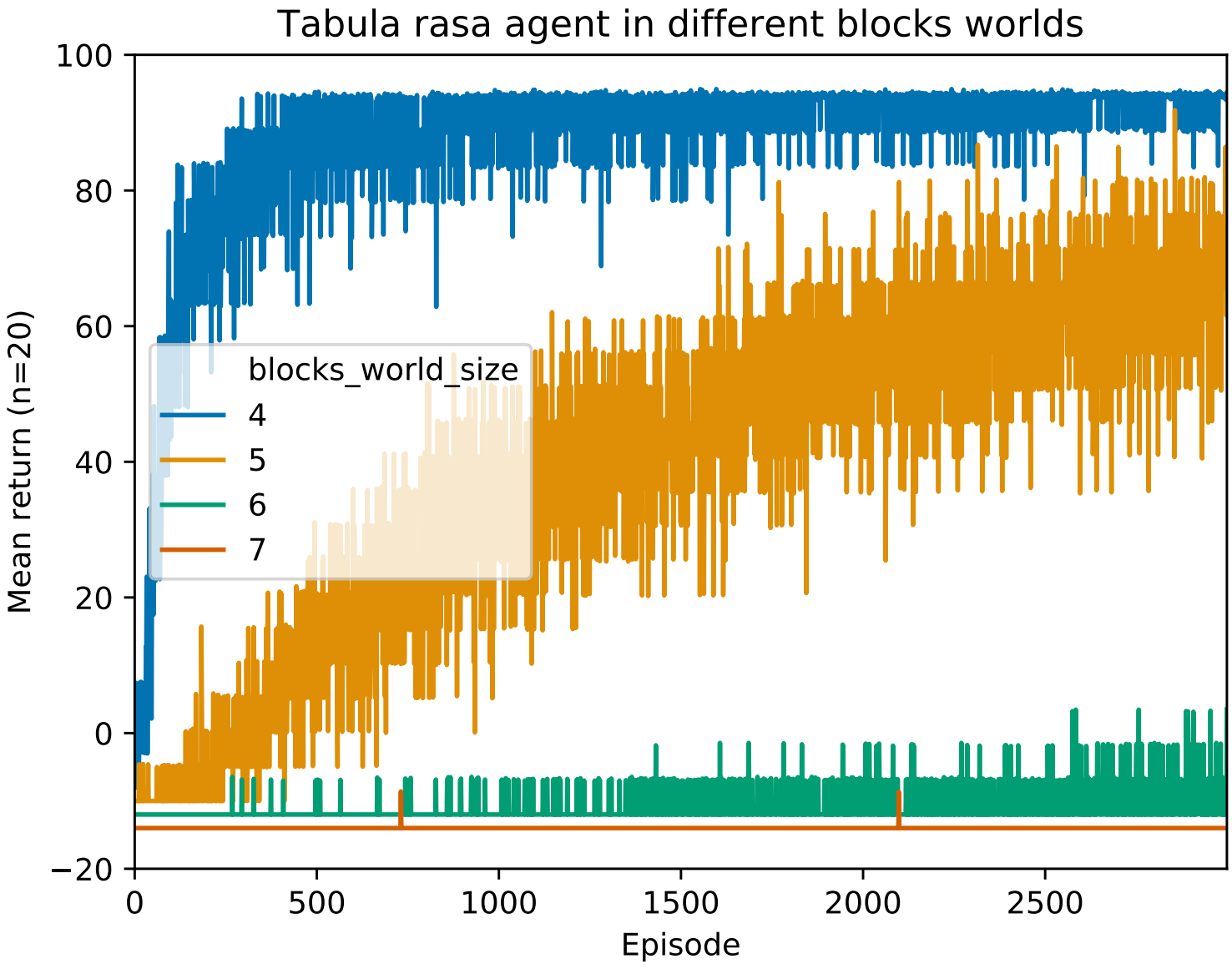
Experiment 1

To reproduce the results from the bachelor's thesis

Experiment 1a



Experiment 1a

Remarks

- Results are as expected.
- Bigger blocks worlds need much more episodes to train.

