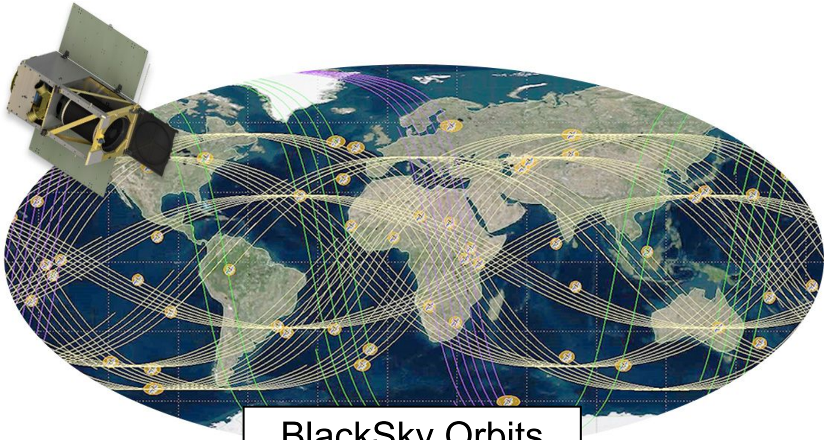
# Deep Learning with Satellite Imagery

Seminar Introduction

# BlackSky Introduction

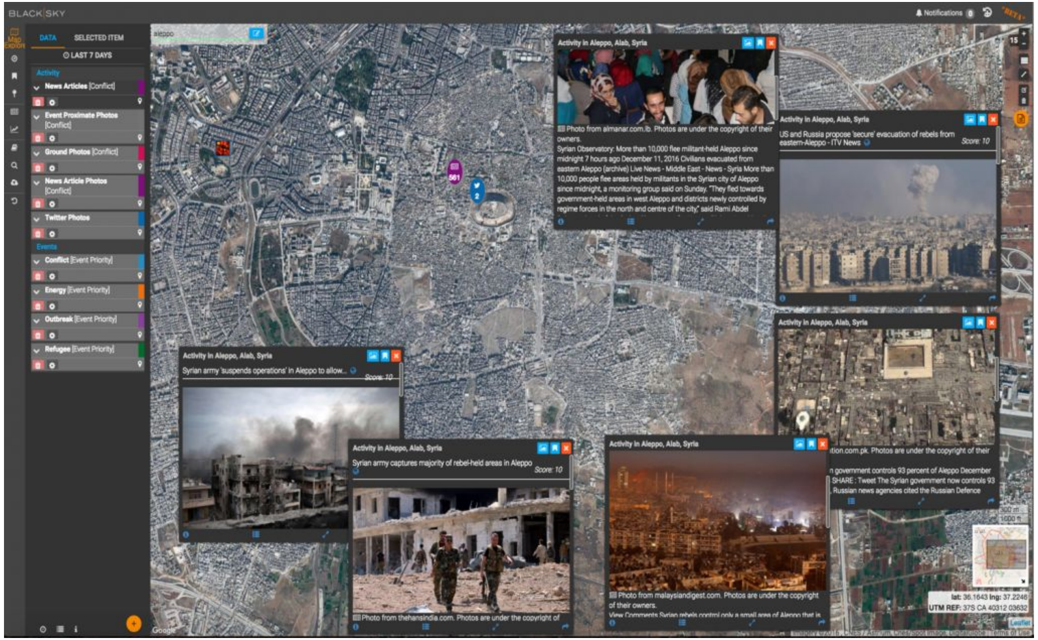
- Geospatial intelligence company with offices in Herndon, VA and Seattle, WA.
- Building constellation of **small sats** with plans of orbiting over 20 satellites.
- **Mid-inclination orbits** yield exceptionally high revisit rates over targets.
- Imagery derived analytics are core part of our mission.
- Growing data science team with heavy specialization in **machine learning**.

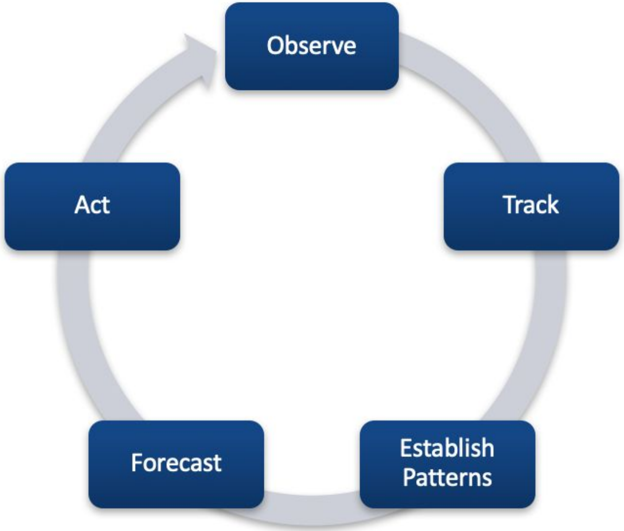


BlackSky Orbits

# BlackSky Introduction

With machine learning, predictive algorithms, and natural language processing, BlackSky delivers critical geospatial insights about an area or topic of interest. We synthesize data from a wide array of sources including social media, news outlets and even earthquake sensors.



