Understand Amazon Deforestation using Neural Network

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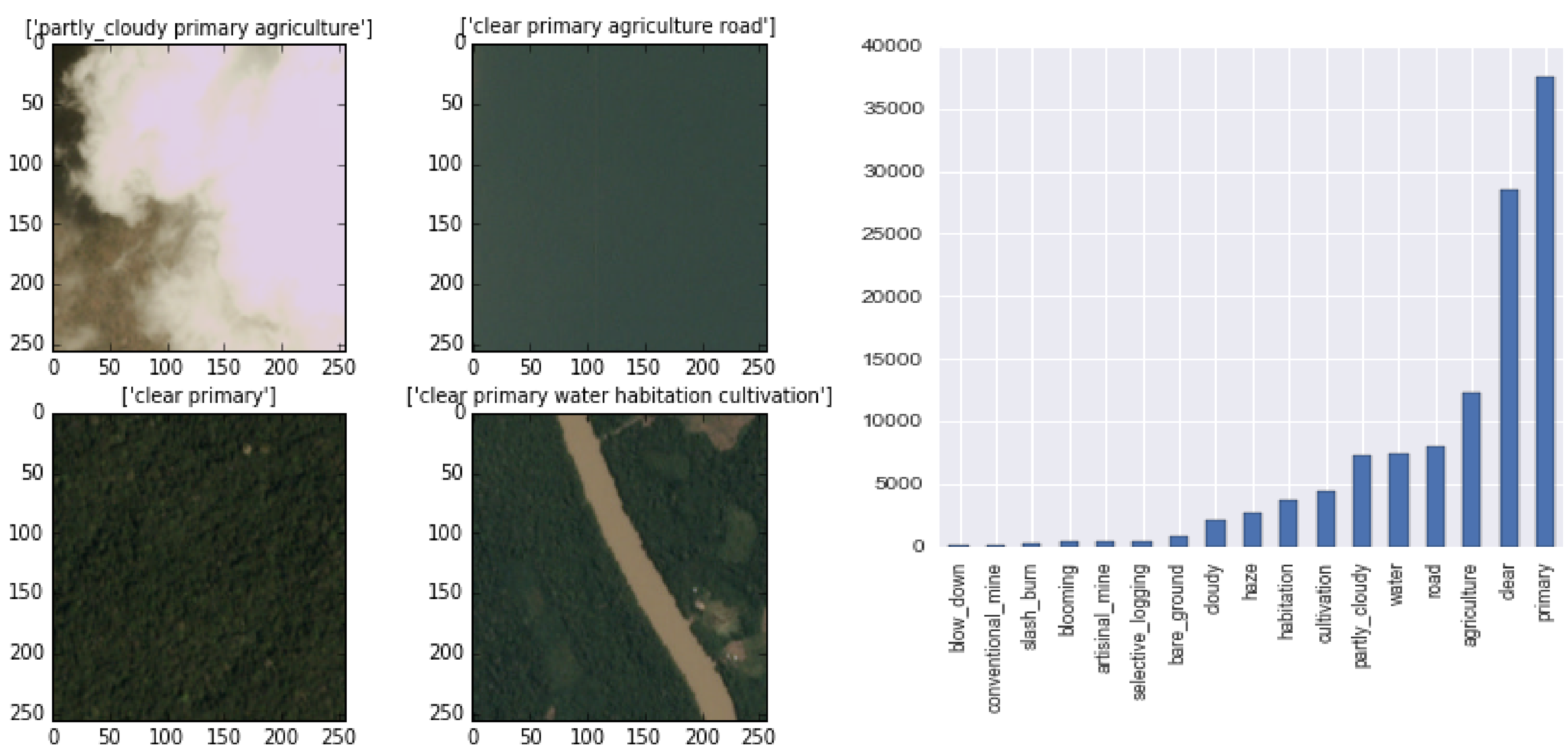
Abstract

The goal of this project is have the computer predict multiple tags for a given satellite image chip to understand the evolution of amazon forest. We fine tune a pretrained VGG16 model to extract low level features from RGB channels for the classification. We use both data augmentation, balancing and more specialized neural nets to overcome the severely skewed class label distribution. Through this project, we explore the effect of data augmentation, training strategy and network architectures on prediction accuracy.

