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Drainage Network Generation using Deep Convolutional Generative Adversarial Neural Networks

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Motivations

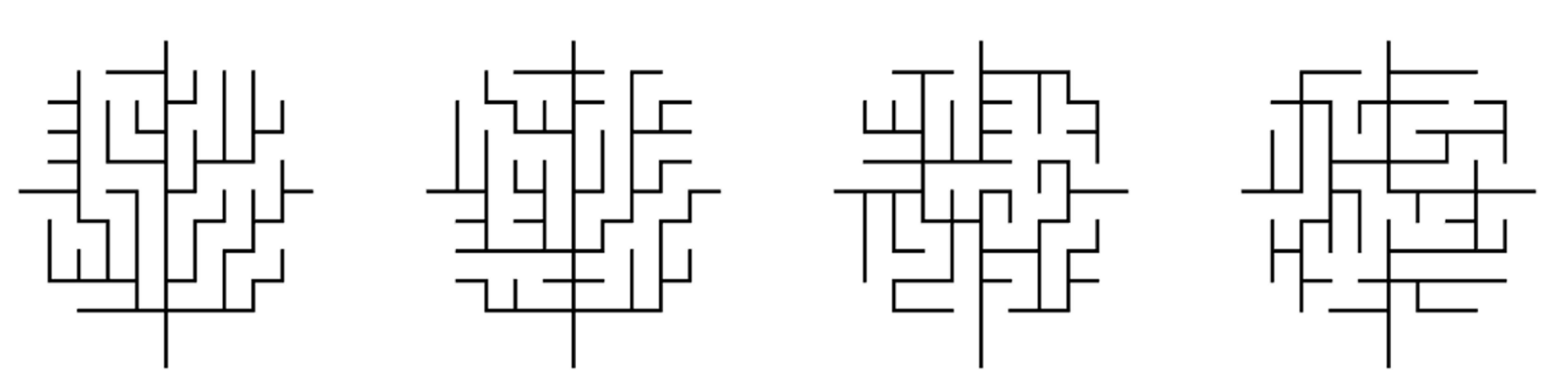
- Topological and geomorphological characteristics of **drainage networks are essential to assess the hydrologic response of catchments.**
- **A stochastic network model** has been applied to regenerate or classify complex river networks.
- **Successful drainage network generation is challenging** because of inherent uncertainty from river systems and its application is **limited by several statistical assumptions.**
- **The stochastic network modeling even gets worse** exponentially in terms of accuracy and computational costs **when the networks are complex**.

Objectives

- We propose a **Deep Convolutional Generative Adversarial Networks (DCGANs)-based, non-parametric approach for stochastic drainage network generation** and apply it to two distinctive drainage networks with different network complexity.

Stochastic network model: Gibb's Model

- Gibbs' model includes both the Scheidegger model and the uniform model depending on the value of a parameter, β.



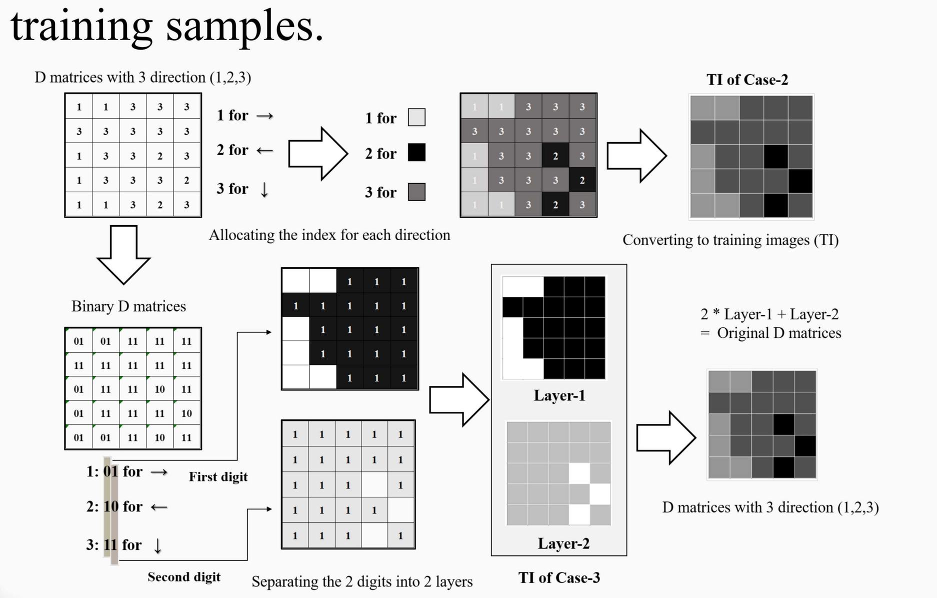
(a) (b) (c) (d)

(a) The Scheidegger model, (b) Gibbs model with $\beta = 10^3$ and (c) $\beta = 10^{-4}$, and (d) the Uniform model

- Two distinctive drainage networks by Gibbs' model with $\beta = 10^3$ and $\beta = 10^{-4}$ were generated and compared with the networks by the proposed model, DCGANs.

