AN IMPROVED APPROACH OF CONTEXTUAL SUGGESTION SYSTEM FOR E-TOURISM

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SULTAN IDRIS EDUCATION UNIVERSITY

2022

AN IMPROVED APPROACH OF CONTEXTUAL SUGGESTION SYSTEM FOR E-TOURISM

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05-4506832 pustaka.upsi.edu.my Perpustakaan Tuanku Bainun Kampus Sultan Abdul Jalil Shah PustakaTBainun ptbupsi

THESIS PRESENTED TO QUALIFY FOR A DOCTOR OF PHILOSOPHY

FACULTY OF ART, COMPUTING AND CREATIVE INDUSTRY
SULTAN IDRIS EDUCATION UNIVERSITY

2022

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ACKNOWLEDGEMENT

This PhD has been a life-changing journey for me, and I could not have done it without the encouragement and support of many individuals.

I gratefully acknowledge the help of, Dr Wang Shir Li, my main supervisor. Her expertise was quite helpful in creating the study objectives, technique, and general research flow. Her insightful remarks encouraged me to improve my thoughts and raise the quality of my work. This PhD would not have been possible without her mentoring and frequent criticism.

I owe a debt of gratitude to my previous supervisors, Dr Kian Lam Tan and Dr Chen Kim Lim, for their unwavering support and a never-ending supply of mindboggling ideas. Their unassuming approach to science and research is an inspiration. This approach is mirrored in their straightforward writing style, which I intend to emulate throughout my career.

I also want to thank Dr Mou Lei (Chengdu University, China) for introducing me to smart tourism-related applications as an external supervisor. I am thankful to Dr Mohammad Aliannejadi for his continuous support, his research guidance enabled me to cope with the technicalities needed to draft the interpretations. I am also thankful to the National Institute of Standards and Technology (NIST, USA) and TREC organizers for providing the Dataset needed to carry out experiments. Lastly, I would like to mention Dr Waseem Tufail from whom I learned the basics of research.

In addition, I am grateful for my family’s unconditional, unequivocal, and loving support. Especially Dr Naveed ur Rehman Khan for pushing us to do the unthinkable. My loving parents Fazal ur Rehman and Shahnaz Sardar Fazal for keep supporting me endlessly. Dr Arsalan Mujahid Ghouri, and Dr Mutahara Khan for unconditional love and blessings. Finally, I couldn't have finished this dissertation without Mustafa Rehman Khan's help, who kept me out of the research by delivering fascinating, intelligent talks. Tayyaba Rehman Khan for her memories cannot wait to meet her again. Omair Haroon for listening to my ideas and making plans after my return. Mohd Ahmed Khan for his countless therapies and warm memories of Ibrahim and Sahab as well as Abha’s cute videos.

ABSTRACT

The contextual suggestion system is defined as "generating a list of venues for a user, based on temporal and geographical context as well as traveller's preferences relating to venues to be suggested". A lack of effective methodologies has compromised the accuracy of the contextual suggestion system in e-tourism. In this regard, the Text Retrieval Conference (TREC) has been organized yearly to focus not only on the development of information retrieval systems but also on the approaches leading to the improvement of the systems. Besides, TREC provides datasets and standard protocols for evaluation to ensure fair comparisons. In the study, an improved approach based on four main phases has been proposed for the contextual suggestion system in e-tourism, namely, (i) Dataset Enrichment, (ii) Profile Enrichment, (iii) User Modelling, and (iv) Ranking Suggestion. The TREC dataset is used to evaluate the proposed approach. In the Dataset Enrichment's improvement, tags prediction, semantic similarity between tags, and correlation between tags are used. The improvement in Profile Enrichment is based on context processing and relevancy between the user and venue profiles in the given context. On the other hand, the improvement in User Modelling is based on content-collaborative filtering and iterative-based approaches. Lastly, a linear combination of true rocchio and cosine similarity is used to improve Ranking Suggestion. The performance of the proposed approach is evaluated based on TREC's standard evaluation protocols consisting of NDCG@5, P@5, and MRR. The experimental results show an increment of 5% to 12% of accuracy in the proposed approach and the increment is significantly better than the baseline run. In conclusion, the proposed approach shows significant improvements consisting of 12.5% in P@5, 4.77% in NDCG@5, and 5.04% in MRR. This study implicates that the use of a contextual-based personalized venue suggestions system enhances the travel experience of a traveller.

PENDEKATAN PENINGKATAN SISTEM CADANGAN KONTEKSTUAL UNTUK E-PELANCONGAN

ABSTRAK

Sistem cadangan kontekstual ditakrifkan sebagai "penjanaan senarai tempat untuk pengguna, berdasarkan konteks temporal dan geografi serta keutamaan pengembara yang berkaitan dengan tempat yang dicadangkan". Kekurangan metodologi yang berkesan telah menjejaskan ketepatan sistem cadangan kontekstual dalam e-pelancongan. Dalam hal ini, anjuran tahunan Text Retrieval Conference (TREC) diadakan untuk memfokuskan bukan sahaja pada pembangunan sistem pencarian maklumat tetapi juga pada pendekatan yang dapat meningkatkan prestasi sistem. Selain itu, TREC menyediakan data dan protokol standard untuk tujuan penilaian yang adil. Dalam kajian tersebut, satu penambahbaikan pendekatan yang berdasarkan empat fasa utama telah dicadangkan untuk sistem cadangan kontekstual dalam e-pelancongan, iaitu, (i) Dataset Enrichment, (ii) Profile Enrichment, (iii) User Modelling, and (iv) Ranking Suggestion. Data dalam TREC digunakan untuk menilai prestasi pendekatan yang dicadangkan. Dalam penambahbaikan Dataset Enrichment, ramalan tag, persamaan semantik antara tag dan korelasi antara tag digunakan. Penambahbaikan dalam Profile Enrichment adalah berdasarkan pemprosesan konteks dan hubungkait antara profil pengguna dan tempat dalam konteks yang diberikan. Manakala, penambahbaikan dalam User Modelling adalah berdasarkan penapisan kolaboratif kandungan dan pendekatan berasaskan berulang. Akhir sekali, satu gabungan linear persamaan rocchio dan kosinus sebenar digunakan untuk penambahbaikan dalam Ranking Suggestion. Prestasi pendekatan yang dicadangkan dinilai berdasarkan protokol penilaian standard TREC yang terdiri daripada NDCG@5, P@5, dan MRR. Keputusan eksperimen menunjukkan bahawa pendekatan tersebut mencapai peningkatan ketepatan sebanyak 5% sehingga 12% dan menunjukkan peningkatan yang ketara berbanding dengan perlaksanaan garis dasar. Kesimpulannya, pendekatan yang dicadangkan menunjukkan peningkatan yang ketara, iaitu 12.5% untuk P@5, 4.77% untuk NDCG@5, dan 5.04% untuk MRR. Kajian ini mengimplikasi bahawa penggunaan sistem cadangan kontekstual yang berdasarkan cadangan tempat secara peribadi dapat meningkatkan pengalaman pengembaraan.

