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IntelliLight: A Reinforcement Learning Approach for Intelligent Traffic Light Control

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* Equal contribution

Hangzhou Traffic Brain

#vehicles

149.92 ▲ 4.80%

congestion

0.46 ▼ 0.08

delay

1.15 ▲ 0.01

major road speed

28.06 ▲ 2.34

highway speed

60.33 ▲ 4.9%

溫度

18°C

Hangzhou City Traffic
11pm March 27, 2018 Tuesday

Hangzhou Traffic Brain

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4.80%

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major road speed

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highway speed

60.33

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温度

18°C

Speed on major arterials is only 28.06 km/h
Speed limit 60km/h
Expect 40-45km/h at night

Hangzhou City Traffic
11pm March 27, 2018 Tuesday

Traffic light **fails to see** the traffic



Traffic light **fails to see** the traffic



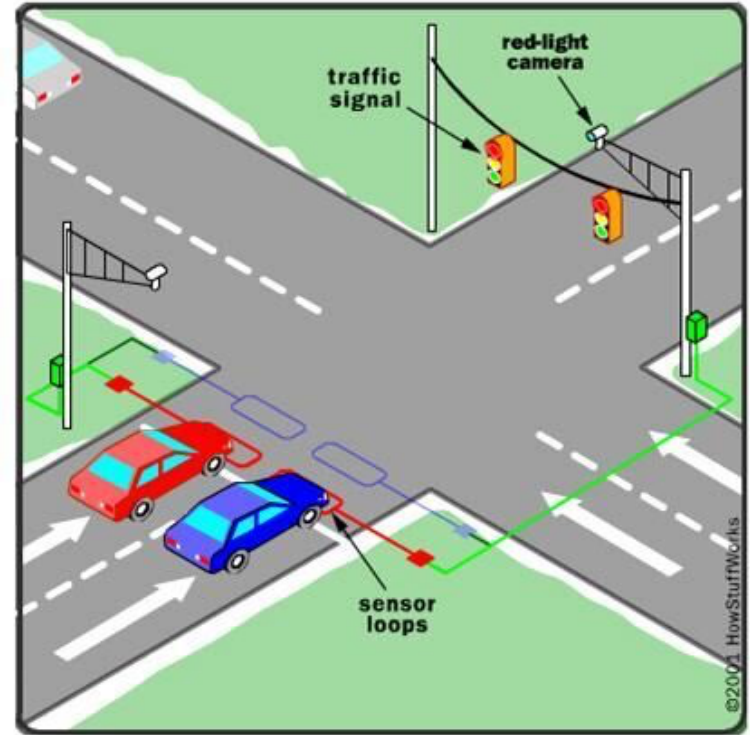
Spillover



Light through movement traffic
heavy left-turn traffic

The current traffic signal control systems

- SCATS
 - Sydney Co-ordinated Adaptive Traffic System
 - Developed in 1980s
 - Each traffic signal: 8~16 **manually designed** signal plans, not learned by data
 - Use loop sensor data to choose the plan



Why today? (we could improve traffic signal)

