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CONTRIBUTION OF DIFFERENT ARTIFICIAL INTELLIGENCE TECHNIQUES FOR THE CLASSIFICATION OF LOW CLOUD SPATIAL ORGANIZATIONS

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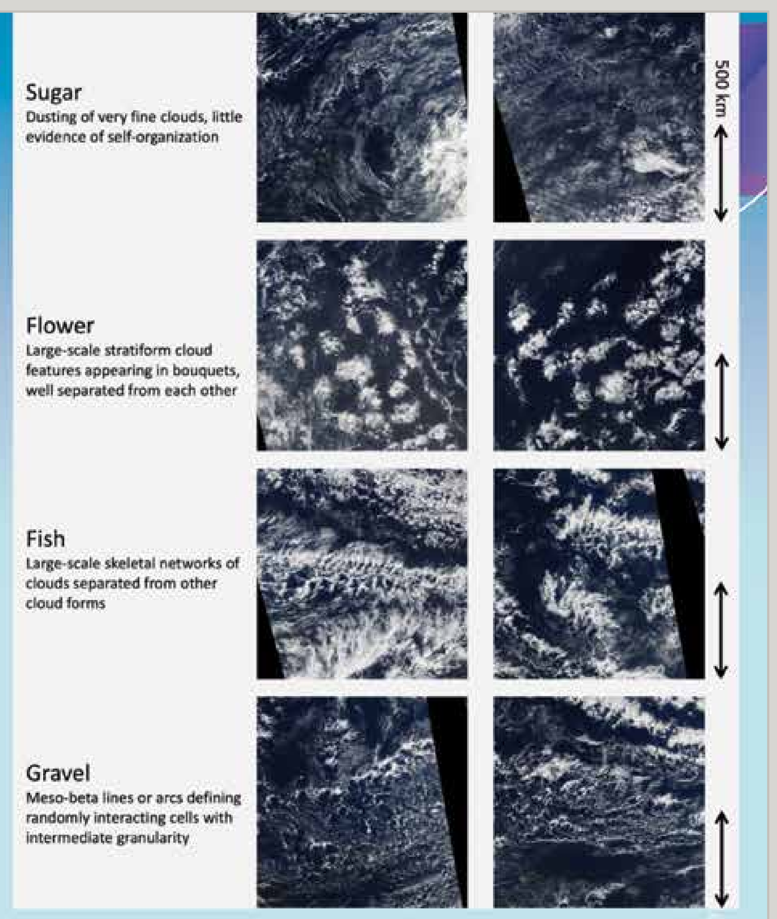
Cloud patterns

The EUREC4A campaign has raised a lot of interest in the international community about the diversity of patterns of low-level cloudiness that can be found in the trade-wind regions. One of the EUREC4A questions is how these different patterns form, and what is their role in climate. With this in mind, an early classification has been made by human as part of the preparation of the campaign. Later on, other initiatives aimed at recognizing and classifying the patterns in a more automatic way, including my using machine learning approaches. And the internship takes place in this context.
The internship objectives are

- Trying to understand the relation between 2 methodologies a supervised one (with human labels) and unsupervised (without human knowledge) and analyze how a model trained without human knowledge would compare to models trained using labeled dataset.
- Studying to what extent we are able to find the cloud spatial characteristics deduced from a supervised learning based on human labellisation with an unsupervised learning?

A recent study has visually identified four prominent mesoscale patterns of shallow convection, referred to as flowers, fish, gravel, and sugar :

