

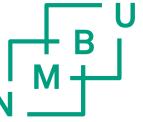
INF250

Hyperspectral imaging 2



Learning goals

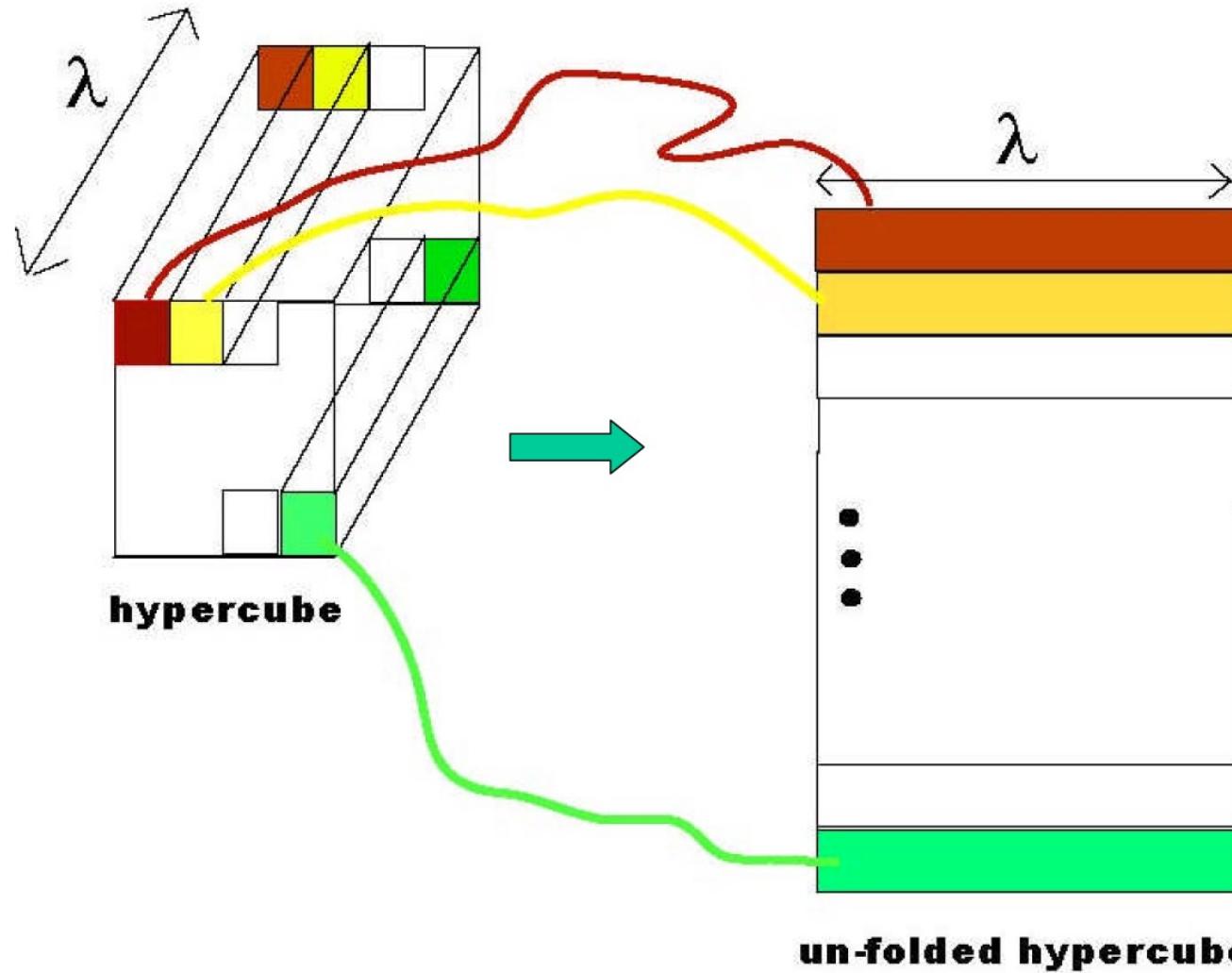
- What is multispectral and hyperspectral imaging ?
- What kind of cameras are used for hyperspectral imaging
- Give som examples of research one can do with hyperspectral imaging
- Describe how PCA works on a hyperspectral image
- Describe how k-means clustering works
- Describe supervised classification



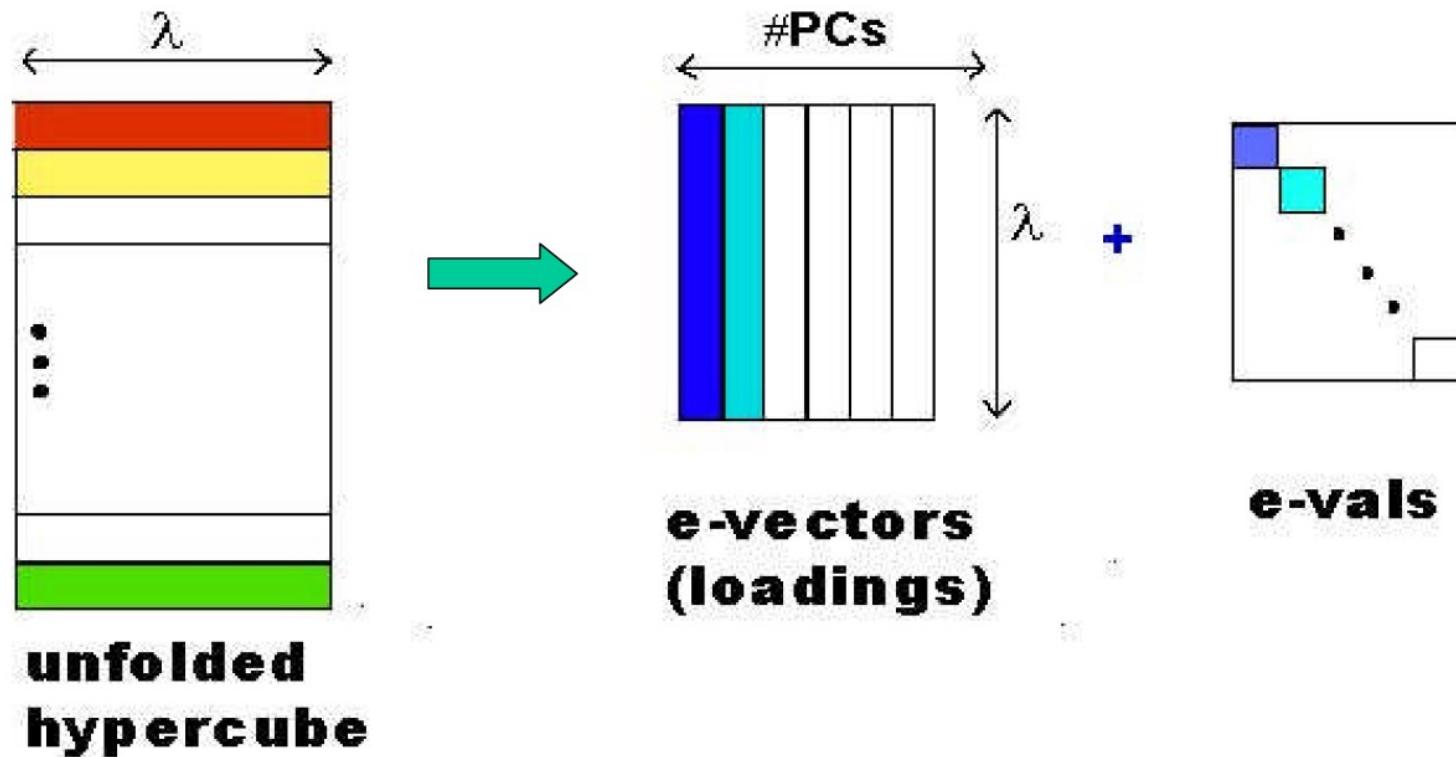
Multivariate image analysis on spectral images^N