Dataset

Training data contains 40479 satellite images with 4 channels (RGB and near infrared) with 16 bits color. Each image comes with a tag, which can include three types of labels: atmospheric condition, common land cover/land use phenomena, and rare land cover/land use phenomena.



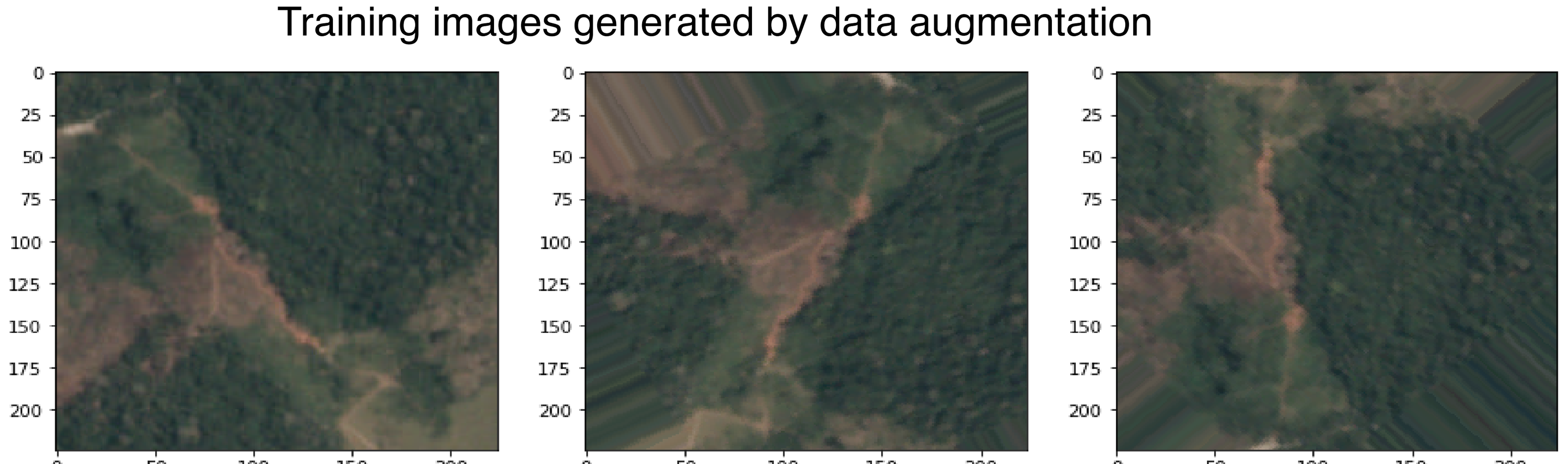
Sample images and skewed class distribution in the dataset

Data augmentation and rebalancing

We randomly flip, rotate and shift the training images while training to infinite flow of transformed training images.

