Personalized Dynamic User Interfaces

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Abstract—We live in an era where most organizations tend to pay the utmost significance to the customer. Most organizations will position their business models to align with the demands put forth by the customer and hence, better cater them. However, more often than not, these organizations fail to accommodate the individuality of each of their customers. While the actual functionality of an application holds prime importance to the user, the presented interface that a user engages with to achieve these functionalities is equally essential. If the user isn’t able to comprehend how to accomplish the functionality as mentioned earlier, the application, more or less, becomes redundant. This consideration can be augmented by simple facts that no two customers will ever be the same and that none of them will ever share a commonality amongst them as to how they interact, manipulate and communicate with an application. This very fact, however, is often overlooked. This very aspect of un-tailored experiences of almost all commercially available applications can hurt business for the worse. A lot can be done simply by learning from user preferences and applying these learned preferences to predict what a user may or may not like.

Keywords—Dynamic User Interfaces, Human-Computer Interaction, Machine Learning, Personalization.

I. INTRODUCTION

In this day and age, we see a growing dependence of humankind on all sorts of Computer softwares. This age of technology enables us to have applications that serve a varied range of purposes. From sophisticated softwares that are able to map the immediate vicinity of the user, to simple applications that aid easy calculations. But as we move from elementary applications to more elaborate ones, the chances of not being able to represent functionality increases accurately. Moreover, since users will have a non-uniform and diverging utilization of softwares, customer dissatisfaction and frustration are bound to occur. This discontentment, nevertheless, can be assuaged by the usage of Dynamic Interfaces. Dynamic user interfaces are, in a general sense, interfaces that alter according to the likings and preferences of users. Such interfaces are able to adjust themselves depending on previously-stored or learned data in a way that the generated interface is able to cater to the user best. Hence, increasing the overall usability and intractability of the application. Not only does this solve the issue of user-dissatisfaction, but this methodology can favorably benefit application owners (Application Developer, Business Organizations, etc.) as well. Since user requirements are paid the utmost importance in such interfaces, customer satisfaction is sure to be attained. Tailoring of applications to coincide with the user priorities and likings is definite to benefit both parties.
Through this paper, we aim at highlighting the usage of Machine learning in conjunction with interfaces to achieve this mechanism, as mentioned above. We also aim at highlighting how usage of such technologies will benefit the user as well as the application owner. This paper proposes the usage of simple techniques that involve K-Means clustering and Recurrent Neural Networks to monitor user statistics and likings and hence, make predictions to generate customized interfaces for diverse sets of users.

II. CURRENT SCENARIO

A. Partial Customization

Customization isn’t a new concept and has been around for a while now. Most applications tend to have some sort of customizability, such as dark/ light usage mode. A very thoughtful implementation to boost the readability of content. This feature also enables the reduction of stress on eyes during various times of the day. This customization forms the basis of what we want to achieve but is very superficial and doesn’t take into consideration the prioritization of application functions. An in-depth approach, wherein the entire look of the application can be changed, is what the ultimate aim of this paper is.

B. User Survey

To thoroughly understand how people prefer their user interface to look, we conducted a survey. Through a closed study of Thirty-Three people, we were able to generate an overall understanding of how the current users feel about stagnant/non-dynamic interfaces. Below is a table that represents the types of users we include in our survey.

| User Type          | Number |
|--------------------|--------|
| Students           | 21     |
| Educators          | 8      |
| Industry Professionals | 4     |

C. Findings

Through the survey that involved thirty-three people, we attained valuable data on the current trends and user moods. Twenty-nine out of the total Thirty-three candidates were firm with their opinion that applications require more customization options so as to boost the usability. The remaining users stated that the current non-customizable applications weren’t hampering the usage.

Moreover, twenty-three users believed that these customizations should be auto-generated by tracking user predilections and likings, and shouldn’t require the user to make decisions manually. These changes should arise from the decisions made in the background to minimize usage stress.

