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The Human-Data-Model Interaction Canvas for Visual Analytics – Supplemental Materials

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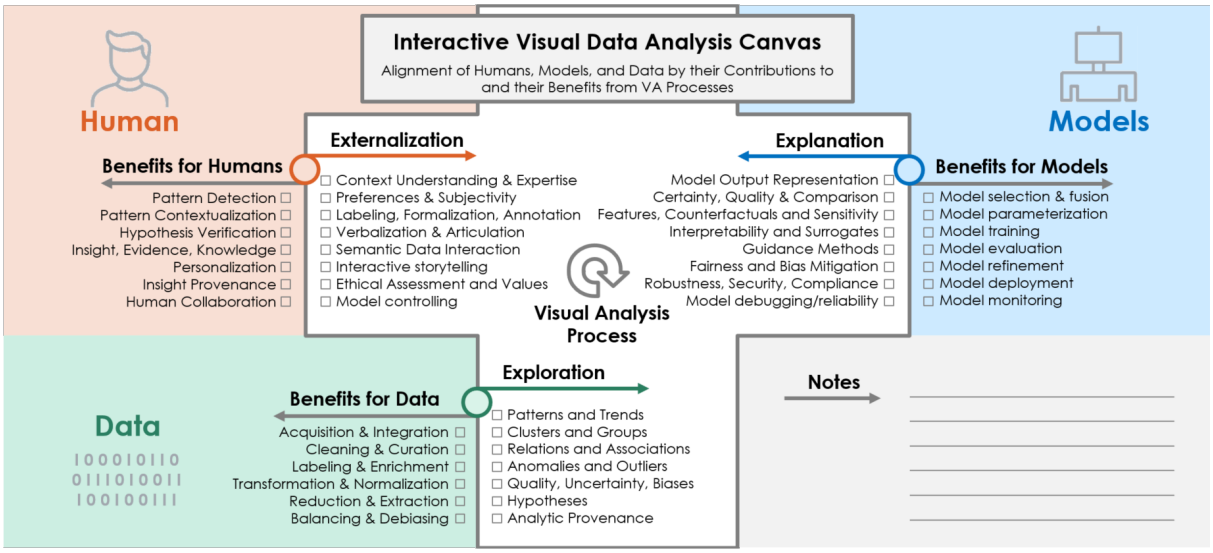

Figure 1: *HDMI Canvas as a fresh perspective to key VA building blocks and their interplay, assembled acrosse humans, models, and data, the main entities. The canvas can be used for both to describe existing VA approaches or for the idation of new VA designs.*

1. Introduction

The supplemental materials document presents values and strengths of for 16 VA process, models, conceptual frameworks, and design spaces in detail. Also, potential extensions for fresh perspectives are indicated, based on observations and reflections.

2. Related Process Models, Frameworks, and Design Spaces

2.1. Knowledge Discovery in Databases and CRISP-DM

Both the KDD [FPSS96] process and the Cross Industry Standard Process for Data Mining (CRISP-DM) [CCK*99, WH00] present a data mining perspective, slightly differing in their research vs. business perspective. Together, these process models describe the process from data to knowledge/decisions, following crucial steps including gaining an understanding for data and task, preparing and processing data, conduct data mining and modeling, process evaluation, and deployment. Both processes keep the human entity as an implicit actor; later VA process models extended this process by emphasizing the interactivity of human-in-the-loop processes.

2.2. Card's InfoVis Pipeline

The Card (InfoVis) Pipeline [CMS99] is a reference model that structures information visualization as a sequential process–from raw data transformation to visual representation. Users are explicitly represented, influencing the pipeline through interactive task execution. The process model emphasizes means such as visualization and interaction, while models are left out entirely. This reflects the strong information visualization focus, limiting its ability to integrate computational reasoning or structured analytical modeling within the visualization pipeline.

2.3. Pirolli & Card's Sense-Making Loop

Pirolli and Card [PC05] present a sense-making [KMH06] process model for data-intensive analyses, structured around multiple stages of information collection, organization, and interpretation. Inspiring for VA, the sense-making process is not linear but iterative, featuring loops between stages. Two major loops are distinguished: the information foraging loop, which focuses on gathering and structuring evidence, and the sensemaking loop, which fo-

cuses on reasoning over structured evidence to produce knowledge outputs. Throughout the process, data and models serve as tools, while control remains with the human analyst, guiding sensemaking through refinement and interpretation.

2.4. Keim's VA Diamond

With the presentation of the Data-Visualization-Model-Knowledge standard model [KAF*08] ("VA Diamond"), VA's [CT05] scope and challenge were formalized in a process model. This was among the first process models to combine automated data analysis (from model to knowledge) with visual data exploration (from visualization to knowledge). Like many process models, its emphasis is on the connections and interactions between the four process elements, supporting the flow from data to knowledge toward the overarching goal of knowledge discovery. However, users remain seen as knowledge carriers and entities enabling connections between process elements. Models and model interaction are kept to the core: model building, parameter refinement, and model visualization; yet models are not conceptualized as active actors or agents in human-AI collaboration. A key innovation was making the feedback loop explicit, allowing knowledge (human engagement) to influence the process, though kept at an abstract level without characterizing types of human feedback further.

