Information Theory:
An Analysis and Design Tool for HCI

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ABSTRACT

Shannon's information theory, since its first introduction in 1948, has received much attention and successful applications in many domains. Apart from Fitts' law and Hick's law, which came out when experimental psychologists were enthusiastic about applying information theory to various areas of psychology, the relation of information theory to human-computer interaction (HCI) has not been clear. Even the two above-mentioned "laws" remain controversial in both psychology and HCI. On the other hand, in recent years, information theory has started to directly inspire or contribute to HCI research.

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This paper examines these information-theoretic applications and discusses the opportunities where information theory can be used to understand, design and optimize human-computer communication.

CCS CONCEPTS

• **Human-centered computing** → **HCI theory, concepts and models**.

KEYWORDS

HCI, information theory, model, performance, optimization, entropy, mutual information

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INFORMATION THEORY CONCEPTS

The communication scheme proposed by Shannon [19] (Fig. 1) has pioneered the modern analysis of digital communication and established *entropy* as a relevant measure of information. It states that a *source* produces messages, modeled as a random variable X, which are adapted by an *encoder* and then sent over a *channel* and decoded by a *decoder* to the final *destination*. The input of the channel is X and the output of the channel to the *receiver* is Y. Since there might be *noise* in the channel, output Y does not always equal input X. The engineering process to transmit a source message X through the channel does not concern the semantic aspect of communication, but is only related to the probability of each possible outcome. Therefore, the channel is completely described by the probability $p(Y|X)$ of Y given X. The key notions that have largely been used in psychology and HCI are *entropy*, *mutual information* and *channel capacity* (see sidebar on page 2).

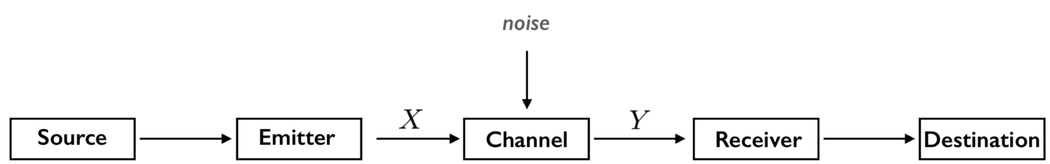

Figure 1. Shannon's communication scheme.

Entropy:

$$H(X) = -\sum_x p(x)\log_2 p(x).$$

where X is drawn according to the probability distribution $p(x) = P(X = x)$ and entropy $H(X)$ is measured in bit.

Mutual Information:

$$I(X;Y) = \sum_y \sum_x p(x,y)\log\frac{p(x,y)}{p(x)p(y)} = H(X) - H(X|Y)$$

where $p(x,y)$ is the joint probability function of X and Y, and $p(x)$ and $p(y)$ are the marginal probability distribution functions of X and Y, respectively.

Channel Capacity:

$$C = \max_{p(x)} I(X;Y)$$

where the maximum is taken over all possible input distributions $p(x)$.

Shannon's Theorem 17:

$$C = B\log_2\left(1 + \frac{S}{N}\right)$$

where B is the bandwidth and S/N is the signal-to-noise ratio.

INFORMATION-THEORETIC APPLICATIONS IN HCI

What is Throughput in Fitts' Law?

One direct application of Shannon's information theory that has been proven useful and has been largely studied in HCI community is *pointing*. Among many experimental psychologists back in the 1950s [1], Fitts conceptualized the human motor system as a communication channel [6] and proposed an operationalized formula [2] to capture the relationship between movement time MT and what we call *index of difficulty* ID. Fitts [6] also derived the *Index of Performance* IP, which is computed by dividing ID by the empirically determined movement time MT: $IP = \frac{ID}{MT}$, to represent the participant's maximum rate. This notion was later borrowed by Mackenzie [14] as *throughput*, which in engineering is widely used to measure an effective speed of data transmission [3]. Building on Card et al. [3], Zhai [23] argued that Mackenzie's throughput "is an ill-defined concept" and instead described the constant b in Fitts' formula as the informational aspect of input performance. Since Fitts' law is an analogy to Shannon's Theorem 17 (see Gori et al. [7] and sidebar on page 2), information theory should provide a straightforward way to analyze throughput. The first author's thesis [11] introduces an information-theoretic notion of throughput that generalizes beyond Fitts' law by considering input as communicating what is in the user's head to the computer over a noisy channel. We demonstrate its consistency compared with two existing notions of throughput and extend it from a single input random variable to sequential input such as text entry, accounting for conditional probability and a stochastic input process.

