Application of Artificial Intelligence for Fluid Typing using Calibrated Compositional Data*

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Abstract

Identifying the type of fluid that will be produced at surface is a significant reservoir characterization challenge that is prone to error and uncertainty in exploration environment. It usually requires rigorous treatment of equation of state coupled with phase envelopes that are usually available in a later stage after drilling the well. The business impact of such errors in fluid identification is remarkable. This can vary from poor completion decisions to incorrect reserves estimation. With the introduction of advanced mud gas logging systems (AMG), quantitative assessment of gas data comparable to PVT analysis is possible in real-time. This facilitates real-time accurate fluid typing. To get the most representative fluid typing results, a framework has to be established where local production data is mapped to compositional data from PVT through model building techniques. The successful application of this technique has many advantages. It allowed for accurate fluid typing in real-time that provided valuable information for reservoir characterization. This information can affect a spectrum of decisions, starting from rig operations to simulation efforts. In this study, a decision tree, which is one form of artificial intelligence, is used to build a model that maps compositional to production data using local data sets. The resulting model is then used as a predictive tool to identify fluid types using AMG data while drilling before any other formation evaluation data, such as wireline logs, becomes available.

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Saudi Aramco

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Contents

Motivation

- To increase confidence in our ability to predict fluid type in real time before running wireline logs
- To integrate different sources of data from new and existing technologies (Advanced mud gas logging, PVT, etc.)
- Extract knowledge from available data in order to help guide in making more informed decisions

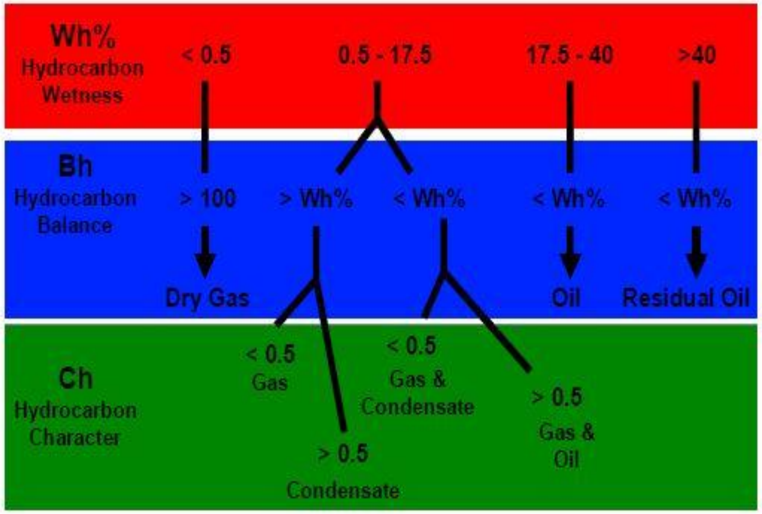
Business Impact

- Utilization of data and knowledge discovery
- Improve reserve estimation, operational, and completion decisions

Advanced Mud Gas Logging

- Slow development in mud gas logging
- Usually used to detect hydrocarbon with little confidence on hydrocarbon fluid typing (Haworth et al 1985)
- Variable operational settings (rig configuration, mud characteristics, mud density, pressure differential…etc)

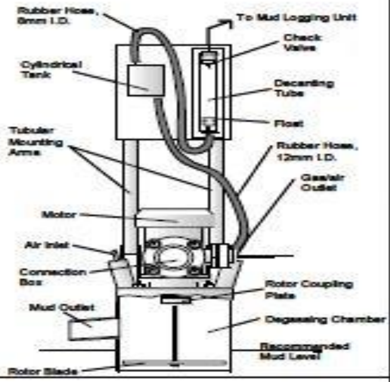
- Wetness Ratio (WH): $[(\sum_{i=2-5} C_i) / (\sum_{i=1-5} C_i)]*100$
- Balance Ratio (BH): $(C1+C2) / (\sum_{i=3-5} Ci)$
- Character Ratio (CH): $(C4+C5)/C3$

