

# Report: Deep RL Arm Manipulation

May 20, 2018

## Objectives

Objectives of the project was to create DQN Agent and tune hyperparameters to achieve the two following tasks:

1. Any part of the robot arm should touch the object with atleast an accuracy of 90%.
2. Only the gripper base of the robot arm should touch the object with at least an accuracy of 80%.

## Reward Functions

Both task are using the same reward function and params except the episode end condition.

Win and loss reward values was selected as following:

```
#define REWARD_WIN 20.0f
#define REWARD_LOSS -20.0f

#define REWARD_ALPHA 0.5f
```

`REWARD_ALPHA` is a smoothing parameter that determine the contribution of a running average delta distance to the goal `avgGoalDelta`. The value of `0.5` was determined experimentally and works great for both tasks.

```
// are we decreasing distance to the goal?
const float distDelta = lastGoalDistance - distGoal;

// compute the smoothed moving average of the delta of the distance to the
avgGoalDelta = avgGoalDelta * REWARD_ALPHA + distDelta * (1 - REWARD_ALPHA);

rewardHistory = 4 * avgGoalDelta - 0.2; // Task #2 WINNING! And works for '...
```

Transitional reward consists of `avgGoalDelta` with a multiplier of `4` - selected experimentally to balance `REWARD_WIN` / `REWARD_LOSS` values.

And the second term `-0.2` is a penalty for each move that prevents the agent to just hold the position and stop moving at all.

The same reward function and values are used for both tasks.

Joint control was selected as positional for both tasks. Also quick experiments show that velocity control works good as well. However the final params wasn't tested with the velocity control and may require further tuning of reward function values and DQN parameters.

## Hyperparameters

Hyperparameters for the DQN Agent was selected as following:

```
#define INPUT_WIDTH    64
#define INPUT_HEIGHT   64
#define OPTIMIZER "RMSprop"
#define LEARNING_RATE  0.01f // Task #1 = 0.01f, Task #2 = 0.1f
#define REPLAY_MEMORY  10000
#define BATCH_SIZE     32
#define USE_LSTM        true
#define LSTM_SIZE      256
```

Above parameters was mainly selected during the tuning of Task #2, which is harder to learn for the agent, and tested again for Task #1 later. During such backward tests were determined that lower `LEARNING_RATE` of `0.01f` works better for Task #1. And higher `LEARNING_RATE` of `0.1f` is more important for Task #1.

During parameters tuning higher `LSTM_SIZE` showed better results thus it's `256` this means that agent can learn more complex feature in it's state and track them during the subsequent actions.

`BATCH_SIZE` higher than `32` showed worse results and wasn't been able to learn past `56%` of accuracy for Task #2.

`Adam` optimizer showed worse results than `RMSProp`.

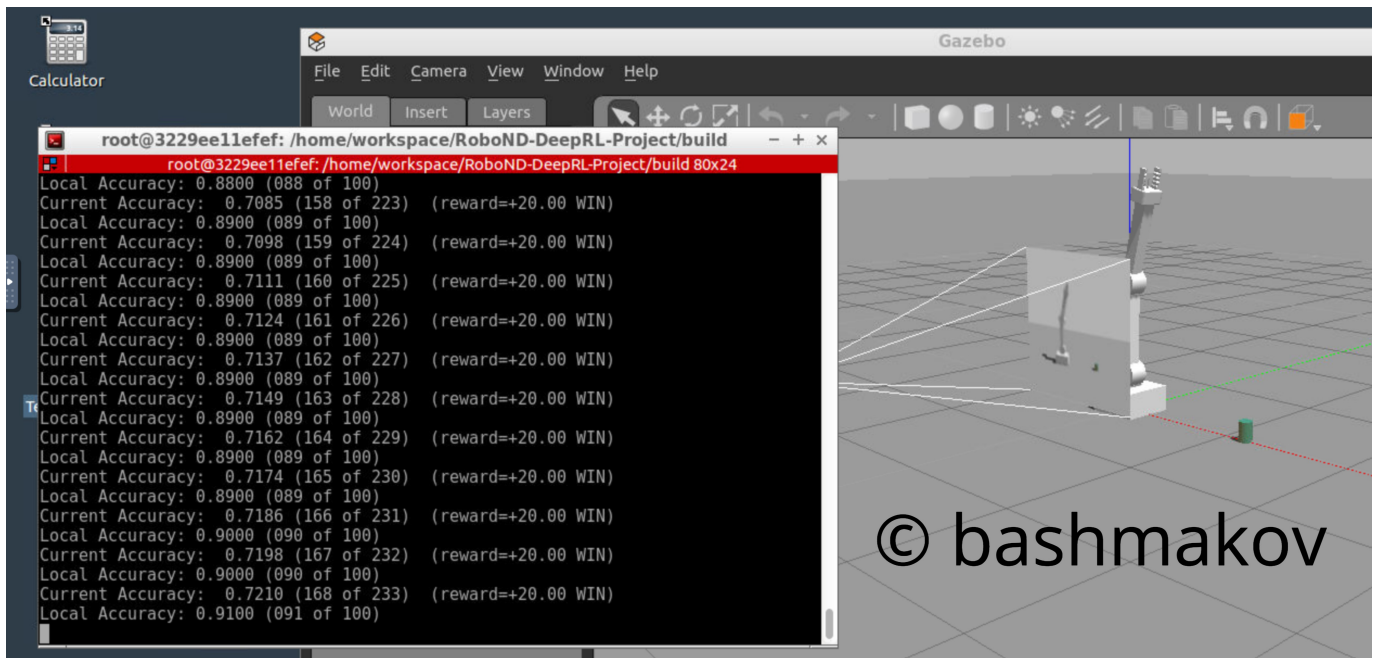
As a result we have one set of hyperparameters that works for both objectives with the only change in `LEARNING_RATE` between them.

