Preparing the Soil in which to Plant a Seismic Facies Analysis Decision Tree

Murphy Cassel

ConocoPhillips School of Geology & Geophysics, The University of Oklahoma

Abstract

With the advances made by Amazon and Google, many geoscientists (and perhaps more so, geoscience management) believe that machine learning will both greatly accelerate and quantify the seismic interpretation process. Since seismic facies analysis is based on pattern recognition, attributes that quantitively measure components of these patterns, will form the basis of future machine learning solutions, the simplest of which is a simple decision tree, or "wizard". Machine learning requires training. The first step in developing a machine-learning based interpretation workflow is to quantify which combination of attributes best characterize a given seismic facies. To this end, I will start by compiling a simple web-based database, or attribute "menagerie".

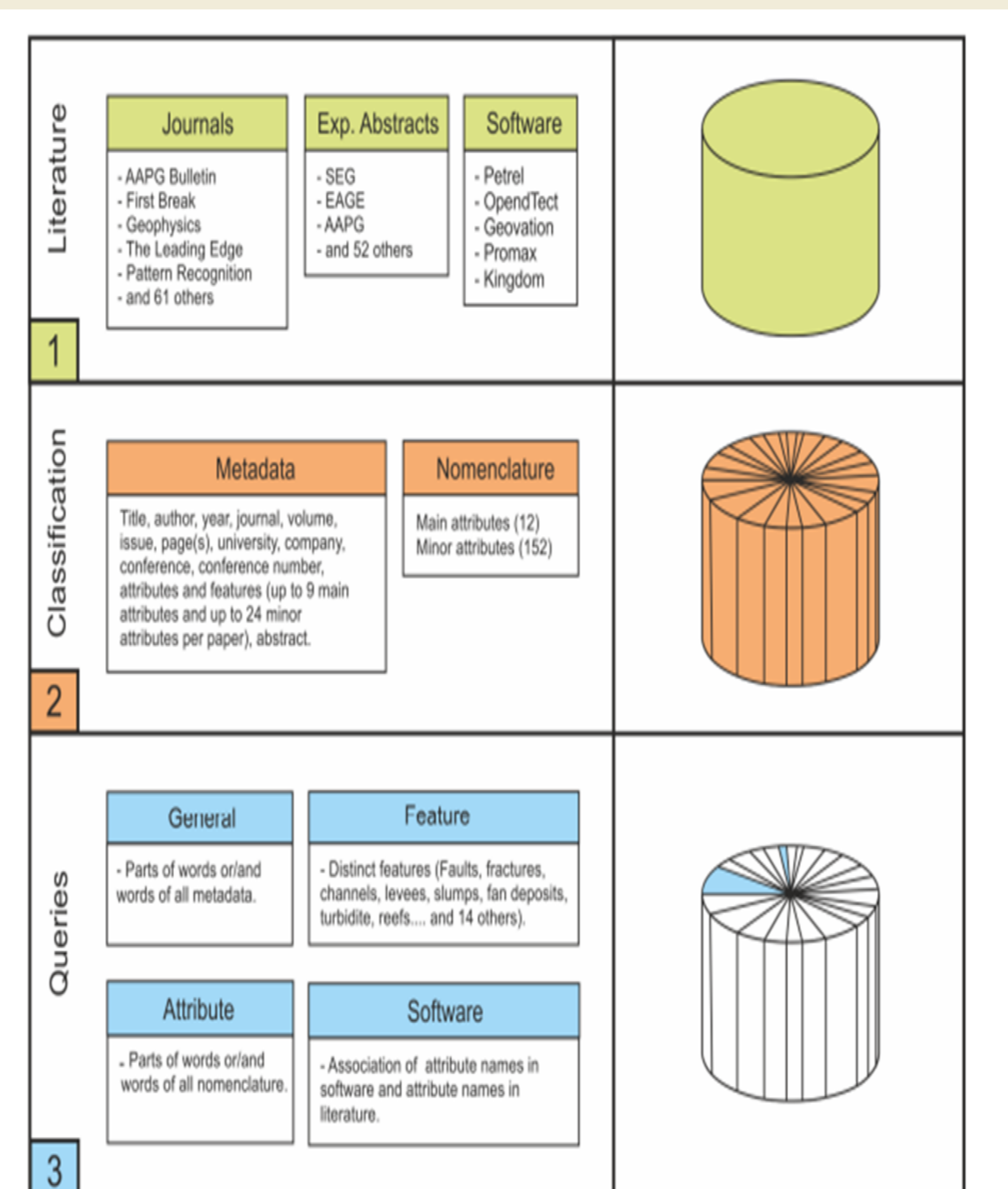


Figure 1: Amtmann et al. (2013) at Joanneum Research Leoben have constructed a data base of attributes provided by multiple technology suppliers, but have not yet started to define which attribute might be "best" for a specific objective.

