# MetaLight: Value-based Meta-reinforcement Learning





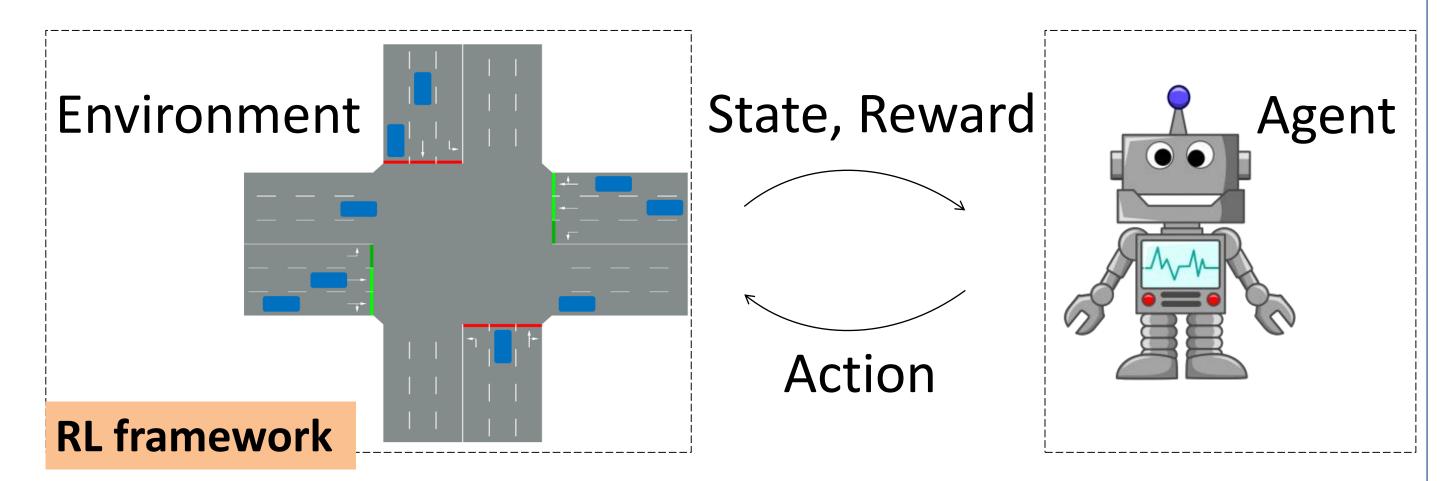


Xinshi Zang, Huaxiu Yao, Guanjie Zheng, Nan Xu, Kai Xu, Zhenhui Li Shanghai Jiao Tong University, Pennsylvania State University, Shanghai Tianrang Intelligent Technology Co., Ltd



### Introduction

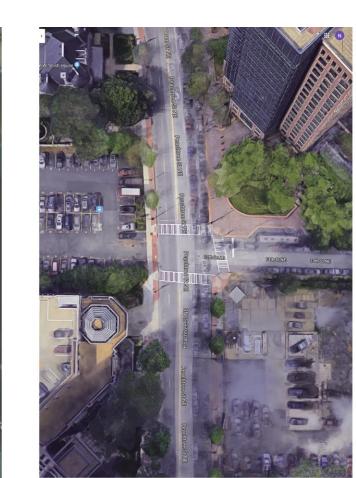
Reinforcement Learning has made traffic signal control more intelligent.



However, the cost of computational resources and learning time is unacceptable in the complicated real world.





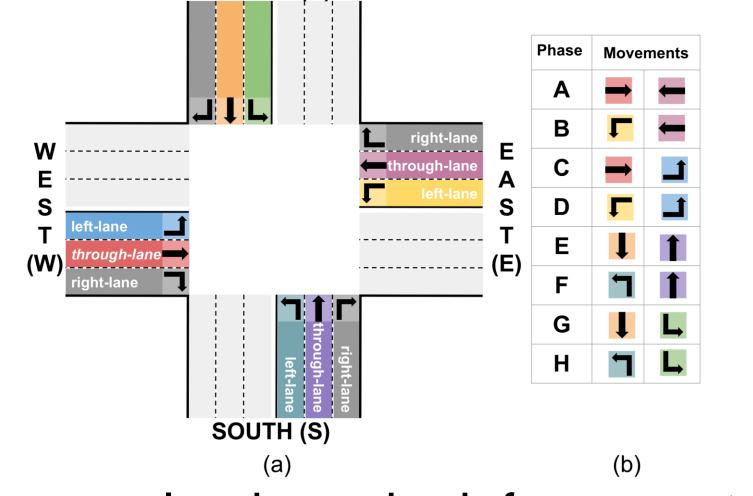




Therefore, how about leveraging the common knowledge shared in all intersection scenarios (Meta-RL)?

