



What's New for Us in Data Analytics, Geostatistics and Machine Learning

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Who am I?



- New **Professor** in UT PGE, started Fall 2017
- 17 years of experience in consulting, teaching and industrial R&D in **data analytics, reservoir modeling and uncertainty characterization, statistical / machine learning**
- **Associate Editor** for Computers and Geosciences Journal
- **Editorial Board** of Mathematical Geosciences Journal
- **Author** of the textbook “Geostatistical Reservoir Modeling” and > 40 peer reviewed publications, patents etc.
- **Program Chair** for SPE Petroleum Data Driven Analytics Technical section (PD²A)



Michael Not Working



Michael Working

Research



Geostatistics, Spatial Statistics, Statistics

- Multivariate, multiscale, spatial modeling with uncertainty
- Grid-free representations
- Uncertainty models for unconventional reservoirs

Data Analytics

- Data cleaning and bias
- Data preparation, imputation, scaling and updating
- Data visualization

Machine Learning

- Fast proxies for real-time feedback and optimization
- Multivariate, spatiotemporal inference and prediction
- Physics informed machine learning

Motivation



Modeling for Decision Support

we only add value when we impact a decision

Integrated Modeling

if it doesn't get in the model, it doesn't matter

Robust Statistics

Statistical learning needs statistics done well

Deployment

New tools, new workflows to improve practice

Examples



- 1. Optimal Well Placement**
- 2. Reservoir Multiscale Flow Modeling**
- 3. Production Forecasting**
- 4. Induced Seismicity**
- 5. Improved Geomodeling**

Optimal Well Placement



Requires fast iteration of flow forecasting to sample from the large potential solution space

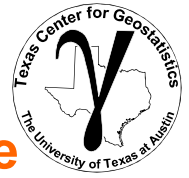
Solution: train and apply a machine learning-based / gradient boosting decision tree (XGBoost Library) for fast proxy for flow forecasting

Standard multivariate machine learning is oblivious of spatial context and connectivity

Solution: apply fast marching to calculate an efficient measure of well-to-well connectivity to include as a feature in the machine learning model

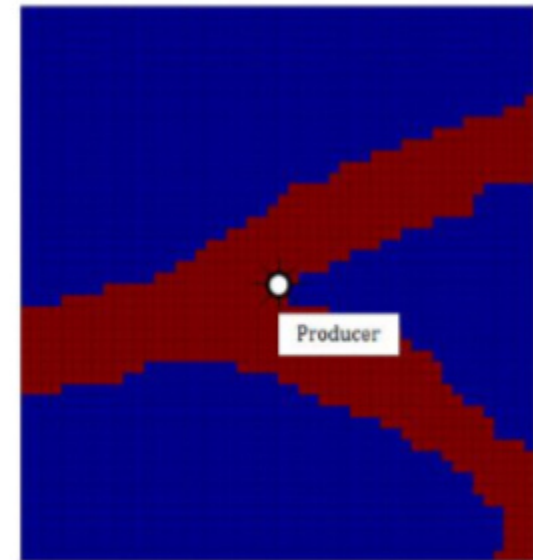
Optimal Well Placement

Student Azor Nwachukwu, Co-supervised with Prof. Larry Lake



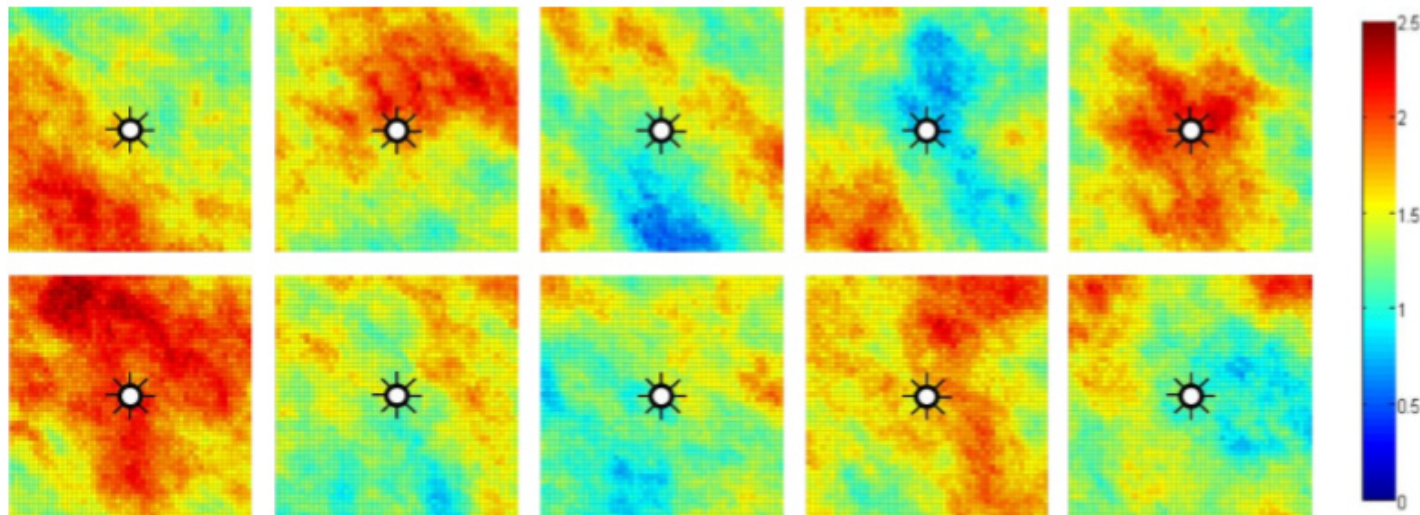
Experiment I:

- Channel facies (30%, 300md)
- Overbank facies (5%, 10 md)
- 2 variable injector locations
- 2000 days of waterflood



Experiment 2:

- Gaussian co-simulation



10 sample models (log of permeability)

