Quantifying the Uncertainty of Elastic Facies Classification*

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Abstract

In order to relate known facies to seismic data, we must first determine how those facies map in an elastic parameter domain. Elastic parameters are based on properties that control how elastic waves propagate in the subsurface. While the three basic properties are P and S velocity and density, there are others such as Vp/Vs, Lambda, Mu, Poisson's Ratio, P and S Impedance, that can be derived from the three fundamental properties. It is important to determine what facies can be distinguished in a given two-dimensional, elastic domain. It is equally important to quantify how certain or uncertain the facies can be mapped in this domain. Surprisingly this is often not done, or if it is done, it is not done in a consistent manner. There are several ways to measure "accuracy". For instance, you can measure what percentage of a certain facies falls within the elastic region that maps to that facies. Another criteria would be to measure how many of the points within a certain region actually belong to the facies associated with that region. It is also important to consider the overall proportions of each facies. Mathematicians try to represent this uncertainty using a "confusion matrix". A confusion matrix is simply a square matrix of numbers showing how the "true" facies map to elastic facies. The problem with the confusion matrix is that it is non-graphical and frankly, confusing. We have developed a facies mapping tool which includes a display with shows the various types of uncertainties in an intuitive, graphical way. Capturing this uncertainty can be done at both log resolution and at seismic resolution. This should be an important part of any feasibility study where seismic is being proposed as a method to determine facies.

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BAHRAIN INTERNATIONAL EXHIBITION & CONVENTION CENTRE

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Kuwait Oil Company

شركة نفط الكويت
Kuwait Oil Company
إحدى شركات مؤسسة البترول الكويتية
A Subsidiary of Kuwait Petroleum Corporation

Outline

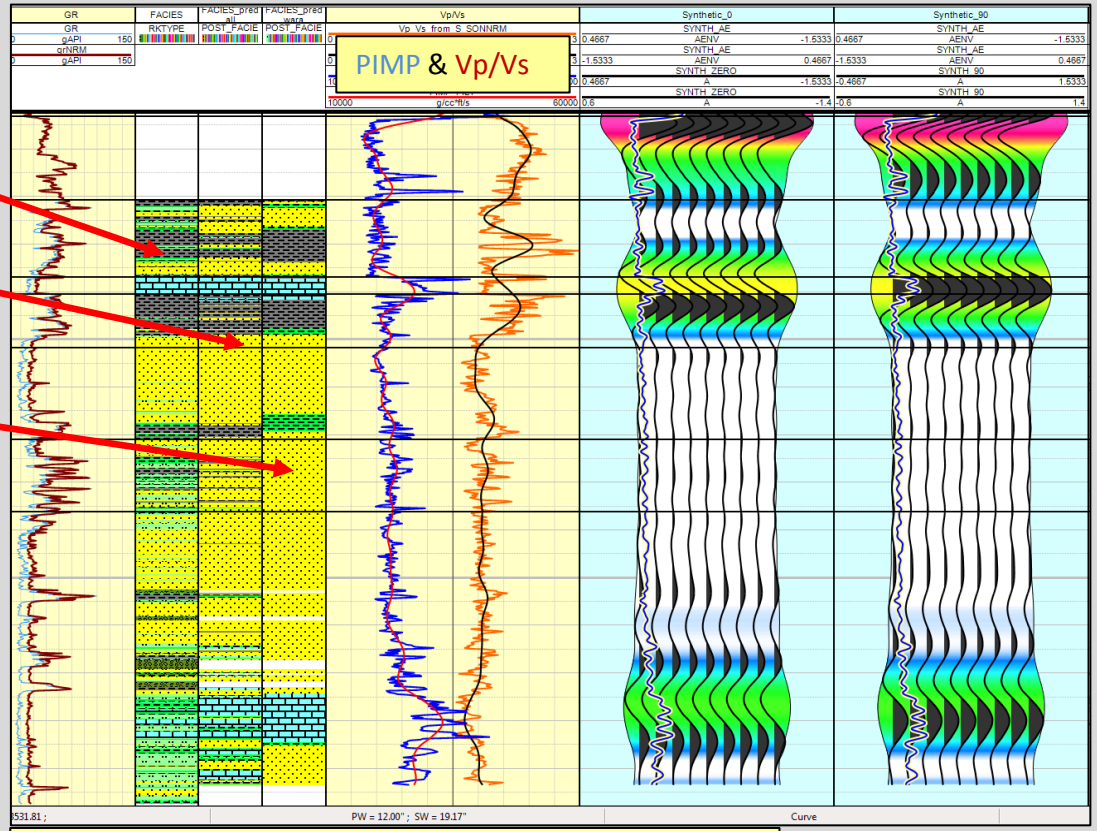
- What is “Elastic Facies Classification?”
- How can we measure the accuracy of a classification scenario?
  - Probability of Assignment
  - Accuracy of Assignment
  - Democratic Accuracy of Assignment
  - Input and Output Histograms
- What is a “confusion matrix”, and can we make it less confusing?
- What about limited seismic bandwidth?
- Summary and Conclusions
- Interactive Facies Classification (bonus if time allows)

What is Elastic Facies Classification

Original Facies or Rock Type

Predicted Rock Class from PIMP,Vp/Vs

Predicted Rock Class from PIMP,Vp/Vs(60hz)



PIMP = P-Impedance = Acoustic Impedance = Vp*Density
Vp/Vs = Compressional Velocity (Vp) / Shear Velocity (Vs)

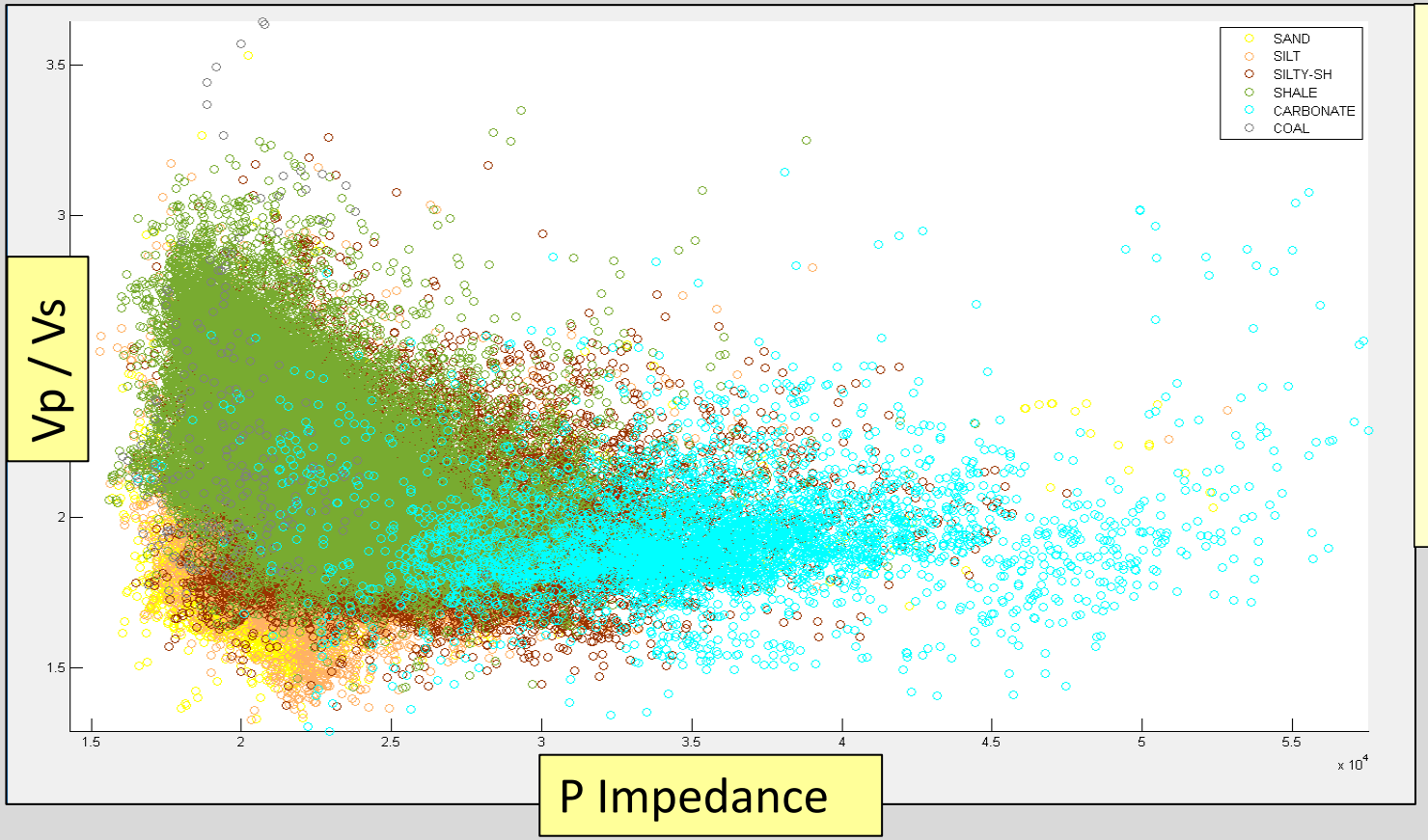
The goal is to predict "true" rock types by using only properties that seismic may be able to measure. We predict rock types by building regions in two dimensional space that will provide an "optimal" estimate of what the true rock type is by grouping all samples in a given region into a single "rock class".

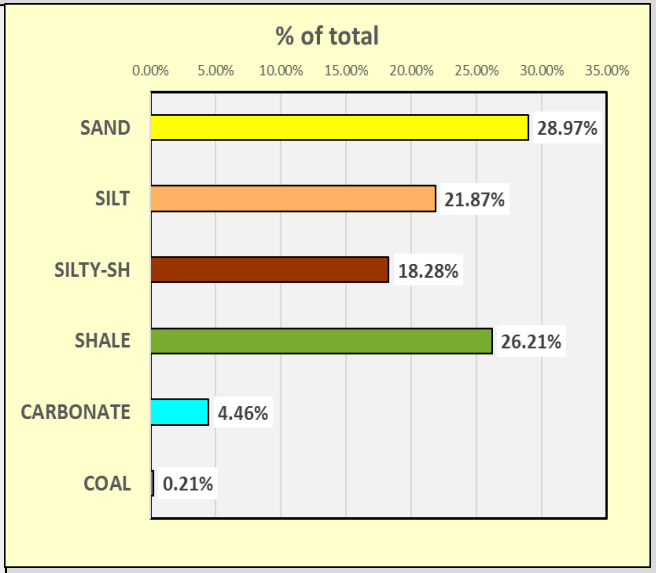
If the rock types do not overlap at all in 2D space, then the rock class will be the same as the rock type.

Supervised Classification

- In this presentation we assume we already know the correct rock type.
- The rock type has already been determined by petrophysical analysis using all available logs.
- How well can we predict rock types, using only “elastic” logs?
- Elastic properties are those that might be extracted from seismic.
- P Velocity, S Velocity and Density and any derivative of these three are elastic properties.
- In this presentation we will use P-Impedance and Vp/Vs ratio.

Input Data From 61 Wells



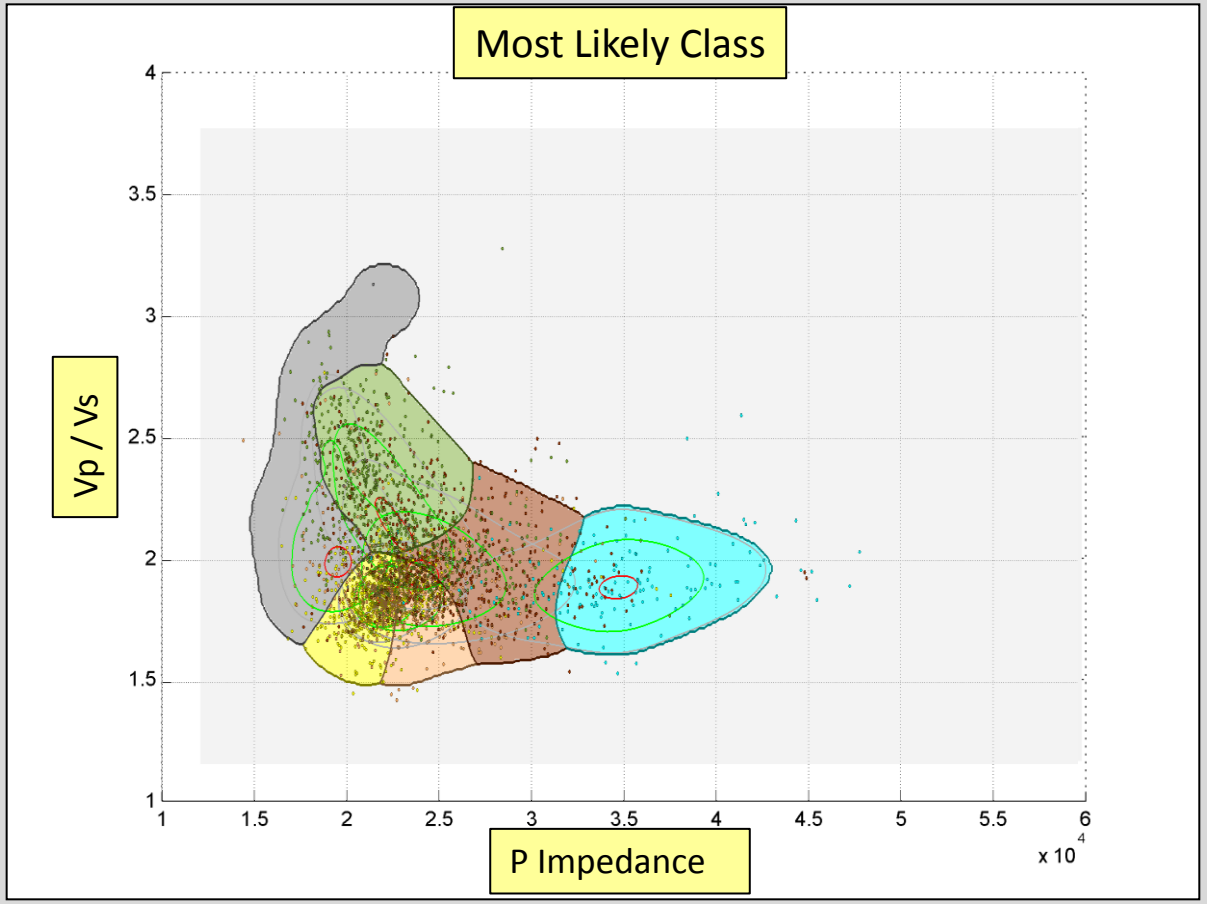


Input Data Classified (decimated 97%)

This data was classified using an Interactive Bayesian Classification technique developed in KOC.

The technique involves adjusting the sizes and shapes of each region until you reach an optimum classification based that will meet your objectives.

How you adjust those regions will depend on what measures of uncertainty are most important to meeting your objectives.



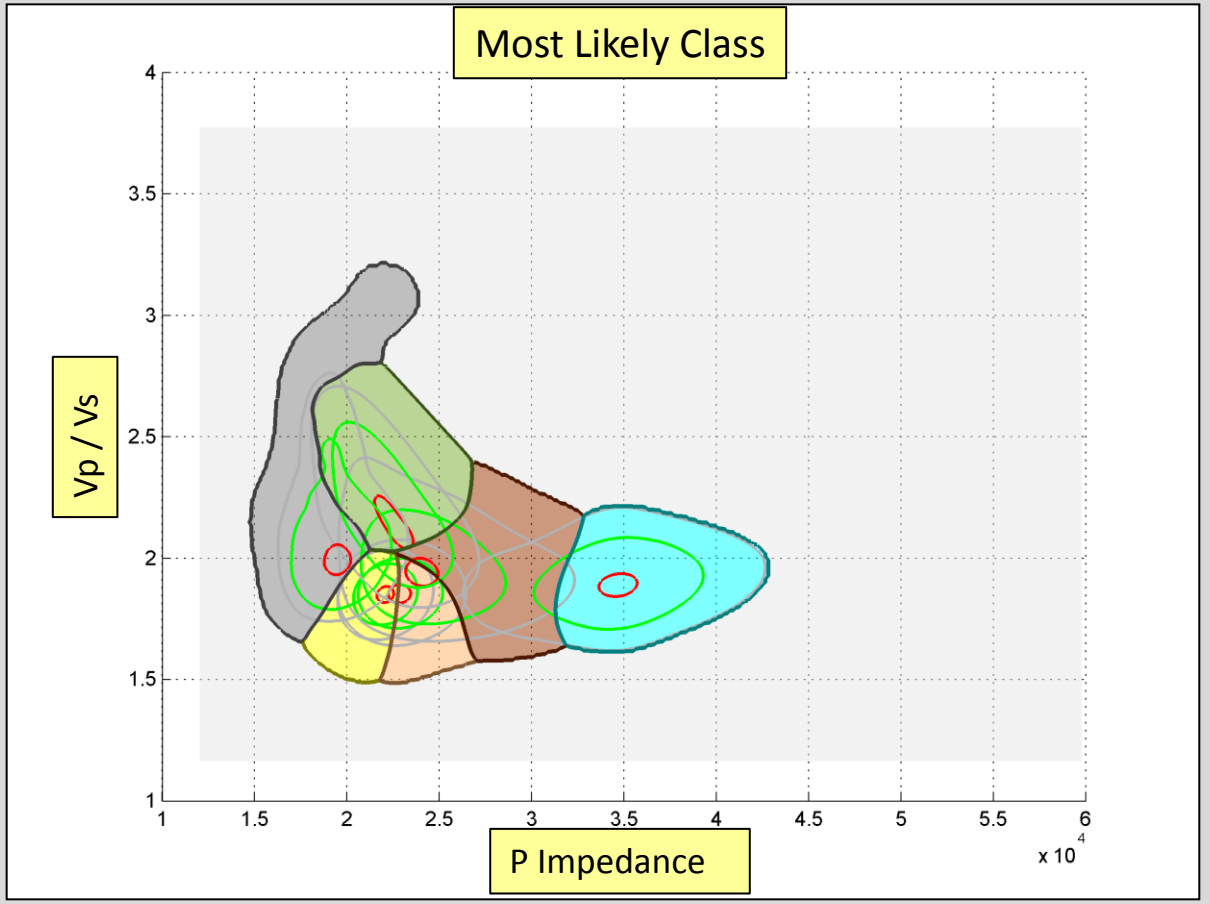
SAND
SILT
SILTY-SH
SHALE
CARBONATE
COAL

Most Likely Class

This data was classified using an Interactive Bayesian Classification technique developed in KOC.

