# Adaptive Subsampling of Temporal Image Sequences

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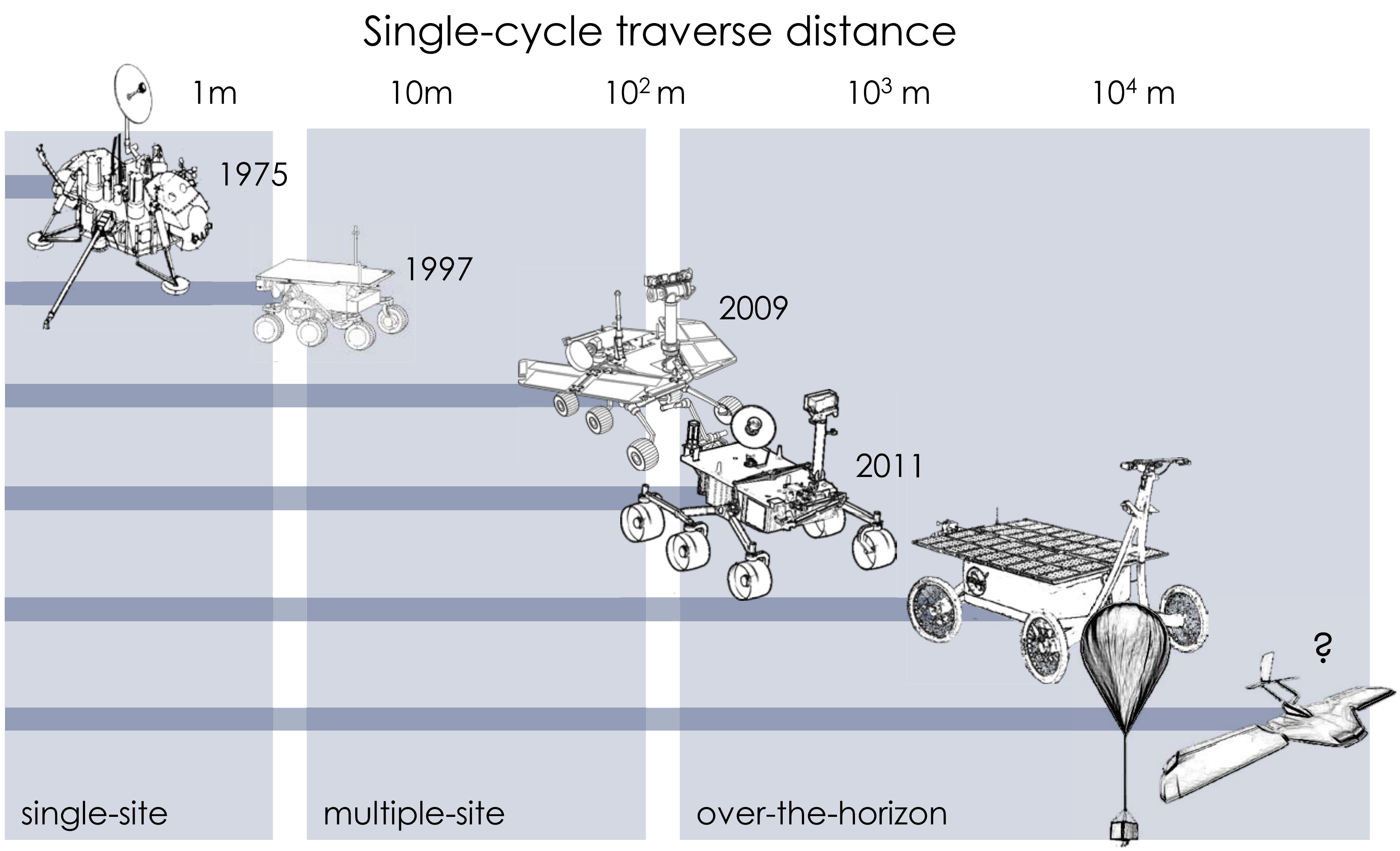
Images courtesy NASA / Caltech JPL / Carnegie Mellon University. This work performed with Carnegie Mellon University, supported by a JPL Strategic University Partnership Grant. Additional support from NASA ASTEP NNG0-4GB66G "Science on the Fly"

