Towards Tackling Multi-Label Imbalances in Remote Sensing Imagery

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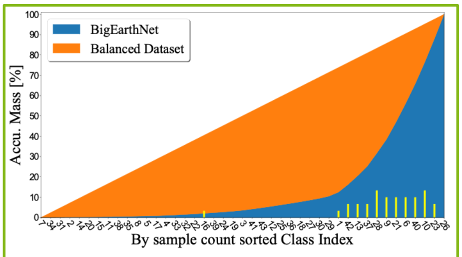
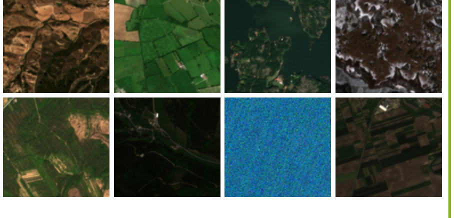
Introduction

- Recently, new and deep learning sizeable datasets with Remote Sensing Multi Spectral Imagery have come forward.
- Earth is not covered equally by semantically meaningful classes, leading to severe class imbalances in Land Cover Datasets and poor recognition results.
- We improve the performance on these minority classes with up to 20 % without strong effects on majority classes.
- Utilizing the CLC Classes as Attributes improves accuracies on new parent classes[3]

Highly Imbalanced Data



- BigEarthNet[1] dataset with nearly 600.000 multi-class multi-label multispectral images
- Sentinel-2 satellite imagery matched with CORINE Land Cover (CLC) inventory
- 12 spectral channels including RGB and IR
- 120 x 120 px with 10 [m]² to 60 [m]² Res.
- 43 Classes with sample counts between 60 in minority and 40.000 in majority classes



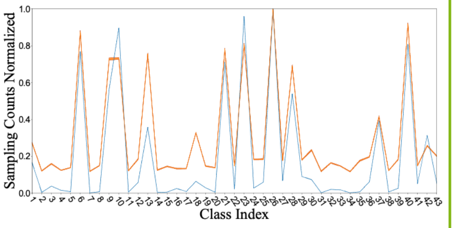
Class Co-Occurrences, normalized by Rows (Read from left to right)

Minority Class Agnostic Sampling

- **M**inority class marginal probability based data **R**andom **O**ver**s**ampling process (**MROS**) produces sample weights

$$\text{Multi}(\mathbf{s}|B, \mathbf{w}_{\text{samples}}) = \binom{B}{s_1 \dots s_M} \prod_{j=1}^{M} \mathbf{w}_{\text{samples},j}^{s_j}$$

Sampling Process of one epoch



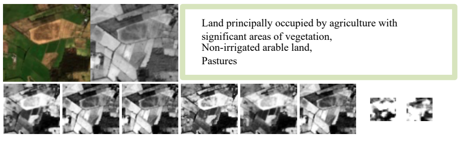
- **D**ynamic **C**lass **W**eight (**DCW**) adjustment in loss during training with BCE.

$$\mathcal{L}_{dbce}(e) = \frac{1}{C} \sum_{i=1}^{C} w_i(e) \times [y_i \log(a_i) + (1 - y_i) \log(1 - a_i)]$$

Minority Agnostic Metric

- Inverse proportional weighting of classes in averaging metrics: **minor weighting**

$$F1_{\text{minor}} = \sum_{\text{classes}} s_n \sum_{\text{classes}} \frac{1}{s_n} \frac{tp_n}{tp_n + fn_n}$$



Experiments

- Densenet121[19] backbone
- Upsampling of all spectral channels
- Different ablations: **CW**, **MROS + DCW**, **PT** (Pretraining on ImageNet)
- Two different data splits [%] with training/test/validation mean Class Probabilities [µC%]
  - 1. **New Split** 70/ 20/ 10 [%] with 70.1/ 19.9/ 10.0 [µC%]
  - 2: **BigEarthNet Split**[1] 52/ 24/ 24 [%] with 61.3/ 20.7/ 17.9 [µC%]

Comparison to SotA

Method	Model	$F1_{macro}$	R_{macro}	P_{macro}
S-CNN-All [1]	S-CNN-All	70.98	77.10	69.93
K-Branch CNN [18]	K-Branch CNN	72.89	**80.00**	-
Base	DenseNet121	77.3	76.46	78.41
CW	DenseNet121	72.0	76.59	68.73
MROS + DCW	DenseNet121	77.66	76.16	79.97
MROS + DCW + PT	DenseNet121	**78.21**	77.18	**80.41**

