

today: continue RKHS in all their glory. ▽

$$\langle k(x, \cdot), k(x', \cdot) \rangle_{\mathcal{H}} = k(x, x')$$

\uparrow \uparrow
 $\Phi(x)$ $\Phi(x')$

"reproducing property"

$$\langle f, k(x, \cdot) \rangle_{\mathcal{H}} = f(x)$$

\uparrow
 $\Phi(x)$

analog: $\langle w, \Phi(x) \rangle$

$$\langle \Phi(x), \Phi(x') \rangle = k(x, x')$$

representer's thm says that (for \mathcal{H} a RKHS)

$$\min_{f \in \mathcal{H}} \frac{1}{n} \sum_{i=1}^n \ell(y_i, f(x_i)) + \lambda \|f\|_{\mathcal{H}}^2$$

is reached for $f^* = \sum_{i=1}^n \alpha_i^* k(x_i, \cdot)$

$(x_i, y_i)_{i=1}^n$
training set

let $f_{\alpha} = \sum_{i=1}^n \alpha_i k(x_i, \cdot)$ $\alpha \in \mathbb{R}^n$

then $\|f_{\alpha}\|_{\mathcal{H}}^2 = \langle f_{\alpha}, f_{\alpha} \rangle_{\mathcal{H}} = \sum_{i,j} \alpha_i \alpha_j k(x_i, x_j) = \alpha^T K \alpha$

$n \times n$ matrix

Gram matrix: $(K)_{i,j} \triangleq k(x_i, x_j) = \langle \Phi(x_i), \Phi(x_j) \rangle_{\mathcal{H}}$

\hookrightarrow inner product of $\Phi(x_i)$ on data

$$\min_{\alpha \in \mathbb{R}^n} \frac{1}{n} \sum_{i=1}^n \ell(y_i, \underbrace{\sum_j \alpha_j k(x_j, x_i)}_{f_{\alpha}(x_i)}) + \lambda \alpha^T K \alpha$$

finite dim. opt.

(thanks to representer's thm)

$$f_{\alpha}(x) = \sum_j \alpha_j \underbrace{k(x_j, x)}_{\langle \Phi(x_j), \Phi(x) \rangle_{\mathcal{H}}}$$

getting a handle on \mathcal{H} : generalize diagonalization of matrices to ∞ -dim

I) start with finite matrices

say X is finite eg. x_1, \dots, x_n

$|X| = n$

$f: X \rightarrow \mathbb{R}$
 \hookrightarrow is finite \Rightarrow just a vector

$$\begin{pmatrix} f(x_1) \\ \vdots \\ f(x_n) \end{pmatrix} \in \mathbb{R}^n$$

("2 norm")

$$(k\alpha)_i = \sum_j \alpha_j k(x_j, x_i)$$

$$= \sum_j \alpha_j k(x_j, x_i) = (k\alpha)_i$$

\dots $n \times n$ "0 1"

\rightarrow vector (function)

$$\mathcal{H} = \text{span} \{ k(x_i, \cdot) : i=1, \dots, n \} = \{ k\alpha : \alpha \in \mathbb{R}^n \} \subseteq \mathbb{R}^n \quad \text{"S}_2\text{-view"}$$

let K be Gram matrix $(k)_{ij} \triangleq k(x_i, x_j)$

if k is a valid kernel (i.e. defines a inner product)

$$\Rightarrow K \succeq 0$$

$$\text{diag}(\lambda_1, \dots, \lambda_n)$$

$$\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_n \geq 0$$

$$\text{spectral thm.} \Rightarrow K = U \Lambda U^T$$

and U is orthonormal basis of \mathbb{R}^n

$$\text{i.e. } U = \begin{pmatrix} \psi_1 & \dots & \psi_n \\ | & & | \\ \psi_1 & & \psi_n \end{pmatrix}$$

$$U^T U = U U^T = I_n \quad \langle \psi_i, \psi_j \rangle_{\mathcal{S}_2} = \delta_{ij}$$

$$\text{we can let } \tilde{\Phi} \triangleq \Lambda^{1/2} U^T$$

$$\Rightarrow K = \tilde{\Phi} \tilde{\Phi}^T$$

$$\tilde{\Phi} = \begin{pmatrix} -\sqrt{\lambda_1} \psi_1^T & \dots & 0 \\ \vdots & \ddots & \vdots \\ -\sqrt{\lambda_d} \psi_d^T & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & 0 \end{pmatrix}$$

$$d = \text{rank}(K) \leq n$$

$$\tilde{\Phi}: \mathcal{X} \rightarrow \mathbb{R}^d$$

$$\Rightarrow \langle \tilde{\Phi}(x_i), \tilde{\Phi}(x_j) \rangle_{\mathbb{R}^d}$$

$$= k(x_i, x_j)$$

$$\Rightarrow$$

$$\tilde{\Phi}(x) = \begin{pmatrix} \sqrt{\lambda_1} \psi_1(x) \\ \vdots \\ \sqrt{\lambda_d} \psi_d(x) \end{pmatrix} \in \mathbb{R}^d$$

