Instance theory predicts information theory: Episodic uncertainty as a determinant of keystroke dynamics

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Abstract

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Theories of cognitive processes run along a continuum. On one extreme, cognitive phenomena are explained in terms specialized and dedicated modules (Fodor, 1983) that give rise to cognition by the principles of their internal processing architecture. On the other extreme, cognitive phenomena are explained in terms of general learning and memory processes (Jacoby & Brooks, 1984; Kolers & Roediger, 1984; Rumelhart & McClelland, 1986) that give rise to cognition through their experience with a structured environment (Clark, 2008). Valid theories produce explanations of phenomena by deduction from their processing assumptions, and then compete with other valid theories on the basis of parsimony. When a phenomena is explained by a general process, specialized accounts become sufficient, but not necessary; and, vice versa. We continue in this tradtion by proposing and validating a general process account of keystroke dynamics in skilled typing performance. We show that keystroke dynamics can emerge from a general memory process sensitive to structure (uncertainty) in the natural language environment.

We identified the following pre-requisites as necessary for our approach. We follow the assumption that specialized or general processes of cognition are constrained to operate upon the structure of their environmental inputs. So, we require a tool for describing the structure of environmental inputs. We assume that performance is driven by learning processes sensitive to the structure in the environment. So, we require a model that articulates how learning about the structure of an environment produces performance. Finally, we require a task where the relation between performance and a structured environment can be measured. We use information theory (Shannon & Weaver, 1998) to measure the structure of the letters that typists' type, instance theory (Logan, 1988) to model how typists' performance is shaped by the typing environment, and the task of continuous typing (Logan & Crump, 2011) to measure keystroke dynamics as a function of the structure in the typing environment.

There are many typing phenomena to explain (Salthouse, 1986), and several existing models of typing (Heath & Willcox, 1990; John, 1996; Rumelhart & Norman, 1982; Wu & Liu, 2008). Our goal here was not to provide another general model of typing, and we expect that our model will fail to explain many aspects of typing performance. Instead, we focus our efforts empirically and theoretically as follows. Empirically, we examine whether typing performance is constrained by structure in the natural language. Theoretically, we propose a general processing account that predicts how structure in the natural language should constrain typing performance. These aims contribute to the broader goals (beyond the scope of this paper) of determining whether specialized or general accounts are neccessary or sufficient to explain typing performance, and then adjucating between them.

We focused on two typing phenomena, the word-initiation/first-letter slowing effect, and the mid-word slowing effect, which are both observed in continuous copy-typing of words presented in sentences. First-letter slowing refers to longer keystroke times for letters in the first position of a word compared to other letters. Mid-word slowing refers to an inverted U shaped pattern, with longer interkeystroke intervals for letters in the middle of a word compared to letters at the beginning and ending of a word. First-letter and mid-word slowing were clearly demonstrated by Ostry (1983), who showed systematic effects of letter position and word length on interkeystroke intervals.

We chose these phenomena for two reasons. First, both phenomena have been explained in terms of specialized processes, and it remains unclear whether those accounts are necessary to explain the phenomena. Second, we have not found work replicating Ostry's (1983) results, and Salthouse (1986) suggested that effects of word length do not systematically influence interkeystroke intervals, so the effects of letter position and word length on interkeystroke interval remain unclear.

First-letter slowing has been explained in terms of planning and buffering processes associated with typing a whole word. For example, the time associated with retrieving a motor program for a word, parsing the word into letters, planning the sequence, or initiating the execution of the sequence after it is buffered, could cause the first letter in a word to be produced more slowly than other letters. Mid-word slowing has been explained in terms of rising interference from ongoing sequencing, or from micro-planning of syllables which often occur in the middle of words (Will, Nottbusch, & Weingarten, 2006). These explanations rely on largely unspecified planning and execution processes that are reverse-engineered by imputing hypotheses about their operation from typing data.

