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Applications of Onboard Analytics and Machine Learning

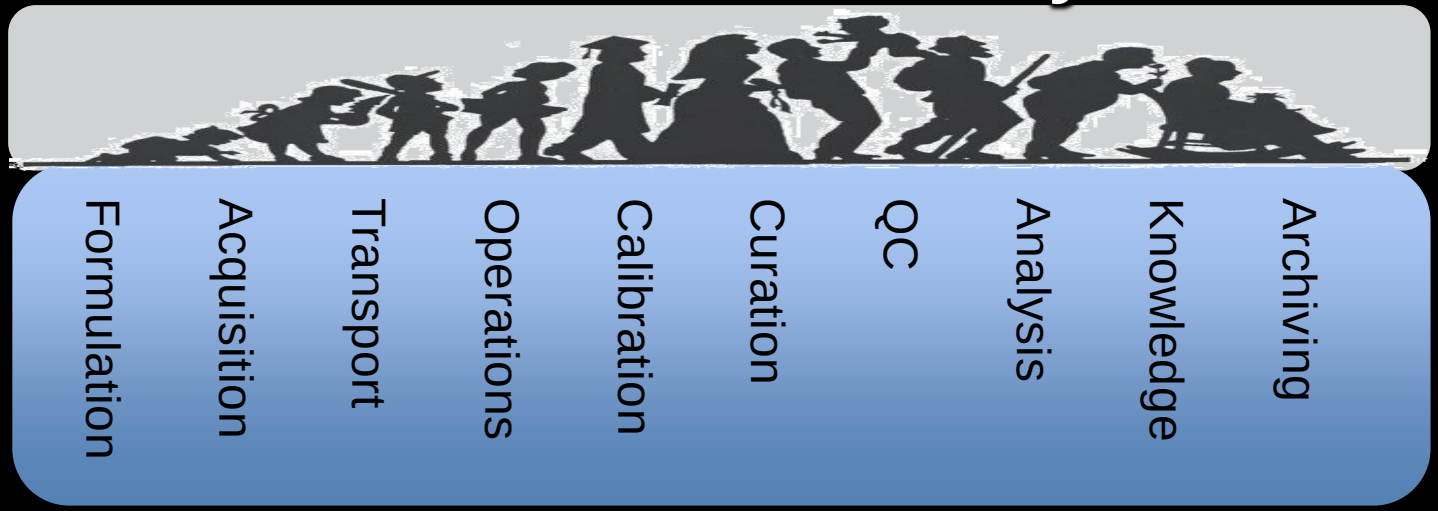
Jack Lightholder

On Behalf of the JPL Machine Learning and Instrument Autonomy Group

This research was carried out by the Jet Propulsion Laboratory, California Institute of Technology, under a contract with the National Aeronautics and Space Administration.

Jet Propulsion Laboratory
California Institute of Technology

Data Science Life Cycle



Historically…

Real-time reaction

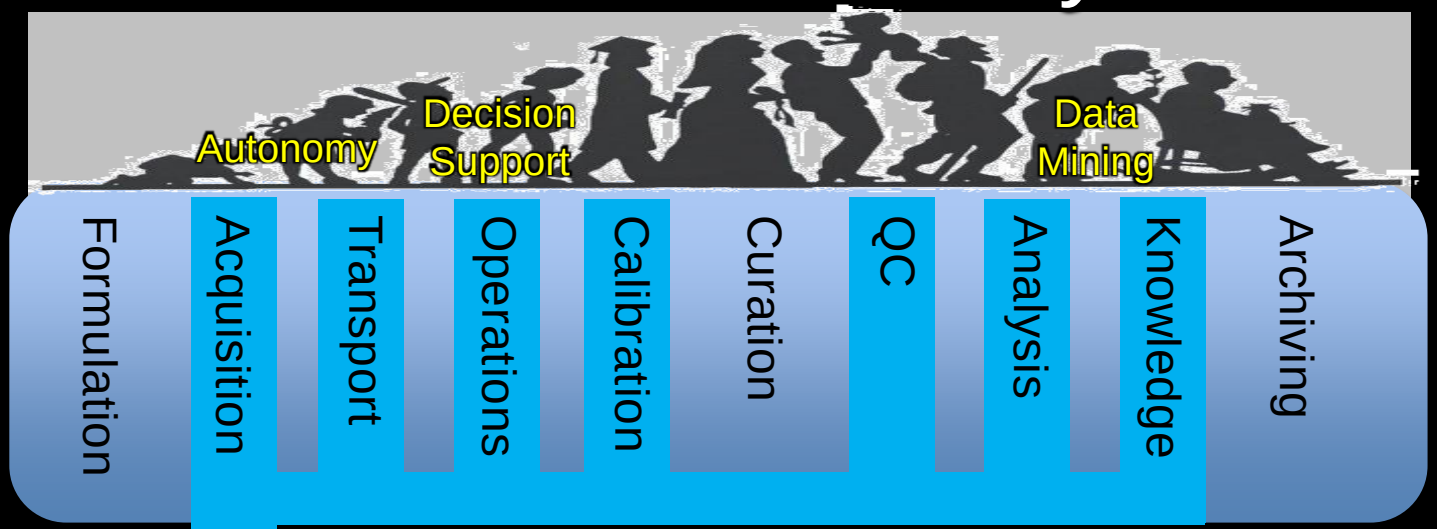
- Humans in the loop
- Fast & loose hand calculation
- Opportunity cost

Thorough Analysis

- Manual rigor
- Exhaustive exploration
- Human-time limited

Courtesy Dr. Lukas Mandrake, JPL

Data Science Life Cycle



- Quick Analysis
  - Quick Calibration
  - Quick QC
  - Quick Analysis
  - Quick Knowledge
- Annotate
- Advise / React
- Repeat

