Modeling Sub-Document Attention Using Viewport Time

Max Grusky[1], Jeiran Jahani[3], Josh Schwartz[3], Dan Valente[3], Yoav Artzi[1,2], and Mor Naaman[2]
{grusky, yoav}@cs.cornell.edu, {jeiran, josh, dan}@chartbeat.com, mor@jacobs.cornell.edu
[1]Computer Science, Cornell University [2]Cornell Tech [3]Chartbeat, Inc.

ABSTRACT
Website measures of engagement captured from millions of users, such as in-page scrolling and viewport position, can provide deeper understanding of attention than possible with simpler measures, such as dwell time. Using data from 1.2M news reading sessions, we examine and evaluate three increasingly sophisticated models of sub-document attention computed from *viewport time*, the time a page component is visible on the user display. Our modeling incorporates prior eye-tracking knowledge about onscreen reading, and we validate it by showing how, when used to estimate user reading rate, it aligns with known empirical measures. We then show how our models reveal an interaction between article topic and attention to page elements. Our approach supports refined large-scale measurement of user engagement at a level previously available only from lab-based eye-tracking studies.

ACM Classification Keywords
H.5.m. Information Interfaces and Presentation: Miscellaneous

Author Keywords
attention; reading; news articles; web analytics; user modeling

INTRODUCTION
The shift to digital media creates a growing need for methods of modeling, visualizing, and more broadly understanding the experiences readers have with text online. Recently, analytic tools have been used to capture user activity at increasing scale and granularity [13]. In this paper, we show how in-page measurements can generate better understanding of reading behavior online, and provide a more accurate picture of reader interests and attention at a scale previously unavailable.

We study methods of measuring sub-document user attention in long-form news articles using *viewport time*, the amount of time a user spends with a certain part of a page visible on their screen. Viewport time strikes a balance between two common measurement techniques: lab-based eye tracking, and standard web analytics such as dwell time and page views. In eye tracking studies, researchers are able to capture detailed information on attention and focus [4, 15]. However, such studies require expensive equipment and are hard to scale to large populations. In contrast, metrics such as dwell time and page views are easy to scale, but cannot capture detailed user behavior [13]. We use scalable, detailed viewport time data, and design models to understand user attention to individual HTML elements that make up an article. Our model design emphasizes scalability and incorporates prior results from small-scale studies of onscreen reading behavior [3, 18].

We compare and validate our models using a large dataset of over 1.2M reading sessions on a popular news site publishing long-form articles. Validating models at such scale is a challenging problem. Unlike lab studies, we are unable to rely on careful instrumentation of the environment, such as in eye tracking studies, and web-scale measurements, where users read and interact in different contexts and with different goals, are noisy. We validate our models by comparing them to existing measurements of reading behavior, and focus on measuring reading rates in multiple languages.

We also demonstrate how models using viewport time can help understand user attention online with an exploratory large-scale study of the amount of attention users give to text versus images in articles of different topics. We measure attention using the time spent by the user on individual page elements as estimated by the different models. Our results highlight specific topics where people spend more time with images, and demonstrate the different qualities of our models.

RELATED WORK
A wide set of methods has been used to model user attention on the Web. Dwell time, while simple, enables to model overall user engagement for various tasks, including scoring pages for recommendation systems [21] and estimating user satisfaction with search results [10, 11]. However, dwell time does not account for sub-document within-page user interactions, among other limitations [13]. Eye tracking has been used to compare website designs [2], to investigate the within-page behavior of different user groups [7], and to understand how users interact with search engines [8]. Most related to our work, eye tracking has also been used to determine whether users are reading a document or if they are only skimming [5].

Other measures of sub-page engagement had been proposed. For example, cursor position has been shown to correlate with user gaze [6]. However, it is computationally difficult to capture at scale and not available on mobile devices. The small screens of mobile devices were shown to be effective for generating attention heatmaps [9] and measuring user attention in the context of advertising [14] and mobile search [12]. Our work focuses on desktop reading but could be applied to mo-

CHI 2017, May 6-11, 2017, Denver, CO, USA.