Training Datasets and Cases

- The drainage network images and their equivalent directional connectivity information matrices (D-matrices) generated by two Gibb's models were used as training samples.



- Connectivity directions of a D-matrices were separated into each layer as soft constraints of training.
- To validate the proposed approach, several cases of the training data set with images and D-matrices.

	Subcase	Gibb's model	Type	Size
Case-1	1	$\beta = 10^3$	Drainage Image	120 x 120
	2	$\beta = 10^{-4}$		
Case-2	1	$\beta = 10^3$	D-matrix	11 x 11
	2	$\beta = 10^{-4}$		
Case-3	1	$\beta = 10^3$	D-matrix with 2 layers	11 x 11 x 2
	2	$\beta = 10^{-4}$	D-matrix with 3 layers	11 x 11 x 3

Deep Convolutional Generative Adversarial Neural Network (DCGANs)

Generative Adversarial Neural Networks (GANs)

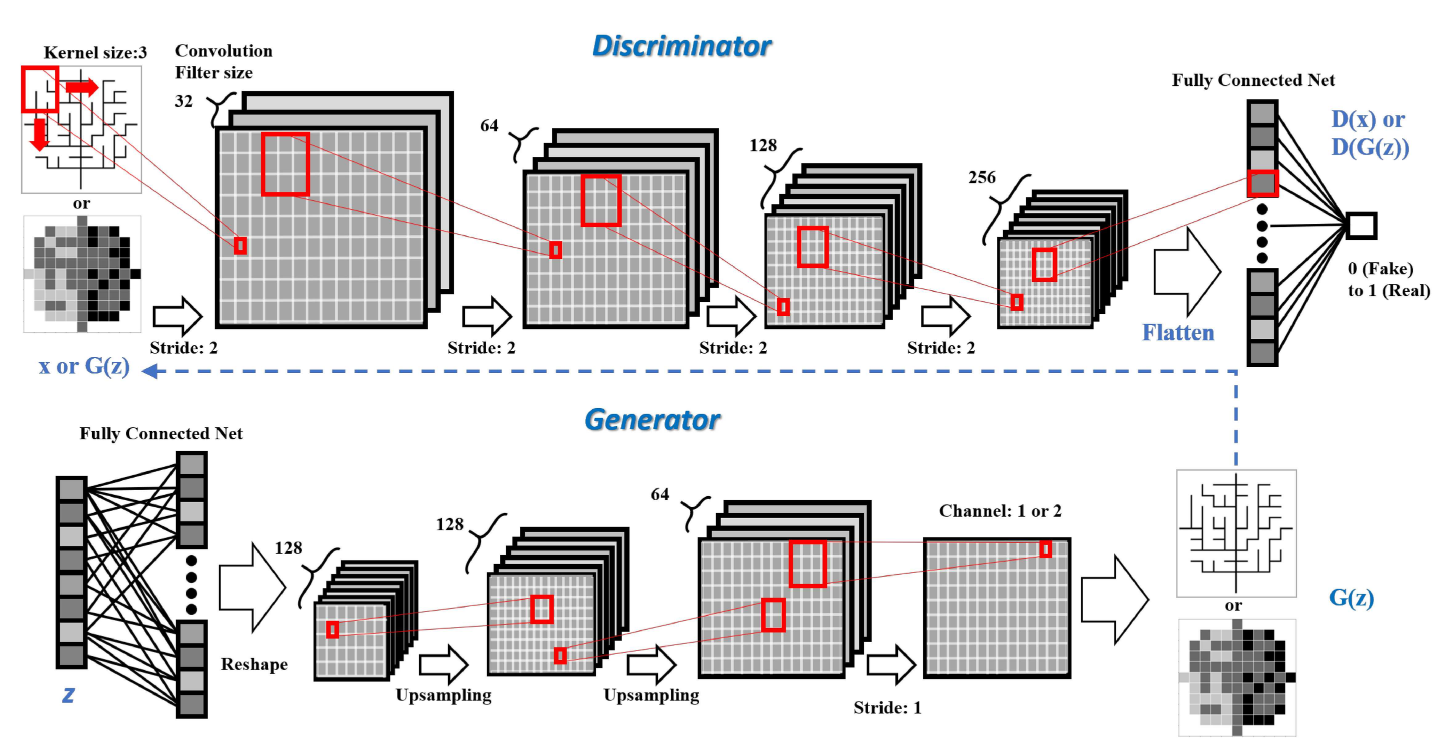
- GANs are one of deep neural networks, which have a new framework for estimating generative models via adversarial two neural network models.
- G model (generator) – a generative model generates samples through learning to map from a latent space to a particular data distribution of real samples
- D model (discriminator) – a discriminative model determines whether given samples were a generated (fake) sample by G model or real samples.
- The loss of DCGANs was estimated by binary cross-entropy function.