Optimal Well Placement

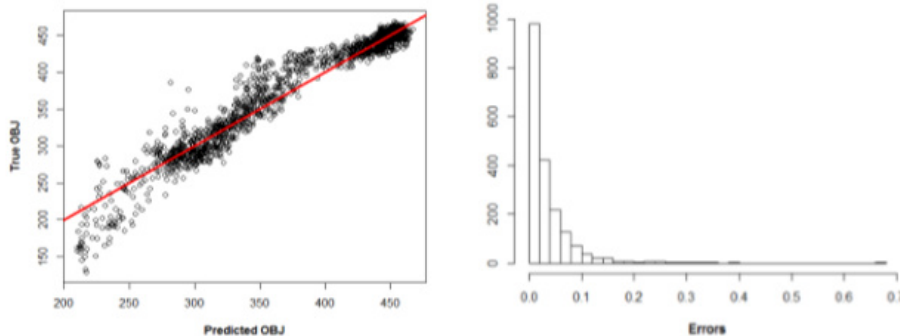
Student Azor Nwachukwu, Co-supervised with Prof. Larry Lake



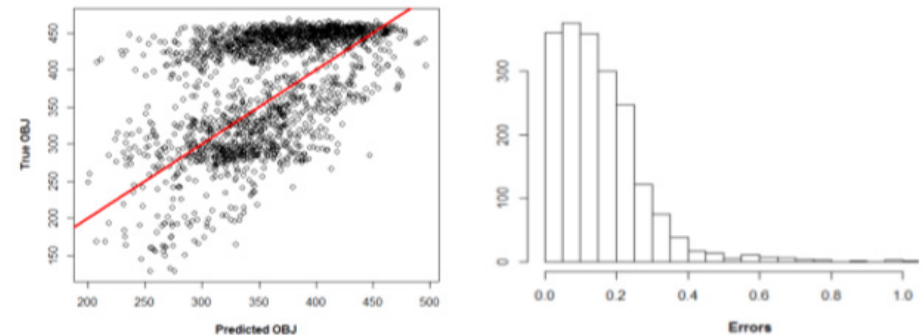
Results:

- Connectivity information is essential for a good machine learning proxy for production rates.

With Connectivity Information

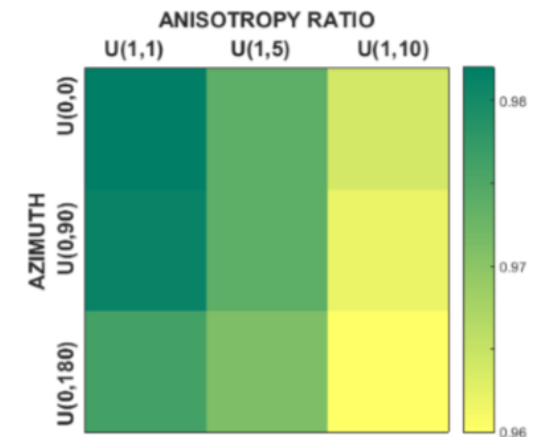


Without Connectivity Information



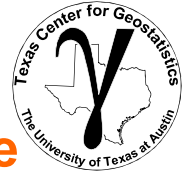
Training Diversity vs. Prediction Accuracy

- Training model diversity is essential for a good machine learning proxy for production rates.



Well Forecasting

Student Azor Nwachukwu, Co-supervised with Prof. Larry Lake



Requires ability to learn from the past and forecast into the future:

Solution: recurrent neural networks for time series prediction, long short term memory networks. Vector to vector encoder-decoder with retraining when new data is available.

LSTM Design for Short Term Updates to Long Term

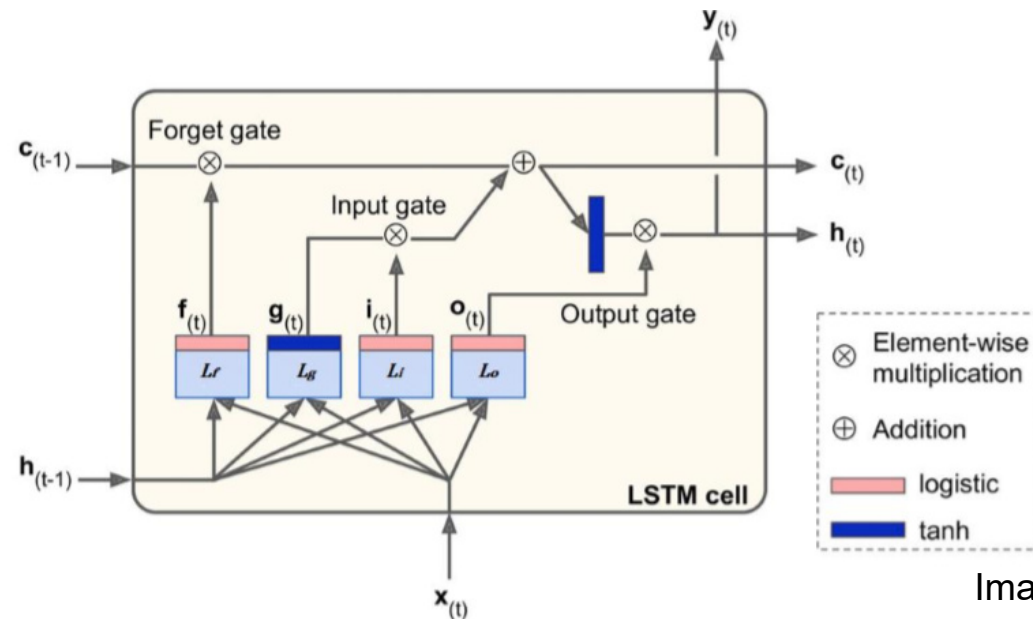
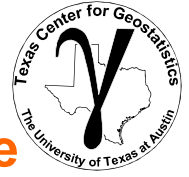


