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ABSTRACT

Cultural venues, such as libraries, theatres, cinemas and galleries, contribute to a city's tourism and economy, and enrich the cultural life of the local residents. In this paper, we propose a novel approach to automatic site selection of cultural venues in an urban area, which requires less expertise in urban planning. The two-stage approach consists of a learning stage for predicting zones as a prior constraint, and an optimisation stage for determining the number of cultural venues and their exact locations according to multiple criteria. Given an input set of urban data, our approach generates an optimal configuration of two-dimensional locations for cultural venues that complies with land use policies and provides easy access for the public. We implemented the approach using reliable methods of deep learning and stochastic optimisation, and the results demonstrate the approach's effectiveness by a comparison to their real-world counterparts.

CCS CONCEPTS

• **Computing methodologies → Shape modeling**;

KEYWORDS

Site selection, Deep learning, Stochastic optimisation, Cultural venues

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1 INTRODUCTION

A modern city would be considered heartless and uncreative without places symbolising its exclusive history, value and the preserved contributions from the community. From the Metropolitan Museum of Art in New York to the Opera House in Sydney, cultural venues serve as a vital part of a city's lifeblood and are conductive to various aspects of the local development. These places satisfy the local residents' need for more vibrant life, and appeal to tourists raising local government revenue and promoting the neighbourhood development. The reasons above enable cultural venues to be an important tool for urban development [Markusen and Gadwa 2010] and hence their strategic locations matter.

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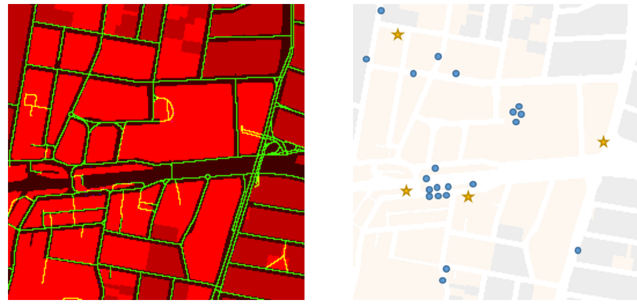

(a) Input: Rasterised urban data **(b) Output: Site selection plan**

Figure 1: Our approach automatically generates a site section plan for cultural venues (b) from an image representing a set of urban data (a). Yellow star markers illustrate the proposed locations of the new cultural venues, and blue dot makers denote the locations of public transport facilities.

Selecting site locations for cultural venues remains a complex decision-making process. Its legislative feature requires new venues to be located in permitted zones according to a land use plan [Nguyen et al. 2017]. In addition, public visitors and tourists are always expecting a smooth travel to cultural venues by public transport systems and convenient access roads [Mardoukhi and Kordzadeh 2016]. In a dynamic scenario, decision makers have to balance the number of new venues against the construction expenditures. These concerns demand expertise in urban planning and usually cause considerable manpower and time for site selection. Therefore, urban planners and policy makers would benefit substantially from automatic approaches to site selection of cultural venues predicting the most optimal configuration.

In contrast to the conventional approaches based on Multi-Criteria Analysis (MCA) [Chabuk et al. 2016; Mardoukhi and Kordzadeh 2016; Nguyen et al. 2017], we aim to formulate site selection of cultural venues as a computational problem. The proposed approach utilises deep learning and stochastic optimisation successively, and generates a site selection plan suggesting an optimal number of cultural venues and their exact locations from a set of urban data. The rest of this paper is organised as follows: in Section 2, we introduce the two-stage approach's pipeline; in Section 3 and 4, we discuss respectively the *learning* stage for predicting zones as a prior information and the *optimisation* stage for determining the number of cultural venues and their exact locations according to multiple criteria; in Section 5, we demonstrate site selection examples generated with our approach and a comparative analysis between them and real-world cases followed by a conclusion in Section 6.

