

Predicting Heavy Oil Viscosity from Well Logs

September 25th CREWES Tech Talk
By: Eric Rops



Presentation Outline

1. Introduction to Heavy Oil and Viscosity
2. Theory of Multi-attribute Analysis
3. Overview of the study wells
4. Viscosity Prediction Results
5. Conclusions
6. Future Work

Introduction – Heavy Oil

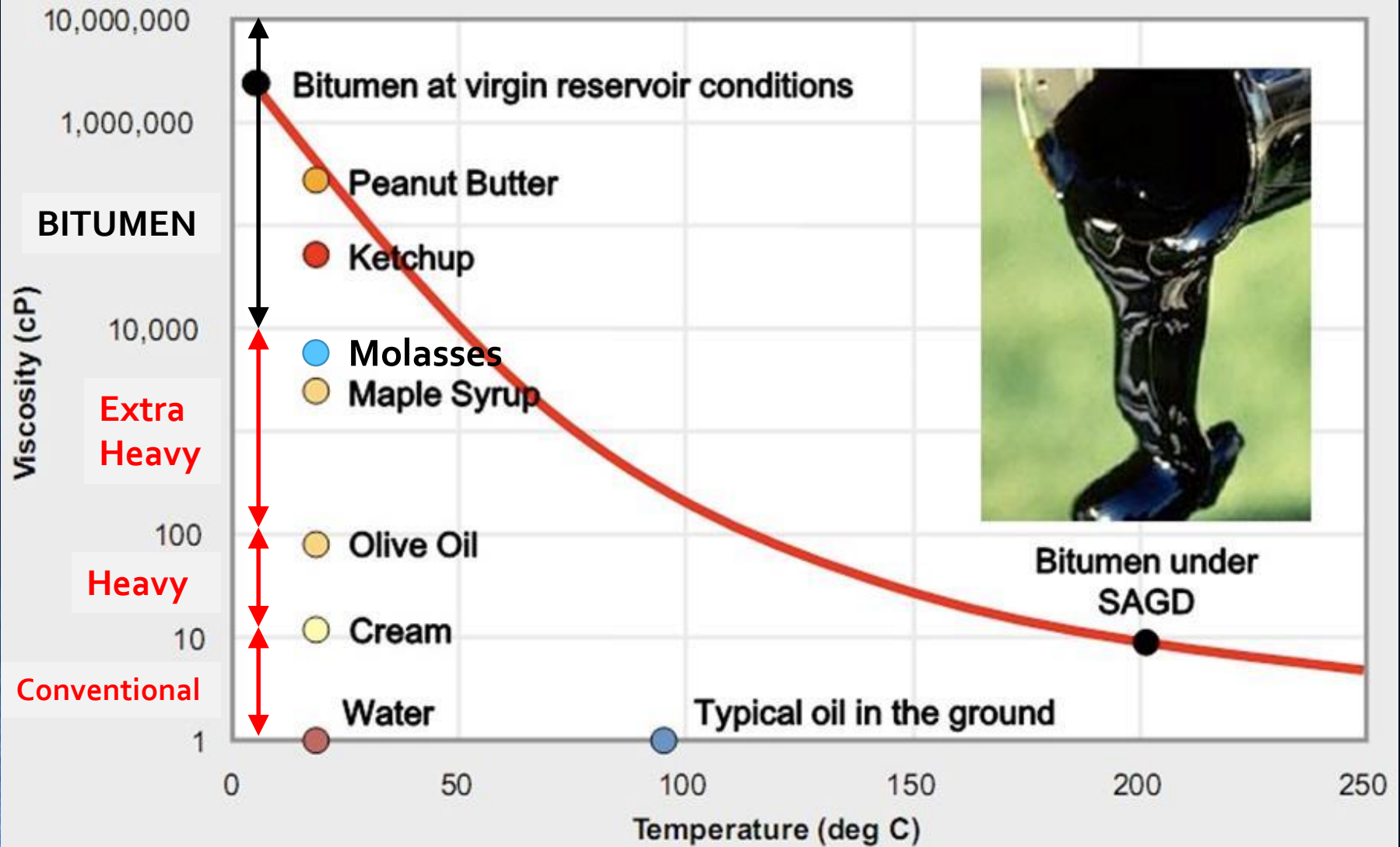
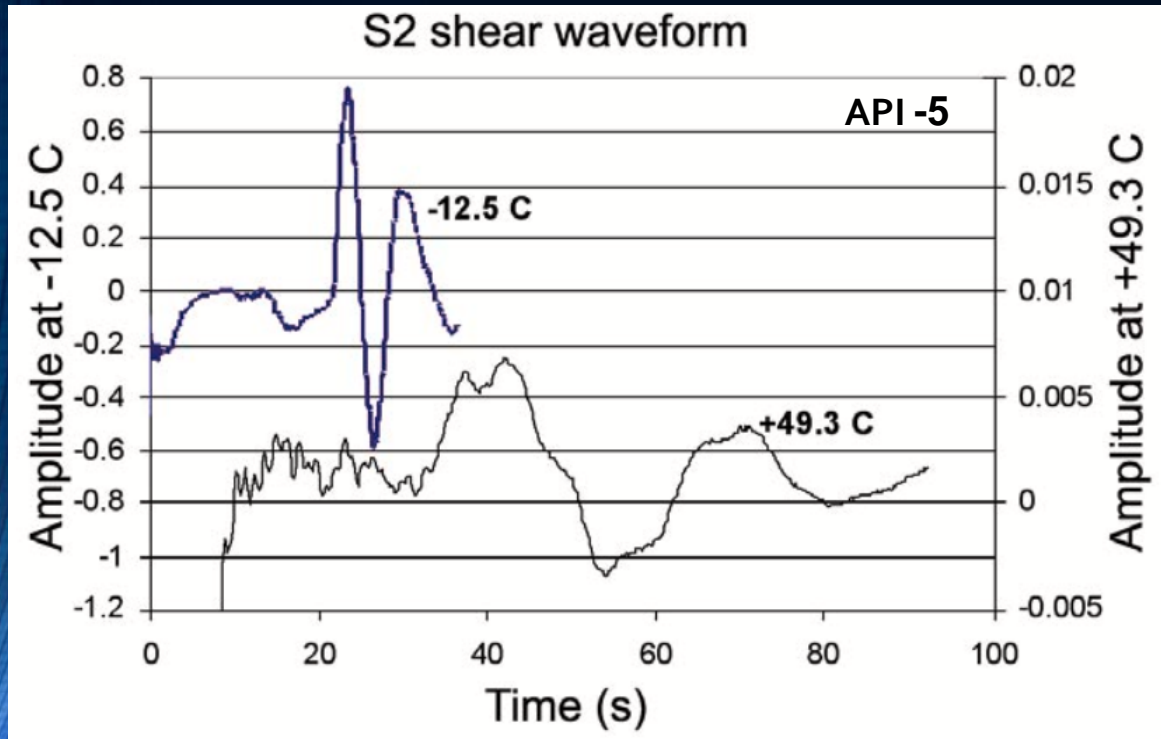


Image Credit: ConocoPhillips Oil Sands website

Why do we Care About Viscosity?

- “Viscosity is the key controlling heavy-oil production and, as we shall see, it also has a strong influence on seismic properties.” (Han & Liu & Batzle, 2008)
- It is used as a main criterion in determining the optimum recovery method.

