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Master's Thesis
修士論文

Transductive Learning for Gaussian Processes via Information Rate
（情報率を用いたガウス過程のトランスダクティブ学習）

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Abstract

Machine learning is a field of computer science and is covering a broad range of topics as represented by its definition such as detecting patterns in the data automatically. Although the goal is to be wide-ranging, machine learning algorithms basically have the same process; after constructing a learning algorithm, we tune some parameters that determine the performance of the method on the basis of data. One of the most succeeded methods is non-parametric estimation. It certainly has a long history, but Gaussian process regression especially have attracted a great deal of attention due to their increased flexibility compared with parametric models. Kernel functions that determine almost all the properties of functions generated from Gaussian process also have hyperparameters that we have to tune. There is a common tuning method known as marginal likelihood estimation which is based on empirical Bayesian learning. It is Bayesian and frequentist strategies because this approach violates the Bayesian principle that any prior should be selected independently of observations. However, it could be regarded as a kind of approximation and have good properties in the aspect of frequentist statistics. Through this thesis, we propose a novel approach for the hyperparameter tuning problems under transduction. In contrast to traditional machine learning, transductive learning algorithms receive a set of samples including unlabeled data and aim to minimize the loss for these unlabeled data. Although there already exists some studies in transductive learning, our approach needs not to take an assumption that existing methods need to. Moreover, the existing methods modify an objective function by just putting KL divergence term as regularization, has no theoretical guarantee for convergence. As contributions of this thesis, we theoretically clarify the relationship between existing and proposed methods. The proposed method succeeded to overcome a kind of drawback in existing methods: train and test data follow the same distribution. This relaxation of the limitation enables us to apply Gaussian Process regression in various fields for application. Besides, we derive a theoretical guarantee and objective function is equipped with a kind of interpretability.