Deep learning Lab
Uni Freiburg

Assignment 3
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Training CNN for visual planning (A* imitation)

1. Implementation and training

Network architecture:
Can be found in model.py script.

Parameters used for training: learning rate 0.001, batch size 50, epochs num 20
All the computations were performed on following architecture:

CPU: **Intel(R) Core(™) i7-6700HQCPU 2.8 GHz**
GPU: **NVIDIA Quadro M1000M**

Validation accuracy was 0.972

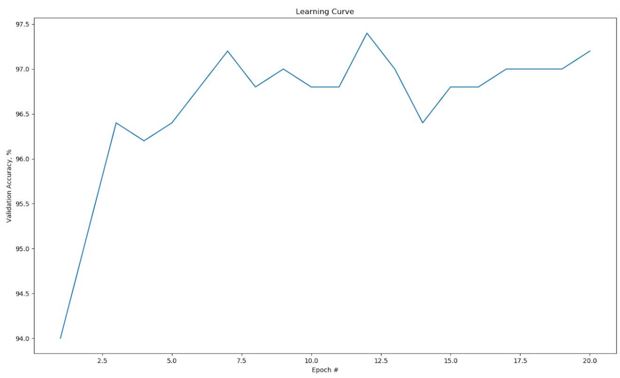

Fig.1. Learning curve

2. Test script evaluation

For default history length of 4 test accuracy of 1.0 was achieved;
However, A* algorithm solved the maze on average on 2 steps faster, than agent.
Fig. 2. Shows the number of steps for A* and agent.

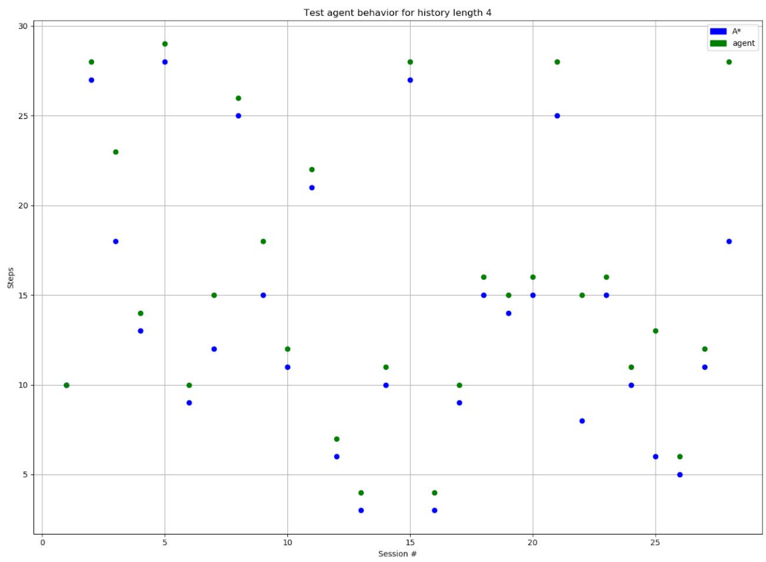

Fig.2. Agent vs. A* performance

3. Results and discussion

3.1.Local view performance

Increasing the field of view for agent will result in higher success rates.
We’ve trained and tested an agent with FOV 3*3, 5*5 (default) and 7*7, all tests gave us success of 1.0, but in case of smaller field of view difference with A* algorithm was higher (3 steps avr.). Obviously, increasing observability helps to achieve target position in fewer number of steps.

3.2 History length influence

We’ve changed history length and performed training and testing of our agent with default history map. Results are summed up in the Table.1.

History length	1	2	3	4	5	6	7	8	9	10
Validation accuracy	0.946	0.968	0.968	0.972	0.966	0.966	0.954	0.964	0.964	0.962
Success rate	0.7	0.96	1.0	1.0	1.0	1.0	0.95	1.0	1.0	1.0
Difference to A* (avr. number of steps)	0	1.56	1.06	2	3.74	4.12	4.2	4.88	6.9	6.7

Table.1. Agent performance evaluation for different history lengths.

We can conclude that optimal performance of our agent using default map was with history length of 3 steps, cause here we have success rate of 1.0 and minimal difference to A* performance (1 step average). Further increasing of history length doesn’t influence the success rate, but increases the difference with A*, so we need more steps to get into target position. Setting minimal history length intuitively results in increased failure rate.

3.3. Map changing (generalization)

Training was performed with default map, and testing with map #1. Agent was still able to reach target position, although the number of steps increased.
Changing the target position during testing lead to increased failure rate. Although if choose target position close to original one (on which the training was performed), the agent performance is still solid enough.

3.4. Generalization options

- ➔ Increasing field of view for agent
- ➔ Increasing history length.
- ➔ Training on different maps with different target positions
- ➔ Implementing RL

Conclusions:

We’ve trained CNN to approximate A* planner behaviour, although for generalization reinforcement learning methods should be applied in order to achieve better performance in unfamiliar environments.