

## Corrected KernelUCB algorithm

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We chose RBF kernel for our tests.

Using the following definitions (clears up inconsistencies):

$$\bullet k_{x^*,t} = [k(x^*, x_1), \dots, k(x^*, x_t)]^\top$$

$$\bullet y_t = [r_1, \dots, r_t]^\top$$

$$\bullet \Phi_t = [\phi(x_1)^\top, \dots, \phi(x_t)^\top]^\top$$

$$\bullet K_t = \Phi_t^\top \Phi_t$$

$$\bullet \hat{\sigma}_{a,t+1} = [\phi(x_{a,t+1})^\top (\Phi_t^\top \Phi_t + \gamma I)^{-1} \phi(x_{a,t+1})]^\frac{1}{2}$$

$$\bullet \hat{\mu}_{a,t+1} = k_{x_{a,t+1},t}^\top (K_t + \gamma I)^{-1} y_t$$

-Here  $\phi(x)$  is the vector transformation of the context vector  $x$ , with kernel function  $k(x,y) = \phi(x) \cdot \phi(y)$ .

$K(t)$  is Kernel Matrix at time  $t$ .

Gaussian probability distribution:-

1.  $\mu(a, t)$  is the mean
2.  $\sigma(a, t)$  is the standard deviation

In  $\mu$  (mean) formula, we are assuming that  $\phi_{upper}$  is square matrix, So, left inverse of  $\phi_{upper}$  = right inverse of  $\phi_{upper}$ . Hence,  $\text{inverse}([\phi_{upper\_tr}][\phi_{upper}])([\phi_{upper\_tr}]) = [\phi_{upper\_tr}][K_{inv}]$ . This enables use of Kernel matrix  $\phi_i[\phi_{upper}] = \text{transpose}[k\_x(a,t+1)]$

**Algorithm 1** KernelUCB with online updates

**Input:**  $N$  the number of actions,  $T$  the number of pulls,  $\gamma, \eta$  regularization and exploration parameters,  $k(\cdot, \cdot)$  kernel function

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1: for  $t \in 1, \dots, T$  do
2:   Receive contexts  $\{x_{1,t}, \dots, x_{N,t}\}$ 
3:   if  $t = 1$  then
4:      $u_t \leftarrow [1, 0, \dots, 0]^\top$ 
5:   else
6:     for  $n \in \{1, \dots, N\}$  do
7:        $\sigma_{n,t} \leftarrow \left[ k(x_{n,t}, x_{n,t}) - k_{x_{n,t},t-1}^\top K_{t-1}^{-1} k_{x_{n,t},t-1} \right]^\frac{1}{2}$ 
8:        $u_{n,t} \leftarrow k_{x_{n,t},t-1}^\top K_{t-1}^{-1} y_{t-1} + \frac{\eta}{\sqrt{\gamma}} \sigma_{n,t}$ 
9:     end for
10:  end if
11:  Choose action  $a_t \leftarrow \arg \max u_t$  and receive reward  $r_t$ 
12:  Store context for action  $a_t$ :  $x_t \leftarrow x_{a,t}$ 
13:  Update reward history:  $y_t \leftarrow [r_1, \dots, r_t]^\top$ 
14:  if  $t = 1$  then
15:     $K_t^{-1} \leftarrow (k(x_t, x_t) + \gamma)^{-1}$ 
16:  else
17:     $b \leftarrow k_{x_t,t-1}$ 
18:     $K_{22} \leftarrow (k(x_t, x_t) + \gamma - b^\top K_{t-1}^{-1} b)^{-1}$ 
19:     $K_{11} \leftarrow K_{t-1}^{-1} + K_{22} K_{t-1}^{-1} b b^\top K_{t-1}^{-1}$ 
20:     $K_{12} \leftarrow -K_{22} K_{t-1}^{-1} b$ 
21:     $K_{21} \leftarrow -K_{22} b^\top K_{t-1}^{-1}$ 
22:     $K_t^{-1} \leftarrow \begin{bmatrix} K_{11} & K_{12} \\ K_{21} & K_{22} \end{bmatrix}$ 
23:  end if
24: end for

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These can be proved to be equal using Woolbury matrix identity.  
\*\* proof included on the next page

