Horizontal Mouse Movements (HMMs) on Web Pages as Indicators of User Interest

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Abstract. Mouse events are widely used as implicit indicators of user attention on web pages. In this study, we investigated a particular pattern of mouse movements, *Horizontal Mouse Movements (HMMs)*, consisting of series of mouse move events in the same horizontal direction, as indicators of users' current interest. We formally defined HMMs and analyzed HMM activity on a sample website in English. We distinguished between LTR (Left to Right) HMMs and RTL (Right to Left) HMMs. LTR HMMs (in the reading direction of the sample website) were found to be more frequent than RTL HMMs (in the opposite direction). Then we investigated leaving web pages immediately after HMMs and found that they are much more frequent after an RTL HMM than after an LTR HMM. The difference can be explained by recent studies, which show that mouse movements in the reading direction are related to reading. Because reading indicates current interest in the web page content, the probability of leaving a web page immediately after LTR HMMs is lower. Accordingly, HMMs in the reading direction may serve as user interest indicators in educational technology, online learning, web analytics, and adaptive websites.

Keywords: Mouse Cursor · Mouse Movement · LTR · RTL · Web Pages · Reading · Human-Computer Interaction · Intention · User Interest · Adaptive Websites · Educational Technology · Web Analytics

1 Introduction

This study analyzes Horizontal Mouse Movements (HMMs) on a sample website as indicators of user interest. User interest is an abstract concept that may be defined differently in different contexts. For the purpose of this study, we assume that staying on a web page reflects more interest in the page (at a given point in time) than leaving the page. This assumption or definition facilitates the collection of precise measurements and statistical analysis.

We analyzed HMMs on a sample website and compared LTR (Left to Right) HMMs (in the direction of reading, as the website is in English) to RTL (Right

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to Left) HMMs (in the opposite direction). The main contribution of this paper is showing that leaving a web page immediately after an HMM is less likely for LTR HMMs than for RTL HMMs. Accordingly, HMMs in the reading direction can be used as indicators of user interest (based on the definition of user interest provided above).

This paper is organized as follows. Section 2 reviews related work. Section 3 defines HMMs. Section 4 shows the experiment results. Section 5 discusses the results and suggests possible directions for further work.

2 Related Work

User attention on areas of a web page can be measured accurately using eye-tracking [6]. However, collecting eye-tracking data from web users is impractical for most websites, because it requires user collaboration and may raise privacy concerns, as it relies on cameras. In addition, accurate results require special cameras on the client-side. Therefore, user actions that can be tracked in modern browsers using JavaScript, such as page scrolling, mouse movements, and clicks, are often used as alternative indicators of user attention [3, 5, 7, 8, 13, 17].

Mouse activity can be used as a valuable indicator of user attention, as studies show that when a user moves or clicks the mouse, the position of the mouse cursor on the screen is correlated with the user's eye-gaze [4, 9, 16]. Cumulative user attention on areas of a web page, based on the mouse activity of users, can be visualized using heatmaps [14, 15]. Mouse activity heatmaps (also known as attention heatmaps) are popular in commercial web analytics services [11].

Recent studies show that mouse movements in the reading direction are often associated with a reading technique where the mouse cursor is used as a pointer to mark the reading position, similarly to finger-pointing when reading a book [10, 12]. This study builds on this new knowledge and investigates whether horizontal mouse movements in the reading direction can be considered as indicators of current interest in web pages.

3 HMM Definition

In order to study HMMs, we need a precise definition. Our definition of HMM is configurable through four numeric parameters (HOR_DIST, VER_RANGE, MIN_TIME, and MAX_TIME), which are discussed below.

Mouse movements can be represented as a sequence of tuples (t, x, y), where each tuple contains a timestamp t, and a mouse cursor position (x, y) at that point in time. We define HMM as a sequence $(t_1, x_1, y_1), \ldots, (t_n, x_n, y_n)$ of such tuples that satisfies the following conditions:

1. **Horizontal Direction:** All horizontal differences $x_2 - x_1, \ldots, x_n - x_{n-1}$ are either non negative (for LTR movements) or non positive (for RTL movements).

2. **Horizontal Distance:** $|x_n - x_1| \geq HOR\_DIST$, i.e. the movement is not too short and is above a specified horizontal distance threshold.
3. **Vertical Range:** For every $1 \leq i, j \leq n$, $|y_i - y_j| \leq VER\_RANGE$, i.e. the movement is approximately horizontal, within a tolerance range of vertical differences.
4. **Time Frame:** $MIN\_TIME \leq |t_n - t_1| \leq MAX\_TIME$, i.e. the movement is not too slow or too fast.

The definition of HMM in this study is flexible (e.g. compared to [10]), and covers also mouse movements that are not perfectly straight, as long as they have a general consistent horizontal direction, either to the left or to the right.

This study focuses on HMMs that may be associated with reading. The default parameter values in the HMM definition have been selected accordingly, as shown in Table 1.

