EMERSON

A GUIDE TO

Emerson E&P Software
MACHINE LEARNING

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MACHINE LEARNING

Improving subsurface knowledge through technology, experience and commitment

Machine Learning and Geoscience

Machine learning is an application of Artificial Intelligence based on the concept that we should give machines access to data and let them learn specific tasks by themselves, without being explicitly programmed.

Machine learning exploits computing systems that learn and predict from data. It is particularly useful when working with large datasets, as it detects patterns and predicts - and in some cases, recommends - outcomes. Its ability to learn from data and build an experience is opposed to deterministic approaches, which require user instructions and a human knowledge base.

Machine learning applications for geoscience data have been in use for over 25 years. With the massive growth in petrotechnical data, they have become a practical necessity, rather than a "nice to have" solution. As machine learning evolves and gains acceptance, it will play an increasingly visible role in analyzing surface and subsurface data.

Emerson is a pioneer in implementing advanced, proven and reliable machine learning solutions. Our machine learning-based technology is able to describe the subsurface from large amounts of various types of data, and employ predictive analytics to prospecting, field development and production optimization.

Artificial Neural Networks and Deep Learning

Among all available computing systems, **Artificial Neural Networks (ANNs)**, inspired by biological neural networks, are some of the ones most often adopted by the Oil & Gas industry to deal with the increasing availability of seismic and well data.

Artificial Neural Network computing is the study of networks of adaptable nodes which learn to perform tasks based on data exposure and experience, generally without being programmed with any task-specific rules.

Deep Learning is a "smarter" new class of Machine Learning techniques which can handle Big Data. Deep learning architectures, such as Convolutional Neural Networks, allow the analysis of all available data, enabling us to better anticipate changes and adapt strategies as needed.

Deep learning algorithms use a cascade of multiple layers of nonlinear processing units for feature extraction and transformation. Each successive layer uses the output from the previous layer as input.

UNSUPERVISED LEARNING

Input data (soft data) is not labeled; the goal is to find similarities in the data point for grouping similar data points together. A model is prepared by deducing structures present in the input data. This may be used to extract general rules. It may be done through a mathematical process to systematically reduce redundancy, or to organize data by similarity. Examples of different algorithms include clustering, dimensionality reduction and association rule learning.

WHAT	WHEN	HOW
Explore data without being driven by a specific output	Let the algorithm find relevant patterns and organize classification	Infer structure from unlabeled data

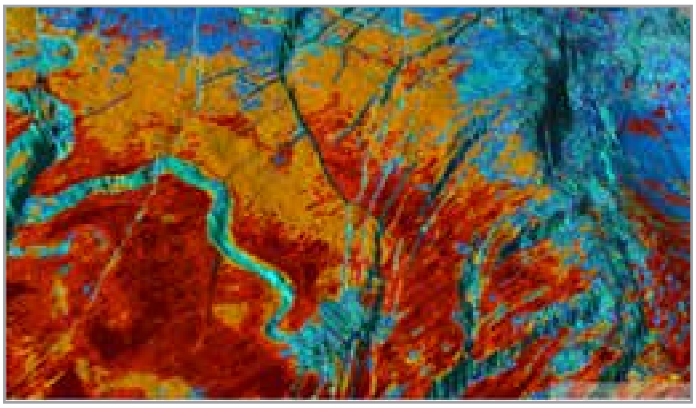
EXAMPLES

Self-Organizing Mapping (SOM)	Multi-Resolution Graphic Clustering	Back Propagation Neural Network
K-means Clustering	Hybrid	Self-Growing Neural Network
Hierarchical Clustering	Gaussian Processes	Principal Component Analysis (PCA)

BUSINESS USE CASES

Self-Organizing Mapping Neural Network is a type of Artificial Neural Network that is trained using unsupervised learning to produce a low-dimensional (typically 2D), discretized representation of the input space of the training samples, called a map. This is therefore a method to reduce dimensionality. Self-organizing maps differ from other artificial neural networks in that they apply competitive learning and use a neighborhood function to preserve the topological properties of the input space (Kohonen, 1982).