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CHAPTER 1

INTRODUCTION

This chapter discusses the introduction of this research. Section 1.1 presents the introduction; while Section 1.2 presents research background; Section 1.3 presents the motivation; Section 1.4 presents the operational definitions; Section 1.5 presents the problem statement; Section 1.6 presents the objective of the study; Section 1.7 presents research questions; Section 1.8 presents the research hypothesis; Section 1.9 presents contributions; Section 1.10 significance of the study; Section 1.11 presents thesis organization.

1.1 Introduction

This research focuses on contextual suggestion system techniques in order to develop and propose an improved approach that can accurately suggest a predicted list of venues to a tourist considering his/her personal interests and context, to improve the travel experience. The main goal of this research is to utilise approaches based on Artificial Intelligence (AI) and Information Retrieval (IR), which must be able to provide a list of venues based on the context and personalized information of the user. This system can help travellers who are looking for places to visit nearby in a new city, based on their context, location, and personal preferences.

1.2 Research Background

Tourism has changed dramatically in recent years as a result of technological advancements, reshaping both the industry and our perceptions of tourism. Information and communication technologies (ICT) are gradually becoming more important in providing competitiveness to the tourism sector, and therefore evolving tourists and tourism business behaviour, which is referred to as e-tourism (Shafqat & Byun, 2020). E-tourism makes extensive use of Facebook, Twitter, YouTube, and other social media platforms, which is bolstered by travellers' increasing usage of social media platforms. Due to the influence of social media, the way people acquire and use tourism information has changed dramatically in recent years (Xiang, Magnini, & Fesenmaier, 2015), around 69% of travellers are influenced by the social media platforms during the trip-planning stage, and 50% of tourists plan their trip based on public assessments and insights about the specific location, according to the ITB World Travel Trends (2012–2013). In a nutshell, e-tourism is the digitalization of all operations and value chains in the travel, tourism, hospitality, and catering industries, allowing businesses to increase efficiency and effectiveness (Buhalis, 2020).

(Gretzel et al., 2020) proposed six novel pillars for transforming e-tourism by critically assessing the existing ones. The proposed pillars are epistemological and ontological based on historic fundamentals, transparency, equity, plurality, reflexivity, and creativity. Furthermore, e-tourism destinations should be innovative, engaging, and enhance visitors' travel experiences. However, as e-tourism develops, new difficulties emerge, such as personalized content recommended to a tourist (Buhalis & Amaranggana, 2015; Kontogianni & Alepis, 2020). If dataset repositories are suitable for dataset extraction and e-tourism services are fed with implicit or explicit feedback, system accuracy improves and privacy issues lessen. Similarly, established ICT infrastructures, such as Wi-Fi, RFID, cellphones, cloud computing, and sensors, can play an important role in developing e-tourism applications (Masseno & Santos, 2019). Currently, a few e-tourism services exist, such as sensor-based services including weather sensors, physical sensors (e.g., CCTV cameras), and social sensors (e.g., social media), to assist a traveller with a limited amount of time to explore a city (Nitti et al., 2017). To perform area-based marketing, location-based tracking services were introduced (Masseno & Santos, 2019). And a recommendation system that suggests the most relevant tourist spot or Point of Interest (POI) based on personal preferences to assume and predict tourists' behaviour (Gavalas, Konstantopoulos, Mastakas, & Pantziou, 2014).

Also, the Internet of Things (IoT) is propelling ICT forward. Similarly, because of the necessity to extract data from millions of documents, systems with sound technologies make it easier to modify search engines in terms of capacity and speed. While technology is always changing, it may be beneficial to e-tourism if a system can automatically assist in tour planning or offer a list of venues based on a tourist's personalized interests. This system can assist millions of travellers across the world take advantage of e-tourism services such as tour planning and automated suggestions and recommendation of places to visit in order to improve their travel experience.

As travellers appear to rely substantially on their cell phones when looking for events to attend or discovering interesting nearby locations or things to do. To comprehend the idea, consider a traveller in a new city who has a set of preferences for locations and activities in his home city; the system would recommend things based on his current context, interests and personal profile.

For example, if a user drinks coffee, the system may recommend a brand of coffee that he likes as well as nearby locations where the specific brand of coffee is sold; this user's user profile is to drink coffee, namely Lattee. When he visits Tanjong Malim, the Contextual Suggestion System can present a list of coffee shops, with the coffee shops that sell Lattee at the top of the list. By combining personal preferences, prior history, and contextual aspects such as the user's location, weather, and time, user profiles can be created from the places he has visited, employing the many data resources accessible in repositories online such as social networks and location-based social networks (LBSN). In comparison to other traditional recommender systems, this concept could be a good fit for creating a list of recommendations or suggestions in the context of e-tourism.

The data repositories social media offers via internet-connected sensors and the internet of things (IoT) are enormously huge (Soldatos, Draief, Macdonald, & Ounis, 2012), consequently, usage of such data repositories provide a profound and intense view of city insights at any time and help in making realistic forecasting and achieving overwhelming results. Therefore, the data collected and stored in these repositories are based on two categories of sensors; physical as well as social sensors. The physical sensors usually include a microphone, CCTV cameras, wearable, and environment sensors whereas social sensors comprise Twitter, Facebook and other social media applications (Deveaud, Albakour, Macdonald, & Ounis, 2014). Keeping given the function and framework of these up-to-date sensors and repositories, new applications have emerged to utilise such huge data by filtering, analysing, and storing the data captured from the physical world (Soldatos et al., 2012). At present, recommendation systems are largely utilising the dataset based on the social sensors, however, data/information extracted from physical sensors is deliberately ignored. Dataset reforestations and repositories based on social and physical sensors can significantly enhance the quality of contextual suggestion and recommendation systems; physical sensors in this way act as a primary source to capture real-time information while social sensors act as a secondary source of capturing additional data for any query in multiple contexts (e.g., realtime/hourly traffic status, and daily/hourly weather reports) (Deveaud et al., 2014).

