Programming Assignment 2: Tetris

Due: Wednesday 12/10/2024 @ 11:59pm EST

The purpose of programming assignments is to use the concepts that we learn in class to solve an actual real-world task. We will not be using Sepia for this assignment: I have developed a game engine for us to use. In this assignment we will be writing agents to play Tetris.

RL with Neural Networks

As we discussed in lecture, reinforcement learning requires us to learn either a single utility per state, or in the case of q-learning, a single q-value per (state, action) pair. This mapping is not feasible to store as a table for all but the simplest toy problems. For most problems (Tetris included), there are simply too many states for us to allocate a single float per entry. When we encounter a scenario like this, we often use a neural network in place of the tabular function. Neural networks learn functions, so we can use them in this setting to learn the function we don't have space to store a table for.

Like all ML models, neural networks learn a kernel function $K(\vec{x}, \vec{y})$: a similarity function. This kernel is both a blessing and a curse. A kernel is a blessing because, if you see an example (that you've never seen before), you can leverage knowledge that you've learned from examples that are similar (the kernel tells you how similar things are). A Kernel is a curse because of how it is constructed. A Neural Network learns a kernel through its parameters. If we change a single parameter (i.e. tweak one of the many parameters inside the network), we change the entire kernel itself and therefore we change how the network views every example it will ever see. This means that if we try to improve performance on a single example, we can potentially destroy the knowledge that the network currently has contained within it. It is for this reason that when we train neural networks, we don't optimize for a single example: we take the average gradient across a batch of examples.

When training a Neural Network in reinforcement learning, we will use temporal difference (TD learning): we will have our agent play a bunch of games, record the transitions from those games, and then update our network. While we technically should update our network as soon as a transition occurs, we will instead aggregate them in a buffer called a *replay buffer*. The purpose of the replay buffer is to account for the curse of the kernel: if we updated our network with a transition the second we observe it, we would be optimizing for a single example and run the risk of our network forgetting all the knowledge it has already learned. So, instead of updating the network as soon as transitions become observed, we will collect them into the replay buffer, and wait until the network has finished playing a bunch of games before using the replay buffer to update the network. To be clear, a replay buffer is a hack: this is a bandaid solution that does not solve the underlying problem. A more meaningful approach would be to address neural networks treating each example as i.i.d, but thats a topic for another time and is an active area of research.

This leads us to the training process for neural networks in reinforcement learning. Training is organized into cycles. Each cycle has the following sections, which are executed in order:

1. Play a bunch of "training games", the sole purpose of which is to observe (and record) trajectories.

2. Convert the replay buffer (which was populated with training game trajectories) into a supervised learning dataset. Train the neural network on this dataset.

3. Play a bunch of "evaluation" games with the updated neural network, the sole purpose of which is to evaluate the performance of the network.

This cycle is repeated an enormous amount of times. Eventually, the network will get really good, and therefore our agent will get really good.

Tetris

The version of tetris in this assignment is slightly different than how humans play tetris. When a human plays tetris, they use a joystick (or arrow keys) to guide a piece as it descends to control where the piece lands on the board. While we could do this same process for our agent, it would take much longer for the agent to learn than with what we will do. The way our agent plays tetris is it gets to choose the "final resting place" of a piece, and then once that decision is made, the piece teleports to the desired location. Essentially, the machine does not have the same dexterity that we humans do: we naturally are pretty good at guiding a piece as it descends to the desired location. The machine is not. If we were to have the machine also guide the pieces itself, then we would be asking the agent to learn multiple things: it would need to learn *where* the piece should go, and it would also need to learn *how* to get it there. This is a much harder problem that would take much longer to learn, so the machine gets assistance in placing pieces where it wants them to go.

The rest of tetris is still the same. You earn points for clearning lines: the more lines you clear at once the more points you earn. A *tetris* is clearning four lines at once, and you get bonus points for doing so. A *perfect clear* is where you clear the board, and you get extra points for doing so.

This version of tetris also implements single and double *t-spins*. A "T"-piece (also called a "T"-block or a "T"-mino) can be squeezed into locations that it normally doesn't fit by rotating the piece at the correct time. If you are able to squeeze a "T"-piece using a single rotation, that is called a *single* t-spin. If you are able to squeeze a "T"-piece using two rotations, that is called a *double* t-spin. You are rewarded extra points for a single t-spin, and even more points for a double t-spin.

1. Copy Files

Please, copy the files from the downloaded lab directory to your cs440 directory. You can just drag and drop them in your file explorer.

