of on-line *User Generated Content* (UGC) (e.g., folksonomies, tags, posts, comments, reviews, multimedia information, etc.) has suggested to consider it for user modeling [175]. UGC provides an important source of evidence for representing the user' interests and building the user profile. The usage of UGC allows to infer the user's interests from information explicitly provided by the knowledge owner herself/himself, which improves the expressive power of the user model.

- **Representation of User-Related Information** The *organization and representation* process implies the selection of an appropriate formal language to define the user model [146]. Gauch et al., 2007 [71] provide a classification of user models based on the used language among which: keyword-based [186], semantic network-based [43, 70] and vector-based models [104]. A vector-based model represents terms and associated weights as a vector. The terms weights are usually determined using a term weighting scheme, e.g., TF-IDF or BM25 [56]. However, keyword-based models present a number of challenges such as ambiguity, polysemy and synonymy. These issues have been largely discussed in user modeling for CBF approaches and have given rise to semantic approaches [70, 172, 190]. A deal of research is addressing the problem of representing the user's interest through a concept-based model. In this model, categorical terms are drawn from external resources to identify concepts in the user-related information. Recently, the use of richer knowledge sources that cover a wide range of concepts and their hierarchies has become popular. External knowledge sources can be either taxonomies or ontologies such as the ODP taxonomy,[6] the Wordnet thesaurus,[7] or the Yago ontology. Several approaches have been proposed, based on the use of ODP, among which the one proposed by Speretta et al.

[6] Open Directory Project http://www.dmoz.org

[7] http://wordnet.princeton.edu

[182], who define a user profile with semantically enriched concepts extracted from the ODP hierarchy. Another research work [136] creates a rich semantic-based user model for context-aware content-based recommendations. The proposed user model utilizes a Wikipedia-based distributional semantic and entity linking framework to create the user model. An important aspect related to user profile representations is the distinction between short-term user interests [70] and long-term ones [51]. The short-term representation of a user profile refers to the user interests collected during a short period of time. The long-term user profile is used to build a stable user profile that considers the user's interests in general. These interests represent persistent user's interests, which are usually inferred from the whole user activities on the Web.

- **Updating of the User Model** An important issue is related to the user profile updating. This aspect generally concerns dynamic user models, which keep track of the user's evolving interests over time [104, 105]. The approaches using short-term user profiles are the more concerned with this issue, because user profile's are frequently updated over multiple search sessions.

Filtering Component The filtering component exploits both the user and the item profiles to predict the item's relevance to the active user. In particular, this component ranks candidate items according to their relevance with respect to the user profile [9]. CBF technique are classified according to whether the employed model is based on: (i) machine learning techniques [124], or use a (ii) heuristic function inspired by Information Retrieval methods [23]. The most common machine learning techniques are probabilistic methods, particularly the Naïve Bayes model [134]. Naïve Bayes estimate the probability to evaluate if an item is relevant or irrelevant based on previously observed ratings. Formally, an item is seen as a document d, for which we generate the posteriori probability $P(c|d)$ that d belongs to a class c (relevant or irrelevant), given a priori probability $P(c)$. The posteriori probability is estimated as follows [124]:

$$P(c|d) = \frac{P(c)P(d|c)}{P(d)} \tag{2.4}$$

where $P(d)$ is the probability of observing d, and $P(d|c)$ the probability of observing the item given the class c.

The most commonly used model for CBF is the *Vector Space Model* (VSM) [165]. This model represents an item by a vector in a n-dimensional space. Formally, an item's content (i.e., its textual description) is seen as a document. The given document is represented as a vector $d_j = \{w_{1j}, w_{2j}, ..., w_{nj}\}$, where w_{kj} is the weight for the term t_{kj} in a document d_j. The commonly used weighting schema is the *Term Frequency-Inverse Document Frequency* $(TF-IDF)$ weighting.

The *Term Frequency* (TF) is defined as the frequency of the term t_k in a document d_j, divided by the number of terms in the document d_j, formally:

$$TF\left(t_k, d_j\right) = \frac{freq_{kj}}{|d_j|} \tag{2.5}$$

The *Inverse Document Frequency* (IDF) is computed as follows:

$$IDF\left(t_k, d_j\right) = log\frac{N}{n_k} \tag{2.6}$$

where N is the number of documents and n_k denotes the number of documents in which the term t_k appears.

Then, the TF-IDF measure is estimated as follows:

$$TF - IDF = TF\left(t_k, d_j\right) * IDF\left(t_k, d_j\right) \tag{2.7}$$

However, keyword-based models such as the Vector Space Model present a number of issues such as ambiguity, polysemy and synonymy. These issues have been largely discussed in CBF and have given rise to semantic approaches [61]. The semantic analysis allows learning more accurate profiles and interpreting documents written in natural language [172].

CBF advantages and limitations CBF is a widely used recommendation method that proved its effectiveness in many RSs such as *YourNews*, described in [6], and *NewT*, described in [176]. The main advantage of CBF is its ability to resolve the new item problem, which was not solved by Collaborative Filtering. CBF is also useful when data sparsity is very high, due to its ability to recommend items that have no rating assigned. CBF requires only knowing the contents of new items to be recommended.

However, CBF suffers from a main issue called *overspecialization* [27]. For instance, CBF suggests items similar to those items user's already consumed, which can not be suitable in some domains like news recommendation, or high-tech products or even in travel recommendations [27]. For example if a traveler used to visit cultural point of interests in all her/his past trips, the system will recommend to her/him a museum even if s/he is on a business trip, which is not suitable for such occasion. Moreover, CBF suffers from the *limited content analysis* problem [124], caused by the limited features/content associated with the users. CBF techniques need enough useful data about users and items to provide good recommendations. In particular, CBF techniques faced the user cold-start problem. This issue, can be solved by inheriting implicit user's feedback through social media stream such as *User-Generated Content* [124].

2.1.2.3 Hybrid Approaches

To overcome CF and CBF limitations and improve their accuracy, hybrid approaches have been proposed in the literature. In [4], a detailed classification of hybrid recommendation approaches is presented:

- **Combining separate Recommender Systems**: the outputs of individual Recommender Systems, i.e., based on CF and CBF techniques are combined. This combination can be released through a linear combination or a voting scheme.

- **Adding content-based characteristics to collaborative models**: a CF approach represents the recommendation core. In this context, CBF techniques are employed for user profiling offering a solution to the new item problem.

- **Adding collaborative characteristics to content-based models**: this technique has been proven to be more effective than the pure CBF approach. Under this category, dimensionality reduction techniques are employed on content-based profiles to create a collaborative view of a collection of user profiles.

- **Developing a single unifying recommendation model**: probabilistic methods are used for combining collaborative and content-based recommendations. Several works used a single statistical model that combines users and items content to predict ratings.

2.1.3 Evaluating Recommender Systems

The evaluation of Recommender Systems is a challenging task that has been widely discussed in the literature [24, 151, 173]. Shani and Gunawardana distinguish between three different kinds of evaluations: *off-line evaluations*, *on-line evaluations*, and *user studies* [173, 199]. The choice of the evaluation strategy should take into account the goal of the system itself. It is important to evaluate the RS effectiveness with respect to the original hypothesis. Hence, the evaluation should concentrate on assessing the effectiveness of a RS in relation to its main objectives.

2.1.3.1 Off-line Evaluations

An *off-line evaluation* (also called system evaluation) [173] is realized by simulating the user's actions after receiving recommendations. This simulation is produced by splitting the data into a training and a test set [24]. The recommendation model is trained on the training set which is considered as an evidence about the users' judgments when receiving the items. Then, the model is tested and evaluated on the test set with several metrics and methodologies.

An off-line evaluation facilitates the comparison of several recommendation algorithms for the same problem because they do not require interactions with real users. Therefore, an off-line evaluation allows to compare a wide range of RSs at a low cost. However, the main limitation of this kind of evaluation is that it does not measure the recommender's influence on the user behavior directly. It allows to evaluate the accuracy of recommendations through a typical simulation that may has no correlation with the recommender system's performance in practice.

2.1.3.2 On-line Evaluations

Many Recommender Systems attempt to improve the accuracy of the recommendations provided, while maintaining high user satisfaction. Therefore, the designer of the system are interested in measuring the change in the user behavior while receiving recommendations. An *on-line evaluation* is one of the best methodologies to measure the change in the user behavior when interacting with the Recommender System. By performing an on-line evaluation – with real users that perform real tasks and interact with the system – we can gather strong evidence about the user true satisfaction through the click-through rate. For example, in the case of a mobile or a Context-Aware Recommender System, the real effect of recommendation depends on a variety of factors including the user's context, the user's intent and the system's interface. Thus, on-line evaluations allow the direct measurement of the the user satisfaction under real circumstances. Despite its advantages, an on-line evaluation is an expensive task. It requires a fully functional implementation and a pool of users to evaluate the system.

2.1.3.3 User Studies

A *user study* [110] is conducted by recruiting a set of *test subjects*. According to Tullis et al. [192], to conduct an accurate user study, a group of at least 12/14 participants (i.e., test subjects) suitably selected is necessary. Participants are asked to perform several tasks requiring an interaction with the RS. During the user study, quantitative and qualitative measurements are observed by means of questionnaires or with the implicit observation of the participants behavior. Many interesting measurements could be observed during user's interaction with the system, including: the accuracy in completing the tasks, what portion of the tasks was completed, or the time taken to perform the tasks.

User studies have been divided into *lab studies* and *field studies* [110]. The *lab studies* are conducted in an artificial setting, where the researchers manipulate some variables. Users perform the task in an environment where a big amount of considered variables are controlled. In *field studies*, the researchers make no attempt to control or manipulate the RS. Users use a tested system in uncontrolled environment. Although it proved its effectiveness in evaluating the RS at many levels, user studies are not suitable for comparing many algorithms because they are truly expensive.

2.1.3.4 Evaluation Metrics

Evaluating RSs strongly depends on the recommendation property we want to assess; thus, different properties could be considered when deciding which recommendation approach is better performing. Many RS proprieties have been investigated in the literature such as accuracy, coverage, novelty and serendipity [173]. The accuracy of recommendations is one of the most discussed property in the RS literature. It is refereed to the ability to find all good items or the top-k ones. Shani and Gunawardana [173] identify three main categories of evaluation metrics: *rating prediction accuracy*, *usage prediction* and *accuracy of rankings*.

Rating Prediction Accuracy In the typical formulation of a recommendation problem, user interests for items are represented as numeric ratings. In relation thereto, *rating prediction accuracy* measures the ability of the system to predict the exact rating. Commonly, the rating prediction accuracy is evaluated by measuring the error between predicted and known ratings through metrics such as the *Root Mean Squared Error* (RMSE) (Equation 2.8) and the *Mean Average Error* (MAE) (Equation 2.9). Formally:

$$RMSE = \sqrt{\frac{1}{T}\sum_{(u,i)\in T}(r_{u_i} - \bar{r}_i)^2} \tag{2.8}$$

$$MAE = \sqrt{\frac{1}{T}\sum_{(u,i)\in T}\left|r_{u_i} - \bar{r}i\right|} \tag{2.9}$$

where $\bar{r}_i$s are the predicted ratings for the set T of user-item pairs (u,i)s, for which the true ratings r_{u_i}s are known. The main difference between RMSE and MAE is that RMSE penalizes errors greater than 1, while it puts less emphasis on small errors. Many versions of these metrics have been proposed and studied in the literature, such as Normalized RMSE (NMRSE), Normalized MAE (NMAE), Average RMSE and Average MAE. The NMRSE and NMAE are normalized by the range of the ratings (i.e., $r_{max} - r_{min}$). The Average RMSE and Average MAE are adjusted for unbalanced test sets.

Usage Prediction It measures the ability of the system to produce a set of positive items, i.e., items liked by the user. For this task it is common to use precision-oriented metrics [24] that measures the amount of relevant and non-relevant retrieved items. These measures are drawing from well-studied methodologies in the Information Retrieval (IR) field [54]. Precision, recall, and F1 are the most popular metrics to evaluate the classification task at a specific cutoffs (i.e., @n) of the recommendation list. As shown in Table 2.2, given the set of recommended items, we classify the suggestions into four possible results according to the user interest on them.

Table 2.2: Classification of the possible result of a recommendation of an item to a user.

	Recommended	Not recommended
Liked	true-positive (tp)	false-negative (fn)
Not liked	false-positive (fp)	true-negative (tn)

The precision (Equation 2.10) is the ratio between the number of items recommended that are liked by the user (tp) and the number of items recommended (i.e. $tp + fp$).

$$Precision = \frac{\#tp}{\#tp + \#fp} \tag{2.10}$$

Accuracy of Rankings The ranking accuracy measures such as *rank score* [37] and *Normalized discount cumulative gain* (nDCG) [97] measure the ability of the system to favor relevant items in top-k positions of the recommendations list. The *normalized Discounted Cumulative Gain* (nDCG) [97] is a measure derived from Information Retrieval, defined to compare IR methods with respect to their ability to favor relevant search results in top-k positions of the ranked list of results [58, 173].

The nDCG measure has been widely adopted to evaluate the ranking prediction accuracy of RSs following the methodology described in [173]. nDCG is calculated by comparing the predicted ranking to a reference ranking as follows [173]:

$$nDCG = \frac{DCG}{iDCG} \tag{2.11}$$

where $iDCG$ is the reference ranking that presents the ideal DCG when all the hits are in the top positions. Therefore the DCG is normalized, i.e., $nDCG$, in the interval [0;1].

DGC is computed as follows:

$$DCG_{pos} = rel_1 + \sum_{i=2}^{pos} \frac{rel_i}{log_2 i} \tag{2.12}$$

where pos denotes the position up to which relevance is accumulated and rel_i presents the relevance of the recommendation at position i.

2.2 Context in Recommender Systems

Current advances in ubiquitous and mobile computing (e.g., the ubiquitous availability of wireless connection), have brought Web application (i.e., search and filtering systems) to migrate to mobile platforms. Indeed, thanks to smartphones' capabilities, mobile users are overwhelmed by information they have not the time to assess. This problem has attract a significant research attention in an attempt to support mobile users in their decision making process while moving around in the world [30, 53, 157]. Many works [135, 180] argue that the context shapes the users behavior and could be a strong trigger for information needs in mobile environment. In last years of research, *context-awareness* has proved to be successful to overcome the information overload problem that burdens users in mobile context.

The concept of context-awareness originated in the ubiquitous computing domain [197] where systems are increasingly sensitive to the context in which they operate. Ubiquitous computing is a paradigm that shifts where technologies become flexible, adaptable, and capable of operating in highly dynamic environments without requiring demands on user attention [78, 198]. For example, a call-forwarding system can monitor the user's context changes using physical sensors. The system detects the user's current location after s/he left her/his office, then, it forwards the call to a nearby phone (e.g., to user's voice mailbox if s/he is in a meeting).

2.2.1 Defining Context

The notion of *context* refers to a multifaceted and multi-dimensional concept that has a grown popularity since its introduction by [170] in the field of of ubiquitous and pervasive computing. Context has been studied and successfully applied in various application domains such as Information Retrieval, Ubiquitous Computing and Recommender Systems.

Therefore, numerous definitions and explanations of context have been proposed and employed since the early 1990s [170]. Schilit and Theimer [170] define the context as: *"where you are, who you are with, and what resources are nearby"*. The definition for context that is widely accepted by the research community were proposed by Dey, 2001 [63] in which the context notion, going beyond location and time. Dey defines the context as *"Any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves"*.

For the purpose of this thesis we shall adopt a restricted version of the definition of context. The primary focus of this thesis will be on: (i) *cognitive context*, such as a the user's topical interests and preferences, and (ii) *spatio-temporal context*, which may affect the user's interests, such as a geographic location, activity or day time. Further, we share the same view detailed in [63], where context refers to all interesting information regarding the user's current situation (physical or personal) that allows the application to automatically adapt its process according to the user's needs.

2.2.2 Context-Aware Recommender Systems

Along over two decades of research, the importance of contextual information in Recommender Systems has been recognized [3] to provide mobile users with accurate recommendations that are suitable for them based on their context [161]. As a result, *Context-Aware Recommender Systems* (CARS)s have been developed [5].

The importance of including context in the recommendation process can be observed through a simple example in the tourism domain: although a user may love swimming and fishing, if s/he receives recommendations about beaches while being in Madrid in a raining day, the recommendation becomes questionable. Such recommendation could be detrimental for the user's trust in the system. In such a scenario, integrating the user's current location along with the weather is fundamental to enhance the system's prediction accuracy. The importance of contextual information in RSs has been recognized by researchers in many disciplines (see Table 2.3) including TV contents and movie recommendations [8, 17], music recommendation [12, 42, 143], shopping assistance [116, 163], learning-related services [196], mobile recommendation [157].

Table 2.3: Most popular web-platforms for Context-Aware recommendation.

Site	Items recommended	Contextual factors
Netflix	Movies	Time, social, behaviours, Geo-information, device info
Facebook	Friends	Location, time, social information and interaction
Spotify	Music	Mood, activities, events
TripAdvisor	Tourism	Trip goal, time, companion

2.2.2.1 Modeling Context in Recommender Systems

Context-Aware Recommender Systems are Information Filtering systems that generate recommendations by exploiting the knowledge of the contextual situation encountered by a user while experienced and rated the item [36]. A context-aware recommendation algorithm predicts the rating of a user u for an item i under a context C that presents the user's current situation. Therefore, an accurate rating prediction should take into consideration real-time contextual situation under which the user asking for recommendation. Unlike two-dimensional

(2D) Recommender Systems that deal with *user-item* pairs to estimate the rating function R (see Equation (2.13)), CARSs incorporate the user's current context c (see Equation (2.14) and Figure 2.4).

$$R : User \times Item \longrightarrow Rating \tag{2.13}$$

Formally, in CARS the rating is modeled as the function of user u, item i and contextual attributes space C as follows:

$$R : User \times Item \times Context \longrightarrow Rating \tag{2.14}$$

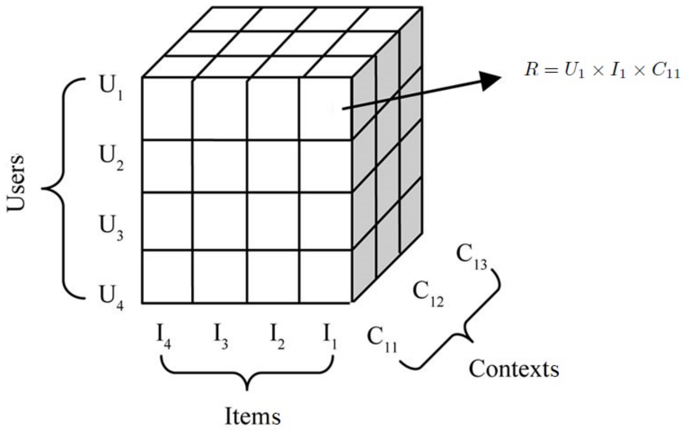


Figure 2.4: Schematic view of rating matrix in Context-Aware Recommender System.

The main interpretation of the notion of context adopted in CARS is provided by Bazire and Brezillon in [20]. They introduce the notion of context as all the information that characterizes the current situation of a user, an item, and the interaction between them while the user evaluating the item. The *contextual situation* refers to a combination of elementary *contextual conditions* that describe the context in which the user experienced the item. Specifically, in the literature, the terms contextual factors, dimensions, variables or attributes, refer to a particular type of the contextual information (e.g., location, weather, etc.) [5], while the term *contextual condition* refers to a specific value of this contextual information [52]. For example, for a tourism recommender system, the contextual situation: "today is cold, it is my first day in Madrid and I am alone at hotel", represents conditions that tend to increase the user's rating for indoor places like museums. Therefore, based on the context influence, recommending *Teatro Real* in Madrid for this user may suit the user's preferences under such circumstances. In general, the contextual situation includes any contextual information that may influence the user's perception of what is a relevant recommendation.

2.2.2.2 Main Paradigms of CARS

Recently, CARSs have been classified by [5] according to the way in which they incorporate contextual information into the recommendation process as follows:

- (i) *Contextual pre-filtering* approaches, which use contextual information to filter out irrelevant items and then use classical IF approaches to generate recommendations (see Figure 2.5.(a));
- (ii) *Contextual post-filtering* approaches, which exploit IF techniques to generate recommendations, and then re-rank the provided suggestions according to contextual information (see Figure 2.5.(b));
- (iii) *Contextual modeling* approaches, which make use of contextual information directly within the recommendation process to generate suggestions (see Figure 2.5.(c)).

In the following, we review the state-of-the-art CARS approaches following this classification proposed by [5].

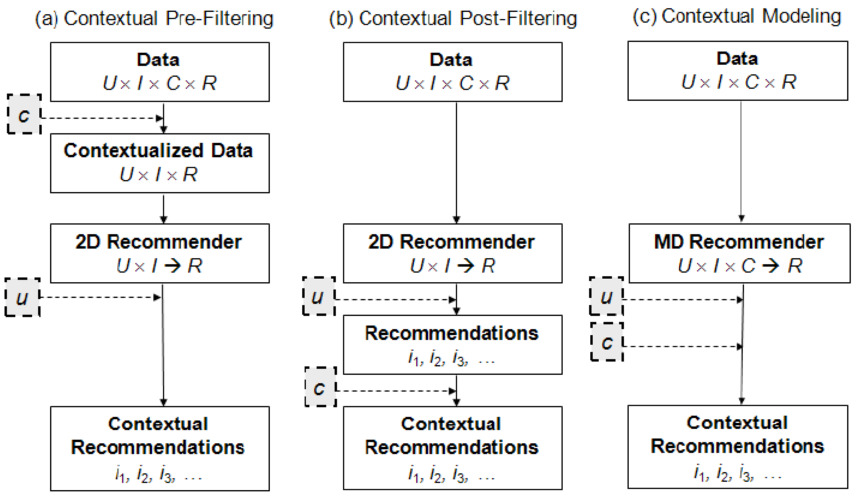


Figure 2.5: Main paradigms for incorporating context in Recommender Systems [5].