Table 1. Default HMM Definition Parameters

Parameter	Default	Motivation
HOR_DIST	400 pixels	Roughly the width of half a text line and approximately 8 words on the sample website (based on the most commonly used resolution) [10].
VER_RANGE	30 pixels	Roughly the height of one text line.
MIN_TIME	2 seconds	A reasonable time for reading half a text line consisting of approximately 8 words [2].
MAX_TIME	5 seconds	A reasonable time for reading a full text line consisting of approximately 16 words [2].

4 Experimental Results

In our experiments, we used web usage data from a sample website.[4] During a three month period (ending in March 2020), mouse movements of visitors to the website have been tracked (using a JavaScript code, referenced from the website pages), reported back to the server, anonymized, and stored in a dedicated database, adhering to industry standards of data anonymization and user privacy. Previous studies provide more details on this website [10] and on the tracking and data collection methods used [12]. The dataset used in the experiments consists of 316,762 views of the 38 web pages of the website that had at least 2,000 page views each (excluding web pages with less than 200 words).

[4] www.objectdb.com, providing technical learning materials for programmers

Figure 1 shows the frequencies of LTR and RTL HMMs for views of each of the 38 web pages in the dataset (based on the default parameters in section 3). In Figures 1, 3, and 4, the pages are in descending order of LTR HMM frequencies.

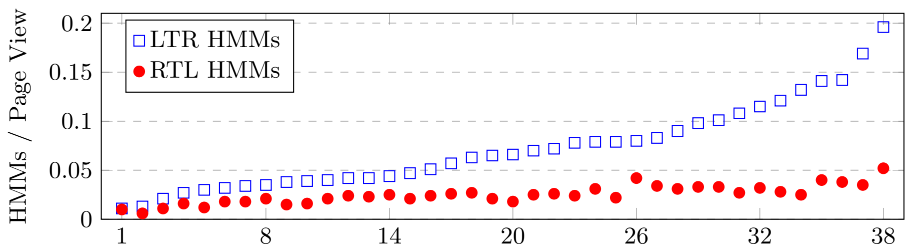

Fig. 1. HMMs Frequency in Views of the 38 Dataset Pages: LTR vs RTL

There were 23,071 LTR HMMs and 8,427 RTL HMMs (in total for all the 38 pages), i.e. an LTR / RTL ratio of 2.74. The difference has a very high statistical significance (p-value $< 0.5^{38} < 0.0000000001$, based on Arbuthnot's method [1], as there were more LTR HMMs than RTL HMMs on each of the 38 web pages).

A recent study on the same website shows that mouse movements in the direction of reading are often related to reading (as discussed in section 2), and accordingly, movements in the reading direction are also more frequent than in other directions [10]. This relation between mouse movements and reading also explains the results in Figure 1.

Figure 2 shows that the LTR / RTL ratio depends on the HMM definition parameters. In general, more restrictive parameter values lead to higher LTR / RTL ratios. A possible explanation is that more restrictive parameters increase the quality of the identified HMMs as indicating reading (higher precision) at the expense of fewer HMMs (lower recall), and accordingly, the frequencies ratio in favor of the reading direction increases.

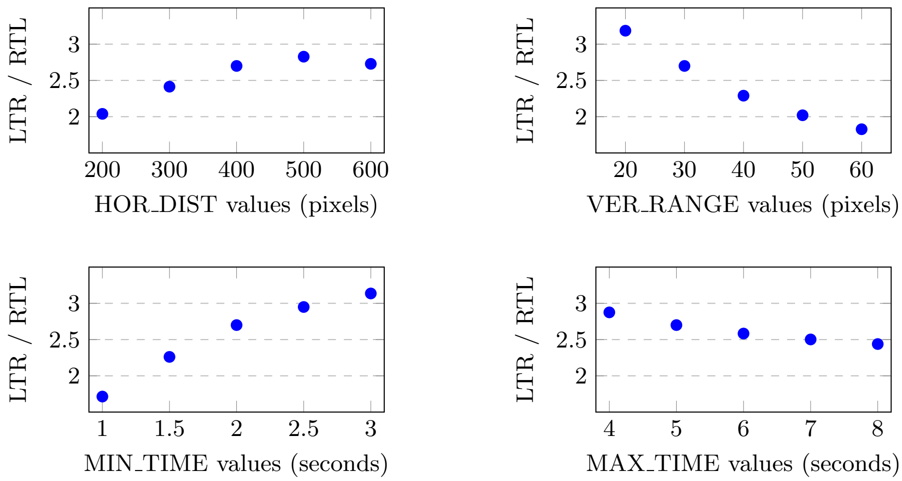

Fig. 2. LTR HMMs / RTL HMMs Ratio with Different Parameters

As discussed in section 1, we consider staying on a page and leaving a page as indicators of user interest and lack of interest in the page, respectively, because a user that is currently interested in a web page is less likely to leave it immediately.

Figure 3 shows the frequency of JavaScript UNLOAD events within 5 seconds of HMMs. The UNLOAD event indicates leaving a web page, by either closing the browser tab, closing the browser completely, or replacing the current page in the browser tab with another page (e.g. by clicking a link). The total frequency (in all 38 pages) of UNLOAD events was 8% after RTL HMMs and 2.4% after LTR HMMs, i.e. the user is more likely to stay on a web page after LTR HMMs than after RTL HMMs.