The dataset captured from these sensors can be utilised subjective to various fields and applications. For instance, in e-tourism, venue recommendations (Aliannejadi, Mele, & Crestani, 2016; Aliannejadi, Rafailidis, & Crestani, 2018) mostly rely on a dataset that is extracted from social sensors only such as location-based social networks (LBSNs) (Bao, Zheng, Wilkie, & Mokbel, 2015). As a result, systems struggle with accuracy in order to recommend a venue, because data from social sensors suffer from sparsity, therefore, the system needs to access users' personal information, which in return raises privacy as well as personal concerns. Thus, these privacy, security concerns and data sparsity issues can be minimized through the digital infrastructure and dataset repositories operating and containing the dataset from multiple sensors in e-tourism.

Therefore, to address these issues, the next generation of recommendation systems in e-tourism applications is highly required. These next generation of recommendation systems should be reliable in providing accurate and effective recommendations by utilising context-specific information from social sensors and adding further details through physical sensors will formulate an instant, effective, and accurate list of recommended venues to tourists and thereby promote and enhance tourism-related experience, activities and services (Sánchez, Cantador, Cediel, & Gil, 2020).

Recently, the initiative to introduce advanced technology in tourism applications is changing our view on tourism. Consequently, the critical role is played by Information and Communication Technologies (ICT) by facilitating the tourism industry and offering a competitive environment to the tourism-related businesses to enhance tourism experience and destination planning. ICT is also evolving tourist behaviour by offering a larger list of interesting places, searching for accommodation and transport planning without the need for any local guidance. Facebook, Twitter and YouTube and other social media platforms' presence are being felt in the tourism industries as exponential growth has been witnessed in terms of user interaction on social media platforms. Moreover, it is reported that travellers are getting more influenced by social networks than any other source. Almost every traveller plans his/her trip using social media and location-based social network applications. Reviews of other travellers and sharing experience on social network encourage the globetrotting instinct at about 40%, whereas 50% of travellers plan their trip on other travelling-related websites and applications which is also based on public reviews and personal experiences about the specific place (Kim, Rasouli, Timmermans, 2018). Moreover, travel bloggers provide recommendations to their followers regarding their recent visited places. Their recommended places are based on personal experiences. Due to their interaction with followers via social media, people trust their recommendations and follow their guidance while making decisions on outdoor trips. They also influence people to visit the recommended places, ask followers for venue recommendations for their next visit and share public personal experiences and reviews of the trip (ITB World Travel Trends, 2012–2013). However, comprehensive information and unbiased insights of a recommended place are also limited, as a single blogger cannot cover all the aspects of recommended places, due to sponsored campaigns and limited time spent on a specific location by the blogger. Therefore, in order to get better insights into the tourism-related places, several location-based social networks (LBSNs) such as TripAdvisor, Yelp, Foursquare and others have emerged to fill the need for tourism.

Currently, ICT is also advancing with the integration of the Internet of Things. Furthermore, ICT facilitates the development of modern search engines by providing the speed and capacity it needs to search and fetch data from million of digital documents, this enables search engines to become the most effective method to search and filter from an enormous amount of data. This advancement in recent technologies can also contribute to the field of recommendation systems especially in tourism-based applications to filter out irrelevant choices from a huge number of venues to make recommendations more accurate.

While technologies are continuously evolving, tourism industries and tourists may benefit if a system can spontaneously help in suggesting a place from the large categories of venues based on users' interests and preferences. In this regard, this system can provide relief and ease to millions of travellers around the world by cherry-picking interesting venues for them to enhance their travel experience. Such modern advancements in the recommendation systems may also facilitate tourists in managing appropriate accommodations, restaurants, outdoor entertainment activities, and cultural heritage for potential recommended places. In addition to this, public ratings, reviews, and tourist personal interest also help to generate a more precise list of venue suggestions (Figueredo et al., 2018).

Moreover, the data explosion that social media and location-based social networks offer may increase tourist choices, which can therefore cause risks of information overload (Lau et al., 2019; Lu & Guo, 2019). Consequently, in order to provide precise recommendations to ease and enhance users' travel experience, the systems must understand brief information about venues, users' interests, personal preferences and users' behaviour. These scenarios have led to the evolution of traditional tourism, which has further evolved into e-tourism (Kontogianni & Alepis, 2020) by integrating the e-tourism experience and ICT.

Besides, tourism usually revolves around travellers' activities that they perform during trips. The activities travellers perform during the journey are mainly different from those of their regular activities and routine practices. The whole travelling duration/trip most of the time involves leisure or business reasons and sometimes miscellaneous purposes that can last for more than a day and less than a year. As one of the world's largest economic sectors, travel & tourism creates jobs, promote an exchange of cultural heritage, preserves export and generates tranquillity around the globe.

An analysis by World Travel and Tourism Council, (2017), shows that the global economic impact of travel & tourism is an important economic activity in most countries around the world, according to their report, the sector is shown to account for 10.4% of global GDP and 313 million jobs or 9.9% of total employment, in 2017 and the growth is expected to exceed to 4% of global GDP and 3% of total employment in 2018 and the increase in spending comprise of domestic spending, leisure and business spending. Table 1.1 shows the details of the fact sheet of growth indicators in 2017 and 2018.

Table 1.1

Growth fact sheet by World Travel Tourism Council (WTTC)

World	**2017 (USDbn)**	**2017 % of Total**	**2018 Growth**
Direct contribution to GDP	2,570.1	3.2	4.0
Total contribution to GDP	**8,272.3**	**10.4**	**4.0**
Direct contribution to employment	118,454	3.8	2.4
Total contribution to employment	313,221	9.9	3.0
Domestic spending	3,970.5	5.0	4.1
Leisure spending	4,233.3	2.5	4.1
Business spending	1230.6	0.7	4.8

The current state of tourism is manifest by the emergence of new markets, presenting a great number of options to tourists and diverse business opportunities for locals. Higher participation from locals in offering tourism-related activities attract more tourist, therefore, resulting in the creation of uncountable activities and attractions nearby making tourist explore more and schedule their vacations more often throughout the year. Therefore, people are more drawn toward e-tourism because of its advanced applications such as Location-based Social Networks (LBSNs) and Social Media to increase the frequency of travel, the simplicity of planning a vacation and necessary information about the venues are the key factors. This reality can be explained by the fact that the Internet is part of our daily life, and no study is found to be denying its significance. Although people must review diverse data of potential places and information related to any specific place before finalizing a destination and planning a trip. Therefore, they will likely prefer to filter unnecessary information and look for those places or activities that match their interests, personal preferences, and context. Each traveller's profiles determine the different places to visit or the different ways to plan a trip. For example, people who travel with children will avoid visiting multiple museums and will consider practising outdoor activities, such as water sports or amusement parks. They will prefer all those activities which will entertain their children, and, in this regard, a system is highly needed that can help the tourist to suggest interesting places and activities according to the context.