Motivation

The most common question we encounter within the AASPI group from both our industry sponsors and from our newer students is "Which attribute is best to delineate such and such?". Until now, such feature-specific recommendations have been documented by our team and other interpreters in the form of published papers and oral presentations. The "best-attribute" data base involves a tedious Google-search of the literature! In 2017, it is time to do better.

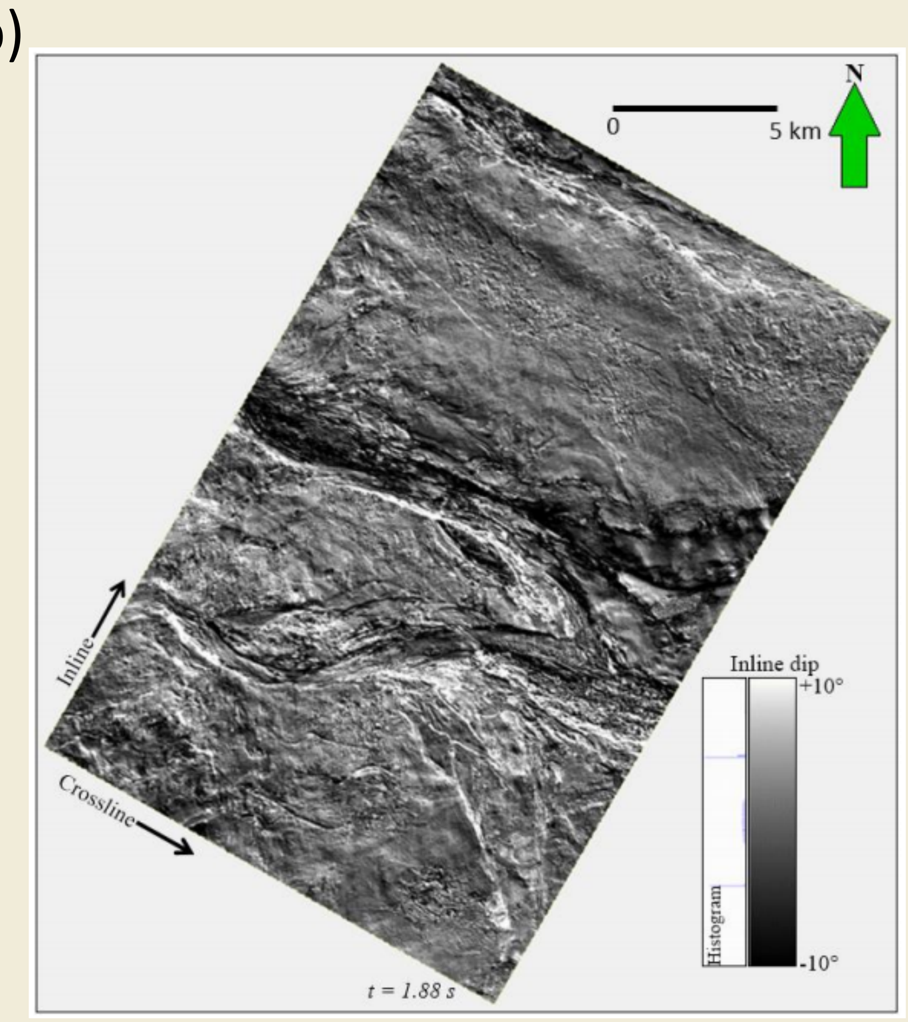
Methodology

The first step to creating this major database is a large scale investigation into all seismic attributes and how and when they are utilized in data sets as seen in Figure 2 with the Facies expression table and in Figure 1. This involves going back through archives of papers to create a general list of attributes and examples of these attributes using a dataset with the best geologic setting for the attribute. Once a general list is created the next step is to create an interactive webpage where the user can search for their geomorphology or facies and see the attribute they can use as a tool to interpret the geology. The references will be displayed as well so that the user can go to the link and follow the publications guidelines for the attribute. Eventually the program will develop into a deterministic facies program where the user can input data and the program can develop an attribute map of the facies within the data set.

