Engineering Design Document

AI Bot for Self-designed Overhead Shooter Game

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TABLE OF CONTENTS

1 INTRODUCTION

1.1 Overview

The game is a 2D overhead shooter game similar to those old-school Atari games. Players can control their characters to fight against AI enemies. To win the game, players must eliminate all enemies and stay alive. The idea of this game came from the combination of MOBA and old-school video games. We would like the game to be simple enough for initial training and we planned to add more complexity throughout the semester.

The game will then be used as a customizable environment to train our reinforcement learning agents. We will compare the performance of a wide range of models on different versions of the game. The game and the model will be designed and developed together so that we can make changes based on model performances.

1.2 Goals

The main goals of this project are to:

1) Construct the custom environment:

Different versions bring flexibility. And we will be able to see models' adaptation to new elements in the game. Our custom game environment allows us to tweak it in response to model performances. The RL agent can potentially help us find bugs in the game.

2) Train our agent to play against an enemy or multiple enemies:

We will start by training RL agents against one enemy, and will increase the number of enemies throughout the project. One advantage of this is that we can apply pre-training techniques.

3) Compare the performance of different models and observe their behaviors:

For each of our models, we will train the agent by playing against pre-scripted enemy(s). Using different models, we hope to find their strengths and weaknesses. Along with training the agents, we expect to learn new strategies from our RL agents.

Models are expected to have fluctuating scores on different versions of the game, so we would like to find out what factors cause the fluctuations and why some models perform better.

1.3 Related Research

Research was conducted to find out what environments and models were suitable for our project. We decided to design our own environment and apply as many models as possible.

Regarding the environment, we narrowed it down to an overhead shooter game. We were inspired by OpenAI's algorithms trained on Atari games. The overhead shooter was similar to those games but different in terms of the gameplay. We expected to discover new findings using such an environment.

When choosing models, we looked for RL models that had good performance in game environments. Since we planned to try out as many different models as possible, we chose DQN as our starting point and added future models such as Genetic Algorithm and Actor-critic methods. From our research, we learned that many models were designed to play games of different kinds, which is exactly what we wanted.

2 DESIGN OVERVIEW

Since all of the models require a standardized game environment to compare their performances, the project can be splitted into two components:

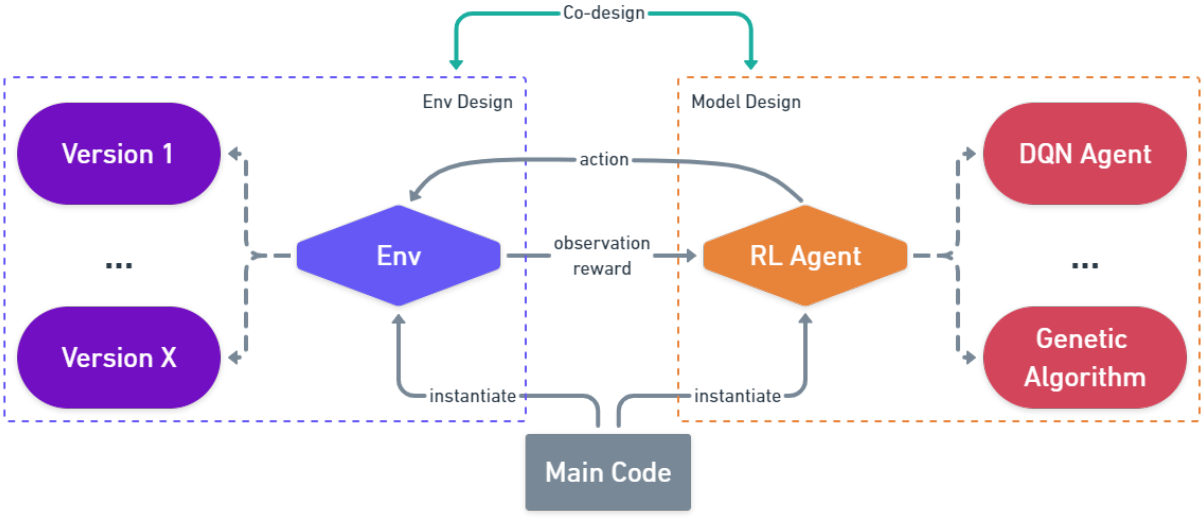
1. The game environment: it provides an interface for different models to use
2. The models: they utilize the game environment to perform training

2.1 System Architecture

The development of game environments and models are separated but co-designed, as shown in the diagram below. Multiple models can be using the same environment while there can be multiple environments.

Each version of the game environment will have the same API. Thus, it can be plugged into any models we choose. Having the same interface will allow us to compare the performance of different models in the same environment.

In addition, each model will own a game environment instance and interact with it. Regardless of the environment version, the model should be able to train and evaluate.



System Architecture

3 GAME ENVIRONMENT DESIGN

3.1 Environment Overview

Our environment is a 2D overhead shooter game wrapped in a ML interface. The player of the game controls a spaceship to fight against two or more enemy spaceships. The player and enemies can move in all directions at constant speed and fire bullets that do constant damage to the opponents. When one enemy dies, a new one will be spawned at a random position. If the player's health drops below zero, the game will be over.

In different versions of the game environment, we added new elements such as additional enemies, shields and treasures. But at the core of the environment, we kept the same goals: the agent must hit enemies, dodge bullets and utilize game elements wisely.

All environment versions share the same ML interface, which inherits from OpenAI Gym Env class. This will facilitate model training, as models can treat the environment as the same.

3.2 Choosing the Right Tool

Prior to the project, multiple researches concerning different game development environments were conducted. We had come down to 2 main options and their features as following:

1) Pygame + Open AI Gym open code resources:
    a) Direct, customizable interaction with Python. ✔
    b) Similar syntax to SDL, easy to learn/use. ✔
    c) Lightweight, small GPU usage. ✔
    d) Basic game development tools with few integrated functions. ×
    e) Less aesthetic graphic interface. ×
2) Unity + ML-agents:
    a) Highly integrated game development tools. ✔
    b) Delicate graphics quality. ✔
    c) Indirect, less customizable interaction with Python. ×
    d) Incompatible API with PyTorch baseline code for training. ×
    e) Steep learning curve. ×
    f) Taking up a lot of GPU memory, hindering training speed. ×

As the main purpose of this project being application of machine learning algorithms in game AIs, instead of making a relatively nice-looking facet, we prioritize the

“intelligence” part of the game, digging into multiple algorithms and having them tested and analyzed in various environments. As a result, we decided not to put much effort into the actual gaming features, but to focus on the machine learning functionalities in which the combination of Pygame and Open AI Gym would give us more freedom in design.

3.3 How PyGame + OpenAI Gym Works?

The game will be built in Pygame, an open-source Python library for game development. In terms of the coding logic, the most important and principal functionality of Pygame is “Sprite” which essentially is the combination of a “game object” and an “image sprite”.

As shown in following diagram, a “pygame.sprite.Sprite” contains:

1) An image representing the object.
2) A “rect” variable storing the rectangular coordinates of the object. This is also where position information is stored.
3) All other customized parameters.
4) Function to display the game canvas.
5) Function to detect collisions between rectangular boxes of itself and other objects’.

