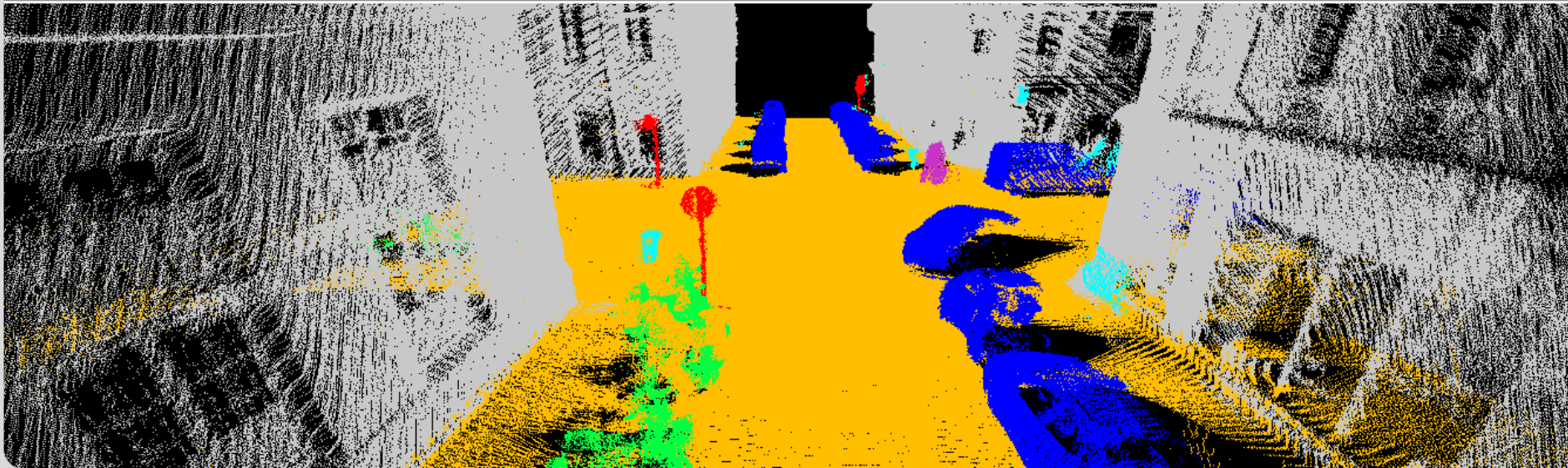


Semantic Segmentation of Dense Point Clouds

Dr.-Ing. Martin Weinmann

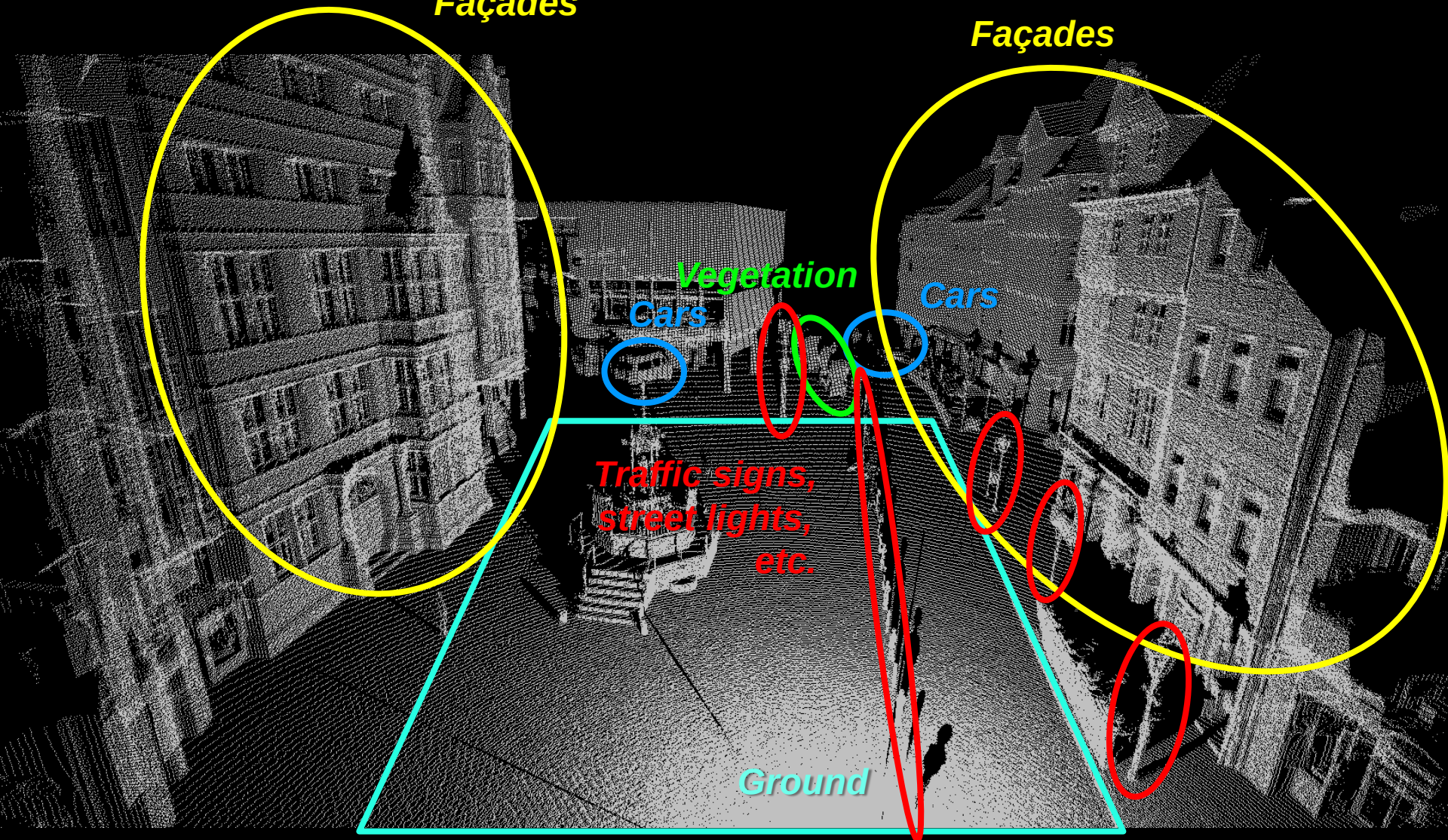
2nd International Workshop Point Cloud Processing



Motivation

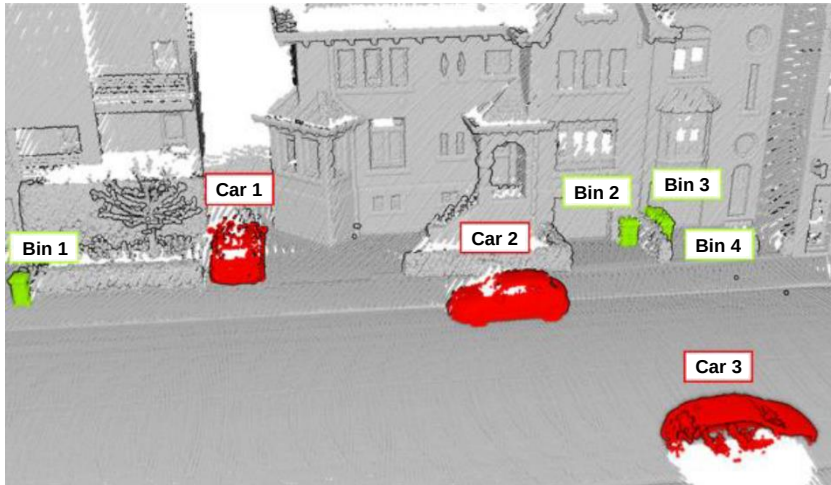
Façades

Façades



Motivation

Instance-Level Segmentation



- Point-based labeling
- Class-aware labels
- Instance-aware labels

Semantic Segmentation

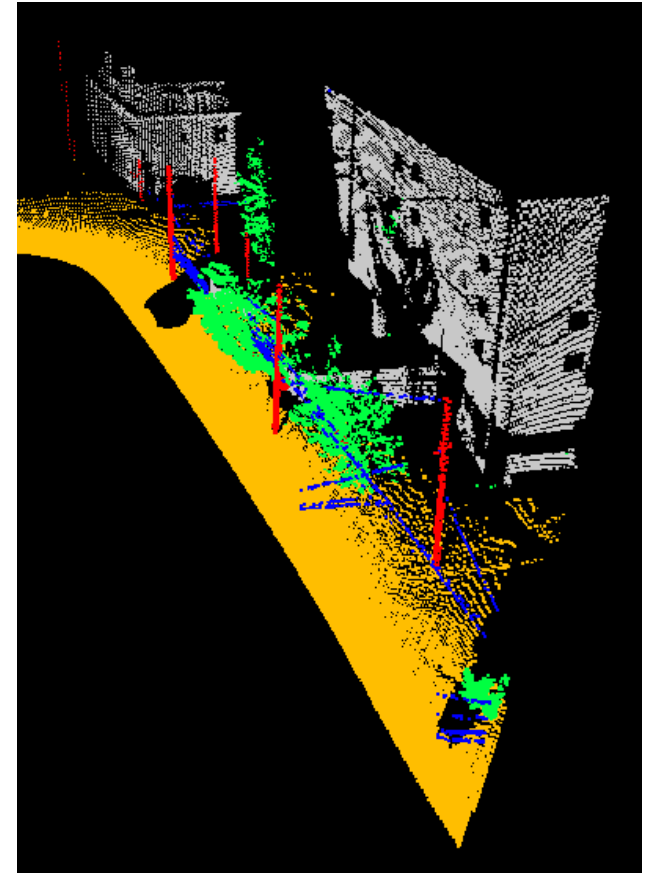


- Point-based labeling
- Class-aware labels
- No instance-aware labels

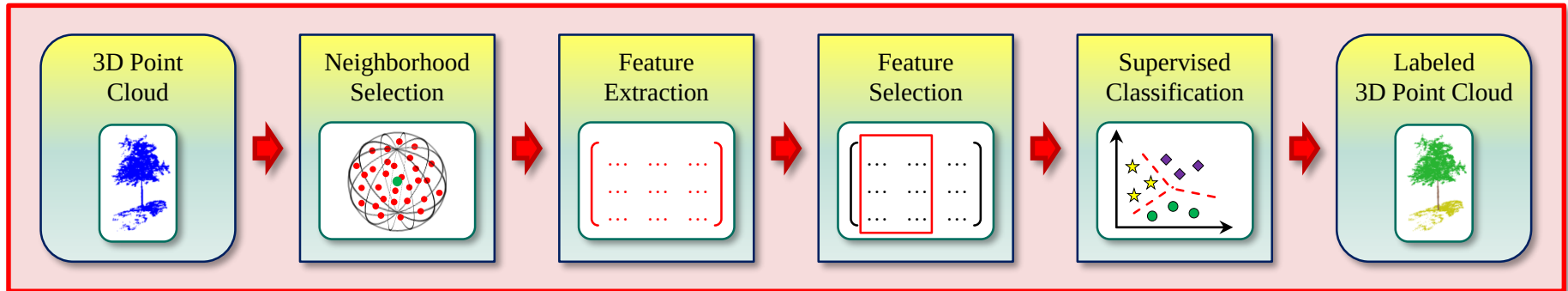
H. Thomas (2019): Learning new representations for 3D point cloud semantic segmentation. PhD Thesis, MINES ParisTech, Université de recherche Paris Sciences et Lettres, Paris, France.

Outline

1. Introduction
2. Methodology
3. Experimental Results
4. Conclusions & Future Work

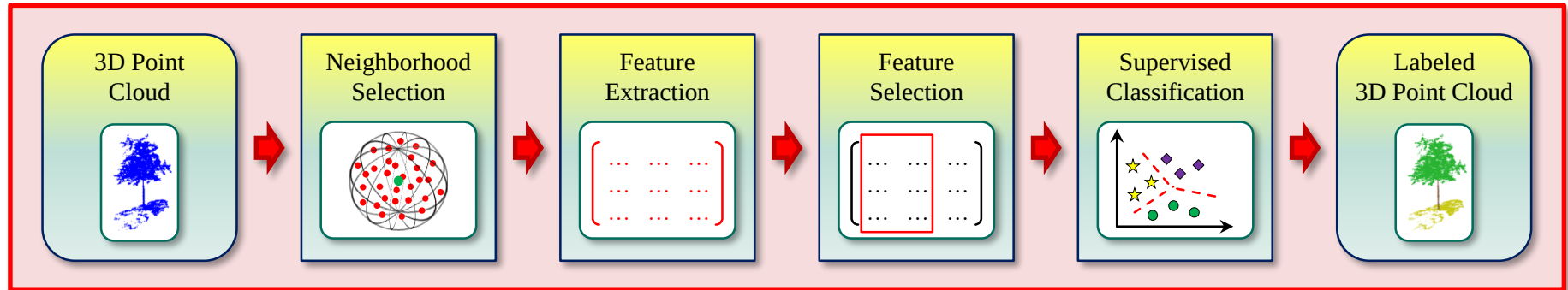


1. Introduction



- Semantic interpretation of 3D point cloud data
 - Unique assignment of a semantic class label to each 3D point (e.g. “ground”, “building” or “vegetation”)
 - General applicability (e.g. for TLS / MLS / ALS or MVS point cloud data)
 - Desired properties
 - Fully automated and efficient approaches
 - Accurate results (without including prior knowledge?)

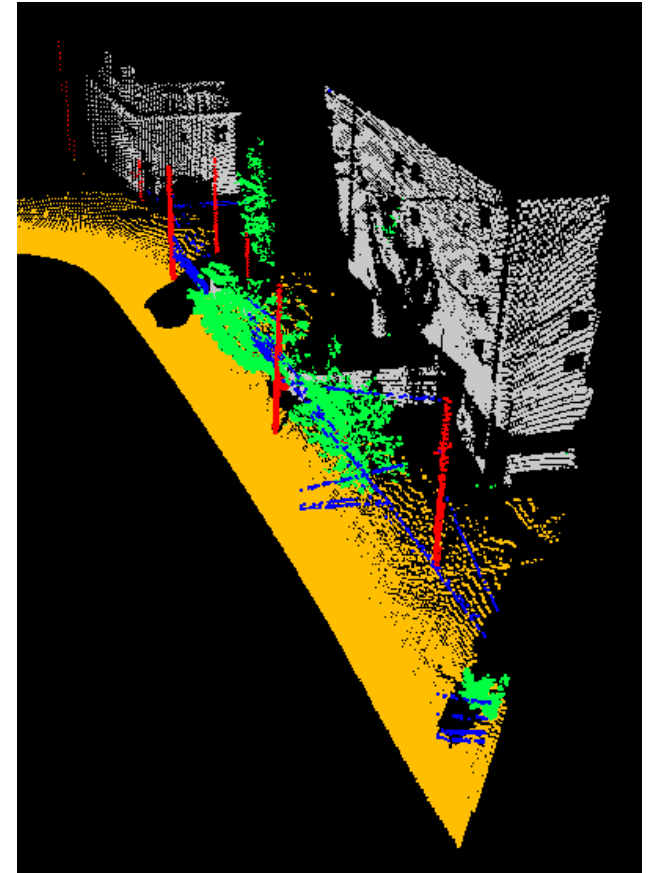
1. Introduction



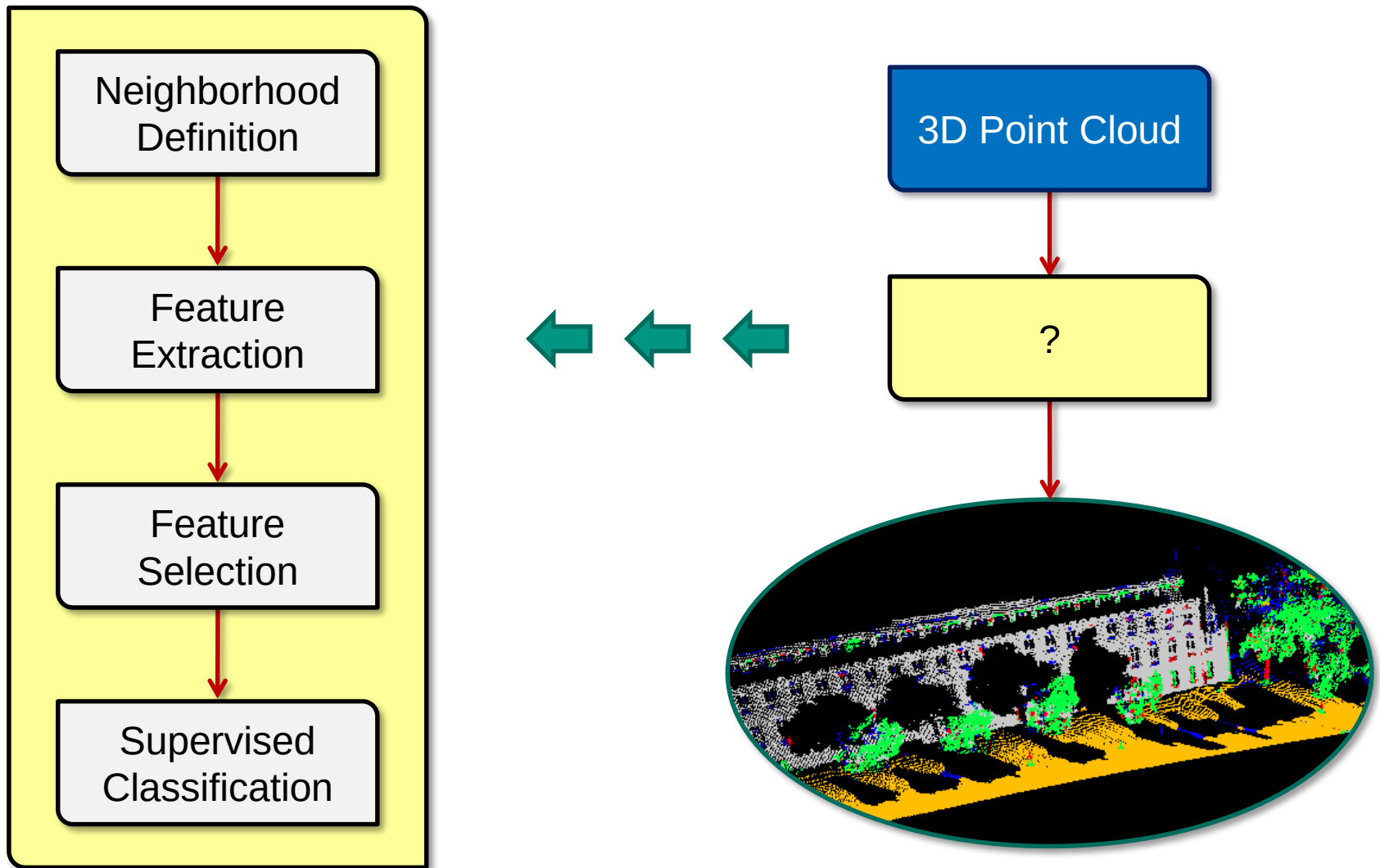
■ Main challenges

- Single-scale representation vs. multi-scale representation
- Interpretable features vs. complex features
- All features vs. relevant features
- Individual classification vs. contextual classification

1. Introduction
2. Methodology
3. Experimental Results
4. Conclusions & Future Work



2. Methodology

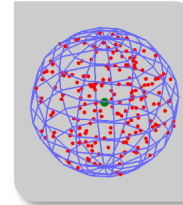


2. Methodology

■ Recovery of local 3D neighborhoods

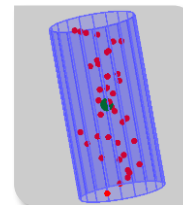
- Spherical neighborhood with fixed radius

→ Which radius ?



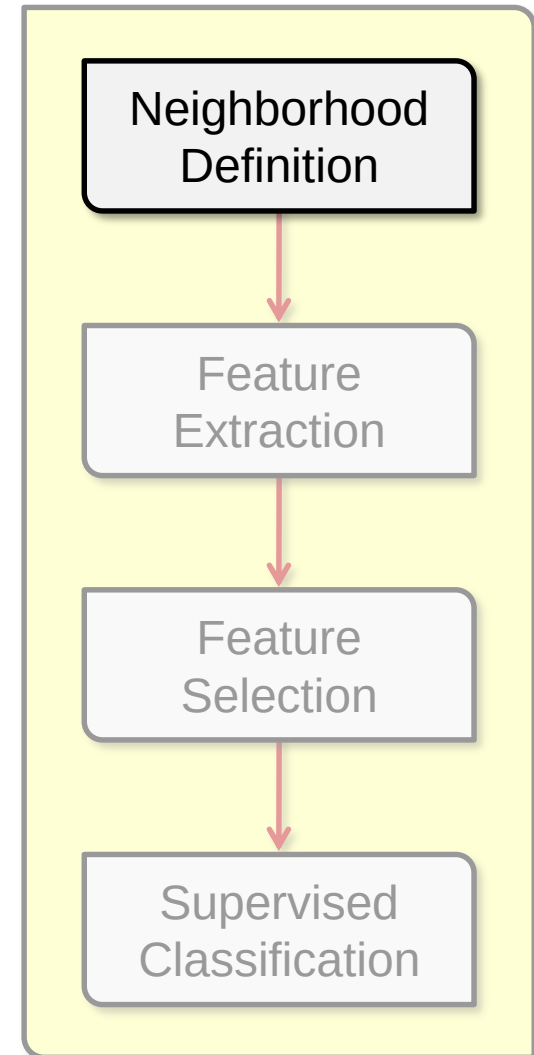
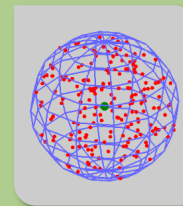
- Cylindrical neighborhood with fixed radius

→ Which radius ?



