Towards Real Estate Analytics using Map Personalisation

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Abstract: The value of global real estate was $217 trillion in 2015 which is 2.7 times world GDP, making up roughly 60% of mainstream global assets and consequently it is considered one of the main drivers of economic growth. The availability of geospatial big data can assist real estate stakeholders to make informed decisions and increase their profits. Location plays a significant role in real estate decision making and so maps represent an excellent resource for real estate planning. Personalisation can assist with real estate decisions by ascertaining a user's interests and preferences which can be captured via interaction with maps. A personalised real estate portal can then use this information to recommend properties on the web aiding property buyers and provide valuable real estate analytics. In this paper, we propose an approach for a personalised real estate platform called Estatech Maps. This will be a pioneer in the real estate industry, the key focus of which is to alter the prevailing management practices by imparting GIS and data analytics as long-term solutions.

1 INTRODUCTION

Global real estate investment volumes are increasing steadily[1]. While some signs of decline are currently being observed, for example, in the UK due to Brexit and in Jakarta due to a new capital formation, many of the other major capital cities (particularly in the Asia Pacific region) are showing a rising trend. "The global real estate value was $217 trillion in 2015 which at that time was 2.7 times the world GDP, making up roughly 60% of mainstream global assets" [2].

Moreover, investors in real estate are concerned about the overestimation of the property prices in comparison to its long-term value. Indeed whenever and wherever prices are well above their long-term value the investor should adopt a strategic approach of lowering the risk of an incorrect investment against the opportunity to make a small investment goes a long way. To assist with this decision an investor should have the right tools. There are currently many online real estate portals and web applications which provide users with relevant data for any real estate investment decision.

The real estate industry still has to mature when it comes to combining both artificial intelligence (AI) with humans in the loop judgments to make suggestions for investment. There are organizations and start-ups involved in research and its consequent development may have the tendency to eventually become a major breakthrough in advancing real estate portals to a much more mature level.

There has been some technology mediated innovation in the real estate market. For example, the leading Australian property portal realestate.com.au has a business model which is based on creating competitive tension in the market[3]. The idea revolves around elevating a real estate item

[1]https://www.imf.org/external/research/housing/index.htm
[2]https://www.valuewalk.com/2016/01/global-real-estate-value/

[3] https://www.realestate.com.au/buy

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as a premium sale item and making it desirable in all aspects. The model ensures that paid advertisement by the investor gets the property listing at the top of the web page. Nowadays the use of maps to show the location of properties and nearby facilities is a common practice. A UK based platform called Rightmove focuses on customers' interaction with the property listings. In this case every aspect of the product is mentioned clearly along with the option of interactive maps where users can outline areas of interest and view listed properties[4]. Daft, an Irish based real estate platform also uses an interactive map for selecting property items[5]. A US based platform called Trulia distinguishes its services in terms of providing richer map features such as neighbourhood overview for the selected area along with providing spatial information for nearest utilities and crime rates in the area[6].

Another portal with a detailed map view of all the property listings, features and relevant tools is Realtor. The website has extensive listings with detailed filtering and multiple calculators for mortgage, re-finance, how much one can afford, rent vs. buy and find my buying power. The listings on the map are displayed in terms of price tooltips which are colour coded as well. The map has separate layers for schools, crime, lifestyle and transit which when selected is displayed along with the selected listings layer[7].

Given the massive real estate target market, our emphasis is on automation at micro level of real estate business procedures and practices. The main aspect of creating a web portal for personalized real estate maps is based on how accurately our system develops user profiles. The system creates profiles based on methods such as implicit and explicit profiling techniques (Mac Aoidh et al, 2007). Implicit profiling considers the movements of the mouse cursor and the interaction of the user with a system where as explicit profiling technique gathers data when the user provides the feedback explicitly about their preferences. In both scenarios the profiling of the user takes place based on the conduct of the user and the set of collaborative/interactive data that is generated after a session. As a result the system can offer response to the user, by visualizing the outcomes of the computation initiated by user activities. Based on our research, the proposed real-estate portal is distinctive which uses such profiling techniques which will provide services for the customer and insight for the real estate company.

