

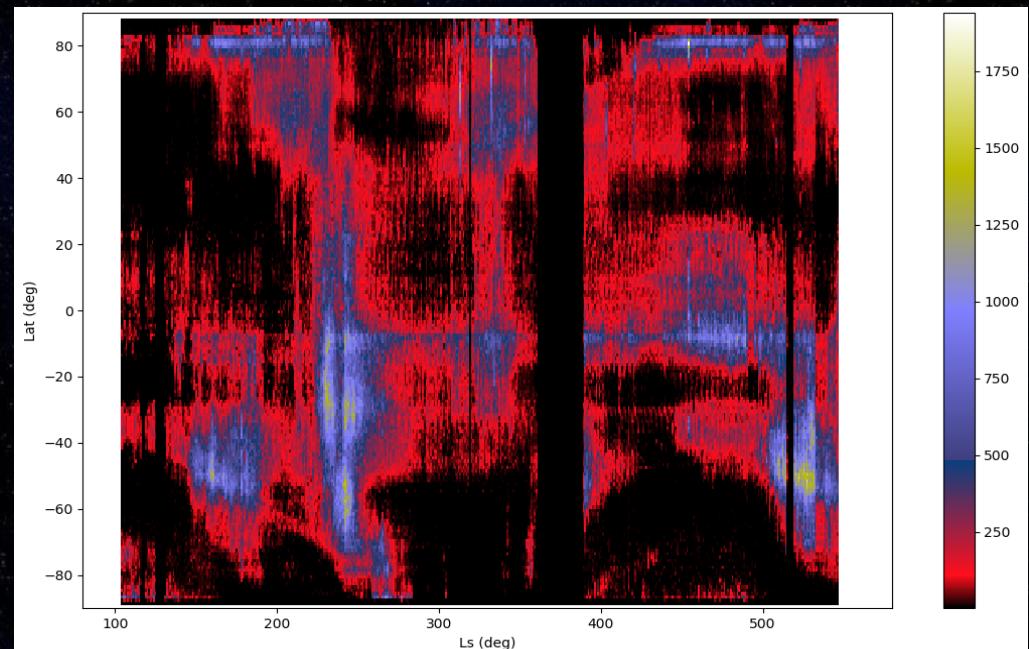
# Unsupervised Machine Learning Algorithms to Detect CO<sub>2</sub> Clouds on Mars



Vincent Caillé<sup>(1)</sup>, Anni Määttänen<sup>(1)</sup>, Aymeric Spiga<sup>(2)</sup>  
Lola Falletti<sup>(1)</sup>, Gregory A. Neumann<sup>(3)</sup>

**Abstract : We automatically detect clouds on Mars using MOLA and machine learning**

- ✓ Introduction & Background
- ⚙️ Methodology & Results
- 💬 Conclusions & Perspectives
- ❤️ Acknowledgements & References



<sup>(1)</sup> LATMOS, Sorbonne Université, UVSQ Paris-Saclay

<sup>(2)</sup> LMD/IPSL, Sorbonne Université

<sup>(3)</sup> NASA Goddard Space Flight Center, Greenbelt, Maryland, USA

# Introduction & Background

To revisit decade-old CO<sub>2</sub> cloud dataset  
To improve on a previous conservative threshold

## The instrument and data : MOLA

- Aboard **Mars Global Surveyor**, in Mars orbit from 1997 to 2006
- **Altimeter** : goal to characterize Mars surface topography with infrared laser pulses toward Mars
- **Huge dataset** from MOLA (1998-2001)
- More sensitive than expected with a good vertical resolution allowed **detection of non surface features, like clouds**  
(Neumann and al. (2003))
- **First data selection** has been made before clustering, to eliminate obvious surface returns

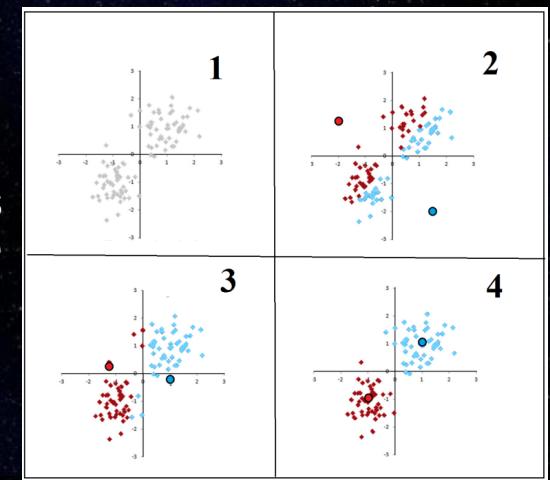
## The method : K-means algorithm

- Each observation point belongs to the cluster with the closest centroid (cluster mean)
- Move clusters centroids to minimize within-cluster variances