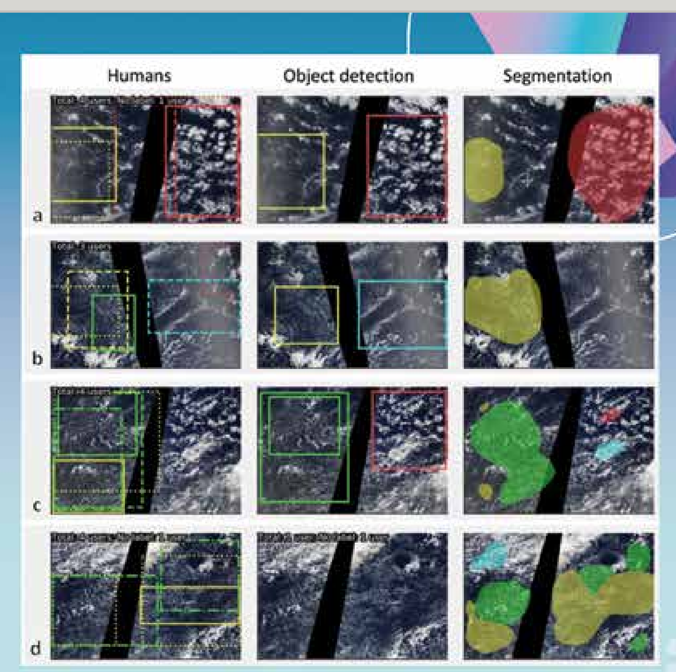
- **Sugar** describes widespread areas of very fine cumulus clouds. Overall these fields are not very reflective, do not have large pockets of cloud-free regions, and, ideally, exhibit little evidence of mesoscale organization.
- **Flower** describes areas with isotropic cloud structures, each ranging from 50 to 200 km diameter, with similarly wide cloud-free regions in between. Flowers, however, are often less densely packed than typical closed cells, which only have narrow cloud-free regions at the edges, and they are identified well outside of regions where stratocumulus are found.
- **Fish** are elongated, skeletal structures that sometimes span up to 1 000 km, mostly longitudinally. As noted by Stevens et al. (2020), these features appear similar to what Garay et al. (2004) called actinoform clouds. They presented examples of these particularly well structured cloud forms taken from all ocean basins, near but typically downwind of regions where stratocumulus maximize.
- **Gravel** describes fields of granular features marked by arcs or rings. The typical scale of these arcs is around 20 km. We suspect that these patterns are driven by cold pools caused by raining cumulus clouds.



Supervised approach

Deep Learning : is a subfield of Machine Learning which itself is a subfield of artificial intelligence, it is based on the usage of deep neural networks (where all neurons are connected and each one of them receives one or more inputs and sums them through activation functions to give an output). Deep Learning had permitted great advancements in the recent years in many domains (autonomous cars, face detection, image segmentation ...) , this data-driven approach has revolutionized the field of computer vision, which, up to 2012, was to a large extent based on hard-coded feature engineering . Deep learning in computer vision is based on convolutional neural networks which exploit the translational invariance of natural images. Deep neural networks also have many potential applications in the Earth sciences, particularly where already existing deep learning techniques can be transferred to geoscientific problems (Reichstein et al. 2019).
Supervised Learning : is a set of algorithms that learn a function that maps an input to an output based on example input-output pairs. It infers a function from *labeled training data* consisting of a set of *training examples*.In supervised learning, each example is a *pair* consisting of an input object (typically a vector) and a desired output value. A supervised learning algorithm analyzes the training data and produces an inferred function, which can be used for mapping new examples. An optimal scenario will allow for the algorithm to correctly determine the class labels for unseen instances. This requires the learning algorithm to generalize from the training data to unseen situations. This statistical quality of an algorithm is measured through metrics like mean squared error.

Specific Study of Supervised Learning on Clouds and Climate :
In the paper from Rasp et. al (2020 (10.1175/BAMS-D-19-0324.1)) images from MODIS were collected and then uploaded on a crowdsourcing platform (Zooniverse) so users can annotate parts of the image with cloud categories as labels.
67 scientists screened 10,000 satellite images on a crowdsourcing platform and classified almost 50,000 mesoscale cloud clusters. This dataset is then used as a training dataset for deep learning algorithms that make it possible to automate the pattern detection and create global climatologies of the four patterns.
The pattern recognition task can be framed as one of two machine learning problems: object detection and semantic segmentation. Object detection algorithms draw boxes around features of interest, essentially mirroring what the human labelers were doing. In contrast, segmentation algorithms classify every pixel of the image.
Both types of algorithm accurately detect the most obvious patterns in the image and agree well with human labels. Neither algorithm is perfect, however the object detection algorithm sometimes misses features.
The model gave good Intersection over Union results, better than the Intersection over Union scores between the different uses which in addition to showing an efficient model, showed that the model predictions were less noisy.



In this paper cloud images from MODIS were classified and localized with rectangles.

MODIS (Moderate Resolution Imaging Spectroradiometer)

MODIS is a payload imaging sensor that was launched into Earth orbit by NASA in 1999 on board the Terra satellite, and in 2002 on board the Aqua satellite.