- PCA (principal component analysis)
- K-means clustering
- Supervised classification

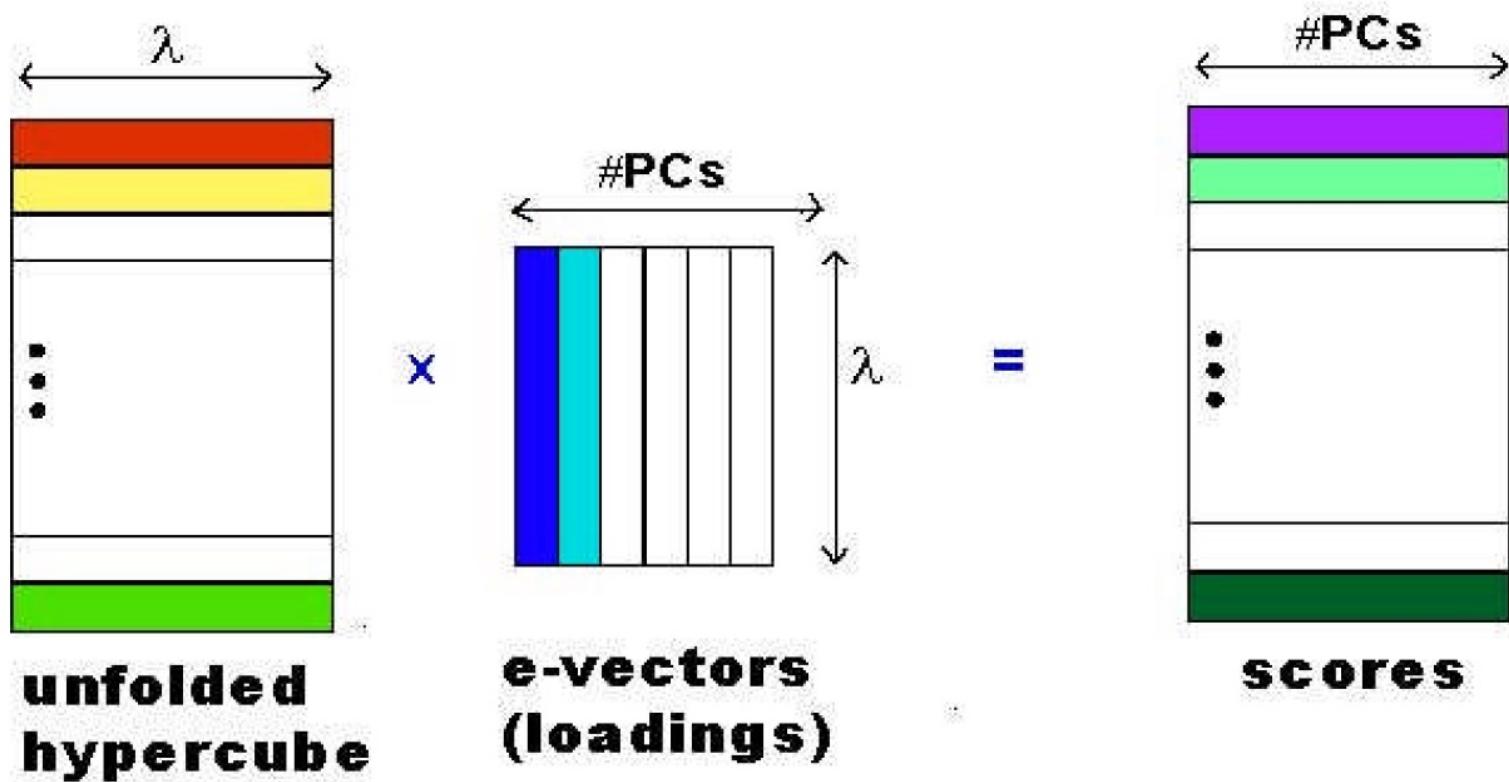
Unfolding the Hypercube



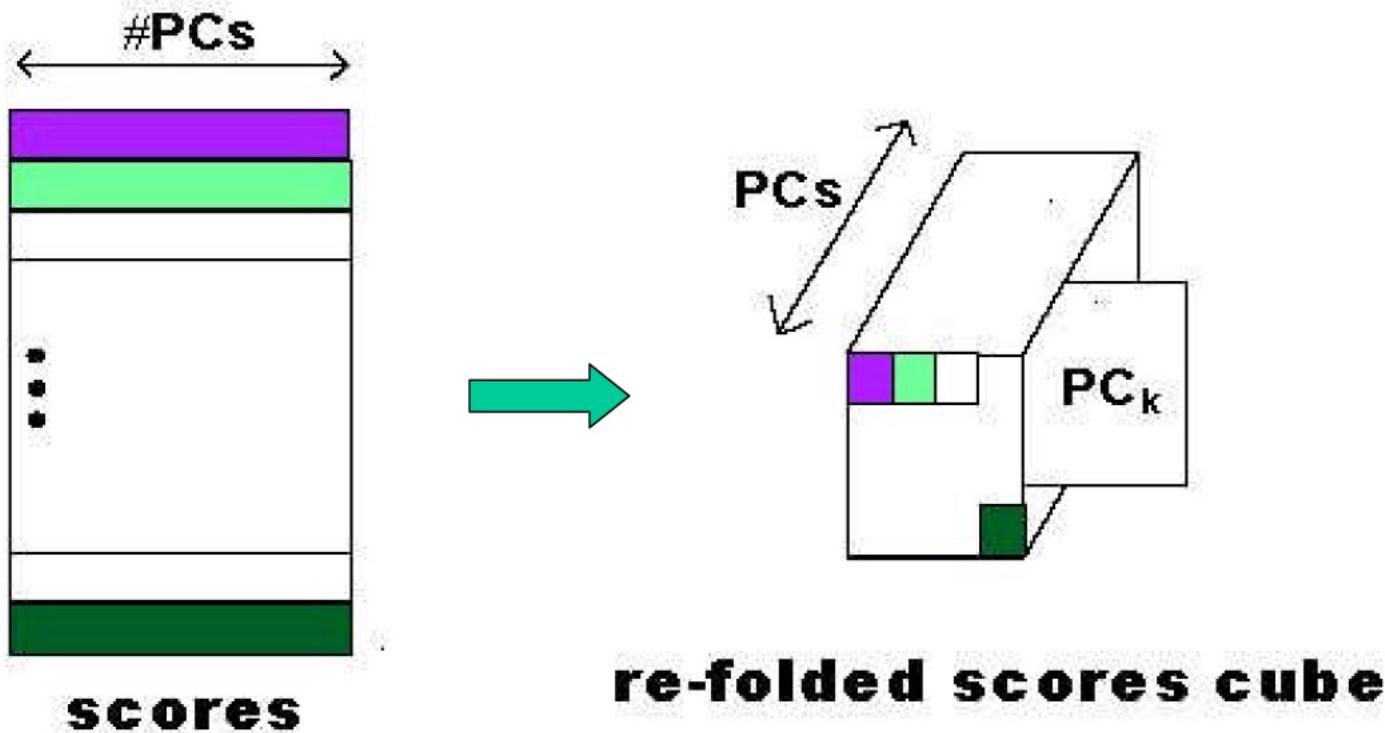
PCA on unfolded hypercube



Calculating Scores



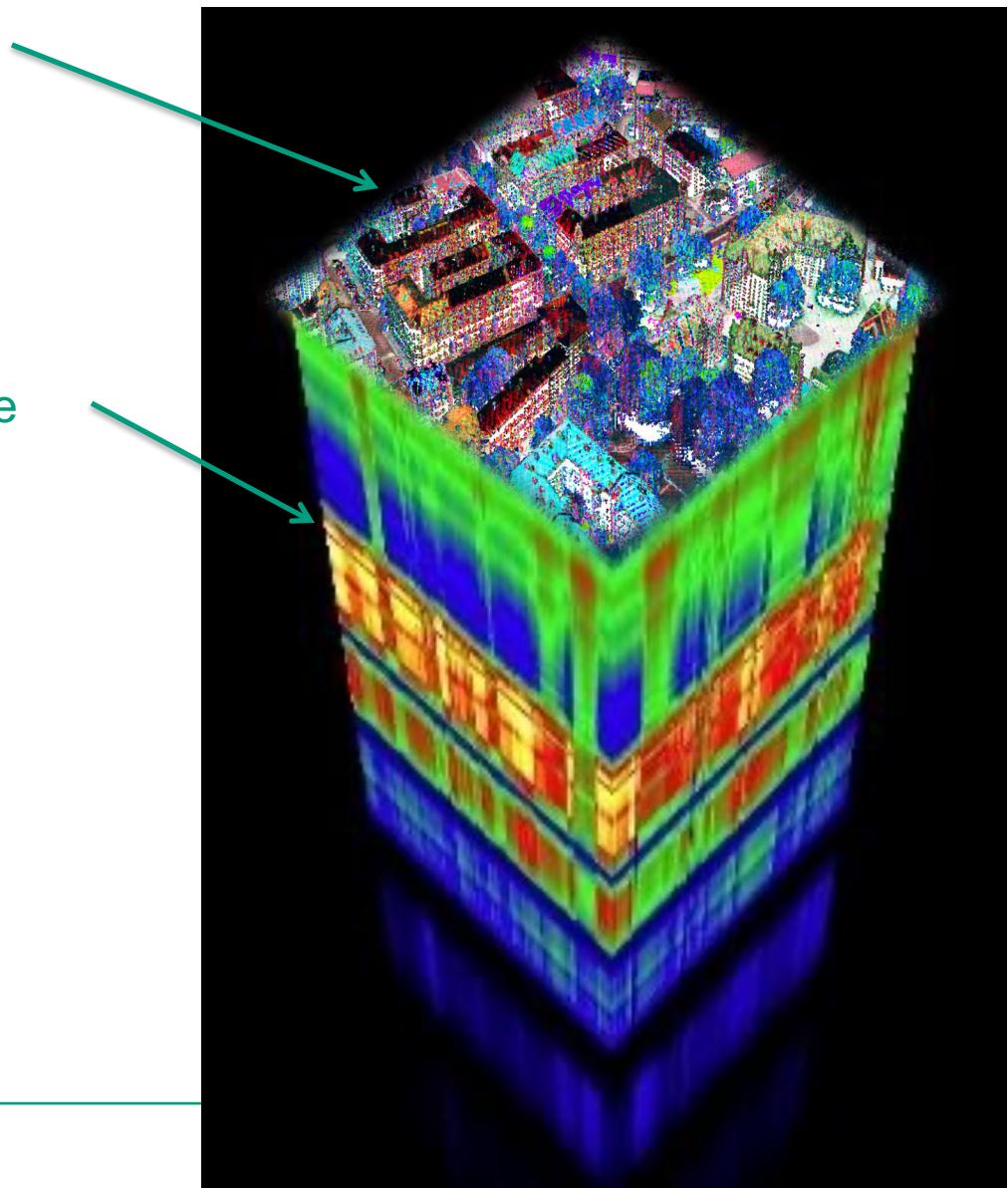
Re-folding Scores



