Learning Phase Competition for Traffic Signal Control

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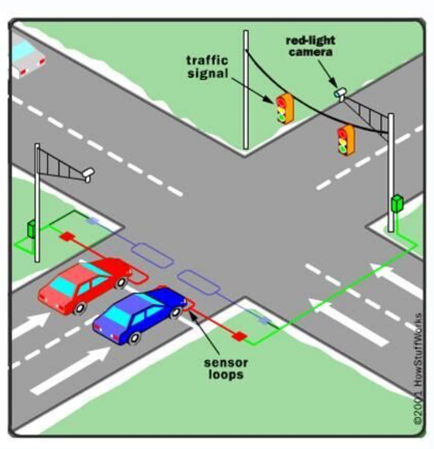
Motivation

Traffic congestion causes additional travel time

	New York	Paris	Tokyo	London
MORNING PEAK	55%	71%	64%	62%
EVENING PEAK	69%	67%	63%	65%

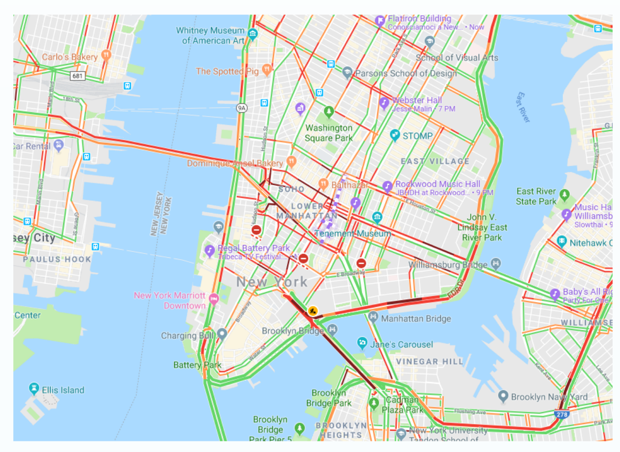
Data and images from https://www.tomtom.com/en_gb/traffic-index/

Problem: how to use traffic data to control the signal?



Loop sensor

Camera



Speed

Image from Google Maps

Related work & Preliminary

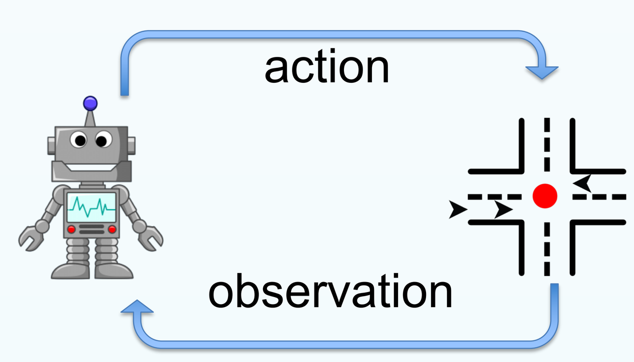
Transportation Methods
Decision based on assumptions

minimize travel time
subject to traffic model

Traffic signal = func (data)

