Optimizing Traffic Control using Bayesian Inference

Wenyu Li, Xiangyu Zhao, Yilin Sun

Structure of Presentation

- Problem Description
- Simulation
- Emulation
- Evaluation

Problem Description

Motivations

- Impact on city planning: suboptimal traffic control leads to higher carbon emissions and waste of time for citizens.
- Adaptable for internet traffic: traffic planning can also be adapted in networking and communication for shorter latency, higher throughput and lower packet drop rate.
- Feasibility: computer modeling is widely used in traffic simulation and optimization.
- This project is inspired by the Google Hash Code 2021 Qualification Round

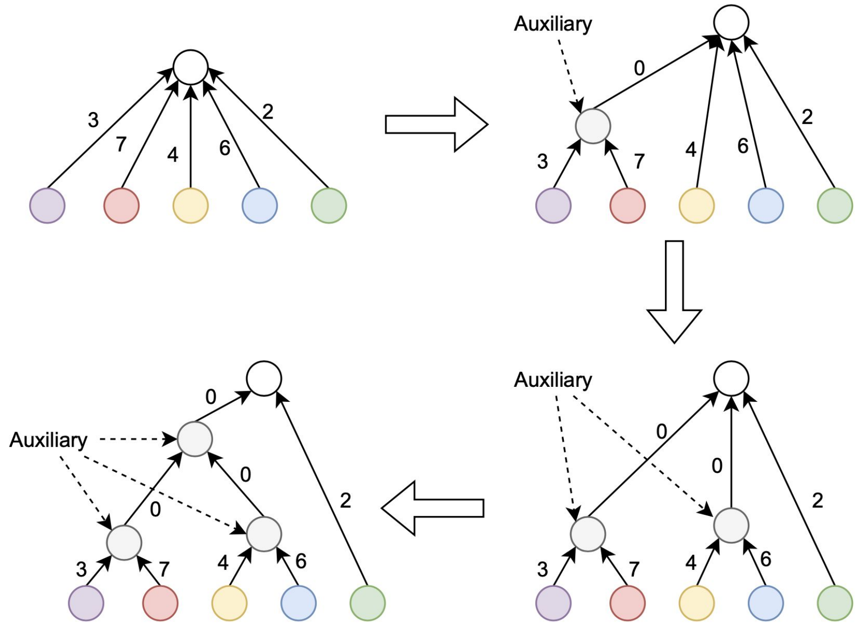
Problem description: network

Network: directed graph

Junctions: vertices

Roads: edges

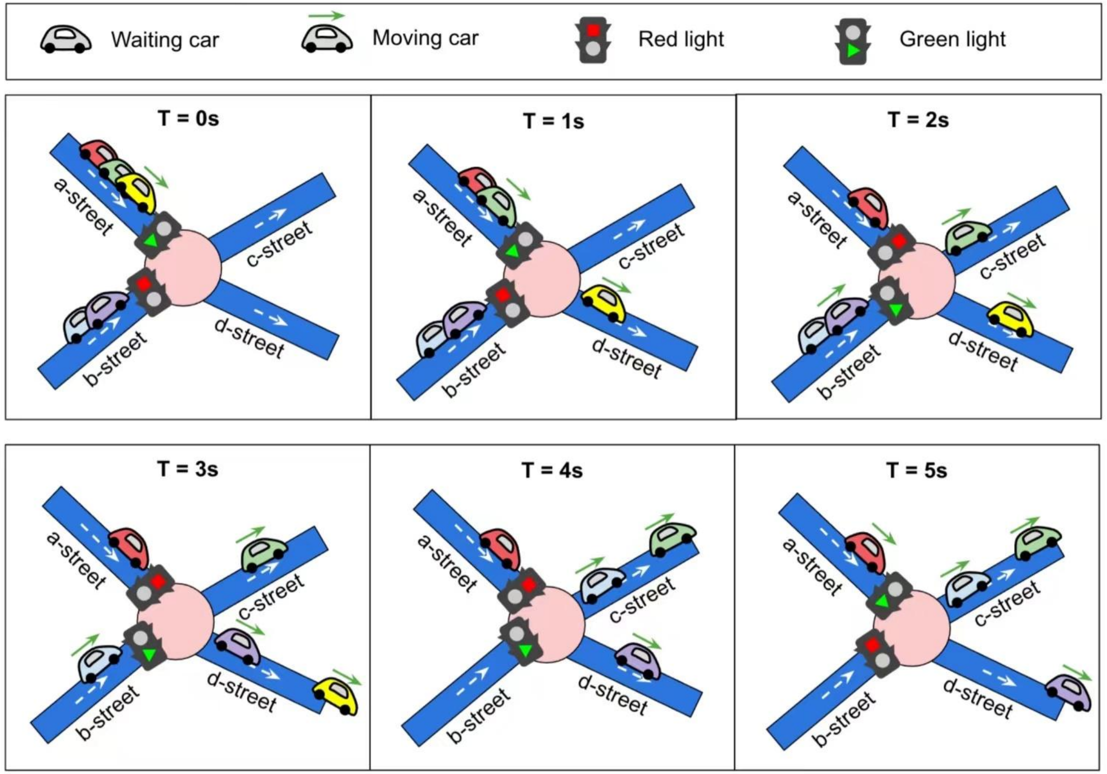
Assumption: Each junction has exactly 2 incoming roads.



