AC297r Fall 2019
Milestone 3
Optimal Real-time Scheduling for Black Hole Imaging

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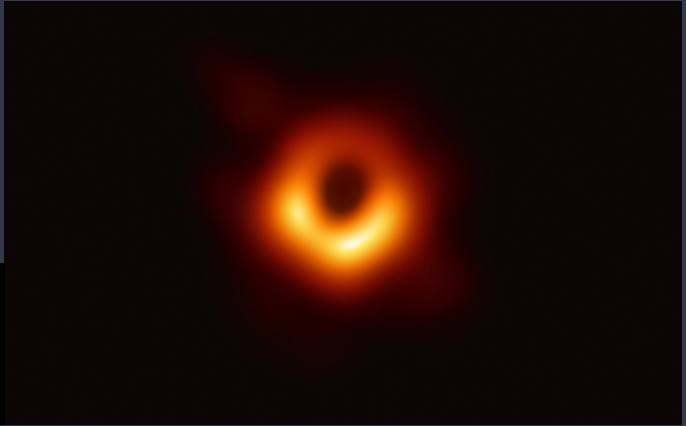
Event Horizon Telescope

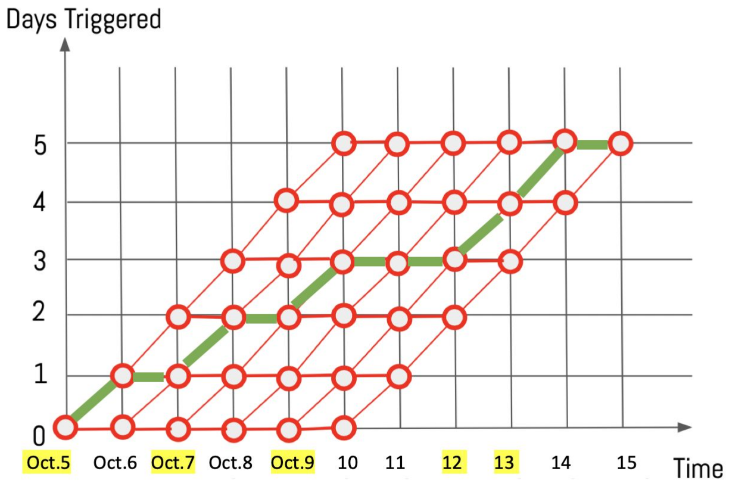


Previously...

Problem Statement

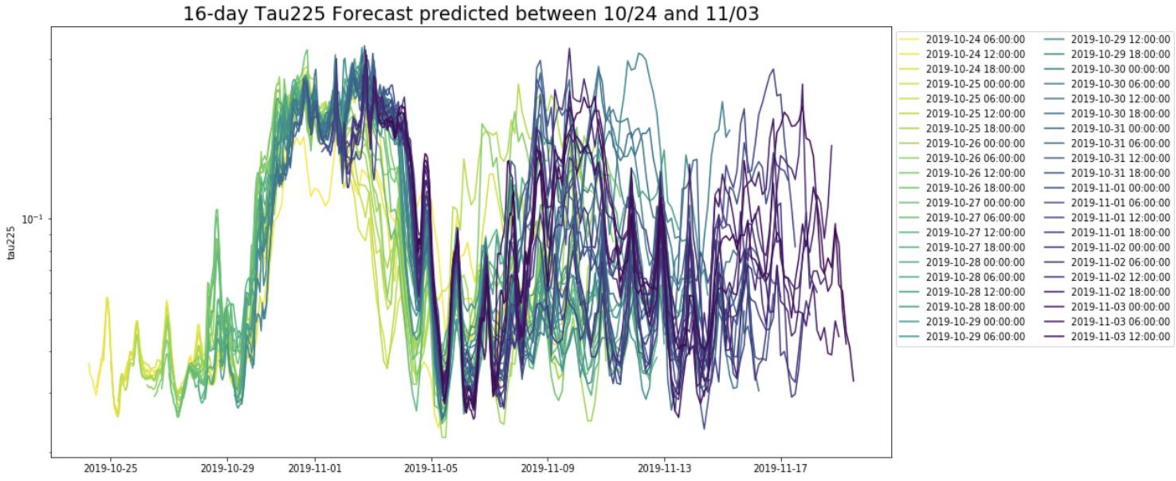
We are going to build a model that can:

1. In total, choose 5 days from a 10-day window
2. On each day, determine the optimal strategy for future remaining days
3. If possible, provide a confidence level on its suggestion
4. Also provide the second optimal strategy



Data

- Every 6 hours, we get 16-day atmosphere forecast from GFS.
- **Tau_225**(absorption directly above head, the smaller the better)



Previously...