New rich data

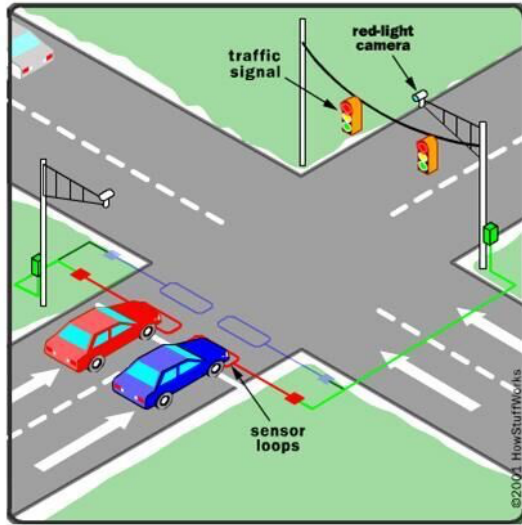
- Loop sensor data vs. camera data

New data-driven models

- Transportation models vs. machine learning data-driven models

Why today? New rich data

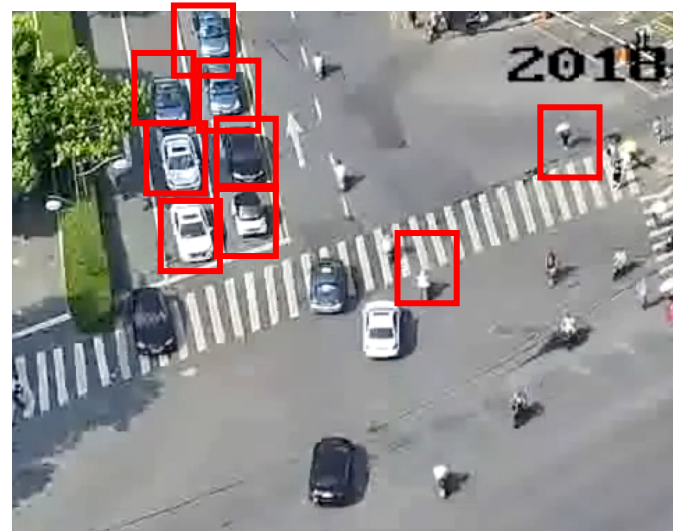
Yesterday



Loop sensor data

Only count the vehicle when it passes the sensor

Today



Camera data

Show positions of all vehicles, pedestrian, and bicycles

Why today? New data-driven model

Traditional Transportation

Optimization under assumptions
of traffic model

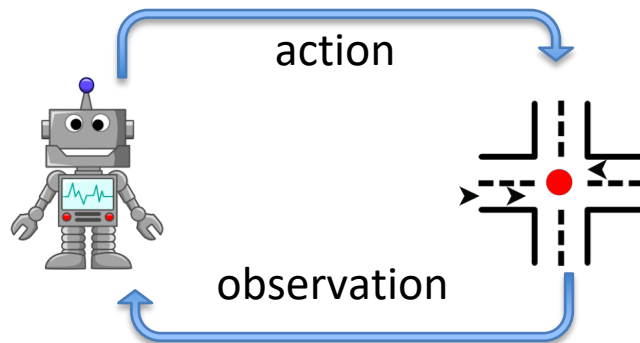
minimize *duration*
subject to *traffic model*

Signal plan = func (traffic data)

Assumptions do not apply in the real world!

