Data Mining at NASA: from Theory to Applications

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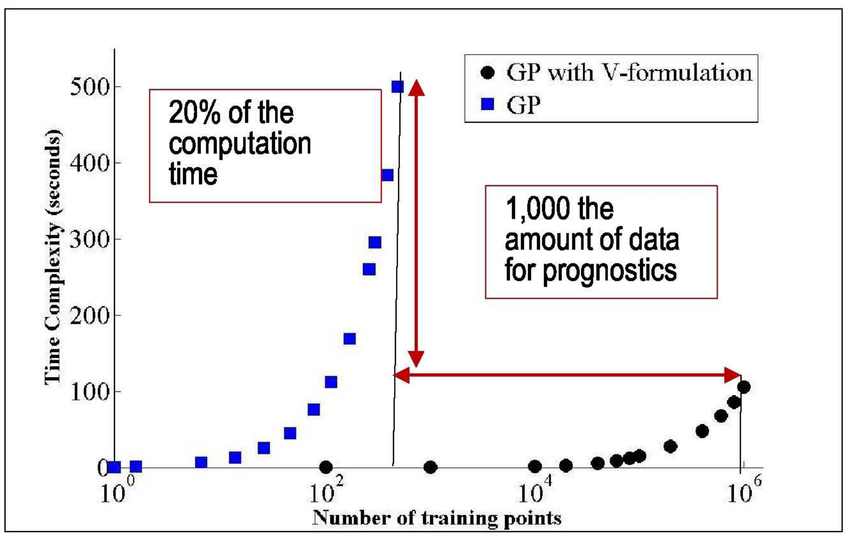
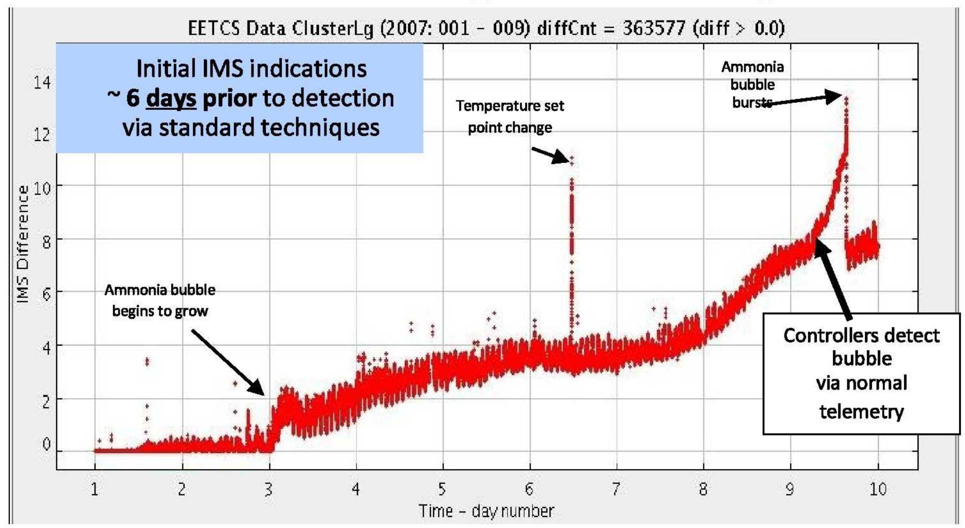
Intelligent Data Understanding Group

The IDU group develops novel algorithms to detect, classify, and predict events in large data streams for scientific and engineering systems.





- In early January 2007, ISS Early External Thermal Control System developed an ammonia gas bubble
- Bubble noted by ISS controllers only ~9 hours before it "burst" and dissipated back into liquid

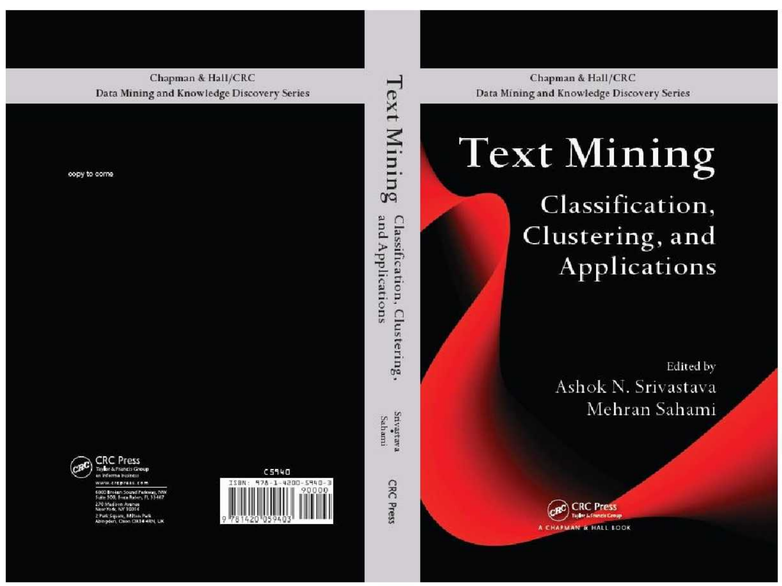
Key areas of research in data mining

Research Topic Areas

- Anomaly Detection
- Prediction Systems
- Text Mining
- Mining Distributed Data Systems and Sensor Networks
- High Performance Time Series Search

Application Areas

- Safety critical systems
- Large scale distributed systems
- Earth Sciences
- Space Sciences
- Systems Health Data from Aeronautical and Space Systems



NASA Data Systems

- Earth and Space Science
  - Earth Observing System generates ~21 TB of data per week.
  - Ames simulations generating 1-5 TB per day
- Aeronautical Systems
  - Distributed archive growing at 100K flights per month with 2M flights already.
- Exploration Systems
  - Space Shuttle and International Space station downlinks about 1.5GB per day.

Developing *Virtual* Sensors

- Virtual Sensors predict the value of one sensor measurement by exploiting the nonlinear correlations between its values and other sensor readings.
- Useful for emulating sensors back in time or estimating the value of one sensor based on other sensor measurements

Z: Sensors measurements
λ: Wavelength or Frequency
u: Position

$$Z(\mathbf{u}, \lambda, t) = [Z_{\mathbf{u}}(\lambda, t)]$$
$$= [Z_{u_1}(\lambda, t), Z_{u_2}(\lambda, t), \ldots, Z_{u_n}(\lambda, t)]^T$$

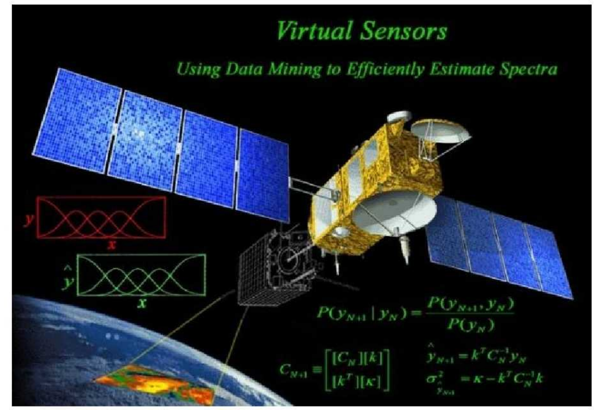
$$\mu(Z(\mathbf{B})) = \int \Gamma(Z(\mathbf{B}))Z(\mathbf{B})d\mathbf{B}$$

Predicted Sensor Measurement

$$\sigma^2(Z(\mathbf{B})) = \int [\Gamma(Z(\mathbf{B})) - \mu(Z(\mathbf{B}))]^2 Z(\mathbf{B})d\mathbf{B}$$

Estimated Uncertainty

Earth and Space Sciences



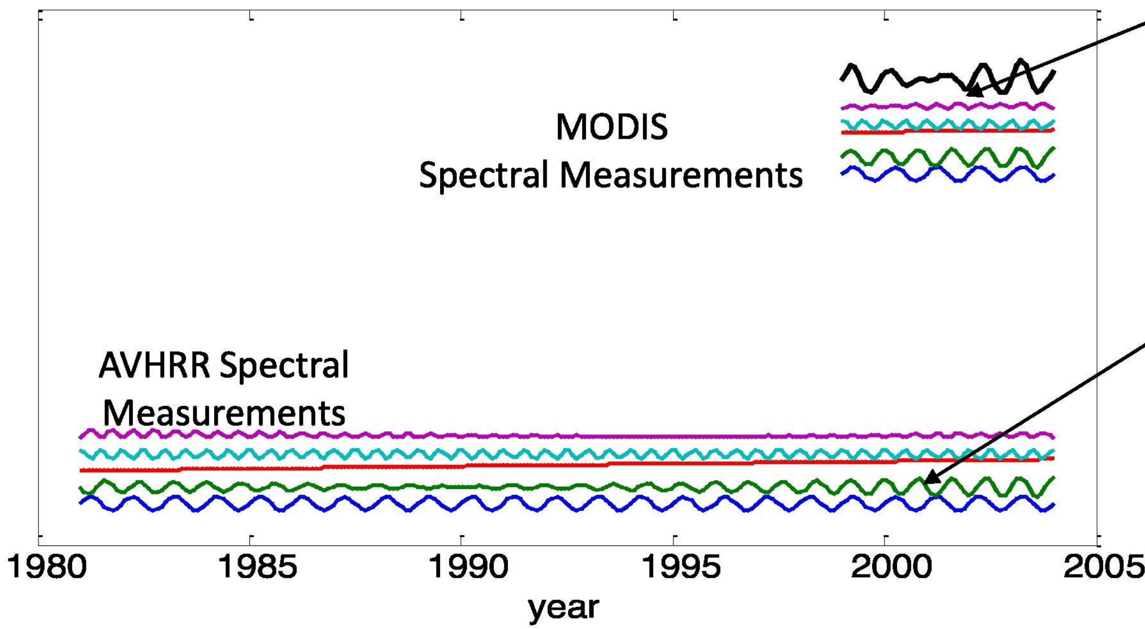
Aeronautics and Space Systems

Virtual Sensors in the Earth Sciences

Collaborators
Ashok N. Srivastava, NASA Ames
Nikunj C. Oza, NASA Ames
Julienne Stroeve, National Snow and Ice Data Center
Ramakrishna Nemani, NASA Ames
Petr Votava, NASA Ames

Has Cloud Cover Changed over Greenland in the past 30 years?

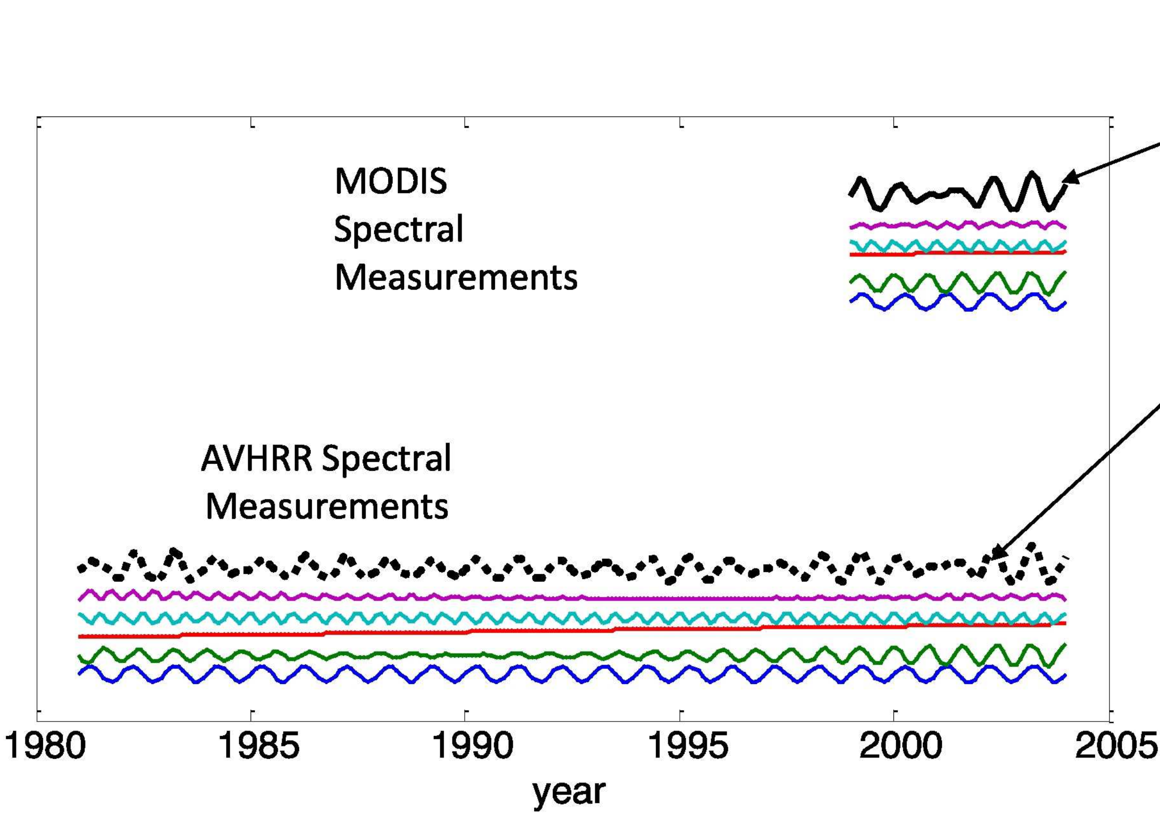
- New sensors on the MODIS system can detect clouds over snow and ice in the 1.6μm band (circa 1999).
- Difficult over snow and ice-covered surfaces because of low contrast in visible and thermal infrared wavelengths.
- Older sensors from the AVHRR system do not detect cloud cover over snow and ice because of poor contrast.

