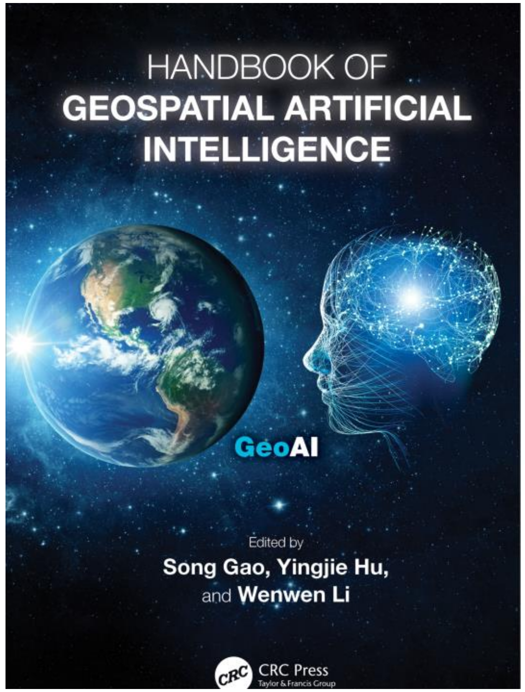

Chapter 4: GeoAI Methodological Foundations

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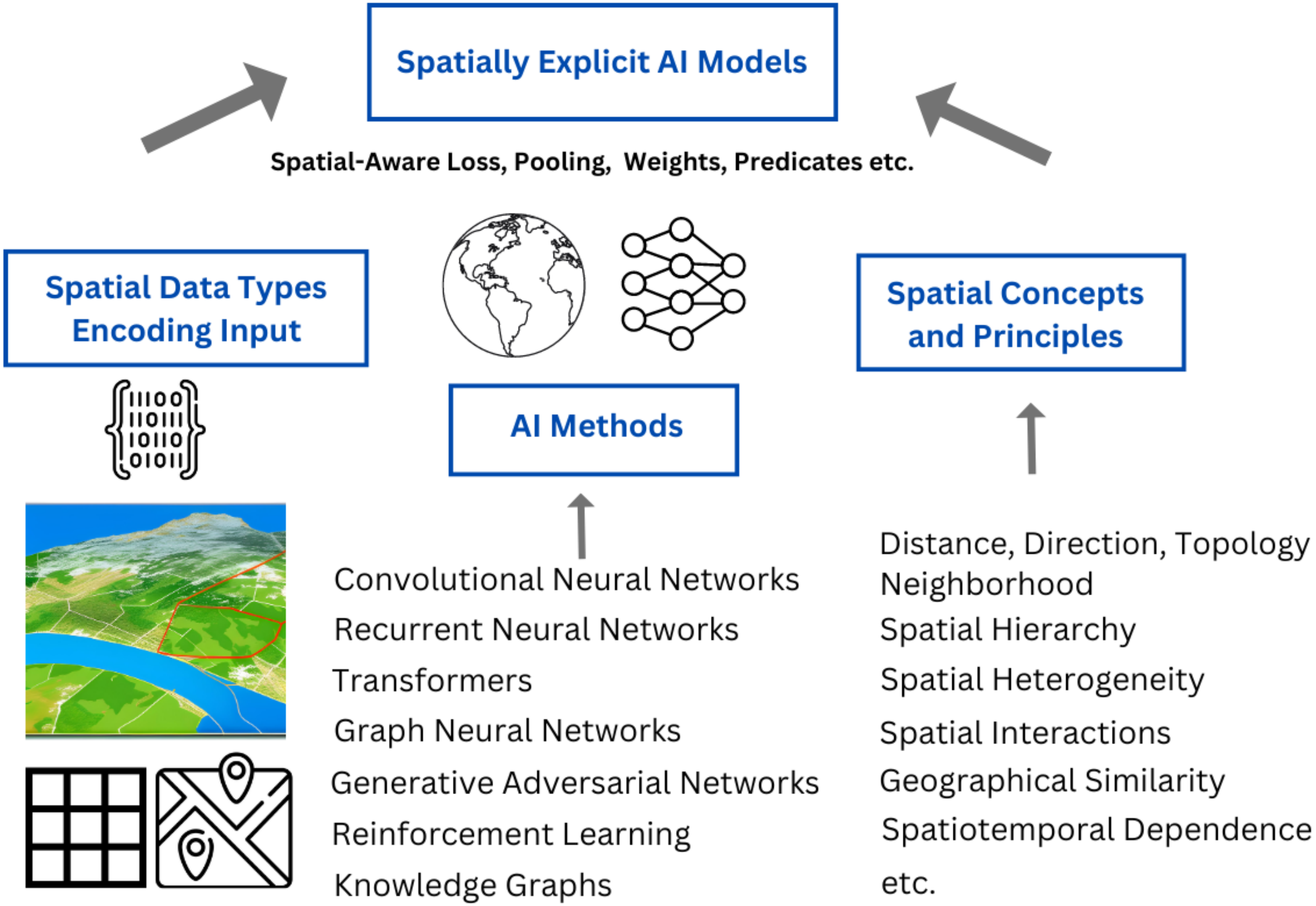
https://doi.org/10.1201/9781003308423

Definitions

- Deep neural network
- Weights
- Biases
- Activation function
- Loss function
- Gradient
- Hyperparameters
- Spatial embedding
- Spatially-explicit AI model
- Geospatial knowledge graph (GeoKG)

Gao et al. (2023, Chapter 4, Handbook of GeoAI)

Spatially-Explicit AI Models



Gao et al. (2023, Chapter 4, Handbook of GeoAI)

Tests for Spatially-Explicit AI Models

- **Invariance test:** The results of spatially explicit models are not invariant under relocation of the studied phenomena.

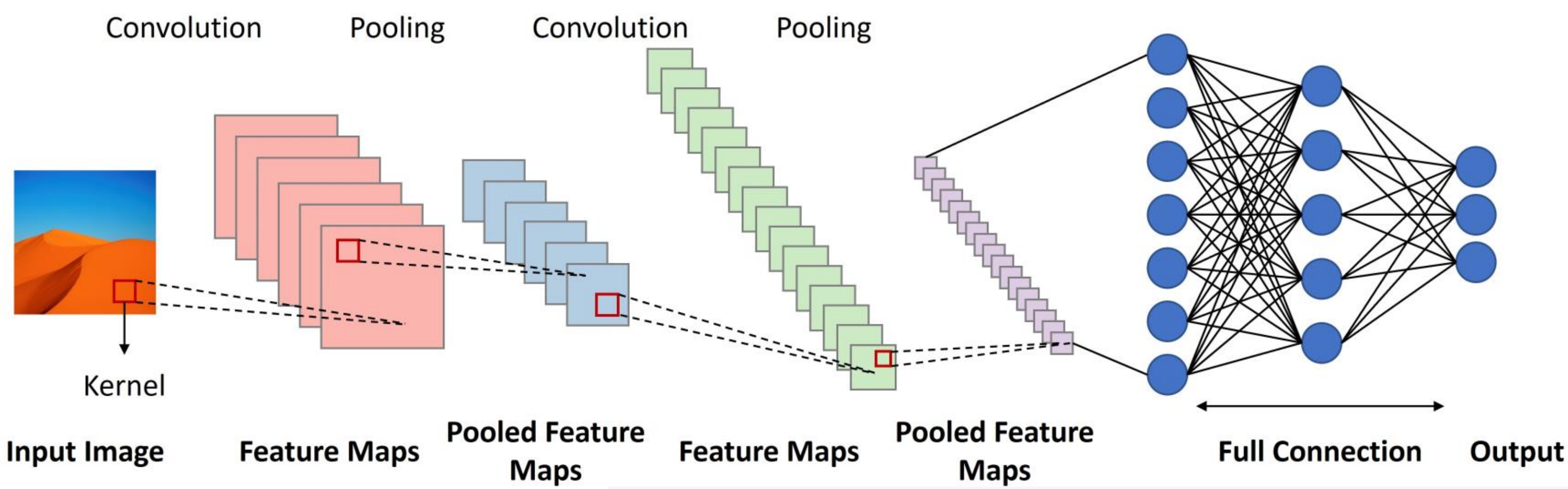
- **Representation test:** spatially explicit models contain spatial representations of the studied phenomena in their implementations.

