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Jul 29 · 11 min read

Reinforcement Learning w/ Keras + OpenAI: DQNs

Quick Recap

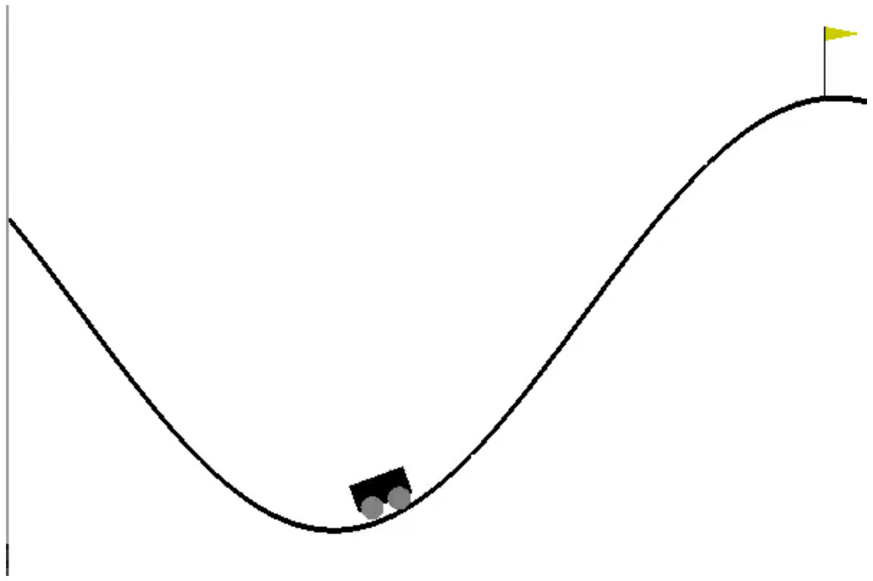
Last time in our Keras/OpenAI tutorial, we discussed a very basic example of applying deep learning to reinforcement learning contexts. This was an incredible showing in retrospect! If you looked at the training data, the random chance models would usually only be able to perform for 60 steps in median. And yet, by training on this seemingly very mediocre data, we were able to "beat" the environment (i.e. get >200 step performance). How is this possible?

We can get directly an intuitive feel for this. Let's imagine the perfectly random series we used as our training data. It is extremely unlikely that any two series will have high overlap with one another, since these are generated completely randomly. However, there **are** key features that are common between successful trials, such as pushing the cart right when the pole is leaning right and vice versa. And so, by training our NN on all these trials data, we extract the shared patterns that contributed to them being successful and are able to smooth over the details that resulted in their independent failures.

That being said, the environment we consider this week is significantly more difficult than that from last week: the MountainCar.

More Complex Environments

Even though it seems we should be able to apply the same technique as that we applied last week, there is one key features here that makes doing so impossible: we can't generate training data. Unlike the very simple Cartpole example, taking random movements often simply leads to the trial ending in us at the bottom of the hill. That is, we have several trials that are all identically -200 in the end. This is practically useless to use as training data. Imagine you were in a class where no matter what answers you put on your exam, you got a 0%! How are you going to learn from any of those experiences?

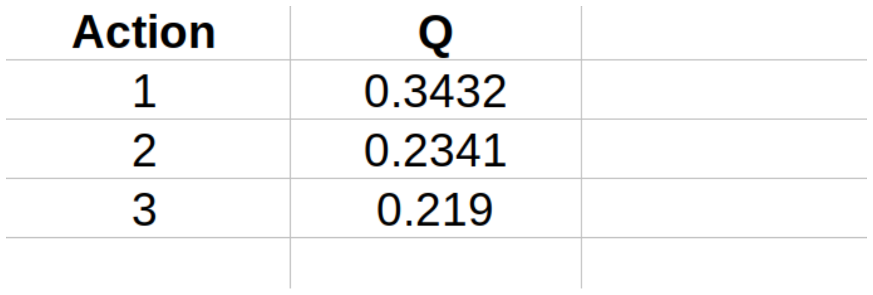


Random inputs for the "MountainCar-v0" environment does not produce any output that is worthwhile or useful to train on

In line with that, we have to figure out a way to incrementally improve upon previous trials. For this, we use one of the most basic stepping stones for reinforcement learning: Q-learning!

