Accurate Segmentation of Hyperspectral Images Using Deep Neural Networks—Are We There Yet?

Jakub Nalepa, Michal Marcinkiewicz, Pablo Ribalta Lorenzo, Krzysztof Czyz,
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The ESA Earth Observation Φ-Week,
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Introduction

About us

KP LABS

HYPERspectral image segmentation using deep neural **NET**works

HYPERNET

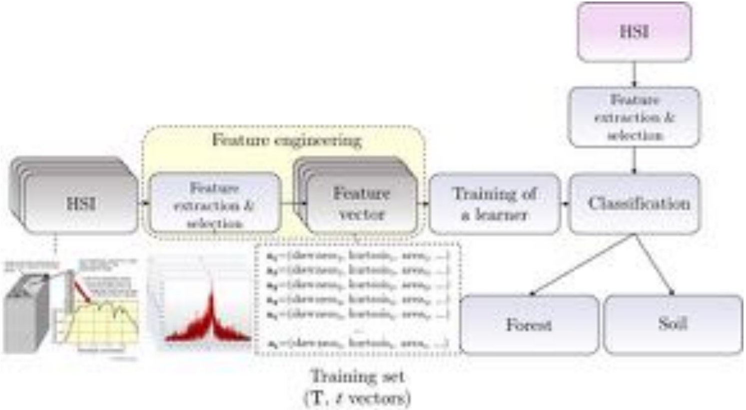
May 2018—May 2019

Polish Industry Incentive Scheme

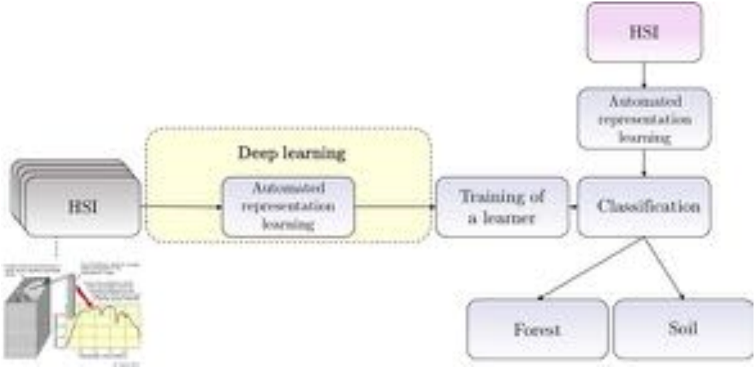
esa


6U CLASS

Segmentation of HSI—conventional machine learning



Segmentation of HSI—deep learning



Deep networks in the wild...

- **Hyperspectral image segmentation**
- Medical imaging
- Object detection
- Text classification
- Temporal and time-series analysis
- Self-driving cars
- Music composition
- Real-time analysis of behaviors
- Translation
- Speech recognition
- Language modeling
- Document summarization
- ...

Deploying a deep neural network in the wild

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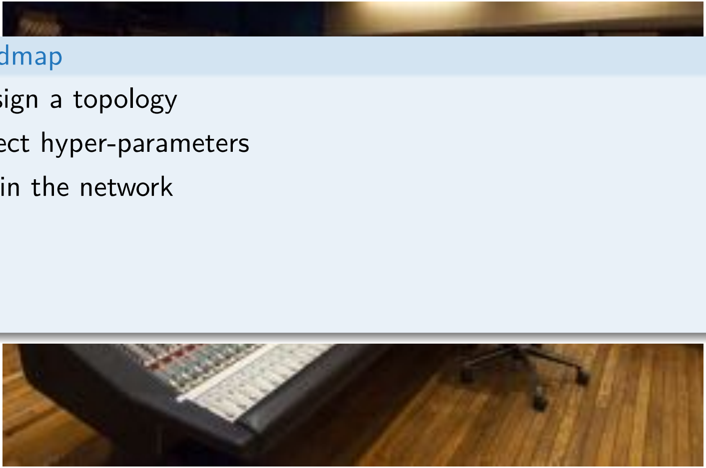


