Jet Propulsion Laboratory
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Estimating Time to Image Areas with Steerable 2D Framing Sensors

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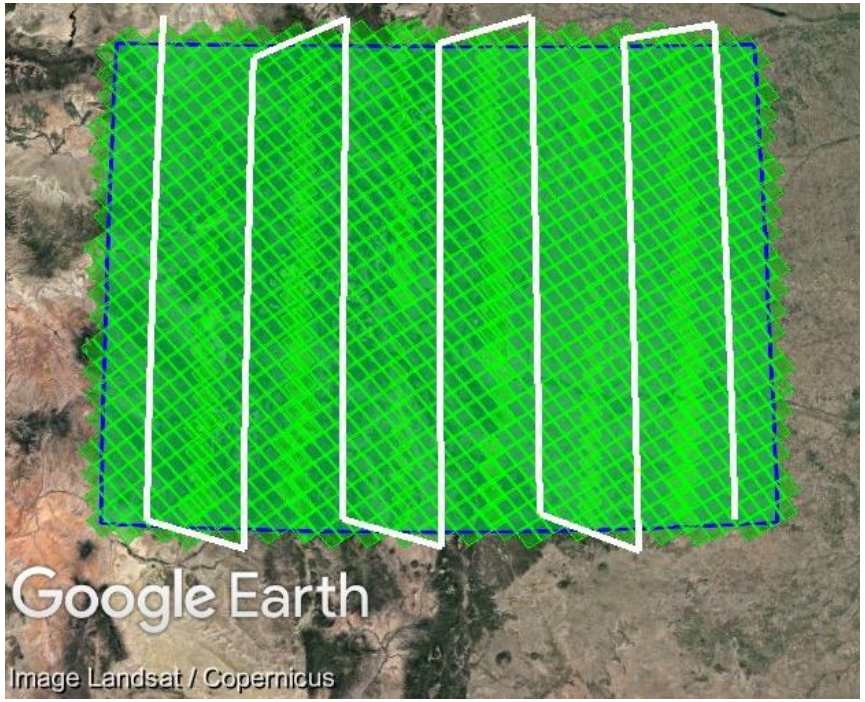
Tile decompositions are slow

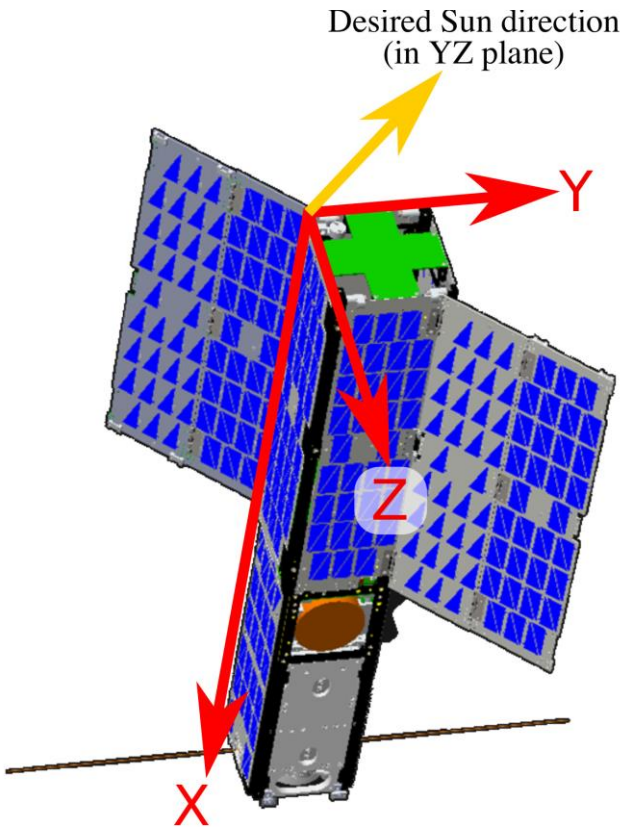
This tile coverage plan



required **50.3** seconds runtime to compute.

