DIRECT: **DI**gital **RE**servoir **C**haracterization **T**echnology

Kick-off Meeting

Michael J. Pyrcz[1], John Foster[1,2], Carlos Torres-Verdín[1], and Eric van Oort[1]

Hildebrand Department of Petroleum & Geosystems Engineering
The University of Texas at Austin
200 E. Dean Keeton St., Stop C0300
Austin, TX 78712-1585

1- Hildebrand Department of Petroleum & Geosystems Engineering, the University of Texas at Austin, 2 – Oden Institute for Computational Engineering and Science, the University of Texas at Austin

Good News – DIRECT is Happening

- The following companies have already joined the consortium:

Anadarko BAZEAN aramco

- There are two other E&P companies that have indicated they will join:

to be announced shortly

DIRECT Kick Off Follow Up

- We have provided a set of initial short-term, mid-term and long-term goals and quite a few exploratory prototypes (see the following slides)

- Participants asked for a ‘menu’ / set of candidate initial research projects to communicate within their organizations to provide line of sight to value

- We will prioritize and update with steering from our pioneering consortium members, Aramco Services, Bazean, Anadarko and 2 other E&P companies to be announced shortly.

- Join now for early steering.

DIRECT Research Menu / Candidate Initial Research Projects

- **Training Models** – machine learning requires a large set of training data. The member companies would benefit the construction of a suite of realistic numerical, consistent 3D multivariate earth models with structural and stratigraphic heterogeneity, petrophysical, geophysical and geomechanical properties, well and production data. We will account for realistic physics and messy, noisy, unbalanced, and incomplete measurements

- **Fair Training and Testing Workflows** – development of training and testing workflows that fairly assess the prediction accuracy of machine learning models. Note: current random selection of testing subsets is not fair. This includes improved methods for design of optimum model complexity and to diagnose model overfit.

- **Data Preparation Methods** – methods for normalization, standardization of subsurface features for input into machine learning. This includes data debiasing, imputation and accounting for measurement and interpretation uncertainty and spatial and scale context.

DIRECT Research Menu / Candidate Initial Research Projects

- **Proxies for Reservoir Production** – rapid production forecasting from subsurface modes of initial and enhanced production and recovery for real-time feedback of reservoir production from subsurface modeling decisions and also for inference of subsurface heterogeneity from complicated production signals.

- **Physical Constraints in Machine Learning Models** – development of methods to encode physical constraints in machine learning methods for improved accuracy and uncertainty models.

- **Reduced Dimensionality Representation of Subsurface Uncertainty** – use of methods such as autoencoders to extracts salient features from complicated systems. This includes the representation of subsurface uncertainty with reduce dimensionality for improved uncertainty modeling and communication.

DIRECT Research Menu / Candidate Initial Research Projects

- **Fast Solutions of Inverse Problems** - estimate (with measures of uncertainty) lithology, petrophysical, elastic, and mechanical properties from noisy surface and borehole geophysical measurements. Approximate numerical solution for ultra-fast deep-learning training.

- **Rock and Fluid Inference from Petrophysical Measures** – modeling of the complex relationships, and data issues to improve inference of rock and fluids from petrophysical measures.

- **Seismic Downscaling** – modeling the relationships between low resolution seismic and high resolution reservoir features and other multi-scale procedures to relate input measurements to output properties.

- **Anomaly Detection** – methods to detect features based on concepts such as production significance and acquisition artifacts from spatiotemporal datasets.

DIRECT Research Menu / Candidate Initial Research Projects

- **Impact of Well Trajectory on Production** - quantify effect / influence of well placement / quality on production to improve well trajectory design.

- **Advanced Optimal Well Placement** - Real-time integration of sub-surface information (geophysics, geostatistics) and drilling data for placing wells optimally for primary & secondary HC recovery.

- **Advanced Optimal Drilling Management** - Real-time characterization of pore-pressure, in-situ stress, rock properties, for optimum mud pressure and properties, etc.

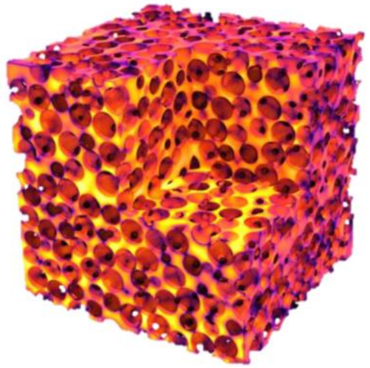
- **Feature Engineering** – methods for encoding spatial and physical constraints while potentially reducing problem dimensionality.

Subject to member company steering. Research, prototype demonstrations and training materials included to support internal use of results.

DIRECT Research Menu / Candidate Initial Research Projects

- **Building Reservoir Models** – machine learning-based reservoir models that honor complicated heterogeneity concepts, seismic information and production data. Integrated approach for estimation of inter-well and missing properties (data imputation).

- **Multiscale Flow Proxy Models** – fast assessments of flow behavior for model upscaling (from pores scale to production scale). We have already demonstrated the use of convolutional neural nets.



Santos et al., 2019, Interpore 11th Annual Meeting

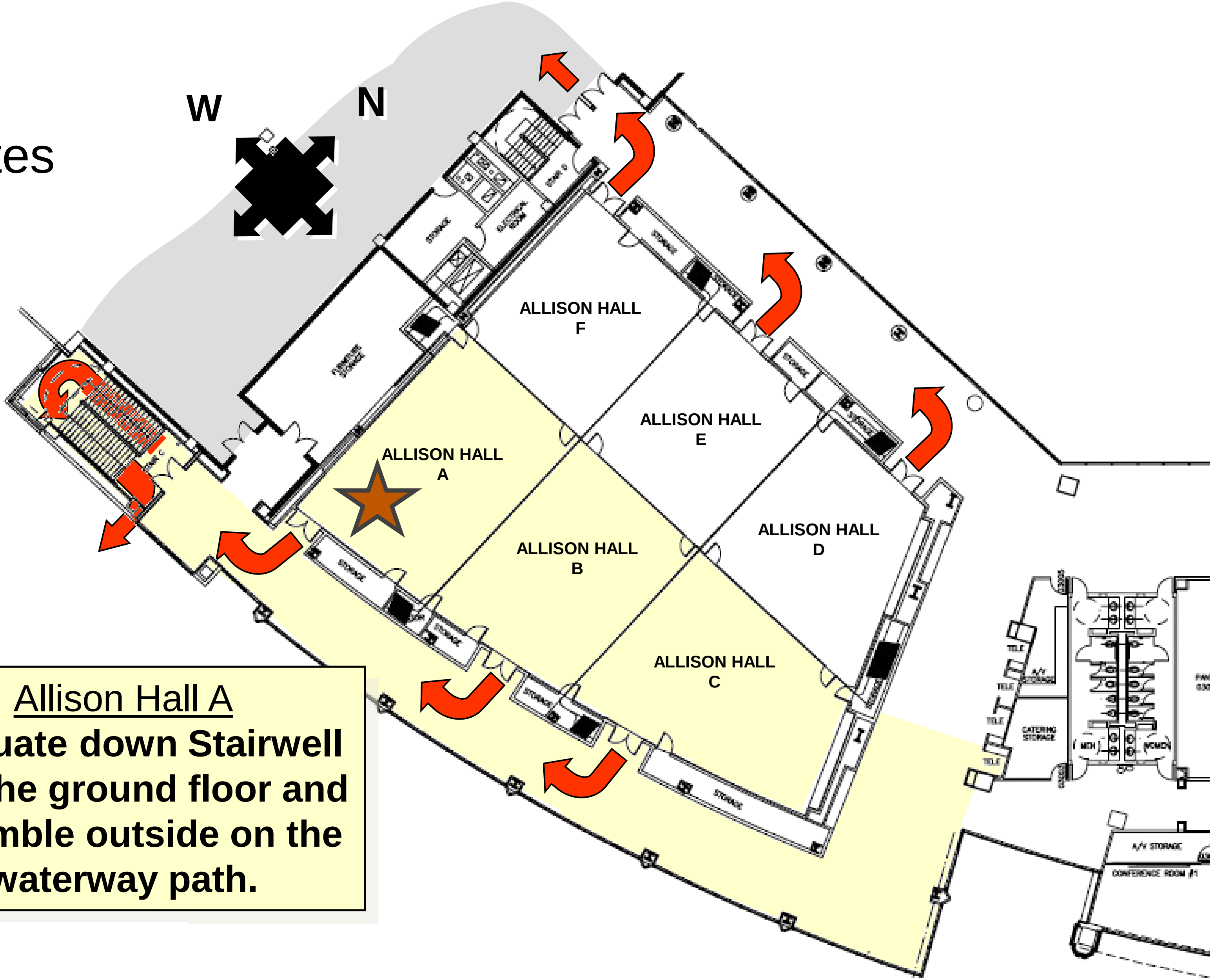
DIRECT: **DI**gital **RE**servoir **C**haracterization **T**echnology

Kick-off Meeting

Welcome to the DIRECT consortium kick-off meeting

- Thank you for making the time.
- Appreciation to Anadarko for providing the venue
  - Advanced Analytics and Emerging Technologies
  - Didi Ooi, Richard Sech and Christian Noll
- Appreciation to individuals from companies that assisted in building the business case

Safety Moment
Allison Hall Fire
Evacuation Routes



Allison Hall A
Evacuate down Stairwell C to the ground floor and assemble outside on the waterway path.

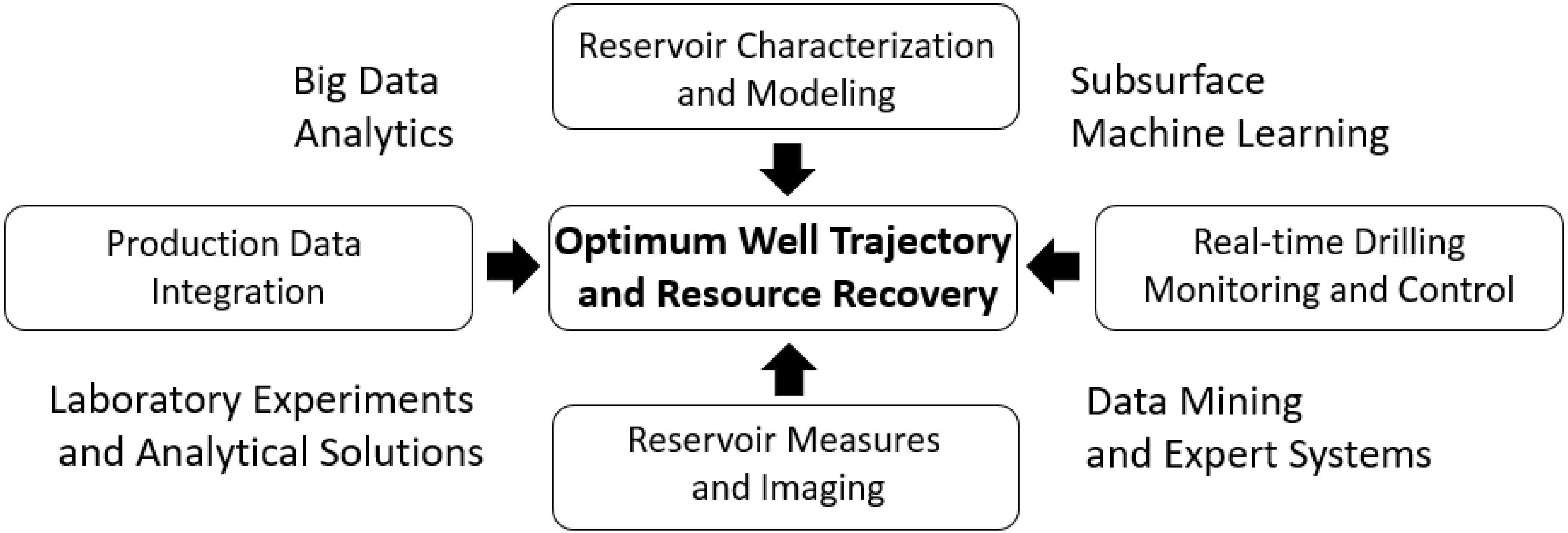
DIRECT: **DI**gital **RE**servoir **C**haracterization **T**echnology

Kick-off Meeting

House Keeping

- Consortium Information Previously Provided
    - Prospectus
    - Kick-off meeting agenda
    - Slide deck with goals short to long-term plans, and exploratory prototypes
- We will provide these slides as a meeting follow up

DIRECT Consortium Goals



Integration across geoscience and engineering disciplines with

data analytics and machine learning

to support optimum field development decision making

DIRECT Consortium Goals

Combine best-practice and cutting-edge technology in

reservoir spatiotemporal characterization and modeling

real-time drilling control

production data integration and forecasting

reservoir petrophysical measures and geophysics

with emerging technology in

big data analytics and machine learning

to optimize well trajectory and resource recovery.

data analytics and machine learning with engineering and geoscience

DIRECT Consortium Leadership

Prof. Michael Pyrcz
UT Petroleum and Geosystems Engineering
Data Analytics and Geostatistics

Prof. John Foster
UT Aerospace, Petroleum and Geosystems Engineering,
Fluid Flow, Computational Engineering

Prof. Eric van Oort
UT Petroleum and Geosystems Engineering
Drilling Automation and Expert Systems

Prof. Carlos Torres-Verdin
Petroleum and Geosystems Engineering
Geophysical / Petrophysical Measurements

DIRECT: **DI**gital **RE**servoir **C**haracterization **T**echnology

Data Analytics, Reservoir Characterization and Modeling

Michael J. Pyrcz[1]

Time	Speaker	Topic
9:00	Michael Pyrcz	Welcome, Introduction Geostatistics and Data Analytics
9:30	John Foster	Introduction Numerical Modeling
10:00	Carlos Torres-Verdin	Introduction Geophysical / Petrophysical Data Integration
10:30		Break
10:45	Eric van Oort	Introduction Drilling Automation and Expert Systems
11:15	Michael Pyrcz	Consortium Details
11:45		Additional Discussion and Feedback
12:00		Lunch Provided

1- Hildebrand Department of Petroleum & Geosystems Engineering, the University of Texas at Austin

DIRECT: **DI**gital **RE**servoir **C**haracterization **T**echnology

Big Data Analytics

Reservoir Characterization and Modeling

Subsurface Machine Learning

Production Data Integration

Optimum Well Trajectory and Resource Recovery

Real-time Drilling Monitoring and Control

Laboratory Experiments and Analytical Solutions

Reservoir Measures and Imaging

Data Mining and Expert Systems

Michael J. Pyrcz, co-PI of DIRECT, Associate Professor
Hildebrand Department of Petroleum & Geosystems Engineering
The University of Texas at Austin

What Am I About to Say?

- We have a great team assembled, faculty, students and member companies.
    - and I have experience delivering products and adding value in industry.
- There is a digital transformation underway.
- But we need unique Energy Data-driven Solutions
    1. Build operational capability / expertise to support implementation
    2. Build novel methods and workflows for Energy problems
- DIRECT is partnering with industry to support this.

Michael in DIRECT

13 years of experience in industrial practice, research, deployment and leadership.

Expertise

Data Analytics / Geostatistics
Probability, statistics, multivariate analytics, spatiotemporal modeling, feature engineering, debiasing, decision making

Engineering
Physics-based models, numerical methods, solution design

Geoscience
Characterization and modeling, geodata integration

Statistical Modeling and Now Machine Learning
Model design, abstraction, training and testing, uncertainty

All lectures recorded on YouTube.

AAPG SEPM Panel Discussion on Modeling

CPGE Webinar on Big Data

University of Texas at Austin Data Analytics and Geostatistics Class

Other Statistics About Michael

- **8 Industry Short Courses** taught to our industry during spring term on data analytics and machine learning
- **Founding Advisor of Daytum** for delivery of Oil and Gas Data Science Boot Camps to industry professionals
- **3 New University Courses** on data analytics, geostatistics and machine learning to geoscience and engineering students
- **1 Python Package** on subsurface data analytics and geostatistics, GeostatsPy
- **Principal Investigator** of the College of Natural Sciences Energy Analytics inventors program (funded by ConocoPhillips)
- **Program Chair** for SPE Data Analytics Technical Section
- **Associate Editor** with Computers and Geosciences and on **Editorial Board** of Mathematical Geosciences
- **Author of the Textbook** Geostatistical Reservoir Modeling

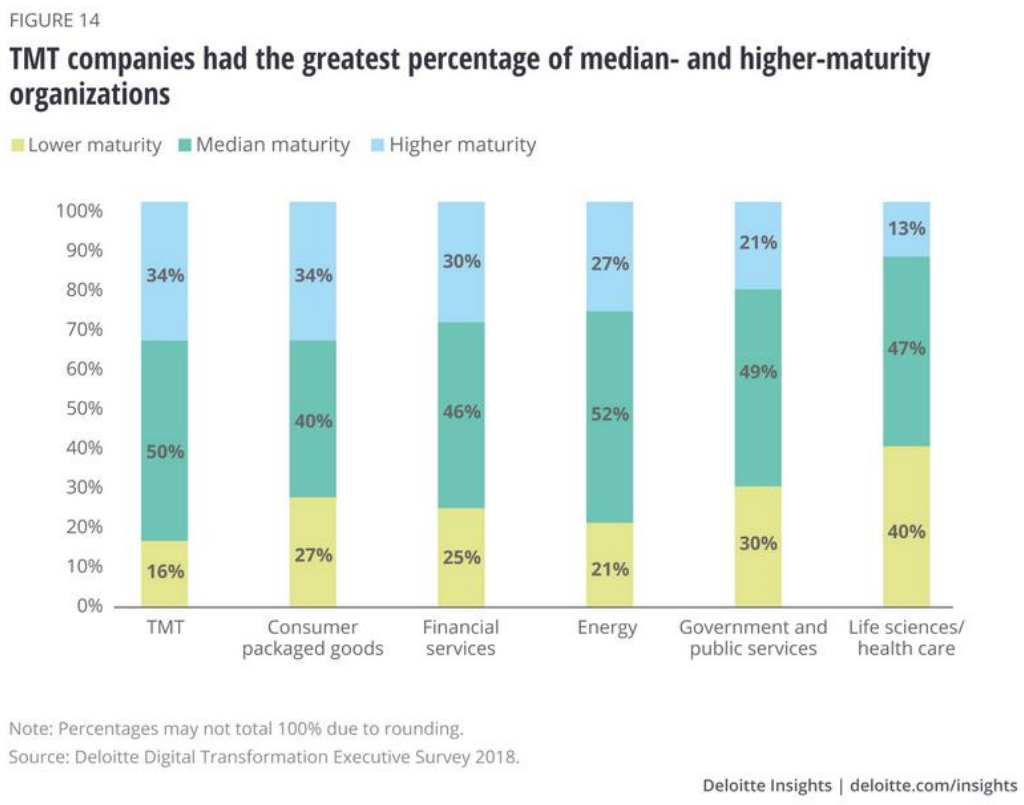
I make data analytics, geostatistics and machine learning accessible for solving practical Energy problems.

The Digital Transformation

Digital transformations are underway in all sectors of our economy.

Each sector is:

- Finding new opportunities to apply technology
- Value is being added through efficiency
- Individuals and organizations are working hard to grow new capability and adopt new technology



Digital transformation study by Deloitte, 2019.

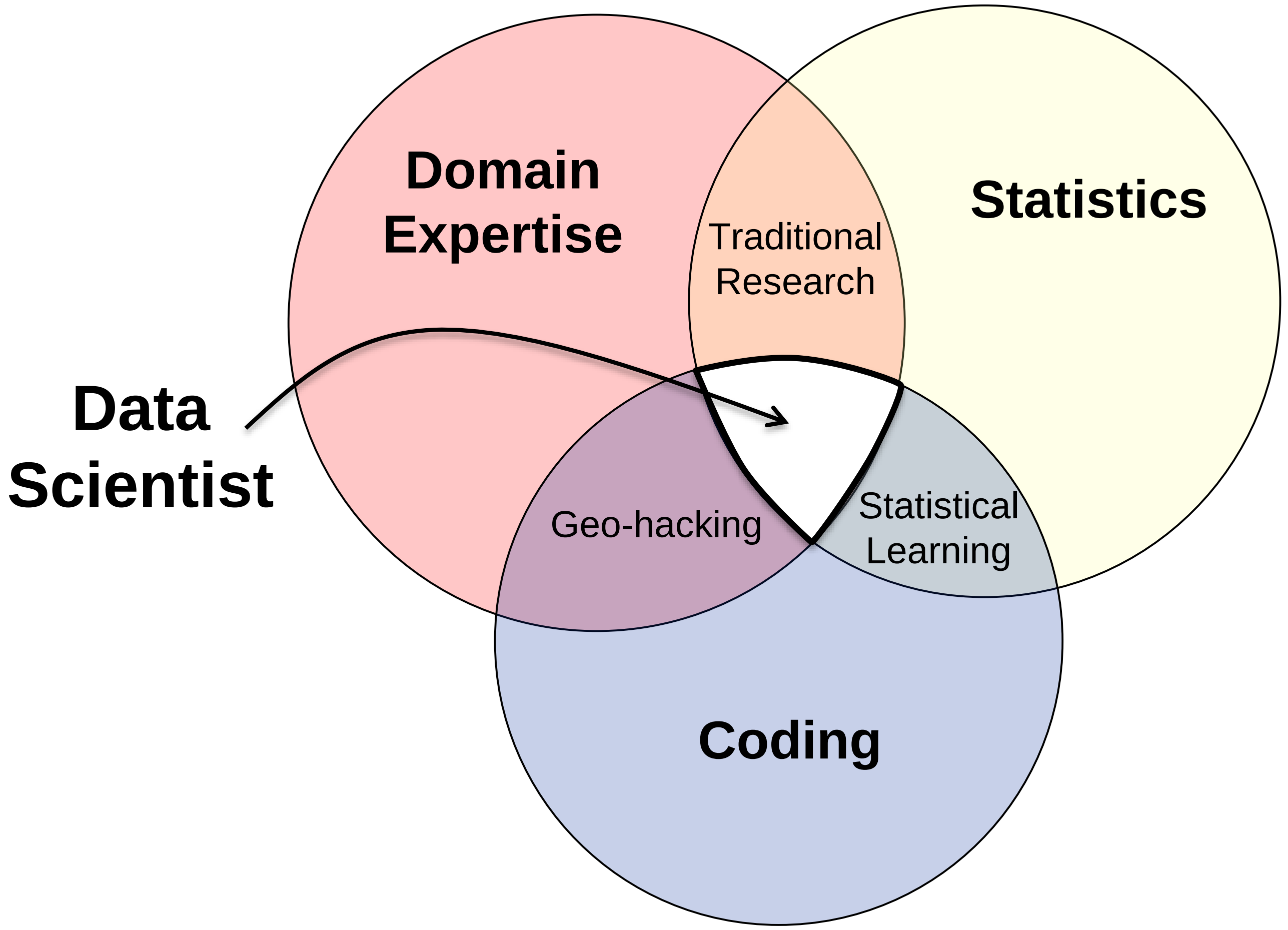
https://www2.deloitte.com/insights/us/en/focus/digital-maturity/digital-maturity-pivot-model.html

Developing Operational Capability

We need Data Scientists

Intersection of:

- Domain Expertise
  - Geoscience
  - Engineering
- Statistics
  - Modeling
- Coding
  - Scripting



Venn diagram the data scientist.

Developing Operational Capability

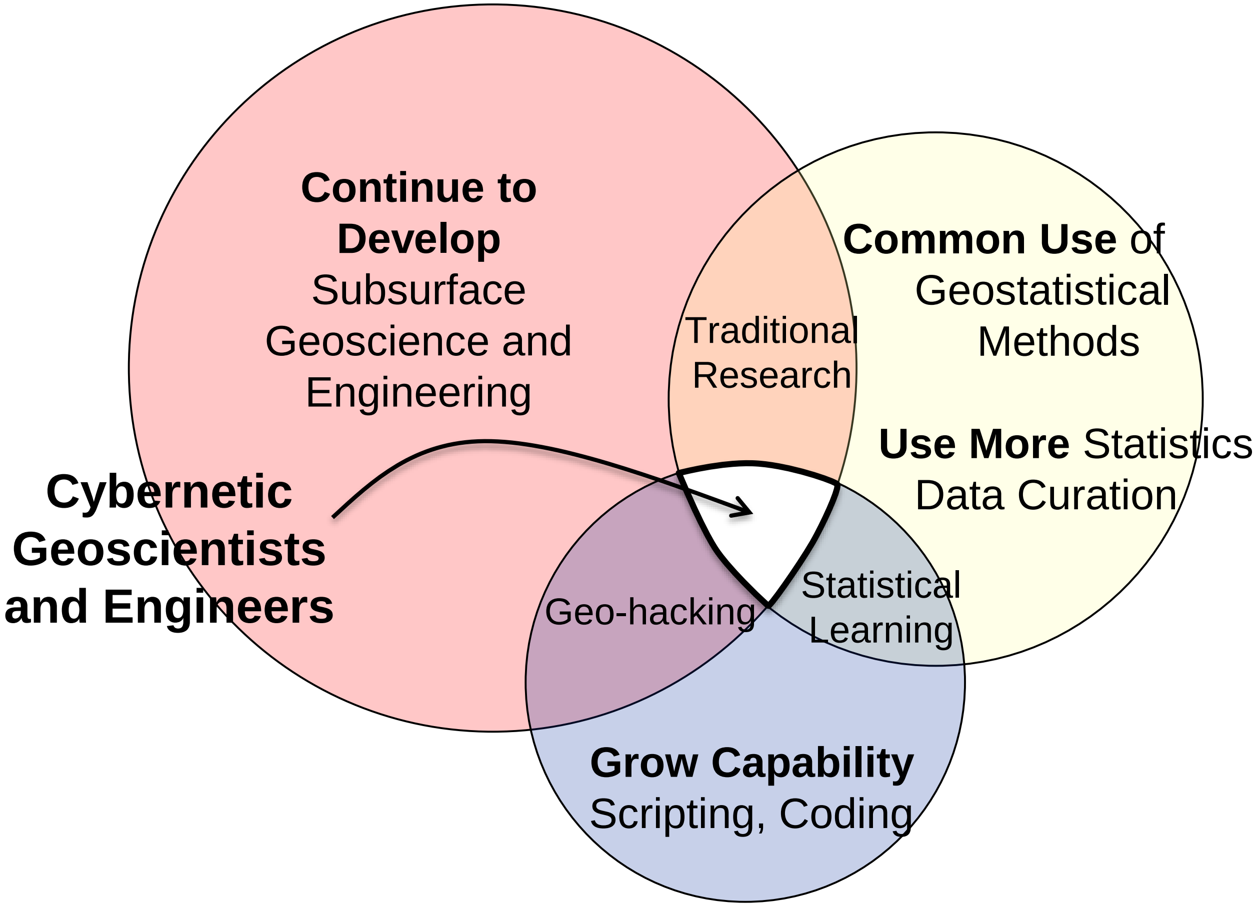
1. Make Engineers and Geoscientists

Well-prepared with data analytics, data-driven knowledge to contribute in our industry

2. Build Capability in the Existing Geoscientist and Engineering Workforce

Geoscience and engineering capability remains core to our work

We will assist with building the cybernetic geoscientists and engineers with abilities extended with data analytics and machine learning.

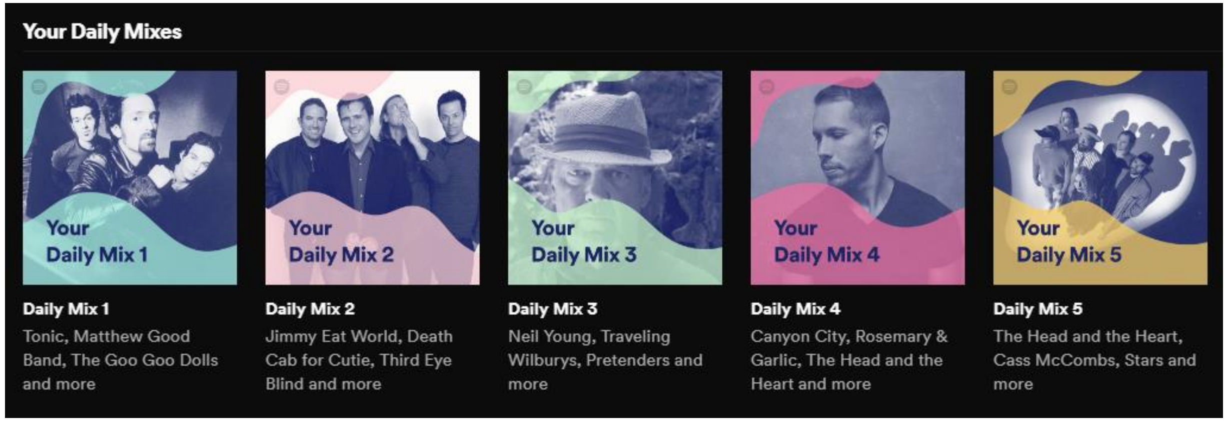


Proposed Venn diagram for a path forward for growing data science capabilities among engineers and geoscientists.

The Energy Industry is Different

Energy is unique among industries:

- **sparse and uncertain data**
- **complicated and heterogeneous**, open earth systems
- high degree of **necessary geoscience and engineering interpretation and physics**
- **expensive, high value decisions** that must be supported
- **We will develop novel methods and workflows tailored to the needs of Energy.**



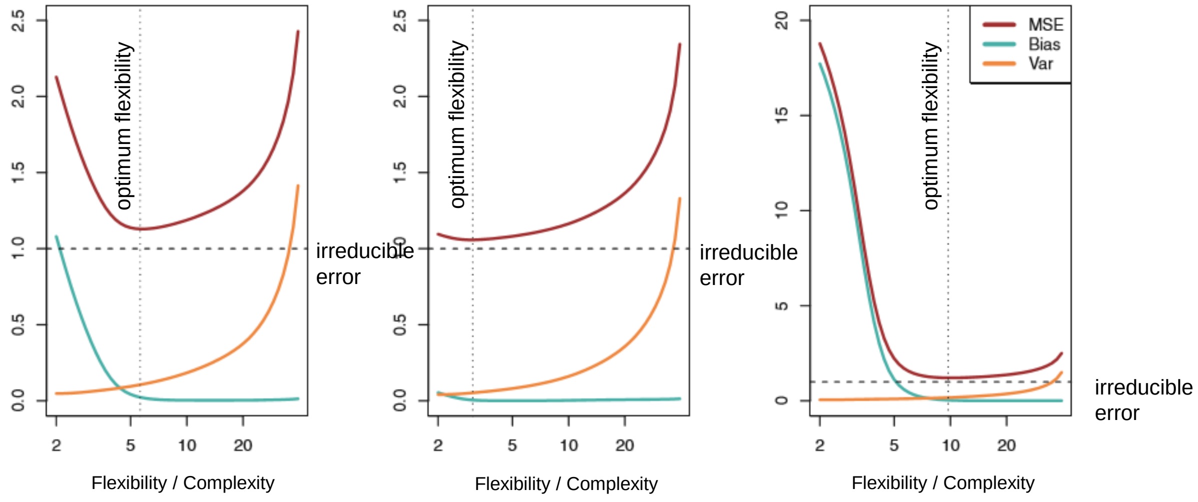
Spotify recommender system

At Times There is Value in Simplicity

We need to build solutions matched to maximize value.

Simpler models have **lower model variance** (more robust with sparse data) and **higher interpretability**.

We will work to build fit-for-purpose, optimum complexity solutions.



Model variance, model bias and test MSE for 3 datasets with variable flexibility (Fig 2.12, James et al., 2013), labels added for clarification.

Interpretability is Critical

New methods may become routine and trusted.

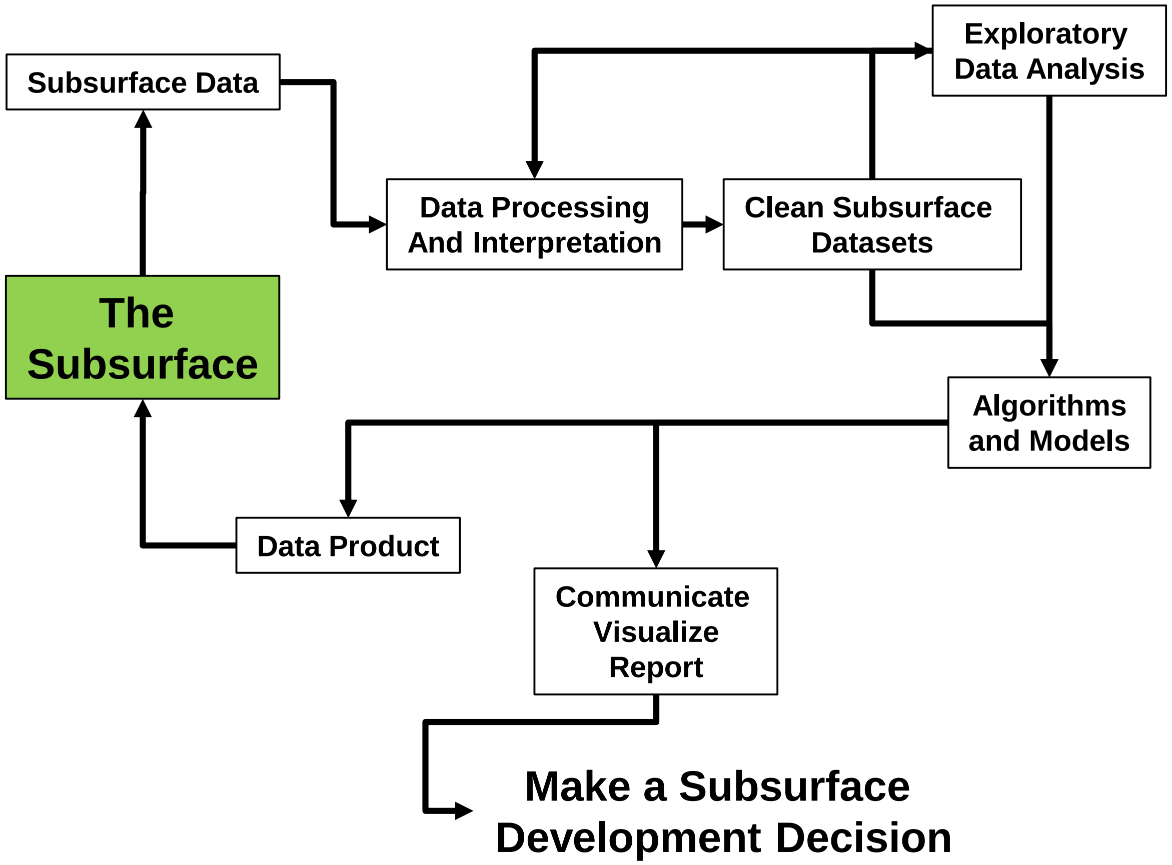
Without interpretability the machine is trusted, becomes an unquestioned authority

We will work to increase interpretability so we learn, support our decisions.

Rideiro et al. (2016) trained a logistic regression classifier with 20 wolves and dogs images to detect the difference between wolves and dogs.

Doing More with Our Data

- Further quantification, standardization, integration
- Improved data curation
- Mitigating data bias, data imputation, feature engineering
- Data preparation remains prerequisite



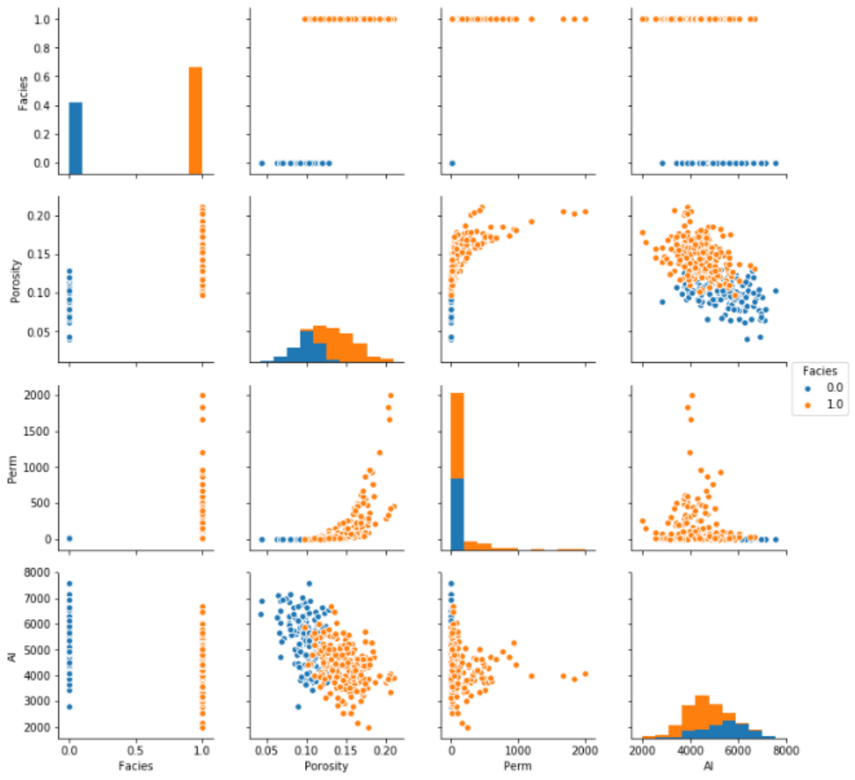
Learning from our data workflows, adapted to subsurface data analytics from Doing Data Science Schutt & O'Neil (2013)

We will work on getting our data 'model ready'.

