Self-Train Seismic data to reveal Your traps

Smaller harder to get targets imply more targets require replacing traditional time and cost consuming play, lead and prospect mapping methods

Lower the risk and make cost savings - Big time

CHALLENGE OF
SEISMIC DATA INTERPRETATION

3D replaces 2D domain seismic interpretation in a larger degree than before.

More data types creates data and attribute overload, not possible to manually screen properly with high degree of confidence and reliability.

Multiple surveys over same areas require governance and comparison/ calibration which is time-consuming and full of potential traps.

4D domain seismic interpretation introduces a full suite of new parameters to take into consideration.

Amount of attributes and lack of clarity in their inter-dependencies and importance to describe the geology or reservoirs have become overwhelming.

Importance of Seismic Attribute

Seismic attributes are any measurable property of seismic data. In turn, these attributes are input to self-organizing-map (SOM) training. Efforts distilling numerous seismic attributes into volumes that are easily evaluated for their geologic significance and improved seismic interpretation. Commonly used categories of seismic attributes include instantaneous, geometric, amplitude accentuating, amplitude-variation with offset, spectral decomposition, and inversion.
Principal component analysis (PCA), a linear quantitative technique, has proven to be an approach for use in understanding which seismic attributes or combination of seismic attributes has interpretive significance. The PCA reduces a large set of seismic attributes to indicate variations in the data, which often relate to geologic features of interest. PCA, as a tool used in an interpretation workflow, can help to determine meaningful seismic attributes

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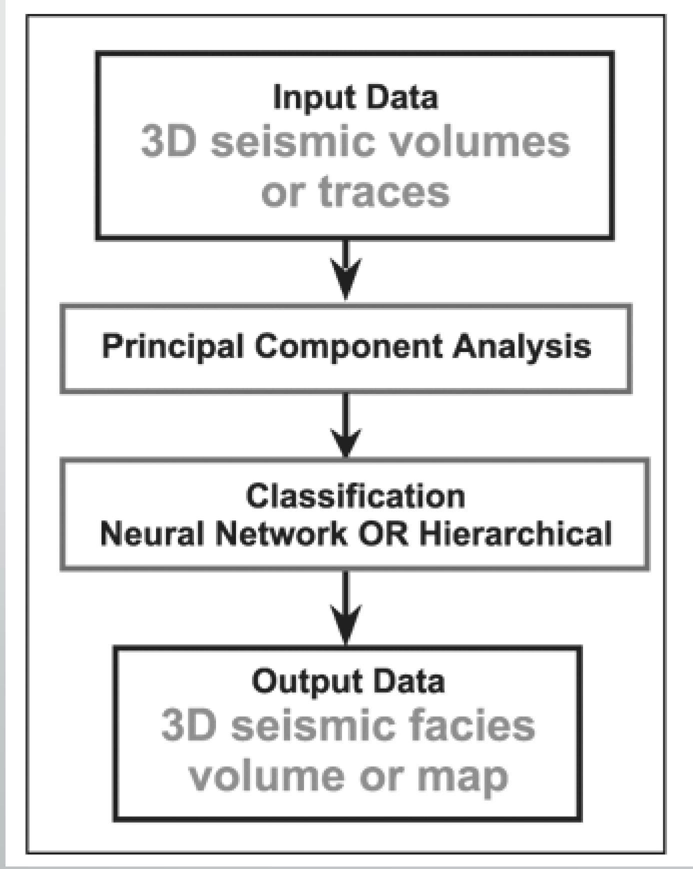
Typical Seismic Attributes

Seismic attribute categories and corresponding types and interpretive uses.

CATEGORY	TYPE	INTERPRETIVE USE
Instantaneous Attributes	Reflection Strength, Instantaneous Phase, Instantaneous Frequency, Quadrature, Instantaneous Q	Lithology Contrasts, Bedding Continuity, Porosity, DHIs, Stratigraphy, Thickness
Geometric Attributes	Semblance and Eigen-Based Coherency/Similarity, Curvature (Maximum, Minimum, Most Positive, Most Negative, Strike, Dip)	Faults, Fractures, Folds, Anisotropy, Regional Stress Fields
Amplitude Accentuating Attributes	RMS Amplitude, Relative Acoustic Impedance, Sweetness, Average Energy	Porosity, Stratigraphic and Lithologic Variations, DHIs
AVO Attributes	Intercept, Gradient, Intercept/Gradient Derivatives, Fluid Factor, Lambda-Mu-Rho, Far-Near, (Far-Near)Far	Pore fluid, Lithology, DHIs
Seismic Inversion Attributes	Colored inversion, Sparse Spike, Elastic Impedance, Extended Elastic Impedance, Prestack Simultaneous Inversion, Stochastic Inversion	Lithology, Porosity, Fluid Effects
Spectral Decomposition	Continuous Wavelet Transform, Matching Pursuit, Exponential Pursuit	Layer Thicknesses, Stratigraphic Variations

Workflow handling Seismic Data in a statistical method.



Seismic facies classification generic workflow: PCA is the statistical method applied for downsizing the amount of available data, especially applied on 3D seismic volume attributes.

Unsupervised Classification of Attributes

Classification without supervision of patterns into groups is formally called clustering.
Depending on the application area these patterns are called data lists, observations or vectors.
For exploration geophysicists, these patterns are usually associated with seismic attributes, seismic waveforms or seismic facies.
The main objective here is to show how one of the most popular clustering algorithms - Kohonen Self-Organizing Maps (KSOM), can be applied to enhance seismic interpretation analysis associated with one and two-dimensional color maps.

Kohonen Self-Organizing Map (KSOM)

The KSOM (Kohonen, 2001) clustering is one of the most commonly used tools for non-supervised seismic facies analysis, with KSOM providing ordered clusters that can be mapped to a gradational color bar (Coléou et al., 2003).
KSOM is closely related to vector quantization methods (Haykin, 1999).

We assume input variables, i.e., the seismic attributes, can be represented by vectors in the space $\Re n$, aj = [aj1, aj2, ..., ajN], j = 1, 2, ..., J; where N is the number of seismic attributes and J is the number of seismic traces when KSOM is applied to surface attributes or is the number of voxels (Matos et al., 2005) when KSOM is applied to volumetric attributes.

The objective of the algorithm is to organize the dataset of input seismic attributes, into a geometric structure called the KSOM.

