How can machine learning improve geophysical interpretation?

Tim Gibbons
Geoscience Sales Consultant

HOOLOCK CONSULTING

Hoolock Consulting

Hoolock Consulting provides sales consulting services to the upstream oil and gas industry, with a focus on geoscience. We provide sales training and consultancy as well as selling products on behalf of a number of clients.

30 years experience in the oil industry

Worked as a geophysicist with BP and Elf

19 years sales experience with Landmark, Paradigm and TGS

3 years with Hoolock Consulting

Maths, Further Maths and Physics

$$x\frac{dy}{dx} + y = x^2y^2$$

$$\left[\frac{dy}{dx}\right]^2 + y = 5x^2$$

$$\frac{d^3y}{dx^3} + \left[\frac{dy}{dx}\right]^2 + y = 6x^3$$

Physics

$$i\hbar\frac{\partial}{\partial t}\Psi(x,t) = -\frac{\hbar^2}{2m}\frac{\partial^2}{\partial x^2}\Psi(x,t) + V(x)\Psi(x,t)$$

$$E\psi(x) = -\frac{\hbar^2}{2m}\frac{\partial^2}{\partial x^2}\psi(x) + V(x)\psi(x)$$

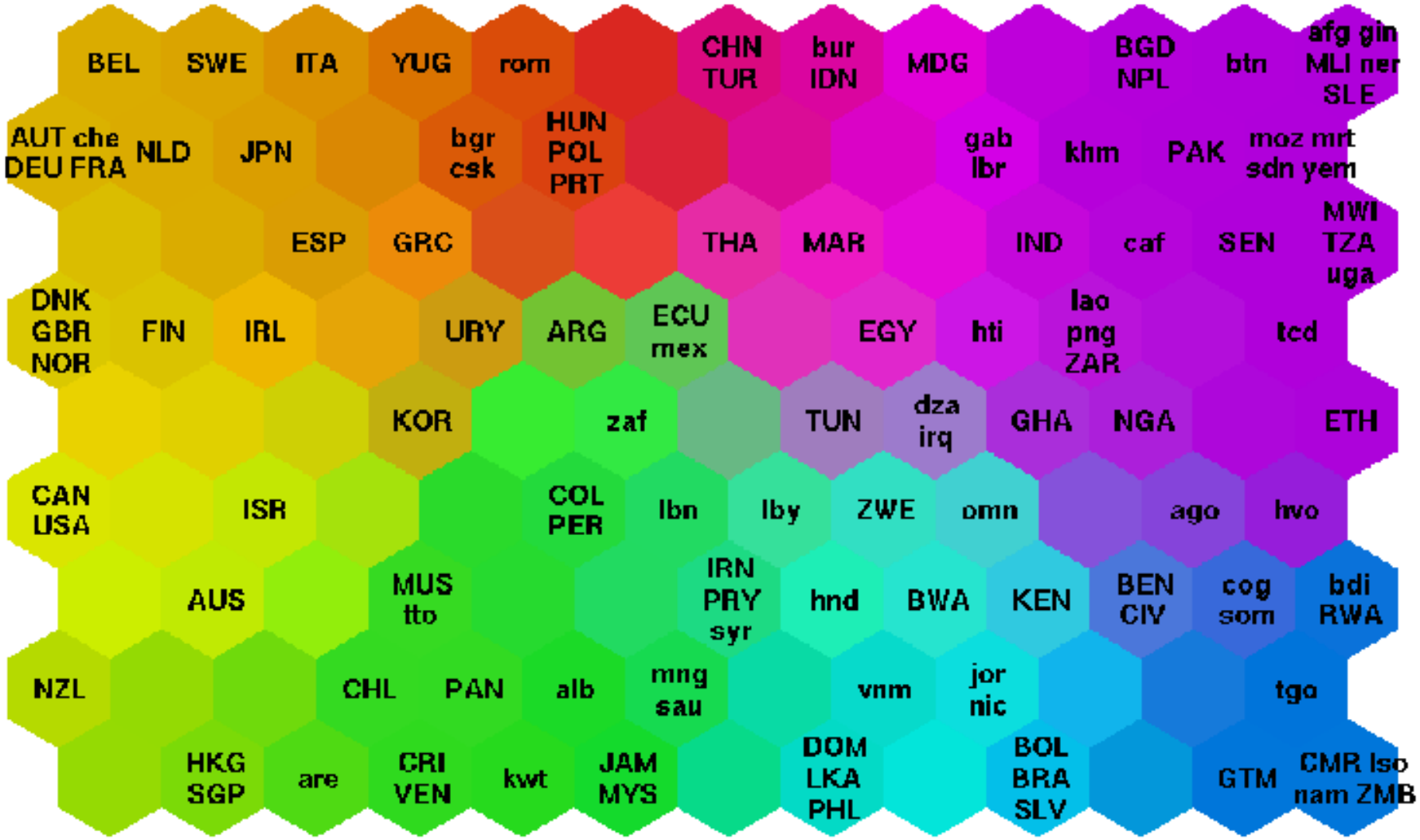
Self Organising Maps

$$W_v(s+1) = W_v(s) + \Theta(u, v, s) \times \alpha(s) \times (D(t) - W_v(s))$$

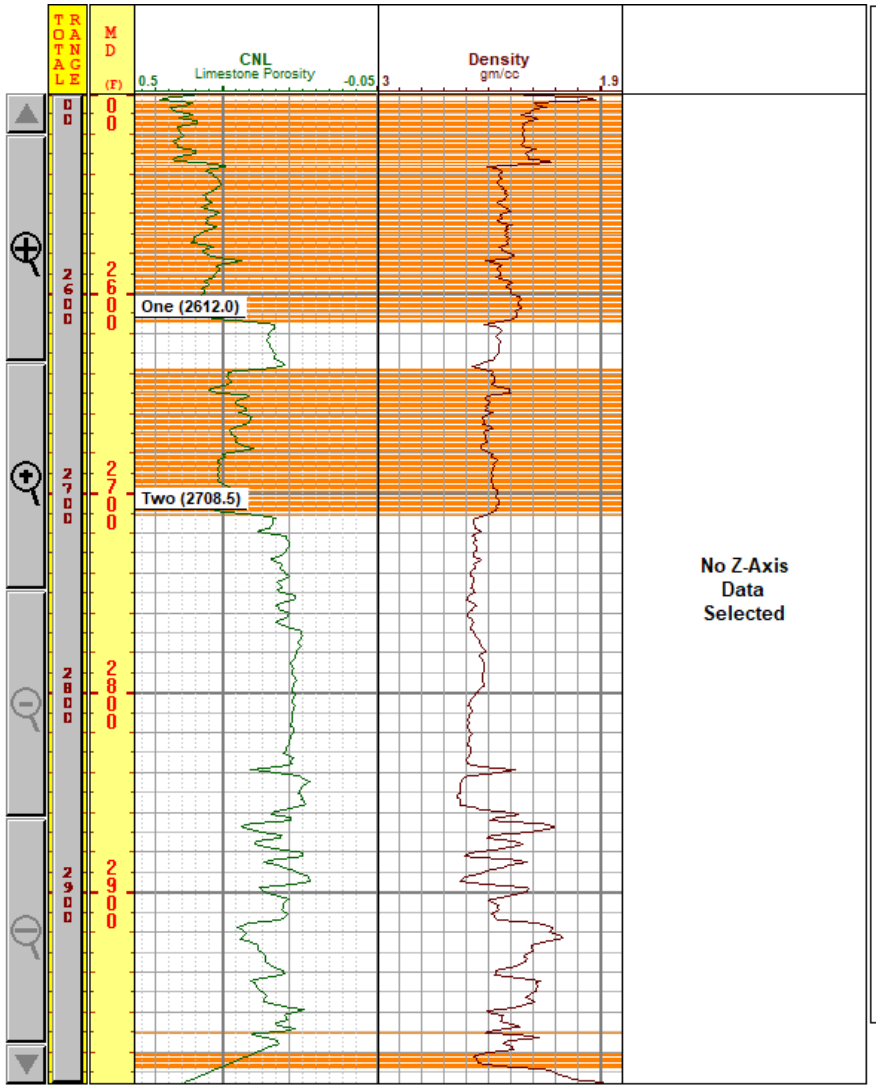
The Self Organizing Map (SOM) process is neural training that adapts to data values in multidimensional space, such as attributes in a seismic volume. After training, the data are classified so each input data sample is assigned a best-fitting neuron. The result of neural training is a two dimensional map that corresponds to how the data (attributes) cluster in “n” dimensions. Based on the attributes used in the SOM analysis, the neural map can often discriminate geologic and stratigraphic features, as well as expose direct hydrocarbon indicators (DHI’s).

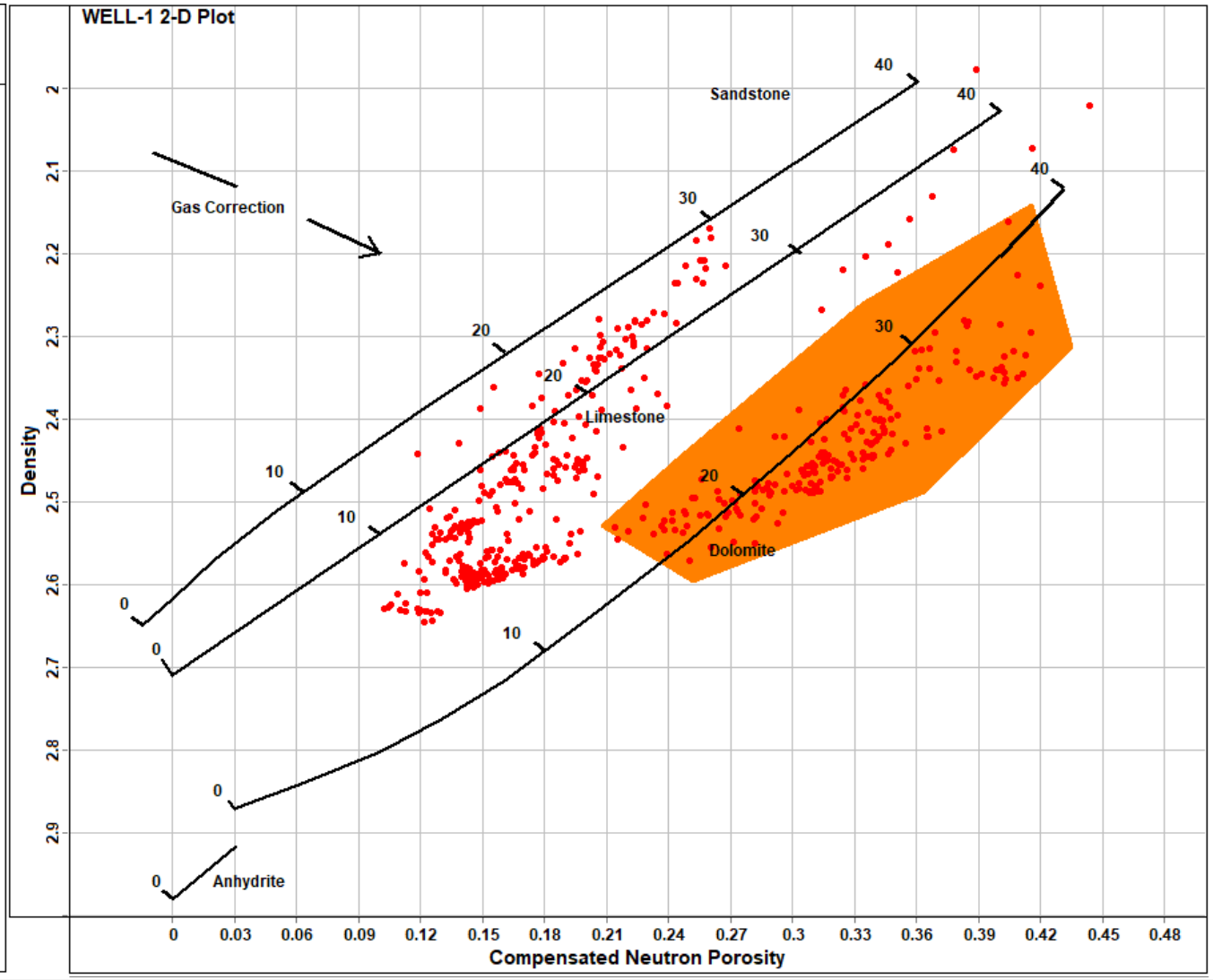
Self Organising Map is a display of data points that are highly probable to be associated with one cluster or another.

Self Organising Maps



Self Organising Maps

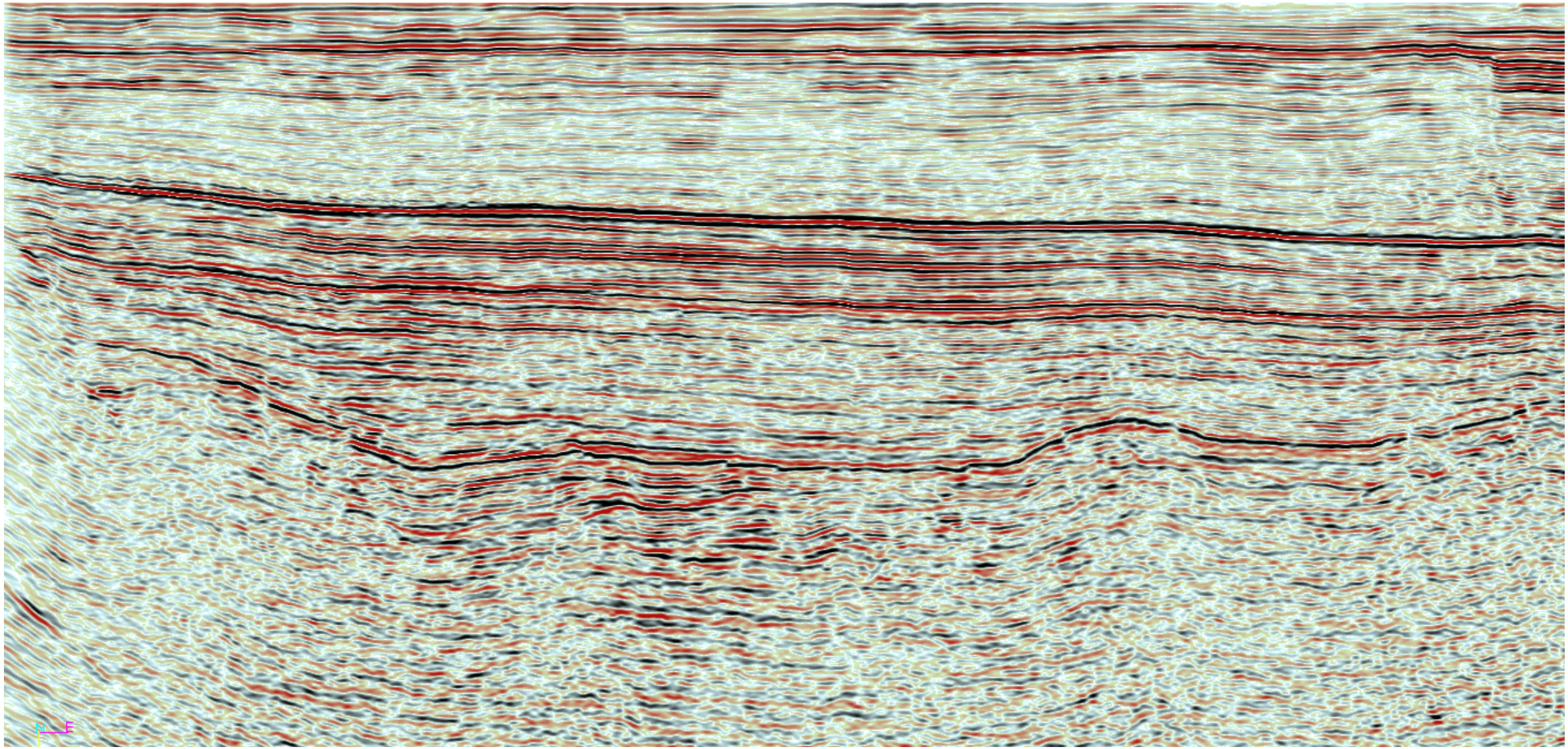




Why SOM is an Appealing Learning Machine

1. Dimensionality Reduction: SOM is tolerant of high dimensionality because of its unique learning strategy through the winning neuron strategy.
2. Vector Quantization: SOM searches for regions of high density => natural clusters in attribute space are geophysical reflections of geologic bodies of interest.
3. Non-parametric: There are no assumptions about statistical properties of the data.
4. Understandable: SOM is easy to understand (really if you spend a little time with it).
5. Dynamic Topology: Learning strategy is dynamic because it changes over time, from cooperative to competitive and from early recognition of group properties to later refinement.
6. Robust Learning: Processes vast amounts of multi-attribute seismic data and insensitive to initial conditions as long as basic learning parameters are honoured.
7. Dimensional Up-reach: After training, it is an easy matter to associate subsets of the data with individual winning neurons which then leads to further statistical analysis.
8. Flexible Architecture: Neural topologies are adaptable to the needs of a variety of geophysical and geological data .