"feature space" pt. of view

$$k(x_i, x_j) = \langle \tilde{\Phi}(x_i), \tilde{\Phi}(x_j) \rangle_{\mathbb{R}^d} = \sum_{l=1}^d \lambda_l \psi_l(x_i) \psi_l(x_j)$$

$$\text{note: } K \psi_i = \lambda_i \psi_i$$

back to \mathcal{S}_2 -view: $\mathcal{H} \subseteq \mathcal{S}_2 \subseteq \mathbb{R}^n$

$$v \in \mathcal{H} \Rightarrow v = k\alpha \text{ for some } \alpha \in \mathbb{R}^n$$

to get $\|v\|_{\mathcal{H}}$, we compute $\alpha_v = K^{\dagger} v$ (pseudo-inverse)

$$\text{so } \|v\|_{\mathcal{H}}^2 = \alpha_v^T K \alpha_v = v^T K^{\dagger} K v$$

$$= v^T U \Lambda^{\dagger} U^T U \begin{pmatrix} I_d & 0 \\ 0 & 0 \end{pmatrix} U^T \quad K = U \Lambda U^T$$

$$= (U^T v)^T \Lambda^{\dagger} (U^T v)$$

$$K^{\dagger} = U \Lambda^{\dagger} U^T$$

$$= U \begin{pmatrix} I_d & 0 \\ 0 & 0 \end{pmatrix} U^T$$

$$\|v\|_{\mathcal{H}}^2 = \sum_{j=1}^d \frac{\langle v, \psi_j \rangle_{\mathcal{S}_2}^2}{\lambda_j}$$

$U^T v$ is projection of v onto $\{ \psi_j \}_{j=1}^n$ basis

$$\text{i.e. } v = \sum_{j=1}^n \beta_j \psi_j \quad \text{i.e. } \beta_j \triangleq \langle v, \psi_j \rangle_{\mathcal{S}_2}$$

more generally, $\|v\|_{\mathcal{H}}^2 = \sum_{j=1}^{\infty} \frac{\langle v, \psi_j \rangle_{\mathcal{S}_2}^2}{\lambda_j}$
 = + ∞ if any $\langle v, \psi_j \rangle_{\mathcal{S}_2} \neq 0$ for $j > d$

$$\|v\|_{\mathcal{H}}^2 \geq \dots \geq 2$$

vs. $\|v\|_{\mathcal{L}_2}^2 = \sum_{j=1}^{\infty} \langle v, \psi_j \rangle_{\mathcal{L}_2}^2$

and $\| \psi_j \|_{\mathcal{L}_2}^2 = \frac{1}{\lambda_j}$
for $j \leq d$

$\| \psi_j \|_{\mathcal{H}} = +\infty$
for $j > d$

so orthonormal basis of \mathcal{H} in \mathcal{L}_2
is $\{ \sqrt{\lambda_j} \psi_j \}_{j=1}^d$

$\langle v, v \rangle_{\mathcal{L}_2} = \sum_{i=1}^n \beta_i^2$
 $\langle v, v \rangle_{\mathcal{H}} = \sum_{i=1}^n \frac{\beta_i^2}{\lambda_i}$

thus $\|v\|_{\mathcal{H}} \leq 1$

↳ makes an ellipsoid in \mathcal{L}_2

ie. higher coordinates are shrunk more?
(since λ_i 's is smaller as $i \uparrow$)

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II) generalization to ∞ -dim \mathcal{H}

suppose X is a compact normed space (e.g. $X = [0,1]$)

+ Lebesgue measure on it

$\mathcal{L}_2(X) \triangleq \{ f: X \rightarrow \mathbb{R} \mid \int_X (f(x))^2 dx < \infty \}$

$\mathcal{L}_2 \triangleq \{ (\alpha_i)_{i=1}^{\infty} \text{ s.t. } \sum \alpha_i^2 < \infty \}$

let k be a cts. psd kernel fct. (note: it is symmetric)

