

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)

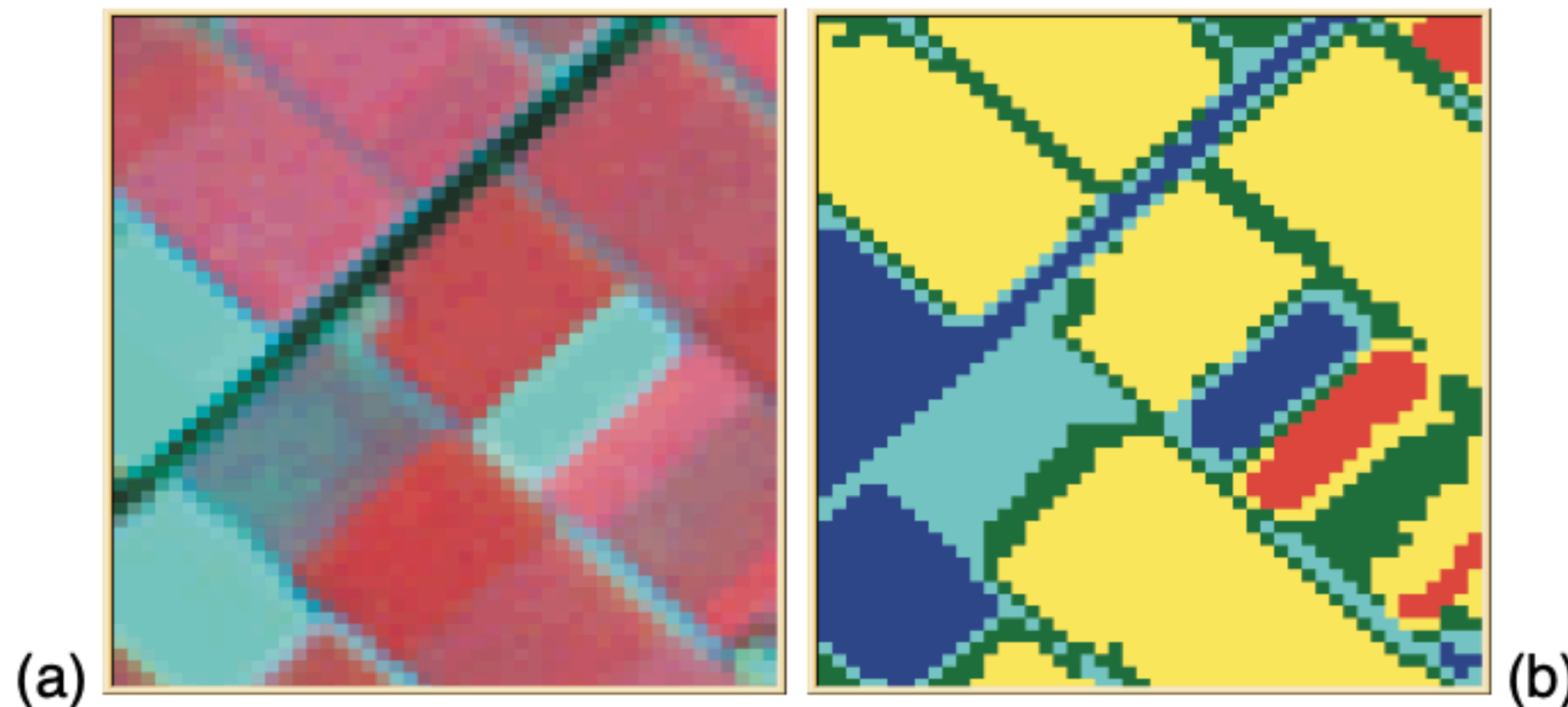


Figure 12.7: The result of classification of a multispectral image (a) is a raster in which each cell is assigned to some thematic class (b).

From satellite images to GIS polygons (land cover polygons)

The screenshot shows the Copernicus Land Monitoring Service website. The main content area displays a map of the Netherlands with land cover polygons in various colors (red, yellow, green, blue). The map is titled "CLC 2018" and includes a legend, metadata, and download options. The website header features the Copernicus logo and navigation links for Global, Pan-European, and Local services. A "User corner" sidebar on the right provides links to "How to access our data", "Technical library", "Factsheets", and "Use cases".

The screenshot shows the OpenStreetMap Wiki page for Corine Land Cover. The page title is "Technical parameters of Corine Land Cover". It lists several technical parameters:

- 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"

The page also includes a "Tagging" section with a table detailing the suggested tag conversion during import. The table has three columns: Code, Description, and Comment.

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

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

From satellite images to GIS polygons (land cover polygons)

CLC 2018

Print

Map View

Metadata

Download

Legend

Web services

CLC2018_WM

Corine Land Cover 2018 vector

- 111: Continuous urban fabric
- 112: Discontinuous urban fabric
- 121: Industrial or commercial units
- 122: Road and rail networks and associated land
- 123: Port areas
- 124: Airports
- 131: Mineral extraction sites
- 132: Dump sites
- 133: Construction sites
- 141: Green urban areas
- 142: Sport and leisure facilities
- 211: Non-irrigated arable land

