The Cartographer in the Loop? Reframing Cartography + GeoAI as a Problem of Interaction (not Automation) in Geovisual Analytics

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Introduction

From its inception, *Visual Analytics* is defined as the use of (1) visual interfaces to (2) computational methods in support of (3) sophisticated human reasoning (Thomas et al., 2005). This definition implies an intentional and productive interaction between humans and machines: computers are tools that help humans reason with information, particularly when the volume, velocity, variety, and veracity of this information exceed our cognitive limits (Robinson, 2017). In this way, the machine scales human capacities to meet the demands of complex problems (Roth & MacEachren, 2016), resulting in the discovery of new insights that are more intricate, deep, contextualized, unexpected, and relevant than if people or machines worked alone (North, 2006).

Fast-forward twenty years, and discussion within Cartography and GIScience about what could be described as *Geovisual Analytics* has slid towards computational automation for tasks ranging from the sensitive to the mundane due to the rise of generative artificial intelligence (*AI*; see Kang et al., 2024 for a recent review). The "moonshot question" around the emergent research domain of *GeoAI* is how to automate geospatial processing, including data collection, analysis, presentation, and decision making (Janowicz et al., 2020). Therefore, one interpretation of GeoAI involves the elimination of (1) the visual interface and (3) human-directed reasoning per the original definition of Visual Analytics, all replaced by (2) computational methods.

We propose Geovisual Analytics as a bridge between Cartography and GeoAI, requiring careful interaction design and not technical automation. In doing so, we adapt and extend a framework of analytical reasoning developed by Gahegan (2005) to consider how cartographic interfaces can be enhanced by GeoAI, centering cartographers in the "analytical loop". Throughout, we use the term "GeoAI" as shorthand for a range of computational methods relevant to Geovisual Analytics, some of which have been described as data mining, geocomputation, and machine learning, but nonetheless are now commonly included under the umbrella of GeoAI.

Background

Analytical reasoning describes the cognitive processes for building explanations from information (Ribarsky et al., 2009). In Psychology and Cognitive Science, reasoning is treated as the progressive suite of cognitive faculties that are engaged when humans apply judgment to construct knowledge from current (i.e., learning) and past (i.e., remembering) experiences (MacEachren, 1995). Accordingly, the "analytical loop" in Psychology and Cognitive Science is not a sequence of programmatic conditions or algorithmic iterations, but instead the human cognitive capacity to reason with information.

In Visual Analytics, analytical reasoning builds *actionable* knowledge to inform, for instance, in the context of collaborative deliberation and decision making (Andrienko et al., 2007). Actionable knowledge is the product of an iterative *sensemaking* process that includes 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 can mirror 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) and results in unreliable explanations ranging from irreproducible workflows to untrustworthy hallucinations (Huang, forthcoming). Often, people using 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 and acting at the behest of the machine (Prestby, 2025). Accordingly, there is as much skepticism as there is optimism amongst cartographers regarding the possibility and value of automating cartographic workflows with AI (Robinson et al., 2023).

However, the semantic web, large language models (LLMs), and new geospatial foundation models (Janowicz et al., 2025) are offering new opportunities for integrating Cartography and GeoAI not for automation, but in support of human-computer interaction. Prompt-based generative AI is an interface, albeit a non-visual one. Shneiderman and Plaisant (2020) describe five interface styles: direct manipulation (reliant almost entirely on visual or "graphical" user interfaces), menu selection, form fill-in, command language, and—notably—natural language (reliant almost entirely on speech or text input). Most existing cartographic design workflows rely on direct manipulation (e.g., through desktop GIS or graphic design software) or command language (e.g., through programming languages and libraries) (Roth, 2013b). However, each interface style exhibits different advantages and disadvantages, and, notably, their flexible combination has the potential to overcome individual limitations (Masson et al., 2024). Therefore, we see a renewed opportunity to integrate (1) visual (cartographic) interfaces to (2) computational (GeoAI) methods in support of (3) sophisticated (geoanalytical) human reasoning, centering the cartographer in the analytical loop.

Framework: Modes of Analytical Reasoning

The sensemaking process crosses different *modes of reasoning* that altogether define a single analytical loop. Gahegan (2005) identified five modes of reasoning that generate different analytical products (Figure 1). While Gahegan originally added “model-based” as an additional, fifth form of reasoning following the fourth paradigm (Gahegan, 2020), we consider how the use of model-based reasoning *writ large* (i.e., computational techniques falling under GeoAI) might be applied throughout the analytical loop using visual interfaces, bringing this analytical workflow in line with DiBiase’s (1990) and MacEachren’s (1994) Stages of Science to inform the design and use of maps for each mode of reasoning.