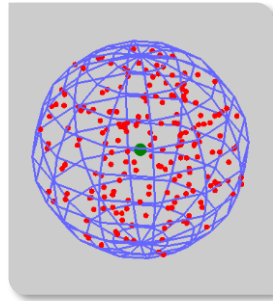
- k closest neighbors in 3D (flexible neighborhood size)

→ Which k ?



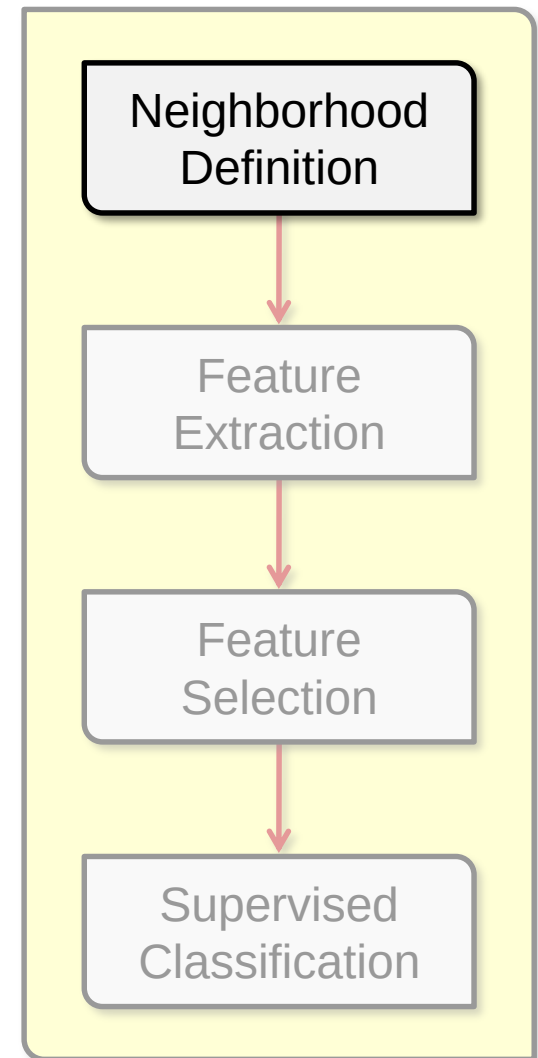
2. Methodology

- Recovery of an optimal value for k
 - Consideration of neighboring 3D points



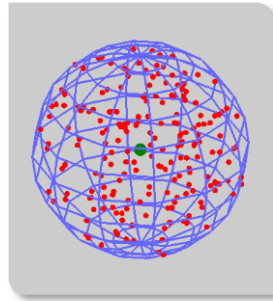
→ 3D structure tensor
= 3D covariance matrix

$$\mathbf{S}_{3D} = \frac{1}{k+1} \sum_{i=0}^k (\mathbf{x}_i - \bar{\mathbf{x}}) (\mathbf{x}_i - \bar{\mathbf{x}})^T$$

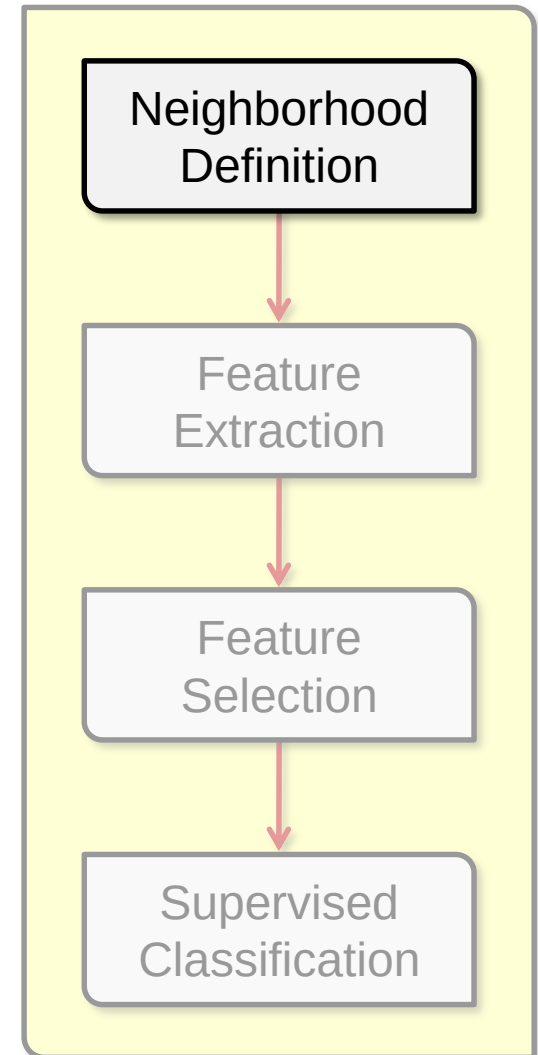
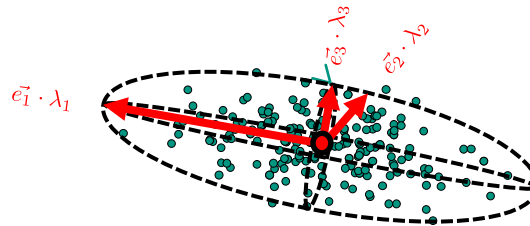


2. Methodology

- Recovery of an optimal value for k
 - Consideration of neighboring 3D points



- 3D structure tensor
= 3D covariance matrix
- Eigenvalues represent the extent of a 3D ellipsoid along its principal axes



2. Methodology

■ Recovery of an optimal value for k

■ *Dimensionality-based scale selection* [Demantké et al., 2011]

→ Idea: favor 1D, 2D or 3D structure and minimize

$$k_{\min} = 10$$

$$k_{\max} = 100$$

$$\Delta k = 1 \quad L_{\lambda} = \frac{\lambda_1 - \lambda_2}{\lambda_1} \quad P_{\lambda} = \frac{\lambda_2 - \lambda_3}{\lambda_1} \quad S_{\lambda} = \frac{\lambda_3}{\lambda_1}$$

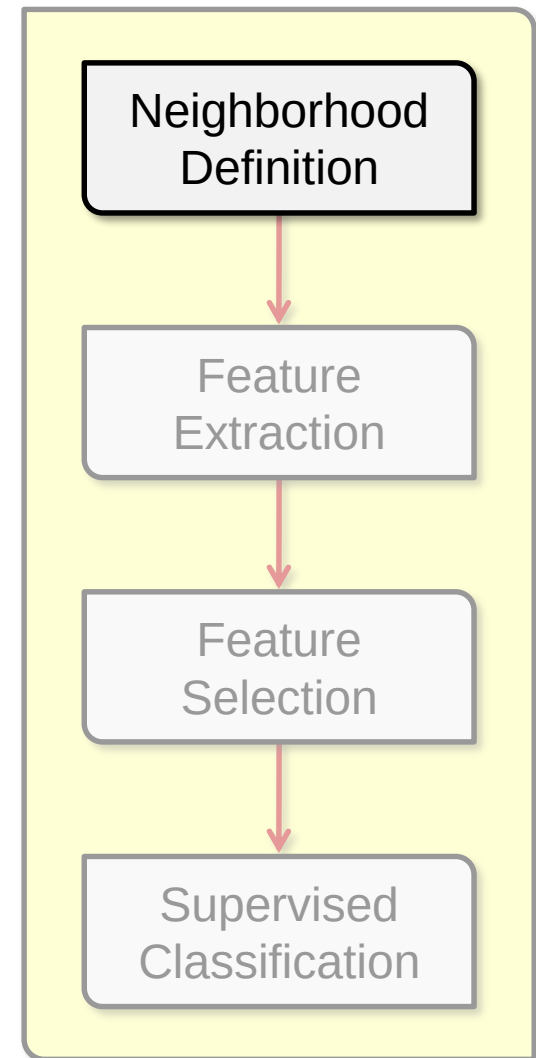
$$E_{\dim} = -L_{\lambda} \ln(L_{\lambda}) - P_{\lambda} \ln(P_{\lambda}) - S_{\lambda} \ln(S_{\lambda})$$

■ *Eigenentropy-based scale selection* [Weinmann et al., PCV 2014]

$k_{\min} = 10$ → Idea: favor the minimal disorder of 3D points and minimize

$$k_{\max} = 100$$

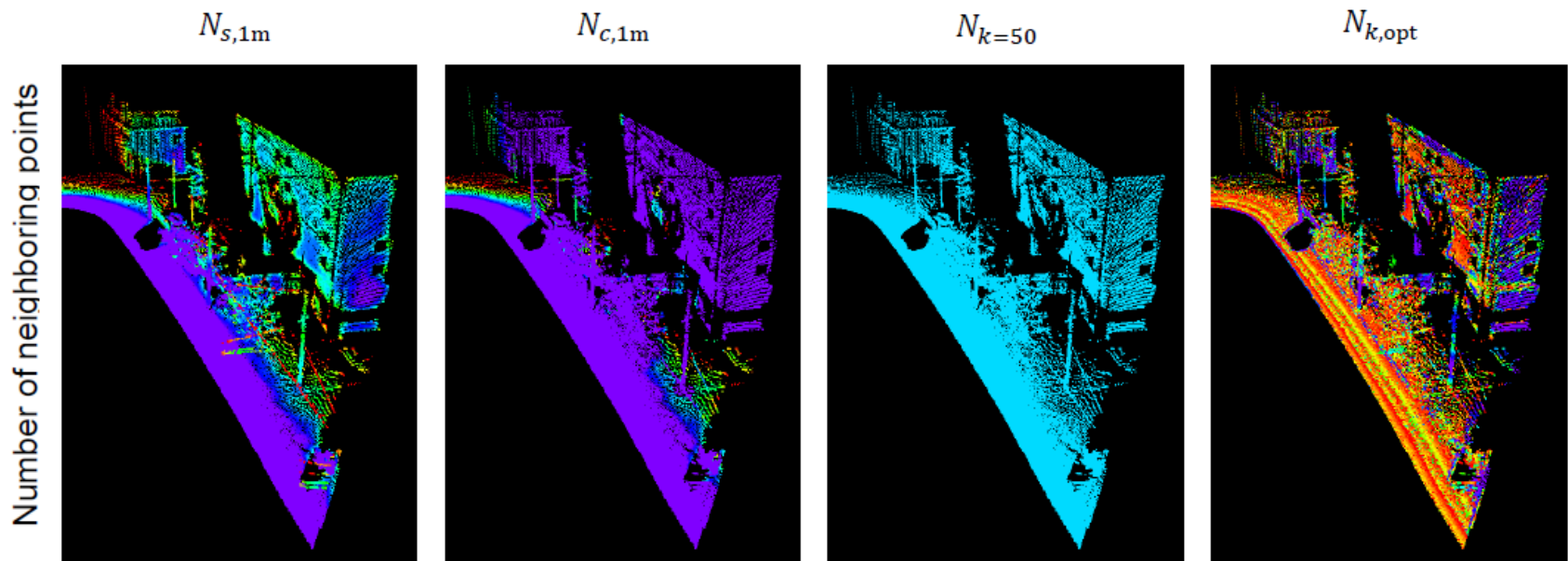
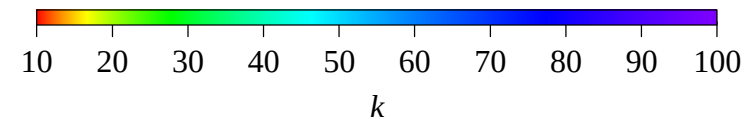
$$\Delta k = 1 \quad E_{\lambda} = -\lambda_1 \ln(\lambda_1) - \lambda_2 \ln(\lambda_2) - \lambda_3 \ln(\lambda_3)$$



2. Methodology

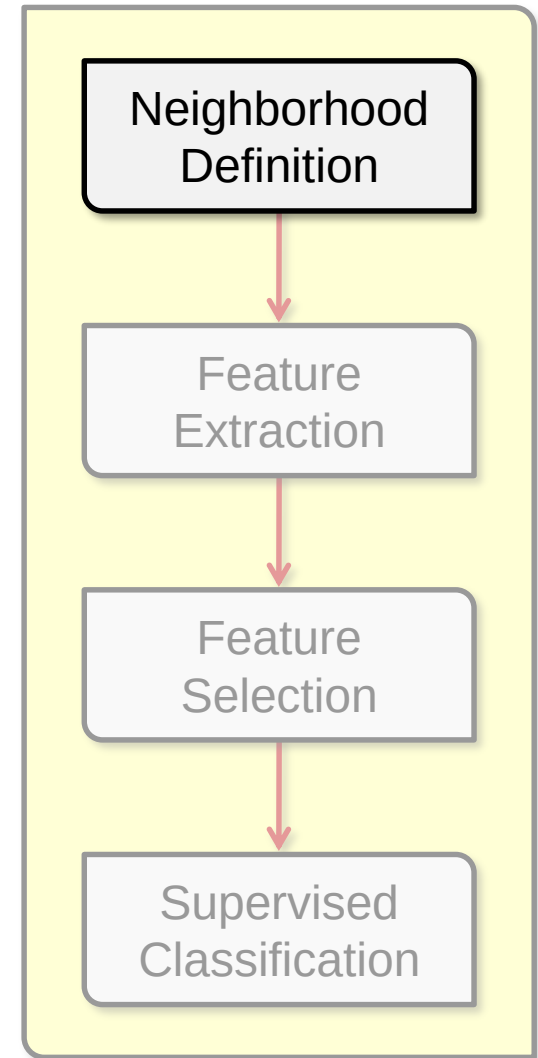
■ Recovery of local 3D neighborhoods

- Spherical neighborhood with fixed radius ($R = 1\text{m}$)
- Cylindrical neighborhood with fixed radius ($R = 1\text{m}$)
- k closest neighbors in 3D ($k = 50$)
- k closest neighbors in 3D (optimal k)

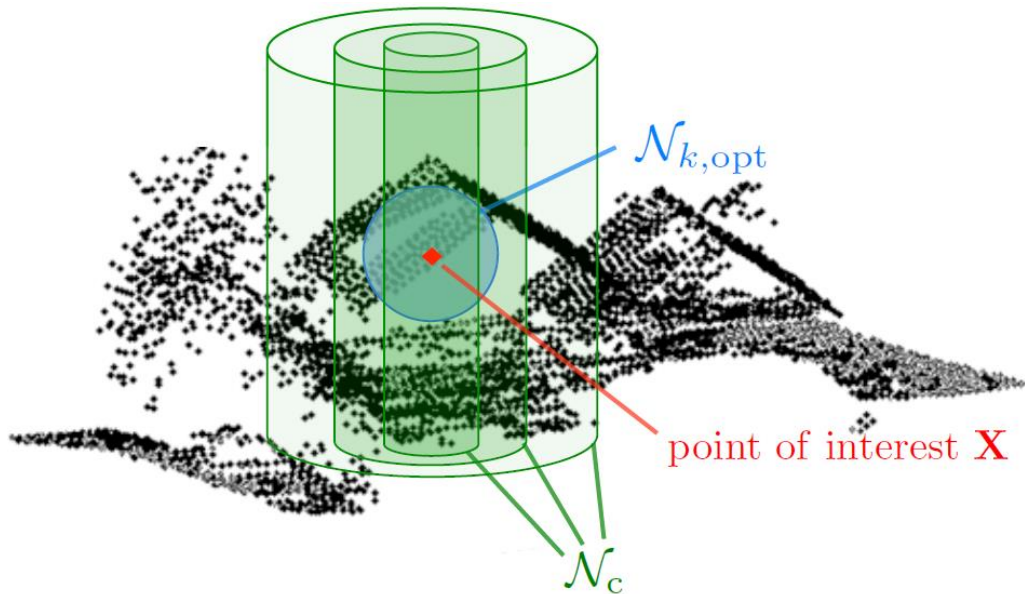


2. Methodology

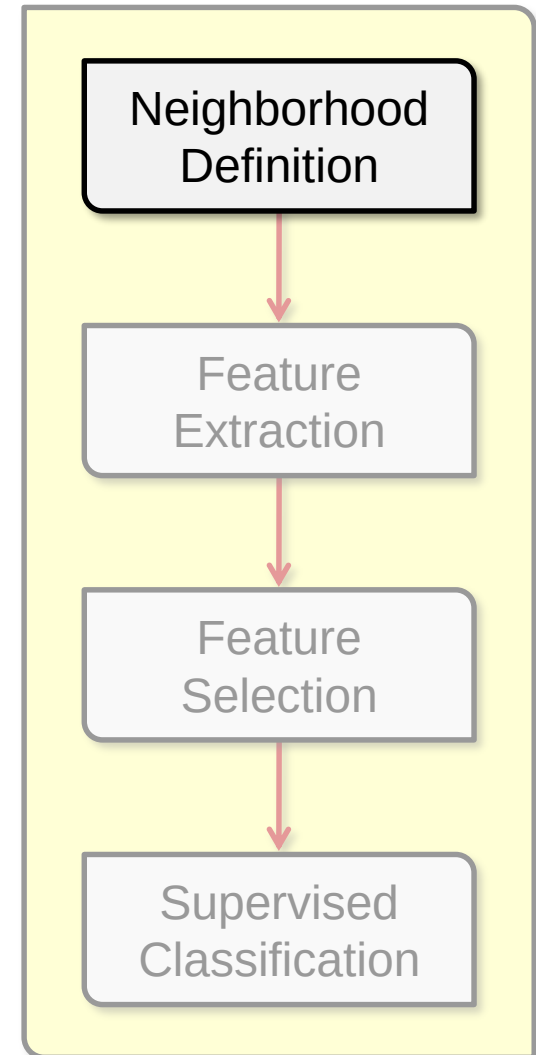
- Recovery of local 3D neighborhoods
 - Multi-scale neighborhood
e.g. [Niemeyer et al., IJPRS 2014]
 - Consider local 3D structure at different scales
 - Describe geometric behavior across different scales
 - Multi-scale, multi-type neighborhood
e.g. [Blomley et al., ISPRS Congress 2016]
 - Consider local 3D structure at different scales
 - Describe geometric behavior across different scales and different neighborhood types



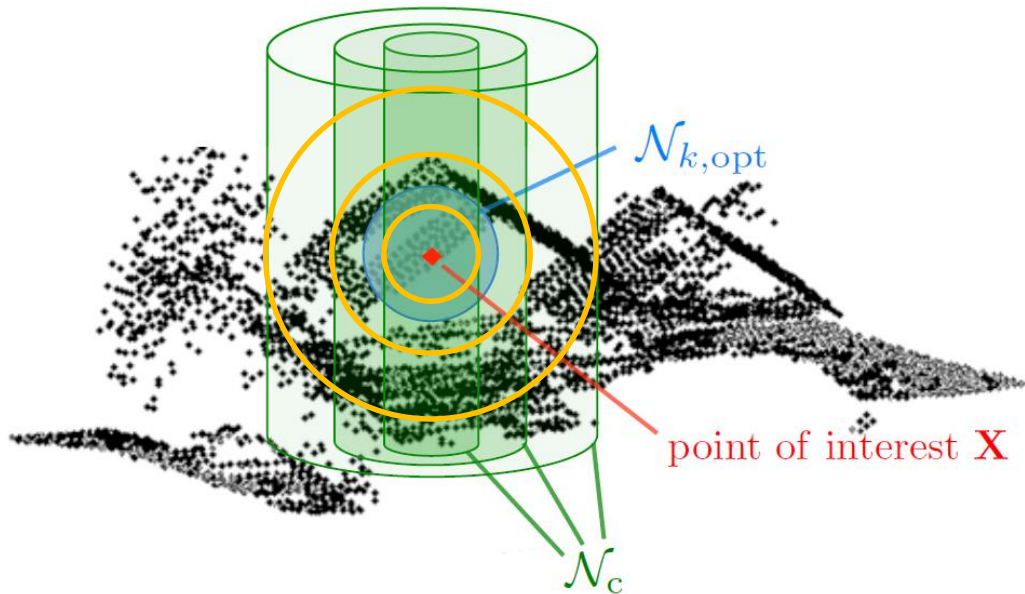
2. Methodology



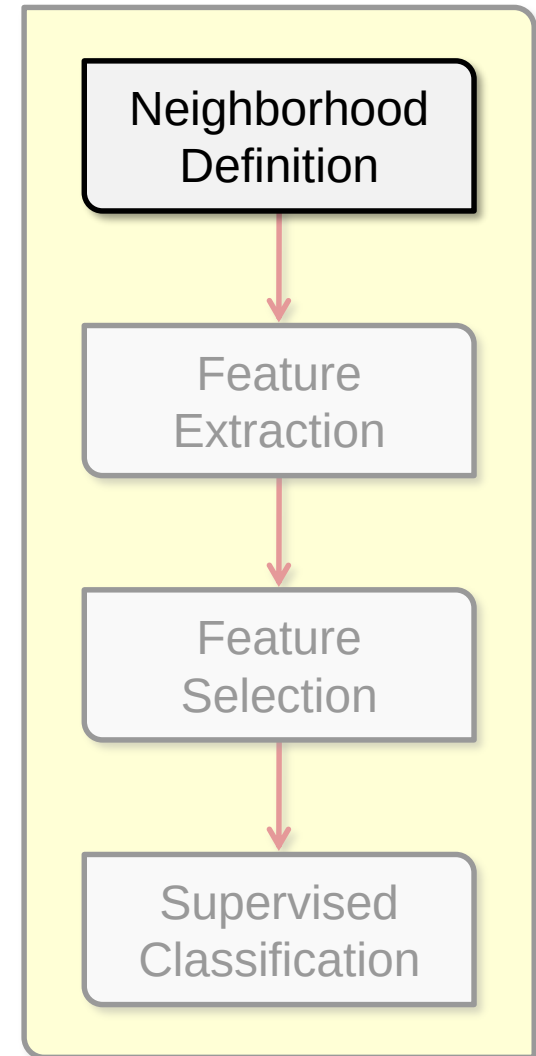
- Multi-scale, multi-type neighborhood
e.g. [Blomley et al., ISPRS Congress 2016]
 - Cylindrical neighborhoods with radii of 1m, 2m, 3m and 5m [Niemeyer et al., IJPRS 2014]
 - k -NN neighborhood with optimal k [Weinmann et al., IJPRS 2015]



