Homework #1

John Karasev STAT 672 January 22, 2020

1 Orthogonal projection in a hilbert space

$$\pi_V(f) \in V;$$

$$\langle f - \pi_V(f), g \rangle = 0 \ \forall g \in V;$$

1.
$$||f||^{2} = \langle f, f \rangle$$

$$= \langle \pi_{v}(f) + (f - \pi_{v}(f)), \pi_{v}(f) + (f - \pi_{v}(f)) \rangle$$

$$= \langle \pi_{v}(f), \pi_{v}(f) \rangle + 2\langle \pi_{v}(f), f - \pi_{v}(f) \rangle + \langle f - \pi_{v}(f), f - \pi_{v}(f) \rangle$$

$$= ||\pi_{v}(f)||^{2} + ||f - \pi_{v}(f)||^{2} \text{ center term cancels since orthogonal}$$
2.
$$\langle f, \pi_{v}(g) \rangle = \langle (f - \pi_{v}(f)) + \pi_{v}(f), \pi_{v}(g) \rangle$$

$$= \langle f - \pi_{v}(f), \pi_{v}(g) \rangle + \langle \pi_{v}(f), \pi_{v}(g) \rangle$$

$$= \langle \pi_{v}(f), \pi_{v}(g) \rangle \text{ by orthogonality}$$

$$\langle g, \pi_{v}(f) \rangle = \langle (g - \pi_{v}(g)) + \pi_{v}(g), \pi_{v}(f) \rangle$$

 $= \langle g - \pi_v(g), \pi_v(f) \rangle + \langle \pi_v(g), \pi_v(f) \rangle$ = $\langle \pi_v(g), \pi_v(f) \rangle$ by orthogonality

$$\langle q, \pi_v(f) \rangle = \langle f, \pi_v(q) \rangle$$

3.

2 A reproducing kernel is positive definite

1. $K(x,y) = \langle K_x(.), K_y(.) \rangle \ by \ reproducing \ property$ $K(y,x) = \langle K_y(.), K_x(.) \rangle \ by \ reproducing \ property$ $K(x,y) = \langle K_x(.), K_y(.) \rangle = \langle K_y(.), K_x(.) \rangle = K(y,x)$

2.
$$for \ any \ n \in \mathbb{N}, \ (a_1, ..., a_n) \in \mathbb{R}^n ,$$

$$(x_1, ..., x_n) \in \mathbb{X}^n$$

$$\sum_{i,j=1}^n a_i a_j K(x_i, x_j) = \sum_{i,j=1}^n a_i a_j \langle Kx_i, Kx_j \rangle_{\mathcal{H}}$$

$$= \left\| \sum_{i=1}^n a_i Kx_i \right\|_{\mathcal{H}} \ge 0$$

$$(1)$$

3.

$$|\langle f, K_x \rangle| \le ||f|| ||K_x|| \text{ true by } Cauchy - Schwartz inequality$$

 $|\langle f, K_x \rangle| \le ||f|| \sqrt{\langle K_x, K_x \rangle} \text{ by norm definition}$
 $|f(x)| \le ||f|| \sqrt{K(x, x)} \text{ reproducing property}$

3 RKHS over a finite set

1.

$$\langle \boldsymbol{f}, \boldsymbol{g} \rangle = \boldsymbol{f}^T \boldsymbol{K}^{-1} \boldsymbol{g} \quad \boldsymbol{f}, \boldsymbol{g} \in \mathbb{R}^{2m+1}$$

$$\mathcal{N}(\boldsymbol{x}; \boldsymbol{\mu}, \boldsymbol{\Sigma}) = \frac{1}{(2\pi)^{\frac{n}{2}} |\boldsymbol{\Sigma}|^{\frac{1}{2}}} exp \left\{ \frac{-(\boldsymbol{x} - \boldsymbol{\mu})^T \boldsymbol{\Sigma}^{-1} (\boldsymbol{x} - \boldsymbol{\mu})}{2} \right\} \quad \boldsymbol{x} \in \mathbb{R}^n$$

$$p(\boldsymbol{f}) = Ce^{-\frac{\|\boldsymbol{f}\|_H^2}{2}}$$

$$= Cexp \left\{ -\frac{\boldsymbol{f}^T \boldsymbol{K}^{-1} \boldsymbol{f}}{2} \right\}$$

$$= \frac{1}{(2\pi)^{\frac{2m+1}{2}} |\boldsymbol{K}|^{\frac{1}{2}}} exp \left\{ -\frac{\boldsymbol{f}^T \boldsymbol{K}^{-1} \boldsymbol{f}}{2} \right\}$$

$$p(\boldsymbol{f}) = \mathcal{N}(\boldsymbol{f}; \boldsymbol{0}, \boldsymbol{K})$$

$$\therefore \quad \boldsymbol{\mu} = \boldsymbol{0}$$

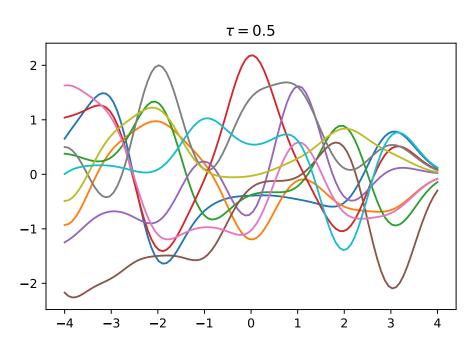
$$\boldsymbol{\Sigma} = \boldsymbol{K}$$

 $2.\ C$ is a normalizing constant so the probability distribution sums to 1

$$C = \frac{1}{(2\pi)^{\frac{2m+1}{2}} |\mathbf{K}|^{\frac{1}{2}}}$$

which is taken from the $\mathcal{N}(f; \mathbf{0}, K)$ normalization constant

3. (a) kernel matrix: $\mathbf{K} = [k_{ij}] = e^{-\frac{(i-j)^2}{2\tau^2}}$



(b) functions become smoother as τ increases

