User-Centric Adaptive User Interface Extended to Augmented Reality application

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***Abstract*—The project proposes an idea to enable user to have a personalised adaptive user interface which can be extended to augmented reality application. With AR becoming the next generation technology it is necessary for making it easy to understand and use. The project aims to revolutionize the user's interaction with webpages and AR content. The primary goal of is to increase user engagement, seamless flow through the UI, scalable to other web and AR applications. The data collected will range from personal information to user interaction logs. The data collected will be identification of navigation pattern, button clicks, swipes, taps and user preference along with the frequency of the actions for getting a personalized view of the usage by the users. It can be used to know how often the user navigates from one link to other? Which area has the highest taps/swipes? The highest/lowest used buttons?**

Index Terms: Adaptive User Interface(AUI) Dynamic Interface Human Computer Interaction

1. Introduction

In an Adaptive User Interface, it is important to identify the user data and impact of features on users. In user interface the user should be easily be able to traverse through the webpages and links and come across the required or desired information. In order to make this easy it is important to take into consideration of relation of sites and how users tend to interact with them. You will notice the use of terms like 'button clicks' in the initial project document, the button clicks are linked to the links and similar to traversing to a webpage. In User Experience it is necessary to identify how the user is interacting with the product and build on the consensus of the data. The User Experience focuses on various factors of usability, interaction design, structure, findability and accessibility. The data for such users on a webpage can be mapped to an AR webpage which will have similar structure. Augmented application of such 2D webpages will have similar traversal and interactions, thus the data can be improvised to implement in an AR version of the application. Popular application like Snapchat uses AR for various interactive filters. The study validates the benefits of Adaptive User Interface (AUIs), they increase the user-machine interactivity and adaptability [1]. An AUI will make the application adaptable and fun to use as well. A case study done in the form of a mobile app called APA (Assistant Personal App), whose adaptability features have been tested in several scenarios [4]. The AUI technique can be used for AR applications as understood from [2] and [3]. We need to understand, which webpages are most important to keep user? Which webpages have the potential to attract more users? What pages require to be improved on the basis of its usage by users?

Intellectual Merit: The project has the potential to be used as a general technique or method to be followed while building web or AR applications to make them more seamless or adaptable. The data collected will be used in real-time analysis for user and can largely exploit cloud computing as a regular practice for individual user interface. It can improve the navigation, advertising and ways to get new users attracted to use the website.

1.1. Research Objectve

In this section, we will look at some of the objectives for the improving online navigation and usage of a webpage which can be extended to Augmented Reality.

1.1.1. Exploratory Visualization.

1) To describe the trends within the page paths (url) for a webpage analytics data.
2) To find the trend on which webpage new users are being attracted to in the unique views and average time on webpage.

1.1.2. Application of a Machine Learning Technique.

1) To predict the class of webpage based on page views and entrances to classify the webpage. (classification)
2) To predict the exit rate on webpages using the exit rate and bounce on webpage analytics data. (regression)

1.1.3. Defensibility of a Machine Learning Technique.

1) To defend the model for performing the prediction of 1.1.2 (1).
2) To defend the model for performing the prediction of 1.1.2 (2)

1.1.4. Ability of Model to provide insight into the relationships.

1) To defend the model for performing the prediction of 1.1.2 (1).
2) To defend the model for performing the prediction of 1.1.2 (2)

2. Related Work

In [1] the paper briefs on various work related to universal usability, plasticity of user interface design and facilitation. It provides a comprehensive review of 165 papers over 55 years for Adaptive User Interface(AUI) and User Modelling (UM). It discuses recent trends and challenges in AUI showcasing complete systems and prototypes.

The [2] paper provides a brief description of AR application used from mobile for urban situation awareness. The paper emhasizes on the need for the Augmented Reality (AR) application to be user friendly and adapt to the environment. AR applications pose great requirement to be versatile and adaptive for user experience. The study supports this with an indepth literature review.

In [3] the paper introduces a framework which adapts user interfaces based on the interactions of users. The agent is trained using unsupervised learning to make decisions based on the user data. The paper [4] proposes a framework, AUIDP (Adaptive User Interface Design Patterns) which is designed based on ontology-based models and UI for generation of an adaptive user interface. The innovation is that the framework has the ability to dynamically assign UI design patterns based on users needs.

