Programming Assignment 4 (Who you going to call?)

Due Dec 9, 2020 by 11:59pm **Points** 25 **Available** after Nov 18, 2020 at 12am

Asgn 4: Ghostbusters

Modified version of UC berkeley CSC188 [Project 4](https://inst.eecs.berkeley.edu/~cs188/fa20/project4/) (https://inst.eecs.berkeley.edu/~cs188/fa20/project4/)

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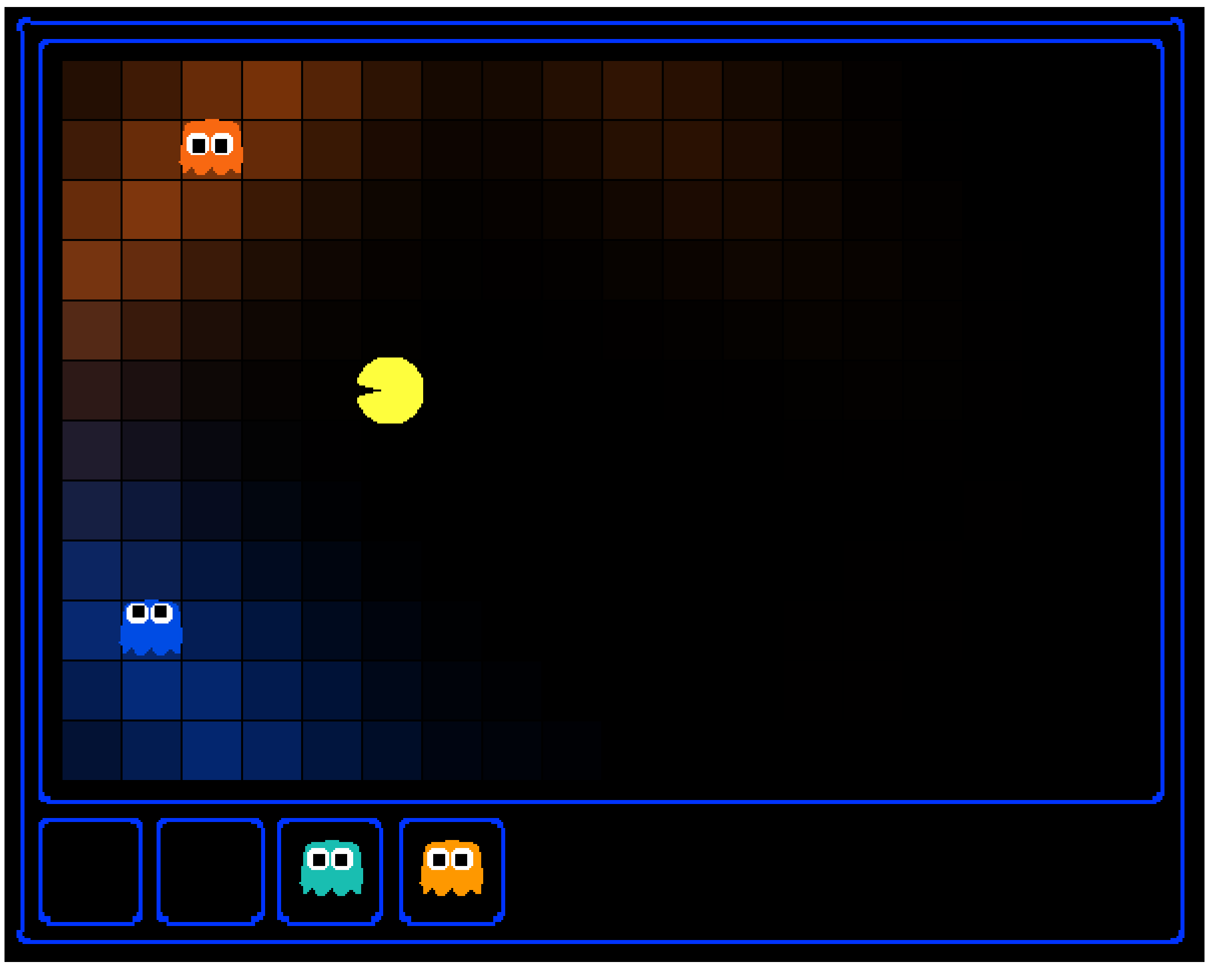


I can hear you, ghost.
Running won't save you from my
Particle filter!