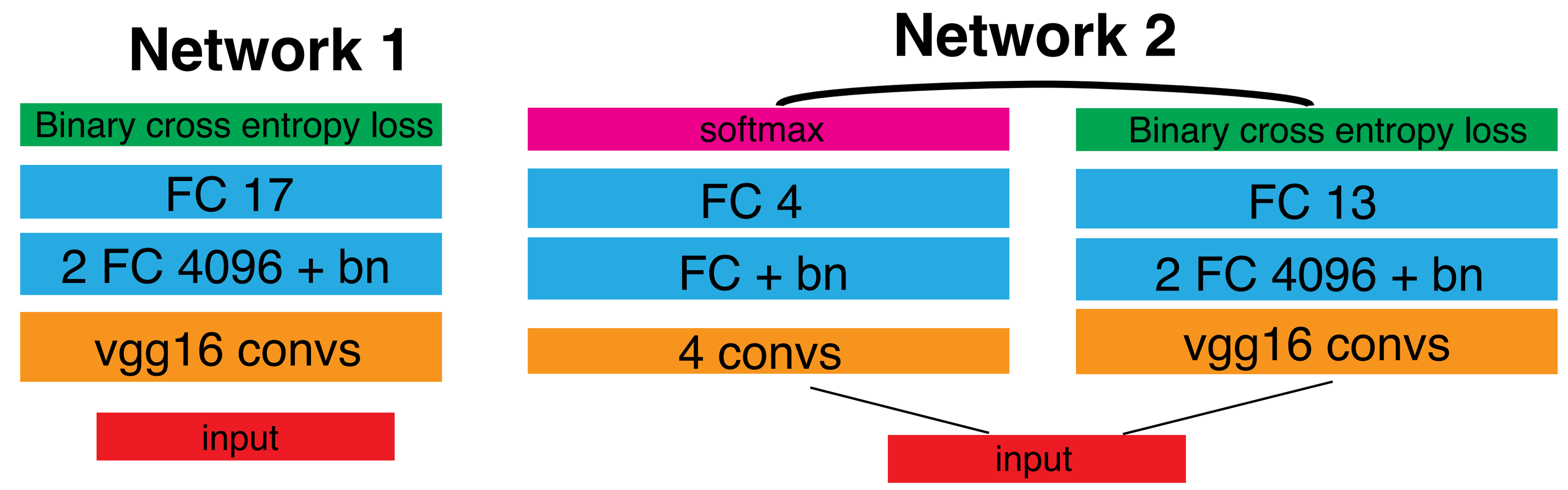
Data balancing is done by randomly downsample the top 5 majoriy labels to the frequncy of the 5th majority labels.

Training images generated by data augmentation



Network architecture

The main network is based on pretrained vgg16. We test two architectures showing in the schematics.



Loss and evaluation metric

Softmax cross entropy loss (weather classes): $L = -\log\left(\frac{e^{s_y}}{\sum_j e^{s_j}}\right)$

Binary cross entropy loss (landform classes):

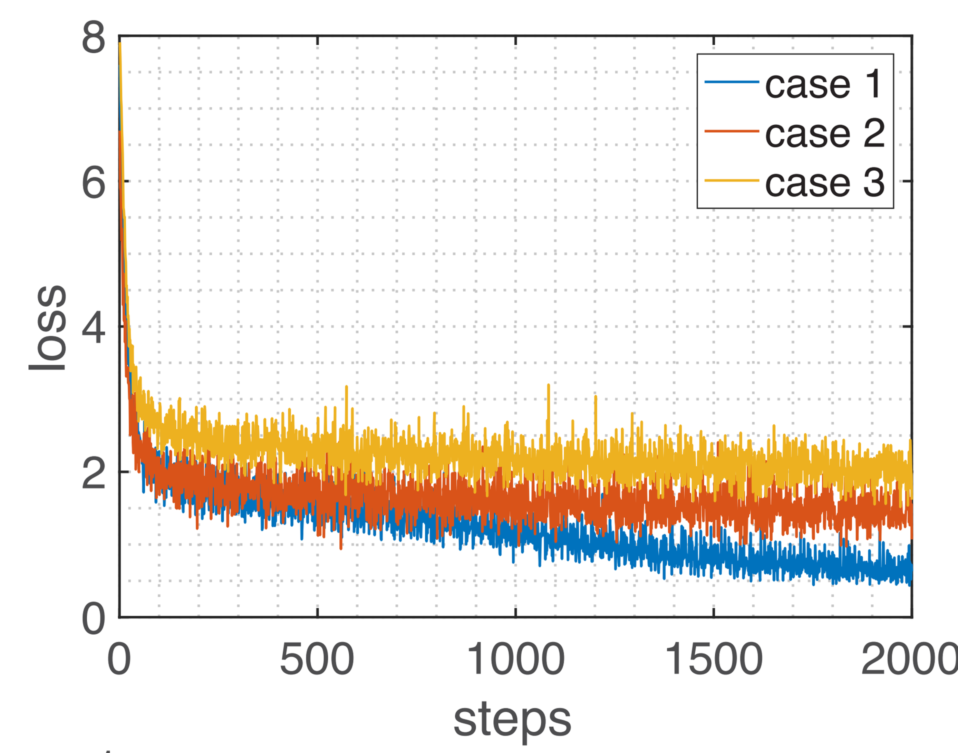
$$L = -\log(\sigma(s))y - (1-y)\log(1-\sigma(s))$$