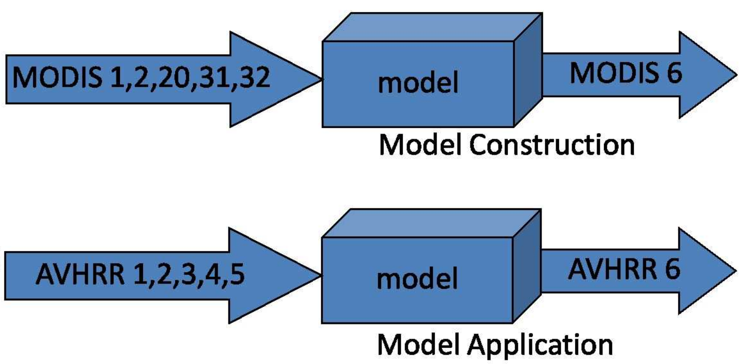


Joint work with Nikunj Oza, Julliene Stroeve, Rama Nemani, Brett Zane-Ulman

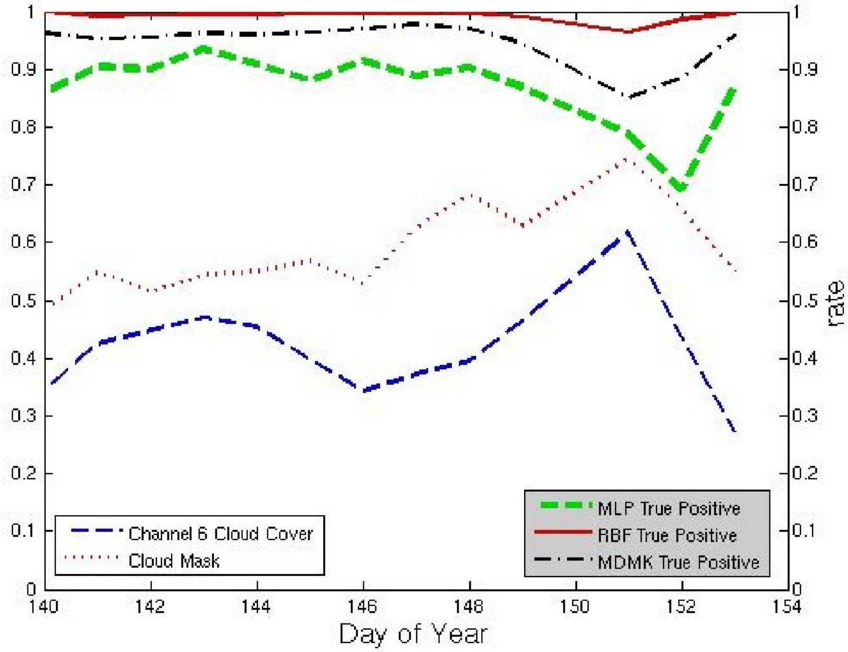
Cloud Detection back in Time

- MODIS 1.6μm has enough contrast for this task.
- However 1.6μm channel not available in AVHRR/2.
- Predict 1.6μm channel using a Virtual Sensor

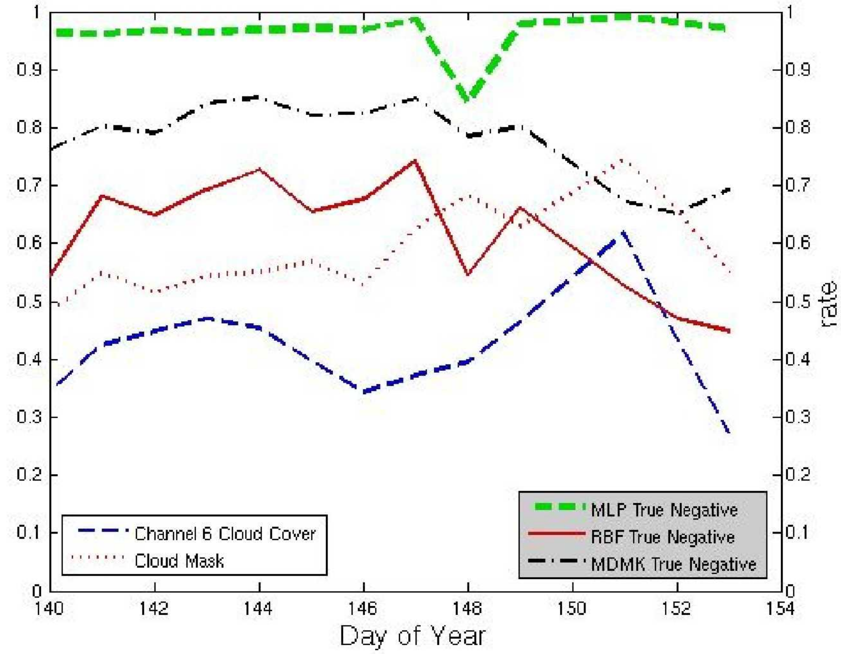




Accuracy Results for Three Models



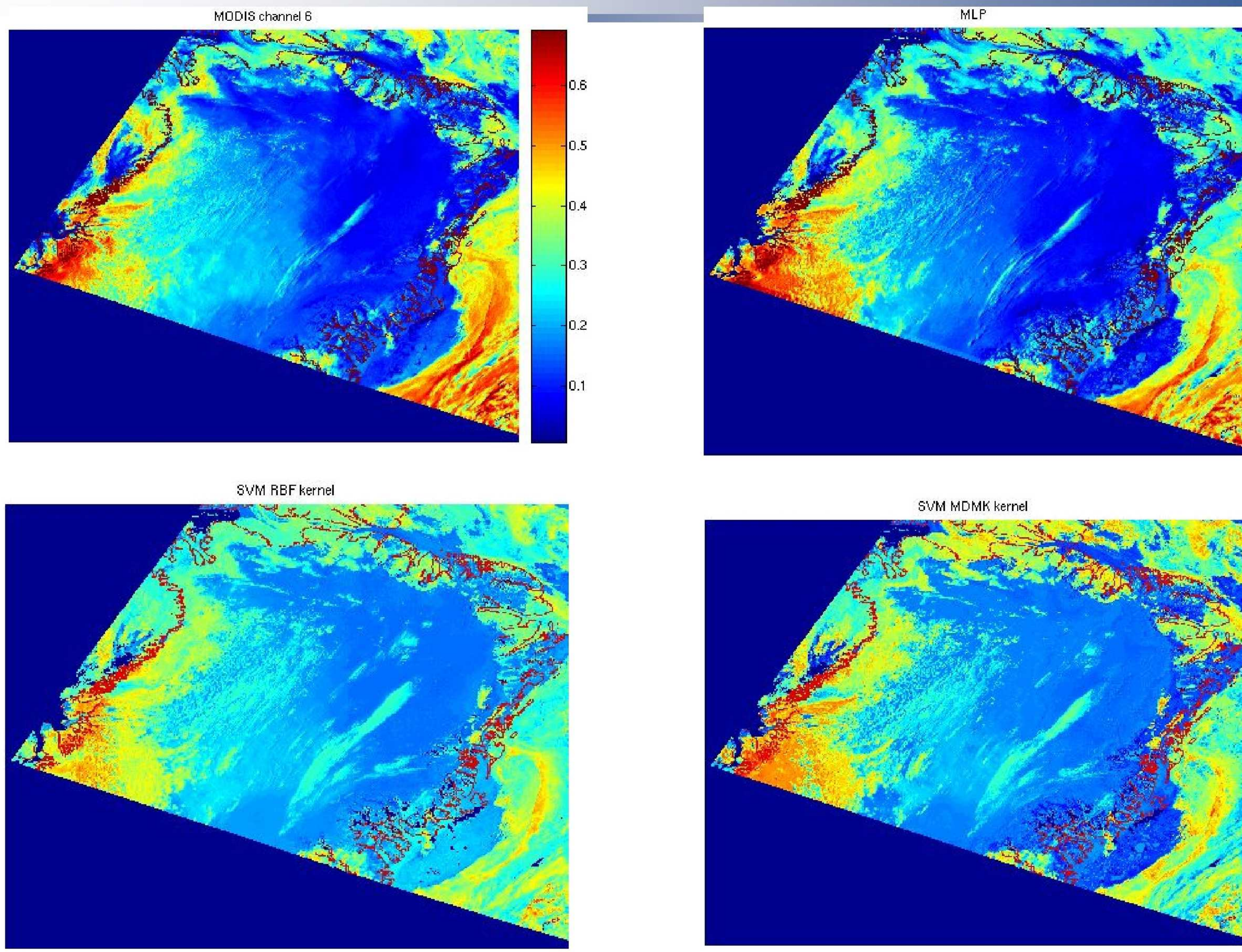
True Positive



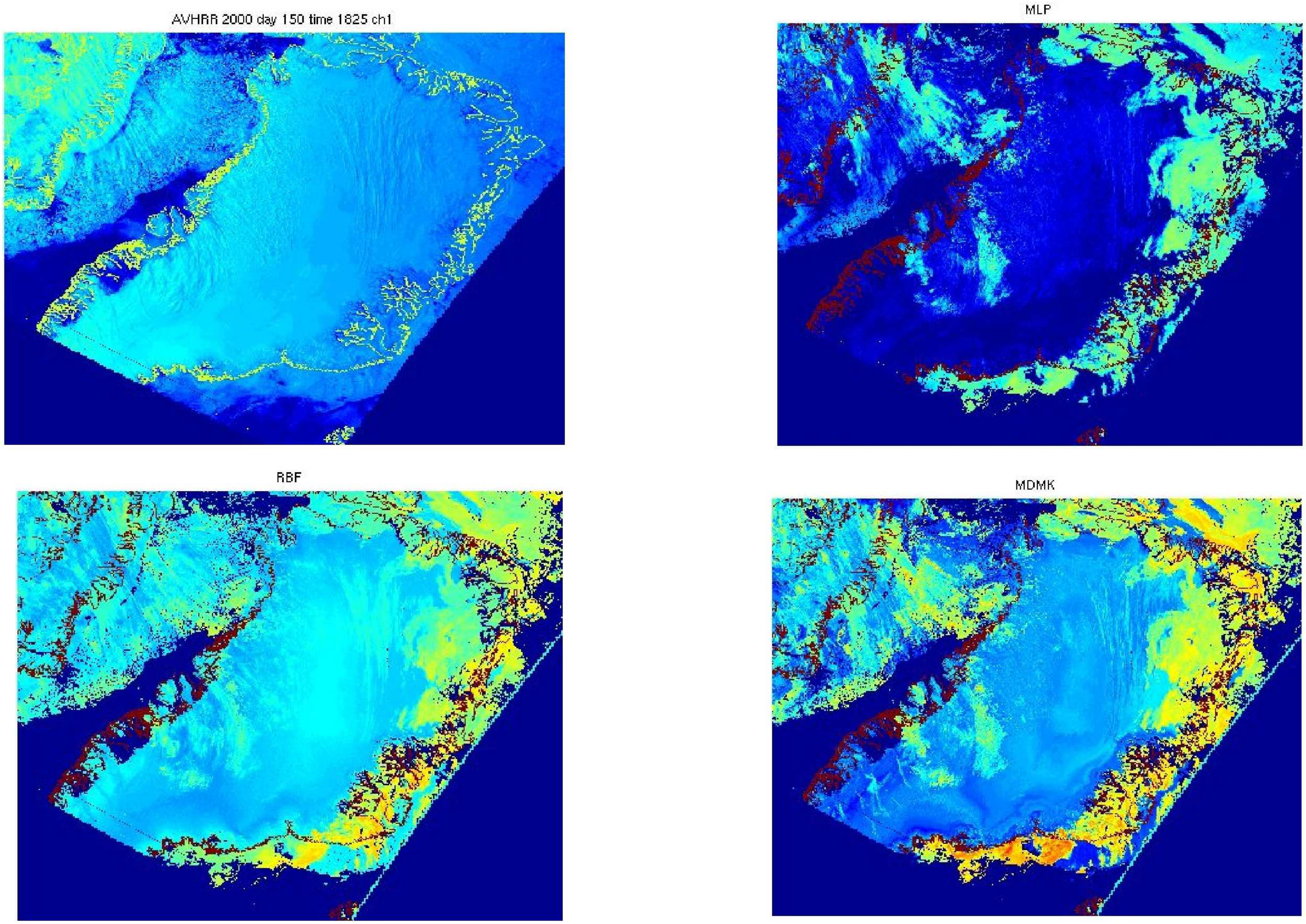
True Negative

- True Positive = number of times channel 6 indicated a cloud and the model predicted cloud
- True Negative = number of times channel 6 indicate no cloud and the model predicted no cloud

Verification of Models on MODIS Data



Application of Models to AVHRR Data



Summary

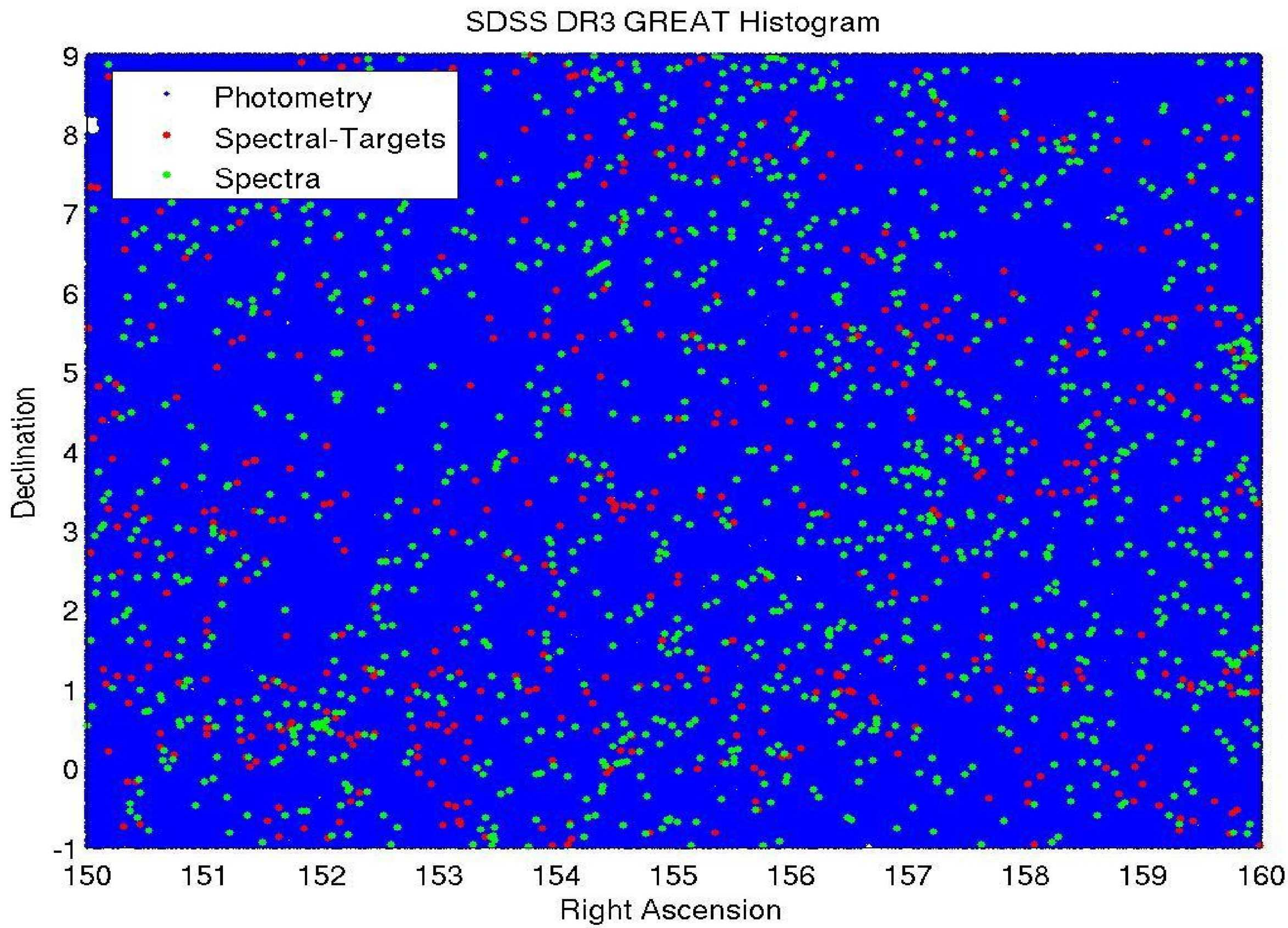
- Application to entire historical record is a significant task because of data quality issues and transitions from one sensor system to another.
- Method applied to emulation of physics models to calculate corrections for surface albedo measurements resulted in an increase in speed by factor of 27 compared to existing methods.
- Potential to deploy Virtual Sensors for generation of a historical cloud mask record.
- Model verification and validation must be done by hand since we have no signal for comparison.