Basic “sprite” Diagram:

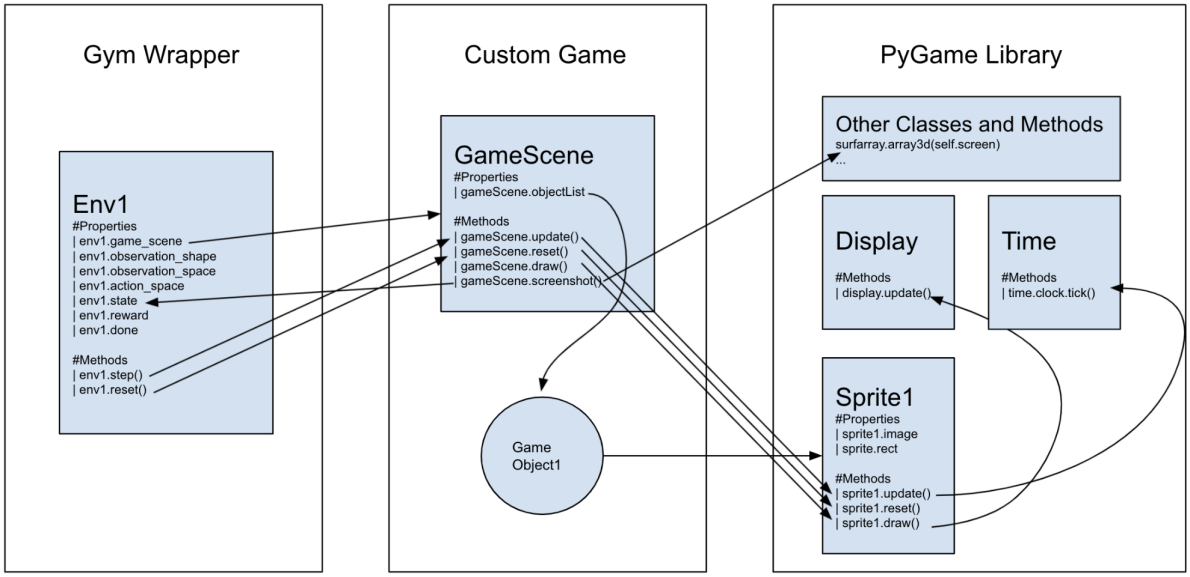
pygame.sprite
| self.image: *pygame.image*
| self.rect: *pygame.rect*
| self.foo: *customizable data type*
| self.draw() -> *None*
    #display on canvas
| self.collide_rect(sprite1: pygame.sprite, sprite2: pygame.sprite) -> *bool*
    #can be called as a static function

Open AI Gym is currently a prevalent API standard for implementing machine learning algorithms in a Pygame project. Simply by wrapping a pygame project inside a black box, developers are provided access to tons of open-source machine learning codebase. As long as the environment is configured accordingly, codes from variant resources can be properly integrated and run without a flaw.

Basic Gym “Env” Diagram:

gym.env
| self.game_scene: *customized data type*
    # a reference to the game project if needed
| self.observation_shape: *Tuple*
    # defines the size of an observation

| self.observation_space: *gym.spaces.Box*
    # defines a rudimental space of an observation
| self.action_space: gym.spaces.Discrete
    # defines all actions that can be performed
| self.state: *customized data type*
    # stores current state
| self.reward: *customized data type*
    # stores a customized evaluation score of current state
| self.done: *bool*
    # record status of the game
|self.info: *dict*
    # stores any additional information if needed
| step() -> *None*
    # takes an action and modifies self.state, self.reward,
    # self.done and self.info
| render() -> *None*
    # displays the game canvas
| reset() -> *None*
    # starts over



Basic Workflow of PyGame + Gym

3.4 Building Up the Environment

3.4.1 PyGame Environment Setup

The game scene is a human-playable Pygame class, which will feed inputs to the *ShooterEnv* class.

GameScene

class GameScene:
Properties:

- self.screen: Pygame screen
- self.clock: Pygame clock to control the FPS
- self.player: Customized game objects as below classes

Methods:

- __init__(self):
    - Initializes Pygame display
    - Initializes player and enemy
    - self.Reset()
- Play()
    - Take an action and get feedback from GameScene
- ScreenShot()
    - Get a vectorized array of screen pixel
- update()
    - Update the GameScene according to current action
- draw()
    - Display the canvas

Spaceship

class Spaceship(pygame.sprite.Sprite):
Properties:

- self.health: current health
- self.start_health: starting health
- self.start_x: starting x position
- self.start_y: starting y position
- self.color: color of this spaceship (used to fill the image)
- self.up_direction: a boolean whether the spaceship is facing upwards
- self.bullets: a pygame.sprite.Group for all its bullets

Methods:

- __init__(self, image: pygame.Surface, screen_rect: pygame.Rect, start_health: int, start_x: int, start_y: int, color: Tuple[int, int, int], up_direction: bool):
    - Initializes self.image and fill using color
    - Initializes self.rect.x and self.rect.y using x and y from arguments
    - Initializes other properties

- update(self, action: Action, others: List[pygame.sprite.Sprite]):
- fire(self):
- reset(self):
- is_dead(self) -> bool:

Bullet

class Bullet(pygame.sprite.Sprite):
Properties:

- self.vel_x: velocity in x direction
- self.vel_y: velocity in y direction
- self.screen_rect: the rect for the entire game screen

Methods:

- __init__(self, x: int, y: int, color: Tuple[int, int, int], vel_x: int, vel_y: int, screen_rect: pygame.Rect):
    - Initializes self.image and fill using color
    - Initializes self.rect.x and self.rect.y using x and y from arguments
    - Initializes other properties
- update(self):
    - Updates x and y position using self.vel_x and self.vel_y
    - Checks if it goes off screen:
        - If it does, kill the bullet sprite

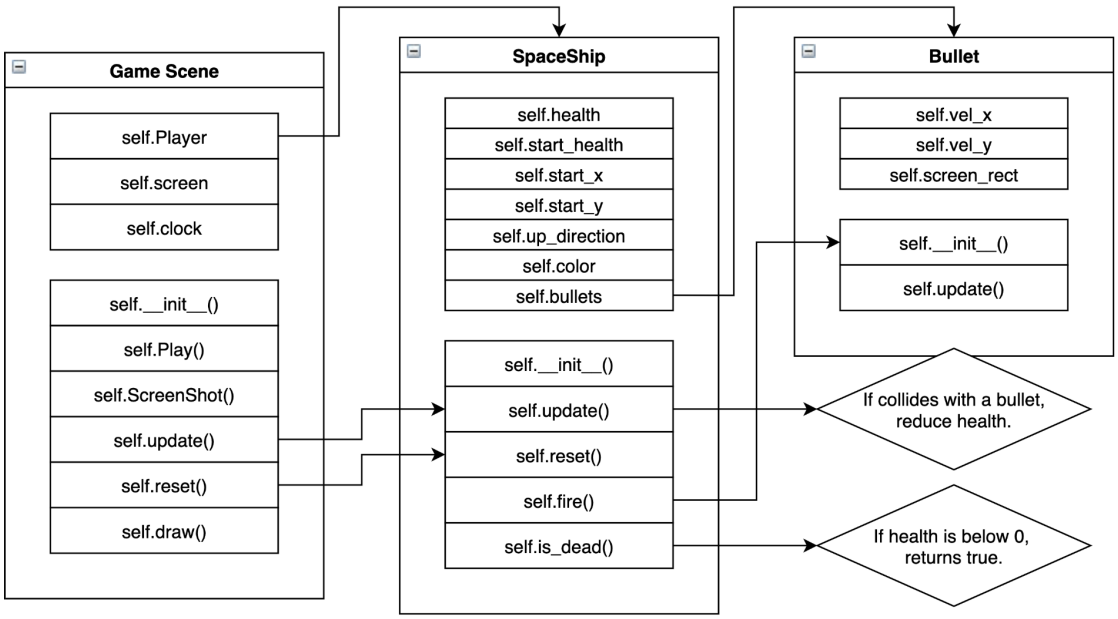
Treasure

class Treasure(pygame.sprite.Sprite):
Methods:

- __init__(self, image: pygame.Surface, x: int, y: int):
    - Initializes self.image and fill using color
    - Initializes self.rect.x and self.rect.y using x and y from arguments

Pre-scripted Enemy

The pre-scripted enemy is designed to facilitate the training of agents. The enemy will constantly move from left edge to right edge and move backward in a loop. It will fire randomly when possible. Its implementation contains a series of “if else” statements and it performs random actions using a random number generator.