ACM ISBN 978-1-4503-4655-9/17/05 ...$15.00.
http://dx.doi.org/10.1145/3025453.3025916

	Original	*Filtered*
Unique Users	3,105,715	30,791
Unique Pages	171,603	45,049
Reading Sessions	9,025,946	1,217,634

Table 1. Dataset statistics for the compelte original dataset and the filtered dataset of article pages and high-activity users.

bile data with different assumptions. Most closely related, user viewport size and article scroll depth have been combined to analyze reader attention across two thousand news articles [13]. The authors focused on differences between pages, using viewport data to examine different types of article reading patterns. In contrast, we examine patterns of *user* behavior by modeling their attention to individual page elements. Our approach is informed by knowledge developed in eye tracking studies [3, 18], while relying on easy-to-capture viewport data.

DATASET

We use a sample of two months of traffic to a popular news and entertainment website collected using client-side scripts developed by Chartbeat.[1] The website content requires user engagement over relatively long periods of time, including long-form articles, stories and interviews. The data contains over 3M readers and 170K pages (Table 1) representing complete activity for a set of randomly selected users.

The data is made of *reading sessions*, where a single user visits and interacts with a single page. For each reading session, Chartbeat captures snapshots of user interaction approximately every fifteen seconds. Each snapshot includes the position of the user viewport on the page, the size of the browser window, and other data. Snapshots also contain second-to-second user interaction between snapshots, including user scrolling, clicking, mouse movement, and viewport resizing. Each article is rendered using a standard screen width (1,024 pixels) and a fixed user agent to determine the size and positions of HTML elements on the page.

Since we focus on desktop reading and user models, we prune non-article pages (e.g., index pages), users who read less than 20 articles, and mobile reading sessions. Within the filtered dataset (Table 1), users on average read 40 articles and view 1,123 page elements (paragraphs and images). This large amount of per-user data allows us to establish a reasonable understanding of individual reading behaviors and attention.

MODELING SUB-DOCUMENT ATTENTION

We describe three models of reading behavior to estimate user attention at the level of individual HTML elements based on viewport time measurements. The models are of increasing complexity, with a baseline model not using viewport time.

We assume that a majority of the attention time users spend on a page is directed toward the inline text (<p>) and image (<img>) elements that make up an article, rather other elements displayed alongside (e.g., navigation links). Therefore, we consider only inline text and image elements in our calculation of element-level dwell time. We also assume that inline text and image elements are arranged linearly in the vertical direction. These assumptions hold for many websites including the one used in this analysis. Text and image elements are "leaf" HTML elements. In our dataset, we do not observe any nesting or onscreen overlap between these HTML elements. Accordingly, we measure element size and position using only the vertical axis of the page.

Formally, a page P with N elements is a set of tuples $\{\langle e_i, \tau_i, \beta_i\rangle\}_{i=1}^{N}$, where e_i is the content of element i, and τ_i and β_i describe its location: τ_i is the percentage of the page from the top where the first pixel of e_i appears, and β_i is the percentage where the last pixel appears. For example, consider a page P with a height of 1,000 pixels that contains, among others, an element i that starts 300 pixels from the top and has a height of 200 pixels, and an element that starts 500 pixels from the top and has a height of 250 pixels. The set P contains the tuples $\langle e_i, 0.3, 0.5\rangle$ and $\langle e_j, 0.5, 0.75\rangle$. For each user reading session, the viewport $V(P,t)$ at time t of page P is a set of K tuples $\{\langle e_i, \tau_i^t, \beta_i^t\rangle\}_{i=1}^{K}$, where each tuple is computed from a corresponding tuple from P: the start τ^t and end β^t percentages are modified according to the viewport and only visible pixels are considered. For example, given the 1000-pixel page P above, consider a time t when only the area between the pixels 600 and 900 is visible on screen, $V(P,t)$ will be the set $\{\langle e_j, 0.0, 0.5\rangle\}$. Finally, let $d(P)$ be the total dwell time (in seconds) for page P, and a reading session be a sequence of viewports, one for each second $t = 0 \dots d(P)$.