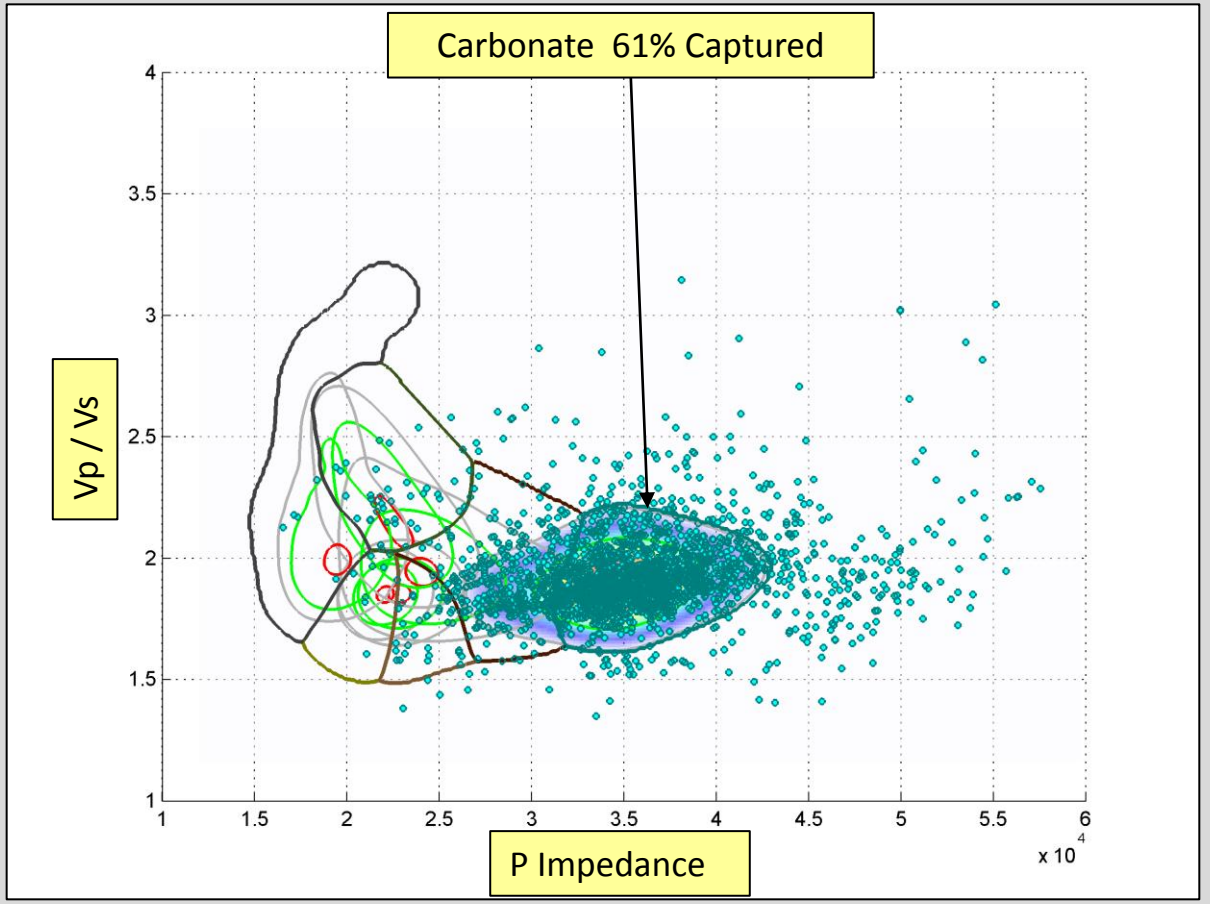
The technique involves adjusting the sizes and shapes of each region until you reach an optimum classification based that will meet your objectives.

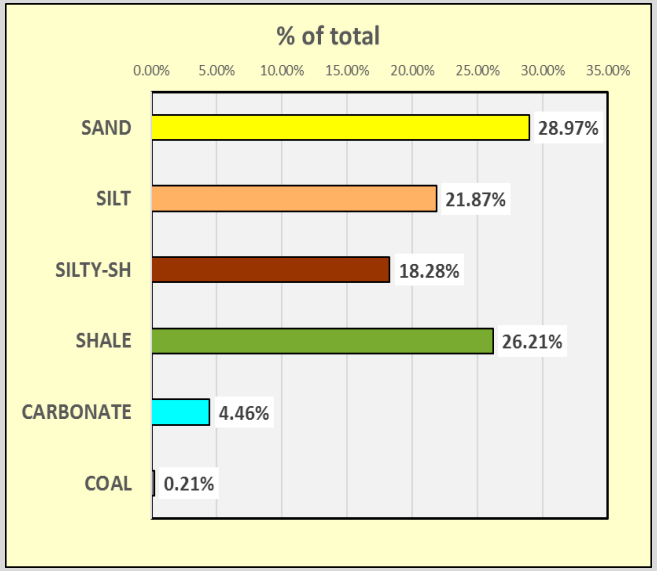
How you adjust those regions will depend on what measures of uncertainty are most important to meeting your objectives.



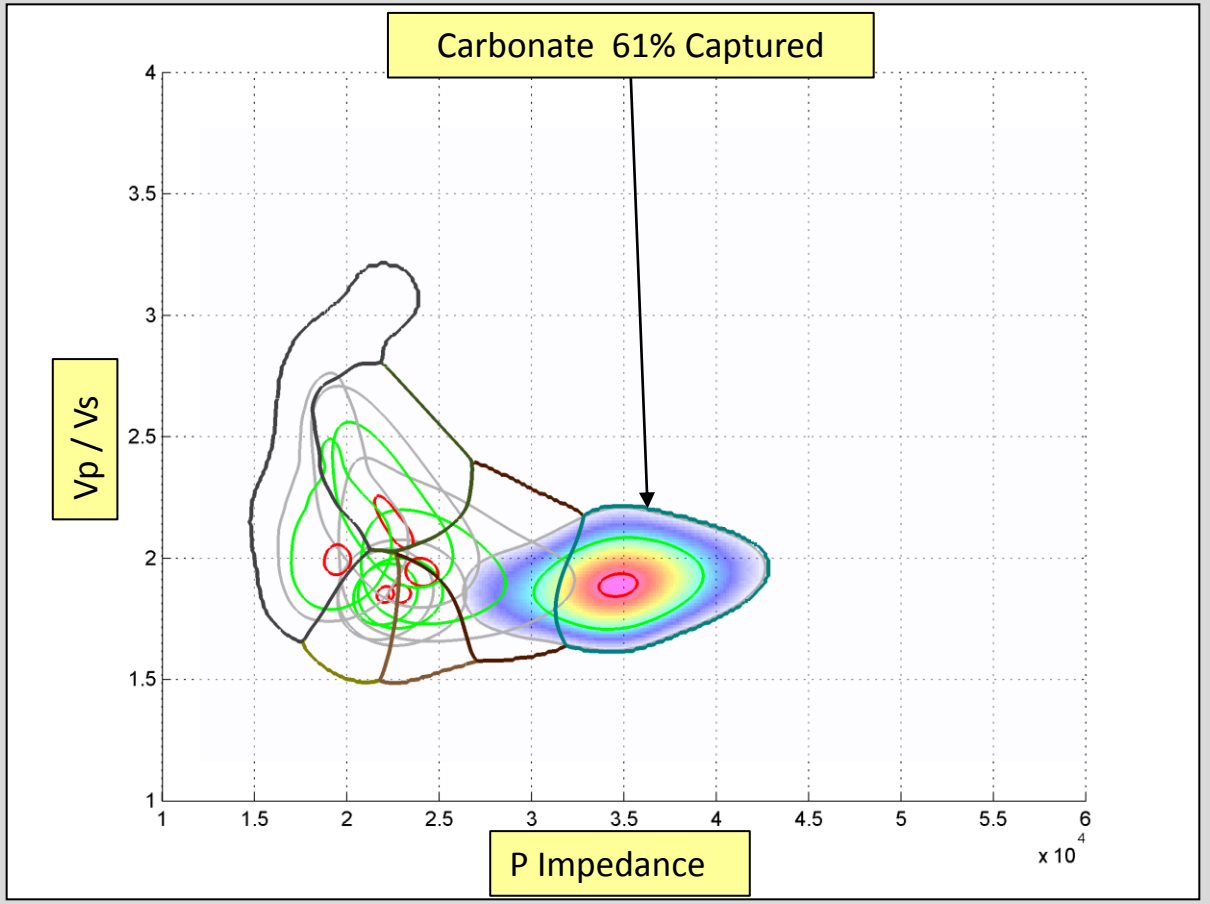
SAND
SILT
SILTY-SH
SHALE
CARBONATE
COAL

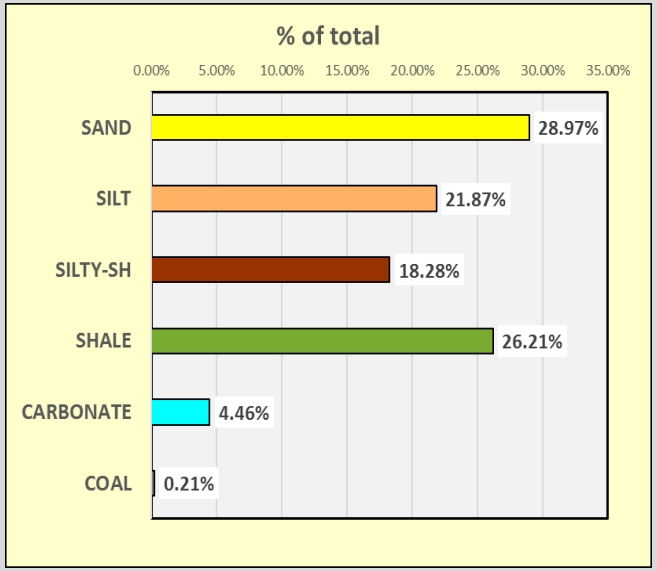
Probability Density Function for Carbonate



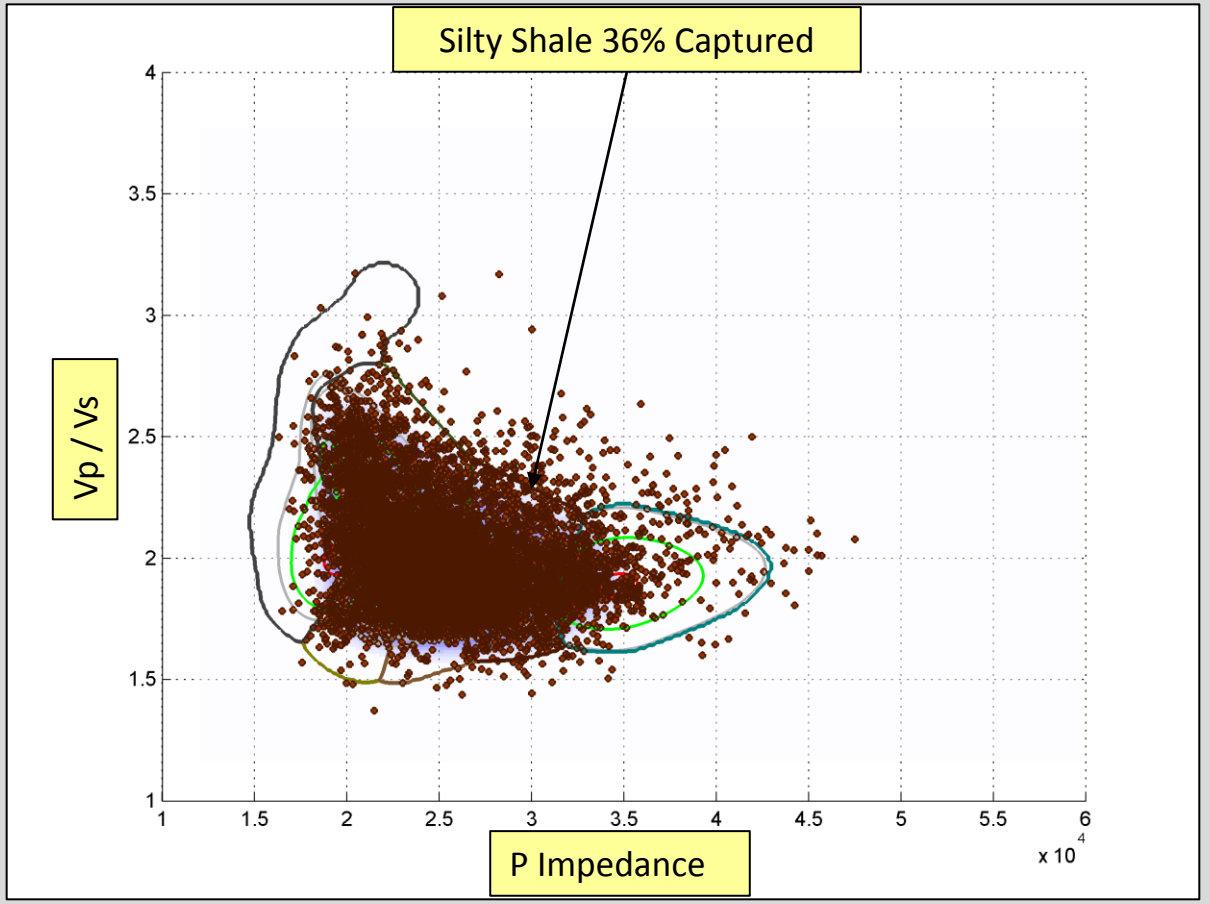


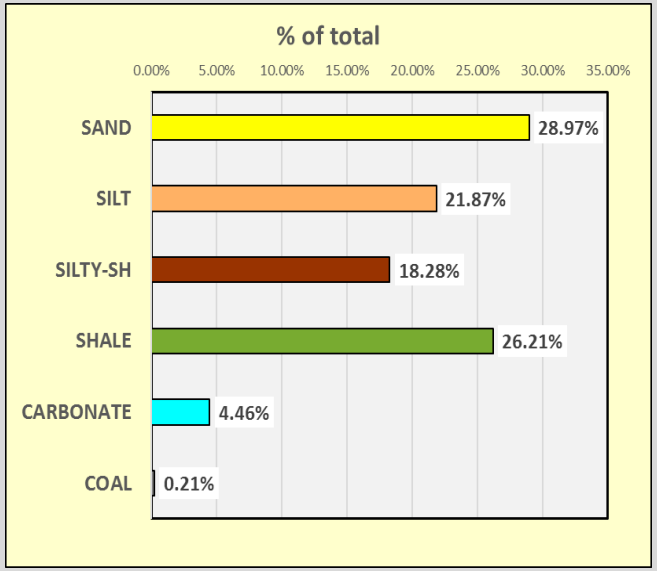
Probability Density Function for Carbonate



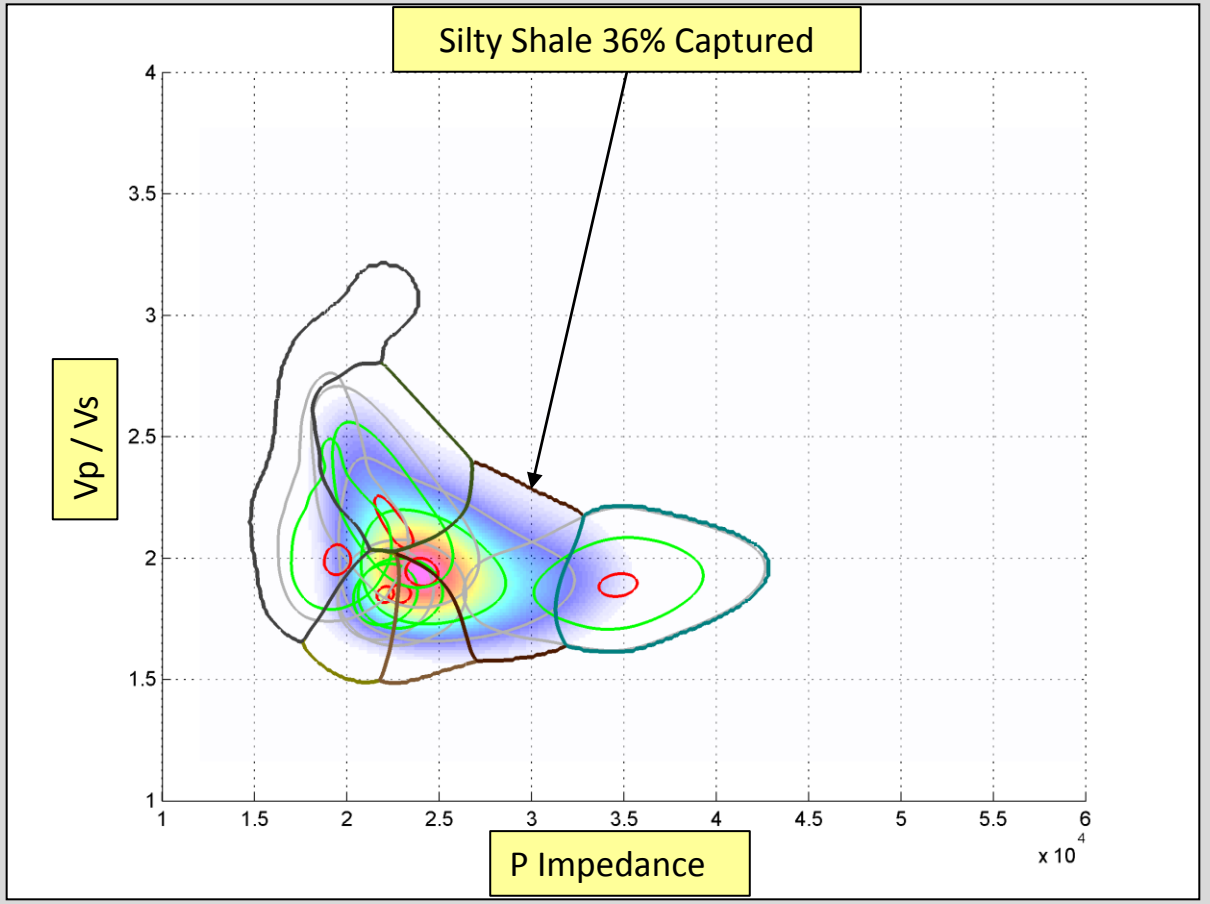


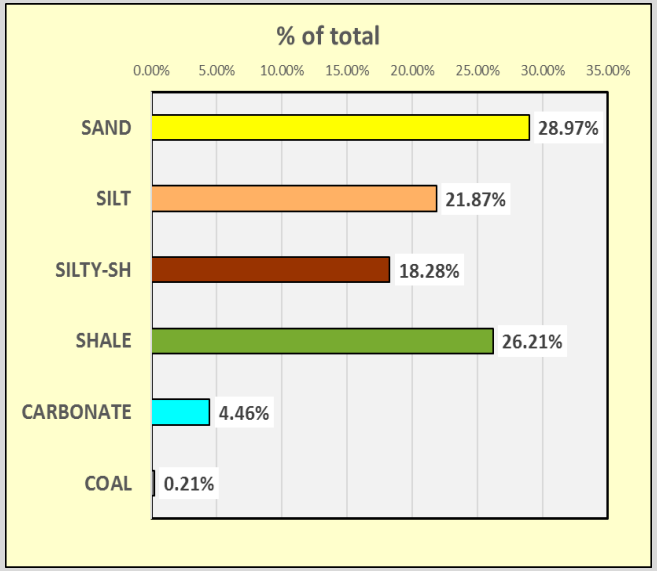
Probability Density Function for Silty Shale



