ABSTRACT
Handwriting is a natural and versatile method for human-computer interaction, especially on small mobile devices such as smart phones. However, as handwriting varies significantly from person to person, it is difficult to design handwriting recognizers that perform well for all users. A natural solution is to use machine learning to adapt the recognizer to the user. One complicating factor is that, as the computer adapts to the user, the user also adapts to the computer and probably changes their handwriting. This paper investigates the dynamics of co-adaptation, a process in which both the computer and the user are adapting their behaviors in order to improve the speed and accuracy of the communication through handwriting. We devised an information-theoretic framework for quantifying the efficiency of a handwriting system where the system includes both the user and the computer. Using this framework, we analyzed data collected from an adaptive handwriting recognition system and characterized the impact of machine adaptation and of human adaptation. We found that both machine adaptation and human adaptation have significant impact on the input rate and must be considered together in order to improve the efficiency of the system as a whole.

Author Keywords
Co-adaptation; handwriting recognition; communication channel;

INTRODUCTION
Handwriting is a natural and versatile method for human-computer interaction, especially on small mobile devices such as smart phones. As handwriting varies significantly from person to person, it is difficult to design a handwriting recognition system that performs well for all users. Modern handwriting recognizers resort to machine learning techniques to adapt and specialize their handwriting models to each individual user. As the recognizer adapts to the human user, the user is likely to adapt to the system as well. We call this situation “co-adaptation” where both human and computer adapt to each other simultaneously.

In general, co-adaptation can manifest in any adaptive system. Designing a system that co-adapts with the users is a challenging problem on its own [1,2,3]. Our goal in this paper is not to address those challenges, but rather to focus on characterizing the impact of machine adaptation and of human adaptation in the context of handwriting recognition. We believe that this study will provide us with useful insights towards designing a more efficient adaptive handwriting recognition system.

In order to evaluate performance of a handwriting recognition system under co-adaptation, we introduce a framework based on the idea of Shannon’s communication channel [4] that considers both the user and the handwriting recognizer in a single system. Under this framework, we define the notion of “channel rate” that measures the amount of information successfully transferred from the user to the computer.

To quantify the effect of machine adaptation and of user adaptation empirically, we developed a handwriting recognition system that is capable of adapting to the handwriting of each individual user over time. We collected usage data from 15 different users and performed an analysis of the channel rate.

The paper is organized as follows. First, in Section I, we present the information-theoretic framework for quantifying the efficiency of a handwriting system where the system includes both the user and the computer. Next, in Section II, we describe our adaptive handwriting recognition algorithm that we developed for our experiment. Then, in Section III, we describe the experiment and present the results in terms of the performance measures derived from the proposed framework. Finally, we draw some conclusions in Section IV.

HANDWRITING RECOGNITION AS A COMMUNICATION CHANNEL
Unlike typing, which transmits information to the computer at discrete time points, handwriting continuously transmits
Next, we can define the channel rate in terms of the mutual information as follows.

\[ R_{\text{MI}} = \frac{I(M; Q_{\text{final}})}{E[T_{\text{final}}]} \]  

(1)

However, the channel rate \( R_{\text{MI}} \) is not suitable for practical implementation for two reasons. First, the estimation of \( H(Q_{\text{final}} | M) \) requires an extensive amount of data. Secondly, suppose the original intent is \( m \), \( R_{\text{MI}} \) yields a high value as long as \( P(Q_{\text{final}} | M = m) \) concentrates any single intent \( n \) even when \( n \neq m \). Thus, we propose an alternative measure to the \( R_{\text{MI}} \) based on the idea of log loss, called \( R_{\text{LL}} \).

We define \( R_{\text{LL}} \) to be

\[ R_{\text{LL}} = \frac{\sum_{m \in \mathcal{E}} P(M = m)(-\log_2 P(Q_{\text{final}} = m | M = m))}{\eta(Q_{\text{final}})} \]  

(2)

The relationship between \( R_{\text{MI}} \) and \( R_{\text{LL}} \) is worth noting. When \( (-\log_2 P(Q_{\text{final}} = m | M = m)) \) is small then the conditional entropy \( H(Q_{\text{final}} | M) \) is also small. As a result, the mutual information \( I(M; Q_{\text{final}}) \) will be close to its maximum possible value of \( H(Q_{\text{final}}) \). In other words, the log loss term \( (-\log_2 P(Q_{\text{final}} = m | M = m)) \) provides an upper bound for the conditional entropy \( H(Q_{\text{final}} | M) \) up to some constant factor. For the remaining of this paper, when we refer to the channel rate, we strictly refer to \( R_{\text{LL}} \).

Intuitively, the channel rate is a measure that quantifies both accuracy and speed of a handwriting recognition channel at the same time. Handwriting, as well as many other motor control tasks, obeys the speed-accuracy tradeoff. It is not sufficient to quantify the efficiency of a handwriting recognition system by its recognition accuracy alone. For example, a system that requires the user to write each character in a specialized form may attain a very high recognition accuracy, but it would require the user more time and effort to use. Such system might not be as efficient as a system that makes more errors but allows the user to write freely. This leads us to believe that the channel rate is a suitable measure that any handwriting recognition system should aim to maximize. In a sense, maximizing the channel rate is equivalent to finding a balance between maximizing the recognition accuracy and minimizing the writing time and effort of the user.