Uniform Attention Model

Our baseline model, the Uniform Attention Model (UAM), makes the naive assumption that user attention is divided uniformly across all article text and image elements present on a page. Given a page P with N elements, the UAM dwell time of e_i is relative to the normalized size of the element:

$$\mathrm{UAM}(e_i) = \frac{\beta_i - \tau_i}{\sum_{j=1}^{N}(\beta_j - \tau_j)} \times d(P) \ .$$

With UAM, elements that take up more space on the page are assumed to receive proportionally more attention from users. As with the two other models, the denominator adjusts for whitespace between page elements and element overlap. UAM is the simplest of the three models, and does not consider viewport size and scroll data.

Uniform Viewport Attention Model

The Uniform Viewport Attention Model (UVAM) considers viewport time and assumes that a user may attend to all pixels on the screen with equivalent probability. The model only assigns dwell time to text and image elements visible in the user viewport. User attention is distributed uniformly across all visible elements. For each element, UVAM only considers the percentage of viewport space occupied by its visible portion. UVAM estimates the dwell time on element e_i as the portion of the viewport occupied by the element normalized for each second, and summed over the length of the session:

$$\mathrm{UVAM}(e_i) = \sum_{t=0}^{d(P)} \frac{\beta_i^t - \tau_i^t}{\sum\limits_{\langle e_j, \tau_j^t, \beta_j^t\rangle \in V(P,t)} (\beta_j^t - \tau_j^t)} \ .$$

[1] https://chartbeat.com

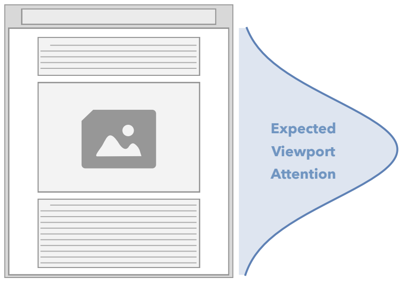

Figure 1. Illustration of normally distributed reading-consistent eye fixation across the viewport [3, 18]. This distribution is used in GVAM to estimate attention on individual page elements across time.

Attention Model:	*UAM*	*UVAM*	*GVAM*
Correlation	0.094	0.425	0.529
Excluding Spanish	0.163	0.490	0.749

Table 2. Correlation between empirical language reading rates and language reading rates estimated by the three models.

Gaussian Viewport Attention Model

Prior results on user attention show the uniform assumption to be overly simplistic. Eye tracking studies of users reading and interacting with web pages found that users mainly read and attend to page elements according to a normal distribution placed over the viewport [3]. More recently, as part of a study of automatic scrolling, researchers tracked user gaze and recorded the coordinates of eye fixations consistent with reading [18]. The user reading-consistent fixations were normally distributed across a screen with a height of 1,024 pixels, with mean location of 49.2% from the top of the screen and a standard deviation of 20.1% of the height of the screen. Figure 1 illustrates the estimated viewport attention.

Our Gaussian Viewport Attention Model (GVAM) estimates user attention to each element, while assuming the attention is distributed across the viewport in accordance with the distribution found by Sharmin et al. [18]. We assume the mean and standard deviation scale proportionally with the screen size. GVAM is computed similar to UVAM:

$$\mathrm{GVAM}(e_i) = \sum_{t=0}^{d(P)} \frac{\mathrm{EVA}(\tau_i^t, \beta_i^t)}{\sum_{\langle e_j, \tau_j^t, \beta_j^t \rangle \in V(P,t)} \mathrm{EVA}(\tau_j^t, \beta_j^t)} ,$$

where $\mathrm{EVA}(\tau_i^t, \beta_i^t)$ is the estimated viewport attention for element e_i at time t, and is defined as the cumulative distribution function of the normal distribution $\mathcal{N}(\mu, \sigma^2)$ evaluated between the visible top and bottom of e_i:

$$\mathrm{EVA}(\tau_i^t, \beta_i^t) = \frac{1}{2}\left[\mathrm{erf}\left(\frac{\mu - \beta_i^t}{\sigma\sqrt{2}}\right) - \mathrm{erf}\left(\frac{\mu - \tau_i^t}{\sigma\sqrt{2}}\right)\right] ,$$

where erf is the Gauss error function [20]. Following Sharmin et al. [18] we set the mean $\mu = 0.492$ and standard deviation $\sigma = 0.201$. Through the normalization of the GVAM computation, the model is designed to ignore (a) the probability mass of the normal distribution that is beyond the viewport boundaries, and (b) gaps between displayed elements. Both are not considered to draw the reader attention.

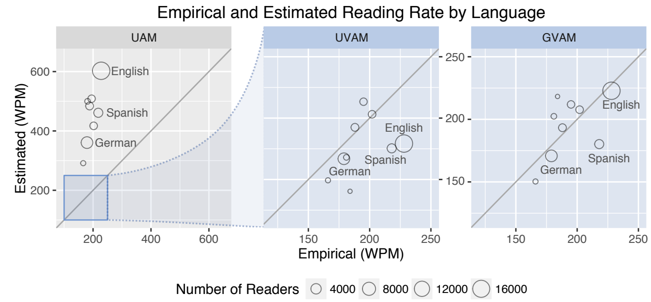

Figure 2. Comparison between user reading rates in each language measured by IReST and estimated by the three attention models. Ideal estimates should be close to the marked identity line. The UVAM and GVAM plots are scaled up for clarity and are equivalent to the space of the blue rectangle in the UAM plot.

MODEL EVALUATION USING KNOWN READING RATES

We evaluate our models by comparing their estimated reading rates to the existing empirical measurements of the International Reading Speed Texts (IReST) study [19], the largest cross-language study of reading rate to date. The study includes 436 readers in 17 languages reading standardized texts. Although the study included only reading on paper, recent studies of reading comprehension found no significant difference between onscreen and paper reading rates [16].

To compute reading rates, we first estimated dwell time $d(e,u)$ for each user u and element e. For each text element e, we computed the reading rate $r(e,u)$ by dividing the word count $wc(e)$ by the user u dwell time: $r(e,u) = d(e,u)/wc(e)$. We computed the median[2] of user element reading rates across all the text elements for each page, and then across pages to get a user reading rate $r(u)$. Finally, we calculated the median reading rate for all users in each language.

While exact measurement of language reading rate is challenging, even with advanced eye tracking, we expect that a more accurate attention model would better capture the way in which users read, and therefore display higher correlation with the empirical rates measured by IReST. Figure 2 compares the reading rates estimated by UAM, UVAM, and GVAM with IReST empirical reading rates. The correlations between the models and IReST are shown in Table 2. Each panel of the figure corresponds to one of the three user attention models. Markers in each panel represent the model-estimated (y-axis) versus empirically-known (x-axis) reading rate for each language, with the size of the marker corresponding to the number of readers of articles in each language in our data. The line drawn in the panels is the identity line, where the estimated rate equals the empirical rate. We expect a successful model to result in markers close to this line. Our results demonstrate that both GVAM and UVAM significantly outperform the UAM baseline in estimating reading rates and that incorporating known biases of attention in GVAM further improves our estimates compared to the simpler models.

[2]Reading rate of users on individual elements vary significantly by user reading style, such as skimming or skipping. To best capture central tendency of readers, we calculate reading rates using the median rather than the mean throughout this study.

With the exception of Spanish, the reading rates of GVAM closely approximate those measured by IReST. It is unclear why GVAM is less effective at approximating Spanish reading rates. Languages such as English and Spanish, with relatively fast readers and higher reader variability (e.g., across countries and cultures), may requires more observations for accurate estimates. While we were able to measure reading speed for over 16K English readers, our dataset only included 2K Spanish readers. Excluding Spanish, the only major outlier, the correlation between GVAM and IReST reaches 0.749.