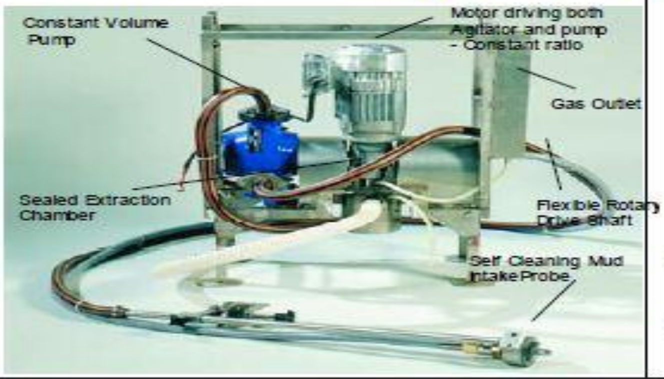


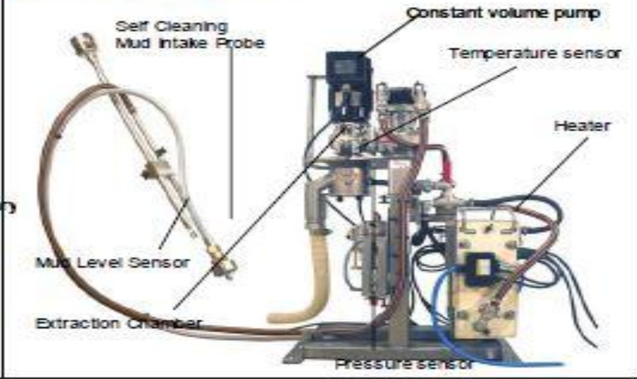
Advanced Mud Gas Logging

- **Constant volume and temperature of analyzed mud**

ADVANCED MUD LOGGING







Standard mud logging with standard degaser	GZG degasser (Geoservices patented)	FLEX Extractor (Geoservices patented)
• In Shaker box • Mud Level • Low Efficiency	• Flow Line • Constant Volume • Constant Rate • High Efficiency • Qualitative	• Flow Line • Constant Volume • Constant Rate • Constant Temperature • Gas Line (Pressure controlled) • Quantitative & Qualitative

Advanced Mud Gas Logging

PVT quality gas data (C1-C5)

Region	Africa		Gulf of Mexico					Middle East	
Component	**HC**	**FLAIR**	**HC**	**FLAIR**	**Trad**	**HC**	**FLAIR**	**HC**	**FLAIR**
C1	73.2	72.3	81.4	80.8	94.6	78.5	76.1	90.1	88.3
C2	9.0	9.1	7.6	8.2	3.7	9.0	10.0	5.8	6.1
C3	7.9	7.9	5.6	5.7	1.3	5.5	6.6	2.1	2.3
i-C4	3.1	3.4	1.0	1.1	0.4	1.2	1.2	0.5	0.7
n-C4	4.1	4.4	2.5	2.3	0.0	2.5	2.9	0.8	1.2
i-C5	2.6	2.7	0.9	0.9	0.0	1.3	1.1	0.4	0.7
n-C5	0.1	0.1	1.0	0.9	0.0	1.3	1.2	0.4	0.6
WH	26.8	27.6	18.6	19.1	5.4	20.9	23.2	10.0	11.6
BH	4.6	4.4	8.1	8.2	57.8	7.4	6.6	22.8	17.2

Important Points

- Existing compositional PVT data is used to recognize fluid types
- AMG positive correlation with PVT data
- We can use local knowledge (experience) to calibrate

Why Artificial Intelligence?

- Many useful applications in the PE

- Examples:

- Anifowose, F., Ewenla, A., Eludiora, S., & Awolowo, O. (2011). Prediction of Oil and Gas Reservoir Properties using Support Vector Machines. IPTC.
- Fedenczuk, L., Hoffmann, K., & Fedenczuk, T. (2002). Predicting Waterflood Responses with Decision Trees. Canadian International Petroleum Conference.

- It can be used for predictive modeling and knowledge discovery

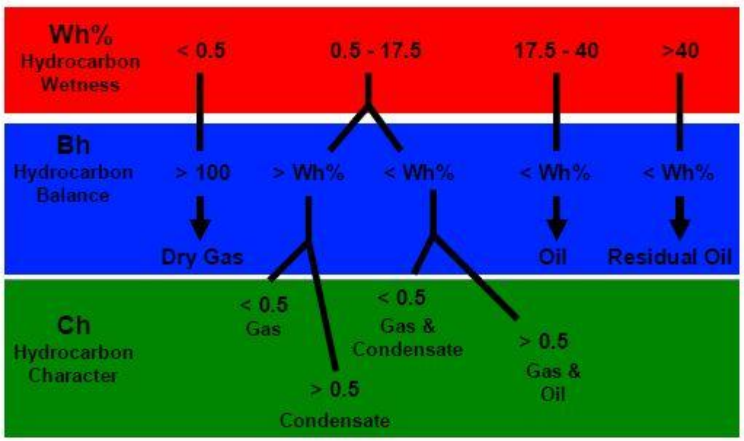
Why Decision Trees?

