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Predicting Users' Behavior using Mouse Movement Information: An Information Foraging Theory Perspective

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Received: date / Accepted: date

Abstract The prediction of users' behavior is essential for keeping useful information on the web. Previous studies have used mouse cursor information in web usability evaluation and designing user-oriented search interfaces. However, we know fairly to a small extent pertaining to user behavior, specifically clicking and navigating behavior, for prolonged search session illustrating sophisticated search norms. In this study, we perform extensive analysis on a mouse movement activities dataset to capture every users' movement pattern using the effects of *Information Foraging Theory* (IFT). The mouse cursor movement information dataset includes the timing and positioning information of mouse cursors collected from several users in different sessions. The tasks vary in two dimensions: (1) to determine the interactive elements (i.e., information episodes) of user interaction with the site; (2) adopt these findings to predict users' behavior by exploiting the LSTM model. Our model is developed to find the main patterns of the user's movement on the site and simulate the behavior of users' mouse movement on any website. We validate our approach on a mouse movement dataset with a rich collection of time and position information of mouse pointers in which searchers and websites are annotated by web foragers and information patches, respectively. Our evaluation shows that the proposed IFT based effects provide an LSTM model a more accurate interpretative exposition of all the patterns in the movement of the users' mouse cursors across the screen.

Keywords Users' Behavior Analysis · Users' Behavior Prediction · Mouse movements · Information Foraging Theory

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1 Introduction

Every day people certainly face convenient search issues (e.g., seeking a particular homepage and interpolating specific attributes with common keywords), which perhaps contented via a distinct query and single click. It typically perceives various searches to extricate new sophisticated norms. The intentions deviate. The search session encompasses a class of user requests for interpreting both what the user is looking for and where (mouse cursor locations, mouse button, and it's a state, etc. in particular) is critical to rank and display resources. It happens to be the searcher who embraces a sort and govern scheme, employing respective queries to assign with a portion of the norm's intention [1]. Earlier studies [2,3] on user search features such as observation over information search, temporal conviction, or topic reconciliation, including the deemed task difficulty subvene their execution. Recent study [4] on task complexity and the user's scattered attention over Web pages[49] based on Information Foraging constructs [5], the outcome of this study were less well-tuned in task closure for users who followed rigorous information search. The search process is interactive, and in itself, an iterative pattern of actions that repeatedly solicit different queries to attain the proper amount of coherent information for intrinsic information needs to be determined.

Human users during the information-seeking process as foraging [24], user behavioral aspects, and insight of the information dependability, value, and quality depend on account of the situation, intuition, and cognition [6]. When users interact with an online information world, websites and Web pages are annotated by information patches such as hypermedia and hypertext documents encompassing the interactive links [7, 8]. These links possessed the visual facets such as cues and objects that emanate information scent [9]. The devolution of the information scent is a major factor in analyzing users' behavior, be it strong or weak information scent, where cues portraits users' judgment and processing of information acquired from the interactive elements. Information cues are exhibited in the form of several interactive facets such as visual cues [10], source cues [11], and informational cues. It has been earlier suggested [12] that these interactive facets emit an information scent by which a user, after identifying the proximal cues means to estimate the relevance and value of information contents. During foraging for information recline, users weigh the associated costs and benefits, i.e., the utility [13], and specify between the uncertainty of the information scent to follow.

Earlier studies [14] demonstrated that searchers' evolving actions are skewed toward retrieving top rank results; usually, systems having high positive predictive value are immensely preferred in web search than systems with high sensitivity. In contrast, systems or humans know only to a small extent about users' behavior in prolonged sessions of sophisticated norm paradigms, specifically those to confer inspection to the online search systems and its evaluation reinforcing prolonged sessions and sophisticated norms. For instance, do users look into more result excerpts and involve in prolonged search sessions of sophisticated norms? Do users seek to gaze credible information more precisely?

To address that gap, it would be meaningful to examine the interactive elements of a user within the websites and web pages are given that the focus on the interaction between a human and an online information environment. The interaction between a user and an online information environment can eventuate over three modalities, such as search by perceiving images, verbally [15], or customarily by typing into a search box. It has been earlier found [39] that a mouse can render much more information than just a user pointing in X, Y direction, which showed a strong relationship between the mouse cursor position and gazes position. In this work, our goal is to find and characterize interactive elements, i.e., mouse cursor movements, and it's a feature in particular.

By relying on users' mouse movement activities as an indicator of facilitating information episodes by means of Information Foraging Theory, it helps us understand user behavior in a session search. The main contributions of this study can be outlined as follows:

1) We present extensive insights depicting user behavior on a mouse movement activities dataset (in Section 5), extending considerably the previous work [16] by characterizing the uniqueness of unknown tasks pattern via users' click. In this analysis, our motivation is: (i) to characterise the user behavior with the usage of our proposed mathematical features, temporal patterns, and summarize the role of users' mouse movements by using Information Foraging Theory [12]; (ii) investigate to simulate the behavior of the users' mouse movements on any website.
2) We standardize the problem of users' behavior prediction as a semi-supervised driven learning task (Section 6) for the given mouse cursor locations (i.e., x, y coordinate pairs on the screen). It is used to investigate unknown tasks patterns of the user on any website using the effects of Information Foraging Theory.
3) We present a novel LSTM-based approach for predicting users' behavior from mouse movement activities dataset based on Information Foraging Theory.
4) We present empirical results (Section 6) that demonstrate the overall perspective proposed in this work. Also, it forms a mouse dynamics-attentive baseline that consolidates mouse curve features, button states, user sessions and clicks events per session by almost 96% success of predicting the behavior of pattern in the movement of users' mouse. We further analyze the importance of various mouse movement features.

The rest of the paper is adopted as follows. Next, we shed light on the related work in terms of user sessions, mouse movement activities, and it's features for users' behavior prediction. Section 5 introduces a detailed analysis of the mouse movement dataset with the introduction of features based on the proposed mathematical properties. Then we explore the role of mouse movements on users' behavior followed by simulating the behavior of the user's mouse. At the same time, Section 6 reports our experimental results followed by our predictive model, with concluding future work following in Section 7.

2 Related Work

Our work is affined to the behavioral aspects of the user on mouse cursor activities: user behavior with mouse movement dataset, user search behavior based on IFT and its effects in predicting users' behavior, and user sessions. We review each area below.