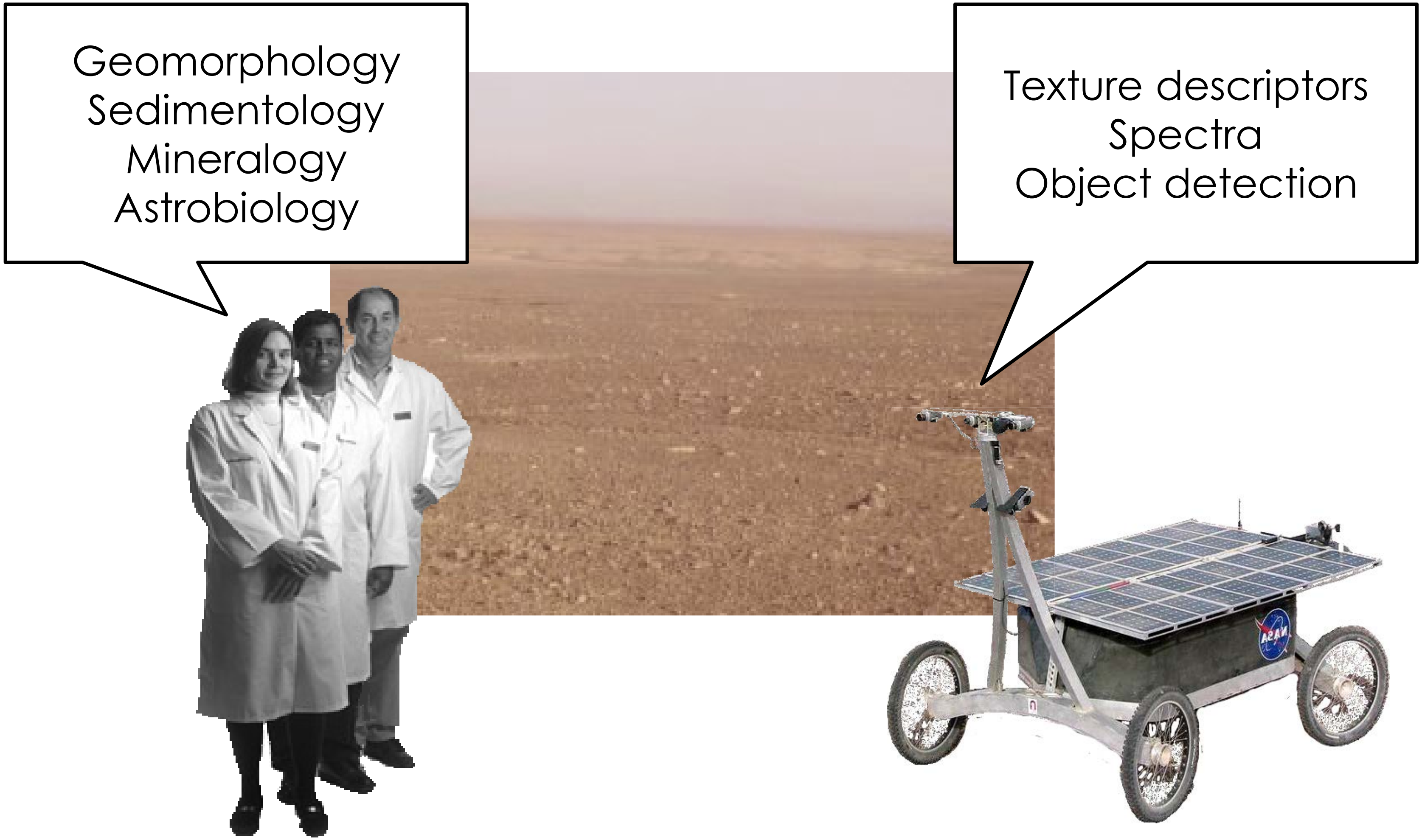
# Agenda

- Motivation: autonomous science for robotic exploration
- Previous work in subsampling image sequences
- A new approach with Gaussian Processes
- Field Trials

# Why subsample image sequences?



# The perception gap



# Information optimal subsampling

- Find subset that provides the most information about the science content of *unreturned* images
- Mutual Information Criterion
- Gaussian process model
- Closed-form analytical expression
- *Does not* require that the robot know the hidden science content!

# A Gaussian Process Primer

- Bayesian Nonparametric Regression

$$f(\mathbf{x}) : \mathbb{R}^n \mapsto \mathbb{R}.$$

- Posterior probability of observations is a multivariate Gaussian

- Entries of covariance matrix are given by a *covariance function*:

$$\kappa(\mathbf{x}_i, \mathbf{x}_j) = \psi_1 + \psi_2 \exp\left\{-\frac{1}{2}\sum_{k=1}^{d}\frac{(x_{ik} - x_{jk})^2}{w_k^2}\right\}$$

# Mutual Information Objective

- Maximize mutual information between returned and unreturned data.

$$I(\mathbf{s}_U;\mathbf{s}_O \mid \mathbf{s}_L,\theta) = h(\mathbf{s}_O \mid \mathbf{s}_L,\theta) + h(\mathbf{s}_U \mid \mathbf{s}_L,\theta) - h(\mathbf{s} \mid \mathbf{s}_L,\theta)$$

$$= \frac{1}{2}\log\frac{2\pi e^m|\kappa(\mathbf{X}_O,\mathbf{X}_O| \;\; 2\pi e^{n-m}|\kappa(\mathbf{X}_U,\mathbf{X}_U)|}{2\pi e^n|\kappa(\mathbf{X},\mathbf{X})|}$$

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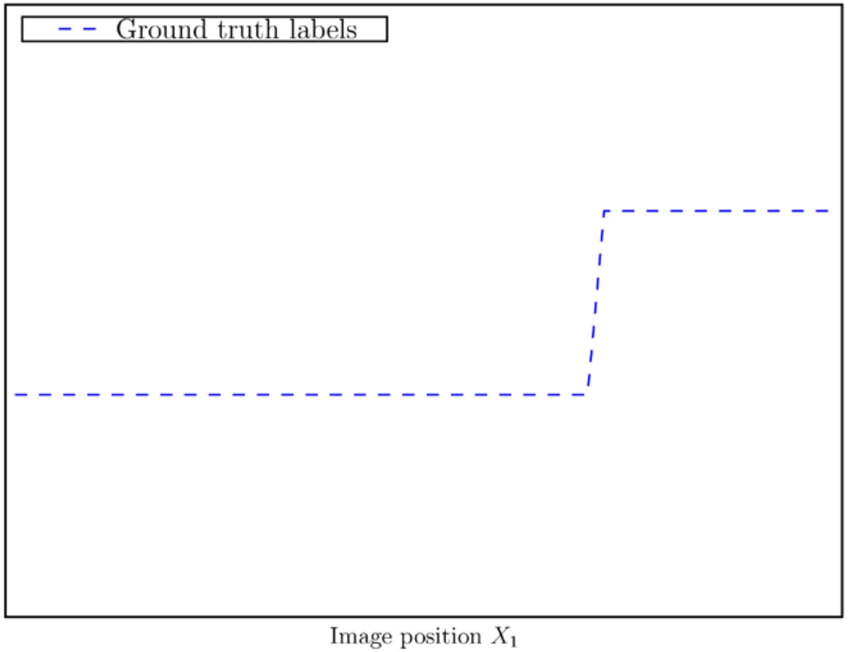
$$= \frac{1}{2} \log \frac{2\pi e^m |\kappa(\mathbf{X}_O, \mathbf{X}_O)| \, 2\pi e^{n-m} |\kappa(\mathbf{X}_U, \mathbf{X}_U)|}{2\pi e^n |\kappa(\mathbf{X}, \mathbf{X})|}$$