Reinforcement Learning

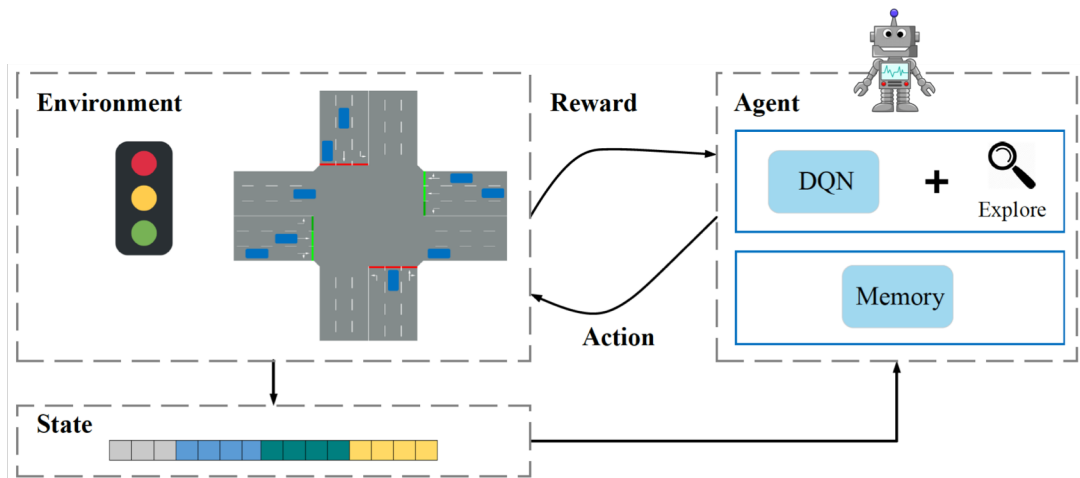
Directly learning from real-world
data



Literature review in RL for signal control

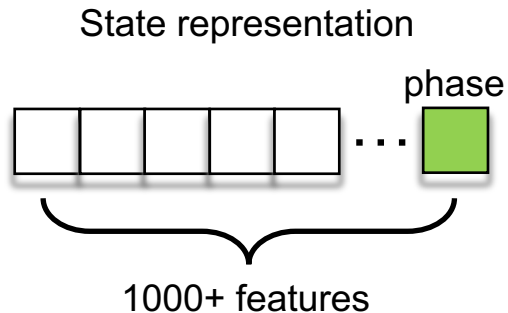
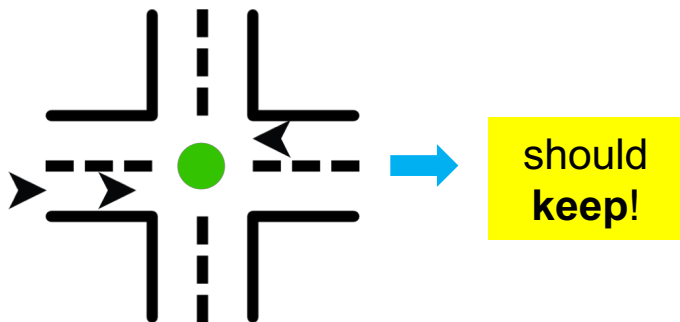
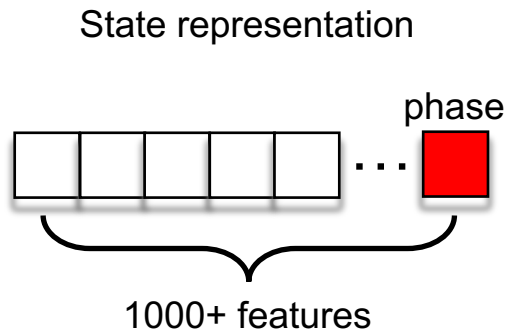
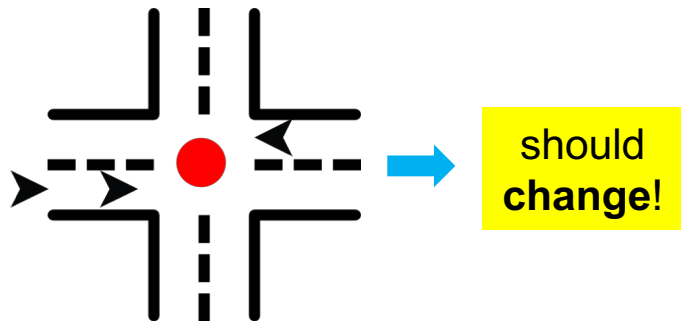
- **Tabular method (discrete state):**
 - Q-learning (El-Tantawy et. al. 2010, El-Tantawy et. al. 2012)
 - Discrete state, can not scale up
- **Approximation method (continuous state):**
 - DQN (Gao et. al. 2017, van der Pol and A. Oliehoek 2016)