Understanding users' behavior on Web pages with the usage of mouse cursor movements, clicks and gaze which has been an engaging topic since a decade ago as an *inherent indicators of interest*. In particular, how users interact with search engine result pages (SERP) is a basic question in information retrieval, dealing with search quality, relevance evaluation, and interface design [17–19]. Earlier studies (before 2003) are in general rooted in the explication of wide-reaching query logs [22], but they do not provide details of how users examine result abstracts. It has been demonstrated that browsing various web pages records all at once in a web browser [20]. The aggregate of mouse cursor movements information on the SERP leads them to predict via a neural network which they presumed user interest as quantified subordinate. In early work [21], they developed the "curious browser" and noticed that the web page's relevance was one of the positive indicators for mouse cursor movement time but could only distinguish exquisite extraneous Web pages. Notably, they found that the number of mouse clicks on a web page was not relevant. Recent studies with eye-tracking [23, 24, 27] additionally decrepit that searchers act multifariously in various norms. It has been demonstrated that searchers may act precisely to varied viewpoints of search result excerpts [25, 26] and except those of result excerpts including SERP attributes such as advertisements and connected searches [27, 23]. Although user behavior studies using eye-tracking data are narrowed due to a limited amount of such sophisticated, accessible devices.

As far as the ongoing research on user behavior studies resides, the search tasks being studied in [27, 23, 14] are simple, such as the "navigational" and "informational" tasks elaborated in [28]. Also, searchers perform online searches on a regular basis, which delineates a significant level of satisfaction with it. A user study has been performed on such an online search scenario [37]. To the best of our knowledge, existing experiments related to search behavior conducted user studies with mouse movements corpora, only [21, 29, 30] considering the tasks of coequal complications to the tasks validated in our paper. Although finding or simulating the unique search patter of users' in a search session is still unexplored in their study. A very recent work [40] employs SERP regions traced by mouse movement to seize the spatial information for learning the sequences from the representation of interactions. In our work, we use the effects of Information Foraging Theory to analyze and simulate the mouse movement activities. Consequently, it is ambiguous to know how users react - specifically how they browse the result excerpts on Web pages and click results - in prolonged sessions of sophisticated norms.

To deal with sophisticated norms, it generally solicits comparatively prolonged search sessions to carry into effect. Prior studies on web search logs [22] described search sessions as multiplex searches beyond fixed time duration in search logs. Moreover, in this context, these varied searches spanned under a session are not radically confined to a coherent topic or search norm. In our work, a session signifies to successive searches that desire to expound relevant norms, which is analogous to the search sessions deliberated in [31].

3 Theoretical Foundations

Based on the previous studies that are relevant to users' behavior research [18, 5, 12, 26, 22], this work aims to study what enforces user behavior on the web also to find dominant traits or factor the behavior rests on. We explored the mouse movement activities corpora representing a vital indicator to understand user behavior in an unknown task session. These attributes can be extracted as features, which can be employed to build a predictive model of user behavior [32]. In contrast to information retrieval, the theoretical foundation relies on Information Foraging Theory, which theorizes that an *information forager* seeks for data to make practical, strategic search preferences so want high-level information (i.e., summaries) and engage in Information Foraging behaviors to accomplish a designated objective [12]. These behaviors incorporate using a particular information diet and following the information scent to search the needful information within or between information patches. *Information diet* refers to the decision making to follow a set of information sources over another that has a perceived value to an information forager, while *information scent* helps an information forager determine the potential information value of specific information based on metadata and navigation cues. An *information patch* refers to the spatial, temporal nature, and/or conceptual space in which information is clustered.

As information foragers in a session, users must reveal an information diet for SERPs on the Web pages to build on IFT. Users then pursue the information scent of each result abstracts based on their information diet for SERPs to seek useful information within or between

SERP patches. Users can have high information scent on a website with fewer clicks matches the information diet of users for the SERP. The extent to which the consecutive presentation of SERP patches matches users' information diet is defined as the *information sequentiality of SERP provision on a website.* A high level of information sequentiality represents a provision of SERP patches that use to match the user information diet for a SERP. Apart from this, the SERP provision embraces a low level of information sequentiality.

On the basis of IFT, we propose the *information sequentiality of SERP provision*, which hypothesizes that the order of the SERP patches available on a website influences the execution performance of users' decisions. Information sequentiality refers to the range to which the consecutive presentation of information patches matches the information diet of users. The concept of information sequentiality of SERP provision differs from other similar concepts, such as the order of information placement [33]. The important differences include the type of object provided and the interactive elements (i.e., mouse cursors) status between information provision and information need. In the perspective of the type of object, previous works focused on investigating the placement order (i.e., relevancy) of information within information patches [34], whereas the current work investigates the provision order of information patches to understand users' behavior. In terms of the role of interaction such as mouse cursor as an interactive qualifier between information provision and information need, this work sees the information sequentiality of SERP provision based on the IFT constructs.

4 Mouse Movement Data

We employed a dataset [35] created by One Identity Inc. (formerly Balabit Corp.) that records mouse cursor activities of 10 users extricated during the remote session from remote desktop protocol connections, and the dataset imperializes 1612 hours of logged mouse cursor activities. Each activity is provided in the form of tuples containing the timestamp, button pressed, state of the mouse, and the mouse pointers' coordinates. Throughout the data collection, users did not have to conduct any specific tasks; however, they usually performed unknown search tasks, which is recorded in several sessions for each user. The mouse movements dataset comprises of a train and test set, containing timestamped and positional information without screen resolutions. So we estimated every users' screen resolution by calculating the maximum coordinate and delineating it to a collection of finite screen resolutions. Our conjecture relies on the certainty that the user selected only one screen resolution, and we select the identical plausible mapping.

5 Mouse Movement Data Analysis

To understand user behavior and characterize in an unknown task session, we analyze a rich collection of mouse cursor activities sampled from ten users collected during a remote session with a time window of more than two months.

We rely on the analysis of a large sample of mouse interactions of the user during a remote session in a time window of more than two months. This analysis aims at

- Understanding the user's mouse movements in an unknown task session: Which part of the screen do users look for when interacting on the web? How does the user behavior change when considering the X or Y position? Does the mouse clicks exhibit any temporal patterns?
- Understanding the user behavior patterns, using the features extracted from the mouse curves, and determining the main interactive elements of user interaction with the site based on large unmarked information structures.

For this purpose, we analyze mouse cursor actions of each user that delineates a click on the web, for which the part of the screen when used most in each mouse state. The data contains several sessions of every user, involving more than sixty sessions with over 0.08 million events per session.

5.1 Revealing Mouse Movement Features

We start our analysis by extracting characteristics that can signalize the user behavior patterns. In general, we are interested in understanding which kind of mouse actions users follow through when they interact with the web.

We try to understand the users' click features in X-Y direction in all sessions, which is reported in Fig. 1.