To develop an alternative, we entertained a simple question: are more predictable letters typed faster than less predictable letters? More specifically, we wondered whether natural variation in letter uncertainty as a function of letter position and word length would magically (in the sense of) correspond to the observed variation in interkeystroke intervals as a function of letter position and word length. Such a demonstration would license consideration of how a general learning process sensitive to letter uncertainty could explain effects of letter position and word length on interkeystroke intervals.

Prior work shows that typists are sensitive to structures in the text the type. For example, IKSIs are negatively correlated with letter frequency, bigram frequency, and trigram frequency. Individual keystroke times are influenced by the immediate letter context in which they occur. IKSIs are also influenced by orthographic structure. Finally, IKSIs are much faster for letter strings from a natural language, compared to random letter strings. These demonstrations suggest that typing performance may be in part determined by a learning process sensitive to structure inherent to natural texts.

Following Shannon (), we use information theory as a tool to measure structure in natural texts. Information theory provides the summary statistic H to measure the entropy or uncertainty in any discrete probability distribution of a set of items. H goes to 0 for distributions that are perfectly predictable (e.g., when one item occurs 100% of the time). H goes to it's maximum value for distributions that are completely unpredictable, fully entropic, or maximally uncertain (e.g., when all items occur with equal probability). Shannon's H is defined as:

$$H = -\sum p \log_2 p$$

where, p is the probability of occurence for each item in a given distribution. H is the number of bits needed to represent the distribution. To apply this to letter uncertainty, consider the set of the 26 lowercase letters from a to z. For this set, H can range from 0 to ~4.7. H approaches 4.7 as letter probabilities approach a uniform distribution, indicating all letters are equiprobable, $H = -\sum \frac{1}{26} \log_2 \frac{1}{26} = 4.7004$. H by definition is less than 4.7 for all unequal letter probability distributions, where some letters occur with higher/lower probabilities than others.

Most important, H can be calculated for any letter probability distribution. For example, if separate letter probability distributions for every letter position across words of every length in natural English text could be obtained, then the letter uncertainty for each position by word length could be calculated; and, correspondence between letter uncertainty and interkeystroke intervals as a function of letter position and word length could be evaluated.

Our empirical question also ties into the well known application of information theory to choice-reaction time performance. For example, Hick and Hyman showed that choice reaction time, which was known to increase as a function of set-size, increases linearly as a function of choice uncertainty in the set (measured by H), rather than set-size persay. Although there are numerous exceptions to the Hick-Hyman law (for a review see), we are not aware of any work that has determined whether typing performance (a continuous 26-AFC choice-task, assuming lower case for convenience) depends on letter uncertainty. If typing performance does depend on letter uncertainty, then a model based explanation of the dependency is required.

Overview of present study

We first reproduce Ostry's (1983) analysis of interkeystroke intervals as a function of letter position and word length. We used the dataset collected by Crump & Behmer (2016), who had 346 typists copy type five paragraphs of natural english text. Then we estimated letter uncertainty in natural english for each letter position in words of different lengths. We used letter frequency counts from google's ngram project provided by Peter Norvig, which gave us letter uncertainty estimates for each position in words of length one to nine. Next, we show that natural variation in letter uncertainty can explain large portions of variance in interkeystroke intervals as a function of letter position and word length. Finally, we show that Logan's (1988) instance theory of automatization provides a working process model explaining how a general memory process could cause typing performance to be constrained by letter uncertainty.

Methods

Participants

400 participants were recruited from Amazon's mechanical turk (restricted to people from the USA, with over 90% completion rate). Data were only analyzed for the 346 participants who successfully completed the task (98 men, 237 women, 11 no response). Additional demographic information is reported in Crump & Behmer (2016). The procedure was approved by the institutional review board at Brooklyn College of the City University of New York.

