Anomaly Detection on Multispectral Satellite Images

using self-supervised Contrastive Learning features extraction

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Abstract

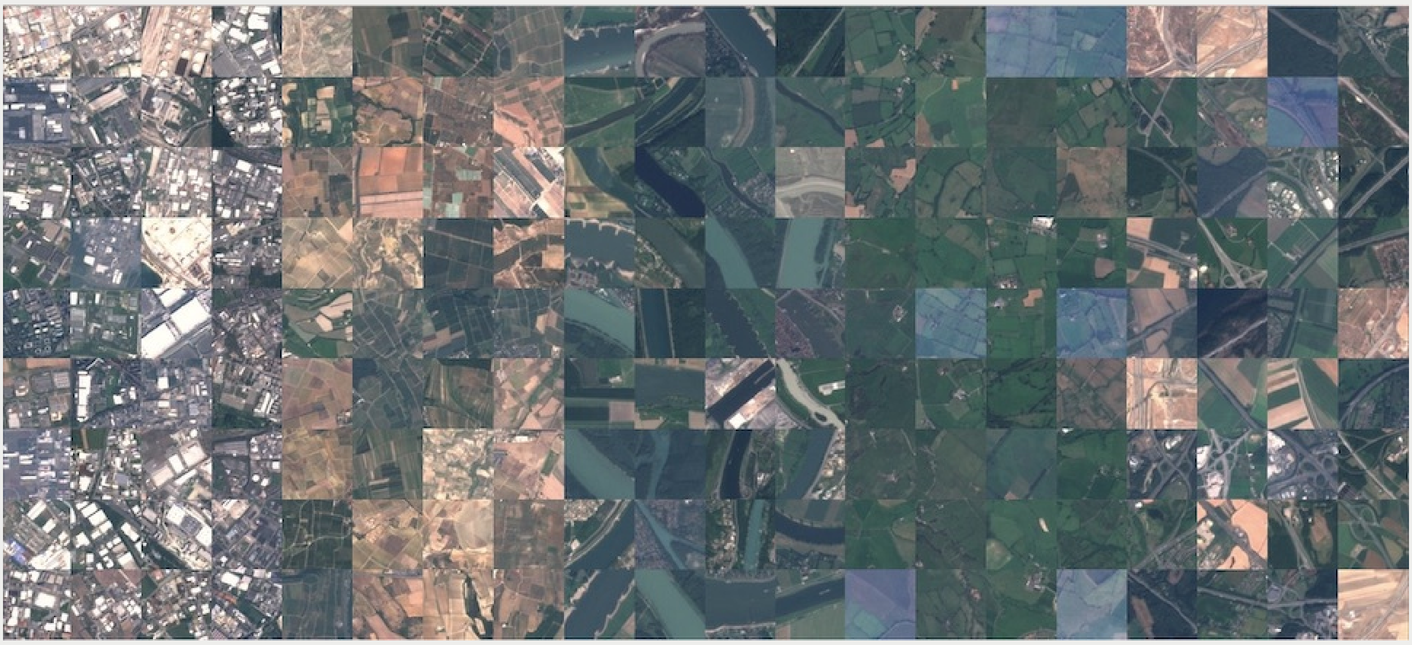
The processing of satellite data provides an in-depth knowledge of the entire globe. However it is as important to be able to process and valorize these data as to be able to collect them.

That's why machine learning methods are at the basis of many revolution in the field. With a shorter processing time, a lower human effort and a much better efficiency, it largely surpasses all traditional methods.

Motivation

1. Each earth observation satellite produces several hundred thousand GBS of data each year, which makes it impossible for a human to process that much data. Machine learning strategies have the benefit of handling massive amounts of data in real time.
2. As the amount of data is too large it is also too tedious to label our dataset. The classical supervised learning methods are therefore in general not suitable. Methods such as self-supervised learning are highly effective on such dataset.

Dataset



The "EuroSAT" is a open source dataset of Sentinel-2 satellite image covering 13 multi-spectral bands (in the visible, near infrared and shortwave infrared part of the spectrum) and composed of 10 classes with a total of 27 000 labeled and georeferenced images.

Sentinel-2 is a Copernicus Earth observation mission that acquires high spatial resolution (10 m to 60 m) optical images of land and near-shore waters. The mission is currently a constellation of two satellites, Sentinel-2A and Sentinel-2B; a third satellite, Sentinel-2C, is being planned for launch in 2024.

Step 1 - SimCLR features extraction

SimCLR is a state of art self-supervised learning model that does not require any human-created labels. As the name suggest, the model learns to supervise itself.