Image from Géron, 2017

Well Forecasting

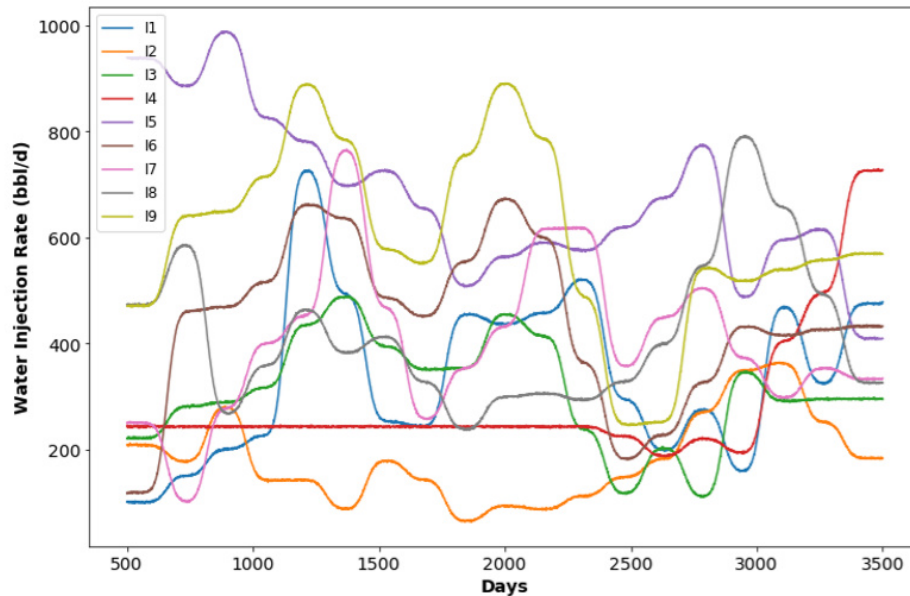
Student Azor Nwachukwu, Co-supervised with Prof. Larry Lake



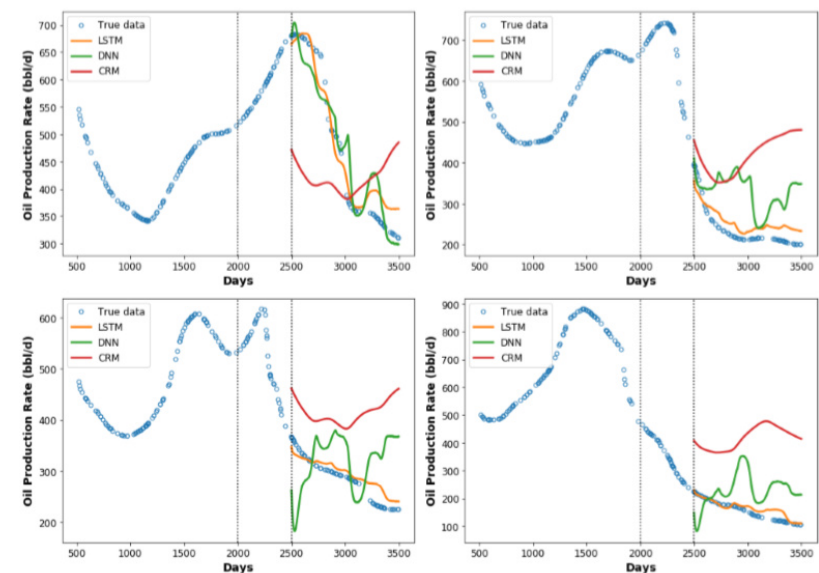
Results:

- Prediction during 3000 days of water flow (500 days of primary not included).
- Inputs included injection and oil rates production rates shifted backward.

Injection Rates Over Train and Test Intervals



Production Over Train and Modeled Over Test



Induced Seismicity

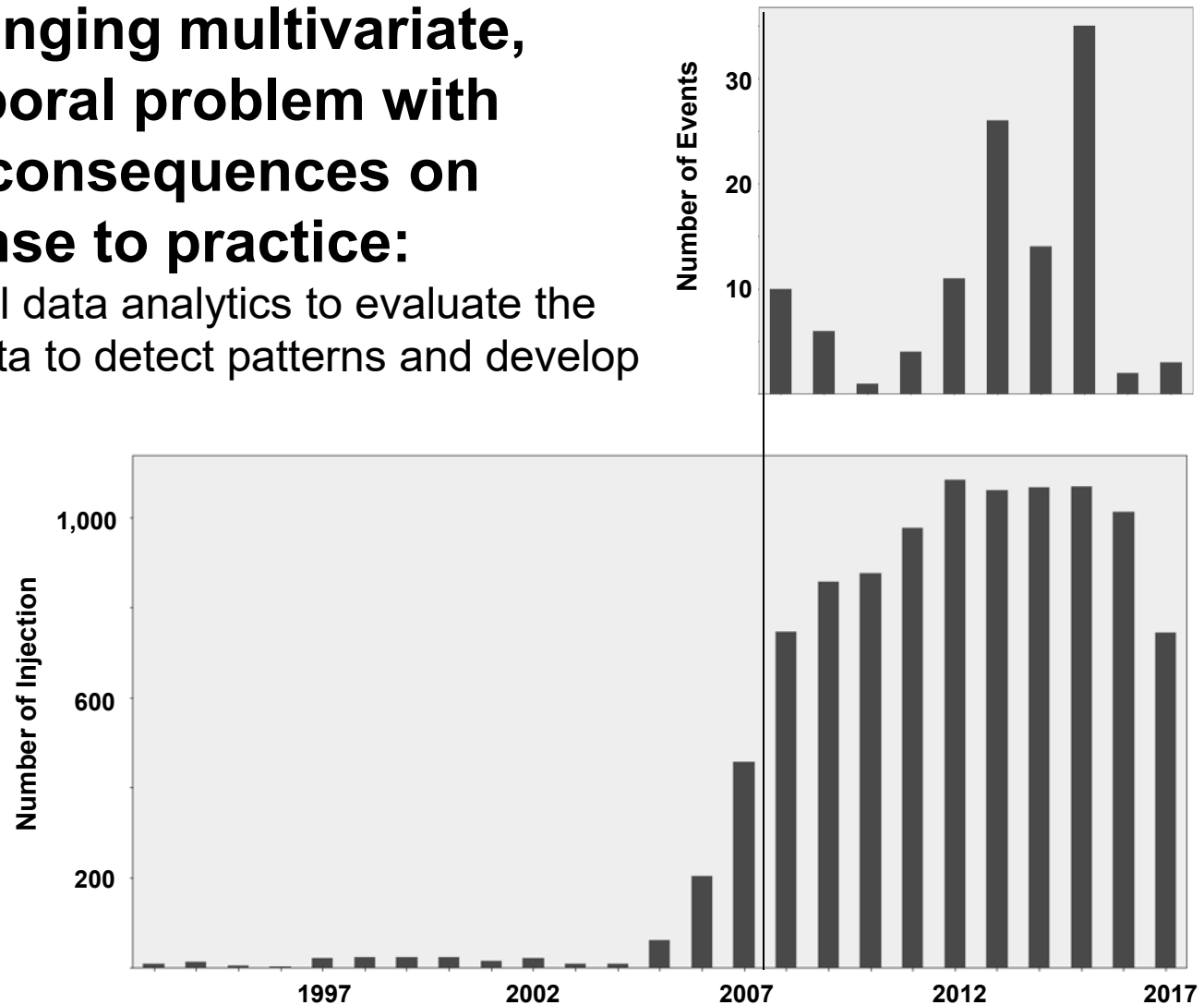
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Very challenging multivariate, spatiotemporal problem with important consequences on social license to practice:

