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# Keystroke-level analysis to estimate time to process pages in online learning environments 

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#### Abstract

It is challenging for students to plan their work sessions in online environments, as it is very difficult to make estimates on how much material there is to cover. In order to simplify this estimation, we have extended the Keystroke-level analysis model with individual reading speed of text, figures, and questions. This was used to estimate how long students might take to work through pages in an online learning environment. The estimates from the model were compared to data collected from 902 volunteer students. Despite the huge differences in reported reading speeds between students, the presented model performs reasonably well and could be used to give learners feedback on how long it takes to work through pages in online learning environments. This feedback could be used to support students' motivation and effort regulation as they work through online course components. Although the model performs reasonably well, we propose giving feedback in the form of intervals to indicate the uncertainty of the estimates.


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Online learning; time estimates; planning; feedback; effort regulation; interface

## 1. Introduction

Time management is an essential skill for both learners (Loomis, 2000; Whipp \& Chiarelli, 2004) and teachers (Goodyear, Salmon, Spector, \& Tickner, 2001) and planning is an important part of the learning process (Bonestroo \& de Jong, 2012). Despite this importance, there is a lack of research on planning (Bonestroo \& de Jong, 2012), but positive effects of planning have been observed from the existing research. Among these are specific goal setting that can lead to increased academic success and in the long run better abilities for lifelong learning (Zimmerman, 2002); control over the pacing of instructional material can lead to more effective learning by computer users (Hattie, 2008) and active involvement in the planning process leads to more structural knowledge (Bonestroo \& de Jong, 2012).

However, it is difficult for students to plan their work sessions in online environments, as it is very difficult to make estimates on how much material there is to cover. When they are reading an ordinary printed book, they can use cues such as page numbers, flip through the pages to get an estimate of the number of formulas and pictures, and they can rest assured that all pages will be of the same physical length. This is not true in online environments. Pages can be anything from a paragraph to multiple sections of text, images, simulations, and problems. Each page can contain links to other pages. Navigation in online learning environments can be both complex and demanding and

[^0]growing with the size of the online material (Liang \& Sedig, 2009). All this makes planning difficult, or at least cumbersome (a student could begin a planning session by clicking through all pages in a section, following all links, to make an estimate of the content).

A better solution would be to provide students with feedback on how much time each page would take for an average student. There are challenges to this, as there are no average students (Rose, 2016), but we could use data from the students' interaction with the system to individualize the feedback.

The goal of this study is to propose a model for how to estimate the time required for student to work through a page in an online environment. This estimate can then be used to inform students how long it takes to complete a page (module) to simplify their planning. In particular, research on metacognition identifies four stages students engage in when working on an academic task: task definition, goal setting and planning, enacting study strategies, and metacognitively revising study strategies (Winne \& Hadwin, 1998). This model can help inform how students define the task, how to plan their approach and effort required to complete the task, and how to adjust their strategies to the task-based model guidelines. The model could also be used by course designers to optimize course content and by subdividing learning modules in more easily digestible chunks. Tools like this model have been pointed out as needed, but so far neglected in computer-supported learning environments (Zacharia, Manoli, Xenofontos, Kamp, \& Ma, 2015).

## 2. Background

While the order of a course is given by the book or online environment, the timing of work sessions is more open. With no information available on how much time a section takes, students have no option but to reserve large chunks of time for each session, but this is not optimal from a learning point of view. The benefits of the spacing effect, dividing and separating the time of study with other activities in-between, rather than using the same time at fewer occasions (massing), have been demonstrated in hundreds of experiments (Kornell, 2009). Kornell's study used stacks of flashcards to investigate the differences between spacing and massing. It also showed that spacing was more effective than cramming, that is study everything, just before the test. Although spacing was more effective than massing for $90 \%$ of the participants, $72 \%$ of them believed the exact opposite: that massing had been more effective (Kornell, 2009). One reason for this may be that participants assumed that the noted ease of short-term retrieval also signified long-term learning (Benjamin, Bjork, \& Schwartz, 1998; Kelley \& Lindsay, 1993).

