Visual Analytics Driven Human-Computer Collaborative Decision Making to Solve Global Challenges

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Abstract
Growing accessibility and availability of data and cloud computing create new opportunities to rethink and redesign critical engineering systems and address outstanding global challenges. The machine learning approaches, having succeeded in many new fields of study, will have many issues as they get adopted in system of increasing complexity, scale and criticality. In this paper, we present the Human-Collaborative Decision Making (HCCD), a framework that leverages both artificial and human intelligences through visual analytics to produce explainable and trustable information that support decision making in complex and critical systems. We demonstrate the generalizability, superiority, impact and potential of HCCD in a wide range of applications.

Key Words: Human-Computer Collaborative Decision Making (HCCD), Decision Making Systems, Explainable AI (XAI), Artificial Intelligence, Visual Analytics, Interactive Machine Learning

1. Introduction

The past decade has witnessed a revolution in technology (Lasi et al., 2014). Data logging devices including smart phones, IoT device and sensors, and microprocessors have become omnipresent due to their decreasing cost and increasing computing power (Atzori et al., 2010). Cloud technologies made accessing and processing of big data possible for anyone (Fox et al., 2009). These drastic changes introduce many opportunities for rethinking and redesigning of existing engineering systems and creating new tools to address outstanding global challenges, e.g. (Ostrom et al., 1999).

Artificial Intelligence (AI) including machine learning has permeated numerous new fields of study, feeding off the growing volumes of data and cloud computing (Nilsson, 2014). Current research and application of data driven AI has primarily focused on processing and modeling of data and performance improvement of existing AI methods (Müller and Bostrom, 2016). We argue that a far more superior solution to extracting knowledge from data is the Human-Computer Collaborative Decision Making (HCCD) environment, particular for critical, complex, large scale systems and consequential decisions. HCCD leverages the speed and memory of artificial intelligences and the cognition and reasoning of human intelligences, and therefore is better at making intelligent, explainable and trustable decisions.

Visual analytics is an interdisciplinary research area that designs and develops real-time software systems that allow users to visually and interactively explore voluminous data and extract knowledge that support decision making (Keim et al., 2008). Visual analytics has been applied in many critical decision systems such as public safety surveillance and sustainable agriculture (Zhang et al., 2014; J. Zhao et al., 2019). As AI gets adopted to more complex and large-scale systems and operations, visual analytics can provide a HCCD environment that ensures outputs of AI components are explainable and trustable. Additionally, visual analytics can also be used to directly explain machine learning models through visualization and interactions among data, models and end users.

In this paper, we present the HCCD, a framework that integrates artificial and human intelligence through visual analytics, to produce explainable and trustable information that support decision-making in complex and large-scale situations. We demonstrate HCCD's wide range of applications in explainable deep learning, public safety, and sustainable agriculture. We will also discuss the open problems and future directions of HCCD.

The rest of the paper is organized as follows. Section 2 provides an overview of related work in Human-Computer Interaction, Human-Computer Collaboration, and the most current AI technologies and applications. Section 3 details the HCCD framework, its advantages and open research problems. Sections 4, 5 and 6 showcases applications of HCCD to a spectrum of complex problems. Section 7 concludes the paper with a discussion on future directions of HCCD.

2. Related work

The study of relationship between human and computer in decision making systems is not new. We discuss selected four research areas that are related to HCCD and support the adoption of HCCD.

2.1 Human Computer Interaction

Human-Computer Interaction (HCI) studies the way computer technology influences human work and activities and uses such knowledge to improve technology usability and user experience (Dix, 2009). Active research in HCI includes augmented reality, knowledge-driven human-computer interaction, and brain-computer interactions (e.g. (Billinghurst et al., 2015; Chen et al., 2015; Ye et al., 2015)

These areas provide new tools beyond visualization for human computer collaboration. Human gesture in HCI for example studies human gestures as an input method to communicate with the computers aiming to bridge the gap between human and computer by making the interaction as natural as human to human as possible (Rautaray and Agrawal, 2015). Gesture-based human-computer interaction often focuses on measuring and analyzing different body parts or objects, especially hand gestures (Karam, 2006). Devices such as CyberGlove II and SoftKnetic HD cameras has further supported the technology needed to make such analysis (Kevin et al., 2004). However, there remain challenges such as analyzing cluttered scenes where nearby objects and surfaces interact, methods not sharing the same evaluation criteria making comparisons difficult, and systems not generalizing beyond training sets (Supančič et al., 2018).