Loss of D model: $$\min J^{(D)} = -\frac{1}{2}\left\{\mathrm{E}_{x\sim P_{data}(x)}[log D(x)] + \mathrm{E}_{z\sim P_z(z)}[log(1-D(G(z)))]\right\}$$

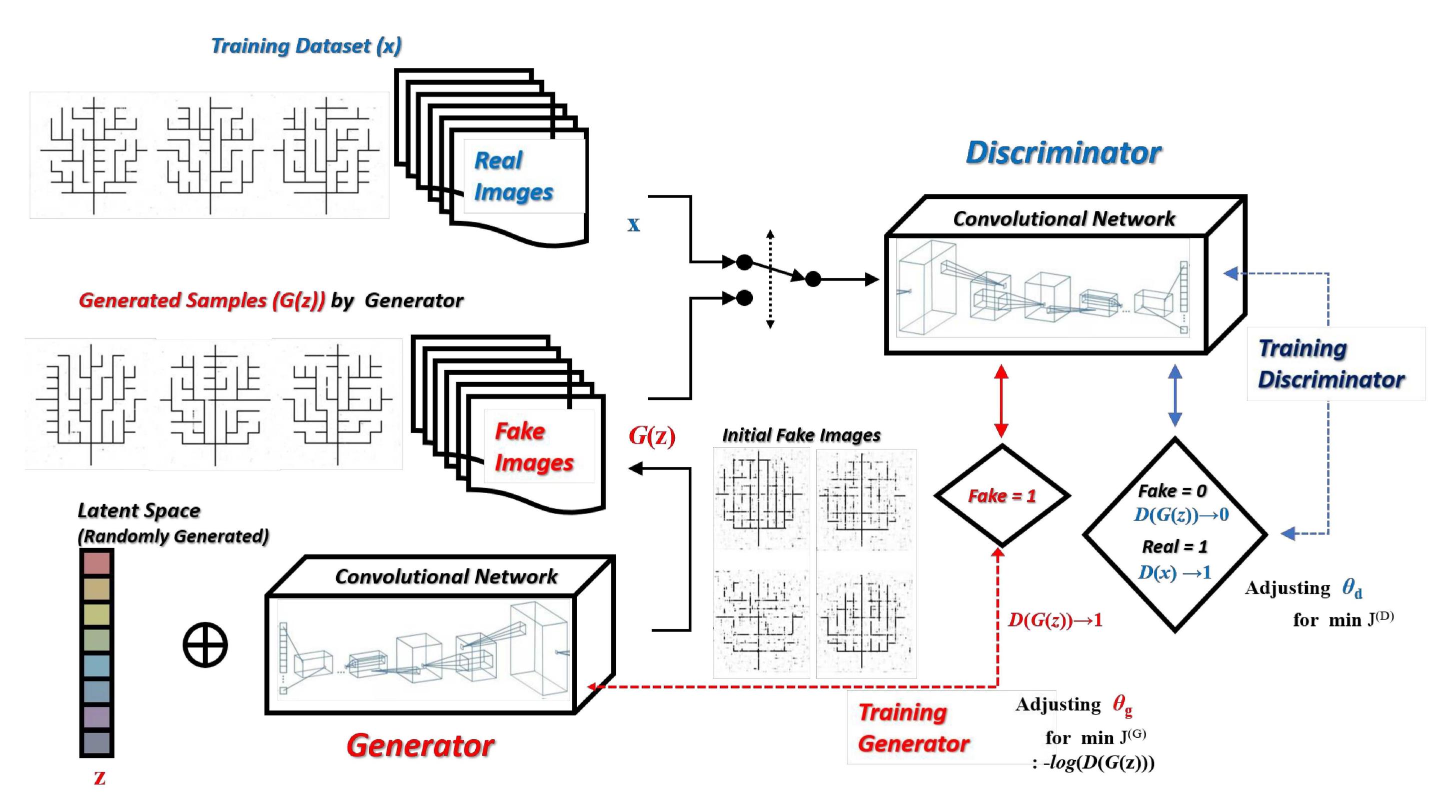
Loss of G model: $$\min J^{(G)} = -\frac{1}{2}\mathrm{E}_{z\sim P_z(z)}[log(D(G(z)))]$$

