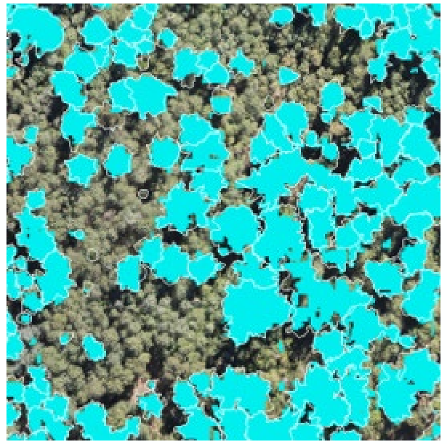
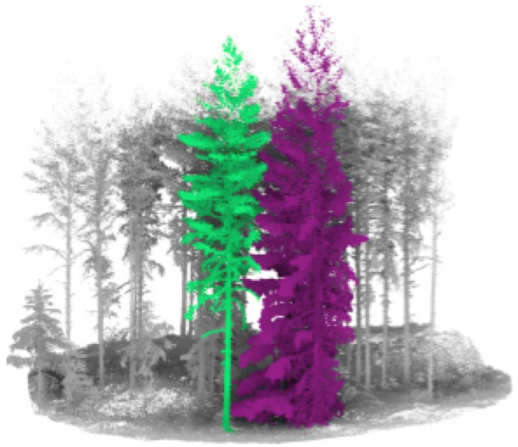
09 – Introduction to Deep Learning

- Image-based pattern recognition
- Point Cloud-based pattern recognition





Chair of Sensor-based Geoinformatics (geosense)
www.geosense.uni-freiburg.de

Image-based Pattern recognition

Image-based Pattern recognition

RGB Drone image

Image Pattern recognition

Sensor-based Geoinformatics
University of Freiburg
geosense.uni-freiburg.de

RGB Drone image

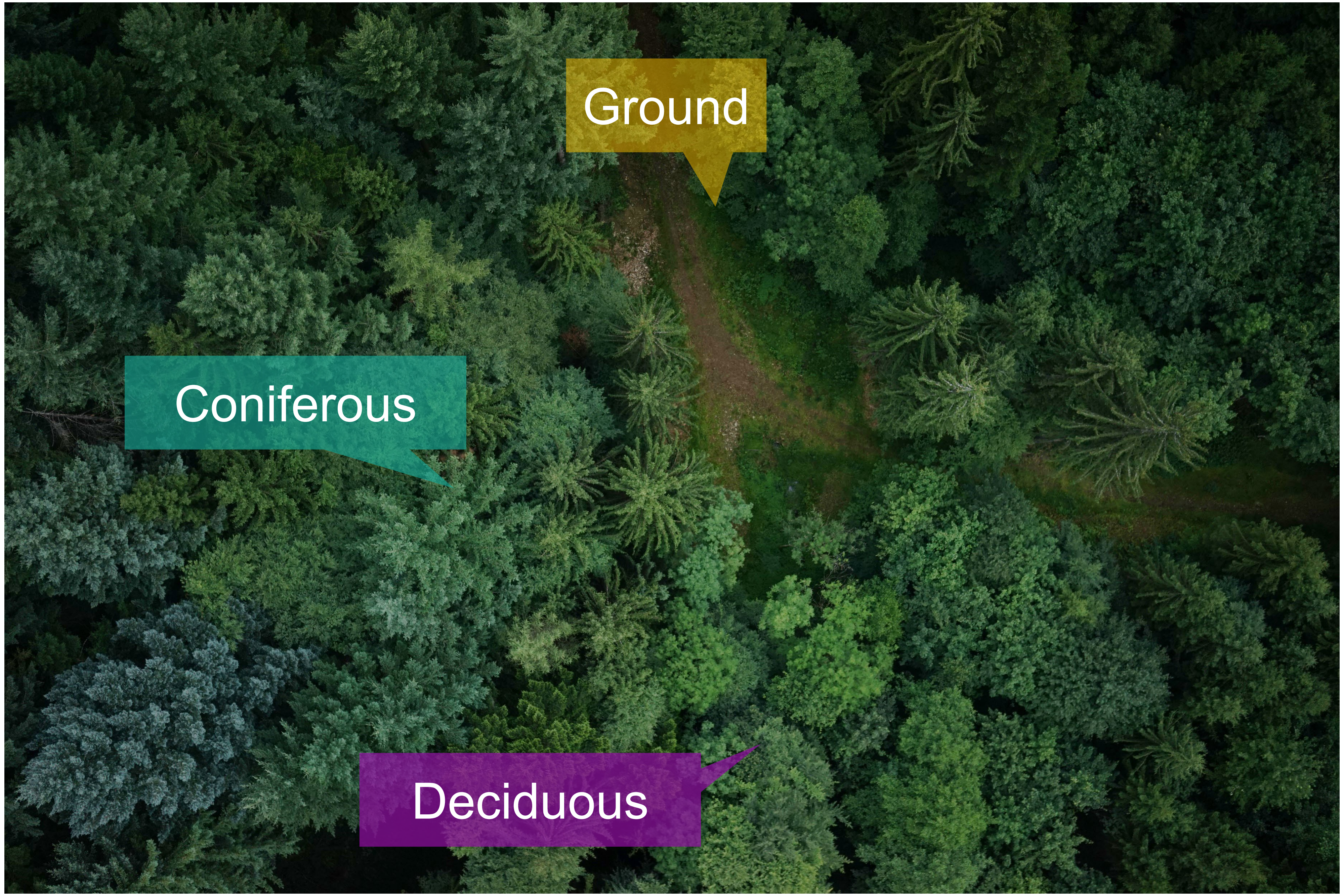


Image Pattern recognition

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University of Freiburg
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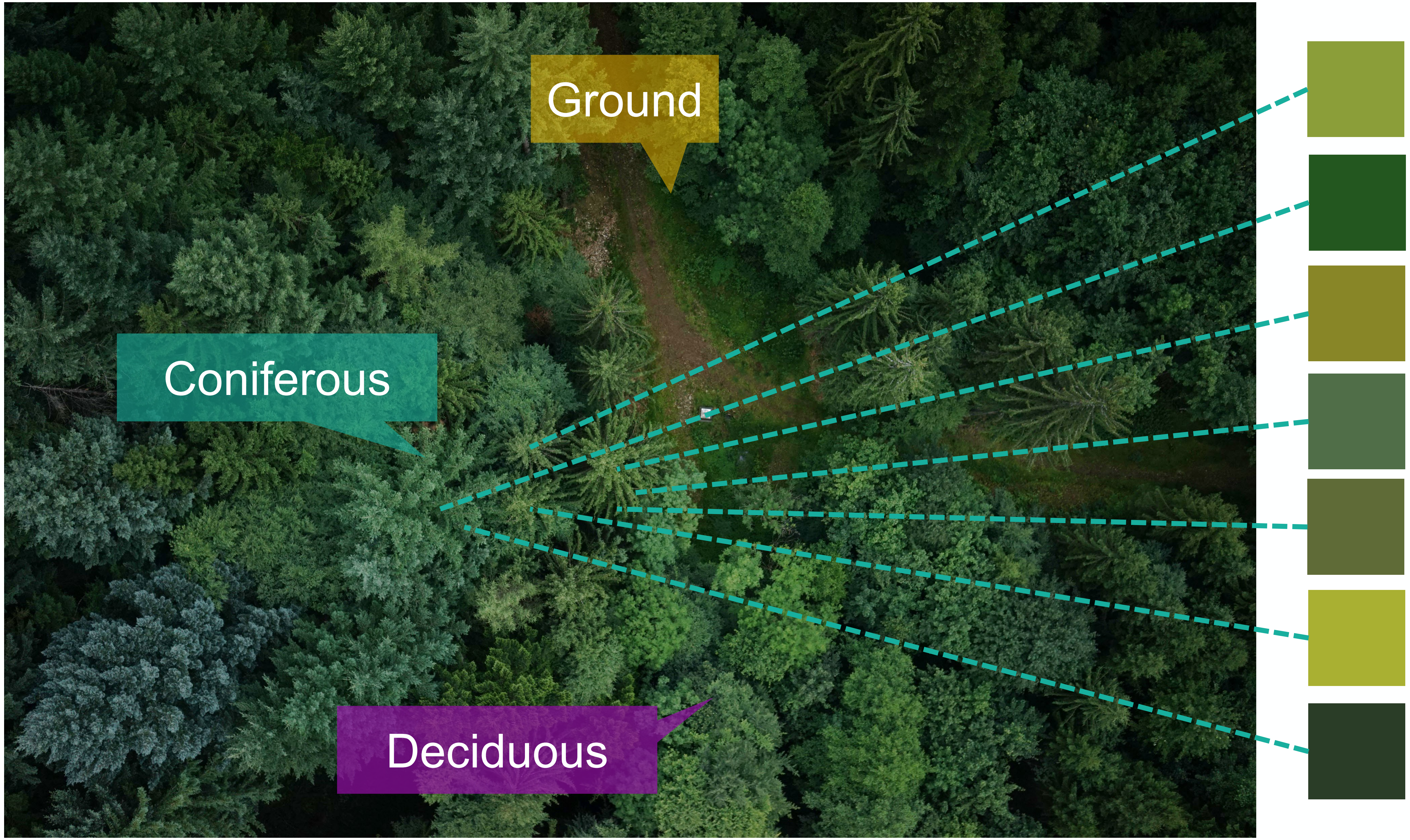
RGB Drone image