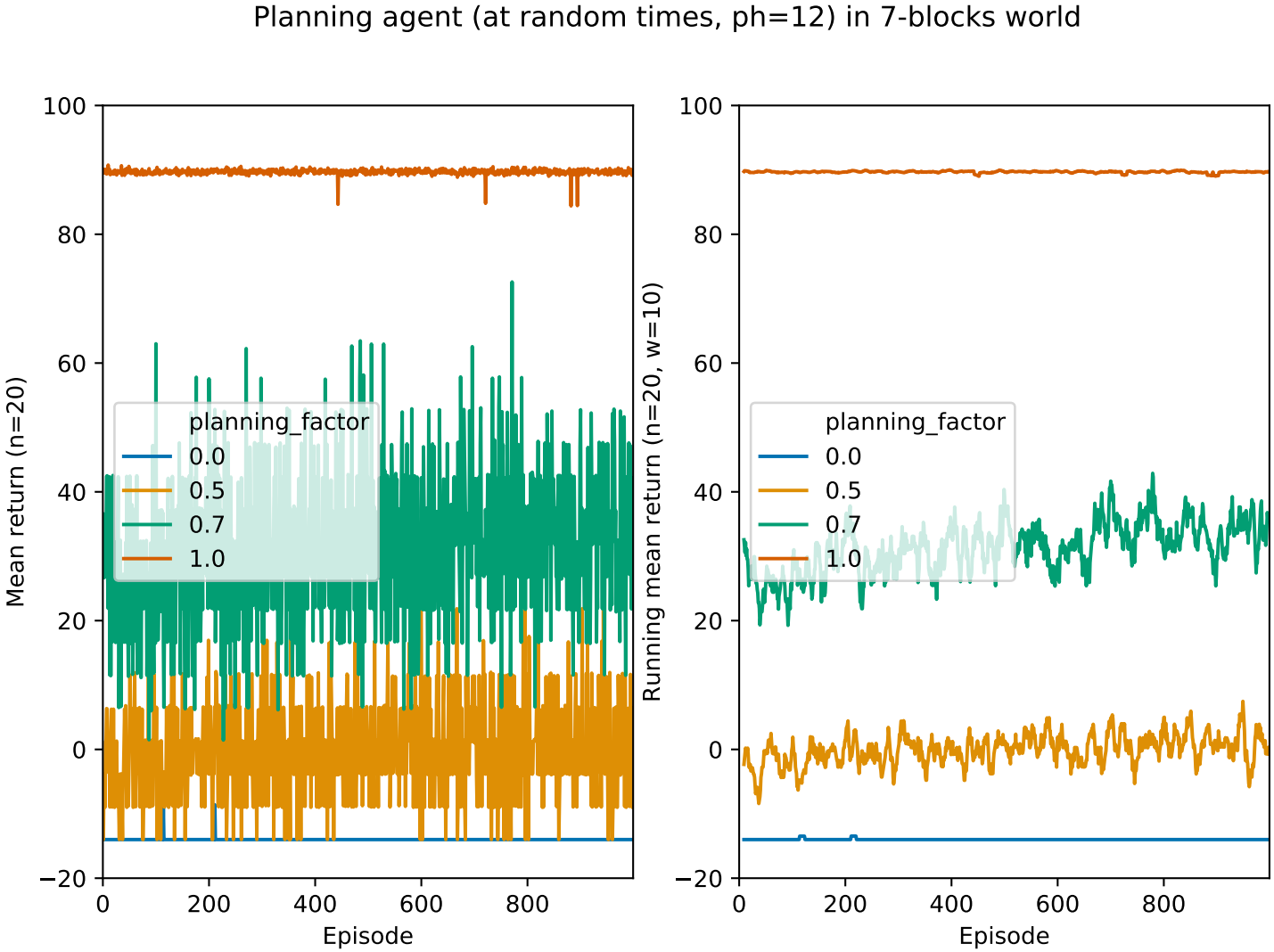
Experiment 1b

Experiment 1b

Remarks

- Adding a planning component clearly speeds up training.
- Already small planning horizons cause significant increase in training speed (compared to the previous experiment).
- Bigger planning horizons speed up training even more.

Experiment 1c



The original output (left) is too messy. Used running average to smooth the result and make it more readable (right).

Experiment 1c

Remarks

- Planning at random times speeds up training as well.
- However, even with near-perfect planning horizons, planning at random times is not as effective as planning for new states.
  - ...except when `planning_factor=1.0`, i.e. when the planner is used at every timestep - too expensive!

