

Enhancing User Experience using Machine Learning

Sumaiya PK

Associate Developer,
SAP Labs Whitefield, Bangalore,
Karnataka, India

Abstract--- Many business solutions are available, but what differentiates the best products is Customer Satisfaction. Customer satisfaction is the key factor in any business. By performing User Activity Tracking we ensure that honest feedback from the customers is passed on to the developers, which helps them analyze the difficulties that customers face. The feedback is collected through intermediators. The customers share the feedback with the consultants, consultants share their understanding to the lead, which then goes to product owner who then share it with the developers. In such a process, the customer feedback is prone to modification based on the stake holders understanding, which sometimes leads to an issue radically different from what the customer had stated. Marinating the sanctity of customer feedback is imperative as it allows the developers to identify the features that would enhance and enrich the User Experience. We can achieve a lossless capture of user feedback with the help of 'Clickstream'. Clickstream will capture all the events triggered along with the time of the event. This difference in the time will be plotted and a peak in the graph would determine a potential pain point for the customer. This instant data retrieval can also help us reduce the number of customer tickets that we encounter, as we would exactly know where there is an issue and can start working on it even before the incident is raised. The huge amount of user activity tracking data can be added into a Machine Learning algorithm which would help us analyze patterns of normal user behavior and abnormal user behavior (When there is any User experience issue). We can't rely on a single set of rules to ascertain that the user is facing an issue. Every application is different, features are different, customers are from different locations etc. Hence a simple rule based algorithm will not be helpful. We need Machine Learning Algorithm to find a lasting solution to the problem.

Index Terms—Clickstream, Machine Learning, MongoDB, User Activity Tracking.

I. INTRODUCTION

Any business solution is considered to be good when it solves the exact problem. However, there are innumerable solutions available in the market. What differentiates the best solution from the rest, is the way the user feels about a solution. The end user is the one who uses the entire solution which is available in the form of websites/web applications/on premise solution. Hence how user feels about the solution is the key factor to be considered, which in simple terms can be called as User Experience. Any business Solution be it a Web application or a Website or Mobile app etc., is always dependent on ongoing user inputs. If user finds

any difficulties in understanding and using the solution itself then the productivity of the user is hampered. The task which can be completed in 5 hours might end up taking up to 7 hours. This causes the end user to be frustrated and unhappy while using the application. When the websites / Web applications/ mobile applications provide easy and self-understandable User Interface then it provides a better user experience leading to happy customers. Customer satisfaction is what determines which company products are best.

II. COMMON USABILITY ISSUES

A) Lack of appropriate name for UI Element

This is one of the biggest issue faced in terms of usability. Many a times the name given to a UI element is not self-explanatory. From a development point of view, there is a tendency to make the UI fancy and use fancy vocabulary. But the problem is, we deal with a variety of customers spread over different regions consisting of users of different age group and different knowledge level. Thus, analysis of what naming format is appropriate is quite difficult. Machine learning can help us analyze and decide on a better naming convention^[8].

B) Self-Understanding

The UI elements should be clearly visible, spacious and self-understandable. The icons used and the color, fonts etc., should be connected to real world for easy grasp^[10]. In many cases, the UI is made to be complicated thereby demanding the users to invest a lot of time understand the flow and find the UI elements on the Screen.

C) Varying perceptions of developer and customer

It is an extremely well-known fact that the understanding level of a beginner and an experienced person is different. We are familiar with things that we use very often. Similarly, when any developer works on an app, they are familiar with the terms they use in a UI, but relying on such knowledge introduces a bias into the application that works against the user. Customers use different apps at different times. E.g. HR of any company will use products for different uses, like payroll, leave request etc., In such a case, one user is using different applications and hence terminology will be different. The UI of Finance app will look entirely different compared to Payroll. The challenge here will be to develop

both in such a way that it is self-explanatory. Hence, we need to know customer's level of understanding to develop user friendly apps.

D) Quick Turnaround time

We all understand the quote 'Time is money'. A user expects issues to be resolved on time, but with multiple stakeholders involved such as, Project Manager, User Representative(s), Developer(s), Support team, the time available for response is depleted^[9]. A significant time is spent by the brokers to identify the issue through mails and calls and then fix the issue.

The amount of data available

Note: Calculating the data based on certain assumptions.