1 : raw points

2 : first cluster estimate

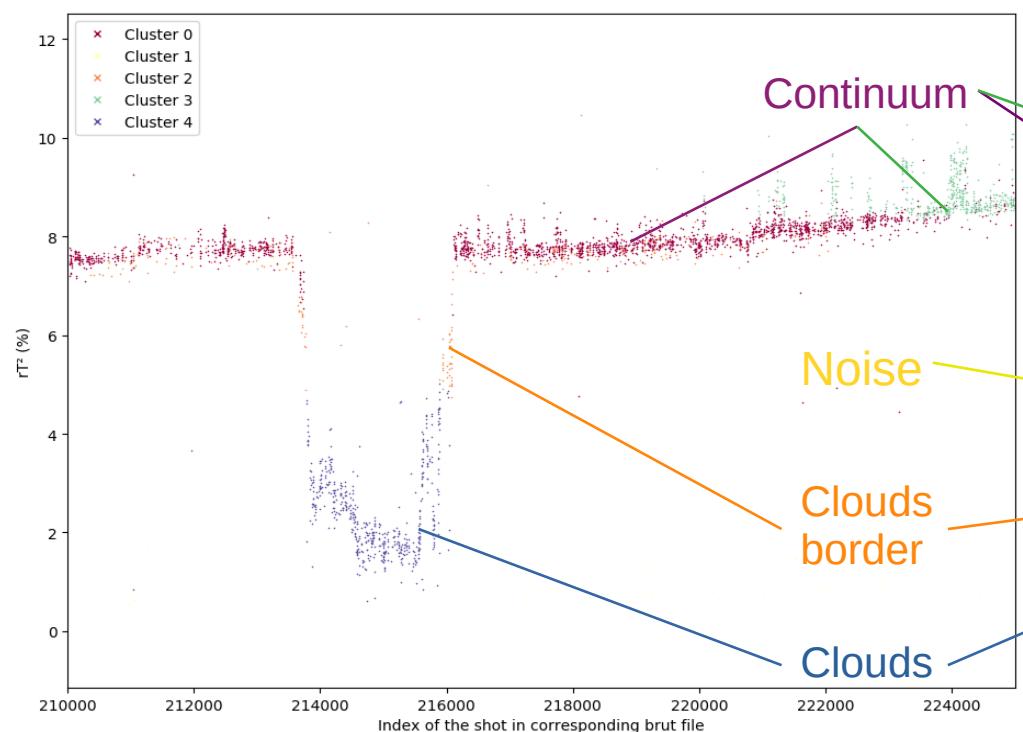
3 & 4 : cluster centroids are moved till variance is minimized  
(Kalmar and al. (2012))



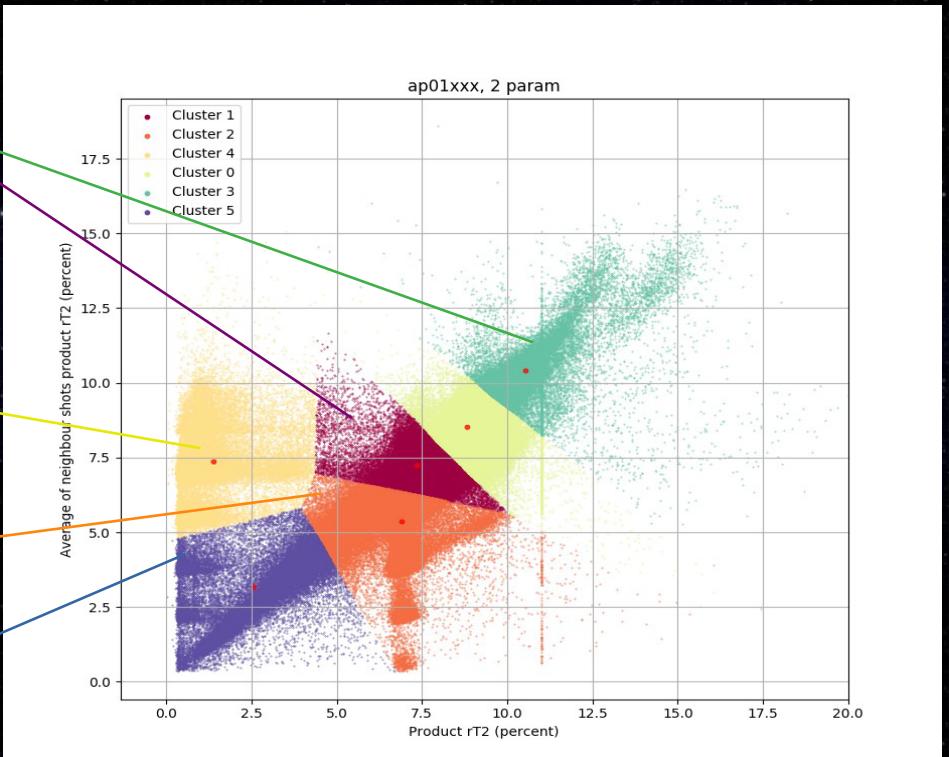
Need to find : - best parameters  
- best number of clusters