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RGB Drone image

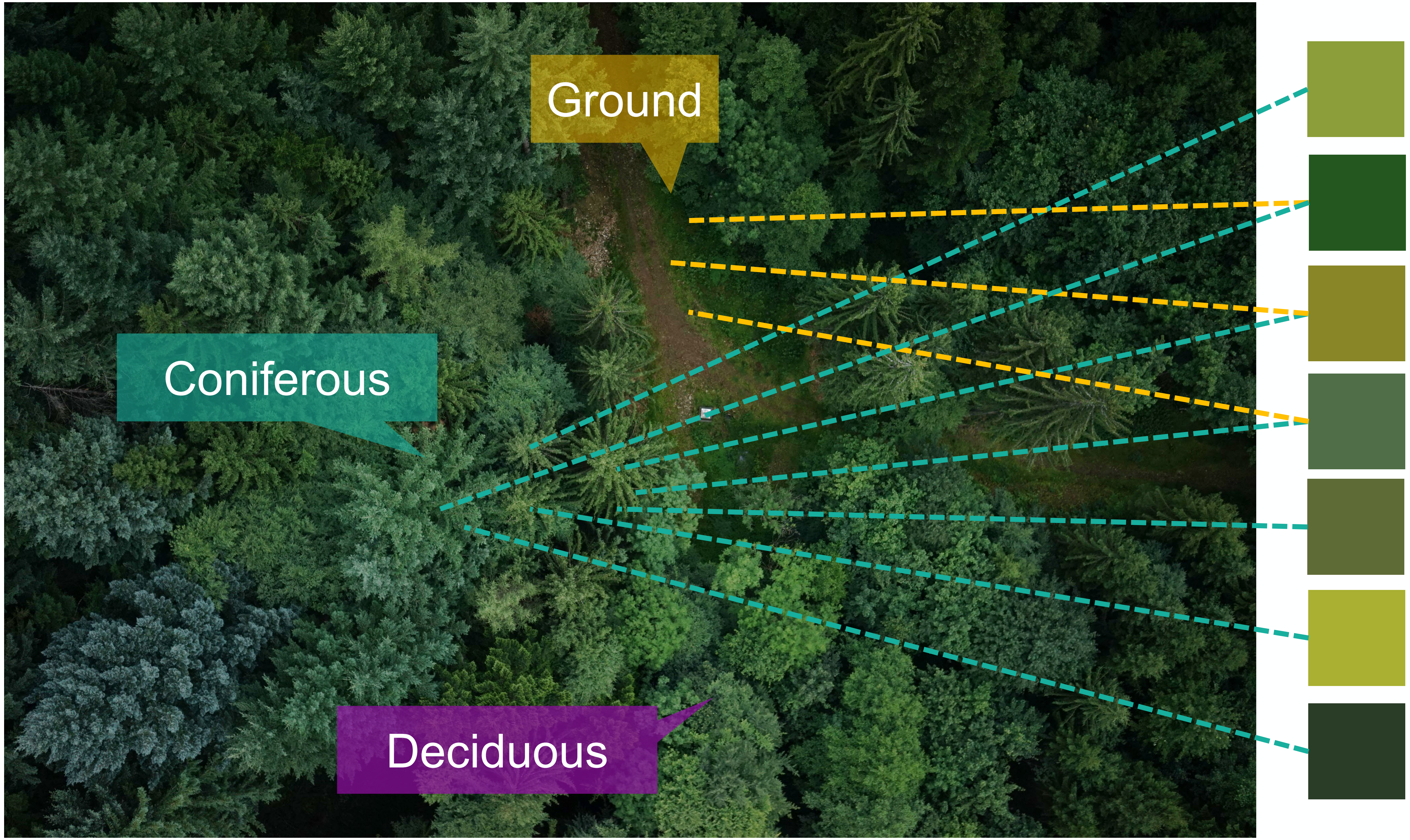

Image Pattern recognition

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RGB Drone image

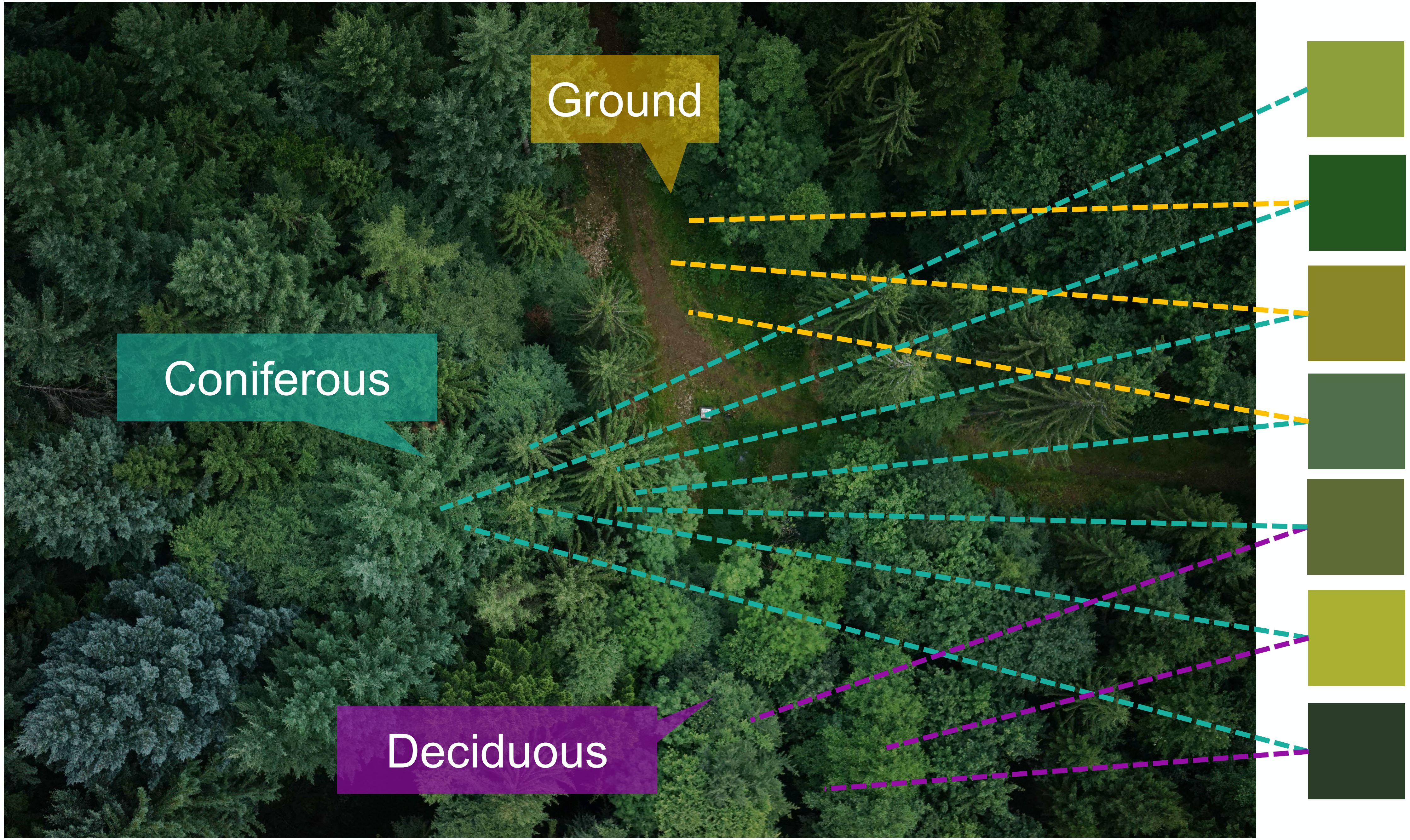

Image Pattern recognition

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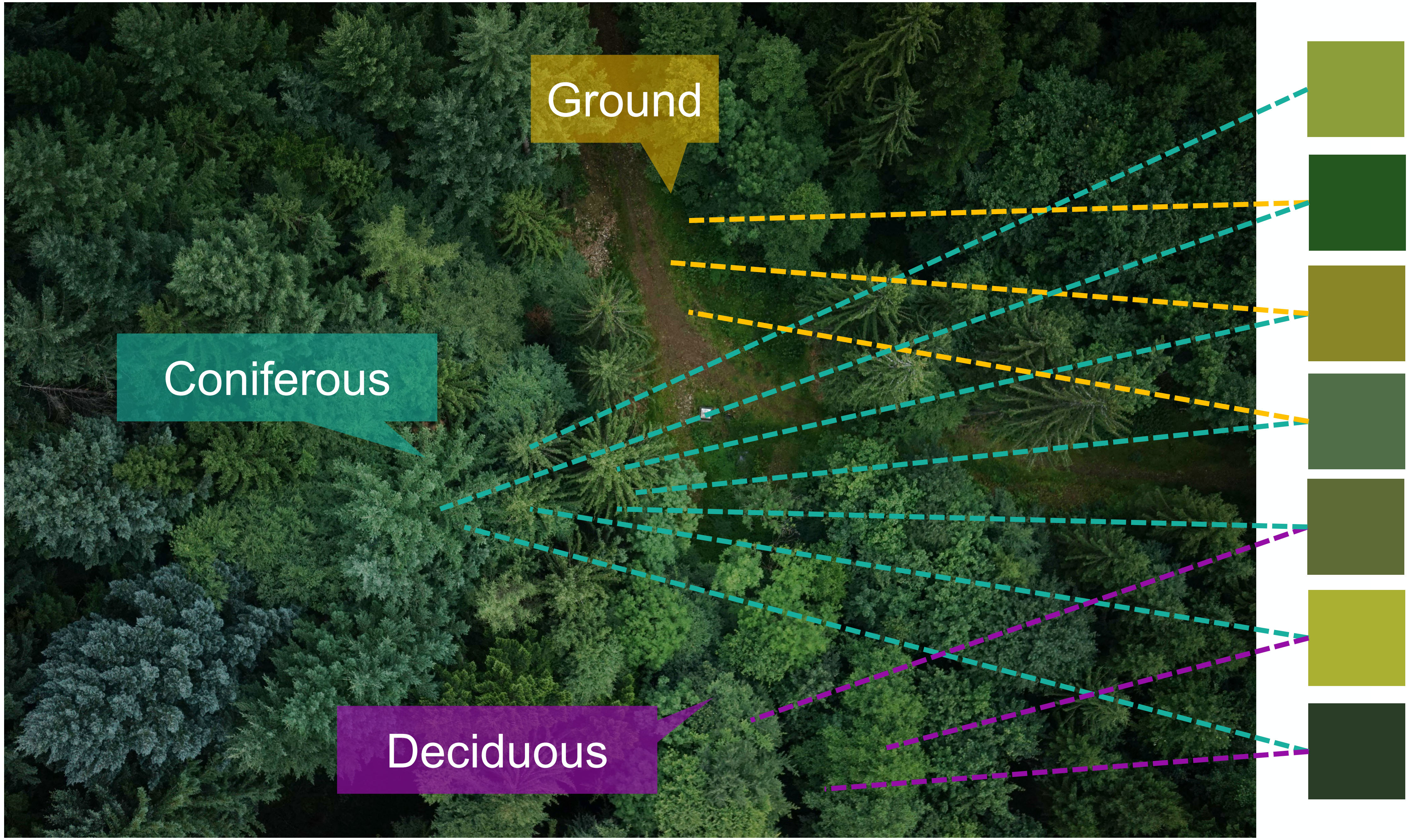

RGB color space:

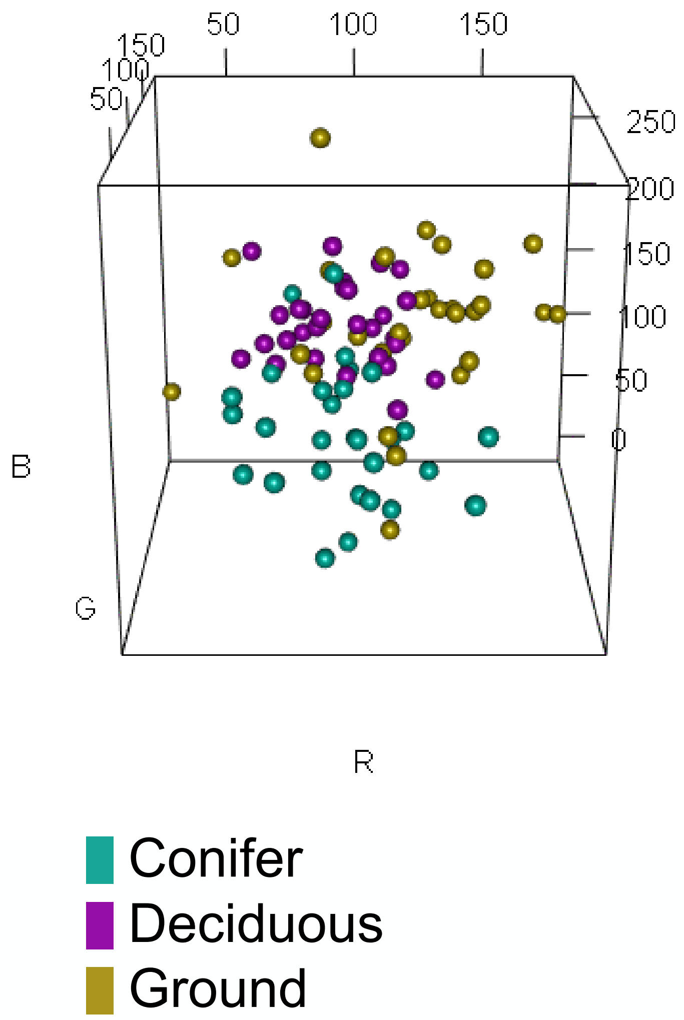

Image Pattern recognition

Image Pattern recognition

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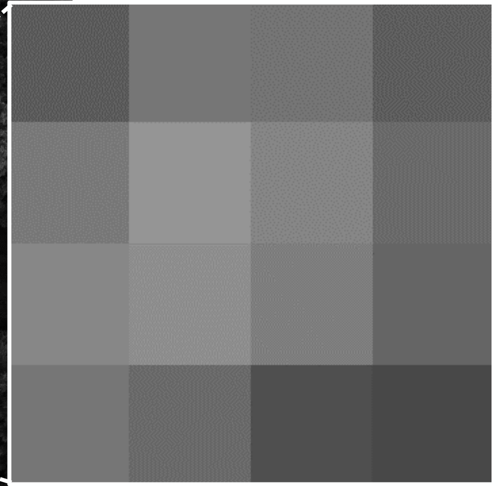


Response (y):

```
Class:
Deciduous
```

Predictors (y):

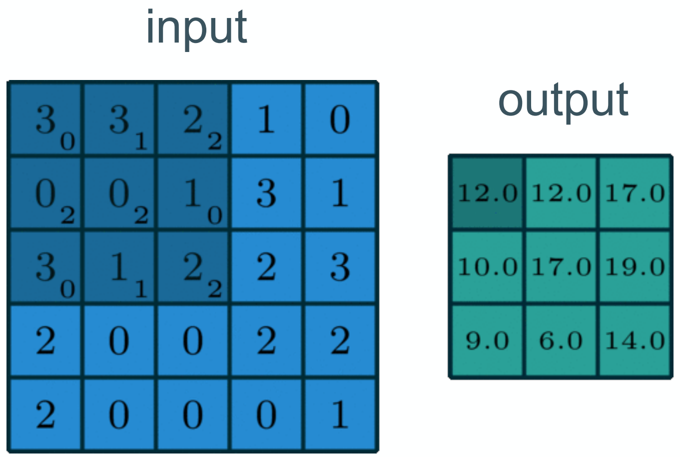
```
089  110  105 075
112 175 125 097
125 167 155 102
131 103 069 052
```