Iteration to create Clustering

If we assume that the Self-Organizing Map has P units, defined as prototype vectors, then, there will exist P N-dimensional prototype vectors mi, mi = [mi1, ..., miN], i = 1, 2, ..., P; connected to its neighbors by a grid of lower dimension than P. Usually, this grid has dimension one or two and is related to KSOM dimensionality. 2D KSOM is most commonly represented by hexagonal or rectangular structural grids. After initializing the KSOM prototype vectors to reasonably span the data space, the next training step in KSOM is to choose a representative subset of the J input vectors. Each training vector is associated with the nearest prototype vector. After each iteration of the training, the mean and standard deviation of the input vectors associated with each prototype vector is accumulated, after which the prototype vectors are updated using a function of the distance between it and its neighbors (Kohonen, 2001). This iterative process stops either when the KSOM converges or the training process reaches a predetermined number of iterations.

Classification according to KSOM

KSOM places the prototype vectors on a regular low-dimension grid in an ordered fashion (Kohonen, 2001) and after training, the prototype vectors form a good representation of the input dataset of seismic attributes. Next, we label each input seismic attribute vector by the index of the closest KSOM prototype vector, i.e., the KSOM index with highest cross-correlation to the input data vector. This labeling process is called classification (Kohonen, 2001). KSOM can be considered an unsupervised classification algorithm because no previous information is used to generate the prototype vectors. KSOM can easily be supervised also (Kohonen, 2001).

Training the Data

The number of prototype vectors in the map determines both its effectiveness and generalization capacity. During the training, KSOM forms an elastic net that adapts to the "cloud" formed by the input seismic attribute data.
Data that are close to each other in the input space will also be close to each other in the output map. Since KSOM can be interpreted as a reduced version of the input n-dimensional data ruled by a lower dimensional grid that attempts to preserve the original topological structure and since seismic data measures the changes in geology.
KSOM approximates the topological relation of the underlying geology.

Cluster Formation of Attributes

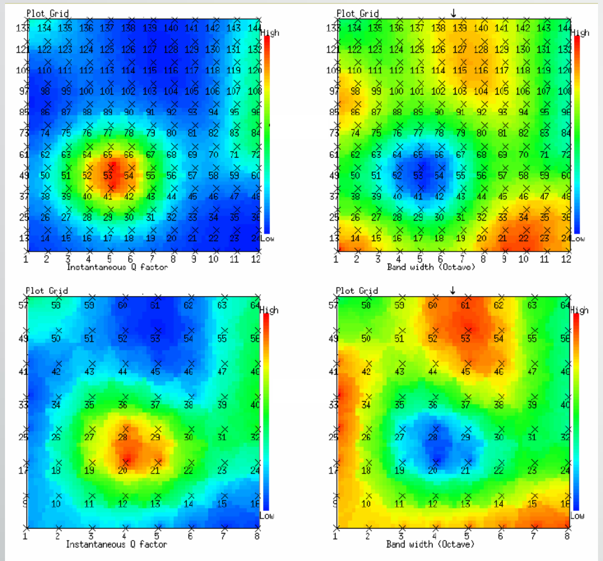
Although the prototype vectors represent the input data very well they have the same dimension of the input data making visualization difficult. For this reason, we exploit the topological relation among the prototype vectors as a visualization tool to display the different data characteristics and structuring. One way to visualize cluster formation of the KSOM prototype vectors is by computing the distance among the vectors thereby generating a U-matrix (Ultsch, 1993). Another way is by mapping continuous 1D, 2D or 3D color bars to the SOM topology to represent the location of each prototype vector.

KSOM can be applied to volumetric or surface attributes.

Color Maps of KSOM

These attributes are input to Self-Organizing-Map (SOM) training. The SOM, a form of Unsupervised Neural Networks (UNN), has proven to take many of these seismic attributes and produce meaningful and easily interpretable results.
SOM analysis reveals the natural clustering and patterns in data and has been beneficial in defining stratigraphy, seismic facies, direct hydrocarbon indicator features, and aspects of shale plays, such as fault/fracture trends and sweet spots.
Visualization and application of 2D color maps, SOM routinely identifies meaningful geologic patterns. Recent work using SOM and PCA has revealed geologic features that were not previously identified or easily interpreted from the seismic data.
The ultimate goal in this multi-attribute analysis is to enable the geoscientist to produce a more accurate interpretation and reduce exploration and development risk.

KSOM of Seismic Attributes



12x12

8x8

Instantaneous Q Bandwidth

Instantaneous Q and Bandwidth have similar patterns.
12x12 and 8x8 cells have comparable shapes.
12x12 cells have slightly clearer clusters.

- Similar weight patterns, but opposite trend should reveal different trend in N dimensional space
- Keep both attributes for classification
- Use high number of classes to give greater discrimination
- Clustering maximas/ minimas indicate ability for strong discrimination
- Similar weight patterns favors Neural Network solution with one attribute based on other criteria

