Interview

Adaptive Learning for network-wide traffic management

- Goal: to maximise the traffic flow by control the density on the main road.
- According to Greenshield's model, the traffic flow reaches the maximum when density equals the critical density. The critical density ρ_c is set to 35.
- Rewards: the rewards is computed based on the estimated flow.

Method: Deep Q-Learning with MLP

- State: current density on the main road & previous target flow. The density is converted to binary representation.
- Action Space: The action space is discretised into 19 actions: a_0 to a_{18} . The action a_i denotes setting the target flow value to $100 \times i$. The final target flow is clipped into the range [60,1800].
- An MLP with skip connections learns to map the state to the Q-values of the 19 actions. During the evaluation, the action with the highest Q-value will be selected.

Method: Deep Q-Learning with temporal convolutional network (TCN)

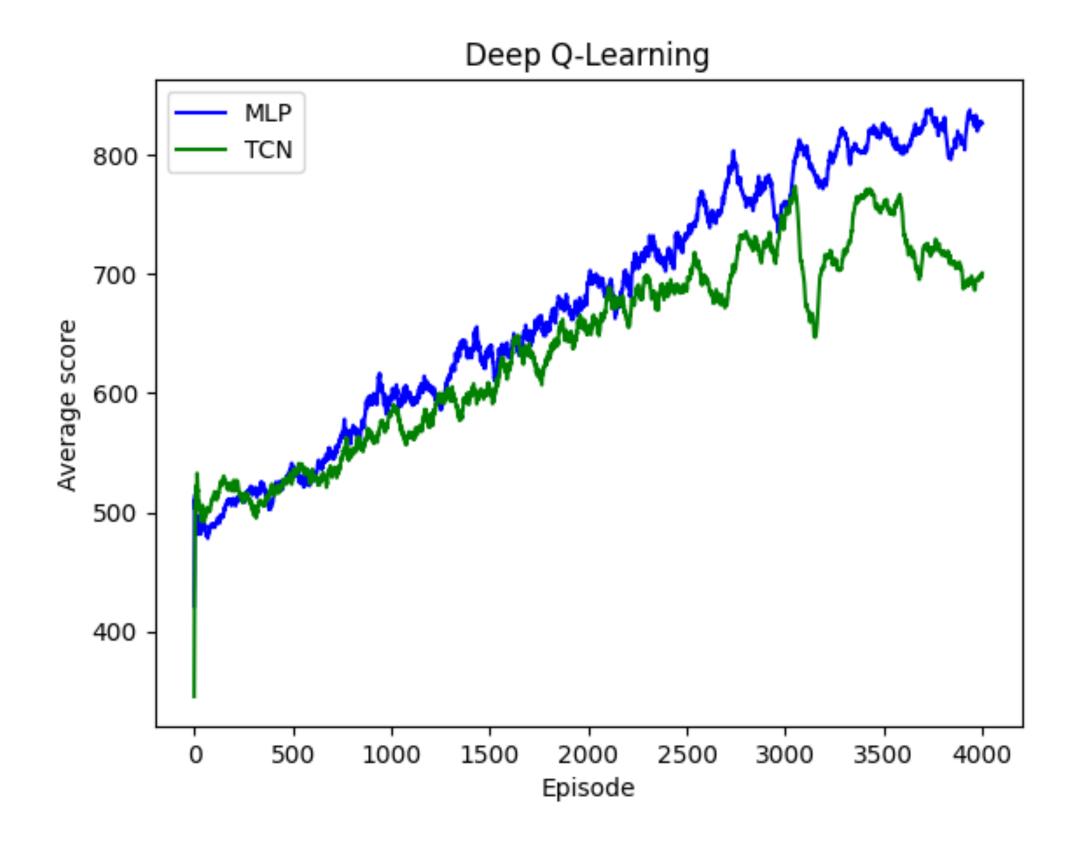
- State: a stack of the densities and the target flows of the last 4 time steps.
 Inspired by the trick of Atari breakout game.
- Action Space: The action space is discretised into 19 actions: a_0 to a_{18} . The action a_i denotes setting the target flow value to $100 \times i$. The final target flow is clipped into the range [60,1800].
- A TCN block with the gated activation and skip connections (proposed by Wavenet [3]) learns to map the state to the Q-values of the 19 actions.

Method: Deep Deterministic Policy Gradient (DDPG)

- State: the current density on the main road with the previous target flow.
- Continuous action space: the action value ranges from [-1,1], which will be mapped to the corresponding target flow ranging from [60,1800].
- An MLP (actor) learns to map the state to the continuous action space.
 Another MLP (critic) learns the Q-values of the state and the corresponding action output by the actor. The actor is trained to maximise the Q-values of the critic.

