DeepStat: learning statistics from images using deep learning

First attempts

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Background

– Sustainable Development Goals (UN 2015)
– MAKSWELL
  - EU-funded project
  - Harmonize indicators on sustainable development and well-being
  - WP3 – measurement of regional poverty
    - Tax register
    - Earth observation
Research questions

- Can we learn poverty from images?
- What is the effect on prediction quality of
  - sample size?
  - sampling design (including non-probability sample)?
  - grid size (image height $\times$ width)?
  - remote sensing indices (image depth)?
- What features are learned?

Statistics Netherlands has the labels needed for this supervised ML task
Data

– Input images

<table>
<thead>
<tr>
<th>Data source</th>
<th>Resolution</th>
<th>Bands</th>
<th>Color depth</th>
<th>Available since</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aerial images</td>
<td>0.25 m</td>
<td>3</td>
<td>8-bit</td>
<td>2016</td>
</tr>
<tr>
<td>Satellite images (Landsat 8)</td>
<td>30 m</td>
<td>11</td>
<td>16-bit</td>
<td>2013</td>
</tr>
</tbody>
</table>

– Grid (coordinate system EPSG:28992)

- 1 ha (100 m × 100 m) – 400 × 400 aerial pixels or 4 × 4 Landsat pixels
- 25 ha (500 m × 500 m) – 2000 × 2000 aerial pixels or 17 × 17 Landsat pixels

– Output labels

- income-related poverty indices
- open grid statistics

Data preparation

- NL 40k km$^2$
  - 4 mln 1-ha squares
  - 160k 25-ha squares
- 300k 1-ha squares after simple random sample and linking grid statistics (unknown/unreliable/undisclosed $\rightarrow$ bias)
- Data augmentation (rotation, shift, zoom, shear, flip)
- 4-class label (quartiles)
  - Number of inhabitants
  - Number of households
  - Number of dwellings
Examples
Convolutional Neural Network (CNN)

- VGG16
- ResNet
- Adjust final layer
- Transfer learning
# Preliminary results

<table>
<thead>
<tr>
<th>Output label</th>
<th># classes</th>
<th>train/test</th>
<th>VGG16</th>
<th>ResNet</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of households quantile</td>
<td>4</td>
<td>20k/10k</td>
<td>0.68</td>
<td></td>
</tr>
<tr>
<td>Number of inhabitants quantile</td>
<td>4</td>
<td>20k/10k</td>
<td>0.65</td>
<td></td>
</tr>
<tr>
<td>Number of dwellings quantile</td>
<td>4</td>
<td>20k/10k</td>
<td></td>
<td>0.69 (0.58*)</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>30k/10k</td>
<td>0.73</td>
<td></td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>50k/20k</td>
<td>0.74</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>20k/10k</td>
<td>0.87  (0.74*)</td>
<td></td>
</tr>
</tbody>
</table>

*min-max normalized
Conclusions

– Statistical information can be learned from images
– CNNs require specialized IT hardware and skills
  - Input is big
  - Algorithms evolve quickly
  - Many (hyper)parameters to estimate/tune
  - Output is privacy-sensitive
Next steps

1. Move to secure environment
   - Link income-related poverty indices
2. Use ordinal loss function
3. Optimize architecture and (hyper)parameters
4. Quantify effect on prediction quality of
   - sample size
   - sampling design
   - grid size
   - remote sensing indices
5. Visualize learned features
6. Compare or combine aerial with satellite images and traditional ML
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