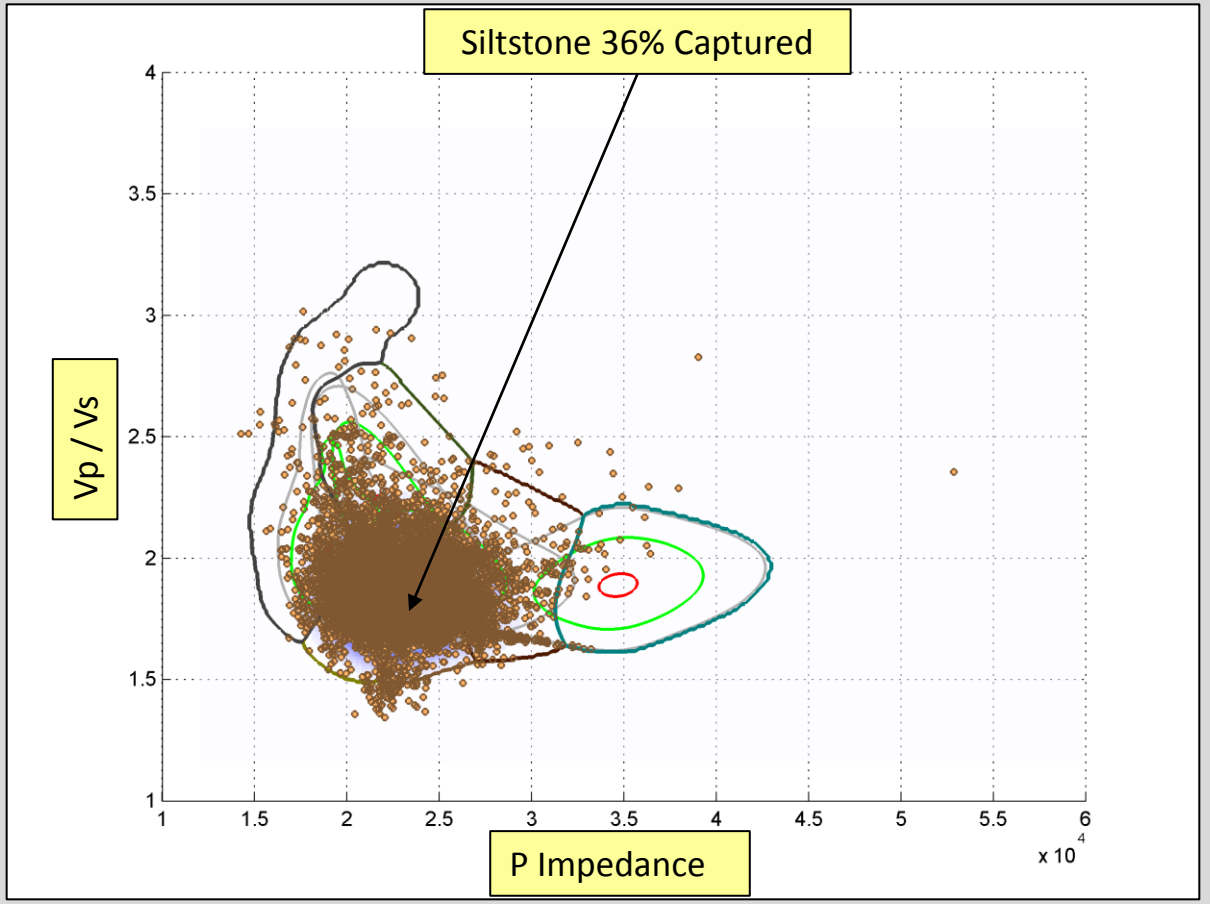


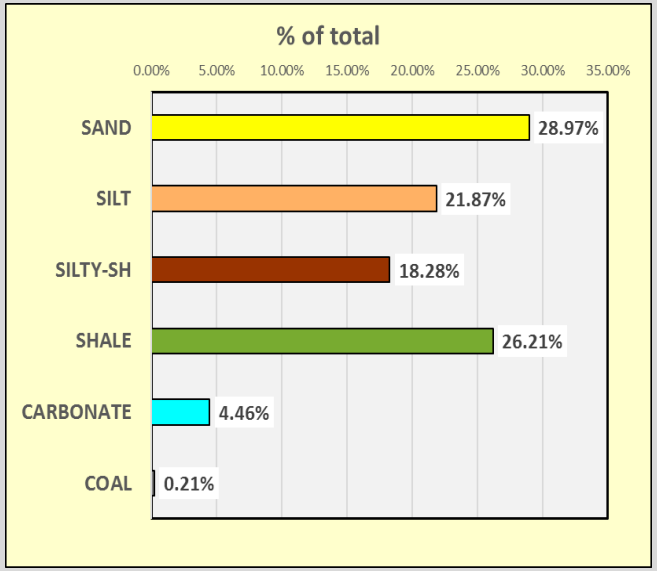
Probability Density Function for Silty Shale



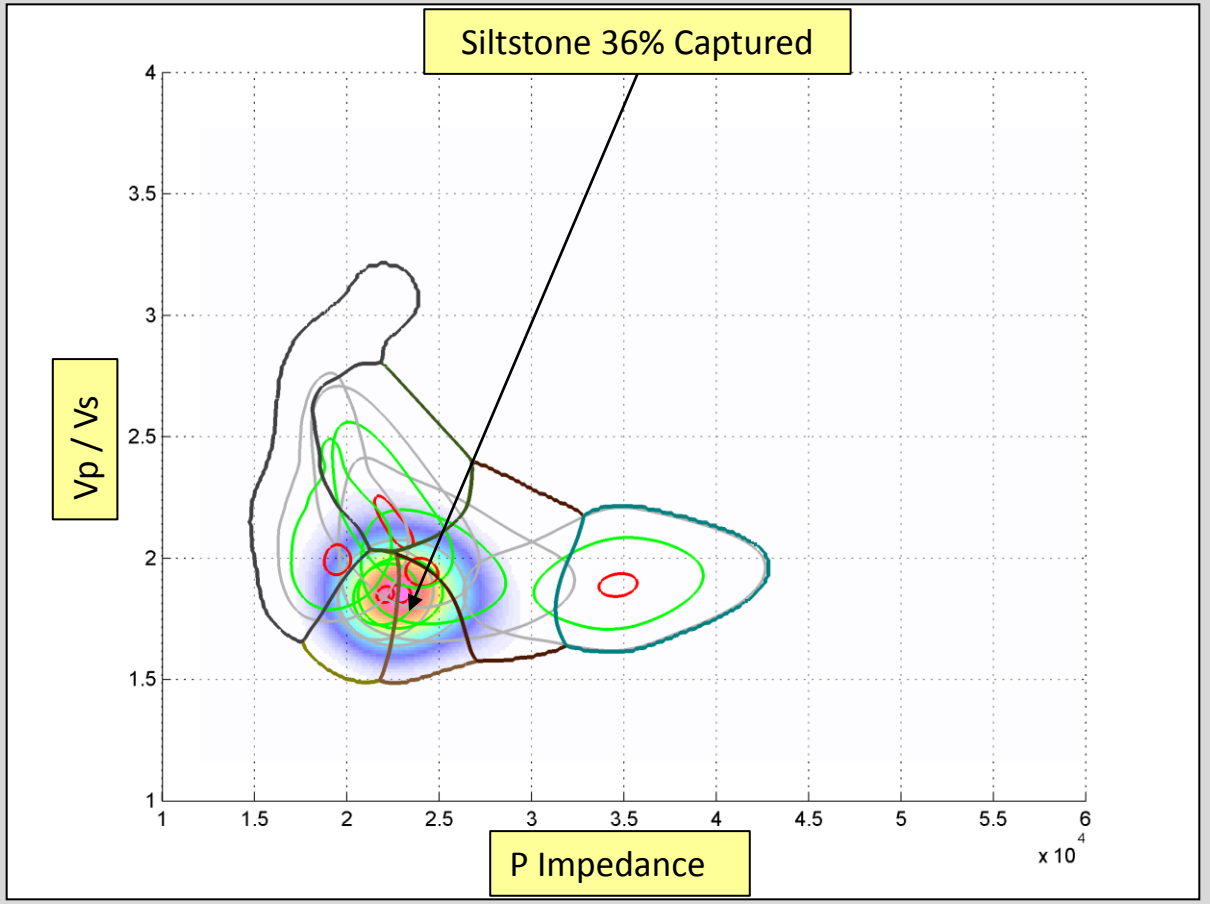


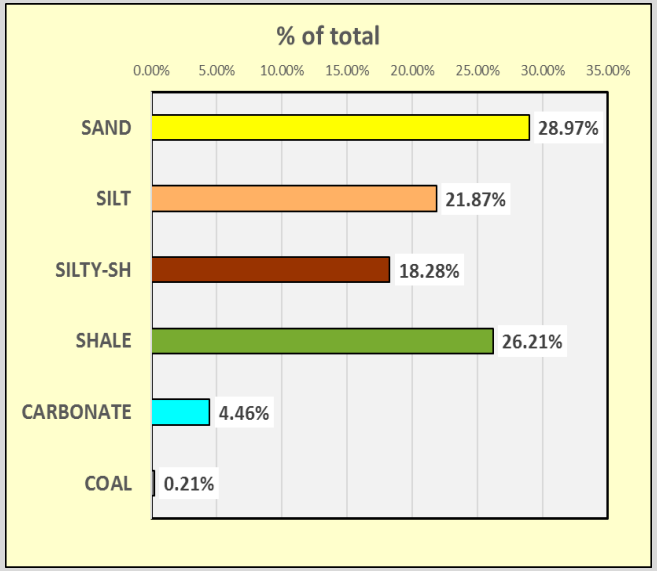
Probability Density Function for Siltstone



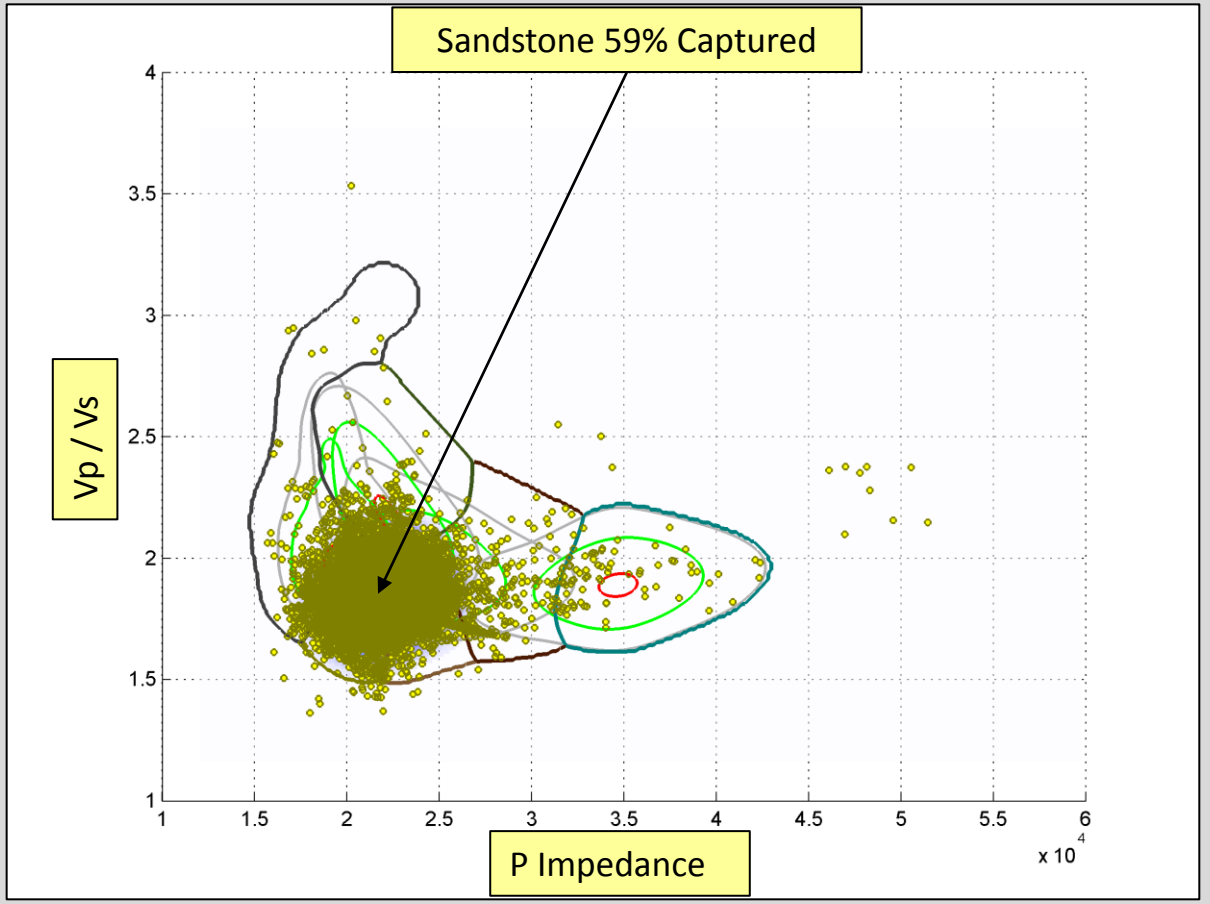


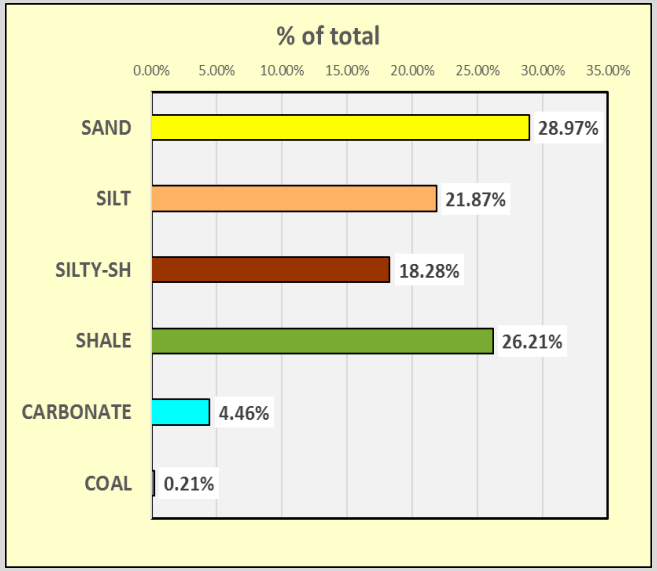
Probability Density Function for Siltstone



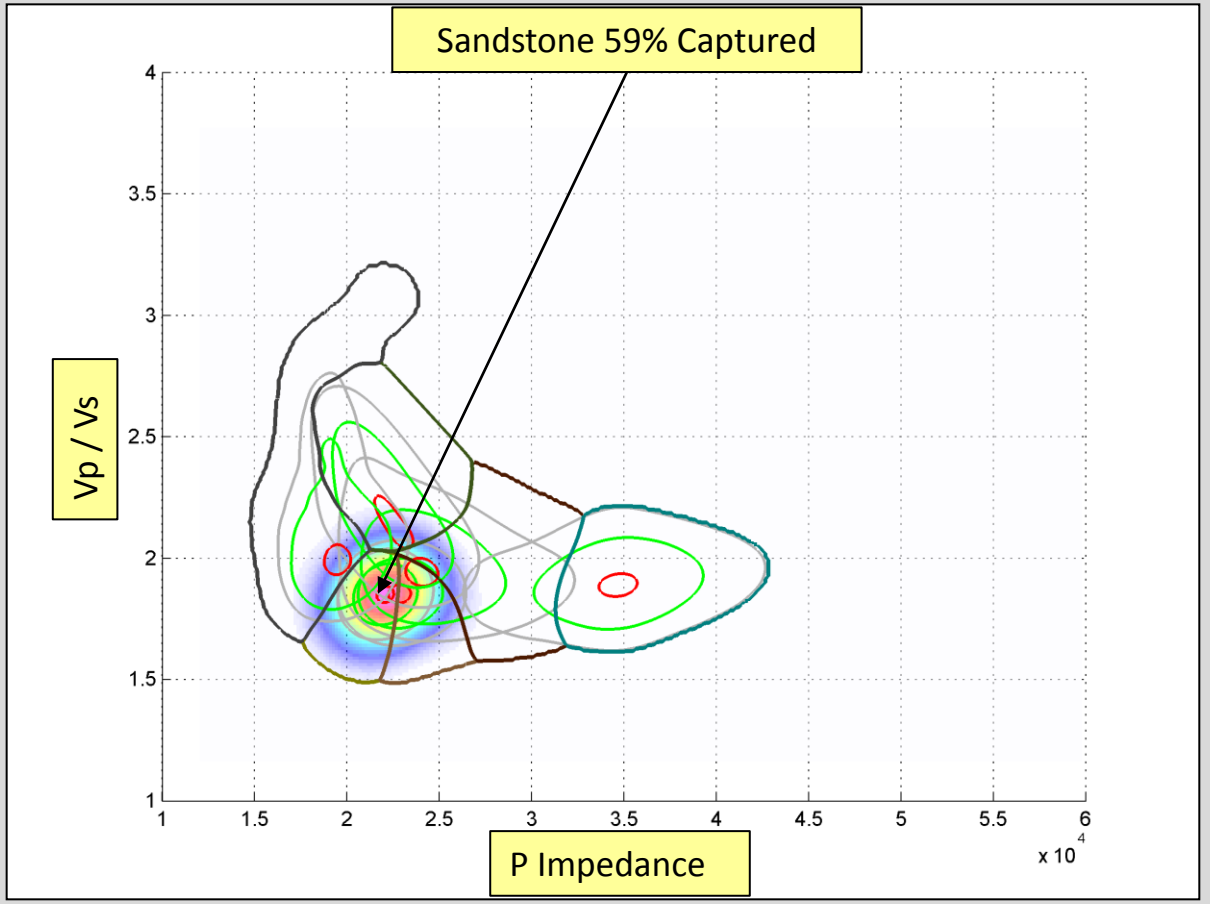


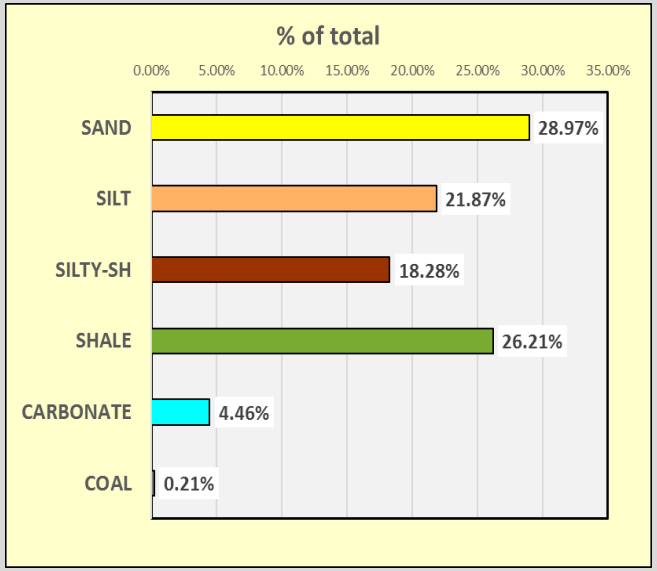
Probability Density Function for Sandstone



