CS577 Project Proposal

Understanding Clouds from Satellite Images

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March 30, 2021

1. Problem statement

Shallow clouds play a huge role in determining the Earth's climate, although they are difficult to understand and to represent in climate models. There are many ways in which clouds can organize, however, even though the human eye is really good at detecting their features, the boundaries between different forms of organization are not usually well defined. This makes it challenging to build traditional rule-based algorithms to separate cloud features.

Therefore, as it is stated in the paper *Combining crowdsourcing and deep learning to explore the mesoscale organization of shallow convection* [1], four subjective patterns of organization have been defined: Sugar, Flower, Fish and Gravel in a total of 10,000 satellite images on a crowd-sourcing platform and deep learning networks have been trained with this dataset to achieve an automated pattern detection and create global climatologies of the four formations, suggesting promising results.

Hence, by classifying different types of cloud organizations, researchers at Max Planck hope to improve the physical understanding of these types of clouds, which in turn will help build better climate models.

2. Proposed Solution

As it is explained in the next section, the aim of the model is to classify different cloud formations in a satellite image. For that reason, the pattern recognition task can be framed with two different deep learning approaches: object detection and semantic segmentation, see Figure 1.

Object detection algorithms draw boxes around features of interest. Here, [1] proposes the model keras-retinanet, an implementation of a modern detection network in Keras. This is basically a ResNet model that matches the speed of one-stage detectors while surpassing the accuracy of all existing state-of-the-art two-stage detectors [2]. It uses a Resnet50 backbone. The original images had a resolution of 2100 by 1400 pixels, hence the images have been downscaled to 1050 by 700 pixels to fit the batch (batch size = 4) into GPU RAM.

In contrast, semantic segmentation algorithms classify every pixel of the image, assigning a category to every pixel from the original image that form the features of interest. For that purpose, a Unet structure with a ResNet50 backbone that uses the fastai Python library v17 is used [3]. A mask will be created by converting the boxes of the cloud formations images to an array with their corresponding categories. In case the bounding boxes are overlapped, the mask will be chosen to represent the value of the smaller box. At the same time, the images will be downscaled to 700 by 466 pixels (batch size = 6).

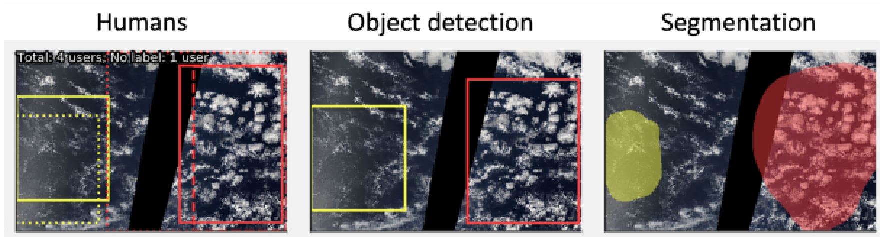

Figure 1: Different approaches to the detection of cloud formations.

3. Data

A total of 9244 satellite images will be used as part of the dataset of the network, and they will be downloaded from the NASA Worldview website [4]. Labels will be retrieved from [5]. These images contain different cloud formations, with label names: Fish, Flower, Gravel, and Sugar. Each image has at least one cloud formation, and can possibly contain up to all four. The labels were created in a crowd-sourcing activity at the Max-Planck-Institute for Meteorology in Hamburg, Germany, and the Laboratoire de météorologie dynamique in Paris, France. A team of 68 scientists identified areas of cloud patterns in each image, and each image was labeled by approximately 3 different scientists.

Three regions, spanning 21 degrees longitude and 14 degrees latitude, will be chosen. 3692 (40%) images will be used for testing the network (*test_images*) and 5546 (60%) will be used for training purposes (*train_images*).

A CSV file (*train.csv*) will also be used for each image-label pair in the training dataset, and will contain their run length encoded segmentations.

4. Team member responsibilities

As a two-member team project, the following tasks are going to be defined for each one:

- Both team members will carry on a prior analysis of the data to determine the useful information and then carry on the appropriate pre-processing for both deep learning approaches.
- Luis will be in charge of the design, training and analysis of the object detection approach.
- Jorge will be in charge of the design, training and analysis of the semantic segmentation approach.
- Finally, the comparison between both models will be carried out together, as well as the development of the final report.

5. References

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