

Lynker Analytics

- Based in Wellington, New Zealand
- Formed in late 2018 in a partnership with US based, Lynker
- 3 primary delivery areas
 - Artificial Intelligence
 - Geospatial Analytics
 - Data Visualisation

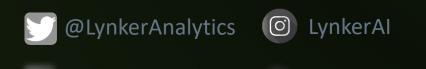


@LynkerAnalytics
 @LynkerAl

Lynker Analytics

- A team of 3 with 20+ years experience in the Geospatial & Data Science domains
- Matt Lythe ~ Managing Director
- **David Knox** ~ Principal, Data Science
- **Phil Woods** ~ Principal, Analytics & Visualisation

...an **"Al First"** geospatial business who specialise in unlocking insights from geospatial datasets through the use of advanced location-informed, **machine learning.**





Lynker Analytics

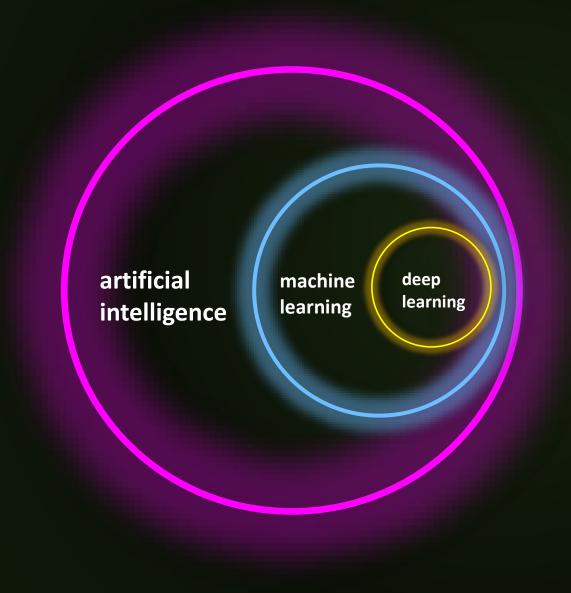
- Recent R&D focused on porting proprietary Machine Learning technology into Esri's ArcGIS Pro
 - Computer Vision
 - Earth Observation (EO) Machine Learning

...an **"Al First"** geospatial business who specialise in unlocking insights from geospatial datasets through the use of advanced location-informed, **machine learning.**





Al vs Machine Learning or Deep Learning



- Both "Machine Learning" &
 "Deep Learning" are subsets of the greater, Artificial Intelligence domain
- Machine Learning and Deep Learning are where most "data science" occurs
- Both are very useful tools for geospatial analytics
- Esri have implemented several Machine Learning / Deep Learning tools within the ArcGIS platform

Machine Learning?

- an evolving way of communicating with computers that allows us to program them by example rather than instruction
- It's an automation tool consistent performance and high accuracy
- *"Anything you can do..."* machine learning processes can do almost any easily repeatable, task oriented procedure humans carry out today
- It's also an analytics tool that's good at identifying patterns and correlations across large, unstructured datasets
- Can be applied to a variety of geospatial disciplines including remote sensing, geospatial analysis and data extraction

How Machines Learn...

In most cases, machine learning processes are "trained" by relating a proportionally representative amount of the desired output against an equivalent amount of the available input... or something like that.

- Supervised
 - Labelled data provided to achieve a good model
- Semi Supervised
 - Human-in-the-loop (active learning)
 - Label propagation
- Unsupervised
 - No labelling required



Machine Learning +



- Esri provide several tools that can be used within or to create Machine Learning workflows, including:
 - Export Training Data for Deep Learning
 - Detect Objects & Classify Pixels using Deep Learning
 - Forest-based Classification and Regression
- Esri don't at this stage provide pre-built models for Object Detection or Classification although there's a simple example for Buildings using RCNN masks here: <u>https://github.com/Esri/raster-deep-learning/tree/master/examples/keras/mask_rcnn</u>

Computer Vision

- Object Detection
 - An object within an image is identified with a bounding geometry
 - Commonly used to locate objects within large imagery datasets for quantitative analytics
- Pixel Classification or Sematic Segmentation
 - Pixels within an image are classified as belonging to a specific object
 - Commonly used within geospatial workflows to extract features from imagery