DQN Theory Background

Q-learning (which doesn't stand for anything, by the way) is centered around creating a "virtual table" that accounts for how much reward is assigned to each possible action given the current state of the environment. Let's break that down one step at a time:



Action	Q	
1	0.3432	
2	0.2341	
3	0.219	

You can imagine the DQN network as internally maintaining a spreadsheet of the values of each of the possible actions that can be taken given the current environment state

What do we mean by "virtual table?" Imagine that for each possible configuration of the input space, you have a table that assigns a score for each of the possible actions you can take. If this were magically possible, then it would be extremely easy for you to "beat" the environment: simply choose the action that has the highest score! Two points to note about this score. First, this score is conventionally referred to as the "Q-score," which is where the name of the overall algorithm comes from. Second, as with any other score, these Q score have *no meaning* outside the context of their simulation. That is, they have **no absolute significance**, but that's perfectly fine, since we solely need it to do comparisons.

Why then do we need virtual table for *each* input configuration? Why can't we just have one table to rule them all? The reason is that it doesn't make sense to do so: that would be the same as saying the best action to take while at the bottom of the valley is exactly that which you should take when you are perched on the highest point of the left incline.

Now, the main problem with what I described (maintaining a virtual table for *each* input configuration) is that this is impossible: we have a continuous (infinite) input space! We could get around this by discretizing the input space, but that seems like a pretty hacky solution to this problem that we'll be encountering over and over in future situations. So, how do we get around this? By applying neural nets to the situation: that's where the D in DQN comes from!

DQN Agent

So, we've now reduced the problem to finding a way to assign the different actions Q-scores given the current state. This is the answer to a very natural first question to answer when employing any NN: what are the inputs and outputs of our model? The extent of the math you need to understand for this model is the following equation (don't worry, we'll break it down):

$$\left(\underbrace{r + \gamma \max_{a`} \hat{Q}(s,a`)}_{\text{Target}} - \underbrace{Q(s,a)}_{\text{Prediction}}\right)^2$$

Q, as mentioned, represents the value estimated by our model given the current state (s) and action taken (a). The goal, however, is to determine the *overall* value of a state. What do I mean by that? The *overall* value is **both** the immediate reward you will get **and** the expected rewards you will get in the future from being in that position. That is, we want to account for the fact that the value of a position often reflects not only its immediate gains but also the future gains it enables (damn, deep). In any case, we discount future rewards because, if I compare two situations in which I expect to get $100 one of the two being in the future, I would always take the present deal, since the position of the future one may change between when I made the deal and when I receive the money. The gamma factor reflects this depreciated value for the expected future returns on the state.

And that's it: that's all the math we'll need for this! Time to actually move on to some code!

DQN Agent Implementation

The Deep Q Network revolves around continuous learning, meaning that we don't simply accrue a bunch of trial/training data and feed it into the model. Instead, we create training data through the trials we run and feed this information into it directly after running the trial. If this all seems somewhat vague right now, don't worry: time to see some code about this. The code largely revolves around defining a DQN class, where all the logic of the algorithm will actually be implemented, and where we expose a simple set of functions for the actual training.

DQN Hyperparameters

First off, we're going to discuss some parameters of relevance for DQNs. Most of them are standard from most neural net implementations:

```
class DQN:
    def __init__(self, env):
        self.env     = env
        self.memory  = deque(maxlen=2000)

        self.gamma = 0.95
        self.epsilon = 1.0
        self.epsilon_min = 0.01
        self.epsilon_decay = 0.995
        self.learning_rate = 0.01
```

Let's step through these one at a time. The first is simply the environment, which we supply for convenience when we need to reference the shapes in creating our model. The "memory" is a key component of DQNs: as mentioned previously, the trials are used to continuously train the model. However, rather than training on the trials as they come in, we add them to memory and train on a random sample of that memory. Why do this instead of just training on the last *x* trials as our "sample?" The reason is somewhat subtle. Imagine instead we were to just train on the most recent trials as our sample: in this case, our results would only learn on its most recent actions, which may not be directly relevant for future predictions. In this environment in particular, if we were moving down the right side of the slope, training on the most recent trials would entail training on the data where you were moving up the hill towards the right. But, this would not be at all relevant to determining what actions to take in the scenario you would soon be facing of scaling up the left hill. So, by taking a random sample, we don't bias our training set, and instead ideally learn about scaling all environments we would encounter equally well.