Enhance Professional Impact

There are opportunities to **teach, develop and adopt new data analytics and machine learning methods** to engineers and geoscientists to improve capabilities:

- Large complicate, high-dimensional datasets
- Complicated, nonlinear, heterogeneous systems
- Sparsely sampled and highly uncertainty
- Incorporate all possible geoscience and engineering



Example of a multivariate, complicated spatial dataset.

We will work to enhance professional impact.

Build Enhanced / Expert Workflows

3. Augmented geoscience and engineering workflows for greater accuracy and efficiency

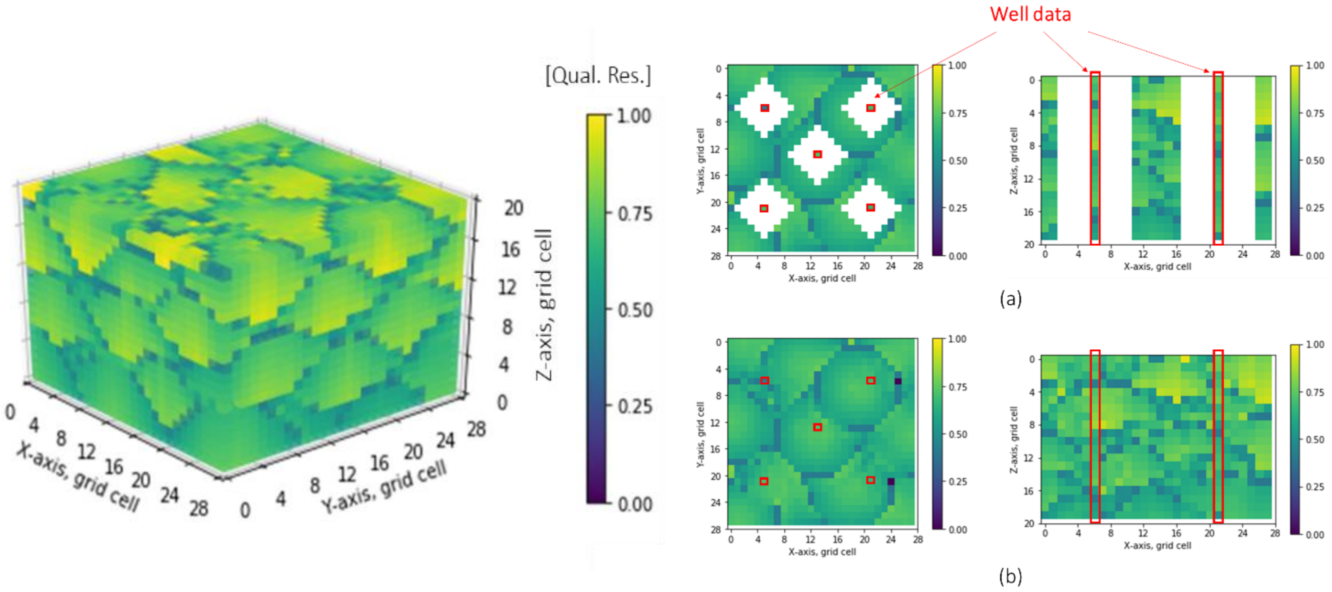
- **Streamline common tasks** to better utilize professional time
- Assist with the **data preparation** for data-driven modeling
- Identify **most interesting subsets** of massive, multivariate datasets
- Provide **real-time feedback** on modeling decisions
- **Decision support** through white box and black box modeling
- **Engineering and geoscience** remains core to our business.

We will build well-documented enhanced prototype methods and workflows.

Initial Exploratory Prototypes

Q3 2018 – Q1 2019 our teams have conducted initial exploratory prototyping to assist with scoping the opportunity to develop student capabilities.

Reservoir Modeling: Subsurface *model conditioning* by semantic image inpainting by Honggeun Jo (2nd Year PhD student).

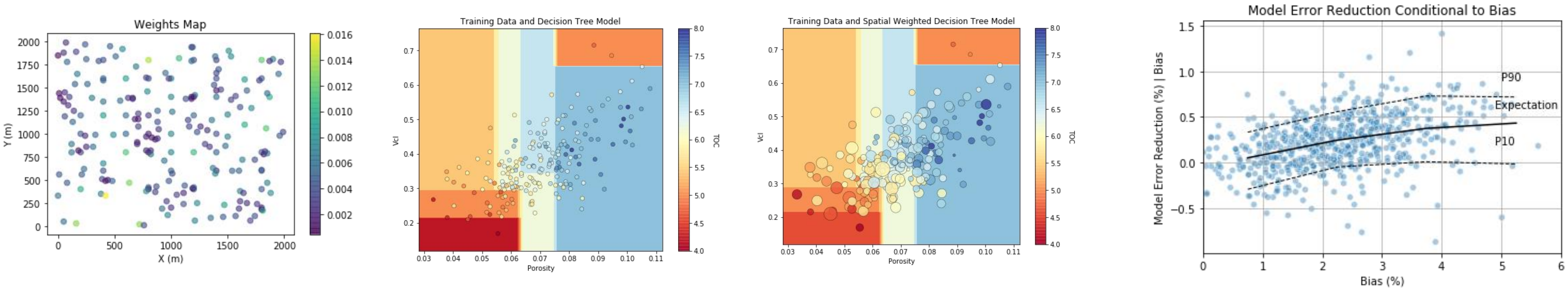


Left - process-mimicking model, Right – well conditioning with semantic image inpainting.

Initial Exploratory Prototypes

Q3 2018 – Q1 2019 our teams have conducted initial exploratory prototyping to assist with scoping the opportunity to develop student capabilities.

Spatial Bias in Machine Learning: Quantification and mitigation of *spatial bias in machine learning* by Wendi Liu (1st Year PhD student).

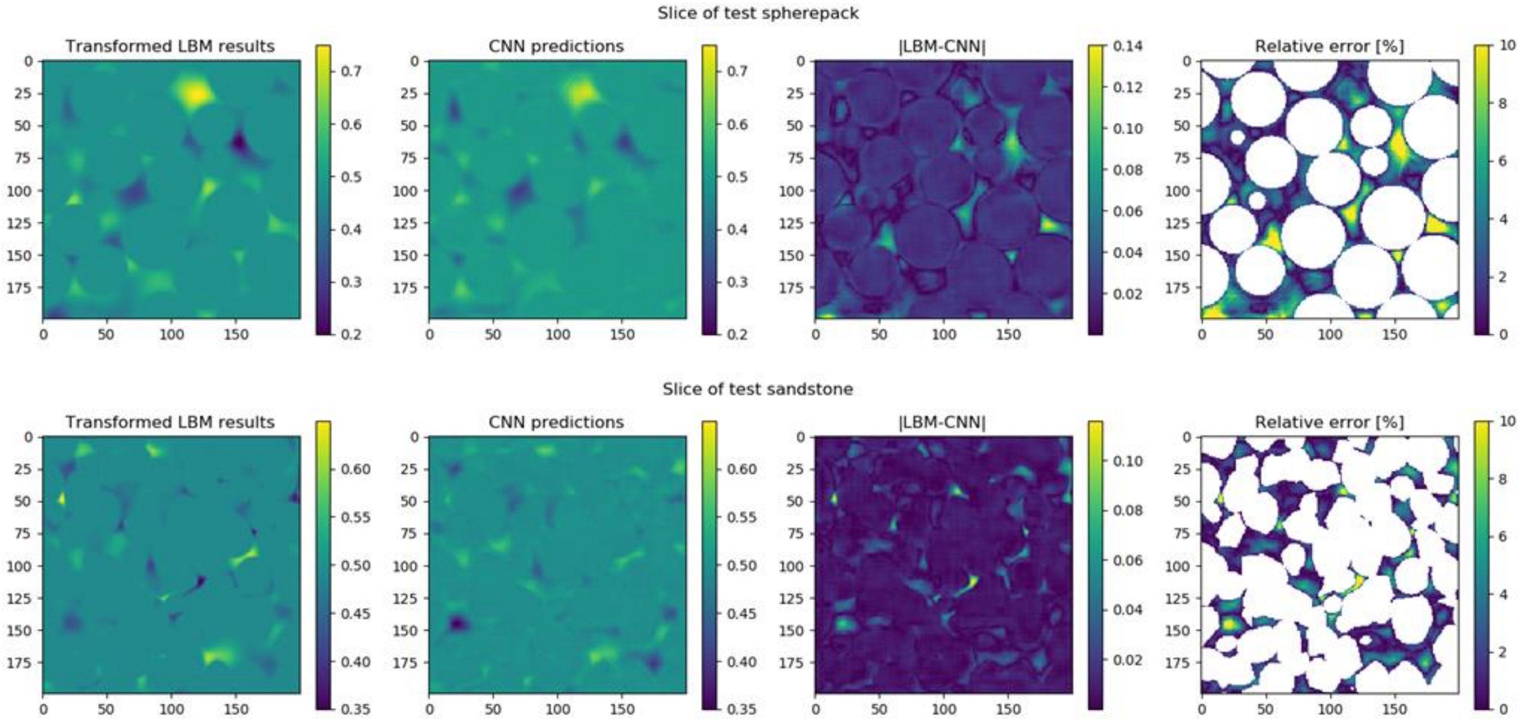


Left – spatial data, decision tree naïve and debiased, Right – error reduction vs. amount of bias.

Initial Exploratory Prototypes

Q3 2018 – Q3 2019 our teams have conducted initial exploratory prototyping to assist with scoping the opportunity to develop student capabilities.

Flow Proxies, Scaling: Machine learning-based *flow proxy* for intragranular flow.
by Javier Santos (1st Year PhD student).



Lattice Boltzmann vs. convolutional neural nets prediction of flow velocity.

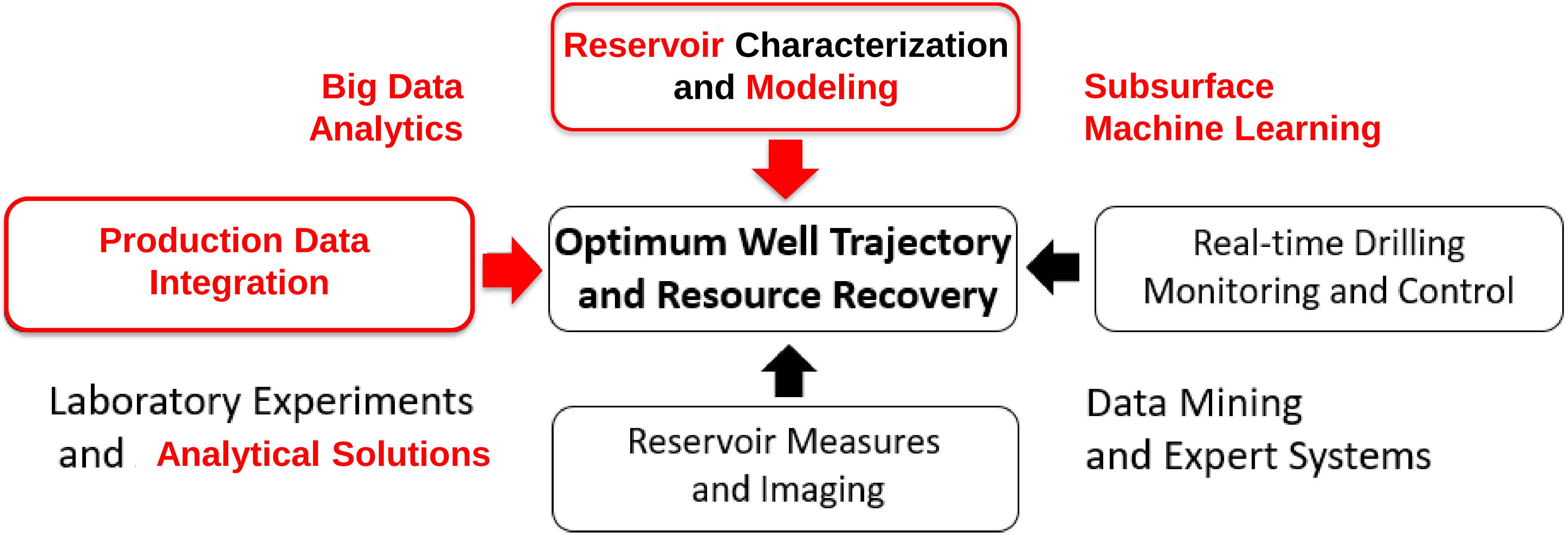
DIRECT: **DI**gital **RE**servoir **C**haracterization **T**echnology

John Foster[1,2]

Time	Speaker	Topic
9:00	Michael Pyrcz	Welcome, Introduction Geostatistics and Data Analytics
9:30	John Foster	Introduction Numerical Modeling
10:00	Carlos Torres-Verdin	Introduction Geophysical / Petrophysical Data Integration
10:30		Break
10:45	Eric van Oort	Introduction Drilling Automation and Expert Systems
11:15	Michael Pyrcz	Consortium Details
11:45		Additional Discussion and Feedback
12:00		Lunch Provided

1- Hildebrand Department of Petroleum & Geosystems Engineering, the University of Texas at Austin, 2 – Oden Institute for Computational Engineering and Science, the University of Texas at Austin

DIRECT: **DI**gital **RE**servoir **C**haracterization **T**echnology



John T. Foster, co-PI of DIRECT, Associate Professor
Hildebrand Department of Petroleum & Geosystems Engineering
The University of Texas at Austin

About me…

Sandia National Laboratories

Technical Staff – 2004-2011

UTSA
The University of Texas at San Antonio™

Mechanical Eng. Faculty 2011-2014

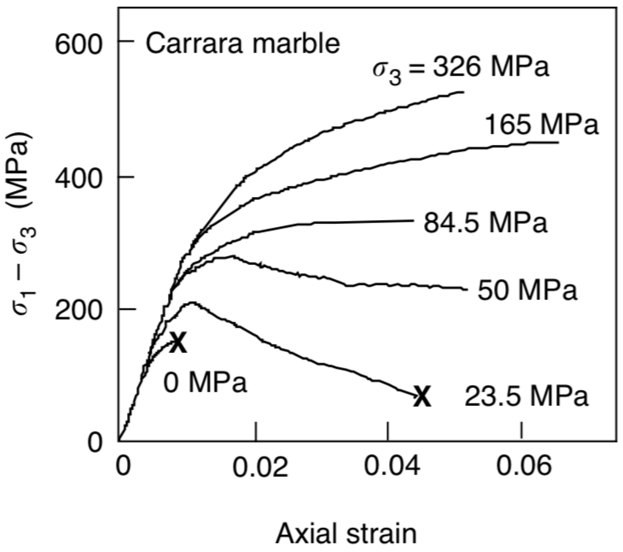
The University of Texas at Austin
Hildebrand Department of Petroleum and Geosystems Engineering
Cockrell School of Engineering

The University of Texas at Austin
Aerospace Engineering and Engineering Mechanics
Cockrell School of Engineering

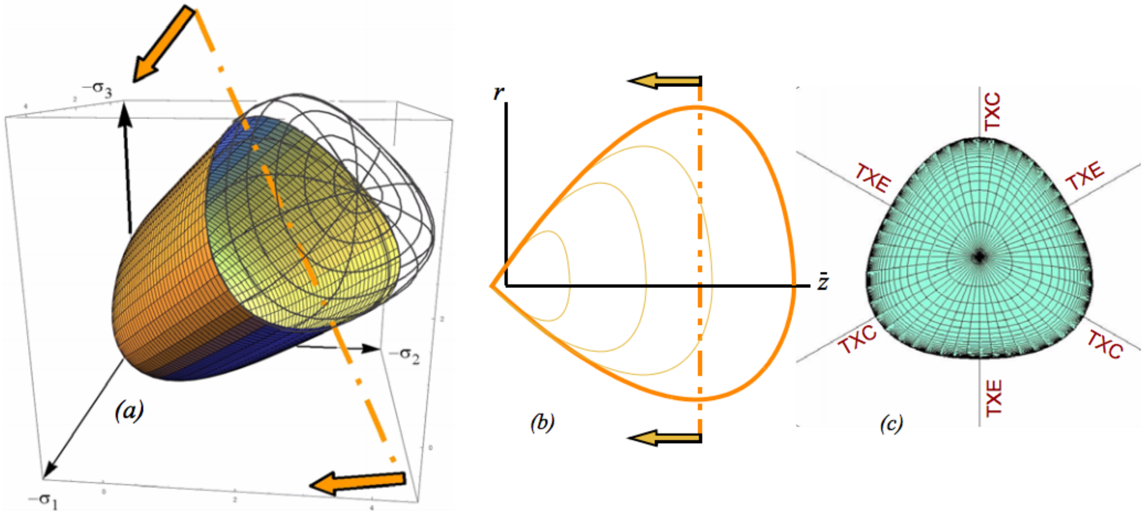
ODEN INSTITUTE
FOR COMPUTATIONAL ENGINEERING & SCIENCES

2014-Present

Expertise: Theoretical and Computational Mechanics



© Blackwell Publishing Jaeger, et al., *Fundamentals of Rock Mechanics* (Fig. 4.5, pp. 86)

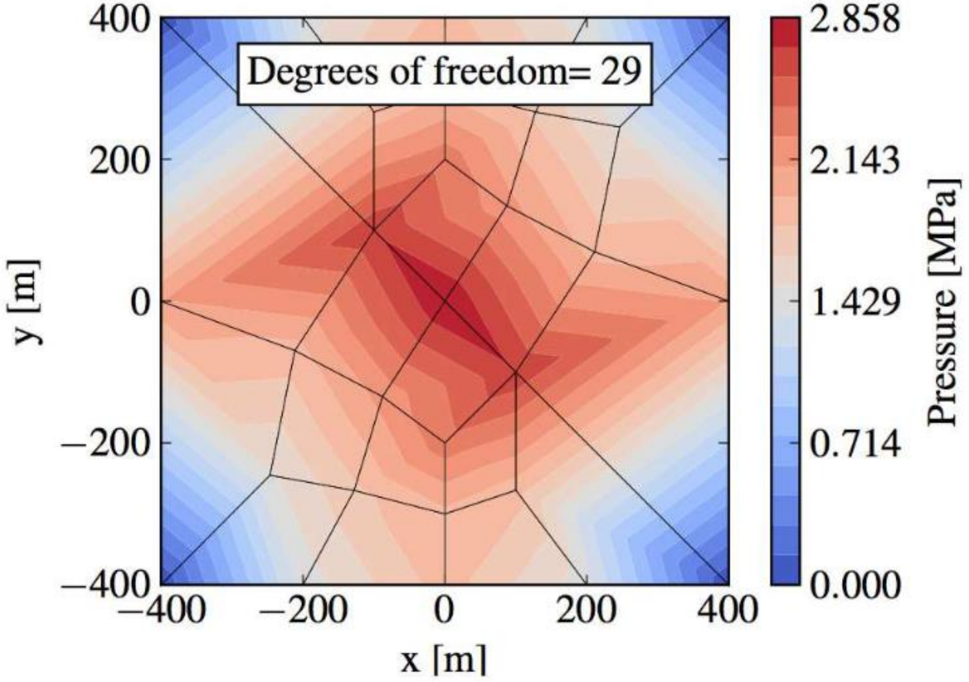


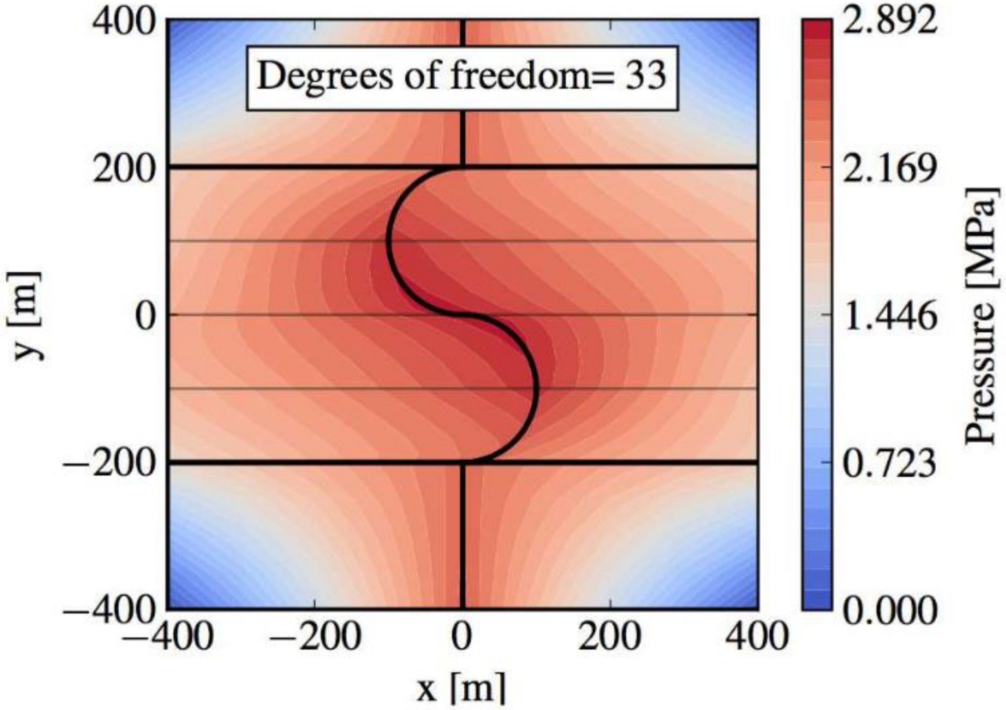
R.M. Brannon, A.F. Fossum, and O.E. Strack: Kayenta: Theory and User's Guide. Tech. rep. Sandia National Laboratories, 2009.

The University of Texas at Austin

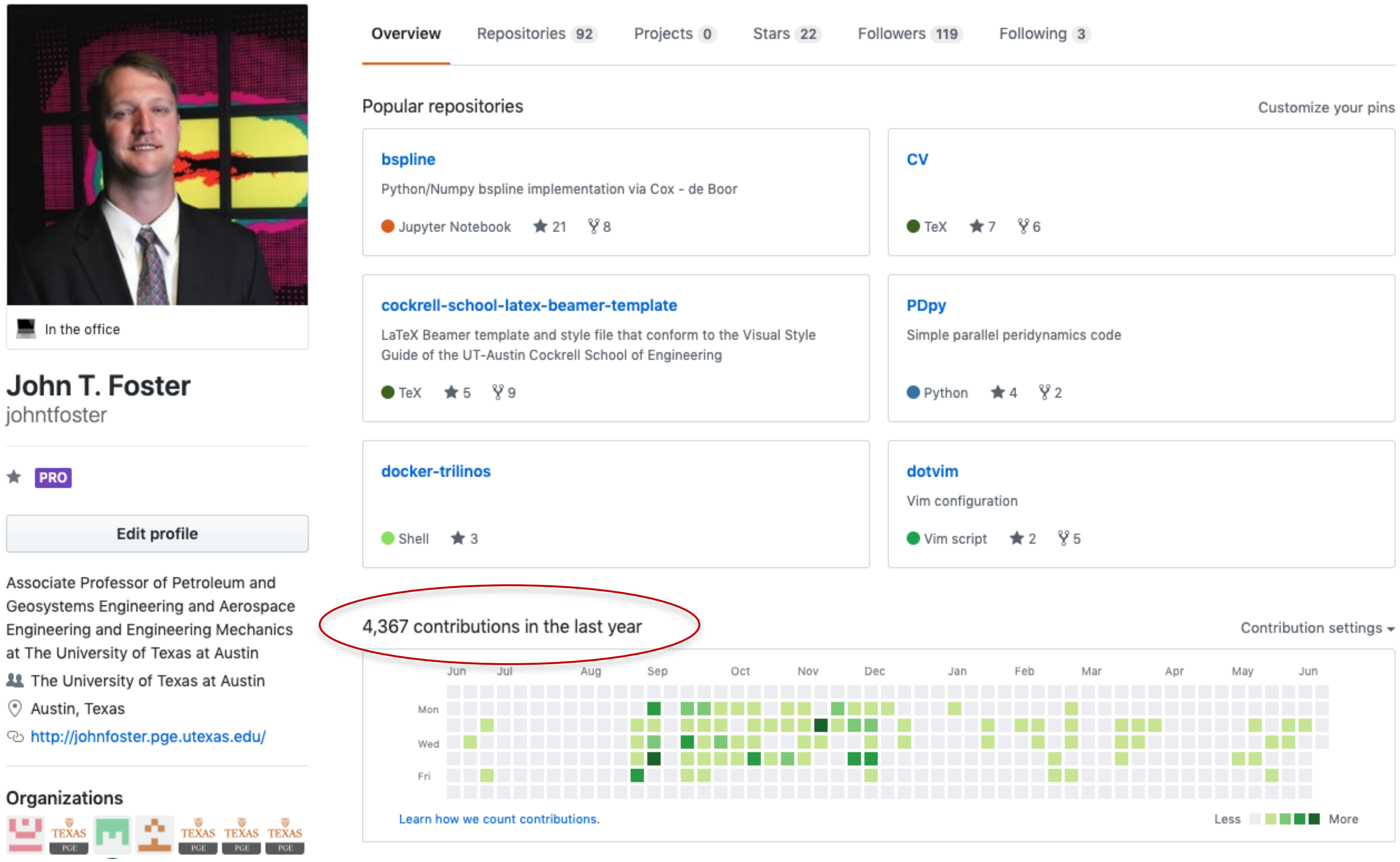
WHAT STARTS HERE CHANGES THE WORLD

Expertise: Computational Mechanics

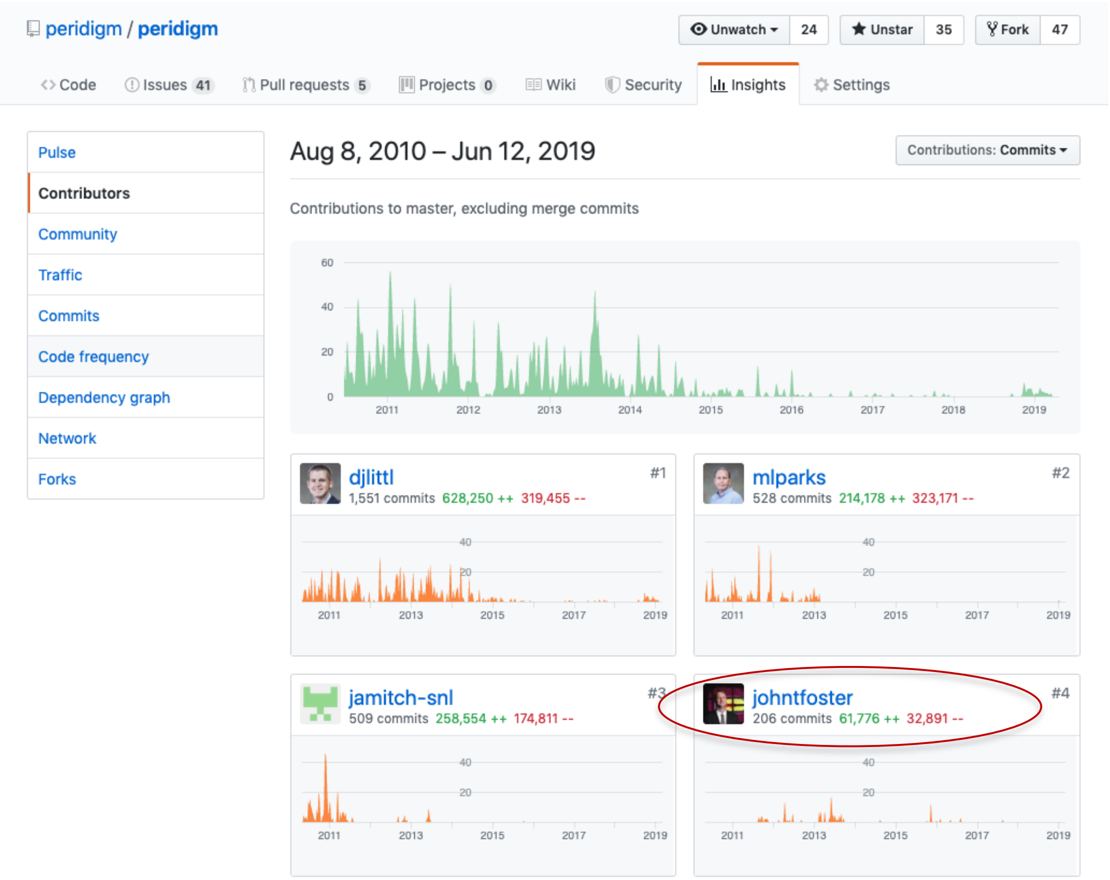




Expertise: HPC / DevOps / Software Engineering

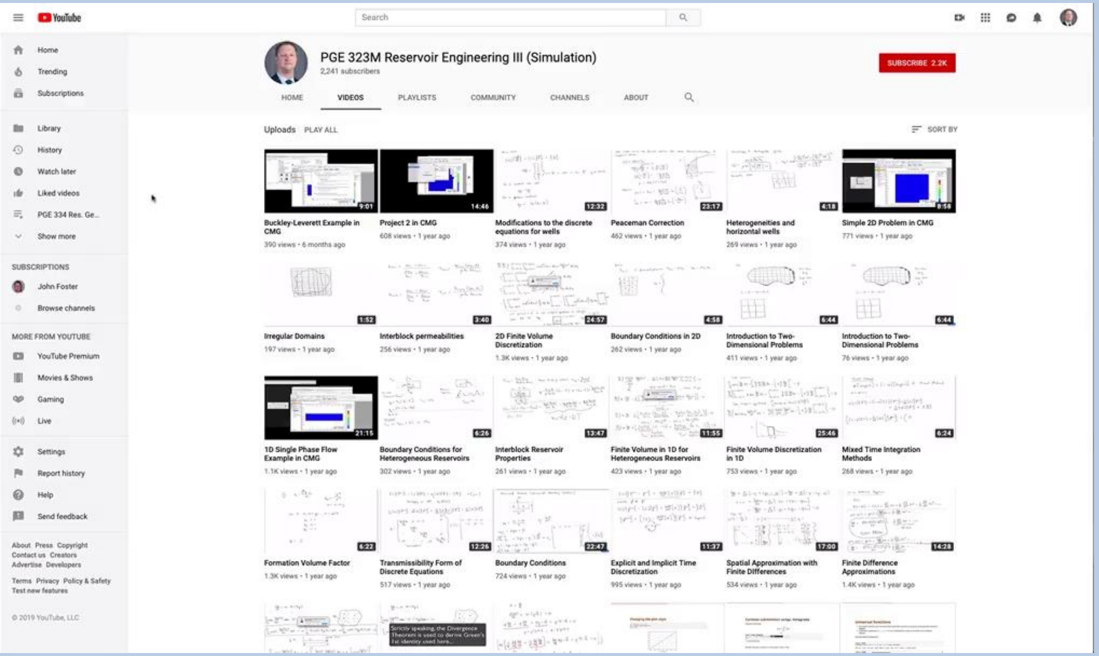


Expertise: HPC / DevOps / Software Engineering

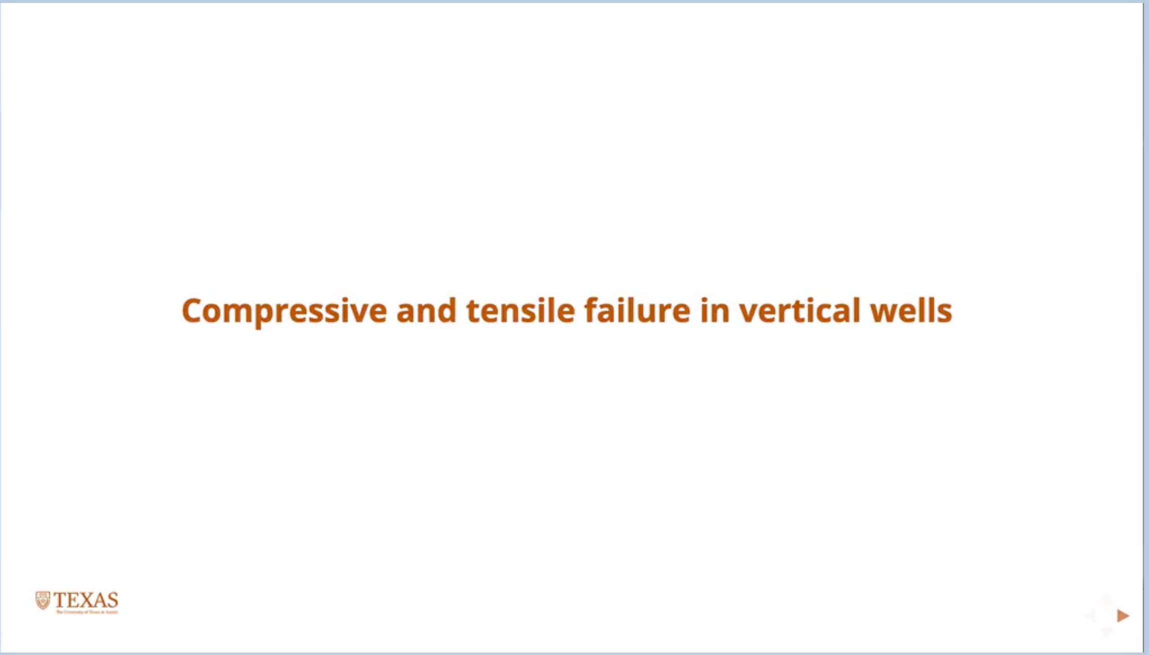


Teaching

>5800 YouTube subscribers

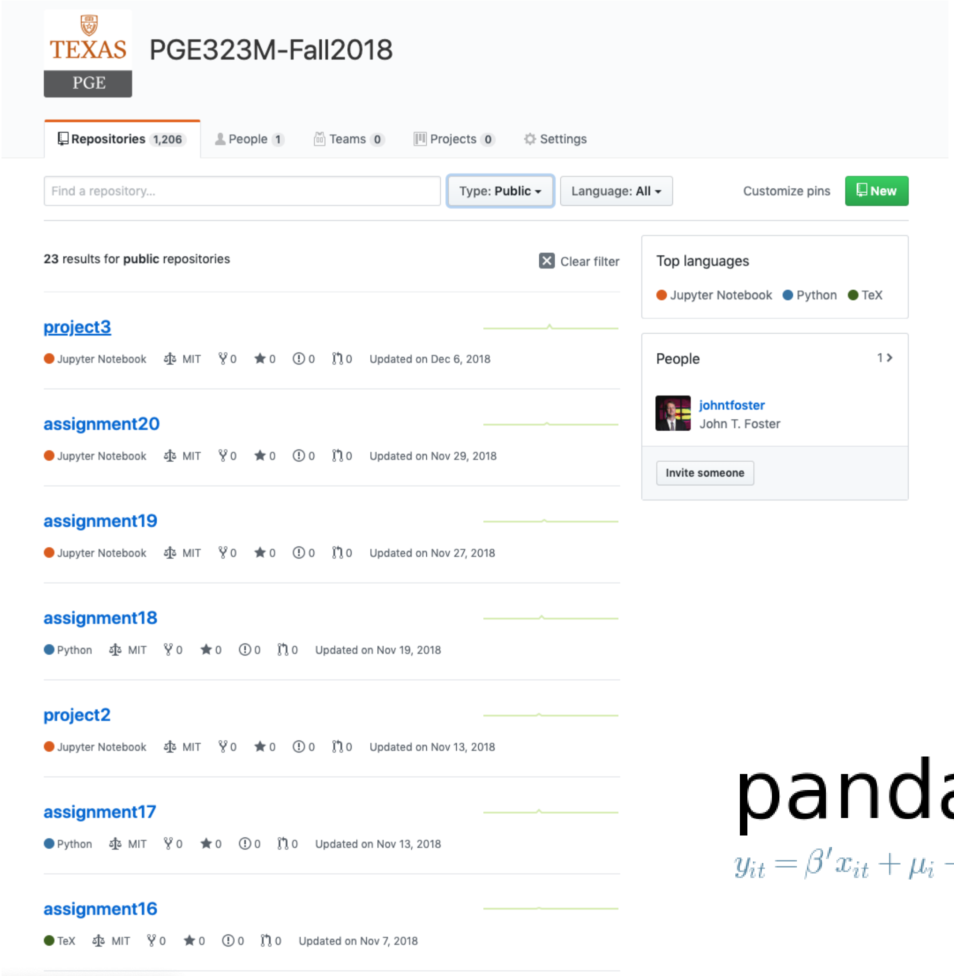


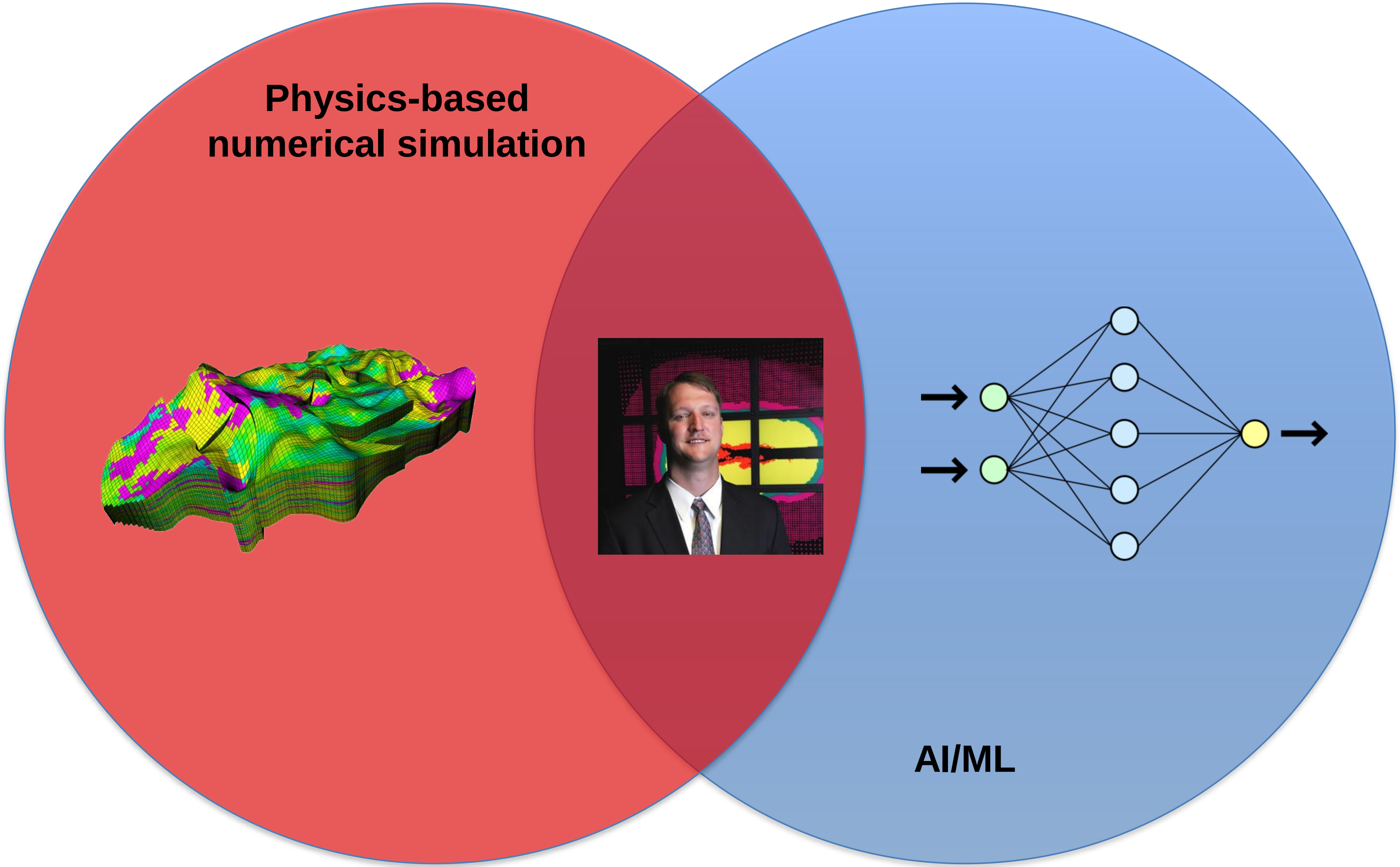
HTML Slides



http://johnfoster.pge.utexas.edu/courses/

Teaching


TEXAS
PGE
PGE323M-Fall2018
Repositories 1,206
People 1
Teams 0
Projects 0
Settings
Find a repository...
Type: Public
Language: All
Customize pins
New
23 results for public repositories
Clear filter
Top languages
Jupyter Notebook
Python
TeX
People
1
johntfoster
John T. Foster
Invite someone
project3
Jupyter Notebook MIT 0 0 0 0 Updated on Dec 6, 2018
assignment20
Jupyter Notebook MIT 0 0 0 0 Updated on Nov 29, 2018
assignment19
Jupyter Notebook MIT 0 0 0 0 Updated on Nov 27, 2018
assignment18
Python MIT 0 0 0 0 Updated on Nov 19, 2018
project2
Jupyter Notebook MIT 0 0 0 0 Updated on Nov 13, 2018
assignment17
Python MIT 0 0 0 0 Updated on Nov 13, 2018
assignment16
TeX MIT 0 0 0 0 Updated on Nov 7, 2018


