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Human Reasoning for Visual Analytics in the Moment of Emergent Artificial Intelligence

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Introduction: From its inception, *Visual Analytics* has been defined as the use of visual interfaces to computational methods in support of sophisticated human reasoning (Thomas et al., 2005). Implicit in this definition is an intentional and productive synergy between humans and machines: computers are tools that help humans reason with data, particularly when the volume, velocity, variety, and veracity of this data exceed the cognitive limits of humans (Robinson et al., 2017). In this way, the machine scales the human to meet the complexity of the problem at hand (Roth & MacEachren, 2016). Fast-forward twenty years, and discussion within Cartography and Geoscience about what could have been *Geovisual Analytics* arguably has slipped towards computational automation for tasks from the sensitive to the mundane due to discriminative and generative artificial intelligence (see Kang et al., 2024 for our recent review). The "moonshot question" around this emergent research thrust of *GeoAI* is how to fully automate geospatial processing including data collection, analysis, presentation, and decision making (Janowicz et al., 2020). In other words, one interpretation of GeoAI is the elimination of the visual, the interface, and the human from the original definition of Visual Analytics to privilege the computational. In this position paper, I reframe Visual Analytics as a bridge between Cartography and GeoAI by extending a Geovisualization framework on modes of human-centered analytical reasoning developed by Gahegan (2005) to consider emergent possibilities with discriminative and generative AI.

Background: Broadly defined, *analytical reasoning* describes the cognitive processes for building explanations from information (Robinson, 2017). In Psychology and Cognitive Science, reasoning is treated as the culminating suite of cognitive faculties that apply human judgement to construct knowledge from current (learning) and past (remembering) experiences (MacEachren, 1995). For Visual Analytics, analytical reasoning has a specific of connotation of building *actionable* knowledge to inform, for instance, collaborative deliberation and decision making (Andrienko et al., 2007). Construction of actionable knowledge follows an iterative *sensemaking* process of collecting data-driven evidence related to a given problem, making assumptions and inferences about patterns within the evidence to establish potential pathways of action, and weighting new evidence against previous inferences to evaluate and change actions (Pirolli & Card, 2005). Visual representations like maps are important for supporting sensemaking, as vision affords the greatest sensory bandwidth to the human brain, enabling reasoning to be offloaded onto visuals or onto computational processes made available through visual interfaces (Hollan et al., 2000). AI arguably mirrors this sensemaking process with training data that exceeds the capacity of human reasoning—a promise similar to the initial proposal for Visual Analytics—but this "artificial reasoning" is made invisible within the "black box" of proprietary discriminative and generative AI algorithms (Ricker, 2017). Accordingly, humans employing AI either have difficulty in understanding how to incorporate the AI output into their own reasoning processes to inform action, or simply must trust the results of AI, giving up their individual agency in favor of mindlessly acting on behalf of the machine (Prestby, 2023).

Framework: Notably, the sensemaking process crosses different *modes of reasoning*, and a potentially viable pathway forward is calibrating AI to support a specific mode within the process, rather than overtaking the reasoning process altogether. Gahegan (2005) identified five unique modes of reasoning that have different resulting analytical products (Figure 1). In the following, I offer brief thoughts on how Visual Analytics might bridge Cartography and GeoAI for each modality to seed workshop discussion on human reasoning in the moment of emergent AI.

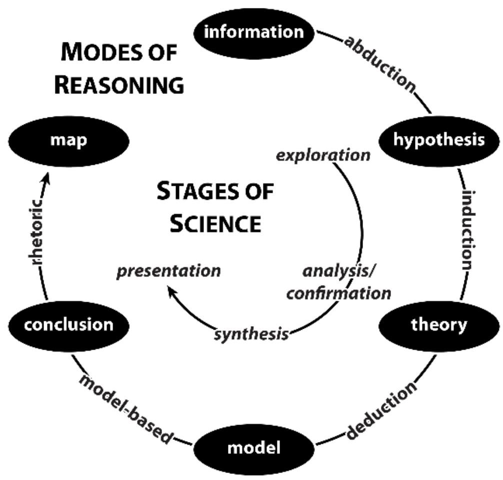

Figure 1. Modes of Reasoning and Analytical Products (after Gahegan, 2005) combined with the DiBiase (1990) and MacEachren (1994) Stages of Science.