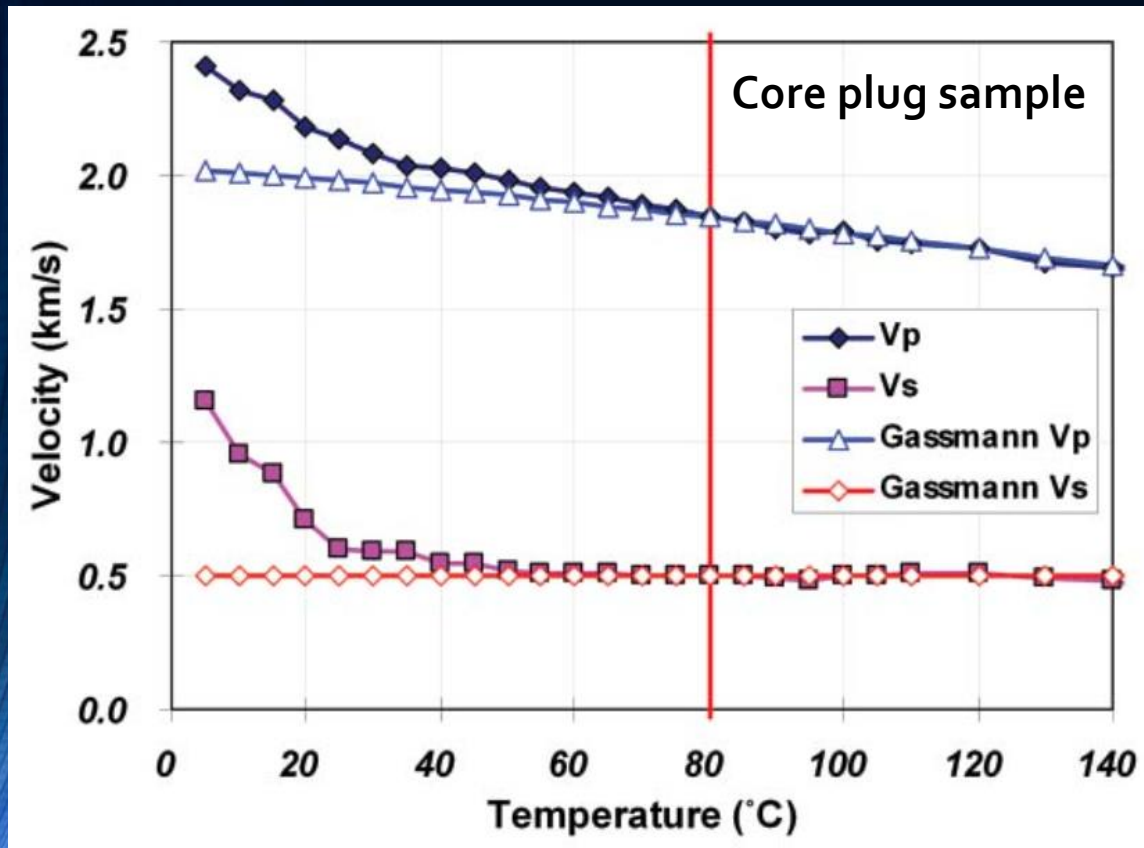
Shear Properties of Heavy Oil (Lab Measurements)



Batzle & Hofmann & Han (2006)

- Because of its high viscosity, heavy oil has a non-negligible shear modulus
- Figure shows sharp shear arrival in a very heavy oil sample (API -5)

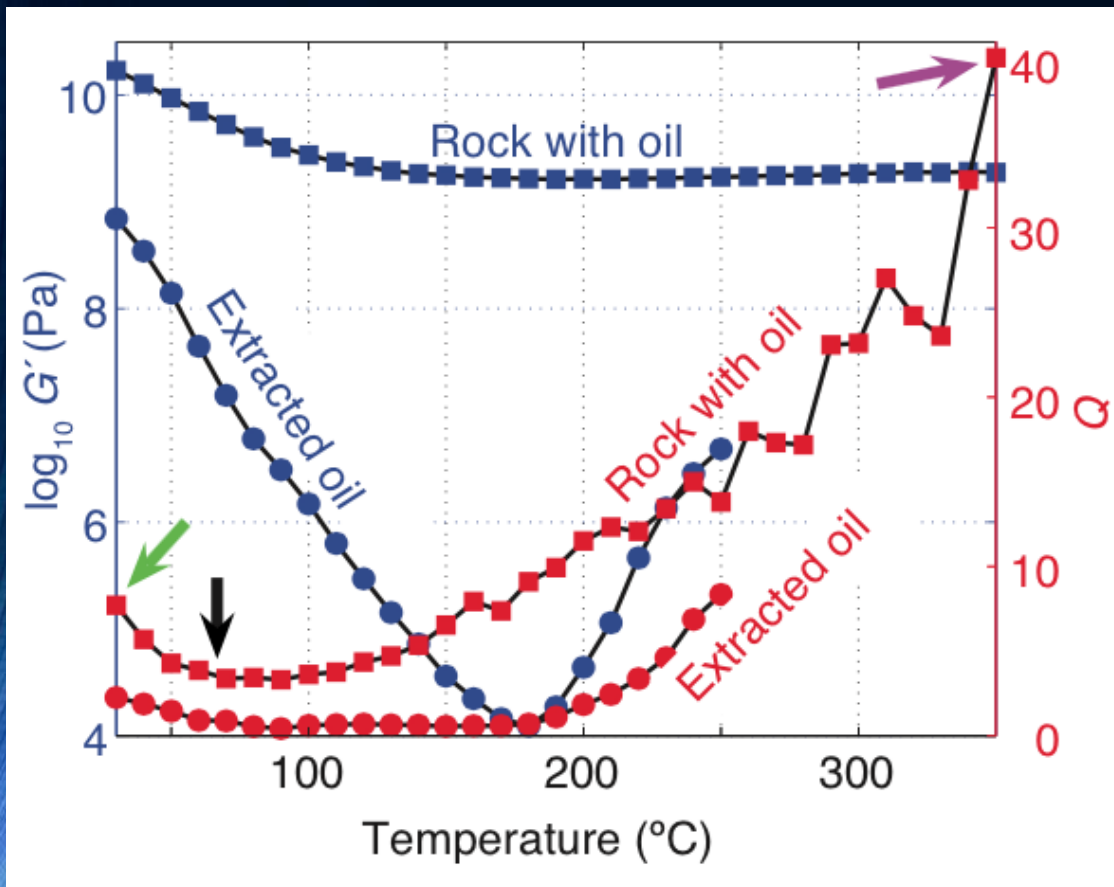
Lab Measurements of Heavy Oil - Rock



Kato & Onozuka & Nakayama (2008)

- Gassmann Equation not valid below a certain temperature once the viscosity starts getting high

Shear Modulus and Attenuation Lab Measurements

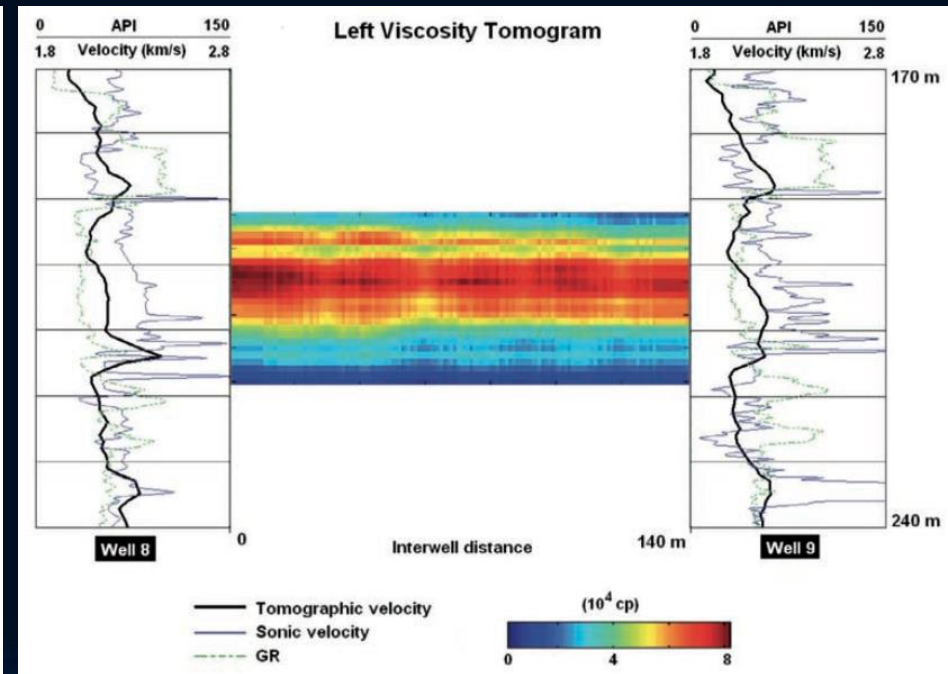
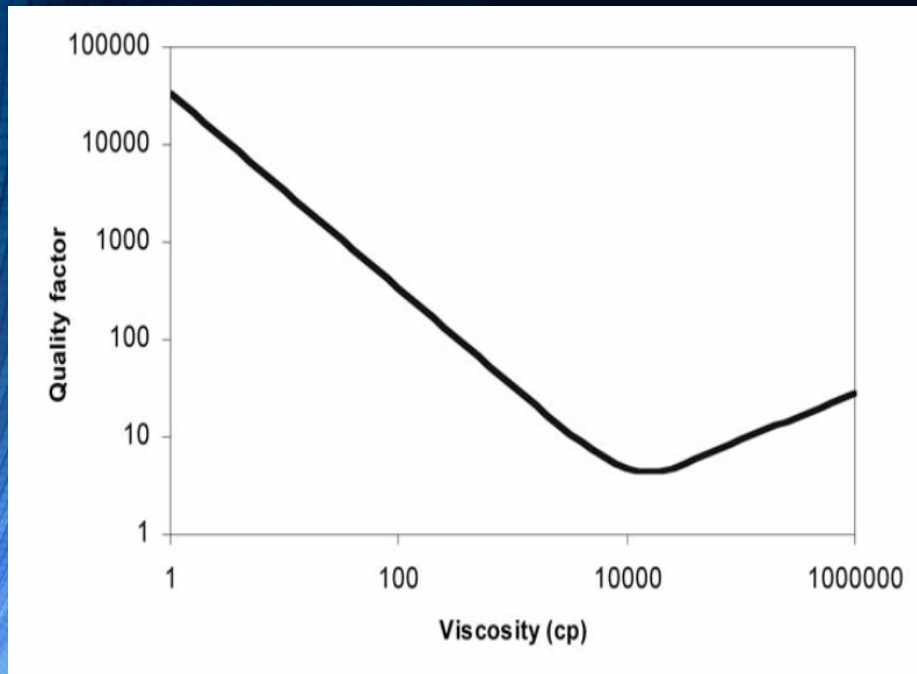


