UNIVERSITY OF TWENTE.

AI & 3D POINT CLOUD CLASSIFICATION

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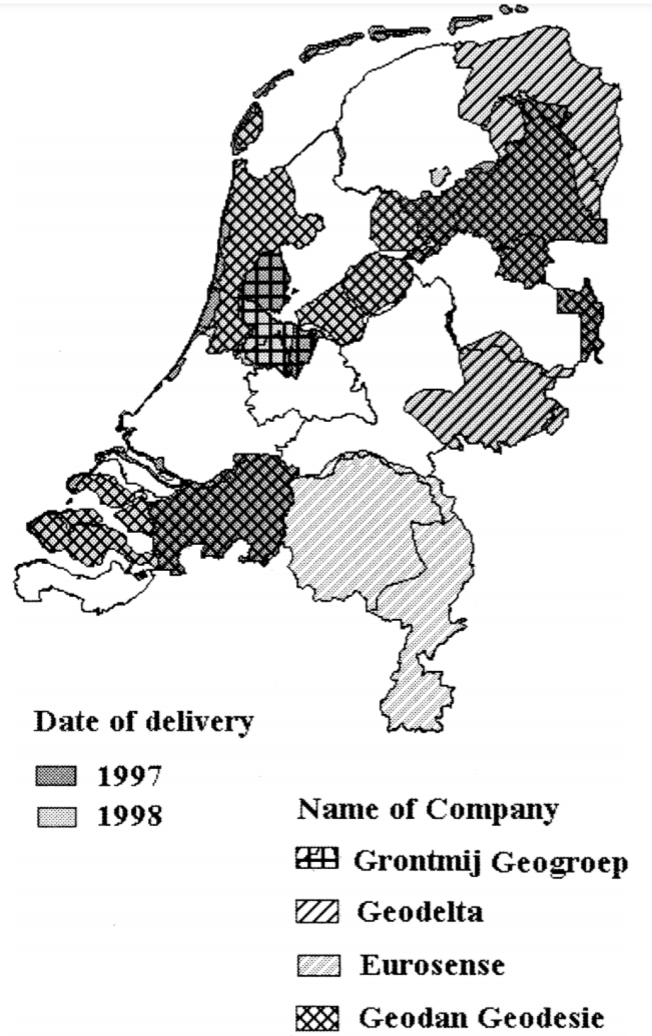
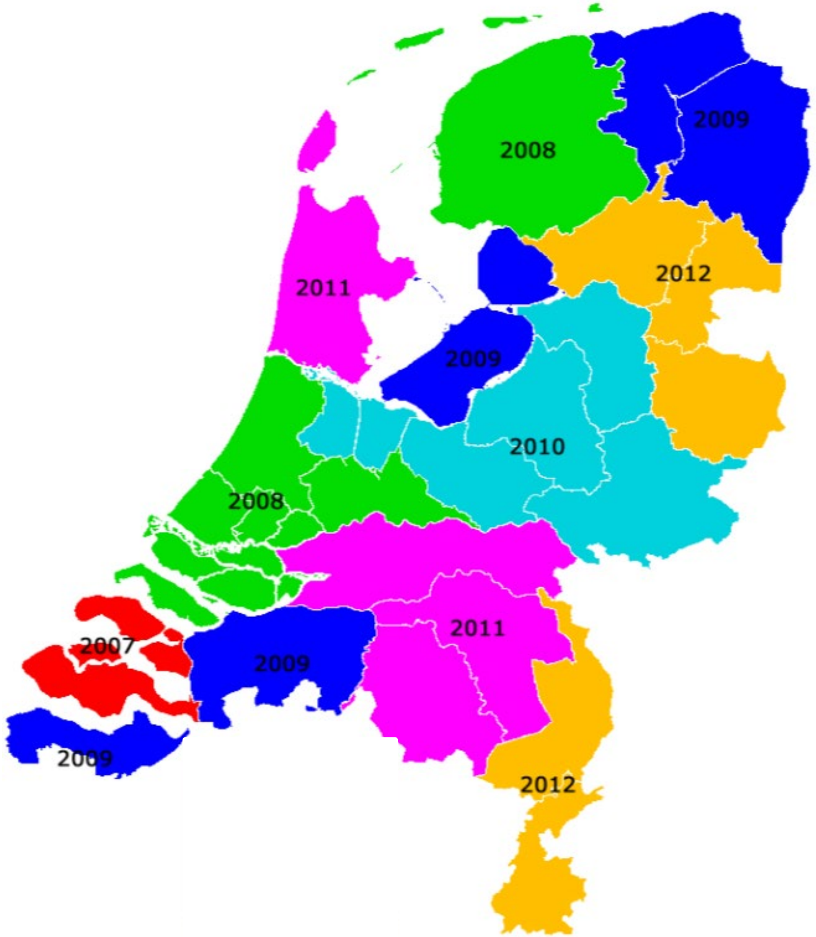
NATIONAL HEIGHT MODEL AHN (1997-2004)

- Actueel Hoogtemodel Nederland
- Rijkswaterstaat, water boards, and provinces
- Point density 1 point / 16 m^2
- 2.5 billion points
- Systematic height error 10 cm
- Stochastic height error 15 cm
- Classification in ground / non-ground
- Government and companies learned a lot…



NATIONAL HEIGHT MODEL AHN2 (2007-2012)

- Rijkswaterstaat and water boards
- Point density 8-10 point / m^2
- 640 billion points
- Systematic height error 5 cm
- Stochastic height error 5 cm
- Classification in ground / non-ground



NATIONAL HEIGHT MODEL AHN3 (2014-2019)

- Rijkswaterstaat, water boards, and provinces
- Unchanged geometric quality specifications
- Classification in
  - Ground
  - Building
  - Water
  - Civil structure (bridges, fly-overs)
  - Other
- Most companies use TerraScan
  - TIN densification (Peter Axelsson)
  - Point grouping, classification trees

NATIONAL HEIGHT MODEL AHN4 (2020-2022)

- Unchanged geometric quality specifications
- Same classes, but more pragmatic choices
  - Accept classification errors
  - Modified class definitions
  - Smart labelling approaches
- Classification takes 20-25% of the project costs

ACCEPT CLASSIFICATION ERRORS

- Ground: No more than 1 hectare per 10,000 hectare classified as non-ground
- Building: No more than 1 building (> 10 m^2) per 1,000 hectares classified as ground
- Building: No more than 1 out of 100 buildings misclassified
- Civil structures: No more than 1 object per 1,000 hectares classified as ground
- Civil structures: No more than 2 out of 100 civil structures misclassified
- Water: No more than 1 object per 10,000 hectares misclassified
- Etc.

MODIFIED CLASS DEFINITIONS

- Silage heaps now part of ground

Source: www.melkvee.nl

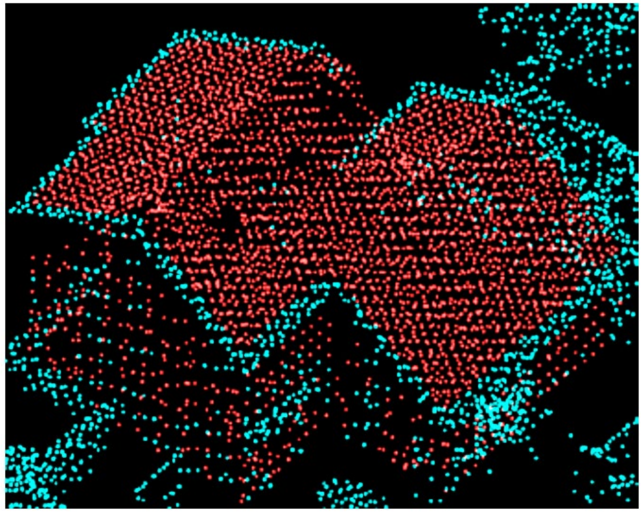
MODIFIED CLASS DEFINITIONS

- Silage heaps now part of ground
- Boat dock if parallel to shoreline now accepted as ground

