Riding the hype wave: Evaluating new AI techniques for their applicability in Earth science

Rahul Ramachandran, NASA/MSFC

Jia Zhang, CMU

Manil Maskey, NASA/MSFC

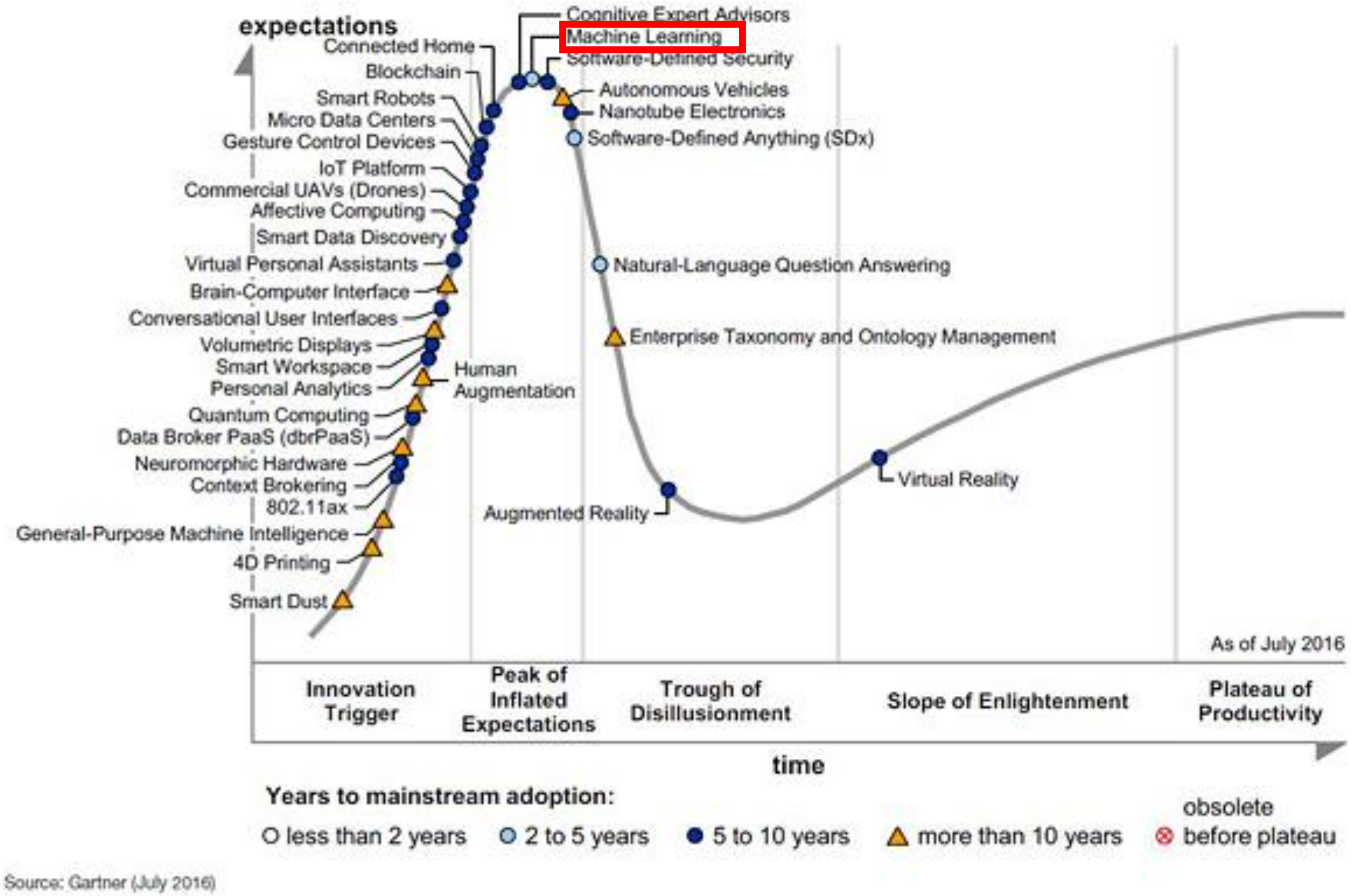
Tsengdar Lee, NASA/HQ

Hype Wave: The Perpetual Smart Machine Age

“Smart machine technologies will be the **most disruptive class of technologies over the next 10 years** due to radical computational power, near-endless amounts of data, and unprecedented advances in **deep neural networks** that will allow organizations with smart machine technologies to harness data in order to adapt to new situations and solve problems that no one has encountered previously. Enterprises that are seeking leverage in this theme should consider the following technologies: *Smart Dust*, ***Machine Learning***, *[Virtual Personal Assistants]*, *Cognitive Expert Advisors, Smart Data Discovery, Smart Workspace, Conversational User Interfaces, Smart Robots, Commercial UAVs (Drones)*, *[Autonomous Vehicles]*, *Natural-Language Question Answering, Personal Analytics*, ***Enterprise Taxonomy and Ontology Management***, *Data Broker PaaS (dbrPaaS), and Context Brokering.”*

Source: Gartner Press Release http://www.gartner.com/newsroom/id/3412017

Hype Cycle for Emerging Technologies (2016)



Source: Gartner Press Release http://www.gartner.com/newsroom/id/3412017

AI Hype

ANALYTICS

Machine Learning Is No Longer Just for Experts

by Josh Schwartz Source: https://hbr.org/2016/10/machine-learning-is-no-longer-just-for-experts

OCTOBER 26, 2016

TECHNOLOGY

The Competitive Landscape for Machine Intelligence

by Shivon Zilis and James Cham Source: https://hbr.org/2016/11/the-competitive-landscape-for-machine-intelligence

