

A pragmatic theoretical framework for geomodelling in hyperspace

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Most Implicit Modelling (IM) techniques are fundamentally the same as dual Kriging. Horowitz et al. already wrote about this mathematical similarity for Radial Basis Functions (RBFs)^[1]. We already extended that mathematical foundation to explain further similarity to Support Vector Machines (SVMs) and Single Layer RBF networks in a blog post (not peer reviewed).

The problem is that these methods require fundamental statistical parameters not directly related to the geological structure, such as range. For complex folded geometries those values can be largely meaningless as they crosscut geometry. To improve reliability, one needs to apply complex unfolding, or apply pseudo-methods such as structural trends that follow the geometry but do not account for grade trends. We propose to re-think these interpolations with lessons learned from Machine Learning to improve modelling of complex geology through non-linear mapping to hyperspace. In our work we focused on SVMs, but the theory can be applied to other methods.

In IM signed distance or indicator interpolation is used with values on either side of a contact receiving opposite signs and contact points having a zero distance. These samples are used to determine a set of weights from a Covariance or Kernel Matrix. Estimates are then calculated via the generic formula: $F(x) = \sum(\omega * \varphi(x)) + b$, where the $\varphi(x)$ is a covariance function between the unknown location and the support vectors. In all cases, ω are interpolation weights derived from the matrix and b is a bias term. We can see that this is similar to a high-dimensional hyperspace defined by the $\varphi(x)$ vectors and where the weights vector acts as a normal vector to a 'decision' hyperplane. The contact points of a continuous geometry in 3D space are all mapped to lie on that hyperplane.

The implication is that after modelling the geological structure, other attributes such as grades, can be mapped to, and interpolated within, that geometric hyperspace. Assuming those other parameters are correlated to the underlying geological structure, this means anisotropy can be relatively easily decomposed as tangential to the hyperplane. Analysis of the second stage covariance can be done via experimental variograms where distances are measured in hyperspace instead of 3D. This allows for interpolation within this hyperspace along the structure of the original geometry.

The advantage of this approach is that it can be applied to any initial interpolation. Intuitively, one would first interpolate the main controlling structure, before applying secondary modelling within the resulting hyperspace. However, the method is not constrained to geometry and one could first create a hyperspace on grade, or alteration before applying secondary analysis. Moreover, once a hyperspace is created it can be applied to various other attributes, or the process can even be repeated: map to geometry for structure, re-map to alteration, then apply analysis and interpolation on grade. This allows for an intuitive and flexible chain of mappings from youngest to oldest events adapted to the project without requiring re-training.

This approach is still undergoing real world testing. In a first trial, we applied the mapping followed by simple cluster analysis. The mineral grade of interest was first interpolated using isotropic interpolation. The resulting hyperspace was then used to map geochemistry information and define clusters of high, medium and low grades. Subsequently, all points were compared to the 3 centers in hyperspace and their hyperspace distances rescaled to relative values (0-100%). We could successfully correlate high grades to particular mineralization, which enables more targeted and reliable resource estimation.