Therefore, e-tourism integrated with the Internet of Things (IoT) via social and physical sensors has the potential to offer innovative applications to the tourist, to improve tourist experiences. In this regard, several tourist applications based on cutting-edge mythologies and techniques are emerging in the process which not only consider users' personal information but also extract users' context to generate a list of suggestions about potential places a user might like interesting to visit. Furthermore, all these applications usually work utilising various dataset repositories. These applications can be effective in enhancing the tourist experience as the generated list of suggestions assist them in their destination planning and compile mandatory information about interesting places. Consequently, the system selects and filters out the most suitable places from large repositories of datasets, by taking the user's profile, interests, personal preferences, and context into account.

Moreover, in order to develop such systems and applications, there is a need to reinvestigate issues related to Information Retrieval (IR) based filtering methods and Artificial Intelligence (AI) based machine learning approaches, to filter and predict a venue from multifarious datasets considering contextual-based queries with regards to user's data and interests. Second Strategic Workshop on Information Retrieval has reported that current e-tourism-based services, applications and methodologies offer limited features, therefore, future e-tourism-based services applications should be based on Information Retrieval that should be able to anticipate places based on contextual factors concerning user's personal preferences and interests without consulting them to provide an explicit query. In a mobile environment, a system can be built with features that suggest interesting places to users based on contextual factors such as their current location weather and time, and previous check-in history (Allan, Croft, Moffat, & Sanderson, 2012). While several pieces of research have been conducted to convert the theory into practice, several studies propose a contextual suggestion system based on IR and AI methodologies and approaches but unfortunately, there are certain limitations which seem to challenge the progress of such innovative systems (Allan et al., 2012).

The system utilises the context and personal preferences of a user while filtering relevant venues from large repositories of datasets called a contextual suggestion system. This system somehow falls between traditional AI-based recommendation systems and information retrieval-based approaches. Although, the query is fixed in contextual suggestion systems based on implicit feedback in order to entertain travellers with context to their travelling history, personal and geo-temporal interests. Dissimilar to recommendation systems in which the query is open to a range of suggestions based on the user's past check-in experience and the potential to filter out relevant venues from large repositories of datasets. Hence, the contextual suggestion system ideally explores the user's desires and can be modified with travel's experience and context at any time (Hall, 2014).

The contextual suggestion system synthesizes data from diverse sources; therefore, it should be precise in predicting interesting venues with an implicit query without considering any explicit data when presenting a list. In this way, the default implicit query will be, "what should I do in this new city?", formerly referring to the question, the system will suggest a list of places while considering the current context (i.e., user's location) and user profile indicating interests, history of visited locations and personal preferences. Figure 1.1 depicts the conventional concept of a contextual suggestion system, where, the context consists of a geo-location, specific time of routine days (morning, evening or afternoon), weekly schedules (weekday or weekend), Seasonal specifics (spring, summer, fall or winter), communal holidays (i.e. Christmas or Halloween) and weather situations. And user profile consists of previous visit history along with interests of users, review-ratings of a venue a user visited recently, age, personal preferences and gender specifics data is integrated and compiled into profiles to predict venues relevant to the user. Whereas the suggestions will be a proactive list of places along with their descriptions based on the anticipatory interest of users. However, there is several challenges which may emerge in the development of contextual suggestion systems such as revealing personal data, travelling history of a tourist, multidimensional contexts, and personalization of the content and places relevant to a traveller (Buhalis & Amaranggana, 2015; Kontogianni & Alepis, 2020). While the repositories of datasets which experts consider are appropriate for contextual suggestion systems; then implicit and explicit feedback both will enhance the accuracy of the system and the concerns related to privacy can be decreased. Similarly, advancements in ICT infrastructure play a critical role in the development of e-tourism applications and services, the infrastructure includes 5th Generation Internet, RFID, cloud computing, out-door/in-door physical and social sensors, smart appliances, phones, and open dataset repositories (Masseno & Santos, 2019).

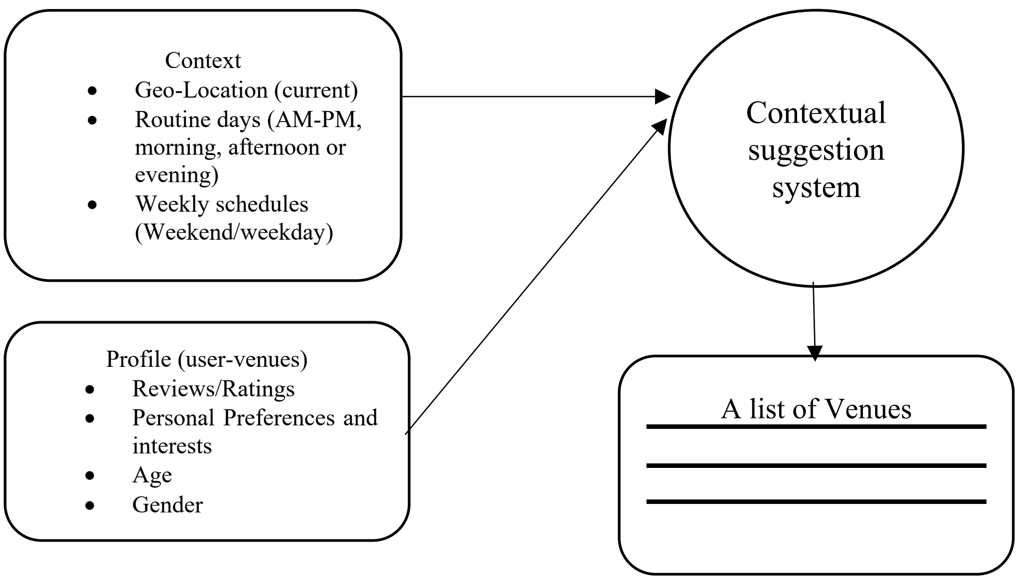

Figure 1.1. Conventional Contextual Suggestion System

Currently, a few e-tourism-based applications and services are accessible, such as travel guide applications (google maps), and location-based social networks LSBNs (Trip Advisor, foursquare and yelp) which provide the interesting venues to visit nearby places (Gavalas, Konstantopoulos, Mastakas, & Pantziou, 2014). Therefore, to forecast and learn about traveller's behaviour, and his context to accurately predict relevant venues, the proposed approach for a contextual suggestion system comprises four key factors as depicted in figure 1.2, dataset enrichment, profile enrichment, user modelling, and ranking suggestions.