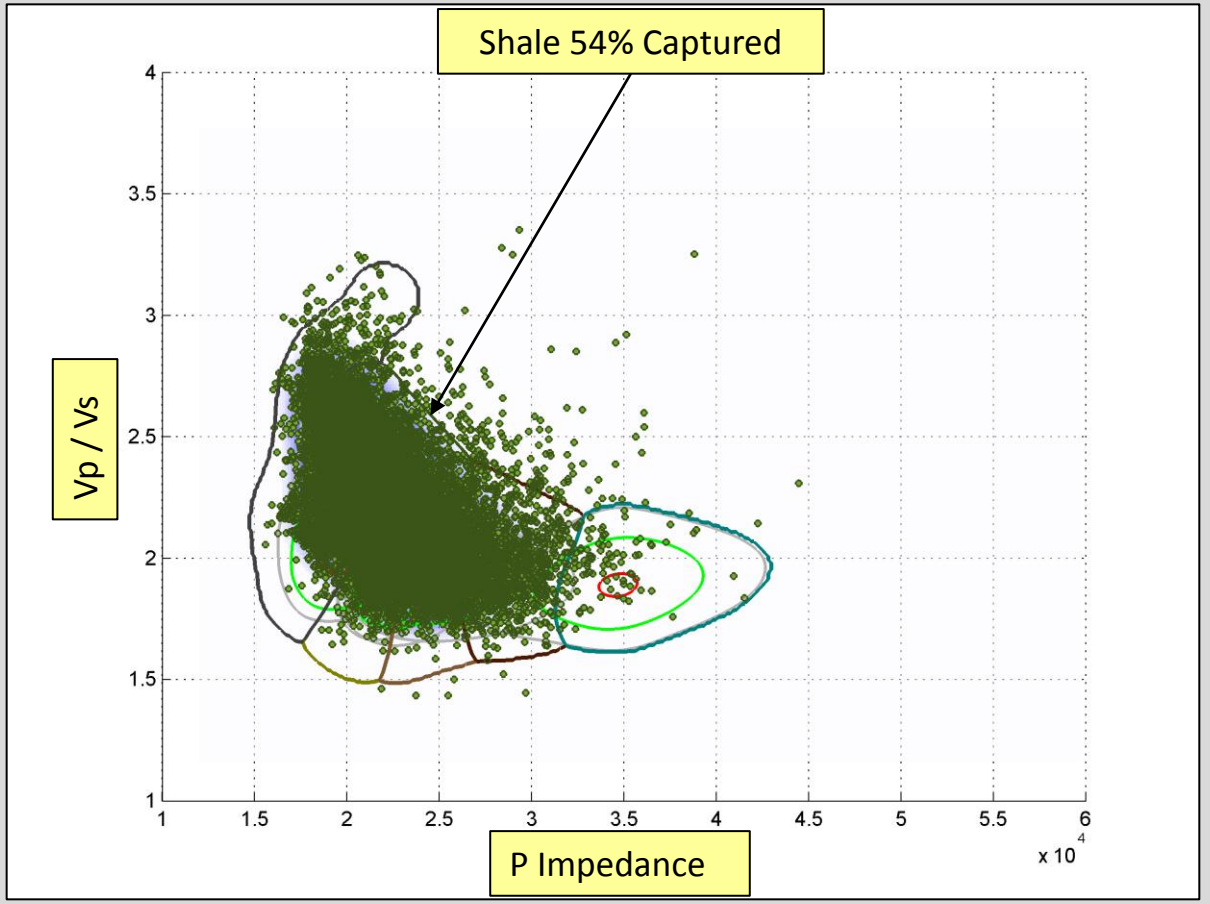


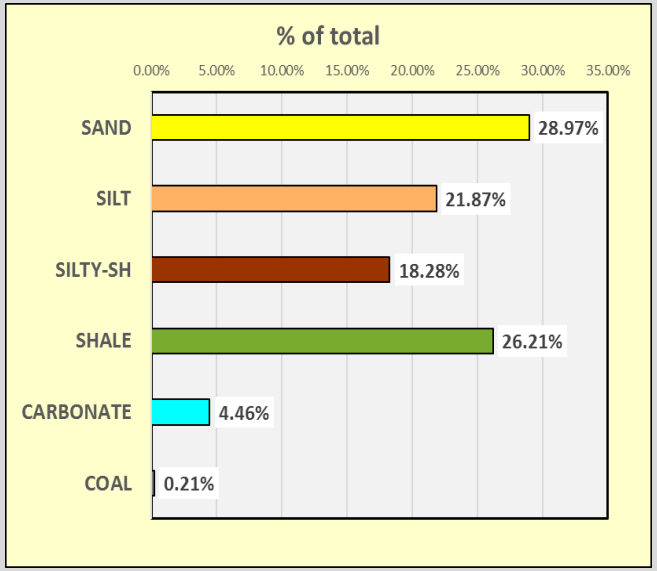
Probability Density Function for Sandstone





Probability Density Function for Shale





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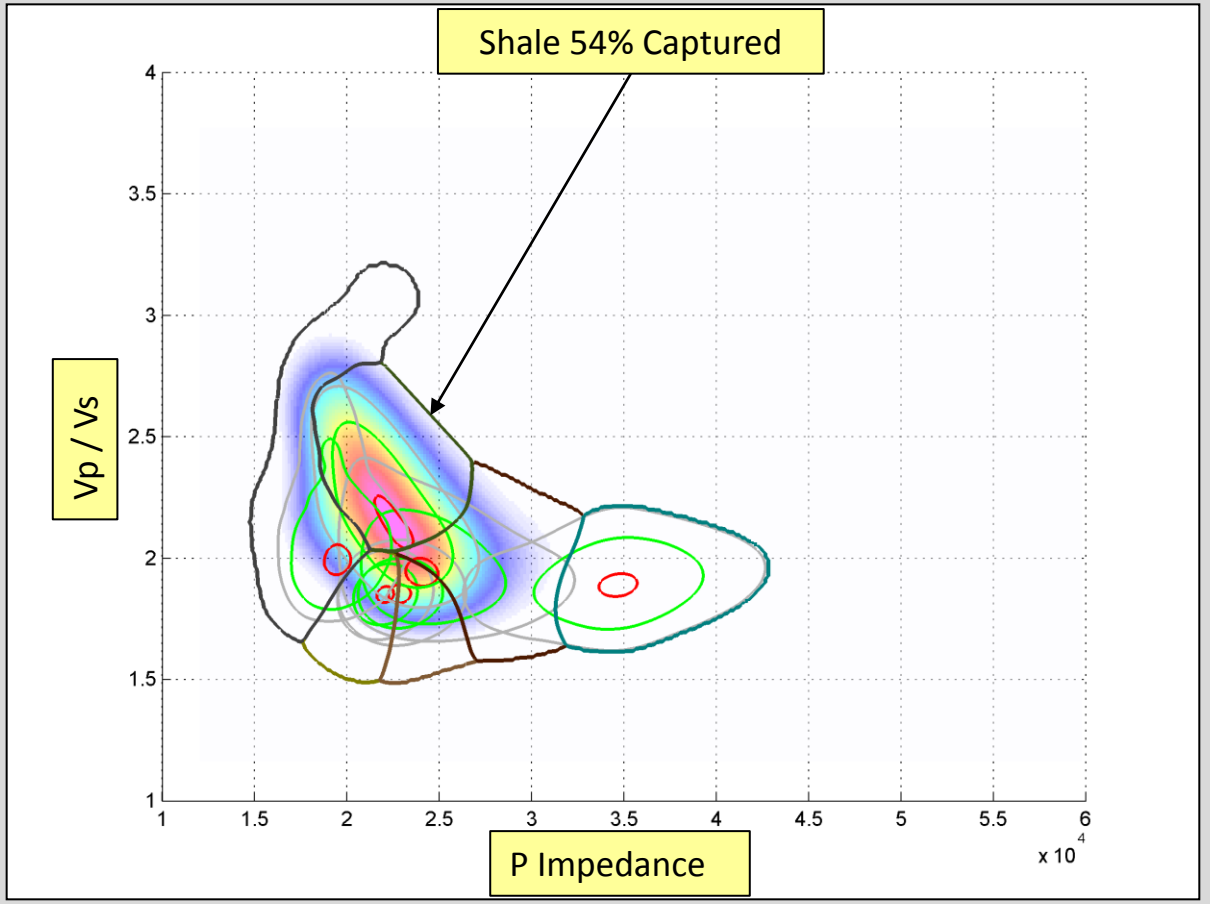
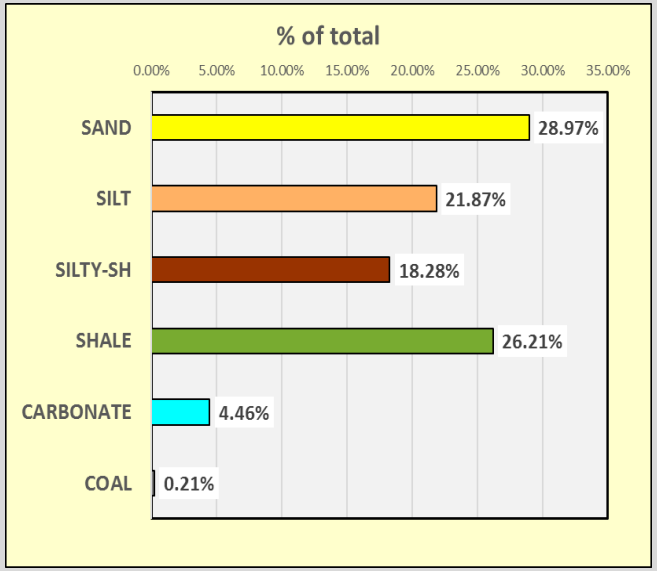
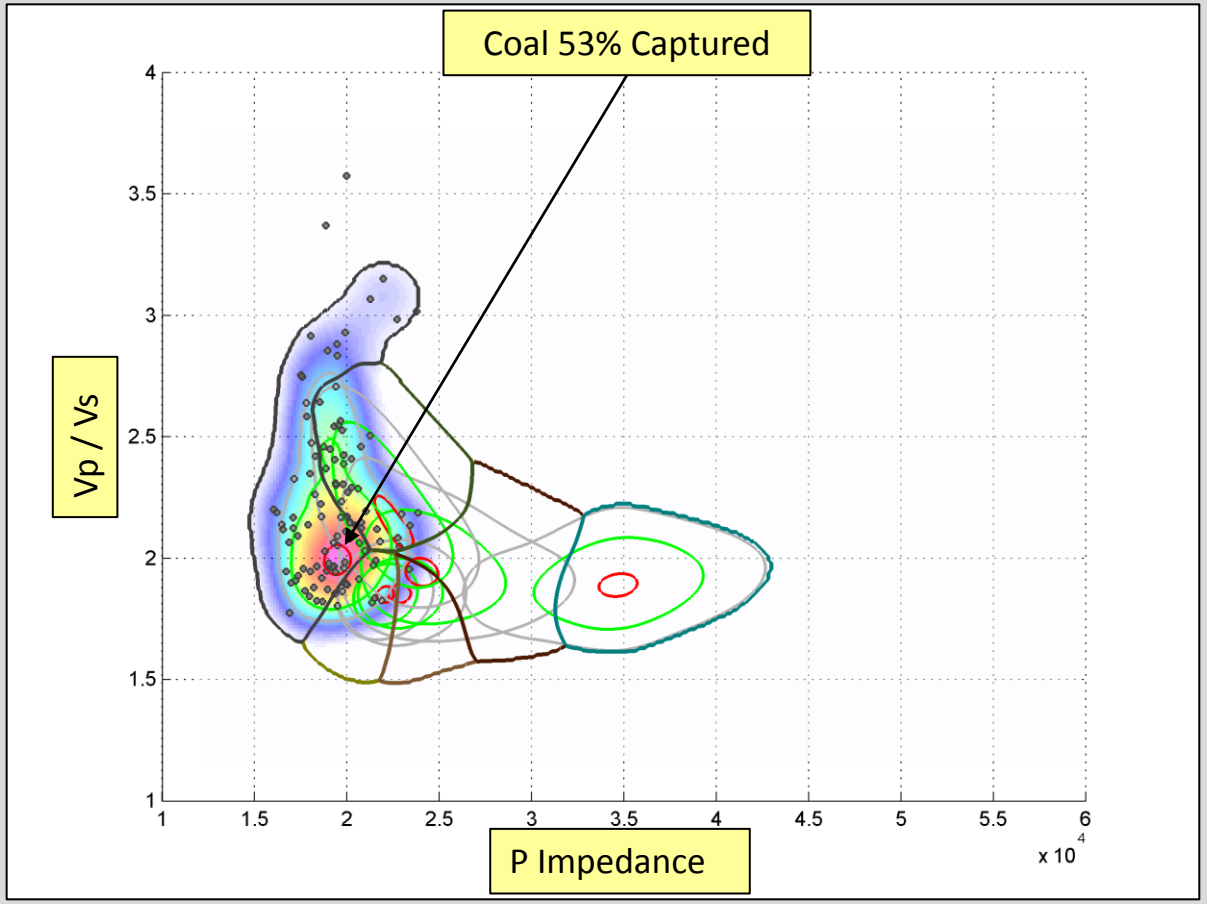
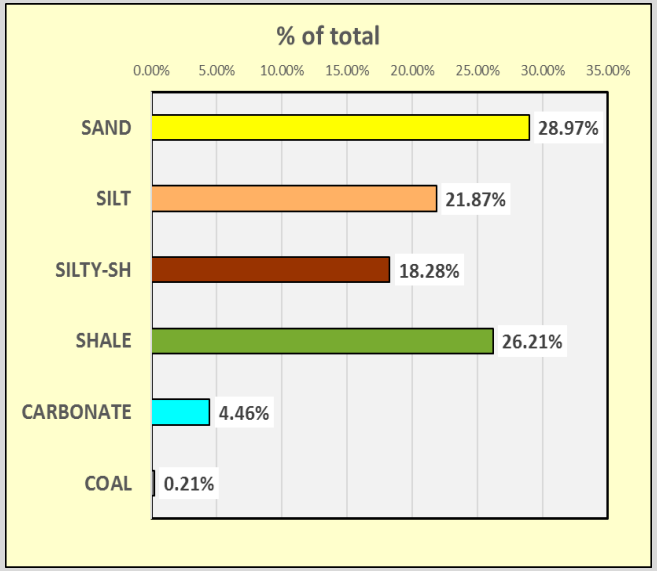




Probability Density Function for Coal





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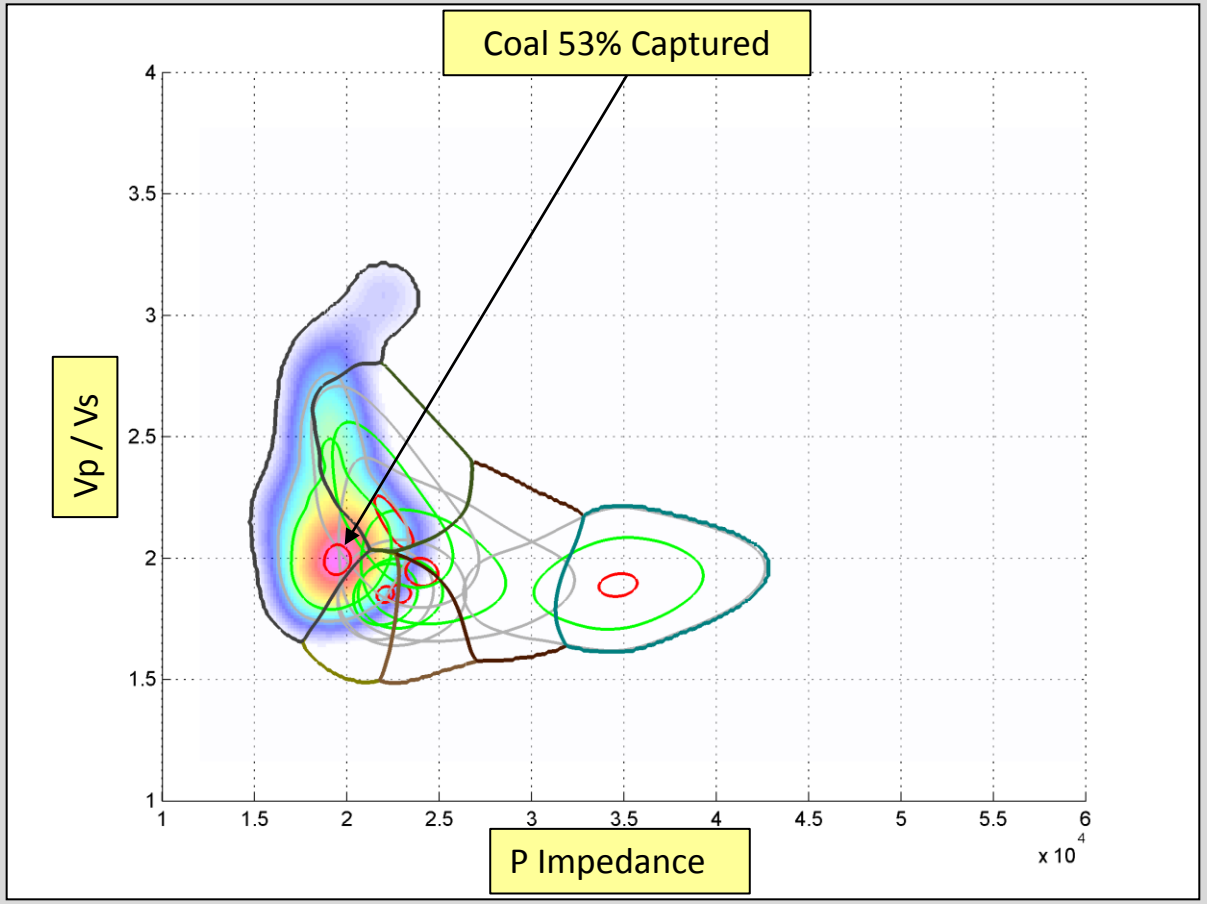

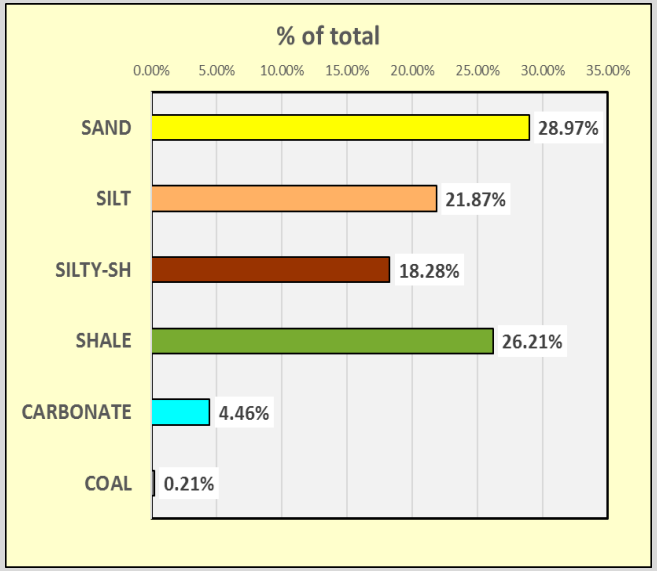

Probability of Assignment

- The percentage of each rock type captured, that we showed in the previous slides, is one measure of how well the classification works.
- We will refer to this as “Probability of Assignment”
- Note that it can be calculated with a single rock type pdf and classified region. It simply shows what percentage of the points are inside the classified region.
- No regard is given to how other rock types may overlap into this region.

The "Confusion Matrix", Probability of Assignment & Accuracy of Assignment

Another measure can be "Accuracy of Assignment", which shows the percentage of points that are predicted correctly.