Contextual Pre-filtering Approaches The *contextual pre-filtering* paradigm uses contextual information to filter out irrelevant items/ratings before their incorporation in the recommendation process. Pre-filtering methods assume the context as a query for discarding rating data [5], and avoid the unnecessary recommendation of items that are not effectively usable by the user.

One of the earlier research using the pre-filtering paradigm was proposed by Adomavicius et al. in [2], which defines a *reduction-based* approach. The approach allows to reduce the multi-dimensional context-aware recommendation problem to a standard (2D) *user-item* space. The major benefit of such approach, is that all approaches on 2D recommendation can be applied for the multi-dimensional contextual recommendation. However, this approach builds a local context model for each situation using exactly the ratings provided with that situation. This method caused the rigidity of the approach, and assumed as its main limitation. To tackle this issue, Adomavicius et al. in [2] proposed the *generalized pre-filtering* method, which allows to generalize the contextual information using a context hierarchy, i.e., an optimal segments. In

[15, 16], Baltrunas and Ricci proposed another strategy among the pre-filtering paradigm. They developed the so-called *Item Splitting*, which dynamically discovers the contextual information relevant to each item. This approach splits an item rating vector into two virtual items. These virtual profiles can be generated if the two virtual items have significantly different ratings in different contextual conditions. The *Item Splitting* approach has been proved to provide more accurate rating predictions than the *generalized pre-filtering* approach, and it reduces the computational cost of the *reduction-based* approach [2].

Contextual Post-filtering Approaches The *contextual post-filtering* paradigm exploits contextual information after a non-contextual recommendation has been generated. The contextual information is used to adjust the recommendation, either (i) by filtering out recommendations that are irrelevant in a given contextual situation, or by (ii) adjusting the ranking of recommendations (i.e., top-k list) [5] according to the target contextual situation. Adomavicius and Tuzhilin [5] explored a classification of post-filtering approaches into *heuristic* and *model-based* techniques (see Figure 2.6). A specific example of a *model-based* technique was proposed in [142]. Panniello et al. [142] introduced a probabilistic post-filtering approach that predicts the ratings of an item by using a CF approach; then, the recommendations are adjusted by filtering out those ratings having a low probability to be relevant for the target user in a given context. Approaches based on *heuristics* focus on finding common item attributes for a given user in a similar context. The selected attributes are used to adjust the recommendations.

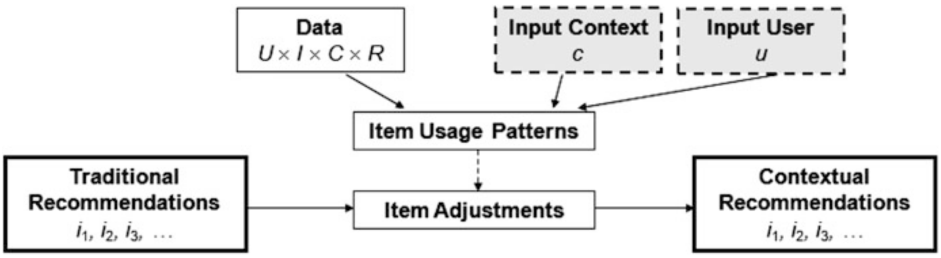


Figure 2.6: Final phase of the contextual post-filtering approach [5].

Contextual Modeling Approaches The contextual modeling paradigm explores the contextual information inside the recommendation algorithm. The contextual modeling paradigm gives rise to multidimensional recommendation functions by incorporating contextual information as part of rating estimation process [5]. In [2], Adomavicius and Tuzhilin extended two-dimensional (2D) neighborhood-based approach to the multidimensional model. The proposed approach incorporates the contextual information, by using a n-dimensional distance metric instead of the user-user or item-item similarity metrics traditionally used in CF approaches.

More recent works propose to fit the rating data to the context using regression models [14, 178]. The regression models including Tensor Factorization [106] allows to incorporate contextual information into the recommendation process by extending the two-dimensional Matrix Factorization (MF) problem into a multi-dimensional version.

Currently, several approaches have extended the MF for context modelling such as *Context-Aware Matrix Factorization* (CAMF) proposed by Baltrunas et al. [13, 14]. CAMF extends MF by using context-aware baseline predictors to represent the interactions of contextual information with both items and users. Similarly, several works proposed Matrix Factorization techniques through the context modeling paradigm [91, 106, 154, 177]. CAMF was proved to be effective in many contextual dataset including the Netflix data set [44, 52]. However, Matrix Factorization and regression models in general introduce a big number of model parameters that grow exponentially with the number of contextual factors. Thus, MF presents a main limitation related to its computational complexity.

Recent empirical analysis by Panniello et al. [141], demonstrated that none of the CARS paradigms uniformly dominates the others across all domains. This analysis was made to study the *pre-filtering*, *post-filtering* and *context modeling* approaches and to compare them to determine which one outperforms the others under which factors or experimental settings. This investigation demonstrates that three factors can affect the performance of CARS methods, including the context granularity, the recommendation task, and the recommendation data. Although no methods outperforms the others, a certain group of contextual modeling methods was proven, by Panniello et al. study, to constitute a reliable approach for CARS, due to their ability to provide balance of accuracy and diversity of contextual recommendations.

2.3 Summary

In this chapter, we introduced the theoretical background and the relevant concepts that form the basis of this thesis. We first gave an overview of Recommender Systems area. In particular, we explained recommendation techniques and we stressed upon the importance of user profile modeling for Content-Based Filtering approaches. Then, we introduced the basic concepts of Context-Awareness computing and main state-of-the-art Context-Aware Recommender Systems.

After covering the essential background related the contributions of this thesis, in the next chapter we will concentrate on the travel recommendation task for mobile users and we will discuss main context-aware approaches that have been proposed for the tourism domain.

CHAPTER 3

RELATED WORKS

This chapter presents an overview of the state of the art about Travel Recommender Systems. The main ideas, approaches, and research works in this field are presented, together with their pros and cons. Specifically, in Section 3.1, we detail and discuss the travel recommendation task, and the main research works that have been presented in the literature. Then, in Section 3.2, we present an overview on language modeling approaches, because language models will be employed in our recommendation approach.

3.1 The Travel Recommendation Task

With the increasing on-line availability of *Travel-Related services*, namely TR services, the development of *Travel* (or *Tourism*) *Recommender Systems* has become very popular for organizing tourist trips while offering a solution to the *information overload* problem [188]. The recommendation of TR services is a task that attempts to support tourists in taking decisions and find relevant services from a large pool of unseen services and/or Point of Interests (POI)s according to their needs. Several Travel Recommender Systems have been proposed over the last years [123]. Most of them are reviewed in [74] and classified according to the offered tourism and leisure services. Travel RS can offer several types of items, such as attractions (POIs) [34, 107], Travel-Related services (restaurants, hotels, transportation services, etc.) [92, 160, 201], routes and tours planning services [150, 193], etc.

3.1.1 Characteristics and Issues of the Tourism Domain

Tourism is a major application area of Recommender Systems. However, as reviewed in [41], this domain has specific characteristics that should be considred when developing a travel RS, thus are:

- *Preference stability* [41]: it indicates the Travel RS ability to consider that the user's preferences evolve over time and have varying degrees of duration. According to [41], the tourism domain is highly concerned with the problem of preference instability (i.e., the user's preferences are affected by the changing contexts) which can be improved through CARS approaches [5].

- *Ubiquity* [157]: it indicates the Travel RS ability to deliver information to mobile users wherever they are, and whenever they need [157]. Due to the advances in mobile technologies, tourists increasingly rely on their smartphones to accomplish various tasks. In particular, tourists are increasingly employing their smartphones to obtain right information 'anytime and anywhere'.

- *Social Influence* [209]: it indicates the Travel RS ability to analyze social information in order to understand the user's interests and practices. In particular, social media plays a significant role in the user's travel-related decisions, especially on-line. Smartphones allows to generate and share a large portion of User-Generated Content, which represents a digital Word-of-Mouth and influences the user's purchase decisions.

- *Heterogeneity* [41]: it indicates the Travel RS ability to consider the fact that the mobile environment requires the use of dynamic set of items that fit in real-time the changes in the user's contextual situation. Hence, the item space is heterogeneous and encompasses many items with different features.

Among the many challenges that can be encountered in the deployment of a Travel RS, the 'data sparsity' problem is one of the main issues that have to be considered. In fact, in the tourism domain, the item space is very large. In addition, even the most active users can only rate a small subset of the available touristic items. More specifically, the number of user's ratings is small in comparison with the total number of items, which causes the 'data sparsity' problem. Hence, the recommendation model should make use of the ratings implicitly inferred from external information sources such as social knowledge (i.e., reviews, tags, likes, etc.) and context knowledge.

In addition, another characteristic to be taken into account is that a mobile user's attention is quite limited, and therefore s/he cannot be engaged in complex tasks that need complicate interaction with the systems interface. Hence, a good travel recommendation methodology should deliver personalized recommendations, while creating at the same time a positive user experience [111]. For this reason, a good Travel RS has to improve the usability of its interface while coping with the information overload problem.

To resume, as discussed in [59], the choice of a touristic destination and/or TR service is strictly related to the user's personal interests and preferences. In addition, under the changing context, the user's preferences become unstable in the tourism domain. This requires building a generic user model that scales with different types of input data. Table 3.1 shows the user model instantiation in a travel recommender system.

Table 3.1: User Model instantiation for travel recommendation.

Demographic information	Age, job, salary rang (to estimate the traveler budget, e.g., high spender)
Goal's existence and nature	In tourism domain, the user's goal is likened to the travel goal. We distinguish between business, health care, education, social event, landscape, fun, sport, religion, visiting friends. All of these goals have different impact on user's preferences.
Level of expectation	high: inaccurate recommendation could be detrimental for the user's usage of system. In travel the recommender is considered central to the user's travel-related decision
Change of expectation over time	yes: expectations of users increase and changes because of the capabilitis of modern mobile devices. Users expect to get the right information whenever and wherever they are.
Importance of user situation	high: the changing contexts affect the tourists' satisfaction and preferences.
Social environment	S/he can be alone, with friends/colleagues, with family, with girlfriend/boyfriend, with children
Trust and privacy concerns	Considered: for example, if the user's receive a poorly rated hotel as a suggestion, such recommendation could be detrimental for the user's trust in system.

3.1.2 Web-based Approaches to Travel Recommender Systems

In the early works, Travel RSs have been developed as an intermediary between tourists and travel agencies [123], or tourist guides that aim to facilitate the tourist decision-making process [208]. Several content-based recommendation approaches focused on the matching between personal preferences against all the available Travel-Related services, for example [29]. Early research efforts in this domain [123, 156] required an explicit interaction of the user with the system, by providing her/his preferences, needs, characteristics and even by exchanging textual messages [123].

In [195] for example, the *CityTrip* planner was proposed to visit five cities in Belgium. This system is essentially a tourist guide that provides a brief questionnaire to users, trying to obtain this way their preferences and constraints. Nowadays, many popular social media or e-tourism Websites develop their own RSs for hotels, restaurants, museum or other POIs recommendation, such as TripAdvisor,[1] or DieToRecs.[2] These on-line platforms also contain social component allowing users to review and rate the systems' suggestions. Some popular travel Web agencies such as Expedia[3] and Trippy[4] use social components (e.g., the average ratings of other users) as an informative data for collaborative recommendation [4] to support tourists in their trip planning. Nevertheless, traditional recommendation purposes in the tourism domain need to be improved, because during a trip the user will be confronted with a large amount of possible combinations of locations, events and activities.

[1]http://www.tripadvisor.com/
[2]http://www.isi.edu/integration/Heracles/
[3]http://www.expedia.com
[4]http://www.trippy.com/

3.1.3 Mobile Travel Recommender Systems

Recently, smartphones offer an environment for a multitude of services giving rise to the field of *mobile tourism* (namely *m-Tourism*), which represents a steadily growing economy [183]. According to Kenteris et al. [107], "the concept of *mobile tourism* has recently emerged wherein users access tourist content through mobile devices". As a consequence, Mobile Recommender Systems have become very popular in the tourism domain [34, 74].

For instance, in [19], *Turist@*, a mobile recommender system for tourism activities, has been proposed. The *Turist@* system exploits the built-in GPS receivers of smartphones to track the position of users. Then a pro-active recommendation is provided when a user is near an interesting activity, based on a distance calculation between the user's position and the activity's location. In [204], the mobile recommender system *iTravel* was proposed. *iTravel* merges a collaborative filtering method with a mobile peer-to-peer network architecture (Bluetooth or Wi-Fi Direct) to provide on-tour travel attractions. Three techniques for data exchange have been developed in *iTravel* to the aim of exploiting neighbors (similar users) evaluations in computing the recommendations for the active user.

Gavalas and Kenteris [72] proposed a mobile tourist guide namely *MTRS* which uses a collaborative filtering based recommendation method. *MTRS* uses wireless sensor network around tourist sites, allowing tourists to upload and share their feedbacks (i.e., ratings) about POIs via their smartphones. Braunhofer et al. [34] presented a mobile Context-Aware Recommender System, named *South Tyrol Suggests* (STS), that leverages weather context in addition to various contextual factors for providing relevant recommendation in tourism domain. The *STS* mobile recommender system takes into account the weather, season, budget, day-time, companion, mood, travel goal and more conditions, to recommend POIs in South Tyrol (Italy).

3.1.4 Context-Aware Approaches to Travel Recommender Systems

Context-awareness is the predominant aspect that has to be considered in travel recommendation due to the richness of available contextual information [13, 14, 119]. For instance, when considering a new destination, the tourist will be confronted to specific constraints that should be taken into account to provide accurate recommendation, e.g., climate change, food constraints (vegetarian, halal, etc.), transportation issues, etc. In this scenario, *Context-Aware Recommender Systems* (CARS)s extract hidden dependencies between the current contextual situation and the user's preferences to adapt the recommendations to the tourists' needs.

An interesting aspect, that emerges when addressing the problem by using CARS for travel recommendation, is the availability of a multi-dimensional model of context, since several dimensions can be incorporated into the recommendation process. As represented in the TREC Contextual Suggestion track [5] [60], the tourists' context includes several contextual information that may affect tourists' satisfaction: the city where the trip will take place, the trip type (e.g., Business), the trip duration (e.g., Weekend trip), the type of group the person is travelling with (e.g., Travelling with a group of friends as "Friends"), and the season the trip will occur (e.g.,

[5] https://sites.google.com/site/treccontext/trec-2016

summer). Although these contextual information have been used differently in the literature [5], they have been integrated in RSs to optimize the prediction accuracy, and to improve the quality of recommendation [161].

Location-Aware Recommender Systems In the early work, the concept of context was initially referred only as the geographic location, which made *Location-Aware Recommender Systems* (LARS)s the more widespread context-aware RSs [118, 204]. The location was mostly considered to provide tourist tours [19, 47], nearby shops [204], restaurants [194], and cultural POIs [7]. For instance, in [92] a collaborative filtering method has been proposed for restaurant recommendation, where location was the key context information for generating recommendations. In the last years, there has been an attempt to exploit social media content such as photo tags in Flickr,[6] or Del.icio.us,[7] to identify the user's location and to predict next places to visit according to it [94, 149]. For instance, in [149] the geo-tagged photos have been used to make inferences about users' behaviors in specific location.

Location presents an important contextual information that allows to many social platforms to enhance their services and recommendations. However, the main limit of LARSs is that they favor items geographically closer to the target users, and ignore other several contextual information (e.g., weather, time, surrounding people, etc.) that can be modeled and utilized to enhance the recommendation accuracy.

Social Context for Travel Recommendation In the last years, many researchers have proposed methods to recommend travel destinations by means of the user preferences inferred from social media [38, 168, 171].

The Travel Recommender System *I'm feeling LoCo* [168] merges contextual information inferred from a user's social network profile and her/his mobile phone's sensors for place discovery. In [207], the authors exploit the 'check-in' data to provide a time-aware POIs recommendation. They recommend POIs to a given user at a specific time in a day. Similarly, in [171], Sebastia et al. propose a travel RS that provides the tourist with a list of the places that are likely to interest her/him. This RS employs the user's demographic information, time, activities, likes and preferences from previous trips, as well as from the current trip. TripBuilder [38] is a POI recommendation system which explore data shared on Flickr including itineraries of different tourists. It provides a set of POI destinations to be visited and an optional set of POIs not to be visited. In [47], the *PlanTour* system has been proposed that creates personalized tourist plans based on User-Generated Content extracted from the traveling social network MINUBE [8].

Recently, several works on Travel RS focused on modeling and exploiting multiple contextual information such as [34–36]. Braunhofer and Ricci [36] proposed a CARS for travel recommendation, a solution that relies on matrix factorization-based prediction model to generate rating predictions under various contextual conditions, i.e., time, location, weather, season, budget, mood, trip goal, etc. To resume, the wide spectrum of CARS that have been proposed

[6] https://www.flickr.com/
[7] https://del.icio.us/
[8] www.minube.com

over the last decade in the travel recommendation scenario offers a context modeling that encompasses *location-aware* [94, 118, 144, 204], *time-aware* [139, 207], and *multi-dimensional* CARS [36, 157, 193].

3.1.5 Limitations of Travel Recommendation Approaches

In Table 3.2, different Travel Recommender Systems are summarized, with respect to different characteristics. As it emerges from the table, the contextual information, mobility and social data have been extensively utilized as a mean for reducing information overload and offering personalized tourism recommendations. These works are compared with respect to our proposal, based on the considered contextual information and on the different recommendation methods previously introduced (see. Section 2.2.2.1), i.e., contextual pre-filtering, post-filtering, and modeling.

Although the Travel Recommender Systems summarized in Table 3.2 allow a 'good' personalization of recommendation outcomes, they present different weaknesses. In particular, they take into limited consideration the user's opinions (i.e., her/his likes and dislikes) expressed differently from one domain to another. The variety of Travel-Related services such as restaurants, accommodations, flights, and cultural point of interest, causes a variety and multitude of ways in which tourists express their needs and preferences. Actually, smartphones users may be different with respect to their opinions, background knowledge, the way of expressing their requirements, or the language employed (a fundamental aspect that is taken into consideration in this paper). For this reason, using only context-aware filtering techniques can be inappropriate when trying to make travel recommendations for multiple service categories at the same time [25].

To eliminate such downsides, the work presented in this thesis is closely related to the main trends and research for the next generation of Recommender Systems in the tourism domain. More specifically, our approach detailed in Chapters 5 and 6, we tackle the previous discussed issues by exploiting both contextual information and the user's interests inferred from social content. In order to consider the user's interest, we focus in the content generated by the user herself/himself in the form of online reviews. This way it is possible to extract the user's topical interests and model the user profile. The online reviews are textual data, hence, the user modeling needs a prior step to extract keywords. In the next section, we provide a brief introduction to language modeling techniques that allow text representations and has been applied successfully in a many fields such as RS and user profile modeling.

3.2 Language Modeling

A statistical *Language Model* (LM) is a probabilistic model that has been successfully applied in different research fields such as Speech Recognition, Machine Translation and Information Retrieval.

Table 3.2: Comparison of the proposed approach against related work approaches. Context-Aware approaches: Pre: pre-filtering; Post: post-filtering; CM: Context modeling. Filtering algorithm: CBF: Content-Based Filtering; CF: Collaborative Filtering.