- Apply spatial data analytics to evaluate the available data to detect patterns and develop hypotheses.

Injection and Seismic Events Over Time



Frequency vs year bar chart for events (top) and injections (bottom).

Induced Seismicity

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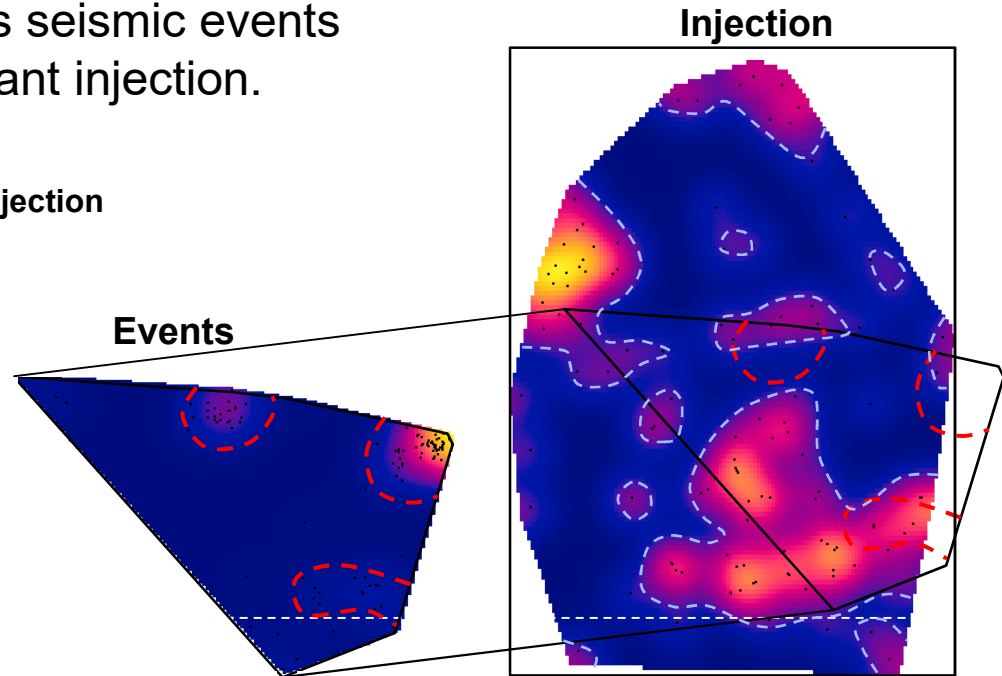
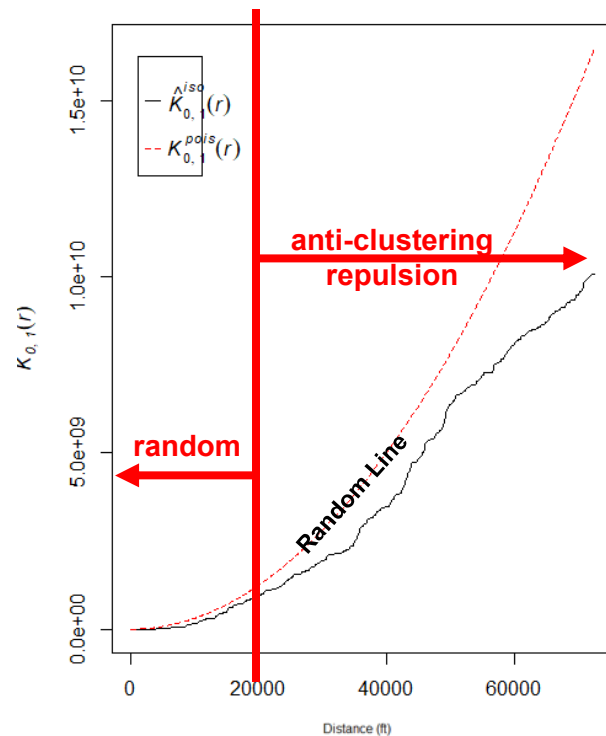


Results:

- Hotspot analysis determines seismic events occur in locations of significant injection.

Hotspot Analysis of Seismic Events and Injection

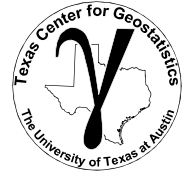
Ripley's K cross function for events, given injection



- Cross Ripley's K function did not detect higher rates of seismic events near injectors than random.

