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Programming Languages ICOM 4036
Class Project - Phase 3: Final Report
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Deep **Q**-learning **B**ox

Developers

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I. Introduction and motivation:

The broad topic of AI and machine learning is slowly entering mainstream conversation due to its recent strides in algorithm development. For the broad audience machine learning is riddled with mysterious concepts and an inevitable sci-fi background; however, companies such as DeepMind have made strides with Deep Learning techniques that proved successful when their AlphaGo[1] project beat the top Korean Go player back in 2016. The topic of AI is mostly very high level since it is a bleeding edge technology currently involved in many research experiments that are trying develop and improve current techniques that allow a computer or a system to make decisions on its own. Our proposed programing language ***DQB*** serves to lower the level of abstraction to those interested in learning one of the basic methods of achieving Deep Reinforcement Learning (DRL), one of the many ways we can achieve the behaviour of a “self-thinking” computer.

DQB will encapsulate the main components and concepts of deep reinforcement learning to provide beginners with a subtle introduction to Q-Learning implementations[2]. In order to continue a steady pace of improvements in AI and machine learning in general we must normalize and facilitate the introduction of complex mathematical notation that scares away brilliance. Hence our project is a virtual box with the tools required to create and train simple reinforcement learning agents in multiple environments. The focus would lie on encapsulating convoluted code but maintaining a clear exoskeleton of what is needed to develop a deep reinforcement learning agent.

The scope of DQB lies within 2D-environments that recreate old atari games via the gym python library by OpenAI. Its purpose is to serve as a playground for developing models with the goal of serving as people’s first encounter.

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[1] AlphaGo is the first computer program to defeat a professional human Go player, the first program to defeat a Go world champion, and arguably the strongest Go player in history.

[2] Q-learning is a RL technique that creates an agent and lets it use the environment's rewards to learn, over time, the best action to take in a given state.

II. Language Tutorial

To get started, clone the repository to your computer. Make sure you have Python 3 and the PLY parsing tool installed. Afterwards, you need to install the external libraries required by using the command:

```
pip install –r requirements.txt
```

Now you have everything to write in DQB!
*Ubuntu or Mac only.

Instructions:

1. First, to get started, use the command:
   ```
   python3 DQB.py
   ```
2. Write the DQB source code on a .txt file called DQB_script.
3. Run the DQB_blackbox which initializes, compiles, and trains the agent.
4. Observe the agent's training process! You have the option to display the environment as it trains and the model's status episode by episode.

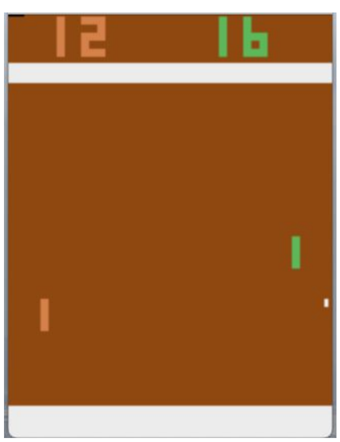
To learn how to write the source code go to the example programs and the reference manual below.

Example program 1: Pong Environment

DQB source code on DQB_script.txt file

```
main(){
 ENVIRONMENT:Pong
 AGENT:AtariPro{

  MODEL_PARAMETERS:{

      Learning_Rate = 0.001
      Discount_Factor = 0.99

      }

 NETWORK:{
             add(ConvolutionalLayers)
          add(PredictiveLayers)
          showModelSummary()

 }

 TRAINING:{
     find_probabilities()
    predict_moves()
    fit()
    displayGame()

  }
}
  Execute()
}
```

Display the environment as it trains and the model's status episode by episode:




```
Episode: 1 - Score: -9.000000.
Episode: 2 - Score: 5.000000.
Episode: 3 - Score: -6.000000.
Episode: 4 - Score: -4.000000.
Episode: 5 - Score: 4.000000.
Episode: 6 - Score: -2.000000.
Episode: 7 - Score: -4.000000.
Episode: 8 - Score: -7.000000.
Episode: 9 - Score: 1.000000.
Episode: 10 - Score: -1.000000.
Episode: 11 - Score: -2.000000.
Episode: 12 - Score: 6.000000.
Episode: 13 - Score: -4.000000.
Episode: 14 - Score: -2.000000.
Episode: 15 - Score: -3.000000.
Episode: 16 - Score: -2.000000.
Episode: 17 - Score: -4.000000.
Episode: 18 - Score: -10.000000.
```

Example program 2: Pong Environment

DQB source code on DQB_script.txt file

```
main(){

ENVIRONMENT:BrickBreaker
AGENT:BBA{

MODEL_PARAMETERS:{
    Learning_Rate = 0.10
    Epsilon_Start = 1.0
    Epsilon_End = 0.10
    Exploration_Steps = 1000000
    Batch_Size = 16
    Discount_Factor = 0.90
    No_Steps = 30
    Action_Size = 3
}
NETWORK:{
  add(ConvolutionalLayers)
  add(PredictiveLayers)
}
TRAINING:{
  predict_moves()
  calculateQ_Values()
  modelCurrentStatus()
  displayGame()
}
}
Execute()
}
```

