Make Planetary Images Searchable: Content-based search for PDS and On-Board Datasets. M. Ono[1], B. Rothrock[1], C. Mattmann[1], T. Islam[1], A. Didier[1], V. Z. Sun[1], D. Qiu[2], P. Ramirez[1], K. Grimes[1], and G. Hedrick[3], [1]Jet Propulsion Laboratory, California Institute of Technology (4800 Oak Grove Drive, Pasadena, CA, 91106, ono@jpl.nasa.gov), [2]Carnegie Mellon University, [3]West Virginia University.

Introduction: We present a new content-based image search approach utilizing deep-learning models. This would benefit the planetary science community in two ways: 1) making PDS (Planetary Data System) images searchable by geological keywords/phrases (e.g., "veins," "nodules," "outcrop with crossbedded layers") or image similarity, just like Google Image Search; and 2) convert a planetary rover with no nominal scientific instruments such as the future Sample Fetch Rover concept for the proposed Mars Sample Return campaign, to a scientifically valuable one by allowing scientists to instruct the rover to find geological features in its navigation camera images.

Recent planetary missions are characterized by a rapid increase in the volume of the data generated by the instruments, particularly from imaging devices. For example, there are over 189k Mastcam and 199k Navcam images from the Mars Science Laboratory (MSL) mission on PDS, totaling to hundreds of gigabytes of data. Even a greater volume of data is produced by the rover, but the limitation in the communication capacity from Mars to Earth does not allow us to downlink all the data. Such an explosion in data volume poses two problems on the planetary science community:

1. **UGMP (the Unnoticed Green Monster Problem)**: a Mars rover could pass by a green monster (a metaphor for a serendipitous encounter with important scientific features) without being noticed by ground operations because image acquisition is not commanded at that moment or the image of the green monster is simply not downlinked due to the limitation in the communication capacity.
2. **GHTMI (Geologists' Headache with Too Many Images)**: even with a filtered collection, a geologist will often have to manually eyeball thousands of images on PDS to find subtle features that s/he is researching (e.g., nodules, veins, layers with a particular geometry).

One related example to the UGMP happened during Opportunity's walkabout at Matijevic Hill between sols 3100 and 3143. The science team surveyed the site in search for the clay minerals detected from orbit [1]. The images sent back from the rover unexpectedly showed interesting boxwork features, which later turned out to be an evidence of neutral water rather than acidic. This site, Esperance, turned out to be so important that the team spent weeks studying it.

To the disappointment of the scientific community, there could be a number of future missions that would send rovers to Mars, the Moon, or beyond with no in-situ science planned. For example, the Sample Fetch Rover concepts being studied by NASA and ESA have no scientific instruments, with the sole mission purpose of fetching sample tubes even though it could drive tens of kilometers on unexplored terrains with potential discoveries. Had Opportunity been the Sample Fetch Rover, Esperance would have an "unnoticed green monster."

Approach: We offer a technical solution to UGMP and GHTMI by introducing deep neural networks. More specifically, our tools allow content-based search of a large planetary image dataset. Users can quickly extract relevant images by specifying geological keywords/phrases such as "outcrop with crossbedded layers." Alternatively, if a user has an image that includes the geologic feature of interest, s/he can present the image to the tool and acquire similar images.

The content-based search capability is supported by two technologies. The first is SCOTI (Science Captioning Of Terrain with Intelligence), which generates a natural language sentence to geologically explain a given image. Figure 1 shows a few examples of image captions autonomously generated by SCOTI. Once SCOTI processes all images in the dataset, the user can quickly search through the dataset by using a standard text-based search tool such as Apache Solr. The second is Image Space which is a forensic toolkit for multimedia exploration and analysis originally funded by the DARPA MEMEX effort. ImageSpace creates an AlexNet FC7 neural net-based "hash code" for each image which allows quick evaluation of visual similarity between two images and otherwise difficult to discover (by hand) relationships.