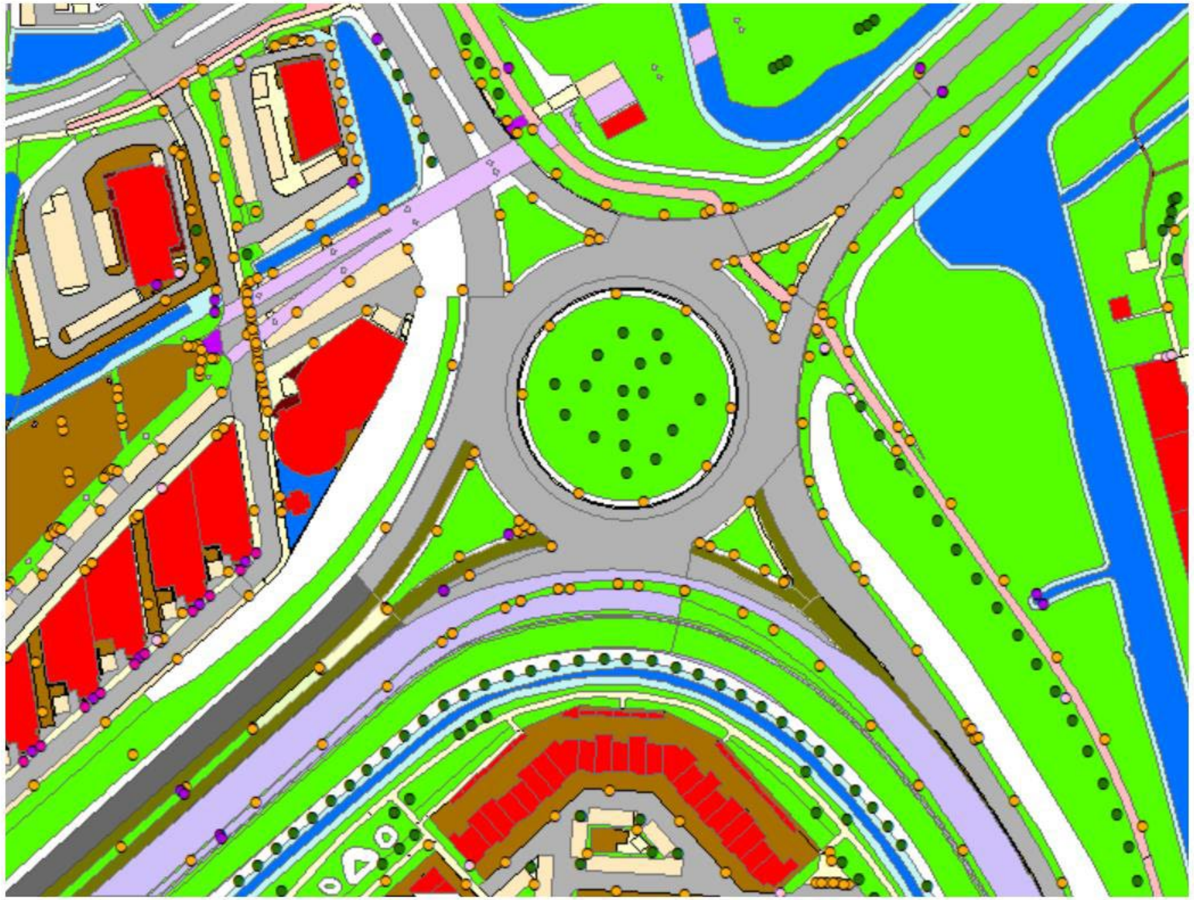
Source: www.hoveniersbedrijf-richard.nl/

SMART LABELLING APPROACHES

- Infer labels from topographic maps
  - Used for buildings and water
  - Buildings not in the map should be classified as “other”
  - No simple point-in-polygon check



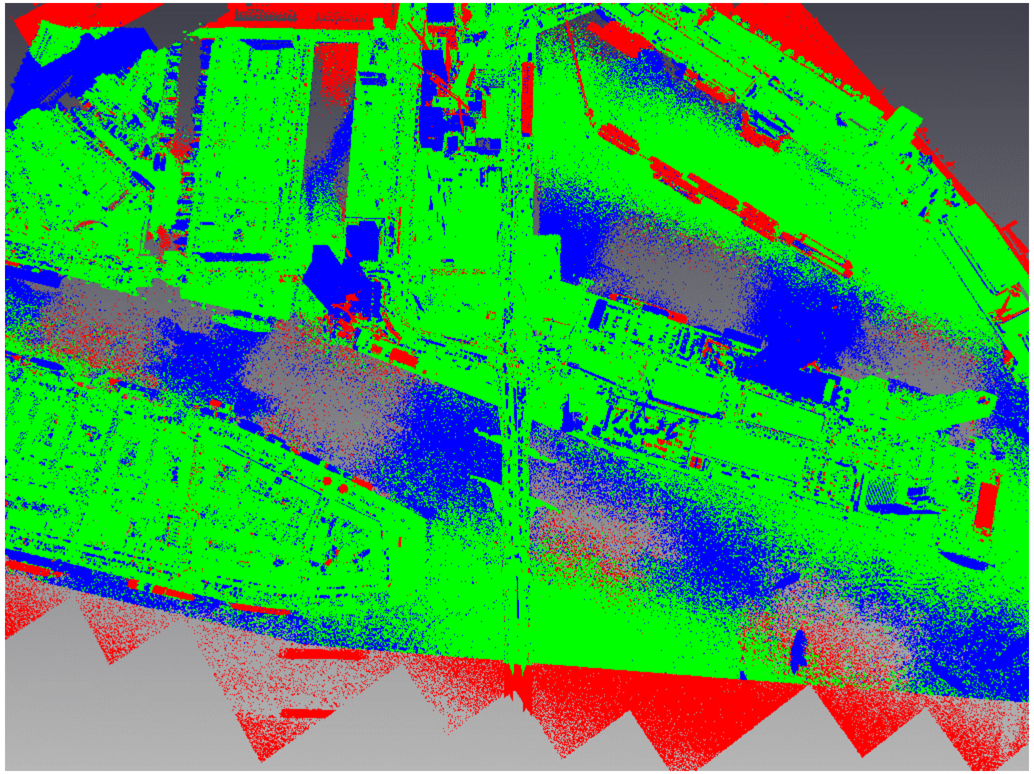
(Wang et al, 2016)



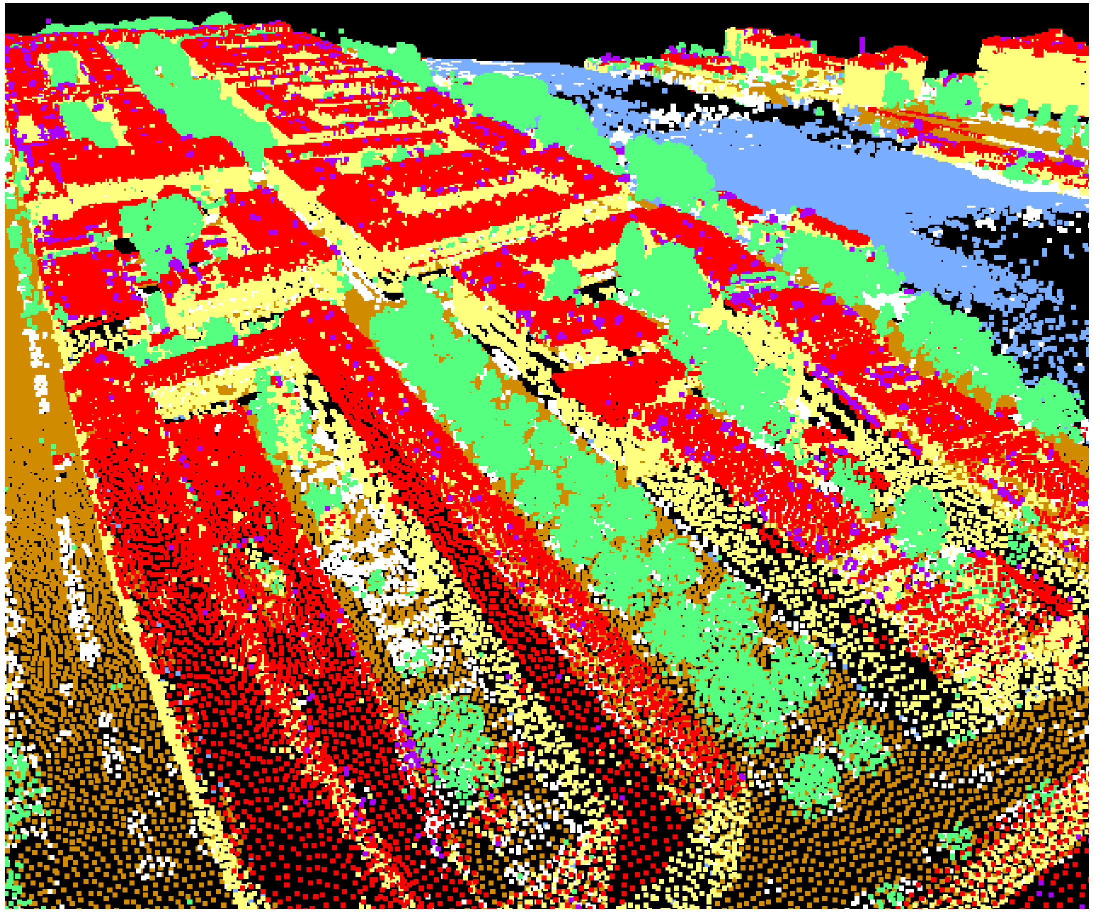
Source: PDOK

SMART LABELLING APPROACHES

- Infer labels from topographic maps
  - Used for buildings and water
  - Buildings not in the map should be classified as "other"
  - No simple point-in-polygon check
- Infer labels from previous AHN version
  - Copy label from nearby point of previous AHN
  - Only changed locations are to be classified and checked



