PGE 383 Subsurface Machine Learning

Lecture 5d: Feature Imputation

Lecture outline:

- **Likewise Deletion**
- **Feature Imputation**
- **Feature Imputation Alternatives**
- **Feature Imputation Hands-on**

Causes of Missing Samples

Most spatial, subsurface datasets are not complete, missing values from the database.

- Data analytics and machine learning require complete data
- Dealing with missing data is an essential part of feature / data engineering, prerequisite for data analytics and machine learning

While you board your flight.

Image from: https://whatsthejam.com/world-news/stunned-passenger-sees-familys-suitcases-left-on-tarmac-just-before-take-off/

Causes of Missing Samples

Cost, too expensive

- Porosity can be calculated from a fast, cheaper density well log
- Permeability typically requires a core sample extraction and laboratory test

Infeasible, Not Possible

- Permeability test of high permeability rock is faster than very low permeability rock

Multiple Vintage, Sampling Campaigns

- Data collected at different times with different sampling methods, and even goals

Blunders, Errors

- Valuable data has disappeared, corrupted, recorded incorrectly

Constant head permeability test.

Image from, https://uta.pressbooks.pub/soilmechanics/chapter/permeability-test/

Missing Data Bias

Missing at random (MAR) is not common and is not evaluated

- Global random omission may not result in data bias and bias in the resulting models

This is typically not the case as missing data often has a confounding feature, e.g.,

- sampling cost, e.g., low permeability test takes too long
- rock rheology sample filter, e.g., can't recover the mudstone samples
- sampling to reduce uncertainty and maximize profitability instead of statistical representativity, dual purpose samples for information and production

Missing data consequences, more than reducing the amount of training and testing data, missing data, if not completely at random will result in:

- Biased sample statistics resulting in biased model training and testing

- Biased models with biased predictions with potentially no indication of the bias!

Impact of Missing Data on Modeling

Samples with Missing Features Cannot be Applied in Many Data Analytics and Machine Learning Methods

Inferential Machine Learning:

PCA, MDS, Cluster Analysis require all the features, $x_{1,i}, \ldots, x_{m,i}$ for each of the data samples $i = 1, \ldots, n$.

- We cannot calculate distance / dissimilarity, projects etc. without placing each sample in the m dimensional space

Predictive Machine Learning:

require all features to train and test the model.

$$\hat{Y} = \hat{f}(X_1, \ldots, X_m)$$

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Likewise Deletion

Most Common / Default Approach in Data Analytics and Machine Learning

Removal of any sample with any missing feature – likewise deletion

If missing at random (MAR)

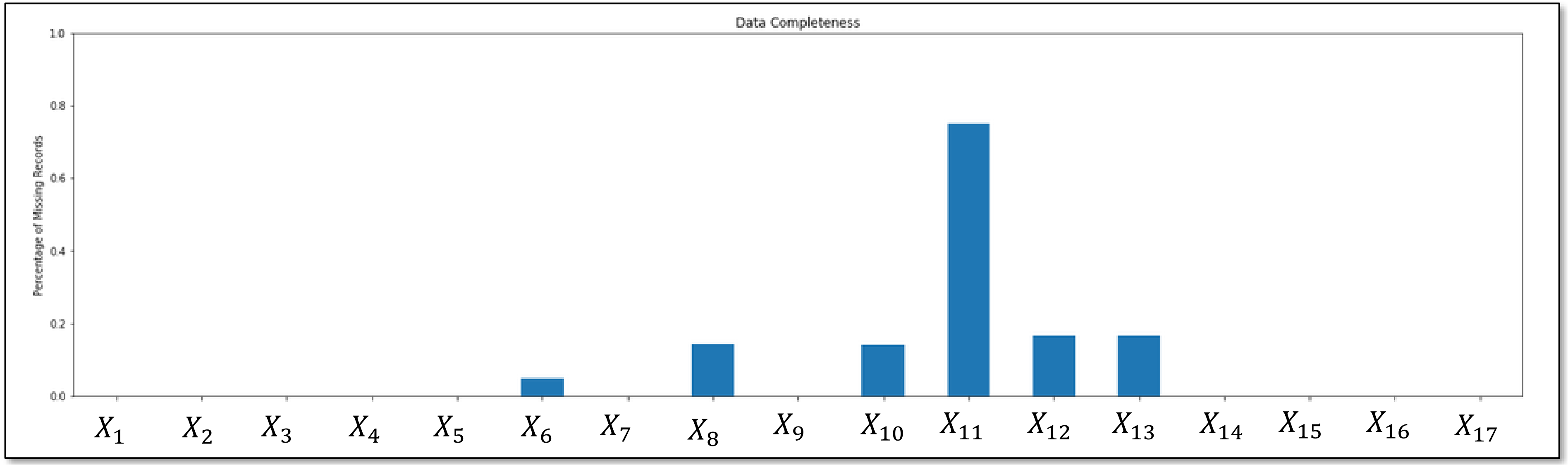
- Should not result in biased (or increased bias)