So, we now discuss hyperparameters of the model: gamma, epsilon/epsilon decay, and the learning rate. The first is the future rewards depreciation factor (<1) discussed in the earlier equation, and the last is the standard learning rate parameter, so I won't discuss that here. The second, however, is an interesting facet of RL that deserves a moment to discuss. In any sort of learning experience, we always have the choice between exploration vs. exploitation. This isn't limited to computer science or academics: we do this on a day to day basis!

Consider the restaurants in your local neighborhood. When was the last time you went to a new one? Probably a long time ago. That corresponds to your shift from *exploration* to *exploitation*: rather than trying to find new and better opportunities, you settle with the best one you've found in your past experiences and maximize your utility from there. Contrast that to when you moved into your house: at that time, you had no idea what restaurants were good or not and so were enticed to explore your options. In other words, there's a clear trend for learning: explore all your options when you're unaware of them, and gradually shift over to exploiting once you've established opinions on some of them. In the same manner, we want our model to capture this natural model of learning, and epsilon plays that role.

Epsilon denotes the fraction of time we will dedicate to exploring. That is, a fraction *self.epsilon* of the trials, we will simply take a random action rather than the one we would predict to be the best in that scenario. As stated, we want to do this more often than not in the beginning, before we form stabilizing valuations on the matter, and so initialize epsilon to close to 1.0 at the beginning and decay it by some fraction <1 at every successive time step.

DQN Models

There was one key thing that was excluded in the initialization of the DQN above: the actual model used for predictions! As in our original Keras RL tutorial, we are directly given the input and output as numeric vectors. So, there's no need to employ more complex layers in our network other than fully connected layers. Specifically, we define our model just as:

```
def create_model(self):
        model   = Sequential()
        state_shape  = self.env.observation_space.shape
        model.add(Dense(24, input_dim=state_shape[0],
            activation="relu"))
        model.add(Dense(48, activation="relu"))
        model.add(Dense(24, activation="relu"))
        model.add(Dense(self.env.action_space.n))
        model.compile(loss="mean_squared_error",
            optimizer=Adam(lr=self.learning_rate))
        return model
```

And use this to define the model and target model (explained below):

```
def __init__(self, env):
        self.env     = env
        self.memory  = deque(maxlen=2000)

        self.gamma = 0.95
        self.epsilon = 1.0
        self.epsilon_min = 0.01
        self.epsilon_decay = 0.995
        self.learning_rate = 0.01
        self.tau = .05


        self.model = self.create_model()
        # "hack" implemented by DeepMind to improve
convergence
        self.target_model = self.create_model()
```

The fact that there are two *separate* models, one for doing predictions and one for tracking "target values" is definitely counter-intuitive. To be explicit, the role of the model (*self.model*) is to do the actual predictions on what action to take, and the target model (*self.target_model*) tracks what action we *want* our model to take.

Why not just have a single model that does both? After all, if something is predicting the action to take, shouldn't it be implicitly determine what model we *want* our model to take? This is actually one of those "weird tricks" in deep learning that DeepMind developed to get convergence in the DQN algorithm. If you use a single model, it can (and often does) converge in simple environments (such as the CartPole). But, the reason it doesn't converge in these more complex environments is because of how we're training the model: as mentioned previously, we're training it "on the fly."

As a result, we are doing training at each time step and, if we used a single network, would also be essentially changing the "goal" at each time step. Think of how confusing that would be! That would be like if a teacher told you to go finish pg. 6 in your textbook and, by the time you finished half of it, she changed it to pg. 9, and by the time you finished half of that, she told you to do pg. 21! This, therefore, causes a lack of convergence by a lack of clear direction in which to employ the optimizer, i.e. the gradients are changing too rapidly for stable convergence. So, to compensate, we have a network that changes more slowly that tracks our eventual goal and one that is trying to achieve those.