Seismic Interpretation



Data from UK NDR

Seismic Amplitude

Seismic amplitude is a function of the impedance contrast across a boundary

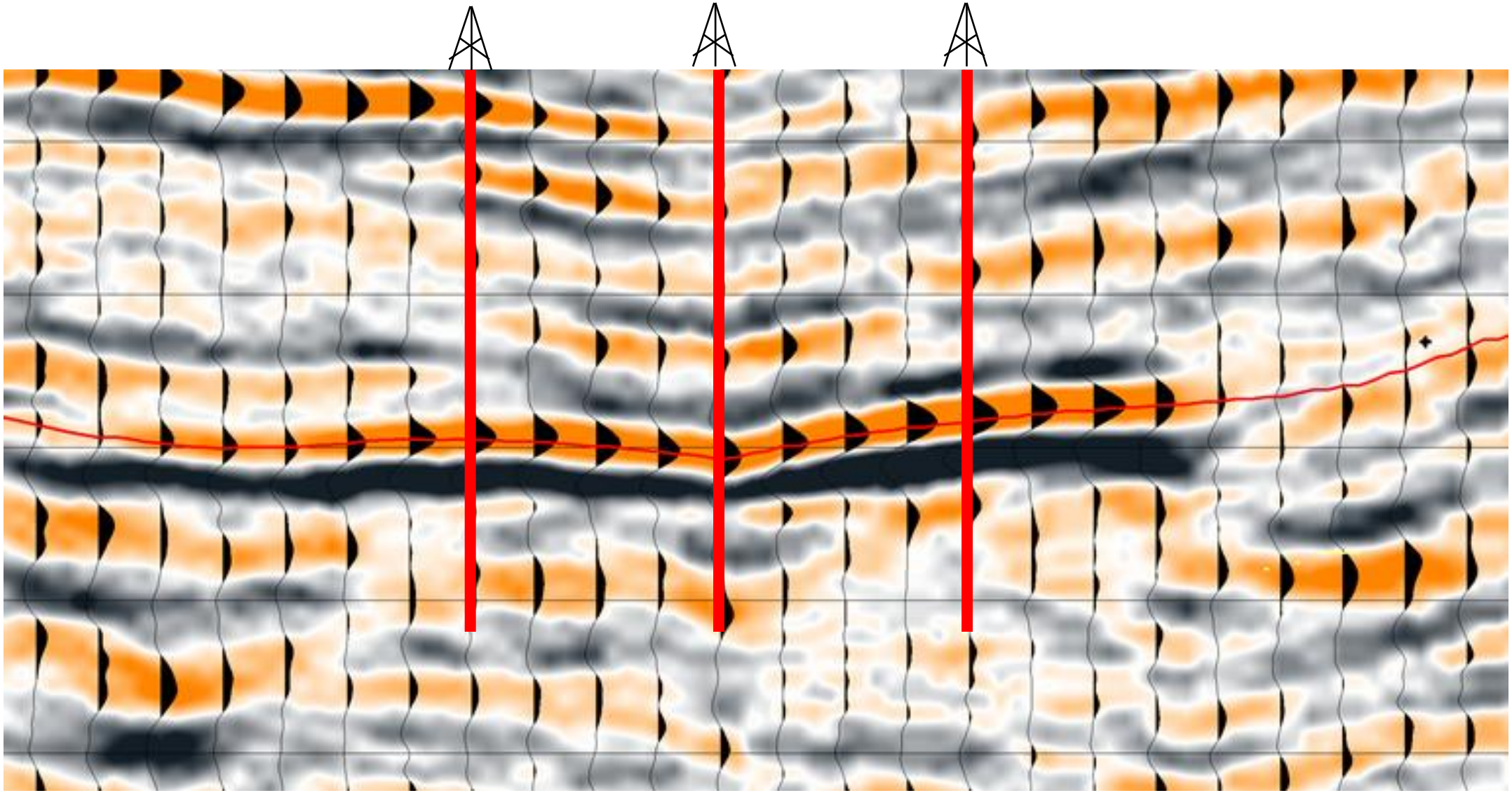
Impedance is the product of seismic velocity and density

Seismic velocity varies due to:

- Porosity
- Density
- Temperature
- Grain size
- Saturation
- Fluid fill
- Pressure
- Stress

Two equal amplitudes do not equal two identical geologies.

Relying just on amplitude



If we are going to use Seismic Attributes…..

How do we know which attributes to use?

How do we use multiple attributes in a meaningful way?

Seismic Attribute Families

Category	Type	Interpretive Use
Instantaneous Attributes	Reflection strength, instantaneous phase and frequency, Quadrature, Instantaneous Q	Lithology contrasts, bedding continuity, porosity, DHI's, Stratigraphy, Thickness
Geometric Attributes	Coherency, curvature, dip etc	Faults, fractures, folds, anisotropy, regional stress
Amplitude Accentuating Attributes	RMS Amplitude, relative AI, Sweetness, Average energy	Porosity, stratigraphic and lithologic variations, DHI's
AVO Attributes	Intercept, gradient, fluid factor, Lambda-Mu-Rho	Pore fluid, lithology, DHI's
Seismic Inversion Attributes	Coloured inversion, sparce spike, elastic impedance	Lithology, porosity, fluid effects
Spectral Decomposition	Continuous wavelet transform, matching pursuit, exponential pursuit	Layer thickness, stratigraphic variations

Principal Component Analysis

Principal Component Analysis a linear mathematical technique to reduce a large set of variables (seismic attributes) to a small set that still contains most of the variation of independent information in the large set.

We need to determine which attributes are the most important and which can be ignored in the final analysis.

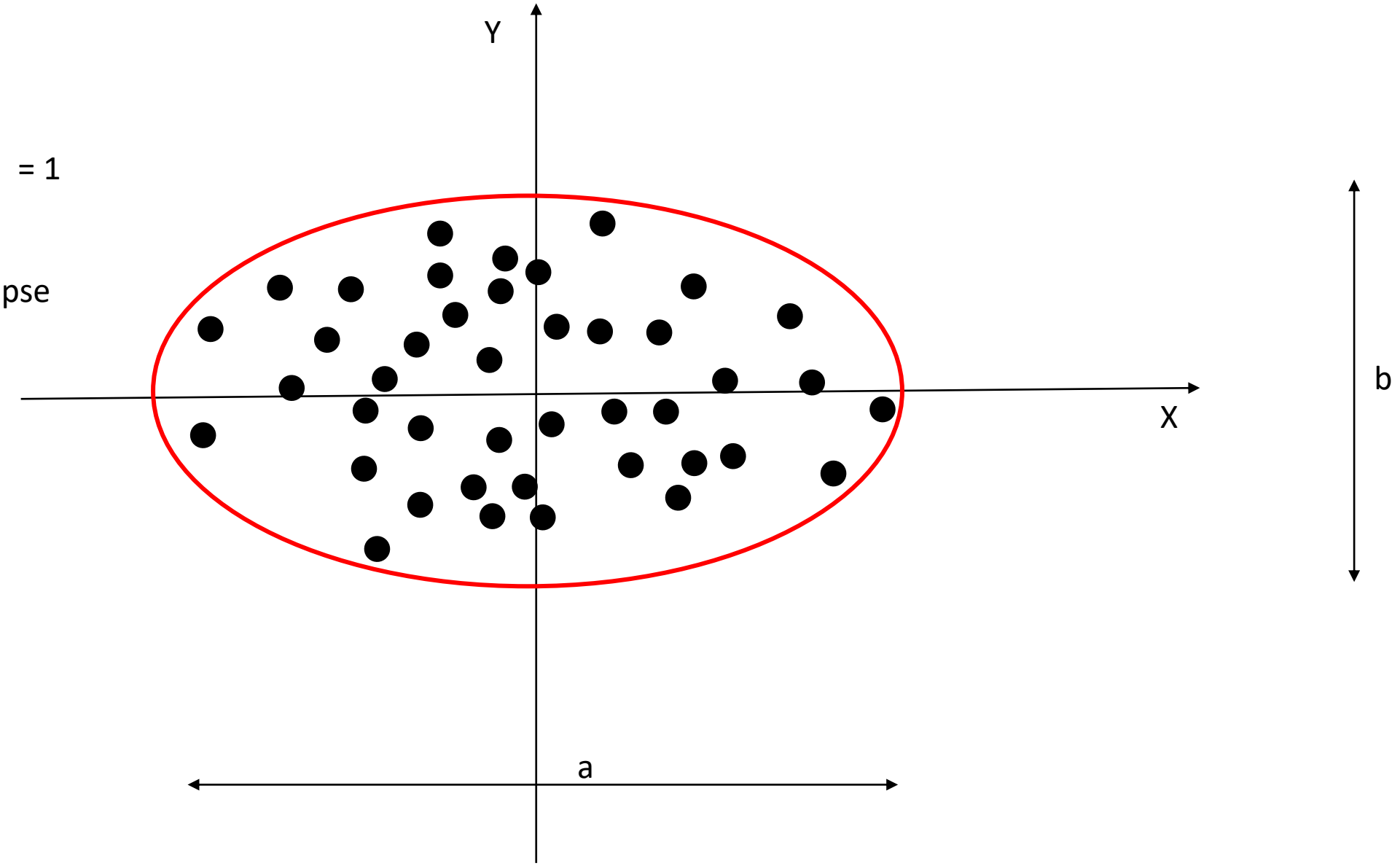
We need it because of the number of attributes involved and therefore the number of dimensions of variation.

We run PCA to effectively choose which attributes are contributing to the overall discrimination in the data so that we can input these into the Self Organising Maps.

Principal Component Analysis

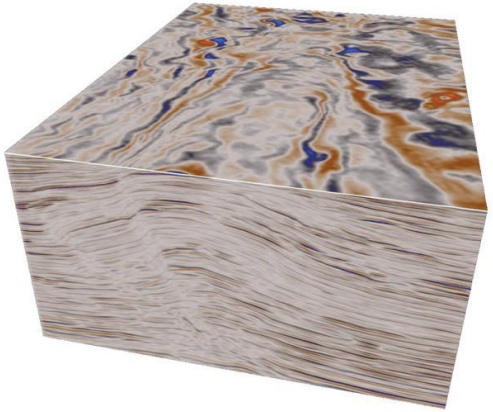
$$\frac{X^2}{a^2} + \frac{Y^2}{b^2} = 1$$

Equation of Ellipse



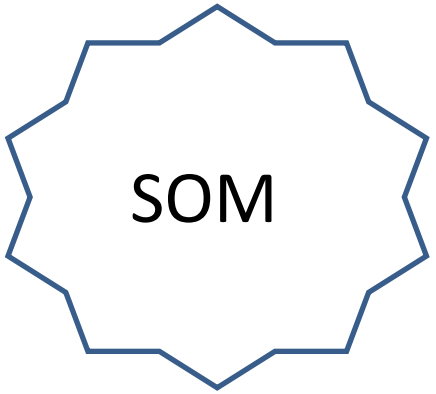
Self Organising Maps

Survey Space



Each sample in “survey space” has “n” attributes associated with it.

Attribute Space

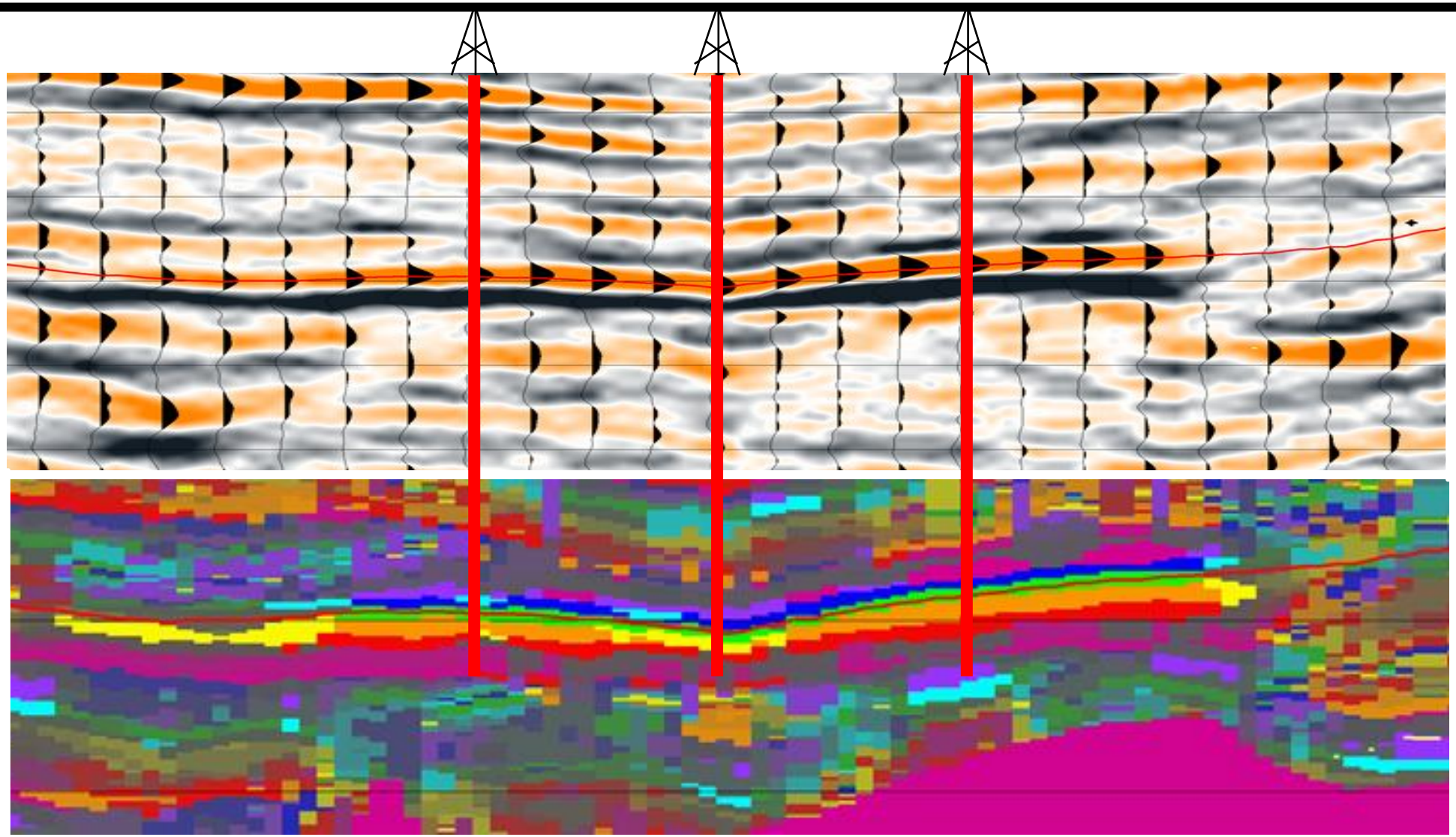


“n” attributes => “n” dimensional space

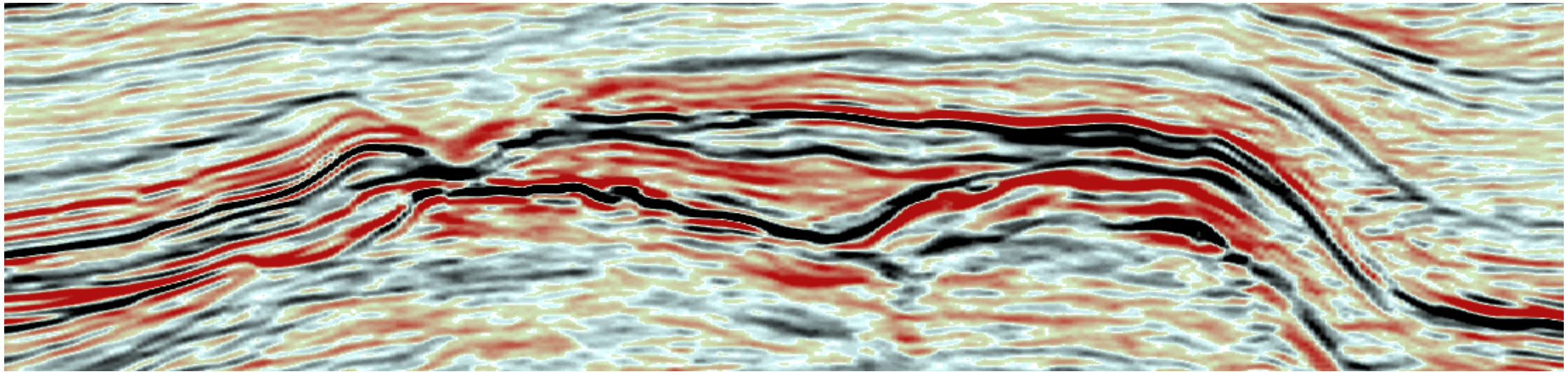
2D Colour Map

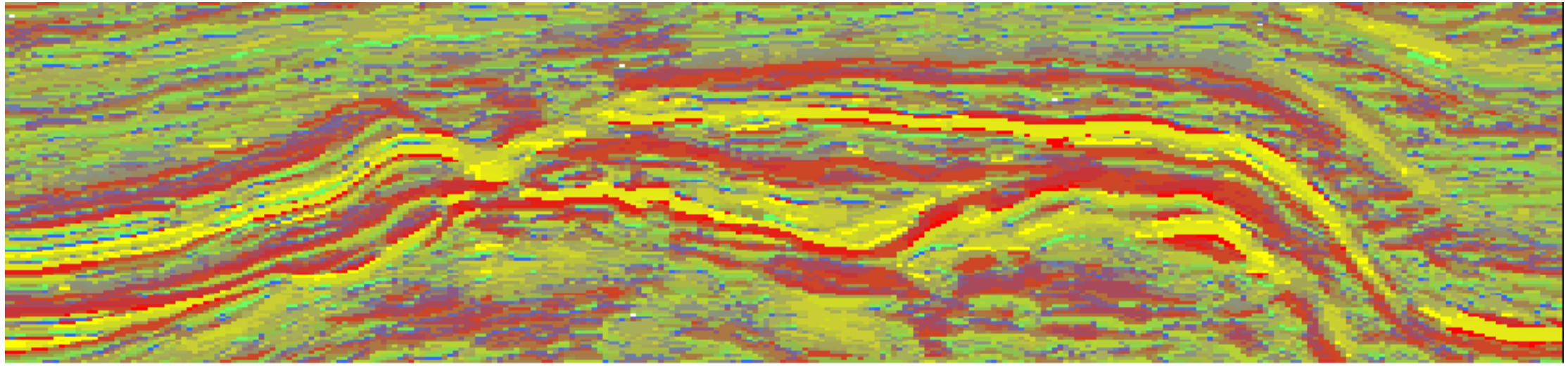
Each neuron represents a cluster of data points that are similar.