# Challenges

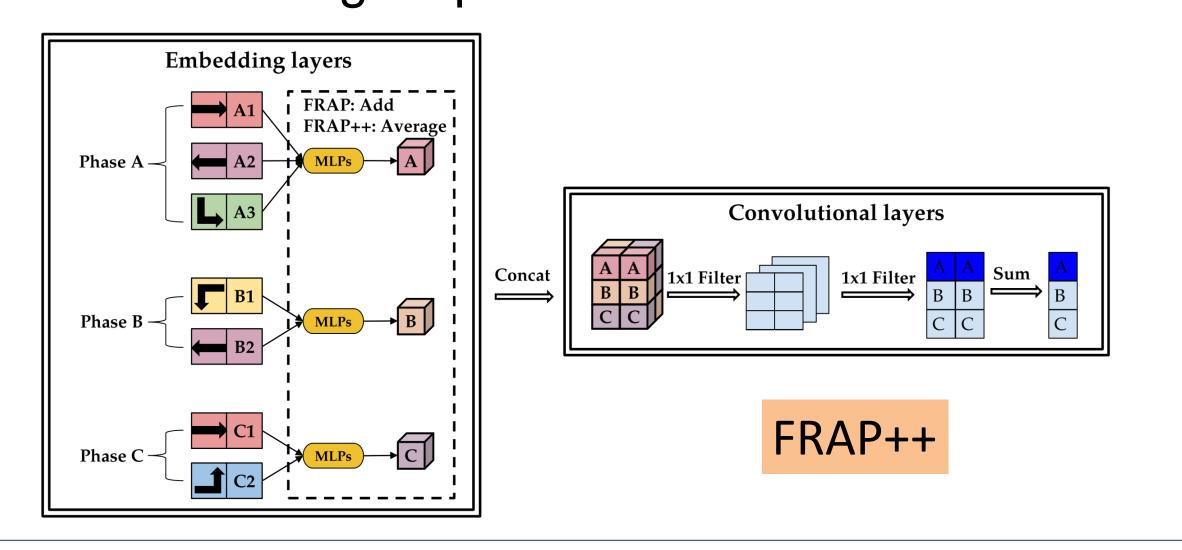
- 1. How to learn and adapt to the complicated and heterogeneous scenarios in traffic signal control?
  - Traffic flow
  - Entering approach/lane
  - Phase Setting



2. How apply meta-learning on value-based reinforcement learning?

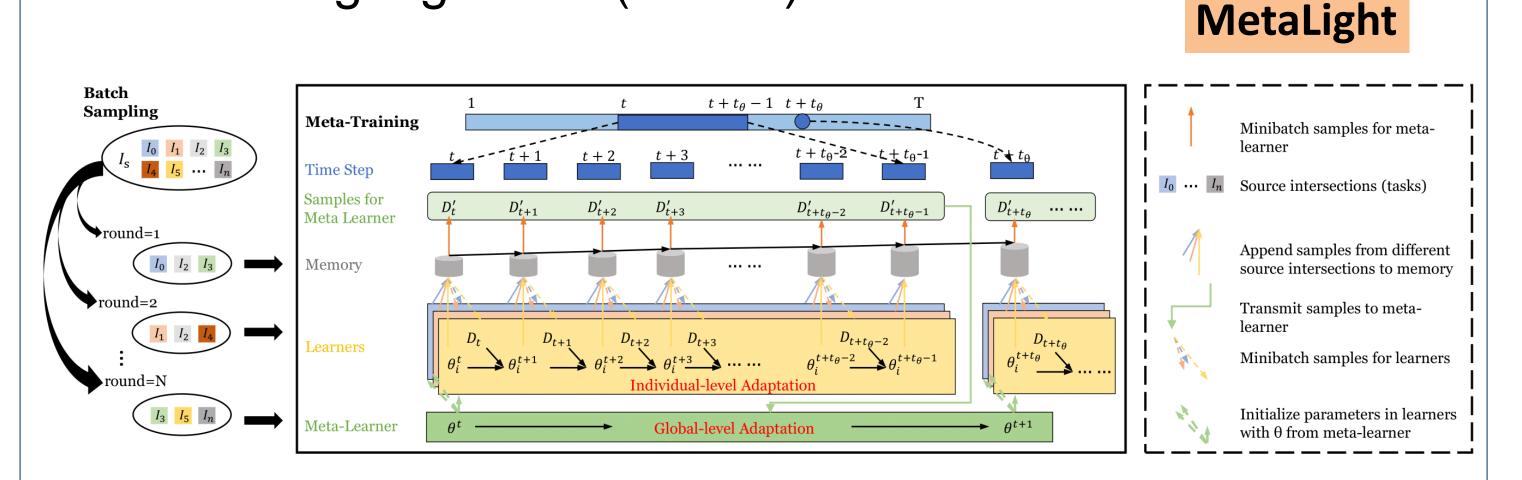
## Framework

- State: number of vehicles on each lane
- Reward: average queue length
- Action: choose signal phase for next time interval



