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T81-558: Applications of Deep Neural Networks

Module 12: Reinforcement Learning

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- For more information visit the class website.

Module 12 Video Material

- Part 12.1: Introduction to the OpenAI Gym [Video] [Notebook]
- Part 12.2: Introduction to Q-Learning [Video] [Notebook]
- Part 12.3: Keras Q-Learning in the OpenAI Gym [Video] [Notebook]
- Part 12.4: Atari Games with Keras Neural Networks [Video] [Notebook]
- **Part 12.5: Application of Reinforcement Learning** [Video] [Notebook]

Google CoLab Instructions

The following code ensures that Google CoLab is running the correct version of TensorFlow.

In [1]:
```
try:
    from google.colab import drive
    %tensorflow_version 2.x
    COLAB = True
    print("Note: using Google CoLab")
except:
    print("Note: not using Google CoLab")
    COLAB = False
```

```
Note: using Google CoLab
```

In [2]:
```
# HIDE OUTPUT
if COLAB:
    !sudo apt-get install - y xvfb ffmpeg x11-utils
    !pip install - q 'gym==0.17.3'
    !pip install - q 'imageio==2.4.0'
    !pip install - q PILLOW
    !pip install - q 'pyglet==1.3.2'
```

```
!pip install -q pyvirtualdisplay
!pip install -q 'tf-agents==0.12.0'
```

```
Reading package lists... Done
Building dependency tree
Reading state information... Done
ffmpeg is already the newest version (7:3.4.8-0ubuntu0.2).
Suggested packages:
  mesa-utils
The following NEW packages will be installed:
  libxxf86dga1 x11-utils xvfb
0 upgraded, 3 newly installed, 0 to remove and 39 not upgraded.
Need to get 993 kB of archives.
After this operation, 2,982 kB of additional disk space will be used.
Get:1 http://archive.ubuntu.com/ubuntu bionic/main amd64 libxxf86dga1 amd64
2:1.1.4-1 [13.7 kB]
Get:2 http://archive.ubuntu.com/ubuntu bionic/main amd64 x11-utils amd64 7.7
+3build1 [196 kB]
Get:3 http://archive.ubuntu.com/ubuntu bionic-updates/universe amd64 xvfb am
d64 2:1.19.6-1ubuntu4.10 [784 kB]
Fetched 993 kB in 0s (3,848 kB/s)
debconf: unable to initialize frontend: Dialog
debconf: (No usable dialog-like program is installed, so the dialog based fr
ontend cannot be used. at /usr/share/perl5/Debconf/FrontEnd/Dialog.pm line 7
6, <> line 3.)
debconf: falling back to frontend: Readline
debconf: unable to initialize frontend: Readline
debconf: (This frontend requires a controlling tty.)
debconf: falling back to frontend: Teletype
dpkg-preconfigure: unable to re-open stdin:
Selecting previously unselected package libxxf86dga1:amd64.
(Reading database ... 156210 files and directories currently installed.)
Preparing to unpack .../libxxf86dga1_2%3a1.1.4-1_amd64.deb ...
Unpacking libxxf86dga1:amd64 (2:1.1.4-1) ...
Selecting previously unselected package x11-utils.
Preparing to unpack .../x11-utils_7.7+3build1_amd64.deb ...
Unpacking x11-utils (7.7+3build1) ...
Selecting previously unselected package xvfb.
Preparing to unpack .../xvfb_2%3a1.19.6-1ubuntu4.10_amd64.deb ...
Unpacking xvfb (2:1.19.6-1ubuntu4.10) ...
Setting up xvfb (2:1.19.6-1ubuntu4.10) ...
Setting up libxxf86dga1:amd64 (2:1.1.4-1) ...
Setting up x11-utils (7.7+3build1) ...
Processing triggers for man-db (2.8.3-2ubuntu0.1) ...
Processing triggers for libc-bin (2.27-3ubuntu1.3) ...
/sbin/ldconfig.real: /usr/local/lib/python3.7/dist-packages/ideep4py/lib/lib
mkldnn.so.0 is not a symbolic link

     |████████████████████████████████| 3.3 MB 5.1 MB/s
  Building wheel for imageio (setup.py) ... done
ERROR: pip's dependency resolver does not currently take into account all th
e packages that are installed. This behaviour is the source of the following
dependency conflicts.
albumentations 0.1.12 requires imgaug<0.2.7,>=0.2.5, but you have imgaug 0.
2.9 which is incompatible.
     |████████████████████████████████| 1.0 MB 5.0 MB/s
ERROR: pip's dependency resolver does not currently take into account all th
e packages that are installed. This behaviour is the source of the following
dependency conflicts.
```

```
gym 0.17.3 requires pyglet<=1.5.0,>=1.4.0, but you have pyglet 1.3.2 which i
s incompatible.
     |████████████████████████████████| 1.3 MB 5.0 MB/s
     |████████████████████████████████| 1.0 MB 83.9 MB/s
```

Part 12.5: Application of Reinforcement Learning

Creating an environment is the first step to applying TF-Agent-based reinforcement learning to a problem with your design. This part will see how to create your environment and apply it to an agent that allows actions to be floating-point values rather than the discrete actions employed by the Deep Q-Networks (DQN) that we used earlier in this chapter. This new type of agent is called a Deep Deterministic Policy Gradients (DDPG) network. From an application standpoint, the primary difference between DDPG and DQN is that DQN only supports discrete actions, whereas DDPG supports continuous actions; however, there are other essential differences that we will cover later in this chapter.