Typical Interpretation Problems



Mapping and Interpretation





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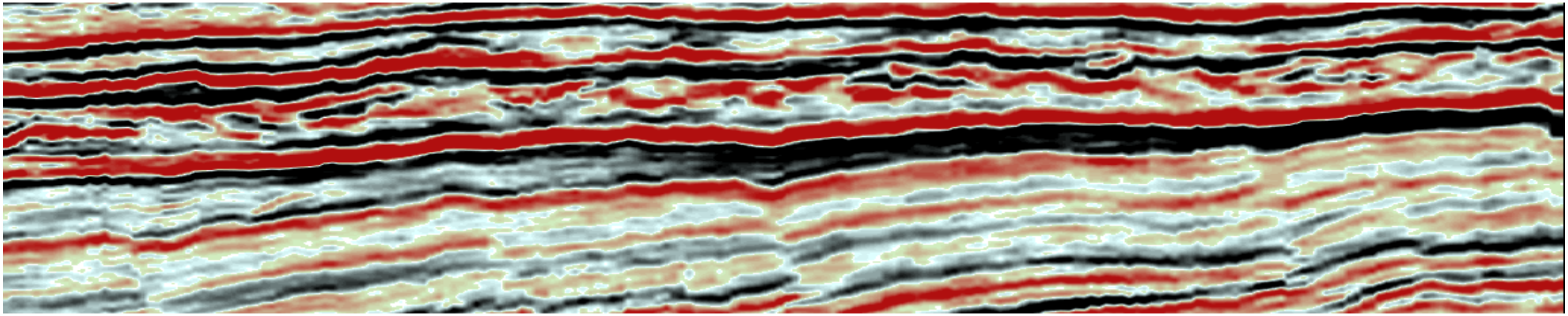

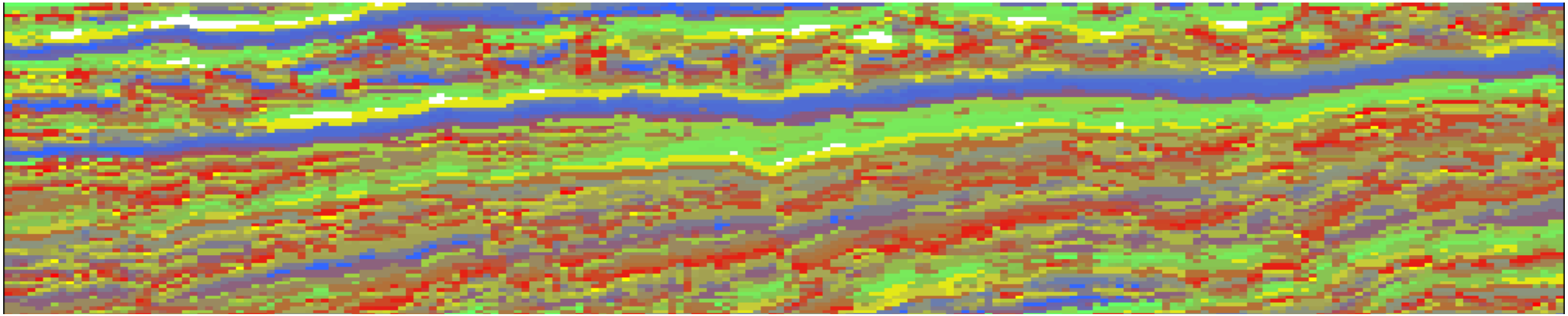

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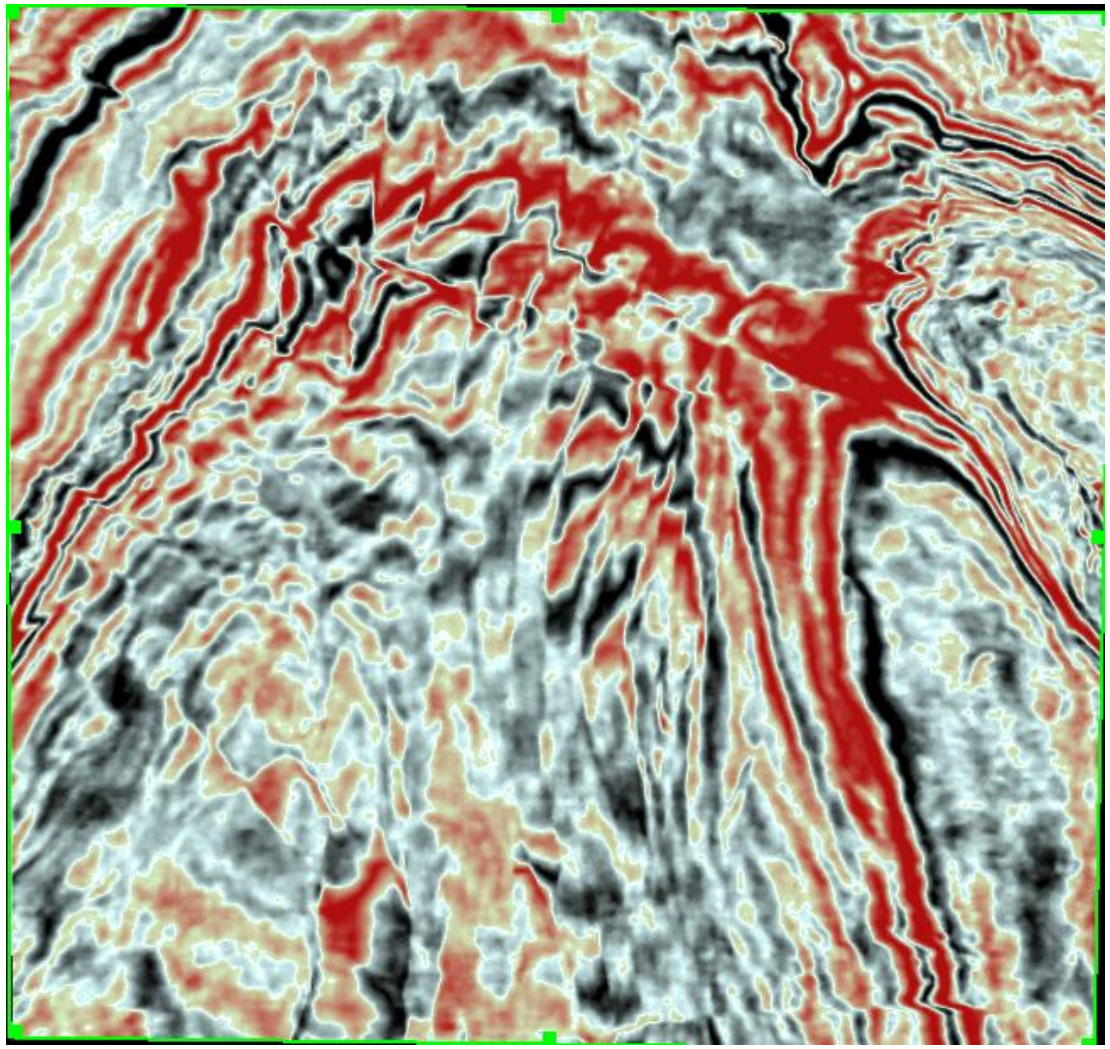
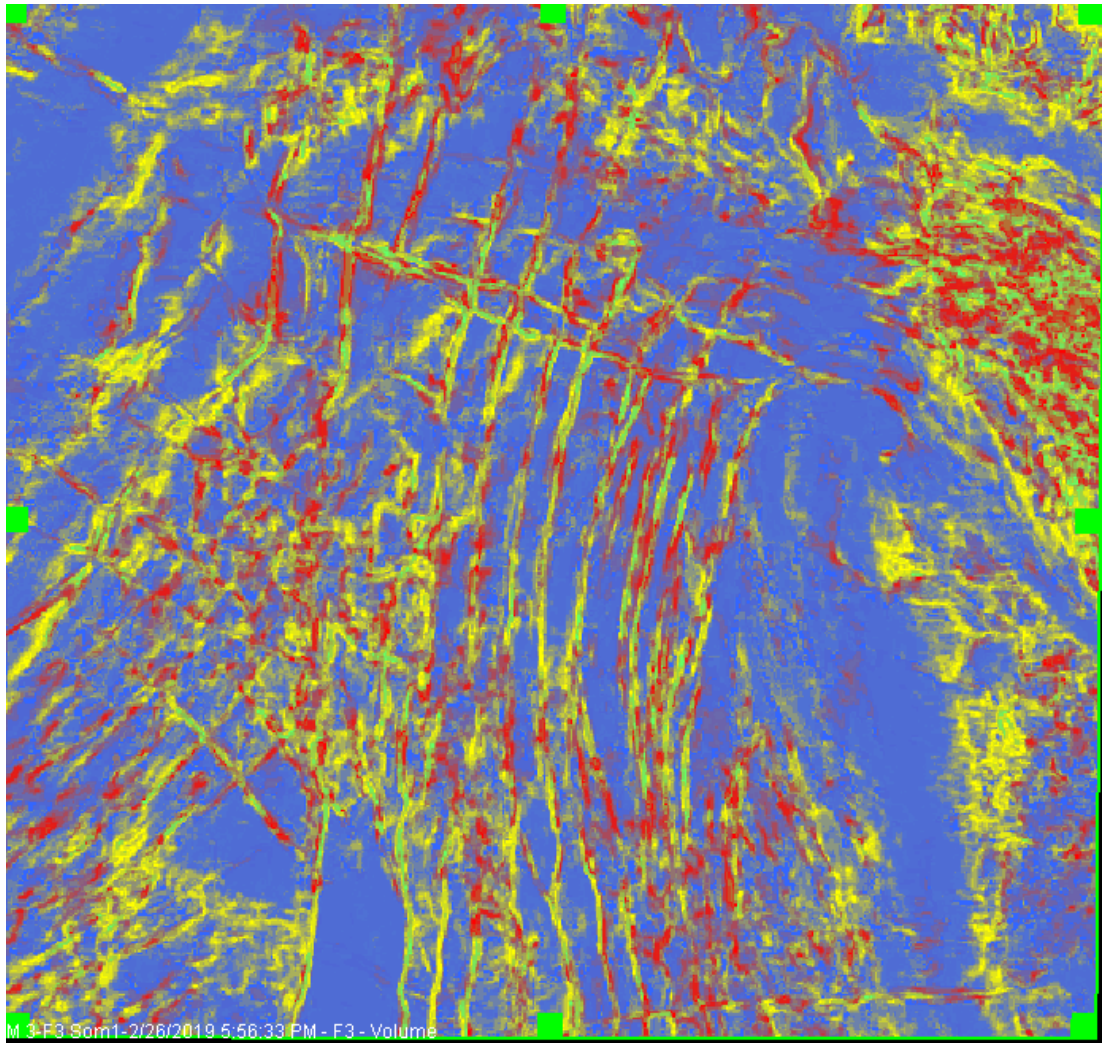
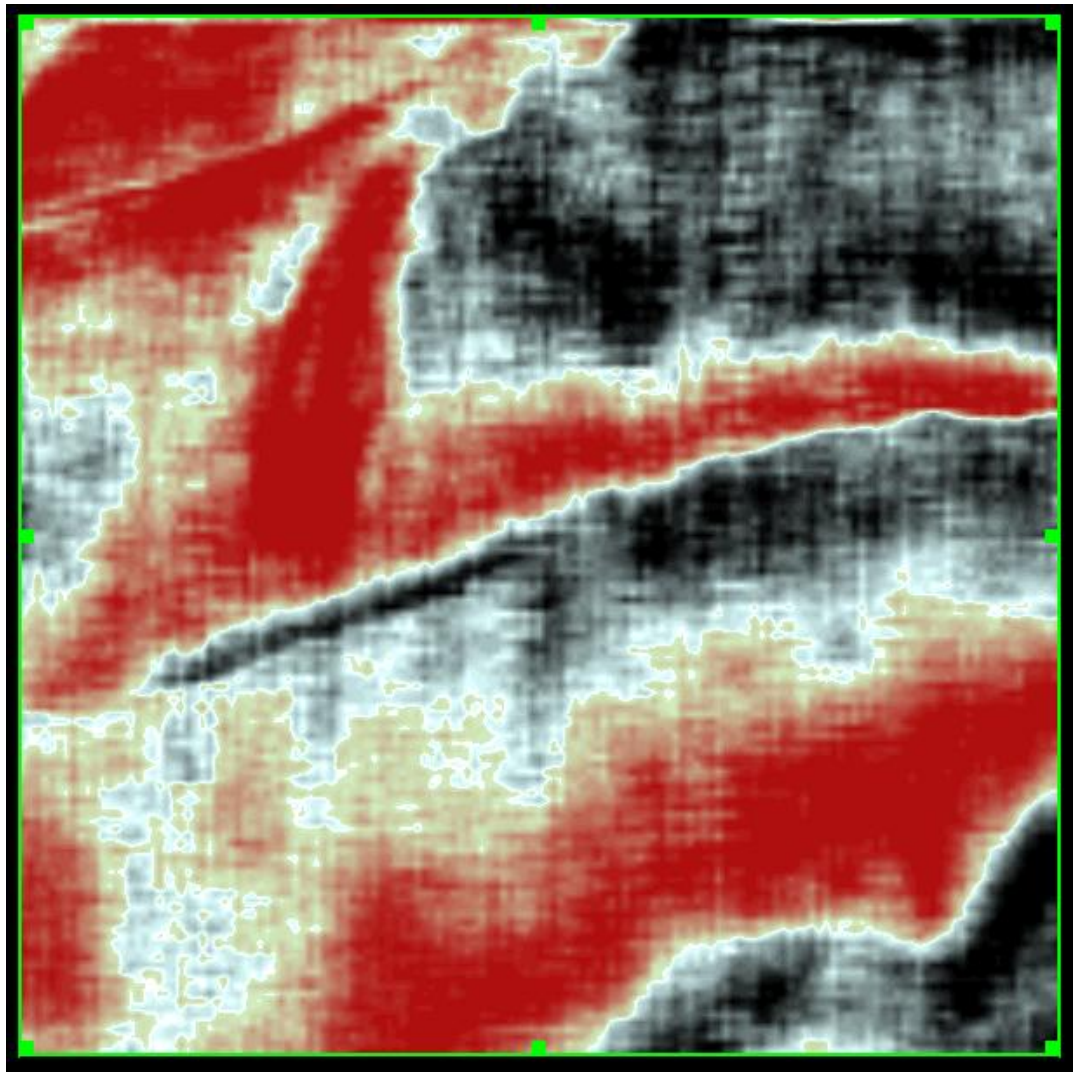