Computer Vision



Object Detection

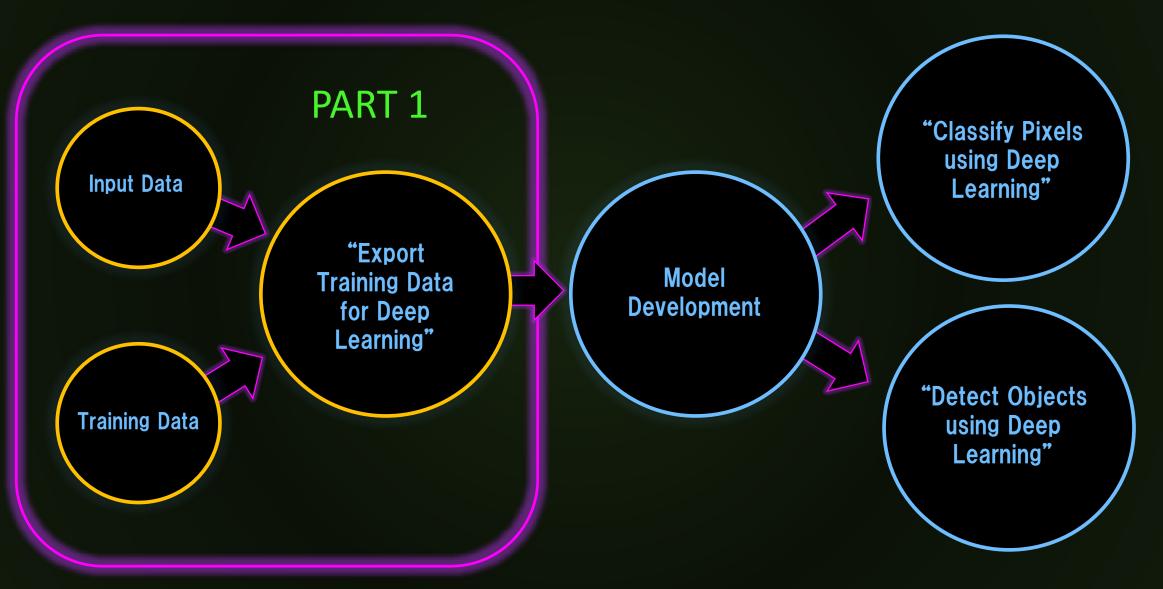
- Quantitative Analytics
- Quantitative Analytics



Semantic Segmentation

- Data Capture
- Data Gapture

Computer Vision ... in Esri



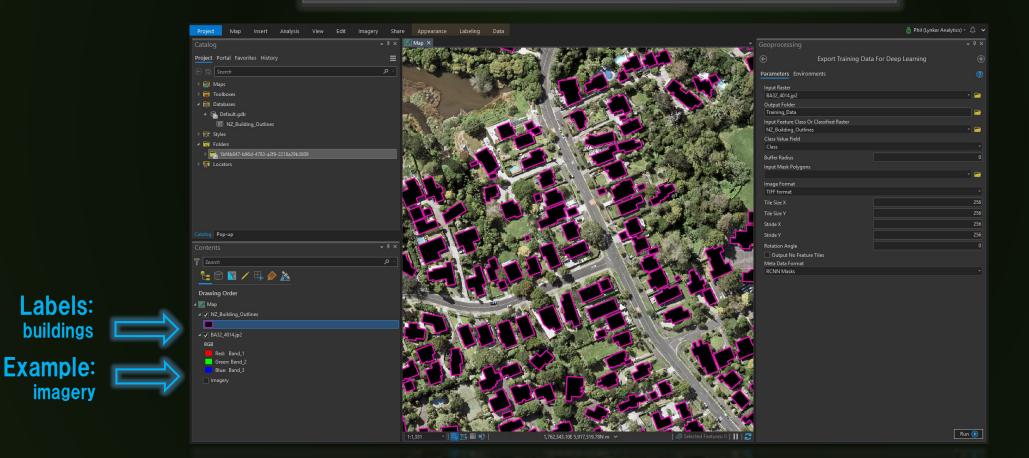


Export Training Data For Deep Learning (Image Analyst Tools) Uses a remote sensing image to convert labeled vector or raster data into deep learning training datasets. The output is a folder of image chips and a folder of metadata files in the specified format.