Stimuli and Apparatus

From Behmer & Crump, "Typists copy-typed five normal paragraphs from the Simple English Wiki, a version of the online encyclopedia Wikipedia written in basic English. Four of the paragraphs were from the entry about cats (http://simple.wikipedia. org/wiki/Cat), and one paragraph was from the entry for music (http://simple.wikipedia.org/wiki/Music). Each normal paragraph had an average of 131 words (range 124–137)."

The apparatus was a website displaying textbox containing a single paragraph. Paragraph text was black, presented in 14 pt, Helvetica font. JavaScript was used to record keystroke timestamps in milliseconds.

Design and Procedure

From Behmer & Crump, “Participants were instructed to begin typing with the first letter in the paragraph. Correctly typed letters turned green, and typists could only proceed to the next by typing the current letter correctly. After completing the task, participants were presented with a debriefing, and a form to provide any feedback about the task. The task took around 30 to 45 minutes to complete. Participants who completed the task were paid $1.”

Data analysis and pre-processing

We used R (Version 3.4.2; R Core Team, 2017) and the R-packages *bindrcpp* (Version 0.2.2; Müller, 2018), *bit* (Oehlschlägel, 2017, Version 1.1.14; 2018), *bit64* (Version 0.9.7; Oehlschlägel, 2017), *Crump* (Version 1.0; M. Crump, 2017), *data.table* (Version 1.10.4.3; Dowle & Srinivasan, 2017), *dplyr* (Version 0.7.4; Wickham, Francois, Henry, & Müller, 2017), *ggplot2* (Version 2.2.1; Wickham, 2009), *ggpubr* (Version 0.1.6; Kassambara, 2017), *knitr* (Version 1.20; Xie, 2015), *magrittr* (Version 1.5; Bache & Wickham, 2014), *papaja* (Version 0.1.0.9655; Aust & Barth, 2018), *Rcpp* (Eddelbuettel, 2017; Eddelbuettel & Balamuta, 2017; Version 0.12.16; Eddelbuettel & François, 2011), *RcppZiggurat* (Version 0.1.4; Eddelbuettel, 2017), *Rfast* (Version 1.8.8; Papadakis et al., 2018), *rlist* (Version 0.4.6.1; Ren, 2016), and *skimr* (Version 1.0.3; McNamara, Arino de la Rubia, Zhu, Ellis, & Quinn, 2018) for all our analyses.

For each subject, we applied the following pre-processing steps. We included IKSIs only for keystrokes involving a lower case letter, and only for correct keystrokes that were preceded by a correct keystroke. Outlier IKSIs were removed for each subject, on a cell-by-cell basis, using Van Selst & Jolicoeur’s (1994) non-recursive moving criterion procedure, which eliminated approximately X% of IKSIs from further analysis.