2. Methodology



- Multi-scale, multi-type neighborhood
e.g. [Blomley & Weinmann, LS 2017]
 - Cylindrical neighborhoods with radii of 1m, 2m, 3m and 5m
 - Spherical neighborhoods with radii of 1m, 2m, 3m and 5m
 - k -NN neighborhood with optimal k



2. Methodology

■ Extraction of 3D features (8)

■ Eigenvalue-based features $\lambda_1 \geq \lambda_2 \geq \lambda_3 \geq 0$

→ Linearity: $L_\lambda = \frac{\lambda_1 - \lambda_2}{\lambda_1}$

→ Planarity: $P_\lambda = \frac{\lambda_2 - \lambda_3}{\lambda_1}$

→ Scattering: $S_\lambda = \frac{\lambda_3}{\lambda_1}$

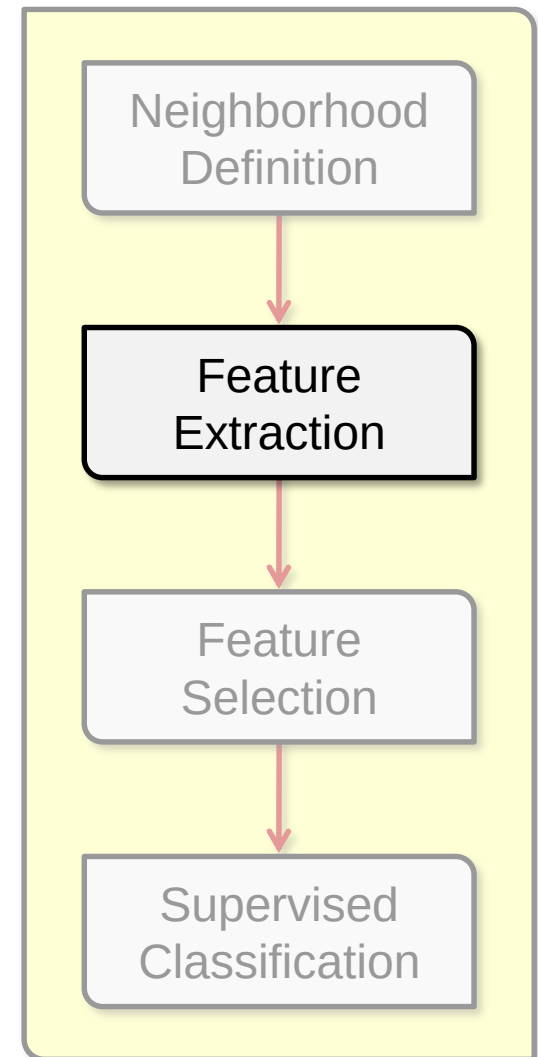
→ Omnivariance: $O_\lambda = \sqrt[3]{\lambda_1 \lambda_2 \lambda_3}$

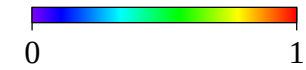
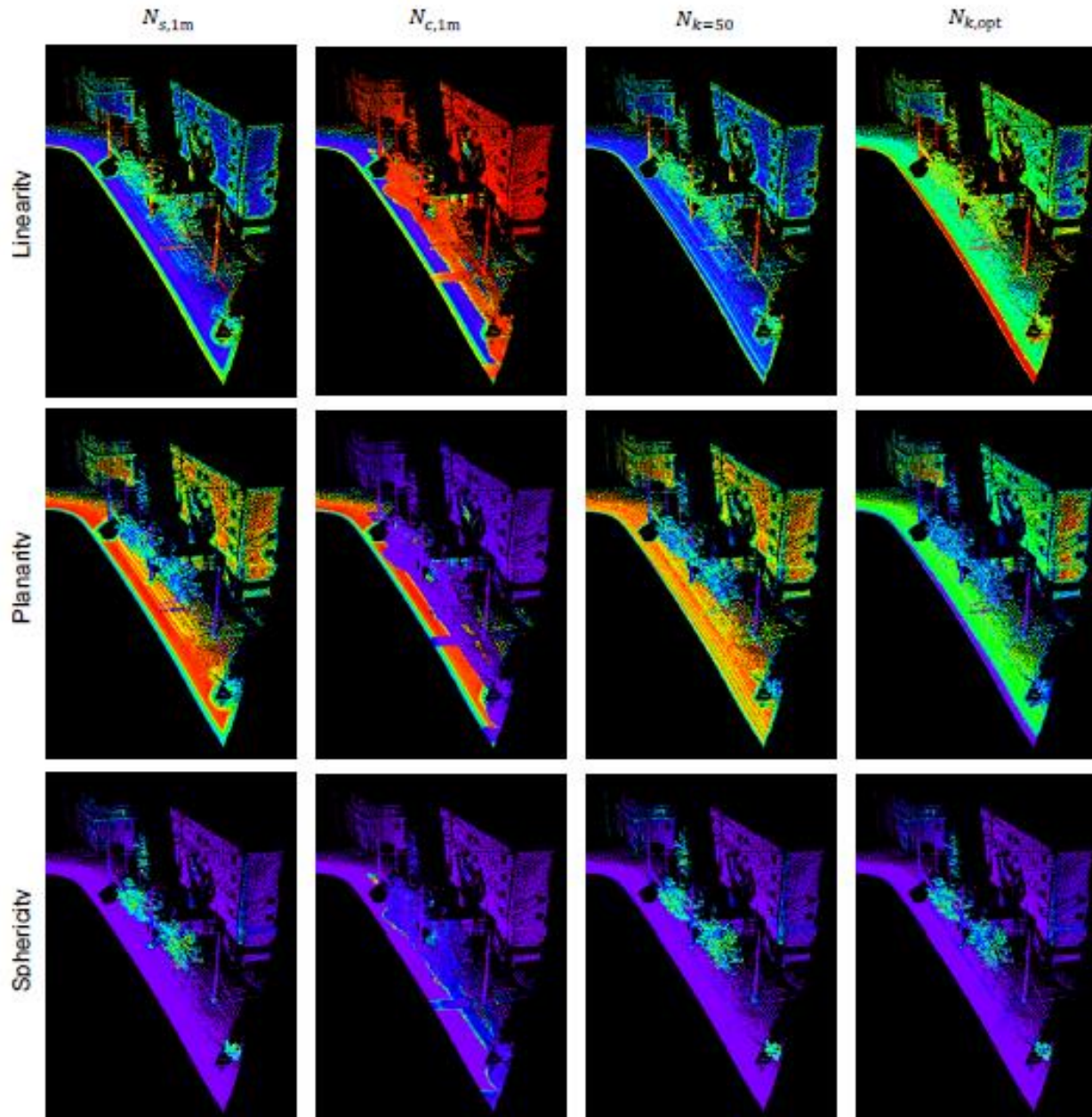
→ Anisotropy: $A_\lambda = \frac{\lambda_1 - \lambda_3}{\lambda_1}$

→ Eigenentropy: $E_\lambda = - \sum_{i=1}^3 \lambda_i \ln(\lambda_i)$

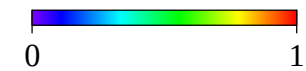
→ Sum of eigenvalues: $\Sigma_\lambda = \lambda_1 + \lambda_2 + \lambda_3$

→ Change of curvature: $C_\lambda = \frac{\lambda_3}{\lambda_1 + \lambda_2 + \lambda_3}$

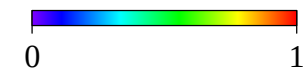




Linearity
(1D)



Planarity
(2D)



Sphericity
(3D)

2. Methodology

■ Extraction of 3D features (8 + 6)

■ Geometric 3D properties

→ Radius of k -NN:

$$r_{k\text{-NN},3D}$$

→ Local point density:

$$D_{3D} = \frac{k + 1}{\frac{4}{3} \pi r_{k\text{-NN},3D}^3}$$

→ Verticality:

$$V = 1 - n_Z$$

→ Absolute height:

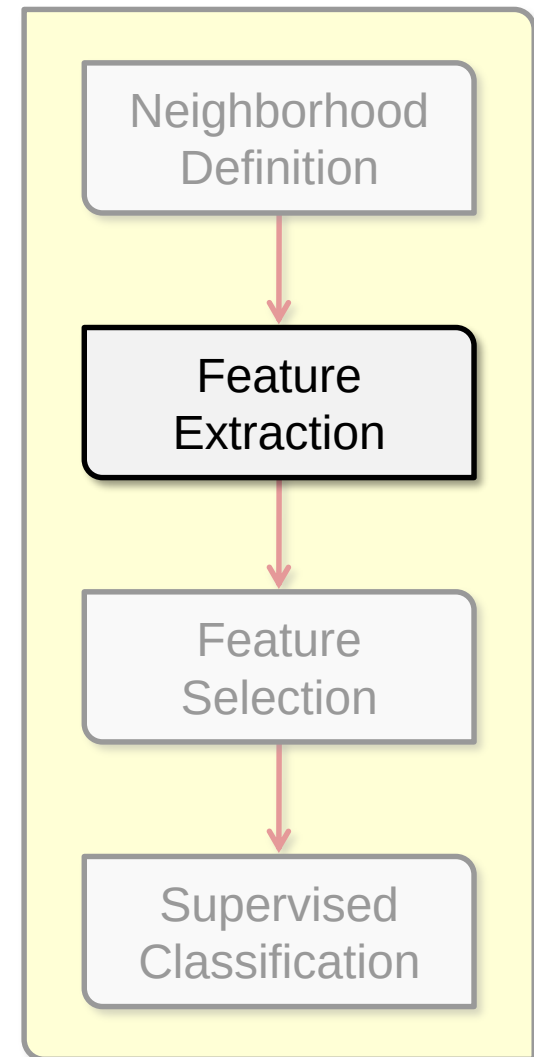
$$H$$

→ Height difference:

$$\Delta H_{k\text{-NN},3D}$$

→ Std.dev. of height values:

$$\sigma_{H,k\text{-NN},3D}$$



2. Methodology

■ Extraction of 2D features (2 + 2 + 3)

■ Geometric 2D properties

→ Radius of k -NN: $r_{k\text{-NN},2D}$

→ Local point density: D_{2D}

■ Eigenvalue-based features

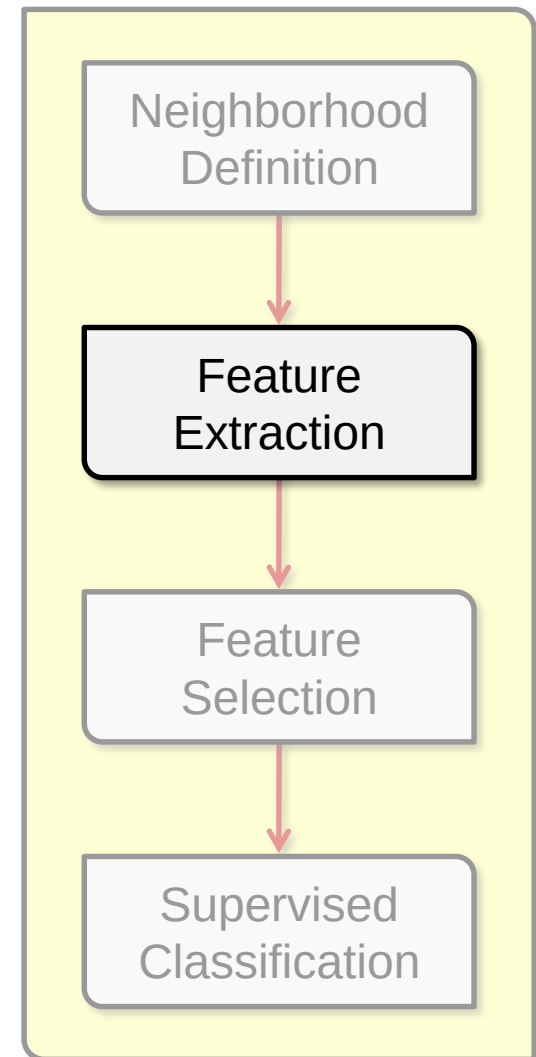
→ Sum of eigenvalues: $\Sigma_{\lambda,2D}$

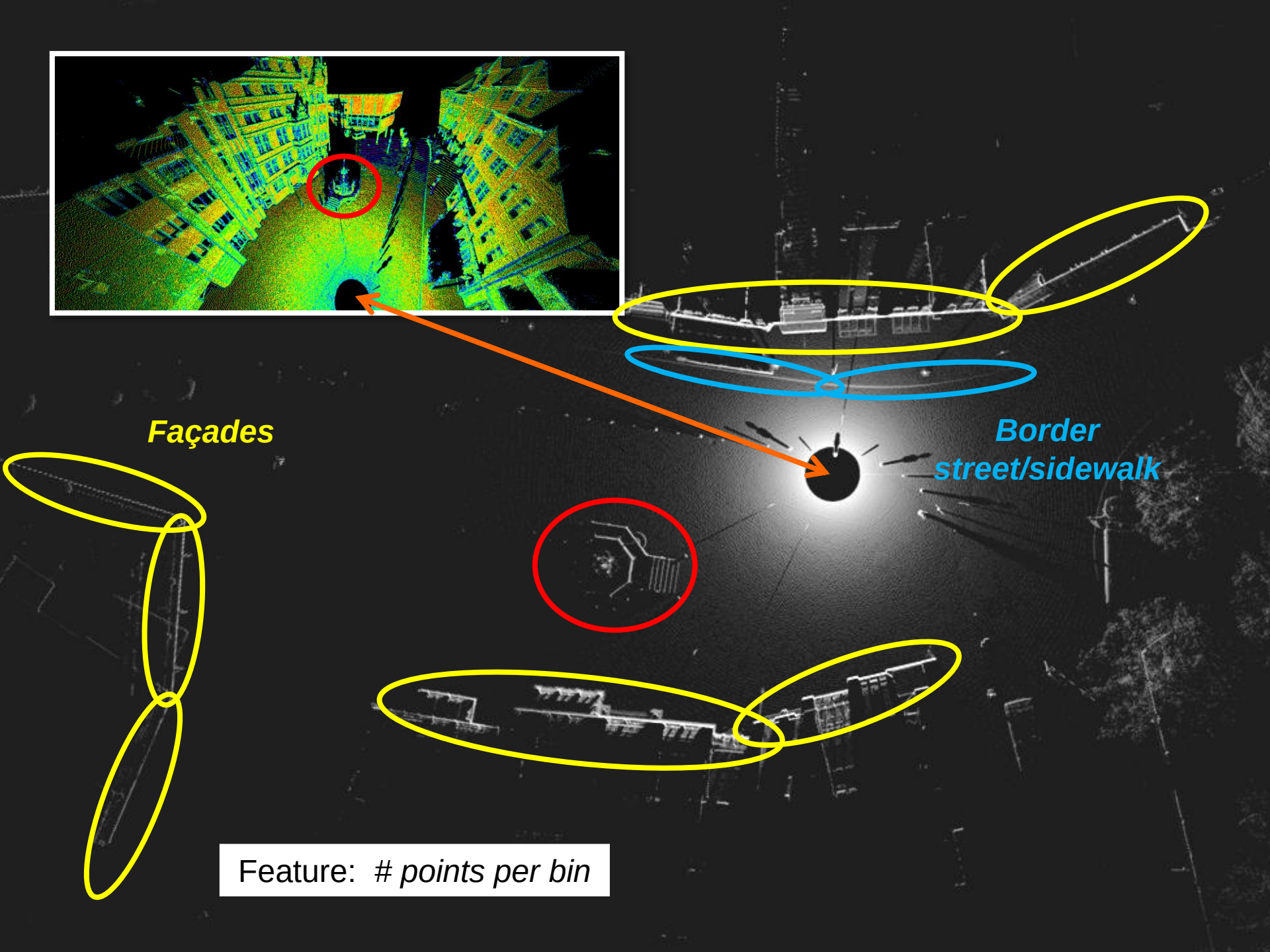
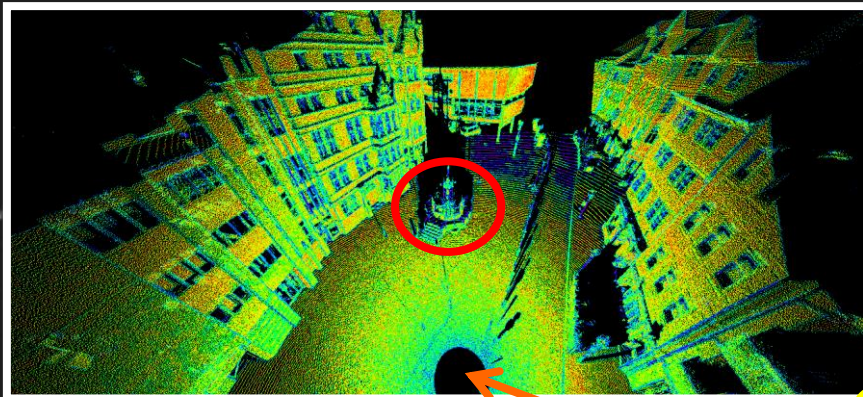
→ Ratio of eigenvalues: $R_{\lambda,2D} = \frac{\lambda_{2,2D}}{\lambda_{1,2D}}$

■ Discretization (e.g. bins of 0.25m x 0.25m)

→ # points per bin: M

→ Properties of a bin: $\Delta H \quad \sigma_H$





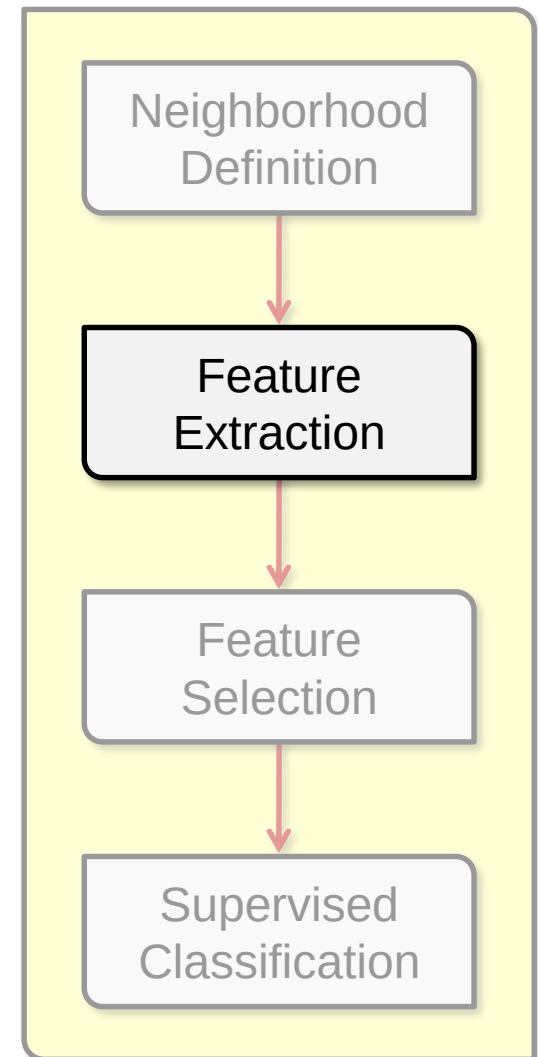
Façades

Border
street/sidewalk

Feature: # points per bin

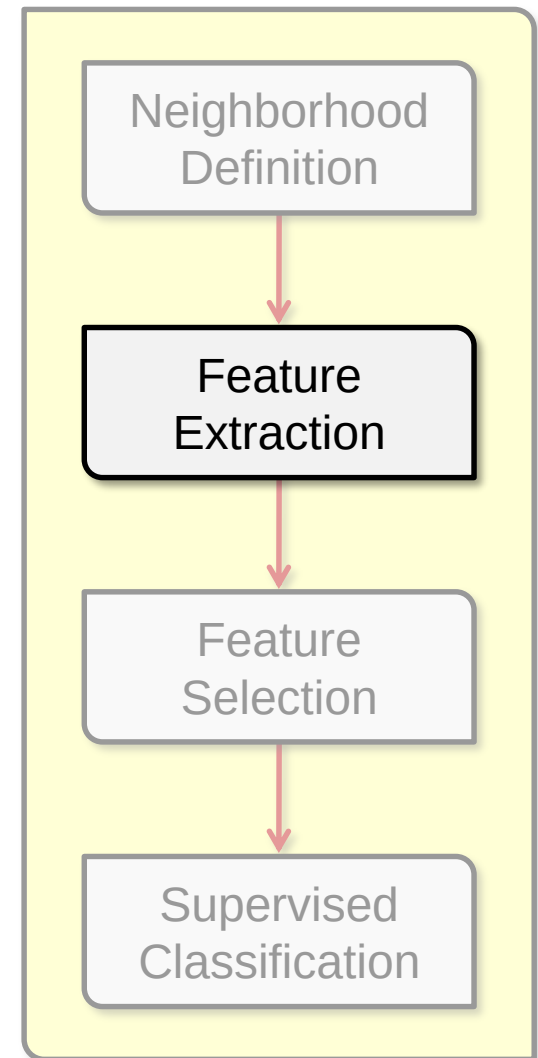
2. Methodology

- Extraction of more complex features
 - 3D Shape Context descriptor
[Frome et al., ECCV 2004]
 - Signature of Histograms of Orientations (SHOT) descriptor
[Tombari et al., ECCV 2010]
 - Point Feature Histograms (PFHs)
[Rusu et al., ICRA 2009]
 - Shape Distributions
[Osada et al., 2002]



