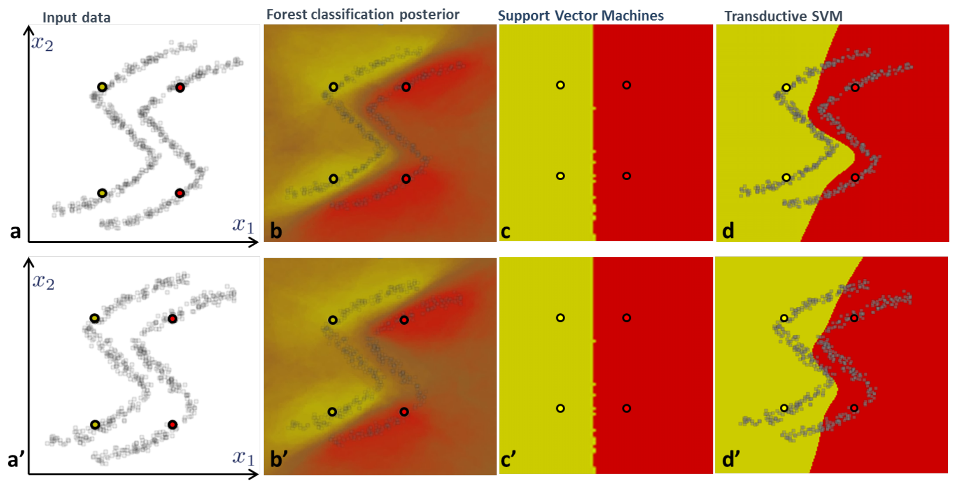

Fig. 7.5: **Comparing semi-supervised forests with SVM and transductive SVM.** **(a)** Input partially labelled data points. **(b)** Semi-supervised forest classification posterior. The probabilistic output captures prediction uncertainty (mixed-colour pixels in the central region). **(c)** Unsurprisingly, conventional SVM produces a vertical separating surface and it is not affected by the unlabelled set. **(d)** Transductive SVM follows regions of low density, but still does not capture uncertainty. **(a')** As in (a) but with larger noise in the point positions. **(b')** The increased input noise is reflected in lower overall confidence in the forest prediction. **(c',d')** as (c) and (d), respectively, but run on the noisier training set (a').

Handling multiple classes. Being tree-based models semi-supervised forests can natively handle multiple (> 2) classes. This is demonstrated in fig. 7.6 with a four-class synthetic experiment. The input points are randomly drawn from four bi-variate Gaussians. Out of hundreds of points only four are labelled with their respective classes (shown in different colours). Conventional one-v-all SVM classification results in hard class assignments (fig. 7.6b). Tree-based transductive label propagation (for a single tree) is shown in fig. 7.6c. Note that slightly different assignments are achieved for different trees. The forest-based