[4] https://www.rightmove.co.uk/
[5] https://www.daft.ie/
[6] https://www.trulia.com/
[7] https://www.realtor.com/

2 RELATED WORK

Exponential increase in spatial information and its consequent storage has been a continuous area of concern (Dragicevic et al, 2016). The massive amount of information to be displayed on digital maps makes the extraction of useful content a tedious task. Personalization techniques are one of the most optimized ways of eliminating these problems. Research in this area focuses on developing profiling techniques for individuals and reducing the overall cognitive load (Stiller et al, 2009). Furthermore, building upon this is the dimension, extensively explored in profiling, regarding the division of the problem into sub-tasks which in turn improves the efficiency and accuracy of the system (Guy, 2017).

Several sub tasks have been devised such as profile extraction, profile integration and user recommendations through which propositions are made to deal with the profiling task. A TCRF (Tree Structured Random Conditional Fields) algorithm has been proposed which helps in the extraction of profile data from the already available web documents. The algorithm devised acquires data through implicit profiling techniques, through which the data is acquired from the user anonymously as per the user's interest and location information (Tang et al, 2007). LCARS (Location content aware recommendation system) provides the user a set of recommended items based on the location of the user and through its offline mode it learns the interests of the user and produces the top recommended items (Yin et al, 2014) Applied examples include RecoMap which is a portal through which every user gets recommendations based on their preferences and the results are in the form of a map interface highlighting the user's choice and corresponding personalized spatial recommendations. The adaptive map also highlights user's preference as well as context which are both perceived implicitly (Ballatore et al, 2010). Another similar study which considers user mouse movement, GPS trajectories and subsequent extraction of useful data which in turn analyses which information can become a part of recommendation system (Huang and Gartner, 2014). These approaches have not been widely used in the property domain.

Recommendation based on a case-based reasoning methodology has been introduced to the real estate domain for personalisation (Alrawhani et al, 2016). Both approaches provide accurate results. The methods used in these approaches utilise an iterative process for refining the search criteria in order to provide polished results to the end user. End users can provide feedback to classify if the recommendations are useful. A similar approach which aims to reduce the computational cost relies on the concept of combining or grouping similar sets of users (Kanoje et al, 2015). This aims to help with the cold start problem of recommender systems so that when a new user starts using the system or if the user is in an unlogged session, suggested content based on the nearest neighbour is displayed (Pereira and Hruschka, 2015).

Further technological advances in the real estate domain come in the form of so called smart real estate investment there is an emphasis on the use of technologies such as drones, internet of things (IoT), cloud, software as a service (SaaS), big data, 3D scanning, wearable technologies, virtual and augmented realities (VR and AR), artificial intelligence (AI) and robotics in order to make decisions which can avoid any bad return on investment (Ullah et al, 2018). However, when it comes to making real time smart investments in real estate, there is a need for a multi criteria evaluation model for selection of an optimal real estate investment. The model needs to account for the factors of alternative options, variant selection and investment resource allocation (Ginevicius and Zubrecovas, 2009).

Smart real estate investment is not void of threats designed for a theoretical reference model for residential real estate risk assessment using fuzzy cognitive mapping. This fuzzy model makes it possible to define and better understand the cause-and-effect relationships between determinants, thus allowing better informed investment decisions. The results show that the use of cognitive maps reduces the number of missing criteria and facilitates focus on how the criteria relates with each other. (Ribeiro et al, 2017).

We suggest a "Multi-Attribute Cogency Method" which takes into account the four basic attributes through which a buyer and seller both can make clear and winning decisions about their investment and return on investment. These attributes include Cost, Utilities, Transport and Environment. These have sub-attributes associated with them as well based on which any user of the portal is able to make a decision which can ensure an effective outcome.

To the best of our knowledge, real estate map personalisation is an emerging research domain with relatively less research work in this field.