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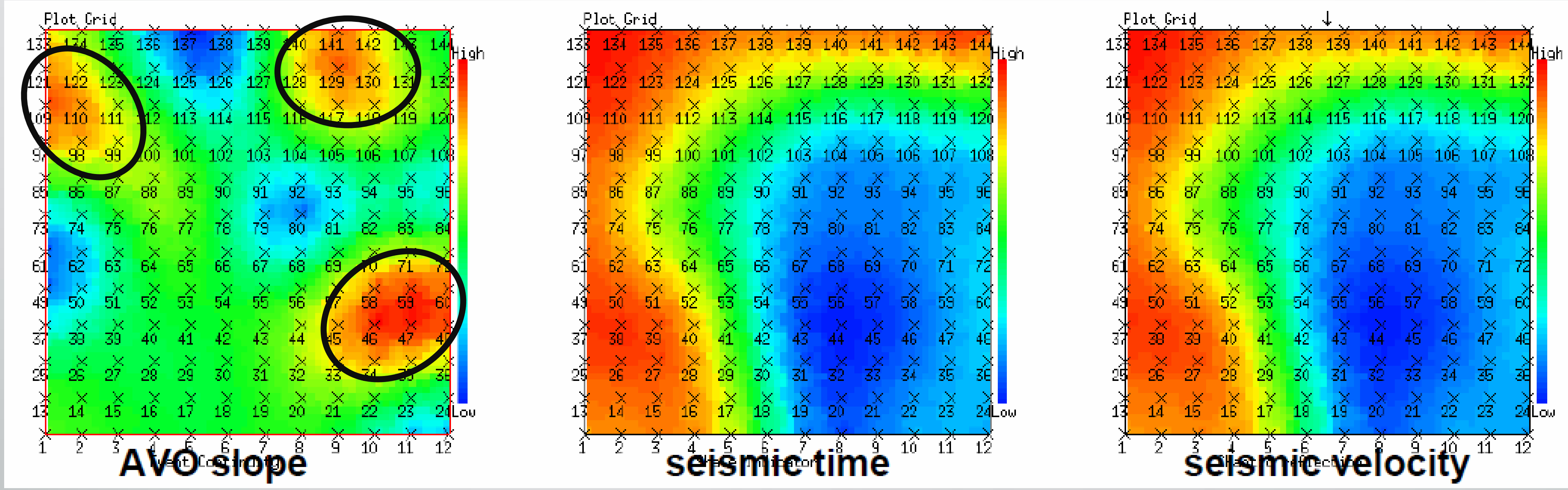
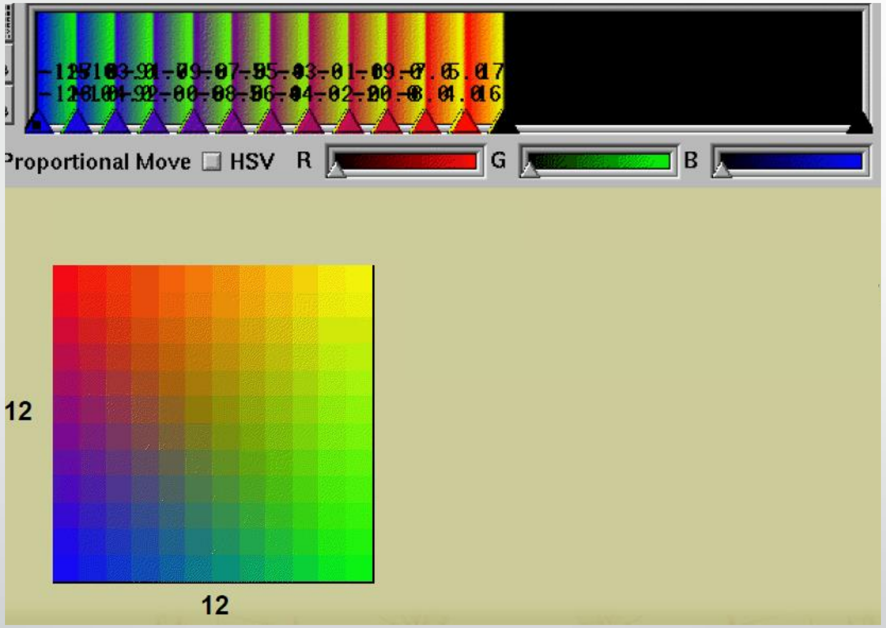
KSOM of Seismic Attributes



Seismic Attributes; AVO slope, Seismic Time and Velocity.
AVO Slope exhibits high clustering degree, as for time and velocity attributes both mimic depth trend only.

Color Map of KSOM result



Linear Color Bar, based on Values obtained in weight diagrams

2D Color Bar map in the linear scheme

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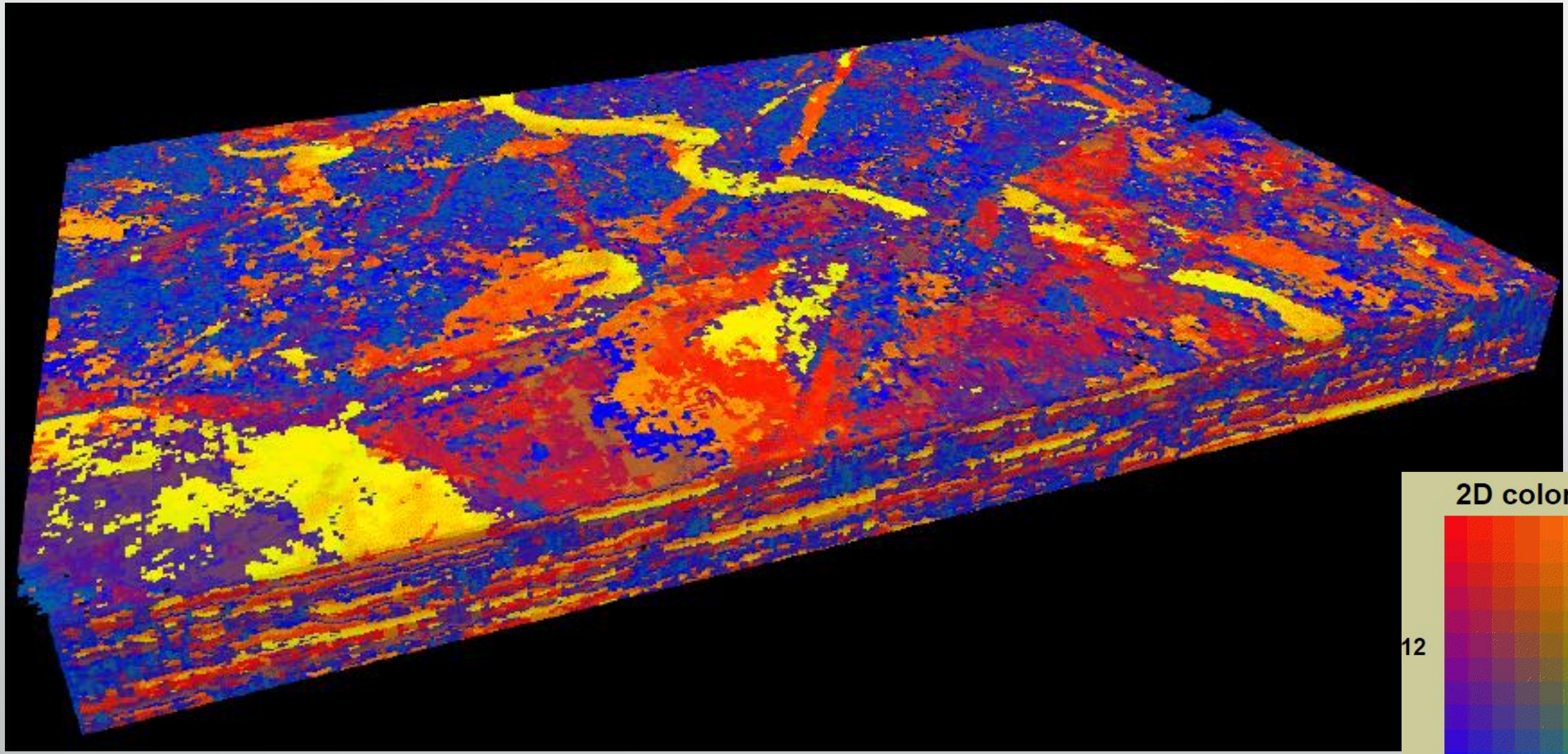
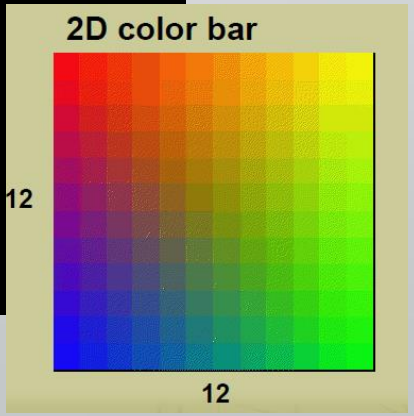
Applied Color Map on Seismic Data