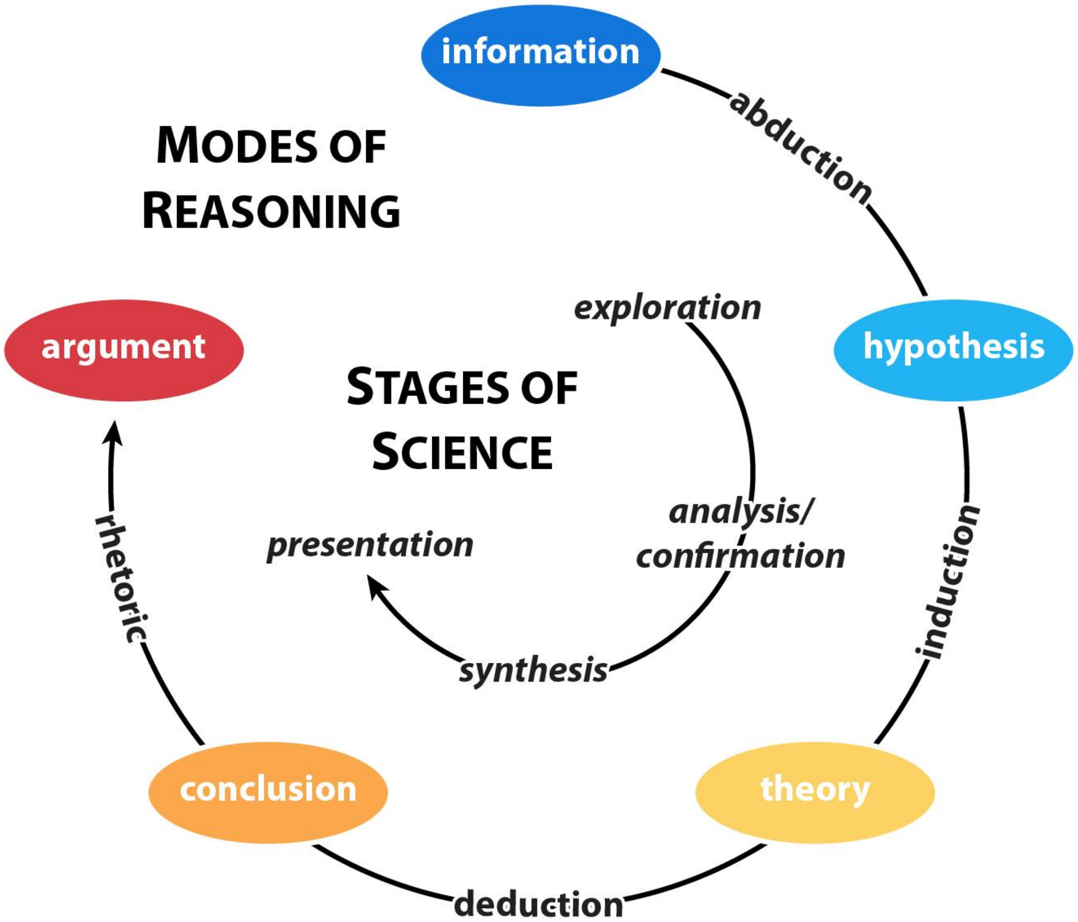

Figure 1. Modes of Reasoning and Analytical Products (Gahegan, 2005) aligned with the DiBiase’s (1990) and MacEachren’s (1994) Stages of Science.

In the following, we introduce each (3) mode of reasoning with its analytical tasks and products and summarize existing (1) visual and non-visual interface solutions that could be paired with (2) computation methods to bridge Cartography and AI using Geovisual Analytics (Table 1):

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 analysis and often is restated in practice as a *hunch* worthy of follow-up investigation (Roth et al., 2015). Visual interfaces for exploratory abduction include re-expression of visual isomorphs, coordinated visualization with linked views (often described as dashboards), and self-organizing maps. Useful GeoAI techniques for abduction include descriptive statistics, data mining (anomaly and outlier detection), and active symbolism. We posit that re-express, arrange, zoom, filter, and retrieve (as defined in Roth, 2013a) are likely valuable interaction operators (regardless of interface style) for pairing interfaces with computation for abduction, following Schneiderman's (1996) information seeking mantra of overview first, zoom and filter, and details on demand.

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 that is less scientifically robust than a theory. In Cartography, induction connects 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 provide statistical measures. Special visual interfaces/interaction strategies for induction include the analysis of competing hypotheses, sand table visualization, and simulations. Useful GeoAI techniques for induction include inferential statistics (correlation, regression), Bayesian statistics (Monte Carlo simulation), cluster detection (LISAs, SaTScan, DBSCAN), and neural networks (ANNs, DCNNs, GCNs). Given the focus from generating new insights to testing theories, we posit that arrange, overlay, sequence, reproject, and calculate are likely valuable bridging interaction operators to support induction.

3. ***Deduction*** infers an explanation for a single instance from an unrefuted general explanation. Deductive reasoning uses the scientific method to "corroborate" theory. The analytical products of deduction—generated via a stage of science known as *synthesis*—can be a *conclusion*, or actionable explanation of past, current, and future observations. Special visual interfaces for deduction include model steering, verifiable visualization, and uncertainty evaluation and visualization. Useful GeoAI techniques for induction include optimization algorithms (ABCs, simulated annealing), decision trees, ontologies (knowledge graph, semantic web techniques), and reinforcement learning. We posit that search, arrange, annotate, zoom, and save are likely valuable bridging interaction operators for deduction based on Robinson (2008).

4. ***Rhetoric*** employs persuasive discourse to argue for a given conclusion. Generalizing Gahegan (2005), the analytical product of rhetoric is an *argument* used for the "presentation" stage of science and visual communication, and thus efforts to automate cartographic design through GeoAI align most closely here (Kang et al., 2024). Special visual interfaces for rhetoric include analytical provenance, re-visualization, automated reporting, and style transfer. Use GeoAI techniques for rhetoric include generative adversarial networks (GANs), large language models (ChatGPT, Claude, Gemini), and text-to-image models (DALL•E, Midjourney). We posit that search, pan, retrieve, resymbolize, and export are likely valuable bridging interaction operators for rhetoric based on Roth and MacEachren (2016).

Mode[1], Stage[2]	Analytical Product(s)	Example Tasks[3]	Visual Interfaces[4]	GeoAI Methods[4]	Interaction Operators[5]
abduction, exploration	hypothesis, hunch	*"where are the highest/lowest values?" (e.g., rank)* *"what attributes that correlate with this one?" (e.g., associate)* *"where are there clusters of high values?" (e.g., delineate)*	• visual isomorph reexpression • coordinated visualization (dashboards) • self-organizing maps	• descriptive statistics (normalization) • data mining (anomaly & outlier detection) • active symbolism	• reexpress • arrange • zoom • filter • retrieve
induction, confirmation/ analysis	theory, conjecture	*"are the clusters significant?" (e.g., LISA)* *"is the pattern scale dependent?" (e.g., MAUP)* *"does the pattern hold over time" (e.g., CUSUM)*	• analysis of competing hypotheses • sand table visualization • simulation	• inferential statistics (correlation, regression) • Bayesian statistics (Monte Carlo simulation) • cluster detection (LISAs, SaTScan, DBSCAN) • neural networks (ANNs, DCNNs, GCNs)	• overlay • sequence • reproject • filter • calculate
deduction, synthesis	conclusion	*"what is the reliability of the values at __?" (e.g., procure)* *"what will the pattern be for the next __?" (e.g., predict)* *"what should we do to get __?" (e.g., prescribe)*	• model steering • verifiable visualization • uncertainty evaluation and visualization	• optimization algorithms (ABCs, simulated annealing) • decision trees • ontologies (knowledge graphs, semantic web) • reinforcement learning	• search • arrange • annotate • zoom • save
rhetoric, presentation	argument	*"describe the map to me" (e.g., accessibility)* *"change the map to a local perspective" (e.g., selection, toponymy)* *"show me a map in the style of __" (e.g., symbolization, aesthetics)*	• analytical provenance • revisualization • automated reporting • style transfer	• generative adversarial networks (GANs) • large language models (ChatGPT, Claude, Gemini) • text-to-image models (DALL•E, Midjourney)	• search • pan • retrieve • resymbolize • export

Table 1: Proposed connections that bridge Cartography and GeoAI using Geovisual Analytics. [1]After Gahegan (2005). [2]After DiBiase (1990) and MacEachren (1994). [3]Based on Roth (2013b). [4]To be expanded in follow-up literature review. [5]Drawn from Robinson (2008), Roth (2013a), and Roth and MacEachren (2016) and require follow-up empirical study.

Outlook

In this short paper, we approach GeoAI as an interface that can be integrated with other common visual cartographic interfaces to propel the next generation of Geovisual Analytics. We argue to reframe the goal of GeoAI for Cartography as interaction as opposed to automation. Cartographic expertise is more vital than ever with contemporary AI, and GeoAI will require us to better formalize our methods and workflows for cartographic research and design (i.e., we need to know what we are doing and why!). We also need to question when GeoAI should be employed for Cartography given its substantial economic, social, and environmental impacts, and relating (1) visual interfaces and (2) computational methods to (3) modes of reasoning contributes to ethical guidelines for the more intentional and sustainable use of AI.

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