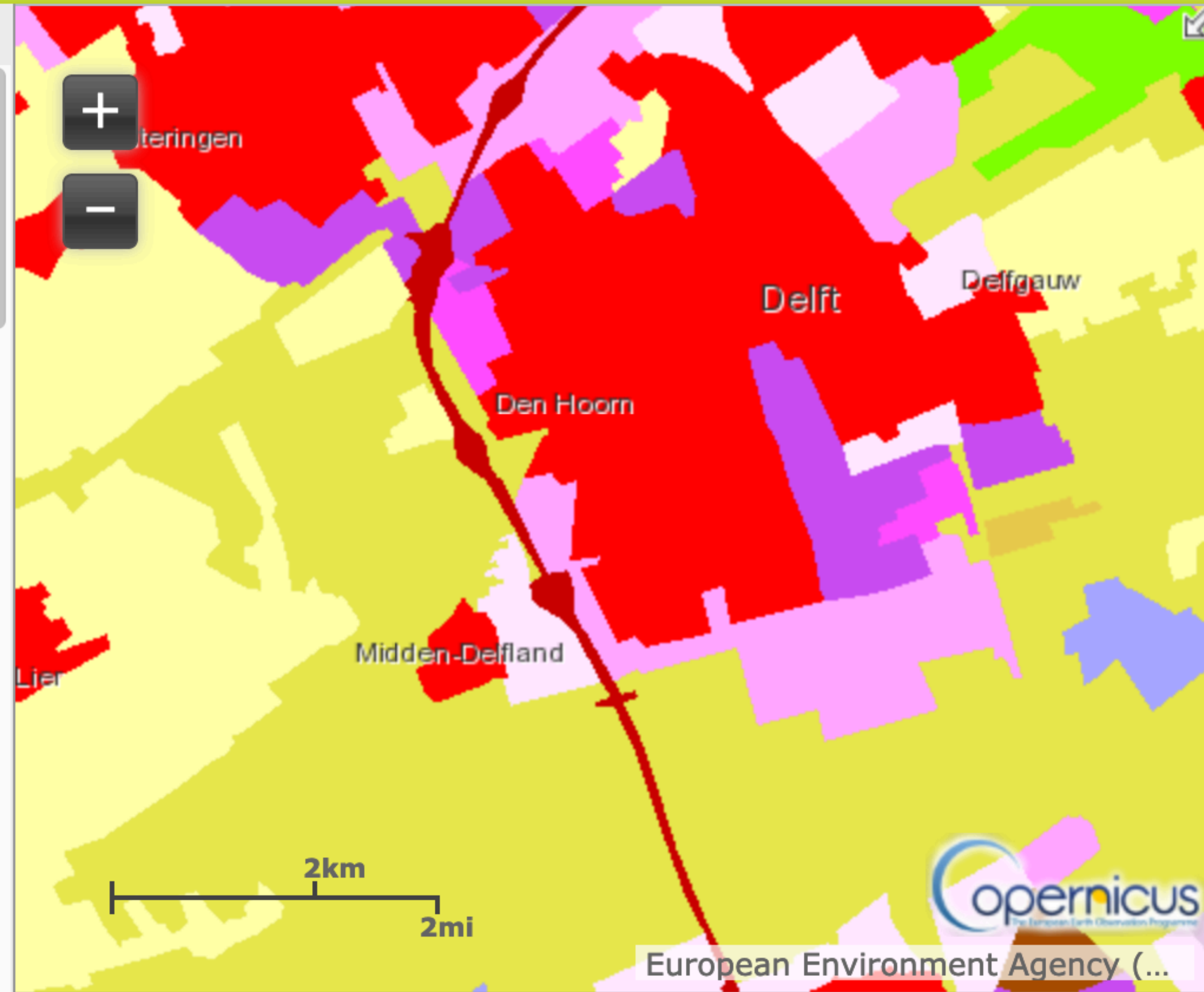


Image classification == differences in spectral signatures

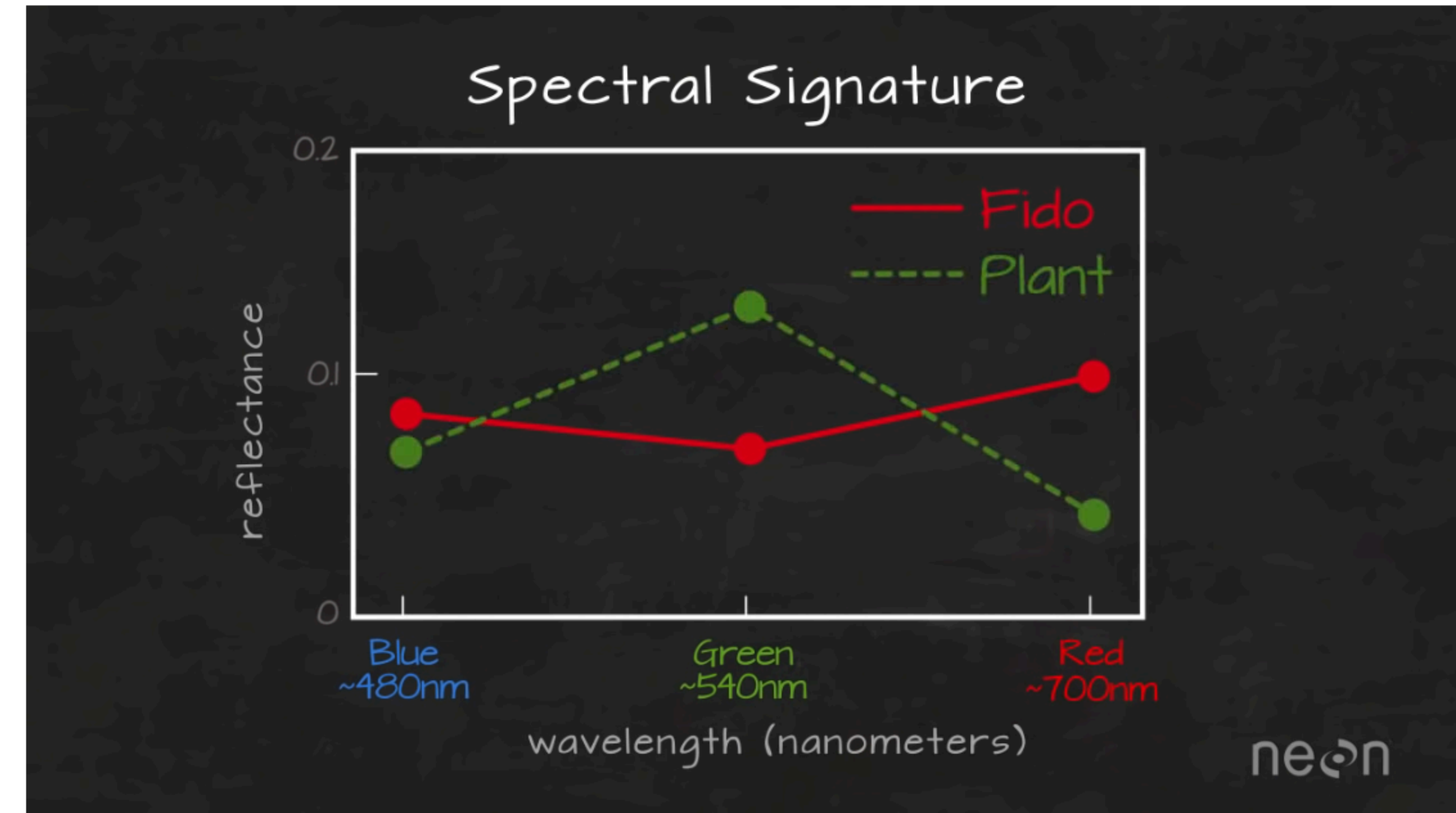
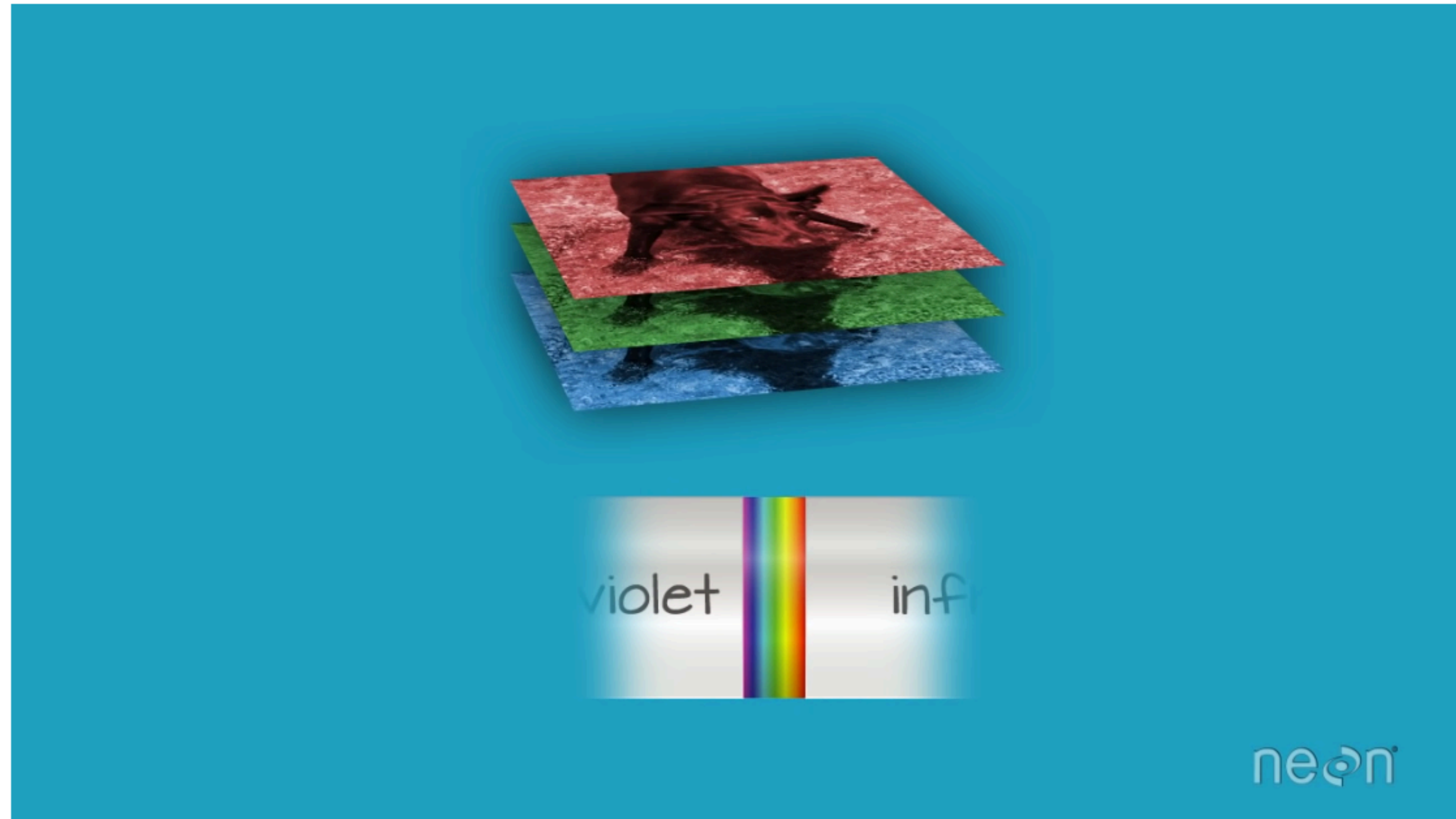
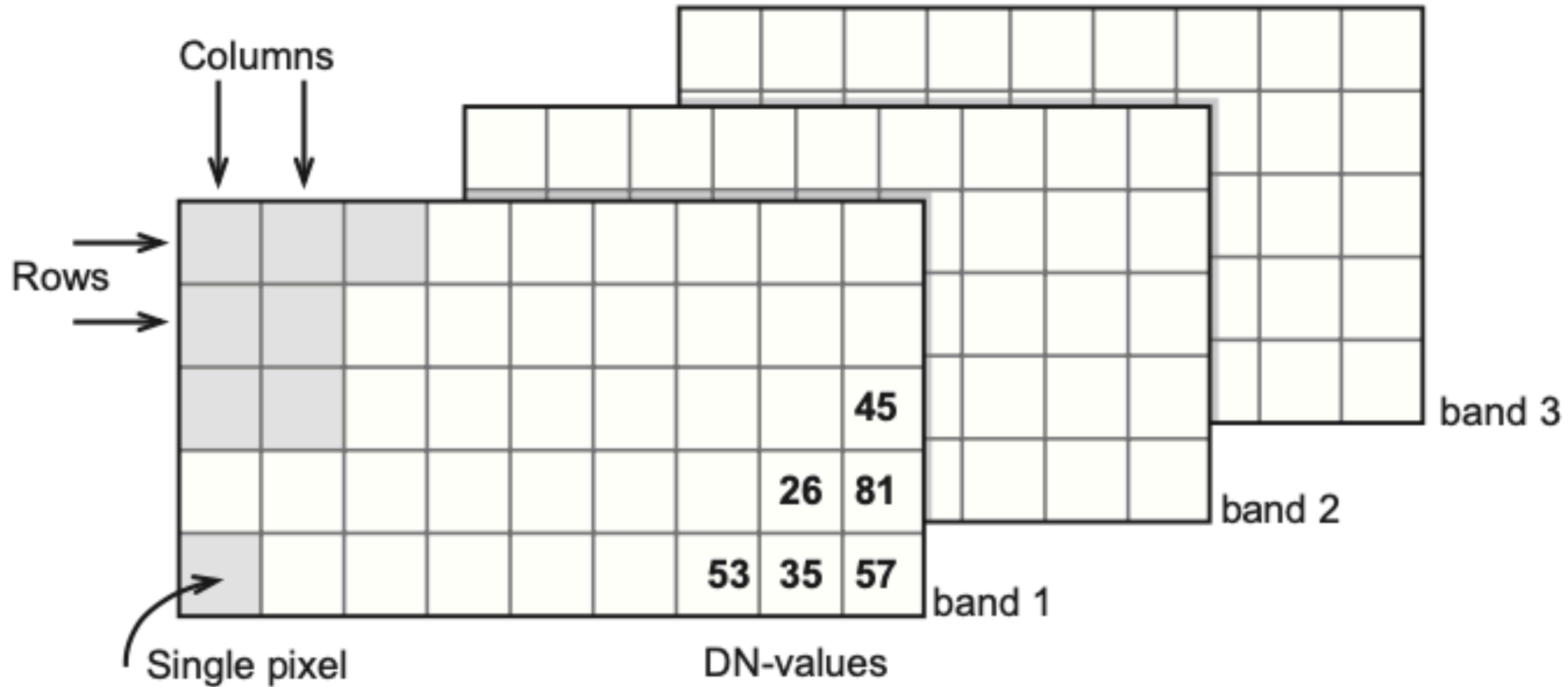
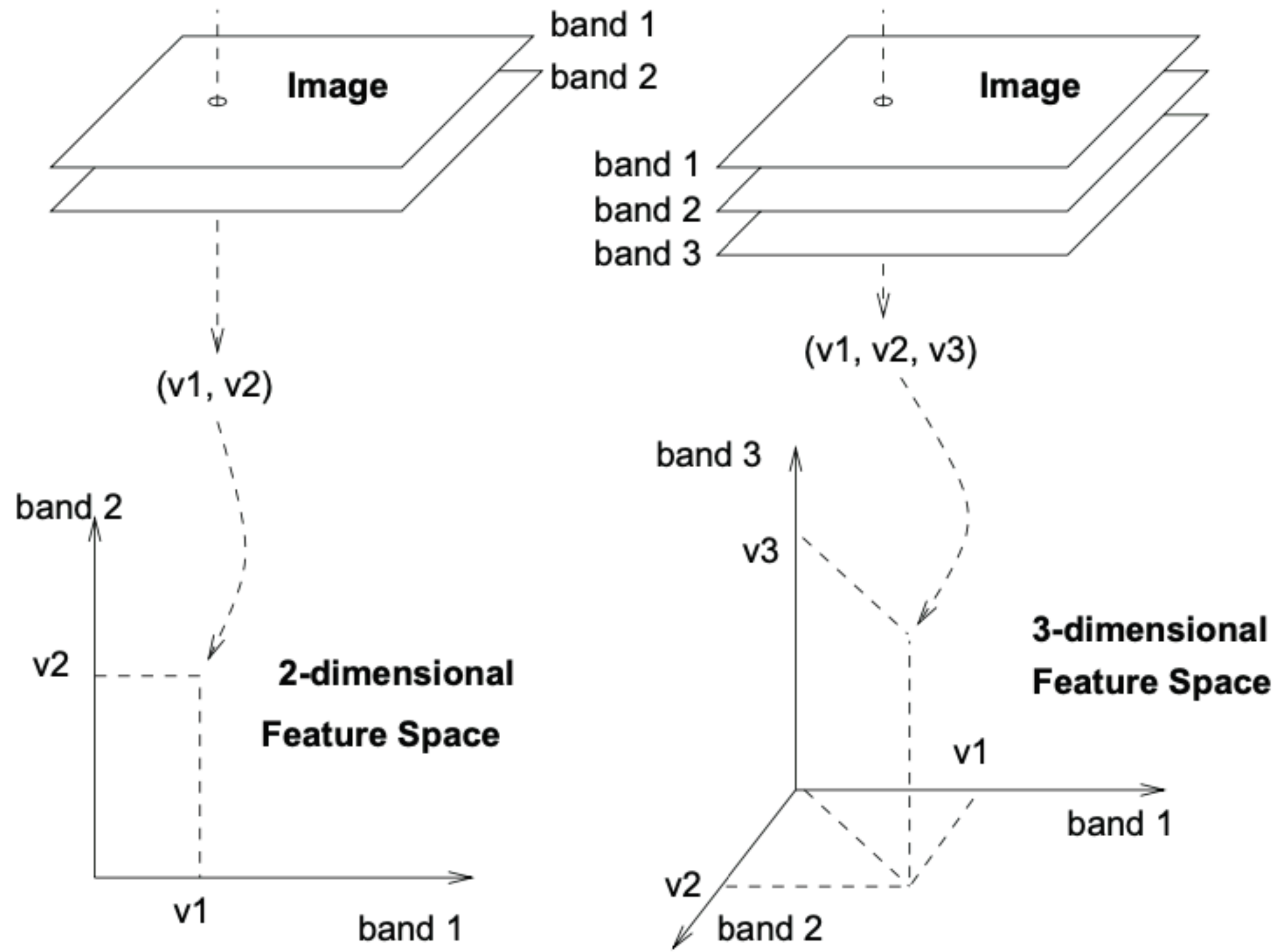