(a)

Facies	Appearance to Interpreter	Attribute Expression
Levee	Structurally high	Stronger dome or ridge shape structural components
	locally continuous	Higher GLCM homogeneity; lower GLCM entropy
	Higher amplitude	Dome or ridge shape component
	Possibly thicker	Lower peak spectral frequency
Channel thalwegs	Shale-filled with negative compaction	Stronger bowl or valley shape structural components; higher peak spectral frequency
	Sand-filled with positive compaction	Stronger dome or ridge shape structural components; lower peak spectral frequency
Channel flanks	Onlap onto incisement, canyon edges	Higher reflector convergence magnitude
Gas-charged sands	High amplitude, continuous reflections	Higher GLCM homogeneity; lower GLCM entropy; high high peak magnitude
Incised floodplain	Erosional truncation	Higher reflector convergence magnitude, Higher curvedness
Floodplain	Lower amplitude	Lower spectral magnitude
	Higher frequency	Higher peak spectral frequency
	Continuous	Higher GLCM homogeneity; lower GLCM entropy
	Near planar events	Lower amplitude structural shape components; lower reflector convergence magnitude
Slumps	Chaotic reflectivity	Higher reflector convergence magnitude; higher spectral frequency; lower GLCM homogeneity; higher GLCM entropy

(b)