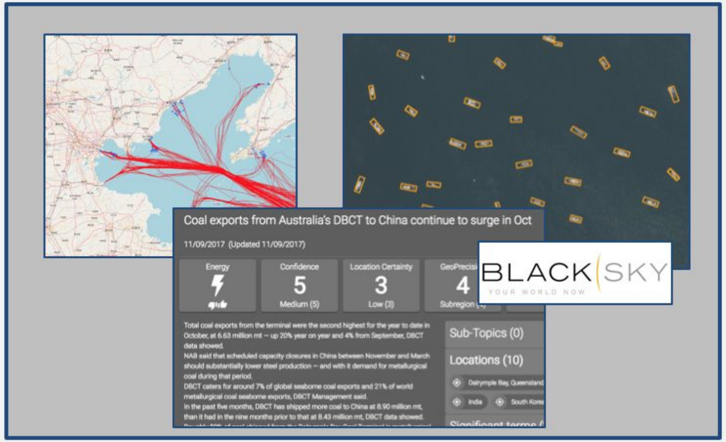



## Our Approach

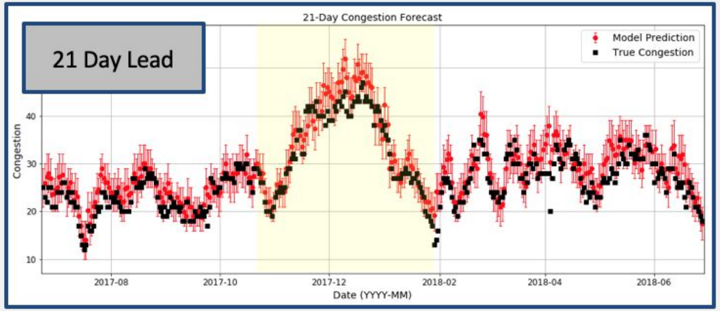
| | |
|---|---|
| **Collection** | Rapid revisit imagery collection capture patterns |
| **Multi-INT** | Fusion of imagery and emerging sensors |
| **Computer Vision** | Scalable analytics deriving insights from raw data |
| **Artificial Intelligence** | Inferring purpose from collections of objects |
| **Pattern of Life** | Identify trends, anomalies, and patterns at facilities |
| **Predictive Analytics** | Predict behavior and performance based on PoL |
| **Course-of-Action** | Automatic generation of action plans |
| **Communication** | Provide intelligence and SA to customers |

## Left of Boom

Predicting Port Congestion 21 Days Prior to Build Up







# BlackSky Introduction

## Patrick O’Neil

- Director of Machine Learning and Artificial Intelligence at BlackSky.
- Working at BlackSky for four years.
- PhD in mathematics from GMU.
- Worked at GeoEye prior to BlackSky.
- Background in topological data analysis and probabilistic modeling.

## Diego Torrejon

- Data Scientist at BlackSky.
- Working at BlackSky for three years.
- PhD in mathematics from GMU.
- Former researcher at NIST.
- Recipient of the NSF Graduate Research Fellowship.

# Seminar Overview

1. Seminar Overview
2. Satellite Imagery (Orbits, Bands, Collection, Resolution, etc)
3. Satellite Image Processing (Orthorectification, Color Correction, Dynamic Range Adjustment, Co-registration, etc.)
4. Classical Computer Vision (Convolutions, Sobel Filters, Watershed and Segmentation)
5. Deep Learning Overview (Deep Neural Networks, CNNs, RNNs, etc)
6. Deep Learning Ingredients (Dropout, Batch Normalization, Vanishing Gradient, etc.)
7. Convolutional Neural Networks
8. U-Net and W-Net
9. ResNet and ODEs
10. Generative Adversarial Neural Networks.

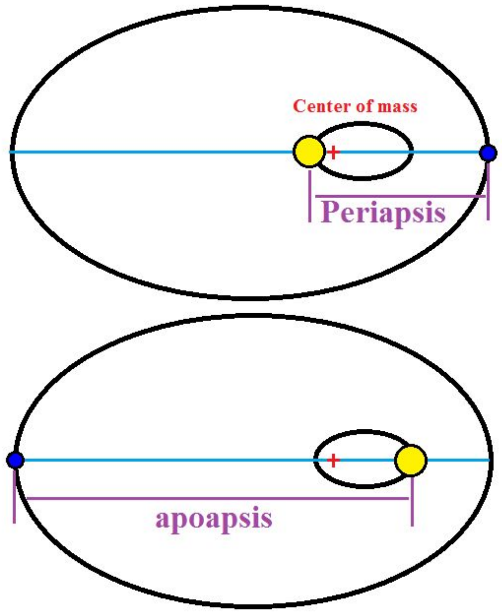
Satellite Imagery

# Getting to Orbit

- Rocket Labs Electron
  - 150–225 kg to 550 SSO
  - $6M per launch
- ISRO PSLV
  - 1,750 kg to SSO
  - $21M-31M per launch
- SpaceX Falcon 9
  - 22,800 kg to LEO
  - $50M per launch
- ULA Atlas V
  - 20,520 kg to LEO
  - $109M per launch
- CNES Ariane 5
  - Over 20,000 kg to LEO
  - $165M-220M per launch

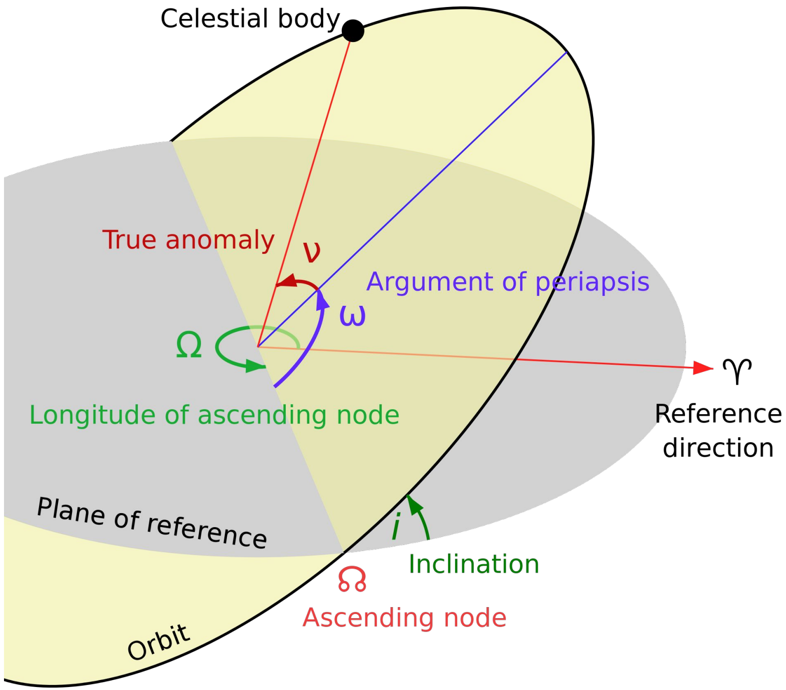

# Orbital Terminology

- Remote sensing requires an understanding of where a satellite is in its orbit.
- **Apoapsis** and **Periapsis**: The furthest and closest points respectively, of an orbit with respect to its host.
- Apogee and Perigee: Same as above with the host being Earth.