- Caution: MAR is rare

- Will result in a decrease in the effective data size and increase in model uncertainty

Likewise Deletion

Most Common / Default Approach in Data Analytics and Machine Learning



Proportion of missing records for each feature.

Data completeness, coverage for each feature

- Missing records in X_{10} may not all be in X_{11} etc.
- May result in loss of much more than the largest proportion of missing

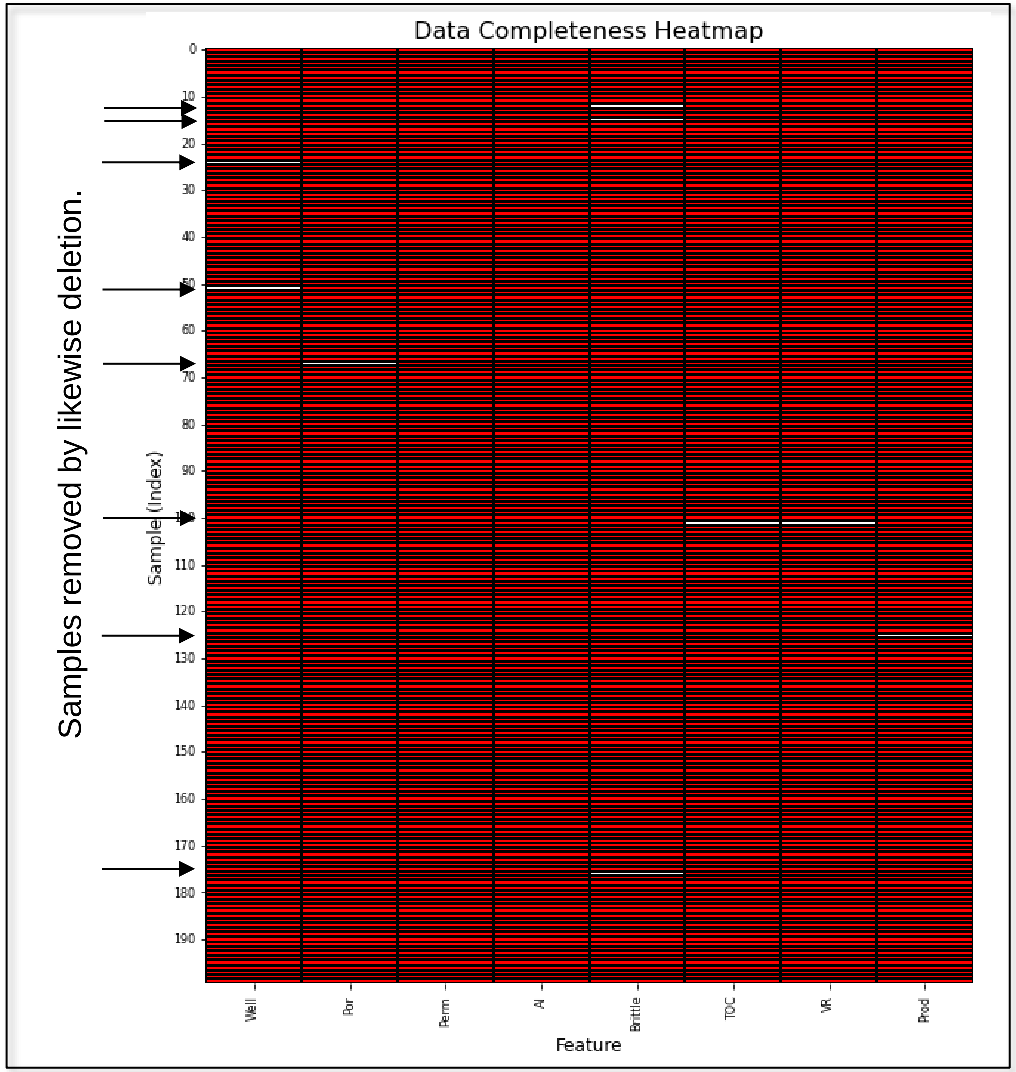
If missing not at random (MNAR), sample bias is increased

- Missing data diagnosis – best method fill in missing data, practical method is to evaluate the conditional statistics of missing samples over other features.