Improved Geomodelling

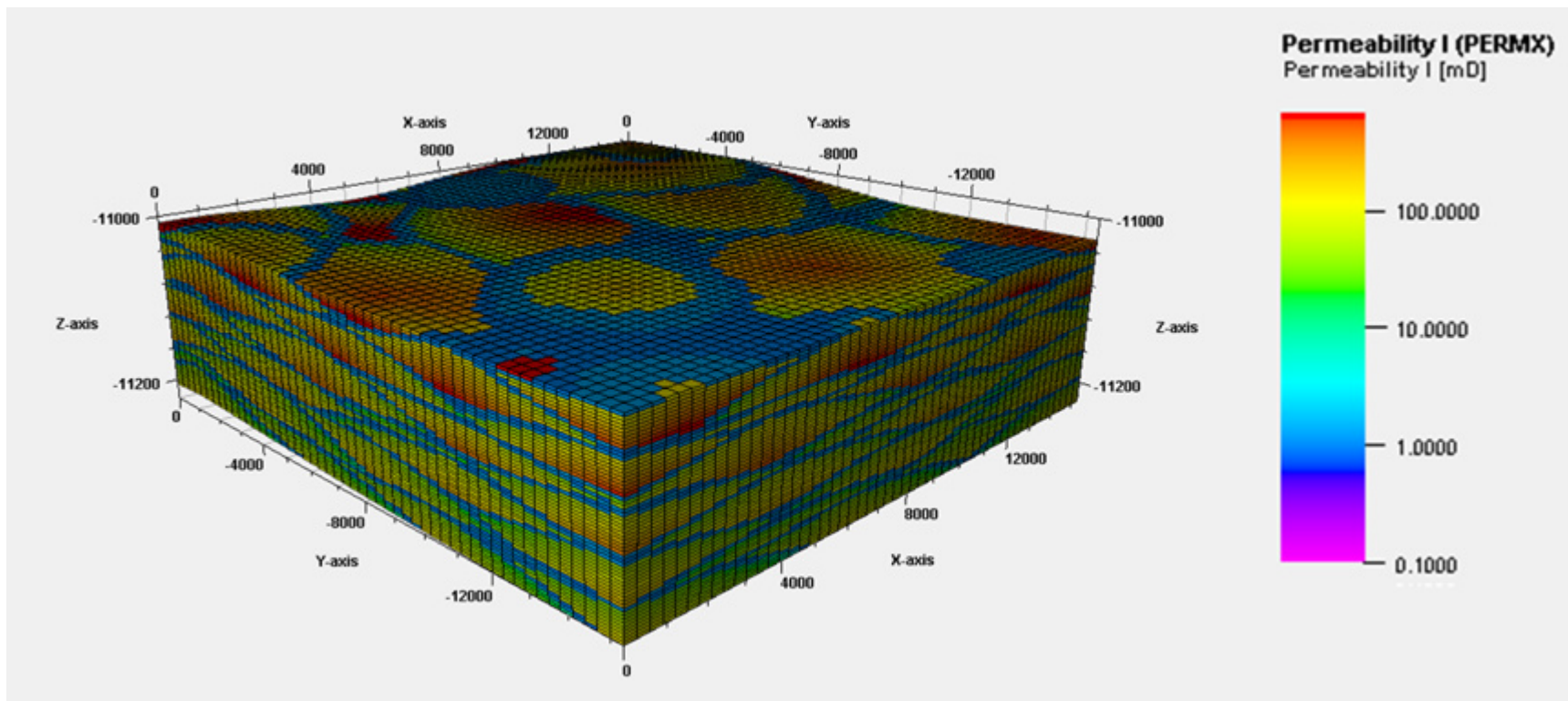
Student Honggeun Jo



Improved reservoir models are required to capture complicated heterogeneity fields:

- New process-mimicking methods that condition to concepts and data
- Rules calibration to geologic observation, robust, artifact free features

Geologically Calibrated, Artifact Mitigated Process-mimicking Model



Improved Geomodelling

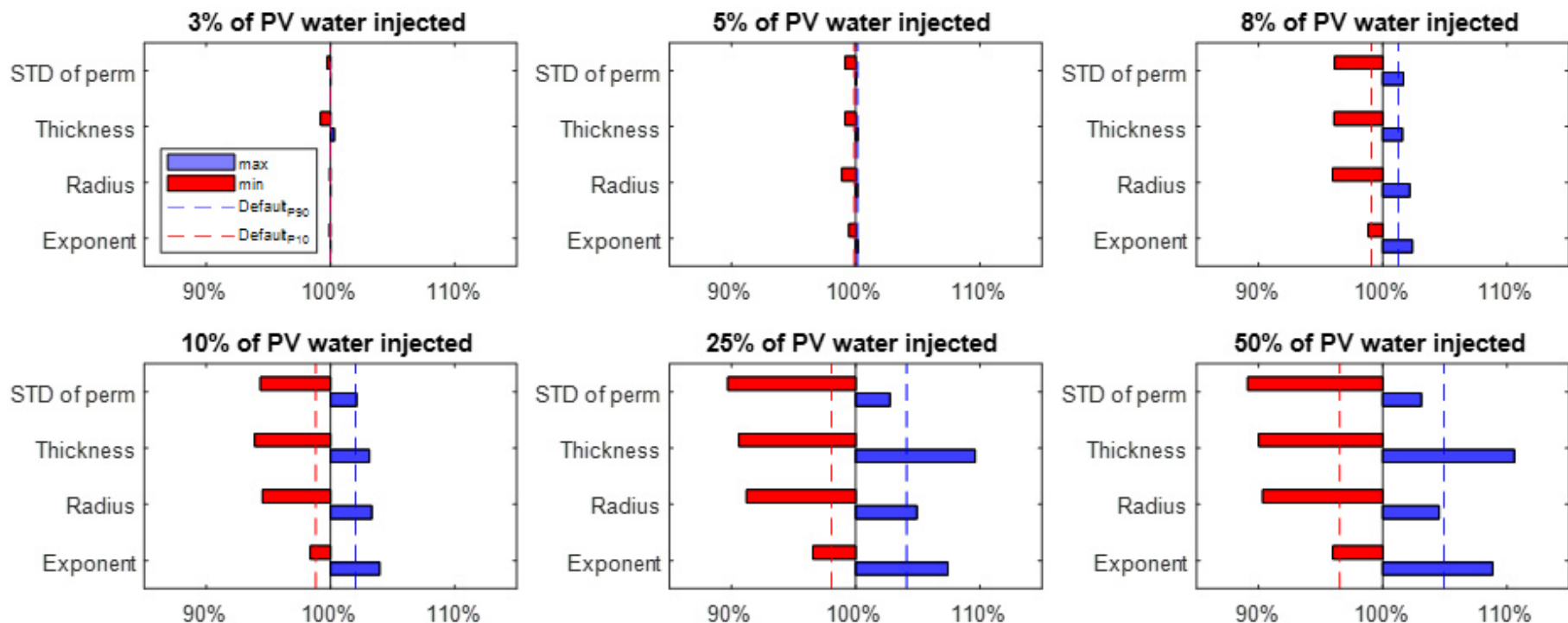
Student Honggeun Jo



Value and impact of architectural complexity in models:

- Standard reservoir models omit architectural complexity
- Inform reservoir modeling and to motivate new methods adoption.