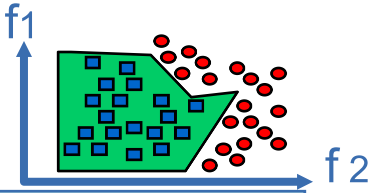
DEEP LEARNING FOR POINT CLOUD CLASSIFICATION



Franz Rottensteiner

What‘s Different in Deep Learning?

- Machine Learning, classical approach:



Input → Compute cleverly defined “hand-crafted” features → $f_1 \dots f_n$ → Machine Learning, Classification → Output

performance only as good as feature set

- **Deep Learning**: Joint learning of features and classification model

Input → Deep Learning [Feature extraction | classification] → Output

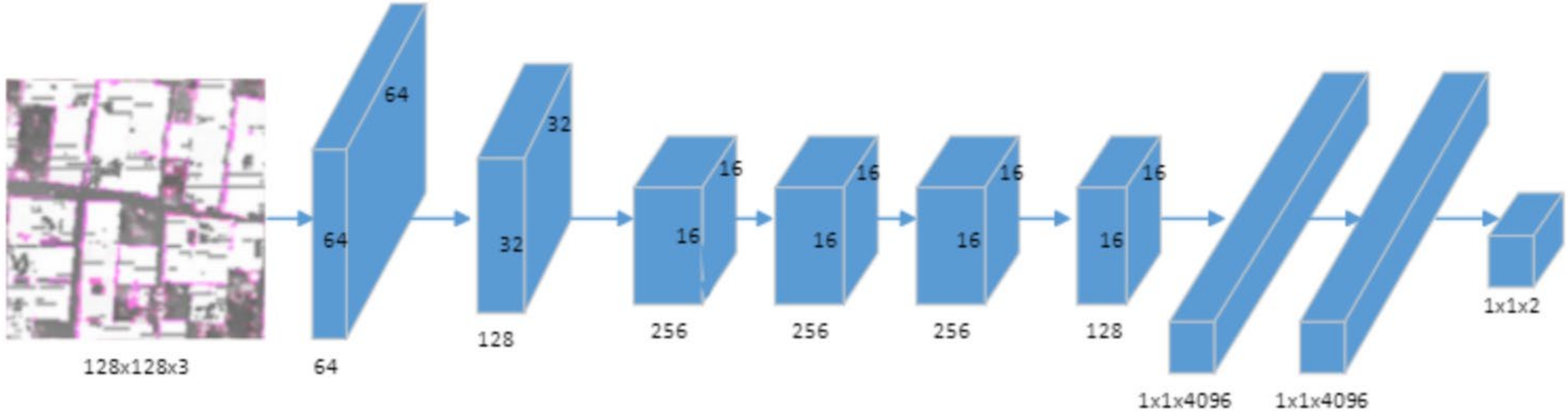
  – “End-to-end learning“, based on artificial neural networks (ANN)

CLASSIFICATION OF RASTERIZED POINT CLOUDS

Convolutional Neural Networks are made for raster data processing

Work-arounds

- Convert point cloud to raster, use Z_{mean}, Z_{max}, Z_{min} instead of RGB values (Hu and Yuan, 2016)



CLASSIFICATION OF RASTERIZED POINT CLOUDS

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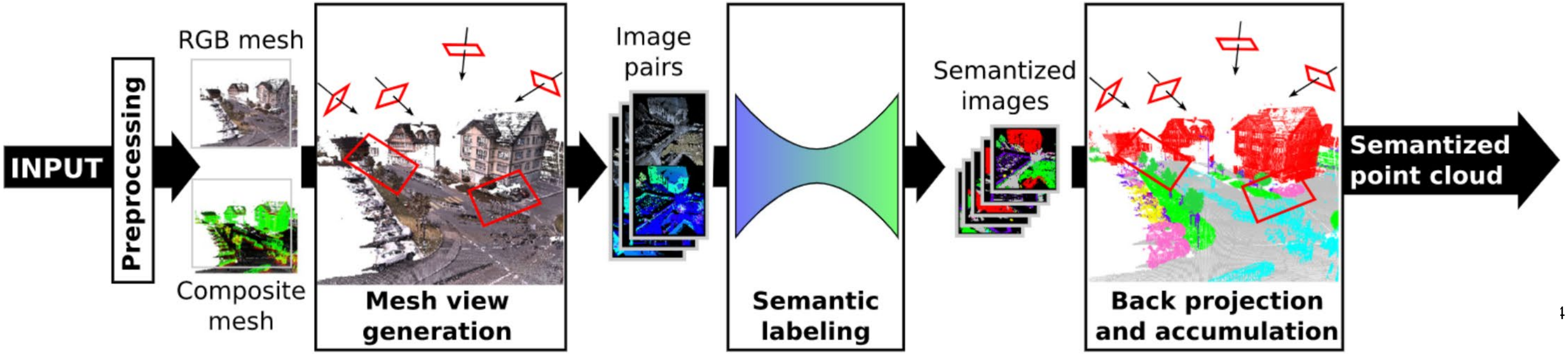

CLASSIFICATION OF RASTERIZED POINT CLOUDS

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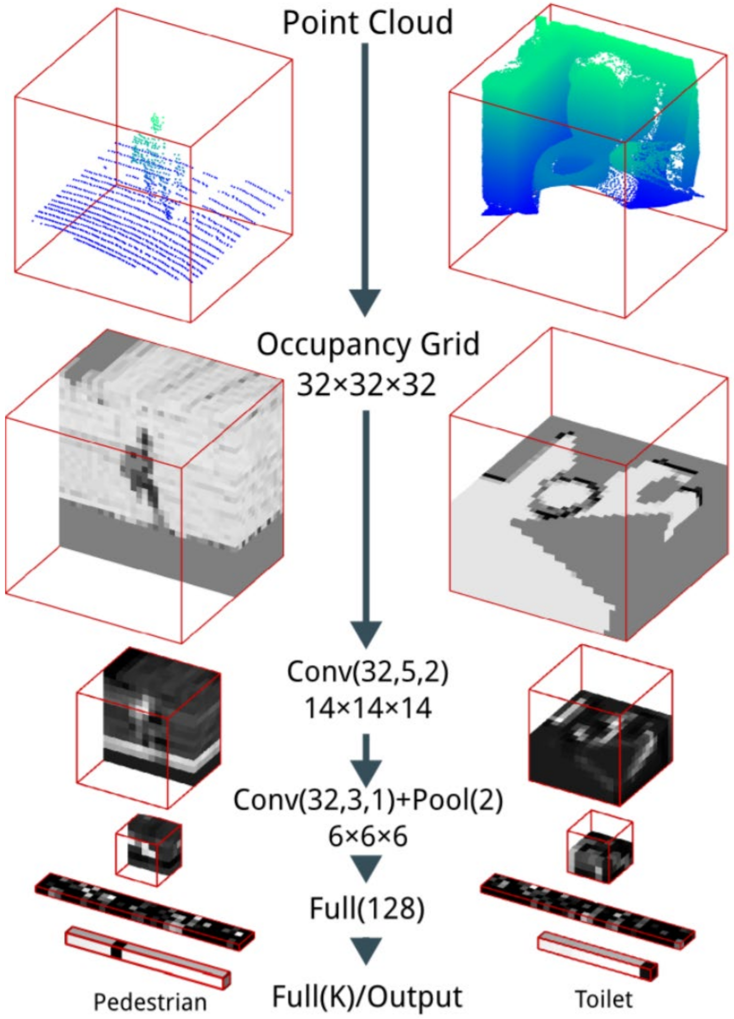
- Convert to multi-view rasters (**SnapNet**, Boulch et al, 2017)
- Convert to 3D raster (**VoxNet**, Maturana and Scherer, 2015)