NOVEMBER 02, 2016

ANALYTICS

How to Make Your Company Machine Learning Ready

by James Hodson Source: https://hbr.org/2016/11/how-to-make-your-company-machine-learning-ready

NOVEMBER 07, 2016

Cautionary Examples

ANALYTICS

What Artificial Intelligence Can and Can't Do Right Now

by Andrew Ng

NOVEMBER 09, 2016

Source: https://hbr.org/2016/10/machine-learning-is-no-longer-just-for-experts

The racist hijacking of Microsoft's chatbot shows how the internet teems with hate

Source: https://www.theguardian.com/world/2016/mar/29/microsoft-tay-tweets-antisemitic-racism

Google says sorry for racist auto-tag in photo app

Source:https://www.theguardian.com/technology/2015/jul/01/google-sorry-racist-auto-tag-photo-app

Challenges for Earth Science Informatics

- How do we evaluate these new technologies?
  - What is this new technology enabling/providing that is innovative and different?
- Can one justify the adoption costs with respect to the research returns?
  - Since nothing comes for free, utilizing a new technology entails adoption costs that may outweigh the benefits.
  - Technologies may require significant computing infrastructure in order to be utilized effectively.

AI Projects – Overview and Lessons Learned

- Building a Knowledge Graph for Earth Science
  - Rahul Ramachandran *NASA/MSFC*, Patrick Gatlin *NASA/MSFC*, Manil Maskey *NASA/MSFC*; Jia Zhang, *CMU*; Amanda Weigel *UAH*, J. J. Miller, *UAH*

- Evaluating deep learning technique for different applications within Earth science using satellite imagery
  - *Multiple projects*

Building a Knowledge Graph for Earth Science

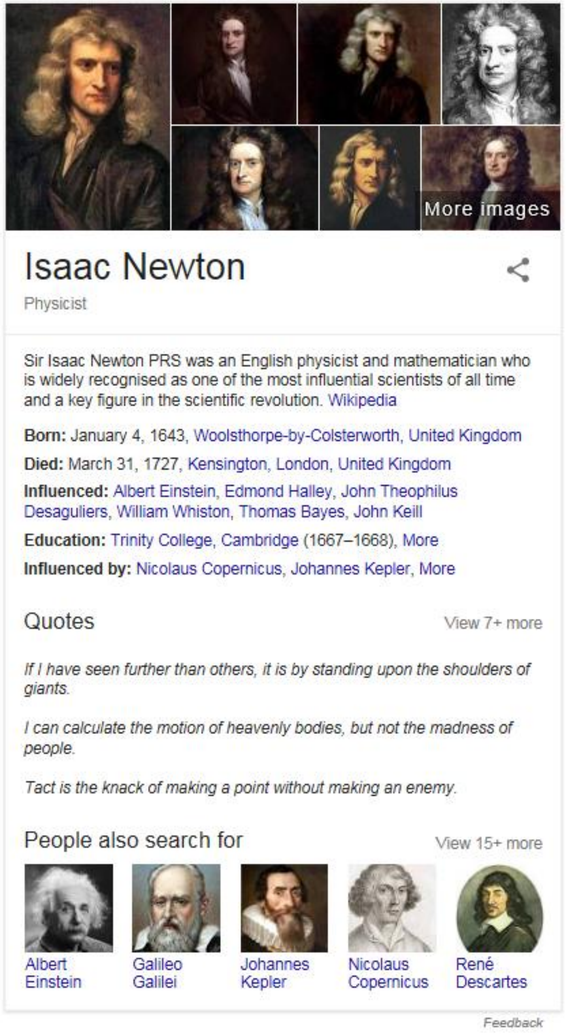
What is a Knowledge Graph?

- Aggregates structured and detailed information about a defined topic, enabling users to resolve their query without having to navigate and assemble information manually
- Developed by Google in 2012 to enhance the results of its search engine by systematically linking information.