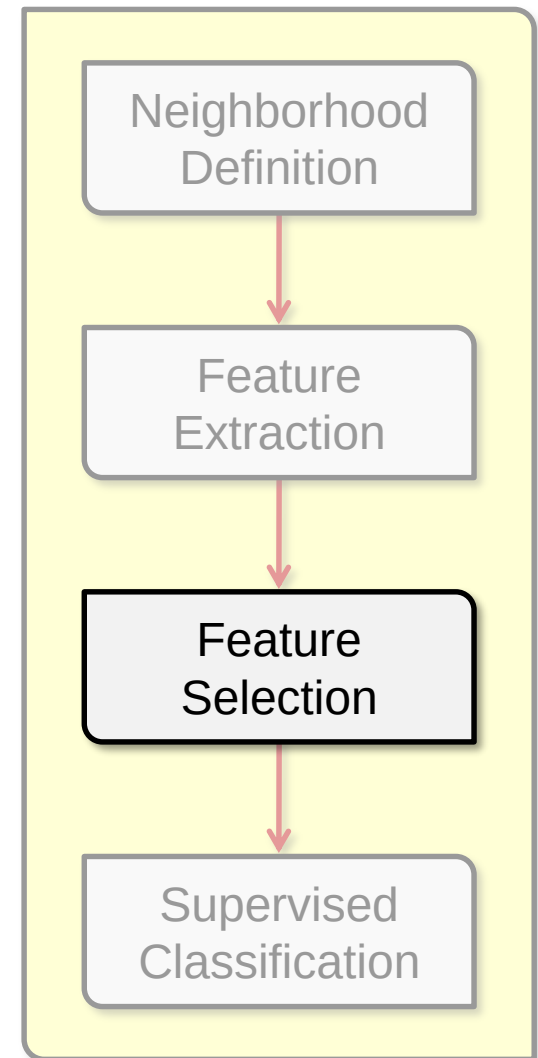
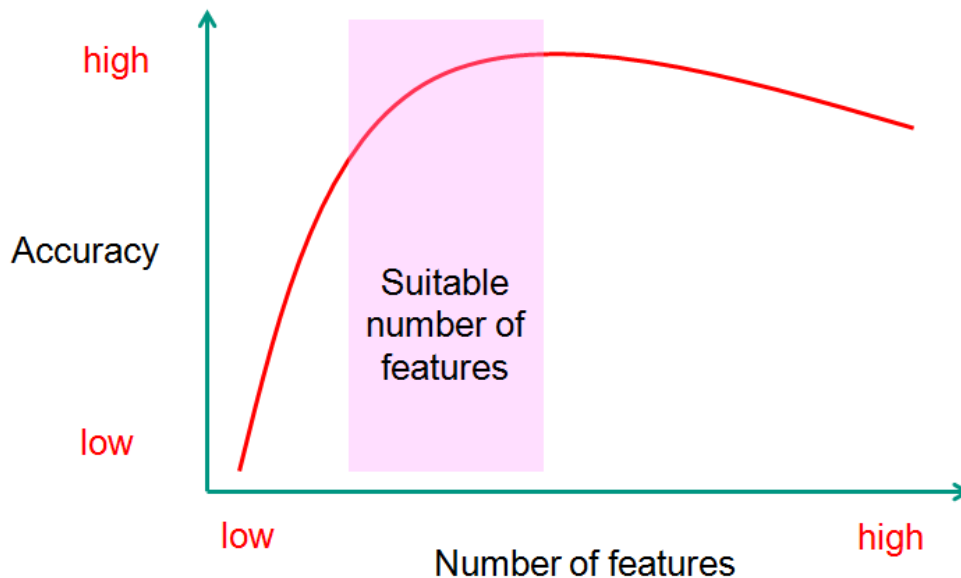
2. Methodology

- Use as many features as possible...



2. Methodology

- Selection of “suitable” features
 - Relevant, irrelevant and redundant features
 - Hughes phenomenon [Hughes, 1968]



2. Methodology

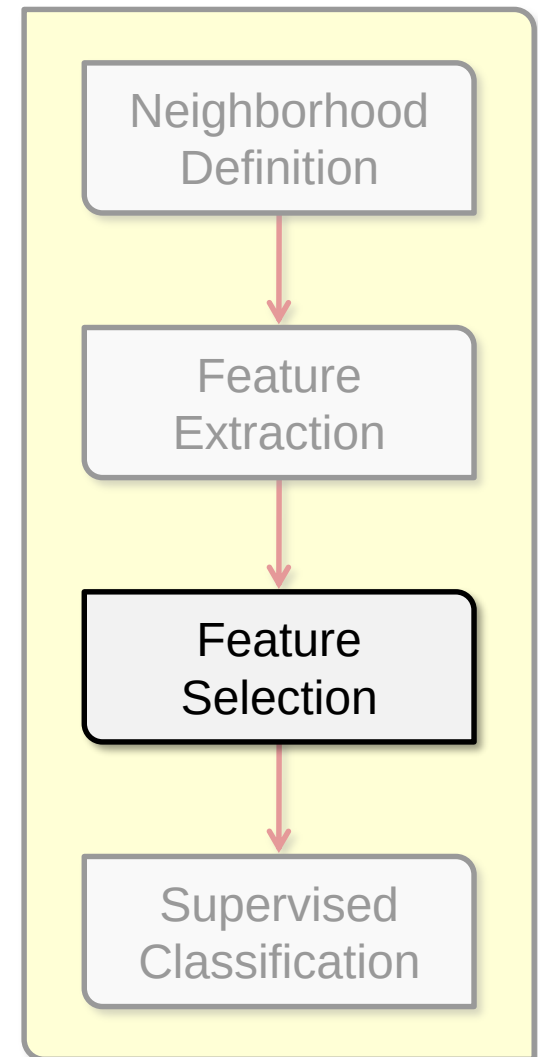
■ Selection of “suitable” features

■ Filter-based methods

- Classifier-independent
- Simple and efficient
- Consideration of intrinsic properties of the given (training) data
- Different criteria

■ Alternative strategies:

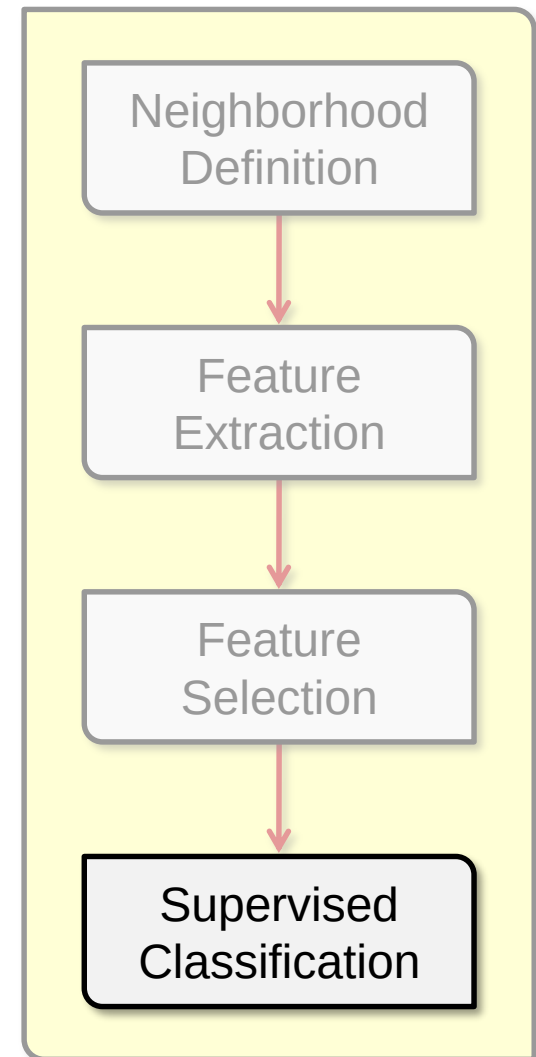
- Wrapper-based methods
- Embedded methods



2. Methodology

■ Individual classification

Learning principle	Involved classifiers
<i>Instance-based learning</i>	- <i>Nearest Neighbor (NN) classifier</i>
<i>Rule-based learning</i>	- <i>Decision Tree (DT)</i>
<i>Probabilistic learning</i>	- <i>Naïve Bayesian (NB) classifier</i> - <i>Linear Discriminant Analysis (LDA)</i> - <i>Quadratic Discriminant Analysis (QDA)</i>
<i>Max-margin learning</i>	- <i>Support Vector Machine (SVM)</i>
<i>Ensemble learning</i>	- <i>Random Forest (RF)</i> - <i>Random Fern (RFe)</i> - <i>AdaBoost (AB)</i>
<i>Deep learning</i>	- <i>Multi-Layer Perceptron (MLP)</i>



2. Methodology

■ Individual classification

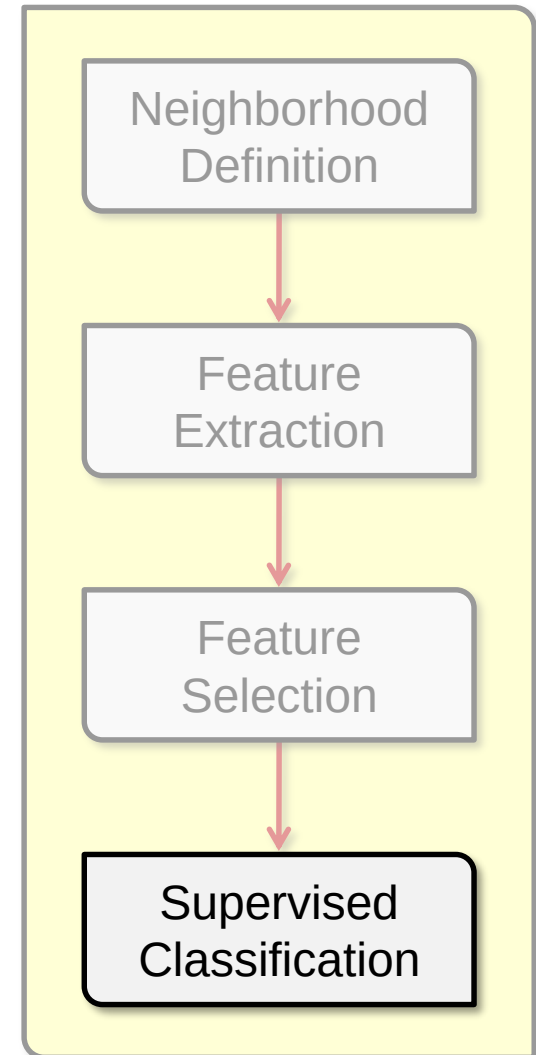
■ Random Forest (RF) Classifier

- Ensemble of randomly trained decision trees (“weak learners”)
- Typically majority vote across all decision trees
- (*Optionally*) Probabilistic interpretation:

$$p\left(c_i = c^l | \mathbf{f}_i(\mathbf{x})\right) = \frac{N_l}{N_T}$$

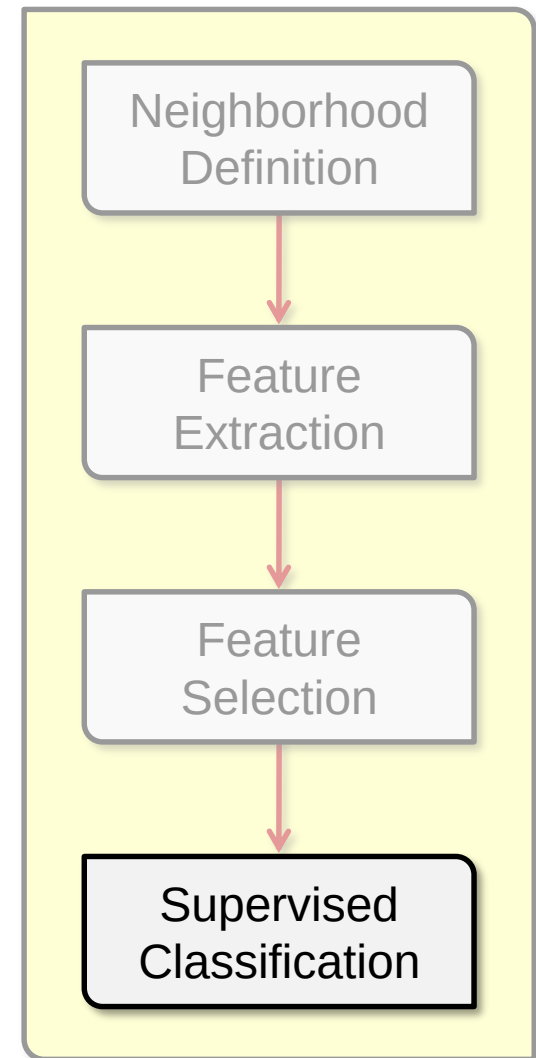
N_T : number of decision trees

N_l : number of votes that are cast for class l



2. Methodology

- Supervised classification
 - Individual classification of 3D points
 - Only classification of feature vectors
 - e.g. Random Forest classifier
 - Noisy appearance of classified data
 - Contextual classification of 3D points
 - Classification based on feature vectors AND relations between 3D points in a neighborhood
 - Statistical models of context
 - e.g. Conditional Random Field (CRF)
 - Locally smooth behavior of classified data enforced



2. Methodology

■ Supervised classification

■ Conditional Random Field (CRF)

- Undirected graphical model that allows to model interactions between neighboring 3D points
- Simultaneous determination of all labels [Kumar & Hebert, 2006] by maximizing

Labels of all points

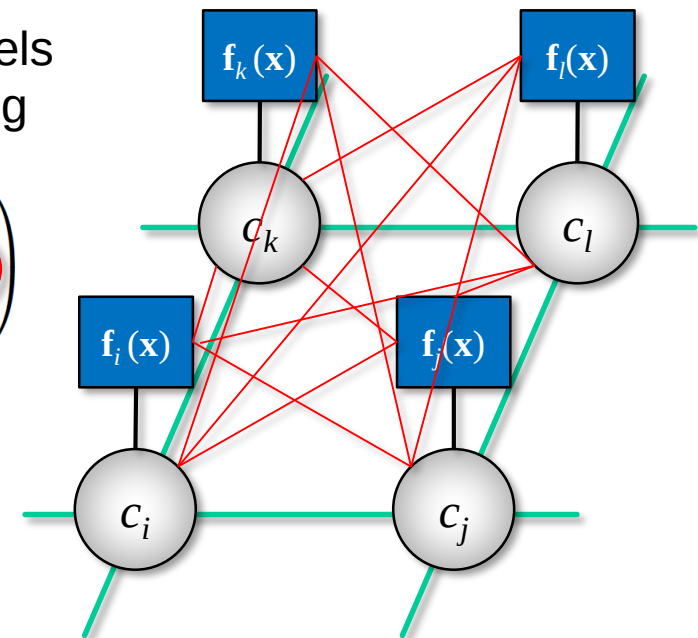
$$p(\mathbf{C}|\mathbf{x}) = \frac{1}{Z(\mathbf{x})} \left(\prod_{i \in n} \phi(\mathbf{x}, c_i) \prod_{i \in n} \prod_{j \in N_i} \psi(\mathbf{x}, c_i, c_j) \right)$$

Partition function *Association potentials* *Neighborhood* *Interaction potentials*

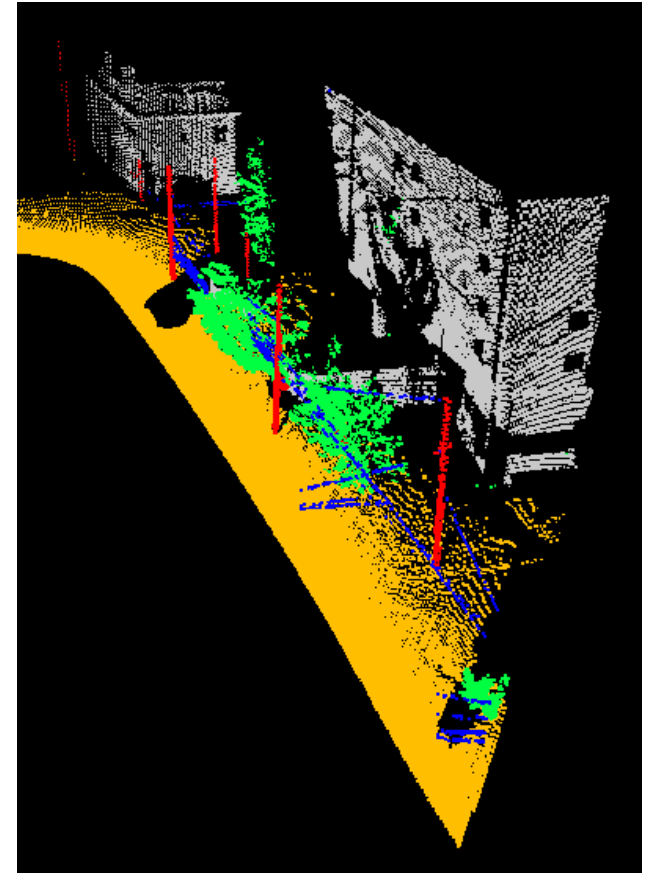
- Inference based on Loopy Belief Propagation [Frey & MacKay, 1998]

Nodes: 3D points

Edges: spatial dependencies



1. Introduction
2. Methodology
3. Experimental Results
4. Conclusions & Future Work



3. Experimental Results

- *Oakland 3D Point Cloud Dataset* [Munoz et al., 2008, 2009]
 - 5 semantic classes: *Wire, Pole/Trunk, Façade, Ground, Vegetation*



	Training	Validation	Test
# 3D points	35,000	91,515	1,324,310
Min. class size	1,000	899	3,794
Max. class size	11,000	67,419	934,146

Reduction of training data

3. Experimental Results

- A. Impact of optimal neighborhood size selection
- B. Impact of the selection of relevant features
- C. Impact of the consideration of context information

M. Weinmann, B. Jutzi, S. Hinz, and C. Mallet (2015): Semantic point cloud interpretation based on optimal neighborhoods, relevant features and efficient classifiers. ISPRS Journal of Photogrammetry and Remote Sensing, Vol. 105, pp. 286-304.

M. Weinmann, B. Jutzi, and C. Mallet (2014): Semantic 3D scene interpretation: a framework combining optimal neighborhood size selection with relevant features. ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Vol. II-3, pp. 181-188.