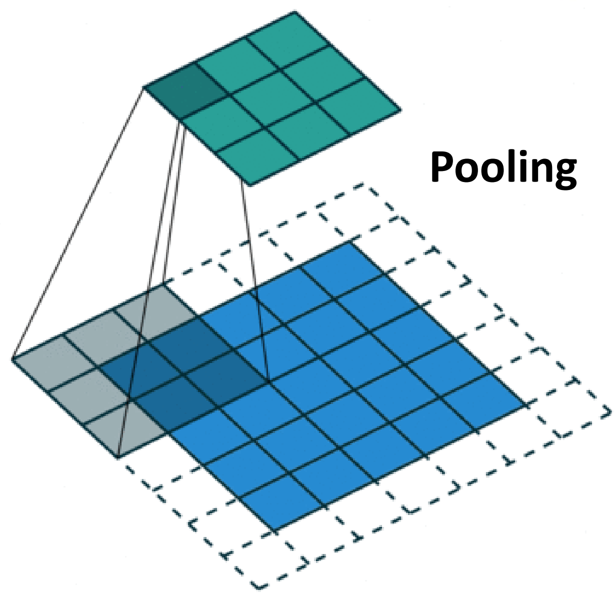
- **Formulation test:** spatially explicit models make use of spatial concepts in their formulations, e.g. the notion of a neighborhood.

- **Outcome test:** spatial structures/forms of inputs and outcomes are different.

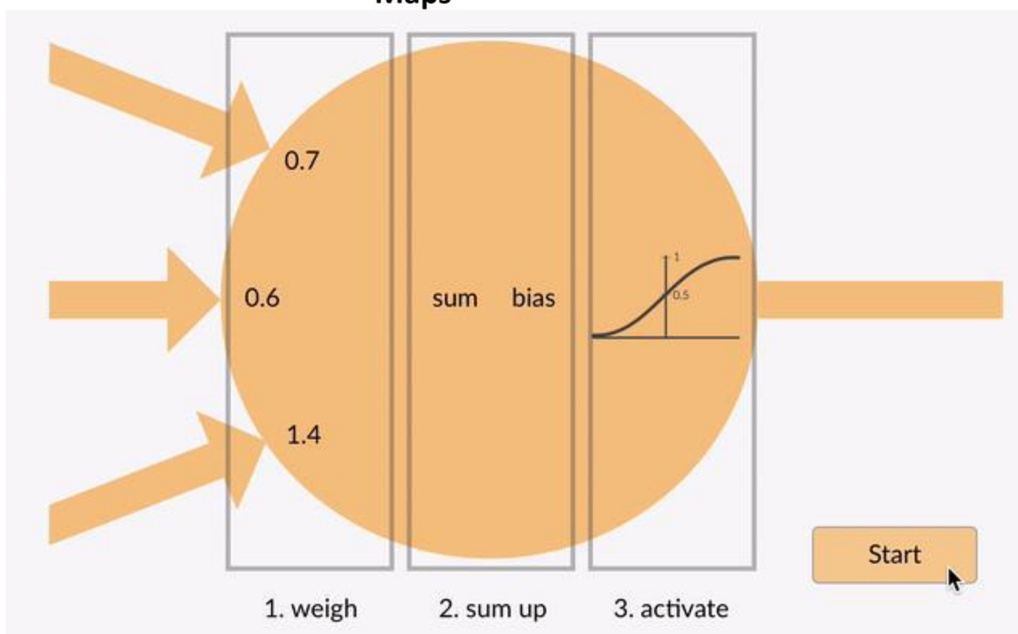
Goodchild, M., (2001); Janowicz et al. (2020, IJGIS)

Convolutional Neural Networks



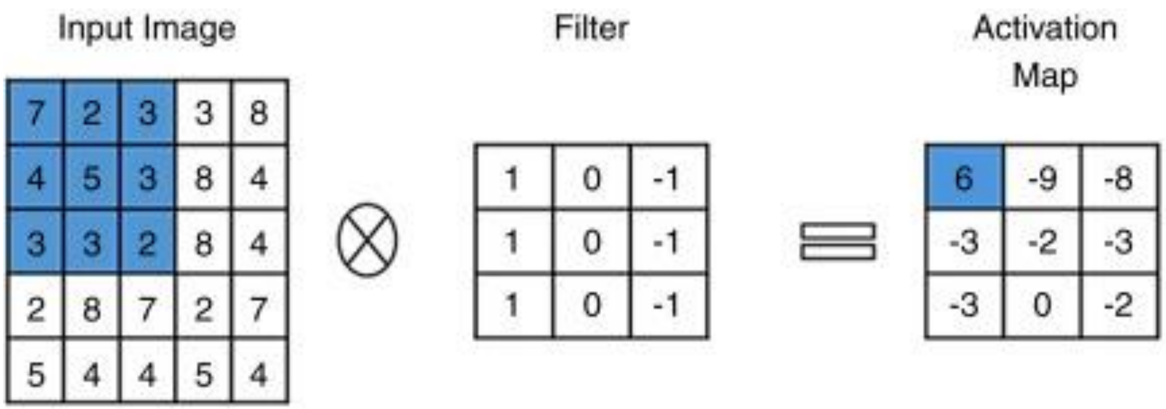


Convolution

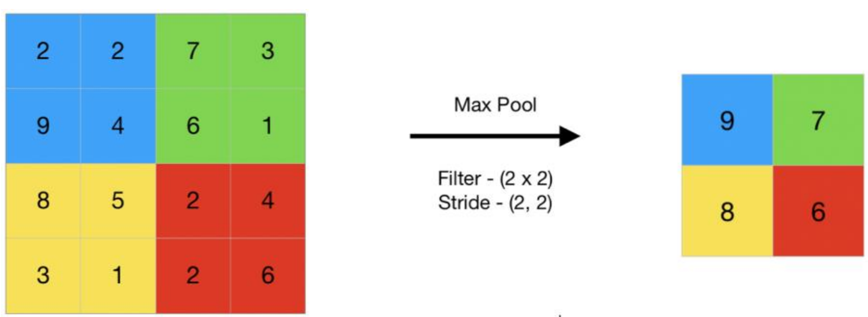


Convolutional Neural Networks

Convolution: A convolutional layer contains a set of filters (or kernels), parameters of which are to be learned throughout the training. Every component of the activation map can be thought to be the output of a neuron. Therefore each neuron is connected to a small local region in the input image.