Physics-based
numerical simulation
AI/ML

Example: Permeability prediction from Garn data

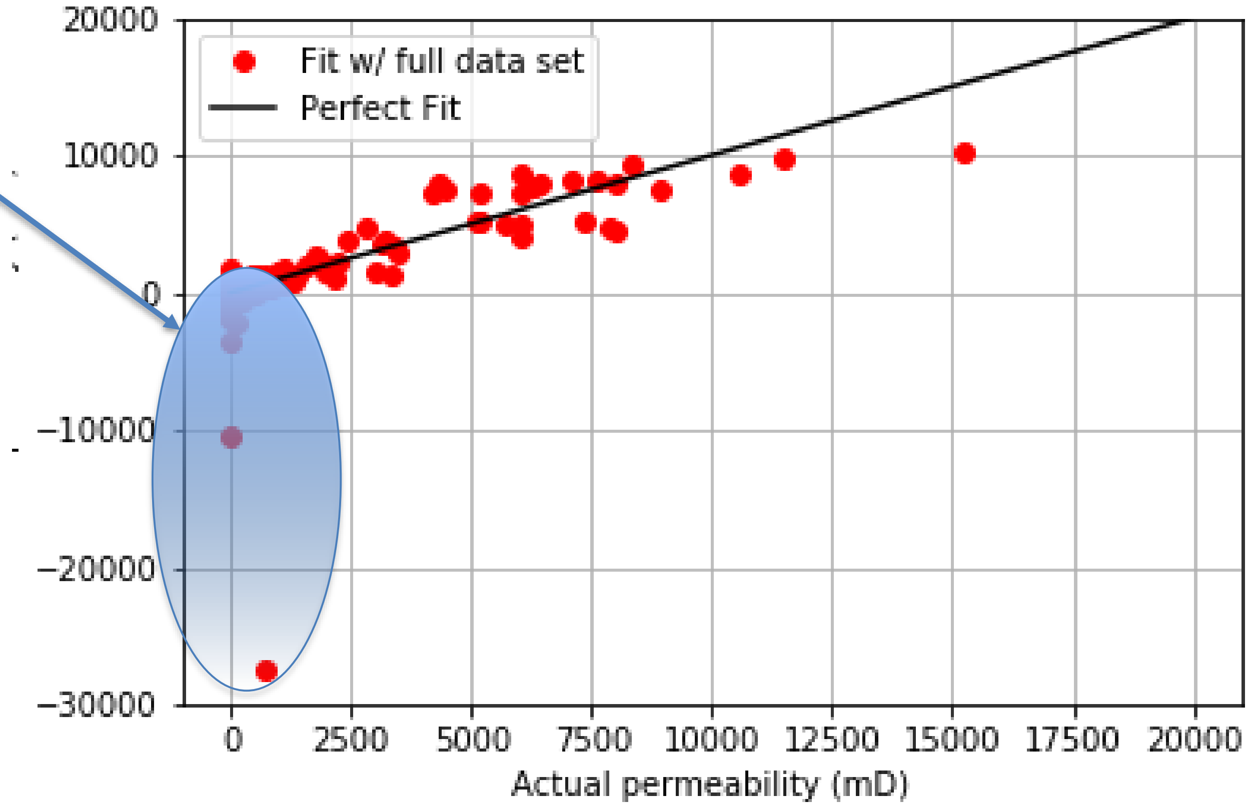
	WELL	CD	LD	SD	FM	POR	KLH	GD	IGV	DG	...	TIO2	AL2O3	FE2O3	MNO	MGO	CAO	NA2O	K2O	P2O5	LOI
0	A	2446.35	NaN	2076.35	G	23.9	2413.00	2.66	29.8	2.0	...	0.14	2.80	0.67	0.01	0.20	0.02	0.13	0.90	0.01	1.69
1	A	2448.35	NaN	2078.35	G	24.1	3112.00	2.66	29.8	1.0	...	0.12	3.45	0.44	0.01	0.23	0.00	0.13	0.98	0.02	1.70
2	A	2450.35	NaN	2080.35	G	23.7	3190.00	2.66	30.3	1.7	...	0.12	3.08	0.61	0.01	0.28	0.03	0.09	0.85	0.02	1.79
3	A	2452.35	NaN	2082.35	G	23.7	6058.00	2.66	28.0	2.3	...	0.21	3.02	0.78	0.01	0.34	0.03	0.18	0.77	0.01	1.41
4	A	2455.35	NaN	2085.35	G	26.5	8026.00	2.68	29.2	1.7	...	0.10	2.90	2.51	0.01	0.22	0.02	0.29	0.80	0.01	2.63
5	A	2456.65	NaN	2086.65	G	24.4	7898.00	2.64	21.5	1.7	...	0.11	3.31	0.19	0.00	0.16	0.00	0.07	1.13	0.01	1.73
6	A	2457.65	NaN	2087.65	G	31.6	5698.00	2.65	34.5	3.0	...	0.16	4.83	0.36	0.01	0.20	0.01	0.24	1.22	0.01	2.36
7	B	3783.20	NaN	3505.20	G	24.8	1573.00	2.65	22.8	0.7	...	0.15	4.49	1.10	0.01	0.27	0.14	0.79	0.14	0.07	1.50
8	B	3784.30	NaN	3506.30	G	23.7	2007.00	2.66	31.5	5.7	...	0.19	3.64	1.33	0.01	0.37	0.17	0.72	0.21	0.05	1.19
9	B	3785.00	NaN	3507.00	G	20.6	206.00	2.66	24.8	2.0	...	0.08	3.47	0.75	0.01	0.25	0.33	0.66	0.43	0.05	1.13

Subset of Panda's Dataframe w/ 300 samples, 57 features each

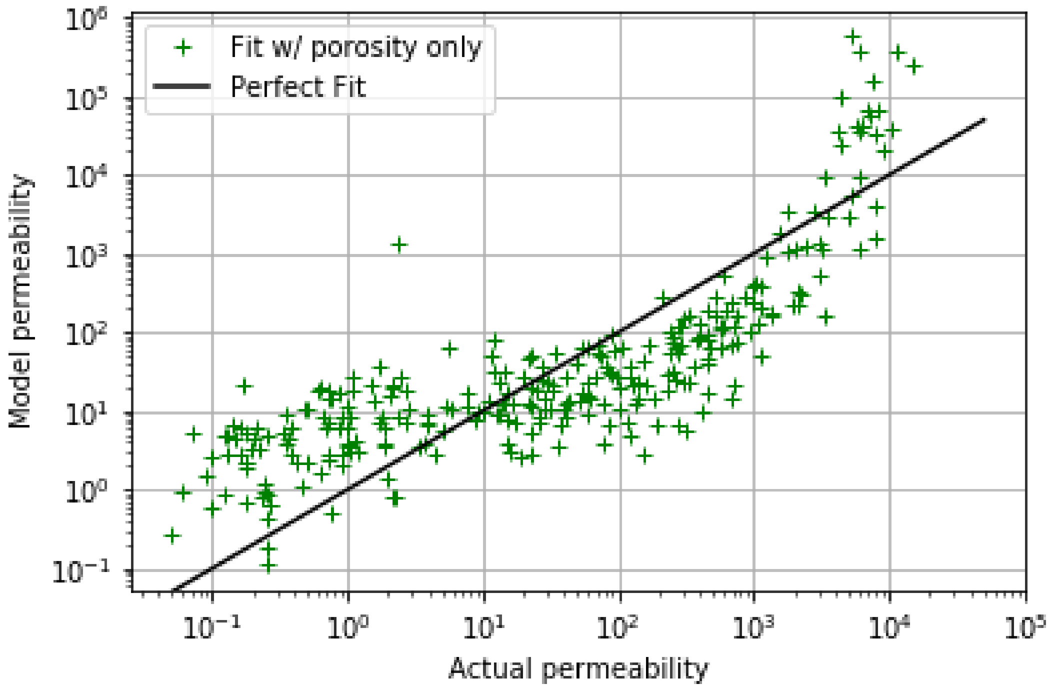
Ehrenberg, S. N. (1990) "Relationship between diagenesis and reservoir quality in sandstones of the Garn Formation, Haltenbanken, mid-Norwegian continental shelf" AAPG Bulletin, v. 74, p. 1538-1558.

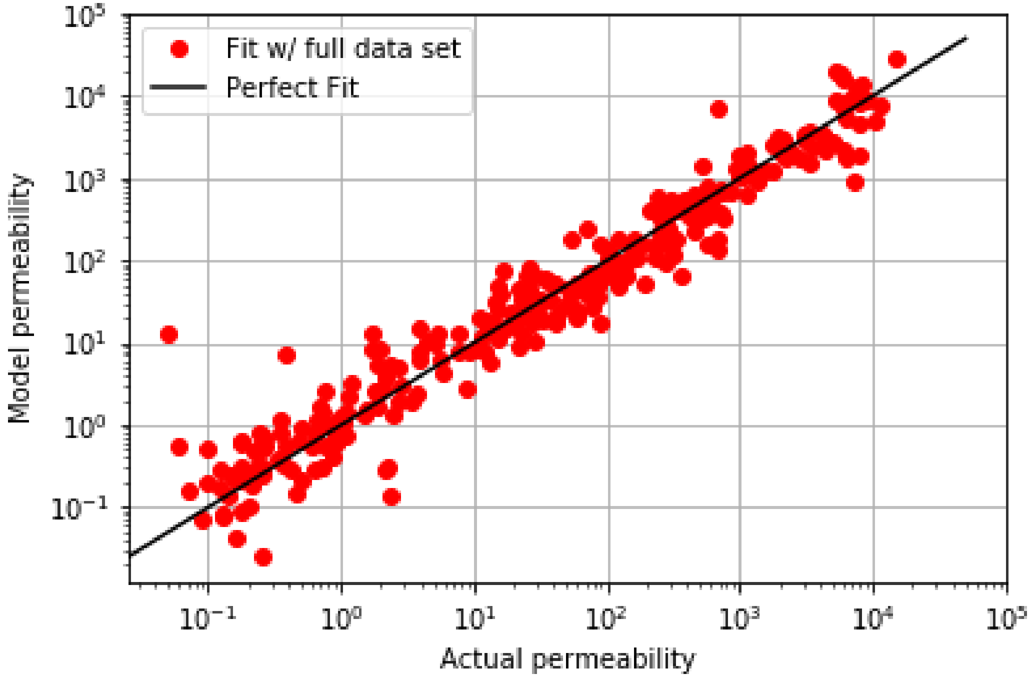
Naïve ML with scikit learn

Negative Permeability?



Physics constrained ML with scikit learn





DIRECT: **DI**gital **RE**servoir **C**haracterization **T**echnology

Carlos Torres-Verdín[1]

Time	Speaker	Topic
9:00	Michael Pyrcz	Welcome, Introduction Geostatistics and Data Analytics
9:30	John Foster	Introduction Numerical Modeling
10:00	Carlos Torres-Verdin	Introduction Geophysical / Petrophysical Data Integration
10:30		Break
10:45	Eric van Oort	Introduction Drilling Automation and Expert Systems
11:15	Michael Pyrcz	Consortium Details
11:45		Additional Discussion and Feedback
12:00		Lunch Provided

1- Hildebrand Department of Petroleum & Geosystems Engineering, the University of Texas at Austin

Introduction to Carlos Torres-Verdín

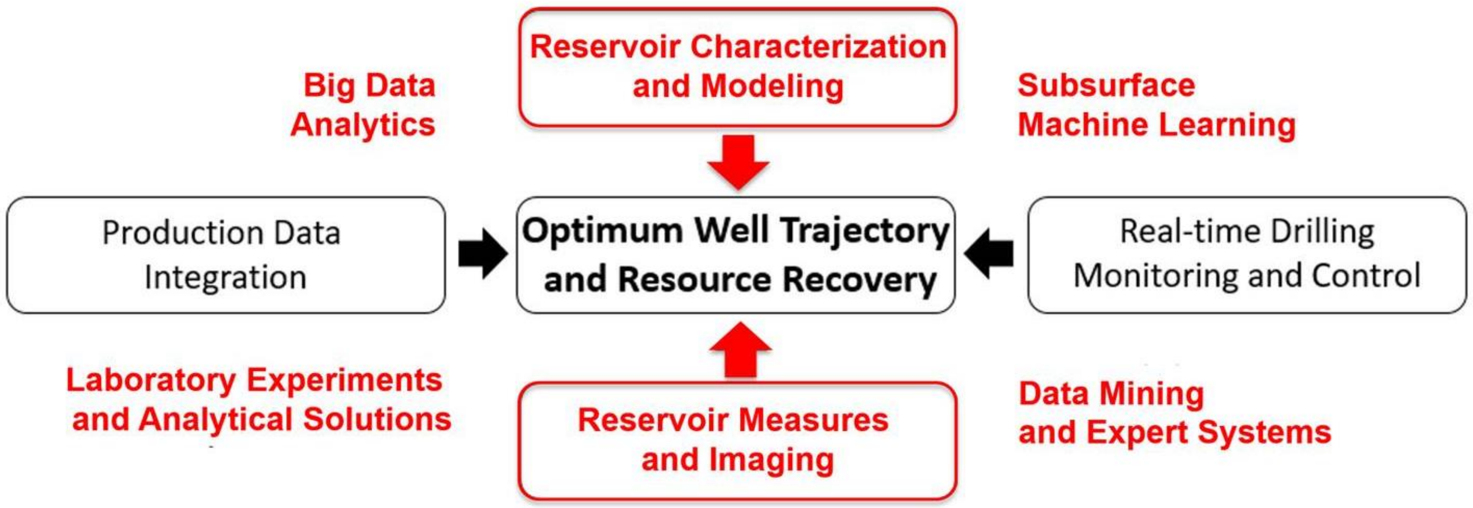
- **Background and Expertise**

  - 10 years of industry experience.
  - 20 years of academic experience.
  - Founder and Director of the Joint Industry Research Consortium on Formation Evaluation, 25 companies and 19 years in operation.
  - Multi-disciplinary research and engineering applications in reservoir description, geophysical reservoir sensing, formation evaluation, borehole geophysics, well logging, rock physics, petrophysics, and multi-physics inverse problems.

I am used to working with industry partners and delivering tangible, valuable, and timely results

Anadarko Petroleum Corporation
ارامكو السعودية Saudi Aramco
BAKER HUGHES a GE company
bhpbilliton
bp
Chevron
ConocoPhillips
COSL
DEA
eni
equinor
ExxonMobil
HALLIBURTON
INPEX
Lundin Norway
nexen A CNOOC LIMITED COMPANY
Oil Search
BR PETROBRAS
REPSOL
Schlumberger
swn Southwestern Energy®
TOTAL
wintershall dea
woodside

DIRECT Consortium Goals



Integration across geoscience and engineering disciplines with data analytics and machine learning to support optimum field development decision making.

Integrated Solutions

Gathered a team of experts in drilling, geophysics, reservoir engineering, Geomodeling to support adoption of data-driven methods.

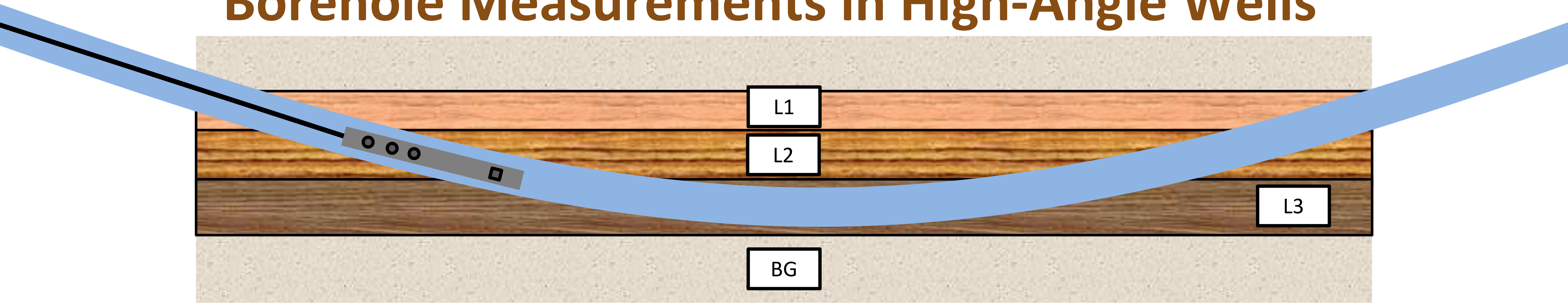
DIRECT by design:

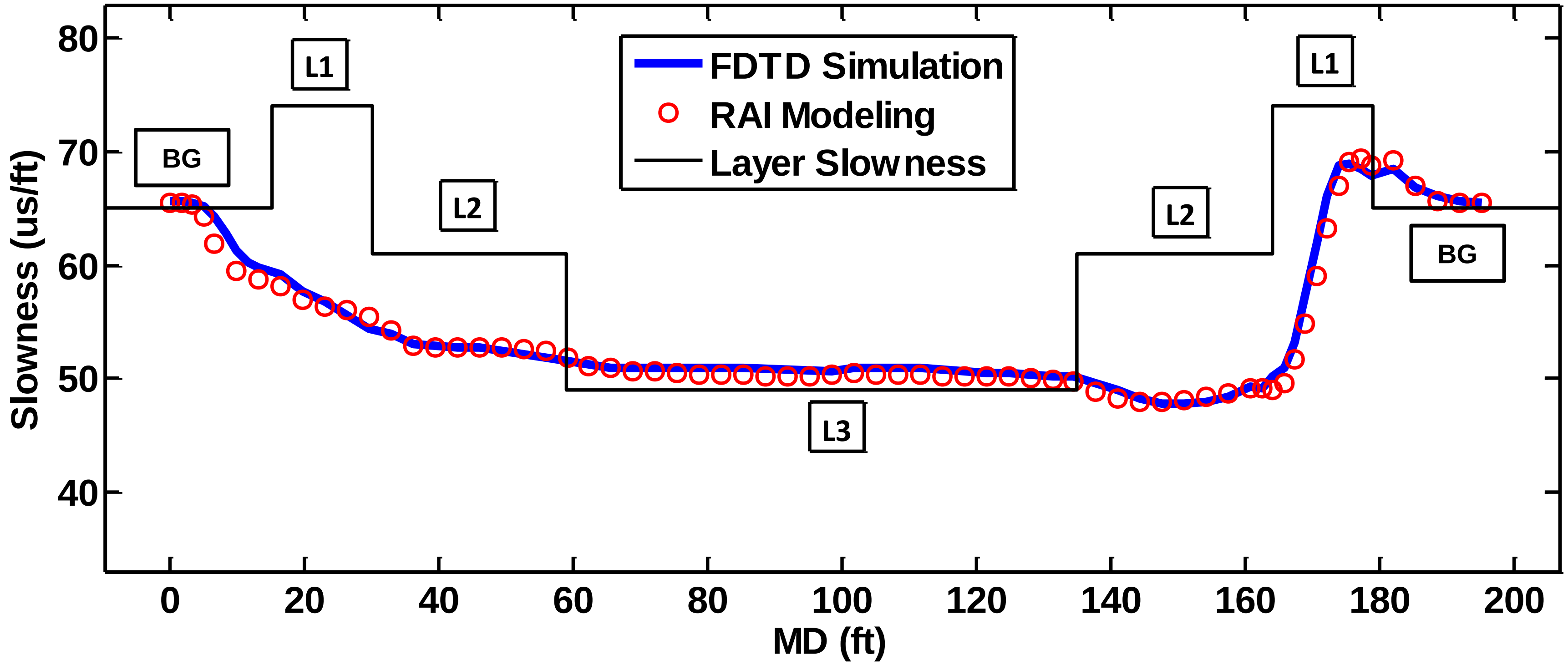
- Rock centric ✓
- Geology centric ✓
- Reservoir (fluid-rock) centric ✓
- Production centric ✓
- Intrinsic and explicit well-seismic tie ✓
- Rock physics calibration at wells ✓
- Time lapse ✓
- Well navigation and geomechanics ✓

Why Machine Learning and AI?

Extreme Rock Complexity requires Expert Knowledge + Computer-Driven Solutions that Assimilate Complex Input-Output Relationships

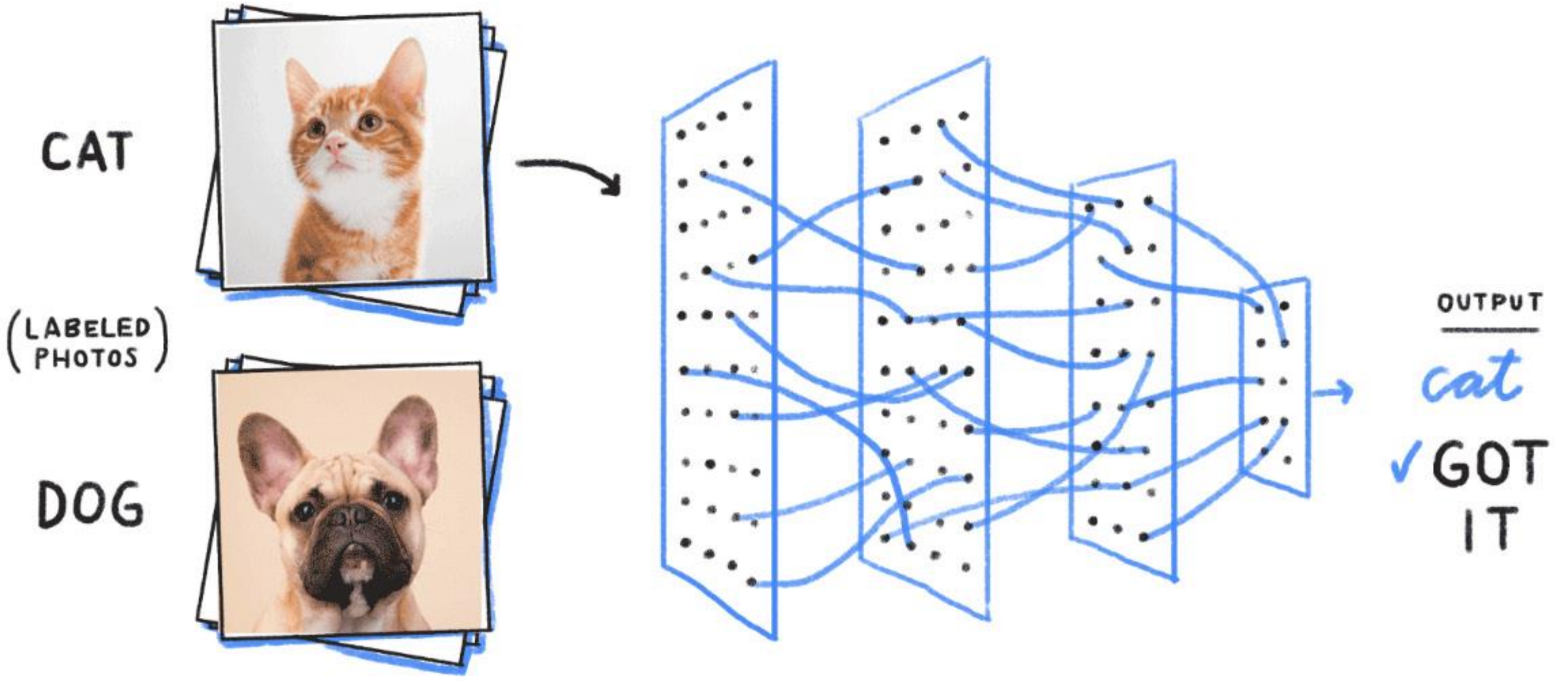
Borehole Measurements in High-Angle Wells





Why Deep Learning

2012: Deep Learning wins ImageNet competition!



2013: They win again, but this time with a larger distance
2014: The competition becomes just about Deep Learning

Machine Learning/AI to Synthesize Production-Oriented Properties

of Spatially Complex Rocks via Multi-Physics and Multi-Scale Geophysical Measurements

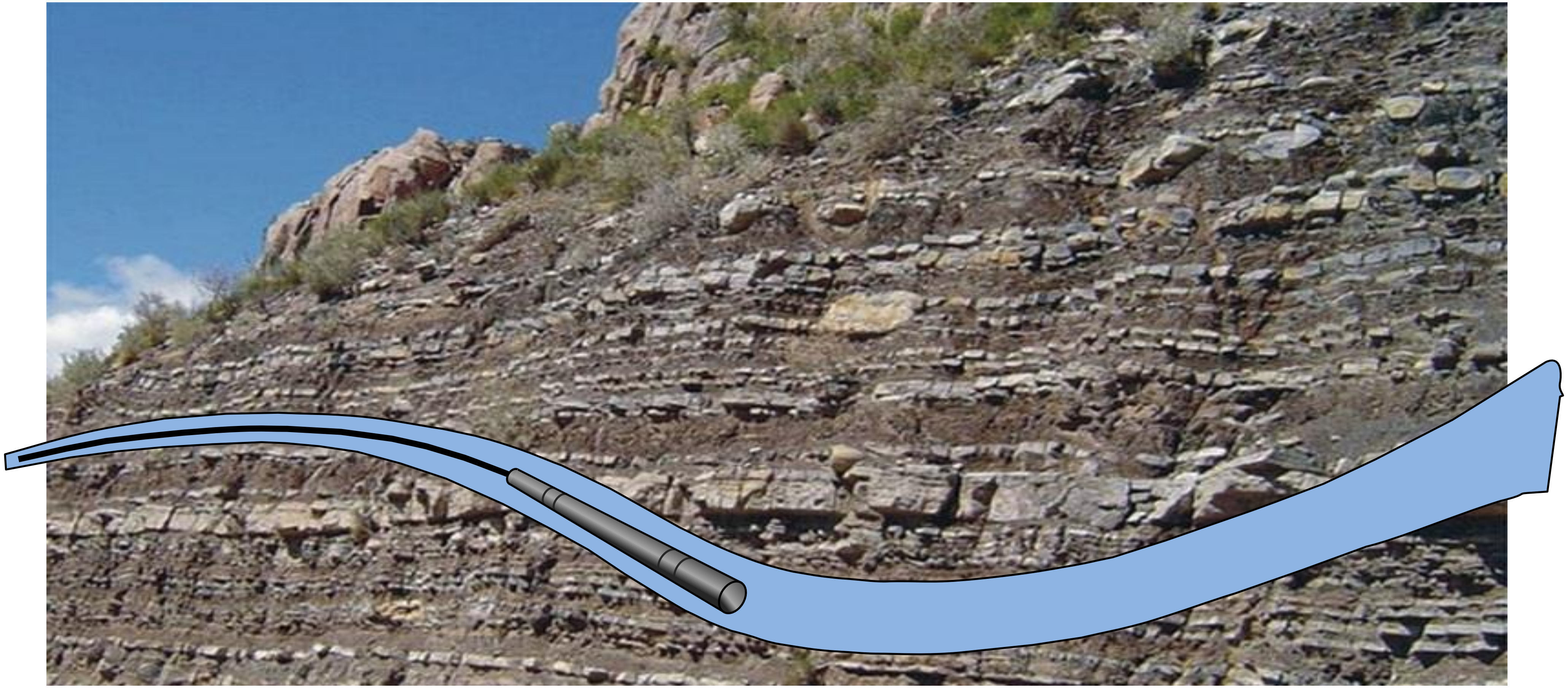
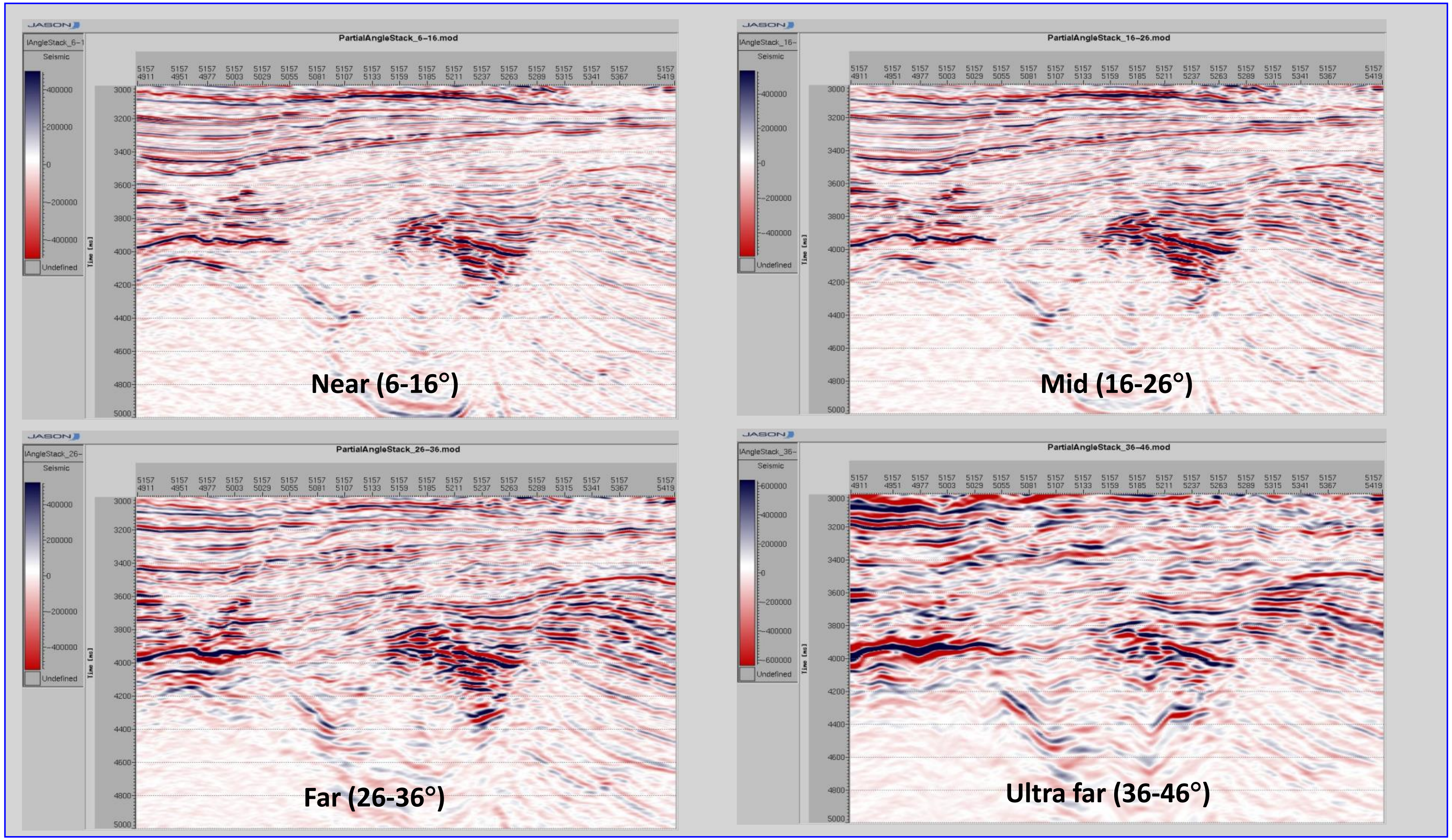
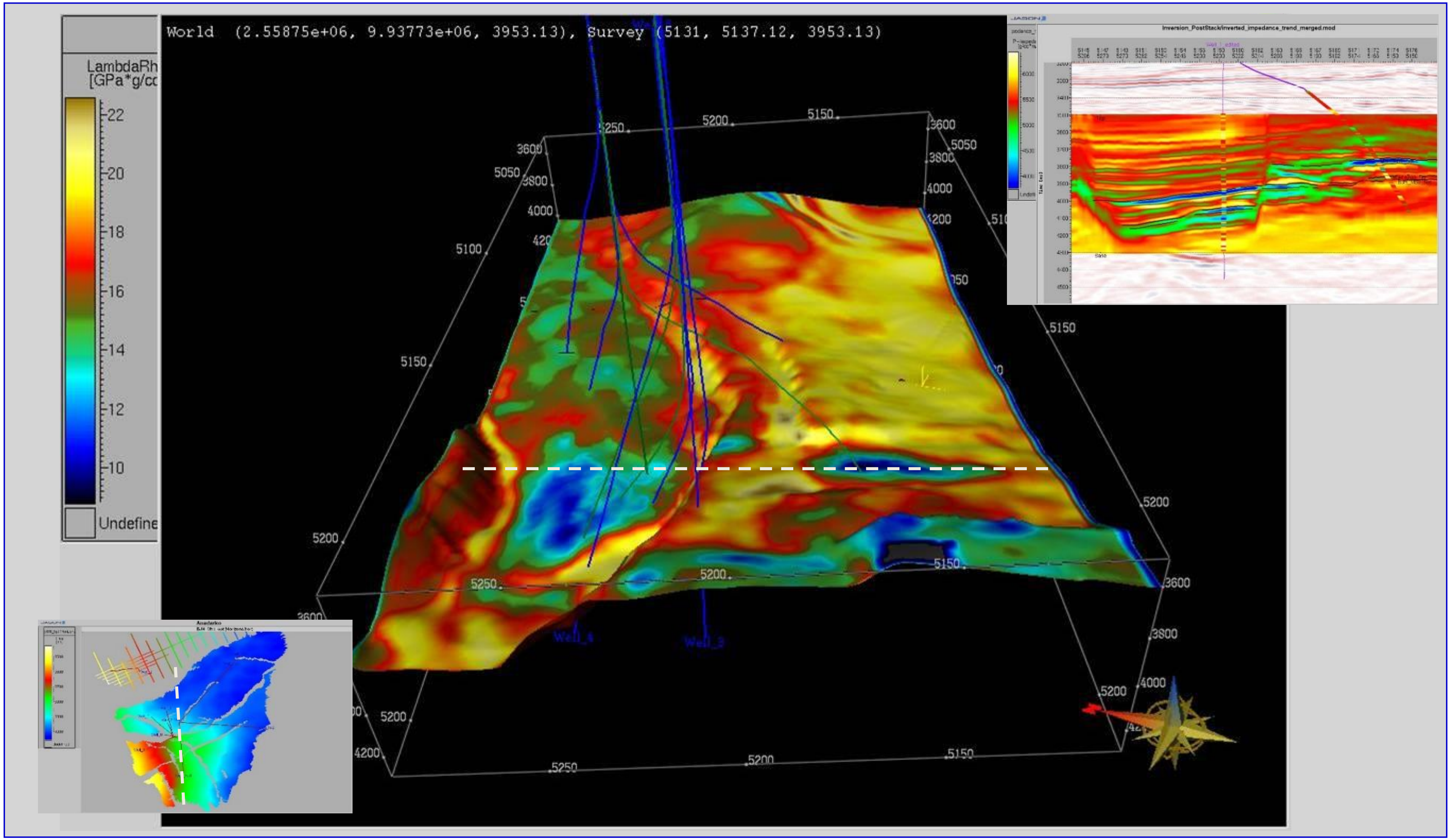