3. Experimental Results (A)

- *Oakland 3D Point Cloud Dataset*, all 21 low-level features:
 - Feature extraction based on different neighborhood definitions
 - Classification: *Random Forest* (100 decision trees)

Mean class recall:	$\mathcal{N}$	Wire	Pole/Trunk	Façade	Ground	Vegetation	
70.78	$\mathcal{N}_{10}$	70.46	68.49	50.29	98.23	66.45	
74.65	$\mathcal{N}_{25}$	69.48	69.59	60.98	98.91	74.29	
72.72	$\mathcal{N}_{50}$	56.86	62.64	68.13	98.84	77.10	
69.99	$\mathcal{N}_{75}$	49.71	58.63	67.51	98.81	75.31	
68.51	$\mathcal{N}_{100}$	49.67	58.27	62.69	98.71	73.20	
81.70	$\mathcal{N}_{\text{opt,dim}}$	85.16	78.90	65.90	98.52	79.99	
82.59	$\mathcal{N}_{\text{opt},\lambda}$	86.05	79.99	67.01	98.48	81.41	Recall (Completeness)
Overall accuracy:	$\mathcal{N}$	Wire	Pole/Trunk	Façade	Ground	Vegetation	
87.53	$\mathcal{N}_{10}$	5.51	7.99	77.62	96.82	94.79	
90.50	$\mathcal{N}_{25}$	7.12	9.46	83.88	98.58	94.87	
91.54	$\mathcal{N}_{50}$	4.81	19.47	83.43	97.77	94.40	
91.06	$\mathcal{N}_{75}$	4.00	18.25	80.28	97.86	93.84	
90.16	$\mathcal{N}_{100}$	3.98	13.55	76.19	97.92	93.55	
91.89	$\mathcal{N}_{\text{opt,dim}}$	7.98	22.09	83.71	97.67	94.97	
92.25	$\mathcal{N}_{\text{opt},\lambda}$	9.03	24.13	84.69	97.18	95.87	Precision (Correctness)

3. Experimental Results (A)

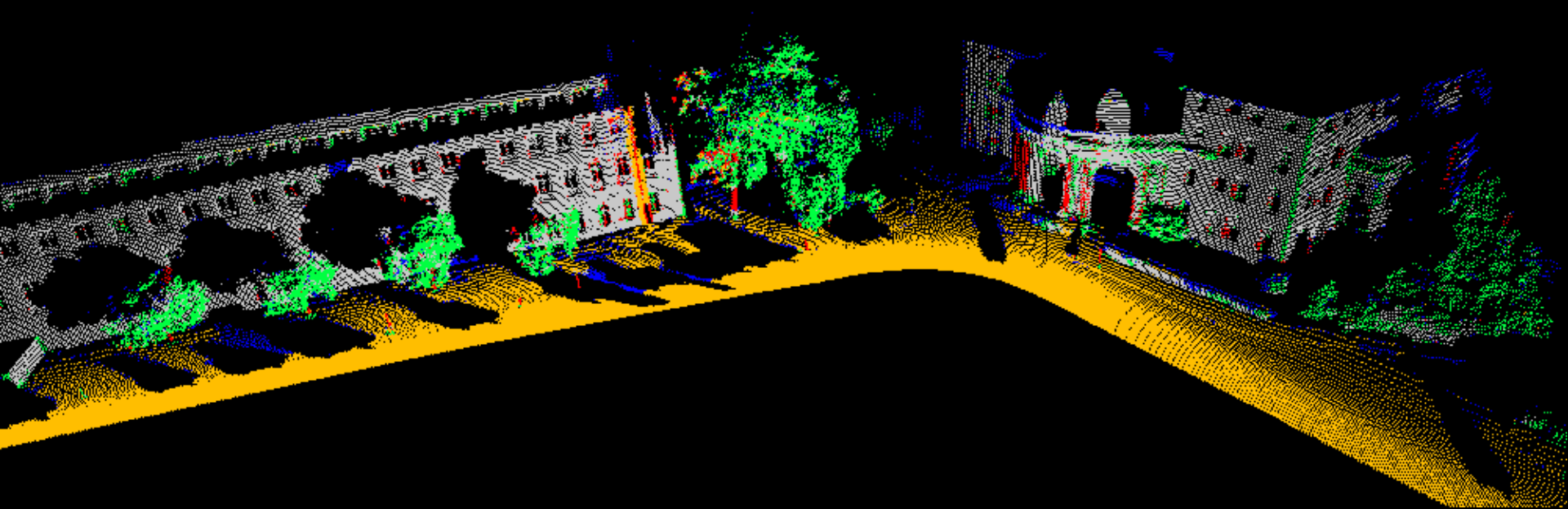
■ *Oakland 3D Point Cloud Dataset*, all 21 low-level features:

■ *Overall accuracy:*

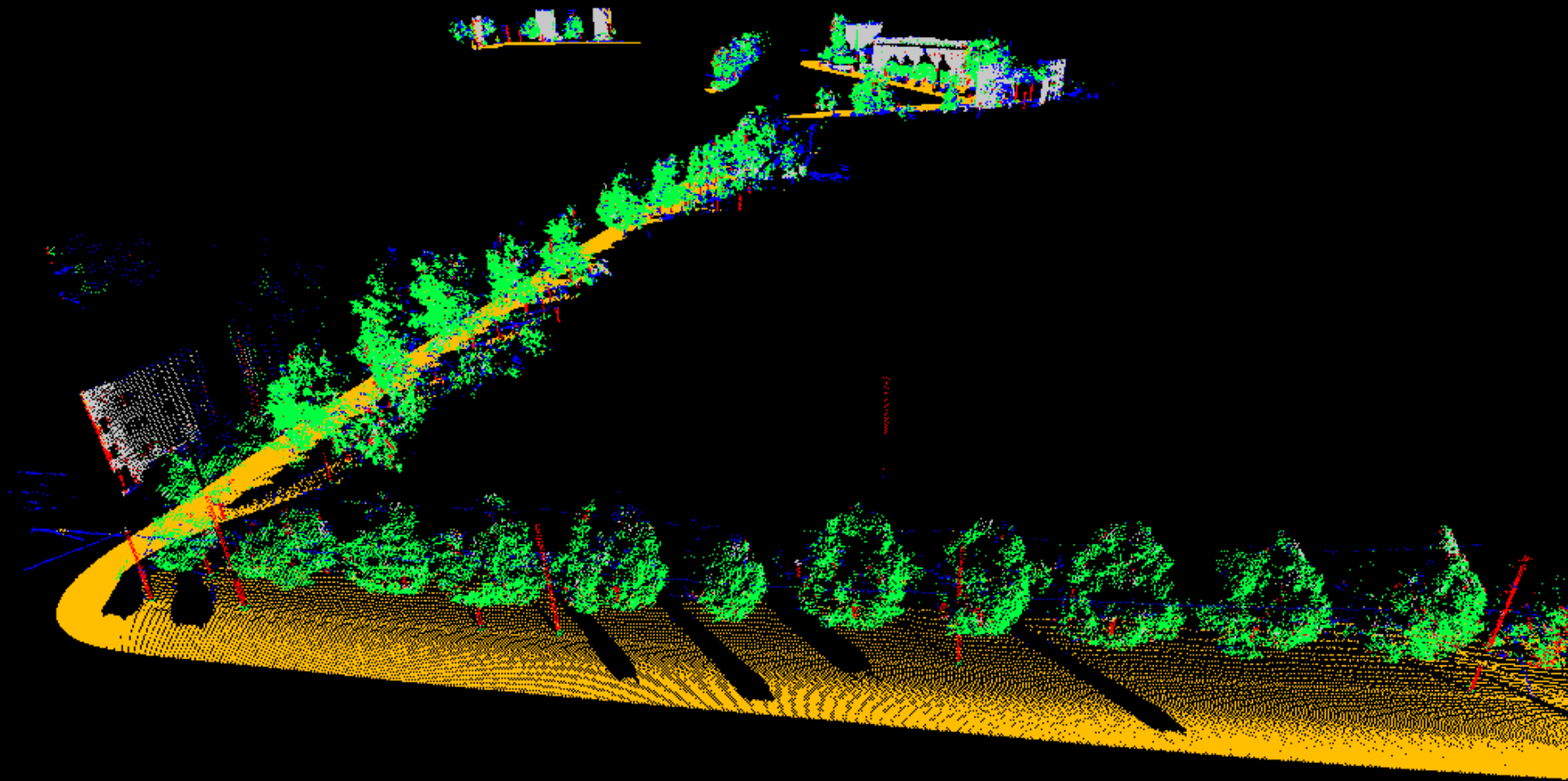
$\mathcal{N}$	NN	DT	NB	LDA	QDA	SVM	RF	RFe	AB	MLP
$\mathcal{N}_{10}$	73.86	65.64	78.88	87.38	78.93	82.93	87.53	81.94	86.78	80.54
$\mathcal{N}_{25}$	86.25	69.30	83.64	90.08	83.62	88.88	90.50	88.77	89.99	78.59
$\mathcal{N}_{50}$	88.89	75.47	85.03	92.83	84.95	92.00	91.54	90.42	91.80	85.68
$\mathcal{N}_{75}$	89.97	76.87	85.00	93.05	84.99	91.99	91.06	91.16	90.56	87.07
$\mathcal{N}_{100}$	89.90	84.45	84.33	92.60	84.43	91.76	90.16	90.59	87.01	84.39
$\mathcal{N}_{\text{opt,dim}}$	79.34	70.71	83.75	91.01	83.80	90.15	91.89	90.12	91.62	85.69
$\mathcal{N}_{\text{opt},\lambda}$	79.87	75.76	85.63	90.39	85.69	89.10	92.25	90.45	92.28	87.29

■ *Mean class recall:*

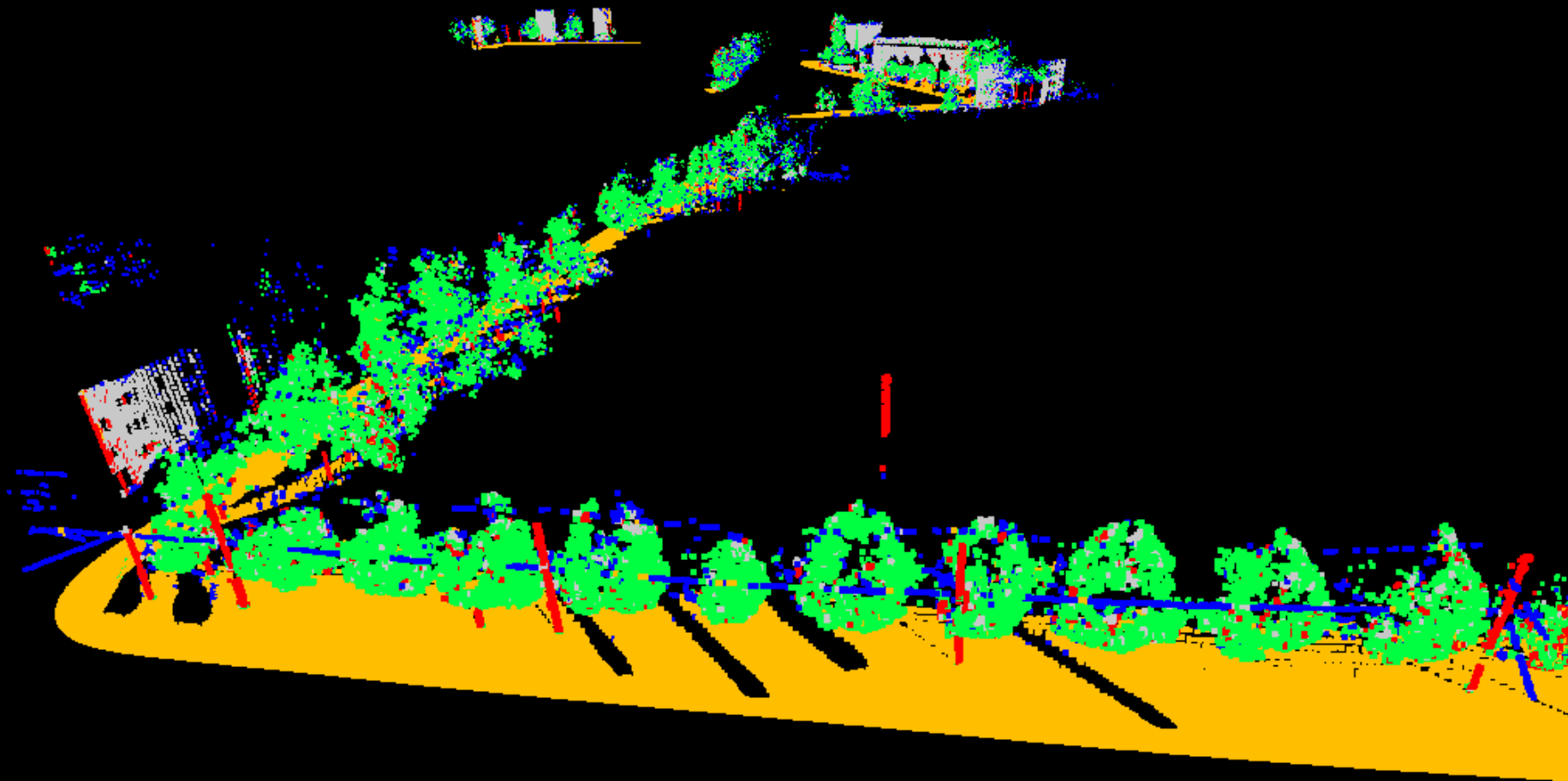
$\mathcal{N}$	NN	DT	NB	LDA	QDA	SVM	RF	RFe	AB	MLP
$\mathcal{N}_{10}$	63.40	54.19	62.29	70.68	62.33	58.86	70.78	63.75	67.52	64.20
$\mathcal{N}_{25}$	70.01	57.41	68.46	75.54	68.47	68.50	74.65	71.48	68.64	68.03
$\mathcal{N}_{50}$	69.47	59.99	67.12	72.76	66.98	68.47	72.72	69.22	71.46	69.13
$\mathcal{N}_{75}$	68.29	57.82	65.49	73.05	65.44	68.00	69.99	68.88	68.19	70.47
$\mathcal{N}_{100}$	66.66	57.96	63.44	72.35	63.46	64.76	68.51	67.16	59.58	68.98
$\mathcal{N}_{\text{opt,dim}}$	74.17	62.15	74.49	81.36	74.35	79.58	81.70	78.35	77.63	78.61
$\mathcal{N}_{\text{opt},\lambda}$	73.98	66.99	76.19	82.05	76.15	79.97	82.59	78.70	79.49	79.92



M. Weinmann, B. Jutzi and C. Mallet (2014): Semantic 3D scene interpretation: a framework combining optimal neighborhood size selection with relevant features. ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Vol. II-3, pp. 181-188.



M. Weinmann, B. Jutzi and C. Mallet (2014): Semantic 3D scene interpretation: a framework combining optimal neighborhood size selection with relevant features. ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Vol. II-3, pp. 181-188.



M. Weinmann, B. Jutzi and C. Mallet (2014): Semantic 3D scene interpretation: a framework combining optimal neighborhood size selection with relevant features. ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Vol. II-3, pp. 181-188.

3. Experimental Results (A)

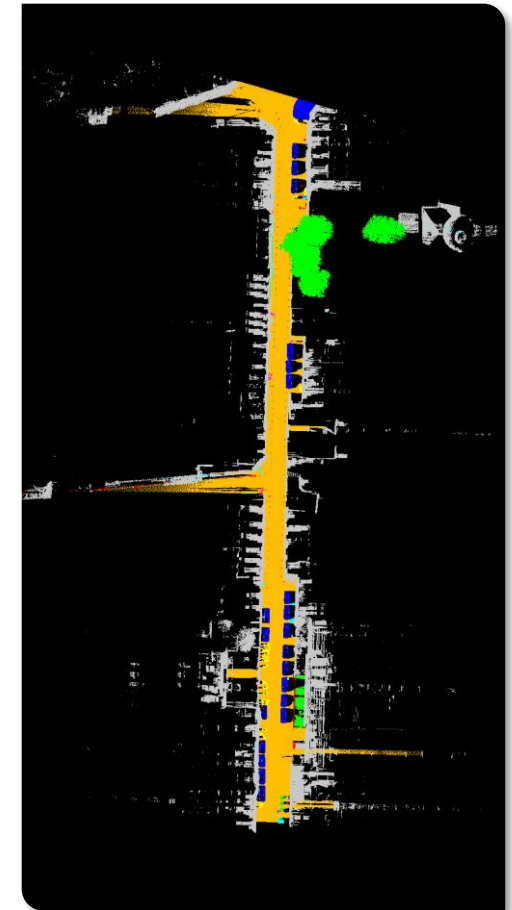
- Paris-rue-Cassette database [Paparoditis et al., 2014]

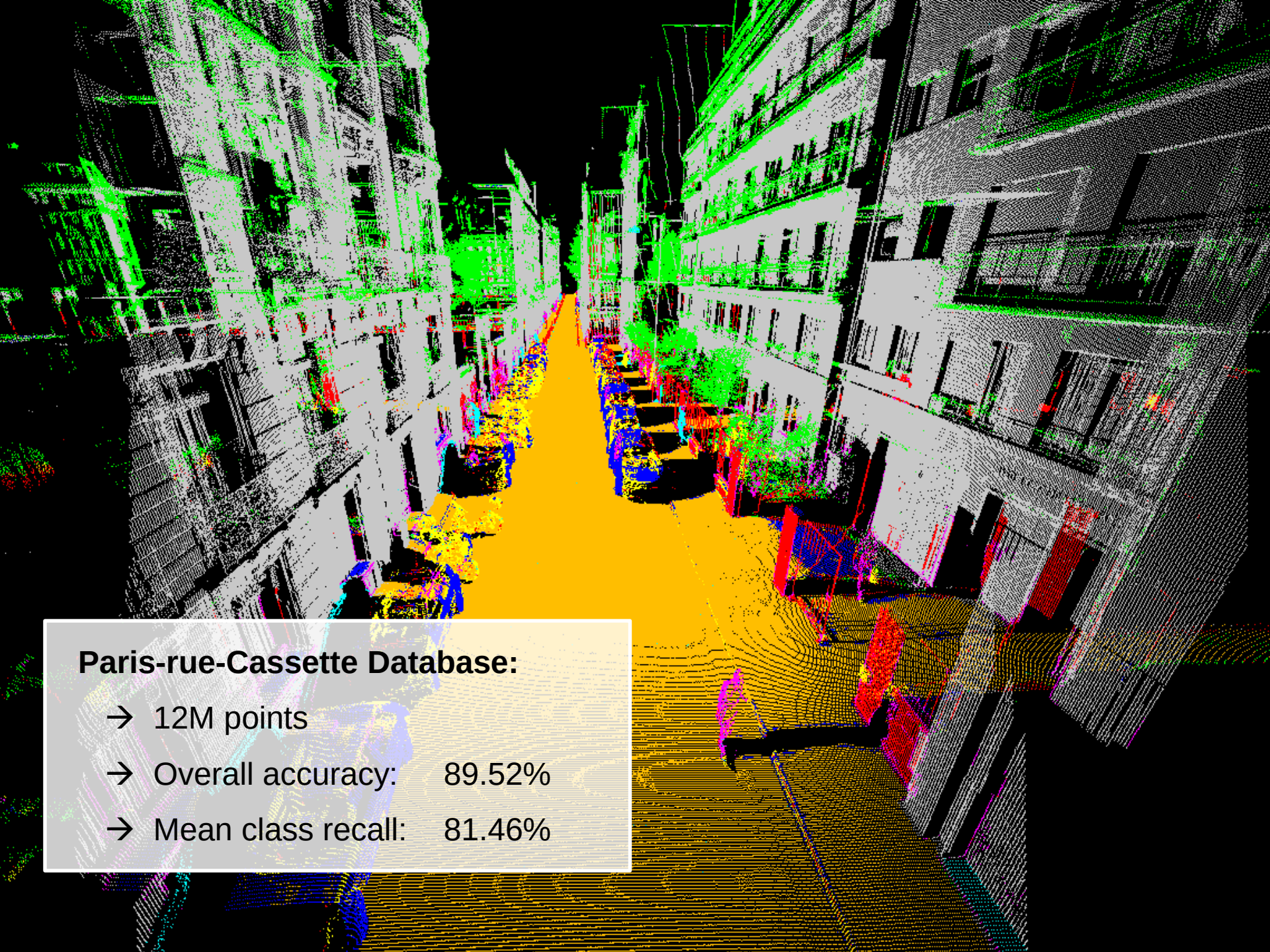
- Learning dataset with 12 million points

- Many different classes and subclasses

- Consideration of 7 significant classes:

1.) Façade:	6,141,405 points
2.) Ground:	4,124,327 points
3.) Cars:	311,902 points
4.) 2 wheelers:	181,940 points
5.) Road inventory:	229,338 points
6.) Pedestrians:	238,094 points
7.) Vegetation:	713,486 points





Paris-rue-Cassette Database:

- 12M points
- Overall accuracy: 89.52%
- Mean class recall: 81.46%

3. Experimental Results

- A. Impact of optimal neighborhood size selection
- B. Impact of the selection of relevant features
- C. Impact of the consideration of context information

M. Weinmann, B. Jutzi, S. Hinz, and C. Mallet (2015): Semantic point cloud interpretation based on optimal neighborhoods, relevant features and efficient classifiers. ISPRS Journal of Photogrammetry and Remote Sensing, Vol. 105, pp. 286-304.

M. Weinmann, B. Jutzi, and C. Mallet (2013): Feature relevance assessment for the semantic interpretation of 3D point cloud data. ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Vol. II-5/W2, pp. 313-318.