Likewise Deletion

Most Common / Default Approach in Data Analytics and Machine Learning

- conservative approach, avoids estimation of missing values
- maximize removal of data, loss of information

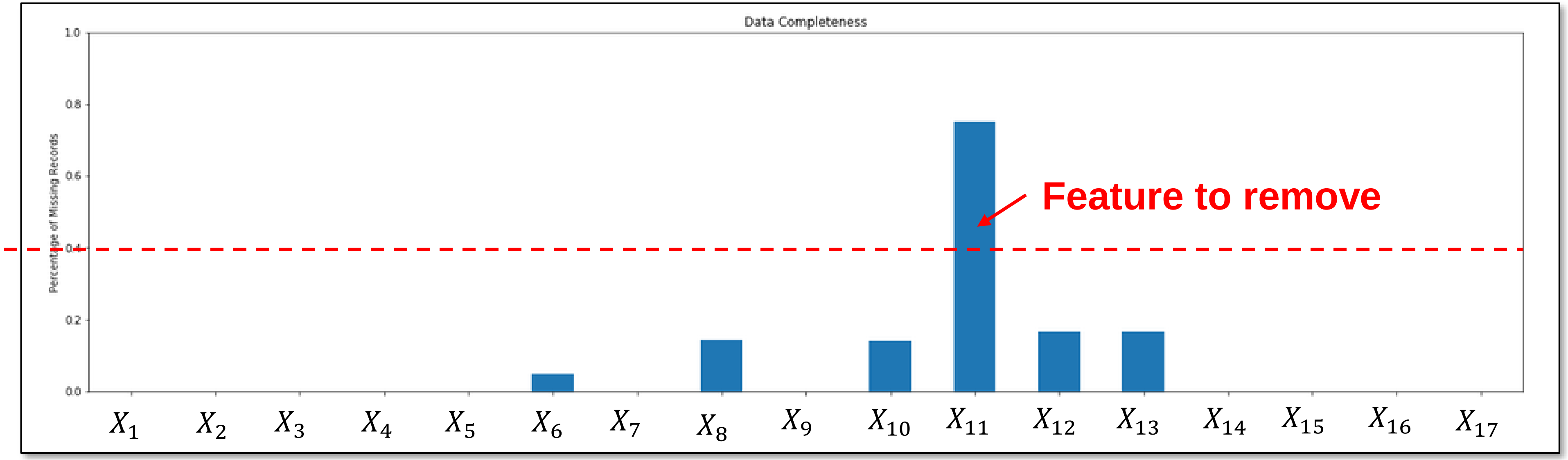


Heat map of data coverage (white = missing feature), and samples to be removed by likewise deletion.

Likewise Deletion

Removal of features low data completeness

Reduces missing data severity, treat data completeness as feature reliability for feature selection



Proportion of missing records for each feature.

Removing the features with low coverage

- Removal of X_{11} and likewise deletion fortunately resulted in a 18% reduction in samples, fortunately missing X_6, X_8, X_{10}, X_{12} and X_{13} coincide (same samples) in this case
- Often not the case, missing features' samples don't perfectly overlap.

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- **Feature Imputation**

What is a Feature Imputation?

Estimating missing values in the dataset, our DataFrame

2 Primary Goals,

- Maximize model accuracy

- Avoid model bias

We could also add this goal for the subsurface, spatial phenomenon,

- Provide fair measure of model uncertainty

Hot and Cold Deck Methods

Hot Deck Imputation

Random selection from a similar record in the current dataset

- One implementation is last observation carried forward (LOCF). After sorting the dataset over features of interest (ordering to maximize similarity of adjacent records)

Cold Deck Imputation

Like hot deck, but from another, analog dataset

Issues:

Likely introduce bias, disrupt correlations

Mean Value Imputation

Substitute the Global Mean

Optimum estimate (minimizes the L2 loss function) given no other information

Do not do this,

- Cause conditional bias in the model in the presence of other features, systematic shift in the expectation of the substituted predictor feature over combinatorials of the other features.