Transformation algorithm

Problem description: traffic light and cars

- Traffic lights are placed at the end of each road.
- For each junction, at any point, exactly one of the light is green.
- During each time step, exactly one car passes the junction.
- Cars have uniform speed of 1
- Passing junction generates no delay.



Problem description: reward function

Reward is defined as the total distance travelled by all cars in the system

$$\text{Reward} = \sum_{c_i \in \text{Cars}} \text{Distance travelled by car } c_i$$

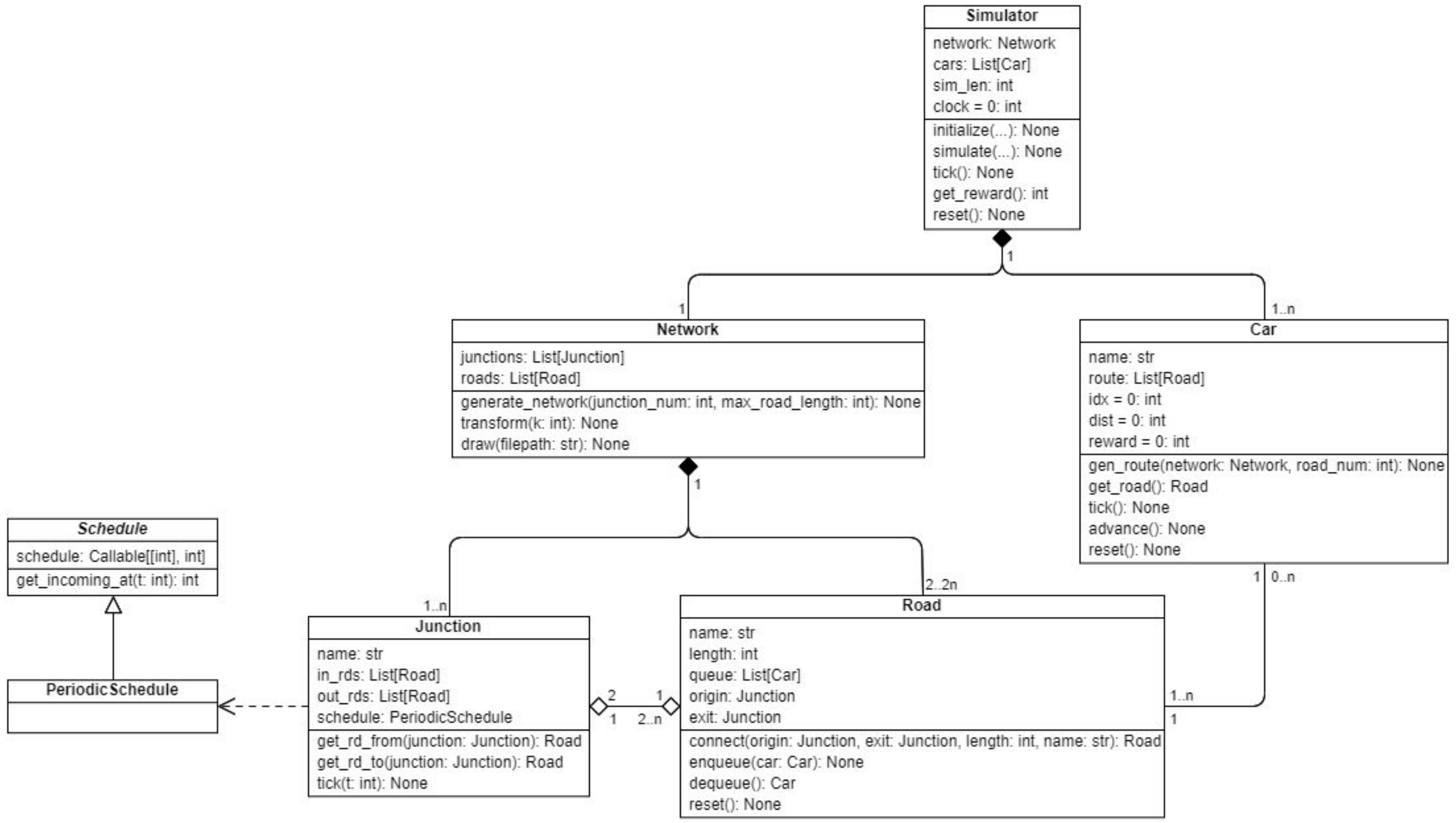
In Google Hash Code, original reward for each car is