Deep Convolutional GANs

- Deep convolution neural networks was adopted to develop the GANs in this study.
- Fully convolutional nature of GANs allows the stable training and the generation of large samples that contains the similar properties with computational efficiency (Radford et al., 2016).



Deep Convolution Neural Nets of G and D model

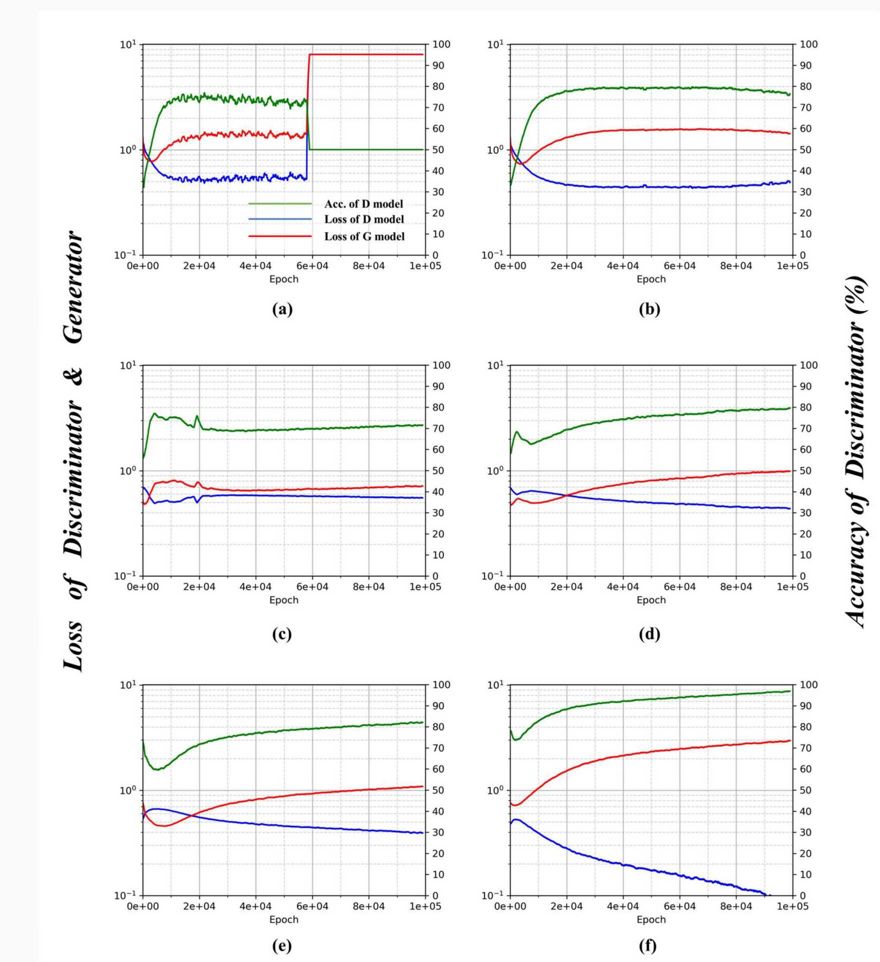


Schematic Diagram of DCGANs for Generating the River Nets

Training and Results

Architecture and parameters of the DCGANs

- Architecture of deep convolution neural networks in GANs was constructed considering the following guidelines proposed by Radford et al. (2016
- DCGANs were trained and evaluated on Ama-55zon AWS equipped with NVIDIA K80 GPUs, Intel Xeon E5-2686 v4 and 6256G RAM



