Context-Aware Intelligent Recommendation System *for* Tourism

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***Abstract*— Increasingly manufacturers of smartphone devices are utilising a diverse range of sensors. This innovation has enabled developers to accurately determine a user's current context. In recent years there has also been a renewed requirement to use more types of context and reduce the current over-reliance on location as a context. Location based systems have enjoyed great success and this context is very important for mobile devices. However, using additional context data such as weather, time, social media sentiment and user preferences can provide a more accurate model of the user's current context. One area that has been significantly improved by the increased use of context in mobile applications is tourism. Traditionally tour guide applications rely heavily on location and essentially ignore other types of context. This has led to problems of inappropriate suggestions, due to inadequate content filtering and tourists experiencing information overload. These problems can be mitigated if appropriate personalisation and content filtering is performed. The intelligent decision making that this paper proposes with regard to the development of the VISIT [17] system, is a hybrid based recommendation approach made up of collaborative filtering, content based recommendation and demographic profiling. Intelligent reasoning will then be performed as part of this hybrid system to determine the weight/importance of each different context type.**

Keywords- Context-Awareness, Tourism, Mobile, Personalisation, Pervasive, Social Media.

I. INTRODUCTION

Tourism is a business that is information intensive. However, contemporary tourists expect to get access to this large body of information at any time using their preferred medium [1]. It is a growing trend that tourists are using their smartphones to help with navigation and discovery, which is sometimes referred to as 'interactive travel'. However, the majority of tourists are still using traditional resources while travelling, such as maps and tour guide books. Consequently they are not getting an individual experience to match their preferences. A tour guide is designed for the 'average' tourist so as a result there is a lot of information available, sometimes leading to what is known as 'information overload' [2]. This is a real problem as often tourist's read a lot of information but still have to spend additional time referencing their selected attraction relative to their current location. This issue can be overcome by a mobile application which allows the user to query which attractions are 'nearby'. For the most part, these applications display the results in order of distance (closest to the user displayed first) and little or no attempt is made to personalise the results for the user. This is not appropriate in most cases as the actions that a tourist takes are highly dependent on their own preferences and contextual conditions [3]. These contextual conditions and user preferences can be managed using context aware recommender systems, which have become ubiquitous in recent years [4]. In the tourism domain, these recommendations should help reduce the problem of information overload, which in turn will give the user more time to explore their current destination.

This paper investigates the hypothesis that all available relevant contextual information should be considered when making decisions about which attractions a user should visit. This decision making process will consider the five main contexts of location, weather, time, sentiment and user preferences. Location and time have been used quite extensively in other applications but the other contexts have been largely ignored. Weather and user preferences have been rarely considered as context, particularly in an implicit way as proposed in this paper. The most novel context considered is using real time social media sentiment to capture the 'mood' of each attraction. Each of the context's associated with the user will have a level of importance (weighting) that will be computed and evolve over time. The role of contextual factors will be quantified and the use of recommendation techniques will be addressed. The intelligent decision making will then be discussed in relation to the proposed artificial neural network and how it will be deployed. Finally, the main points of the paper will be deliberated and the future plans for this research will be outlined.

II. CONTEXT AWARENESS & RECOMMENDATION

"Context is any information that can be used to characterise the situation of an entity. An entity is a persona, place, or object that is considered relevant to the interaction between a user and an application (including the user and the application themselves)" [5]. When the system uses this context to provide services or information to the user, this is known as Context Awareness. There has been research in this area since the introduction of Ubiquitous Computing, however adoption of contexts other than location have been slow with application developers. There are various sensors available on contemporary mobile devices such as assisted GPS (Global Positioning System) for location, accelerometer and compass. However, in order for this raw

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sensor data to make sense to the application layer it needs to be preprocessed either within the application or using an API (Application Program Interface) [6]. Once this data is processed it is possible to use it to make assumptions about the user's current context in order to then make recommendations.

The evolution of recommender systems has been rapid in recent years. They are moving away from the crude rule based design to a more intelligent probabalistic / network model [7]. Recommendation techniques can be broadly categorised into three areas, these are content based recommendation, collaborative filtering and hybrid recommenders. Content based recommenders make decisions based on what the user has previously rated or what the user is currently looking at. In most areas this is requesting direct feedback from the user with a rating scale or a like/dislike button. Collaborative filtering takes into consideration the views/ratings of other people when deciding on recommendations; sometimes this is narrowed down into a specific demographic with similar interests. The hybrid recommender is a combination of the collaborative filtering and content based recommendation techniques. These are used in conjunction to resolve the weaknesses in each of the techniques [8]. For example, a content based recommender would find it difficult to make a decision when there is no previous user data; in this regard collaborative filtering can provide initial data, based on the user's demographic profile.

III. A Context Aware Tourist App

The five main types of contextual data that will be used in this research are location, time, weather, social media sentiment and personalisation.