We do so by analyzing the state-wise distribution of mouse in X-Y direction associated with users' mouse positions and click events, which is reported in Fig. 2 and Fig. 3, including the distribution of user-wise distinctive X-Y movements, which is reported in Fig. 4. Based on the analysis, it depicts that most of the users follow to "Pressed" in X as well as Y direction followed by "Released" in Y direction giving similar patterns for other states, whereas most of the users' mouse states in

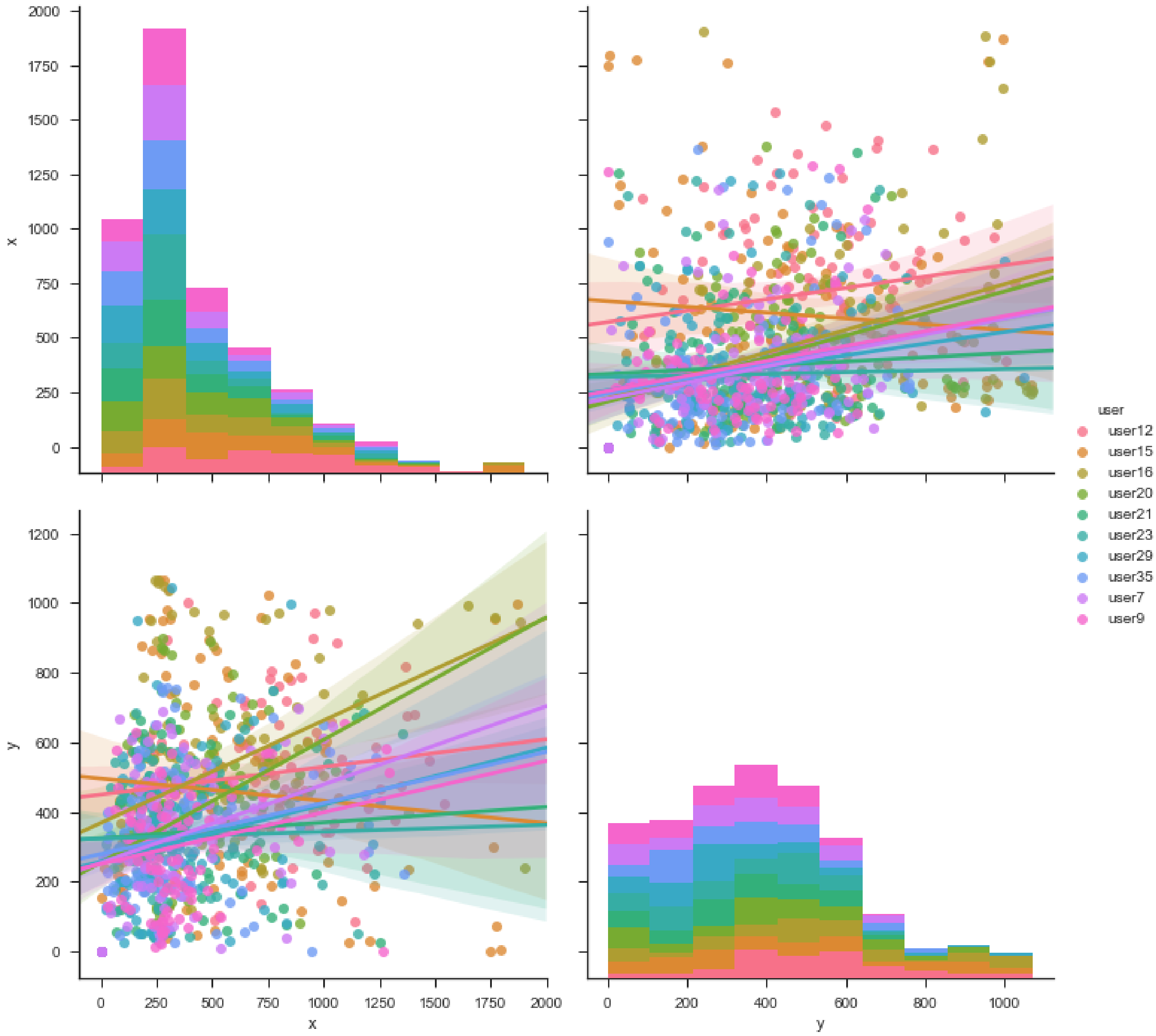

Fig. 1: User-wise mouse actions in every session w.r.t. X & Y direction

the X direction is comparatively less followed for other states in comparison to actions in the Y direction. An extensive analysis of the mouse state of every user has been conducted given in Fig. 10 in terms of state-wise distribution with respect to user in X and Y direction, reported in Fig. 11 and Fig. 12.

We now break down the analysis of mouse movement activities on features into mouse coordinates and mouse actions, collected from users during various sessions. The successive coordinates of the mouse are classed within so-called *curves* that matches to the pioneer featured actions of the mouse (move, drag-drop, point-and-click), which is reported for user35 in Fig. 6. To introduce a user to follow a single curve does not provide assurance of giving substantial information, and following this, we put the curves together under sessions in sequence to analyze the analytical, behavioral features spotted during an individual session. In contrast to the mouse curve, a *session* is defined for a user possessing multiple curves, we have recorded a mouse movement session for 15586.994000 seconds which is reported in Fig. 5.

To evaluate if mouse cursor location predicts users' click position in x- and y-coordinate space, we conducted regression analyses considering the use of movements of the mouse cursor to enormously index users' search patterns, reported in Fig. 8.

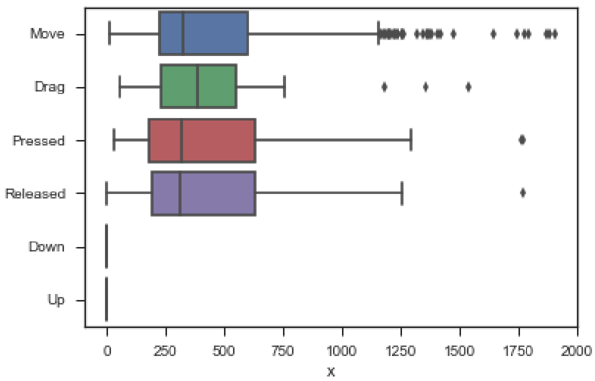

Fig. 2: Mouse state-wise distribution in X direction indicate which part of the screen used most in each state

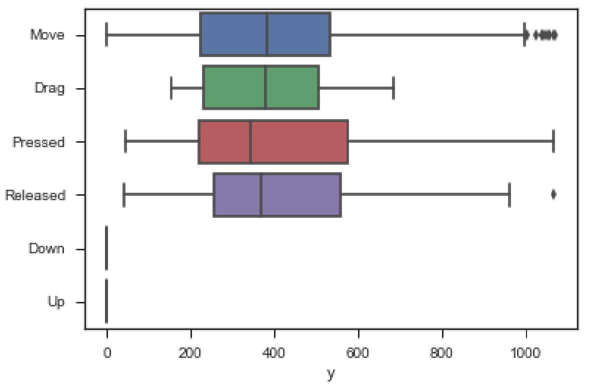

Fig. 3: Mouse state-wise distribution in Y direction indicate which part of the screen used most in each state

To interpolate a single mouse curve, we introduce six varied features, where each feature allows only one value as a delineator of the curve. As far as we are concerned, we introduce these characteristics for the first time in the domain of behavioral aspects based on IFT. However, we propose our adopted implementation for these characteristics.