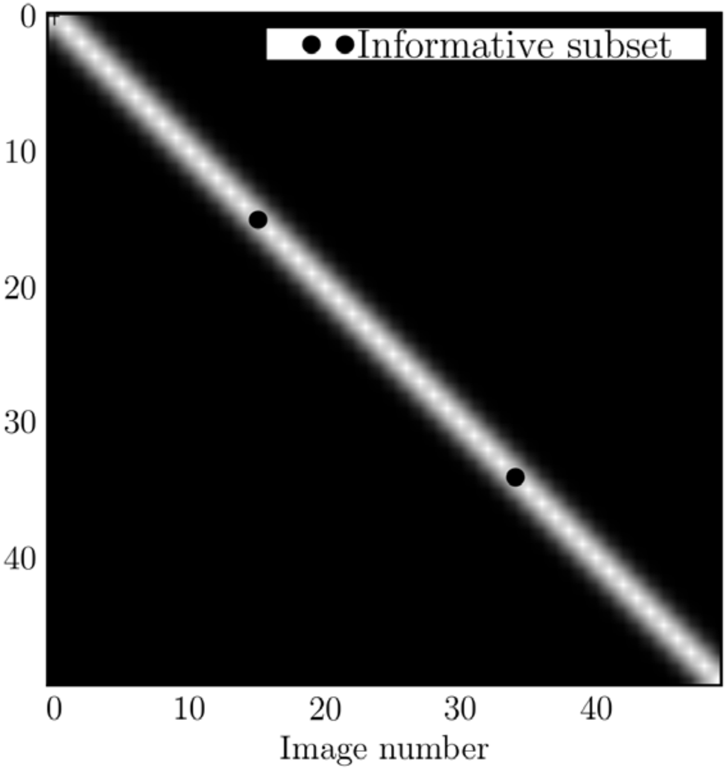
returned total unreturned

- Stationary covariance function: mutual information objective is **independent of images' contents**!

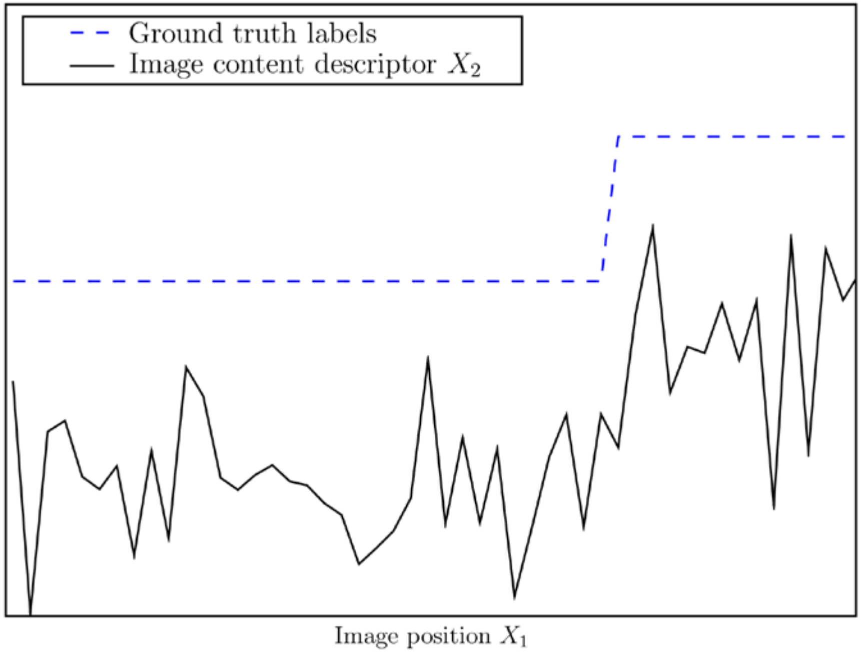
- **Use explorer's observations as latent inputs**, and learn how they correlate with changes in science content.

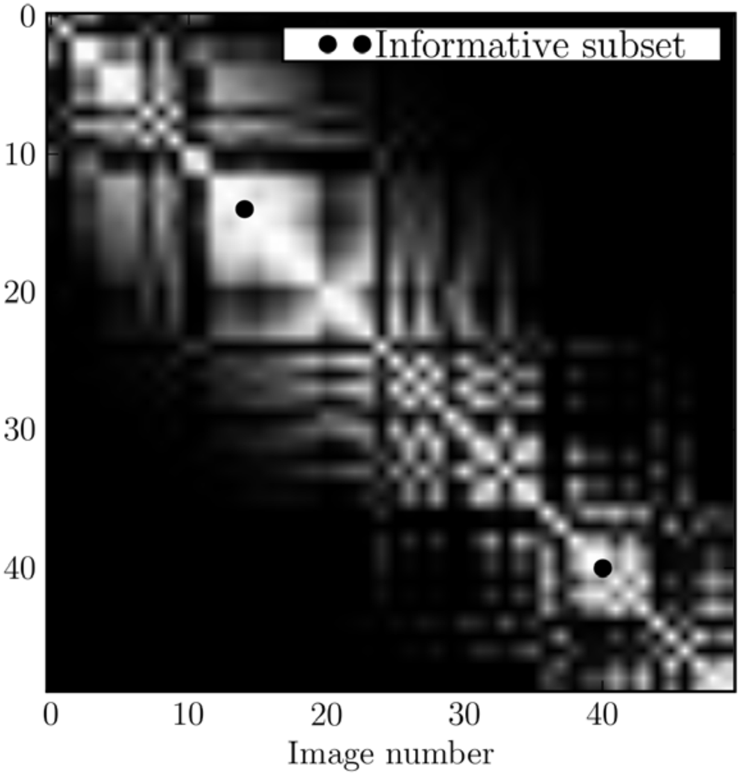
# Synthetic example observing only location



