

# 2020 Machine Learning Homework 5

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## Gaussian Process

- Training data:

$$\circ \begin{bmatrix} x_1 & y_1 \\ \cdot & \cdot \\ \cdot & \cdot \\ \cdot & \cdot \\ x_n & y_n \end{bmatrix} = [X \quad Y]$$

- Kernel function:

$$\circ k(x_n, x_m) = \sigma^2 \left( 1 + \frac{\|x_n - x_m\|^2}{2\alpha\ell^2} \right)^{-\alpha}$$

There is a function  $f$  could transfer each  $x_i$  into corresponding  $y_i$  ( i.e.,  $f(x_i) = y_i$  ).

Assume that  $y_i = f(x_i) + \epsilon$ , where  $\epsilon \sim N(0, \beta)$  and  $f \sim N(0, K_n)$ .

(i.e.,  $Y \sim N(f, \beta)$ )

On estimate the  $x_*$  point, we have formula  $\begin{bmatrix} Y \\ y_* \end{bmatrix} \sim N\left(\begin{bmatrix} Y \\ y_* \end{bmatrix} \mid 0, K_{n+1}\right)$

After the [derivation of probability](#), we get the

- $\mu(x_*) = k(x, x_*)^T (K_n + \beta I)^{-1} Y$
- $cov(x_*) = k(x_*, x_*) - k(x, x_*)^T (K_n + \beta I)^{-1} k(x, x_*)$

This form is almost the same as the formula mentioned by Prof. Chiu in the class.

The tiny difference is that it take the  $\beta$  out of the matrix  $K$ , but the course slide takes it into the matrix.

Thus, we could apply the  $x_*$  to describe our model.

We notice that the kernel method is decided by some kernel parameters ( e.g.,  $\sigma, \alpha, \ell$  ), so we need to find the parameters which could have the maximum likelihood.

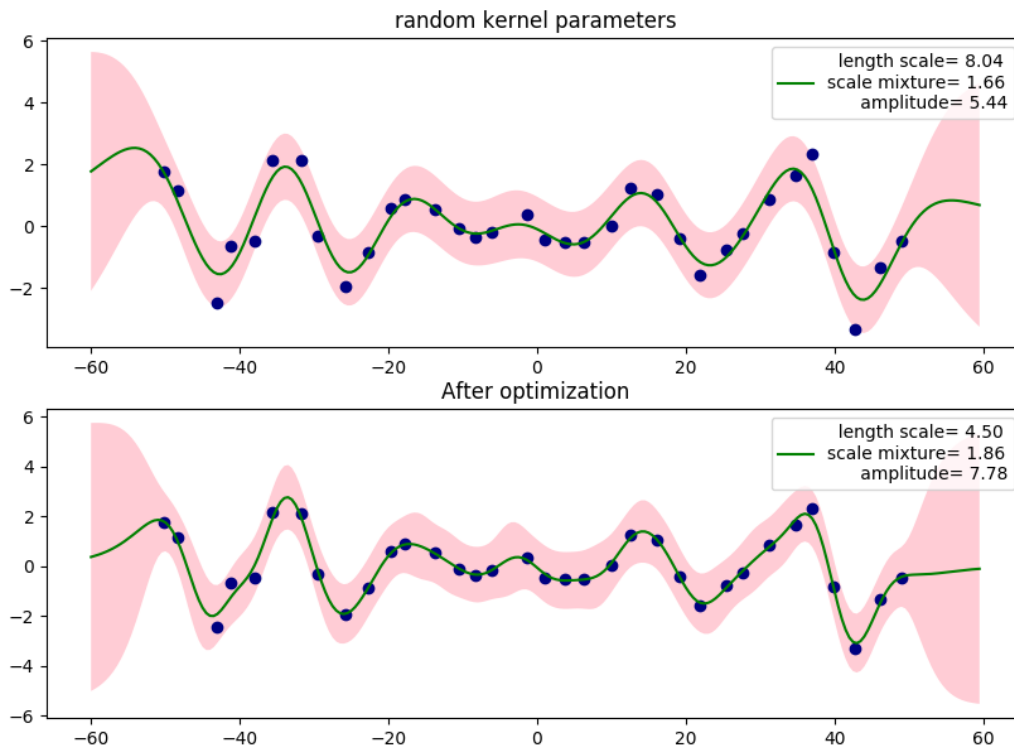
In my practice, I choose the random value of all parameter between 0 and 10, and call the

`scipy.optimize.minimize` to optimize it.

The relative formula is shown below,

$$\begin{aligned} \operatorname{argmax}(\ln p(y \mid \theta)) &= -\frac{1}{2} \ln |C_\theta| - \frac{1}{2} y^T C_\theta^{-1} y - \frac{N}{2} \ln (2\pi) \\ &\propto -\ln |C_\theta| - y^T C_\theta^{-1} y \\ &= \operatorname{argmin}(\ln |C_\theta| + y^T C_\theta^{-1} y) \end{aligned}$$

result:



## Reference

- <https://www.csie.ntu.edu.tw/~cjlin/mlgroup/tutorials/gpr.pdf>