- The instruments capture data in 36 spectral bands ranging in wavelength from 0.4 µm to 14.4 µm and at varying spatial resolutions, together they image the entire Earth every 1 to 2 days, they are designed to provide measurements in large-scale global dynamics including changes in Earth's cloud cover,
- With its low spatial resolution but high temporal resolution, MODIS data are useful to track changes in the landscape over time

Dataset link : https://www.zooniverse.org/projects/raspstephan/sugar-flower-fish-or-gravel/classify

Unsupervised approach

Unsupervised Learning : In contrast to supervised learning where data is tagged by a human is a type of algorithm that learns patterns from untagged data. Unsupervised learning exhibits self-organization that captures patterns as neuronal predilections or probability densities. The hope is that, through mimicry, the machine is forced to build a compact internal representation of the data.

The second paper from one of my supervisors (Denby 2020 (10.1029/2019GL085190)) is treating the problem in an unsupervised way, it approaches the problem of cloud classification by understanding that the way in which we classify clouds is based on their relative difference (or visual difference/distance) to other clouds.
From that he developed a model that learns to create a dimensional space (that we would call embedding space) for this visual difference metric, the objective of the model is to learn to assign coordinates in a multi-dimensional space for an image.
The way the model learns this new dimensional space is by taking a first tile (where a tile is a 256 by 256 shaped image extracted from a domain) called anchor tile and a neighbor tile (within a random direction and a distance of 125 px and a 50% overlap to guarantee a minimum visual similarity) and learns a to assign them a small distance, and then it takes a distant tile extracted from a random different day and try to maximize the learned distance to it.
The 3 images are passed through an architecture composed of a pre trained neural network (a ResNet) using a technique called Transfer Learning (which consists of using a model trained on big dataset of other domains and which its convolutional learned to extract features and apply it to another context with fixed parameters) and then to a multi-layer fully connected neural network with a 100 sized vector which correspond to the coordinates on a 100-dimensional embedding space.