- Reduce variance of the substituted predictor feature limiting the training and testing data coverage

Mean Value Imputation

Mean Value Imputation

Replace the missing value with the global mean of the feature

$$x_i = E\{X_i\}$$

- avoids global bias in the specific feature

Conditional Mean Value Imputation

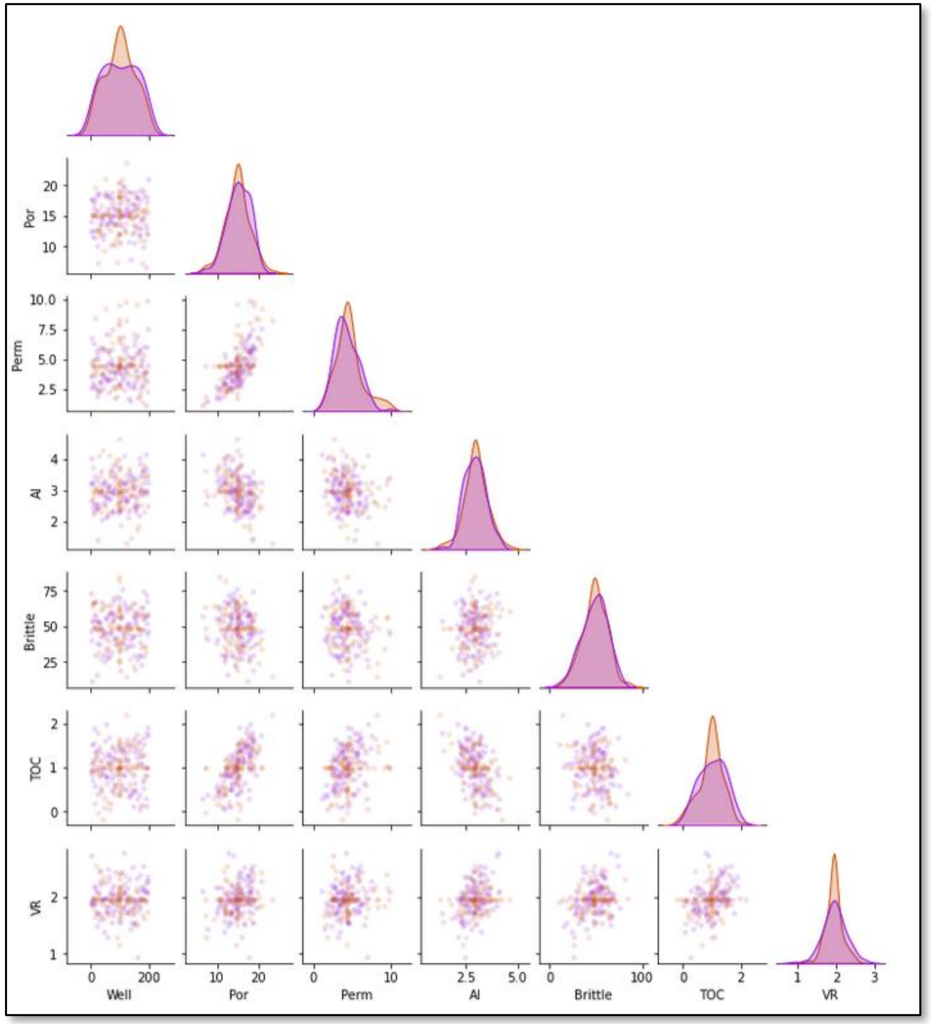
- Replace the missing value with the conditional mean of the feature

$$x_i = E\{X_i | X_{j=1,\dots,m, j \neq i}\}$$

- avoids global and conditional bias

Issues:

- these methods may attenuate correlations



Matrix scatter plot after mean value imputation (orange), from MachineLearning_feature_imputation chapter of e-book.

