The application of deep generative models in urban form generation based on topology: a review

Abstract: Integrating deep generative models into urban form generation is an innovative and promising approach to support the urban design process. However, most deep generative urban form models are based on image representations that do not explicitly consider topological relationships among urban form elements. Toward developing an urban form generation framework aided by deep generative models and considering topological information, this paper reviews urban form generation, deep generative models/deep graph generation, and the state of the art of deep generative models in architectural and urban form generation. Based on the literature review, a topology-based urban form generation framework aided by deep generative models is proposed. The hypotheses of street network generation by deep generative models for graph generation and plot/building configuration generation by deep generative models/space syntax and the feasibility of the proposed framework require validation in future research.

Keywords: deep generative models; urban form generation; topology

1. Introduction

According to National Unions (2014), 66% of the world's population is expected to live in urban areas by 2050. By 2030, the global urban area will triple compared with that of the start of the twentieth century (Seto, Güneralp, and Hutyra 2012). An increasing significance is attached to urban design to fulfill the requirement of rapid urbanization.

Urban design is a complicated process. The UK's former Social Science Research Council located the discipline of urban design at "the interface between architecture, landscape architecture, and town planning, drawing on the design tradition of architecture and landscape architecture and the environmental management and social science tradition of contemporary planning"(Bentley and Butina 1991). Carmona (2021) argues urban design is not only a simple interface but also encompasses and sometimes subsumes many disciplines and activities, such as architecture, town planning, landscape architecture, surveying, property development, environmental management, and protection, etc. Cowan (2001) has similar arguments to Carmona and contends that producing an urban design framework or masterplan needs a lot of skills, such as interpreting policy, assessing the local economy and property market; appraising a site or area in terms of land use, ecology, landscape, ground conditions, social factors, history, archaeology, urban form and transport, managing and facilitating a participative process, drafting and illustrating design principles, and programming the development process. Urban designers need to consider all these aspects and work with various clients frequently with conflicting interests and aims. Instead of one single solution, varied solutions have to be developed. The process requires a lot of time and labour. When drawing urban masterplans, designers should define the street network, blocks, parcels, and buildings (Miao, Koenig, Knecht, Konieva, Buš, and M. C. Chang 2018). In the early stage of urban design, urban designers have to spend a lot of time in designing urban forms with different characteristics. Extensive urban forms are required in the early stage of urban design to ensure high urban performance in the final construction.

To improve the efficiency and creativity of urban design, multiple generative urban design methods have been put forwards, which are effective in urban design to some extent (Beirão, Duarte, & Stouffs 2011; Luca 2007; Miao, Koenig, Bus, et al. 2017; Miao et al. 2018; Rakha & Reinhart 2012). However, the influence of these approaches is still limited in the mainstream practice of urban design. These urban form generation methods are based on procedural modelling with a series of manually defined rules. Although these approaches significantly reduce the cost of designing urban forms, many tedious processes are still required as these rules are hand-engineered and inflexible to use (Hartmann et al. 2017). For example, repetitive manual tuning of many parameters is demanded to generate urban forms similar to targeted real urban forms.

With the rapid development of artificial intelligence (AI), technology is updated continuously, especially machine learning. Machine learning gives computers the ability to learn how to perform a given task from demonstrations without being explicitly programmed (Samuel 2000). With AI, people will not need to define the rules manually as discussed above. Instead, the "rules" can be learned from data. It revolutionized many scientific fields, such as computer vision and natural language processing. Deep generative models, an approach of machine learning that learns from and interprets data to synthesize designs through multiple layers of artificial neurons, have shown the ability to generate realistic images of faces and everyday objects (Karras, Laine, and Aila 2019; Ruthotto and Haber 2021; Wang et al. 2018; Zhu et al. 2017). Many researchers have made a lot of effort to translate this success to the urban form generation. Hartmann et al. (2017) and Kempinska and Murcio (2019) attempt to generate road network layouts automatically by deep generative models. Shen et al. (2020) put forward an urban filling method assisted by deep generative models.

However, most urban form generation approaches assisted by deep generative models rely on pixel or image representations. There are limitations of this data format, although the data format of the two-dimensional (2D) images seems compatible with the representation of the urban design which is mainly demonstrated through city plans and drawings. The urban space is complicated and topologically associated, and the topology is important in urban form. Images only encode topology information implicitly. On the other hand, graphs encode topology information explicitly. This potentially makes graphs a more suitable representation for modelling urban forms and in turn applying machine learning to urban forms. A promising method to generate urban forms with topological information is deep generative models for graph generation, which is a novel research topic in general (Borgwardt et al. 2020; Kriege and Mutzel 2012; Orsini, Frasconi, and De Raedt 2015). To date, most works have considered the problem of generating graphs corresponding to molecules (Cao and Kipf 2018; Jin, Barzilay, and Jaakkola 2018; Popova et al. 2019; Samanta et al. 2019; You, Liu, et al. 2018). Astrazeneca uses such models for drug discovery (Mercado et al. 2020). Only a handful have considered the problem of generating graphs corresponding to street networks (Chu et al. 2019; Owaki and Machida 2020). Molecules are small graphs while street networks are very large graphs, so the problems are different. To generate urban form with topological information, we should understand the topological information of urban form first. Space Syntax, a technique developed under the theory of city as flows, is a well-known quantitative analysis approach to describe urban form based on topology. Regarding the configurational relations, urban space is represented as a graph in which discrete spatial elements (e.g., convex space, segment, axial line, or isvoist[1]) are shown as nodes, and the connection between each other is denoted as an edge (UCL Space Syntax, 2021).