A *mouse curve* refers to a tuple containing timestamp and Cartesian coordinate pairs:

$$M_C = (p_1, p_2, ..., p_n) : n \geq 2 \quad (1)$$

where $p_i = (\textit{VARIATION-TYPE}, \text{t}, x_i, y_i) \in \mathbb{R}^4$, n is the number of points, *VARIATION-TYPE* is the type of mouse variations (such as move, drag-drop, point-click) and t is the timestamp of the mouse variation. Timestamps in the used benchmark dataset [35] are collected in seconds.

A feature of this curve is merely a function of the mouse coordinate points:

$$F(M_C) : R^{2n} \rightarrow S \subseteq R \quad (2)$$

where S is a subset of real valued numbers.

Primarily, these features can be an unconnected task depicting any user characteristics to be positioned, independent of size, and the curve inclination, which could be used to characterize users. So the functions of these features should meet the following mathematical properties:

Translational Invariance

$$F(p_1 + u, p_2 + u, ..., p_n + u) = F(p_1, p_2, ..., p_n), \quad (3)$$

where $u \in R^2$ is a multidimensional translational vector.

Scale Invariance

$$F(lp_1, lp_2, ..., lp_n) = F(p_1, p_2, ..., p_n), \quad (4)$$

where l refers to a scaling factor.

Viewpoint Invariance

$$F(Ap_1, Ap_2, ..., Ap_n) = F(p_1, p_2, ..., p_n), \quad (5)$$

$$where\ A = \begin{pmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{pmatrix}$$

is a 2D viewpoint matrix which rotates about the origin via an angle θ in anticlockwise direction.

Efficiency: A single mouse movement intends to elongate from the initial cursor position p_1 to the final cursor p_n pointing to result location. The minimum spacing, while movement is a straight line while curve varying, will result in no efficiency. Efficiency refers to the ratio of initial distance during cursor pointing on the screen to the curve's length.

$$E = \frac{\sqrt{(u_n - u_1)^2 + (v_n - v_1)^2}}{\sum_{i=1}^{n-1} \sqrt{(u_{i+1} - u_i)^2 + (v_{i+1} - v_i)^2}} \in [0, 1] \quad (6)$$

It helps to measure how *efficient* a curve could be, in stating its goal. The value of efficiency varies between zero and one. The shortest path between the initial and final points is equal to one and the most efficient if a curve with value converging to zero is one that crawls a lot instead of going beyond. A user curve containing high-efficiency value approaches the mouse spotlessly to target locations in the absence of several idle movements. It may be noted that users generally have poor efficiency and web robots have high efficiency, so this

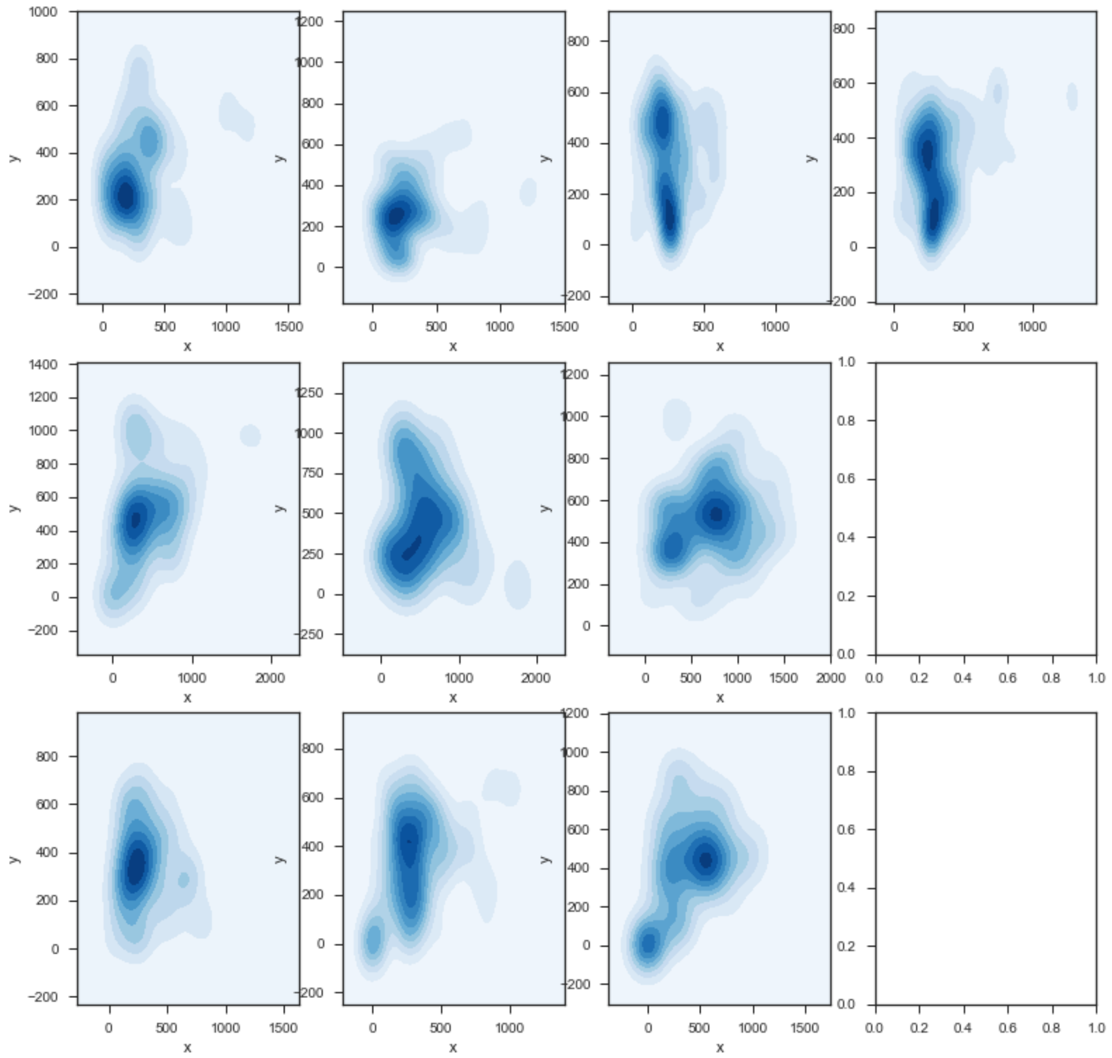

Fig. 4: Distribution of Unique mouse movements in X-Y direction of every user

may be very useful in differentiating between the two from mouse movements.