Work	Items and Services recommended	Method		CA Approach			Contextual Information	Architecture
		CBF	CF	Pre	Post	CM		
CATIS (Pashtan et al., 2003) [145]	Restaurants, hotels	✓					User location, time of day, speed, direction of travel and personal preferences	Web-based
CRUMPET (Poslad et al., 2001) [150]	Travel tips, tour suggestions	✓					User location, visited POIs	Web-based
MobiDENK (Krosche et al., 2004) [114]	Monuments					✓	location	Web to mobile
MTRS (Gavalas and Kenteris, 2011) [72]	POIs		✓	✓			User location, time, weather, user's mobility history, peer users ratings	Web-based
I'm feeling LoCo (Savage et al., 2011) [168]	Restaurants, hotels, bars, walking trails	✓					User location, user preferences, transportation mode, user's mood	Web-based
MobyRek (Ricci and Nguyen, 2007) [160]	Restaurants	✓	✓		✓	✓	User location, critics, restaurant information (location, average cost, opening days)	Web-based
iTravel (Yang & Hwang, 2013)	On-tour attraction		✓	✓			User location	Web-based
STS (Braunhofer and Ricci, 2013) [34]	POIs		✓	✓			Weather, season, budget, mood, transport, companion	Web-based
Turist@ (Batet et al., 2012) [19]	Tourist attraction	✓	✓	✓			User location	Web-based
PlanTour (Cenamor et al., 2017) [47]	Tourist plans, restaurants, POIs		✓			✓	User location, time, User preference	Web-based
eTourism (Sebastia et al., 2009) [171]	Tourist plans, list of activities	✓			✓		User tastes, time, activities(duration, opening hours, location)	Web-based
MobyRek (Ricci and Nguyen, 2007) [159]	Restaurants	✓	✓			✓	User location, critiques, restaurant data	Web-based
PECITAS (Tumas and Ricci, 2009) [193]	Public transportation, routes	✓					User location, travel preferences	Web-based
DailyTRIP (Gavalas et al., 2012) [73]	Multiple-days tour planning	✓					User location, travel preferences, time	Web-based
(Bouzeghoub et al., 2009) [33]	Events, buildings, available resources	✓				✓	User location, preferences	Web to mobile
YummyKarachi (Qureshi et al., 2014) [152]	Restaurants		✓			✓	Location, Tweets	Web to mobile
Proposed Approach	Restaurants, health, shops, attractions	✓		✓			User location, user preference, user generated content	Web to mobile

3.2.1 Basic Concepts

Language Models are used to represent textual data. A Language Model assigns a probability distribution to words that appear in a text. This probability determines how likely a word w occurs in an indexed vocabulary V [56]. That is, for a Language Model M over a vocabulary V:

$$\sum_{w \in V} p(w) = 1 \tag{3.1}$$

where $p(w) \geq 0$ is the probability of occurrence of $w \in V$. The probability $p(w)$ is calculated as follows:

$$p(w) = \frac{count(w)}{count(V)} \tag{3.2}$$

where $count(w)$ denotes the frequency of occurrence of word w in V, and $count(V)$ is the total number of words in V. This reformulation represents a simple kind of language model which is the '*unigram*' model. The *unigram* language model can be treated as the combination of a finite automaton that consists of a single node with a single probability distribution over the entire vocabulary of the model, so that $\sum_{w \in V} p(w) = 1$ [128]. In this model the $p(w)$ of a word depends on that word's own probability occurring in the vocabulary for which previous words has no impact. In an *n-gram* model, the LM allows to predict the next word in a sequence on the previous $n-1$ words [49]. If we treat a sentence W that can be formed by using a sequence of words $w_1, ..., w_n$, then, the probability of observing W is $p(W) = p(w_1, ..., w_n)$, which can be formally expressed as follows:

$$p(w_1, ..., w_n) = \prod_{i=1}^{n} p(w_i | w_1, ..., w_{i-1})$$

The *bigram* (n=2) and *trigram* (n=3) are the most common *n-gram* language models employed.

3.2.2 The Query Likelihood Model

Language Models have been successfully applied in *Information Retrieval* (IR) since their introduction by Ponte & Croft in 1998 [148]. In IR, the relevance of a document D with respect to a query Q can be seen as the probability of producing the query terms from the document language model. Several approaches have been proposed to estimate this probability. The most common is the *query likelihood model* [148] estimated as follows:

$$P(Q|D) = \prod_{w \in Q} P(w|D) \tag{3.3}$$

where w is a query word and $P(w|D)$ is the probability of w within the document language model. Estimating $P(w|D)$ can be establish using the maximum likelihood $P_{ML}(w|D)$ of individual words estimated as follows:

$$P_{ML}(w|D) = \frac{nocc(w,D)}{|D|} \tag{3.4}$$

where $nocc(w,D)$ denotes the frequency of the word w within the document D, and $|D|$ is the total number of words in that document.

In this model a query word w that does not occur in D has a $P(w|D)$ equal to zero, making the overall score $P(Q|D)$ zero. To address this zero probability problem, a number of smoothing techniques (Jelinek-Mercer [99], Dirichlet [127] or Absolute discount [137]) have been proposed. These methods assign a nonzero probability to unseen query words in documents. Smoothing methods adjust low probabilities. They make an adjustment of the maximum likelihood estimator of a language model to be more accurate. For example, using the Dirichlet prior smoothing method, the maximum likelihood is calculated as follows:

$$P_{ML}(w|D) = \frac{nocc(w,D) + \mu \frac{nocc(w,C)}{\sum_w nocc(w,C)}}{\sum_w nocc(w,d) + \mu} \tag{3.5}$$

where $nocc(w,C)$ represents the frequency of occurrence of the word w in the collection of documents C. μ represents a smoothing parameter in the interval $[0,+\infty[$.

By using Language Models it is possible to address well known problems in Information Retrieval, such as polysemy and synonymy, by considering dependencies such as n-grams, word relationships or phrasal-concepts.

3.3 Summary

This chapter covered important related works with regards to the contributions of this thesis. We focused on mobile and Context-Aware approaches to Travel Recommender Systems. First, we explained various aspects of the travel recommendation area. We highlight main challenges concerning the development of Travel RSs. Second, we discussed the importance of user profile modeling for travel recommendation. Then, a broad overview of various approaches that consider the contextual information and the social media content for travel recommendation have been discussed. Works related to utilization of mobile RS techniques, in particular, were covered. In the last part of the chapter, we focused on Language Modeling. We discussed basic concepts and the query likelihood model since they will be used in Chapters 4 and 5, respectively, to the aim of search re-ranking and user profile modeling.

CHAPTER 4

A Context Modeling and Acquisition Method for Mobile Search

In this chapter, we address the issue of context modeling and acquisition to improve mobile search systems. In respect with the first challenge discussed in Section 1.3 (Chapter 1), we proposed a novel context acquisition method that deems a contextual information as relevant if it has an impact on the user's preferences. First, we provide a formal context model that explores the *Context Modeling Language* (CML) technique to model contextual factors and their metadata. Then, we propose a selective context acquisition method. The proposed method was instantiated to the mobile search domain which allows to estimate the relevance of contextual factors with respect to the user's need formally sketched in a query.

4.1 Introduction and Motivations

With the improvement of the mobile technology and smartphones capabilities, contextual information can be gathered from a variety of sources. Consequently, the integration of contextual factors into mobile search systems is a natural fit. Recent research has increasingly assumed that developing context-aware applications should be supported by adequate context information modeling techniques [205]. Most recent research has focused on modeling multiple contextual information. Therefore, many context models have been developed. They range from early simple, flat models [166, 191] to more sophisticated and complex models such as ontological models [48, 83]. However, the granularity and the type of contextual factors that may effect the effectiveness of the retrieval process are still open issues. Existing approaches such as [30, 79, 93, 185] proposed to meet mobile user's information needs by exploiting a multi-dimensional user's context (e.g., time, location, season, weather, companion). They are taking for granted that context matters, i.e., that the relevance of an information is sensitive to several contextual factors. Few works such as Bouidghaghen and Tamine [30] discuss the mobile queries dependency to the user's context. They define five types of query dependency: *interests-based query*, *location-based query*, *time-based query*, *situation-based query* and *conversation-based query*. This classification is not restrictive and the context can influence the query as it may not have any impact on the user's information need (i.e., query). Most existing mobile search systems adapt the retrieval process automatically to the current contextual situation, without underlying the relevance of each factors, which can result in inaccurate information. Thereby, an initial issue is the assessment of contextual factors relevance [14, 100]. We illustrate the raised issue with the following example: Let u be a mobile user who is planning for a business trip. S/he submits a search query Q to the mobile search engine.

– Q is "*hotel Vienna*".

The user's current context F includes a set of contextual factors that are:

– Task: planing a business trip;

– Activity: searching;

– Time: Weekend;

– Location: Home;

– Companion: Family.

The query Q is short and ambiguous, so, the mobile search system incorporates the contextual factors to provide accurate results. If the search system considers the 'Family' factor, the search results will include inaccurate information such as: *10 best family resorts*. Hence, the contextual factor 'Family' is a noise leading to biased search results. Clearly, not all of the contextual factors are relevant for contextualizing the search process. Obviously, context-aware applications should be supported by adequate context information gathering and reasoning techniques. In [108, 184, 216], it is shown that providing relevant search results depends not only on the choice of the contextual retrieval process, but also on the quality of the incorporate contextual factors. The noise injected in a context model affects the accuracy of the produced results. The problem of selecting appropriate contextual factors remains a challenging problem that we address in this chapter.

In this thesis, we address the issue of selecting relevant contextual factors that should be acquired to enhance the contextual retrieval process. In summary, we apply a selective context acquisition method, which estimates the relevance of a contextual factor by mean of a new metric measure namely *"Context Relevance"*. The proposed measure estimates the deviation of the user's predicted preference for a document if the system considers or not a specific contextual factor. The method then dynamically selects the contextual factors to be integrated in the search process. The selected contextual factors are those that improve the search system accuracy.

4.2 The Proposed Method

We provide a context modeling and acquisition method that deems a contextual factor relevant to be elicited, if: (i) it is related to the user's query and (ii) influences user's preferences. Therefore, we propose a two steps method that includes:

- An effective context model: that formally represent the contextual factors;
- A context acquisition method: that selectively gathers relevant contextual factors.

4.2.1 Context Model

We provide a context model that allows to capture and present the contextual factors and relations between them. we adopt the *Context Modeling Language* (CML) technique [89] derived from Object Role Modeling (ORM) [26]. CML is a powerful approach for context modeling that allows to capture the pertinent object types and relationships between them. It reduces the application complexity level.

Our proposed model describes the common contextual factors that can highly influence the user's preferences and behavior. We define five dimensions of mobile user's context including *Location*, *Time*, *Task*, *Activity*, and *Surrounding people*. As shown in Figure 4.1 the CML-based context model allows to define dynamic mappings between users and entities implied in their context. Moreover, it encompasses relationships between entities (i.e., mobile user, surrounding people), and their activities, which provides a good explanation of the user's context.

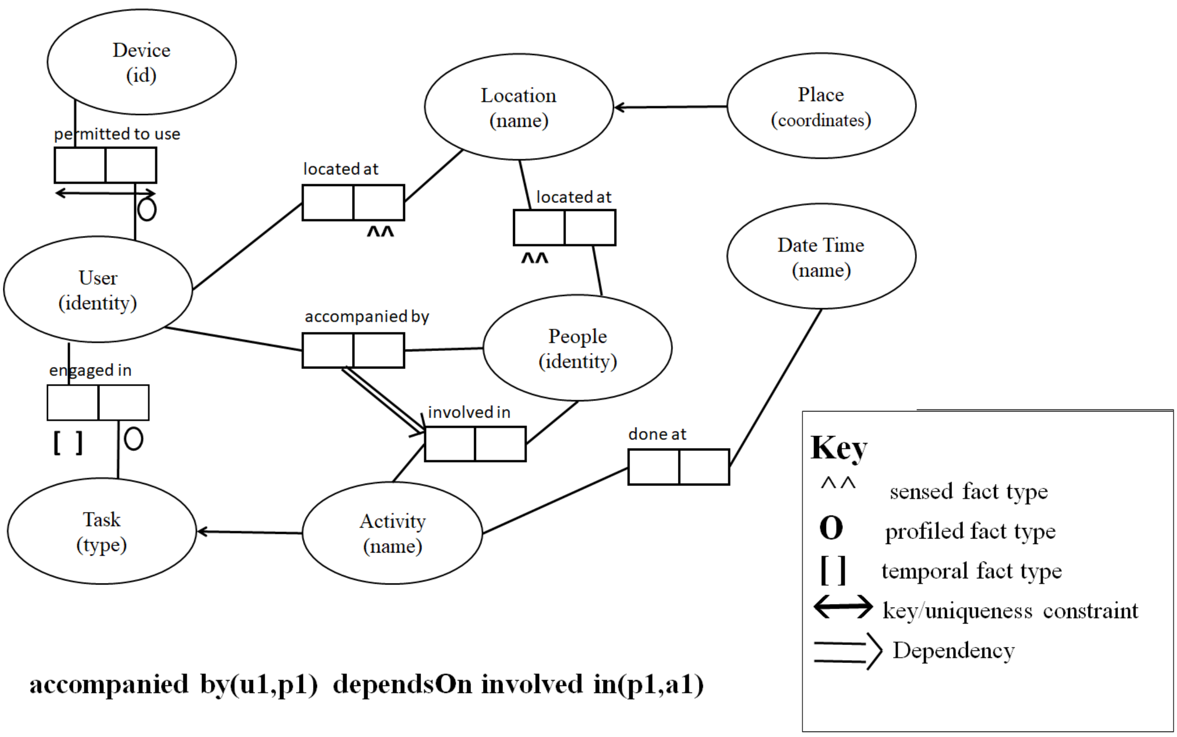


Figure 4.1: A CML model for a mobile user.

We adopt a specific interpretation of the context model, which introduces the situation of a mobile user following the representational view of context discussed in Section 2.2.2. To illustrate our model (see Figure 4.1), let U_1 be a mobile user's and F designs her current context. F denotes the contextual situation that encompasses a set of contextual factors $F = \{f_1, ..., f_n\}$. We instance the model with five factors: **People**, **Task**, **Activity**, **Location**, **Place**, **Date Time**. The contextual factors are designed as objects which undergoes a fact: ***engaged in, located at, done at, surrounded by*** from another object in the same context. In the proposed model we define a primary dependency as follows:

- ***accompanied by*** depends on ***involved in***: which means that for a user u_1 to be ***accompanied by*** a people p_1, p_1 should be ***involved in*** the same activity a_1 realized by u_1 at location l.

Each contextual factors $f_i \in F$ can be considered as *Relevant* or *Irrelevant* depending on their influence on the user's preferences.

4.3 Context Acquisition Method: Instantiation to the Mobile Search Domain

In this section, we detailed our selective context acquisition method. The proposed method aims to identify and acquire the relevant contextual factors that influence the user's perception of what is a relevant information.

Relevant contextual factors are selected according to their impact on both: (i) the user's information need formally sketched in a query; and (ii) the user's preferences. More specifically, we measure the impact of each dimension on mobile queries performance according to two statistical language models:

(1) Query Language Model,

(2) Preferences Language Model.

4.3.1 Query Language Model

The language modeling approach in Information Retrieval models depict a document as a language sample generated according to some probability distribution of word sequences [210]. The relevance of a document d with respect to a query Q is seen as a probability of generating the query from the document language model [55]. Then, documents are ranked in the document collection according to their likelihood of having generated the query. Using this ranking, a *query language model*, $P(w|Q)$ is built out of the top-k documents D [31, 57]. Formally:

$$P(w|Q) = \sum_{d \in D} P(w|d) \frac{P(Q|d)}{\sum_{d' \in D} P(Q|d')} \quad (4.1)$$

where w denotes a word. We adopt a *query language model* to estimate the relevance of a contextual factor. More specifically, we estimate the sensitivity of a query to the contextual factors using the *query language model*. Formally, given a user U, who submits a search query Q in a contextual situation F, we adopt the following process:

- Initially, the documents in the collection C are ranked under the language model framework [148] using the query likelihood retrieval function (discussed in Section 3.2).
- The top-k documents D from the initial result set are used to build the *query language model* $P(w|Q)$.
- The query Q is then reformulated with the the contextual factor $f_i \in F$.
- The reformulated query Q_i is used to reproduce a new ranking list.
- The top-k documents D_i from the new list are used to estimate a *query language model* $P(w|Q_i)$ for Q_i.
- The divergence between $P(w|Q)$ and $P(w|Q_i)$ is estimated to identify the content-based relevance of the contextual factor f_i.

We estimate the divergence between $P(w|Q)$ and $P(w|Q_i)$ within the language model based on Kullback Leibler divergence [115] as follows:

$$RVS_{content}(f_i,Q) = D_{KL}(P(w|Q_i) \| P(w|Q)) = \sum_{w \in W} P(w \mid Q_i) log \frac{P(w \mid Q_i)}{P(w \mid Q)} \tag{4.2}$$

4.3.2 Preferences Language Model

We are interested in estimating the impact of the context on the user's preferences. We measure the ability of a contextual factors to enhance search results in response to the user's preferences. We measure "preference language model" of a query Q before and after reformulating it with the contextual factor f_i. By analogy with the query language model described above, we define a *preferences language model* as:

$$P(Pre|Q) = \sum_{d \in D} P(Pre|d) \frac{P(Q|d)}{\sum_{d' \in D} P(Q|d')} \tag{4.3}$$

Where Pre is a user's preferences or topical interests presented as a bag of words in a database, for example, $Pre = Art$, $Pre = Jazz$, $Pre = Music$, etc.

$$P(Pre|d) = \begin{cases} 1 & \text{if } Pre \in Pre_d \\ 0 & \text{otherwise} \end{cases}$$

We smooth the maximum likelihood models $P(Pre|Q)$ using the distribution of terms Pre over the collection C as a background model. Formally, the distribution $P(Pre|C)$ is defined as follows:

$$P(Pre|C) = \frac{1}{|C|} \sum_{d \in C} P(Pre|d) \tag{4.4}$$

The *preference query model* is estimated using the Jelinek-Mercer smoothing method [49] as follows:

$$P(Pre|Q) = \alpha P(Pre|Q) + (1-\alpha)P(Pre|C) \tag{4.5}$$

Following the same process defined in 4.3.1, we estimate the divergence between the *preferences query models* for the query Q and the reformulated query Q_i. This divergence represents the *preference-related relevance* of a contextual factor f_i and it is estimated as follows:

$$RVS_{preferences}(f_i,Q) = D_{KL}(P(Pre|Q_i) \| P(Pre|Q)) = \sum_{Pre \in W_{pre}} P(Pre \mid Q_i) log \frac{P(Pre \mid Q_i)}{P(Pre \mid Q)} \tag{4.6}$$

where W_{pre} denotes the bag-of-words representing the user's preferences.

4.3.3 Context Relevance Measure

We introduce a new measure namely *Context Relevance Score* that allows to estimate the relevance of a contextual factor. It estimate the effectiveness of the contextual factor at enhancing the mobile query. Our proposed measure linearly combines the $Preferences - related Relevance(f_i,Q)$ and the $Content - based Relevance(f_i,Q)$ as follows:

$$Relevance(f_i,Q) = \beta D_{KL}(P(Pre|Q_i) \| P(Pre|Q)) + (1-\beta) D_{KL}(P(w|Q_i) \| P(w|Q)) \tag{4.7}$$

This relevance is normalized on $[0,1]$ interval. To acquire the set of relevant contextual situation F_{rel}, we experimentally define a threshold value λ. A relevant contextual factor f_i must have a relevance degree that goes beyond λ, otherwise it is considered as irrelevant. Then, the n factors with highest estimated Relevance are selected to enhance the retrieval process. We notice that a query Q could be sensitive to one or many contextual factors simultaneously.

4.3.4 Context-based Re-Ranking Module

Our approach consists of exploiting relevant contextual factors as a source of evidence to be taken into account in the re-ranking model. We follow a strategy in which non-contextualized search results returned from a search system are re-ranked with the help of the relevant contextual factors to return results that are more relevant to the user.

We rely on language models to combine topical relevance of a given document to a query and its contextual relevance modeled as a linear score. Formally, given a query Q and the set of relevant contextual factors F_{rel}, a re-ranking score for the initial set of retrieved documents D is estimated as follows:

$$Score_{re-rank}(d,Q,F) = P(f_i|d) + P(d|Q) \tag{4.8}$$

where $P(d|Q)$ is estimated using the maximum likelihood estimation approach [148] (see Section 3.2 in Chapter 3 for more details). We exploit language models to estimate the contextual relevance of a document d $P(f_i|d)$ as follows:

$$P(f_i|d) = \frac{nocc(w_{f_i},d) + \mu \frac{nocc(w_{f_i},D)}{\sum_{w_{f_i}} nocc(w_{f_i},D)}}{\sum_{w_{f_i}} nocc(w_{f_i},d) + \mu} \tag{4.9}$$

Where w_{f_i} words represents the contextual factors f_i. For instance, if f_i is the location *Tunis*, w_{f_i} is a bag of words that includes terms such as *sidi-bousaid, Marsa, carthage*, etc. $nocc(w_{f_i}, d)$ denotes the frequency of occurrence of the word w_{f_i} in the document d. $nocc(_{f_i}, D)$ represents the frequency of occurrence of the word w_{f_i} in the set of retrieved documents D. μ represents a smoothing parameter in the interval $[0, +\infty[$.

In summary, more higher the $Score_{re-rank}$ is, more the document is considered as relevant to the user's intent given her current context. Finally we re-rank documents belongs to D in descending order of $Score_{re-rank}$.

4.4 Experimental Evaluations

In this section we describe the performed experiments and discuss the results. To evaluate our approach, we conducted a series of experiments on real-world dataset. We compared our contextual search, which takes into account the relevance of contextual factors, with the baseline formed by only topical relevance. Our goals in these experiments are:

- to evaluate the effectiveness of relevance contextual information acquisition method.
- to evaluate the impact of acquisition method on search accuracy.

4.4.1 Dataset

For the experiments reported in this chapter, we used a real-world dataset which is a fragment submitted to the America Online search engine. We had access to a portion of the 2006 query log of AOL[1]. The statistics of these data are displayed in Table 4.1.

Table 4.1: Statistics about the dataset.

Statistics	Quantity
Number of users	1730
Number of queries	2000
Number of context factors	7896
Sparsity	0.042

We had relied on three experts in the field of Information Retrieval to pick manually 2200 initial set of queries based on the signification of their terms. Experts selected queries which may be related to the user's search context. After a filtering step to eliminate duplicate queries, we obtained a set of 2000 queries, where four contextual factors (i.e., Date time, Location, Place and Activity) are assigned to each query. This process allows simulating the user's current contextual situation. More details about the contextual factors used in our experiments are given in Table 4.2.

