Optimal Real-Time Scheduling for Black Hole Imaging

INSTITUTE FOR APPLIED COMPUTATIONAL SCIENCE AT HARVARD UNIVERSITY

Shu Xu, Yiming Xu, Ziyi (Queena) Zhou

Harvard Institute of Applied Computational Sciences (IACS)

Event Horizon Telescope

ABSTRACT

Every year, the Event Horizon Telescope (EHT) Collaboration is granted a 10-day window in which they can utilize the virtual telescope formed by 11 radio dishes across the globe to observe a black hole. Due to other contraints, they can only choose five days out of this 10-day window. To facilitate the EHT in making decisions on how to select the five days, the authors decided to build a software that encompasses the procedures of processing the data, running the optimization models, and making suggestions with provided uncertainty measurement. During this project, the authors designed and implemented four main models that can make use of future days' weather forecast data. The authors also built a nice and clean graphical user interface for the users to customize the settings and visualize the model outputs.

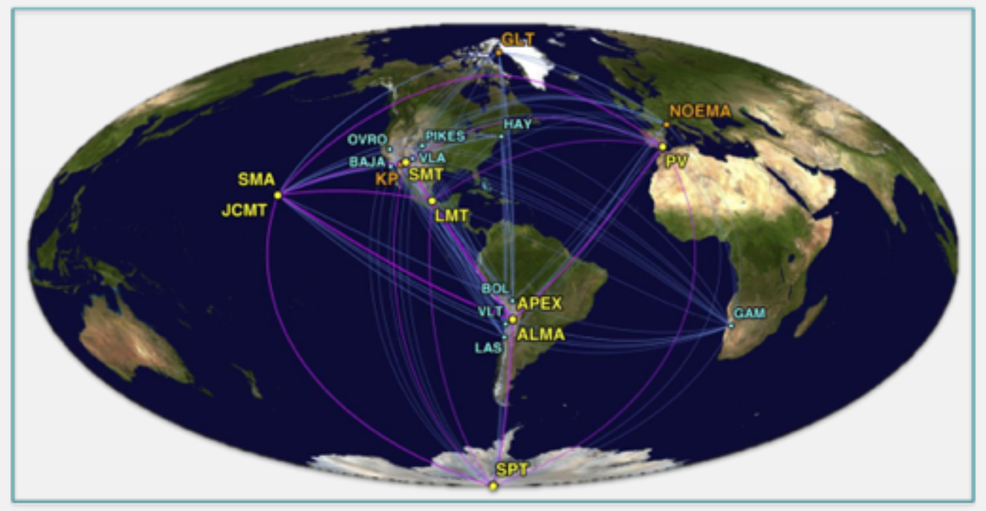
INTRODUCTION

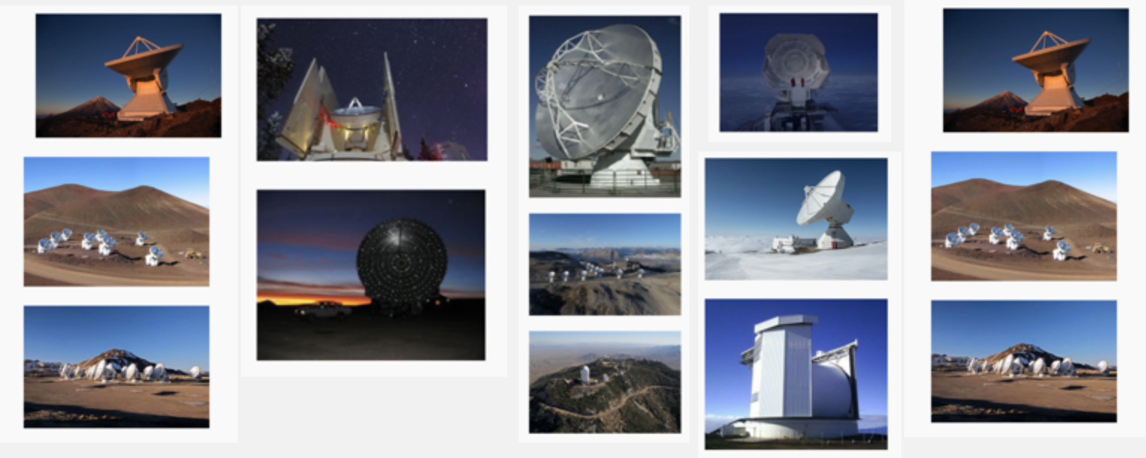
On April 10, 2019, the EHT released this image of a black hole. They won the 2020 Breakthrough Prize in Fundamental Physics.