↳ with respect to standard norm on $X \times \mathbb{R}$

define $L_k: \mathcal{L}_2 \rightarrow \mathcal{L}_2$ $k(\cdot, x)$
s.t. $[L_k f](\cdot) \triangleq \int_X k(x, \cdot) f(x) dx$

$Kv = \sum_i K_{i,j} v_j$

then can show that

L_k is a "compact self-adjoint positive" operator

and yields an (countable) orthonormal basis (for \mathcal{L}_2)
[Hilbert basis]

of e -functions for L_k $\{ \psi_i \}_{i=1}^{\infty}$

with non-negative e -values $\lambda_1 \geq \lambda_2 \geq \dots \geq 0$

ie. $L_k \psi_i = \lambda_i \psi_i$

and we have $k(x, z) = \sum_{i=1}^{\infty} \lambda_i \psi_i(x) \psi_i(z)$

$\langle f, L_k g \rangle_{\mathcal{L}_2}$
 $= \langle L_k f, g \rangle_{\mathcal{L}_2} \quad \forall f, g$

finite version: $\langle v, K w \rangle$

$= v^T K w$
 $= v^T K^T w$ use $k = k^T$
 $= \langle K v, w \rangle$

" $U \Lambda U^T$ "

and we have
$$K(x, x') = \sum_{i=1}^{\infty} \lambda_i \psi_i(x) \psi_i(x')$$

Mercer's thm

" $U \Lambda U^T$
like $K = \tilde{\Phi} \tilde{\Phi}^T$
of before

a) feature space $\mathcal{H} \subseteq \ell_2$
view of \mathcal{H}

$\Phi: X \rightarrow \ell_2$ with $(\Phi(x))_i \triangleq \sqrt{\lambda_i} \psi_i(x)$

here: $k(x, x') = \langle \Phi(x), \Phi(x') \rangle_{\ell_2}$

"diagonalized representation"

here identify $k(x, x') \in \mathcal{L}_2$ as $\Phi(x) \in \ell_2$

$\sum_i (\Phi(x))_i^2 = \sum_i \lambda_i \psi_i^2(x) = k(x, x) \leq \lambda_0$

\downarrow valid element of ℓ_2 because

(do not know what $\mathcal{H} \subseteq \ell_2$ looks like though) $\beta_i \downarrow \|f\|_{\mathcal{H}}^2 < \infty$

b) \mathcal{L}_2 view

$$\mathcal{H} \subseteq \mathcal{L}_2 : \mathcal{H} = \left\{ f \in \mathcal{L}_2 : \sum_{i=1}^{\infty} \frac{\langle f, \psi_i \rangle_{\mathcal{L}_2}^2}{\lambda_i} < \infty \right\}$$

$$\langle f, g \rangle_{\mathcal{H}} \triangleq \sum_{i=1}^{\infty} \frac{\langle f, \psi_i \rangle_{\mathcal{L}_2} \langle g, \psi_i \rangle_{\mathcal{L}_2}}{\lambda_i}$$

\rightarrow ellipsoid in \mathcal{L}_2

\otimes if K is "universal"

$\Rightarrow \mathcal{H}_K$ is dense in \mathcal{L}_2 i.e. for any $f \in \mathcal{L}_2$

\exists a sequence $h_n \in \mathcal{H}_K$ st. $\|h_n - f\|_{\mathcal{L}_2} \xrightarrow{n \rightarrow \infty} 0$

note: if $f \notin \mathcal{H} \Rightarrow \|h_n\|_{\mathcal{H}} \rightarrow \infty$

* non-parametric learning:

$$\hat{f}_n = \operatorname{argmin}_{f \in \mathcal{H}} \underbrace{\frac{1}{n} \sum_{i=1}^n \mathcal{L}(y_i, f(x_i))}_{n \rightarrow \infty \mathbb{E} \mathcal{L}(f)} + \lambda_n \|f\|_{\mathcal{H}}^2$$

$f^* \triangleq \operatorname{argmin}_{f \in \mathcal{L}_2} \mathbb{E} \mathcal{L}(y, f(x))$ perhaps $f^* \notin \mathcal{H}$

but \mathcal{H} dense in \mathcal{L}_2

\rightarrow regularity property $\lambda_n \rightarrow 0$ at correct rate
 \Rightarrow consistency of \hat{f}_n i.e. $\hat{f}_n \xrightarrow{n \rightarrow \infty} f^*$

$\| \hat{f}_n - f^* \|_{\mathcal{L}_2}$

e.g. SVM with RBF kernel is "universally consistent"
when $\lambda_n \rightarrow 0$ at correct rate