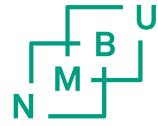


Laser data (LiDAR) yields a 3D model of the surface in the form of a point cloud

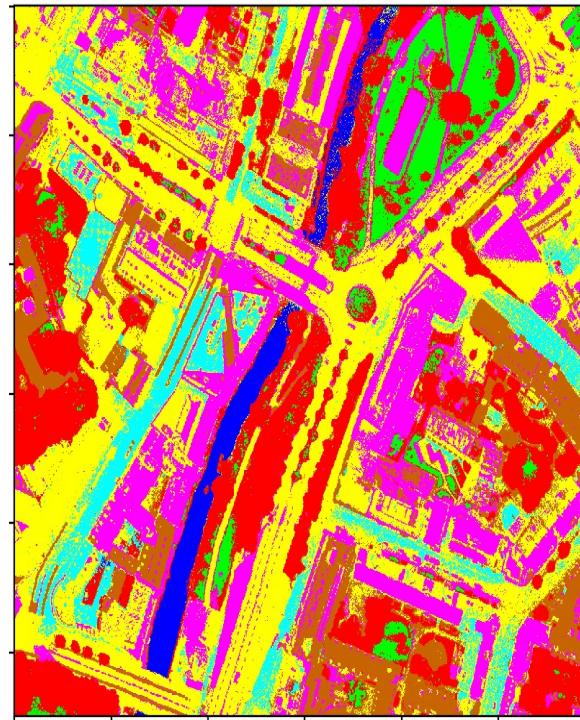
Hyperspectral data gives a detailed spectrum of channels in the visible and the near infrared and shortwave infrared, bringing out «invisible» differences in the surface material