To achieve a high resolution in this image, they used the technique of very long baseline interferometry, in which radio dishes across the globe are synchronized to form a virtual telescope with the highest angular resolution currently possible from the surface of the Earth.

To operate in this way, the EHT requires reasonably good weather across most of the array at the same time. Currently there are eleven radio dishes in the array.

The EHT is only provided with a 10-day window in each year, and they want to perform the observation in 5 days.

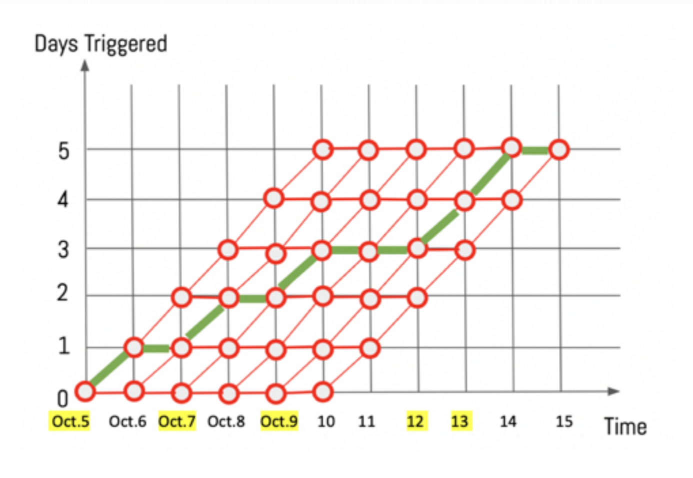




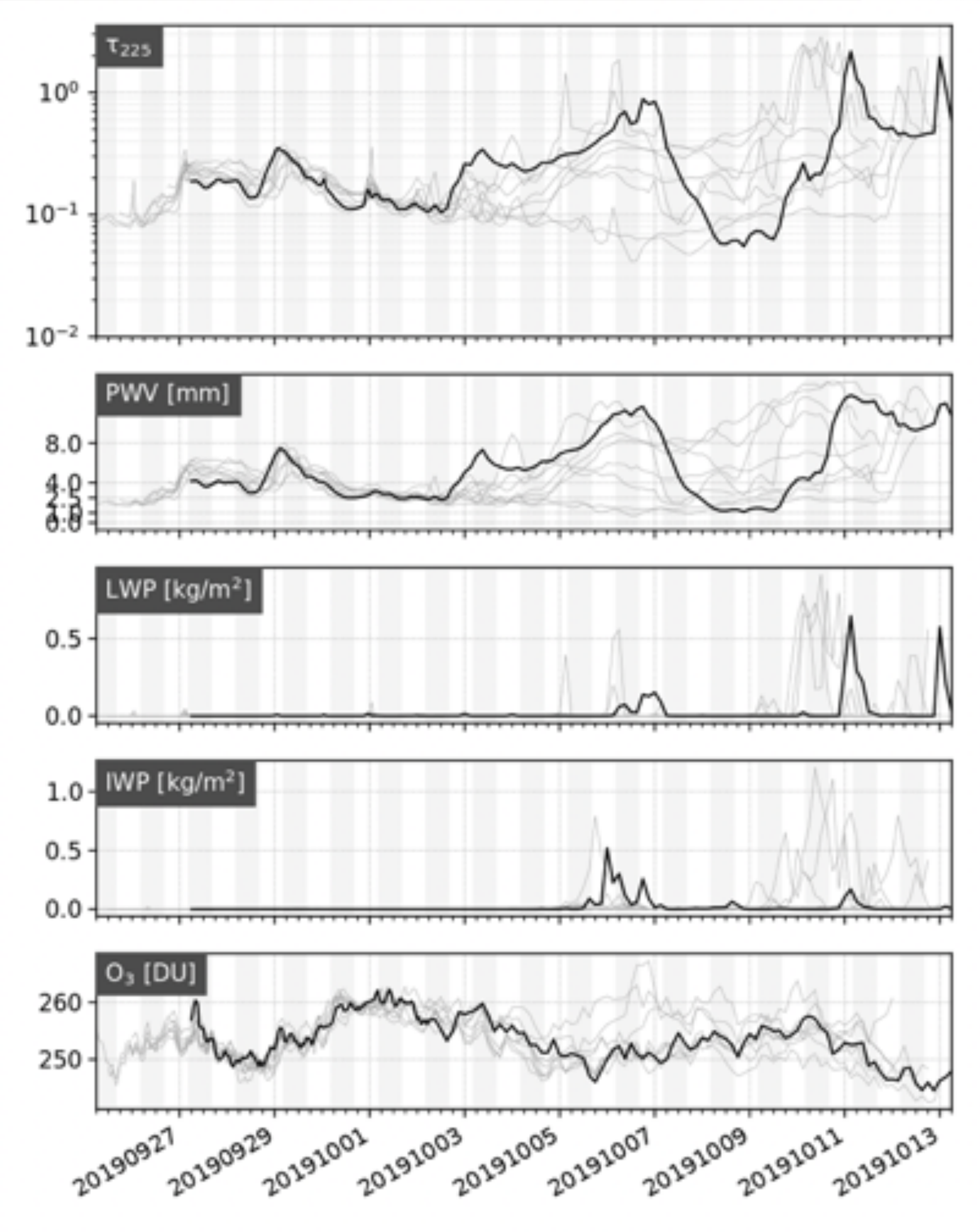
PROBLEM STATEMENT

Given the weather data and the dates information, we need to build an algorithm that makes suggestions on-the-go, namely whether to trigger on that day, and the optimal strategy for the future remaining days. In total, we can only select five days out of consecutive 10 days.

If possible, the EHT also wants our model to output the confidence level and second optimal strategy.



DATA



We collected our data from the GFS, which is a weather forecast model produced by the national centers for environmental information.