Newly classified rock type (rock class) is in columns

Rock Class

Rock Type

Original "True" Rock type is in rows

Confusion Matrix

	SAND	SILT	SILTY-SH	SHALE	CARBONATE	COAL	uncl	Sub Total	% of total	Probability of Assignment
SAND	17567	7863	1578	961	140	1559	100	29768	28.97%	59%
SILT	8205	7499	3667	1483	55	1339	227	22475	21.87%	33%
SILTY-SH	2137	3080	6735	4336	1231	742	524	18785	18.28%	36%
SHALE	1682	1995	4915	14445	190	3317	386	26930	26.21%	54%
CARBONATE	17	64	853	73	2791	6	775	4579	4.46%	61%
COAL	26	2	3	63	0	113	8	215	0.21%	53%
	0	0	0	0	0	0	0	0		
Sub Total	29634	20503	17751	21361	4407	7076	2020	102752		
Accuracy of Assignment	59%	37%	38%	68%	63%	2%				

The "Confusion Matrix", Probability of Assignment & Accuracy of Assignment

Another measure can be "Accuracy of Assignment", which shows the percentage of points that are predicted correctly.

For Coal, these are "False Positives"

For Coal these are "False Negatives"

Confusion Matrix

	SAND	SILT	SILTY-SH	SHALE	CARBONATE	COAL	uncl	Sub Total	% of total	Probability of Assignment
SAND	17567	7863	1578	961	140	1559	100	29768	28.97%	59%
SILT	8205	7499	3667	1483	55	1339	227	22475	21.87%	33%
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	0	0	0	0	0	0	0	0		
Sub Total	29634	20503	17751	21361	4407	7076	2020	102752		
Accuracy of Assignment	59%	37%	38%	68%	63%	2%				

The "Confusion Matrix", Probability of Assignment & Accuracy of Assignment

What if we normalized the input percentages to be the same?

Confusion Matrix

	SAND	SILT	SILTY-SH	SHALE	CARBONATE	COAL	uncl	Sub Total	% of total	Probability of Assignment
SAND	17567	7863	1578	961	140	1559	100	29768	28.97%	59%
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	0	0	0	0	0	0	0	0		
Sub Total	29634	20503	17751	21361	4407	7076	2020	102752		
Accuracy of Assignment	59%	37%	38%	68%	63%	2%				

The "Confusion Matrix", Probability of Assignment & Democratic Accuracy of Assignment

We call this "Democratic" because each rock type gets equal weight.

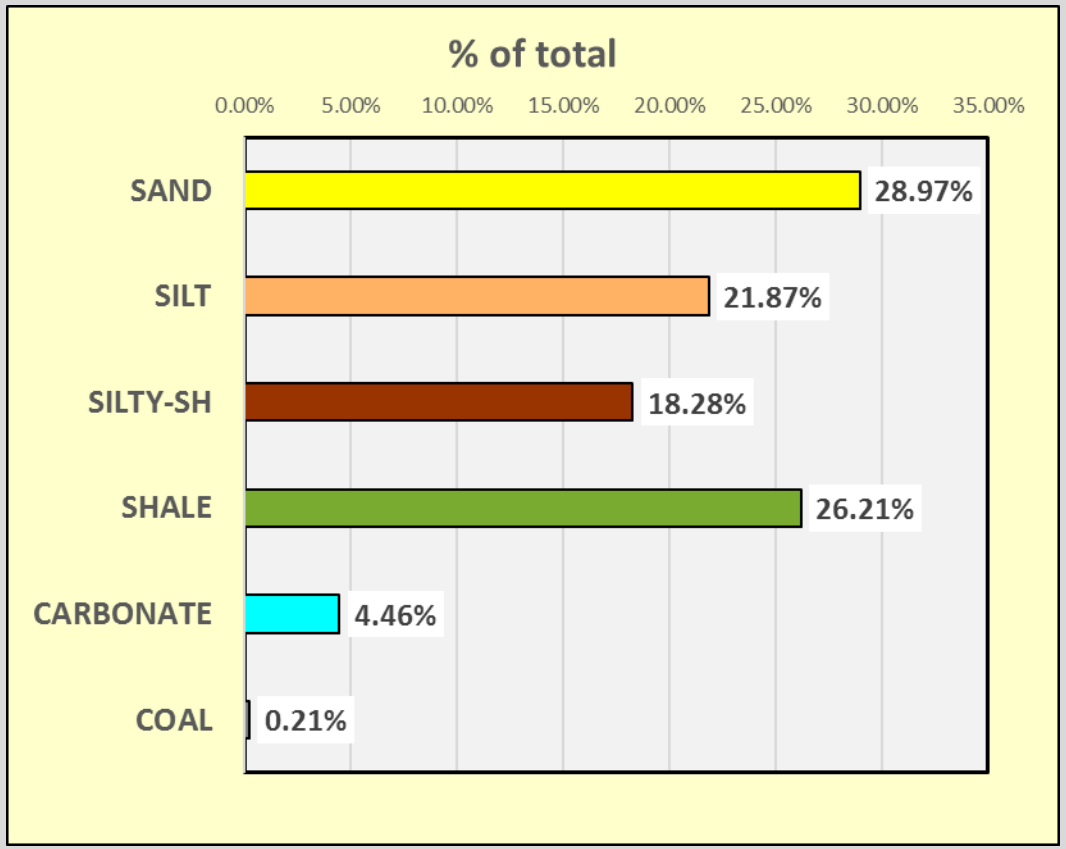
What if we normalized the input percentages to be the same?

Confusion Matrix

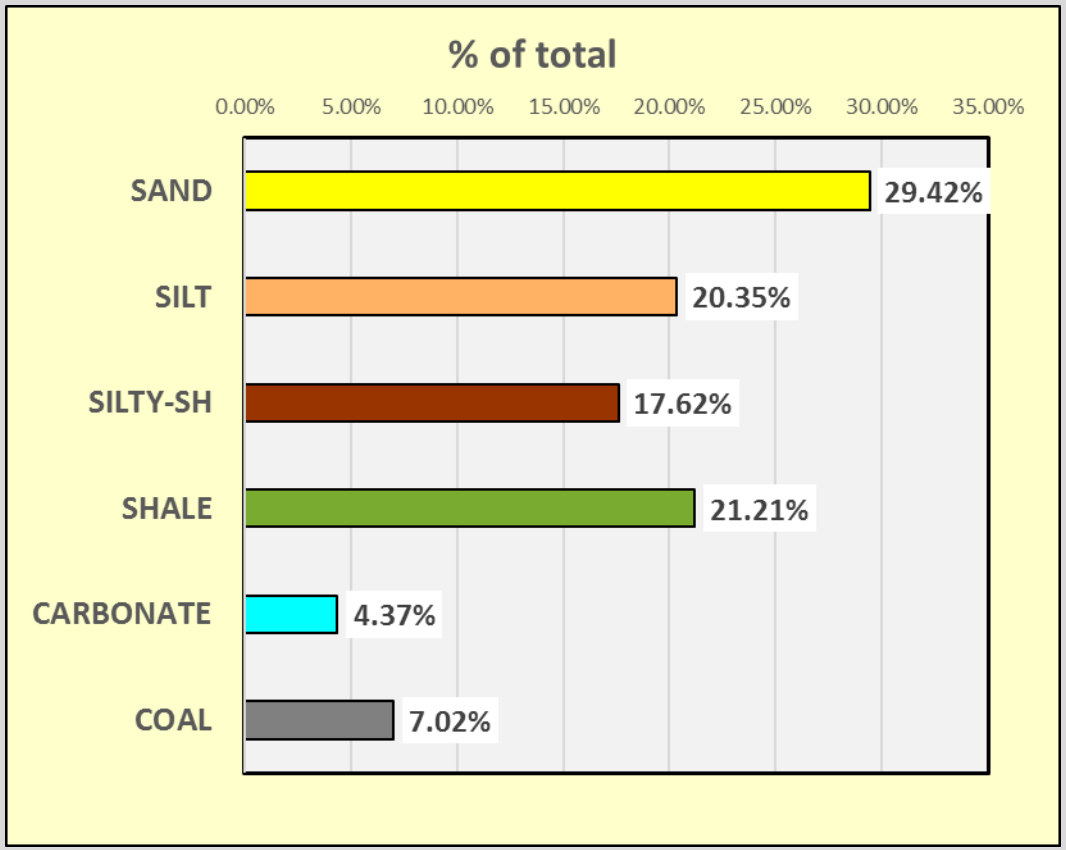
	SAND	SILT	SILTY-SH	SHALE	CARBONATE	COAL	uncl	Sub Total	% of total	Probability of Assignment
SAND	10106	4524	908	553	81	897	58	17125	16.67%	59%
SILT	6252	5714	2794	1130	42	1020	173	17125	16.67%	33%
SILTY-SH	1948	2808	6140	3953	1122	676	478	17125	16.67%	36%
SHALE	1070	1269	3126	9186	121	2109	245	17125	16.67%	54%
CARBONATE	64	239	3190	273	10438	22	2898	17125	16.67%	61%
COAL	2071	159	239	5018	0	9001	637	17125	16.67%	53%
	0	0	0	0	0	0	0	0		
Sub Total	21511	14713	16397	20113	11804	13726	4489	102752		
Accuracy of Assignment	47%	39%	37%	46%	88%	66%				

What About Input and Output Percentages?

Input (Rock Type) Histogram



Output (Rock Class) Histogram

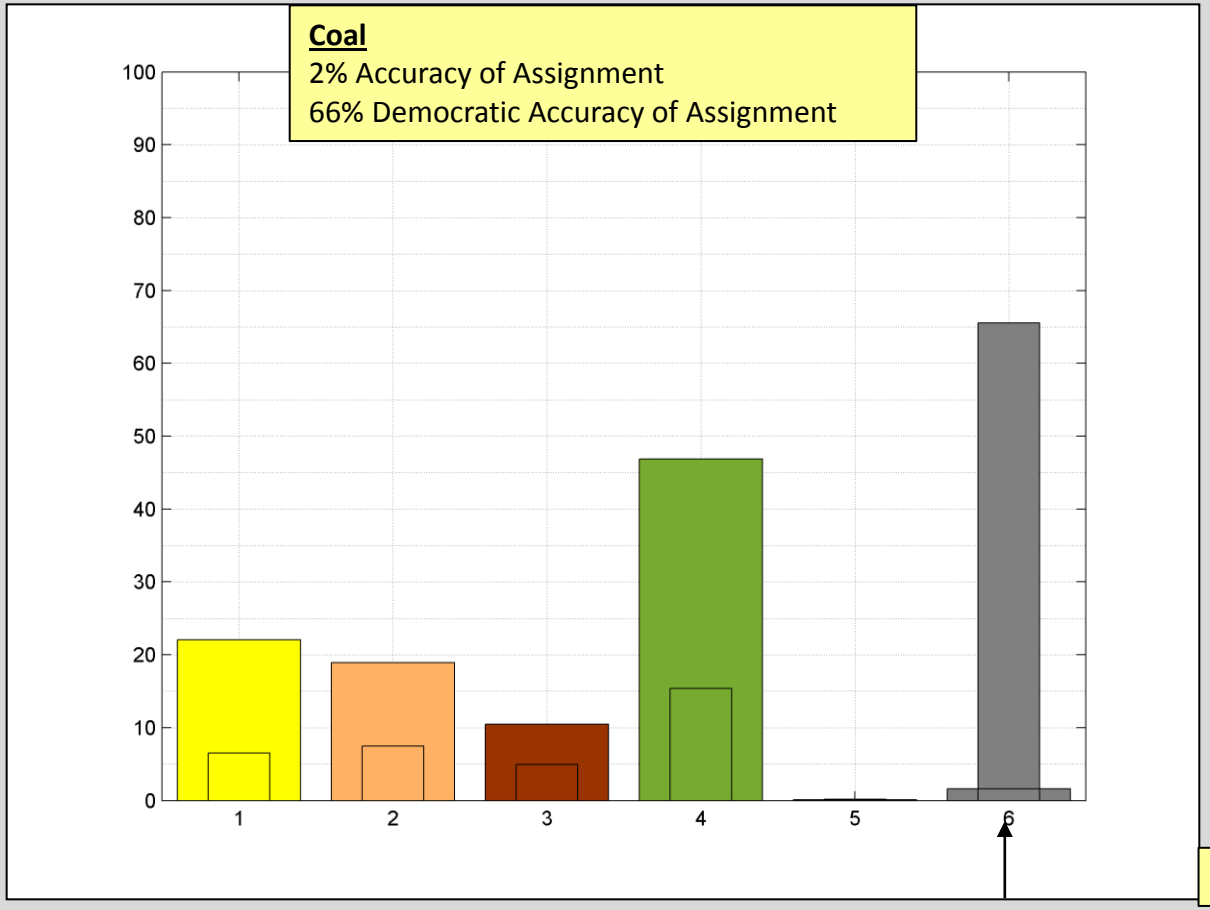


Can we display the confusion matrix graphically?

- Since we have a two dimensional array of numbers that can be normalized by rows or columns, we would have to display histograms for each column and another set of histograms for each row.

Accuracy of Assignment Histogram for Coal Class

The values in each column of the confusion matrix can be shown as a histogram. This shows how much of each rock types end up being classified as coal.



COAL
1559
1339
742
3317
6
113
0
7076
2%

No Normalization

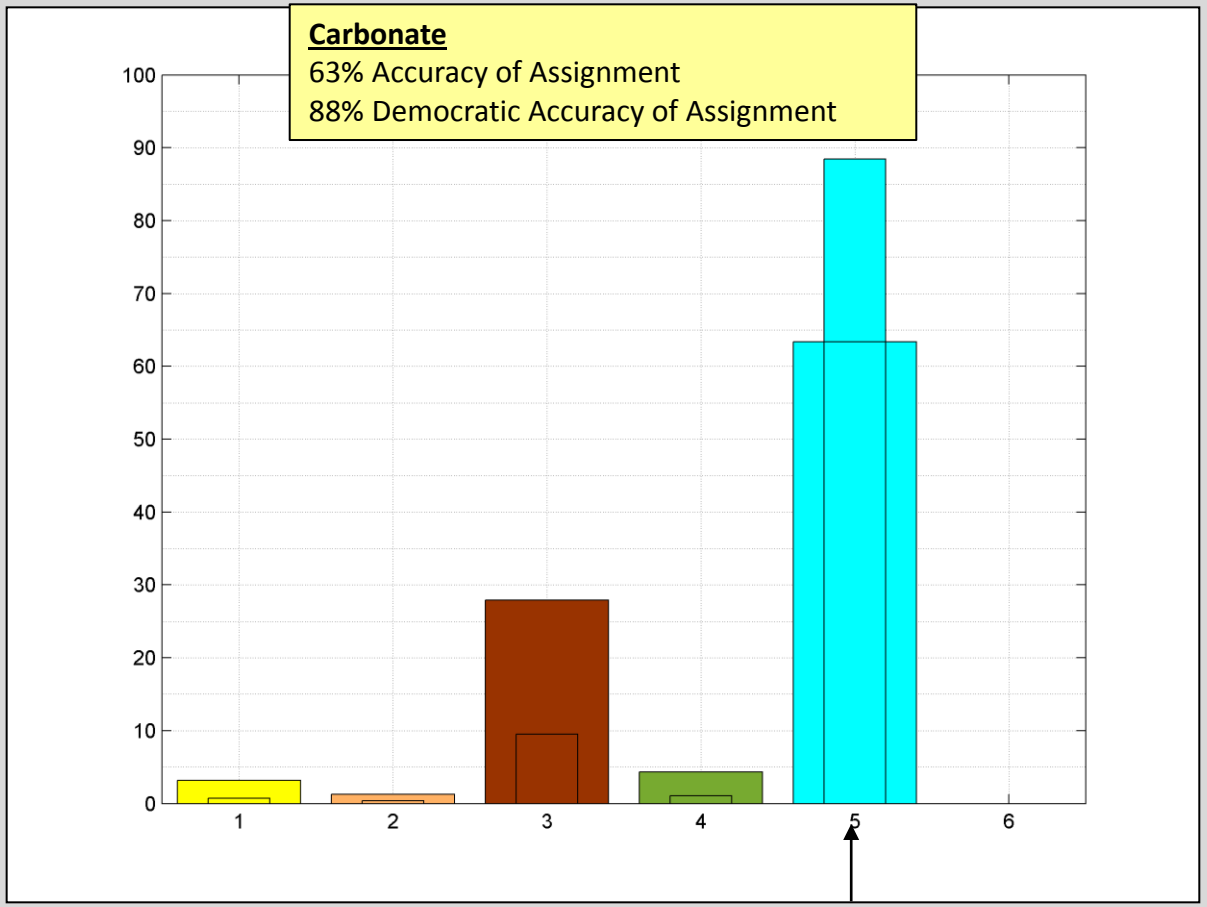
COAL
897
1020
676
2109
22
9001
0
13726
66%

Normalized

Wide bar = No normalization
Narrow bar = Normalized

Accuracy of Assignment Histogram for Carbonate

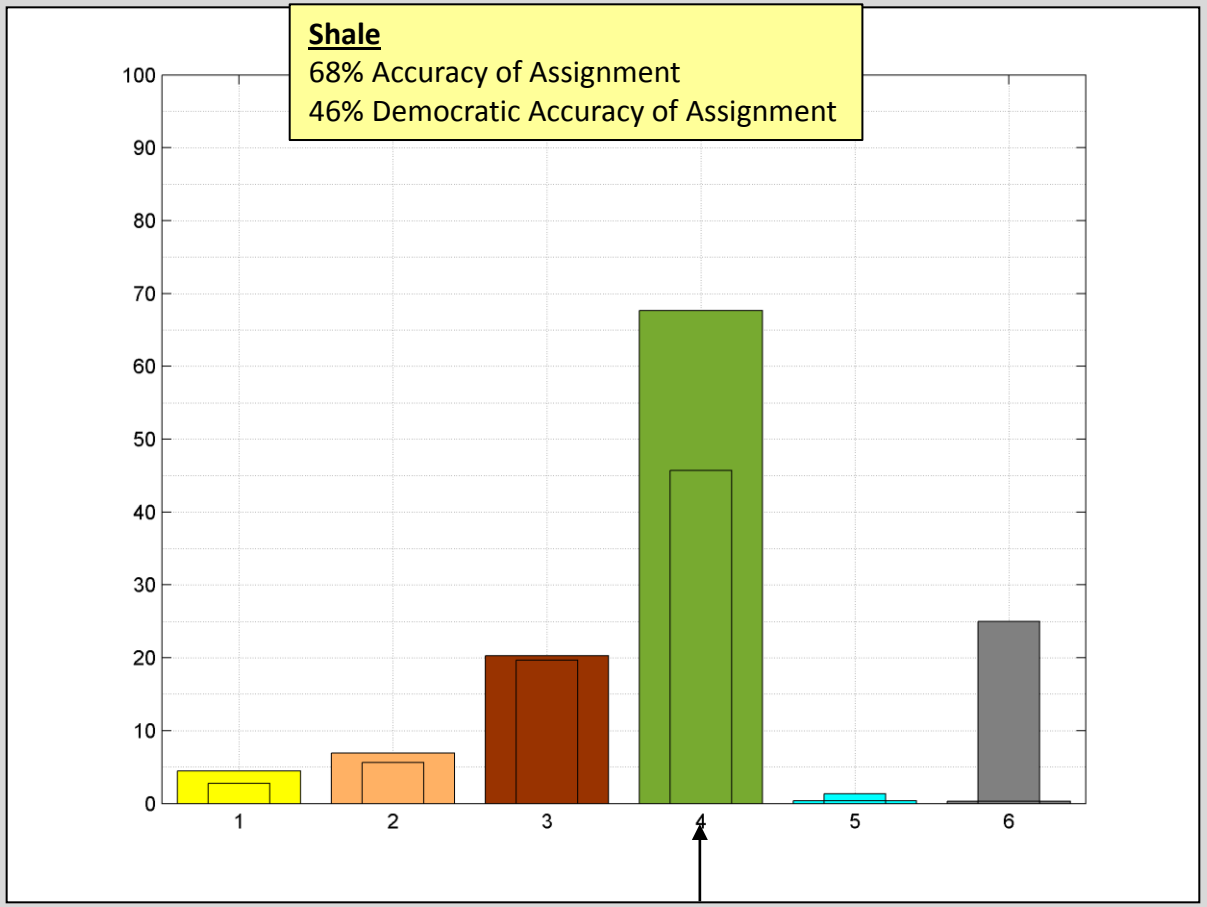
The values in each column of the confusion matrix can be shown as a histogram. This shows how much of each rock types end up being classified as coal.