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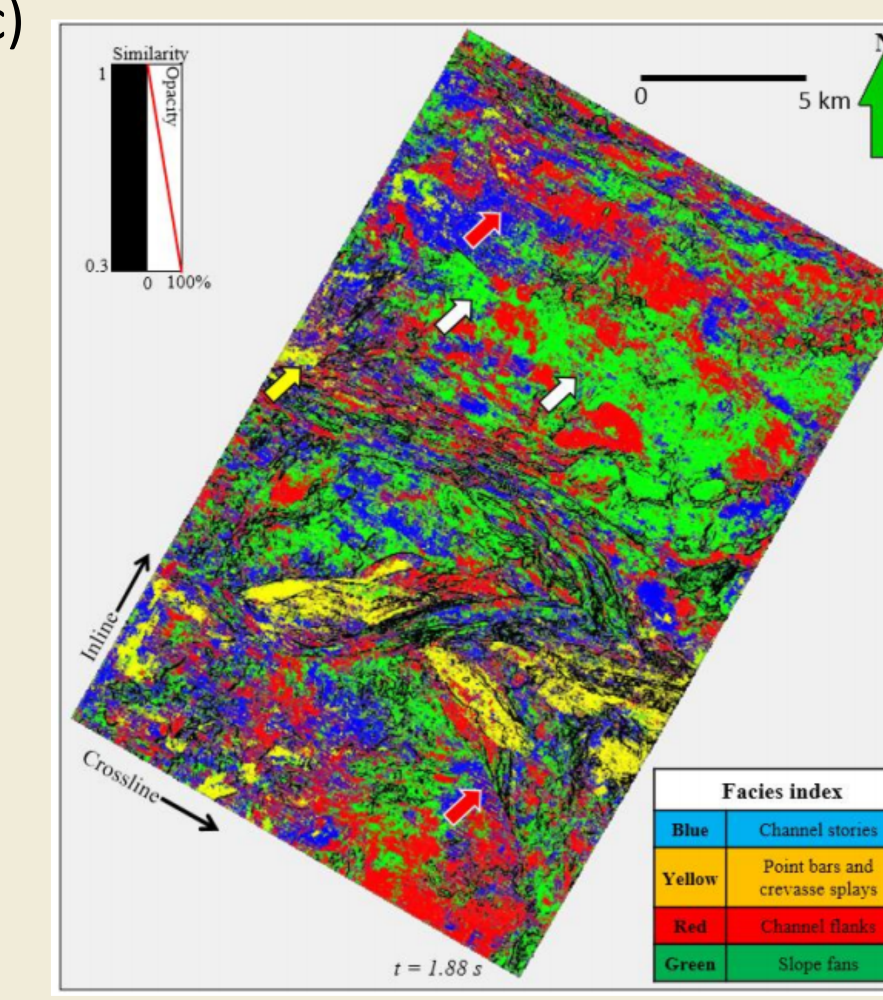
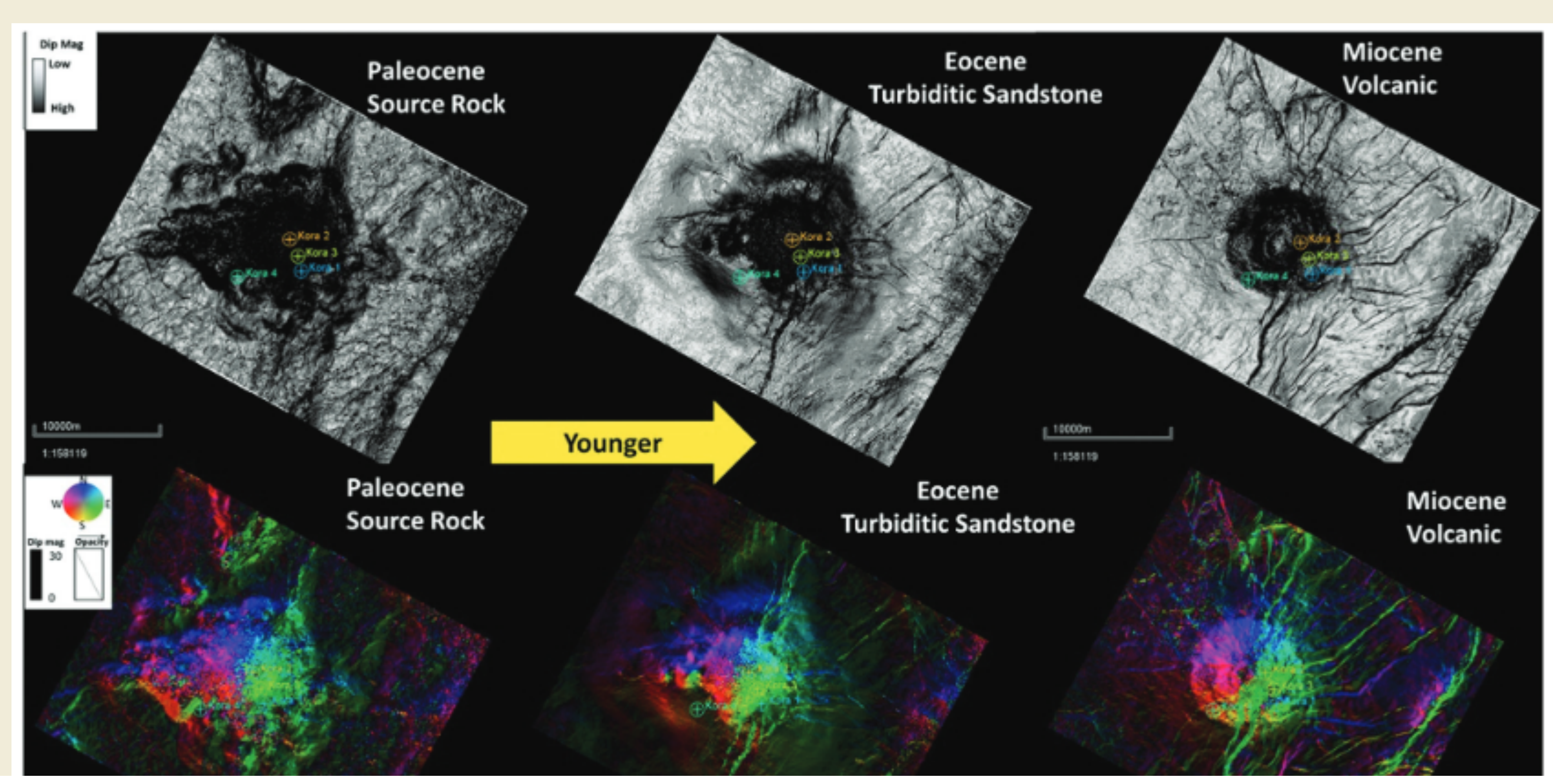
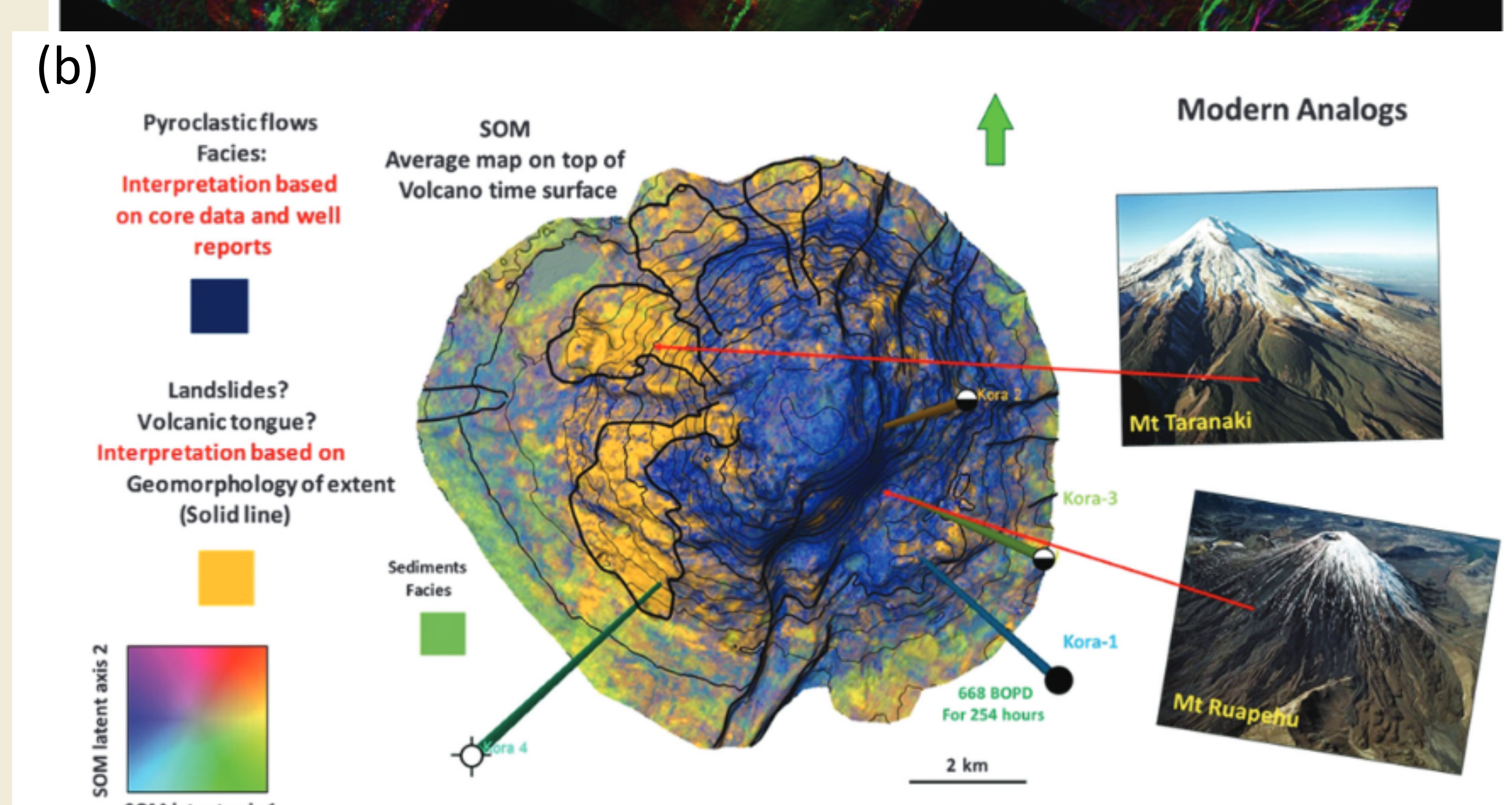


