Geophysical Corner

Unsupervised Machine Learning for Characterizing a Geothermal Sandstone Reservoir

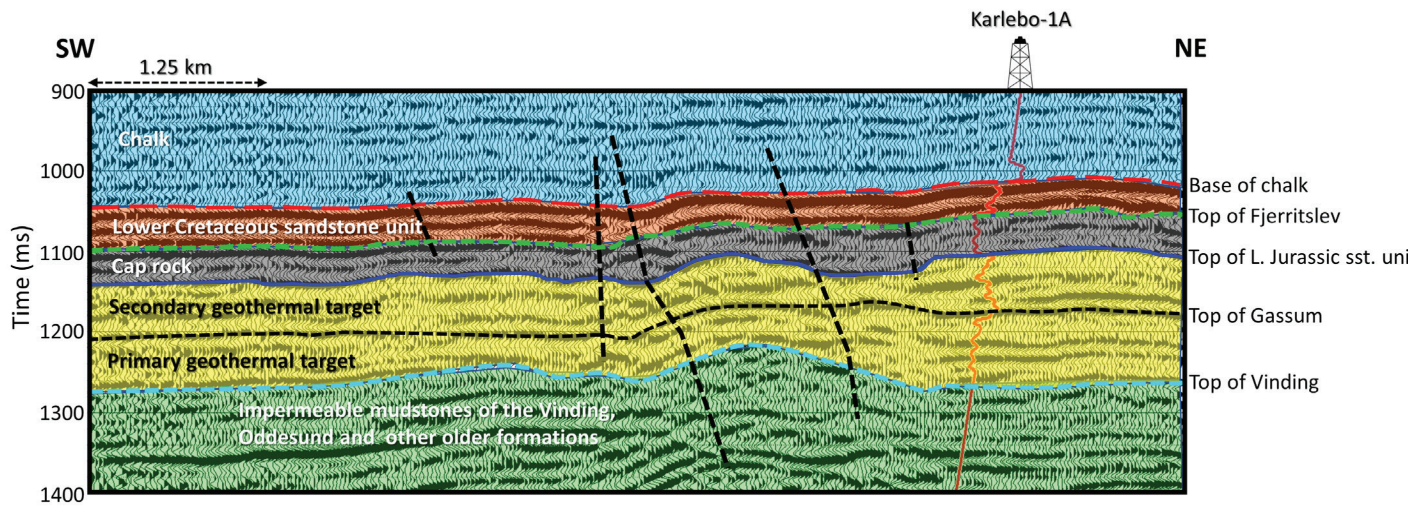

Figure 1: Seismic profile 5 shown overlain by the main geological units with the projected location of the Karlebo-1A well. Yellow indicates the primary and secondary geothermal targets.

The estimated hydrocarbon reserves around the world, when produced, can keep us going for the next several decades. But scientific records and our own experiences are enough evidence that climate change is indeed happening. Addressing it requires energy extraction from non-fossil fuels. One such resource is the natural heat of the Earth, or geothermal energy.

There are different ways in which the heat of the Earth can be utilized. We hear of natural hot springs at certain places, where, somehow, groundwater emerges through the porous and fractured rocks after contact with the deeper and hotter layers of the Earth's crust. Geysers spout columns of hot water and steam through vents in the Earth's surface. Under suitable conditions, the geothermal system in place can be enhanced to our advantage. For instance, a fluid circulation cycle could be set up by injecting (pumping) cold water through a well to the depth of, say, a hot sandstone reservoir rock and then drawn up as hot water through another well a certain distance away. Of course, such an initiative requires the right kind of rocks through which a steady water flow rate can be established. Such geothermally heated water (usually more than 75 degrees C) is used to heat buildings constructed in their proximity, where hot water from the producing well transfers the heat to the housing heating grid.

The feasibility and success of such a geothermal reservoir are dependent on finding the candidate reservoir rock that will allow the water to percolate through. This would need good porosity and permeability, the presence or absence of faults and fractures, high enough temperature and knowledge about the structural component of the target reservoir.

Danish Geothermal Potential

The Danish subsurface hosts low-enthalpy reservoirs (40-80 degrees C) of Jurassic, Triassic and Cretaceous age. The available geothermal energy has the potential to supply district heating for hundreds of years into the future, and three geothermal plants have been set up in Denmark.