Ablation Study

Metric	Base	CW	MROS + DCW	MROS + DCW + PT
$BAcc_{\text{micro}}$	**92.6**	88.39	90.89	90.34
$F1_{\text{micro}}$	**86.22**	78.37	83.03	82.01
P_{micro}	**86.22**	78.37	83.03	82.01
R_{micro}	**86.22**	78.37	83.03	82.01
$BAcc_{\text{macro}}$	87.61	87.35	87.32	**87.78**
$F1_{\text{macro}}$	77.3	72.0	77.66	**78.21**
P_{macro}	78.41	68.73	79.97	**80.41**
R_{macro}	76.46	76.59	76.16	**77.18**
$BAcc_{\text{minor}}$	83.4	**87.01**	84.86	86.41
$F1_{\text{minor}}$	69.45	69.89	73.03	**77.23**
P_{minor}	72.92	66.86	77.91	**84.04**
R_{minor}	66.9	**74.18**	69.79	72.9

Attribute Representation

- Problem complexity reduction by class merging is leading to loss of information
- Instead the 43 classes of BigEarthNet are linearly transformed and used as attributes to derive the new classes

	DenseNet121		Resnet50	
	Base	**MROS + DCW**	**Attr.**	[3]
New Class (Attribute Encoding)	✓	✓	✓	-
Agro-forestry areas (1)	77.54	77.01	**78.09**	70.49
Arable Land (26,30,32)	**86.53**	84.59	85.94	83.85
Beaches, Dunes and Sands (5)	56.55	54.48	58.75	**61.46**
Broad leaved forest (6)	**78.09**	75.50	77.59	74.05
Coastel wetlands (34,35)	61.88	57.52	**62.61**	47.71
Complex cultivation patterns (9)	**71.75**	67.11	70.40	66.03
Coniferous forest (10)	86.81	85.82	**87.50**	85.41
Industrial or commercial units (18)	51.98	49.08	**53.67**	48.55
Inland Waters (42,43)	**85.93**	82.77	85.11	83.69
Inland wetlands (19,29)	**63.59**	61.01	62.87	60.64
Land principally occupied ... (21)	**69.14**	65.53	64.51	60.94
Marine Waters (15,37)	98.06	97.70	**98.14**	97.53
Mixed Forest (23)	**83.06**	81.44	82.61	79.44
Moors (24,36)	**66.54**	62.39	66.35	59.41
Natural grassland and ... (25,38)	**54.10**	51.99	52.52	47.55
Pastures (28)	**75.68**	72.95	74.99	72.38
Permanent crops (3,16,27,41)	**63.90**	58.97	62.53	51.91
Transitional woodland-shrub (40)	**71.79**	68.31	71.28	53.47
Urban fabric (12,13)	**78.40**	74.88	77.07	74.84
$F1_{\text{macro}}$	**72.7**	69.95	72.24	67.33

Conclusion

- Our method pushed the detection of semantically very meaningful minority classes in multi-label remote sensing imagery
- **MROS** and **DCW** increase the performance of minority classes by up to 20\ % with only minimal changes to the majority classes
- Pre-Training on ImageNet is especially beneficial for minority classes.
- Better analysis of model performances on highly imbalanced multi-label data through minority agnostic metric
- Attribute based class encoding produces superior classification performances for a reduced set of parent classes and is identified as a promising research direction

Selected References

[1] G. Sumbul, M. Charfuelan, B. Demir, and V. Markl, “BigEarthNet: A large-scale benchmark archive for remote sensing image understanding,” , *IGARSS 2019 - IEEE International Geoscience and Remote Sensing Symposium,* pp. 5901–5904.
[3] G. Sumbul, J. Kang, T. Kreuziger, F. Marcelino, H. Costa, P. Benevides, M. Caetano, and B. Demir, “BigEarthNet Deep learning models with a new class-nomenclature for remote sensing image understanding,” *January 2020 preprint*
[19] G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, “Densely connected convolutional networks,” in Proceedings of the *IEEE conference on computer vision and pattern recognition*, 2017, pp. 4700–4708.

Acknowledgements

This work has been supported by the Deutsche Forschungs-gemeinschaft (DFG, German Research Foundation) - Project number 26966170

Deutsche Forschungsgemeinschaft
German Research Foundation