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# Dynamic Learning of Embeddings for Cognitive Classification from High-dimensional Data

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**Abstract**—Supervised machine learning provides a powerful set of tools for data classification and pattern recognition, in particular, for static data or for data inheriting more stationary temporal structures. However, for classification tasks involving time-series data presenting active dynamic features, many of the state-of-the-art classifiers may not perform well. This is because these methods are based on pure statistical or information-theoretic approaches, such as Bayesian types or mutual information, while overlooking the underlying dynamic temporal properties of the data that are generated through the measurements of a dynamical system. In this work, we develop a dynamic learning approach, integrating the Koopman operator theory and support vector machines (SVMs), to create embeddings of high-dimensional data to a low-dimensional space for classification. Adopting such embeddings, we construct a linear approximation of the flow of the nonlinear dynamical system associated with each time-series using spectral methods, such as the Arnoldi method. Each approximating linear system (ALS) is represented in an observability canonical form determined by the coefficients of the characteristic polynomial of its system matrix. Our classification process is based on utilizing these coefficient vectors or the trajectories of the ALS's as feature inputs of the SVM algorithms, because these trajectories are projections of the dynamics of the high-dimensional time-series data onto a low-dimensional observable subspace. We apply and validate the developed method for cognitive classifications using fMRI visual cognition datasets. We formulate each cognition task as a multi-class classification problem, and tackle it as a dynamical learning process. It is shown that the established approach achieves comparable or better classification accuracy with high computational efficiency compared to state-of-the-art classifiers developed based on machine learning techniques.