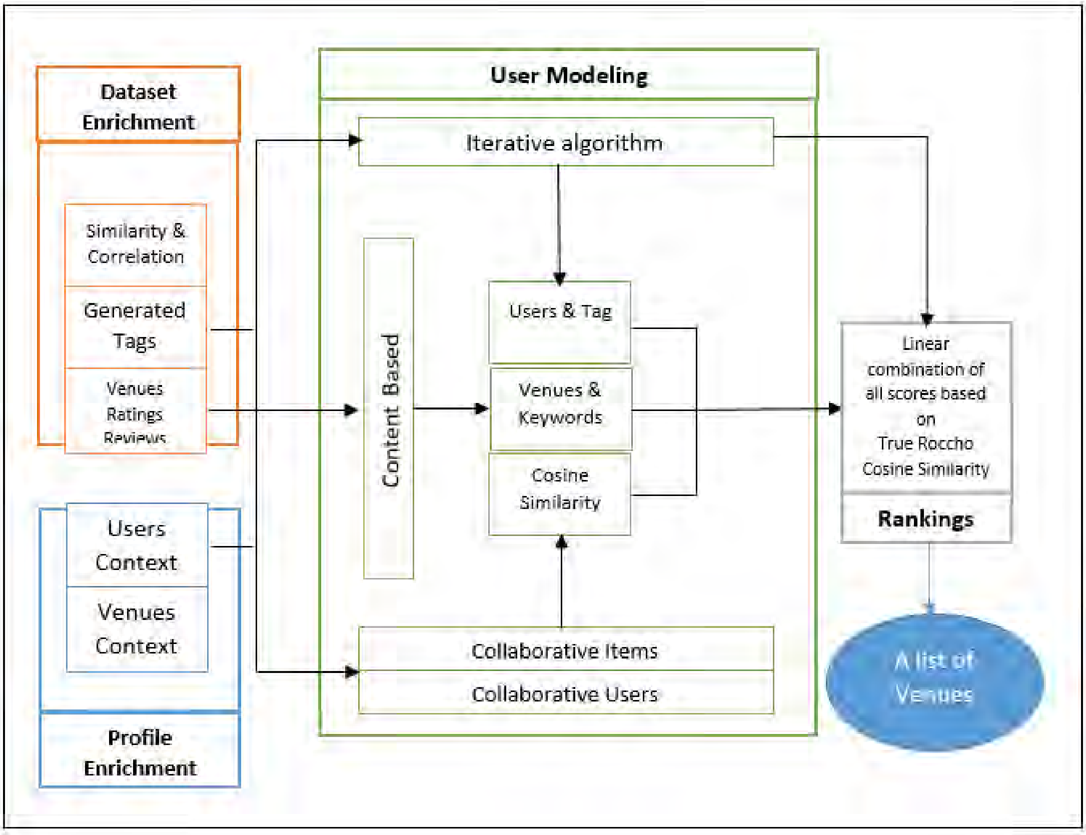

Figure 1.2. Proposed Contextual Suggestion System

A few studies were found focusing on contextual suggestion systems, which analyse contextual factors and personal preferences of users in order to predict a list of places or venues. The system formulates a list of venues within the city using implicit/explicit feedback queries, related to user model processing implicitly in the system or the explicit responses taken from the users (Braunhofer, Elahi, Ricci, & Schievenin, 2013). AI and machines learning-based approaches such as collaborative filtering (CF) and content-based filtering approaches incorporate primary contextual factors such as time of a day, weather, a season of the year, user's current location, travelling week and days of the weeks (weekends/weekdays) (Aliannejadi & Crestani, 2018). Similarly, the user's budget and secondary information such as familiarity or visiting history can also be used as contextual data (Baltrunas, Ludwig, Peer, & Ricci, 2012). Apart from these studies, finding a research gap between contemporary approaches and primitive studies based on contextual suggestion systems is a primary challenge as studies are limited and datasets to run such huge experimentations are not publicly available. Furthermore, most of the researchers preferred self-designed evaluation measures due to the limited standard analytical protocols accessible for evaluations of the systems, such as measuring performance, outcome and effectiveness of the proposed approaches and experiments.

Consequently, to assist future researchers in the field of contextual suggestion systems, the Text Retrieval Conference (TREC) recommended a series of test collections, a raw dataset collected by their teams to run experiments. TREC also proposed a standard evaluation method to measure performance and comparison of the proposed approaches for fair analysis (Hall, Clarke, & Kamps, 2015). During TREC, participants were asked to complete a specific task assigned to their teams. The task assigns to the teams is to propose an approach, based on a detailed description of the venues including ratings and reviews, incorporate with context such as location, and predict a list of venues relevant to user's interests and contexts (Hall et al., 2015).

Several participants were also assigned to gather or crawl data from various travelling websites and location-based social network resources. The data collection and the evaluation measures utilised in the TREC conferences were later declared as standard protocols to evaluate the approaches and performance of contextual suggestion systems.

Consequently, the basic purpose of TREC Contextual Suggestion Track conferences is to standardize the process of testing, assessment, and evaluation against proposed approaches for comparison to facilitate future studies. Also, there is a shift of paradigm in tourism owing to the advancement in technology such as IoT, electronic devices, AI etc. Therefore, a contextual suggestion system needs to be able to provide accurate suggestions by taking into consideration users' contextual and personal preferences through their previous implicit feedback. The four key factors that contribute to the development of contextual suggestion systems, i.e., Dataset Enrichment, Profile Enrichment, User Modelling and Ranking Suggestion are defined as; The dataset enrichment deals with making raw data homogeneous and making the information more meaningful for the AI and IR based systems. The profile enrichment assists in extracting additional information (context) for user-venue profiles in order to make the prediction more accurate. The user modelling deals with learning the user's profiles based on users' behaviour and activities such as personal interest, preferences, activities, and history of checked-in data. And the ranking suggestion ranks a list of venues based on relevancy score amid venue profiles and user profiles. In this regard, several approaches were proposed using TREC's evaluation protocols such as a contextual suggestion system based on ratings (positive and negative), incorporated with content and textual relevancy between the user profile and venues (Hall & Clarke,

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2015). On the contrary various proposed approaches are based on contextual factors, travelling history, reviews, and categories of venues relevant to user's interests (Hall et al., 2014; Hall & Clarke, 2015).

