Context-Aware Intelligent Recommendation System *for* Tourism

Kevin Meehan, Tom Lunney, Kevin Curran, Aiden McCaughey
School of Computing and Intelligent Systems
University of Ulster, Derry, Northern Ireland
E-mail: meehan-k@email.ulster.ac.uk

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 is a hybrid based recommendation approach made up of collaborative filtering, content based recommendation and demographic profile. 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.

1. 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' [2]. 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 [3]. 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' [4]. This is a real problem as often tourist's read a lot of information but still have to spend additional time locating their selected attraction relative to their current location. This issue can be overcome by a mobile applications 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 processing takes place to personalise the results for the user [5]. This is not appropriate in most cases as the actions that a tourist takes are largely dependent on their own preferences and contextual conditions [6]. These contextual conditions and user preferences can be managed using context aware recommender systems, which have been growing in recent years [7]. 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 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 other contexts have been largely ignored. Weather and user preferences have been considered rarely as context, particularly in an implicit way as proposed in this paper. The most novel context is using real time social media sentiment to capture the 'mood' of each attraction and using this in the decision making process. Each of the context's will have a different level of importance (weighting) depending on the user. This will be faciliated by using machine learning techniques such as an Artificail Neural Networks. Machine Learning been used extensively in other areas of computing, however, it is rarely used in mobile applications or recommender systems. We outline the meaning of context awareness, as well as discussing each of the individual contextual factors. We also summarise recommendation techniques and how these relate to the application being proposed. The intelligent decision making will then be discussed in relation to the artificial neural network and how it will be deployed. Finally, the main points of the paper will be summarised and the future plans of this research will be outlined.

2. Context Awareness & Recommendation Techniques

"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)" [8]. 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 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) [9]. Once this data is processed it is possible to use it to make assumptions about the user's current context in order to make recommendations.

The evolution of recommender systems has been substantial in recent years. They are moving away from the crude case based design to a more intelligent predictive model[23]. 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 [24]. 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 [25]. 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 [26]. 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.

3. 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.

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. There are varying degrees of accuracy with these technologies [10]. GPS is the most accurate using satellites to triangulate an area of up to a few metres. However, GPS does not work as well indoors or in built up areas where line of sight to the satellite is not always available. This is why mobile devices use a combination of these techniques in the form of assisted GPS. Location will ultimately be important to the user as they would like to know what type of tourist attractions are near their current location. Knowledge of location is also important as the user will want information about the point of interest they are currently visiting and directions for visiting this attraction [11]. 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 see 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.

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

B. *Time* - The combination of other contexts with time can provide an extra level of intelligence to the application from the user's perspective [***12***]. This will allow the application to determine if a point of interest is open before suggesting it to the user. It is also possible to use timespan to calculate the amount of time that a user stays at each attraction [***13***]. This data in turn could be used to determine their level of interest in that particular attraction.

C. *Weather* - Weather data from APIs can provide the weather conditions for the user's current location. Web services can return a textual representation of the current position 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 [14]. The distance a user is prepared to travel will alsobe dependant on weather conditions. .

D. *Social Media Sentiment* - Now that 65% of internet users maintain a profile on a social network site and Facebook is boasting user levels of more than 800 million people worldwide, this has provided a great corpus of messages [15]. These messages can be better understood 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 [16]. The aim is to determine if a selection of text contains positive, negative or neutral sentiment. In this research sentiment analysis will be performed on twitter messages (tweets) in real time to determine to current "mood" of each tourist attraction [17]. The result of this analysis will be a percentage of positive tweets and a percentage of negative tweets about a point of interest. It is considered that tourism content created by tourists is more reliable than content created by a marketing or tourist information organisation so this will ensure the user receives un-biased information about each point of interest [18]. It is also assumed that if a twitter message is forwarded to others (in the form of a retweet) then there is 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 [19] and after testing this on a corpus of 5313 tweets (one calendar month of data) we are finding 86.01% of the tweets to be classified correctly.

