

1. Positive (semi) definite

a) A symmetric matrix has real eigenvalues.

The complex version of an inner product

$$\langle s, t \rangle = s^T t^*, \quad t^* \text{ is the complex conjugate.}$$

Some properties

$$\langle Ks, t \rangle = \langle s, K^T t \rangle \quad \text{if } K \text{ is real}$$

$$\langle \lambda s, t \rangle = \lambda^* \langle s, t \rangle$$

$$\langle s, \lambda t \rangle = \lambda \langle s, t \rangle.$$

Observe for symmetric A that is real

$$\begin{aligned} \lambda^* \langle s, s \rangle &= \langle \lambda s, s \rangle = \langle As, s \rangle \\ &= \langle s, As \rangle = \langle s, \lambda s \rangle \\ &= \lambda \langle s, s \rangle. \end{aligned}$$

So $\lambda = \lambda^*$ since $\langle s, s \rangle \neq 0$.

b) If $\lambda_1, \dots, \lambda_n > 0$ then $\alpha^T K \alpha > 0 \quad \forall \alpha \in \mathbb{R}^n$,

$$K = U \Lambda U^T, \quad \Lambda_{ii}^{1/2} = \lambda_i^{1/2}.$$

$$\alpha^T U \Lambda^{1/2} \Lambda^{1/2} U^T \alpha = \alpha^T K \alpha,$$

$$r = \Lambda^{1/2} U^T \alpha$$

$$r^T = \alpha^T U (\Lambda^{1/2})^T = \alpha^T U \Lambda^{1/2}$$

$$r^T r = \|r\|^2 \geq 0.$$

i) if $\lambda_1, \dots, \lambda_n > 0 \Rightarrow r \neq 0 \Rightarrow \|r\|^2 > 0$

ii) if $\lambda_1, \dots, \lambda_n \geq 0 \Rightarrow r$ can be 0 ~~set~~
so $\|r\|^2 \geq 0$.

The eigenvalues state the matrix is positive definite if $\lambda_1, \dots, \lambda_n > 0$ and if $\lambda_1, \dots, \lambda_n \geq 0$ then positive semi-definite.

2. In words: If for any finite collection of size $n \in \mathbb{N}$ the matrix is positive definite, then the kernel function is positive definite.

$$\begin{aligned} 1) a) K(u, v) &= \langle u, v \rangle \\ &= (\langle u, v \rangle + 1)^d, \quad d > 0, d \in \mathbb{N} \end{aligned}$$

$$K(u, v) = \exp(-\kappa \|u - v\|^2)$$

are all positive (semi) definite

$$\begin{aligned} b) K(u, v) &= au^2 + 2buv + cv^2 \quad u, v \in \mathbb{R} \\ a < 0, \quad c < 0. \end{aligned}$$

Problem 2.

~~a~~

$$a. \arg \min_{f \in \mathcal{H}_k} \left[\frac{1}{n} \sum_{i=1}^n \log(1 + \exp(-\gamma_i f(x_i))) + \lambda \|f\|_k^2 \right]$$

$f_{\parallel} \in \text{span}(\phi(x_1), \dots, \phi(x_n))$ where

$$\phi(x_i) = \begin{pmatrix} \sqrt{\lambda_1} \phi_1(x_i) \\ \vdots \\ \sqrt{\lambda_k} \phi_k(x_i) \end{pmatrix}$$

$$f_{\perp} \in \text{span}(\mathcal{H}_k) \ominus f_{\parallel}.$$

$$f = f_{\perp} + f_{\parallel}$$

From notes

$$\frac{1}{n} \sum_{i=1}^n \log(1 + \exp(-\gamma_i f(x_i))) = \frac{1}{n} \sum \log(1 + \exp(-\gamma_i f_{\parallel}(x_i)))$$

because $f(x_i) = \langle f, \phi(x_i) \rangle$
 $= \langle f_{\parallel}, \phi(x_i) \rangle$

$$\|f_{\parallel} + f_{\perp}\|_K^2 > \|f_{\parallel}\|_K^2 \quad \text{if } f_{\perp} \neq 0.$$

So $f_{\perp} = 0$ ~~for~~ for minimizer, or

$$f(x) = \sum_{i=1}^n \alpha_i k(x, x_i)$$

b) $\arg \min_{\alpha \in \mathbb{R}^n} \left[\frac{1}{n} \sum \log(1 + \exp(-y_i K \alpha)) + \lambda \alpha^T K \alpha \right]$

c) $K(u, v) = (1 + u^T v)^2, \quad u, v \in \mathbb{R}^2$

$$\phi(u) = \begin{pmatrix} \frac{1}{\sqrt{2}} u \\ u^2 \end{pmatrix}, \quad \phi(v) = \begin{pmatrix} \frac{1}{\sqrt{2}} v \\ v^2 \end{pmatrix}$$

$$\begin{aligned} \phi^T(u) \phi(v) &= 1 + 2uv + u^2 v^2 \\ &= (1 + uv)^2 \end{aligned}$$

Problem 3,

Go look at

fourier.eng.hmc.edu/e161/lectures/

[gaussian process/](#)

[node7.html](#)

Problem 4.

a) Primal:

$$\min_c \quad \frac{1}{2} c^T K c + C \sum \xi_i$$

$$\text{s.t.} \quad y_i \left(\sum_j c_j k(x_i, x_j) \right) \geq 1 - \xi_i, \quad i=1, \dots, n$$

$$\xi_i \geq 0$$

Dual:

$$L(c, \xi, \alpha, \eta) = \frac{1}{2} c^T K c + C \sum \xi_i - \sum_i \alpha_i \left[y_i \left(\sum_j c_j k(x_i, x_j) \right) - 1 + \xi_i \right]$$

$$- \sum_i \eta_i \xi_i$$

$$\frac{\partial L}{\partial \xi_i} = 0 \Rightarrow C - \alpha_i - \eta_i = 0 \Rightarrow$$

$$L^R(c, \alpha, \eta) = \frac{1}{2} c^T K c$$

$$- \sum \alpha_i \left[y_i \left(\sum_j c_j k(x_i, x_j) \right) - 1 \right]$$

also $0 \leq \alpha_i \leq C$

$$L^R(c, \alpha, \lambda) = \frac{1}{2} c^T K c + \sum \alpha_i - \sum_i \alpha_i \left[\sum_j c_j K(x_i, x_j) \right]$$

$$\frac{\partial L^R}{\partial c} = 0 \Rightarrow \text{Dual} \quad c_i = \alpha_i y_i$$

$$\min_{\alpha \in \mathbb{R}^n} \quad \sum \alpha_i - \alpha^T Q \alpha, \quad Q_{ij} = K_{ij} y_i y_j$$

$$\text{s.t.} \quad 0 \leq \alpha_i \leq C.$$

b) KKT conditions

$$C - \alpha_i - \eta_i = 0$$

$$y_i \left(\sum_j y_j \alpha_j k(x_i, x_j) \right) - 1 + \xi_i \geq 0, \quad i=1, \dots, n$$

$$\alpha_i \left[y_i \left(\sum_j y_j \alpha_j k(x_i, x_j) \right) - 1 + \xi_i \right] = 0, \quad i=1, \dots, n$$

$$\eta_i \xi_i = 0, \quad i=1, \dots, n$$

$$\xi_i, \alpha_i, \eta_i \geq 0, \quad i=1, \dots, n$$

$$\sum_j c_j k(x_i, x_j) - \sum_j y_j \alpha_j k(x_i, x_j) = 0, \quad i=1, \dots, n,$$