- Copy `Downloads/tetris/lib/tetris.jar` to `cs440/lib/tetris.jar`.
  This file is the custom jarfile that I created for you.
- Copy `Downloads/tetris/lib/argparse4j-0.9.0.jar` to `cs440/lib/argparse4j-0.9.0.jar`. This is a jarfile that `tetris.jar` depends on. It provides similar functionality to Python's `argparse` module. The documentation for `argparse4j` can be found here.
- Copy `Downloads/tetris/src` to `cs440/src`.
  This directory contains our source code `.java` files.
- Copy `Downloads/tetris/tetris.srcs` to `cs440/tetris.srcs`.
  This file contains the paths to the `.java` files we are working with in this assignment. Just like in the past, files like these are used to speed up the compilation process by preventing you from listing all source files you want to compile manually.
- Copy `Downloads/tetris/doc/pas` to `cs440/doc/pas`. This is the documentation generated from `tetris.jar` and will be extremely useful in this assignment. After copying, if you double-click on `cs440/doc/pas/tetris/index.html`, the documentation should open in your browser.
- Copy `Downloads/tetris/learning_curve.py` to `cs440/`. This is a python script that will be useful for plotting the performance of your agent as a function of how many games its played. More on this later in this document.

2. Test run

If your setup is correct, you should be able to compile and execute the following code. A window should appear:

```
# Mac, Linux. Run from the cs440 directory.
javac -cp "./lib/*:." @tetris.srcs
java -cp "./lib/*:." edu.bu.tetris.Main

# Windows. Run from the cs440 directory.
javac -cp "./lib/*;." @tetris.srcs
java -cp "./lib/*;." edu.bu.tetris.Main
```

NOTE: There are several command line options available to you. If you want to see the exhausive list, please add a `-h` or `--help` argument to the command line and see the help message! Most of these command line arguments are your way of configuring the way you train your model (such as learning rate, batch size, etc.).

Task 1: `TetrisQAgent.java` (100 points)

Please complete the implementation of `TetrisQAgent.java`. In this file, I am asking you to devise and implement several different methods which are crucial for a good RL agent. I have listed them below in order of priority:

1. method `getQFunctionInput`. This method takes a `GameView` object which contains all the information about the current state of the game (i.e. the *state*), as well as a `Mino` object. A `Mino` (short for `Tetramino`) are the pieces that you can place in a game of tetris. The `Mino` provided here as an argument is a possible resting place for the `Mino` that needs to be placed on the board (i.e. the *action*).

   Your method needs to convert these two objects into a row-vector which will be used as input to your neural network. You are responsible for engineering the representation, i.e. for engineering the conversion of game information into a vector. You want you vector to contain all the information necessary for the neural network to provide a meaningful ranking (q-value) of the `Mino` placed on the board.

2. method `getReward`. You have to engineer your reward function. This method takes a single `GameView` object as input, and your method should calculate the reward for being in that state of the game. If this state is bad, you should produce a small number (you are allowed to go negative), and if this state is good, you should produce a large number. I encourage you to be creative when devising your reward function, we want to determine "goodness" and "badness" that correlates to actual good tetris behavior. Don't forget that you are responsible for assigning a reward for terminal states as well as a reward for nonterminal states.

3. method `initQFunction`. Once you have designed your vector representation and figured out your reward function, you will now need to actually build your neural network object. You are only allowed to use feed-forward neural networks in this project: I could not get convolutions working in time for use this semester. The size of the input vector is now fixed: you had to decide this when implementing `getQFunctionInput`, so your input layer should expect a vector of that size. The output of your neural network should be an unbounded (i.e. no output layer activation function) scalar value (i.e. the q-value).

The difficulty part will be how many hidden layers do you use, how big are each hidden layer, and what are their activation functions? I have implemented a little library of layers for you to take a look at, just know that convolutions are not ready yet, so please don't use them.

4. methods `shouldExplore` and `getExplorationMove`. These methods are how we implement curiosity into our agent. As your agent learns, it will start to discover actions that it thinks are good, and start suggesting them more frequently. This can be a blessing and a curse. The blessing is that the model is doing things that are "good" (as measured by the reward function). The curse is that as we continue to follow the policy, we will stop exploring and gaining novel experiences, and we risk getting stuck. This isn't really a problem if our policy happens to stumble upon really good actions, however this is unlikely, and instead our policy will get stuck on (what it deems to be the best its seen so far but are actually) mid-tier actions.

   To encourage the agent to ignore the policy (sometimes) and instead explore for novel experiences, we need to implement a version of curiosity. The first method, `shouldExplore` should return `true` when the agent determines that it should explore in this state (and ignore what the policy recommends), and `false` otherwise. The second method, `getExplorationMove` is how we generate an action that will (hopefully) lead to a novel experience (assuming we have decided to ignore the policy in the first place). You should implement some notion of curiosity here.

To earn full credit, you must demonstrate that your agent has learned. If your agent can score an average of 10 points when playing 500 games of tetris, then I will award you full credit.

Training

To train your agent, you should develop your code locally and make sure that it doesn't error, and that it measures quantities the way you intend them to be measured. Once you have that working, you will want to train your agent on tens of thousands, if not hundreds of thousands of games. To do this, I am providing you access to one of the big machines in my office. This machine has 256 logical cpu cores and 1TB of RAM, so it should be able to handle all you can throw at it. Since this machine is my personal property and not that of BU's, you do not have an account on it. Please shoot me an email or post on piazza asking for access. Of course, you do not have to use my machine, but the other alternative is for you to use your laptop and have it running for days.