Regularity: This feature may be very useful to measure how regular a user follow a mouse curve while seeking information from a distance to the computer screen which follows from its geometrical centre.

$$\bar{u} = \frac{1}{s}\sum_{i=1}^{s} u_i, \bar{v} = \frac{1}{s}\sum_{i=1}^{s} v_i$$

$$d_i = \sqrt{(u_i - \bar{u})^2 + (v_i - \bar{v})^2}$$

Regularity interprets in the form of mean and standard deviation of those distances which is given below

$$R = \frac{\mu_d}{\mu_d + \sigma_d} \in [0, 1], \quad (7)$$

where $\mu_d = \frac{1}{s}\sum_{i=1}^{s} d_i$, $\sigma_d^2 = \frac{1}{s}\sum_{i=1}^{s}(d_i - \mu_d)^2$

Whenever a curve retracts in the form of regular polygons (such as squares or equilateral triangle), then

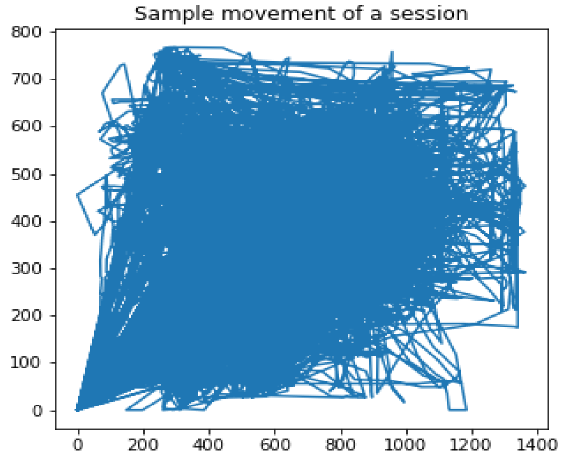

Fig. 5: Mouse movements of a user in a session

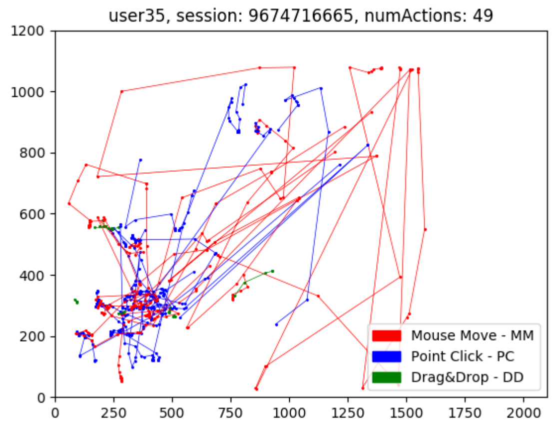

Fig. 6: Mouse actions of user35 in a test session

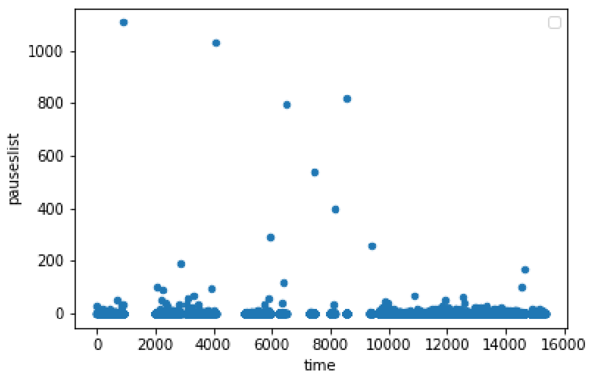

Fig. 7: Variation of mouse pauses with time in a session

the variance of the distance becomes zero, and regularity becomes one due to the equal distance of all the corners from its center. In general, when a user moves straight to the target, then regularity is 1; otherwise, in other cases, it should be between 0 and less than 1.

We now define four compact positional metrics: edging, the curvature of the mouse cursor, curvature spacing of mouse cursor, and pause-and-click. These newly-defined metrics can purely reflect a user's unique behavior during his/her cursor movement, which is system independent.

Edging: We collect overall movements forth the line $\overrightarrow{PQ}$ among at least two gradually recorded points P and Q. The edging is equal to the inclination about the line $\overrightarrow{PQ}$ and the parallel.

Curvature of Mouse Cursor: The viewpoint of curvature of mouse cursor of is defined as the inclination ($\angle PQL$) among the line from P to Q ($\overrightarrow{PQ}$) and the line from Q to L ($\overrightarrow{QL}$) among at least three gradually recorded points P, Q, and L.

Curvature Spacing of Mouse Cursor: Presumably, the length of the line joining P to L ($\overrightarrow{PL}$). The curvature spacing of mouse cursor is the ratio of the cursor length ($\overrightarrow{PL}$) to the perpendicular distance from point Q to the line $\overrightarrow{PL}$ among at least three recorded points P, Q, and L. As the ratio of spacing of two cursors makes this metric unit less. Combining features such as curvature spacing of mouse cursor and curvature of the mouse cursor helps to assess the mouse movement arc curvature, which is reported in Fig. 9.

Point and click: For every action follows point, then click, we compute the elapsed time in linking the click event and the end of the movement. Note that this metric computes the elapsed time halting between indicating to any result abstracts and substantially clicking on it. Fewer mouse pauses of a session are reported in Fig. 7.

Our method aims to characterize users' behavior throughout the mouse movement as the curves are assessed on their own characteristics. Also, even if the curves are connected to the identical user, it alters the considerable amount of values of those characteristics. Although, every user has a unique probability distribution, which may be used as his/her signature of mouse cursor movements deduced from each feature. We can compute every feature's probability distribution by employing an extensive set of curves following some spe-