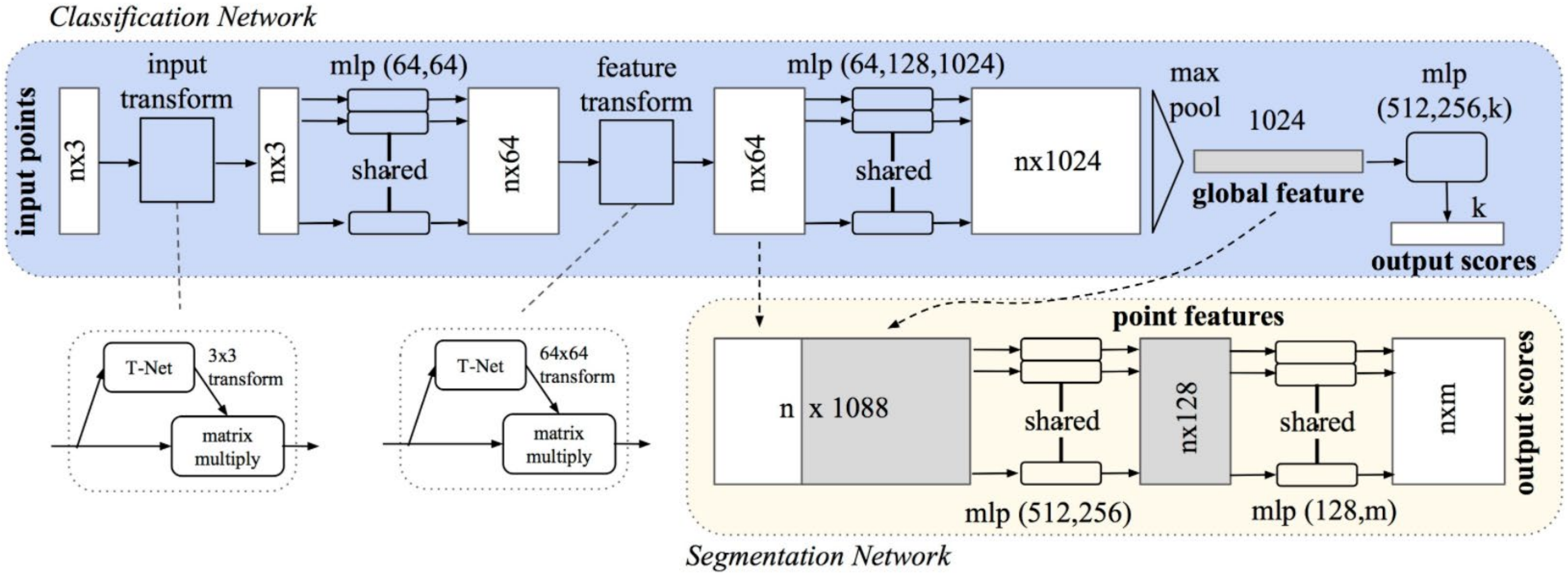
DEEP LEARNING FOR POINT CLOUD CLASSIFICATION

PointNet (Qi et al., 2017)

Learning affine transformation of a point cloud and features

Multi-layer perceptrons (MLP)

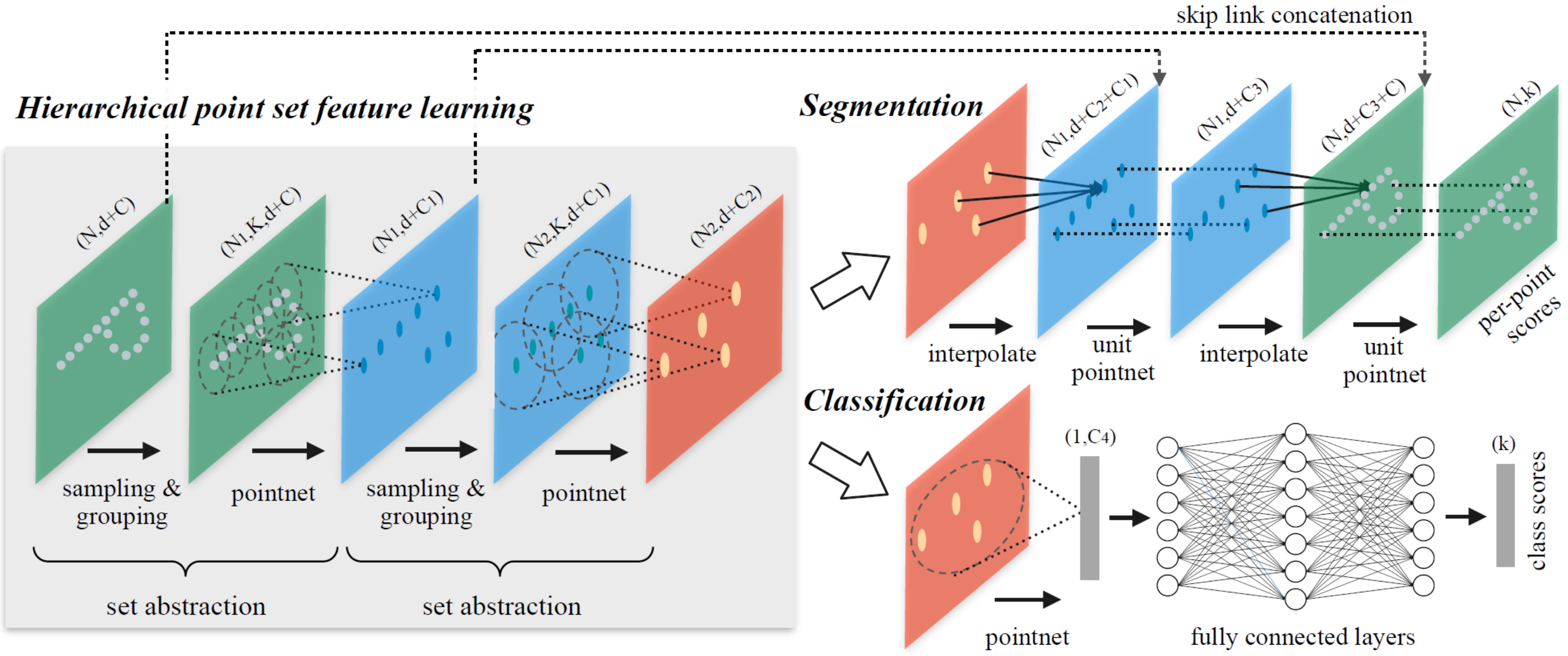
Networks for classifying the whole point cloud and labelling each point



DEEP LEARNING FOR POINT CLOUD CLASSIFICATION

PointNet++ (Qi et al., 2018)

Hierarchical application of PointNet to capture more global point cloud structure