3 METHODOLOGY

The real estate market is continually evolving and various factors must be understood. It has become a necessity to develop new analytical tools and methods within this emerging area. Our focus is on basic attributes of a property item through which a buyer can make clear and objective decisions about their investment. These attributes include characteristics of the property and utilities. There are sub-attributes associated with them such as cost, size, facilities around the property etc. based on which any user of our proposed real estate portal, *Estatech Maps*, is able to make a decision, which may ensure an effective outcome. *Estatech Maps* is an extension of Estatech, which is more of an ERP (Enterprise Resource Planning), commercially available product built on open source technologies. The web application we propose makes suggestions and recommendations based on user profiling techniques, which provide an interactive map-based experience. The following section describes the complete system flow, proposed profiling methods and the open source technology stack.

3.1 System Description

Estatech Maps is a web based real estate portal which presents properties for sale and rent to end users. A map is used to display property locations and features. The portal allows simple search options such as search by city, society (a planned settlement comprising of all essential living facilities), sector or block. Furthermore, using the advanced search option the user can refine the criteria by selecting options such as area or size, number of bedrooms, type (house or apartment), price etc. Search for nearby properties allows the user to see properties around them on the map which are under the radius of say 5km (radius can be customized). The show path option displays the shortest route between the user's current location and the selected property. This usage data is utilized to form a user profile. The profile is used to drive a personalization feature to produce relevant recommendations for the end-user. The profile also provides user analytics for estate agents.

The proposed workflow of the system is illustrated in Figure 1. It describes the process for the case when the user profile exists as well as when it does not. If a user is not logged in then the profiling is done implicitly, otherwise both implicit and explicit profiling is performed for building the user profile. The user profile keeps on updating with a time-decay function which places more emphasis on recent interactions with the system to generate recommendations for the user. The recommendations are built on attributes such as user position, preferred area, filters set for the properties, map extent, zoom level, saved properties and previous interactions of the users with the system. The users interact with the map or the listings of the property and a user profile is generated and updated accordingly, if the user is registered then the interaction data is stored permanently otherwise the data is stored temporarily until the user session ends.

3.2 User Profiling

Multiple approaches can be followed for building the user profile however based on our research explicit, implicit and group based profiling techniques will be adopted, which have not been implemented at this stage but will be part of the final system. One of the most fundamental aspects of system development is reduction of computational cost which is done through "group profiling technique". The technique serves the purpose of delivering quick results, but the accuracy or quality of those results may vary since the results are not based on a specific user but represent combined group preferences.

The user implicit and explicit profile building approaches can be seen in detail in Figure 2, implicit profiling can be termed as profile evolution and explicit profiling as profile determination. After implicit and explicit profiling are performed collaborative filtering approach is adopted which involves predicting preferences or choices. Collaborative filtering (Schafer et al, 2007) method uses the known partialities of a set of prior users to suggest recommendations for the next set of users. This approach assists system which in turn would be able to generate group profiles of the user by combining those individual user profiles which have similar interests (Herlocker et al, 2004). A detailed explanation of the interaction between the user and the suggested system on the basis of user inputs is shown in Figure 3. The system aids the user by providing personalized recommendations based on the set preferences which were learnt by the system using implicit or explicit techniques.

3.3 Technology Stack

The technology stack being used to develop Estatech Maps comprises of a framework and multiple libraries. On the client side we have used LeaftletJS [8] for visualization of spatial data, which are properties, schools, hospitals and the current location of the user. Open street map (OSM) is used as the background base map. Moreover, the prototype uses TurfJS [9] for the spatial analysis of the data; in particular it is being used to filter properties near the user's current location. Axios[10] is being used for data acquisition from the database. VueJS[11] is the front-end framework, which is being used for building the user interface, with the plugin Vuetify[12] to give the application a material design appearance. The application is running on a VM instance on amazon cloud[13] and the database is PostgreSQL[14].

4 DISCUSSION

The initial prototype of the portal yielded optimum results along with successful testing of certain features such as filters, buffer around the user's location, route buffers for the user to assist in selecting the best available property. Figure 4 shows the initial concept and design of the interface. The right side shows the interactive map section while the left panel displays the property items which match the user's criteria. The filtering can be done based on property type, purpose, number of rooms, property size. Whereas a customisable buffer will be generated as per the user's current location (if allowed by user), visualizing the filtered properties on the map within the user's immediate area of interest as depicted in Figure 5. The size of the buffer can be changed as per the user's requirement.