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1. ***Abduction*** infers a preliminary explanation from limited evidence. Abduction is the primary mode of reasoning employed by Exploratory Data Analysis (Tukey, 1980), and therefore is the conceptual basis for sensemaking within Exploratory Geovisualization (MacEachren, 1994). The analytical product of abduction is a *hypothesis*, or proposed explanation for a phenomenon that can be confirmed or refuted through subsequent evidence, which often is restated in practice as a *hunch* worthy of follow-up investigation (Roth et al., 2015). Accordingly, GeoAI can be used to suggest and generate alternative *visual isomorphs*, or different visual structures of the same information, which might include different map types or map designs, or different kinds of non-map visualizations altogether. Each newly generated visual isomorph may lead to a spontaneous new insight for follow-up analysis.

2. ***Induction*** infers a general explanation from comprehensive evidence. The analytical product of induction is a *theory*, or general explanation yet to be disproven by counter evidence, which often in practice is a less robust *conjecture* suggesting a generally helpful expectation or guideline but less scientifically robust than a theory. For Cartography and GIScience, induction is related to the “confirmation” or “analysis” stage of science (DiBiase, 1990), and therefore can be supported with GeoAI through the automation and evaluation of complex spatial analysis techniques that supply a measure of statistical significance. Notably, induction can be made actionable through an *analysis of competing hypotheses*, or the processing of weighting specific evidence against alternative explanations. Accordingly, GeoAI may be used to produce alternative simulations, linked with Visual Analytics through a sandtable interface supporting user-directed inspection of alternative scenarios.

3. ***Deduction*** infers a pattern of a single instance from an unrefuted general explanation. Notably, deductive reasoning follows the scientific method to “corroborate” theory. Deductive reasoning for Cartography aligns with *verifiable visualization*, and GeoAI can be used to evaluate the potential for Type I (seeing wrong) and, in particular, Type II (not seeing) map reading errors that may be meaningful in statistical or historical space but less visually obvious because of the volume of mapped data (MacEachren, 1995). The analytical product of deduction can be (although does not need to be) a *model* that combines multiple general explanations into a complex system for predicting unknown or future observations. Accordingly, the deductive mode of reasoning relates to the “synthesis” stage of science underdeveloped in Cartography and Visual Analytics (Robinson, 2008). Discriminative and generative AI can help with this synthesis projects, finding observations and patterns similar to those identified visually to further corroborate a general explanation.

4. ***Model-based reasoning*** infers from a trained model the most likely of several possible explanations. Gahegan’s (2005) addition of model-based reasoning today most closely matches the implementation of GeoAI, and “fourth paradigm” data-driven scientific discovery broadly. The analytical product of model-based reasoning—and really the entire analytical process up to this point—is a *conclusion*, or actionable explanation of past, current, and future observations. GeoAI as computational techniques for automation arguably replaces human-centric abduction, induction, and deduction with model-based conclusions, and therefore has pitfalls with transparency and trust listed above. However, model-based reasoning does not need to be a black-box, as users can *steer* models through visual interfaces, amplifying interesting model outcomes and recalibrating model parameters when suboptimal results are returned.

5. ***Rhetoric*** employs persuasive discourse to argue for a given conclusion. To Gahegan (2005), the analytical product of rhetoric is a *conventional map* used for the “presentation” stage of science and visual communication, and thus efforts to automate cartographic design through GeoAI align most closely here. Rather than just generating a single map, however, GeoAI can be used to generate alternative rhetorical *framings* about a visual conclusion, such as different geographic locations, intersectional identities, political ideologies, and other individual differences to the end of considering the conclusion from multiple perspectives beyond one’s own. GeoAI also can help retain *analytical provenance* about the reasoning process from exploration to presentation, enabling numerous loops through the sensemaking process, as well as support automated reporting about the analytic process for collaboration.

Outlook: In this position paper, I argue that Visual Analytics can serve as a bridge between Cartography and GeoAI to support sophisticated, human-centered reasoning. Rather than handing over reasoning to machines—and thus our capacity to reason about and act on complex geographic problems—Visual Analytics provides a potential common ground to refocus discriminative and generative AI as a tool for supporting rather than automating Cartography. The updated Gahegan (2005) framework offers a useful, albeit preliminary foundation for understanding what outcomes we are seeking from GeoAI through different modes of reasoning as well as for brainstorming new visual interfaces to computational methods to support analytical reasoning with GeoAI.

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