Assuming 10000 users of one application

One application requires around 200 clicks (User activity)

So, we have $10000 * 200 = 2000000$ data points in one day

One month $2000000 * 30 = 60000000$ data points in one month

Just in ERP there are around 12 major fields; considering each field as one app

We have $60000000 * 12 = 720000000$ data points in one month

Then we have $720000000 * 12 = 8640000000$ data points in one year.

The process of user feedback involves many mediators.

Customer → Customer Lead → Customer manager → Consultant → Consultant lead → Consultant manager → Product Owner → Developer Team Lead → Developer

In this process of feedback everyone explains their understanding to the next level. In the process, the actual feedback might get corrupted or modified.

Hence the suggestion here is to make user experience better based on data collected at the source. While the customer is using the app, all the activities are recorded in background and added to a Machine Learning algorithm. This algorithm will help developers identify any unusual behavior in the data. The machine will learn using the data fed, and learn to identify unusual behavior. E.g.: consider one user using an application where there is a list of tasks, and user needs certain amount of time to complete the task. Now when there is an issue, the time taken will be much different compared to the normal pattern. Machine Learning algorithm will help us identify this outlier and show the cause of it.

Note: Any observation that appears to be inconsistent when compared to the remaining data set available is termed as an Outlier.

III. INDEX TERMS ELABORATED

A) Clickstream

The process of recording and analyzing the user actions or mouse movements in any Web browser or any software application is called Clickstream. The cumulative data will

contain details of the path the user takes in any browser/application and in what order. When the user clicks/types anywhere in the web browser or any software application, the user's activity will be recorded. The activity log will consist of which browser/application is loaded, time required for loading, the page/view in the browser/application, number of pages viewed, frequency of the pages viewed, different featured used, User details, etc., This data will provide hints on user's flexibility in using the browser/application and where the user finds difficulty while using the app.

B) Machine Learning

Machine Learning (ML) involves the process of training the machine. In this process, we try to convert experience into Knowledge. The Machine is trained using large amounts of data, this data acts as an input. The input will be added to a training algorithm, which analyzes the data and recognizes patterns. The outcome will be the knowledge^[2].

C) Why machine learning

We have many users providing huge amount of data. Every user exhibits different behavior in using the app. This User Experience is influenced by a wide range of behavioral parameters like emotional, experiential, affective and aesthetics^[11]. It's not easy to identify the behavior of each user and analyze it only when the user is facing a difficulty in using the app. Users are spread all over the world, working in different time zones, having different levels of experience, different knowledge level etc.^[1]

Users are spread over a wide range. Even within the same continent users belonging to different country exhibit different behavior. This applies to different states in the same country and different cities in the same state. All these combinations are based on just one parameter, geographic locations, we can include many other parameters such as experience level, requirement, type of data base needed, etc., Hence we need a framework that is capable of adjusting to the ever-changing customer scenario. Machine learning algorithms can learn continuously and provide analysis.

D) MongoDB

MongoDB is a document oriented database. The data will be stored in JSON style documents. Different documents come together to form a Collection. Each document is independent of the other in terms of fields, content, size etc. MongoDB is easy to scale which makes it extensively used in Big Data use-cases^[6].

E) User activity tracking

With the help of Clickstream, we can record the activities performed by the user. This tracking will be done with the help of Clickstream. The data captured will include the URL, Application Name, the pages viewed, amount of time spent of different pages, texts entered/edited/deleted in Text boxes, checkbox etc., any item in the UI can be captured.

NOTE: The data will be captured adhering to the Data Privacy Rules as agreed on the Non-Disclosure Agreement (NDA).

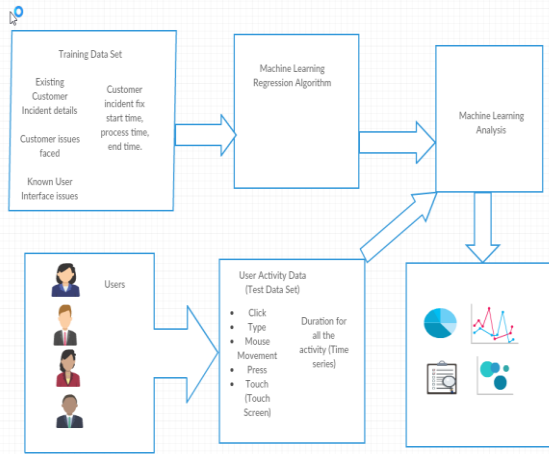


Fig. 1: Basic Architecture Diagram

TABLE I: List of User Data that can be recorded

User ID	App Name	Page/View Name	Control ID	Event	Time
001	CloudReportingDemo	__page0	__button0	press	2017-09-13 :14:07.19
001	CloudReportingDemo	__page0	__xmlview0--userid_input_id	liveChange	2017-09-13 :14:08.21
001	CloudReportingDemo	__page0	__xmlview0--userid_input_id	Change	2017-09-13 :14:09.42
001	CloudReportingDemo	__page0	__button1	press	2017-09-13 :14:19.37
001	CloudReportingDemo	__page0	__xmlview1--userid_input_id	Change	2017-09-13 :14:20.33