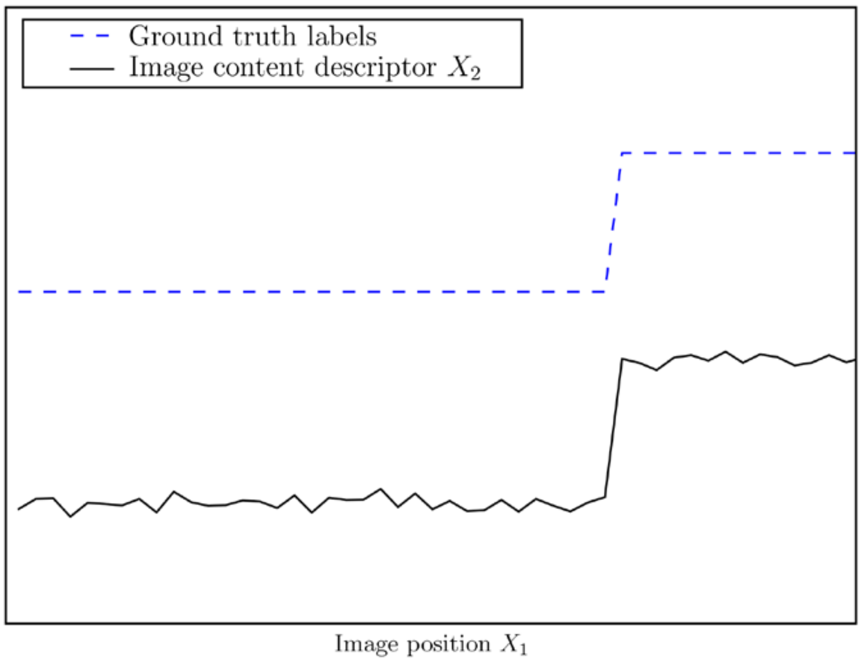



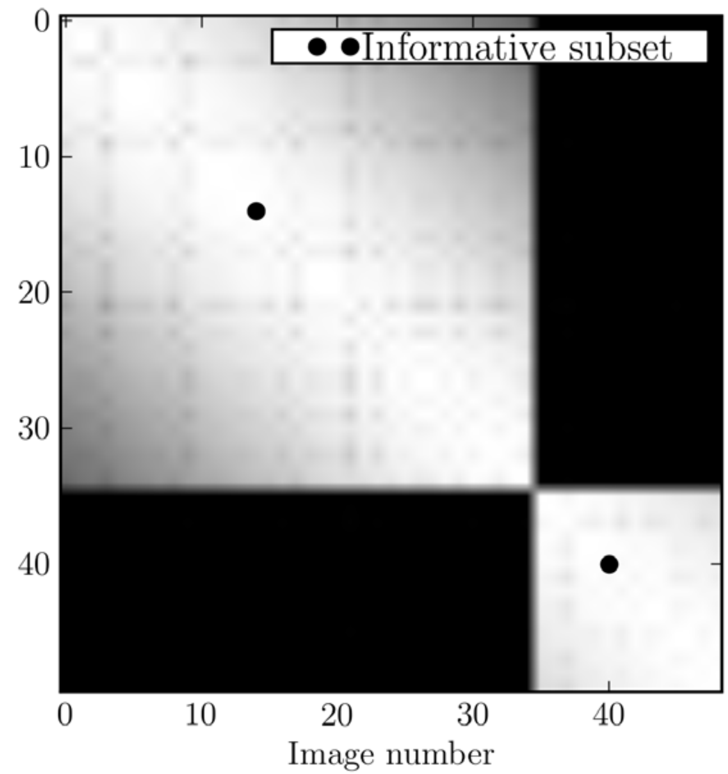
# Synthetic example observing location and one noisy feature