# Orbital Mechanics Terminology

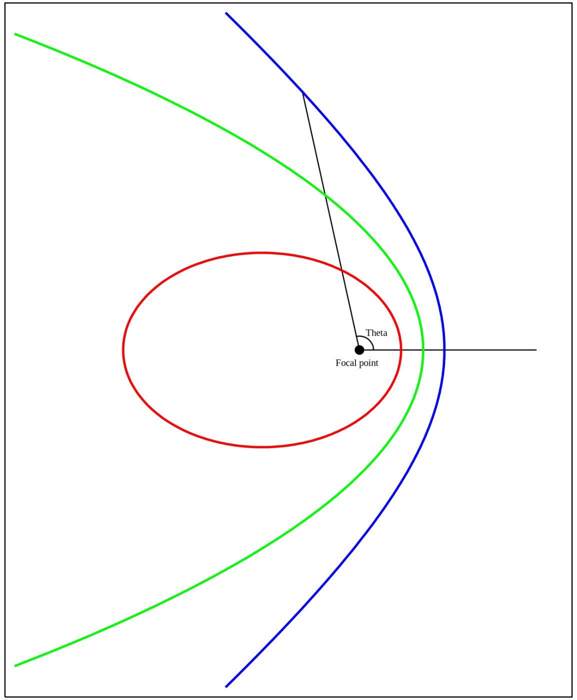
- **Inclination** describes the angle of an orbital plane with respect to a reference plane.
- For Earth the reference plane is taken to be the equatorial plane.



# Orbital Mechanics Terminology

- Orbital **eccentricity** describes the amount by which an orbit deviates from a perfect circle.
- All satellites we will be discussing have an eccentricity below one and usually pretty close to zero.

| | |
|---|---|
| Earth | 0.0167 |
| Mars | 0.0934 |
| Jupiter | 0.0484 |
| Halley's Comet | 0.9671 |
| ‘Oumuamua | 1.20 |



# Orbital Terminology

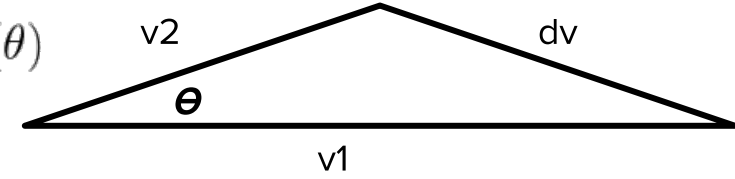
Semi-major Axis: $a = \frac{r_a + r_p}{2}$ where $r_a$ is the apoapsis and $r_p$ is the periapsis

Orbital Velocity: $v^2 = GM\left(\frac{2}{r} - \frac{1}{a}\right)$

$$G = 6.67 \times 10^{-11} m^3 kg^{-1} s^{-2}$$
$$M = 5.97 \times 10^{24} \text{ kg}$$
$$\mu = GM = 4 \times 10^{14}$$

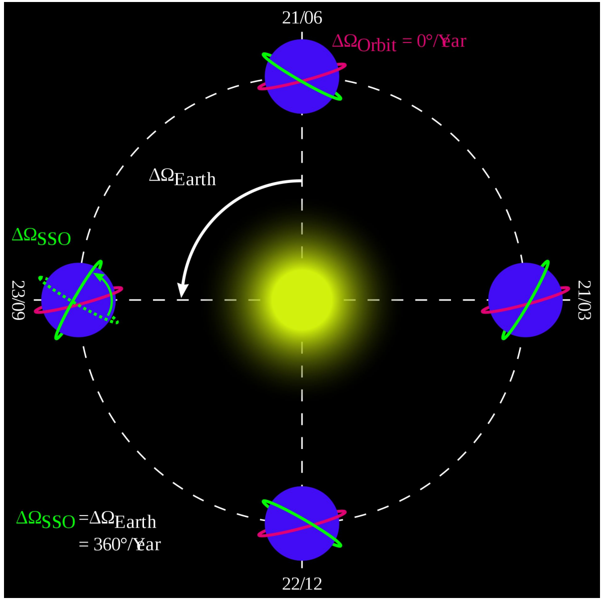
Eccentricity: $$e = \frac{r_\text{a} - r_\text{p}}{r_\text{a} + r_\text{p}} = 1 - \frac{2}{\frac{r_\text{a}}{r_\text{p}} + 1}$$

Delta-V for Inclined Orbit: $\Delta v_2^2 = v_1^2 + v_2^2 - 2v_1v_2\cos(\theta)$



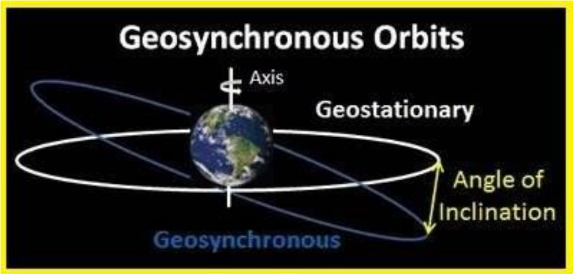
# Important Types of Orbits

- Low-Earth Orbit (LEO): Lower than 2000 Kilometers
    - Optimal for remote sensing due to proximity to Earth
    - Small field of view
    - **Sun-Synchronous Orbit**
- Geosynchronous Earth Orbit (GEO)
    - Orbital period matches Earth's rotation on its axis
    - GEO is at a 35,786 km altitude above the Earth
    - Useful for communications satellites
- Orbits around Earth are often described by their Two-Line Element Set (TLE).



