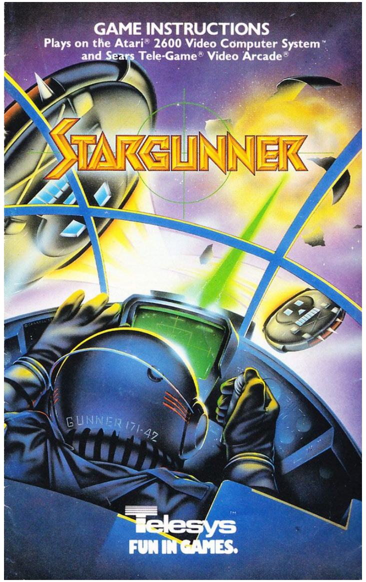
DQN Project

Important Note

Let me reiterate that all submissions will be run through a program that automatically detects copies including minor variations and duplicate parts (e.g., doesn't have to be the whole code).
Please do not risk copying code from anywhere. If you copy the whole or part of a code, including web sources, we will find out and immediately refer the student(s) to the university as an academic dishonesty case.

Objective

You are going to implement a DQN agent that plays the Atari 2600 game StarGunner.



Required Readings

Please read carefully **both**:

- Human-level control through deep reinforcement learning: https://web.stanford.edu/class/psych209/Readings/MnihEtAlHassibis15NatureControlDeepRL.pdf
- Section 16.5 of the textbook

before attempting to solve the project.

Environment

StarGunner is available in the OpenAI Gym:
https://gym.openai.com/envs/StarGunner-v0/

To get started with the OpenAI Gym, please read this tutorial:
https://gym.openai.com/docs/

To create the game environment and preprocess the game frames:

```
import gym
env = gym.make('StarGunner-v0')
env = gym.wrappers.AtariPreprocessing(env)
```

Implementation

You can use any machine learning library of your choice to implement DQN's architecture. We recommend Keras (https://keras.io/) because it is easy to use.

You can use Google Colaboratory so you don't need to install anything locally.

The next several slides provide some hints on how to implement the learning algorithm.

Algorithm 1: deep Q-learning with experience replay.

Initialize replay memory D to capacity N ← E.g., a python list

Initialize action-value function Q with random weights θ

Initialize target action-value function $\hat{Q}$ with weights $\theta^- = \theta$

For episode = 1, M **do**

  Initialize sequence $s_1 = \{x_1\}$ and preprocessed sequence $\phi_1 = \phi(s_1)$

  For $t = 1$,T **do**

    With probability ε select a random action a_t

    otherwise select $a_t = \mathrm{argmax}_a Q(\phi(s_t), a; \theta)$

    Execute action a_t in emulator and observe reward r_t and image x_{t+1}

    Set $s_{t+1} = s_t, a_t, x_{t+1}$ and preprocess $\phi_{t+1} = \phi(s_{t+1})$

    Store transition $(\phi_t, a_t, r_t, \phi_{t+1})$ in D

    Sample random minibatch of transitions $(\phi_j, a_j, r_j, \phi_{j+1})$ from D

    Set $y_j = \begin{cases} r_j & \text{if episode terminates at step } j+1 \\ r_j + \gamma \max_{a'} \hat{Q}(\phi_{j+1}, a'; \theta^-) & \text{otherwise} \end{cases}$

    Perform a gradient descent step on $\left(y_j - Q(\phi_j, a_j; \theta)\right)^2$ with respect to the network parameters θ

    Every C steps reset $\hat{Q} = Q$

  End For

End For

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$$\text{Set } y_j = \begin{cases} r_j & \text{if episode terminates at step j+1} \\ r_j + \gamma \max_{a'} \hat{Q}\left(\phi_{j+1}, a'; \theta^-\right) & \text{otherwise} \end{cases}$$

Perform a gradient descent step on $\left(y_j - Q\left(\phi_j, a_j; \theta\right)\right)^2$ with respect to the network parameters θ

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E.g., create a Keras model and add Conv2D layers, Dense layers, etc. Use the hyperparameters described in the paper.

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The same as the previous step; create another model with identical architecture.

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For episode = 1, M **do**

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E.g., a Python deque that maintains 4 game frames

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E.g., create two lists *x* and *y*; *x* is the states, and *y* is the targets. Use the Keras function *fit* to train the model.

Submission (via Course Site)

Please submit two files:

- Your code
- A 1-page PDF file with the following information about your system:
  - Plotting on the x-axis (training episodes) and the y-axis (episodic reward)
  - A description of the results

The most significant portion of the grade will be dependent on the performance of your agent.

Deadline: Monday, December 16, 2019, 7:00 AM

Meeting with Instructor - REQUIRED

- Each group is required to meet with the instructor
- In the meeting the group will demonstrate their system
- The instructor will ask questions about the code
- **The code submitted via Course Site must be identical to the one in the demonstration**
- **Registration information for these meetings will be available on Course Site (first come, first serve)**
- Meetings dates: Monday December 16, Tuesday December 17