```
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1. Value iteration
     TI opt
                  V_{opt}^{(t)}(s) = \max_{\alpha \in A_{crowl}(s)} \sum_{s'} T(s,\alpha,s') [Roward(s,\alpha,s') + YV_{opt}^{(t-s)}(s')]
Q 20+0) + 20% (-5+0) = 15
a=> 70% (20+0) + 30% (-5+0) = 12.5
80\% (-5+0) + 2\% (-5+0) = -5
0 = -1 \text{ or } 1
0 = -1 \text{ or } 1
(1) a=1 80/(-5+0) + 20/ (100+0) + 16
  a=1 > 70% (-5+0) + 30% (100+0) = 26.5
update
     Vopt
          0 15 -5 26.5 0
     0=-1 $0% (20+0) + 20% (-5+-5) = 14 

0=-1 70% (20+0) + 30% (-5+-5) = 11
0 70% (-5+15) + 20% (-5+26.5) = 12.3 = 0=1
0 80/. (-5-5) + 20/. (0+100) = 12
0=13 70/. (-5-5) + 30/. (0+100) = 23
 update
   Vopt
               0 14 13.45 23 U
  Tope
```

For the small data set, only 1 out of the 27 states have different actions. The percentage of different items is 3.7%. The reinforcement learning performed pretty good.

For the large data set, 937 out of 2745 states have different actions. The percentage of different items is 34%. The reinforcement learning performed bad, because the large problem has far more states, and the identityFeatureExtractor is a bad choice, because the feature it generates is very sparse, and does not generalize. So the function approximation is bad

4 (d)

FixedRLAlgorithm with policy obtained from original MDP gets average reward of average of 6.84. However, when using Q-Learning, the average reward is 9.38. Q-learning is better result because it adapts to the new problem and adjusts the weights according to what it see, while FixedRLAlgorithm will stick to a fixed policy and can not adapt to the new problem.