Isaac Newton

Google Search

I'm Feeling Lucky



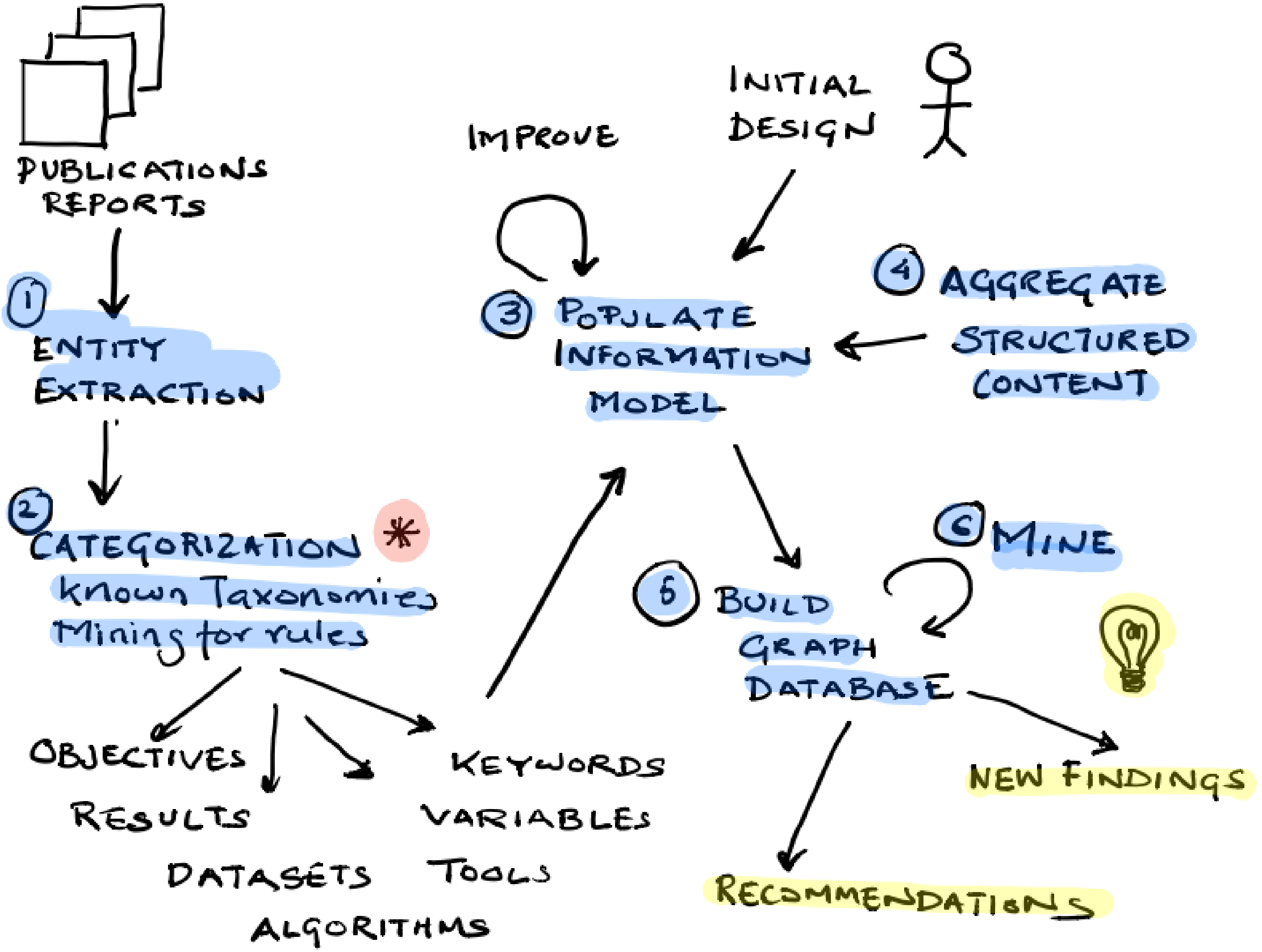
Benefits to NASA Earth Science

- New knowledge/knowledge augmentation services
  - Hypothesis formulation and testing:
    - Automate the search for and compilation of background information
    - Given a topic, what hypotheses have been tested?
    - What data/tools are being used to test a hypothesis?
    - Common paths to knowledge discovery
  - Mission development/review:
    - What kinds of instruments/parameters are needed to specify science objectives?
    - Impact of a mission by linking it with publications and dataset distribution
- Recommendation service based on the knowledge base to broaden usage of NASA EOS datasets and computational resources

Methodology

Earth Science Research consists of both Structured and <u>Unstructured Content</u>

How do we extract and link valuable information from the vast distributed heterogeneous resources?



Initial Results

299 Publications

Paper Title	Authors	Publication Channel	Year
Laser observations of wave growth and foam density for fetch limited 25 M/SEC winds	Ross D. B., Cardone V.		1970
Atmospheric probing by Doppler radar	Lhermitte R. M.		1969
Experimental approaches to remote atmospheric probing in the infrared from satellites	Bandeen W. R.		1969
The role of remotely sensed and relayed data in the Delaware River Basin	Paulson R. W.		1970
Third Annual Earth Resources Program Review. Volume 2: Agriculture, forestry, and sensor studies		1-3 Dec. 1970; Houston, TX; United States	1970
Spectral reflectance from plant canopies and optimum spectral channels in the near infrared	Wiegand C. L., Gausman H. W., Allen W. A.		
Exploration of Marine Resources by Photographic Remote Sensing	Duntley S. Q., Boileau A. R., Stevenson R. E.		1971
The Role of Remotely Sensed and Relayed Data in the Delaware River Basin	Paulson R. W.		1971
Sources of Asian dust and role of climate change versus desertification in Asian dust emission	Wang Y. Q., Zhou Z. J., Zhang X. Y., ...	GEOPHYSICAL RESEARCH LETTERS	2003
Saharan dust particles nucleate droplets in eastern Atlantic clouds	Ismail Syed, Heymsfield Andrew J., Anderson Bruce E., ...	GEOPHYSICAL RESEARCH LETTERS	2009
A new Saharan dust source activation frequency map derived from MSG-SEVIRI IR-channels	Heinold B., Laurent B., Tegen I., ...	GEOPHYSICAL RESEARCH LETTERS	
Summer dust aerosols detected from CALIPSO over the Tibetan Plateau	Winker David, Liu Zhaoyan, Aye	GEOPHYSICAL RESEARCH	200
Multiangle Imaging Spectr assessment by compariso			

MetaData | Figures and Captions | Analytics | Sections | Micro Article | References | Evaluation | Proofread

