## CPTS 570 Machine Learning, Fall 2016 Homework #5

Due Date: Nov 29

1. (40 points) Implementation of Expectation Maximization (EM) algorithm and experimentation.

You will implement the EM algorithm and Gaussian Mixture Models (GMMs) to cluster the data into k clusters. As we discussed in the class, we assume a GMM with k components for the data and we find the parameters of the model using maximum likelihood estimation.

Implement the EM algorithm for one-dimensional GMMs (assume that each data point has only one feature). You are provided with one-dimensional dataset. Use the algorithm to cluster the data. Run the algorithm multiple times from a number of different initialized values (random) and pick the one that results in the highest log-likelihood.

Run the algorithm for different values of k (3, 4, 5) and report the parameters you get for each value of k.

You can use WEKA (http://weka.sourceforge.net/doc.dev/weka/clusterers/EM.html) to debug your implementation.

- 2. (10 points) Devise two example tasks of your own that fit into the reinforcement learning framework, identifying for each its states, actions, and rewards. Make the two examples as different as possible.
- 3. (50 points) Implementation of Q-Learning algorithm and experimentation.

You are given a Gridworld environment that is defined as follows:

**State space**: GridWorld has 10x10 = 100 distinct states. The start state is the top left cell. The gray cells are walls and cannot be moved to.

Actions: The agent can choose from up to 4 actions (left, right, up, down) to move around.

**Environment Dynamics**: GridWorld is deterministic, leading to the same new state given each state and action

**Rewards**: The agent receives +1 reward when it is in the center square (the one that shows R 1.0), and -1 reward in a few states (R -1.0 is shown for these). The state with +1.0 reward is the goal state and resets the agent back to start.

In other words, this is a deterministic, finite Markov Decision Process (MDP). Assume the discount factor  $\beta$ =0.9.

Implement the Q-learning algorithm (slide 46) to learn the Q values for each state-action pair. Assume a small fixed learning rate  $\alpha$ =0.01.

Experiment with different explore/exploit policies:

- 1)  $\epsilon$ -greedy. Try  $\epsilon$  values 0.1, 0.2, and 0.3.
- 2) Boltzman exploration. Start with a large temperature value T and follow a fixed scheduling rate. Give these details in your report.

How many iterations did it take to reach convergence with different exploration policies?

Please show the converged Q values for each state-action pair.

0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
0.00					0.00				0.00
0.00	0.00	0.00	0.00 <b>R</b> -1.0		0.00	0.00	0.00	0.00	0.00
0.00	0.00	0.00	0.00		0.00 ♠ R-1.0	0.00 <b>R</b> -1.0	0.00	0.00	0.00
0.00	0.00	0.00	0.00		0.00 ♣ R 1.0	0.00 ★ R -1.0	0.00	0.00 ♠ R-1.0	0.00
0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00 ♠ R-1.0	0.00
0.00	0.00	0.00	0.00 ♠ R-1.0		0.00 ★ R-1.0	0.00 ♠ R-1.0	0.00	0.00	0.00
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

 ${\bf Figure \ 1:} \ {\bf Grid \ world \ domain \ with \ states \ and \ rewards}.$ 

- 4. Additional instructions for submitting the programming code. This will greatly help the TA in grading your code.
  - 1. Please use the data files in the given format.
  - 2. Please print only the desired outputs.
  - 3. Please mention the python version in your code. Without the version information, it's hard to run the code.
  - 4. Please avoid submitting the homework in iPython Notebook.
  - 5. For C/C++ code, please provide the Makefile/run command with proper parameters.
  - 6. Please provide one example to run the code in a stand-alone mode with some valid parameters. For example, python decisiontree.py -dataDirectory  $\tilde{HW}/data/data$