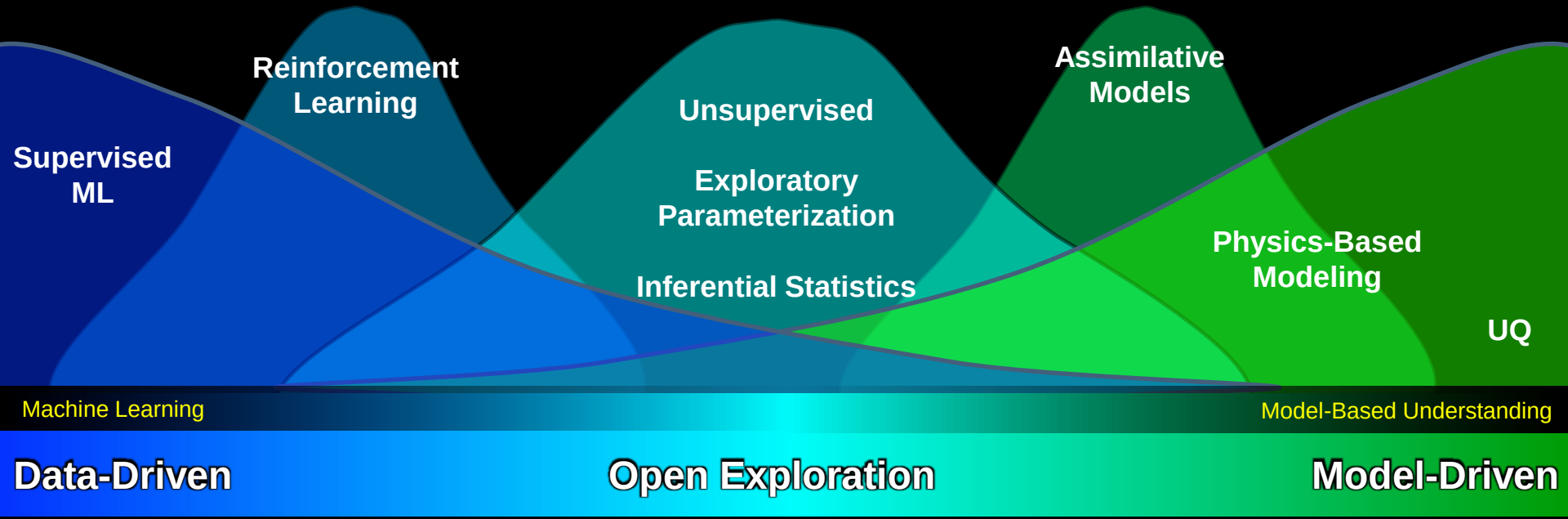
Quick-Look products enable earlier reaction

Advisory systems direct focus

Courtesy Dr. Lukas Mandrake, JPL

Data Science Technology Spectrum

Real-world systems often combine several techniques



Expert Knowledge in Data + Labels
Model (mostly) determined by D + L

Expert Knowledge in Model Details
Data refines model parameters

Courtesy Dr. Lukas Mandrake, JPL

What is Machine Learning?

Algorithms that inductively self-assemble from examples.

Expert Examples
(e.g. Estimates 1-10 of attractiveness of picture)

Training Data
(Encompasses domain of responsibility)

Functional System
- Interpretable as required
- Fixed code (V&V ready)
- Not ever-learning (mostly)
- **EASILY UPDATED**

Strength:
Don't specify rules Don't explain "how"

Machine Learning simplifies & systematizes the building and updating of Autonomy / Advisory systems

Courtesy Dr. Lukas Mandrake, JPL

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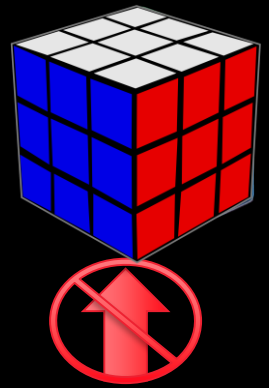

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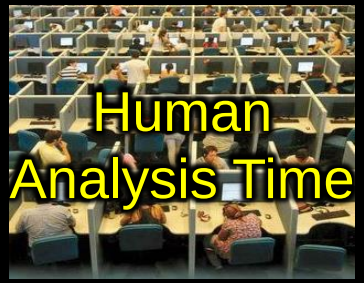
Courtesy Dr. Lukas Mandrake, JPL

When to Use ML / Autonomy?

Reaction Time

Human Decision Time



Courtesy Dr. Lukas Mandrake, JPL

ML ≠ Expert Replacement

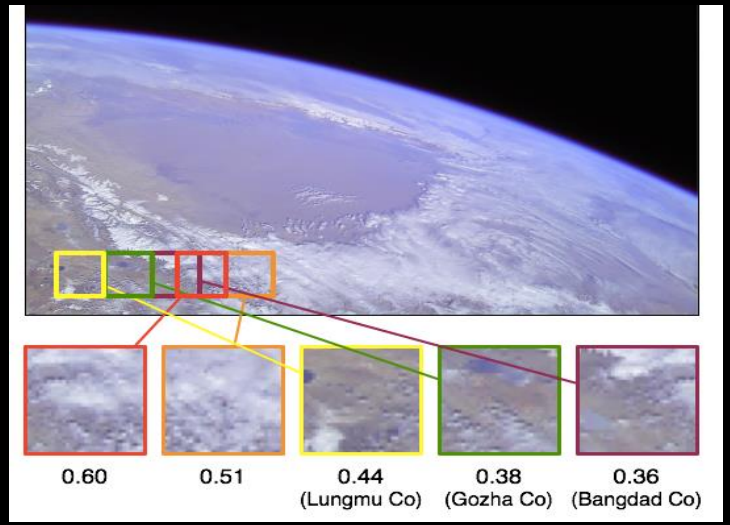
- Eliminates drudgery
- Operates impossibly fast
- Focuses experts on interesting cases
- Enables larger human feats

Data Science asks: “Would you like to have the same output with $^{1}/_{6}$ the experts or x6 the output with your current experts?”

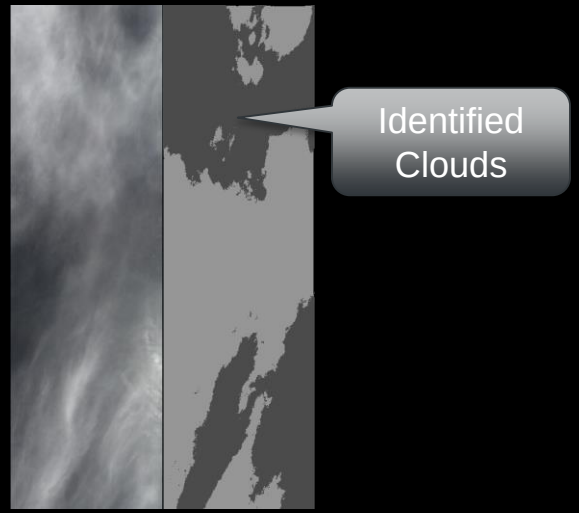
Courtesy Dr. Lukas Mandrake,

Low Earth Orbit Examples

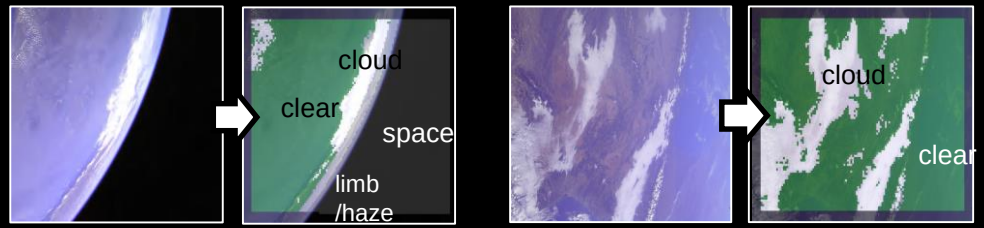
Detecting Features of Interest



Visual Salience: Identified areas of the image that differ from surrounding areas.



