Abstract

Machine learning, a scientific study of algorithms and statistical models that enable computer systems to learn from data, has played an important role in a wide range of real-world applications such as email filtering, speech recognition, computer vision and self-driving cars. Traditional machine learning often explicitly or implicitly assumes that the data used for training a model comes from the same distribution as that of the test data. However, dataset shift is prevalent in practice due to non-stationary environments.

Covariate shift, a typical type of dataset shift, frequently happens when the training and test data are drawn from different time periods, different but related domains, or via different sampling strategies. Under covariate shift, standard learning techniques such as empirical risk minimization no longer produce consistent estimators, but weighted variants according to the ratio of test and training input densities do. Therefore, most existing work focuses on how to accurately estimate the density ratio, which is called the importance, and then use it to reweight the loss for training the classifier or the regressor.

In this thesis, we follow the philosophy of Vapnik's principle, that is, one should avoid solving a more general problem as an intermediate step when solving a target problem, and propose a one-step approach to directly solving the covaritate shift problem. We establish a generalization error bound based on the Rademacher complexity to give a theoretical guarantees for the proposed method. Experiments on toy and benchmark datasets highlight the advantage of our method over previous two-step approaches.