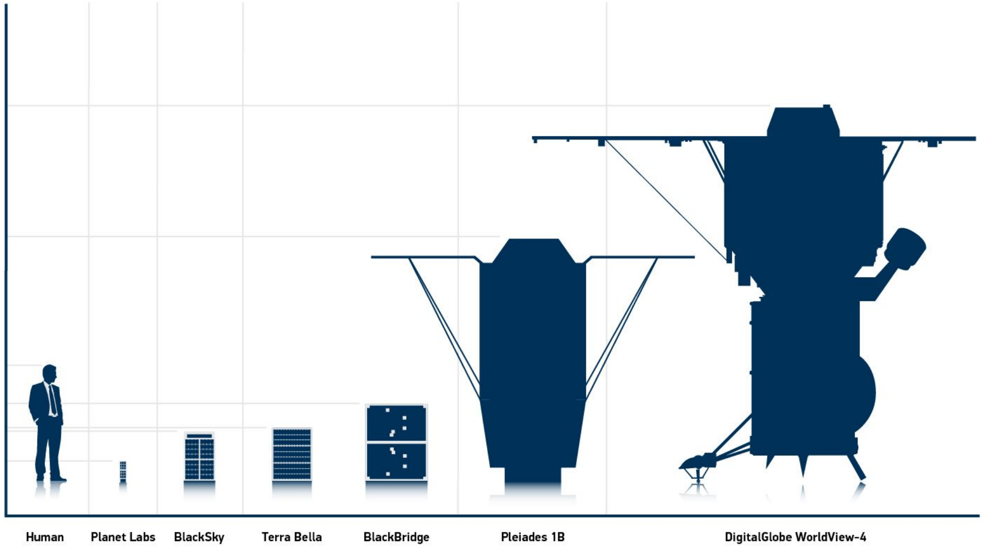

BLACKSKY GLOBAL 2
1 43812U 18099BG  19040.20317408  .00000356  00000-0  37510-4 0  9998
2 43812  97.7571 113.6950 0014563  47.2297 313.0146 14.95340708  9661

BlackSky TLE



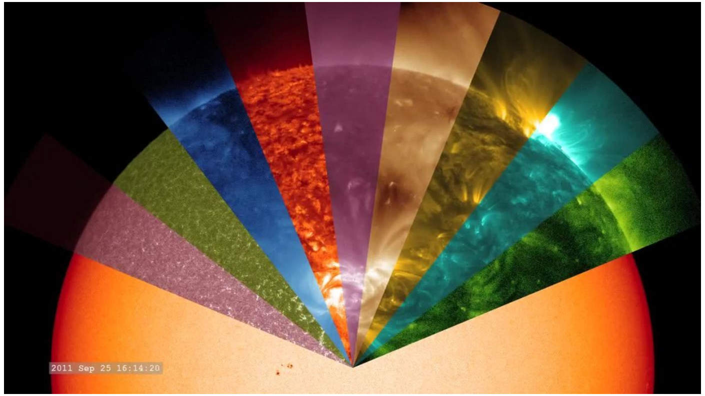
# Satellite Imagery: Major Players

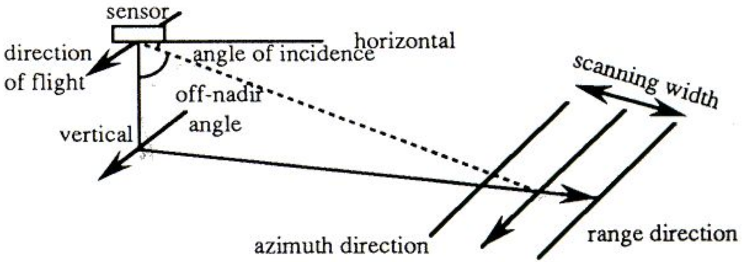
- Globals (BlackSky)
- Worldview Constellation (DigitalGlobe)
- Sentinel (ESA)
- LandSat (NASA & USGS)
- Pleiades (Airbus)
- Kompsat (SIIS)
- Dove & SkySat (Planet)



# Characteristics of Satellite Imagery

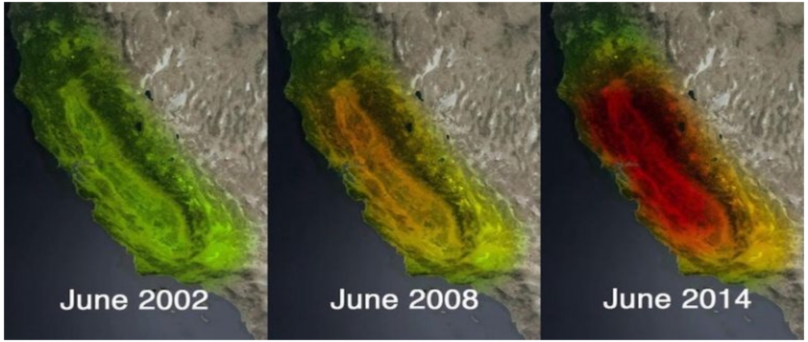
- Spectral Bands: Satellite imagery may contain additional bands beyond the visible spectrum (e.g. SWIR, NIR, Thermal IR, etc).
  - In a tensor framework, multiple band imagery is viewed as third order tensors.
- Ground Sample Distance: the distance between pixel centers* measured on the ground (related to resolution).
- Observation Angle. The angle at which the image was taken relative to the ground.

