Chapter_8_Reinforcement_Learning

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1 Ch 08: Concept 01 Reinforcement learning

1.1 Practical explanation

1.1.1 Introduction

RL is about training a NN to be able to decide on an action based on the best chances to get a reward. This reward doesn't need to be immediate, i.e. it can anticipate long term changes and adapt to gain long-term rewards rather than short-term.

1.1.2 Algorithm

Step 1 - Initialize Initialise algorithm so that there is an initial state. In our example the state is a vector with the prices of stocks over a time period (in the "past"), the available budget and the number of shares we have bought.

$$\textbf{state} = \begin{pmatrix} price_1 \\ price_2 \\ \vdots \\ price_n \\ budget \\ share_{number} \end{pmatrix}$$

The size of the time period in the past that we are going to consider is a hyperparameter that determines the size of **state**.

In the code the state is initialised in function `run_simulation`

```
current_state = np.asmatrix(np.hstack((prices[i:i+hist], budget, num_stocks)))
```

Step 2 - Select action Selection action to perform. The action is selected either randomly or using the NN model. In the start of algorithm steps we want to do more `exploration` rather than `exploitation` since at first our model will not know that much.

This step is performed in the `select_action` method

```
def select_action(self, current_state, step):
    threshold = min(self.epsilon, step / 1000.)
    if random.random() < threshold:
        action_q_vals = self.sess.run(self.q, feed_dict={self.x: current_state})
```

```
        action_idx = np.argmax(action_q_vals)
        action = self.actions[action_idx]
    else:
        action = self.actions[random.randint(0, len(self.actions) - 1)]
    return action
```

The important code line is `action_q_vals = self.sess.run(self.q, feed_dict={self.x: current_state})` here we run our state through the NN model and get back the `relu` activation values. These are trained to predict the `utility` of each action, which is our `reward` taking into account long-term rewards. `action_q_vals` is a vector with size equal to the size of our actions. So each element represents the potential `utility` of taking an action. We take the action that can maximize the `utility` using `action_idx = np.argmax(action_q_vals)`.

Step 3 - Calculate new state Based on the results of step 2, we take an action. In the case of our example it's either `sell`, `buy`, `hold`. So if the action is to `buy` we buy the stock at it's current share value, which is not part of the **state**.

$current_{value} = price_{n+1}$.

We calculate the new state based on our action.

$$\mathbf{state_{new}} = \begin{pmatrix} price_2 \\ price_3 \\ \vdots \\ price_{n+1} \\ budget_{new} \\ share_{number_{new}} \end{pmatrix}$$

Step 4 - Calculate reward Now we calculate our `reward`, this is our immediate gain.

$reward = (budget_{new} + share_{number_{new}} \times current_{value}) - (budget_{old} + share_{number_{old}} \times current_{value})$

Step 5 - Correct utility of current action Based on $\mathbf{state_{old}}$ and $\mathbf{state_{new}}$ we update our `policy`. This is the part we train the NN model.

This step takes place in the `update_q` function

```
    def update_q(self, state, action, reward, next_state, writer, i):
        action_q_vals = self.sess.run(self.q, feed_dict={self.x: state})
        next_action_q_vals = self.sess.run(self.q, feed_dict={self.x: next_state})
        next_best_action_idx = np.argmax(next_action_q_vals)
        current_action_idx = self.actions.index(action)
        action_q_vals[0, current_action_idx] = reward + \
                                self.gamma * next_action_q_vals[0, next_best_action_idx]
        action_q_vals = np.squeeze(np.asarray(action_q_vals))
        _, lossSumm = self.sess.run([self.train_op, self.loss_summary],
                                    feed_dict={self.x: state, self.y: action_q_vals})
```

We get our current `utility` function values for each action using `action_q_vals = self.sess.run(self.q, feed_dict={self.x: state})`(this is done in the `select_action` function also).

Then using our calculated $\textbf{state}_{\textbf{new}}$ we get the `utility` function values for each action based on our new state, which depends on the previous state: `next_action_q_vals = self.sess.run(self.q, feed_dict={self.x: next_state})`

We calculate, based on the utility function values, which is the best **next action** to take: `next_best_action_idx = np.argmax(next_action_q_vals)`. This allows to "correct" the reward of our **current action** based on long term consequences.

The correction is performed using the following equation:

$$utility_{current} = reward + \gamma \times utility_{next}$$

Note that this changes the utility of the current action only, so only an element of the `action_q_vals`

If γ is zero then we don't take into account long term consequences of our actions. This equation is implemented by `action_q_vals[0, current_action_idx] = reward + self.gamma * next_action_q_vals[0, next_best_action_idx]`.