## Results

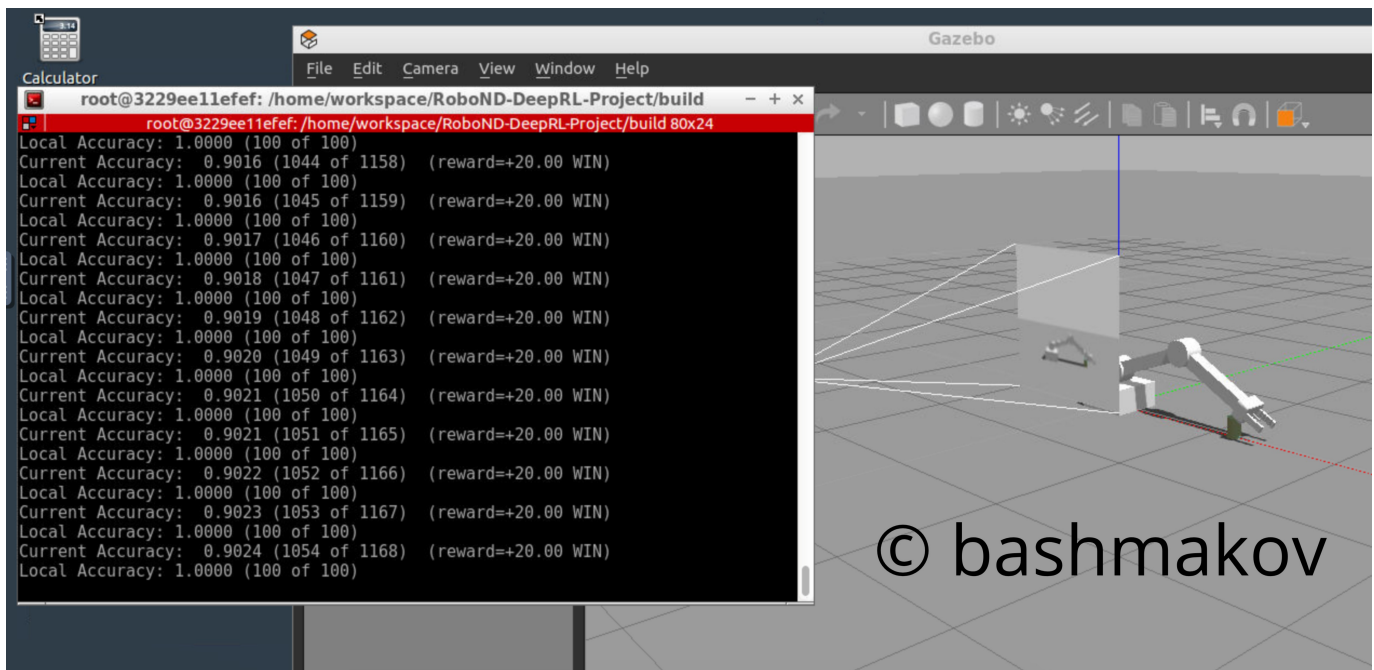
Training environment - Udacity's Project Workspace with enabled GPU.

