Segmentation of cloud patterns from satellite images to improve climate models

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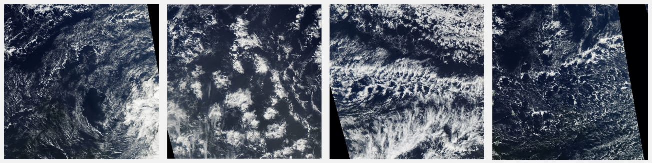
Motivations

Climate change has been at the top of our minds and at the forefront of important political decision-making for many years.

Shallow clouds play a large role in the Earth's radiation balance and yet they are poorly represented in **climate models**. Classification of different types of clouds is substantial for understanding climate change.

ML techniques demonstrate their ability to mimic the human capacity for identifying patterns in the clouds using satellite images.

This work focuses on **segmentation** of 4 subjective patterns of clouds organization.



(a) Sugar (b) Flower (c) Fish (d) Gravel

FIGURE – Canonical examples of the four cloud organization patterns.

Dataset

Dataset : Gathered by the scientists of two meteorologic institutions and later was used to host a Data Science **competition on Kaggle**.

Problematics : The ground-truth masks presented in the **dataset** are quite **noisy** meaning they include a lot of areas that actually do not contain clouds at all. Also, the masks of different classes can overlap. These two facts significantly increase **problem complexity**.

Metric : Mean Dice coefficient $\frac{2|Y_{\text{pred}} \cap Y_{\text{gt}}|}{|Y_{\text{pred}}| + |Y_{\text{gt}}|}$

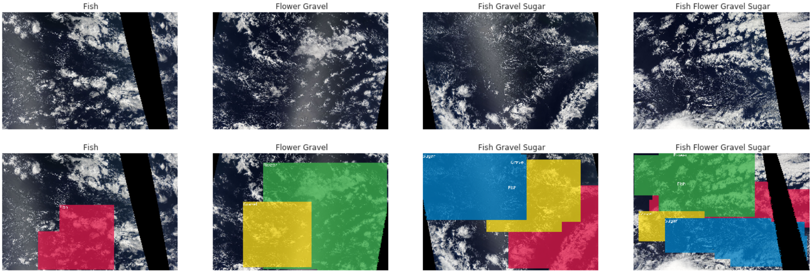


FIGURE – Images of clouds with corresponding masks.

Architecture

Sematic segmentation of 4 classes

U-Net with **EfficientNet-B0** as encoder

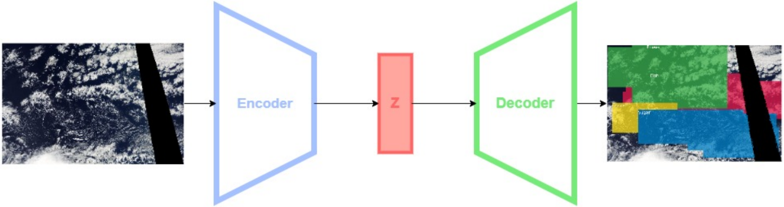


FIGURE – Simplified schematic view of the architecture.

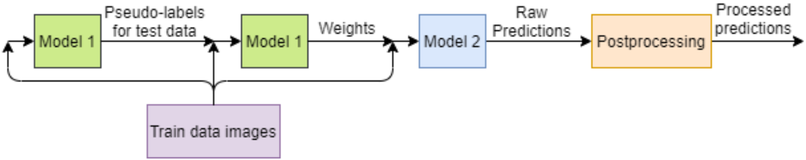
Larger encoders didn't work due to overfitting

Could use the same strategy as in NoisyStudent
$\hookrightarrow$ Pseudo-labeleing strategy

Pipeline

Two-stage segmentation pipeline with **progressive resizing** & **pseudo-labelling**. accepts images with corresponding ground-truth masks and outputs raw (non-normalized) predictions for each of four classes.

Post-processing procedure after the model generates predictions, namely, drop all the masks which **pixel size** [1] is less than some **parameter *k*** (can be optimized). predictions are normalized with sigmoid function to eliminate masks of insufficient-size. Thus, final processed predictions were generated.



How training on different **image sizes** and different sets of **pseudo-labels** affects the convergence ?

1. Pixel size is defined as a number of pixels which belong to the same connected component

Research

Two sets of pseudo-labels were generated :

Confident pseudo-labels only [if its value either <0.3 or >0.7 after sigmoid]

All images from test data selected for pseudo-labels

Hyperparameters :

Encoder : EfficientNet-B0

Augmentations : all with 50% probabilities

- HorizontalFlip
- VerticalFlip
- ShiftScaleRotate
- GridDistortion
- OpticalDistortion
- RandomBrightnessContrast

Optimizer : Adam with lr 1e-3

Scheduler : ReduceLROnPlateau

Stopping criteria : Early Stopping with patience = 5 and min_delta = 5e-4

Post-processing :
activation threshold = 0.4, min_mask_size – depends on image resolution

352×512 – 2.5k pixels $\quad$ 512×768 – 5k pixels $\quad$ 768×1152 – 11k pixels

Loss :

- Stage 1 : BCE Dice Loss
- Stage 2 : Symmetric Lovasz Loss

Results

	352×512	512×768	768×1152
352×512	0.64958	0.65486	0.65087
	0.64941	0.65356	**0.65553**
	0.64840	**0.65603**	0.65389
	0.64518	0.64925	0.64763
512×768		0.65109	0.65318
		0.65590	**0.65582**
		0.65663	0.65394
		0.65313	0.64665
768×1152			0.65041
			0.65118
			0.65141
			0.64528
	Pseudo-labels confident **only stage 1 stage**		
	Pseudo-labels all **only stage 1**		
	Pseudo-labels all **stage 1 + stage 2**		
	Pseudo-labels confident **stage 1 + stage 2**		

TABLE – Summary of the results.

Conclusion

We have developed a **two-stage segmentation pipeline** with post-processing procedure which identifies location of four cloud organization patterns.

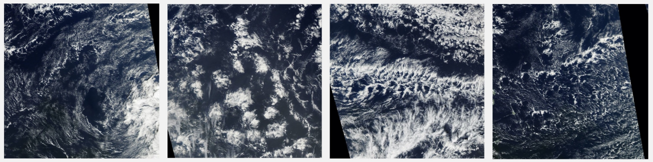
We have studied how choice of pseudo-labels and image resolution affects the final results.

Surprisingly, training on the biggest image resolution (768×1152) didn't yield the best results.

Moreover, training with the confident pseudo-labels consistently couldn't outperform the result obtained from training with a set of all test images chosen as pseudo-labels.

Vishnyakov, K., Organokov, M., "Understanding Clouds from Satellite Images", GitHub repository, `https://github.com/LightnessOfBeing/kaggle-understanding-cloud-organization`

Q&A



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