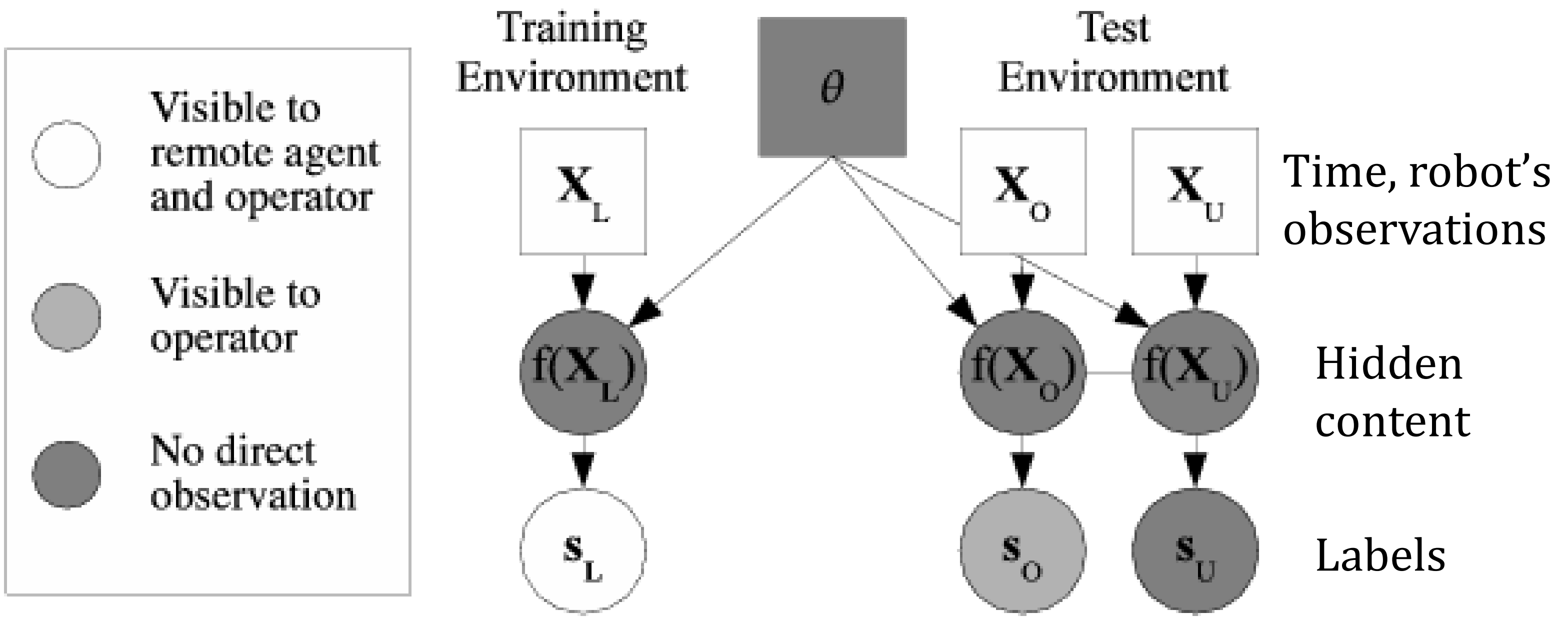



# Synthetic example observing location and one clean feature



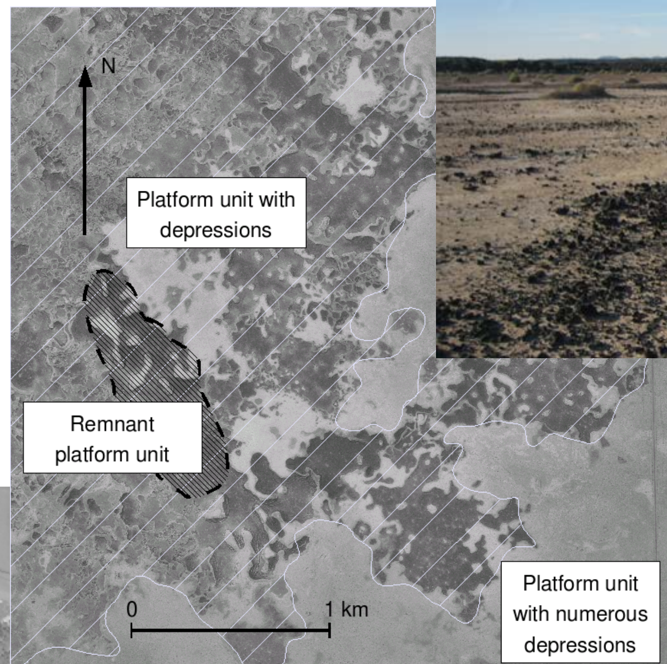



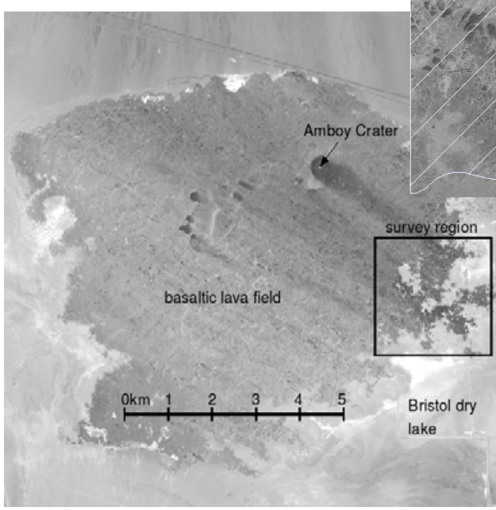
# Gaussian process model



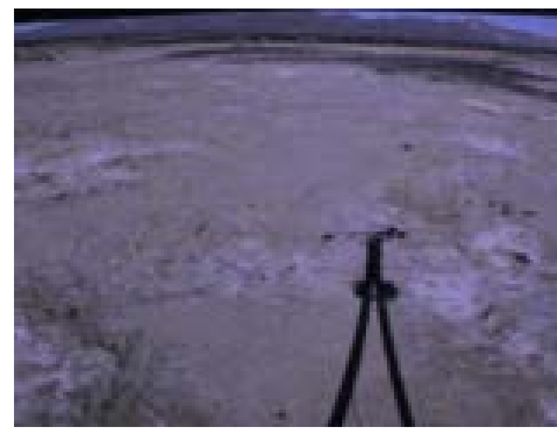

1. Learn θ from training data
2. Predict how new images differ in science content based on their separation in observable features