To obtain the top-k documents that match each query, we used Lucene Apache.[2] We considered only the first 30 retrieved results to build the initial set of documents D_0. This

[1] http://www.gregsadetsky.com/aol-data/
[2] https://lucene.apache.org/core/

amount of results is reasonable for a mobile users, who are not likely to scroll through long lists of retrieved results. Then, for each query in the data set we classified manually their related contextual factors. Each factor is associated to a label to indicate whether it is relevant or irrelevant. The criterion to assess the relevance of a contextual factor, is based on whether a mobile user expects to see search results, dependent on the contextual factor, ordered high on the retrieved results list or not. For instance, for a query such as "*weather*" the user can express her intention to see search results related higher to Location and Time factors. So, these factors are judged relevant. These steps left us, in our dataset, with 65.6% relevant and 34% irrelevant contextual factors.

Table 4.2: Type of contextual factors in our dataset.

Contextual Factor	Value
Location	Home,Work,Out
Place	City name
Date Time	Morning(7:00-11:00), Noon(11:00-14:00), Afternoon(14:00-18:00), Evening(18:00-21:00), Night(21:00-Next day 7:00)
Activity	Traveling, in a business trip, working, in a conversation, attending a meeting, shopping.

4.4.2 Evaluation Procedure and Baselines

We have performed an off-line experiment aimed at simulating as closely as possible the user's behavior in a mobile contextual situation. We have simulated user-system interaction, i.e., the relevance of contextual factors have been assessed manually by domain experts. First, we randomly partitioned all available data into two subsets in the ratio: 80% as training set and 20% as test set. Then, we evaluate and compare the proposed context acquisition method based on its precision performance. The precision of the method at selecting relevant contextual factors has been evaluated by comparing its result to the classification made by the experts. Therefore, for a given pair user-query we denote by:

- *true positive* (TP): the contextual dimension labeled relevant in the dataset and classified as relevant (by the proposed method),
- *false negative* (FN): the contextual dimension labeled relevant in the dataset and classified as non-relevant.
- *false positive* (FP): the contextual dimension labeled non-relevant in the dataset and classified as relevant by our approach.

- *true negative* (TN): the contextual dimension labeled non-relevant and classified as non-relevant.

This classification allows computing the Precision, Recall, and Accuracy measures with respect to the identification of relevant contextual information as follows:

$$Precision = \frac{TP}{TP+FP}$$

$$Recall = \frac{TP}{TP+FN}$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$$

We have compared the effectiveness of the context acquisition method with a state-of-the-art approach proposed by Keßler [108]. In this work, the author proposes a cognitively plausible dissimilarity measure "DIR", to automatically select relevant contextual information. This approach is based on the comparison of result rankings stemming from the same query posed in different contexts. Such measure aims to calculate the effects of context changes on the IR results. Furthermore, we compare the effectiveness of our approach against the well-known learning algorithm Naive Bayes [102] as implemented in Weka 3.7 [85] using default parameters. We have implemented this algorithm for relevant contextual factor selection based on the estimated probabilities.

4.5 Results and Discussion

4.5.1 Evaluation of the Context Acquisition Effectiveness

Figure 4.2, 4.3 and 4.4 show the analysis of the Relevance measure (see Equation 4.7) for different contextual factors. Figure 4.2 shows relevance distributions of four contextual factors (i.e., Date Time, Location, Place, and Activity) over different queries. This analysis has been made under a specific scenario. We select a set of 9 queries with the same contextual situation and we assess the relevance of each factors with respect to all queries. Selected queries are: computers, motors, lottery, museum, business lunch, train schedule, hotel, restaurant, weather. Moreover, the simulated contextual situation includes: $Date-time = \{Noon - 19\,Juin\}$; $Place = Sousse$; $Location = Work$; $Activity = in\,a\,business\,Trip$.

We aimed to compare the effect of the same contextual situation on different queries. In this figure we notice remarkable drops and peaks in the relevance distribution for the Location contextual factor. Moreover, the time factor got nearly the same importance for all the queries. In the meanwhile, the activity factor has an uniform distribution over all the queries.

The uniform distribution of Date-time factor along all queries in the above analysis motivated us to conduct another in depth analysis. In Figure 4.3, we shed the light on the importance of Date-Time factor for the "*movies in theaters now*" query in different time slots. The query has been ranked in 3 different time slot Morning, Afternoon, Evening and Night. The results reported in Figure 4.3 has a clear variation with multiple values which means that the time factor could influence the search results in different ways.

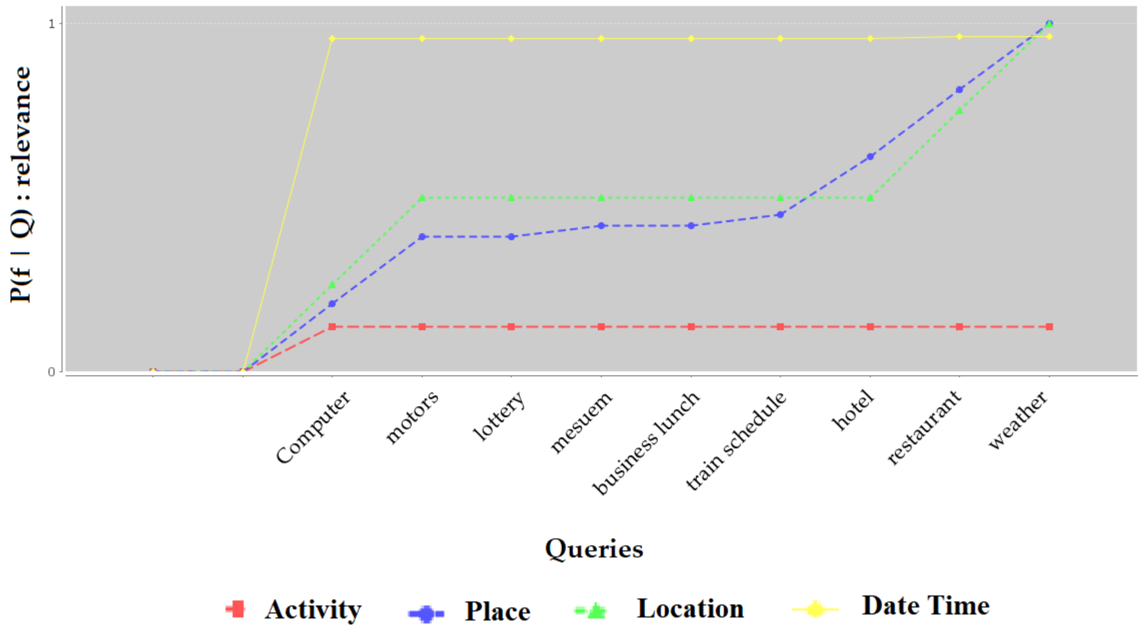


Figure 4.2: Comparison between the *Location*, *Place*, *Date-time* and *Activity* factors based o their relevance for different queries.

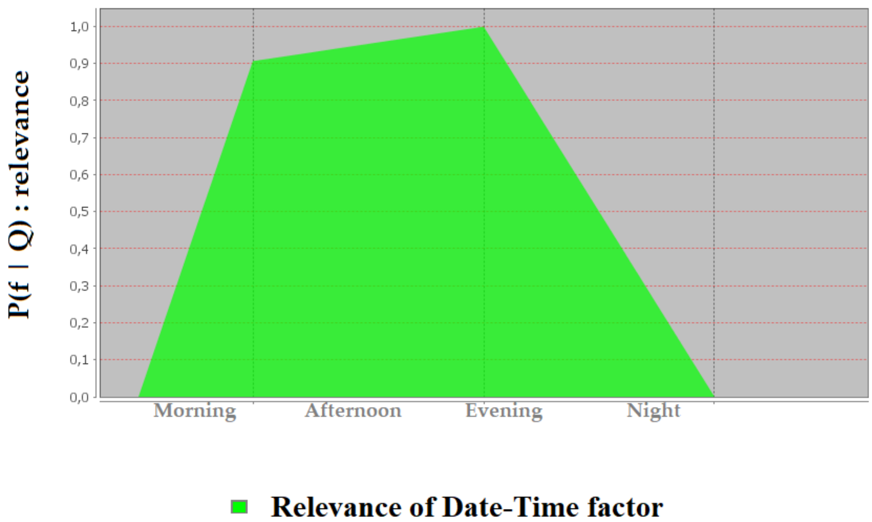


Figure 4.3: Relevance of the *Date-time* factor for the same query at different time slots.

In Figure 4.4, we report the analysis of Place factor relevance over different queries. For all the identified queries in Figure 4.4, we specified the contextual condition Place as Sousse. The obtained results show a high relevance probability for restaurant, hotel, festival, job, and health; however for the query lottery, the Place factor seems to be not too important. All the previous analysis results clearly support our assumption that not all contextual factors are equally important for the user's information need to be acquired. Hence, it is important to

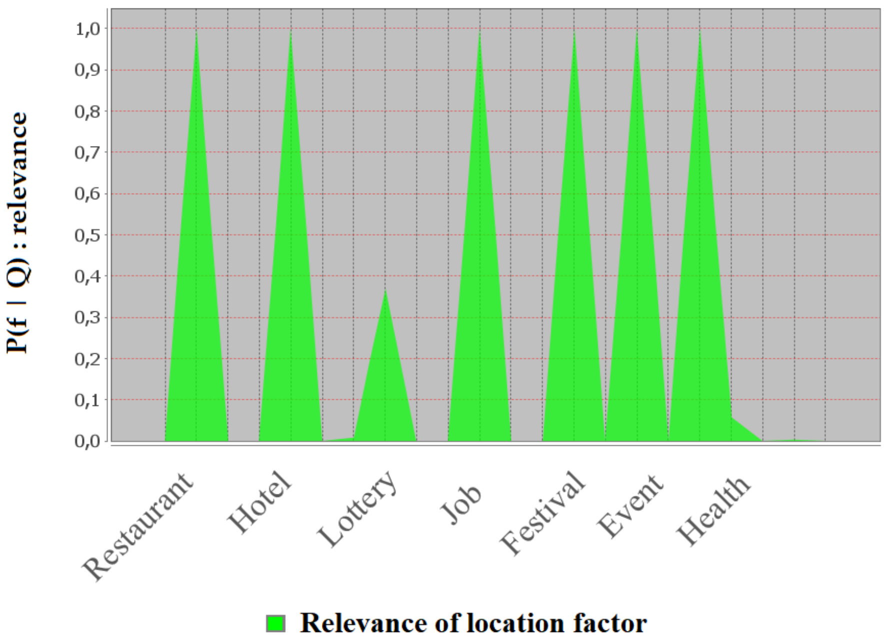


Figure 4.4: Comparison between the relevance of *Place* factor for different queries.

identify only those relevant factors that truly affect the user information need. Indeed, the relevance of a contextual factor depends on the query, specifically on the user's intent behind the query. To conclude, those analysis show the reliability of our language model-based method to measure the relevance of contextual factor for a query, i.e., the sensitivity of user's query to a contextual dimension.

In the following, we apply the precision oriented metrics to assess the effectiveness of the proposed method in selecting relevant contextual factors. We measure precision, recall and accuracy to compare the precision accuracy of the proposed method against baselines. The Naive Bayes [102] baseline have been implemented for relevant contextual factor selection based on the estimated *Context Relevance Score* $Relevance(f_i, Q)$ (see Section 4.3.3). The experimental results are reported in Table 4.3.

Table 4.3: Relevant contextual factors acquisition results.

	50% of the Training Data			80% of the Training Data		
	Precision	Recall	Accuracy	Precision	Recall	Accuracy
DIR approach [108]	0.393	0.350	0.363	0.486	0.372	0.413
Naive Bayes	0.301	0.343	0.345	0.436	0.461	0.421
Our Statistical Method	0.491	0.539	0.473	0.552	0.596	0.602
*Improvement**	63.123%	57.143%	37.101%	26.606%	60.215%	42.993%

*The percentage of improvement is calculated between the higher and the lowest values of the given measure over all methods.

In this experiment, we split the whole data on two sets with different numbers of training samples, to avoid the effect brought by the size of the training data.

Looking at the results for the first round of experiments (50% of training set), we notice that the proposed method significantly outperforms all compared approaches in terms of precision, recall and accuracy. Our method outperforms DIR [108] model by more than 37% in term of accuracy, 63% for precision and more than 57% for recall. Indeed Table 4.3 allows comparing the precision and recall of our method when training sets vary from 50% to 80%. As it can be expected the effectiveness of the all models are correlated with the size of the training data. To conclude, the experiment indicates that our method outperforms other models in selecting relevant contextual information under an increasing number of data. In Table 4.4, we provide more details about the queries and their topic and percentage of the relevant contextual factor for each topic in the whole dataset.

Table 4.4: Number of queries per topic and the most relevant contextual factor per topic.

Topics	#Queries	Most Relevant Contextual Factors (*)
Science	190	Time sensitive
Music and Art	370	Time sensitive
Travel-related queries	580	Time, location and activity sensitive
Health	210	Time and location sensitive
Computers and Smartphones	650	Time, location and activity sensitive

* The identification of query sensitivity is based on the percentage of most relevant contextual factors identified per query topic.

4.5.2 Evaluation of Context Acquisition Impact on the Search Accuracy

In this study, we aim to evaluate the impact of selected contextual factors in the search accuracy. We realize two experimental tasks.

In this study, we realize two experimental tasks that consists on:

1. Implementing our re-ranking model with different number of relevant contextual factors to assess their impact.

2. Evaluating the system performance with context selection method by comparing the performance of the ranking model against state-of-the-art-approaches.

Task 1: In this task, we aim to evaluate the effectiveness of our model at various levels of contextual data granularity. For the first task, we implement 4 instances of our re-ranking model. In each model, we removed a number of contextual factors. Then, we evaluate $precision@10$ and $precision@20$ of each model instance.

As it emerges from Figure 4.5, all the selected contextual factors are essential for the retrieval model. As shown in the Figure 4.5, the most effective model is model 1, in which we incorporate all relevant contextual factors for the re-ranking model. Obviously, if we eliminate all contextual factors as in model 4, the precision decreases by more than 24.5%.

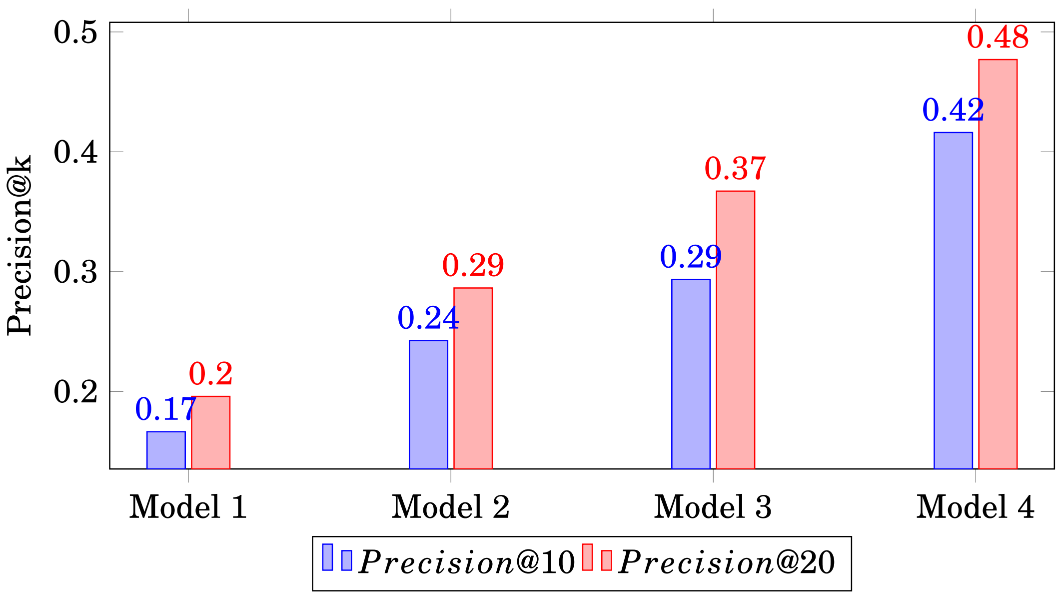


Figure 4.5: Precision@k results for the four instances of our model: impact of the number of selected contextual factors on the search accuracy.

These results show a positive impact of contextual information on the retrieval accuracy. To a large extent, context dependent queries require all relevant contextual factors to retrieve accurate results.

Task 2: In this task, we evaluate the performance of our search approach with context selection method against the following state-of-the-art models:

- *Context-aware Ranking approach* (CRA) [200]: The authors implement different ranking principles for different types of contexts. They adopt a learning-to-rank approach and integrate the ranking principles to RankSVM [101] by encoding the context information as features of the model. To the aim of the comparison study, we choose the *Generalization* principle which fits more our work strategy. For this principle the context of a previous query in the search session is considered as helpful to personalize the search outcomes.
- *Query Reformulation for Context-aware Ranking* (QRCR) [174]: This approach is the most related to our proposed approach. The authors enrich the query by using contextual information, and then employed the reformulated query into language models for retrieval.

The contextual information used in both previous baselines includes previous search queries and click-through information. We replace these information by the contextual factors available in our dataset to perform the comparison study.

Figure 4.6 reports Precision@10 and Precision@20 of all comparison models discussed above. Looking at the results, we can find that the proposed model significantly outperforms all compared approaches in terms of precision of top-10 to top-20.

Our approach outperforms QRCR model by more than 35% and outperforms the CRA model by 16%. Moreover, we notice that there is only minor differences between CRA and

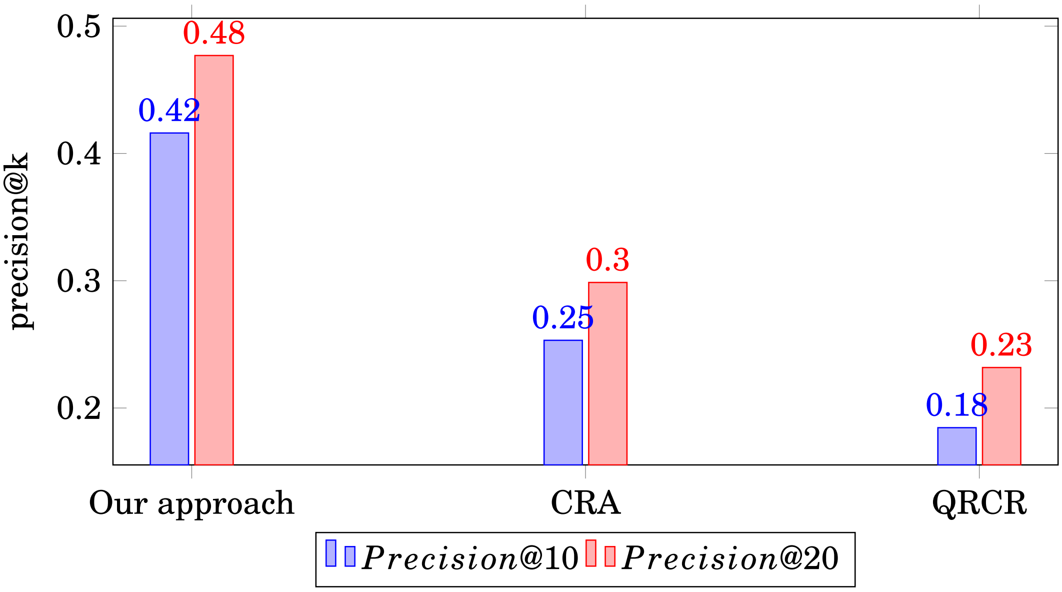


Figure 4.6: Precision@k results: Comparison with baseline models.

QRCR approaches in terms of precision@k. Both approach take into limited consideration the importance of contextual factors in the search process. They focus on the click-through data a ignore other contextual factors. As it can be observed in this chart, the proposed contextual re-ranking module significantly outperforms CRA and QRCR models confirming that retrieval model can be significantly accurate when they are improved by contextual information when it matters (especially for mobile search).

4.6 Summary

In this chapter we investigated two important research questions in the contextual Information Retrieval field. First: which contextual information should be integrated in the search process? Second: how to integrate it into the ranking model?

We have proposed a new contextual data selection method to contextual information retrieval system in mobile context. The aim of our approach is to estimate the relevance of contextual factor in respect with the user's query. This method attempts to enhance the context modeling methods by identifying relevant data and eliminating irrelevant factor that may cause noise to the search process. Then, we proposed a language model based re-ranking model in order to predict the relevance of document in respect with these contextual information. Therefore, we exploit and integrate several contextual information namely date time, location, place and activity independently to enhance the retrieval process.

We evaluated the effectiveness of the Context-based approach and we studied the impact of each factor of the user's context on the retrieval accuracy. To investigate the impact of selected relevant factors on ranking model we implemented four instances of the proposed approach. We found that if the query is dependent on the search context, so, relevant contextual information should be used to improve the search accuracy. We empirically evaluate our approach using a large search log data set obtained from a popular search engine (AOL). In our evaluation, we used human judgments and simulation. The experimental results clearly show that our context-aware ranking approach improves the ranking of a context dependent queries.

The experiments demonstrate also that contextual information can increase the system ranking accuracy for mobile search.

CHAPTER 5

A Language Modeling Approach for Travel-Related Services Recommendation

In this chapter, a language modeling approach for user profile construction is proposed. Based on this user profile representation, a content-based recommendation algorithm is also proposed. Concerning the first issue, we employ the *User-Generated Content* (UGC) in social media as a source of evidence to infer the user's topical interests and model the user profile. In an attempt to address the research questions 2 and 3 presented in Section 1.3 (Chapter 1), we proposed to employ language models to formally represent the user profile and to generate personalized recommendations in a restricted geographical area.