Simulated Annealing

Simulated Annealing (SA) based classification systems can be used in seismic mapping. SA has been shown to be able to overcome the local minimum problem that is typical with many unsupervised classification approaches.
SA-based classification systems could help overcome the local minimum problem in one of such approaches, K-means, and thus improve the classification performance. We have two SA based classification systems, the Single SA-based (S-SA) system is developed based on the standard SA algorithm and the Integrated SA-based (I-SA) system developed by combining the standard SA algorithm and K-means into a two-level classification system. Experimental results have demonstrated that the SA-based systems significantly improved the classification accuracy over that of the K-means algorithm when appropriate parameters were chosen. The I-SA system was shown to produce a satisfactory classification more efficiently than the S-SA system.

WHAT ABOUT THE TRAPS?

So far, we have talked about how to reveal the most important attributes of seismic data, regardless of data types, and then how to then use these in an unsupervised manner to classify the Seismic data.

This should assist us in a more robust and timely manner a seismic dataset which should be able to assist us in better identify traps to search for hydrocarbons.

As the new classified data set now should have the ability to better reveal geological and potentially fluid and rock properties, the interpreter is now standing in front of the task to be able to identify traps, or should we use the word geometries.

Reveal the traps with help of Convergent Neural Network

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TRAIN YOUR DATA TO SEE THE TRAPS

The current excitement about Artificial Intelligence (AI) stems, in great part, from groundbreaking advances involving what are known as Convolutional Neural Networks (CNN).

This machine learning technique promises dramatic improvements in things like computer vision, speech recognition, and natural language processing.

You probably have heard of it by its more layperson-friendly name: **"Deep Learning."**

MASSIVE AMOUNT OF DATA IN NEED OF TRAINING

You have Terabytes upon Terabytes of various seismic data, either in its raw, amplitude or derivative formats. Most of the time it lies there idle, and waiting for the geoscientist to log in and take it into use.

Why not let the data work when it is not used by the geoscientist, and outside working hours for the poor geoscientist being home an getting a well deserved sleep?
The data can in the meantime do its exercise and training and get ready for the geoscientist logging in and begin his/her work with a more intelligent data set than last time.

A dataset which now can tell the geoscientist much more, and reveal much more, making it possible to make the next discovery of hydrocarbons with larger chance of success at a much lower cost and less time efforts.

RECOGNISE SEISMIC FACIES WITH IMAGE RECOGNITION PLATFORMS

The rapid rise of computer vision technology and the increasing number of companies developing image recognition platforms are enormous.

Until recently, computer vision technology has been used primarily for detecting and recognizing faces in photos. While facial recognition remains a popular use of this technology, there has been a rapid rise in the use of computer vision for automatic photo tagging and classification.

This increase is largely due to recent advances in artificial intelligence (AI), specifically the use of convolutional neural networks (CNNs) to improve computer vision methods.

So far, this technology has not won any major terrain within the Oil and Gas Industry.

PATTERN RECOGNITION

Stratigraphic interpretation of seismic data is a time consuming and highly subjective methodology where the result is highly dependent upon the operators skills, training and mostly experience to recognize depositional environments and their associated geometrical attitude and occurrence.

Combine this with varying quality of the data foundation, seismic data quality and type, there are many ways this could go wrong.

The task at hand is to identify geometric patterns in the data, generate image captions/ descriptions

CONVOLUTIONAL NEURAL NETWORKS AND SEISMIC FACIES

Why not use computer vision algorithms to analyze digitized images of seismic data (original or attribute versions, does not matter). The algorithms could be trained to detect and understand visual similarities in seismic facies pattern and automatically classify these based on style, occurrence etc.

Utilize Convolutional Neural Networks (CNN) that are able to learn complex visual concepts using massive amounts of data,, could save time and efforts, but not only that; create a more objective analysis of the data.

The use of machine learning and image processing algorithms to analyze, recognize and understand visual content could prove to be a ground breaking way to analyze large amount of data, both in Supervised Neural Networks (SNN), but also as Unsupervised Neural Networks (UNN), like the CNN.

The computer gets trained to find patterns within the data with the use of deep learning-based computer vision technology to analyze, recognize and understand the content of an image.

COMPUTER VISION TECHNOLOGY COMES TO AID SEEING THE SEISMIC FACIES

The concept of CNN has been around since the 1940s, it is only within the last few years that the use of CNNs has really taken off.

CNNs are being used to significantly improve computer vision, speech recognition, natural language processing and other related technologies.

Companies are doing amazing research in the field of artificial intelligence, and democratizing breakthroughs in AI.

With so many advances in deep learning-based computer vision technology happening just within the last few years, it will be exciting to see how we can use this field of computer vision in the not-too-distant future within Seismic Stratigraphy applications.

WHAT IS SEISMIC STRATIGRAPHY AND WHY IS IT SO IMPORTANT?

Seismic Stratigraphy is basically a geologic approach to the stratigraphic interpretation of seismic data.

Seismic reflections allow the direct application of geologic concepts based on physical stratigraphy.

Primary seismic reflections are generated by physical surface in the rocks, consisting mainly of strata surface and unconformities with velocity-density contrasts.

Therefore, possible to identify primary seismic reflections parallel strata surface and unconformities.