Other researchers have also observed the benefits of spaced practice compared to massed practice (e.g. Yeh \& Park, 2015). They also conclude that testing produces better learning and knowledge retention than to re-study, especially if tested as retrieval (short answer) rather than recognition (mul-tiple-choice). These authors also claim that learners should choose learning strategies that challenge them and require deeper cognitive processing and repeat others' conclusions that cramming is highly inefficient and results in rapid forgetting (Yeh \& Park, 2015).

However, a literature review examined what advice on how to do spacing could be offered with confidence. Although these researchers were confident of the potential of spaced practice, they could not state what is the most efficient use of study time (Pashler, Rohrer, \& Cepeda, 2006).

A prerequisite of students being able to do spacing on their own is the ability to plan work sessions and this requires the ability to accurately estimate the effort needed for the material to be covered. With time feedback, it will be possible for students to utilize shorter time periods for working through online materials and thereby increase spacing and reduce the need for cramming. Being able to estimate learning time could also support micro learning (see e.g. Hug, 2006).

Providing students with information essential for planning could improve their opinion on the learning environment, a factor that correlates with course satisfaction (Rubin, Fernandes, \& Avgerinou, 2013). It could also improve the learner-content interaction which is a strong predictor for student satisfaction (Kuo, Walker, Schroder, \& Belland, 2014).

The challenge is that despite all the data we have from learners interacting with online courses, we have no good measures of time spent on a page. We do not have sufficient knowledge of who has been away from the keyboard, who has only skimmed the page (perhaps to be able to plan her/his work session), and who is really struggling with the content. The time data we have is just not useful. Therefore, we decided to develop a model for time engagement with online course materials based on the Keystroke-level analysis and reading speed estimates.

### 2.1. Keystroke-level analysis

The Keystroke-level analysis is an analysis method that can predict time for users to accomplish given tasks, without developing a prototype and measuring actual users. The method has been tested empirically with good results (Card, Moran, \& Newell, 1980) for a long time and been successfully used to estimate complex tasks, for example, email message storage and retrieval times (Bälter, 2000). It estimates the execution time of a task with the sum of the time for six operators: $K$ (key stroking), $P$ (pointing), $H$ (homing), $D$ (drawing), $M$ (mental preparing), and $R$ (a system response operator):

$$
\begin{equation*}
\text { Time to execute a task }=T_{K}+T_{P}+T_{H}+T_{D}+T_{M}+T_{R} . \tag{1}
\end{equation*}
$$

The total time for all keystrokes ( $T_{K}$ ) can then be estimated as the time to perform one single keystroke $\left(t_{K}\right)$ multiplied by the total number of keystrokes $\left(n_{K}\right): T_{K}=t_{K} \bullet n_{K}$.

The second parameter, time to move the mouse to point at a target on the screen, can be estimated with Fitts's law (Fitts \& Posner, 1967):

$$
\begin{equation*}
T_{P}=A+B \lg _{2}(D / S+C) \tag{2}
\end{equation*}
$$

where $A, B$, and $C$ are constants whose value can be determined experimentally; $D$ is the distance to the target and $S$ is the surface area of the target.

The homing, drawing, and the system response operators are not used in the model below. The last one is excluded, as the system response time is negligible for the current task. $T_{M}$ represents the time the user mentally prepares to execute the physical operators described above. Experiments have been made to estimate values of these operators for different types of users (Card, Moran, \& Newell, 1983). These values include 0.28 s for $K, 0.8+0.1 \lg _{2}(D / S+0.5)$ estimate for $P$, and 1.35 s for $M$. The model can be used to establish a minimum time to perform a task, which assumes that the user does not make mistakes. This assumption will lead to underestimates of the time spent, as users, in general, do make mistakes.