This research aims to develop a topology-based urban form generation framework aided by deep generative models. The studies on urban form generation, deep generative models/deep graph generation, and the application of deep generative models in urban form generation are reviewed. Consequently, there are three parts to this review. We review the approaches to urban morphology, urban form elements, classification of urban forms, and generative urban design models in section 2, and deep generative models/deep graph generation in section 3, and the state of the art of deep generative models in architectural and urban form generation based on topology in section 4. Following these reviews, a topology-based urban form generation

[1] An isvoist means a group of points visible from a defined vantage point and related to the environment (Benedikt 1979).

framework aided by deep generative models is proposed in section 5. Finally, section 6 summarizes the study and puts forward an outlook on future research.

2. A review of urban form generation

This subsection presents the review of urban form generation by introducing approaches to urban morphology, urban form element, classification of urban form, and generative urban design models.

2.1 Approaches to urban morphology

Different approaches have different perspectives on understanding urban form. Kropf (2009, 2017) proposed four broad approaches, namely, typo-morphological, configurational, historico-geographical, and spatial analytical. Oliveira (2016) presented four similar main morphological approaches: the historico-geographical approach, process typological approach, space syntax, and spatial analysis. Shi (2017) reviewed the approaches to urban morphology and put forwards five approaches: historico-geographical approach, complex-systematic approach, typological approach, functional zoning, and defining the constraints that build up an urban design prototype. This section presents the following four approaches to urban morphology, i.e., historico-geographical approach, configurational approach (Space Syntax), typological approach, and spatial analytical approach. The historico-geographical approach and spatial analytical approach have the same origin of the geography field, and the typo-morphological and configurational approaches come from the fields of architecture and urbanism (Kropf 2017).

(1) Historico-geographical approach

The historico-geographical approach to urban morphology explains the urban form through analysis of urban constituent elements and the process of urban development. This approach originated from the early 19 century when people attempted to identify and explain the diversity of places, such as von Humboldt's holistic approach to geography, cultural landscape, and urban geography (Kropf 2017). The research of German geographers in the early twentieth century had an significant influence on urban morphology until the 1930s. A lot of research was conducted on the plan of medieval towns in Germany (Oliveira 2016; Zhang 2010). Most of the research focused on the layout and rarely considered the integration of urban social, economic, and architectural research. A town should be regarded as an organism in a regional economic system rather than merely a layout (Hofmeister 2004). After the 1930s, this approach lost weight in German human geography. However, the historico-geographical approach gained new vitality and further developed in UK when MRG Conzen emigrated to the UK. Conzen published "Alnwick, Northumberland: A Study in Town-Plan Analysis" and provided a comprehensive framework for analysing and designing the urban physical forms (Conzen 1960). The method of urban form evolution in the process of urban development was utilized to analyze urban elements: streets and their arrangement in a street system, plots and their aggregation in blocks, and block plans of buildings. Afterward, the historico-geographical approach was consistently developed by the Urban Morphology Research Group (UMRG) at the University of Birmingham established by Jeremy Whitehand in 1974. There were many well-regarded researchers in UMRG, such as Kropf, Lilley, Slater, and the research topics included medieval towns, suburban expansion and transformation in the 20th century, the relationship among urban economics, real estate development mechanisms, and urban forms, etc. (Kostof 1999a, 1999b; Kropf 2009, 2011, 2014, 2017; Lilley 2009; Slater 1990).

The historico-geographical approach focuses on hierarchy and time (Shi et al. 2017). The research objects of the urban landscape include the town plan, the building fabric and land, and building utilization (Conzen 1960). The town plan has a hierarchy of plan elements, including streets, plots, and buildings (Conzen 1960). In terms of time, this approach is an evolutionary research approach analyzing the chronological sequence of town plans. The historico-geographical approach explains the settlements' complexity through the elements' morphogenetic processes at different levels (Kropf 2017).

(2) Configurational approach

The ideas of the configurational approach stem from the mathematical and quantitative study of architectural and urban forms conducted in the 1960s, especially in the UK. Inspired by the allometric studies (Thompson 1992) and the analytical potential of graph theory and topology (Euler 1741), many studies have been conducted on the configurational approaches. These approaches focus on the geometric and topological attributes of built form to understand the relationships among different measures and attributes and how spatial configurations influence the use of urban buildings and environments (Kropf 2017). Besides, these approaches also aim to predict and improve the function and performance of architectural and urban forms. The research methods of the configurational approach include topological and quantitative methods, combinatorial analysis, and the idea of possible forms (Kropf 2017). There are four similarities in the configurational approaches. Firstly, the elements are defined by positions in the configuration. Secondly, the interdependence of geometric parameters is demonstrated through the exploration of forms and configurations. Thirdly, the spatial form is the result of the generation process. Fourthly, the form is generated by local generative rules.