# Amboy Crater



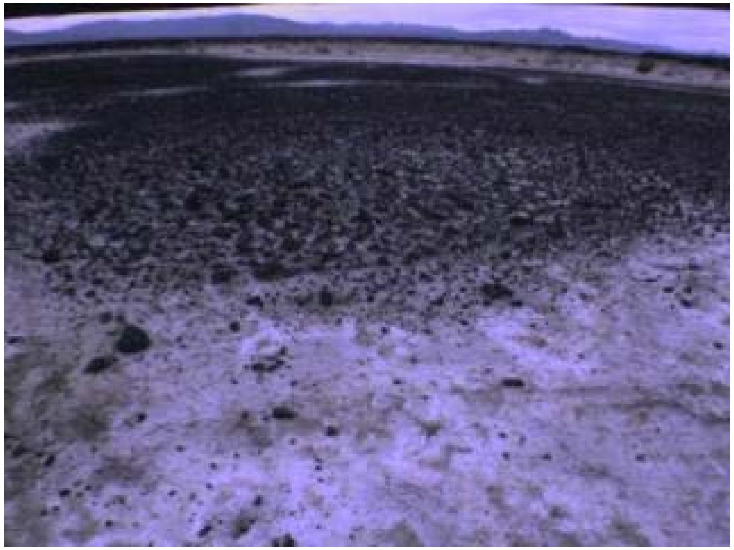



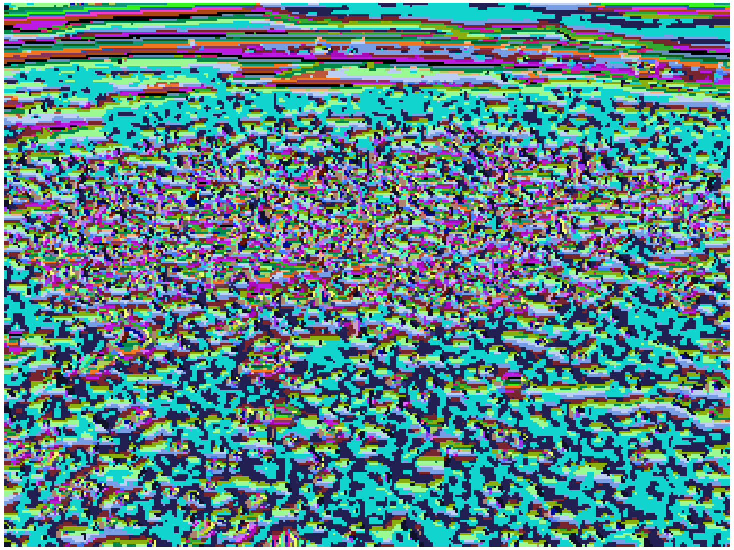

[Hatheway '79]



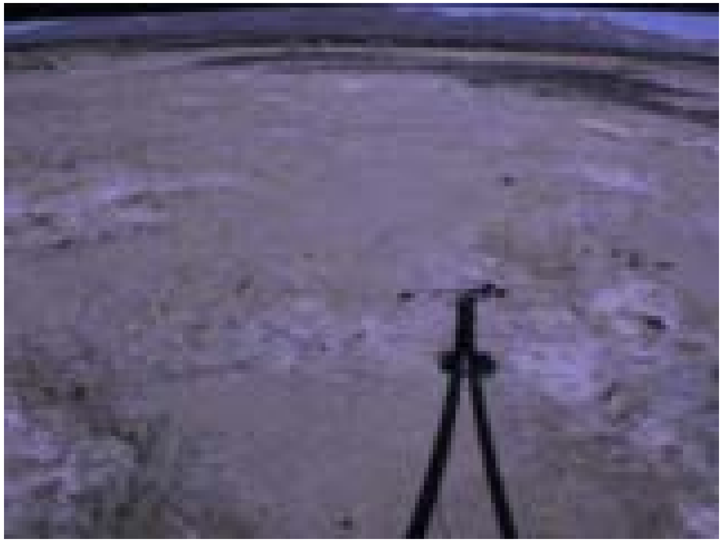
# Texton image features

- Discrete classification of each pixel into texture classes learned from a universal training set
- Here, PCA-project class histogram to a scalar