Image space



Sentinel-2 has 12 bands

Feature space



Feature space

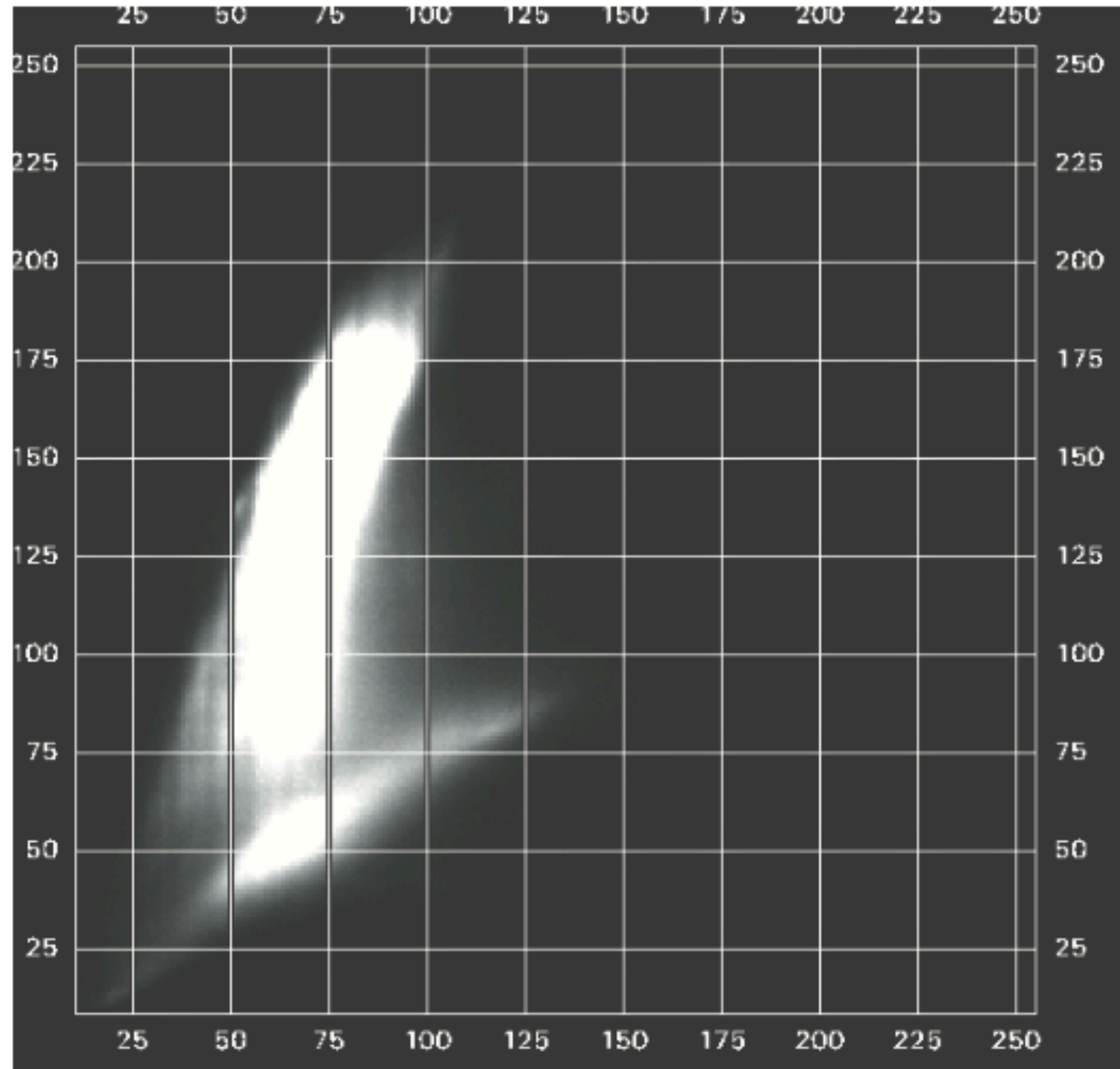
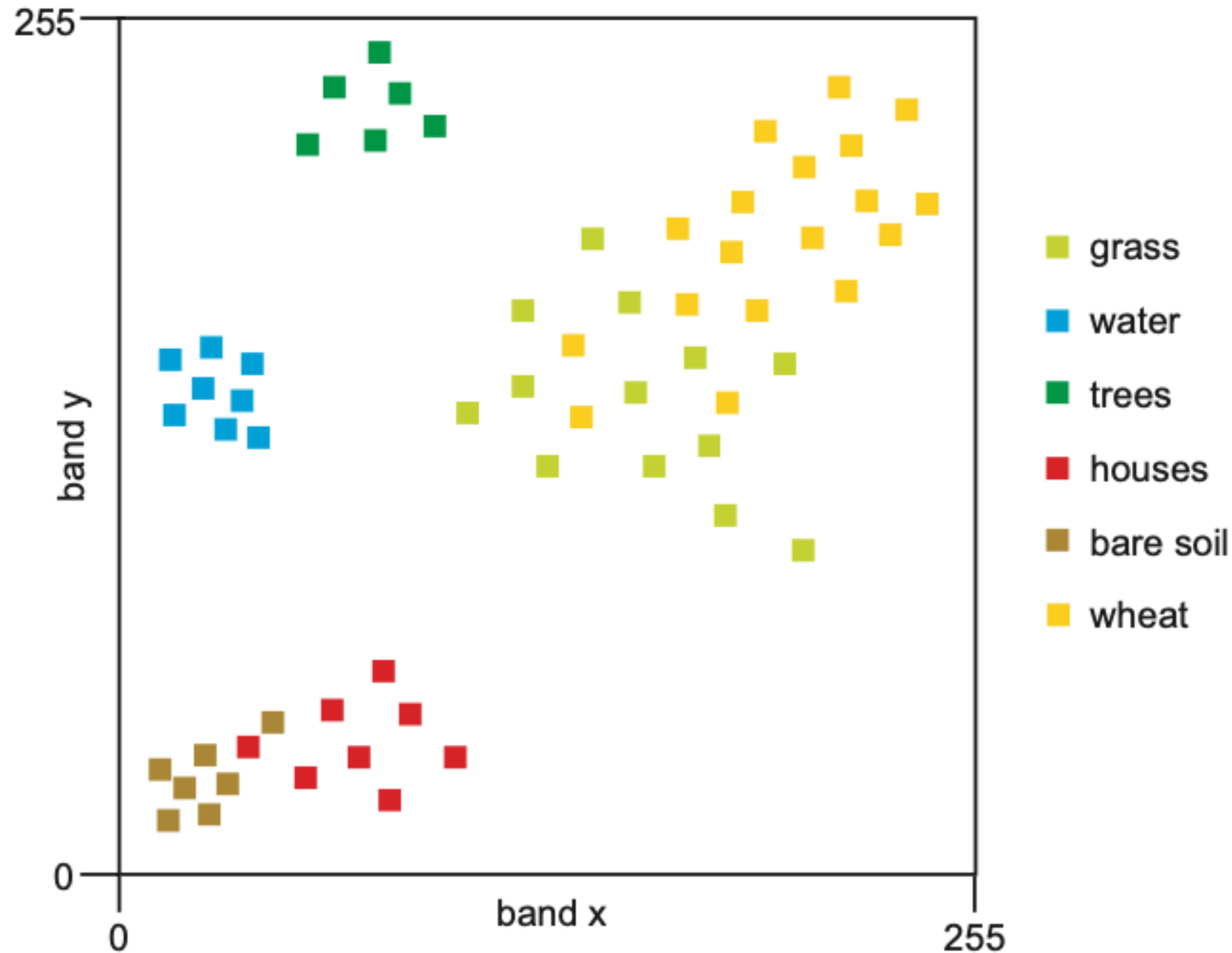