### 2.2. Reading speed

In addition to the model above, a major part of learning consists of reading (or watching videos). Video watching time could, as a first approximation, be set equal to the running time of the video; however, there are studies showing that learners pause and jump back in videos, while others play the video at higher speed. However, interacting with the video to do this is something that can be registered and averaged, unlike pauses in reading. We know from other studies that the average reading speed in English is 228 words per minute (wpm) or 3.8 words per second (wps) (Trau-zettel-Klosinski \& Dietz, 2012), but reading for learning is reportedly slower at 100-200 wpm ("Reading (process)," n.d.), or on average 2.5 wps .

### 2.3. Information on the course

The statistics dataset is comprised of student data from the OLI Probability \& Statistics open and free course delivered on the Stanford University Open edX platform (data collected February-June 2016). This course introduces students to the basic concepts and logic of statistical reasoning. In addition, the course helps students to gain an appreciation for the diverse applications of statistics and its
relevance to their lives and fields of study. The course does not assume any prior knowledge in statistics and its only prerequisite is basic algebra. This open and free course is offered as the self-paced course where learners can enroll at any time and there are no deadlines or end dates by when learners must complete activities in the course. The course does not offer certificates of completion, so learners enrolling in this course are doing so because of their own interest in the subject.

## 3. Methods

When the OLI Probability and Statistics open and free course on Stanford's Open edX platform was launched in February 2016, it included instructions and a timer on six pages (of the 287 pages) in the course where participating learners could volunteer timer data for how long time that page took them to complete. These six pages were selected to be representative for the variety of the pages in the course and appear early in the course when student engagement tends to be highest. Key data outlining the elements on each page are shown in Table 1. The tables and figures all had corresponding text descriptions for accessibility purposes that were used to get a word count for these.

In addition to the items mentioned in Table 1, two of the pages ( 63 and 70 ) also had interactive simulations. The former included a simulation asking learners to summarize a set of 12 numbers and 8 numbers, the latter included a simulation placing and dragging values on a scale to illustrate how the mean and median are affected. The time for these was estimated by a stopwatch by a learner who already knew the content, for example, an expert, in line with the Keystroke-level analysis model to estimate the minimum time. This will likely lead to underestimates of those pages.

One scroll per page is due to the timer that was placed at the beginning of the page. While reading the text, our model assumes using a touch pad, mouse or similar technology so the scrolling can be done while reading, without adding time. However, on the interactivity pages, the learner had to scroll up and down in order to be able to answer questions. Each such scroll is estimated to 3.95 seconds (Card et al., 1980).

The number of questions affects the number of points and clicks necessary to answer all questions. Each point and click is estimated to 2.73 seconds (Card et al., 1980).

The number of words in the answer affects the time to write the answer. In line with the model, we have used the shortest possible answer to the question. The writing speed is estimated to 0.7 seconds per word (Card et al., 1980).

## 4. Results

### 4.1. Background on participants

On 7 June 2016 when we downloaded the dataset, we had a total of 11,678 students enrolled in the course. From these students, who at this date had progressed at their own pace through the course, we have self-reported demographic information available from 11,127 students. The reported gender was $20 \%$ women and $70 \%$ men ( $10 \%$ did not answer). The same share ( $10 \%$ ) did not report highest completed education, but those who did were 9\% Doctorate, 37\% Master's, 31\% Bachelor's, 3\% Associate, $8 \%$ Secondary (high school), $1 \%$ Middle school, and $1 \%$ Other. The median age was 33

Table 1. Data on the six pages used for gathering timer data.

| Page \# | Text words | Figure words | Questions | Question words | Words in answer | Scrolls |
| :--- | :---: | :---: | :---: | :---: | :---: | ---: |
| 25 | 230 | 47 |  |  |  | 1 |
| 41 | 547 | 388 |  |  | 1 |  |
| 63 | 237 | 80 | 8 | 761 | 2 | 13 |
| 70 | 517 | 21 | 6 | 421 | 7 |  |
| 74 | 468 | 666 |  |  | 10 | 1 |
| 178 | 947 |  |  |  | 1 |  |

years. One-fifth (20\%) were 25 or under, a majority (52\%) were 26-40 years and the remainder (28\%) 41 years or over. The largest proportion of students (35\%) came from the United States, with India at $11 \%$ and the United Kingdom at 4\%. The remaining half came from 159 different countries, but all less than $3 \%$ of the total.