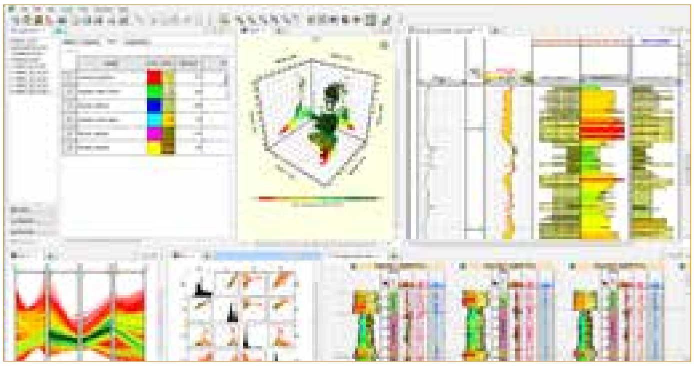
Business Use Case: Generate a seismic facies map or volume from single or multiple seismic attributes.



▲ Neural Network Self-Organizing Mapping in Paradigm Stratimagic

Multi-Resolution Graphic Clustering (MRGC) is a multi-dimensional dot-pattern recognition method based on non-parametric K-nearest neighbor and graph data representation. The underlying structure of the data is analyzed, and natural data groups are formed that may have different densities, sizes, shapes, and relative separations. MRGC automatically determines the optimal number of clusters, yet allows the geologist to control the level of detail actually needed to define the electrofacies (Shin-Ju Ye & Rabiller Philippe, SPWLA 41st Symposium, 2000).

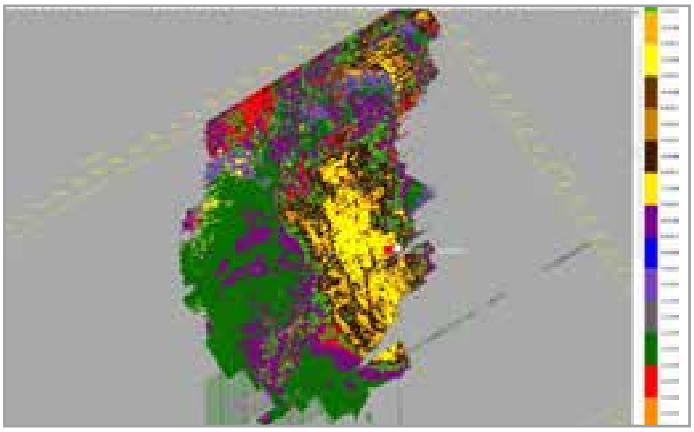
Business Use Case: Electrofacies analysis and core data modeling, making it an invaluable tool for petrophysicists and geologists.



▲ Multi-Resolution Graphic Clustering in Paradigm Geolog Facimage

Self-Growing Neural Network is a dynamic adaptive neural network approach based on Growing Neural Gas (GNG) (Fritzke 1995). This approach broadens the use of classification techniques to more than seismic facies analysis.

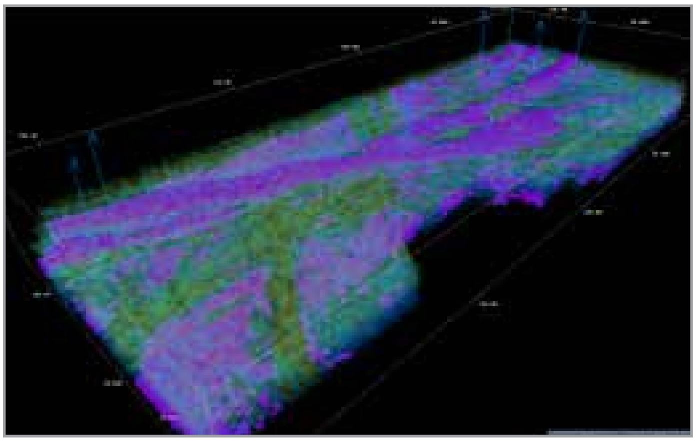
Business Use Cases: Structural delineation from multiple seismic attributes, AVO analysis from prestack data and AVO attributes, outlier detection, unsupervised seismic facies.



▲ Self-Growing Neural Network in Paradigm SeisEarth Integrated Canvas

Hierarchical Clustering is based on an agglomerative approach. It uses a "bottom up" method: Each observation starts in its own cluster, and pairs of clusters are merged as one moves up the hierarchy. Hierarchical Clustering can be used for all data types.