Results

Typing Performance

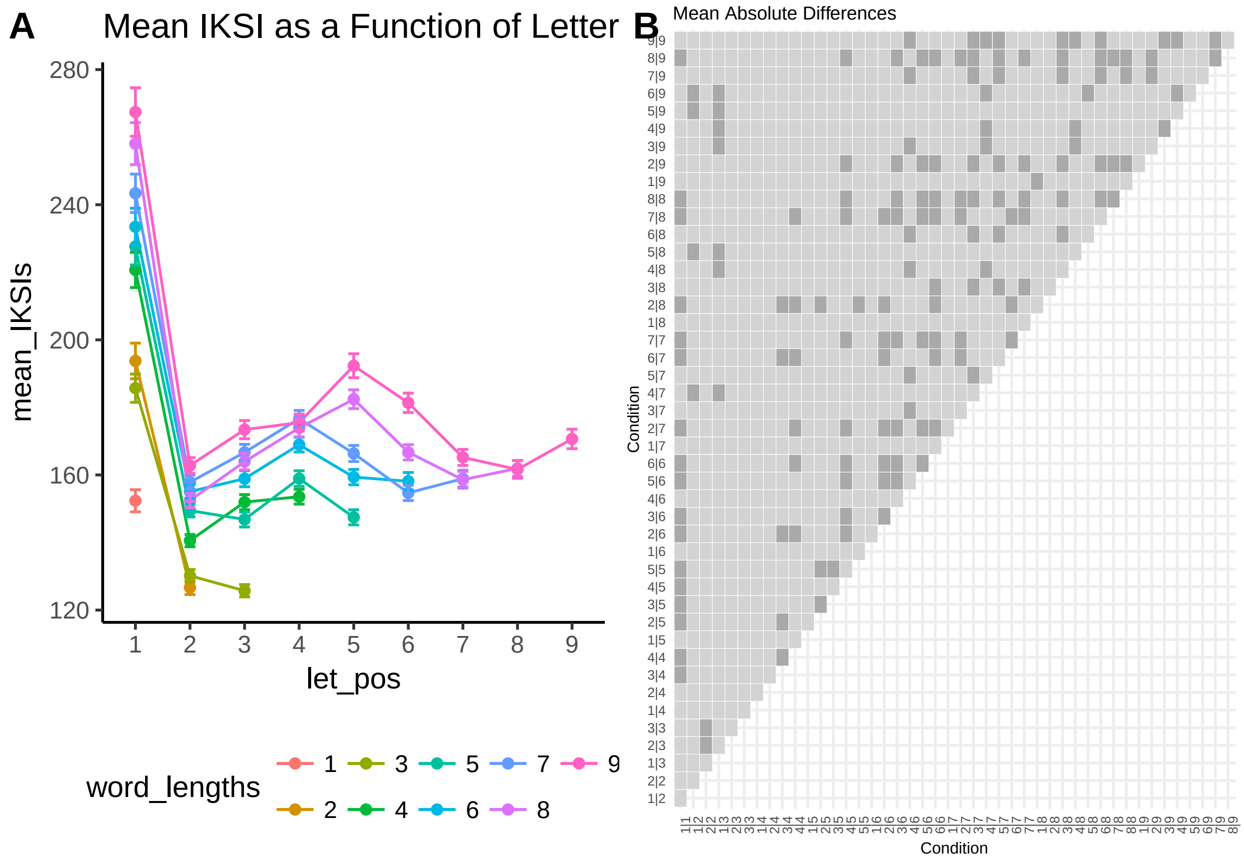

Figure 1

For each subject, we calculated mean IKSIs as a function of letter position and word length. The letter position and word length factors were not factorially crossed. To determine whether there were differences among the means we submitted the means to a single factor repeated measures design with 45 levels (e.g., letter position|word length: 1|1, 1|2, 2|2, ... 9|9). Figure 1 shows mean IKSIs collapsed over subjects, as a function of letter position and word length.

The omnibus test indicated differences among the means were not likely due to chance, F (44,15180) = 276.74, MSE = 1,269.66, $p < .001$. Visual inspection of figure X shows several trends across the means consistent with first-letter slowing and mid-word slowing reported by Ostry (1983).

Our more important aim was to determine whether variation among these means can be explained by variation in letter uncertainty. For this reason we do not exhaustively discuss all of the possible 990 differences among these 45 conditions. Nevertheless, we did conduct all 990 comparisons using bonferroni corrected paired samples t-tests. The results are displayed Figure 2, which shows absolute mean differences between conditions color coded for significance (light grey is significant).

Letter Uncertainty by position and word length

The primary question of interest was whether natural variation in letter uncertainty explains variance in mean IKSI by position and word length. We estimated letter uncertainty by position and word length from google's ngram database, which provides frequency counts of letters and words occuring in Google's massive corpus (X million) of digitized books. Letter frequency counts for letters a to z, for each position in words from length one to nine, were obtained from Norvig ().