This chapter begins by an introduction that provides an overview of the proposed approach and presents the main contributions. Then, we present the travel recommendation approach within which we detail the proposed user profile model. We discuss the novelty of our proposal and explain the assumption behind using UGC in the form of textual reviews for user profiling. Then, the content-based filtering algorithm is detailed. Finally, the experimental evaluation of the proposed approach is presented and discussed.

5.1 Introduction and Motivations

User-Generated Content constitutes nowadays a vast source of information for the user's decision making. Its increasing volume have created a growing need for effective systems able to support users both (i) in keeping informed about certain topics of interest and (ii) in taking decisions based on information they obtain from the Social Web. In particular, it has become a necessity to provide relevant information to users even before they submit any explicit query [161].

In relation thereto, Content-Based Filtering approaches are able to recommend relevant items based on both the item content and the user model that formally represents the user's topical interests [124]. Content-based recommendation approaches need reliable sources to take into consideration the user's interests. As explained in Chapter 2, Section 2.1.2.2, most existing approaches employ tag-based models for building the user profile. However, according to [95], the exploitation of the user's tags tend to be too ambiguous for describing personal interests, and profiles tend to loose specificity. To overcome this problem, in the tourism context, we propose an algorithm that explores User-Generated Content in the form of textual reviews to implicitly infer the user's topical interests.

As illustrated in Section 2.1.2.2, the use of textual reviews has not, with exception of a few works [162, 203], been explored as a source of information for user profiling. We undertake such a direction and we explore textual UGC as a source of user profile construction for personalized recommendation. In particular, the language employed by the user offers a basis for modeling the user's topical interests. Reviews hosting sites (e.g., Yelp, TripAdvisor) provide access to textual reviews and associated ratings that constitute sources of evidence for both: (i) the creation of a rich user profile; and (ii) the creation of item model to provide personalized recommendations.

Therefore, we rely on the fact that users express their opinions about distinct entities (e.g., restaurants, hotels, shops, cultural point of interest, etc.) using different terms and vocabularies to model the user profile. More specifically, we define a user profile which expresses in a formal way the user's opinions with respect to a particular entity (i.e., a given category of TR services). Then, we exploit the user profile to determine the relevance of an item to the user's topical interests within a Content-Based Filtering algorithm. In particular, the proposed approach formally models the UGC connected to a group of reviews for each entity, and compares it with a statistical language model representing the target user profile associated with that entity.

The novel aspects of our proposed recommendation approach are listed as follows:

1. We proposed a statistical language modeling approach to user profile construction. The statistical language models are proposed to model the probability distribution of words within a user's language that s/he employs in textual reviews.

2. We proposed a content-based recommendation algorithm, for which the user profile is employed to recommend personalized *Travel-Related services* namely TR services (e.g., restaurants). In particular, the proposed approach formally models the User Generated Content connected to a group of reviews (written by expert users) to model an item profile, and compares it with the model representing the target user profile associated with that entity (e.g., restaurants).

3. We proposed different scoring methods within the statistical language models framework. These scoring methods incorporated two similarity measures based on the user's positive and negative profiles to estimate the relevance of an item.

We conduct experiments on a publicly available real-world dataset (from a multi-domain hosting site), which demonstrate that the proposed approach outperforms the considered baseline models. Through the extensive experiments, we verify that the effectiveness of our system is accurate for multiple Travel-Related services domains.

5.2 The Content-based Approach to Travel Recommendation

We propose a Content-Based Filtering approach for the recommendation of Travel-Related services (e.g., restaurants) in the mobile context. Based on the user's location, we first select a subset of TR services that are close to her/him. Among this subset, we aim at recommending those services whose content is more similar to the target user's interests.

As illustrated in Figure 5.1, our approach is based on the following sub-tasks:

1. The definition of a user profile for a given category of TR services based on the user's interests. These interests are represented by the content s/he generates in the form of textual reviews about previously rated TR services (belonging to the same category);
2. The definition of Travel-Related services profiles (within the same category), through the analysis of the content posted by other (expert) users concerning candidates services;
3. The comparison between the profile of the candidate Travel-Related service with the interests of the target user, represented by her/his user profile;
4. The recommendation of those services matching (i.e., having a high similarity w.r.t.) the target user's interests.

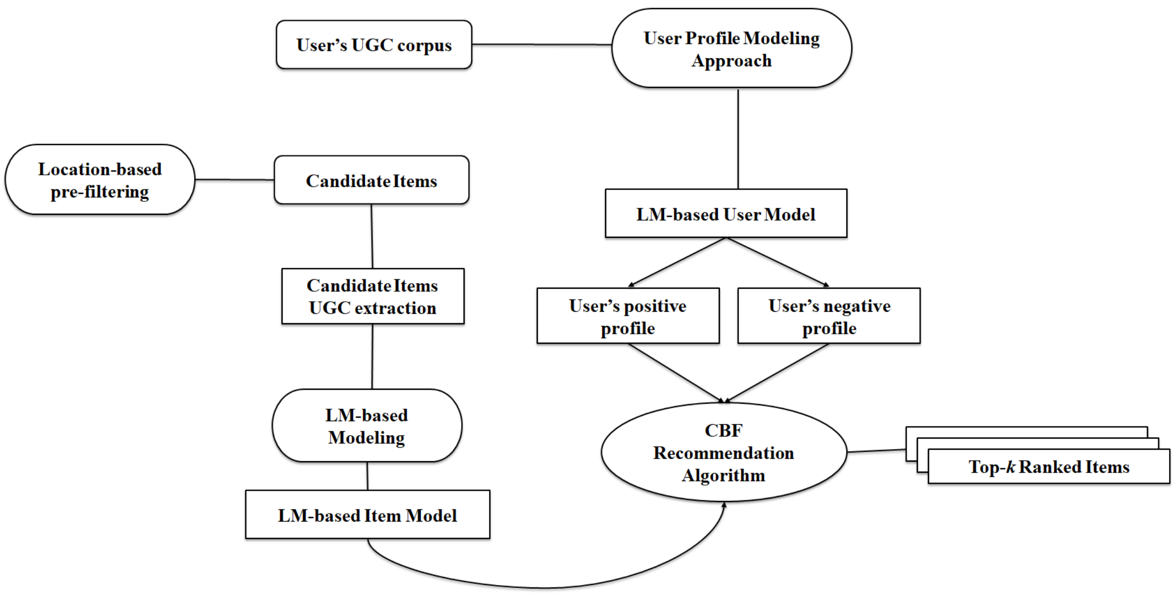


Figure 5.1: Overview of our approach

In order to illustrate our approach, we consider the review site Yelp, the reviews of the target user and of expert users (i.e., Elite members) for a specific TR service category: i.e., restaurants. As the profile (user profile and TR service profile) construction relies on the content written by users, we formally represent it by a *statistical language model*.

5.2.1 Modeling the User Profile: Inferring User Interests from User Generated Content

Individuals often express their opinions about different domains and subjects using different terms and vocabularies. In social media, comments and reviews may well express this peculiarity. Hence, we aim to identify from a set of reviews related to a given TR service category (i.e., restaurants) the target user's interests. These reviews are written by the target user on previously experienced TR services. We consider the user's reviews as a source of evidence that allows us to update the user profile and provide personalized recommendation.

For instance, let us consider a user who wrote a set of online reviews on restaurants including the following:

Review 1: *"This **restaurant** is **located** at the Scottsdale Plaza Resort with a **beautiful outside view** and **nice decors** also. The **staff** was very **friendly** and very **helpful** with a **warm hospitality**."* **(Rate= 4 stars)**.

Review 2: *"Really **disappointed** with the **food** here, it is **expensive** and **mediocre**... the **portions** were **atrocious** and the **dessert terrible**. The **worst** dining experience I have had in Reno area **service terrible**.* **(Rate= 1 star)**.

Indeed, by analyzing the language that the user employed over the textual reviews, we can get an idea of the user's interests for restaurants. The "unigram" language model [148] is a probability distribution over the terms in the language. The language model can be employed to associate a probability of occurrence with every term in the index vocabulary for a collection [56]. In Figure 5.2, we provide an example for such probability distribution of words within the set of target user's reviews. We present the top-word probability distributions over both the user's positive and negative feedbacks.

In summary, the user profile model presented in this chapter is motivated by the idea that textual reviews are written evidence explicitly provided by the user [140]. For this purpose, we adopt a language model based on unigrams [148] to model a user's interests. Formally, given a TR service category c, and a target user $u_i \in U = \{u_1, \ldots, u_n\}$ in a particular geographic location, we generate two probability distributions, which represent: (i) a *positive user profile* and (ii) a *negative user profile*. The positive user profile represents a user's positive feedback about past experienced TR services that s/he liked, i.e., the positive reviews that a user explicitly provided. Formally, the set of these positive reviews is denoted by $R^+_{u_i} = \{r_i \in R_{u_i} : \sigma > 3\}$; where σ represents the star rating associated with each review r_i. Conversely, the negative user profile describes a user's negative feedback about TR services that s/he disliked, i.e., the reviews for which the user explicitly provided negative opinions. Formally, the set of these reviews is denoted by $R^-_{u_i} = \{r_i \in R_{u_i} : \sigma \leq 3\}$. The positive and negative distributions are estimated through a *language model* based on *unigrams* [148]. The positive user profile built on $R^+_{u_i}$ (resp.

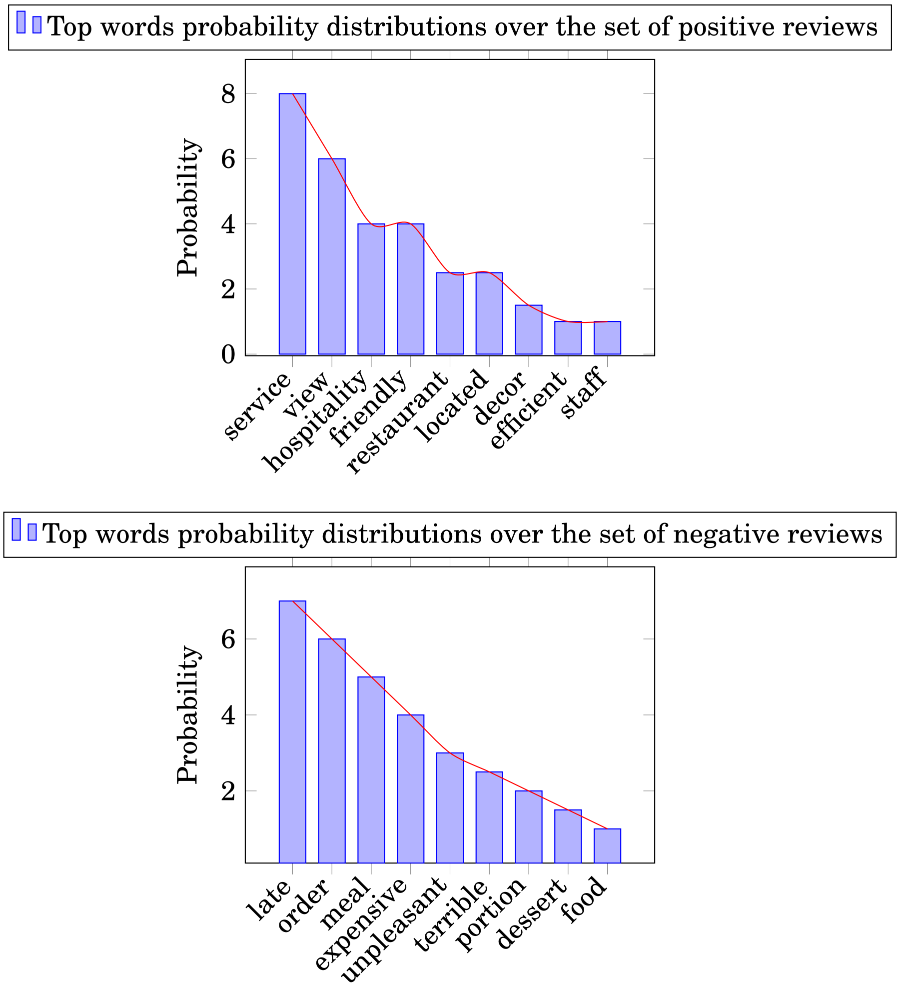


Figure 5.2: Language model for the target user's reviews (top terms)

$R^-_{u_i}$), and denoted by $\theta^+_{u_i}$ (resp. negative user profile $\theta^-_{u_i}$) is formally defined as follows:

$$P(w|R^{\pm}_{u_i}) = \frac{1}{|R^{\pm}_{u_i}|} \sum_{r \epsilon R^{\pm}_{u_i}} P(w|r) \tag{5.1}$$

where the notation $R^{\pm}_{u_i}$ indicates respectively $R^+_{u_i}$ and $R^-_{u_i}$ for the positive and negative user profiles. The words distribution over a user's review r are computed via Dirichlet prior smoothing as follows:

$$P(w|r) = \frac{nocc(w,r) + \mu \frac{nocc(w,R_{u_i})}{\sum_w nocc(w,R_{u_i})}}{\sum_w nocc(w,r) + \mu} \tag{5.2}$$

where:

- $r \in R_{u_i} = \{r_1, ..., r_n\}$ represents a review written by the user u_i,
- $nocc(w,r)$ is the frequency of occurrence of the word w in the review r,
- μ represents a smoothing parameter in the interval $[0, +\infty[$,
- and $nocc(w,R_{u_i})$ represents the frequency of occurrence of the word w in R_{u_i}.

5.2.2 Modeling the Travel-Related Service Profile

The *Travel-Related service profile* is based on the reviews written by other Yelp users on the considered service. However, the limits behind the usage of users' reviews for TR services profiling are related to the fact that the information collected may be biased, due to the presence of spam and low quality data [147]. To alleviate this problem, we rely on trusted users' reviews: *Elite members*' reviews or voted reviews (i.e., that have received *users' votes*[1]) on Yelp. Figure 5.3 shows a small sample of reviews written about the candidate item. We explore Elite members' reviews that provide reliable feedbacks.

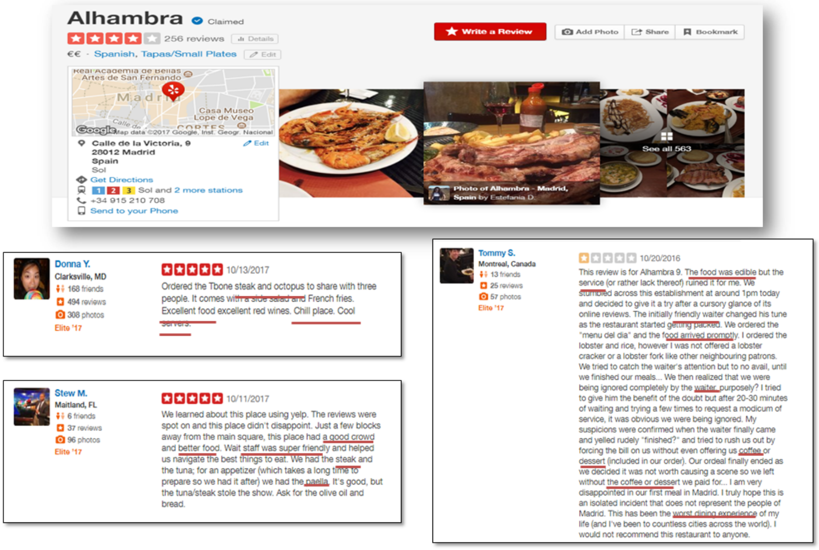


Figure 5.3: Elite members' reviews about candidate item (positive and negative feedbacks).

We consider the set of Elite members' reviews for each travel-related service, formally $R_{s_j} = \bigcup_{e=1}^{m} r_{ej}$, where $s_j \in S$ denotes the TR service belonging to the set S of candidate TR services, and r_{ej} is the review written by an Elite member e about the jth TR service. Then, we build a TR service profile constituted by a positive profile $P(w|R^+_{s_j})$, denoted by $\theta^+_{s_j}$, and a negative profile $P(w|R^-_{s_j})$, denoted by $\theta^-_{s_j}$, where $R^+_{s_j} = \{r_{ej} \in R_{s_j} : \sigma > 3\}$ and $R^-_{s_j} = \{r_{ej} \in R_{s_j} : \sigma \leq 3\}$. Item profile (positive and negative) are estimated through a *language model* based on *unigrams* [148], and are defined as follows:

$$P(w|R^{\pm}_{s_j}) = \frac{1}{|R^{\pm}_{s_j}|} \sum_{r_{ej} \epsilon R^{\pm}_{s_j}} P(w|r_{ej}) \tag{5.3}$$

where the notation $R^{\pm}_{s_j}$ indicates respectively $R^+_{s_j}$ and $R^-_{s_j}$ for the positive and negative TR service profiles. The likelihood of generating a word w given a review r_{ej} is denoted by $P(w|r_{ej})$, and it is computed via Dirichlet prior smoothing as follows:

$$P(w|r_{ej}) = \frac{nocc(w, r_{ej}) + \mu \frac{nocc(w, R_{s_j})}{\sum_w nocc(w, R_{s_j})}}{\sum_w nocc(w, r_{ej}) + \mu} \tag{5.4}$$

[1] users' votes are features associated with the text of a review and can describe how *useful*, *funny* or *cool* the review is.

where $nocc(w, r_{ej})$ denotes the frequency of occurrence of the word w in the review r_{ej}. $nocc(w, R_{s_j})$ represents the frequency of occurrence of the word w in R_{s_j}. μ represents a smoothing parameter in the interval $[0, +\infty[$.

5.2.3 The Content-Based Filtering Algorithm

Once the user profiles and the item profiles have been generated, the recommendation strategy that we adopt consists of two steps. The first step involves the selection of the nearest n travel-related services to a target user based on the user's geographic location. Those TR services constitute the set of candidate restaurants that will be considered for recommendation. Then, using the previously defined user and TR service profiles, we estimate the recommendation score for each service, by comparing the target user profile with the TR service profile.

The intuition behind this choice is that the top-k recommended TR services should be the services: e.g., restaurants, which are more similar to the ones that the user likes and vice versa. Based on the way user and TR service profiles have been defined (i.e., constituted by a positive and a negative language models), the problem of recommending items to users becomes the task of evaluating the similarity between the two components (positive and negative) of the profile of a user u_i in the category c, and the two components of the profile of the travel-related service s_j belong to c. With respect to this issue, we explored different scoring methods to evaluate similarity among user and TR service profiles based on kullback leibler divergence [115] as discussed in the following.

5.2.3.1 Similarity to User Positive Profile

In this similarity-based scoring method, we rely only on the user positive profile $P(w|R^+_{u_i})$ to judge if a user likes or dislikes a travel-related service (see Figure 5.4). Considering the positive

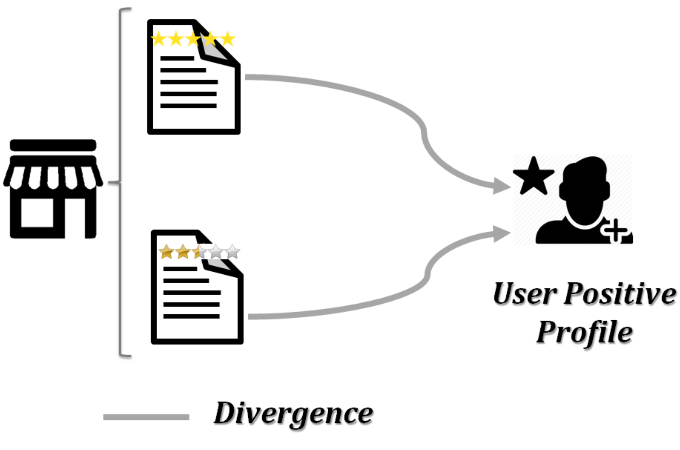


Figure 5.4: Schematic view of the scoring method.

and negative profiles associated with a TR service s_j, i.e., $P(w|R^+_{s_j})$ and $P(w|R^-_{s_j})$, we employ the *Kullback-Leibler* (KL) divergence [21, 115] to measure the divergence between the profile of

u_i and the profile of s_j, and hence to assess their similarity as follows:

$$Score_{positive}\left(s_j \| u_i\right) = \frac{1}{D_{KL}\left(\theta_{s_j} \| \theta_{u_i}\right)} \tag{5.5}$$

with

$$D_{KL}\left(\theta_{s_j} \| \theta_{u_i}\right) = \alpha D_{KL}\left(\theta^+_{s_j} \| \theta^+_{u_i}\right) - \beta D_{KL}\left(\theta^-_{s_j} \| \theta^+_{u_i}\right) \tag{5.6}$$

where α and β are parameters that balance the impact of the both divergences to the final similarity score. Their values are chosen in the interval [0,1]. We assume $D_{KL}\left(\theta_{s_j} \| \theta_{u_i}\right) \neq 0$ for each $s_j \in S$. Furthermore,

$$D_{KL}\left(\theta^+_{s_j} \| \theta^+_{u_i}\right) = \sum_{w \in W} p\left(w \mid R^+_{s_j}\right) log \frac{p\left(w \mid R^+_{s_j}\right)}{p\left(w \mid R^+_{u_i}\right)} \tag{5.7}$$

and

$$D_{KL}\left(\theta^-_{s_j} \| \theta^+_{u_i}\right) = \sum_{w \in W} p\left(w \mid R^-_{s_j}\right) log \frac{p\left(w \mid R^-_{s_j}\right)}{p\left(w \mid R^+_{u_i}\right)} \tag{5.8}$$

Then, for a user, we recommend each 'more similar' travel-related service, i.e., each TR service that (i) minimizes the divergence between the user profile and its positive profile, i.e., $D_{KL}\left(\theta^+_{s_j} \| \theta^+_{u_i}\right)$, and (ii) maximizes the divergence between the user positive profile and its negative profile, i.e., $D_{KL}\left(\theta^-_{s_j} \| \theta^+_{u_i}\right)$.

