Lesson B3

Image classification

GEO1001.2020

Hugo Ledoux

(Digital) image classification?

- Previous lecture == human doing the interpretation
- Image classification == computer performs the interpretation
- (according to some criteria that we humans define)

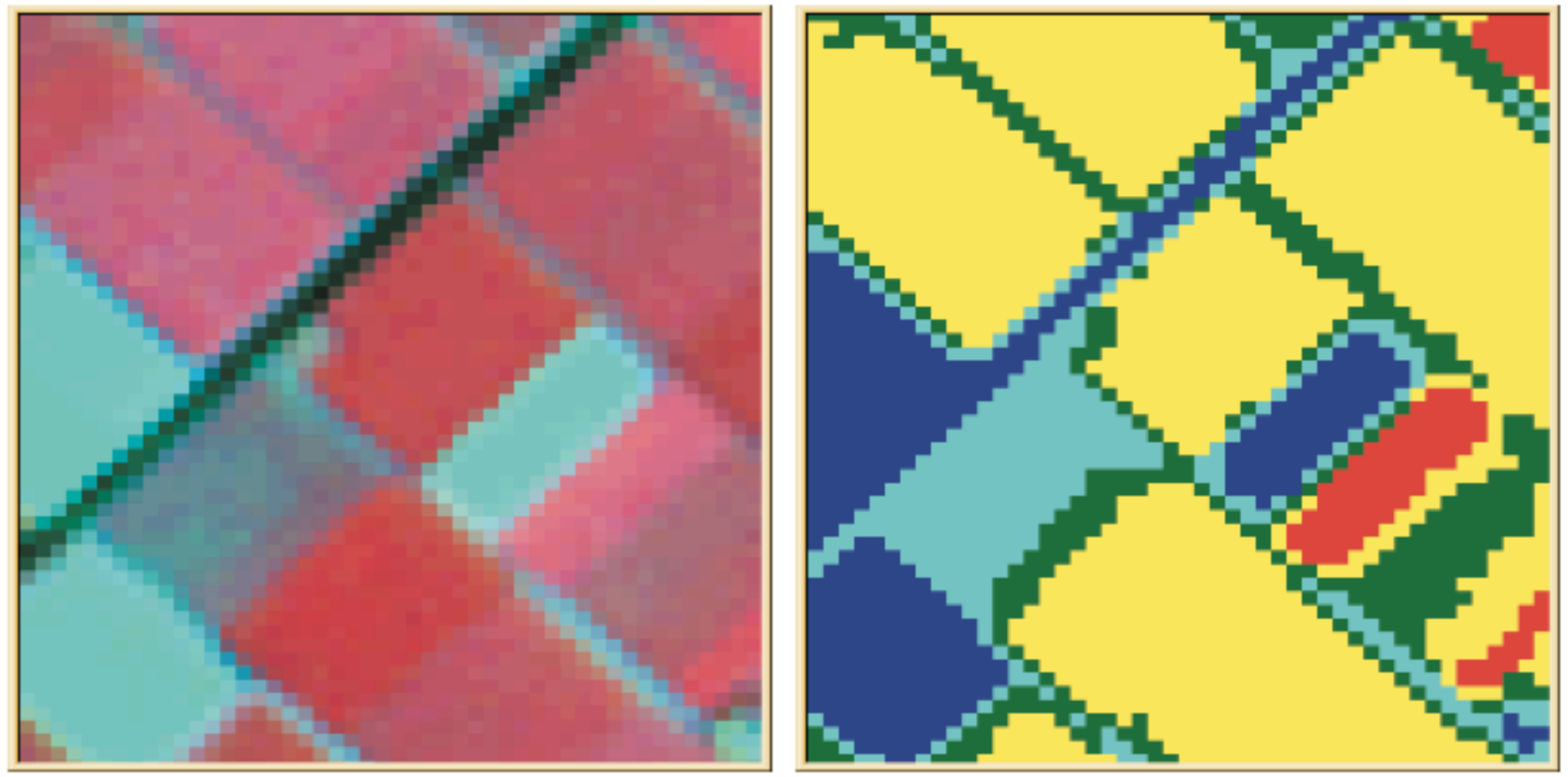
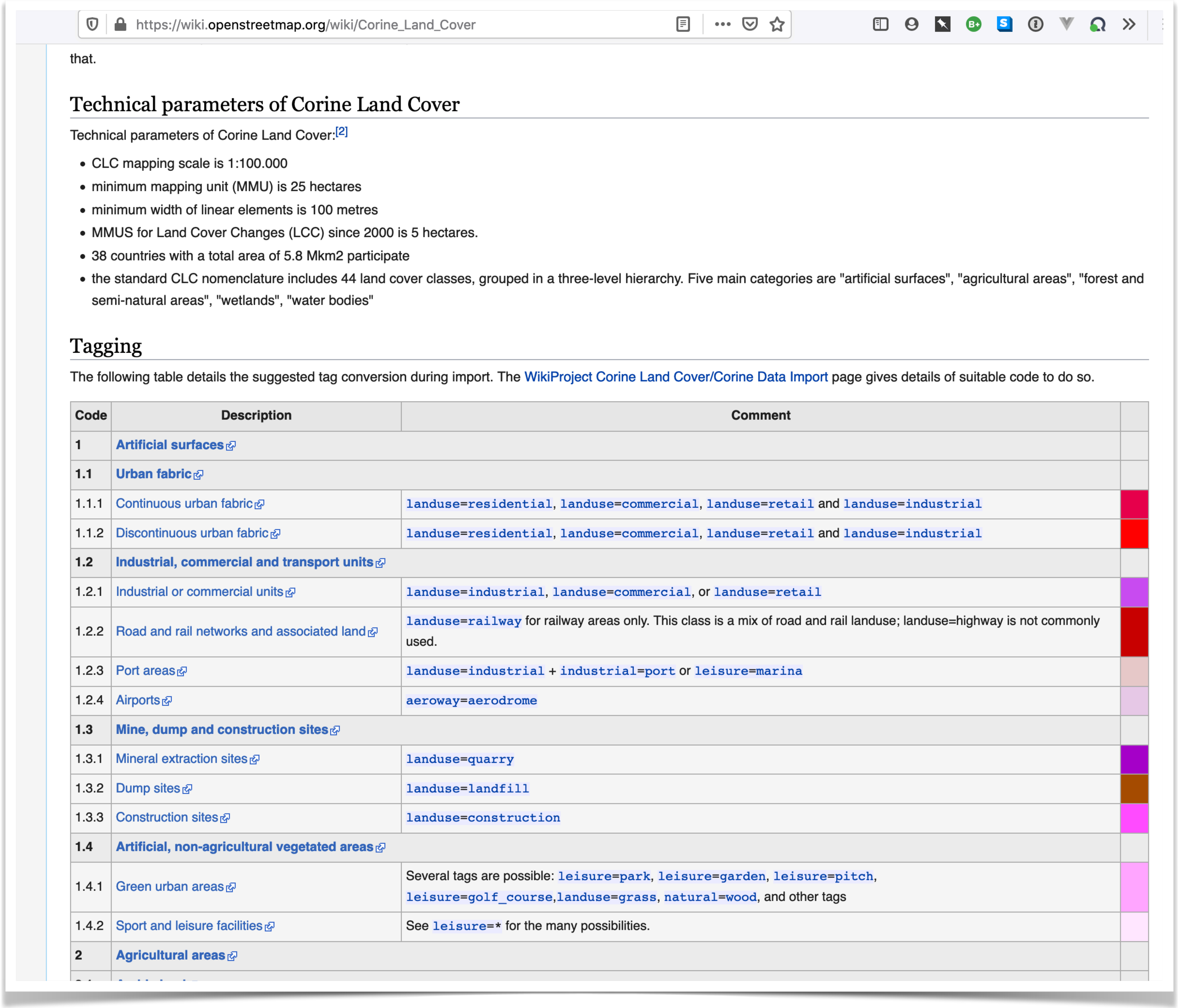
(a)  (b)

Figure 12.7: The result of classification of a multispectral image (a) is a raster in which each cell is assigned to some thematic class (b).

From satellite images to GIS polygons (land cover polygons)

https://land.copernicus.eu/pan-european/corine-land-cover



that.

Technical parameters of Corine Land Cover

Technical parameters of Corine Land Cover:[2]

- CLC mapping scale is 1:100.000
- minimum mapping unit (MMU) is 25 hectares
- minimum width of linear elements is 100 metres
- MMUS for Land Cover Changes (LCC) since 2000 is 5 hectares.
- 38 countries with a total area of 5.8 Mkm2 participate
- the standard CLC nomenclature includes 44 land cover classes, grouped in a three-level hierarchy. Five main categories are "artificial surfaces", "agricultural areas", "forest and semi-natural areas", "wetlands", "water bodies"

Tagging

The following table details the suggested tag conversion during import. The WikiProject Corine Land Cover/Corine Data Import page gives details of suitable code to do so.