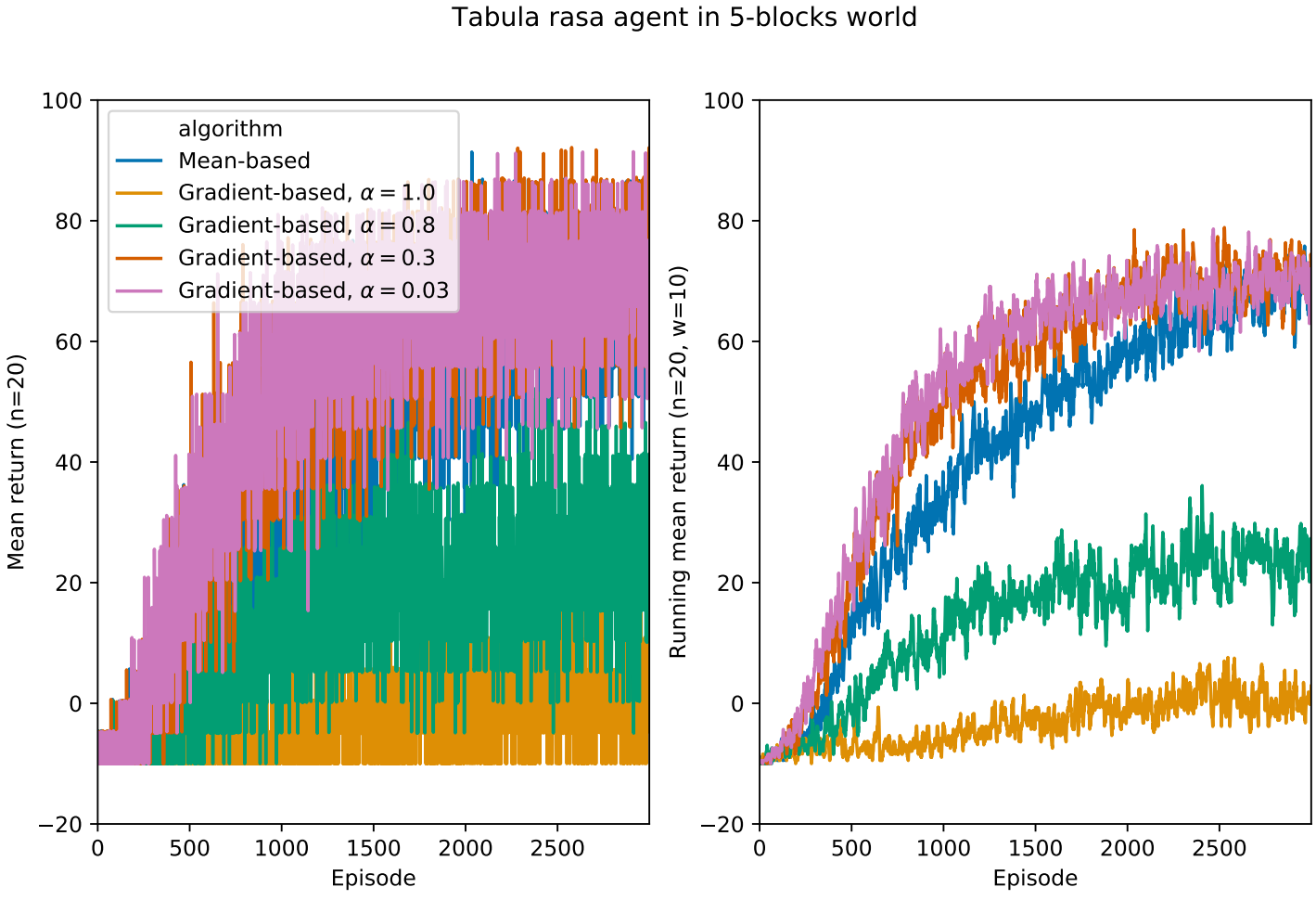
Conclusion

- Overall, the results seem to be in line with that of the bachelor's thesis.
- Planning clearly improves the training process.

Experiment 2

To compare the mean-based First-visit Monte-Carlo method from the bachelor's thesis with a gradient-based every-visit monte-carlo method.