Space syntax is an acknowledged configurational approach. Similar to spatial analytical approaches, space syntax argues that the configuration is complex and emergent and the global configuration develops from local processes (Batty 2007). The theoretical basis of space syntax is the relations between spatial structure and movement (Hillier 1996). Configuration of urban form is the primary generator of movement (Hillier et al. 1993). In terms of form notion, space syntax emphasizes the space and spatial configuration rooted in the analysis of buildings (Hillier 2003). Spatial configuration means the relationships between two spaces in a global system considering relationships with all the other spaces in the system rather than only considering the spatial relationship between two spaces (Hillier, Hanson, and Graham 1987). In the urban scale, space syntax mainly focuses on the voids of structure and the urban form is presented as a graph constituted by discrete spatial elements, such as convex space, axial line, segment, or isvoist (Hillier 2003). The topological measures can be extracted from graphs to quantify the characteristics of spatial configuration. Integration and choice are two main measures reflecting two elements of movement: the selection of a destination and the selection of route. Integration measures accessibility and choice measure the passing flow. Space syntax can be developed as interpretive models to analyze, describe, explain, and predict spatial and socio-economic phenomena, such as urban movement, urban crime, centrality, spatial intelligibility (UCL Space Syntax 2021). Besides, space syntax can be utilized to help generate urban form and predict the distribution of building use based on topology (Al-Sayed 2013; Thirapongphaiboon and Hanna 2019; Xie 2011).

(3) Typological approach

The typological approach refers to typo-morphological approach or process typological approach. This approach developed based on the architectural and urban design practice and education in the first half of 20 century, mainly in France and Italy. The typological approach studies the built environment as a context for development and formative processes and evolution of building types to inform architectural and urban design proposals (Cataldi, Maffei, and Vaccaro 2002). It aims to develop a design with local tradition and in harmony with the context. Saverio Muratori was a representative of researchers supporting this approach in the early stage who combined the research methods of architectural typology and urban morphology to protect the sense of historical continuity in architectural and urban design through the study of architectural and urban history (Cataldi 2003). These researchers opposed modernist architecture and emphasized the protection of historical and cultural heritage in the 1950s and 1960s (Zhang 2010). Afterward, Caniggia, Rossi, and Krier were another three influential researchers. Caniggia (2003) connected the urban typological processes to the different phases of urban history. Rossi (1999) defined typology as elements that cannot be further reduced. Rossi's typological approach mainly reflected people's way of living rather than a physical form itself. He argued that a city should be built with the typology of the city. Many European cities developed with the remained urban physical form and evolving program behind the form. Krier (1984) proposed to guide design through typological study and imitated the pre-industrial cities for design. However, the typology of a city is not always constant, and the urban elements are continuously transforming with the change in people's lifestyles (Moundon 1997). Thus, the prediction of urban typology in the future through the study of the evolution of people's lifestyles is important in urban form generation (Shi et al. 2017).

(4) Spatial analytical approach

The spatial analytical approach mainly focuses on people's activity as sets of spatial interaction. It utilizes a series of quantitative methods, such as mathematical models (entropy-based, fractal, and other non-linear forms in particular), agent-based models, cellular automata, graph theory, and network analysis (Kropf 2017). This approach originates from initial analytical ideas, such as economic geography and the dynamic models of urban structure (Adams 2005; Thünen 1966). According to the spatial analytical approach, cities are complicated adaptive systems involving the relationships of social and economic interactions and settlements' physical forms. In a city, there are flows of people and resources (including natural flows, such as sunlight, wind, and water, and people-related flows, such as goods, energy, information, and waste) (Batty and Cheshire 2011; Kropf 2009). Flows mean the changes occur among points defined by locations and time in Eulerian and Lagrangian frames of reference (Batty and Cheshire 2011). The city is regarded as a network of flows (Batty 2013). The pattern of people and resource flows generate urban physical forms and are also influenced by urban physical forms. Thus, in the early phase of projects, designers should figure out the principles and relationships of flows in the system. The elements are defined and differentiated by their positions in a structure or configuration. The interrelationships of elements and the elements working as a whole are analyzed. The form and structure are the results of the generative process of formation and transformation.

2.2 Urban form elements

The urban physical form consists of several elements. Scheer (2001) divided the urban form into five layers, i.e., site, superstructure (e.g. highways and boundaries before urban settlements), infill (e.g. paths, plots), buildings, and objects (e.g. vegetation, fences). Beirao et al. (J. Beirão 2012) proposed City Ontology with five main elements, i.e., networks, blocks, zones, landscapes, and focal points. In Koenig's model of DecodingSpace, the urban form consisted of three basic urban elements, i.e., street networks, parcels, and buildings (Miao, Koenig, Bus, et al. 2017). Oliveira proposed that all cities and their urban tissues were comprised of four urban elements, i.e., streets, street blocks, plots, and buildings (Oliveira 2016). A well-accepted simple urban form includes three basic elements, i.e., streets, plots, and buildings (Conzen 1960; Kropf 2009, 2017; Moundon 1997; Whitehand 2001). Single space shelters are organized to create buildings; buildings and enclosures are combined to generate plots; plots and routes form streets (Kropf 2017). These urban elements come together organically and form a compositional hierarchy.

