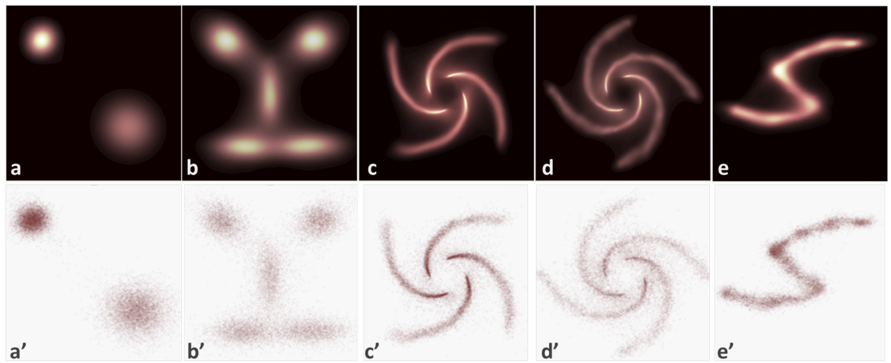

Fig. 5.10: **Sampling results (Top row)** Densities learned from hundreds of training points, via density forests. **(Bottom row)** Random points generated from the learned forests. We draw 10,000 random points per experiment (different experiments in different columns).

a simple algorithm produces good results both for simpler, Gaussian-mixture distributions (figs. 5.10a,b) as well as more complex densities like spirals and other convolved shapes (figs. 5.10c,d,e).

5.6 Dealing with non-function relations

Chapter 4 concluded by showing shortcomings of regression forests trained on inherently ambiguous training data, *i.e.* data such that for a given value of x there may be multiple corresponding values of y (a *relation* as opposed to a *function*). This section shows how better predictions may be achieved in ambiguous settings by means of density forests.

5.6.1 Regression from density

In fig. 4.10b a regression forest was trained on ambiguous training data. The corresponding regression posterior $p(y|x)$ yielded a very large uncertainty in the ambiguous, central region. However, despite its inherent ambiguity, the training data shows some interesting, multi-modal structure that if modelled properly could increase the prediction confidence