$$\text{Score for car } i = F + (D - T) \text{ if finishes else } 0$$

Goal: To maximize the reward function in a given time period T

Simulation

Simulator structure



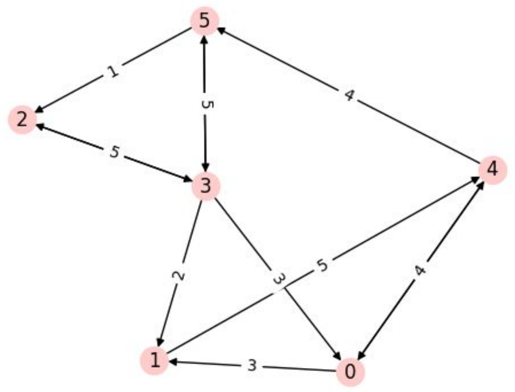
Network initialisation

Problems of most naïve random network generation algorithms:

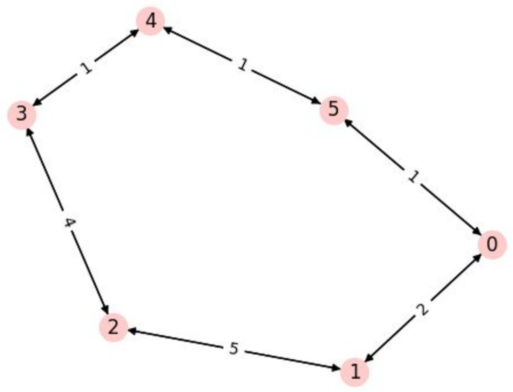
- Deadends: junctions with no outgoing roads
- Disjoint clustering: network becoming multiple disjoint clusters

Network initialisation

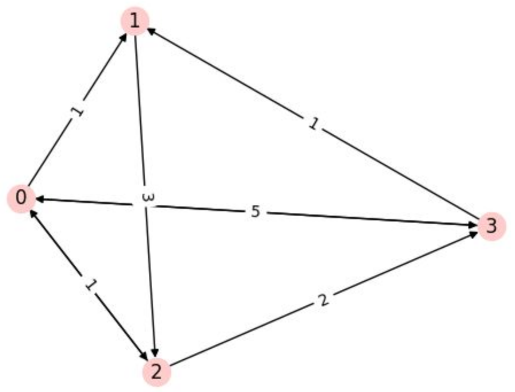
- Random network



- Ring network



- Text input



Simulation mechanism

Ticking: take turns to simulate every junction and every car at every time frame

- Junction: picks a road whose traffic light is green, and dequeue a car from that road (if any)
- Car: travels a distance of 1 along a road, or pushed into the queue at the end of the road

Emulation

Methods and Techniques

- For our emulator, we used Gaussian Process and Bayesian Optimization
- Rationale behind the choice:
  - Traffic Simulation is costly => minimize number of evaluations
  - Traffic Simulation analogous to a black box, very limited understanding
- The Bayesian Optimization library of choice is `GPyOpt`
- Pipeline:
  - Scheduler → Simulator → Bayesian Optimizer

Models and Parameters

In addition to our basic model as mentioned in the simulator, we also added certain simplification of assumptions to facilitate the efficient emulation.