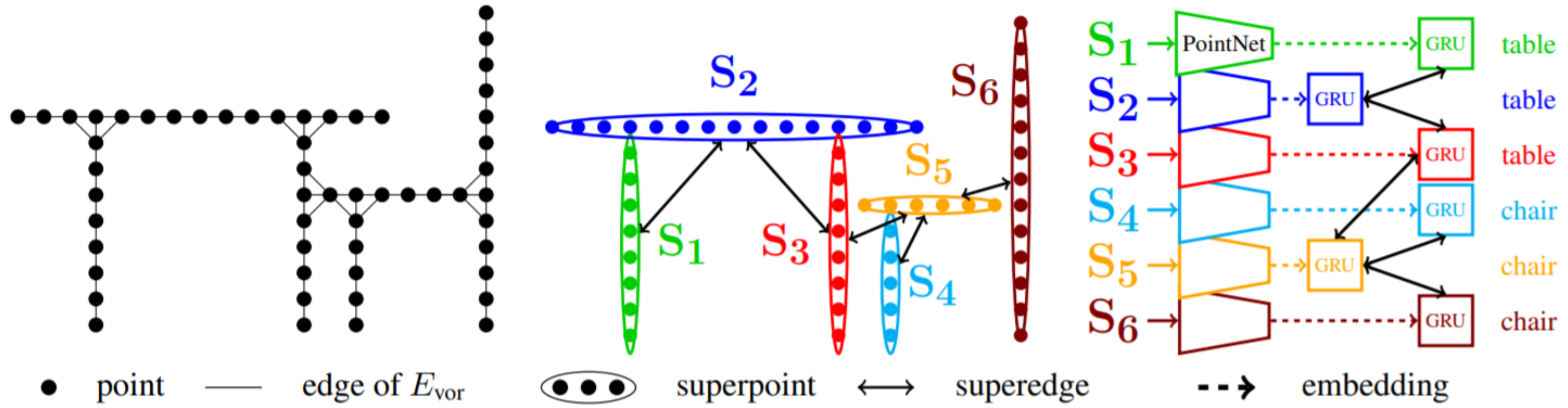
DEEP LEARNING FOR POINT CLOUD CLASSIFICATION

SuperPointGraphs (Landrieu and Simonovsky, 2018)

Segmentation of point cloud into segments (called superpoints)

Extract features for superpoints using PointNet

Contextual classification of superpoints by interative use of gated recurrent units



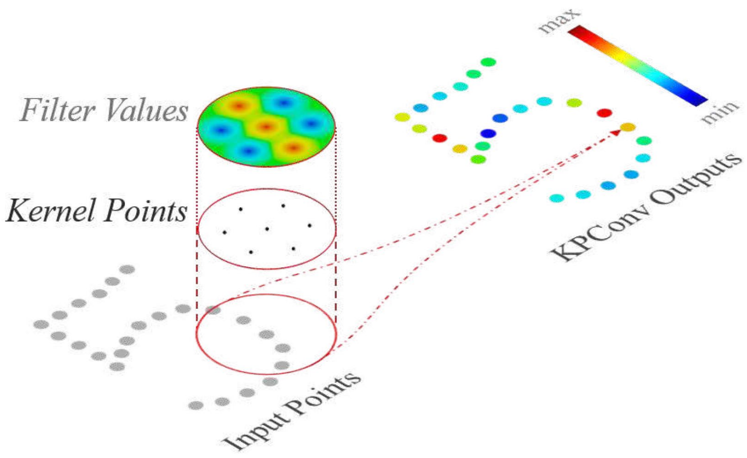
(a) Input point cloud (b) Superpoint graph (c) Network architecture

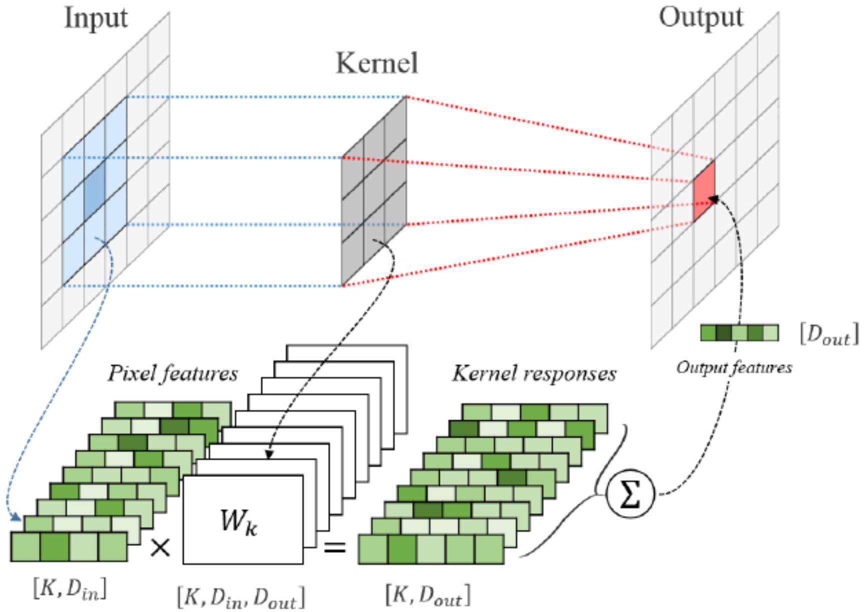
CONVOLUTIONS ON POINT CLOUDS

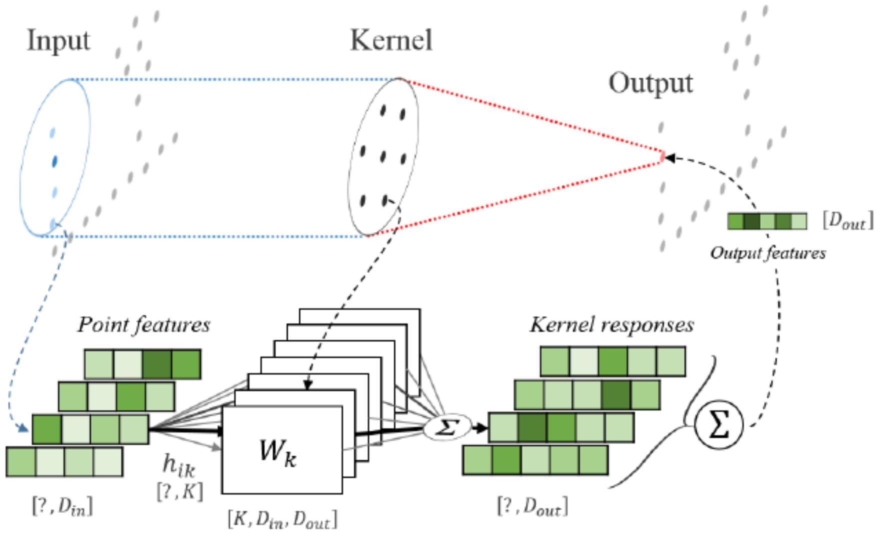
KPConv (Thomas et al., 2019)

Convolution at kernel points

Learnable kernel point locations







LOT OF ONGOING RESEARCH ON POINT CLOUD CLASSIFICATION

Segmentation of unbalanced and in-homogeneous point clouds and its application to 3D scanned trees
J Morel, A Bac, T Kanai - The Visual Computer, 2020

[PDF] Road Mapping In LiDAR Images Using A Joint-Task Dense Dilated Convolutions Merging Network
Q Liu, M Kampffmeyer, R Jenssen, AB Salberg - arXiv preprint arXiv:1909.04588, 2019

[PDF] ShellNet: Efficient Point Cloud Convolutional Neural Networks using Concentric Shells Statistics
Z Zhang, BS Hua, SK Yeung - arXiv preprint arXiv:1908.06295, 2019

A geometry-attentional network for ALS point cloud classification
W Li, FD Wang, GS Xia - ISPRS Journal of Photogrammetry and Remote …, 2020

Two-Stage Point Cloud Super Resolution with Local Interpolation and Readjustment via Outer-Product Neural Network
G Wang, G Xu, Q Wu, X Wu - Journal of Systems Science and Complexity, 2020

An Adaptive Filter for Deep Learning Networks on Large-Scale Point Cloud
W Zhao, R Yi, YJ Liu - 2019 IEEE International Conference on Image …, 2019

[PDF] LightConvPoint: convolution for points
A Boulch, G Puy, R Marlet - arXiv preprint arXiv:2004.04462, 2020

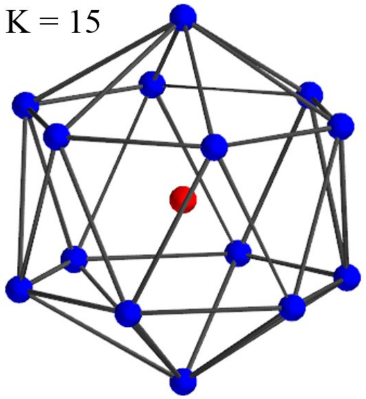
SqueezeSegV3: Spatially-Adaptive Convolution for Efficient Point-Cloud Segmentation
C Xu, B Wu, Z Wang, W Zhan, P Vajda, K Keutzer… - arXiv preprint arXiv …, 2020