Behura et al. (2007)

- Dynamic behavior of shear modulus and attenuation with temperature. (Measured at 12.6 Hz)

Estimating Viscosity from Crosswell Seismic Data

- Attenuation tomography used to extract Q, then related Q to viscosity using Biot Squirt Theory



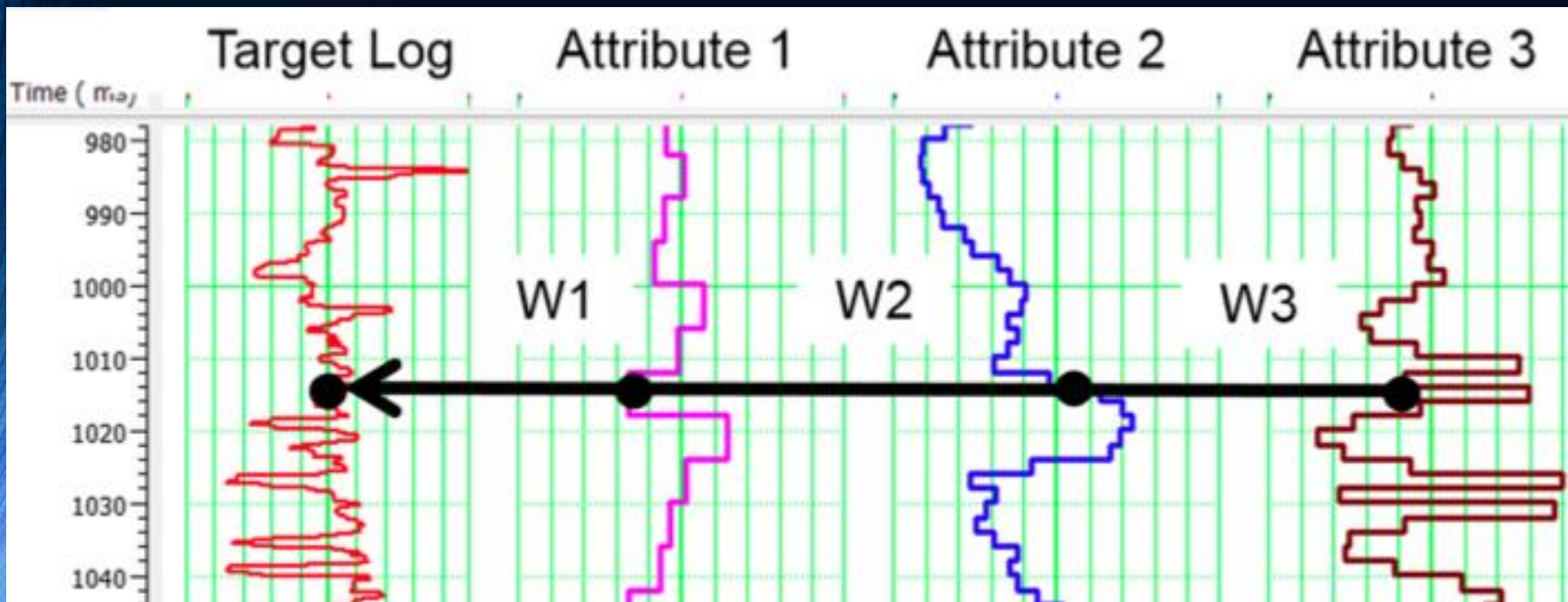
Goal of this Study

- 13 wells acquired from the Athabasca region of northern Alberta
- Each well had viscosity measurements, and dipole sonic logs
- *Can we train a relationship between viscosity and the well log data in only some of the wells, and then successfully predict the viscosity in the remaining wells?*

Theory of Multi-Attribute Analysis

Multi-Attribute Analysis

- At each time sample, the target log is modeled as a linear combination of several attributes.
- "Attribute" and "Well log curve" mean the same thing



Example: Predicting P-wave velocity with 3 Attributes

$$V_p(z) = w_0 + w_1 D(z) + w_2 G(z) + w_3 R(z)$$

where: $V_p(z)$ = P-wave velocity (m/s)

$D(z)$ = Bulk density (kg/m³)

$G(z)$ = Gamma ray (API units)

$R(z)$ = Resistivity (Ohm*m)

Or in matrix form:

$$\begin{bmatrix} V_{p_1} \\ V_{p_2} \\ \vdots \\ V_{p_N} \end{bmatrix} = \begin{bmatrix} 1 & D_1 & G_1 & R_1 \\ 1 & D_2 & G_2 & R_2 \\ \vdots & \vdots & \vdots & \vdots \\ 1 & D_N & G_N & R_N \end{bmatrix} \begin{bmatrix} w_0 \\ w_1 \\ w_2 \\ w_3 \end{bmatrix}$$

Or more compactly as:

$$V_p = AW$$

The regression coefficients can be solved for using least-squares:

$$W = [A^T A]^{-1} A^T V_p$$

What are the best Attributes to use?

Goal is to **minimize the prediction error**:

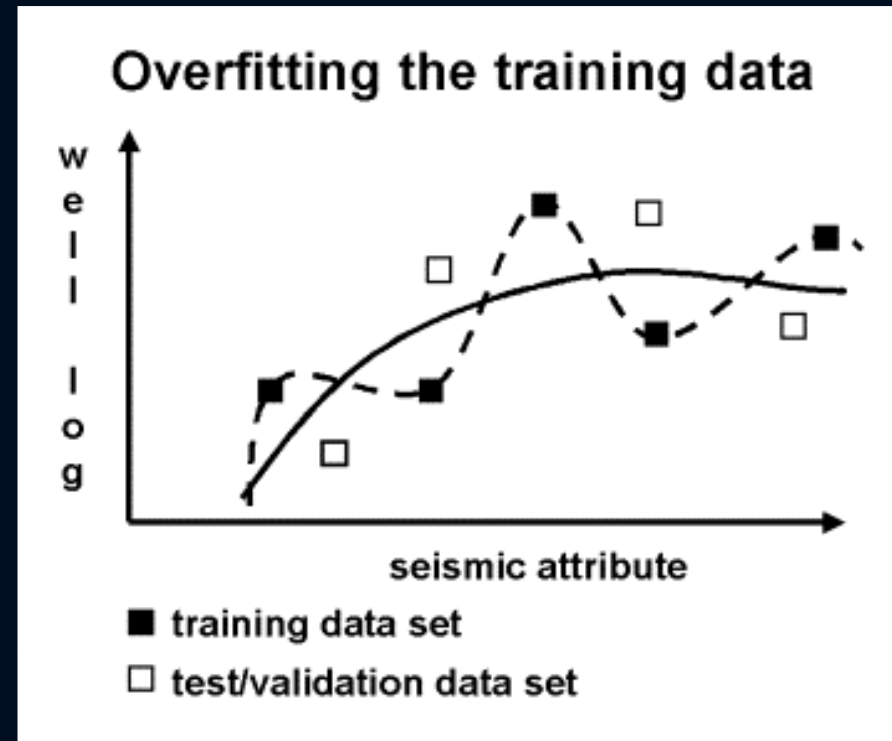
$$PE = \sqrt{\frac{\sum_{i=1}^N (V_{pTrue,i} - V_{pPredicted,i})^2}{N}}$$

Step-wise regression:

1. Find the single best attribute
2. Find the best pair of attributes
3. Find the best triplet of attributes
4. Carry on as long as desired

When do we Stop Adding Attributes? (why would we want to stop?)