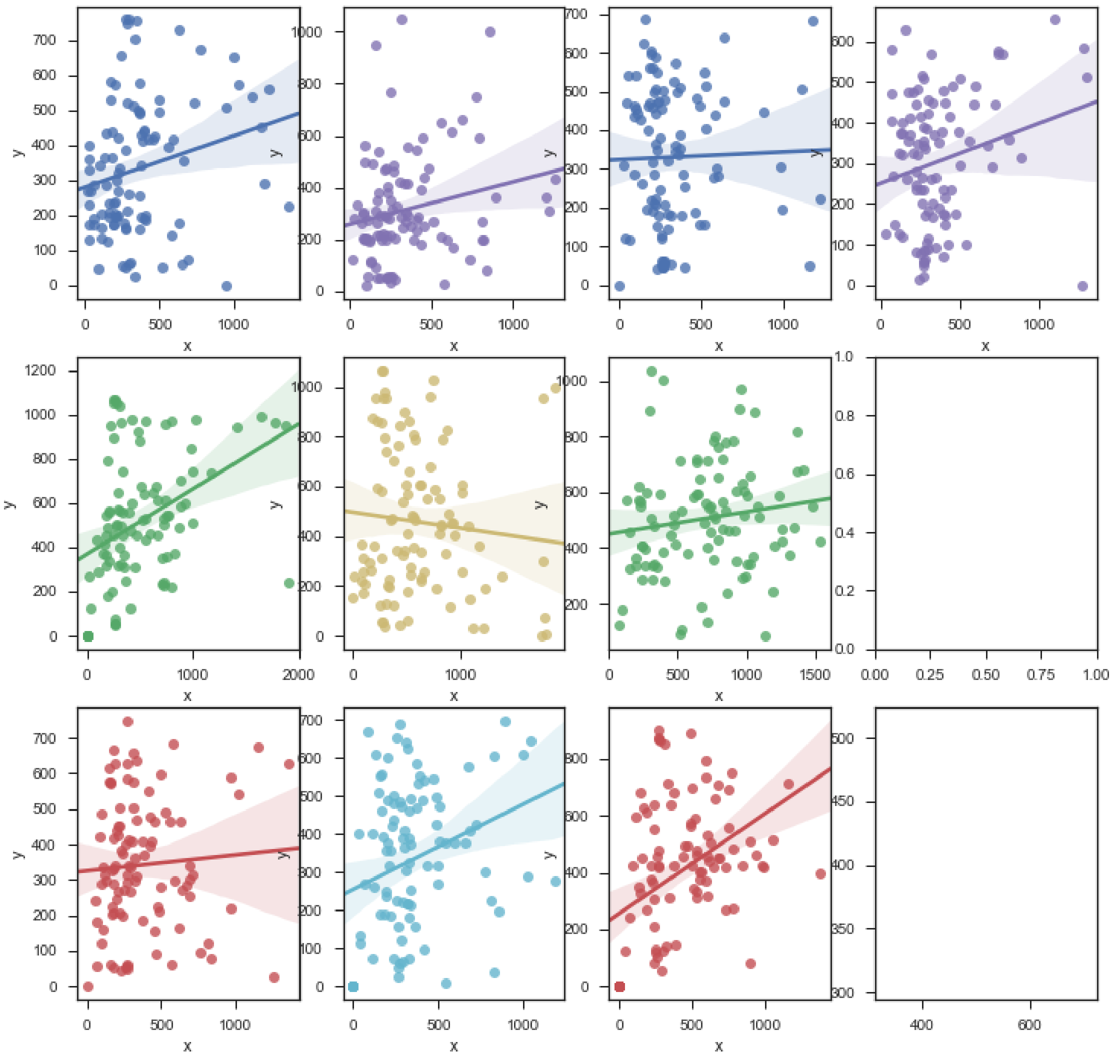

Fig. 8: Regression Line - Analysis of mouser cursor position as a predictor for user click behavior

cific user of a session by normalizing histogram, as reported in Fig. 15.

5.2 Temporal Patterns

To assess if the users' mouse clicks activities in a session exhibit temporal patterns, we investigate the users' mouse movement pattern spanned from the active clicks. We do it by separating the mouse position values with active clicks. The main purpose is to cluster the mouse cursor points on the screen into main groups and then cluster groups as information patches, which represents a set of interactive site elements (i.e., information features), with which the user most often interacts. We predicted the user mouse movement patterns, using K-means clustering, an unsupervised learning method for clustering unlabeled data based on the mouse movements pattern across all samples. We divided the clusters into users who visited the site, given that the activity of users is divided into sessions. The predicted search

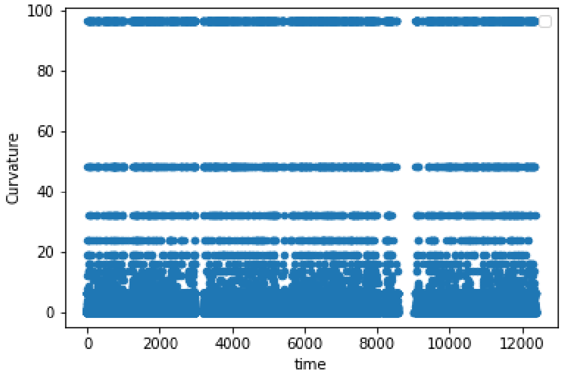

Fig. 9: Variation of curvature & time

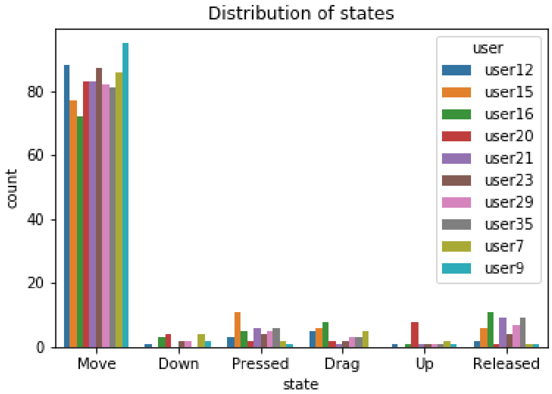

Fig. 10: Distribution of states with # of count a user followed during their mouse position

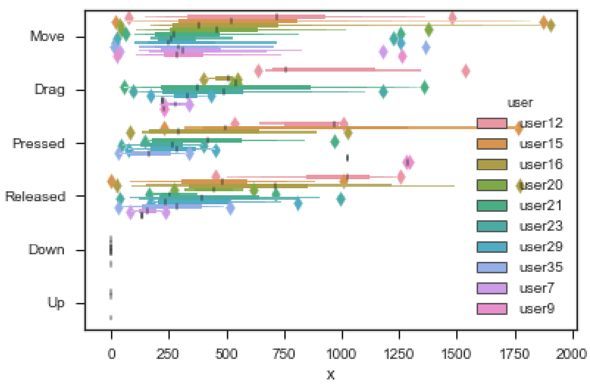

Fig. 11: Mouse state-wise distribution with respect to users' in X direction

patterns are reported in Figure 13, where colored dots are according to the clusters found. We identify the best number of clusters using the elbow method found at K = 3.