Introduction

Pacman spends his life running from ghosts, but things were not always so. Legend has it that many years ago, Pacman's great grandfather Grandpac learned to hunt ghosts for sport. However, he was blinded by his power and could only track ghosts by their banging and clanging.

In this project, you will design Pacman agents that use sensors to locate and eat invisible ghosts. You'll advance from locating single, stationary ghosts to hunting packs of multiple moving ghosts with ruthless efficiency.

The code for this project contains the following files, available as a zip archive.

Files you'll edit:	
`bustersAgents.py`	Agents for playing the Ghostbusters variant of Pacman.

`inference.py`	Code for tracking ghosts over time using their sounds.
Files you will not edit:	
`busters.py`	The main entry to Ghostbusters (replacing Pacman.py)
`bustersGhostAgents.py`	New ghost agents for Ghostbusters
`distanceCalculator.py`	Computes maze distances
`game.py`	Inner workings and helper classes for Pacman
`ghostAgents.py`	Agents to control ghosts
`graphicsDisplay.py`	Graphics for Pacman
`graphicsUtils.py`	Support for Pacman graphics
`keyboardAgents.py`	Keyboard interfaces to control Pacman
`layout.py`	Code for reading layout files and storing their contents
`util.py`	Utility functions

Files to Edit and Submit: You will fill in portions of `bustersAgents.py` and `inference.py` during the assignment. Please *do not* change the other files in this distribution.

Evaluation: Your code will be autograded for technical correctness. Please *do not* change the names of any provided functions or classes within the code, or you will wreak havoc on the autograder. Also do not change any of the other files, as your code will be tested against the original versions of these files. We may also run some additional tests on your code, in addition to the tests run by the autograder supplied in the zip file. Nevertheless, the marks given by the autograder should be a good indication of the final mark you will obtain.

Getting Help: You are not alone! If you find yourself stuck on something, contact the course staff for help. Office hours, section, and the discussion forum are there for your support; please use them. If you can't make our office hours, let us know and we will schedule more. We want these projects to be rewarding and instructional, not frustrating and demoralizing. But, we don't know when or how to help unless you ask.

Piazza Discussion: Please be careful not to post spoilers.

Ghostbusters and BNs

In this assignment the goal is to hunt down scared but invisible ghosts. Pacman, ever resourceful, is equipped with sonar (ears) that provides noisy readings of the Manhattan distance to each ghost. The game ends when Pacman has eaten all the ghosts. To start, try playing a game yourself using the keyboard.

```
python3 busters.py
```

The blocks of color indicate where the each ghost could possibly be, given the noisy distance readings provided to Pacman. The noisy distances at the bottom of the display are always non-negative, and always within 7 of the true distance. The probability of a distance reading decreases exponentially with its difference from the true distance.

Your primary task in this project is to implement inference to track the ghosts. For the keyboard based game above, a crude form of inference was implemented for you by default: all squares in which a ghost could possibly be are shaded by the color of the ghost. Naturally, we want a better estimate of the ghost's position. Fortunately, Bayes Nets provide us with powerful tools for making the most of the information we have. Throughout the rest of this project, you will implement algorithms for performing both exact and approximate inference using Bayes Nets. The project is challenging, so we do encourage you to start early and seek help when necessary.

While watching and debugging your code with the autograder, it will be helpful to have some understanding of what the autograder is doing. There are 2 types of tests in this project, as differentiated by their `.test` files found in the subdirectories of the `test_cases` folder. For tests of class `DoubleInferenceAgentTest` , you will see visualizations of the inference distributions generated by your code, but all Pacman actions will be pre-selected according to the actions of the staff implementation. This is necessary to allow comparison of your distributions with the staff's distributions. The second type of test is `GameScoreTest` , in which your `BustersAgent` will actually select actions for Pacman and you will watch your Pacman play and win games.

As you implement and debug your code, you may find it useful to run a single test at a time. In order to do this you will need to use the `-t` flag with the autograder. For example if you only want to run the first test of question 1, use:

```
python3 autograder.py -t test_cases/q1/1-ObsProb
```

In general, all test cases can be found inside `test_cases/q*` .

For this project, it is possible sometimes for the autograder to time out if running the tests with graphics. To accurately determine whether or not your code is efficient enough, you should run the tests with the `--no-graphics` flag. If the autograder passes with this flag, then you will receive full points, even if the autograder times out with graphics.