Preliminary Cloud Classification results from EO-1



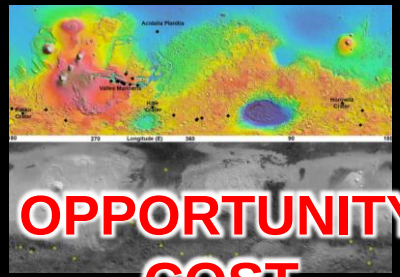
TextureCam: Pixel classification for cloud screening, downlink prioritization

[Chien et al. 2016 JAIS; Thompson et al., i-SAIRAS 2012; Wagstaff et al., *GRL* 2013; Bekker et al., *Astrobiology* 2014; Altinok et al. JFR 2015, Thompson et al. TGARS 2011]

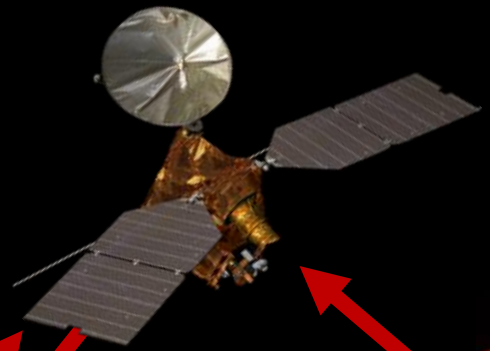
Current Model

On-board Processing
Observe, Thumbnails, transmit

Science Investigation
Manual Inquiry



OPPORTUNITY COST



OPPORTUNITY COST

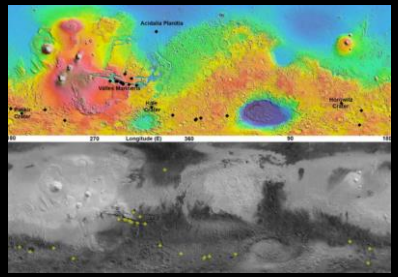
Martian Orbit
Unmapped / Changing Surface

Ops Decision Support
Host of Scientists, Manual Selection

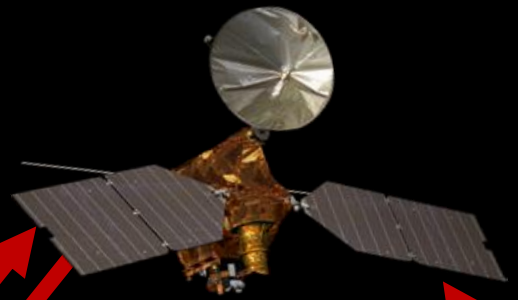
Courtesy Dr. Lukas Mandrake, JPL

Data-Driven Assistance

Science Support
Data Mining



On-board Science
Detect Transients, Summarize Content



Ops Decision Support
Focus of Attention Tools

Martian Orbit
Unmapped / changing surface

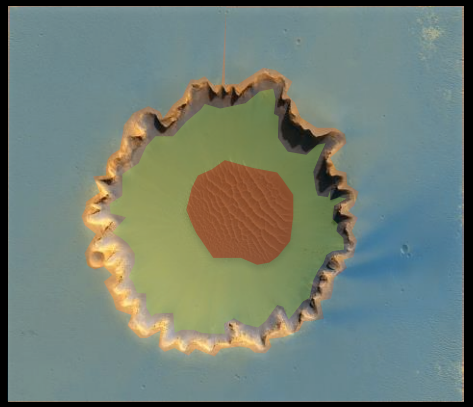
Courtesy Dr. Lukas Mandrake, JPL

Summarization Technology

Scene-Wide Labels

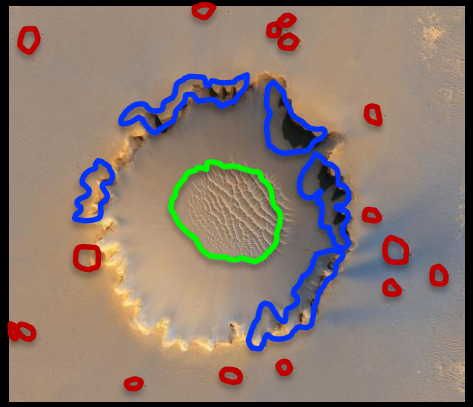
Scene Feature	Present
Dunes	**Yes**
Barchan Dunes	No
Small Craters	**Yes**
Large Craters	**Yes**
Fresh Impacts	No
RSL	No

Terrain Classification



Terrain Type	Image %
Flat Plain	50%
Crater Slope	25%
Dune Field	10%
Ridges	15%

Landmark Identification



Landmark Type	Number
Small Craters	16
Ridges	4
Dunes	1

Courtesy Dr. Lukas Mandrake, JPL

Landmark Recognition

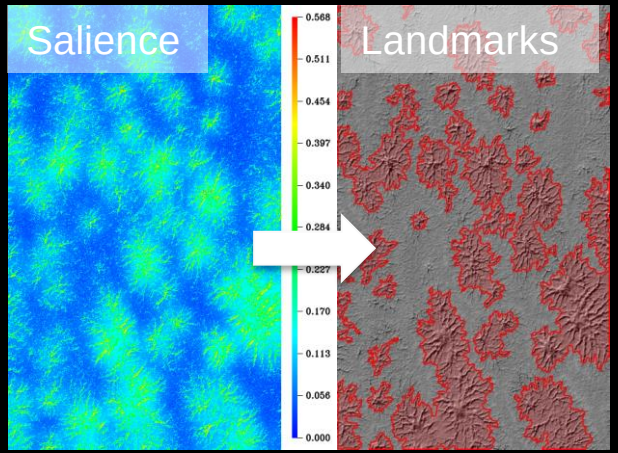
Drs. Kiri Wagstaff
Gary Doran
Ravi Kiran
Lukas Mandrake
Norbert Schorghofer
Alice Stanboli

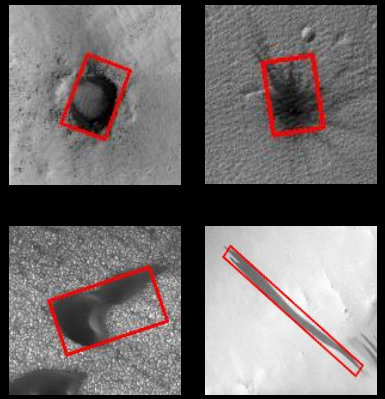
Techniques

- **Salience Estimation**
  - Created by Genetic Algorithm
  - Finds optimal blend of leading techniques
- **Landmark Classification**
  - Naïve Bayes
  - Support Vector Machines
  - Neural Network (deep learning)

Successfully ported to:

- PDS / Planetary Image Atlas
- IPEX: Atmel 400 MHz





Landmark Classification

Landmark Type	Number
Small Craters	16
Ridges	4
Dunes	1

Summarization

Scene Labeling

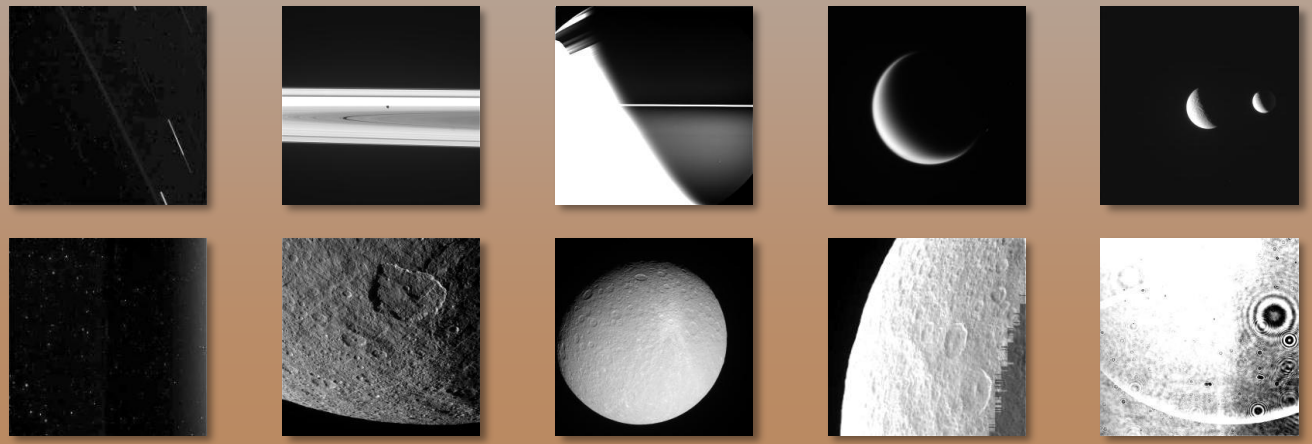
Drs. Alphan Altinok
Brian Bue
Alice Stanboli
Kiri Wagstaff

“Scalable Scene Analysis” System

- Convolutional Neural Network
- Implemented on PDS Atlas
- Currently trained for Cassini & MSL Images

craters transients rings surface horizon clouds plume
sky view starfield body types multiple objects phases
artifact eclipse haze over exposure noise ripple camera distance

19 categories – 53 labels



Terrain Classification

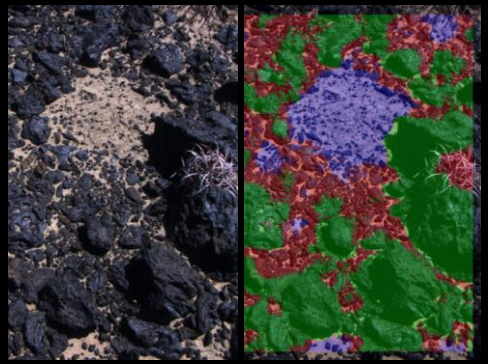
Drs. David Thompson
Alphan Altinok
Brian Bue
Gary Doran
Kiri Wagstaff

TextureCam System

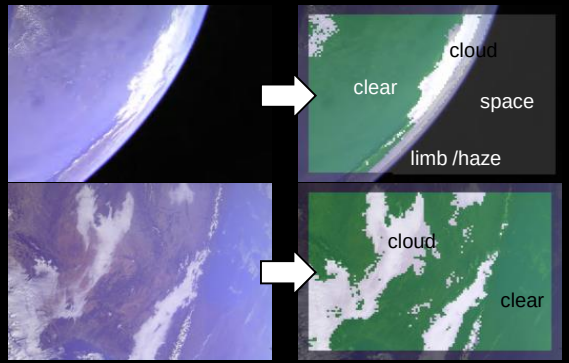
- Random Forest based pixel classifier
- Extremely fast & parallelizable

Successfully ported to:

- MSL VSTB Flight Testbed (RAD750) = ~100 HiRise images/day
- EO-1: Mongoose V (M5) processor
- IPEX: Atmel 400 MHz



Cima Lava Fields



IPEX Cube-Sat Feature Identification & Cloud Mask

Collaboration MLIA & MV

A Landed Mission Example

AEGIS

Autonomous Exploration for Gathering Increased Science

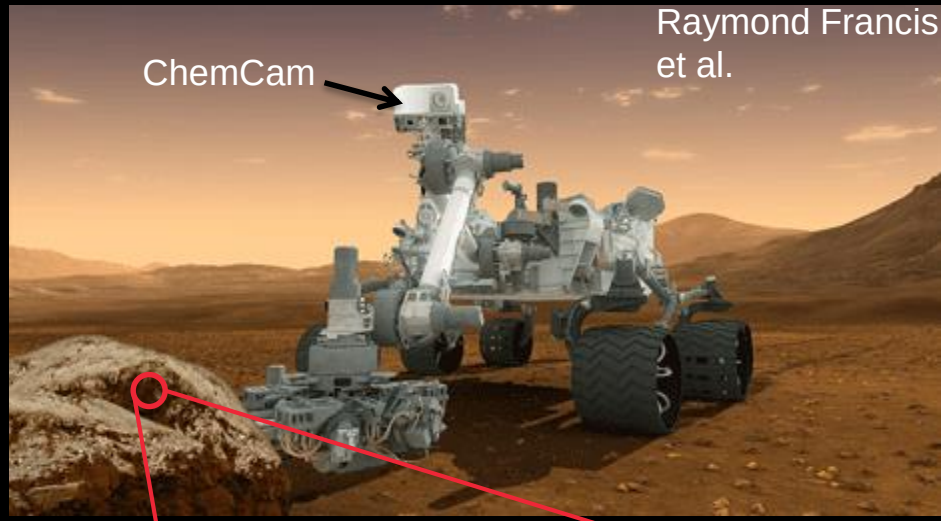
Drs. Tara Estlin
Dan Gaines
Gary Doran
Raymond Francis
et al.