- Surface intercepts
- Constraint checks

for a steerable 2D framing sensor



Hayden, I. 2013. ALL-STAR structure overview. Image courtesy Colorado Space Grant Consortium. Used with permission.

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Motivation: higher level schedule optimization

- Problem: optimization requires comparing different schedule times.
  - n^3 permutations for n area observations if we use insertion search with time propagation
  - n=10 requests would need 14 hours runtime
- Approximation: use a heuristic
  - Defer tiling until the very end
  - Make a guess of total schedule time and memory needed to satisfy the tiling, reserve as a block
  - Faster to compute: 50.3s → 0.0053s

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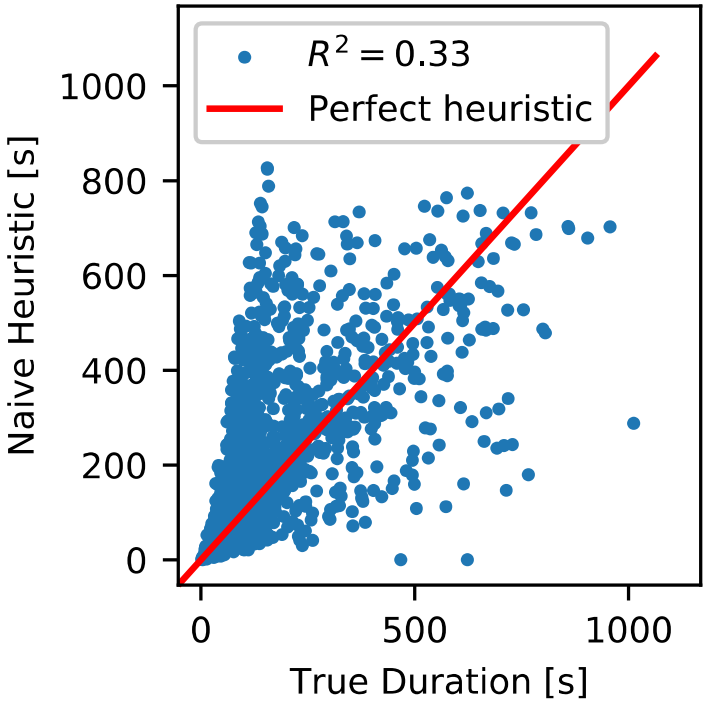
But heuristics can be tricky…



The Naïve Heuristic is a poor predictor of actual spacecraft resources needed.

Naïve Heuristic (area ratio):

$$n_{\text{tiles}} = \frac{a_{\text{target}}}{a_{\text{IFOV}}\left(t_{\text{center}}\right)} \frac{c_{\text{images}}}{\text{tile}}$$

Memory:

$$m\left(t_{\text{center}}\right) = c_1 n_{\text{tiles}} \frac{m_{\text{bits}}}{\text{image}}$$

Duration:

$$d\left(t_{\text{center}}\right) = c_2 n_{\text{tiles}} \frac{\Delta t}{\text{image}}$$

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Outline

- Formulation
- Methodology/Experiment
- Results
- Recommendations for future work
- Conclusion

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Formulation

Duration and memory are still quantities to be estimated

$$d = f_d\left(t, \mathrm{target}, \mathrm{observer}, \mathrm{algorithm}\right)$$
$$m = f_m\left(t, \mathrm{target}, \mathrm{observer}, \mathrm{algorithm}\right)$$

... just do it less naively.