Experiment 2a



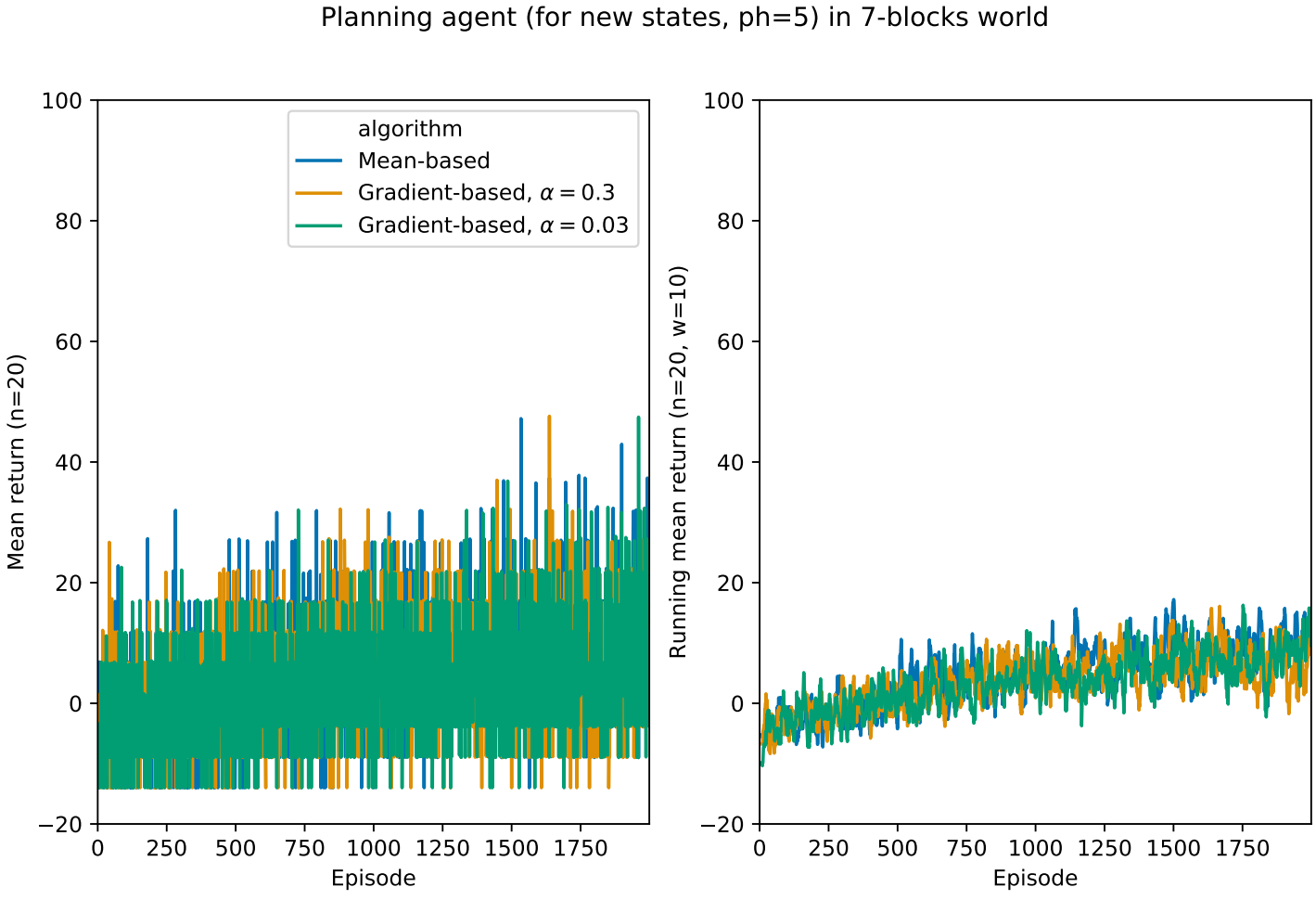
The original output (left) is too messy. Used running average to smooth the result and make it more readable (right).

Experiment 2a

Remarks

- There is no clear difference between the mean-based and the gradient-based algorithm at its best.
  - It may look like the gradient-based algorithm is better, but this is just a coincidence. Re-running the experiment may cause the mean-based algorithm to perform better.
  - *Note* Probably a good idea to re-run this experiment with a higher sample size.
- Both $\alpha = 0.3$ and $\alpha = 0.03$ seem to be good parameter choices.
- There seems to be a decrease in performance for higher values ($\alpha \geq 0.8$), which is expected.

Experiment 2b



The original output (left) is too messy. Used running average to smooth the result and make it more readable (right).

Experiment 2b

- Planning still speeds up training, also for the gradient-based algorithm.
- There is no clear difference between the mean-based and gradient-based algorithms.

Conclusions

- Overall, the gradient-based method seems to work as well as the mean-based method.
- The gradient-based method handles planning as well as the mean-based method.

Experiment 3

This experiment is for profiling the framework and identifying possible bottlenecks.