For each letter frequency distribution, we computed Shannon's H (entropy) to quantify letter uncertainty. We converted each letter frequency distribution to a probability distribution then calculated H for each distribution. Figure 3 displays estimates of letter uncertainty (H) as a function of letter position and word length. Visual inspection of the graph shows that variation in letter uncertainty maps closely onto variation in mean IKSI (Figure 1) as a function of position and word length. In particular, letter uncertainty and mean IKSI for position one as a function of word length appear highly similar. And for the remaining positions, letter uncertainty shows an inverted U- shape with greater letter uncertainty in the middle rather than the beginning and endings of words. This suggests that natural variation of letter uncertainty across position and word in English may account for aspects of the first-letter and mid-word slowing phenomena in typing.

Letter Uncertainty and Mean IKSI

If the Hick-Hyman law applied to continuous typing we would expect a neat linear relationship between mean IKSIs and letter uncertainty. Figure 4 shows a plot of mean IKSIs taken from all positions and word lengths against letter uncertainty. The scatterplot shows a general trend for mean IKSI to increase as a function of letter uncertainty.

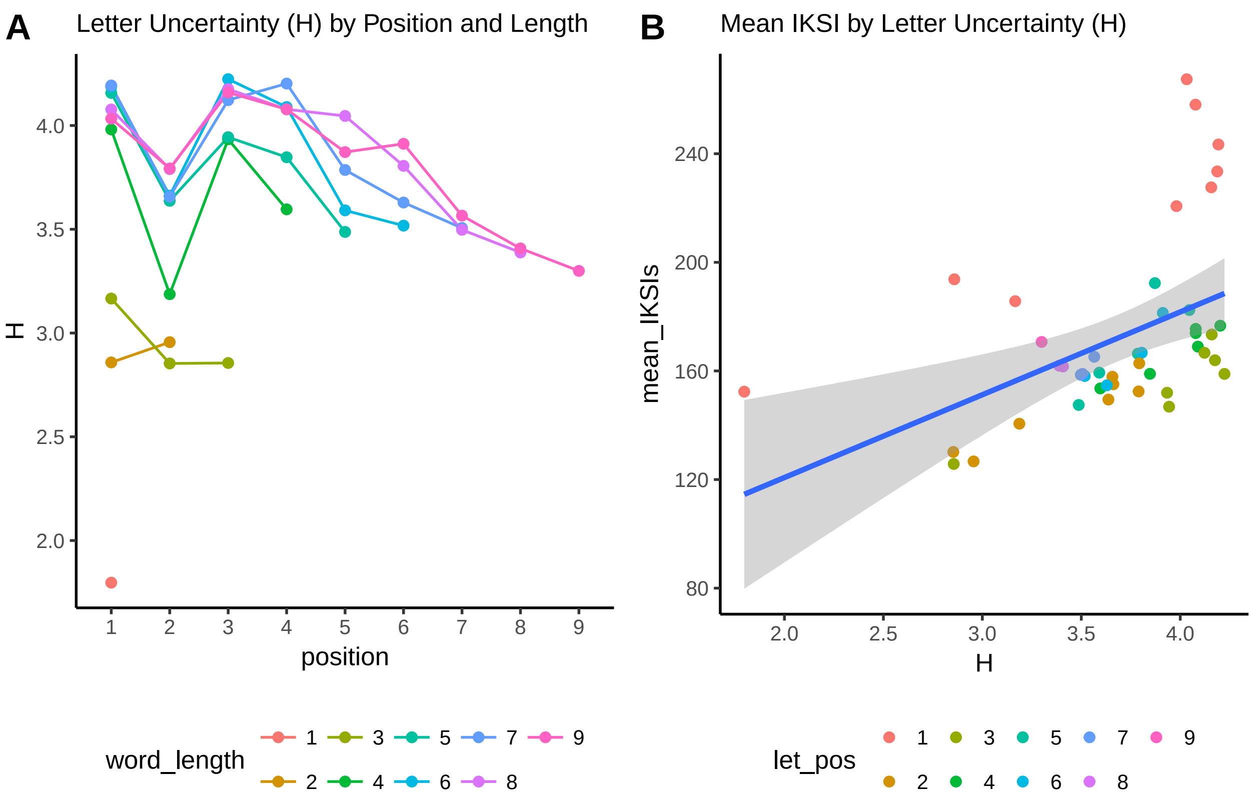

Figure 2

A linear regression with group mean IKSIs (collapsed over subjects) as the dependent variable, and letter uncertainty as the independent variable showed a significant positive trend, F(1, 43) = 11.82, p = 0.0013, $R^2 = 0.22$ (meanIKSI = 59.75 + 30.49 $*H$). We also conducted separate linear regressions for each subject and found similar results. For example, the mean correlation was r = 0.44 (SE = 0.0085); mean $R^2 = 0.22$ (SE = 0.0072); and mean p = 0.047 (SE = 0.0072).

Interim Discussion

We can conclude that letter uncertainty as a function of position and length explains a small amount variation in mean IKSIs during continuous typing. The present analysis does not provide strong evidence that a process sensitive to letter uncertainty causes both first-letter and mid-word slowing. For example, all of the first position mean IKSIs are longer than mean IKSIs for other positions at comparables levels of letter uncertainty. And, a linear regression on the group mean IKSIs including letter uncertainty and position (first letter vs. other letter) as independent variables explains much more variance, $R^2 = 0.86$, $p < .001$, than the regression only including letter uncertainty.