Workflow of the PyGame Environment

3.4.2 OpenAI Gym Environment Setup

To use our game environment as inputs to learning agents, it is necessary to wrap the game in a gym.Env class.

class ShooterEnv(gym.Env):
Properties:

- self.game_scene: a GameScene class
- self.observation_shape: (WIDTH, HEIGHT, 3)
- self.observation_space: a screenshot of the game screen in RGB colors
- self.action_space: NOOP, LEFT, RIGHT, and FIRE
- self.state: a screenshot of the game screen in RGB colors
- self.reward: the current reward
- self.done: done status
- self.info: information

Methods:

- __init__(self):
    - Initializes everything and defines observation and action space
- step(self, action_num: int):
    - Performs the action
    - Returns done status, reward, and state from the game scene
- reset(self):

    - Resets game scene
    - Returns state

3.4.3 Parameters Setup

All tunable parameters are stored in one file for easy tuning. Some of the important ones are:

- PURE_COLOR_DISPLAY = True
- NEGATIVE_REWARD_ENABLED = True
- NEGATIVE_REWARD = 0.005
- REWARD.BULLET_HIT_ENEMY = 10
- REWARD.BULLET_HIT_PLAYER = -10

3.5 Preprocessing

We defined some utility functions/classes that are used across different models. The *make_env* function is used to preprocess raw frames from *ShooterEnv*.

Methods:

- def plot_learning_curve(x, scores, epsilons, filename, lines=None):
    - Plots stats using matplotlib
    - Saves the plot to a file
- def make_env(env_name, shape=(84,84,1), repeat=4, clip_rewards=False, no_ops=0, fire_first=False):
    - Instantiates env using env_name
    - env = RepeatActionAndMaxFrame(...)
    - env = PreprocessFrame(...)
    - env = StackFrames(...)
    - Returns env

Classes:
class RepeatActionAndMaxFrame(gym.Wrapper):

- Wraps reset() and step() functions to repeat actions and only returns the max frame

class PreprocessFrame(gym.ObservationWrapper):

- Wraps observation() function to resize the frame to customized shapes (the most frequent one is 84 x 84

class StackFrames(gym.ObservationWrapper):

- Wraps reset() and observation() functions to stack 4 frames

3.6 Environment Versions

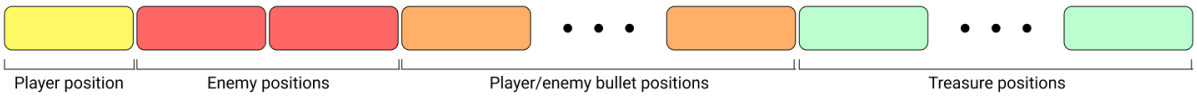
Below is a summary of the different game versions we have. Throughout our development, the difficulty of the game gradually increases.

Version	Action space	Features
Env 1.0	{NOOP, LEFT, RIGHT, FIRE}	Vanilla version
Env 2.0	{NOOP, LEFT, RIGHT, FIRE}	Two enemies, consecutive shooting disabled
Env 3.0	{NOOP, LEFT, RIGHT, FIRE, UP, DOWN}	Two enemies, treasures, consecutive shooting disabled

Summary of environment versions

3.7 Vector Input Variants

For some of our models that require vector inputs, we built a customized environment for them. The vector contains the position of all interactable elements in the game, as shown in the diagram below.



We added the below methods for those variants.

GameScene:
Methods:

- StateVector(self, extra_padding: bool) -> np.ndarray:
    - Gets coordinates of player, enemies and bullets
    - Puts them into state_arr
    - Returns state_arr

ShooterEnv:
Enum:

- StateMode(Enum):
    - SCREENSHOT_MODE = 0
    - VECTOR_MODE_1 = 1
    - VECTOR_MODE_2 = 2

Methods:

- __init__(self, state_mode: StateMode = StateMode.SCREENSHOT_MODE):
    - self.state_mode = state_mode
    - ...
    - if self.state_mode == StateMode.SCREENSHOT_MODE:
        - Use screenshot as state
    - else:
        - Use vector as state
    - …
- step(self, action_num: int) / reset(self):
    - ...
    - if self.state_mode == StateMode.SCREENSHOT_MODE:
        - Use screenshot as state
    - else:
        - Use vector as state
    - ...

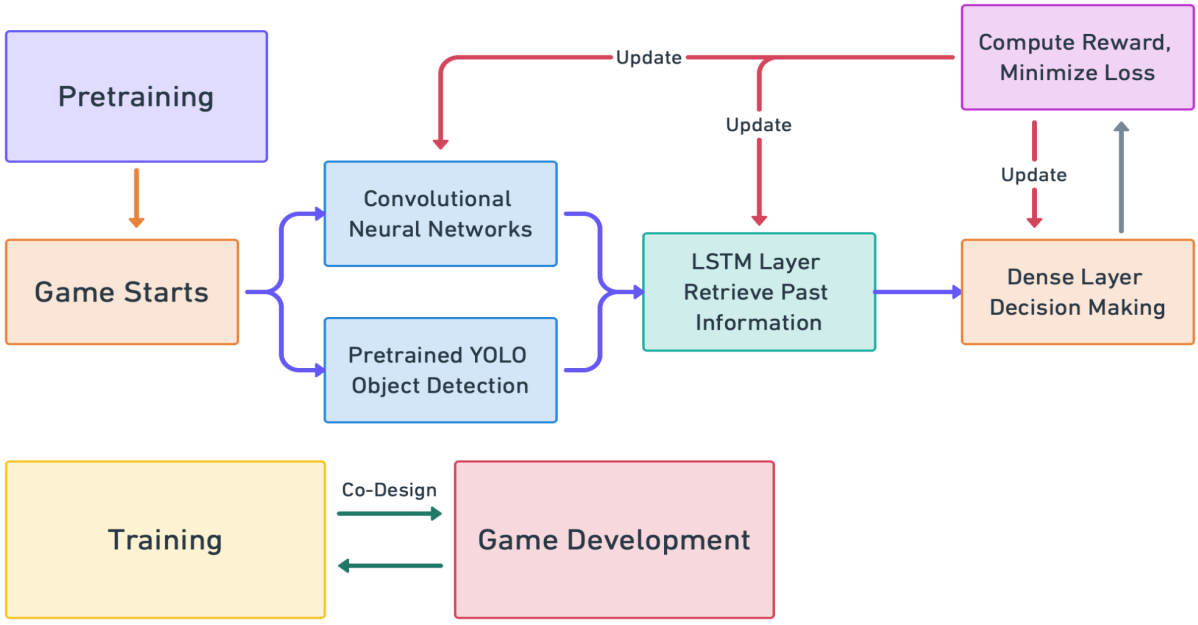
4 MODEL DESIGN

4.1 Model Overview

As we discussed in our design overview, different models use their own agents, but they share the same main code and game environments. In the below diagram is the workflow of different models and the interaction between environments and agents.

Different modules are used for different tasks. For feature extraction, models either use convolutional neural networks or pre-trained YOLO object detection. An optional LSTM layer can be plugged into any model to retrieve past information. Several identical dense layers are used for decision making. And reward and loss are computed in a common way. Some models also utilize pre-training for faster training speed and better performances.

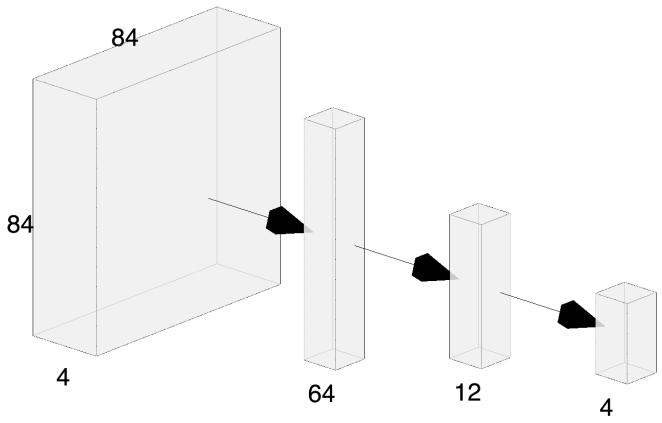
This kind of modular design allows us to quickly design new models and fix bugs in our code. When we compare the performance of models, it is easy to interpret the results.



Model Architecture

4.2 Genetic Algorithm

GA simulates an evolution situation where 20 separate learning agents count as one generation. Within one generation, models from different agents are combined through genetic processes such as mutation, crossover and inversion to form the next generation. In current progress, RNN is used as a single learning agent.