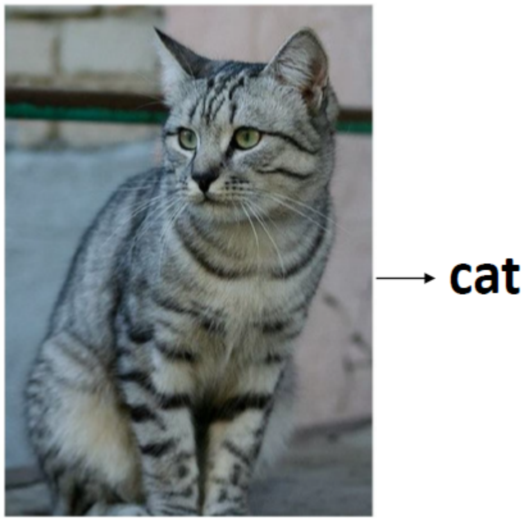
Pooling: Pooling layer is used in CNNs to reduce the spatial dimensions (width and height) of the input feature maps while retaining the most important information.

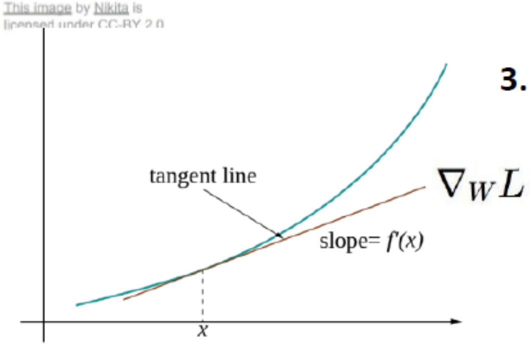


https://www.geeksforgeeks.org/cnn-introduction-to-pooling-layer/

Training CNNs

Supervised learning



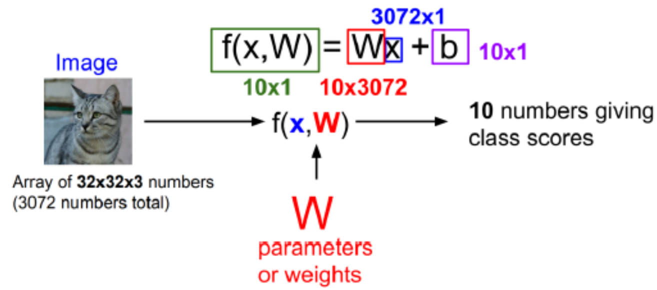


Assume given 10 labels {dog, cat, truck, plane, …} and labeled images

Goal: The desired category has the highest score for each image.

Mechanism:

1. Linear classifier



2. Objective / Loss function $L = \frac{1}{N} \sum_i L_i(f(x_i, W), y_i)$

- Measuring the error (or distance) between the output scores and the scores of the desired category;
- Used to modify internal adjustable parameters (i.e., weights) to reduce this error, i.e., the process of optimization;

3. Loss gradient vectors & gradient descent (follow the "slope")

- How the error changes as a function of the weights;
- Updating the weights in such a way that makes the error decrease as fast as possible

$$\mathbf{w}^{(\tau+1)} = \mathbf{w}^{(\tau)} - \eta \nabla E(\mathbf{w}^{(\tau)})$$

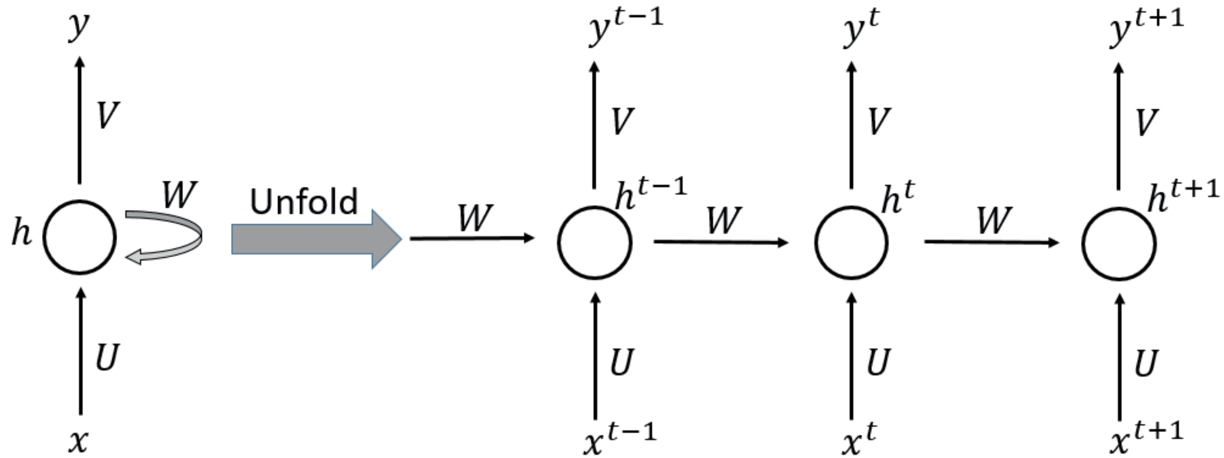
Time

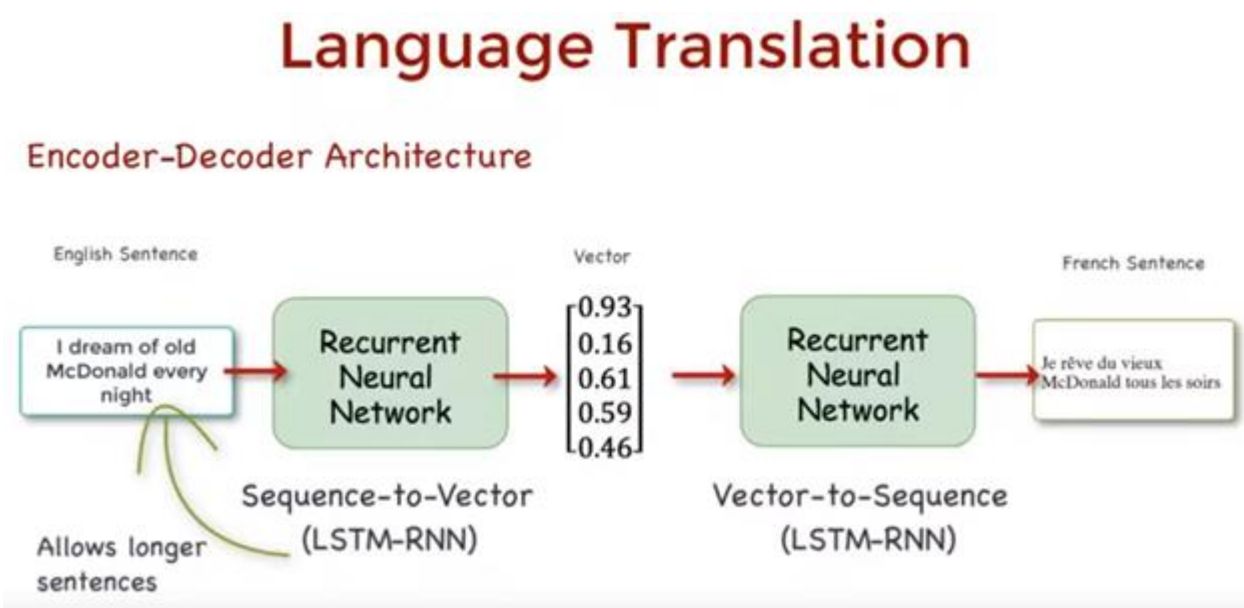
Learning rate

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, *521*(7553), 436-444.