Impact of Architectural Complexity Varies with Production Stage



Improved Geomodelling

Student Javier Santos, Co-supervised by Prof. Prodanovic



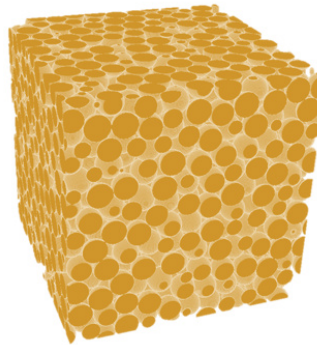
Integrating pore scale flow behavior into reservoir scale models:

- Train fast machine learning models to predict velocity and pressure
- Image segmentation into training sets
- Train convolution neural net with various measures e.g. distance transform

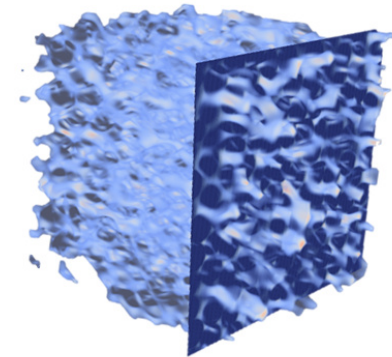
Pore Scale Model and Flow Model

Dataset

Sandstone

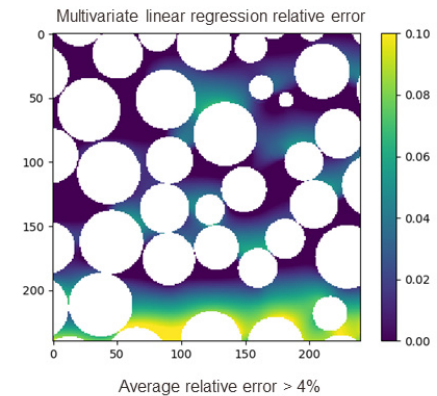
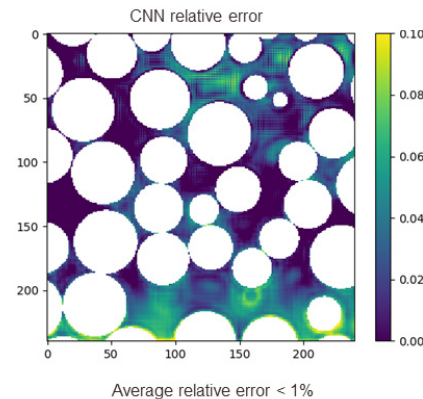


Velocity tensor (MRT-LBM simulation)



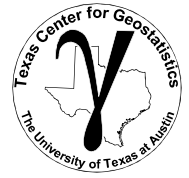
Pressure Field Prediction Error Machine Learning and Simple Regression

Pressure field



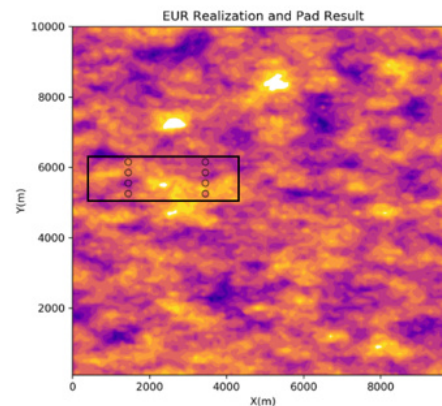
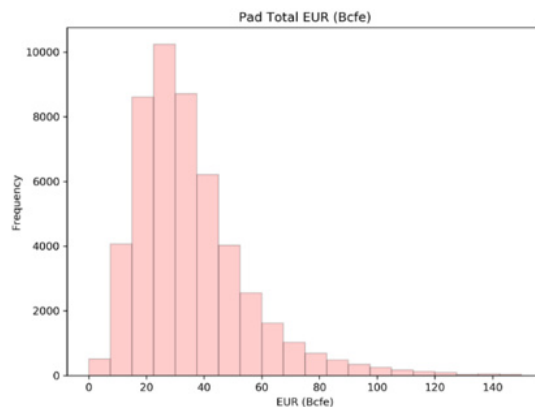
Uncertainty for Unconventionals

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Uncertainty models are needed for unconventional reservoirs:

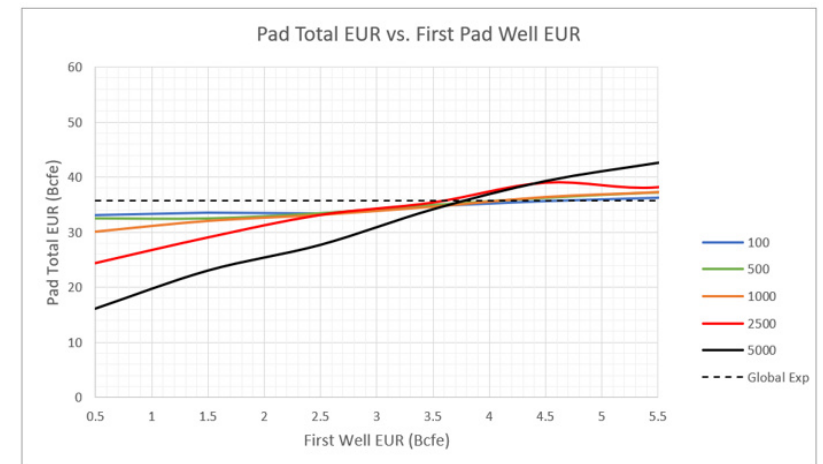
- Empirical model resampling for spatially constrained uncertainty