- Target & Zap Rock
- Manually Scheduled Targets

- Round Trip Delays
- Trouble hitting 1st time
- Targeted science not possible right after drive

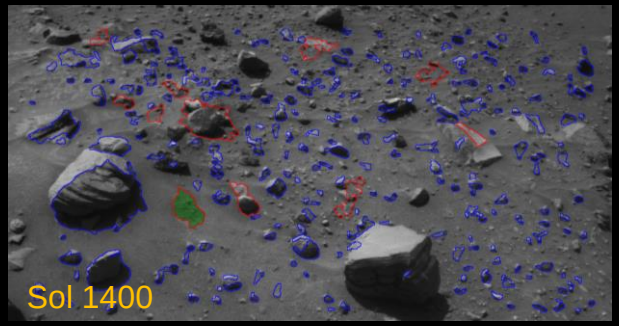
- Autonomy selects interesting targets
- Refines targeting automatically

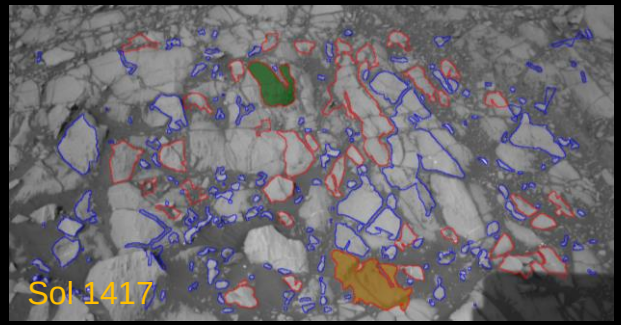
- ~30-100% additional ChemCam science targets on drive sols



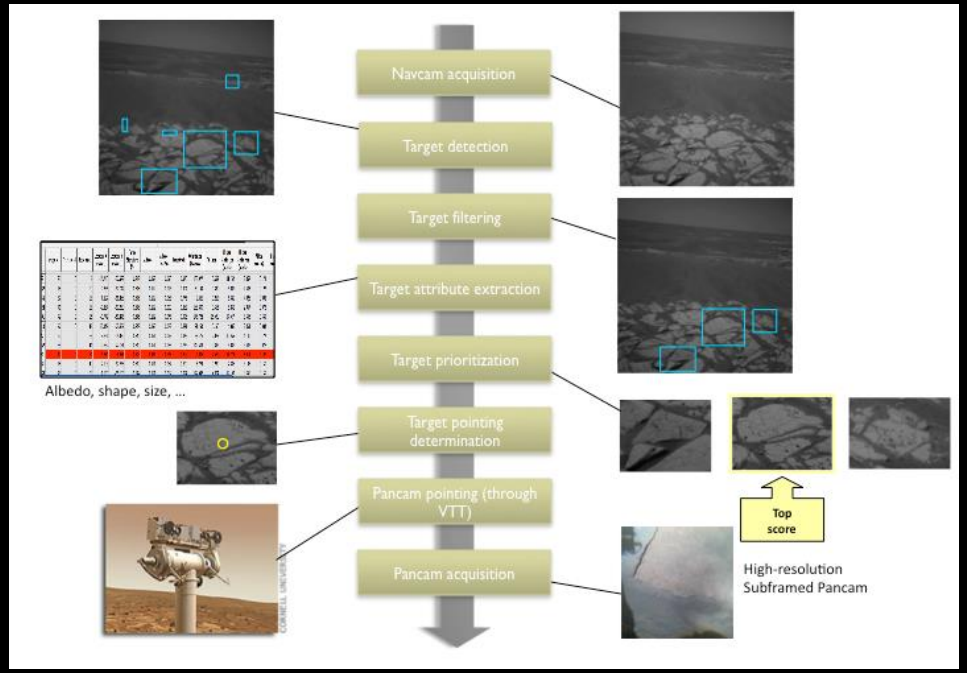
Mars Exploration Rover (2009)

Mars Science Laboratory (2012)





[Estlin et al. 2011]

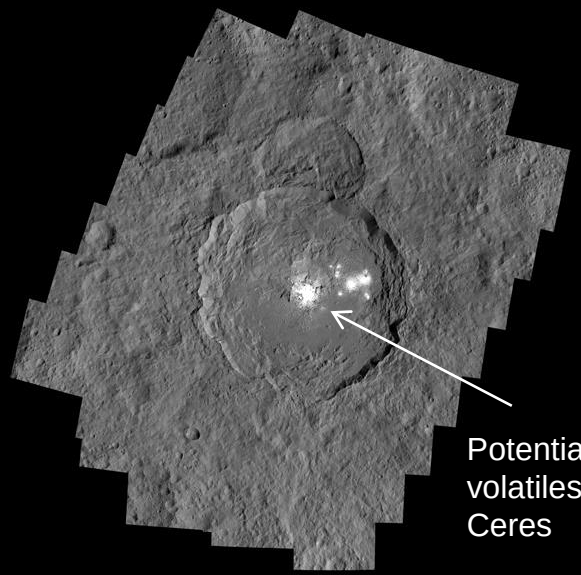


- Provides **intelligent targeting and data acquisition** by:
  - analyzing images of the rover scene
  - identifying high-priority science targets (e.g., rocks)
  - taking follow-up imaging of these targets with no ground communication required