2.2 Human Computer Interaction

Human Computer Collaboration (HCC) is another general research area which studies the collaboration among at least one human user and one computation machine to accomplish a common goal (Terveen, 1995). HCC is a unique approach to benefit from both high computation power and empirical domain knowledge. The central theme of HCC is facilitating human users to gain understandable and trustable insights from the results provided by computation machines.

HCC has been widely applied to knowledge discovery (Valdés-Pérez, 1999), collaboration between multiple users (Dillenbourg and Baker, 1996), designing visual analytics framework for big data (Crouser and Chang, 2012). More recently, crowdsourcing (Howe, 2006) and social computing (Parameswaran and Whinston, 2007) that integrate knowledge from a large population pool, has gain great research interest. HCC can also provide theories, methods and principles for optimizing the designs of complex HCCD environments.

2.3 Human Computer Collaboration

Artificial intelligence (AI) can broadly be described as the science of designing computational artifacts for performing various human tasks or, related to cognition, the science of knowledge representation and reasoning (Pomerol, 1997). AI-driven decision-making has become increasingly relevant in recent years with advances in natural language processing, machine and deep learning, and speech recognition (Jarrahi, 2018). In recent years, AI has been widely adopted in many traditional scientific disciplines to leverage increasing data and computing power. For example, computer vision and pattern recognition methods have been increasingly used to monitor grain production (Patrício and Rieder, 2018) in agriculture.

While AI-driven agents' rate of learning and reasoning is impressive, they are limited by their inability to use common sense and adapt to new areas. However, AI-human collaboration has emerged as a powerful area, combining both the strengths of humans and computers. For example, while a pathologist was able to outperform a deep learning system in identifying metastatic breast cancer, combining the system's predictions with the pathologist's resulted in an approximately 85% reduction in human error (Wang et al., 2016).

3. Visual Analytics Driven HCCD

This section details the proposed HCCD framework, including the components and the process and operational environment of HCCD. Section 3.1 describes the HCCD components, process and operational environment. Section 3.2 discusses the scope of applications and benefits of HCCD.

3.1 Human-Computer Collaborative Decision-Making (HCCD)

Components of the proposed framework HCCD are shown in Figure 1. HCCD integrates three components, real-time information, historical information, and computerized knowledge into one visual analytics platform that collaborates with users or stakeholders in decision making. The real-time information come from physical IoT sensors such as in-situ sensors and remote sensing, or cyber sources such as social media, in geographically distributed transportation, environment and other large-scale systems. The second component, historical information, refers generally to other existing or available data that stakeholders have used and can use for decision making, including current database and known policies. Finally, HCCD requires the assembly of related scientific (e.g. physical, dynamics, economical, sociological, and data) models as well regulatory and operational constraints which can be computerized.