How Relevant is Hick's Law for HCI?

Together with Fitts' law, Hick's law [8, 9] was introduced to HCI in the early 1980s as a contribution of psychology to the design of human-computer interfaces [4]. It has been used in a number of HCI contexts but its applications have been controversial: Some researchers found that the law did not apply to HCI tasks while others regard it as a fundamental law of interface design. Hick and Hyman originally studied the relationship between the number of alternate stimuli and choice-reaction time by considering each alternate stimulus as the message; the sensory-perceptual system as the channel and the participant as the receiver. Choice-reaction time increases with uncertainty, captured by the information-theoretic notion of entropy (sidebar on page 2). HCI researchers, however, have applied it to various scenarios, including expert users' decision time by Cockburn et al. [5] and novice users' visual search time by Soukoreff & Mackenzie [20]. Even though Sears et al. [18] showed the incompatibility of the law with visual search, Wobbrock & Myers [22] used it to model visual search time. In the design community (e.g. [10]), on the other hand, the law seems to work universally. Our review of the state of the art of Hick's law as well as the historical context of the choice-reaction paradigm leads to the conclusion that Hick's law is in fact not very relevant for HCI [11].

[1] Most of these applications were summarized in a book by Attneave [1].

[2] Fitts' formula:

$$MT = a + b \times ID.$$

where a and b are empirically determined constants.

[3] Throughput captures the successfully transmitted information rate. It is computed by dividing the amount of successfully transmitted information $I(X;Y)$ by the average time T required to transmit such information and is measured in bits per second: $TP = I(X;Y)/T$.

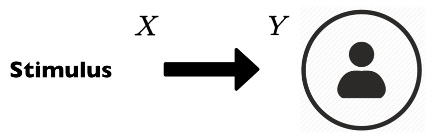

Figure 2. A model of communication system where users are the receivers [8, 9].

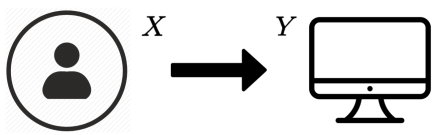

Figure 3. A model of communication system where users are the information source [2, 13, 15, 17].

A Human-Computer Communication Framework?

Several recent works have investigated the information transmission process from the user to the computer using the tools of information theory. Table 1 and Fig. 3 summarize these direct applications of information theory to HCI. We believe that these and the above-mentioned studies can be synthesized and expanded into a general human-computer communication framework. If we consider that the purpose of any input technique is to let users send information to the computer, the information-theoretic approach is well-suited to their characterization. For example, we have introduced the Bayesian Information Gain (BIG) framework [12] that quantifies the information in the user input to reduce the computer's uncertainty about the user's goal, expressed in a probabilistic model. One can use this framework to measure the information sent by the user to the computer. Moreover, by maximizing the expected information gain from the user's subsequent input through a proper choice of feedback, the computer can play a more active role in the interaction. By leveraging the notion of information gain, we can shift the balance of who is in control and investigate the notion of combining human intelligence with machine power.

Table 1. Recent HCI studies that leveraged the information-theoretic concepts.

Reference	*Area*	*Description*
Oulasvirta et al. [16]	Movement	Throughput is calculated from mutual information of two or more deliberately repeated movement sequences.
Berdahl et al. [2]	Gesture	A model to account for human subject controlling a single, continuous sensor where the signal-to-noise ratio of the recorded gestures determines channel capacity.
Williamson and Murray-Smith [21] & Liu et al. [12]	Human Intention	Computer reduces the information-theoretic notion of uncertainty about the user intention.
Roy et al. [17] & Liu et al. [13]	Performance Measures	Using information-theoretic notions for measuring interaction techniques.
Zhang et al. [15]	Text Entry	A text entry throughput metric inspired by information-theoretic concepts.

CONCLUSION

The full spectrum of conceptual and practical benefits of Shannon's information theory seems to have a lot to offer to HCI. We hope that this paper will spur discussion and inspire more work that uses information theory to clarify our understanding of existing models and to design future user interfaces.

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