# Artificial Intelligence Automates Seismic Reservoir Characterization: A Novel Approach using Unsupervised Learning

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## Abstract

Seismic Reservoir characterisation is a critical step in understanding the depositional environment and reservoir property distribution. The conventional way approach integrates multiple, yet relevant seismic attributes to effectively predict the distribution of reservoir facies and hydrocarbon presence beyond well control. However, these conventional approaches are computation intensive, association of human subjectivity and oversights, and time consuming, which sometimes yet may not produce desired outcomes. To address these challenges, a novel approach is proposed for fully automated Seismic facies classification using AI/ML driven unsupervised algorithms. These automated seismic facies classification will be beneficial within the reservoir characterization process to map the depositional environment and reservoir properties in an area. Well data has been integrated as posteriori information with the outcomes for understanding the seismic facies classification and calibrating the interpretation.

This AI/ML driven seismic facies classification approach can combine any number of relevant seismic attributes, constrained with/without interpreted horizon/s. This approach integrates robust algorithms such as SOM (Self-Organizing Map), t-SNE (t-distributed stochastic neighbour embedding), and DBSCAN (Density-based spatial clustering of applications with noise) algorithms.

Here, the application of these algorithms for automated reservoir characterisation on a 3D dataset from Sable basin, Offshore Nova Scotia (Open Source) is demonstrated. The automated seismic facies classification technique resulted in better and meaningful seismic facies as compared to the conventional methods, when posterior analysis was performed with well data. Also, this technique is able to capture the lateral continuity of facies better as compared to conventional clustering techniques like K-Means (Roy et al, 2020).

## Introduction

One of the major objectives of seismic data interpretation is to effectively predict the distribution of reservoir facies and hydrocarbon presence, away from well control. Facies classification is an important step in understanding the depositional environment and reservoir properties. Seismic attributes can be quantitatively related to reservoir properties through calibration with well data (Bakdi et al., 2020) and thereby help in performing the task of reservoir characterisation effectively. The main objective of automated facies classification using machine learning techniques is to perform facies classification fast and effectively using number of relevant seismic attributes for mapping the reservoir facies distribution.

With the advent of increasing number of meaningful attributes, it is time consuming and laborious to analyze them through conventional analytical methods. Artificial Intelligence techniques analyze higher dimensional data points fast and effectively. Automated seismic facies classification techniques are increasingly becoming important in identifying the potential hydrocarbon bearing zone and favorable facies. Such facies classification techniques, or, automated clustering algorithms, help to organize similar seismic traces based on the waveform shape, amplitude, phase, frequency and other relevant seismic attributes derived from the characteristics mentioned above (Ray et al., 2020). First, the relevant number of pre-processed seismic attribute volumes are trained using SOM algorithm. These outputs are then fed into a combination of t-SNE and DBSCAN algorithms. This technique (t-SNE and DBSCAN) preserves the nonlinear nature of the data, which is not addressed by the classical linear clustering algorithms such as K-Means. This novel technique filters out the misclassified datapoints identified as noise and subsequently generating the maximum number of clusters based on Silhouette score, hence defining number of clusters as a-prior input parameter for model building is not needed. The results of this pipeline are processed to generate outputs in industry standard files in segy format, with cluster labels and two projection axis volume attributes, characterizing reservoir geometries automatically from all input seismic attributes.

Prior to applying SOM technique, robust seismic data enhancement steps needed to be performed using edge-preserving, structure-oriented filtering to eliminate undesired noise from the seismic data so that meaningful attributes can be derived.

## Method

The automated approach of AI/ML: The automated seismic facies characterization has been carried out using fAIcies MVP (Minimum Viable Product), which is a an indigenously developed advanced technique for automated facies characterization. The study is based on the workflow comprising of advanced data enhancement techniques, relevant attribute extraction and application of robust automated clustering & pattern recognition technique (SOM, t-SNE and DBSCAN) for effective facies classification from seismic data.

**SOM** (Self-Organising Map): Kohonen SOM is an artificial neural network (ANN) algorithm based on competitive learning and is a robust unsupervised pattern recognition technique. Here higher dimensional data is projected into a much lower dimensional latent – Map space (usually 2D) through statistical process, preserving the geometrical relationship between the data points (Roy et al, 2012). This technique is effectively used for the automatic classification and clustering of seismic facies. Unlike the other clustering methods, there is no aprior requirement of defining the number of facies in the analysis for SOM technique. Instead, using the relevant multi-attributes SOM will create natural clusters of data points with similar properties in 2D latent space and thereby help in automatic identification of different facies effectively.

**t-SNE** (t-Distributed Stochastic Neighbor Embedding ): This is an unsupervised non-linear dimensionality reduction technique primarily used for data exploration and visualization. The t-SNE algorithm calculates a similarity measure between pairs of instances in the high dimensional space and low dimensional space, and then it tries to optimize these two-similarity measure using a cost function.