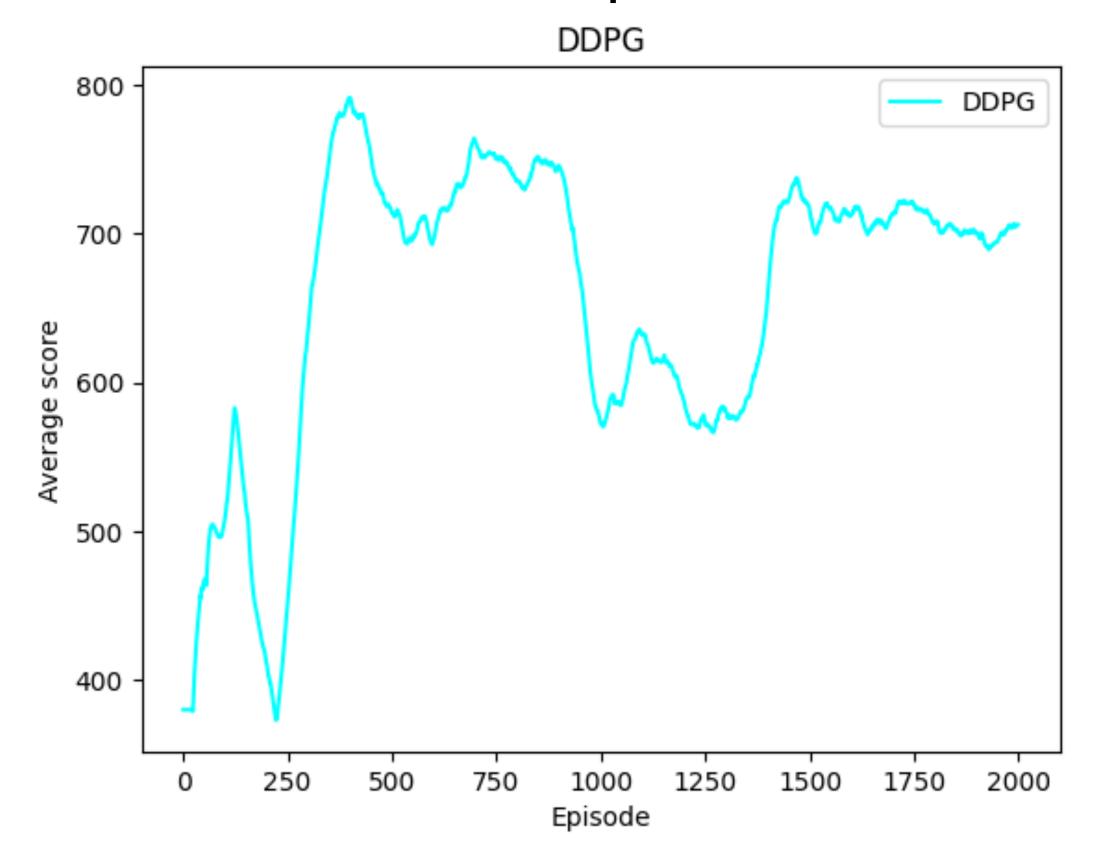
Training: Deep Q-Learning

The two DQN models are trained for 4000 episodes.



Training: DDPG

The DDPG model is trained for 2000 episodes.