A. N. Srivastava, N. C. Oza, and J. Stroeve, "Virtual Sensors: Using Data Mining Techniques to Efficiently Estimate Remote Sensing Spectra," Special Issue on Advanced Data Analysis, IEEE Transactions on Geoscience and Remote Sensing, March 2005.

Virtual Sensors in Astrophysics

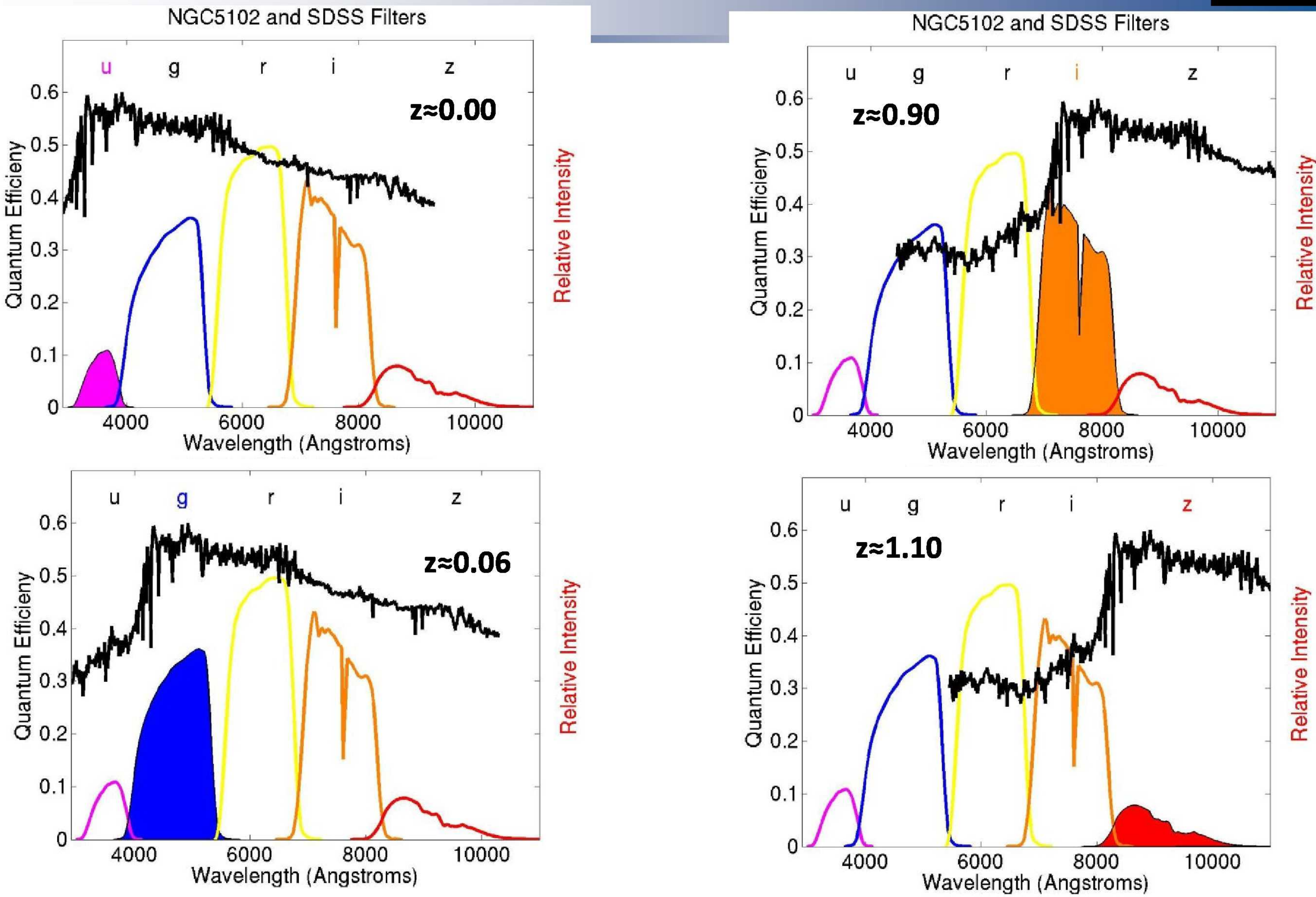
Collaborators
Michael J. Way, NASA Goddard Institute of Space Science
Leslie Foster, San Jose State University
Ashok N. Srivastava, NASA Ames
Paul Gazis, NASA Ames
Jeffery Scargle, NASA Ames

Estimating Photometric Redshifts in the Sloan Digital Sky Survey



Joint work with Michael J. Way, Leslie Foster, Paul Gazis, and Jeffrey Scargle

Photometric Redshifts are Broadband Measurements of Spectra



Gaussian Process Regression

- Can have high accuracy and also measure of uncertainty
- **some *low-rank matrix approximations* work well** but can have numerical problems.

Training Data:

- X – data matrix of observations – $n \times d$
- y – vector of target data – n $\times$ 1

Testing Data:

- X^* – matrix of new observations – $n^* \times d$

Goal:

- predict y^* corresponding to X^*

- Form covariance matrix K ($n \times n$), cross covariance matrix K^* ($n^* \times n$) and select parameter λ
- predict y^* using

$$\hat{y}^* = K^*(\lambda^2 I + K)^{-1} y$$

- the $n \times n$ matrix $(\lambda^2 I + K)$ is large for large data sets

- Memory: Storing covariance matrix – $O(n^2)$
- Time: Solving linear system – $O(n^3)$
- Numerical stability: accurate calculations.

Standard Least Squares Problems

- Given:

  $n \times m$ matrix A, $\quad n \geq m$

  $n \times 1$ vector y

- Solve $\min ||y - Ax||$
- Normal Equations: $x = (A^T A)^{-1} A^T y$

  potential numerical instabilities

- QR: $A = QR$, $x = R^{-1} Q^T y$

  stable calculation

Computational Challenges

- Subset of Regressors [Wahba, 1990]

$$\widehat{y}^* \cong K_1^*(\lambda^2 K_{11} + K_1^T K_1)^{-1} K_1^T y$$

- Memory: Storing covariance matrix – $O(nm)$
- Time: Solving linear system – $O(nm^2)$
- Numerical stability: ???.

Cures for Numerical Instability: *The V-Method*

Approach

1. Select columns to make K_1 well conditioned
2. Use stable technique for least squares problem such as
   - QR factorization
   - V method
3. Requirement: maintain $O(nm)$ memory use and $O(nm^2)$ efficiency.

Column Selection

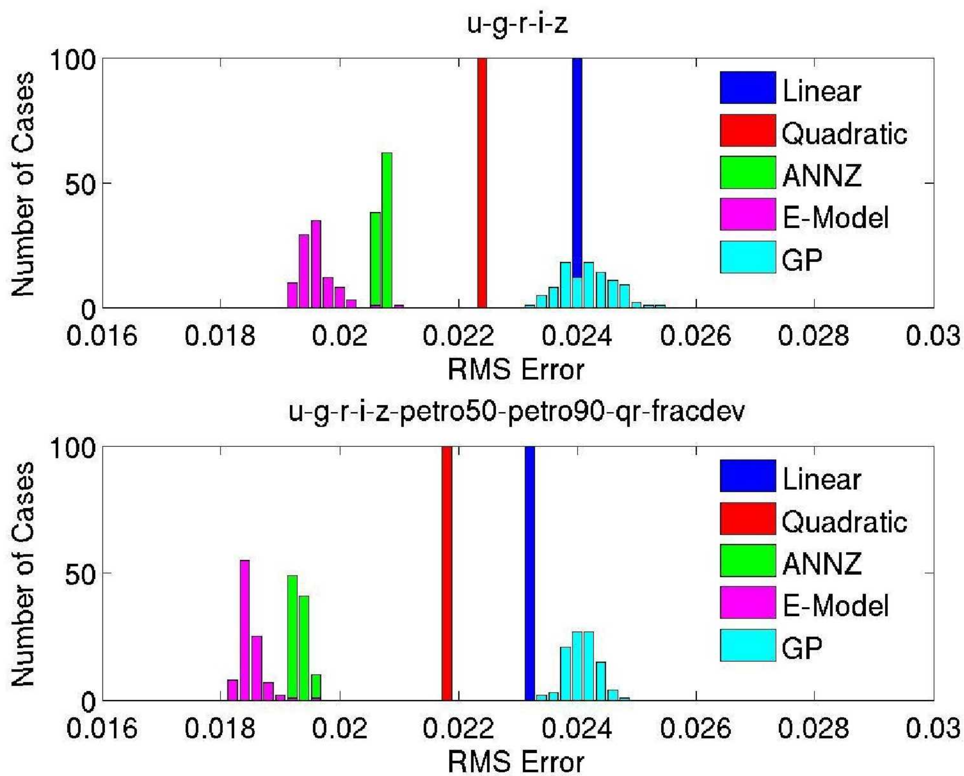
1. Use Cholesky factorization with pivoting to partially factor K
2. selects appropriate columns for K_1
3. K_1 will be well conditioned if $cond(K_1)$ is O(condition of optimal low rank approximation).

The V-Method is the innovation of Leslie Foster and his students at San Jose State University

The V-Method

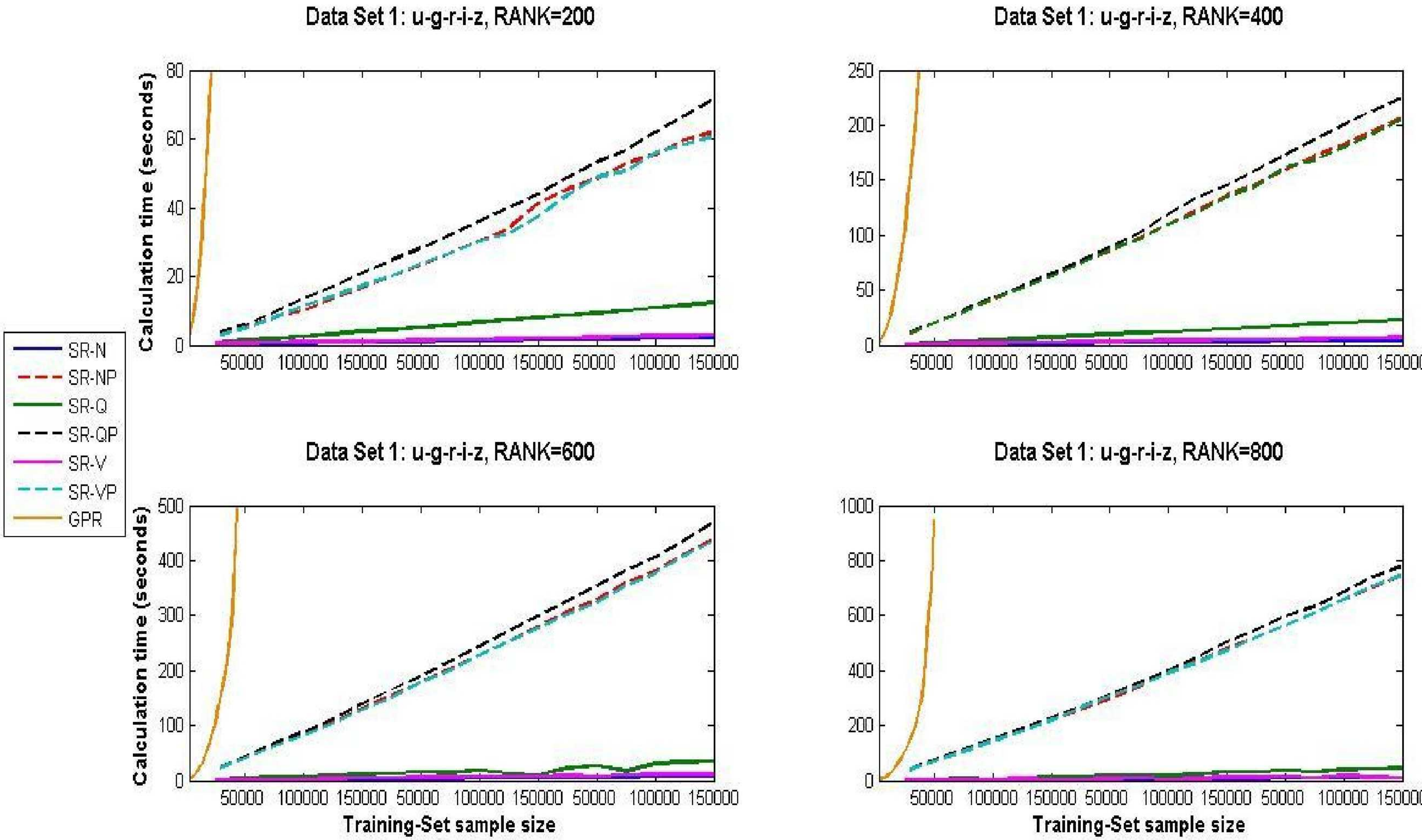
- Factor $K_1 = VV_{11}^T$ where V is $n \times m$ and V_{11} is $m \times m$ lower triangular
- $\widehat{y}^* = K_1^* V_{11}^{-T} (\lambda^2 I + V^T V)^{-1} V^T y$
- V is a rescaling of a well conditioned matrix
- method is numerically stable
- can be faster and need less memory
- related to [Peters and Wilkinson, 1970], [Wahba, 1990]

