

Using Mouse Movement Heatmaps to Visualize User Attention to Words

Ilan Kirsh

kirsh@mta.ac.il

The Academic College of Tel Aviv-Yaffo
Tel Aviv, Israel

ABSTRACT

User attention on web pages is commonly visualized using heatmaps. Substantial mouse activity in an area of a web page may indicate substantial user attention. Accordingly, areas of web pages are painted with hot and cold colors based on the frequency of mouse clicks and movements in these areas. This paper introduces a new type of web page heatmap, the Word Attention Heatmap (WAH), which visualizes user attention to text words based on mouse movements. Naturally, complex words and unclear text may draw more attention and increase reading time, and therefore, may be painted in hotter colors. Consequently, WAHs may help in identifying complex words and challenging sentences as part of a process of improving and simplifying textual web content.

CCS CONCEPTS

• **Human-centered computing** → **Heat maps; Pointing devices**; • **Information systems** → **Browsers**.

KEYWORDS

Visualization, Heatmap, Website, Web Analytics, Mouse Cursor, Pointer Assisted Reading (PAR), User Behavior, Text Simplification, Complex Word Identification (CWI).

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1 INTRODUCTION

Web analytics is essential for understanding the interests, preferences, needs, and actions of website users. The effectiveness of web analytics has been demonstrated in a wide range of industries, including online learning [21], online news [11], e-commerce [9], and digital marketing [3, 12]. Web analytics concepts, principles, and methods are described in detail in various books [1, 5, 13, 14].

During mouse activity (movement and clicks) there is a correlation between the position of the mouse cursor on the screen and the user's eye gaze [4, 10, 25]. Consequently, the mouse cursor position is often used to estimate which areas of a web page capture the

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user's attention. This has been used successfully in various applications, including online surveys [2], task execution [23], e-commerce [26], web marketing [28], and web search [8, 10, 24, 25].

The cumulative attention of all the visitors can be visualized using heatmaps [19, 20, 29]. Areas with high mouse activity are displayed with hot background colors (e.g. red) and areas with low mouse activity with cold background colors (e.g. blue). Different shades of hot and cold colors represent different levels of activity. The visualization can help website maintainers in improving and optimizing the structure and the user interface of websites. Attention heatmaps, based on mouse activity, are offered by various commercial web analytics services [17].

This paper introduces a new type of heatmap, the Word Attention Heatmap (WAH), with a different goal. Instead of visualizing user attention to web page areas, WAHs visualize the user's attention to specific text words while reading, highlighting words that require longer reading time. Unlike a hot region in a standard web page heatmap, which is usually (not always) a positive sign of user interest, a "hot" word on a WAH may indicate user difficulties in reading (similarly to frequent copying of a word to the clipboard, which may also indicate complexity [15]). Identifying complex words that challenge users can help in improving content and is the first step in text simplification processes [27].

2 IMPLEMENTATION ARCHITECTURE

Figure 1 shows the architecture of a WAH implementation. The client-side is on the left, and the server-side is on the right. At the top, we can see a standard HTTP client-server communication between a browser and a web server.

To track mouse activity, a reference to a *Tracking Script* is embedded in all the relevant website pages. As a result, loading a web page from the web server is followed by loading the *Tracking Script* from the WAH server. The script tracks mouse events and reports them to the *Collector* component in the WAH server, which stores the data (following anonymization) in a dedicated database. Mouse event data include event types (mouse move, click, etc.), event times, and event positions (x,y) in pixels on the web pages. Mouse move events are sampled at a rate of up to 10 events per second. In addition, the script maps text words to positions in pixels, and that mapping is also reported and stored in the database. This is required in order to link mouse events to words because the layout of words on a web page is client dependent (e.g. if the browser window is wider, text lines can be longer and contain more words).

To see a WAH, a web analyst visits a web page through the *Visualizer* component, which serves as a proxy server. The Visualizer retrieves original web pages from the web server, paints them with heatmap colors based on the mouse activity data in the database