A Deep Space Example

Mission Agility Through Onboard Analysis

Analyze data acquired onboard spacecraft and respond based on analysis



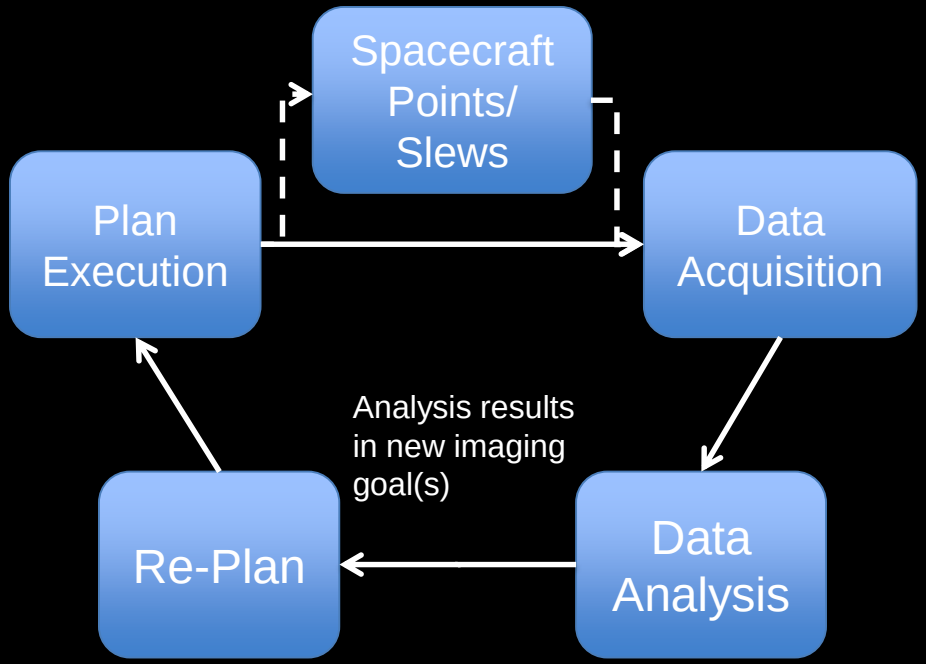
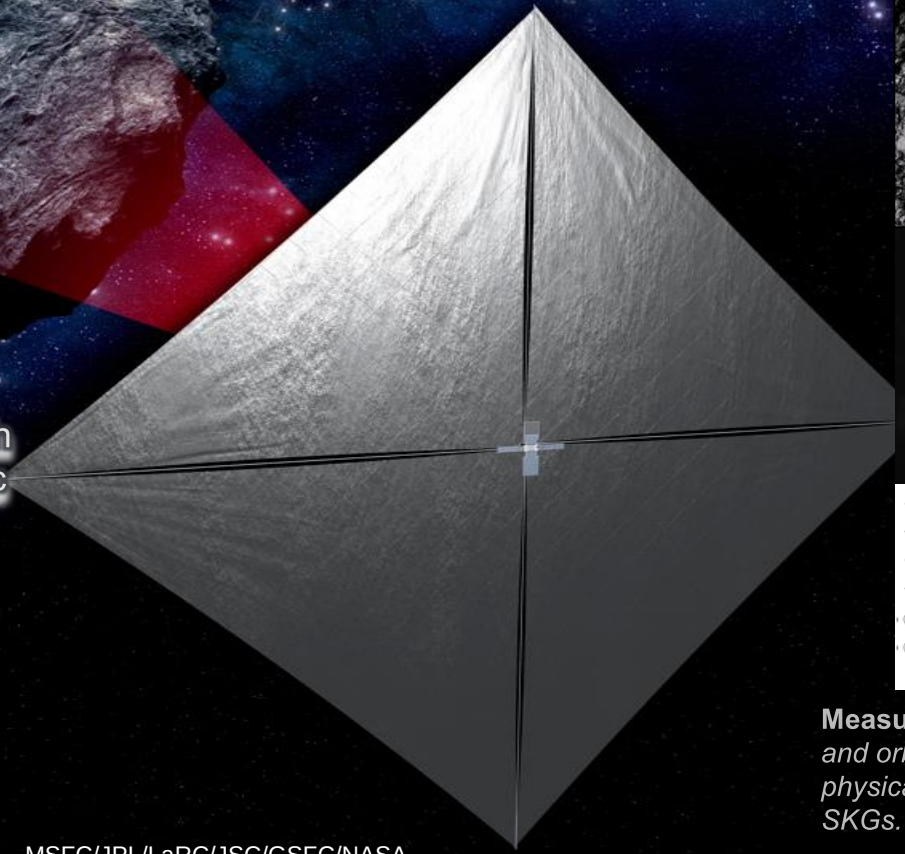
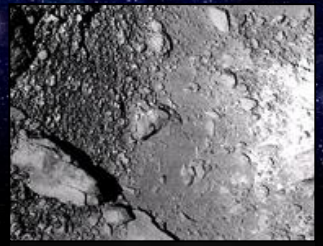
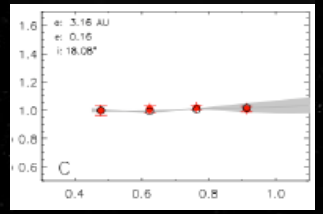


Image Credit: NASA/JPL/Dawn Mission

Near Earth Asteroid Scout







GOALS

Characterize one candidate NEA with an imager to address key Strategic Knowledge Gaps

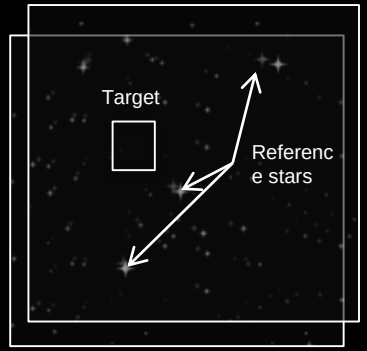
Demonstrates low cost capability for HEOMD for NEA detection and reconnaissance

Measurements: *NEA volume, spin and orbital properties, address key physical and regolith mechanical SKGs.*

MSFC/JPL/LaRC/JSC/GSFC/NASA

G-66840

Imaging Challenges



Target Detection and Approach
Ephemeris determination

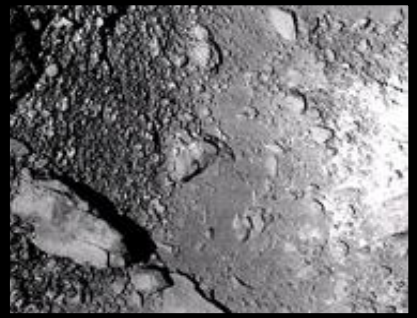
Target Position Uncertainty

Spacecraft Pointing and Camera Limitations

Medium Field Imaging
Shape, spin, and local environment

Short Flyby Time (<30 minutes)

Uncertain Environment



Close Proximity Imaging
Local scale morphology, terrain properties

Data Value Analysis and Sorting

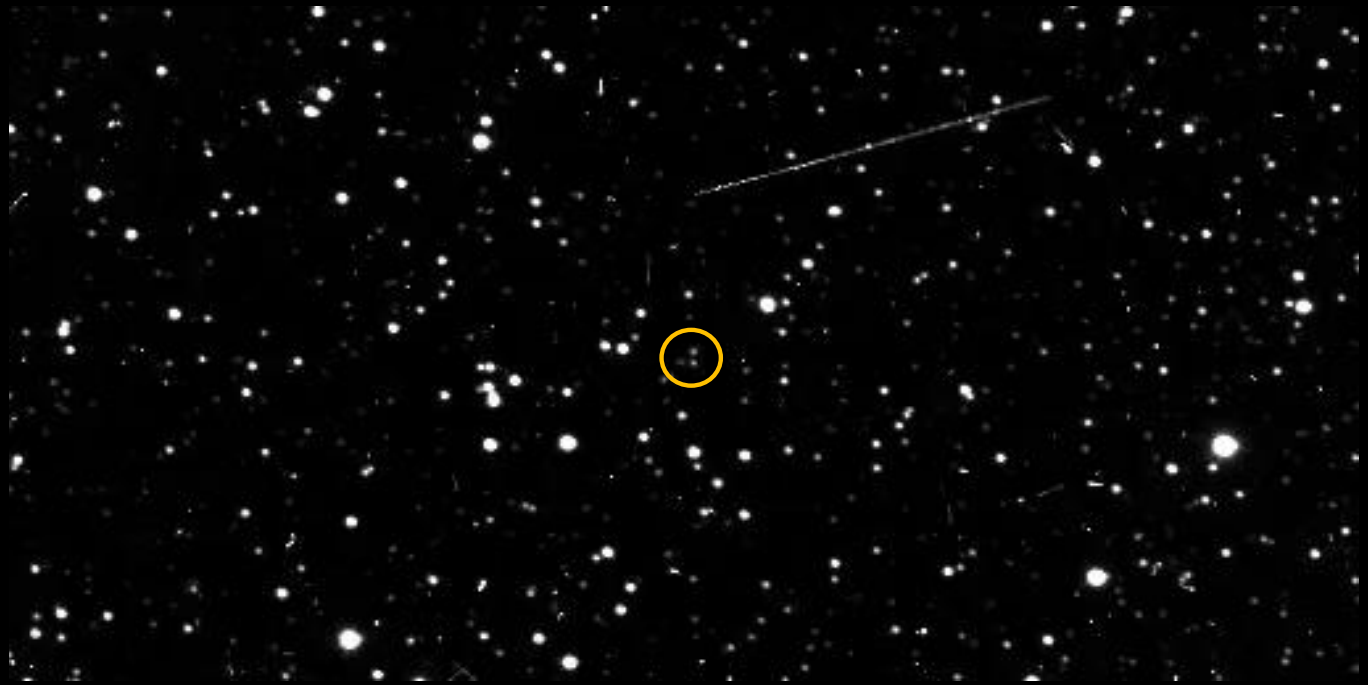
Short Time at Closest Approach (<10 minutes)

