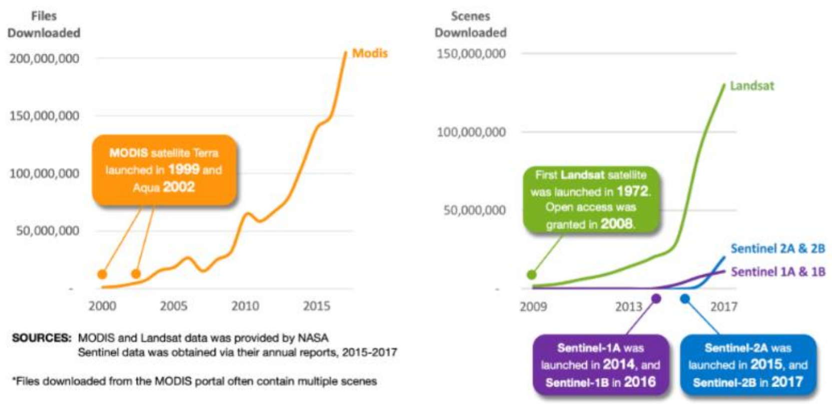
Satellite Imagery Feature Detection

Daniel Smoot 11/7/2020

Overview

The earth observation market has an emerging need for fast, accurate, machine-led image analysis. As the chart below demonstrates, access to satellite imagery is increasing exponentially. A number of other advancements are increasing the importance of machine learning analysis of satellite images. Cloud storage and compute solutions provide wider access to imagery and are improving the capabilities of machine learning [1]. This is occurring alongside increased production of images with the proliferation of smallsat launches from companies like Planet [2]. Meaningful analysis of imagery data demands an algorithmic approach that can match the pace of this substantial increase in volume and access. This is acknowledged by commercial leaders in the space industry who seek to capitalize on the market opportunity by adding analytical services to traditional earth observation imagery production and delivery. Maxar, for example, projects that "with the advancement of AI solutions to power EO data analysis...there is potential for the VAS portion of the EO market to grow to $12.1 billion by 2026. It is increasingly likely that value in the EO market will be driven by AI-enabled data analytics" [3].



Courtesy of the Radiant Earth Foundation

Image source: Azavea blog

This project will deliver a model that addresses that need for satellite image analysis. The project will take on the completed "Dstl Satellite Imagery Feature Detection" competition hosted on Kaggle. The goal of the competition is to label features within the provided satellite images. Labelling is a regular task for imagery analysis and DSTL's specific goal is to "alleviate the burden on their image analysts."

However, this labelling model can be adapted and applied to many different problems in the future. At its core, satellite image analysis provides information about the observed region, and that information can be useful to a variety of industries. In the future, this workflow could address issues such as crop analysis, mapping areas impacted by natural disaster, tracking for logistics, and others.

Datasets and Inputs

All data will be obtained from the original competition page on Kaggle. There are 25 1km x 1km images provided in the train set, and 32 images in the test set. These images include both 3-band and 16-band formats. There are 10 object classes labeled in the dataset:

1. Buildings - large building, residential, non-residential, fuel storage facility, fortified building
2. Misc. Manmade structures
3. Road
4. Track - poor/dirt/cart track, footpath/trail
5. Trees - woodland, hedgerows, groups of trees, standalone trees
6. Crops - contour ploughing/cropland, grain (wheat) crops, row (potatoes, turnips) crops
7. Waterway
8. Standing water
9. Vehicle Large - large vehicle (e.g. lorry, truck,bus), logistics vehicle
10. Vehicle Small - small vehicle (car, van), motorbike

The images were sourced from DigitalGlobe's Worldview 3 satellite, which has the sensor properties listed below. The impact sensors have on analysis are beyond the scope of this project proposal, but more information can be found on National Resource Canada's website.

Wavebands

- Panchromatic: 450-800 nm
- 8 Multispectral: (red, red edge, coastal, blue, green, yellow, near-IR1 and near-IR2) 400 nm - 1040 nm
- 8 SWIR: 1195 nm - 2365 nm

Sensor Resolution (GSD) at Nadir

- Panchromatic: 0.31m
- Multispectral: 1.24 m
- SWIR: Delivered at 7.5m

Dynamic Range

- Panchromatic and multispectral : 11-bits per pixel
- SWIR : 14-bits per pixel

Solution Statement

The goal of the project is to build a model that accurately predicts the competition's object classes within the satellite image. This is an image segmentation problem. A convolutional neural network will be constructed to label the features. The output will be a submission file in the submission format required by the competition.

Benchmark

Kaggle's public leaderboard will be used to benchmark the success of this model. A score of **0.39720** or better is required to get into the top 100 on the public leaderboard and this project will use that as the model's performance target.

Evaluation Metrics

The evaluation metric defined by the competition is the Jaccard Index:

"The Jaccard Index for two regions A and B, also known as the "intersection over union", is defined as:

$$Jaccard = \frac{TP}{TP + FP + FN} = \frac{|A \cap B|}{|A \cup B|} = \frac{|A \cap B|}{|A| + |B| - |A \cap B|}$$

where TP is the true positives area, FP is the false positives area, and FN is the false negatives area.

For each object class, of each image, we calculate the TP, FP, and FN areas. We then sum the total TP, total FP, and total FN across all the images, then the Jaccard is calculated for that class using total TP, total FP, and total FN. Then, we average all the Jaccard Indexes for all the 10 classes."

Project Design

1. Understand and interpret the data
   a. Images need to be loaded.
   b. The class features must be investigated via visual inspection, class histograms, and any other process that will provide information about the data.
2. Preprocess the data
   a. The images will be normalized.
   b. Define specific defining features that will separate nuanced classes - for example, waterways and standing water will likely return the same reflectance, so additional features will need to be created to better inform the model.
3. Train and test model(s)
   a. This project will use Keras build the CNN. It is possible that multiple models will be trained for the different classes.
   b. Given the size of the image data and computational demand of the model training, this model will be trained using Amazon SageMaker.
4. Postprocess the data
   a. The output should be an array with a mask identifying the rasters that match the predicted class.
   b. Process any additional changes required to distinguish the classes.
5. Evaluate model performance
   a. The model will be evaluated against the benchmark.
   c. Make any necessary model improvements and return to step 3.
6. Create submission
   a. Create submission file in the format required by the competition.
7. Analyze project and consider future applications and improvements. Potential further applications could include:
   a. A web application that receives an image and returns predicted classes.
   b. Expansion of classes to predict.
   c. Choose a specific industrial application to focus on, such as crop analysis.
   d. Add in a temporal factors for change detection.
   d. Expand the type of imagery that the application can analyze, for example drone and UAV imagery with lower quality sensors.

Sources:
(1): Radiant Earth foundation: https://medium.com/radiant-earth-insights/observing-the-earth-fueling-global-development-solutions-1c69fd5632bc
(2): Radiant Earth foundation: https://medium.com/radiant-earth-insights/how-earth-observations-cloud-computing-and-machine-learning-enables-global-development-solutions-9ad1c2e60762
(3): Maxar Technologies 2019 10-k: https://www.sec.gov/Archives/edgar/data/1121142/000155837020001895/0001558370-20-001895-index.htm