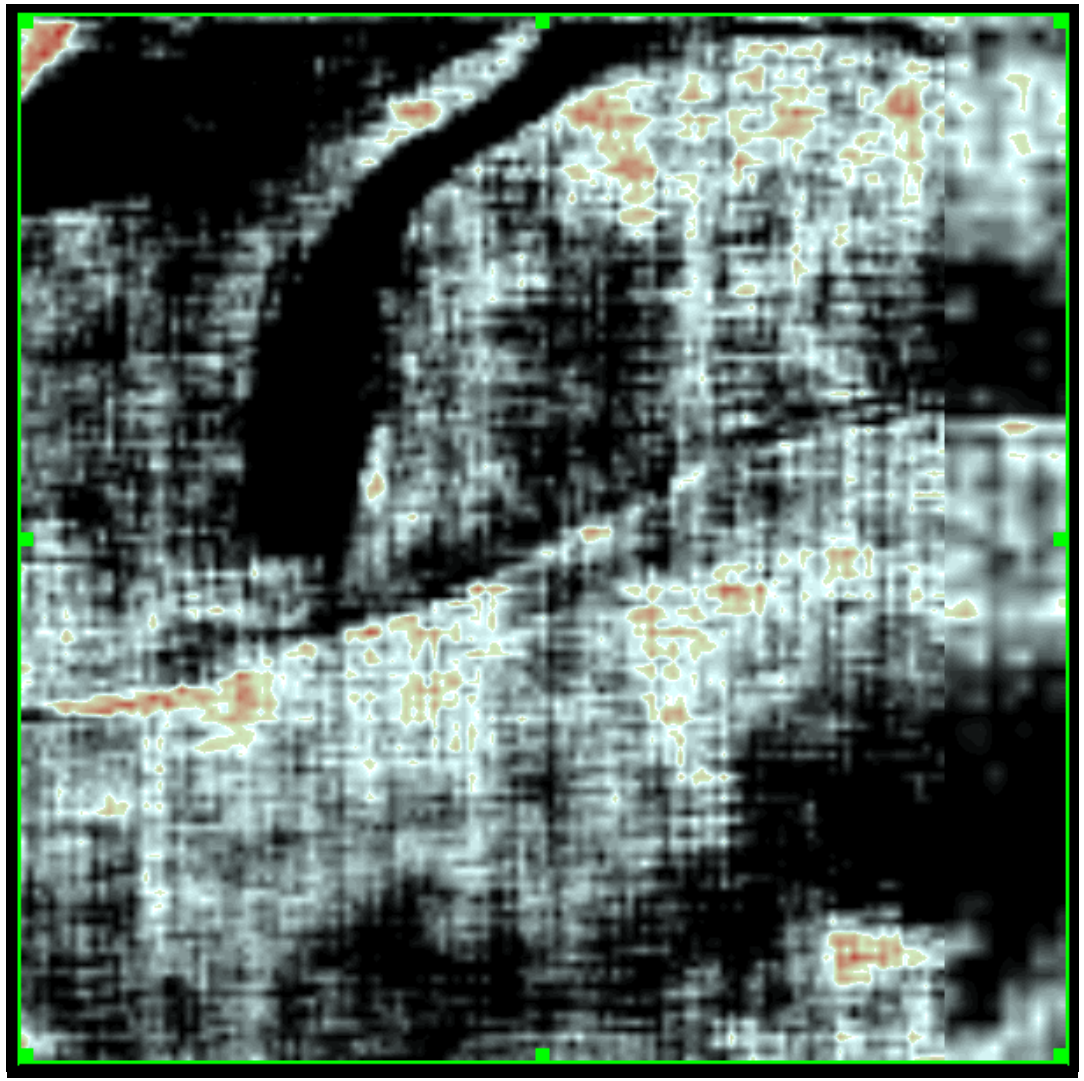


So what happens if we vary the input and the parameters?

Golden 3D Seismic, Onshore US

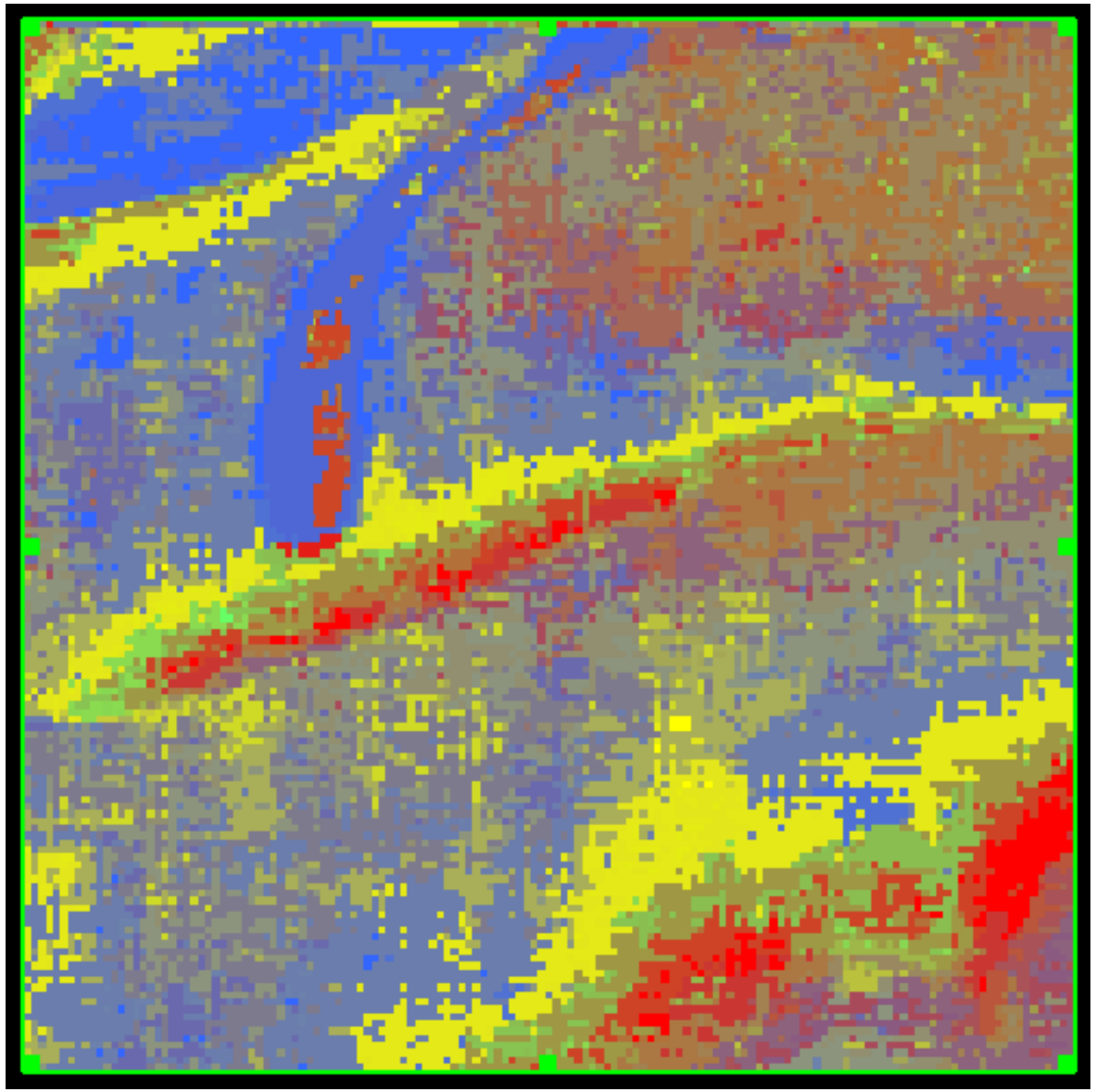


1.234s

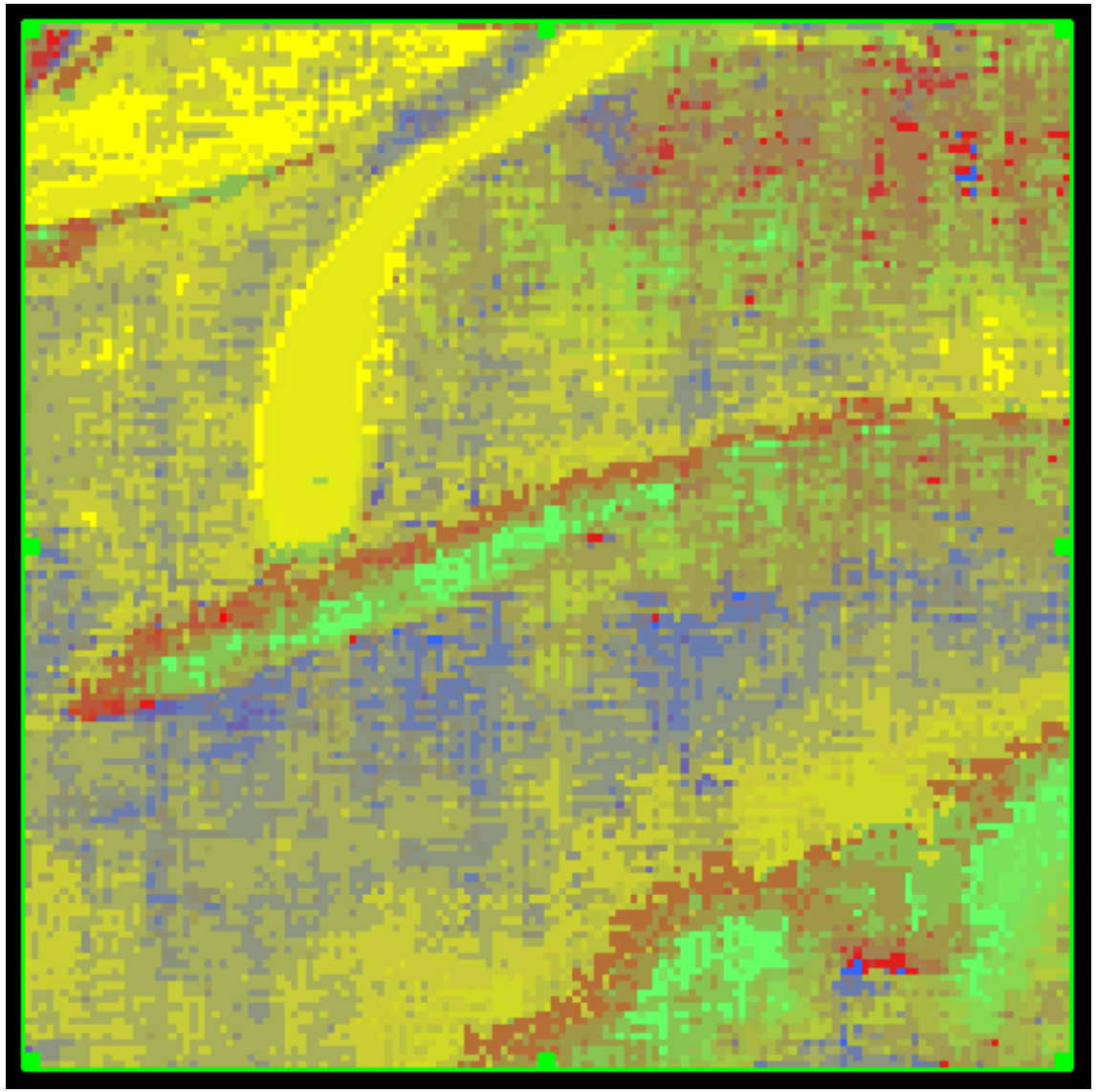


Top 10 Attributes

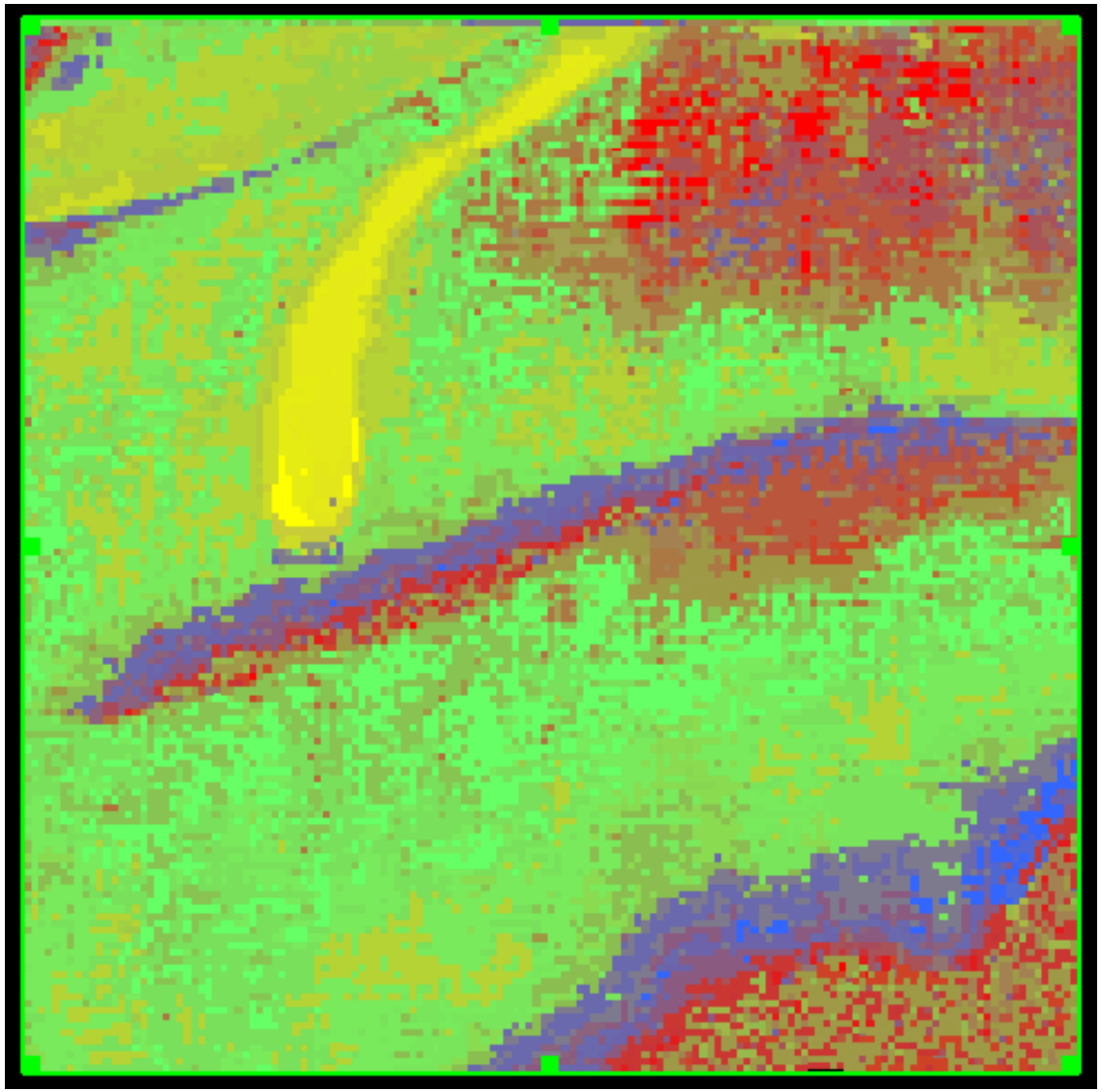
1. Instantaneous Frequency
2. Thin Bed
3. Hilbert
4. Relative Acoustic Impedance
5. Instantaneous Phase
6. Sweetness
7. Envelope
8. Envelope Slope
9. Instantaneous Q
10. Normalised Amplitude