The target reservoir discussed in this study is a Triassic-Jurassic deep geothermal sandstone reservoir, north of Copenhagen, onshore Denmark. The data available for this study were a 2-D seismic survey from 2013 (comprising five profiles with 3 kilometers offset, designed for structural mapping, and outlining potential geothermal reservoirs), a local well (Karlebo-1A), and another well that penetrated the reservoir of interest.

The geothermal interval is the sandstone-dominated Upper Triassic-Lower Jurassic Gassum Formation, which is being exploited for geothermal production and storage in Denmark. Figure 1 displays seismic profile 5 with geologic interpretation with the Karlebo-1A well projection overlaid on it. The Lower Jurassic sandstone unit that overlies the Gassum Formation is a secondary geothermal target. Both these units lie at a depth of about 2 kilometers below the ground level. Above the Lower Jurassic sandstone unit is the Fjerritslev Formation that is dominated by marine mudstones and shales, which is the regional caprock. The Lower Cretaceous sandstone unit sits on top of the Fjerritslev Formation, and in turn is overlaid by the high-velocity chalk formation that generates interfering multiples and converted waves, which makes processing of the seismic data challenging. Below the Gassum Formation are the impermeable mudstones of the Vinding, Oddesund and other older formations. The observations from Karlebo-1A well indicate that while the Lower Jurassic reservoir unit is a homogeneous unit, the Gassum sandstone contains interlacing of thinly bedded shale. The reservoir temperature ranges between 50 and 65 degrees C in the target interval.

The exploration well Karlebo-1A drilled for hydrocarbon exploration is located approximately 140 meters from profile 5. It has a limited number of log curves (gamma ray, sonic and porosity), while a nearby well penetrates the same set of formations as the Karlebo-1A well and contains a complete set of log curves. Thus, the latter well was used to derive empirical relations between pairs of variables and used to determine additional curves such as density, shear sonic and shale volume for Karlebo-1A well.

The earlier work on seismic reservoir characterization of these different lithounits was carried out using prestack simultaneous impedance inversion and predicting facies and reservoir properties using the available data. Their results demonstrated that several porous and clean water-bearing sandstones are potential high-quality geothermal reservoirs within the two target layers, namely the Lower Jurassic sandstone unit and the Gassum Formation. Given the availability and quality of the data and geological complexities, the results were influenced by high uncertainty, but highlighted the possible target layers. We decided to repeat the prestack simultaneous impedance inversion on the same data by following a somewhat different workflow and made use of the available unsupervised machine learning techniques for facies classification and assess their comparison. Our results indicated a superior impedance inversion product such as P- and S-impedance, which along with other seismic attributes were used for ML facies prediction.

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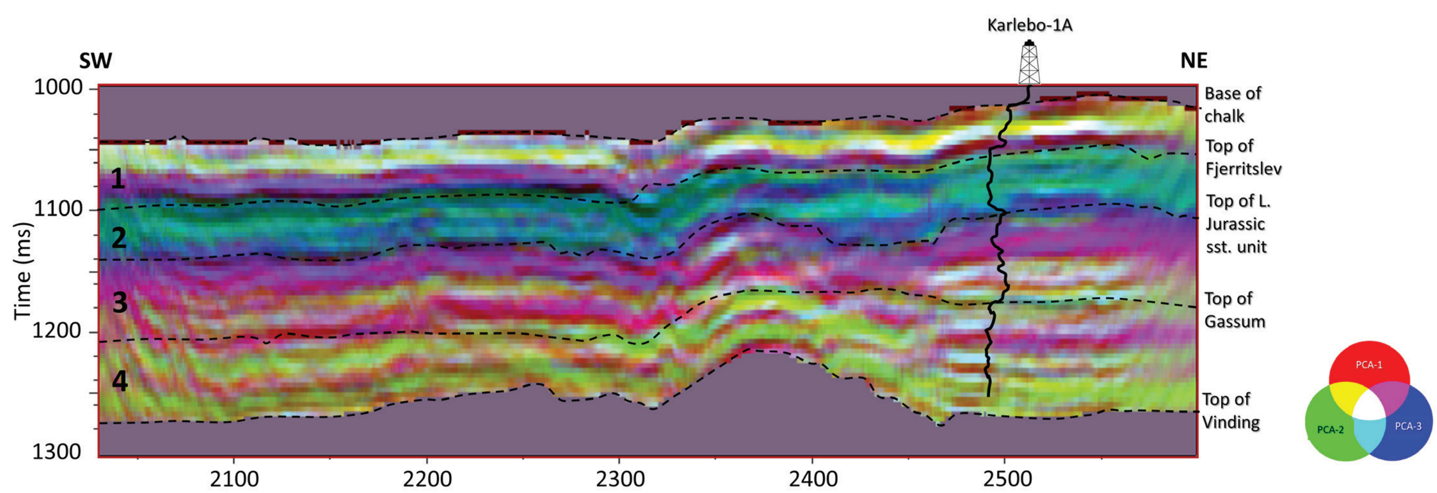