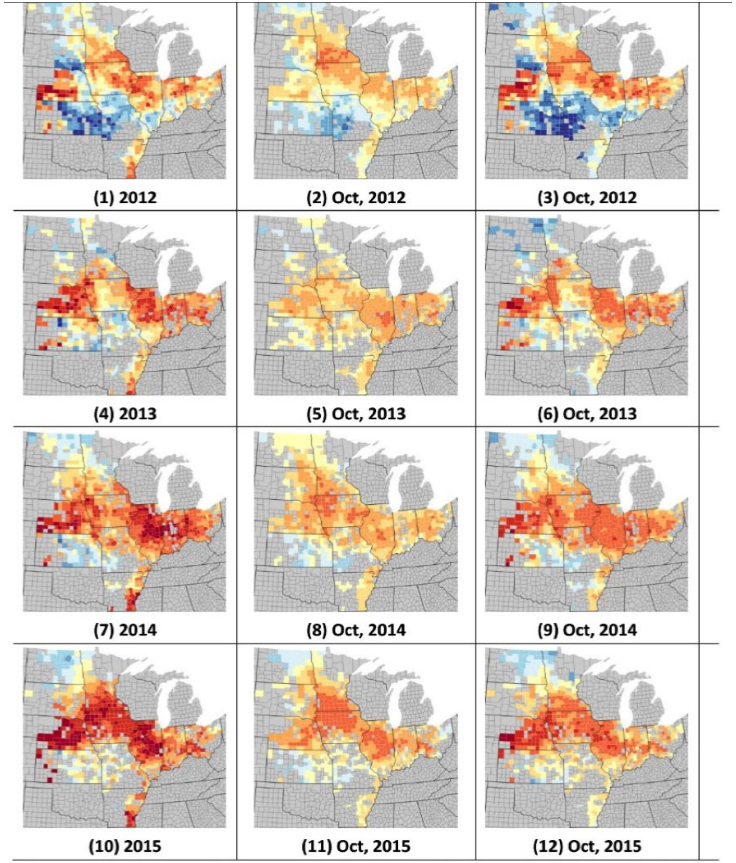


# Applications of Remote Sensing

- Mapping missions.
- Prediction of crop yield (right).
- Military surveillance.
- Rescue missions.
- Size estimation of oil spills.
- Monitoring ice caps.
- Natural disaster assessment.
- Fresh water estimation (bottom).