4.1 Web Application Features

An innovative feature of Estatech Maps is "properties on the go" option through which a user can find a route towards a selected property. The path will be calculated and shown on the map and similar properties nearest to the user's route which

[8] https://leafletjs.com/
[9] https://turfjs.org/
[10] https://www.npmjs.com/package/axios
[11] https://vuejs.org/
[12] https://vuetifyjs.com/en/
[13] https://aws.amazon.com/cloudfront/
[14] https://www.postgresql.org/

match the user profile will also become visible on the map as shown in Figure 6. Other features which are included are area selection on the basis of presence of basic utilities like supermarkets, schools and hospitals as well as heat maps depicting the areas where there is a higher concentration of properties for sale. Depictions of properties with price visibility on the map along with the trends of any price reduction are also available. Estatech Maps is also optimized for use on mobile devices.

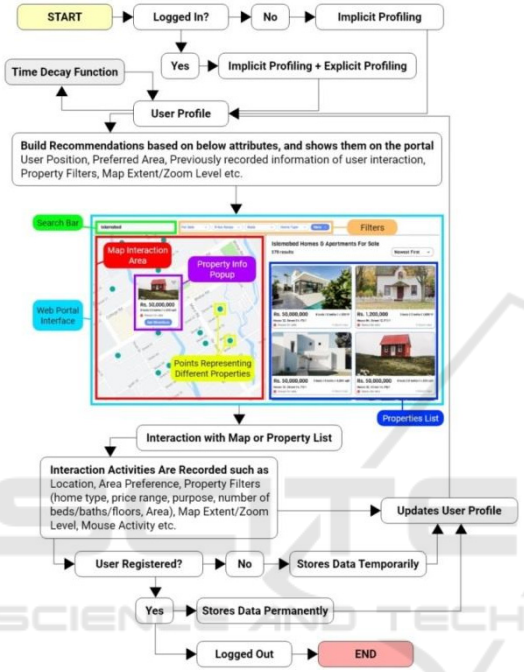

Figure 1: User session and recommendation process.

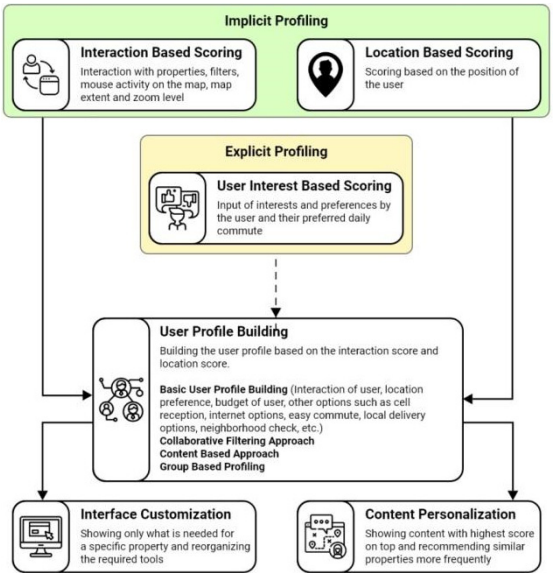

Figure 2: User profile building process.

Additionally, the features which will be added as the portal matures will comprise of individual map view for the user which will be based on what type of interest user has whether it's only for property decrease trends, property value below the market locations or the interest level lies only in areas which are in pre-development stage etc.