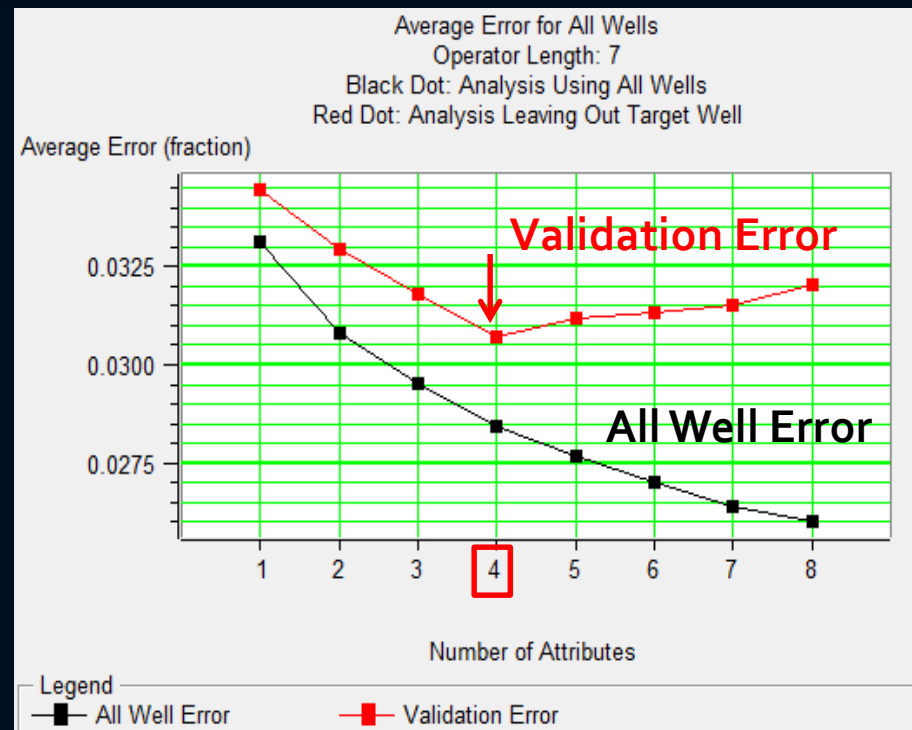
- Adding attributes is similar to fitting a curve through a set of points, using a polynomial of increasing order
- A higher order polynomial can “**overfit**” the data
- **Emerge™** uses Cross Validation to determine when to stop adding attributes



Hampson-Russell **Emerge™** Course Notes

Cross Validation

1. **Leave out a test well**, and solve the regression coefficients using only the remaining wells
2. Use these coefficients to predict the target attribute in the test well
3. The prediction error is the validation error for that test well
4. Repeat for each training well, and compute the average validation error



Hampson-Russell Emerge™ Course Notes

Data and Results

Location of the 13 Study Wells



- Located within the Athabasca oil sands

Image from Google Earth®

Summary of the 13 Study Wells

Each well has:

- Lab Viscosity Measurements from AccuMap®
- Dipole sonic logs
- Full suite of standard well log curves

- Viscosity ranges from **6,685 cP** to **18,374 cP** (measured at 20°C)

* Well 13 not included in the analysis until the very end

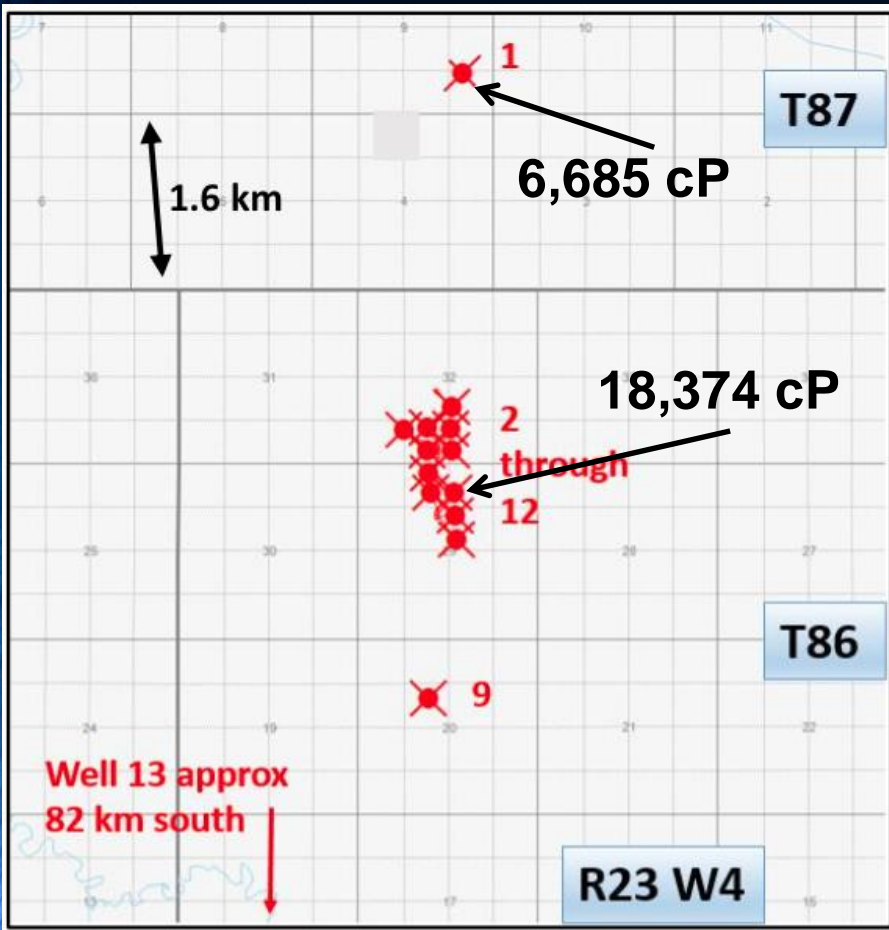


Image from AccuMap®

Type Well for the Study Area (Well 2)

