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A Deep Learning Approach to Learning a Conditional Distribution

PRESENTED BY

COLLEGE OF PUBLIC HEALTH'S DEPARTMENT OF BIOSTATISTICS

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WHEN & WHERE

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PRESENTATION ZOOM INFORMATION:

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Jian Huang is a Professor in the Department of Statistics and Actuarial Science at the University of Iowa. His research interests include machine learning, high-dimensional statistics, bioinformatics, statistical genetics and survival analysis. He has published over 150 peer-reviewed papers in the fields of statistics, biostatistics, machine learning, bioinformatics, and statistical genetics. He has been recognized as a highly cited researcher by the Web of Science group. He is a fellow of the American Statistical Association and the Institute of Mathematical Statistics.

Abstract: We propose a deep generative approach to learning a conditional distribution based on a unified formulation of conditional distribution and generalized nonparametric regression function using the noise-outsourcing lemma. The proposed approach aims at learning a conditional generator so that a random sample from the target conditional distribution can be obtained by the action of the conditional generator on a sample drawn from a reference distribution. The conditional generator is estimated nonparametrically with neural networks by matching appropriate joint distributions. An appealing aspect of our method is that it allows either of or both the predictor and the response to be high-dimensional and can handle both continuous and discrete type predictors and responses. We show that the proposed method is consistent in the sense that the conditional generator converges in distribution to the underlying conditional distribution under mild conditions. Our numerical experiments with simulated and benchmark image data validate the proposed method and demonstrate that it outperforms several existing conditional density estimation methods.