[PA-6] Hidden Markov Model - Benjamin Cape

Description

How do your implemented algorithms work? What design decisions did you make? How you laid out the problems? In particular, for this specific assignment, explain your model precisely, and explain exactly how you compute each new distribution of possible states.

• How do your implemented algorithms work?

My algorithm(Problem), takes a maze and a list of observations to determine where we are on the grid. It loops over each observation(reading) and updates the state based on that observation. We first create a new state, with empty expectations, and the current reading. We use the reading to print out the next process nicely in the console. We then loop over each location, find all of it's neighbors, and sum the probabilities of all the neighbors into the current location - this accounts for the **conjunction over the possible moves from all the neighbors**. The next step is to consider the **disjunction over the sensor reading**, this is accomplished by multiplying the transition model by the sensor model for each location given the proper reading correctness. The final step is **normalizing** all the probabilities such that we retain constant 100% likelihood for all outcomes.

• What design decisions did you make?

I decided to take, once again, and object oriented approach to split out functionality into respective entities. The markov_model.py files is generic, over any board with data at each location. The maze.py file contains all the maze related specific functionality, and the main.py file specifies the specific problem with the colors. I chose this to make it as generic as possible. I considered splitting the markov_chain even to allow for any generic markov chain, rather than board specific, but didn't seem necessary.

• How did you lay out the problems?

See above.

• In particular, for this specific assignment, explain your model precisely, and explain how you compute each new distribution of possible states.

The model is a hashmap of expectations for locations on a board. Each location is given a probability (expectation) that the robot is in that location. Therefore, updating probabilities is very fast and efficient, and clear. We can update probabilities in O(n) time by looping over each location. See Implementation for information on how we compute the new distribution of possible states.

Evaluation

Do your implemented algorithms actually work? How well? If it doesn't work, can you tell why not? What partial successes did you have that deserve partial credit? Include a comparison of running time results using different heuristics and inference.

• Do your implemented algorithms actually work? How well?

Yes, in fact they seem to work very well. After running a various randomly generated mazes, the robot is generally very good at localizing itself.

• What partial successes did you have that deserve partial credit?

I believe that I deserve full credit.

 Include a comparison of running time results using different heuristics and inference.

There are no heuristics for this assignment, nor is there any inference. But here is an evaluation of state determination based on some randomly generated maps:

See bottom...

This one shows very well that with a proper path from (1,1) -> (1,0) -> (2,0) that is G, R, B and no other such path, we are placed INCREDIBLY likely at location (2,0) and very unlikely at the remaining locations of the board.

Discussion

1. What is the state transition model?

The state transition model is adding up all of the neighboring state's probabilities, because we assume uniform provability that the robot moves in any direction, so summing up is essentially saying, we were either in neighbor 1, 2 3 or 4 (max being 4 for 4 neighbors).

2. What is the sensor model?

The sensor model is multiplying the retrieved probability from summing the neighboring state probabilities with the probability that our reading was correct given the actual color of the square. I.e. if we just read a RED, and the square we are on is in fact red, then we multiply by 0.88, whereas for all other colors we would multiply by 0.04

3. How do you implement the filtering algorithm, given that there are several possible values for the state variable (the state variable is not boolean).

The filtering algorithm is simply keeping track of the previous state, and rather than re-computing everything on each transition, using the previous state to calculate the new state. That is described above, but simply put we create a new board, fill in initial probabilities given the transition model, and then update those probabilities with the sensor model.

Extra Credit

I implemented a viterbi algorithm that backtracks from the final state to find the best path.

This is visible with the following output from a random generated path and map. The * indicates where the robot thinks it is.

