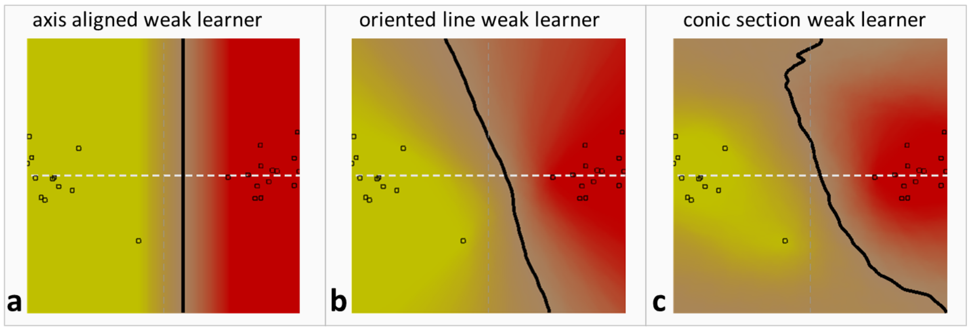

Fig. 3.10: **The effect of the weak learner on forest margin. (a)** Forest posterior for axis aligned weak learners. **(b)** Forest posterior for oriented line weak learners. **(c)** Forest posterior for conic section weak learners. In these experiments we have used $\rho = 50, D = 2, T = 500$. The choice of weak learner affects the optimal, hard separating surface (in black). Individual training points influence the surface differently depending on the amount of randomness in the forest.

forests with $|\mathcal{T}_j| = 50, D = 3, T = 400$. The only difference between the two forests is the fact that the first one uses an oriented line weak learner and the second a conic weak learner. Figures 3.11b,c show the corresponding testing posteriors. As usual grey pixels indicate regions of higher posterior entropy and lower confidence. They roughly delineate the four optimal hard classification regions. Note that in both cases their boundaries are roughly placed half-way between neighbouring classes. As in the 2-class case the influence of individual training points is dictated by the randomness parameter ρ.

Finally, when comparing fig. 3.11c and fig. 3.11b we notice that for conic learners the shape of the uncertainty region evolves in a curved fashion when moving away from training data.

3.4.4 The effect of the randomness model

This section shows a direct comparison between the randomized node optimization and the bagging model.

In bagging randomness is injected by randomly sampling different