2.5. Sacha's Knowledge Generation Model (KGM)

Sacha's KGM [SSS*14] is an influential process model that puts the VA Diamond [KAF*08] stronger in the context of knowledge generation. It introduces three sense-making loops: the inner exploration loop, the verification loop, and the outer knowledge generation loop. This concept extends Pirolli and Card's sense-making process, consisting of a foraging loop and a sense-making loop [PC05]. At its core, the KGM treats data, visualization, and models as means toward the ultimate goal of knowledge generation Like the HDMI Canvas, it dives deeper into the individual components, but keeps human contributions focused on mechanical actions such as data preparation, model building, visual mapping, and model-vis mapping. A key strength is its level-of-detail approach, integrating Card's InfoVis Pipeline [CMS99] (data-to-visualization) and Fayyad's KDD Process [FPSS96] (data-to-models) as means towards an end. This inspired the characterization of ingoing and outgoing information flows per entity in the HDMI Canvas. The KGM differs in its focus on connections, combinations, and coupling mechanisms between components, a complexity the HDMI Canvas avoids. For combinations of human, model, and data, please refer to the discussion section.

2.6. Human-Centered Machine Learning

The conceptual framework by Sacha et al. [SSZ*16, SSZ*17] nicely extends traditional ML process models with human-centered and interactive ML concepts, aligning with VA principles inspired by the KGM [SSS*14]. It structures human-centered ML into four steps (Data, Preprocessing, Model, Visualization), and explicitly adds the human analyst as a fifth process element. Analysts observe, interpret, validate, and refine the entire process through visualization and exploration interfaces, and interactions across all four steps. Like most conceptual frameworks of its time, models are treated as a means: as tools selected, parameterized, and refined by humans. Consequently, novel forms of human-model collaboration are not intensively explored. Focusing mainly on model building in the interactive ML context, the framework discusses human knowledge externalization, mainly through data enrichment and labeling for ground truth, but not yet in its full spectrum.

2.7. VIS4ML

An important subarea of VA is VA-assisted ML or VIS4ML, focusing on understanding, interpreting, and improving ML models. The VIS4ML ontology by Sacha et al. [SKKC19] provides a profound theoretical foundation for model-centered VA workflows, describing concepts and relations based on traditional VA models [KAF*08, SSS*14]. Like the HDMI Canvas, it identifies and maps a series of VA building blocks, offering strong descriptive and generative power. While it considers human and model capabilities, its primary focus remains on model building, covering only a subarea of the broader HDMI Canvas scope. Within that subarea, the complex structures and pathways formed by the ontology's common concepts, relations, and syntactic rules may challenge external stakeholders without VA expertise.

2.8. ML4VIS

ML4VIS uses ML techniques to support or automate decisions in visualization and VA processes, while ML integrations into VA processes promote sensemaking and analytical reasoning [ERT*17]. It optimizes visualization design, layout, recommendation, or interaction based on data characteristics or user behavior. By learning from examples, feedback, or historical usage, ML4VIS improves efficiency, personalization, scalability, and adaptability. Examples include class separation in scatterplots [SA15], perception-driven dimensionality reduction [WFC*18], cluster pattern quality [AASB19], and general visualization learning [HGH*19]. Inspiring for the HDMI Canvas is the strong focus on user feedback and preferences, as the basis for ML. This highlights how users can contribute to VA processes in modern forms of externalization, calibrating visualization and analysis for more human-centered usage.

2.9. Knowledge Generation and Externalization

Van Wijk's value of visualization [vW05] process describes knowledge generation from an economic perspective, showing how data transforms into images to enable human perception and insight. Green et al. (20XX) extend this by emphasizing interactive exploration for knowledge acquisition, aligning with the HDMI Canvas. Another related extension is knowledge externalization, rooted in social sciences [MH98, KTST15, KCM89, CSS00]. Wang et al. and Federico et al. [WJD*09, FWR*17, CGM*16] propose making knowledge externalization an explicit process component, transforming tacit knowledge [NT95] into externalized knowledge through interactive visual interfaces for direct application.

2.10. Human-in-the-loop vs. The-Human-is-the-Loop

Human-in-the-loop (HITL) is a widespread concept often used for computational and AI-driven processes where humans actively participate in training, refining, and guiding an algorithm, model, or

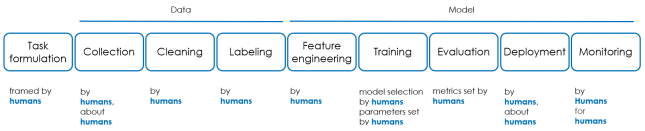

Figure 2: *machine learning process in nine key step, all with essential human contributions. Recreated from a Fred Hohman talk.*

decision-making system, as a means to overcome shortcomings of black box [KAF*08] and/or AutoML [RAB*24] approaches. In contrast, the "The Human is the Loop" principle shifts the perspective, making human involvement an integral, continuous, and adaptive part of the system rather than just an oversight mechanism. Beyond, it is inherent to VA to advance this concept by shifting from HITL to a "Human is the Loop" perspective, embedding analytics seamlessly within analysts' natural workflows [EHR*14], rather than requiring periodic and possibly tedious human oversight [ACKK14]. "The Human is the Loop" is a cornerstone to put the human at the center of the design experience, and put "computers-in-the-loop" [Shn21]. To complete the picture, an inspiring extension of these principles is referred to as "Humans in the group, computers in the loop", as coined by Ben Shneiderman.