Baselines

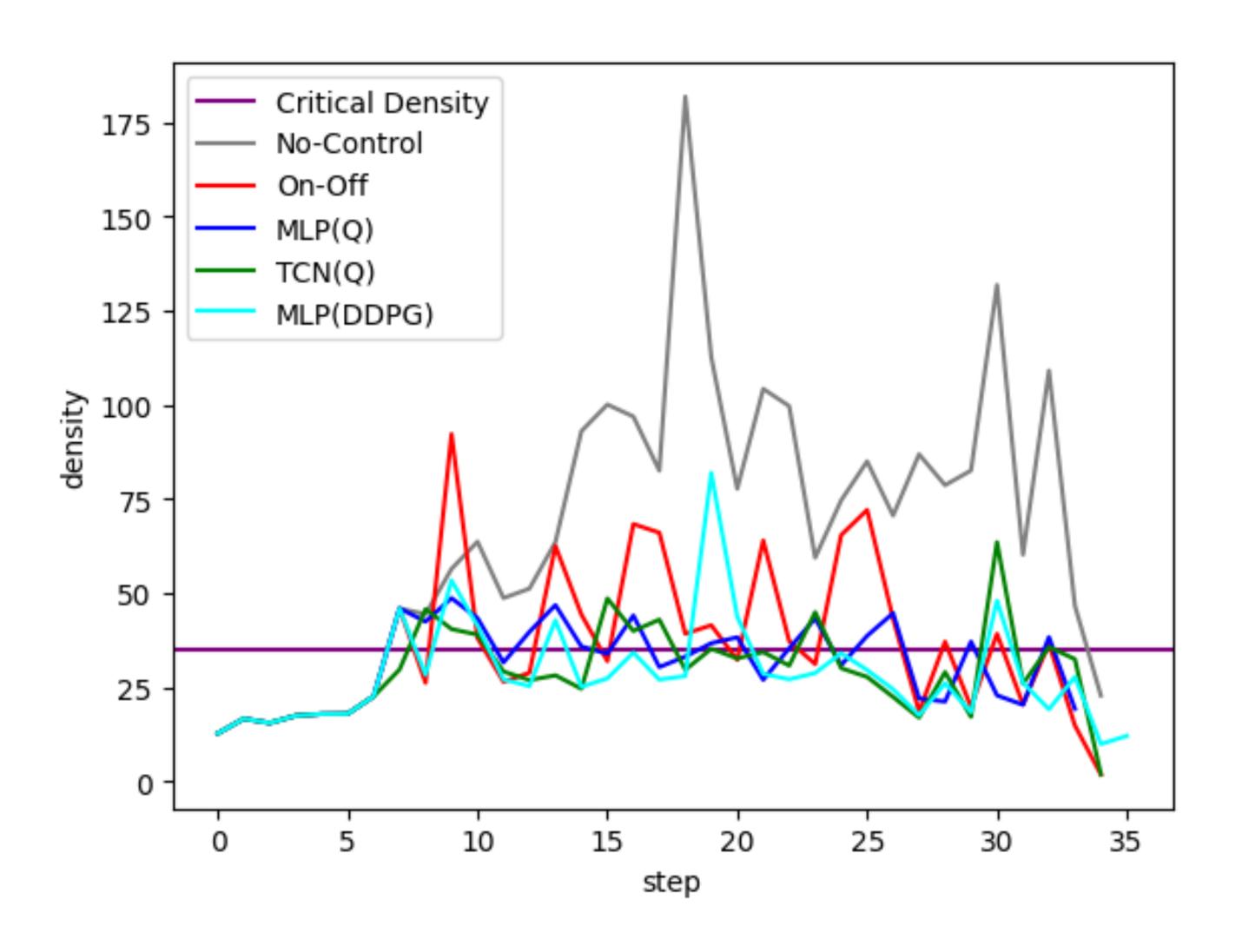
- No-Control: The target flow is always set to the capacity (1800).
- On-Off: When the density equals to the critical density (35), set the target flow to 0. Otherwise the target flow is set to the capacity.

Results: densities over time

Average error:
$$\overline{e} = \sqrt{\frac{\sum_{t} (\rho_{t} - \rho_{c})^{2}}{T}}$$

- No-Control: 49.460
- On-Off: 20.218
- MLP(Q): 11.135
- TCN(Q): 13.117
- MLP(DDPG): 15.085