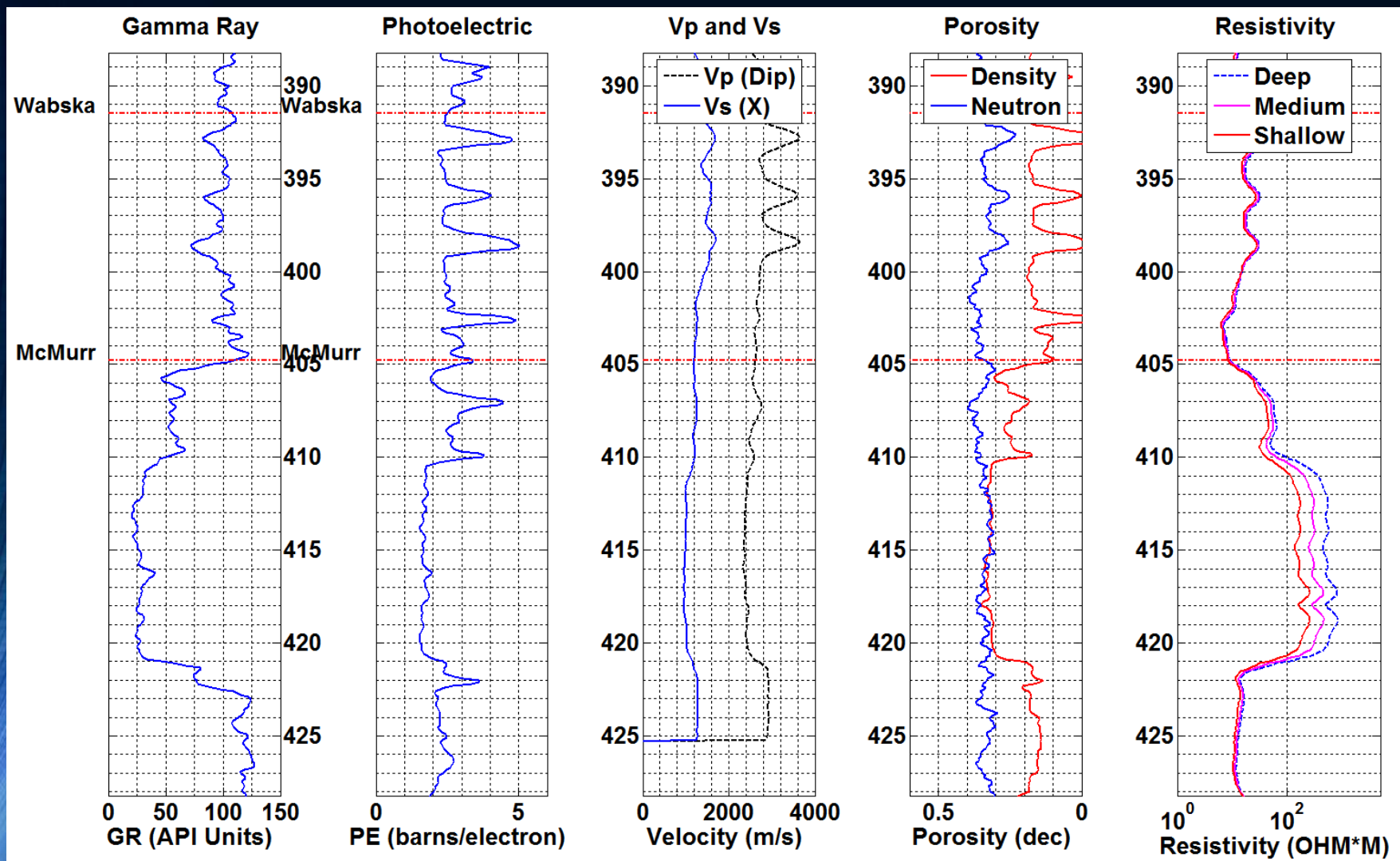


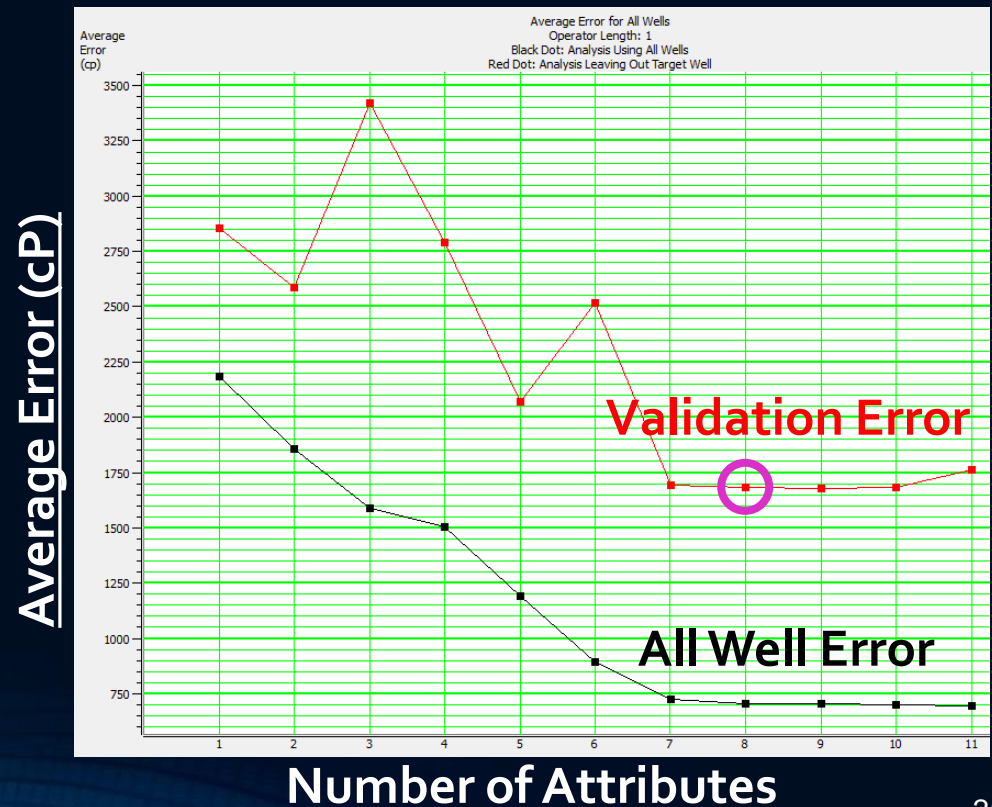
Image generated using *Matlab*® 2014a

Initial Training Results

- Wells 1 to 5 were used to train the multi-attribute relation
- Viscosity is then *blindly predicted* in the remaining wells

Most important attributes:

1. (1 / S-wave)
2. (1 / SP) ← !!!
3. (1 / Gamma Ray)
4. (1 / Res Shallow)
5. (Res Deep)^{1/2}
6. (Res Medium)^{1/2}
7. (1 / Neutron Porosity)
8. (1 / P-wave)

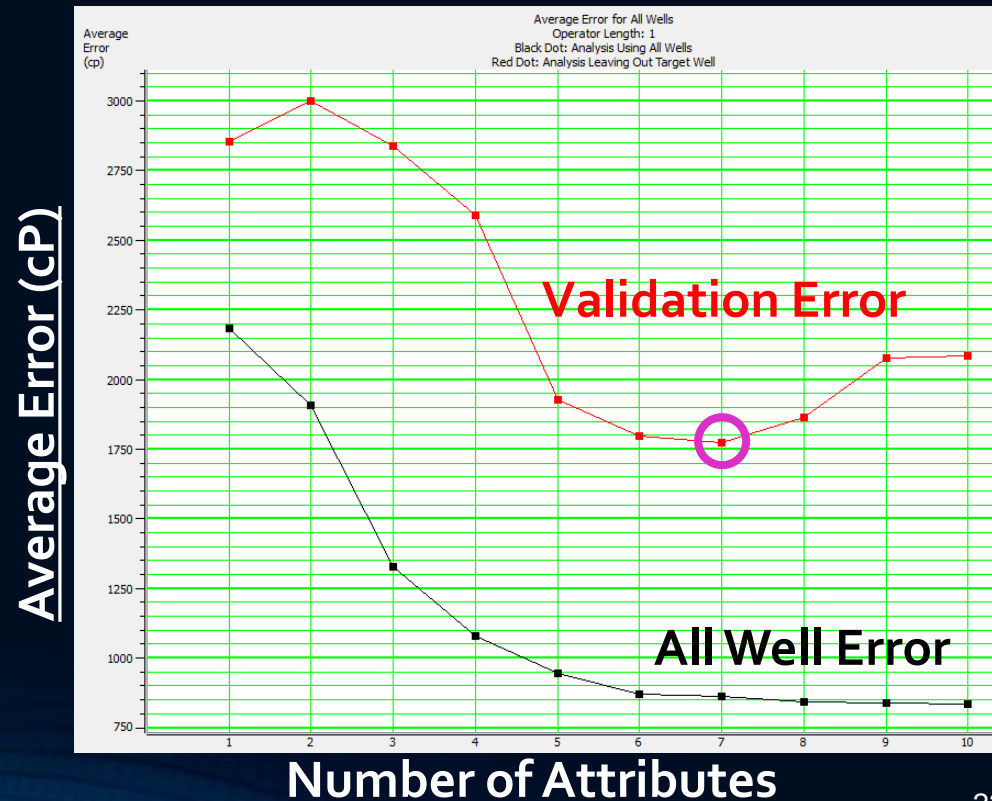


Modified Training Results (No SP)

- Validation error curve is much smoother
- Optimum fit between viscosity and our 5 training wells is found using 7 attributes

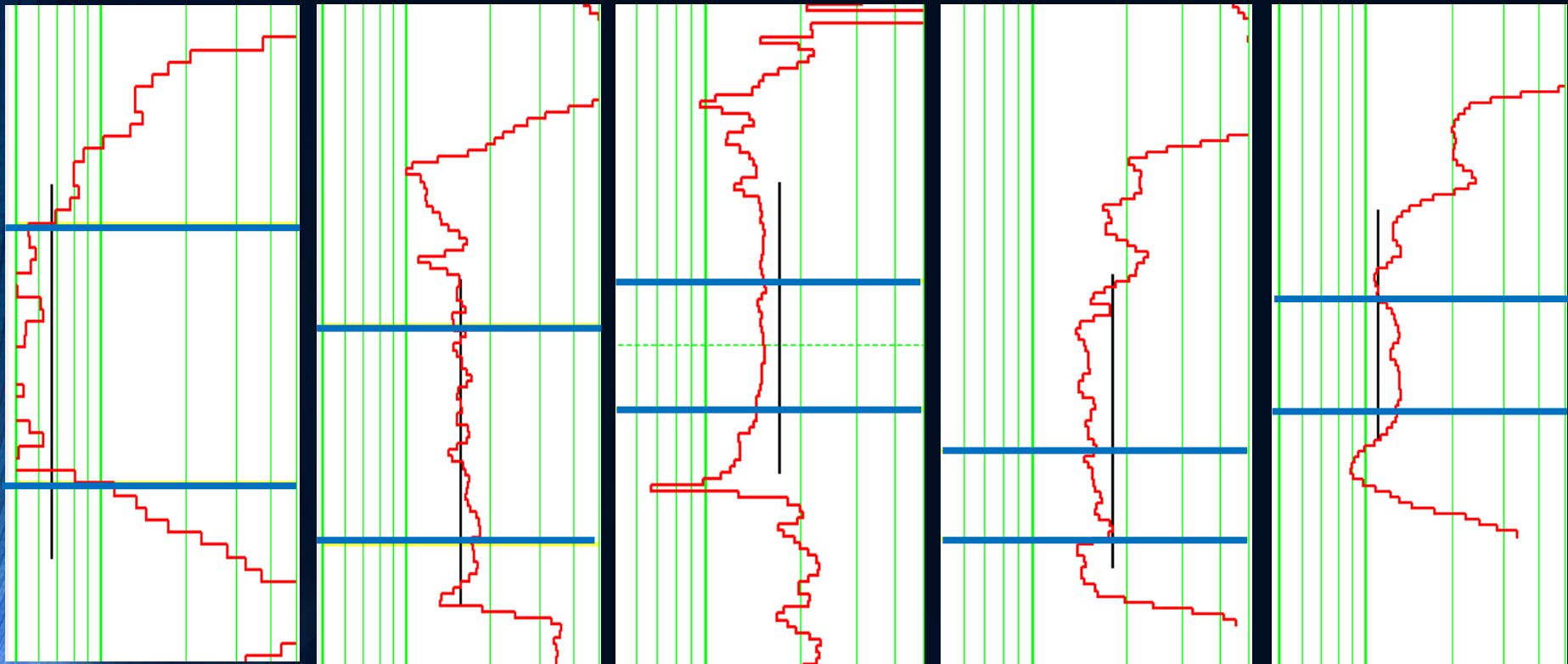
Most important attributes:

1. $(1 / S\text{-wave})$
2. *Res Deep*
3. *Res Medium*
4. $(1 / Res\ Shallow)$
5. $(1 / Neutron\ Porosity)$
6. $(1 / Photoelectric)$
7. $(1 / Density\ Porosity)$



Cross Validation Results for the 5 Training Wells

← (Log scale from 5,000 cP to 50,000 cP) →



Well 1
Avg RMSE
1830 cP

Well 2
Avg RMSE
1205 cP

Well 3
Avg RMSE
2199 cP

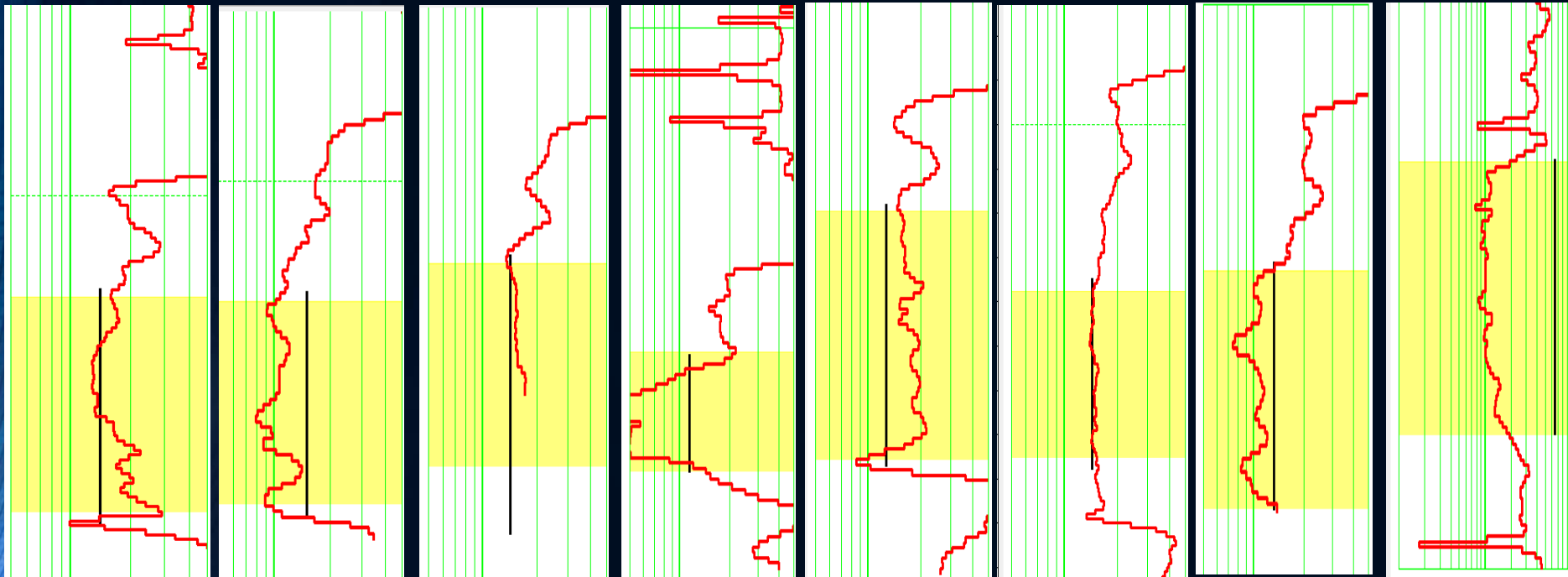
Well 4
Avg RMSE
2190 cP

Well 5
Avg RMSE
1716 cP

Blind Viscosity Predictions of the Remaining Wells

← (Log scale from 5,000 cP to 50,000 cP) →

82 km South



Well 6
Avg
Error:
2011 cP

Well 7
Avg
Error:
4584 cP

Well 8
Avg
Error:
1060 cP

Well 9
Avg
Error:
8390 cP

Well 10
Avg
Error:
5162 cP








Well 11
Avg
Error:
384 cP

Well 12
Avg
Error:
2901 cP

Well 13
Avg
Error:
55697 cP

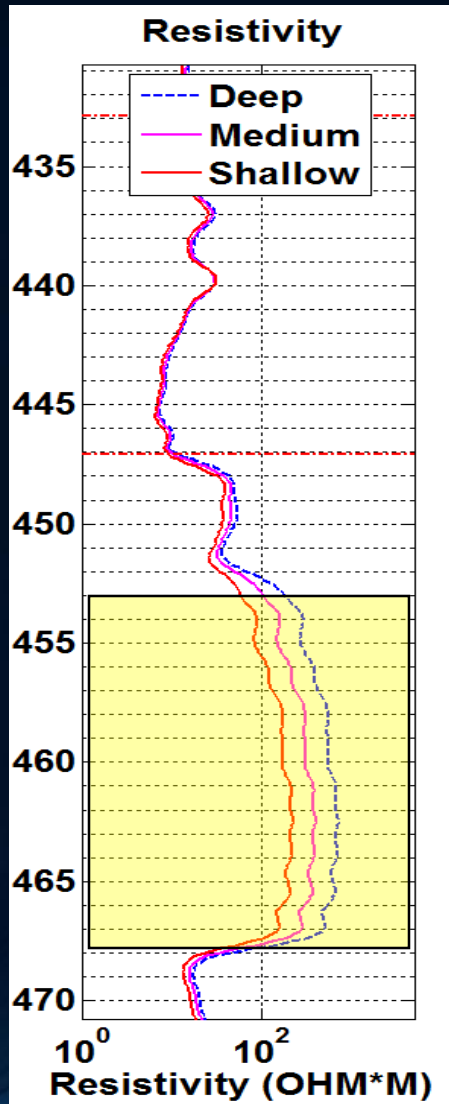
Which Wells Did Good? Which Wells did not?

- Using a cutoff error of 25% of the total viscosity range (2922 cP)

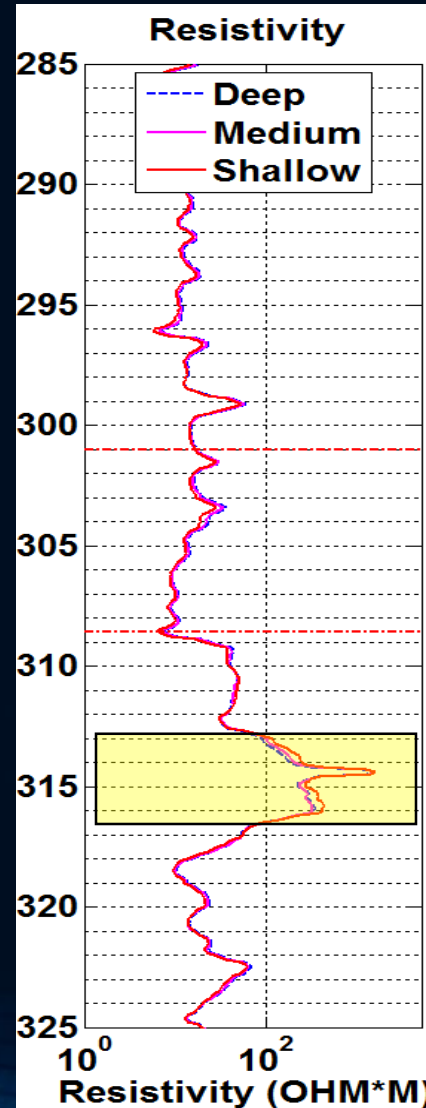
| <u>Well 6</u> | <u>Well 7</u> | <u>Well 8</u> | <u>Well 9</u> | <u>Well 10</u> | <u>Well 11</u> | <u>Well 12</u> | <u>Well 13</u> |
|--|---|---|---|---|---|---|----------------|
| Avg | Avg | Avg | Avg | Avg | Avg | Avg | Avg |
| Error: | Error: | Error: | Error: | Error: | Error: | Error: | Error: |
| 2011 cP | 4584 cP | 1060 cP | 8390 cP | 5162 cP | 384 cP | 2901 cP | 55697 cP |
|  |  |  |  |  |  |  | 82 km South |

Why Would Some Wells Predict Viscosity Better than Others?

