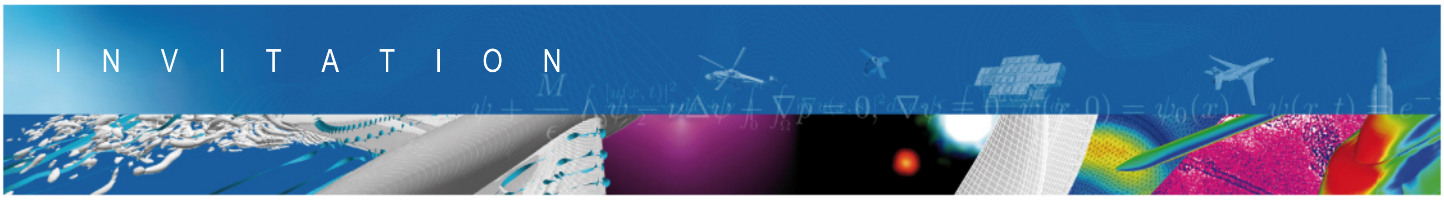


# Riemannian Geometry for Statistical Estimation and Learning: Application to Remote Sensing

Soutenance de thèse – Antoine Collas
**25 novembre 2022 à 10h00**
CentraleSupélec, 3 Rue Joliot Curie, 91192 Gif sur Yvette
Salle : Amphithéâtre F3.05, Bâtiment Bréguet

**Devant le jury composé de :**

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**Abstract:**
Remote sensing systems offer an increased opportunity to record multitemporal and multidimensional images of the earth's surface by improving temporal and spatial resolution. This opportunity greatly increases the interest in data processing tools based on multivariate image time series. In this thesis, we propose a clustering-classification pipeline to segment these data. To do so, robust statistics are estimated and then clustered or classified to obtain a segmentation of the original multivariate image time series. A large part of the thesis is devoted to the theory of Riemannian geometry and its subfield, the information geometry, which studies Riemannian manifolds whose points are probability distributions. It allows to estimate robust statistics very quickly, even on large scale problems, but also to compute Riemannian centers of mass. Indeed, divergences are developed to measure the proximities between the estimated statistics. Then, groups of statistics are averaged by computing their Riemannian centers of mass associated to these divergences. Thus, we adapt classical machine learning algorithms such as the K-means++ or the Nearest centroid classifier to Riemannian manifolds. These algorithms have been implemented for many different combinations of statistics, divergences and Riemannian centers of mass and tested on real datasets such as the *Indian Pines* image and the large crop type mapping *Breizhcrops* dataset.

**Keywords:** Signal processing, machine learning, Riemannian geometry, optimization, robust statistics, Earth observation.