Display the environment as it trains and the model's status episode by episode:


```
episode: 0   score: 3.0   memory length: 245   epsilon: 1.0   global_step: 245   average_q: 0.021846184947965096   average loss: 0.0
episode: 1   score: 2.0   memory length: 444   epsilon: 1.0   global_step: 444   average_q: 0.023213150035870735   average loss: 0.0
episode: 2   score: 1.0   memory length: 590   epsilon: 1.0   global_step: 590   average_q: 0.021619951952095717   average loss: 0.0
episode: 3   score: 2.0   memory length: 767   epsilon: 1.0   global_step: 767   average_q: 0.021686944005600478   average loss: 0.0
episode: 4   score: 1.0   memory length: 924   epsilon: 1.0   global_step: 924   average_q: 0.022075470169163815   average loss: 0.0
episode: 5   score: 1.0   memory length: 1087   epsilon: 1.0   global_step: 1087   average_q: 0.021686089470799714   average loss: 0.0
episode: 6   score: 1.0   memory length: 1232   epsilon: 1.0   global_step: 1232   average_q: 0.023459750863498656   average loss: 0.0
episode: 7   score: 2.0   memory length: 1396   epsilon: 1.0   global_step: 1396   average_q: 0.02182683106738983   average loss: 0.0
episode: 8   score: 3.0   memory length: 1635   epsilon: 1.0   global_step: 1635   average_q: 0.024080044780877344   average loss: 0.0
episode: 9   score: 5.0   memory length: 1941   epsilon: 1.0   global_step: 1941   average_q: 0.021638349356020197   average loss: 0.0
episode: 10   score: 1.0   memory length: 2099   epsilon: 1.0   global_step: 2099   average_q: 0.023378281123181688   average loss: 0.0
episode: 11   score: 1.0   memory length: 2252   epsilon: 1.0   global_step: 2252   average_q: 0.021170890311789668   average loss: 0.0
episode: 12   score: 2.0   memory length: 2436   epsilon: 1.0   global_step: 2436   average_q: 0.02250012611646367   average loss: 0.0
episode: 13   score: 0.0   memory length: 2529   epsilon: 1.0   global_step: 2529   average_q: 0.022584119010516393   average loss: 0.0
episode: 14   score: 1.0   memory length: 2669   epsilon: 1.0   global_step: 2669   average_q: 0.024462294724902935   average loss: 0.0
episode: 15   score: 4.0   memory length: 2949   epsilon: 1.0   global_step: 2949   average_q: 0.023460897460712917   average loss: 0.0
episode: 16   score: 1.0   memory length: 3116   epsilon: 1.0   global_step: 3116   average_q: 0.022065567376906285   average loss: 0.0
episode: 17   score: 0.0   memory length: 3217   epsilon: 1.0   global_step: 3217   average_q: 0.0214828350166283   average loss: 0.0
```

III. Reference Manual

DQB is a simple high-level reinforcement scripting language, developed on PLY capable of building , training and modeling on top of TensorFlow, Keras and Gym. It is focused on introducing fast experimentation with agents training on environments. It features two training environments, Pong and Brick Breaker.

A. Language Structure

They both implement 4 functions each:

a. main(){ … } - Initializes the environment, the agent and the operations it performs.
b. MODEL_PARAMETERS:{...}- Initializes the trainable model parameters which are:
    i. Learning rate: parameter that controls how much the weight of he neural network are updated with respect to the loss gradient. Its value is usually between 0.001 and 0.100.
    ii. Epsilon start: Initial value of the epsilon parameter. Controls the rate between exploration and exploitation steps. This number decreases as the training progresses.
    iii. Epsilon End: Final value of the epsilon parameter.
    iv. Exploration Steps: number of training steps the algorithm performs.
    v. Batch Size: number of samples per gradient update.
    vi. Discount Factor: value multiplied by future rewards as discovered by the agent. Future rewards worth less than immediate rewards. It is a value between 0 and 1.
    vii. Action Size: number of distinct steps the agent is capable performing in each exploration step.
c. Network: {...} - initializes the internal neural network to the agent.
    i. Add{...} - adds layers to the network.
        1. ConvolutionalLayers: process the current environment state
        2. PredictiveLayers: performs optimization and backpropagation.
d. Training:{...} - calls the methods that perform additional training and assigns score to each move.
    i. PredictMoves: performs calculations of training algorithms
    ii. CalculateQvalues: calculates the Q-values of each exploration step

iii. modelCurrentStatus: displays in the console the value of each trainable parameter as the training goes on.
iv. displayGame: displays an image of the model's current status.

IV. Language Development

Deep Q-Learning Box is meant to be a beginners introduction to machine learning and reinforcement learning algorithms, and it was kept in mind when building the language's design. It was built using python so it would enable us to ue the most popular ML libraries used today such as Keras and tensorflow along with PLY for the lexical and syntactical construction of the language. In order to allow for a simplification of the complicated Reinforcement Learning algorithms and serve as a stepping stone for future machine learning engineering aspirants. The language has uses 2 prebuilt atari environments from the gym libraries that use two different algorithms in which we can modify some of the algorithms most important parameters to modify its performance.

We built the language through a python class generator so one is able to view the full python class that implements and runs the algorithm in naivte python. This was achieved through the use of a code generator class named ML code generator that generates strings and attaches them to a file in order to compress the algorithm and break them down to their basic actions to facilitate the learning experience while also recording what was used behind the scenes.

The main class DQB_blackbox merely serves as a hub that brings together the lexer and parser built to traduce our language. In order to maintain the language lightweight the communication between the developer and the program is established via a .txt file named DQB script held within the projects files this is our "IDE" through which one writes the program. DQB_blackbox merely imports the parser and translates the file to generate the classes and executes the native python code that activates.

V. Conclusion

Deep Q-learning Box (DQB) serves to lower the level of abstraction to those interested in learning one of the basic methods of achieving Deep Reinforcement Learning (DRL). It normalizes and facilitates the introduction of complex mathematical notation used in Deep Reinforcement Learning. The focus lies on encapsulating convoluted code but maintaining a clear exoskeleton of what is needed to develop a deep reinforcement learning agent. It is focused on introducing fast experimentation with agents training on environments, giving the user basic knowledge of DRL concepts, like Learning rate, Epsilon Start, Epsilon End, Batch Size, Q-values, and more. DQB serves as a playground for aspiring DRL developers.