NeurIPS Wednesday

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1 Morning Poster Session

1.1 Learning Bayesian Networks with Low Rank Conditional Probability Tables

Summary: Bayesian networks can be used to model complex interactions amongst constituent variables of a system. In this paper, they provide a method to learn the directed structure of a Bayesian network using data. Existing methods are typically NP-hard. They propose a method to learn exact structure of a class of Bayesian networks by making black-box queries with theoretical guarantees. Under rank k conditional probability distribution setting, theire main contributions are

- Introduction of Low rank CPTs: CPT can be treated as summation of multiple simple tables, each of them depending only on a handful of parents;
- Connect this notion of rank of a CPT to the Fourier transformation of a specific real valued set function;
- Use compressed sensing techniques to show that the Fourier coefficients of this set function can be used to learn the structure of the Bayesian network.

Improvement: Please add some experiments: simulations on time or comparison with alternative methods.

1.2 Dynamic Ensemble Modeling Approach to Non-stationary Neural Decoding in Brain-Computer Interfaces

Summary: Existing modeling methods typically use a static model, while assuming the data distribution is fixed and stable in time as well. However, the data distribution is not fixed or stable under some situations such as brain sights. This paper proposes a model that changes over time. The idea is first to give a few alternative static models. Next, they train all the models simultaneously, select the one with largest likelihood at different time according to the data. The proposed method can provide valuable solutions for robust neural decoding tasks and nonstationary signal processing problems.

Comments: This is a well-executed paper. The formulation is clear. The flow of ideas is natural and easy to understand. Theoretical analysis and comprehensive experiments are provided.

1.3 A Regularized Approach to Sparse Optimal Policy in Reinforcement Learning

Summary: The regularized Markov Decision Process (MDP) is based on original MDP with an additional regularization function $\phi(\cdot)$ and a coefficient λ. The aim of this work is to find an optimal policy that maximizes the expected discounted total reward plus a policy regularization term. Moreover, many regularization terms can bring multi-modality and sparsity under their framework, which are potentially useful in reinforcement learning.

2 Afternoon Poster Session

It is our poster presentation time.