Well 11
Best
Viscosity
Predictor



Well 9
Worst
Viscosity
Predictor



Conclusions

- Predicting viscosity using multi-attribute regression of well logs was done successfully, **within 25% error in 4 out of the 7 blind test wells.**
- It is important to use the entire range of desired viscosities when training the regression
- The shear sonic log was found to be the most important viscosity predictor
- The next most important attributes were: *the 3 resistivity logs, neutron porosity, photoelectric factor, and density porosity*
- Observations suggest that viscosity can be predicted most accurately in a well where the reservoir has separation between resistivity curves (ie. is porous and permeable)

Future Work

- **Nexen – CNOOC** has provided viscosity data for ~ **150 wells** with **multiple measurements per well**
- **Goal:** define an **empirical relationship** to predict a wide range of viscosities using only standard well log curves
- **If time:** develop a Matlab code to do this analysis, but test more **non-linear transformations** of the attributes

Acknowledgements

- **Larry Lines** (supervisor)
- **Nexen / David Gray** (expanded viscosity dataset)
- **Scott Keating & Bobby Gunning** (discussions / dry runs)

Questions?

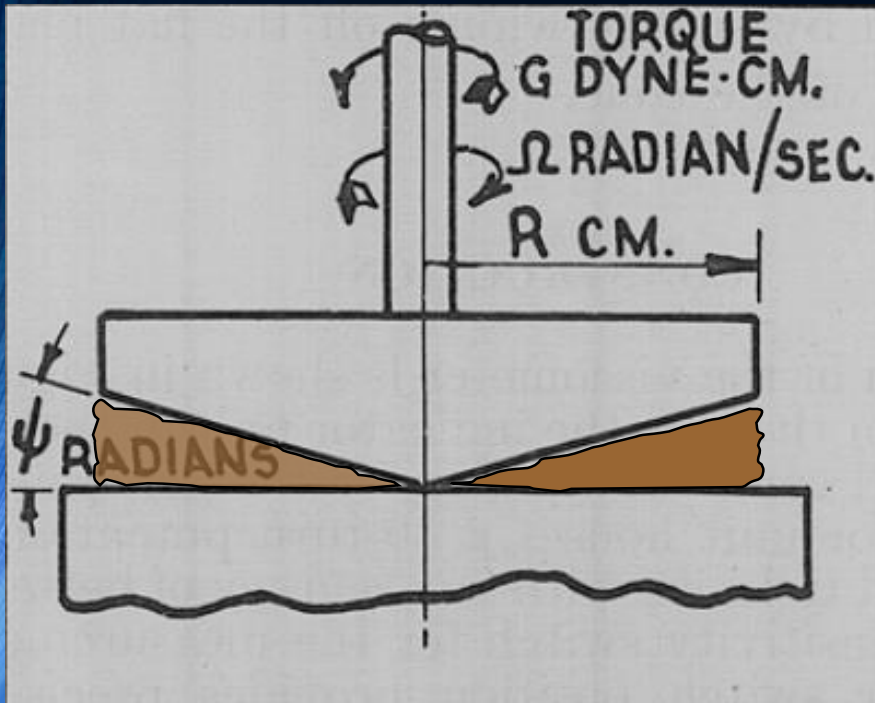


Viscosity Regression Equation

$$\begin{aligned}\eta = & 2331.90 + 8751259.00 \left(\frac{1}{S_{wave}} \right) + 49.33(ResDeep) - 72.02(ResMedium) \\ & + 566728.13 \left(\frac{1}{ResShallow} \right) - 2788.40 \left(\frac{1}{NPHI} \right) + 16271.04 \left(\frac{1}{PEF} \right) \\ & - 1551.46 \left(\frac{1}{DPHI} \right)\end{aligned}$$

Viscosity Measurement

- **Cone and Plate Viscometer** is typically used for heavy oil
- The resistance to the rotation of the cone produces a torque that is proportional to the shear stress in the fluid



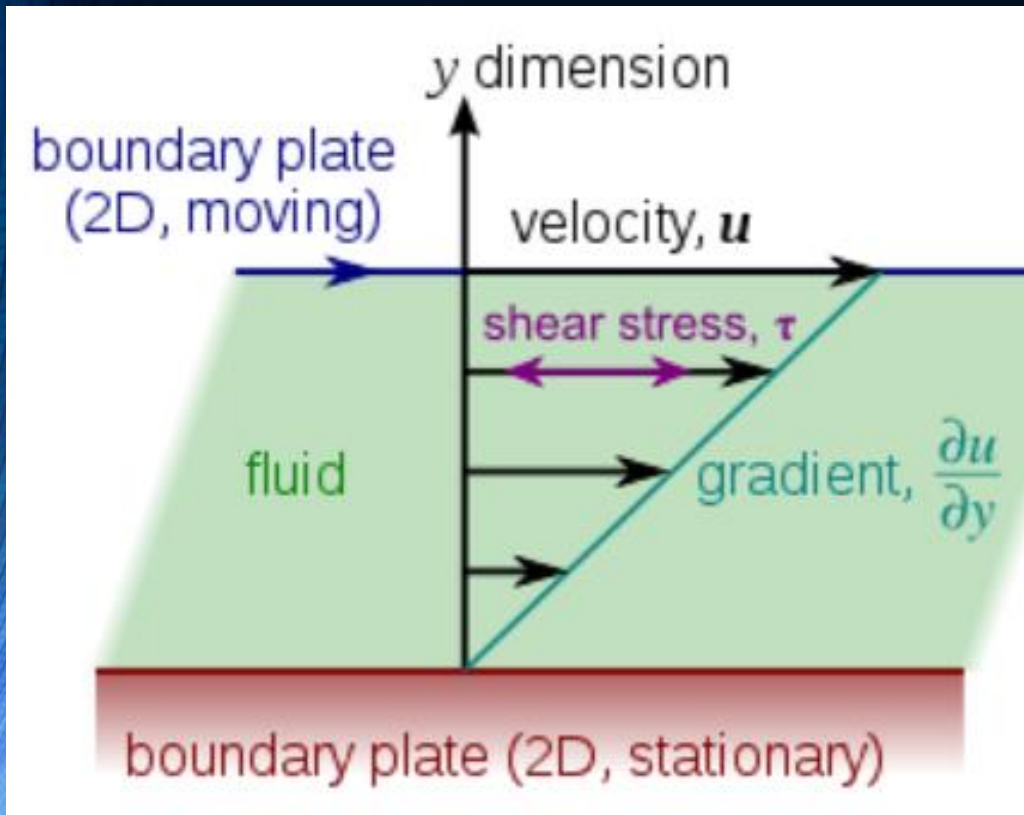
$$\text{Viscosity} = \frac{\text{Shear Stress}}{\text{Shear Rate}}$$

$$\eta = \frac{3G}{2\pi R^3} / \frac{\Omega}{\psi}$$

McKinnell (1956)

Viscosity Concept

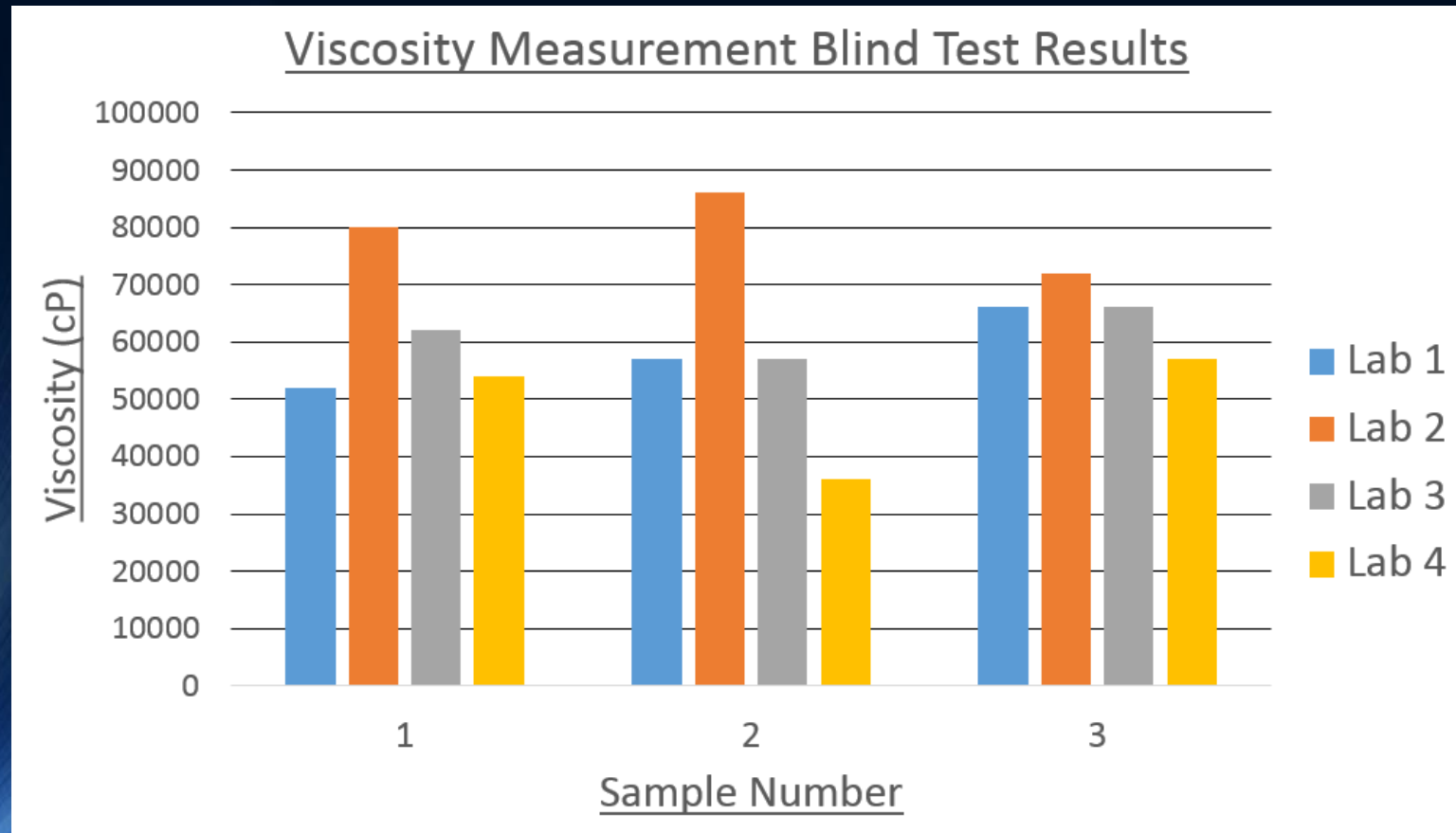
$$1 \text{ cP} = 1 \text{ mPa} \cdot \text{s} = 0.001 \text{ Pa} \cdot \text{s} = 0.001 \frac{\text{N}}{\text{m}^2} \cdot \text{s} = 0.001 \frac{\text{kg}}{\text{m} \cdot \text{s}}$$