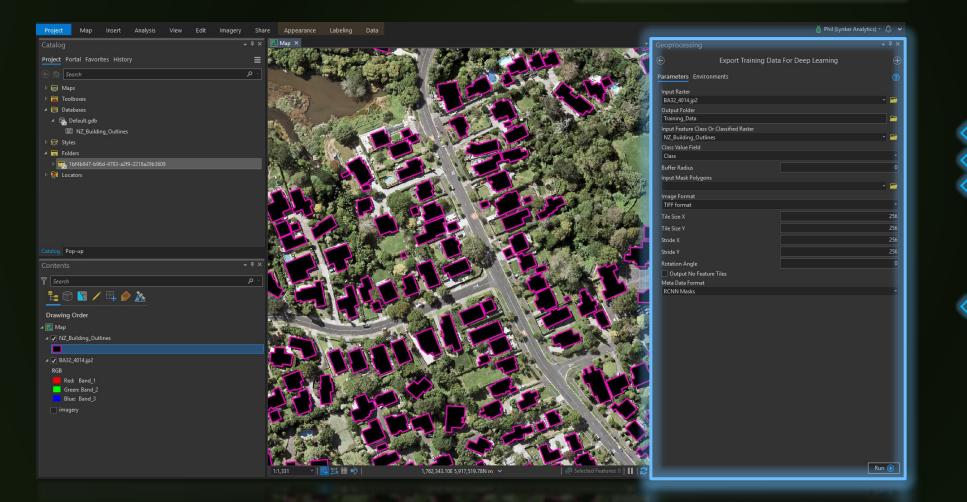
- Converts labelled vector or raster data into training datasets (known as 'image chips')
- Training data produced by this tool is provided to a data scientist to create the associated machine learning model

Export Training Data For Deep Learning (Image Analyst Tools)

Uses a remote sensing image to convert labeled vector or raster data into deep learning training datasets. The output is a folder of image chips and a folder of metadata files in the specified format.



Export Training Data For Deep Learning (mage Analyst Tools) Uses a remote sensing image to convert labeled vector or raster data into deep learning training datasets. The output is a folder of image chips and a folder of metadata files in the specified format.

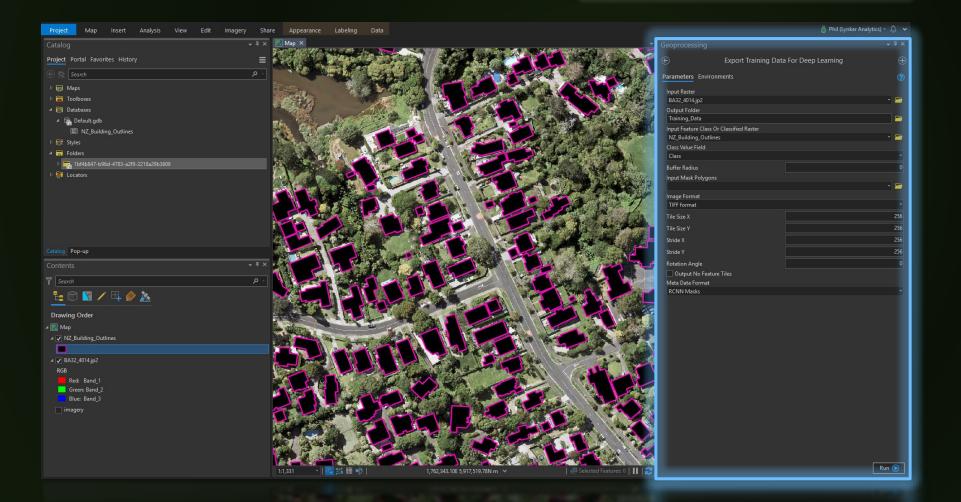


Training Image – RGB Training Data – Buildings Class Value – Single Value



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Export Training Data For Deep Learning (mage Analyst Tools) Uses a remote sensing image to convert labeled vector or raster data into deep learning training datasets. The output is a folder of image chips and a folder of metadata files in the specified format.



