Non-parametric Models for Non-negative Functions

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Prototypical machine learning task

Goal : find $f_* : \mathcal{X} \to \mathbb{R}$ using *n* training points $(x_i)_{1 \leq i \leq n}$.

$$f_{\star} \in \arg\min_{f \in \mathcal{F}} \frac{1}{n} \sum_{i=1}^{n} \ell(f(x_i)) + \Omega(f)$$
(1)

Prototypical machine learning task

Goal : find $\theta_{\star} \in \mathcal{H}$ using *n* training points $(x_i)_{1 \leq i \leq n}$.

$$\boldsymbol{\theta}_{\star} \in \arg\min_{\boldsymbol{\theta} \in \mathcal{H}} \frac{1}{n} \sum_{i=1}^{n} \ell(\boldsymbol{\theta}^{\top} \boldsymbol{\varphi}(\boldsymbol{x}_{i})) + \Omega(\boldsymbol{\theta})$$
(1)

Linear Models

Features : $\varphi(x) \in \mathcal{H}$ (built features, kernels...) **Parametrization** : by a vector $\theta \in \mathcal{H}$, $f_{\theta} : \mathcal{X} \to \mathbb{R}$

 $f_{\theta}(x) = \theta^{\top} \varphi(x), \ \theta \in \mathcal{H}$

Prototypical machine learning task

Goal : find $\theta_* \in \mathcal{H}$ using *n* training points $(x_i)_{1 \leq i \leq n}$.

$$\theta_{\star} \in \arg\min_{\theta \in \mathcal{H}} \frac{1}{n} \sum_{i=1}^{n} \ell(\theta^{\top} \varphi(x_i)) + \Omega(\theta)$$
(1)

Linear Models have good properties

- preserve convexity of ℓ
- rich classes of functions when \mathcal{H} infinite dimensional (kernel methods)
- finite dimensional representation with *n* degrees of freedom:

$$\theta_{\star} = \sum_{i=1}^{n} \alpha_i \varphi(\mathbf{x}_i)$$

What if we want $f \ge 0$?

$$f_{\star} \in \arg\min_{\substack{f \in \mathcal{F} \\ f \ge 0}} \frac{1}{n} \sum_{i=1}^{n} \ell(f(x_i)) + \Omega(f)$$
(2)

Linear models do not work anymore !

What if we want $f \ge 0$?

$$f_\star \in rgmin_{\substack{f \in \mathcal{F} \\ f
eq 0}} rac{1}{n} \sum_{i=1}^n \ell(f(x_i)) + \Omega(f)$$

Classical models lack crucial properties

- (2) becomes **non-convex**;
- $f_{\star} \ge 0$ only on a grid;
- Poor approximation properties.

(2)

What if we want $f \ge 0$?

$$f_\star \in rg\min_{\substack{f \in \mathcal{F} \ f \geqslant 0}} rac{1}{n} \sum_{i=1}^n \ell(f(x_i)) + \Omega(f)$$

We propose a model for non-negative functions :

 $f_A(x) = \varphi(x)^\top A \varphi(x), A$ symmetric matrix $A \succeq 0$

$$A \succeq 0 \implies f_A \geqslant 0$$

(2)

What if we want $f \ge 0$?

$$A_{\star} \in \arg\min_{\substack{A \in \mathcal{S}(\mathcal{H}) \\ A \succeq 0}} \frac{1}{n} \sum_{i=1}^{n} \ell(\varphi(x_i)^{\top} A \varphi(x_i)) + \Omega(A)$$
(2)

We propose a model for non-negative functions :

 $f_A(x) = \varphi(x)^\top A \varphi(x), A \text{ symmetric matrix } A \succeq 0$ $A \succeq 0 \implies f_A \ge 0$

The proposed model keeps the interesting properties

$$A_{\star} \in \arg\min_{\substack{A \in \mathcal{S}(\mathcal{H}) \\ A \succeq 0}} \frac{1}{n} \sum_{i=1}^{n} \ell(\varphi(x_i)^{\top} A \varphi(x_i)) + \Omega(A)$$
(2)

We prove that it has all the good properties of linear models:

- (2) is convex
- approximation properties match those of linear models, ${\cal H}$ infinite dimensional
- finite dimensional representation with *n*² parameters:

$$A_{\star} = \sum_{i,j=1}^{n} a_{ij} \ arphi(x_i) arphi(x_j)^{ op}$$

- dual representation using only *n* parameters;
- statistical complexity matches that of linear models
- and many more ... Check the paper !