In the process of tracking the User Activity, we need to analyze what data is needed to fulfill our outcome. Table 1 shows the sample data that can be collected and used as training data set into Machine Learning Algorithm.

IV. MACHINE LEARNING ALGORITHM

Of the various algorithms available, the scenario determines which one is to be used. In the process of analyzing User behavior, we use some concepts of Distance based Algorithm of detecting outliers [18].

There are 2 major datasets in ML Process.

- A. Training Dataset
- B. Test Dataset

A) Training Dataset

In this step, we input all the existing experience data which is the training data for the Machine. Making use of all the existing experience the Machine will be trained to analyze different patterns and perform set of grouping.

The scenario here demands the user activity data as the training dataset to perform the grouping. With the help of the existing user activity data, grouping will be performed by using time as one of the parameters. By analyzing all the data, major grouping can be done which depicts the approximate time consumed to perform different sets of activities.

Consider User Activities as

$$A_1, A_2, A_3, A_4, \dots, A_n$$

In Fig. 2 the User activity data with respect to time consumption is shown. The Graph shows different users performing activities consuming certain amount of time. The activities which consume approximately similar time to complete will be grouped into one.

Hence, Group1 (G_1) will have set of activities that fall into

certain time range.

$$G_1 = \{A_1, A_2, A_5, A_8, A_{67}, A_{102}, \dots\}$$

Similarly, we will have G_2, G_3, \dots, G_n .

In Fig. 3 the grouping of different activities is shown by using color coding. Each color depicts different group.

e.g. The Red color depicts the activities which consume much more time when compared to other colors.

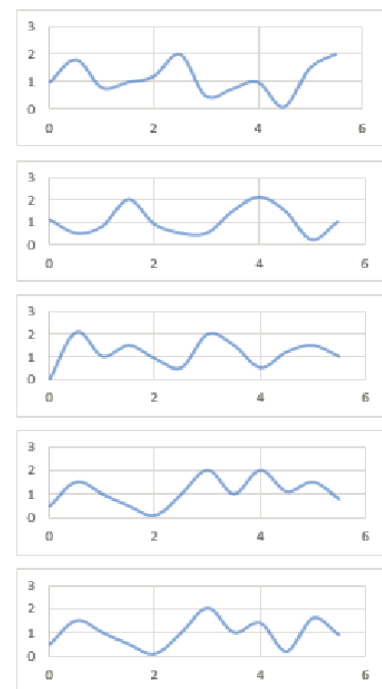


Fig. 2. Training dataset of User Activity(event) against Time

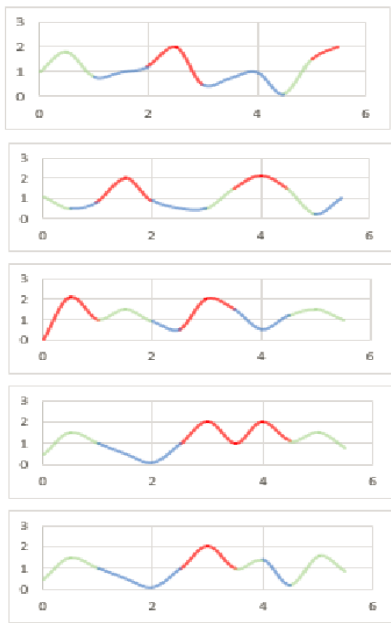


Fig. 3. Grouping of Training dataset of User Activity(event) against Time

B) Test Dataset

Once the analysis of training dataset is accomplished, we input the actual dataset (test data) to obtain results.

Consider User Activities represented as A_1 to A_n .

Time Consumed for each Activity can be represented as T_1 to T_n

Initial mapping of activity to the respective group will be performed.

Considering Activity A_1 to A_{10} belongs to G_1 .