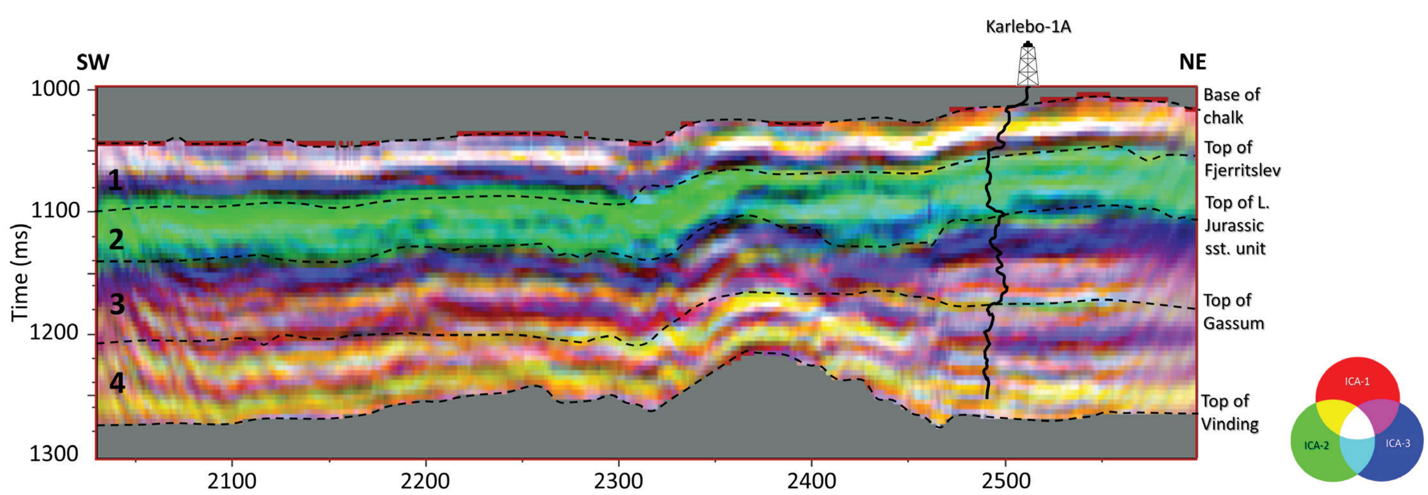

Figure 2 (top): Section display for seismic profile 5 for PCA1, PCA2 and PCA3 corendered using RGB blending. The P-impedance well log for well Karlebo-1A is shown overlaid on each section. Of the four rock types marked to the left of the composite section, not only does rock type 2 stand out in a different color pertaining to shale facies, but the variation in facies can also be seen in units 3 and 4 as well.

Figure 3 (bottom): Section display for seismic profile 5 for ICA1, ICA2 and ICA3 components corendered using RGB blending. Compared with the composite display in figure 2, the lateral resolution and contrast appears to be better on this display in each of the four intervals defined by the five horizons shown overlaid. The colors representing the different facies in the intervals also seem to jive well with the overlaid P-impedance log. The variation in the individual facies in the four intervals seems to be defined somewhat better on this display than the PCA composite display in figure 2.