Wide bar = No normalization
Narrow bar = Normalized

Accuracy of Assignment Histogram for Shale

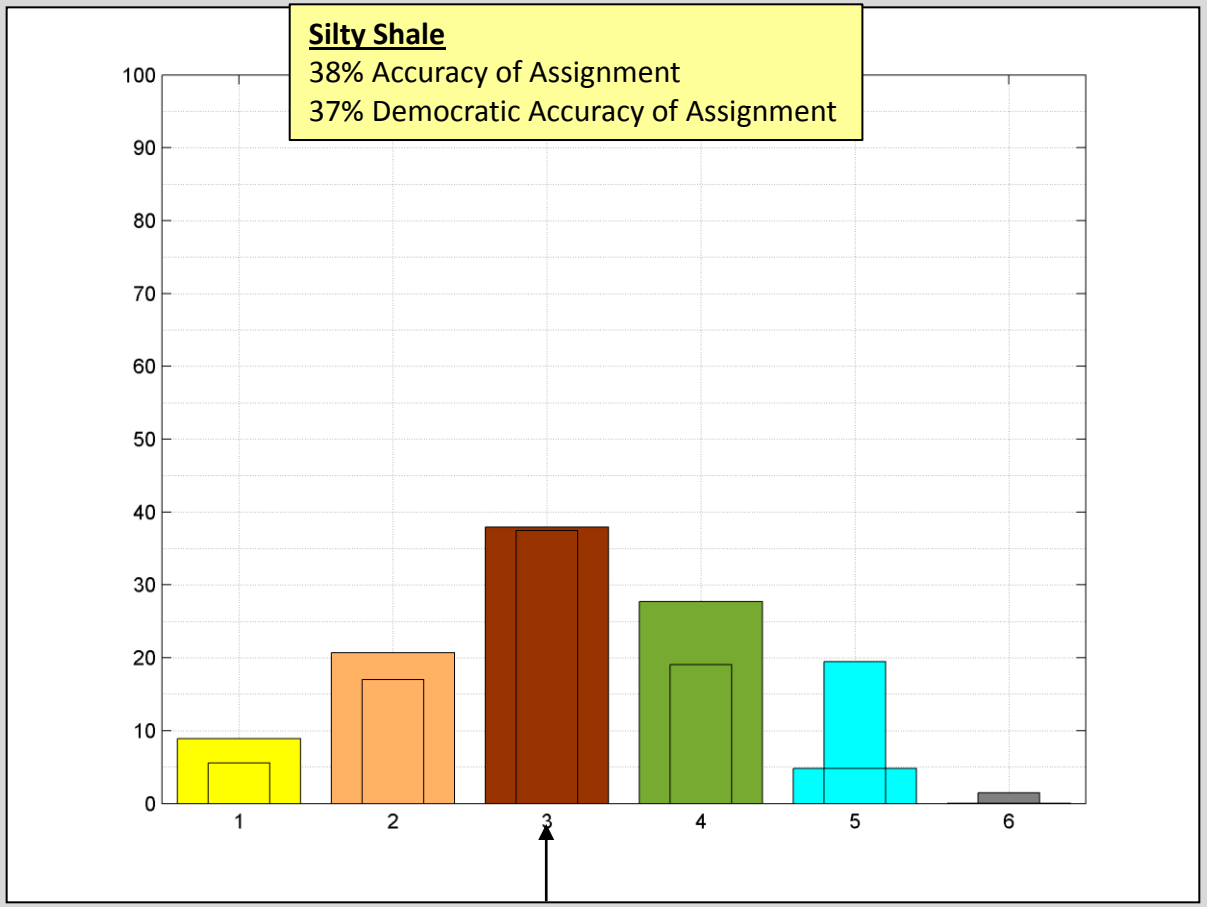
The values in each column of the confusion matrix can be shown as a histogram. This shows how much of each rock types end up being classified as coal.



Wide bar = No normalization
Narrow bar = Normalized

Accuracy of Assignment Histogram for Silty Shale

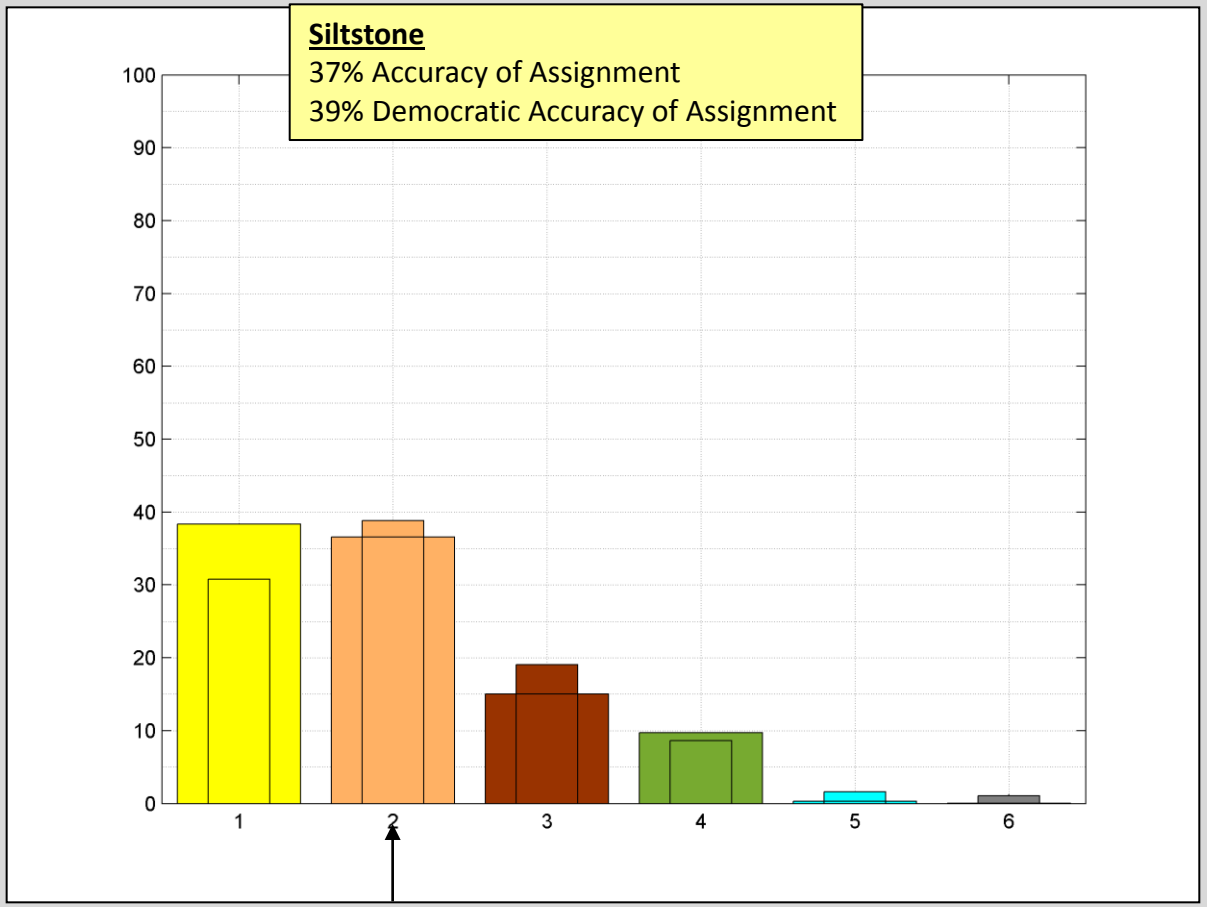
The values in each column of the confusion matrix can be shown as a histogram. This shows how much of each rock types end up being classified as coal.



Wide bar = No normalization
Narrow bar = Normalized

Accuracy of Assignment Histogram for Siltstone

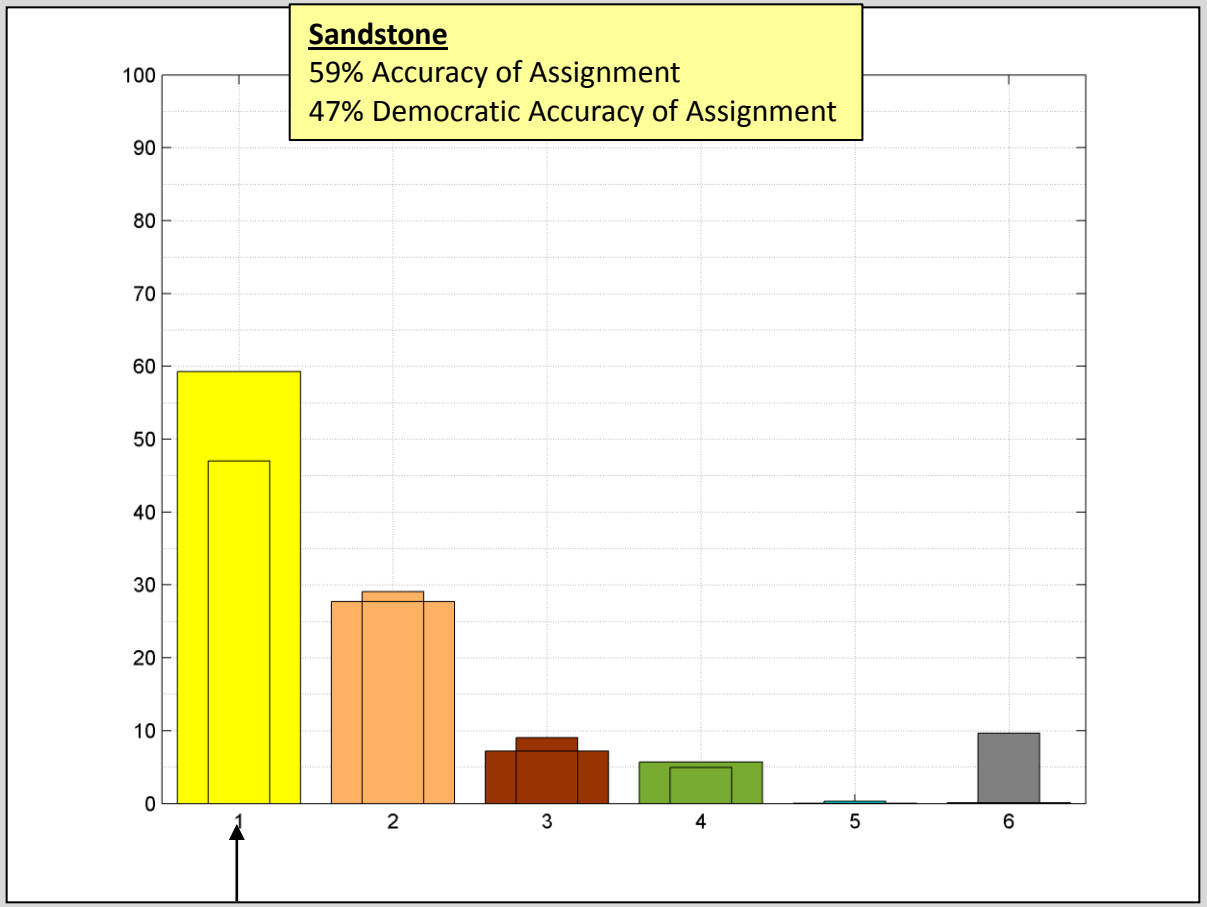
The values in each column of the confusion matrix can be shown as a histogram. This shows how much of each rock types end up being classified as coal.



Wide bar = No normalization
Narrow bar = Normalized

Accuracy of Assignment Histogram for Sandstone

The values in each column of the confusion matrix can be shown as a histogram. This shows how much of each rock types end up being classified as coal.



Wide bar = No normalization
Narrow bar = Normalized

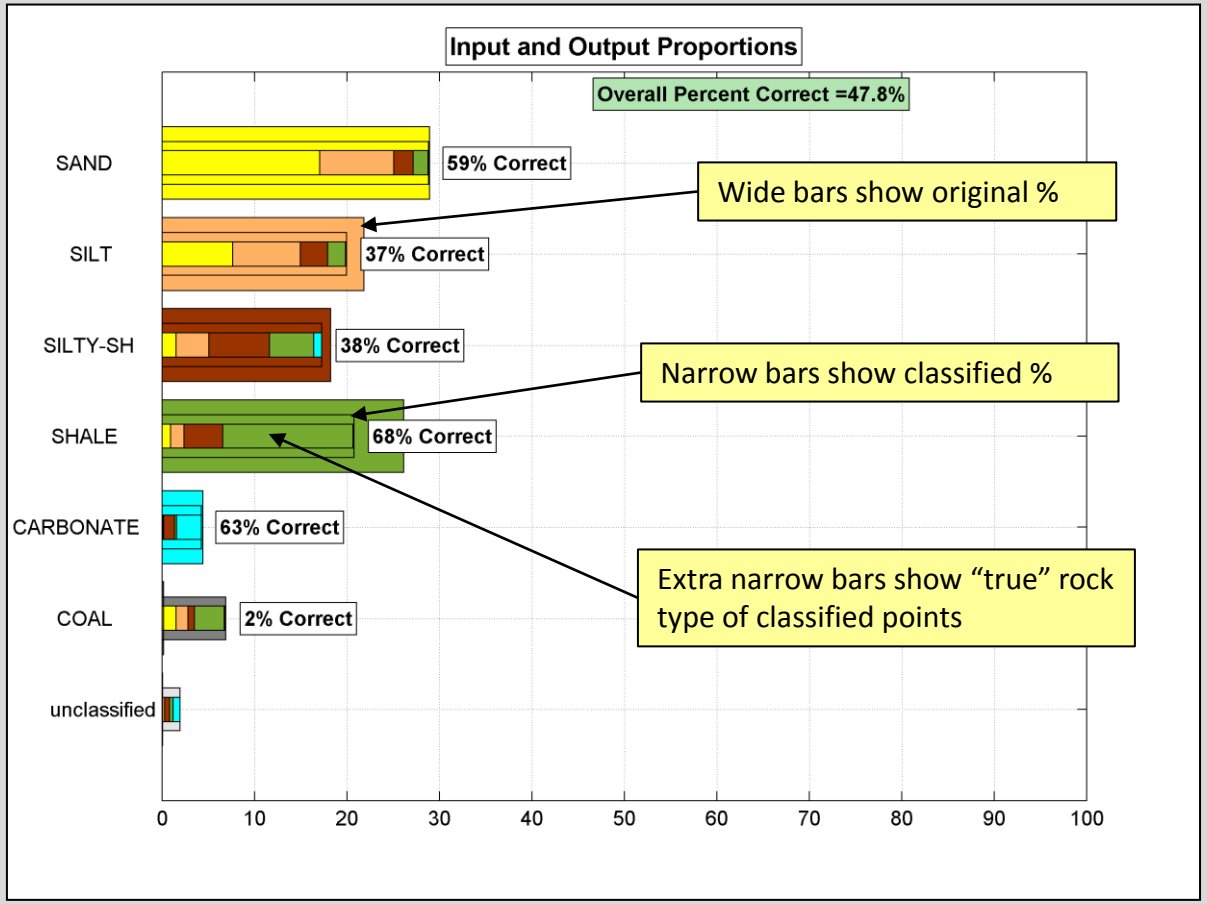
One Display Shows All (almost).

With this display we try to take the confusion out of the confusion matrix.

You can clearly see input and output percentages of each rock type.

You can see how “contaminated” each predicted rock type is. (Accuracy of Assignment)

You can see how each rock type leaks into other classes. (Probability of Assignment)



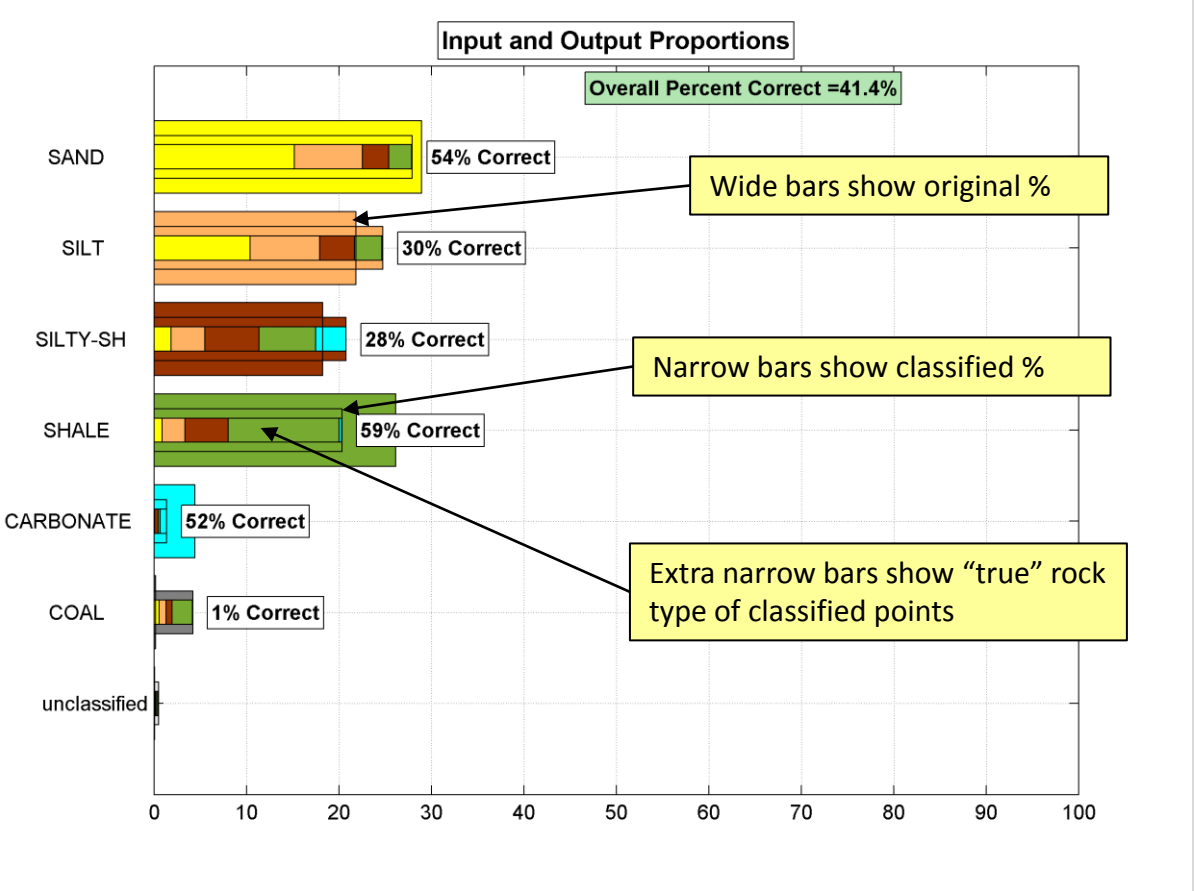
One Display Shows All For Logs Filtered to Seismic Frequency (60 Hz).