Figure 12.3: Scatterplot of two bands of a digital image. Note the units (DN-values) along the x - and y -axes. The intensity at a point in the feature space is related to the number of pixels at that point.

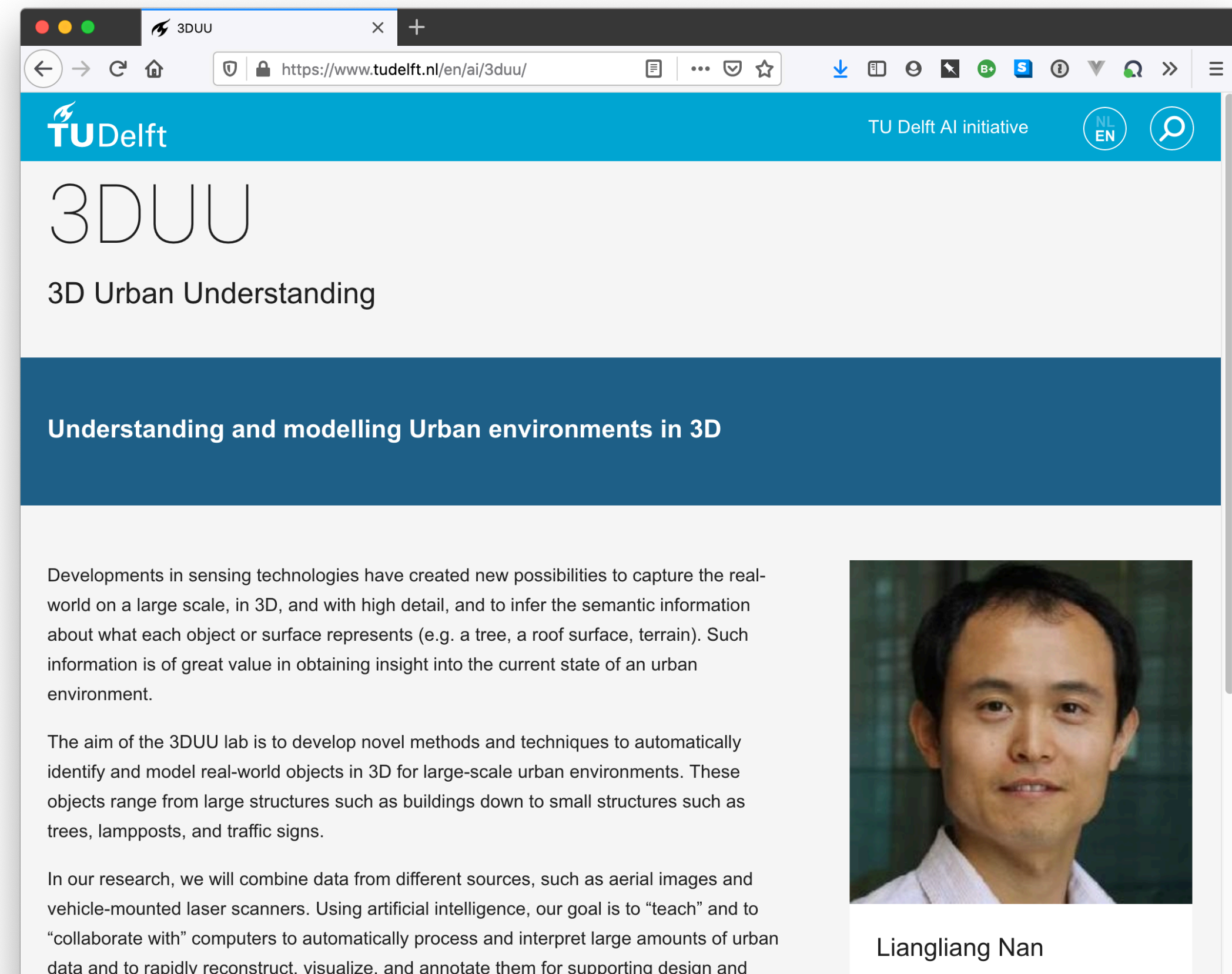
Image classification == clusters in feature space



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*

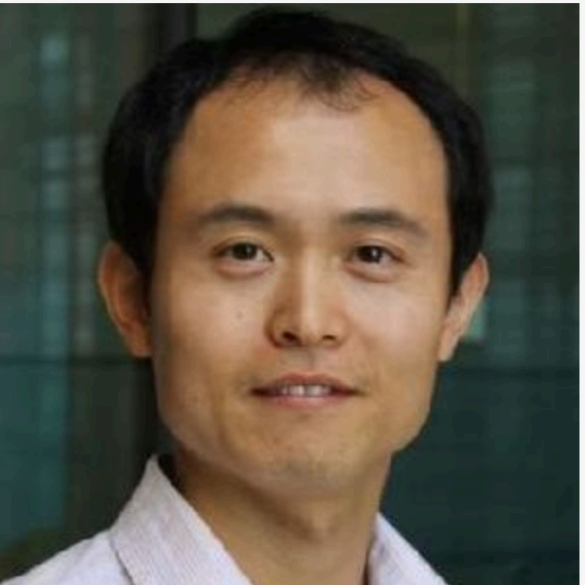


The screenshot shows a web browser window displaying the TU Delft website for the 3DUU (3D Urban Understanding) initiative. The browser's address bar shows the URL <https://www.tudelft.nl/en/ai/3duu/>. The page features the TU Delft logo and the text "TU Delft AI initiative" in the top right corner. The main heading is "3DUU" with the subtitle "3D Urban Understanding". Below this, a dark blue banner contains the text "Understanding and modelling Urban environments in 3D". The main content area includes a paragraph about sensing technologies, a paragraph about the 3DUU lab's aim, and a paragraph about research methods. A portrait of Liangliang Nan is shown on the right side of the page.

Developments in sensing technologies have created new possibilities to capture the real-world on a large scale, in 3D, and with high detail, and to infer the semantic information about what each object or surface represents (e.g. a tree, a roof surface, terrain). Such information is of great value in obtaining insight into the current state of an urban environment.

The aim of the 3DUU lab is to develop novel methods and techniques to automatically identify and model real-world objects in 3D for large-scale urban environments. These objects range from large structures such as buildings down to small structures such as trees, lampposts, and traffic signs.

In our research, we will combine data from different sources, such as aerial images and vehicle-mounted laser scanners. Using artificial intelligence, our goal is to “teach” and to “collaborate with” computers to automatically process and interpret large amounts of urban data and to rapidly reconstruct, visualize, and annotate them for supporting design and



Liangliang Nan

Machine learning (ML)

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

Definition of the clusters in the feature space

1. **supervised classification:**

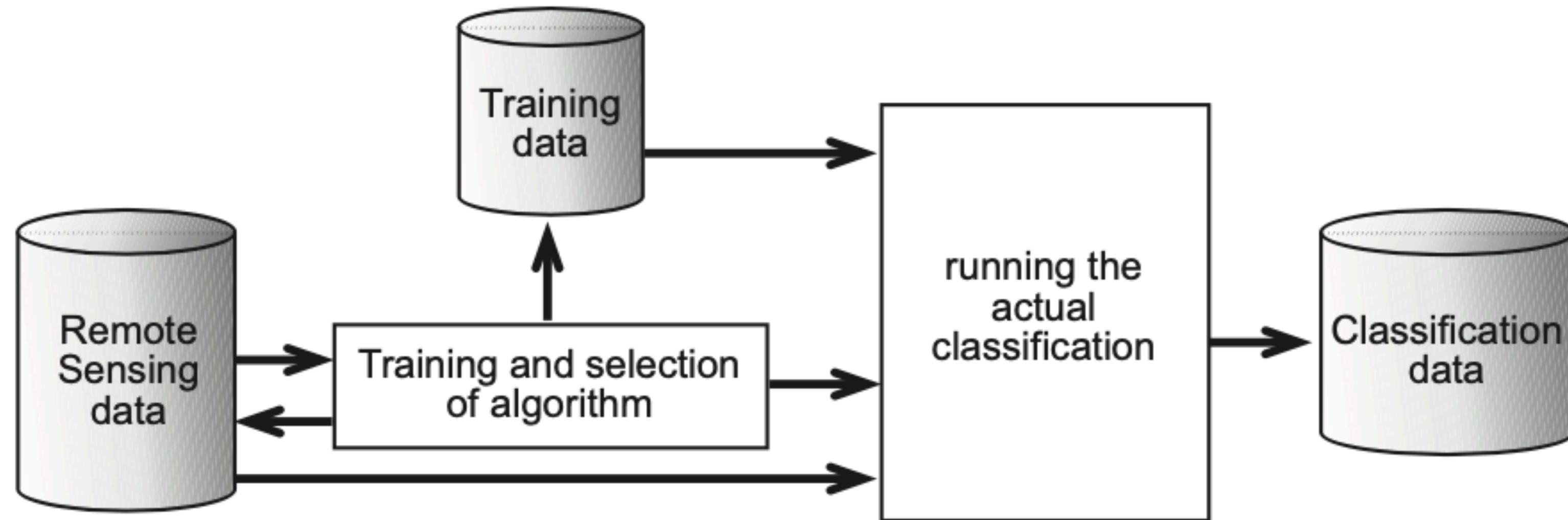
- the computer is presented with example inputs and their desired outputs, and the goal is to learn a general rule that maps inputs to outputs.
- operator defines the clusters (the partitioning of the feature space) during the training process
- done based on spectral characteristics of the classes, 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