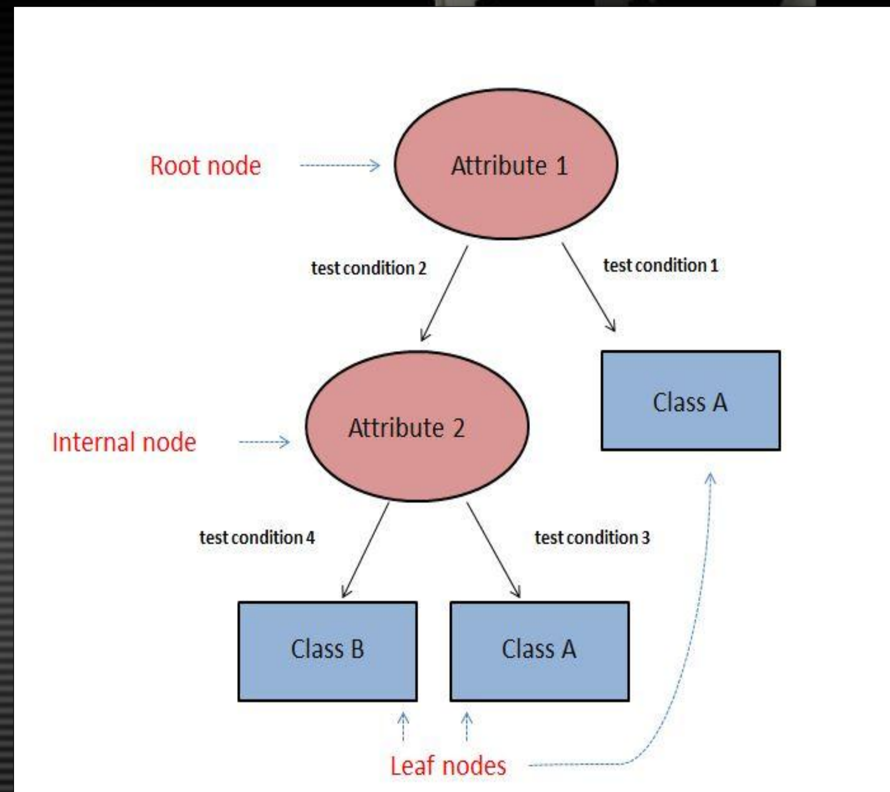
- They are suitable for classification tasks.
- They classify data using simple rules that are easy to apply to new instances.
- The trees' model will highlight the most important parameters or attributes controlling classification, this is particularly important for knowledge discovery.
- They resemble Haworth method, which is an industry accepted method for hydrocarbon classification using mud logs (Haworth, et al. 1985).

The difference is that the modeled decision tree will be constructed based on local data

Artificial Intelligence for PVT Calibration

- **Wetness Ratio (WH):** $[(\sum_{i=2-5} C_i) / (\sum_{i=1-5} C_i)]*100$
- **Balance Ratio (BH):** $(C1+C2) / (\sum_{i=3-5} Ci)$
- **Character Ratio (CH):** $(C4+C5)/C3$

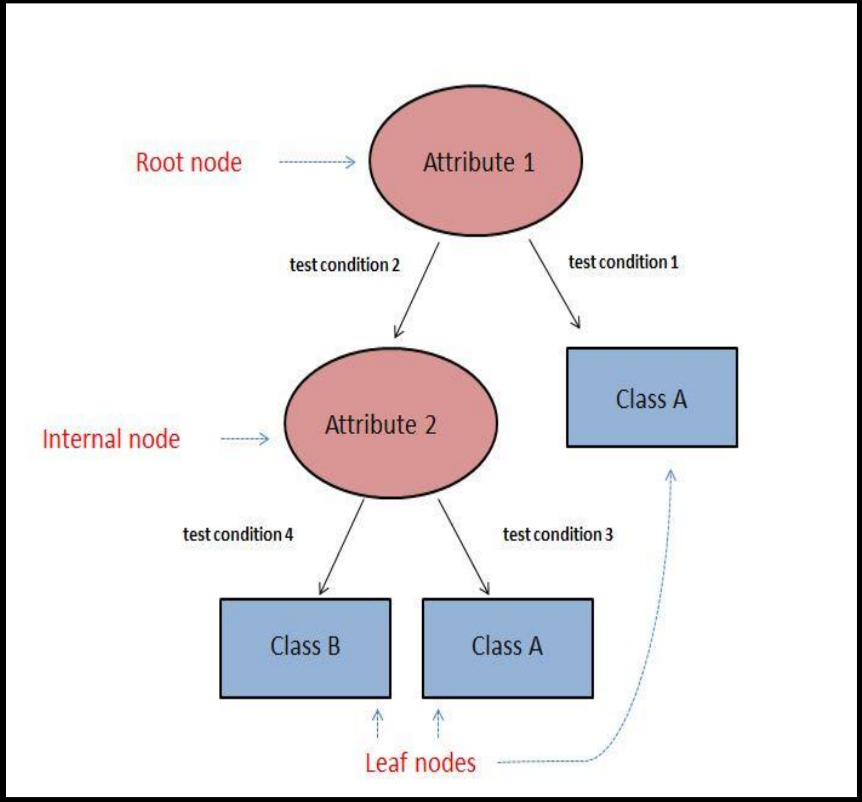




If Attribute 1 test condition 1 = true then Class = A
Else
If Attribute 2 test condition 3 = true Then Class = A
Else
Class = B

