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Sean Ahearn is a Professor of Geography and Director of the Center for Analysis and Research of Spatial Information (CARSI) at Hunter College–CUNY. He received his M.S. and Ph.D. in Environmental Remote Sensing from the University of Wisconsin-Madison. His research interests include agent-based models, deep learning, spatial-temporal models, digital image analysis, ecological modeling, location-based systems, emergency response and urban geographic systems. He has published in a wide range of journals including *IEEE Geoscience and Remote Sensing*, *Photogrammetric Engineering and Remote Sensing*, *International Journal of Geographic Information Science*, *American Journal of Epidemiology*, *Emerging Infectious Disease*, *Ecological Modeling*, *Conservation Biology*, and *Methods in Ecology and Evolution*. He has consulted extensively in the field of geo-spatial science and technology. From 2001 to 2005 he was vice-president of GIS for Linkspoint Inc., a location-based services startup. He was an expert witness for Larry Silberstein in the $5 billion insurance case concerning the World Trade Centers. As Founder and Director of CARSI at Hunter College, Ahearn played a major role in managing the design, development, and implementation of the digital geographic base-map (GIS) for the City of New York, called NYCMap, in the 1990s and early 2000. NYCMap was instrumental in enabling the City of New York to respond to the 9/11 crisis. Ahearn's role was highlighted in the History Channel's "The Twin Towers: Rise and Fall of an American Icon." He was PI on a National Science Foundation Grant titled *Geographic Information Science and Technology BoK2: Foundational Research* from 2010–2013. He directed the Solar NYS Portal software development effort in collaboration with Sustainable CUNY, in a project funded by the US Department of Energy (www.nysolarmap.com). He is past president of the University Consortium for Geographic Information Science (UCGIS). He was appointed by the United States Secretary of Interior to the National Geospatial Advisory Committee (NGAC) as a Charter Member in 2008. Professor Ahearn received the prestigious 2013 IBM faculty award.

Spatial Data Science in the Context of Deep Learning and AI

Over the past seven years there has been a revolution in AI especially Deep Learning. This is a result of a convergence of access to vast amounts of data for training, advancements in Neural Network architecture, faster computing and new approaches to learning systems.

The **Convolutional Neural Network (CNN)**, first conceived in 1989, famously came to the fore with the creation of AlexNet, which won the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) contest in 2012 (Krizhevsky et. Al., 2012). Refinements have followed but the general principals of AlexNet holds. The intriguing aspect of CNNs are that they address one of the early problems in computer vision posed by David Marr in 1982, how to combine the multiple frequencies of an image that relate to objects and their components at different scales (Marr, 1982). The CNN solves this problem through the cascading of multiple CNN layers with pooling between each operation. The number of CNN layers selected should relate to the range of spatial frequencies occurring in the subject image. A fully connected layer then "assembles" these components into templates of the object being trained on.

In 2014 Ian Goodfellow and collogues wrote the founding paper on **Generative Adversarial Networks (GAN)** (Goodfellow et al., 2014) in what Yan LeCun called "the most interesting idea in the last 10 years in Machine Learning". One could argue that this was the first true push into the realm of Artificial Intelligence, though, in many ways the term is more aspirational than tangible. This system in short, poses two competing networks, with one getting better at generating an "artificial" instance of an entity and the other getting better at detecting if that instances is a "fake" generated by the other network. Both receiving feedback from the other.

Another major development is the use of **neural networks in Reinforcement Learning (RLNN)** (Sutton and Barlo, 2018). These systems use agents that perceive and act in a given environment. The agents have a state, they take actions and seek rewards. A value function is assigned to a state that reflects benefits that are both immediate and occur in the future. They can learn through interaction with the environment and optimization through rewards.

A forth type is the **Recurrent Neural Network (RNN)**. The RNN handles sequences and can retain contextual information but unlike the Hidden Markov Model, it doesn't assume a Markov condition where the current state is solely dependent upon the previous state. The RNN's predominant use has been Natural Language Processing, however, recently it has been applied to spatial temporal trajectories (Kulkarni and Garbinato 2017).

The question posed here is how does **Spatial Data Science (SDS)** relate to Deep Learning and AI and what is its potential contribution to this domain?

The **Convolutional Neural Network's (CNN)** use for image classification initially focus on sets of constrained images (e.g., cats and dogs) and has expanded to more general scenes and satellite images (Kussul, et al., 2017). Contextual information supplied through social media has been combined with standard statistical classifications (Cervone et. al., 2015) and could be an interesting source of context for increasing CNN classification accuracy. The contribution of SDS seems possible but limited.

Generative Adversarial Networks (GAN) have some interesting corollaries with species competition, but this will need more teasing-out to relate them to evolutionary phenomena like niche differentiation.

One of the more salient possible contribution of Spatial Data Science to AI and Deep Learning is the relationship between traditional Agent Based Models (ABM), used widely in SDS, and **Reinforcement Learning Neural Network (RLNN)**. Agent Based Models have been used in a wide range of applications to model everything from wildlife (Ahearn et al., 2001) to urban systems (Batty, 2005). Agents were programmed through, in pre-GPS times, field information about states, related behavior, events and patterns of movement. With the acquisition of GPS data these models are increasingly calibrated through reliance on the relationships between movement, environment, interaction and behavior as determined through GPS trajectories (Ahearn et al., 2016). The focus on strong conceptual models developed by geospatial scientists has been a differentiator in this arena (e.g,. Crooks, et al., 2014). How to combine the principles of ABM, with RNN's learning through sensory exploration of the environment is a research endeavor with great potential.

The **Recurrent Neural Network** (**RNN)** shows great promise for both its modeling and generative potential of spatial-temporal trajectories (e.g. GPS trajectories). These trajectories have been studied for their form and function (Dodge et al., 2008) and multiscale properties (Ahearn & Dodge, 2018). The unique ability of RNN to model sequence data and incorporate context with **Long Short-term Memory RNNs** (Hochreiter and Schmidhuber, 1997) could have significant advantages over current approaches.

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