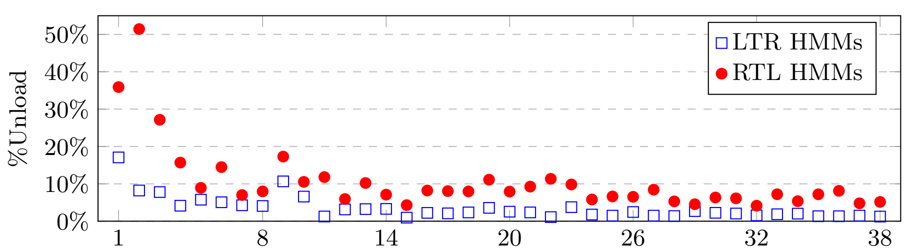

Fig. 3. %UNLOAD Within 5 Seconds of an HMM on the 38 Dataset Pages

Note that UNLOAD events may be partly related to movements to the left side menu and quitting the page with a menu link. It seems that this did not have a major effect on the results because the left side menu is only shown on the top of the page, HMMs are identified only in the textual content area, and usually, movements to the left menu are too fast to be categorized as valid HMMs.

The other main way to leave a web page, switching to another browser tab, is not related to horizontal mouse movements in the content area. The JavaScript HIDE event indicates switching a browser tab (without closing the page, so at least a temporary leave). Figure 4 shows the frequency of HIDE events within 5 seconds of HMMs. The total frequency (in all 38 pages) of HIDE events was 14.8% after RTL HMMs and 5.8% after LTR HMMs.

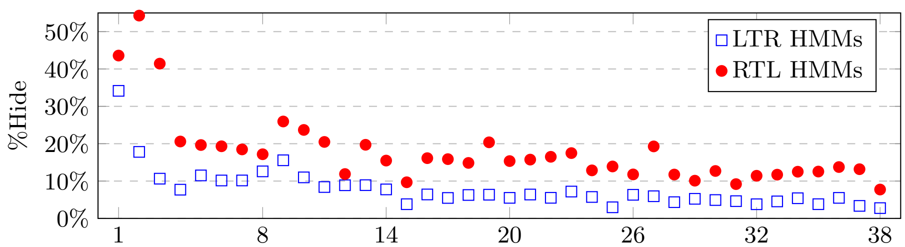

Fig. 4. %HIDE Within 5 Seconds of an HMM on the 38 Dataset Pages

The results show that users are less likely to leave the page immediately after HMMs in the direction of reading compared to leaving immediately after HMMs in the opposite direction, with either UNLOAD or HIDE. As Figures 3 and 4 show, these results were obtained for each of the 38 web pages in the dataset separately. Consequently, these differences have a very high statistical significance (p-value < 0.0000000001, following the same considerations as in the analysis of the results in Figure 1).

5 Discussion and Conclusions

This study compares LTR and RTL HMMs on a sample website and shows that leaving a web page immediately after an LTR HMM is less likely than after an RTL HMM. Based on our assumption that staying on a web page signifies more user interest than leaving it, we conclude that LTR HMMs can be considered as indicators of user interest on this English-based website. On websites in RTL languages (e.g. Hebrew and Arabic) we expect RTL HMMs to be indicators of user interest, although this requires further research.

Figure 5 illustrates an example of mouse movements during reading. The green lines represent mouse movements to the right, and the red lines represent mouse movements to the left. Lines connecting adjacent circles represent movements during one-tenth of a second. This visualization method is introduced and explained in detail in another study [12]. Figure 5 shows that in the context of reading, our definition of HMM covers more LTR HMMs than RTL HMMs, as movements to the left, to the beginning of the next text line, are often too fast and less flattened horizontally. This explains why RTL HMMs were less frequent.

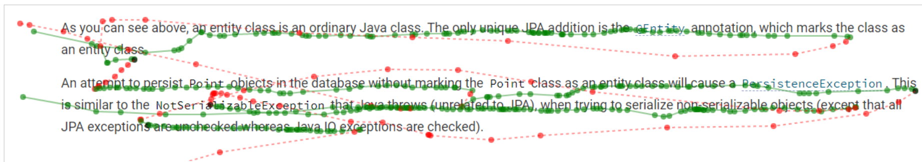

Fig. 5. Visualization of Mouse Movements Indicating Reading

Note, however, that RTL HMMs have been used as a control group, but there is no evidence to suggest that they indicate a lack of interest. On the contrary, mouse movements in general indicate user attention, as discussed in section 2. The comparison emphasizes the uniqueness of HMMs in the reading direction as stronger indicators of attention and interest.

The total frequency of RTL HMMs (using the default parameter values) was approximately 7.3% of the page views. This low frequency is not sufficient on its own to learn about every individual user. However, HMMs might be useful, combined with other indicators, for adaptive websites. They might be useful also for web analytics, for example, for ranking website content by user interest, as feedback from sample users is also beneficial for analytics purposes. Further work should explore these potential uses.

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