Data Analytics for Greenfield Production Forecasting - A Case Study of Antelope Shale*

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Abstract

In this article, we discuss the case study of four vertical wells drilled in the McKittrick Field in San Joaquin Valley targeting the Opal CT and Quartz phases of the Antelope Shale reservoir. All four wells came on at good Initial Production (IP), followed by a steep decline. The results showed opportunities for a horizontal development plan but were challenged by operational issues, limited analog data set, higher cost, poor economics, and comparison with traditional heavy oil projects.

An analog study of unconventional shale plays with both vertical and horizontal producers in San Joaquin Valley and the Permian was done to understand the relative performance of horizontal and vertical wells. This, along with the actual production data from the four vertical wells was used to forecast the horizontal wells production using Decline Curve Analysis (DCA). This statistical method of production forecasting is an inverse problem that is well suited to multivariate correlating technique like Support Vector Machine (SVM). A stochastic model using SVM was developed incorporating the geological, geomechanical, fracture stimulation, production, and zonal contribution data. This model was trained, tested, and then used to forecast oil production. The results of the SVM model compared reasonably well with the analog method of production forecasting, thus validating the DCA forecast using analog data set.

In lack of a reservoir simulation model, the SVM model offers a relatively quick and less expensive way of forecasting oil production using parametric supervised learning. As more production data becomes available, the uncertainty associated with the SVM model should decrease (or the accuracy of the SVM model should increase) which will enable using a deterministic SVM model rather than a stochastic model. This practical application of machine learning opens the opportunity to utilize large volumes of multi-dimensional data and translate them into actionable insights. Use of machine-led intelligence can result in cost and time savings while providing a technology roadmap for forecasting production in a greenfield in lack of suitable analog data and reservoir simulation model. This can be particularly more useful in a low oil price environment.

DATA ANALYTICS FOR GREENFIELD PRODUCTION FORECASTING – A CASE STUDY OF ANTELOPE SHALE

PSAAPG, 23 April 2018, Bakersfield, CA

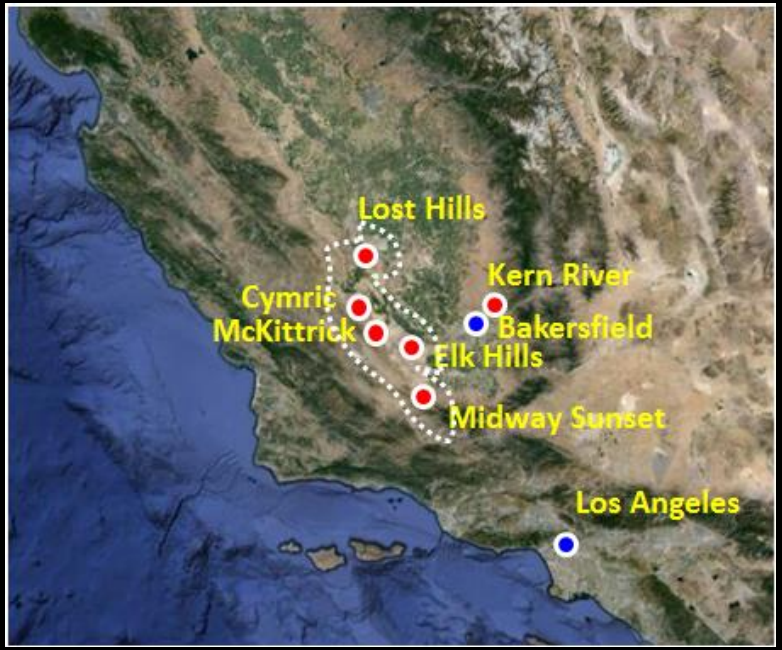
By: Manish K Lal & Tae Kim, Chevron

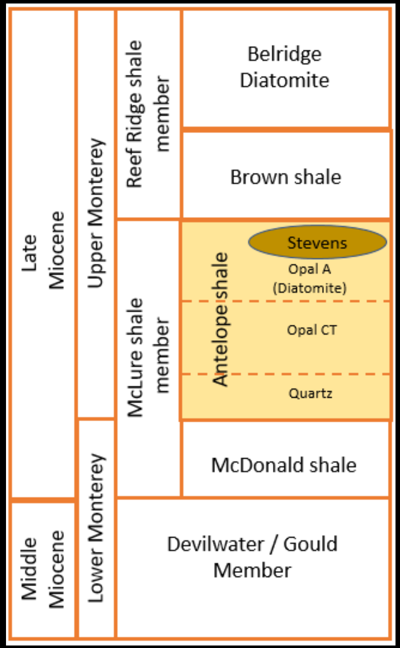
OUTLINE

- Antelope Shale
  - Background
  - Current Status
  - Development Plan
- Support Vector Machine (SVM)
  - Model Training
  - Production Forecast
  - Accuracy & Reliability
  - Future Applications
- Lessons Learned / Best Practices / Challenges