Experiment 3a

Tabula-rasa agent in a 7-blocks world, 150 episodes

```
Fri Sep  4 12:14:58 2020    exp3a_profile_raw.txt

         1164209 function calls (1156493 primitive calls) in 6.990 seconds

   Ordered by: internal time
   List reduced from 2708 to 20 due to restriction <20>

   ncalls  tottime  percall  cumtime  percall filename:lineno(function)
     2251    2.993    0.001    2.993    0.001 {method 'ground' of 'clingo.Control' objects}
     4501    1.252    0.000    1.252    0.000 {method 'load' of 'clingo.Control' objects}
     8852    0.536    0.000    0.536    0.000 {method 'add' of 'clingo.Control' objects}
      150    0.324    0.002    5.735    0.038 MonteCarlo.py:49(generate_episode)
     2100    0.323    0.000    5.007    0.002 markov_decision_procedure.py:31(transition)
   301064    0.301    0.000    0.301    0.000 blocksworld.py:88(<genexpr>)
        1    0.199    0.199    0.644    0.644 blocksworld.py:88(<listcomp>)
    39883    0.162    0.000    0.162    0.000 {method 'symbols' of 'clingo.Model' objects}
     2251    0.070    0.000    0.070    0.000 {method 'solve' of 'clingo.Control' objects}
    51/50    0.069    0.001    0.071    0.001 {built-in method _imp.create_dynamic}
      257    0.051    0.000    0.051    0.000 {built-in method marshal.loads}
        1    0.039    0.039    0.039    0.039 {built-in method mkl._py_mkl_service.get_version}
      257    0.038    0.000    0.044    0.000 <frozen importlib._bootstrap_external>:914(get_data)
     1391    0.032    0.000    0.032    0.000 {built-in method posix.stat}
     4530    0.025    0.000    0.039    0.000 posixpath.py:338(normpath)
     2467    0.023    0.000    0.039    0.000 inspect.py:613(cleandoc)
      150    0.022    0.000    0.360    0.002 markov_decision_procedure.py:13(__init__)
      150    0.020    0.000    0.338    0.002 markov_decision_procedure.py:91(_compute_available_actions)
 1061/970    0.015    0.000    0.059    0.000 {built-in method builtins.__build_class__}
16318/16314    0.014    0.000    0.025    0.000 {method 'join' of 'str' objects}
```

Experiment 3b

Planning agent (on empty policy, ph=5) in a 7-blocks world, 150 episodes

```
Fri Sep  4 12:15:22 2020    exp3b_profile_raw.txt

         1332591 function calls (1324875 primitive calls) in 22.789 seconds

   Ordered by: internal time
   List reduced from 2712 to 20 due to restriction <20>

   ncalls  tottime  percall  cumtime  percall filename:lineno(function)
     3532   11.088    0.003   11.088    0.003 {method 'ground' of 'clingo.Control' objects}
     3532    3.833    0.001    3.833    0.001 {method 'solve' of 'clingo.Control' objects}
     8422    2.027    0.000    2.027    0.000 {method 'load' of 'clingo.Control' objects}
     1359    1.871    0.001   15.146    0.011 planner.py:17(suggest_next_action)
      150    1.308    0.009   21.602    0.144 MonteCarlo.py:49(generate_episode)
    13976    0.818    0.000    0.818    0.000 {method 'add' of 'clingo.Control' objects}
     2022    0.335    0.000    4.764    0.002 markov_decision_procedure.py:31(transition)
   301064    0.292    0.000    0.292    0.000 blocksworld.py:88(<genexpr>)
        1    0.209    0.209    0.647    0.647 blocksworld.py:88(<listcomp>)
    41164    0.175    0.000    0.175    0.000 {method 'symbols' of 'clingo.Model' objects}
      257    0.048    0.000    0.048    0.000 {built-in method marshal.loads}
     7093    0.041    0.000    0.062    0.000 posixpath.py:338(normpath)
    51/50    0.040    0.001    0.042    0.001 {built-in method _imp.create_dynamic}
        1    0.039    0.039    0.039    0.039 {built-in method mkl._py_mkl_service.get_version}
     2467    0.022    0.000    0.038    0.000 inspect.py:613(cleandoc)
21443/21439    0.021    0.000    0.037    0.000 {method 'join' of 'str' objects}
      150    0.021    0.000    0.321    0.002 markov_decision_procedure.py:91(_compute_available_actions)
      150    0.020    0.000    0.342    0.002 markov_decision_procedure.py:13(__init__)
     7202    0.019    0.000    0.026    0.000 posixpath.py:75(join)
     1391    0.019    0.000    0.019    0.000 {built-in method posix.stat}
```

Experiment 3

Observations

- Let's compare these results to the last implementation:
  - The tabular rasa agents runtime decreased from $17.9s$ to $7.0s$ (-60%)
  - The planning agent runtime decreased from $34.5s$ to $22.7s$ (-34%)
- The tabula-rasa agent spent ~5s in transition to next states and ~1s iterating all 7-blocks world states.
- The planning agent spent ~5s in transition, ~1s iterating all states and ~15s planning.