**Motivation**

Deforestation contributes to reduced biodiversity, habitat loss, climate change, and other devastating effects.

Understanding the location of deforestation and human activity on forests can help governments and local authorities to respond quickly and effectively.

**Data and Labels**

The data-set consists of 40,479 training images with labels (both in TIFF and JPEG format).

The training images and labels were divided into 90% train, 5% development, and 5% test sets and used for the project.

**Results**

The synthesis of some of the experiments can be seen in the table below. It is important to note that L2 regularization and the change in loss significantly improved the test results, therefore, only results with regularization are included.

<table>
<thead>
<tr>
<th>Experiment</th>
<th>recall</th>
<th>accuracy</th>
<th>precision</th>
<th>loss</th>
<th>F2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Preprocess</td>
<td>0.805</td>
<td>0.952</td>
<td>0.898</td>
<td>0.123</td>
<td>0.822</td>
</tr>
<tr>
<td>2 Loss weight1,5</td>
<td>0.759</td>
<td>0.935</td>
<td>0.841</td>
<td>0.659</td>
<td>0.773</td>
</tr>
<tr>
<td>3 Loss weight4</td>
<td>0.888</td>
<td>0.935</td>
<td>0.766</td>
<td>0.721</td>
<td>0.860</td>
</tr>
<tr>
<td>4 Loss weight16</td>
<td>0.961</td>
<td>0.896</td>
<td>0.624</td>
<td>0.897</td>
<td>0.867</td>
</tr>
<tr>
<td>5 Loss weight1</td>
<td>0.967</td>
<td>0.813</td>
<td>0.473</td>
<td>1.370</td>
<td>0.800</td>
</tr>
<tr>
<td>6 Resnet34</td>
<td>0.882</td>
<td>0.902</td>
<td>0.656</td>
<td>0.977</td>
<td>0.825</td>
</tr>
<tr>
<td>7 Resnet50</td>
<td>0.888</td>
<td>0.862</td>
<td>0.556</td>
<td>1.161</td>
<td>0.793</td>
</tr>
<tr>
<td>8 Resnet101</td>
<td>0.869</td>
<td>0.900</td>
<td>0.653</td>
<td>1.103</td>
<td>0.815</td>
</tr>
<tr>
<td>9 Resnet152</td>
<td>0.955</td>
<td>0.864</td>
<td>0.557</td>
<td>1.002</td>
<td>0.836</td>
</tr>
</tbody>
</table>

**Discussion**

When fine tuning a CNN it is important to remember what is the metric that we are trying to optimize. In our specific case, changing the loss function significantly improved the results.

Additionally, simpler models might sometimes outperform more complex model. Our best model consisted of the following steps:

1. Re-size the images from 256x256 to 64x64 for ease of learning.
2. Add data augmentation.
3. Build the CNN with several blocks. For each block, the architecture was the following, 3x3 conv -> batch norm -> relu -> 2x2 maxpool.
4. Add two fully connected layers at the end.
5. Calculate the loss with sigmoid cross entropy for the 17 classes.

**References**

[1] Jeff Pyke. Understanding the Amazon from Space with Convolutional Networks.

**Acknowledgements & Future Work**

The author wish to sincerely thank the CS230 course staff for for all the support during all the stages of the project. A special thank to Lacio Dery for all the guidance and support.

Future work for this project includes trying and fine-tuning different CNN architectures such as DenseNets. DenseNets might be tried before the final submission of the project.

**Source Code**

The source code and intermediate results of the project are available at:

https://github.com/bernardocasares/CS230_Final_Project