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Unsupervised Machine Learning Facies Classification

Unsupervised learning provides a means to determine if the seismic response can be related to flow units or rock types that can be calibrated with additional well control, but for which we do not understand the underlying petrophysical or geological theoretical support. Still, seismic interpreters face a perpetual challenge of extracting heterogeneous seismic facies on different generated attributes. The common analysis tools include corendering, crossplotting and visualization, which can help to an extent in terms of simultaneous display of the input attributes. The data reduction approach resorted to at times applies mathematical techniques to reduce the number of attributes to a manageable subset. Clustering is another way to identify elements within the data that have similar expressions.

Here we compare the application of some established ML techniques, namely principal component analysis, independent component analysis, self-organizing mapping and generative topographic mapping. We find such an application promising as the facies results exhibit higher vertical and lateral resolution. The PCA and ICA applications of unsupervised machine learning for facies classification have been discussed earlier in the August 2018 installment of Geophysical Corner.

Below we briefly describe the machine learning techniques and their application to the geothermal sandstone reservoir in Denmark, which has been described above.

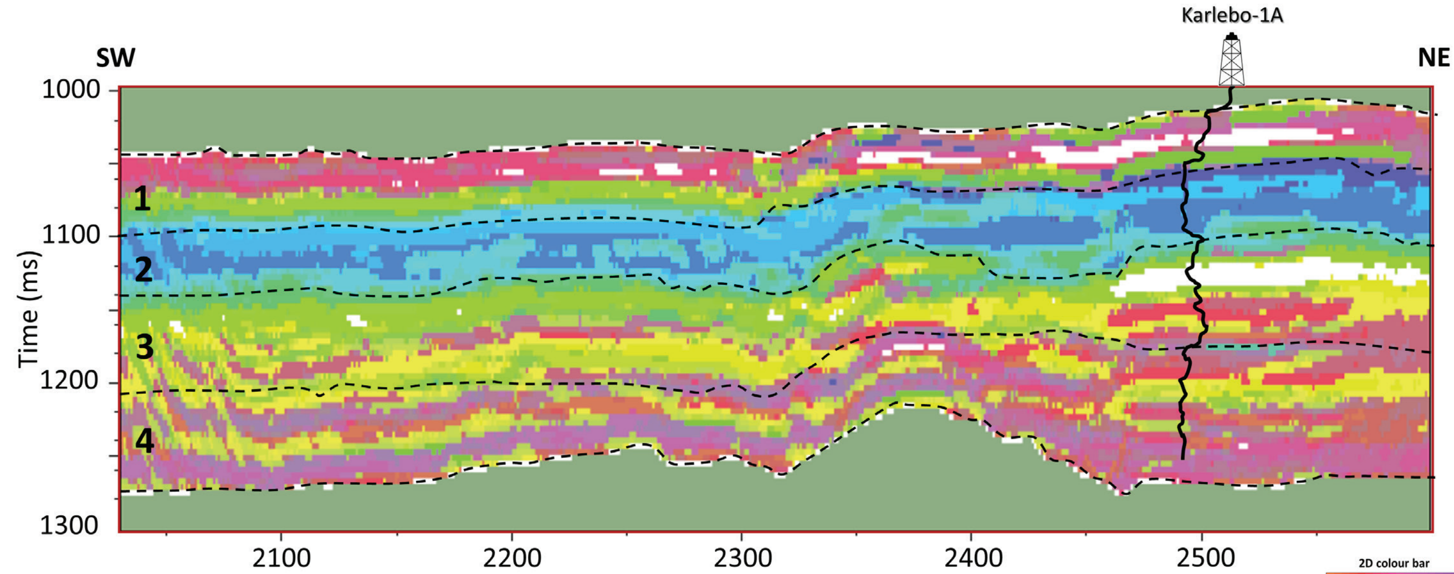
PCA aims to identify patterns in the input attributes by detecting correlation between them. If a strong correlation exists between some of them, then those attributes can be lumped together. Thus, PCA is a useful dimensionality reduction tool and assumes that the input seismic attributes exhibit a Gaussian distribution.

The attributes used for PCA computation were the instantaneous amplitude, spectral magnitude (40 hertz), P-impedance, V_P/V_S, Lambda-Rho, and porosity. All these attributes are seismic amplitude-derived through prestack simultaneous impedance inversion or otherwise, which expectedly should furnish information on the rock types better than some of the other attributes.

In figure 2 we show a section display for seismic profile 5 for the RGB co-rendered PCA-1, PCA-2 and PCA-3 components. This display is particularly useful in that the facies information contained in each of the three principal components can be conveniently interpreted on a single display.