- Exhaustively sample the system
- Choose better features
- Machine learning to discover the model

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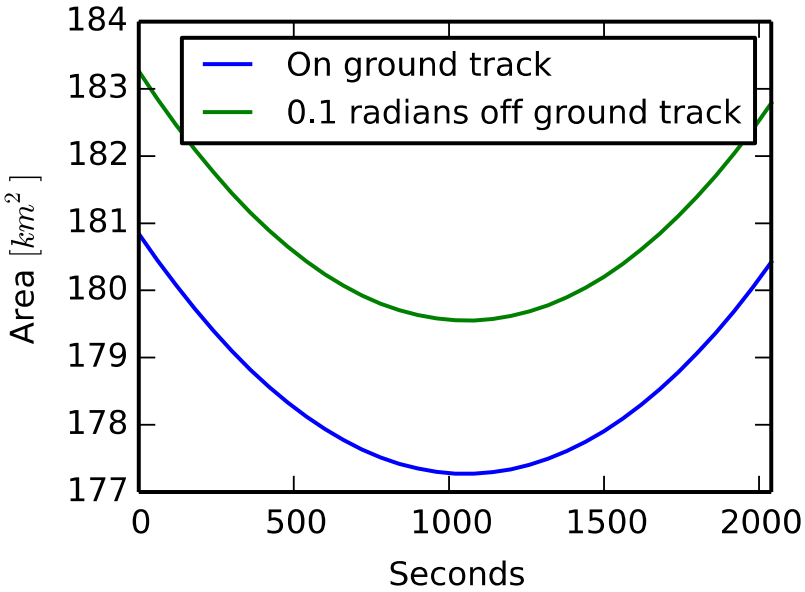
Tile area changes over time

Choose better features: domain-specific insight



- Relative motion and rotation between the observer and the target
- Also sensitive to off-nadir angle (skew effects)

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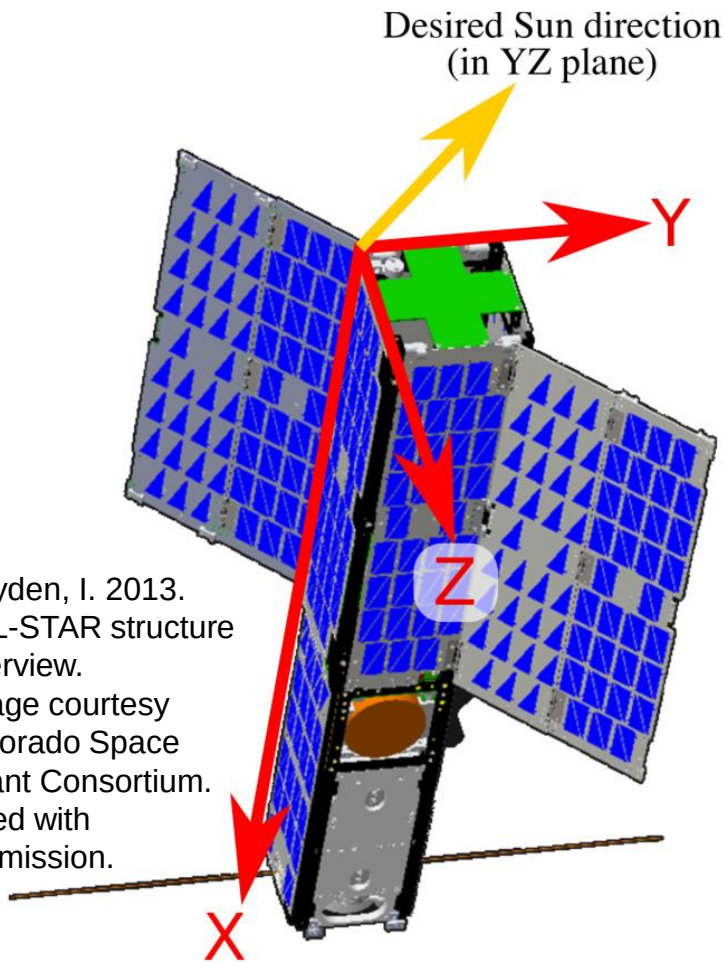
Solar orientation policies

Choose better features: domain-specific insight



Hayden, I. 2013. ALL-STAR structure overview. Image courtesy Colorado Space Grant Consortium. Used with permission.