This pattern invites a dual-process interpretation. For example, first-letter slowing could be explained by a planning process that increases first position IKSIs as a function of word length. Longer words have more letters, thus plan construction and buffering is assumed to take more time before sequence production begins. At the same time, the finding that letter uncertainty does explain some variance in mean IKSI across position suggests that sequence production is also influenced by a process sensitive to letter uncertainty.

Letter Uncertainty by position, word length, and n-1 letter identity

Determining whether first-letter and mid-word slowing could emerge from a process sensitive to letter uncertainty depends on how letter uncertainty is calculated. Letter uncertainty can be calculated from any discrete probability distribution of letters. In the previous section we somewhat arbitrarily calculated letter uncertainty separately for each letter position in words of length one to nine. However, the number of alternative schemes is vast. For example, we could further conditionalize our postion by word length probability distributions by the letter identities of letters occuring in any position n-1 to n-x, or n+1 to n+y of a specific position. Furthermore, we could conditionalize letter distributions upon any permissible number of preceding or succeeding n-grams (groups of letters).

Although an exhaustive calculation of letter uncertainty is beyond the scope of this paper, we nevertheless took one further step and calculated letter uncertainty by position and word length, conditionalizing upon n-1 letter identity. Fortunately, Norvig () also provided bigram frequency counts from the google ngram corpus as a function of position and word length. We calculated letter uncertainty in the following manner. First position letters have no preceding letter, so H as a function of word length was identical to our prior calculation. For letters in positions two to nine, for all word lengths, we calculated H for every n-1 letter identity, and then took the mean H for each position and length. For example, the second position of a two-letter word has a maximum of 26 letter probability distributions, one for each possible n-1 letter (a to z). We calculated H for all n-1 distributions, then took the mean H as our measure of letter uncertainty for each position and word length. Figure X shows mean H conditionalized by n-1 letter identity, as a function of letter position and word length.