Formats:

- RCNN Masks
- Classified Tiles
- KTTI Rectangles
- Pascal VOC

import arcpy from arcpy.ia import * from datetime import datetime import fnmatch import os

start = datetime.now()

rotation angle = "0"

arcpy.CheckOutExtension("SpatialAnalyst") except: e = sys.exc_info()[1] print(e.args[0])

arcpy.AddError(e.args[0])

project = "C:/Projects/Esri Machine Learning"

geodatabase = project + "/MachineLearning.gdb"

in raster = project + "/mosaic.tif" out_folder = project + "/buildings_training_data" in class data = geodatabase + "/training buildings" image chip format = "" tile size x = "256" tile_size_y = "256" stride x = "256" # chip side overlap stride y = "256" # chip forward overlap output nofeature tiles = "ONLY TILES WITH FEATURES" # FEATURES metadata format = "RCNN Masks" # KITTI rectangles, PASCAL start_index = "0" class value field = "CLASS" # attribute in featureclass buffer radius = "" in mask polygons = "" # geodatabase + "/bounding box"

ExportTrainingDataForDeepLearning(in raster , out folder , in class data , image chip format , tile_size_x , tile size y , stride x , stride y

e = sys.exc info()[1]

arcpy.AddError(e.args[0])

print(e.args[0])

print("Exporting training data...")

print("Process completed in " + str(datetime.now() - start)) result = out folder + "/images/" file_count = (len(fnmatch.filter(os.listdir(result), '*.tif'))) if file_count == 0:

, output_nofeature_tiles

, metadata format

, class value field , buffer radius , in_mask_polygons

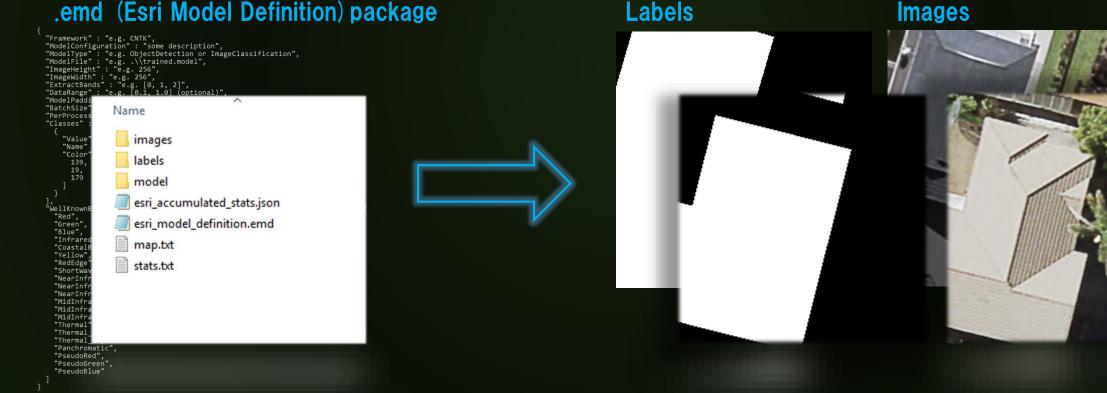
, start index

, rotation_angle) print("No errors but something's wrong no training data was produced!") print(str(file count) + " training tiles were produced.")

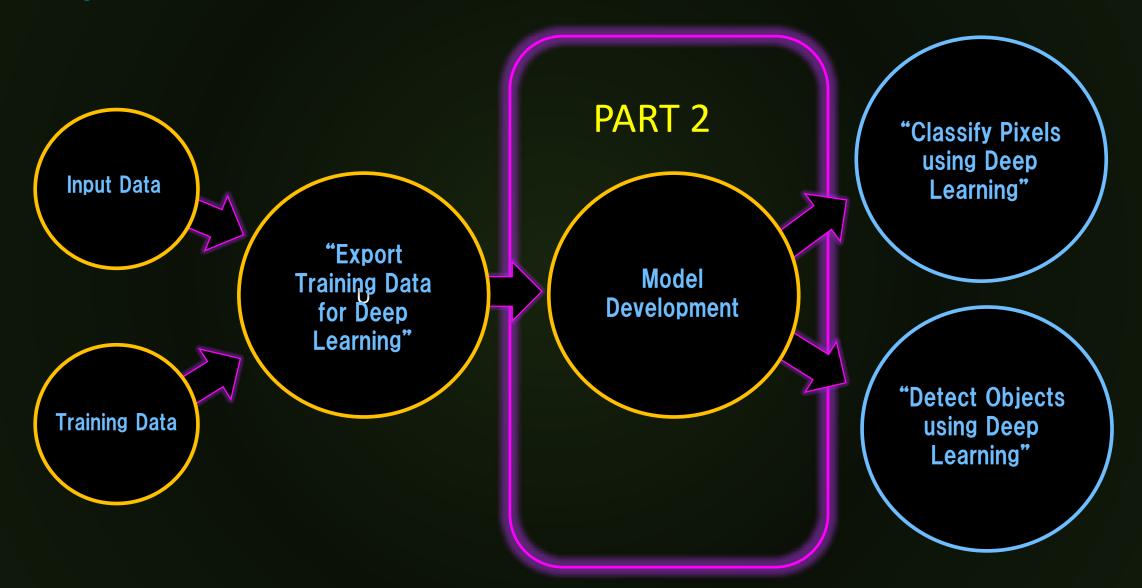
Export Training Data For Deep Learning (Image Analyst Tools)