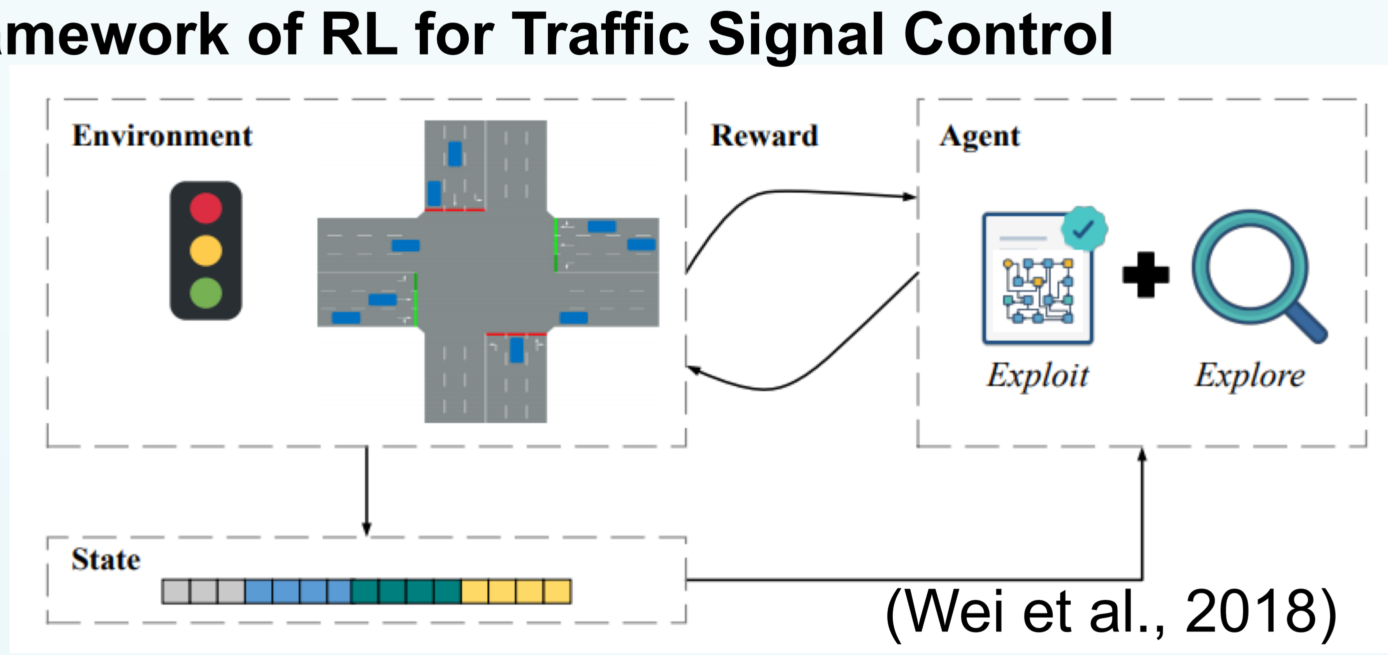
Decision = func (data) is static

Data Driven Methods
Directly learning from real-world data



Decision = func (data) is online learned

- **A framework of RL for Traffic Signal Control**



(Wei et al., 2018)

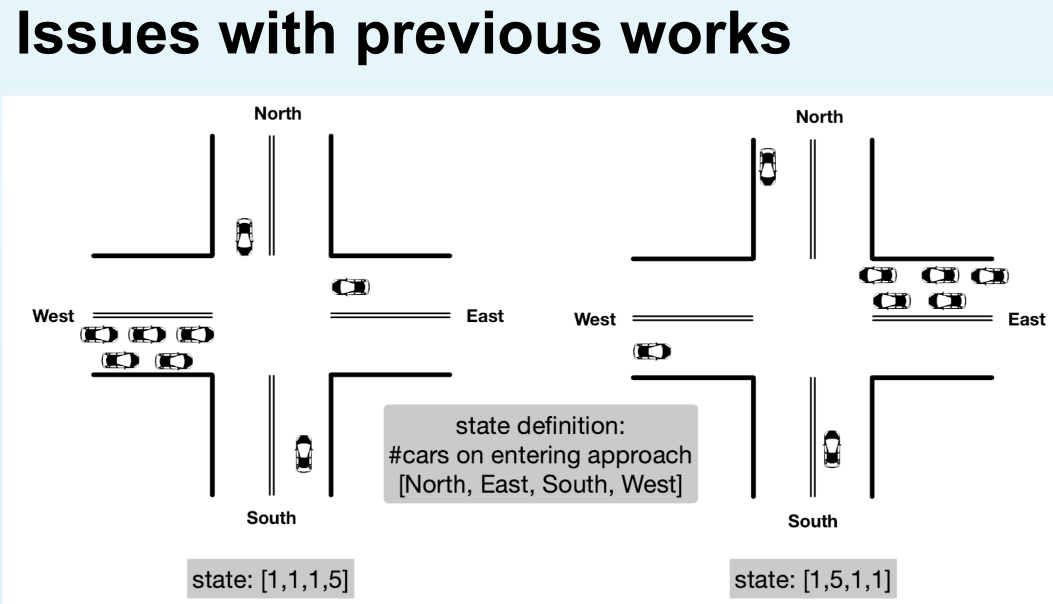
- Reward: queue length
- Action: signal phase for next time interval
- State: number of vehicles

- **Previous works in RL for Traffic Signal Control**

Problem design
- State
- Reward
- Action

Method
- Value-based v.s. policy based
  Q-learning, policy gradient, actor-critic
- Model-based v.s. model-free