1.3 Motivation

In the e-tourism and travel planning process, the dynamic information available on the internet about a venue can be excessive to a user, therefore overwhelmed by the quantity of information presented to the users, make it difficult for them to finalize a venue in a limited time. Furthermore, recent development in Internet-connected devices and the appearances of contemporary tools assist users to resolve this problem manually such as query searching on search engines to discover interesting places nearby and following traveller bloggers on social media to visit nearby places and replicate their pattern of the tour. These tools help explorers to plan and schedule a trip and assist travellers to use the excessive information to their advantages such as prices of fares and accommodation.

Besides, several technicalities arise during the process of taking a travelling decision or planning a trip without refereeing to alternative e-tourism applications. This is the reason for the enrolment of third parties travel agencies before planning a trip to a new city. People rather than taking a verdict of their own prefer third parties to choose a location on their behalf. In this regard, the internet plays an important role. It provides access to various e-tourism resources such as location-based social networks and tourism-related web applications, such systems also try to tackle the existing problem by avoiding the information overload by filtering and selection methods to verify and validate the information related to a potential venue. This manual process ultimately facilitates the decision-making process to explore a specific place.

Simultaneously, the capability of contextual suggestion systems in filtering relevant information from the dynamic dataset repositories available in e-tourism services makes it particularly required in tourism-based applications. Moreover, a countless variety of venues and alternatives present to tourists, a lack of user's willpower to explore such huge information and inexperience in several travel planning sectors make the usage of contextual suggestion system effective and accurate. This system is capable to solve several problems relating to travel and tourism by suggesting a list of interesting venues a user might find interested to visit and assist users in the decision-making process.

In addition, the field of information retrieval (IR), deals with large repositories of datasets, filtering relevant information by taking user's explicit/implicit queries. In recent years IR is rapidly evolving and integrated with AI and Machine Learning (ML) techniques. Currently, IR is dealing with problems that are diverse and dissimilar from traditional IR such as blogs and tweets filtering and retrieval, topic detection and tracking systems based on ML, knowledge-based acceleration and prediction accuracy based on AI, and Temporal summarization, geo locations and context processing with novelty detection etc. IR is based on a great number of techniques applicable to the contextual suggestion systems integrated with AI can make contextual suggestion systems fully equipped to provide a solution to the information overload problem by filtering out and suggesting a relevant venue from huge dataset repositories of venues considering contextual factors and user's personal preferences. Similarly, in recent years, the constant increase in the utilisation of location-based social networks (LBSNs) such as Yelp, TripAdvisor, and Foursquare has been witnessed. LBSNs gather valuable data about users such as travelling history, search history, most checked-in places and ratings and reviews provided by the users. However, in contrast with contextual suggestion systems, they lack multidimensional contextual factors, user's personal preferences, venue filtration and precise prediction of the most relevant places from a large set of venues. Being able to suggest personalized venues to users plays a key role in satisfying the user needs and success factors for such systems.

1.4 Operational Definitions

The operational definition of the terms used in this study is defined in table 1.2.

Table 1.2

Operational definitions

Term	Operational Definition
Model	Refers to a combination of multiple algorithms.
Approach	A basic structure of the research comprises multiple models.
Venues and Point of Interest (POI)	A place of attraction that may be interesting to the user. Examples, Indian Museum, Victoria Palace, Peter Cat, Howrah Bridge, Botanical Garden etc.
Profile (User)	The user profile is a single user's preferences (list of locations rated by a user with their tags/endorsements), gender and age.
Profile (Venue)	Venue profile consists of the venue's content, ratings, and reviews of venues as well as categories, tags, and context.
Suggestions	A list of relevant venues to be predicted and suggested for the users
Context	It is additional information based on changing circumstances of users relevant to the target places (i.e., target location) of the trip, trip type, trip duration, type of group the person is travelling with and season of the trip.

Table 1.2

Operational definitions

Internet of things	Computing devices embedded in everyday objects that are interconnected using the internet and can send and receive data.
Information and Communication Technology	A combination of computer applications and communication technology of electronics, computing, and telecommunications for gathering, processing, storing, and disseminating information.
E-tourism	The digitization of all processes and value chains in the tourist, travel, hospitality, and catering industries, allows businesses to increase their efficiency and effectiveness.
Recommendation System	It is a type of information filtering system that attempts to predict how a user would rate or favour an item. In basic terms, it is an algorithm that provides users with relevant items
Contextual Suggestion System	It considers changing context or circumstances that may influence a user's mood and interests when modelling the user's preferences while filtering and predicting relevant items for users in the given context.
Dataset Enrichment	Making raw data homogeneous and making the information more meaningful for the AI and IR-based systems.
Profile Enrichment	Extracting additional information (context) for users and venues profiles to make the prediction more accurate
User Modelling	A process of building up and modifying a conceptual understanding of the user profile.
Ranking Suggestions	Ranks a list of venues based on relevancy score amid the user and venue profiles.
Semantic network	A knowledge structure that shows how concepts are related to one another and how they are linked

1.5 Problem Statement

The problem statement of this research is categories into dataset enrichment, profile enrichment, user modelling and ranking suggestion, below sub-section discusses the problems raised in each subsection.

1.5.1 Dataset Enrichment

With the availability of location-based social networks (LBSNs), such as Yelp, TripAdvisor and Foursquare, users can share check-in data using their mobile devices. LBSNs collect valuable information about users' mobility records with check-in data including user feedback, such as ratings, tags, and reviews (Crestani, 2018; Seyler, Chandar, & Davis, 2018; Ren et al., 2018; Chakraborty, 2018; Marran, 2017). However, lack of complete information about a venue results in compromised accuracy of suggestions, even though a large amount of data is available but no study has found to be combining the available information from different databases to make a complete database, moreover, automated tagging or tags generation for the venues from datasets can be applied, while, limited studies are found with the same focus despite tag generation approaches are likely to increase the accuracy on the bases of computing similarity and correlation between multiple tags/keywords. In a contextual system's scenario, a system being able to suggest personalized venues to a user would play a key role in satisfying the user's needs (Hashemi & Kamps, 2017; Efraimidis, Arampatzis, Stamatelatos, Athanasiadis, & Drosatos, 2016; Wang & Yang, 2016; Albakour, Deveaud, Macdonald, & Ounis, 2014), for example when exploring a new venue or visiting a city. In this regard, several different LBSNs are widely used, however, a single LBSN does not have a comprehensive coverage over all venues and all types of information. For instance, Booking.com mainly focuses on hotels. Here combining multimodal information e.g., ratings, tags, and reviews of previously visited venues from different LBSNs can improve the accuracy of venue suggestions. In the literature some studies found to be discussing the lack of complete information, available on LBSNs, extracting comprehensive information integrated with tags generation approaches such as similarity and correlation would make those databases homogeneous, hence resulting in improved accuracy, is fascinating research area to focus on. However, studies which are filling this gap found to be limited, (Kiseleva & Kamps, 2014; Albakour et al., 2014; Wing & Yang, 2014; Yang & Fang, 2013; Milne, Thomas, & Paris, 2012).