Well EUR realization and candidate pad location and aggregate performance

- Decision criteria with pad early indicator

Pad Abandonment First Well Decision Criteria



Data Analytics for Unconventionals

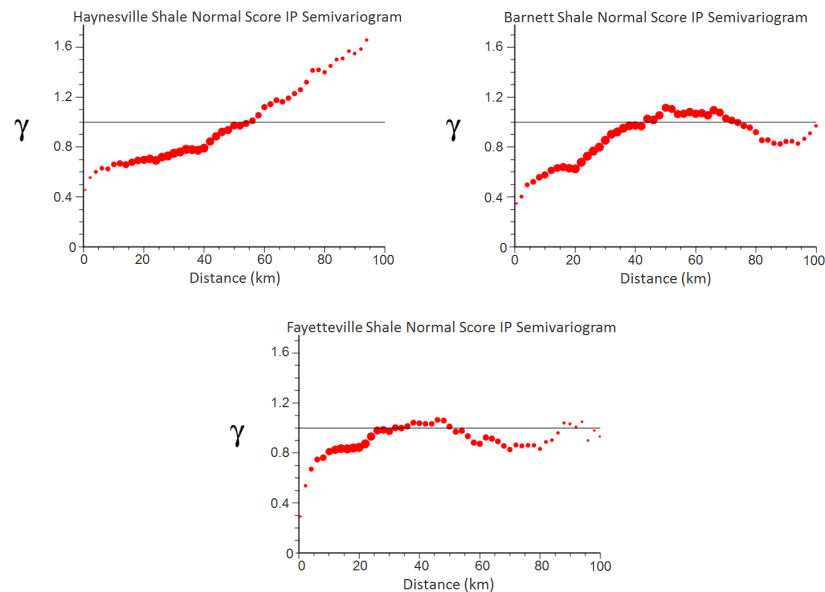
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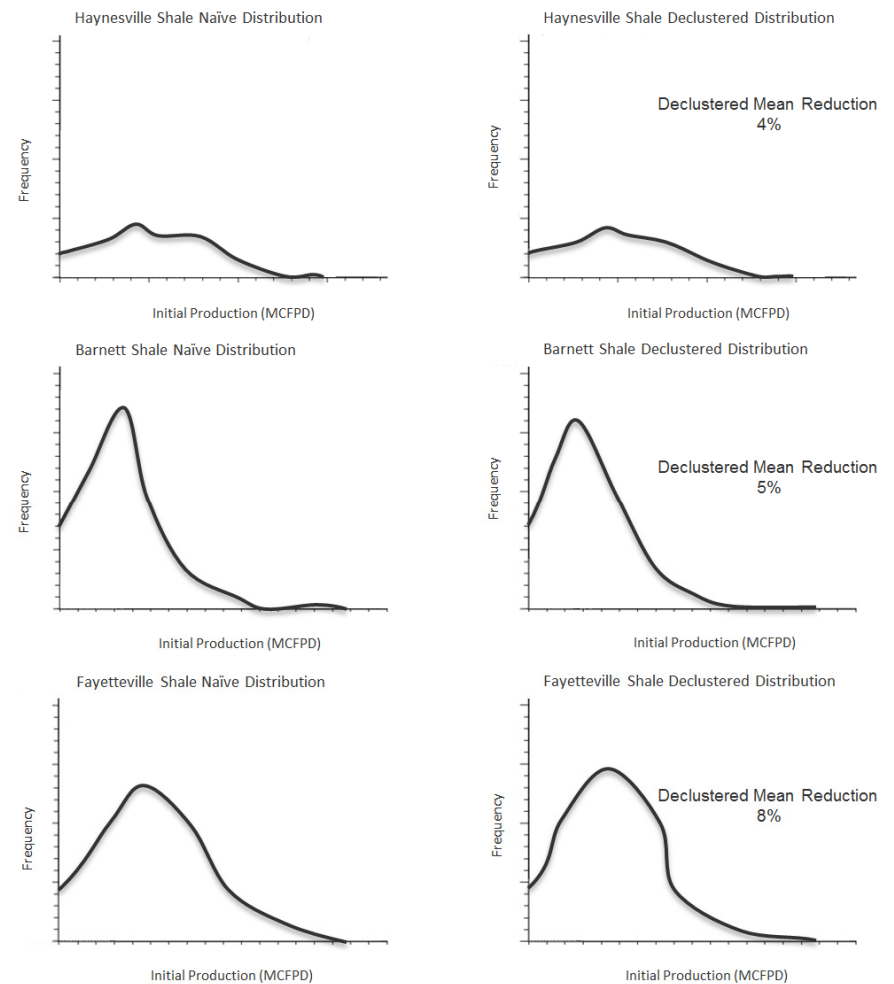
Formulation of representative statistics for unconventional data analytics and machine learning:

- Spatial declustering and continuity measures.

Spatial Correlation for US Domestic Shale Gas Production



Declustered Distributions for US Domestic Shale Gas Production



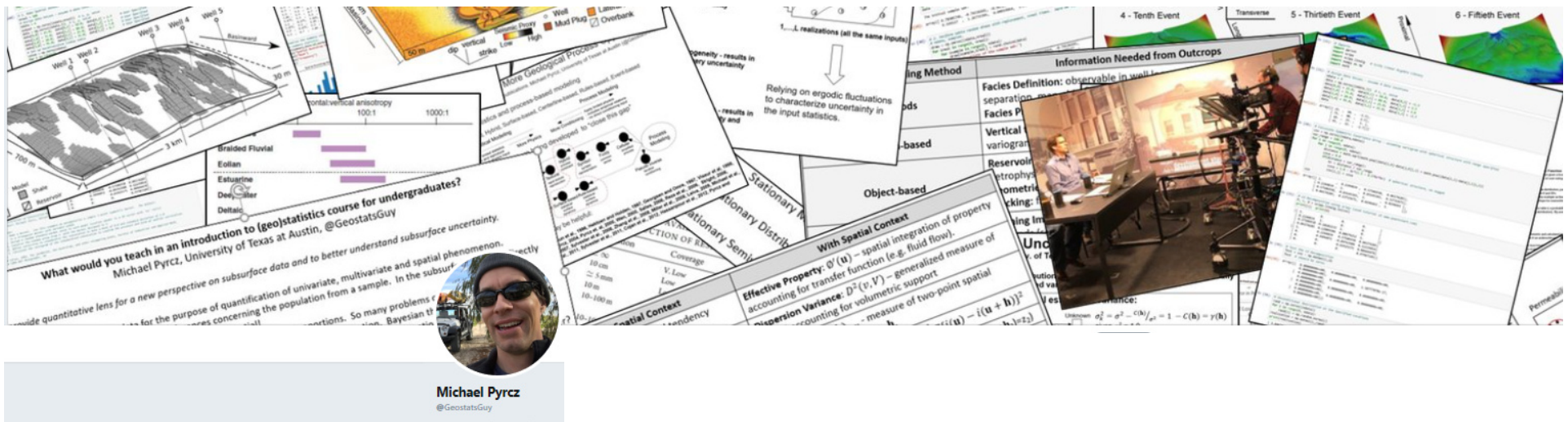
Subsurface Data Analytics and Machine Learning Consortium