Photo Courtesy: Instituto De Estudios Andinos Don Pablo Groeber

Example: From Partial-Angle-Stack Seismic Data to Rock/Fluid Properties Calibrated Along Wells



3D Estimation of Elastic Properties via AI



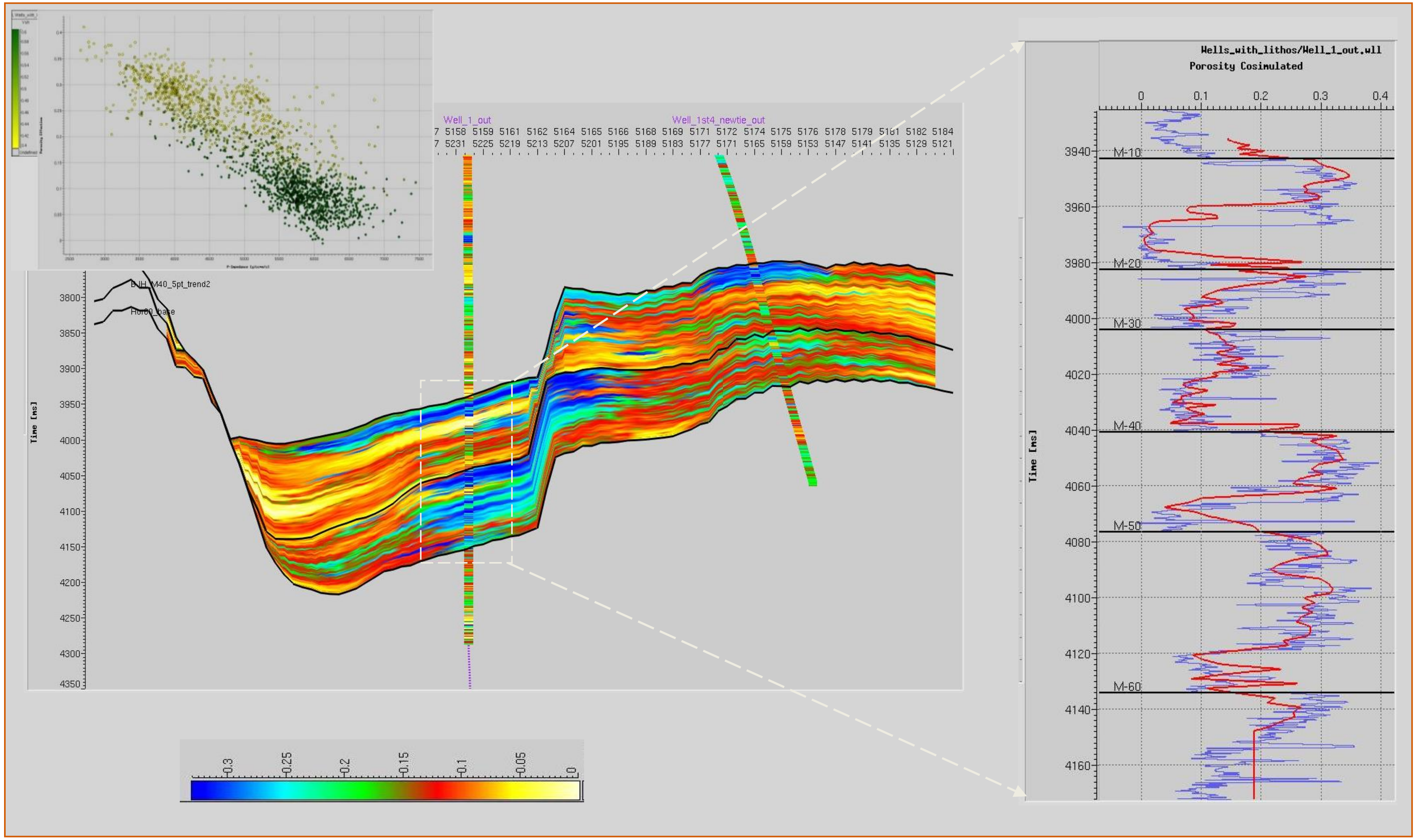
DIRECT by design:

- Reservoir window (time and depth).
- Driven by wells and borehole/core measurements.
- High spatial resolution and low uncertainty.
- Honors rock complexity evidenced by borehole measurements (e.g., type of anisotropy).
- Seismic imaging and amplitude preservation explicitly driven by existing wells and borehole measurements.
- Data acquisition + Imaging + Seismic amplitudes + Rock Physics in explicit harmony.
- Updatable with new wells and other measurements (e.g. EM, pressure).

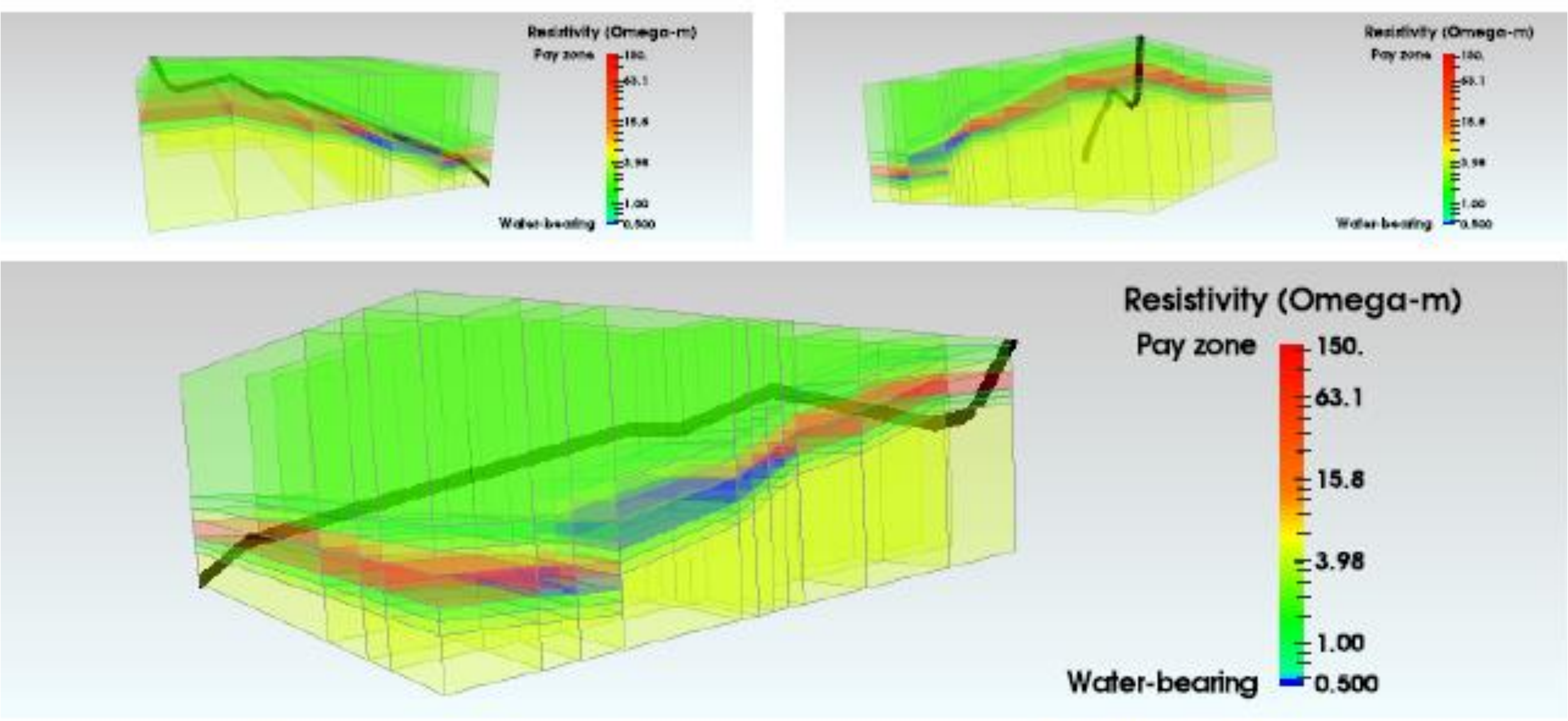
DIRECT: Proposed AI-Based Strategies

- Fast solution of inverse problems to estimate (with measures of uncertainty) lithology, petrophysical, elastic, and mechanical properties from noisy surface and borehole geophysical measurements.
- Numerical modeling to be used for training/deep learning.
- Account for messy, noisy, unbalanced, and incomplete measurements: data normalization!
- Multi-scale procedures to relate input measurements to output properties.
- Approximate numerical solution for ultra-fast deep-learning training.
- Integrated approach for estimation of inter-well properties.

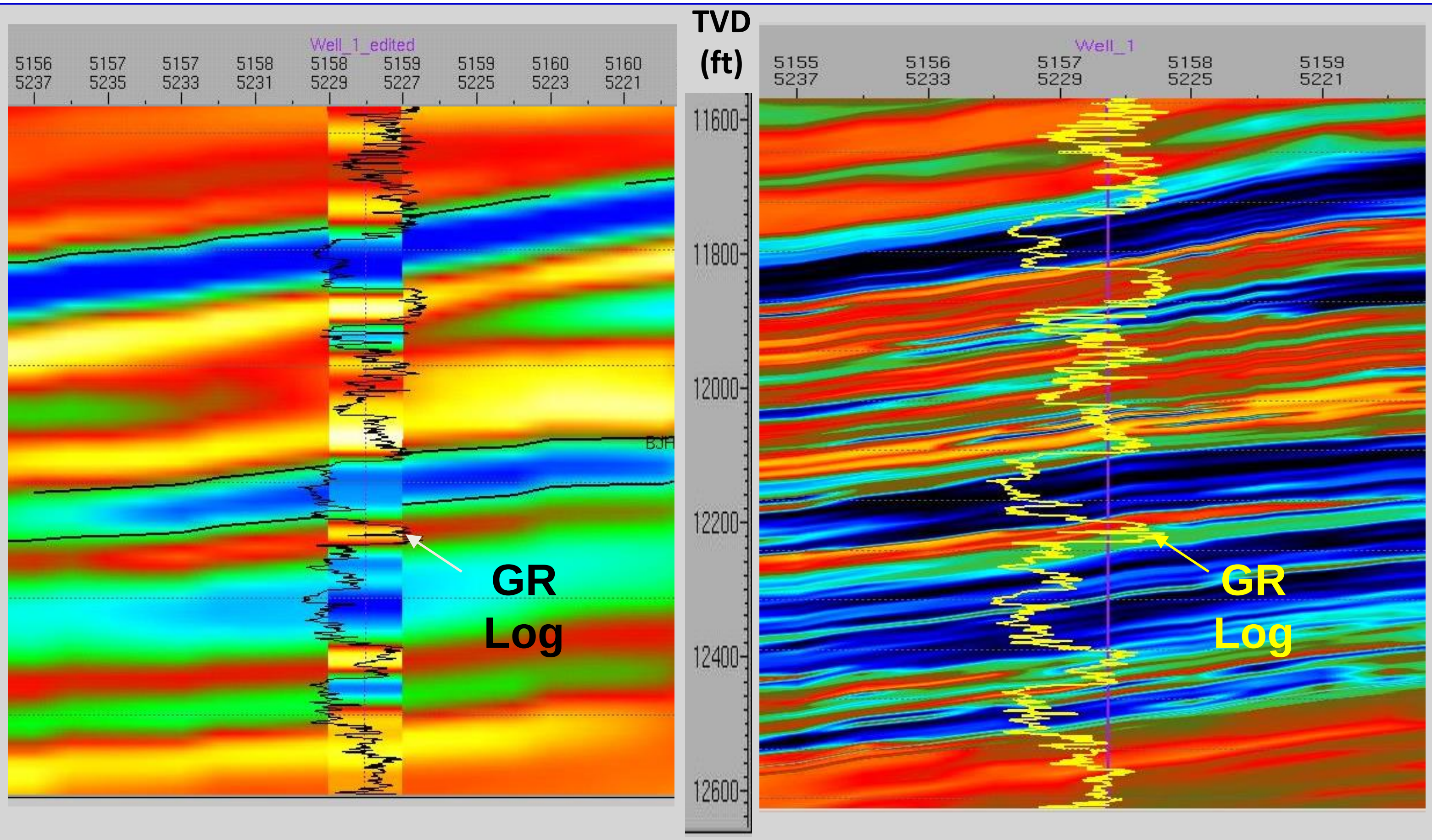
High-Resolution Seismic Inference: Well Logs + Pre-Stack Seismic Amplitude Data



Rapid Reservoir Access via Well Drilling and Construction: Machine Learning guided by Fast Numerical Modeling



Deterministic vs. Well-Driven Bayesian Seismic Inversion

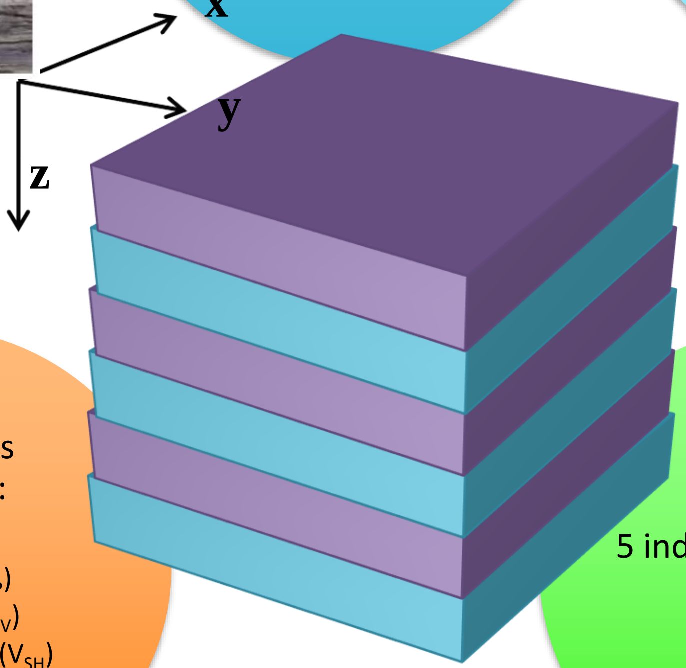


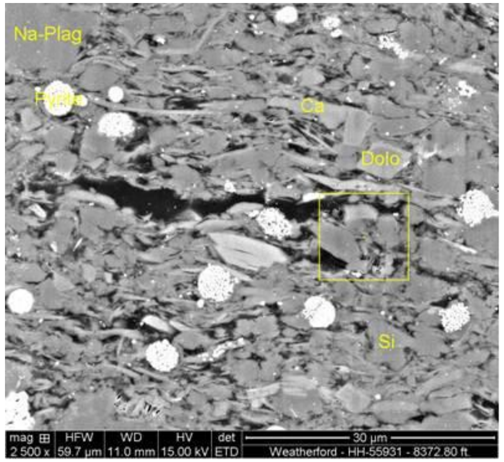
Deterministic Ip
(Sample Rate: 4 ms)

Stochastic Ip
(Sample Rate: 1 ms)

(Vertical) axis normal to a plane of anisotropy

$$\begin{bmatrix} C_{11} & C_{12} & C_{13} & 0 & 0 & 0 \\ C_{12} & C_{11} & C_{13} & 0 & 0 & 0 \\ C_{13} & C_{13} & C_{33} & 0 & 0 & 0 \\ 0 & 0 & 0 & C_{44} & 0 & 0 \\ 0 & 0 & 0 & 0 & C_{44} & 0 \\ 0 & 0 & 0 & 0 & 0 & C_{66} \end{bmatrix}$$





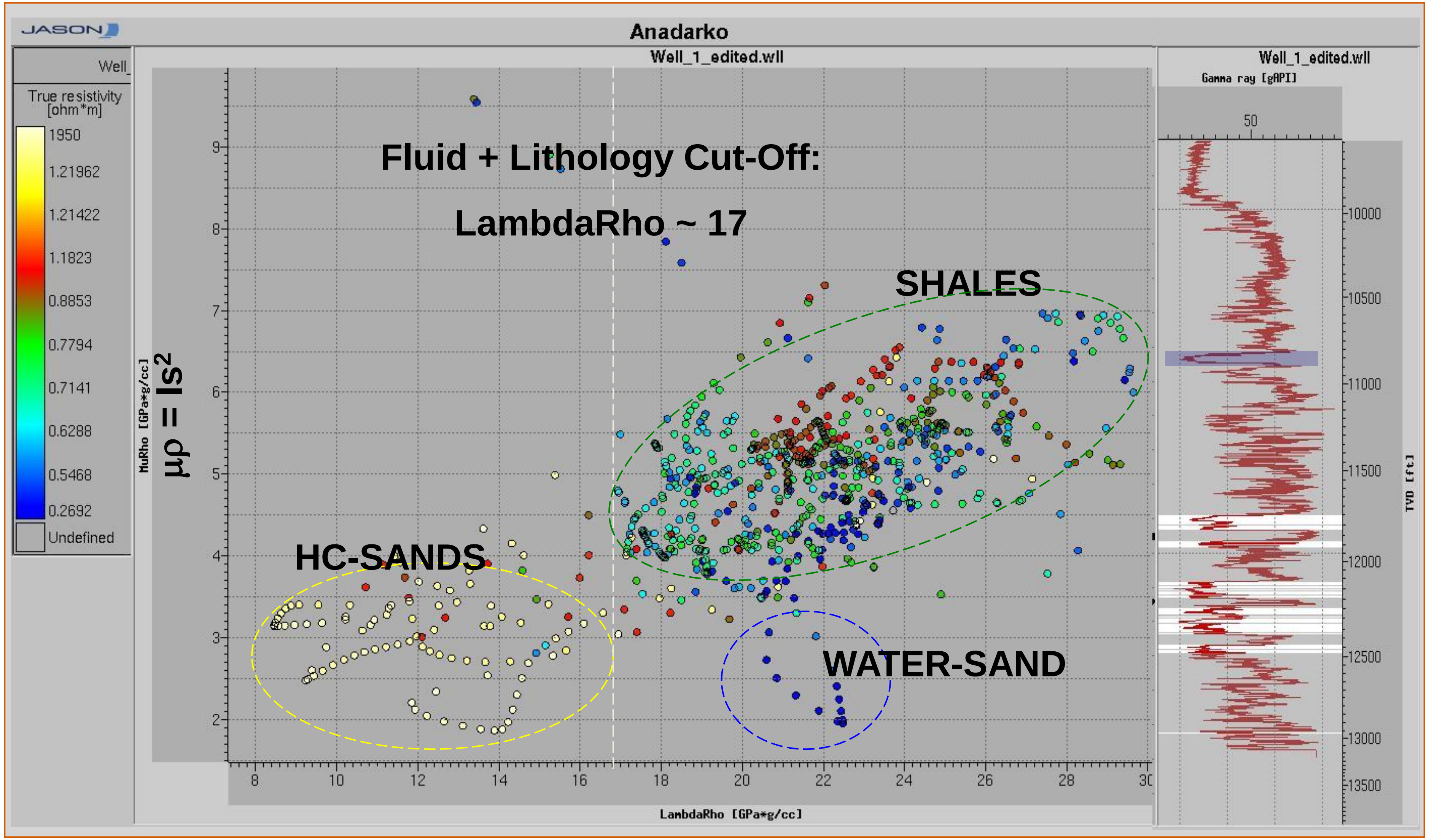
Stiffness matrix is characterized by:

- Sonic log data
  - Vertical P-wave (V_P)
  - Vertical S-wave (V_{SV})
  - Horizontal S-wave (V_{SH})
- Density log data (ρ)

5 independent elastic constants

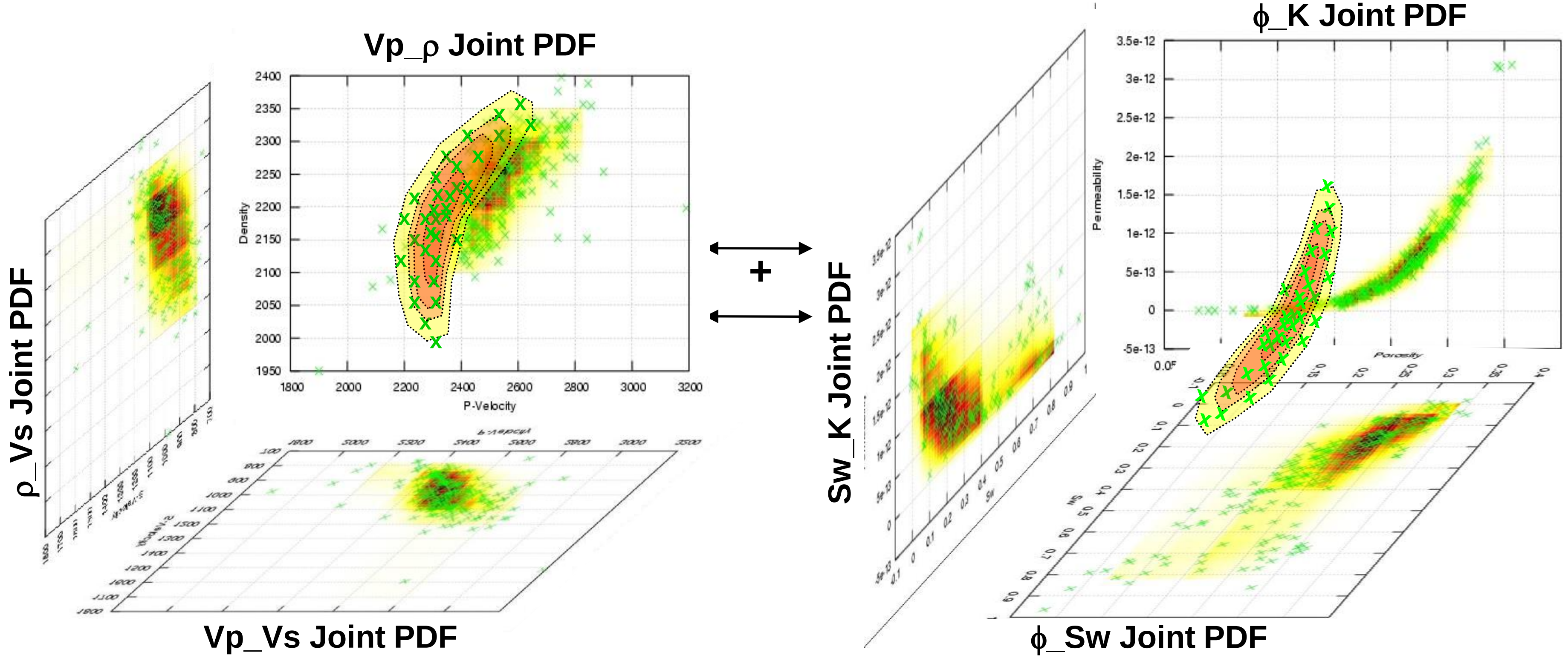
Rock Physics

Modulus Attributes ($\lambda\rho$ vs. $\mu\rho$)



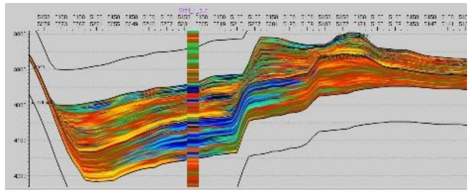
$\lambda\rho = Ip^2 - 2Is^2$

Co-Simulation of Petrophysical Properties (Via Multivariate Statistics)

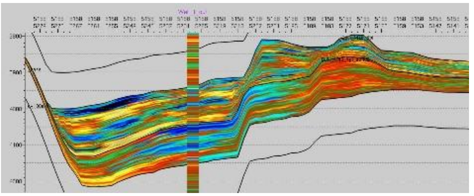


<u>Layer and Lithotype–dependent</u> multidimensional joint distributions

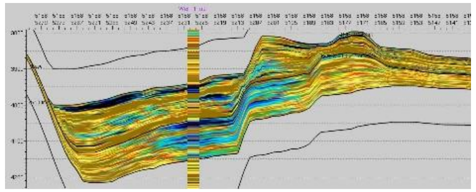
AI-Driven Petrophysical Inversion/Post Processing



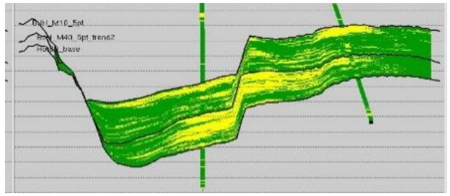
P-Velocity



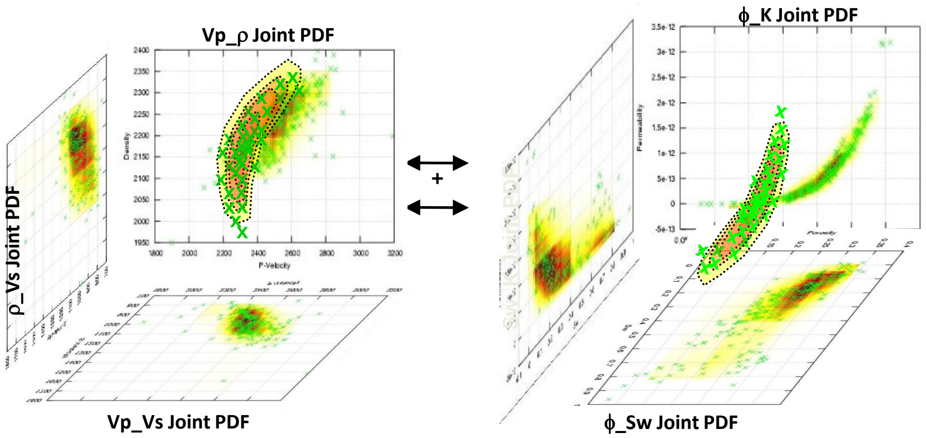
S-Velocity

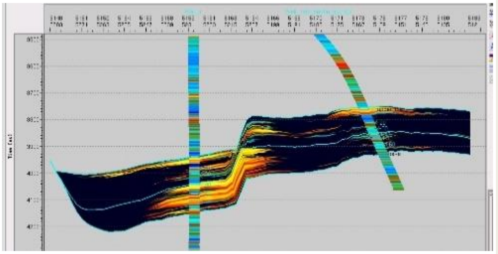


Density

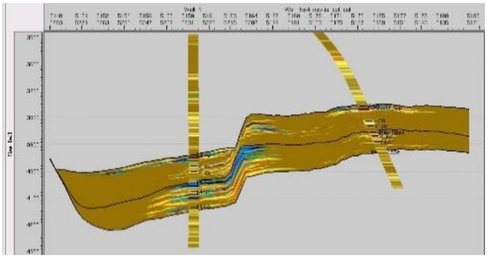


Lythotypes

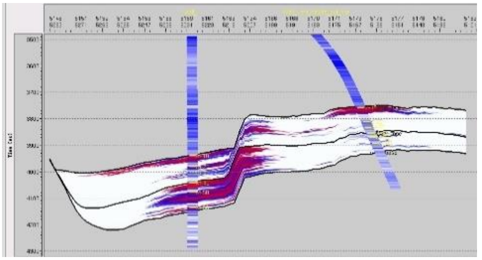




Porosity

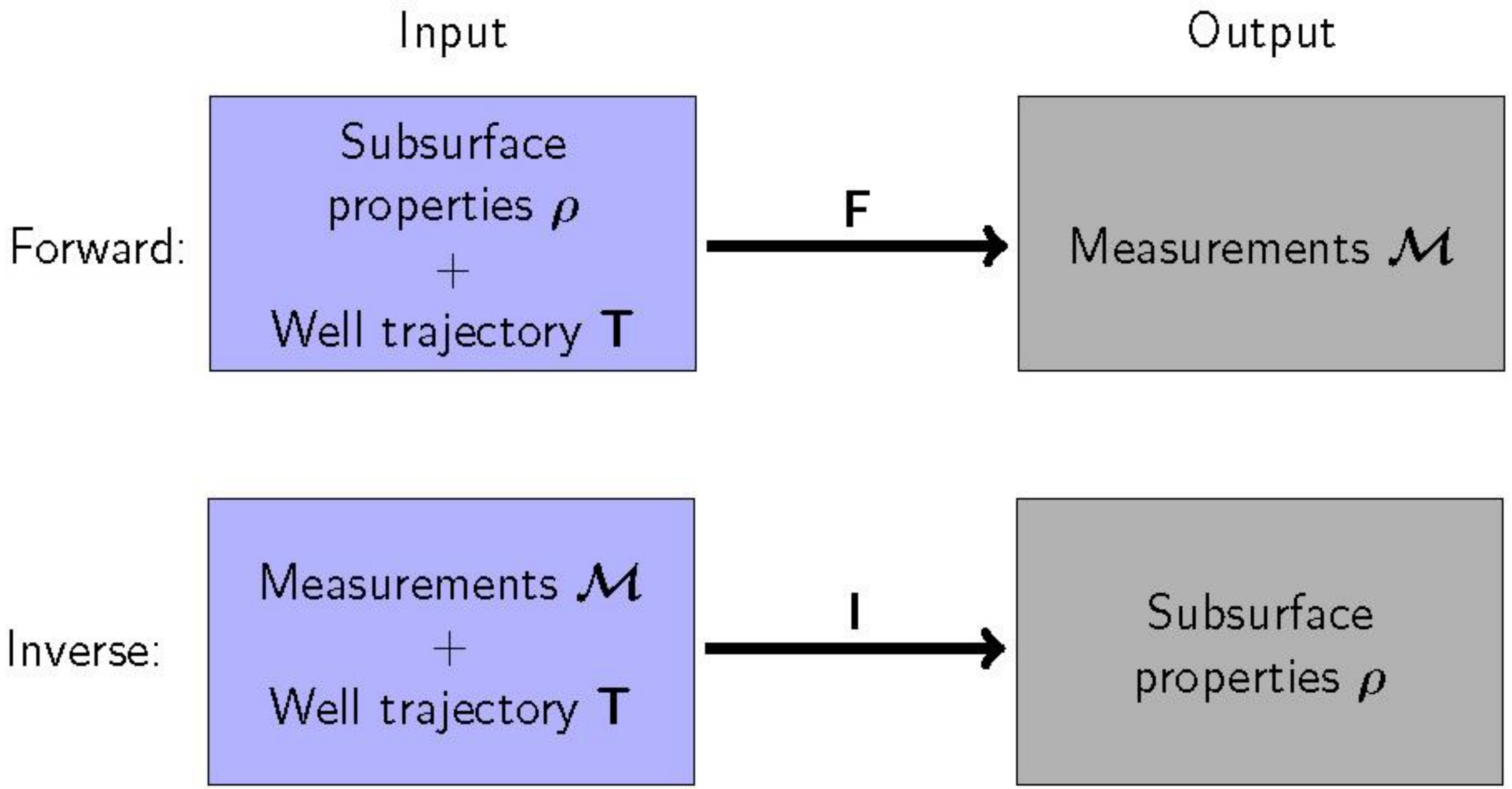


Permeability



Water Saturation

Formulation of Inverse Problems



Formulation of Inverse Problems

Cost Functional:

$$C(\rho) = \underbrace{\| F(\rho) - \mathcal{M} \|^2_{l^2_{W_M}}}_{MISFIT} + \underbrace{\lambda \| \rho - \rho_0 \|^2_{L^2_{W_{\rho_0}}}}_{REGULARIZATION},$$

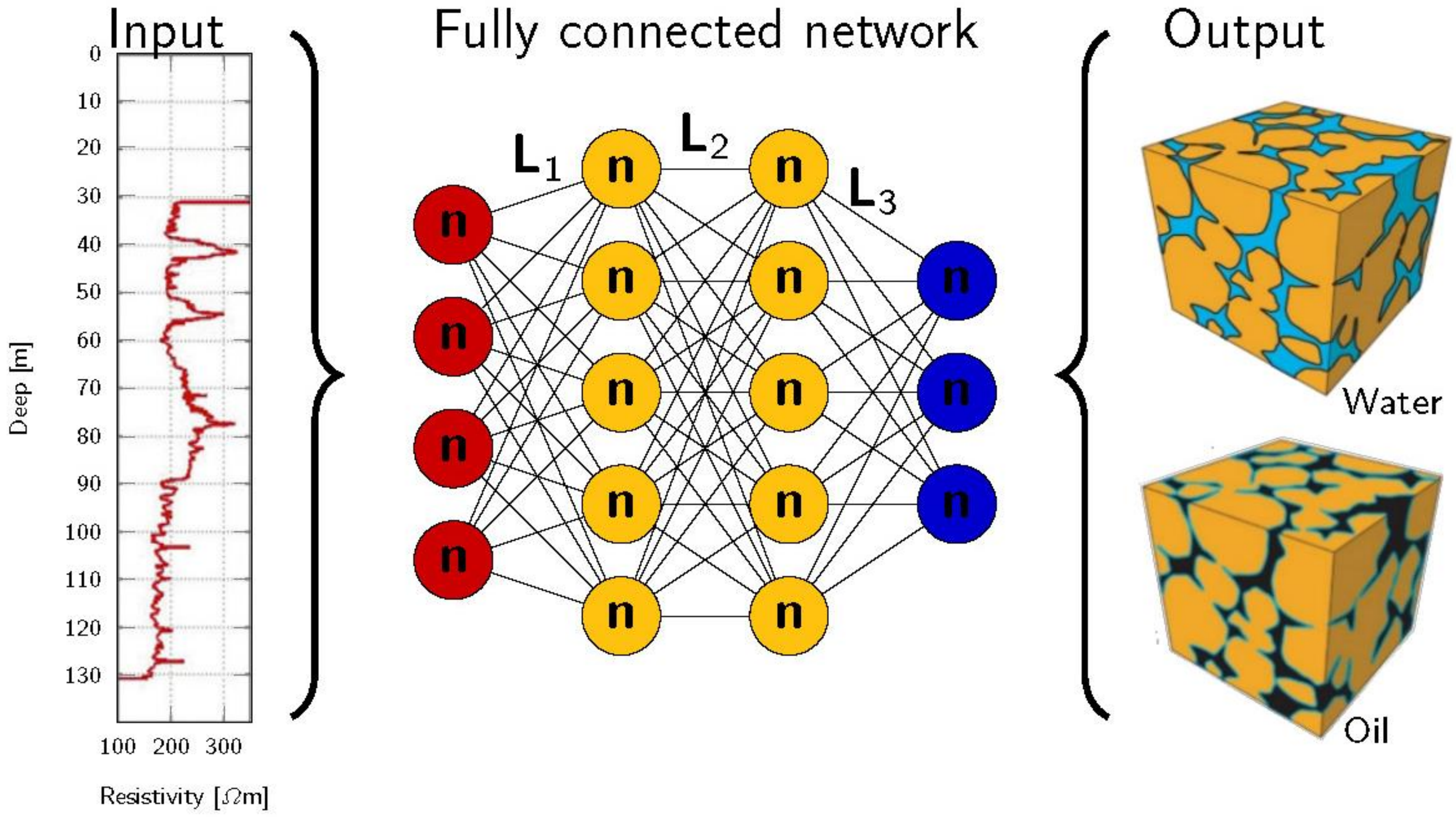
where

- $\rho = \sum_i \rho_i \chi_i(\mathbf{x})$ is the resistivity,
- $F(\rho)$ is the set of simulated measurement for ρ,
- $\mathcal{M}$ is the set of actual (or synthetic) field measurements,
- λ is a regularization parameter, and
- ρ_0 is an *a priori* distribution of ρ.