ATTENTION TO IMAGE AND TEXT ACROSS TOPICS

We apply our models to a sample task of characterizing user activity. We extend previous eye-tracking work examining attention to text and images [4, 7] to understand attention to text and images across different article topics. This type of topic-based analysis of user behavior is enabled, likely for the first time, by the scale of our data

We compute topic distributions with Latent Dirichlet Allocation [1, 17] for 44,315 English articles. We set the number of topics to 50. For each document, given the topic distribution, we pick the max probability topic as the *document topic*. We analyze the ten most common document topics, which include 9,105 articles read by 16,829 users. We estimate user dwell time $d(e,u)$ for each element using the three attention models, and the median value of $d(e,u)$ for each user u on image and text elements for each page P to produce values $d_{\text{images}}(P,u)$ and $d_{\text{text}}(P,u)$. We calculate the median image and text dwell times across articles for each topic.

Figure 3 shows text and image element dwell time for articles of different document topics.[3] The GVAM estimates suggest users spend a consistent amount of time on text elements across topics. However, there are large differences in attention to images across topics. While for most articles, we estimate users dedicate under 5 seconds per image, users spent roughly 15 and 30 seconds on images in "music" and "sex" articles.

In terms of differences between the models, while UVAM and GVAM results are similar, UVAM estimated paragraph dwell time to be higher by time by 13% on average compared to GVAM and image dwell time to be lower by 28%. As expected, the difference between UAM and GVAM was even larger: UAM estimated paragraph dwell 74% below GVAM's estimate and image dwell 41% below GVAM's estimate.

DISCUSSION AND CONCLUSIONS

We used *viewport time* to perform a first large-scale study of reading behavior and attention to news articles on the Web, estimating the amount of attention users give to individual paragraph and image elements on a page. We showed that GVAM, a Gaussian model of attention in the viewport informed by prior lab work [3, 18], results in estimates of reading rates that track closely to known empirical values. Applying the same model to studying time spent on images versus text in articles of different topics results in different and potentially more accurate estimates than the baselines. GVAM is able to capture much of the complexity of sub-document user attention to individual HTML elements, while only requiring viewport time, which is reasonably easy to computationally capture and store. Our results indicate that viewport time effectively balances between rich-but-costly eye tracking data, which is difficult to capture at scale, and cheap-but-limited dwell time data, which does not offer in-page insights.

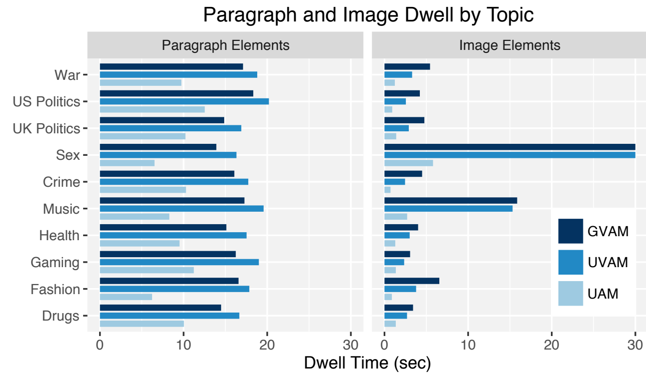

Figure 3. Median dwell time on text paragraphs and images across articles in the ten most popular document topics. The x-axis shows element dwell time in seconds. We show the inferred time based on each model.

Our study has several limitations. While GVAM showed reasonable correlation with known reading metrics, we have no way to verify that it is indeed more accurate than other measures. While it is informed by lab-validated results [18], the evidence we provide above is just a first step in asserting the model validity in realistic conditions. Further, GVAM was developed and intended to measure only vertical variations in attention. Although effective for measuring attention in applications with highly linear layout, such as articles or search results, GVAM cannot measure variation in horizontal user attention. Expanding our models to include dynamic elements, such as image galleries and videos, is left for future work.