Horizon Constrained

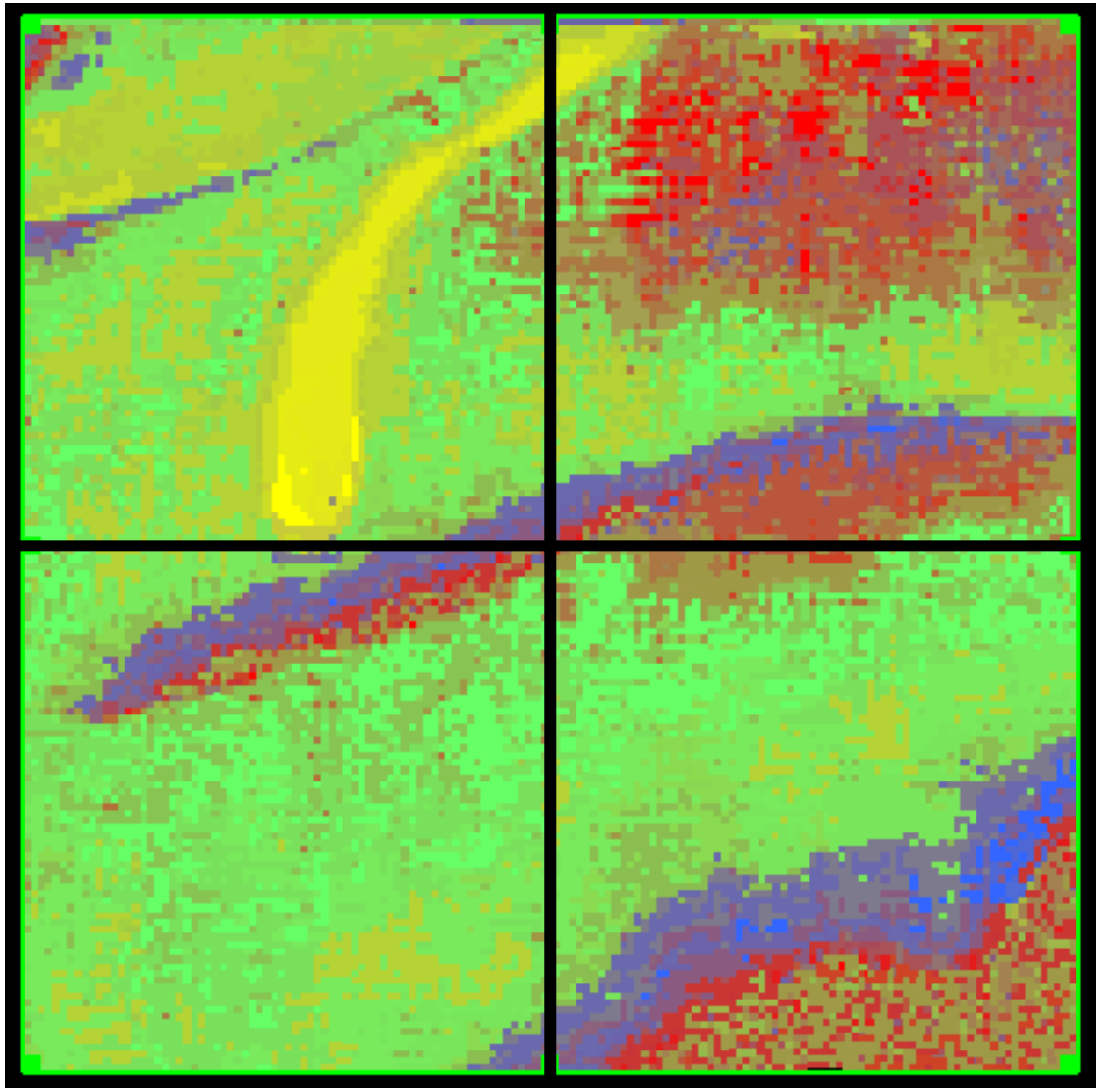


1-2 seconds of data



Horizon constrained

Harvesting



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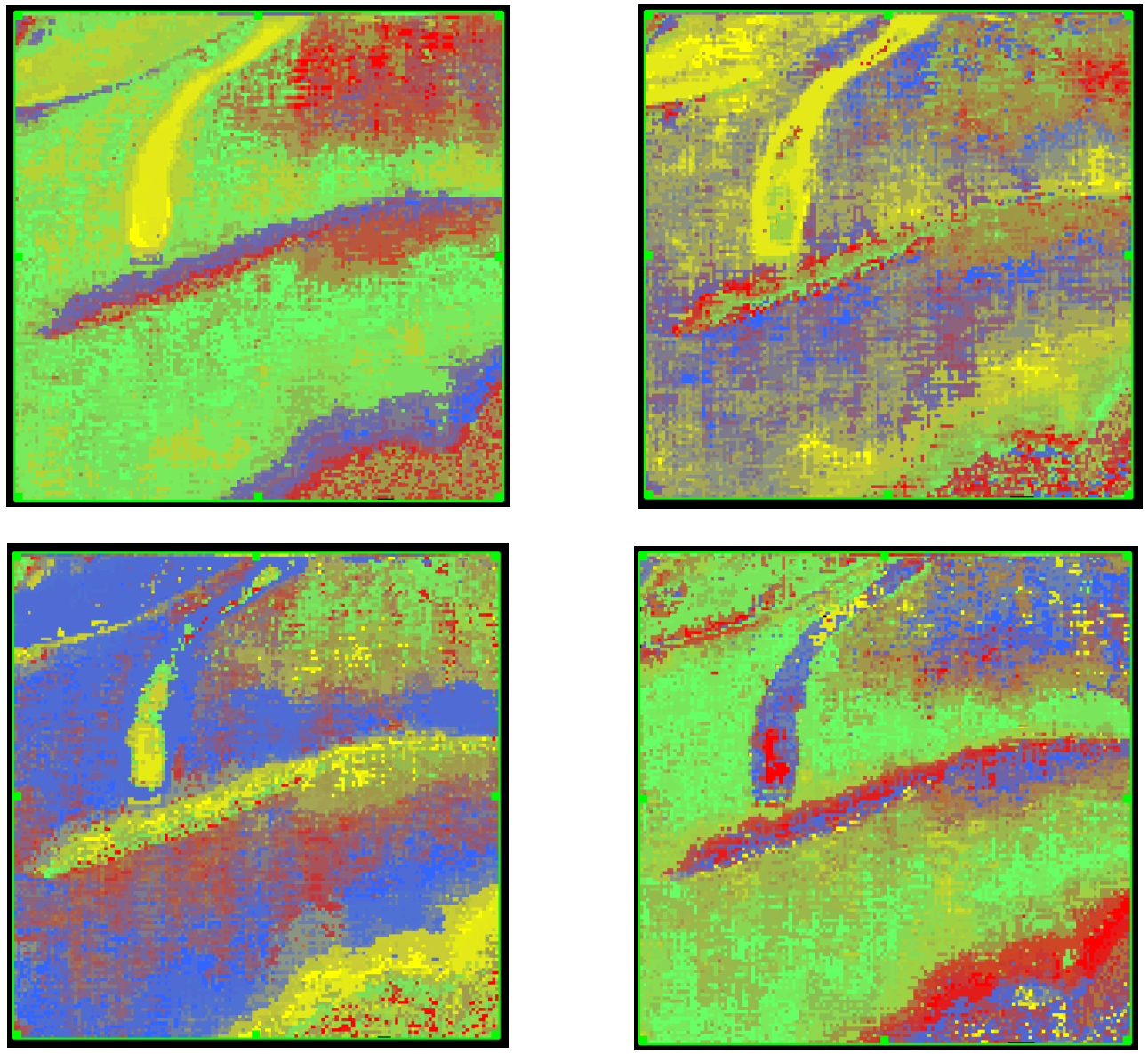
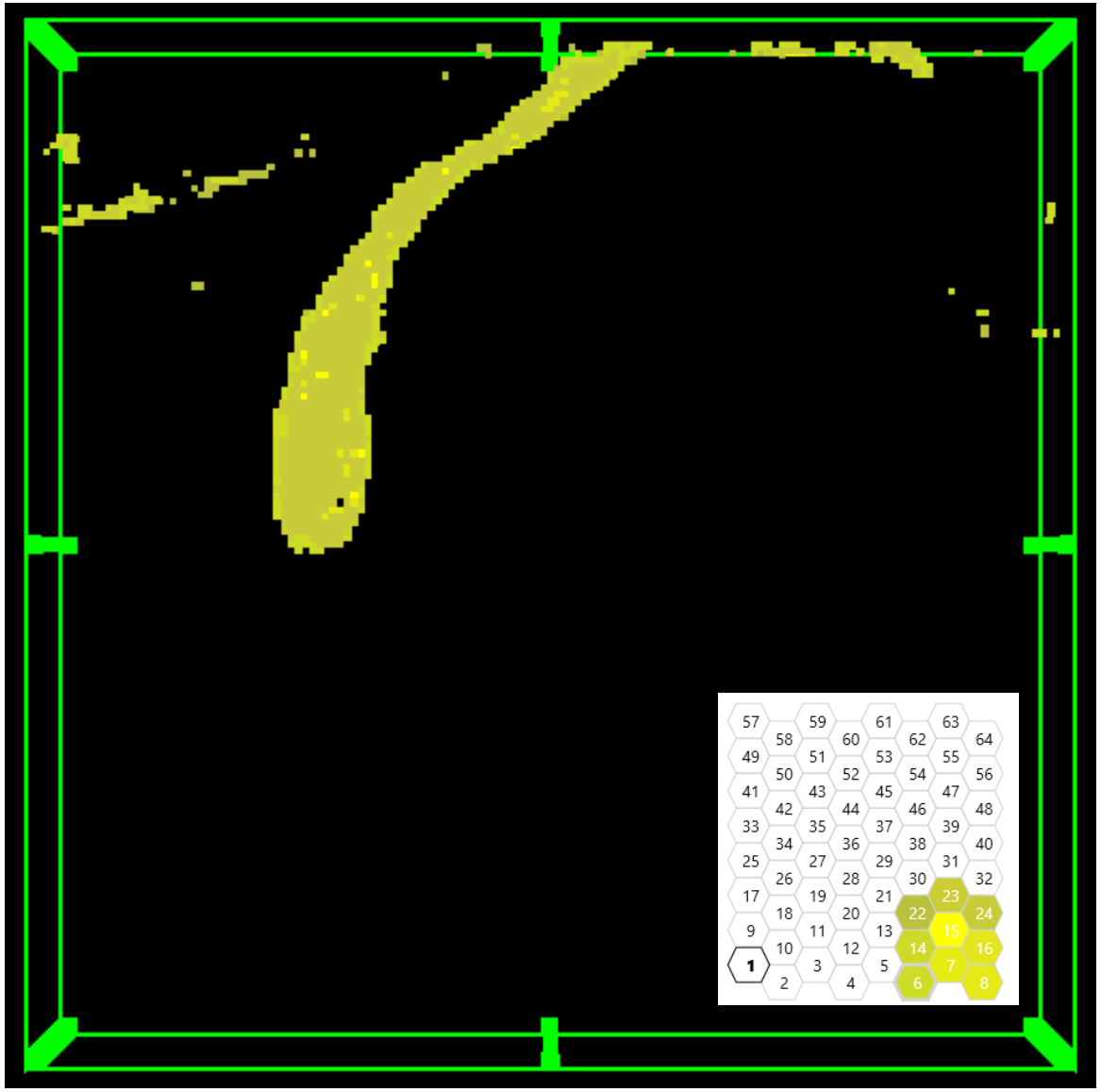
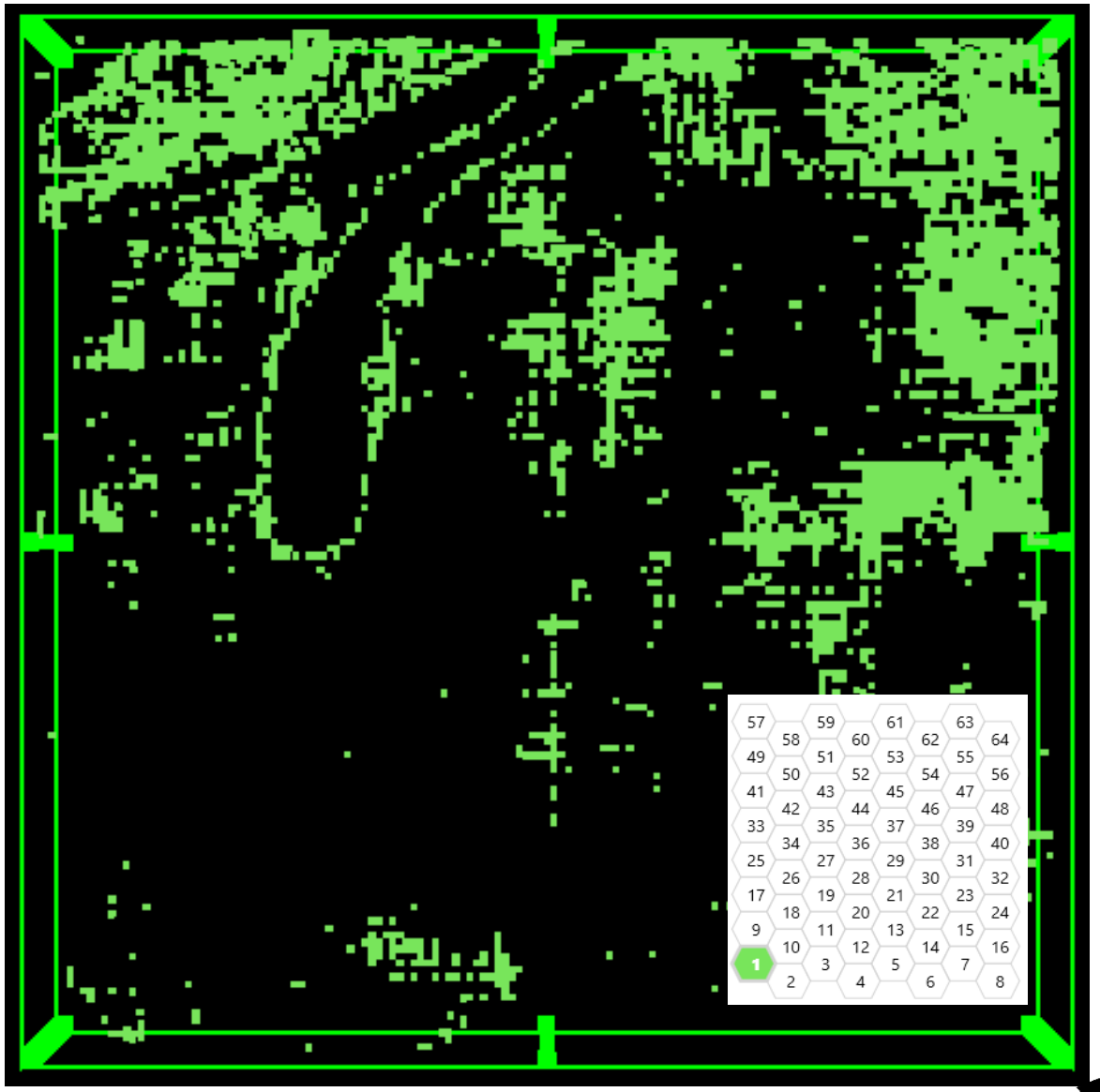
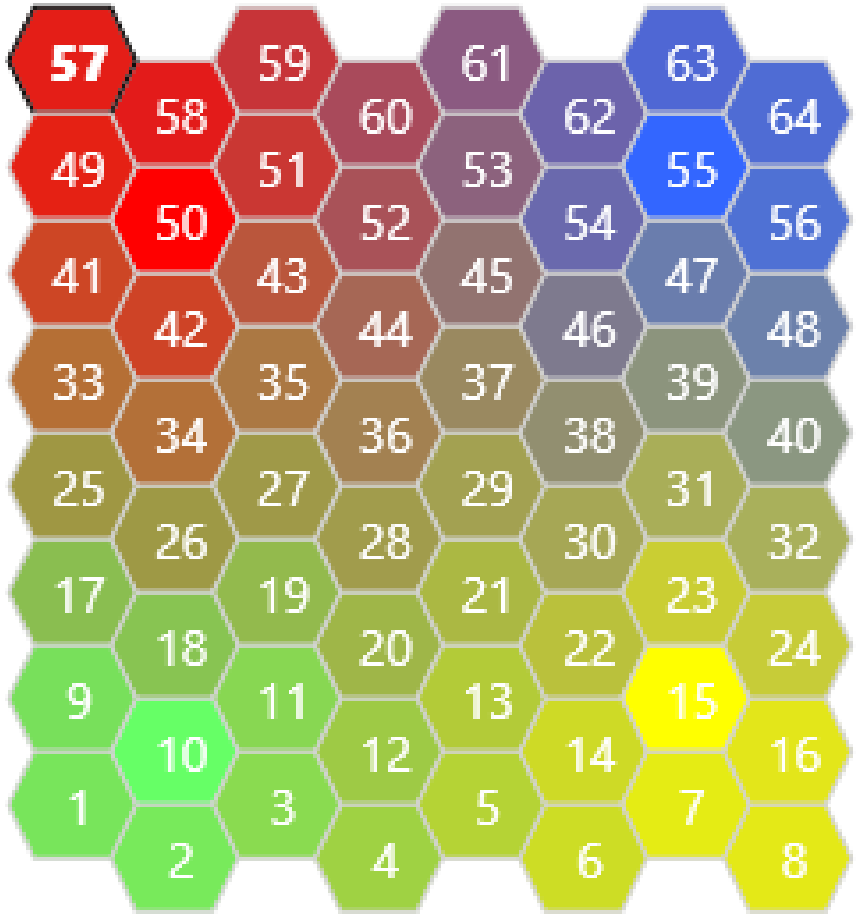