Prediction Accuracy

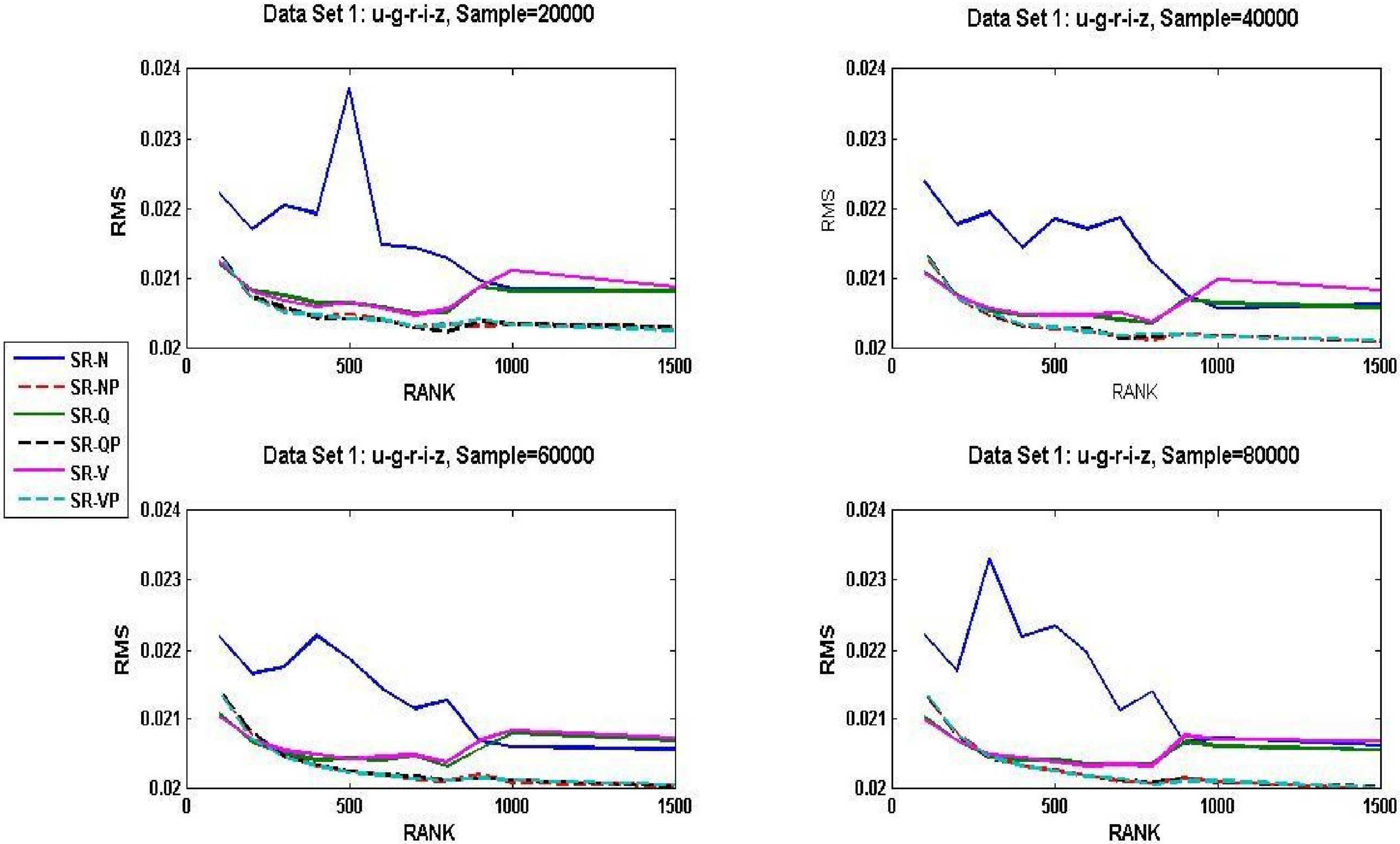


- Our ensemble models produce the best redshift estimates published to date.
- We are developing Gaussian Process Regression methods to scale to 10^6 galaxies and beyond.

Scalability Results



Best Published Results so far*…



* To the best of our knowledge

Results for Redshift Predictions

- The V-Formulation provides an extremely scalable and numerically stable method to compute Gaussian Process Regression for arbitrary kernels.
- With *low-rank matrix inversion approximations* GPs performed better than all other methods.
- Allows us to compute GPs for O(200K) points in a few seconds on a standard desktop PC.

L. Foster, A, A. Waagen, N. Aijaz, M. Hurley, A. Luis, J. Rinsky, C. Satyavolu, M. J. Way, P. Gazis, and A. N. Srivastava, "Stable and Efficient Gaussian Process Calculations," Journal of Machine Learning Research, 10(Apr):857--882, 2009.

Data Mining Supporting the Flight Readiness Review for STS-119

Collaborators

Ashok N. Srivastava, NASA Ames

Dave Iverson, NASA Ames

Bryan Matthews, SGT

Bill Lane, NASA Johnson Space Center

Bob Beil, NASA Kennedy Space Center

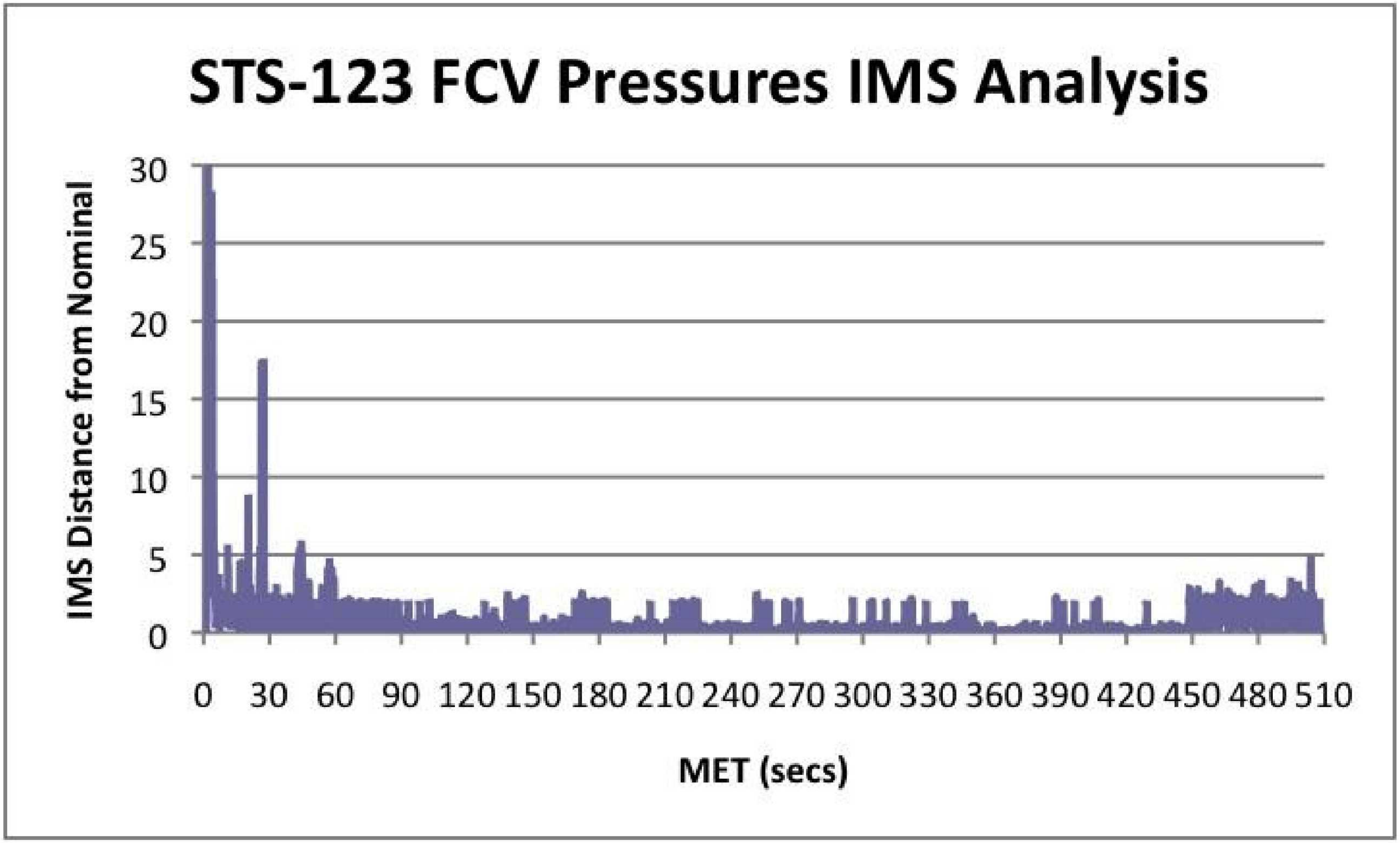
Overview

- Ashok received a request to support the Flight Readiness Review for STS-119 which was scheduled for 2/20/09 as the Data Mining Subject Matter Expert.
- Data mining algorithms developed at NASA were applied to these data to determine whether any anomalies can be detected in STS-126 and its predecessor flight STS-123 for Space Shuttle Endeavor.

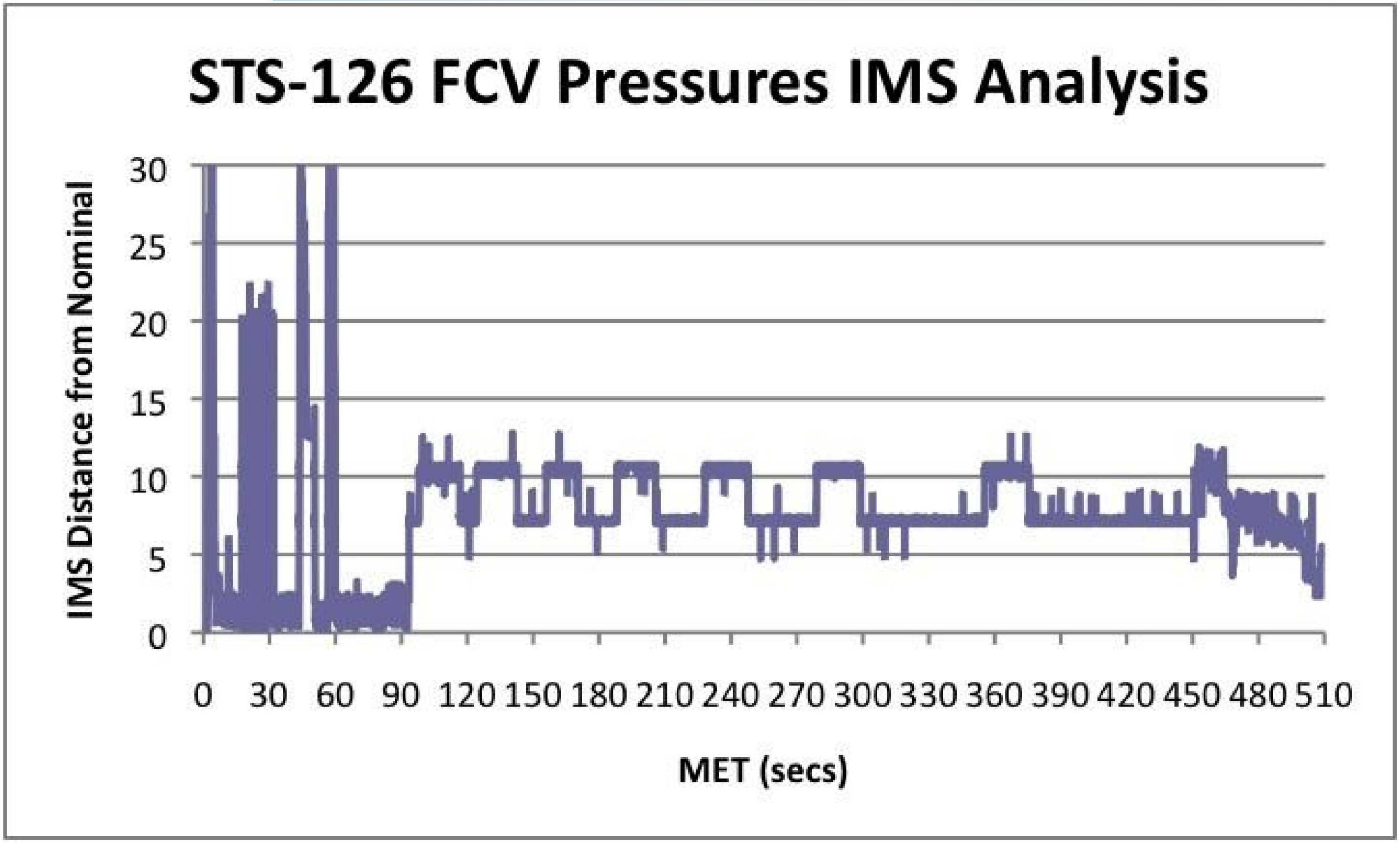
Algorithms and Data

- IMS (Inductive Monitoring System): a data point is anomalous if it is far away from clusters of nominal points.
- Orca: a data point is anomalous if it is far away from its nearest neighbors.
- Virtual Sensor: a data point is anomalous if the actual value is far away from the predicted value.
- Data: 13 pressure, temperature, and control variables related to the Flow Control Valve subsystem.