With this display we try to take the confusion out of the confusion matrix.

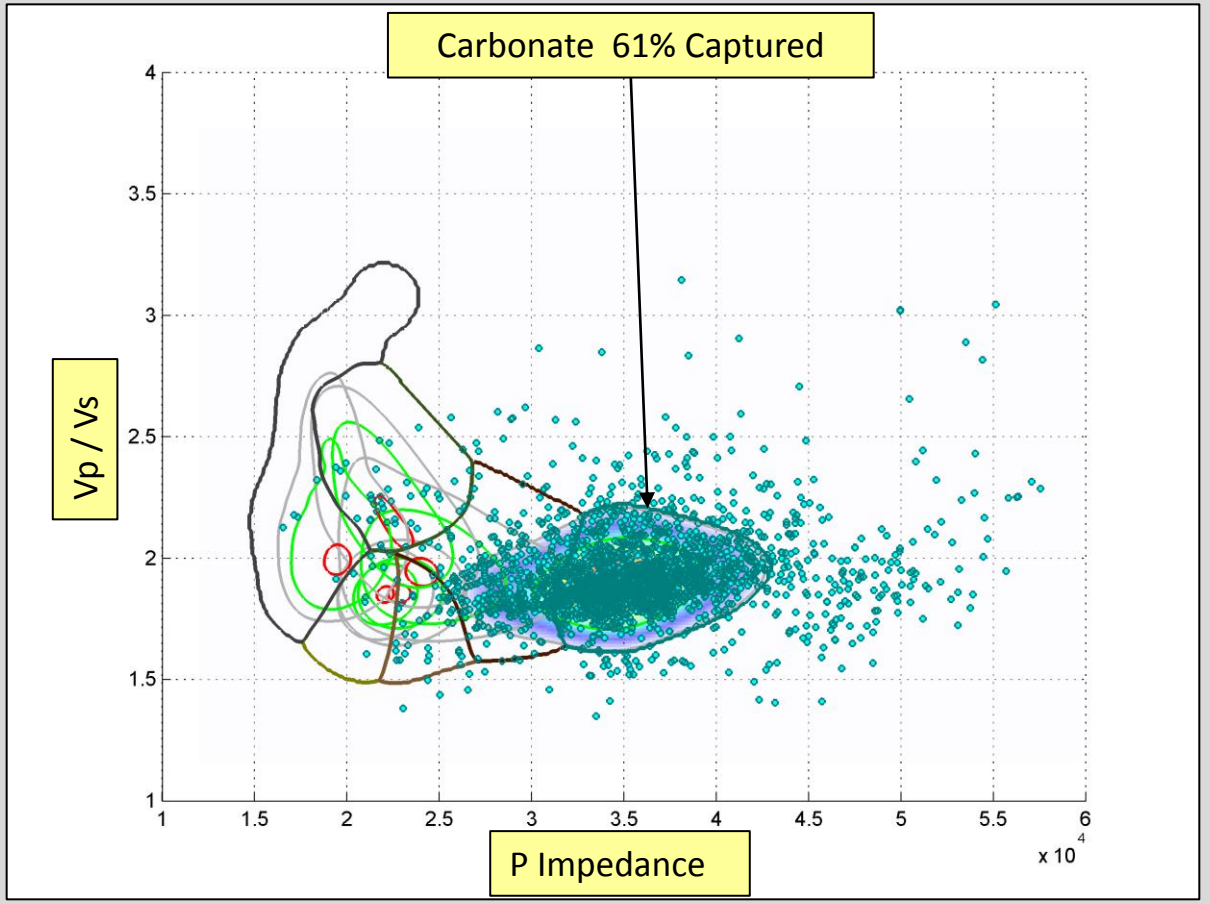
You can clearly see input and output percentages of each rock type.

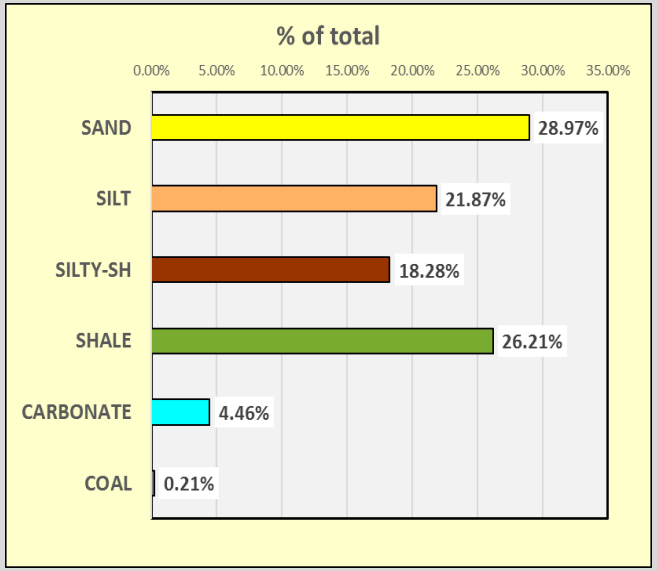
You can see how "contaminated" each predicted rock type is. (Accuracy of Assignment)

You can see how each rock type leaks into other classes. (Probability of Assignment)



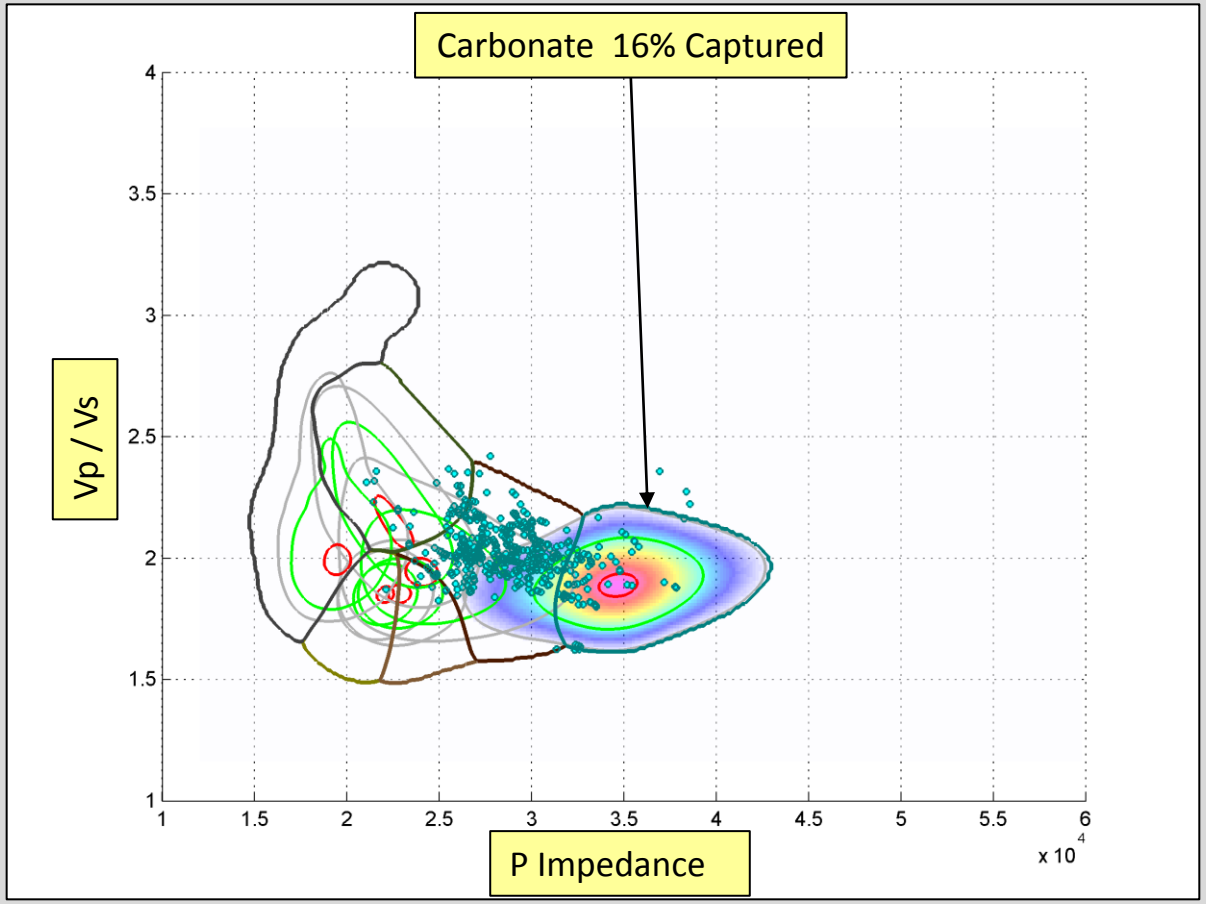
Probability Density Function for Carbonate

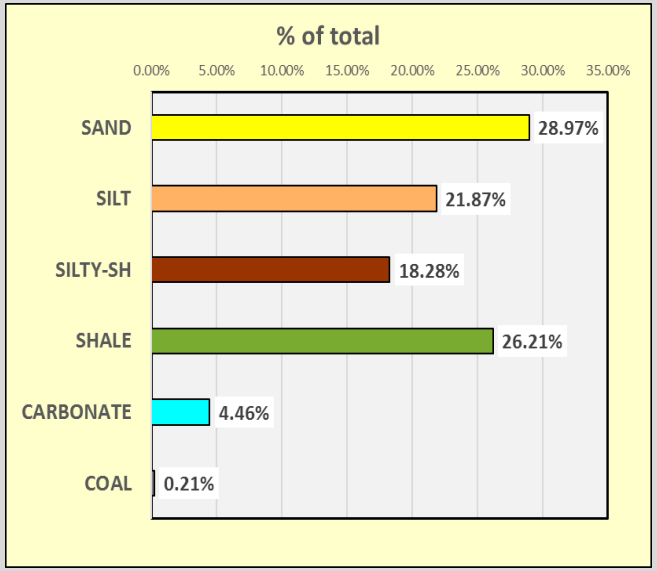




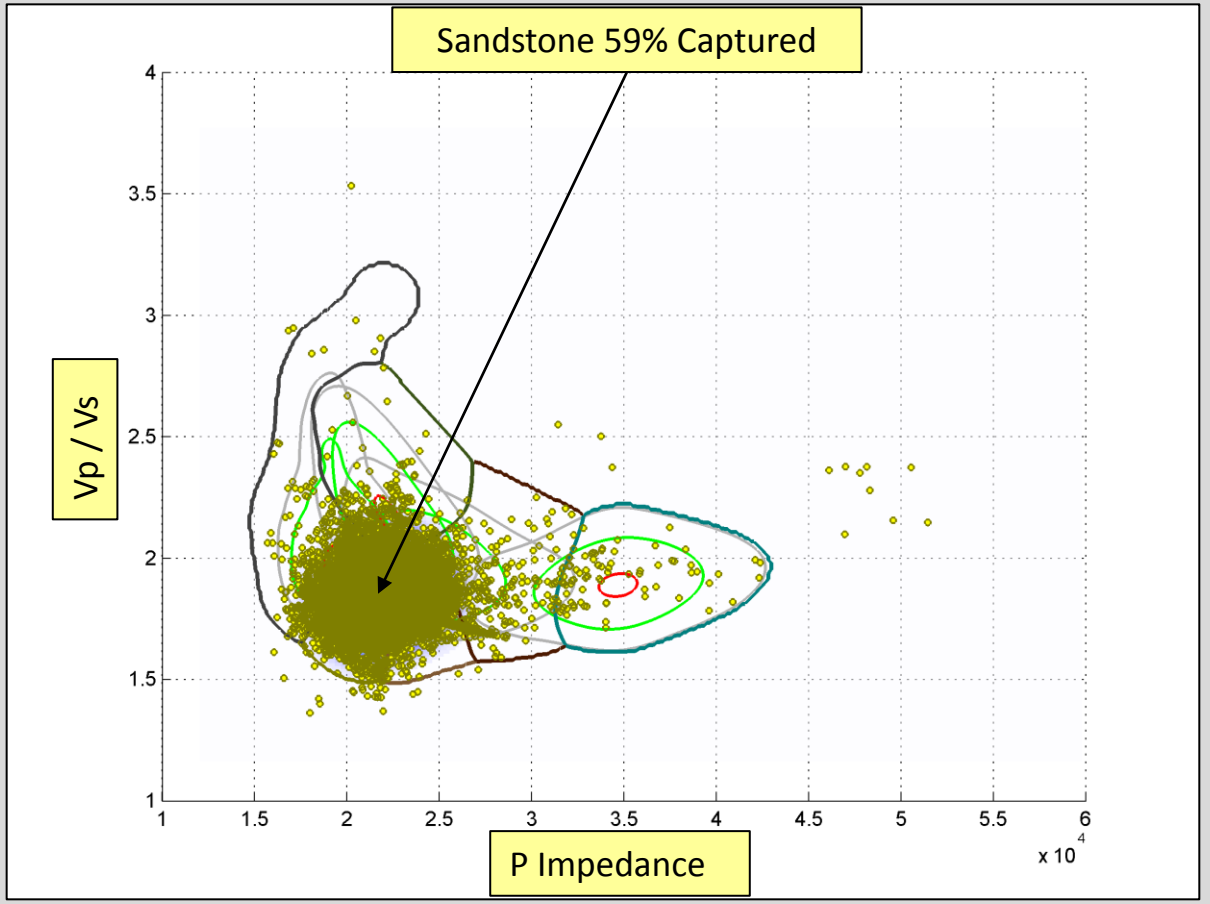
Probability Density Function for Carbonate with 60Hz Filter Applied to Logs.

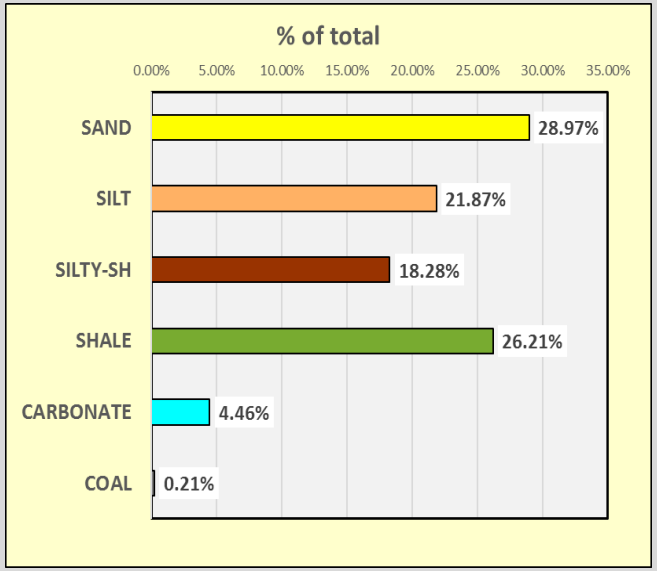
Notice how the points are drawn to other rock types which exert influence because the carbonate layers are thin and below seismic resolution. This causes mixing with other layers above and below.





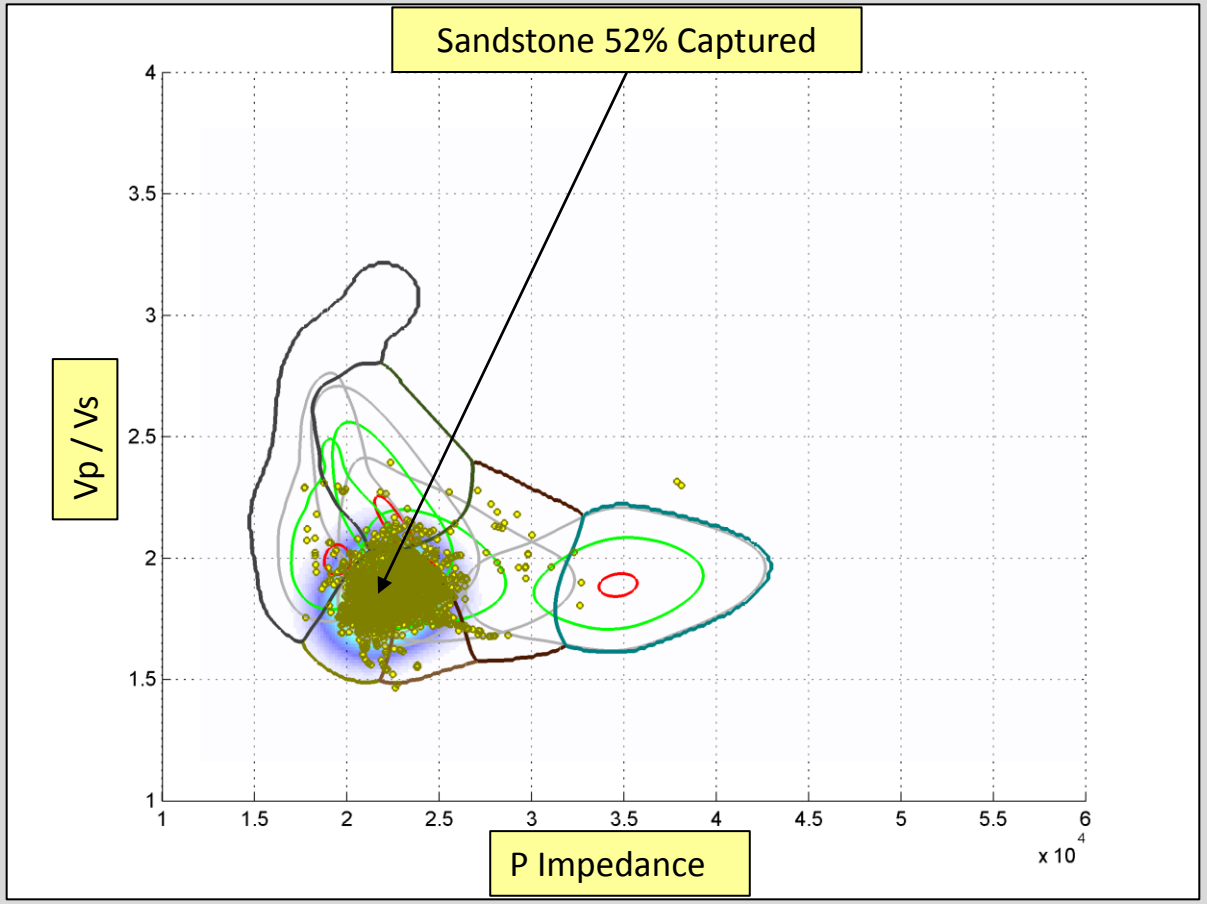
Probability Density Function for Sandstone

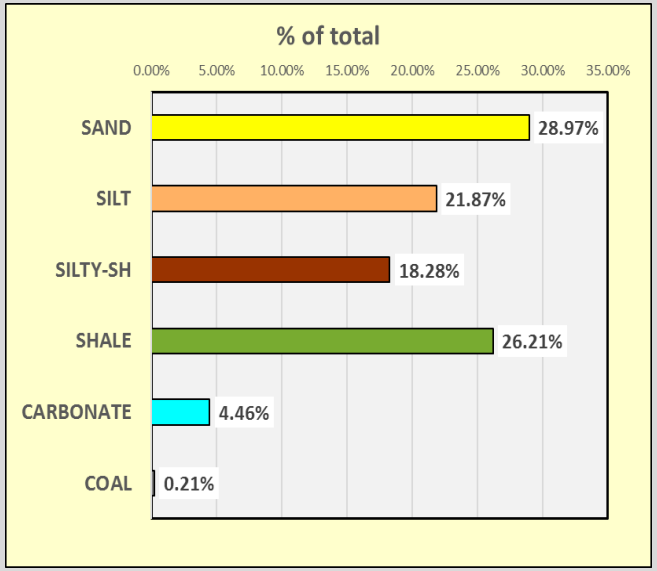




Probability Density Function for Sandstone with 60Hz Filter Applied to Logs.