4 x 4 pixel matrix
(2D-tensor)

Image Pattern recognition

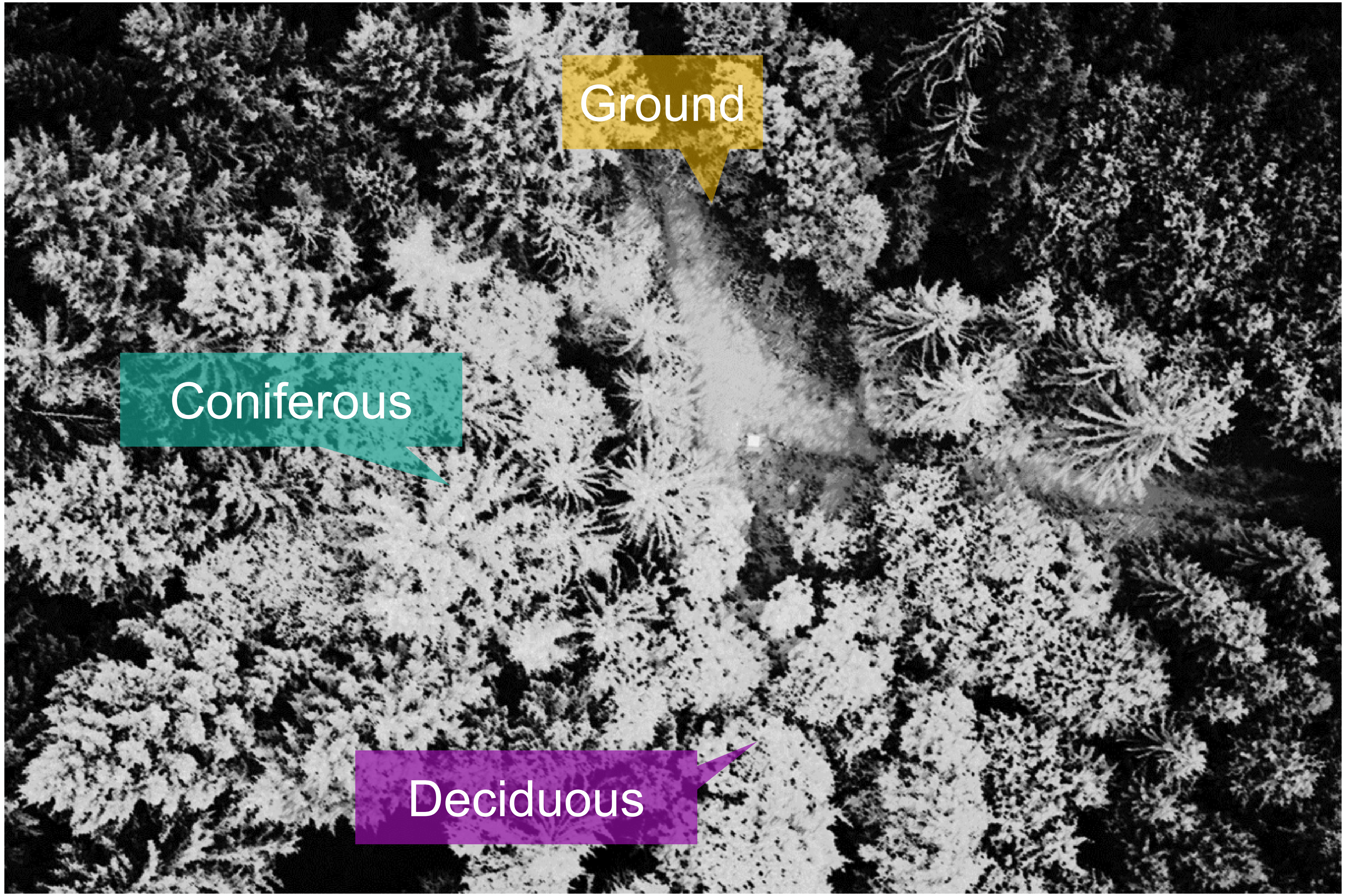
Texture Metrics

- Entropy
- Variance
- Mean
- Homogenity
- etc…



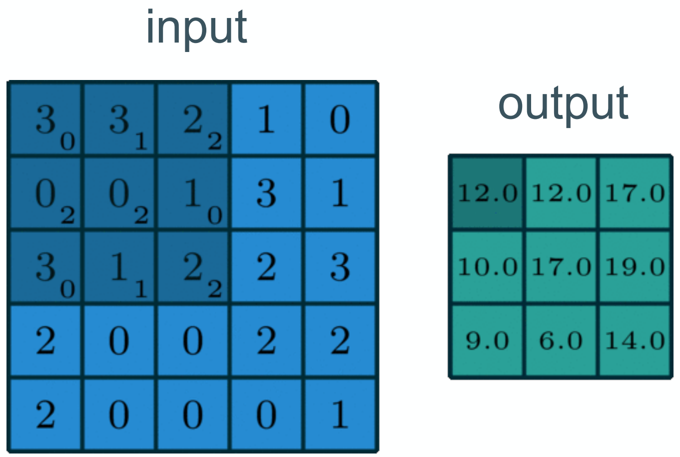
Haralick, R. M., & Shanmugam, K. (1973). Textural features for image classification. *IEEE Transactions on systems, man, and cybernetics*, (6), 610-621.

Image Pattern recognition



Texturmetriken

- Entropy
- Variance
- Mean
- Homogenity
- etc…



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Convolutional Neural Networks

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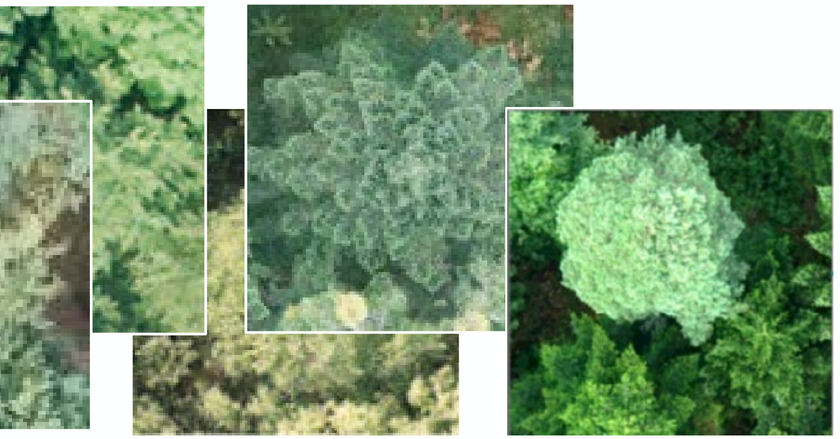
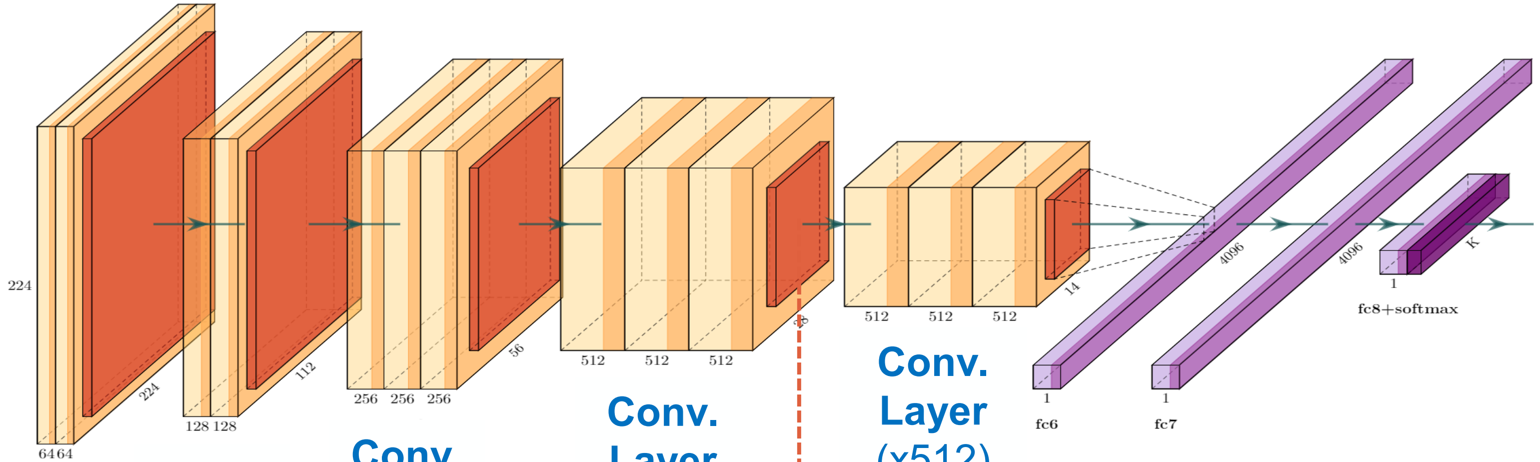
Image Classification (VGG)

Predictors (x, image data)





Conv. Layer (x64)

Conv. Layer (x128)

Conv. Layer (x256)

Conv. Layer (x512)

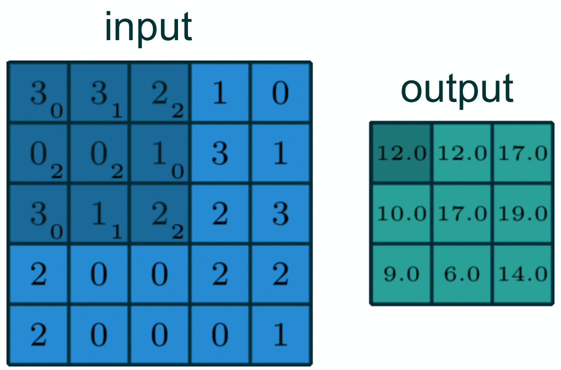
Conv. Layer (x512)

Response (y, Class)

Klasse	Probability
Deciduous	0.39
Coniferous	0.37
Ground	0.26

Spatial aggregation (Pooling)

Convolutions



https://github.com/HarisIqbal88/PlotNeuralNet
https://github.com/vdumoulin/conv_arithmetic

Kattenborn et al. 2022; Review on Convolutional Neural Networks for vegetation remote sensing, ISPRS.