Figure 2: (a) Seismic facies in column 1, followed by a traditional description of their appearance on seismic amplitude data in column 2, and the corresponding attribute quantification in column 3. (b) A horizon slice through one of the attribute volumes - dip magnitude. (c) A horizon slice through a self-organizing map that successfully breaks out different facies, although without extra user input, are "unlabeled" as to which facies is which. (After Zhao et al., 2017).

(a)



(b)



Recent Examples

Tao Zhao conducted an attribute classification of a turbidite system imaged by a survey in the Canterbury Basin, New Zealand. He started with a traditional description of geologic facies, followed by their expression by seismic amplitude and seismic attributes (Figure 2a). He then computed these attributes (e.g. Figure 2b) and analyzed them using an SOM facies classification algorithm (Figure 2c). In general, SOM provides an unsupervised classification. However, using Jane Zhang's stratigraphy expertise, he was able to apply labels to the different colored facies.

Lennon Infante used a similar workflow to classify volcanoclastic facies imaged by a survey in the Taranaki Basin, New Zealand. Again, he first defined the alternative facies in terms of seismic amplitudes and amplitude patterns. He then used selected attributes that quantitatively measure these patterns. For example, dip magnitude delineates the Kora Seamount and major faults (Figure 3a). Reflector convergence quantified sequence stratigraphic changes, while GLCM textures quantified reflector continuity or roughness. Five of these attributes were analyzed using SOM, resulting in the image of pyroclastic flows and lava flows as well as sediment facies seen in Figure 3b.