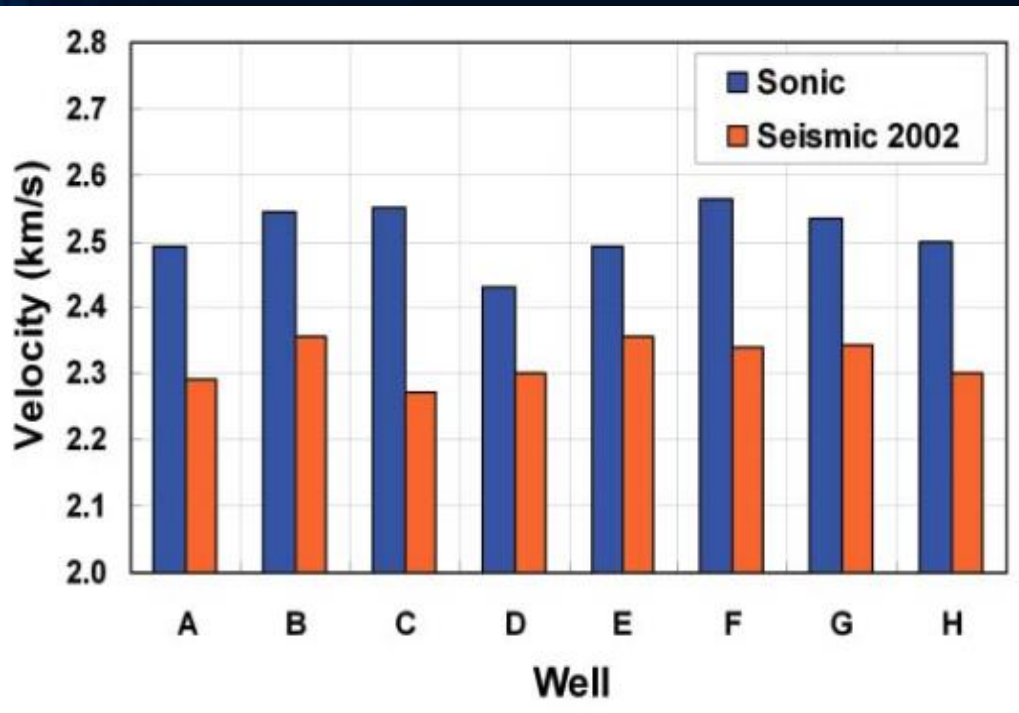
- If a fluid is placed between two plates with distance 1 m , and one plate is pushed sideways with a shear stress of 1 Pa , and it moves at " u " m/s , then it has viscosity of " u " $\text{Pa} \cdot \text{s}$

Uncertainty of the Viscosity Measurement

- Miller et al (2006): Should you Trust your Heavy Oil Viscosity Measurement?



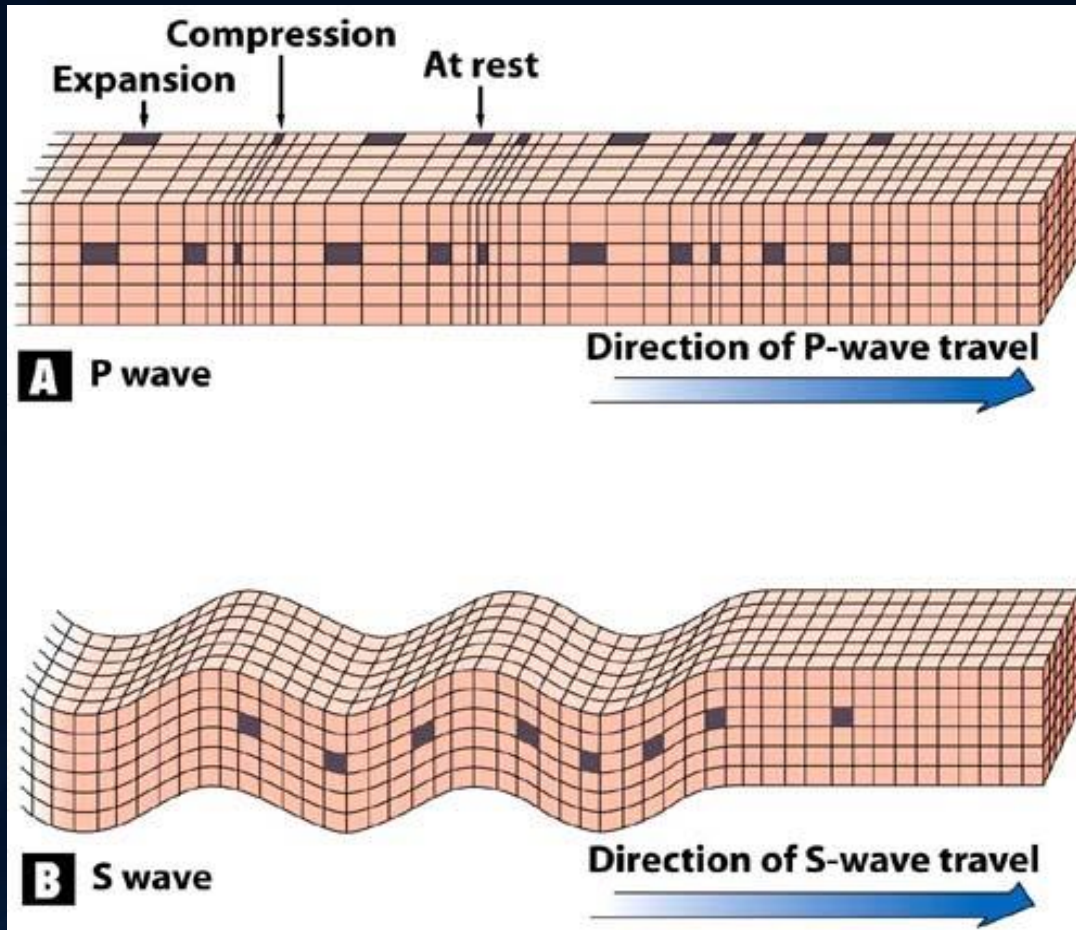
Velocity Dispersion



Kato & Onozuka & Nakayama (2008)

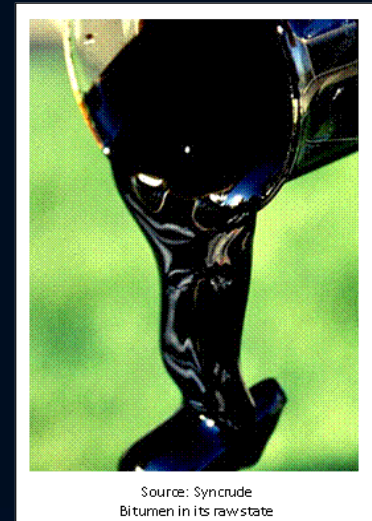
- Velocities tend to increase with measurement frequency
- Laboratory measurements give higher velocities than sonic logs or seismic data
- Example from a heavy oil field 50km SW of Fort McMurray

Wait ... S-waves travel through heavy oil?



Non-negligible
Rigidity

Zero Rigidity



Source: Syncrude
Bitumen in its raw state

Image Credit: academic.brooklyn.cuny.edu