This paper provides a two-fold contribution: (a) it solves the problem of site selection for cultural venues computationally; and (b) it proposes an automatic approach using deep learning and stochastic optimisation, which enables the user to cost-efficiently

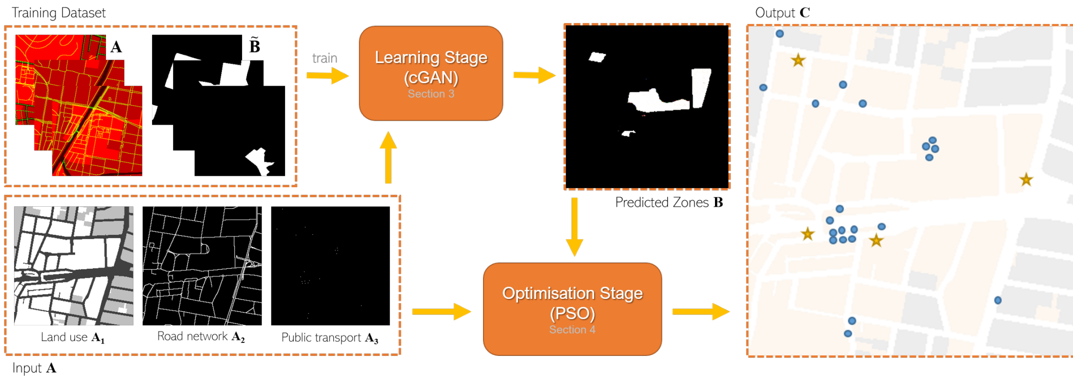

Figure 2: The approach's pipeline. From an input image A, the learning stage predicts zones B as a prior constraint using a cGAN trained on a real-world dataset $\{(A, \tilde{B})\}$, and the optimisation stage utilises the PSO algorithm to generate a site selection plan C for cultural venues from A and B.

Table 1: Definition of image pixel values.

Pixel Value	*Image* A A_1	A A_2	A A_3	B	C
0	Unsuitable	Void	Void	Void	Void
0.5	Residential	-	-	-	-
1.0	Service	Road segment	Bus stop / Train station	Predicted zone	Site location

generate a site selection plan for cultural venues by trading off among multiple criteria.

2 OVERVIEW

We propose a two-stage *coarse-to-fine* approach as illustrated in Figure 2. Given an input image **A** representing a set of urban area, the initial *learning* stage predicts zones **B** where cultural venues are likely to be located using a deep learning model trained on a real-world dataset $\{(\mathbf{A}, \tilde{\mathbf{B}})\}$. The following *optimisation* stage explores the search space of the problem, in order to determine an optimal number of cultural venues and their exact locations using a stochastic optimisation algorithm from **A** and **B**. The approach generates a site selection plan **C**.

The input image **A** consists of three bands $\{\mathbf{A}_1, \mathbf{A}_2, \mathbf{A}_3\}$ respectively corresponding to *land use*, *road network* and *public transport*. $\mathbf{A}_1$ is converted from a land use plan and each of its pixels represents a land use type. In this work, we categorised all urban zones into three land use types: *service*, i.e., zones for commercial and public activities, *residential*, i.e., zones for housing, and *unsuitable*, i.e., zones for roads and railways or prohibited areas for new construction. $\mathbf{A}_2$ and $\mathbf{A}_3$ are obtained by rasterising a road map and their binary pixels indicate the existence of road segments and transport facilities, i.e., bus stops and train stations. Single-band images **B** and **C** depict the geographic distributions of predicted zones and generated site locations for cultural venues. We processed the aforementioned images using 32-bit single-precision floating-point representation. The pixel values of these images are defined in Table 1.

3 LEARNING

We observed that most public places, including cultural venues, are usually located in certain zones according to a land use plan that has been approved by a local authority [Collins et al. 2001; Nguyen et al. 2017]. Therefore, we believe that prediction of possible zones is able to provide useful information as a prior constraint for site selection of cultural venues. Similar *image-to-image* problems has been solved with deep learning methods in recent years, among which *conditional Generative Adversarial Nets* (cGANs) [Mirza and Osindero 2014] are outstanding for their sound capability to achieve example-based synthesis [Isola et al. 2016].