Limited Downlink of 1 Kbps

Raw Data is Messy

Rosetta OSIRIS Narrow Angle Camera Detection of 2867 Steins

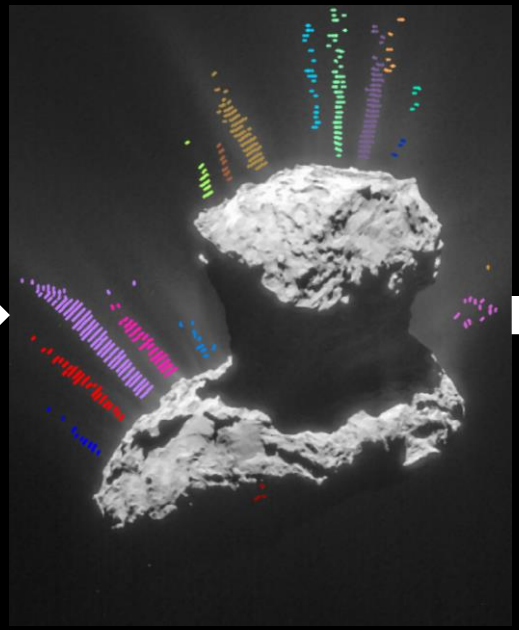
Raw Data is Messy



Rosetta OSIRIS Narrow Angle Camera Detection of 2867 Steins

Mission Operations Flexibility

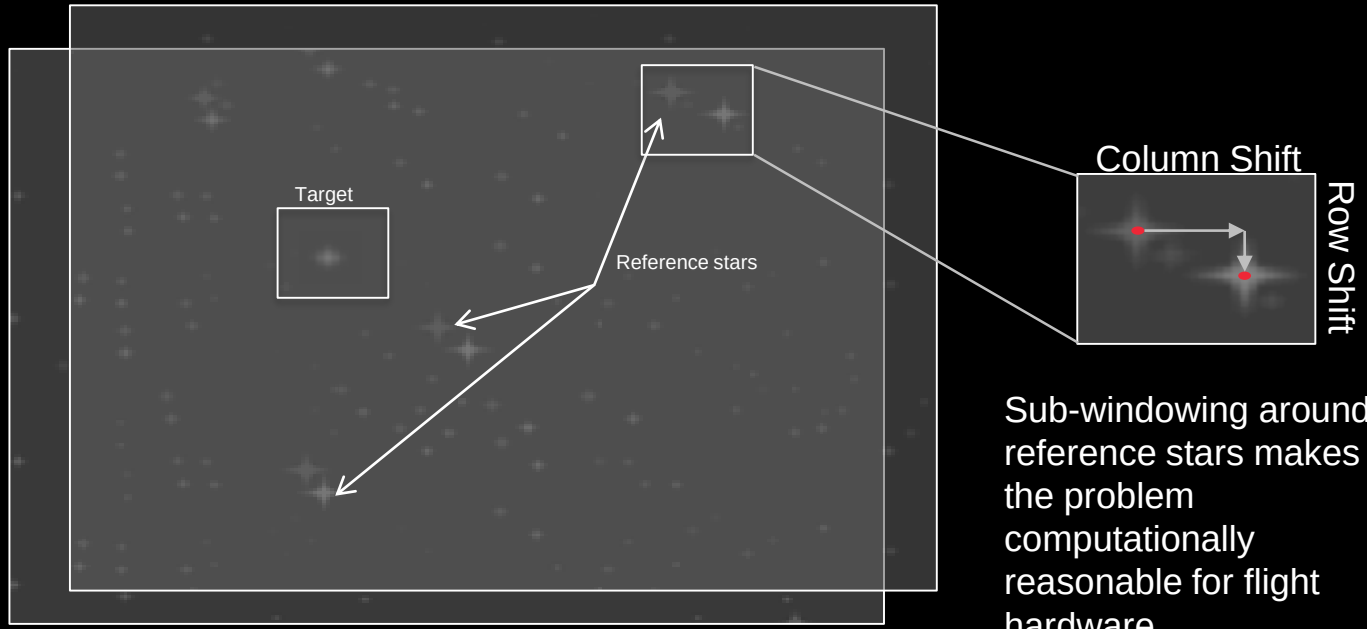
Data Calibration



Feature Detection

Operational Decisions

Cleaning Up the Noise



Sub-windowing around reference stars makes the problem computationally reasonable for flight hardware.

Onboard co-registration of images improves SNR and reduces downlink requirements

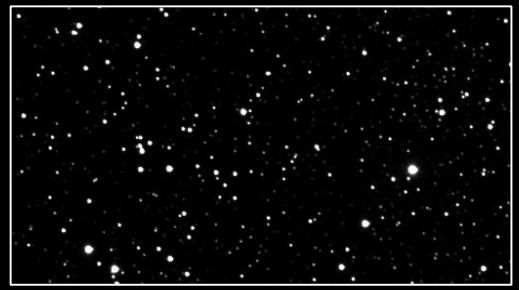
[Thompson et al. 2015]

Processed Data

Rosetta OSIRIS Narrow Angle Camera Detection of 2867 Steins

Identifying Targets

-



=

Determine the shift between two images, subtract with (x,y) offset.

This type of information has many mission applications.

