On Human Information Processing in Information Retrieval (Position Paper)

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ABSTRACT

Experimental psychology, cognitive science or, more recently, cognitive neuroscience, is the main framework to place human information processing under extensive empirical scrutiny. The last decade has seen a surge of interest in the application of psychological measurements for evaluating increasingly complex human-technology interactions. While most welcome from the psychological perspective, we propose that the use of these methodologies should not rely only on the application of sophisticated measurement tools, but also on the application of contemporary knowledge on psychological phenomena and dynamics of human information processing. In addition, we argue that the latest developments in multimodal signals and data mining techniques offer a unique opportunity to extend psychological methodologies to large scale testing grounds. Thus, the application of psychological knowledge to information retrieval research will not only be beneficial for the latter, but for the former as well, inasmuch as information retrieval provides a real field of application for its hypotheses about human information processing.

Categories and Subject Descriptors

H.1.2 [**Models and Principles**]: User/Machine Systems—*Human factors*; H.3.3 [**Information Storage and Retrieval**]: Information Search and Retrieval

Keywords

cognitive neuroscience; information retrieval; human information processing; experimental methodology

1. INTRODUCTION

Our approach is grounded on cognitive psychology, a view that is dominant in psychological research and in which people are characterised as "information processors". In this framework, perception is the first stage in information processing, and refers to the processes whereby sensory information from the environment is made available to information processing systems. In turn, cognitive reactions refer to those processes by which information is manipulated (e.g., filtered, coded, compared, retrieved). The most interesting psychological variables and processes for the study of information retrieval (IR) are those related to attentional and emotional phenomena.

Regarding attention, cognitive science has provided large amounts of evidence that conscious information processing is primarily serial. When processing information in situations that require to shift the focus of attention between different tasks or stimuli, this results in an increase in the effort required to process that information [13]. In the field of basic cognitive psychology, this phenomenon has been extensively studied by means of experimental paradigms that allow to determine, for example, the degree to which performance on a given task is affected by concurrently performing a secondary task [13, 20], or the actual performance cost of attention shifts [21, 22]. Regarding emotions, a theoretical approach that has proven useful in quantifying emotional reactions defines emotions [15] as a function of two components: affective or hedonic valence, that is if the emotion is positive or negative, and arousal, meaning the intensity of the emotion. However, several other theories and methods have been employed in the field of emotion research. For a detailed review we refer the reader to [19].

A wide collection of methods is available to measure such aspects, grounded on different methodologies depending on the type of question explored. First, to analyse conscious processes, there are standardised questionnaires for measuring perceptual aspects, perceived usability [17], cognitive working load [12], or affective reactions [7, 31], among others. Nevertheless, since it is unlikely that people can report information about processes over which they have little or no awareness [4, 24], psychological research has traditionally favoured methods that allow exploring unconscious or automated psychological processes. Such methods provide online, moment by moment information, and are not dependent on subjective biases such as social desirability. A broad classification of these methods could be: (i) behavioural, that is, measurement of psychophysical thresholds (e.g., reaction times, motion, eye tracking), and (ii) neurophysiological, which entail measuring physiological changes in users in response to psychological stimuli.

Behavioural methods (with the exception of tracking measures) often require designing specific tasks where different variables are manipulated in order to to measure psychological effects associated with different aspects of their performance. Neurophysiological signals on the other hand, al-

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low psychological measurements while users are interacting with the assessed technology, and have been favoured in media research [2, 10, 14, 23, 28, 30]. When the central nervous system is the object of measurement, electrical brain activity (EEG) is the most widely used method, as it can can provide information about attention and cognitive effort [11], as well as about emotional reactions [8]. Peripheral nervous system activity measurements are very informative when measuring emotional reactions as well, and can also signal some of the attentional reactions. The most popular methods are electrodermal activity, which provides information about emotional arousal and cognitive effort [13], facial electromyography, which can inform about the valence of emotional reactions [16], and phasic and tonic changes in heart rate, which are related to attention, cognitive effort and stress, and emotional reactions [26].

2. APPROACH

As mentioned above, research on human information processing has consistently demonstrated that human beings are not consciously aware of the mental processes determining their behaviour [24, 27]. Such unconscious influences do not need to be restricted to basic or low-level mental processes, but can also reach high-level psychological processes like motivations, preferences, or complex behaviours [5]. This has obvious implications when it comes to the assessment of user experience in human-computer interaction (HCI) contexts. For example, previous research in the context of web search has shown that response latency values lower than a certain threshold are unnoticeable by the users and, therefore, inconsequential in terms of user experience [3, 6].