Future work may incorporate GVAM with cursor position, which has been shown to correlate with eye movement [6], to help estimate horizontal engagement. Another potential direction is incorporating user data and similar detailed analytics to design user-specific models. Models of sub-document attention have the potential to help better understand users and adapt to their preferences. Measuring paragraph- and image-level changes in attention may be useful in determining whether a user enjoys an article and in recommending articles, while variation in reading rate between paragraphs could signal loss of interest or confusion. Finally, aggregating element-level information on user attention by page, topic, and user demographics may be helpful in automatic customization and adaptation of pages for different groups of users.

The ability to accurately estimate large-scale sub-document attention at the element-level opens up new possibilities for massive and detailed studies of usability, multivariate testing, personalization, and recommendation on the Web.

ACKNOWLEDGMENTS

This work was funded by AOL as part of the Connected Experiences Laboratory at Cornell Tech. We thank the anonymous reviewers and area chairs for their thoughtful comments.

[3]The topic of each of cluster is labeled by hand based on its highest probability words.

REFERENCES

1. David M Blei, Andrew Y Ng, and Michael I Jordan. 2003. Latent Dirichlet Allocation. *Journal of Machine Learning Research* 3, Jan (2003), 993–1022.
2. Agnieszka Bojko. 2006. Using Eye Tracking to Compare Web Page Designs: A Case Study. *Journal of Usability Studies* 1, 3 (May 2006), 112–120. http://dl.acm.org/citation.cfm?id=2835663.2835665
3. Georg Buscher, Ralf Biedert, Daniel Heinesch, and Andreas Dengel. 2010. Eye Tracking Analysis of Preferred Reading Regions on the Screen. In *CHI '10 Extended Abstracts on Human Factors in Computing Systems (CHI EA '10)*. ACM, New York, NY, USA, 3307–3312. DOI: http://dx.doi.org/10.1145/1753846.1753976
4. Georg Buscher, Edward Cutrell, and Meredith Ringel Morris. 2009. What Do You See when You'Re Surfing?: Using Eye Tracking to Predict Salient Regions of Web Pages. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '09)*. ACM, New York, NY, USA, 21–30. DOI: http://dx.doi.org/10.1145/1518701.1518705
5. Christopher S. Campbell and Paul P. Maglio. 2001. A Robust Algorithm for Reading Detection. In *Proceedings of the 2001 Workshop on Perceptive User Interfaces (PUI '01)*. ACM, New York, NY, USA, 1–7. DOI: http://dx.doi.org/10.1145/971478.971503
6. Mon Chu Chen, John R. Anderson, and Myeong Ho Sohn. 2001. What Can a Mouse Cursor Tell Us More?: Correlation of Eye/Mouse Movements on Web Browsing. In *CHI '01 Extended Abstracts on Human Factors in Computing Systems (CHI EA '01)*. ACM, New York, NY, USA, 281–282. DOI: http://dx.doi.org/10.1145/634067.634234
7. Soussan Djamasbi, Marisa Siegel, and Tom Tullis. 2010. Generation Y, Web Design, and Eye Tracking. *International Journal of Human-Computer Studies* 68, 5 (May 2010), 307–323. DOI: http://dx.doi.org/10.1016/j.ijhcs.2009.12.006
8. Laura Granka, Matthew Feusner, and Lori Lorigo. 2008. Eye Monitoring in Online Search. *Passive Eye Monitoring* (2008), 347–372. DOI: http://dx.doi.org/10.1007/978-3-540-75412-1_16
9. Jeff Huang, Ryen White, and Georg Buscher. 2012. User See, User Point: Gaze and Cursor Alignment in Web Search. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '12)*. ACM, New York, NY, USA, 1341–1350. DOI: http://dx.doi.org/10.1145/2207676.2208591