Artificial Intelligence for PVT Calibration

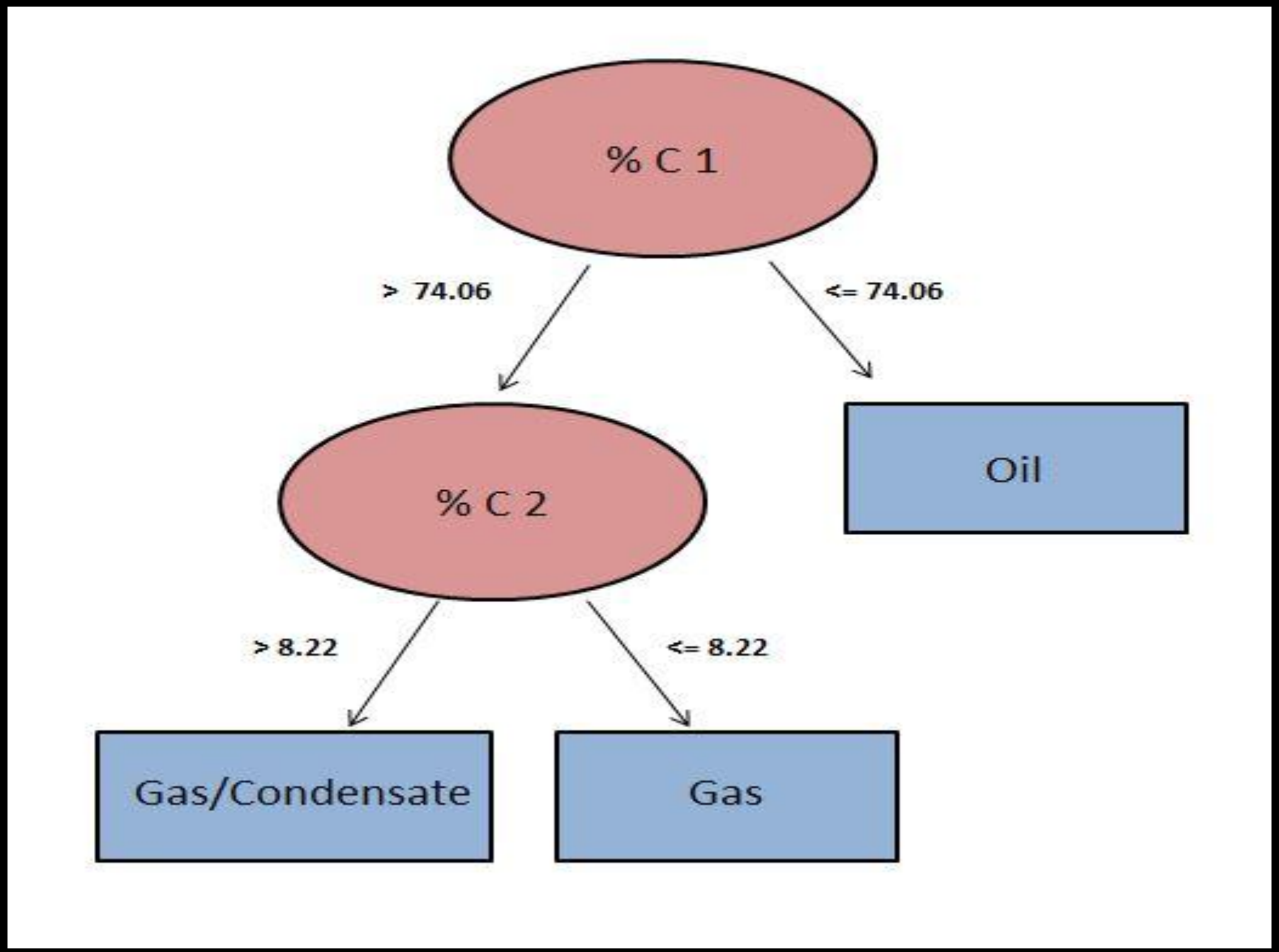
- **Entropy (t) =** $-\sum_{i=0}^{c-1} p(i|t) log_2\, p(i|t)$
- **Gini (t) =** $1 - \sum_{i=0}^{c-1}[p(i|t)]^2$
- **Classification Error (t) =** $1 - max_i\, [p\, (i|t)]$