Uses a remote sensing image to convert labeled vector or raster data into deep learning training datasets. The output is a folder of image chips and a folder of metadata files in the specified format.

.emd (Esri Model Definition) package



Computer Vision ... in Esri



The Data Scientist...

.emd package

["Framework" : "e.g. CNTK", "ModelConfiguration" : "some description", "ModelType" : "e.g. ObjectDetection or ImageClassification", "ModelTie" : "e.g. .\trained.model", "ImageHeight" : "e.g. 256", "ImageWidth" : "e.g. 256", "ExtractBands" : "e.g. [0, 1, 2]", "DataRange" : "e.g. [0, 1, 2]", "ModelPadding" : "e.g. 6(, 1, 2]", "BatchSize" : "e.g. 8 (optional)", "Classes" : ["Classes" : ["Value" : 1 'Name" : "Color" : [139, "WellKnownBandNames (FYI, these band names can be used in ExtractBands)" : ["Red", "Green", "Blue", "Infrared", "CoastalBlue", "Yellow", "RedEdge", "ShortWaveInfrared", "NearInfrared", "NearInfrared_1" "NearInfrared_2", "MidInfrared" "MidInfrared_1", "MidInfrared_2", "Thermal", "Thermal_1" "Thermal_2", "Panchromatic", "PseudoRed", "PseudoGreen" "PseudoBlue"

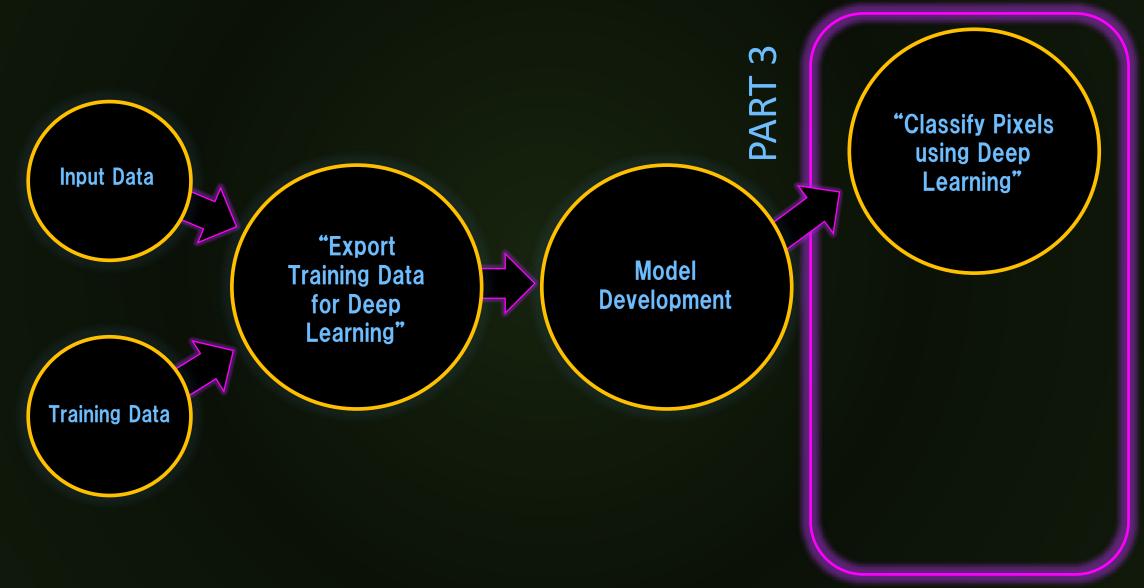
Trained Models

K Keras



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Computer Vision ...in Esri



Classify Pixels Using Deep Learning



Classify Pixels Using **Deep Learning** (Image Analyst Tools) Runs a trained deep learning model on an input raster to produce a classified raster, with each valid pixel having a class label assigned.