# Task 1

Tests of the selected parameters on Task #1 showed good results around episode ~240 with the achieved accuracy 91% for the last 100 episodes.



Continue training for the next 1000 episodes showed the further improvements up to the accuracy 100% of the last 100 episodes.

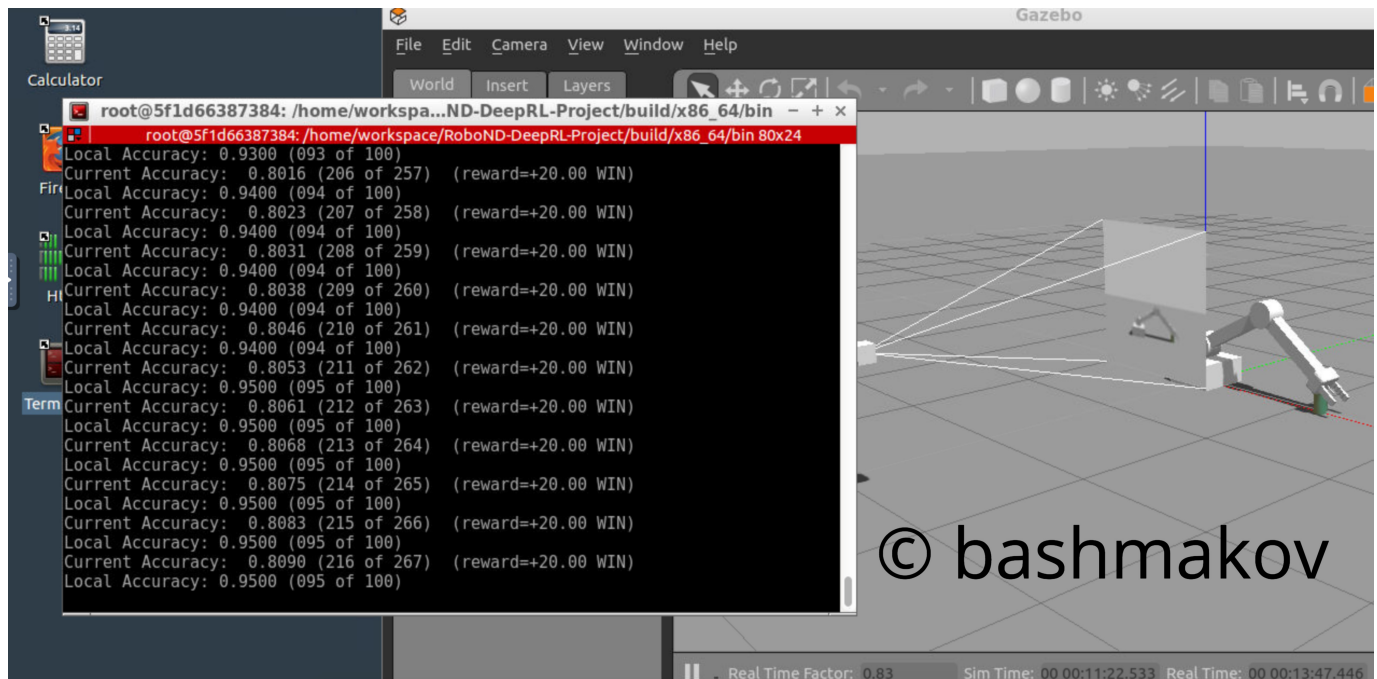


Video [result for the Task #1](#) after >1000 episodes.

# Task 2

Second task was much harder to find the right balance of the hyperparameters but after ~20 hours of tests on GPU it converges at start showing good enough results.

In just 267 episodes local accuracy of 95% on the last 100 episodes were achieved for Task #2.



## Future Work

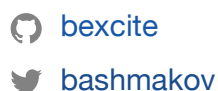
Training for Task #1 on the parameters tuned for the Task #2 is much longer than was achieved without Task #2 in mind. Interesting question is 'How we can achieve the best result in the shortest amount of episodes with the same parameters of DQN Agent and reward function for both tasks simultaneously?'

Perhaps joint training of the agent on both task simultaneously can help with it.

Other interesting task is to try the trained agent on different arm configurations (link length, joint shapes, etc) and see how transferable our agent between different arms.

## Capsules Bot

Pavlo Bashmakov



Exploring autonomous systems, robotics and mapping world around us.