Recurrent Neural Networks

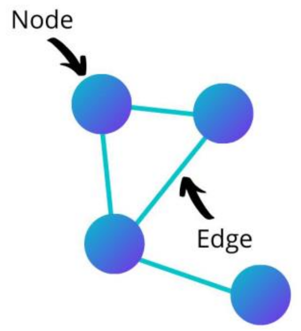
learning patterns in sequential data, such as text, audio, and video

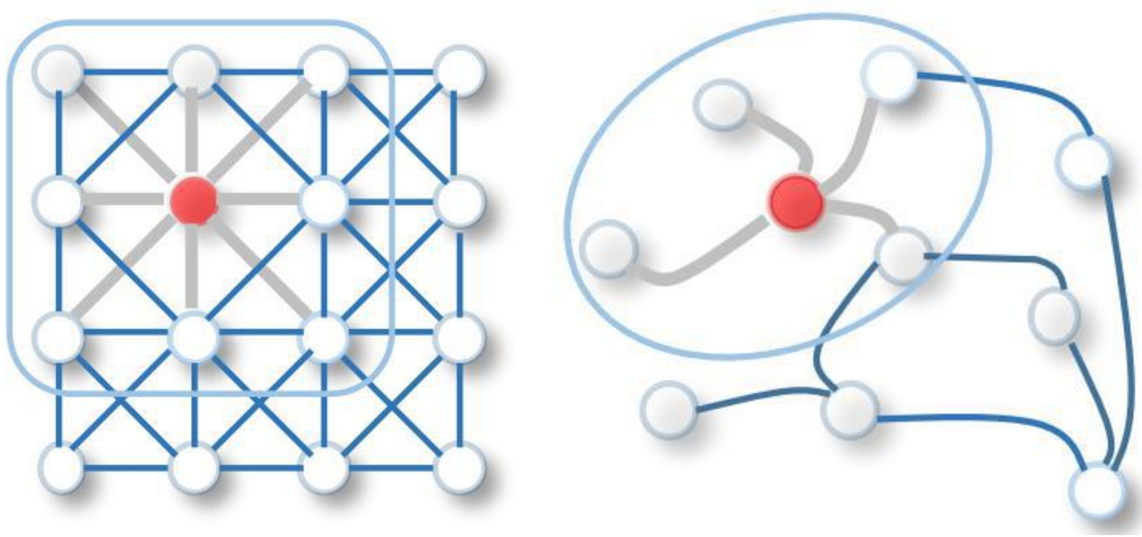




Graph Neural Networks

- Nodes: geographical units
- -Eg., Grids, traffic analysis zones
- - Node Attributes
- Edges: spatial interaction flows
- -Model spatial dependency + relations



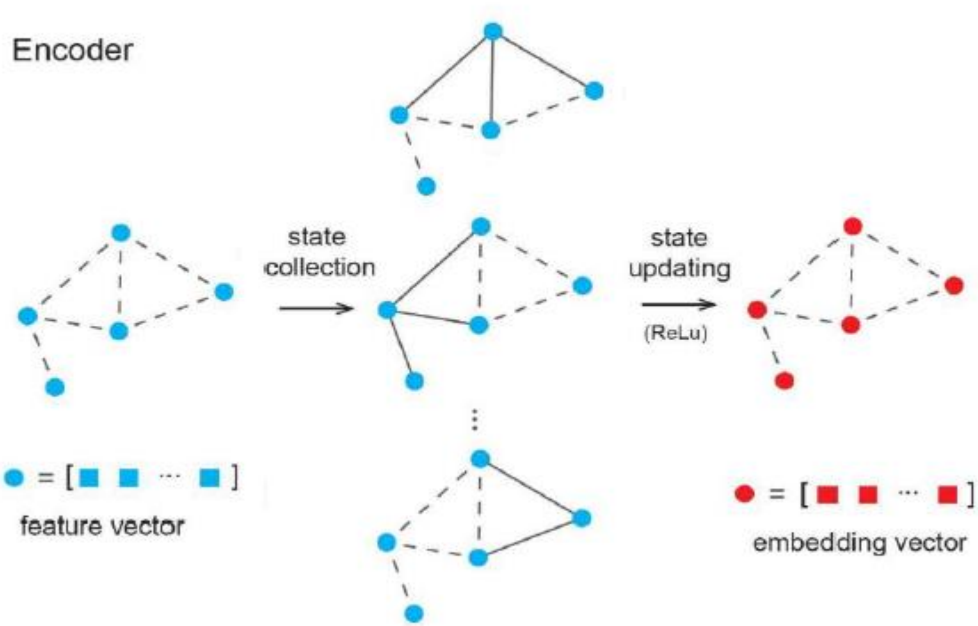


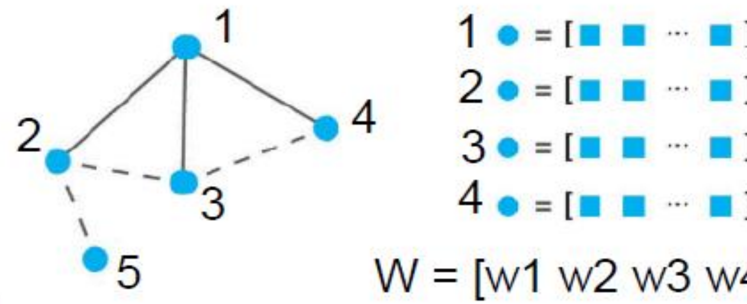
Generate hidden representation of nodes

2D Convolution vs. Graph Convolution

Graph Neural Networks

- Generate latent representation





W = [w1 w2 w3 w4]