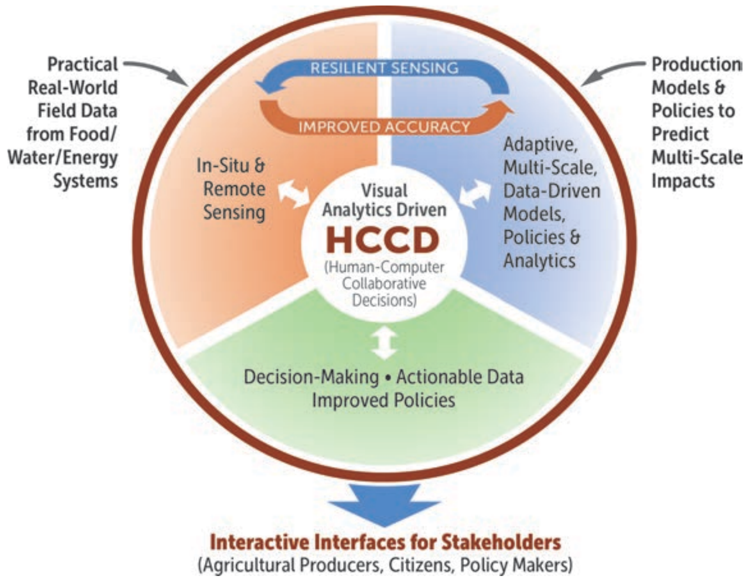

Figure 1: Illustration of HCCD for decision making in agriculture

These three components are the raw material for an HCCD environment, where visual analytics is then applied to for an interface that facilitates the knowledge discovery of end users. Data and computerized knowledge will need to be organized in a hierarchy that represent different levels of abstraction and addresses needs in the targeted application. The interaction between data and computerized knowledge, e.g. machine learning models, will also help users understand the context of the model outputs. In certain cases, HCCD can be used solely for this purpose (e.g. Section 4). This process will require knowledge of artificial intelligence, cognitive science, human factor and uses an iterative user-centered design approach to meet specific requirements of the end users and optimize the effectiveness the collaborative environment.

3.2 Applications and advantages of HCCD

The HCCD is a generalizable and scalable framework that can be applied to a spectrum of problems. The need for HCCD increases when the application problem at hand grows in complexity, scale and/or criticality. Examples of such problem range from interpretation of AI models (e.g. deep learning) to criminology to Food-Water-Energy systems to climate change. Figure 2 exemplifies the interactions between HCCD environment with external sources of real-time information, historical information, and computerized knowledge as well as the range of domains these sources. Sections 4, 5 and 6 will showcase some successful applications of HCCD in these areas.

In these applications, HCCD is an inherently advantageous environment compared with the stand-alone AI solutions. We summarize these benefits as follows:

- Provides a balance of automated computerized analysis and human cognition to amplify human-centered decision making.
- Leverages both human knowledge and visual analysis to increase analytical efficiency and guide simulations and analysis
- Enables interactive simulations, dimensional reduction, clustering, analytics to improve decision making
- Creates interactive discovery, planning and decision-making environments

- Discovers knowledge about role of visual display and interfaces in discovery and decision-making