In [6], the authors performed a controlled experiment and demonstrated the effects of small increases in response latency, using physiological measures of emotional arousal and valence. These physiological signals were then compared against data gathered from self-reports. Results showed that the former were more effective in capturing the attentional and emotional reactions to increasing response latency. Although such short latency increases of under 500ms were not available to self-report, they had sizeable physiological effects. This leads to an obvious question, what is the actual effect that such delays might have on the engagement of users? As mentioned earlier, research in psychology has demonstrated that our motivations and preferences are not always determined by conscious objectives or reasons. Indeed, by means of a large-scale query log analysis, the same study [6] revealed a significant decrease in users' engagement with the search result page, even at small increases in latency.

The interest in integrating the information provided by psychological measures in modelling user interaction with IR systems is therefore obvious. However, our approach to modelling user experience will not only consist in applying measuring methodologies, but also in applying the knowledge about a plethora of well-known phenomena in human information processing. In this sense, it is worth noting that information processing is intrinsically dynamic and, for instance, it is well known that previous events have a significant effect on the processing of current events [21, 25]. Although this phenomenon has been extensively studied in laboratory conditions with artificial tasks and stimuli, its study in the context of IR research offers a unique opportunity to observe how this phenomena affect real-world tasks. One of the main problems of scientific psychology has been one of external validity: psychological experiments too often test micro-hypothesis about concrete processing phenomena in tightly controlled laboratory conditions, thus making difficult its application to real-life situations. Aspects of HCI, such as user studies of IR, provide precisely these real-life grounds in which to observe the actual validity of our models of human information processing. Therefore, building bridges between IR research and experimental psychology will clearly be a mutually beneficial endeavour for both fields.

Finally, let us comment a further beneficial aspect of this approach that makes reference to its scalability. There is plenty of evidence on how modelling of psychological phenomena from audio-visual data is possible, as exemplified from recent advances in social computing [1]. For example, it has been shown how fusion of audio-visual data is significant for the prediction of various behavioural patterns and phenomena in social dialogue in human-human interactions, such as dominance [29]. Many HCI studies have shown how, when it comes to conversational interaction with or through computers, in addition to verbal cues, people display a lots of nonverbal cues such as body posture, head and hands movements, interpersonal distance, direction of gaze, smiling or frowning, and many other nonverbal behaviours [9].

Accordingly, in recent years, computer vision and speech analysis tools (e.g. eye tracking, emotional expression analysis [9, 18] or emotional speech analysis) have become available to measure the user responses from data retrieved with off-the-shelf hardware, such as web-cameras and microphones. However, despite the worthy advances made in the last years towards obtaining robust measures of cognitive and emotional variables by means of audiovisual measures (i.e., measures based on audiovisual recordings of users), the thrust has been mainly on the technological challenges. Therefore, there is an increasing need to understand the key elements of the user experience in specific contexts of use, given that it is the particular context of use what will determine which variables are most informative and which methods for collecting behavioural information are available and optimal.

Our approach here will be to develop contextual models of the specific use conditions that establish the putative relationships between the observable user behaviour (physiological and audiovisual signals), psychological indicators (such as arousal, valence, cognitive load, etc.), and high-level psychological variables defining the key aspects of the user experience, such as user engagement, satisfaction or performance. These contextual models would then inform the training of machine learning or deep learning models aimed at predicting the relevant, high-level psychological variables in the specified contexts of use. These are emerging opportunities that are beginning to allow for truly user-centred analysis in ecological environments far beyond what has been previously possible. In this context, our approach targets the emerging scenario in which the interaction is enhanced with the employment of motion and biometric sensors. This will allow for a robust, real-time, behaviour analysis where information can be used for the purpose of research on human behaviour and user experience. Imagine for example that in the study described above, we had access to this kind of psychological measures at large scale. The opportunity is ripe to move beyond experimental laboratory settings into large-scale, controlled experimentation.

3. CONCLUSIONS

The use of neuro-physiological methods in IR research is essential in order to obtain a complete picture of the mental processes underlying user search behaviour, as exemplified in our own initial research on the topic. However, the collaboration between psychological and IR research can go far beyond the application of sophisticated measuring methodologies, and bring actual knowledge on the dynamics of human information processing into a real-world testing ground. Moreover, the use of multimodal signals holds the promise of allowing large-scale, controlled studies that will undoubtedly foster the progress of both research fields.

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