Change-point Estimation in High-dimensional Markov Random Fields

Sandipan Roy, Yves Atchadé and George Michailidis

Abstract

We consider a change-point estimation problem in the context of high-dimensional Markov Random Field (MRF) models. Change-points represent a key feature in many dynamically evolving network structures. The change-point estimate is obtained by maximizing a profile penalized pseudo-likelihood function under a sparsity assumption. We also derive a tight bound for the estimate, up to a logarithmic factor, even in settings where the number of possible edges in the network far exceeds the sample size. We have established the rate of convergence of $O(\log(dT))$ for the estimated change-point to the truth. The usual rate of convergence in the low dimensional setting is $O(1)$, as discussed in Bai(1997); Kosorok(2007). The logarithmic factor seems to be the cost that one has to account for the high dimensionality of the problem. Another key aspect that we investigate in our theoretical analysis is the model misspecification in high dimensional setting which can be of independent interest in some other problems as well. The performance of the proposed estimator is evaluated on synthetic data sets and is also used to explore voting patterns in the US Senate in the 1979-2012 period.