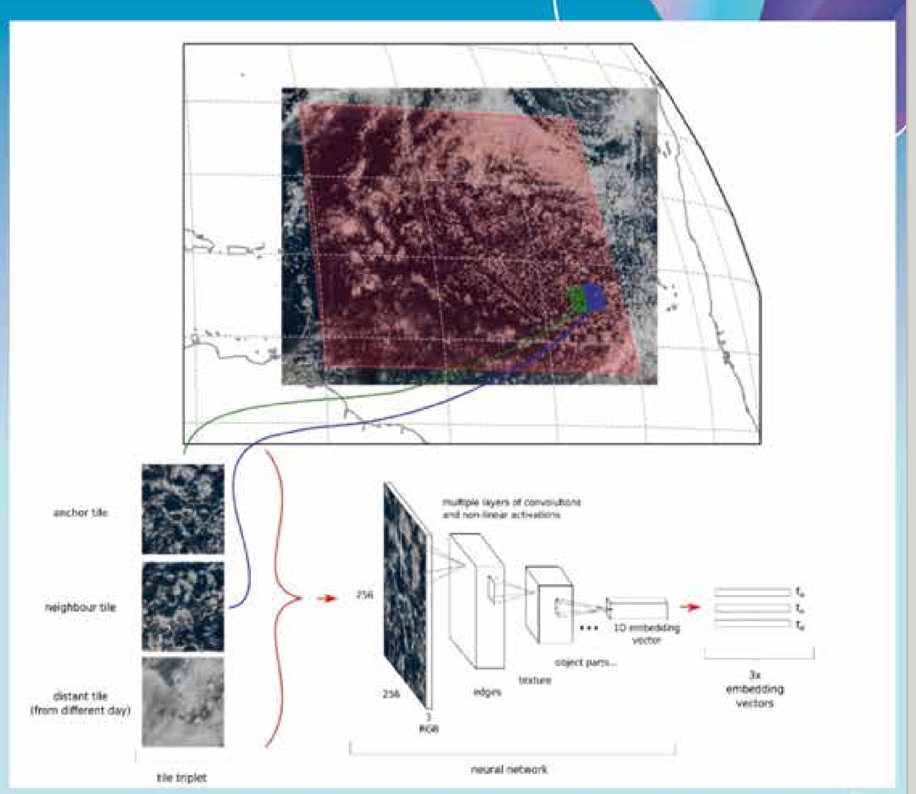


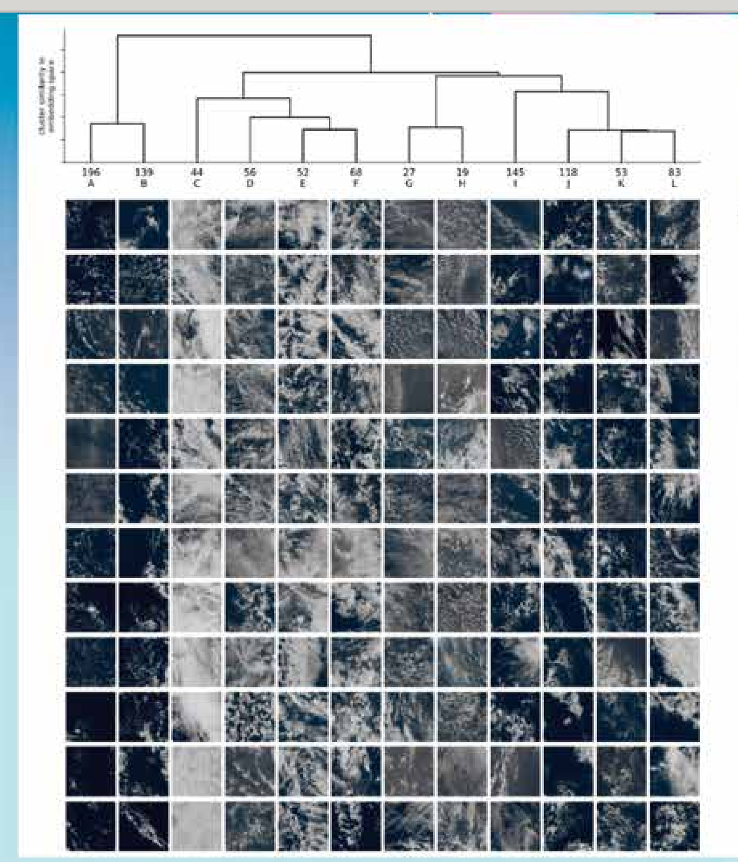
Figure : representation of the model architecture
source : Denby (2020)

Unsupervised clustering

This graph is a demonstration of clustering for embeddings produced by the trained neural network in form of a dendogram.
In the top we can see on the y-axis the intra-cluster variance in the embedding space and only 12 clusters are fixed.
In the bottom part are shown 12 random tile examples from each cluster belonging to the leaf or cluster immediately above in the dendrogram.
Each node cluster is annotated with the number of tiles that were associated with it and an alphabetical labellisation to aid discussion. The persistence in the dendrogram indicates for example clusters A and B are much more similar to each other than to any other cluster.
We can see in the figure :
A number of visibly distinct structures have been identified, for example,

- A-B : scattered small clouds
- C-D-G-H : cellular structures.
- D-F : larger cloud cellular
- I-J-K-L : broken cloud structures.

The clusters were created without prior knowledge about the human labellisation of the tiles. The objective of the internship is then to apply the model on labelised images and see if there would be clusters having strong correlation with known cloud categories.



MODIS images (Amazon Dataset) dendogram clustering
source : Denby (2020)

First Results

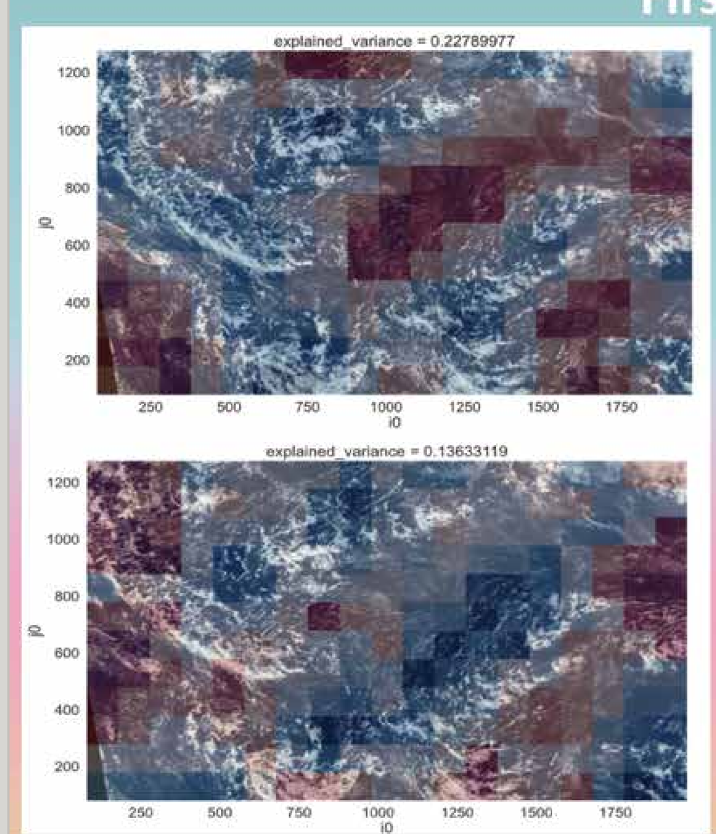


Figure 1 : Visual domain with principal component as heat value.

