UNIVERSITY OF COPENHAGEN
FACULTY OF SCIENCE

A Bachelor of Science thesis

Super Learners

and their oracle properties

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Contents

1 Introduction

Let X_n be n-i.i.d. observations distributed according to $P \in \mathcal{P}$ on some measurable space $(\mathcal{X}^n, \mathcal{A})$ where $X_i \in \mathcal{X}$ for each i and $\mathcal{P}$ is our statistical model. For a parameter set $\Theta \subseteq \mathbb{R}^p$ we define the corresponding loss function $L : \mathcal{X} \times \Theta \to [0, \infty)$ as a measurable map such that our goal is to find an estimator $\hat{\theta}$ that minimizes the true risk function $R : \Theta \to \mathbb{R}$ given as

$$R(\theta) = \int L(x, \theta) \mathrm{d}P(x) = EL(X_1)$$

Definition 1 (Estimator of θ_0)**.** An estimator for $\theta_0 \in \Theta$ is a measurable map $\hat{\theta} : \mathcal{X}^n \times \mathcal{P} \to \Theta$. In the context where the estimator is fitted from our observations, we write $\hat{\theta}(P_n) : \mathcal{X}^n \to \Theta$ to denote the estimator fitted on the empirical distribution, P_n, of our observations.

Example 1 (The true estimator θ_0). If we have knowledge of the true distribution P of our observations, then we can define the true estimator $\theta_0(P) : \mathcal{X}^n \to \Theta$ simply as the constant function which that outputs the true value θ_0 for any input in $\mathcal{X}^n$.

We would like to consider a set estimators $\{\hat{\theta}_i(P_n) | 1 \leq i \leq p\}$, where we find $\hat{\theta}_{\hat{i}}(P_n)$, which denotes the estimator that minimizes R and $\hat{i}$ may depend on the observations.

In order to find $\hat{i}$ we have to proceed via cross validation. In cross validation, we randomly split our data into a training set and a test set. Let $S = (S_1, ..., S_n) \in \{0, 1\}^n$ independent of $X_1, ..., X_n$ such that $S_i = 0$ indicates that X_i should be in the training set and $S_i = 1$ indicates that X_i belongs to the test set. We can define the empirical distributions over these two subsets, $P^0_{n,S}$ and $P^1_{n,S}$ as

$$P^0_{n,S} = \frac{1}{n_0} \sum_{j:S_j=0} \delta_{X_j}$$
$$P^1_{n,S} = \frac{1}{1 - n_0} \sum_{j:S_j=1} \delta_{X_j}$$

Where n_0 would be the number of S_i's that are marked 0.

Definition 2 (True risk of i'th estimator averaged over splits)**.** Given the data $X \in \mathcal{X}^n$ and a set of estimators $\{\hat{\theta}_i \mid 1 \leq i \leq p\}, p \in \mathbb{N}$. The risks of these estimator averaged over the splits specified by some S is given as a function of i

$$i \mapsto E_S \int L(x, \hat{\theta}_i(P^0_{n,S})) \mathrm{d}P(x) = E_S R(\theta_i(P^0_{n,S}))$$

Where P is the true distribution for our data X.

Definition 3 (Oracle selector)**.** The oracle selector is a function $\tilde{i} : \mathcal{X}^n \to \{1, ..., p\}$ which finds the estimator that minimizes the true risk given our data $X \in \mathcal{X}^n$.

$$\tilde{i}(X) = \underset{1 \leq i \leq p}{\arg\min}\, E_S R(\theta_i(P^0_{n,S}))$$

Where $P^0_{n,s}$ is the empirical distribution over the training set of X as specified by some split-variable S.

In light of the above definitions, we will define the cross-validation risk and the cross-validation selector for our estimators

Definition 4 (Cross-validation risk of i'th estimator averaged over splits)**.** Given the data $X \in \mathcal{X}^n$ and a set of estimators $\{\hat{\theta}_i \mid 1 \leq i \leq p\}, p \in \mathbb{N}$. The cross-validation risks of these estimator averaged over the splits specified by some S is given as a function of i

$$i \mapsto E_S \int L(x, \hat{\theta}_i(P^0_{n,S}))\mathrm{d}P^1_{n,s}(x) = E_S \hat{R}(\theta_i(P^0_{n,S}))$$

Where $P^1_{n,S}$ is the empircal distribution over the validation set for our data X. We write $\hat{R}$ for empirical risk over the validation set.

Definition 5 (Cross-validation selector)**.** The cross-validation selector is a function $\hat{i} : \mathcal{X}^n \to \{1, ..., p\}$ which finds the estimator that minimizes the cross-validation risk given our data $X \in \mathcal{X}^n$.

$$\hat{i}(X) = \underset{1 \leq i \leq p}{\arg\min}\, E_S \hat{R}(\theta_i(P^0_{n,S}))$$

Where $\hat{R}$ is the empirical risk over the validation set and $P^0_{n,s}$ is the empirical distribution over the training set of X as specified by some split-variable S.

We are interested in the risk difference between the cross-validation selector and and the oracle selector, we remark that the optimal risk is attained at the true value θ_0

$$R(\theta_0) = \int L(x, \theta_0)\mathrm{d}P(x),$$

and clearly it is the case that $R(\theta_0) \leq R(\hat{\theta})$ for any estimator $\hat{\theta}$ of θ_0. Given a set of estimators $\hat{\theta}_k$, we define the centered conditional risk as the difference

$$\begin{aligned}\Delta_S(\hat{\theta}_{\hat{i}}, \theta_0) &= R(\theta_{\hat{i}}(P^0_{n,S})) - R(\theta_0) \\ &= E_S \int L(x, \theta_{\hat{i}}(P^0_{n,S})) - L(x, \theta_0)\mathrm{d}P(x)\end{aligned}$$

Theorem 6 (Asymptotic equality)**.** *The cross validation selector $\hat{i}$ performs asymptotically as well as the oracle selector $\tilde{i}$ in the sense that*

$$\frac{\Delta_S(\hat{\theta}_{\hat{i}}, \theta_0)}{\Delta_S(\hat{\theta}_{\tilde{i}}, \theta_0)} \to 1 \qquad \textit{in probability for } n \to \infty$$

2 The discrete super learner, dSL

2.1 Finite sample properties

3 The ensemble super learner, eSL

4 Simulation results

5 Discussion

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