Figure 3: (a) Horizon slices through the volumetric dip magnitude volume showing lateral variation in source rock, turbidite, and volcanic facies. (b) Horizon slice through the SOM facies volume computed showing pyroclastic flows, lava flows, and sediments. (After Infante et al., 2017).

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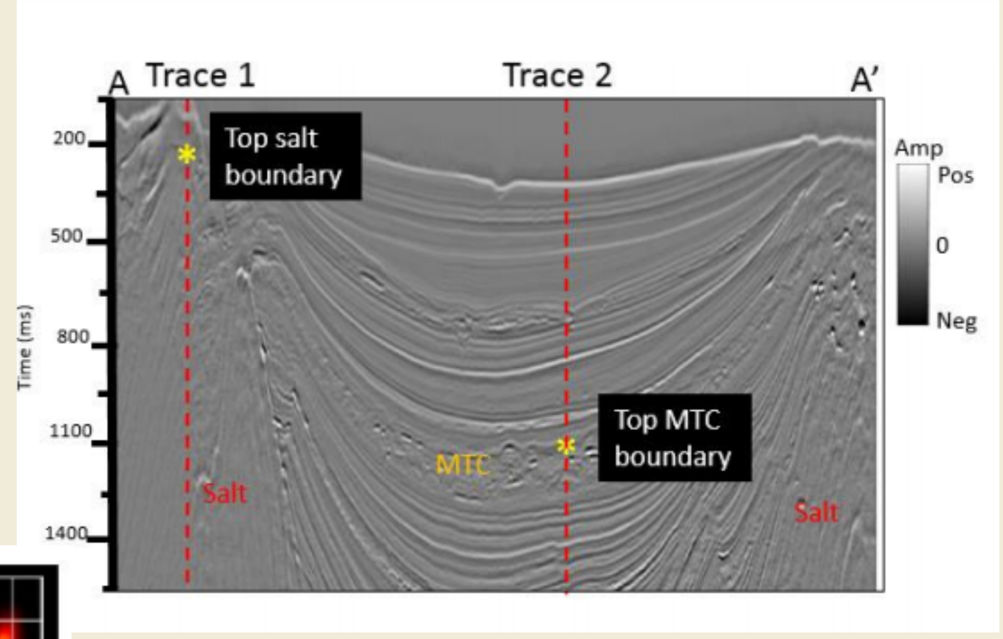
Recent Examples (continued)

Jie Qi tackled as somewhat different problem – differentiating salt from mass transport complexes (MTCs) in a Gulf of Mexico survey dominated by conformal sand and shale sediments. Like Zhao et al. (2017) and Infante and Marfurt (2017), Qi et al. (2016) first constructed a table defining the seismic facies seen in the survey, then their amplitude expression, followed by their attribute quantification. These attributes were subsequently smoothed and blocked using a Kuwahara filter and analyzed using a generative topological mapping (GTM) algorithm. Figure 4a shows a vertical slice seismic amplitude. Figure 4b shows the same slice after classification without Kuwahara filtering while Figure 4c shows it with Kuwahara filtering. Then end product is a geobody extraction (Figure 4d).

(a)



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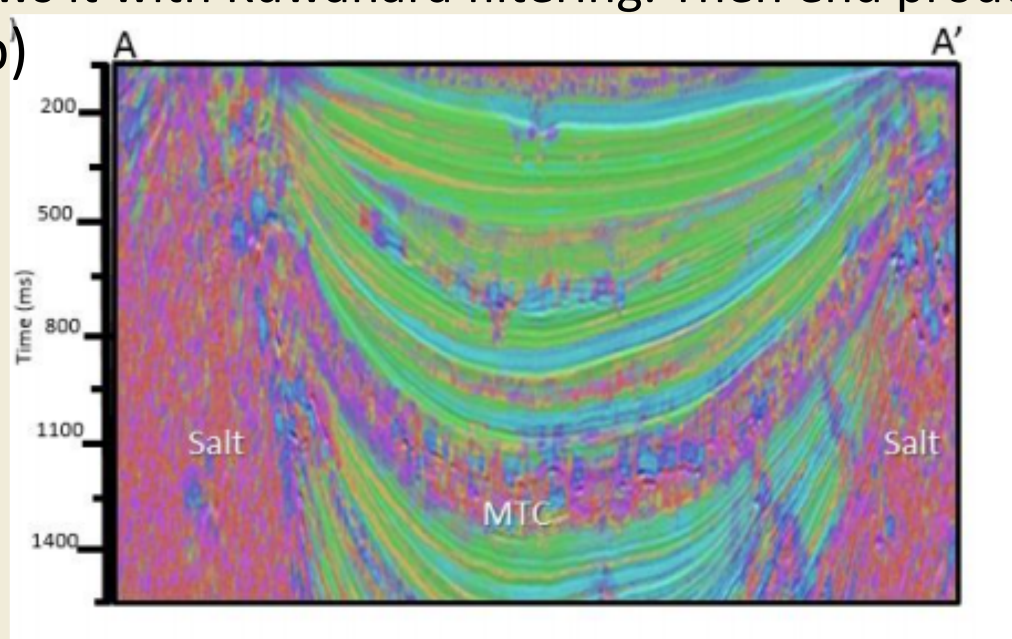

