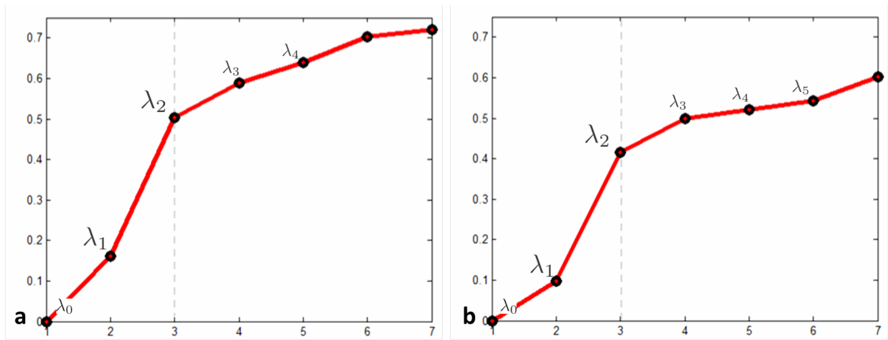

Fig. 6.8: **Discovering the manifold intrinsic dimensionality. (a)** The sorted eigenvalues of the normalized graph Laplacian for the "Swiss Roll" 3D example, with binary affinity model. **(b)** As above but with Gaussian affinity. In both curves there is a clear elbow in correspondence of λ_2 thus indicating an intrinsic dimensionality $d' = 2$. Here we used forest size $T = 100$, $D = 4$ and weak learner = linear.

the optimal dimensionality of the target space. On the flip side it is important to choose the forest depth D carefully, as this parameter influences the number of clusters in which the data is partitioned and, in turn, the smoothness of the recovered mapping. In contrast to existing techniques here we also need to choose a weak-learner model to guide the way in which different clusters are separated. The forest size T is not a crucial parameter since, as usual, the more trees the better the behaviour.

The fact that the same decision forest model can be used for manifold learning and nonlinear dimensionality reduction is an interesting discovery. This chapter has only presented the manifold forest model and some basic intuitions. However, a more thorough experimental validation with real data is necessary to fully assess the validity of such model. Next, we discuss a natural continuation of the supervised and unsupervised models discussed so far, and their use in semi-supervised learning.