

Formulating Machine Learning Problems for Satellite Imagery (and solving them)

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- Discussion on different ML formulations of satellite imagery problems
- Overview of popular computer vision tasks and how they have been addressed with the recent deep learning advances
 - demystify some jargon
 - provide references to Python implementations
- Go through a couple of example notebooks
- Steps for building our own training datasets

Supervised Learning

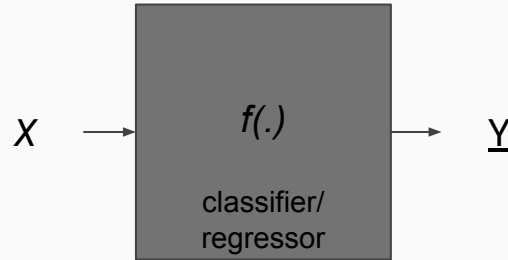
Labeled observations:

X_1, Y_1

X_2, Y_2

...

X_n, Y_n



Find f to minimize the expected $loss(f(X), Y)$.

Diagram illustrating the Iris dataset structure. The table shows samples (instances, observations) with features (attributes, measurements, dimensions) and class labels (targets). The features are Sepal length, Sepal width, Petal length, and Petal width. The class labels are Setosa, Versicolor, and Virginica. The diagram also shows a visual representation of the Iris flower with arrows indicating measurements for Sepal, Petal, and Class labels.

	Sepal length	Sepal width	Petal length	Petal width	Class label
1	5.1	3.5	1.4	0.2	Setosa
2	4.9	3.0	1.4	0.2	Setosa
...
50	6.4	3.5	4.5	1.2	Versicolor
...
150	5.9	3.0	5.0	1.8	Virginica

Source:

<https://setscholarsanalytics.podia.com/applied-machine-learning-using-python-classification-with-iris-dataset>

Supervised Learning for Satellite Imagery

What are X and Y?

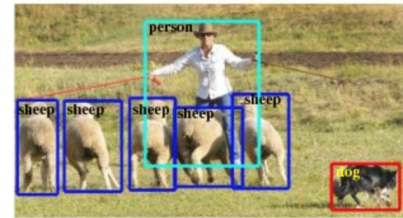
- **Images:** Collection of images with corresponding labels
 - categories: rural/urban, cloud/no cloud, snow/cloud, etc.
 - Image pairs: other modalities, other sensors, other time stamps, other resolutions
- **Pixels:** One (or more) image with each pixel labeled to be a certain class (land cover segmentation)
- **Regions:** represented by bounding boxes, polygons, or masks
 - Labels for each pixel
 - Labels only for objects of interest

Supervised Learning for Satellite Imagery

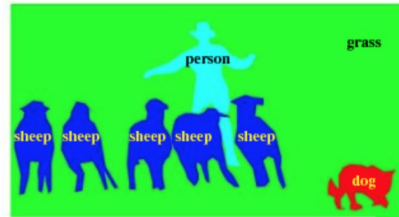
Popular Computer Vision Tasks



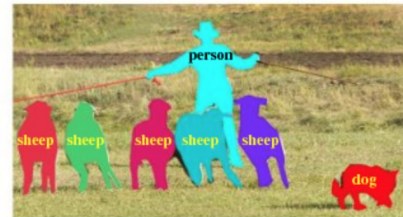
(a) Object Classification



(b) Generic Object Detection
(Bounding Box)



(c) Semantic Segmentation



(d) Object Instance Segmentation

Fig. 3 Recognition problems related to generic object detection. (a) Image level object classification, (b) bounding box level generic object detection, (c) pixel-wise semantic segmentation, (d) instance level semantic segmentation.

