

# LatticeKrig Vignette

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# 1 Introduction

In this document, we will briefly explain what kriging is, explore the functions in the LatticeKrig package, and show examples of how they can be used to solve problems.

## 1.1 What is Kriging?

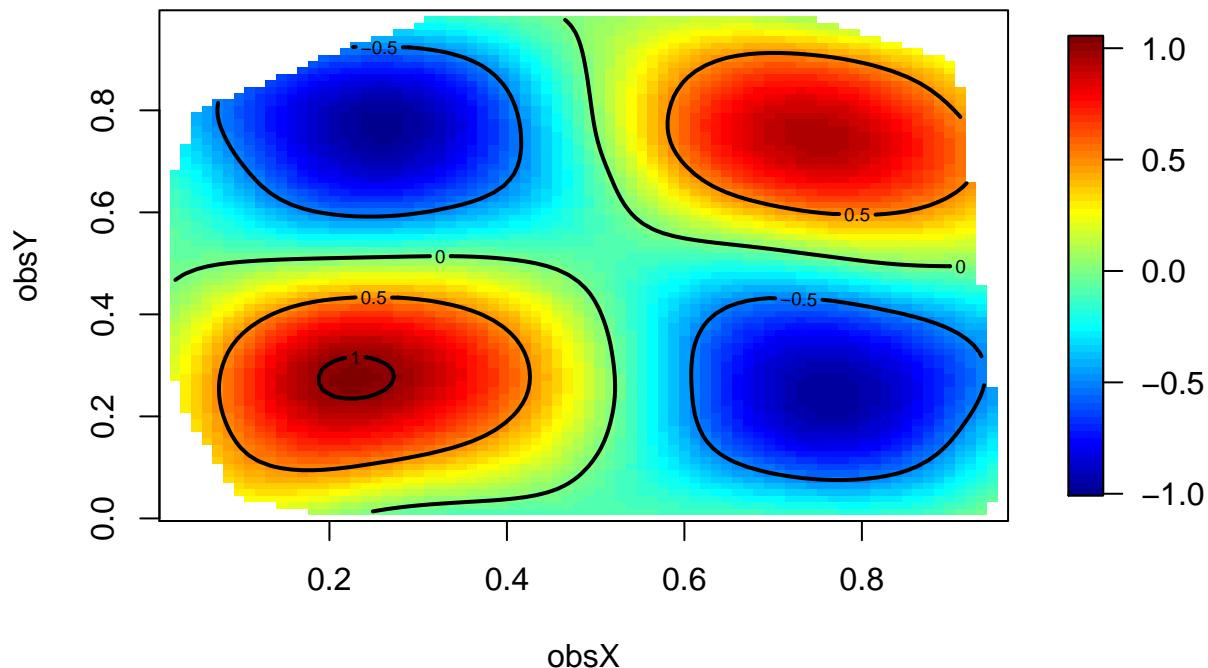
Kriging (named for South African statistician Danie Krige) is a method for making predictions from a data set. It is designed to be used on spatial data – that is, our data contains the observed variable and the location it was observed at, and pairs of observations taken close together have similar values. As such, it can be applied to a variety of physical data sets, from geological data to atmospheric data.

The goal of kriging is to create a model, based on data from some locations, that can predict the observed variable at any location.

## 2 The LatticeKrig Function

Use LatticeKrig to make all your worries go away.

```
set.seed(31734)
obsX <- runif(100);
obsY <- runif(100);
obsXY <- cbind(obsX, obsY);
obsZ <- sin(2*pi*obsX) * sin(2*pi*obsY) + 0.1*rnorm(100);
kFit <- LatticeKrig(obsXY, obsZ)
surface(kFit)
```



### 3 Appendix A: The Linear Algebra of Kriging

Suppose we have a vector of observations, where each observation  $y_i$  is taken at location  $\mathbf{s}_i$ , and a covariate matrix  $X$ . Assuming that the observations are a linear combination of the covariates with a Gaussian process of mean 0, we have

$$\mathbf{y} = X\beta + \epsilon$$

where  $\epsilon \sim MN(\mathbf{0}, \Sigma)$  for some covariance matrix  $\Sigma$ . We can then make assumptions to determine the form of  $\Sigma$ : Assuming the process is stationary,  $\sigma_{ij}$  will only depend on the vector  $\mathbf{s}_i - \mathbf{s}_j$ ; assuming the process is isotropic,  $\sigma_{ij}$  will only depend on the scalar  $\|\mathbf{s}_i - \mathbf{s}_j\|$ , which also means that  $\Sigma$  will be symmetric. This then allows us to establish a covariance function,  $f$ , such that  $\sigma_{ij} = f(\|\mathbf{s}_i - \mathbf{s}_j\|)$ . The covariance function describes how strongly correlated observations at varying distances are; as such, we would expect that  $f(0) = 1$  and  $\lim_{x \rightarrow \infty} f(x) = 0$ .