Based on this framework, it follows that the channel rate can be improved by a combination of human learning and machine learning, which corresponds to improving the handwriting process and the recognition process respectively. Ideally, \( Q_{\text{final}} \) will always be concentrated on the original intent \( M \). This would mean that the channel is perfect and works without error. However, in real-world scenarios, errors will occur. One source of errors comes from mistakes made in the recognition process. These recognition errors can be reduced using training data and machine learning. The harder problem is when there is a significant overlap between \( P(\mathbf{W} | M) \) for different intents. In this situation, we will need to rely on the user to make their handwriting less ambiguous. Although the effect of human learning is always present, we believe that it can be enhanced by giving useful feedback to the user in the form of guidance or lessons.

**ADAPTIVE RECOGNITION ALGORITHM**

We developed an adaptive handwriting recognition algorithm that, for every time step \( t \), maps a partial handwriting trajectory \( W_{1:t} \) to a posterior distribution over \( \mathcal{E} \), denoted by \( Q_{\text{final}} \).

By realizing that the effect of user adaptation is likely to be...
The initial adaptation is critical for any intelligent system. It is unquestionable that the performance of any well-behaved intelligent system increases as the system learns more about the user. If the initial adaptation is poor, the users might get frustrated with the system and stop using it even before it can fully adapt to them.

We address the problem of initial adaptation by sharing data across different users. Typically, people do have similar handwriting especially when they share the same educational culture. The process of the initial adaptation can be described as follows. In the very first interaction with the user \( u \), our system has no information about the user and, therefore, assign a set of typical prototypes which has been trained using data from multiple users in the past. Specifically, the typical prototypes are the centroids of the clusters returned by running a clustering algorithm (k-means) on a set of training handwriting instances. We refer to this set of prototypes as \( \mathcal{P}_0 \). After the first interaction, the system creates a new set of prototypes \( \mathcal{P}_{(u,1)} \) by recomputing the centroids of the clusters after adding the examples from the user to the pool with significantly higher weights than the rest.

**Adapting the prototypes over time**

After collecting a few examples of the user’s handwriting, the system again performs the weighted clustering algorithm on the data to generate a new set of prototypes \( \mathcal{P}_{(u,i+1)} \). In this stage, only examples from the user and previous prototypes are considered. This adaptation process happens after 3-5 new examples are acquired.

To improve real-time performance, we need to keep the lengths (number of states) of the prototypes as small as possible. After the new prototypes are chosen, the system performs an additional step to shorten the length of each prototype. This pruning process is similar in spirit to removing and merging unnecessary hidden states in an HMM. The basic idea is to remove unwanted states while maintaining the same recognition power using a variant of forward-backward algorithm \( [11] \). Figure 2 shows the hidden states before and after the reduction step.

**Decoding**

Our decoding algorithm is based on the standard Bayesian inference. Namely, given a trajectory \( W_{1:T} \) and the current set of prototypes \( \mathcal{P}_u \), the algorithm computes the distance from \( W_{1:t} \) to each of the prototypes in \( \mathcal{P}_u \) for all \( 1 \leq t \leq T \). The distances are then transformed into a probability distribution.
Figure 2: The hidden state reduction process is applied to each prototype to remove rarely visited states with respect to the training set. The originally trained prototype is shown on the left and the reduced prototype is shown on the right. The intensity of the colors corresponds to the expected number of times the state being mapped to.

\( Q_t \). We use \( e^{-x} \) as the transfer function. When a single prediction is expected, the algorithm simply returns the prediction with the maximum likelihood.

**EXPERIMENT**

The main objective of our experiment is to determine and quantify the effect of machine adaptation and of human adaptation when the users interact with the system over some period of time. We implemented the handwriting recognition system described in Section as an application on Apple iOS platform. The application was presented to the users as a writing game. In each session, each participant was presented with a random permutation of the 26 lowercase English alphabets i.e. \( \mathcal{E} = \{a \ldots z\} \) and \( P(M) \) is uniform. The objective of the game was to write the presented characters as quickly as possible and, more importantly, the handwritten characters should be recognizable by the system. A score, which is the average channel rate of the session, was given to the user right after each session to reflect the performance of the session. There were 15 participants in this experiment. We asked them to play our game for at least 20 sessions over multiple days in his/her own pace. We did not control past experience of the participants. Some of them had more experience with touch screens than others.

The experiment was set up to demonstrate a condition called **co-adaptation** where both the user and the computer were allowed to adapt together. We denote this condition \( R_{\text{adapt}} \).