Code	Description	Comment	
1	**Artificial surfaces**		
1.1	**Urban fabric**		
1.1.1	Continuous urban fabric	`landuse=residential`, `landuse=commercial`, `landuse=retail` and `landuse=industrial`	
1.1.2	Discontinuous urban fabric	`landuse=residential`, `landuse=commercial`, `landuse=retail` and `landuse=industrial`	
1.2	**Industrial, commercial and transport units**		
1.2.1	Industrial or commercial units	`landuse=industrial`, `landuse=commercial`, or `landuse=retail`	
1.2.2	Road and rail networks and associated land	`landuse=railway` for railway areas only. This class is a mix of road and rail landuse; landuse=highway is not commonly used.	
1.2.3	Port areas	`landuse=industrial` + `industrial=port` or `leisure=marina`	
1.2.4	Airports	`aeroway=aerodrome`	
1.3	**Mine, dump and construction sites**		
1.3.1	Mineral extraction sites	`landuse=quarry`	
1.3.2	Dump sites	`landuse=landfill`	
1.3.3	Construction sites	`landuse=construction`	
1.4	**Artificial, non-agricultural vegetated areas**		
1.4.1	Green urban areas	Several tags are possible: `leisure=park`, `leisure=garden`, `leisure=pitch`, `leisure=golf_course`, `landuse=grass`, `natural=wood`, and other tags	
1.4.2	Sport and leisure facilities	See `leisure=*` for the many possibilities.	
2	**Agricultural areas**		

From satellite images to GIS polygons (land cover polygons)

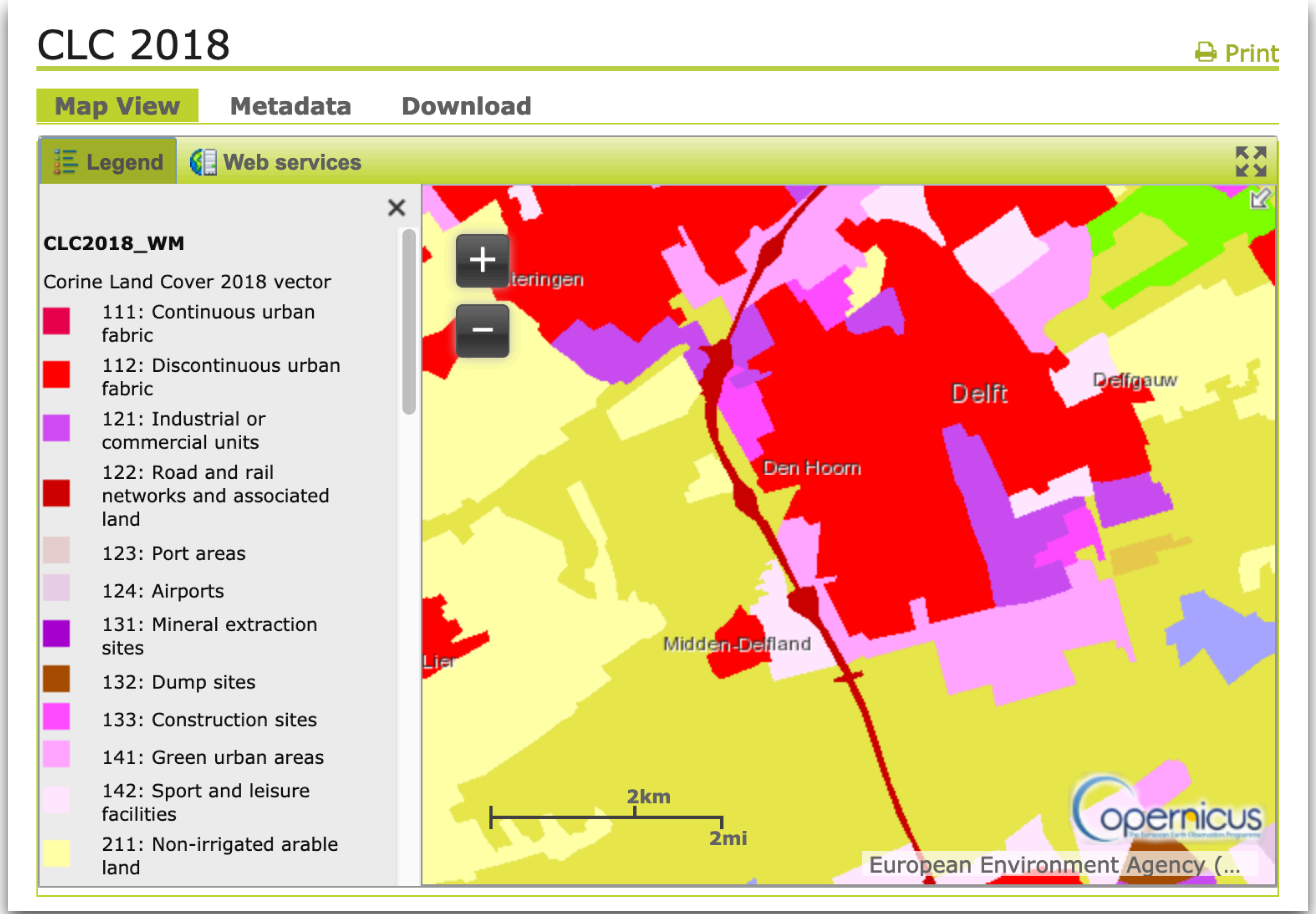
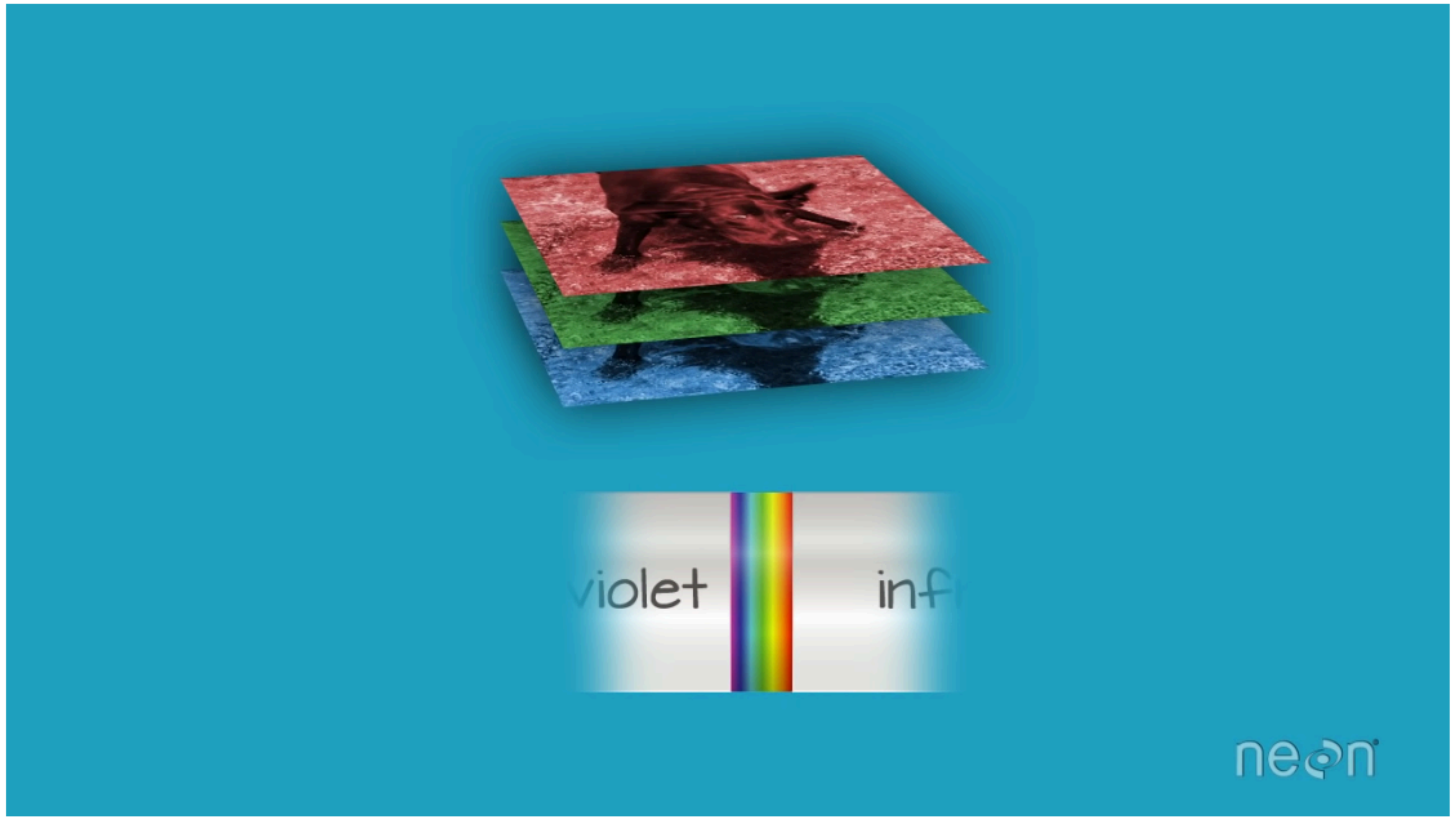