Our proposed RL framework

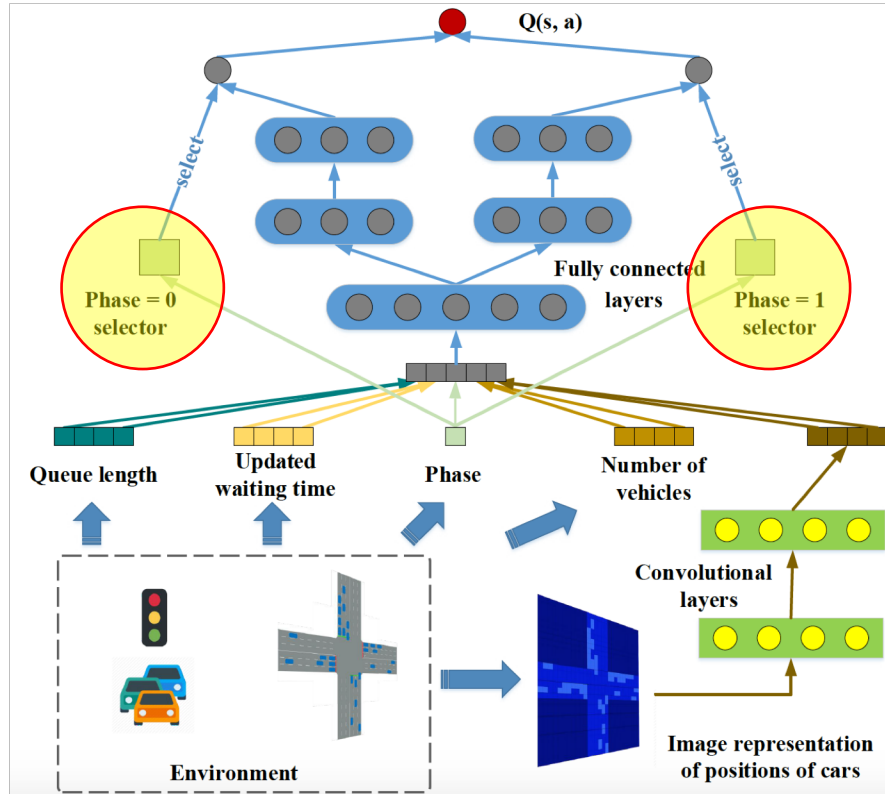


- **Setting:** One intersection, no turns
- **Reward:** queue length, average waiting time, sum of delay
- **Action:** keep the signal or change the signal
- **State:** queue length, #cars, waiting time, traffic situations (image), signal

Q1: Represent state as plain features?