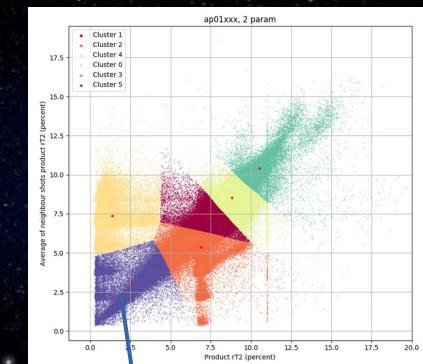
# Methodology & Results

The  $rT^2$  plotted against time shows clouds cause a dip in this parameter  
 ⇒ cloud returns have a low  $rT^2$  and low neighboring  $rT^2$

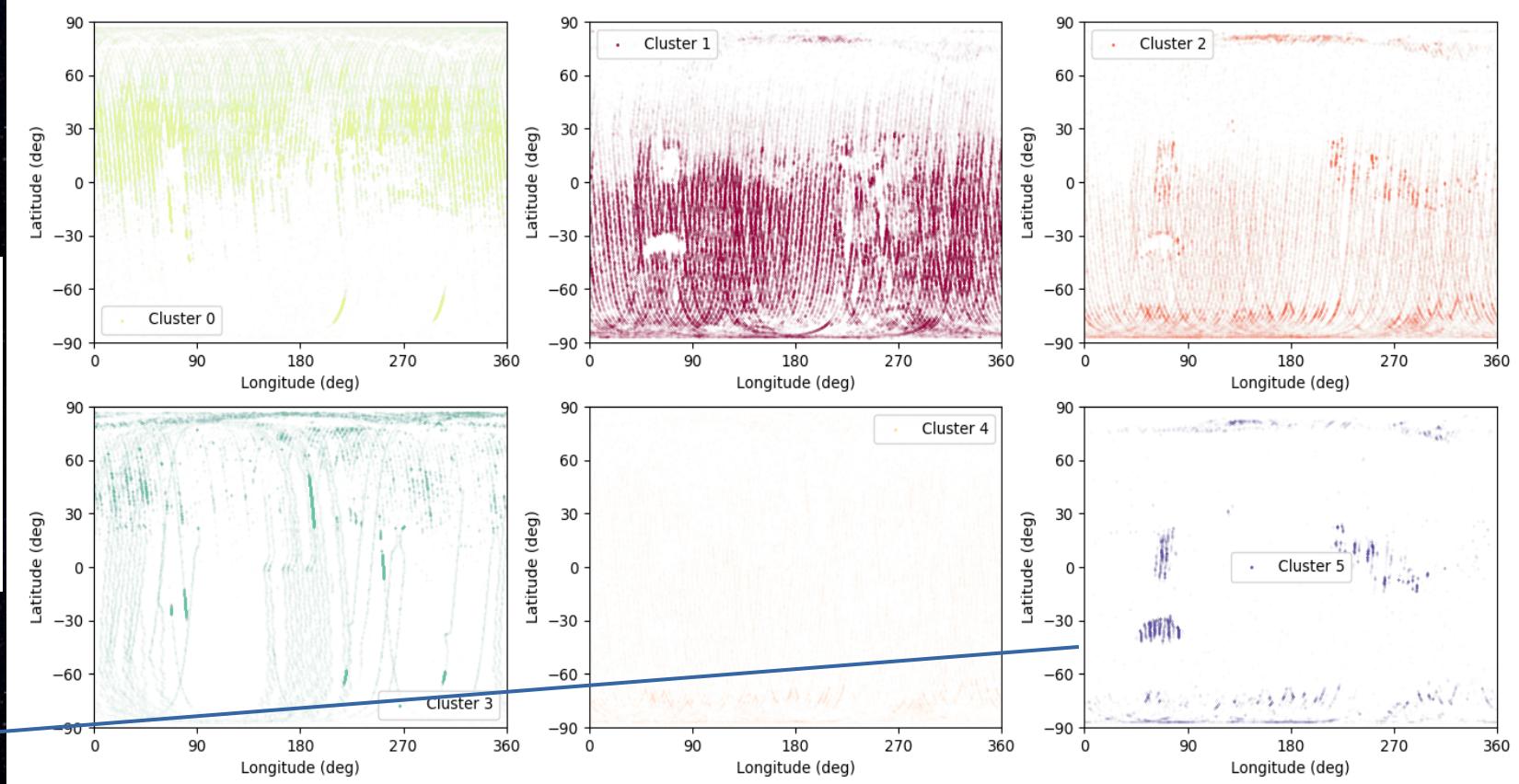


Parameter : Reflectivity<sub>surface</sub> \* Transmissivity<sub>atmosphere</sub><sup>2</sup>  
 3 independent methods converge to 6 clusters