Image classification == differences in spectral signatures



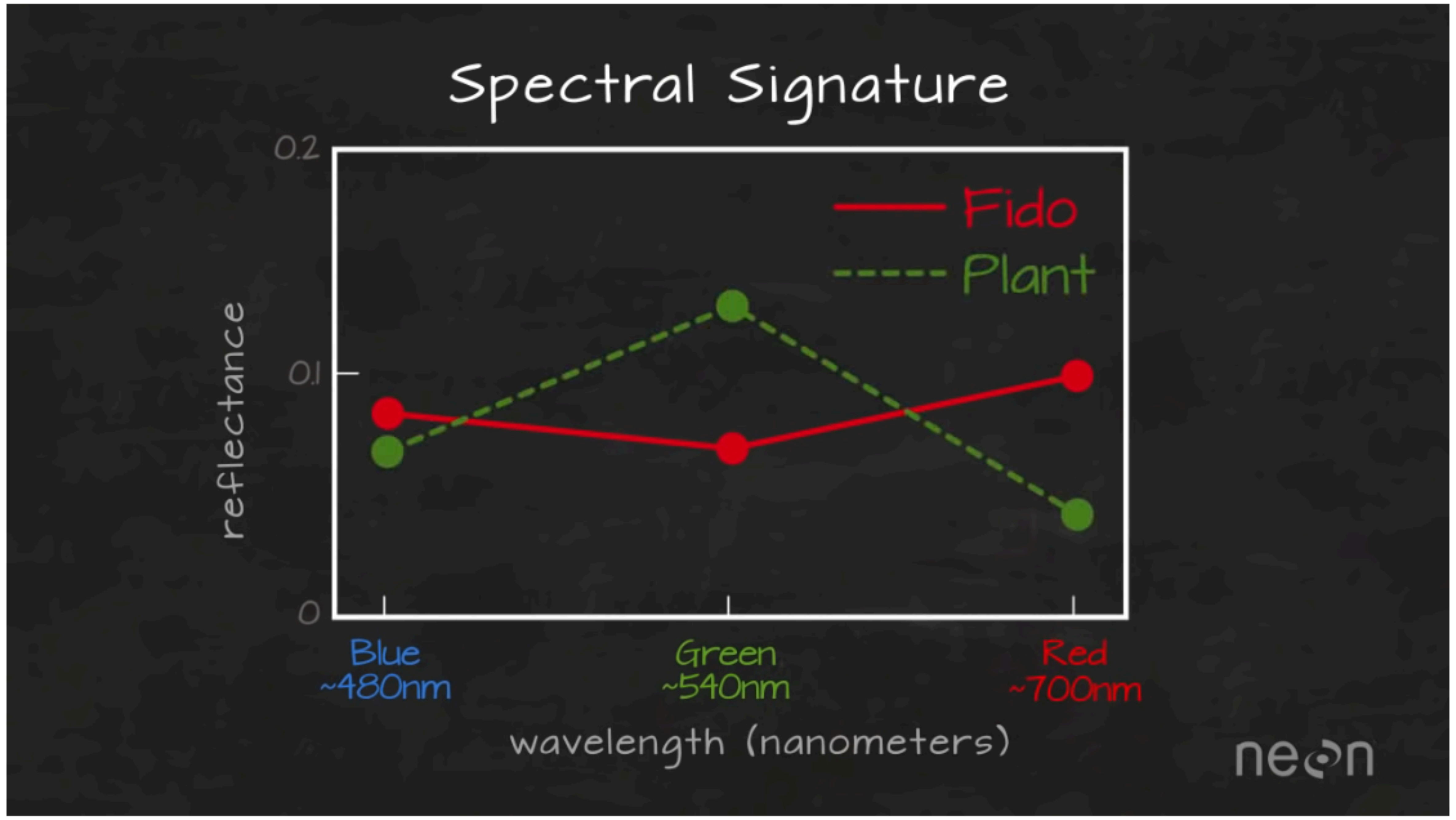
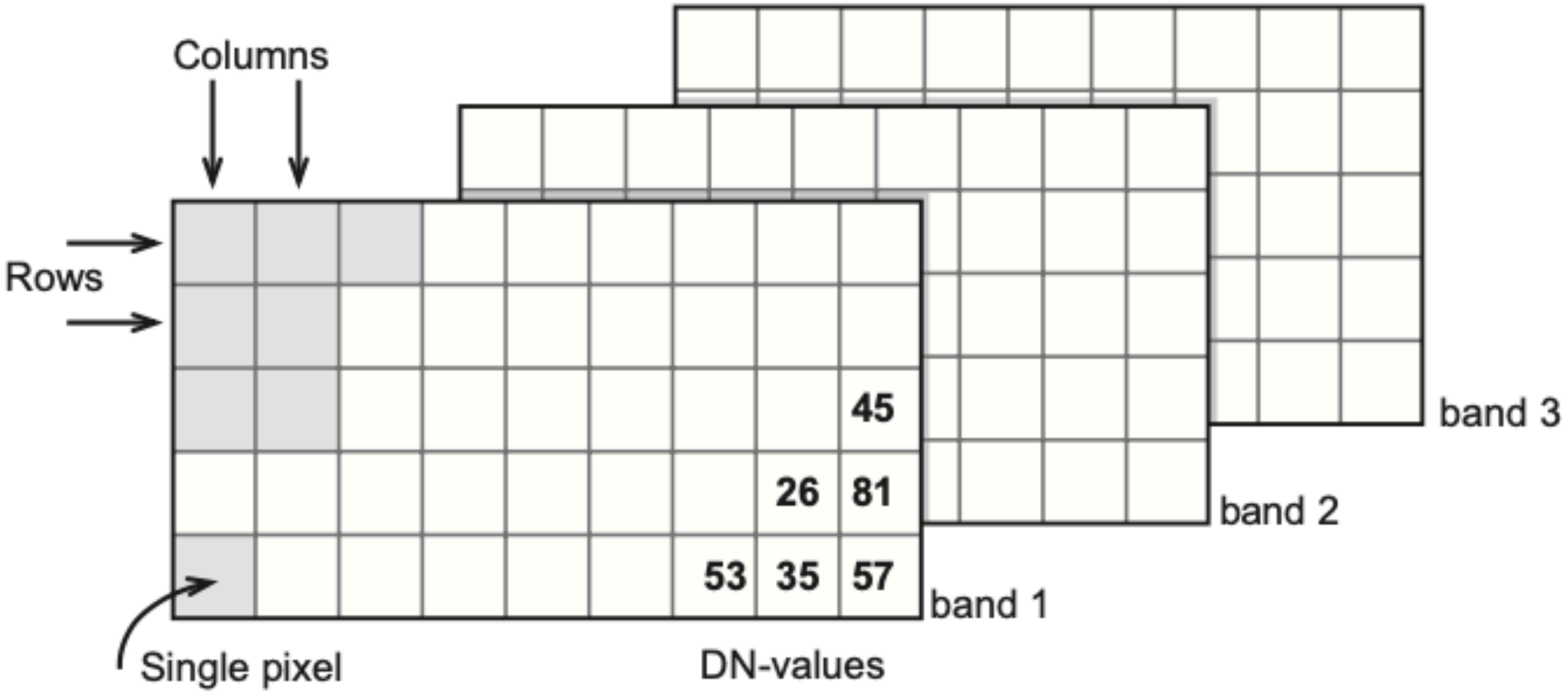
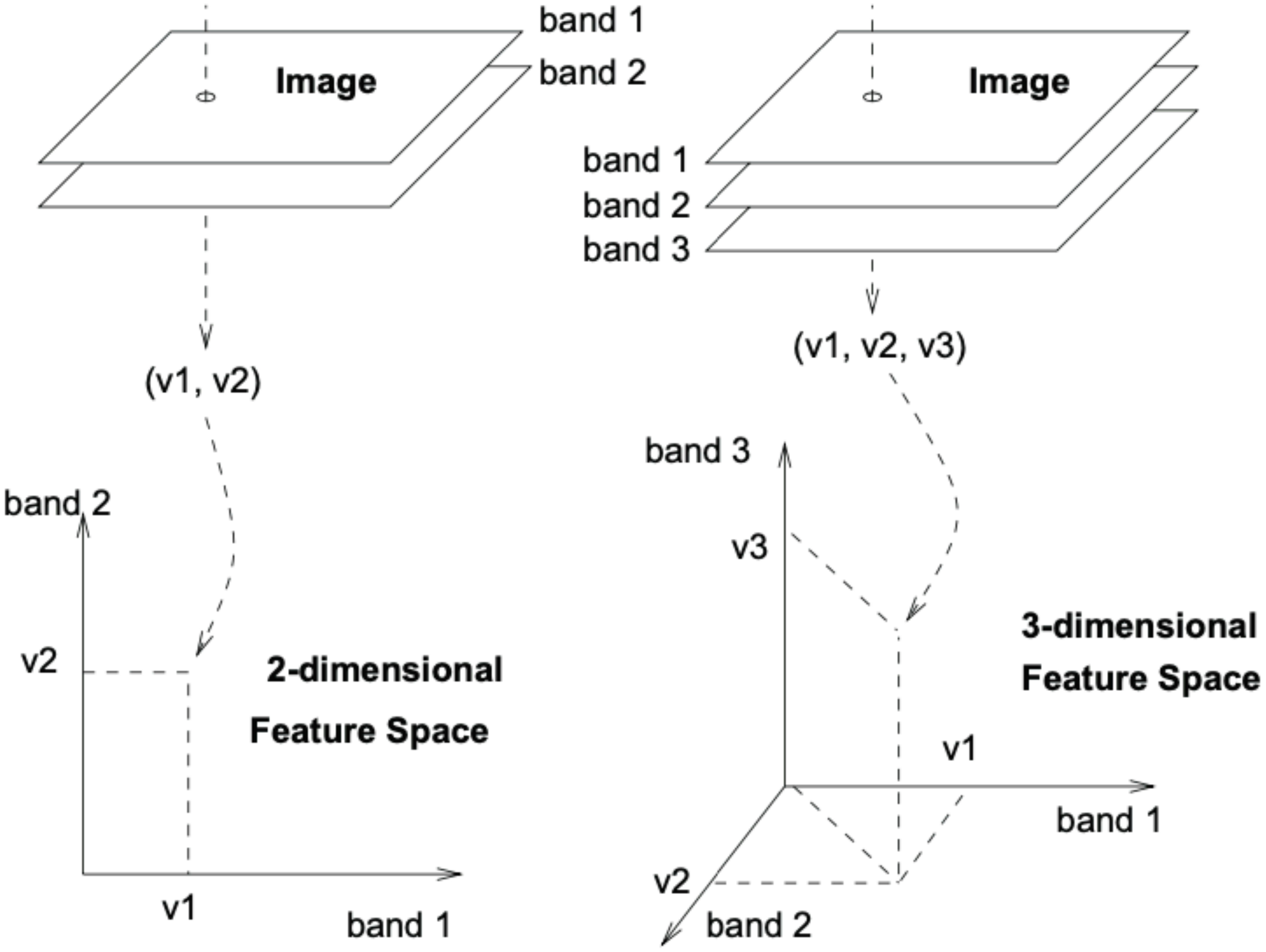