`DiscreteDistribution Class`

Throughout this project, we will be using the `DiscreteDistribution` class defined in `inference.py` to model belief distributions and weight distributions. This class is an extension of the built-in Python3 dictionary class, where the keys are the different discrete elements of our distribution, and the corresponding values are proportional to the belief or weight that the distribution assigns that element.

The class contains a number of useful methods. One of them is the `normalize` method, which normalizes the values in the distribution to sum to one, but keeps the proportions of the values the same.

Another useful method is the `sample` method, which draws a sample from the distribution, where the probability that a key is sampled is proportional to its corresponding value. This method can be called on any distribution that does not have all of its values as zero.

Question 1 (2 points): Observation Probability

In this question, you will implement the `getObservationProb` method in the `InferenceModule` base class in `inference.py` . This method takes in an observation (which is a noisy reading of the distance to the ghost), Pacman's position, the ghost's position, and the position of the ghost's jail, and returns the probability of the noisy distance reading given Pacman's position and the ghost's position. In other words, we want to return

`P(noisyDistance | pacmanPosition, ghostPosition)` .

Note that the distance sensor returns a `noisyDistance` but does not return a direction. For example, if `noisyDistance` is `10` then the sensor thinks that the ghost is Manhattan distance 10 from the packman. So this function, is returning the probability that the sensor returns `noisyDistance` given that the pacman is actually located at `pacmanPosition` and the ghost is actually located at `ghostPosition` .

The distance sensor has a probability distribution over distance readings (i.e., particular `noisyDistance` readings) given the true distance from Pacman to the ghost. This distribution is given by the function `busters.getObservationProbability(noisyDistance, trueDistance)` , which returns `P(noisyDistance | trueDistance)` and is provided for you. You should use this function to help you write this function, and use the provided `manhattanDistance` function to find the true distance between Pacman's location and the ghost's location.

There is, however, one special case that has to be handled. This special case involves when the pacman captures a ghost and send it to the jail location (i.e., when the ghost position is equal to the jail position). The distance sensor will return `None` as its `noisyDistance` value if and only if the ghost position is equal to the jail position. That is, when ghost position is equal to the jail position, the probability of `noisyDistance==None` is one, and every other values of `noisyDistance` has probability zero. Furthermore, `noisyDistance==None` has probability 0 if the goal position is not equal to the jail position.

To test your code and run the autograder for this question:

```
python3 autograder.py -q q1
```

As a general note, it is possible for some of the autograder tests to take a long time to run for this project, and you will have to exercise patience. As long as the autograder doesn't time out, you should be fine (provided that you actually pass the tests).

Question 2 (3 points): Exact Inference Observation

In this question, you will implement the `observeUpdate` method in `ExactInference` class of `inference.py` to correctly update the agent's belief distribution over ghost positions given an observation from Pacman's sensors. You are implementing the online belief update for observing new evidence. The `observeUpdate` method should, for this problem, update the belief at every position on the map after receiving a sensor reading. You should iterate your updates over the variable `self.allPositions` which includes all legal positions plus the special jail position. Beliefs represent the probability that the ghost is at a particular location, and are stored as a `DiscreteDistribution` object in a field called `self.beliefs` , which you should update.

Before typing any code, write down the equation of the inference problem you are trying to solve. You should use the function `self.getObservationProb` that you wrote in the last question, which returns the probability of an observation given Pacman's position, a potential ghost position, and the jail position. You can obtain Pacman's position using `gameState.getPacmanPosition()` , and the jail position using `self.getJailPosition()` .

In the Pacman display, high posterior beliefs are represented by bright colors, while low beliefs are represented by dim colors. You should start with a large cloud of belief that shrinks over time as more evidence accumulates. As you watch the test cases, be sure that you understand how the squares converge to their final coloring.

Note: your busters agents have a separate inference module for each ghost they are tracking. That's why if you print an observation inside the `observeUpdate` function, you'll only see a single number even though there may be multiple ghosts on the board.

To run the autograder for this question and visualize the output:

```
python3 autograder.py -q q2
```

If you want to run this test (or any of the other tests) without graphics you can add the following flag:

```
python3 autograder.py -q q2 --no-graphics
```

IMPORTANT: In general, it is possible sometimes for the autograder to time out if running the tests with graphics. To accurately determine whether or not your code is efficient enough, you should run the tests with the `--no-graphics` flag. If the autograder passes with this flag, then you will receive full points, even if the autograder times out with graphics.