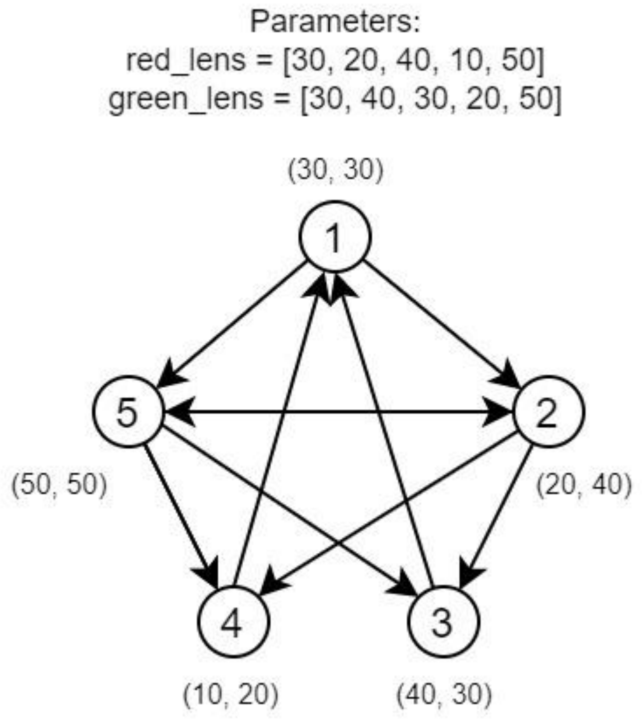
We started off by considering two basic cases:

1. Distinct Scheduling
2. Uniform Scheduling

We then move on to the hybrid of the two:

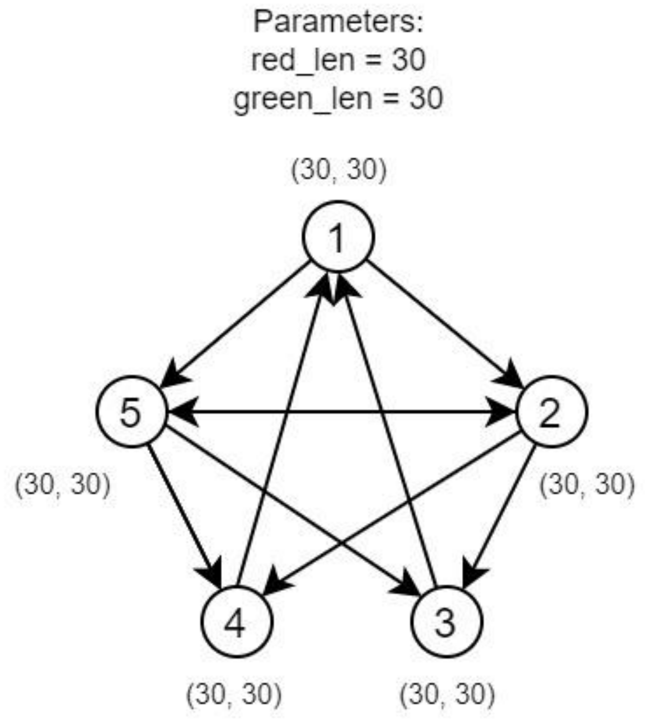
3. Preset scheduling

Distinct Scheduling


Parameters:
red_lens = [30, 20, 40, 10, 50]
green_lens = [30, 40, 30, 20, 50]
(30, 30)
1
5
2
(50, 50)
(20, 40)
4
3
(10, 20)
(40, 30)

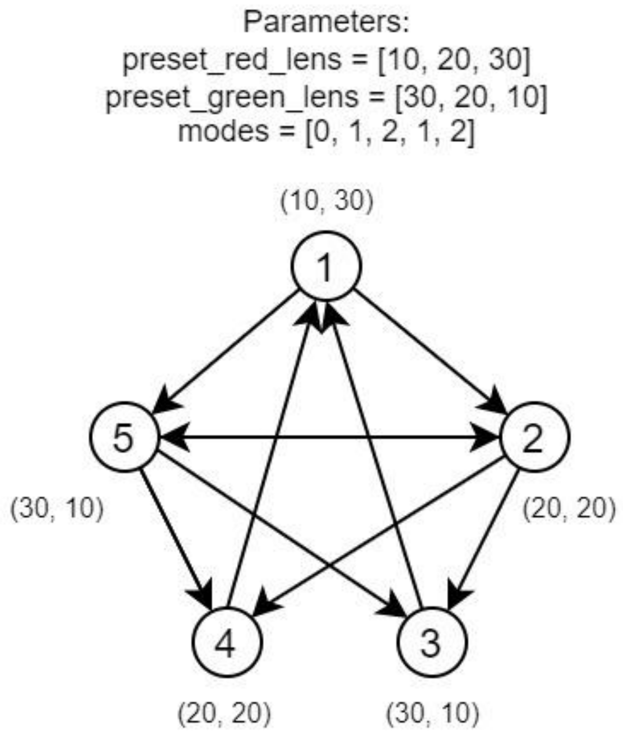
- Treat every junction separately, assign two parameters: `red_len_n` and `green_len_n` to describe the scheduling at n-th junction
- (Pro) Very descriptive, covers all possible search space
- (Con) Explosion of search space, take extremely long to converge, impractical to carry out in real time
- (Con) Large search space also leads to higher risk to settling in local minima instead of global minima