5.2.3.2 Cross-similarity

Given a target user u_i, and a TR service s_j, our goal is to find the highest similarity between them by using the symmetrized Kullback-Leibler divergence [103], considering both user positive and negative profiles. In this scoring method, we start from the idea to promote a TR service that fits a user's positive opinions, or that does not fit user's negative opinions. Figure 5.5 shows an explanation of the scoring method. This means to recommend a TR service that, at

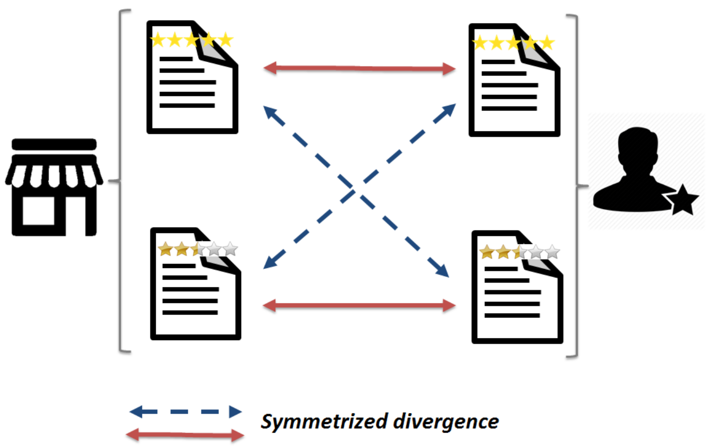


Figure 5.5: Schematic view of the cross similarity scoring method.

the same time, (i) minimizes the symmetrized divergence between the user positive profile and its positive profile, i.e., SymKL($\theta^+_{s_j}$, $\theta^+_{u_i}$); (ii) maximizes the symmetrized divergence between the user negative profile and its negative profile, i.e., SymKL($\theta^-_{s_j}$, $\theta^-_{u_i}$); (iii) maximizes the 'cross' symmetrized divergences, i.e., SymKL($\theta^+_{s_j}$, $\theta^-_{u_i}$) and SymKL($\theta^+_{s_j}$, $\theta^-_{u_i}$). The overall similarity score is computed as follows:

$$Score_{cross} = \frac{1}{SymKL(\theta^+_{s_j},\theta^+_{u_i})} - \frac{1}{SymKL(\theta^+_{s_j},\theta^-_{u_i})} - \frac{1}{SymKL(\theta^-_{s_j},\theta^+_{u_i})} + \frac{1}{SymKL(\theta^-_{s_j},\theta^-_{u_i})} \tag{5.9}$$

where the symmetrized Kullback-Leibler divergence SymKL($\theta^\pm_{s_j}$, $\theta^\pm_{u_i}$) between the travel-related service profile θ_{s_j} and the user profile θ_{u_i} is defined as follows:

$$SymKL\left(\theta_{s^\pm_j} \| \theta_{u^\pm_i}\right) = \frac{1}{2}\sum_{w\in W} p\left(w \mid R^\pm_{s_j}\right) log\frac{p\left(w \mid R^\pm_{s_j}\right)}{p\left(w \mid R^\pm_{u_i}\right)} + \frac{1}{2}\sum_{w\in W} p\left(w \mid R^\pm_{u_i}\right) log\frac{p\left(w \mid R^\pm_{u_i}\right)}{p\left(w \mid R^\pm_{s_j}\right)} \tag{5.10}$$

As previously introduced, ± denotes respectively the positive and the negative language models.

Once we have computed for each TR service s_j geographically close to a user u_i the similarity between its profile and the user profile – using Equation (5.9) – we rank the top-k TR closest services in descending order of similarity, and we recommend them to the user u_i.

5.3 Evaluation of the Proposed Approach

In this section we describe the experimental evaluation that has been conducted to verify the effectiveness of the proposed approach. Our recommendation approach presents to the user a list of recommendations, in which items are ordered according to the user's preferences. For this reason, we follow a methodology that evaluates the the top-k ranked recommendation lists with precision-based metrics, as suggested in [24].

5.3.1 Dataset

Experiments have been carried out on the Yelp Challenge Dataset[2]. We have pre-processed this dataset to select only TR services belonging to the restaurant category, which have received trusted reviews. We judge the truthfulness of a review based on two criteria: (i) it has been written by trustworthy Yelp users, i.e., Elite members, and/or (ii) it has received a *user vote*. This way, we obtained a reduced set denoted by $T \subseteq U \times S$, which is the subset of user-service pairs for which the review and the rating are known. We denote by $R_{s_j} = \{r_1, ..., r_{n_s}\}$ the set of reviews written about a TR service $s_j \in S$, with $n_s \geq 30$. T also includes 1090 target users (they can be both Elite and non-Elite members) that have written at least 25 reviews with a rating

[2] https://www.yelp.com/dataset_challenge

$\sigma > 3$, and 25 reviews with a rating $\sigma <= 3$ about previously visited restaurants $\in S$. Formally, $R_{u_i} = \{r_1, ..., r_{n_u}\}$ denotes the set of reviews written by the user u_i (i.e., the user's corpus), with $n_u \geq 50$.

Some information on the dataset is provided in Table 5.1.

Table 5.1: Statistics of the dataset used in the conducted experiments.

Yelp Dataset Challenge	
Users	1090
Average number of reviews per user	42.25
Average number of reviews per item	53
Reviews	81365
Items (Restaurants)	15176
Sparsity	0.042%

By using the Lucene open-source API[3], we have performed a pre-processing phase on the text of reviews, i.e., stemming, stop-words removal, and tokenization. Furthermore, unigrams (single words) frequencies have been counted and stored into a document-term matrix of counts.

5.3.2 Evaluation Methodology

The evaluation of the proposed approach is based on the *TestItems* methodology described by Bellogín *et al.* in [24]. First, the set T of user-service pairs with known reviews and associated star ratings is split into a training set Tr and a test set Te [24].

In particular, for a user u, we denote as $Te_u = \{s_j \in S \mid \sigma(u, s_j) \in Te\}$ the set of restaurants rated by u in the test set, where σ denotes the known star rating for s_j by u; these star ratings in the test set will be used as graded relevance judgments. In the same manner, we denote Tr_u the set of restaurants rated by u in the training set.

In order to evaluate a ranked list of recommendations for a target user u, we consider a set L_u of target services (i.e., recommendation corpus) to be ranked and recommended to u. In the *TestItems* methodology, L_u includes: (i) TR services rated by u and other users in the test set denoted as Te_v, and (ii) no training ratings by the target user u, since the rational behind this methodology is that it makes no sense to predict known training ratings. Formally, $L_u = \bigcup_v Te_v \setminus Tr_u$. For all users the recommendation corpus denoted by L has the following cardinality:

$$|L| = \sum_{u \in U} |L_u| = 15176$$

5.3.3 Metrics and Baselines

Precision and *normalized Discounted Cumulative Gain* (nDCG) [97] are used as suitable precision-oriented metrics to evaluate the proposed approach. nDCG in particular is used for quantifying the quality of the ranking by using the ratings in the test set as graded relevance

[3] https://lucene.apache.org/core/

judgments. The effectiveness of the proposed recommendation approach has been compared against two widespread baselines:

- GeoWhiz [92]: A restaurant recommender system that uses traditional user-based collaborative filtering techniques coupled with location-based partitioning (labeled UCF). The proposed a collaborative filtering approach for recommending points of interest (POI) in a given location. The system selects the available POIs, then, similarities between the target user and other users are computed using a person-to-person correlation. The system predicts a vote on each of the selected POIs by taking a weighted combination of similar users votes. Finally, the point of interest with the highest vote are recommended to the user.

- A Ranking-based Strategy for Contextual Suggestion [202]: The approach provides a list of recommendations, for which candidate items are ranked based on their similarity to the user profile. The similarity between the profile of the target user and an item is computed based on: (i) the similarity between a suggestion and the places that the user liked, and (ii) the dissimilarity between the suggestion and the places disliked by the user. The similarity is computed based on the either the category of the item or its content description.

5.3.4 Effectiveness of the Language Modeling Approach for Personalized Recommendation

For each user, every restaurant in the test set has been evaluated with respect to the two distinct scoring schemes illustrated in Section 6.2.2.2, i.e., $Score_{positive}$, and $Score_{cross}$. This produces for each user two different ranked lists where the Travel-Related services are sorted by their estimated similarity with respect to the user profile. For each ranking we analyze the top 20 restaurants. We then compute the $precision@k$ and $nDCG@k$, with k = 5, 10, and 20. Then, an average of the measures over all users has been provided.

Table 5.2: The results of the $precision@k$ measure computed on the rankings produced by considering all users.

	$p@5$	$p@10$	$p@20$
$CBF - Score_{cross}$(our approach)	0.6165	0.5531	0.5102
$CBF - Score_{positive}$(our approach)	0.6815	0.5817	0.5623
UCF (baseline)	0.5967	0,5217	0.444
CAT-F (baseline)	0.4615	0.4396	0,3779

Table 5.2 shows the comparison of the $precision@k$ values averaged for all users. As it emerges from the table, our CBF approach (with respect to both the $Score_{positive}$ and $Score_{cross}$ scoring methods) clearly improves compared with the baselines in terms of $precision@k$. In the three cutoffs (k = 5, 10, 20), there are not significant differences between $Score_{positive}$ and $Score_{cross}$. The obtained $nDCG@k$ values are reported in Figure 5.6. In general, the

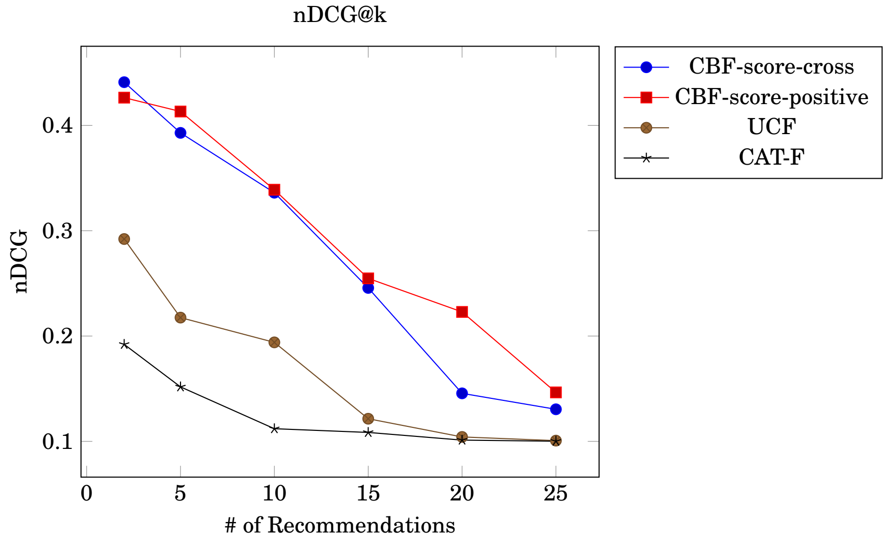


Figure 5.6: nDCG@k computed on the ranks produced by considering all users.

CBF approach based on the $Score_{positive}$ scoring scheme outperforms with respect to other approaches, as expected from ranking models taking into account both user's positive and negative opinions at the same time.

These results show that modeling a user profile through her/his positive feedbacks using language model (while also taking into consideration the context and her/his evolving opinions) can significantly improve the recommendation process compared to methods based on different (and simpler) models, or taking simply into account both users' positive and negative opinions.

5.3.5 Addressing the Data Sparsity Problem

In this study, we evaluate the system performance with an increasing proportion of ratings. This study is conducted to get an insight about our approach effectiveness against data sparsity issue.

As discussed in Chapter 2, the data sparsity arises due to the fact that users only rate a small portion of items (i.e., give small set of textual reviews about a travel-related services category). In relation thereto, we studied the system performance with an increasing proportion of ratings and reviews collected from the simulated users. Hence, we randomly divided the user-item pairs of our dataset into $n = 7$ subsets. We then vary the portion of sets to be considered for training data by repeatedly selecting training set rating in 10% steps.

For each set, we evaluate the system performance with MAE and *Precision@20* measures.

Figure 5.7 reports the obtained MAE and precision when test sets increase from 20% to 80%. As it is clearly shown the *precision@20* results increase at a slower space, and they are not affected by data sparsity. In the meanwhile, the MAE results decrease (lower is better). Overall, from this graph, we can clearly notice that the proposed approach is effective in all the states with big amount of training data, i.e., when more data of user's preferences are known for the system. In fact, our approach relies on training data to build the user's profile. Thus, the more

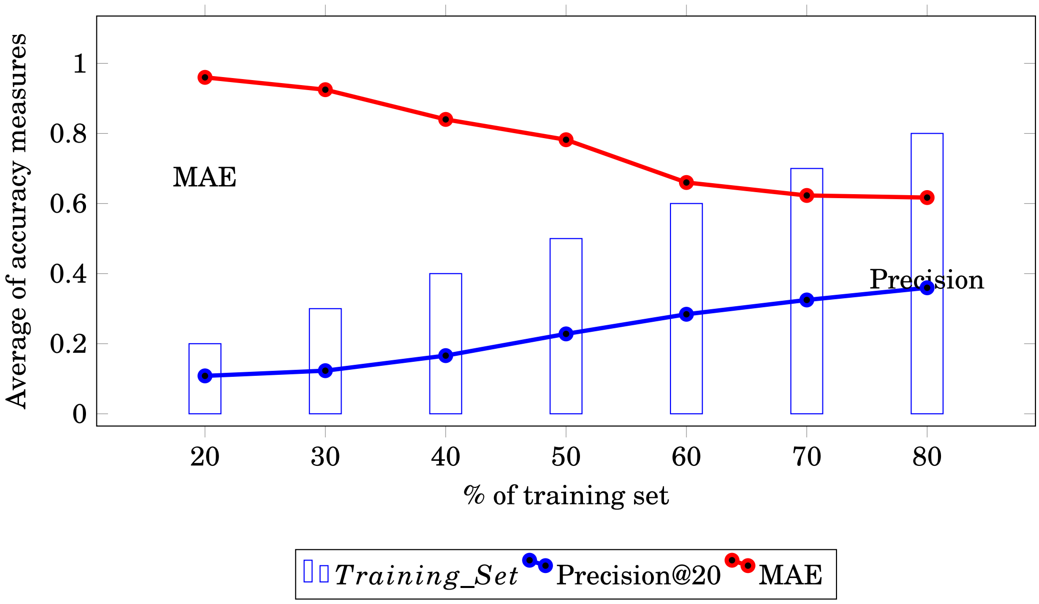


Figure 5.7: Evaluating the performance of the proposed approach in terms of MAE and precision@20 at different sizes of test set.

rich the user's profile, the more precise the recommendation.

5.4 Summary

In this chapter, we have proposed a content-based filtering approach for Travel-Related services recommendation in the mobile context. The proposed approach explore the use of statistical language models in travel recommendation to represent both user and item profiles. In particular, we presented details of our idea to identify users' opinions and interest by means of the content they generate, and which is diffused on Social Media. In the tourism context, the user profile is built upon the user's own reviews generated about previously visited TR services, and formalized by means of a statistical language model. Employing the user-generated content better reflects the user's topical interests; therefore, this contributes to have better recommendations.

Then, we described the content-based filtering algorithm for Travel-Related services recommendation. First, considering a location-based pre-filtering step, we generate a subset of candidate items (considered as context-aware TR services) to be loaded into a content-based recommendation process and that to avoid unnecessary search in items the user will not want to see. Then, the recommendation algorithm provided for each user a list of top-k recommended TR services among the initial subset. Recommended TR services are services: e.g., restaurants which are more similar to the ones that the user liked in the past and more dissimilar to the ones s/he disliked. We proposed two scoring methods within the recommendation algorithm, which compute in a different way the similarity between the user's profile and the TR service profile.

We evaluated the effectiveness of the the proposed way of representing the user's profile by measuring the recommendation accuracy using a publicly available dataset. We studied the impact of of considering both positive and negative profiles in the recommendation process. We also compared the proposed approach with state-of-the-art approaches: The first one is based on collaborative filtering technique, while the second is based on the items category and descriptions. The evaluation provided good results comparing to both methods in terms of precision and nDCG. The obtained results confirm the effectiveness of our approach based on the proposed way of modeling the user's interests despite missing data. It is different from previous related work in the following aspects:

- We explore the use of user-generated content for user profile modeling to personalize travel recommendation.
- We explore UGC that other users share to infer items' hidden features and improve recommendation accuracy.

CHAPTER 6

LOOKER: A CONTEXT-AWARE AND CONTENT-BASED MOBILE RECOMMENDER SYSTEM FOR THE TOURISM DOMAIN

In this chapter, a mobile Recommender System for Travel-Related services is proposed. The proposed system combines context-aware recommendation with a content-based filtering (CBF) algorithm to make personalized suggestions, and provide tourists with items of their interest. This chapter focuses on the main research question: how can the user experience of mobile recommendation systems be improved by maintaining accuracy? In the tourism context, we consider also an important problem of constructing a rich and multi-domain user profile that formally represents the user's topical interests about different travel-related services categories. In summary, this chapter presents two main contributions:

- The enrichment of the user profile described in Chapter 5 as a multi-layer user profile, since the idea is that each layer represents the user's preferences with respect to a distinct Travel-Related services categories.

- A mobile recommender system for tourism, namely LOOKER, implemented as a *rich mobile application* on the top of Android operating system.

LOOKER has been developed within the MobiDoc program,[1] which is hosted by PASRI[2] and funded by the European Union.

This chapter is organized as follows: Section 6.2 presents the context-aware and content-based recommendation approach. The, Section 6.3 defines the LOOKER architecture and the requirement of implementation. We also point out the characteristics and the interaction

[1]http://www.pasri.tn/mobidoc-doctorant

[2]Project Supporting Research and Innovation Systems: http://www.pasri.tn/

design of the developed prototype and highlight its distinctions. Then, Section 6.4 presents the conducted evaluation. The goals of the overall evaluation and the conducted the user study was described. Later, the undertaken questionnaires and their results were reported and discussed.

6.1 Motivation and Positioning

Mobile technologies have recently evolved in such a way to significantly influence the user's experience. Smartphones, in particular, offer an environment for a multitude of social media applications, which represent a steadily growing economy, in particular in the tourism domain [183]. As discussed in Chapter 3 Section 3.1, given its growth, tourism constitutes an important application area for *Recommender Systems* (RS)s. In a ubiquitous environment where tourists are often in a hurry, they cannot engage in complex search tasks that require a direct interaction with the system. In such a scenario, it has become a necessity to proactively provide relevant information to travelers even before they submit any explicit query, by taking into account their needs and preferences. A considerable amount of research has addressed this task by proposing *Travel Recommender Systems* [67, 156], which are based on different models and approaches for organizing and planning touristic trips. In recent years, in particular, a lot of attention has been paid to design more effective and user-friendly mobile applications for the tourism industry, to address a wide variety of tourists' information needs [32, 46]. Within this area, the importance of contextual information has been recognized by researchers as the dominant factor affecting the user's decisions.

As discussed in Chapter 2 Section 2.2.2, a number of recent studies have proposed *Context-Aware Recommender Systems* (CARS)s [5, 74], where context-awareness is considered by Recommender Systems to adapt their suggestions to the user's changing context. Context can refer to simple environmental information, such as the user's location and time, or to more detailed information, such as the entities surrounding the user (e.g, devices, services, and persons), or particular environmental characteristics (e.g., light, humidity, noise) [63, 80]. Although context-aware approaches for tourism recommendation provide an effective personalization of recommendation outcomes, they take into limited consideration the user's opinions (i.e., her/his likes and dislikes), which can be expressed differently from one domain to another. To tackle this issue, it becomes necessary to integrate another source of evidence – other than the context – into travel recommender systems. To this purpose, the growing amount of *User-Generated Content* (UGC) in the form of opinionated *on-line reviews* in social media represents an incredibly rich source of information that can be employed to provide decision support and recommendations to on-line tourists [125].

By considering the above described aspects, in this chapter we describe LOOKER, a mobile and adaptable recommender system developed for the Tunisian market. LOOKER provides personalized suggestions of *Travel-Related services*, namely TR services, by taking into account not only the tourist's context, but also the user's dynamic interests. To do this, the system combines a *Context-Aware* [94, 118, 144] and a *Content-Based Filtering* (CBF) strategies. In particular, the context-aware strategy considers both location and time as context dimensions.

The CBF strategy employs a user profile built by using the content that the user has generated on social media, i.e., the reviews previously provided with respect to TR services that s/he liked/disliked. This UGC represents an explicit evidence about the user's preferences that has been specifically collected on Facebook,[3] Twitter,[4] and TripAdvisor.[5] These social media are widely-used in Tunisia to share opinions in general, and on TR services in particular, usually in the form of reviews. LOOKER has been fully developed for the Android operating system; a user study has been conducted to evaluate the usefulness and the usability of the mobile application.