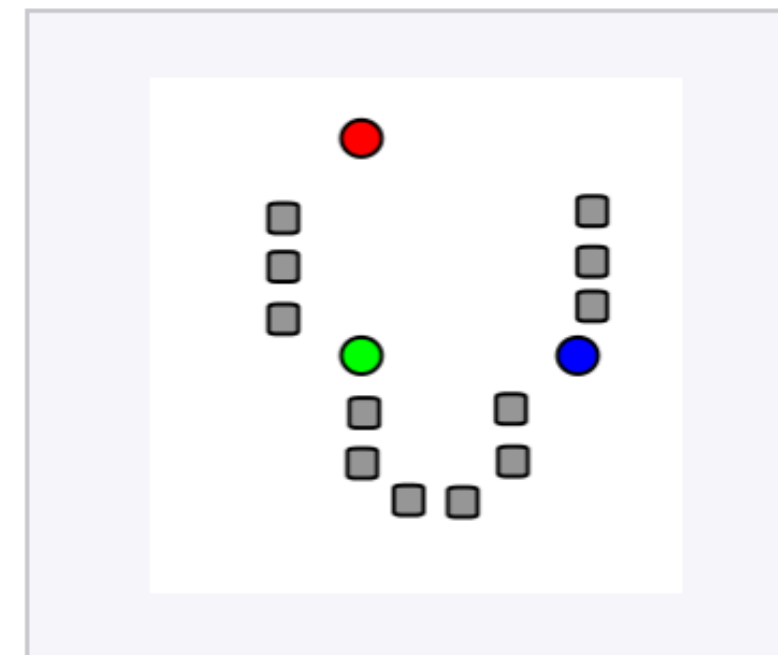
Classification process



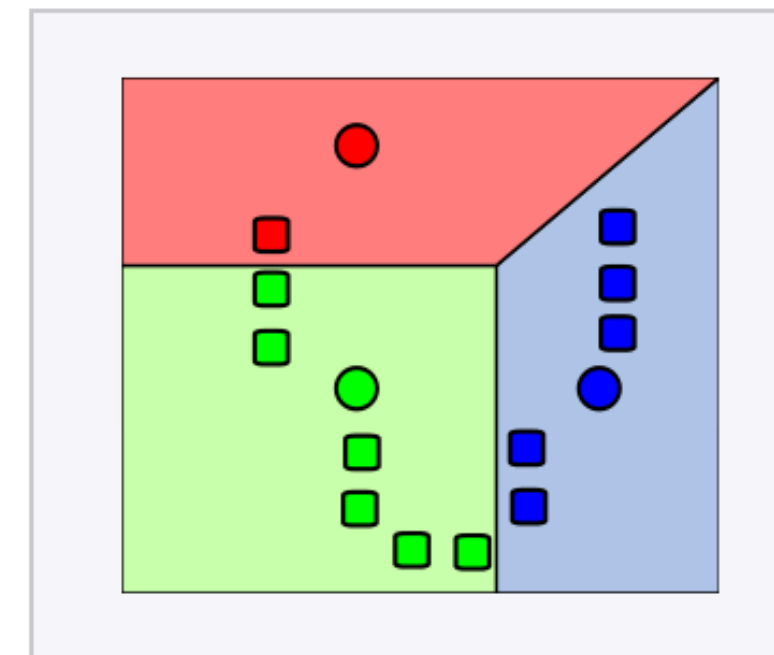
k-means clustering

- 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

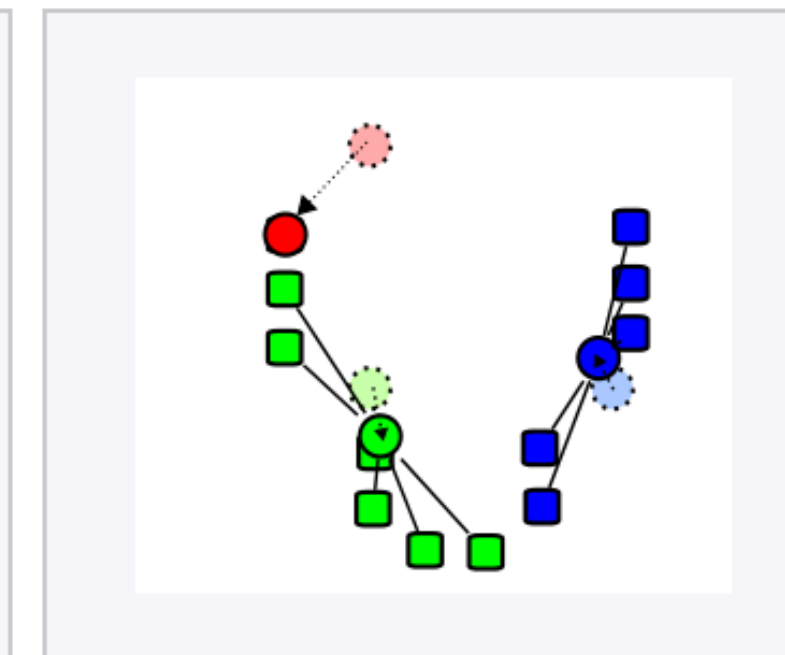
Demonstration of the standard algorithm



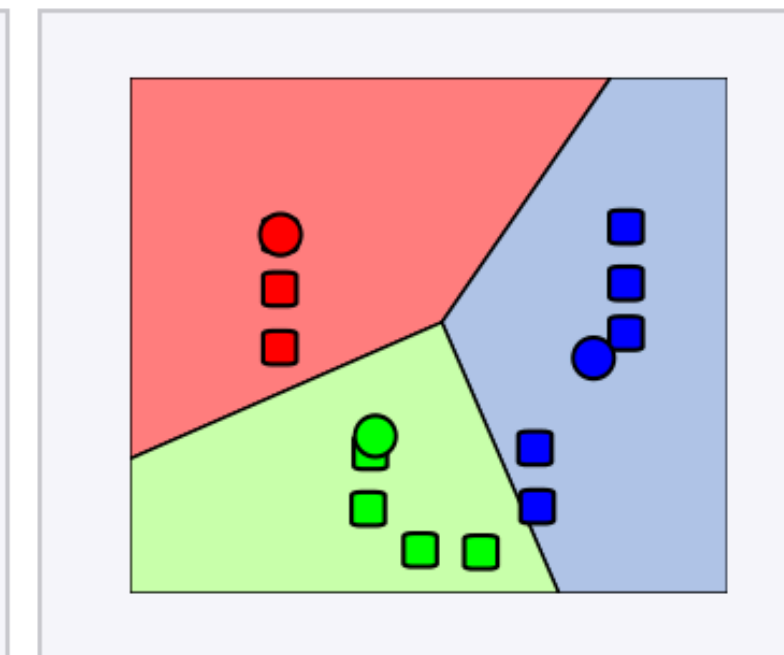
1. k initial "means" (in this case $k=3$) are randomly generated within the data domain (shown in color).



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.

