94% at the subject level (i.e. using several assessment nights to classify each subject) and an average accuracy of 89% in classifying each single night. In addition, patients were classified as well according to their disease severity level and dyspnoea grade with 94% and 93% accuracies, respectively. Standard features such as total night sleeping time, number of nocturnal sleeping bouts and duration of sleeping bouts were able to differentiate between healthy subjects and patients with COPD with good accuracy. However, in agreement with Hartman et al. [99] who did not find significant associations between night's rest parameters and GOLD or MMRC, these features were not able to discriminate between different disease severity stages and dyspnoea grades. Discovered latent structures in night-time data, instead, were sufficiently sensitive to pick up subtle differences existing between the four groups of COPD subjects and five groups of dyspnoeic patients. Based on the target outcome, the settings in the latent model should be adapted. In particular, a lower number of latent structures is required to get the best classification performance for a two class problem compared to the classification of more classes. For the four classes and five classes problems, a higher number of latent structures, in turn more specific, led to better classification results. It is worth noting that the classification accuracies were always greater than 80% regardless the number of sleep modalities and eigenvectors selected. We believe our contribution represents a step forward towards a better support to the diagnosis of a complicated disease that will hopefully lead to better patient care. With the aim of learning different disease subspaces in mind, an open question for follow-up work is whether it is possible to use (fully or partially) structures provided by clinicians using known clinical relevant features instead of hidden structures extracted from the data.