Radiant MLHub:

A Repository for Machine Learning Ready Geospatial Training Data

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LOCATION POWERS: DATA SCIENCE

Mission



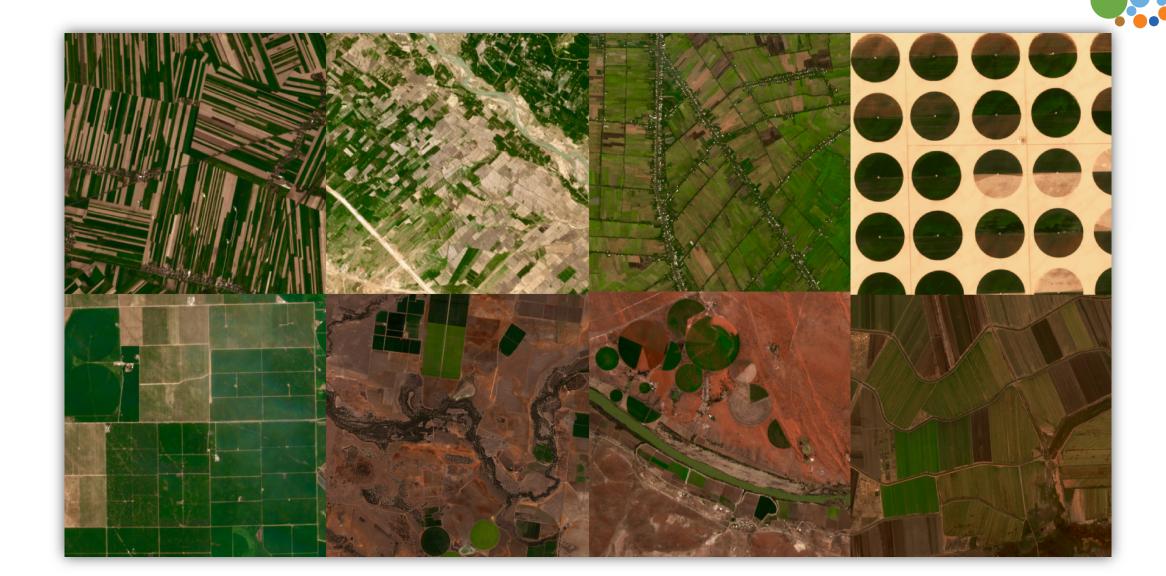
Empowering organizations and individuals globally with open Al and EO data, standards and tools to address the world's most critical international development challenges.

Vision



A strengthened global development community that benefits from highquality and trusted AI and EO resources for positive global impact.

Motivation



Benchmark for Computer Vision



- ▶ 14 M annotated images including 1 M with object bounding boxes.
- ▶ 20 K categories of objects
- Open access
- ► Annual competition since 2010



BigEarthNet



- ▶ 590,326 Sentinel-2 image patches
- Each patch is a section of i) 120 × 120 pixels for 10m bands; ii) 60 × 60 pixels for 20m bands; and iii) 20×20 pixels for 60m bands.
- Each image patch is annotated by multiple land-cover classes
- ▶ 95% of images have at most 5 multi-labels.

- Images are selected across 10 EU countries.
- Data available for download on the web



permanently irrigated land, sclerophyllous vegetation, beaches, dunes, sands, estuaries, sea and ocean



coniferous forest, mixed forest, water bodies



non-irrigated arable land, fruit trees and berry plantations, agro-forestry areas, transitional woodland/shrub



non-irrigated arable land



discontinuous urban fabric. non-irrigated arable land, land principally occupied by agriculture, broad-leaved forest

SpaceNet



- ▶ A corpus of commercial satellite imagery and labeled training data to use for machine learning research.
- ▶ Training data available for open access on AWS

AOI	Area of Raster (Sq. Km)	Building Labels (Polygons)	Road Labels (LineString)
Rio	2,544	4,082,529	N/A
Vegas	216	151,367	3685 km
Paris	1,030	23,816	425 km
Shanghai	1,000	92,015	3537 km
Khartoum	765	710,960	1030 km
Atlanta	655 x 27	126,747	3000 km

Challenges in Geospatial ML



Geospatial Training Data Catalogs:

- ▶ Lack of Geo-Diversity
- Scarce data sources
- Data Accessibility
- ▶ Inter-Operability
- Machine learning-readiness

Result of Gaps in Training Data Catalogs:

- Biased or incorrect results
- Inability to capture wide range of possible outcomes in space and time

ML Commons for Earth Observation





Hub

- EO training datasets
- ML Models
- High impact competitions
- Image annotation + groundreferencing