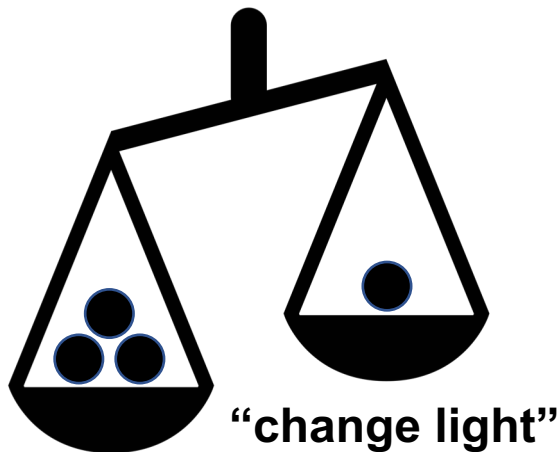


Q1-Solution: Phase-gated Deep Q-Network



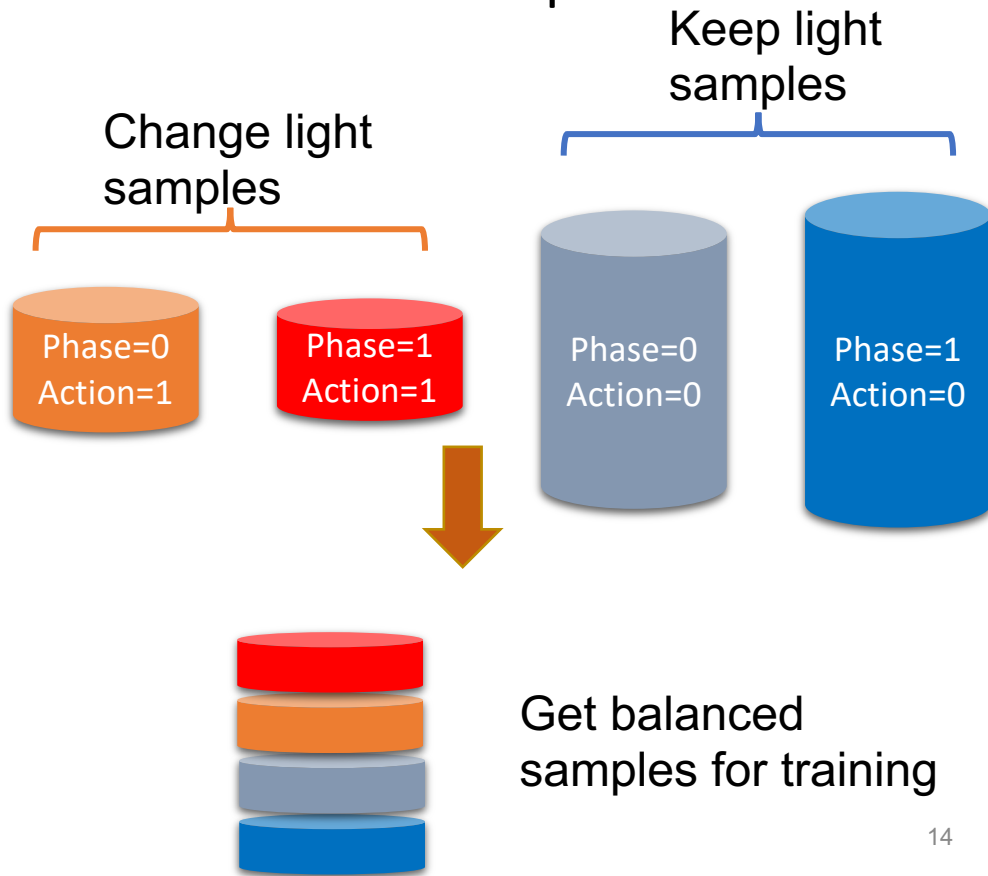
Phase as a gate to
separate decision making

Q2: How to avoid unbalanced samples?



“keep light”

#keep is way more than #change



Do these two special designs help?

Model name	Reward	Queue length	Delay	Duration
Fixedtime	-1.670	4.601	2.883	39.707
Base	-5.030	5.880	3.432	39.021
Base + MP	-3.329	5.358	2.238	44.703
Base + MP + PS	-0.474	0.548	2.202	25.977