The roadmap

- Design a topology
- Select hyper-parameters
- Train the network

Deploying a deep neural network in the wild

The roadmap

- Design a topology
- Select hyper-parameters
- Train the network

- **Topology**: P. Ribalta and J. Nalepa, pp 505-512, Proc. GECCO, ACM 2018.
- **Hyper-params**: P. Ribalta and J. Nalepa, et al., pp 481-488, Proc. GECCO, ACM 2017.
- **Hyper-params**: P. Ribalta and J. Nalepa, et al., pp 1864-1871, Proc. GECCO, ACM 2017.

Deep networks for hyperspectral image segmentation

Spectral

Spatial-spectral

Deep networks for hyperspectral image segmentation

Spectral

Spatial-spectral

(Selected) Open issues:

- Validation of hyperspectral image segmentation algorithms
- Resouce-frugality of deep neural networks
- Robustness of deep neural networks

Validation of hyperspectral image segmentation algorithms

Selection of training, validation, and test sets

How to select training, validation, and test sets?
What are the benchmark (ground-truth) datasets?

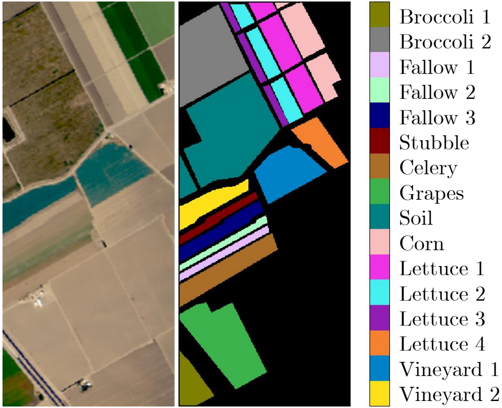
Selection of training, validation, and test sets

Method	Datasets*	Settings
Multiscale superpixels (Dundar & Ince, 2018)	IP, PU	Random
Watershed + SVM (Tarabalka et al., 2010)	PU	Arbitrary
Clustering (SVM) (Bilgin et al., 2011)	Washington DC, PU	Full image
Multiresolution segm. (Amini et al., 2018)	Three in-house datasets	Random
Region expansion (Li et al., 2018)	PU, Sa, KSC	Full image
DBN (spatial-spectral) (Li et al., 2014)	HU	Random
DBN (spatial-spectral) (Chen et al., 2015)	IP, PU	Random
Deep autoencoder (Chen et al., 2014)	KSC, PU	Monte Carlo
CNN (Zhao & Du, 2016)	PC, PU,	Random
CNN (Chen et al., 2016)	IP, PU, KSC	Monte Carlo
Active learning + DBN (Liu et al., 2017)	PC, PU, Bo	Random
DBN (spectral) (Zhong et al., 2017)	IP, PU	Random
RNN (spectral) (Mou et al., 2017)	PU, HU, IP	Random
CNN (Santara et al., 2017)	IP, Sa, PU	Random
CNN (Lee & Kwon, 2017)	IP, Sa, PU	Monte Carlo
CNN (Gao et al., 2018)	IP, Sa, PU	Monte Carlo
CNN (Ribalta et al., 2018)	Sa, PU	Random

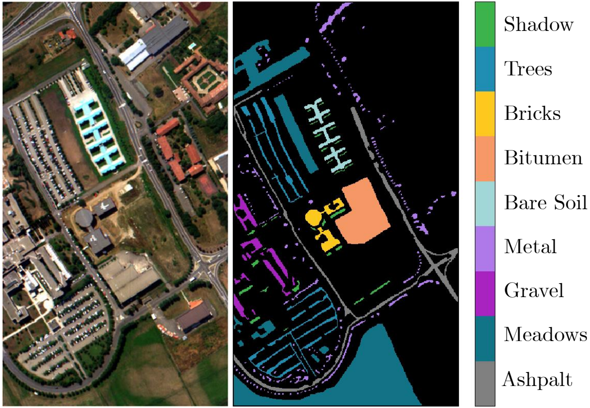
* IP—Indian Pines; PU—Pavia University; Sa—Salinas; KSC—Kennedy Space Center; HU—Houston University; PC—Pavia Centre; Bo—Botswana