The environment that I will demonstrate in this chapter simulates paying off a mortgage and saving for retirement. This simulation allows the agent to allocate their income between several types of accounts, buying luxury items, and paying off their mortgage. The goal is to maximize net worth. Because we wish to provide the agent with the ability to distribute their income among several accounts, we provide continuous (floating point) actions that determine this distribution of the agent's salary.

Similar to previous TF-Agent examples in this chapter, we begin by importing needed packages.

In [3]:

```
import base64
import imageio
import IPython
import matplotlib
import matplotlib.pyplot as plt
import numpy as np
import PIL.Image
import pyvirtualdisplay
import math
import numpy as np

import tensorflow as tf

from tf_agents.agents.ddpg import actor_network
from tf_agents.agents.ddpg import critic_network
from tf_agents.agents.ddpg import ddpg_agent

from tf_agents.agents.dqn import dqn_agent
from tf_agents.drivers import dynamic_step_driver
```

```
from tf_agents.environments import suite_gym
from tf_agents.environments import tf_py_environment
from tf_agents.eval import metric_utils
from tf_agents.metrics import tf_metrics
from tf_agents.networks import q_network
from tf_agents.policies import random_tf_policy
from tf_agents.replay_buffers import tf_uniform_replay_buffer
from tf_agents.trajectories import trajectory
from tf_agents.trajectories import policy_step
from tf_agents.utils import common

import gym
from gym import spaces
from gym.utils import seeding
from gym.envs.registration import register
import PIL.ImageDraw
import PIL.Image
from PIL import ImageFont
```

If you get the following error, restart and rerun the Google CoLab environment. Sometimes a restart is needed after installing TF-Agents.

```
AttributeError: module 'google.protobuf.descriptor' has no
    attribute '_internal_create_key'
```

We create a virtual display to view the simulation in a Jupyter notebook.

In [4]:
```
# Set up a virtual display for rendering OpenAI gym environments.
vdisplay = pyvirtualdisplay.Display(visible=0, size=(1400, 900)).start()
```

Create an Environment of your Own

An environment is a simulator that your agent runs in. An environment must have a current state. Some of this state is visible to the agent. However, the environment also hides some aspects of the state from the agent. Likewise, the agent takes actions that will affect the state of the environment. There may also be internal actions outside the agent's control. For example, in the finance simulator demonstrated in this section, the agent does not control the investment returns or rate of inflation. Instead, the agent must react to these external actions and state components.

The environment class that you create must contain these elements:

- Be a child class of **gym.Env**
- Implement a **seed** function that sets a seed that governs the simulation's random aspects. For this environment, the seed oversees the random fluctuations in inflation and rates of return.
- Implement a **reset** function that resets the state for a new episode.
- Implement a **render** function that renders one frame of the simulation. The rendering is only for display and does not affect reinforcement learning.

- Implement a **step** function that performs one step of your simulation.

The class presented below implements a financial planning simulation. The agent must save for retirement and should attempt to amass the greatest possible net worth. The simulation includes the following key elements:

- Random starting salary between 40K (USD) and 60K (USD).
- Home loan for a house with a random purchase price between 1.5 and 4 times the starting salary.
- Home loan is a standard amortized 30-year loan with a fixed monthly payment.
- Paying higher than the home's monthly payment pays the loan down quicker. Paying below the monthly payment results in late fees and eventually foreclosure.
- Ability to allocate income between luxury purchases and home payments (above or below payment amount) and a taxable and tax-advantaged savings account.

The state is composed of the following floating-point values:

- **age** - The agent's current age in months (steps)
- **salary** - The agent's starting salary, increases relative to inflation.
- **home_value** - The value of the agent's home, increases relative to inflation.
- **home_loan** - How much the agent still owes on their home.
- **req_home_pmt** - The minimum required home payment.
- **acct_tax_adv** - The balance of the tax advantaged retirement account.
- **acct_tax** - The balance of the taxable retuirement account.

The action space is composed of the following floating-point values (between 0 and 1):

- **home_loan** - The amount to apply to a home loan.
- **savings_tax_adv** - The amount to deposit in a tax-advantaged savings account.
- **savings taxable** - The amount to deposit in a taxable savings account.
- **luxury** - The amount to spend on luxury items/services.

The actions are weights that the program converts to a percentage of the total. For example, the home loan percentage is the home loan action value divided by all actions (including a home loan). The following code implements the environment and provides implementation details in the comments.

