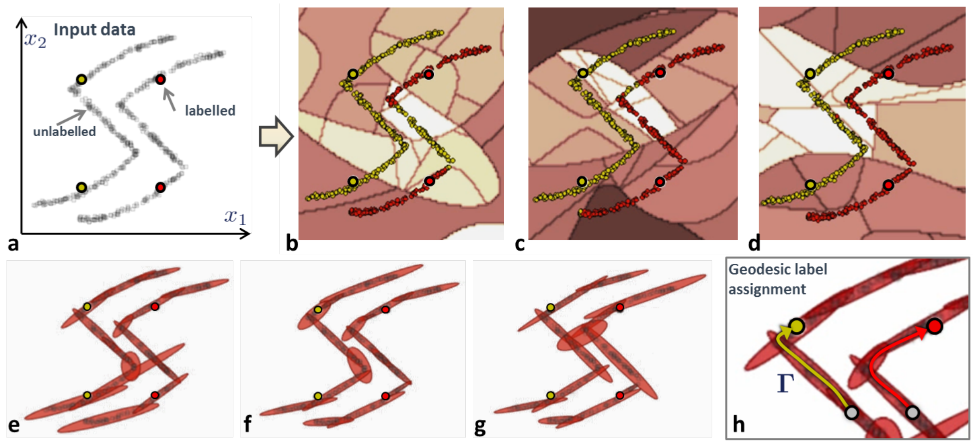

Fig. 7.2: **Label transduction in semi-supervised forests. (a)** Input points, only four of which are labelled as belonging to two classes (red and yellow). **(b,c,d)** Different transductive trees produce different partitions of the feature space. Different regions of high data density tend to be separated by cluster boundaries. Geodesic optimization enables assigning labels to the originally unlabelled points. Points in the central region (away from original ground-truth labels) tend to have less stable assignments. In the context of the entire forest this captures uncertainty of transductive assignments. **(e,f,g)** Different tree-induced partitions correspond to different Gaussian Mixture models. **(h)** Label propagation via geodesic path assignment.

dataset (as in fig. 7.2a) which we use to train a transductive forest of size T and maximum depth D by maximizing the mixed information gain (7.1).

Different trees produce randomly different partitions of the feature space as shown in fig. 7.2b,c,d. The different coloured regions represent different clusters (leaves) in each of the three partitions. If we use Gaussian models then each leaf stores a different Gaussian distribution learned by maximum likelihood for the points within. Label transduction from annotated data to unannotated data can be achieved directly