Question 3 (3 points): Exact Inference with Time Elapse

In the previous question you implemented belief updates for Pacman based on his observations. Fortunately, Pacman's observations are not his only source of knowledge about where a ghost may be. Pacman also has knowledge about the ways that a ghost may move; namely that the ghost can not move through a wall or more than one space in one time step.

To understand why this is useful to Pacman, consider the following scenario in which there is Pacman and one Ghost. Pacman receives many observations which indicate the ghost is very near, but then one which indicates the ghost is very far. The reading indicating the ghost is very far is likely to be the result of a buggy sensor. Pacman's prior knowledge of how the ghost may move will decrease the impact of this reading since Pacman knows the ghost could not move so far in only one move.

In this question, you will implement the `elapseTime` method in `ExactInference` . The `elapseTime` step should, for this problem, update the belief at every position on the map after one time step elapsing. Your agent has access to the action distribution for the ghost through `self.getPositionDistribution` . In order to obtain the distribution over new positions for the ghost, given its previous position, use this line of code:

```
newPosDist = self.getPositionDistribution(gameState, oldPos)
```

Where `oldPos` refers to the previous ghost position. `newPosDist` is a `DiscreteDistribution` object, where for each position `p` in `self.allPositions` , `newPosDist[p]` is the probability that the ghost is at position `p` at time `t + 1`, given that the ghost is at position `oldPos` at time `t`. Note that this call can be fairly expensive, so if your code is timing out, one thing to think about is whether or not you can reduce the number of calls to `self.getPositionDistribution`.

Before typing any code, write down the equation of the inference problem you are trying to solve. In order to test your predict implementation separately from your update implementation in the previous question, this question will not make use of your update implementation.

Since Pacman is not observing the ghost, this means the ghost's actions will not impact Pacman's beliefs. Over time, Pacman's beliefs will come to reflect places on the board where he believes ghosts are most likely to be given the geometry of the board and what Pacman already knows about their valid movements.

For the tests in this question we will sometimes use a ghost with random movements and other times we will use the `GoSouthGhost`. This ghost tends to move south so over time, and without any observations, Pacman's belief distribution should begin to focus around the bottom of the board. To see which ghost is used for each test case you can look in the `.test` files.

To run the autograder for this question and visualize the output:

```
python3 autograder.py -q q3
```

If you want to run this test (or any of the other tests) without graphics you can add the following flag:

```
python3 autograder.py -q q3 --no-graphics
```

IMPORTANT: In general, it is possible sometimes for the autograder to time out if running the tests with graphics. To accurately determine whether or not your code is efficient enough, you should run the tests with the `--no-graphics` flag. If the autograder passes with this flag, then you will receive full points, even if the autograder times out with graphics.

As you watch the autograder output, remember that lighter squares indicate that pacman believes a ghost is more likely to occupy that location, and darker squares indicate a ghost is less likely to occupy that location. For which of the test cases do you notice differences emerging in the shading of the squares? Can you explain why some squares get lighter and some squares get darker?

Question 4 (2 points): Exact Inference Full Test

Now that Pacman knows how to use both his prior knowledge and his observations when figuring out where a ghost is, he is ready to hunt down ghosts on his own. This question will use your `observeUpdate` and `elapseTime` implementations together, along with a simple greedy hunting strategy which you will implement for this question. In the simple greedy strategy, Pacman assumes that each ghost is in its most likely position according to his beliefs, then moves toward the closest ghost. Up to this point, Pacman has moved by randomly selecting a valid action.

Implement the `chooseAction` method in `GreedyBustersAgent` in `bustersAgents.py` . Your agent should first find the most likely position of each remaining uncaptured ghost, then choose an action that minimizes the maze distance to the closest ghost.

To find the maze distance between any two positions `pos1` and `pos2` , use `self.distancer.getDistance(pos1, pos2)` . To find the successor position of a position after an action:

```
successorPosition = Actions.getSuccessor(position, action)
```

You are provided with `livingGhostPositionDistributions` , a list of `DiscreteDistribution` objects representing the position belief distributions for each of the ghosts that are still uncaptured.

If correctly implemented, your agent should win the game in `q4/3-gameScoreTest` with a score greater than 700 at least 8 out of 10 times. Note: the autograder will also check the correctness of your inference directly, but the outcome of games is a reasonable sanity check.