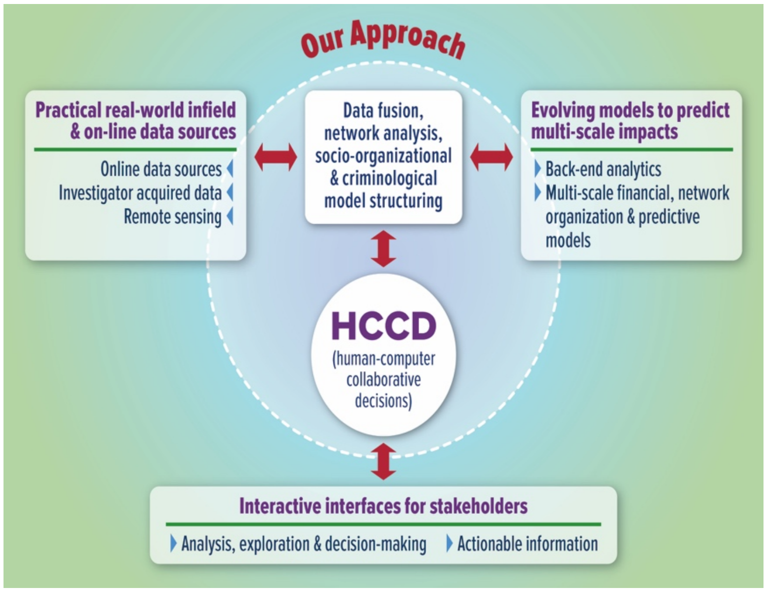

Figure 2: HCCD operational environment

4. HCCD and Deep Learning

4.1 Limitation of Deep Learning Models

4.1.1 Limitation of training data

Deep learning symbolizes the current state of AI technologies and machine learning research. The standard machine learning process includes data preparation, feature engineering, training, evaluation and implementation. It is common practice to spend 80% of time to prepare data for model training. Since learning is retroactive, the model will not adapt to evolutions of system dynamics, future significant events, and new patterns. This issue exacerbates with deep learning models, as the data relies on extremely large dataset and requires extended time to train.

Data are information collected about real-world processes, which follows the laws of physics and established theories in respective disciplines. Data models, with machine learning or not, is an approximation of the generative real-world process, whose dynamics models may already exist. Machine learning models train exclusively on input data and does not account for science-based physical and dynamical models. Integrating the two models remain an open research problem.

4.1.2 Interpretability and Trust

There also exists a trust issue with deep learning in practice. Like other machine learning models, deep learning takes a black-box approach, where learning follows predetermined automated procedures and has limited options for domain experts to incorporate even common sense and basic human knowledges (Adadi and Berrada, 2018).

While per defined metrics, e.g. precision and recall, deep learning may produce satisfactory performances for different tasks, in many scenarios, e.g. critical information is sparse, it will have little practical value. For example, deep learning models may have 99.99%

accuracy detecting pedestrian obstacles in autonomous vehicles, a single mistake may result in a fatal casualty and creating far-reaching legal, policy and public trust issues for adoption of self-driving cars.

4.1.3 Lack of context
Machine learning models require data to be transformed into numeric representations, unlike cognitive processes of a human. The inputs are also treated as independent variables, when in most cases they are not. Connections among different inputs, often critical in human's sense-making, are lost in the processing of input data. In natural language processing for example, many vectorization methods focus on the frequencies and orders of words, whereas humans rely on semantics for comprehension.

Predictions of machine learning are provided without explanation. In many cases, it is not sufficient to make decisions based on predictions with uncertainties, but why the prediction is made, e.g. responsible variables and patterns. Since the training process is a "black-box", the results are not explainable.

4.2 HCCD for Deep Learning
4.2.1 HCCD for model analysis
HCCD can compensate the limitation of machine learning by allowing human users to explore and experiment with training data and deep learning models. Visualization can be developed to understand parameter influence, training process and convergence of the model. In this process, user can iteratively better model performances, develop confidence on the model, and understand data and model limitations informed model implementations.

For example, Wongsuphasawat et al. designed the TensorFlow Graph Visualizer, providing a high-level overview of the model's graph structure as well as individual inputs and outputs of each layer (or node) in the model, such as the weights or bias (Wongsuphasawat et al., 2017). This visualizer allows users to more effectively understand a model's complex structure and operations, the high- and low-level workflow, and potential limitations that would otherwise be difficult to identify.

4.2.2 Mixed-Initiative and Interactive Machine Learning
With both artificial and human intelligences in the HCCD environment, there is an opportunity for the mixed-initiative learning, where knowledge extraction may originate from either machine learning models or the human agents. Endert has explored many different scenarios of how to integrate the human and computer effectively in analysis problems (e.g. (Endert et al., 2011; Endert et al., 2012).

Interactive machine learning in which users iteratively train machine learning models is especially important for finding relevant information during evolving situations and events since models that are trained offline may not perform well as the definition for relevancy changes over time. Figure 3 shows an example (Snyder et al., 2019) of an interactive learning framework for facilitating situational awareness in which social media analysts incrementally train text classifiers by correcting (relabeling) the relevancy of real-time tweets during evolving events, outperforming state-of-the-art offline models. The underlying HCCD environment in this example demonstrates the interactivity between human users and the machine learning process. HCCD allow users to develop better understanding and confidence of the developed models as a result.