Evaluation (F score):

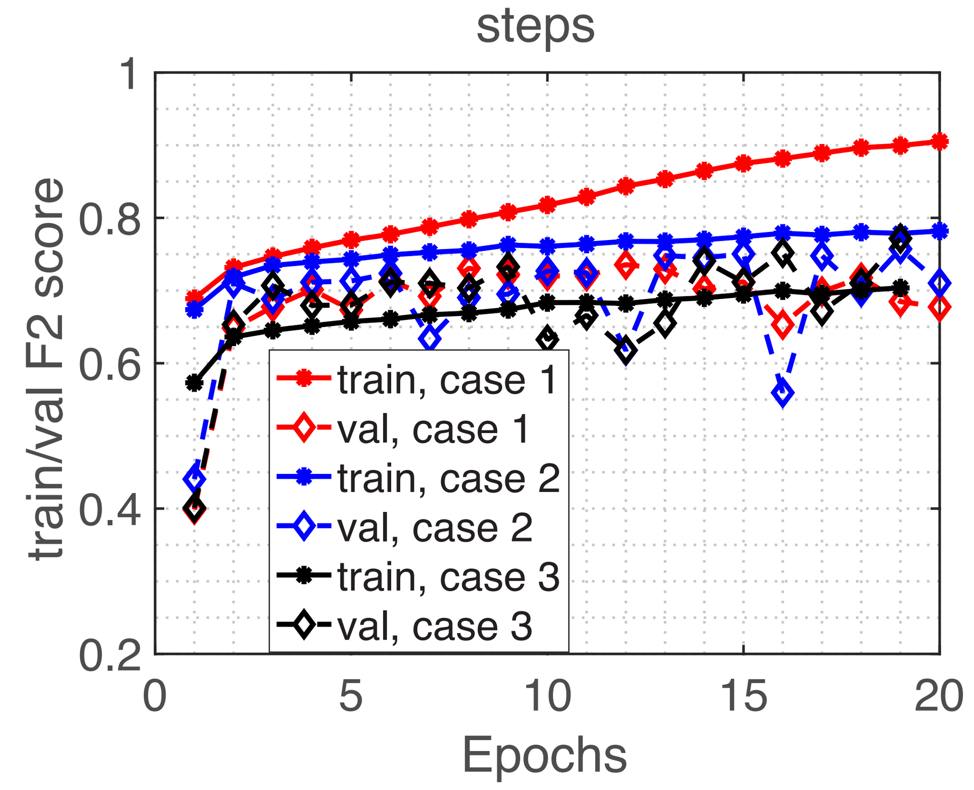
$$F_\beta = 1 + (1+\beta^2)\frac{pr}{\beta^2 + r} \quad \text{where } p = \frac{tp}{tp+fp}, r = \frac{tp}{tp+fn}, \beta = 2$$

Training Model

We compare the results of three models trained on a subset (5000 images) of large dataset.



Case 1:
skew, no augmentation.
Case 2:
skew, augmentation.
Case 3:
balanced, augmentation.