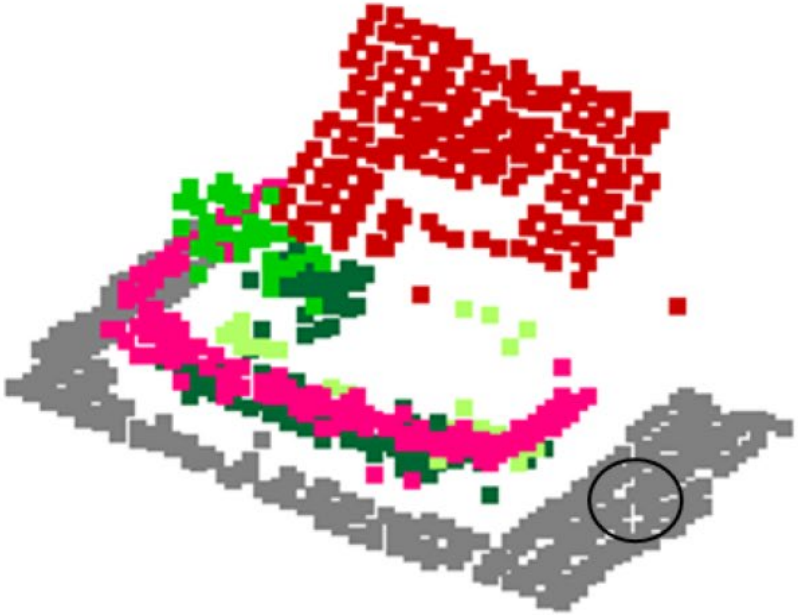
[PDF] LU-Net: A Simple Approach to 3D LiDAR Point Cloud Semantic Segmentation
P Biasutti, V Lepetit, M Brédif, JF Aujol, A Bugeau - 2019

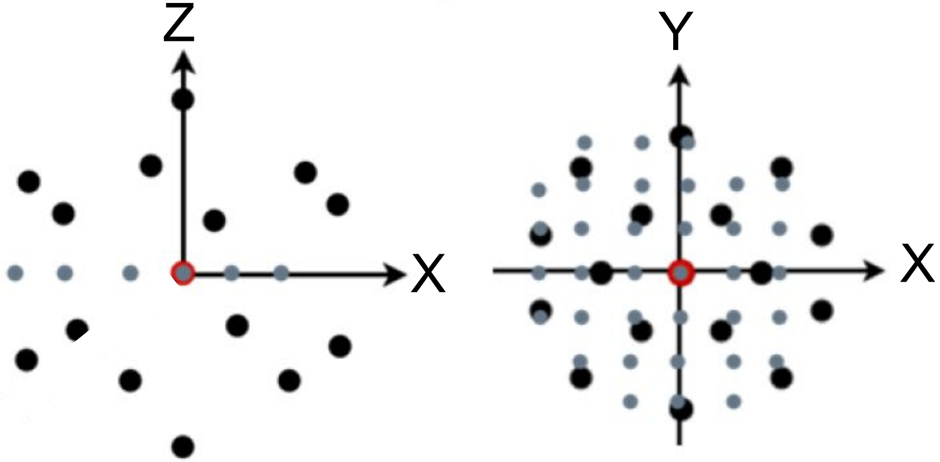
PFCN: A Fully Convolutional Network for Point Cloud Semantic Segmentation
J Lu, T Liu, M Luo, H Cheng, K Zhang - Electronics Letters, 2019

OPTIMIZING KPCONV – ADDING 2D CONVOLUTIONS

KPConv (Thomas et al., 2019) uses 3D kernels

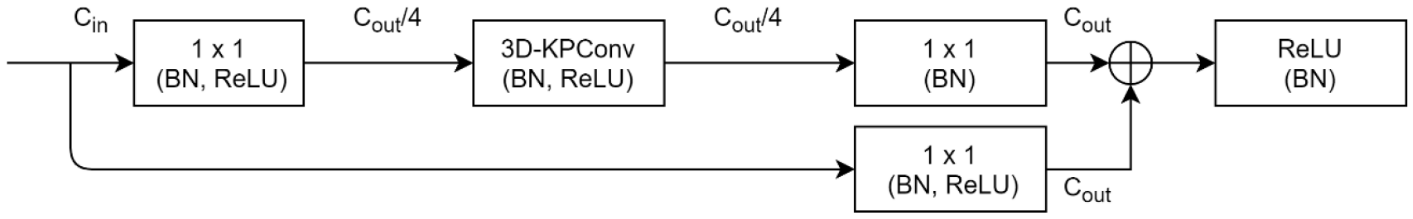


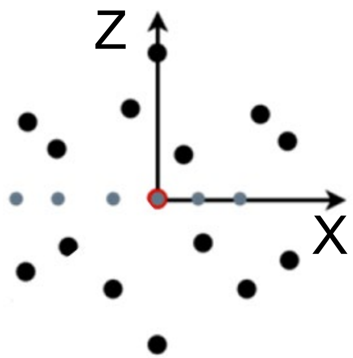




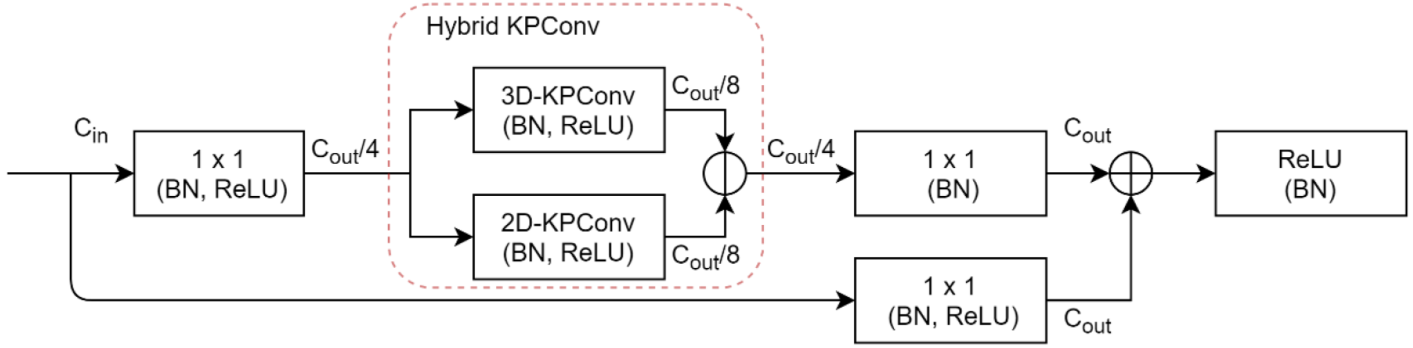
OPTIMIZING KPCONV – ADDING 2D CONVOLUTIONS