We could also generalize and take into account more actions than just the next, i.e. the one after next etc.

$$utility_0 = reward + \gamma_1 \times utility_1 + \gamma_2 \times utility_2 + ... + \gamma_k \times utility_k$$

There is also another equation that intoduces another parameter α, which aims to make newly available information less/more important than historical records.

$$utility_{current} = (1 - \alpha) \times utility_{current} + \alpha \times (reward + \gamma \times utility_{next})$$

If α is increased then we expect our `agent` (the decision maker) to learn to solve tasks faster but not optimal.If α is decreased our `agent` is allowed more time to explore and exploit.

Step 6 - Train NN model Now we train our NN based on the input, our current state `state` and the corrected `utility` values of our current action that takes into account future consequences.

The training call is in function `_, lossSumm = self.sess.run([self.train_op, self.loss_summary],feed_dict={self.x: state, self.y: action_q_vals})`. This will update our NN model parameters so that our state produces `relu` activations that better agree with the corrected utility values of our current action `action_q_vals`, rather than the original that were derived from the same input `state`.

1.2 Code

The **states** are previous history of stock prices, current budget, and current number of shares of a stock.

The **actions** are buy, sell, or hold (i.e. do nothing).

The stock market data comes from the Yahoo Finance library, `pip install yahoo-finance`.

In [1]:
```
%matplotlib inline
from yahoo_finance import Share
from matplotlib import pyplot as plt
import numpy as np
import random
import tensorflow as tf
```

```
import tqdm
import datetime as dt
```

Define an abstract class called `DecisionPolicy`:

```
In [2]: # it's a good idea to create a class with the relevant methods to
        # reference later, such as an abstract class or interface
        class DecisionPolicy:
            # Basically, reinforcement learning needs two operations well defined:
            def select_action(self, current_state, step):
                # (1) how to select an action
                pass

            def update_q(self, state, action, reward, next_state):
                # (2) how to improve the utility Q-function
                pass
```

Here's one way we could implement the decision policy, called a random decision policy:

```
In [3]: # let's inherit from `DecisionPolicy` superclass to implement a random decision policy
        # it's a good idea to test our poly against a random policy or a "greedy" policy (not
        # just takes the action that maximizes current reward
        class RandomDecisionPolicy(DecisionPolicy):# Inherit from DecisionPolicy to implement
            def __init__(self, actions):
                self.actions = actions

            def select_action(self, current_state, step):
                # Randomly choose the next action
                action = random.choice(self.actions)
                return action
```

That's a good baseline. Now let's use a smarter approach using a neural network:

```
In [4]: class QLearningDecisionPolicy(DecisionPolicy):
            def __init__(self, actions, input_dim):
                # Set the hyper-parameters from the Q-function
                self.epsilon = 0.95
                self.gamma = 0.3
                self.actions = actions
                output_dim = len(actions)
                # Set the number of hidden nodes in the neural networks
                h1_dim = 20
                # Define the input and output tensors
                self.x = tf.placeholder(tf.float32, [None, input_dim])
                self.y = tf.placeholder(tf.float32, [output_dim])
                # Design the neural network architecture
                W1 = tf.Variable(tf.random_normal([input_dim, h1_dim]))
                b1 = tf.Variable(tf.constant(0.1, shape=[h1_dim]))
                h1 = tf.nn.relu(tf.matmul(self.x, W1) + b1)
```

```
        W2 = tf.Variable(tf.random_normal([h1_dim, output_dim]))
        b2 = tf.Variable(tf.constant(0.1, shape=[output_dim]))
        # Define the op to compute the utility
        self.q = tf.nn.relu(tf.matmul(h1, W2) + b2)
        # Set the loss as the square error
        self.loss = tf.square(self.y - self.q)
        # set loss summary for tensorboard
        self.loss_summary = tf.summary.scalar('loss', tf.reduce_mean(self.loss))
        # Use an optimizer to update model parameters to minimize the loss
        self.train_op = tf.train.AdagradOptimizer(0.01).minimize(self.loss)
        # Set up the session and initialize variables
        self.sess = tf.Session()
        self.sess.run(tf.global_variables_initializer())


    def select_action(self, current_state, step):
        # select minimum between epsilon and step/1000 because
        # at the begining we want to explore so that our algorithm learns
        # before it can make policies
        threshold = min(self.epsilon, step / 1000.)
        if random.random() < threshold:
            # Exploit best option with probability epsilon
            action_q_vals = self.sess.run(self.q, feed_dict={self.x: current_state})
            action_idx = np.argmax(action_q_vals)  # TODO: replace w/ tensorflow's arg
            action = self.actions[action_idx]
        else:
            # Explore random option with probability 1 - epsilon
            action = self.actions[random.randint(0, len(self.actions) - 1)]
        return action

    def update_q(self, state, action, reward, next_state, writer, i):
        """Update the Q-function by updating its model parameters"""
        # calculate utilities of each action for current state
        action_q_vals = self.sess.run(self.q, feed_dict={self.x: state})
        # calculate utilities of each action for next state
        next_action_q_vals = self.sess.run(self.q, feed_dict={self.x: next_state})
        # find next action that will maximise the utility when we are in the next stat
        next_best_action_idx = np.argmax(next_action_q_vals)
        # find index of current action
        current_action_idx = self.actions.index(action)
        # now we need to "correct" the utility of current action by looking at the uti
        # conditional on the current state. In other words the next state depends on th
        # the higher the gamma hyperparameter the more we take into account future rew
        # if gamma is zero then we ignore any long term rewards (consequences of our a
        # I guess we could add more future states and best actions to make our algorit
        # i.e. action_q_vals[0, current_action_idx] = reward + self.gamma1 * next_acti
        # + self.gamma2 * next_next_action_q_vals[0, next_next_best_action_idx]
        action_q_vals[0, current_action_idx] = reward + \
```

```
                                              self.gamma * next_action_q_vals[0, next_
        action_q_vals = np.squeeze(np.asarray(action_q_vals))
        # have the nn learn a function that minimizes the difference between the
        # current uncorrected action and the corrected
        # ones based on future consequences
        _, lossSumm = self.sess.run([self.train_op, self.loss_summary],
                                    feed_dict={self.x: state, self.y: action_q_vals})
        writer.add_summary(summary=lossSumm, global_step=i)
        writer.add_graph(self.sess.graph)
        writer.flush()
```