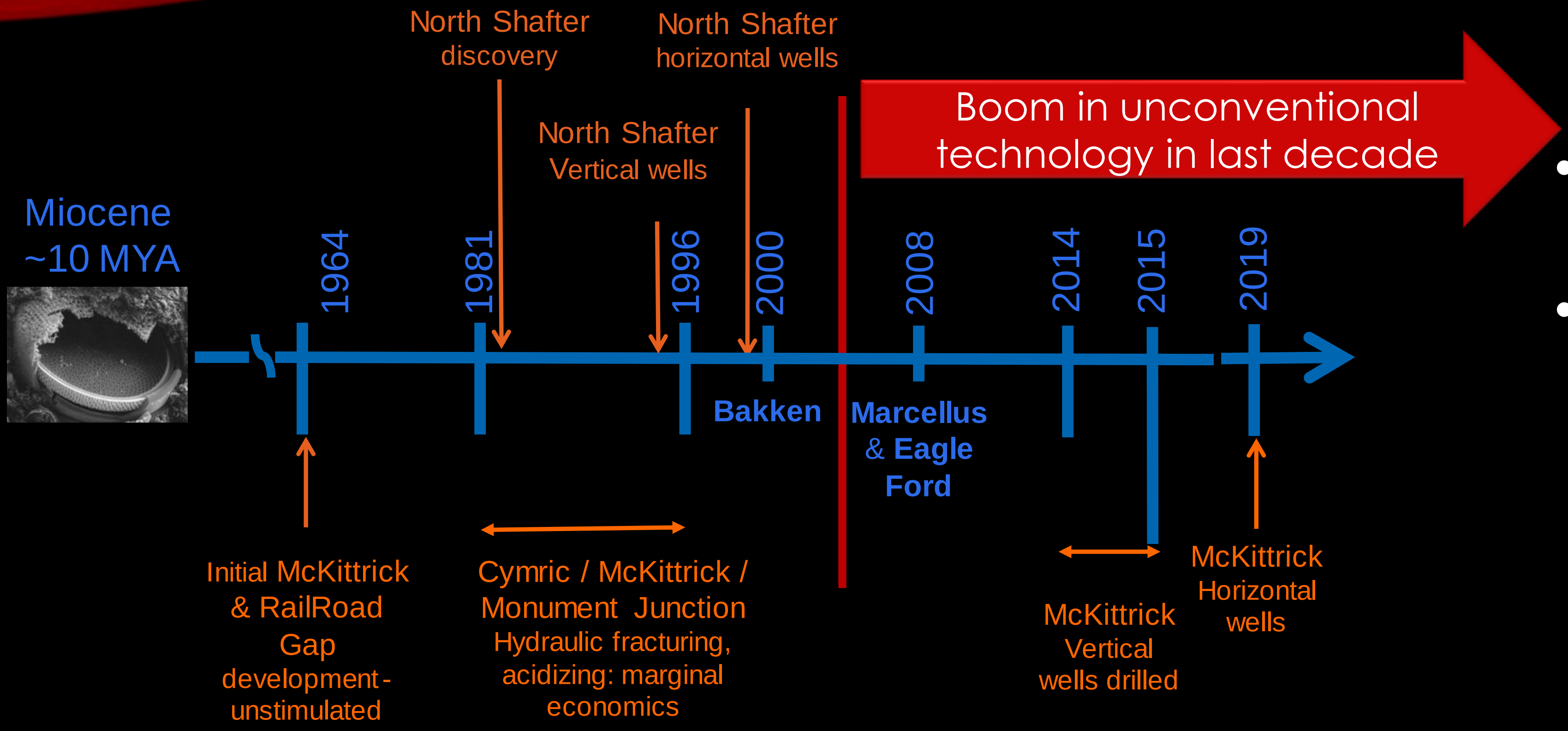
BACKGROUND

- Monterey produces from reservoirs in all three silica phases: Opal A (Diatomite), Opal CT, and Quartz
- Silica-rich diatom deposition in the Monterey formation
- Miocene age
- Naturally fractured, migrated oil, normally pressured
- Decent porosity (27-53%), low matrix permeability (0.001 -10 mD)
- 26 API oil with associated gas





