Time-Varying Semantic Representations of Planetary Observations for Discovering Novelties

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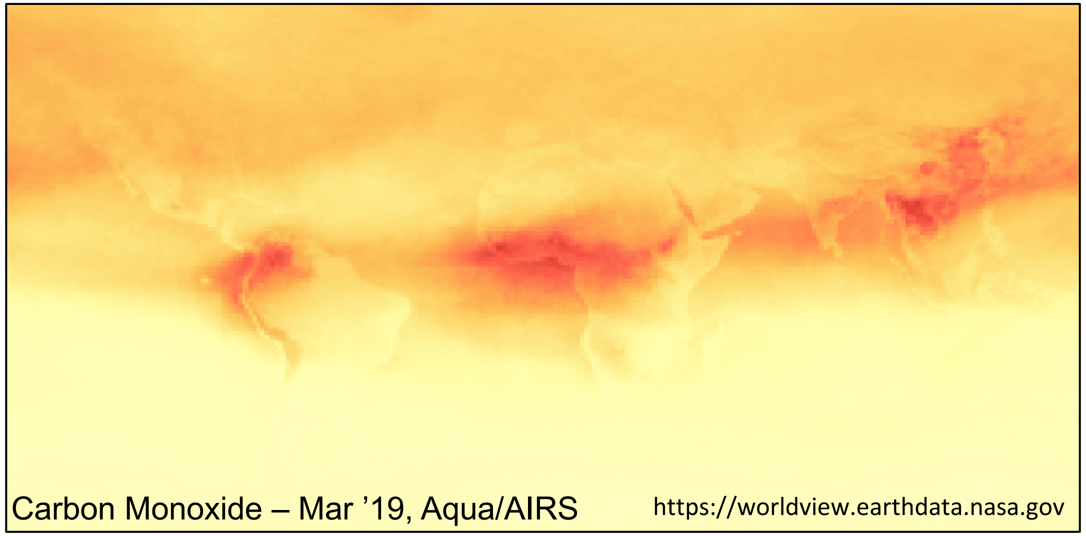
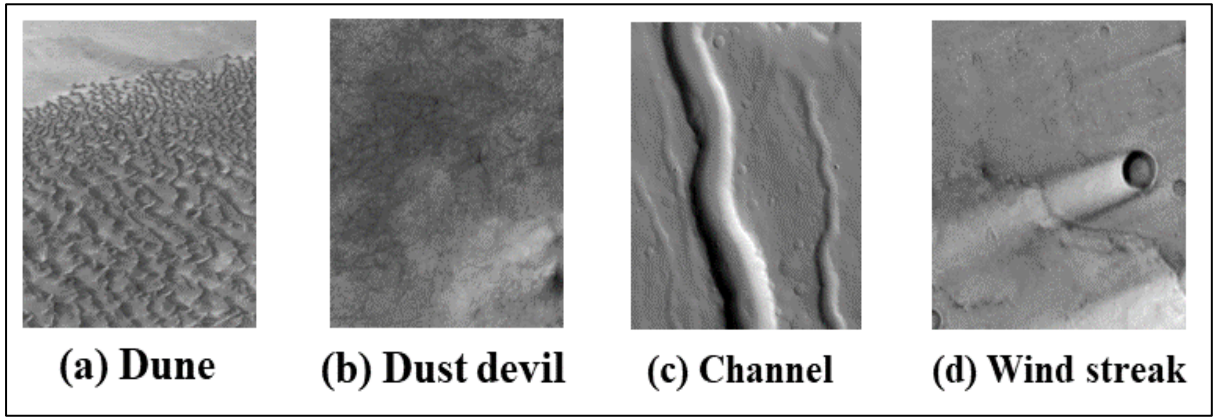
Novelty Detection from Remote Sensing Observations

Increasing volume of the data collected by the growing number of Earth and Planetary observation satellites

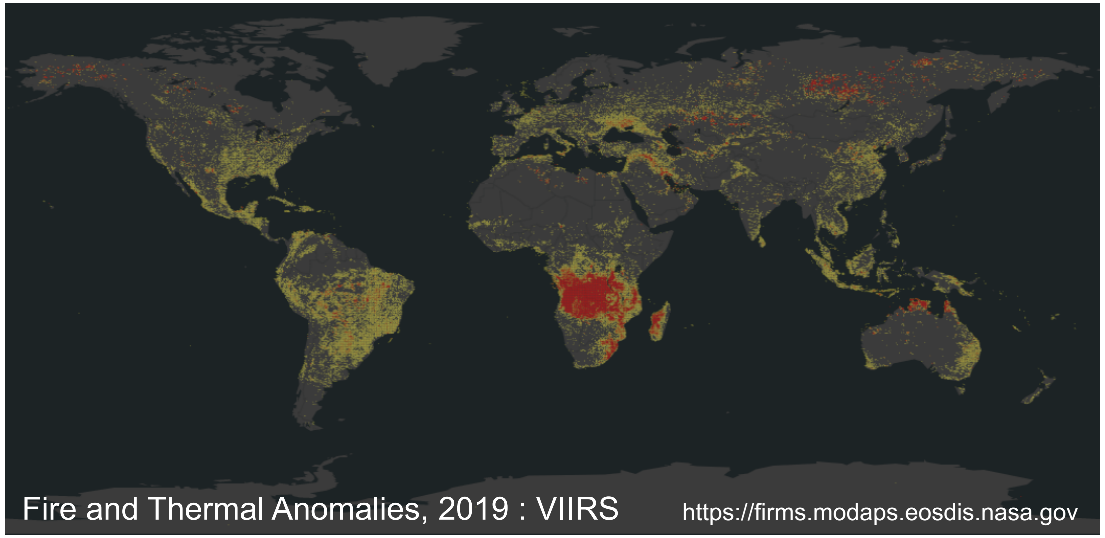
Classes of Interest

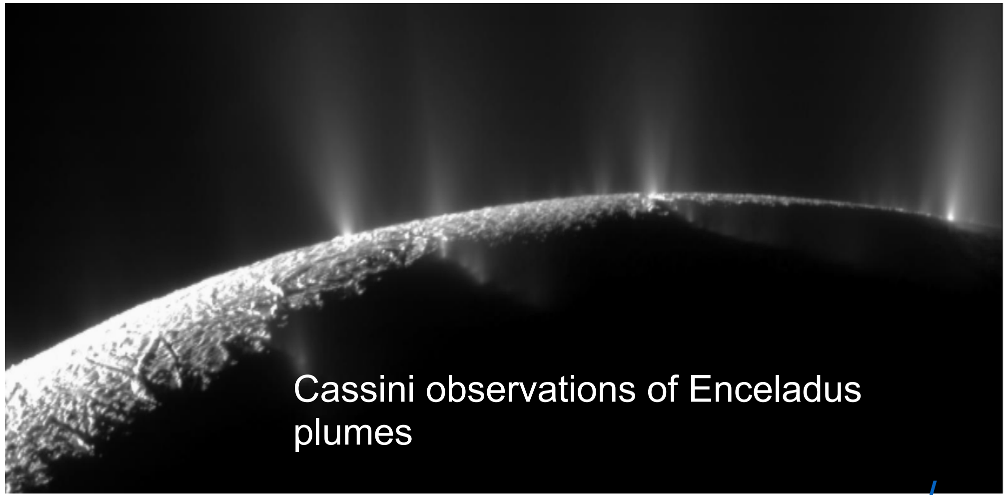

Carbon Monoxide – Mar ’19, Aqua/AIRS https://worldview.earthdata.nasa.gov



http://themis.asu.edu

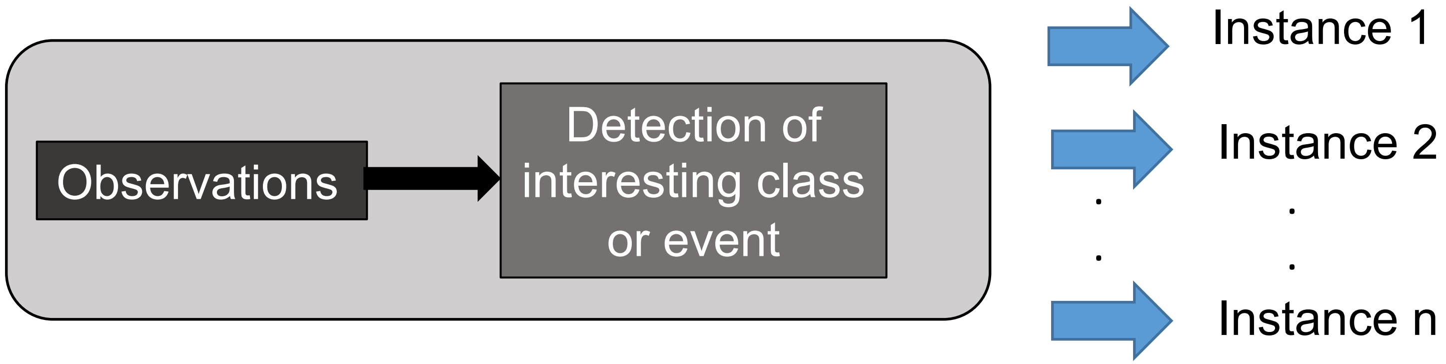
Events


Fire and Thermal Anomalies, 2019 : VIIRS https://firms.modaps.eosdis.nasa.gov


Cassini observations of Enceladus plumes

https://solarsystem.nasa.gov/news/13020/the-moon-with-the-plume/

Expert-like Analysis of Novelty



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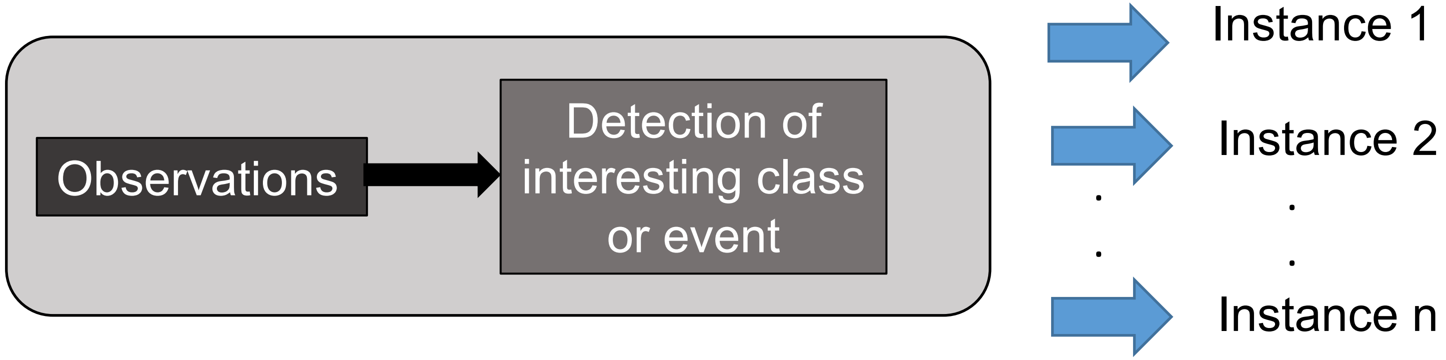

Are all detections equally interesting to an expert?

Unusual context of an event

- Spatially associated with other classes; previously unseen
- Observed it in an unusual location or season
- Increases the need for an expert to further analyze the observation

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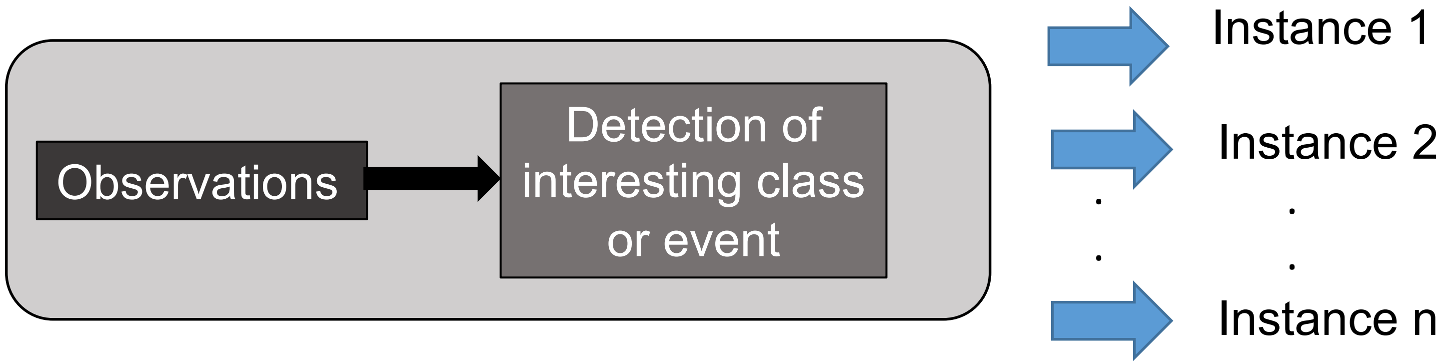

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Refines our knowledge of event/ class
 - better model of where and when to expect a natural hazard or a landform
- Better understanding of driving factors or triggers of the hazard or how these morphologies formed

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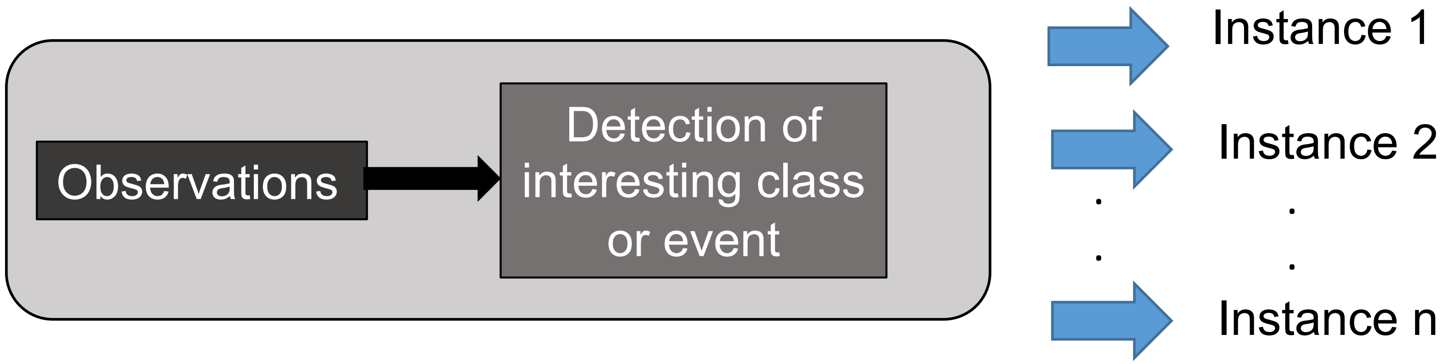

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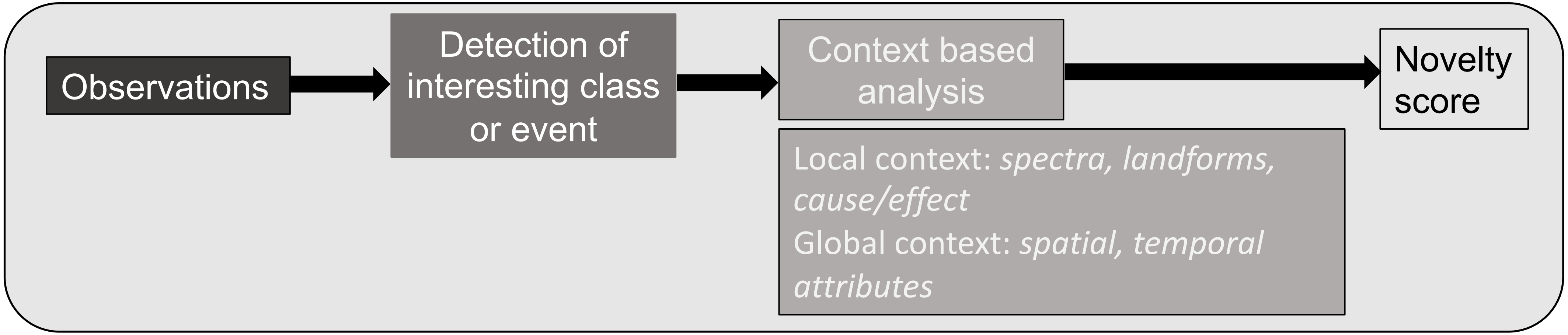
Ranking anomalies to improve our ability to interpret extremes, targeting future observations, support scientific discovery and planetary exploration

Context-based Representations of Events and Classes of Interest



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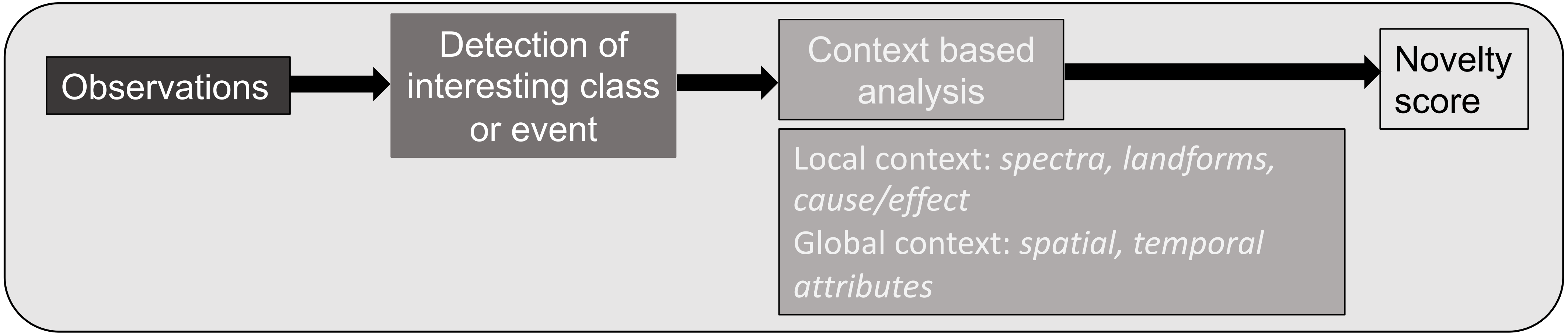

Towards expert-like interpretation of observations:

- Representations that learn local and global context
- Update this representation to indicate the shift in the understanding of the process through discovered anomalies
- Explored on multispectral Mars (THEMIS) VIS/IR images and currently on (MODIS, VIIRS) wildfire

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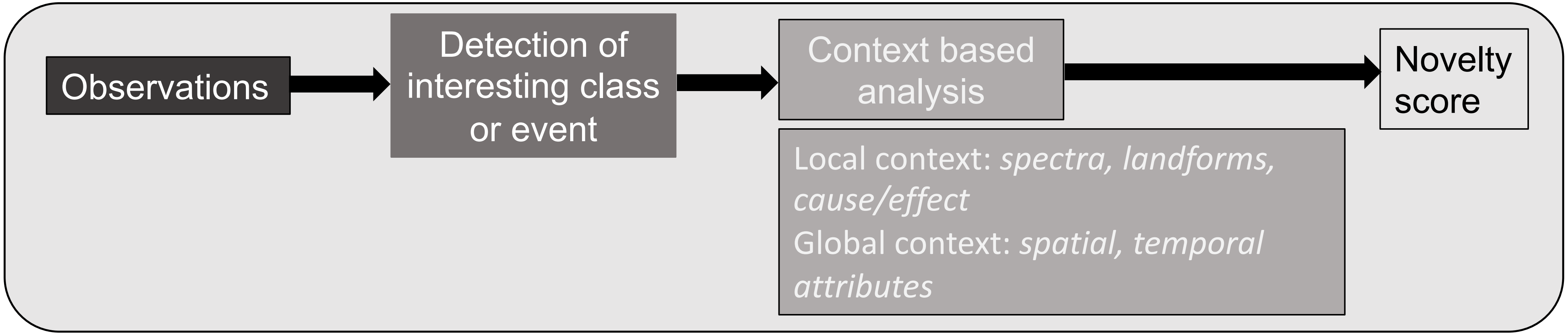

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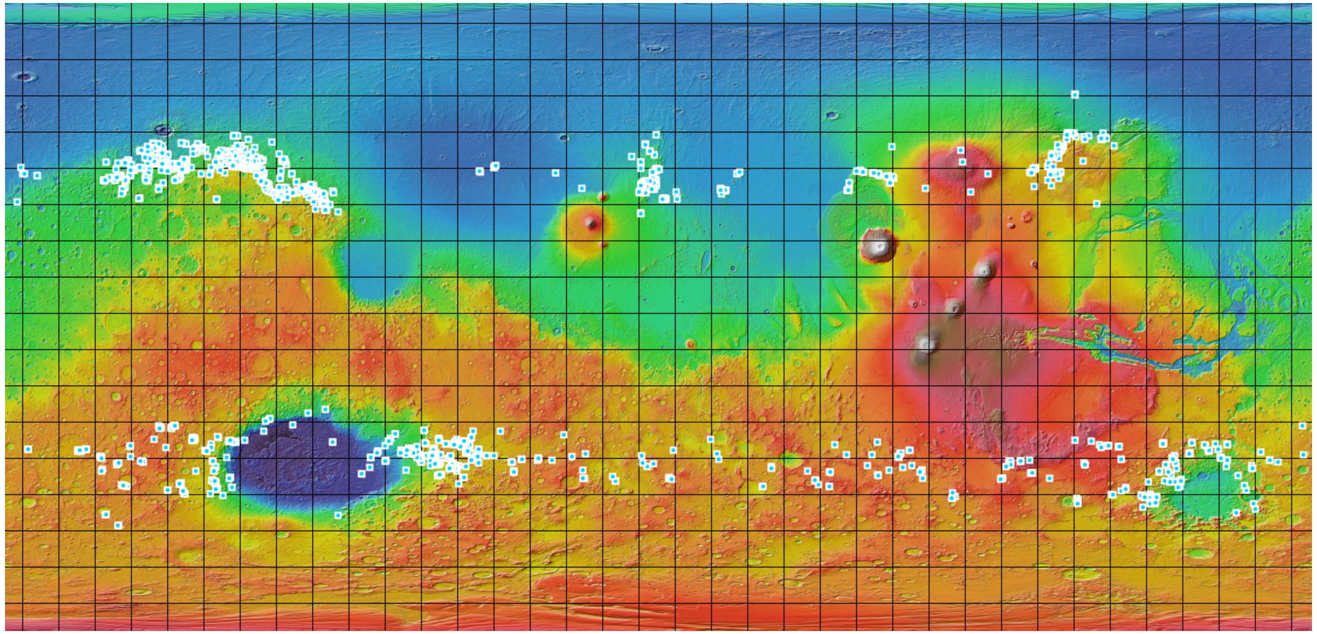
$\mathrm{O} = \{\mathrm{o}_1, \mathrm{o}_2, \ldots, \mathrm{o}_\mathrm{N}\}$ Data Repository of all N past observations

$D = \{o_j | C_j \in C, D \subseteq O\}$ Total observations N_C with C classes of interest

Representations: o_j: $< \boldsymbol{detected\ classes, (lat, long), seasons, surface\ properties} >$

Identify Spatial Locations

Based on our past observations, where do we expect to find the given landform?



Spatial Location of glacier-like forms

R_i: < expected interclass association, **expected location**, expected season, surface properties >

For every instance θ_i in D belonging to class i:

Expected Spatial locations: $\Omega_i = \{(X_{\omega_i} + \sigma_{lat_{\omega_i}}, Y_{\omega_i} + \sigma_{long_{\omega_i}})\}$,
where $(X_{\omega_i}, Y_{\omega_i})$ are centers of ω clusters (by grouping observations within a spatial bound)
$\sigma_{lat_{\omega_i}}, \sigma_{long_{\omega_i}}$ *after assigning all* θ_i of class i to the closest center

Souness, C. et al., 2012. An inventory and population-scale analysis of martian glacier-like forms. Icarus 217, 243–255. http://dx.doi.org/10.1016/j.icarus.2011.10.020.

Learning Most Prevalent Season

Based on our past observations, when do we expect to observe the given landform?

Mar year[a]	Spring equinox ($L_s = 0°$)[b]	Summer solstice ($L_s = 90°$)[b]	Autumnal equinox ($L_s = 180°$)[b]	Winter solstice ($L_s = 270°$)[b]
25	05-31-2000	12-16-2000	06-17-2001	11-11-2001
26	04-18-2002	11-03-2002	05-05-2003	09-29-2003
27	03-05-2004	09-20-2004	03-22-2005	08-16-2005
28	01-21-2006	08-08-2006	02-07-2007	07-04-2007
29	12-09-2007	06-25-2008	12-25-2008	05-21-2009
30	10-26-2009	05-13-2010	11-12-2010	04-08-2011

R_i: < expected interclass association, expected location, **expected season**, surface properties >

For every instance θ_i in D belonging to class i:

Expected season of prevalence, μ_i at each spatial cluster:
probability mass function from binary seasonal vector $\mathbf{t}$, $|\mathbf{t}| = \Phi$ (number of seasons on the surface)

$$t_{\theta_i}[k] = \begin{cases} 1, & k = \varphi, \\ 0, & \text{otherwise} \end{cases}$$

$$T_i = E[k_i] = \sum_{k=1}^{\phi} k.\, f(k)_i, \quad \sigma(k_i) = \sum_{k=1}^{\phi} (k - E[k_i])^2.\, f(k)_i, \qquad \text{where } f(k)_i = \frac{1}{N_{c_i}} \sum_{\theta_i \in i} t_{\theta_i}[k]$$

Cantor, B.A. et al., 2006. Mars Orbiter Camera observations of Martian dust devils and their tracks (September 1997 to January 2006) and evaluation of theoretical vortex models, Journal of Geophysical Research, vol. 111(E12)

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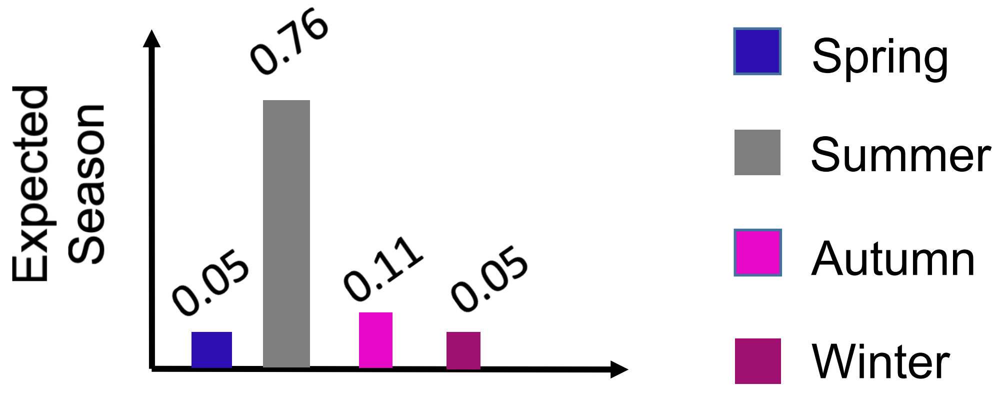

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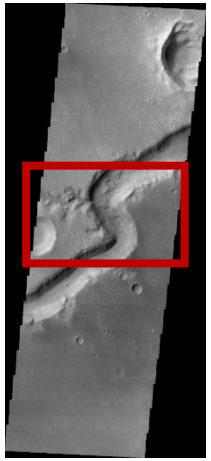
Learning Spatial Association

Based on our past observations, what other landforms co-occur with a given landform?



Channel

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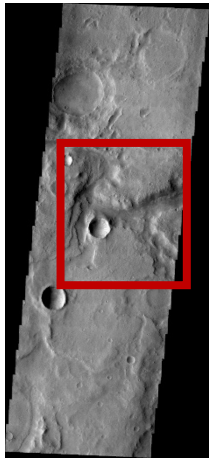

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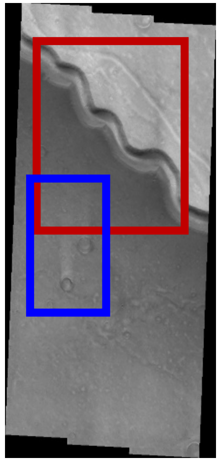


Channel,
Wind streak

$$R_i: < \textbf{expected interclass association}, \text{expected location}, \text{expected season}, \text{surface properties} >$$

For every instance θ_i in D belonging to class i:

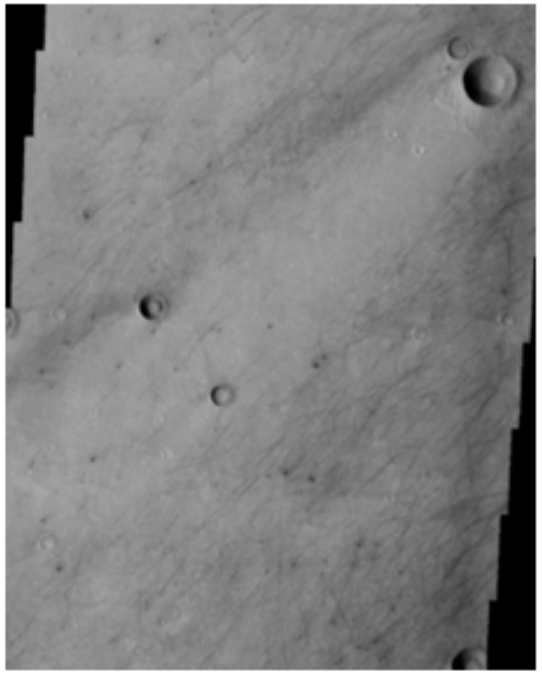
Interclass (i, j, …, n) association in each spatial cluster: $s_{i,j,\ldots,n} = \frac{|\theta_s|}{N_c}$,
where $|\theta_s|$ - frequency of co-occurrence of (i, j, …, n) in D

Refining Spatial Association through Expert Feedback

For each ILF observed association $(\mathrm{i}, \mathrm{j}, \ldots, \mathrm{n}) \in D$:

Expert feedback on how rare or important the association is

Scale: 1= (Low downlink priority/common, not interesting); 5= (High downlink priority / rare, very interesting)



class: dust devil, wind streak; lat: -15; long: 302 E; date: 2002/3/31; Mars year=25

	0	1	2	3	4	5
How important or rare is this association	○	○	○	○	○	◉

$w_{\theta_{i,e}}$

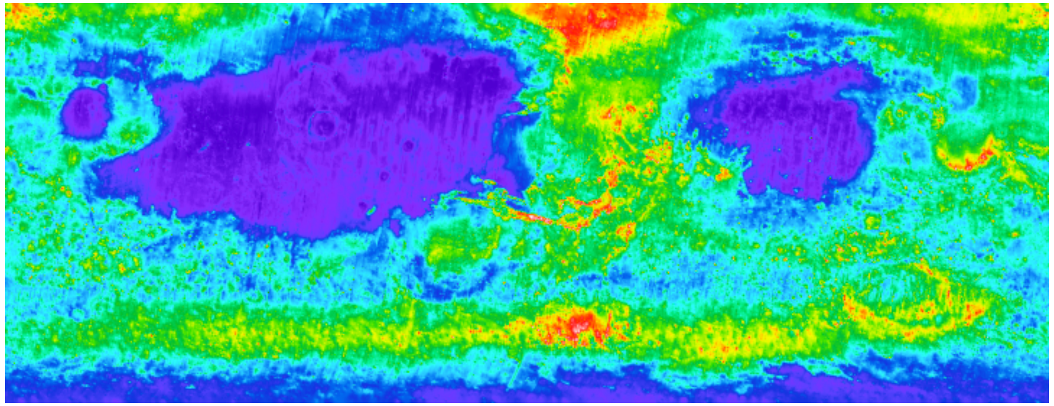
$$w_{i,j,..,n} = \frac{1}{E}\sum_{e=1}^{E} w_{\theta_{i,e}}$$

Weight or importance of the association from E experts

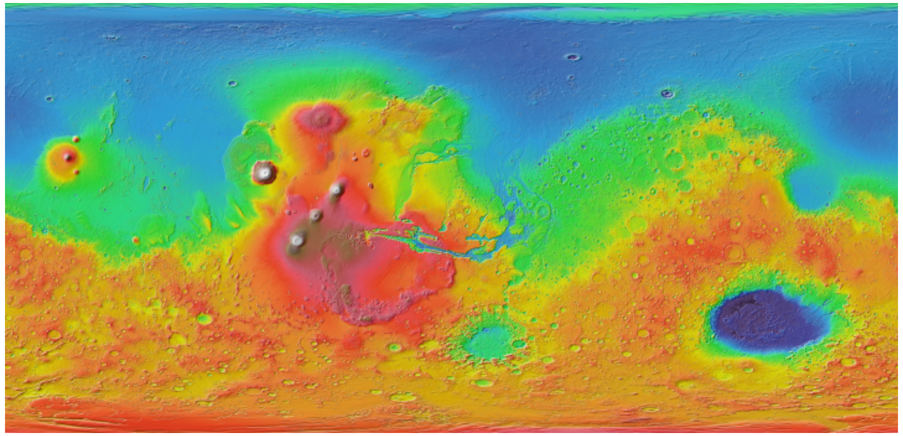
R_i: < **expected interclass association**, expected location, expected season, surface properties >

Learning Surface Properties

Based on our past observations, what can we infer about surface properties where a given landform appears?



TES Thermal inertia



MOLA Elevation

R_i: < expected interclass association, expected location, expected season, **surface properties** >

Joint representation $p_i \sim \mathcal{N}(\mu_i, \Sigma_i)$ of surface properties
Multivariate normal distribution for each class of interest at each spatial location

Provides local (terrain) context

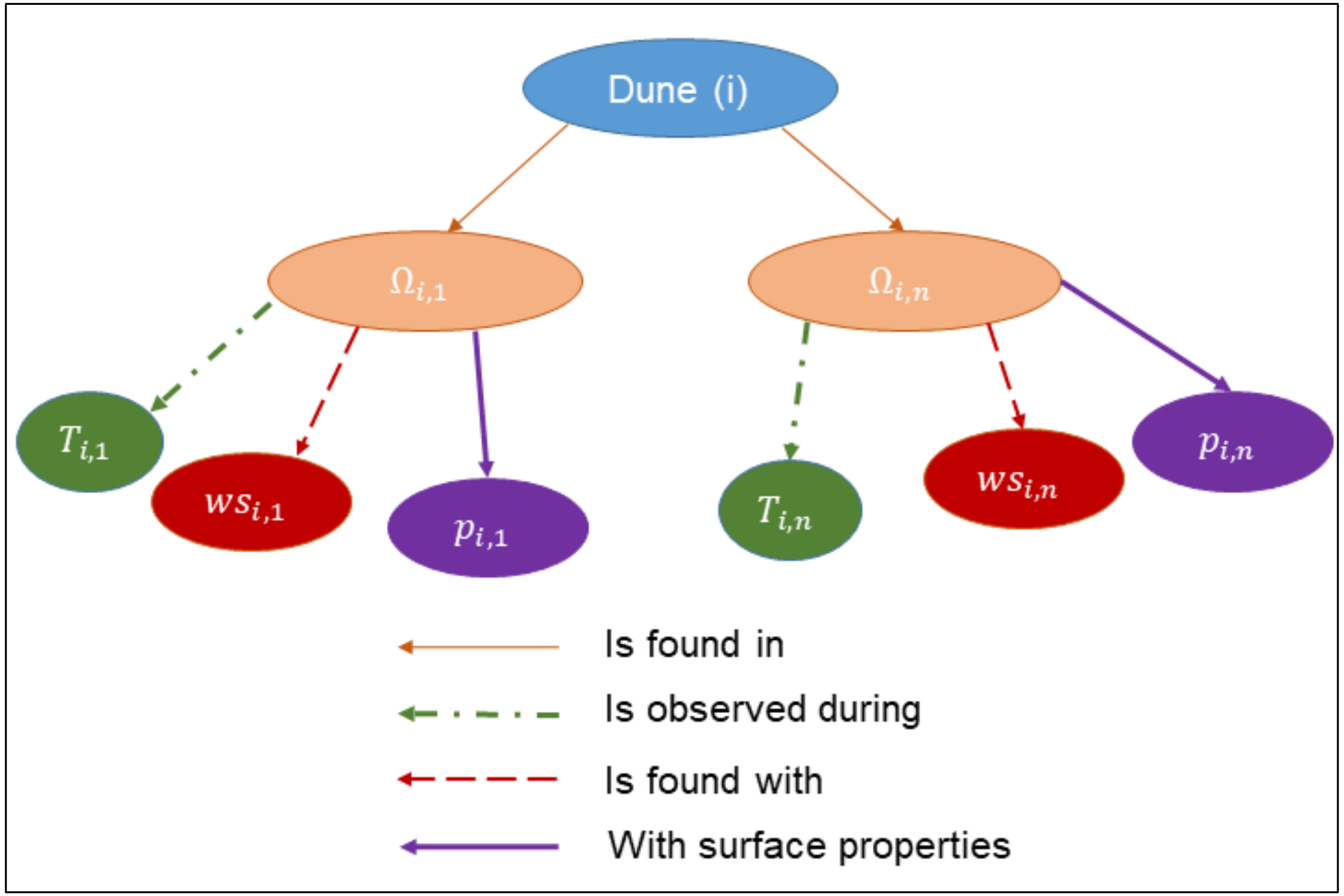
Integrating observations from multiple instruments

Christensen, P.R.; Engle, E.; Anwar, S.; Dickenshied, S.; Noss, D.; Gorelick, N.; Weiss-Malik, M.; *JMARS – A Planetary GIS*, http://adsabs.harvard.edu/abs/2009AGUFMIN22A..06C

Christensen, P. R., and H. J. Moore (1992), The martian surface layer, in Mars, edited by H. H. Kieffer, et al., pp. 686-729, University of Arizona Press, Tucson, AZ.

https://pds-geosciences.wustl.edu/missions/mgs/mola.html

Context-aware Novelty Detection



Learned representations (for each class/ event of interest)

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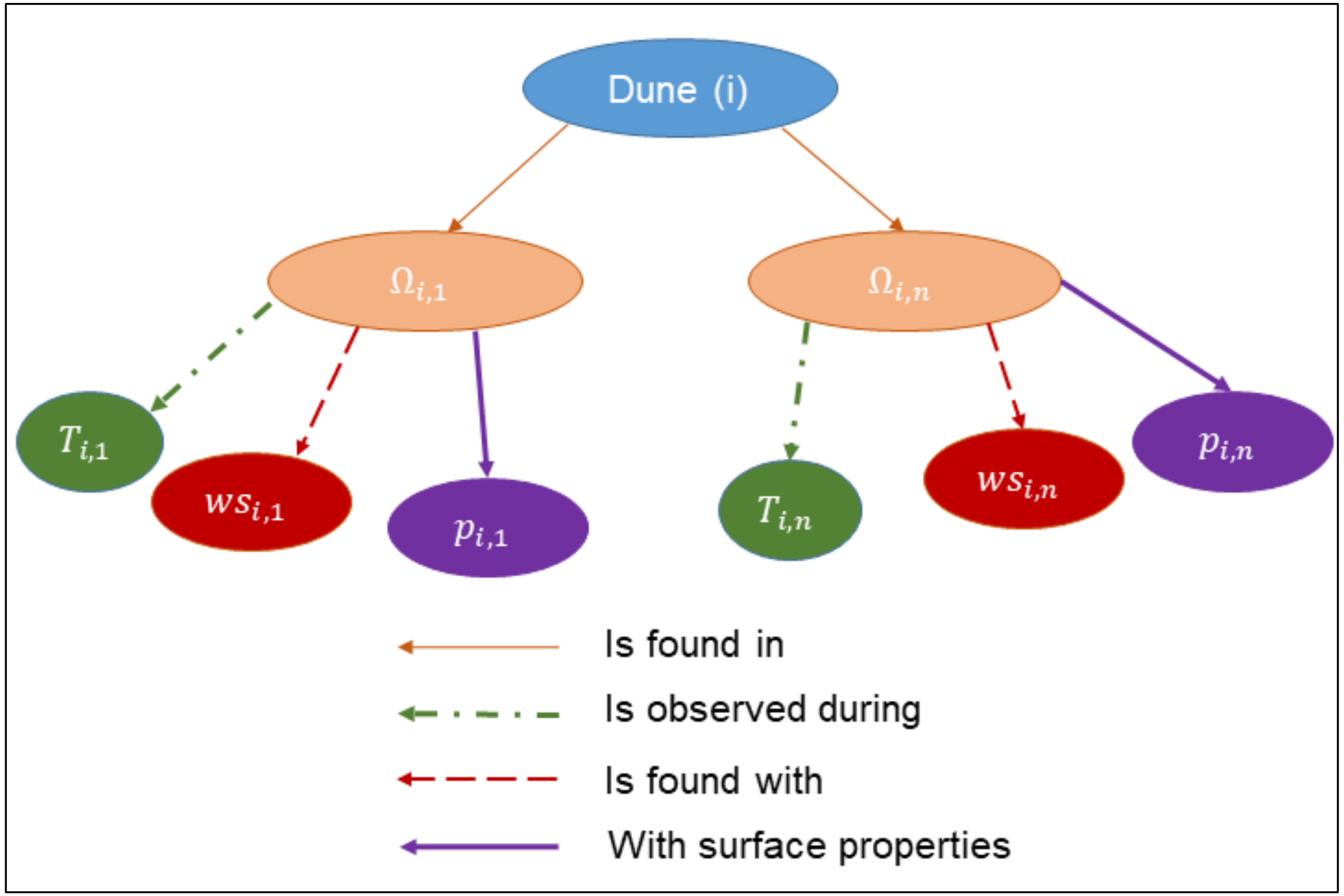

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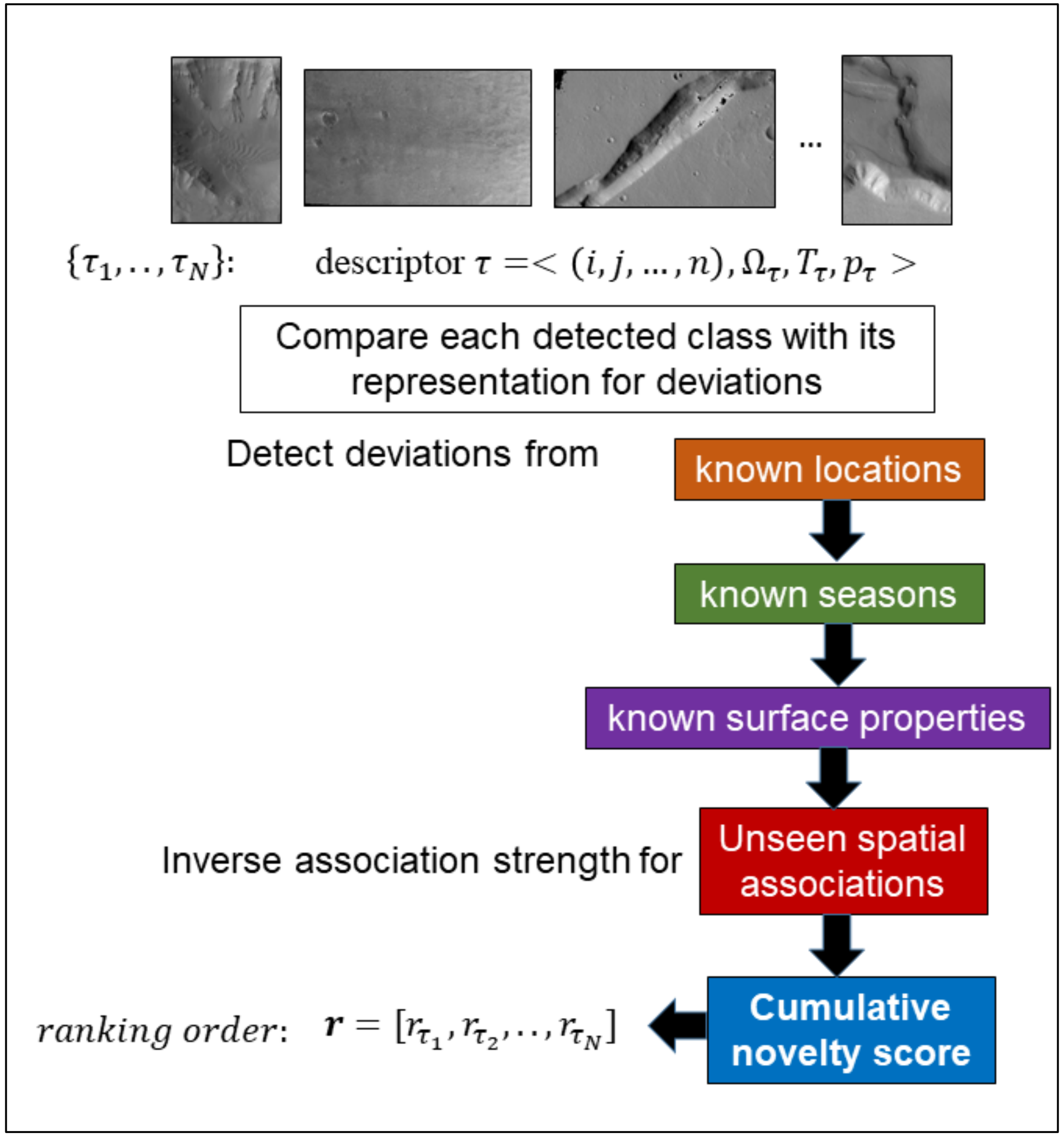
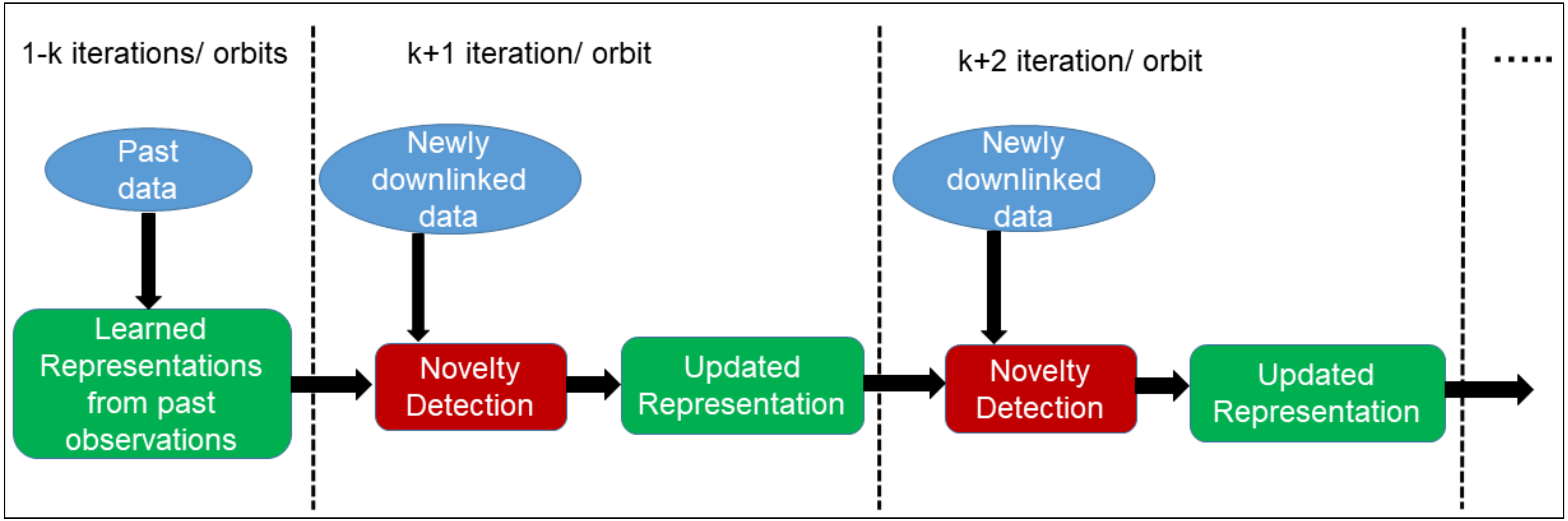


Novelty detection from learned representations

Iterative Representation Update



Updated with expert guidance

- Merging clusters
- Updating weights of spatial association importance
- Updating list of interesting classes/ events

Acceptability of Novelty Detection to Experts

Mean average precision (MAP): Average precision at every position b where $r_\tau = e_\tau$, over all test set batches Q

$$MAP = \frac{1}{Q.B}\sum_{q=1}^{Q}\sum_{b=1}^{B}\gamma_b$$

r_τ- rank generated by the module

e_τ- rank from experts

where $\gamma_b = \begin{cases} p_b, & r_\tau = e_\tau \\ 0, otherwise \end{cases}$

Spearman Rank Correlation (SRC) between r_τ and e_τ

Acceptability of novelty ranking to experts

Representation	MAP	SRC
Standalone	0.1864	0.5482
Expert Guided	**0.765**	**0.984**

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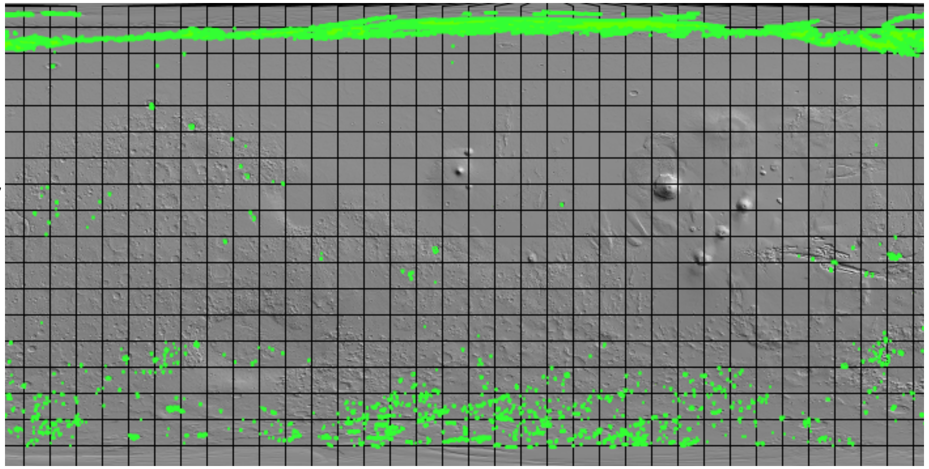
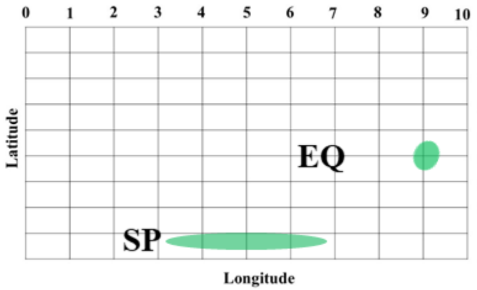
Examples of Detected Novelties:

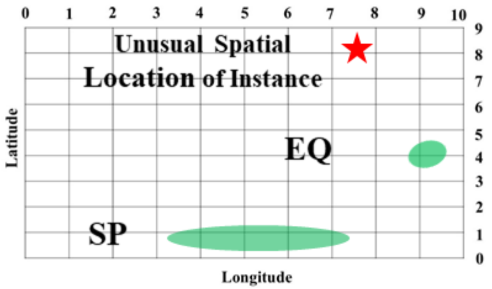
EQ- Equatorial; SP- South Polar; NP – North Polar



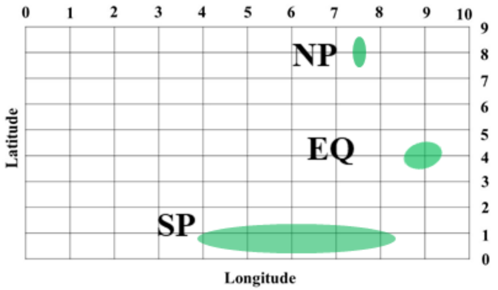
Dune locations:18 years of THEMIS observation



Iteration 1:
- Known spatial locations of dunes

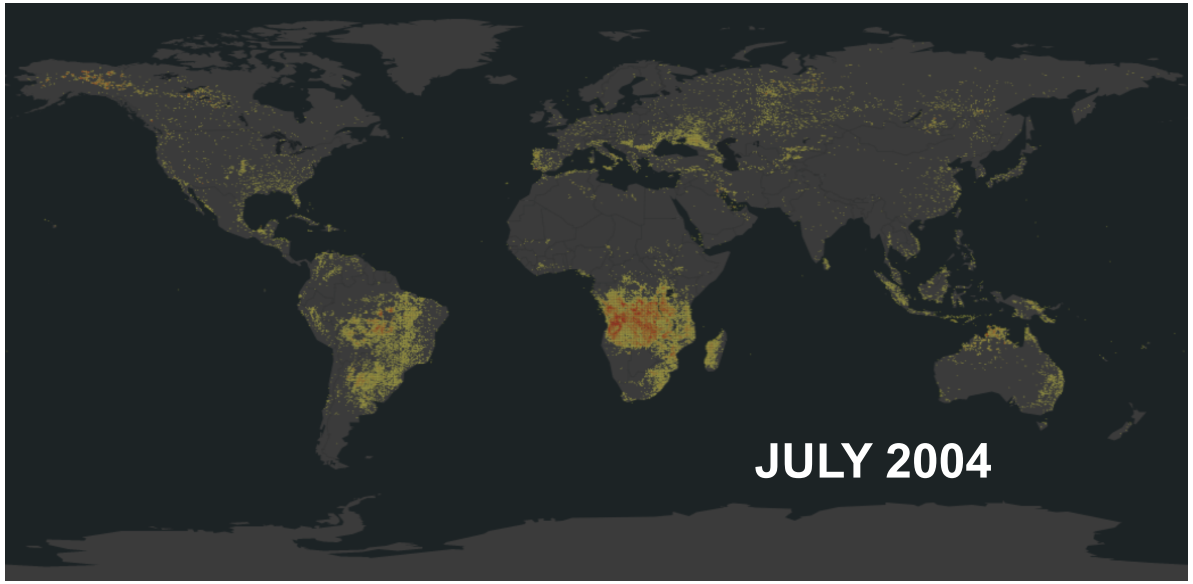


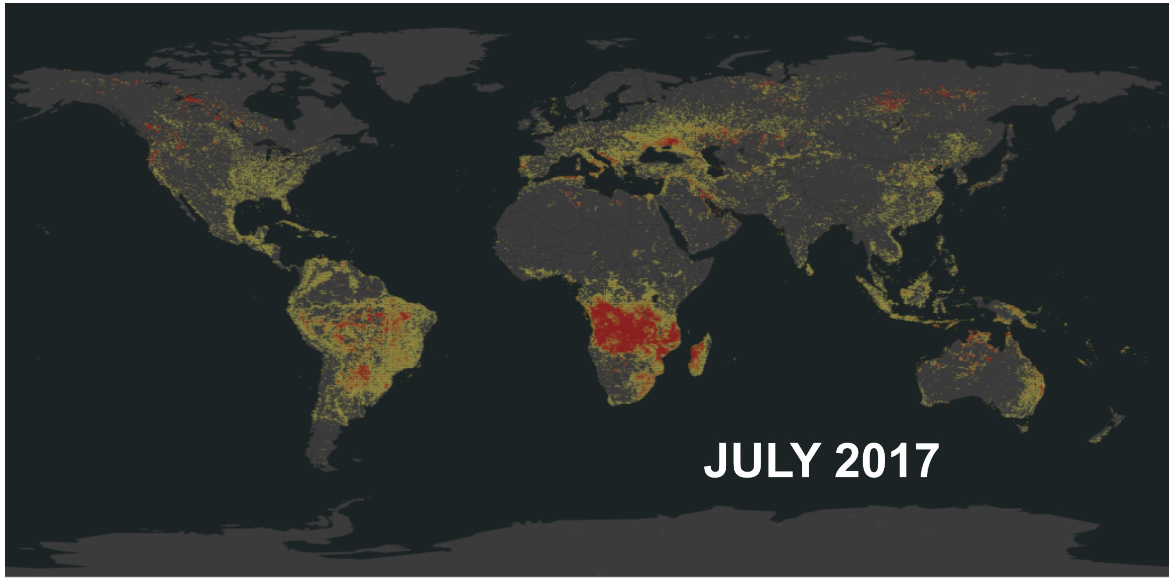
Iteration 2:
- Known spatial locations of dunes modified
- Dune observed at an unusual location



Iteration 3:
- Known spatial locations of dunes modified to include north pole

Context-Based Representation of Natural Hazards





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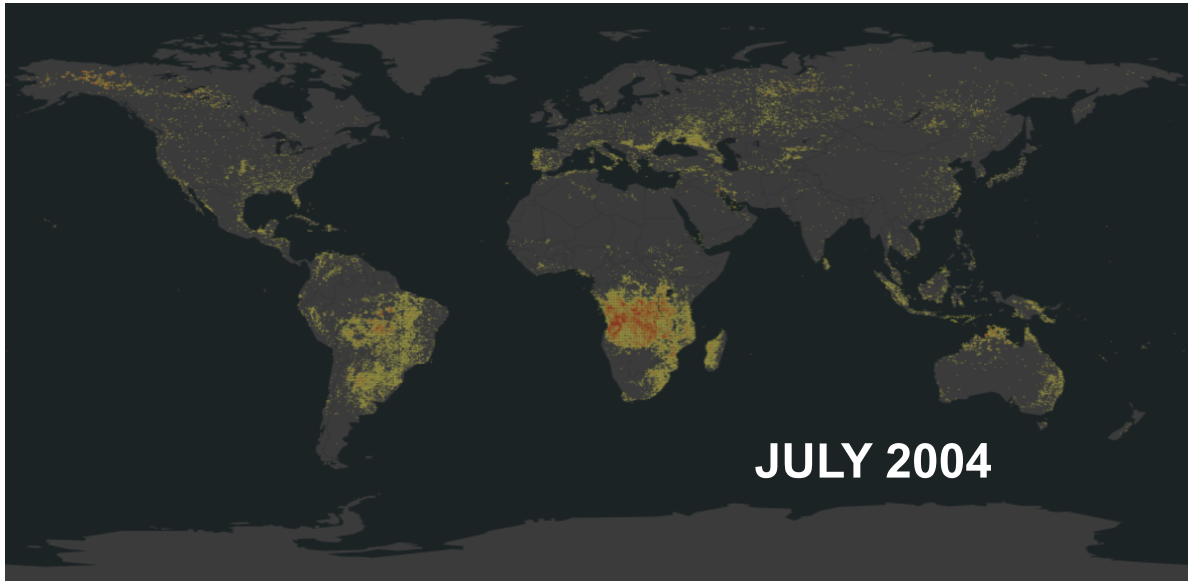
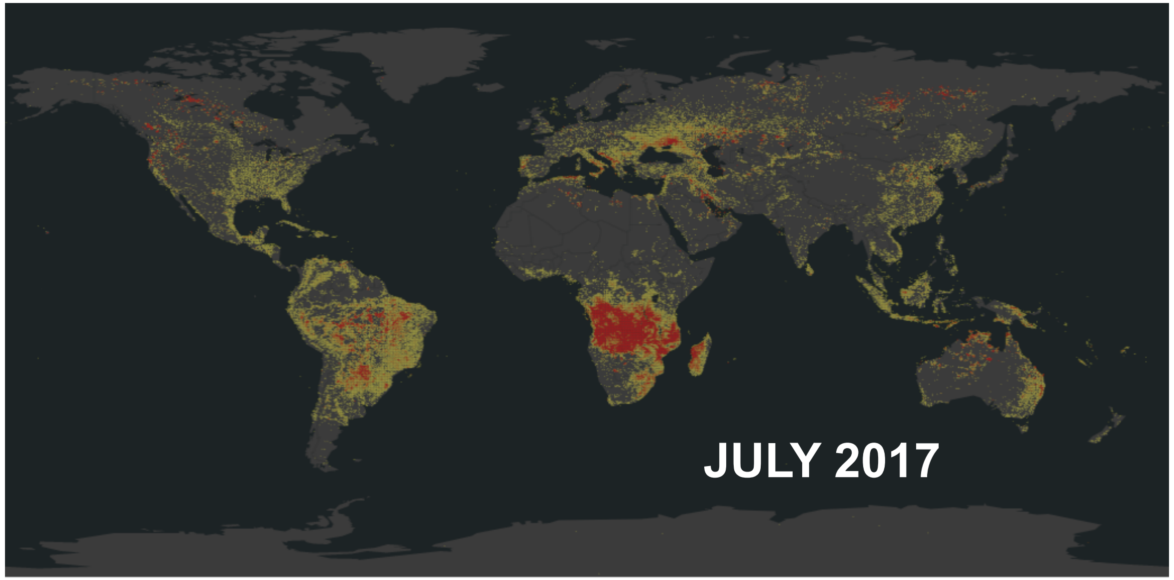




- Location
- Temporal information
- Temperature
- Precipitation
- Slope
- Land Cover Class
- Vegetation/ Fuel type
- Regional Deviation from Driving Factors

Factors that are known to cause or trigger the natural hazard

- Other Disturbances in Spatial/ Temporal Neighborhood

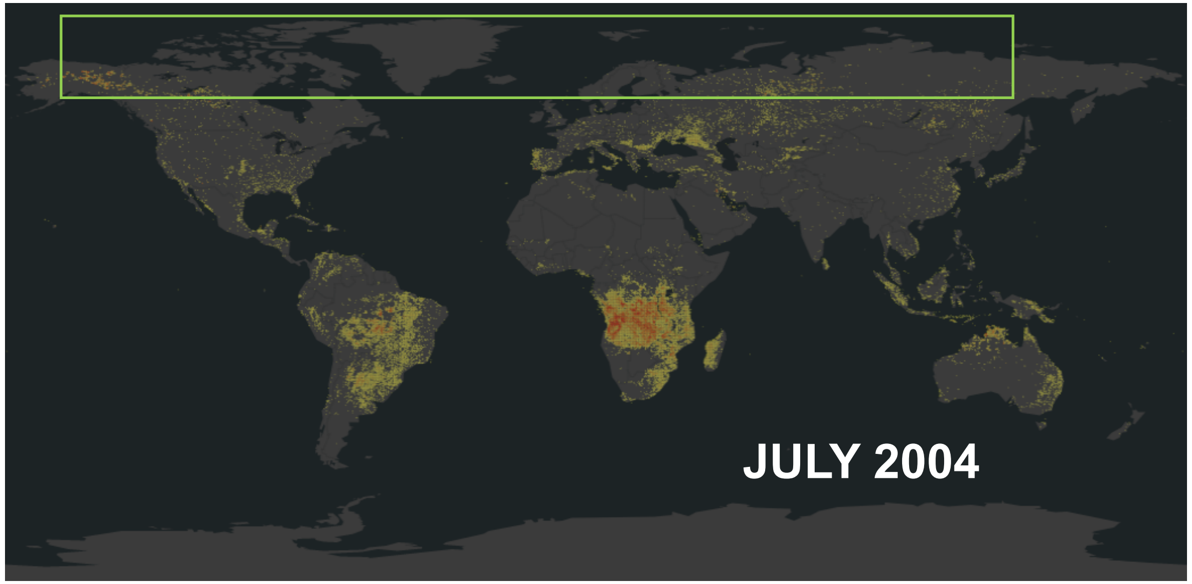
Contributing factors & effects

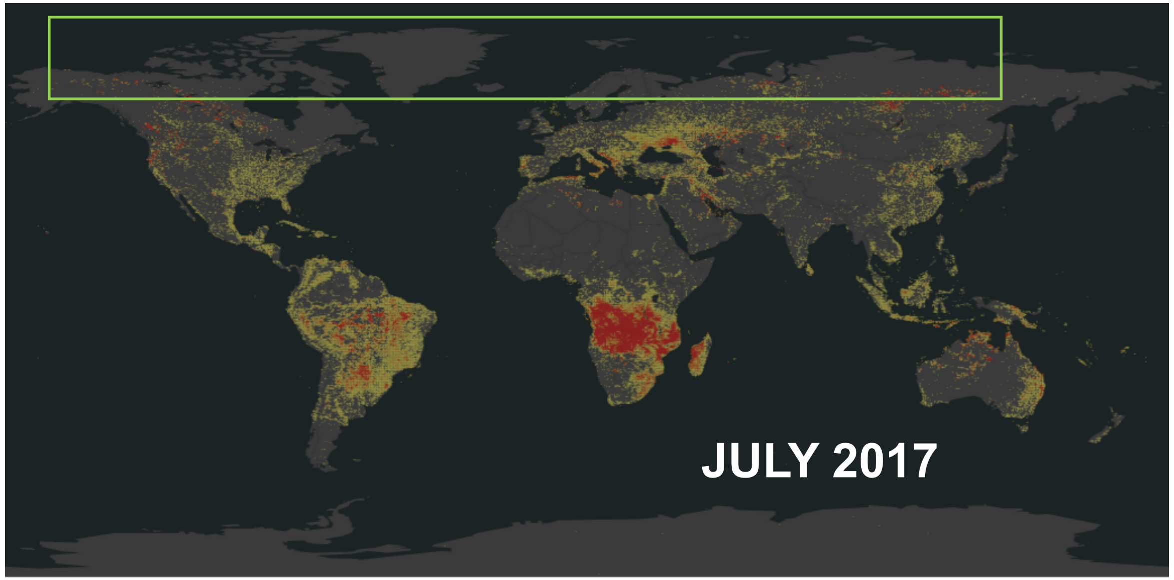
- Emission and air quality
- Burned Area

Effects of the natural hazard

Wildfire representations updated over time with every novel detection

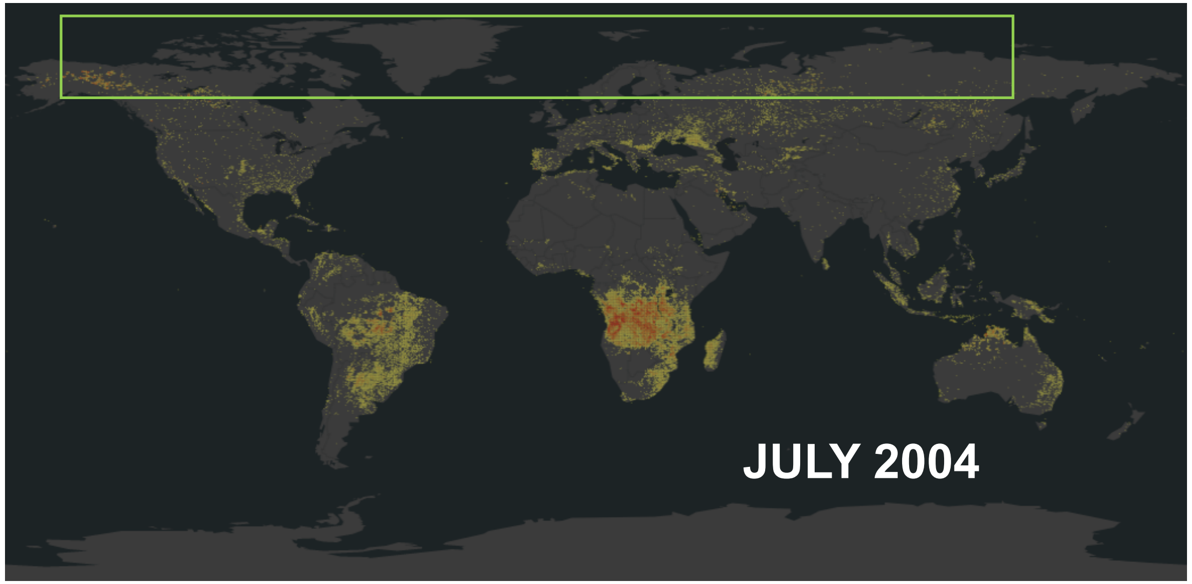
Novelty Detection from Context-Based Representation

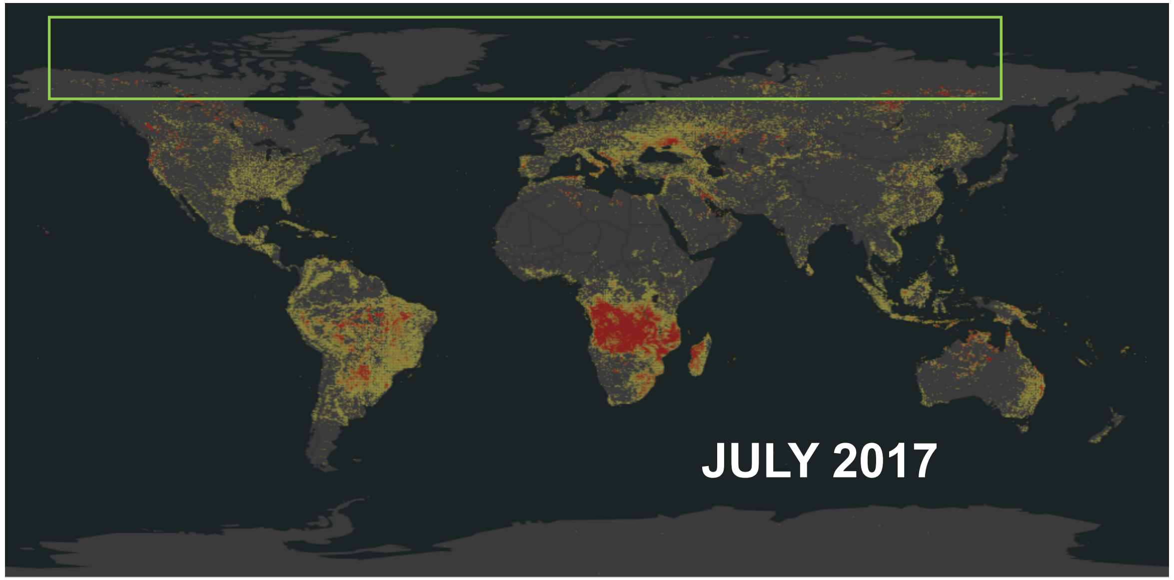


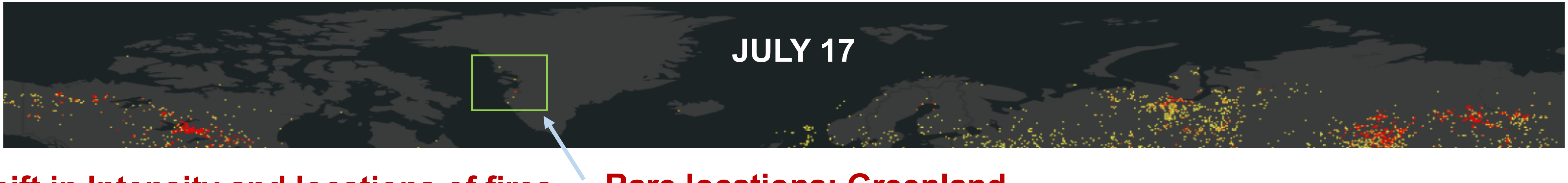


Shift in Intensity and locations of fires

Novelty Detection from Context-Based Representation







Shift in Intensity and locations of fires

Rare locations: Greenland

Future Directions

- Towards a more interpretable representation of novelties
- Applicable for retrieval, identifying context-based rare observations
- Incorporate additional relevant features and models (different modality)
  - data dimensionality
- Learn representations from varying volumes of data
  - early stages of an instrument/ less explored surfaces – low data volume
  - increasing data volume over time
- Expert feedback for adapting to an application (attributes, weights), evaluation
  - “interestingness” often relative, difficult to quantify

Acknowledgements

- JMARS: https://jmars.asu.edu/
- https://themis.mars.asu.edu/
- https://search.earthdata.nasa.gov/search
- Philip Christensen
- Mars Space Flight Facility