Collaboration with Terratec



Maximum Likelihood Classification

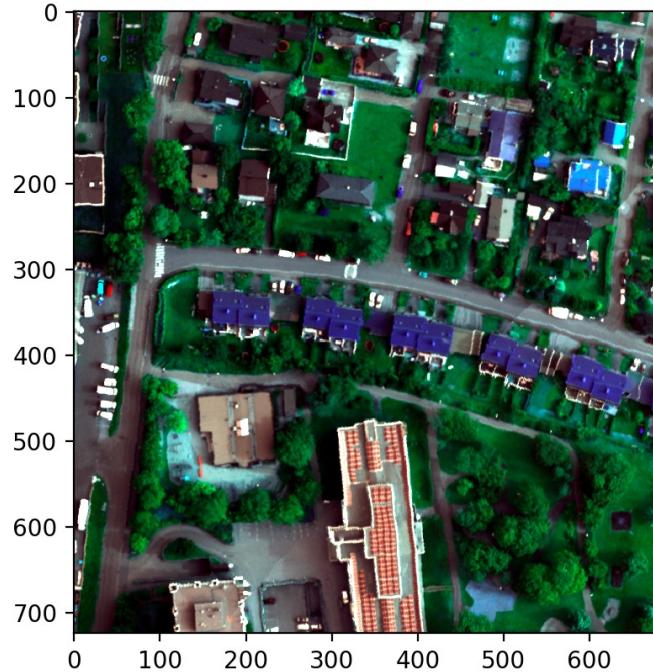


- [Yellow square] Asphalt
- [Green square] Grass
- [Red square] Trees
- [Magenta square] Dark rooftops + sand
- [Brown square] Red rooftops
- [Cyan square] Shadowed areas (asphalt)

```
from spectral import *
import numpy as np
import matplotlib.pyplot as plt
import skimage

hyperim = np.load("Oslo_hsi.npy")

imshow(hyperim, (10, 48, 70), stretch=((0.02,0.98),(0.02,0.98),(0.02,0.98)))
```



```
z = np.array(hyperim[521,520,:].reshape(-1,1))
z2 = np.array(hyperim[635,214,:].reshape(-1,1))
z3 = np.array(hyperim[441,36,:].reshape(-1,1))
plt.figure()
plt.plot(ww,z)
plt.plot(ww,z2)
plt.plot(ww,z3)
plt.show()

#plot as fct of pixel values
plt.figure()
plt.plot(z)
plt.show()

#compute mean of all spectra
m1 = hyperim.mean(axis=0)
m2 = m1.mean(axis=0).reshape(-1,1)
plt.figure()
plt.plot(ww,m2)
plt.show()

#ndvi

ndvi_ima = (hyperim[:, :, 108] - hyperim[:, :, 94]) / (hyperim[:, :, 108] + hyperim[:, :, 94])
plt.imshow(ndvi_ima, vmin=0, vmax=0.7)

# ndvi from spectral python
vi = ndvi(hyperim, 94, 108)
plt.figure()
plt.imshow(vi, vmin=-0.3, vmax=0.6)
```

```
# pca

pc = principal_components(hyperim)

pc_0999 = pc.reduce(fraction=0.999)

loading = pc_0999.eigenvectors

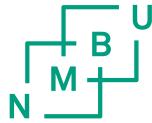
#loading of pc1
plt.figure()
plt.plot(loading[:,0])

#score of pc1
img_pc = pc_0999.transform(hyperim)
plt.figure()
plt.imshow(img_pc[:, :, 0], vmin=-0.1, vmax=0.15)
```

```
# kmeans

(m, c) = kmeans(hyperim, 7, 20)
plt.imshow(m, 'spectral')

plt.figure()
for i in range(c.shape[0]):
    plt.plot(c[i])
```



```
shape = hyperim.shape
groundtruth = np.zeros([shape[0],shape[1]])

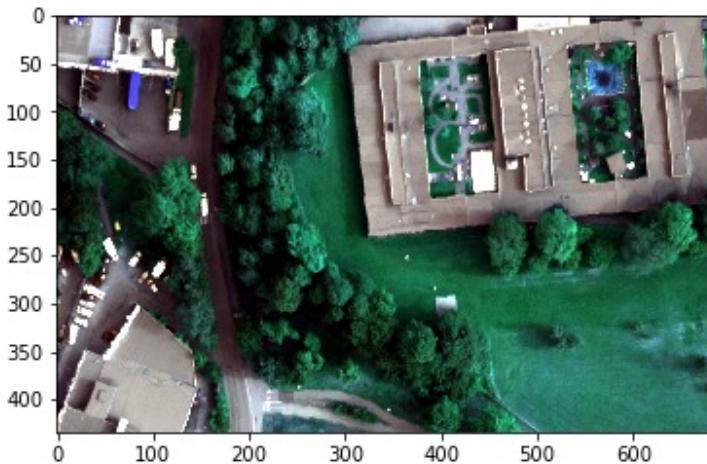
groundtruth[128:168, 336:366] = 1.0    #grass
groundtruth[623:650, 200:250] = 2.0 # asphalt
groundtruth[460:480, 150:170] = 3.0 # roof1

groundtruth[350:370, 300:320] = 3.0 # roof1

plt.figure()
plt.imshow(groundtruth)
```

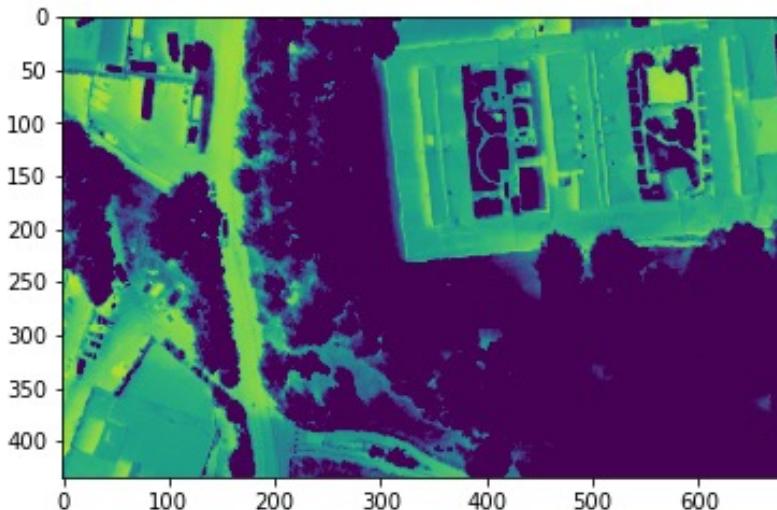
Gaussian Maximum Likelihood classification

```
classes = create_training_classes(hyperim, groundtruth)
gmlc = GaussianClassifier(classes)
clmap = gmlc.classify_image(hyperim)
imshow(classes=clmap)
```

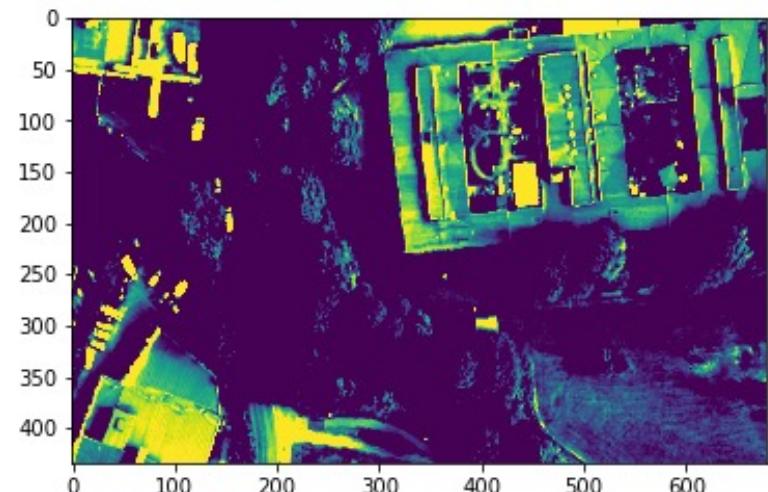


```
# pca  
  
pc = principal_components(hyperim)  
  
pc_0999 = pc.reduce(fraction=0.999)  
len(pc_0999.eigenvalues)  
img_pc = pc_0999.transform(img)  
plt.imshow(img_pc[:, :, 0], vmin=0.0, vmax=0.3)  
plt.imshow(img_pc[:, :, 1], vmin=0.0, vmax=0.1)
```