#### Framework

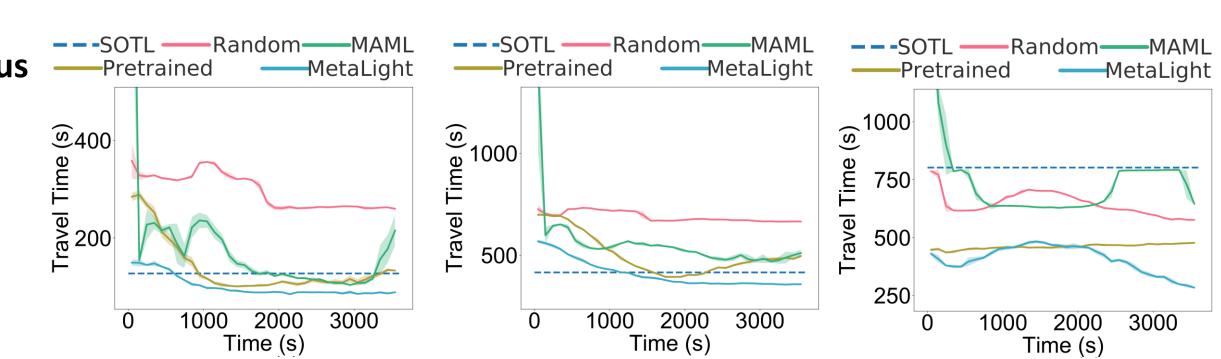
Value-based Meta-RL workflow based on the gradient-based meta-learning algorithm (MAML)



## Experiments

Table: P	erformances	s on Tas	k-1, 2,	3. Trav	el time	e is rep	orted	
Homogeneous	Phase Setting	4a	4b	6a	6c	6e	8	
	Random	102.71	292.51	90.41	461.78	105.49	73.62	
	Pretrained	82.87	191.83	85.47	200.06	111.94	67.88	
	MAML	82.95	191.53	161.41	404.04	132.26	77.07	
	MetaLight	<b>74.67</b>	199.55	<b>78.92</b>	195.92	98.58	66.93	
	Improvement	9.89%	\	7.66%	2.07%	6.56%	1.41%	
Heterogeneous	Phase Setting	4c	4d	6	ōb	6d	6f	
	Random	254.70	662.8	35 298	3.53 5	70.55	474.20	
	Pretrained	95.94	385.7	74 233	3.64 4	30.74	307.98	
	MAML	101.41	440.6	55 369	9.82 6	14.09	345.46	
	MetaLight	81.07	352.8			73.58	226.82	
	Improvement	15.50%	8.53	% 25.9	99% 30	6.49%	26.35%	
	City	Homogeneous			Heterogeneous			
Different Cities		JN	ĂT	LA	JN	ΑT	LA	
•	Random	451.88	379.16	262.23	363.59	602.60	684.15	

		JN	AI	LA	JN	Al	LA
	Random	451.88	379.16	262.23	363.59	602.60	684.15
	Pretrained	128.20	186.86	104.59	156.04	351.39	331.75
	MAML	173.13	301.29	135.11	335.81	618.84	393.58
	MetaLight	95.01	161.37	77.23	137.02	310.39	308.71
	Improvement	25.89%	13.64%	26.16%	10.17%	11.67%	6.94%
Heterogeneous	SOTLRandom- Pretrained	—MAML – MetaLight –		RandomM Metal		OTL ——Rande etrained –	omMAML MetaLight



(a) Phase setting: 4c (b) Phase setting: 4d (c) Phase setting: 6d Figure: Meta-testing curves for Task-2

# Acknowledgements

The work was supported in part by NSF awards #1652525 and #1618448. The views and conclusions contained in this paper are those of the authors and should not be interpreted as representing any funding agencies

#### References

[KDD'18] Wei et al., IntelliLight: A Reinforcement Learning Approach for Intelligent Traffic Light Control

[CIKM'19] Zheng et al, Learning Traffic Signal Control from Demonstrations [ICML'17] Finn et al, Model-agnostic meta-learning for fast adaptation of deep networks [arXiv:1904.08117] Wei et al., A Survey on Traffic Signal Control Methods [arXiv:1905.04716] Zheng et al., Diagnosing Reinforcement Learning for Traffic Signal Control

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