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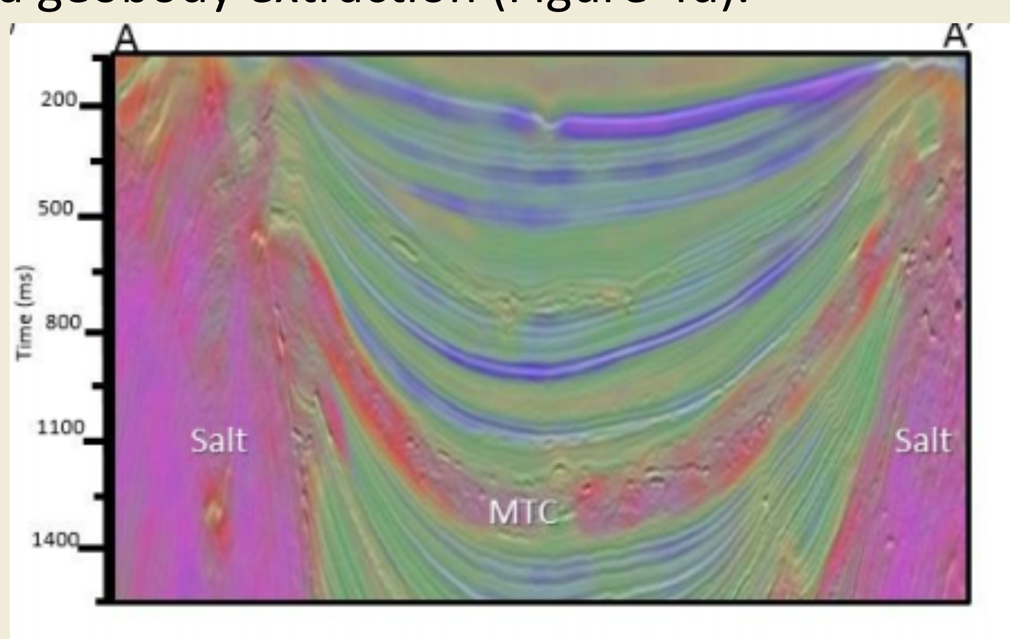


(d)