Figure 1: City description and image based on phone's location

Figure 2: Attraction information & options available.

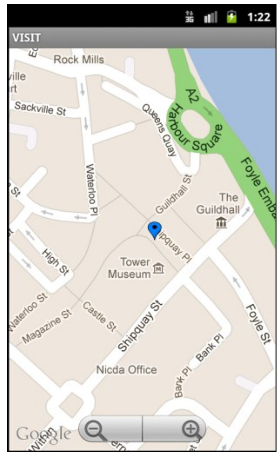

Figure 3: Map with a pushpin showing location of attraction

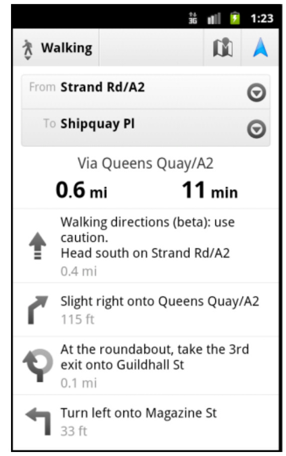

Figure 4: Walking directions from current location to attraction

A. *Location* – The three main location sensing techniques used outdoors are GPS, GSM and Wi-Fi. These methods use triangulation and proximity to detect a location. Knowledge of location is important as the user will want information and directions for each point of interest (POI) around their current location [9]. Figures 1 and 2 show how the location data may be used to provide a user with information about the city they are visiting and also view a list of points of interest for that city. For each point of interest the user will have the ability to view a map, get directions (see figure 3 & 4), see a video, hear audio and finally view social media messages about the attraction.

B. *Time* - The combination of other contexts with time can provide an extra level of intelligence to the application from the user's perspective, allowing the application to determine if a point of interest is open before suggesting it to the user. It is also possible to calculate the amount of time that a user stays at each attraction [10]. This data could be used to determine their level of interest in that particular attraction.

C. *Weather* - Weather data from the WorldWeatherOnline API can provide the weather conditions for the user's current location. Web services can return a textual representation of the current conditions as well as temperature and other weather data. If the prevailing conditions are not favourable for visiting outdoor attractions then the user suggestions can be modified to take this into account [11]. The distance a user is prepared to travel may depend on weather conditions.

D. *Social Media Sentiment* - 65% of Internet users maintain a profile on a social network site. Facebook is boasting user levels of more than 800 million people worldwide. This has created an excellent corpus of messages [12] as they can be 'trawled' for emotion or opinion by a process known as sentiment analysis. Sentiment analysis is a task that aims to identify sentiment expressions and determine the polarity of the expressed sentiment [13]. In this research, sentiment analysis will be performed on twitter messages (tweets) in real time to determine to current "mood" of each tourist attraction. The result of this analysis will be a percentage of positive, negative and neutral tweets about a point of interest. Tourism content created by tourists is more reliable than content created by tourist information organisations. It is also assumed that if a twitter message is forwarded to others (in the form of a retweet) then there is probably more support for this sentiment. In this research the user will have the ability to view real-time messages for each of the points of interest. These messages will be displayed on the screen and colour coded (red for negative, green for positive and white for neutral); an example of this is displayed in Figure 5. The sentiment analysis is performed by Alchemy API [14] and after manual testing performed on a corpus of 5370 tweets (one calendar month of data) we are finding 86.01% of the tweets to be classified correctly.

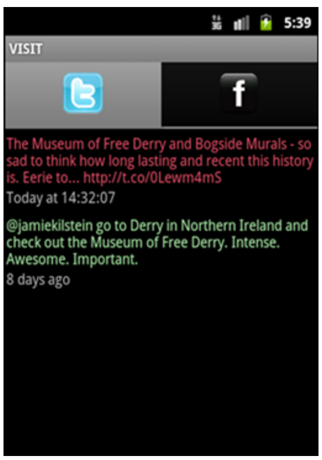

Figure 5: Tweets for POI

Figure 6: Explicit user profile

E. *Personalisation (User)* - The tourists themselves will be one of the main contributors to their current context. Personalisation will ensure that the suggestions are more relevant to the current user [15]. However, it is also important when generating personalisation data implicitly that the user remains in control. This can be facilitated by allowing the user to explicitly change any incorrect assumptions made for personalisation purposes, in the proposed system this will be done using a drag and drop menu. There are various types of personal data that are stored within a social network site. The main types of data that can be used to describe a person are age, gender, relationship status and number of children [16]. This social network data can be used as a starting point for the application when first launched with no previous history. In this case a family cycle status will be determined and the user profile will be initially set to match this status. The application will continue to learn implicitly from user behaviour and update the profile incrementally. In the case that social media is not available, a user can enter their profile explicitly when the application starts, see Figure 6.