2.11. Mixed Initiative

Mixed-initiative [AGH99, Hor99] is a collaborative HCI approach where humans and computational systems actively contribute to problem-solving, decision-making, and task execution. Instead of a single driver, initiative shifts dynamically between humans and AI based on context, expertise, and system intelligence. Humans provide guidance, control, and refinement, and feedback, while models handle data analysis and prediction, automating computationally intensive tasks. Though mixed-initiative frameworks do not explicitly account for data-centered goals like exploration, their focus on humans and models as active agents–rather than mere tools–is inspiring for this work.

2.12. Interactive Machine Learning

Interactive ML (iML) [FOJ03, RMS*20, WBV22] brings more power to the people [ACKK14] by enhancing more direct human involvement. Humans are iteratively feeding training parameters, inspecting model outputs, and providing feedback on intermediate results, simplifying model creation [WBV22]. While ML is traditionally model-centered, iML adopts a human-centered approach, making it an iterative and incremental process [ACKK14] with human-in-the-loop methods [RMS*20]–closely linked to VA. Users provide interactive feedback to refine model predictions, with stronger focus on interpretability, usability, and trust. A key aspect for the HDMI Canvas is the structured articulation of formal types for ML tasks, e.g., provided by humans through VA systems. By integrating human insights into learning, iML makes AI systems more adaptive, transparent, and explainable, enhancing decision-making through real-time adjustments based on user feedback.

2.13. Fred Hohman's Interpretable Machine Learning Pipeline

In his SIGCHI Dissertation [Hoh21] Award Talk, Fred Hohman presents the nine key steps of a machine learning process (task formulation, data collection, data cleaning, data labeling, feature engineering, model training, model evaluation, model deployment, and monitoring) and makes an important point: for all nine steps of the process, he explicitly maps human activities and contributions to the process, highlighting that even very model-centered processes with strong benefits for the modeling end would not work without human contributions, possibly implemented in a human-in-the-loop notion. The level of detail of highlighting human involvement is interesting, as it inspires to reflect on which types of human contributions modern VA and human-AI systems offer. Finally, Hohman advocates the human-centered approach, focusing on understanding what people need to design and develop the right tools for interpretability.

2.14. Model Explainability and Interpretability

Explainable AI is certainly one of the hot topics that, one year ago, may not have been on the radar of most VA process models and research agendas. More recent state-of-the-art reports have explored the space for explainable AI and interpretable ML techniques, enhancing transparency and finally: more trust in AI models. Examples include the exploration of VA methods for explainable Deep Learning [RBB*23], general explainable AI [GSC*19], interactive and explainable ML [SSSE20], interpretable ML [Hoh21], or enhancing trust in ML models with reliable visualizations [CMJ*20]. This fresh perspective on VA as an enabler of model explainability and interpretability would be worth having as building blocks in VA process models.

2.15. Human-Centered AI

Human-Centered AI (HCAI) [Rie19, Shn21, Shn22, Rus22] is an approach that prioritizes human needs, values, and agency in AI design, development, and deployment. It focuses on collaboration between humans and AI, ensuring AI systems are transparent, interpretable, fair, and aligned with human goals [Shn21]. Instead of fully automating decisions, HCAI aims to augment human intelligence by enabling users to understand, control, and refine AI outputs [Shn22]. HCAI is human-centered, the AI is designed to enhance human decision-making rather than replace it. Model-centered aspects of HCAI include the use of explainable models and iterative learning to align models with human preferences. Taking a data-centered perspectives in HCAI, the focus is on high-quality, unbiased data to ensure AI makes fair and transparent decisions [LOS20].

2.16. Human-AI Collaboration

Another source for inspiration for the HDMI Canvas are recent frameworks that analyze human-AI collaboration [RM23, FDKN24]. Unlike traditional automation where AI replaces human roles, human-AI collaboration combines human intelligence, creativity, and ethical reasoning with AI's computational power and efficiency. Humans provide contextual understanding, ethical judgment, and experiential knowledge, setting objectives and making nuanced decisions requiring moral considerations beyond AI's capabilities. AI models act as partners, handling repetitive tasks, analyzing data, and offering insights to augment human decision-making. Holter and El-Assady [HE24] describe the strengths of entities for human-AI collaboration in a design space with three dimensions: *Agency* (balancing control between humans and AI),

Interaction (facilitating seamless communication), and *Adaptation* (enabling dynamic learning and evolution for improved joint performance over time). The design space highlights novel forms of human-model collaboration as acting entities, central to the HDMI Canvas which focuses on how entities benefit from VA processes, and what they contribute. HDMI Canvas further extends this perspective of a tandem of actors (human, model) to a triplet, creating a space opened by human, model, and data.

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