Benchmark hyperspectral images—examples

Salinas Valley (512x217px, AVIRIS, 3.7m, 224 bands)



Pavia University (610x340px, ROSIS, 1.3m, 103 bands)



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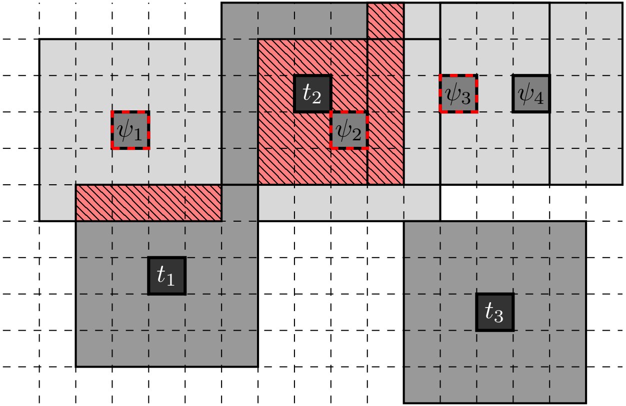
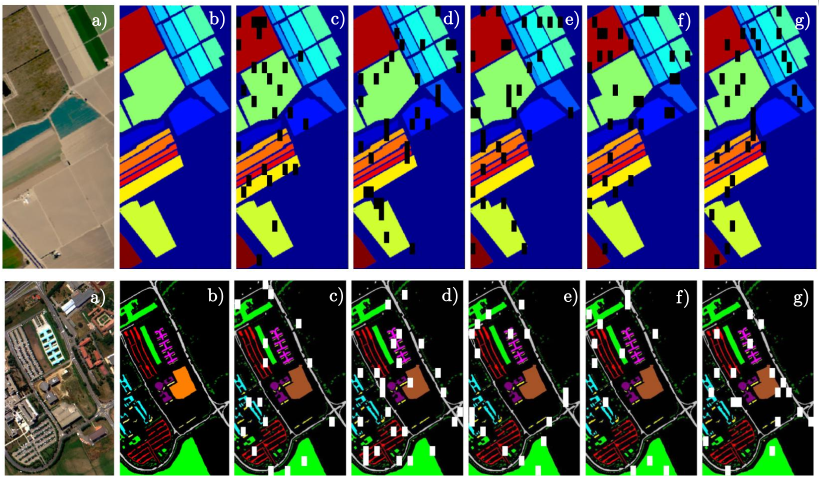
Training-test information leak



Training (t_i) and test (ψ_i) pixels with their spatial neighborhoods.

Patch-based training-test splits



a) True-color composite, b) ground-truth, c)–g) 5 folds (black/white patches are for training).

Do train-test splits matter (Monte-Carlo vs. Patch-based)?

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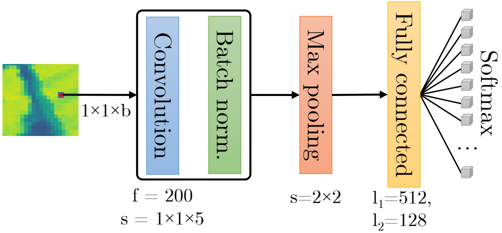
- Deep neural network architectures
  - **Spatial-spectral** (3D) CNN (Gao et al., Remote Sens., 2018)
  - **Spectral** (1D) CNN



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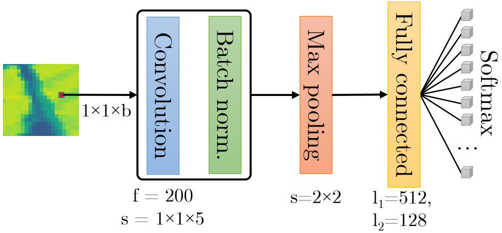

- Training-test subset cardinalities: as in Gao et al., 2018 (balanced and imbalanced)

Sneak-peek from the results (Salinas Valley). . .