Specifically, a cGAN is trained offline and utilised at the learning stage to generate an image **B** predicting possible zones where cultural venues are likely to be located from **A**. It contains a generator $\mathcal{G}$, which produces **B** from **A**, and a discriminator $\mathcal{D}$, which makes binary decisions to differentiate *artificial* pairs $(\mathbf{A}, \mathbf{B})$ from *genuine* pairs $(\mathbf{A}, \tilde{\mathbf{B}})$ belonging to a training dataset, i.e., $\mathcal{D}(\mathbf{A}, \mathbf{B}) = 0$ and $\mathcal{D}(\mathbf{A}, \tilde{\mathbf{B}}) = 1$. The training process aims to enable $\mathcal{G}$ to generate images indistinguishable to $\mathcal{D}$, while $\mathcal{D}$ attempts not to be deceived by $\mathcal{G}$, which can be described as a mini-max game as follows:

$$\mathcal{G}^* = \arg\min_{\mathcal{G}} \max_{\mathcal{D}} \mathbb{E}_{\mathbf{A},\tilde{\mathbf{B}}} \log \mathcal{D}(\mathbf{A}, \tilde{\mathbf{B}}) + \mathbb{E}_{\mathbf{A},\mathbf{B}} \log(1 - \mathcal{D}(\mathbf{A}, \mathbf{B})) + \mathbb{E}_{\mathbf{B},\tilde{\mathbf{B}}} \|\mathbf{B} - \tilde{\mathbf{B}}\|, \tag{1}$$

We adapt the network architecture and the training specifics proposed by Isola [Isola et al. 2016]. Our generator $\mathcal{G}$ is constructed as an encoder-decoder whose encoder contains convolutional layers and decoder connected upsampling layers. The numbers of features in $\mathcal{G}$'s layers are respectively 64, 128, 256, 512, 512 , 512, and 512. Our cGAN for predicting zones achieves an overall accuracy about *82.98%* in a ten-fold cross validation on the training dataset. Figure 3 demonstrates the examples predicted by the cGAN compared to the corresponding real-world zones.

4 OPTIMISATION

In order to obtain an accurate site selection plan for cultural venues considering multiple criteria, we have to carry out a further exploration of the search space constrained by the predicted zones. We observed that stochastic optimisation algorithms have been prolonged exploited to solve complex modelling problems [Feng et al. 2016; Garcia-Dorado et al. 2017; Wu et al. 2018], and hence apply the same strategy to achieve our goal. In this paper, we focus on the *Particle Swarm Optimisation* (PSO) [Kennedy and Eberhart 1995] algorithm for seeking an optimal site selection plan.

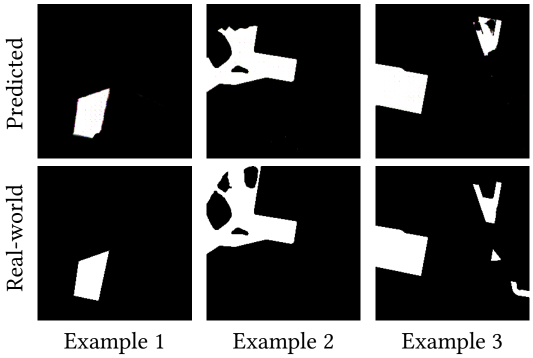

Figure 3: Zone examples predicted at the learning stage and their real-world counterparts. Our cGAN is capable to accurately predict convex, concave and multi-part zones.

