Discussion 7 No free lunch theory

田鹏超

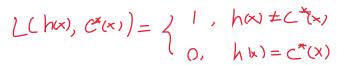
tianpch@shanghaitech.edu.cn

PAC/SLT models for Supervised Learning

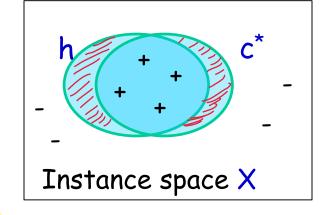
- X feature or instance space; distribution D over X e.g., $X = R^d$ or $X = \{0,1\}^d$
- Algo sees training sample S: $(x_1,c^*(x_1)),...,(x_m,c^*(x_m)),x_i$ i.i.d. from D
 - labeled examples assumed to be drawn i.i.d. from some distr.
 D over X and labeled by some target concept c*
 - labels $\in \{-1,1\}$ binary classification

 $C^*: X \rightarrow 303$

- Algo does optimization over S, find hypothesis h.
- Goal: h has small error over D. $\neq C^*(x)$ $= err_D(h) = \Pr_{x \sim D}(h(x) \neq c^*(x))$



Need a bias: no free lunch.





NFL (no free lunch) Theorem:

(无万金油算法定理)

- $P(h \mid X, \mathscr{A})$: the probability of finding hypothesis h when applying learning algorithm \mathscr{A} on training set $X \subset \mathscr{X}$
- f is the target function, $X \subset \mathcal{X}$ is noise-free
- Consider the o-1 error
- Purpose: compare the performance of different A

The out-of-sample error of \mathcal{A} is given by:

$$E(\mathcal{A} \mid X, f) = \sum_{h} \sum_{x \in \mathcal{X} - X} P(x) \delta(h(x) \neq f(x)) P(h \mid X, \mathcal{A})$$

- 1. D. H. Wolpert, "The Lack of A Priori Distinctions Between Learning Algorithms," in *Neural Computation*, vol. 8, no. 7, pp. 1341-1390, Oct. 1996.
- 2. David H. Wolpert and William G. Macready, "No Free Lunch Theorems for Optimization", *IEEE TRANSACTIONS ON EVOLUTIONARY COMPUTATION*, VOL. 1, NO. 1, APRIL 1997
- 3. https://www.kdnuggets.com/2019/09/no-free-lunch-data-science.html

无万金油算法定理

$$E(\mathcal{A} \mid X, f) = \sum_{h} \sum_{\mathbf{x} \in \mathcal{X} - X} P(\mathbf{x}) \mathbb{I}(h(\mathbf{x}) \neq f(\mathbf{x})) P(h \mid X, \mathcal{A})$$

If you apply \mathcal{A} to any problem (any f), the overall out-of-sample error of \mathcal{A} is given by:

$$\sum_{f} E(\mathcal{A}|X,f) = \sum_{f} \sum_{h} \sum_{x \in \mathcal{X}-X} P(x) \mathbb{I}(h(x) \neq f(x)) P(h|X,\mathcal{A})$$

$$= \sum_{h} \sum_{x \in \mathcal{X}-X} P(x) P(h|X,\mathcal{A}) \sum_{f} \delta(h(x) \neq f(x))$$

$$= \sum_{x \in \mathcal{X}-X} P(x) \sum_{h} P(h|X,\mathcal{A}) \sum_{f} \delta(h(x) \neq f(x))$$

$$= \sum_{x \in \mathcal{X}-X} P(x) \sum_{h} P(h|X,\mathcal{A}) \frac{1}{2} \mathbb{I}^{|\mathcal{X}|}$$

$$= \frac{1}{2} 2^{|\mathcal{X}|} \sum_{x \in \mathcal{X}-X} P(x) \cdot 1 = 0.5 \cdot 2^{|\mathcal{X}|}$$