This assignment consists of three parts. This is the final assignment for this course.

Use Python for implementation using only standard python libraries (e.g., numpy, matplotlib etc.). Please do not use any third party libaries/implementations for algorithms.

Submission is due at 5pm on Sunday, May 02, 2021. No late submissions please. Points will be awarded out of 120. This assignment will carry 20% of the total grade.

You may work individually or in pairs (with the same partner as the previous assignment or with a new partner). The choice is entirely yours.

Code implementation must be from your own independent efforts. Do not use an existing or previous implementations done by others. Please do not violate the honor code (refer to the course policy on honor code violations).

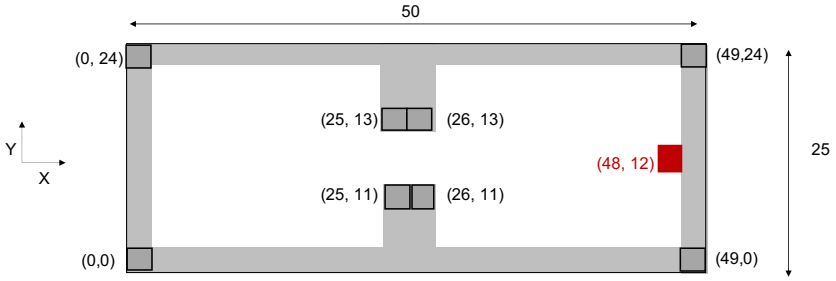
Ensure the reproduction of graphs (modulo probabilistic execution) for your submission. The implementation should be accompanied with a report that includes responses and the desired plots/graphs. Briefly describe the key findings/insights for the graphs.

For parts (a) and (b), please submit a two individual files named as A2-PartA-{EntryNumber}.py and A2-PartB-{EntryNumber}.py. For part (c), submit a presentation in the standard Powerpoint format named as A2-PartC-{EntryNumber}.pptx. Submit the material (code, report and presentation) as a single .zip file named as {A2-EntryNumber}.zip on Moodle.

If the assignment is done in pairs then include both entry numbers as {EntryNumber1-EntryNumber2} in naming the file(s). If you do the assignment in pairs then only one person should submit on Moodle. The submission should be self-contained without external links to a file on Google drive/Dropbox/OneDrive etc. Non-compliance with the submission guidelines will lead to a 10% reduction.

1. (35 points) **Solving an MDP.** Consider a mobile robot in the grid world domain. Please see the figure drawn below. Note that the figure is indicative and not drawn to scale. Some of the grid cells are drawn with the associated coordinates written along side. The other grid cells are implicit in the diagram.

   - The world is a grid of dimensions (50×25). The grid boundary that links the grid indices $(0, 0)$, $(0, 24)$, $(49, 24)$, $(49, 0)$ are walls. There is a wall in the middle portion of the grid (coordinates shown) with a gap of one grid cell between the bottom and the top half. All grid cells constituting walls are shown in *gray* colour.
   - The robot has a choice of four actions: $\uparrow, \downarrow, \rightarrow, \leftarrow$ that can move the agent to an adjacent grid cell in the *north*, *south*, *east* or *west* directions respectively.
   - The action model is such that the nominal outcome (when the robot moves in the intended direction) occurs with probability 0.8, and the other three outcomes occur with probability $0.2/3$. If an action results in a collision with a grid cell part of a wall, then the robot *does not* move and remains in the same grid cell.
   - The robot receives a reward of $(+100)$ if it transitions into the goal state. If the robot stays in the goal state, it will continue to collect a reward of $(+100)$. In case the final state during a transition leads to a collision with a wall in the grid then the robot receives a reward of (-1). In all other cases, a reward of (0) is collected.
   - The robot intends to move to a goal located at grid cell $(48, 12)$ as shown in *red* colour.



   (a) Solve for a policy using value iteration for the problem stated above (refer to lecture 9 slide 28). Use a discount factor of $\gamma = 0.1$ and a threshold of $\theta = 0.1$ as the *max-norm* distance in the successive value functions to determine convergence. You may simulate 100 iterations. To show the result of value iteration, generate an image, where each grid cell is a pixel in the image. Scale the values of the value function obtained to a gray scale value between $[0, 255]$. Show the action (e.g., as arrows) for each state (grid cell) as prescribed by the final policy.