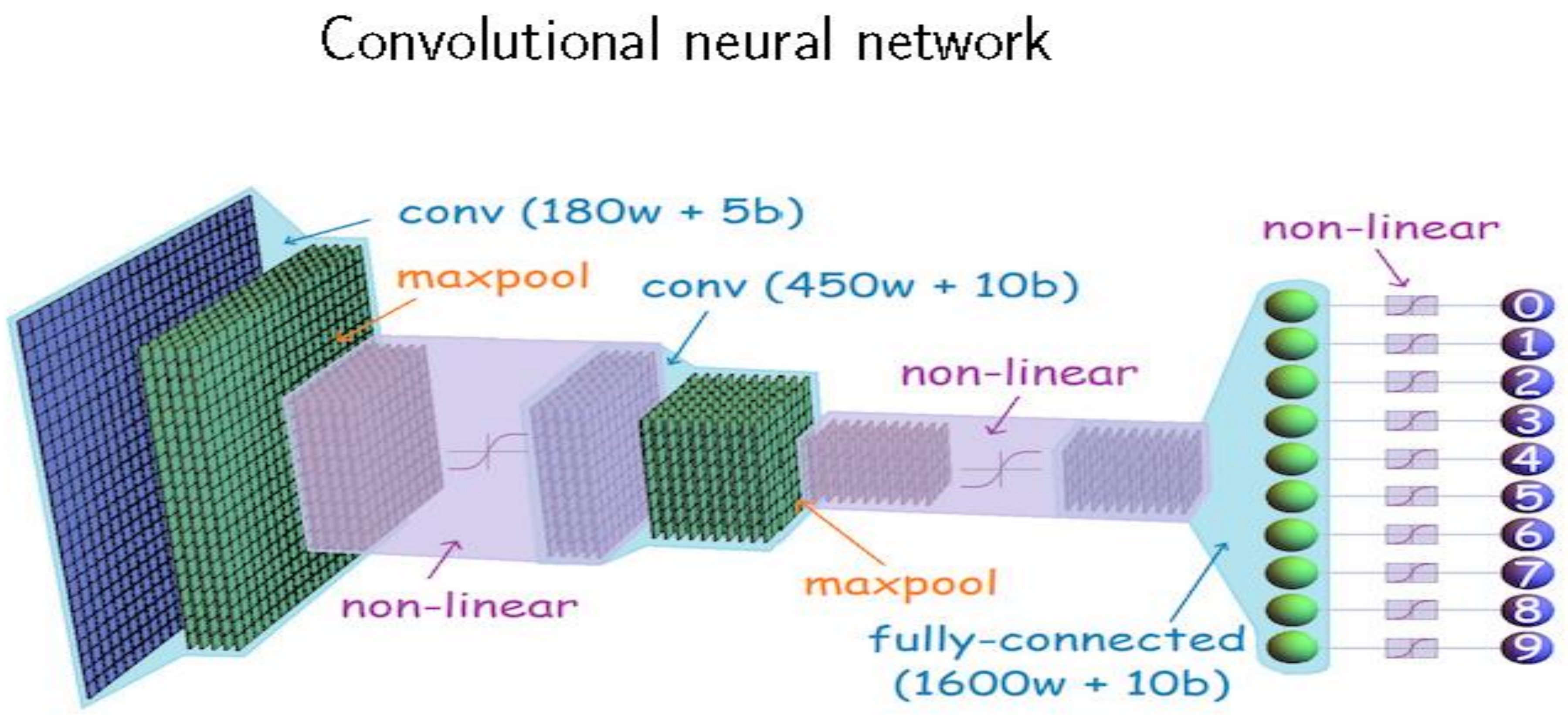
Goal: To find $\rho^* := \arg\min_{\rho} C(\rho)$.

Neural Networks for Inverse Problem

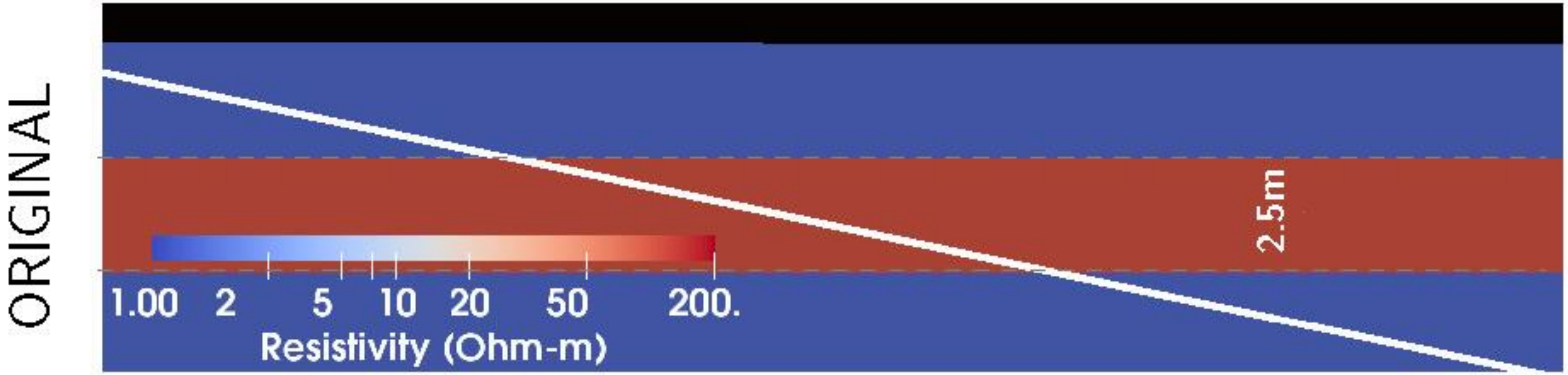
Approximate: $\mathbf{I} \approx \mathbf{I}_h := \mathbf{N} \circ \mathbf{L}_k \circ \mathbf{N} \circ \mathbf{L}_{k-1} \circ \cdots \circ \mathbf{L}_1 \circ \mathbf{N}$

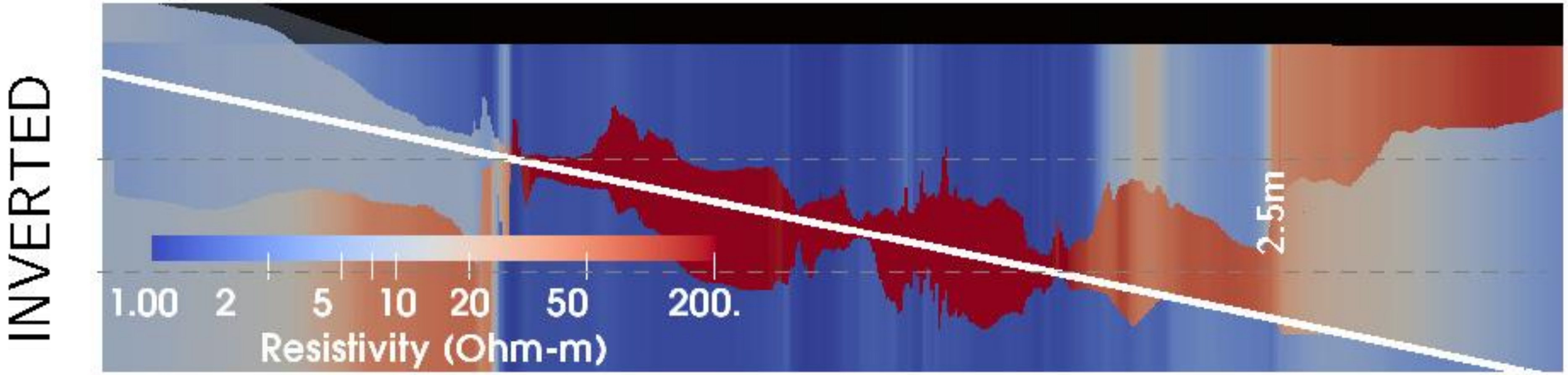


Deep Convolutional Network

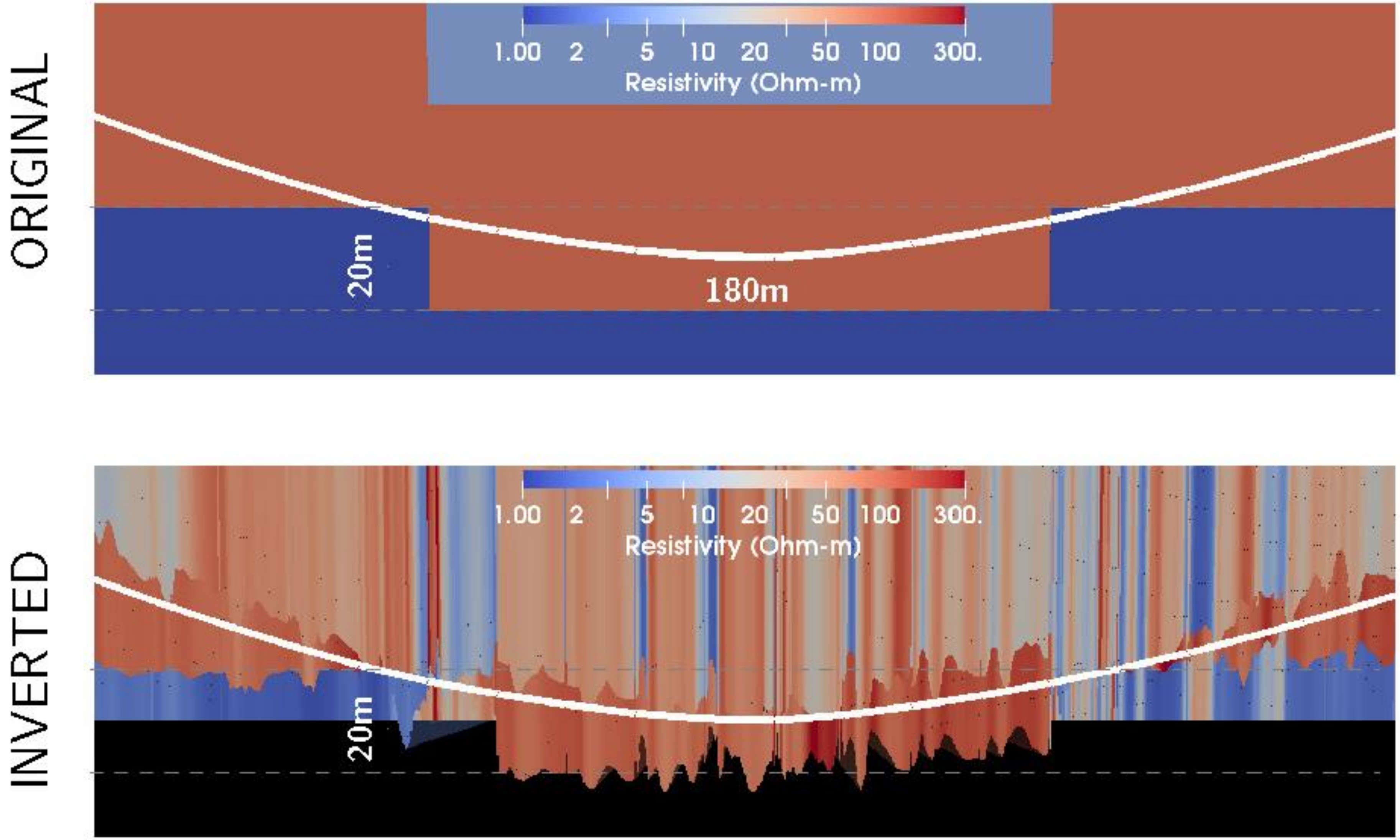


Synthetic Example I: Dip=88°

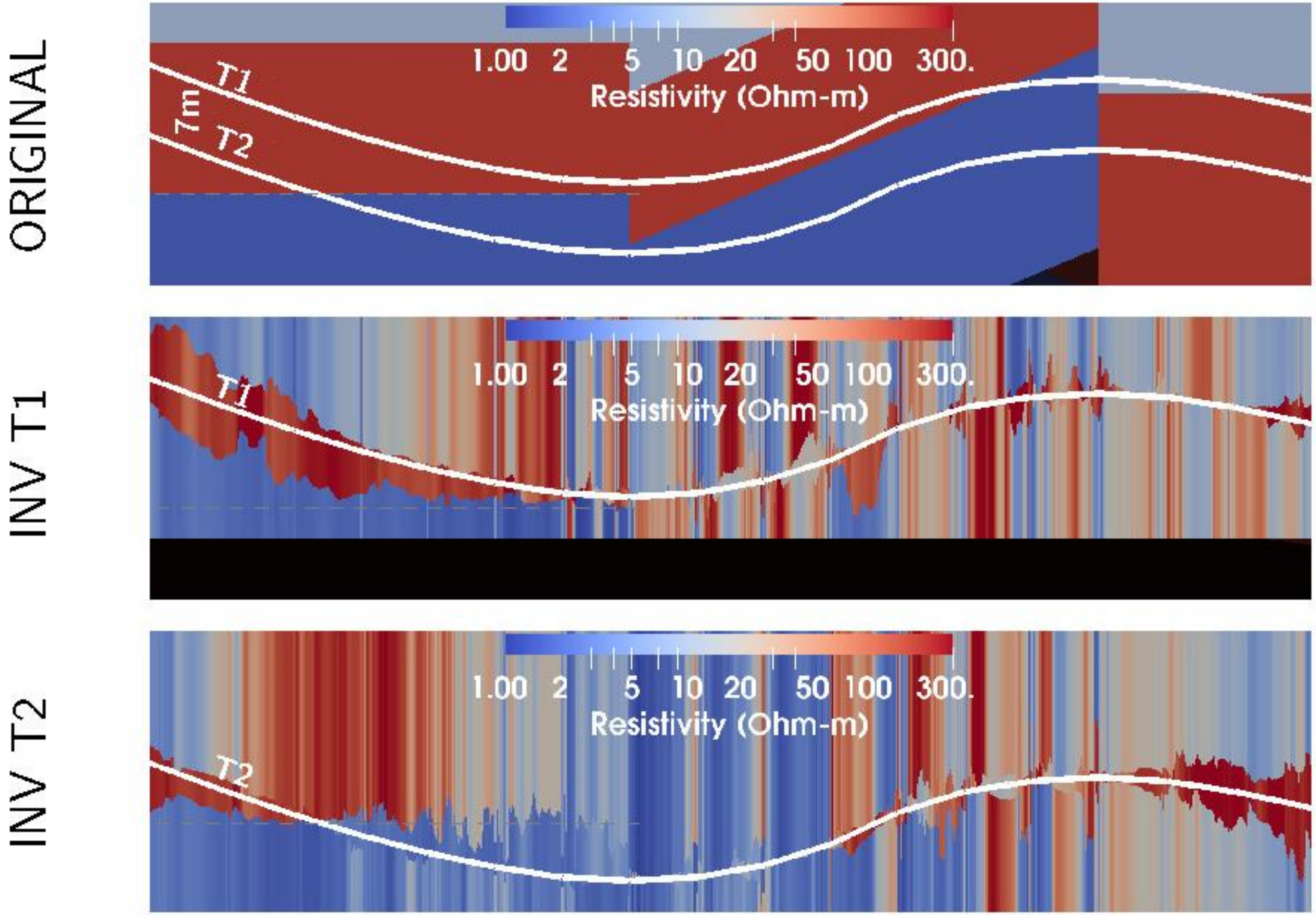




Example II: Curved Well Trajectory

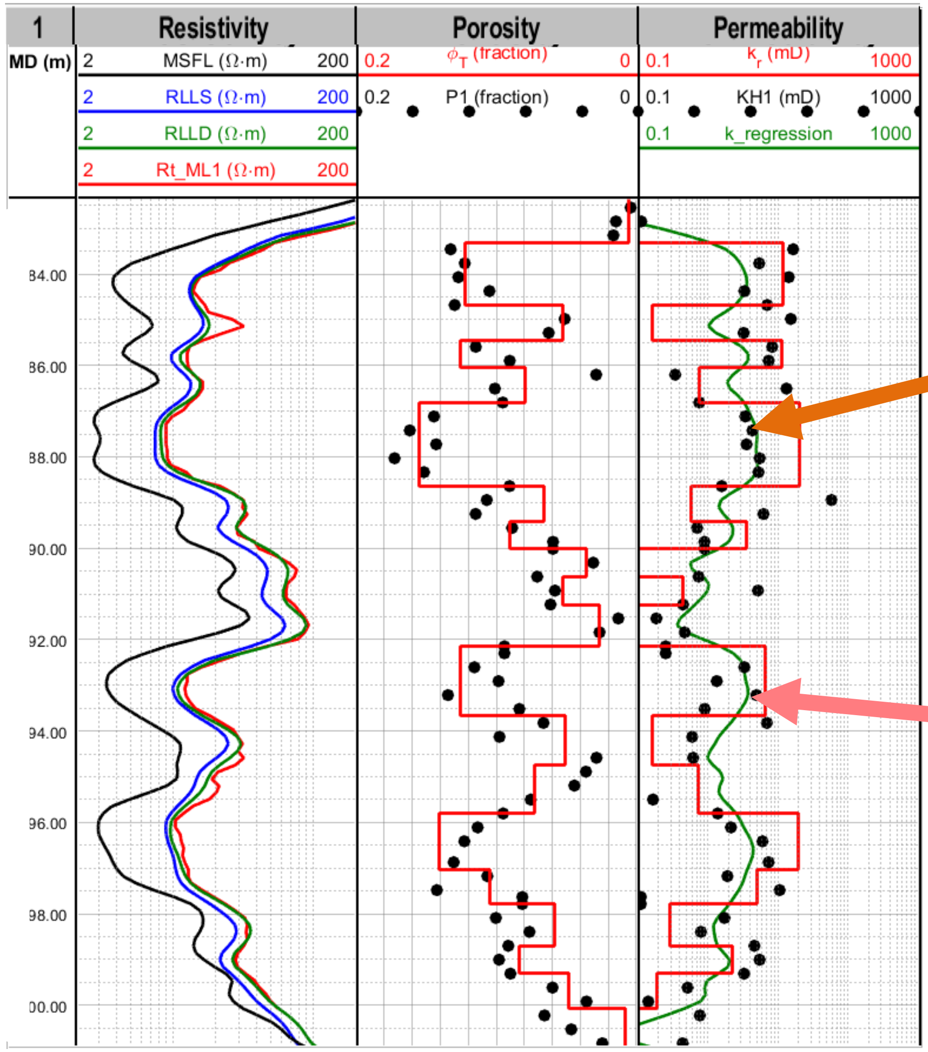


Synthetic Example III



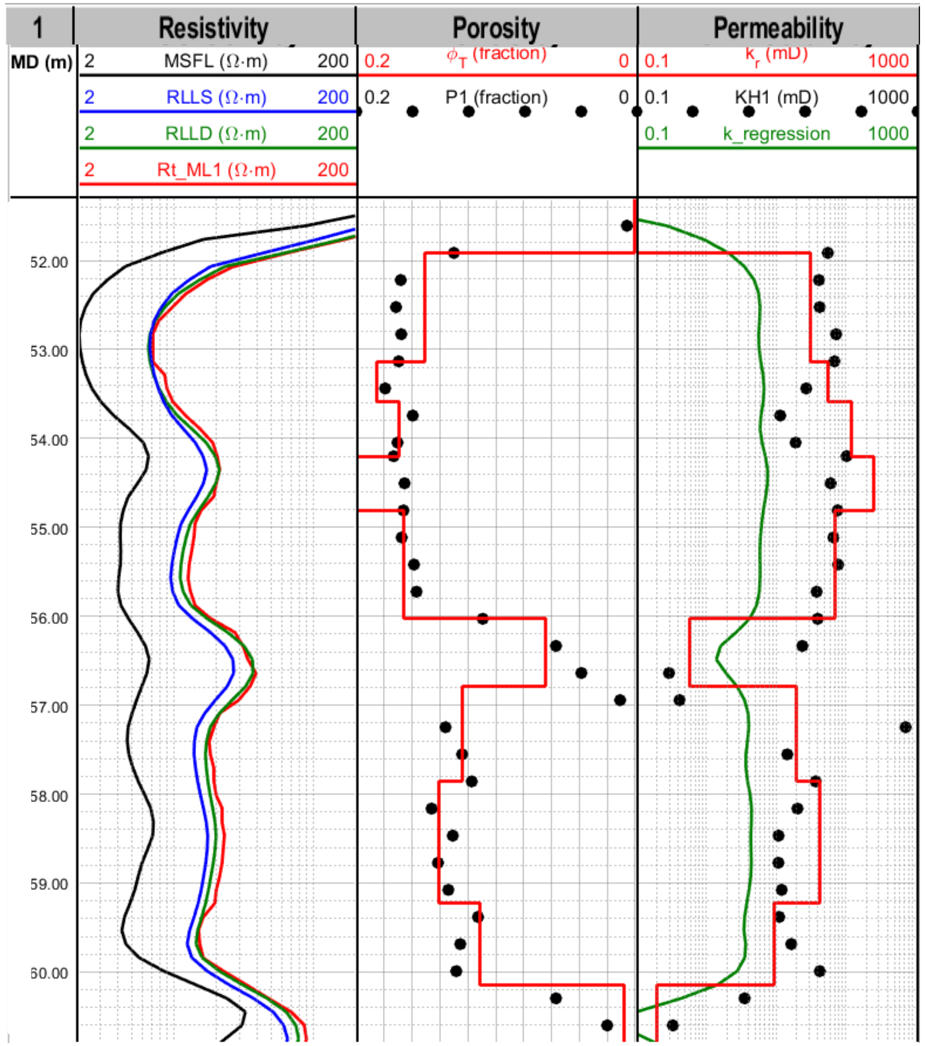
Field Case: Multi-Well Interpretation in a Carbonate Reservoir

Calibration of Petrophysical Parameters in Cored Intervals



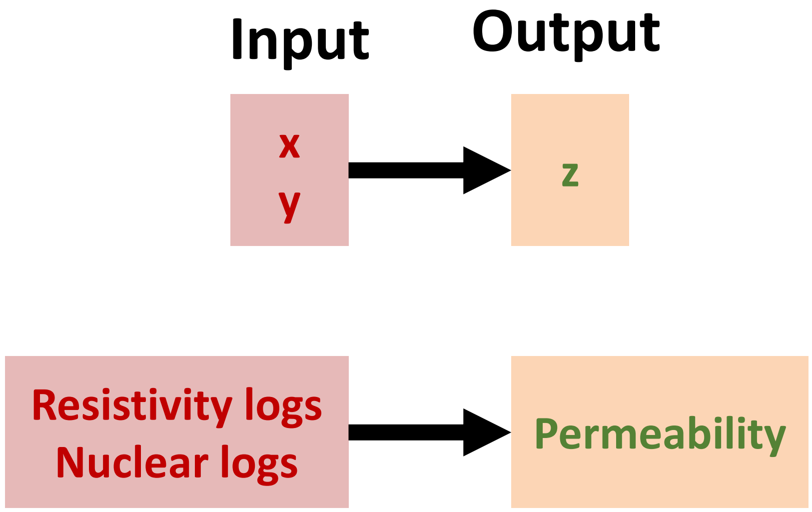
Permeability estimated from porosity-permeability regression line

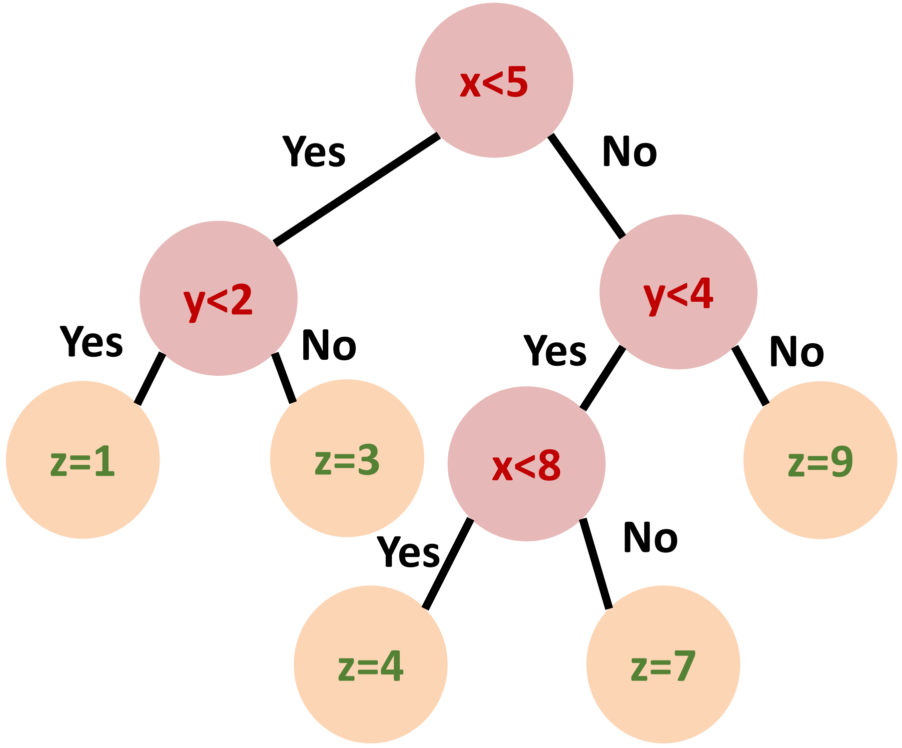
Permeability estimated from a machine learning model



Method: Random Forests for Inverse Problems

Decision Trees



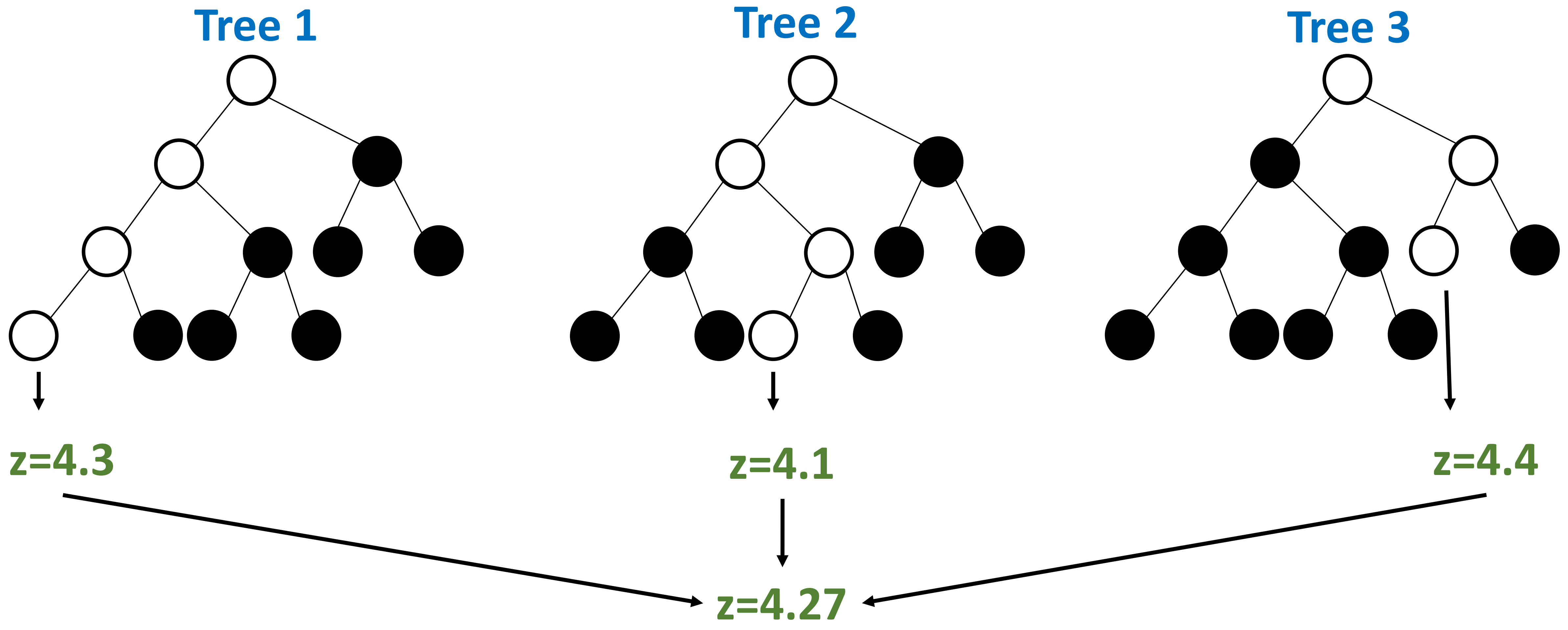


Disadvantages of using only one tree:

- **Non-uniqueness**
- **Over-fitting**

Method: Random Forests for Inverse Problems

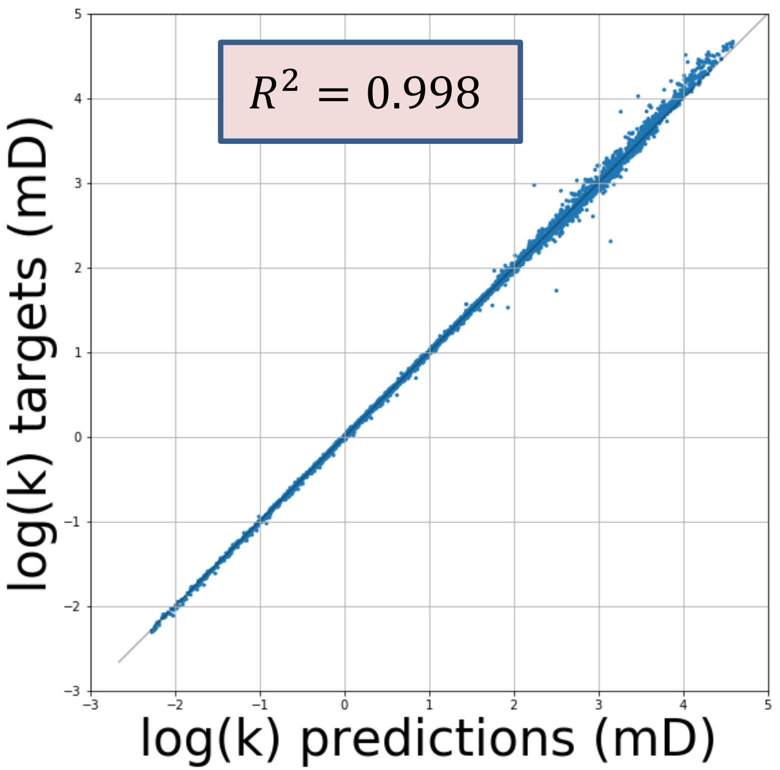
Random Forests



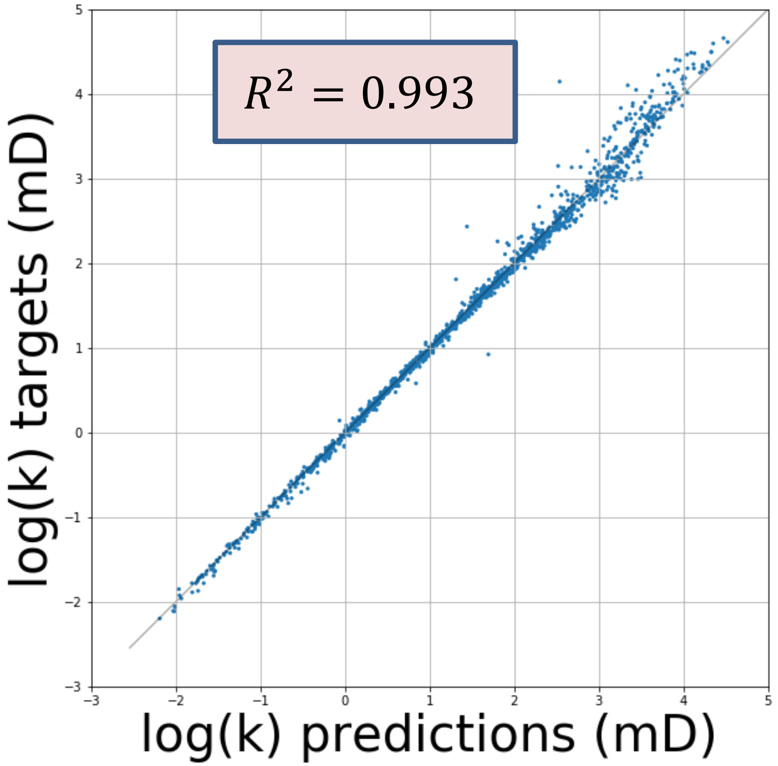
Synthetic Case No. 1: Permeability of a Water-Saturated Formation

Build a machine learning model to estimate permeability.