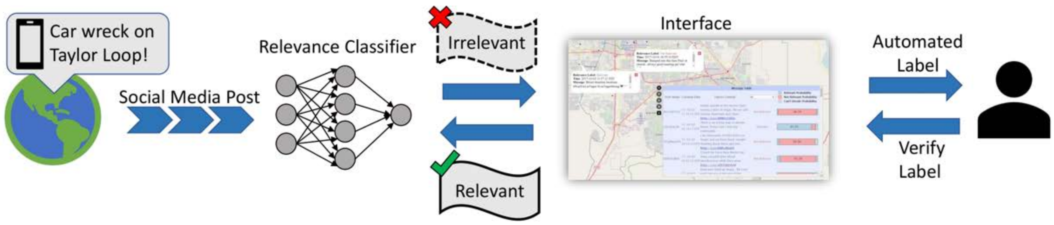

Figure 3: Example of interactive machine learning (Snyder et al., 2019)

5. HCCD and Public Safety

5.1 Background

Social media is a rich source of eyewitness accounts and field information. There is a great value as well as challenge in harnessing social media analytics to improve public safety and security, and improve safety during a terrorist attack, natural disaster and other emergency events. Meanwhile, significant increases in text, image, and video data (with limited quality, relevance, and reliability) can reduce first responder sensemaking and coordination capabilities in time-critical event detection, isolation, and response tasks due to information overload.

5.2 Social Media Analytics and Reporting Tool (SMART)

SMART is a visual analytics application that streams real-time, geotagged tweets to facilitate situational awareness. SMART provides a number of advanced visualizations and tools for spatial clustering, textual filtering, topic modeling, and anomaly detection. SMART's design and selection of visual tools is inherently human-centered and effectively supports situational awareness through automated algorithms and interactive machine learning. However, system training is needed for effective use, and users must know which visualization tools to apply for quickly understanding an evolving situation, especially when it is time-critical, as well as identifying potentially important information. Figure 4 shows the user interface of SMART which enables a HCCD environment.

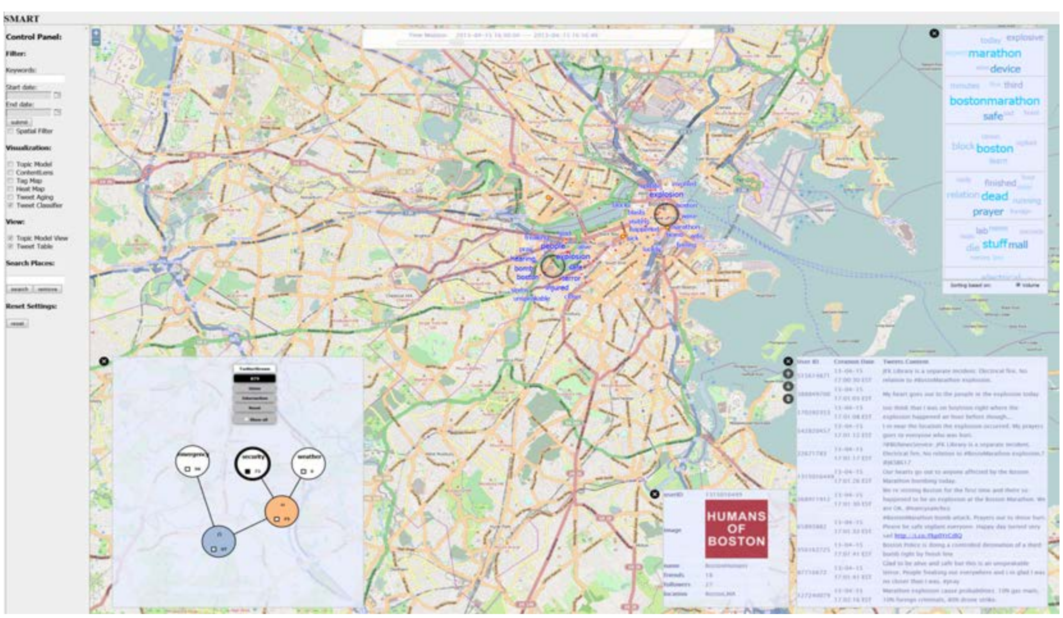

Figure 4: User Interface of HCCD in SMART (Zhang et al., 2014)