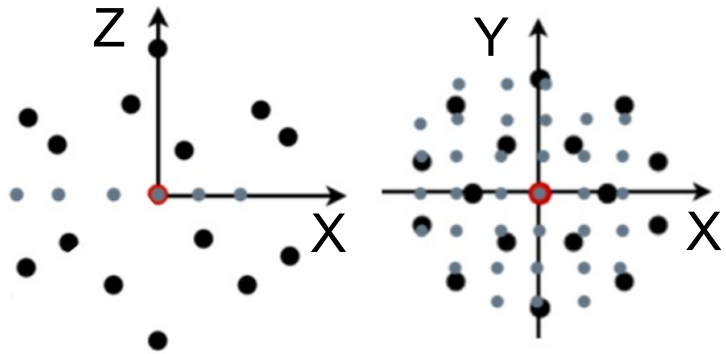
KPConv - 3D point convolutions





Hybrid KPConv - Combining 3D and 2D point convolutions





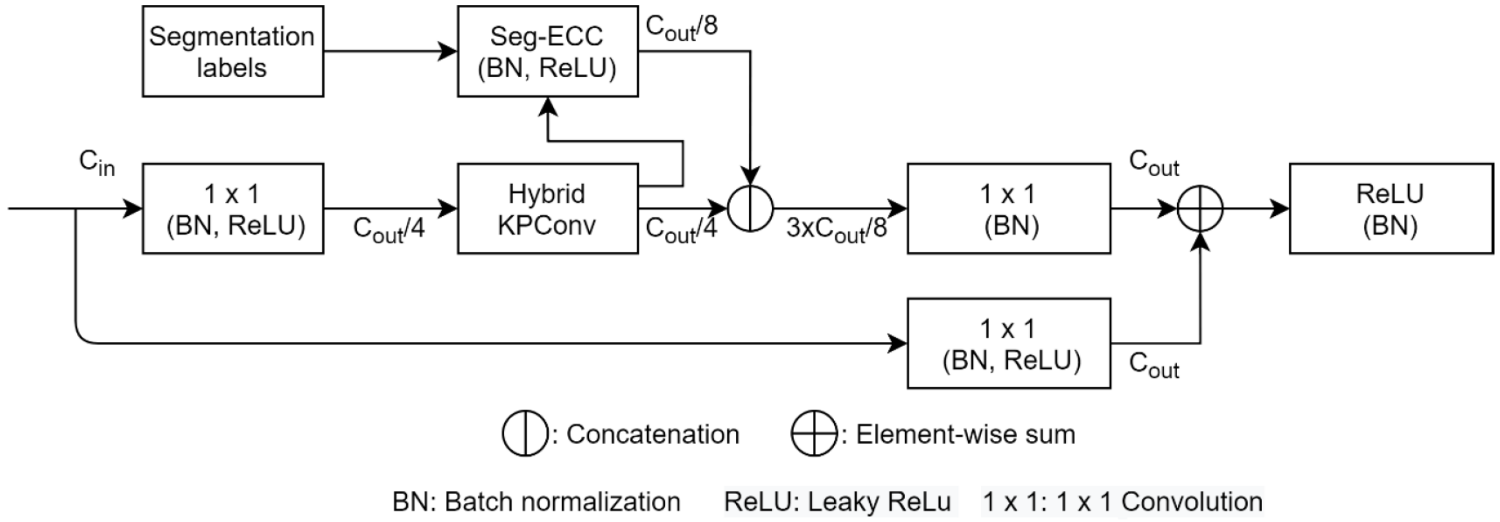
⦶: Concatenation ⊕ : Element-wise sum

BN: Batch normalization ReLU: Leaky ReLu 1 x 1: 1 x 1 Convolution

OPTIMIZING KPCONV – ADDING SEGMENT INFORMATION

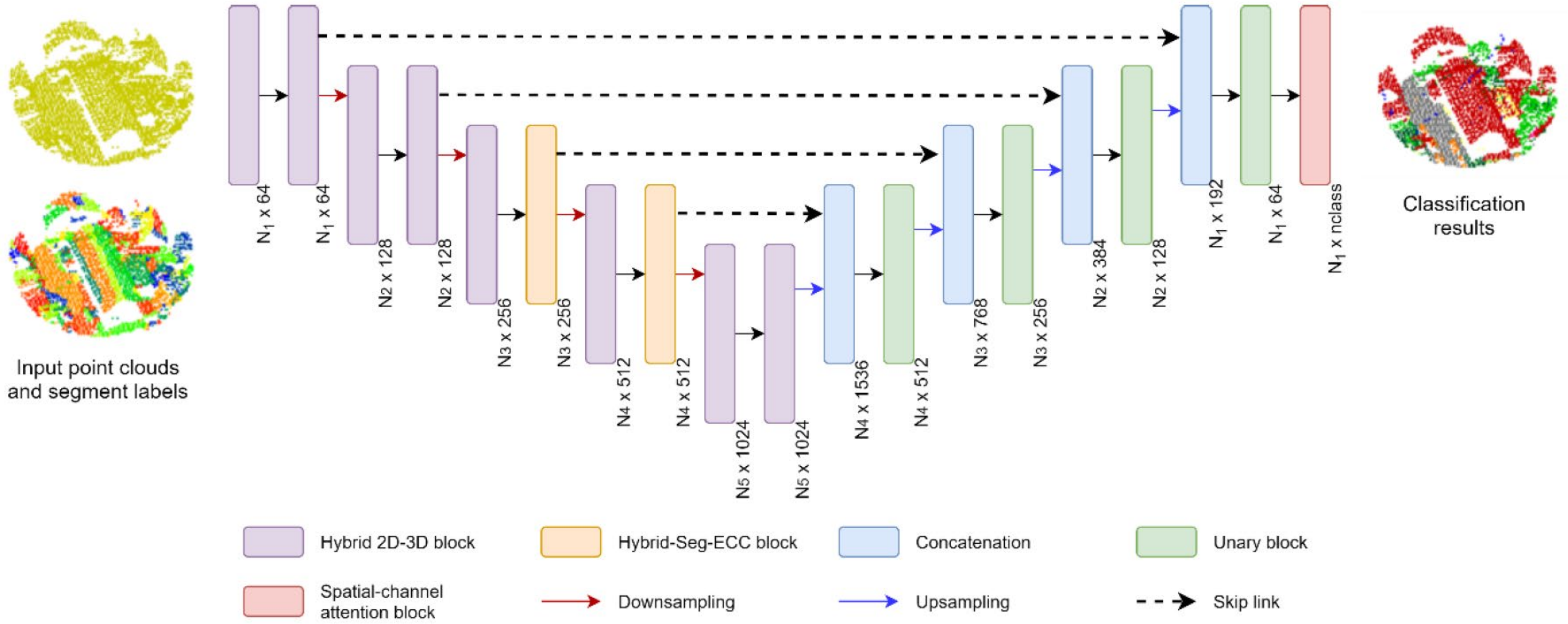
SuperPointGraphs - Classification of segments

Adding segment-based edge-conditioned convolution (Seg-ECC)



OPTIMIZING KPCONV

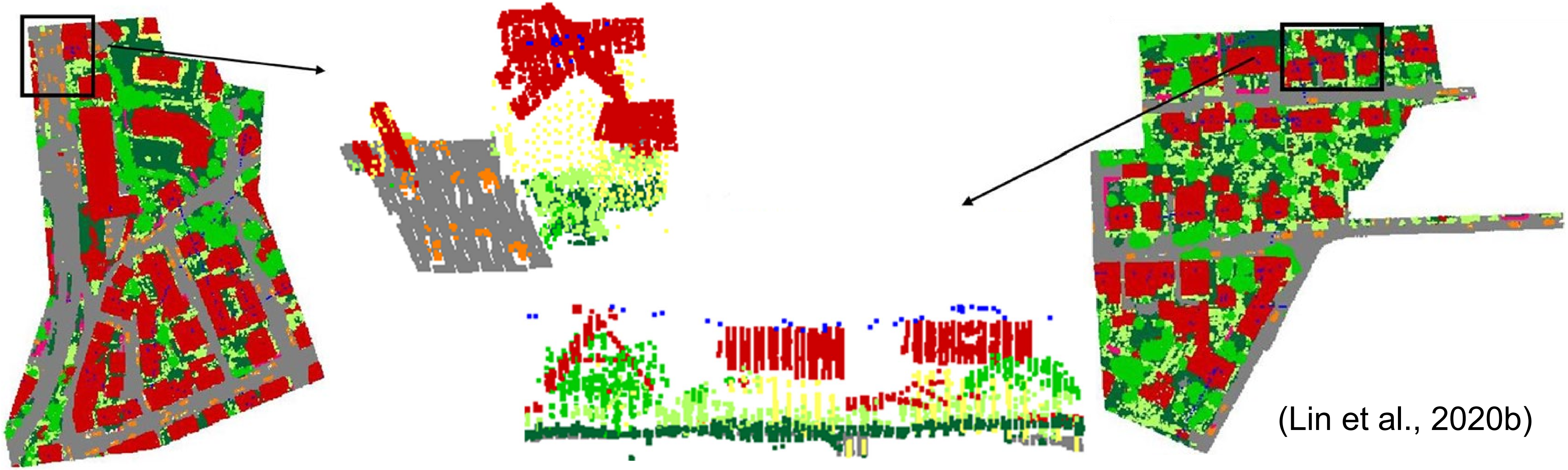
Combining all elements and adding spatial and channel attention modules



OPTIMIZING KPCONV – RESULTS ON ISPRS BENCHMARK

Combining all elements and adding spatial and channel attention modules

	Power	Low_veg	Imp_surf	Car	Fence/Hedge	Roof	Facade	Shrub	Tree	Av. F1	OA
KPConv	0.735	0.787	0.880	0.794	0.330	0.942	0.613	0.457	0.820	0.706	0.817
Hybrid	0.703	0.811	0.908	0.757	0.381	0.939	0.632	0.495	0.826	0.717	0.837



(Lin et al., 2020b)