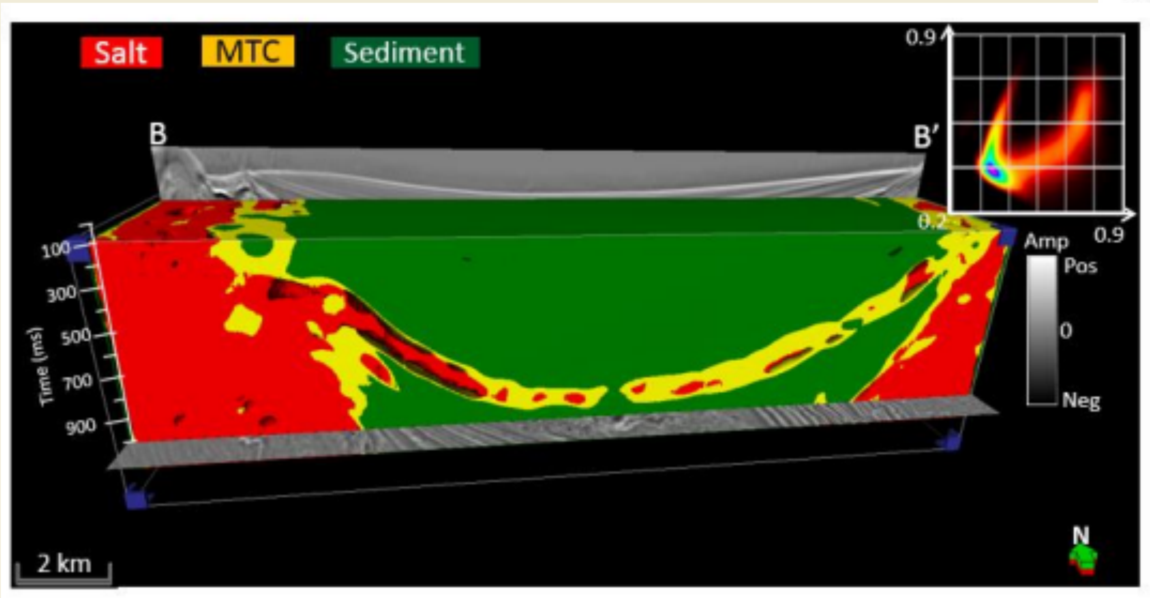
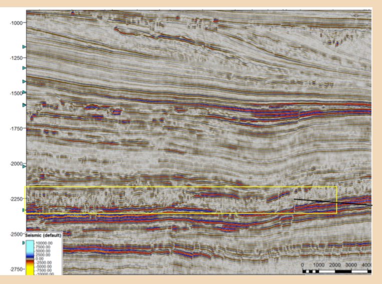
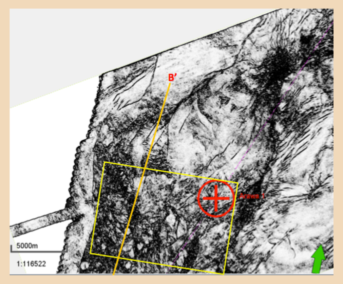
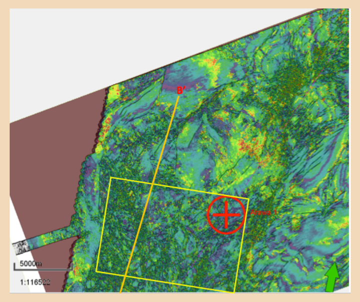
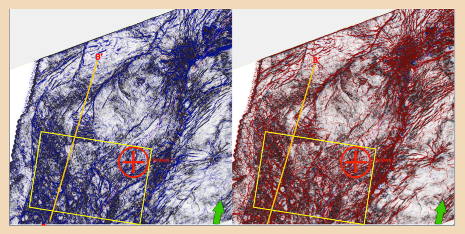
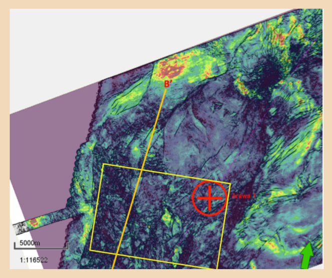
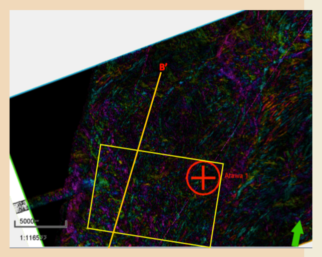


Figure 4: Vertical slices from a Gulf of Mexico survey through (a) seismic amplitude, and GTM classification (b) before and (c) after Kuwahara filtering. (d) The final facies classification volume. (After Qi et al., 2016).

Attribute Menagerie

Geologic Facies	Visual Expression		Attribute Expression					
	Internal Reflection	External Forms	Amplitude	Coherence	Similarity Variance Co-render with Homogeneity	Most positive and negative curvature	Similarity Variance Co-render with Entropy	K convergence modulated by K convergence Magnitude
Sea Floor Valley Teranaki Basin Infante et al 2017	Parallel reflectors with some chaotic features	Pinchout along edges of reflectors as well as structural lows from V-shape valleys						

Digging the Hole for the Decision Tree

Some seismic facies are easy, while others are more difficult to analyze using a computer. The easiest facies are those that exhibit a distinguishing voxel-by-voxel expression that differs from their neighboring facies. For example, a karst collapse may exhibit lower peak frequency, greater entropy, more negative curvature, and lower coherence than the limestone facies within which it occurs. Mass transport complexes are somewhat more difficult, but by increasing the spatial scale (smoothing and blocking) using Kuwahara filtering, it will appear to be less conformal, higher entropy and less coherent than the surrounding sediments, but higher amplitude and more coherent than the neighboring salt. Faults often exhibit low coherence, high aberrancy, high amplitude curvature, and higher entropy than their neighboring unfaulted facies. More difficult facies such as channels and progradations need to be put into a sequence stratigraphic framework and often exhibit multiple, spatially separated "architectural elements" each of which has its own attribute expression (onlap, offlap, downlap, high dip,…) but form part of larger unit.

References

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