- **Issues with previous works**



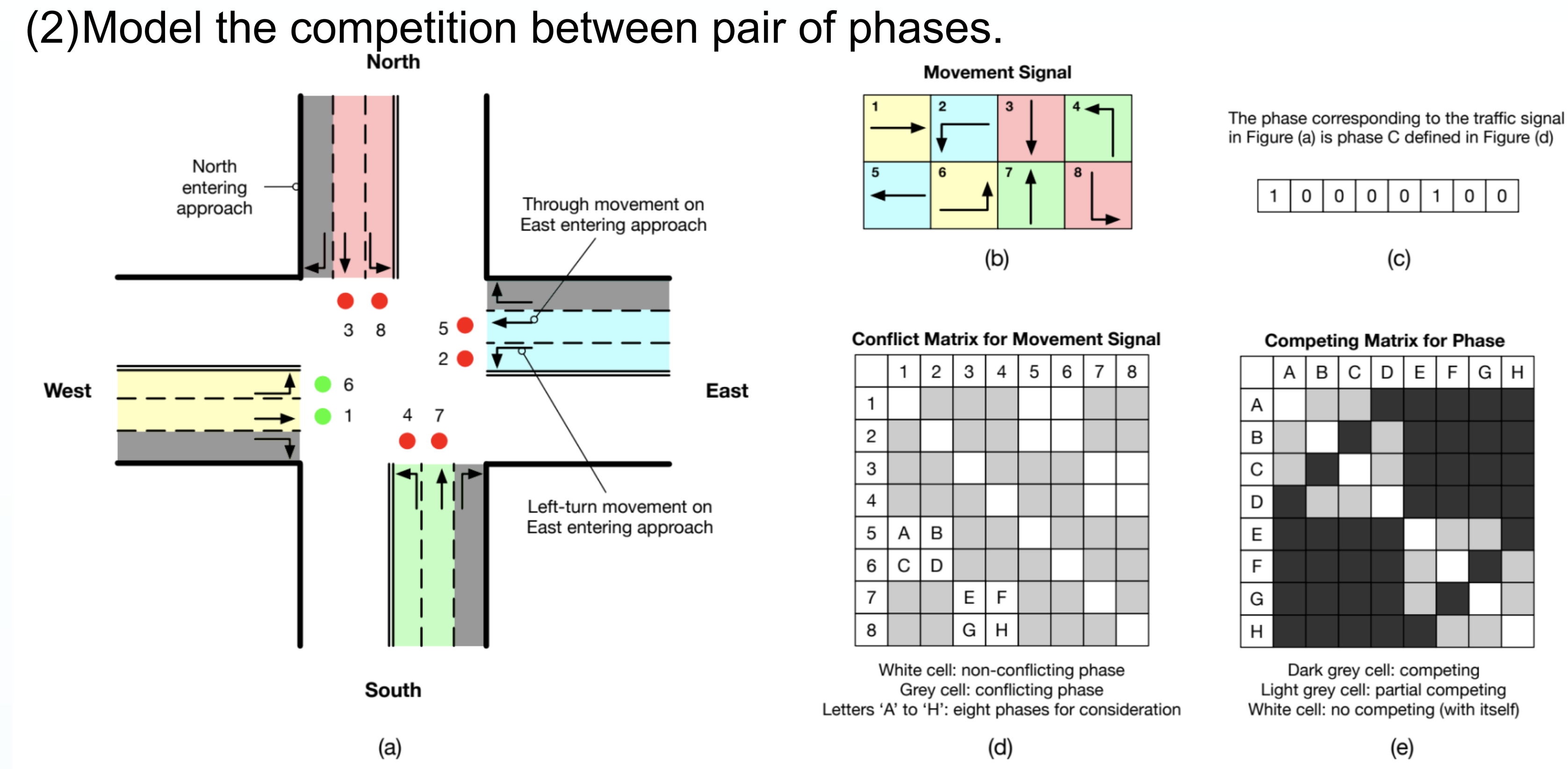
Similar cases are considered repetitively.

Algorithms will struggle in multiple-phase scenarios with larger state space!