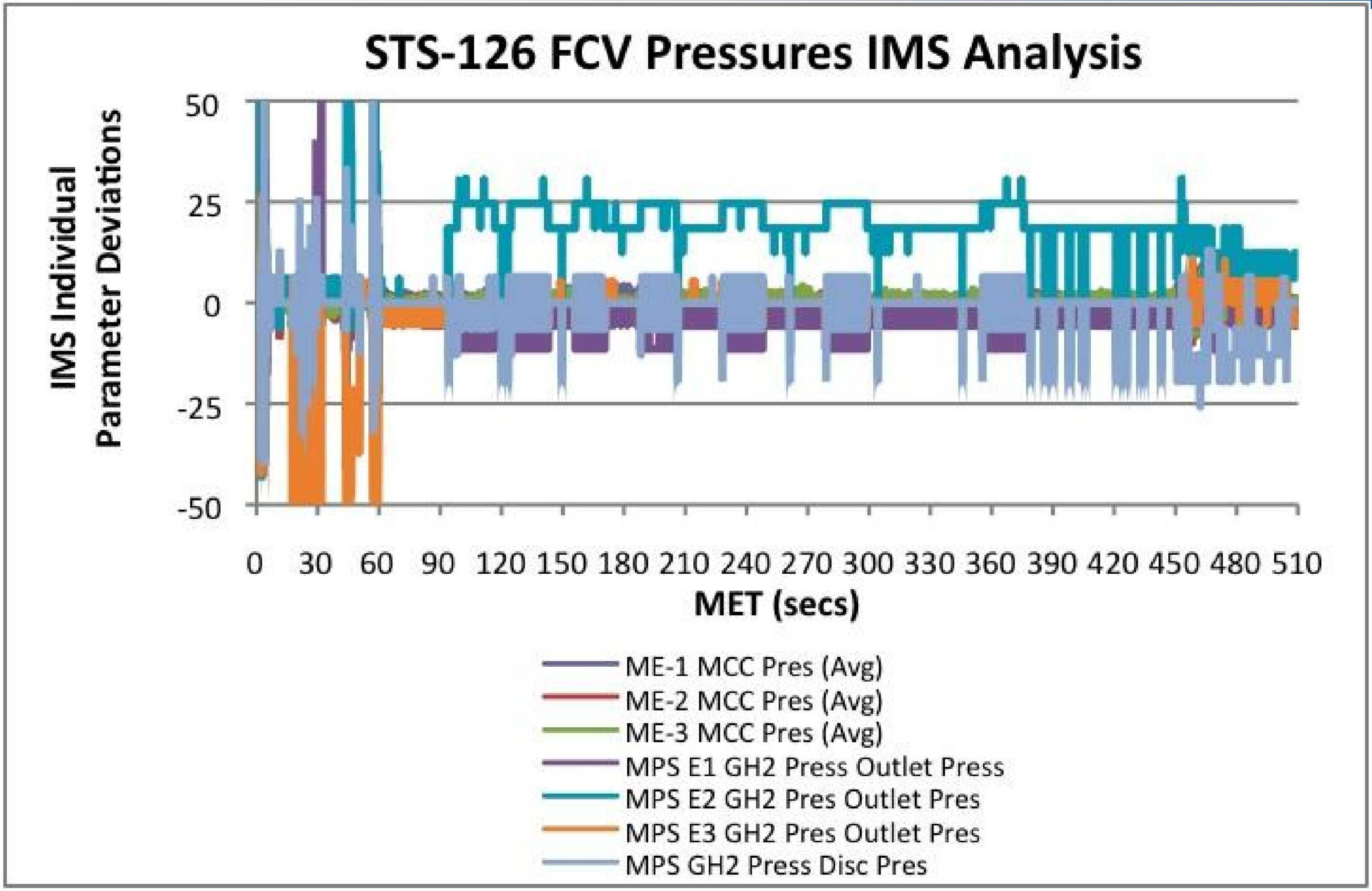
IMS Anomaly Score



IMS Anomaly Score



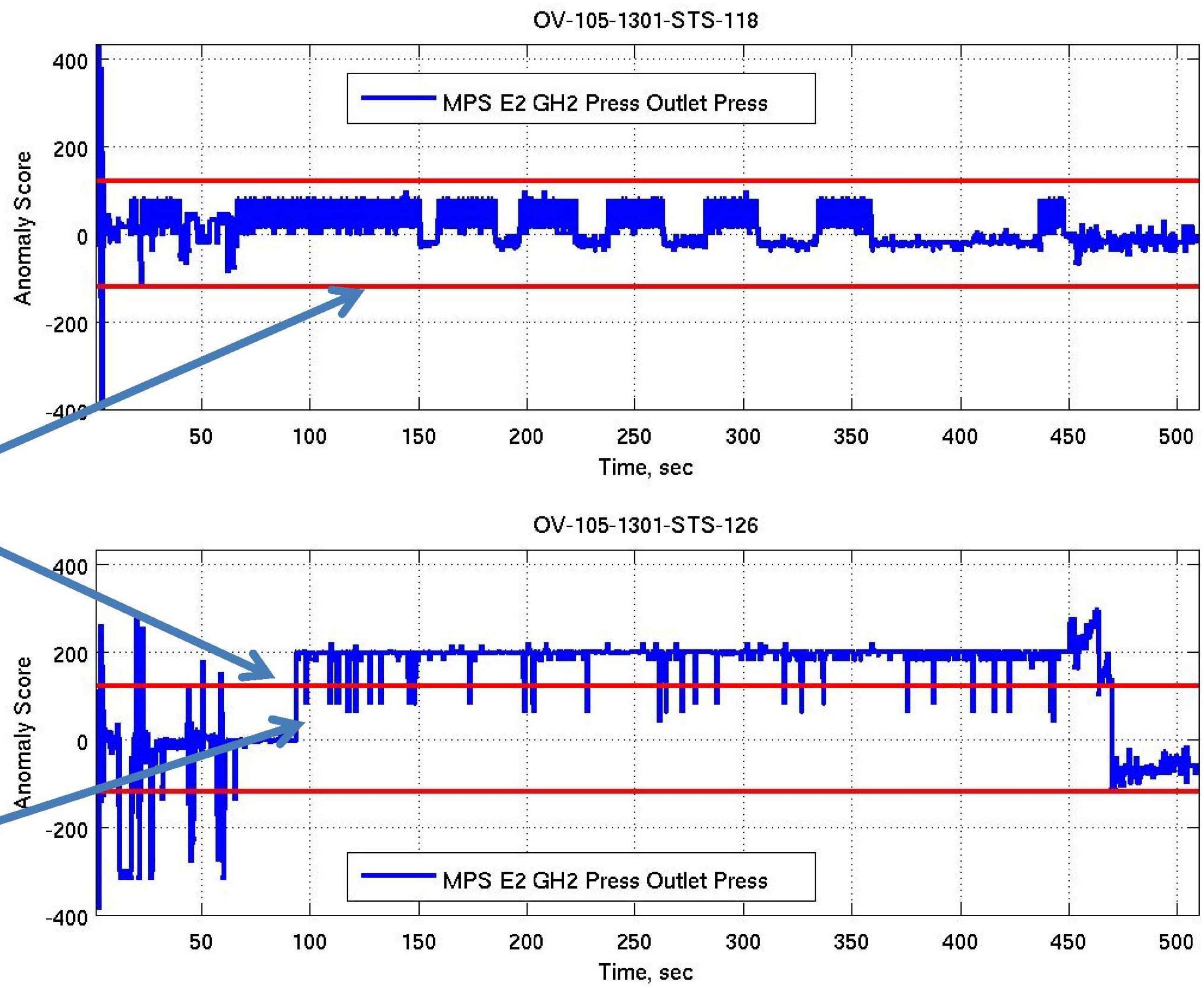
IMS Anomaly Score



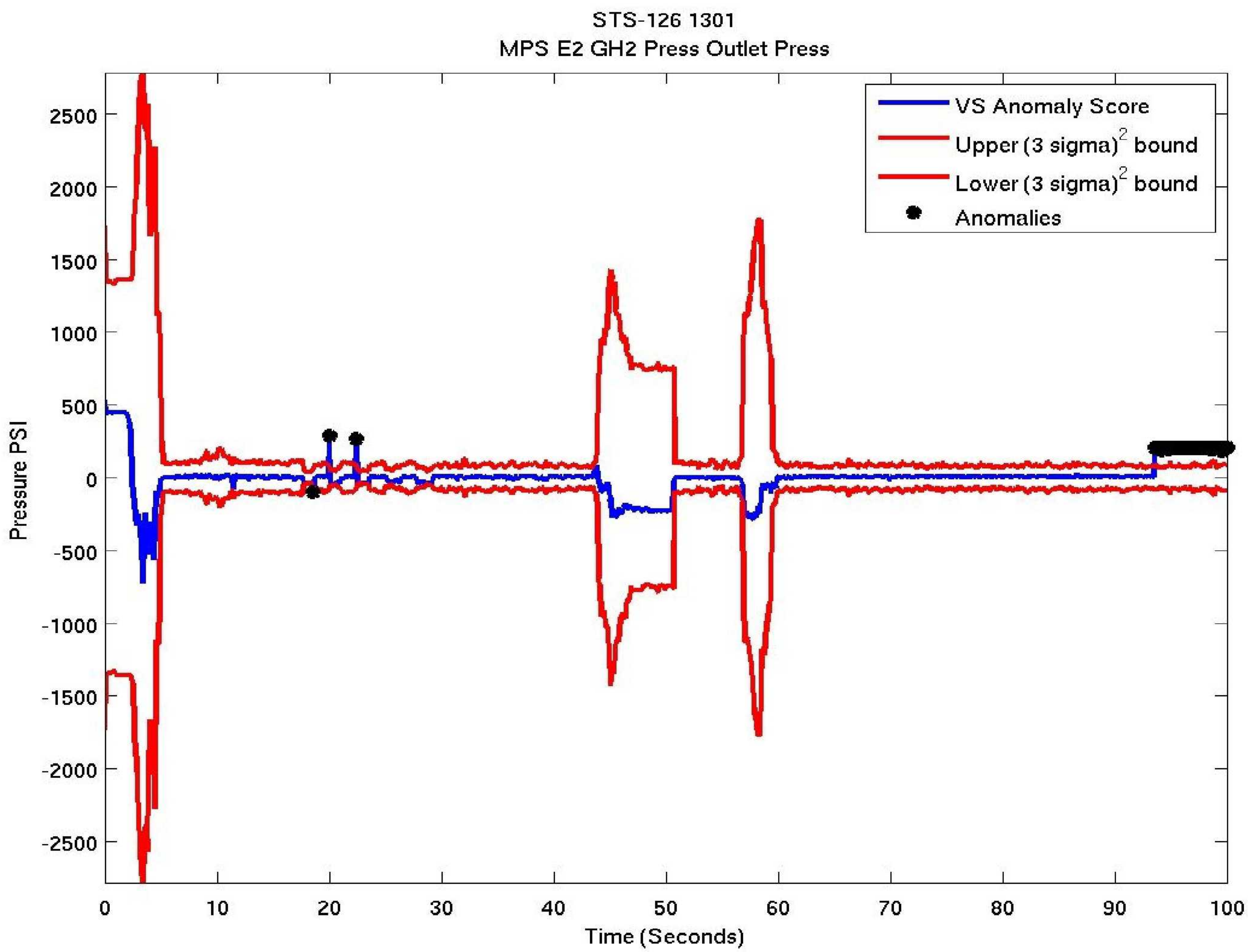
Virtual Sensor: STS-118 and STS-126

• Redlines correspond to 3-sigma nominal error rate on STS-118.

•STS-126 shows anomalous behavior after 93.6 seconds.



Virtual Sensors with Adaptive Thresholds

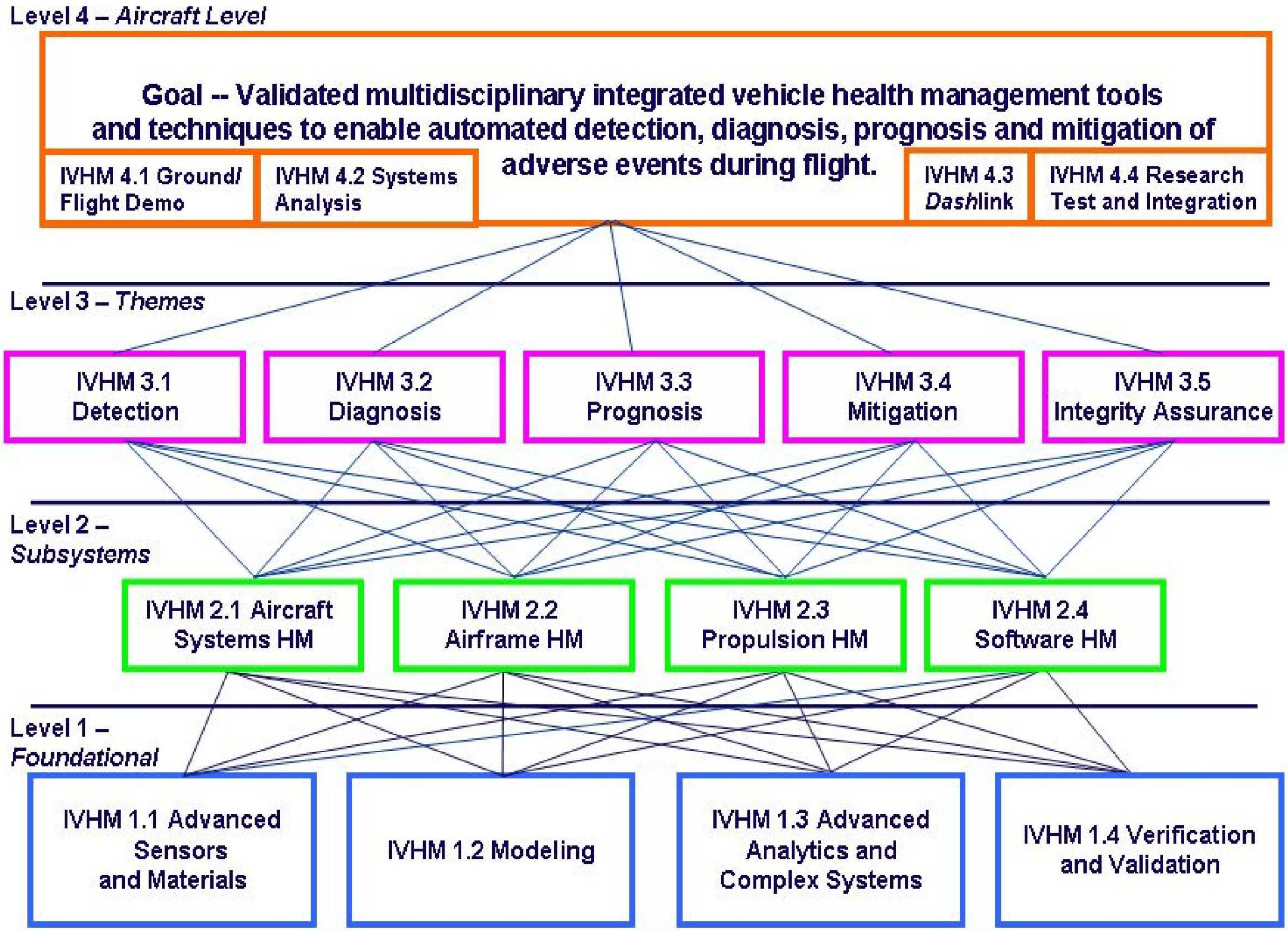


A. N. Srivastava, B. Matthews, D. Iverson, B. Beil, and B. Lane, "Multidimensional Anomaly Detection on the Space Shuttle Main Propulsion System: A Case Study," submitted to IEEE Transactions on Systems, Man, and Cybernetics, Part C, 2009.