ICA is another machine learning technique, which classifies the different input seismic attributes into independent components but does not require them to have a Gaussian distribution. More description on this technique can be picked up from the August 2018 Geophysical Corner.

In figure 3 is shown a section display for seismic profile 5 from the ICA-1, ICA-2 and ICA-3 RGB co-blended data. Notice the appearance of the clusters in different colors resemble the cluster patterns obtained from the PCA co-blended data display in figure 2, except they appear to be somewhat better defined and exhibiting better spatial resolution in terms of color.



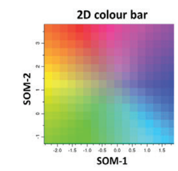
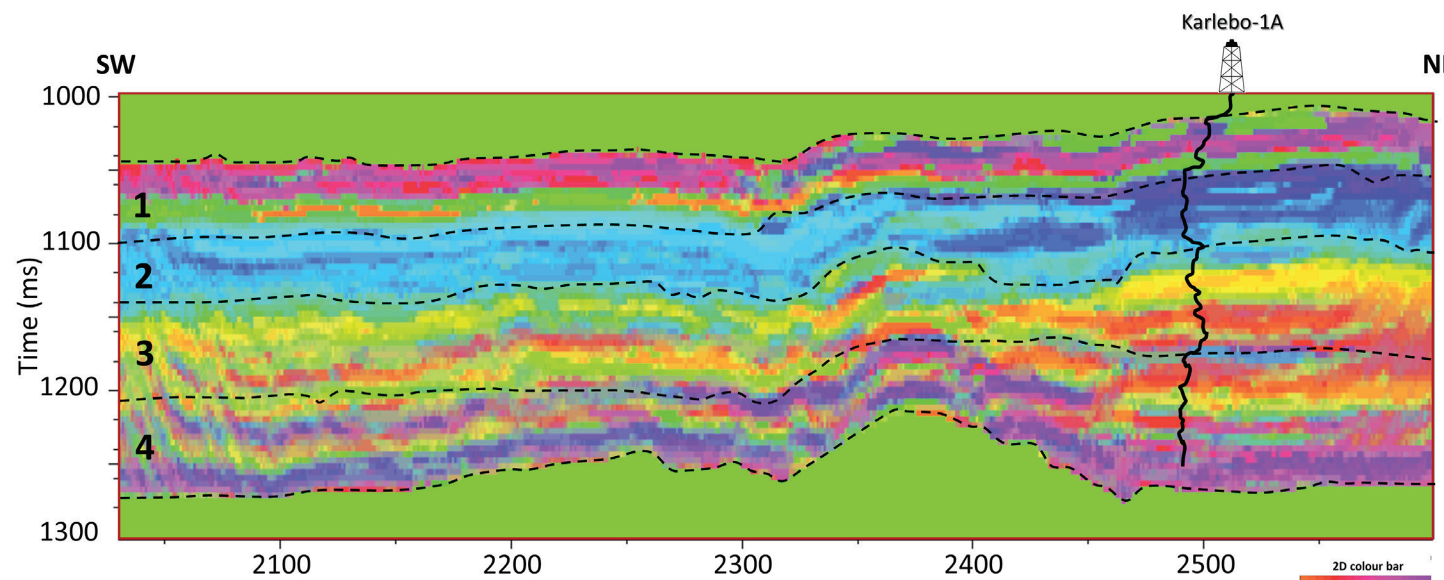


Figure 4: Section display for seismic profile 5 from the SOM1 and SOM2 crossplotted using a 2-D color bar. As compared with the earlier methods, besides better spatial resolution in intervals 3 and 4, even in interval 2, the resolution is seen to be superior.



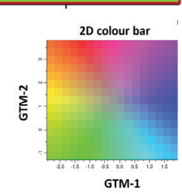


Figure 5: Section display for seismic profile 5 from co-rendered GTM1 and GTM-2 using a 2-D color bar. Multiplexed color bar shown in the above display. This display exhibits the best spatial resolution in all four intervals 1 to 4 compared with all the other methods discussed in this exercise.