In [5]:
```
class SimpleGameOfLifeEnv(gym.Env):
    metadata = {
        'render.modes': ['human', 'rgb_array'],
        'video.frames_per_second': 1
    }

    STATE_ELEMENTS = 7
    STATES = ['age', 'salary', 'home_value', 'home_loan', 'req_home_pmt',
              'acct_tax_adv', 'acct_tax', "expenses", "actual_home_pmt",
              "tax_deposit",
              "tax_adv_deposit", "net_worth"]
```

```
    STATE_AGE = 0
    STATE_SALARY = 1
    STATE_HOME_VALUE = 2
    STATE_HOME_LOAN = 3
    STATE_HOME_REQ_PAYMENT = 4
    STATE_SAVE_TAX_ADV = 5
    STATE_SAVE_TAXABLE = 6

    MEG = 1.0e6

    ACTION_ELEMENTS = 4
    ACTION_HOME_LOAN = 0
    ACTION_SAVE_TAX_ADV = 1
    ACTION_SAVE_TAXABLE = 2
    ACTION_LUXURY = 3

    INFLATION = (0.015)/12.0
    INTEREST = (0.05)/12.0
    TAX_RATE = (.142)/12.0
    EXPENSES = 0.6
    INVEST_RETURN = 0.065/12.0
    SALARY_LOW = 40000.0
    SALARY_HIGH = 60000.0
    START_AGE = 18
    RETIRE_AGE = 80

    def __init__(self, goal_velocity=0):
        self.verbose = False
        self.viewer = None

        self.action_space = spaces.Box(
            low=0.0,
            high=1.0,
            shape=(SimpleGameOfLifeEnv.ACTION_ELEMENTS,),
            dtype=np.float32
        )
        self.observation_space = spaces.Box(
            low=0,
            high=2,
            shape=(SimpleGameOfLifeEnv.STATE_ELEMENTS,),
            dtype=np.float32
        )

        self.seed()
        self.reset()

        self.state_log = []

    def seed(self, seed=None):
        self.np_random, seed = seeding.np_random(seed)
        return [seed]

    def _calc_net_worth(self):
        home_value = self.state[
            SimpleGameOfLifeEnv.STATE_HOME_VALUE]
        principal = self.state[
```

```
            SimpleGameOfLifeEnv.STATE_HOME_LOAN]
        worth = home_value - principal
        worth += self.state[
            SimpleGameOfLifeEnv.STATE_SAVE_TAX_ADV]
        worth += self.state[
            SimpleGameOfLifeEnv.STATE_SAVE_TAXABLE]
        return worth

    def _eval_action(self, action, payment):
        # Calculate actions
        act_home_payment = action[
            SimpleGameOfLifeEnv.ACTION_HOME_LOAN]
        act_tax_adv_pay = action[
            SimpleGameOfLifeEnv.ACTION_SAVE_TAX_ADV]
        act_taxable = action[
            SimpleGameOfLifeEnv.ACTION_SAVE_TAXABLE]
        act_luxury = action[
            SimpleGameOfLifeEnv.ACTION_LUXURY]
        if payment <= 0:
            act_home_payment = 0
        total_act = act_home_payment + act_tax_adv_pay\
            + act_taxable + \
            act_luxury + self.expenses

        if total_act < 1e-2:
            pct_home_payment = 0
            pct_tax_adv_pay = 0
            pct_taxable = 0
            pct_luxury = 0
        else:
            pct_home_payment = act_home_payment / total_act
            pct_tax_adv_pay = act_tax_adv_pay / total_act
            pct_taxable = act_taxable / total_act
            pct_luxury = act_luxury / total_act

        return pct_home_payment, pct_tax_adv_pay, pct_taxable, pct_luxury

    def step(self, action):
        self.last_action = action
        age = self.state[SimpleGameOfLifeEnv.STATE_AGE]
        salary = self.state[SimpleGameOfLifeEnv.STATE_SALARY]
        home_value = self.state[SimpleGameOfLifeEnv.STATE_HOME_VALUE]
        principal = self.state[SimpleGameOfLifeEnv.STATE_HOME_LOAN]
        payment = self.state[SimpleGameOfLifeEnv.STATE_HOME_REQ_PAYMENT]
        net1 = self._calc_net_worth()
        remaining_salary = salary

        # Calculate actions
        pct_home_payment, pct_tax_adv_pay, pct_taxable, pct_luxury = \
            self._eval_action(action, payment)

        # Expenses
        current_expenses = salary * self.expenses
        remaining_salary -= current_expenses
        if self.verbose:
            print(f"Expenses: {current_expenses}")
```

```
            print(f"Remaining Salary: {remaining_salary}")

        # Tax advantaged deposit action
        my_tax_adv_deposit = min(salary * pct_tax_adv_pay,
                                 remaining_salary)
        # Govt CAP
        my_tax_adv_deposit = min(my_tax_adv_deposit,
                                 self.year_tax_adv_deposit_left)
        self.year_tax_adv_deposit_left -= my_tax_adv_deposit
        remaining_salary -= my_tax_adv_deposit
        # Company match
        tax_adv_deposit = my_tax_adv_deposit * 1.05
        self.state[SimpleGameOfLifeEnv.STATE_SAVE_TAX_ADV] += \
            int(tax_adv_deposit)

        if self.verbose:
            print(f"IRA Deposit: {tax_adv_deposit}")
            print(f"Remaining Salary: {remaining_salary}")

        # Tax
        remaining_salary -= remaining_salary * \
            SimpleGameOfLifeEnv.TAX_RATE
        if self.verbose:
            print(f"Tax Salary: {remaining_salary}")

        # Home payment
        actual_payment = min(salary * pct_home_payment,
                             remaining_salary)

        if principal > 0:
            ipart = principal * SimpleGameOfLifeEnv.INTEREST
            ppart = actual_payment - ipart
            principal = int(principal-ppart)
            if principal <= 0:
                principal = 0
                self.state[SimpleGameOfLifeEnv.STATE_HOME_REQ_PAYMENT] = 0
            elif actual_payment < payment:
                self.late_count += 1
                if self.late_count > 15:
                    sell = (home_value-principal)/2
                    sell -= 20000
                    sell = max(sell, 0)
                    self.state[SimpleGameOfLifeEnv.STATE_SAVE_TAXABLE] \
                        += sell
                    principal = 0
                    home_value = 0
                    self.expenses += .3
                    self.state[SimpleGameOfLifeEnv.STATE_HOME_REQ_PAYMENT] \
                        = 0
                    if self.verbose:
                        print(f"Foreclosure!!")
                else:
                    late_fee = payment * 0.1
                    principal += late_fee
                    if self.verbose:
                        print(f"Late Fee: {late_fee}")
```

```
            self.state[SimpleGameOfLifeEnv.STATE_HOME_LOAN] = principal
            remaining_salary -= actual_payment

        if self.verbose:
            print(f"Home Payment: {actual_payment}")
            print(f"Remaining Salary: {remaining_salary}")

        # Taxable savings
        actual_savings = remaining_salary * pct_taxable
        self.state[SimpleGameOfLifeEnv.STATE_SAVE_TAXABLE] \
            += actual_savings
        remaining_salary -= actual_savings

        if self.verbose:
            print(f"Tax Save: {actual_savings}")
            print(f"Remaining Salary (goes to Luxury): {remaining_salary}")

        # Investment income
        return_taxable = self.state[
            SimpleGameOfLifeEnv.STATE_SAVE_TAXABLE]\
            * self.invest_return
        return_tax_adv = self.state[
            SimpleGameOfLifeEnv.STATE_SAVE_TAX_ADV]\
            * self.invest_return

        return_taxable *= 1-SimpleGameOfLifeEnv.TAX_RATE
        self.state[SimpleGameOfLifeEnv.STATE_SAVE_TAXABLE] \
            += return_taxable
        self.state[SimpleGameOfLifeEnv.STATE_SAVE_TAX_ADV] \
            += return_tax_adv

        # Yearly events
        if age > 0 and age % 12 == 0:
            self.perform_yearly()

        # Monthly events
        self.state[SimpleGameOfLifeEnv.STATE_AGE] += 1

        # Time to retire (by age?)
        done = self.state[SimpleGameOfLifeEnv.STATE_AGE] > \
            (SimpleGameOfLifeEnv.RETIRE_AGE*12)

        # Calculate reward
        net2 = self._calc_net_worth()
        reward = net2 - net1

        # Track progress
        if self.verbose:
            print(f"Networth: {nw}")
            print(f"*** End Step {self.step_num}: State={self.state}, \
          Reward={reward}")
        self.state_log.append(self.state + [current_expenses,
                                            actual_payment,
                                            actual_savings,
                                            my_tax_adv_deposit,
```

```
                                                    net2])
        self.step_num += 1

        # Normalize state and finish up
        norm_state = [x/SimpleGameOfLifeEnv.MEG for x in self.state]
        return norm_state, reward/SimpleGameOfLifeEnv.MEG, done, {}

    def perform_yearly(self):
        salary = self.state[SimpleGameOfLifeEnv.STATE_SALARY]
        home_value = self.state[SimpleGameOfLifeEnv.STATE_HOME_VALUE]

        self.inflation = SimpleGameOfLifeEnv.INTEREST + \
            self.np_random.normal(loc=0, scale=1e-2)
        self.invest_return = SimpleGameOfLifeEnv.INVEST_RETURN + \
            self.np_random.normal(loc=0, scale=1e-2)

        self.year_tax_adv_deposit_left = 19000
        self.state[SimpleGameOfLifeEnv.STATE_SALARY] = \
            int(salary * (1+self.inflation))

        self.state[SimpleGameOfLifeEnv.STATE_HOME_VALUE] \
            = int(home_value * (1+self.inflation))

    def reset(self):
        self.expenses = SimpleGameOfLifeEnv.EXPENSES
        self.late_count = 0
        self.step_num = 0
        self.last_action = [0] * SimpleGameOfLifeEnv.ACTION_ELEMENTS
        self.state = [0] * SimpleGameOfLifeEnv.STATE_ELEMENTS
        self.state_log = []
        salary = float(self.np_random.randint(
            low=SimpleGameOfLifeEnv.SALARY_LOW,
            high=SimpleGameOfLifeEnv.SALARY_HIGH))
        house_mult = self.np_random.uniform(low=1.5, high=4)
        value = round(salary*house_mult)
        p = (value*0.9)
        i = SimpleGameOfLifeEnv.INTEREST
        n = 30 * 12
        m = float(int(p * (i * (1 + i)**n) / ((1 + i)**n - 1)))
        self.state[SimpleGameOfLifeEnv.STATE_AGE] = \
            SimpleGameOfLifeEnv.START_AGE * 12
        self.state[SimpleGameOfLifeEnv.STATE_SALARY] = salary / 12.0
        self.state[SimpleGameOfLifeEnv.STATE_HOME_VALUE] = value
        self.state[SimpleGameOfLifeEnv.STATE_HOME_LOAN] = p
        self.state[SimpleGameOfLifeEnv.STATE_HOME_REQ_PAYMENT] = m
        self.year_tax_adv_deposit_left = 19000
        self.perform_yearly()
        return np.array(self.state)

    def render(self, mode='human'):
        screen_width = 600
        screen_height = 400

        img = PIL.Image.new('RGB', (600, 400))
        d = PIL.ImageDraw.Draw(img)
        font = ImageFont.load_default()
```

```
        y = 0
        _, height = d.textsize("W", font)

        age = self.state[SimpleGameOfLifeEnv.STATE_AGE]
        salary = self.state[SimpleGameOfLifeEnv.STATE_SALARY]*12
        home_value = self.state[
            SimpleGameOfLifeEnv.STATE_HOME_VALUE]
        home_loan = self.state[
            SimpleGameOfLifeEnv.STATE_HOME_LOAN]
        home_payment = self.state[
            SimpleGameOfLifeEnv.STATE_HOME_REQ_PAYMENT]
        balance_tax_adv = self.state[
            SimpleGameOfLifeEnv.STATE_SAVE_TAX_ADV]
        balance_taxable = self.state[
            SimpleGameOfLifeEnv.STATE_SAVE_TAXABLE]
        net_worth = self._calc_net_worth()

        d.text((0, y), f"Age: {age/12}", fill=(0, 255, 0))
        y += height
        d.text((0, y), f"Salary: {salary:,}", fill=(0, 255, 0))
        y += height
        d.text((0, y), f"Home Value: {home_value:,}",
               fill=(0, 255, 0))
        y += height
        d.text((0, y), f"Home Loan: {home_loan:,}",
               fill=(0, 255, 0))
        y += height
        d.text((0, y), f"Home Payment: {home_payment:,}",
               fill=(0, 255, 0))
        y += height
        d.text((0, y), f"Balance Tax Adv: {balance_tax_adv:,}",
               fill=(0, 255, 0))
        y += height
        d.text((0, y), f"Balance Taxable: {balance_taxable:,}",
               fill=(0, 255, 0))
        y += height
        d.text((0, y), f"Net Worth: {net_worth:,}", fill=(0, 255, 0))
        y += height*2

        payment = self.state[SimpleGameOfLifeEnv.STATE_HOME_REQ_PAYMENT]
        pct_home_payment, pct_tax_adv_pay, pct_taxable, pct_luxury = \
            self._eval_action(self.last_action, payment)
        d.text((0, y), f"Percent Home Payment: {pct_home_payment}",
               fill=(0, 255, 0))
        y += height
        d.text((0, y), f"Percent Tax Adv: {pct_tax_adv_pay}",
               fill=(0, 255, 0))
        y += height
        d.text((0, y), f"Percent Taxable: {pct_taxable}", fill=(0, 255, 0))
        y += height
        d.text((0, y), f"Percent Luxury: {pct_luxury}", fill=(0, 255, 0))

        return np.array(img)

    def close(self):
        pass
```

