GIS & Artificial Neural Networks:
Does Your GIS Think?

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Introduction

The purpose of a GIS is to provide both the individual and organization with increased knowledge and understanding of spatial data. Often GIS users overlook the 'decision making' capability these systems can provide, instead, focusing on the presentation. GIS information can become increasingly more valuable for decision making when coupled to artificial intelligence (AI). Artificial intelligence has evolved in recent years to the point that many applications can be run using desktop computing – thus within reach of many GIS professionals. When linked to GIS, artificial intelligence can be useful for evaluating, monitoring and decision-making. Neural networks, fuzzy logic, nano-technology and evolutionary computation and others are directed toward decision-making functionality. In the case of artificial neural networks (ANN), computing methodologies are being used to simulate how the human brain processes spatial data problems. It is anticipated that many future spatial applications will incorporate elements of artificial intelligence. These networks have many potential applications in GIS including; land use, oceanography, forestry, consumer movement, transportation, bio-sphere studies, image analysis, environmental, entertainment, anti-terrorism, pattern analysis and health. In fact, in almost every instance where GIS is being used, AI applications could potentially be developed for the purpose of enhancing decision-making capabilities. In this article I will briefly describe ANN and discuss the relationship of ANN to GIS.

The Artificial Neural Network

What are neural networks? Neural networks are models that are designed to imitate the human brain through the use of mathematical models. The neural 'network' consists of a series of processing "units" which are collectively "connected" – like synapses in the human brain. The network consists of an input, output and hidden layer (Fig 1). Numeric data moves from connection to each unit whereupon it is processed. Processing takes place locally at each unit and between connections – in a parallel fashion. That is - ANN's are parallel processors rather than iterative processors, which alternates from processor to processor. Let's briefly describe an ANN in a simple manner.

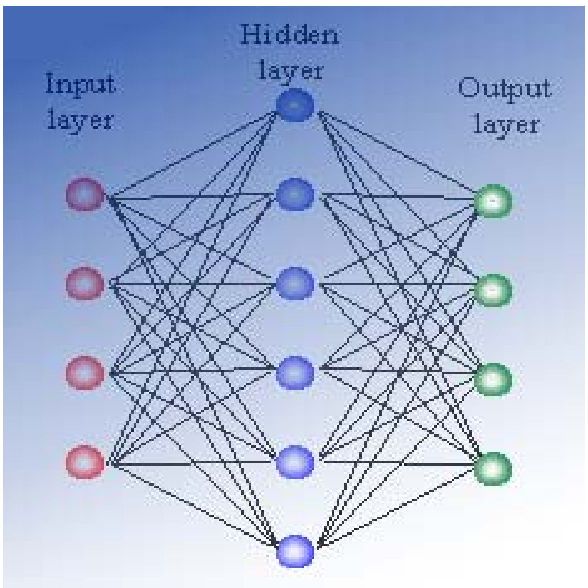

Fig 1. Neural Network

Think of tossing a rock into a pond where a ripple emanates from the rock hitting the water. Then imagine tossing five rocks together into a pond. The resulting ripples collide amongst themselves (particularly those closest to each other) then break into small ripples until they eventually fade. The 'units' would be the individual points where the rock hits the ponds surface, while the ‘connections’ would be the ripples- those closest to each other having more ‘local’ impact.

Since those ripples closest to each other collide more, we could ‘weight’ them using a rule we devise independently, assigning them higher values than those further away. The process of weighting them we refer to as ‘training’. If you toss the rocks into the pond again, you will get differing ripples and therefore have to re-adjust the weightings. Over time, repeatedly tossing the rocks into the pond and refining the weightings will yield higher levels of probabilities that certain ripples will occur – both around each individual unit and for the whole network, thereby ‘training’ the network. If you put a small floating ball into the pond then toss the rocks into the water you could expect at any given location of the ball, certain types of waves would be present – thus how the ball might be affected. The key features of neural networks to remember are that they:

- Operate (learn) locally and asynchronously at the ‘units’ – rocks on pond

- Strength of the connections between ‘units’ is important - ripples

Now, imagine I give you numeric data relating to trees- height, diameter, branching and so on (input data). In doing so you would be ‘training’ to actually meet a tree face to face and know it is a tree, but how does that recognition come about? We know that trees exist (output data) and what they should look like, but we must somehow evaluate the input data through the weightings we assign in the (hidden layer) to arrive at that conclusion. The number of weightings times their occurrence will yield an answer leading to the desired output. If the output answer is used again as input and the weightings adjusted, slowly the network reaches a state where it understands a tree can be recognized – this is similar to humans mulling over a problem until finally reaching a conclusion, having thought of all the possibilities related to the problem!

In this way, data are processed mathematically to ‘think’ like the human brain – to connect data with a real object. This is a very simple example to allow the reader to understand ANN. Most neural networks are slightly more complex. By now though, you are probably wondering what this has to do with GIS!