Define a function to run a simulation of buying and selling stocks from a market:

```
In [5]: def run_simulation(policy, initial_budget, initial_num_stocks, prices, hist, writer):
            # Initialize values that depend on computing the net worth of a portfolio
            budget = initial_budget
            num_stocks = initial_num_stocks
            share_value = 0
            transitions = list()
            for i in tqdm.tqdm(range(len(prices) - hist - 1)):
                # The state is a `hist+2` dimensional vector. Well force it to by a numpy matr
                current_state = np.asmatrix(np.hstack((prices[i:i+hist], budget, num_stocks)))
                # Calculate the portfolio value
                current_portfolio = budget + num_stocks * share_value
                # Select an action from the current policy
                action = policy.select_action(current_state, i)
                share_value = float(prices[i + hist])
                # Update portfolio values based on action
                if action == 'Buy' and budget >= share_value:
                    budget -= share_value
                    num_stocks += 1
                elif action == 'Sell' and num_stocks > 0:
                    budget += share_value
                    num_stocks -= 1
                else:
                    action = 'Hold'
                # Compute new portfolio value after taking action
                new_portfolio = budget + num_stocks * share_value
                # Compute the reward from taking an action at a state
                reward = new_portfolio - current_portfolio
                next_state = np.asmatrix(np.hstack((prices[i+1:i+hist+1], budget, num_stocks)))
                transitions.append((current_state, action, reward, next_state))
                # Update the policy after experiencing a new action
                # This is when we train our model
                policy.update_q(current_state, action, reward, next_state, writer, i)
            # Compute final portfolio worth
            portfolio = budget + num_stocks * share_value
            return portfolio
```

We want to run simulations multiple times and average out the performances:

```
In [6]: def run_simulations(policy, budget, num_stocks, prices, hist):
            # Decide number of times to re-run the simulations
            num_tries = 3
            # Store portfolio worth of each run in this array
            final_portfolios = list()
            # initial portfolio value
            portfolio = budget
            for i in range(num_tries):
                # tensorboard writer
                # *** TENSORBOARD ***
                # set directory to collect saved summary tensors with each run
                # based on run time
                now = dt.datetime.now()
                currentDir = "./logs/" + now.strftime("%Y%m%d-%H%M%S") + "/"
                # create writer and set directory and graph
                writer = tf.summary.FileWriter(currentDir)
                print('Running simulation {}...'.format(i + 1))
                print('Starting budget portfolio: ${}'.format(portfolio))
                final_portfolio = run_simulation(policy, budget, num_stocks, prices, hist, wri
                final_portfolios.append(final_portfolio)
                print('Final portfolio: ${}'.format(final_portfolio))
                writer.close()
            # Average the values from all the runs
            avg, std = np.mean(final_portfolios), np.std(final_portfolios)
            return avg, std
```