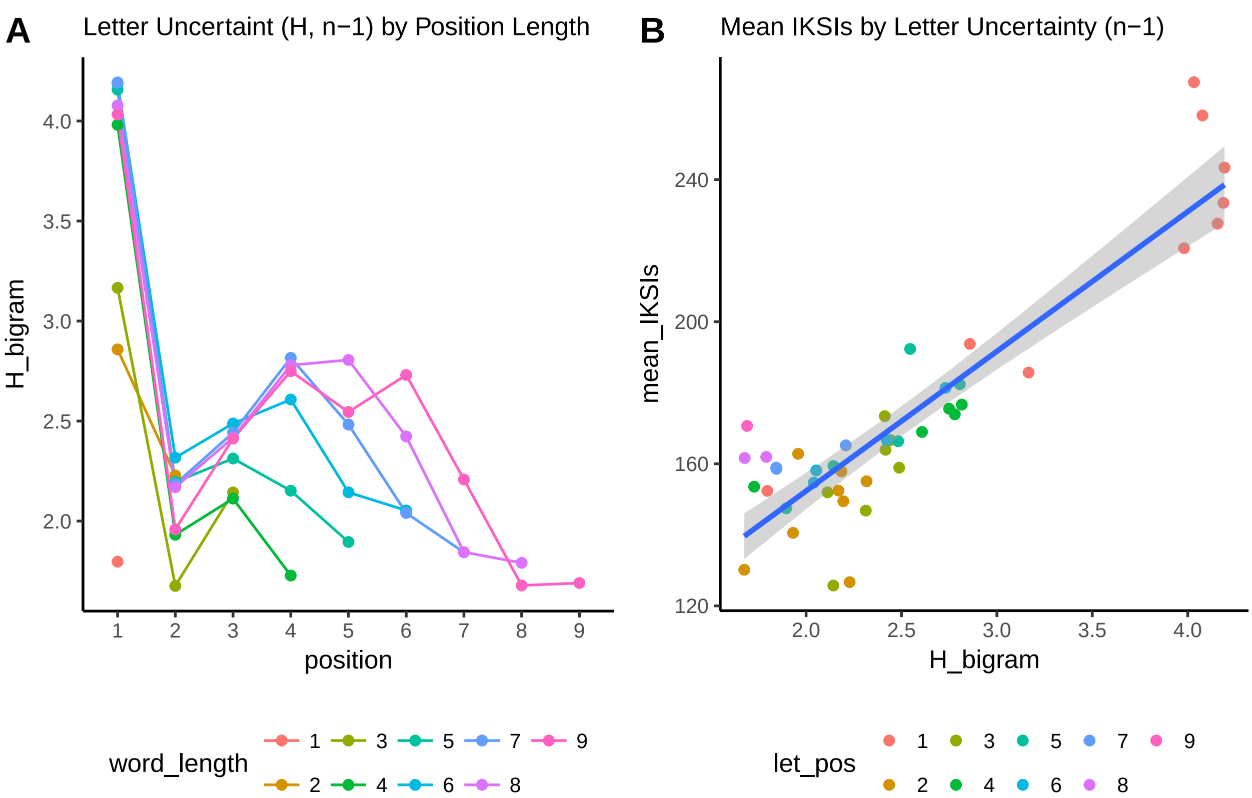

Figure 3

Unsurprisingly, letter identity becomes more predictable when n-1 letter identity is known. Compared to the letter uncertainty measures in Figure X, we see that H for letters in positions two to nine is much lower when n-1 letter identity is taken into account. More important, the pattern of H in Figure X much more closely resembles the pattern of mean IKSIs in Figure X.

Figure X displays a scatterplot of mean IKSIs as a function of letter uncertainty conditionalized by letter n-1 identity across positions and word length. A linear regression on mean IKSIs using our new measure of letter uncertainty as the independent variable showed a strong positive relationship, F(1, 43) = 182.44, p = 4.5e-17, $R^2 = 0.81$ (meanIKSI = 73.72 + 39.31 $*H$).

An instance-based model

We have shown that variation in mean IKSIs as a function of letter position and word length can be well explained by natural variation in letter uncertainty conditionalized by letter n-1 identity by letter position and word length. This finding licenses consideration of the claim that first-letter and mid-word slowing are caused by a single process sensitive to letter uncertainty. However, the plausibility of this causal claim is empty in the absence of a working process model. Next, we establish theoretical plausibility by showing that letter uncertainty influences on performance can be explained in terms of Logan's (1988) instance-based memory model of automatization.