New Industrial Affiliates Proposal:

- Maximizing the integration of deterministic engineering, geological description, target oriented drilling, geophysical measurements, borehole formation evaluation, and core data while preserving expert geoscience information to construct high-resolution reservoir models subject to production forecasts.
- Development of spatial data analytics and machine learning methods and workflows to support geomodeling and reservoir forecasting.
- Automated, expert systems, improved visualization and decision support
- Dr. Carlos Torres-Verdin – geophysics, data analytics and machine learning
- Dr. Eric van Oort – geomechanics, data analytics and machine learning
- Dr. John Foster – numerical simulation, flow and data analytics
- Dr. Michael Pyrcz – geostatistics, reservoir modeling, data analytics and machine learning

Learn More - Twitter



For tweets with Subsurface Geostatistical, Data Analytics and Machine Learning resources -

follow **@GeostatsGuy**

Learn More - GitHub

GitHub GeostatsGuy

Excel, R and Python

- Distributions
- Bootstrap
- Cellular Automata
- Hypothesis Testing
- Lorenz Coefficient
- Decision Making
- Bayesian Updating
- Kriging
- Simulation
- Volume-variance



Michael Pyrcz GeostatsGuy

I'm an Associate Professor with University of Texas at Austin in the Petroleum and Geosystems Engineering Department. Geostatistical Subsurface Modeling.

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<http://www.michaelpyrcz.com/>

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2DayCourse

2 day short course.

★ 20 🍴 2

PythonNumericalDemos

A collection of Python demos for geostatistical methods.

🍴 Jupyter Notebook ★ 10 🍴 5

ExcelNumericalDemos

A set of numerical demonstrations in Excel to assist with teaching / learning concepts in statistics and geostatistics.

★ 9 🍴 3

2DayCourse_Exercises

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GeostatsPy

Wrapper / Reimplementation of GSLIB in Python

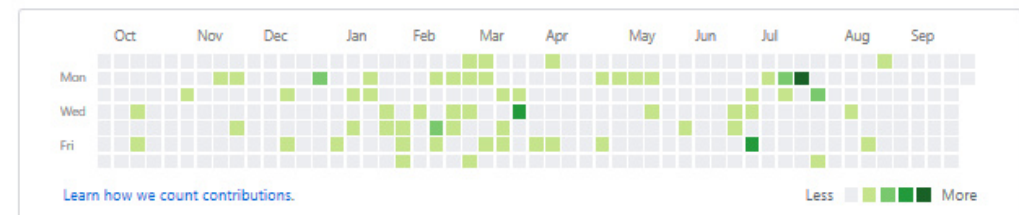
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GeostatsLectures

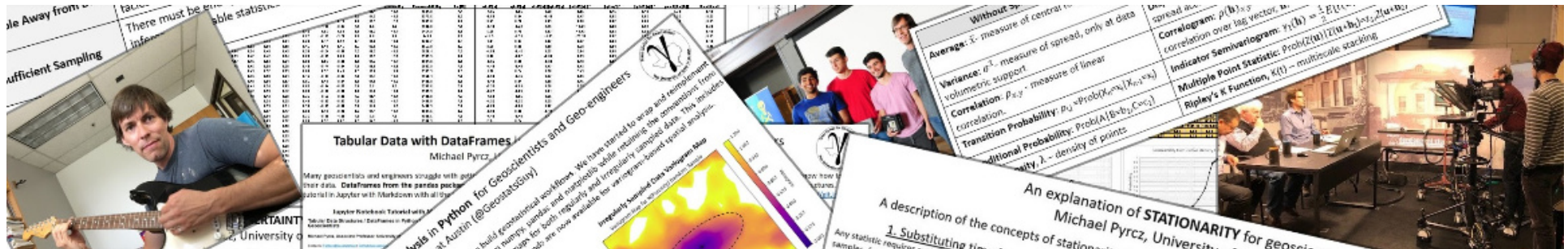
(Geo)statistical course materials released for anyone to use (.pdf format). Enjoy! I'm happy to discuss.

★ 2 🍴 2

177 contributions in the last year




Learn More - YouTube



For my lectures check out my YouTube Channel, 'GeostatsGuy Lectures'.


Example Topics:

- probability theory
- frequentist vs. Bayesian statistics
- binomial distribution to model exploration success



Binomial Distribution

Use for multiple trials with binary (0,1) result.



• PDF:

$f(x) = \binom{N}{x} p^x (1-p)^{N-x}$

Probability of x success in N trials

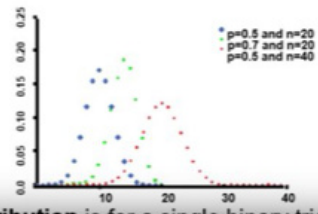
CDF:

$F(x) = \sum_{i=0}^x \binom{N}{i} p^i (1-p)^{N-i}$

Recall for independent events $P(A,B,C) = P(A) \cdot P(B) \cdot P(C)$

E.g. $\binom{3}{2} = \frac{3 \cdot 2 \cdot 1}{2 \cdot 1 \cdot 1} = 3$, E.g. for coin toss: HHT, HTH, THH

Example: distributions with variable attempts and probability of success.



Note: a Bernoulli distribution is for a single binary trial.