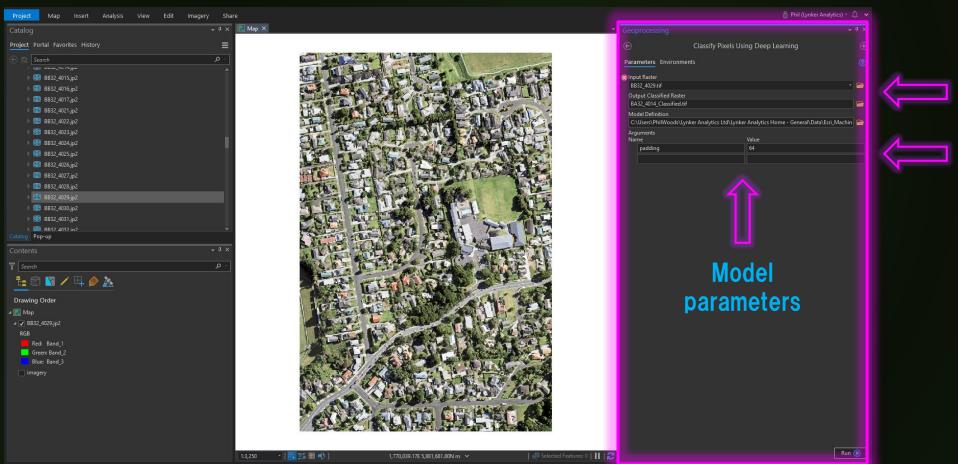


Classifies pixels within an image to produce a segmented image

 Highly recommend a computer with a high-end Nvidia GPU with CUDA and Tensor Core support. This makes a huge difference.

Classify Pixels Using Deep Learning

Classify Pixels Using Deep Learning (mage Analyst Tools) Runs a trained deep learning model on an input raster to produce a classified raster, with each valid pixel having a class label assigned.



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Image to capture Esri Model Definition (.emd)



Forest-based Classification and Regression (Spatial Statistics Tools)

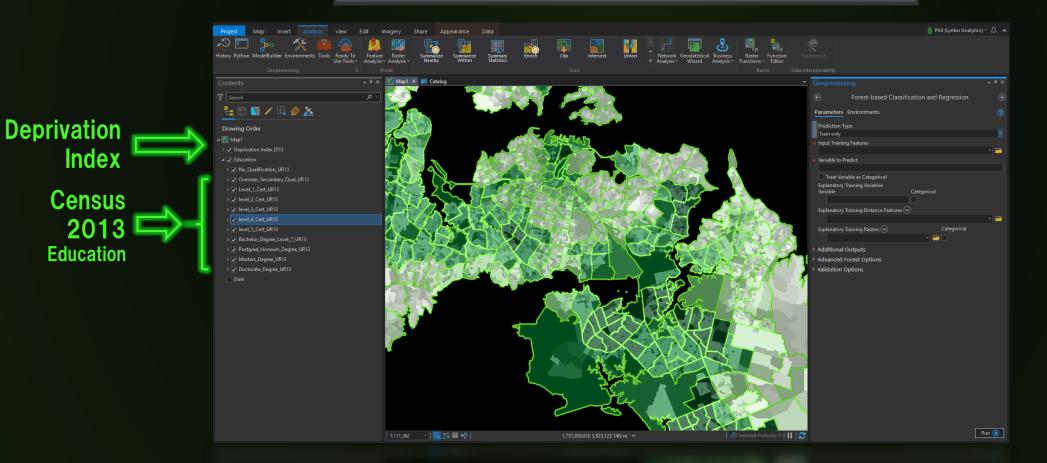
Creates models and generates predictions using an adaptation of Leo Breiman's random forest algorithm, which is a supervised machine learning method. Predictions can be performed for both categorical vari...