Self-Organizing Maps

SOM is another unsupervised machine learning technique based on the clustering approach that generates a seismic facies map from multiple seismic attributes. In this technique the initial cluster centroids are defined in an N-dimensional attribute data space by fitting a plane defined by the first two eigen vectors of the covariance matrix to the data in a least-squares sense. With centroid still locked to this plane, it is iteratively deformed into a 2-D surface that fits the data still better. Once convergence is reached, the N-dimensional data are projected onto this 2-D surface. Thus, SOM may be considered as projection from a multidimensional attribute space to a 2-D space or "latent" (hidden) space. Usually, the output from SOM computation is obtained in the form of two projections on the two SOM axes, which can then be directly crossplotted and displayed using a 2-D RGB color bar.

Figure 4 shows section display for seismic profile 5 for the SOM-1 and SOM-2 crossplotted together using a 2-D color bar as shown to the lower right. Some of the clusters seen on this display are better defined than the ones shown earlier from PCA and ICA analysis in figures 1 and 2.

Generative Topographic Mapping

Though the Kohonen SOM method described above is easy to implement, is computationally inexpensive, and thus is a popular unsupervised clustering approach, it does have limitations. First, there is no theoretical basis for the selection of parameters such as training radius, neighborhood function and learning radius, as all of these are data dependent. Secondly, no cost function is defined in the method that could be iteratively minimized indicating convergence during the training process.

Finally, as a measure of confidence in the final clustering results, no probability density is defined. An alternative approach to the Kohonen SOM method, called

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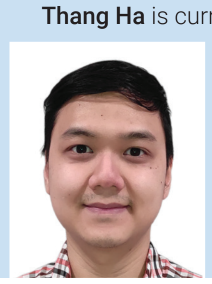
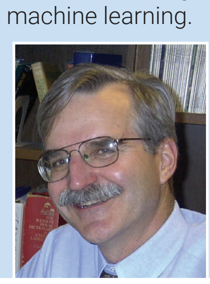
Kenneth Bredesen works as a geophysicist at the Geological Survey of Denmark and Greenland. He received a doctorate in geophysics from the University of Bergen in 2017. He has previously worked as a QI geophysicist at Spike Exploration and as a postdoctoral researcher at Aarhus University. His core competencies are quantitative seismic interpretation, rock physics modeling, seismic attribute and amplitude analysis.



Thang Ha is currently a post-doctoral researcher in geophysics, advised by Kurt Marfurt, at the University of Oklahoma. He obtained his bachelor's, master's and doctoral degrees in geophysics at the same university. He is a member of AAPG, the Society of Exploration Geophysicists, the European Association of Geoscientists and Engineers and the Geophysical Society of Oklahoma City. His research interests are seismic processing, 3-D seismic attributes, data conditioning and automatic classification of geological facies via machine learning.



Kurt Marfurt serves as serves as research professor of geophysics at the University of Oklahoma in Norman's Department of Geosciences.

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"generative topographic mapping," overcomes the above-stated limitations. It is a nonlinear dimension reduction technique that provides a probabilistic representation of the data vectors in latent space.

Thus, as the above descriptions suggest, the PCA, ICA, SOM and GTM methods project data from a higher dimensional space (8-D when eight attributes are used as input) to a lower dimensional space, which may be a 2-D plane or a 2-D deformed surface. Once projected on to these planes, the data can be clustered in that space, corendered with RGB or crossplotted using a 2-D color bar.

In figure 5 we show a section display for seismic profile 5 for the GTM-1 and GTM-2 crossplotted together using a 2-D color bar as shown to the lower right. This display exhibits the best spatial resolution in all four intervals 1 to 4 compared with all the other methods discussed in this exercise. The individual-colored patches or facies are crisper and could lead to more accurate interpretations.

Conclusions

We have shown a comparison of seismic facies classification using the machine learning methods such as PCA, ICA, SOM and GTM to a seismic profile from the Danish area.

In summary, we find that some of the machine learning methods hold promise as they exhibit better vertical and spatial resolution. Among the machine learning methods discussed, the ICA furnishes more detail than the PCA. Both the SOM and GTM methods provide promising results, with the latter yielding more accurate definition as seen on the displays.

(Editors Note: The Geophysical Corner is a regular column in the EXPLORER, edited by Satinder Chopra, Founder and President of SamiGeo, Calgary, Canada, and a past AAPG-SEG Joint Distinguished Lecturer.)