Uniform Scheduling



- Another extreme, let every junction share the same schedule
- (Pro) Number of parameters reduce significantly to 2, much faster to emulate and optimize
- (Con) Lack of descriptiveness, unable to adjust for the differences in junctions
- Performs surprisingly well in uniform networks (e.g. ring networks), but poorly in more complex ones. Overall an adequate choice for fast, real-time optimization.

Preset Scheduling



- A hybrid between uniform and distinct scheduling
- Assume there are only a fixed set of schedules (preset schedules), let the junctions choose within this fixed set
- Reduces search space drastically, but still exponential due to the combinatorial nature of the model.
- Could be an inspiration for more efficient optimization techniques.
- Variant: forced preset - we force the preset schedules to span an even range, then let the junctions choose within the set

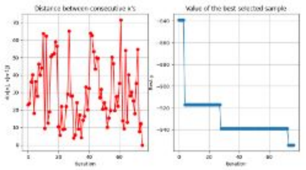
Can we achieve constant-time optimization?

- Preset scheduling achieves reasonable convergence speed
- But it is subjected to exponential increase in search space.
- As size of network increases, we observe that the time its takes to converge to optimal values becomes much longer.

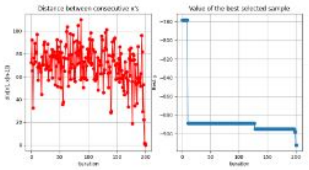
It might be possible to achieve constant-time optimization using following method:

1. Pretrain the model to assign `modes`, either using GP or assign using graph properties such as degrees/centrality of nodes.
2. In the real-time system, we only finetune `preset schedules`, which have constant number of parameters and constant upper-bound on converge time.

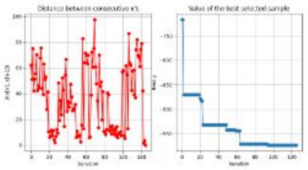
Evaluation of the models



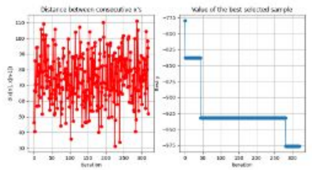
(a) Uniform scheduling



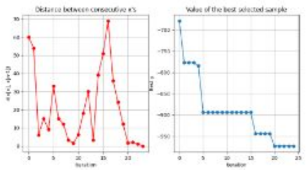
(b) Distinct scheduling



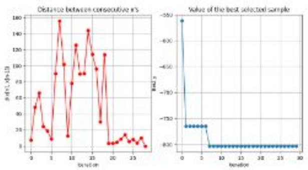
(c) Preset scheduling with 2 modes



(d) Preset scheduling with 5 modes



(e) Forced-preset scheduling with 2 modes



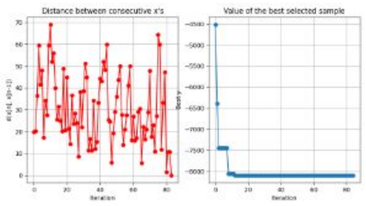
(f) Forced-preset scheduling with 5 modes

Figure 4. Convergence graph for running Bayesian optimisation on a 5-junction network

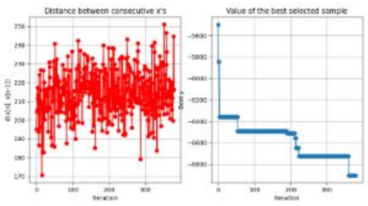
Schedule	Opt. schedule	Opt. reward	Convergence iter.
Uniform	[17, 12]	931	78
Distinct	[(21, 38), (30, 41), (26, 13), (32, 29), (26, 36)]	964	200
Preset (2 modes)	schedules: [(16, 29), (54, 9)] modes: [0, 0, 0, 1, 0]	**1014**	125
Preset (5 modes)	schedules: [(15, 13), (40, 47), (31, 17), (14, 7), (29, 31)] modes: [0, 2, 2, 2, 0]	984	322
Forced-preset (2 modes)	cycle length: 6 modes: [0, 0, 0, 1, 1]	**992**	**24**
Forced-preset (5 modes)	cycle length: 48 modes: [1, 2, 2, 3, 3]	939	**29**