You must register the environment class with TF-Agents before your program can use it.

In [6]:
```
register(
    id='simple-game-of-life-v0',
    entry_point=f'{__name__}:SimpleGameOfLifeEnv',
)
```

Testing the Environment

This financial planning environment is complex. It took me some degree of testing to perfect it. Even at the current state of this simulator, it is far from a complete financial simulator. The primary objective of this simulator is to demonstrate creating your environment for a non-video game project.

I used the following code to help test this simulator. I ran the simulator with fixed actions and then loaded the state into a Pandas data frame for easy viewing.

In [7]:
```
env_name = 'simple-game-of-life-v0'
env = gym.make(env_name)

env.reset()
done = False

i = 0
env.verbose = False
while not done:
    i += 1
    state, reward, done, _ = env.step([1, 1, 0, 0])
    env.render()

env.close()
```

In [8]:
```
import pandas as pd

df = pd.DataFrame(env.state_log, columns=SimpleGameOfLifeEnv.STATES)
df = df.round(0)
df['age'] = df['age']/12
df['age'] = df['age'].round(2)
for col in df.columns:
    df[col] = df[col].apply(lambda x: "{:,}".format(x))

pd.set_option('display.max_columns', 7)
pd.set_option('display.max_rows', 12)
display(df)
```

	age	salary	home_value	...	tax_deposit	tax_adv_deposit	net_worth
0	18.08	4,876	214,749	...	0.0	1,880.0	24,578.0
1	18.17	4,876	214,749	...	0.0	1,875.0	25,791.0
2	18.25	4,876	214,749	...	0.0	1,875.0	27,039.0
3	18.33	4,876	214,749	...	0.0	1,875.0	28,321.0
4	18.42	4,876	214,749	...	0.0	1,875.0	29,640.0
...	...	...	...	...	...	...	...
740	79.75	6,830	302,304	...	0.0	683.0	3,990,102.0
741	79.83	6,830	302,304	...	0.0	683.0	3,989,629.0
742	79.92	6,830	302,304	...	0.0	683.0	3,989,157.0
743	80.0	6,830	302,304	...	0.0	683.0	3,988,684.0
744	80.08	6,816	301,724	...	0.0	683.0	3,987,632.0

745 rows × 12 columns

1810888.5833333335

Hyperparameters

I tuned the following hyperparameters to get a reasonable result from training the agent. Further optimization would be beneficial.