- The Sun moves relative to the observer
- Ideal solar alignment may cause poor tiling
- Possible features: solar elevation angle, phase angle

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Geometric features

Choose better features

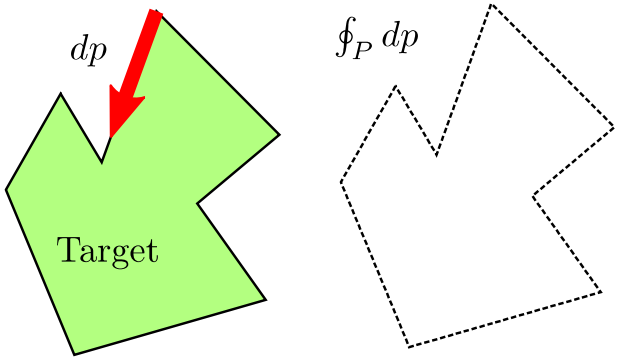
- Point
  - Off-nadir angle
  - Solar off-zenith angle
  - Cross-track angle
  - Along-track angle
- Area
  - Target area a
  - Instrument tile area derivative

$$\dot{a}_{\mathrm{IFOV}}$$

- Perimeter-based
  - Inspired by Greene's theorem: trace perimeter
  - Slew time line integral

$$\oint_P dt_{\mathrm{slew}}$$

  - Instrument tile area line integral $\oint_P da_{\mathrm{IFOV}}$



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Computational complexity of features

Feature	Complexity
Off nadir angle	$O(1)$
Solar off-zenith angle	$O(1)$
Cross-track angle	$O(1)$
Along-track angle	$O(1)$
$\oint_P da_{\mathrm{IFOV}}$	$O(\lvert p \rvert)$
$\oint_P dt_{\mathrm{slew}}$	$O(\lvert p \rvert)$
Polygon area a	$O(\lvert p \rvert)$
$\dot{a}_{\mathrm{IFOV}}$	$O(1)$

- All time-varying except target polygon area a
- p: number of vertices in target polygon

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Machine Learning Models Considered

- Ordinary Least Squares

$$\underset{\theta}{\operatorname{argmin}} \sum_i (\langle x_i, \theta \rangle + \beta - y_i)^2$$

- Support Vector Regression (Smola and Vapnik 1997)
  - Linear kernel
  - Radial Basis Function (RBF) kernel

- Empirical Conditional Expectation

$$\mathbb{E}(Y|\theta, \phi) = \sum_{y \in \mathcal{D}} y \hat{p}(y|\theta, \phi)$$

- Generalized Regression Neural Networks (Specht 1991)

$$f(x|X, Y) = \frac{\sum_i^n y_i \exp\left(-\langle x - x_i \rangle / 2\sigma^2\right)}{\sum_i^n \exp\left(-\langle x - x_i \rangle / 2\sigma^2\right)}$$

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Experiment

Corpus (white circles)

- Random (uniform) sampling of 2000 target polygons
  - Center location
  - Area U(0,10000 km^2)
- Sample the system
  - Compute detailed tiling
  - Record features X at
  - Measure response variables Y=(d,m) after scheduling
- Produce models Y=f(X)
- Evaluate models
  - 60 iterations random subsampling, 80%/20% training/test split (Han and Kamber 2006)

