Towards Tackling Multi-Label Imbalances in Remote Sensing Imagery

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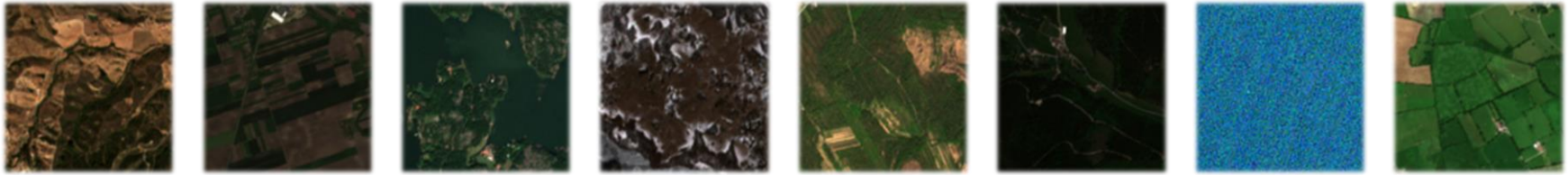
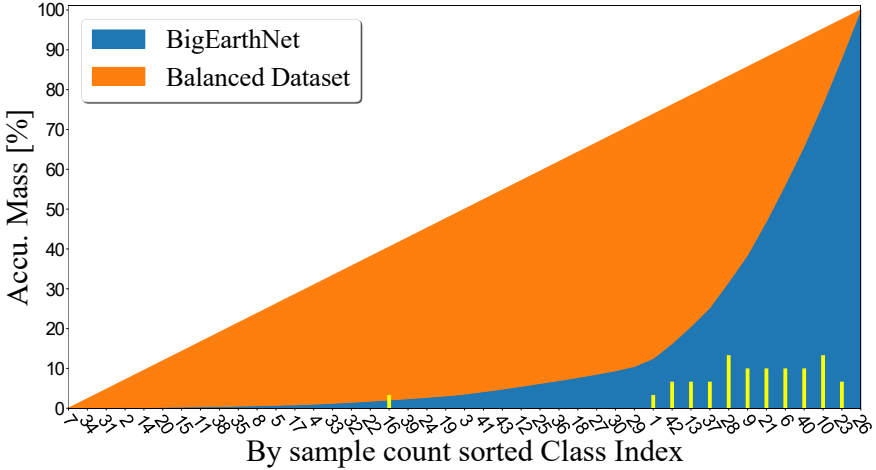


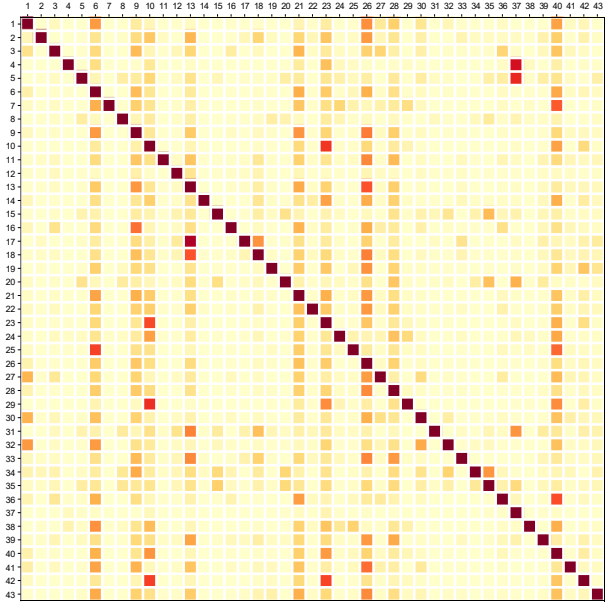
Introduction - Imbalanced Data



- Earth not covered equally in semantically meaningful classes
- BigEarthNet[1]: ~600000 images, 12 multispectral channels, matched **C**orine **L**and **C**over inventory with Sentinel 2 imagery
- 43 classes (airports, urban areas, forest, agriculture, water sides …)
- Forest ~ 40.000 samples vs. Airports ~ 60 samples (imbalance factor ~600)
- 120 x 120 [px] images, 10 – 60 [m] Res.

[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.

Multilabel Data from Segmentation?



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

- Multilabel data from pixel labels results to huge differences inside inter class conditional probabilities
- Small regions can denote class instances without context
- Standard Oversampling (ROS) or class weighting schemes insufficient to deal with these imbalances