10. Youngho Kim, Ahmed Hassan, Ryen W. White, and Imed Zitouni. 2014a. Comparing Client and Server Dwell Time Estimates for Click-level Satisfaction Prediction. In *Proceedings of the 37th International ACM SIGIR Conference on Research & Development in Information Retrieval (SIGIR '14)*. ACM, New York, NY, USA, 895–898. DOI: http://dx.doi.org/10.1145/2600428.2609468
11. Youngho Kim, Ahmed Hassan, Ryen W. White, and Imed Zitouni. 2014b. Modeling Dwell Time to Predict Click-level Satisfaction. In *Proceedings of the 7th ACM International Conference on Web Search and Data Mining (WSDM '14)*. ACM, New York, NY, USA, 193–202. DOI: http://dx.doi.org/10.1145/2556195.2556220
12. Dmitry Lagun, Chih-Hung Hsieh, Dale Webster, and Vidhya Navalpakkam. 2014. Towards Better Measurement of Attention and Satisfaction in Mobile Search. In *Proceedings of the 37th International ACM SIGIR Conference on Research & Development in Information Retrieval (SIGIR '14)*. ACM, New York, NY, USA, 113–122. DOI: http://dx.doi.org/10.1145/2600428.2609631
13. Dmitry Lagun and Mounia Lalmas. 2016. Understanding User Attention and Engagement in Online News Reading. In *Proceedings of the 9th ACM International Conference on Web Search and Data Mining (WSDM '16)*. ACM, New York, NY, USA, 113–122. DOI: http://dx.doi.org/10.1145/2835776.2835833
14. Dmitry Lagun, Donal McMahon, and Vidhya Navalpakkam. 2016. Understanding Mobile Searcher Attention with Rich Ad Formats. In *Proceedings of the 25th Conference on Information and Knowledge Management (CIKM '16)*. ACM, New York, NY, USA, 599–608. DOI: http://dx.doi.org/10.1145/2983323.2983853
15. Pascual Martínez-Gómez, Tadayoshi Hara, and Akiko Aizawa. 2012. Recognizing Personal Characteristics of Readers using Eye-Movements and Text Features. *Proceedings of COLING 2012* December (2012), 1747–1762. http://www.aclweb.org/anthology/C12-1107
16. Jan M Noyes and Kate J Garland. 2008. Computer- vs. paper-based tasks: are they equivalent? *Ergonomics* 51, 9 (2008), 1352–1375. DOI: http://dx.doi.org/10.1080/00140130802170387
17. Radim Řehůřek and Petr Sojka. 2010. Software Framework for Topic Modelling with Large Corpora. In *Proceedings of the LREC 2010 Workshop on New Challenges for NLP Frameworks*. ELRA, Valletta, Malta, 45–50. http://is.muni.cz/publication/884893/en.
18. Selina Sharmin, Oleg Špakov, and Kari-Jouko Räihä. 2013. Reading On-screen Text with Gaze-based Auto-scrolling. In *Proceedings of the 2013 Conference on Eye Tracking South Africa (ETSA '13)*. ACM, New York, NY, USA, 24–31. DOI: http://dx.doi.org/10.1145/2509315.2509319
19. Susanne Trauzettel-Klosinski and Klaus Dietz. 2012. Standardized assessment of reading performance: The new international reading speed texts IReST. *Investigative Ophthalmology and Visual Science* 53, 9 (2012), 5452–5461. DOI: http://dx.doi.org/10.1167/iovs.11-8284

20. Eric W Weisstein. 2002. Erf. http://web.archive.org/web/20080207010024/http://www.808multimedia.com/winnt/kernel.htm. (2002). Retrieved December 2016.

21. Xing Yi, Liangjie Hong, Erheng Zhong, Nanthan Nan Liu, and Suju Rajan. 2014. Beyond Clicks: Dwell Time for Personalization. In *Proceedings of the 8th ACM Conference on Recommender Systems (RecSys '14)*. ACM, New York, NY, USA, 113–120. DOI: http://dx.doi.org/10.1145/2645710.2645724