The Role of Data Mining in Aviation Safety

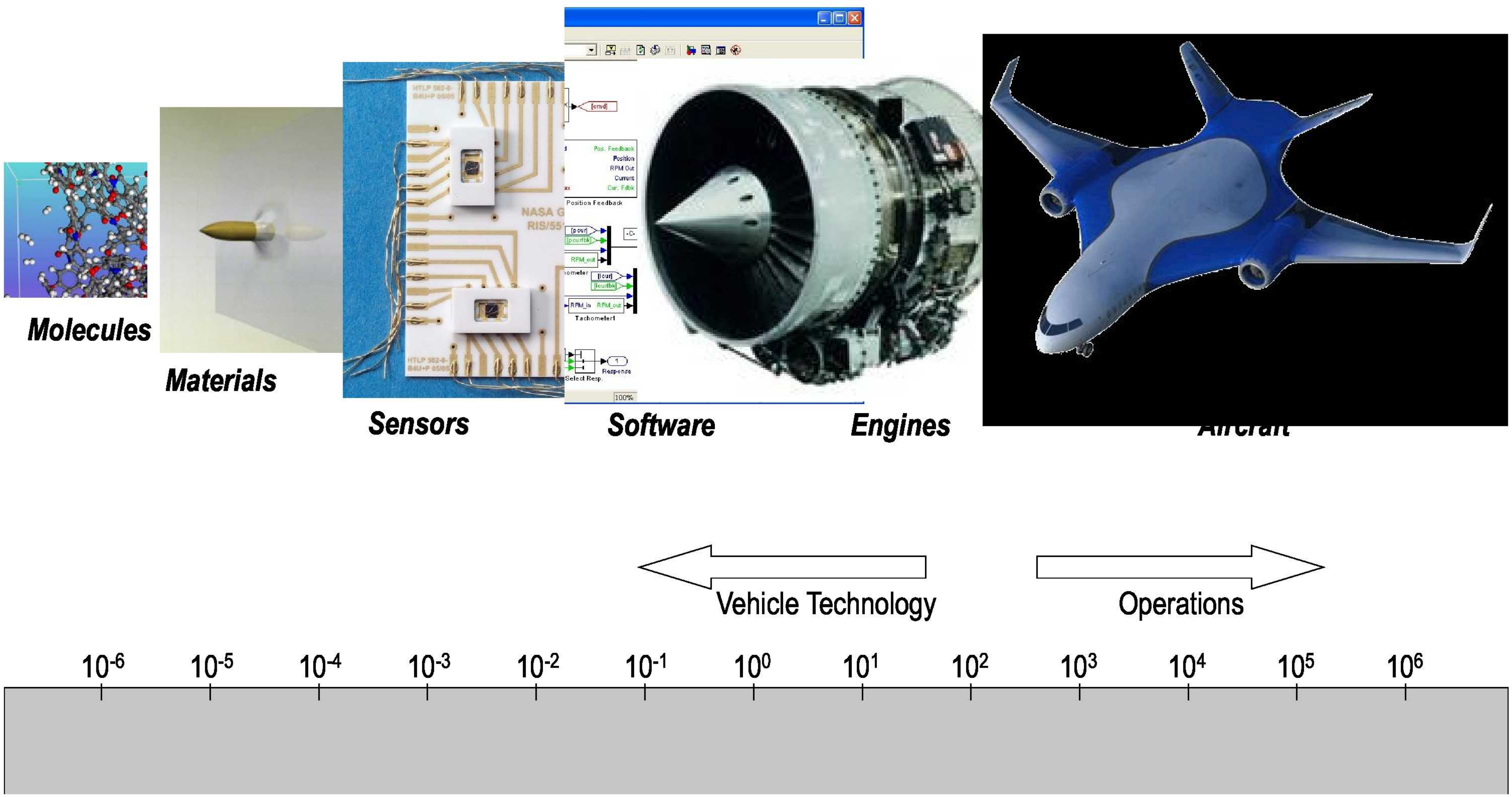
Ashok N. Srivastava, Principal Investigator
Claudia Meyer, Project Manager
Robert Mah, Project Scientist

Integrated Vehicle Health Management: An Aviation Safety Project

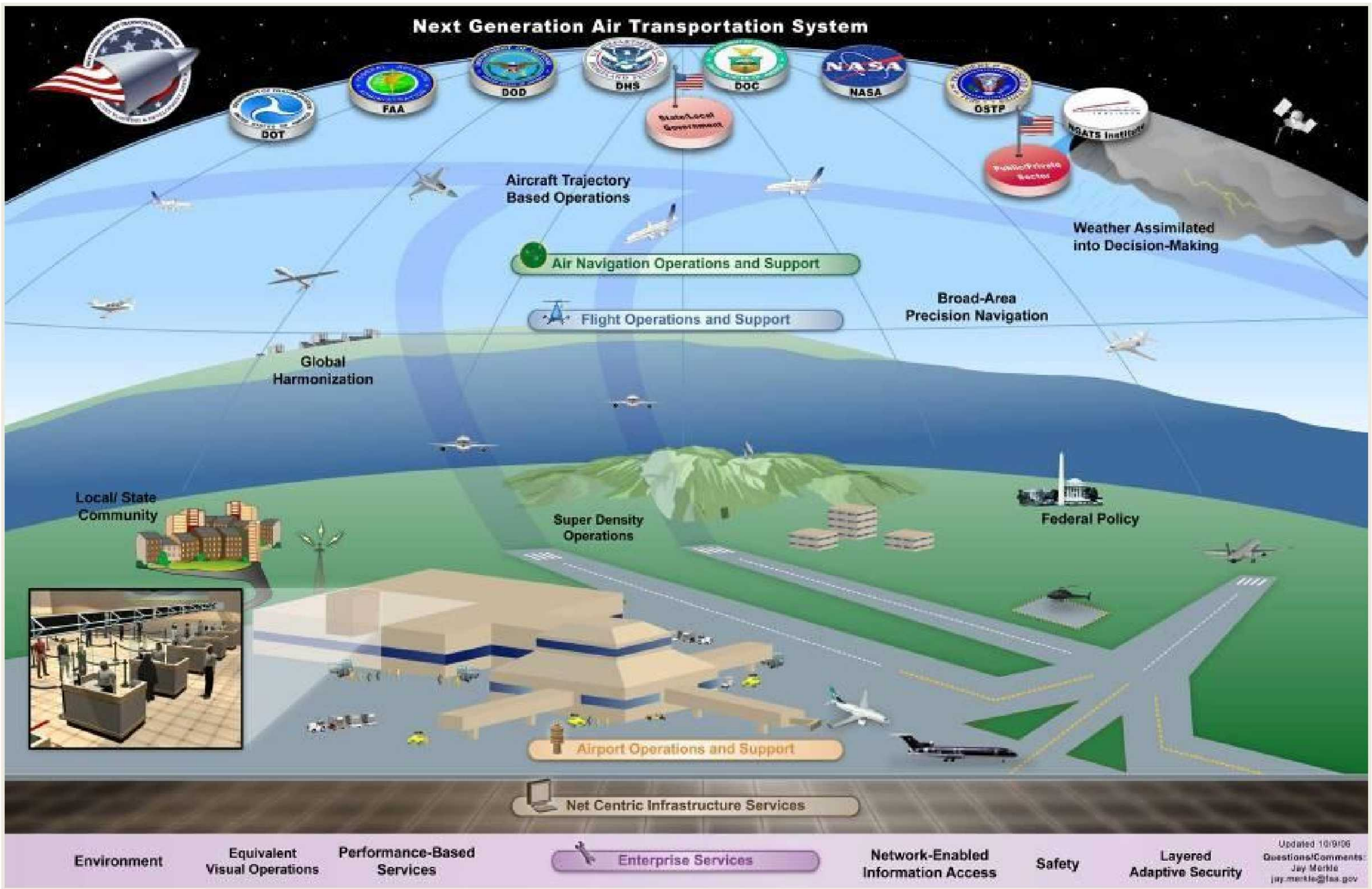


Some Partners of the IVHM Project

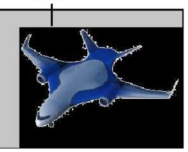
IVHM Covers a broad range of technology



Data Mining in Support of Global Operations



10^{-6} 10^{-5} 10^{-4} 10^{-3} 10^{-2} 10^{-1} 10^{0} 10^{1} 10^{2} 10^{3} 10^{4} 10^{5} 10^{6}



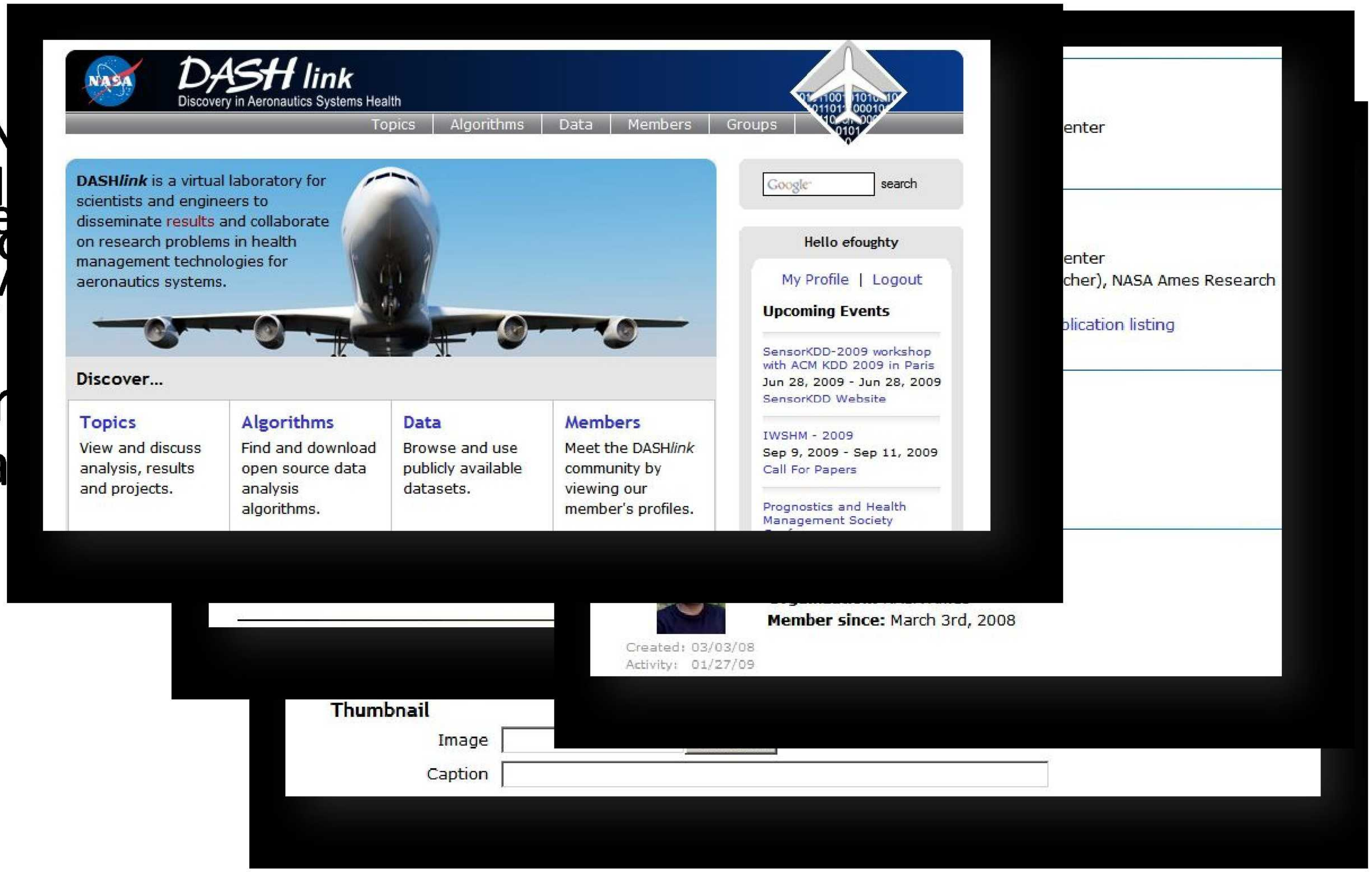
DASHlink.arc.nasa.gov

DASHlink harnesses the power of web 2.0 to further Systems Health and Data Mining research

Download N… papers, and… (including s… in this talk).

Find and inte… Data Mining/… researchers.

Easily shar… own resea…



Organization of IVHM

Principal Investigator: Ashok Srivastava
Project Scientist: Robert Mah
Project Manager: Claudia Meyer

•Project Operations
Manager: Jeff Rybak

•NRA
Manager: Lilly Spirkovska

ARC, DFRC, GRC, LaRC Center POCs

ARC APM: Steve Jacklin
DFRC POC: Mark Dickerson
GRC APM: Bob Kerczewski
LaRC APM: Sharon Graves

•Level 4

- **•Multidisciplinary Ground/ Flight Demos** — •Leads: PI, PS, PM
- **•Systems Analysis for Health Management** — Lead: Mary Reveley
- **•Research Test and Integration** — Lead: Robert Mah
- **•DASHlink** — Lead: Elizabeth Foughty

•Level 3 Associate Principal Investigators

- **•Detection** — API: John Lekki
- **•Diagnosis** — API: Rick Ross
- **•Prognosis** — API: Kai Goebel
- **•Mitigation** — API: Eric Cooper
- **•Integrity Assurance** — API: Eric Cooper

•Level 2

- **Aircraft Systems**
- **Airframe**
- **Propulsion Systems**

***Traditional** Aircraft Subsystems – well represented in Levels 1,3 and 4*

- **Software** — **Lead: Paul Miner**

***Newly Recognized** Aircraft Subsystem*

•Level 1 Lead Researchers

- **•Advanced Sensors and Materials** — Lead: Tim Bencic
- **•Modeling** — Lead: Kevin Wheeler
- **•Advanced Analytics and Complex Systems** — Lead: Nikunj Oza
- **•Verification and Validation** — Lead: Steve Jacklin

The Data Mining Team

Group Members

Kanishka Bhaduri, Ph.D.
Santanu Das, Ph.D.
Elizabeth Foughty
Dave Iverson
Rodney Martin, Ph.D.
Bryan Matthews
Nikunj Oza, Ph.D.
Mark Schwabacher, Ph.D.
John Stutz
David Wolpert, Ph.D.

Funding Sources

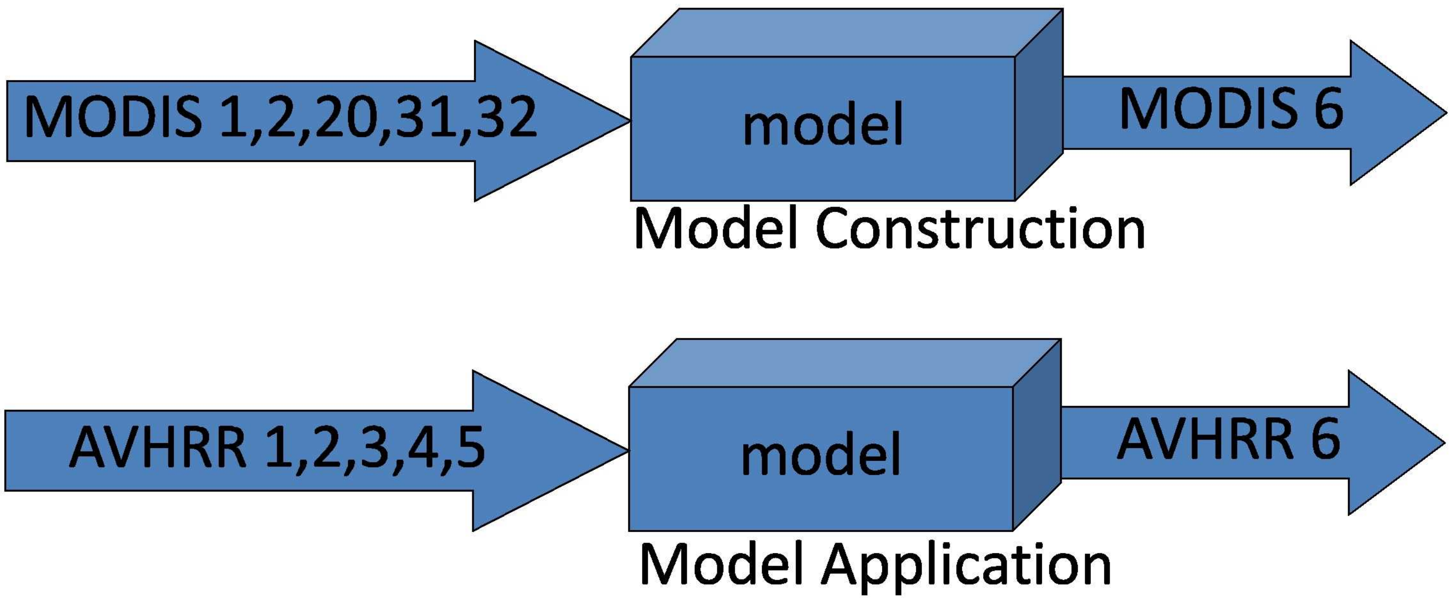
- NASA Aeronautics Research Mission Directorate- IVHM Project
- NASA Engineering and Safety Center
- Exploration Systems Mission Directorate Exploration Technology Development Program, ISHM Project
- Science Mission Directorate

Team Members are NASA Employees, Contractors, and Students.