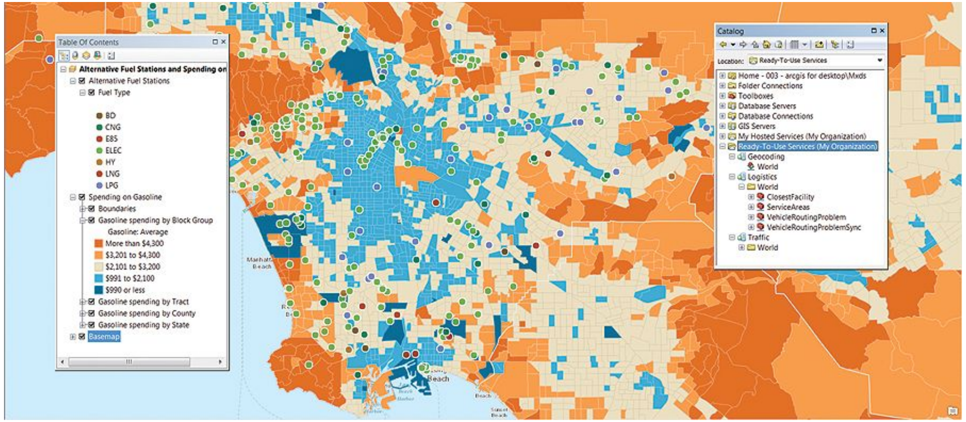


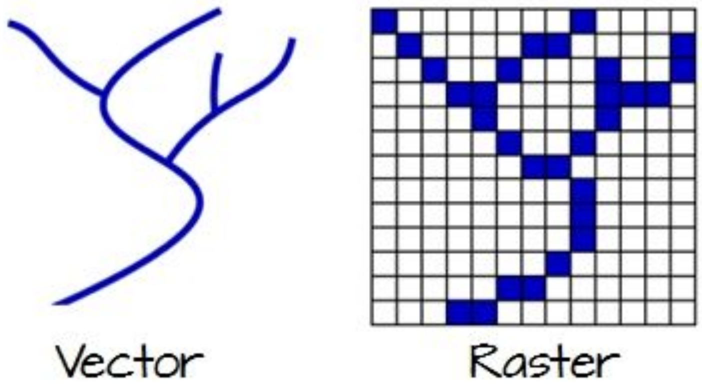




**Left**: True soybean yield. **Middle**: Previous Model. **Right**: Deep learning Model.

# Geospatial Data Tools

- Raster vs Vector
- QGIS and Esri ArcGIS
- GDAL
- Rasterio
- geopy

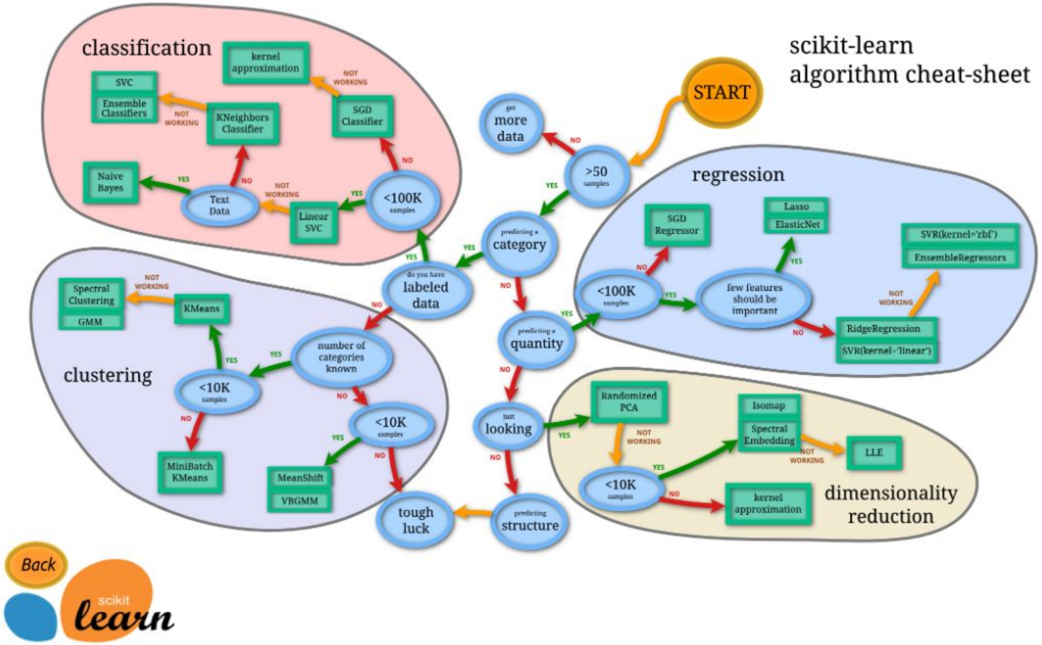


Machine Learning

# What is Machine Learning?

- The goal of machine learning is to teach a computer program to perform a task.
- **Classification**: To label an email as spam or not.
- **Regression**: To estimate US population in 2020.
- **Dimensionality Reduction**: To extract keywords of a news article.
- **Clustering**: To find cliques in Facebook.



# Types of Machine Learning

There are many types of machine learning, the following classification highlights the type of data utilized.

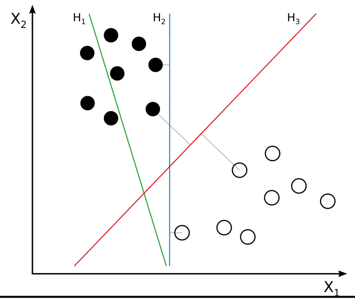
## Supervised

Training data has associated labels.

We want to learn the function

p(y | x) or p(x, y)

**Example**: Support vector machines (classification).



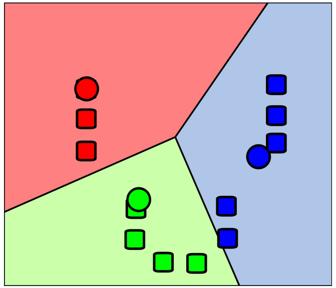

## Unsupervised

Training data doesn't have associated labels.

We may attempt to learn

p(x)

**Example**: K-nearest neighbors (clustering).



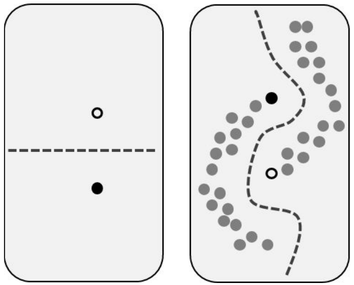
## Semi-supervised

Some training data has associated labels.

**Pro:** Faster training and simpler gathering of data.

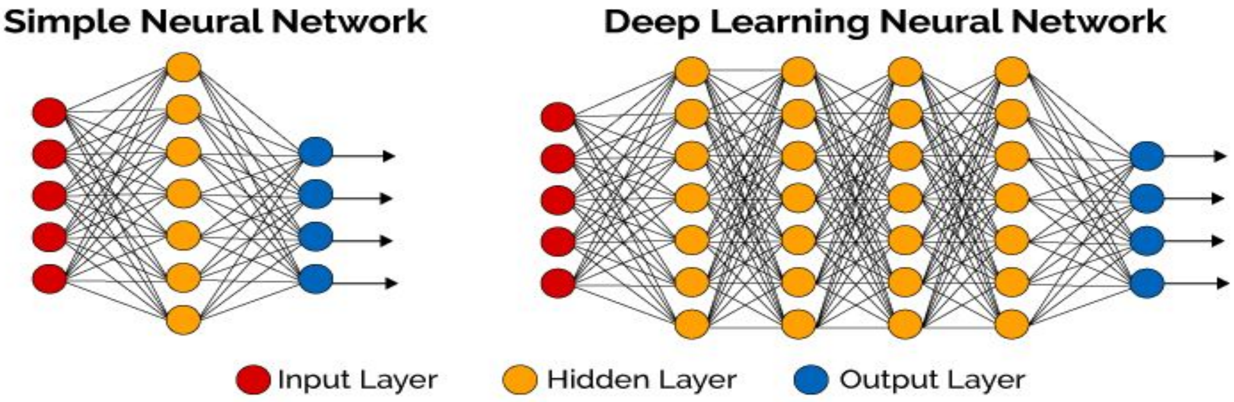
**Con**: Models tend to be more complex.

**Example**: GAN + Classifier

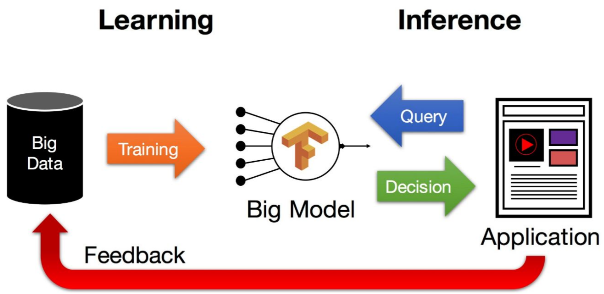


# What is Deep Learning?

- A **Neural Network** consist of multiple nodes which mimic the biological neurons of a human brain.
- **Deep learning** uses a hierarchy of these layers, which serve to extract more abstract representations/features from the data.



# Why Machine Learning?




- Machine learning can now automate many tasks that were thought to be only performed by humans (e.g. image recognition).
- Address the issue of needing a huge number of analysts to look at immense quantities of data.
- Models have been trained to beat humans in board games such as chess and go; and in live video games such as Dota 2 and Starcraft II.
- These accomplishments have shown that the AI models pick up on hidden patterns in the data, previously missed by humans.

