

• Functional : function  $\mapsto \mathbb{R}$

e.g.

evaluation functional :  $E_x(f)$  is evaluating at  $x$      $E_x(f) = f(x)$

summation functional :  $S_{x_1, \dots, x_n}(f) = \sum_i f(x_i)$

integration functional :  $I_{[a, b]}(f) = \int_a^b f(x) dx$

the composition of a function  $g: \mathbb{R} \rightarrow \mathbb{R}$  with a functional is also a functional

• Derivative of functionals

let  $k$  be a kernel,  $\mathcal{H}$  be the RHTS of  $K$ ,  $E: \mathcal{H} \rightarrow \mathbb{R}$  be a functional

$D_E(f): \mathcal{H} \rightarrow \mathcal{H}$  is the functional gradient of  $E$  at  $f$

s.t.  $\lim_{\|h\|_{\mathcal{H}} \rightarrow 0} \frac{\|E(f+h) - E(f) - \langle D_E(f), h \rangle_{\mathcal{H}}\|}{\|h\|_{\mathcal{H}}} \Rightarrow f \in \mathcal{H}$  gets

e.g.  $E_x(f) = f(x)$

$$E_x(f+h) = f(x) + h(x) = f(x) + \langle h, k(x) \rangle_{\mathcal{H}}$$

$$D_E(f) = k(x)$$

$$\lim_{\|h\|_{\mathcal{H}} \rightarrow 0} \frac{\|E_x(f+h) - E_x(f) - \langle D_E(f), h \rangle_{\mathcal{H}}\|}{\|h\|_{\mathcal{H}}} = \lim_{\|h\|_{\mathcal{H}} \rightarrow 0} \frac{|f(x) + h(x) - f(x) - \langle k(x), h \rangle|}{\|h\|_{\mathcal{H}}} = 0$$

e.g.  $E(f) = \|f\|_{\mathcal{H}}^2$

$$E(f+h) = \|f+h\|_{\mathcal{H}}^2 = \|f\|_{\mathcal{H}}^2 + \|h\|_{\mathcal{H}}^2 + 2\langle f, h \rangle_{\mathcal{H}}$$

$$D_E(f) = 2f$$

$$\lim_{\|h\|_{\mathcal{H}} \rightarrow 0} \frac{\|E(f+h) - E(f) - \langle D_E(f), h \rangle\|}{\|h\|_{\mathcal{H}}} = \lim_{\|h\|_{\mathcal{H}} \rightarrow 0} \frac{\|h\|_{\mathcal{H}}^2}{\|h\|_{\mathcal{H}}} = 0$$

let  $E: \mathcal{H} \rightarrow \mathbb{R}$      $f: \mathbb{R} \rightarrow \mathbb{R}$      $h(f) = g(E(f))$

$$D_h(f) = g'(E(f)) \cdot D_E(f) \quad \text{chain rule}$$

## Eg. Kernel Regression



given data  $\{(x_i, y_i)\}_{i=1}^m$

$$\text{model: } f = \sum_{i=1}^m \alpha_i K(x_i, \cdot) \in \mathcal{H}$$

$$K(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right)$$

$$\min_{f \in \mathcal{H}} L(f) = \frac{1}{m} \sum_{i=1}^m (f(x_i) - y_i)^2 + \lambda \|f\|_H^2$$

$$\begin{aligned} D_L(f) &= \frac{2}{m} \sum_{i=1}^m (f(x_i) - y_i) K(x_i, \cdot) + 2\lambda f \\ &= \frac{2}{m} \sum_{i=1}^m [(f(x_i) - y_i) + 2\lambda \alpha_i] K(x_i, \cdot) \quad \frac{\partial f}{\partial x_i} = \frac{2}{m} (f(x_i) - y_i) + 2\lambda \alpha_i \end{aligned}$$

$$\begin{aligned} \|D_L(f)\|_H^2 &= \frac{4}{m} \sum_{i=1}^m \sum_{j=1}^m (f(x_i) - y_i) K(x_i, x_j) (f(x_j) - y_j) \\ &\quad + 4\lambda^2 \|f\|_H^2 \\ &\quad + 2 \left\langle \frac{2}{m} \sum_{i=1}^m (f(x_i) - y_i) K(x_i, \cdot), 2\lambda f \right\rangle_H \\ &= \frac{4}{m^2} (f - y)^T K (f - y) + 4\lambda^2 \alpha^T K \alpha + \frac{8}{m} (f - y)^T f \end{aligned}$$

Backtracking Line search

$$\text{while } L(f) - t c \|D_L(f)\|_H^2 < L(f - t D_L(f))$$

$$t := 0.5t$$