	State	(Read: None)			
	0	1	2	3	4
4:	G0.05	#	G0.05	RO.05	Y0.05
3:	#	RO.05	B0.05	RO.05	#
2:	#	YO.05	G0.05	GO.05	Y0.05
1:	Y0.05	GO.05	B0.05	B0.05	#
0:	Y0.05	RO.05	G0.05	GO.05	B0.05
	State	(Read: B)			
	0	1	2	3	4
4:	G0.008	#	G0.008	RO.008	Y0.008
3:	#	RO.008	B0.187	RO.008	#
2:	#	Y0.008	*0.008	G0.008	Y0.008
1:	Y0.008	G0.008	B0.187	B0.187	#
0:	Y0.008	RO.008	G0.008	G0.008	B0.187
	State	(Read: Y)			
	0	1	2	3	4
4:	G0.004	#	G0.025	RO.004	Y0.088
3:	#	RO.025	B0.004	RO.025	#
2:	#	*0.088	G0.046	G0.025	Y0.088
1:	Y0.088	G0.025	B0.025	B0.046	#
	Y0.088	RO.004	G0.025	G0.046	B0.067
	State	(Read: G)			
	0	1	2	3	4
4:	G0.015	#	G0.055	R0.006	Y0.012
3:	#	RO.006	B0.005	R0.002	#
2:	#	Y0.008	GO.134	GO.194	Y0.012
1:	Y0.012	*0.194	B0.006	B0.006	#
0:	Y0.012	RO.006	G0.094	GO.174	B0.011
	State				
	0	1	2	3	4
4:	G0.003	#	G0.005	R0.003	Y0.038
3:	#	RO.001	B0.008	RO.009	#
2:	#	*0.32	GO.009	G0.007	Y0.216
1:	Y0.216	G0.001	B0.018	B0.016	#
0:	Y0.039	RO.013	G0.012	G0.012	B0.009

	State	(Read:	G)	_		
	0	(1	2	3	4
4:	G0.007		#	GO.015	R0.002	Y0.004
3:	#		RO.01	B0.001	RO.001	#
2:	#		Y0.01	GO.24	GO.17	Y0.02
1:	Y0.015		*0.385	B0.001	B0.002	#
0:	Y0.009		R0.002	GO.038	G0.033	B0.001
	C+-+-	(Daad.	M)			
	0	(Read:	None)	2	3	4
4:	GO.05		Y0.05	RO.05		
3:	#		#	#	B0.05	RO.05
2:	# RO.05		# B0.05	# GO.05	YO.05 GO.05	B0.05 #
1:	B0.05					
0:	GO.05		GO.05 RO.05	Y0.05 Y0.05	RO.05 #	B0.05 Y0.05
		(Poad:	G)		#	10.05
	0	(neau.	1	2	3	4
4:	GO.172		Y0.008	RO.008	B0.008	RO.008
3:	#		#	#	Y0.008	B0.008
2:	TO.008		т ВО.008	*0.172	GO.172	#
1:	B0.008		GO.172	Y0.008	RO.008	B0.008
0:	GO.172		RO.008	Y0.008	#	Y0.008
			в)		"	10.000
	0	(IIIGuu.	1	2	3	4
4:	G0.018		Y0.007	RO.001	B0.023	RO.001
3:	#		#	#	Y0.007	B0.023
2:	RO.001		*0.267	GO.012	G0.012	#
1:	B0.267		G0.001	Y0.012	RO.007	B0.023
0:	G0.012		RO.012	Y0.001	#	Y0.001
			G)			
	0		1	2	3	4
4:	GO.044		Y0.001	RO.001	B0.001	RO.002
3:	#		#	#	Y0.002	B0.002
2:	RO.018		B0.009	G0.221	G0.027	#
1:	B0.009		*0.407	Y0.001	R0.002	B0.002
0:	G0.221		RO.001	Y0.001	#	Y0.001
			Y)	_		
	0		1	2	3	4
4:	GO.006		Y0.05	RO.O	B0.0	RO.O
3:	#		#	#	Y0.034	B0.0
2:	R0.003		B0.032	G0.012	G0.012	#
1:	B0.032		G0.001	*0.67	R0.002	B0.0
0:	G0.022		RO.03	Y0.004	#	Y0.005
	State	(Read:	Y)	_		
	0		1	2	3	4
4:	G0.003		Y0.086	R0.002	B0.001	RO.0

3:	#	#	#	Y0.038	B0.001
2:	RO.003	B0.002	G0.027	G0.002	#
1:	B0.002	G0.028	Y0.015	RO.025	B0.0
0:	G0.004	R0.002	*0.577	#	Y0.012