The number of students volunteering timer data started out at 956 for the first timer page in the course (page 25). As expected, the number dropped with the order in the course and on the sixth and last timer page (178) was down to 229 . We wrote a parser to identify the times entered and used manual inspections for the numbers the parser could not identify. After manual interpretation, we could identify 902 entries on the first page and 207 on the last.

### 4.2. Original KLM-model

Using the model described above and comparing it to the median time collected from the volunteers for the six pages, we get the data summarized in Table 2. We can see that the model is fairly close to four pages, but significantly off for the two remaining pages ( 41 and 74 ).

As reading speed is such an important factor in the model, it is, of course, essential to get that factor right. In our case, we have one page, Sampling, containing only text and a single scroll (for the timer). This gives us the possibility to estimate a reading speed, in this case 2.9 wps . This is rather high, but we should bear in mind that these students are by no means average, with more than $85 \%$ reporting at least a Bachelor's degree (see Section 4.1). Table 3 shows the updated values adjusted for reading speed equal to 2.9 wps .

In Table 3, we can see that the model overestimates all pages with figures, with the exception of the interactivity pages ( 63 and 70 ), which we above have explained would likely lead to an underestimate. Considering that a figure is used because it explains something better than can be done in words, otherwise there would be no reason to have the figure at all, it is reasonable to assume that reading speed for (the text description of) a figure would be higher than "normal" text. Also, it is reasonable to argue that when you are answering questions, you read more carefully, hence slower, compared to the normal text. We, therefore, refined our model by separating the figure and question reading speed from the text reading speed.

### 4.3. Model with separated figure and question reading speed

It is, of course, difficult to come up with a general value for figure and question reading speeds, as it depends so much on what the figure is attempting to explain or illustrate, and how complex the question is. However, since we have the model, we can optimize the values of the figure reading speed and question reading speed. We, therefore, wrote a program that searched for a minimal sum of absolute errors in the range of figure reading speeds between 1.5 and 1200 wps and a question reading speed between 0.3 and 6 wps . In those ranges, the optimum values are 175 and 2.17 wps , respectively, with a sum of absolute errors of $28 \%$. The question reading speed stabilizes at 2.2 wps when the figure reading speed is above 6.74 wps . However, as we do not have data to run several competing tests for figure reading, we settled for a figure text reading speed of four

Table 2. Comparison between the model and the reality with reading speed at 2.5 wps .

| Page \# | Content | Model (s) | Median (s) |
| :--- | :--- | :---: | :---: |
| 25 | WF | 115 | 88.5 |
| 41 | WF | 378 | 197 |
| 63 | WFQI | 579 | 580 |
| 70 | WFQI | 505 | 616 |
| 74 | WF | 458 | 168 |
| 178 | W | 383 | 328 |
| Sum of absolute errors: $312 \%$ |  |  | 130 |

Table 3. Comparison between the model and the reality with reading speed at 2.9 wps .

| Page \# | Content | Model (s) | Median (s) | Model/median (\%) |
| :--- | :--- | :---: | :---: | :---: |
| 25 | WF | 99 | 88.5 | 112 |
| 41 | WF | 326 | 197 | 166 |
| 63 | WFQI | 520 | 580 | 90 |
| 70 | WFQI | 452 | 616 | 73 |
| 74 | WF | 395 | 168 | 235 |
| 178 | W | 331 | 328 | 101 |
| Sum of absolute errors: $250 \%$ |  |  |  |  |

times the text reading speed, which is an upper limit of skimming text ("Reading (process)," n.d.). The anatomy of the eye gives limits for how fast a text can be decoded. With reading text defined as capturing and decoding all the words on every page, this limit is 15 wps (Bremer, 2011). Also, as there are figures on all pages, with the exception of the last page used to determine the text reading speed, the figure reading speed will be very sensitive to the reading speed. In our case, we are trying to estimate a first-order approximation of figure interpretation speed that works well enough for our model. In lack of such studies, our selection of four times the text reading speed seems reasonable. The updated model data are shown in Table 4 with a sum of absolute errors of $69 \%$.