Model Design & Baseline Model

1. Reward Function
2. Uncertainty Measurements
3. Optimization
4. Model Evaluation

f_i
reward of a single telescope i.

$F(f_1, \ldots, f_n)$
Total reward for all telescopes

1. Reward Function

$$f_i(\tau 225) = -\tau 225$$

$$F = \sum_{i}^{N_{telescope}} w_i f_i$$

where w_i is the weight for each telescope (total GBytes data sent from the telescope used by EHT).

2. Uncertainty Measurement：

None

Reward Function

- 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

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

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

Model Design

1. Reward Function

2. Uncertainty Measurements

3. Optimization

4. Model Evaluation

$$f_i$$

reward of a single telescope i.

$$F(f_i, \ldots, f_n)$$

Total rewards for all telescopes

Uncertainty of atmosphere forecast (how far in the future)

Uncertainty associated with a specific date

Measure performance based on real weather afterwards.

Compare with:

1. Baseline Model
2. Random path
3. Best path afterwards

Uncertainty I

Uncertainty of atmosphere forecast: only depends on how far in the future the weather forecast model is predicting

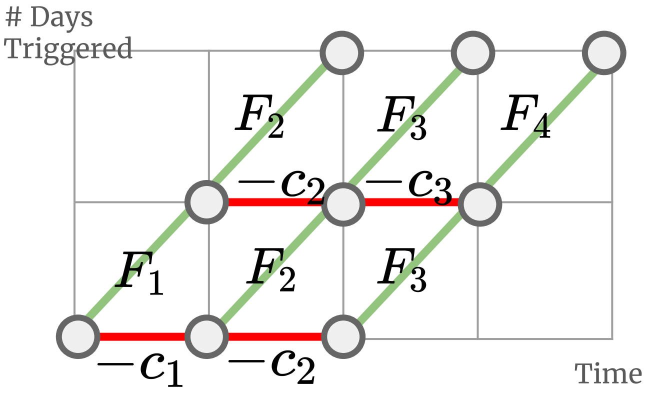
- **Method 1: discount factor**

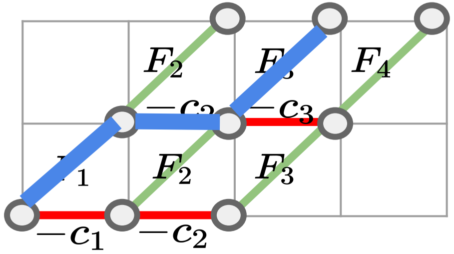
Day1	Day2	Day3	Day4	Day5	Day6	Day7	Day8	Day9	Day10
19.03	13.93	16.24	16.38	18.80	12.99	17.02	19.03	18.81	14.06
$\times$	$(1-r)$	$(1-r)^2$	$(1-r)^3$	$(1-r)^4$	$(1-r)^5$	$(1-r)^6$	$(1-r)^7$	$(1-r)^8$	$(1-r)^9$