The GFS makes predictions for five variables at a time. On each graph, there is one black line and seven gray lines. This is because for each 6 hours, we get a new set of weather forecast data, so the black line represents the most updated forecast data, while the grey lines are predictions made in the past 48 hours.

We were told by the experts that the first variable, which is Tao-225 is the most important one to indicate clarity of the atmosphere, as it is the absorption rate directly above head. A smaller Tao-225 is more preferred than a larger one.

METHODS

We borrowed the idea of reward functions from reinforcement learning. Each telescope would get a reward value based on its weather condition. The reward function of each telescope is being called the small f.

Each day is assigned a reward value, for which the reward function is called the big F.

- f_i : reward of a single telescope i

$$f_i(\tau_{225}) = -\tau_{225}, -\log(\tau_{225}), \exp(-\tau_{225}), \ldots$$

- $F(f_1, \ldots, f_n)$: total reward of all telescopes on a given date

$$F = \sum r_i^2 f_i \quad \text{where r is the radius of each telescope}$$

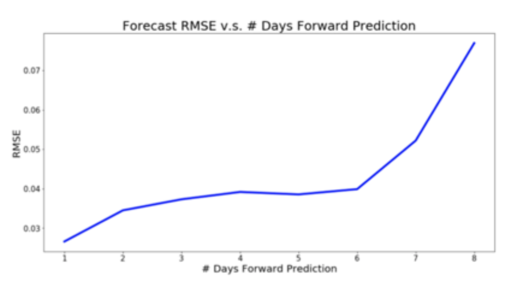
$$F = [f_1, \ldots, f_n] D [f_1, \ldots, f_n]^T \quad \text{where D is the distance matrix}$$

Once we calculate the reward values for each day, we then want to solve the optimization problem, which is to choose the days to trigger the telescopes. We try to incorporate uncertainty in the following models.

