EPSC Abstracts
Vol. 13, EPSC-DPS2019-539-1, 2019
EPSC-DPS Joint Meeting 2019

EPSC
EPSC-DPS Joint Meeting 2019
15–20 September 2019 | Geneva, Switzerland

Mapping Saturn using deep learning

Ingo Waldmann (1) and Caitlin Griffith (2)
(1) Dept. Physics & Astronomy, University College London, UK (ingo@star.ucl.ac.uk), (2) Lunar & Planetary Laboratory, University of Arizona, USA

Abstract

In this talk, we present a deep learning algorithm, PlanetNet, to map cloud patterns on Saturn using Cassini/VIMS data. This work was recently published in Nature Astronomy [**?**]. Clouds and aerosols provide a unique insight into the chemical and physical processes of gas-giant planets. Mapping and characterising the spectral features indicative of the cloud structure and composition, enables an understanding of a planet's energy budget, chemistry and atmospheric dynamics (e.g. [**?**, **?**, **?**, **?**]). Current space missions to solar-system planets produce high-quality data sets, yet the sheer amount of data obtained often prohibits detailed 'by hand' analyses. Current techniques mainly rely on two approaches: 1) identify the existence of spectral features by dividing fluxes of two or more spectral channels; 2) perform full radiative transfer calculations for individual spectra. The first method suffers from accuracy whilst the second from scalability to the whole planetary surface. Here we developed a deep learning algorithm, PlanetNet, able to quickly and accurately map spatial/spectral features across large, heterogeneous areas of a planet. We demonstrate PlanetNet on Saturn's 2008 storm[**?**], enhancing the scope of the area previously studied. Our spectral-component maps indicate compositional and cloud variations of the vast region affected by the storm showing regions of vertical upwelling, and diminished clouds at the centre of compact storms. This analysis quickly and accurately delineates the major components of Saturn's storm, thereby indicating regions that can be probed deeper with radiative transfer models.

1. Introduction

PlanetNet is capable of non-parametrically identifying faint features in hyperspectral images and once trained on a given feature, able to search for it across highly heterogeneous data sets. The algorithm consists of two parts: 1) a spectral clustering algorithm to identify an initial feature set; 2) a double-stream deep convolutional neural network (CNN). We demonstrate our algorithm on a rare detection of an ammonia ice cloud in the southern hemisphere of Saturn. The observations of Saturn's 2008 storm[**?**] are particularly well suited for this work as they encompass multiple, adjacent storms, providing a complex atmospheric feature space to be analysed by PlanetNet. In particular, the rare ammonia ice feature, detected by [**?**], which projects a "S" shaped feature on Saturn's disk. This data cube, along with two spatially adjacent cubes, has previously been analysed by the spectral band devision (I/F) method[**?**], which allows comparison to our approach. In this study we re-analyse the three original cubes along with three additional adjacent data cubes, all of which were obtained on February 9^{th} 2008.

2. PlanetNet

PlanetNet is a convolutional neural network (NN), trained on feature clusters derived from spectral clustering. The NN contains two branches, a spatial and a spectral channel. The spectral branch takes each remaining spectrum and trains a two layer CNN using ReLu activation functions and two pooling layers. Surrounding each spectrum, we compute a 20x20 spatial image by averaging the spectral cube along the spectral axis. This is the input for the spatial channel which otherwise follows the same NN architecture as the spectral channel. By analysing both spectral and spatial information, we can take into account the morphological and spectral signatures of atmospheric features on Saturn. In other words, a dark storm, for example, will have a distinct spectrum and spatial morphology that correlate together. By including these spatial-spectral correlations, the neural network will take all possible information available into account. A schematic of the network is given in figure **??**.

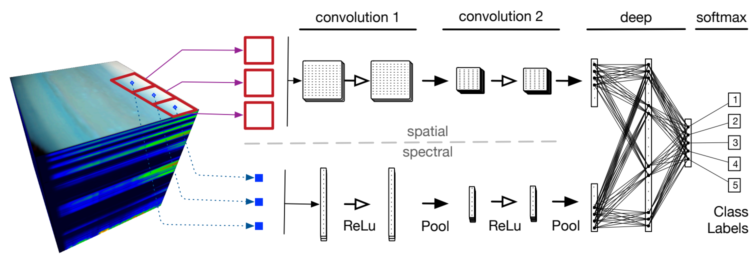

Figure 1: **Flowchart of the PlanetNet algorithm**. The blue dots indicate the central pixel at which the spectrum is extracted from the Cassini/VIMS data cube. The red squares indicate the corresponding spatial patches centred on the central spectral pixels. The spatial and spectral data is fed into two convolutional neural networks for the spatial (top network) and spectral (bottom network) information respectively. Both convolutional networks are linked to a fully connected layer combining spatial and spectral convolutional outputs. The output of the fully connected layer is mapped to the class labels.

3. Results

In figure **??** we show the 5 spectral clusters identified. Here, the blue region corresponds to a large stormy region (SR) surrounding the central dark storm (purple/green) with the previously detected "S" feature being on the western most part of the blue ammonia region. Each cluster is distinguished by its absorption and scattering characteristics, indicative of the cloud structure and gas composition. Most salient are the spectral differences between the region surrounding the dark storm features (blue region) in contrast to the unperturbed regions (red/orange), and the unique signatures of the black storms (purple/green). These SR features, based on their 1 - 2 μm spectra and low 5 μm flux, contain relatively large particles. We find the "S" feature to be the proverbial "tip of the iceberg" of a much larger region of upwelling. Baines et al.[**?**] hypothesise that the particles found in the "S" feature are condensed NH_3 as indicated by colour maps of the continuum (0.93 μm), methane (0.90 μm) and the NH_3 ice feature (2.73 μm). Our analysis defines the relative spectrum of the "S" and find that the "S" spectrum displays an absorption feature at roughly 2.74 μm – 2.85 μm. This is part of a broader continuum that resembles the NH_3 ice spectrum characteristic of that observed in Jupiter's storms[**?**]. Similarly, the averaged spectrum of the full SR region indicates a similar although weak ammonia ice feature.