If you want to use my machine, after you get an account, you will need to ssh into it. I will post more information on piazza about how to ssh for those unfamiliar. When ssh'd into my machine, you will have to transfer your files from your local machine to mine. There are a variety of ways of doing this, but I think the simplest is to use a program called `rsync`. However, if you prefer another way, that is fine with me.

Ok, lets say that you have an account, can ssh into my machine, and have copied all of your files over. Now it is time to launch a long training run. The trouble is, if you launch a run in your ssh shell, you will have to leave the ssh connection open the entire time the program is running, or else it will be killed when you disconnect. To avoid this, you will need to learn how to use a program called `screen`. `screen` screen is a program that lets you detach your current terminal and have it run in the background. Instructions for screen can be found here (note you dont have admin privileges on my machine so you can skip the install parts of that tutorial).

The Tl;dr of screen is that you can create a screen using a command that looks something like this:

```
screen -h 10000 -S tetris_train
```

This would create a screen that stores the latest 10000 console messages and is called tetris_train. If you run this command you will be in the screen (just another terminal). You can always detach the current screen by typing `Ctrl + a + d`. The detached screen will continue running in the background.

You can view you screens with

```
screen -ls
```

You can reattach a background screen with

```
screen -r <name_of_screen_to_reattach>
```

, so for me that would be

```
screen -r tetris_train
```

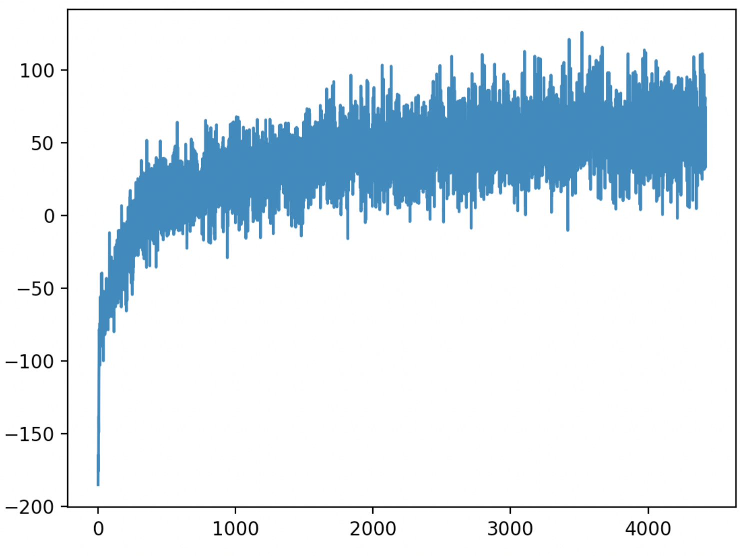
Once youre in a screen, you compile your code, launch it, hang around for a few minutes to make sure it works, and then detach it and logout of the ssh. You can come back at any point in the future, reattach the screen and check on its progress!

Checking on Performance

When training your agent (which will take days), you will want to check in on it periodically. My code will, after every cycle, save your neural network to disk in a directory called `params`. When should you stop training, and which version of your network is the best? These are questions answered by the evaluation section of every cycle. The average trajectory utility is printed out after every cycle: this is information you will want to keep and to plot. To do so, when it is time for you to launch your agent's massive training run, you should run it like so (only shown for linux since I am assuming you'll be running this on my machine):

```
java -cp "./lib/*:." edu.bu.tetris.Main ... | tee my_logfile.log
```

The `| tee my_logfile.log` part of this command (the `...` stands for your specific settings) will pipe stdout to a file called `my_logfile.log` which will exist in the same directory that the shell is in when the command was run. Periodically, you can download your `my_logfile.log` to your laptop, and then use `learning_curve.py` to plot the average trajectory utility as a function of time. The way you will know your model is learning is if you get something that looks like this



The x-axis is the number of cycles that the model has run for (this curve shows 4000 cycles), and the y-axis is the average trajectory utility.

Task 2: What to Submit

This time you will need to submit more than just your Java source code. As your model trains, my code will write the parameters of the model to files on your machine after every phase. You need to pick one of these files (ideally the file that corresponds to the model that has the best performance), rename it to `params.model`, and submit it along with your `TetrisQAgent.java` file on gradescope.

Task 3: Extra Credit (50 points)

If your agent can earn an average of 30 points when playing 500 games of tetris, then I will award you full credit.

Task 4: Tournament Eligibility

In order for your submission to be eligible in the tournament, your submission must satisfy all of the following requirements:

- Your submission must be on time.
- You do not get an extension for this assignment.
- Your agent compiles on the autograder.
- Your agent can play 1000 games of tetris and earn an average of 20 points or more.