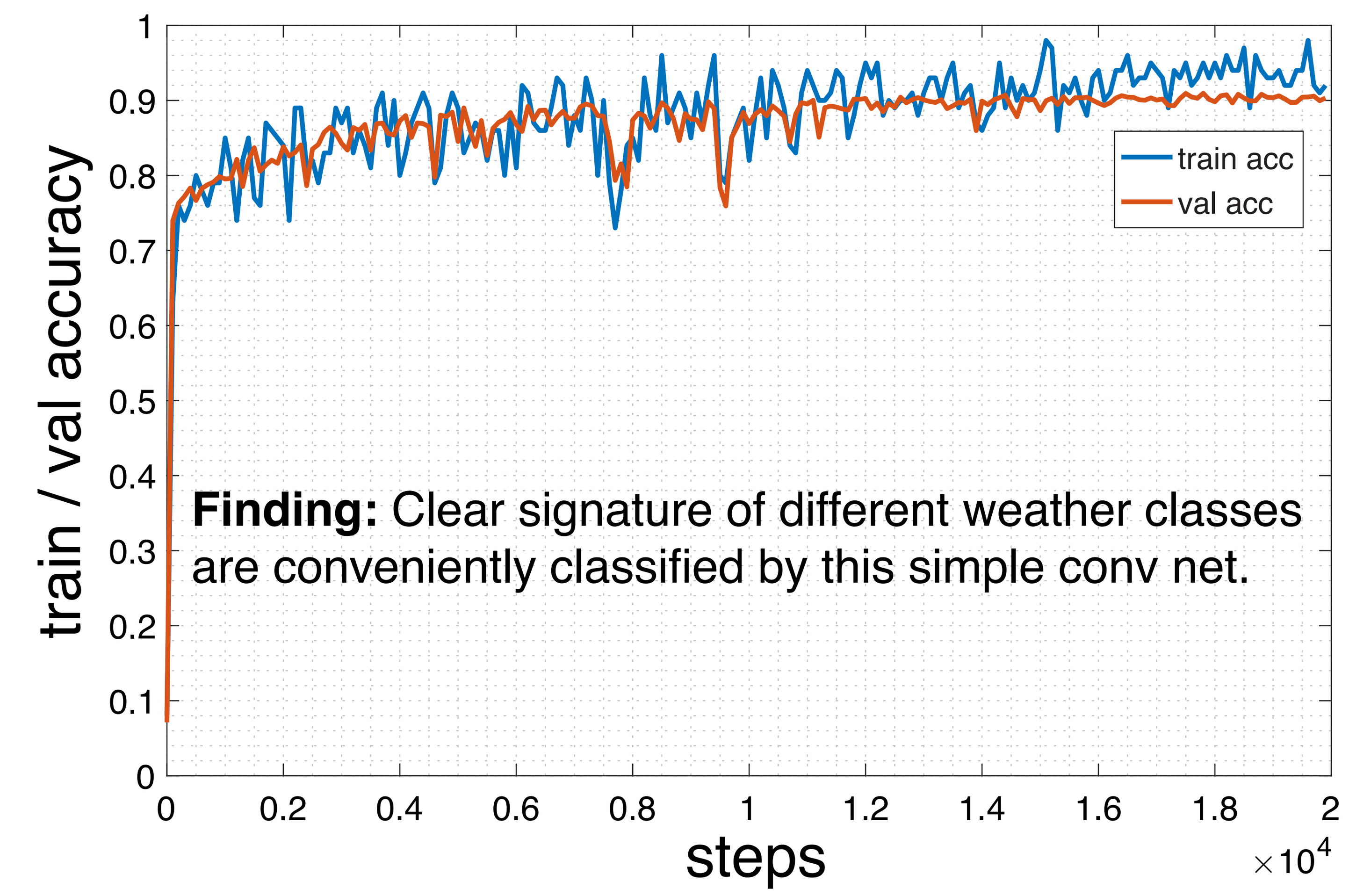
Findings:

1. Data augmentation helps preventing overfitting.

2. More challenging to train on a balanced dataset. (need more data, training more epochs)

Training weather classes

Since the 4 weather classes ('clear','haze','partially cloudy','cloudy') are mutually exclusive, we designed a small CNN network to classify them separately from the network that focuses on classify the landforms. This rather simple net acchieves 91% test accuracy.



Discussion and conclusion

- Direct training on dataset with highly skew class distribution can bias the model to predict the majority class.
- Data augmentation is helpful in improving learning and preventing overfitting.
- Data balancing is helpful in preventing the model fitting to the majority class but also more difficult to learn well.
- Clear signature of different weather classes can be classified separately by simpler net, which reduce the "burden" of the other net by letting it focused on classifying different landforms.

Reference

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