AI & 3D POINT CLOUD CLASSIFICATION

GEORGE VOSSELMAN
NATIONAL HEIGHT MODEL AHN (1997-2004)

- Actueel Hoogtemodel Nederland
- Rijkswaterstaat, water boards, and provinces
- Point density 1 point / 16 m²
- 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 / m²
- 640 billion points
- Systematic height error 5 cm
- Stochastic height error 5 cm
- Classification in ground / non-ground
• 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 m²) 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

Source: PDOK (Wang et al, 2016)
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
What’s Different in Deep Learning?

• Machine Learning, classical approach:

  Compute cleverly defined “hand-crafted” features

  \[ f_1 \ldots f_n \]

  Machine Learning, Classification

  \[ f_1 \quad f_2 \]

  performance only as good as feature set

• Deep Learning: Joint learning of features and classification model

  Deep Learning

  Input

  Feature extraction

  classification

  Output

  “End-to-end learning“, based on artificial neural networks (ANN)
Convolutional Neural Networks are made for raster data processing

Work-arounds

- Convert point cloud to raster, use $Z_{\text{mean}}$, $Z_{\text{max}}$, $Z_{\text{min}}$ instead of RGB values (Hu and Yuan, 2016)
CLASSIFICATION OF RASTERIZED POINT CLOUDS

Convolutional Neural Networks made for raster data processing

Work-arounds
- Convert point cloud to raster, use $Z_{\text{mean}}$, $Z_{\text{max}}$, $Z_{\text{min}}$ instead of RGB values (Hu and Yuan, 2016)
- Convert to multi-view rasters (SnapNet, Boulch et al, 2017)
Convolutional Neural Networks made for raster data processing

Work-arounds
• Convert point cloud to raster, use $Z_{\text{mean}}$, $Z_{\text{max}}$, $Z_{\text{min}}$ instead of RGB values (Hu and Yuan, 2016)
• 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 interactive use of gated recurrent units
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

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

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

Road Mapping In LiDAR Images Using A Joint-Task Dense Dilated Convolutions Merging Network

ShellNet: Efficient Point Cloud Convolutional Neural Networks using Concentric Shells Statistics

LightConvPoint: convolution for points

SqueezeSegV3: Spatially-Adaptive Convolution for Efficient Point-Cloud Segmentation

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

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

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**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**

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

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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
Combining all elements and adding spatial and channel attention modules

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<thead>
<tr>
<th></th>
<th>Av. F1</th>
<th>OA</th>
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<tbody>
<tr>
<td>KPConv</td>
<td>0.735</td>
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<td>Hybrid</td>
<td>0.703</td>
<td>0.811</td>
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(Lin et al., 2020b)
NEED FOR TRAINING DATA

Deep learning networks contain millions of parameters
Benchmark datasets increase in size

<table>
<thead>
<tr>
<th>Name and Reference</th>
<th>Year</th>
<th>Spatial size $^1$</th>
<th>Classes $^2$</th>
<th>Points</th>
<th>RGB</th>
<th>Sensors</th>
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<td>S3DIS [16]</td>
<td>2017</td>
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<td>Matterport</td>
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<td>ScanNet [17]</td>
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<td>5×5×2</td>
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<td>Paris-rue-Madame [22]</td>
<td>2014</td>
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<td>IqMulus [23]</td>
<td>2015</td>
<td>850×800×450</td>
<td>8 (22)</td>
<td>300M</td>
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<td>Semantic3D [20]</td>
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<td>Paris-Lille-3D [24]</td>
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<td>200×280×30</td>
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<td>SemanticKITTI [19]</td>
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<td>150×100×10</td>
<td>25 (28)</td>
<td>4549M</td>
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<td>Toronto-3D [25]</td>
<td>2020</td>
<td>260×350×40</td>
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<td>78.3M</td>
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<td>ISPRS [26]</td>
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<td>1.2M</td>
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<td>DALES [27]</td>
<td>2020</td>
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<td>505M</td>
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<td>SensaUrban (Ours)</td>
<td>2020</td>
<td>1700×1700×100</td>
<td>13 (31)</td>
<td>2847M</td>
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<td>UAV Photogrammetry</td>
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*Hu et al., 2020*
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)

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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
REFERENCES


Wang, Y, Oude Elberink, S.J., 2016. Map based segmentation of airborne laser scanner data. 6th International Conference on Geographic Object-Based Image Analysis GEOBIA.