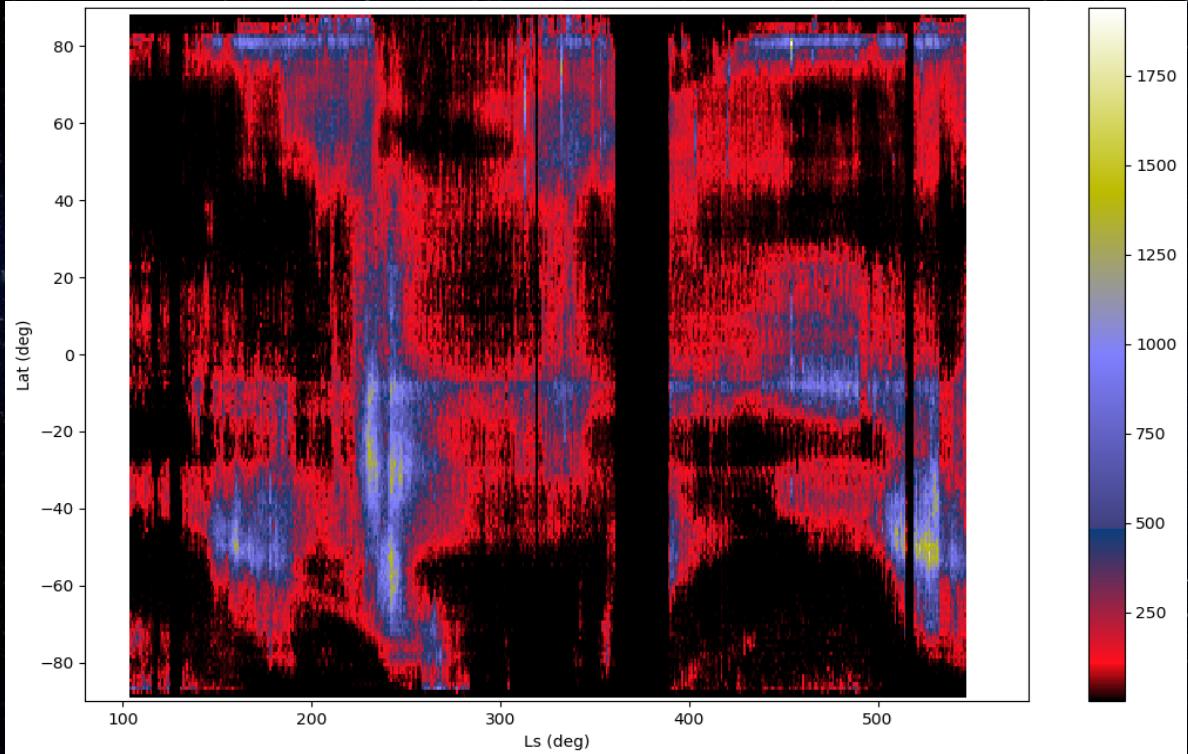




**Clouds**



This method can also allow to map clouds during the mission duration  
 ⇒ other clusters only draw the instrument orbit (while cloud one is more patchy)



**Cloud distribution** as a function of latitude and solar longitude from our cloud cluster.

High point density areas are in agreement with reference studies including both reflective and absorptive clouds maps (Neumann and al. (2003) results).

## Conclusions

- To apply Machine Learning on MOLA data, we've been able to find the best parameters for our clustering algorithms.
- Clustering method enabled us to distinguish continuum / noise and clouds laser returns in MOLA data.
- Unsupervised machine learning allows less stringent criteria than previous studies, leading to more cloud detections

## Perspectives

- Work only with cloud returns to cluster different kinds of particles (absorptive/reflective clouds, CO<sub>2</sub>, H<sub>2</sub>O, dust...)
- Test several parameters to find the best way to distinguish different kinds of clouds, and eventually move on to another clustering method
- Compare the observations with model results (developed by LATMOS and LMD)

## Acknowledgements



We thank the Agence National de la Recherche for funding (projet MECCOM, ANR-18-CE31-0013).

## References

- Neumann, G. & Smith, D & Zuber, M.. (2002). Two Mars Years of Clouds Detected by the Mars Orbiter Laser Altimeter. *Journal of Geophysical Research E: Planets*. 108. 10.1029/2002JE001849.
- Kalmar, Andras & Öllös, Gergely & Vida, Rolland. (2012). Analysis of an Event Forecasting Method for Wireless Sensor Networks. *Acta Universitatis Sapientiae-Electrical & Mechanical Engineering*.