Business Use Case: Applied on samples (blocks), maps, traces and multi-traces, this approach generates facies maps or facies volume/2D sections.



▲ Multi-attribute classification (Ascending Hierarchical Clustering) in Paradigm SeisFacies

k-means clustering is a type of unsupervised learning, originally used in signal processing, and popular for cluster analysis in data mining. k-means clustering aims to partition n observations into k clusters, in which each observation belongs to the cluster with the nearest mean, and serves as a prototype of the cluster. Data points are clustered based on feature similarity.

Business Use Case: Generate electrofacies and seismic facies volumes in a reservoir properties analysis and modeling workflow.

Principal Component Analysis (PCA) is a statistical process used for data reduction. It identifies redundant data and keeps only correlated information that contributes to further classification. PCA analyzes the relationships between a rich set of attributes to generate principal components, related to the variability in the data.

Business Use Case: Reduce dimensionality to avoid redundancy when working with large amounts of seismic data.

SUPERVISED LEARNING

The input data is training data with a known label (hard data). A model is prepared through a training process which requires predictions, and corrections are made when those predictions are wrong. The training process continues until the model achieves the desired level of accuracy on the training data. Example problems are classification and regression.

WHAT	WHEN	HOW
Learn from data for which input variables and theoretical responses are known and correct	Capture the user's expertise and predict from new data	Train the algorithm to determine the relation between input and output; apply operator to new data

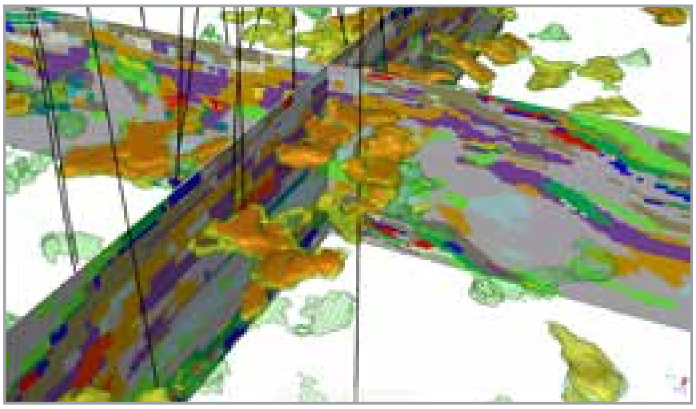
EXAMPLES

Neural Network Ensemble	Convolutional Neural Networks	Deep Learning for Seismic Feature Recognition

BUSINESS USE CASES

Neural Network Ensemble or DNNA (DEMOCRATIC NEURAL NETWORK ASSOCIATION): A combination of several naïve independent networks running simultaneously (Tetko, 2002) where each network learns differently from the same labeled dataset, increasing accuracy while reducing overfitting.

Business Use Case: DNNA generates the most probable facies distribution and probability volumes associated with each facies defined at the well. Apply to rock type prediction from core, logs and prestack and/or poststack seismic data.



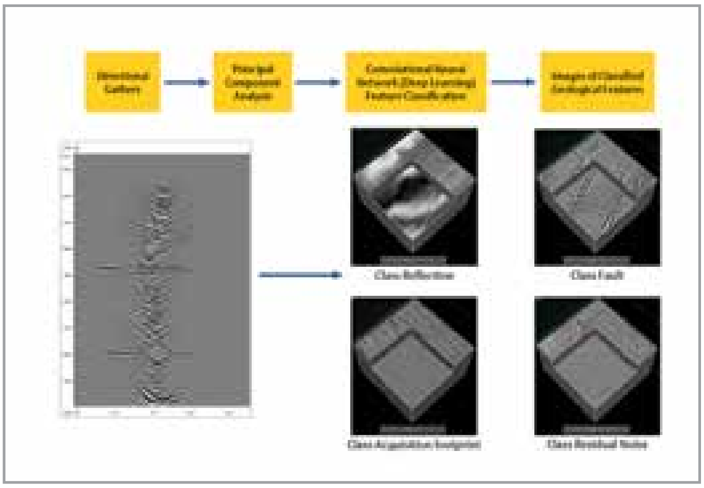
▲ Democratic Neural Network Association in Paradigm SeisEarth

Convolutional Neural Networks (1D, 2D, 3D): A network of many connected perceptrons often used for image recognition and to detect shapes and patterns inside of a dataset. CNN infers reservoir properties from logs and seismic attributes.