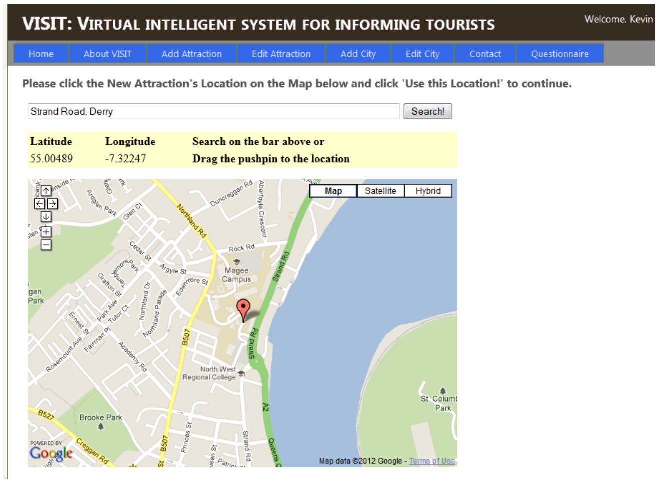

Figure 7: Server-side data capture for entering and editing attraction/city information

The data that is used on the mobile application is generated and stored on a web server; this allows for more control when updating attractions. In an ideal scenario this would be maintained by the tourist information service and they would have the flexibility to add and remove attractions. This is particularly important in an evolving city where new tourist attractions are being added regularly. Also, opening times and exhibits will change depending on the season so this will ensure the tourist has the most up to date information available. In Figure 7 you can see the start of the process of adding a new attraction. You must select the attraction location to continue. Then further information will be entered on a data capture form and once submitted it will be immediately available on the mobile application.

	Location	Weather	Time	POI Sentiment	Personalisation	Device Independence	Scalable
COMPASS	✓	P	✓	×	✓	×	✓
Cyberguide	✓	×	✓	×	✓	✓	×
GUIDE	✓	P	✓	×	✓	×	×
INTRIGUE	✓	×	✓	×	✓	✓	✓
MyMap	✓	✓	✓	×	✓	✓	✓
UbiquiTO	✓	×	✓	×	✓	✓	✓
Proposed System	✓	✓	✓	✓	✓	✓	✓

Table 1: Comparison of Tour Guide Systems

Table 1 shows that the COMPASS and GUIDE applications have only partially implemented (P) weather into their application. Weather forecast is available for the user to see in these applications but they are not used within the reasoner or the recommendation process. The MyMap application is the most similar to proposed system as it uses every context apart from sentiment analysis of each point of interest. This context is important as it ensures that the attraction is represented in the decision making process to ensure the best recommendation for the user. For example, if there was a queue at the attraction and there was a temporary increase in negative tweets it would impact the tourist's decision on whether to visit the attraction. It would be useful to temporarily give the attraction less priority in the recommended list in this case.

IV. INTELLIGENT DECISION MAKING

Our hybrid system model will need to utilize various intelligent techniques to facilitate optimum decision making. The specific techniques used will be artificial neural networks, fuzzy logic and principal component analysis.

Neural Network- An Artificial Neural Network (ANN) is a biologically inspired series of inter-connected nodes and weighted links that are modeled on the architecture of the human brain. The perceptron model of ANN will be used to determine the weighting / importance of each context type for each user [8].

Fuzzy Logic- Fuzzy techniques use probability (or degrees of truth) rather than assuming the logic is exactly true or false. This technique has been used successfully in recommender systems as uncertainty is perfect for representing a user's profile. Fuzzy logic will be used to represent user's interest in each attraction and current weather conditions (e.g. good weather = 1, neutral weather = 0.5 and bad weather = 0). These values will be determined for each weather condition and stored on the server as part of the context manager.

Principal Component Analysis -This is a statistical method to detect the level or variance between data and reduce the dimensionality of data with a small contribution to the variance [8]. PCA will be used to reduce the dimensionality of any distance travelled that has a small contribution to the variance. The remaining distances will then be averaged after PCA is performed to determine the location boundaries and "how far is too far" for travelling in the current city.

V. CONCLUSIONS

The importance of using other potential contexts in conjunction with the widely used location context was discussed. The importance of using time, weather, social media sentiment and user preferences was concluded in relation to the problem. Examples of how the different types of contextual data would be used in the application to provide a more accurate result for the user was explored. Each of the recommendation techniques were explained and it was decided that a hybrid recommender would be the most appropriate solution for this research problem. Finally, intelligent decision making was outlined with reference to the three main techniques that will be used in the proposed VISIT (Virtual Intelligent System for Informing Tourists) application [17]. VISIT is the mobile application that is currently being developed to prove the concepts of this research.

Further research will be undertaken in the areas of machine learning for recommender systems to ensure that the proposed solutions are the most appropriate. The prototype of the VISIT application will continue to be developed, refined and evaluated. The majority of contextual factors are specified at this stage. However, time and personalisation require more work to effectively use these contexts in the proposed intelligent model. Finally, the recommender system will be developed and refined using the intelligent techniques discussed within this paper.

VI. REFERENCES

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