



Learning a forest of Hierarchical Bayesian Networks to model dependencies between genetic markers

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— *KnOwledge and Decision (KOD)* —



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Abstract

We propose a novel probabilistic graphical model dedicated to represent the statistical dependencies between genetic markers, in the Human genome. Our proposal relies on building a forest of hierarchical latent class models. It is able to account for both local and higher-order dependencies between markers. Our motivation is to reduce the dimension of the data to be further submitted to statistical association tests with respect to diseased/non diseased status. A generic algorithm, CFHLC, has been designed to tackle the learning of both forest structure and probability distributions. A first implementation of CFHLC has been shown to be highly-scalable: benchmarks describing 10^5 variables for 2000 individuals were parsed in about 45 hours on a standard personal computer.

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