A seismic section is a record of chronostratigraphic (time-stratigraphic) depositional and structural patterns and not a record of the time-transgressive lithostratigraphy (rock-stratigraphy)

SEISMIC STRATIGRAPHIC INTERPRETATION IS A MASSIVE PATTERN RECOGNITION EFFORT

It is possible to make the following types of stratigraphic interpretation from the geometry of seismic reflections correlation patterns:

- geologic time correlations
- definition of genetic depositional units
- thickness and depositional environment of genetic units
- paleo bathymetry
- burial history
- relief and topography on unconformities
- paleogeography and geologic history

SEISMIC STRATIGRAPHIC INTERPRETATION PROCEDURE

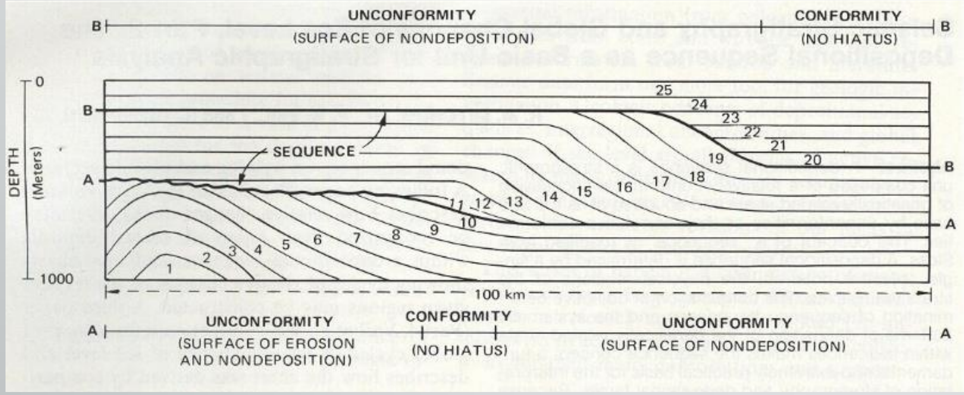
To accomplish these geologic objectives you follow three step interpretational procedure:

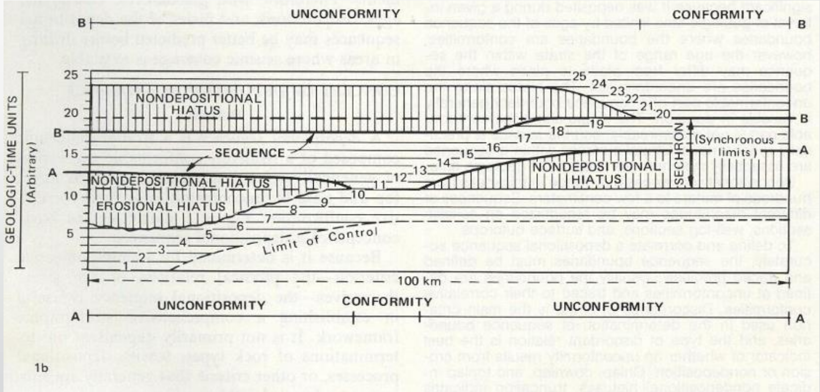
- seismic sequence analysis
- seismic facies analysis
- analysis of relative changes of sea-level

Seismic sequence analysis is based on the identification of stratigraphic units composed of a relatively conformable succession of genetically related strata termed depositional sequence

The upper and lower boundaries of depositional sequences are unconformities or their correlative conformities.

CONVOLUTIONAL NEURAL NETWORKS (CNN) TO IMPROVE IDENTIFYING DEPOSITIONAL SEQUENCES



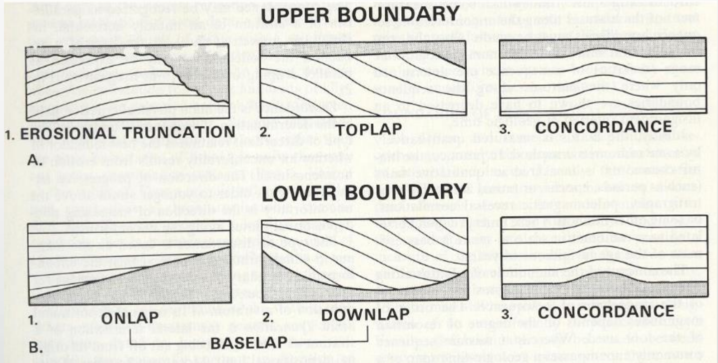


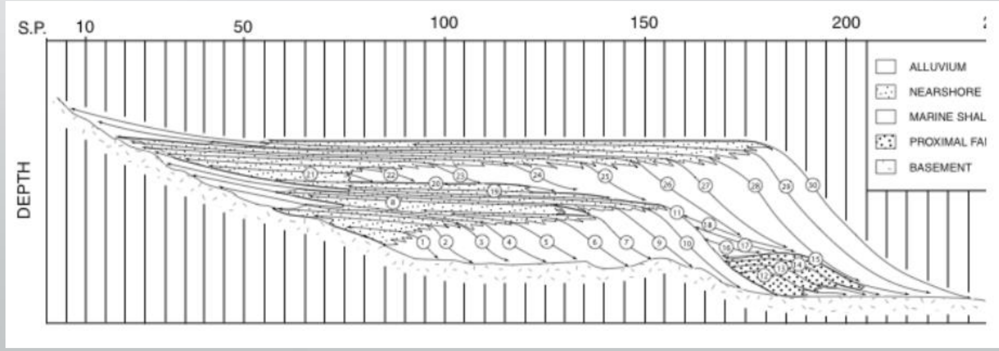
Depositional sequence boundaries are recognized on seismic data by identifying reflections caused by lateral terminations of strata