GIS linked to Neural Networks

Imagery Example - GIS data often includes satellite and other remotely sensed imagery. Analysis of imagery involves either supervised or unsupervised classification. Unsupervised classification of imagery involves the analysis of colour or black and white pixels of the image for the purposes of classifying image objects and entities, where, tone, texture and hue are used. Supervised classification of imagery involves referencing the pixels to actual field or site conditions and colour balancing of the image for similar classification purposes. ANN is increasingly being used for the purpose of determining spatial patterns. In the area of landscape ecology, landscape pattern is an important factor enabling classification. Landscape patterns can be ascertained through analysis of pixels; their shape, colour, connectivity, direction, edges and patchiness. Using ANN, the weighting of pixels and their inter-relatedness provides clues about the relationships of objects on the landscape. Indeed, more recent developments in the area of remote sensing analysis involve ANN for the analysis of images for the purposes of classifying objects.

Transportation Example – On any given day vehicular traffic will vary through a city with respect to time of day, road network capacity and weather amongst other factors. A GIS can map the road network easily enough, but imagine an accident or some other event causing this flow of traffic to change. Traffic congestion would change with respect to other routes, those nearer the event becoming more congested. ANN input might include the location of the accident causing resultant congestion on arterial roadways, current weather conditions which influence speed and time of day, which relates to load. Using ANN all variables with respect to the accident could be processed resulting in a determination of optimum re-routing until the traffic flow is stabilized. In such a case, GIS mapping is used and spatial data acts as one of the input variables into the ANN. Taken one step further, a map server could update with latest conditions and transfer those to vehicles and or PDA – allowing individual drivers to follow the best selected re-routing. This would also be quite useful for emergency vehicle access purposes.

Facial Feature Example – Recent terrorist events have led to increased security at airports and other facilities. GIS mapping of such facilities is useful for anti-terrorism reasons for numerous reasons including; emergency access, utility and services and crowd control. Movement of individuals within these environments is increasingly being monitored. ANN can be used with GIS to locate problematic situations while ANN pixel/pattern analysis can be used to determine facial features. Granted there is much work to be done in this area, however, facial tones and patterns are good candidates for future ANN applications, particularly where very large groups of individual faces must be processed quickly.

Delivery / Business Example – Similar to the transportation example, delivery vehicles circulate throughout a road network. Delivery time is important for providing prompt service and determining vehicle and personnel allocation. Through the use of GIS network analysis, travel times can be ascertained and updated with location-based networks coupled to GPS. In the event a truck breaks down, then a companies entire delivery network may be affected. ANN can be used to determine potential optimum re-allocation, where all vehicle locations are inventoried (input), assessed (weighted) and re-routing (output) are used for alternate decision-making to allow for the continued speedy delivery of products.

A Closer Look at ANN:

Let's use a real transportation situation to explain ANN in more detail. For this we will use a road network and assume green vehicles are moving through a city from point A to point B (Fig 2.) and that an accident occurs at the red box. As time passes, the traffic begins to back up (Fig 3.)

To keep things simple we will call the cars ANN inputs. As the number of inputs increase, the cars begin to search for alternate routing. To do this they move within the same area or 'intra-layer' to the left side as compared to 'inter-layer', which crosses the accident area. In evaluating the road network in this state the cars search for other access routes (layers). If they

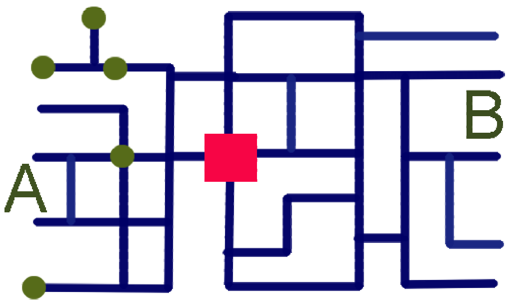

Fig 2. Road Network with cars – accident at red.

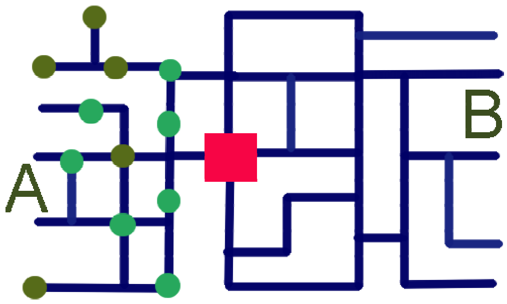

Fig 3. Traffic back up

can move forward then the condition would be called 'fully connected'. All neurons (roads) could then accept traffic. That however is not the situation with the road blockage. The cars may circle around to the left of the accident in which case we have a 'feed lateral' connection. Alternatively, if they could only move to the right we would have a 'feed forward' connection. Some drivers might even go around and around in circles – a 'recurrent' connection.