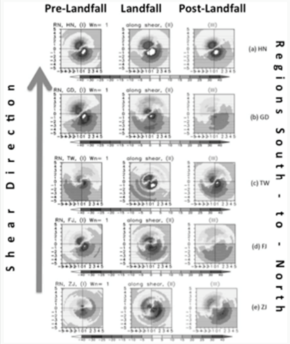
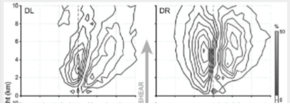
Paper Title	Impact of Vertical Wind Shear on Tropical Cyclone Rainfall
Authors	Cecil Dan , Marchok Tim
Publication Channel	WMO International Workshop on Tropical Cyclone Landfall Processes; 3rd; 2-10 Dec. 2014; Jeju; Korea, Republic ofWMO International Workshop on Tropical Cyclones; 8th; 2-10 Dec. 2014; Jeju; Korea, Republic of
Financial Sponsor	NASA Marshall Space Flight Center; Huntsville, AL, United States
Organization Source	NASA Marshall Space Flight Center; Huntsville, AL, United States
Meeting Sponsor	World Meteorological Organization; Geneva, SwitzerlandKorea Meteorological Administration; Seoul, Republic of Korea
Report/Patent Number	M14-4117
NASA Terms	TROPICAL STORMS; CYCLONES; VERTICAL AIR CURRENTS; WIND SHEAR; PRECIPITATION (METEOROLOGY); DOWNBURSTS; WIND DIRECTION; IMPACT PREDICTION; ASYMMETRY; CHINA; TAIWAN; HYDROMETEORS; METEOROLOGICAL RADAR; REFLECTANCE
Subject Category	METEOROLOGY AND CLIMATOLOGY
Date	Dec 02
Year	2014
Abstract	While tropical cyclone rainfall has a large axisymmetric component, previous observational and theoretical studies have shown that environmental vertical wind shear leads to an asymmetric component of the vertical motion and precipitation fields. Composites consistently depict a precipitation enhancement downshear and also cyclonically downwind from the downshear direction. For consistence with much of the literature and with Northern Hemisphere observations, this is subsequently referred to as "Downshear-Left""""""""". Stronger shear magnitudes are associated with greater amplitude precipitation asymmetries. Recent work has reinforced the prior findings, and explored details of the response of the precipitation and kinematic fields to environmental vertical wind shear. Much of this research has focused on tropical cyclones away from land, to limit the influence of other processes that might distort the signal related to vertical wind shear. Recent evidence does suggest

MetaData | Figures and Captions | Analytics | Sections | Micro Article | References | Evaluation | Proofread

Topic	TROPICAL/CYCLONES
Topic Keywords	Regions, Landfall, Hurricane, Tropical, Rate, Rates, Storm, Cyclone
Instruments	
Datasets	
Variables	Altitude, X wind, Y wind
Organizations	
Tool-model	SHIPS(Statistical Hurricane Intensity Prediction Scheme)
Statistical Technology	
Filters	
Projection Type	azimuthal
Projects	TRMM(Tropical Rainfall Measuring Mission Project)
Aircraft	
Satellite	
Ground	
Algorithms	
Visualizations	Horizontal, Schematic, Frequency distribution
Conclusions	
Hypothesis	

MetaData | Figures and Captions | Analytics | Sections | Micro Article | Evaluation | Proofread

4 Extracted Figure/Table

Eorganizationsxtracted Figure/Table	Caption
	Figure 1. S... rainfall asymmetry before (left), during (middle), and after (right)
	Figure 2. Anomaly Contoured Frequency by Altitude Display (CFAD) of eyewall vertical velocity for each shear-relative quadrant, relative to a CFAD for the eyewall in general. Contours represent the frequency anomaly, contoured every 5%, where red contours are positive anomalies and blue contours are negative anomalies. From DeHart et al. (2014)

Lessons Learned

- Entity extraction tools work well; however, categorization of entities is hard.
- Using domain control vocabularies and taxonomies help, but they only get you so far.
- Mining for rules within sentences may work but requires extensive number of labeled samples (training data).

Deep Learning Applications

- Browse Imagery Retrieval Service for Different Phenomena
  - Manil Maskey, NASA/MSFC
- Study Transverse Cirrus Cloud Bands
  - JJ Miller, UAH and NASA/MSFC DSIG; U.S. Nair, UAH
- Tropical Cyclone Intensity Estimation
  - Manil Maskey, NASA/MSFC; Dan Cecil, NASA/MSFC