MP: memory palace

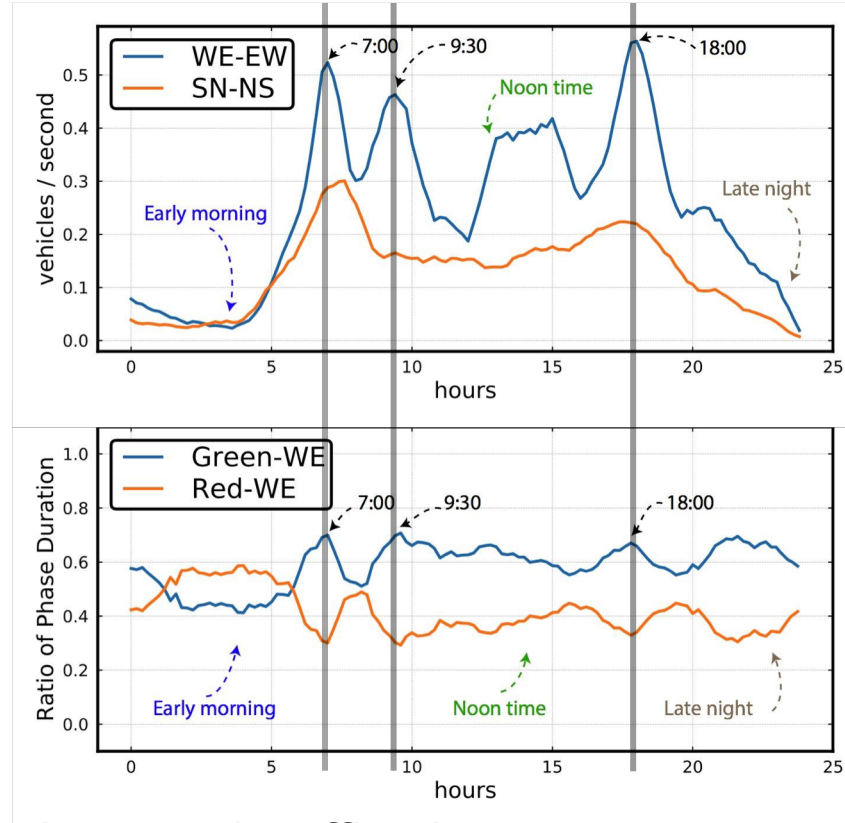
PS: phase selector

Experiment results using real data (from a city in China)

Methods	Reward	Queue Length	Delay	Duration
<i>FT</i>	-5.727 ± 5.977	19.542 ± 22.405	3.377 ± 1.057	84.513 ± 60.888
<i>SOTL</i>	-35.338 ± 65.108	16.603 ± 17.718	4.070 ± 0.420	64.833 ± 23.136
<i>DRL</i>	-30.577 ± 26.242	54.148 ± 43.420	4.209 ± 1.023	166.861 ± 93.985
<i>IntelliLight</i>	-3.892 ± 7.609	10.238 ± 20.949	2.730 ± 1.086	50.487 ± 46.439

- **FT**: Fixed Time
- **SOTL**: Self-Organizing Traffic Light Control (changing the light when #cars waiting > threshold)
- **DRL**: Deep Reinforcement Learning (van der Pol et al, 2016)

Policy learnt from real data



Traffic volume and learned traffic signal on a real world intersection ¹⁷

Modern city traffic is complex. We still have open questions

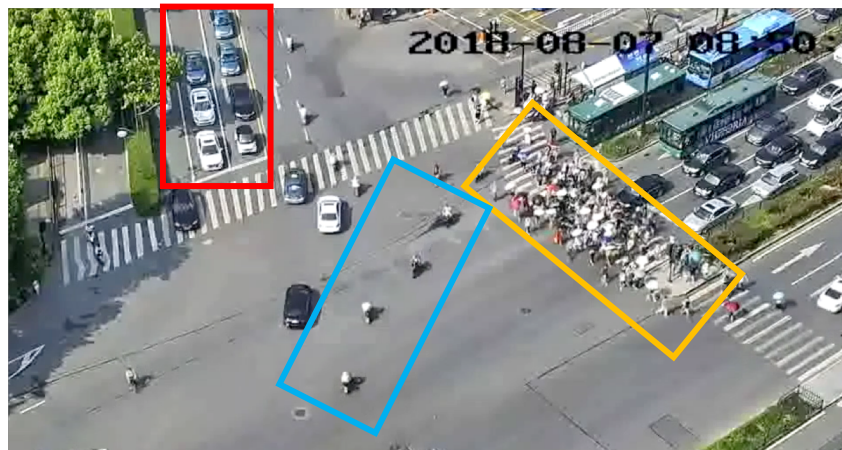
- How to mitigate **trial-and-error** cost when applying RL in real world?



<https://www.swlexledger.com/single-post/2018/09/10/All-state-office-and-schools-in-Lexington-County-closed-tomorrow>

Modern city traffic is complex. We still have open questions

- How to mitigate trial-and-error cost when applying RL in real world?
- How to design a “fair” reward function?



Cars scooters pedestrians

Modern city traffic is complex. We still have open questions

- How to mitigate trial-and-error cost when applying RL in real world?
- How to design a “fair” reward function?
- Real **data** are messy and incomplete.



<https://www.insideedition.com/inquisitive-owl-videobombs-traffic-camera-finland-40999>

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Interested in working on traffic problem in Hangzhou?



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Thanks for your attention! Any questions?