1.5.2 Profile Enrichment

The absence of multi-dimensional context in user profiles needs a focus and no study is defining an approach which predicts context for a new venue in the given context by modelling empirically the mapping between keywords and the context relevancy with the user's defined context utilised for a venue and content. (Aliannejadi, Mele, et al., 2017).

Moreover, another gap found by analysis of the literature review is to find relevance between the user profile and venue profile in the given context. A relation between user-given context, user profile and venue profile can be found to make a list of suggestions more accurate by calculating contextual appropriateness for the list of the venue being suggested to a user (Crestani, 2016; Hall & Clarke, 2015; Kiseleva & Voorhees, 2016; Yang & Fang, 2013). Therefore, relationship analysis between available tags and venue can be performed by using the semantic network to get a better idea of the user's taste and interest, and it needs to consider their liked/disliked categories. However, it is not clear exactly which category or subcategory a user likes/dislikes or in which context. For example, check the corresponding categories to three attractions a user likes: a) Pizzeria - Italian - Takeaway – Pizza; b) Restaurant - Pasta - Pizza – Sandwich; c) Restaurant - American - Pizza – Burger. So, it can be assumed that the user likes Pizza, since it is the only category in common.

The discussion above on the need for further research in contextual processing to clarify the gaps in relevant literature specifically highlighted by (Aliannejadi & Crestani, 2017; Samar, Bellogín, & Vries, 2016; Dehghani, 2016; Aliannejadi, Bahrainian, Giachanou, & Crestani, 2015; Hall & Clarke, 2015; Bao, Zheng, Wilkie, & Mokbel, 2015 Yang & Fang, 2013).

1.5.3 User Modelling

Lack of user ratings for one user and limitation of reviews in another user, this phenomenon results in compromised prediction when making a list of venues based on users' interests. This study is focusing on the user modelling based on personal preferences, user checked-in history and venue rating and reviews (e.g., the ratings of previously visited venues, and activities he likes).

In the past, researchers (Aliannejadi, Zamani, Crestani, & Croft, 2018; Sappelli & Kraaij, 2018; Aliannejadi & Crestani, 2018; Hashemi & Kamps, 2017; Gonçalves, Lincs, Martins, & Magalhães, 2017; Aliannejadi, Mele, & Crestani, 2017) proposed to make venue suggestions based on the similarity between the users' preferences and the venues' descriptions and categories. Others leveraged the opinions of users about a given place, which are, for example, extracted from the users' online reviews.

In this research, the intention is to present a novel approach for suggesting venues to users, where the users are modelled based on venues' content as well as users' reviews and similar users. Many studies such as, (Yang & Fang, 2013; Mele, & Crestani, 2016; Hashemi, 2008; Deveaud, Albakour, Macdonald, & Ounis, 2014; Deveaud et al., 2014; Hubert & Cabanac, 2012), highlighted the same problem, however, no study has found to be utilising content-based, ratings/review based and similar users' modelling in a single approach.

1.5.4 Rank Suggestions

Lack of work on ranking approaches to rank and judge a list of the suggestion which results in compromised scores, traditionally, ranking is based on judgments of document relevance, by using naïve Bayes, Rocchio classifier, cosine similarity and probabilistic variants of all (Hall, Clarke, Kamps, Thomas, & Voorhees, 2014; Hall, Thomas, Clarke, Simone, & Voorhees, 2013; Hubert & Cabanac, 2012). These judgments are used to compute via standard measures such as precision@k, mean reciprocal rank (MRR), discounted cumulative gain, rank biased precision, expected reciprocal rank, and many others.

However, all these measures implicitly assume that the user works their way down a ranked search result list at a fixed rate, eventually stopping, perhaps due to boredom, tiredness, or because they found what they are seeking. None of these measures appropriately account for document length, duplicate documents, and snippets (i.e., short captions describing a document, which may allow non-relevant results to be quickly skipped).

Relevance is generally viewed in positive terms only, indicating the degree to which a user likes a document. The TREC contextual suggestion track (CCT) needs to focus on determining the best working ranking approach, as TREC CCT uses precision@5 and mean reciprocal rank (MRR). Unfortunately, precision@5 assumes that a user will look at exactly the first five results, no more and no less, while MRR assumes that the user stops at the first useful result (Seyler et al., 2018; Palaiokrassas, Karlis, Litke, Charlaftis, & Varvarigou, 2017; Hadi, Charles, Jaap, Julia, & Ellen, 2016).

1.6 Objective of the Study

The objectives of this research are as follows:

1. **Systematic Review:** To review existing work and identify the differences between the approaches used in the recommendation and contextual suggestion systems.

2. **Dataset Enrichment:** To propose an effective approach based on IR and AI algorithms for calculating similarity and correlation between multiple tags to increase relevancy and to make the raw datasets homogeneous.

3. **Profile Enrichment:** To propose an approach to predict the multidimensional contextual appropriateness of places and contextual relevancy of users.

4. **User Modelling:** To propose an approach based on multiple AI algorithms to learn users' personal preferences and to increase the accuracy of prediction.

5. **Rank Suggestions:** To propose a ranking approach to rank a list of suggestions based on multiple ranking algorithms to learn the scores of highly relevant places.

1.7 Research Question

The research question of this research are as follows:

i. How to enrich dataset by introducing various insights based on tags to make raw dataset homogeneous. Which technique is the most suitable for tags acquisition, and which approach can be appropriately adopted to find the similarity and correlation between multiple tags in order to increase the relevancy of places?

ii. How contextual appropriateness can be predicted in a multidimensional contextual environment for users and places to make precise predictions?

iii. How a user can be modelled as per his interest and opinion based on his/her check-in record, which approaches can be utilised to model users and make suggestions more precise?

iv. How to integrate different aspects of information to generate a ranking for suggestions considering both users' personal interests and contextual constraints and evaluation of the system by using standard evaluation protocols?