Instance theory provides an account of how performance becomes automatized with practice. Among other things, it provides a theoretical explanation of learning curves that follow a power function (). We will show that the instance theory process also develops sensitivity to uncertainty in the stimuli it encounters over practice. More specifically, instance theories predictions for performance are nearly identical to the hick-hyman law which posits that reaction times are a linear function of the uncertainty in a choice set.

Instance theory models learning as a function of practice in terms of cue-driven retrieval of stored memory traces. A new unique trace is preserved in memory every time a response is given to a stimulus. When a familiar stimulus is encountered again, it automatically triggers the retrieval of all stored instances of the stimulus. The timing of the memory-based response to a current stimulus is treated as a race. Whichever memory trace is retrieved first wins the race. As a result, the memory-based reaction time to respond to a stimulus is determined by the retrieval time associated with the fastest memory trace for that stimulus. The retrieval times for every memory trace are assumed to vary, and can be sampled from any desired distribution.

So, instance theory models practice based performance speed-ups in terms of sampling extreme values from a growing retrieval time distribution. As the number of memory traces grows the range of the retrieval time distribution also grows. As a result, the minimum value of the distribution (fastest retrieval) is more likely to be smaller for distributions with more than fewer memory traces. In other words, reaction times will tend to be faster for higher than lower frequency stimuli.

We can now draw a more transparent connection between instance theory and information theory. Information theory provides H as a summary statistic of probability distributions for any discrete set of stimuli. Empirical probability distributions for natural occuring stimuli, such as letters, are found by counting stimulus frequencies, and then dividing a stimulus frequency distribution by it's sum. Instance theories predictions for response times in a stimulus set will be monotonically decreasing as a function of each stimulus frequencies. We should also expect that a summary statistic of instance theories predictions for mean reaction time, collapsing across all items in the set, will behave in a similar manner to information theory's summary statistic, which also collapses over the expected frequency of each item in the set. We demonstrate these relationships by monte-carlo simulation.

Our goal was to model instance theory predictions for keystroke production times for typing natural english sentences as a function of letter position and word length. We treated all 26 letters that could possibly occur in any position for any word length as completely unique and independent stimuli. We modeled the structure of natural english using the 45 letter probability distributions derived from Norvig's letter frequence counts by position and word length, from Google's n-gram corpus.

We modelled keystroke times for specific letters in the following manner. At different practice intervals each letter, occuring in each position for each word length, had occured in the model's history with specific frequency. We estimated reaction time as a function of frequency by monte-carlo simulation. We assumed that the retrieval time distribution for each stimulus was sampled from a normal distribution with mean = 500, and standard deviation = 100. Using R, we sampled retrieval times from the normal distribution n times, where n was the current number of memory traces. Then we took the minimum value from the sampling distribution as the reaction time. We repeated this process 1000 times to estimate the expected mean reaction time (expected minimum retrieval time) for the given frequency value. In this way, we estimated mean keystroke production times for every letter position across different word lengths. Last, we evaluated model predictions across four practice intervals.

Figure X displays the instance model predictions, across increasing amounts of practice, for mean keystroke production times as a function of letter position and word length. As expected, simulated keystroke times shorten with practice. More imporant, at each stage in practice, simulated keystroke times show the same qualitative pattern of variation across letter postion and word length. Notably, these appear very similar to human typing performance, and to letter uncertainty as a function of position and word length.

Finally, we conducted linear regressions on simulated mean typing times using letter uncertainty as the independent variable. We found that letter uncertainty nearly perfectly explains the variance in simulated keystroke time, with Rˆ2 increasing across practice.

Conclusion

Future studies should investigate the role of probability of repetition in regulating response times.

Kornblum in 1969 found that with constant H, trials that had higher chances of sequentially repeating stimuli experienced faster response times.

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