TRAINING THE LEARNING COMPUTER THROUGH ARTIFICIAL INTELLIGENCE

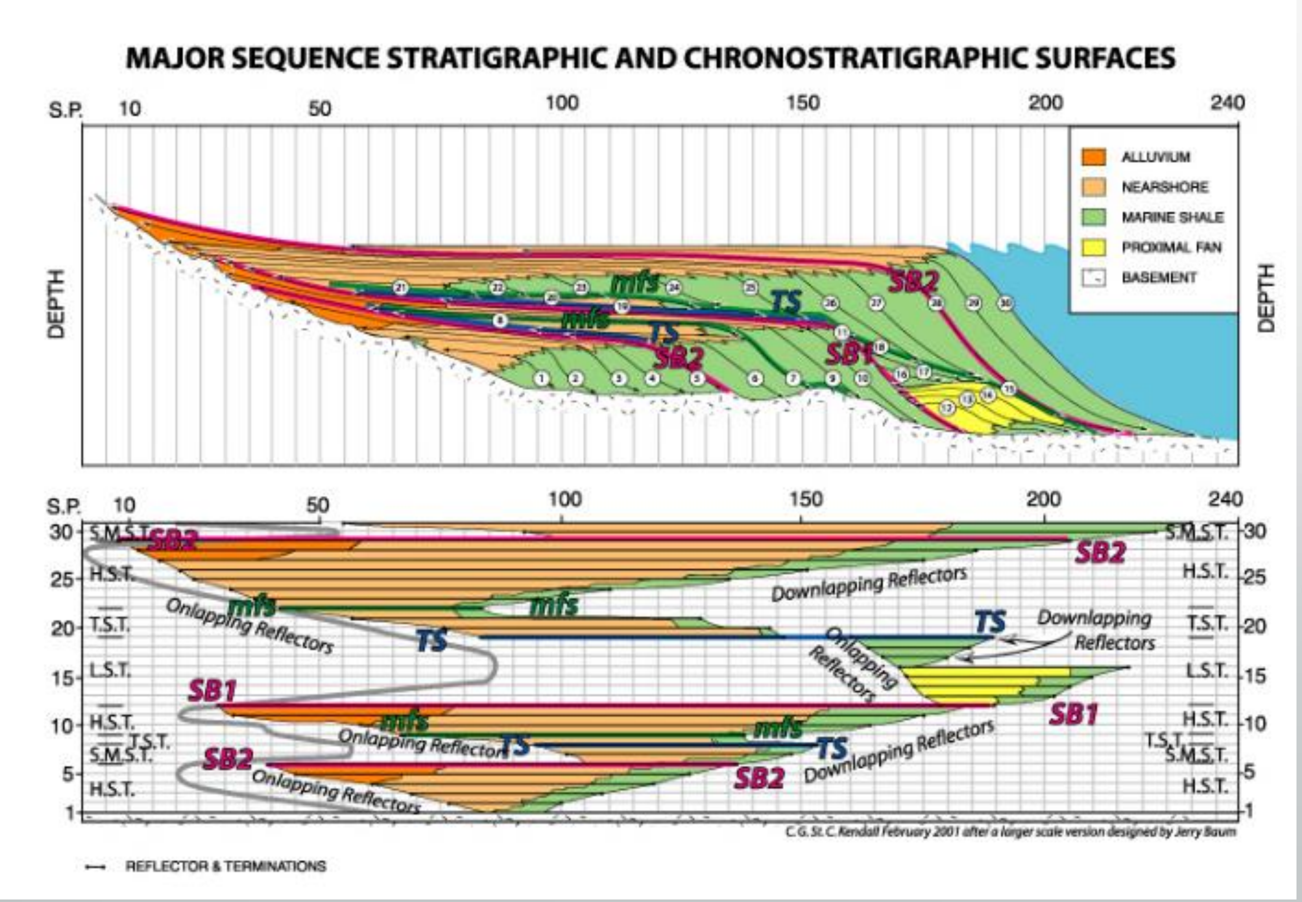
Depositional sequence boundaries are recognized on seismic data by identifying reflections caused by lateral terminations of strata termed:

- onlap
- downlap
- toplap
- truncation

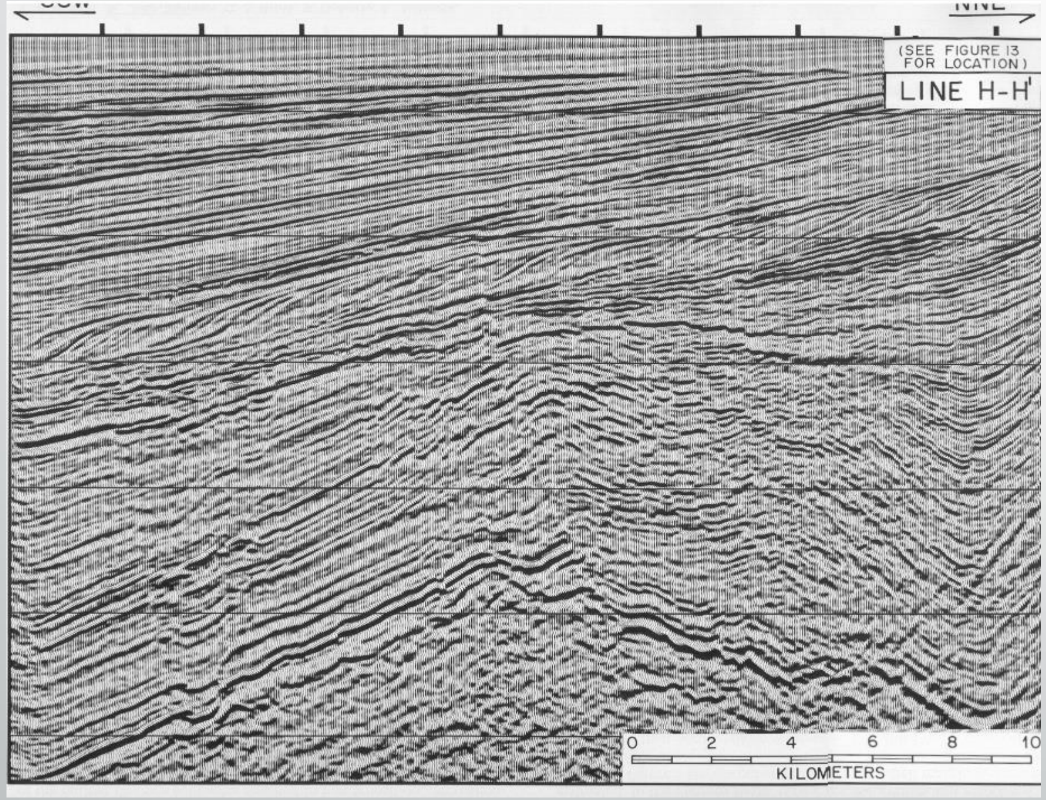


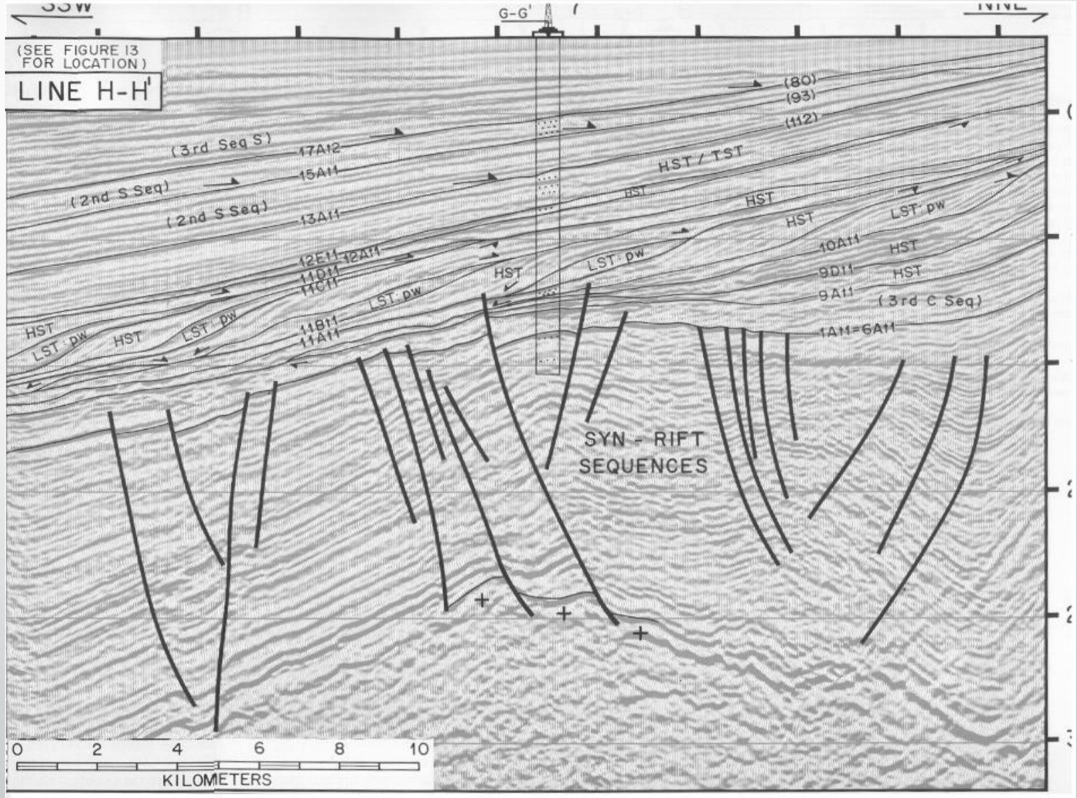


USE OF VISION TECHNOLOGY TO PERFORM CLASSIFICATION OF SEISMIC STRATIGRAPHIC GEOMETRIES

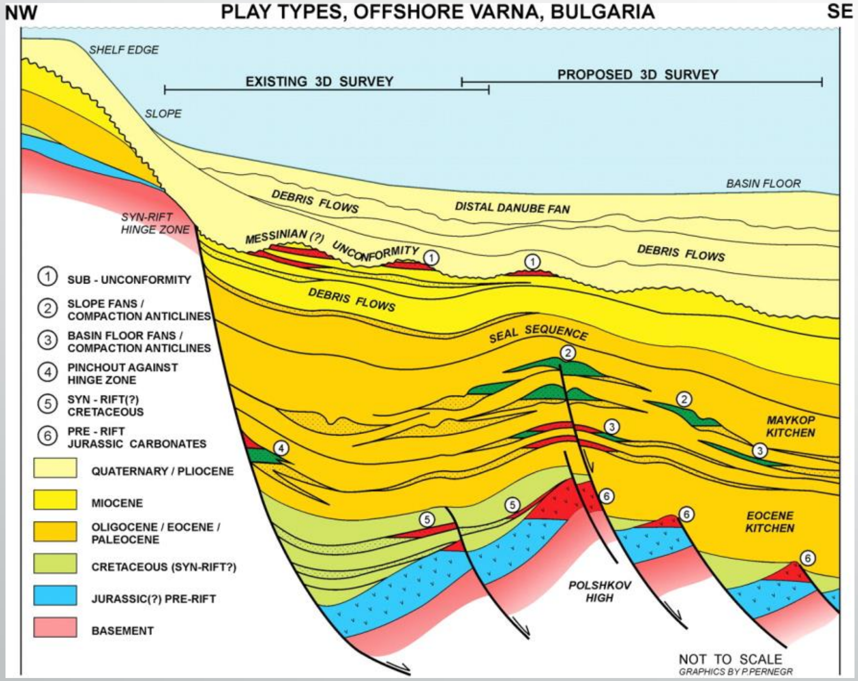


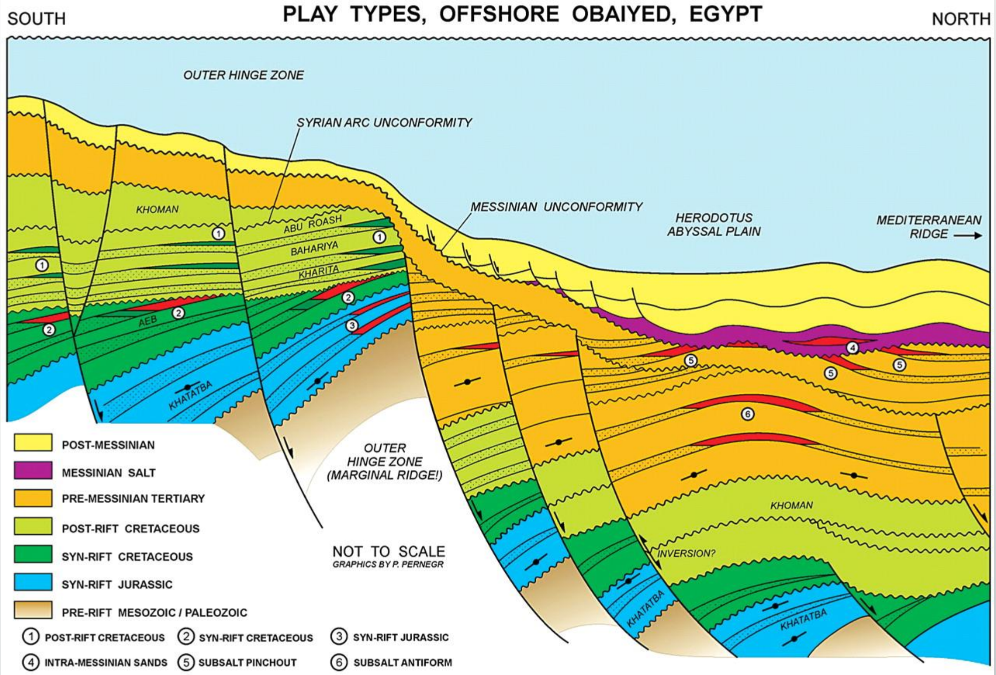
AUTOMATIC IDENTIFICATION OF
Seismic Stratigraphic Patterns