Method 1: Discount Factor

Day1	Day2	Day3	Day4	Day5	Day6	Day7	Day8	Day9	Day10
-1.90	-1.39	-1.62	-1.64	-1.88	-1.29	-1.70	-1.90	-1.88	-1.40
$\times$	$(1-r)$	$(1-r)^2$	$(1-r)^3$	$(1-r)^4$	$(1-r)^5$	$(1-r)^6$	$(1-r)^7$	$(1-r)^8$	$(1-r)^9$

Method 2: Forecast Penalty



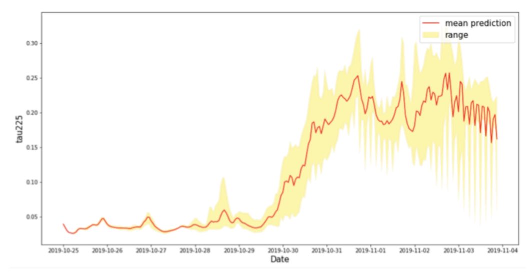
For a single telescope i on day d:

$$f_{i,d} * \boxed{e^{\text{penalty\_level} * \text{RMSE}_{[i][t]}}}$$

penalty term

t: how far is day d from the current

Method 3: Prediction Difficulty of Specific Time

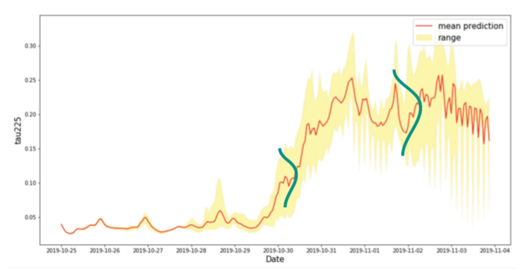


For a single telescope i on day d:

$$\text{latest}(f_{i,d}) \times \boxed{e^{\text{penalty\_term} * RMSE_{i,d}}}$$

penalty term

Method 4: Sampling from Normal Distribution



For a single telescope i on day d:

$$\text{reward} \sim \mathbb{N}(latest(f_{i,d}), \text{RMSE}_{i,d})$$

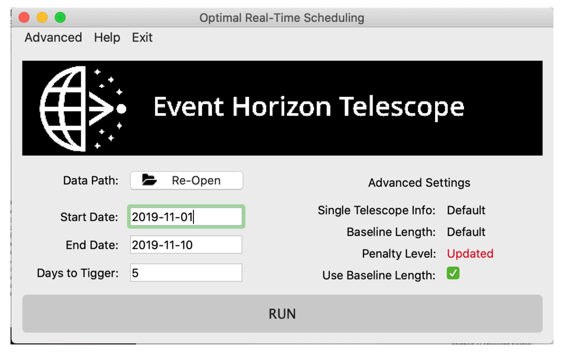
MODEL EVALUATION

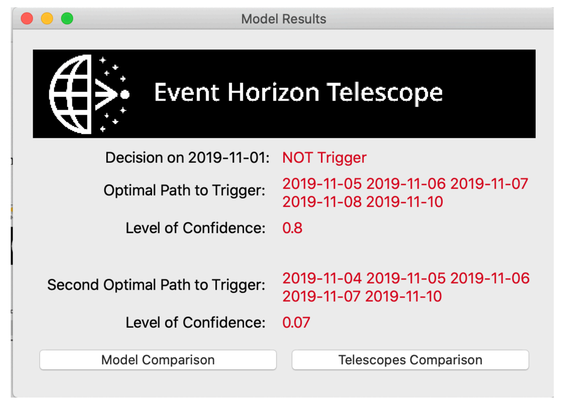
We collected GFS data dated from 10/25 to 11/30 and ran simulations in each consecutive 10-day window. We cross-validated the best punishment level for each model as well as the best model in 'back-testing' style. We chose as metric the mean squared error between the best path score and the path chosen by a model with a particular punishment level. The result is as below:

Method 3 with punish = 1	0.000015
Method 2 with punish = 0.6	0.000016
Method 1 with punish = 0.03	0.000017
Method 4	0.000028