Street network is public and democratic of the city, where we meet and interact in social terms. Streets define the street blocks and are accessible to everyone (Oliveira 2016). There are many categories of streets with different functions, shapes, sizes, and relations to other streets. The characters of streets are affected by plots on one or two sides of the street, the buildings of their height, the location of buildings in plots (the distance from buildings and street), the length of frontage, and the distribution of the movement of pedestrians and vehicles (Gehl 2011; Oliveira 2016).

Plot is also known as parcel, property, and lot. The plot system is the organizational framework of urban form separating the public domains and the different private domains (Bobkova et al. 2019). The definition of plots involves the relation of the plot to the street, the position of the plot within the plot system, and the shape, dimension, and proportion of the plot. The plots influence the buildings within these plots and further affect the urban landscape. The dimension of street blocks and plots is a significant element in describing the physical urban form. In general, the dimension of blocks and plots increases from the historical center to the peripheral parts of the city except for some conditions, such as the fringe belt (Oliveira 2016). On the contrary, the number of plots per street block decreases from the historical center to the peripheral parts of the city generally (Oliveira 2016).

Building is one of the most important and visible elements of urban form. Buildings have the character of the positions in plots, the dimension of buildings and the utilization of buildings, etc. The position of buildings within their plots is an important characteristic of urban form. According to Oliveira (2016), buildings were aligned continuously in an apparent organization in most cities before the end of the nineteenth century. However, many theories developed over the twentieth century supporting the variation in the position of buildings within plots. There are two critical indicators of building dimension: building height and the relationship between building height and the width of the street where the buildings are located. The building height and street width influence the sense of street space. The sense of eclosure in street space increases if the ratio of building height to street width increases. The utilization of buildings lays out the activities within a building. The use of buildings includes residential, commercial, service, mix of use, etc. There are other essential characteristics of buildings, such as facade, building material, organization of dwellings.

2.3 Classification of urban forms

The urban form demonstrates a series of repeating arrangements or configurations of urban elements: street networks, plots, and buildings (Conzen 1960; Kropf 2009, 2017; Moundon 1997; Whitehand 2001). The repeating patterns are regarded as form types and represent the organization of urban form. Different types of urban elements are combined in different patterns (streets incorporate plots and plots incorporate buildings) and generate different types of urban forms. There are various classification methods for urban form. Table 1 shows the classification of urban forms, including urban indicators for classification, urban form types, and classification method. Table 2 demonstrates the most used urban indicators quantifying urban form, i.e., connectivity, centrality, density, dimension, shape, and usage.

In summary, the urban indicators describing urban elements are utilized to classify urban types. The most used indicators quantifying urban form are connectivity, centrality, density, dimension, shape, and usage. The most used classification methods are clustering analysis and self-organizing maps (SOM). The different urban form types result from the classification of urban forms using different urban indicators and classification methods.

2.4 Generative urban design models

There are multiple urban form generation models. In this section, several widely accepted urban generative design models are introduced.

Koenig et al.'s model consists of three steps (Koenig et al. 2017; Miao, Koenig, Bus, et al. 2017; Miao, Koenig, Knecht, Konieva, Buš, and M.-C. Chang 2018; Miao, Koenig, and Knecht 2017). Firstly, street networks are generated. Then, through extraction from the street networks, blocks are defined. Finally, buildings are placed on the parcels, which are sliced from blocks. This model has the advantage of being able to generate a fast prototype of urban design. However, the generation of plots relies on street networks based on the defined parameter and initial street segments. Also, no component is integrated for data analysis and evolutionary multi-criteria optimization.

Beirão put forward an urban form generation model called CItyMaker in 2012. It consists of three modules, i.e., formulation module, generation module, and evaluation module (Beirão, Duarte & Stouffs 2011; J. N. Beirão 2012). The formulation module analyses the urban context of the site. The generation module leverages the generative method of shape grammar. The evaluation module evaluates the generated design and leads the design to meet the target. The rules of urban induction patterns are used to define the compositional guidelines of the plan, grids or the main street structure, urban units including squares and other public spaces, and designing details (e.g., street profiles and materiality) (Beirão, Duarte and Stouffs 2011; J. N. Beirão 2012). However, this model lacks integrated calculations or tools for topology evaluation.

Rakha and Renhart's model (Rakha and Renhart 2012) has two steps, i.e., the generation of street networks and buildings and the optimization based on walkability by genetic algorithms. The advantage of this model is that it can work on terrain. However, the types of building massing in this model are limited, and the void open space is not considered.

Luca (2007) utilizes cellular automata and agent-based modeling for generation on the urban and regional scales. This model has two steps, namely, data collection and form generation. The forms generated to meet the tasks in the spatial, temporal, and scale hierarchy are based on the dataset. However, Luca’s model does not generate urban and building functions.