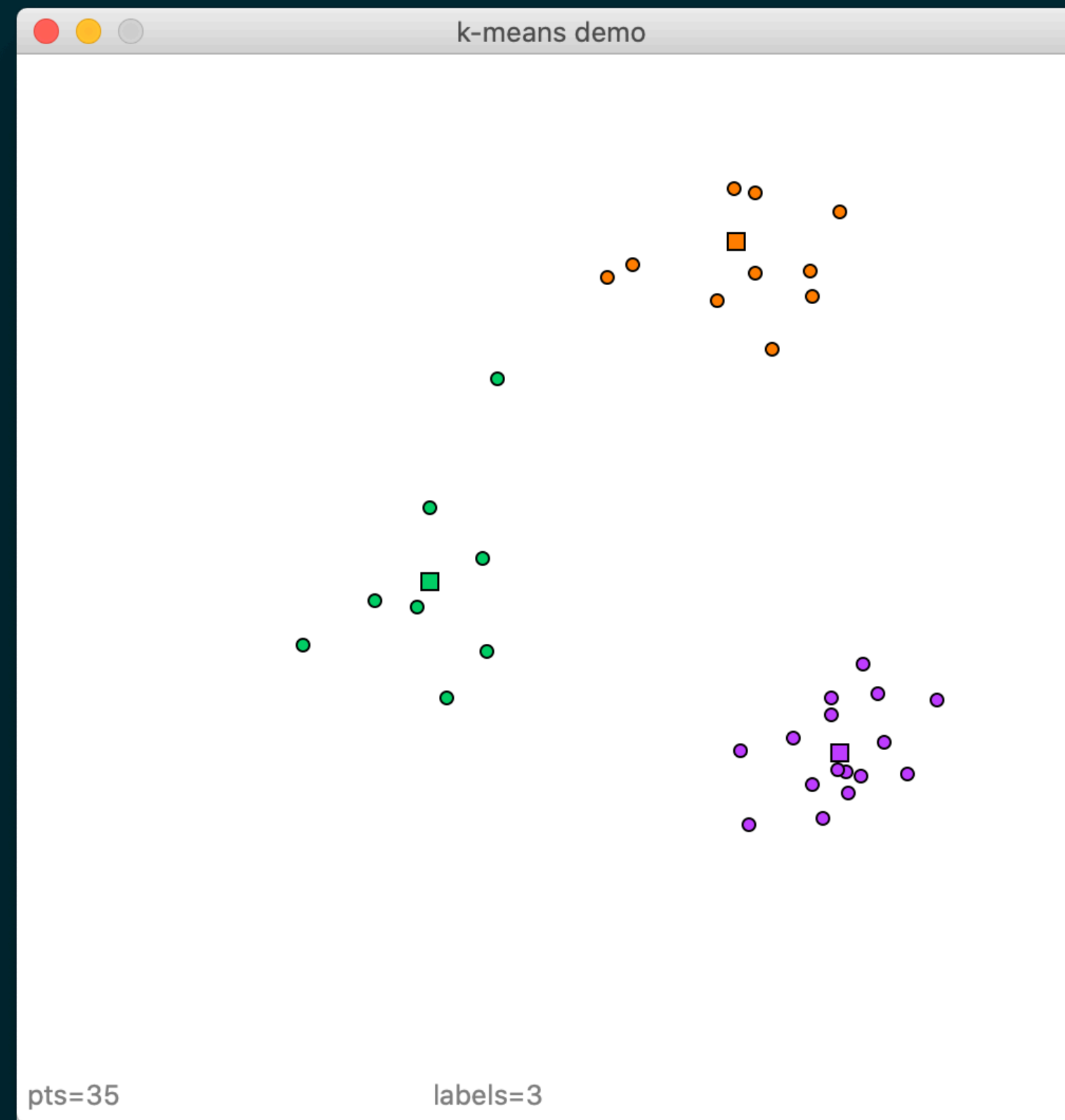


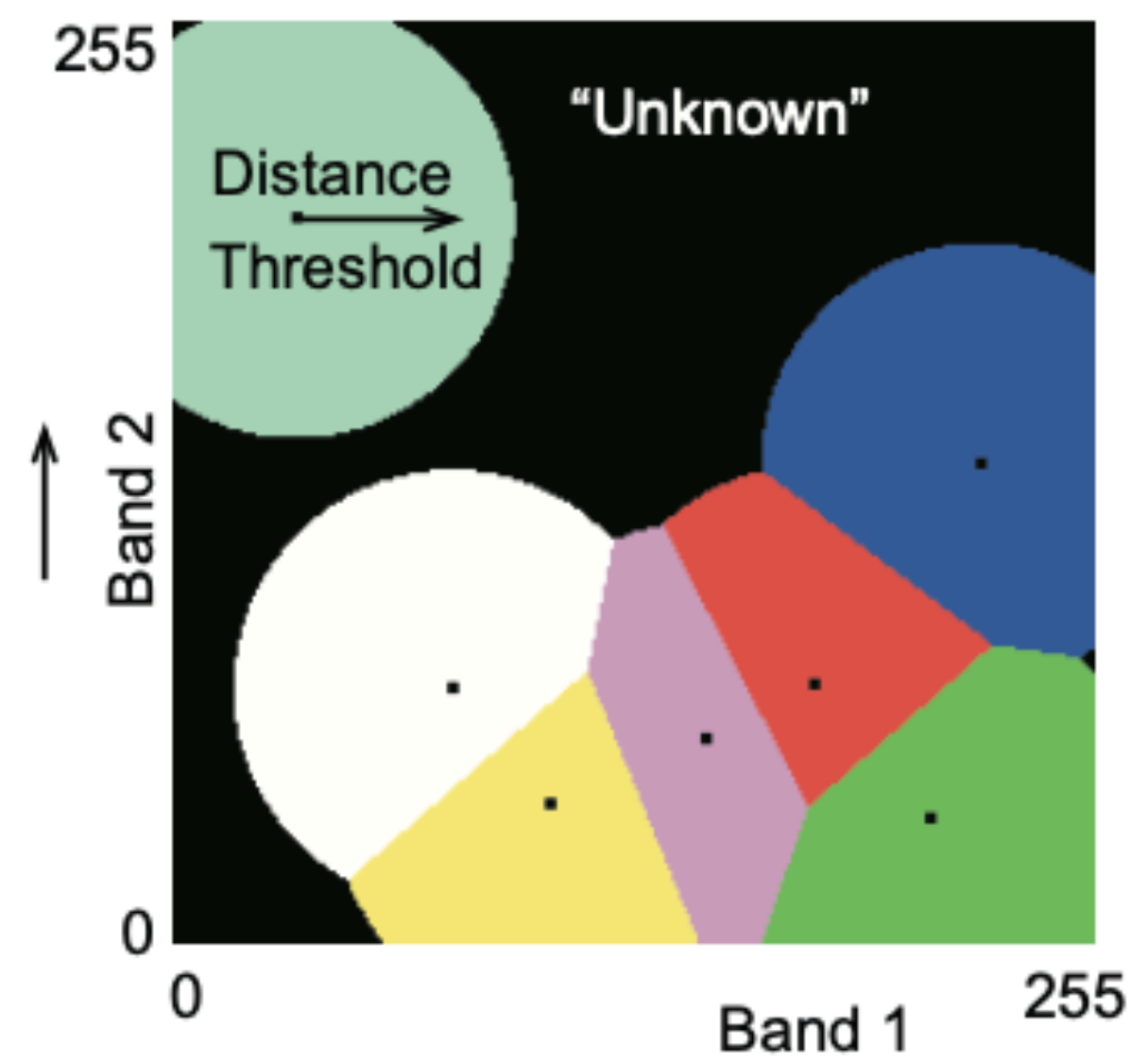
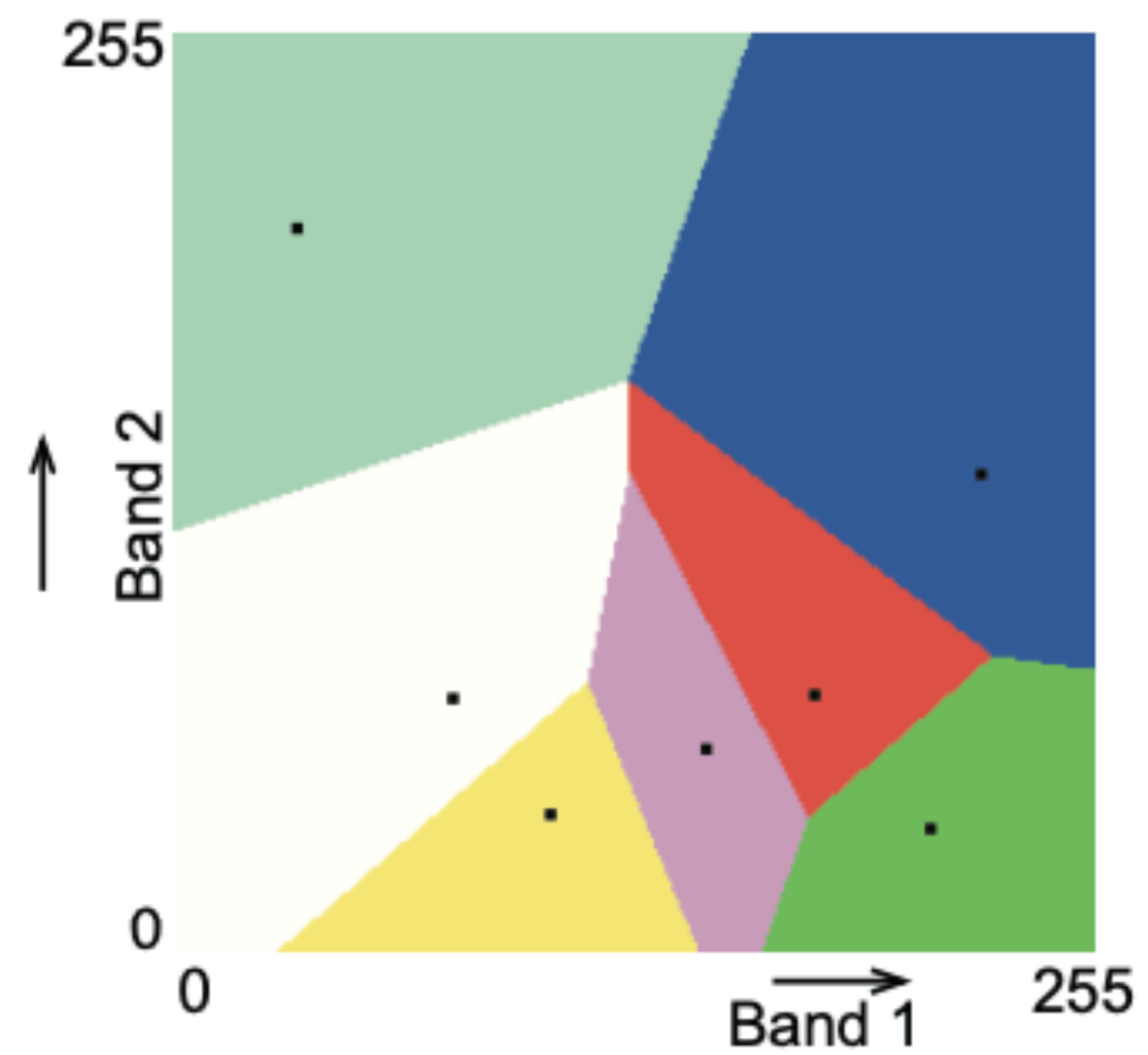
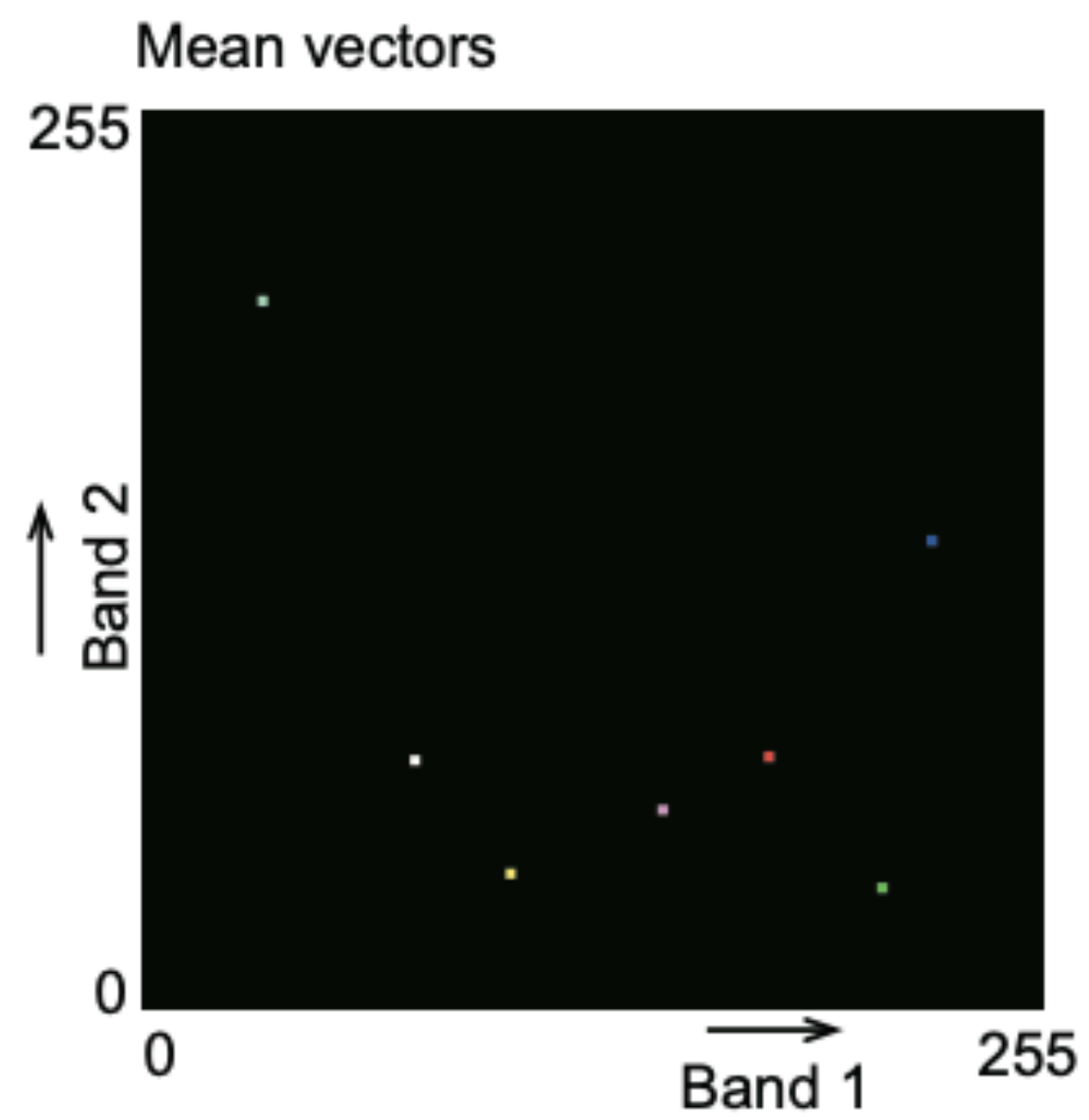
4. Steps 2 and 3 are repeated until convergence has been reached.

