Advanced Remote Sensing

Sample assignments



ADVANCED REMOTE SENSING ASSIGNMENT

Part II : Object features for classification



EXAMPLE 1 + 2



chess/1 XY 5,184 Objects



Create a new project.

XY 5,184 Objects

QUESTION 1:

What becomes obvious if you compare the values for the two objects of the chessboard segmentation?

• The object representing a part of the boat is more reflective in all bands than the river which absorbs most wavelenghts

QUESTION 2:

Which features don't make that much sense in the case of the chessboard classification?

• The geometry , since all the objects have the same geometry.

• The multisegmentation classification gives more meaningful objects since it takes into consideration the shape as well as the spectral properties:



EXAMPLE 3 + 4





Vorkspace

📕 Default Workspace 🗌 Name

🦉 File View Image Objects Analysis Architect Classification Process Tools Window Help

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* QB_MGI31_subset_SBG







Ready

🦉 File View Image Objects Analysis Architect Classification Process Tools Window Help



multires_200/1 XY 132 Objects



What happens if you collapse the vegetation super-class?

• The extra subclasses taking into consideration the air quality aren't displayed and only the superclass Vegetation (classified from only NDVI values) is shown.

🎽 File View ImageObjects Analysis Architect Classification Process Tools Window Help



QUESTION 3:

How many objects were classified as "water"?

• There were **3** objects classified as water

QUESTION 4

What is the area of the whole vegetation class (if you select the vegetation class to generate the feature, it will summarize the values from the grouped sub-classes)?

•Yes. If only the vegetation class is selected, its subclasses (High and Low Quality vegetation) will be summarized.

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Ē.	Is end of super-object				
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🔳 🌱 Object features

Workspace Source View

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main

QUESTION 5

What is the meaning of the distance value when you create the feature?

• The distance value refers to the hierarchal relation between the objects in the finer segmentation (scale 50) and the super objects in the coarser segmentation (scale 200). A distance value of 1 for the vegetation means that if an object from segmentation 50 exists within an object of the segmentation 200, it will be detected and considered as belonging to the same class.



Hyperspectral unmixing

Hyperspectral imagery assignment

Data Sources 3 Filter Value Name Rasters (2) enmap_berlin.bs hires_berlin.bsq Vectors (5) enmap_srf_librar 🗱 landcover_berlin landcover_berlin library_berlin.gp

veg-cover-fracti

Classification workflow **X**

> Classification Workflow (advanced) Classification Workflow (deprecated) EnPT (EnMAP Processing Tool) EO Time Series Viewer

GFZ EnGeoMAP

Image Math (deprecated)

Raster math

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- Regression Dataset Manager
- Regression workflow
 - Regression Workflow (deprecated)
- Regression-based unmixing



Launching the Unmixing application

Property



Regression-Based Unmixing

Parameters Log		` F	Regression-based	
Endmember dataset			Inmixing	
	🗱		nplementation of the regression- ased unmixing approach <u>"Ensemble</u>	
Raster layer	-	Create classi	fication dataset (from categorized	vector layer and feature ras
enmap_berlin.bsq [EPSG:32633]		Create classi	fication dataset (from categorized	raster layer and feature rast
Regressor	8	Create classi	fication dataset (from categorized	spectral library)
RandomForestRegressor		Create classi	fication dataset (from categorized	vector layer with attribute t
1 from sklearn.ensemble import RandomForestRegressor		Create classi	fication dataset (from table with c	ategories and feature fields)
2 regressor = RandomForestRegressor(n_estimators=100,	°° 🥏	Create classi	fication dataset (from Python code	e)
		Create classi	fication dataset (from text files)	
		Create classi	fication dataset (from JSON file)	
		A	raster layer to be unmixed.	
		R	Regressor	
		s	cikit-Learn Python code specifying a	

Creating a classification dataset

Number of mixtures per class.

Scikit-learn python code. See <u>RandomForestRegressor</u> for information on different parameters.

Proportion of background mixtures (%)



raster)

Create a classification dataset by sampling data for pixels that match the given categories and store the result as a pickle file.

If the layer is not categorized, or the field with class values is selected manually, categories are derived from the sampled target data y. To be more precise: i) category values are derived from unique attribute values (after excluding no data or zero data values), ii) category names are set equal to the category values, and iii) category colors are picked randomly.

Categorized vector layer

Categorized vector layer specifying sample locations and target data y. If required, the layer is reprojected and rasterized internally to match the feature raster grid.

Setting up the classification dataset

Excecuting the Regression model

A

	Scikit-learn python code. See LinearRegression for information on different parameters.
Parameters Log	Number of mixtures per class
Endmember dataset	1000
/Users/turki/AppData/Local/Temp/processing_jBEyaM/a4eaa7df52234d128b1a0915ce90700c/outputClassificationDataset.pkl 🗴 🔆 🦊	Proportion of background mixtures (%)
Raster layer	n *
• enmap_berlin.bsq [EPSG:32633]	V Takida adalah sakarakara
Regressor	Include original endmembers
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	Ensemble size 1 Robust decision fusion [optional] Ensemble
	Output class fraction layer Python i
Scikit-learn python code. See LinearRegression for information on different parameters.	C:/Users/turki/OneDrive/Assignment/Hyperspecrtral/RegressionUnmixing/CLassFractionLayer.tif
Number of mixtures per class	Open output file after running algorithm Default v Output classification layer [optional]
Proportion of background mixtures (%)	C:/Users/turki/OneDrive/Assignment/Hyperspecrtral/RegressionUnmixing/ClassificationLayer.tif
D *	Open output file after running algorithm
Include original endmembers	Output class fraction variation layer [optional]
Mixing complexity probabilities [optional]	[Skip output]
0.5, 0.5 Allow within-class mixtures Class probabilities [optional]	Open output file after running algorithm
	0%
0%	Advanced 🚽 Run as Batch Process



Comparing results

Water

• Water is well distinguished from other endmembers

• We can see that the linear regression performed well in distinguishing water and water fraction, although it is sometimes confused with vegetation





Vegetation (dense – trees)

• Dense vegetation is discerned with fuzzy limits, but with areas with major fraction



Vegetation (thin – grass)

• Thin vegetation and grass has a mixed fraction and cannot be detected simply



2

Impervious

 Impervious areas have very mixed fractions and cannot be detected clearly