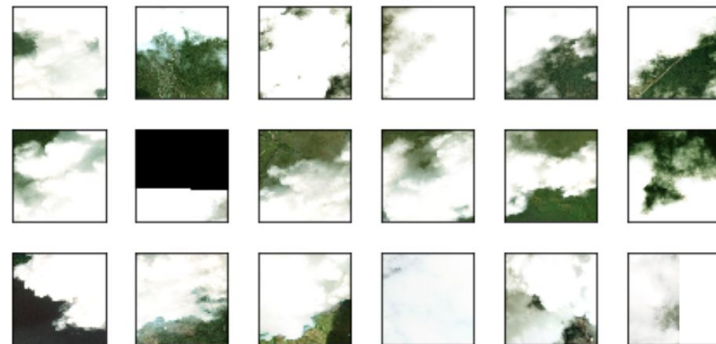
Image Classification

Approach 1:

- Extract features & apply scikit-learn classifiers

Approach 2:

- Use Convolutional Neural Networks on the full images
 - There exist pretrained models which can be used as a starting point
 - [VGG](#), [ResNet](#), [MobileNet](#)
 - Easy implementation in Keras
 - Image augmentation
 - Rotation
 - Translation
 - Affine transformation (nadir)
 - Resolution/blur
 - Light, color
 - Cloud occlusion



Evaluation:

- Standard classification metrics apply:
 - Accuracy, precision, recall, F1 score

Object Detection

How can we identify more than one object in an image?

Approach 1:

Split into small windows and classify each window

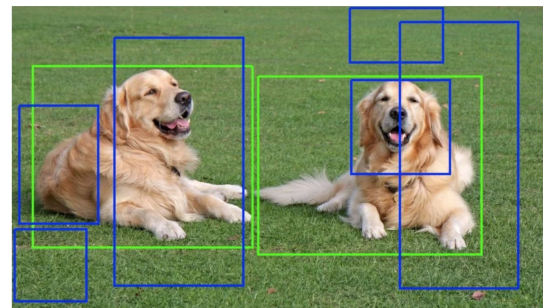
- hopefully only one object falls into the small window
- too expensive to apply classification to each small window

Approach 2:

- 1) propose regions (using a small network)
 - 2) classify only those regions, combine bounding boxes
- Faster RCNN (Region Conv. Neural Networks)
 - YOLOv3 (You Only Look Once)
 - SSD (Single Shot Detector)

https://github.com/tensorflow/models/tree/master/research/object_detection
<https://github.com/qgwweee/keras-yolo3>

Evaluation: [mean Average Precision \(mAP\)](#)



Blue Boxes: False Positives; Green Boxes: True Positives

Semantic Segmentation

X_i - image, Y_i - mask

Approach 1:

- Pixel by pixel classification (assume independence)

Approach 2:

- Fully convolutional neural networks (keep pixels together)
- U-net (developed for biomedical imaging, works with little training data)
- Easy Implementation in keras

Evaluation:

- Evaluation based on standard metrics (like pixel accuracy, F1 scores): no geometric information
- Intersection/total area, boundary F1 scores

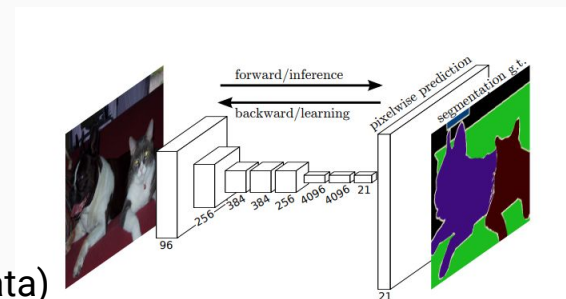
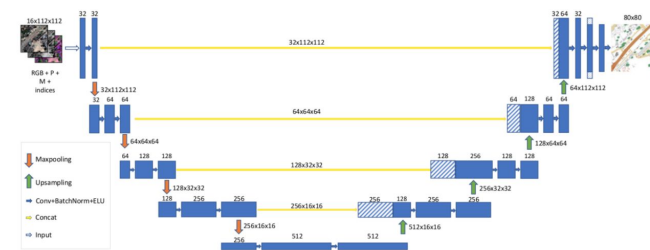


Figure 1. Fully convolutional networks can efficiently learn to make dense predictions for per-pixel tasks like semantic segmentation.