DEVELOPMENT HISTORY

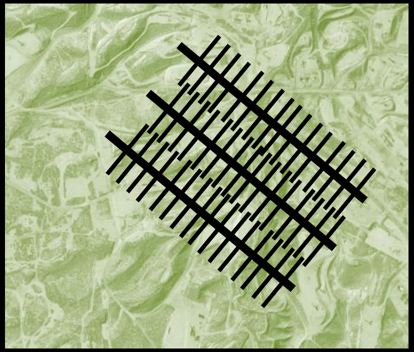


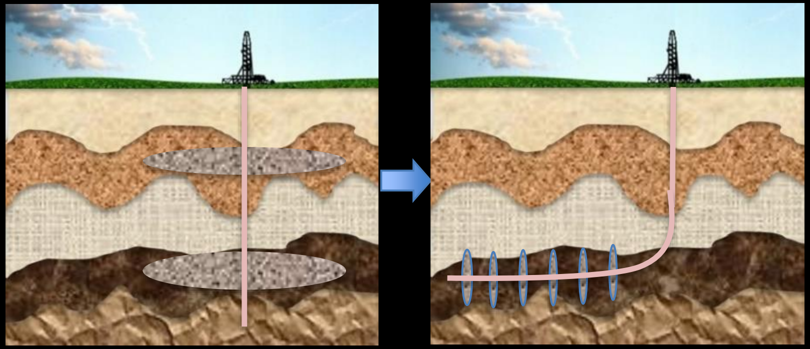
- Four vertical wells drilled in McKittrick field in 2015
- Objective of vertical drilling was data gathering and reservoir characterization

LEARNING OBJECTIVES OF VERTICAL WELLS

- ECONOMIC Field Development Plan
- Identify BEST Formation
- OPTIMUM Completion and Stimulation Design
- EARLY and LOW-COST Learning

- KEY DECISIONS
- Vertical or Horizontal Wells
- Well Spacing
- Horizontal Well Orientation
- Well Landing Depth
- Distance between fractures
- Completion Type