4. Summary and Conclusions

Past and current planetary missions produce a wealth of data, too abundant to be analysed by "hand". More traditional data analysis techniques force us to consider only small volumes of data and a global understanding of spatial distributions of spectroscopic features (e.g. clouds on gas giants) is often lost. Maps produced by PlanetNet can give us insight into large-scale dynamics of a planet, while identifying regions of interest for more traditional radiative transfer calculations. This technique is significantly more sensitive and robust than simple I/F spectral band subtraction or division and can reveal previously unseen dynamics in the atmospheres of giant planets. The ability to identify features in data sets markedly different to the training data (both in pixel scale and observed angle) allows this technique to be easily scalable to large, planet-wide mapping of spectral features. PlanetNet can easily be adapted to other data sets and missions, making it a potentially invaluable tool in the global analysis of planetary mission data in the future.

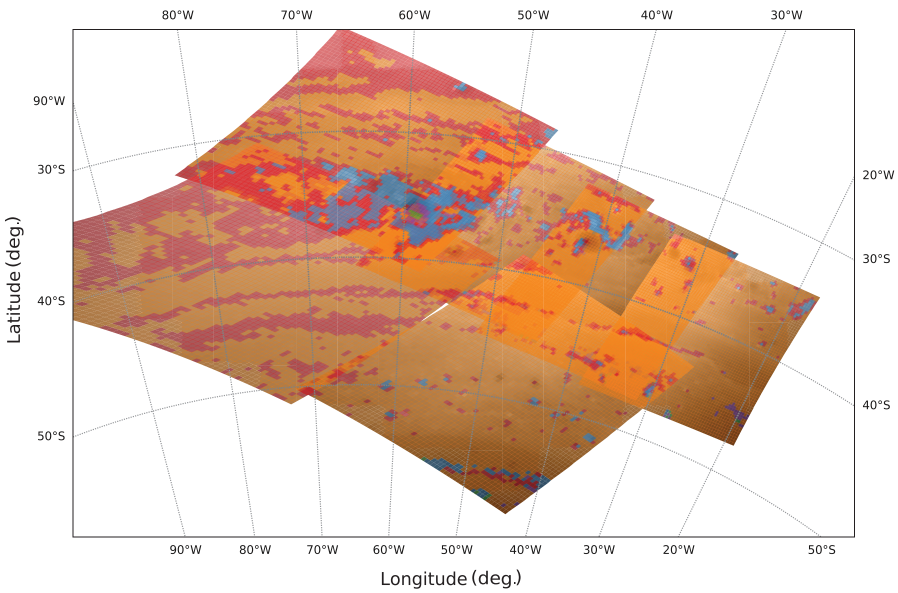

Figure 2: **Cloud distribution as mapped by PlanetNet across six overlapping data sets.** Colours indicate different types of cloud distributions: Blue: Ammonia upwelling, purple & green the inner edges of the most prominent dark storm, orange & red high altitude methane clouds. It is apparent that the SR feature (blue) occurs in the vicinity of dark storms but covers significantly larger areas than previously thought.

Acknowledgements

This project has received funding from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme (grant agreement No 758892, ExoAI) and under the European Union's Seventh Framework Programme (FP7/2007-2013)/ ERC grant agreement numbers 617119 (ExoLights). IPW furthermore acknowledges funding by the Science and Technology Funding Council (STFC) grants: ST/K502406/1 and ST/P000282/1 and support from Microsoft Azure for Research cloud computing. CAG is funded by the University of Arizona.

References

[1] Waldmann,I. P., Griffith,C. A., Mapping Saturn using deep learning. *Nature Astronomy* **10.1038/s41550-019-0753-8**, 308 (2019).

[2] Fouchet, T. *et al.* Stratospheric aftermath of the 2010 Storm on Saturn as observed by the TEXES instrument. I. Temperature structure. *Icarus* **277**, 196–214 (2016).

[3] Fletcher, L. N. *et al.* Thermal Structure and Dynamics of Saturnś Northern Springtime Disturbance. *Science* **332**, 1413 (2011).

[4] Barstow, J. K., Irwin, P. G. J., Fletcher, L. N., Giles, R. S. & Merlet, C. Probing Saturnś tropospheric cloud with Cassini/VIMS. *Icarus* **271**, 400–417 (2016).

[5] Sánchez-Lavega, A. *et al.* An enduring rapidly moving storm as a guide to Saturn's Equatorial jet's complex structure. *Nature Communications* **7**, 13262 (2016).

[6] Baines, K. H. *et al.* Storm clouds on Saturn: Lightning-induced chemistry and associated materials consistent with Cassini/VIMS spectra. *Planetary and Space Science* **57**, 1650–1658 (2009).

[7] Baines, K. H., Carlson, R. W. & Kamp, L. W. Fresh Ammonia Ice Clouds in Jupiter. I. Spectroscopic Identification, Spatial Distribution, and Dynamical Implications. *Icarus* **159**, 74–94 (2002).