Time consumed for each Activity will be as

$$G_n T A_n = G_n (T_{n+1} - T_n)$$

e.g. $G_1 T A_1 = G_1 (T_2 - T_1)$ - Time consumed for completing Activity1 which belongs to Group1.

$G_1 T A_2 = G_1 (T_3 - T_2)$ - Time consumed for completing Activity2 which belongs to Group1.

Approximate Time for each group is provided by the Analysis which can be represented as $G_1 T_{Approx}$

The difference of $G_1 T_{Approx}$ with data $G_1 T A_1$ to $G_n T A_n$ will be calculated which can be represented as Check C .

$$G_n C_n = G_n T_{Approx} \sim G_n T A_n$$

e.g. $G_1 C_1 = G_1 T_{Approx} \sim G_1 T A_1$

$$G_1 C_2 = G_1 T_{Approx} \sim G_1 T A_2$$

Then the Cluster is made of all the data for $G_1 C_1$ to $G_n C_n$. Any data which has more than allotted time difference will be considered as an Outlier.

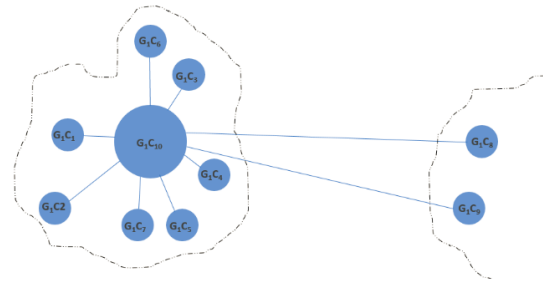


Fig. 4. Outlier detection of unusual user behavior

V. IMPLEMENTATION PROCESS

Key steps involved

- Implement custom event listener
- Store event data in a repository
- Feed the event data to our ML Algorithm
- Analysis of output produced by ML

These steps are described in detail below.

A) Implement custom event listener

This step involves creating a custom event listener for the purpose of capturing all the data related to a User activity. Table 1 provides a probable list of interesting data points, which can be extended to include more data points based on requirement.

B) Store event data in a repository

Event data captured by the event listener should be stored in a repository. Accumulation of this data would lead to more accurate results provided by the ML Algorithm. Repository should be interchangeable to allow for quick changes in database technology e.g. Switching repository from standard SQL to MongoDB.

C) Feed event data to our ML Algorithm

Machine Learning Algorithm will process the data stored in the repository. We will make use of Regression analysis of ML and perform outlier detection, which will help us identify the event where the user is facing an issue

D) Analysis of output produced by ML

The outcome obtained by the ML can be used as needed. The time series captured along with the event will point to the exact issue faced by the user (described in detail in Scenario 1). And the analysis of number of users with respect to the event/controller will help us identify the most used features

in an application which will be used for future enhancements (described in detail in Scenario 2).

VI. REAL TIME CUSTOMER ISSUE HANDLING.

The test data from the Customers(Users) are uploaded in the ML algorithm and the outcome is described in detail in the below two scenarios.

A) Scenario 1: Help fixing the issue

Machine Learning has the ability to find different patterns which provide valuable analysis by using large data sets. Our scenario requires the need to identify an issue. Machine is trained with the previous experience (Dataset), so any data other than the usual pattern will be identified. We make use of Novelty Detection where the machine will determine unusual pattern given a set of past experience data. The term unusual is very subjective, hence the approach here can be that each observation will be given some rating based on a degree of novelty [3]. Pattern recognition is one of the application of Novelty Detection. Pattern recognition focuses on recognizing different patterns from a given set of data. Using these concepts the analysis based on assumed data is described. The Chart below shows the connection between user performing different activity in one app vs the time duration. The data is plotted as, User1 performing activity 1 to activity 10. User1 takes 1 minute to complete activity 1, 2 minutes to complete activity 2 and so on. Which means on an average User1 takes 1 minute per activity. But when it comes to activity 8 User1 takes 13 minutes to complete just one activity. This is clearly visible in the chart shown in Fig 5. When we consolidate the data, this behavior is present for other users as well. Fig 6 shows the user behavior with respect to different controls used in the UI. With such graph, it is easy to analyze other parameters as well which is shown on hovering. This consolidated data will be directly sent to the developer. Now the developer can easily figure out which part of UI the customer actually finds it difficult and instantly fix this and upgrade in the immediate next release. This will help optimize human performance and improve user satisfaction [12]. And we might be even able to fix the issue, before the customer even creates the ticket. This will save money and more importantly save time.

