Palynology of the Jurassic–Cretaceous transition, Surat Basin

The formations around the Jurassic–Cretaceous transition in the Surat Basin are the last of that basin to undergo systematic palynological study. They represent the most complete record of deposition for the period in the state and contain a number of important aquifers.

This project will result in:
- A systematic description of the palynomorphs from the strata and the description of several new species
- Confirmation of how well the pan-Australian palynostratigraphic zones (Fig. 1) work for this region and possible new units allowing for a finer subdivision of the strata
- An improved understanding of the flora and climate of the period of deposition.

Work to date
- Sample for palynology have been taken from 3 GSQ Stratigraphic holes (Fig. 2)
- A systematic survey of palynomorphs has been conducted for DRD 26 and Roma 2 finding 237 species across 111 genera.
- Species counts have begun for samples from Roma 2

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Machine Learning for Coal Seam Gas Production

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How do we construct a PCE surrogate model?
- A PCE represents the model as a sum of carefully chosen polynomials each individually weighted to give an accurate approximation.

\[ M(x) = c_0 + c_1 x_1 + c_2 x_2 + \ldots \]

- The method naturally generalises to multiple input parameters.
- The polynomials are orthogonal with respect to the input parameters' statistical distributions:
  - reducing the complexity;
  - capturing the uncertainty in the input parameters;
  - allowing for efficient identification of key parameters and key parameter interactions.

How does it honour the geophysics?
- The weights \( c_0, c_1, c_2, \ldots \) are derived from the underlying data (often via evaluations of the original model).

How do we apply machine learning?
- A surrogate model is built to approximate a computationally expensive model.
- It emulates the behaviour of the original model, honouring the underlying physics.
- It accurately and efficiently performs:
  - uncertainty propagation; and
  - sensitivity analysis.
- It facilitates processes such as EUR calculations and history matching.

How do we optimise the construction process?
- Construct surrogate models using moments or approximations of the moments for the inputs, thus allowing for unknown distributions.
- Use regression techniques for approximating key coefficients, thus reducing the required number of training points.
- Two types of regression techniques to solve the same minimum argument equation; Ordinary Least Squares (OLS) and Least Angle Regression (LARS).
- LARS is preferred for higher dimensionality cases as it preferences the 'most important' coefficients and hence can generate a higher order surrogate model.

Example – Identifying the sources of uncertainty. Sobol' indices are used to rank the impact of the porosity and permeability of the various coal bodies.

Example – Using a surrogate to predict cumulative gas production.

Future directions.
1. Exploring the relationship between the size of the training set, the number of input parameters and the accuracy of the surrogate model.
2. Machine learning from field data, cutting out the middleman, i.e. no requirement for an established model.