Structure of RNN used in GA

4.2.1 Implementation

Individual

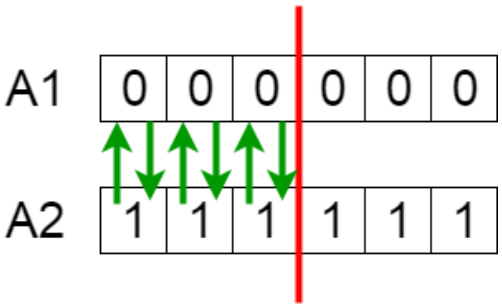
Individual is a class for each “creature” or learning agent. A customized RNN is used to play the game and some genetic processes are included to perform evolution between parents and offspring.

class Individual
Properties:
| self.nn: *NeuralNetwork*
    # stores a customized RNN class object
| self.fitness: *float*
    # stores the score of the RNN, in GA’s terminology, fitness
| self.weight_biases: *np.array*

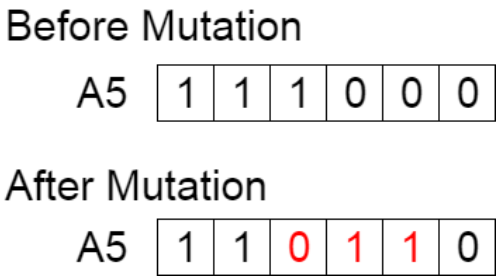
Methods:
| self.__init__(input_size: *int,* hidden_size: *int*, output_size: *int*) -> *None*
    # initialization of a single learning agent
| self.calculate_fitness(env: *gym.env*) -> *None*

```
            # run a single episode of a game and get the feedback information
        | self.update_model() -> None
            # update RNN mode weights with current result and biases

        # Abstract methods for future definition
        | self.get_model(input_size: int, hidden_size: int, output_size: int) ->
NeuralNetwork
            # method of getting a learning agent
        | self.run_single(env: gym.env, episode: int, render: bool) -> Tuple[float, np.array]
            #method for a single episode game simulation

# Static Functions:
| crossover(parent1_weights_biases: np.array, parent2_weights_biases: np.array, p: float)
-> Tuple[np.array, np.array]
| inversion(child_weights_biases: np.array) -> np.array
| mutation(parent_weights_biases: np.array, p: float, scale: int) -> np.array
| ranking_selection(population: List[Individual]) -> Tuple[Individual, Individual]
| roulette_wheel_selection(population: List[Individual])-> Individual
| statistics(population: List[Individual]) -> float, float, float
```

Genetic Crossover of a Vector



Genetic Mutation of a Vector



Population

Population is a class for the “entire world” including 500 generations. It’s a generalization class for the GA model.

```
        class Population
        # Properties:
        | self.pop_size: int
        | self.max_generation: int
        | self.p_mutation: float
            # probability of mutation
```

| self.p_crossover: *float*
        # probability of crossover
| self.p_inversion: *float*
        # probability of inversion

Methods:
| self.__init__() -> *None*
        # initialization of a generation
| self.run()-> *None*
        # Run GA simulation until max generation is achieved.
        # Inside each generation, 20 individuals are called one by one to start a single game episode.

Basic Parameter

- RNN:
  Input size: 84 * 84 * 3
  Hidden layer1 size: 40
  Hidden layer2 size: 12
  Output size: 4
- GA:
  Max iteration in one game: 2000
  Population size: 20
  Max generation size: 500
  Mutation rate: 0.2 ~ 0.1
  Crossover rate: 0.7 ~ 0.8
  Inversion rate: 0

Further modification and tests are needed to find out the best and most quickly-converging settings of the parameters.

4.3 DQN

DQN evolves from Q learning. Q learning keeps a Q table to evaluate the desirability of each state/action pair. The Q table is updated using the temporal different method. However, it is unscalable in large games because the number of states is too large, and the Q table will be intractable. So, we replace the Q table with Q network for generalization. Q network also updates itself by minimizing the loss function within the framework of temporal difference (TD) algorithm.

4.3.1 Pseudocode

Algorithm 1 Deep Q-learning with Experience Replay

Initialize replay memory $\mathcal{D}$ to capacity N
Initialize action-value function Q with random weights
for episode $= 1, M$ **do**
  Initialise sequence $s_1 = \{x_1\}$ and preprocessed sequenced $\phi_1 = \phi(s_1)$
  for $t = 1, T$ **do**
    With probability ϵ select a random action a_t
    otherwise select $a_t = \max_a Q^*(\phi(s_t), a; \theta)$
    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 $\mathcal{D}$
    Sample random minibatch of transitions $(\phi_j, a_j, r_j, \phi_{j+1})$ from $\mathcal{D}$
    Set $y_j = \begin{cases} r_j & \text{for terminal } \phi_{j+1} \\ r_j + \gamma \max_{a'} Q(\phi_{j+1}, a'; \theta) & \text{for non-terminal } \phi_{j+1} \end{cases}$
    Perform a gradient descent step on $(y_j - Q(\phi_j, a_j; \theta))^2$ according to equation 3
  end for
end for

4.3.2 Implementation

class DeepQNetwork(nn.Module):
Properties:

- self.conv1, self.conv2, self.conv3: convolutional layers
- self.fc1, self.fc2: fully connected layers
- self.optimizer: RMSprop optimizer
- self.loss: MSE loss

Methods:

- forward(self, state):
  - Forwards the input state through each layer of the network
  - Returns action

class DQNAgent(object):
Properties:

- self.q_eval: a DeepQNetwork
- self.q_next: a DeepQNetwork
- self.memory: a replay buffer
- self.epsilon

Methods:

- choose_action(self, observation):
  - If np.random.random() > self.epsilon:
    - Chooses action using q_eval
  - else:
    - Chooses random action
  - Return action
- store_transition(self, state, action, reward, state_, done):

    - Stores transition in self.memory
- sample_memory(self):
    - Samples memory from self.memory
    - Return states, actions, rewards, states_, dones
- replace_target_network(self):
    - Copies eval network to target_network for every 1000 steps
- decrement_epsilon(self):
    - Decreases self.epsilon by fixed amount

Main:

- agent = DQNAgent(...)
- env = make_env(...)
- for i in range(n_games):
    - done = False
    - observation = env.reset()
    - score = 0
    - while not done:
        - action = agent.choose_action(observation)
        - observation_, reward, done, info = env.step(action)
        - agent.store_transition(observation, action, reward, observation_, done)
        - agent.learn()
        - observation = observation_
    - Print out stats

4.4 DDQN

DQN uses the same Q network for both evaluation and selection, Such estimation creates a maximum bias. Double DQN alleviates the problem by introducing a separate Q' prime network soly for action selection in the max operator. The weights of Q' are periodically copied from Q.

4.4.1 Implementation

The only difference from DQN:

- Second Q' network

4.5 Dueling DDQN

Dueling architecture takes this into account by designing an advantage function Athat subtracts the state value $V^{\pi}(s)$ from the action value $Q^{\pi}(s, a)$. The DQN network is split into two streams to compute the action and the state value.

4.5.1 Implementation

The only difference from DQN:

- Uses an advantage function that subtracts the state value V(s) from the action value Q(s, a) as the output of the q_eval and q_next networks

4.6 DRQN

The original DQN learning captures temporal information by having 4 consecutive frames as inputs. DRQN has only one frame as input but can retain past information by using an LSTM layer to replace the linear layer in the original DQN. And we are sampling a sub-sequence from an episode.

4.6.1 Implementation

The only difference from DQN:

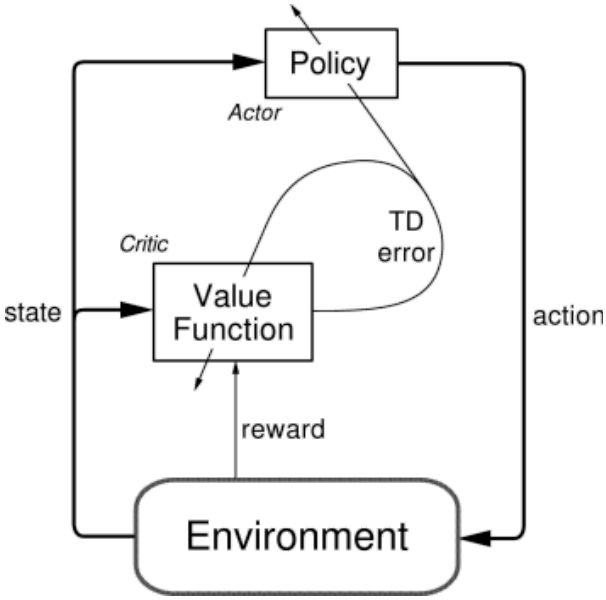
- One of the fully connected layer is replaced by an LSTM layer

4.7 Actor-Critic

Actor-critic algorithm is the combination of value-based and policy-based algorithms. The model consists of two networks: an actor choosing action based on current game state and a critic to calculate the Q value of the actor's action. The learning of the actor is using policy gradient while the learning of the critic is using temporal difference (TD).