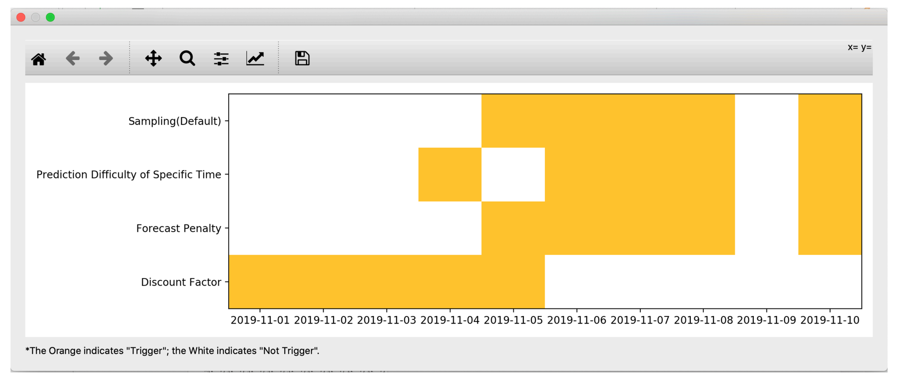
FINAL DELIVERABLE

We built a software that packaged all the models and features in an easily accessible way. Here are the main functionalities, in which data and date information are the inputs and suggested decisions are the outputs.

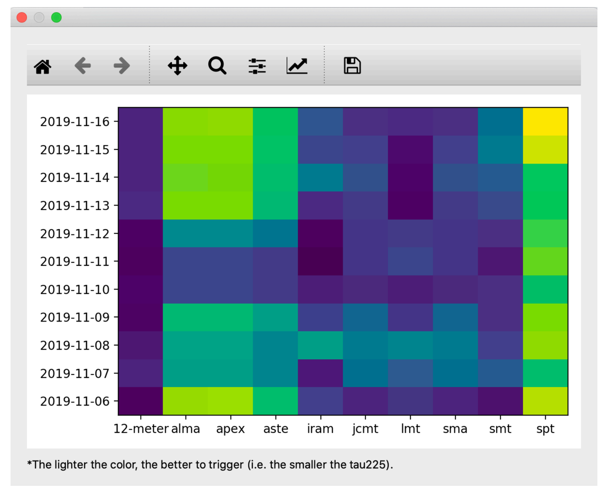




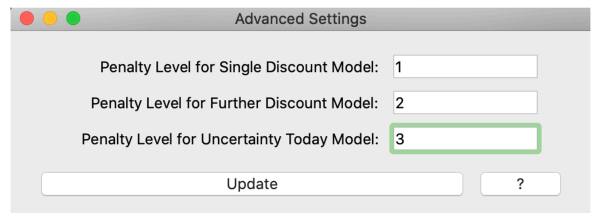
Comparison of models:

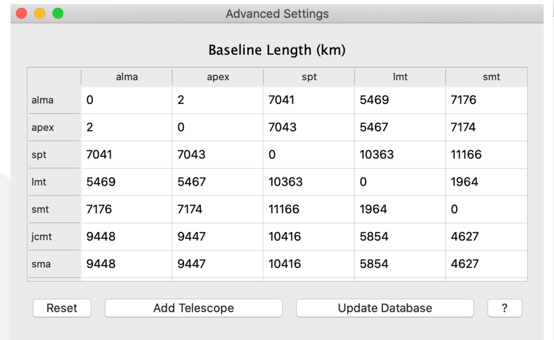


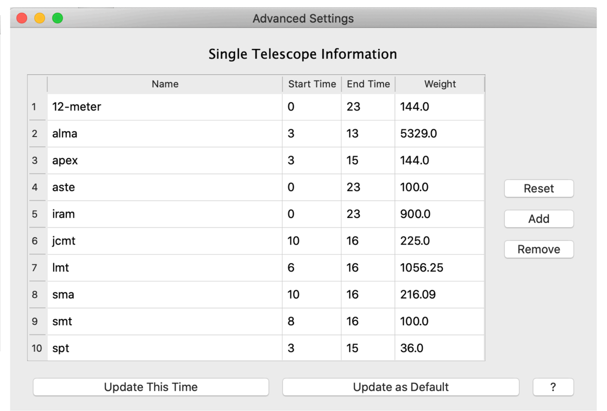
Visualization of telescope's weather condition using heat map:



Settings adjustments:







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