

kernels

Part 1

- A kernel is an inner product for a Hilbert space
 - ↑ symmetric, bilinear strictly pos def
 - ↑ vector space inner product complete
- If the world is finite and k is its inner product, then k is symmetric and norms ≥ 0 \rightarrow "Gram" matrix $K = \begin{bmatrix} \ddots & \ddots & \ddots \\ & k(x_i, x_i) & \\ \vdots & & \ddots \end{bmatrix}$ is symmetric & pos semidef
- Def kernel: symmetric & has pos. semidef Gram matrices

Part 2

Create an infinite dimensional map ϕ

Use it to create a vector space

$$\begin{array}{ccc} & \phi & \\ & \searrow & \\ \dot{x} & & \phi(x)(\cdot) \end{array}$$

"Vector" $f(\cdot) = \sum_{i=1}^m \alpha_i \overbrace{k(\cdot, x_i)}^{\phi}$

"another vector" $g(\cdot) = \sum_{j=1}^{m'} \beta_j k(\cdot, x'_j)$

with inner product defined $\langle f, g \rangle_{\mathcal{H}_k} := \sum_{i=1}^m \sum_{j=1}^{m'} \alpha_i \beta_j k(x_i, x'_j)$

What if we compute: $\langle k(\cdot, x), f \rangle_{\mathcal{H}_k} = \langle k(\cdot, x), \sum_{i=1}^m \alpha_i k(\cdot, x_i) \rangle_{\mathcal{H}_k}$

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

So, $\left. \begin{array}{l} \langle k(\cdot, x), f \rangle_{\mathcal{H}_k} = f(x) \\ \langle k(\cdot, x), k(\cdot, x') \rangle_{\mathcal{H}_k} = k(x, x') \end{array} \right\} \text{"reproducing property"}$

Our vector space is thus a reproducing kernel Hilbert space (RKHS)

$$x \xrightarrow{\phi} k(\cdot, x)$$

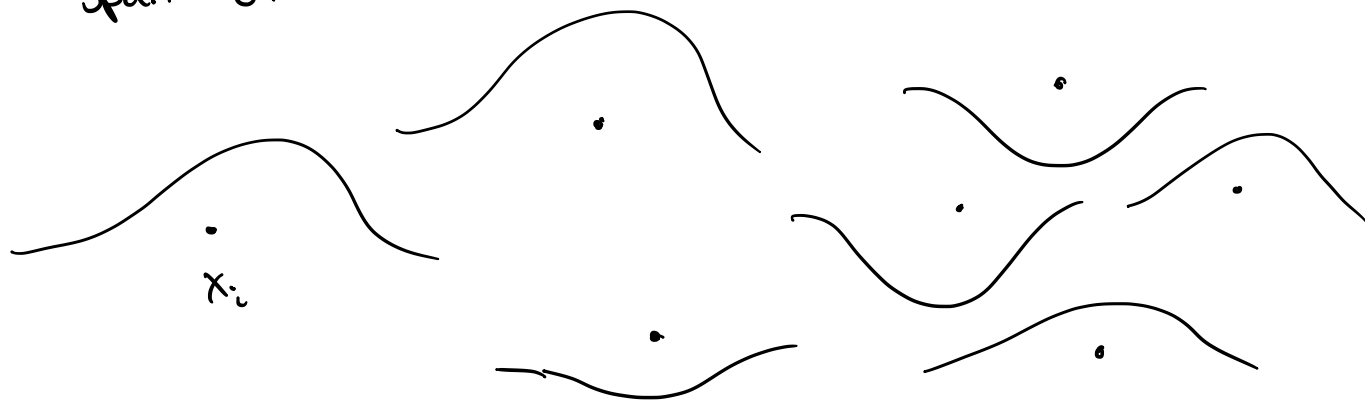
Part 3 Representer Theorem

set X , kernel k , RKHS \mathcal{H}_k , loss $l: \mathbb{R}^2 \rightarrow \mathbb{R}$

Consider $f^* \in \operatorname{argmin}_{f \in \mathcal{H}_k} \sum_{i=1}^n l(f(x_i), y_i) + \|f\|_{\mathcal{H}_k}^2$.

Theorem $f^*(\cdot) = \sum_{i=1}^n \alpha_i k(x_i, \cdot)$.

Even if RKHS is infinite dimensional, and x_i 's are chosen arbitrarily, for any loss l , the solution lies in the span of kernels centered on x_i 's !



Part 4 Show that gaussian kernel is a valid kernel.