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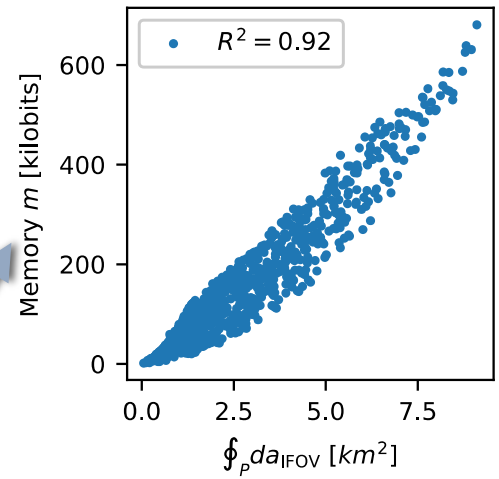
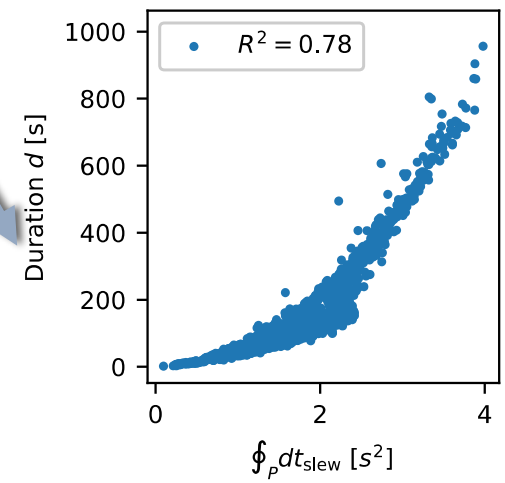
Results

Good Features

Table 2: Coefficients of Determination

Feature	Duration	Memory
Area line integral	0.89	0.92
Slew line integral	0.78	0.81
Off-nadir angle	0.43	0.44
Area	0.32	0.33
$\dot{a}_{\mathrm{IFOV}}$	0.12	0.12
Along-track angle	0.08	0.07
Solar emission angle	0.07	0.07
Cross-track angle	0.00	0.00





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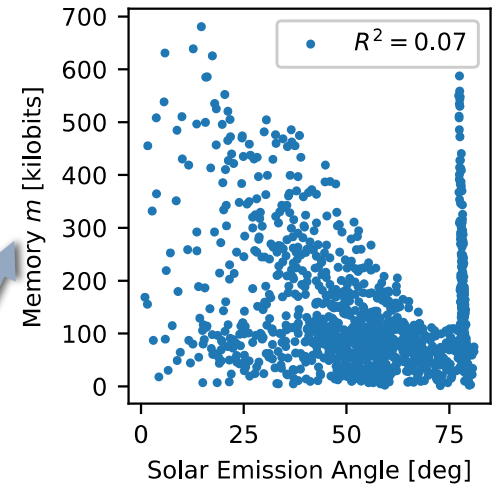

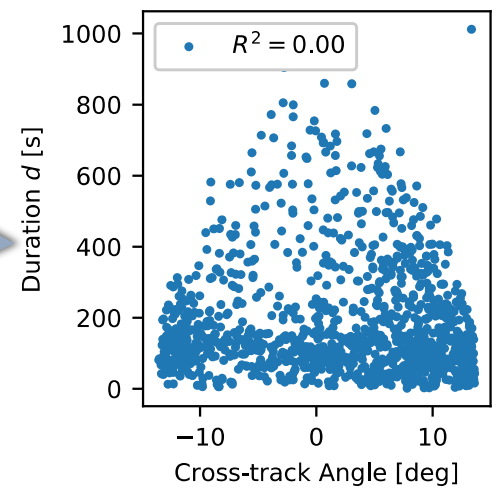

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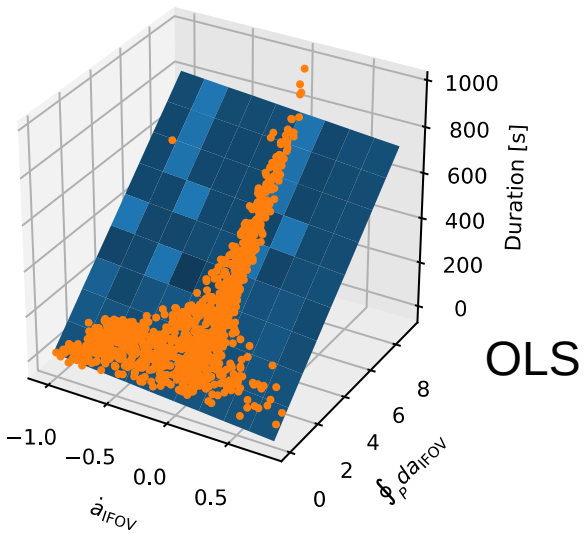
Results

