

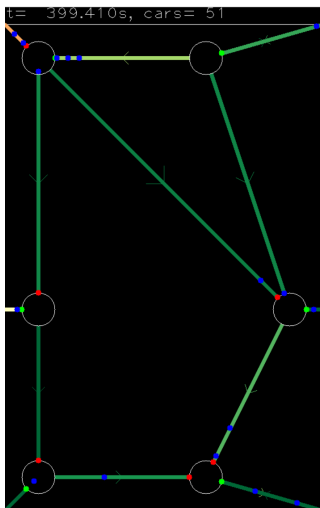
gym-traffic

Controlling traffic lights with Reinforcement Learning

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The Environment



- Street network as **directed graph**
 - ▶ The world consists of multiple **intersections**.
 - ▶ Intersections are connected with **streets**.
 - ▶ Intersections have **traffic lights** for each incoming street.
 - ▶ Traffic lights can either be **red or green**.
 - ▶ For each intersection there **cannot be more than one green light**.
 - ▶ **Vehicles** can spawn at some intersections with a predefined route.
 - ▶ Vehicles drive on streets and **stop at red traffic lights**.
 - ▶ Vehicles **do not crash** into each other.

~> **An Agent has to control the traffic lights.**

- ▶ “Traffic flow” should be maximized

Observation- and Actionspace

Observationspace

- For each intersection t :
 - ▶ For each incoming street s :

$$\begin{cases} -1 & \text{if } |v(s)| = 0 \\ \sum_{v \in v(s)} \frac{v.pos}{|v(s)|} & \text{else} \end{cases}$$

↪ observation $\in \mathcal{R}^{n \times 1}$ with one entry for each (relevant) street

But:

- ↪ Requires knowledge about the street network
- ↪ Agent only works for a specific street network

Actionspace

- For each intersection t :
 - ▶ Index of green street

↪ Multidiscrete Actionspace

Reward

- r_1 Mean Velocity \forall vehicles
- r_2 Mean Acceleration \forall vehicles

$$r' = \frac{1}{|n_v|} \sum_{v \in world} v.velocity$$

$$r_1 = \frac{r' - 5}{5}$$

$$r_2 = \frac{r_{1,2} - r_{1,1}}{\Delta t}$$

More generalized approach

Idea:

- Add empty fake-streets so that each intersection has k incoming streets. (in practice: append -1 's)
- In each time step:
 - ▶ Only provide observation for one intersection and ask to control only this traffic light.
- Reward: Stays the same as before.

~> Generalized observation and action space

Pro:

- Can transfer knowledge to other street networks
- Training is more efficient
 - ▶ No need to learn correlation of streets far away from intersection
 - ▶ Effect of good/bad action is more predictable

Drawback:

- Intersections cannot “communicate” between each other

Results

- stable-baselines3: PPO with MlpPolicy (network architecture: (64,64))
 - ▶ Supports Multi-Discrete Actionspace and Multi-Processing
- Horizon: 1000, World: 3x3circle
- At least 5 episodes to evaluate an algorithm.

Conventional approach

Algorithm	<i>velocity</i>	$\sum reward$	Training duration
random	4.200	2.626	-
PPO-acceleration	6.120	4.672	1.5M steps ($\sim 10h$)

Generalized approach

Algorithm	<i>velocity</i>	$\sum reward$	Training duration
random	5.525	5.645	-
argmax	8.115	8.023	-
PPO-velocity	6.383	5.815	1.5M steps ($\sim 9h$)
PPO-velocity-shuffled	7.736	8.548	1.25M steps ($\sim 7.5h$)
PPO-acceleration-shuffled-1	7.991	7.522	1.25M steps ($\sim 7.5h$)
PPO-acceleration-shuffled-2	7.987	5.775	1.25M steps ($\sim 7.5h$)

- Does Markov assumption holds true?
 - ▶ Yes, especially in generalized approach.

Possible Extensions:

- Communication between intersection
 - ▶ For each incoming street: add observation of preceding intersection
 - ▶ Use RNN to generate a fixed sized representation of all intersection states
- Automatic world generation for different training models
- More complex traffic-light rules
 - ▶ In reality 2 lanes are allowed to drive in parallel if they do not cross each other
 - ▶ In reality left turner wait until opposing lanes drive
- Multiple lanes per street