To run the autograder for this question and visualize the output:

```
python3 autograder.py -q q4
```

If you want to run this test (or any of the other tests) without graphics you can add the following flag:

```
code>python3 autograder.py -q q4 --no-graphics
```

IMPORTANT: In general, it is possible sometimes for the autograder to time out if running the tests with graphics. To accurately determine whether or not your code is efficient enough, you should run the tests with the `--no-graphics` flag. If the autograder passes with this flag, then you will receive full points, even if the autograder times out with graphics.

Question 5 (2 points): Approximate Inference Initialization and Beliefs

Approximate inference is very trendy among ghost hunters this season. For the next few questions, you will implement a particle filtering algorithm for tracking a single ghost.

First, implement the functions `initializeUniformly` and `getBeliefDistribution` in the `ParticleFilter` class in `inference.py`. A particle (sample) is a ghost position in this inference problem. Note that, for effective performance from a relatively small number of particles (as we use here) it is important that the particles be evenly (not randomly) distributed across legal positions in order to ensure a uniform prior. (A randomly placement of the particles is unlikely to be evenly distributed unless there is a very large number of particles). Consider placing 103 particles evenly in 10 different legal positions. We could place ten particles in each position and then remaining 3 can placed in the first, second, and third positions. Think about how you can use the mod operator to achieve this in `initializeUniformly`.

Note that the variable you store your particles in must be a list. A list is simply a collection of unweighted variables (positions in this case). Storing your particles as any other data type, such as a dictionary, is incorrect and will produce errors. The `getBeliefDistribution` method then takes the list of particles and converts it into a `DiscreteDistribution` object.

To test your code and run the autograder for this question:

```
python3 autograder.py -q q5
```

Question 6 (3 points): Approximate Inference Observation

Next, we will implement the `observeUpdate` method in the `ParticleFilter` class in `inference.py` . This method constructs a weight distribution over `self.particles` where the weight of a particle is the probability of the observation given Pacman's position and that particle location. Then, we resample from this weighted distribution to construct our new list of particles.

You should again use the function `self.getObservationProb` to find the probability of an observation given Pacman's position, a potential ghost position, and the jail position. The sample method of the `DiscreteDistribution` class will also be useful. As a reminder, you can obtain Pacman's position using `gameState.getPacmanPosition()` , and the jail position using `self.getJailPosition()` .

There is one special case that a correct implementation must handle. When all particles receive zero weight, the list of particles should be reinitialized by calling `initializeUniformly`. The total method of the `DiscreteDistribution` may be useful.

To run the autograder for this question and visualize the output:

```
python3 autograder.py -q q6
```

If you want to run this test (or any of the other tests) without graphics you can add the following flag:

```
python3 autograder.py -q q6 --no-graphics
```

IMPORTANT: In general, it is possible sometimes for the autograder to time out if running the tests with graphics. To accurately determine whether or not your code is efficient enough, you should run the tests with the `--no-graphics` flag. If the autograder passes with this flag, then you will receive full points, even if the autograder times out with graphics.

Question 7 (3 points): Approximate Inference with Time Elapse

Implement the `elapseTime` function in the `ParticleFilter` class in `inference.py`. This function should construct a new list of particles that corresponds to each existing particle in `self.particles` advancing a time step, and then assign this new list back to `self.particles`. When complete, you should be able to track ghosts nearly as effectively as with exact inference.

Note that in this question, we will test both the `elapseTime` function in isolation, as well as the full implementation of the particle filter combining `elapseTime` and `observe`.

As in the `elapseTime` method of the `ExactInference` class, you should use:

```
newPosDist = self.getPositionDistribution(gameState, oldPos)
```

This line of code obtains the distribution over new positions for the ghost, given its previous position (`oldPos`). The sample method of the `DiscreteDistribution` class will also be useful.

To run the autograder for this question and visualize the output:

```
python3 autograder.py -q q7
```

If you want to run this test (or any of the other tests) without graphics you can add the following flag:

```
python3 autograder.py -q q7 --no-graphics
```