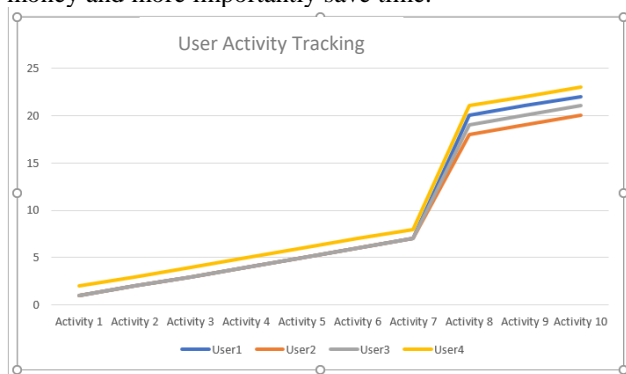


Fig. 5. Plot of User Activity(event) against Time

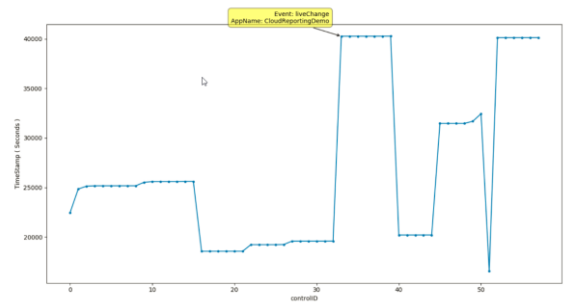


Fig. 6. Plot of User Activity (Control ID) against Time

B) Scenario 2: Future Enhancement

Customers use many applications and features across the world. We can use the past behavior of the customer to obtain a pattern of the most used features. This analysis will help predict the features that can be planned for enhancement. The patterns are obtained based on the behavior of similar users; hence it is collaborative in nature. This analysis is termed as collaborative filtering [4]. With this honest feedback development team, will also know the need and choice of the customers. By getting the plot against the customers and the apps used we can identify which app is used by most customers, allowing the development team to plan enhancements on the same. In Fig. 7, it's very clear that App1 has more number of users. So, the development team can plan more enhancements for the same. Similarly, App3 and App4 have a lesser percentage of users, which indicates that there might be an issue.

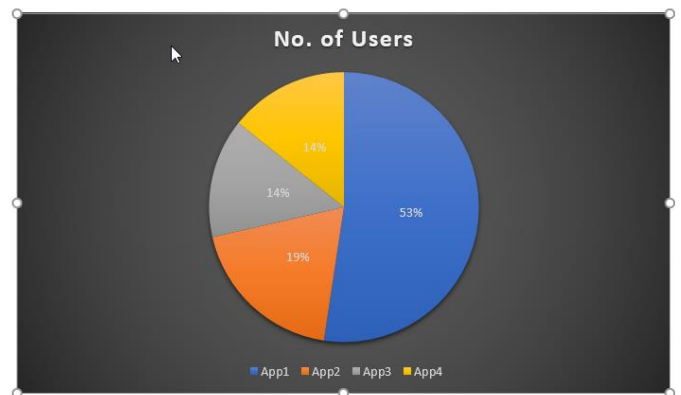


Fig. 7: Plot showing number of users for different applications

VII. CHALLENGES

- Performance – The Performance of the Customer system will get affected when the tracking data hits the backend very often. Hence, intervals of capturing data should be decided based on the Performance needed.
- Scaling – In the Process of tracking the user activity, the controllers developed should be scalable so that any number of features can be tracked.
 More Scaling → better performance for ML analysis
 More Scaling → Reduced System Performance

VIII. FURTHER ENHANCEMENT

The analysis obtained from the ML will help us solve various usability issues. The Solution suggested in this paper needs manual effort from the development team to analyze the ML outcome and decide which issues need to be fixed. In future, this process can as well be automated. The ML analysis will exhibit different patterns which displays any unusual behavior of the user while using any Website/Web Application/On-Premise products etc., We can integrate an automated voice recorded system or a pop-up help message in the User's Screen, which will be triggered when any such pattern is recorded. With this the user, can type or speak out the issue faced and with help of AI we can show a set of possible solutions and important links to refer. So, the customer incidents will come up only when User faces issues beyond the help of AI system.

ABBREVIATION

- AI- Artificial Intelligence
- DB- Data Base
- JSON- Java Script Object Notation
- ML- Machine Learning
- NDA-Non-Disclosure Agreement
- SQL - Sequential Query Language
- UI- User Interface

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