Deep Learning based methods for remote sensing data
Doing more with buildings

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ESA Φ-week
13/11/2018
June 28th 2018: *Bing releases 125 million Building Footprints in the US as Open Data*
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How?

Apply ResNet [He et al., 2015] + smart postprocessing
June 28th 2018: Bing releases 125 million Building Footprints in the US as Open Data

IGARSS 2018: Large-scale semantic classification: outcome of the first year of Inria aerial image labeling benchmark [Huang et al., 2018]
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IGARSS 2018: Large-scale semantic classification: outcome of the first year of Inria aerial image labeling benchmark [Huang et al., 2018]
Winner:

Apply U-Net [Ronneberger et al., 2015] with a modified inference method
Is it always sufficient to apply off the shelf methods?
Semantic segmentation vs Instance segmentation
Semantic segmentation

- Many off the shelf algorithms
- No info about structure
Semantic instances segmentation

- Can encode geometry priors
- Can export GIS footprints
- No off the shelf algorithm
Segmenting buildings

Based on:

Learning deep structured active contours end-to-end
Diego Marcos, Devis Tuia, Benjamin Kellenberger, Lisa Zhang, Min Bai, Renjie Liao, Raquel Urtasun
in CVPR 2018
In the 80’s: people used Active Contour Models
Example of snakes [Kass et al., 1988]:
- A contour = set of points
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Example of snakes [Kass et al., 1988]:

- A contour = set of points
- Model enforce:
  - A data term (e.g. gradients)
  - Penalization of length
  - Penalization of curvature
  - Balloon term
In the 80’s: people used Active Contour Models
Example of snakes [Kass et al., 1988]:

- A contour = set of points
- Model enforce:
  - A data term (e.g. gradients)
  - Penalization of length
  - Penalization of curvature
  - Balloon term
- Each term is balanced
Tuning ACM parameters

Should we penalize more length and curve?
Tuning ACM parameters
Segmenting building

Tuning ACM parameters

What about the other buildings?
Segmenting building

Tuning ACM parameters

Input image → CNN → Data term → Penalize curvature → Balloon term
Tuning ACM parameters

Input image → CNN → Data term

Penalize curvature → Balloon term

Snake model
Tuning ACM parameters

Input image -> CNN -> Data term

Penalize curvature -> Balloon term

Snake model

Loss

Ground truth

Backpropagation
Results and conclusion

- In a nutshell: learning the ACM parameters leading to desired convergence

- Comparison on the TorontoCity dataset [Wang et al., 2016] (over 12000 building instances):

<table>
<thead>
<tr>
<th>Method</th>
<th>WeighCov</th>
<th>PolySim</th>
</tr>
</thead>
<tbody>
<tr>
<td>ResNet [He et al., 2015]</td>
<td>0.40</td>
<td>0.29</td>
</tr>
<tr>
<td>Deep Watershed [Bai and Urtasun, 2016]</td>
<td>0.52</td>
<td>0.24</td>
</tr>
<tr>
<td>Proposed model</td>
<td>0.58</td>
<td>0.27</td>
</tr>
</tbody>
</table>

WeighCov: IoU-based weighted coverage
PolySim: shape similarity
(see [Wang et al., 2016])
Correcting building annotations

Based on:

Correcting rural building annotations in OpenStreetMap using convolutional neural networks
John Edgar Vargas Muñoz, Sylvain Lobry, Alexandre Xavier Falcão, Devis Tuia
Building annotations can be:

1. Misaligned (because imagery has changed)
2. Missing
3. There, but building has disappeared
Correcting building annotations

Problem

Building annotations can be:

1. Misaligned (because imagery has changed)
2. Missing
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Question

Can we correct these annotations instead of starting from scratch?
Correcting building annotations

**Problem**

Building annotations can be:

1. **Misaligned** (because imagery has changed)
2. Missing
3. There, but building has disappeared

**Question**

Can we correct these annotations instead of starting from scratch?
Correcting building annotations

Solution: Aligning

Input image  
Convolutional layers  
Hypercolumns  
Probability map

Upsampling  
MLP
Correcting building annotations

Solution: Aligning

Annotations

MLP

Deep learning for urban remote sensing
Correcting building annotations

Solution: Aligning

Annotations

MLP
Solution: Aligning

Use a Markov Random Field which:
- Maximize the correlation between annotations and probability map
- Enforce alignment vectors to be similar (in a group of buildings)
### Results

<table>
<thead>
<tr>
<th>Method</th>
<th>F-score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Semantic segmentation [Maggiori et al., 2017]</td>
<td>0.657</td>
</tr>
<tr>
<td>Proposed method</td>
<td>0.725</td>
</tr>
</tbody>
</table>

F-score: harmonic mean of precision and recall (higher is better)
Results

<table>
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<th>Input</th>
<th>Semantic segmentation</th>
<th>Proposed method</th>
</tr>
</thead>
</table>

Conclusion

It is better to use (potentially inaccurate) OpenStreetMap data than starting from scratch.
How to characterize buildings

Land use classification

Based on:

Understanding urban landuse from above and ground perspectives: a deep learning, multimodal solution.
Shivangi Srivastava, John Edgar Vargas Muñoz, Devis Tuia
in Remote Sensing of Environment (under review)
How to characterize buildings

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Land use classification

Problem

Using overhead imagery alone is not enough!

→ Use ground-based pictures (e.g. Google Street View)
Land use classification
Land use classification
Conclusion

Applying off the shelf methods from computer vision to remote sensing data works but, as a community, we can do better.

- We do not always have the same problems
- Using priors
- Using auxiliary data
Thank you!

The team:

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