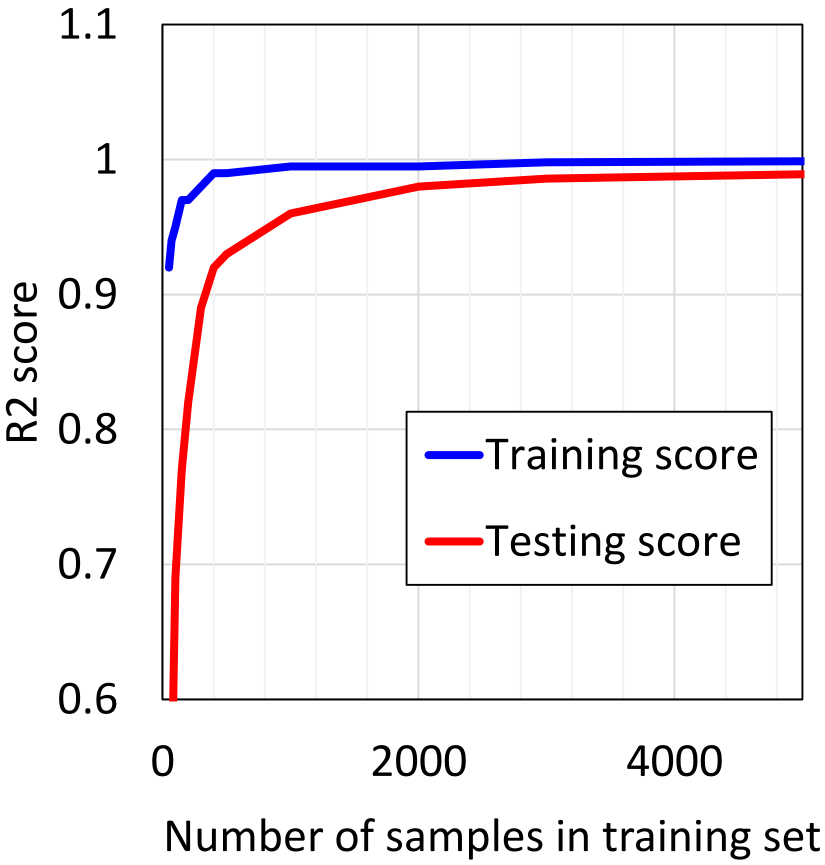
Training



Testing

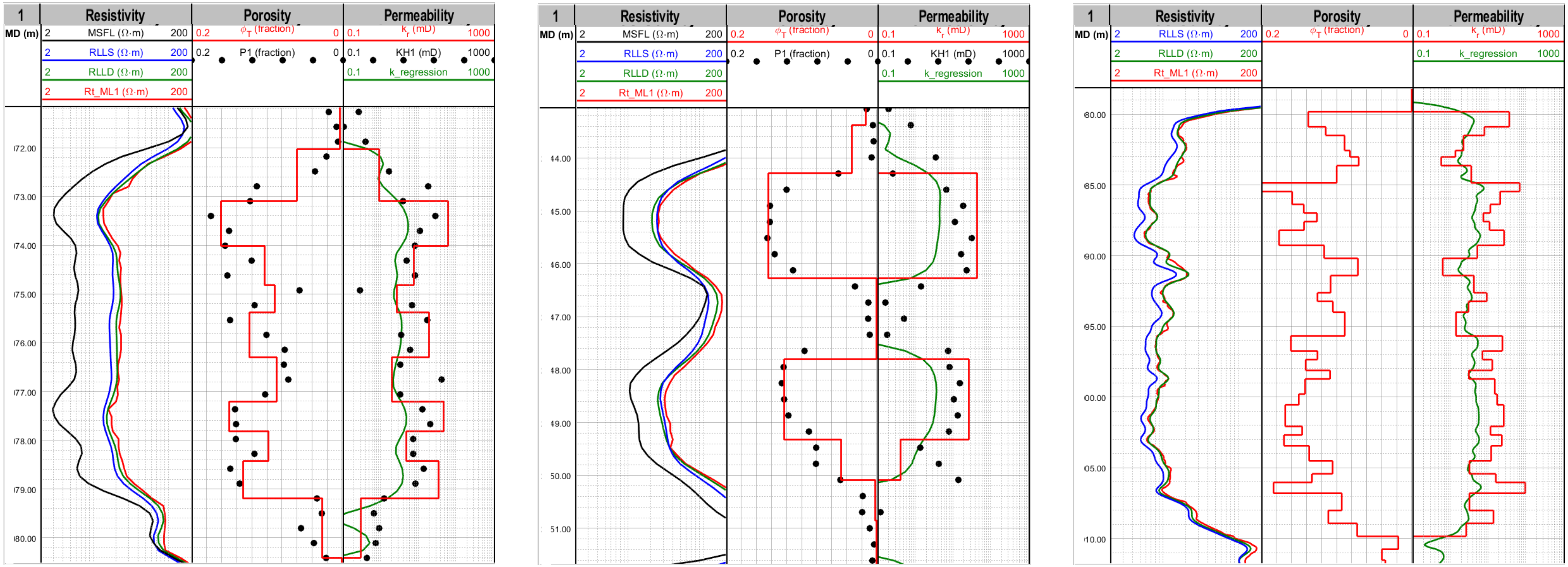


Learning Curve



Field Case: Multi-Well Interpretation in a Carbonate Reservoir

Testing the Machine Learning Model in Nearby Wells



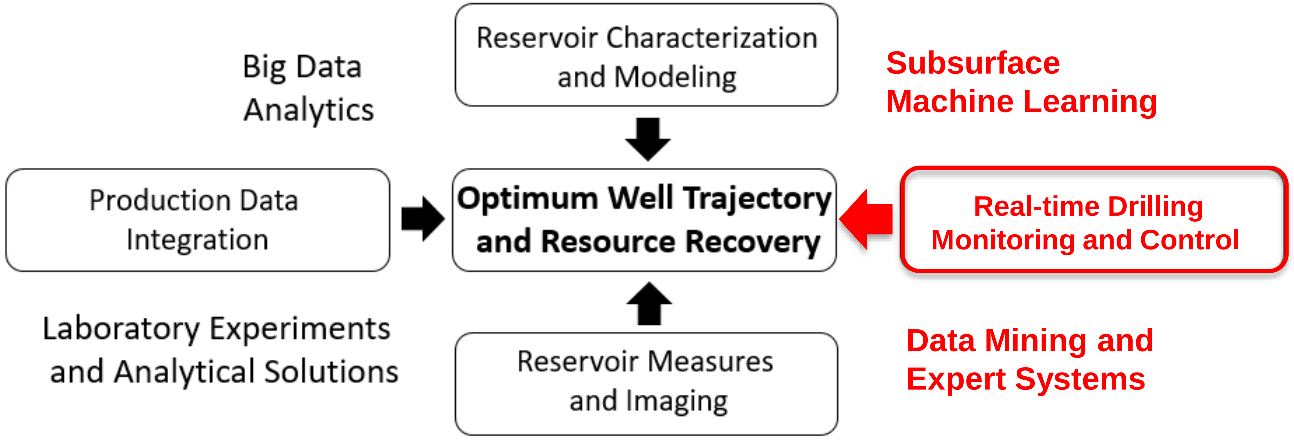
DIRECT: **DI**gital **RE**servoir **C**haracterization **T**echnology

Eric van Oort[1]

Time	Speaker	Topic
9:00	Michael Pyrcz	Welcome, Introduction Geostatistics and Data Analytics
9:30	John Foster	Introduction Numerical Modeling
10:00	Carlos Torres-Verdin	Introduction Geophysical / Petrophysical Data Integration
10:30		Break
10:45	Eric van Oort	Introduction Drilling Automation and Expert Systems
11:15	Michael Pyrcz	Consortium Details
11:45		Additional Discussion and Feedback
12:00		Lunch Provided

1- Hildebrand Department of Petroleum & Geosystems Engineering, the University of Texas at Austin

Drilling & Geomechanics



Overarching Theme:

"*Optimum Drilling & Well Placement for Production (primary, secondary)*"

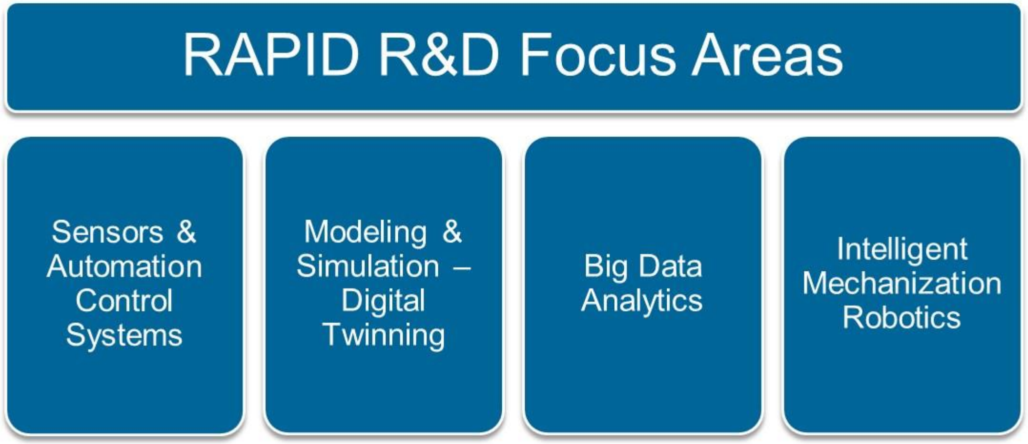
Key Elements:

- Automated Directional Drilling
- Automated Geosteering
- Automated Wellbore Stabilization
- Real-Time Geophysics/ Petrophysics Data Processing
- Real-Time Geomechanics
- Downhole EDGE Computing
- Pre-/RT-/Post-Well Data Analysis

DIRECT: Interface with RAPID - 1

RAPID will continue to focus on “hard-core” drilling optimization and automation subjects & tasks:

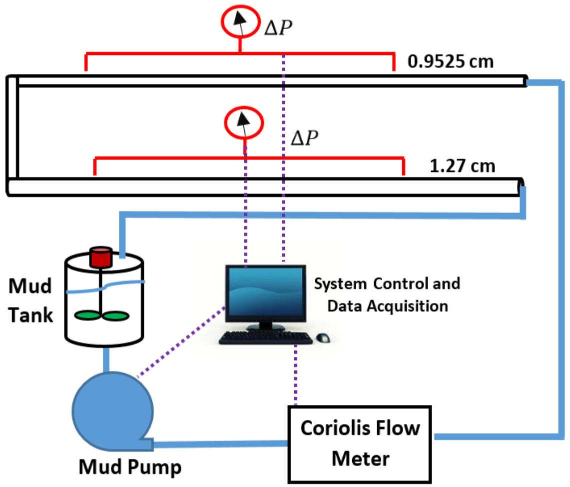
- Wellbore Quality Assessment & Optimization
- Closed-Loop Automated Drilling Routines
- Drilling Mechanics Optimization:
    - Drilling Vibration Optimization
    - Drilling Hydraulics Optimization
    - Drilling NPT / ILT Mitigation
    - Drillstring Fatigue/Wear Mitigation
    - Drilling-Related Condition-Based Monitoring
- In-Depth Drilling Data Analysis
- Drilling Automation, Mechanization & Robotics
- Drilling Control Systems
- Etc.

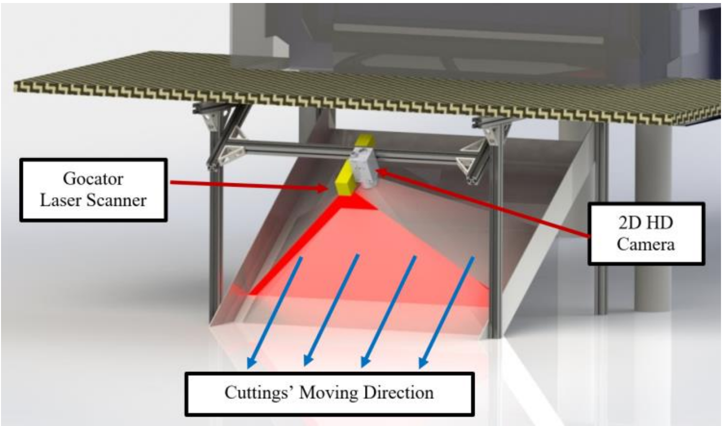


DIRECT: Interface with RAPID - 2

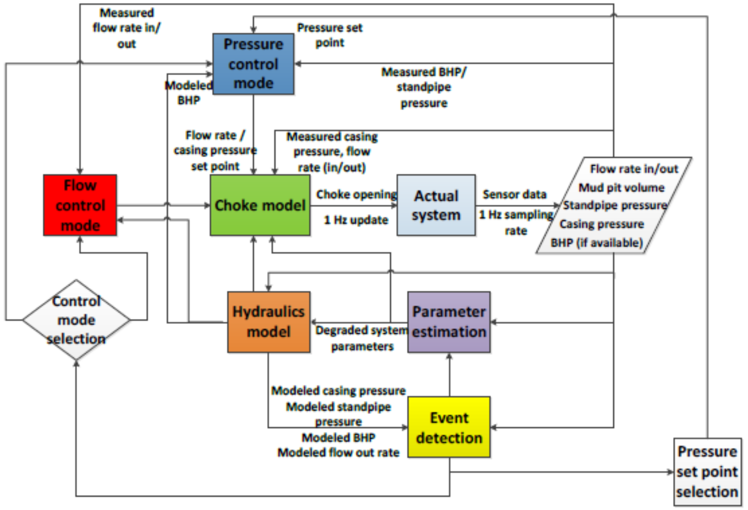
Examples of RAPID Activities & Technologies

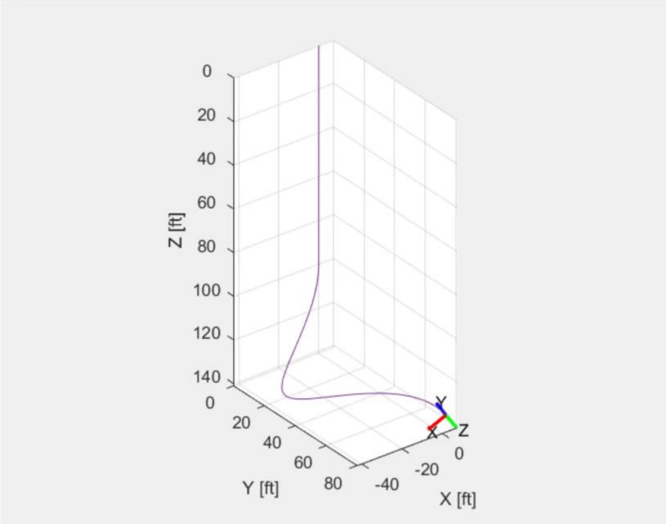
Sensors & Automation

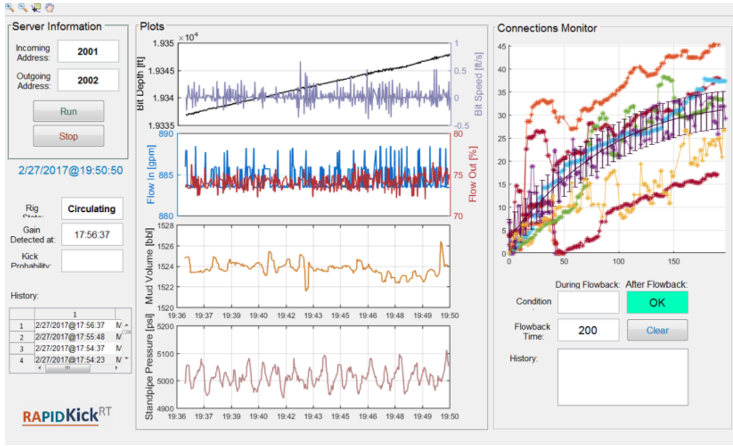


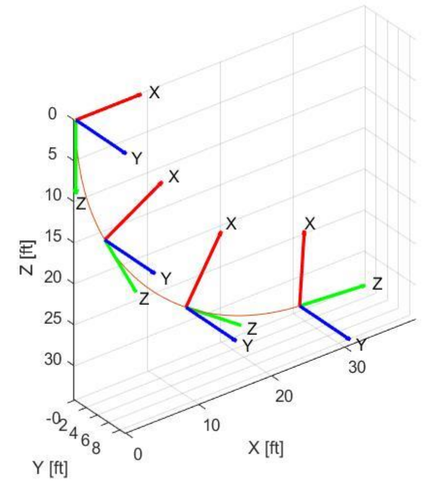


Algorithms & Control Systems







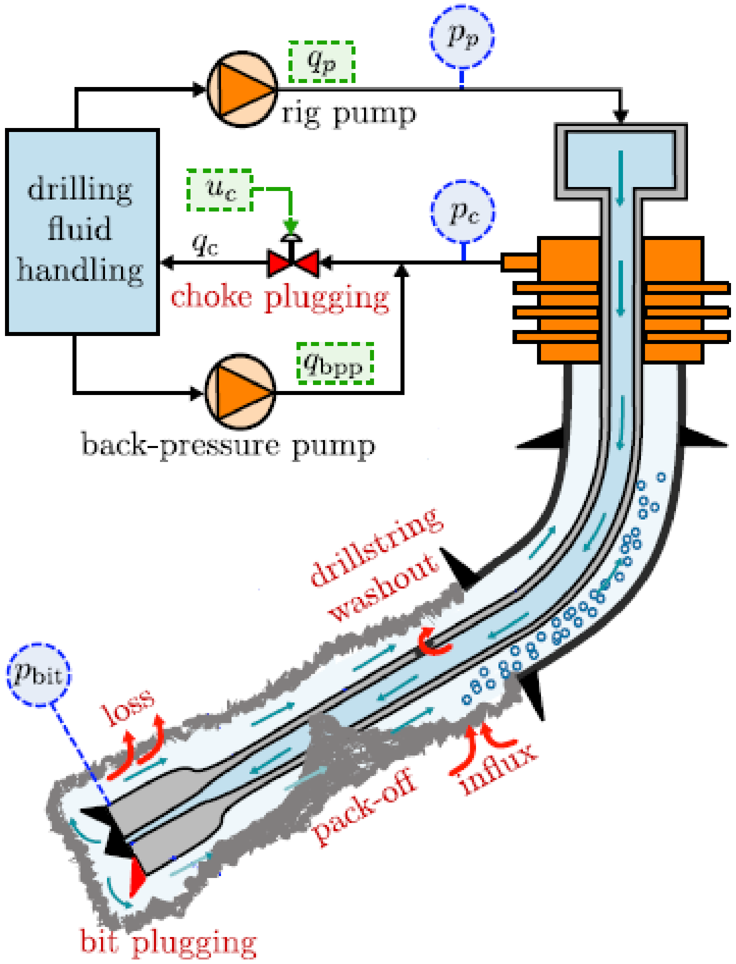


DIRECT: Interface with RAPID - 3

RAPID will not duplicate or "double-dip" with DIRECT (e.g. on well data analytics)

RAPID & DIRECT will have a clear interface where DIRECT can leverage activities / achievements by RAPID, and allows for the integration of DIRECT's sub-surface expertise / data with drilling expertise / data that will enable e.g.:

- Automated Geosteering
- Optimum Well Placement for Production
- Optimum Near-Wellbore Geomechanics Management
    - Avoid Wellbore Instability / Stuck Pipe
    - Avoid Lost Circulation
    - Avoid Well Control Incidents
    - Avoid Geohazard Problems (Salt, Tar, etc.)



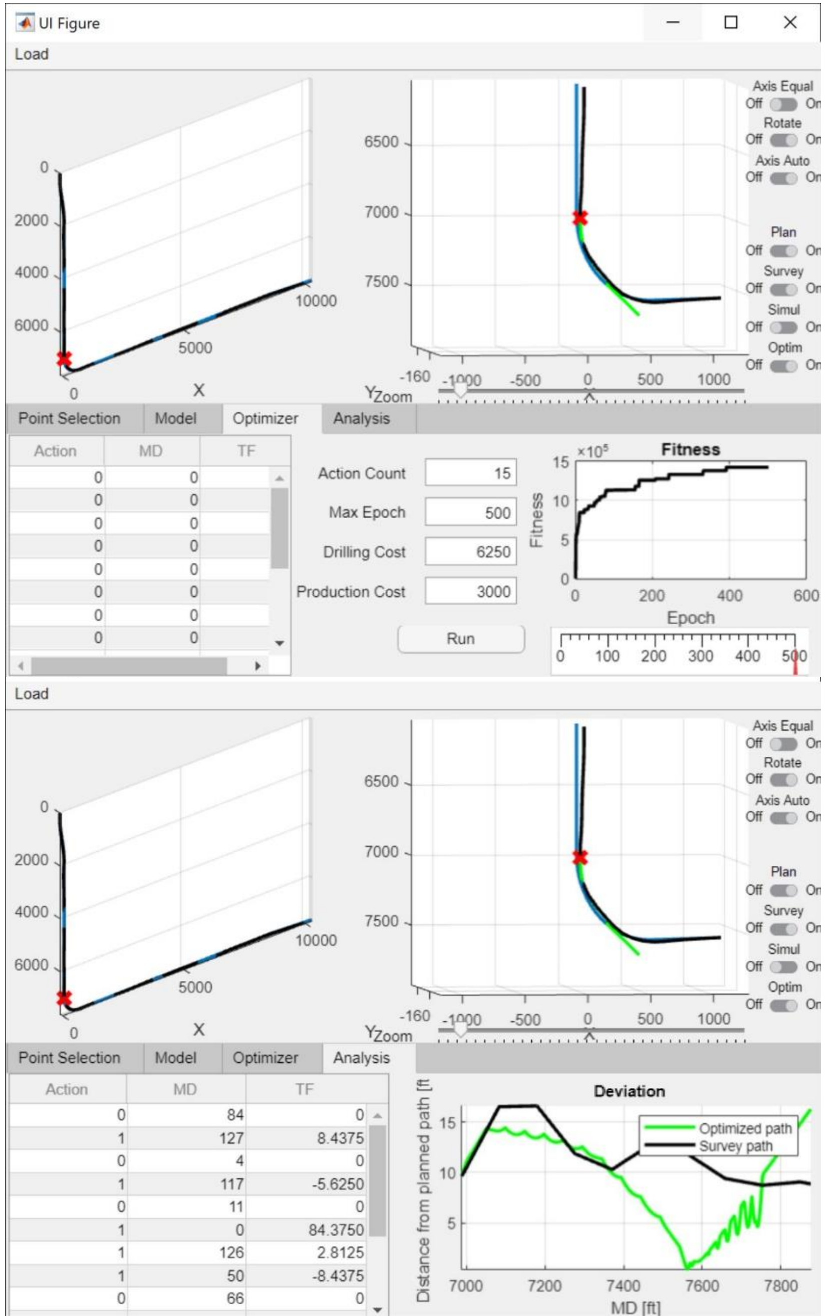
[Willersrud et. al, 2013]

TEXAS
The University of Texas at Austin

WHAT STARTS HERE CHANGES THE WORLD

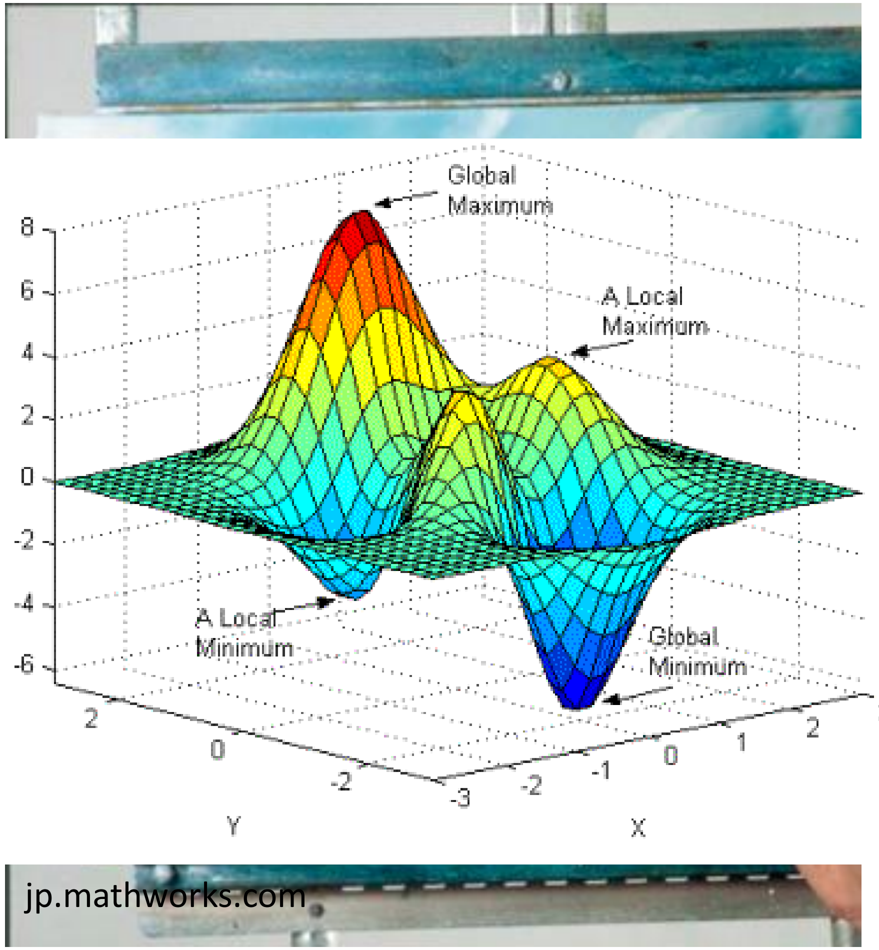
Introducing: John D’Angelo

- Introduction
- Wellbore Tortuosity
- Directional Drilling Guidance
- Geosteering
- Moving Forward
- Questions/Feedback



Introduction

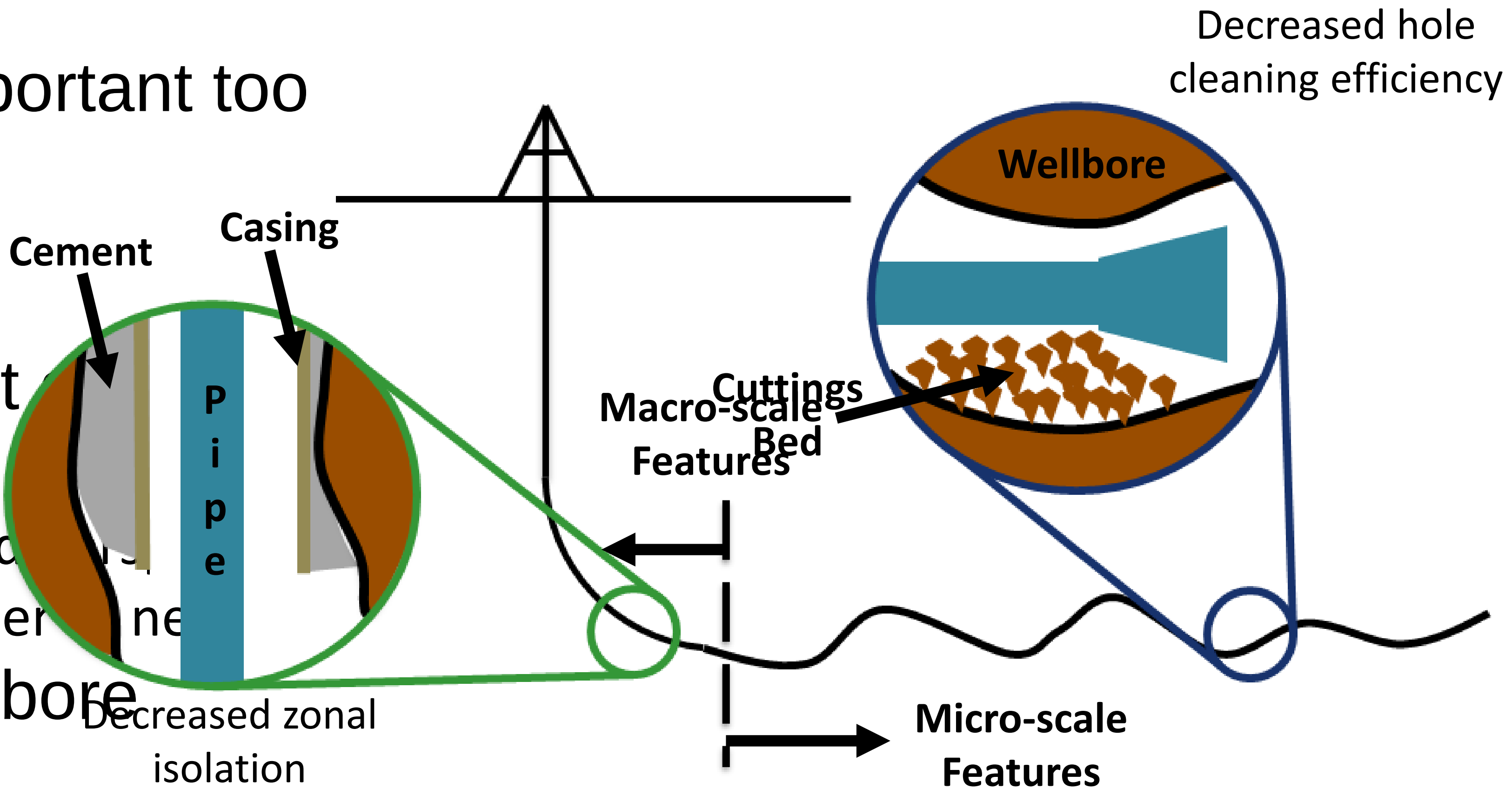
- Directional drilling still widely treated as an art:
  - Quality is rarely quantified
  - Ignores optimality
  - Lacks strict repeatability
  - Leaves drilling decisions to experience instead of calculations
- There is a lot to be gained from a method that:
  - Considers **optimality**
  - Aims at repeatably increasing well **value**
  - Integrates with **Geosteering workflow**



www.bobross.com

Wellbore Tortuosity

- Drilling to targets quickly is a cost-reduction priority
- Wellbore quality is important too
  - Hole-cleaning capability
  - Casing and cementation
  - Etc…
- Wellbore geometry not easy to interpret in 3D
  - Warping due to scale and
  - Subjective from one driller ne
- Need quantitative wellbore quality metrics



Wellbore Tortuosity

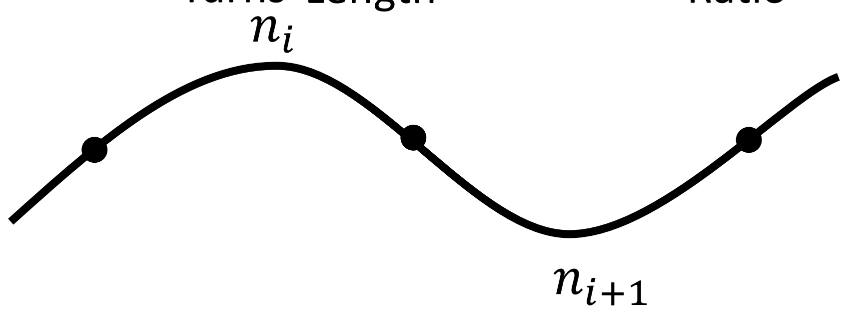
- Wellbore surveys are easily accessible
  - Use a wellbore's geometry to quantify its quality → tortuosity
- Tortuosity is deviation from a planned or straight path
- Numerous wellbore quality metrics

Macro-scale (90+ ft via MWD survey)

$$TI = \boxed{\frac{n}{n+1}}\boxed{\frac{1}{L_c}}\sum_{i=1}^{n}\boxed{\left(\frac{L_{csi}}{L_{xsi}} - 1\right)}$$

Curve Turns | Path Length | Arc to Chord Ratio

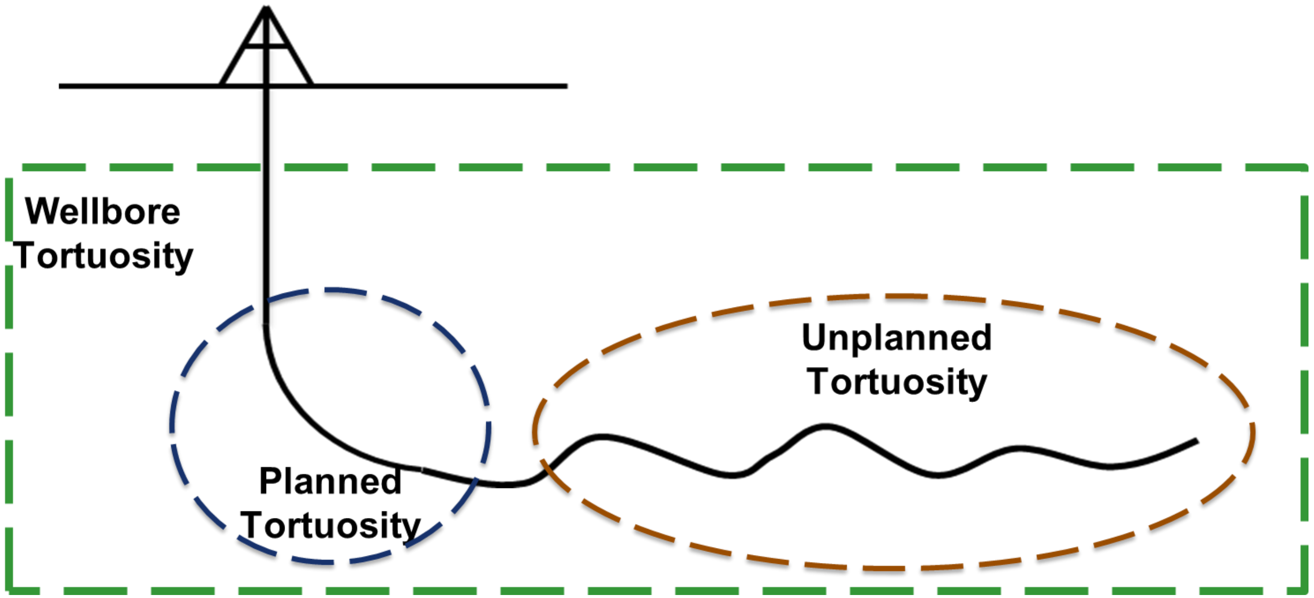
ous or



Wellbore Tortuosity Index (TI)
Zhou, Yang, et al. 2016

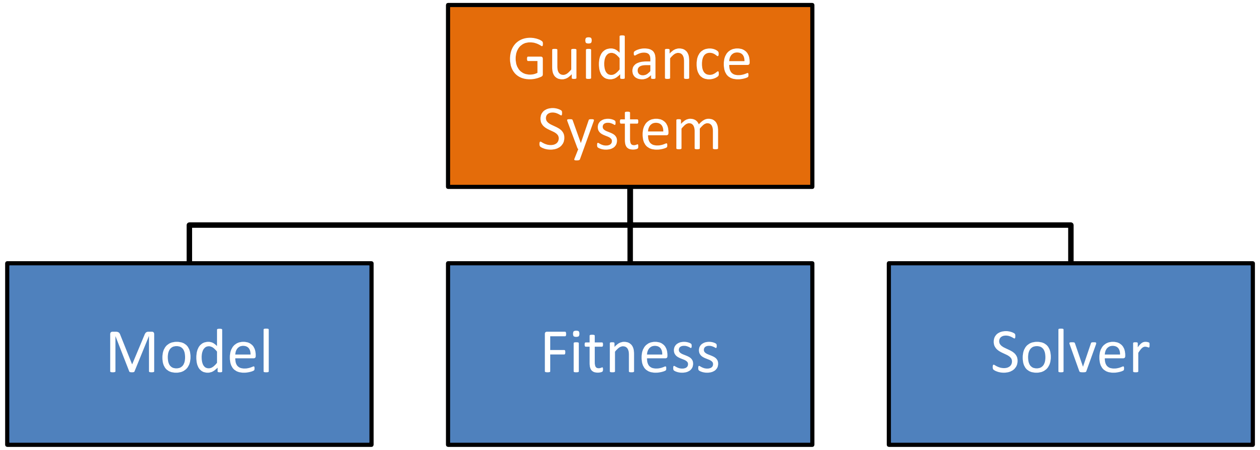
Wellbore Tortuosity

- Tortuosity can fall into different bins
- Differentiating planned from unplanned tortuosity impacts definition of wellbore “quality”
  - May need curved features to reach certain targets



Directional Drilling Guidance

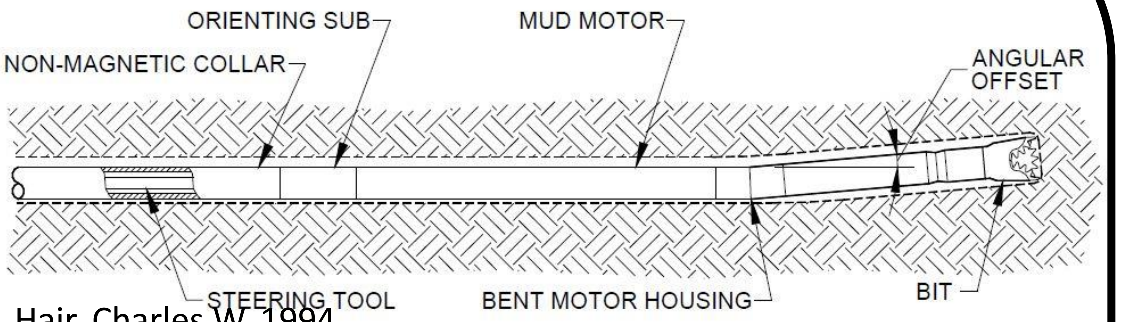
- **Directional drilling guidance system** targeted at downhole motors and slide drilling
- Generate optimal well path as **slide drilling instructions**



Typical Slide Sheet Format

Action	*MD(ft)*	*TF*
Slide	*131*	*10R*
Slide	*89*	*20R*
Rotate	*25*	*0*
Slide	*65*	*30R*
Rotate	*40*	*0*
…	…	…
Rotate	*60*	*0*

Model: Directional Drilling Approaches



Hair, Charles W. 1994

Bent-Sub Downhole Motor

- Slide and Rotate
- Fixed build rate

halliburton.com

Rotary Steerable System

- Rotate
  - Continuous input possible
- Build rate has an upper bound

Fitness

- Main objectives of method is to increase **value** of the well and satisfy **constraints**
- Modular costs are considered instead of shortest path:

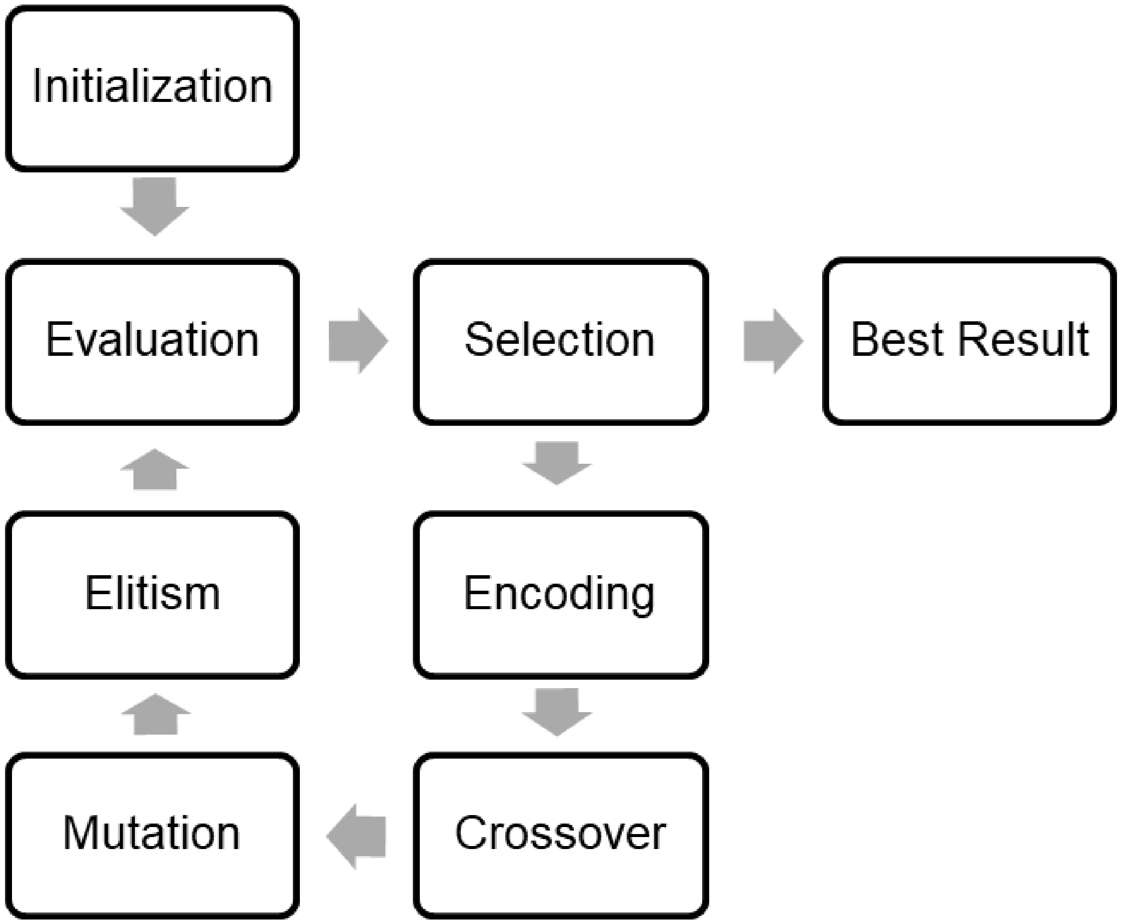
$$J(x) = J_1(x) + J_2(x) + J_3(x) + \cdots$$

Cost	Representation	Weight
Proximity cost	$J_1(r) = c_1 * P(r) * MD$	$c_1, predicted\ revenue\ per\ foot$
Drilling time cost	$J_2(t) = c_2 * \left(\frac{\sum MD_s}{ROP_s} + \frac{\sum MD_R}{ROP_R}\right)$	$c_2, drilling\ cost\ per\ hour$
Tortuosity and control authority cost	$J_3(r) = c_3 * \left(TI(r_i) - TI(r_f)\right)$	$c_3, tortuosity\ constant$
Insert New Cost Here	…	…

Solver

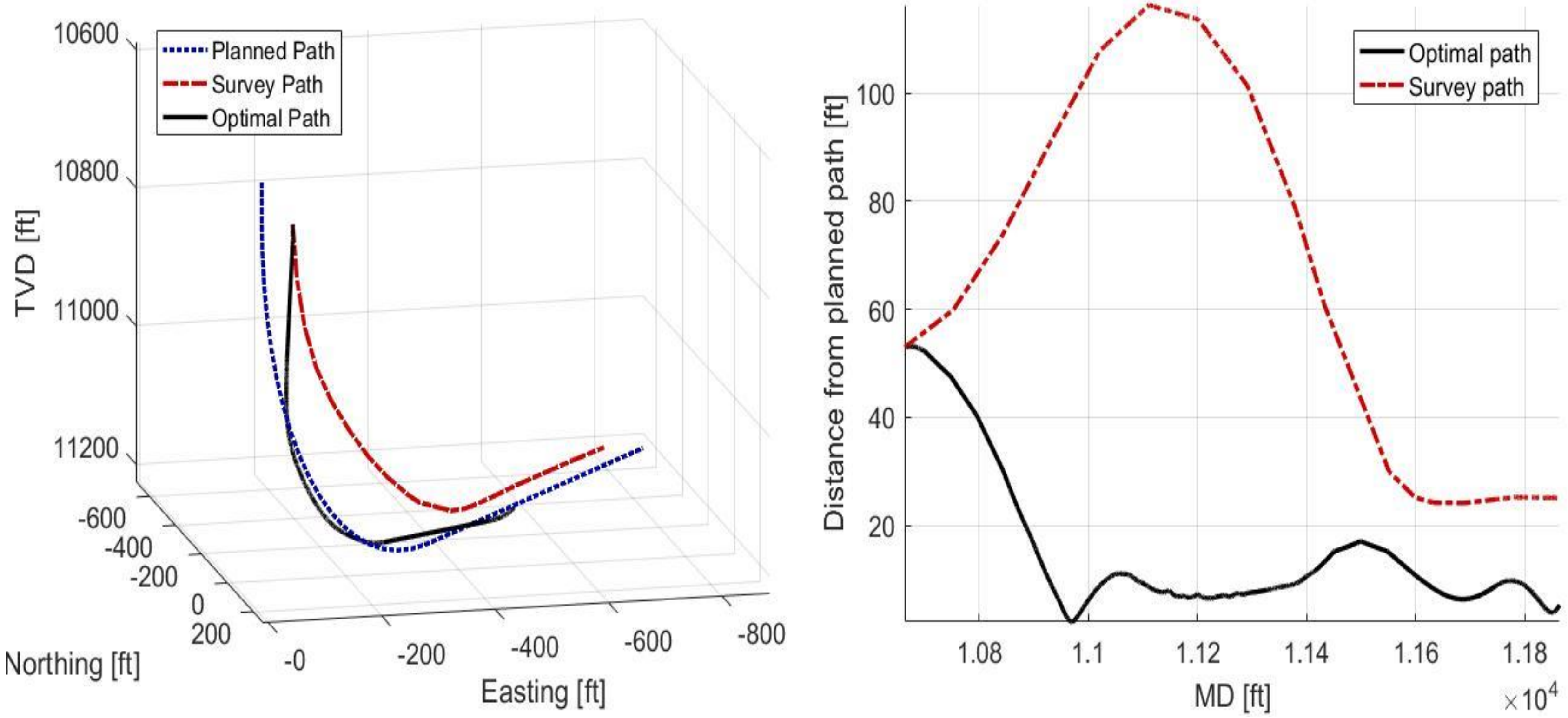
- High-dimensional problem
- Objective and constraint functions potentially nonconvex and nondifferentiable
- Ideal use case for Genetic Algorithm
  - Robust to problem properties
  - Anytime algorithm

Genetic Algorithm Workflow



Tracking a Path

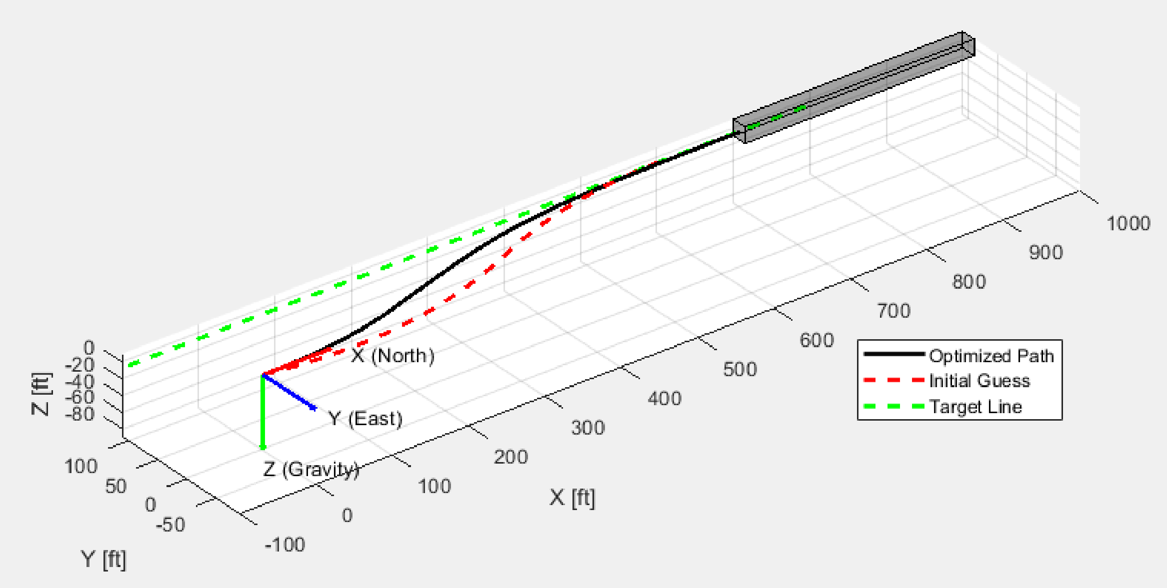
- Given a planned path, follow it as closely as possible



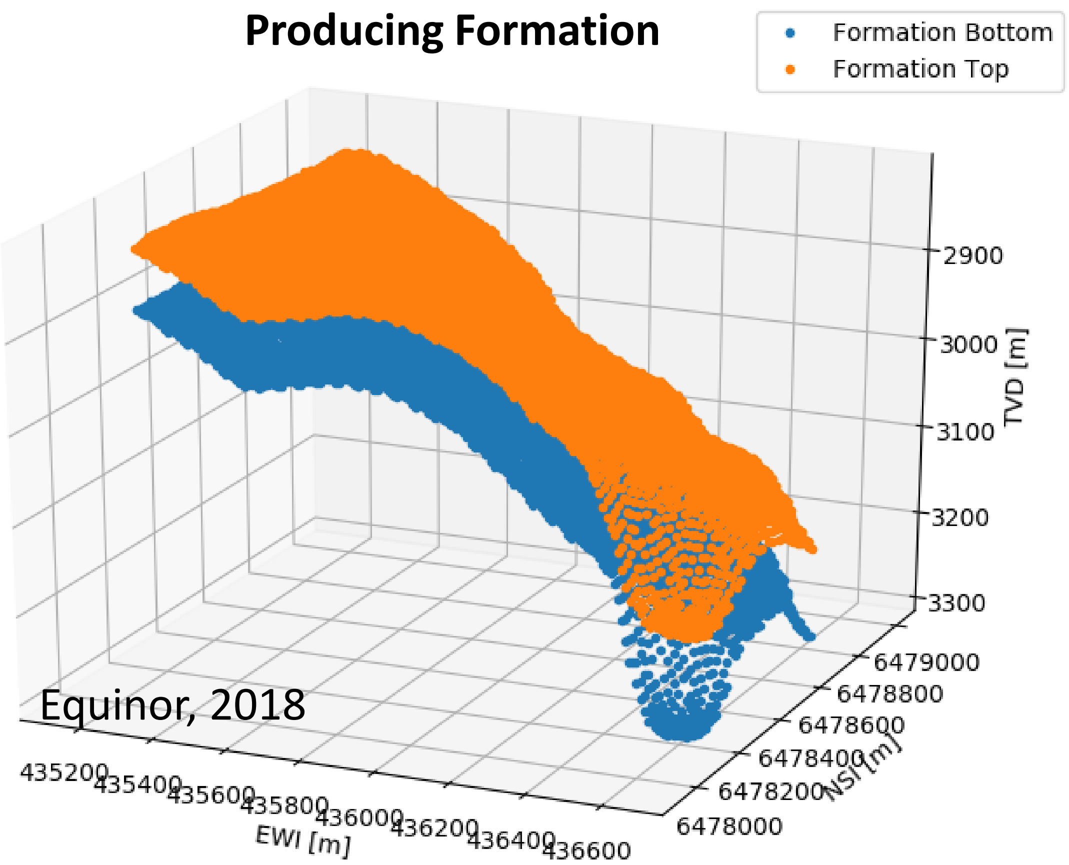
Source: Can Pehlivantürk

Maintaining Pay-Zone Contact

- Given a pay-zone, land inside while minimizing path constraints
  - Volume or point cloud (right)
  - Target line and tolerance (left)



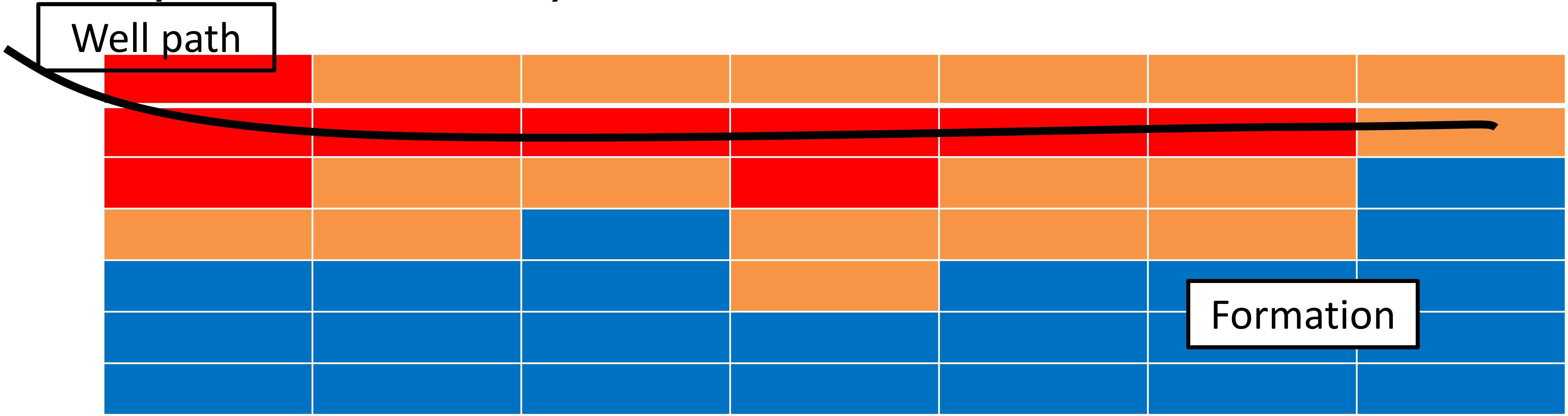
Source: Can Pehlivantürk



Equinor, 2018

Productive Regions of Reservoir Formation

- Given a region of interest, search for path that maximizes sum of desirable property values (under path constraints)



Moving Forward

- Working on validation of the wellbore propagation model and guidance system against field data
- Testing constraint handling framework on more complex constraints
    - Formation boundaries, point clouds, etc…
- Looking into more realistic objectives
    - Production over well life
    - Pay-zone contact
    - Other geophysical criteria
- Exploring most efficient ways to compute objectives and check constraints to maintain real-time applicability

DIRECT: **DI**gital **RE**servoir **C**haracterization **T**echnology

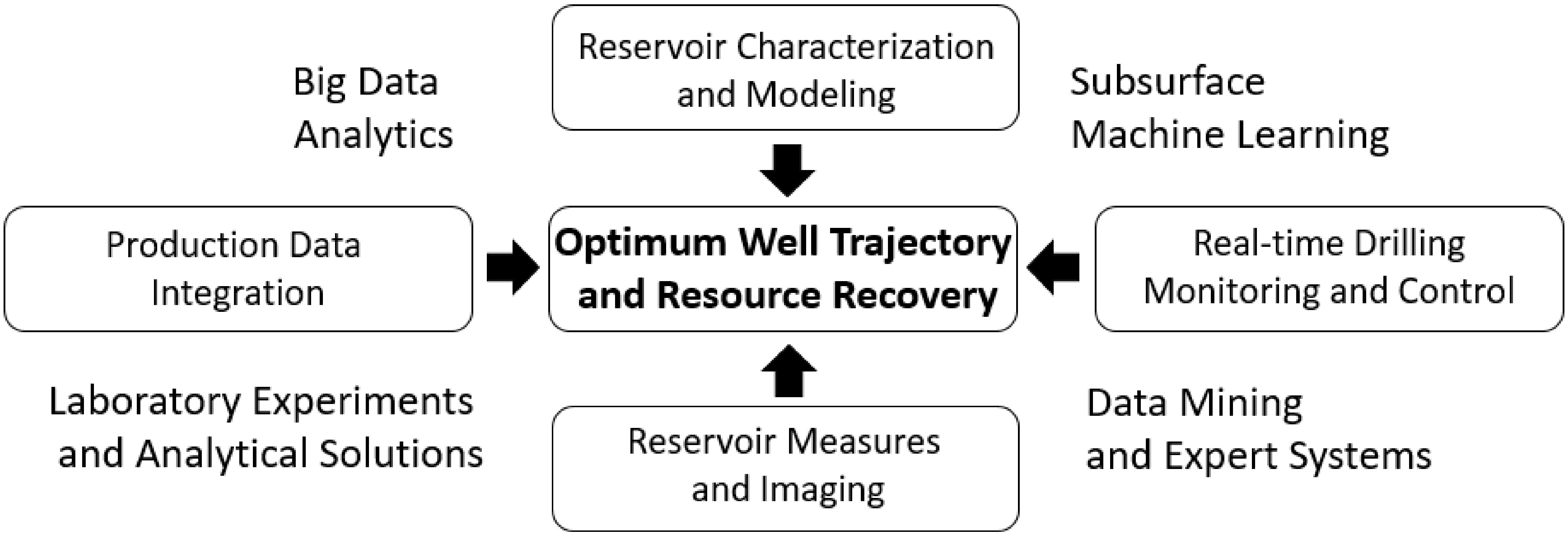
Consortium Details

Michael J. Pyrcz[1], John Foster[1,2], Carlos Torres-Verdín[1], and Eric van Oort[1]

Time	Speaker	Topic
9:00	Michael Pyrcz	Welcome, Introduction Geostatistics and Data Analytics
9:30	John Foster	Introduction Numerical Modeling
10:00	Carlos Torres-Verdin	Introduction Geophysical Data Integration
10:30		Break
10:45	Eric van Oort	Introduction Geomechanical Data Integration
11:15	Michael Pyrcz	Consortium Details
11:45		Additional Discussion and Feedback
12:00		Lunch Provided

1- Hildebrand Department of Petroleum & Geosystems Engineering, the University of Texas at Austin, 2 – Oden Institute for Computational Engineering and Science, the University of Texas at Austin

DIRECT Consortium



Integration across geoscience and engineering disciplines with

data analytics and machine learning

to support optimum field development decision making

Direct Consortium

- Consortium Details

Good News – DIRECT is Happening

- The following companies have already joined the consortium:

Anadarko BAZEAN aramco

- There are two other E&P companies that have indicated they will join:

to be announced shortly

What Specifically Do Members Get by Joining?

- Early access to DIRECT **research results, technology prototypes, workflows, and manuscripts**.
- Emphasis on **transfer of developed technologies** and efficient commercialization.
- Spectrum of short-term, mid-term and long-term **goals for adding value**.
- Steerable consortium with **embedded approach** for collaboration.
- Early priority **access to the geoscience and engineering researchers** with exceptional data analytics and machine learning skills.
- Early **access to training materials** to support with demonstration workflows to support development of operational capability in your organization.

How Specifically Do Members Get This?

- Will develop a private website to share consortium results
- Quarterly newsletters to all members
- Comprehensive annual research report and research presentations
- Annual DIRECT Review Meeting and additional informal meeting for the end of each term
- Host periodic onsite engagements and webinars with member companies

Who Owns the Intellectual Property

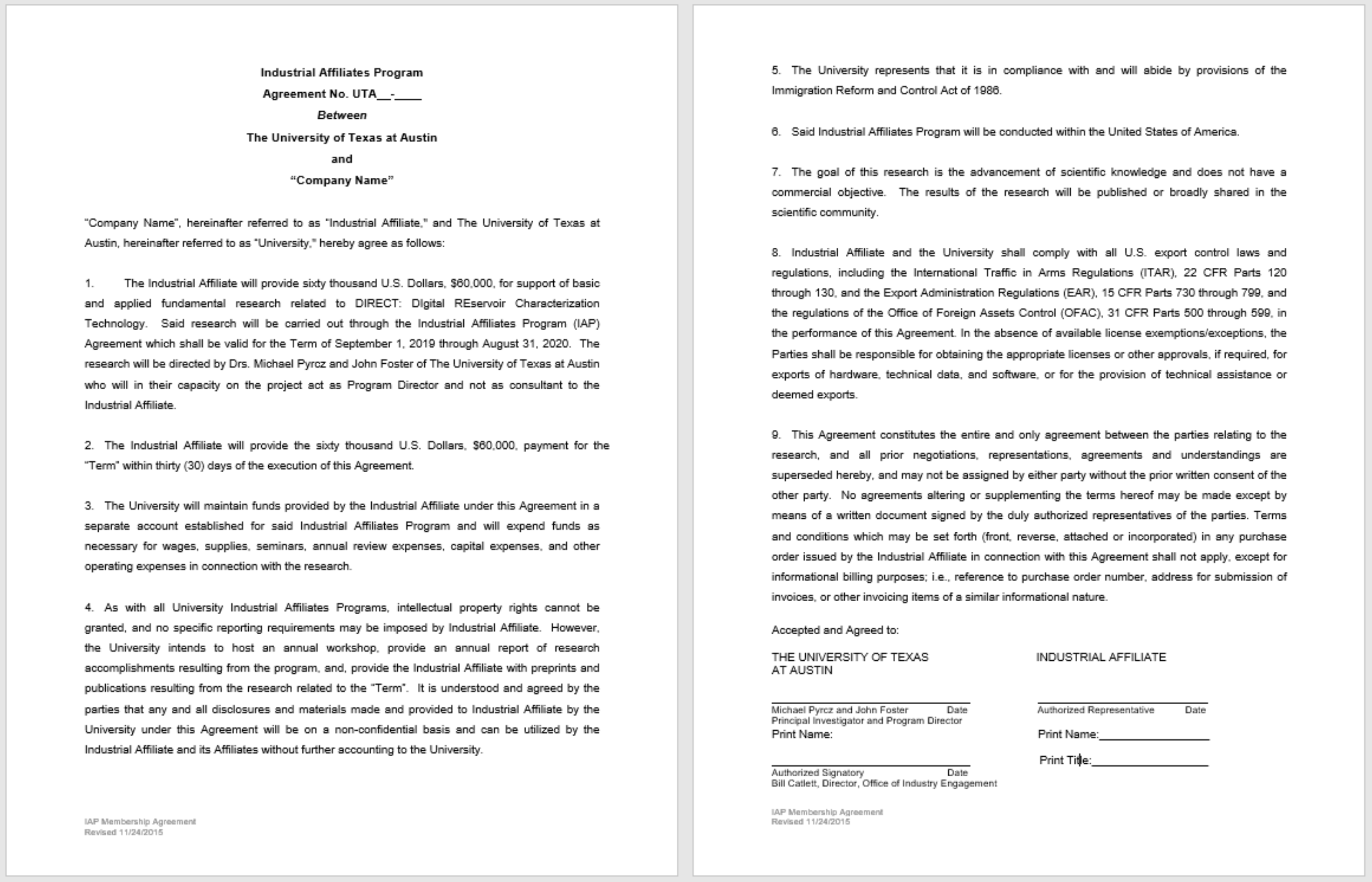
- We support the adoption of the consortium products within our member companies.

4. As with all University Industrial Affiliates Programs, intellectual property rights cannot be granted, and no specific reporting requirements may be imposed by Industrial Affiliate. However, the University intends to host an annual workshop, provide an annual report of research accomplishments resulting from the program, and, provide the Industrial Affiliate with preprints and publications resulting from the research related to the "Term".

From the IAP Agreement

How to Join DIRECT?

- Sign the Industrial Affiliate Program Agreement
- Provide payment for the “Term” within 30 days.
- Leilani Swafford can walk you through the process.
- Renew annually.



Industrial Affiliates Program
Agreement No. UTA__-____
Between
The University of Texas at Austin
and
“Company Name”

"Company Name", hereinafter referred to as "Industrial Affiliate," and The University of Texas at Austin, hereinafter referred to as "University," hereby agree as follows:

1. The Industrial Affiliate will provide sixty thousand U.S. Dollars, $60,000, for support of basic and applied fundamental research related to DIRECT: DIgital REservoir Characterization Technology. Said research will be carried out through the Industrial Affiliates Program (IAP) Agreement which shall be valid for the Term of September 1, 2019 through August 31, 2020. The research will be directed by Drs. Michael Pyrcz and John Foster of The University of Texas at Austin who will in their capacity on the project act as Program Director and not as consultant to the Industrial Affiliate.

2. The Industrial Affiliate will provide the sixty thousand U.S. Dollars, $60,000, payment for the "Term" within thirty (30) days of the execution of this Agreement.

3. The University will maintain funds provided by the Industrial Affiliate under this Agreement in a separate account established for said Industrial Affiliates Program and will expend funds as necessary for wages, supplies, seminars, annual review expenses, capital expenses, and other operating expenses in connection with the research.

4. As with all University Industrial Affiliates Programs, intellectual property rights cannot be granted, and no specific reporting requirements may be imposed by Industrial Affiliate. However, the University intends to host an annual workshop, provide an annual report of research accomplishments resulting from the program, and, provide the Industrial Affiliate with preprints and publications resulting from the research related to the "Term". It is understood and agreed by the parties that any and all disclosures and materials made and provided to Industrial Affiliate by the University under this Agreement will be on a non-confidential basis and can be utilized by the Industrial Affiliate and its Affiliates without further accounting to the University.

IAP Membership Agreement
Revised 11/24/2015

5. The University represents that it is in compliance with and will abide by provisions of the Immigration Reform and Control Act of 1986.

6. Said Industrial Affiliates Program will be conducted within the United States of America.

7. The goal of this research is the advancement of scientific knowledge and does not have a commercial objective. The results of the research will be published or broadly shared in the scientific community.

8. Industrial Affiliate and the University shall comply with all U.S. export control laws and regulations, including the International Traffic in Arms Regulations (ITAR), 22 CFR Parts 120 through 130, and the Export Administration Regulations (EAR), 15 CFR Parts 730 through 799, and the regulations of the Office of Foreign Assets Control (OFAC), 31 CFR Parts 500 through 599, in the performance of this Agreement. In the absence of available license exemptions/exceptions, the Parties shall be responsible for obtaining the appropriate licenses or other approvals, if required, for exports of hardware, technical data, and software, or for the provision of technical assistance or deemed exports.

9. This Agreement constitutes the entire and only agreement between the parties relating to the research, and all prior negotiations, representations, agreements and understandings are superseded hereby, and may not be assigned by either party without the prior written consent of the other party. No agreements altering or supplementing the terms hereof may be made except by means of a written document signed by the duly authorized representatives of the parties. Terms and conditions which may be set forth (front, reverse, attached or incorporated) in any purchase order issued by the Industrial Affiliate in connection with this Agreement shall not apply, except for informational billing purposes; i.e., reference to purchase order number, address for submission of invoices, or other invoicing items of a similar informational nature.

Accepted and Agreed to:

THE UNIVERSITY OF TEXAS AT AUSTIN	INDUSTRIAL AFFILIATE
____________________ Michael Pyrcz and John Foster Date Principal Investigator and Program Director Print Name:	____________________ Authorized Representative Date Print Name:____________ Print Title:____________
____________________ Authorized Signatory Date Bill Catlett, Director, Office of Industry Engagement	

IAP Membership Agreement
Revised 11/24/2015

The IAP Agreement

What is an Industrial Affiliate Program?

What you **need** to do:

- Sign the IAP agreement every year and pay the membership fee.

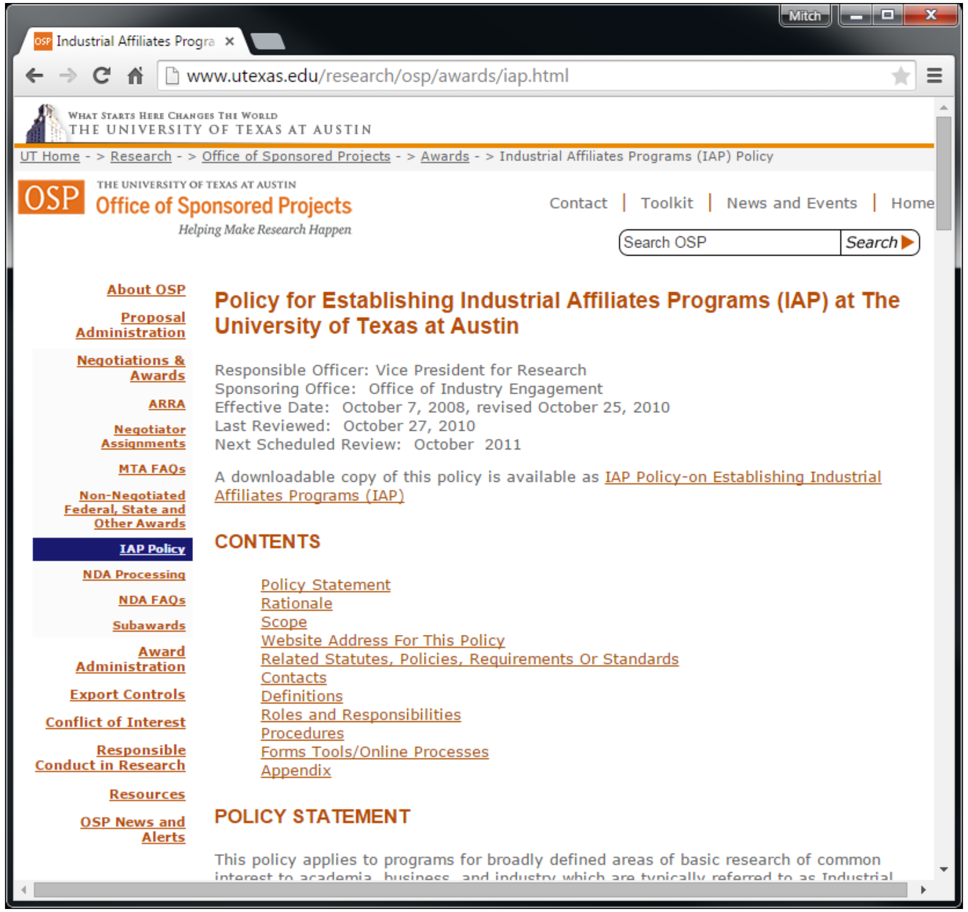
What we **hope** you do:

- **Participate** in the annual meetings, interact with our students, and read our reports.
- **Utilize** our novel methods and workflows to work with your data and add value.
- Identify technologies developed by DIRECT that can be **commercialized** and work with us to make that a reality.
- Provide valuable experience and **employment opportunities** for DIRECT students which enable data analytics and machine learning in the industry.
- Provide candid and constructive **feedback** on our research and steering focus areas.

What is an Industrial Affiliate Program?

DIRECT is an IAP

- UT programs for basic [and applied] research of common interest to academia, business, and industry.
- Supported by multiple companies through membership fees
- Facilitate the transfer of knowledge and topical discussion
- For more information, go to:
  www.utexas.edu/research/osp/awards/iap.html
- DIRECT Program Directors:
  Michael Pyrcz and John Foster
- DIRECT coPIs:
  Carlos Torres-Verdin and Eric van Oort
- Program Coordinator(s):
  Leilani Swafford (Leilani.Swafford@austin.utexas.edu)



Office of Sponsored Projects Website

What if Someone Wants to Join in the Future?

- Great news!
- Each year the members only web site will be archived.
- Members have access to the archives for each year they are a member
- Members in good standing for three consecutive years will be given access to the entire archive.

How does DIRECT internally distribute its funding?

Maintain research in focus areas and viable graduate programs to support our member companies.

Focus areas may be updated with feedback from DIRECT members.

Will prioritize efforts to deliver a balance of short-term benefits and longer terms research efforts.

DIRECT Schedule and Events

Year 1

- Jan 1st - DIRECT IAP launches scoping and exploratory prototypes
- June 13th - Kick-off meeting
- Sept. TBD – Informal event to network and present initial results
- December 4th (or 11th or sometime in between) – Informal Review Meeting

Year 2, 3, 4,……

- Mar, June, Sept (quarterly newsletters)
- Jan – Informal Meeting
- September TBD – Informal event to network present research plans
- May TBD – Annual report released
- May TBD – DIRECT annual meeting

Initial Plans

Here is a draft list of initial topics for DIRECT:

Data Preparation: Novel big data analytics methods and workflows for data debiasing, imputation of missing data, feature and anomaly detection. Getting the data model-ready.

Information Integration: Novel reservoir-oriented methods for geophysical data processing and interpretation for high-resolution reservoir description and updating.

Novel Subsurface Data Analytics and Machine Learning: new methods to learn from data (real time feedback), fast forecasting and spatial / physical constraints on data-driven models.

Operational Capability Development: Well-documented examples, best practice workflows and case studies, training and mentoring for development of member company operational capability.

Early Deployment: Provide source code and workflows with training materials to support early partner adoption of new technologies.

DIRECT: **DI**gital **RE**servoir **C**haracterization **T**echnology

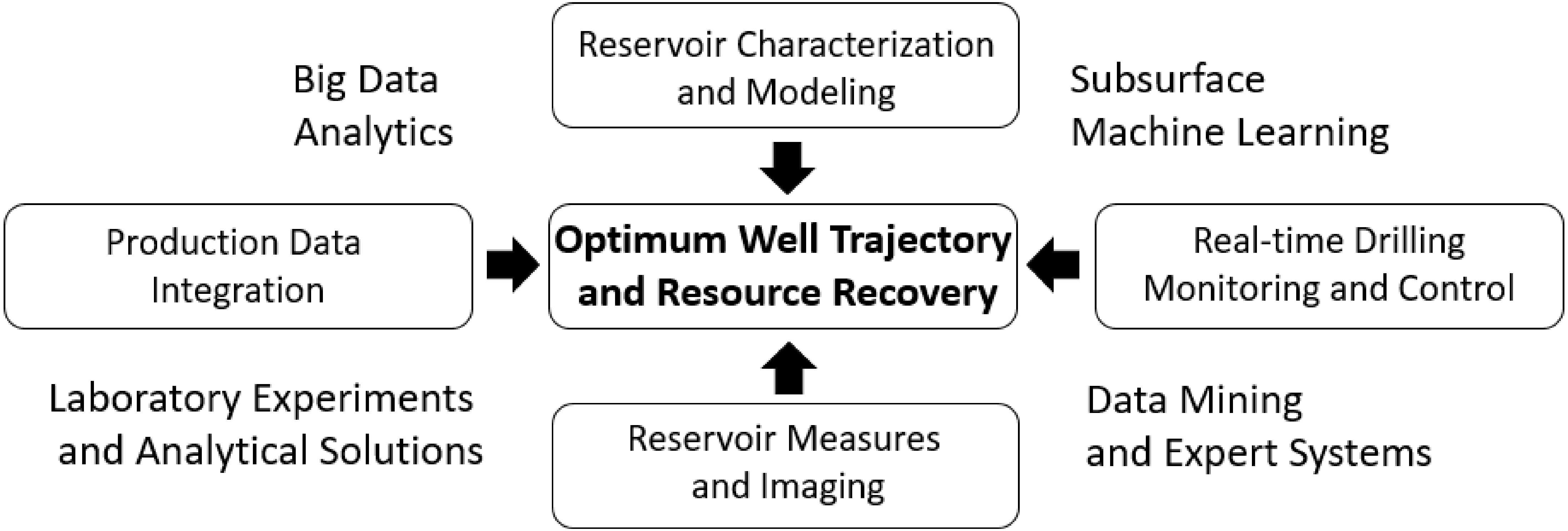
Additional Discussion

Michael J. Pyrcz[1], John Foster[1,2], Carlos Torres-Verdín[1], and Eric van Oort[1]

Time	Speaker	Topic
9:00	Michael Pyrcz	Welcome, Introduction Geostatistics and Data Analytics
9:30	John Foster	Introduction Numerical Modeling
10:00	Carlos Torres-Verdin	Introduction Geophysical Data Integration
10:30		Break
10:45	Eric van Oort	Introduction Geomechanical Data Integration
11:15	Michael Pyrcz	Consortium Details
11:45		Additional Discussion and Feedback
12:00		Lunch Provided

1- Hildebrand Department of Petroleum & Geosystems Engineering, the University of Texas at Austin, 2 – Oden Institute for Computational Engineering and Science, the University of Texas at Austin

DIRECT Consortium



Consortium Goals, Plans and Timeline

Initial Plans

Here is a draft list of initial topics for DIRECT:

Data Preparation: Novel big data analytics methods and workflows for data debiasing, imputation of missing data, feature and anomaly detection. Getting the data model-ready.

- **Unconventional feature engineering for machine learning applications for production forecasting**
- **Bayesian decline curve analysis for early forecasting**
- **Unconventional anomaly detection**

Information Integration: Novel reservoir-oriented methods for geophysical data processing and interpretation for high-resolution reservoir description and updating.