Convolutional Neural Networks

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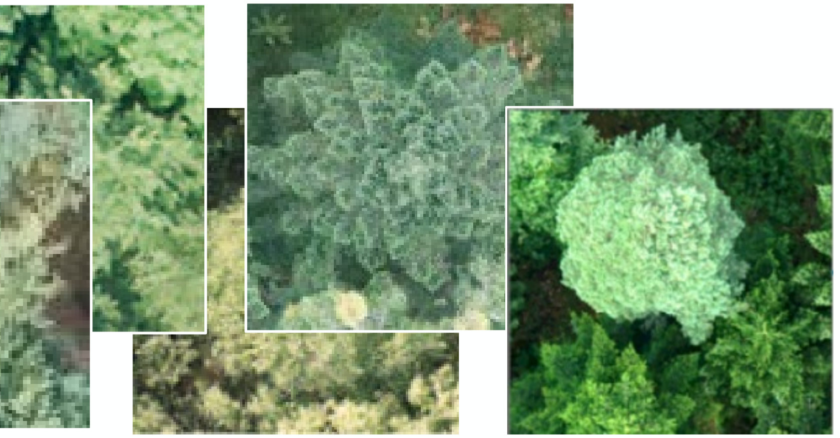
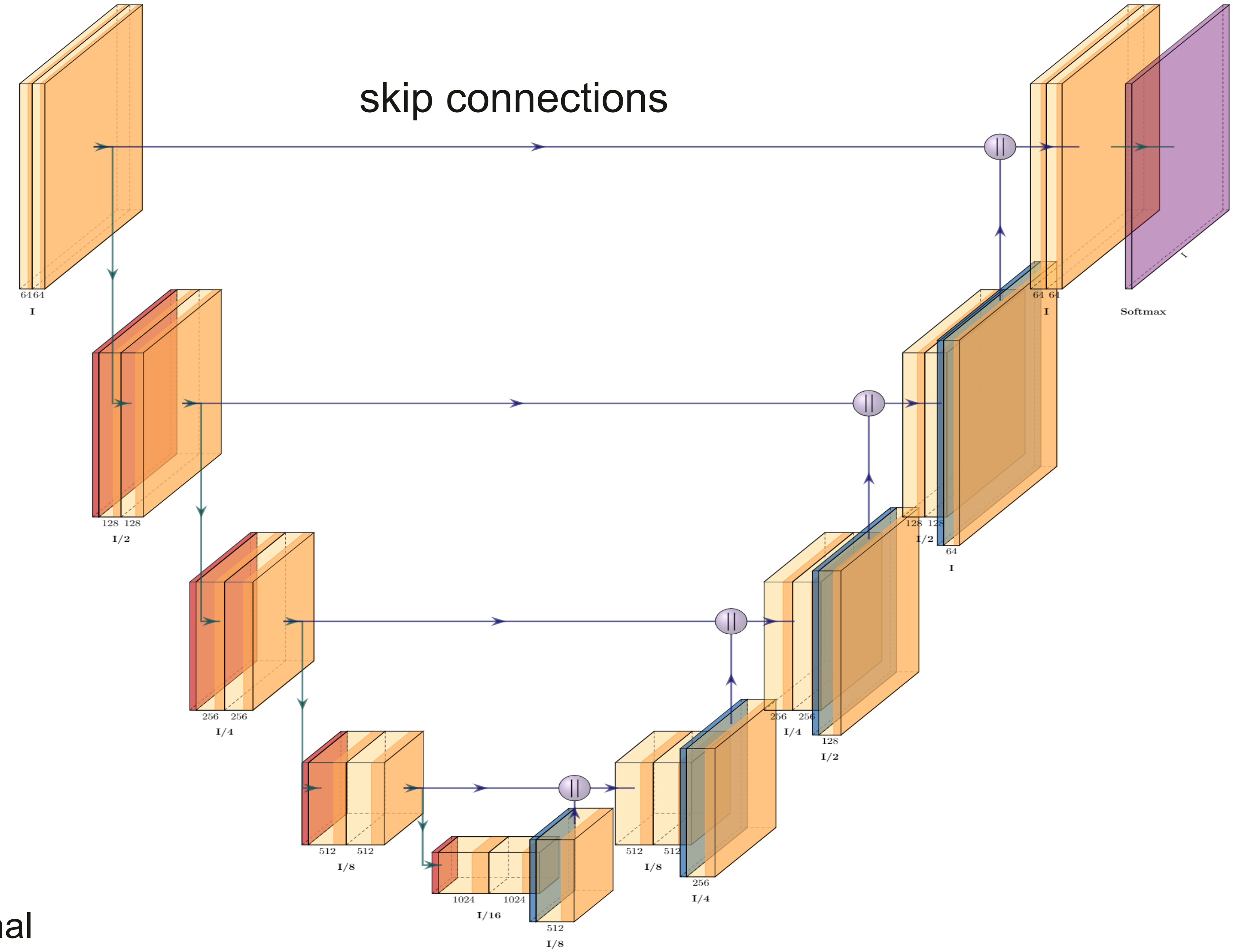
Image Segmentation (Unet)

Predictors (x, image data)





Output: Segmentierung

- Deciduous
- Coniferous
- Ground

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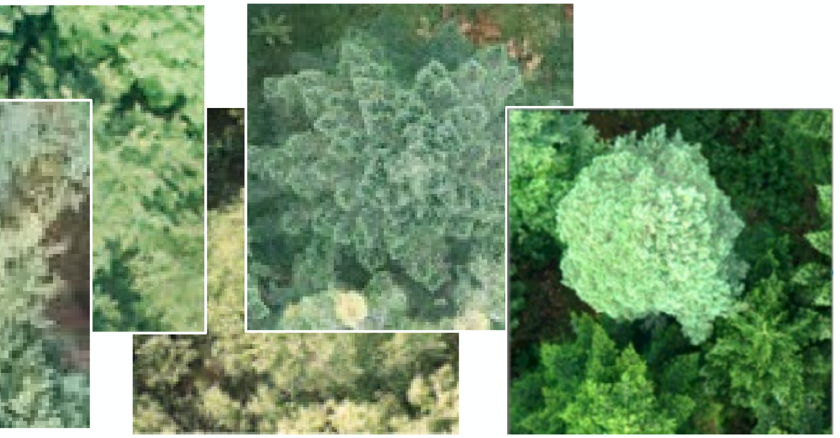
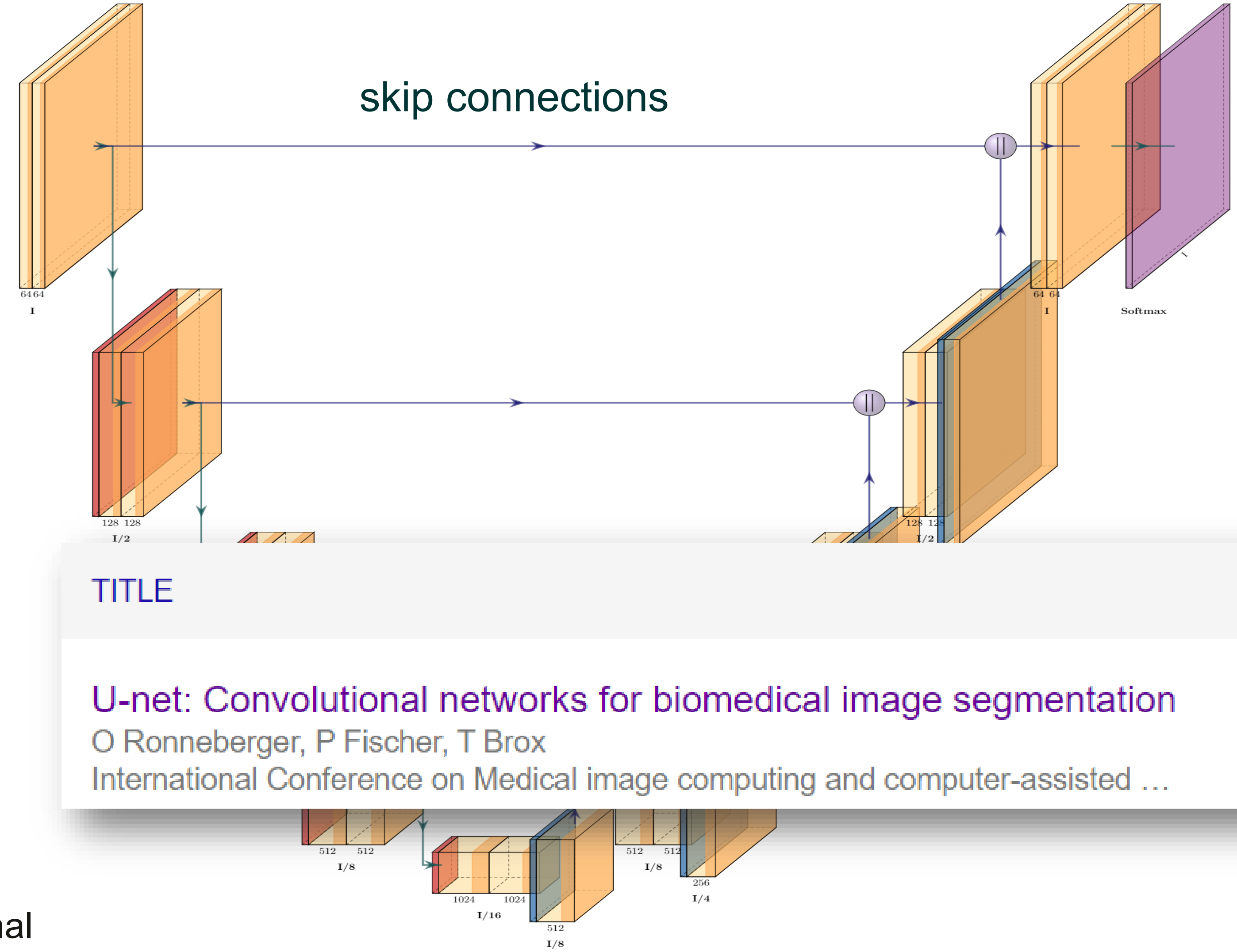
Image Segmentation (Unet)

Predictors (x, image data)





Output: Segmentation mask

TITLE	CITED BY	YEAR
U-net: Convolutional networks for biomedical image segmentation O Ronneberger, P Fischer, T Brox International Conference on Medical image computing and computer-assisted …	52248	2015

(Google Scholar)

https://github.com/HarisIqbal88/PlotNeuralNet

Kattenborn et al. 2022; Review on Convolutional Neural Networks for vegetation remote sensing, ISPRS.

Convolutional Neural Networks

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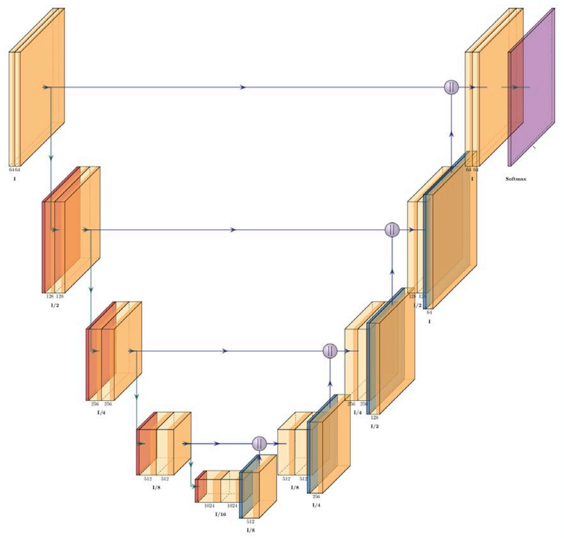
CNN Training
(Training phase with reference data)

Visual
Interpretation

Drone Orthomosaic
2 cm Resolution
> 56 Mio Pixel

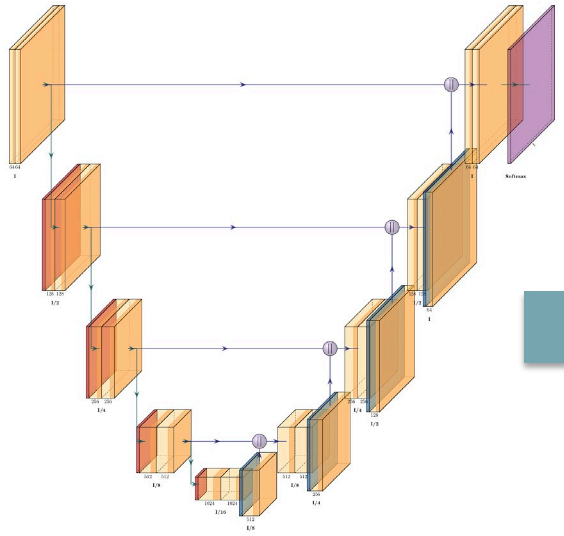


Trained
Convolutional Neural Network
(Segmentation, UNet)

Convolutional Neural Networks

CNN Training
(Training phase with reference data)