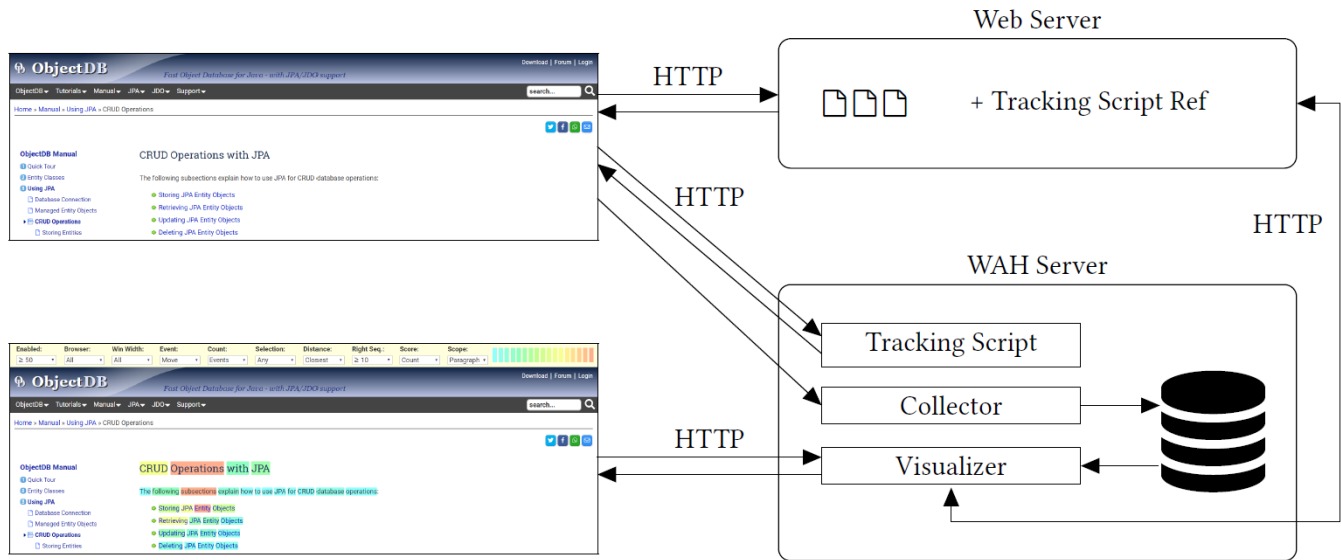


Figure 1: High-Level Architecture of the Word Attention Heatmap (WAH) Implementation

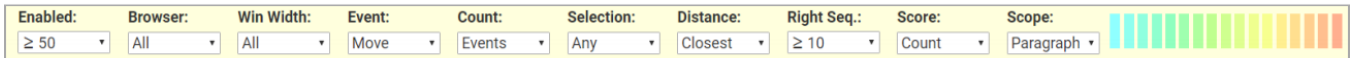


Figure 2: Word Attention Heatmap (WAH) Control Toolbar

(and the current settings), and then returns the modified heatmap pages to the analyst’s browser with an additional settings toolbar at the top. Any setting change is reported back to the Visualizer and an updated heatmap, based on the new settings, is created by the Visualizer and loaded by the browser.

3 WORD SCORING AND SETTINGS

This section explains how the Visualizer component (see Figure 1) ranks words and sets their colors. We start with a description that is based on the default settings (which are used in all the examples in section 4 below).

The score of a word is the number of mouse move events that are associated with it. Only mouse move events that represent movements to the right and are part of sequences of at least 10 mouse move events to the right are counted. The motivation is to focus on mouse movements that may be related to Pointer Assisted Reading, which is reading text with the aid of the mouse (as defined in [16, 18]), i.e. from left to right in English (the website language). Every mouse event in the text area is associated with the closest text word. The heatmap is disabled for paragraphs in which the maximum word score is less than 50 (insufficient amount of data). Figure 2 shows the settings toolbar. The legend on the right side presents the fixed palette of colors from cold (left) to hot (right). The word with the highest score in the paragraph receives the hottest color, whose index is 16 (red), and that sets the scale for the other words in that paragraph, which receive colors proportionally to their scores. For example, a word with half of the highest score

receives the color with index 8 (green). Unlike ordinary web page attention heatmaps, in WAH every paragraph is processed separately from other paragraphs, to neutralize differences in popularity of paragraphs.

Many of the default settings that are described above are configurable using the settings toolbar, including the threshold score that enables heatmaps (50 by default) and the right sequence threshold (minimum 10 events by default). The toolbar supports filtering data by browser type (e.g. Chrome) and client window width (e.g. 1920 pixels). Other options include visualizing mouse clicks and text selections, counting multiple events on the same page view only once, different methods for associating mouse events with words (e.g. associating a mouse event with multiple words within a radius), and various score normalization methods. The results are relatively stable with most of the settings. The default settings are somewhat arbitrary, and further work is needed to explore the effect of different options. There is also an option for ranking words relative to the page rather than to the paragraph, generating heatmaps that are more similar to ordinary web page attention heatmaps.