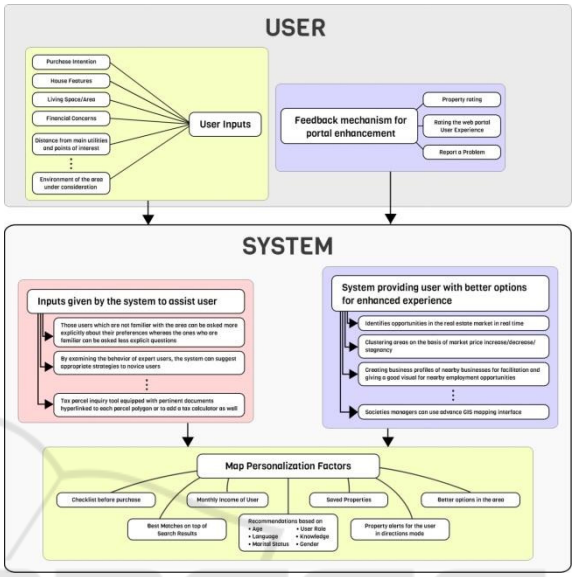

Figure 3: User and system interaction.

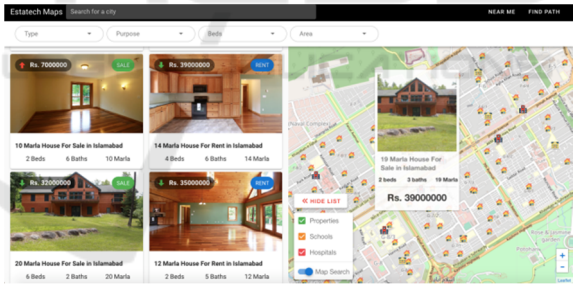

Figure 4: Main interface real estate map portal.

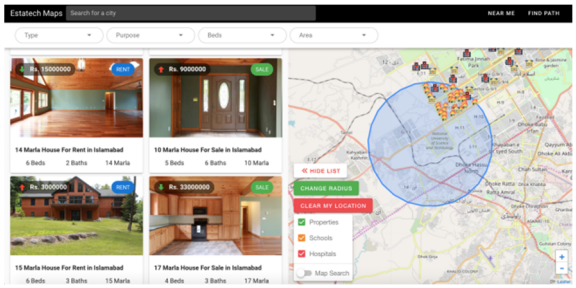

Figure 5: Real estate map portal with basic spatial analysis.

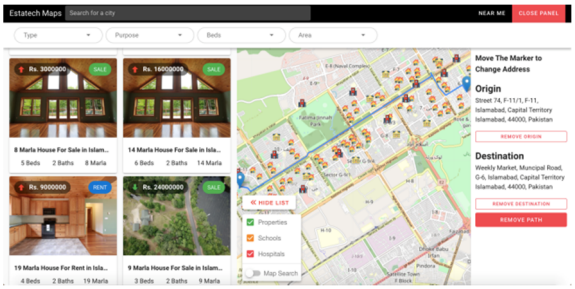

Figure 6: A tool for "on the go" suggestions for matching properties.

5 CONCLUSIONS

This real estate portal will bring forward an exceptional experience for the stakeholders of this domain in order to select, manage and handle properties. The strength of the recommendation system and the accurate user profile building are the core components of this portal. The next step to evaluate the impact of Estatech Maps is with the use of AI and ML algorithms (Syam and Sharma, 2018; Shahhosseini et al, 2019). Machine learning approaches for real estate can be categorized based on specific objectives, including: finding the market value of a building, predicting long term value (LTV) of new listings, predicting value of property, classification of seller score, predicting time to close, effective lead management.

Prediction making systems in the real estate are in developing stages and machine learning algorithms which can be utilized for the purpose of predicting the current and future prices of the properties are: ANN, support vector machines, k-nearest neighbours and regression trees (Ottomanelli et al, 2014). Specifically, our system can be further enhanced by the use of Artificial Neural Networks (ANNs) which are beneficial in developing input-output relations, acquiring data from existing real estate statistics, the model proposed to be used for evaluation is KERAS model which is a high-level neural networks API written in Python. The capability of this model can be very beneficial in complicated systems like real estate where rationale, perceptions and existing resources do not tend to obey coherent course of actions.

Whereas machine learning approaches for real estate can be categorized as: finding the market value of a building, predicting long term value (LTV) of new listings, predicting value of property, classification of seller score, predicting time to close, effective lead management are some of the approaches which can be effectively determined. Similarly, the ethical and privacy issues implementation are left for future work.

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