Improving Science Yield for NASA Swift with Automated Planning Technologies

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Objectives

To quickly and safely build highly optimized Pre-Planned Science Timelines (PPST) for the spacecraft:

- Quickly turn observational priorities into precise spacecraft maneuvers.
- Continue to exploit and extend *Swift*'s unique capabilities as a fast-response satellite observatory.
- Don't break the spacecraft!

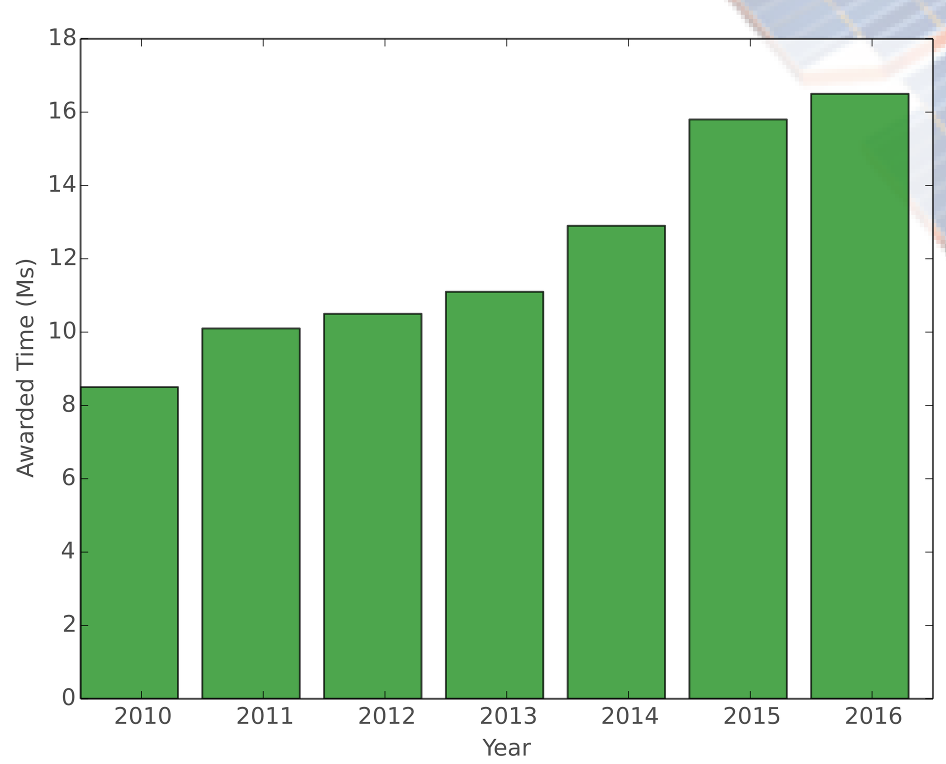
PPST Build time:

Current	Goal
5-7 hrs.	30 min.

Motivation

Since launch in 2004 the demands put on the spacecraft have increased substantially in terms of amount of awarded observing time, types of targets, number of observations/day, co-pointing and trigger agreements, etc.

Year	Avg. # Obs./day
2005	74
2010	85
2016	112



Amount of time awarded, in megaseconds, through the *Swift* Target of Opportunity (TOO) program, from 2010-2016.

Framing the problem

Building an optimized PPST for a single day is equivalent to solving a traveling salesman problem on the sky with ~130 sites, and thousands of dynamic constraints both astronautical and scientific.

Spacecraft Constraints

There are a host of constraints, some of the most important and/or difficult to wrangle are:

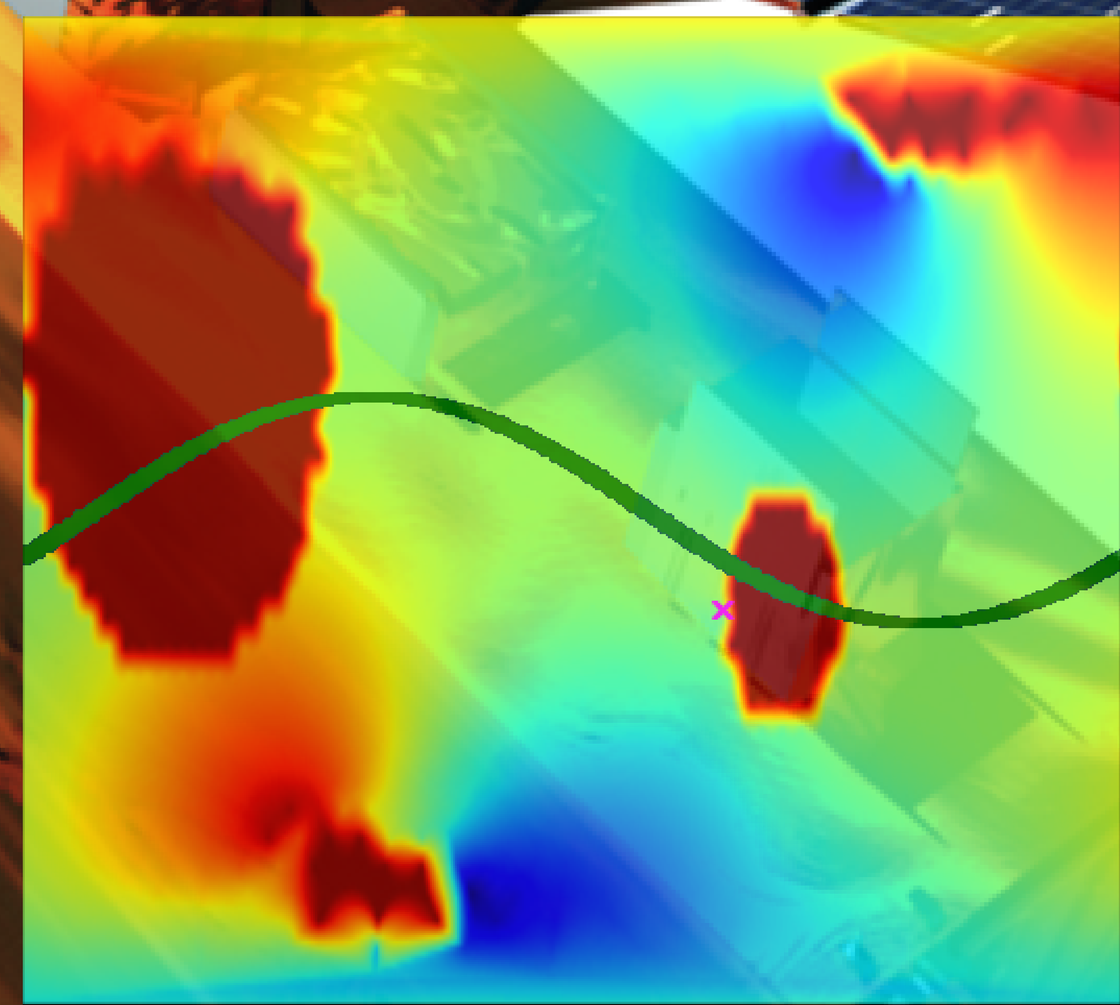
- Changing target visibility windows.
- Passively maintaining the XRT CCD temperature between -55 and -65° C.
- Complex slew path constraints.
- Roll is constrained by solar panel pointing and star-tracker catalog.
- Slew resources (# of degrees able to slew/orbit) are limited.
- Preventing momentum build-up in the reaction wheels.