3. Experimental Results (B)

■ *Oakland 3D Point Cloud Dataset*

- Feature extraction based on different neighborhood definitions

- Feature selection:

- All features (21)
- Dimensionality features (3)
- Eigenvalue-based 3D features (8)
- 5 best-ranked features according to [Weinmann et al., 2013] (5)
- *Correlation-based Feature Selection* [Hall, 1999] (12-16)
- *Fast Correlation-Based Filter* [Yu & Liu, 2003] (6-9)
- *Minimal-Redundancy-Maximal-Relevance* [Peng et al., 2005] (10)

3. Experimental Results (B)

Overall accuracy:

$\mathcal{N}$	$\mathcal{S}_{\text{all}}$	$\mathcal{S}_{\text{dim}}$	$\mathcal{S}_{\lambda,3D}$	$\mathcal{S}_5$	$\mathcal{S}_{\text{CFS}}$	$\mathcal{S}_{\text{FCBF}}$	$\mathcal{S}_{\text{mRMR}}$
$\mathcal{N}_{10}$	87.50	58.36	74.33	85.66	87.43	87.29	82.11
$\mathcal{N}_{25}$	90.78	68.80	82.48	89.60	90.59	91.78	84.70
$\mathcal{N}_{50}$	91.64	73.19	81.38	91.01	91.71	92.69	85.64
$\mathcal{N}_{75}$	91.00	73.63	80.12	90.24	91.17	91.47	85.99
$\mathcal{N}_{100}$	90.11	72.99	81.96	89.84	90.31	90.94	85.76
$\mathcal{N}_{\text{opt,dim}}$	91.92	69.59	77.69	91.41	91.83	91.55	86.82
$\mathcal{N}_{\text{opt},\lambda}$	92.28	63.61	84.88	91.44	92.27	92.78	84.28
# Features	21	3	8	5	12-16	8-9	10

Mean class recall:

$\mathcal{N}$	$\mathcal{S}_{\text{all}}$	$\mathcal{S}_{\text{dim}}$	$\mathcal{S}_{\lambda,3D}$	$\mathcal{S}_5$	$\mathcal{S}_{\text{CFS}}$	$\mathcal{S}_{\text{FCBF}}$	$\mathcal{S}_{\text{mRMR}}$
$\mathcal{N}_{10}$	70.83	48.41	59.95	58.24	69.28	70.08	62.46
$\mathcal{N}_{25}$	75.48	55.68	65.22	73.30	74.24	76.58	63.61
$\mathcal{N}_{50}$	72.71	54.41	64.43	65.91	72.64	74.14	60.90
$\mathcal{N}_{75}$	69.75	52.12	61.37	59.86	70.19	68.66	58.35
$\mathcal{N}_{100}$	68.49	50.33	61.37	60.22	69.02	66.34	56.05
$\mathcal{N}_{\text{opt,dim}}$	81.79	61.53	67.65	75.57	81.33	80.83	74.72
$\mathcal{N}_{\text{opt},\lambda}$	82.60	59.48	69.17	78.50	82.39	82.93	69.37

3. Experimental Results

- A. Impact of optimal neighborhood size selection
- B. Impact of the selection of relevant features
- C. Impact of the consideration of context information

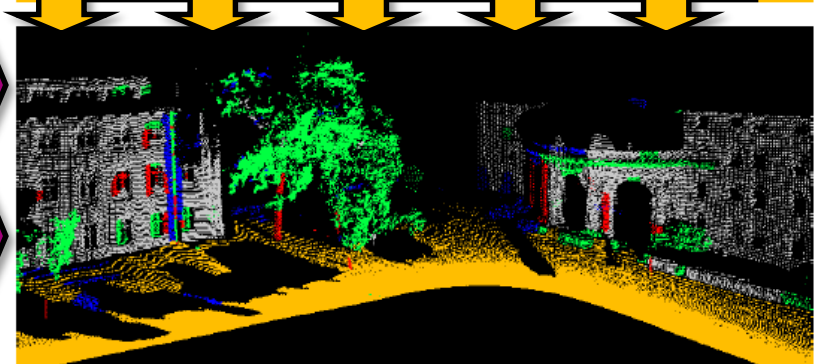
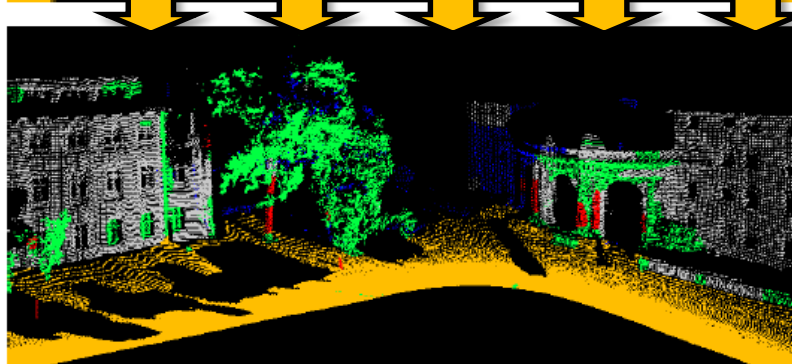
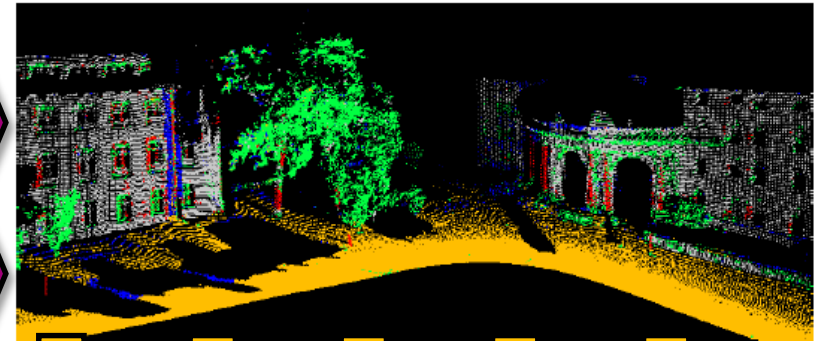
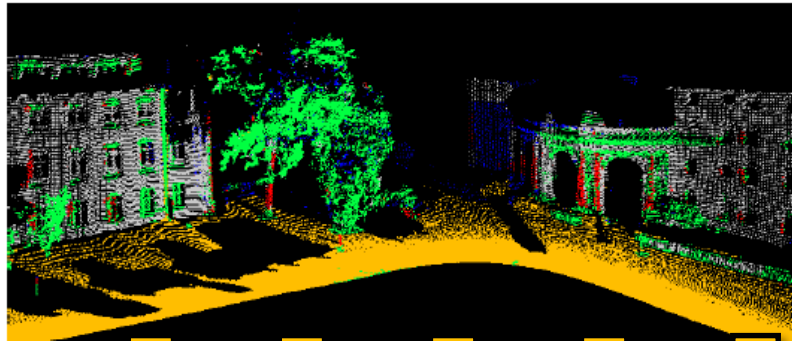
M. Weinmann, A. Schmidt, C. Mallet, S. Hinz, F. Rottensteiner, and B. Jutzi (2015): Contextual classification of point cloud data by exploiting individual 3D neighborhoods. ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Vol. II-3/W4, S. 271-278.

L. Landrieu, H. Raguette, B. Vallet, C. Mallet, and M. Weinmann (2017): A structured regularization framework for spatially smoothing semantic labelings of 3D point clouds. ISPRS Journal of Photogrammetry and Remote Sensing, Vol. 132, pp. 102-118.

3. Experimental Results (C)

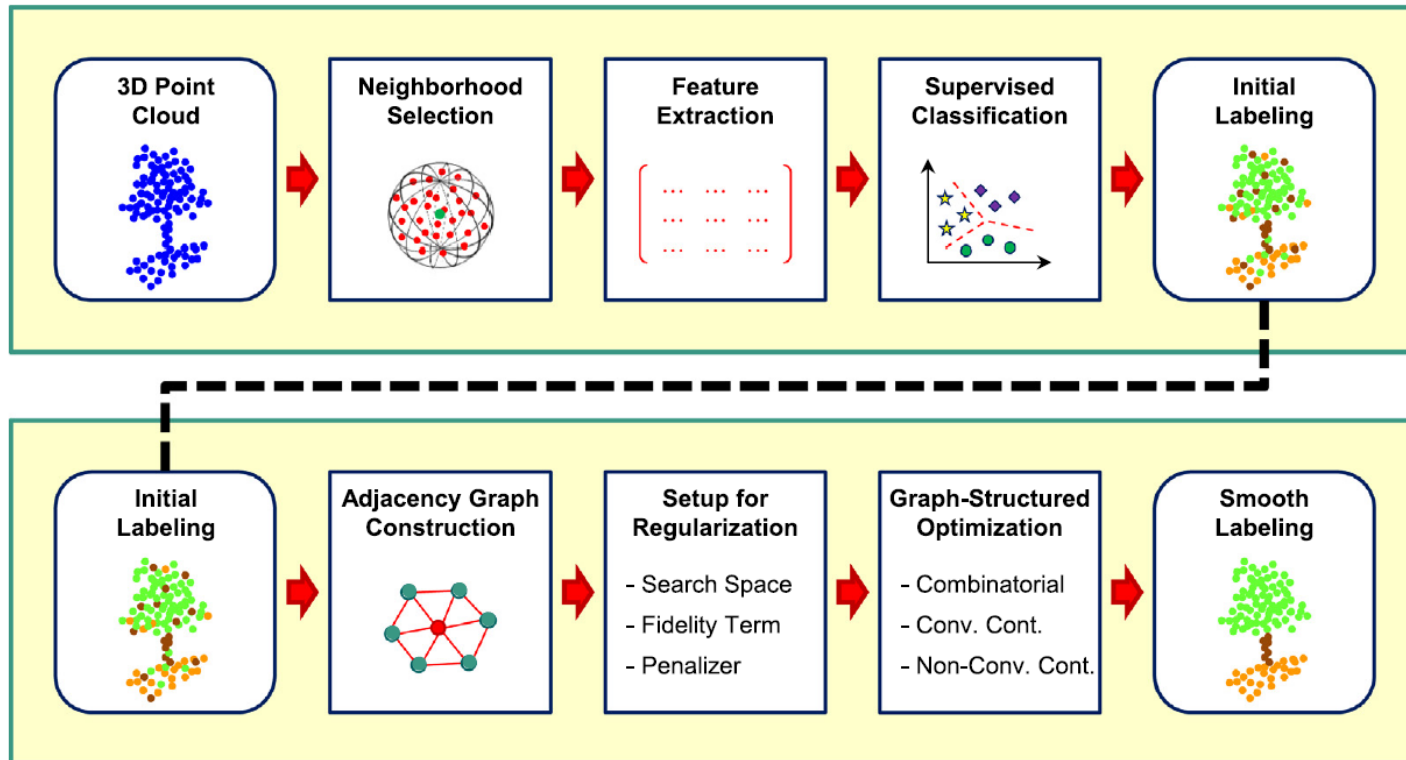
- *Oakland 3D Point Cloud Dataset*, all 21 features:

- Different definitions of the local 3D neighborhood
- Individual classification (RF) vs. contextual classification (CRF)

 $\mathcal{N}_{50}$
 $\mathcal{N}_{\text{opt}, \lambda}$
 RF_{200}

 CRF_{200}^5

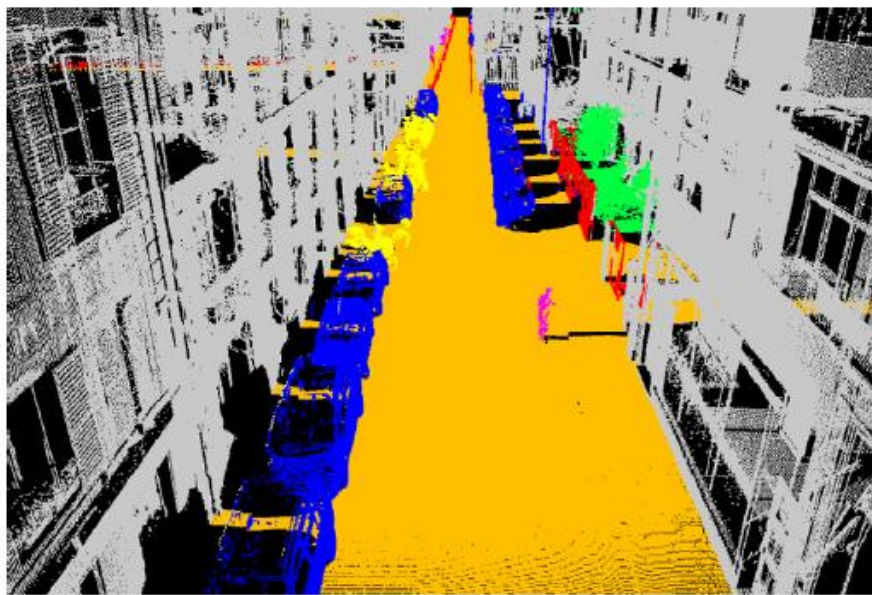
3. Experimental Results (C)

Step 1: Pointwise Probabilistic Classification

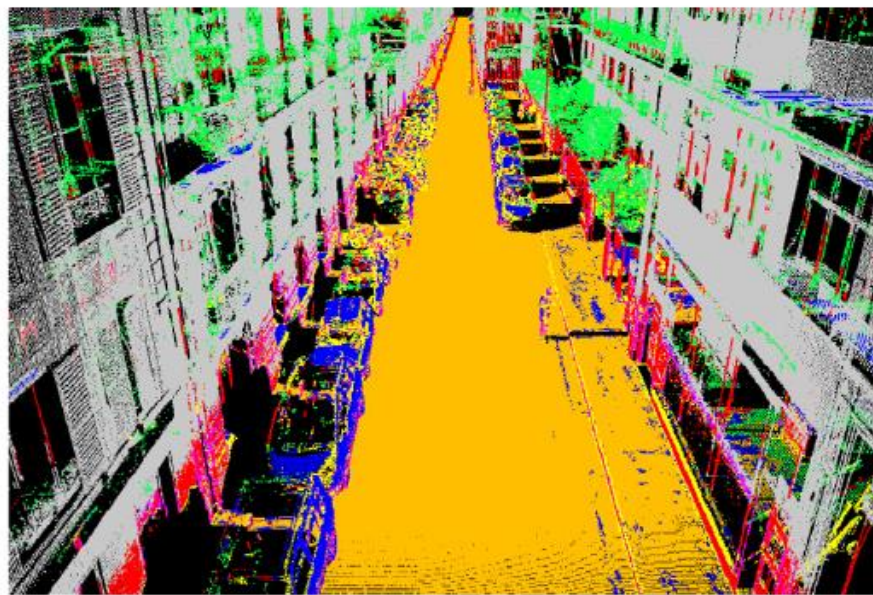


Step 2: Structured Regularization

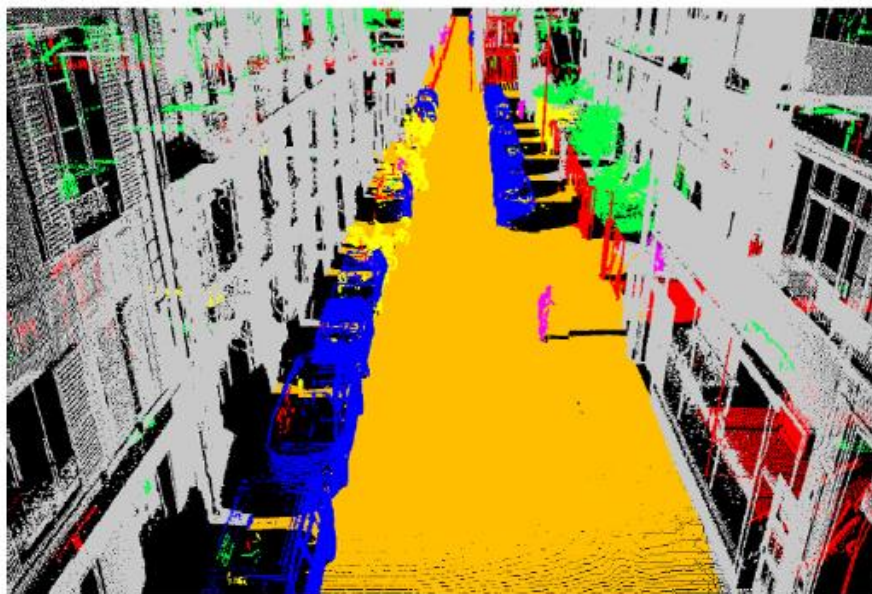
L. Landrieu, H. Raguette, B. Vallet, C. Mallet, and M. Weinmann (2017): A structured regularization framework for spatially smoothing semantic labelings of 3D point clouds. ISPRS Journal of Photogrammetry and Remote Sensing, Vol. 132, pp. 102-118.



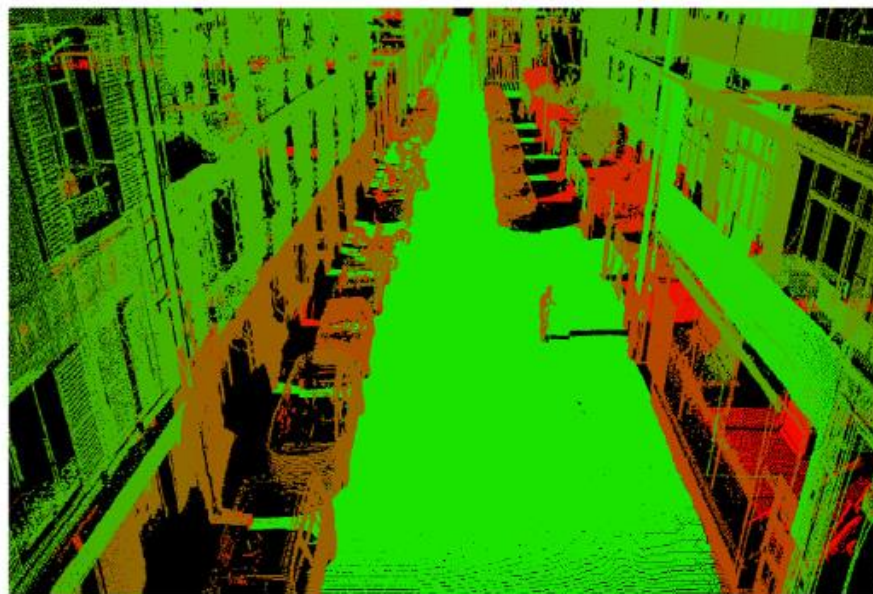
(a) Ground truth



(b) Pointwise classification

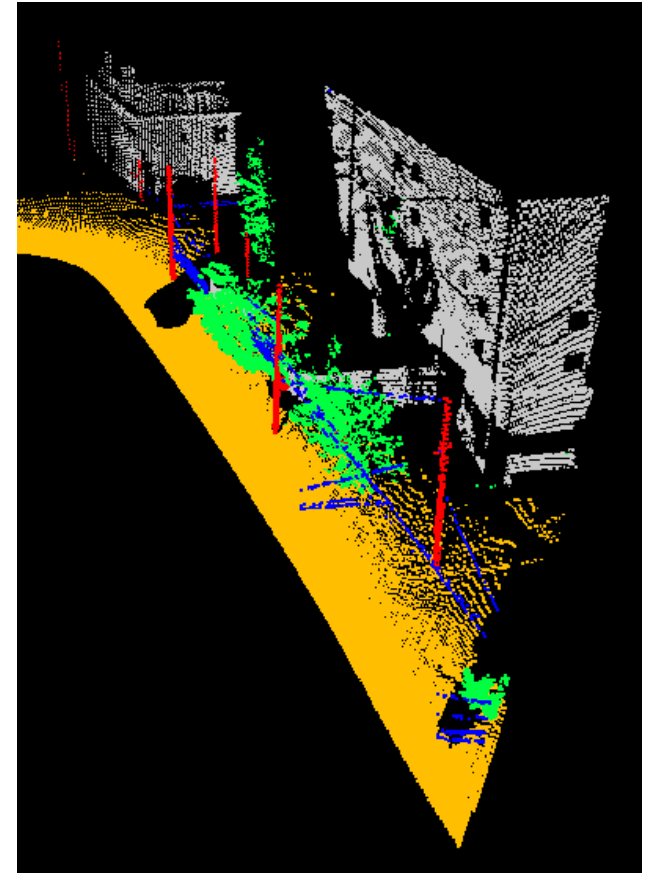


(c) Regularized classification

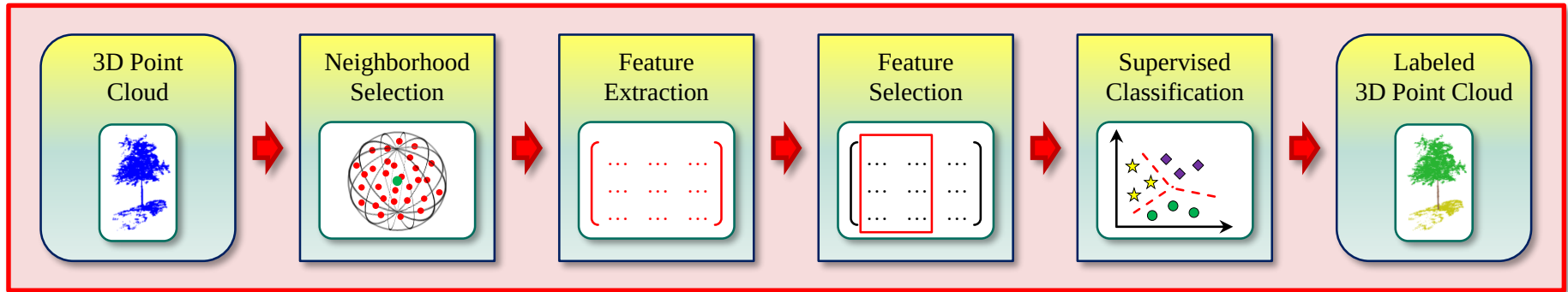


(d) Confidence map

1. Introduction
2. Methodology
3. Experimental Results
4. Conclusions & Future Work



4. Conclusions & Future Work



- Semantic interpretation of 3D point cloud data
 - Selection of individual 3D neighborhoods of optimal size
 - Significant improvement of classification results
 - Selection of relevant features
 - Increase in efficiency w.r.t. processing time and memory consumption
 - Consideration of (local) context information
 - Further improvement of classification results (“spatial regularity”)