Data Collection

#	% C1	% C2	% C3	% i-C4	% n-C4	% i-C5	% n-C5	Type/Class
1	51.47	17.10	15.29	3.17	7.04	2.95	2.95	oil
2	50.55	16.11	16.08	3.25	7.72	3.26	3.01	oil
3	54.16	14.80	14.77	3.07	7.15	3.12	2.91	oil
4	75.69	11.27	7.06	1.38	2.63	1.06	0.89	gas/condensate
5	64.75	11.27	10.80	2.67	4.89	2.80	2.25	oil
6	88.55	7.88	2.24	0.41	0.55	0.21	0.14	gas
7	87.27	8.22	2.81	0.50	0.59	0.25	0.21	gas
8	85.16	8.72	3.50	0.69	1.15	0.43	0.32	gas/condensate
9	85.97	8.46	3.57	0.59	0.89	0.29	0.20	gas/condensate
10	84.07	8.91	4.12	0.76	1.25	0.49	0.36	gas/condensate
11	82.62	8.93	4.50	1.01	1.71	0.67	0.47	gas/condensate
12	84.07	7.90	4.11	0.82	0.82	1.54	0.65	gas
13	83.74	8.03	4.14	0.94	1.51	0.77	0.84	gas/condensate
14	84.47	8.22	3.88	0.79	1.41	0.65	0.55	gas
15	84.59	8.62	4.00	0.71	1.29	0.44	0.32	gas/condensate
16	99.12	0.25						gas
17	100.00							gas
18	99.49	0.47	0.03					gas
19	86.41	8.35	3.16	0.60	0.79	0.36	0.33	gas/condensate
20	74.06	10.08	7.56	2.35	3.5	1.8	0.65	oil

Model Construction Results



Model Performance on Training

		Predicted Class		
		Oil	Gas/Condensate	Gas
Actual Class	Oil	3	0	0
	Gas/Condensate	0	5	1
	Gas	0	1	4

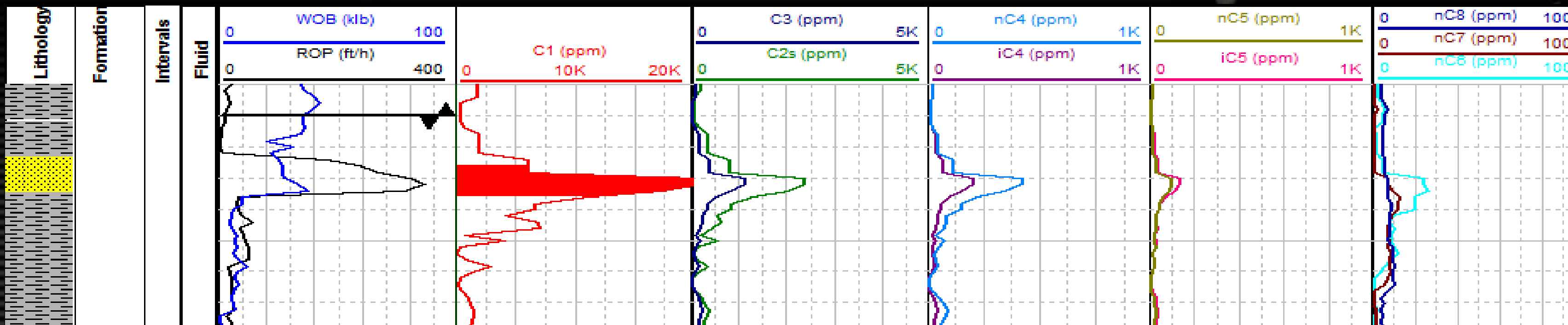
- **Using a single number to describe the performance of the model**
- **Accuracy is defined as the ratio of the number of correct prediction to total number of predictions. On the other hand, error rate represents the number of wrong prediction to the total number of predictions**
- **Using accuracy as a measure, the model is able to have 12 out of 14 correct predictions. A value of 0.857, given 1 represents the perfect score.**

Model Performance on Testing

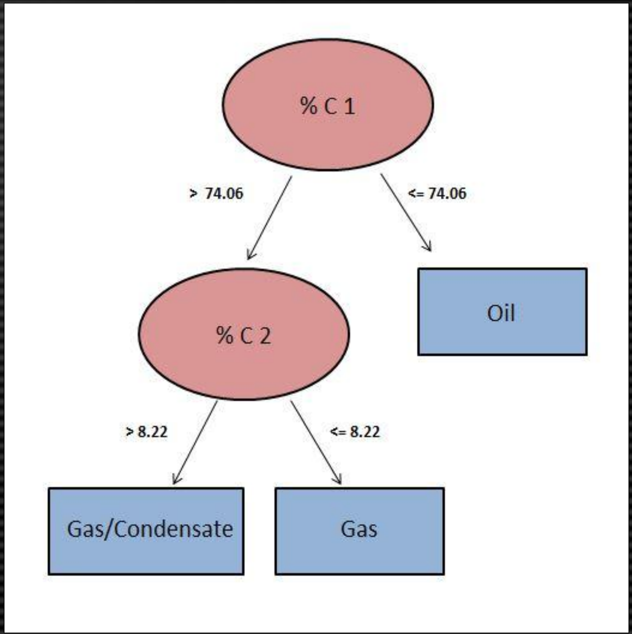
		Predicted Class		
		Oil	Gas/Condensate	Gas
Actual Class	Oil	2	0	0
	Gas/Condensate	0	2	0
	Gas	0	0	2