Training Results of DCGANs

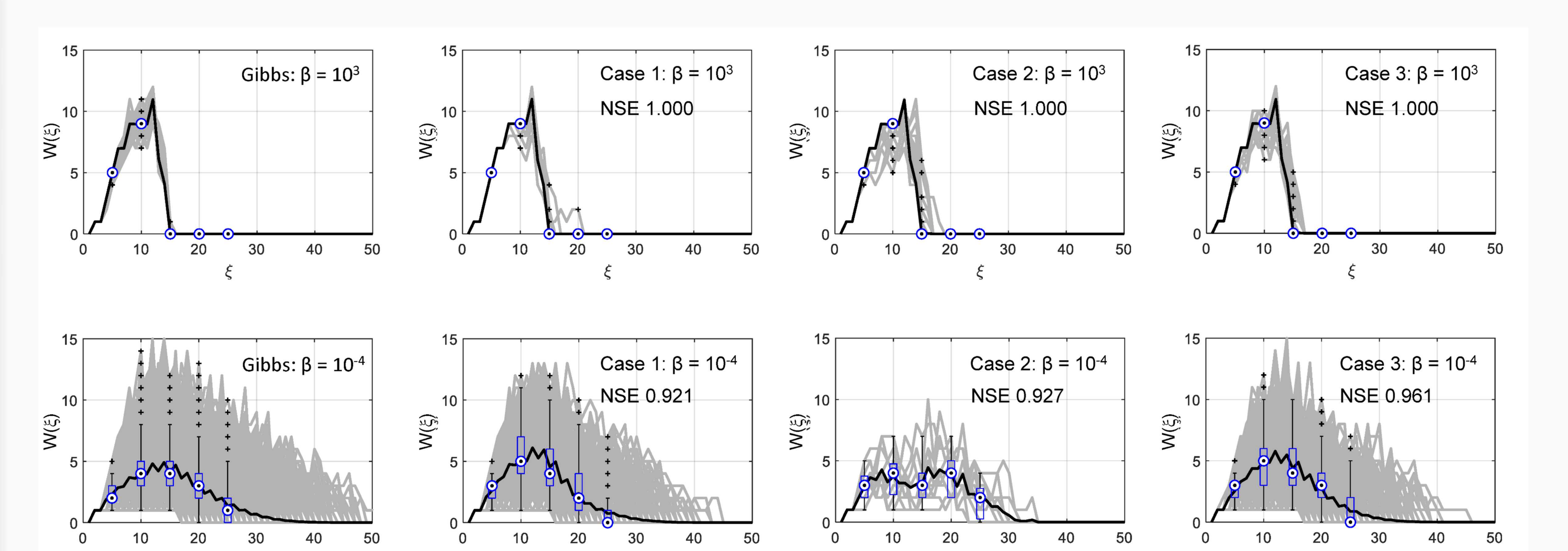
- Stride convolutions instead of any pooling layers
- Batch normalization in both the generator and the discriminator
- No hidden layers in fully connected net in both the generator and the discriminator
- ReLU activation in generator for all layers except for the output, which uses Tanh
- LeakyReLU activation in discriminator for all layers except for the output, which uses sigmoid

Architecture and Parameters

	Architecture & Parameters	
Latent Space (z dimension)	100	
Convolution Layer	Generator	128 / 64 Filters with kernel size : 3
	Discriminator	64 / 128 Filters with kernel size : 3
Optimizer	Adam with mini-batch	
	Learning Rate	0.0002
	Momentum	$\beta_1 = 0.5$, $\beta_2 = 0.999$
	Batch Size	256
Regularization	Generator	Batch Normalization with momentum 0.8
	Discriminator	Dropout with 25 %, Batch Normalization with momentum 0.8
Activation Func.	Generator	ReLu, Tanh (output layer)
	Discriminator	LeakyReLu (alpha = 0.2), Sigmoid (output layer)
Loss Func.	Binary Cross-entropy	

Comparison of river nets by Gibb's model and DCGANs

- The similarity of the two distinct groups of drainage network generated by DCGAN was evaluated based on width functions at the outlet of a drainage network.
- Two distinct width functions of the drainage network by DCGANs and Gibb's model are almost the same.
- NSE ~ 1.0 for Gibbs' model $\beta = 10^3$, NSE > 0.92 for Gibbs' model $\beta = 10^{-4}$



Comparison of the Stochastic Properties of the Drainage Nets by Gibb's Model and DCGANs

- **The proposed approach using DCGANs can successfully capture the distinct stochastic property of the drainage networks by Gibbs model.**

References

- A. Radford, L. Metz, and S. Chintala. "Unsupervised representation learning with deep convolutional generative adversarial networks," International Conference on Learning Representations (ICLR), 2016

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