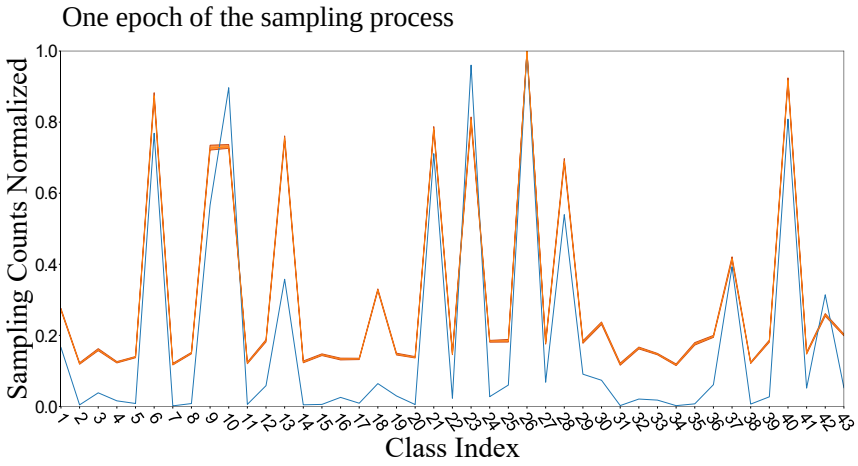
CLC Segmentation Map

https://land.copernicus.eu/pan-european/corine-land-cover/clc-2012

Sampling and Dynamic Weighting

- Class weighted sampling (CW)
- Minority Class focused sample weights (MROS)
- Dynamic Class Weights in Loss (DCW)

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



Experiments - SotA

- Upsampling of all spectral channels
- Different ablations:
  - **CW** (Standard Class Weighting)
  - **MROS + DCW**
  - **PT** (Pretraining)

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**

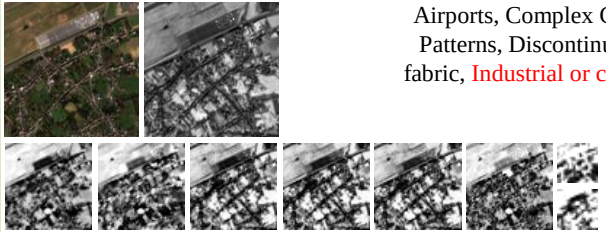
[1] G. Sumbul, M. Charfuelan, B. Demir, and V. Markl, "BigEarthNet: A large-scale benchmark archive for remote sensing image understanding," , *IGARSS 2019 - IEEE International Geoscience and Remote Sensing Symposium*, pp. 5901–5904.
[18] G. Sumbul and B. Demir, "A novel multi-attention driven system for multi-label remote sensing image classification," in *IGARSS 2019-2019 IEEE International Geoscience and Remote Sensing Symposium*, 2019, pp. 5726–5729

Experiments – Class F1 Score

Index	Class	Count	Base	CW	MROS + DCW	MROS + DCW + PT	Transf.
1	Agro-forestry areas	6199	**92.58**	84.05	90.96	90.99	1
2	Airports	**173**	50.14	47.11	58.39	**61.48**	-
3	Annual crops associated with permanent crops	1408	78.66	70.6	83.92	**83.98**	17
4	Bare rock	**584**	84.57	78.33	84.96	**85.43**	-
5	Beaches, Dunes and Sands	**314**	86.89	87.97	87.25	**91.94**	3
6	Broad-leaved forest	28144	**86.36**	77.34	82.06	81.0	4
7	Burnt areas	**60**	56.31	65.6	59.26	**73.08**	-
8	Coastal lagoons	**287**	95.99	91.14	**96.59**	93.27	12
9	Complex cultivation patterns	20785	**81.24**	72.36	76.6	75.3	6
10	Coniferous forest	32731	**91.82**	86.65	89.55	88.76	7
11	Construction sites	**232**	56.59	63.41	64.5	**71.72**	-
12	Continuous urban fabric	2127	**89.28**	84.94	83.12	83.65	19
13	Discontinuous urban fabric	13188	**84.5**	76.11	78.53	78.71	19
14	Dump sites	**148**	50.75	56.09	53.62	**66.67**	-
15	Estuaries	**210**	86.12	77.17	**88.67**	81.65	12
16	Fruit trees and berry plantations	**937**	64.77	53.56	66.86	**67.76**	17
17	Green urban areas	**325**	57.63	54.14	**60.07**	59.83	-
18	Industrial or commercial units	2388	70.71	62.37	70.3	**71.35**	8
19	Inland marshes	1097	**61.35**	50.16	58.97	61.21	10
20	Intertidal flats	**184**	80.43	76.38	80.21	**81.65**	-
			...				
Average			77.3	72.0	77.66	78.21	

Less Problem Complexity: Attributes

Land principally occupied by agriculture with significant areas of vegetation, Non-irrigated arable land, Pastures



Airports, Complex Cultivation Patterns, Discontinuous urban fabric, Industrial or commercial units

	DenseNet121		Resnet50	
New Class (Attribute Encoding)	**Base** ✓	**MROS + DCW** ✓	**Attr.** ✓	[3] -
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

[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*

Conclusion

- Better detection of semantically very meaningful minority classes in multi-label remote sensing imagery
- Increased Accuracy on minority classes (up to 20 %) with only minimal changes to majority classes
- Pre-Training on ImageNet beneficial for minority classes.
- Better analysis on highly imbalanced multi-label data through minority agnostic metric
- Superior classification performances for reduced set of parent classes by attribute encoding

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