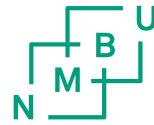
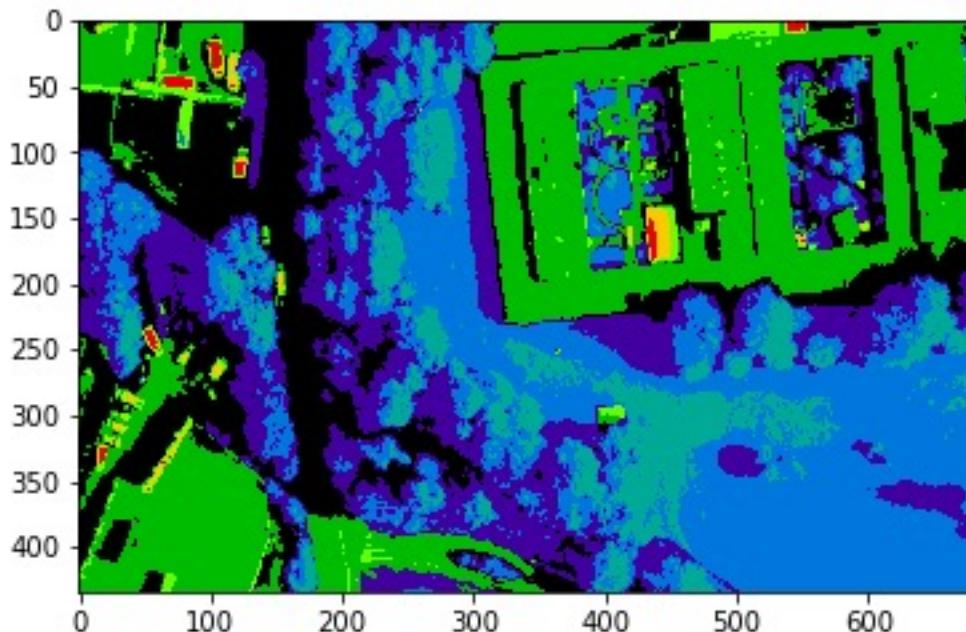
Hyperspectral image composite
of band 20,40 and 60



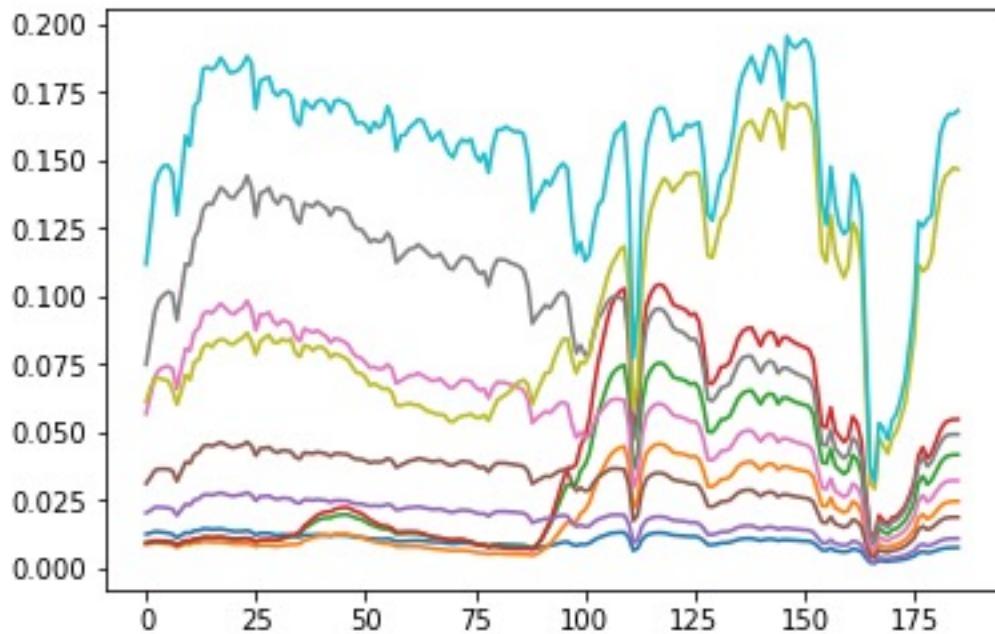
PC 1



PC 2



```
# kmeans  
(m, c) = kmeans(hyperim, 10, 30)  
plt.figure()  
plt.imshow(m, 'spectral')  
plt.show()  
  
for i in range(c.shape[0]):  
    plt.plot(c[i])
```

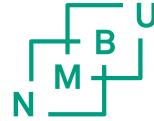


Classification

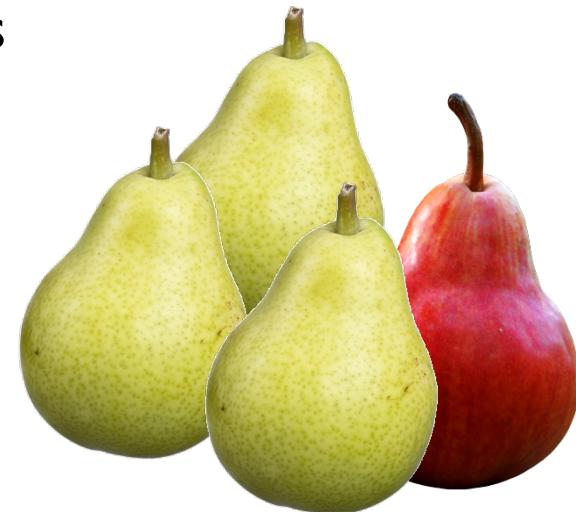
Assigning predefined labels to objects based on their features