In [9]:
```
# How long should training run?
num_iterations = 3000
# How often should the program provide an update.
log_interval = 500

# How many initial random steps, before training start, to
# collect initial data.
initial_collect_steps = 1000
# How many steps should we run each iteration to collect
# data from.
collect_steps_per_iteration = 50
# How much data should we store for training examples.
replay_buffer_max_length = 100000

batch_size = 64

# How many episodes should the program use for each evaluation.
num_eval_episodes = 100
# How often should an evaluation occur.
eval_interval = 5000
```

Instantiate the Environment

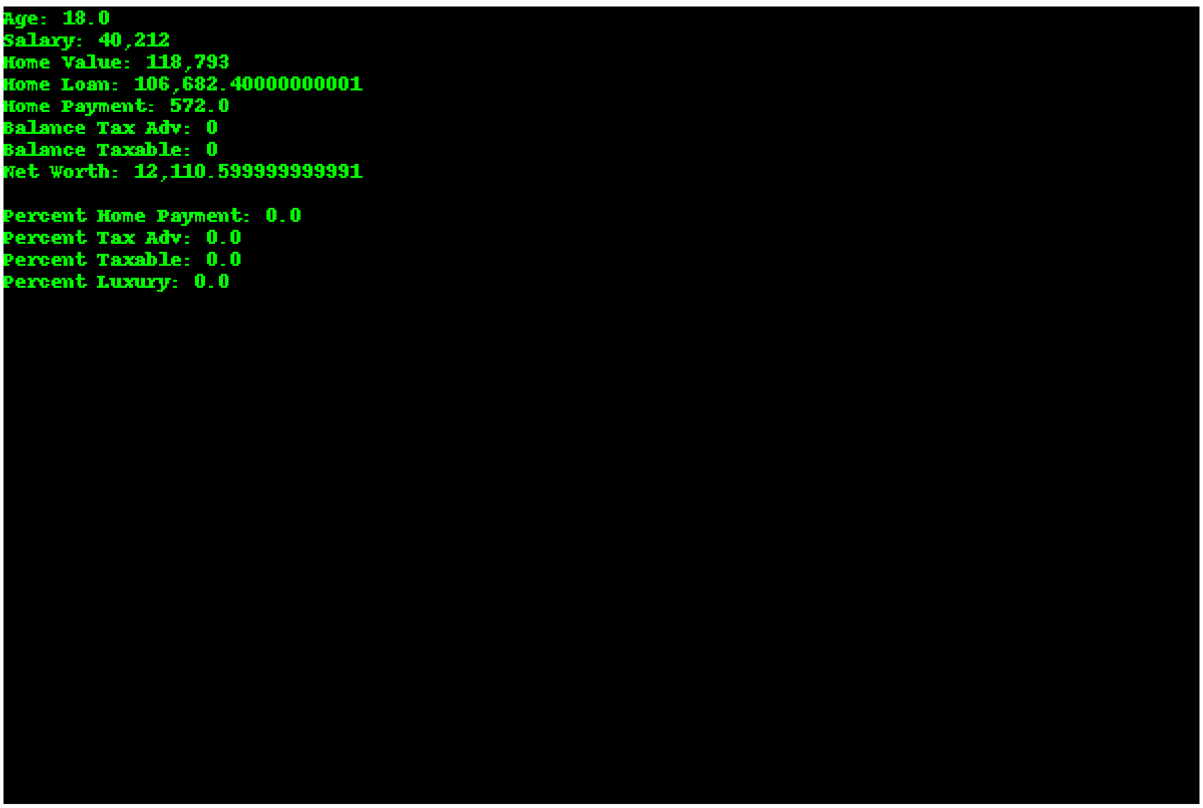
We are now ready to make use of our environment. Because we registered the environment with TF-Agents the program can load the environment by its name "simple-game-of-life-v".

In [10]:
```
env_name = 'simple-game-of-life-v0'
#env_name = 'MountainCarContinuous-v0'
env = suite_gym.load(env_name)
```

We can now have a quick look at the first state rendered. Here we can see the random salary and home values are chosen for an agent. The learned policy must be able to consider different starting salaries and home values and find an appropriate strategy.

In [11]:
```
env.reset()
PIL.Image.fromarray(env.render())
```

Out[11]:



Just as before, the program instantiates two environments: one for training and one for evaluation.