The actor and the critic networks can share a large part of a neural network. Both of them need several convolutional layers to extract features from the input images and one or two fully connected layers. The only difference is the final output layer. The actor network has an output size equal to the number of actions while the critic network has an output size of one (Q value).

The loss of actor-critic networks has two parts as well. The first part is policy loss, computed by policy gradient. And the second part is value loss, computed by temporal difference (TD).



Actor-critic workflow

4.7.1 Pseudocode

In each training step:

1. Observe the state
2. Randomly sample action a_t according to $\pi(\cdot \mid s_t; \theta_t)$
3. Perform a_t and observe new state s_{t+1} and reward r_t
4. Update ω(in value network) using temporal difference (TD)
5. Update θ(in policy network) using policy gradient

4.7.2 Implementation

class ActorCriticNetwork(nn.Module):
Properties:

- A neural network with two output layers:
  - self.pi: output for actor network
  - self.v: output for critic network

Methods:

- forward(self, state):
  - Given a game state, return pi and v

class ActorCriticAgent:
Properties:

- self.actor_critic: an ActorCriticNetwork
- self.gamma
- self.lr: learning rate

Methods:

- choose_action(self, observation):
    - Forwards self.actor_critic network to get action probabilities
    - Randomly samples an action and return it
- learn(self, state, reward, state_, done):
    - Forwards self.actor_critic network to get critic value
    - Calculates actor and critic losses
    - (actor_loss + critic_loss).backward()
    - Steps optimizer

Main:

- agent = ActorCriticAgent(...)
- env = make_env(...)
- for i in range(n_games):
    - done = False
    - observation = env.reset()
    - score = 0
    - while not done:
        - action = agent.choose_action(observation)
        - observation_, reward, done, info = env.step(action)
        - score += reward
        - agent.learn(observation, reward, observation_, done)
        - observation = observation_

4.8 PPO

Proximal Policy Optimization, one of popular reinforcement learning models in recent years, is an improvement of the policy gradient descent algorithm.

PPO also uses actor-critic agents, but the difference is that it combines the idea of TRPO. It uses clipped surrogate objectives to penalize large policy updates.

4.8.1 Implementation

class Policy(nn.Module):
Properties:

- self.base: CNN base
- self.dist: distribution of size num_outputs to decide action

Methods:

- act(self, inputs):
    - Gets value and actor_feature from CNN
    - Returns return value, action, action_log_probs
- get_value(self, inputs):
    - Returns value from CNN

- evaluate_actions(self, inputs, action):
    - Returns value, action_log_probs from CNN

class A2C_ACKTR:
Properties:

- self.actor_critic: a Policy network
- self.optimizer: optimizer

Methods:

- update(self, rollouts):
    - self.actor_critic.evaluate_actions(rollout buffer data)
    - Calculates value and policy loss
    - loss.backward()
    - self.optimizer.step()

Main:

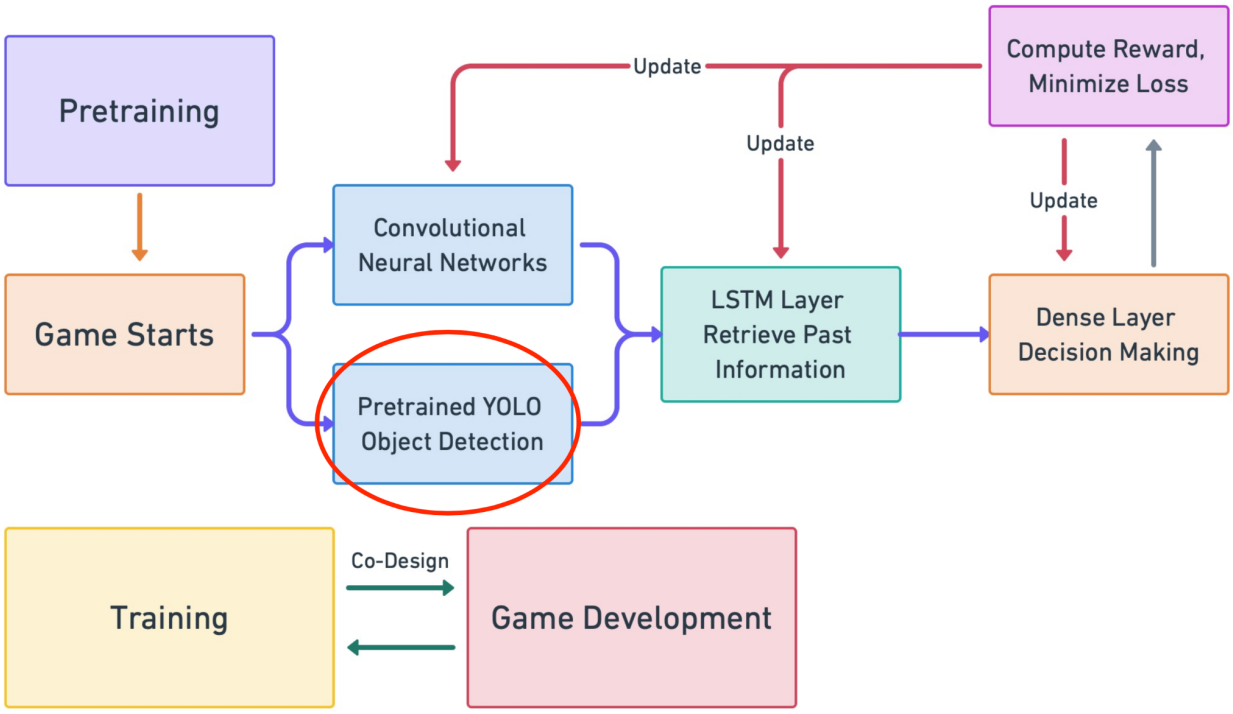
- actor_critic = Policy(...)
- agent = A2C_ACKTR(actor_critic, ...)
- env = make_env(...)
- for j in range(num_updates):
    - for step in range(args.num_steps):
        - obs, reward, done, infos = envs.step(action)
        - Puts input to rollout buffer
        - next_value = actor_critic.get_value(...)
        - Determines reward based on action
        - agent.update(rollouts)

4.9 YOLOv3

YOLO (You Only Look Once) is an object detection algorithm that can efficiently extract object positions from image inputs. To date, there are five versions of YOLO, of which version 3 (YOLOv3) is used in this paper.

In YOLOv3, images first go through deep convolutional layers for feature extraction. Then, the outputs are divided into three different sizes of grids to accommodate size variation of objects. To stabilize initial stages of training, anchor boxes are pre-computed with k-means clustering methods.

Object positions are represented by vectors of normalized relative positions between bounding boxes and anchor boxes. The difference between the predicted object positions and the ground truths is computed as the loss function and iteratively minimized.



Project Architecture

As shown in the chart above, YOLO is used in our project mainly for pre-processing screenshots of states. For its promising performance in object detection, we are able to split our task into two goals. First, extract position information from a pixel image. Second, inject position information of a state into different reinforcement learning agents to retrieve a proper decision that hits the highest score.