Shi et al. (2017) propose a general workflow with three steps of data collection, generation, and optimization for simulation-based urban form generation and optimization modeling. However, the computation cost of the simulation is rather high, and the simulations and analysis in the research are not validated by measurement data.

All the models mentioned above have the steps of data collection and generation. The collected data step includes physical, social-economic data of the environment, the context of the site, and users’ preferences. The generation step is the generation of urban form elements based on generative methods and constraint sets, and the primary urban form elements include street networks, plots, and buildings.

3. A review of deep generative models and deep graph generation

3.1 Deep generative models

In general, deep generative models are the models with many layers of stochastic or deterministic variables to approximate complex and high dimensional probability distributions (Beirão 2012; Beirão et al. 2011). According to Turhan and Bilge (2018), deep generative models can be categorized into five types, namely, unsupervised fundamental models, Autoencoder (AE) based models, autoregressive models, Generative Adversarial Networks (GAN) based models, and AE-GAN hybrid models. At the end of 2019, another kind of deep generative model, i.e., diffusion models, became very popular (Dieleman 2022). These six types of deep generative models are introduced as follows.

(1) Unsupervised fundamental models

A lot of research has been conducted on using unsupervised fundamental models for texture synthesis and classification of handwritten digits, but the generated images are blurry (Creswell and Bharath 2016; Hu et al. 2018; Ou 2018; Ruthotto and Haber 2021). Boltzmann Machine, introduced by Geoffrey Hinton et al. in 1983, aims to search for combinations of "hypotheses" satisfying some constrained input maximally (Turhan and Bilge 2018). Restricted Boltzmann Machine is inspired by the binary Boltzmann Machine and has more freedom and flexibility (Ackley, Hinton, and Sejnowski 1985; Fahlman, Hinton, and Sejnowski 1983). Deep Boltzmann Machines and Deep Belief Networks are more powerful generative models based on the building block of Restricted Boltzmann Machine (Oussidi and Elhassouny 2018). Deep Boltzmann Machine can generate images based on latent representation by generative decoders with Gibbs sampling (Salakhutdinov 2015; Xu, Li, and Zhou 2015) and Deep Belief Network can provide features from representations at high levels (Salakhutdinov and Hinton 2009). The unsupervised fundamental models are widely applied in image processing, speech recognition, information retrieval, etc. (Fischer and Igel 2012).

(2) Autoencoder models

Autoencoder models are neural networks trained to reconstruct input as output consisting of two parts, i.e., encoder and decoder. These models aim to learn the pattern and characteristics of the data distribution and generate new examples similar to the training examples. There are four kinds of autoencoder models, i.e., undercomplete autoencoders, denoising autoencoders, sparse autoencoders, and variational autoencoders (VAE) (Salakhutdinov 2015; Xu et al. 2015). VAE is one of the widely used and efficient deep generative models (Nikolaev 2018). It is a direct model using learned approximate inference and trained through the gradient based method (Nikolaev 2018). Through VAE, the input image can be encoded as a low-dimensional representation storing the input information.

(3) Autoregressive models

Autoregressive models use a linear combination of past values of valuables to forecast the target variables, and they are very flexible in dealing with different kinds of time series (Kingma and Welling 2014). In terms of images, autoregressive models handle images pixel by pixel rather than whole images (Hyndman 2018). Masked Autoencoder for Distribution Estimation (MADE), an autoregressive model modified by autoencoder network, uses the autoregressive property to forecast the distribution from a set of samples (Turhan and Bilge 2018). PixelCNN Decoder, an autoregressive model based on Convolutional Neural Network (CNN), can generate images conditionally (Uria et al. 2016). PixelRNN uses the dependency between pixels closer together to generate images sequentially based on Long Short-Term Memory (LSTM) (Oord et al. 2016). Recurrent Neural Networks (RNN) are a class of neural networks modeling the information in sequential order, widely used in time series and natural language (Guo and Zhao 2020). However, RNN only performs well in short-term dependency and has not been proven useful in long-term dependency. LSTM, a special type of RNN, can seamlessly store and repeatedly utilize long-term information (Oussidi and Elhassouny 2018; Tensorflow n.d.). PixelVAE is a VAE model with an autoregressive model based on pixelCNN for natural image modeling (Oussidi and Elhassouny 2018). Variational Lossy Autoencoder learns the global representation for 2D images by combining VAE with neural autoregressive models, such as RNN, MADE, PixelCNN, and PixelRNN (Gulrajani et al. 2017). Graphgen, GraphRNN, and DeepGMG utilize autoregressive models to generate graphs (Goyal, Jain, and Ranu 2020; Li et al. 2018; You, Ying, et al. 2018).