Model Comparison

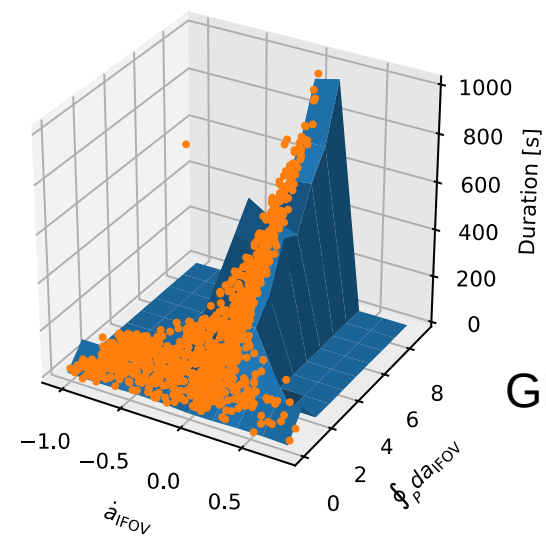
- GRNN, OLS, SVR have similar accuracy
- ECE and Naïve heuristic are least accurate

Table 3: Mean error (μ) and RMSE (σ) of models in estimating duration, features: $\dot{a}_{\mathrm{IFOV}}$, $\oint_P da_{\mathrm{IFOV}}$.

Model	Train μ	Train σ	Test μ	Test σ
OLS	0.00	55.61	-0.65	54.88
Linear SVR	-3.82	55.62	-3.66	57.60
RBF SVR	-2.23	52.83	-3.26	52.59
ECE	0.00	37.48	4.24	81.23
GRNN	1.44	48.00	1.31	52.56
Naive	0.00	0.00	51.81	173.02



OLS



GRNN

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Comparing different feature sets

Table 5: Mean error (μ) and RMSE (σ) of OLS models by feature set (test only).

Feature Set	Duration [s]		Memory [kbits]	
	μ	σ	μ	σ
$\dot{a}_{\mathrm{IFOV}}$, $\oint_P da_{\mathrm{IFOV}}$	-0.01	54.94	0.23	34.28
$\dot{a}_{\mathrm{IFOV}}$, $\oint_P da_{\mathrm{IFOV}}$, $\oint_P dt_{\mathrm{slew}}$	0.52	45.65	0.08	24.84
Off nadir angle, $\oint_P dt_{\mathrm{slew}}$	0.07	61.44	-0.05	40.02
Off nadir angle, Solar angle, $\oint_P dt_{\mathrm{slew}}$	0.23	61.64	-0.32	40.11
$\dot{a}_{\mathrm{IFOV}}$, $\oint_P dt_{\mathrm{slew}}$	-0.17	70.81	0.12	49.65
Off nadir angle, Solar angle	-0.89	126.55	-1.07	92.42
Cross-track angle, Along-track angle	1.93	163.59	-1.47	117.80

- The most accurate OLS model used both of the perimeter integral features
- Even adding only one perimeter integral was significantly better than using all constant-time features

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Recommendations for Future Work

- Metaheuristics/portfolio approach (Engelhard and Chien 2000, Cowling, Kendall and Soubeiga 2000).
  - Make more models from more features
  - Choose the model(s) most likely to succeed for the observational being estimated
- Examine log-features
  - Area is quadratic, so log(area) may linearize better
  - May provide better fits for OLS models

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Conclusions

- All machine learning models were more accurate than the naïve heuristic
- Worst: Empirical Conditional Expectation (ECE)
- Best: Generalized Regression Neural Network (GRNN)
  - Slowest to generate and evaluate
  - Recommend GPU or other specialized hardware
- Least Squares (OLS) is probably good enough
  - Faster to generate and evaluate
  - Less complicated to implement, no special hardware

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