$$z_i^{l+1} = \sigma\left(k_i \sum_{j \in N_i} W^l z_j^l\right)$$

$$\text{ReLu: } \sigma(x) = \max(0, x)$$

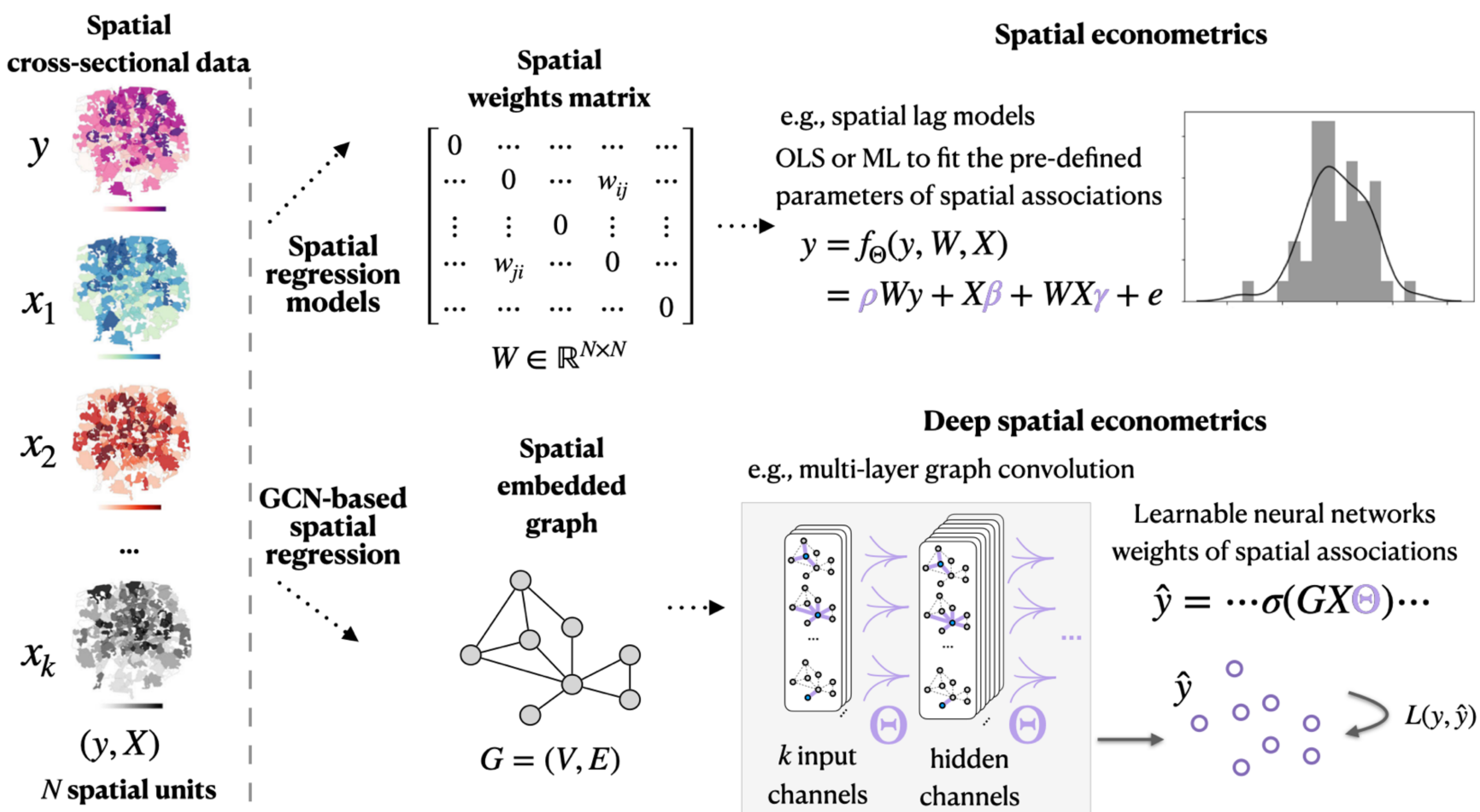
- Generate similar representation vectors for similar geographical units.

Spatially-Explicit Graph Neural Networks

- Spatial relationships when constructing the input graph
- Spatial effects in the aggregation process to assign weights to neighboring nodes
- Spatial constraints when optimizing the model
- GNNs can also be combined with other models such as RNN and LSTM to process spatiotemporal data

Gao et al. (2023, Chapter 4, Handbook of GeoAI)

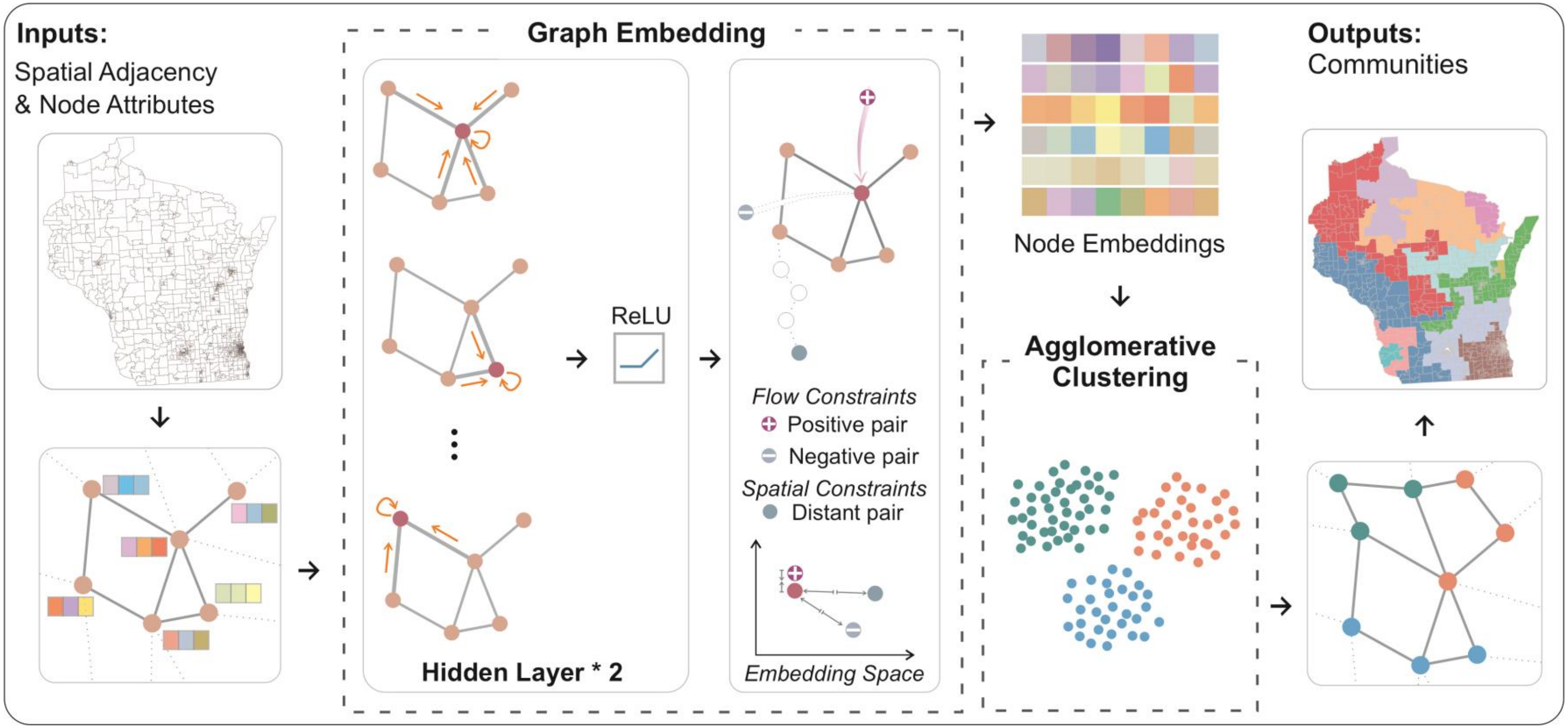
Intelligent Spatial Prediction and Interpolation