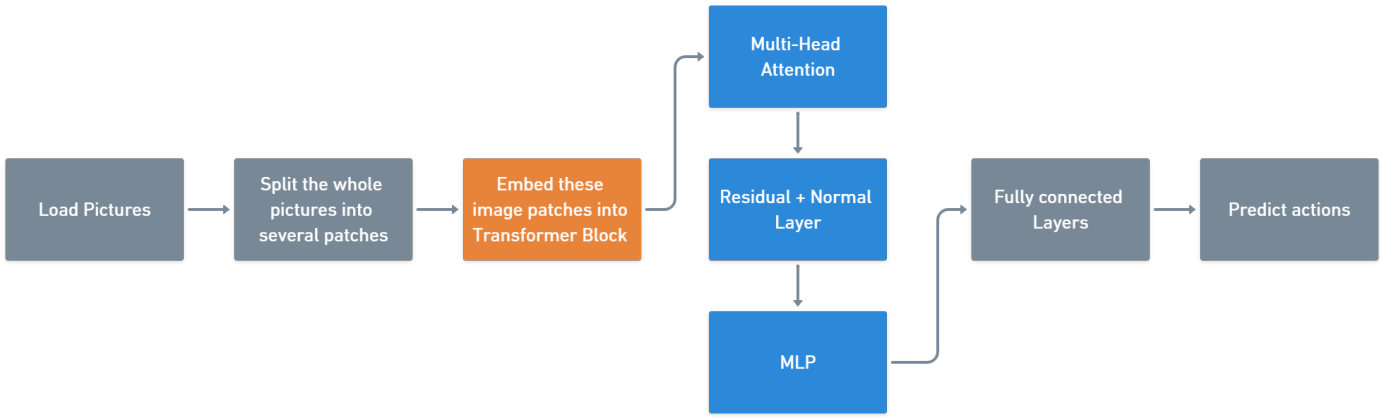
With YOLO, we can handle the goals separately and the best part of it is that a decently pre-trained YOLO model is an once-for-all solution to convert a complicated screenshot of thousands of pixels into a vectorized representation of a state featuring a huge decrement of entropy.

4.10 Vision Transformer (ViT)

Vision Transformer, presented by Google, is a vision model based closely on the Transformer architecture originally for some NLP tasks. When trained with sufficient data, Vision Transformer outperforms state-of-art CNN with fewer computational computational resources which shows broad prospects in many common vision tasks such as image classification, image classification, object detection. In our project, We also explored applying the Vision Transformer model into our game.
Compared with the previous model, Vision Transformer is used to extract features from the input images and construct feature vector space instead of two conventional layers.

What's more, We combined Vision Transformer and DQN and trained this end-to-end model. The output of this new model will be the next action of the agent in our game.

4.10.1 Implentmention



Vision Transformer Workflow

This picture shows the workflow of Vision Transformer in our model. First, We load the input pictures and then split them into several patches. Second, We input these patches into the embedding layer. Then the output embedding vectors will be input into the Vision Transformer units. Finally, we obtain the result from the transformer blocks and then use the result to predict actions. The whole pipeline can be viewed as an end-to-end model in the image classification task.

Input Size	Layer name	hyper-parameter	Output Size
[64*4*84*84]	PatchEmbedding	in_channels: int = 4, patch_size: int = 4, emb_size: int = 64, img_size: int = 84	[64*442*64]
[64*442*64]	MultiHeadAttention	emb_size: int = 64, num_heads: int = 8, dropout: float = 0	[64*442*64]
[64*442*64]	Multilayer Perceptron	emb_size: int=64 expansion: int = 4, drop_p: float = 0.	[64*442*64]

[64*28288]	Fully Connected Layer	in_features: 28288, out_features: 512	[512*1]
[512*1]	Fully Connected Layer	in_features: 512, action space size	[action space size*1]

Table: Network Structure Description

The above table gives detailed information about the implementation of our model. We use the Pytorch framework to build our model. Because our game is self-designed which means it is difficult to find a suitable pre-trained transformer model to fit our game scene. So we trained our model from the very beginning.