Small Python program to help

Code in GitLab repo "lectureB3"

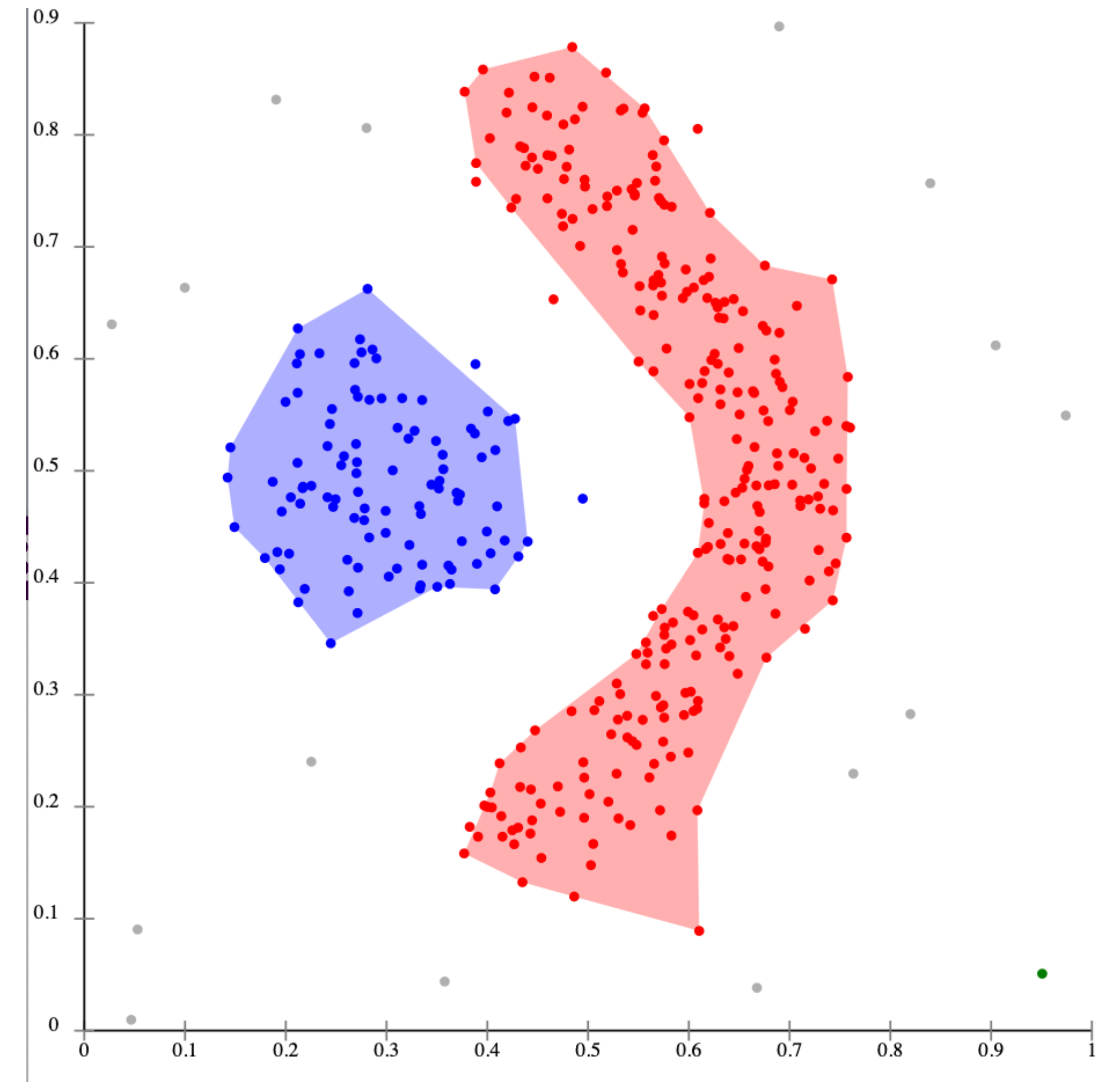
```
python main.py
[[227 347 2]] 8
[[389 170]
 [340 412]
 [195 251]]
[[400 212 0]
 [385 196 0]
 [392 161 0]
 [421 160 0]
 [435 195 0]
 [407 198 0]
 [410 175 0]
 [388 162 0]
 [376 155 0]
 [367 177 0]
 [342 171 0]
 [346 136 0]
 [381 139 0]
 [393 151 0]
 [399 159 0]
 [385 188 0]] 16
[[308 514 1]
 [357 361 1]
 [279 395 1]
 [291 401 1]
 [349 397 1]
 [349 435 1]
 [339 437 1]
 [331 384 1]
 [389 426 1]
 [375 398 1]
 [376 386 1]] 11
[[195 286 2]
 [135 221 2]
 [203 196 2]
 [189 239 2]
 [169 242 2]
 [220 262 2]
 [222 218 2]
 [227 347 2]] 8
```