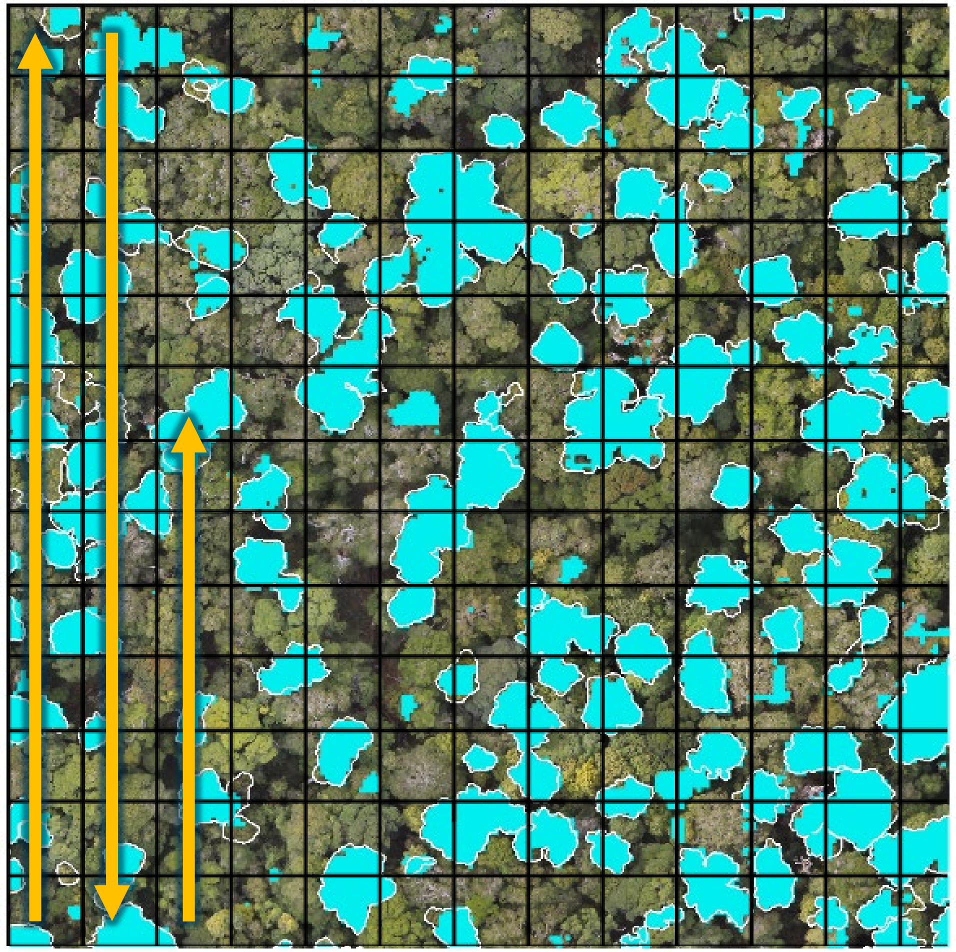
Visual
Interpretation



Drone Orthomosaic
2 cm Resolution
> 56 Mio Pixel

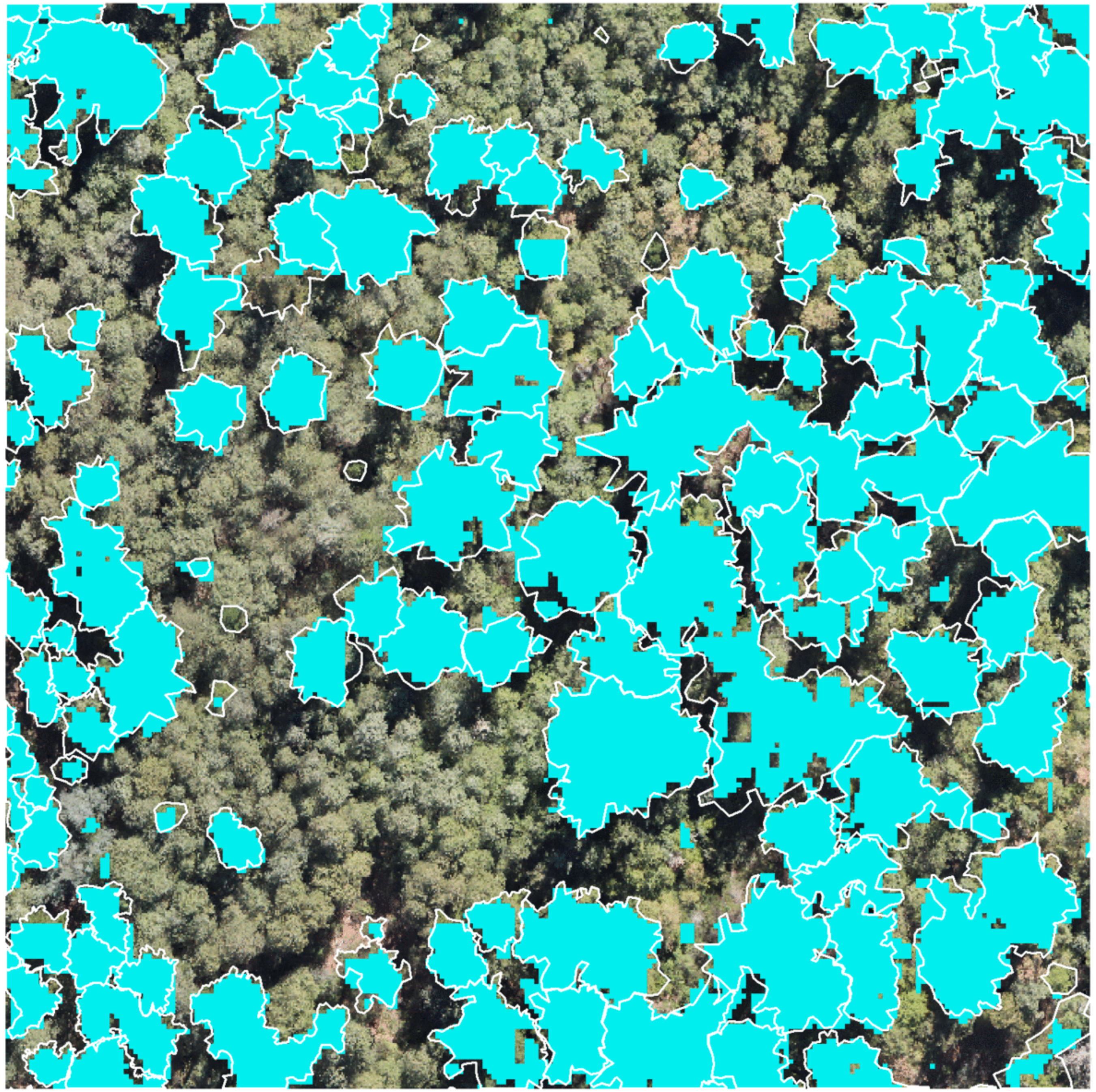
Trained
Convolutional Neural Network
(Segmentation, UNet)

CNN Inference
(Application to new data)



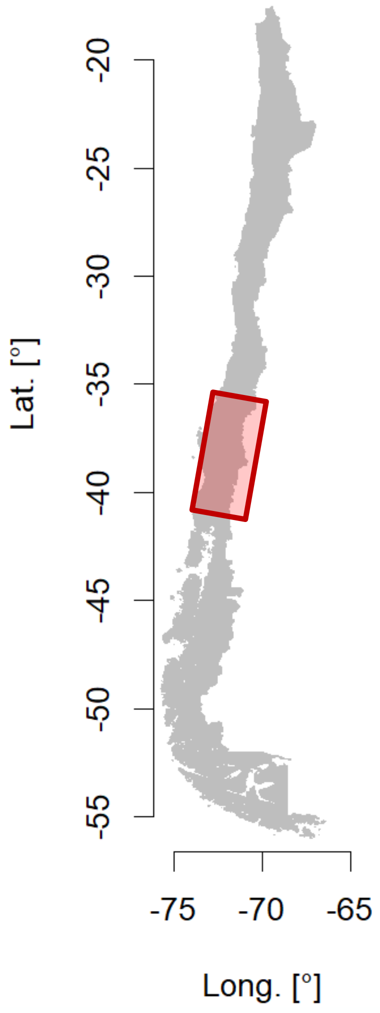
Convolutional Neural Networks

Kattenborn et al. 2019, Scientific Reports



20 m

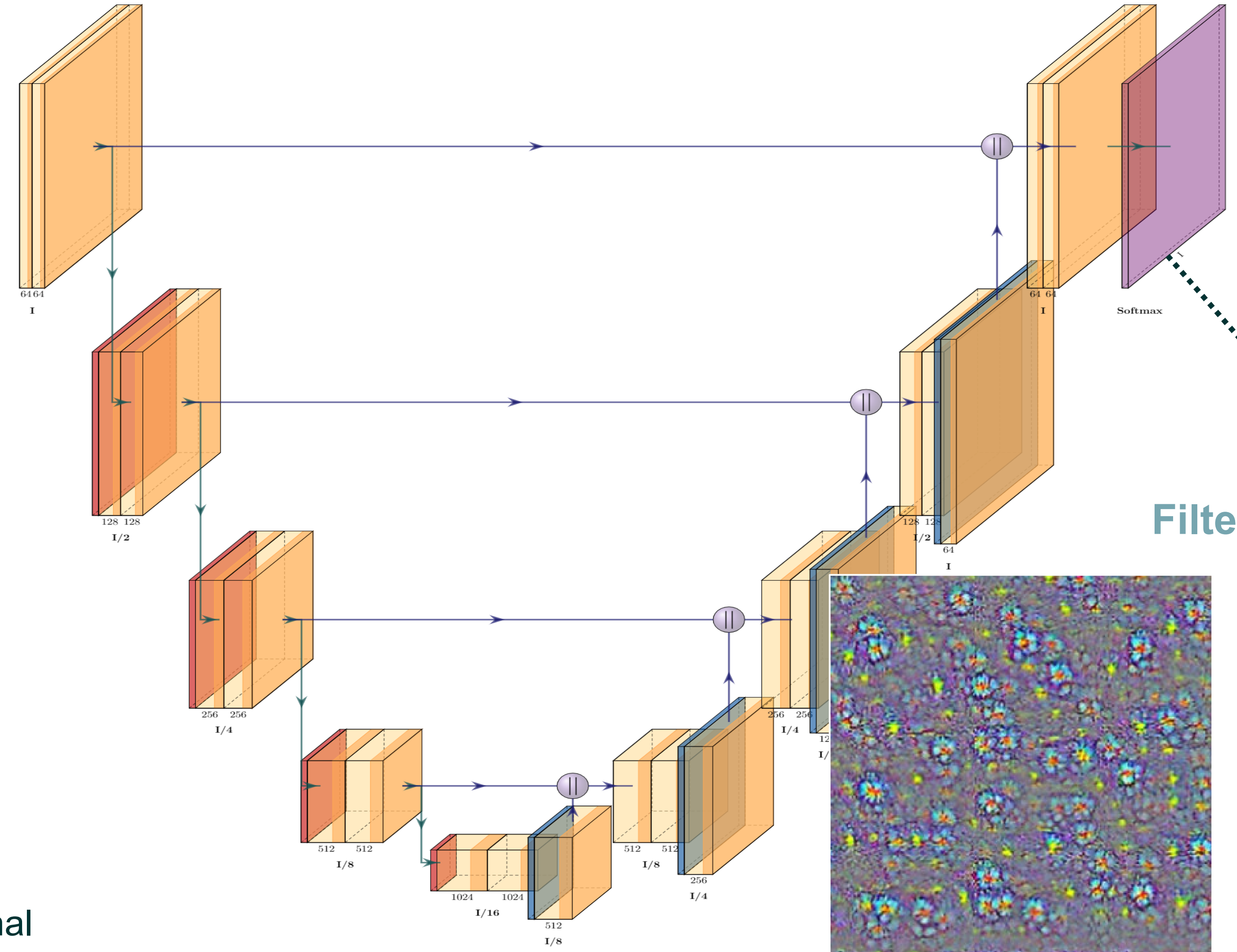
Study area:
Central Chile



Convolutional Neural Networks

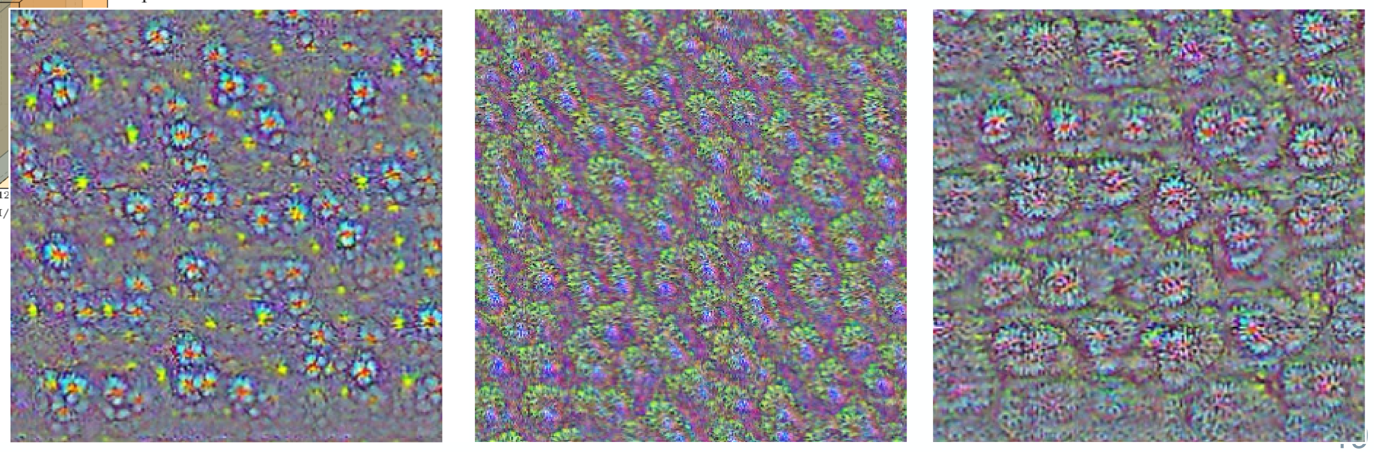
Image Segmentation (Unet)

Input (Image data)



Output: Segmentation mask

Filter representations



https://github.com/HarisIqbal88/PlotNeuralNet

Kattenborn et al. 2022; Review on Convolutional Neural Networks for vegetation remote sensing, ISPRS.