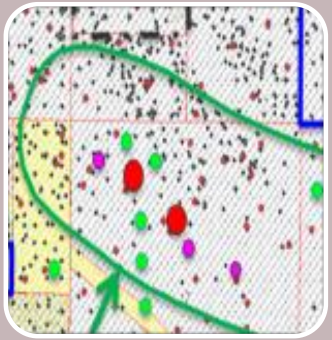




Early and Low-cost learning from vertical wells

Identify future field development Plan

LEARNING STRATEGY



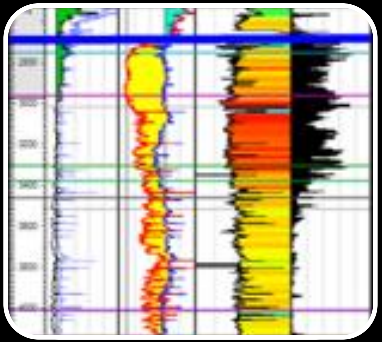
Vertical Wells

Gather critical data

Reservoir Characterization

Coring

Logging



Stimulation & Completion

Downhole microseismic

Tiltmeter

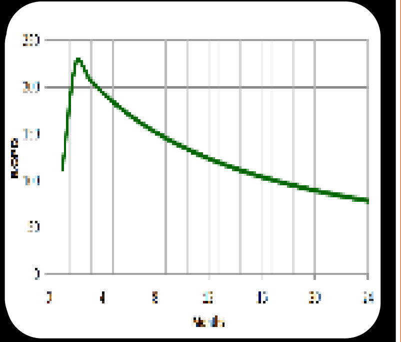
DFIT

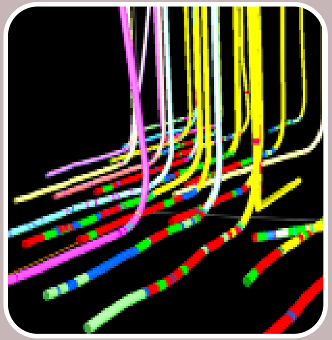
Production

Tracer results

Artificial lift

Operational challenges

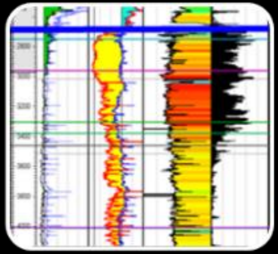


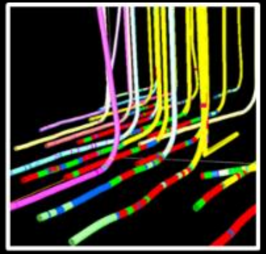


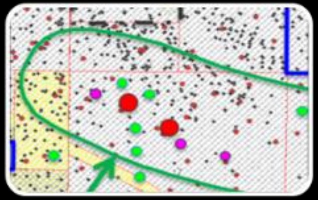
Horizontal Development

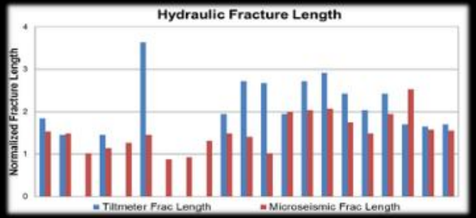
LEARNING SUMMARY

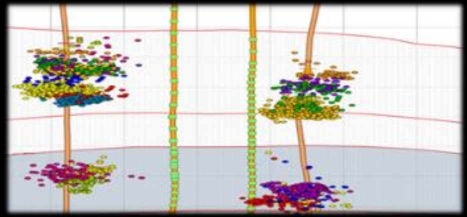
Key Decision Queries	Completion Plan for Field Development
Vertical or Horizontal Wells	Horizontal Well
Well Spacing	600 ft Fracture half length: 350 ft
Horizontal Well Orientation	perpendicular to N30 degree (transverse frac)
Well Landing Depth	Zone 4 in Opal CT Fracture height: 250 ft
Distance between fractures	100 ft
Completion Type	Single cluster CT sand-jet perf



