International Cartographic Association
Association Cartographique Internationale

Interpreting morphological prototype of urban form using CNN and prototype learning

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Keywords: urban morphology, urban form, morphological prototype, explainable AI, prototype learning

Abstract:

Urban morphology is a research field that focuses on revealing general patterns of urban forms and summarizing paths towards sustainable urban development (Zhang *et al.* 2023). Urban form refers to urban physical space shaped by natural, history, political factors, etc., and has an impact on the spatial organization of urban systems. A good urban form can enhance urban vitality (Lynch 1964), e.g., economic, resilient, cultural developments of cities. Historically, urban designers have proposed a multitude of professional urban design prototypes, e.g., Ebenezer Howard's Garden City (Howard 2013) and Le Corbusier's Radiant City (Corbusier 1967), in an effort to address the specific needs of cities at given time periods, including enhancing housing capacity and balancing built-up and green areas. Hence, urban morphologists have sought to derive universal principles of good urban form through comparative analysis and the extraction of global lessons (Porta *et al.* 2014).

Qualitative interpretation of figure-ground maps is a traditional approach to urban morphology. A figure-ground map, also called a figure-ground diagram, refers to the 2D map of urban space revealing the relationship built-up and open space (Wang *et al.* 2024). It is an effective tool for urban planners to explore complex urban systems, however, complex spatial relationships of figure-ground elements are difficult to interpret directly. Accordingly, the conventional approach among urban planning experts has been to abstract the figure-ground maps into city models, e.g., the concentric zone model and the sector model (Hoyt 1964), thereby facilitating a qualitative summary of the general patterns of urban form. The qualitative interpretation of urban form can be regarded as an approach of structuralism in urban morphology. Nevertheless, the oversimplification of qualitative interpretation often results in the loss of relevant details and ambiguous type identification. In contrast, the urban morphometric approach represents a development of deconstruction in urban morphology as an alternative research method to summarize general patterns of urban form. It challenges the conventional wisdom regarding the holistic nature of urban form by focusing on the fundamental components and their combinations (Fleischmann *et al.* 2020). Urban forms are characterized by both simple metrics of fundamental elements, such as areas of building footprints, and more complex indicators that illustrate the interconnections between individual elements, such as building adjacency, or encapsulate the attributes of the street profile, which is shaped by the interplay of streets and buildings (Zhang *et al.* 2023). However, the urban morphometric approach may be inadequate for discerning certain implicit regional patterns, such as the grid street pattern, which are challenging to quantify.

The exponential growth of computer vision technology has sparked a surge of interest in visual analysis methods for urban morphology based on figure-ground maps. Convolutional neural networks (CNNs) have proven effective in the classification of natural images, object detection and instance segmentation. Consequently, some urban morphology scholars have attempted to apply CNNs to urban form characterisation studies (Chen *et al.* 2021; Wu and Biljecki 2023; Wang *et al.* 2024), with the aim of addressing the limitations of qualitative analysis and urban morphometric methods. The overarching idea is to use CNNs, which are capable of discerning implicit visual characteristics, to capture implicit regional patterns from figure-ground maps. CNNs are categorized as supervised or unsupervised. Supervised CNNs classify known urban forms but struggle with new, undefined categories (Chen *et al.* 2021). However, the paucity of known classes of urban forms, coupled with the existence of numerous undefined urban form classes, renders the supervised CNNs to urban morphological classification highly constrained. Hence, the current mainstream for urban morphology is unsupervised CNNs (Wu and Biljecki 2023; Wang *et al.* 2024), which do not rely on known classes or existing knowledge. Nevertheless, they are limited to discovering data-driven knowledge. Consequently, current CNN-based research into urban form often lacks connection to the accumulated knowledge in the field of urban morphology (e.g. classic urban design prototypes), which spans over two hundred years. Furthermore, the interpretability of CNNs is a significant challenge for urban morphologists when evaluating classification results. A more transparent model is required to improve understanding of urban form.

https://doi.org/10.5194/ica-abs-10-34-2025

Prototype learning has a great potential for the studies of CNNs-based urban morphology. It refers to a classic paradigm in machine learning, which determines the category of a sample via the distance between the sample and the prototypes. Prototype-based CNNs are a special few-shot type of supervised CNNs, which required a modest number of predefined prototypes (Cheng *et al.* 2022). In addition to its high compatibility with urban morphology which already has some well-defined morphological prototypes as well as the accumulated knowledge, it has two more advantages. 1) It is compatible with unseen types of urban forms, which is beneficial for urban morphology as lots of undefined morphological prototypes exist worldwide. 2) It provides explanations through distances to prototypes. It makes the decisions made by the CNNs more transparent, which in turn contributes to a more comprehensive understanding of the outcomes of urban form classification. Therefore, the prototype learning method holds great value in classifying and explaining comprehensive urban form.

This work is committed to developing prototype-based CNN models which will serve to classify urban forms in figure-ground maps, identify new categories of urban forms, and elucidate the nature of an urban form as a prototype (Figure 1). The explicable results of prototype learning can be applied to guide and evaluate automatic map generalization. Smaller-scale figure-ground maps can be effectively and explicably derived from a large-scale map based on the generated knowledge of prototypes. It provides a potential way towards intelligent map generalization.

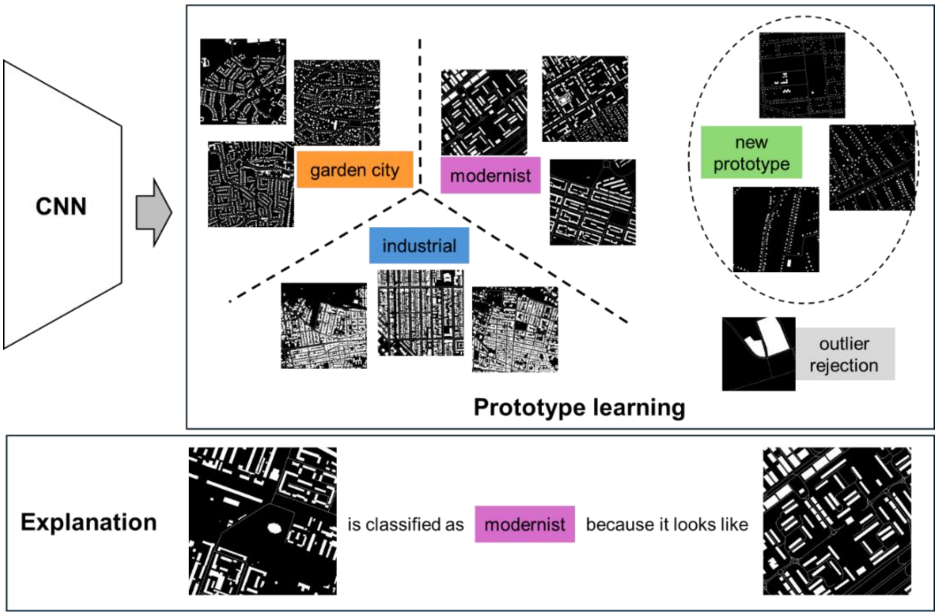

Figure 1. The working principle of the prototype-based CNN model for urban morphology

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Abstracts of the International Cartographic Association, 10, 34, 2025
32nd International Cartographic Conference (ICC 2025), 17–22 August 2025, Vancouver, Canada.
https://doi.org/10.5194/ica-abs-10-34-2025