Harvesting



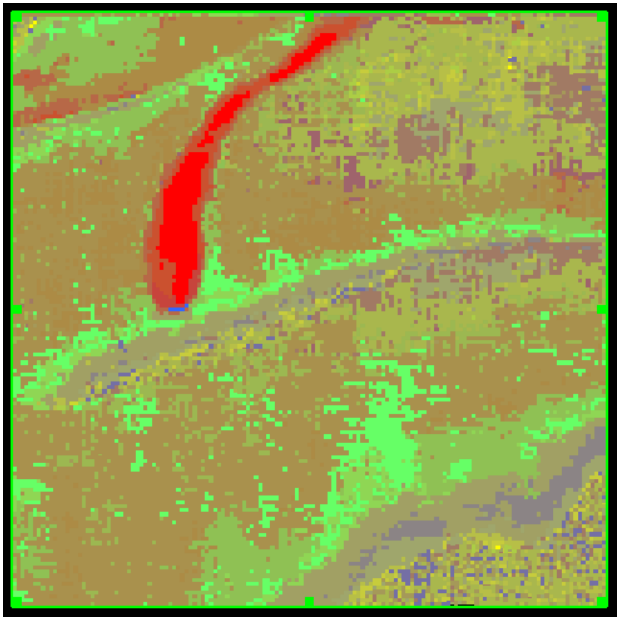


Neuron Count

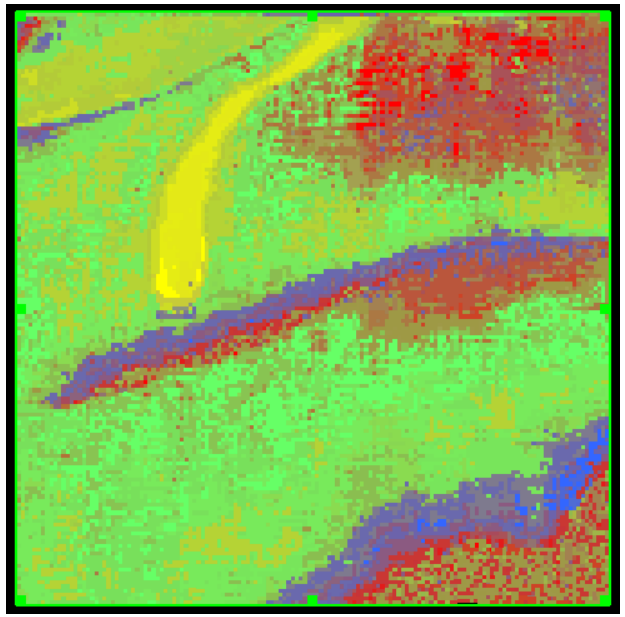


Standard Colour Maps:
5 x 5
8 x 8 (default)
10 x 10
12 x 12

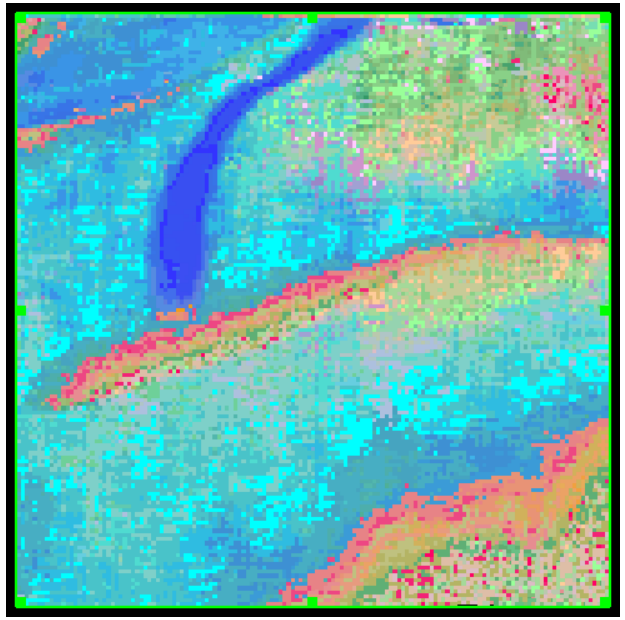
Neuron Count



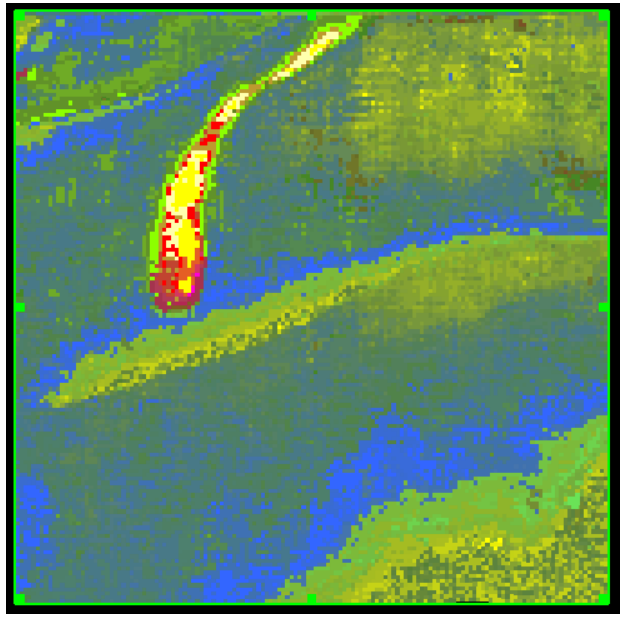
5 x 5



8 x 8



10 x 10



12 x 12

Varying SOM Parameters

1. Randomize the node weight vectors in a map
2. Randomly pick an input vector $D(t)$
3. Traverse each node in the map
   a. Use the Euclidean distance formula to find the similarity between the input vector and the map's node's weight vector
   b. Track the node that produces the smallest distance (this node is the best matching unit, BMU)
4. Update the weight vectors of the nodes in the neighbourhood of the BMU (including the BMU itself) by pulling them closer to the input vector
   a. $W_v(s+1) = W_v(s) + \theta(u, v, s) \cdot \alpha(s) \cdot (D(t) - W_v(s))$
5. Increase s and repeat from step 2 while $s < \lambda$

(Source: Wikipedia)

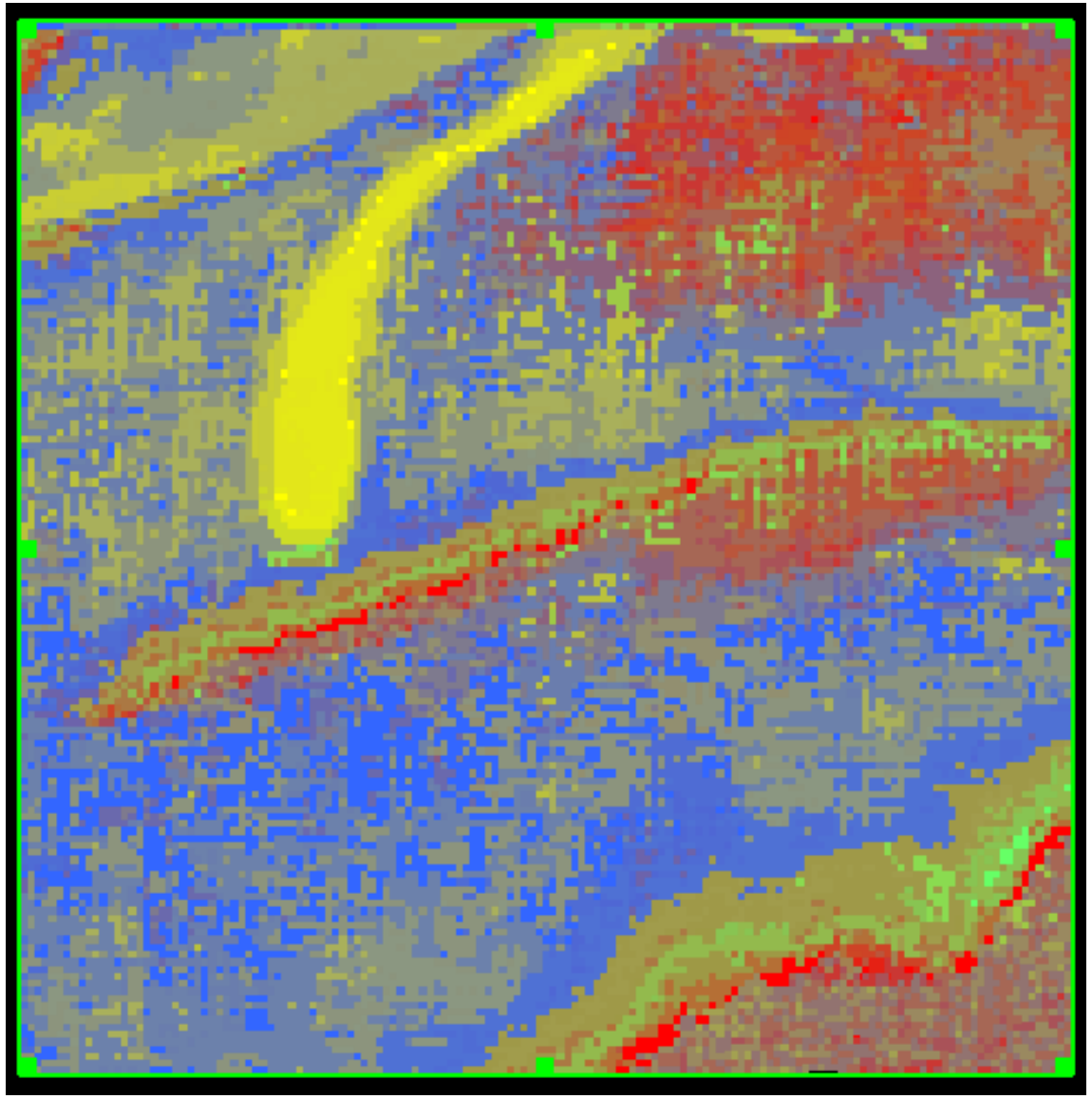
Neuron Pattern Topology

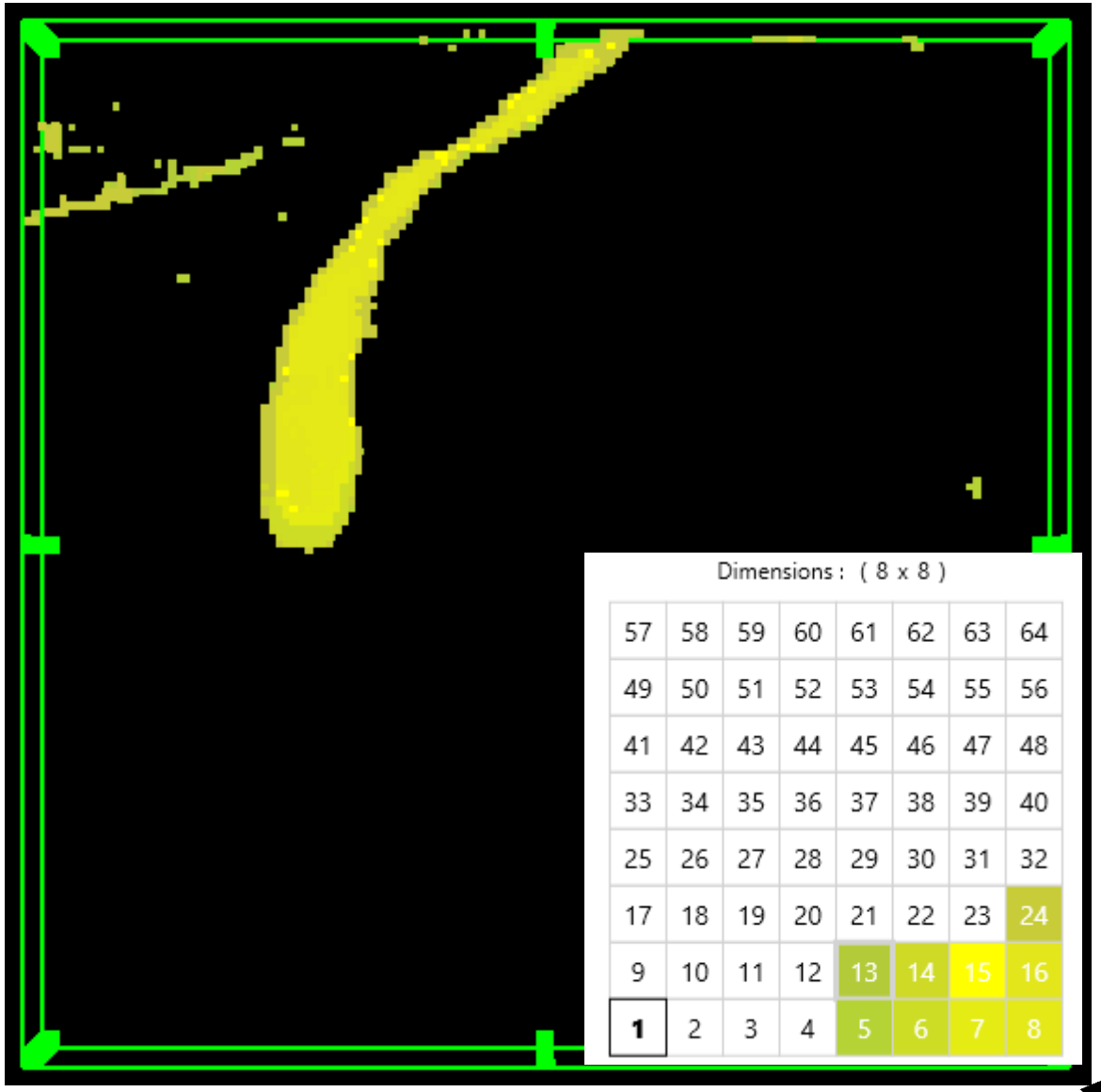
Defines the neurons' spatial relationship to each other within the Self Organizing Map and is used to determine the influence neighboring neurons have on each other. When the winning neuron moves in a direction, it pulls neighboring neurons with it and adjusts by Square or Hex.

•Square – From left to right on a square shape, the centre to centre is one unit away for those neurons on a grid that is left to right and top to the bottom. The neurons that are Northeast, Southeast, Northwest and Southwest are not exactly one unit away - slightly more than one unit away.

•Hex – From all sides, the neurons are exactly one unit away. Northeast centre to centre is the same distance as all of the other sides.

Neuron Pattern Topology





Initial Neuron Position

Defines the position of the neurons in Eigen-space at the beginning of the neural net job.

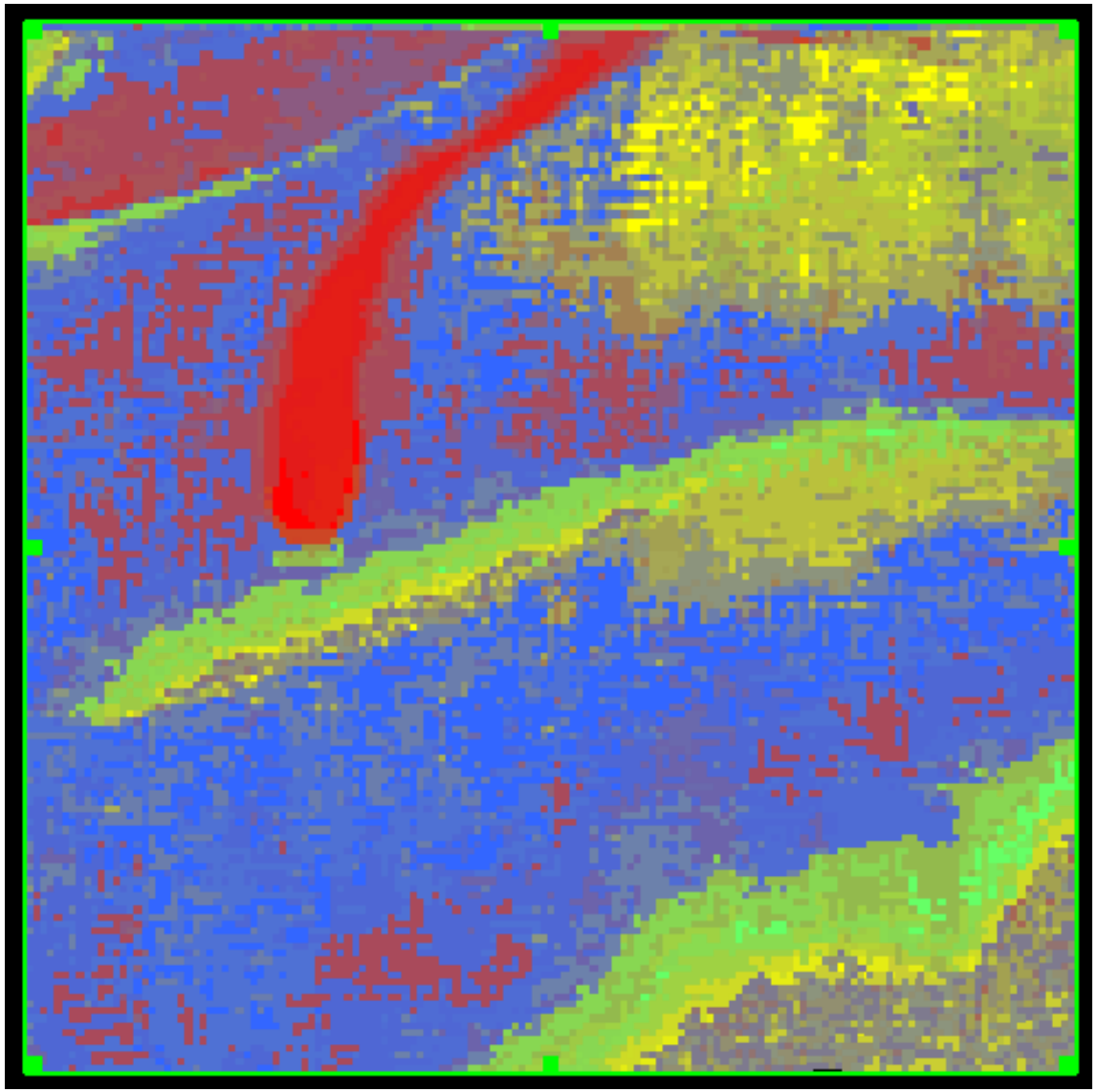
The available positions are:

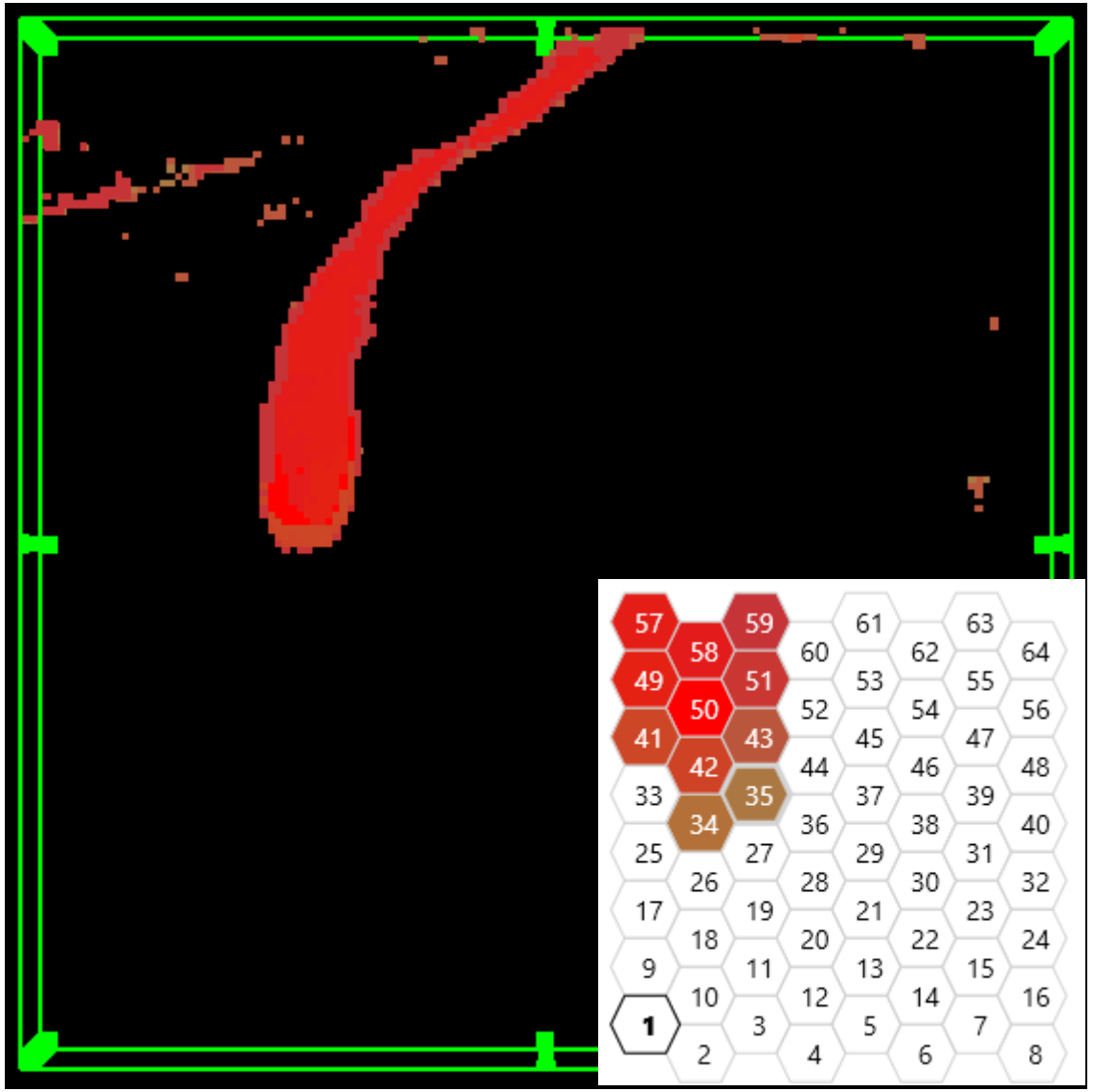
- First Samples – neuron based on a number of samples.
- Random – randomly dispersed at the beginning, depending on the seed value.
- True Random – the number of samples is never repeated.
- Set to Origin

Default is Random.

Test uses Set to Origin

Initial Neuron Position





Initial Learning Rate

This defines how strongly the neurons will adjust toward the data at the beginning of the process.

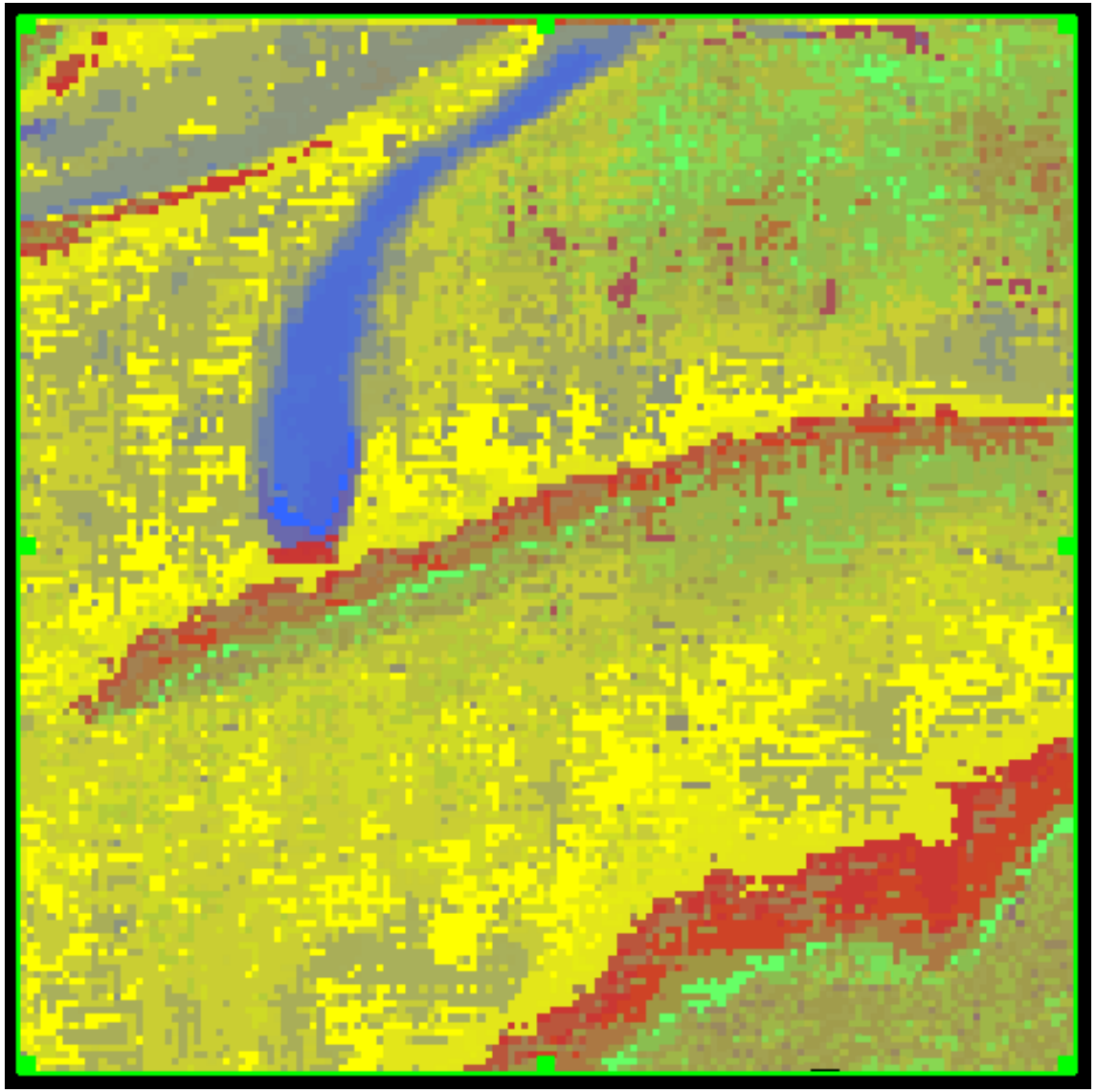
The range is from 0.1 to 0.5.

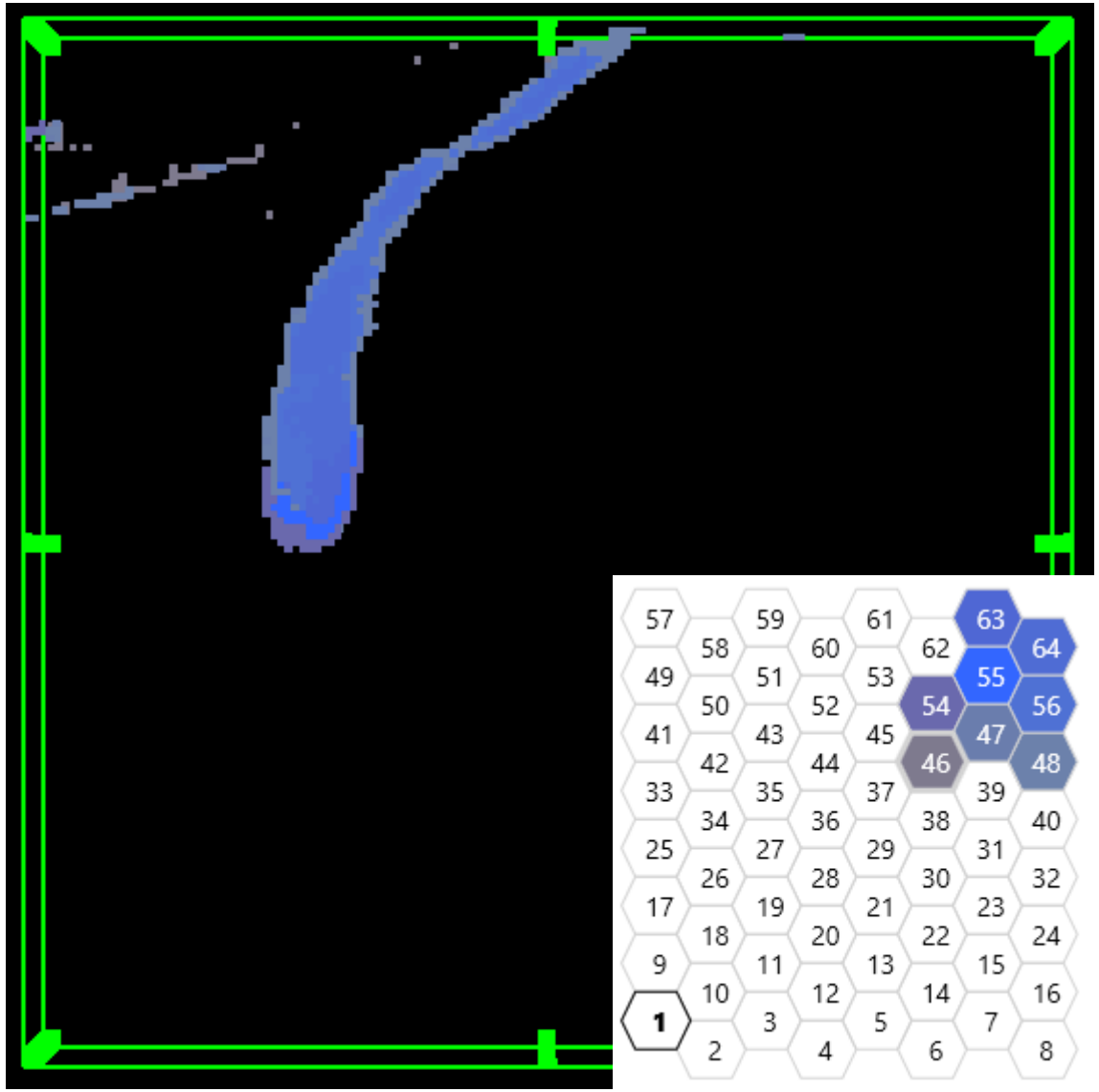
The default is set at 0.3.

If the rate is set too low, the neurons do not move far from where they start and are not moving anywhere and adjusting.

Test uses 0.5

Initial Learning Rate





Learning Decay Factor

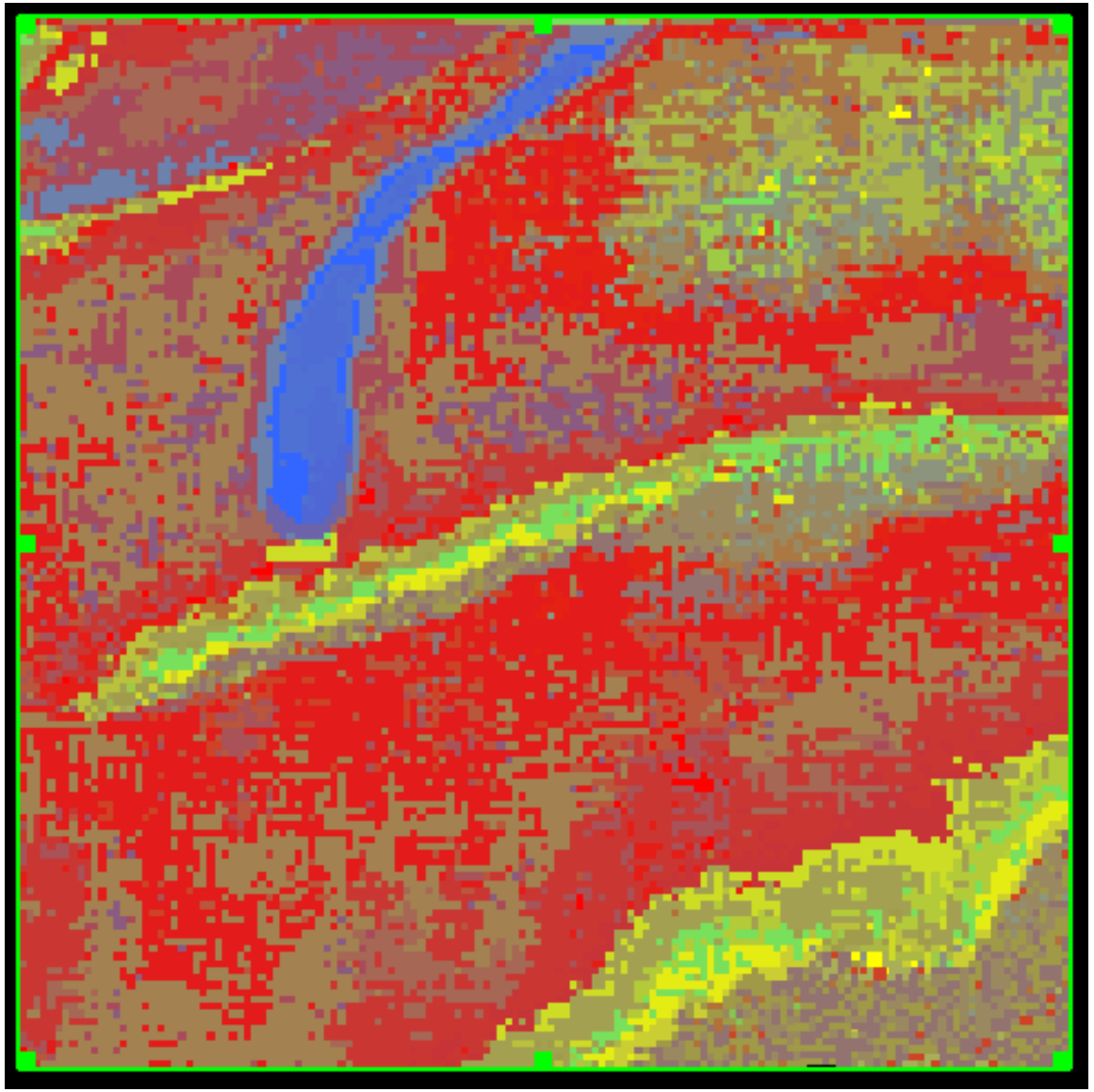
This defines the rate at which, over time, neurons lose its ability to adjust to more data.