Business Use Case: Highlight patterns in well logs, detect structures from seismic. Estimate the non-linear relation between logs and seismic attributes to be propagated away from well bores.

Deep Learning for Seismic Feature Recognition: An evolution of Emerson's full-azimuth imaging to characterize subsurface features from migrated seismic data. The system decomposes the recorded seismic wavefield into full-azimuth components comprised of thousands of dips and azimuths. Deep Learning is particularly adapted to handle such large input data and their complex relationship patterns in order to classify them into geological features such as reflectors and faults, and remove ambient noise or acquisition footprint.

Business Use Case: Identify subsurface structural features with high accuracy, low cost, simple yet scalable implementation, and reduced time-to-result.



▲ Deep Learning approach - poststack extraction of different classes

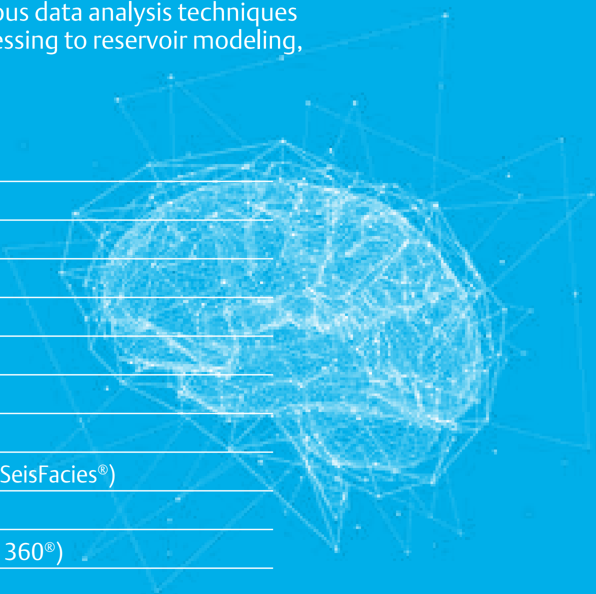
EMERSON MACHINE LEARNING TECHNOLOGIES

Our integration of machine learning is used to solve, or optimize, linear and non-linear problems. It is suitable for solving a broad range of problems related to petrotechnical data, including classification, automation, transformation, and integration of multi-resolution data.

- Back Propagation Neural Networks
- Ascending Hierarchical Clustering
- Neural Network “Ensembles”
- Hybrid Classification Methods
- Deep Learning
- Self Organizing Maps
- Multi-Resolution Graph-based Clustering
- Simple Convolutional Neural Networks
- Gaussian Processes
- K Means Cluster Analysis
- Principal Component Analysis

EMERSON SOLUTIONS THAT USE MACHINE LEARNING

Emerson E&P Software solves many challenges using machine learning and statistical tools. The analysis of big data volumes, and many types of data, requires rigorous data analysis techniques to extract relevant information for geoscientists. From seismic processing to reservoir modeling, machine learning enables faster and more accurate data mining.



- First Break Picking (Echos®)
- Seismic to Well Log Transformation (Vanguard® QSI)
- Rock Type Classification (SeisEarth®, QSI)
- Multi-Attribute Seismic Data Classification (Stratimagic®, SeisFacies®)
- Prestack Seismic Data Interpretation (SeisEarth®, Vanguard® QSI)
- Prestack Wavefield Separation using Deep Learning (EarthStudy 360®)
- Seismic Facies Classification (Stratimagic®, SKUA-GOCAD™)
- Electrofacies Classification (Geolog® Facimage, SKUA-GOCAD™)
- Well Log and Seismic Multi-attribute Classification (Geolog®, Stratimagic®, SeisFacies®)
- Uncertainty Analysis and History Matching (Tempest ENABLE™)
- Neural Network Data Preparation (Stratimagic®, SeisFacies®, EarthStudy 360®)

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