1 Particle Filters

Consider the following proposition: There is no point in using a particle filter if the number of distinct states at any time is no more than the number of particles one plans to allocate to the particle filter. Justify or refute this statement.

2 Particle Filters II

Consider a particle filter defined over a discrete set of events and observations. Assume that you initially draw a sample from $P(X_0)$ at time $0$ and that the first observation is made at time $t+1$. Show that for some randomly selected particle $Y$ at time $t+1$, $P(Y = x|o_{t+1}) = P(X_{t+1} = x|o_{t+1})$.

3 Decision Trees

Do problem 18.10.

4 Decision Trees

Do problem 18.15.

5 Neural Networks

Do problem 20.15.

6 Neural Networks II

Do problem 20.11.

7 Neural Networks III

Prove that a multilayer network can compute any boolean function.

8 Clustering

In class, we discussed how k-means could be interpreted as maximizing the probability of the data, under the assumption that they are coming from spherical Gaussians centered at the cluster centers. If we think of our cluster centers as a model, $M$, we can think of k-means as maximizing $P(D|M)$. There is one thing a little strange about this view: The output of k-means is a model, so it seems like we should be maximizing $P(M|D)$ and not $P(D|M)$. Explain what assumptions are necessary to make maximizing $P(D|M)$ equivalent to maximizing $P(M|D)$.
9 Clustering II

Give an example of a set of points and initial guess of cluster centers where k-means will terminate with some clusters having no points assigned. Note that you may need to pick an initial cluster position that does not equal one of your point positions.