Current trajectory verification and refinement

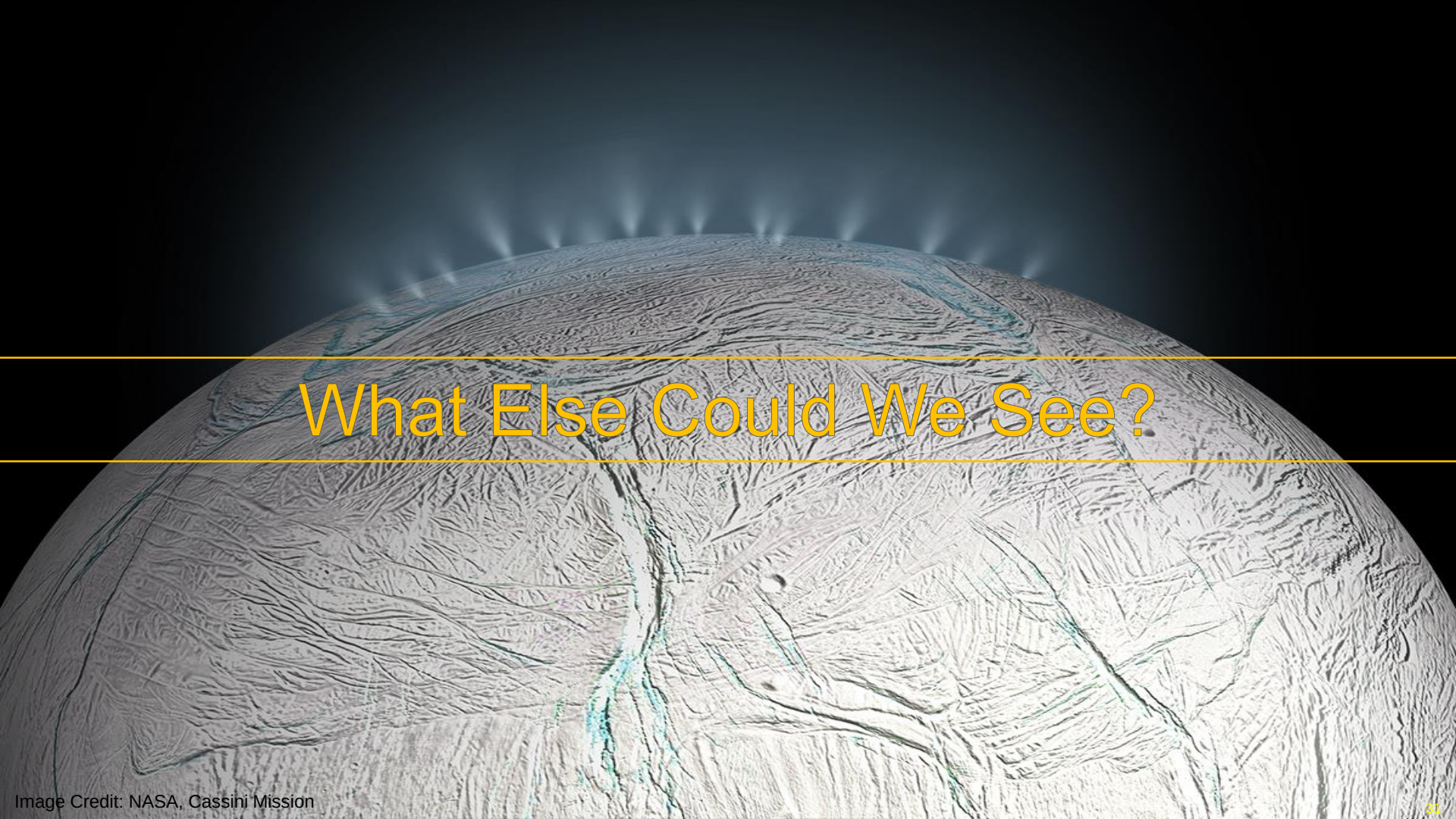
Automated target tracking

Target of opportunity detection

Target survey and classification

Does Your Target Look “As Expected”?

New Horizons Long Range Reconnaissance Imager Detection of Pluto/Charon



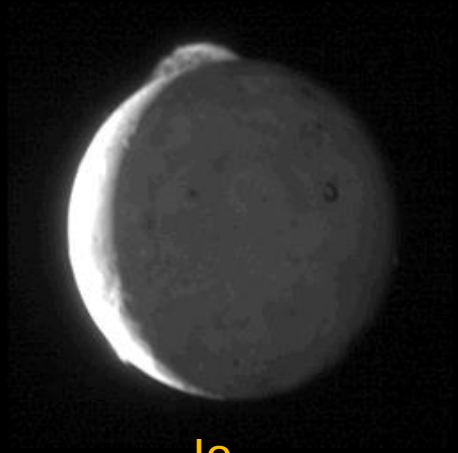
What Else Could We See?

Image Credit: NASA, Cassini Mission

Plumes are Scientifically Exciting

Enceladus

Comet 67P



Io

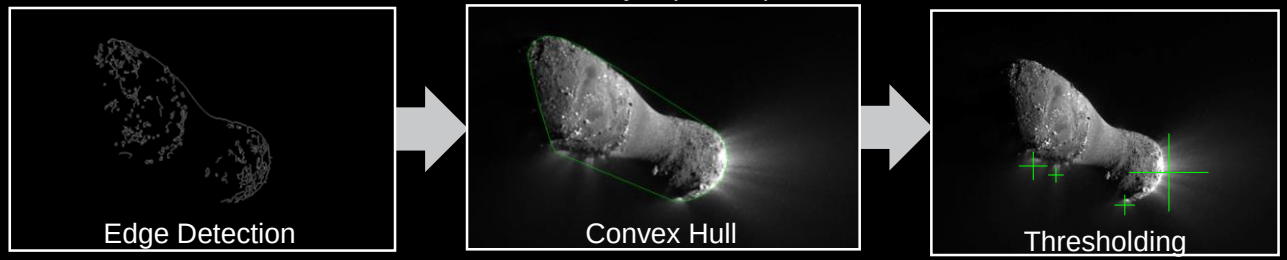
Plumes gives scientists insights into the volatiles located throughout the solar system.

Unfortunately, they're not scheduled. We have to react fast.

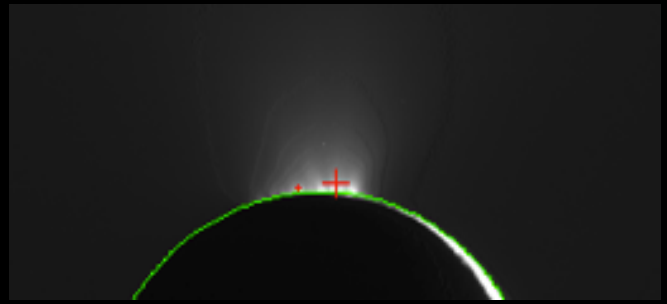
Image Credit: NASA, Cassini Mission (Left), ESA, Rosetta Mission (Center), NASA, New Horizons Mission(Right)

Plume Detection

Hartley 2 (*EPOXI*)



- Detects bright material beyond the limb
- Enables monitoring campaigns, target-relative data acquisition
- Detects most plumes with zero false positives



Enceladus (*Cassini*)

[Thompson et al., PSS 2012, Wagstaff et al, ApJ 2014]

Comet Tracking

Hartley 2 flyby
Original Sequence

Agile Science Planning

Target and plume detection using MRI-VIS on EPOXI. Tracking Comet Hartley 2.

Jet Propulsion Laboratory
California Institute of Technology

jpl.nasa.gov