Deep Learning Architecture

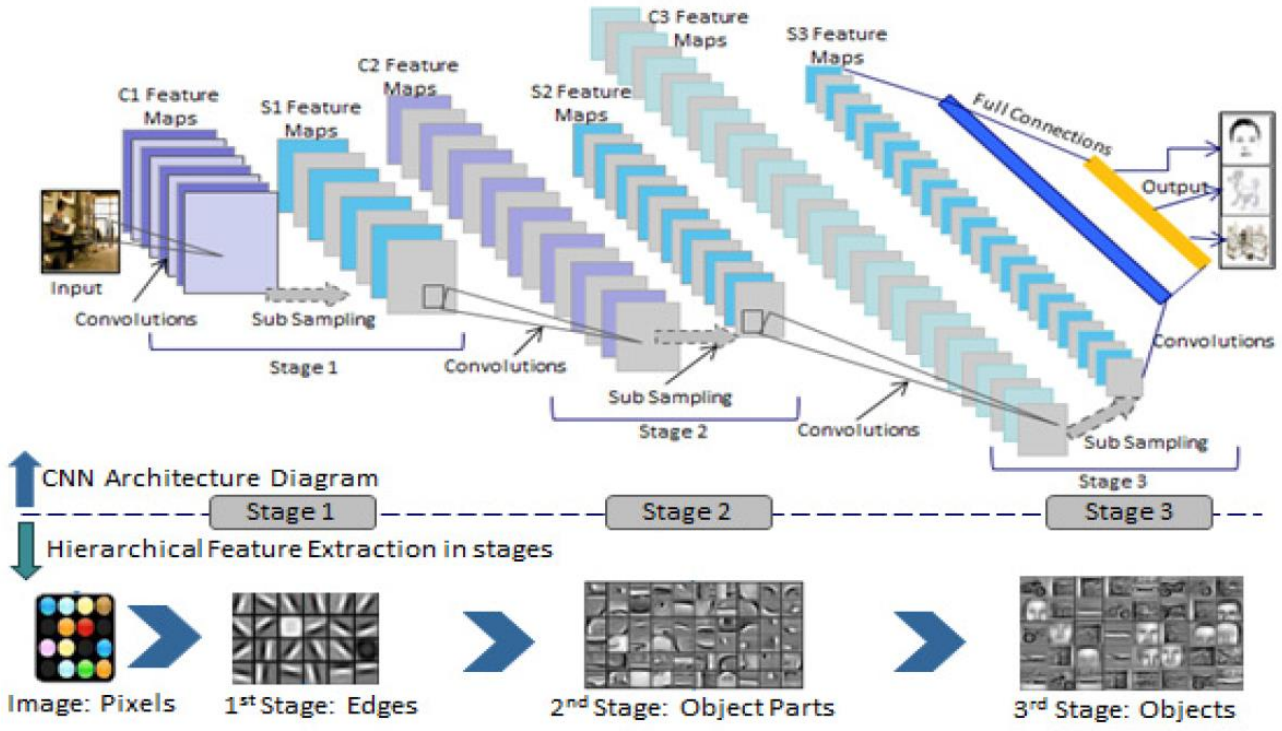


Figure source: Katole et al., 2015 Hierarchical Deep Learning Architecture for 10K Objects Classification, Computer Science & Information Technology (CS & IT), DOI : 10.5121/csit.2015.51408

- Deep Learning
  - Hierarchical Learning
  - Mimics the human brain which is organized in a deep architecture
  - Processes information through multiple stages of transformation and representation
- Key Advantage
  - Automates features engineering (learns)

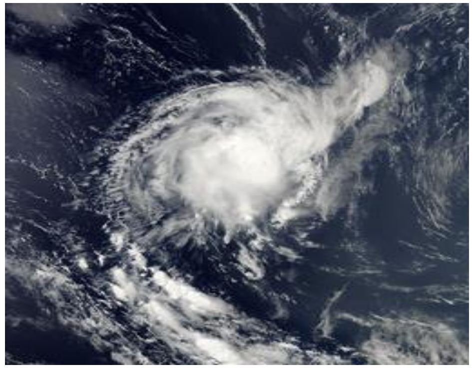
Image Retrieval Application

Objective:

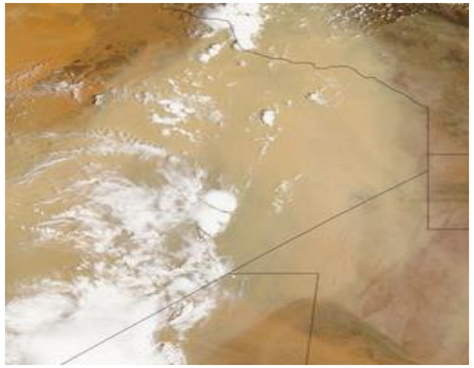
- Test deep learning (Convolution Neural Network) to identify Earth science phenomenon in browse imagery (RGB)

Results (MODIS Rapid Response Test Images)

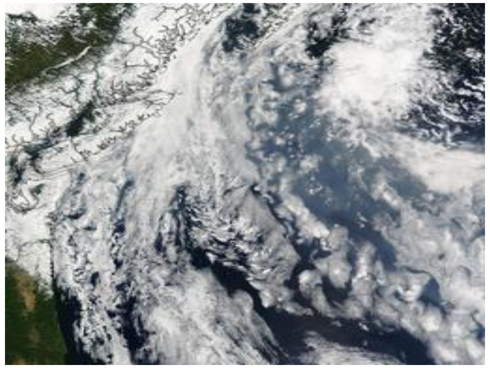
True/Pred	Dust	Hurricane	Smoke	Other
Dust	**287**	8	32	33
Hurricane	0	**379**	1	10
Smoke	12	12	**443**	9
Other	33	9	23	**211**