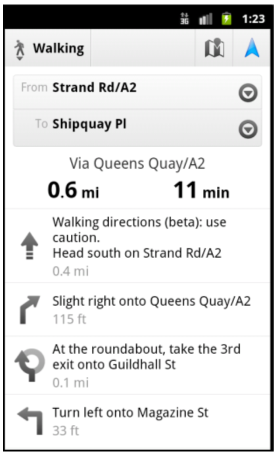

Figure 4: Walking directions from current location to attraction

Figure 5: Tweets for "Free Derry Museum" point of interest

Figure 6: Explicit user profile survey

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 [20]. 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 [21]. 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 [22]. 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 as appropriate. In the case that social media is not available a user can enter their profile explicitly when the application starts, see Figure 6.

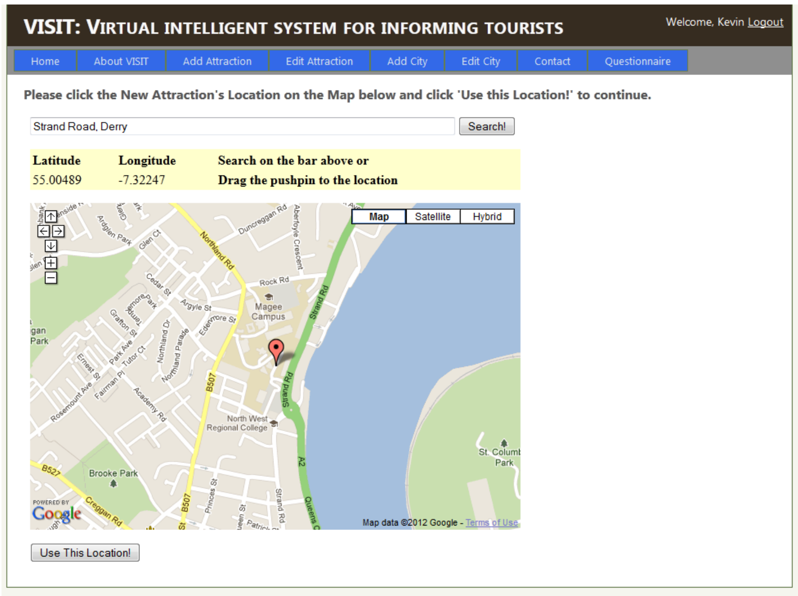

Figure 7: Server-side data capture for entering and editing attraction/city information

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 search or select the attraction location to continue. Then further information about the attraction will be entered on a data capture form and it will then be available on the mobile application.

4. Intelligent Decision Making

Our hybrid system model utilises 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 between these nodes that are modeled on the architecture of the human brain [27]. In this research the perceptron model of ANN would be most appropriate as it is simple and computationally efficient to accommodate for running in real time. This activity involves the process of setting a threshold and putting the output results in order of the highest weighting, then comparing this to the training data [26]. The main challenges with this model is the difficulty involved in setting up the network topology because there are no semantics for inferring meaning.

Fuzzy Logic- Fuzzy techniques are similar to case based or rule based reasoning in the way that a set of rules need to be devised when considering each of the attributes [28]. The difference however is that fuzzy logic uses 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 systems when used as a recommender, however, can have difficulty dealing with incomplete data when contexts are not available. In this research the fuzzy logic will be used to make decisions regarding explicit contextual data such as weather.

Principal Component Analysis -This is a statistical method used in high dimensionality data sets to find patterns. It achieves this by detecting the level or variance between the data and reducing the dimensionality of the data with a small contribution to the variance [26]. We use it to determine the distance travelled for each tourist before it is sent to the artificial neural network, this will help decide how far a tourist is willing to travel in each different contextual situation.

5. Conclusion

The importance of using other contexts in conjunction with the widely used location context was discussed. The importance of using time, weather, social media sentiment and user preferences was expressed in relation to the problem. Examples of how the different types of contextual data would be used in the application to provide a more intelligent result for the user wasprovided. Each of the recommendation techniques were explained and it was decided that a hybrid recommender would be the most appropriate solution to this research problem. Using this hybrid approach will benefit from both the content based recommender and the collaborative filtering techniques. 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 [29].

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 intelligentmodel. The recommender system will be developed and optimised using the intelligent techniques discussed within this paper.. Finally, user testing will be performed to evaluate an benchmark this application against an application using only the location context

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