# Example



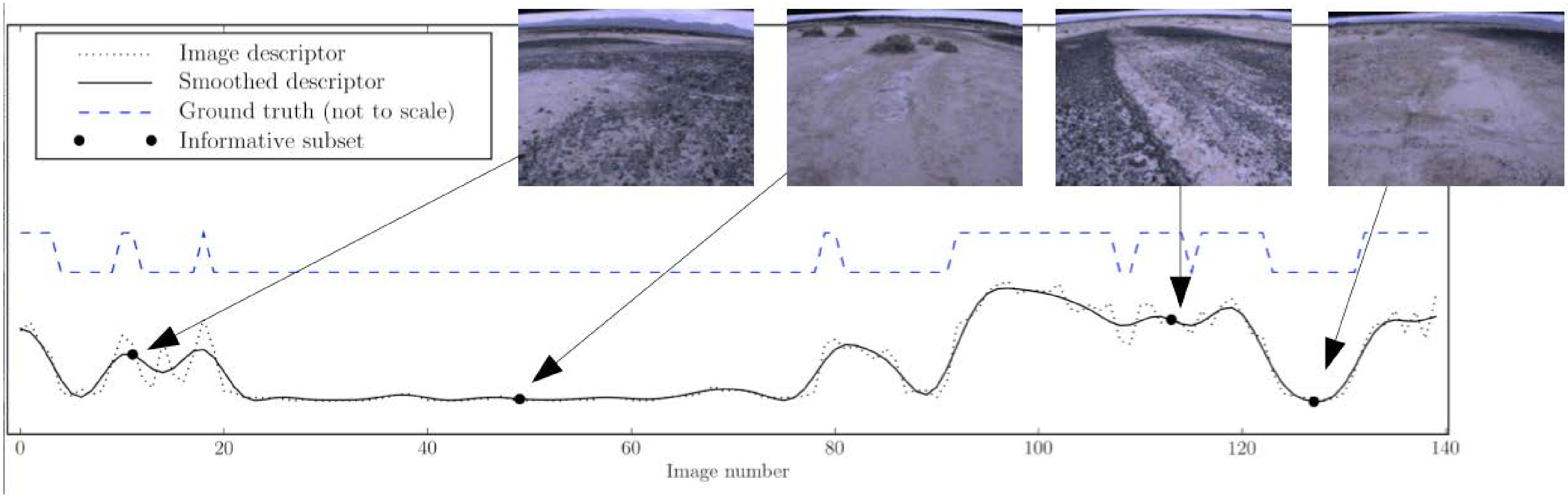
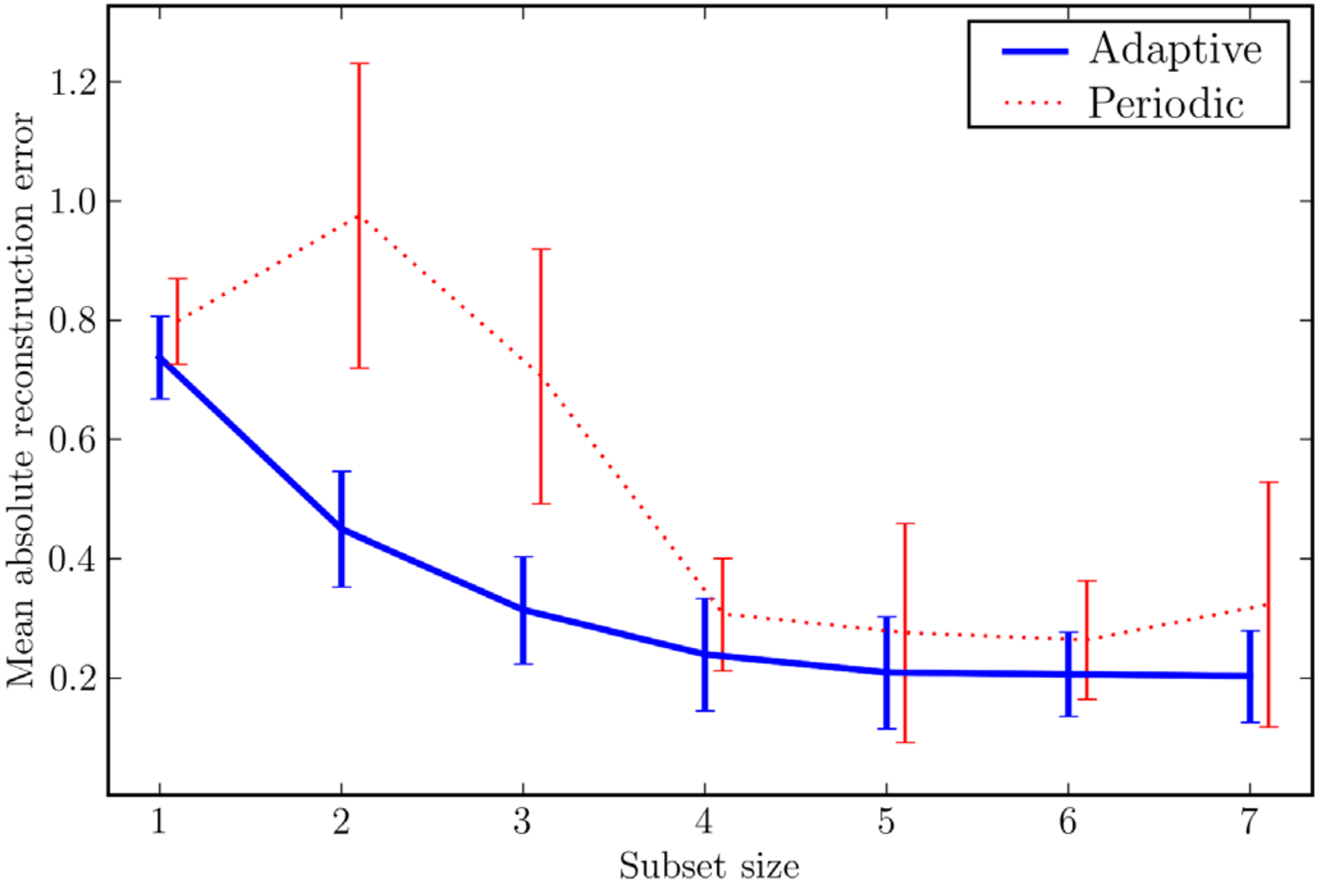
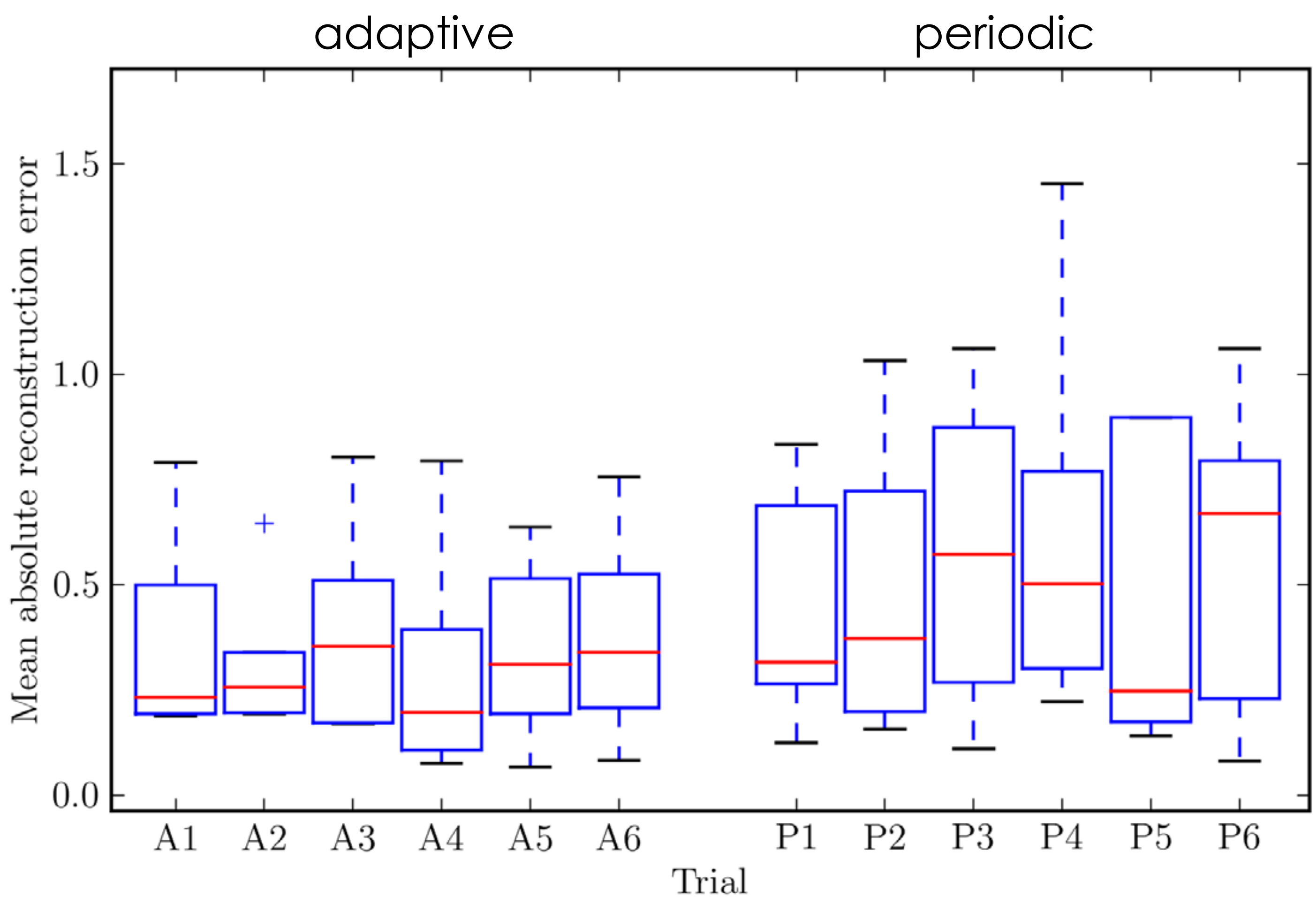


