Dimension Reduction in Time Series

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In this talk, we will give an overview of our work to date on dimension reduction in time series. More specifically, first we develop a sufficient dimension reduction theory for time series, X_t, based *Central Subspace*, which does not require specification of a model but seeks to find a $p \times d$ matrix Φ_d with the smallest number $d(\leq p)$ such that the conditional distribution of $X_t|\mathbf{X}_{t-1}$ is the same as that of $X_t|\Phi_\mathrm{d}^T\mathbf{X}_{t-1}$, where $\mathbf{X}_{t-1} = (X_{t-1}, ..., X_{t-p})^T$. Here, we use a nonparametric estimation method based on Kullback-Leibler divergence. We also construct a *Central Mean Subspace*, where reduction in dimension is aimed at the conditional mean function $E(X_t|\mathbf{X}_{t-1})$. Two well known data sets, *Sunspot* and *Canadian Lynx*, are analyzed to illustrate these methods. Finally, we present an approach to modeling the conditional variance of a time series, X_t, whose conditional mean is zero. We consider the squared series and propose a sufficient dimension reduction approach, which aims at reducing the dimension in the conditional variance of X_t without imposing any model assumption. The approach here is based on *Density Power Divergences* (DPD) with a view to achieving robustness in estimation. A volatility index data is analyzed to illustrate that our DPD approach yields viable models for the conditional variance, which are superior to ARCH/GARCH models.

This is a joint work with Drs. Xiangrong Yin and Jin-Hong Park.