DQN Training

The training involves three main steps: remembering, learning, and reorienting goals. The first is basically just adding to the memory as we go through more trials:

```
def remember(self, state, action, reward, new_state, done):
        self.memory.append([state, action, reward,
new_state, done])
```

There’s not much of note here other than that we have to store the *done* phase for how we later update the reward function. Moving on to the main body of our DQN, we have the train function. This is where we make use of our stored memory and actively learn from what we’ve seen in the past. We start by taking a sample from our entire memory storage. From there, we handle each sample different. As we saw in the equation before, we want to update the *Q* function as **the sum of** the current reward **and** expected future rewards (depreciated by gamma). In the case we are at the end of the trials, there are no such future rewards, so the entire value of this state is just the current reward we received. In a non-terminal state, however, we want to see what the maximum reward we would receive would be if we were able to take any possible action, from which we get:

```
def replay(self):
        batch_size = 32
        if len(self.memory) < batch_size:
            return

        samples = random.sample(self.memory, batch_size)
        for sample in samples:
            state, action, reward, new_state, done = sample
            target = self.target_model.predict(state)
            if done:
                target[0][action] = reward
            else:
                Q_future = max(
                    self.target_model.predict(new_state)[0])
                target[0][action] = reward + Q_future *
self.gamma
            self.model.fit(state, target, epochs=1,
verbose=0)
```

And finally, we have to reorient our goals, where we simply copy over the weights from the main model into the target one. Unlike the main train method, however, this target update is called less frequently:

```
def target_train(self):
        weights = self.model.get_weights()
        target_weights = self.target_model.get_weights()
        for i in range(len(target_weights)):
            target_weights[i] = weights[i]
        self.target_model.set_weights(target_weights)
```

DQN Action

The final step is simply getting the DQN to actually perform the desired action, which alternates based on the given epsilon parameter between taking a random action and one predicated on past training, as follows:

```
def act(self, state):
        self.epsilon *= self.epsilon_decay
        self.epsilon = max(self.epsilon_min, self.epsilon)
        if np.random.random() < self.epsilon:
            return self.env.action_space.sample()
        return np.argmax(self.model.predict(state)[0])
```

Training Agent

Training the agent now follows naturally from the complex agent we developed. We have to instantiate it, feed it the experiences as we encounter them, train the agent, and update the target network:

```
def main():
    env     = gym.make("MountainCar-v0")
    gamma   = 0.9
    epsilon = .95


    trials  = 100
    trial_len = 500


    updateTargetNetwork = 1000
    dqn_agent = DQN(env=env)
    steps = []
    for trial in range(trials):
        cur_state = env.reset().reshape(1,2)
        for step in range(trial_len):
            action = dqn_agent.act(cur_state)
            env.render()
            new_state, reward, done, _ = env.step(action)


            reward = reward if not done else -20
            print(reward)
            new_state = new_state.reshape(1,2)
            dqn_agent.remember(cur_state, action,
                reward, new_state, done)

            dqn_agent.replay()
            dqn_agent.target_train()


            cur_state = new_state
            if done:
                break
        if step >= 199:
            print("Failed to complete trial")
        else:
            print("Completed in {} trials".format(trial))
            break
```

Complete Code

With that, here is the complete code used for training against the "MountainCar-v0" environment using DQN!

```
import gym
import numpy as np
import random
from keras.models import Sequential
from keras.layers import Dense, Dropout
from keras.optimizers import Adam

from collections import deque

class DQN:
    def __init__(self, env):
        self.env     = env
        self.memory  = deque(maxlen=2000)

        self.gamma = 0.85
        self.epsilon = 1.0
        self.epsilon_min = 0.01
        self.epsilon_decay = 0.995
        self.learning_rate = 0.005
        self.tau = .125

        self.model        = self.create_model()
        self.target_model = self.create_model()

    def create_model(self):
        model   = Sequential()
        state_shape  = self.env.observation_space.sha
        model.add(Dense(24, input_dim=state_shape[0],
        model.add(Dense(48, activation="relu"))
        model.add(Dense(24, activation="relu"))
        model.add(Dense(self.env.action_space.n))
        model.compile(loss="mean_squared_error",
            optimizer=Adam(lr=self.learning_rate))
        return model

    def act(self, state):
        self.epsilon *= self.epsilon_decay
        self.epsilon = max(self.epsilon_min, self.eps
        if np.random.random() < self.epsilon:
            return self.env.action_space.sample()
        return np.argmax(self.model.predict(state)[0]

```

Keep an eye out for the next Keras+OpenAI tutorial!

Comment and click that ❤ below to show support!