To move from point 'A' to point 'B' the vehicles must select the open routes. In this case there is only one – north of the accident scene. Subsequently, we give a higher weighting to that open stretch of road while decreasing the weighting to the road where the accident is (Fig 4). As vehicles move past the accident area, the nearby roads could receive higher weightings since they could lead to point 'B' ultimately. The traffic is still congested and some drivers get lost (recurrently connecting in circles) while others move slowly toward point 'B' (Fig 5).

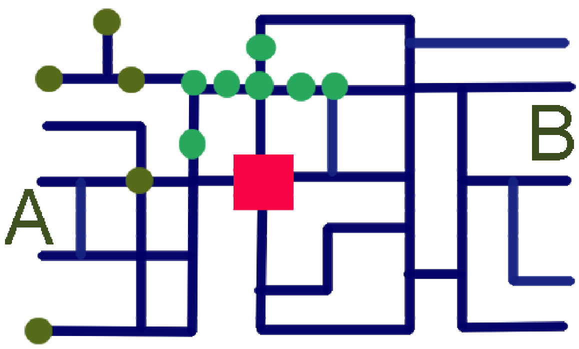

Fig 4. Higher weighting on open route

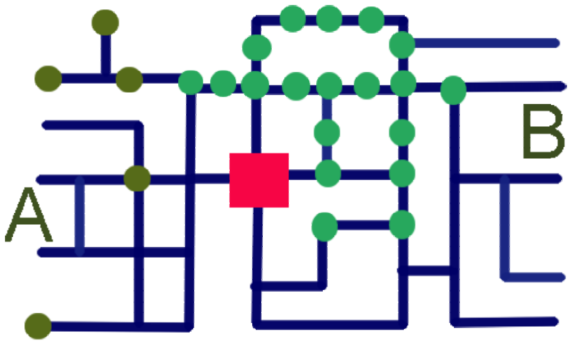

Fig 5. Alternate re-routing

Each of the re-routes (Fig 5) could have a different weighting due to the fact some are more preferred than others in terms of final distance to point ‘B’. After some time all the vehicles would arrive at point ‘B’ or the output point.

If this exercise were repeated over and over, changing the weightings for the re-routes in the hidden middle layer the optimum solution (selection) of roads would be determined and the road network would be trained for an accident occurring at the red box. It is not that simple though. In this case we used only one hidden layer, that being the roads themselves. We could have added weather, time, road condition and other pieces of information, in which case we would have had more layers in the middle – a ‘multi-layered’ ANN. Naturally the more layers we include to more realistically represent the situation, then the more complex the ANN becomes. Since more layers would then be added, then each would have a different weighting contributing to the overall neural structure and operation. This can become complex very quickly.

Neural networks are not capable of re-learning, meaning that once we set up above network and optimise it, training it for the re-routing, we cannot add other factors like age of drivers or type of vehicles without beginning the whole process over again. That is a distinct disadvantage to ANN since that takes time – but not unlike humans who do not learn from their mistakes! Continuing with the example, a steady state will be reached until the accident is removed at which point the network will once again change weightings back to the original traffic movement patterns.

Summary:

Artificial neural networks when coupled to GIS can be used for many applications for the purposes of improved decision-making. The design of an ANN will entail numerous layers, all of which can have varying weightings. There are many examples where ANN is useful, for example, in agriculture these could include crop inputs related to the output of yield. In forestry they may include silvicultural operations as inputs computed to outputs of increased annual forest growth while in health they may be related to population demographics and disease rate of spread. The process of training an ANN involves changing the weightings over time until the network reaches the optimum firing or static state as is desired – that process is called ‘training’. Once trained an ANN can be used for applications consistently and effectively. Through the application of an ANN, GIS professionals can add another dimension to their spatial capabilities.

Additional Information:

- **Neural Network Classifiers for GIS Data: Improved Search Strategies**
- **GIS Supported Modeling of Water Quality Using Artificial Neural Network (ANN) in the Tomorrow/Waupaca River Watershed**
- **Baltimore's Urban Environment Using GIS and Neural Networks**
- **AI & Neural Networks**
- **What is an ANN?**
- **Artificial Neural Networks**
- **Application of Neural Net Based Techniques to Vegetation Management Plan Development**
- **Merging Technologies: Linking Artificial Neural Networks to Geographic Information Systems for Landscape Research and Education.**
- **comp.ai.neural-nets newsgroup FAQ**
- **Neural Network Software Programs**

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Biography:

Jeff Thurston holds a MSc. in Geographic Information Science and is European Director for Integral GIS, Inc. in Berlin, Germany. He is a graduate of the UNIGIS program at Simon Fraser University, Vancouver, Canada and has previously taught GPS, GIS, photogrammetry and visualization as well as writing for numerous publications internationally. (jeff@integralgis.com).