5 EVALUATION

1. Scores: we evaluate the model by summation of agent's reward scores.

$$scores = \sum_{i=1}^{n} reward_{T=i} \ (When\ T = n,\ Game\ ends\ up)$$

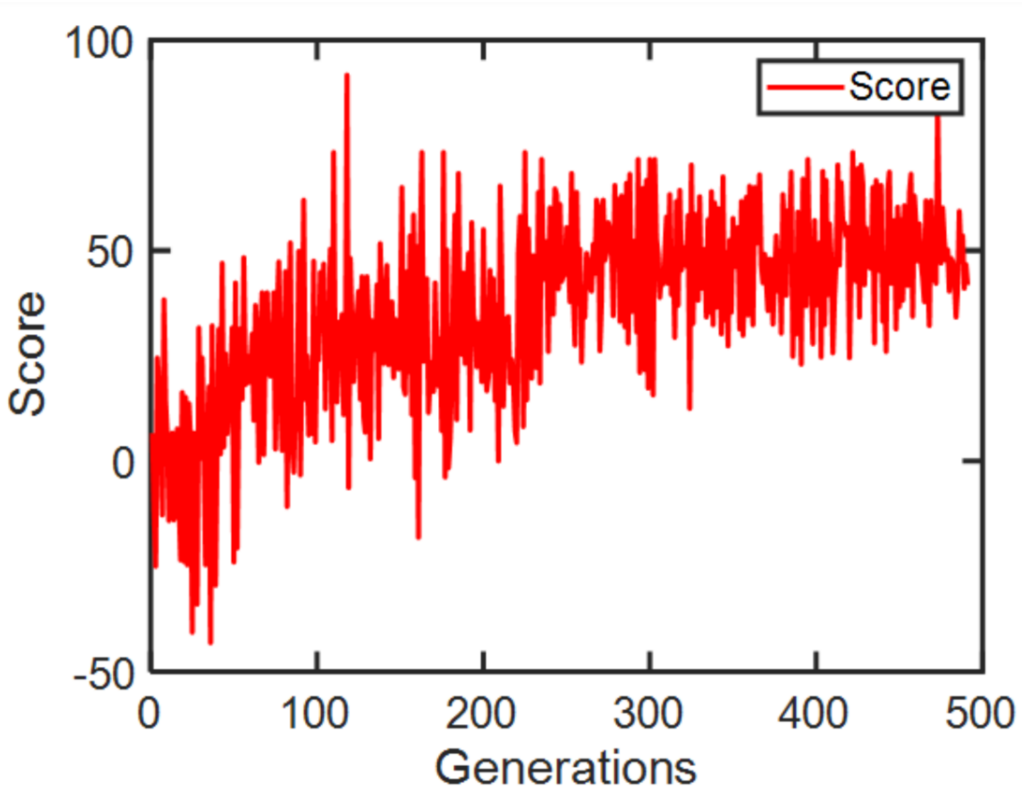
$$-100 \leq scores \leq 100$$

2. The convergence speed of training the model.

6 RESULTS

6.1 Env v1.0

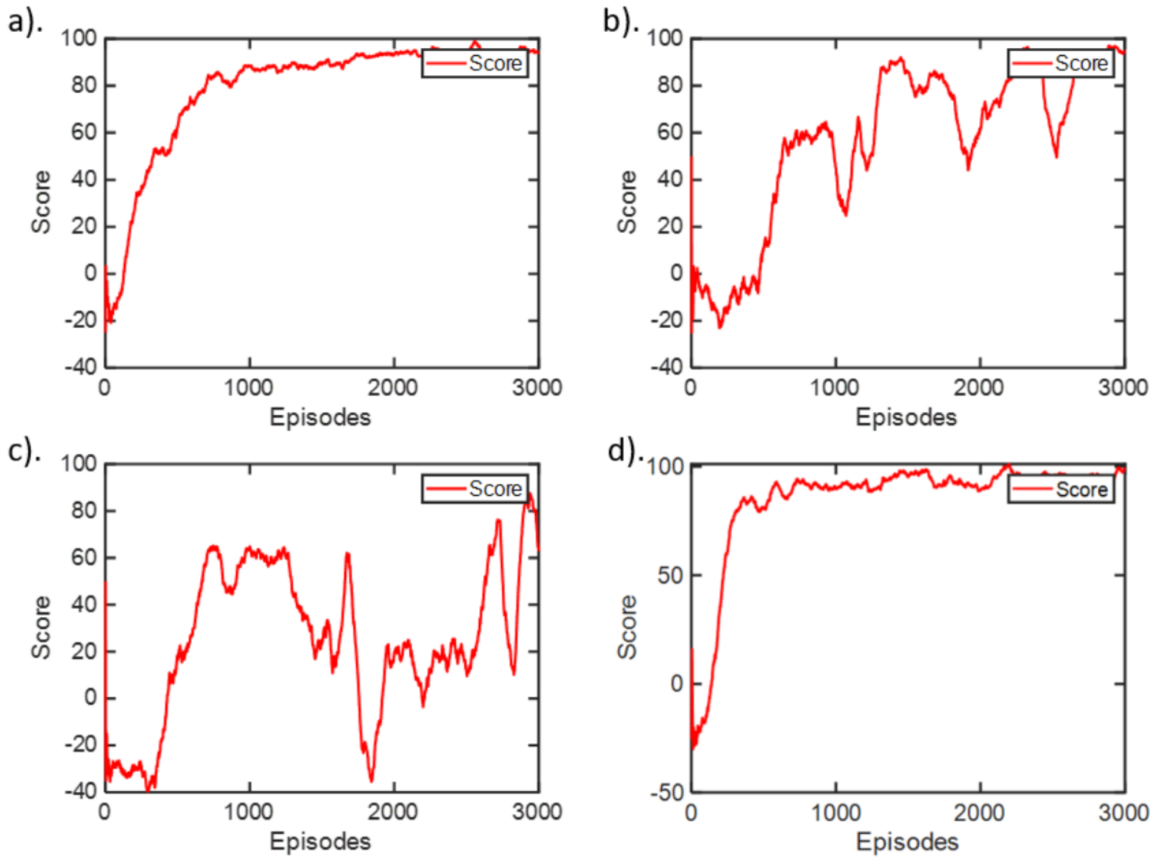
6.1.1 Genetic Algorithm



Results of Genetic Algorithm

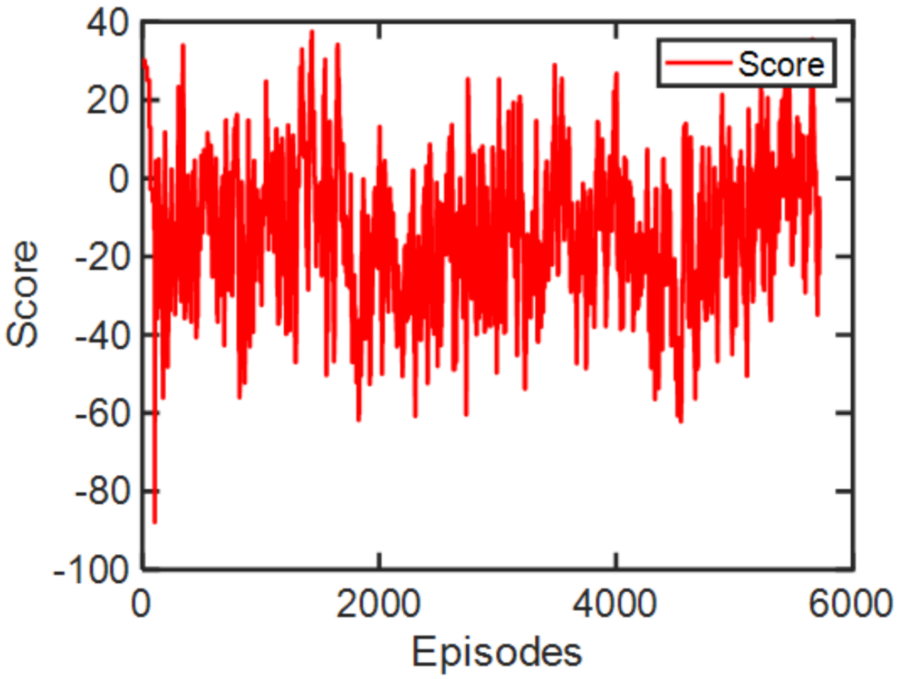
The plots above show the performance of Genetic Algorithms. We see that after significant score increase in the first 200 generations, the model ceases to improve and oscillates at around 50 points. Note that the full score is 100 points.

6.1.2 DQN, DDQN, Dueling DQN



Plots of DQN (a.), DDQN (b.), Dueling DDQN (c.) and DRQN (d.)

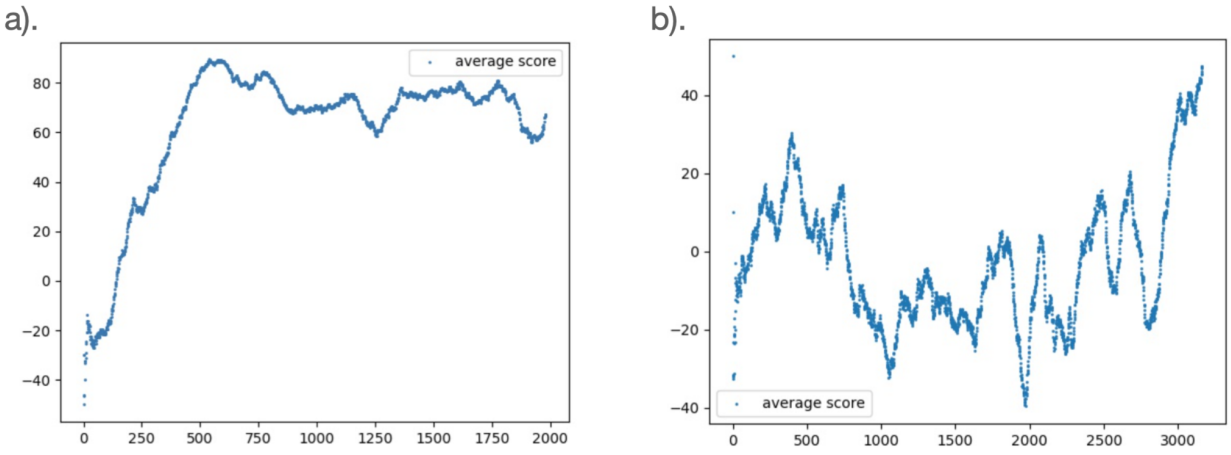
The plots above show the perfor-mances of the DQN model and its variants, DDQN, Dueling DDQN, DRQN. We see that the DQN and DRQN agent is able to achieve close to full score, 100 points. DDQN also approaches full score but oscillates more. Dueling DDQN does not converge.



The Training Curve of PPO

The plots above show the performances of the PPO model. It strongly oscillates around 0 scores and does not display a strong learning behavior beyond this point.

6.1.3 LSTM Frame-skipping

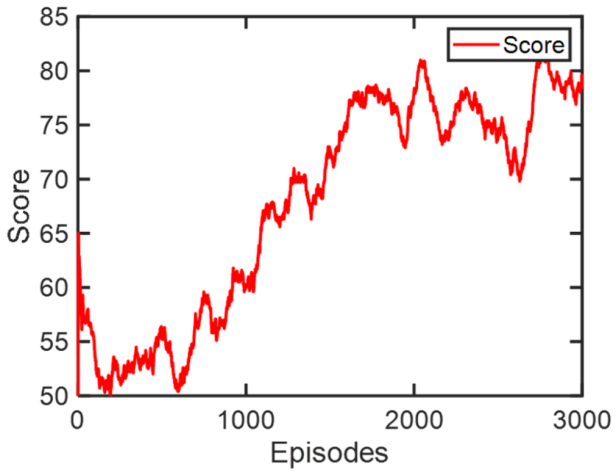


Performance of DRQN (a.) and DQN (b.) on Frame-skipping Environment

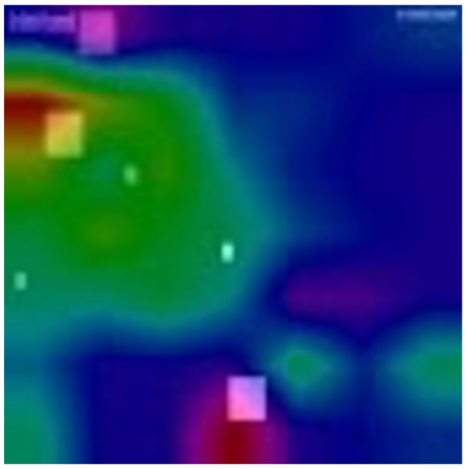
The plots above show DQN and DRQN in a frame-skipping environment. It can be observed that the DQN model collapsed due to the loss of information. On the other hand, the DRQN model only experiences a slight drop in scores. This experiment confirmed our hypothesis that the usage of LSTM layers can indeed preserve past information and is more resilient to loss of frames.