(4) Generative Adversarial Networks (GAN) based models

GAN is based on the game theory of the minimax game, where a generator and a discriminator compete with each other (Chen et al. 2017). The generator learns to generate new data from the stochastic noise and the discriminator learns to distinguish the generated fake data from the real data. GAN is one of the most successful generative models based on deep learning, especially in generating realistic high-resolution images. Based on GAN, there are many improved models developed, such as Conditional Generative Adversarial Networks (CGAN) (Goodfellow et al. 2014), Deep Convolutional Generative Adversarial Networks (DCGAN) (Gauthier 2014), Style-Based Generator Architecture for Generative Adversarial Networks (StyleGAN) (Radford, Metz, and Chintala n.d.), Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks (CycleGAN) (Karras et al. 2019), Image-to-Image Translation with Conditional Generative Adversarial Networks (Pix2Pix) (Zhu et al. 2017). Pix2PixHD is also proposed for high-resolution image synthesis and semantic manipulation with conditional GAN (Wang et al. 2018). In addition to the models for 2D image generation, GAN is extended to generate three-dimensional (3D) objects (Wu et al. 2016) and graphs (Fan, Tech, and Huang 2019; Wang et al. 2021).

(5) Autoencoder-GAN hybrid models

Many studies have been conducted to combine autoencoder and GAN. VAE/GAN can learn to encode, generate, and discriminate information (Fan and Huang 2019). The discriminative feature learned by GAN is used as the reconstruction objective of VAE. Deep perceptual similarity metrics (DeePSiM) uses VAE and GAN to prevent blurry reconstructed image in image generation (Anders Boesen Lindbo et al. 2016). Lamb et al. propose an autoencoder-GAN hybrid model and show that this model can generate samples with higher quality than standard VAE (Dumoulin et al. 2017). 3D-VAE-GAN is an autoencoder-GAN hybrid model for learning an 2D image to 3D model mapping (Lamb, Dumoulin, and Courville 2016).

(6) Diffusion models

Diffusion models define a Markov chain[2] of diffusion steps to add random noise to data gradually, and then train a neural network that learns to invert the diffusion process to construct expected data samples from the noise (Weng 2021). Diffusion models were inspired by non-equilibrium thermodynamics (Sohl-Dickstein et al. 2015) and developed rapidly after 2019, when noise-conditioned score network was proposed (Song and Ermon 2019). Building on Sohl-Dickenstein et al.'s research, Ho et al. (2020) put forwards denoising diffusion probabilistic models (DDPM), which could match GAN on image generation. Afterward, Denoising Diffusion Implicit Models (DDIM) was proposed to accelerate diffusion model sampling to improve DDPM (Song, Meng, and Ermon 2020). In 2021, Nichol et al. (2021) released GLIDE for text-conditional image synthesis and Dhariwai and Nichol (2021) demonstrated a better performance than GAN with diffusion models. Besides, SR3 and Cascaded

[2] Markov chain is a chain formed by a sequence of possibilities of states in a long-run steady-state level in which the probability of a state relies on the previous state (Glantz and Mun 2011).

Diffusion Models (CDM) models were released by Google, which could convert low-resolution images to high-resolution (Ho et al. 2022; Saharia et al. 2022).

3.2 Deep graph generation

Graphs are complicated data structures with rich underlying values, and they can represent relational and structural information, such as social networks, molecule structures, citation networks, traffic networks, biology networks. There are many applications of graph generation, for example, drug design, model architecture search, network science (Wu et al. 2016). As the wide application, there is a long development history of graph generation dating back to the 1960s (Liao et al. 2019). The traditional graph generative models focus on modeling families of graphs with specific properties, such as random graphs (Erdös and Rényi 1960), small-world networks (Erdös and Rényi 1960), and scale-free graphs (Watts and Strogatz 1998). However, these models can only model a few statistical properties of graphs and have limited ability to model complicated dependencies. Besides, these models only focus on the structural property and neglect the assignment of labels to individual graph vertices and edges. Considering the limitations of the traditional methods, an increasing amount of research pays attention to the deep generative models that can directly learn from a set of graphs to generate new and novel graphs with similar properties to the set or distribution of training graphs. The use of deep generative models can improve the fidelity of generated graphs. Deep generative models for graph generation are also called deep graph generation (Albert and Barabási 2002).

According to Guo and Zhao (2020), there are two kinds of deep generative models for graph generation, namely, unconditional generation and conditional generation. Unconditional generation is using deep generative models to learn the distribution based on a set of observed realistic graphs from the real distribution. Conditional generation is using deep generative models to learn the distribution based on a set of observed realistic graphs and auxiliary information, such as labels, semantic context, graphs from other distribution spaces, etc.

There are three critical areas in deep graph generation, i.e., domain-agnostic modeling, labeled graph generation, and data scalability (Goyal, Jain and Ranu 2020). Many techniques have limitations in these areas. Table 3 demonstrates the limitations of deep graph generation techniques. Only Graphgen is domain-agnostic, data scalable, and with node labels and edge labels.

In terms of evaluation metrics for deep graph generation, there are three kinds of methods, namely, statistics-based, classifier-based evaluation, and self-quality-based evaluation (Guo and Zhao 2020). Statistics-based evaluation first computes graph statistics measuring different graph properties (including node degree distribution, clustering coefficient distribution, orbit count distribution, largest connected component, triangle count, characteristic path length, and assortativity) and then measures the distance between the distributions of generated graph properties and test graph properties. There are two major metrics for calculating the distance between two distributions of graph properties, namely, the Kullback-Leibler Divergence and the Maximum Mean Discrepancy. There are two ways for the distance metrics for scalar-valued statistics (including largest connected component, triangle count, characteristic path length, and assortativity). The first is the calculation of the disparity between the averaged value of the scalar-valued statistic of the real graph and the generated graph. The second is the calculation of the distance between the distribution of the scalar-valued statistic of the real graph and the generated graph. The classifier-based evaluation compares the generated graphs and real graphs through a graph classifier without explicitly defining the graph statistics, including accuracy-based and Fréchet Inception Distance-based methods. The classifier is trained on the real graphs and then is tested on the generated graphs. The self-quality-based evaluation directly assesses the generated graphs' properties, i.e., the generated graph's validity, uniqueness, and novelty.

The application of deep graph generation continuously extends to an increasing number of fields, such as molecular chemistry, semantic parsing in natural language processing, code modeling, and pseudo-industrial Boolean Satisfiability instance generation (Guo and Zhao 2020).

4. State of the art of deep generative models in architectural and urban form generation

Many studies explore applying deep generative models in architectural and urban form generation (see Table 4). To date, there have been four kinds of deep generative models applied in architectural and urban form generation, i.e., GAN, CNN, VAE, and autoregressive models. According to Table 4, GAN is the most widely used deep generative model in architectural and urban form generation. Most generation objectives model properties relating to building configuration, floor plan, building facade, building massing, and street network structure. Evaluating the quality of output is a challenge for deep generative models. The metrics refer to measures of similarity to determine how similar the generated architectural and urban forms are to the set of architectural and urban forms used to train the model. Useful measures of similarity are required to train the model. Otherwise, we cannot define whether the generated architectural and urban forms have similar properties to the real architectural and urban forms used to train the model. There are various metrics to evaluate the qualities of architectural and urban forms generated by the deep generative models. The metrics can be categorized into two groups, namely, visual metrics and statistical metrics. There are two kinds of statistical evaluation. One is scoring the indicators manually, and the other one is quantitative indicators, such as density, area, and connectivity. Most models use image representations to generate the architectural and urban forms. However, the architectural and urban spaces are complicated and topologically associated. These models neglect the topological relationship among architectural and urban elements. This topological information is modeled in the corresponding graph or network representation of architectural and urban spaces. On the other hand, image representations do not explicitly encode topological information and therefore deep generative models based on such representations generate architectural and urban spaces with inaccurate or highly unusual topology. The other common limitations of these studies include the low quality of design output, limited control over the design output, long training time, limited training data, and training based only on one single example.

5. Topology-based urban form generation framework aided by deep generative models

Through the literature review, two hypotheses are raised:

- Deep generative models for graph generation can be used for street network generation based on topology.
- Deep generative models and space syntax can be used for plot and building configuration generation based on topology.

Based on the two hypotheses, a topology-based urban form generation framework aided by deep generative models is proposed to overcome the most common limitations of previous studies of deep generative models in architectural and urban form generation:

- rarely considering topological relationships among urban form elements
- low quality of design output
- limited control over the design output
- limited training data
- training based only on one single example

The topology-based urban form generation framework aided by deep generative models consists of six modules, i.e., the establishment of the dataset, the selection of sub-datasets, the street network generation, the selection of generated street networks, the plot and building configuration generation, and the selection of generated plots and building configurations (see Figure 1). The user-machine interaction workflow is presented in Figure 1. Among the six modules, establishment of the dataset, street network generation, and plot and building configuration generation are highly automized, and the other three parts require the participation of designers.

This framework consists of tools, data, and interfaces. The tools include clustering analysis or SOM for division of sub-dataset, deep generative models for graph generation, and deep generative models/space syntax for plot and building configuration generation. The urban forms are made up of street networks, plots, and building configurations, and there are three interfaces, i.e., sub-dataset decision interfaces, design decision interface for street networks, design decision interface for plots and building configurations. These interfaces achieve the interaction between designers and the machine and allow the designers to influence the process of design generation. Figure 2 demonstrates the detailed workflow of the proposed framework. In the establishment of the dataset, the data of urban form (including street network, plot, and building configuration) is classified into different types, making up several sub-datasets, by the classification method of clustering analysis or SOM through the urban indicators of connectivity, centrality, density, dimension, usage, and shape. Through the sub-dataset decision interface, designers select a sub-dataset whose urban form fits the site for learning, considering the context of the site. Then, the street networks in the sub-dataset are used for training, and new street networks are generated by deep generative models for graph generation. In these generated street networks, an optimum street network is selected by designers through the design decision interface. Afterward, space syntax is used to analyze the centrality of the generated street network and the street networks from the selected sub-dataset. Based on the training of a pair of street network centrality analysis maps and plot/building configuration maps from the sub-dataset, new plots and building configurations are generated with the input of the generated street network in the last step by deep generative models. Through the design decision interface, designers choose a set of plots and building configurations from the generated plots and building configurations. This set of plots and building configurations, together with the generated street network selected by designers, makes up the generated urban form as design output. This generated urban form is stored in the urban form dataset simultaneously.

This framework combines the four approaches to urban morphology, i.e., historico-geographical approach, configurational approach, typological approach, and spatial analytical approach. According to historico-geographical approach, the proposed framework dissects the urban form into three components, i.e., street networks, plots, and building configurations. The configuration approach is reflected by generating urban forms based on topology. The structures of urban forms, i.e., street networks, are presented as graphs. The trained deep generative model generates new urban forms with similar geometric and topological attributes to the urban forms in the training set. In the plot and building configuration generation, space syntax is leveraged to analyze the centrality of street networks. Besides, this framework utilized a typological approach to divide the urban form dataset into several sub-datasets for users to select. In addition, the spatial analytical approach is applied in the plot and building configuration generation. In this stage, the city is regarded as a network of flows visualized through the street network centrality analysis map. Deep generative models learn how flows generate urban physical forms through pairs of street network centrality analysis maps and plot/building configuration maps. Plots and building configurations are defined and differentiated by their positions by trained deep generative models in the street network generated in the last step.

Besides, this framework overcomes the most common limitations of the previous applications of deep generative models in urban form generation. The limitation of rarely considering topological relationships among urban form elements is surmounted by using deep generative models for graph generation, deep generative models, and space syntax to generate urban forms based on topology. Besides, the training of deep generative models for graph generation (such as Graphgen) and deep generative models (such as Pix2PixHD) is based on multiple data. Also, the limitation of low-quality design output is overcome through deep generative models that can synthesize high-resolution images, such as Pix2PixHD. In addition, designers' controllability of the model can be improved by dividing the urban form dataset into several sub-datasets based on typology. Designers can influence the design process by selecting the sub-dataset based on typology of urban form and by choosing the optimum street network and the optimum set of plots and building configurations from the generated street networks and generated plots and building configurations, respectively. Moreover, the problem of limited training data can be surmounted through data collection from OpenStreetMap and Digimap, which contain data on street networks, plots, and building configurations for most urban areas.

6. Conclusion and outlook

In this research, a critical literature review is conducted. At first, the urban form generation is reviewed. The approaches to urban morphology are presented, i.e., historico-geographical approach, configurational approach, typological approach, and spatial analytical approach. The main urban form elements of street networks, plots, and buildings are demonstrated. The urban form classification is conducted using the different urban indicators and classification methods of clustering analysis or SOM. The well-accepted urban indicators include connectivity, centrality, density, dimension, usage, and shape. Most generative urban design models involve the steps of data collection and generation. The main urban form elements generated include street networks, plots, and buildings. Then, deep generative models and deep graph generation are reviewed. All the six types of deep generative models (i.e., unsupervised fundamental models, autoencoder models, autoregressive models, GAN based models, autoencoder-GAN hybrid models, and diffusion models) might be helpful for urban form generation. Afterwards, the state of the art of deep generative models in architectural and urban form generation is presented. The most common limitations of previous studies of deep generative models in architectural and urban form generation include:

- rarely considering topological relationships among urban form elements
- low quality of design output
- limited control over the design output
- limited training data
- training based only on one single example

Through the literature review, two hypotheses are raised:

- Deep generative models for graph generation can be used for street network generation based on topology.
- Deep generative models and space syntax can be used for plot and building configuration generation based on topology.

Based on the two hypotheses, a topology-based urban form generation framework aided by deep generative models is proposed to overcome the five most common limitations of previous studies of deep generative models in architectural and urban form generation mentioned above. This framework integrates historico-geographical approach, configurational approach, typological approach, and spatial analytical approach acquired from the review of approaches to urban morphology in section 2.1. There are six modules in this framework, i.e., the establishment of the dataset, the selection of sub-datasets, the street network generation, the selection of generated street networks, the plot and building configuration generation, and the selection of generated plots and building configurations. This framework has three kinds of data, three tools, and three interfaces. The urban forms are composed of street networks, plots, and building configurations summarized from the review of urban form elements in section 2.2. The tools used in the framework include clustering analysis or SOM for urban form classification, deep generative models for graph generation leveraged for street network generation, and deep generative models/space syntax used for plot and building configuration generation. These tools are summarized from the review of classification of urban forms in section 2.3, deep generative models in section 3.1, deep graph generation in section 3.2, and approaches to urban morphology in section 2.1. The three interfaces, including sub-dataset decision interface, design decision interface for street networks, and design decision interface for plots and building configurations, allow the designers to intervene in the design process, which overcomes the common limitation of restrained control over the design output by the users in the previous studies summarized in the state of the art of deep generative models in architectural and urban form generation in section 4.

However, this framework is still at a conceptual level. The classification of urban form based on typology using clustering analysis and SOM in the step of data collection and analysis is validated by previous studies. However, the generation of street networks using deep generative models for graph generation and the generation of plot and building configurations using deep generative models and space syntax are still hypotheses. In future research, these hypotheses and the feasibility of the proposed framework will be validated through a design practice methodology engaging inputs in concert with the digital generation. We will qualitatively evaluate the rationality of the design output and quantitatively test whether the urban form type of the output is the same as the type of the urban forms in the selected sub-dataset through the urban indicators of connectivity, centrality, density, dimension, shape, and usage. Besides, the technology acceptance model will be utilized to obtain feedback from early users of the proposed framework through a survey and further improve the proposed framework.

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No potential conflict of interest was reported by the authors.

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