Image space



Sentinel-2 has 12 bands

Feature space



Feature space

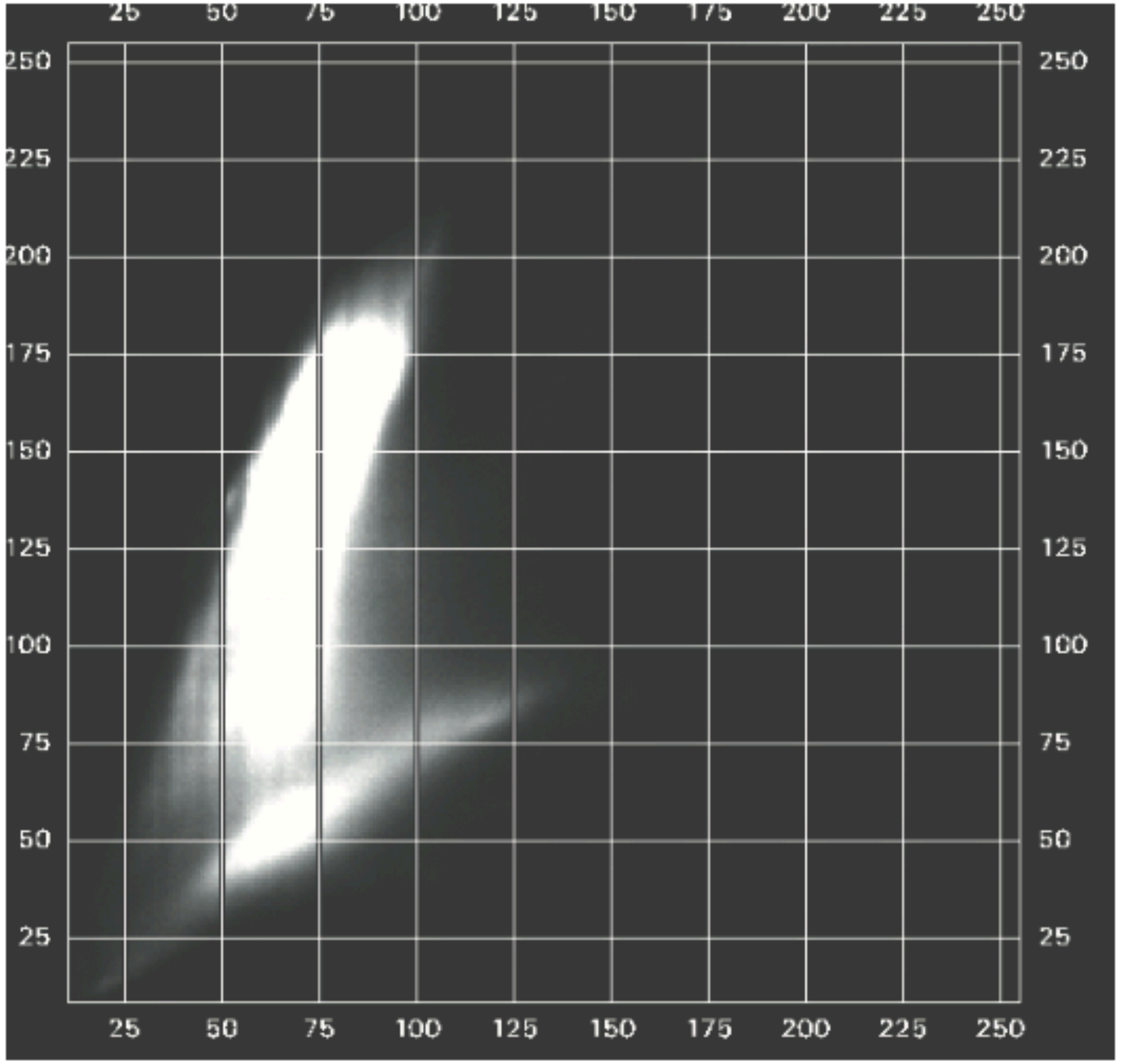
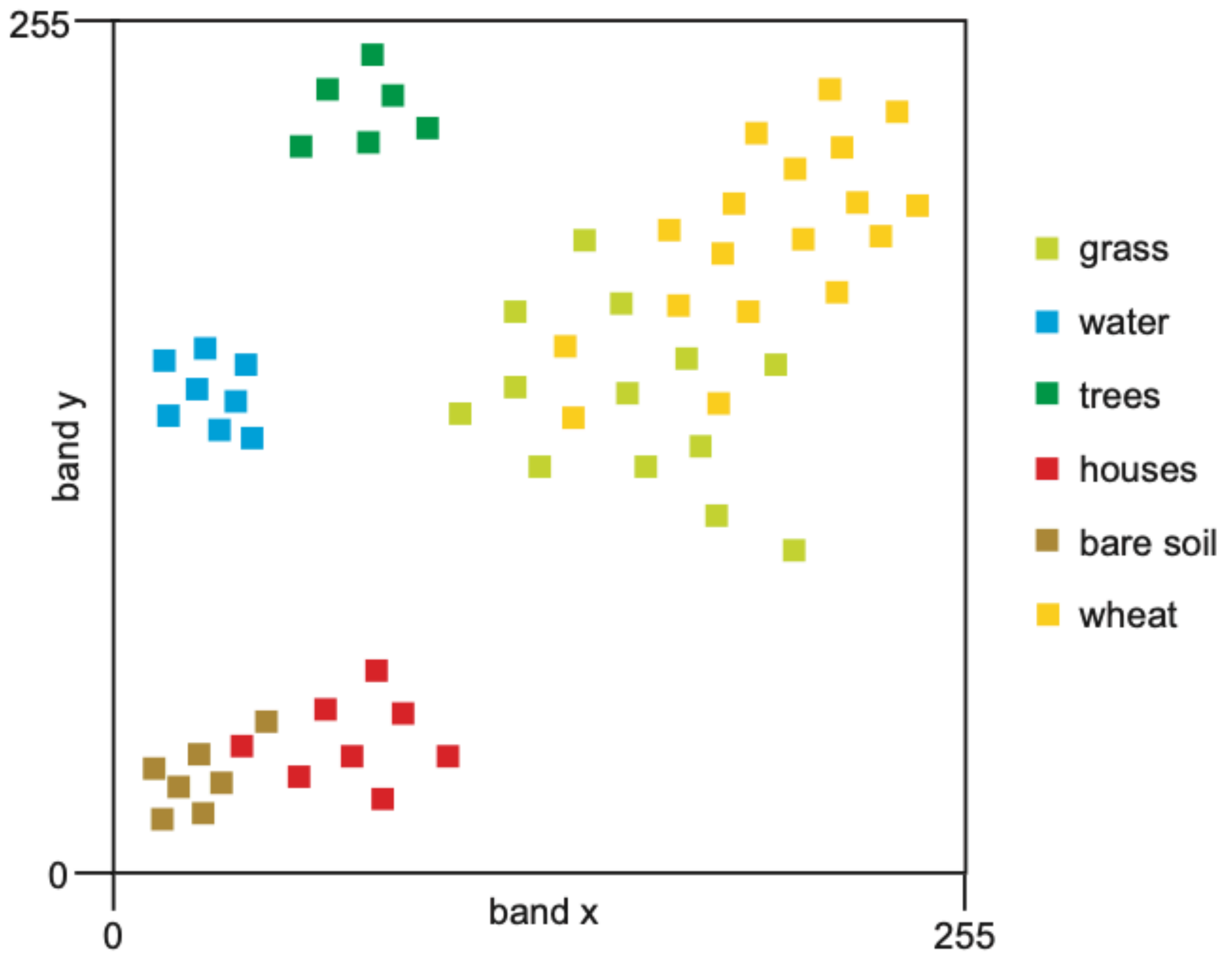


Figure 12.3: Scatterplot of two bands of a digital image. Note the units (DN-values) along the x- and y-axes. The intensity at a point in the feature space is related to the number of pixels at that point.

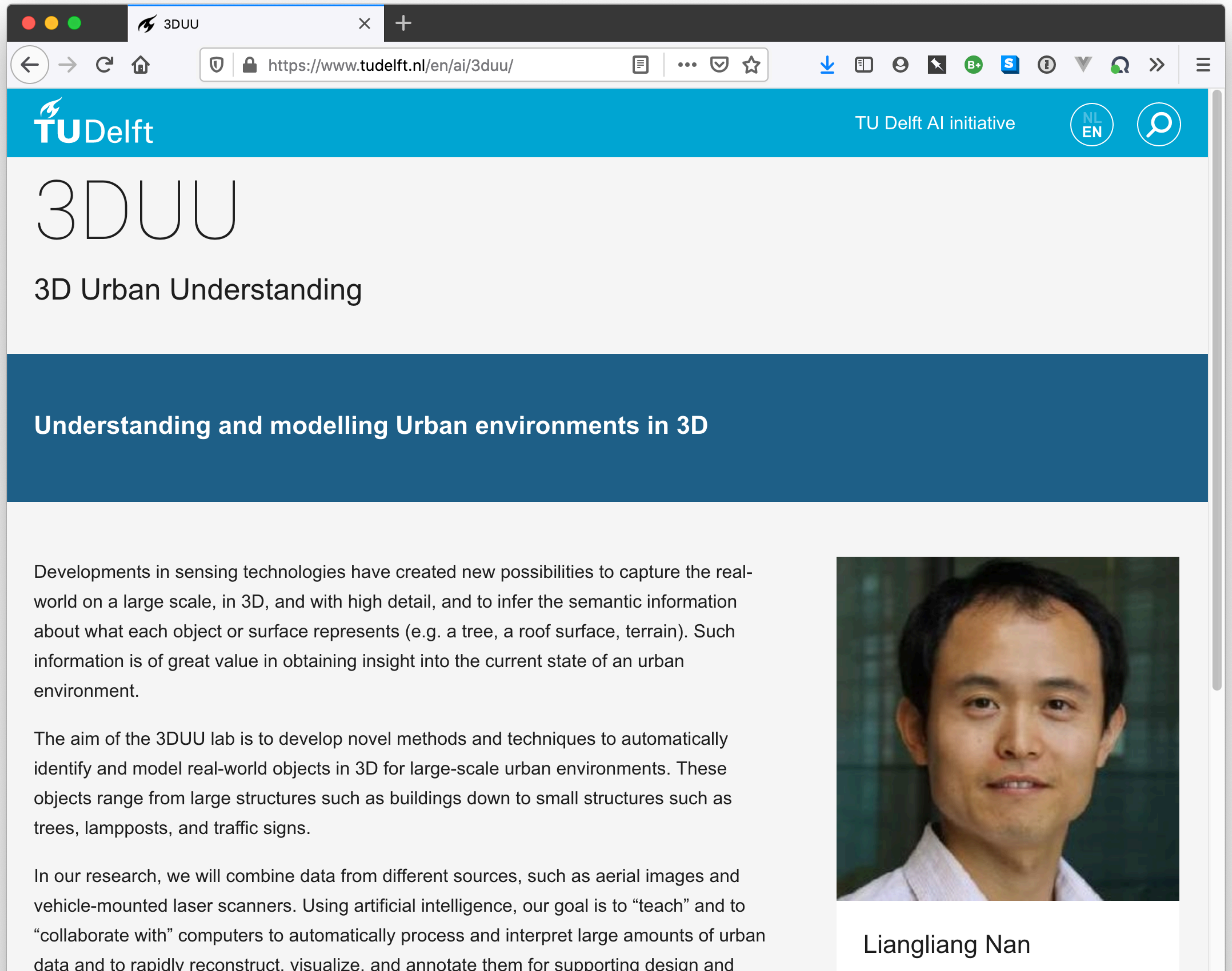
Image classification == clusters in feature space



Definition of the clusters is an interactive process and is carried out during the training process.