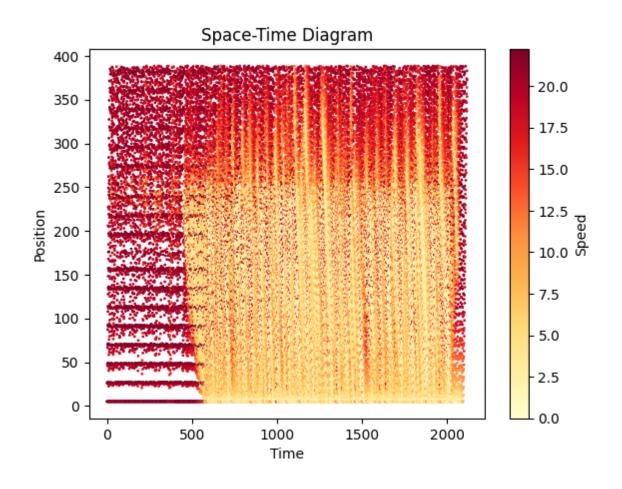
Results: densities over time



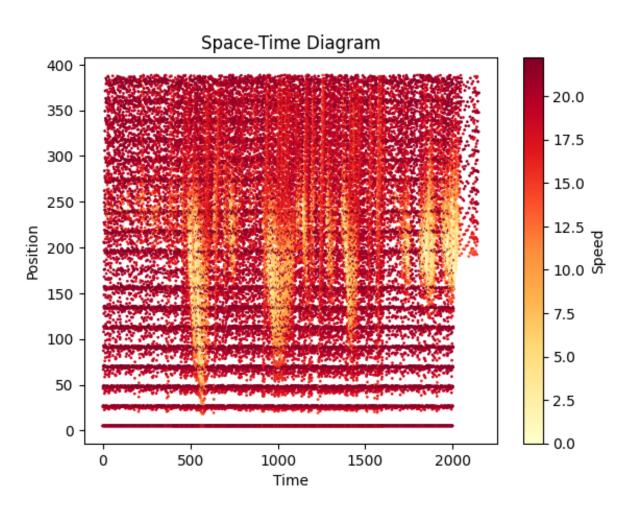
Results: Estimated Traffic Flow & Velocity

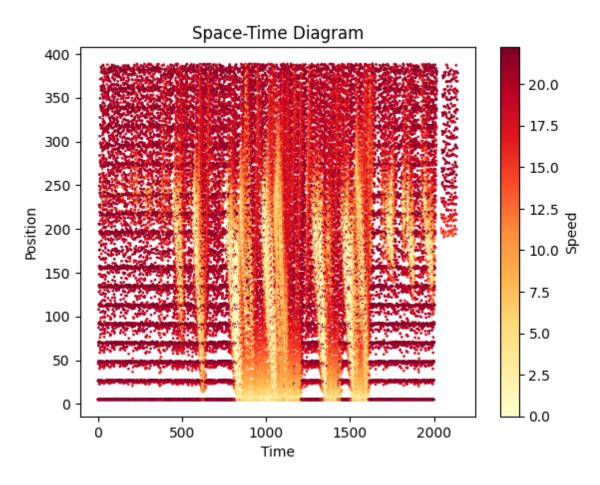
Method	Estimated Traffic Flow	Velocity
No-Control	380.272	8.822±6.767
On-Off	753.516	14.470±6.852
MLP (Q)	943.716	15.953±6.049
TCN (Q)	902.529	17.688±4.766
MLP (DDPG)	878.206	17.532±5.005

Results: Congestion

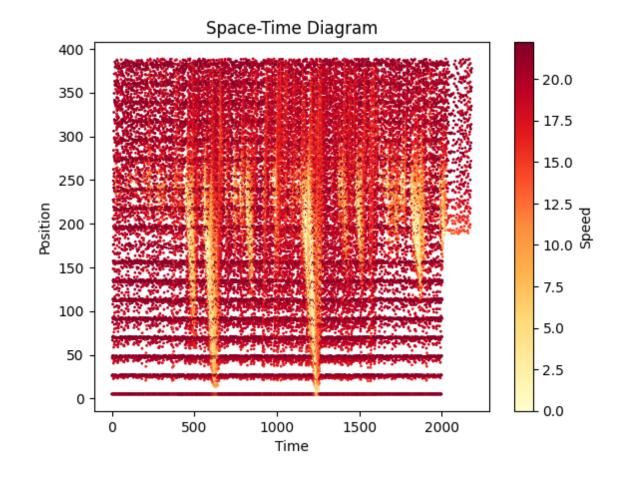


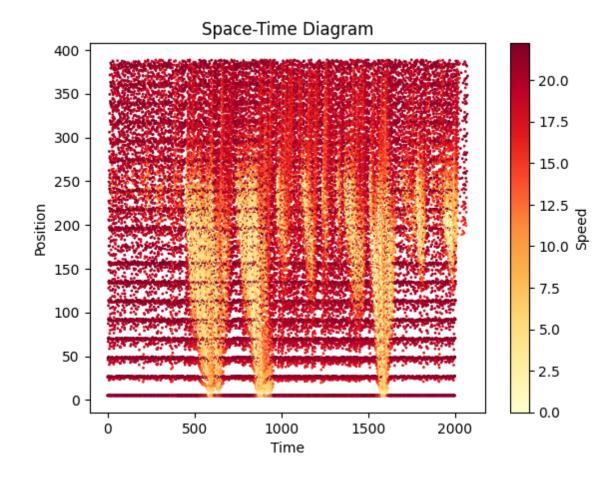
No Control





On-Off





MLP (Q)

TCN (Q)

MLP (DDPG)

Future work

- Since the roads can be modelled as a network, it is worth studying how to combine Graph Neural Networks (GNN) with Reinforcement Learning (RL) to this problem.
- Design a new reward mechanism that can reflect the traffic flow, congestion and other measurements.

Thank you for your listening