Deep Learning-based Point Cloud Classification on Multiple Airborne LiDAR Datasets

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Guideline

• Introduction
• Public ALS Datasets
• How to Use Multiple Datasets
• The First Experiment
• Conclusion & Open Questions
Introduction
Introduction

- The task of **point cloud classification (semantic segmentation)** is to associate each point with a semantic label.
Introduction

• Deep learning brings new possibilities in point cloud processing.
Introduction

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Introduction

• More public point cloud datasets than ever provide available research materials to test “data-hungry” algorithms.
Public ALS Datasets
Public ALS Datasets

- ISPRS Vaihingen Dataset
- Data Fusion Contest 2018 (DFC2018)
- Data Fusion Contest 2019 (DFC2019)
- Actueel Hoogtebestand Nederland 3 (AHN3)
Datasets  ISPRS Vaihingen

• Only 1.1 million points in total:
  ✓ Ca. 700,000 as the training data
  ✓ Ca. 400,000 as the test data

• 9 classes: powerline, low vegetation, impervious surfaces, car, fence/hedge, roof, façade, shrub and tree.

• Density: ca. 6 points / m²

Datasets  \textit{DFC2018}

- Multispectral LiDAR point clouds (1550 nm, 1064 nm, and 532 nm)
- 20 urban land use and land cover classes
- However, no \textit{direct} point-wise semantic labels

Datasets  *DFC2018*

- A solution to create point-wise labels:

*2D Ground Truth*  \[\rightarrow\]  *Point Clouds*
Datasets  

- Tens of millions of points
- Captured in two American cities, Jacksonville and Omaha
- 5 classes: ground, building, tree, water and bridge
- Density: 3-6 points / m²

Datasets \textit{AHN3}

• A very large ALS LiDAR point cloud project, covering almost the entire Netherlands

• 5 classes: ground, building, water, artwork (including bridges and other man-made structures) and “others” (mostly vegetation)

• Density: 10-20 points / m²

\url{https://www.pdok.nl/nl/ahn3-downloads}
Limitations of Above Datasets

• ISPRS Vaihingen:  
  Limited amount of points over a small region

• DFC2018:  
  No direct point-wise labels

• DFC2019:  
  Only 5 classes in total

• AHN3:  
  Only 5 classes labeled roughly
How to Use Multiple Datasets
How to Use Multiple Datasets

Relationship 1: $a_i \in A = b_j \in B$

“Buildings” in DFC2019 Dataset

“Buildings” in AHN3 Dataset
How to Use Multiple Datasets

Relationship 1: $a_i \in A = b_j \in B$

“Ground” (blue) in DFC2019 Dataset

“Impervious Surfaces” (blue) in ISPRS Vaihingen Dataset
How to Use Multiple Datasets

Relationship 2: \( a_i \) in \( A = (b_1 + b_2 + \ldots + b_n) \) in \( B \)

“Trees” in DFC2019 Dataset

“Shrubs” (blue) and “Trees” (green) in ISPRS Vaihingen Dataset
The First Experiment
Data Preparation

• Data selection:
  ✓ Training data: *ISPRS Vaihingen (training set)*
  ✓ Validation data: *ISPRS Vaihingen (test set)*
  ✓ Test data: 11 files from DFC2019 dataset
Data Preparation

• Modify original data:
  ✓ Delete unnecessary classes
  ✓ Renumber labels

0 Powerline
1 Low vegetation
2 Impervious surfaces
3 Car
4 Fence/Hedge
5 Roof
6 Façade
7 Shrub
8 Tree

1 Ground (Impervious surfaces)
2 Tree
3 Building (Roof + Façade)
4 Shrub

*ISPRS Vaihingen Ground Truth Re-labeling*
Data Preparation

• Modify original data:
  ✓ Delete unnecessary classes
  ✓ Renumber labels

0 Unlabeled
2 Ground
5 Tree
6 Building
9 Water
17 Bridge

1 Ground
2 Tree
3 Building

DFC2019 Ground Truth Re-labeling

DFC2019 Ground Truth Re-labeling
Data Preparation

- Modify original data:
  - Delete unnecessary classes
  - Renumber labels

Training & Validation (ISPRS Vaihingen):
1. Ground
2. Tree
3. Building
4. Shrub

Test (DFC2019):
1. Ground
2. Tree
3. Building
Data Preparation

• Re-organize the data structure of points:

\{x, y, z, i, number of returns, return number...\}

\downarrow

\{x, y, z\}
Methodology (PointNet++)

Results

Ground Truth

Prediction Results
## Results

<table>
<thead>
<tr>
<th>( \text{GT} )</th>
<th>( \text{PR} )</th>
<th>Ground</th>
<th>Tree</th>
<th>Building</th>
<th>Shrub</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Ground</strong></td>
<td></td>
<td>3310099</td>
<td>132924</td>
<td>33527</td>
<td>8718</td>
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<tr>
<td><strong>Tree</strong></td>
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<td>186347</td>
<td>1569767</td>
<td>65750</td>
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<tr>
<td><strong>Building</strong></td>
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<td>402201</td>
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<td>38627</td>
</tr>
<tr>
<td><strong>Shrub</strong></td>
<td></td>
<td>?</td>
<td>?</td>
<td>?</td>
<td>?</td>
</tr>
</tbody>
</table>

*Confusion Matrix*
## Results

- **Overall Accuracy**: 81.12%
- **IoU_Ground**: 81.25%
- **IoU_Tree**: 69.40%
- **IoU_Building**: 18.09%

*Accuracy and IoUs*
Discussion

• Roof type difference
• Different land cover distribution

Training Data (ISPRS Vaihingen)  Test Data (DFC2019)
Discussion

- The subclass shrub can be recognized.
- A possible way to improve re-annotating efficiency

*Trees (green) in the Ground Truth*  
*Trees (green) and Shrubs (yellow) in Prediction Results*
Conclusion & Open Questions
Conclusion

• A very initial work
• An idea to use multiple public datasets
• An example to test its feasibility
Q & A
Open Questions

• How many classes do we actually need?

• The difference between TLS (small-area dense point clouds) and ALS (large-area sparse point clouds) data when processed by deep learning techniques

• Are there other ways to utilize multisource semantic point clouds?