Exploring Effective Decision Making through Human-Centered and Computational Intelligence Methods

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Abstract
Decision-making has long been studied to understand a psychological, cognitive, and social process of selecting an effective choice from alternative options. Its studies have been extended from a personal level to a group and collaborative level, and many computer-aided decision-making systems have been developed to help people make right decisions. There has been significant research growth in computational aspects of decision-making systems, yet comparatively little effort has existed in identifying and articulating user needs and requirements in assessing system outputs and the extent to which human judgments could be utilized for making accurate and reliable decisions. Our research focus is decision-making through human-centered and computational intelligence methods in a collaborative environment, and the objectives of this position paper are to bring our research ideas to the workshop, and share and discuss ideas.

Author Keywords
Human-centered decision-making, human-in-the-loop machine learning, user-centered design

Introduction
Decision-making is a cognitive process of selecting an effective and logical choice from several available and

alternative options [5]. It happens at all times in one's life from trivial cases to important events and many times is influenced by one's psychological needs, situated contexts, and personal traits. When it goes beyond a personal level (e.g., group or organization), decision-making becomes more complex, and its success is critical for cost reduction and risk mitigation in the organizational context [3].

Decision-making used to be studied at an individual, personal level, but over time, more elements (e.g., social, collaborative, etc.) were considered together. In the early 19th century, scientists and scholars envisioned that computers would improve human decision-making. After the 1990s, there were a number of computer-aided decision support systems developed by scientists and used by employees in organizations. This trend was fueled and expanded after the emergence of the Internet and personal computers, opening up an opportunity for individuals and experts in different domains to utilize networked computers to identify and solve problems, and provide new insights [3].

Decision-making systems consist of four fundamental components; namely, data management, model management, knowledge management, and user interface management [17]. Data management refers to the function of storing and maintaining the information. Model management represents relationships among variables in the data and provides practical and sometimes experimental results and analyses. Knowledge management provides information about the relationship among data that needs human knowledge or heuristics to manage alternative options properly. Lastly, user interface management allows experts to access and interact with system outputs and combine their knowledge for the analysis through the interface.

Over the years, computational power, ability, and capacity of computer technology have significantly increased, which enable the evolution of decision-making systems that incorporate various intelligence methods such as complex machine learning, data mining, automated inference, visualizations, etc. This also affects all four components of decision-making systems. For example, a large amount of data can be collected, stored, and managed (data). A large dataset can be used, trained, and tested through different machine-learning models (model). Results can be presented in interactive interfaces such as visualizations, allowing experts to identify problems and patterns, and make right decisions (knowledge and user interface). At the same time, however, there exist many challenges. Data itself is heterogeneous and highly complex, and its volume keeps on increasing. Even state-of-the-art machine learning algorithms do not produce perfect predictions or solutions. As such, experts need to consider these limitations when dealing with system outputs and make their decisions carefully.

It is possible that developing a more robust and reliable machine-learning algorithm would mitigate this challenge. However, researchers have expanded their focus not only on algorithmic and computational aspects, but also on the possibility of utilizing human knowledge to improve a performance of underlying machine learning algorithms in the system. This refers to human-in-the-loop machine learning in decision-making.

The idea of human-in-the-loop machine learning emerged to counteract situations where humans tend to be passive recipients with little control over system outputs, even if they are active in making decisions. It emphasizes that humans should play an active role in changing the outcome of an event or process [1]. It assumes that, given incomplete outputs from the model, humans can provide supervised labels or additional information in an active learning environment, which in turn would drive the system toward end users' intended behaviors and purposes and increase the overall accuracy and reliability of system outputs and decision-making.