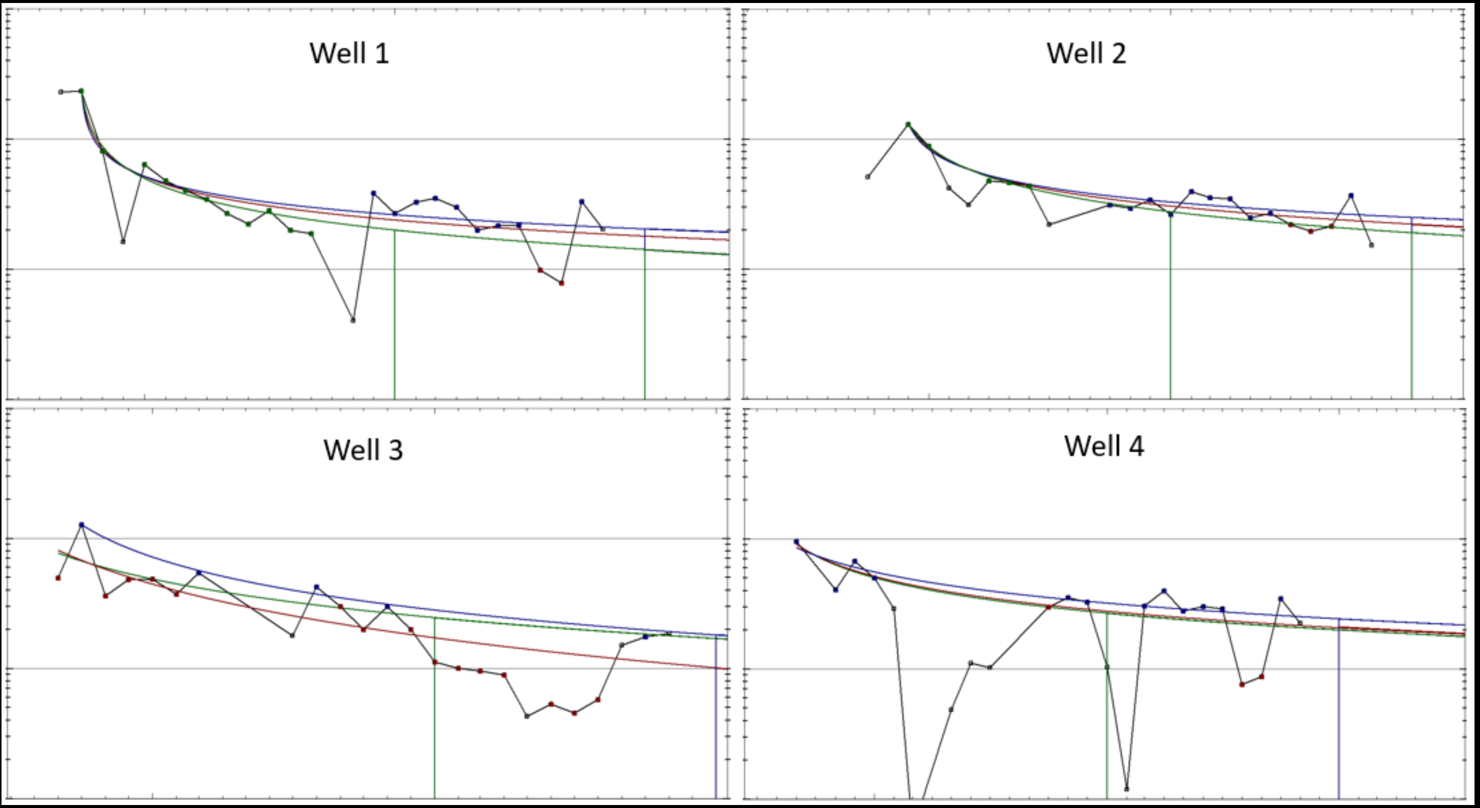








VERTICAL WELLS: GOOD INITIAL PRODUCTION, STEEP DECLINE

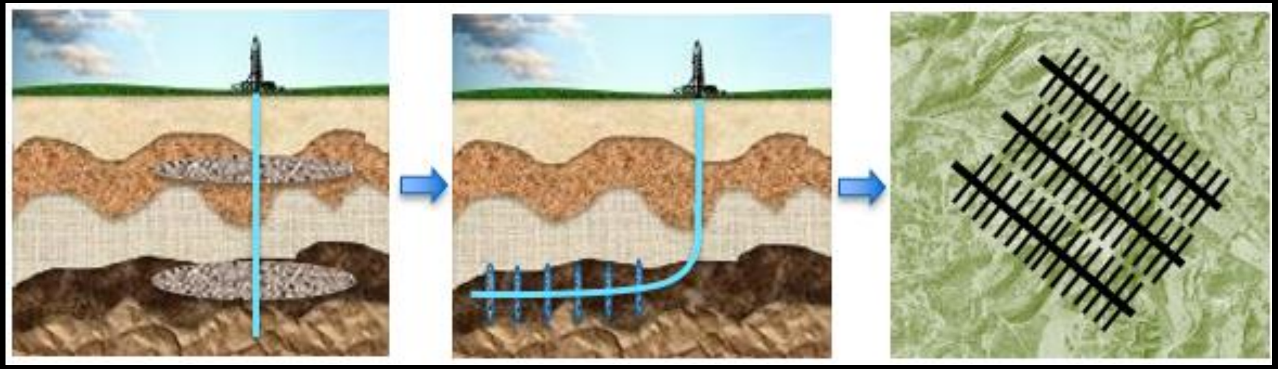


EUR with Time [months]	6 mo	12 mo	24 mo
Well 1	0.6	0.8	1.0
Well 2	0.6	0.8	1.0
Well 3	1.0	0.6	1.0
Well 4	0.7	0.9	1.0

OPPORTUNITY: HORIZONTAL DEVELOPMENT PLAN

- Encouraging early production response from vertical wells and generally expected better economics of drilling and completion for horizontal wells led to the selection of a horizontal development opportunity