▷ initialise kernel matrix inverse

▷ online update of kernel matrix inverse

# Proof of Standard Deviation formula, in Kernel-UCB algorithm, using Woodbury Matrix Identity

Anubhav Singh

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## Proof

According to the Woodbury Matrix Identity:

$$(\mathbf{A} + \mathbf{B}\mathbf{D}^{-1}\mathbf{C})^{-1} = \mathbf{A}^{-1} - \mathbf{A}^{-1}\mathbf{B}(\mathbf{D} + \mathbf{C}\mathbf{A}^{-1}\mathbf{B})^{-1}\mathbf{C}\mathbf{A}^{-1} \quad (1)$$

Now, assign the following to matrices A, B, C and D

$$\mathbf{A} = \gamma\mathbf{I}_d, \mathbf{B} = \Phi_{\text{dxt}}^T, \mathbf{C} = \Phi_{\text{txd}}, \mathbf{D} = \mathbf{I}_t \quad (2)$$

Using equation (1),

$$\begin{aligned} (\gamma\mathbf{I}_d + \Phi^T\Phi)^{-1} &= (\gamma\mathbf{I}_d + \Phi^T\mathbf{I}_t^{-1}\Phi)^{-1} \\ &= \gamma^{-1}\mathbf{I}_d^{-1} - \gamma^{-1}\mathbf{I}_d^{-1}\Phi^T(\mathbf{I}_t + \Phi(\gamma^{-1}\mathbf{I}_d^{-1})\Phi^T)^{-1}\Phi\gamma^{-1}\mathbf{I}_d^{-1} \\ &= \gamma^{-1}\mathbf{I}_d - \gamma^{-1}\mathbf{I}_d\Phi^T(\mathbf{I}_t + \Phi(\gamma^{-1}\mathbf{I}_d)\Phi^T)^{-1}\Phi\gamma^{-1}\mathbf{I}_d \\ &= \gamma^{-1}\mathbf{I}_d - \gamma^{-2}\Phi^T\gamma(\gamma\mathbf{I}_t + \Phi\Phi^T)^{-1}\Phi \\ &= \gamma^{-1}(\mathbf{I}_d - \Phi^T(\gamma\mathbf{I}_t + \Phi\Phi^T)^{-1}\Phi) \\ &= \gamma^{-1}(\mathbf{I}_d - \Phi^T(\gamma\mathbf{I}_t + \mathbf{K})^{-1}\Phi) \end{aligned} \quad (3)$$

Applying the results obtained in (3) to the Standard Deviation Formula, we get the formula used in Algorithm-1

$$\begin{aligned} \sigma_{\mathbf{n},t} &= [\phi_{\mathbf{x}_{\mathbf{n}},t}^T(\gamma\mathbf{I} + \Phi_{t-1}^T\Phi_{t-1})_{t-1}^{-1}\phi_{\mathbf{x}_{\mathbf{n}},t}]^{1/2} \\ &= [\gamma^{-1}\phi_{\mathbf{x}_{\mathbf{n}},t}^T(\mathbf{I} - \Phi_{t-1}^T(\gamma\mathbf{I} + \mathbf{K}_{t-1})^{-1}\Phi_{t-1})\phi_{\mathbf{x}_{\mathbf{n}},t}]^{1/2} \\ &= [\gamma^{-1}\{(\phi_{\mathbf{x}_{\mathbf{n}},t}^T\phi_{\mathbf{x}_{\mathbf{n}},t}) - (\phi_{\mathbf{x}_{\mathbf{n}},t}^T\Phi_{t-1}^T)(\gamma\mathbf{I} + \mathbf{K}_{t-1})^{-1}(\Phi_{t-1}\phi_{\mathbf{x}_{\mathbf{n}},t})\}]^{1/2} \\ &= \gamma^{-1/2}[\mathbf{k}(\mathbf{x}_{\mathbf{n}},t, \mathbf{x}_{\mathbf{n}},t) - \mathbf{k}_{\mathbf{x}_{\mathbf{n}},t,t-1}^T(\gamma\mathbf{I} + \mathbf{K}_{t-1})^{-1}\mathbf{k}_{\mathbf{x}_{\mathbf{n}},t,t-1}]^{1/2} \end{aligned} \quad (4)$$