5.3 Evaluation and Impact

SMART 2.0 (Snyder et al., 2019) an extended version of SMART that provides interactive machine learning, resulted in significant improvements in tweet relevancy classification performance (F_1 score) by allowing users to iteratively train text classifiers as opposed to using a statically trained model. SMART 2.0 users also found that the interactive learning noticeably expedited the process of locating important information during events such as basketball games, shootings, and widespread wildfires (e.g. specific blood drive and wildfire locations).

6. HCCD and Agriculture

6.1 Background

Smart agriculture catches the attention of plant breeders and becomes increasingly popular due to its benefits of capturing plant status with remote sensing technologies. For instance, various sensing cameras (e.g., RGB, LiDAR, hyperspectral, thermal cameras) can be mounted on Unmanned Aerial Vehicles (UAVs) to collect the physical appearance of plants. Instead of traditional hand-measured plant characters, which is an expensive and time-consuming manual process, remote sensing technologies can efficiently obtain a large amount of data for numerous plants throughout the entire growing season. Usually, the plant characters, which the plant breeders are interested in, takes extra steps to derive, such as the end of season plant biomass. Biomass is a critical indicator for the estimation of productivity and yield.

The prediction of plant biomass involves the application of regression models that taking a series of hyperspectral images as input. For hyperspectral images, each pixel on a photograph records the spectrum of visible light (range from 400 nm to 900 nm) and then binning by 5 nm. Therefore, the dimension of input data samples is high and demands a long computation time. To help domain experts to understand how the regression models perform as well as identify the critical set of input features that impacts the performance. We collaborated with remote sensing experts and plant scientists to design an interactive exploration system to assist the feature selection and model exploration.

6.2 FeatureExplorer

FeatureExplorer (Zhao et al. 2019) is a visual analytics system designed to facilitate the evaluation of regression models and interactive feature selection. As shown in Figure 5, FeatureExplorer consists of 3 panels: *a*) the control panel to support the interactive selection of features, *b*) the feature correlation panel with a sorted correlation matrix and a scatter plot for a selected pair of features, *c*) the evaluation panel to display the prediction results of regression models and the importance ranking of features. The correlation matrix in Panel *b* and the feature importance ranking in Panel *c* are two methods to rank the features. The correlation matrix displays the linear relationship between a pair of features in a tabular visualization. The feature importance ranking shows the predictive contribution of features in regression models, and it captures the latent features that can be generated from input features. The users can explore the ranking of features for these two methods and interactively select the features that have both high correlation with biomass and feature importance.