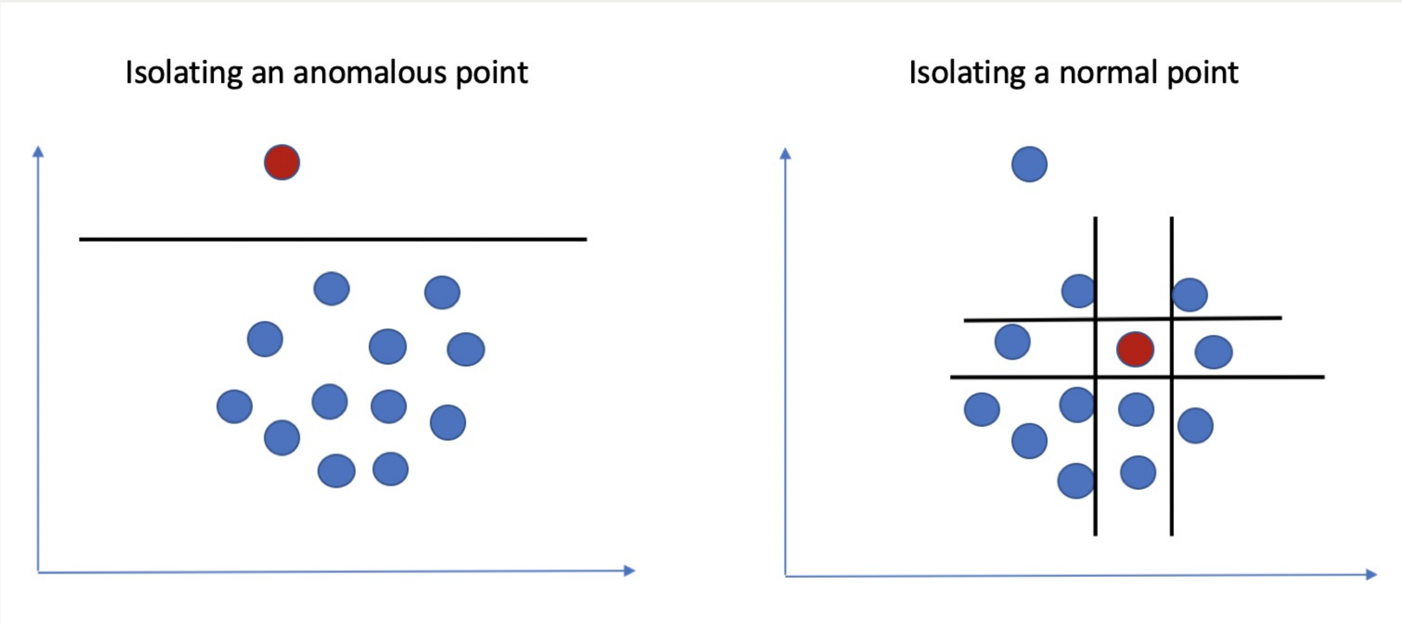
To do so we first apply 2 random augmentations (τ) on a same original image (x) making x_i and x_j. And we let the model learn that these images still contain the same visual information after a ConvNet Neural Network (CNN) and a projection head (MLP) forming z_i and z_j. This leads to the model learning a similar latent representation for the same objects.

The model is fitted against the "NT-Xent loss" define as $\ell_{i,j} = -\log \frac{\exp(\mathrm{sim}(z_i, z_j)/\tau)}{\sum_{k=1}^{2N} 1_{k \neq i}\exp(\mathrm{sim}(z_i, z_k)/\tau)}$

Step 2 - Isolation Forest Anomalie Detection

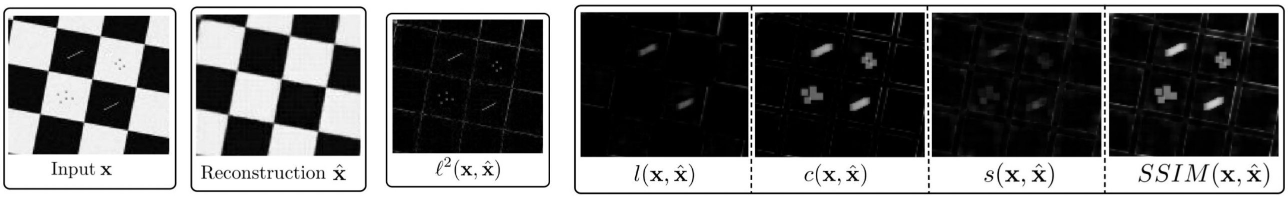
Once trained the latent space of SimCLR (representation / feature extraction) gives a good representation of the image in terms of features.

It is then possible to differentiate different classes of images. Like for example a field or a forest



This feature extraction can also be used for anomaly detection with an Isolation Forest approach. If the representation of a satellite image is too far from what can be found normally, it is a potential anomaly. For example a burning field will be classified as an anomaly

Reconstruction-based method



(a) (b) (c) (d)

[redacted]

Results and conclusion

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Based on this open source project