### 4.3.1. Comparing the static model to individual students

How well does this model fit individuals? In Figure 1, we can see the distribution of the reported time compared to the median for page 25 . The distribution for page 25 as well as other pages resembles a log normal with a very long upper tail. It is impossible to say whether these upper tail timer reports are what we intended: time to work through the page, without any interruptions, or if some of the students took pauses without stopping the timer.

However, time feedback to students on the granularity of number seconds would not be helpful. For the shortest page, it would make more sense to state "less than three minutes", which would be true for $87 \%$ (outliers included) of the participating students. For the longest page, the feedback could be "between 5 and 15 minutes" which would be true for $75 \%$ of the respondents. In Table 5, we can see how large percentage of the respondents would be covered by model-based time feedback depending on how this feedback is articulated. The page most difficult to give time feedback on is page 70 that includes both figures, questions, and interactivity. As we have mentioned before, the time for interactivity is the most difficult to estimate, as some students probably will spend more time interacting with the simulation.

### 4.4. Individual modeling

Of the 982 students who volunteered their timer data, 102 did so on all six pages. This gives us a possibility to use the model for individual students, with their individual reading speed (as defined by their report of the Sampling page). Of those 102, there are three outliers above 1400 seconds on the Sampling page that the model fails to capture. To make comparisons between the static

Table 4. Comparison between the model and the reality with reading speed at 2.9 wps , figure reading speed at four times that and question reading speed at 2.2 wps .

| Page \# | Content | Model (s) | Median (s) | Model/median (\%) |
| :--- | :--- | :---: | :---: | :---: |
| 25 | WF | 87 | 88.5 | 98 |
| 41 | WF | 225 | 197 | 114 |
| 63 | WFQI | 587 | 580 | 101 |
| 70 | WFQI | 494 | 616 | 80 |
| 74 | WF | 221 | 168 | 132 |
| 178 | 328 | 328 | 100 |  |
| Sum of absolute errors: $69 \%$ |  |  |  |  |



Figure 1. Histogram over reported time in seconds for page 25 ( 28 outliers above 550 s removed) and median at 89.
model above and this individual model possible, we have removed the same outliers from these 102 respondents as we did above.

In Table 6, we can see that the individual model is 4-8 percentage units better than the static model. The only page not close to or above $90 \%$ is page 70 . The remaining students are in general within three minutes, but it is clear that the model has the largest misses on the two pages with interactivity ( 63 and 70 ) where 6 and 7 reports, respectively, were outside even three minutes.

One conclusion might be that using a single page to estimate reading speed might not be optimal. Considering the importance of getting this estimate right, it should probably be an average of more than one page. We simulated this by using the page with the least amount of figure text as all text and this improved the model's estimates slightly as shown in Table 7.

## 5. Discussion

We have extended the Keystroke-level analysis model with reading speed to make estimates of how long pages in an online learning environment take to work through for students and compared the model to data collected from students. Despite the huge differences between the students, the presented model performs reasonably well and could be used to give learners feedback on how long it takes to work through pages, and aggregated also for modules, sections, and chapters.

There are two different ways course designers could use these results: in simpler learning management systems, the time estimates could be done once and time information added to pages statically. In more advanced systems, data could be collected from the learners to estimate each individual's reading speed and present this dynamic information on the course pages. Learners who perceive

Table 5. Percentage of non-outlier responses covered by an interval ( $\pm 50 \%$ ) estimated by the static model and rounded down and up to whole minutes.

| Page \# | Min | Max | Covered by interval (\%) | Under max (\%) | $N$ |
| :--- | :---: | :---: | :---: | :---: | :---: |
| 25 | 0 | 3 | 90 | 90 | 874 |
| 41 | 1 | 6 | 79 | 83 | 596 |
| 63 | 4 | 15 | 80 | 83 | 368 |
| 70 | 4 | 13 | 62 | 66 | 319 |
| 74 | 1 | 6 | 81 | 90 | 324 |
| 178 | 2 | 9 | 74 | 78 | 198 |