Estimation / Regression Methods

Regression Imputation

- Replace the missing value with a model-based estimate of the feature

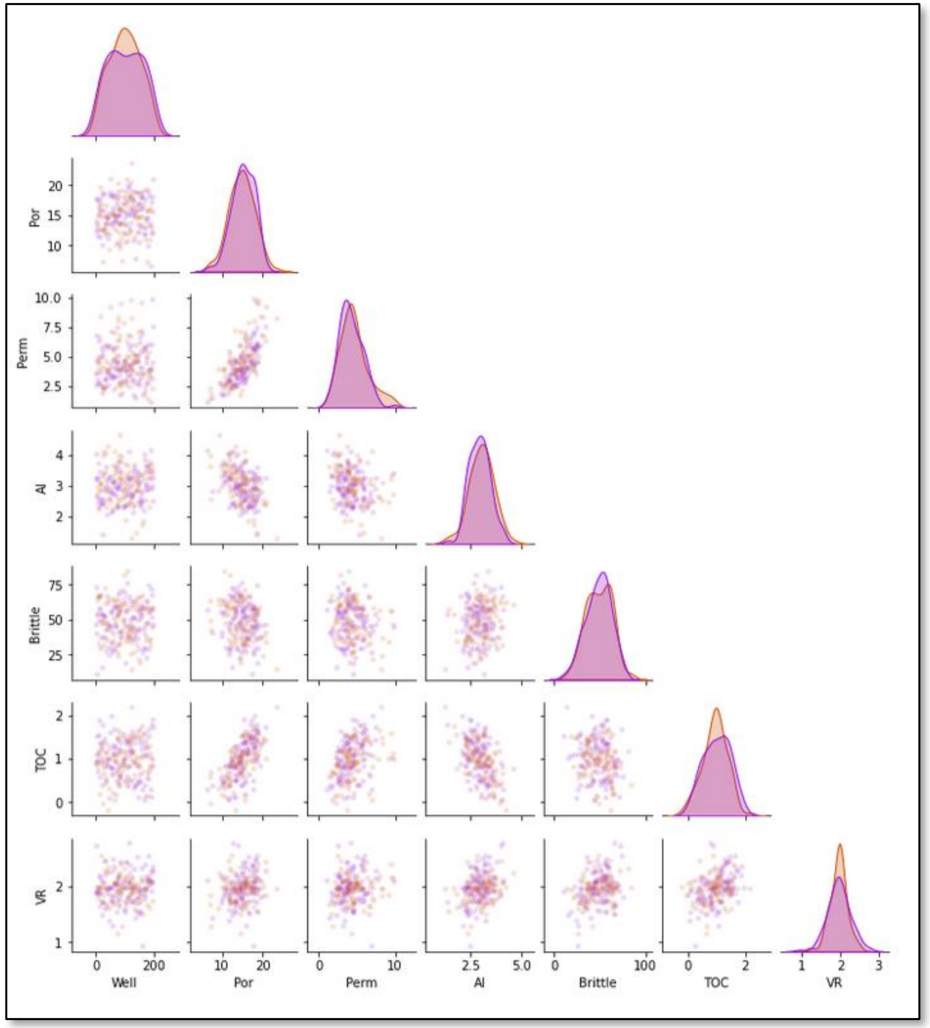
$$x_i = \hat{f}(X_{j=1,\ldots,m,j\neq i})$$

- Reduce the global and local bias, but prediction models often have conditional bias.

- The full range / variance of the response feature(s) is not represented.
- Conditional bias can be checked and improved with model training and tuning (more later).

Issues:

- The imputed values are represented as hard data and fail to represent the uncertainty associated with their estimation
- This method will underestimate the uncertainty models



Matrix scatter plot after mean value imputation (orange), from MachineLearning_feature_imputation chapter of e-book.

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- **Feature Imputation Alternatives**

Feature Imputation Alternatives

Geo-imputation / Geographical Imputation

by spatial analog, similar locations

General Interpolation

a wide variate of interpolation methods including geostatistics for spatial and temporal problems

Censoring / Indicator Coding

include a bound / constraint on the missing value, for subsequent methods that integrate soft data

Multiple Imputation

Multiple Imputation

Replace the missing value with a suite of realizations, with multiple model-based estimates (and even scenarios) of the feature

$$x_i^{\ell} = \hat{f}^{\ell}(X_{j=1,\ldots,m,j\neq i})$$

- subsequent workflows must now integrate data realizations to integrate uncertainty

Alternatives:

- Bootstrap, geostatistics / spatial bootstrap

Multiple Imputation

Multiple Imputation by Chained Equations (MICE) Approach:

1. Substitute placeholder (constant, random values from $F_{X_{i=1,\ldots,m}}(X_{i=1,\ldots,m})$) for missing values

2. Sequentially predict missing values for one feature at a time with all other features
   – set placeholders in one feature to missing and predict with all values (actual and placeholders) for the other features.