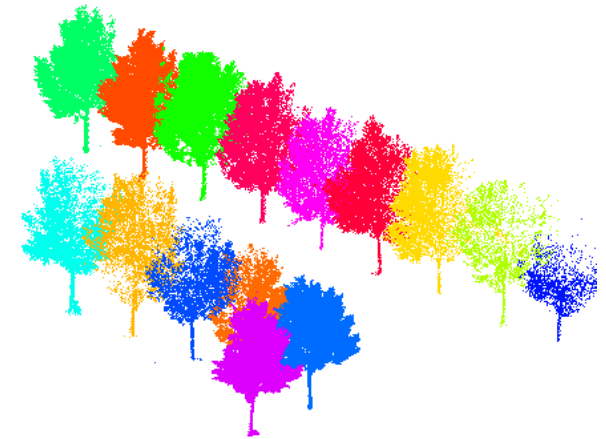
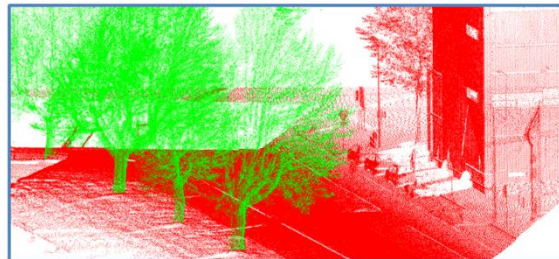
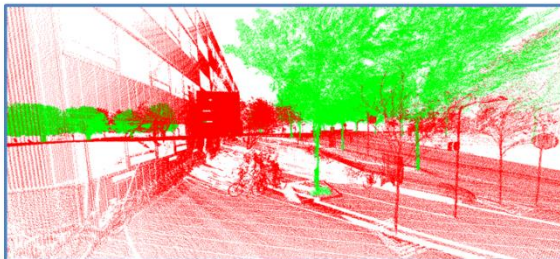
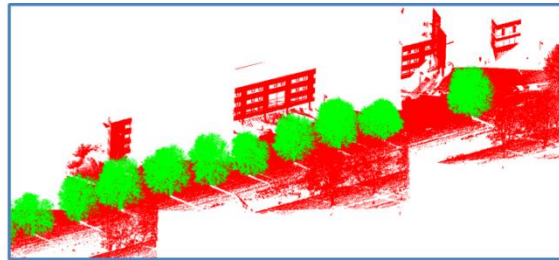
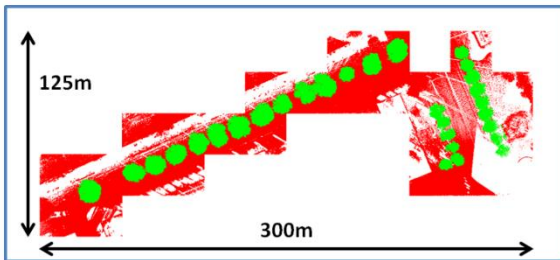
4. Conclusions & Future Work

■ Outlook

■ Tree detection, segmentation and localization (→ IQmulus)

→ Binary classification (“tree” vs. “non-tree”)

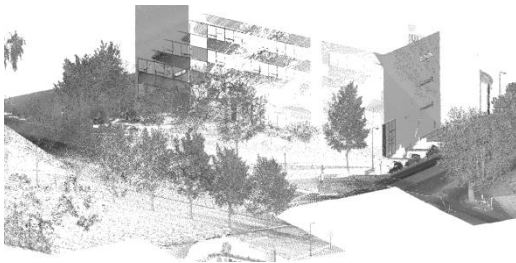
→ Tree individualization via segmentation



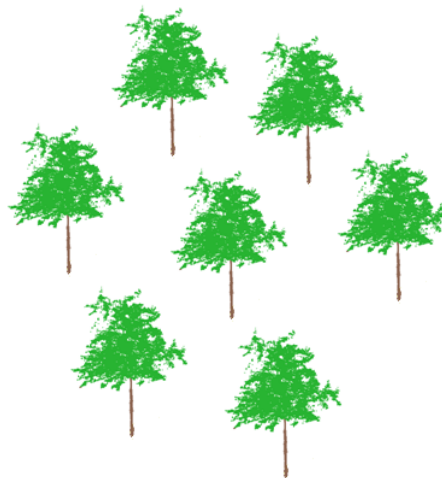
4. Conclusions & Future Work

- IQPC'15 – Track 3: *Tree Separation and Classification*
[Gorte et al., 2015]

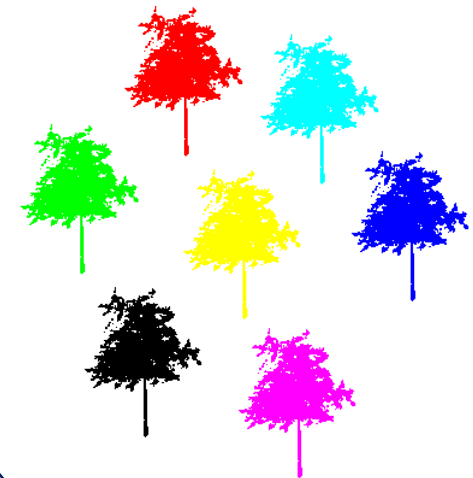
Input Point Cloud



(1) Classification



(2) Segmentation



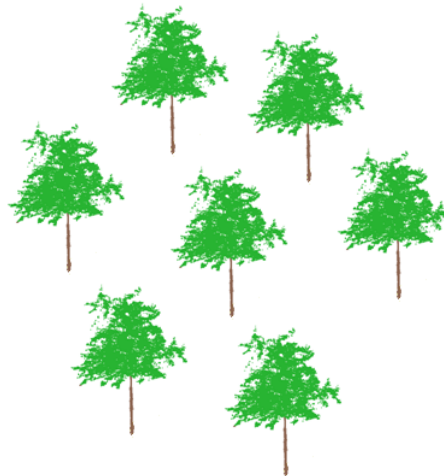
- Task 1: Binary classification of 3D points with respect to the classes “*tree points*” and “*other points*”
- Task 2: Separation of “*tree points*” with respect to “*individual trees*”

4. Conclusions & Future Work

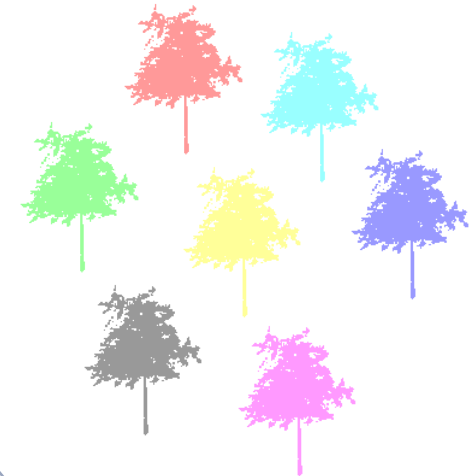
Input Point Cloud



(1) Classification

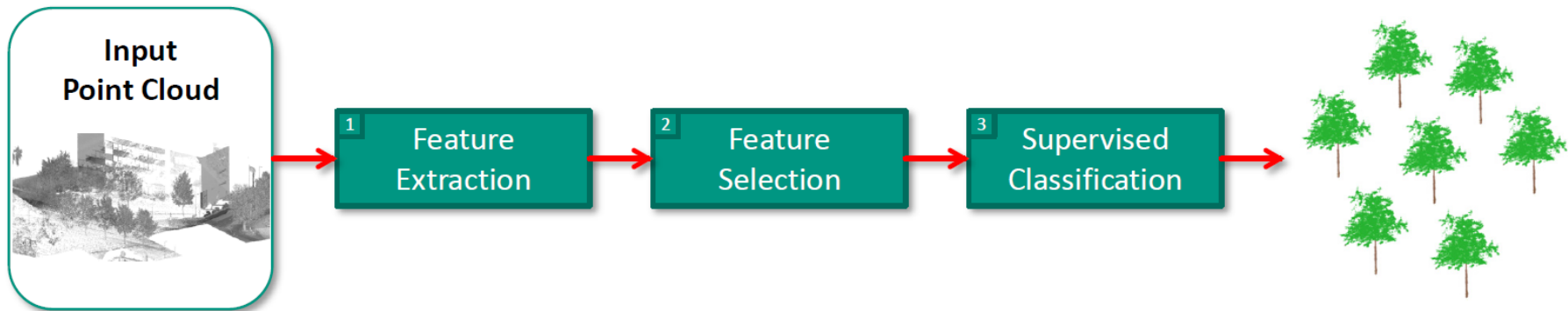


(2) Segmentation



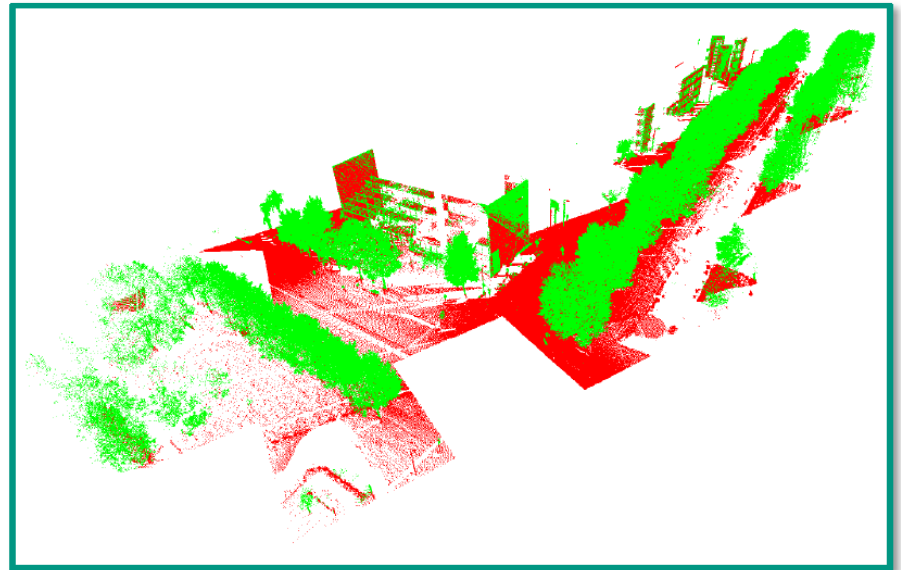
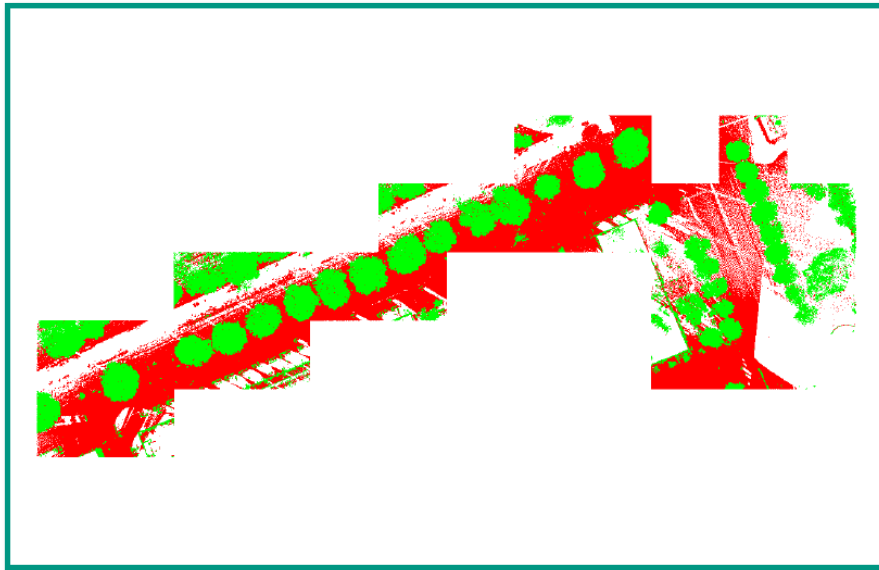
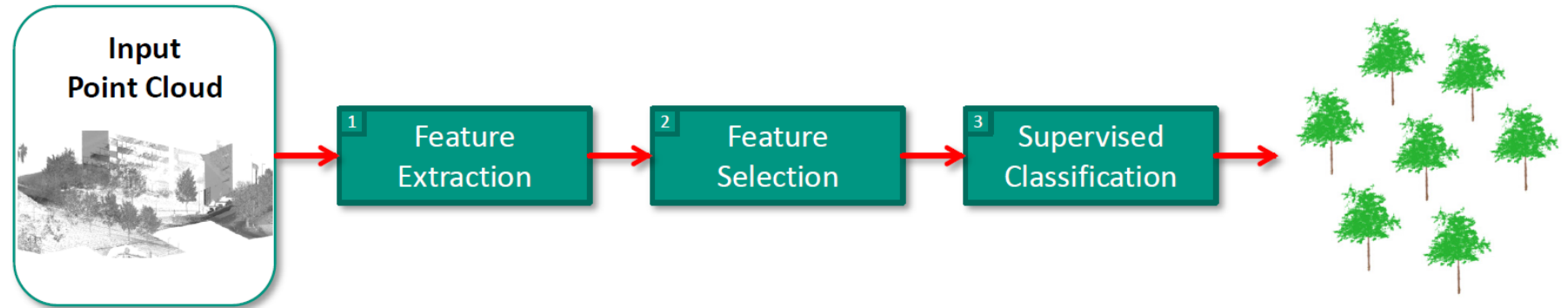
4. Conclusions & Future Work

- Task 1: Binary classification of 3D points with respect to the classes “*tree points*” and “*other points*”



- Consideration of local neighborhoods → geometric features
- (*optional*) Selection of relevant features via feature selection techniques
- Use of a classifier with suitable properties

M. Weinmann, Mi. Weinmann, C. Mallet, and M. Brédif (2017): A classification-segmentation framework for the detection of individual trees in dense MMS point cloud data acquired in urban areas. Remote Sensing, Vol. 9, No. 3, pp. 1-28.



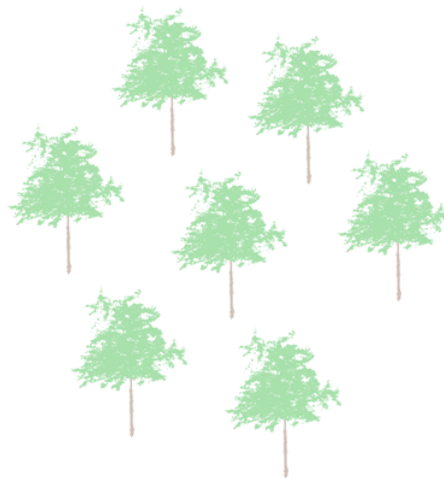
M. Weinmann, Mi. Weinmann, C. Mallet, and M. Brédif (2017): A classification-segmentation framework for the detection of individual trees in dense MMS point cloud data acquired in urban areas. *Remote Sensing*, Vol. 9, No. 3, pp. 1-28.

4. Conclusions & Future Work

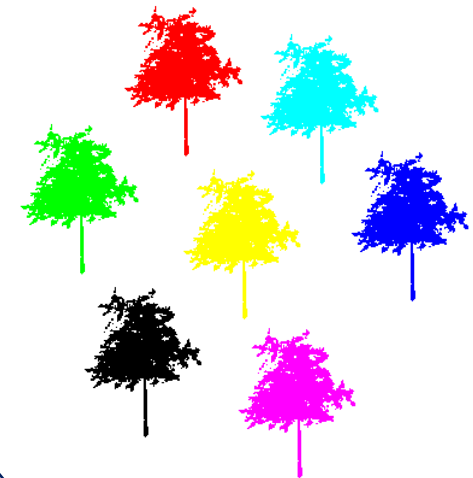
Input Point Cloud



(1) Classification

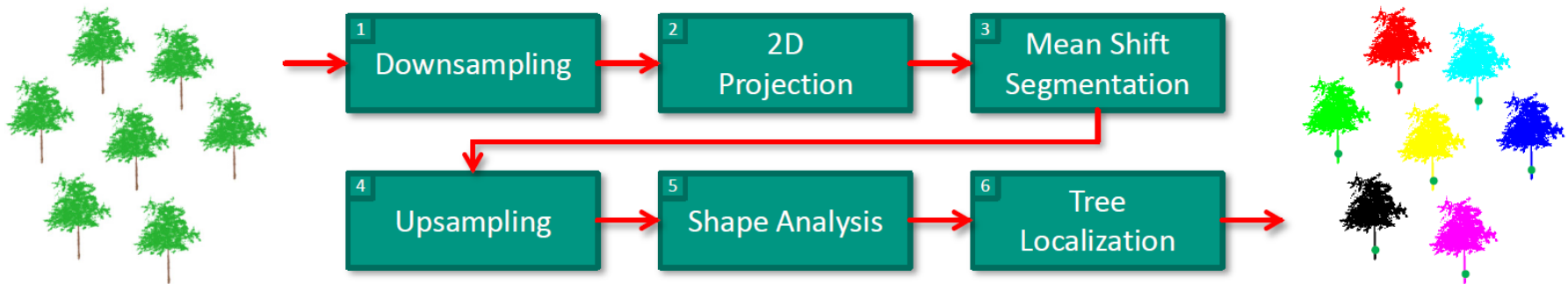


(2) Segmentation



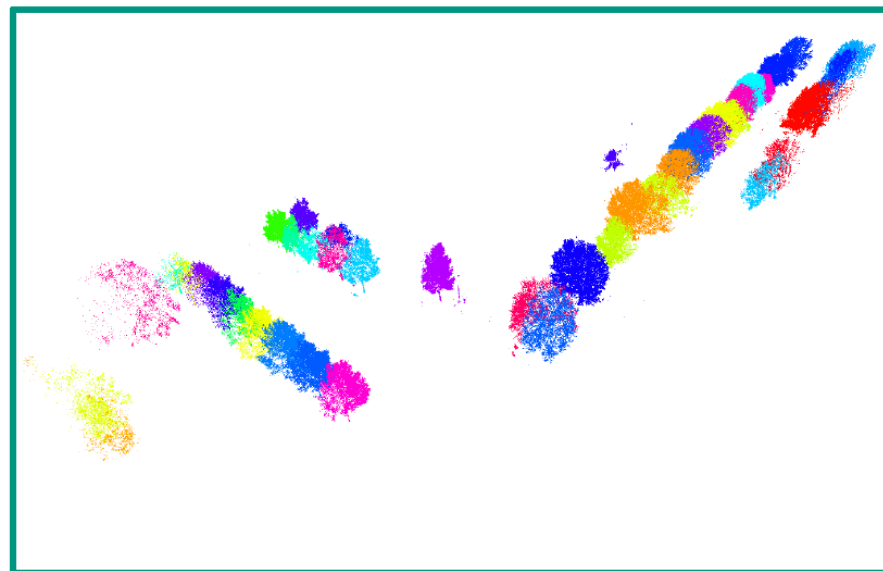
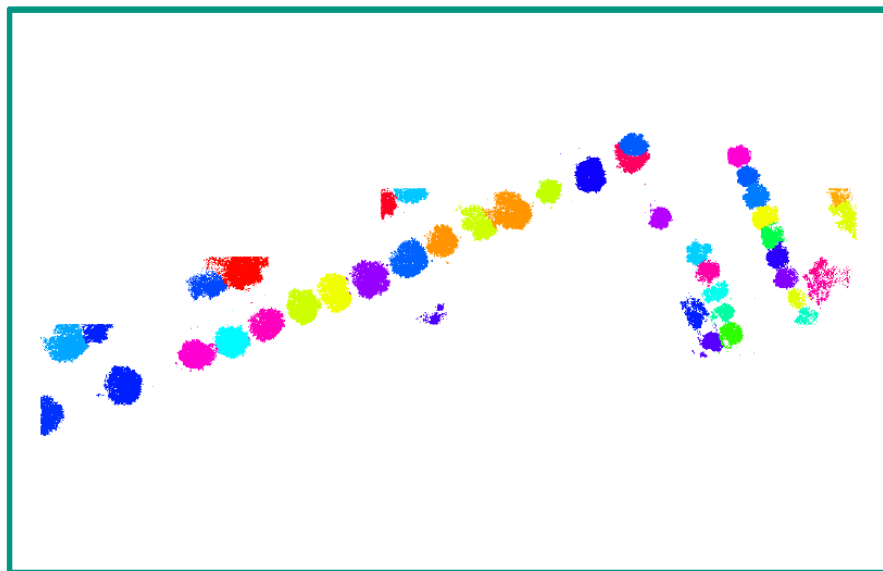
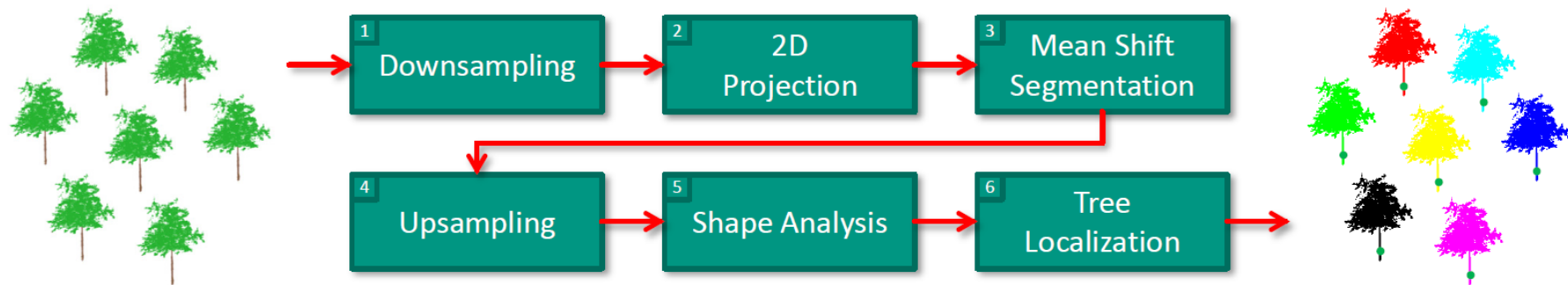
4. Conclusions & Future Work