1.8 Research Hypothesis

RQ1: How to enrich the dataset by introducing various insights based on tags to make the raw dataset homogeneous. Which technique is the most suitable for tags acquisition, and which approach can be appropriately adopted to find the similarity and correlation between multiple tags in order to increase the relevancy of places?

$H1_0$ The tag generation approach is not linked with frequency, diversity, and rank aggregation.

$H1_1$ The tag generation approach is positively linked with diversity and rank aggregation.

$H2_0$ WordNet and Semantic distance cannot enhance the quality of suggestion by measuring similarity between tags.

$H2_1$ WordNet and Semantic distance enhance the quality of suggestion by measuring similarity between tags.

$H3_0$ Computing correlation between tags by using Jaccard similarity will not improve the accuracy of the suggestion.

$H3_1$ Computing correlation between tags by using Jaccard similarity will significantly improve the accuracy of suggestions.

RQ2: How contextual appropriateness can be predicted in a multidimensional contextual environment for users and places in order to make precise predictions?

$H4_0$ Relevancy between the user profile and venue profile score will not improve accuracy in the given context i.e location, time of the day, and day of the week.

$H4_1$ Relevancy between the user profile and venue profile score will improve accuracy in the given context i.e location, time of the day, and day of the week.

$H5_0$ Using taste keywords will not improve relevancy any further between the user profile and venue profile in the given context i.e location, time of the day, day of the week.

$H5_1$ Using taste keywords will further improve relevancy between the user profile and venue profile in the given context i.e location, time of the day, and day of the week.

$H6_0$ There will be no improvement in the accuracy of suggestions by using binomial classification & support vector machine (SVM).

$H6_1$ There will be a significant improvement in the accuracy of suggestions by using binomial classification & support vector machine (SVM).

RQ3: How a user can be modelled as per his interest and opinion based on his/her check-in record, which approaches can be utilised to model users and make suggestions more precise?

$H7_0$ Combining collaborative filtering and content-based will not be an effective approach to user modelling.

$H7_1$ Combining collaborative filtering and content-based are effective approaches in user modelling.

$H8_0$ Preference tags using an Iterative algorithm will not improve the accuracy of the suggestion.

$H8_1$ Preference tags using an Iterative algorithm will significantly improve the accuracy of the suggestion.

RQ4: How to integrate different aspects of information to generate a ranking for suggestions considering both users' personal interests and contextual constraints and evaluation of the system by using standard evaluation protocols?

$H9_0$ True Rocchio algorithm will not work for the ranking suggestion.

$H9_1$ True Rocchio algorithm will significantly work better for the ranking suggestion.

$H10_0$ Cosine similarity algorithm will not be fit for the ranking suggestion.

$H10_1$ Cosine similarity algorithm will positively be fit for the ranking suggestion.

$H11_0$ Linear combination of true rocchio and cosine similarity will not work for the ranking suggestion task.

$H11_1$ Linear combination of true rocchio and cosine similarity will positively enhance the ranking list of places in the suggestion task.

1.9 Contributions

The contribution of this research is as follows:

i. To perform a systematic review to compile the work and findings of the previous studies, to find research gaps and research trends in the field.

ii. To gather useful information such as profiles for each venue suggestion from known sources such as Yelp, TripAdvisor and Foursquare, and turn the collected dataset into homogeneous information by generating tags, based on frequency, similarity, and correlation.

iii. To propose and test an efficient approach for profile enrichment using multi-dimensional contextual semantic representation, concept-based.

iv. To model user profiles based on content-based filtration, collaborative filtering, and iteration of each content by including additional weight keywords associated with the context.

v. To rank suggestions by testing different ranking models to find which ranking models suit better for contextual suggestion system.

1.10 Significance of the Study

A contextual suggestion system can try to emulate offline travel agents by providing users with knowledgeable travel suggestions based on context to facilitate their decision-making processes. Using a contextual suggestion system, we assume that a user's needs and constraints can be mapped into a specific set of alternatives or a list of suggestions from which the user will be able to choose the best way to plan his/her trip. It can obsolete the traditional e-tourism way of planning a trip where a user needed to use different LSBNs to find activities and nearby venues where suggestions are very general to influence a user in order to make him decide what to do.

1.11 Scope of the Research

The scope of the research is to test algorithms based on artificial intelligence (AI) and information retrieval (IR) to propose an improved approach for contextual suggestion systems in e-tourism. TREC contextual suggestion track dataset is utilised in the experimentations that focus only on venue's profiles extracted from on LBSNs with limited users-related data. The predicted list of suggestions focuses only on venue prediction related to tourism. In terms of context, a context can be multidimensional, however, in this study context utilised are; the user's location, specific time of a day or week (i.e. morning and evening, weekdays and weekend), a trip type (i.e. business or family), and location (i.e. city). Due to the dynamic nature of the data and contextual factors, the datasets need to be fixed and separated the contextual effect from the personalization effects which cannot be done in a single study, therefore it is ignored.

Several approaches and algorithms based on AI and IR were tested in the experimentation, however, approaches with statistically proven significant results were reported in this study. The evaluation was performed using the standard evaluation protocol proposed by TREC contextual suggestion track.

1.12 Thesis Organization

The remainder of this thesis is structured as follows:

- **Chapter 2:** Section 2.1 presents the introduction while Section 2.2 presents the review protocol, Section 2.3 presents methods, Section 2.4 presents taxonomy analysis, Section 2.5 presents a discussion, Section 2.6 presents critical review and 2.7 presents the summary of the literature review.

- **Chapter 3:** This chapter describes the overall methodology, and the flow of the research process and discusses the technique that can be utilised to perform an experiment on the datasets and the techniques that can be used for evaluation and comparison of the results.

- **Chapter 4:** Presents the Approach for the key elements 1) Dataset Enrichment, 2) Profile Enrichment, 3) User Modelling and 4) Ranking Suggestions. It also presents Findings, Evaluation, and Results along with Hypothesis Testing.

- **Chapter 5:** This chapter is comprised of a Summary of Results, Discussion of the Findings, Comparison of Approaches, Theoretical Contribution of this study, Practical Implications, Academic Implications, Limitation of the Study, Future Direction of Research, and Conclusion.