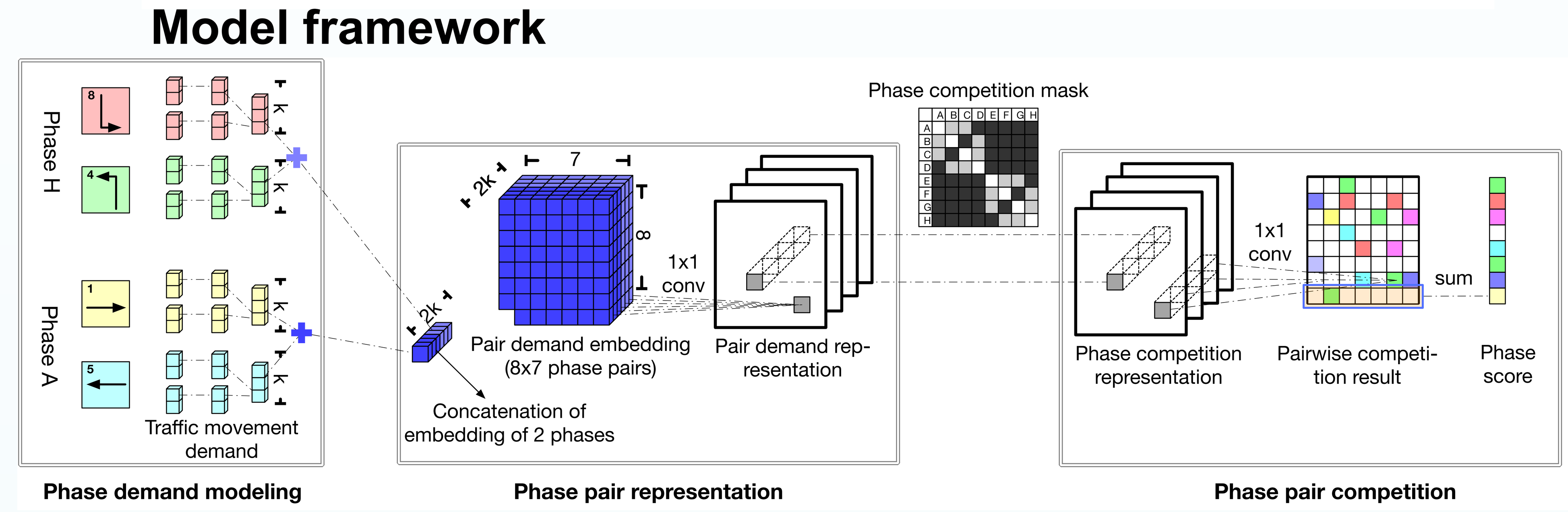
Methodology

Key idea

(1)Combine the compatible traffic movements into signal phase.
(2)Model the competition between pair of phases.



Model framework



Experimental Results

Table 1: Overall performance. Travel time is reported in the unit of second.

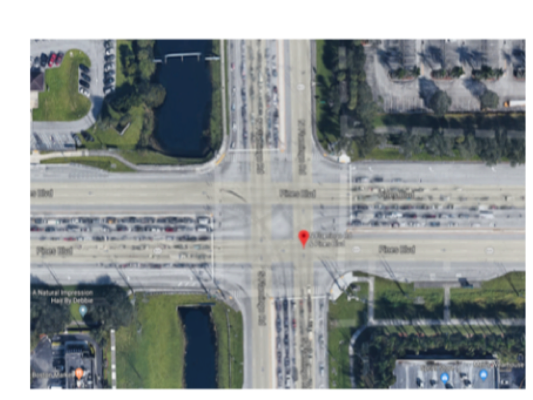
Model	Jinan 1	Jinan 2	Jinan 3	Jinan 4	Jinan 5	Jinan 6	Jinan 7	Hangzhou 1	Hangzhou 2	Hangzhou 3	Hangzhou 4	Hangzhou 5	Hangzhou 6
Fixedtime	118.82	250.00	233.83	297.23	101.06	104.00	146.66	271.16	192.32	258.93	207.73	259.88	237.77
Formula	107.92	195.89	245.94	159.11	76.16	100.56	130.72	218.68	203.17	227.85	155.09	218.66	230.49
SOTL	97.80	149.29	172.99	64.67	76.53	92.14	109.35	179.90	134.92	172.33	119.70	188.40	171.77
DRL	98.90	235.78	182.31	73.79	66.40	76.88	119.22	146.50	118.90	218.41	80.13	120.88	147.80
IntelliLight	88.74	195.71	100.39	73.24	61.26	76.96	112.36	97.87	129.02	186.04	81.48	177.30	130.40
A2C	135.81	166.97	226.82	43.28	67.05	148.69	236.17	110.91	98.56	187.41	86.56	116.70	128.88
FRAP	**66.40**	**88.40**	**84.32**	**33.83**	**54.43**	**61.72**	**72.31**	**80.24**	**79.43**	**110.33**	**67.87**	**92.90**	**88.28**
Improvement	25.17%	40.79%	16.01%	47.69%	11.15%	19.72%	33.87%	18.01%	33.20%	35.98%	15.30%	23.15%	32.30%

Table 3: Performance on different intersection structures.

Model	3-approach	4-approach	5-approach
Fixedtime	166.16	93.21	211.26
Formula	159.12	67.17	231.33
SOTL	123.43	65.39	124.71
DRL	108.94	125.84	140.33
IntelliLight	108.27	60.38	151.92
A2C	132.56	52.64	172.60
FRAP	**81.57**	**48.83**	**110.66**

Table 4: Performance in a multi-intersection environment.

Model	Jinan	Hangzhou	Atlanta
Fixedtime	880.18	823.13	493.49
Formula	385.46	629.77	831.34
SOTL	1422.35	1315.98	721.15
DRL	1047.52	1683.05	769.46
IntelliLight	358.83	634.73	306.07
A2C	316.61	591.14	244.10
FRAP	**293.35**	**528.44**	**124.42**



Images from Google Maps

Acknowledgements

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We are implementing our model in Hangzhou China!

Try to find more related researches? Just scan QR code on the right or visit https://traffic-signal-control.github.io