NEED FOR TRAINING DATA

Deep learning networks contain millions of parameters

Benchmark datasets increase in size

	#Name and Reference	#Year	#Spatial size[1]	#Classes[2]	#Points	#RGB	#Sensors
Object-level	ShapeNet [15]	2015	-	55	-	No	Synthetic
	PartNet [21]	2019	-	24	-	No	Synthetic
Indoor	S3DIS [16]	2017	10×5×5	13 (13)	273M	Yes	Matterport
Scene-level	ScanNet [17]	2017	5×5×2	20 (20)	242M	Yes	RGB-D
	Paris-rue-Madame [22]	2014	35×90×20	17	20M	No	MLS
	IQmulus [23]	2015	850×800×450	8 (22)	300M	No	MLS
Outdoor	Semantic3D [20]	2017	250×260×80	8 (9)	4000M	Yes	TLS
Roadway-level	Paris-Lille-3D [24]	2018	200×280× 30	9 (50)	143M	No	MLS
	SemanticKITTI [19]	2019	150×100×10	25 (28)	4549M	No	MLS
	Toronto-3D [25]	2020	260×350× 40	8 (9)	78.3M	Yes	MLS
	ISPRS [26]	2012	-	9	1.2M	No	ALS
Urban-level	DALES [27]	2020	500×500×65	8 (9)	505M	No	ALS
(Hu et al., 2020)	**SensatUrban** ~~(Ours)~~	2020	1700×1700×100	13 (31)	2847M	Yes	UAV Photogrammetry

LEARNING STRATEGIES

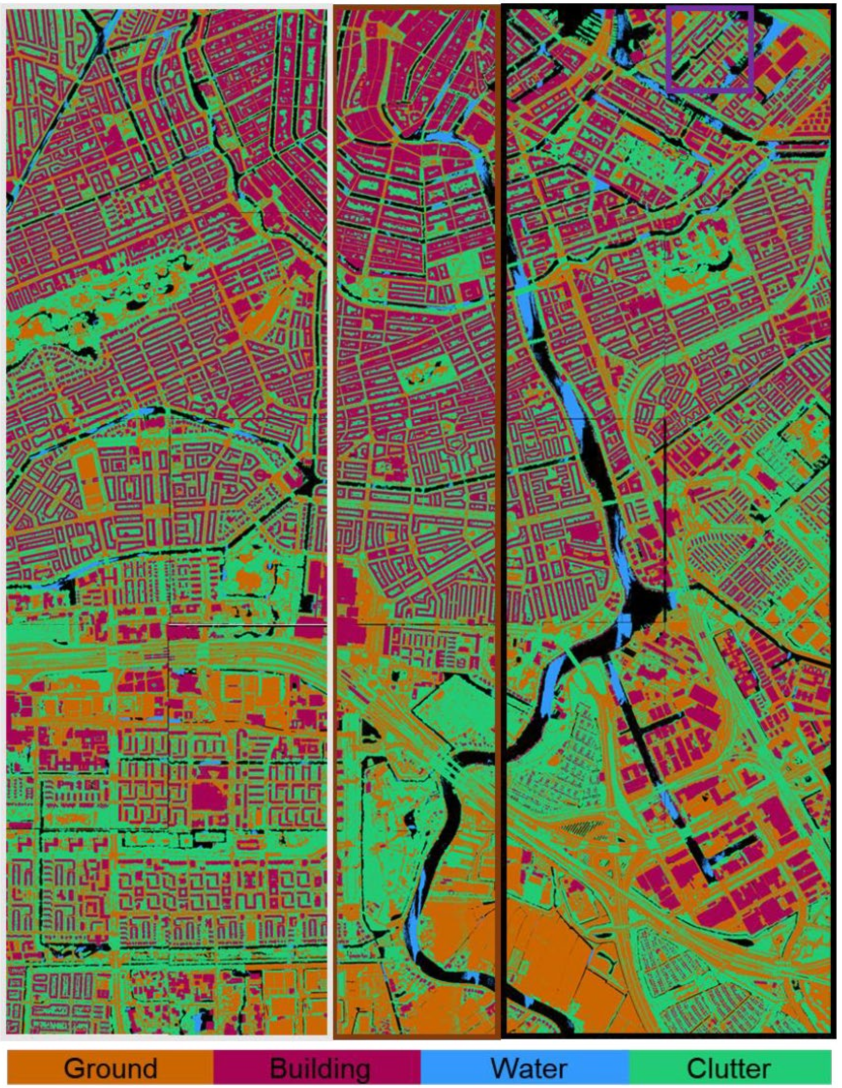
Transferring of map labels to point clouds

Smart selection of additional training samples

- Focus on areas with largest label uncertainty

Minimize required amount of training data

- Active learning
  - Retrain from scratch with increased training data
- Incremental learning
  - Updating old model with a mix of old and additional training data
  - Reduced time required for training (Lin et al., 2020a)



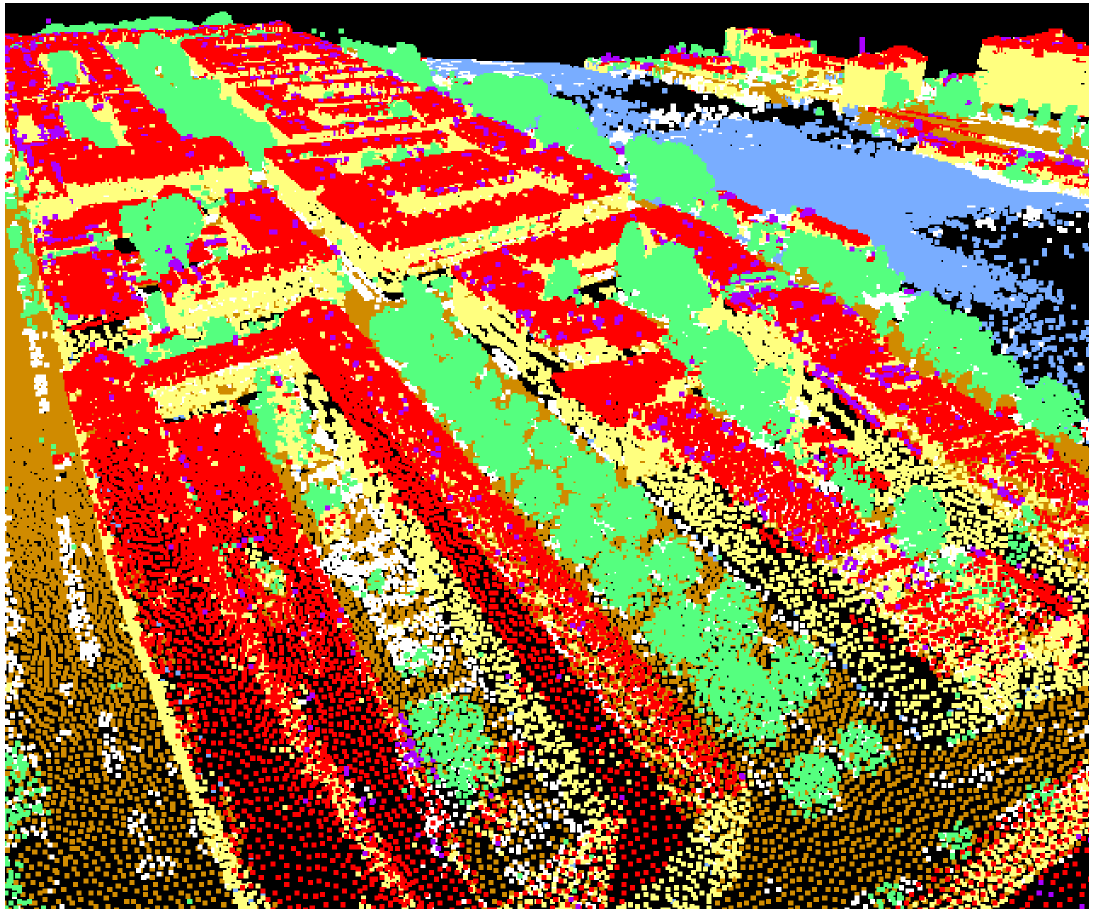
CONCLUSIONS

Classification of nationwide point clouds

- Doable, but be pragmatic

Deep learning for point cloud classification

- Not yet used by companies involved in the Dutch national point cloud acquisition
- Very active research field
- Need for manual editing will be reduced, but not eliminated
- Classification costs will be reduced



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