6.2 Env v2.0

a).



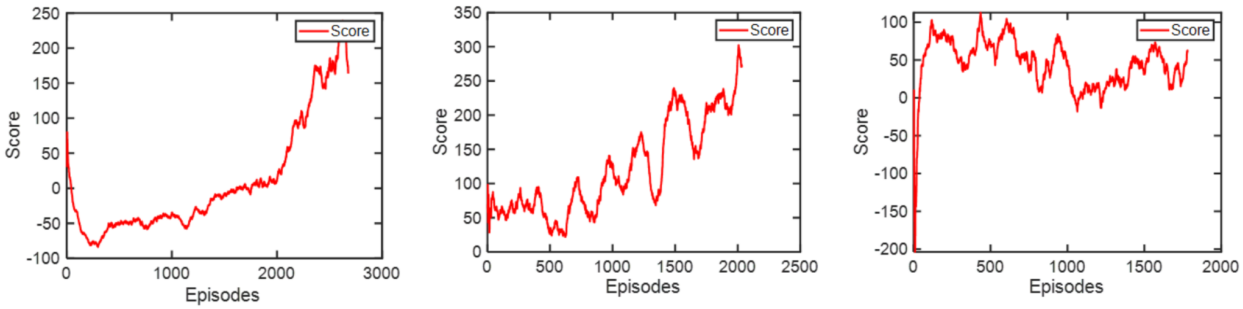
b).



Performance of DQN in Env 2.0 (a.) and the Heatmap the Trained Network (b.)

As shown in plot (a,), in this more complex game environment, the DQN model is taking longer time to converge and achieves a lower score than it does in Env v1.0. Graph (b.) shows the heat map of the trained deep Q network. We see that the network focuses more on the red regions where enemy and player spaceships are located; the network focuses less on the green regions where the bullets are more sparsely distributed; the network totally ignores the blue regions, where there are no objects at all. These results verify that our train deep Q network looks at the right places on the image.

6.3 Env v3.0



Performance of DQpixel-input DQN, vector-input DQN, and pre-trained DQN on Env v3.0

From the plots above, we observe that vector-input DQN outperforms pixel-input DQN, which makes sense because the former takes much more accurate information about the game state. The pre-trained DQN increases its score much faster than other models, which shows the merit of pre-training. However, its scores soon stabilize and stop increasing. This is most likely due to the low exploration rate that causes the model to have less diverse experiences and converge into local minimums.

6.4 Discussion

We first diagnosed the causes of the relative poor performances of GA, PPO, and Dueling DDQN in Env v1.0. We loaded each of these models and observed how AI behaves. We discovered that they all share one common syndrome—AI agents like to move to the corner and stay there forever. This happens because our pre-scripted enemy is always a few pixels away from the side of the window; therefore, staying at the corner can help AI avoid the enemy's bullets. This is certainly a safe policy, but it also makes it impossible for AI to shoot the enemy either, and the total score will always stay at around 0. We consider such a situation as the local minimum, because it is a stable yet sub-optimal situation. One potential cure is to add another penalty if the AI agent is too close to the side of the window to force it to stay in the center.

We then loaded the models of DQN in Env v1.0, which can achieve close to full scores, and observe the agent's behavior. We find the agent to be remarkably intelligent. The agent is not only able to follow the enemy but also able to predict its movement and fire bullets ahead of time. In addition, the agent can adjust its movement when bullets are close. What's more, the agent prefers to fire bullets consecutively to maximize the chance of hitting the enemy. Lastly, the agent actively moves in the center part of the window, rather than staying at the corner.

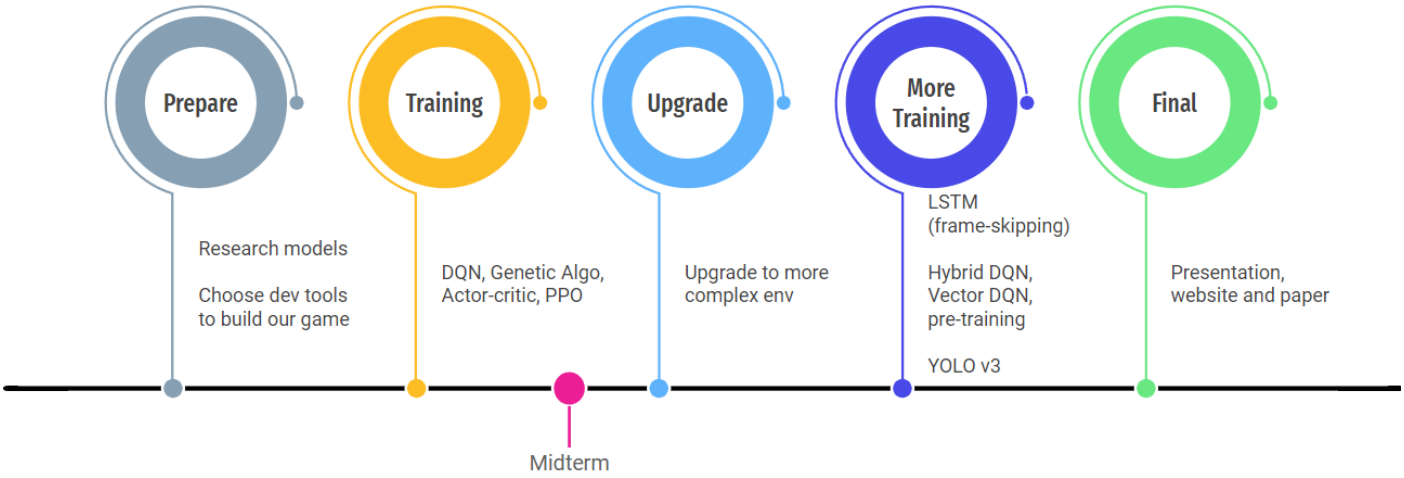
We also loaded the models of DRQN in Env v1.0 and observed a similar behavior as DQN. However, one difference is that DRQN runs considerably more smoothly than DQN agent does. This is because while DQN takes in four stacked frames as inputs, DRQN only takes only one frame at each time step and can therefore process images much faster. In addition, DRQN also shows a superior resilience to the frame-skipping issue. These results imply that under certain hardware conditions, such as resource-limited edge devices, we may want to switch to the DRQN agent that is less resource-hungry and more immune to low-quality inputs.

In Env v2.0, we loaded the trained DQN model and observed its behavior. We observed that even though the consecutive shooting is disable, the agent is still capable of adjusting its position and shooting at appropriate times. We observed that when the enemies move along the same direction, the agent still can predict their movements and fire ahead of their arrival. The corresponding heap map corroborates our observation because the agent focuses more on spaceships, less on bullets, and not at all on empty objects. However, when the enemies move in opposition directions or are farther apart, the agent becomes a little disoriented. We think that this disorientation happens because the action values of chasing either enemy is similar and weakens the agent's decisiveness.

In Env v3.0, DQN-vector's superior performance over vanilla DQN is expected, because the input vector can more accurately and reliably capture all relevant information of a state than CNN does. The pre-trained DQN shows a much faster convergence speed at the initial stage of training, which is expected because it has better-initialized model weights. It is not expected that the score quickly stops increasing at some point; we think it is because of the low exploration rate that causes the agent to form a fixed pattern and settle in the local minimum point.

The YOLO training curve shows strong evidence of training. The final model is extremely good at detecting treasures but poor at detecting bullets. We think it is due to (1) the inherent difficulty of YOLO to detect ultra-small objects. We could add additional, finer girding in YOLO to better capture ultra-small objects (2) the insufficient training data. While mainstream data sets, we only have 300 images as training data. A larger training data set may be beneficial.

7 TIMELINE



Phase 0 (Week 4)

- Construct game environment using PyGame

Phase 1 (Week 5 - 6)

- Train 1 AI player against 1 pre-scripted enemy
- DQN

Phase 2 (Week 7 - 10)

- Train 1 AI player against multiple pre-scripted enemies
- DQN + LSTM + Actor-critic + PPO

Phase 3 (Week 11 - 14)

- Train multiple AI player against multiple pre-scripted enemies
- Extend from 1 player model to include teammates' observation space

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