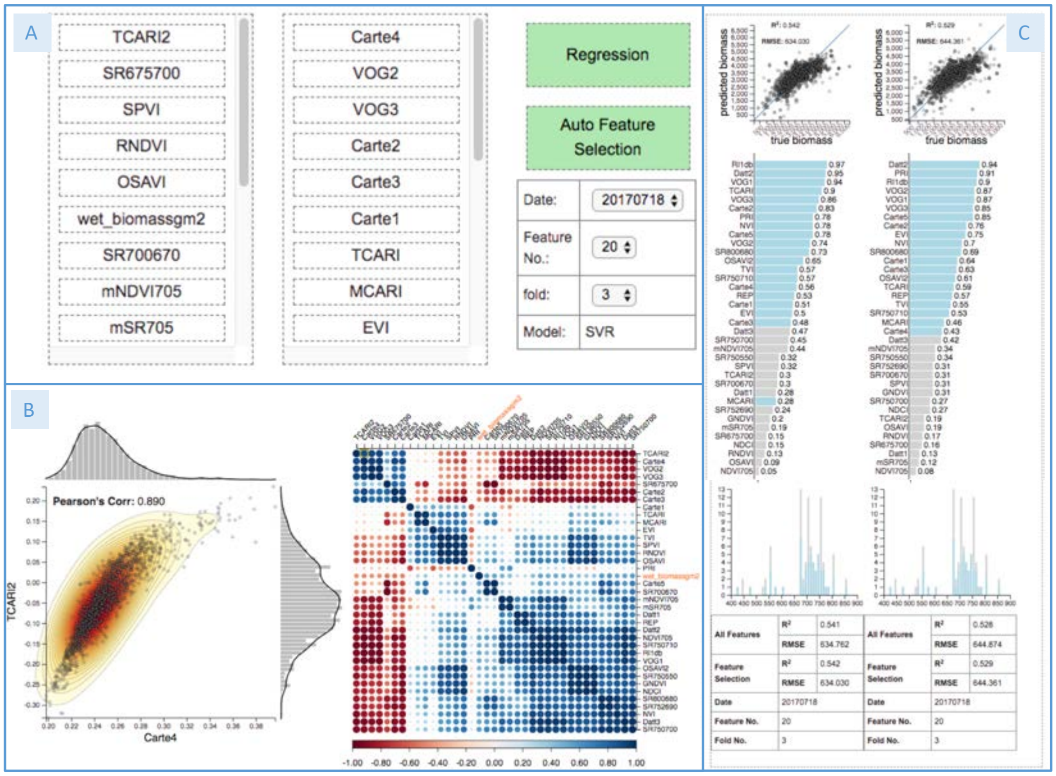

Figure 5: User Interface of FeatureExplorer (Zhao et al., 2019)

6.3 Evaluation

During the collaborative analysis process with domain experts, it is found that iteratively selected subset of features can achieve better performance than an automatic selection method because domain experts pick more robust features for different datasets. Domain experts take advantage of knowledge on the biophysical meaning of features as well as choosing the features suggested by an automatic algorithm. The evaluation shows the advantage of the HCCD environment for complicated decision-making tasks.

7. Discussion and Research Opportunities

7.1 "Infobesity"

One primary challenge to be addressed in designing an HCCD environment is "infobesity" (Rogers et al., 2013). Information exists in a wide range of formats, modalities, scales, and sources. While cloud and IoT have made access to information extremely easy, the velocity, volume and veracity of the various data has made synthesis of them, and fusion of their underlying information a daunting task.

Many design decisions have to be made on the VA interface, i.e. what and how data will be transformed and presented to end users. Preparatory analysis will need to be conducted to understand relationships of the data. Developers will then need to innovate on the ways related data are presented to users without introducing bias and misinterpretations. The interactivity of VA systems also requires data rendering to be of low latency. Sampling methods for VA system can be used to mitigate this issue and remains an active research area.

7.2 Interdisciplinary system design

Another major challenge in developing HCCD is the interdisciplinary task to optimize human and computer intelligence collaborations. The raw data is transformed into interconnected visualizations for users to interactively extract knowledge. Designing the interface of HCCD will require domain knowledge of multiple disciplines.

For example, developers must understand the cognitive workload of the HCCD users and the operational environment prior to developing and implementing these visualizations. For example, there is a distinction between on-line and off-line applications. Users that manage on-line or real-time processes will have limited bandwidth to process information and the development of events in real-time puts hard constraints on time available for locating and interpreting critical information. Whereas, for off-line analytical tasks, users might want access to all possible information, can accommodate longer wait time and may be interested in exploring historical data as well as real-time data. Further complexity is introduced when levels of expertise are taken into accounts. It is recommended that a user-centered design be used with HCCD to tailor the interface for the specific needs of the application, problem and user population. Interdisciplinary research, methods and theories to address the above problems will also be developed to ensure the effectiveness of the HCCD environment.

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