Algorithm	Fold	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	OA	AA
3D(P)	1	85.69	97.19	0	0	95.23	0	0	61.59	94.02	92.09	91.09	0	46.72	83.42	78.64	0.06	56.69	51.47
3D(P)	2	99.64	99.07	87.88	98.78	0	96.16	91.54	96.65	96.66	93.34	92.76	97.7	99.43	96.8	2.92	0	72.32	75.58
3D(P)	3	99.89	41.27	30.71	99.23	78.12	99.69	97.25	84.03	99.67	67.98	79.37	92.17	99.63	43.02	71.15	77.73	79.8	78.63
3D(P)	4	98.12	96.88	43.78	12.73	0	100	97.9	59.18	6.11	96.35	0	93.71	99.07	87.53	98.76	12.79	61.96	62.17
3D(P)	5	99.11	41.75	77.06	97.31	87.54	100	97.37	72.36	95.05	78.7	93.99	98.85	58.65	0	65.53	74.42	77.81	77.4
3D(P)	Avg	96.49	75.15	39.89	61.61	51.79	79.21	76.81	74.84	78.14	85.69	71.56	76.49	80.86	62.15	63.8	33	69.72	69.09
3D(B)	—	99.84	99.3	93.68	99.83	97.51	99.98	99.71	82.82	99.17	96.71	99.42	99.79	99.75	99.73	82.83	99.86	93.01	96.91
3D(BB)	—	99.17	99.21	91.52	99.58	97.37	99.97	99.73	90.03	99.68	96.28	96.46	99.52	99.35	99	80.43	96.53	94.27	96.51
3D [16]	—	100	99.92	99.65	99.78	99.07	99.97	99.75	94.28	99.97	99.63	99.81	100	100	99.91	97.4	100	99.34	99.33
1D(P)	1	94.62	99.23	0	0	98.5	0	0	73.93	91.1	91.51	87.11	45.62	98.31	88.52	67.32	0.89	60.65	58.52
1D(P)	2	97.84	79.77	58.94	99.32	29.96	99.71	99.41	95.48	94.81	91.54	88.92	99.09	83.73	97.35	4.68	0	73.27	70.28
1D(P)	3	99.63	70.59	13.61	98.51	98.03	99.91	99.36	82.98	96.75	69.15	89.35	97.69	99.29	83.78	59.53	88.04	83	85.39
1D(P)	4	97.49	99.83	55.5	98.46	0	98.75	99.56	19.37	67.97	92.72	0	86.24	97.67	90.55	90.22	18.15	63.9	69.59
1D(P)	5	35.99	19.97	20.53	33.29	5.59	98.8	69.61	89.04	8.7	21.01	97.19	26.65	0	0	3.41	5.63	40.19	33.71
1D(P)	Avg	85.91	73.88	33.72	65.92	46.42	79.63	73.59	72.16	71.87	73.11	72.51	71.06	75.8	72.08	45.03	22.54	64.2	64.7
1D(B)	—	93.74	94.42	85	98.47	81.19	99.53	98.98	59.05	92.49	85.37	90.87	88.94	91.3	92.71	63.33	93.93	80.87	88.12
1D(BB)	—	93.78	96.13	76.48	97.68	81.95	99.34	99.21	83.13	97.55	81	68.80	93.89	97.72	88.28	43.14	99.93	83.57	86.7

OA—overall accuracy, AA—average accuracy

Sneak-peek from the results (Salinas Valley)...

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OA—overall accuracy, AA—average accuracy

Conclusion: Monte-Carlo cross-validation renders over-optimistic insights into classification performance.