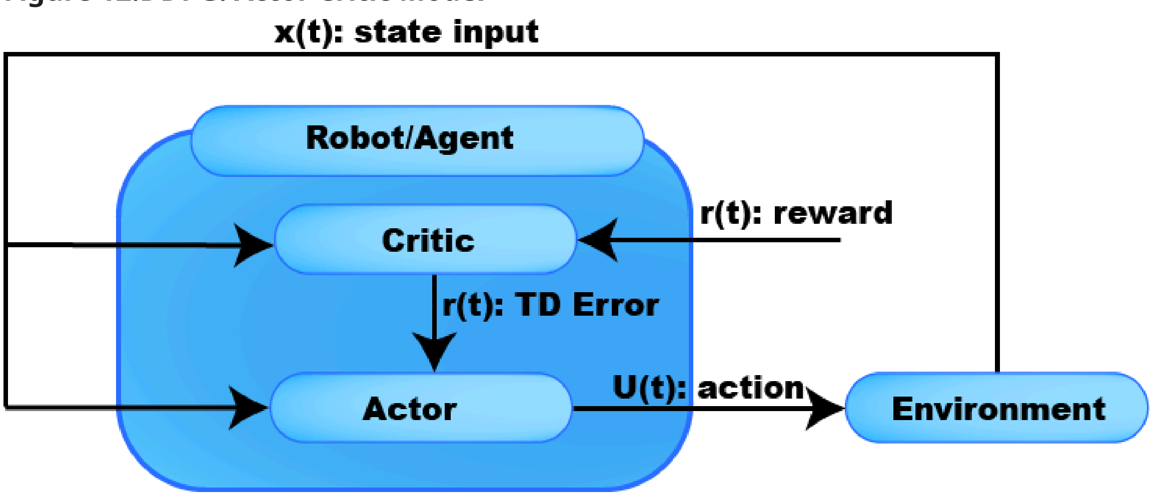
In [12]:
```
train_py_env = suite_gym.load(env_name)
eval_py_env = suite_gym.load(env_name)

train_env = tf_py_environment.TFPyEnvironment(train_py_env)
eval_env = tf_py_environment.TFPyEnvironment(eval_py_env)
```

You might be wondering why a DQN does not support continuous actions. This limitation is that the DQN algorithm maps each action as an output neuron. Each of these neurons predicts the likely future reward for taking each action. The algorithm knows the future rewards for each particular action. Generally, the DQN agent will perform the action that has the highest reward. However, because a continuous number represented in a computer has an effectively infinite number of possible values, it is not possible to calculate a future reward estimate for all of them.

We will use the Deep Deterministic Policy Gradients (DDPG) algorithm to provide a continuous action space. [Cite:lillicrap2015continuous] This technique uses two neural networks. The first neural network, called an actor, acts as the agent and predicts the expected reward for a given value of the action. The second neural network, called a critic, is trained to predict the accuracy of the actor-network. Training two neural networks in parallel that operate adversarially is a popular technique. Earlier in this course, we saw that Generative Adversarial Networks (GAN) used a similar method. Figure 12.DDPG shows the structure of the DDPG network that we will use.

Figure 12.DDPG: Actor Critic Model



The environment provides the same input ($x(t)$) for each time step to both the actor and critic networks. The temporal difference error ($r(t)$) reports the difference between the estimated reward and the actual reward at any given state or time step.

The following code creates the actor and critic neural networks.

In [13]:
```
actor_fc_layers = (400, 300)
critic_obs_fc_layers = (400,)
critic_action_fc_layers = None
critic_joint_fc_layers = (300,)
ou_stddev = 0.2
ou_damping = 0.15
target_update_tau = 0.05
target_update_period = 5
dqda_clipping = None
td_errors_loss_fn = tf.compat.v1.losses.huber_loss
```

```
gamma = 0.995
reward_scale_factor = 1.0
gradient_clipping = None

actor_learning_rate = 1e-4
critic_learning_rate = 1e-3
debug_summaries = False
summarize_grads_and_vars = False

global_step = tf.compat.v1.train.get_or_create_global_step()

actor_net = actor_network.ActorNetwork(
    train_env.time_step_spec().observation,
    train_env.action_spec(),
    fc_layer_params=actor_fc_layers,
)

critic_net_input_specs = (train_env.time_step_spec().observation,
                          train_env.action_spec())

critic_net = critic_network.CriticNetwork(
    critic_net_input_specs,
    observation_fc_layer_params=critic_obs_fc_layers,
    action_fc_layer_params=critic_action_fc_layers,
    joint_fc_layer_params=critic_joint_fc_layers,
)

tf_agent = ddpg_agent.DdpgAgent(
    train_env.time_step_spec(),
    train_env.action_spec(),
    actor_network=actor_net,
    critic_network=critic_net,
    actor_optimizer=tf.compat.v1.train.AdamOptimizer(
        learning_rate=actor_learning_rate),
    critic_optimizer=tf.compat.v1.train.AdamOptimizer(
        learning_rate=critic_learning_rate),
    ou_stddev=ou_stddev,
    ou_damping=ou_damping,
    target_update_tau=target_update_tau,
    target_update_period=target_update_period,
    dqda_clipping=dqda_clipping,
    td_errors_loss_fn=td_errors_loss_fn,
    gamma=gamma,
    reward_scale_factor=reward_scale_factor,
    gradient_clipping=gradient_clipping,
    debug_summaries=debug_summaries,
    summarize_grads_and_vars=summarize_grads_and_vars,
    train_step_counter=global_step)
tf_agent.initialize()
```

Metrics and Evaluation

Just as in previous examples, we will compute the average return over several episodes to evaluate performance.

In [14]:
```
def compute_avg_return(environment, policy, num_episodes=10):

    total_return = 0.0
    for _ in range(num_episodes):

        time_step = environment.reset()
        episode_return = 0.0

        while not time_step.is_last():
            action_step = policy.action(time_step)
            time_step = environment.step(action_step.action)
            episode_return += time_step.reward
        total_return += episode_return

    avg_return = total_return / num_episodes
    return avg_return.numpy()[0]


# See also the metrics module for standard implementations of
# different metrics.
# https://github.com/tensorflow/agents/tree/master/tf_agents/metrics
```

Data Collection

Now execute the random policy in the environment for a few steps, recording the data in the replay buffer.