Image descriptor
Smoothed descriptor
Ground truth (not to scale)
Informative subset
0
20
40
60
80
100
120
140
Image number

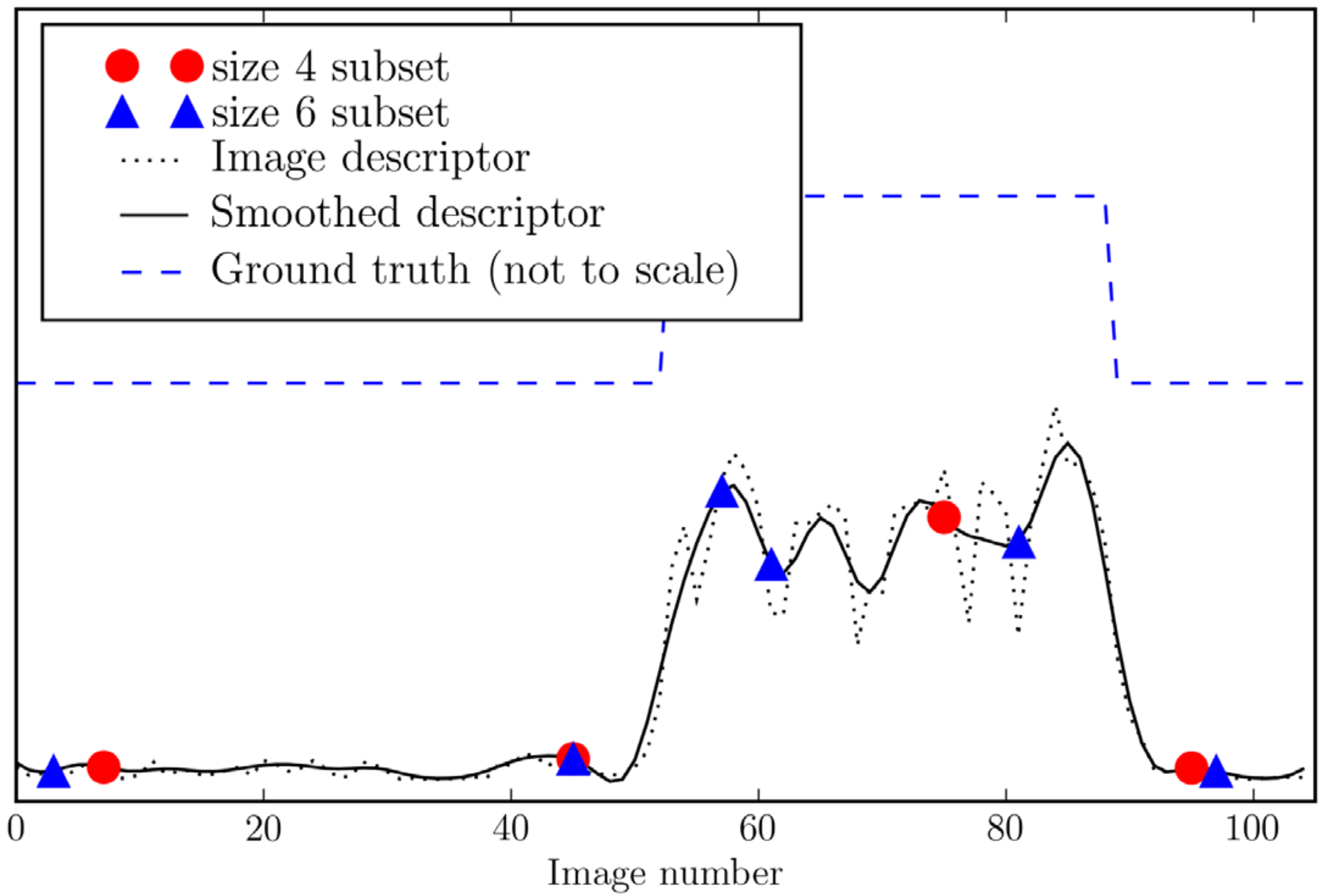
# Performance by image budget (lower is better)



# Performance by trial (lower is better)



# Effect of varying image budgets



# Conclusions: Information-theoretic formulation of selective image return

- Information-theory formulation of selective image return
  - Principled
  - Intuitive, reasonable results
  - Can leverage training data
- Stationary GPs
  - Elegant solution for Mutual Information Objective
  - Must describe content of interest as real-valued scalar (for now)

# Thanks!

- This work performed with Carnegie Mellon University, supported by a JPL Strategic University Partnership Grant.  Additional support from NASA ASTEP NNG0-4GB66G "Science on the Fly"
- Support from JPL Early Career Hire Grant
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