

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 × width)?
 - remote sensing indices (image depth)?
- What features are learned?

Statistics Netherlands has the labels needed for this supervised ML task



Data

- Input images

| Data source | Resolution | Bands | Color depth | Available since |
|------------------------------|------------|-------|-------------|-----------------|
| Aerial images | 0.25 m | 3 | 8-bit | 2016 |
| Satellite images (Landsat 8) | 30 m | 11 | 16-bit | 2013 |

- Grid (coordinate system EPSG:28992)

- 1 ha ($100 \text{ m} \times 100 \text{ m}$) – 400×400 aerial pixels or 4×4 Landsat pixels
 - 25 ha ($500 \text{ m} \times 500 \text{ m}$) – 2000×2000 aerial pixels or 17×17 Landsat pixels

- Output labels

- income-related poverty indices
 - open grid statistics

<https://www.cbs.nl/nl-nl/dossier/nederland-regionaal/geografische-data/kaart-van-100-meter-bij-100-meter-met-statistieken>



Data preparation

- NL 40k km²
 - 4 mln 1-ha squares
 - 160k 25-ha squares
- 300k 1-ha squares after simple random sample and linking grid statistics (unknown/unreliable/undisclosed → bias)
- Data augmentation (rotation, shift, zoom, shear, flip)
- 4-class label (quartiles)
 - Number of inhabitants
 - Number of households
 - Number of dwellings



Examples

Density: 1



Density: 2



Density: 3

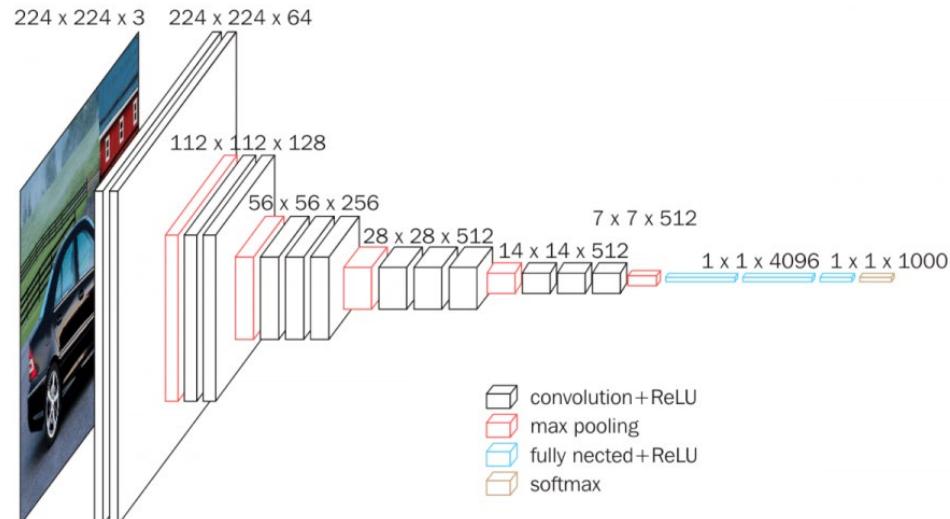


Density: 4



Convolutional Neural Network (CNN)

- VGG16
- ResNet
- Adjust final layer
- Transfer learning



Preliminary results

| Output label | # classes | train/test | Accuracy | |
|--------------------------------|-----------|------------|----------|--------------|
| | | | VGG16 | ResNet |
| Number of households quantile | 4 | 20k/10k | 0.68 | |
| Number of inhabitants quantile | 4 | 20k/10k | 0.65 | |
| Number of dwellings quantile | 4 | 20k/10k | | 0.69 (0.58*) |
| | 4 | 30k/10k | | 0.73 |
| | 4 | 50k/20k | | 0.74 |
| | 2 | 20k/10k | | 0.87 (0.74*) |

*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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