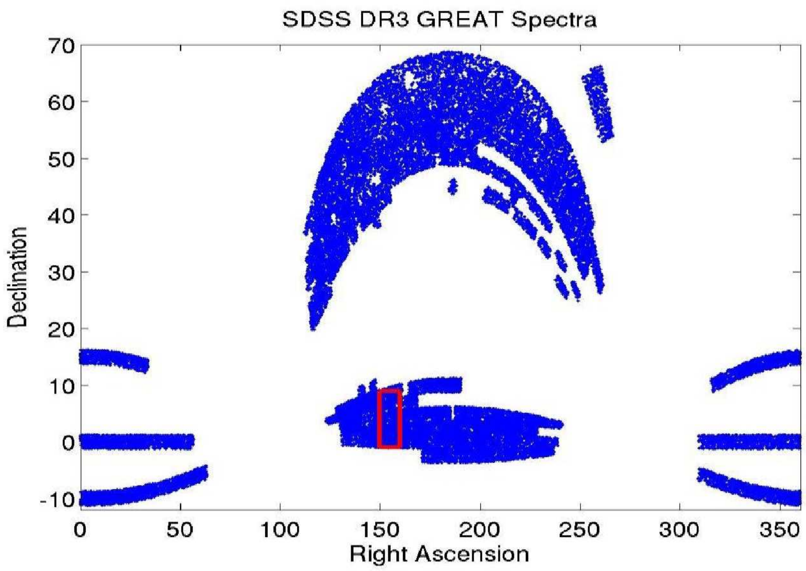
APPENDIX

Virtual Sensors Approach

- Given MODIS channels 1, 2, 20, 31, 32 correspond to five AVHRR/2 channels
- Develop a model for MODIS channel 6 (1.6mm) as a function of these channels
- Use function to construct estimate of 1.6mm channel for AVHRR/2



Characterizing the Large Scale Structure of the Universe

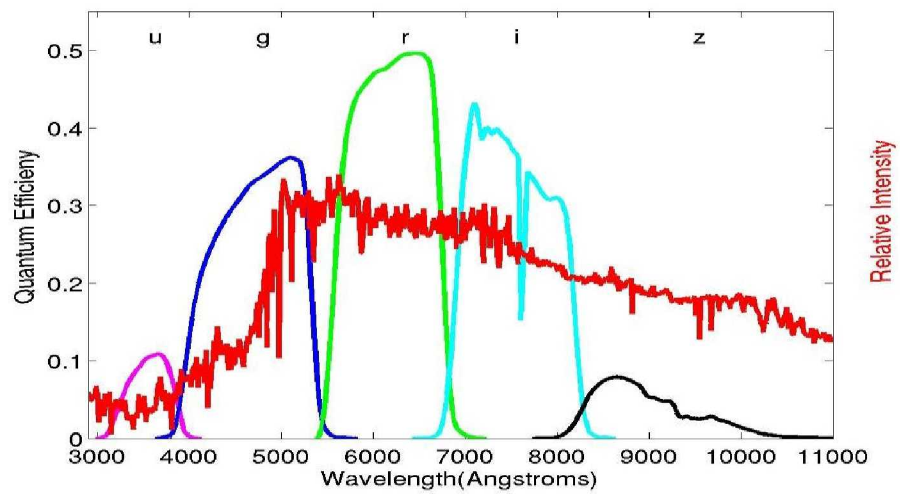


There are between 125 and 500 billion galaxies in the universe.

Obtaining a good estimate of their 3-D position in the sky would help determine the filamentary structure of the universe to constrain cosmological models.

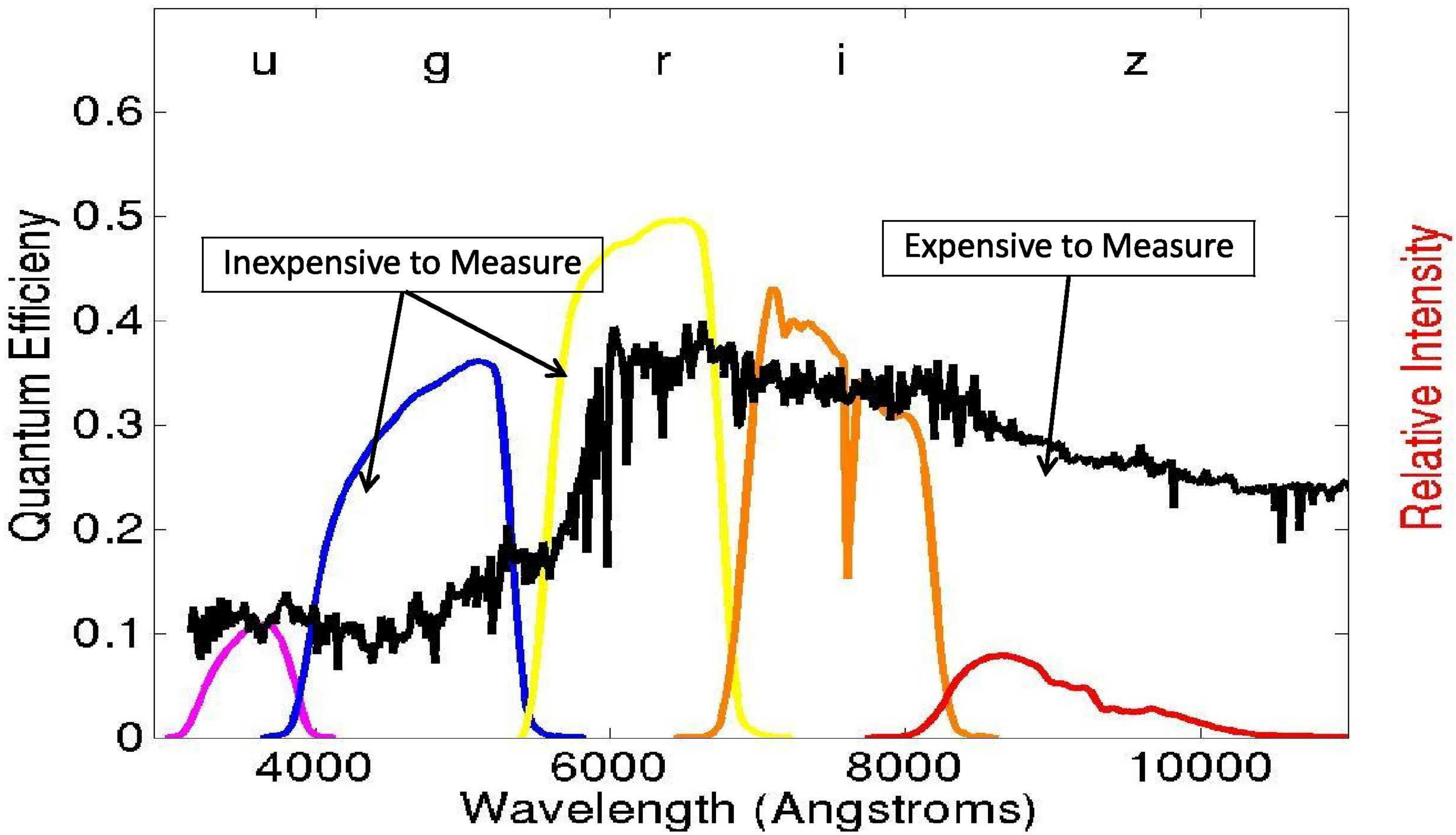
We are building machine learning methods to estimate the redshift of galaxies using broad-band photometry.

If these estimates are of high enough accuracy, it would enable a better understanding of how the universe evolved after the Big Bang.



What are Photometric Redshifts?

Photometric Redshifts: A **rough** estimate of the redshift of a galaxy without having to measure a spectrum.



The Empirical Approach to Redshift Estimation

Training sample consists of galaxies with

- known spectroscopic redshift
- a comparable range of **magnitudes (**u g r i z**)** to our photometric survey objects

Galaxy Photometric Redshift Prediction History

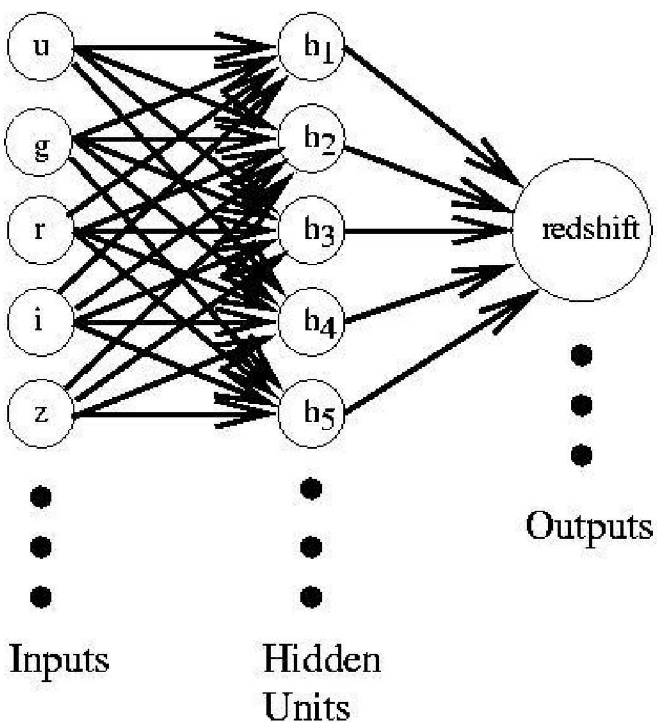
- Linear Regression was first tried in the 1960s
- Quadratic & Cubic Regression (1970s)
- Polynomial Regression (1980s)
- Neural Networks (1990s)
- Kd Trees & Bayesian Classification Approaches (1990s)
- Support Vector Machines & GP Regression (2000s)

Kernels Incorporate Prior Knowledge

Gaussian Process Regression

A large # of hidden units in a Neural Network

Gaussian Process Regression (Neal 1996).



Johann Carl Friedrich Gauss (1777–1855), painted by [Christian Albrecht Jensen] (wikipedia)

Large Scale Gaussian Processes

With our SDSS (DR3) Main Galaxy spectroscopic sample (180,000 galaxies) the matrix size is 180,000 x 180,000

- Need a supercomputer with a LOT of ram and cpu time?
- One can take a random sample of ~1000 galaxies & invert that while bootstrapping n times from full sample
- **However, some *low-rank matrix approximations* work well** such as Cholesky Decomposition, Subset of Regressors but can have numerical problems.
- Solution: V-method (Cholesky decomposition with pivoting)

The V-Method is the innovation of Leslie Foster and his students at San Jose State University

Numerical Instability in Subset of Regressors Method

- In SR formula consider special case $\lambda = 0$
- $\widehat{y}^* = K_1^*(K_1^T K_1)^{-1} K_1^T y$
- Exactly normal equations solution to the least squares prediction problem: min $||y - K_1 x||$ and $\widehat{y}^* = K_1^* x$
- Note: can be easily extended for $\lambda \neq 0$
- Potential numerical instability

Low Rank Approximations

$$K = \begin{array}{cc} & \begin{array}{cc} m & n-m \end{array} \\ \begin{array}{c} m \\ n-m \end{array} & \begin{pmatrix} K_{11} & K_{12} \\ K_{21} & K_{22} \end{pmatrix} \end{array} = \begin{array}{cc} & \begin{array}{cc} m & n-m \end{array} \\ n & \begin{pmatrix} K_1 & K_2 \end{pmatrix} \end{array}$$

$$K^* = \begin{array}{cc} & \begin{array}{cc} m & n-m \end{array} \\ n^* & \begin{pmatrix} K_1^* & K_2^* \end{pmatrix} \end{array}$$

$$K \cong \widehat{K} \equiv K_1 K_{11}^{-1} K_1^T$$

$$K^* \cong \widehat{K}^* \equiv K_1^* K_{11}^{-1} K_1^T$$

Results from Other Authors

Method Name	σ_{rms}	Dataset[1]	Inputs[2]	Source
CWW	0.0666	SDSS-EDR	ugriz	Csabai et al. (2003)
Bruzual-Charlot	0.0552	SDSS-EDR	ugriz	Csabai et al. (2003)
ClassX	0.0340	SDSS-DR2	ugriz	Suchkov et al. (2005)
Polynomial	0.0318	SDSS-EDR	ugriz	Csabai et al. (2003)
Support Vector Machine	0.0270	SDSS-DR2	ugriz	Wadadekar (2005)
Kd-tree	0.0254	SDSS-EDR	ugriz	Csabai et al. (2003)
Support Vector Machine	0.0230	SDSS-DR2	ugriz+r50+r90	Wadadekar (2005)
Artificial Neural Network	0.0229	SDSS-DR1	ugriz	Collister & Lahav (2004)