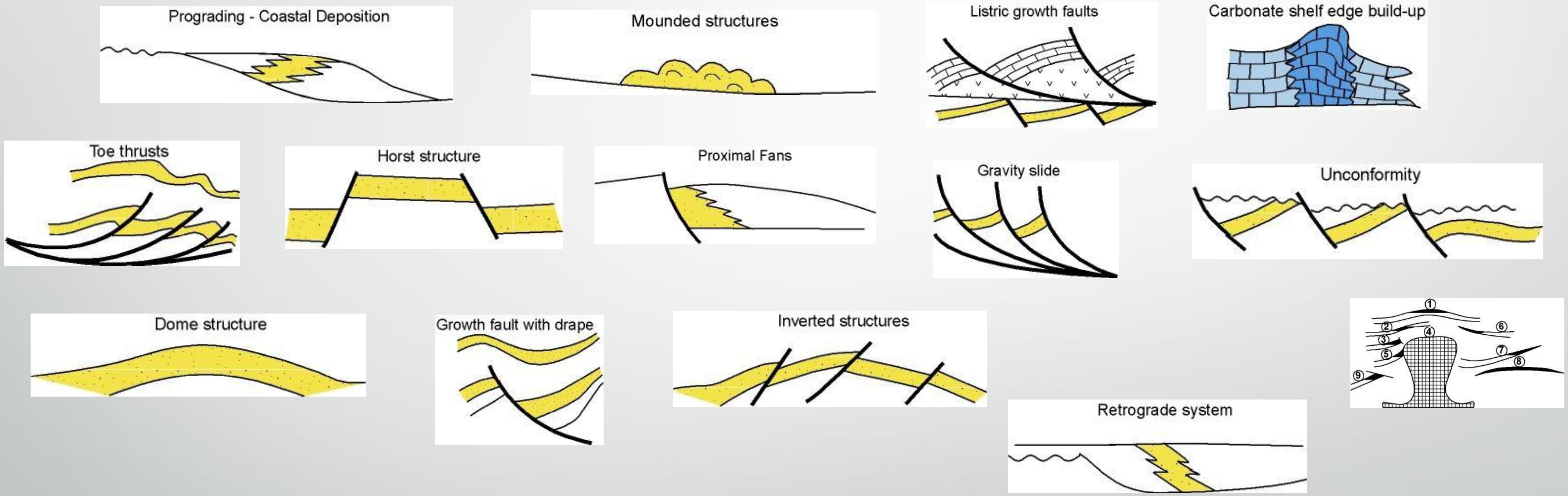


AUTOMATIC IDENTIFICATION OF PLAY TYPES



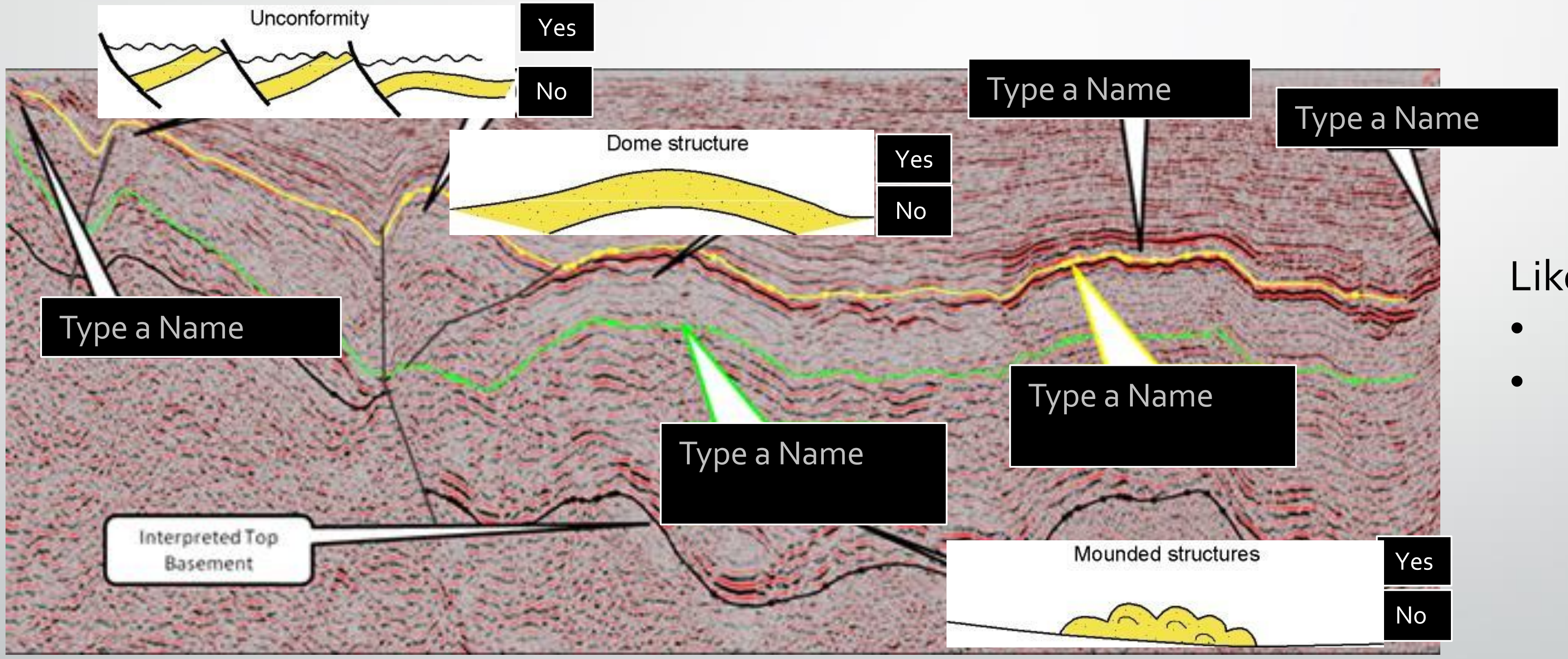


AUTOMATIC IDENTIFICATION OF PLAY TYPES, LEADS and PROSPECTS



Train your data towards well-known play types, trap types in the region and part of the stratigraphy. In addition have a library of known types from other areas,
you never know, you might find it in your data too.

TAG YOUR play types, LEADS and PROSPECTS



Like the way you do in

- Facebook or
- iPhoto

You give input to the unsupervised training of your data. It will automatically identify similar ones and/or give you a choice of places it finds similar, and you choose to tell its right or wrong.