Convolutional Neural Networks

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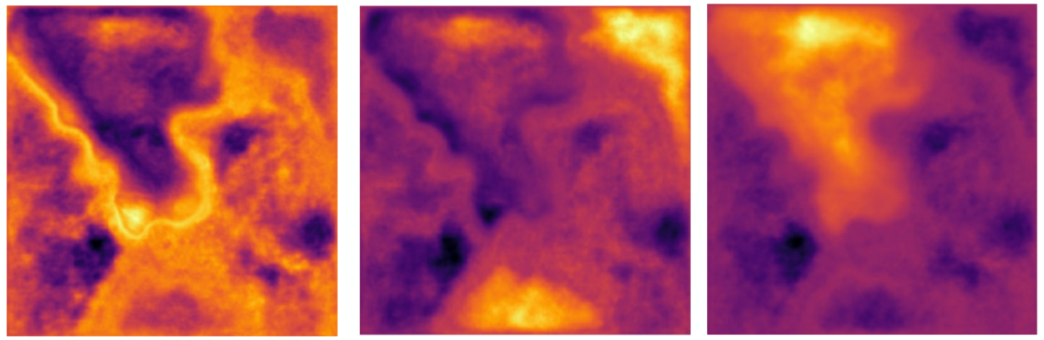
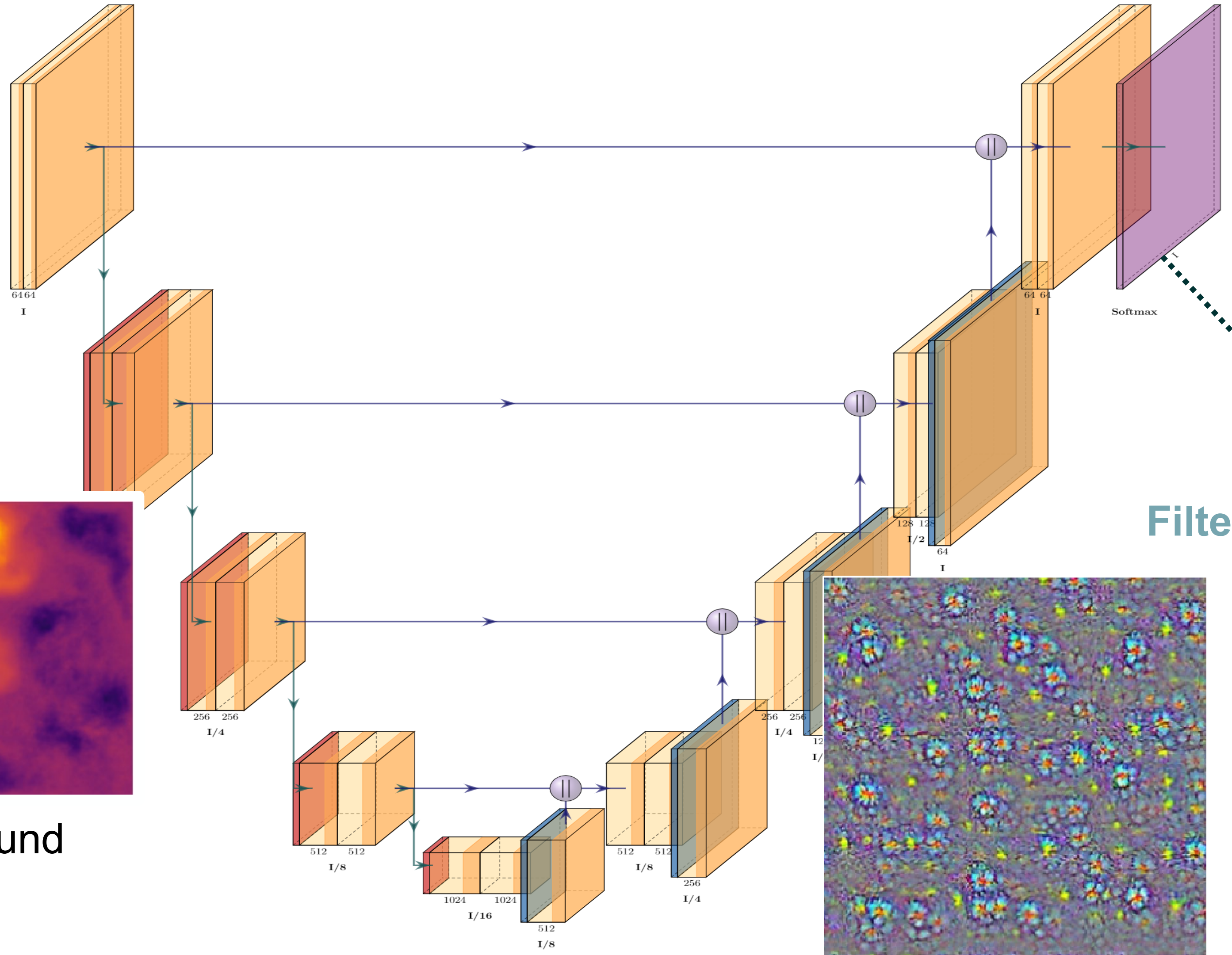
Image Segmentation (Unet)

Predictors (x, image data)

Feature Attribution



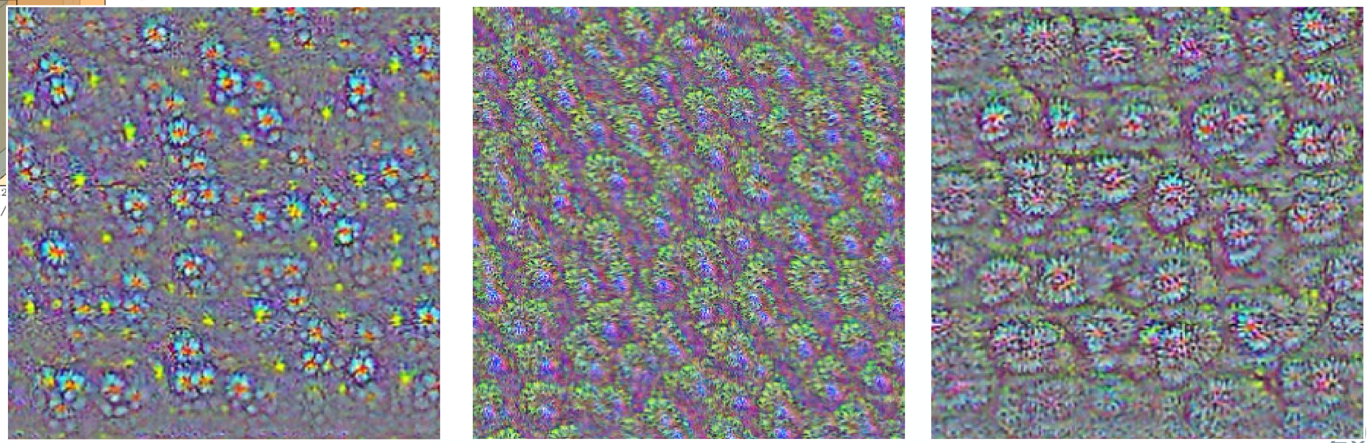
Deciduous Coniferous Ground



Output: Segmentation mask

Deciduous
Coniferous
Ground

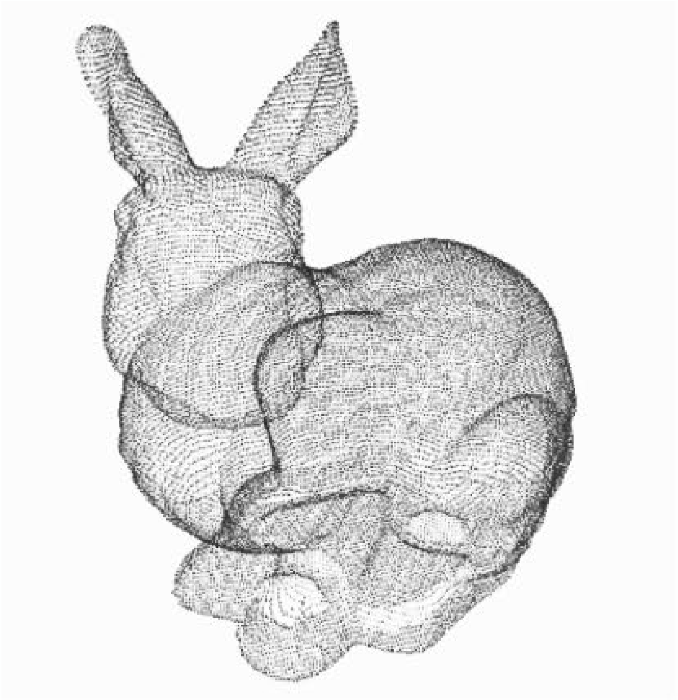
Filter representations

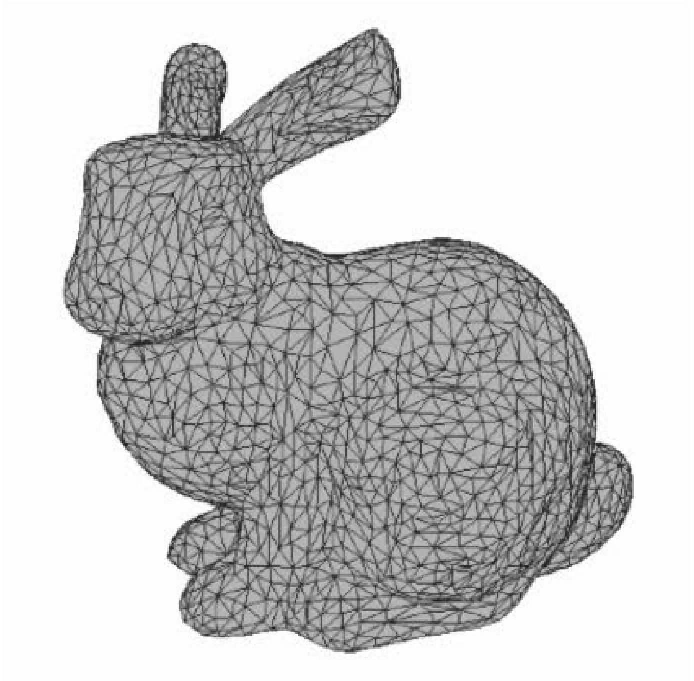


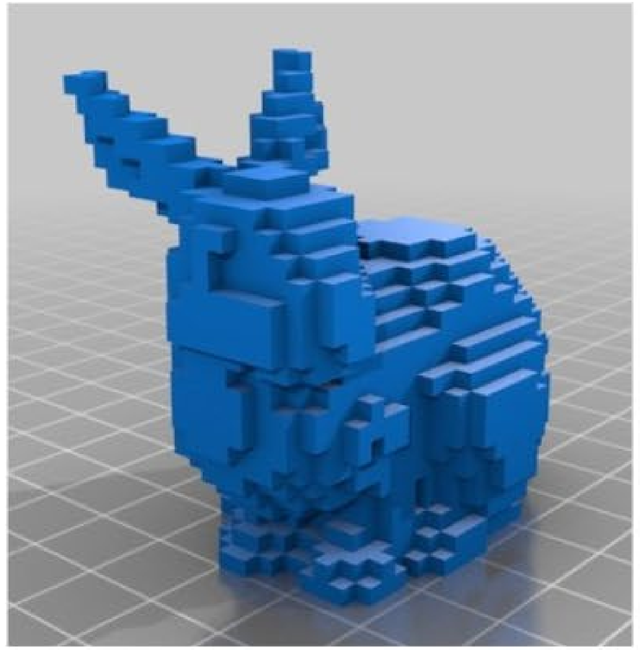
Kattenborn et al. 2022; Review on Convolutio
Neural Networks for vegetation remote sensing, ISPRS.