- Utilized analog and Machine Learning to forecast horizontal wells production



Early and Low-cost learning from vertical wells

Identify future field development concept

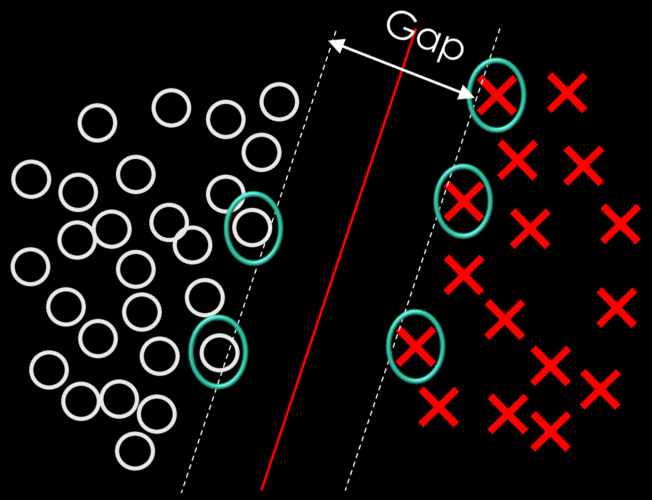
Field Development Plan

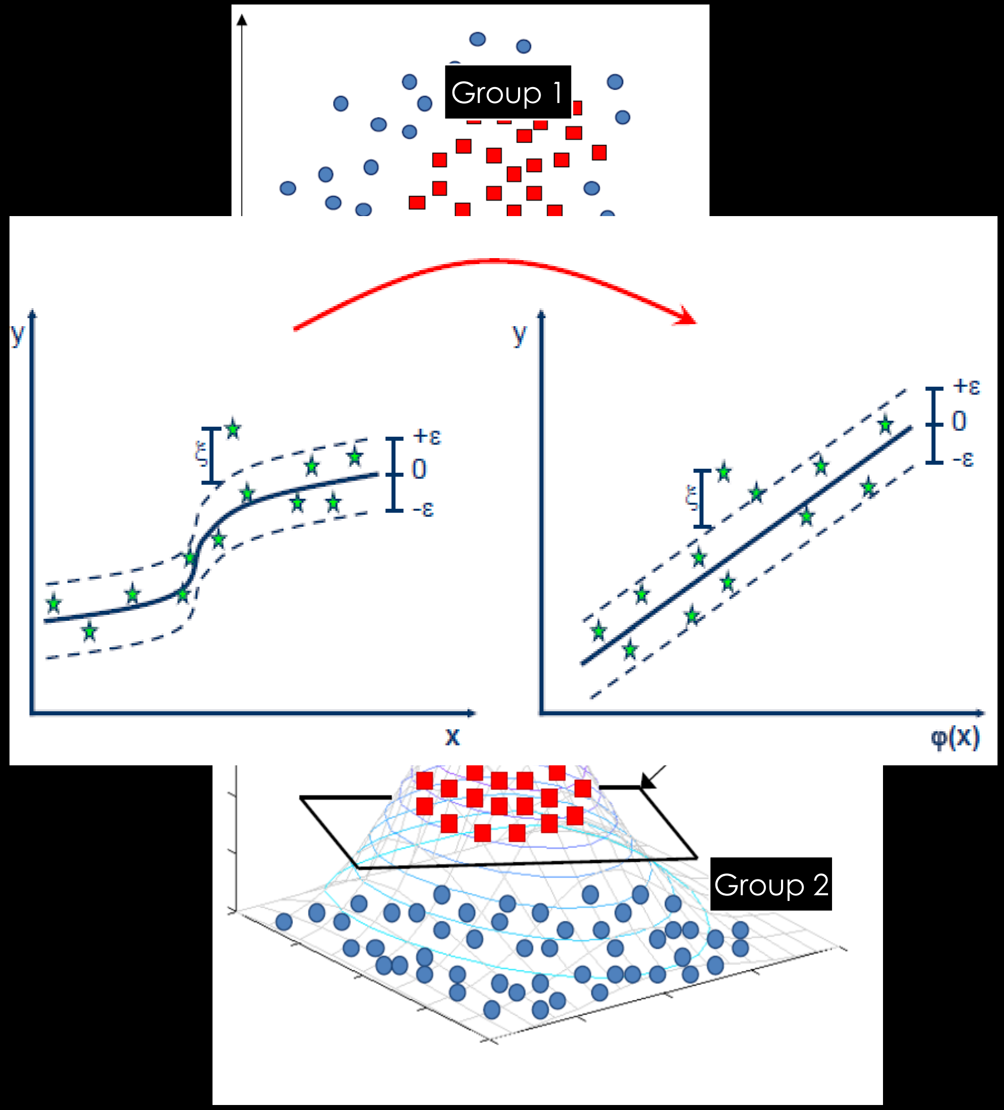
INTRODUCTION TO MACHINE LEARNING (ML)

- ML is a field of computer science that gives computers the ability to “learn” with data without being explicitly programmed
- Classified supervised and unsupervised learnings
- Used for multi-dimensional non-linear regression, clustering, anomaly detection, etc.
- Artificial neural network, deep learning, SVM, decision tree, K-means clustering, etc.
- Works good when plenty of data exists and physical model is not certain or unavailable

SUPPORT VECTOR MACHINE (SVM)

- One of supervised learning algorithms
- Main usages are for classification and regression