- Task 2: Separation of “*tree points*” w.r.t. “*individual trees*”

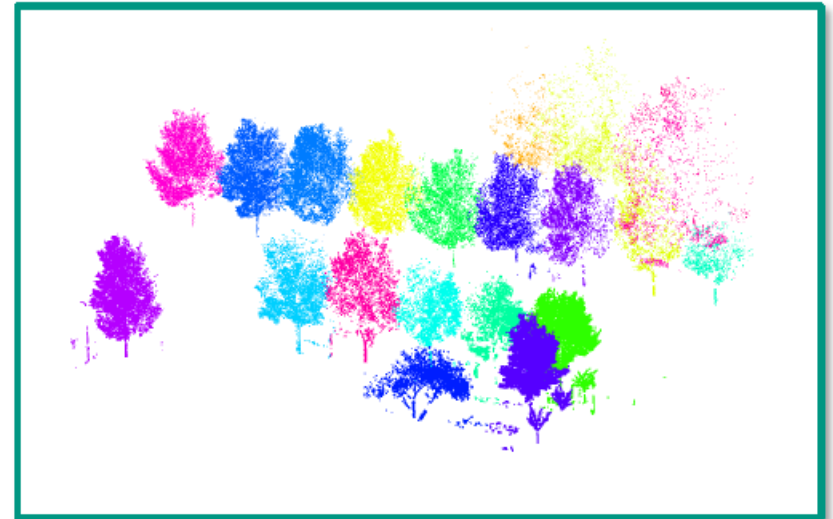
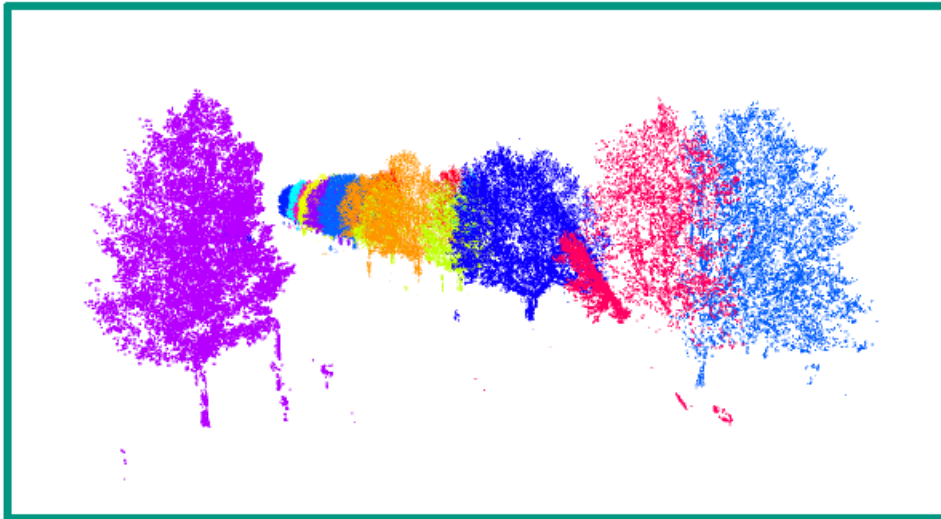
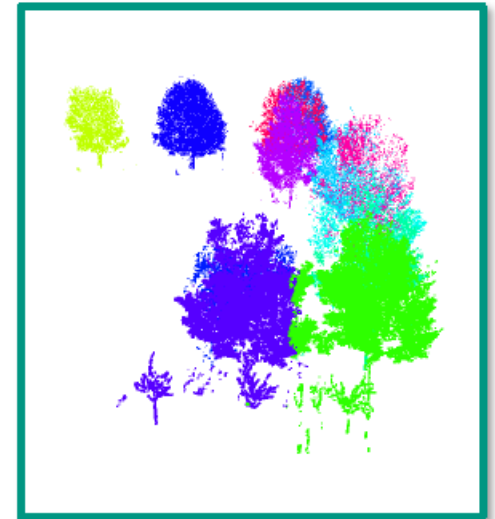
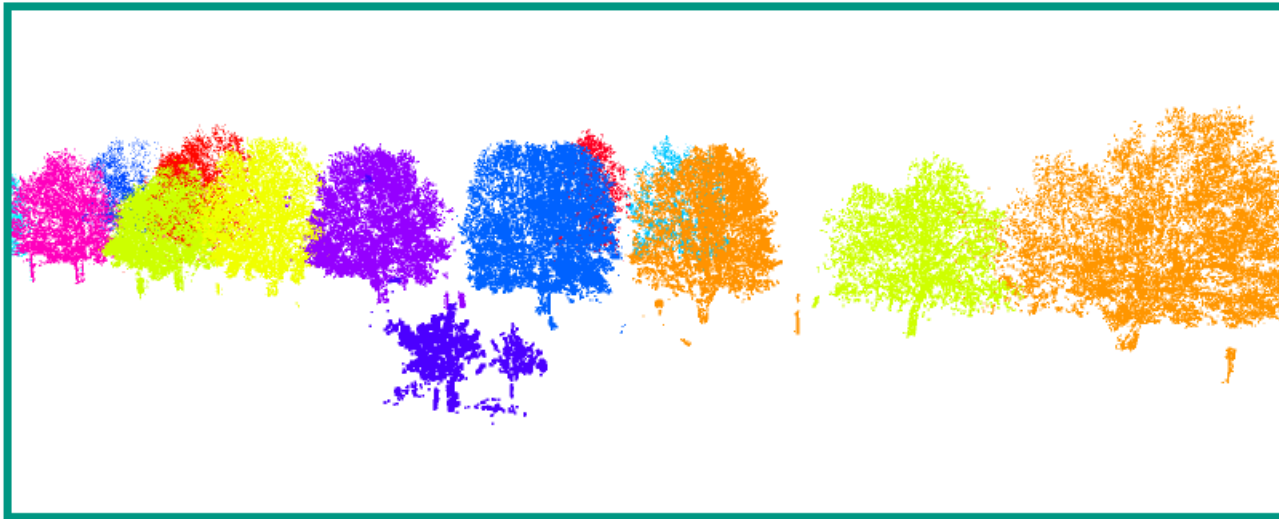


- Efficient approach for extracting individual trees
- Scalability towards the processing of large geospatial data
- Data processing on point level (→ no voxelization)

M. Weinmann, Mi. Weinmann, C. Mallet, and M. Brédif (2017): A classification-segmentation framework for the detection of individual trees in dense MMS point cloud data acquired in urban areas. Remote Sensing, Vol. 9, No. 3, pp. 1-28.



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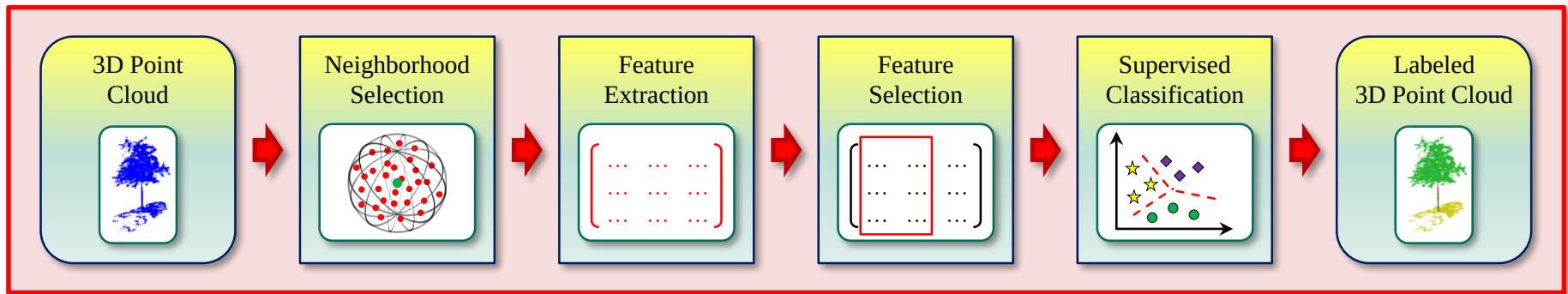


M. Weinmann, Mi. Weinmann, C. Mallet, and M. Brédif (2017): A classification-segmentation framework for the detection of individual trees in dense MMS point cloud data acquired in urban areas. *Remote Sensing*, Vol. 9, No. 3, pp. 1-28.

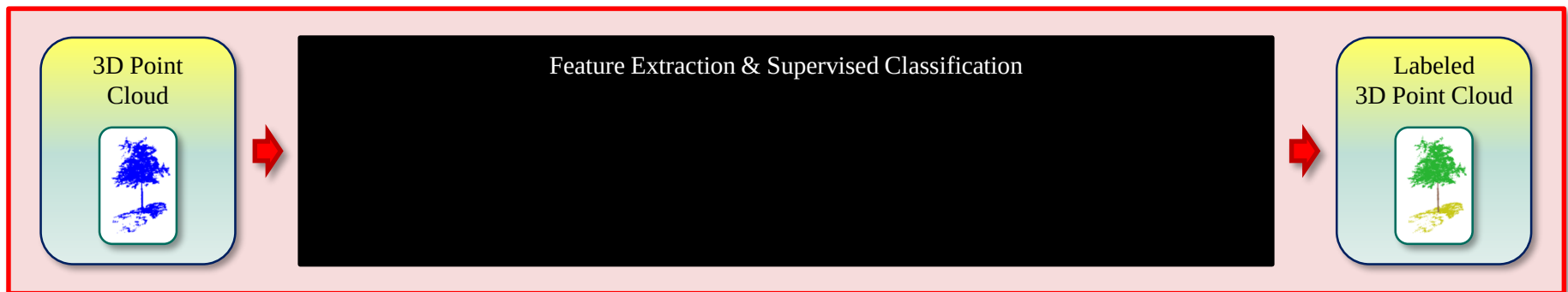
4. Conclusions & Future Work

■ Outlook

■ From the classic approach ...



■ ... to the use of modern deep learning techniques



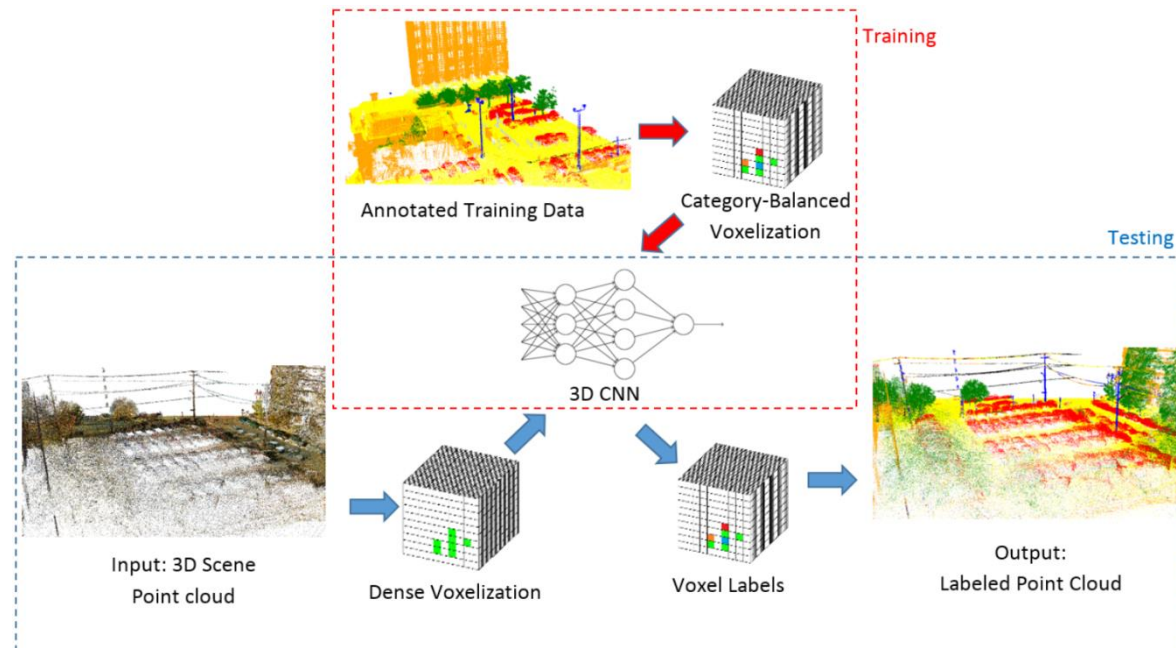
4. Conclusions & Future Work

■ Outlook

■ ... to the use of modern deep learning techniques

→ Adaptation of Convolutional Neural Networks (CNNs) to 3D data

- Local Neighborhood → Voxel-Occupancy Grid → 3D-CNN
[Savinov, 2017; Hackel et al., 2016a; Huang and You, 2016]



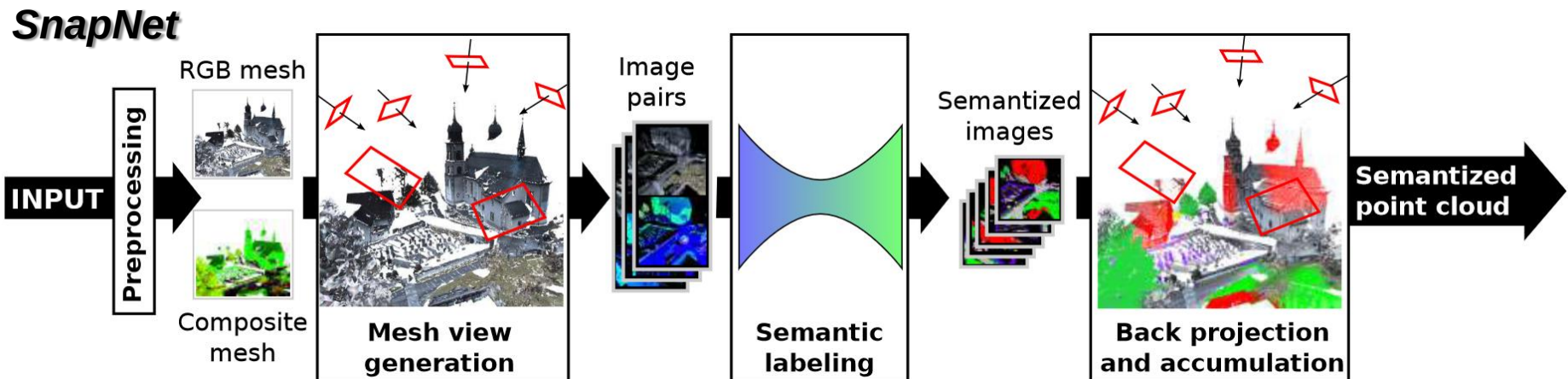
4. Conclusions & Future Work

■ Outlook

■ ... to the use of modern deep learning techniques

→ Exploitation of 2D projections

- Use of standard CNNs for semantic segmentation and back-projection of the classification results to 3D space [Boulch et al., 2017; Lawin et al., 2017]



A. Boulch, B. Le Saux, and N. Audebert (2017): Unstructured point cloud semantic labeling using deep segmentation networks. Proceedings of the Eurographics Workshop on 3D Object Retrieval, pp. 17-24.

4. Conclusions & Future Work

■ Outlook

■ ... to the use of modern deep learning techniques

→ ... and many more advanced approaches

- e.g. via superpoint graphs
[Landrieu and Simonowsky, 2018]
- etc.

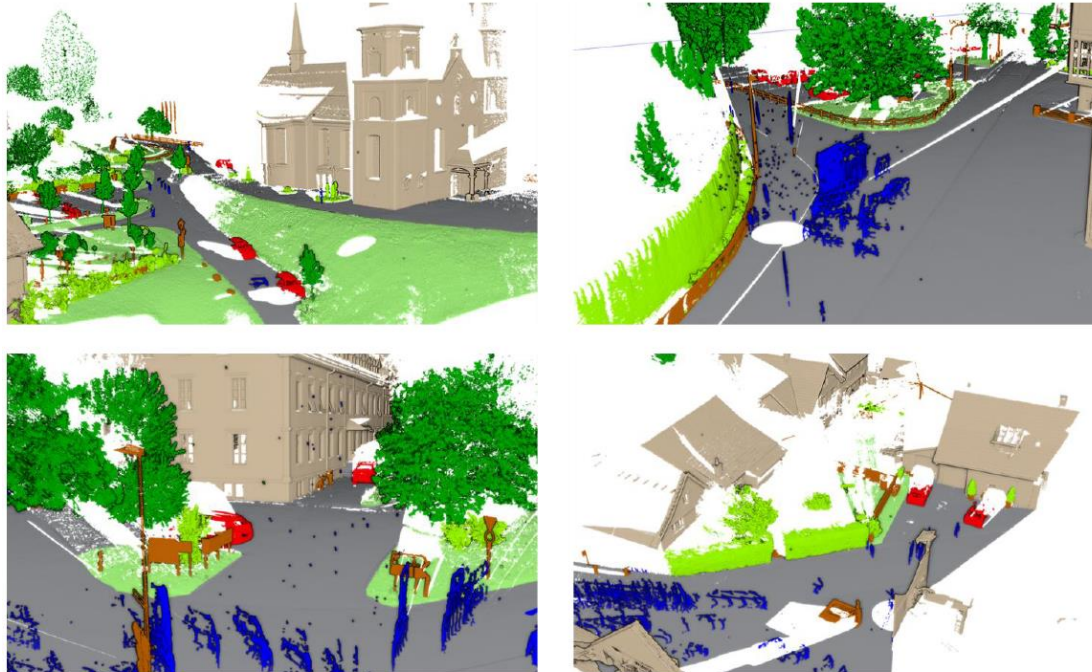
SPGraph



L. Landrieu and M. Simonowsky (2018): Large-scale point cloud semantic segmentation with superpoint graphs. Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 4558-4567.

4. Conclusions & Future Work

■ But ...



 Unclassified	 High vegetation	 Hard scape
 Man-made terrain	 Low vegetation	 Scanning artefacts
 Natural terrain	 Buildings	 Cars

H. Thomas (2019): Learning new representations for 3D point cloud semantic segmentation. PhD Thesis, MINES ParisTech, Université de recherche Paris Sciences et Lettres, Paris, France.

4. Conclusions & Future Work

■ But ...

TMLC-MSR = Traditional Machine Learning with Covariance based features in Multi-Scale

Method	man-made terrain	natural terrain	high vegetation	low vegetation	buildings	hard scape	scanning artefacts	cars	mean
TMLC-MSR (Hackel et al., 2016b)	89.8	74.5	53.7	26.8	88.8	18.9	36.4	44.7	54.2
DeePr3SS (Lawin et al., 2017)	85.6	83.2	74.2	32.4	89.7	18.5	25.1	59.2	58.5
SnapNet (Boulch et al., 2017)	82.0	77.3	79.7	22.9	91.1	18.4	37.3	64.4	59.1
SEGCloud (Tchapmi et al., 2017)	83.9	66.0	86.0	40.5	91.1	30.9	27.5	64.3	61.3
SPGraph (Landrieu and Simonovsky, 2017)	97.4	92.6	87.9	44.0	93.2	31.0	63.5	76.2	73.2
RF_MSSF (ours)	87.6	80.3	81.8	36.4	92.2	24.1	42.6	56.6	62.7

RF_MSSF = Random Forest with Multi-Scale Spherical Features

H. Thomas (2019): Learning new representations for 3D point cloud semantic segmentation. PhD Thesis, MINES ParisTech, Université de recherche Paris Sciences et Lettres, Paris, France.

4. Conclusions & Future Work

■ But ...

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RF_MSSF = Random Forest with Multi-Scale Spherical Features

H. Thomas (2019): Learning new representations for 3D point cloud semantic segmentation. PhD Thesis, MINES ParisTech, Université de recherche Paris Sciences et Lettres, Paris, France.

An aerial, high-angle view of a city street, likely in New York City, showing a grid of buildings and a yellow-paved road. A large, light-blue oval with a dark blue border is centered over the street. The text "Thank you for your attention !" is written in bold red font inside the oval. The image has a halftone or dithered texture.

**Thank you for your
attention !**