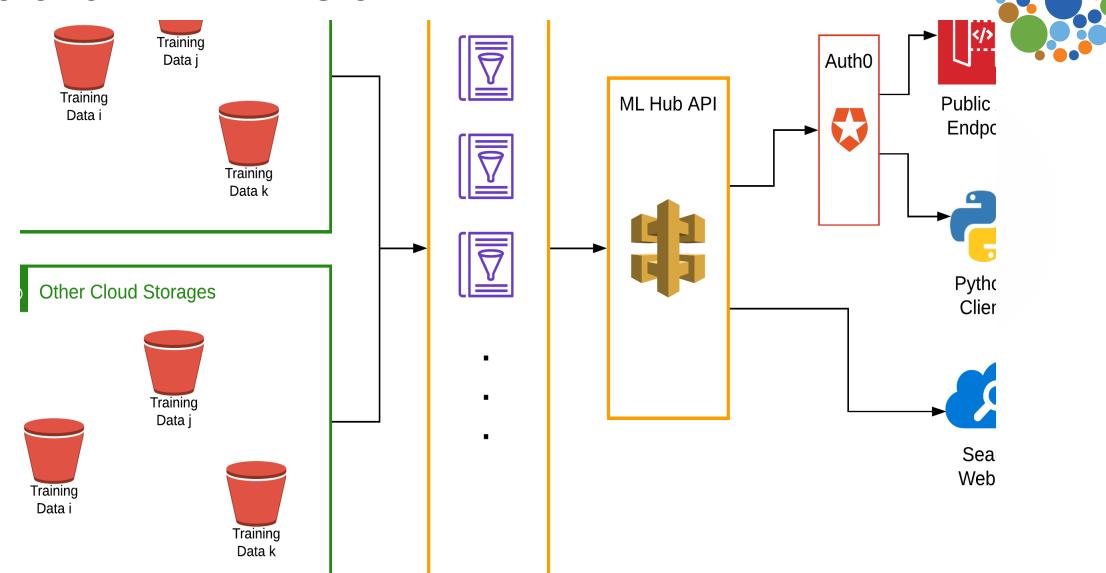
Community

- Convenings to develop standards around ML on EO
- Interoperability of datasets
- Technical Working Groups
- White Papers

Educations

- EO market information
- Best practices on use of ML and EO
- Speaking engagements
- Media outreach

Radiant ML Hub



An Open Source Standard



SpatioTemporal Asset Catalog (STAC)

An open specification to increase the interoperability of searching for geospatial data.

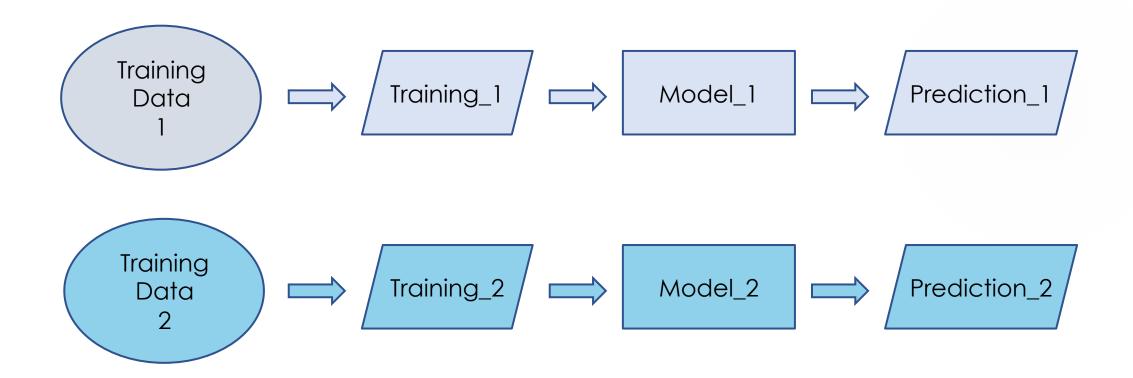


MAXAR (Digital Globe), Azavea, Google Earth Engine, Harris, CBERS, Development Seed, USGS, Geoscience Australia, Planet, Astraea, Element-84, Radiant Earth Foundation



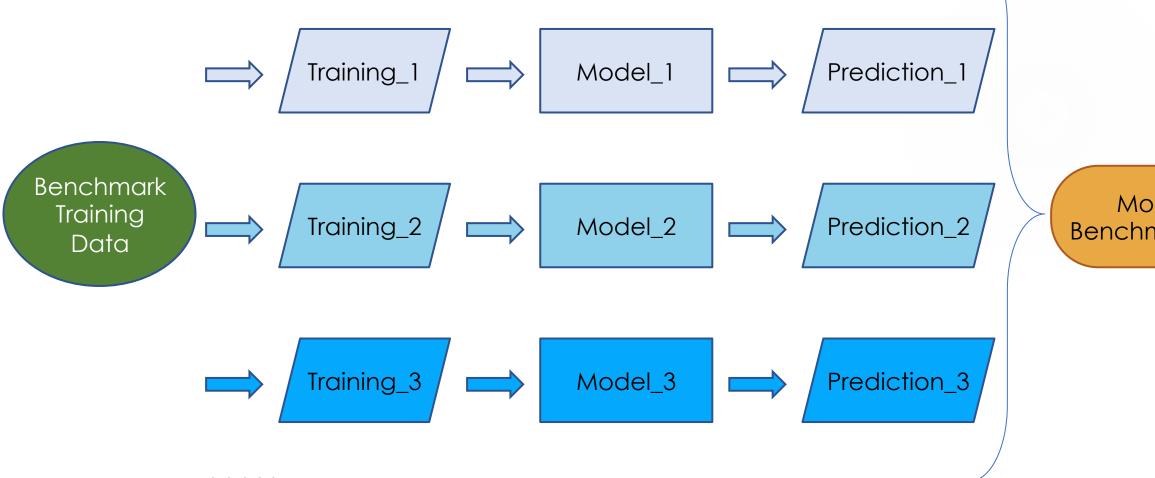
Existing Workflows





Ideal Workflow





Model Benchmarking

How will it look like in practice?



```
In [1]: import mlhubearth as mle
In [2]: demo bbox = [
                    (37.176361083984375, -6.815989239380505),
                     (37.24365234375, -6.7559877474853325)
In [3]: td id = mle.datasets(keywords = "maize", bbox = demo bbox)
        { 'data provider': 'Radiant Earth Foundation',
         'docs': 'www.mlhub.earth/datasets/tanzania crop 2017',
         'id': '87472972523egb7365288157394uyhs6352527e',
         'license': 'CC BY',
         'name': 'Tanzania Crop Type Dataset 2017',
         'version': '1.0'}
In [4]: (x train, y train) = td id.load data()
In [ ]:
```

Thanks!











Funders

OMIDYAR NETWORK