4 DEMONSTRATION

WAHs are demonstrated in this section on pages of the ObjectDB Developer Guide (www.objectdb.com/java/jpa). Mouse tracking data were collected for a period of three months ending in March 2020 for all visitors.

The examples in this section are from pages that had between 6,049 to 26,674 views. The score of the hottest words (i.e. number

If `orphanRemoval=true` is specified the `disconnected` `Address` instance is automatically removed. This is useful for cleaning up dependent objects (e.g. `Transient` entity fields are fields that do not participate in persistence and their values are never stored in the database (similar to transient fields in Java that do not

Figure 3: Complex Words: “disconnected” (2234), “participate” (3189), and “persistence” (3158)

A persistent field whose type is `embeddable` may optionally be marked with the `@Embedded` annotation, requiring `ObjectDB` to verify that the type is indeed `embeddable`:

When a managed entity object is `serialized` and then `deserialized`, the `deserialized` entity object (but not the original `serialized` object) is constructed as a detached entity object

Figure 4: Complex Technical Words: “embeddable” (563), “serialized” (1085), and “deserialized” (1223)

Every `serializable` class (user defined or system defined) is also `persistable`, but relying on `serialization` in persisting data has a severe drawback in lack of portability. The internal

Every `enum` type (user defined or system defined) is `persistable`. But, if future portability to other platforms is important, only values of user defined `enum` types should be

Figure 5: Another Complex Word: “persistable” (232, 96)

Notice that `construction` of a new `managed` object during retrieval uses the `no-arg` constructor. Therefore, it is recommended to avoid unnecessary time consuming

`ObjectDB` does not enforce registration of all the `managed` classes. However, it might be useful to register classes that define generators and named queries (by annotations).

Figure 6: A Simple Word with a Challenging Meaning in This Context: “managed” (374, 132)

of mouse move events) is shown in parentheses in the captions of Figures 3, 4, 5, and 6 and is considerably lower than the number of views. This is expected, as Pointer Assisted Reading (reading with the aid of the mouse) is occasional [16, 18]. Moreover, most visitors do not read whole pages, so not all page views feed into the scores of each individual word in the page.

Words with more syllables are considered complex in classic readability tests such as the Gunning fog index [7] and the SMOG grade [22] (this rule has exceptions, e.g. “Wikipedia” is not a complex word for most web users). It is easy to see in the following examples that short words are indeed “colder”. Each one of Figures 3, 4, 5, and 6 shows two independent heatmaps of separate paragraphs. The focus in each heatmap is on the “hottest” word in the paragraph (colored red) and its close environment. Hot words, with substantial user attention relative to other words in their close environment (based on mouse move events), demonstrate slower average reading speed and potentially higher complexity to users.

In Figure 3, the words “disconnected”, “participate”, and “persistence” are marked as hot. These are long words with 3-4 syllables. Note that the longest word, “automatically” (6 syllables), attracts less user attention, as well as the words “dependent”, “database”, “entity”, and “specified” (3 syllables), which are frequently used in this developer guide. These words may be less challenging to users of this website.

The technical terms, “embeddable”, “serialized”, and “deserialized” in Figure 4 are colored red. These terms are explained on the website but, apparently, some users find them challenging (for example, users that arrive at these paragraphs directly). Note that each one of these words appears twice in these examples. The first occurrence is hot (red), and the second is colder (yellow / green). Reading the same word again in the same paragraph is expected to be easier.

The word “persistable” is another complex technical word. It appears several times in the examined web pages, and most of its occurrences (Figure 5 shows two of them) are colored red.

The word “managed” (2 syllables, #2,591 in the list of the most frequent words in Google’s Trillion Word Corpus [6]), is a relatively simple word. However, in this context (see Figure 6), it may be unclear. Readers may ask themselves what is a “managed object” and what are “managed classes”. These are, again, technical terms that are explained elsewhere in the developer guide. The last examples are particularly important as they show that tracking the behavior and the mouse activity of real users can reveal text complexity, which could be more difficult to find using static text analysis.

5 CONCLUSIONS AND FURTHER WORK

The new proposed heatmaps highlight words that attract more mouse movements than other words in their paragraphs. Previous works show that cumulative mouse movements reflect cumulative user attention and that some users read with the aid of the mouse. Excess attention and reading time may indicate potential issues in the readability and understandability of the text. The examples in this paper support this idea visually. Further work should build on the visual aspects that this paper presents by carrying out quantitative research of this user behavior. The ability to identify complex text in websites could be useful in the process of content improvement and text simplification.

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