The link in [5] briefs on how user experience works and its aspects. The blog provides an idea of how designing can and user experience can be improved looking at its various aspects.

The book in [6] dives deep into what adaptive user interface is to how it can used and evaluated. It explores various techniques and approaches towards an AUI. The User interface modelling section dives into the methodology to approach building an AUI based on the desired problem.

The paper [7] analyzes user data to generate adaptive user interface.The study emphasizes on the use of clustering to automate the complete process. The study evaluates the clustering technique used and showcases its use. The wiki link in [8] briefs on Adaptive Web Interfaces, it provides a brief knowledge of how collected data can be selected and used. The study in [9] provides the use of user interface logs to determine the user behaviour. The paper emphasizes on the need of user behaviour to build an AUI for the system.

3. Exploratory Data Analysis

The dataset is provided by Information Services (Government Baton Rogue). The dataset is updated daily on the analysis of webpage usage by users. The dataset can be found on https://data.brla.gov/Government/Website-Analytics/n9u7-h9i7 .

1) WEBSITE : This field contains the websites of open baton rougue. The Open Data BR provides names of main websites. (Qualitative) Interpretation: The data contains the websites which are used by the public to view data. This can tell me how many distinct main websites are available in the data set. We can find out the most used website or the most recorded website on the basis. This data is highly meaningfull as it identifies the unique websites
2) YEAR : The year the data of the fields was collected. (Quantitative)
3) PAGE PATH : The path and filename of the website. (Qualitative) This can help me understand the requirement of which page is most common and least common to decide which page should be given as a header or easily accesibleon the main page for viewers. This data is meaningfull to show information of the specific file of webpage which the data is about.
4) PAGE URL : The complete url of the page the row contains data about. (Qualitative) Interpretation: This can help me understand number of times the page was viewed and how often the page file is viewed. The importance and frquency of requirement of this data can be understood. It can also show the trend in the usage of the page. This is a meanigful data which indicates page views for wepage.
5) PAGE VIEWS : The number of times the page was viewed. (Quantitative)This can help me understand number of times the page was viewed and how often the page file is viewed. The importance and frquency of requirement of this data can be understood. It can also show the trend in the usage of the page. This is a meanigful data which indicates page views for wepage.
6) UNIQUE VIEWS : The unique views are the unique users viewing the url. (Quantitative)This can help me understand number of times the page was viewed by a unique user. This will help us understand the importance of the page for new users and its capability to attract new users. This data is meaningful for the uniqueness of the viewers.
7) AVERAGE TIME ON PAGE (SECONDS) : The average seconds spent on the webpage by viewers. (Quantitative)This can help me understand if the website has high traffic and impact as user spend more or less time. This will also show if the description of the link clearly describes it contains and attracts appropriate users. Is the link description accurate?
8) ENTRANCES : This field shows number of viwers who entered the website from the pages. (Quantitative)This can help me understand where the entrances are occuring from and increase the priority of the link in the website.
9) BOUNCE RATE (%) : This is the rate at which