Zhu and Cao (2023, Chapter 7, Handbook of GeoAI)

Region2Vec

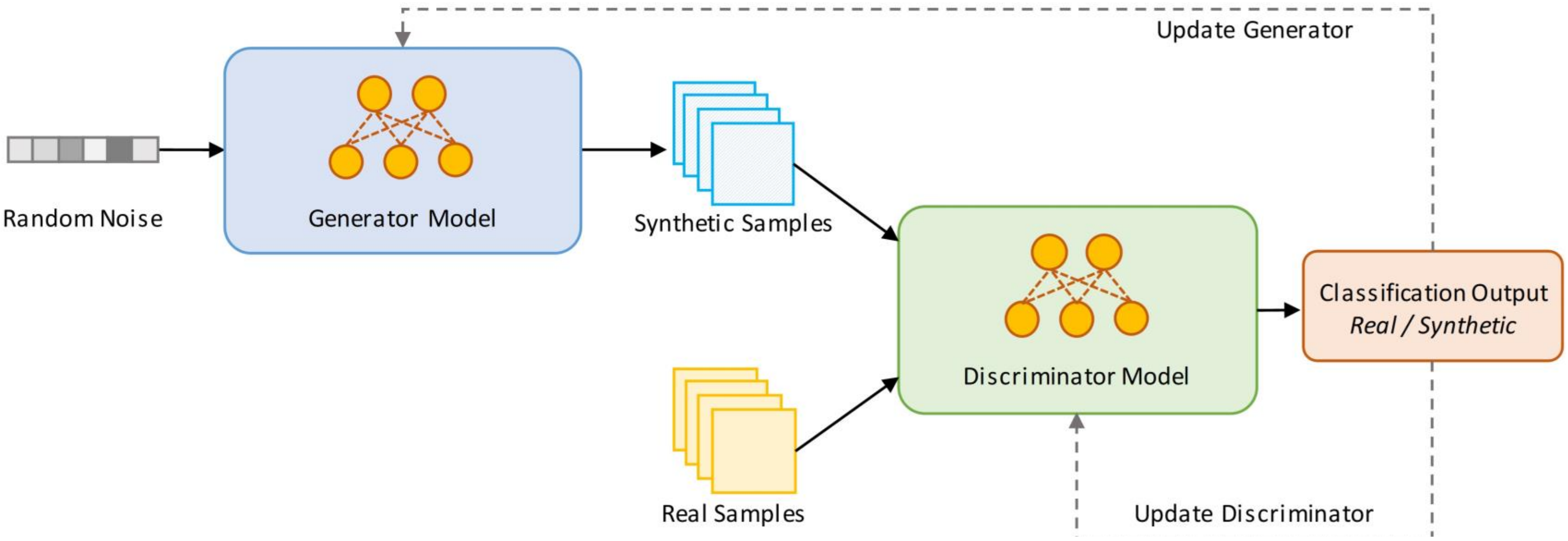
GeoAI for Community Detection on Spatial Networks Using Graph Neural Embedding with Node Attributes and Spatial Interactions



Liang et al. (ACM SIGSPATIAL 2022) https://github.com/GeoDS/Region2vec

Generative Adversarial Networks (GAN)

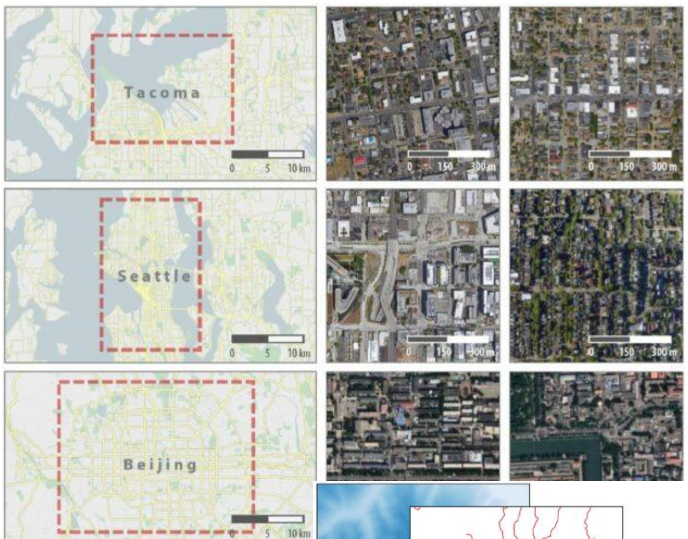
- GANs have been widely used in data generation, style transfer, and super-resolution tasks.

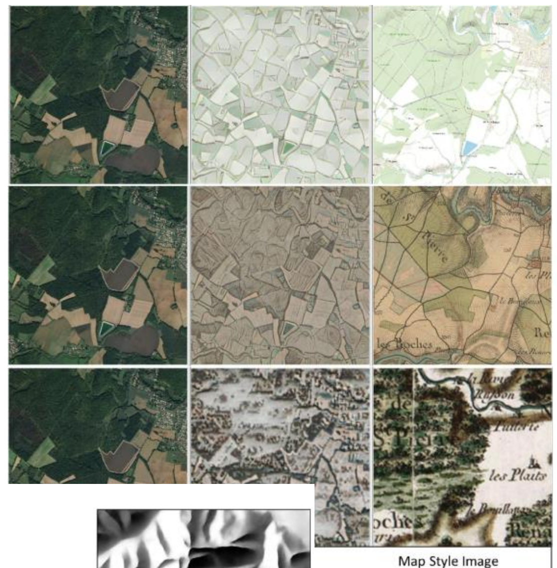


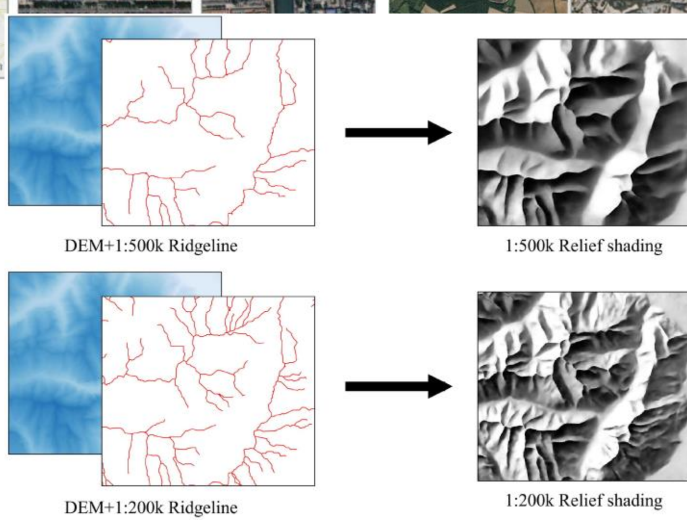
$$\min_G \max_D \mathbb{E}_{x\sim p_{\text{data}}(x)}[\log D(x)] + \mathbb{E}_{z\sim p_z(z)}[1 - \log D(G(z))]$$

Generative Adversarial Networks (GAN)

