Tensor-Based Multi-Modality Multi-Target Regression for Alzheimer's Disease Diagnosis

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Background: Multi-Target Regression (MTR) has recently attracted great interest in the research community including healthcare, computational medicine, machine learning, etc. The inherent property of jointly learning multiple tasks can contribute task-correlated information to these regressions, thus leading to a better performance than Single-Target Regression (STR). Existing methods focus more on the identification of a specific feature set for different regression tasks, which predefines a suboptimal condition that different tasks are separately modeled but share the common feature space. Thus, how to simultaneously build inter-target correlations and input-target relationships into a task-integrated learning framework is greatly concerned in MTR. In addition, heterogeneous features obtained in a real-world dataset containing multiple modalities or views might complicate this concern via the curse of dimensionality.

Methods: We propose a general Tensor-based Multi-modality MTR (TMMTR) method to address this problem via boosted sparse and low-rank learning. Specifically, we leverage the tensor structure to exploit high-level and inter-target correlation information inherent in the multi-modality multi-target data and investigate tensor-level sparsity in the multilinear regression model. The intrinsic tensor structure is explored to strengthen and capture the complex relationships among multiple regression tasks. In this study, we apply the TMMTR to analyze multimodal imaging data (VBM-MRI, FDG-PET, and AV45-PET) from ADNI cohort with three clinical parameters of Disease Severity (DS) score, AD Assessment Scale–Cognitive 13-item (ADAS-Cog-13) score, and Mini-Mental State Examination (MMSE) score as targets for Alzheimer's disease diagnosis.

Results: The experimental results demonstrate the outstanding performance of our proposed method against both the state-of-the-art STR and MTR methods for the AD diagnosis. The results also show that the significant correlation between the three clinical scores boosts the proposed model's capacity for disease prediction. At the same time, our proposed model learns a better biomarker identification of disease-specific brain regions and modality-related differences from its inherent property of feature selection and competes with other baseline methods in terms of running time. The interpretable coefficients of our model coincide with the clinical findings in AD diagnosis and thus further validate the superiority.

Conclusions: The tensor-structured sparsity, inter-target correlation and input-target relationship are simultaneously exploited to learn the interpretable coefficients in our proposed model, which also successfully identifies biomarkers related to AD with multiple clinical scores and achieves higher predictive performance than the state-of-the-art methods. Our approach is of wide general interest as it can be generalized to other diseases when high dimensionality data is available.

Keywords (up to six words): Alzheimer's disease, multi-target regression, tensor, feature selection, factorization, interpretability