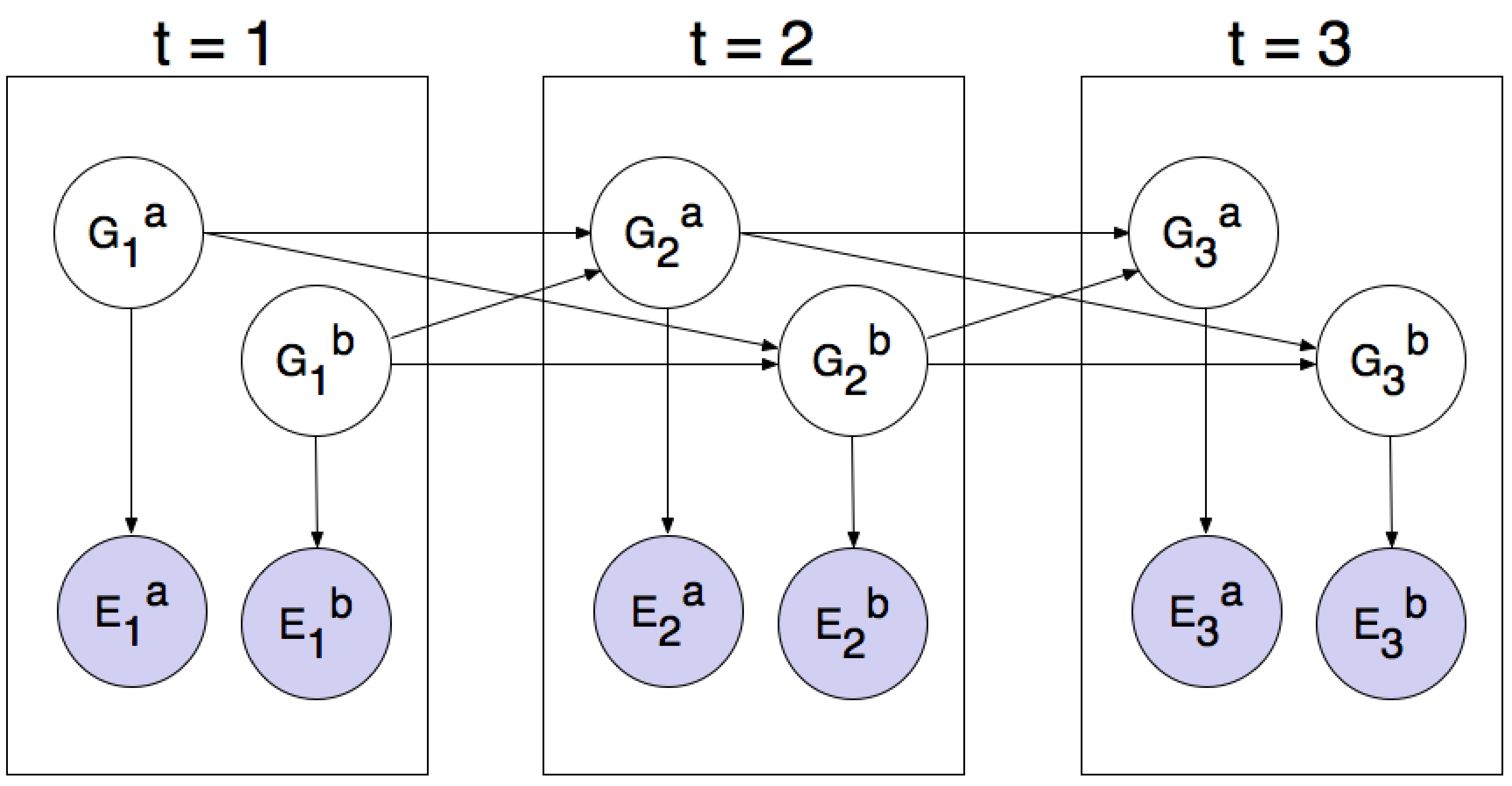
Note that even with no graphics, this test may take several minutes to run.

IMPORTANT: In general, it is possible sometimes for the autograder to time out if running the tests with graphics. To accurately determine whether or not your code is efficient enough, you should run the tests with the `--no-graphics` flag. If the autograder passes with this flag, then you will receive full points, even if the autograder times out with graphics.

Question 8 (1 points): Joint Particle Filter Observation

So far, we have tracked each ghost independently, which works fine for the default `RandomGhost` or more advanced `DirectionalGhost`. However, the prized `DispersingGhost` chooses actions that avoid other ghosts. Since the ghosts' transition models are no longer independent, all ghosts must be tracked jointly in a dynamic Bayes net!

The Bayes net has the following structure, where the hidden variables G represent ghost positions and the emission variables E are the noisy distances to each ghost. This structure can be extended to more ghosts, but only two (a and b) are shown below.