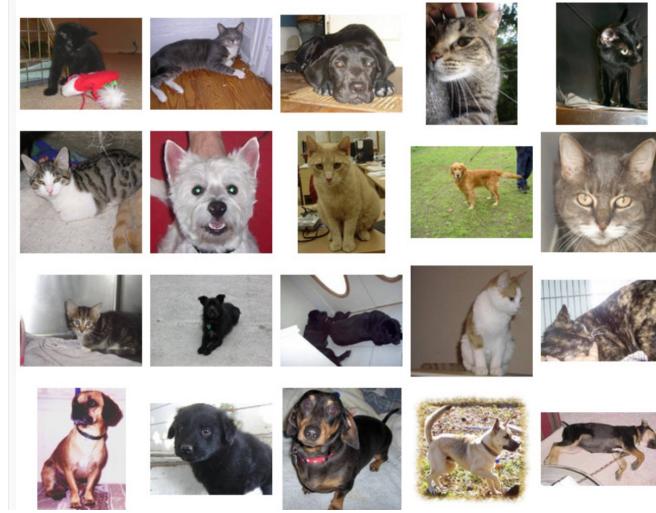
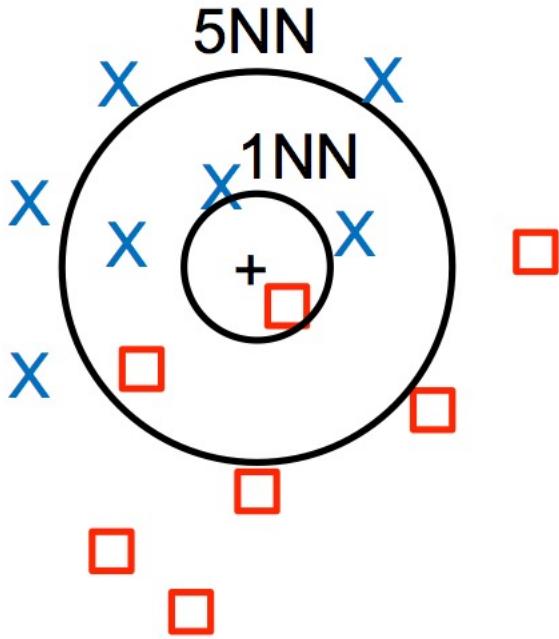
Clustering



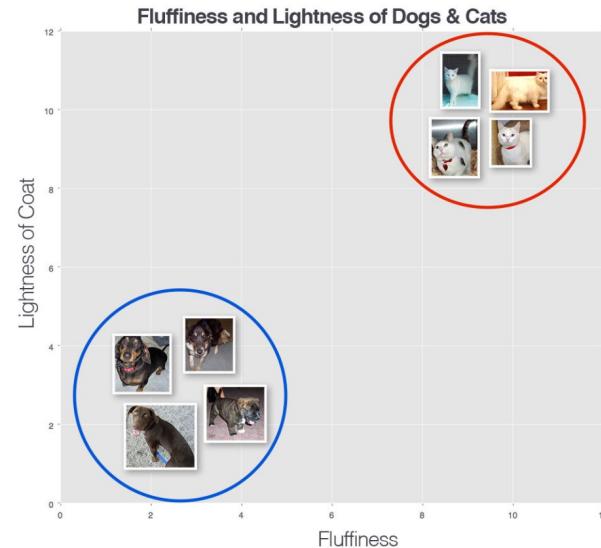
Grouping a set of objects in such a way that objects in the same group are more similar in some sense than objects in other groups



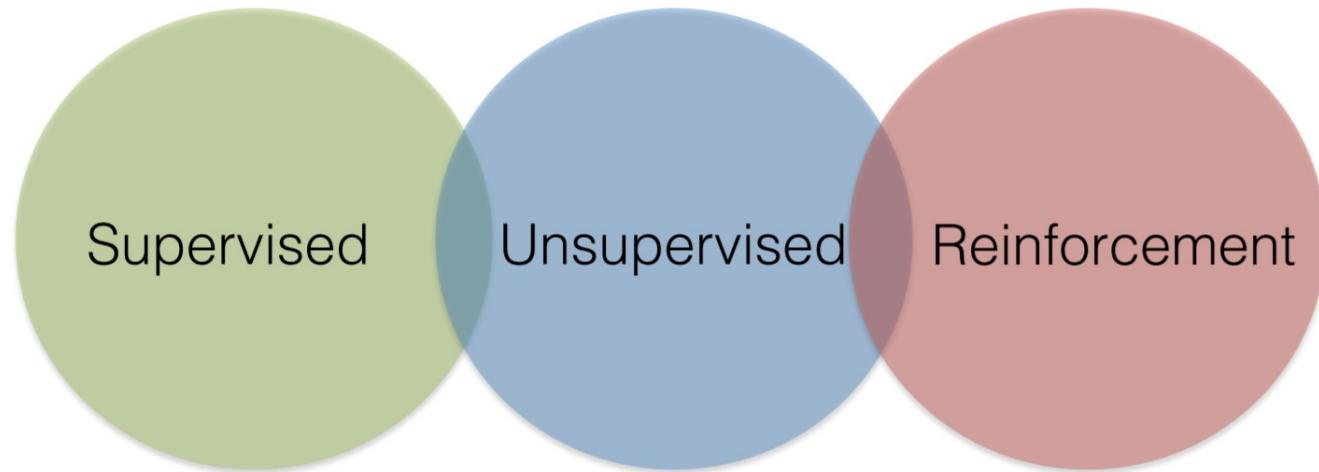
KNN – K nearest neighbours



U
B
M



Classification in images



Supervised

Unsupervised

Reinforcement

Learning from
“labelled” data

Discover structure
in “unlabelled” data

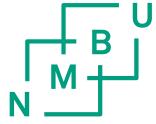
Learning by “doing”
with delayed reward

Non supervised vs supervised classification



Unsupervised classification is where the outcomes (groupings of pixels with common characteristics) are based on the software analysis of an image without the user providing sample classes. The computer uses techniques to determine which pixels are related and groups them into classes. The user can specify which algorithm the software will use and the desired number of output classes but otherwise does not aid in the classification process. However, the user must have knowledge of the area being classified when the groupings of pixels with common characteristics produced by the computer have to be related to actual features on the ground (such as wetlands, developed areas, coniferous forests, etc.).

Supervised classification is based on the idea that a user can select sample pixels in an image that are representative of specific classes and then direct the image processing software to use these training sites as references for the classification of all other pixels in the image. Training sites (also known as testing sets or input classes) are selected based on the knowledge of the user. The user also sets the bounds for how similar other pixels must be to group them together. These bounds are often set based on the spectral characteristics of the training area, plus or minus a certain increment (often based on "brightness" or strength of reflection in specific spectral bands). The user also designates the number of classes that the image is classified into. Many analysts use a combination of supervised and unsupervised classification processes to develop final output analysis and classified maps.