**DBSCAN**: This is a density-based clustering algorithm, it is focused on finding neighbours by density on a sphere with radius $\epsilon$ with minimum number of points (MinPts). It classifies points into

- Core points: The points which contains at least same or more points than the parameter MinPts in its neighbourhood defined by $\epsilon$.
- Border points: The points that lie in a cluster, but its neighbourhood doesn't contain more points than MinPts
- Outliers: The points that doesn't lie in any cluster and its neighbourhood doesn't contain more points than MinPts

Finally, the clustering is done on all those points based on density. The cluster labels, t-components are combined and written it back in a segy format. The output is generated as 3D segy volume.

Figure 1 shows the Overall Flowchart of fAIcies MVP.

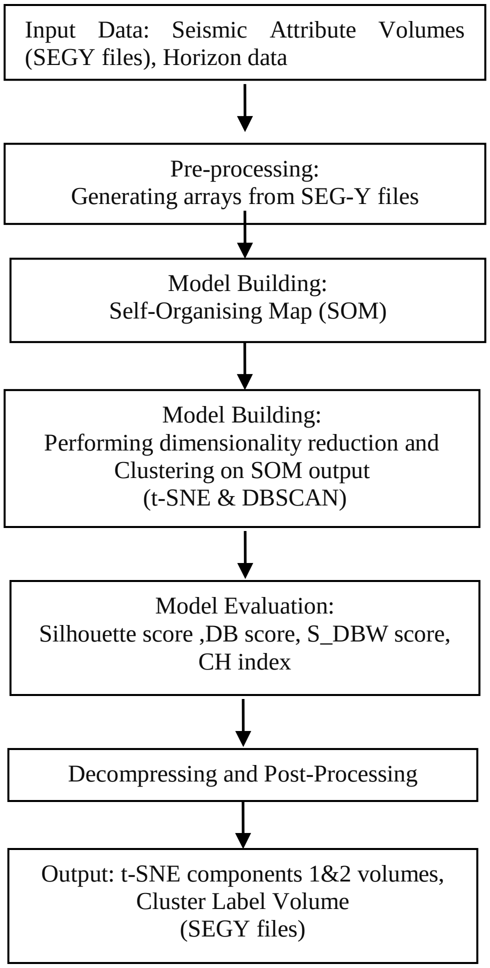


Figure 1: Overall Flowchart of fAIcies MVP

In this study, we demonstrate the application of this automated AI/ML approach algorithm for facies classification to a dataset from Sable basin in Offshore Nova Scotia.

## Model Input

Seismic Attribute volumes such as Coherent energy, Sobel-filter similarity, Textural attributes based on grey level co-occurrence matrix (GLCM) attributes – GLCM Energy & Entropy, Spectral Decomposition volumes, Principal Curvature attributes and Relative Acoustic Impedance (RAI) were considered. The reflectivity seismic section (Xline) passing through the well L-30 is shown in the Figure 2. The Zone of interest considered from Logan Canyon top to Logan Canyon+ 400ms. The analysis is done around the stratigraphic level at Logan Canyon +300ms, marked in the section (Figure 2) as Channel sand.

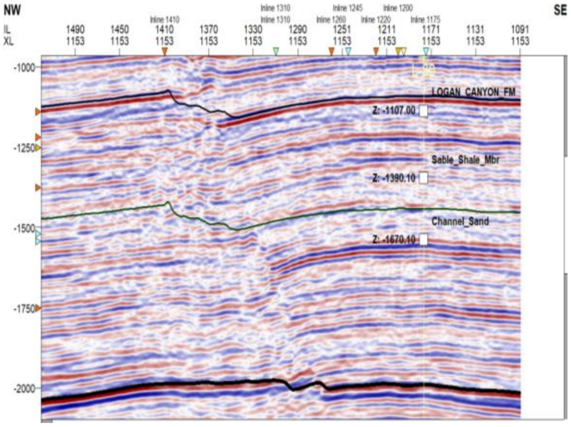
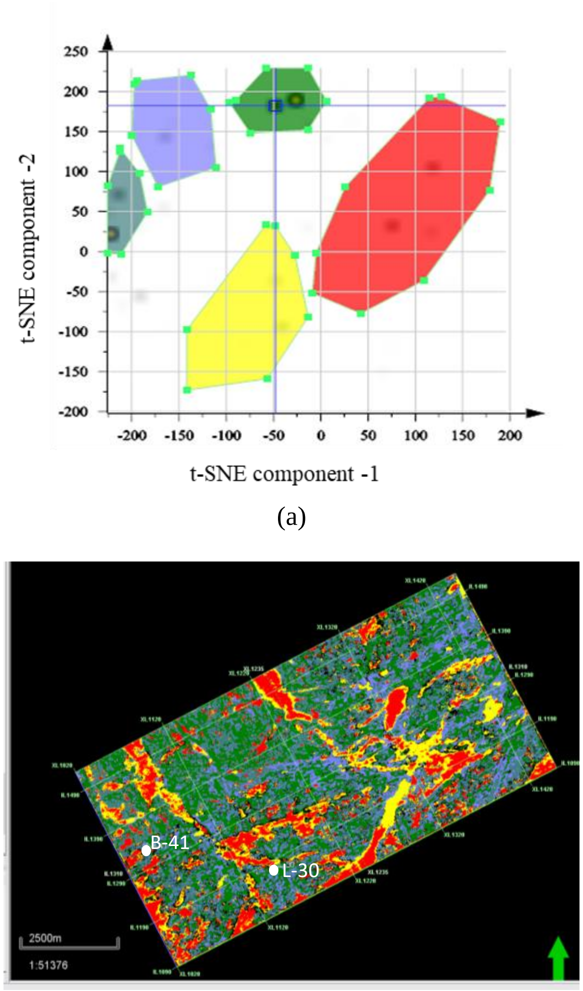