6.2 A Context-Aware and Content-Based Model for Personalized Recommendation in the Tourism Domain

As previously outlined, LOOKER is based on a model for the recommendation of *Travel-Related services* – abbreviated as *TR services* – which is constituted by: (i) a *context-aware pre-filtering module* and (ii) a *content-based filtering module*. The first module performs a pre-filtering of TR services based on the geolocation of a target user and on the opening hours of TR services. The second module applies a content-based filtering algorithm that employs the user's preferences extracted from travel-related UGC to build a user profile. Based on these two modules, LOOKER is able to identify the nearest open travel-related services with respect to the user's geolocation. Then, it recommends the most relevant ones by taking into account the user's preferences. In LOOKER, four distinct categories of TR services are considered:

- *Food*, which includes restaurants and bars, coffee bars, food trucks, etc;
- *Shopping*, which includes fashion stores, bookstores, cosmetics and beauty supply, children's clothing, etc;
- *Health*, which is related to healthcare services such as dentistry, nursing, medicine, optometry, midwifery, emergency and hospitals;
- *Attractions*, which refers to points of interest for tourists such as beaches, national parks, mountains and forests, or cultural attractions including historical places, monuments, museums and art galleries.

Details concerning the two modules are presented in the following Sections 6.2.1 and 6.2.2.

6.2.1 Context-Aware Pre-filtering Module

Based on the assumption that places that the user visits vary depending on her/his location and the time of the day, two main contextual information are considered in the proposed system: location and time. Therefore, the context-aware module performs a pre-filtering on TR services based on this dual contextual information. The subset of the closest TR services to the target

[3] https://developers.facebook.com/
[4] https://dev.twitter.com/overview/api
[5] https://www.tripadvisor.fr/

user, which are open at the current time, are considered for recommendation. This aims at selecting only relevant items (with respect to spatio-temporal context) to be further analyzed with respect to the user's interests.

In this module, the distance between the user's geolocation and the TR service is simply computed by using the geographic coordinates (i.e., GPS coordinates, latitude and longitude) captured using the user's smartphone (with her/his consent). A subset of TR services is selected in a predefined radius (set a priori by the user) around the user's geographic position using the *Google Places* API.[6] Furthermore, also opening hours of TR services are used as a filter, to restrict the subset of selected items and avoid the unnecessary recommendation of items that are not effectively usable by the user.

Within this subset, the Content-Based Filtering module described below selects the TR services which are more similar to the target user's interests.

6.2.2 Content-Based Filtering Module

The Content-Based Filtering module exploits the content generated by users in the tourism context as a source of information for representing users' preferences and building user profiles. Specifically, to build each user profile, this module takes into account the *textual content* in the form of *on-line reviews* that each target user has previously provided with respect to distinct TR services on different social media.

Here below, the main components of the Content-Based Filtering module are described: (i) the *multi-layer user profile*, (ii) the *TR-service profile*, and (iii) the *content-based filtering algorithm* which is used for the final recommendation of TR services.

6.2.2.1 Multi-layer User Profile

The CBF module employs a *multi-layer user profile*, based on the idea that each layer represents the user's preferences with respect to a distinct TR-service category. As detailed in Section 6.2, four TR-service categories are considered by the proposed mobile application: *food*, *shopping*, *health*, and *attractions*. To model each layer, a *statistical language modeling* [148] technique has been employed, which consider on-line reviews written by the user about TR services (in a given category) and collected from the apps installed on the user's smartphone (with her/his consent). The idea of employing the content written by a user and language models to build user profiles has been taken from the literature [206]; in LOOKER, only 'positive' reviews are considered to build the user profile, since they reflect the user's positive feedbacks and provide evidence to understand her/his preferences. To detect a positive review, it is possible to use either the *ratings* associated with the review, i.e., ratings in the form of 'stars' (in a $[1-5]$ range) which provide an evaluation for the considered TR service, or the content of the review. When ratings are provided, a review is considered as positive if the assigned evaluation is greater than or equal to 3 stars. In the absence of ratings, a simple *polarity analysis* that takes into account the ratio between 'positive' and 'negative' terms that appear in the review is performed.

[6] https://developers.google.com/places/

Formally, for a given target user u, a set $R_c = \bigcup r_i$ of the user's positive reviews about a given TR-service category c is identified. The *user profile*, denoted as θ_u, is composed of many distinct layers (one for each considered TR services category) each of which is built by aggregating the *word distributions* of the user's reviews belonging to R_c. These distributions are estimated through a simple *language model* based on *unigrams* [148]. Each layer of the user profile is formally denoted as θ_c, and is estimated, by taking inspiration from [206], as follows:

$$\theta_c = P(w|R_c) = \frac{1}{|R_c|}\sum_{r_i \in R_c} P(w|r_i) \tag{6.1}$$

In Equation (6.1), w represents a given word in the subset of reviews R_c, and $P(w|r_i)$ is estimated by using a language model for r_i via *Dirichlet prior smoothing* [211] as follows:

$$P(w|r_i) = \frac{nocc(w,r_i) + \mu \frac{nocc(w,R_c)}{\sum_w nocc(w,R_c)}}{\sum_w nocc(w,r_i) + \mu} \tag{6.2}$$

where $nocc(w,r)$ is the number of occurrences of the word w in the review r_i, μ is a smoothing parameter, and $nocc(w,R_c)$ represents the number of occurrences of the word w in R_c.

6.2.2.2 Content-Based Filtering Algorithm

The *content-Based Filtering* algorithm, proposed in this chapter, followed the same process described in Chapter 5, Section 5.2. The CBF algorithm estimates a *recommendation score* for each of the TR services, by using the previously defined multi-layer user profile and TR-service profiles. As illustrated in algorithm 1, the proposed CB compares the user profile (i.e., the layer corresponding to the category c) with the TR-service profile to estimate their similarity. The intuition behind this choice is that the top-k recommended TR services should be the services that are more similar to the ones that the user likes. Based on the way both user and TR-service profiles have been defined, the problem of recommending items to users becomes the task of evaluating the *similarity* between the two profiles, in particular the θ_c layer of user profile belonging to u, and θ_s for the travel-related service s belong to the same category c. To compute similarity, as proposed in [181], the *Kullback-Leibler* (KL) divergence [21, 115] has been employed as follows:

$$Score_{rank}(\theta_c, \theta_s) = \frac{1}{D_{KL}(\theta_c \| \theta_s)} \tag{6.3}$$

where $D_{KL}(\theta_c \| \theta_s)$ corresponds to measure the divergence between two probability distributions, which can be computed as follows:

$$D_{KL}(\theta_c \| \theta_s) = \sum_w P(w \mid R_s) log \frac{P(w \mid R_s)}{P(w \mid R_c)} \tag{6.4}$$

It is assumed that $D_{KL}(\theta_c \| \theta_s) \neq 0$ for each s. The higher the score, the more similar the service and the user profile are; thus, the k services with the highest similarity values are selected and ranked in the top list of returned recommendations.

Algorithm 1 Content-Based Filtering algorithm (CBF)

Input : TR services category c; a user u profile θ_u; a set of candidate TR services S;
Output : top-k recommended TR services

procedure CB
  Initialize $\theta_u = \theta_c$, for all s belongs to c
  repeat
    for $s \in \mathcal{S}$ **do**
      $\theta_s \leftarrow P(w|R_s)$
      Calculate $Score_{rank}(\theta_c, \theta_s) = \frac{1}{D_{KL}(\theta_c \| \theta_s)}$
  until $S = \emptyset$
  Rank S based on $Score_{rank}$ ▷ The higher the score is, the more relevant the service is.

6.3 LOOKER Implementation

LOOKER has been implemented to recommend travel-related services to tourists in Tunisia. The first LOOKER prototype has been developed with the TUNAV private company[7] for the city of Tunis. Then, in order to evaluate the effectiveness of the system with respect to the system usability, a set of four different cities has been selected: Tunis, Ariana, Sousse and Monastir. LOOKER has been developed for the Android mobile operating system, on top of Android Studio version 6 to support all smartphones running the Android 'Marshmallow' version[8] or higher. Android is currently the largest mobile platform, it dominates the smartphone market with a share of 83%,[9] which allows to the proposed app to be exposed to the largest part of mobile users globally.

6.3.1 System Architecture

LOOKER has been implemented as a *rich mobile application* (RMA) [1], to leverage the hardware capabilities and specifically the GPS sensors of smartphones intended to run the contextual pre-filtering module. The LOOKER *client-server* architecture is illustrated in Figure 6.1. Specifically, its components are organized in a *two-tier* client-server design in which each tier plays a specific role based on the individual roles of its modules.

In details, the *client side* includes a *graphical user interface* (GUI) and a *presentation logic* component. The presentation logic component handles and manages the user's interactions with the mobile application. It includes data validation, response to the user's actions, and communication between the GUI components. All information gathered by means of the GUI is sent to the LOOKER server. Here, data referring to travel-related services and to the user's preferences are stocked and treated.

At the *server side*, the *Google Places* and the *Google Maps* APIs as well as others APIs – illustrated in Table 6.1 – are used to obtain details about TR services, such as opening hours, popular visiting times, reviews, and photos. The server includes two main components: (i) the *data repository* (DR) and (ii) the *recommendation engine*, which is in turn composed of distinct

[7] http://www.tunav.com/
[8] http://www.frandroid.com/tag/android-6-0-marshmallow
[9] Source IDC, 2016 :http://www.idc.com/getdoc.jsp?containerId=prUS41962716

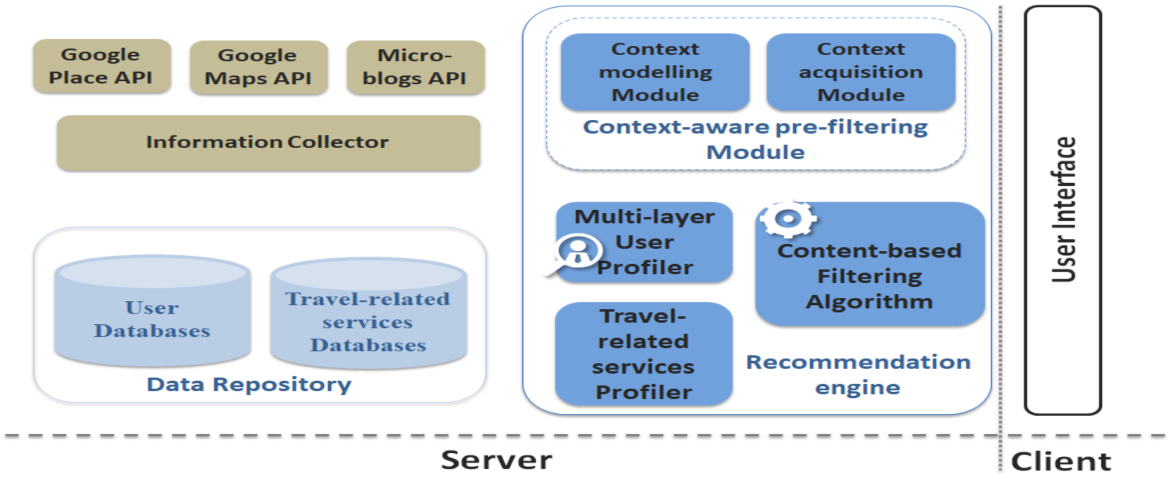


Figure 6.1: The architecture of LOOKER.

modules, among which the *context-aware pre-filtering module*, and the *content-based filtering module* previously described. The DR acts as a back-end system for the recommendation process, and it is responsible for data persistence; data include the user-generated content (i.e., online reviews, ratings, etc.), and the user's context (i.e., her/his geolocation).

Table 6.1: Overview of the employed APIs.

API	Description
Google Places API	It allows to get the current location, get periodic location updates, and addresses. It provides the estimated distance between two locations. It gives further details about services, including opening hours and popular visiting times, reviews and photos.
Google Maps API	It allows to add maps to the application, and to customize them with additional content and imagery provided by LOOKER.
TripAdvisor API	It allows to get information for different points of interest. Information include locations, categories, reviews, ratings, etc.
Facebook API	It allows the integration of the Facebook's Graph API, to get information like the user's name, likes and interests.
Twitter API	It allows to get a collection of tweets posted by the target user.

A brief description of the global functioning of LOOKER is provided below, by emphasizing the associations among the components of the architecture. Here, the different phases of the recommendation process outlined in Section 6.2 are described. For each target user who installed the mobile application:

- The *Android client* gets access through different social media apps installed in the user's smartphone and picks-up all textual UGC from her/his social accounts (i.e., Twitter, Facebook) with her/his consent.

- The *Android client* uses the location data from smartphone's GPS sensor (e.g., longitude and latitude) to track the position of the user; then, it communicates it to the LOOKER *server*.

- The LOOKER *server*, by means of the *Context-Aware pre-filtering module*, selects a subset of TR services based on the user's current location.
- The LOOKER *server*, based on the UGC received, builds the user's profile (as described in Section 6.2.2.1) by means of the *Content-Based Filtering module*.
- The LOOKER *server* executes the recommendation process by means of the *Content-Based Filtering algorithm*. The recommendation engine ranks the TR services by comparing them to the specific user profile layer corresponding to the services category (e.g., food, shopping, health, or attraction) chosen by the user.
- The LOOKER *server* sends the ranked list of recommended travel-related services back to the *Android client*.
- Finally, the top-k ranked TR services are shown to the user by means of the user interface provided by the *Android client* as illustrated in Figure 6.3.

6.3.2 Interface Design

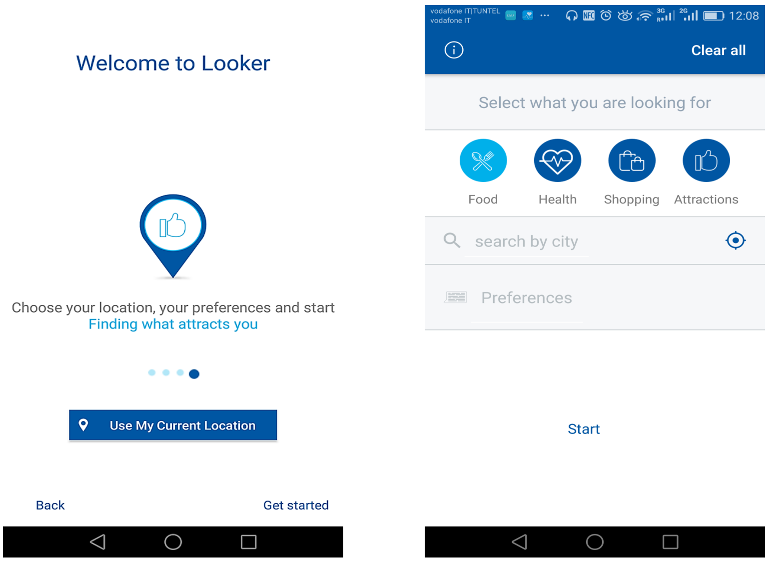
To get the highest level of usability, the first interaction that a user has with LOOKER is constituted *on-boarding* screens[10] illustrated in Figure 6.2 (a), which introduce to a new user the LOOKER application, its operation, and some practical hints on how better exploit the app. The purpose of the on-boarding screens is twofold: (i) to provide the user with a 'learning by doing' methodology to interact with the application, and (ii) to show to the user the ease of use of LOOKER and how fun and useful it can be.

After the *on-boarding process*, the participants are requested to provide some permissions to LOOKER. Firstly, they must allow to LOOKER to interact with different social media apps which are installed on their smartphones. This permission allows to the *Android client* to collect the user's textual UGC. Secondly, the user is required to give permission to LOOKER to identify her/his geographic location (i.e., using the latitude and longitude information obtained by the GPS).

Once the permissions have been granted, the user must specify to which travel-related service category s/he is interested in, to receive touristic suggestions accordingly. S/he can select the chosen TR-service category by clicking on one of the top buttons (i.e., food, health, shopping, attractions) (see Figure 6.2). Moreover, each time the user requests a recommendation for a travel, s/he can specify and add other (optional) preferences that s/he thinks can be useful to enhance the results (see Figure 6.2). Figure 6.3 shows an example of a ranked set of recommendations in the 'food' category (e.g., restaurants), which can be easily scrolled by the user. By clicking on the 'map' button the user is able to visualize the set of results on a map, and to verify their distance with respect to her/his current location. Besides the visualization on the map, the user can see more details about each item in the raked list by clicking on it. As illustrated in Figure 6.4, the detailed view obtained this way provides various information

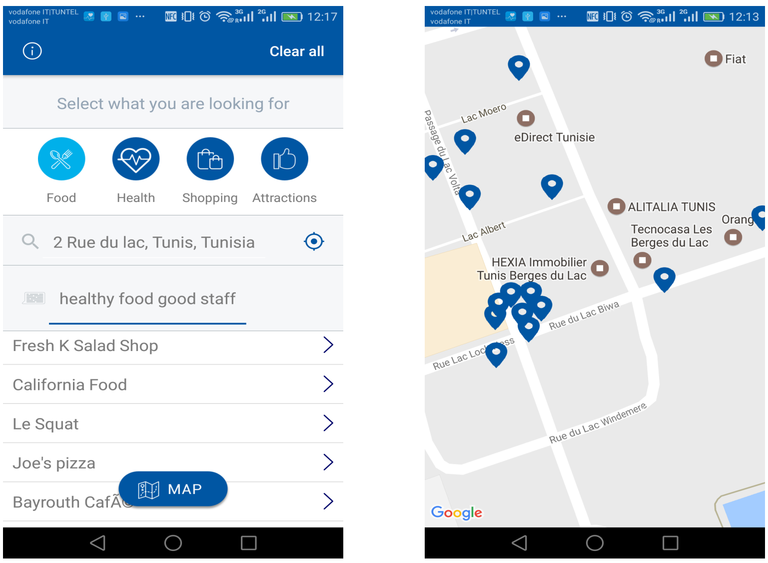
[10] The *on-boarding process*, in mobile application, refers to the mechanism through which new users are informed and educated about the application. A strong on-boarding process is essential for the success of the mobile app [117].

about the recommended TR service, such as: name, address, description, web site link, average rating given by other users, as well as the reviews written about it, and finally the geolocation on the map.



(a) On-boarding Interface (b) Main Interface

Figure 6.2: LOOKER mobile Travel Recommender System

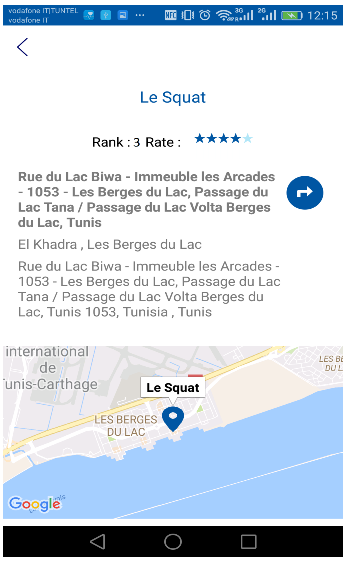


Set of food recommendations. Map view of the results.

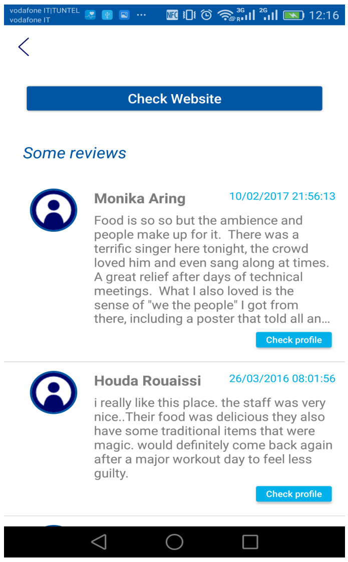
Figure 6.3: Results of restaurants recommendation.

6.4 LOOKER Evaluation: A User Study

As discussed in Chapter 2 Section 2.1.3, the evaluation of Recommender Systems is a challenging task that has been widely discussed in the literature [24, 151, 173]. In general, it is possible to employ *user studies*, *off-line experiments*, and *on-line experiments* for RSs evaluation [173]. The choice of the evaluation strategy of an RS must take into account the goal of the system itself



The detailed view of a recommended restaurant.



A set of reviews about the selected restaurant.

Figure 6.4: Details of LOOKER recommendation results.

[84]. Our proposed mobile recommender system rely on the interaction of users with the system, and thus, offline testing are difficult to conduct. In order to properly evaluate LOOKER, which is a mobile application, we employed a user study to collect real user interactions with the system. This study allows to measure the user's satisfaction and attitude towards our system.

The main motivation for performing a user study is its ability to take into account the user's experience [110] in interacting with a system. Our user study focuses in particular on a user-centered evaluation, based on two popular questionnaires. Thanks to them it is possible to assess both the *usability* of the system and its *usefulness* according to the users' judgments.

6.4.1 Selecting Participants and Main Activities

The user study has been conducted by recruiting a set of participants with distinct characteristics. In fact, according to Tullis et al., [192], to conduct an accurate user study [110], a group of at least 12/14 participants suitably selected is necessary. In the proposed study, in order to have a bigger set of users, 48 participants of various age, educational background and current profession have been chosen. Among the 48 people, 23 were female and 25 were male. Participants were teachers, graduate and undergraduate students from three Tunisian universities (ISG Sousse,[11] ESC Manouba,[12] and IHEC Carthage[13]), computer science engineers (Android developers) who represent 'experts', and simple travelers not related to the academic environment. In general, they were young smartphone users who like to travel and whose ages ranged between 21 and 33 years.