Examples of supervised classification

- Gaussian Maximum Likelihood Classifier (GMLC)
- Spectral Angle Mapper (SAM)
- Discriminant Analysis

Gaussian Maximum Likelihood Classifier (GMLC)

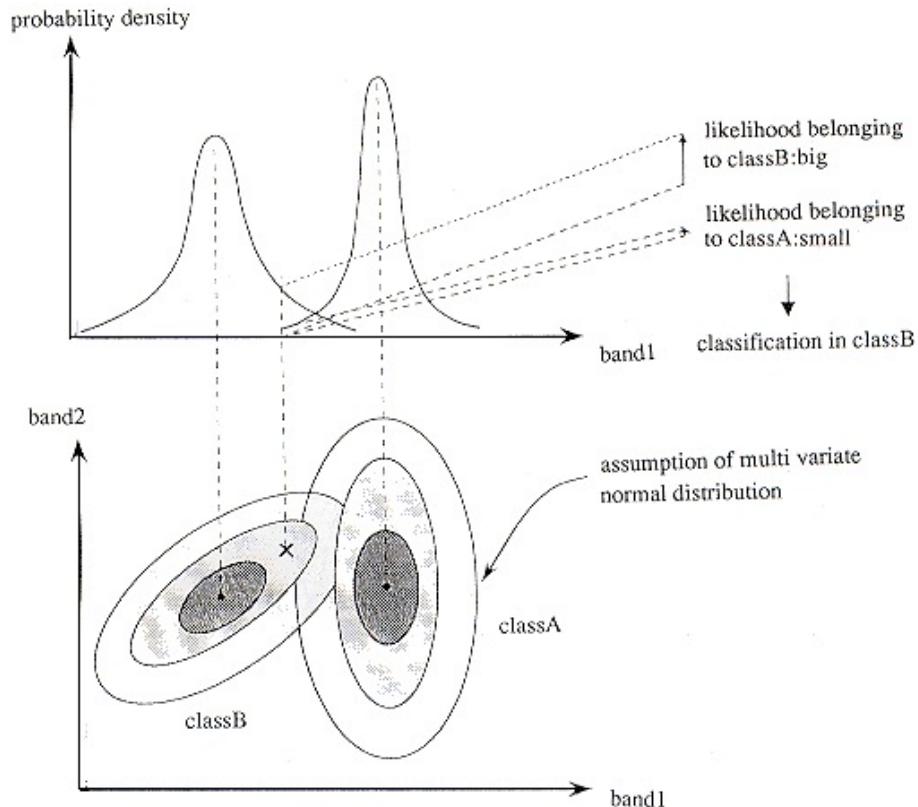
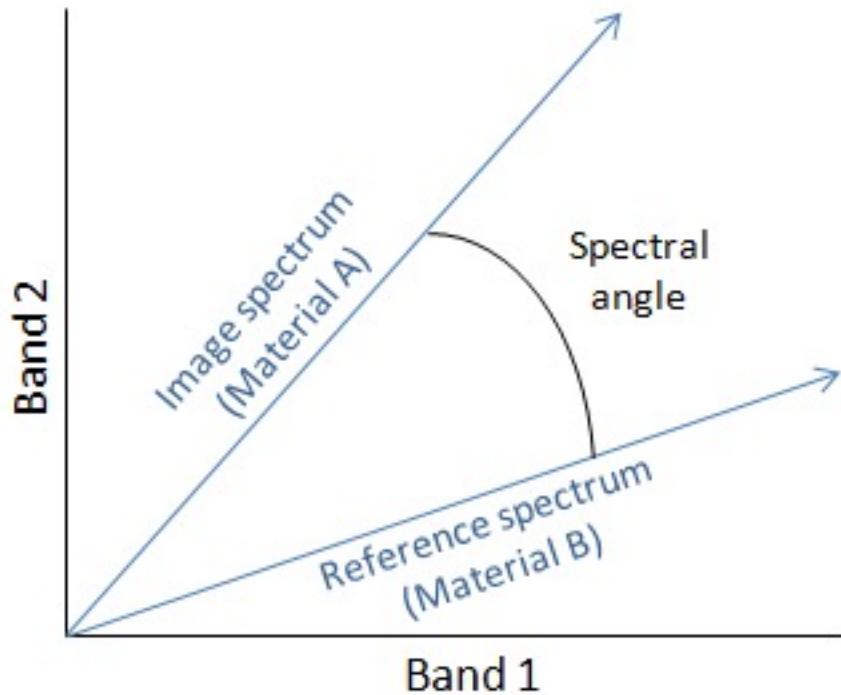