Point cloud-based Pattern recognition

Point Cloud Pattern Recognition

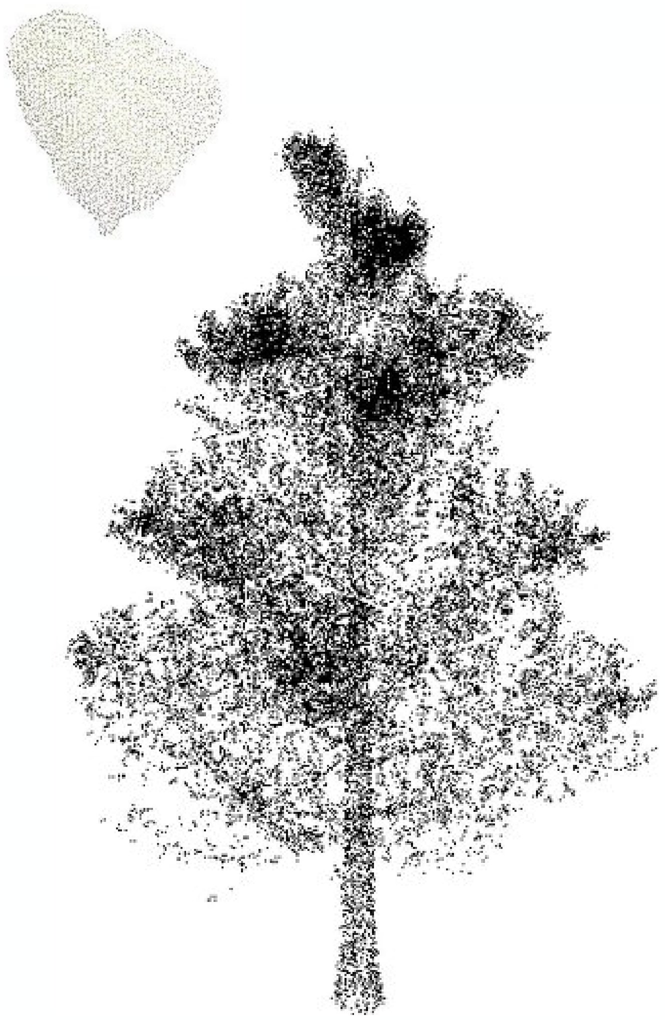

Point Cloud


Mesh

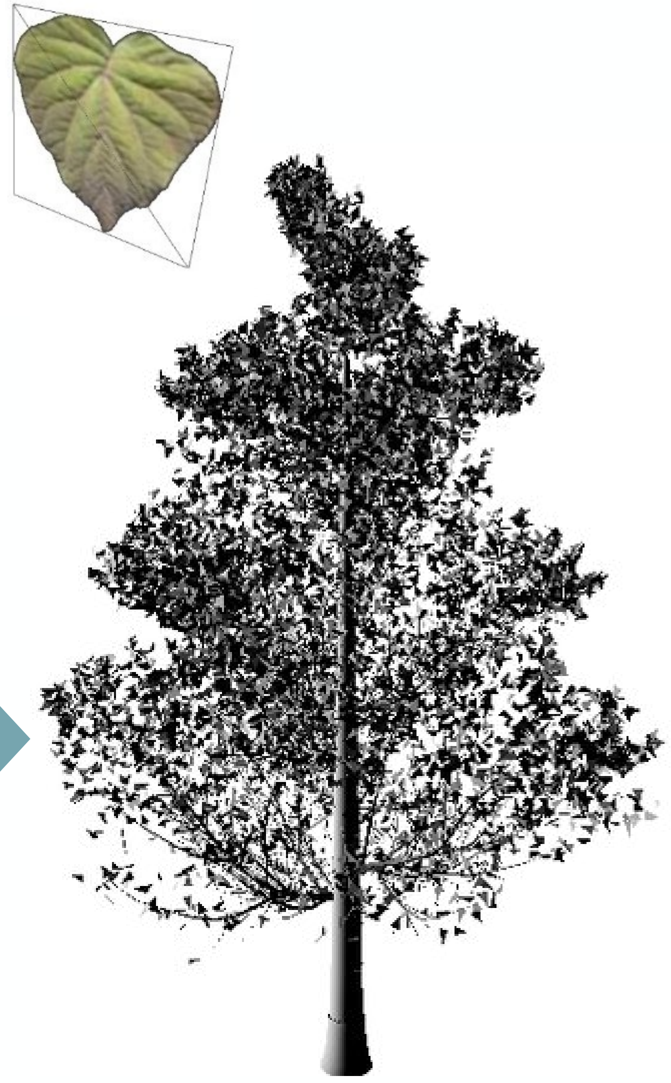

Volumetric


Projected View

Point Cloud Pattern Recognition

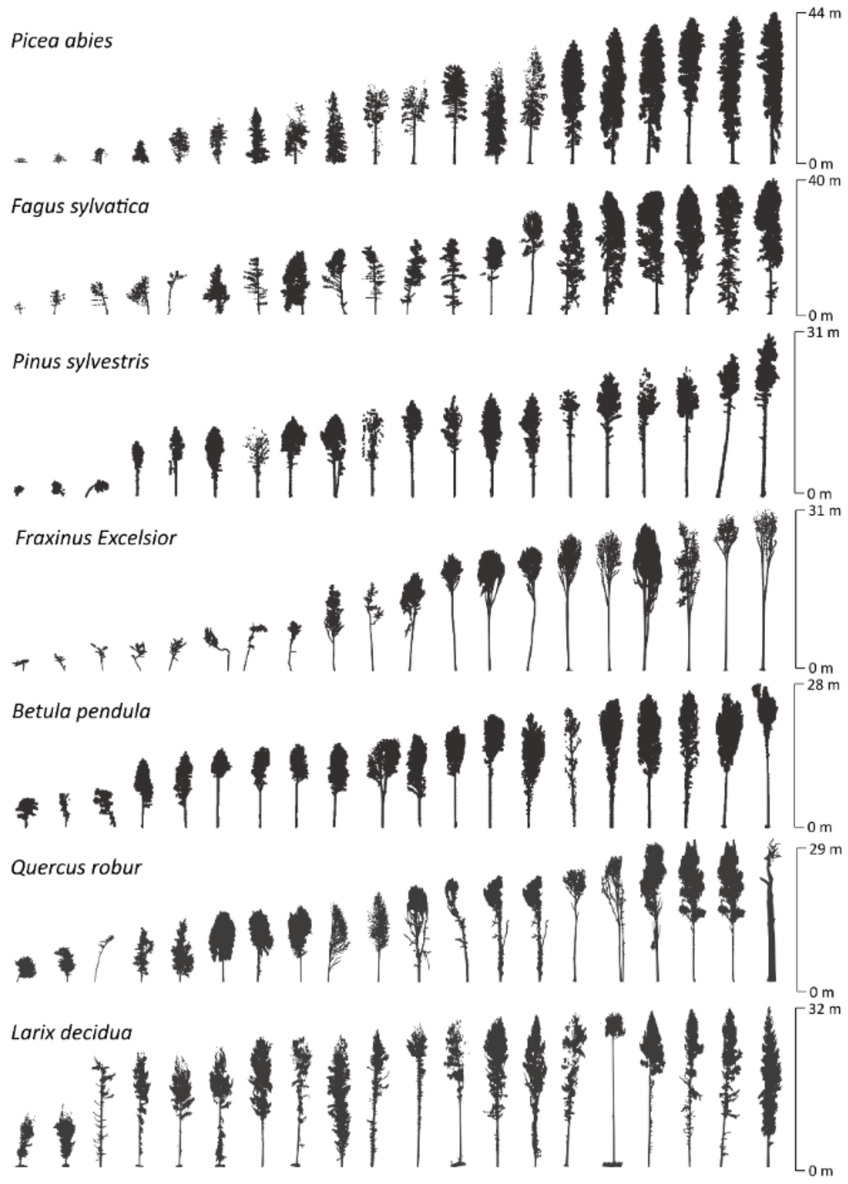


Point Cloud



Mesh

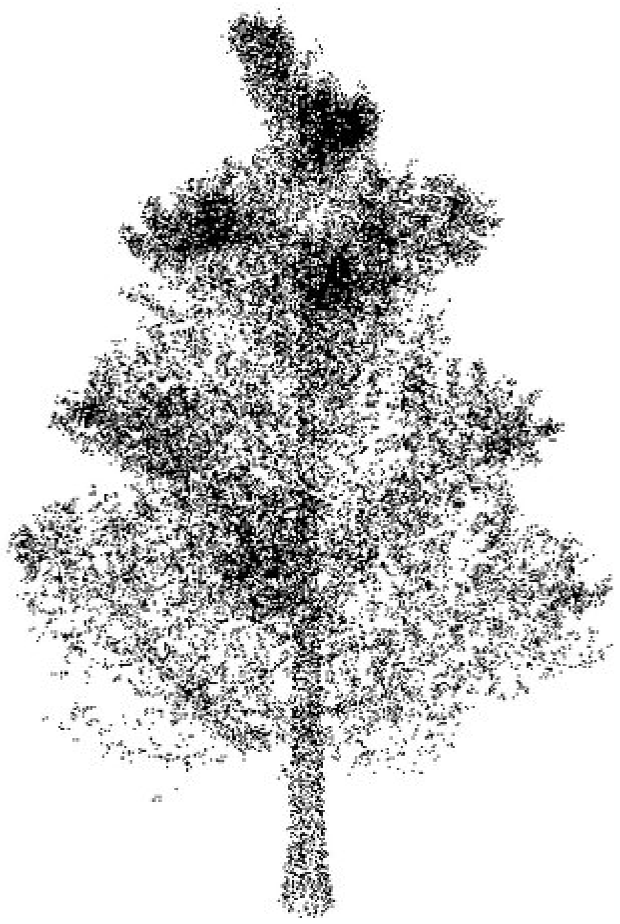
Volumetric



Projected View

https://peterwonka.net/Publications/pdfs/2005.PBG.Rovira.PointSamplingUniformLines.pdf
https://doi.org/10.1016/j.ufug.2021.127324
https://doi.org/10.48550/arXiv.2408.06507

Point Cloud Pattern Recognition



Preferably **extract information from point clouds**

- no information loss

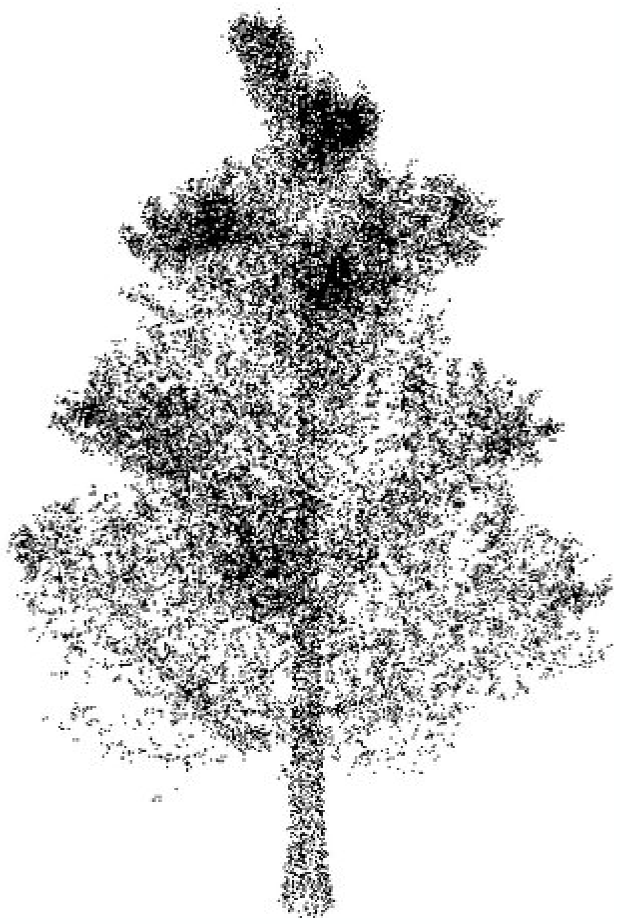
Challenges with points

- Unstructured, Unordered
- Needs to be rotation invariant

  > point cloud rotation should not alter classification result

https://peterwonka.net/Publications/pdfs/2005.PBG.Rovira.PointSamplingUniformLines.pdf

Point Cloud Pattern Recognition



How is it done?

