classification using deep rl code documentation

swakshar.sd

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1 Introduction

The documentation follows the paper "Classification with costly feature using deep reinforcement learning" [1].

This is a documentation on the code of classification with costly feature using deep reinforcement learning. I forked the code from this Github code

The code contains many modules, so I thought of writing documentation to ease the understanding of the code.

2 Parameters

There are some parameters which I find important:

DATA FILE = training file location

DATA VAL FILE = validation file location

META FILE = meta file location

CLASSES = number of classes = must start from 0

FEATURE DIM = number of features

ACTION DIM = feature dimension + number of classes

AGENTS = number of samples collected in one step

MAX MASK CONST = used for not considering any repeated action = 10^6

3 Some visualization

Before starting the function class, let's introduce ourself with some of the important variables.

Action space : classes dimension + feature dimension

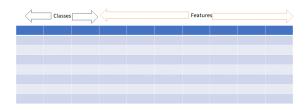


Figure 1: Action space

 $\textbf{State space}: \ \text{feature dimension} + \max k \ \text{dimension} \\ (\max k \ \text{dimension}) \\ \text{as feature dimension})$

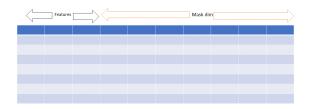


Figure 2: State space

Mask: use to keep track of whether a feature is present or not. Since we are replacing NaN features with zero, we should keep track of whether a feature value is zero or it is Nan.

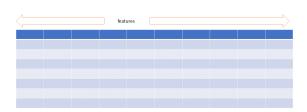


Figure 3: Mask

4 Functions

4.1 Main Functions

 $\mathbf{main.py} = \mathbf{main}$ code section for the whole program. Run this file to train the agent

4.2 Modules

4.2.1 Agent

In agent class, we reset the state(initialize it to zero) and make environment and Brain object.

store: Convert state, action, next state, reward into tensor and store them to replay memory via $put(fucntion\ inside\ pool\ class).$

act: Return the Q-values into numpy array via predict_np(function inside brain class).

step: Call the *store*(function inside agent class).

update_epsilon: update epsilon.

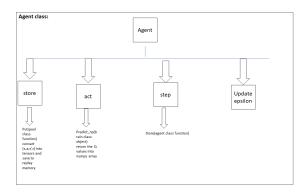


Figure 4: Agent class

4.2.2 Pool

First Initialize state, action, next state, reward tensors.

 $\mathbf{Put:}$ store state, action, next state, reward into replay memory.

sample: sample random index from memory.

cuda: store state, action, next state, reward into GPU.

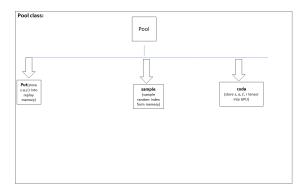


Figure 5: Pool class

4.2.3 Net

Build the neural network, calculate loss and backpropagate the loss.

copy_weight: soft update of target network.

train_network: Calculate loss and backpropagate.

set_lr: learning rate scheduler.

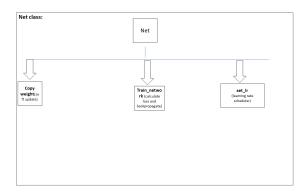


Figure 6: Net class

4.2.4 Brain

Initialize the target and local network. load: load the local and target network. save: save the local and target network.

predict_pt: predict Q-values in form of tensor.
predict_np: convert predicted Q-values into numpy.
train: We use double Q learning to train the agent.

Figure 7: Brian class

4.2.5 Environment

Inside Environment class we first perform those things:

- \blacksquare Get the whole dataset containing features and labels
- Set the cost of each feature and make an cost array
- \blacksquare Initialize the mask to zero
- Initialize an array that contain a batch of features

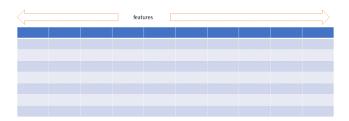


Figure 8: contain a batch of features

■ Initialize an array that contain a batch of labels for those features.

reset: Initialize the input state to zeros. reset: randomly chose a data point.

_generate_sample: randomly chose a data point.
_get_state: Make an input state for the network.

step: Return next state and reward.

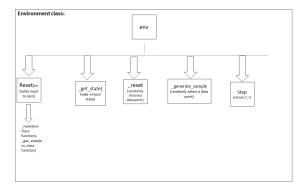


Figure 9: Net class

4.3 Some extra functions

conv_filename.py

- Load the dataset.
 - Make train, validation, test file, and store those files.
 - Make a 'meta' file. Meta file consist of mean, standard deviation, and cost of each feature.
 - Store this meta file.

eval_filename.py

■ For the testing purpose of the model.

Note that: In 'eval_filename.py' file 'Predicted_labels' variable contain all the labels predicted by the agent. 'data_y' variable contain all the true labels.

References

[1] Jaromír Janisch, Tomáš Pevnỳ, and Viliam Lisỳ. Classification with costly features using deep reinforcement learning. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 33, pages 3959–3966, 2019.