We trained the unsupervised architecture on MODIS images (from Zooniverse crowdsourcing) sliced in (256, 256) shaped tiles.

On the 2 images of figure 1 we can visualize a process where we took a domain, splitted it in tiles, and passed it through the model to get the vector of embedding values, then we applied PCA algorithm to get the first 2 principal components of the embedding dimensions that we represented then as a temperature level. We can see higher values of the first component on large cloud-free parts the second component seems to target squared cloud parts.

Number of :
Training images :
35 126 triplets
Clustered images :
11 836

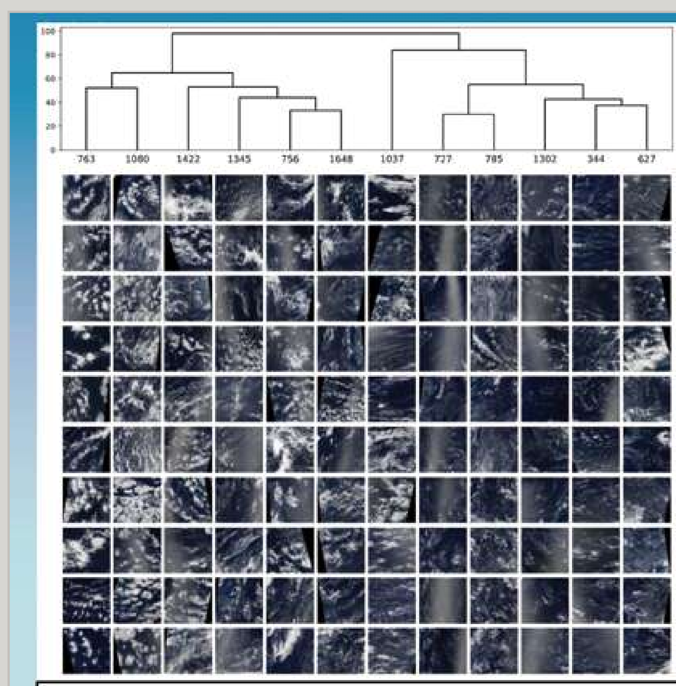


Figure 2 : Dendogram of clouds clustering by their embedding values.

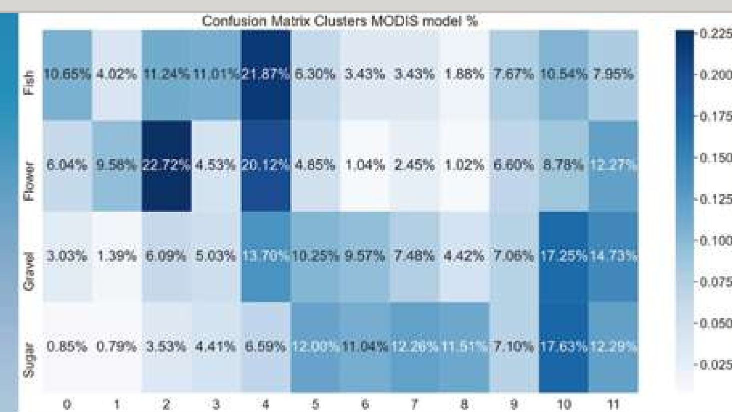


Figure 3 : Confusion Matrix between images labels (classes) and predicted clusters.

We used the trained model to clusterize user's rectangles (of Zoonivers dataset) resized to a shape of (256,256)

We obtained, as we can see in figure 2 interesting clustering which separates nicely different kind of clouds, for examples the first split of clusters seems to separate images with high concentration of clouds and the ones with far less concentration.

The figure 3 shows a confusion matrix where each line represents the true human label of the image and each column the associated cluster from the unsupervised model, so, for example the value from the first line and first column says that 10.65% of images were actually labeled to cluster 0 where they were initially classified as Fish.
From this matrix we can see that the model has learned to do a strong separation between 2 groups of cloud categories on one part Fish and Flower, and on the other Gravel and Sugar.

Outlook

- **Train different architectures of unsupervised learning.**
- **Apply algorithms for the interpretation of neural networks predictions to understand the way the model works.**
- **Develop segmentation algorithm from the feature extracted.**
- **Construct cloud tracking algorithms or models.**
- **Experiment with different hyper-parameters for the creation of the image datasets.**

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