For more results, see J. Nalepa et al., `https://arxiv.org/abs/1811.03707`, 2018 (submitted to IEEE Geoscience and Remote Sensing Letters)

Resource-frugality of deep neural networks

Hardware-constrained environment

Reduction of:

- Memory footprint
- Inference time

Hardware-constrained environment

Reduction* of:

- Memory footprint
- Inference time

***Without** adversely affecting classification performance. . .

Quantization of deep neural networks

Quantization of deep neural networks

- During DNN training
- Post-training

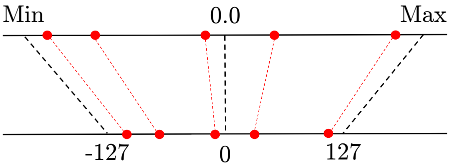
Quantization of deep neural networks

Quantization of deep neural networks

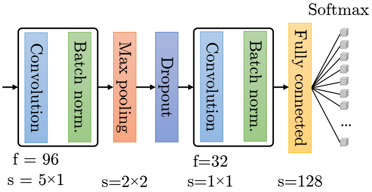
During DNN training

Post-training

- Prune redundant network nodes
- Compress constants
- Map weights/parameters to 8-bit precision



Sneak-peek from the results. . .



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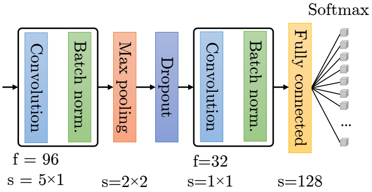

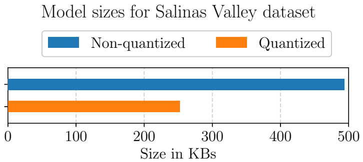

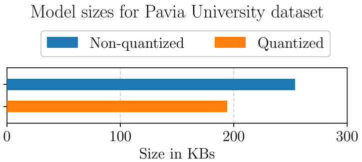

OA: 84.62% → 83.45% (drop of 1.17%) OA: 78.30% → 77.02% (drop of 1.28%)

For more results, see: P. Ribalta, M. Marcinkiewicz, J. Nalepa, Proc. IEEE DSD, pp 260-267, 2018.

Robustness of deep neural networks

Are deep networks robust (against noise)?

Simulation: Gaussian noise, SNR wavelength-dependent
Deep network: Spatial-spectral CNN

(Thanks to Adam Popowicz for the noise model.)

Are deep networks robust (against noise)?

Simulation: Gaussian noise, SNR wavelength-dependent
Deep network: Spatial-spectral CNN

OA: 90.59% OA: 31.90% OA: 48.39% 65.78%

(Thanks to Adam Popowicz for the noise model.)

Conclusions

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- **Open issues** in hyperspectral image analysis
  - Lack of ground-truth data
  - Resource-frugality of deep neural nets for HSI segmentation
  - Robustness of deep neural nets for HSI segmentation
  - Better generalization for unseen data ($\rightarrow$ better regularizers)
  - Efficient pre-/post-processing of HSI data (e.g., band selection)

HYPERNET—code and beyond

`https://github.com/ESA-PhiLab/hypernet`

HYPERNET Team: Jakub Nalepa, Michal Kawulok, Michal Myller, Lukasz Tulczyjew, Marek Antoniak, Rafal Zogala

- State-of-the-art spectral and spatial-spectral deep nets for HSI (and beyond)
- Band selection using **attention-based convolutional neural nets** (P. Ribalta, L. Tulczyjew, M. Marcinkiewicz, J. Nalepa, `https://arxiv.org/abs/1811.02667`, after the first round of reviews in IEEE Transcations on Geoscience and Remote Sensing)
- Data augmentation (generative adversarial nets, noise-based,. . .)
- Visualization of HSI
- Patch-based benchmark generation, and more. . .

HYPERNET—code and beyond

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- **All in Python (Keras/Pytorch)** with **Jupyter-notebook** examples

Wanting more? Drop me a line at jnalepa@ieee.org

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The ESA Earth Observation Φ-Week,
Frascati, Italy. November 14, 2018