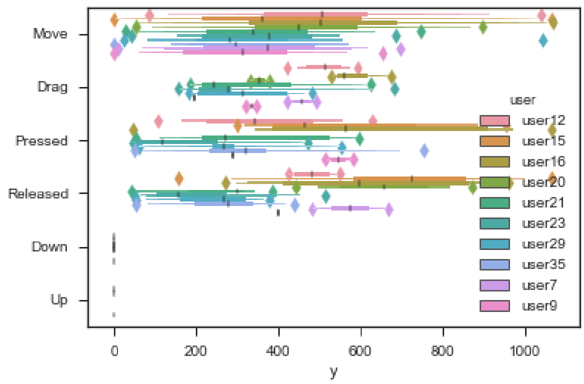

Fig. 12: Mouse state-wise distribution with respect to users' in Y direction

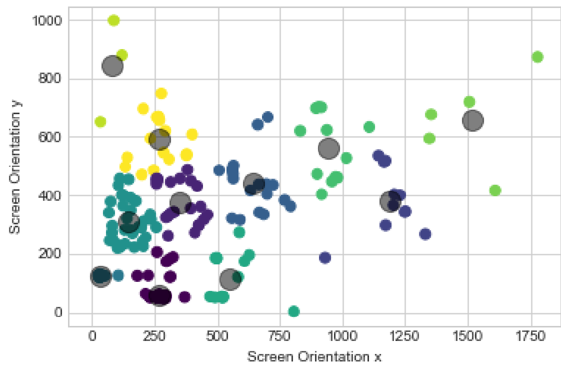

Fig. 13: Formed categories for the location of active elements

5.3 Role of Mouse Movements on User Behavior

Based on the following analysis, we aim at highlighting the most active site elements (i.e., clickable) in comparison to the main categories of interaction, and how, the user behavior with respect to interactive elements changes when considering other factors, such as the mouse clicks, its states, and so on. Fig. 14 shows the number of users' unique click points on X-Y axes based on the separation of mouse position values with active clicks during mouse state "Pressed", which is reported in Table 1.

Total # positions	**# Unique positions**
11422	9111

Table 1: Mouse positions based on active clicks

Fig. 15 depicts the most active interactive elements present among 11 clusters in the distribution between the click frequency and the cluster. As we can see in the histogram, clusters under the number 1 and 10 represents the highest number of clicks. It is illustrated by the fact that the X and Y positions of the mouse in these clusters correspond to the two upper corners of the screen, where *cluster 1* corresponds to the upper left corner of the screen, and *cluster 10* corresponds to the right upper corner of the screen. It is possible to assume that the main attention of users was accounted for by elements that are located in the area of clusters 2, 3, 4, and 5. It is given that our predictive model (LSTM model) did not know anything about the websites and pages on which the click statistics were conducted. The structure was reproduced on the dynamics of user behavior based on the mouse movement dataset.

6 Experimental Evaluation

Based on the prediction task defined in Section 1 including the model description, we detail our findings below.

6.1 Datasets

To calculate the predictive accuracy in the norm of characterizing user behavior in a session, we focus on the mouse movement activities. In this sense, we used Balabit mouse dynamics [35] data were used in our experiments. The dataset field description is given in Table 2.

Field	**Description**
Event	Cursor move or click
Cursor Position	x- and y-coordinates of the cursor
Timestamp	Elapsed time
Button	Mouse button state
State	Mouse movement state
User	User id
Session	Session id

Table 2: Fields in Balabit dataset

We have outlined the detailed description of mouse movement dataset in Section 4.

6.1.1 Data Preprocessing

The conviction of preprocessing is to predict the patterns in the movement of users' mouse across the screen. We do optimize the mouse movement dataset for a recurrent neural network, by performing normalization, scaling and vectorization. We first convert categorical data types such as mouse button and its state to one-hot matrix, followed by the normalization of quantitative data types such as timestamp to the range from 0 to 1.

So, we have the following main list of categories, given in Table 3.:

Button	**State**
Left	Down
Middle	Drag
No Button	Move
Right	Pressed
Scroll	Released
	Up

Table 3: List of main categorical data types

The final step of preprocessing is vectorization, where we formed two vectors X and Y from the training data , and changed the form of input data to a three-dimensional tensor using the step length 20 as a hyperparameter for tuning. In next section, we discuss about the predictive model.

6.2 Model

The learning task considered in this study can be formalized, as user behavior prediction employing clicks that exist or deprive as labels in mouse movement activities dataset.

To address these learning problems of long-term dependencies, we resort to a long short-term memory approach and collected the features from mouse movements that help to predict the patterns during the movement of the users' mouse.

Recurrent Neural Networks (RNNs)
A family of neural networks that demonstrate mutable behavior in view of convened connections among units of a distinct layer are referred as recurrent neural network. As earlier described in [36], the hidden state **h** at a specific time t is calculated as follows:

$$h_t = \tanh(Wh_{t-1} + Ix_t), \tag{8}$$

where **W** is a matrix of knowledgeable parameters, **I** is a symmetric idempotent matrix and tanh is the hyperbolic tangent function. We predict by applying the hidden state **h**