For sandstone there is not much change because the sand layers are thick.





Four Ways to Quantify Uncertainty

- Probability of Assignment
- Accuracy of Assignment
- Democratic Accuracy of Assignment
- Input and Output Histograms

How should we measure performance of supervised classification

Measure how much of a particular rock type is classified as that rock class. (Probability of assignment).

This measure is only dependent on the pdf of a single rock type and the classification region. If you are primarily focused on capturing a single rock type then maximize this.

For example, if you know a rare and valuable tree grows in one region of the forest and you have an opportunity to buy some land in that forest, you would want to buy all the land where that tree grows. This is true even if many other trees grow there.

How should we measure performance of supervised classification

Measure the likelihood that the predicted rock class is true. (Accuracy of assignment).

This may be the most intuitive. It is the likelihood of a true prediction. For example, if your prediction is pay, what percentage of the time will you be correct.

This will not tell you how much of the pay was or was not classified correctly.

How should we measure performance of supervised classification

Measure the accuracy of assignment after equalizing all rock types. (Democratic accuracy of assignment)

This is a variation of the accuracy of assignment except each rock type is given equal probability. Rare rock types such as coal may score very low on simple accuracy of assignment due to the small number of samples of coal. By equalizing the probability of all rock types, this would show the coal can be readily separated from other rock types.

How should we measure performance of supervised classification

Compare input and output histograms

In general, you would like the amounts predicted in each rock class, to match the amounts actually present for each rock type. You may, however, favor accuracy and only want to classify the points associated with a high degree of confidence.

Summary and Conclusions

- The answer is that you must consider all measures of classification performance in order to truly understand if your predictions will optimal for your meeting your objectives.
- If you are reviewing work done by others, it is important to understand what is meant if they say a prediction is *x%* accurate.
- By allowing this process to be performed interactively, the classification regions can be adjusted to best meet your objectives.

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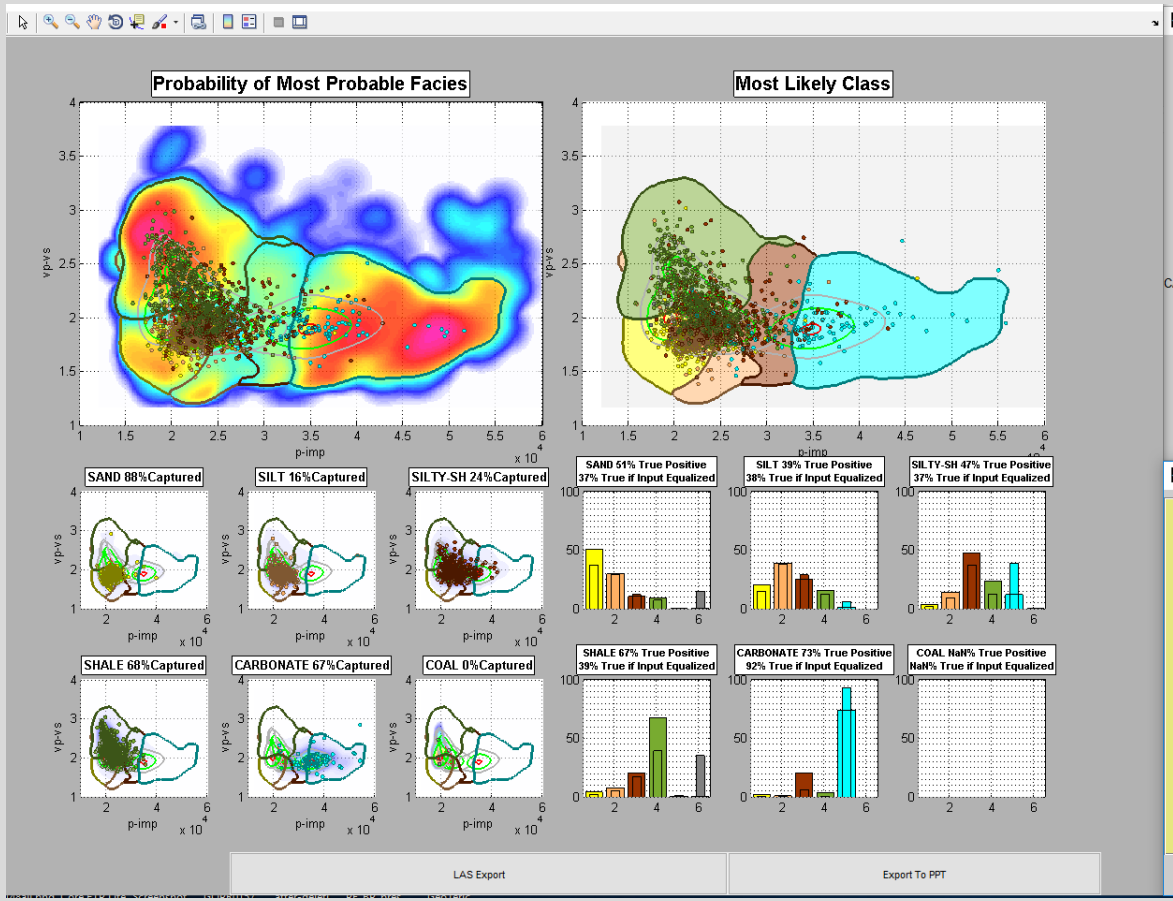
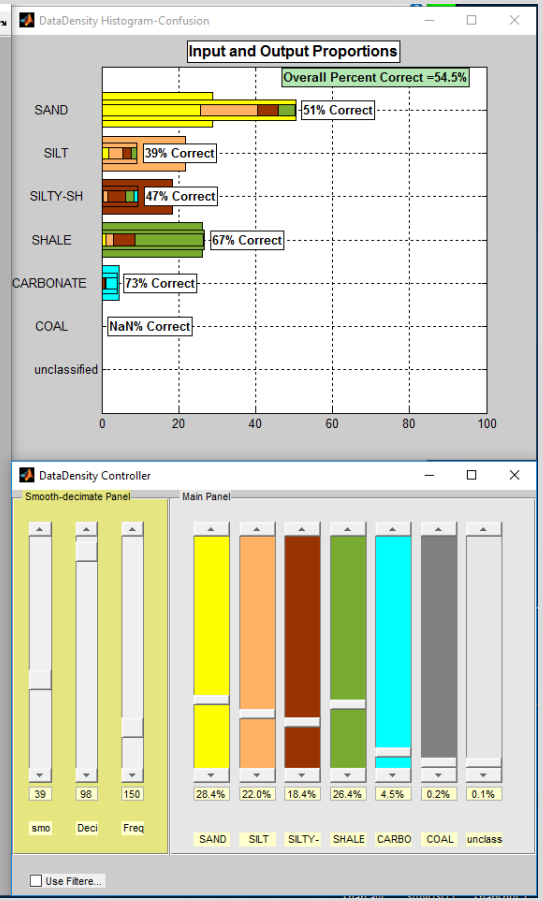
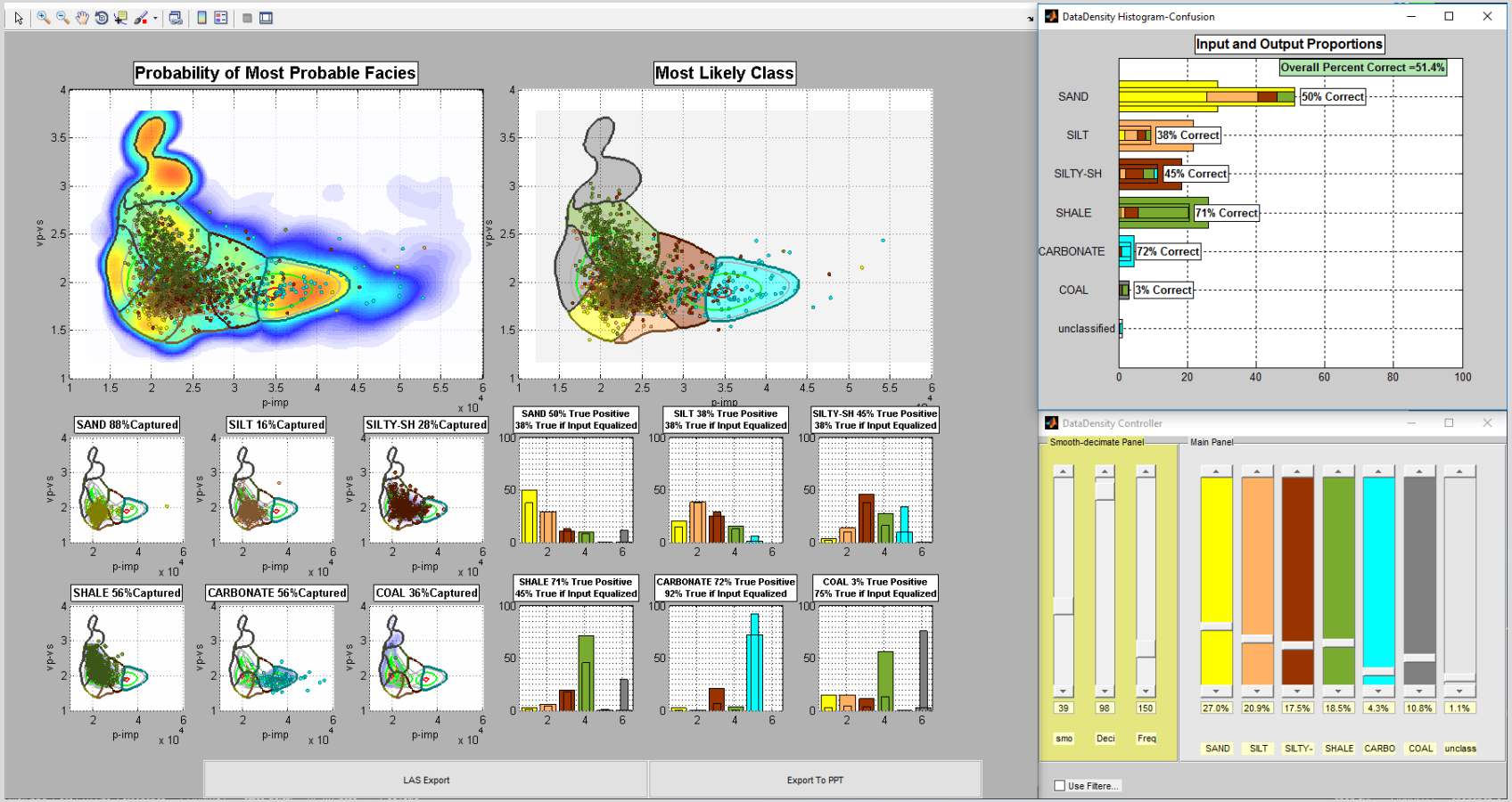
Interactive Facies Classification in the Elastic Domain

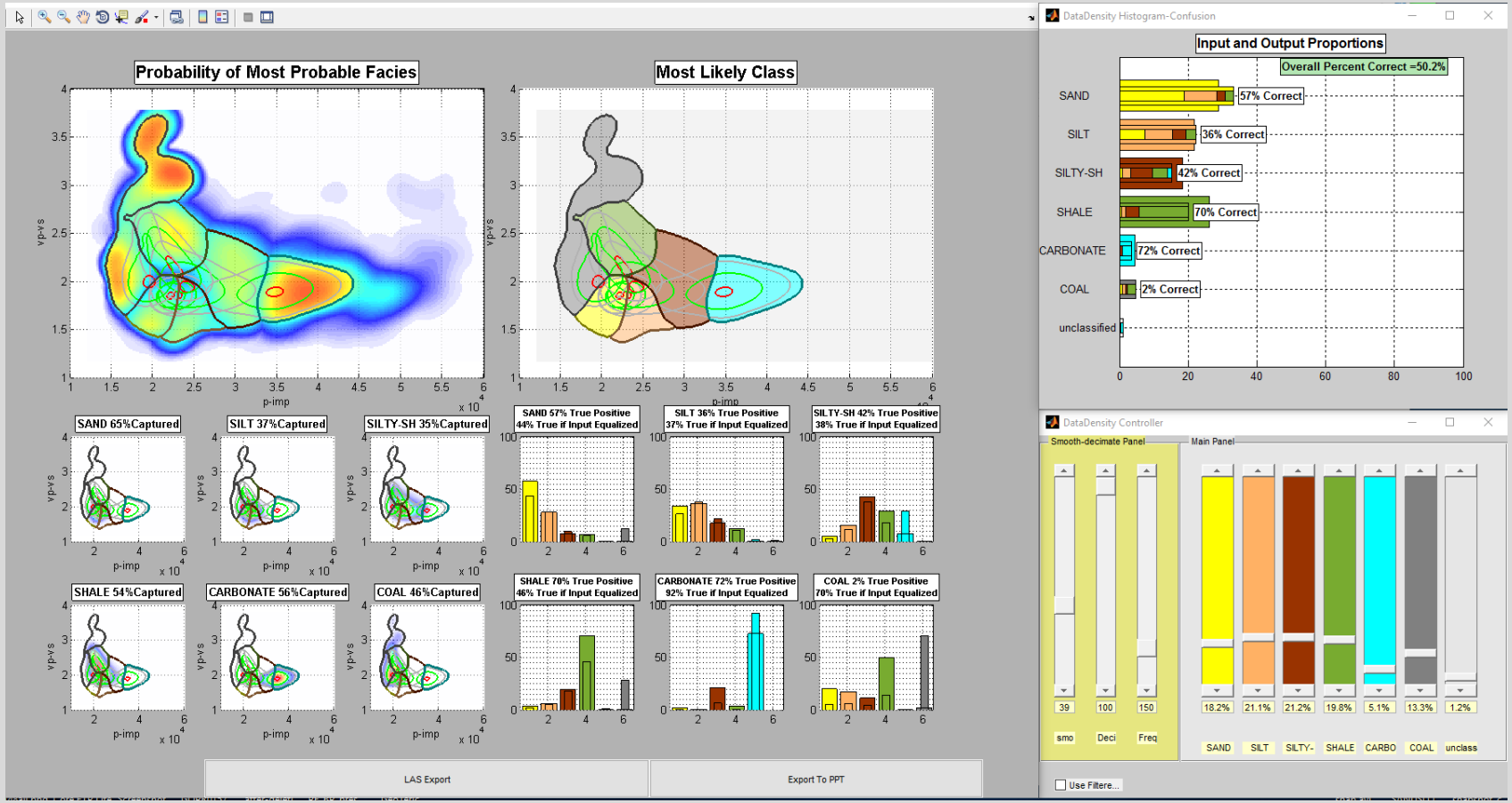




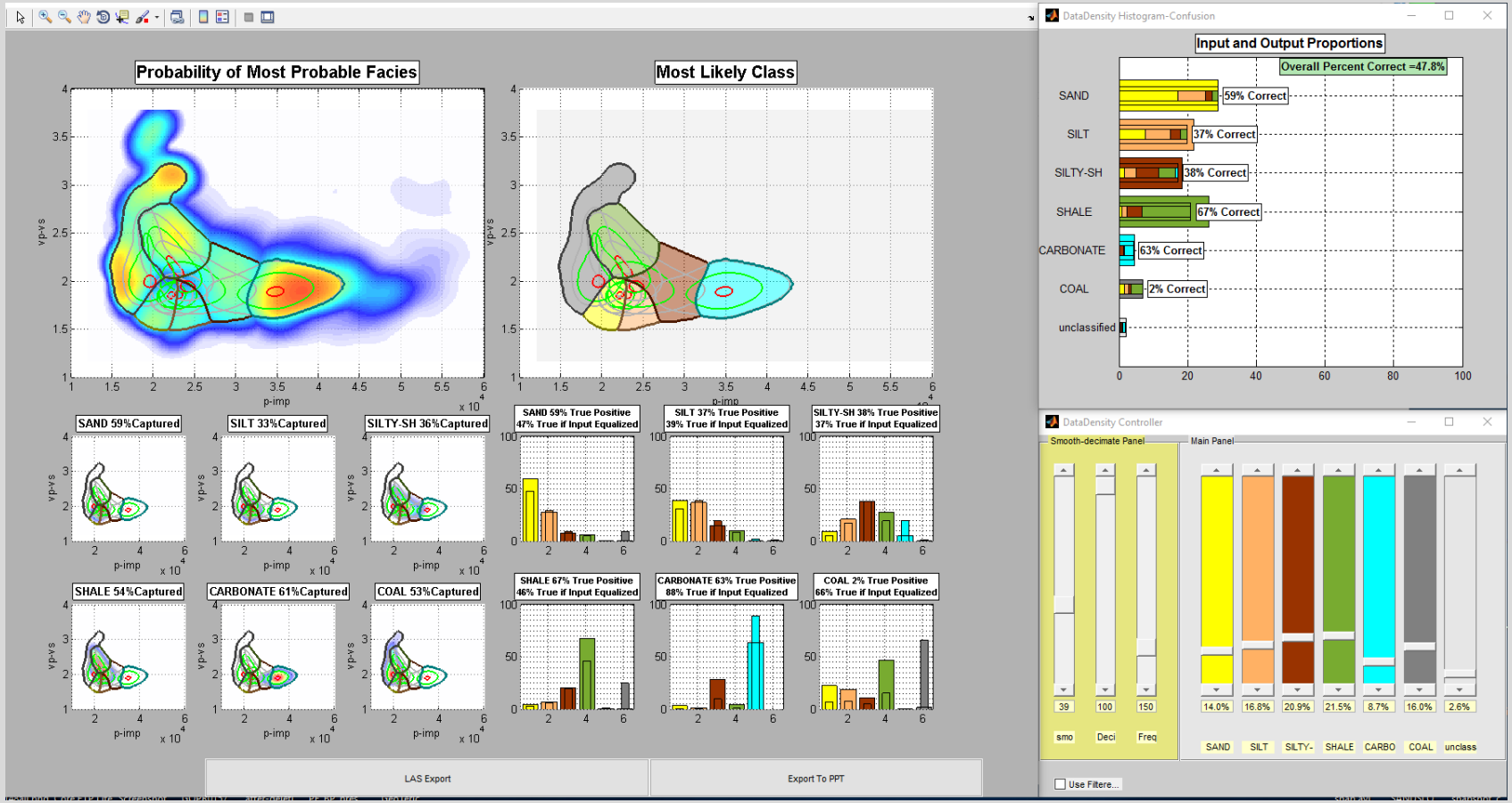
Interactive Facies Classification in the Elastic Domain



Interactive Facies Classification in the Elastic Domain



Interactive Facies Classification in the Elastic Domain



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Thank You