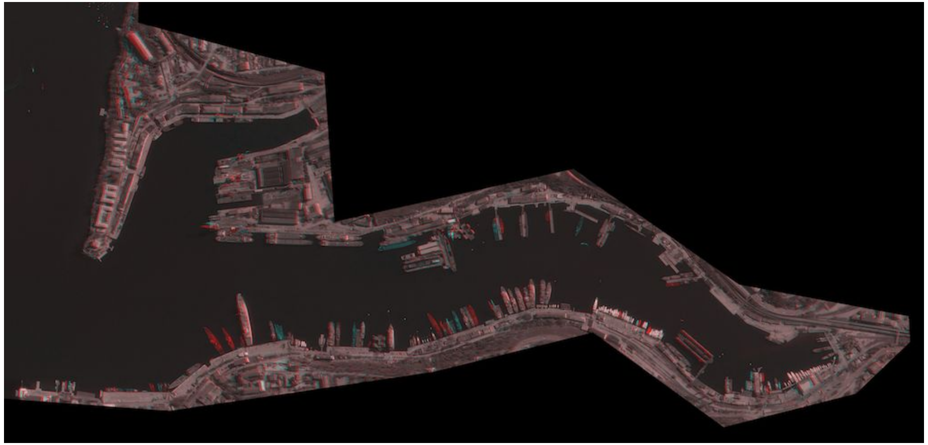
# Machine Learning and Satellite Imagery

Machine learning can be applied to satellite imagery in the following tasks:

- Change detection at a site of interest.
- Object detection (buildings, ships, planes, etc).
- Image segmentation (cities, roads, water, forest, etc).
- Resolution enhancement of imagery.

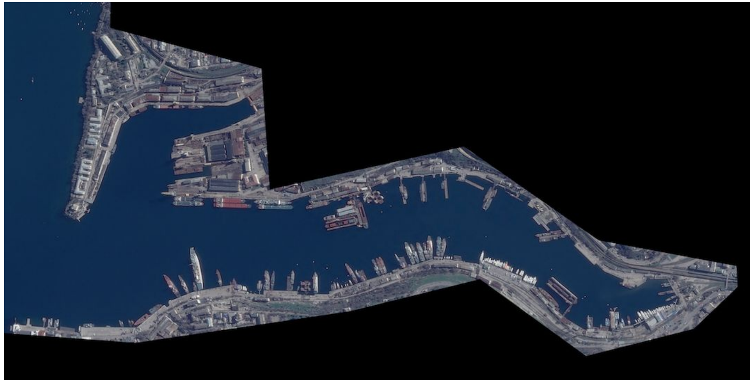
# Change Detection

Change Detection Image

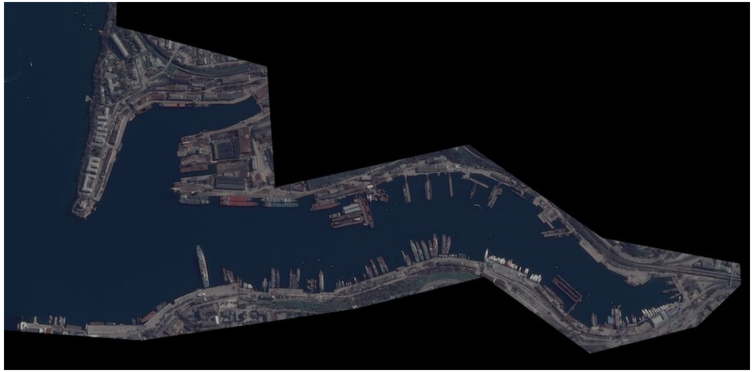


**Red**: Objects in the before image and not in the after image.
**Blue**: Objects in the after image and not in the before image.