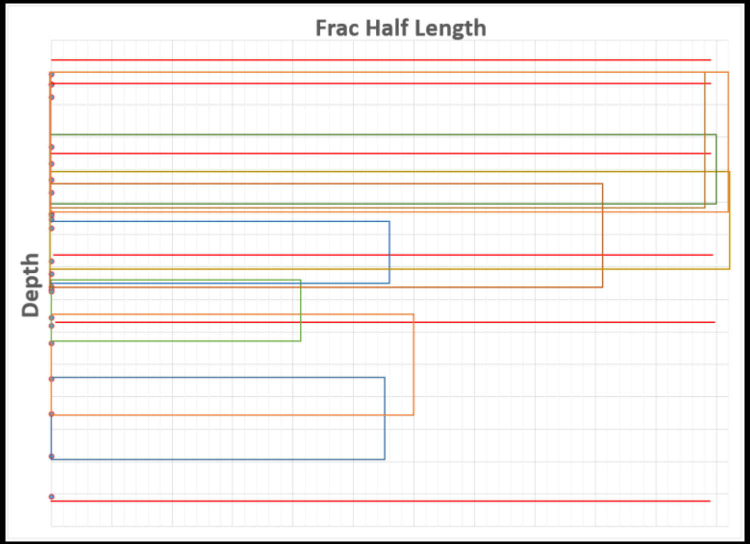


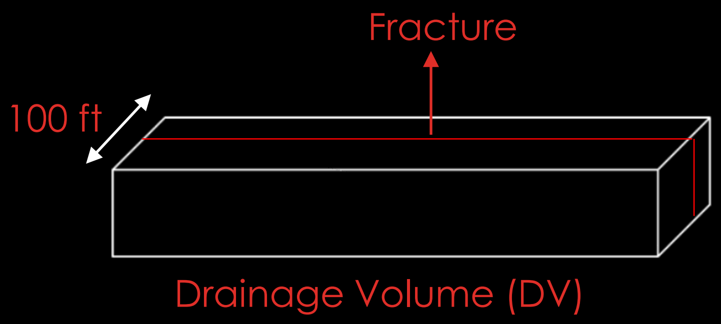


DATA ANALYSIS FOR SVM TRAINING

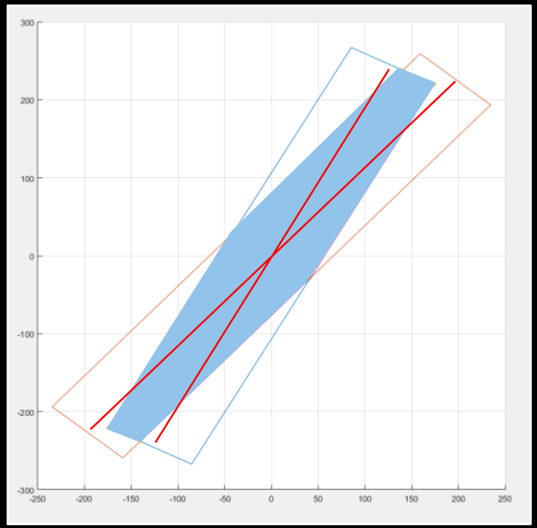
- Measured data from vertical wells
  - Reservoir properties
  - Mechanical properties of reservoir
  - Hydraulic fracture azimuths and dimensions
  - Hydraulic fracture data
  - Production data
- To mitigate complex hydraulic fracture geometry, overlapped area was treated as a separate fracture
- Drainage volume was assumed as rectangular parallelepiped of 100 ft. width