- An ensemble-based learning method primarily used for classification and regression
- "Random Forests" are made up of multiple "decision trees" and can be used to rank the importance of variables in a regression or classification problem
- Interpolate / predict missing data
- Requires Scikit Learn Python library

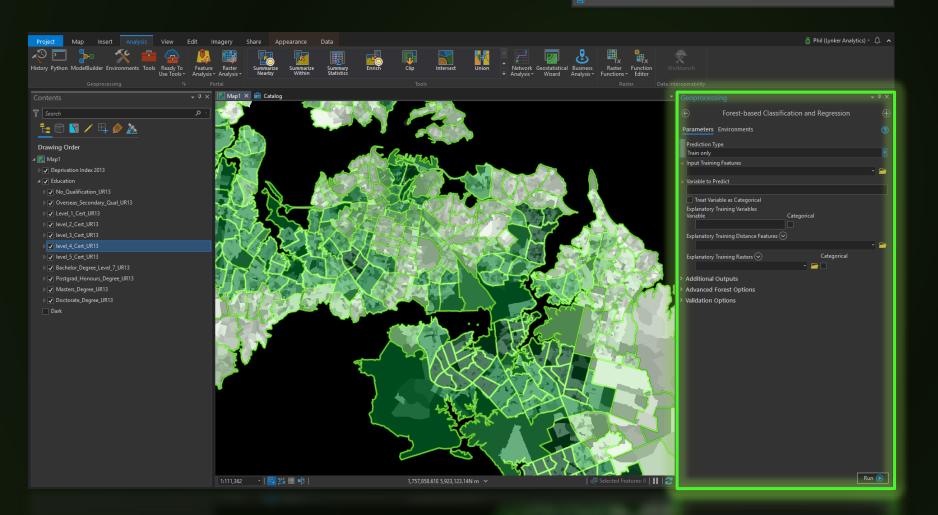


Forest-based Classification and Regression (Spatial Statistics Tools)

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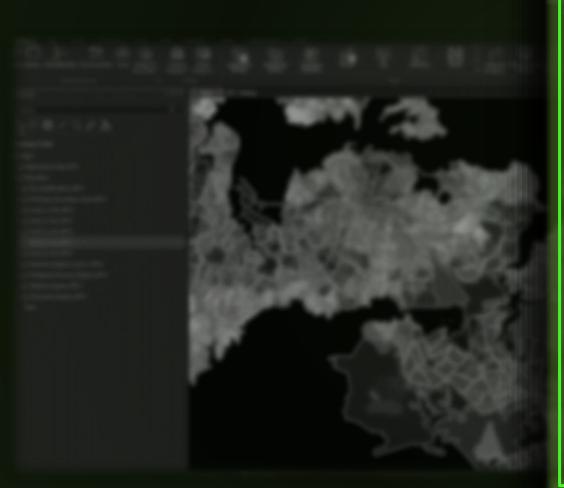


Forest-based Classification and Regression (Spatial Statistics Tools) Creates models and generates predictions using an adaptation of Leo Breiman's random forest algorithm, which is a supervised machine learning method. Predictions can be performed for both categorical vari...



Key variables:

- Prediction Type
- Input Features
- Variable to Predict
- Explanatory Rasters
- Validation Options



Geoprocessing					
Forest-based Classifica Parameters Environments	tion and Regression				
Prediction Type Predict to raster					
Input Training Features					
DeprivationIndex_2013_AreaUnit					
Variable to Predict					
NZDep2013					
Treat Variable as Categorical					
Explanatory Training Variables Variable 🛇 C	ategorical				
Explanatory Training Distance Features 🛇					
Explanatory Training Rasters 🕑	Categorical				
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Postgrad_Honours_Degree_UR13	• 🗁 🗆				
Masters_Degree_UR13	• 🗁 🗖				
Doctorate_Degree_UR13	- 🗁 🗆				
	• 😁 🗆				
Additional Outputs					
Advanced Forest Ontions					

Run 🕟

Validation Options

Key variables:

- Prediction Only
- Deprivation Index
- NZDep2013
- Census Education
- 10% data excluded for validation

Messages

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validation is occurring with incomplete data.+ Ranges of the training data and prediction data do not coincide and the tool is attempting to extrapolate.

Completed script Forest-based Classification and Regression...

Succeeded at Thursday, 8 August 2019 11:53:40 PM (Elapsed Time: 7 minutes 25 seconds)

the second se	

Key variables:

- Prediction Only
- Deprivation Index
- NZDep2013
- Census Education
- 10% data excluded for validation

Thanks

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