Table 6. Percentage of non-outlier responses covered by an interval based on individual reading speeds.

| Page \# | Covered interval (\%) | Covered max (\%) | $N$ |
| :--- | :---: | :---: | :---: |
| 25 | 93 | 94 | 96 |
| 41 | 87 | 90 | 97 |
| 63 | 79 | 87 | 98 |
| 70 | 71 | 74 | 97 |
| 74 | 85 | 96 | 96 |

Note: The sampling page (178) used for measuring this reading speed would have $100 \%$ regardless of interval.
the time feedback generally as overestimates or underestimates could then adjust their reading speed setting to match their reality.

This time we counted words by hand (copy-paste word count) for this proof of concept, but as long as tagging of the pages is done properly, it is possible to write a program that automatically does the word count for all course pages.

It should be noted that from a student's point of view, it is probably worse to underestimate than overestimate the time feedback. If it is underestimated, learners will be led to believe that they are slower than the average student, which might be disheartening and lower motivation.

The timer we added to the six pages could have been better designed by adding a stop button at the bottom of the page as well. This would have eliminated the need for students to scroll up to the beginning again to stop the timer. Also, we have no way of knowing if some students preferred to use their own timer, for example, on their phone, and for these, we erroneously added scrolling time.

The estimated reading speed for figures is a part that needs to be examined further. We used four times the text reading speed, but that is based only on our estimate of what seems reasonable. According to the total search we did, this speed should be much higher (about 60 times the text reading speed) to minimize the differences between reported time and the model, but as we describe above, first we must establish a question reading speed, and this should be done in a separate study. When dynamic reading speed is integrated in an online environment, we could assemble data on this. In this study, we came to $74 \%$ of the text reading speed.

This model is the first attempt and there are several steps to investigate, the first examining how the learners perceive time feedback. There are some design issues to discuss: should we present the model's result in minutes or symbolic (e.g. portions of a pie chart)? While the first would add clarity, it might also add frustration for slower learners. Symbolic feedback has the benefit of avoiding the exact measures (which often will be wrong) while still giving information to the learners on the relative size of pages. Also, to avoid frustrating slower learners, should we pad the time feedback with, for example, $25 \%$ longer times, or would that make the estimates useless for faster and average learners? The granularity of the time feedback can also be a factor. Stating that a page would take "less than 3 minutes" would also be an indication of how exact we assume our model to be.

We should add a note of caution when interpreting these results. First, the course from which these data were taken is a self-paced course with no due dates or deadlines. Therefore, students enrolling in this course may be more motivated than the typical college student to engage with the materials. Secondly, over $85 \%$ of the learners enrolled in this course have a Bachelor's degree or higher indicating a highly educated set of learners working on these materials. Lastly, we asked

Table 7. Percentage of non-outlier responses covered by an interval based on individual reading speeds estimated by the average of the first and last page.

| Page \# | Covered interval (\%) | Covered max (\%) | $N$ |
| :--- | :---: | :---: | :---: |
| 25 | 96 | 96 | 96 |
| 41 | 90 | 92 | 97 |
| 63 | 80 | 88 | 98 |
| 70 | 71 | 76 | 97 |
| 74 | 85 | 96 | 96 |

learners to voluntarily provide time feedback on six pages as they worked through them (all data were collected anonymously). It could be that individuals who voluntarily participated in this study were more comfortable with the content or differed in some way from all learners enrolled in the course. We hope to replicate this study with more traditional college students enrolled in a forcredit course to determine how well the model works with that population of students.

## 6. Conclusions

The Keystroke-level analysis model performs reasonably well to estimate time usage in an online learning environment. The method presented in this paper could be used to provide learners either with static time feedback or in more advanced learning environments with individualized time feedback. More research is necessary to understand how this feedback should be presented for the learners, in both self-paced open and free courses and instructor-led for-credit courses.

## Compliance with ethical standards

All procedures performed were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. Informed consent was obtained from all individual participants included in the study.

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No potential conflict of interest was reported by the authors.

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