In [15]:
```
def collect_step(environment, policy, buffer):
    time_step = environment.current_time_step()
    action_step = policy.action(time_step)
    next_time_step = \
        environment.step(action_step.action)
    traj = trajectory.from_transition(\
        time_step, action_step,\
        next_time_step)

    # Add trajectory to the replay buffer
    buffer.add_batch(traj)


def collect_data(env, policy, buffer, steps):
    for _ in range(steps):
        collect_step(env, policy, buffer)


random_policy = random_tf_policy.RandomTFPolicy(\
```

```
    train_env.time_step_spec(),\
    train_env.action_spec())

replay_buffer = tf_uniform_replay_buffer.TFUniformReplayBuffer(
    data_spec=tf_agent.collect_data_spec,
    batch_size=train_env.batch_size,
    max_length=replay_buffer_max_length)

collect_data(train_env, random_policy, replay_buffer, steps=100)

# Dataset generates trajectories with shape [Bx2x...]
dataset = replay_buffer.as_dataset(
    num_parallel_calls=3,
    sample_batch_size=batch_size,
    num_steps=2).prefetch(3)
```

```
WARNING:tensorflow:From /usr/local/lib/python3.7/dist-packages/tensorflow/py
thon/autograph/impl/api.py:377: ReplayBuffer.get_next (from tf_agents.replay
_buffers.replay_buffer) is deprecated and will be removed in a future versio
n.
Instructions for updating:
Use `as_dataset(..., single_deterministic_pass=False) instead.
```

Training the agent

We are now ready to train the agent. Depending on how many episodes you wish to run through, this process can take many hours. This code will update on both the loss and average return as training occurs. As training becomes more successful, the average return should increase. The losses reported reflect the average loss for individual training batches.

In [16]:
```
iterator = iter(dataset)

# (Optional) Optimize by wrapping some of the code in a graph using
# TF function.
tf_agent.train = common.function(tf_agent.train)

# Reset the train step
tf_agent.train_step_counter.assign(0)

# Evaluate the agent's policy once before training.
avg_return = compute_avg_return(eval_env, tf_agent.policy,
                                num_eval_episodes)
returns = [avg_return]

for _ in range(num_iterations):

    # Collect a few steps using collect_policy and
    # save to the replay buffer.
    for _ in range(collect_steps_per_iteration):
        collect_step(train_env, tf_agent.collect_policy, replay_buffer)

    # Sample a batch of data from the buffer and update the
```

```
    # agent's network.
    experience, unused_info = next(iterator)
    train_loss = tf_agent.train(experience).loss

    step = tf_agent.train_step_counter.numpy()

    if step % log_interval == 0:
        print('step = {0}: loss = {1}'.format(step, train_loss))

    if step % eval_interval == 0:
        avg_return = compute_avg_return(eval_env, tf_agent.policy,
                                        num_eval_episodes)
        print('step = {0}: Average Return = {1}'.format(step, avg_return))
        returns.append(avg_return)
```

```
step = 500: loss = 0.00016351199883501977
step = 1000: loss = 6.34381067357026e-05
step = 1500: loss = 0.0012666243128478527
step = 2000: loss = 0.00041321030585095286
step = 2500: loss = 0.0006321941618807614
step = 3000: loss = 0.0006611005519516766
```

Visualization

The notebook can plot the average return over training iterations. The average return should increase as the program performs more training iterations.

Videos

We use the following functions to produce video in Jupyter notebook. As the person moves through their career, they focus on paying off the house and tax advantage investing.

In [18]:

```
# HIDE OUTPUT
def embed_mp4(filename):
    """Embeds an mp4 file in the notebook."""
    video = open(filename, 'rb').read()
    b64 = base64.b64encode(video)
    tag = '''
  <video width="640" height="480" controls>
    <source src="data:video/mp4;base64,{0}" type="video/mp4">
  Your browser does not support the video tag.
  </video>'''.format(b64.decode())

    return IPython.display.HTML(tag)


def create_policy_eval_video(policy, filename, num_episodes=5, fps=30):
    filename = filename + ".mp4"
    with imageio.get_writer(filename, fps=fps) as video:
        for _ in range(num_episodes):
            time_step = eval_env.reset()
            video.append_data(eval_py_env.render())
```

```
            while not time_step.is_last():
                action_step = policy.action(time_step)
                time_step = eval_env.step(action_step.action)
                video.append_data(eval_py_env.render())
    return embed_mp4(filename)


create_policy_eval_video(tf_agent.policy, "trained-agent")
```

```
WARNING:root:IMAGEIO FFMPEG_WRITER WARNING: input image is not divisible by
macro_block_size=16, resizing from (400, 600) to (400, 608) to ensure video
compatibility with most codecs and players. To prevent resizing, make your i
nput image divisible by the macro_block_size or set the macro_block_size to
None (risking incompatibility). You may also see a FFMPEG warning concerning
speedloss due to data not being aligned.
```

Out[18]: