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Exploring cartographic language for AI

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Abstract:

Applications of generative artificial intelligence (AI) become available to a wider public, in general for the creation of text, images or videos. AI pilots in office environments help to analyse and summarize written text, answer emails, write code, generate 3D models or even perform text to speech conversions in unprecedented quality [Kingma 2013]. The rapid development of the AI toolset and its impressive results [Ashish 2017] lead to the question, when automated and high quality map production will be covered by AI agents [Mnih 2013]. The authors of this contribution have identified the importance and formalization of "cartographic language" as key factor for cartographic AI agents and cornerstone for future reliable GeoAI developments.

Maps play a key role in describing and assigning information to space [Kitchin et al. 2011]. Several rules in map production aim at the effective and efficient communication of spatial knowledge [Brodersen 2017]. This aim of successful geo-communication leads to the use of a well defined cartographic language in order to express geospatial information and make use of indicators of truth. These indicators are able to relate to the individual experience imagery of the users by expressing accuracy and precision, highlighting data sources and their provenance and exploiting map projections and their distortions. From the communication point of view, cartographic language is a powerful tool for expressing geospatial information, but it is also important to recognize that maps are not neutral reflections of geospatial truth. While aiming to represent reality, selective and interpretive processes may lead to artificial constructions. This means that maps are not neutral reflections of truth but rather constructions that can be influenced by various factors. By understanding the limitations of cartographic language and being aware of potential biases, users can critically evaluate maps and use them responsibly [Lloyd 2018].

In terms of AI any embedded model needs to consider inherited limitations and biases in order to enable reliable AI. At the same time "indicators of truth" form facts and especially logical building blocks that can complement stochastic AI models and therefore offer enhanced reasoning, improved explainability, robustness and reliability. This crucial role of extending stochastic AI with logical models is often done by RAG, Retrieval Augmented Generation, and GraphRAG, which extends the stochastic model with a knowledge graph [Edge et al 2024]. It provides a mechanism to ground stochastic models on external geospatial knowledge and factual information. As result the RAG approach reduces hallucinations and enables complex reasoning [Lewis et al 2020] [Bianchi et al 2020] [Zhou et al 2020]. These explorations of cartographic language as logical component that extends stochastic AI may help to put more effort into an AI-ready formalization of the cartographic ruleset.

Many Large Language Model (LLM) embeddings for cartography base on informal cartographic rulesets, like descriptions from unstructured text. Therefore the LLM is used to understand the question and demand of a user based on mere natural language descriptions [Zhang et al 2024]. Subsequently the machine is able to automatically invoke appropriate tools and functions to process geospatial data and prepare a map. As consequence the dimension of styling, cartographic language and linguistic expressiveness develop to future research topics in geospatial AI.

The input for a cartographic LLM extends unstructured text and will include - or just exclusively use - masses of cartographic samples including styled vector format, instead of rasterized tiles. These data are already available e.g. as

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vector tile caches and their styling definitions. In case of inclusion of cartographic samples the LLM follows the principles of multimodal LLM´s [Chen 2024]. The concept of a cartographic LLM could even support the creation of 3D maps as soon as the amount of 3D cartographic samples exist and the definition of a 3D cartographic language exists. First principles of a semiotic model for 3D has been developed by Jobst (2008).

The implementation of a cartographic language to graphically express geospatial information directs towards an own cartographic Large Language Model (carto-LLM) extended by a foundational ontology that describes an appropriate topographic knowledge graph. Foundations for this approach and requirements have been identified by the authors and go into a step-by-step evaluation and implementation.

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