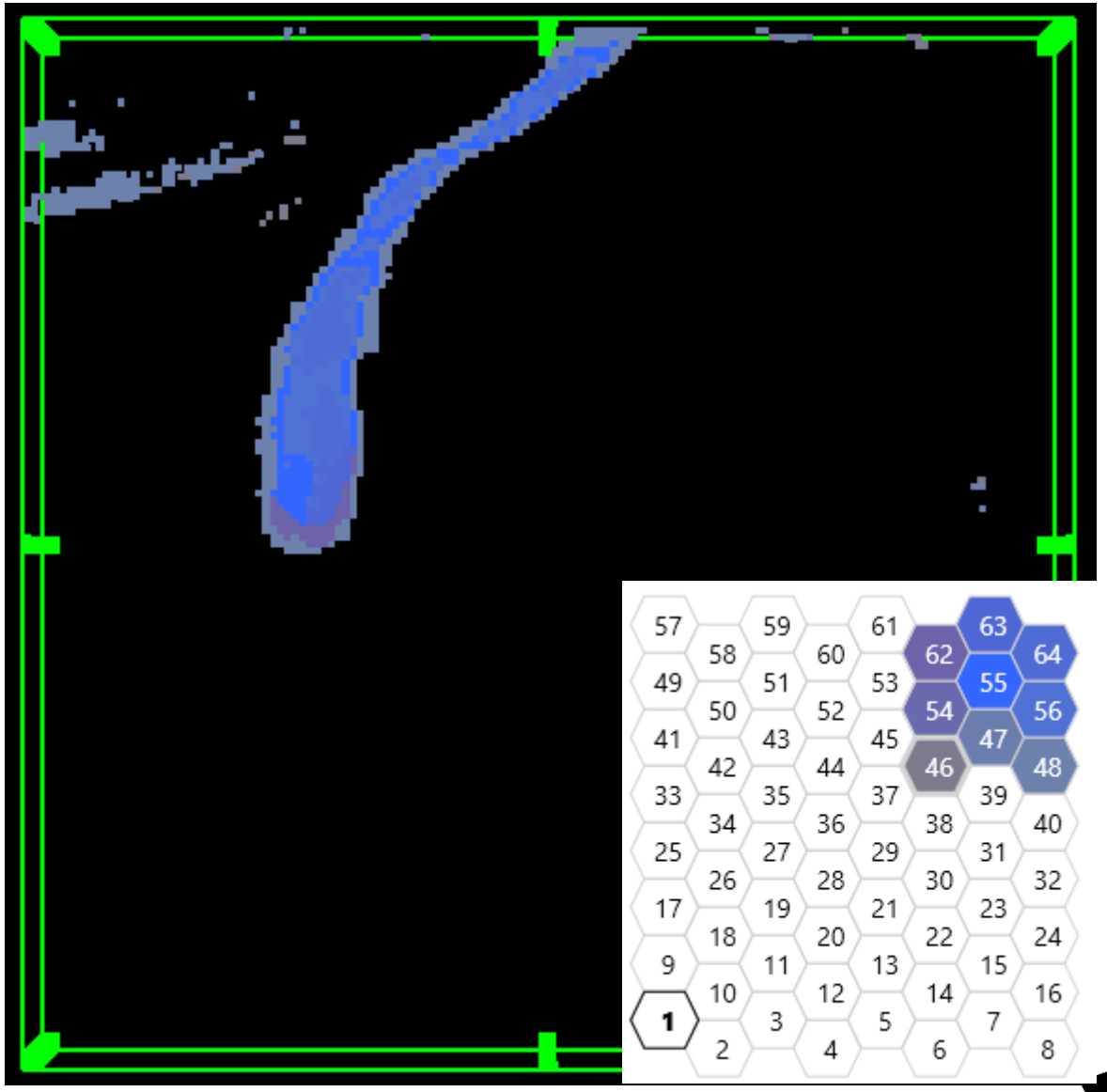
The range is from 1 to 100.

The default is 10.

Test uses 90.

Learning Decay Factor





Initial Neighbour Distance

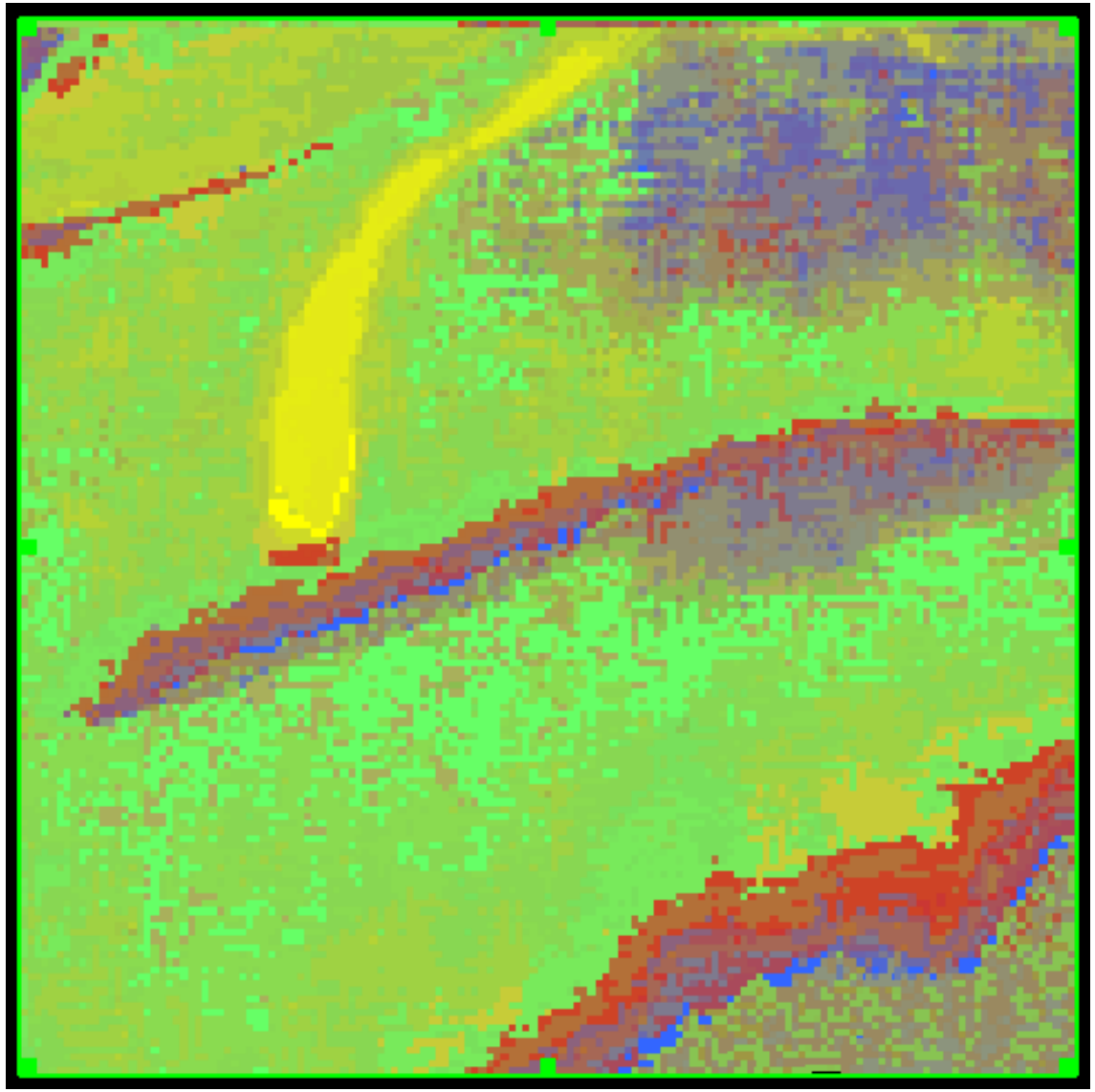
This is the distance within the SOM where a neuron has influence on its neighbours, so that when it adjusts, it also adjusts its neighbours.

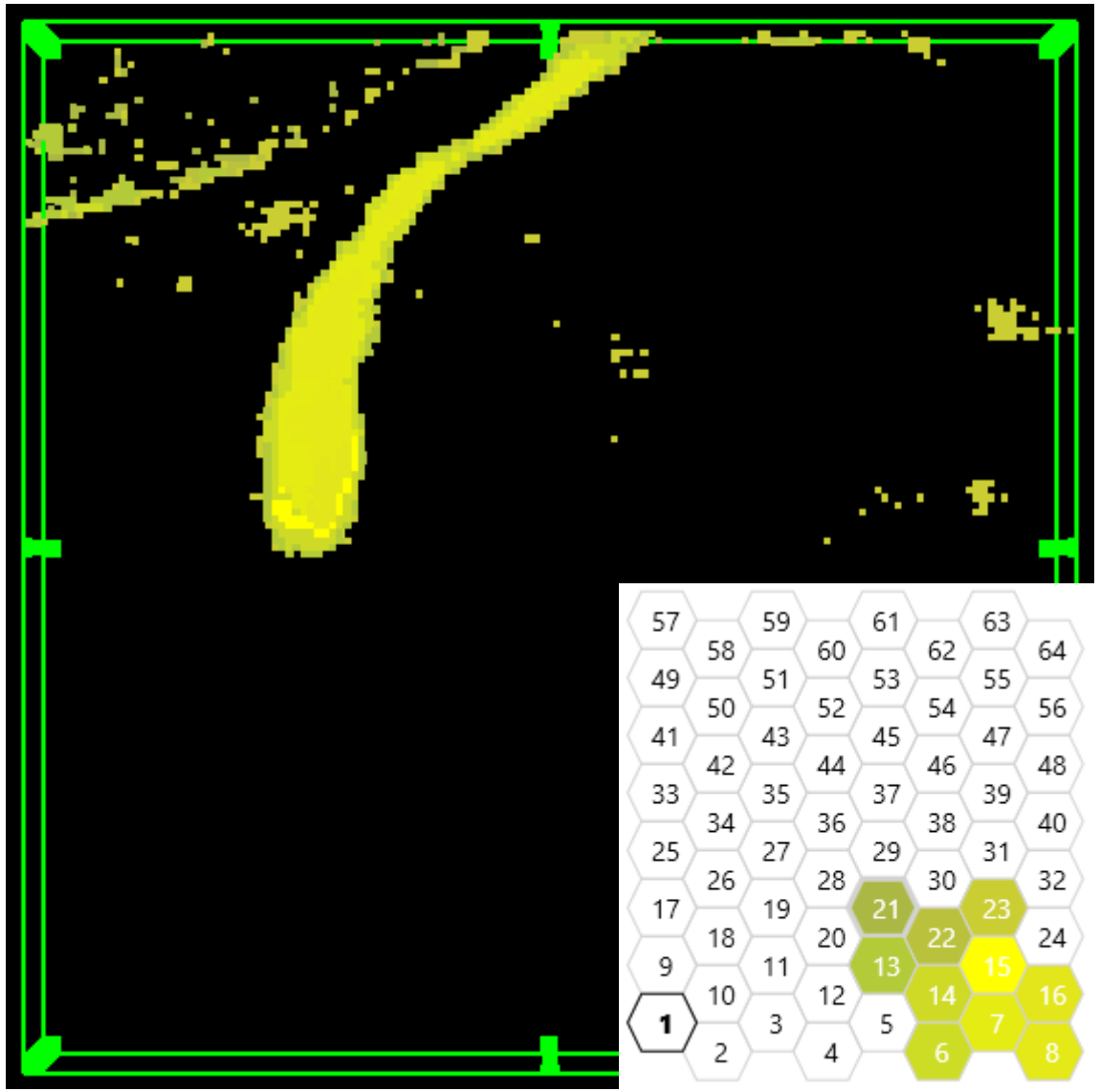
The range is from 0.5 to 10.

Default is 7.

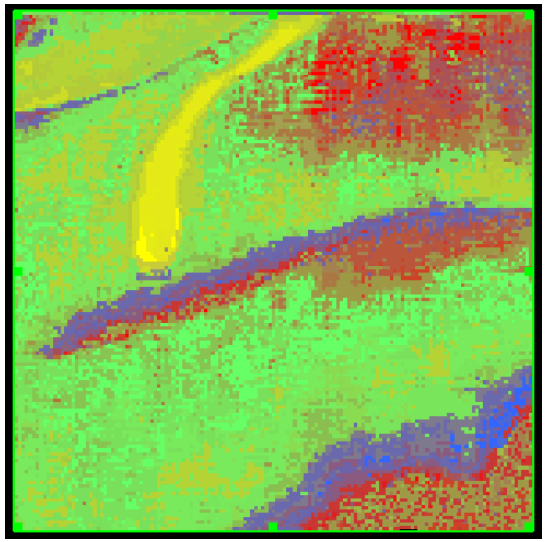
Test uses 1

Initial Neighbour Distance

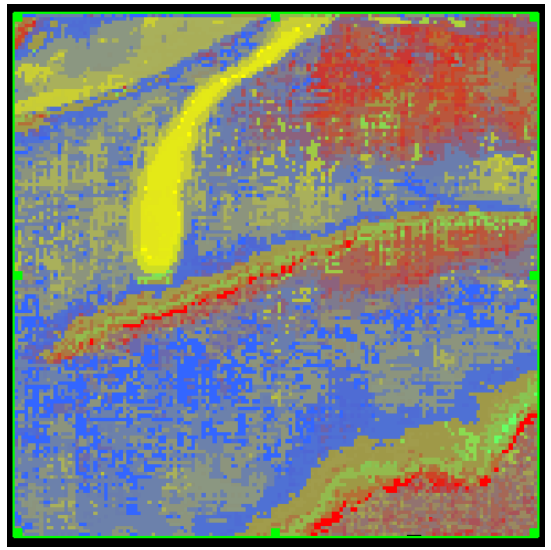




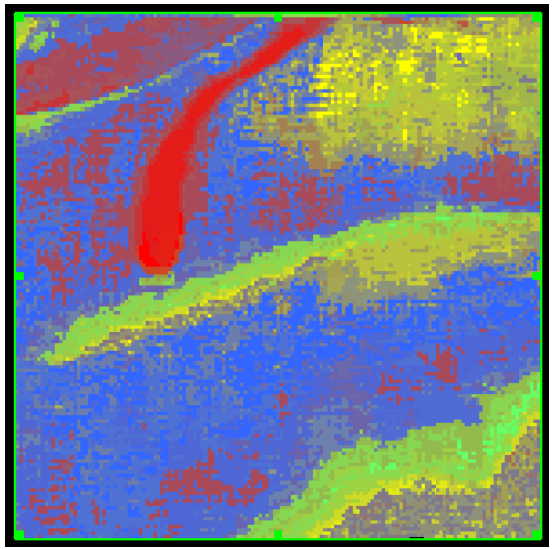
Comparison



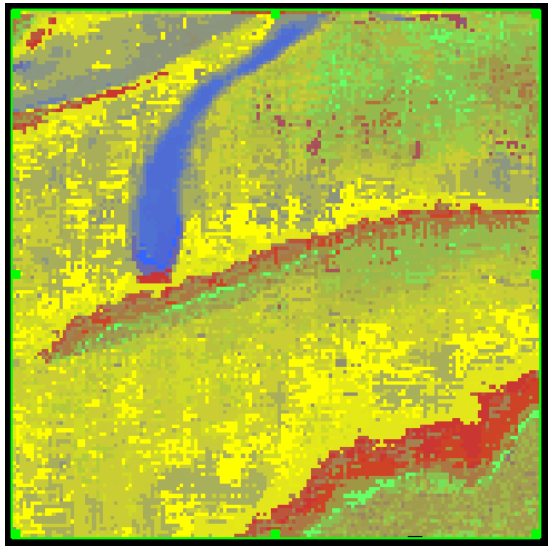
Base



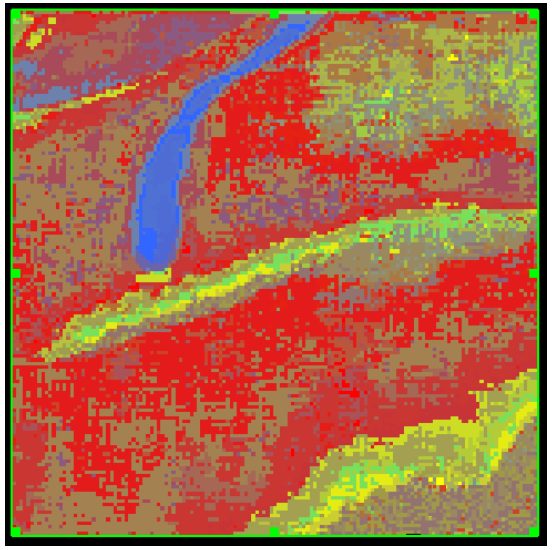
Test 1



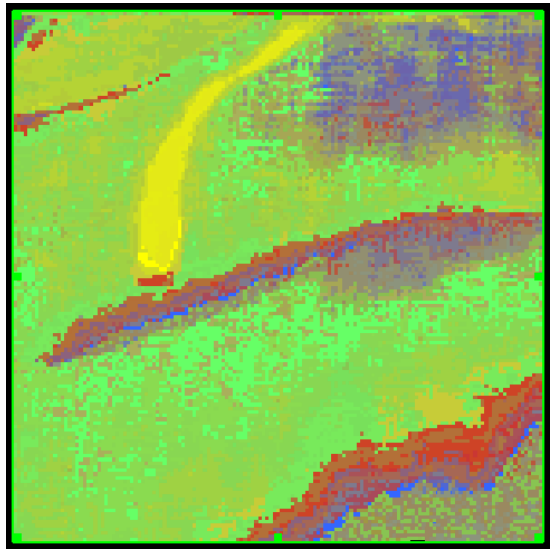
Test 2



Test 3



Test 4



Test 5

Self Organising Maps

Is a machine learning technique that can be applied to seismic attributes

It reduces a large data problem into a manageable problem;

It enables the user to

- reduce the risk in drilling marginal/dry holes;
- provide a better definition of internal reservoir geometries;
- improves correlation in difficult stratigraphic environments;

Still requires a geoscientist to interpret the results!

Thank You

Tim Gibbons
+44 7766 024602
tim@hoolock-consulting.com