Research Motivations

A person's ability to utilize the system outputs for decision-making depends on the information presented to them by the system interface; therefore, designing an effective interface is of the upmost importance. Prior research in human-in-the-loop machine learning has primarily focused on increased accuracy after utilizing human judgments for generating new training data and classifiers through relatively simple tasks such as answering questions that have few selections [10], drawing contours of a requested item [6], annotating texts [11], etc. However, this may not be sufficient in a complex, collaborative, data streaming environment that demands iterative human-in-the-loop interactions. Studies have shown the positive effects of providing information such as validity, reliability, etc. of computerized decision aids on human judgment performance [12,16]; however, its research focus emphasizes primarily the technical aspects and pays very little attention to identifying and articulating *user needs* and *requirements* — to name a few, *comprehension, knowledge, mistake, satisfaction, frustration, preference, environment*, etc. — in understanding and assessing system outputs, making their decisions, and the extent to which human judgments could be utilized for making accurate and reliable decisions. In fact, prior research has already identified a lack of design principles and guidelines for interactive machine learning systems that require in-depth understandings of users and calls for action to study and articulate them [1].

With these research motivations in mind, we would like to investigate how to leverage both machine and human capabilities in making accurate and reliable decisions. Our collaborators are climate scientists at Pacific Northwest National Laboratory who use decision making systems to understand and analyze large volumes of multidimensional data; for example, how ecosystems will respond to climate changes. They are situated in a complex and collaborative environment where data is constantly generated, and machine learning algorithms and visualizations are extensively used. With this specific domain, the objectives of our research are as follows:

1. Understand the flow of decision-making and unpack user needs and requirements for developing evaluation techniques and standards for interactive machine learning systems.
2. Design and develop an interactive decision support prototype that reflects those needs and requirements.
3. Assess the impacts of the prototype on decision-making and discuss theoretical and design implications.

Our research idea asks for the careful design of user studies, the development of a prototype, and the collaboration with domain experts. We will employ contextual design [2], a user-centered design process to collect data about users in the field (understanding how they make decisions collaboratively through interviews, observations, and surveys), interpret and consolidate the data in a structured way, identify user needs, use the data to create and prototype product and service concepts, and iteratively test and refine those concepts with users. We will directly leverage our prior research on user-centered research [7,13] and decision-making support systems and processes [14,15]. This will allow us to discover and articulate user needs and requirements when users interact with machine learning outputs.

Research Goals and Interests

As one of our research interests, we want to investigate a decision making process with particular emphasis on *improvement* and *tradeoff*. Prior research has shown that when people access multiple alternatives in parallel they produce higher quality and more diverse work with higher self-confidence [4]. Conversely, according to Hick's Law [8], the complexity of a given decision increases with the log of the number of alternatives which results in increased cognitive load in the decision-making process. We will investigate how these conflicting aspects are operationalized in a collaborative and streaming data environment with the following two hypotheses (and we expect that these hypotheses might be changed or further developed depending on what user needs and requirements identified in our first study).

- H1: Providing multiple alternatives will lead to less cognitive bias, improve accuracy of the results, and boost confidence of decision choices.
- H2: Providing too many alternatives will increase cognitive load, reduce accuracy of the results, and lower confidence of decision choices.

Our prototype designed based on user study results will allow users to generate alternatives depending on their own criteria and access other user-generated alternatives along with the result from ordinary machine learning.

Another interesting research question that we want to investigate is understanding how/what experts do and use computer systems to make their decisions through a collection and analysis of explicit and implicit user behaviors and interactions, aiming at enhancing group collaboration for making better decisions. This builds on the idea of Meeting Mediator [9], measuring social signals in real time for the quality of conversations, but our focus extends this idea and is more on the overall process of decision-making in a collaborative environment. Through our interface, experts can explicitly indicate their feedback on system results, and the system can be designed to implicitly collect their system usage logs. User behaviors then will be mined by machine learning and visualized, which can be used to improve interactions among experts and further make better decisions.

Given that this is our initial step for this research (and also human-centered machine learning is a relatively new research area), we would like to bring our research ideas, discuss our research questions, study design, evaluations, etc., and share insights with participants who have different background and expertise at this workshop.

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