III. APPLICATION OF MACHINE LEARNING

The core application of Machine Learning in HCI for many years has been using it to improve interaction. Our aim here isn’t to provide an in-depth analysis, but alternatively is to direct attention towards the advances this work has made. Machine Learning, already, has
been used to expand the possible sources of interactions. Marking out a few, these span from utilizing people’s skin as a touch interface, to gesture recognition and motion capturing using cameras. Our aim here is to dwell deeper into these interactions and attune these interactions in accordance with separate users.

We have chosen K-means clustering for our methodology because of its relatively more straightforward implementation and fast computation. We have selected the aforementioned methodology because of its high accuracy, and the fact that approximate nearest neighbor searches in our learned embedding space allow for an order of magnitude decrease in query times a result particularly relevant for real-time interactivity and adaptation.

A. Data Set

Through a survey of self-reported preferences, we were able to curate data from 102 users across various age groups. These preferences were randomized in a CSV datasheet. Shown below is The Representation of the data.

| Id | text | ui | gender | age | Species |
|----|------|----|--------|-----|---------|
| 1  | 3    | 2  | 1      | 30  | g       |
| 2  | 1    | 2  | 1      | 35  | g       |
| 3  | 2    | 2  | 2      | 17  | g       |
| 4  | 2    | 2  | 2      | 28  | g       |
| 5  | 3    | 1  | 1      | 21  | f       |
| 6  | 3    | 3  | 2      | 25  | f       |
| 7  | 3    | 3  | 1      | 20  | p       |
| 8  | 1    | 3  | 2      | 18  | p       |

As can be inferred from above, Text can either be Bold, Medium, or Thin and hence has been given the identities 1, 2, and 3, respectively.

The User interface again, has three options, namely Squared, Curved, and Rounded and has hence been given the identities 1, 2, and 3, respectively.

Gender has been identified as Male, Female, and Others and has hence has been given the identities 1, 2, and 3, respectively, again.

Numerical values have been used to represent age.

The type of design language one likes represented by species is identified as, G- google material design, F-facebook/colorful style type and P- Apple/IOS design style type.

B. K-Means Clustering

Using an iterative refinement technique the K-means clustering algorithm can give out the end result. The number of clusters K and the corresponding data set are the algorithm inputs. The algorithms begin with opening estimates for the K centroids, which were either arbitrarily produced or randomly chosen from the data set. The algorithm then iterates between two steps:

1. Data assignment:
Each centroid defines one cluster. Within this step, every data point is allocated to its nearest centroid, depending upon the squared Euclidean distance. Further, supposing \( c_i \) is the collection of centroids in set \( C \), then corresponding to each data point, \( x \) is associated with a cluster by the relation given by

Here \( \text{dist}(\cdot) \) is the standard (L2) Euclidean distance. Here, Consider the group of data point

\[
\arg\min_{c_i \in C} \text{dist}(c_i, x)^2
\]

assignments for each \( i \)th cluster centroid to be \( S_i \).

2. **Centroid update:**

Within this step, the revaluation of centroids occurs, achieved by computing the mean of all data points associated with that centroid’s cluster. The relation can be accurately defined by one below

\[
c_i = \frac{1}{|S_i|} \sum_{x_i \in S_i} x_i
\]

The algorithm iterates amongst steps one and two until a finishing criterion is achieved (i.e., no data points alter between clusters, the sum of the distances is minimized, or certain upper-limit of iterations is reached).

![Figure 1: Original Data and Clustered Data](image)

Using the K-means algorithm, our primary aim is to be able to form clusters of related users. These clusters, however, can be a little challenging to deal with for such massive data.

![Figure 2: Final Result analysis Graph](image)
3. Choosing $K$

We then use Within-Cluster Shortest Square (WCSS) or the elbow method to accurately calculate the optimal number of centroids that will give the best results upon computation.

3. Results and Discussion

The developed framework effectively made predictions about user likings. Results attained from this algorithm were used to generate the cosmetics or the appearance of the user interfaces. To show its implementation, and it is in its elementary state, we decided upon creating three interfaces that would correspond to the 3 clusters obtained with the help of K-means clustering aided by WCSS.

4. Future Scope

We can implement this in real time using Artificial Intelligent techniques and more over several volume of data set can be consider in future to improve the machine learning model accuracy.

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