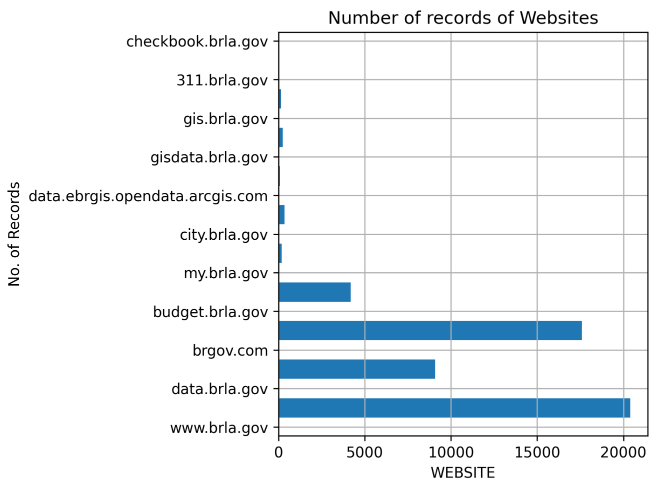

Figure 1. No. of Records vs Websites

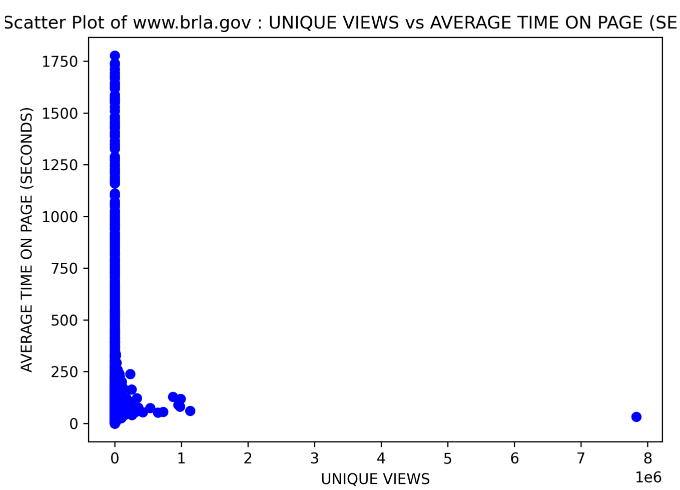

Figure 2. Unique Views vs Average Time

viewers entered but did not interact on it. (Quantitative)The bounce rate will help identify if the website is usefull or misleading the users. This will also help identify miss clicks and give more precise data of the views.

10) EXIT RATE (%) : The rate of users that viwed the page and exited. (Quantitative)The exit rate will help identify if the webpage was left abruptly or traversed within the website to different webpage from the website.

The table 1 briefs about the maximum count of the significant fields used for data modelling.

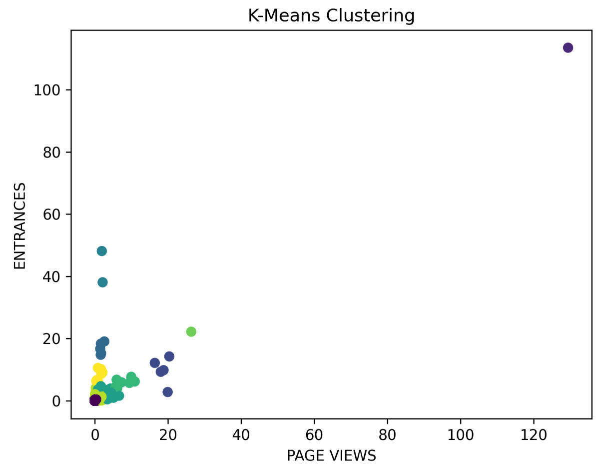

Figure 3. K-Means clustering

4. Visualization

4.1. Websites

The fig 1 histogram describes the histogram of frequency of data of websites. This visualization soundly showcases the frequency of the unique websites with their datasets. This will help identify which website has most entries and point to the direction of which website data should be explored. It can identify important websites or atleast point towards it. This trend for path url as mentioned in 1.1.1 (1) is explored.

4.2. 'UNIQUE VIEWS' vs 'AVERAGE TIME ON PAGE (SECONDS)

The fig 2 scatter plot will identify the relation of unique views with time spent on them. This will tell which page has higher impact and should be prioritized. The time for each webpage is spent on it by users, both higher indicates making it easier to navigate will make the users easy to use the webpage. Many users who are unable to find this page may also find it easier after changing the interface. This will increase the interaction of users on the webpages. This trend in Section 1.1.1(2) is explored.

5. Methodology

5.1. K-Means Clustering

The K-means clustering is valuable for web analysis, it provides an insight in the users behaviour and website optimization. The clustering can identify user patterns on the webpage such as frequency of visits and viewer for that. This is used to analyze the typical behaviour of user journey through the website. I have selected fields of 'PAGE VIEWS', 'ENTRANCES', to cluster the pages based on

TABLE 1. WEBSITE STATISTICS

Websites	Dataset Entries	Total Views	Max Views	Max Avg Time	Max Uni Views
www.brla.gov	20392	52574616	8402179	1777.0	7829387
brgov.com	17595	15210331	552104	1764.0	254168
data.brla.gov	9088	2229916	301899	2794.26	98329
budget.brla.gov	4180	54424	14324	1446.0	12926
city.brla.gov	355	124927728	58076519	984	1637099
gisdata.brla.gov	245	52777	6114	245.95	965
my.brla.gov	185	849768	560249	1008.0	298706
gis.brla.gov	147	897623	110198	991.0	89931
data.ebrgis.opendata.arcgis.com	78	10597	5620	1547.0	2020
311.brla.gov	35	700000	56486	190.87	46082
checkbook.brla.gov	2	29141	27993	23.36	20953

these features eventually leading to a prediction of which cluster a page will lie in. The clusters helps me identify which website should be given optimal priority. We achieve the Section 1.1.2 (1) by performing K-means clustering.