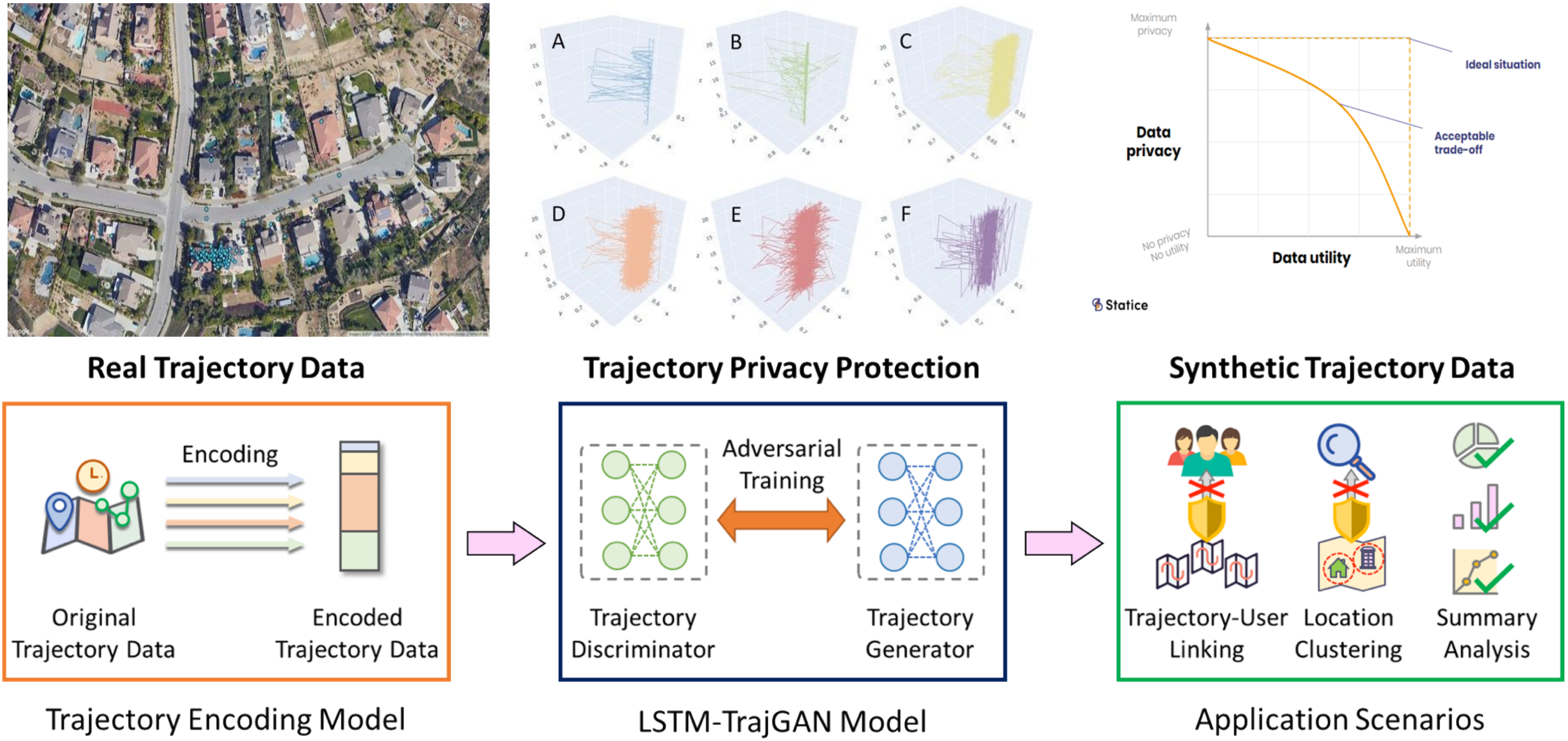
- Deepfake geography (Zhao et al 2021, CaGIS)
- Map style transfer (Kang et al 2019, Christophea 2022)
- Terrain hillshade generation (Yan et al 2024, IJGIS)





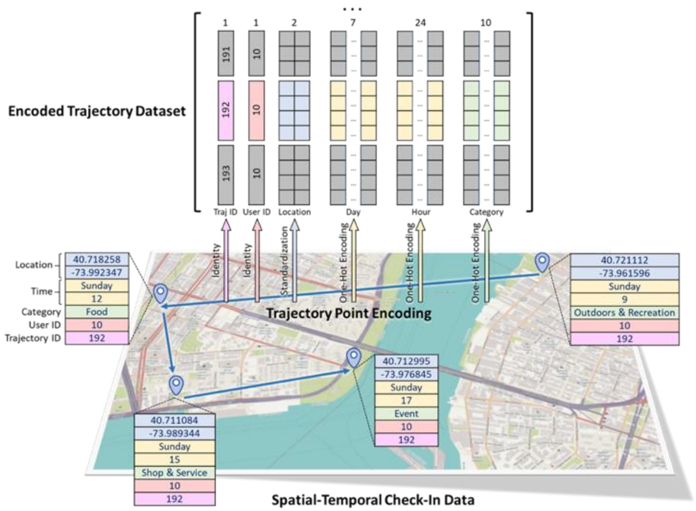


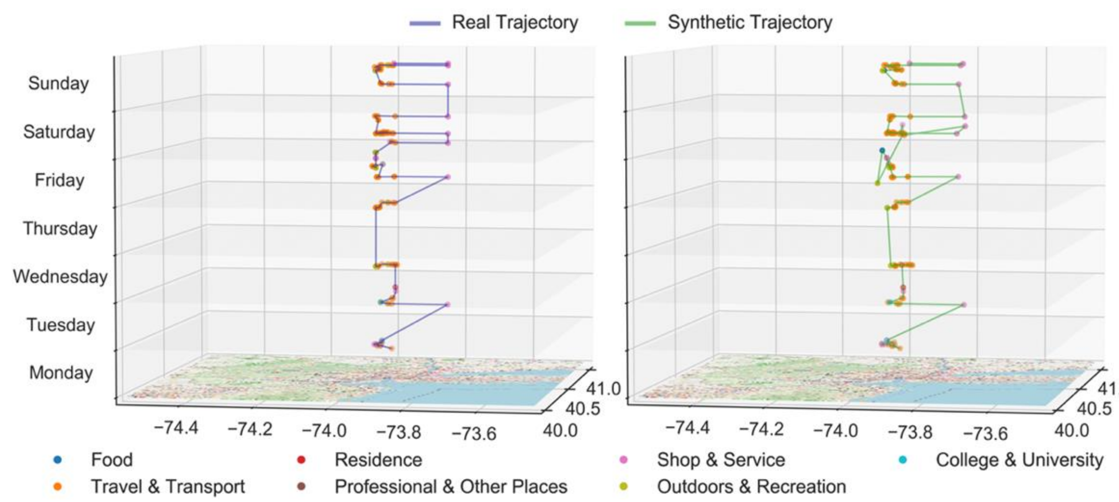
GeoAI for Trajectory Privacy Protection



Rao et al. (GIScience 2021) https://github.com/GeoDS/LSTM-TrajGAN

Spatially-Explicit AI Model: LSTM-TrajGAN





$$TrajLoss(y^r, y^p, t^r, t^s) = \alpha L_{BCE}(y^r, y^p) + \beta L_s(t^r, t^s) + \gamma L_t(t^r, t^s) + c L_c(t^r, t^s)$$

Trajectory Loss Function

https://github.com/GeoDS/LSTM-TrajGAN

Group Discussion:

- Can you think of any further directions that were not mentioned in the deep learning paper (2015, Nature)?