$$y_t = softmax(Wh_{t-1}), \tag{9}$$

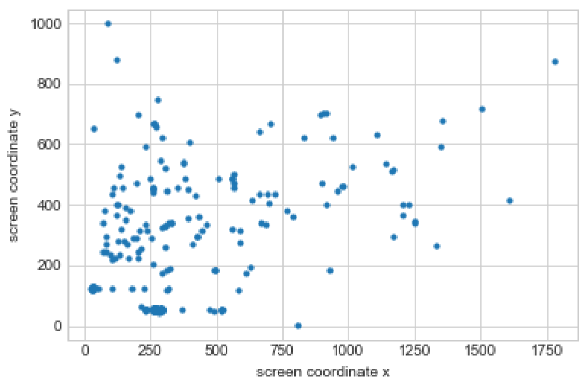

Fig. 14: The position of users' unique points on the axes

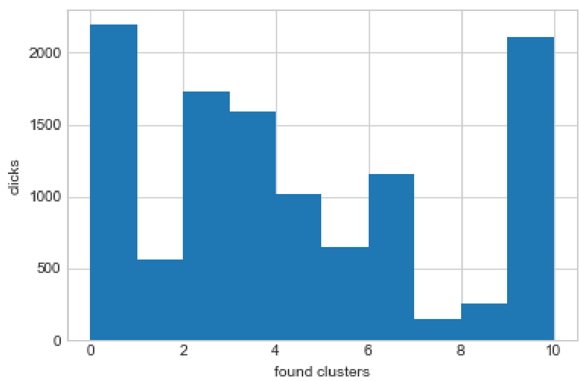

Fig. 15: Frequency of clicks in the clusters

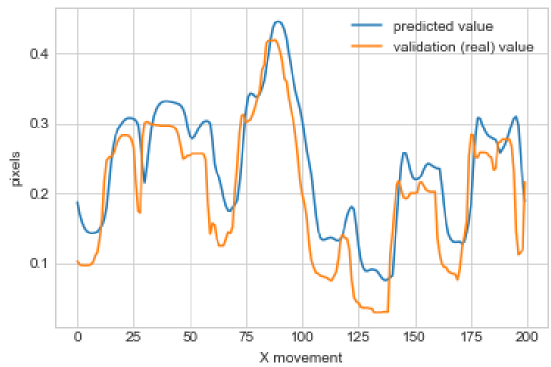

Fig. 16: The ratio of the movement of the mouse along the X axis

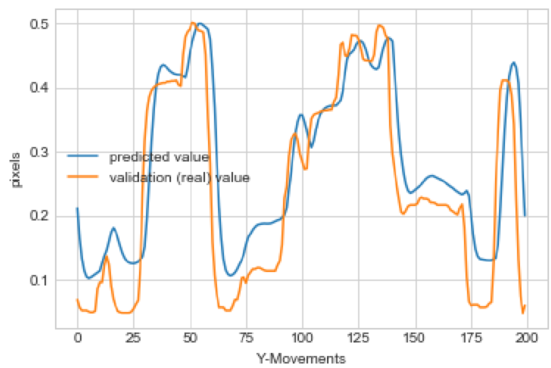

Fig. 17: The ratio of the mouse movement along the Y axis

the available groups have a standardized probability distribution availed via softmax, where σ is the logistic sigmoid function.

We can perform stacking of RNN forming a deep architecture by inputting **h** to another RNN

$$h_t^l = \sigma(W h_{t-1}^l + I h_t^{l-1}). \tag{10}$$

Long Short-Term Memory (LSTM) RNNs The underlying RNNs are enhanced via the inclusion of vanishing ascent issue, which we refer to as LSTM. It usually consolidates the previous state functions among state dynamics, which commonly underlies recurrent neural networks by tracing the vanishing ascent issue. An LSTM accounts for restraining state outputs and renovates at each step of time by updating a hidden vector **h** and memory vector. In fact, [38] describe the calculation at a given time t:

$$\begin{aligned}
g^u &= \sigma(W^u h_{t-1} + I^u x_t) \\
g^f &= \sigma(W^f h_{t-1} + I^f x_t) \\
g^o &= \sigma(W^o h_{t-1} + I^o x_t) \\
g^c &= \tanh(W^c h_{t-1} + I^c x_t) \\
m_t &= g^f \odot m_{t-1} + g^u \odot g^c \\
h_t &= \tanh(g^o \odot m_t)
\end{aligned} \tag{11}$$

Where σ is the logistic sigmoid function, $\odot$ depicts element-wise multiplication, W^u, W^f, W^o, W^c are input weight, and recurrent weight matrices of Cartesian coordinate pairs and symmetric idempotent matrices are I^u, I^f, I^o, I^c. It also strengthens to memorize contemporary dependencies in sequences. In this work, we used a long short-term memory model to predict the users' mouse movement behavior, where one hidden layer consists of 64 neurons with batch length 6000, which is the average value of one session. Our model contains one dense layer containing 2 neurons attached to the LSTM layer. The experiments were reported on the test set.

6.3 Performance Measures

Our evaluation measures are mean squared error (MSE), and root mean squared error (RMSE) as the quality of fidelity indicator to evaluate our LSTM model's efficiency. We note that both metric sets are assessed on the same sets of labels.

Model	MSE	RMSE
LSTM	0.157	0.396
LSTM 4-hidden layer	0.273	0.436
LSTM 3-hidden layer	0.264	0.431
GRU	0.196	0.442

Table 4: Results - Model Comparison. Best model is shaded with blue colour. GRU acronym refers to gradient recurrent unit.

6.4 Results

Based on the prediction task defined in Section 1, we detail our findings below.

Our results (Fig. 16, 17 and 18) shows the mouse movement forth the X and Y axes among the predicted data and validation ratio, which depicts that our neural network understood (reported in Table 4) almost every movement of the users' mouse along the screen's axes, whereas Figure 18 show that the neural network very clearly understood all the patterns in the movement of the users' mouse across the screen.

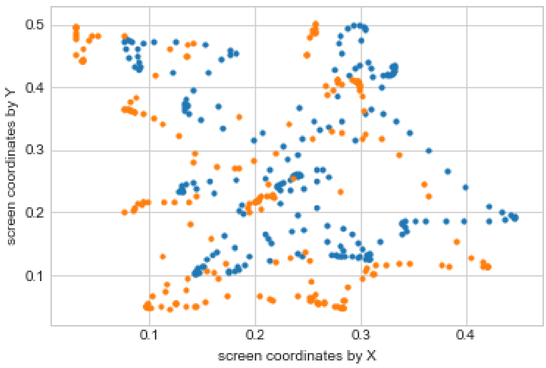

Fig. 18: The ratio of the movement of the mouse along the two axes X, Y

ever, we know fairly to a small extent pertaining to user behavior, specifically

The model trained by LSTM successfully learned to predict the next position of the mouse cursor along the XY axes, taking into account the specified sequence of previous movements.

Based on the above RMSE value, the success of predictions is almost 96%, which indicates that the performance of the model successfully predicted the behavior of the users' mouse.

7 Conclusion & Future Work

We have revealed that users' behavior can be predicted with a long short-term memory model using foraging based effects on the mouse movement features. Specifically, we identify the interactive elements present among clusters that can predict the patterns in the movement of the users' mouse across the screen. Additionally, we demonstrated that mouse cursor positions and other attributes such as state and timestamps could be used to reinforce the top ranks of the search results page, as grossly anxious users are inclined to explore the upper part of the screen. The user mouse movement patterns drawn from prediction could be substantially employed to deduce the intention of the user's query, which constitutes mouse movement activities [29], and utilize it in assessing the design of the interface. Another area where our work is important is modeling user behavior based on our earlier conjecture on Information foraging constructs, such as information patch and information diet.

This work may also be useful to elicit user data collected from Internet-of-Things (IoT) sensors [45,46,44, 47,43,48].

While the experimental results of this work are of significant value, the future direction is to scale up the proposed method using different neural network models such as Spiking neural network [42] and Kalman filter [41] to better understand the user's behavior. This finding suggests that mouse movement information can potentially offer a way to infer the user's intent and experience on the web.

Code Availability

https://github.com/amitkumarj441/PUBMMI

Conflict of Interest

The authors declare that they do not have any conflict of interests.

Acknowledgements M. Shamim Hossain is grateful to the Deanship of Scientific Research at King Saud University, Riyadh, Saudi Arabia for funding through the Vice Deanship of Scientific Research Chairs: Chair of Pervasive and Mobile Computing

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