Source: [Fully Convolutional Networks for Semantic Segmentation, Long et. al.](#)



Source: [U-net architecture](#)

Mask RCNN

X_i - image, Y_i - mask

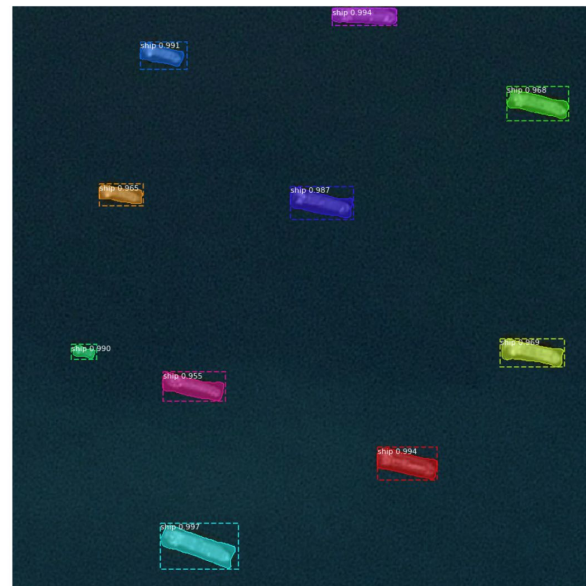
Approach 1:

- Segment directly

Approach 2:

- Detect bounding box
- Segment within bounding box

https://github.com/matterport/Mask_RCNN



Model predicting mask segmentations and bounding boxes for ships in a satellite image

Source: <https://towardsdatascience.com/mask-r-cnn-for-ship-detection-segmentation-a1108b5a083>

Example Notebooks

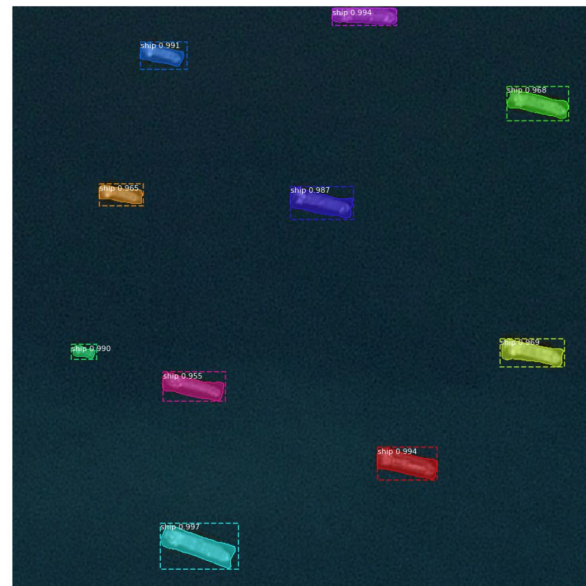
[Kaggle Airbus Ship Detection Challenge](#)

- Segmentation with U-net

<https://www.kaggle.com/valcoder/ship-detection-using-keras-u-net>

- Segmentation with Mask RCNN

<https://www.kaggle.com/valcoder/mask-r-cnn-ship-detection-minimum-viable-model-1>



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Data Preparation

Getting data into the right format for Machine Learning:

- Chipping images and preserving labels
- Geospatial coordinates \Leftrightarrow pixel coordinates
- Mask \Leftrightarrow boundary coordinates \Leftrightarrow geospatial coordinates
- Overlapping geospatial regions on geotiff images
- Merging chips for mapping

Tools:

- [rasterio](#), [geopandas](#), [shapely](#)
- [robosat](#)

Special Formats:

- [COCO \(Common Objects in Context\) format](#)
- [Slippy Map Format \(from OSM\)](#)
- [Run Length Encoding](#) for storing masks