Hurricane – True Positive



Dust – True Positive



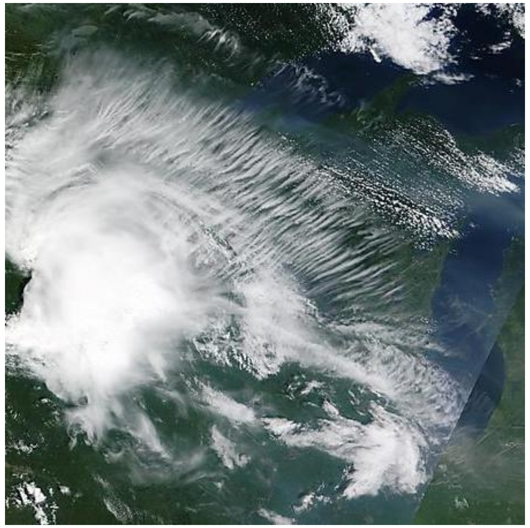
Smoke– True Positive

Producer's Accuracy
Dust 86.45%
Hurricane 92.89%
Smoke 88.78%
Other 80.23

User's Accuracy
Dust 79.72%
Hurricane 97.18%
Smoke 93.07%
Other 76.45%

Overall Accuracy = **87.88**%

Study Transverse Cirrus Bands

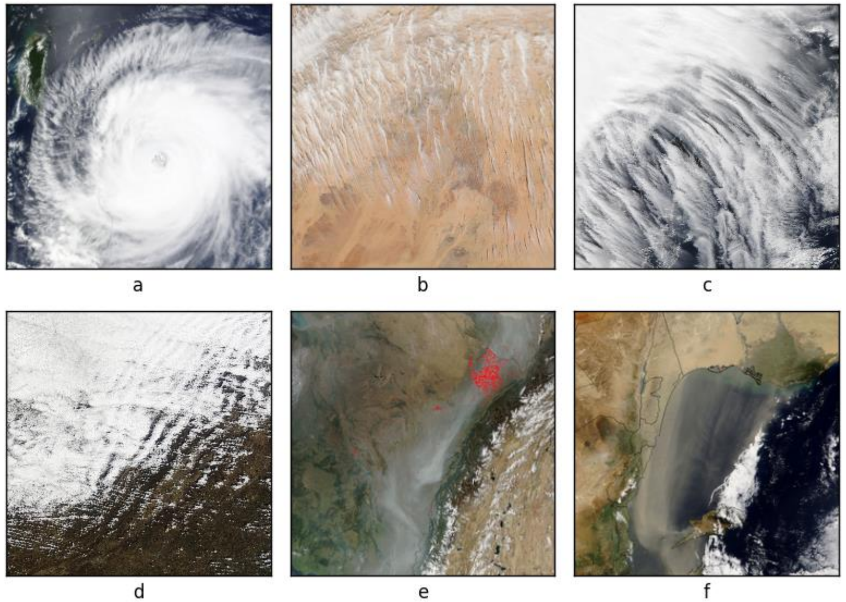


Methodology

- Gathered 5440 images (1 km MODIS RGB)
  - 1741 with transverse bands
  - 3699 without transverse bands
- 20% were used for validation during training
- Test set consisted of 600 separate images not used in training
- Use trained network to classify ~~a~~ one year's worth of MODIS tiles from Global Imagery Browse Service (GIBS)

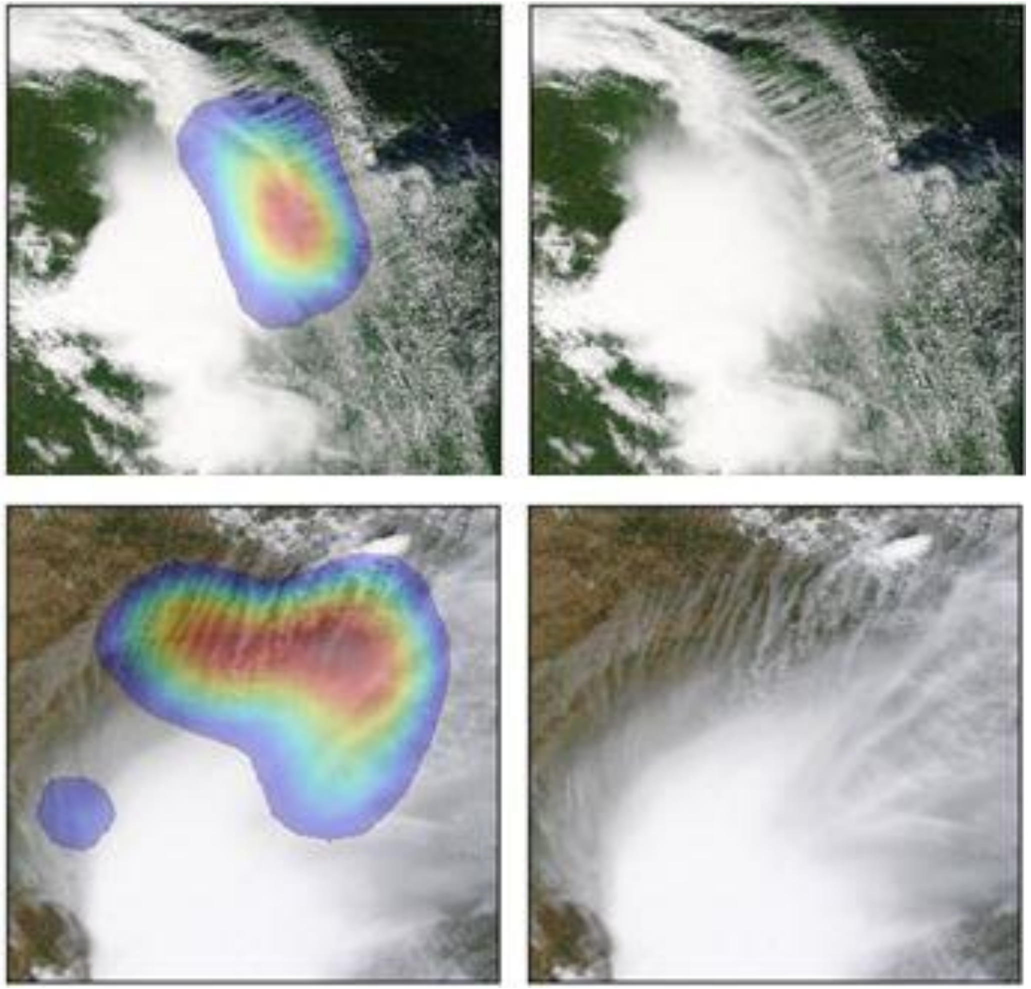
Transverse Cirrus Bands

- Form in and around a variety of meteorological phenomena
  - Hurricanes
  - Mesoscale Convective Systems (MCS)
  - Jet-streaks
- Associated with aviation turbulence
- Still no consensus on exactly what causes them to form



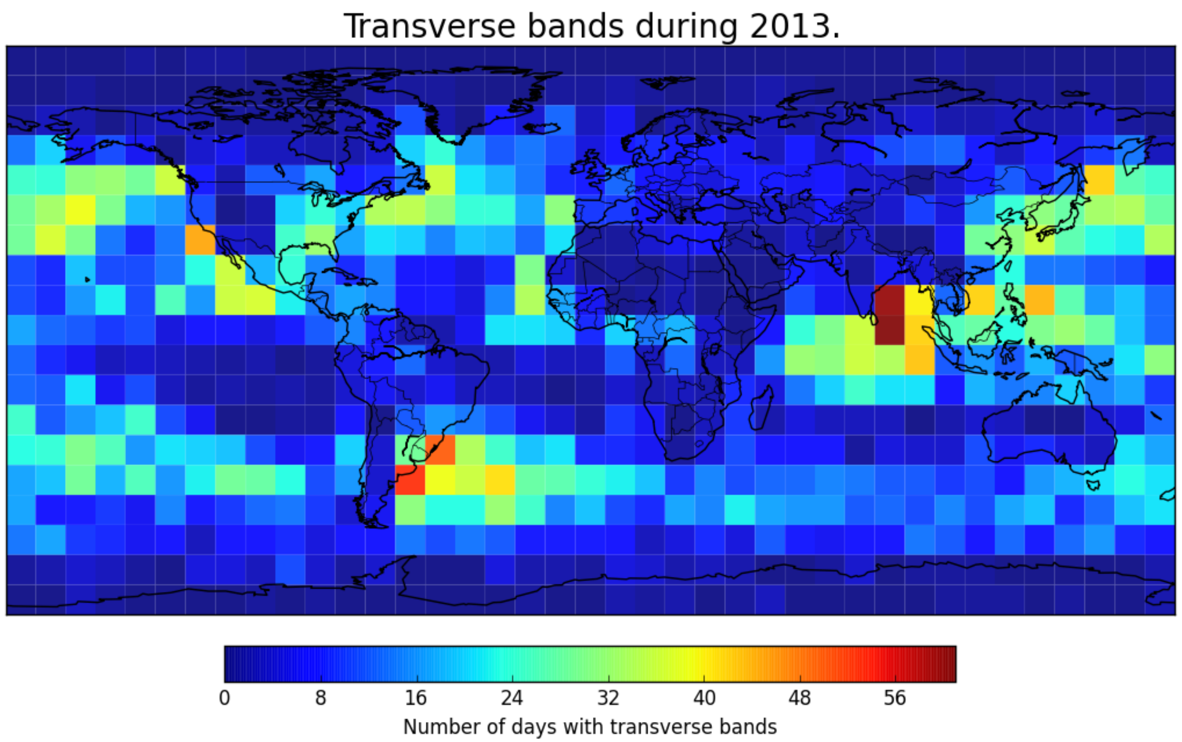
Training Results

- Model trained for 52 epochs (6 hours)
- Highest validation accuracy occurred at epoch 41 (0.937)
- Testing on the test set:
  - Accuracy: 94.67%
  - Recall: 0.95
  - Precision: 0.95
- Class activation maps (right) show that the network is able to identify the regions of the image that contain transverse bands.



		Predictions	
		Bands	Not Bands
Truth	Bands	**107**	22
	Not Bands	10	**461**

Climatology Study: Spatial Distribution

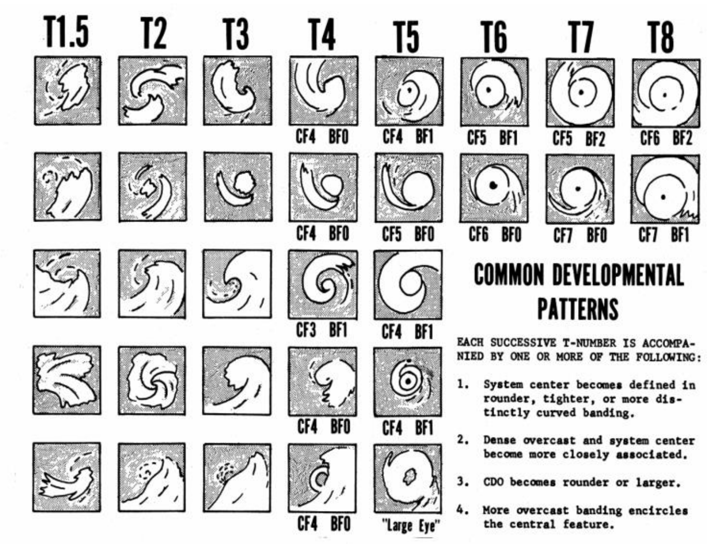


- Some interesting areas stand out
  - Eastern coast of India
  - Western coast of Mexico/California
  - Southeastern coast of South America
- Eastern and Central US more than likely due to MCSs
- Analysis still ongoing…

Tropical Cyclone Intensity Estimation

Goal

- Use deep learning to objectively estimate intensity



Source: Dvorak, V. F., 1973: A technique for the analysis and forecasting of tropical cyclone intensities from satellite pictures. NOAA Tech. Memo. NESS 45, Washington, DC, 19 pp.

Dvorak technique developed in 1970s still used to estimate intensity from satellite imagery

- Inconsistent as estimation is subjective

Image data

- US Naval Research Laboratory (http://www.nrlmry.navy.mil/tcdat)
- 1998 to 2014
- 15 minute interval
- 98 cyclones (68 Atlantic and 30 Pacific)

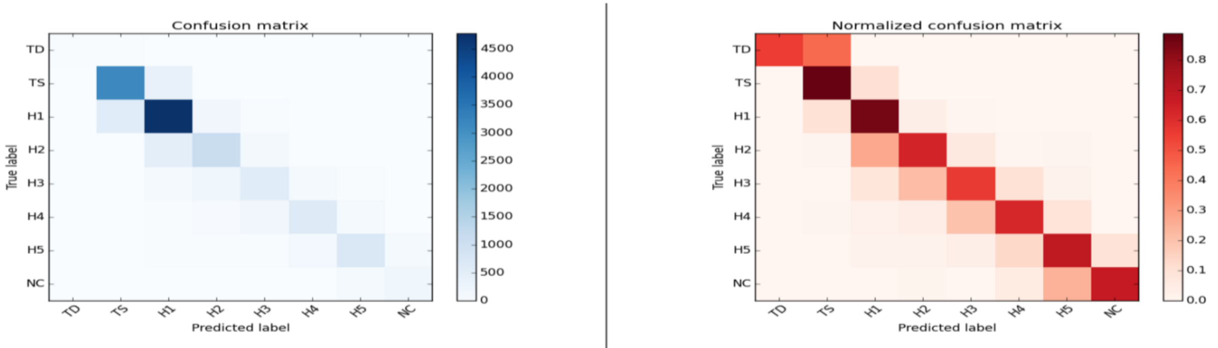
Wind speed data (Truth set)

- National Hurricane Center (http://www.nhc.noaa.gov) (Best track data: HURDAT and HURDAT2)
- Hurricane Research Division (http://www.aoml.noaa.gov/hrd/hurdat/Data_Storm.html)
- 6 hour interval

Results

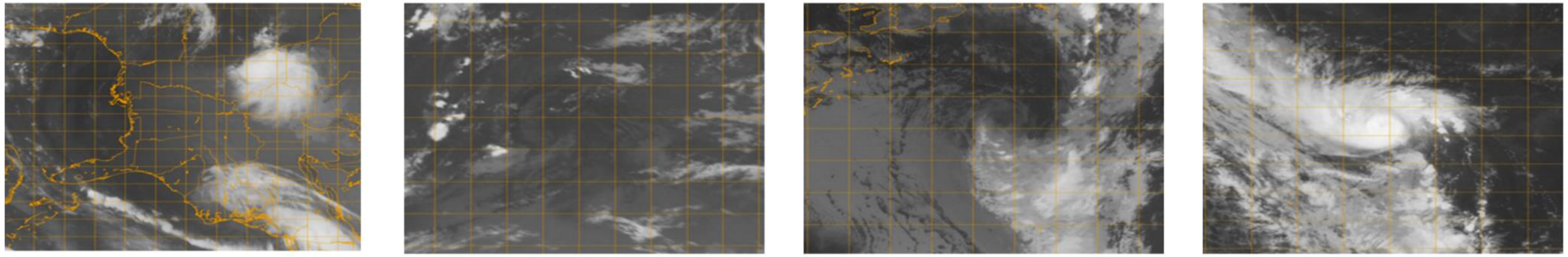
- Precision – 0.80
- Recall – 0.81
- 14,345 test images (Atlantic + Pacific)

		Predicted Category								
		NC	TD	TS	H1	H2	H3	H4	H5	Total
Actual Category	NC	32	20	2	0	0	0	0	0	54
	TD	9	3174	393	0	0	0	0	0	3576
	TS	1	488	4838	208	25	10	3	2	5575
	H1	0	16	423	1235	115	20	7	0	1816
	H2	0	0	70	193	614	98	19	0	994
	H3	0	0	35	37	156	657	106	1	992
	H4	0	0	14	4	24	117	816	57	1032
	H5	0	0	0	0	1	14	86	205	306
	Total	42	3698	5775	1677	935	916	1037	265	14345

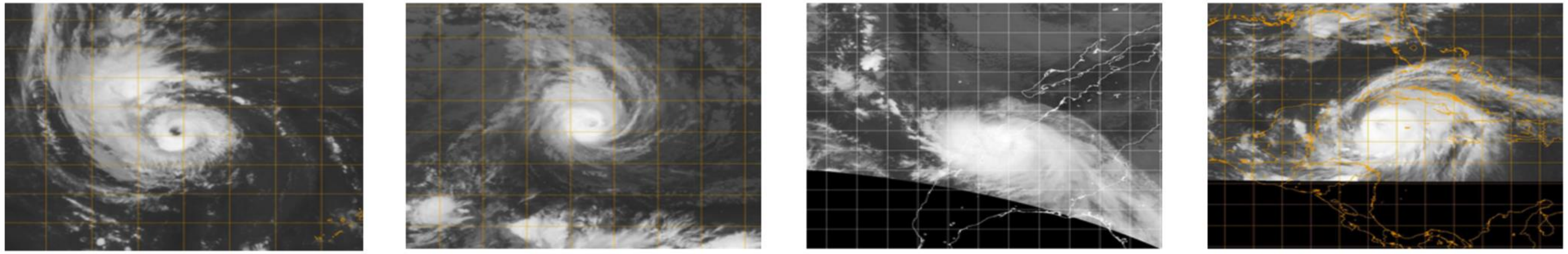


(a) (b)

True Positives



(a) **NC:** ['NC': 99.4] (b) **TD:** ['TD': 87.46] (c) **TS:** [TS: 100] (d) **H1:** [H1: 56.8]



(e) **H2:** [H2: 78.54] (f) **H3:** [H3: 95.73] (g) **H4:** [H4: 86.04] (h) **H5:** [H5: 58.26]

Lessons Learned

- Compute intensive (requires GPUs)
- Requires extensive amounts of training data
    - Learning from *a few thousand training samples* is unrealistic
- Suitable for applications where "labeled (training) data" can be obtained from another instrument or data stream
- For some applications transfer learning may work
    - Use internal representation learned from one classification task to another
        - AlexNet architecture - Krizhevsky et. al.
        - Weights learned from ImageNet 1.3 million high-resolution images
        - State-of-the-art classification accuracy

A. Krizhevsky, I. Sutskever, and G. Hinton, "ImageNet Classification with Deep Convolutional Neural Networks," Advances in Neural Information Processing Systems 25, Curran Associates, Inc., pp: 1097-1105, 2012.

Want more details?

Attend the following presentations:

- **Knowledge Graph: Tsengdar Lee et al.**
  - IN14A-08 Building Knowledge Graphs for NASA's Earth Science Enterprise
    Monday, 12 December 2016, 17:45 - 18:00, Moscone West - 2000
- **Deep Learning: Manil Maskey et al.**
  - IN52A-04 Deep Learning-Powered Insight from Dark Resources
    Friday, 16 December 2016, 11:20 - 11:32, Moscone West - 2000

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rahul.ramachandran@nasa.gov