3. Repeat for multiple realizations of the dataset

Iterative until convergence criteria is met, usually multivariate statistics

Multivariate and Spatial Imputation

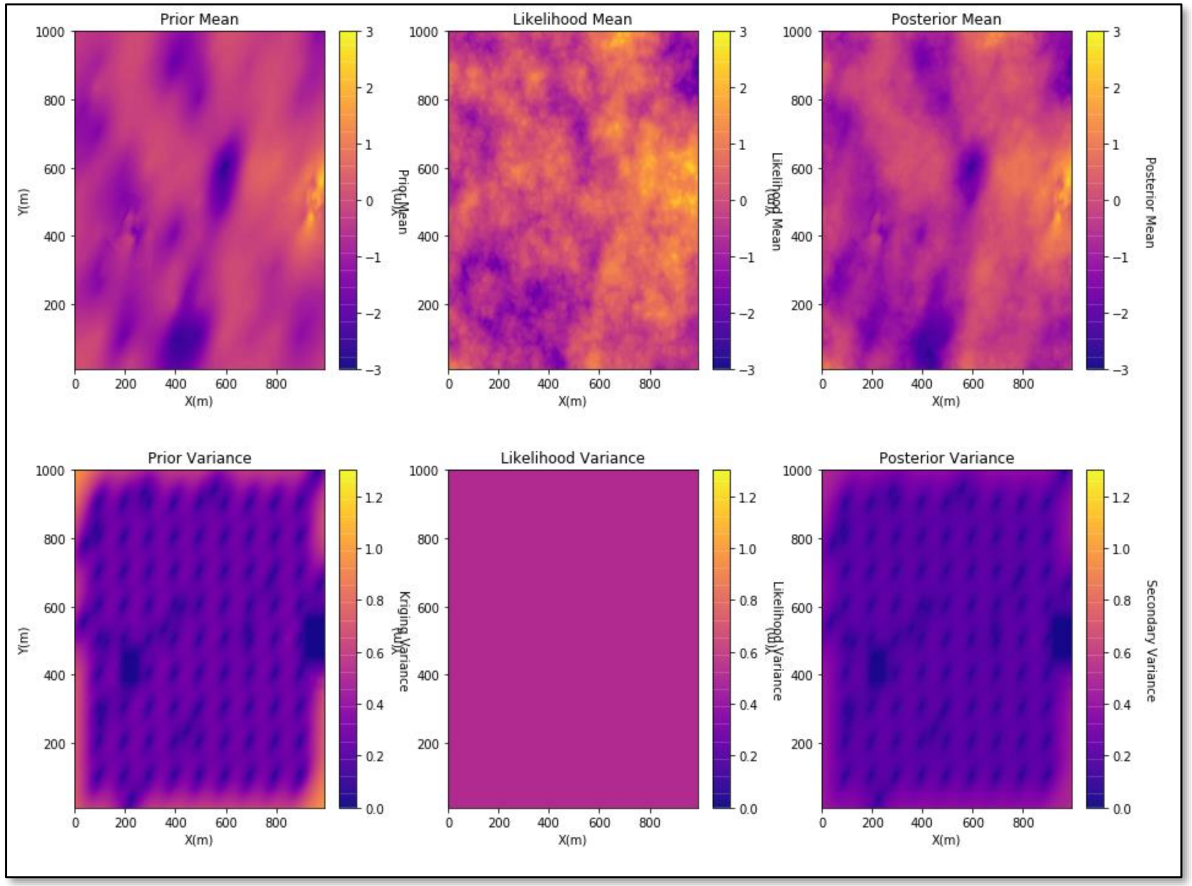
Super Secondary Approach (Deutsch and Zanon, 2004)

1. Transform the selected property to Gaussian
2. **Spatial Primary Information**: Calculate prior through kriging estimate and variance and the Gaussian assumption
3. **Multivariate Secondary Information**: Calculate the likelihood through multivariate relationship with other collocated features
4. **Bayesian Updating to Combine Spatial and Multivariate**: Update to calculate the Gaussian distributed posterior
5. Back transform the property to Gaussian
6. Visualize diagnostics on the impact of the spatial and multivariate on informing the local estimate.

Super Secondary Demonstration

Super Secondary Approach Demonstration – 2D Map

- Prior from well data primary feature, likelihood from multivariate mapped features and posterior.



Example of multivariate and spatial estimation of uncertainty distributions.

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