

Applications of generative methods in cartography on the example of creating pictorial maps

Dirk Burghardt*, Alexander Dunkel, Malte Stüllein, Ronny Techt

Institute of Cartography, TU Dresden, firstname.lastname@tu-dresden.de

* Corresponding author

Keywords: generative methods, Neural Style Transfer, pictorial maps, text-to-image methods

Abstract:

Research on the use of generative methods in cartography, visualization, and map generation is still in a very early phase. Schetinger et al. (2023) describe the potential of using generative text-to-image methods for the different phases of visualization, starting with 1) identifying relevant data, 2) converting data into visualized formats, 3) visualization and diagram recommendation, and 4) interaction and personalization of visual designs. The first experiments on map creation using a text prompt were conducted by Kang et al. (2023) with DALL-E 2. Prompt inputs of the following structure were used: "A {MapType} of {Region} on {Place} with {Description}". When comparing manually and AI-generated maps, four potential error categories were identified: inaccuracies, misleading information, unexpected features, and non-reproducibility. Observed inaccuracies can be due to unclear borderlines, inconsistent place shapes, and truncated content. Zhang et al. (2024) present a "MapGPT prototype" that uses voice input instead of interactions to control the map production process. In the background, 59 map modules are utilized for various map production tasks. Initial approaches in cartography attempt to use Neural Style Transfer (NST) to transfer graphic image styles to map representations. Bogucka and Meng (2019) experimented with NST to transform emotional image representations onto a topographic base map of Berlin. Christophe et al. (2022) used NST to transfer historical map styles (maps by Cassini, 18th century and Etat-Major, 19th century) to orthophotos. With PictoAI (Drews et al. 2024), a custom GPT tool¹ integrated with DALL-E 3 was developed for the derivation of thematically appropriate pictograms.

In the following, two methods for generating pictograms using generative methods are presented. Neural Style Transfer is used to transfer the graphical styles of an input image to a photo for the derivation of the pictorial maps. In the second example, textual inputs from geosocial media are used to generate pictorial map signatures using the text-to-image generator "Stable Diffusion".

1. Using Neural Style Transfer to Generate Pictograms

The presented method uses Neural Style Transfer to transfer artistic styles to photos of landmarks and derive cartographic pictograms from them. The basis is the TensorFlow implementation of NST. Figure 1a) shows the Frauenkirche in the style of an oil painting, which was created using image processing filters. Fig. 1b) presents the results of the style transfer using NST to photos of other sights and Fig. 1c) shows the placement of the position signatures on a topographic base map.



Figure 1. Transferring the graphic style of an oil painting (a) using Neural Style Transfer to photos of landmarks (b) and subsequent generation of pictograms for pictorial map representation (c) (Techt, 2020)

¹ <https://chatgpt.com/g/g-1465GB5y0-pictoai>

While the derivation of single pictograms using NST delivers promising results, the style transfer to an entire map is associated with geometric distortions and topological errors, as well as the generation of "pseudo" labels that are not meaningfully readable and is, therefore, the subject of future research.

2. Utilisation of Stable Diffusion for the generation of pictorial maps

The development of models and technologies in the field of generative AI is very dynamic. Stable Diffusion² is an open-source text-to-image generator that is based on a latent diffusion model and, compared to alternative approaches such as generative adversarial networks or pixel-based diffusion models, achieves a very high level of image diversity and image quality with reduced computational effort. The workflow for creating pictograms for display in pictorial maps can be implemented in three stages (Dunkel et al. 2024). In the first step, textual input data is obtained from public APIs of geosocial media. This involves spatial and thematic clustering to record the most frequently used terms. In the second step, the prompt formulation takes place to generate the icons. The following prompt template was used for this: (a picture of {element}), (simple outline: 1.3), (masterpiece), high quality, ..., where {element} stands for the textual input. In addition to the positive prompt described, a negative prompt can also be specified, the aim of which is to suppress undesirable image properties or elements. The parameter settings of the basic model and the Low-Rank Adaptation (LoRA) models based on it for specific style adaptation (e.g. "Niji - Minimal Vector Style", see Fig. 2) are relevant for generating the icons. In the third step, the background of the icon must be automatically removed (e.g. using Rembg³), and the scaling and placement as a position signature in the base map must be done.



Figure 2. Icon variants for (a) London landmarks created with "Niji - Minimal Vector Style" and (b) derived pictorial map representation (Stillein, 2024).

These first tests show that stable diffusion is suitable for generating pictorial map presentations. However, a strong dependence on the models used and the various parameter settings are evident, so training of adapted models (LoRAs) to implement specific graphic styles remains a task for future research and development work in cartography.

References

- Bogucka, E. P. and Meng, L. (2019). Projecting emotions from artworks to maps using neural style transfer. *Proceedings of the ICA*, 2, 1–8. <https://doi.org/10.5194/ica-proc-2-9-2019>
- Christophe, S., Mermet, S., Laurent, M., and Touya, G. (2022). Neural map style transfer exploration with GANs. *International Journal of Cartography*, 8(1), 18–36. <https://doi.org/10.1080/23729333.2022.2031554>
- Drews, J., Edler, D., Keil, J. and Dickmann, F. (2024). PictoAI: Increasing the Meaningfulness of Cartographic Pictograms Using Artificial Intelligence? In: *Abstracts of the International Cartographic Association*, 7, 33, 2024. European Cartographic Conference – EuroCarto 2024, 9–11 September 2024, TU Wien, Vienna, Austria. <https://doi.org/10.5194/ica-abs-7-33-2024>
- Dunkel, A., Burghardt, D. and Gugulica, M. (2024). Generative Text-to-Image Diffusion for Automated Map Production Based on Geosocial Media Data. *KN J. Cartogr. Geogr. Inf.* (2024). <https://doi.org/10.1007/s42489-024-00159-9>
- Kang, Y., Gao, S. and Roth, R. (2024). Artificial intelligence studies in cartography: a review and synthesis of methods, applications, and ethics, *Cartography and Geographic Information Science*, <https://doi.org/10.1080/15230406.2023.2295943>

² <https://stability.ai/news/stable-diffusion-public-release>

³ <https://github.com/danielgatis/rembg>

- Kang, Y, Zhang, Q. and Roth, R. (2023). The Ethics of AI-Generated Maps: A Study of DALLÉ 2 and Implications for Cartography <https://arxiv.org/abs/2304.10743>
- Techt, R. (2020). Entwicklung eines semi-automatischen Workflows zur Ableitung ikonographischer Kartenzeichen. Masterarbeit Institut für Kartographie, TU Dresden.
- Schetingner, V., Bartolomeo, S. D., El-Assady, M., McNutt, A., Miller, M., Passos, J. P. A. and Adams, J. L. (2023). Doom or Deliciousness. Challenges and Opportunities for Visualization in the Age of Generative Models. <https://doi.org/10.31219/osf.io/3jrcm>
- Stillein, M. (2024). Generative KI für die Kartenerstellung unter Verwendung von Deep-Learning-Text-zu-Bild-Generatoren. Masterarbeit Institut für Kartographie, TU Dresden.
- Zhang, Y., He, Z., Li, J., Lin, J., Guan, Q. and Yu, W. (2024). MapGPT: an autonomous framework for mapping by integrating large language model and cartographic tools. *Cartography and Geographic Information Science*, 51(6), 717–743. <https://doi.org/10.1080/15230406.2024.2404868>