- **Validation set is used to estimate generalization error**
- **The model was able to predict the correct class for every single record in the validation set. The accuracy measure of the model is a perfect score of 1.**
- **The model is believed to be representative of the data set and can accurately map the fluid composition to the correct fluid type (class).**

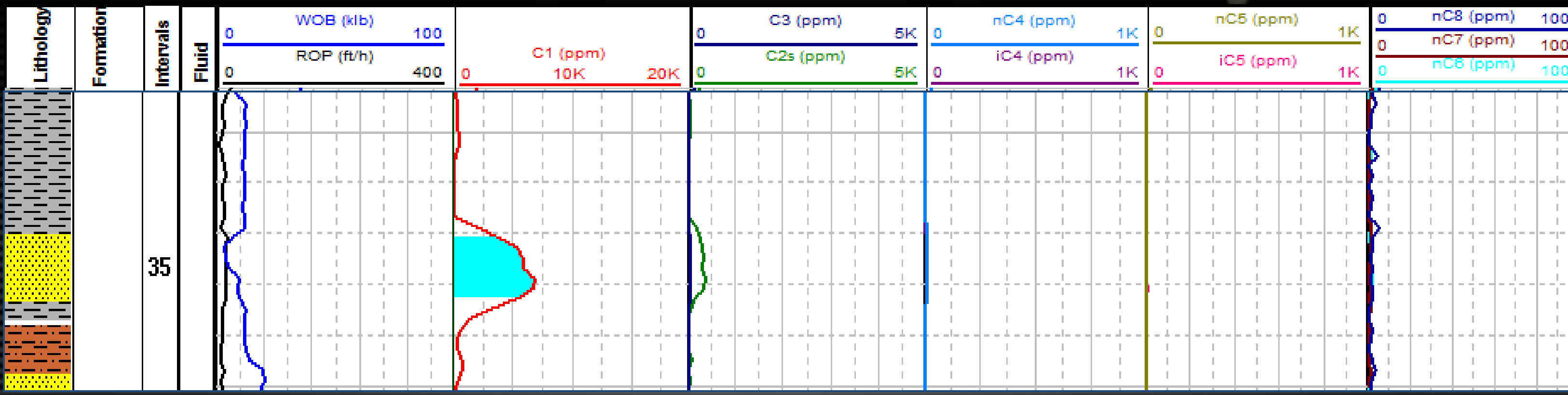
Application to Real Time Data



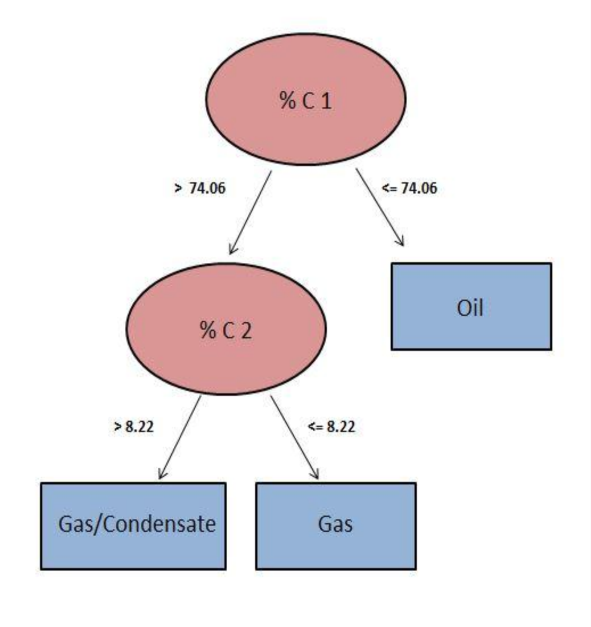
Composition and Classification Results for Zone A								
Zone A normalized composition							Predicted Class From Decision Tree	Produced Fluid from Production Test
% C1	% C2	% C3	% i-C4	% n-C4	% i-C5	% n-C5	Oil	Oil
73.9	11.0	6.53	1.57	3.76	1.76	1.43		