Figure 11.7.1 Concept of Maximum Likelihood Method

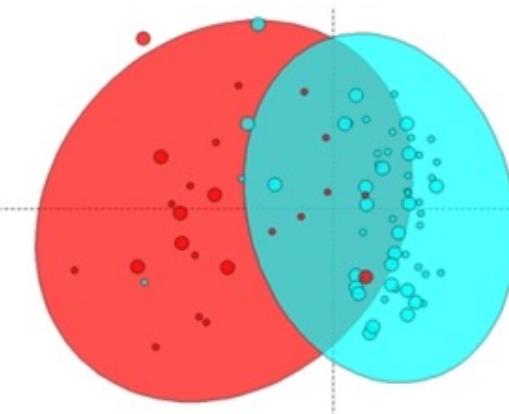
Spectral Angle Mapper



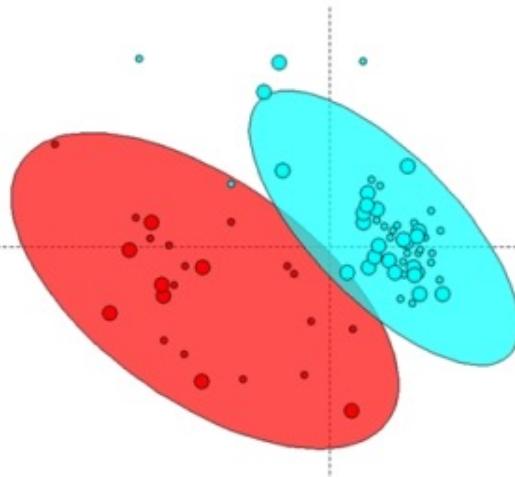
PLS-DA

Rotation of PCA score plot so as to separate classes

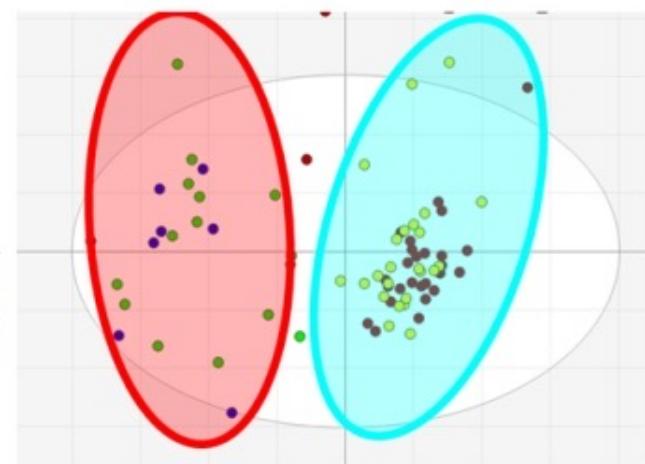
PCA

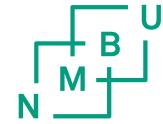


PLS-DA

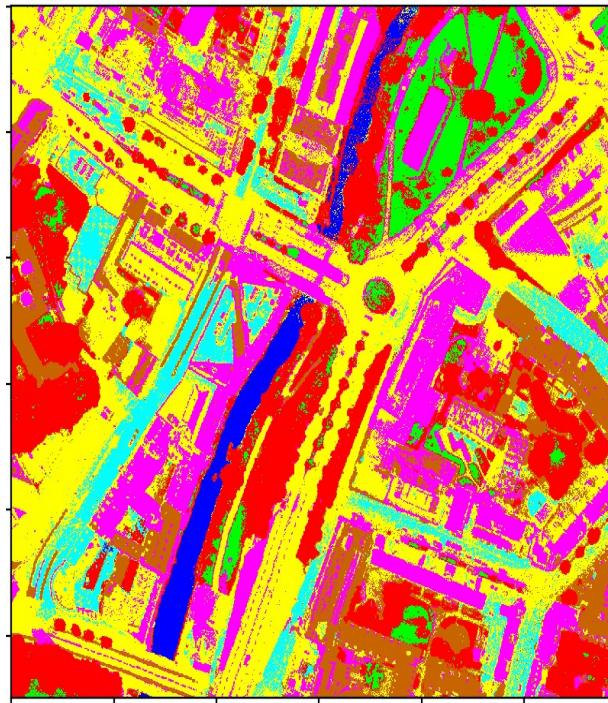
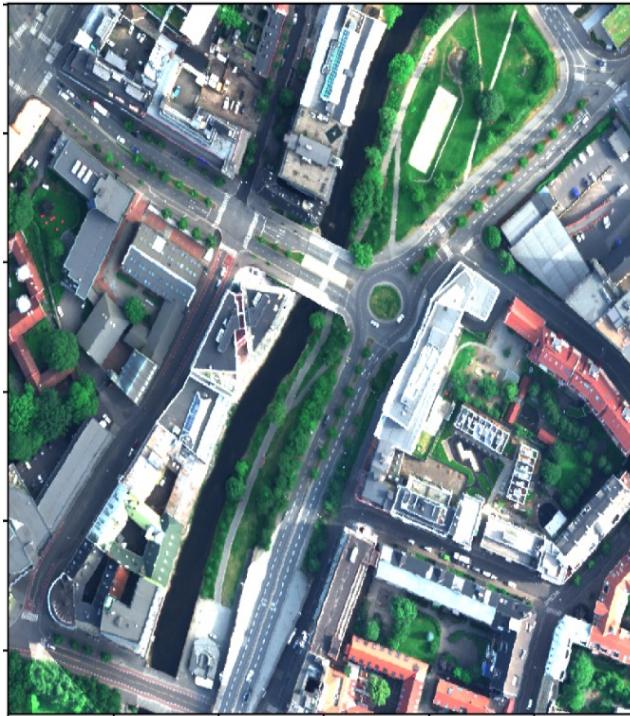


O-PLS-DA



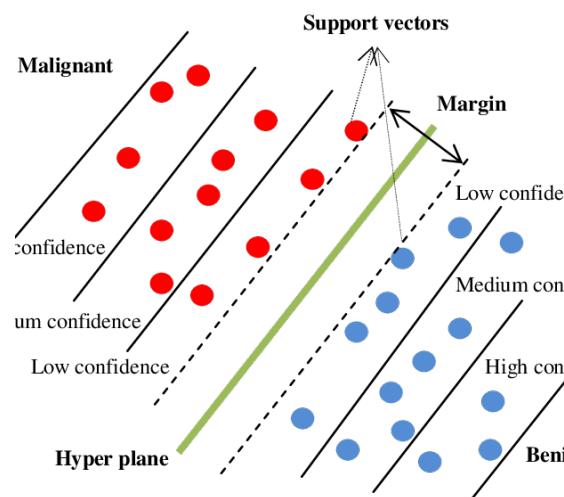
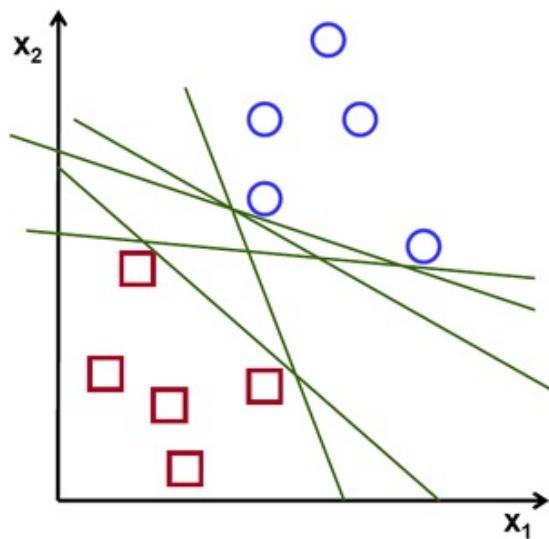


Maximum Likelihood Classification



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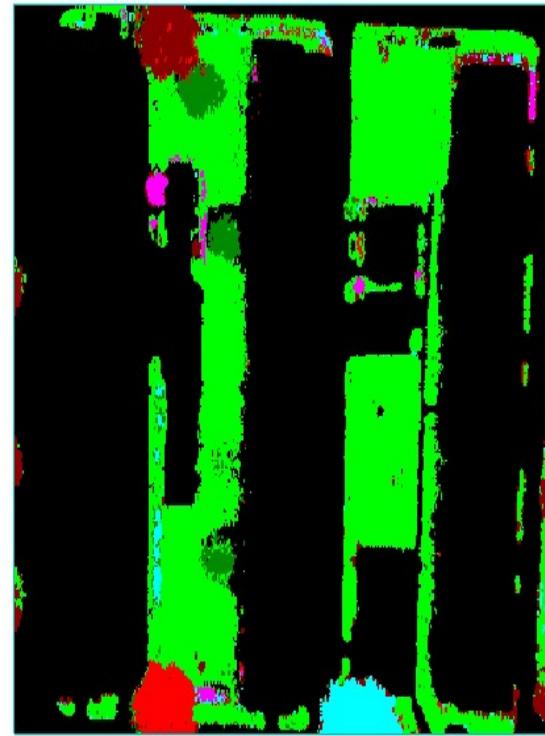
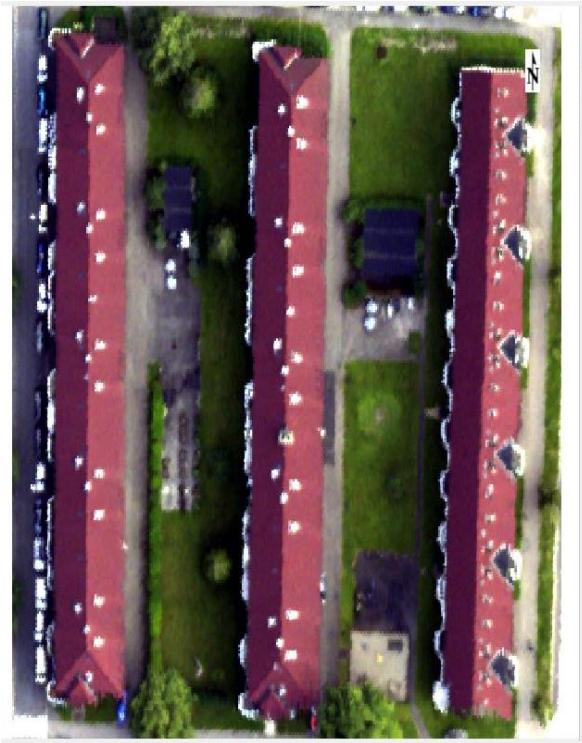
Support Vector Machine



Classification of tree species

Different tree species have different leaf area, which is related to capacity of absorb polluting particles in the air

Support Vector machine classification



Validation