Machine learning (ML)

- extraction of knowledge from data
- a subset of artificial intelligence
- closely related to (computational) statistics
- builds a mathematical model based on sample data that contain both the inputs and the desired outputs (known as training data), in order to make predictions or decisions without being explicitly programmed to do so
- From September 2021 we should offer as new course as elective: *Machine learning for geomatics*



Machine learning (ML)

1. **Supervised learning**
2. **Unsupervised learning**

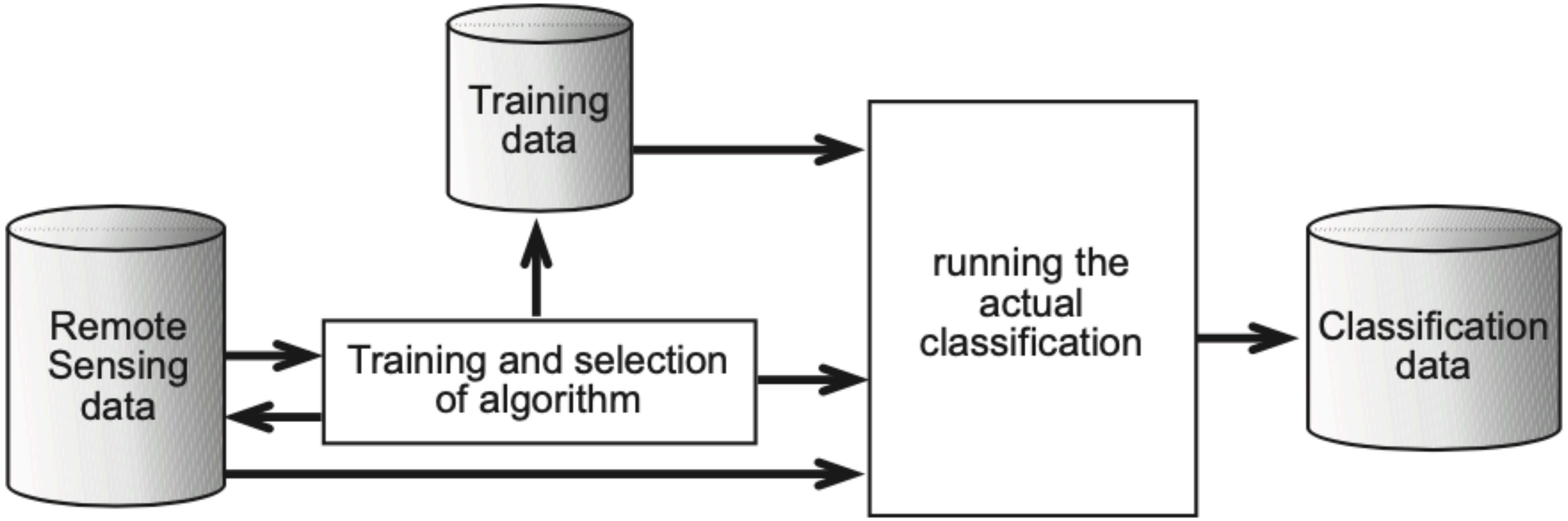
Definition of the clusters in the feature space

1. **supervised classification**:
   - the computer is presented with example inputs and their desired outputs, and the goal is to learn a general rule that maps inputs to outputs.
   - operator defines the clusters (the partitioning of the feature space) during the training process
   - done based on spectral characteristics of the classes, by identifying sample areas (training areas)
   - requires that the operator knows the area, or that there is a *ground truth*
   - *a* subset of the image can be used as training pixels
   - A popular method would be “Random Forest”

Definition of the clusters in the feature space

2. **unsupervised classification**
   - no labels (no “outputs”, no category, just the input) are given to the learning algorithm, leaving it on its own to find structure in its input.
   - can be a goal in itself (discovering hidden patterns in data) or a means towards an end (feature learning).
   - used if no knowledge of area (ground truth) or if the classes of interest are not yet defined
   - clustering algorithms are used to partition the feature space into a number of clusters.
   - number of cluster can be pre-defined or automatically extracted

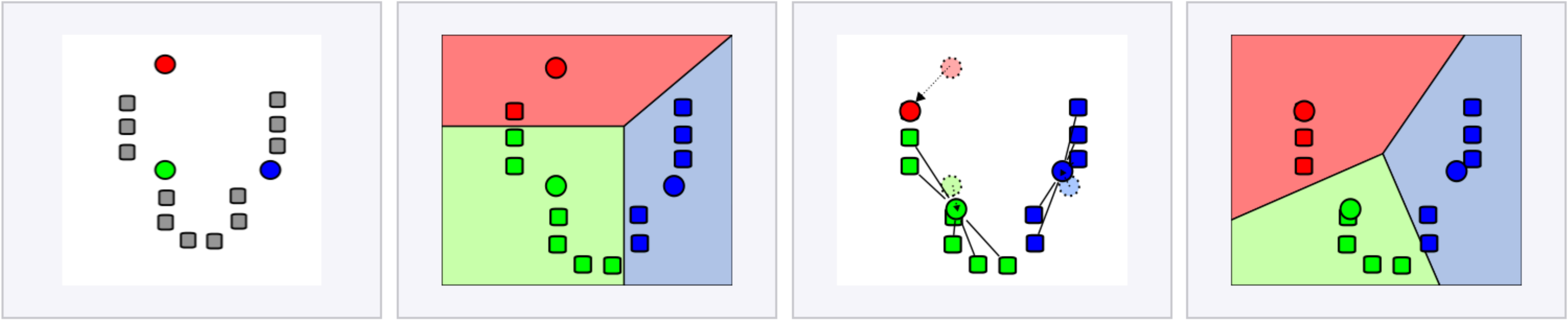
Classification process



k-means clustering

- Our book calls it *minimum distance to mean classifier* (p.201)
- aims to partition *n* observations into *k* clusters in which each observation belongs to the cluster with the nearest mean (cluster centroid/centre)
- Operator needs to define maximum number of clusters

Demonstration of the standard algorithm



1. *k* initial "means" (in this case *k*=3) are randomly generated within the data domain (shown in color).

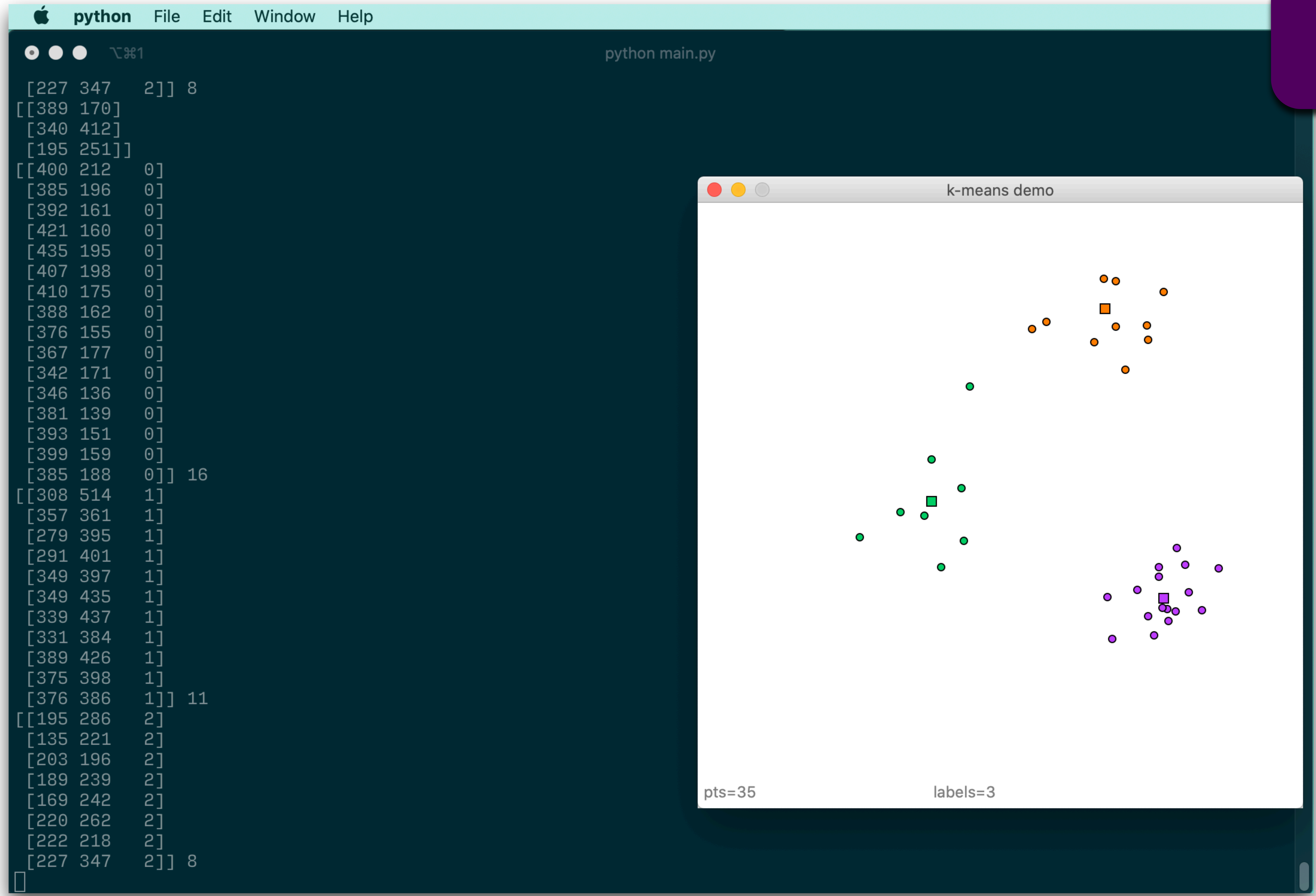
2. *k* clusters are created by associating every observation with the nearest mean. The partitions here represent the Voronoi diagram generated by the means.