- **Integrating Physical Constraints into Machine Learning Flow Proxies**

DIRECT Consortium Goals

Combine best-practice and cutting-edge technology in

reservoir spatiotemporal characterization and modeling

real-time drilling control

production data integration

reservoir geophysics

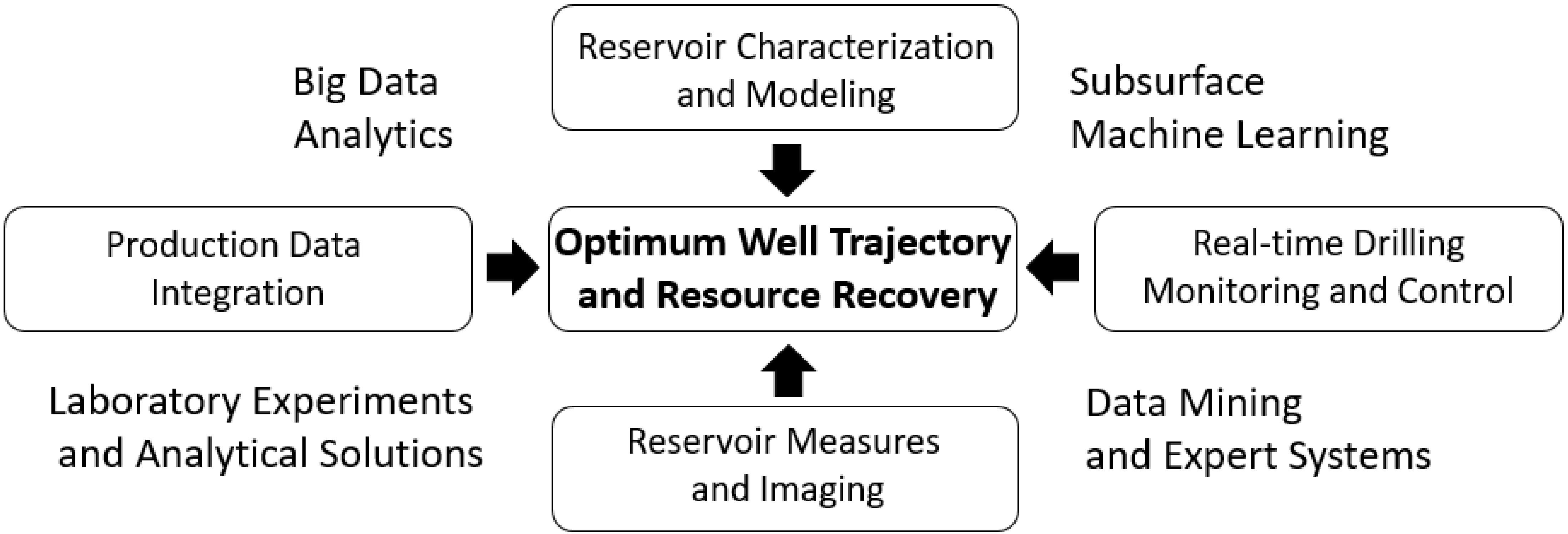
with emerging technology in

big data analytics and machine learning

to optimize well trajectory and resource recovery.

data analytics and machine learning with engineering and geoscience

DIRECT Consortium Goals



Integrated Solutions

Gathered a team of experts in drilling, geophysics, reservoir engineering, geomodeling to support adoption of data-driven methods.

Opportunity

Develop integrated modeling and decision support systems to solve the following outstanding problems:

Integration: Maximizing the integration of deterministic engineering, geological description, target-oriented drilling, geophysical measurements, borehole formation evaluation, production history and core data to construct high-resolution reservoir models for improved production forecast accuracy.

Characterization: Improving the spatial resolution of reservoir description and modeling based on enhanced data integration for improved development decision-making.

Grey Box Modeling: Development of big data analytics and machine learning methods that fully account for geospatial and engineering knowledge.

Opportunity

Develop integrated modeling and decision support systems to solve the following outstanding problems:

Robust Decision Making: Automated, expert systems to support consistent evaluation of subsurface and production data.

System Interpretability: Advanced system summarization and spatial visualization for model interrogation and learning from models for credible decision support.

Optimum Drilling: Development of modern, production-oriented drilling strategies by designing trajectories for optimum well placement to maximize reserves intersection and recovery factors by primary or secondary production means.

Opportunity

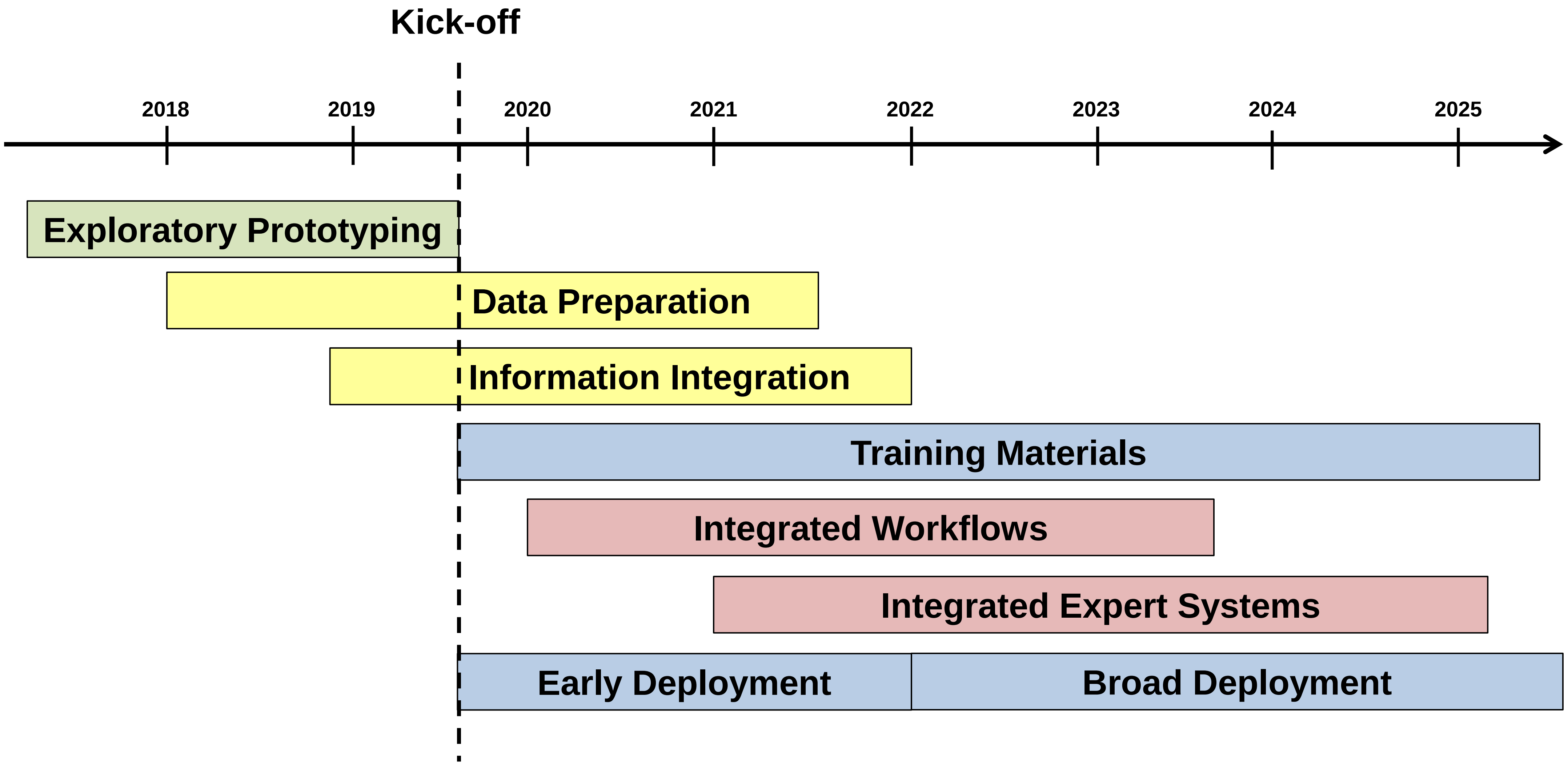
Develop integrated modeling and decision support systems to solve the following outstanding problems:

In-fill Drilling: Development of modern, efficient, and cost-effective strategies to evaluate in-fill drilling, primary or secondary production, and intelligent feedback control systems for reactive production under variable geological, fluid and financial constraints.

Uncertainty Quantification: Development of modern methods to ascertain the value of measurements and the uncertainty of descriptions and quantifications.

Modern Software Solutions for Reservoir Characterization: Development of modern computer and software solutions for rapid and efficient 3D collocated multi-physics description, visualization, modeling, well geosteering, and production forecasting.

Our Plan


Kick-off
2018
2019
2020
2021
2022
2023
2024
2025
Exploratory Prototyping
Data Preparation
Information Integration
Training Materials
Integrated Workflows
Integrated Expert Systems
Early Deployment
Broad Deployment

Our Short-term Plan

Q3 2019 – Q3 2021 our consortium will develop new methods and workflows in spatial, big data analytics for petrophysical, geophysical, reservoir engineering and geomechanical integration into subsurface models for optimum well trajectories and reservoir recovery, including:

Data Preparation: Novel big data analytics methods and workflows for data debiasing, imputation of missing data, feature and anomaly detection.

Information Integration: Novel reservoir-oriented methods for geophysical data processing and interpretation for high-resolution reservoir description and updating.

Novel Subsurface Data Analytics and Machine Learning: initial opportunities, steering from member companies to demonstrate value.

Operational Capability Development: Well-documented examples, best practice workflows and case studies, training and mentoring for development of member company operational capability.

Early Deployment: Provide source code and workflows with training materials to support early partner adoption of new technologies.

Our Mid-term Plan

Q3 2021 – Q3 2023 our consortium will develop novel machine learning-based geomodeling and forecasting methods and workflows.

Best Practice Modeling Workflows: Novel machine learning methods and workflows for spatiotemporal, multivariate modeling that account for data bias, spatial correlation and trends, multivariate physics-based constraints that are robust in the presence of sparse data and big data.

Novel Subsurface Data Analytics and Machine Learning: opportunities, steering from member companies to demonstrate value.

Early Deployment: Provide source code and workflows with training materials to support early partner adoption of new technologies.

Operational Capability Development: Well-documented examples, best practice workflows and case studies, training and mentoring for development of member company operational capability.

Our Long-term Plan

Q3 2023 – Q3 2025 our consortium will develop real-time updateable expert systems for optimum field development.

Integrated Expert Systems: Novel integrated systems for optimum production-oriented well geo-steering and completion.

Broad Deployment: Port algorithms and key findings into a modern computer and software architecture and protocols for user-friendly interactions, diagnostics, learning and decision support.

Delivering Value to Consortium Members

These are the follow results from this consortium that will add value to consortium members.

- **Novel Methods and Workflows:** tailored to subsurface datasets and development decisions as well-documented prototypes in Python.
- **Training Materials:** documentation of research, new methods and workflows, best practice and pitfalls.
- **Steering of Leveraged Research and Development:** agile consortium, responsive to members' technical needs.

Communication and Steering

We will work closely with consortium members on projects of interest:

- Steering is available through regular consortium updates and meetings.
- We welcome close interaction and partnership.
- We welcome the opportunity to test consortium member datasets and to report results.
- We are in Houston at least once every couple of weeks.

Strategy and Steering

- Consortium Leadership, Opportunity and Goals
- Consortium Plans
- Consortium Strategy

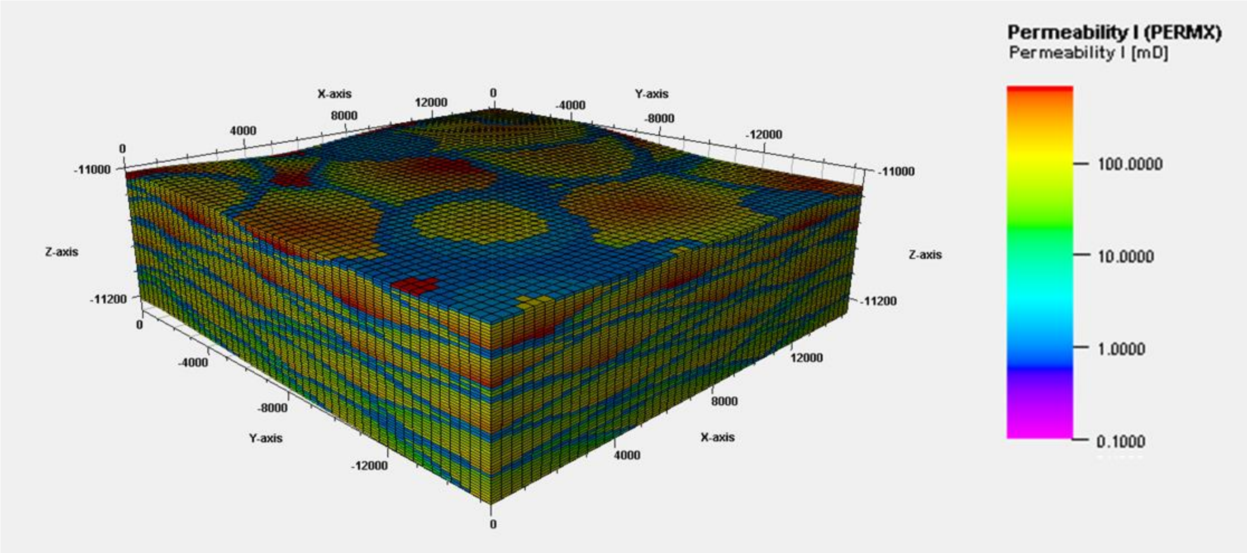
Initial Exploratory Prototypes

- Reservoir Modeling / Numerical Testing Laboratory
- Impact of Spatial Bias
- Data-driven, Multiscale Forecasting
- Unconventional Data Analytics

Initial Exploratory Prototypes

Q3 2018 – Q3 2019 our teams have conducted initial exploratory prototyping to assist with scoping the opportunity to develop student capabilities.

Reservoir Modeling: Methods for advanced, grid-free heterogeneity modeling for a *numerical testing laboratory* by Honggeun Jo (2nd Year PhD student)

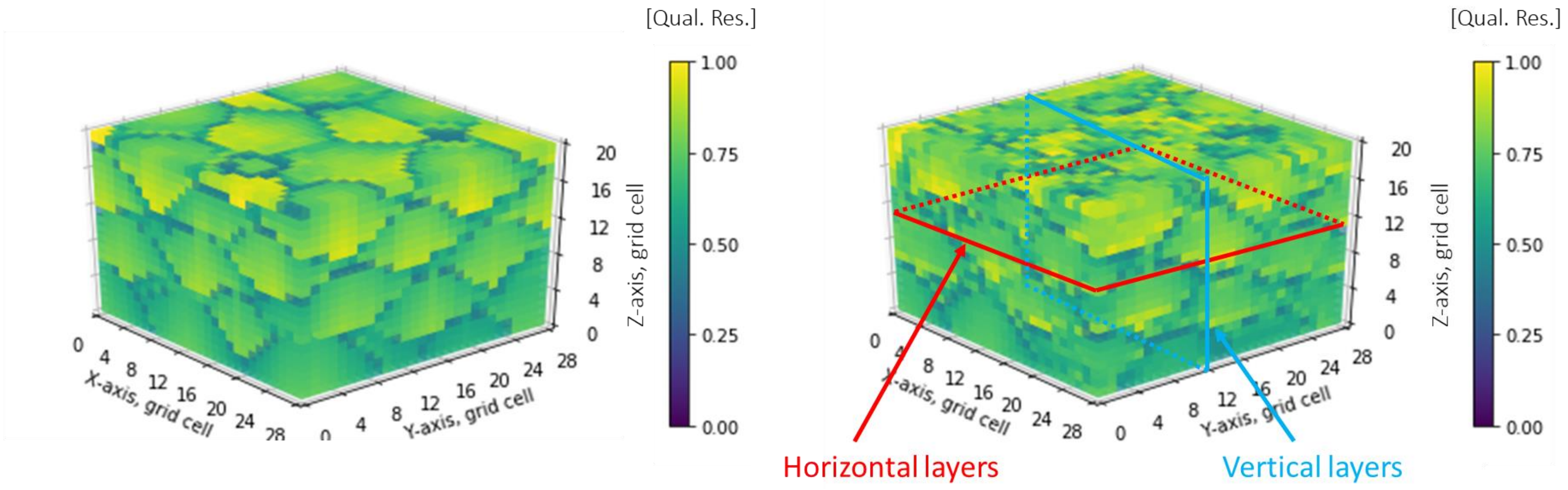


Process-mimicking model for deep-water lobe depositional system: dimension of 5 km x 5 km x 60 m, perfect compensational stacking pattern.

Initial Exploratory Prototypes

Q3 2018 – Q3 2019 our teams have conducted initial exploratory prototyping to assist with scoping the opportunity to develop student capabilities.

Reservoir Modeling: Machine learning based *subsurface heterogeneity models* by Honggeun Jo (2nd Year PhD student).

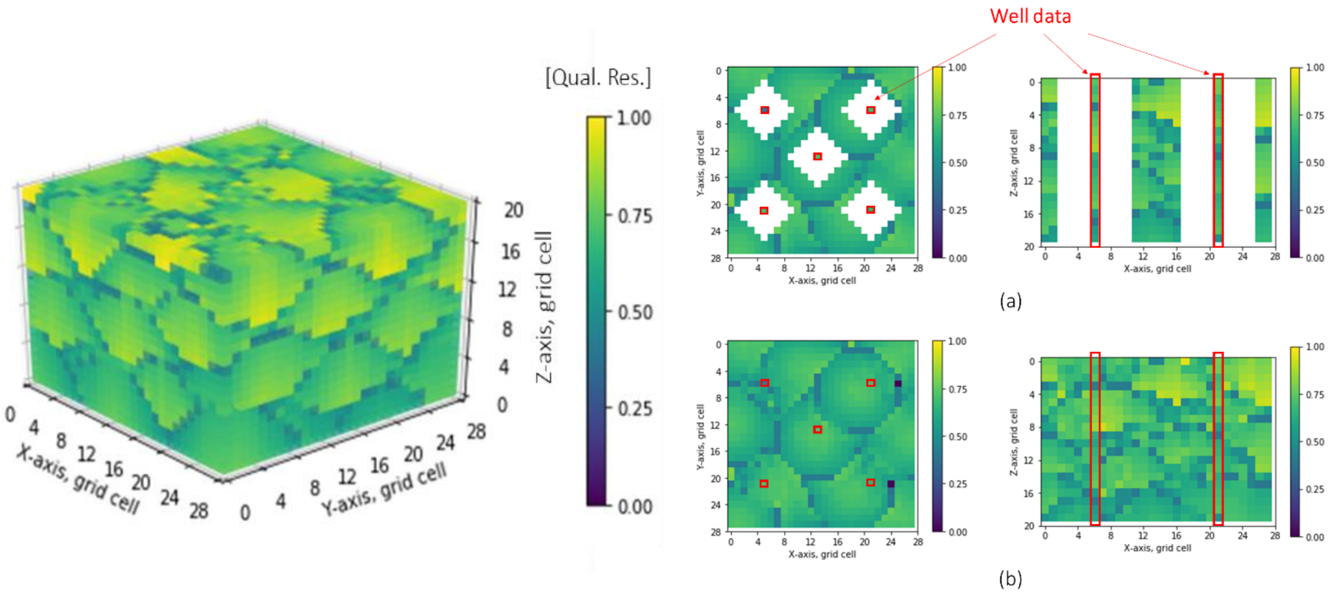


Left - process-mimicking model, Right - result from deep convolutional generative adversarial networks (DC-GANS).

Initial Exploratory Prototypes

Q3 2018 – Q3 2019 our teams have conducted initial exploratory prototyping to assist with scoping the opportunity to develop student capabilities.

Reservoir Modeling: Subsurface *model conditioning* by semantic image inpainting by Honggeun Jo (2nd Year PhD student).



Left - process-mimicking model, Right – well conditioning with semantic image inpainting.

Initial Exploratory Prototypes

Q3 2018 – Q3 2019 our teams have conducted initial exploratory prototyping to assist with scoping the opportunity to develop student capabilities.

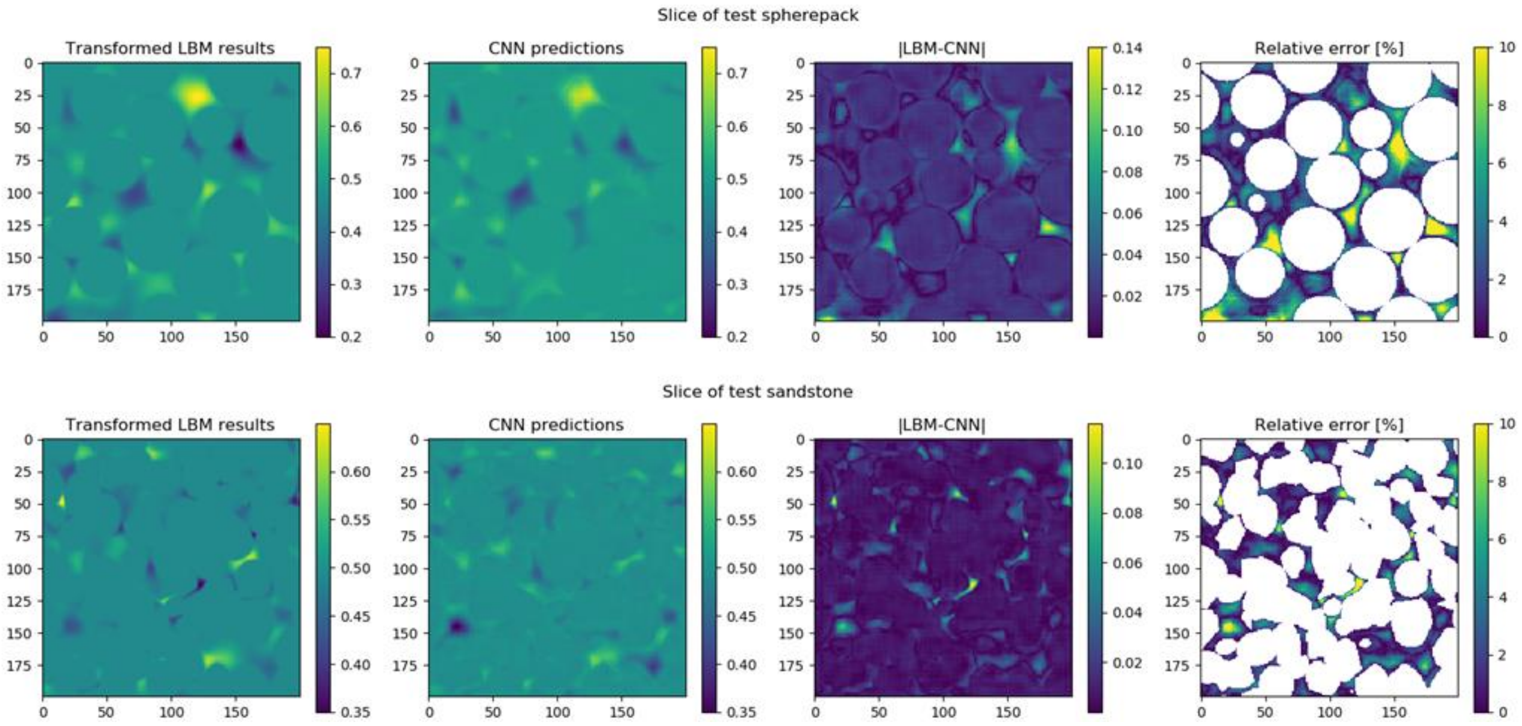
Spatial Bias in Machine Learning: Quantification and mitigation of *spatial bias in machine learning* by Wendi Liu (1st Year PhD student).

Left – spatial data, decision tree naïve and debiased, Right – error reduction vs. amount of bias.

Initial Exploratory Prototypes

Q3 2018 – Q3 2019 our teams have conducted initial exploratory prototyping to assist with scoping the opportunity to develop student capabilities.

Flow Proxies, Scaling: Machine learning-based *flow proxy* for intragranular flow.
by Javier Santos (1st Year PhD student).



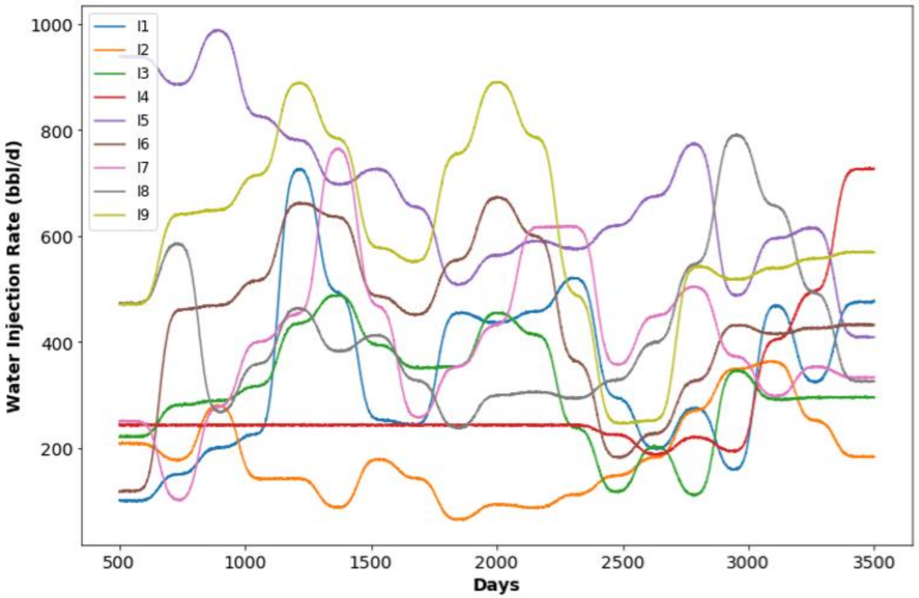
Lattice Boltzmann vs. convolutional neural nets prediction of flow velocity.

Initial Exploratory Prototypes

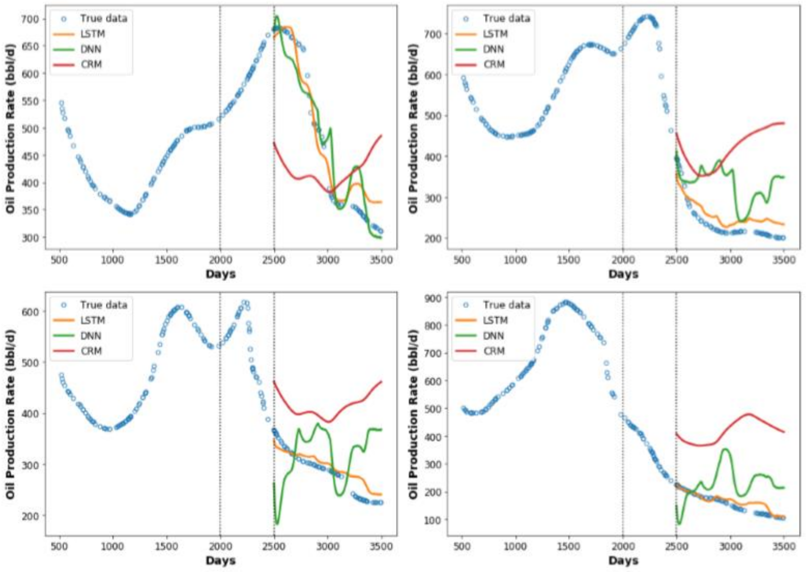
Q3 2018 – Q3 2019 our teams have conducted initial exploratory prototyping to assist with scoping the opportunity to develop student capabilities.

Flow Proxies, Scaling: Machine learning-based *flow forecasting* given multiple well injection and history. by Azor Nwachukwu (Completed PhD Dec., 2018).

Injection Rates Over Train and Test Intervals



Production Over Train and Modeled Over Test



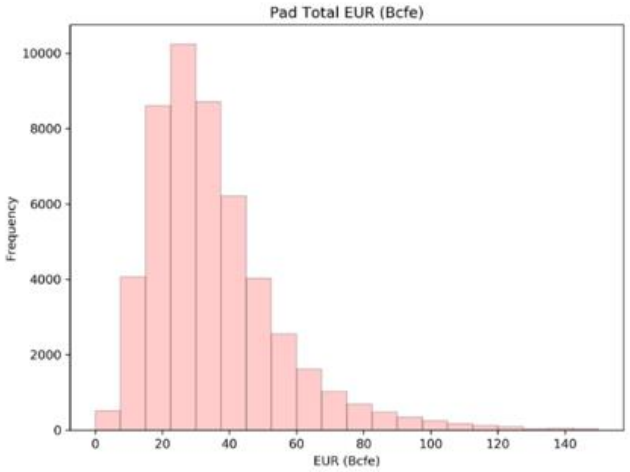
Recurrent neural nets for multiple well injection to prediction model.

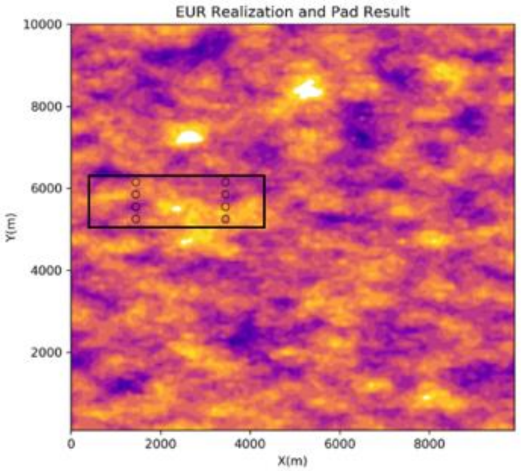
Initial Exploratory Prototypes

Q3 2018 – Q3 2019 our teams have conducted initial exploratory prototyping to assist with scoping the opportunity to develop student capabilities.

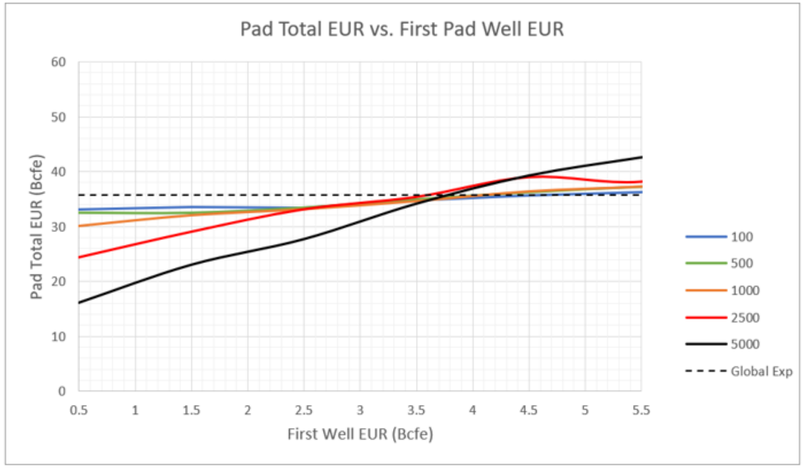
Data Analytics, Value of Information: Model resampling to evaluate the value of information for early pad production by Michael Pyrcz.

EUR Distributions





Early Indicator for Pad Aggregate Performance



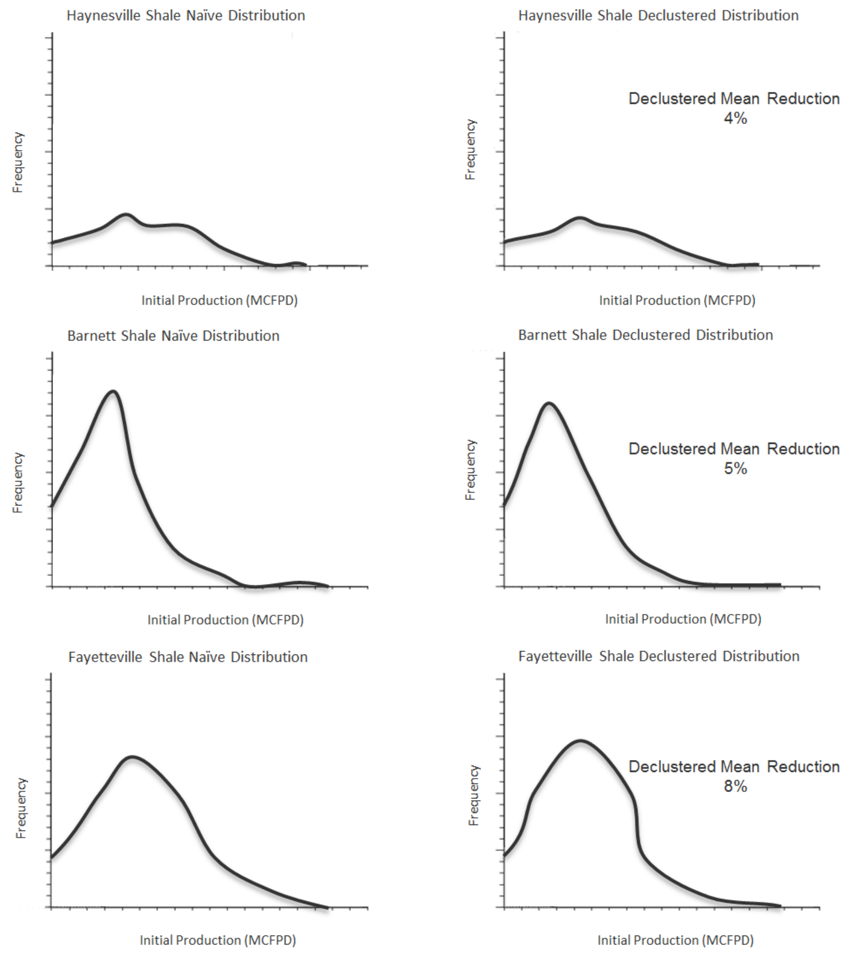
Determination of the value of early production information relative to spatial continuity of production.

Initial Exploratory Prototypes

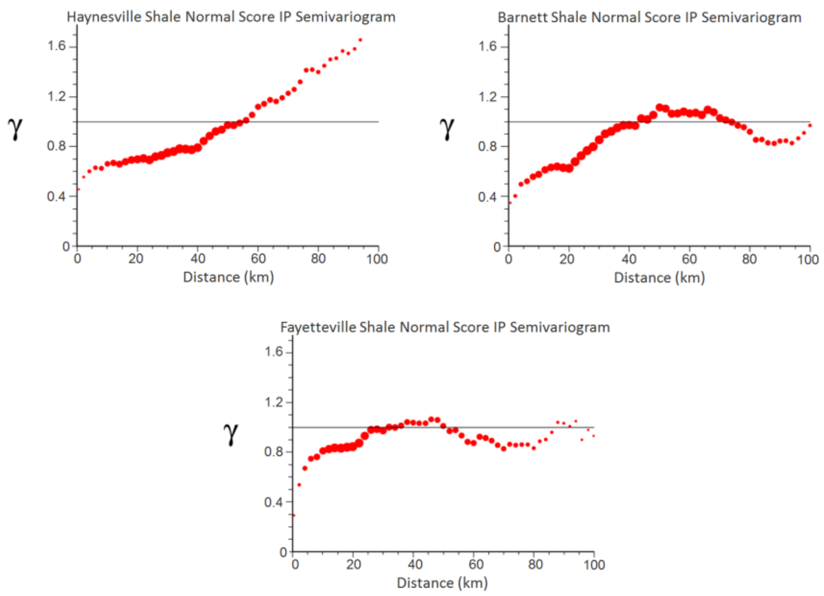
Q3 2018 – Q3 2019 our teams have conducted initial exploratory prototyping to assist with scoping the opportunity to develop student capabilities.

Data Analytics, Geostatistics: Spatiotemporal analysis, anomaly detection by Michael Pyrcz.

Spatial Sample Declustering for Unconventionals



EUR Spatial Continuity for Unconventionals



Spatial continuity analysis and formulation of representative distributions.

For More Information

Join early for the opportunity for early steering.

To join contact the DIRECT manager Leilani Swafford (Leilani.Swafford@austin.utexas.edu).

For further information concerning the consortium goals, plans and membership contact:

Prof. Michael J. Pyrcz, Ph.D., P.Eng.

mpyrcz@austin.utexas.edu

Prof. Carlos Torres-Verdin, Ph.D.

cverdin@austin.utexas.edu

Prof. John Foster, Ph.D.

jfoster@austin.utexas.edu

Prof. Eric van Oort, Ph.D.

vanoort@austin.utexas.edu

Hildebrand Department of Petroleum & Geosystems Engineering
The University of Texas at Austin
200 E. Dean Keeton St., Stop C0300
Austin, TX 78712-1585