Uncertainty I

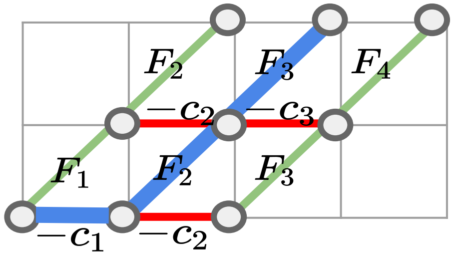
- **Method 2: constant penalty term**

$$c_1 > c_2 > c_3$$





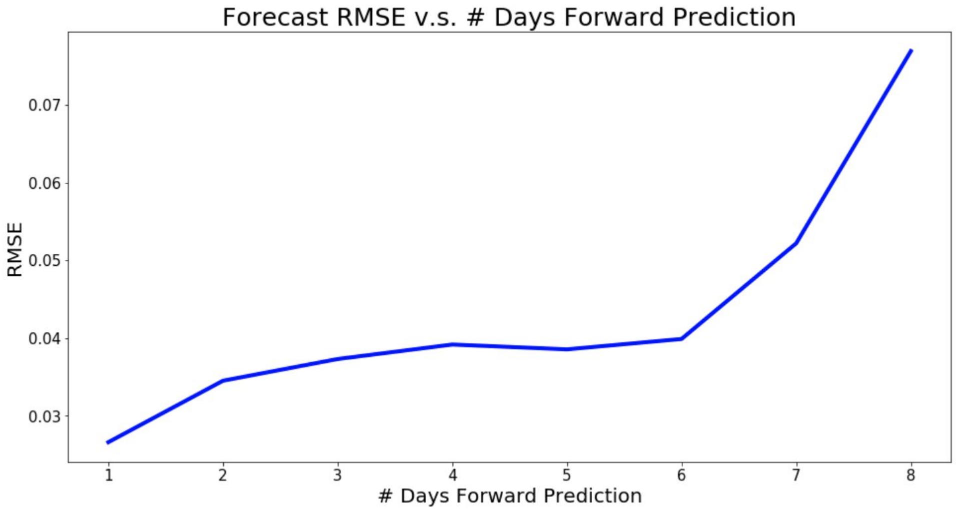
$$F_1 - c_2 + F_3$$



$$-c_1 + F_2 + F_3$$

Uncertainty I

- ## Method 3: RMSE forecast penalty



For a single telescope i on day d:

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

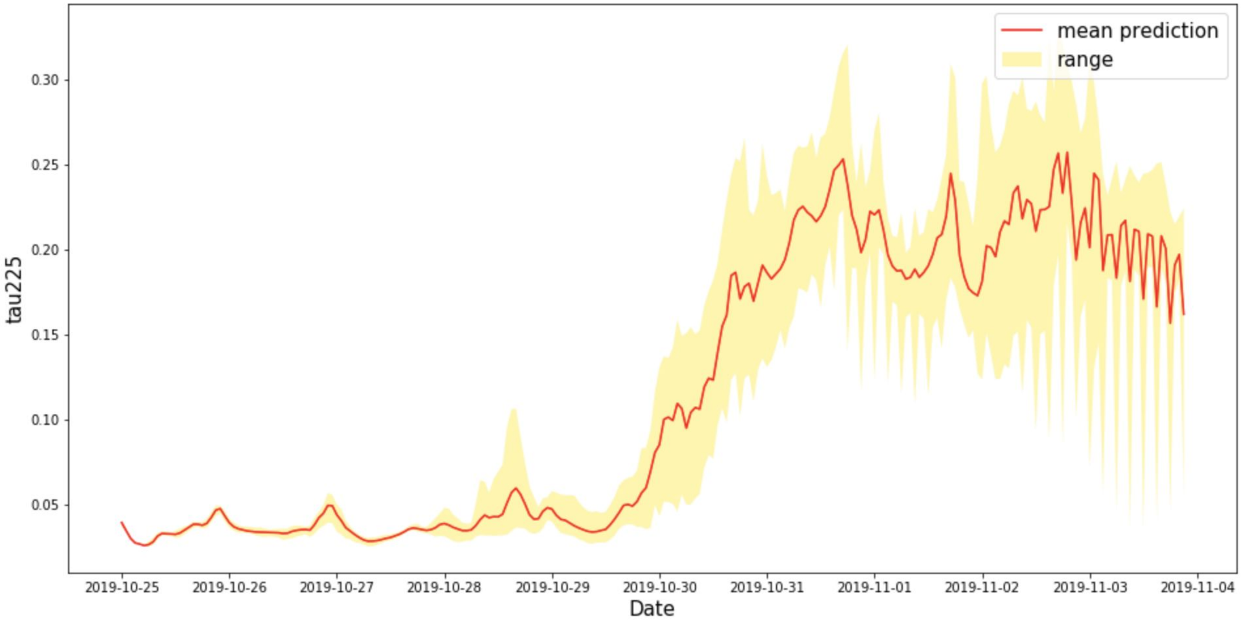
t: how far is day d from the current

Design Choice of Exponential:

1. penalty_level = 0 -> penalty term = 1
2. exaggerate the difference between small and large RMSE when penalty_level is large

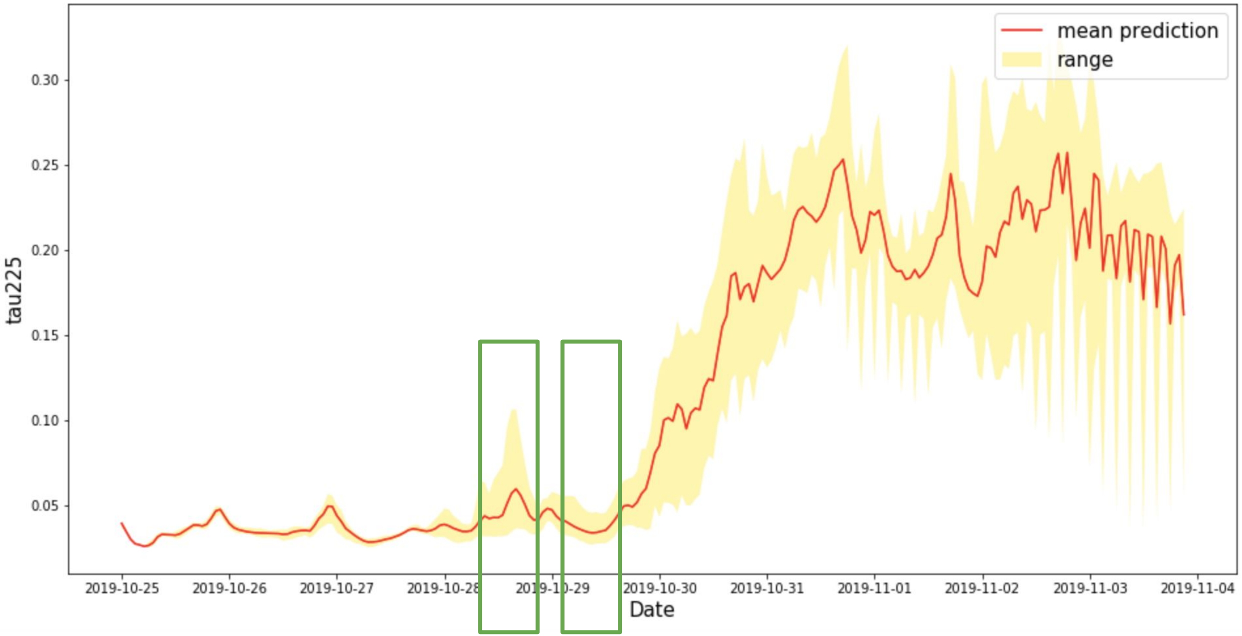
Uncertainty II

Incorporating uncertainty associated with a specific date

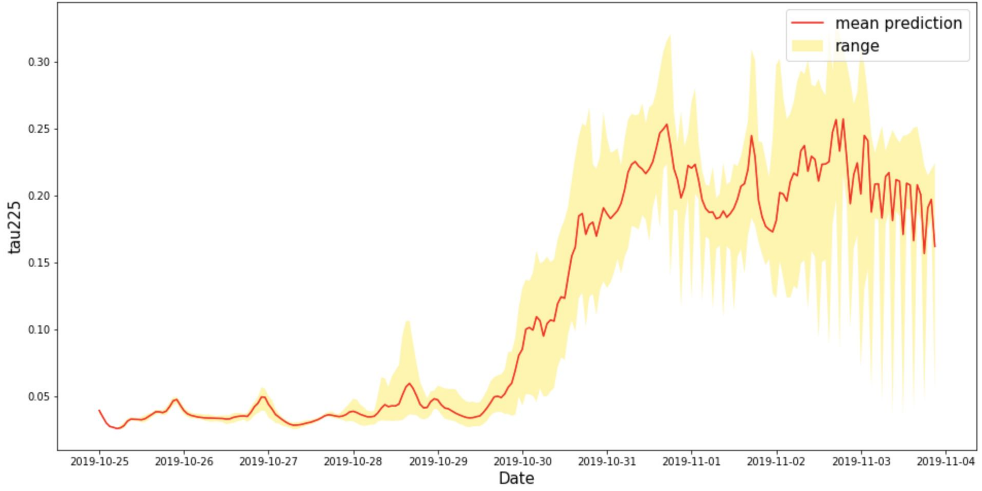


Uncertainty II

Incorporating uncertainty associated with a specific date



Uncertainty II



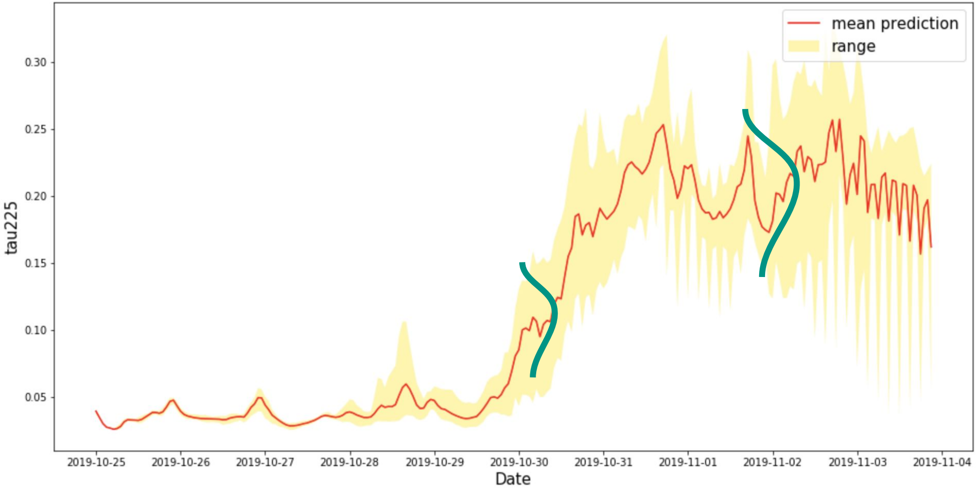
For a single telescope i on day d:

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

penalty term

Uncertainty II

- **Method 2: Sampling from Distribution**

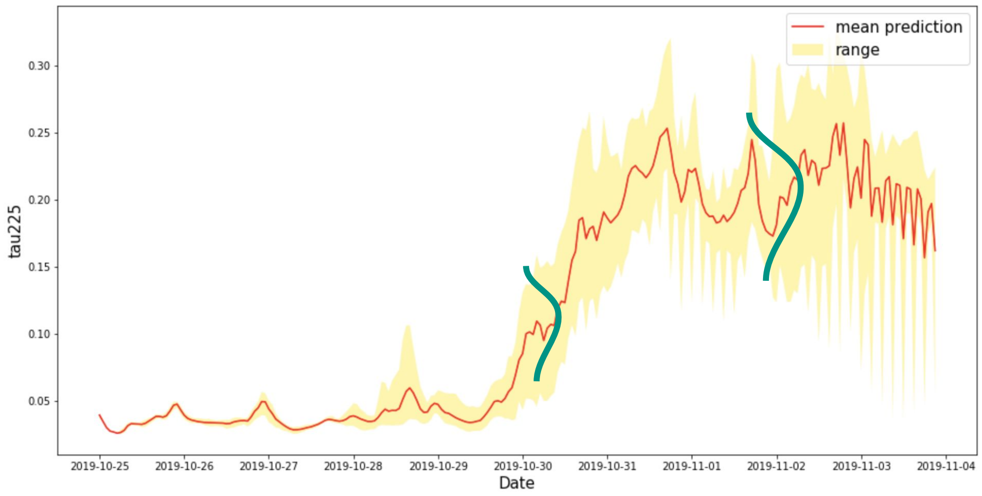


For a single telescope i on day d:

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

Uncertainty II

- **Method 2: Sampling from Distribution**



For a single telescope i on day d:

$$\text{True Reward}_{i,d} \sim N(mean(f_{i,d}), std^2(f_{i,d}))$$

Algorithm:

1. Sample ***N*** samples for $\text{True Reward}_{i,d}$

2. Perform optimization for the ***N*** trails and generated path w.r.t each trail

3. Provide the most frequent path as the final suggested path, and use its frequency as our level of confidence.

Model Evaluation

Choose 5 days From Oct.25 - Nov.03, 2019

	Model	Oct 25	Oct 26	Oct 27	Oct 28	Oct 29	Oct 30	Oct 31	Nov 1	Nov 2	Nov 3	Final Score
	Ground-Truth Best											0.59
	Random Pick											0.42
	Baseline											0.57
I	Discount Factor											0.59
I	RMSE forecast penalty											0.59
II	STD of Date											0.57
II	Sampling Distribution	0.93	0.82	0.72	0.88	0.96	0.99					0.57

Model Next Steps

1. data, Data, DATA!
2. Detailed setting & Possible Combinations

Choose 5 days From Oct.25 - Nov.03, 2019

	Model	Oct 25	Oct 26	Oct 27	Oct 28	Oct 29	Oct 30	Oct 31	Nov 1	Nov 2	Nov 3	Total Reward
	Ground-Truth Best											0.59
	Random Pick											0.42
	Baseline											0.57
I	Discount Factor											0.59
	RMSE forecast penalty											0.59
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Challenges & Next Steps

What tells:

- Uncertainty can help us adjust to a better path
- Different models have different behaviors

Doesn’t tell:

(can’t compare between models)

- The case is too special…
- Overfit

Next Steps for Modeling:

1. data, Data, DATA!
2. Detailed setting & Possible Combinations

Final Deliverable

Input

Must Enter

1. Atmosphere Prediction
2. Window Info:
   Start/end date, # days to trigger

Could Change

1. Telescope Info:
   schedule, availability, weight
2. Reward Function Formula
3. Penalty Term
4. Baseline length matrix

……

Output

1. Suggested Optimal Path
   (with level of confidence)

2. *Second Optimal Path**
   (with level of confidence)

3. Explanation of our suggestion:
   The reward for each telescope;
   Visualization of the path;
   ……

Software Organization

```
scheduling_tool\
    scheduling_tool\
        test\
            __init__.py
            test_schedule.py
        user_interface.py
        read_data.py
        processing_data.py
        make_suggestions.py
        Run.py
        setup.py
        requirements.txt
        LICENSE
        README.md
```

GUI Showcase

Challenges & Next Steps

What tells:

- Uncertainty can help us adjust to a better path
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Doesn’t tell:

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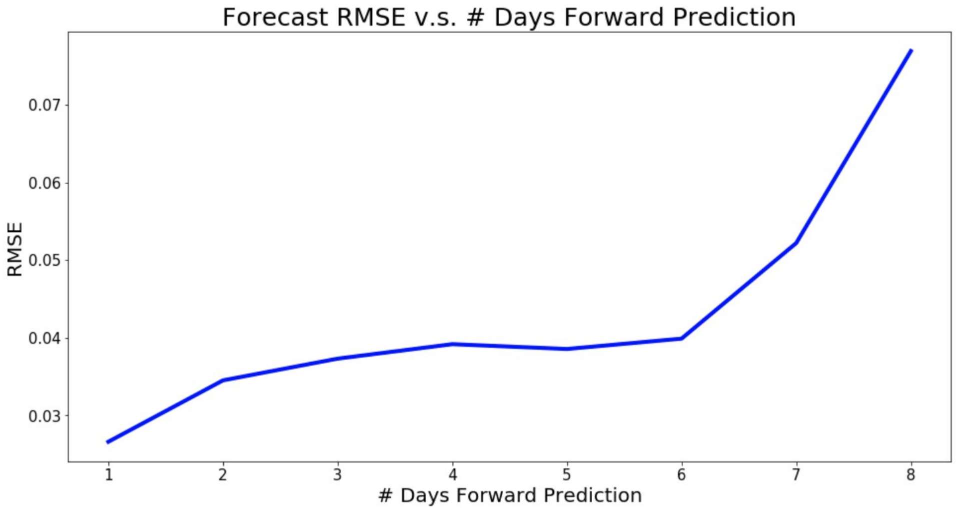
- Overfit

Uncertainty I

- **Method 3: RMSE forecast penalty**



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penalty term

t: how far is day d from the current