3. The centroid of each of the *k* clusters becomes the new mean.

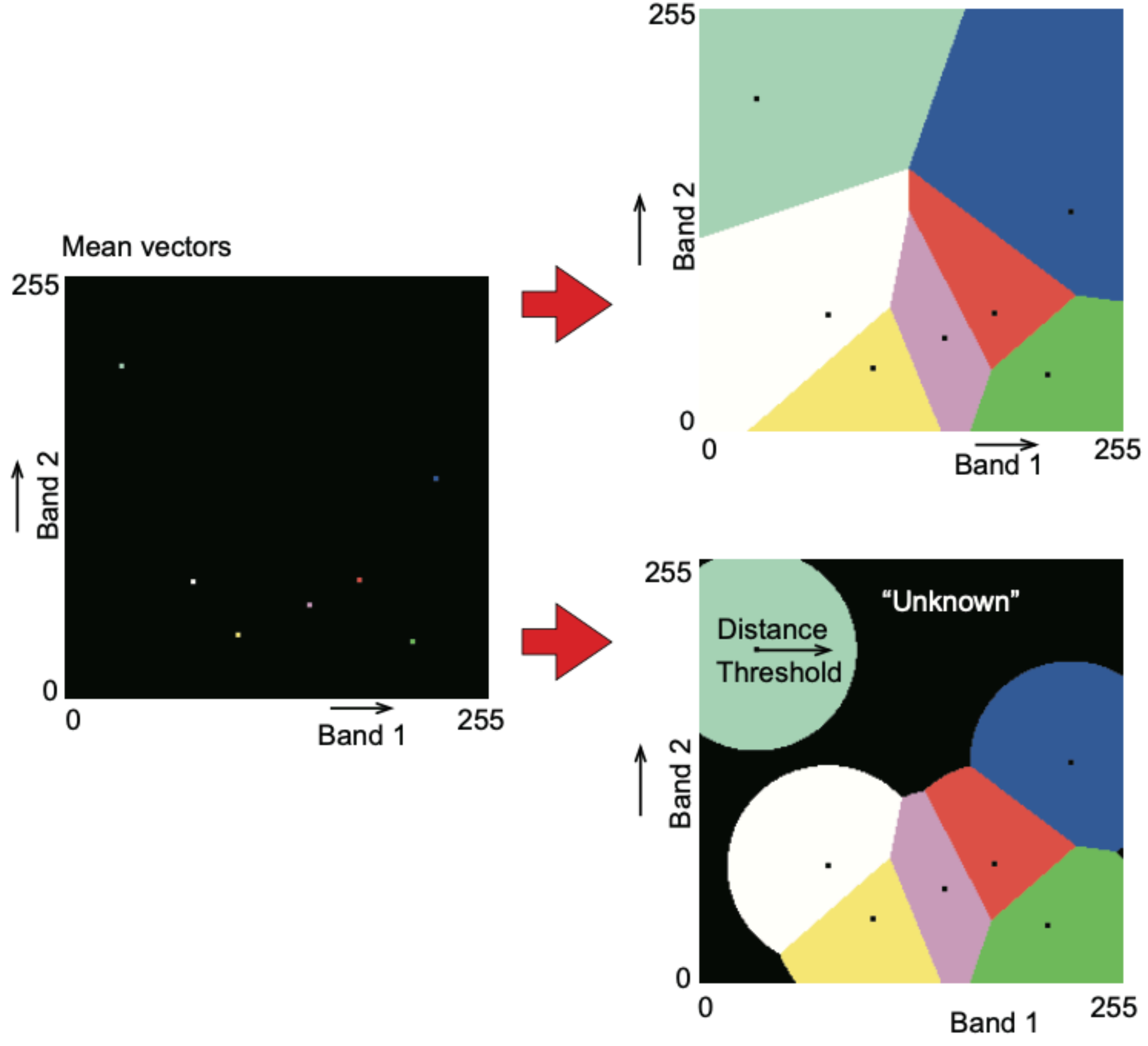
4. Steps 2 and 3 are repeated until convergence has been reached.

https://en.wikipedia.org/wiki/K-means_clustering

Small Python program to help



Code in GitLab repo “lectureB3”

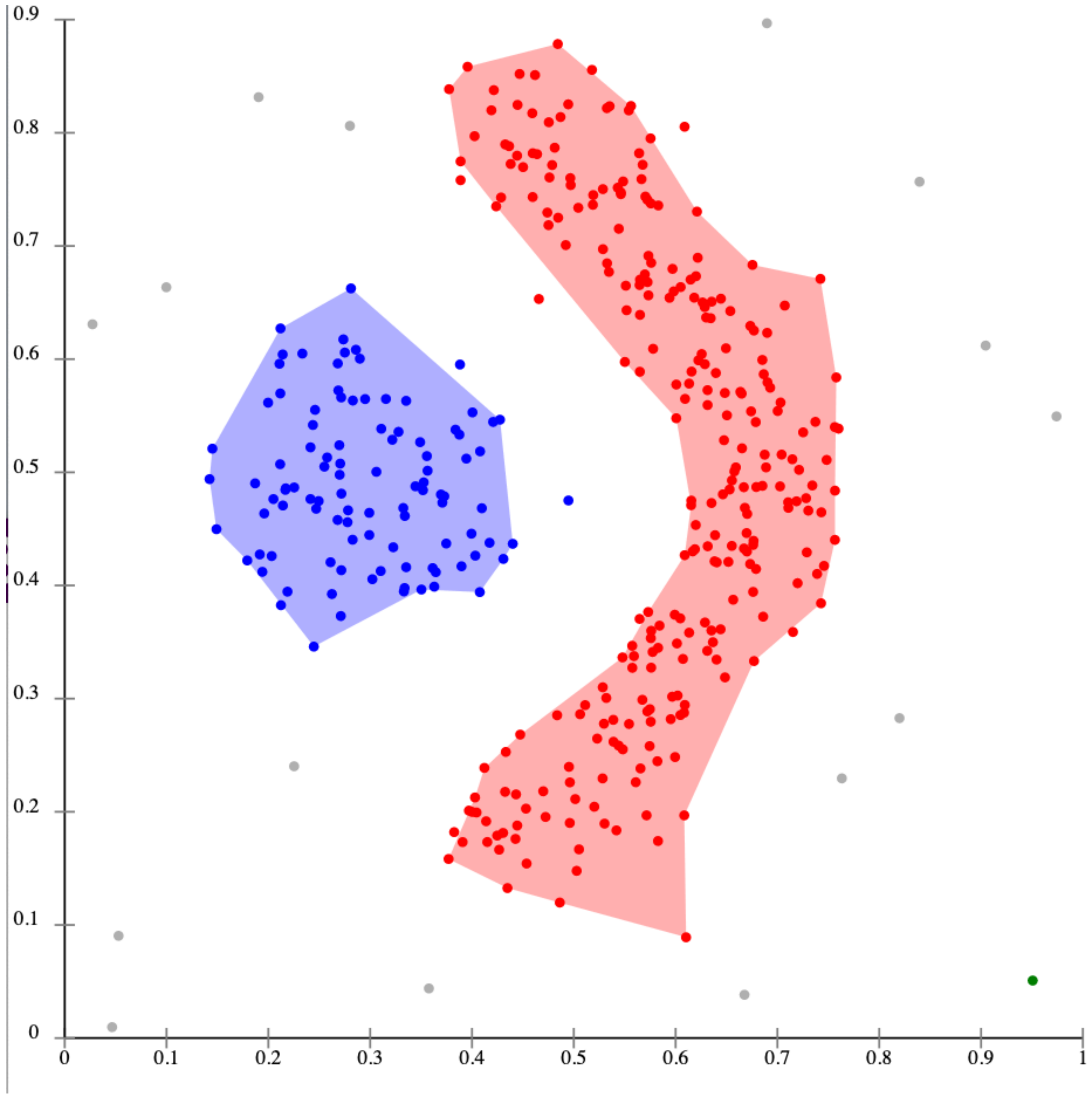


Mean vectors
255
0
Band 2
0
255
Band 1
255
0
Band 2
0
Band 1
255
255
"Unknown"
Distance
Threshold
0
Band 2
0
Band 1
255

Density-based spatial clustering of applications with noise (DBSCAN)