Application to Real Time Data



Composition and Classification Results for Zone B								
Zone B normalized composition							Predicted Class From Decision Tree	Produced Fluid from Production Test
% C1	% C2	% C3	% i-C4	% n-C4	% i-C5	% n-C5	Gas	Gas
92.2	6.15	0.73	0.22	0.29	0.19	0.21		

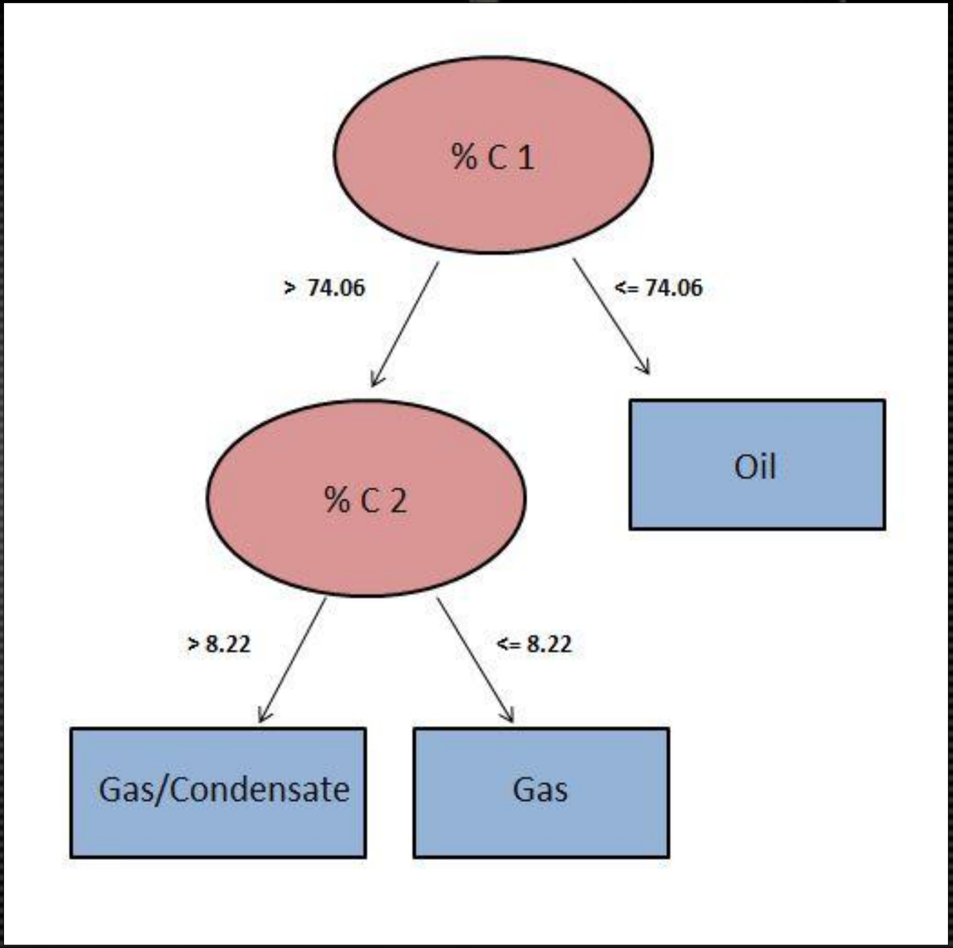


AMG vs PVT Comparison

Comparison Between PVT and AMG Data				
Normalized Composition	Zone A		Zone B	
	AMG	PVT	AMG	PVT
%C1	73.9	73.66	92.21	93.14
%C2	11.05	11.88	6.15	5.16
%C3	6.53	7.3	0.73	0.81
%i-C4	1.57	1.81	0.22	0.19
%n-C4	3.76	2.83	0.29	0.33
%i-C5	1.76	1.3	0.19	0.17
%n-C5	1.43	1.12	0.21	0.17