You will now implement a particle filter that tracks multiple ghosts simultaneously. Each particle will represent a tuple of ghost positions that is a sample of where all the ghosts are at the present time. The code is already set up to extract marginal distributions about each ghost from the joint inference algorithm you will create, so that belief clouds about individual ghosts can be displayed.

Complete the `initializeUniformly` method in `JointParticleFilter` in `inference.py`. Your initialization should be consistent with a uniform prior. You may find the Python `itertools` package helpful. Specifically, look at `itertools.product` to get an implementation of the Cartesian product. However, note that, if you use this, the permutations are not returned in a random order. Therefore, must select your particles from this list of possible joint positions of the ghosts so that you get a uniformly distributed set of particles.

It is important to note that unlike q5 in q8 some tests have `self.numParticles` being less than the total number of joint positions of the ghosts. **Therefore the technique you used in q5 for placing particles will not work here**. But a similar technique can be used if you first randomly shuffle the list of possible joint positions before you apply the technique of q5. For example, if `self.numParticles=10` and there are 100 different joint positions of the ghosts, you will select joint positions 1 to 10 for your particles. However, since these joint positons were randomly shuffled, your particles will be randomly placed even if you are not placing a particle in every possible joint position.

As before, use `self.legalPositions` to obtain a list of positions a ghost may occupy. Also as before, **the variable you store your particles in must be a list**.

To run the autograder for this question and visualize the output:

```
python3 autograder.py -q q8
```

If you want to run this test (or any of the other tests) without graphics you can add the following flag:

```
python3 autograder.py -q q8 --no-graphics
```

IMPORTANT: In general, it is possible sometimes for the autograder to time out if running the tests with graphics. To accurately determine whether or not your code is efficient enough, you should run the tests with the `--no-graphics` flag. If the autograder passes with this flag, then you will receive full points, even if the autograder times out with graphics.

Question 9 (3 points): Joint Particle Filter Observation

In this question, you will complete the `observeUpdate` method in the `JointParticleFilter` class of `inference.py` . A correct implementation will weight and resample the entire list of particles based on the observation of all ghost distances.

To loop over all the ghosts, use:

```
for i in range(self.numGhosts):
        ...
```

You can still obtain Pacman's position using `gameState.getPacmanPosition()`, but to get the jail position for a ghost, use `self.getJailPosition(i)`, since now there are multiple ghosts each with their own jail positions.

Your implementation should also again handle the special case when all particles receive zero weight. In this case, `self.particles` should be recreated from the prior distribution by calling `initializeUniformly`.

As in the update method for the `ParticleFilter` class, you should again use the function `self.getObservationProb` to find the probability of an observation given Pacman's position, a potential ghost position, and the jail position. The sample method of the `DiscreteDistribution` class will also be useful.

To run the autograder for this question and visualize the output:

```
python3 autograder.py -q q9
```

If you want to run this test (or any of the other tests) without graphics you can add the following flag:

```
python3 autograder.py -q q9 --no-graphics
```

IMPORTANT: In general, it is possible sometimes for the autograder to time out if running the tests with graphics. To accurately determine whether or not your code is efficient enough, you should run the tests with the `--no-graphics` flag. If the autograder passes with this flag, then you will receive full points, even if the autograder times out with graphics.

Question 10 (3 points): Joint Particle Filter Time Elapse and Full Test

Complete the `elapseTime` method in `JointParticleFilter` in `inference.py` to resample each particle correctly for the Bayes net. In particular, each ghost should draw a new position conditioned on the positions of all the ghosts at the previous time step.

As in the last question, you can loop over the ghosts using:

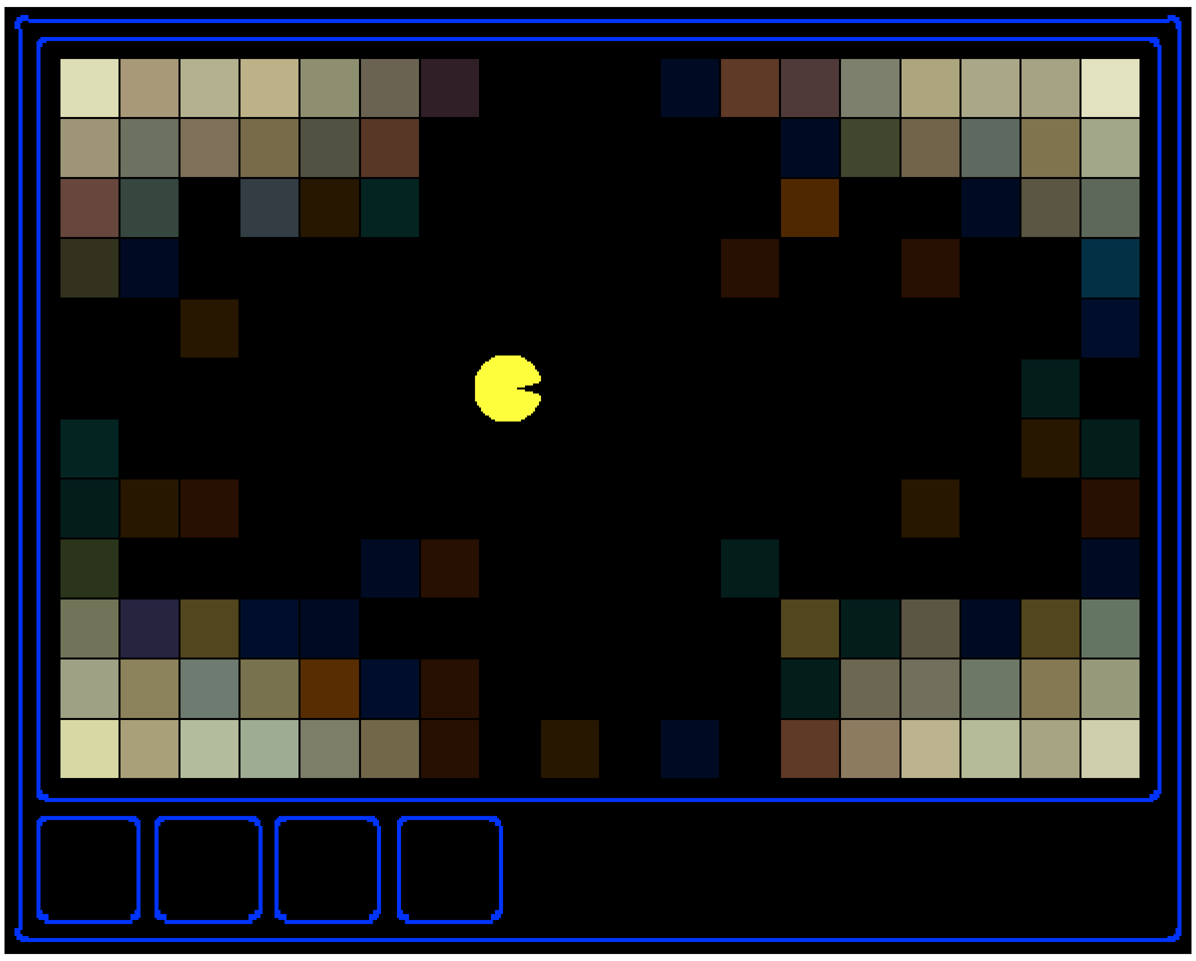
```
for i in range(self.numGhosts):
        ...
```

Then, assuming that `i` refers to the index of the ghost, to obtain the distributions over new positions for that single ghost, given the list (`prevGhostPositions`) of previous positions of all of the ghosts, use:

```
newPosDist = self.getPositionDistribution(gameState, prevGhostPositions, i, self.ghostAgents[i])
```

Note that completing this question involves grading both question 9 and question 10. Since these questions involve joint distributions, they require more computational power (and time) to grade, so please be patient!

As you run the autograder note that `q10/1-JointParticlePredict` and `q10/2-JointParticlePredict` test your `predict` implementations only, and `q10/3-JointParticleFull` tests both your `predict` and `update` implementations. Notice the difference between test 1 and test 3. In both tests, pacman knows that the ghosts will move to the sides of the gameboard. What is different between the tests, and why?



To run the autograder for this question and visualize the output:

```
python3 autograder.py -q q10
```

If you want to run this test (or any of the other tests) without graphics you can add the following flag:

```
python3 autograder.py -q q10 --no-graphics
```

IMPORTANT: In general, it is possible sometimes for the autograder to time out if running the tests with graphics. To accurately determine whether or not your code is efficient enough, you should run the tests with the `--no-graphics` flag. If the autograder passes with this flag, then you will receive full points, even if the autograder times out with graphics.

Submission

Make sure you submit your code files `bustersAgents.py` and `inference.py` to Markus.