These participants were first requested to provide background information about themselves, such as demographic information and their knowledge about tourism mobile RSs and

[11] http://www.isgs.rnu.tn/
[12] http://www.esct.rnu.tn/site/
[13] http://www.ihec.rnu.tn/

mobile applications in general. Then, they were asked to provide reviews for already experienced TR services, which are necessary to build their user profiles. We asked them to provide at least 60 reviews in English for TR services belonging to different categories (i.e., food, shopping, health, attractions).

Then, the LOOKER application was briefly introduced to participants, and the purpose of the user study was presented. After introducing the participants to the task, they installed the LOOKER application on their smartphones. They were asked to test LOOKER for 15 days in different locations; after having performed this phase, participants were asked to fill two popular questionnaires that are often employed for the evaluation of different kinds of applications, i.e., the *System Usability Scale* (SUS) questionnaire, and the *Computer System Usability Questionnaire* (CSUQ). Specifically, the SUS allows to measure to the usability of a system in general, while the CSUQ allows to assess four aspects of the usability of a system: interface quality, information quality, system usefulness and overall satisfaction. Both questionnaires have a higher accuracy with an increasing sample size with respect to the other questionnaires. [192]. Details on both questionnaires are provided in the following sections.

6.4.2 SUS Questionnaire

The *System Usability Scale* (SUS) questionnaire [39] represents a simple and reliable tool for system's usability evaluation. As illustrated in Figure 6.5, it is a short questionnaire that includes 10 question where participants indicate their rate of approval on a 5-point Likert scale, whose values corresponds to 1: Strongly disagree, 2: Disagree, 3: Neutral, 4: Agree, and 5: Strongly agree.

		Strongly disagree				Strongly agree
1.	I think that I would like to use this system frequently.	☐	☐	☐	☐	☐
2.	I found this system unnecessarily complex.	☐	☐	☐	☐	☐
3.	I thought this system was easy to use.	☐	☐	☐	☐	☐
4.	I think that I would need assistance to be able to use this system.	☐	☐	☐	☐	☐
5.	I found the various functions in this system were well integrated.	☐	☐	☐	☐	☐
6.	I thought there was too much inconsistency in this system.	☐	☐	☐	☐	☐
7.	I would imagine that most people would learn to use this system very quickly.	☐	☐	☐	☐	☐
8.	I found this system very cumbersome/awkward to use.	☐	☐	☐	☐	☐
9.	I felt very confident using this system.	☐	☐	☐	☐	☐
10.	I needed to learn a lot of things before I could get going with this system.	☐	☐	☐	☐	☐
		1	2	3	4	5

Figure 6.5: The System Usability Scale questionnaire.

The SUS questionnaire has been tested throughout almost 30 years of use, and has proven to be an effective method of evaluating the usability of systems including software, websites, and mobile devices. SUS yields a single number representing a composite measure of the overall usability of the system under analysis. For this reason, scores for individual items are not meaningful on their own. For further details on how calculate the SUS score, please refer to [40, 153].

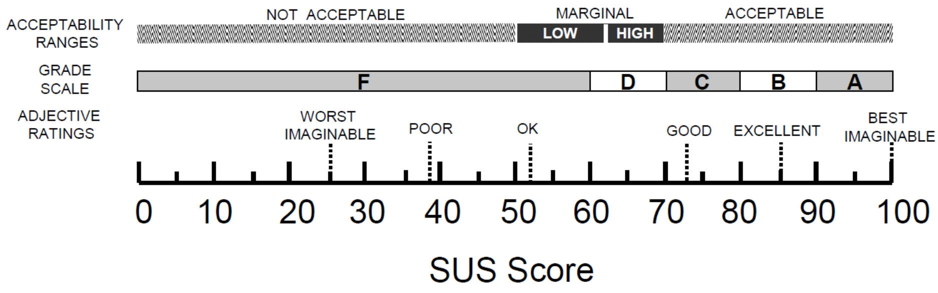


Figure 6.6: A comparison between the SUS and and other grade rankings reproduced based on [18]. Reprinted with permission.

Figure 6.6 illustrates the correspondence between the scores that the SUS questionnaire can produce (on a $[0-100]$ range) and the values of other scales proposed in [18]. This allows to evaluate in a clear way the overall score obtained via the SUS questionnaire after having used LOOKER. In particular, the global score obtained by aggregating the rating provided by our group of participants after trying the LOOKER application during 15 days is 82.9. According to the correspondence between the SUS scores and other scales (see Figure 6.6), LOOKER has an 'excellent' level of usability.

The SUS questionnaire to evaluate the impact of the on-boarding process As previously illustrated, to improve the application usability, an *on-boarding process* [117] has been implemented, with the aim of helping users in understand the key functionalities of LOOKER and to improve the user's first impression about the application. To evaluate the impact of the on-boarding process on the application usability, we divided the participants into two equal groups. The first group was composed of 24 users and filled the SUS questionnaire after using the application without the *on-boarding process*. The rest of the participants assigned their score values in the SUS questionnaire after using a LOOKER version improved with on-boarding screens. Figure 6.7 shows the global SUS scores obtained for each of the two groups of users after using our application with and without on-boarding screens. The SUS score is 80.3 without on-boarding, while it achieves 82.9 with the on-boarding process, with a growth of 3.23%. These results demonstrate that a solid on-boarding process allows to improve the overall system usability.

6.4.3 Computer System Usability Questionnaire

The *Computer System Usability Questionnaire* (CSUQ) [120] has been employed to measure the user satisfaction in using LOOKER under different aspects. The CSUQ consists of 19 questions, for which users were required to provide ratings on a 7-point Likert scale. As illustrated in Figure 6.8, the possible ratings range from 1: 'Strongly disagree', to 7: 'Strongly agree'. The CSUQ questions can be classified into three categories (or sub-scales):

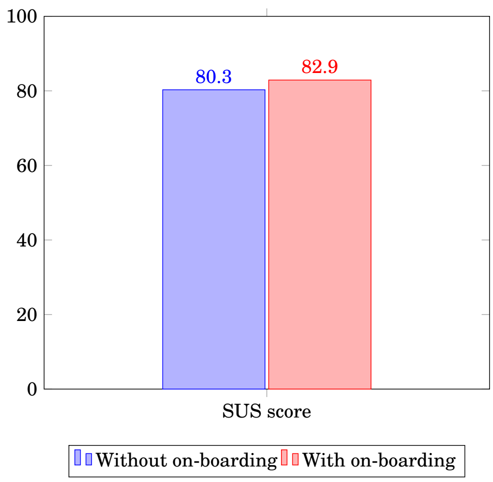


Figure 6.7: Evaluation, by means of the SUS questionnaire, of the impact that on-boarding screens have with respect to the LOOKER overall usability.

- *System Usefulness*: questions 1 – 8 report the system usefulness;
- *Information Quality*: questions 9 – 15 evaluate the user's perceived satisfaction with respect to the quality of the information associated with the system (e.g., information clarity);
- *Interface Quality*: questions 16 – 19 allow to assess the interface quality.

		Strongly disagree						Strongly agree	N/A
1.	Overall, I am satisfied with how easy it is to use this system.	☐	☐	☐	☐	☐	☐	☐	☐
2.	It was simple to use this system.	☐	☐	☐	☐	☐	☐	☐	☐
3.	I can effectively complete my work using this system.	☐	☐	☐	☐	☐	☐	☐	☐
4.	I am able to complete my work quickly using this system.	☐	☐	☐	☐	☐	☐	☐	☐
5.	I am able to efficiently complete my work using this system.	☐	☐	☐	☐	☐	☐	☐	☐
6.	I feel comfortable using this system.	☐	☐	☐	☐	☐	☐	☐	☐
7.	It was easy to learn to use this system.	☐	☐	☐	☐	☐	☐	☐	☐
8.	I believe I became productive quickly using this system.	☐	☐	☐	☐	☐	☐	☐	☐
9.	The system gives error messages that clearly tell me how to fix problems.	☐	☐	☐	☐	☐	☐	☐	☐
10.	Whenever I make a mistake using the system, I recover easily and quickly.	☐	☐	☐	☐	☐	☐	☐	☐
11.	The information provided with this system is clear.	☐	☐	☐	☐	☐	☐	☐	☐
12.	It is easy to find the information I needed.	☐	☐	☐	☐	☐	☐	☐	☐
13.	The information provided for the system is easy to understand.	☐	☐	☐	☐	☐	☐	☐	☐
14.	The information is effective in helping me complete the tasks and scenarios.	☐	☐	☐	☐	☐	☐	☐	☐
15.	The organization of information on the system screens is clear.	☐	☐	☐	☐	☐	☐	☐	☐
16.	The interface of this system is pleasant.	☐	☐	☐	☐	☐	☐	☐	☐
17.	I like using the interface of this system.	☐	☐	☐	☐	☐	☐	☐	☐
18.	This system has all the functions and capabilities I expect it to have.	☐	☐	☐	☐	☐	☐	☐	☐
19.	Overall, I am satisfied with this system.	☐	☐	☐	☐	☐	☐	☐	☐
		1	2	3	4	5	6	7	N/A

Figure 6.8: The Computer System Usability Questionnaire.

The CSUQ scores have been first computed with respect to the three sub-scales: the *System Usefulness*, which corresponds to 5.52, the *Information Quality*, equal to 5.53, and the *Interface*

Quality, equal to 5.23. All these scores are averaged on a 7-point scale, where high scores are better than low scores due to the anchors used in the 7-point scales, as it emerges from figure 6.8. The global CSUQ score is equal to 5.25 computed on the 7-point scale, which implies a high level of usability. These scores have been obtained as described in [120].

The global score has also been normalized on a $[0-100]$ scale, to compare it with the result produced by the SUS score. The obtained result, equal to 74.4, indicates that the LOOKER app is generally perceived as 'good' (see Figure 6.6). To a greater level of detail, the proposed approach has been particularly appreciated with respect to *Information Quality* (the normalized score for this sub-scale is 76.75).

In the following, Table 6.2 analyze the SUS and the CSUQ scores according to different demographic factors; the scores of each group of participants (with respect to demographic factors) are reported along with their standard deviation (SD). Spearman correlation [88] was conducted and revealed that SUS score was significantly associated with CSUQ (r_s= 0.71619, n=48, $p < 0.05$). Hence, the association between the two scores would be considered statistically significant. This correlation between both questionnaires results allows confirming the usability of LOOKER app.

Table 6.2: A summary of mean values of CSUQ and SUS scores for different categories of participants.

Demographic Factor	Response	CSUQ score		SUS score	
		Mean	SD	Mean	SD
Gender	Male	74.38	6.85	85.30	8.04
	Female	77.67	7.84	85.62	8.18
Education background	Graduate	79.17	6.15	86.66	8.74
	Undergraduate	73.54	8.13	84.37	7.34
Occupation	Teacher	72.77	9.14	84.61	8.65
	Software Engineer	71.03	7.62	84.16	7.01
	Others	72.29	6.19	86.15	8.13

6.5 Summary

In this chapter, we have presented a new approach for personalized recommendation in tourism domain. We have presented a mobile application prototype LOOKER that provides mobile users with relevant TR services recommendation and helps them to find point of interests in different categories. Our approach is a context-aware and content-based recommender system. It applies a pre-filtering Context-Aware module to select a subset of contextually relevant items. Then, we apply a Content-Based Filtering module, which employ UGC to infer user preferences and to predict the accuracy of candidates TR services to the target user based on her/his profile in the current context. We conducted a user study, to evaluate the usability of the proposed application with a set of users in four big cities in Tunisia.

In the future work, we plan to enhance the pre-filtering context-aware module with more contextual dimensions that can affect the user perception of what is a relevant recommendation, i.e., travel time, weather, travel partners, budgets, etc.

CHAPTER 7

CONCLUSIONS

This chapter provides a summary of the work presented in this thesis. In Section 7.1, we begin by summarizing the main contributions that our work brings to the Recommender System research field. In Section 7.2, we review the above mentioned contributions with respect to the research questions that emerge from the literature and that was stated in Chapter 1. Then, in Section 7.3, we review and discuss the significance of our research outcomes. Finally, in Section 7.4, we discuss future directions for the research conducted in this thesis.

7.1 Summary of Contributions

In the literature, *Recommender Systems* (RS)s have been extensively explored as a solution to the information overload problem. In the tourism domain, in particular, RSs have been applied to provide tourists with personalized suggestions just in time whenever and wherever they need. However, recommending items in the tourism domain is a challenging task due to: (i) the difficulty in considering the user's changing preferences, (ii) the changing user's context. From a technical point of view, in different recommendation approaches, those focusing on Collaborative Filtering (CF) in particular, the sparsity of context-tagged user-item rating matrix is an important issue: the number of rated items by a user under different contextual situations is very low. Hence, the user's topical preferences along with her/his context should be implicitly inferred from evident sources of information.

This thesis presented a number of contributions towards the goal of predicting the user's preferences to improve *Travel-Related services* (TR-services) recommendation in a mobile context. We provided significant contributions with regard to the use of context-awareness techniques and language models to represent the user's interests in Travel Recommender Systems. Specifically, we contributed to the demonstration of the utility of the use of User-Generated Content as an effective way for user modeling and personalized recommendation. In the following, we present a focused summary of the contributions of this dissertation:

1. **An effective method to model and acquire relevant contextual factors**

   We proposed a context modeling and acquisition method that encompasses two main contributions:

   - A context model that allows capturing and presenting the contextual factors within the user's current context. We adopted the *Context Modeling Language* (CML) to capture the pertinent information and their meta-data. This model reduces provides an explanation of the dynamic mappings between users and the entities involved in their context.
   - A context data acquisition method that identifies relevant contextual factors with respect to their influence on the user's perception of what is relevant information.

   Then, we applied the proposed method to a mobile search system. This demonstrated that considering the user's context and specific contextual factors is an effective means for providing accurate search results.

2. **A multi-layer user profile based on the on-line content generated by the user**

   We proposed a dynamic user profile that enables to infer the user's topical interests about different entities (i.e., different Travel-Related service categories). In particular, the user profile is represented by a language model that, for each TR service category, models the probability distribution of the words within the user's language employed over social media in the form of textual reviews. The profile built in this way is easily interpretable, and it was explored for TR-services recommendation in a restricted geographical area.

3. **A context-aware and content-based approach for recommendation in the tourism domain**

   We proposed a context-aware and content-based recommendation approach that jointly integrates User-Generated Content and contextual factors to improve mobile recommendation. This approach applies a contextual pre-filtering strategy that estimates the relevance of items with respect to the user's current context. Then, we employed statistical language models to model TR service profiles in the tourism domain for providing content-based recommendations. The proposed recommendation approach incorporates two similarity-based scoring measures, whereby services that fit the user's positive opinions, (or that do not fit the user's negative opinions) are recommended. The approach has been evaluated by using the Yelp challenge dataset with precision-oriented measures. Experimental results clearly demonstrate that the incorporation of both user's positive and negative opinions into the user model enhance the recommendation accuracy. In addition to producing effective recommendations for Travel-Related services, the proposed approach alleviated the data sparsity problem and served as a significant basis towards the incorporation of social information in the recommendation process.

4. **A rich mobile application for travel recommendation**

We developed LOOKER, a mobile recommender system for Travel-Related services that incorporates the above described contributions. It is an adaptable application developed for the Android platform, which combines context-aware recommendation with a content-based filtering model to make personalized suggestions, and provide tourists with items of their interest. To evaluate the usefulness and the usability of the LOOKER mobile application, a user study has been conducted. The good results obtained illustrate the potential of LOOKER to provide a good user experience while maintaining good recommendation accuracy.

7.2 Answers to Research Questions

Let us now review our findings with respect to our research questions illustrated in Chapter 1.

1. **Which contextual factors should be considered to improve the system accuracy?**

   This question has been answered by means of the context modeling and acquisition method illustrated in Chapter 4. The method was tuned to be applied to the mobile search framework. It yielded useful insights in terms of the impact of contextual factors in improving search results accuracy with respect to the user's information need (formally sketched in a query).

2. **Is it possible to utilize social information (for example textual UGC) in order to create a richer and multi-domain user profile?**

   This question led to our user modeling efforts, and was initially derived by the need of a relevant source of information to infer the user's topical interest in a changing context. As reported in Chapter 5, we explored the possibility of utilizing on-line User-Generated Content in the form of textual reviews for the user profile creation. The effectiveness of user modeling was improved by developing a generic and multi-domain model reported in Chapter 6. We explored the richness of on-line UGC in order to infer the user's preferences in different Travel-Related service categories. Experimental outcomes demonstrated the usefulness of the use of UGC as a source for user profile construction in mobile recommendation.

3. **How to handle natural language in UGC to identify the user's opinions and interests?**

   This question has been answered by means of the use of language models to build the user profile. Statistical language models was used to model the probability distribution of words within a user's language employed over social media in the form of textual reviews. The experimental results in Chapter 5 demonstrated that this way of modeling user profiles is easily interpretable, and it can enhance the recommendation accuracy.

4. **How to exploit the user's context accurately in the recommendation process while dealing with the context-data sparsity issue?**

The data sparsity issue in context-aware recommendation approaches has been addressed by mean of a context-aware and content-based recommendation approach illustrated in Chapter 5. More specifically, the answer to this question lies in: (i) a context pre-filtering strategy that selects only relevant items (with respect to the spatio-temporal context) to be further analyzed; (ii) the exploration of the user profile for content-based filtering to select the items which are more similar to the user's interests in the current context. Our findings revealed that the contextual pre-filtering strategy helps to restrict the subset of TR services and avoid the unnecessary recommendation of items that are not effectively usable by the user. In addition, considering the user's topical interest improve the recommendation results and consequently the system accuracy.

5. **How can the user satisfaction increase toward mobile recommendation systems while maintaining accuracy?**

   This question has been answered by means of a rich mobile application: LOOKER. We investigated the interaction design of a mobile travel recommender system. Different challenges have been addressed when designing the system prototype, e.g., the smaller screen size, the integration of information about the mobile context, etc. The designed solution meets these requirements and produced a user-friendly application. After having conducted a user-study for evaluation, we was able to state that our system helps in improving the user experience of a mobile recommender system while maintaining the user's satisfaction together with the recommendation accuracy.

7.3 Significance of Research Outcomes

In general, the contributions described in this thesis serve as a significant basis for integrating User-Generated Content and useful contextual information in the recommendation process. In particular:

- Utilizing User-Generated Content in social media as a source of evidence for user profile creation: (i) alleviates the problems encountered in explicit user modeling techniques (see Section 2.1.2.2 of Chapter 2), and (ii) reduces the noise injected in the user's profile because UGC represent a direct evidence about those experiences that the user already made in person.

- Utilizing useful contextual factors in the pre-filtering process deals with the data sparsity problem observed in CARS approaches. In particular, it allows to reduce the multi-dimensional context-aware recommendation problem to a standard (2D) space for which we are able to introduce the user's topical interests.

- Developing a rich mobile application for travel recommendation allows to retrieve and use contextual information. This allows to potentially improve the recommendation accuracy and and enhance the user experience in the tourism domain.

7.4 Future Directions

As a further work, we aim to extend the proposed recommendation model to include the following improvements:

- **Enhancing user profile through n-gram language models**

  Utilizing UGC for user profile construction remains challenging due to the UGC characteristics. The short-text format and and real-time nature of UGC leads to two well-known problems such as polysemy, or term mismatch, and synonymy. We aim to address these issues by considering dependencies by means of bigrams language models, and by considering word relationships [56].

- **Considering Recommendation Transparency:**

  Existing travel RSs mostly produce suggestions to users for items or contents based on the user's explicit or implicit feedbacks. Such systems rely on what users previously consumed or by the adaptation of social networking features to enable users with similar interests (i.e., identification of similarities with other users). However, from a user's viewpoint they remain a *black box* that suggests services, without understand the reason why they are included in the recommendation list. Thereby, RSs are faced with the emerging issue of *Recommendation Transparency* [82]. Travel RSs in particular should provide users with an understandable representation of recommendations, allowing them to have more confidence with the system. Recommendation Transparency affects how recommendations are perceived as accurate by the user. To enhance the capability of the system to be not only accurate, but also perceived as accurate, the goal of this research is to incorporate Recommendation Transparency to travel recommendation.

- **Considering Group Recommendations:** In the tourism domain, users' preferences could be truly influenced by collective behaviors. However, most existing works on Travel Recommender Systems focus on recommending items to individual users [11, 125]. The challenge for travel recommendation is how to decide what would be relevant for an individual user in a changing context. When the user profile does not contain enough information, the individual recommendations will not be effective. Therefore, we aim to investigate how a user could obtain better recommendations looking at the group recommendations. Group recommendation can be interpreted as a particular form of context recommendation, where the user's preferences are adapted from her/his social context (friends or companion preferences) [13].

- **Evaluating alternative contextual information for travel recommendation:** To develop our context-aware and content-based recommender system, we employed a context pre-filtering strategy based on spatio-temporal context. Although this module has already shown good performances, it is clear that many contextual factors could be used in the recommendation process [34]. This includes weather, season, temperature and companion. The contextual information should be actively incorporated to enhance the recommendation accuracy. We aim to provide context-aware and just in time suggestions. Unlike other contributions related to the tourism domain, our proposal is intended to recommend TR services as schedules rather than as contents, i.e., the best check-in time at the closest restaurant with the actual companion.

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