To investigate the effect of co-adaptation, we create a controlled condition called \( R_{\text{fixed}} \) where the computer was not allowed to adapt with the user. In other words, we ran a simulation to figure out what the channel rates would have been if the prototype sets were never changed from \( P_0 \). Ideally, it would be more preferable to have \( R_{\text{fixed}} \) determined by another control group where the prototypes were kept fixed and never changed. However, the results from the simulated condition can be seen as a lower bound on the amount of the improvement attributable to human learning and, therefore, it is sufficient to demonstrate our point.

**RESULTS AND DISCUSSION**

The average channel rates per session of the two conditions \( R_{\text{adapt}} \) and \( R_{\text{fixed}} \) are shown in Figure 3a and Figure 3b respectively. In both conditions, the results show increases of the channel rate over time where the improvement in the early sessions seems to be larger than in the later sessions. Figure 3c shows the difference of \( R_{\text{adapt}} \) and \( R_{\text{fixed}} \) which corresponds to the channel rate of the system when we ignore the effect of user adaptation. From the result, we observe that the impact of machine adaptation tapers off after 10 sessions.
that the channel rate of $R_{adapt}$ is significantly higher than that of $R_{fixed}$ with $p < 0.0006$. This result confirms that the machine adaptation helps improving the overall channel rate. In addition, we calculate the theoretical maximum of the channel rate under the assumption of the perfect recognition, denoted by $R_{ideal}$. The maximum rates are given by $H(Q_{final})/E[T_{final}]$ and we approximated $H(Q_{final}) = \log_2(26)$.

In the case of perfect recognition, a simple way to increase the channel rate is to expand the character set $\mathcal{E}$ to include more symbols. However, in reality, doing so can lead to a recognition error rate which impairs the channel rate. An interesting future direction is to design a character set that would maximize the channel rate. Figure 5b reveals the efficiency of each letter for our handwriting channel. Characters with complex strokes, such as ‘q’, ‘g’, ‘k’, are not as efficient as characters with simple strokes such as ‘c’, ‘o’, ‘l’. While this finding is not surprising, it implies that, for a handwriting system to be truly efficient, it must allow the user to write in a less complex style while not losing recognition accuracy. How to exactly design such system is still an open problem and requires a more elaborate study.

**CONCLUSIONS**

We presented a information-theoretic framework for quantifying the information rate of a system that combines a human writer with a handwriting recognition system. Using the notion of channel rate, we investigated the impact of machine adaptation and human adaptation in an adaptive handwriting recognition system. We analyzed data collected from a small deployment of our adaptive handwriting recognition system and concluded that both machine adaptation human adaptation have significant impact on the channel rate. This result led us to believe that, for a handwriting recognition system to achieve the maximum channel rate, both machine adaptation and human adaptation are required and must be present together. Specifically, such system should be able to adapt to the user and, at the same time, allow the users to write or scribble using simple hand movement as improving writing.
speed is crucial for attaining a higher channel rate. Additionally, the system should have a mechanism to giving feedback to the user when their handwriting cannot be recognized.

REFERENCES
1. K. Höök, Steps to take before intelligent user interfaces become real, Interacting with computers 12 (2000) 409–426.
2. P. Maes, Agents that Reduce Work and Information Overload, Communications of the ACM.
3. B. Y. Lim, A. K. Dey, Assessing demand for intelligibility in context-aware applications, Proceedings of the 11th international conference on Ubiquitous computing - Ubicomp ’09 (2009) 195.
4. C. E. Shannon, A Mathematical Theory of Communication, Bell System Technical Journal 27 (July 1928) (1948) 379–423.
5. P. M. Fitts, The information capacity of the human motor system in controlling the amplitude of movement, Journal of Experimental Psychology 47 (6) (1954) 381–391.
6. S. D. Connell, A. K. Jain, Writer adaptation for online handwriting recognition, Pattern Analysis and Machine Intelligence, IEEE Transactions on 24 (3) (2002) 329–346.
7. N. Matic, I. Guyon, J. Denker, V. Vapnik, Writer adaptation for on-line handwritten character recognition, in: Proceedings of the Second International Conference on Document Analysis and Recognition (ICDAR ’93), IEEE, 1993, pp. 187–191.
8. W. Kienzle, K. Chellapilla, Personalized handwriting recognition via biased regularization, in: Proceedings of the 23rd International Conference on Machine Learning (ICML ’06), no. Section 6, Pittsburgh, Pennsylvania, 2006, pp. 457–464.
9. T. Plötz, G. a. Fink, Markov Models for Handwriting Recognition, SpringerBriefs in Computer Science, Springer, 2011.
10. L. Rabiner, B.-H. Juang, Fundamentals of Speech Recognition, Vol. 103 of Prentice Hall signal processing series, Prentice Hall, 1993.
11. J. Bilmes, A Gentle Tutorial of the EM Algorithm and its Application to Parameter Estimation for Gaussian Mixture and Hidden Markov Models, Tech. rep., ICSI (1997).
12. A. Newell, P. S. Rosenbloom, Mechanisms of skill acquisition and the law of practice, in: J. R. Anderson (Ed.), Cognitive skills and their acquisition, Vol. 6 of Cognitive skills and their acquisition, Erlbaum, 1981, Ch. 1, pp. 1–55.