- Translation from X,Y,Z into artifical higher order space
- Symmetric functions (functions that do not care about order)
- Transformation (e.g. rotation on the fly, learned by the model)

→ **Global features**

- The overall pattern of points and their properties

→ **Local features**

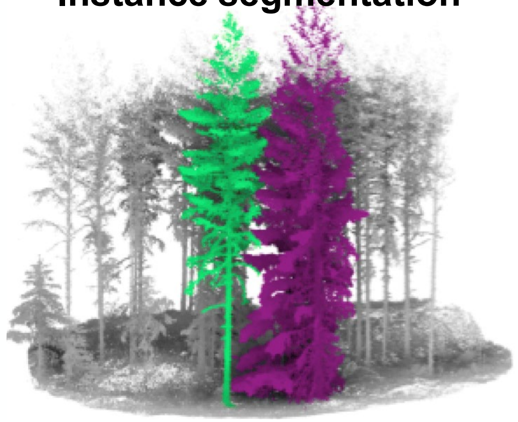
- Relation between points (e.g. curvature)
- Enables segmentation tasks (e.g. which trees belong to the trunk, which are leaves, what are ground points)

https://peterwonka.net/Publications/pdfs/2005.PBG.Rovira.PointSamplingUniformLines.pdf

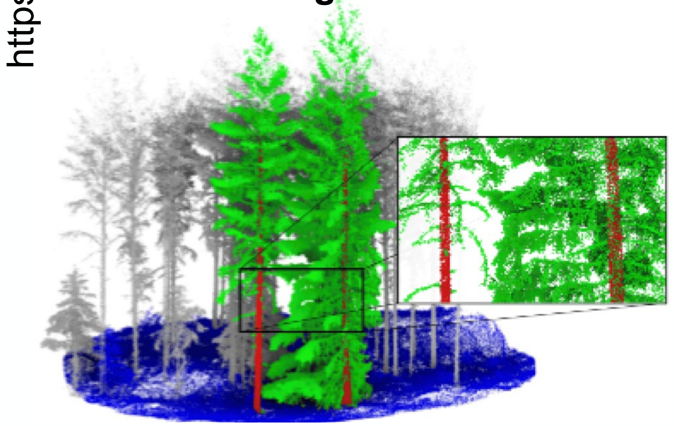
Point Cloud Pattern Recognition

Raw point cloud

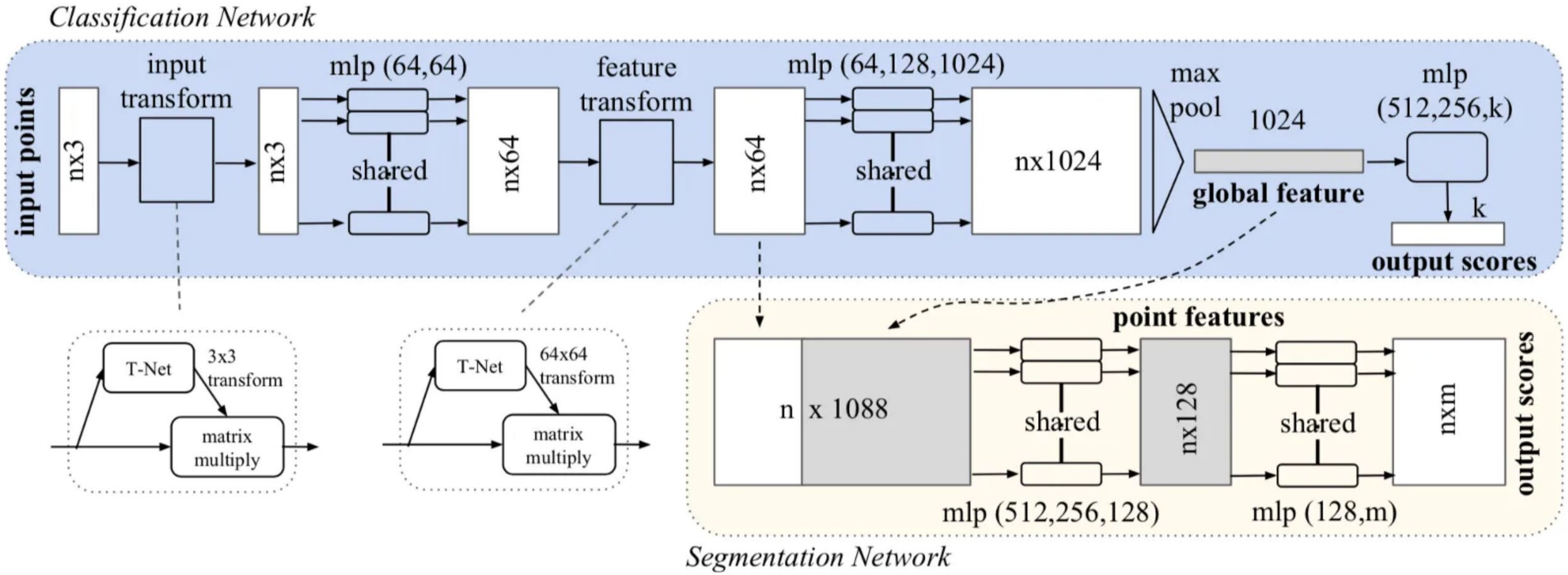
Instance segmentation



Semantic segmentation



https://www.mdpi.com/2072-4292/15/15/3737



Point Cloud Pattern Recognition

Raw point cloud

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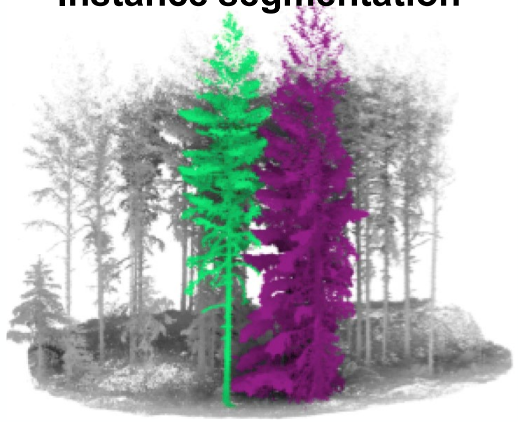

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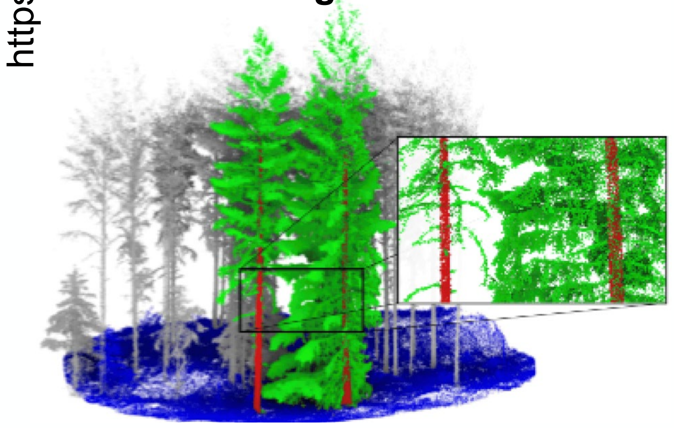


https://www.mdpi.com/2072-4292/15/15/3737

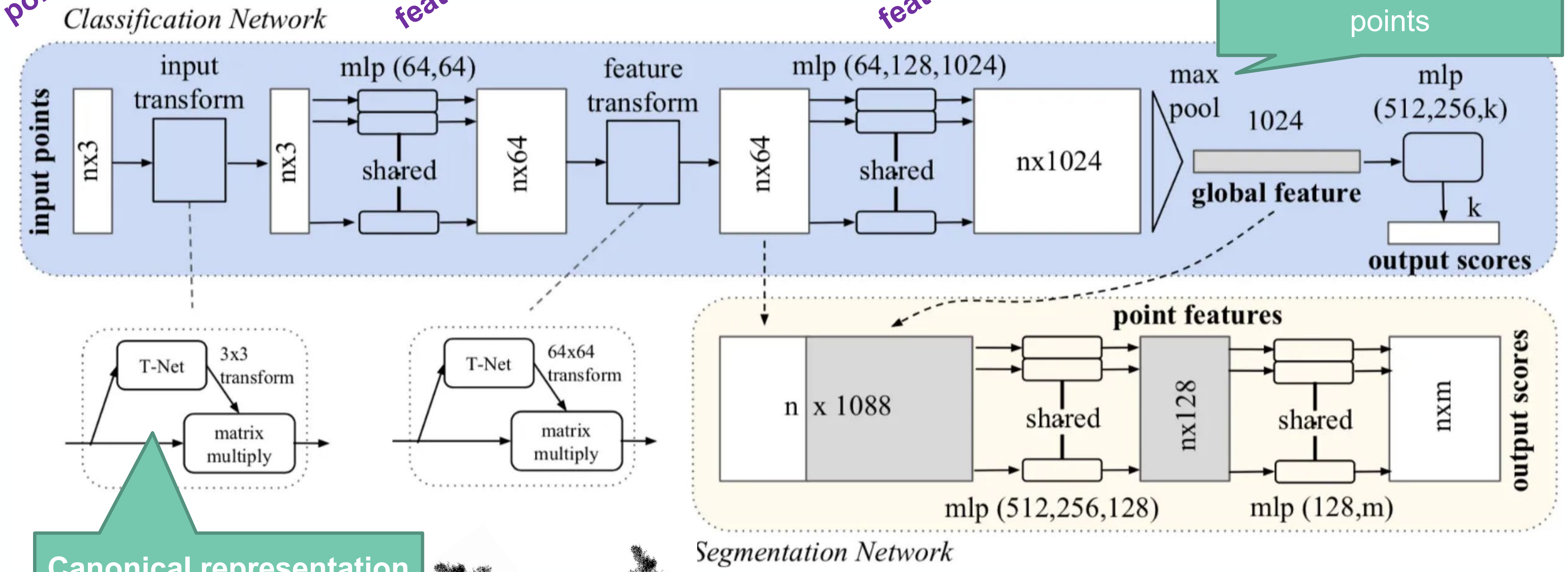
From **XYZ** to **higher order** (abstract) **representation**

point1= (5.2, 3.1, 2.2)
→ length of 3 (x,y,z)

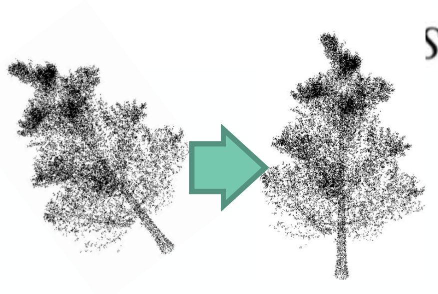
featureA1 = (0.4, 3.3, 5.2, ….)
→length of 64

featureB1 = (0.2, 0.8, 4.2, …,)
→ length of 1024

Symmetric functions (e.g. max) that do not care about the order of points

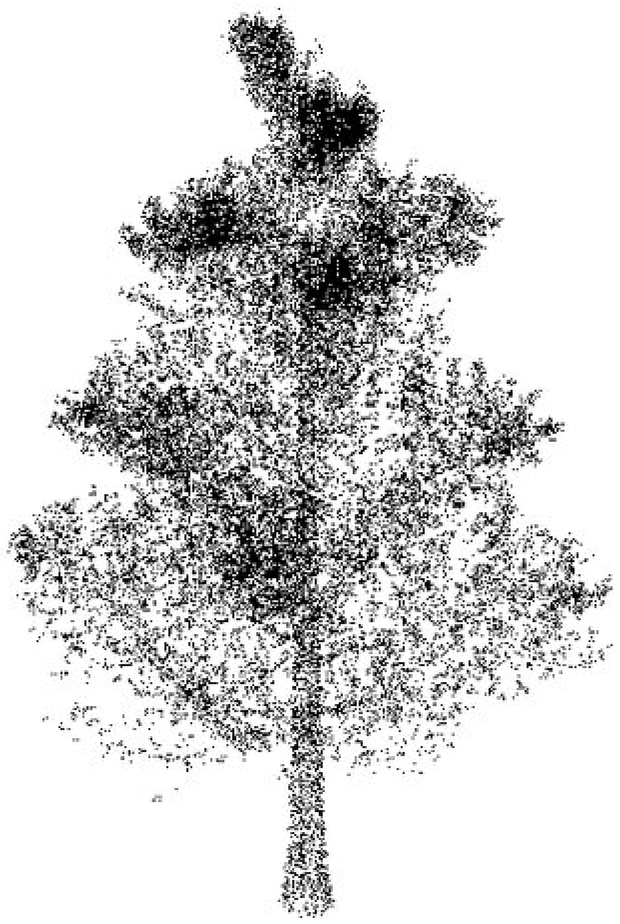


Canonical representation (Model will „rotate“ objects on the fly)



Relation between neighbouring points

Point Cloud Pattern Recognition



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Hands-on on:
Evaluation of Point Cloud-based Segmentation

ELSEVIER

Remote Sensing of Environment
Volume 313, 1 November 2024, 114367

SegmentAnyTree: A sensor and platform agnostic deep learning model for tree segmentation using laser scanning data

Maciej Wielgosz [a 1], Stefano Puliti [a 1], Binbin Xiang [b], Konrad Schindler [b], Rasmus Astrup [a]

Highlights

- Developed a versatile deep learning method for tree segmentation with lidar.
- Evaluated model performance across various platforms with sparsity impact analysis.
- Showed that gradual sparsification as a training strategy is effective for lidar.
- Improved understory tree detection with lower computational needs than others.
- Set new performance standards in Wytham Woods and TreeLearn datasets.