Figure 2: Seismic section passing though well L-30, showing the Channel Sand horizon (Logan Canyon Horizon + 300ms)

## Results

The generated model output, in segy format, was loaded in the geotechnical software. Analysis and calibration of the results were performed along with the well log facies. Two SOM t-SNE principal axis components were coss-plotted considering a small window around the analysis window. The clusters of points have been enclosed by different polygons in the cross-plot space and highlighted with the similar colors in the map shown in Figure 3b for the Channel sand horizon as shown in Figure 2. It is observed that different natural clusters derived from this approach and shown in the cross-plot (Figure 3a), represent different facies associated with the channel complex. This is clearly illustrated in the corresponding map as shown in Figure 3b. QC also carried out in vertical section of t-SNE components using available well data. The well L-30 found to be at the fringe of the channel axis which is also corroborated from the GR log at the Channel Sand level as shown in the Figure 4. The warmer colour in the t-SNE component section represents the anomaly in the Channel Sand horizon as marked in the red box.



(a)

(b)

Figure 3: (a) Cross-plot of t-SNE components, (b) fAIcies map showing different facies associated with the natural clusters of Channel sand horizon

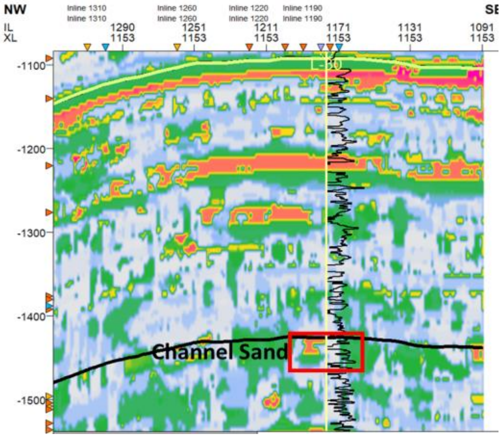


Figure 4: t-SNE Component section passing though well L-30, showing the Channel Sand anomaly (marked in red box with Warmer colour).

## Conclusions

This automated SOM+t-SNE+DBSCAN approach has higher accuracy and better facies classification compared to conventional techniques and can be horizon constrained and can take multiple attributes, without any limitation and without any prior parameterisation required for number of clusters. Parameter and hyper-parameter determination for unsupervised Seismic Facies Classification processes remain a challenge in Machine Learning and Geoscience, and the present study addresses this problem in a novel and effective way.

## Reference

Bakdi, S., Masini, S.R., Kannan, N., Goswami, S., Chennakrishnan, B., 2020, Reservoir Rock Typing Using Unsupervised Clustering Techniques; EAGE/AAPG Digital Subsurface for Asia Pacific Conference & Exhibition, Volume 2020, p.1 – 6. DOI: https://doi.org/10.3997/2214-4609.202075033

https://scikit-learn.org/stable/modules/generated/sklearn.manifold.TSNE.html https://scikit-learn.org/stable/modules/generated/sklearn.cluster.DBSCAN.html

Kohonen, T., 2001, Self-Organizing Maps, 3rd ed.: Springer-Verlag.

Ray, A. K., Dandapani, R. and Verma, S., 2020, Seismic facies classification using Generative Topographic Mapping and Self Organizing Maps; EAGE/AAPG Digital Subsurface for Asia Pacific Conference & Exhibition, Volume 2020, p.1 – 3. DOI: https://doi.org/10.3997/2214-4609.202075034

Roy, A., B. L. Dowel, and K. J. Marfurt, 2012, Characterizing a Mississippian tripolitic chert reservoir using 3D unsupervised seismic facies analysis and well logs: An example from Osage County, Oklahoma: 82nd Annual International Meeting, SEG, Expanded Abstracts.

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