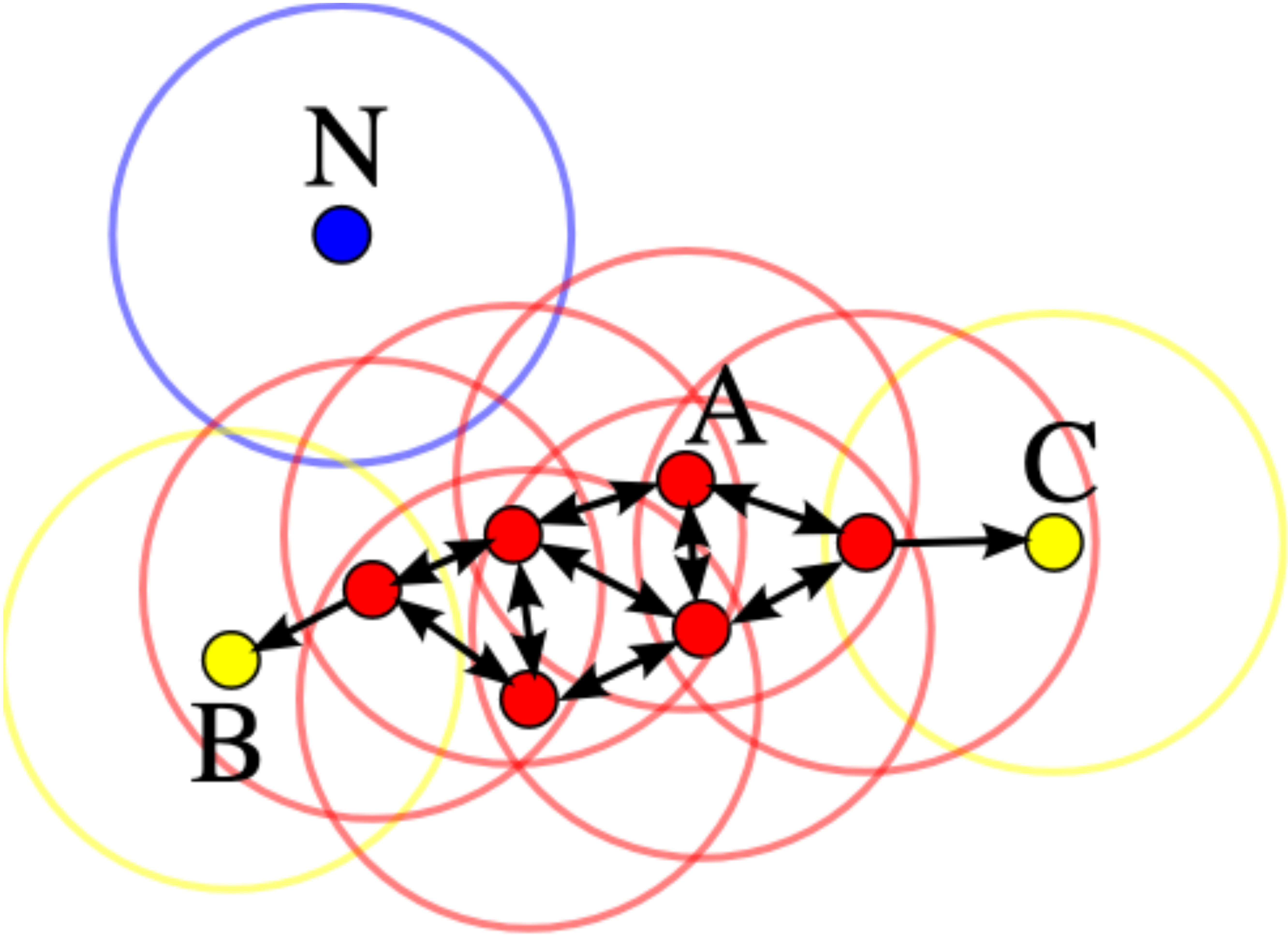
- 👍 No need to specify number of clusters
- 👍 Adapts to arbitrarily-shaped clusters
- 👍 Noise is considered (and output has *outliers*)

- 👎 Parameters must be defined (tricky in practice)

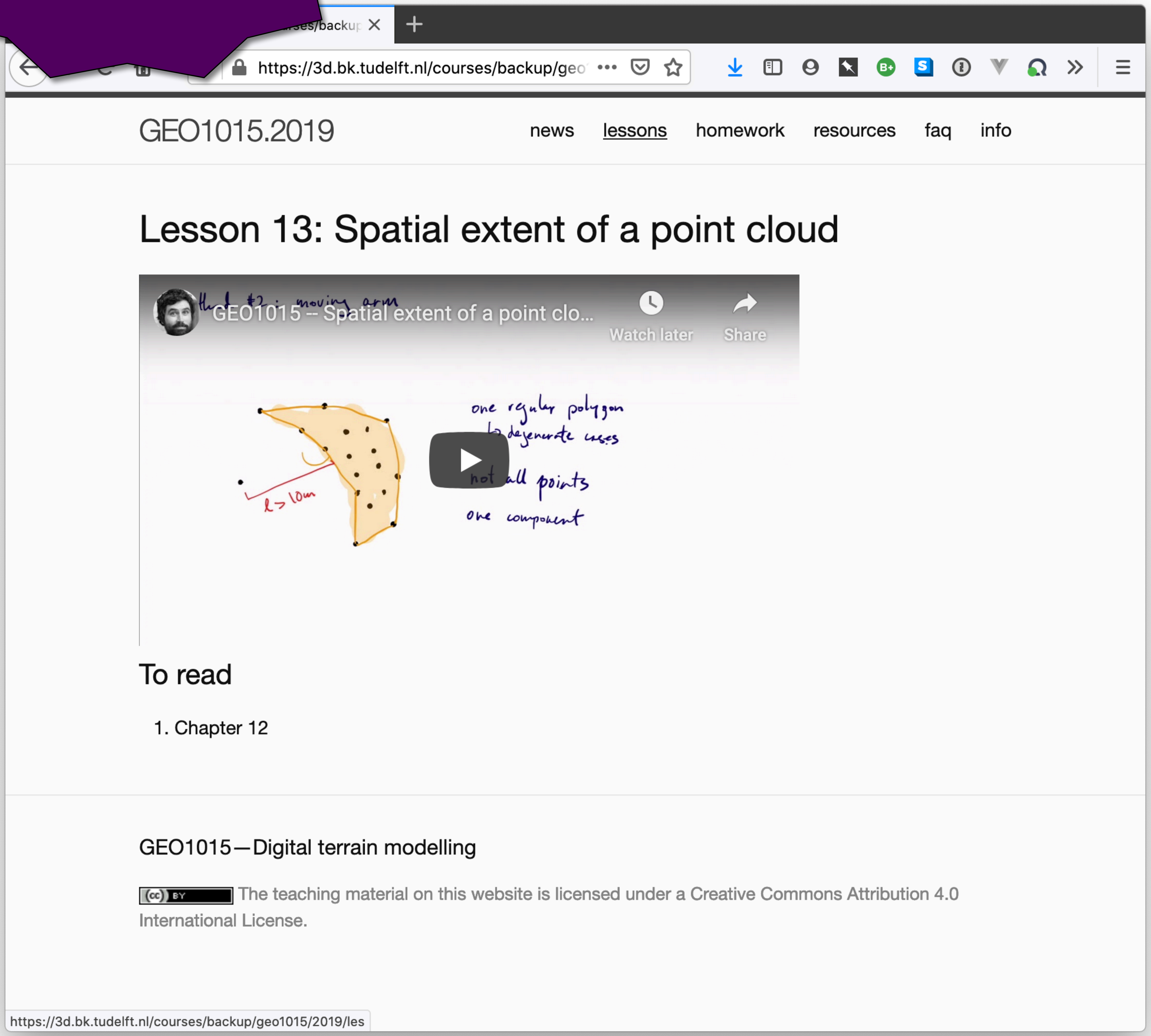


https://en.wikipedia.org/wiki/DBSCAN

Density-based spatial clustering of applications with noise (DBSCAN)



One lesson in GEO1015


https://3d.bk.tudelft.nl/courses/backup/geo

GEO1015.2019

news lessons homework resources faq info

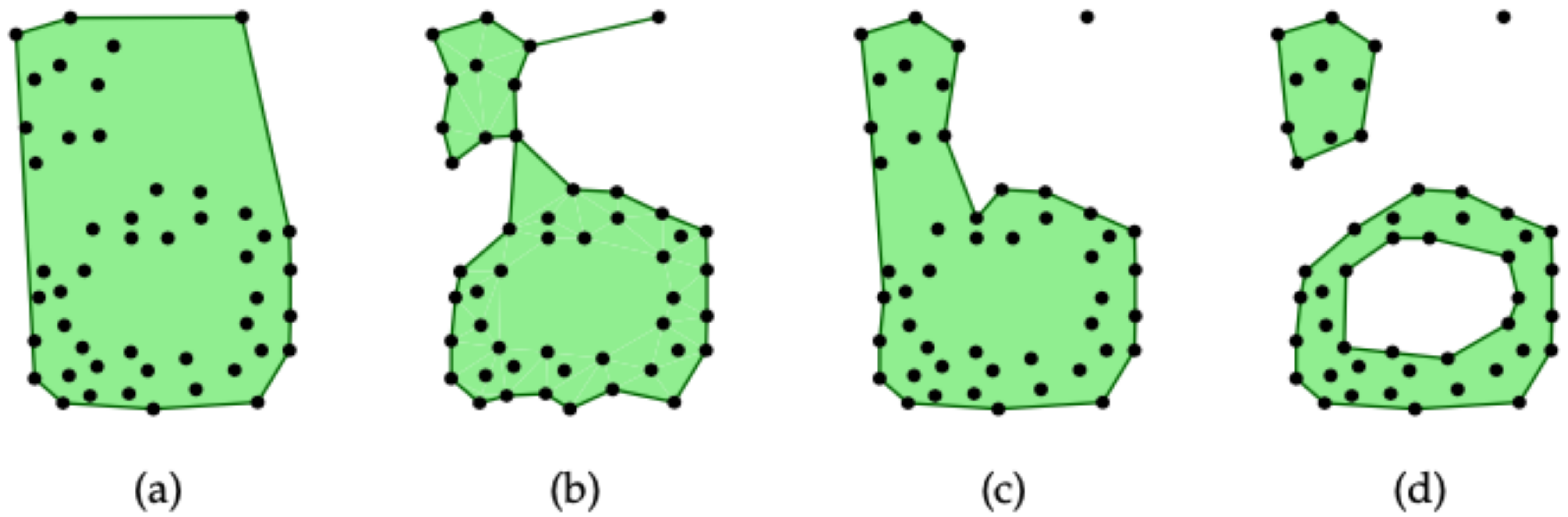
Lesson 13: Spatial extent of a point cloud