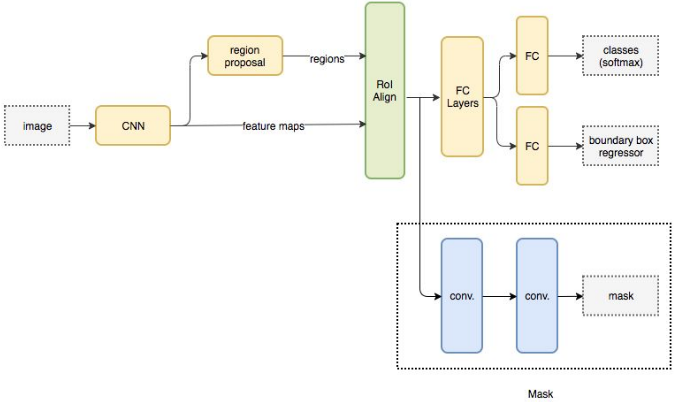
Before Image



After Image

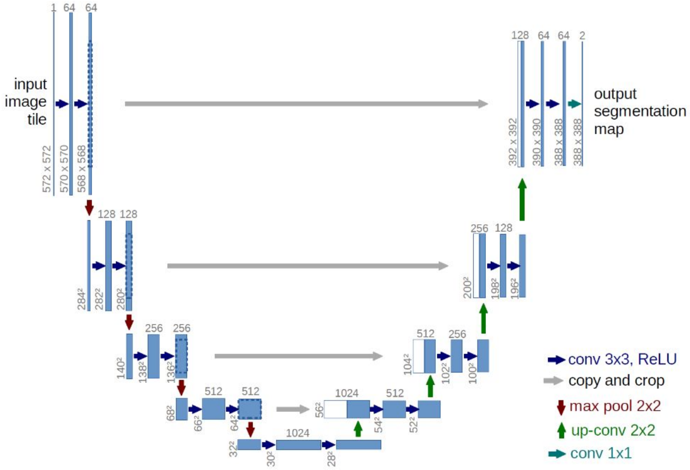


# Object Detection

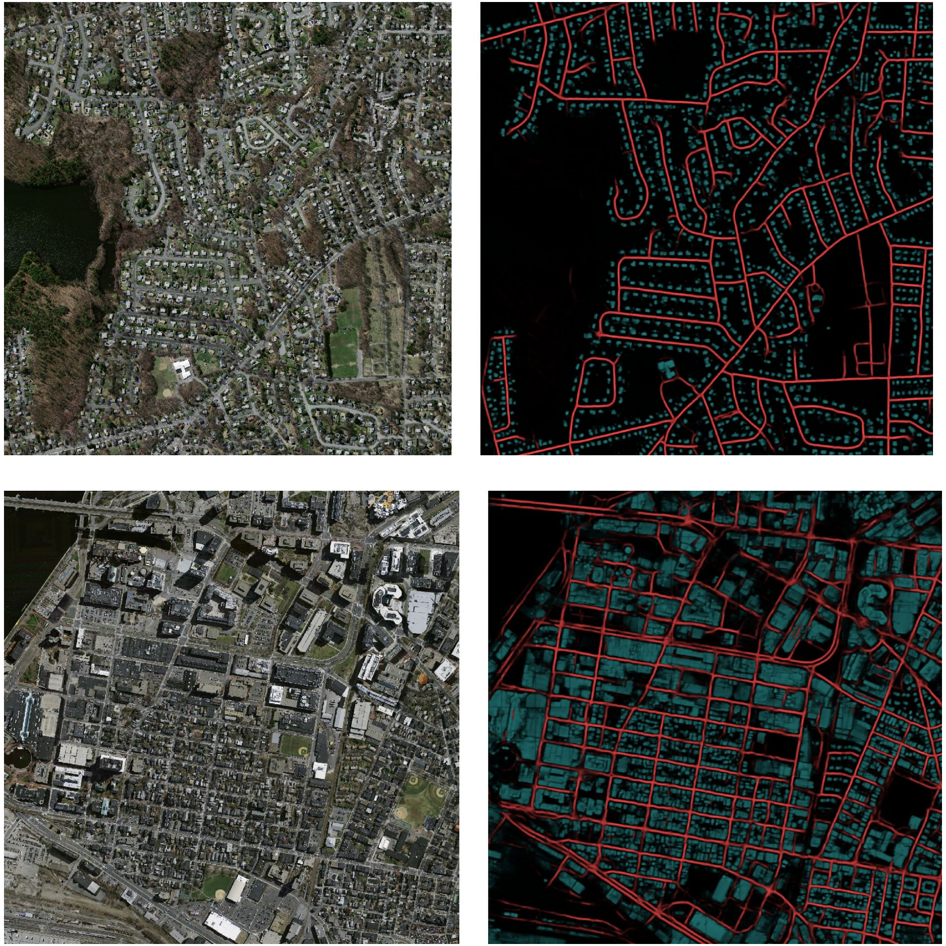



Mask R-CNN Architecture

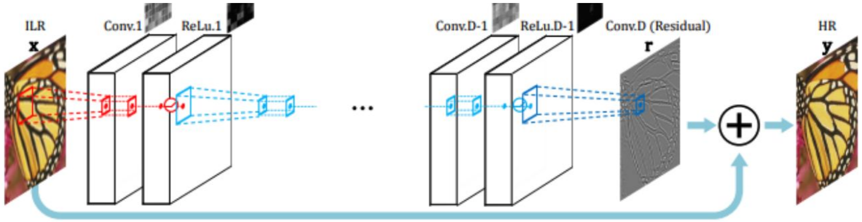
# Semantic Segmentation




U-Net Architecture

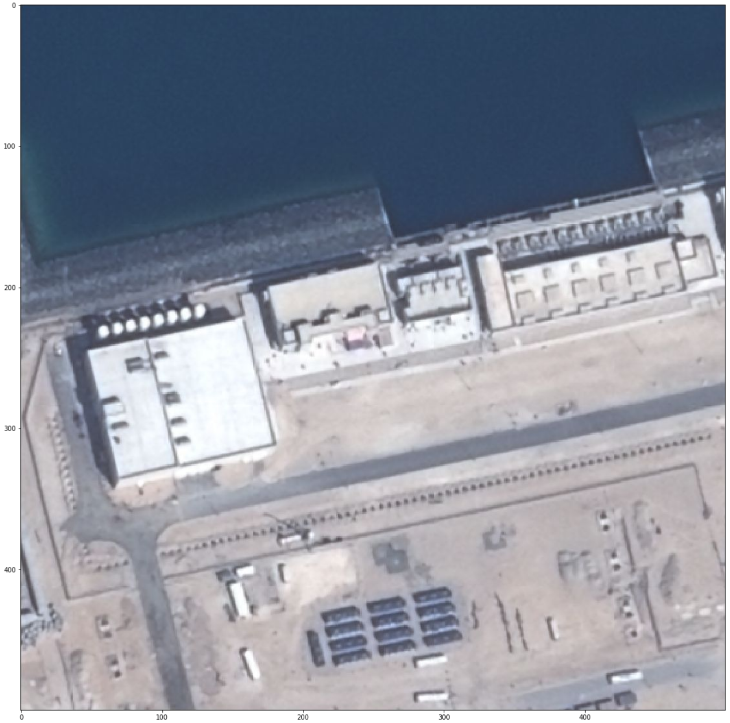


# Imagery Enhancement




Original Image


Enhanced Image



# Python & Keras

Keras is a Python library which provides a layer of abstraction for Tensorflow, PyTorch, and other deep learning frameworks.

Examples in this seminar will use Keras.

NVIDIA GPUs can be used to drastically increase the training and inference speed.

# Example Keras Model

```
# For a single-input model with 10 classes (categorical classification):
model = Sequential()
model.add(Dense( 32, activation='relu', input_dim=100))
model.add(Dense( 10, activation='softmax'))
model.compile(optimizer= 'rmsprop',
              loss='categorical_crossentropy' ,
              metrics=[ 'accuracy'])

# Generate dummy data
import numpy as np
data = np.random.random(( 1000, 100))
labels = np.random.randint( 10, size=(1000, 1))

# Convert labels to categorical one-hot encoding
one_hot_labels = keras.utils.to_categorical(labels, num_classes= 10)

# Train the model, iterating on the data in batches of 32 samples
model.fit(data, one_hot_labels, epochs= 10, batch_size=32)
```