The silhouette score is done for K-means clustering model.The features indicate the behaviour of the user and clusters them in a region. This clustering for 0 will give web-paths which show tendency for higher page views and entrances. The higher the silhouette score, i.e. closer to 1 it indicates the more defined clustering of the data. The score should be higher in order to get an accurate decision of the classification. The Davies-Bouldin metric is used to evaluate the clustering algorithms. It is an efficient, robust and complementary to other metrics for evaluation. A lower Davies-Bouldin score indicates defined clustering classes. It is necessary to consider other metrics along with this. The 2 tests defend the K-Means model as mentioned in Section 1.1.3 (1)

5.2. Linear Regression

The model uses simple linear regression to predict the exit rate i.e the rate of the users that leave the website after clicking or performing action on the website. The model is constructed by training data of Entrances and Bounce rate to get the Exit rate. The Exit rate helps us identify the rate of users which use the webpage rather than just visit or bounce off it. The bounce rate plays a crucial role in predicting the exit as it directly influencing the factor for the web page activity. The model performs this for all the paths of a webpage, as the fact of bounce rate for a path of website also influences the activity of webpage.

The model is evaluated based on the MSE score of the predicted value of the exit rate. We calculate the R square value to check the variance in target. The metrics defend the algorithm as mentioned in Section 1.1.3 (2)

6. Results and Discussion

6.1. K-Means Clustering Results

The page views is the views a page gets from the users. This has a high impact on the need of the webpage as a higher page view would significantly increase the need of the website. The page views with low value clusters towards the higher number of cluster group. The cluster in this field shows smaller values for high page views. The entrances clustering shows tending towards the higher values or a significantly important cluster i.e. 1 as the value increases. The cluster closes in to lower value class as 'page views' and 'entrances' both increase. This trend shows that the web path becomes more important as the 'page views' and 'entrances' vary simultaneously. The cluster is affected by the inverse proportion when page views and entrances are significantly different. The trend leads them towards a low value cluster if the entrances are high but leads to higher value when page views are extremely low. The cluster balances to a central value when the values are significantly different and low. Different is the difference in the numerical value. The clustering can be seen in fig3.

K-Means Clustering (clusters 10) :
Silhouette Score: 0.9461139974973565
Davies-Bouldin Index: 0.4508606553227736
Prediction :

1) WEBSITE: www.brla.gov
2) PAGE PATH: [", '2191', 'pillar-3-culture-and-art-engagements']
3) PAGE VIEWS: 18
4) ENTRANCES: 50
5) K-Means cluster: 4

The k-means prediction helps identify the cluster with the closest proximity. The cluster indicates that the web path selected belongs to cluster 4 and shows similar trends to paths of cluster 4. In this cluster the values for entrances and page views are close but low. Indicating the path has small activity and is required to be optimized. This cluster has low potential but should be further looked into for improvement. This shows feasibility of prediction as mentioned in Section 1.1.4 (1)

6.2. Linear Regression Results

The Linear regression model shows high mean squared error and an average R squared value. The model is determined to be accurate if the mean squared error should be low, the value is extremely high for the model to be effective. The model cannot provide definitive predictions but can be used with other models where it can support with the predictions. As mentioned in Section 1.1.4 (2), the predictions are feasible but with low accuracy.

Mean Squared Error : 311.28370933504226

R^2 Score : 0.5875860033836517

7. Conclusion

The project focuses on improving the User Interface of the user by analyzing the navigation patterns and user behaviour. The study is able to classify web pages into categories which can be marked based on priority for what improvement or action is required. The work aims to use the web analysis to improve the UI to be extended to Augmented Reality application which has shown challenges in user experience. This can improve the idea of AR applications and show hidden potentials.

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