Side View



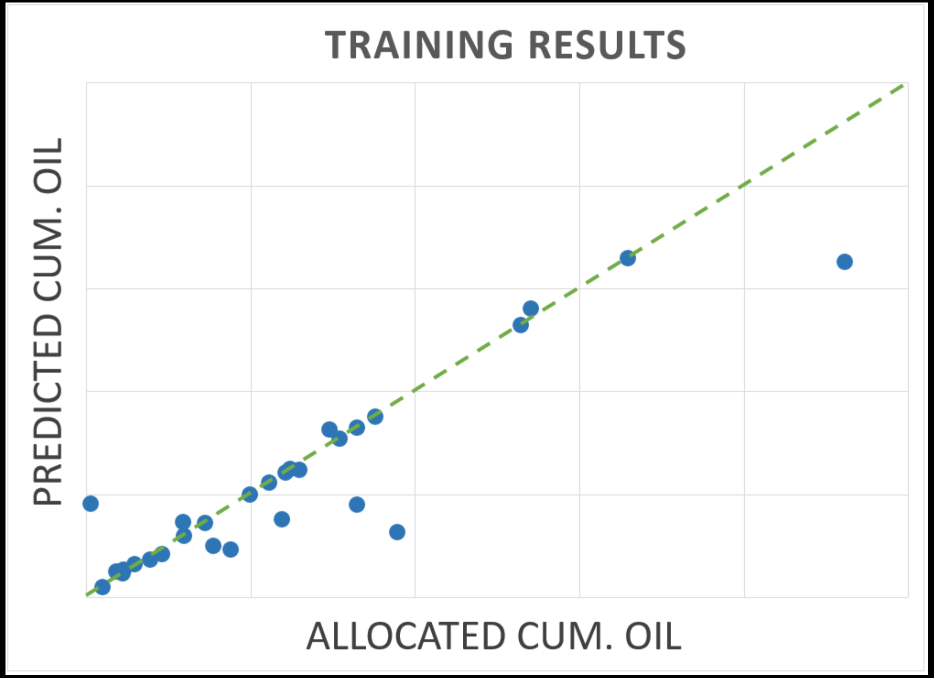


Top View of DV



SVM TRAINING RESULTS & PREDICTION ACCURACY

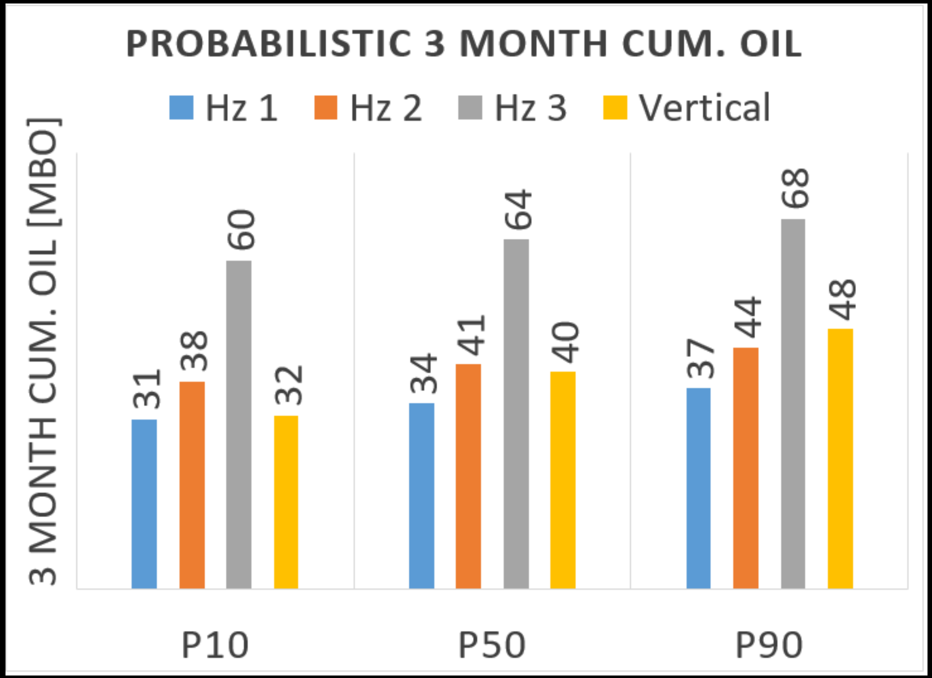
- 8 attributes used as inputs and the model trained against 3 months cumulative oil production:
  - Height of sub-stages, drainage volume, S_o, ϕ, rock compressibility, proppant, pad, & slurry volume
- Trained model's Pearson coefficient is 0.92
- Accuracy of predicting 3 month cum oil:
  - NRMSE: 0.1473



$$NRMSE = \sqrt{\frac{\sum(\hat{y}_i - y_i)^2}{n}} \Big/ \bar{y}$$

PRODUCTION FORECAST FOR HORIZONTAL WELLS

- Based on planned fracturing designs, 3 months cumulative oil production of 3 horizontal wells was forecasted
- To mitigate uncertainties of input attributes, Monte Carlo simulation was used
- Length of Hz 3 is about 60% longer than other two wells



RESULTS

- SVM offers a relatively quick and less expensive way of forecasting oil production using supervised learning
  - Applied to forecast oil production for horizontal wells

- Practical application of machine learning opens up the opportunity to utilize large volumes of multi-dimensional data for forecasting production in a greenfield in lack of suitable analog data and reservoir simulation model

FUTURE APPLICATION OF ML IN ANTELOPE SHALE

- Clustering of hydraulic fractures for analyzing characteristics on production
- Recommend next drilling locations

COMPARISON OF DIFFERENT MODELING METHODS

	Simulation	Statistical	Machine Learning
Require Historical Data	No	Yes	Yes
Require Physical Properties	Yes	No	Not necessary
Require Model Tuning	Yes	Yes	Yes
Time and Cost	High	Low	Low
For Green Field (Extrapolation)	Yes	No	No
For Brown Field (Interpolation)	Yes	Yes	Yes
Capability of Solving Highly Non-Linear Problems	High	Low	High

CHALLENGES, BEST PRACTICE, & LESSONS LEARNED

- Lessons Learned
  - Understanding physics (including reservoir properties) is crucial to build a ML model and increase the reliability of the prediction
- Best Practice
  - Combine Machine Learning with statistical experiment (Monte Carlo simulation)
  - Use a secondary method to validate results
- Challenges
  - Limited data set for quality data analytics
  - Application of machine learning is novice in the upstream industry
  - Practical applications are limited and there is lack of skill set

Thank you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