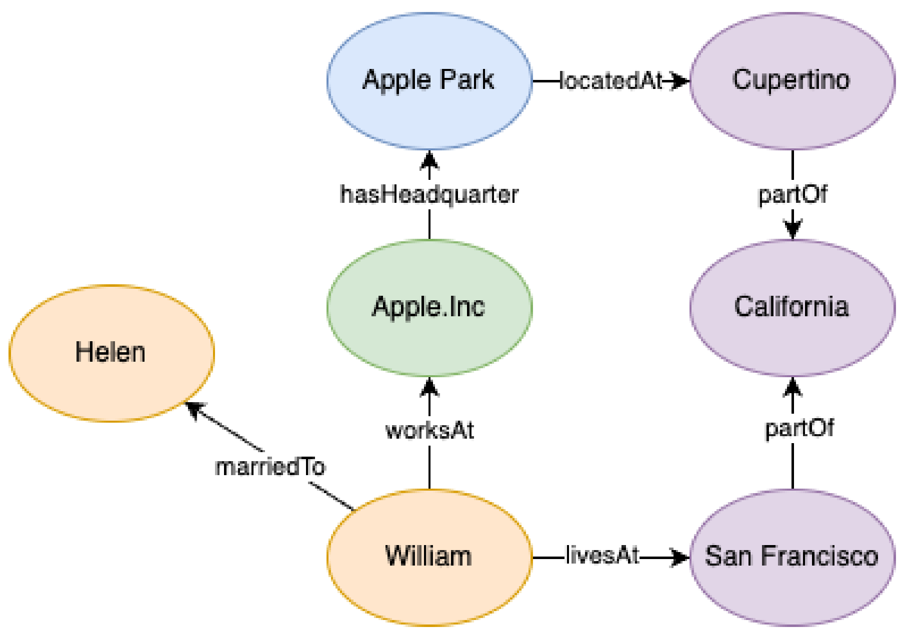
- Deep learning has passed the peak of its development curve. How would you predict its growth in GeoAI?

- Do you think the development of GeoAI would also fuel the development of deep learning? If yes, How?

- Share your thoughts on different approaches to the development of spatially-explicit AI models?

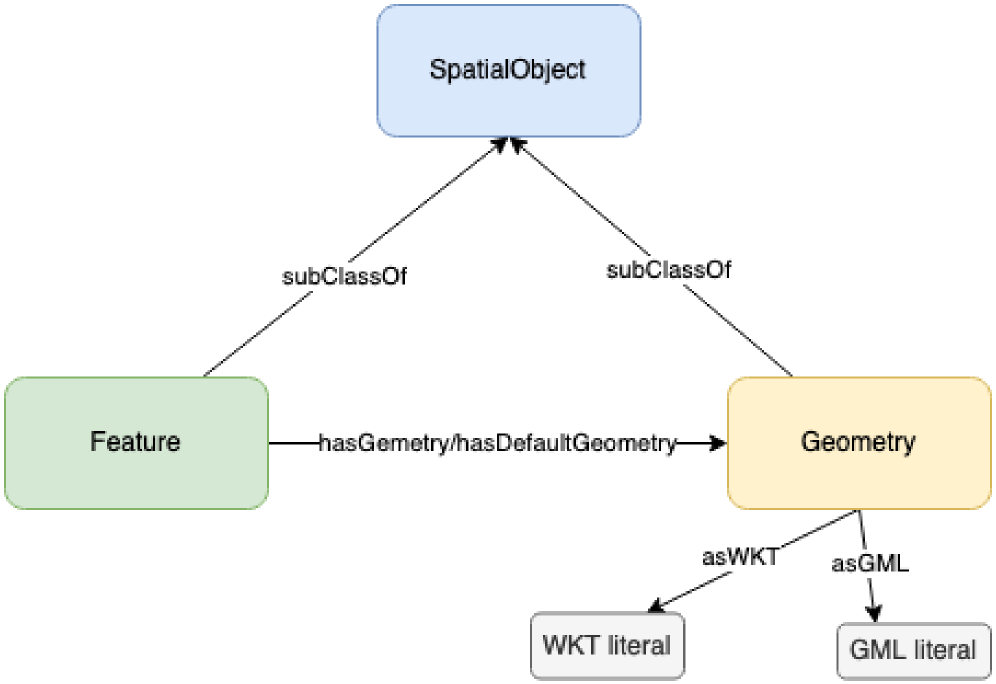
Knowledge Graphs (KG)

- Use a graph to abstract data, in which nodes are used to represent any kinds of entities, such as places, people, organizations, etc., and edges are the relations between these entities, such as friendship, located in et al.



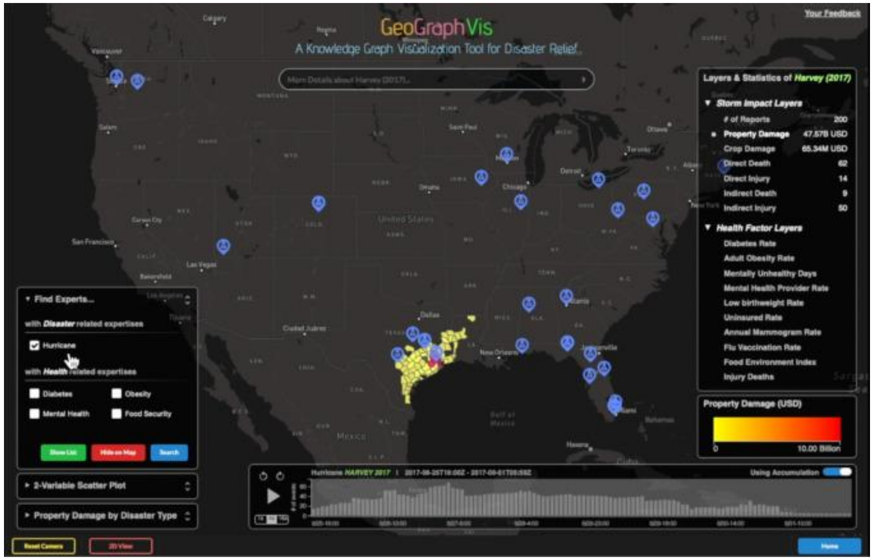
Geospatial KG

- GeoKG is a spatial extension to a knowledge graph, which contains symbolic representations of geographic entities (e.g., places) and other types of entities (e.g., people, organizations, and events), including attributes and their relations, often empowered by geo-ontologies



KnowWhereGraph

- A geo-knowledge graph that is based on existing standards like RDF, OWL and GeoSPARQL, incorporates custom ontologies, and uses a hierarchical grid for spatial representations. The integrated **KWG schema** provides a holistic view of the graph modeling. Its current size exceeds 12 billion information triples, and the covered data support pilot scenarios in disaster relief, agricultural land use and food-related supply chains.



https://knowwheregraph.org/