To read

1. Chapter 12

GEO1015—Digital terrain modelling

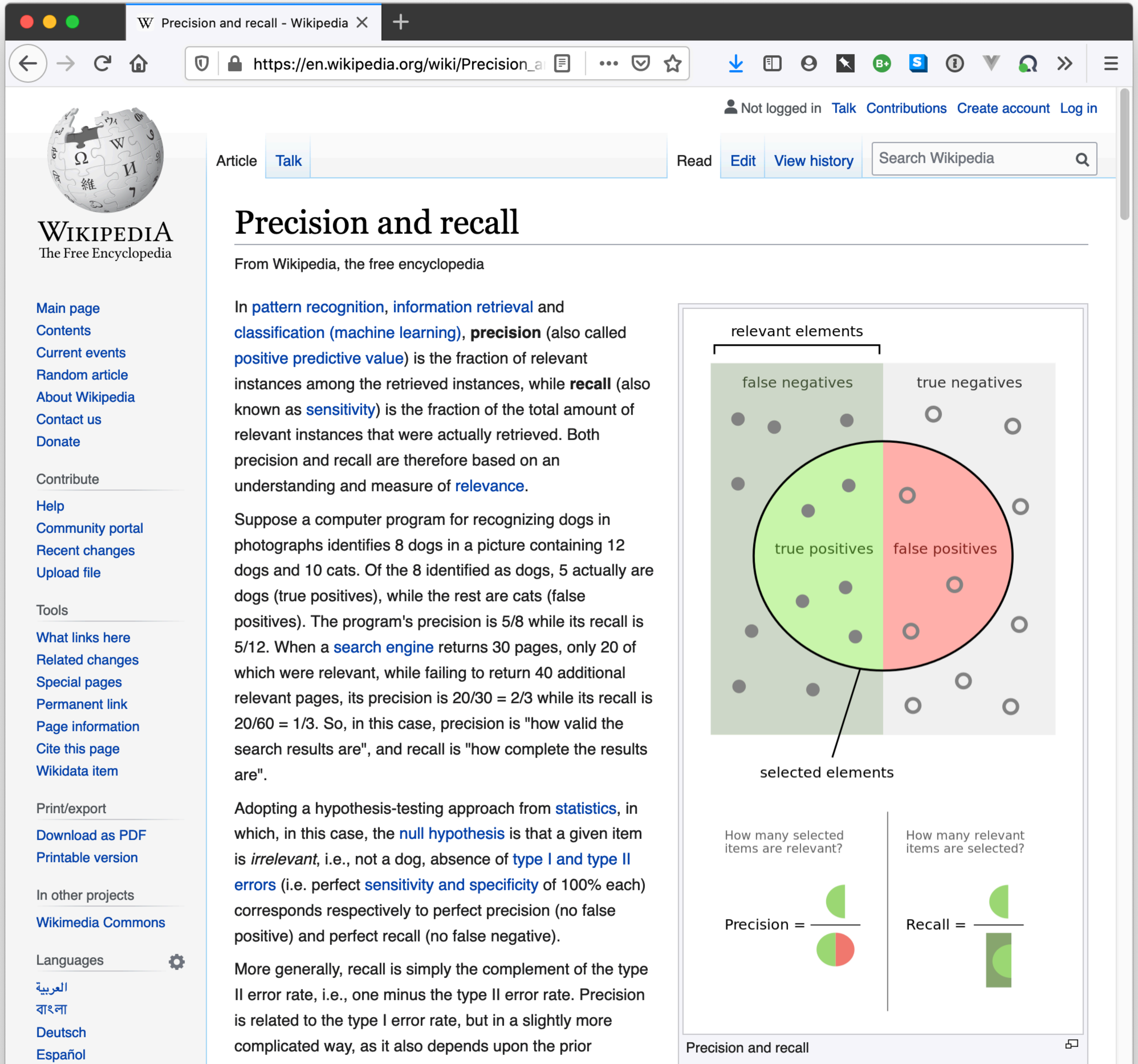
https://3d.bk.tudelft.nl/courses/backup/geo1015/2019/les



Validation of the results: error matrix

	A	B	C	D	Total	Error of Commission (%)	User Accuracy (%)
a	35	14	11	1	61	43	57
b	4	11	3	0	18	39	61
c	12	9	38	4	63	40	60
d	2	5	12	2	21	90	10
Total	53	39	64	7	163		
Error of Omission	34	72	41	71			
Producer Accuracy	66	28	59	29			

Validation of the results: in ML we speak more of "precision" and "recall"



Precision and recall - Wikipedia

https://en.wikipedia.org/wiki/Precision_a

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Precision and recall

From Wikipedia, the free encyclopedia

In pattern recognition, information retrieval and classification (machine learning), **precision** (also called positive predictive value) is the fraction of relevant instances among the retrieved instances, while **recall** (also known as sensitivity) is the fraction of the total amount of relevant instances that were actually retrieved. Both precision and recall are therefore based on an understanding and measure of relevance.

Suppose a computer program for recognizing dogs in photographs identifies 8 dogs in a picture containing 12 dogs and 10 cats. Of the 8 identified as dogs, 5 actually are dogs (true positives), while the rest are cats (false positives). The program's precision is 5/8 while its recall is 5/12. When a search engine returns 30 pages, only 20 of which were relevant, while failing to return 40 additional relevant pages, its precision is 20/30 = 2/3 while its recall is 20/60 = 1/3. So, in this case, precision is "how valid the search results are", and recall is "how complete the results are".

Adopting a hypothesis-testing approach from statistics, in which, in this case, the null hypothesis is that a given item is *irrelevant*, i.e., not a dog, absence of type I and type II errors (i.e. perfect sensitivity and specificity of 100% each) corresponds respectively to perfect precision (no false positive) and perfect recall (no false negative).

More generally, recall is simply the complement of the type II error rate, i.e., one minus the type II error rate. Precision is related to the type I error rate, but in a slightly more complicated way, as it also depends upon the prior

Precision and recall

Precision =
positive predictive value

Recall =
sensitivity

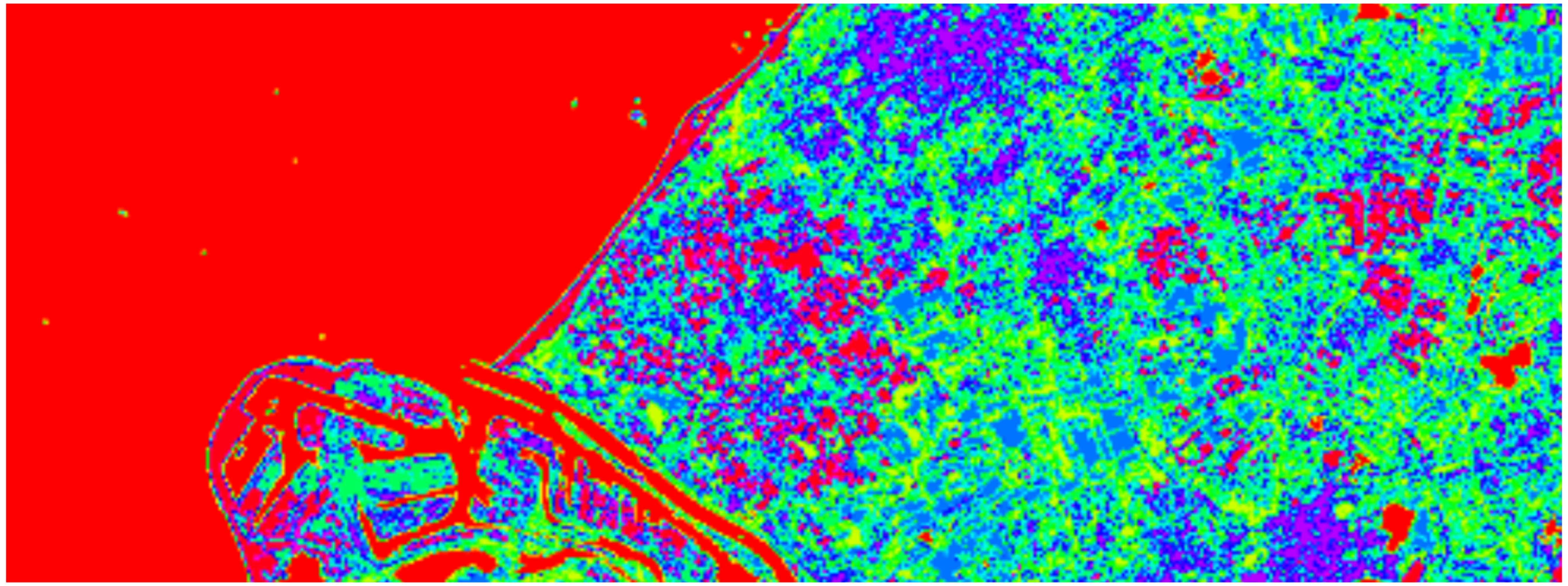
Assignment 02

Classification of a Sentinel-2 image

Deadline is **6 October 2020 at 10:00**.

Late submission? 10% will be removed for each day that you are late.

You're allowed for this assignment to work in a **group of 2** (and thus submit only one solution for both of you). You are free to form a group yourself; if you're looking for a partner let me know (Hugo), or let others know on Discord. If you prefer to work alone it's also fine.



https://3d.bk.tudelft.nl/courses/geo1001/