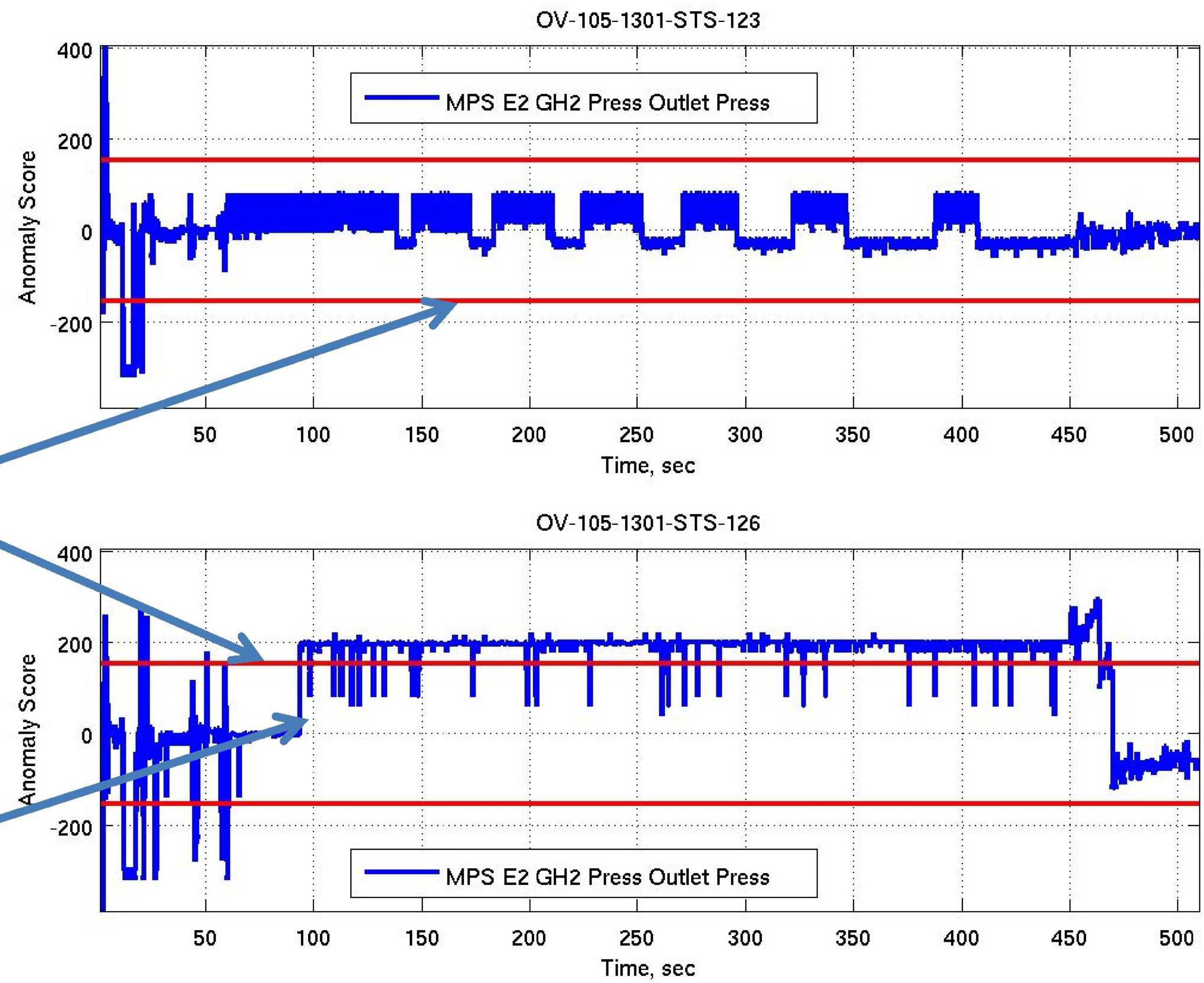
Summary of Our Results

Results: SDSS (DR3) Main Galaxy Sample

- Paper I: Compared linear, quadratic, Neural Networks and GPs on the SDSS
- With ONLY 1000 samples GPs performed well compared to the other methods
- Paper II: With *low-rank matrix inversion approximations* GPs performed better than all other methods

Virtual Sensor: STS-123 and STS-126

- Redlines correspond to 3-sigma nominal error rate on STS-123.
- STS-126 shows anomalous behavior after 93.6 seconds.



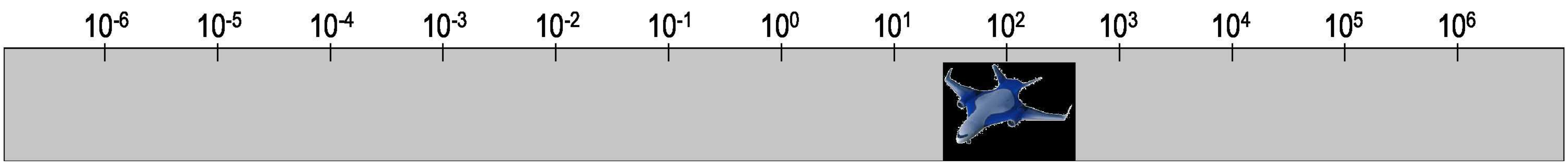
Summary of Research Needs in Aviation Safety

- Aircraft aging and durability
  - Full fundamental knowledge about legacy aircraft
  - Start on knowledge about likely emerging materials and structures
- On-board system failures and faults – airframe, propulsion, aircraft systems (physical and software)
  - Early prediction, detection and diagnosis
  - Prognosis
  - Mitigation
- Monitoring for problems before they become accidents
  - Vehicle issues
  - Airspace issues
- Loss-of-control
  - Understanding aircraft dynamics of current and future vehicles in damaged and upset conditions
  - Control systems robust to the unanticipated and anticipated
  - Aircraft guidance for emergency operation
- Flight in hazardous conditions
  - Modeling and sensing airframe and engine icing and icing conditions
  - Sensing and portraying environmental hazards
- New operations
  - Design of robust collaborative work environments
  - Design of effective, robust human-automation systems
  - Information management and portrayal for effective decision making

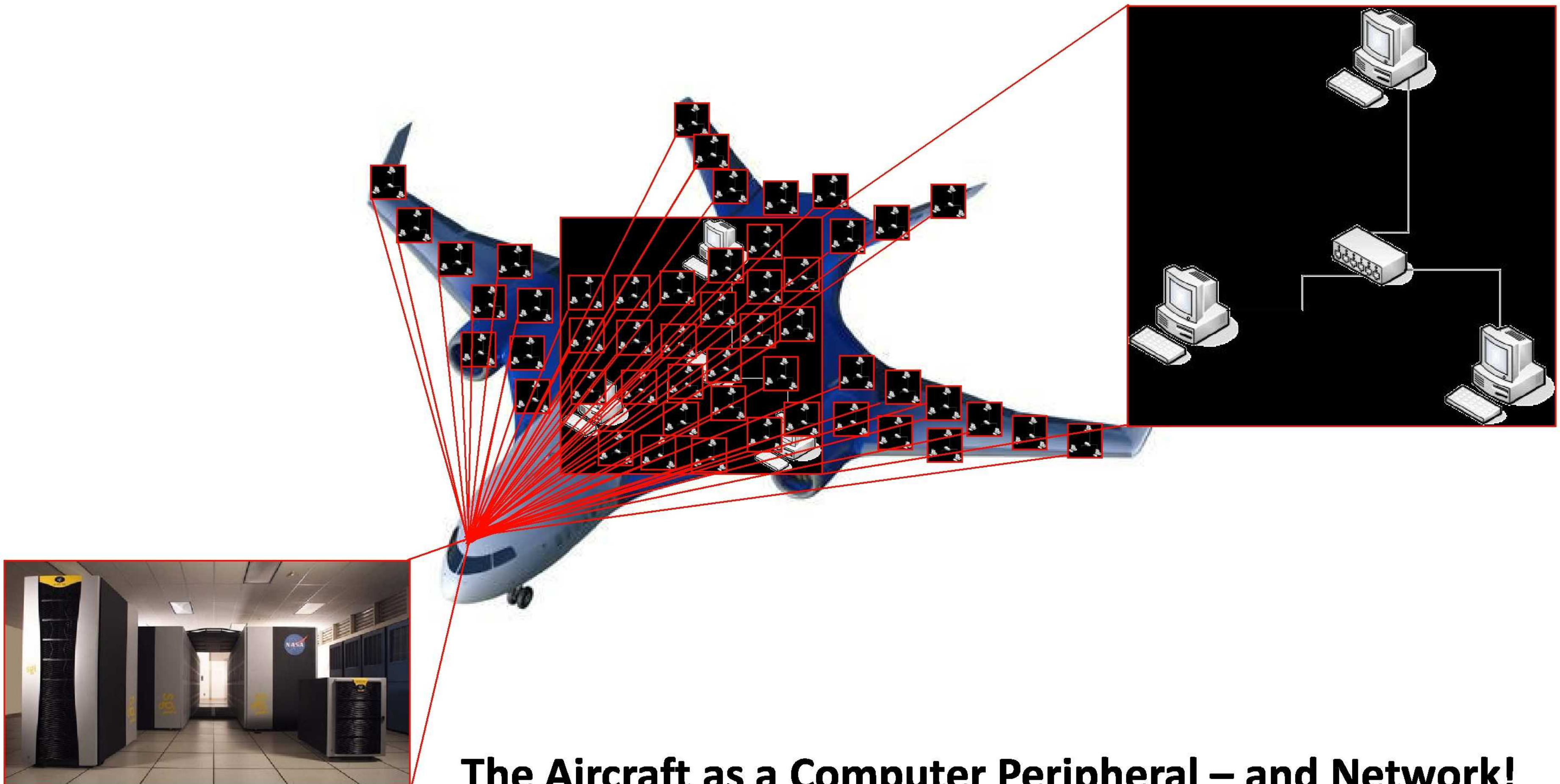
Integrated Vehicle Health Management

The Powers of Aviation Safety – 10^{-6} - 10^{6}

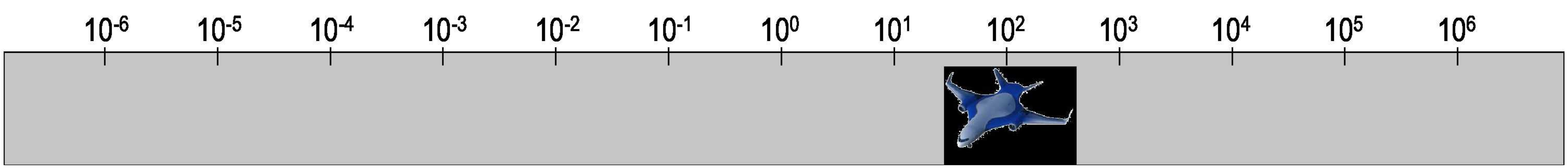
- There is no one 'silver bullet' – we must look at all contributors to safety
- Consider the space we must consider:
  - Safety at the smallest level
  - Safety spanning the nation (and the world!)
- Let us consider these different sizes, expressed as 'Powers of Ten'



10^2 – The Aircraft



The Aircraft as a Computer Peripheral – and Network!



Organization of IVHM

Principal Investigator: Ashok Srivastava
Project Scientist: Robert Mah
Project Manager: Claudia Meyer

- **Project Operations**
  Manager: Jeff Rybak
- **NRA**
  Manager: Lilly Spirkovska

ARC, DFRC, GRC, LaRC Center POCs

ARC APM: Steve Jacklin
DFRC POC: Mark Dickerson
GRC APM: Bob Kerczewski
LaRC APM: Sharon Graves

- ***Level 4***

- **Multidisciplinary Ground/ Flight Demos**
  - Leads: PI, PS, PM
- **Systems Analysis for Health Management**
  Lead: Mary Reveley
- **Research Test and Integration**
  Lead: Robert Mah
- **DASHlink**
  Lead: Elizabeth Foughty

- ***Level 3 Associate Principal Investigators***

- **Detection**
  API: John Lekki
- **Diagnosis**
  API: Rick Ross
- **Prognosis**
  API: Kai Goebel
- **Mitigation**
  API: Eric Cooper
- **Integrity Assurance**
  API: Eric Cooper

- ***Level 2***

Aircraft Systems | **Airframe** | **Propulsion Systems**

***Traditional** Aircraft Subsystems – well represented in Levels 1,3 and 4*

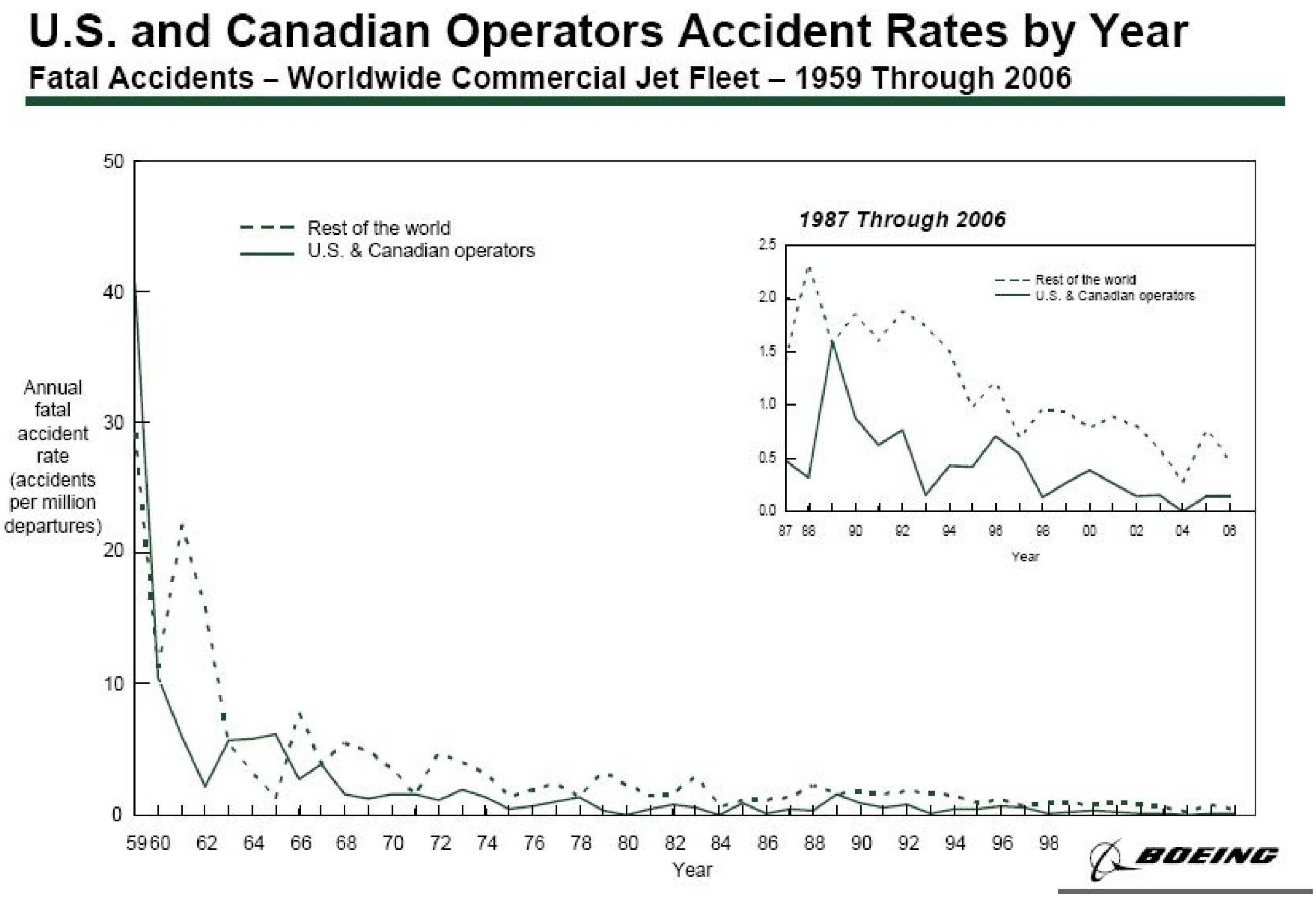
Software
Lead: Paul Miner

***Newly Recognized** Aircraft Subsystem*

- ***Level 1 Lead Researchers***

- **Advanced Sensors and Materials**
  Lead: Tim Bencic
- **Modeling**
  Lead: Kevin Wheeler
- **Advanced Analytics and Complex Systems**
  Lead: Nikunj Oza
- **Verification and Validation**
  Lead: Steve Jacklin

Recent Safety Advances



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