Call the following function to use the Yahoo Finance library and obtain useful stockmarket data.

```
In [7]: def get_prices(share_symbol, start_date, end_date, cache_filename='stock_prices.npy'):
            try:
                stock_prices = np.load(cache_filename)
            except IOError:
                share = Share(share_symbol)
                stock_hist = share.get_historical(start_date, end_date)
                stock_prices = [stock_price['Open'] for stock_price in stock_hist]
                np.save(cache_filename, stock_prices)

            return stock_prices.astype(float)
```

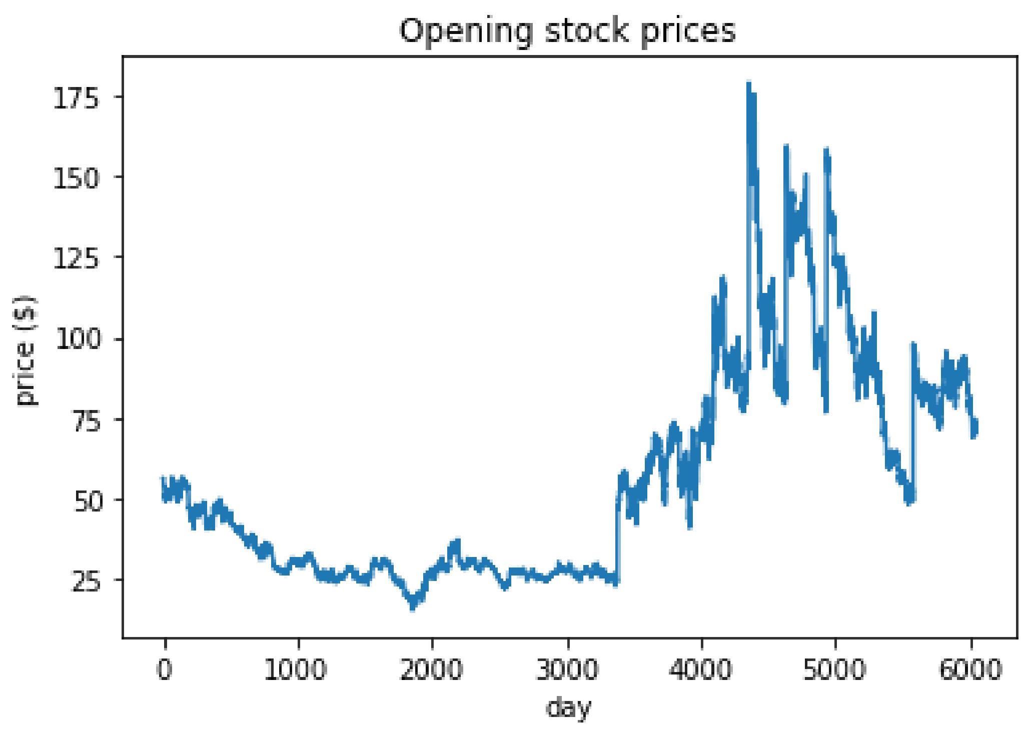
Who wants to deal with stock market data without looking a pretty plots? No one. So we need this out of law:

```
In [8]: def plot_prices(prices):
            plt.title('Opening stock prices')
            plt.xlabel('day')
            plt.ylabel('price ($)')
```

```
        plt.plot(prices)
        plt.savefig('prices.png')
        plt.show()
```

Train a reinforcement learning policy:

```
In [9]: if __name__ == '__main__':
            prices = get_prices('MSFT', '1992-07-22', '2016-07-22')
            plot_prices(prices)
            # Define the list of actions the agent can take
            actions = ['Buy', 'Sell', 'Hold']
            hist = 200
            # Initial a random decision policy
            # policy = RandomDecisionPolicy(actions)
            policy = QLearningDecisionPolicy(actions, hist + 2)
            # Set the initial amount of money available to use
            budget = 1000.0
            # Set the number of stocks already owned
            num_stocks = 0
            # Run simulations multiple times to compute expected value of final net worth
            run_simulations(policy, budget, num_stocks, prices, hist)
```




```
0%|          | 14/5846 [00:00<00:42, 135.67it/s]
```

```
Running simulation 1...
Starting budget portfolio: $1000.0


100%|| 5846/5846 [00:39<00:00, 146.70it/s]
  0%|          | 19/5846 [00:00<00:30, 188.74it/s]

Final portfolio: $1573.7650420000004
Running simulation 2...
Starting budget portfolio: $1000.0


100%|| 5846/5846 [00:36<00:00, 170.98it/s]
  0%|          | 21/5846 [00:00<00:27, 209.27it/s]

Final portfolio: $1617.4550170000002
Running simulation 3...
Starting budget portfolio: $1000.0


100%|| 5846/5846 [00:36<00:00, 160.76it/s]

Final portfolio: $1620.3799610000003
```