The PSO algorithm is based on a swarm of particles, each of which represents a candidate site selection plan, i.e., locations of a specified number of cultural venues. A particle is initialised as a vector of two-dimensional coordinates randomly sampled from the predicted zones in **B**, and advects using a cost function calculated from **A**. In particular, *best known positions*, which achieve the current minimal costs respectively at particle-level and swarm-level, are updated in each iteration of the optimisation and guide the movements of the particles in the search space. The iterative process terminates upon its convergence and the particle travelling to the best know position within the entire swarm then is interpreted into a site selection plan with the two-dimensional coordinates which it represents. In this paper, we define the cost function of the PSO algorithm as follows:

$$C(\mathbf{P}) = w_{\mathrm{L}}C_{\mathrm{L}}(\mathbf{P}) + w_{\mathrm{R}}C_{\mathrm{R}}(\mathbf{P}) + w_{\mathrm{T}}C_{\mathrm{T}}(\mathbf{P}) + w_{\mathrm{N}}C_{\mathrm{N}}(\mathbf{P}), \tag{2}$$

where $\mathbf{P}$ denotes a particle containing the n two-dimensional coordinates, C_{L}, C_{R}, C_{T} and C_{N} four cost functions about *land use*, *road network*, *public transport* and *number of cultural venues*, and w_{L}, w_{R}, w_{T} and w_{N} the weights corresponding to the cost functions.

Although a cultural venue would be generally planned in a *service* zone, we observed some real-world cases located in *residential* zones, e.g., community libraries and art centres. Hence, we define a cost function for ensuring that the locations of cultural venues will be located inside appropriate *land use* zones as follows:

$$C_{\mathrm{L}}(\mathbf{P}) = 1 - \frac{1}{n}\sum_{\mathbf{P}}^{\mathbf{p}} \mathbf{A}_1(\mathbf{p}), \tag{3}$$

where $\mathbf{p}$ represents a two-dimensional coordinate in $\mathbf{P}$, and $\mathbf{A}_1(\mathbf{p})$ the corresponding pixel value in $\mathbf{A}_1$. This cost function advocates a location in a *service* zone, conditionally allows one in a *residential* zone, and penalises one in a *unsuitable* zone.

In order to serve the local residents and promote the commercial and touristic activities in the neighbourhood, a cultural venue is supposed to be connected with adequate roads. To address such a concern, we define a cost function about *road network* as follows:

$$\begin{aligned} C_{\mathrm{R}}(\mathbf{P}) &= 1 - \frac{sum(\mathbf{A}_2(\mathbf{P}, r))}{sum(\mathbf{A}_2)} \\ &= 1 - \frac{sum(\{\mathbf{a}|d(\mathbf{a},\mathbf{p}) \leqslant r, \mathbf{a} \in \mathbf{A}_2, \mathbf{p} \in \mathbf{P}\})}{sum(\mathbf{A}_2)}, \end{aligned} \tag{4}$$

where $sum(\bullet)$ denotes a function summing the values of the input pixels, $\mathbf{A}_2(\mathbf{P}, r)$ a set of pixels representing a road segment in $\mathbf{A}_2$ with an Euclidean distance of less than r to any coordinate $\mathbf{p}$ in the particle $\mathbf{P}$. his cost function penalises a site selection plan with a less coverage of roads.

As a tourist attraction in most cases, a cultural venue is expected to be easily accessed using public transport, e.g., bus and train. We formulate a cost function about *public transport* as follows:

$$\begin{aligned} C_{\mathrm{T}}(n) &= 1 - \frac{1}{n}\sum_{\mathbf{P}}^{\mathbf{p}} \frac{sum(\mathbf{A}_3(\mathbf{p}, r))}{sum(\mathbf{A}_3)} \\ &= 1 - \frac{1}{n}\sum_{\mathbf{P}}^{\mathbf{p}} \frac{sum(\{\mathbf{a}|d(\mathbf{a},\mathbf{p}) \leqslant r, \mathbf{a} \in \mathbf{A}_3\})}{sum(\mathbf{A}_3)}, \end{aligned} \tag{5}$$

where $\mathbf{A}_3(\mathbf{p}, r)$ denotes a set of pixels representing a public transport facility in $\mathbf{A}_3$, e.g., a bus stop and a train station entry, with an Euclidean distance of less than r to a $\mathbf{p}$ in $\mathbf{P}$. This cost function penalises a site location lacking of public transport facilities within the surrounding area.