   (b) Increase the discount factor to $\gamma = 0.99$ and plot the value function at iterations 20, 50 and 100.

   (c) Draw a sample execution of the policy starting from an initial state $(1, 1)$. Next, simulate policy execution 200 times and determine the number of times a state is visited. You may keep an upper bound for the length of each episode (say 1000 steps). Visualize the state-visitation counts of the entire grid as an image.

   (d) Study how the *max-norm* for the successive value functions decreases over successive iterations for the discount factors $\gamma = 0.99$ and $\gamma = 0.01$. Typically, the policy is extracted once value iteration has converged. For experimentation, extract the policy after each value function iteration and study when the policy stops changing (when the policy can be considered as converged).

2. (45 points) **Q-Learning.** We consider a mobile robot in the grid world domain as described in the previous question. The problem setup remains the same as the previous question with the following modifications.

   The robot receives a (+100) reward for *arriving* in the goal state. Note that once the robot has arrived at the goal state (it will remain in the goal state) and collect a reward of 0 for being in the goal state. As before, the agent receives a reward of (-1) reward for colliding with a wall, and a reward of 0 otherwise. You may assume a discount factor of $\gamma = 0.99$.

   Assume that the robot does not have access to the transition function and the reward model. The robot receives an instantaneous reward upon making a transition and the successor state obtained after taking a transition comes from the environment simulator. Note that you have access to the transition model and the reward model specified above and can simulate it, but this is not available to the robot.

   (a) Implement Q-learning to help the robot explore and learn a good policy via model-free RL (refer to lecture 11 and slide 24). You may initialize the agent with a learning rate of $\alpha = 0.25$ and an exploration rate of $\epsilon = 0.05$ for the ϵ-greedy exploration during Q-learning. Simulate at least 4000 episodes with the robot interacting in the environment. Assume that each episode starts from a randomly selected feasible state (not the goal state) and terminates if the agent reaches the goal state or the episode reaches a maximum length of 1000 steps.

   (b) Please visualize the resulting *state-value* function for the grid world as an image. As before, generate an image by scaling the value function on a gray scale value between $[0, 255]$. Note that the Q-learner operates on the *state-action* value functions. Hence, convert the state-action value function to the state value function before plotting. Overlay the policy determined by the learner showing the prescribed action for each grid cell.

   (c) How does changing the exploration parameter affect the behaviour of the Q-learner? Vary the exploration parameter as $\epsilon = 0.005$, $\epsilon = 0.05$ and $\epsilon = 0.5$ and examine the resulting value function and the estimated policy.

   (d) Plot the reward accumulated per episode against the number of training episodes. Study the plots for $\epsilon = 0.05$ and $\epsilon = 0.5$.

3. (40 points) **Paper Presentation.** This part involves reading, critiquing and presenting a technical paper. Please select a paper from a prescribed list drawn from prominent conferences in the Robotics & AI or Embodied AI. The paper list appears at this link. Please select any one paper from the list by writing your name(s) alongside. Selection is on a first come first serve basis. The papers can be accessed at this link.

   Please study the selected paper. The paper would build on the basic themes discussed in class and would require some exploration to understand the work (e.g., the problem domain or the AI technique being used). Prepare a 15-minute presentation (max. 20 slides) organized as follows:

   (a) Problem Statement. What problem does the paper attempt to solve? Formally state the technical gap.

   (b) Baseline: What is the baseline? You may briefly state 1-2 works only.

   (c) Technical approach: Describe the key technical details for the proposed solution.

   (d) Results: What are the central results. What is the agent now able to do that it could not do before this paper?

   (e) Others: How can the work be improved or applied to a new problem?

   Use a standard Powerpoint format (16:9 format). A presentation schedule will be notified in due course. Evaluation will be on the clarity of technical ideas and not on the aesthetics/speaking aspects of your presentation. Try to present the key technical ideas through your own understanding of the material. Try to avoid a direct reproduction of descriptive text from the paper (you should of course use the mathematical material, results and the overall structure from the paper).