Scientific Constraints

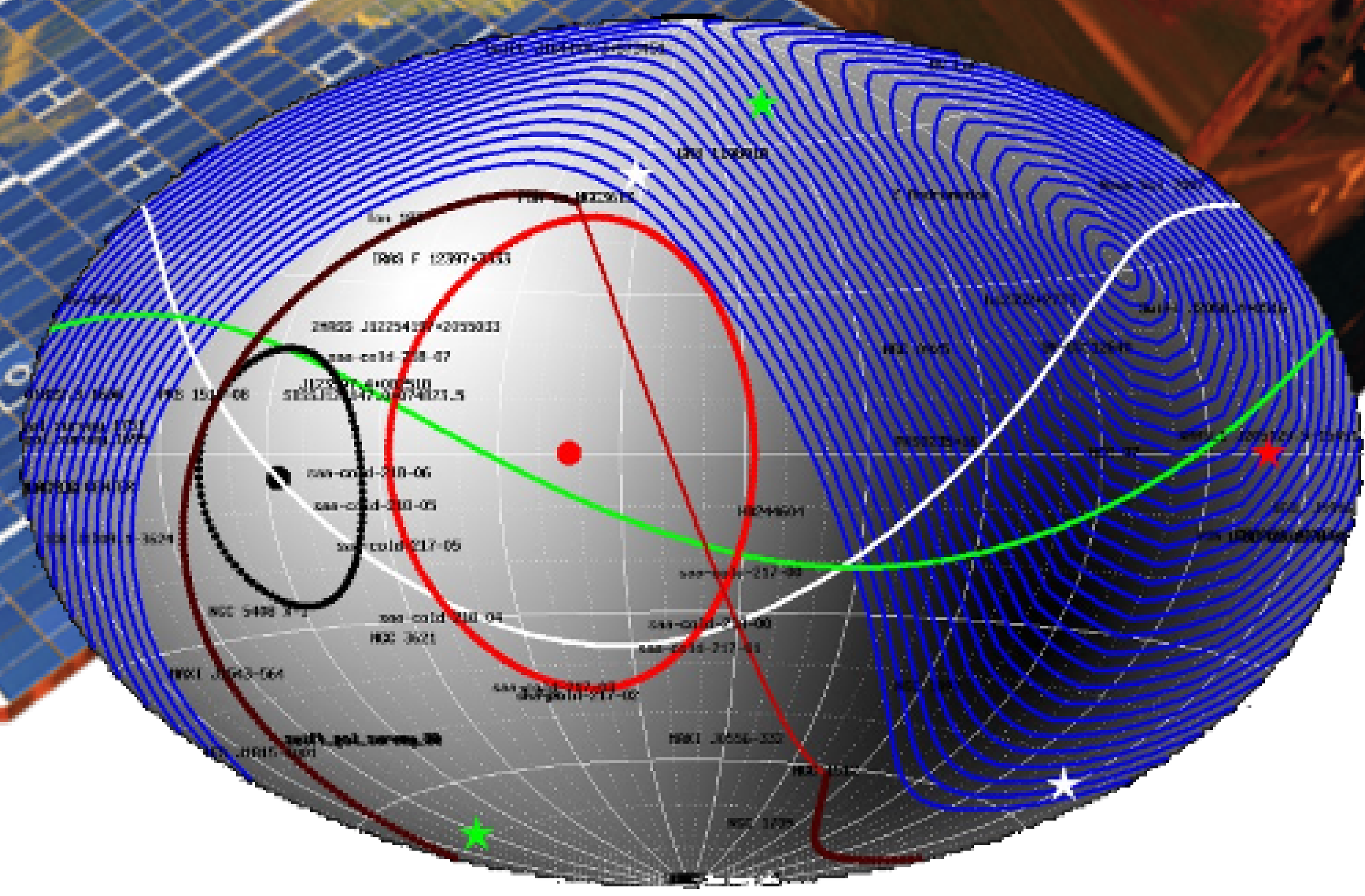
- Different targets require different observing strategies.
- Some observing modes have longer/shorter minimum snapshot lengths.
- Co-pointing and trigger agreements with other observatories put hard time constraints on some observations.

Optimization Goals

- Maximizing observing/slew time ratio.
- Minimizing # of UVOT filter wheel rotations.
- Maximizing time spent observing targets > 8 hrs. from the Sun.



Average temperature on the sky for the XRT CCD on a particular day with large Sun-Moon separation.



A long slew, trying to avoid many competing constraints. The blue region is everything hidden behind the Earth at the time of the slew maneuver. The large red circle and smaller black circle are the sun and moon constraints, respectively. The maroon path is the great-circle distance between the two targets on the sky, and the brown path is the only safe *Swift* slew maneuver between the two at that time.

Constraint Modeling with ML

With 13 years of empirical data (~350,000 individual observations) to train on, ML methods are the appropriate tool for building better models of many of the spacecraft constraints, particularly temperature, and momentum. Preliminary results show:

- Increase of ~13% in accuracy of temperature prediction over previous (linear) model with a LSTM network consisting of 6 input nodes, 3 hidden layers of 40 nodes each, and two output nodes.
- Longer periodicity trending in momentum than previously known, still under investigation.

PPST Simulation via SAT Solver

The scheduling problem was reduced to the form of a Boolean Satisfiability Problem (SAT) and the open-source MiniSAT (N. Een et al.) solver was adapted to the problem at hand. This was used to run large sets of PPST-build simulations under various scenarios, yielding target scheduling heuristics for different classes of PPSTs.

Conclusions

Given the number and complexity of the dynamic constraints, it is not possible to find the strictly optimal PPST that solves the traveling salesman problem in the necessary time frame. A combination of SAT solver, genetic algorithms, improved constraint modeling through machine learning with RNNs, and heuristics derived from long-run-time PPST simulations is the required approach. Moreover, the challenge of PPST creation and optimization can often be made significantly easier with an *intelligent* long-range planning system. This is in development.

References

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Acknowledgements

This work was performed at Penn State's *Swift* Mission Operations Center under support from the NASA *Swift* contract NAS5-00136. The author thanks his colleagues on the *Swift* FOT for their help in better understanding the spacecraft health & safety constraints, and Alex Ledger for useful discussion pertinent to algorithmic optimization.