Existing work: CBIR (Content-Based Image Retrieval) has garnered significant interest recently, primarily in the pursuit of improving how we search image data on the web [2]. Furthermore, the recent advent of deep learning methods has provided significant advancements in performance of these systems [3]. These models are typically designed to understand scenes of common and generic objects and trained on large datasets of daily life images. Application of these techniques to support scientific exploration of large image datasets has largely been unexplored, however, especially as it pertains to deep learning approaches. Models tailored toward science exploration require finer-grained understanding of scene structure, and the incorporation of the relevant vocabulary and semantics appropriate for the science task. Prior work on CBIR for science exploration includes [4,5] for exploring craters, dunes, and slopes on lunar and Mars orbital imagery using traditional non-deep learning features and models.

PDS Deployment: We will have completed the preliminary integration of SCOTI into PDS by March 2019. At that point, all the Mastcam and Navcam images from MSL will be searchable by text. We will provide a live-demo at the conference, and will encourage the public to experiment with the beta integration with the PDS Image Atlas.

On-Board Deployment: To solve UGMP, we are also developing on an on-board version of the content-based search capabilities, with the main infusion target being the Sample Fetch Rover. The Fetch Rover would be a highly automated vehicle which is expected to autonomously drive up to ~1km per Sol (Curiosity typically drives tens of meters per Sol). Autonomous driving on Mars requires taking navigation images about every meter. Therefore, the rover would generate up to ~1,000 images per Sol, but it is unlikely that all the images can be downlinked due to limitations in communication. Our tools can help increasing the scientific values of the Fetch Rover without interfering its main mission in two ways. First, SCOTI can create captions for all the images on-board, which can be easily downlinked. The ground scientists can later decide which images to downlink based on the captions, which can capture subtle geological features that would be unrecognizable in the reduced resolution thumbnails. Second, by pre-specifying the geological features of interest by text or example images, the rover can perform on-board data triage. This on-board capability could also be useful for current and future scientific missions. In fact, there have been multiple cases where rover operators searched for specific geological features. For example, on sols 2969-2970, Opportunity was looking for wide veins around the northern part of Cape York at Endeavour Crater for APXS experiments. As another example, during sols 1900-2250, Curiosity searched for crystal molds and dark Fe-rich concretions (informally called "sticks") during much of its traverse on the Vera Rubin Ridge. The on-board analytic capabilities would allow the Fetch Rover to perform similar activities despite the likely inhibition of ground-in-the-loop search for scientific purposes.

Future Work: SCOTI and the image similarity search are based on machine learning, which requires training on example datasets generated by scientists. It also means the tool can adapt to scientists' needs (e.g., learn new vocabularies, learn image features to best represent geological interests). The volume and quality of training data is crucial. We will add a capability to provide training data (i.e. image captions) to PDS and would like to solicit support from the LPSC community in order to mature our capabilities and to better serve the planetary community and future missions.

References: [1] Arvidson et. al (2014) *Science,* **343** (6169), 1248097. [2] Liu et al. (2007) Pattern recognition 40.1. [3] Wan et al. (2014) ACM Multimedia. [4] Hua et al. (2014) ASEE. [5] Wagstaff et al. (2015) Second Planetary Data Workshop.

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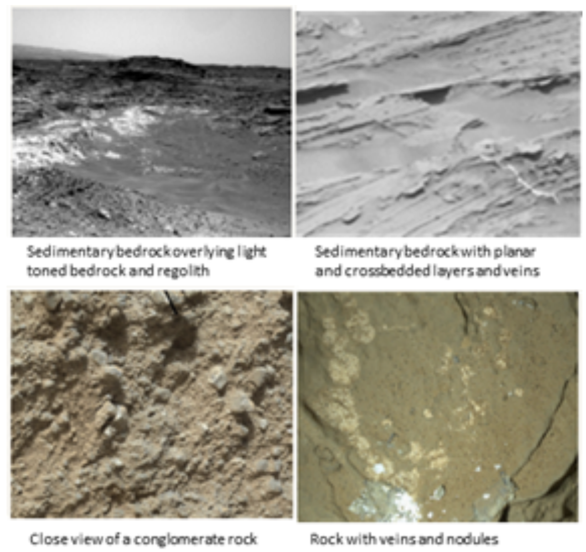

Figure 1: Examples of auto-generated captions by SCOTI

Figure 2: Search result for "nodules"