$\mathcal{GP}$ Write Up 7

October 15, 2018

Experimental results

1. Results comparison Naive vs Convolutions with Conjugate gradient loss

All the experiments are performed using the squared exponential kernel:

$$k(x,y) = \sigma_f^2 exp(\frac{(x-y)^T(x-y)}{2l^2}) \tag{1}$$

In the naive way we maximize the marginal log likelihood wrt to σ_f and l:

$$logp(y|X) = -0.5y^T(K+\sigma_n^2 I)y - 0.5log|K+\sigma_n^2 I| - 0.5nlog(2\pi) \tag{2}$$

For the training data we used three different smooth functions on a grid of size 50×50, with 5% of the observations missing and are filled with $\mathcal{N}(0, 10^{100})$.

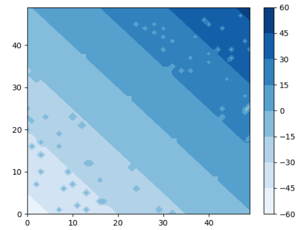
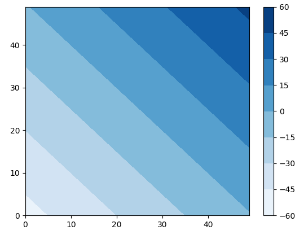
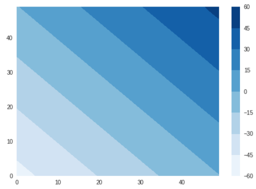
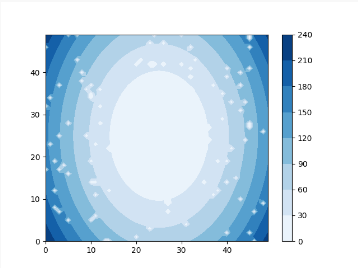
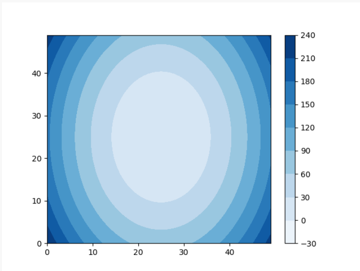
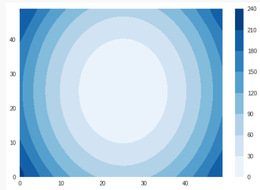
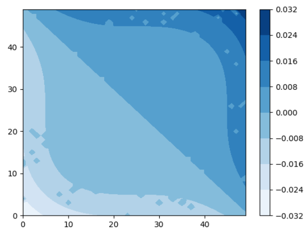
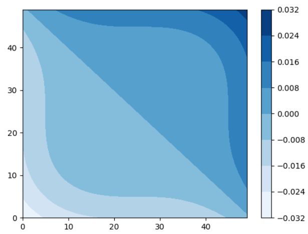
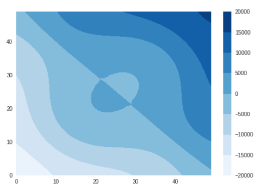
The convolution implementation uses the conjugate gradient loss and the network is run for 10k iterations, with σ_f, l set to 0.1 and 10 respectively.

We compare the performance between the methods by taking the predicted mean for the naive and convolution methods and obtaining the squared l2 norm between the predicted mean and the training data without the imaginary observations:

$$L(y\_pred, y\_train) = ((y\_pred - y\_train) * mask)^2 \tag{3}$$

For the functions described below:

$$X \in [-25, 25], Y \in [-25, 25] \tag{4}$$

Function	Train	Naive Predict	Conv Predict
$X+Y$			
X^2+Y^2			
X^3+Y^3			

Function	Naive , σ_f, l	Naive loss	Conv Loss
$X+Y$	5.6,10.7	1.8×10^{-5}	464.6
X^2+Y^2	5.9,9.8	0.0014	4k
X^3+Y^3	4.7,10.9	9.6×10^{-11}	10^{10}