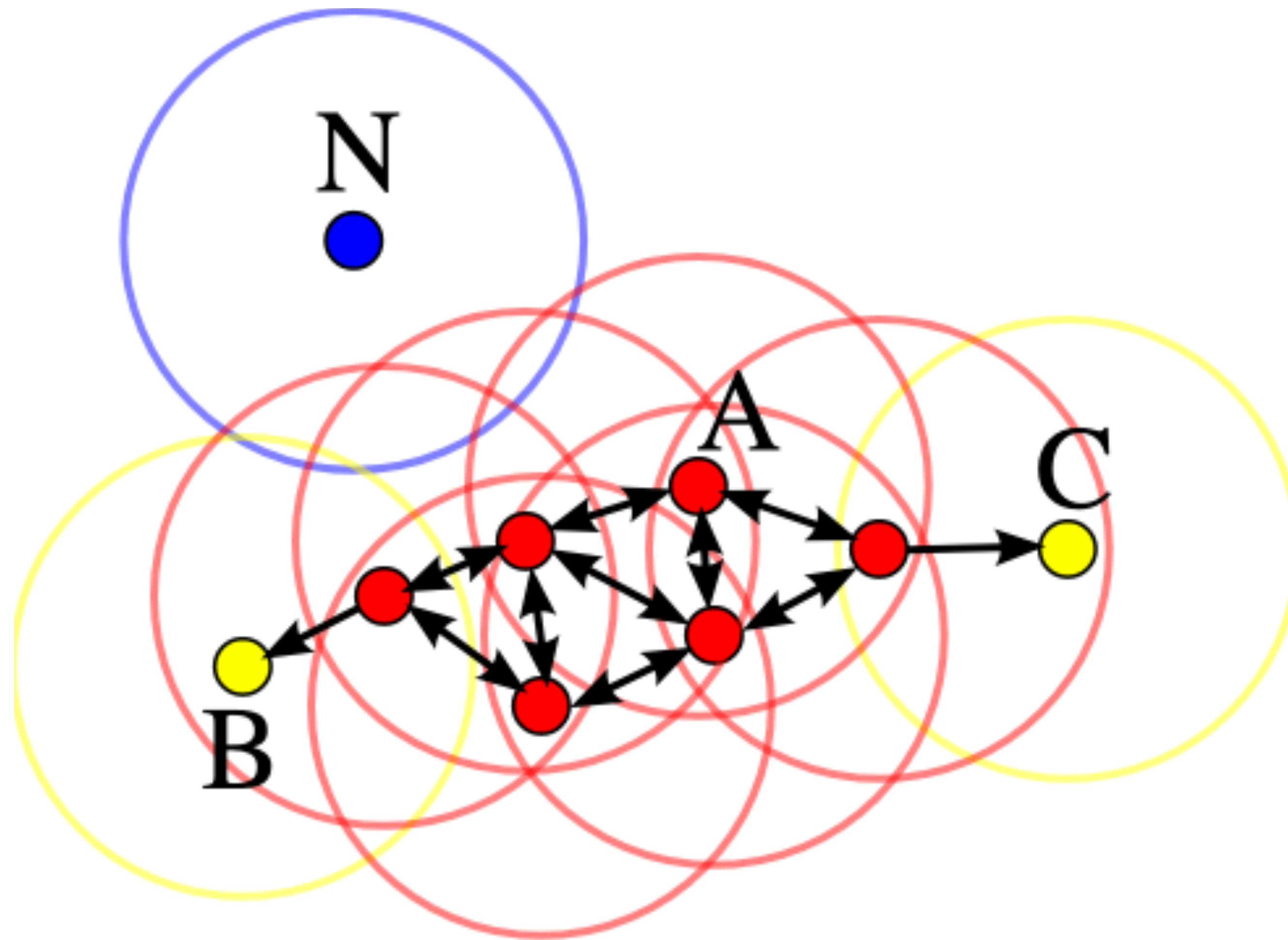


Density-based spatial clustering of applications with noise (DBSCAN)

- 👍 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)



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

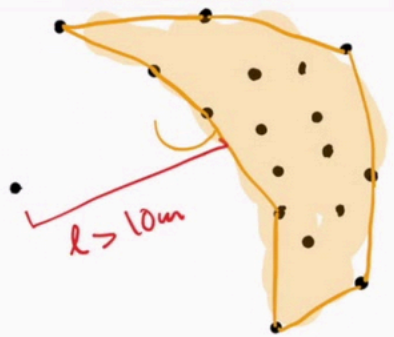


One lesson in GEO1015

https://3d.bk.tudelft.nl/courses/backup/geo...
GEO1015.2019 news lessons homework resources faq info

Lesson 13: Spatial extent of a point cloud

Hand #2: moving arm
GEO1015 – Spatial extent of a point clo...
Watch later Share




one regular polygon
↳ degenerate cases
not all points
one component

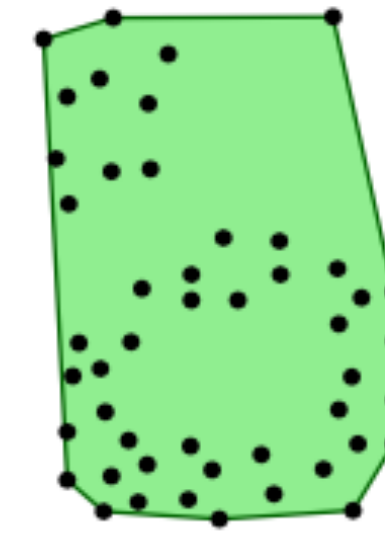
To read

1. Chapter 12

GEO1015—Digital terrain modelling

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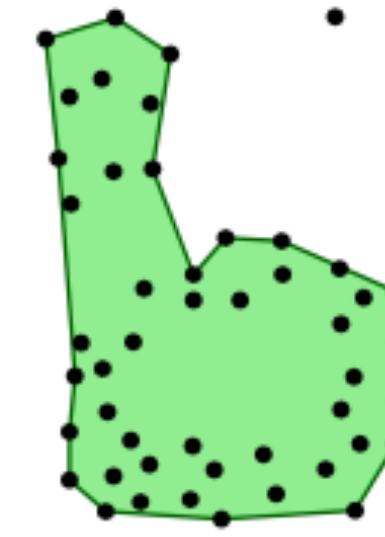
https://3d.bk.tudelft.nl/courses/backup/geo1015/2019/les



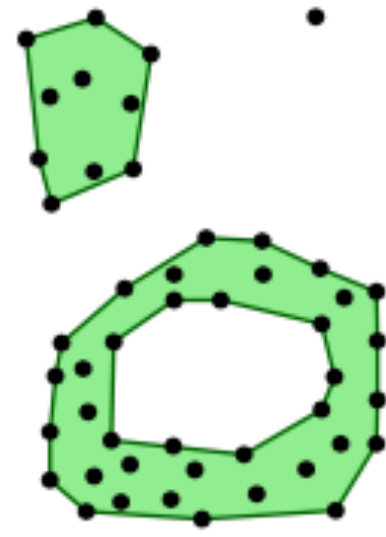
(a)



(b)



(c)



(d)

Validation of the results: error matrix

	A	B	C	D	Total	Error of Com- mission (%)	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”

The screenshot shows the Wikipedia article for "Precision and recall". The article title is "Precision and recall" and it is categorized under "Article" and "Talk". The article text explains that 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 based on an understanding and measure of relevance. An example is provided: 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". The article also mentions 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

The diagram in the article illustrates the concepts of precision and recall using a scatter plot of relevant elements. A circle highlights a subset of these elements, labeled "selected elements". The relevant elements are divided into "false negatives" (grey dots) and "true negatives" (white circles). The selected elements are divided into "true positives" (green dots) and "false positives" (red circles). Below the diagram, two questions are posed: "How many selected items are relevant?" and "How many relevant items are selected?". The first question is answered by the equation $\text{Precision} = \frac{\text{true positives}}{\text{true positives} + \text{false positives}}$, and the second question is answered by the equation $\text{Recall} = \frac{\text{true positives}}{\text{true positives} + \text{false negatives}}$.

Precision =
positive predictive value

Recall =
sensitivity

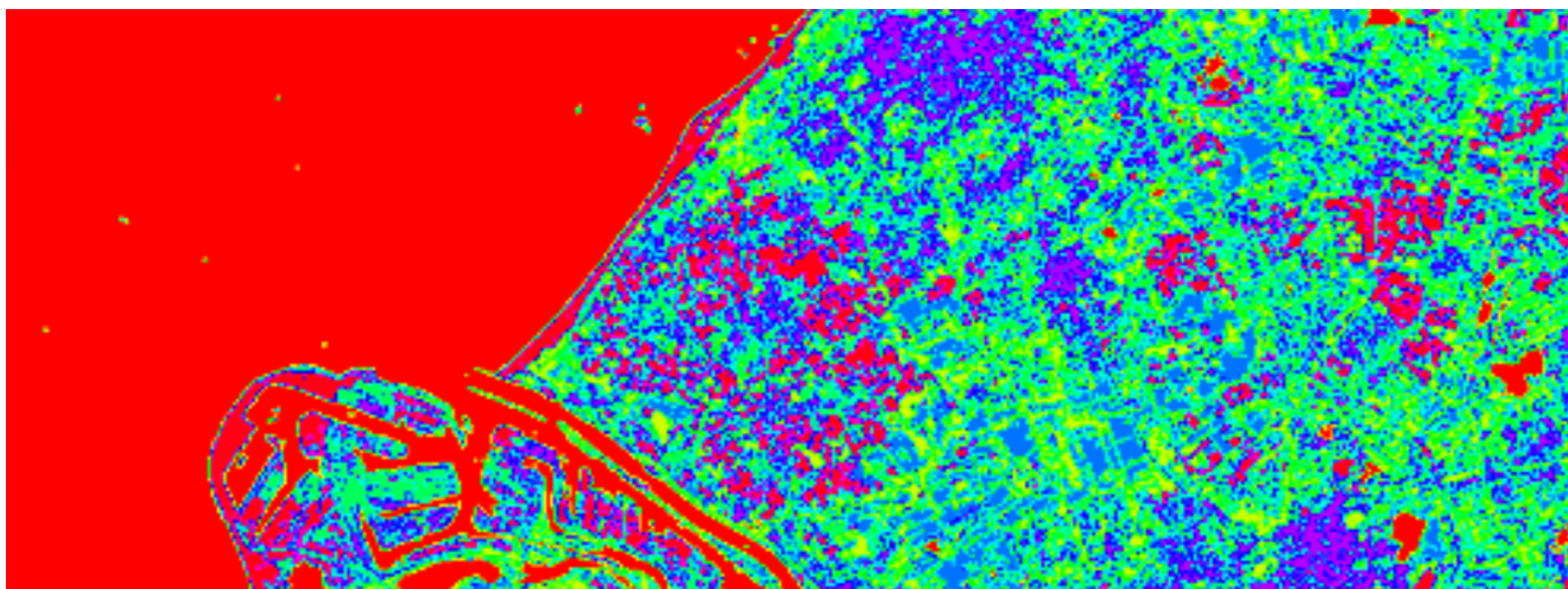
Assignment 02

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.



- Overview
- What you are given to start
- Classification
- Subset of the 10m image
- Python packages
- Tips
- Deliverable

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