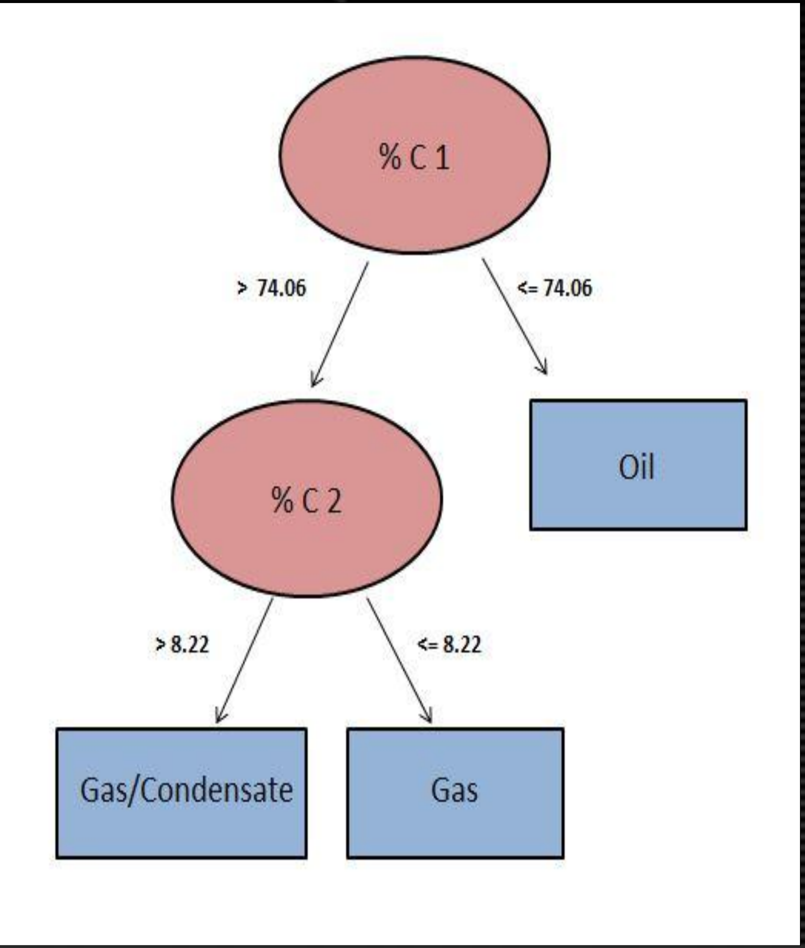
Discussion of Results

- Successful application.
- Decision tree was able to classify using simple model.
- Computationally inexpensive.
- Dynamic process.
- Limitation.



Conclusion

- Artificial intelligence can offer interesting solutions to petroleum engineering problems.
- Better utilization of local data can improve knowledge about the behavior of physical properties in the area.
- Decision tree can be used as descriptive and predictive models.
- AMG data is comparable to PVT for (C1-C5) compositions.
- Uncertainty in fluid typing using AMG if a model is built and calibrated using PVT data from local setting
- Using AMG for fluid typing can make sampling using expensive formation tester or even production tests more efficient and targeted.



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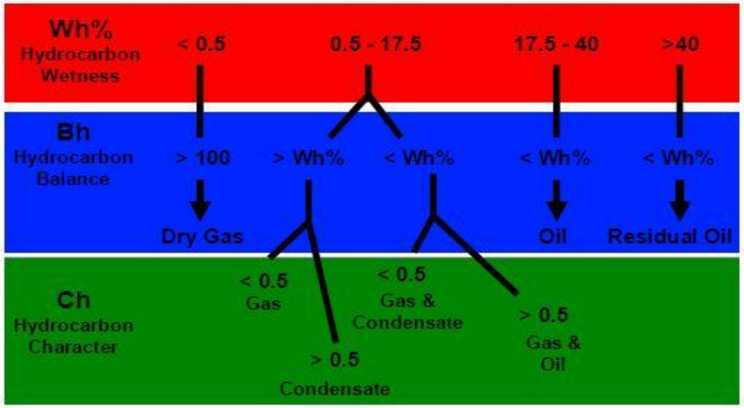

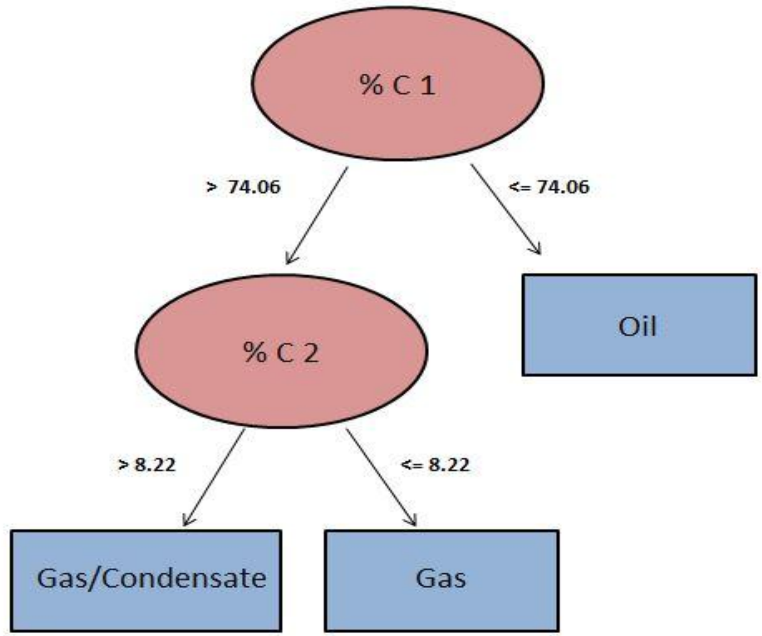

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