A decision maker needs to balance the benefits of new cultural venues against the costs of construction and daily operation. The *number of cultural venues* should be seriously specified, and hence we introduce a corresponding cost function as follows:

$$C_{\mathrm{N}}(\mathbf{P}) = 1 - \frac{n}{m}, \tag{6}$$

where m denotes the upper bound of the number of venues. This cost function penalises a site selection plan with any excessive venues.

In order to guarantee the optimisation's convergence, we apply the constriction coefficients [Clerc and Kennedy 2002] to the PSO algorithm. The optimal number of cultural venues and their locations are obtained by running the PSO algorithm while enlarging n from 1 to m and finding among all optimal particles the one with the lowest cost.

5 RESULTS

We implemented the PSO algorithm using Matlab™ 2018a and trained the cGAN using Python 3.6 and Tensorflow r1.10. All experiments were performed on a desktop computer with an Intel™ Xeon E5 CPU at 3.50 GHz and an NVidia™ GeForce GTX 1080 graphics card with 8 Gb of memory at 1.74 GHz.

5.1 Implementation Details

We collected the land use plan and the road map of the Greater Sydney Region, Australia from the NSW Planning Portal [NSW Planning 2018] and OpenStreetMap [OSM Foundation 2018]. These data contains information on land use, road network, public transport and public places, which contributed to the generation of a three-layered map $\mathcal{A}$ as input dataset and a single-layered map $\tilde{\mathcal{B}}$ of zones containing any cultural venues. In particular, we defined public places in the following categories from OpenStreetMap as cultural venues, including *artwork*, *arts centre*, *cinema*, *gallery*, *library*, *museum*, *statue* and *theatre*, and utilised ArcGIS™ 10.6 to select zones geographically containing any such venues. Both maps were rasterised into two 10843 × 10189 images with a scale of 5 m / pixel. Each of these images was then split into 998 patches with a 256×256 resolution after excluding those without adequate information for building the training dataset $\{(\mathbf{A}, \tilde{\mathbf{B}})\}$.

The cGAN was trained on the training dataset for 200 epochs to reduce artifacts, each of which was divided into 32 steps with a batch size of 32 and required approximately 70 seconds to compute. The PSO algorithm converged in up to 200 iterations and costed less than 5 seconds to finish. In the experiments, we set the four weights in Equation 2 to 0.25, r to 40 pixels, equivalent to 200 meters - the common length of a city block in Australia, and m to 16, the largest number of cultural venues in the training dataset.

5.2 Comparisons

Figure 4 shows four generated plans using our approach compared to the corresponding real-world maps. We observed some obvious improvements in the generated plans as follows:

- In all four cases, the cultural venues in the generated examples were distributed sparsely to serve a wider area than the real-world ones that clustered.
- In Case 1, 3 and 4, our approach located the cultural venues in the surrounding areas of the primary roads and the public transport hubs for easy access.
- In Case 1 and 4, our approach removed the excessive venues in the remote areas as they could not provide cost-efficient services for the public. An additional venue, however, was generated in Case 3 to satisfy the huge demand caused by the roads and the transport hubs nearby.

In the experiments, our approach occasionally located cultural venues in a residential zone for accessing public transport facilities. Such a pattern contradicted the real-world case that prioritises a service zone and can be adjusted by reconfiguring the weights for the cost functions. Our results achieved lower costs than the real-world ones did using the objective function defined in Equation 2.

Figure 4: Site selection examples generated using our approach compared to the corresponding real-world maps.

6 CONCLUSION

We introduced a novel approach to the automatical site selection of cultural venues. In order to satisfy multiple criteria multiple constraints, we solve the problem computationally using deep learning and stochastic optimisation. Our approach enables cost-efficient site selection for cultural venues and is flexible to work with various learning and optimisation techniques to serve different purposes. The presented approach can benefit decision makers in urban planning and city administration, allowing them to make better informed decisions about selecting sites for cultural venues.

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