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 Corine Land Cover 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.

Multilabel Data from Segmentation?

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


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

<table>
<thead>
<tr>
<th>Method</th>
<th>Model</th>
<th>F1\text{macro}</th>
<th>P\text{macro}</th>
<th>P\text{macro}</th>
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</thead>
<tbody>
<tr>
<td>S-CNN-All [1]</td>
<td>S-CNN-All</td>
<td>70.98</td>
<td>77.10</td>
<td>69.93</td>
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<tr>
<td>K-Branch CNN [18]</td>
<td>K-Branch CNN</td>
<td>72.89</td>
<td>80.00</td>
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<tr>
<td>Base</td>
<td>DenseNet121</td>
<td>77.3</td>
<td>76.46</td>
<td>78.41</td>
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<tr>
<td>CW</td>
<td>DenseNet121</td>
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<tr>
<td>MROS + DCW + PT</td>
<td>DenseNet121</td>
<td>78.21</td>
<td>77.18</td>
<td>80.41</td>
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</table>


## Experiments – Class F1 Score

<table>
<thead>
<tr>
<th>Index</th>
<th>Class</th>
<th>Count</th>
<th>Base</th>
<th>CW</th>
<th>MROS + DCW</th>
<th>MROS + DCW + PT</th>
<th>Transf.</th>
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<td>2</td>
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<td>47.11</td>
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<td>61.48</td>
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<td>3</td>
<td>Annual crops associated with permanent crops</td>
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<td>84.96</td>
<td>85.43</td>
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<td>5</td>
<td>Beaches, Dunes and Sands</td>
<td>314</td>
<td>86.89</td>
<td>87.97</td>
<td>87.25</td>
<td>91.94</td>
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<td>6</td>
<td>Broad-leaved forest</td>
<td>28144</td>
<td>86.36</td>
<td>77.34</td>
<td>82.06</td>
<td>81.0</td>
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<td>7</td>
<td>Burnt areas</td>
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<td>56.31</td>
<td>65.6</td>
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<td>93.27</td>
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<td>9</td>
<td>Complex cultivation patterns</td>
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<td>Construction sites</td>
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<td>Dump sites</td>
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<td>53.62</td>
<td>66.67</td>
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<td>88.67</td>
<td>81.65</td>
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<tr>
<td>16</td>
<td>Fruit trees and berry plantations</td>
<td>937</td>
<td>64.77</td>
<td>53.56</td>
<td>66.86</td>
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<td>Green urban areas</td>
<td>325</td>
<td>57.63</td>
<td>54.14</td>
<td>60.07</td>
<td>59.83</td>
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<tr>
<td>18</td>
<td>Industrial or commercial units</td>
<td>2388</td>
<td>70.71</td>
<td>62.37</td>
<td>70.3</td>
<td>71.35</td>
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<tr>
<td>19</td>
<td>Inland marshes</td>
<td>1097</td>
<td>61.35</td>
<td>50.16</td>
<td>58.97</td>
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<td>20</td>
<td>Intertidal flats</td>
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<td>80.43</td>
<td>76.38</td>
<td>80.21</td>
<td>81.65</td>
<td>-</td>
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</tbody>
</table>

Average: 77.3, 72.0, 77.66, 78.21
Less Problem Complexity: Attributes

<table>
<thead>
<tr>
<th>New Class (Attribute Encoding)</th>
<th>DenseNet121</th>
<th>ResNet50</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Base</td>
<td>MROS + DCW</td>
</tr>
<tr>
<td>Agro-forestry areas (1)</td>
<td>77.54</td>
<td>77.01</td>
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<tr>
<td>Arable Land (26,30,32)</td>
<td>86.53</td>
<td>84.59</td>
</tr>
<tr>
<td>Beaches, Dunes and Sands (5)</td>
<td>56.55</td>
<td>54.48</td>
</tr>
<tr>
<td>Broad leaved forest (6)</td>
<td>78.09</td>
<td>75.50</td>
</tr>
<tr>
<td>Coastal wetlands (34,35)</td>
<td>61.88</td>
<td>57.52</td>
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<td>Complex cultivation patterns (9)</td>
<td>71.75</td>
<td>67.11</td>
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<td>Coniferous forest (10)</td>
<td>86.81</td>
<td>85.82</td>
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<td>Industrial or commercial units (18)</td>
<td>51.98</td>
<td>49.08</td>
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<td>Inland Waters (42,43)</td>
<td>85.93</td>
<td>82.77</td>
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<td>Inland wetlands (19,29)</td>
<td>63.59</td>
<td>61.01</td>
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<td>Land principally occupied ... (21)</td>
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<td>Marine Waters (15,37)</td>
<td>98.06</td>
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<td>Mixed Forest (23)</td>
<td>83.06</td>
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<td>Moors (24,36)</td>
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<td>62.39</td>
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<tr>
<td>Natural grassland and ... (25,38)</td>
<td>54.10</td>
<td>51.99</td>
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<td>Pastures (28)</td>
<td>75.68</td>
<td>72.95</td>
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<td>Permanent crops (3,16,27,41)</td>
<td>63.90</td>
<td>58.97</td>
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<tr>
<td>Transitional woodland-shrub (40)</td>
<td>71.79</td>
<td>68.31</td>
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<tr>
<td>Urban fabric (12,13)</td>
<td>78.40</td>
<td>74.88</td>
</tr>
</tbody>
</table>

\[ F_{\text{macro}} = 72.7 \]

\[ F_{\text{macro}} = 69.95 \]

\[ F_{\text{macro}} = 72.24 \]

\[ F_{\text{macro}} = 67.33 \]

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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