Table 1. Experimental results for running Bayesian optimisation on a 5-junction network

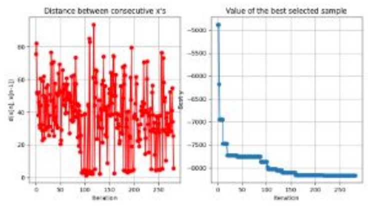
Evaluation of the models



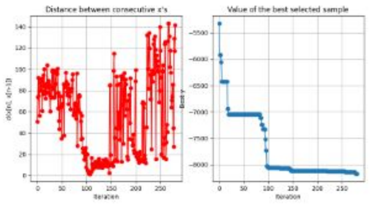
(a) Uniform scheduling



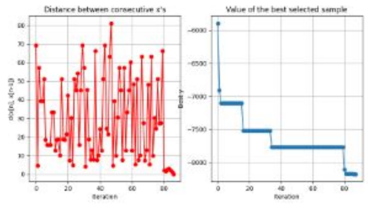
(b) Distinct scheduling



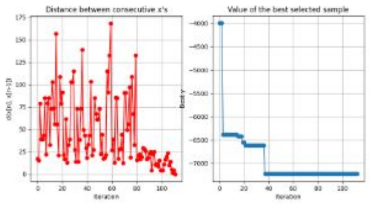
(c) Preset scheduling with 2 modes



(d) Preset scheduling with 5 modes



(e) Forced-preset scheduling with 2 modes



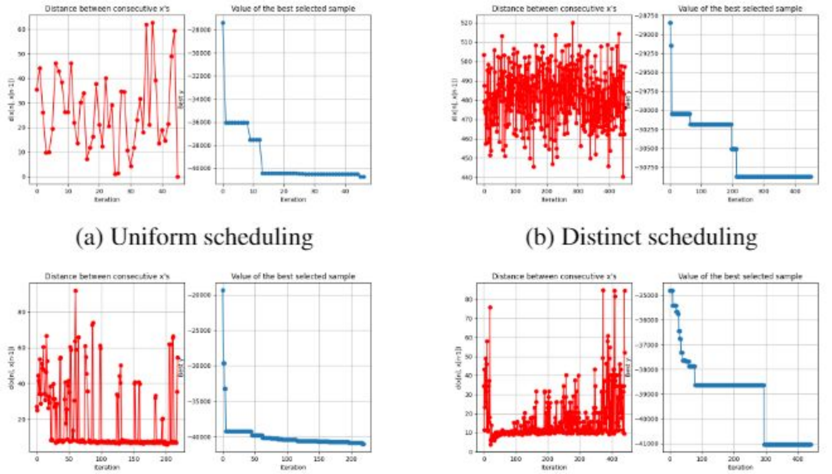
(f) Forced-preset scheduling with 5 modes

Figure 5. Convergence graph for running Bayesian optimisation on a 40-junction network

Schedule	Uniform	Distinct	Preset (2)	Preset (5)	Forced-preset (2)	Forced-preset (5)
Opt. reward	8096	6904	8164	**8176**	**8175**	7320
Convergence iter.	**83**	391	285	117	**88**	112

Table 2. Experimental Results for Bayesian optimisation on a 40-junction network

Evaluation of the models



(a) Uniform scheduling (b) Distinct scheduling

(c) Preset scheduling with 2 modes (d) Forced-preset scheduling with 2 modes

Figure 6. Convergence graph for running Bayesian optimisation on a 200-junction network

Schedule	Uniform	Distinct	Preset (2)	Forced-preset (2)
Opt. reward	40705	30873	**41062**	**41030**
Convergence iter.	**45**	475	**218**	432

Table 3. Experimental Results for Bayesian optimisation on a 200-junction network

Conclusion

Conclusion

- We explored the possibility of traffic optimization using GP and BO
- We have obtained results that confirmed our conjectures
- However, there are certain outliers that are worth looking into
- Ways forward:
    - Attempt other optimization techniques (e.g. Reinforcement Learning)
    - Look deeper into the anomalies
    - Explore the likelihood of our models (evidence)
    - Visualization

Thank you!