Solar array detection on aerial photography based on convolutional neural networks: impact of the solar array characteristics and image backgrounds on the out-of-domain generalization

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1. Context

→ Deep learning remote sensing of aerial images is widely used for large scale solar array mapping.
→ However, current models do not generalize well to out-of-domain (OOD) locations.
→ We empirically study the impact of **image background** and **solar array type** on OOD generalization.

2. Research questions

1. Is the failure to generalize predominantly due to unseen backgrounds or unseen solar arrays?
2. Has the type of background or of solar array in the training data an influence on OOD performance?
3. Can we quantify which types of backgrounds or solar arrays are better for generalization?

3. Methods

Synthetic dataset

We study the effect of different visual instances of the solar arrays and of the different backgrounds on OOD generalization.

The dataset is designed to study the impact of varying visual instances and varying backgrounds on OOD generalization.

Quantification of the semantic factors

We apply the method of [1]. This consists in computing the mutual information between two representations z of two images that depict the same concept (e.g. solar array). By doing so, we can estimate the dimension of this concept in the representations computed by the model.

We want to see whether the number of dimensions that encode the semantic concepts varies with the visual instance of the semantic concept.

Figure 1: Sample images from the source dataset (left) and the OOD dataset (rightmost image)

4. Results

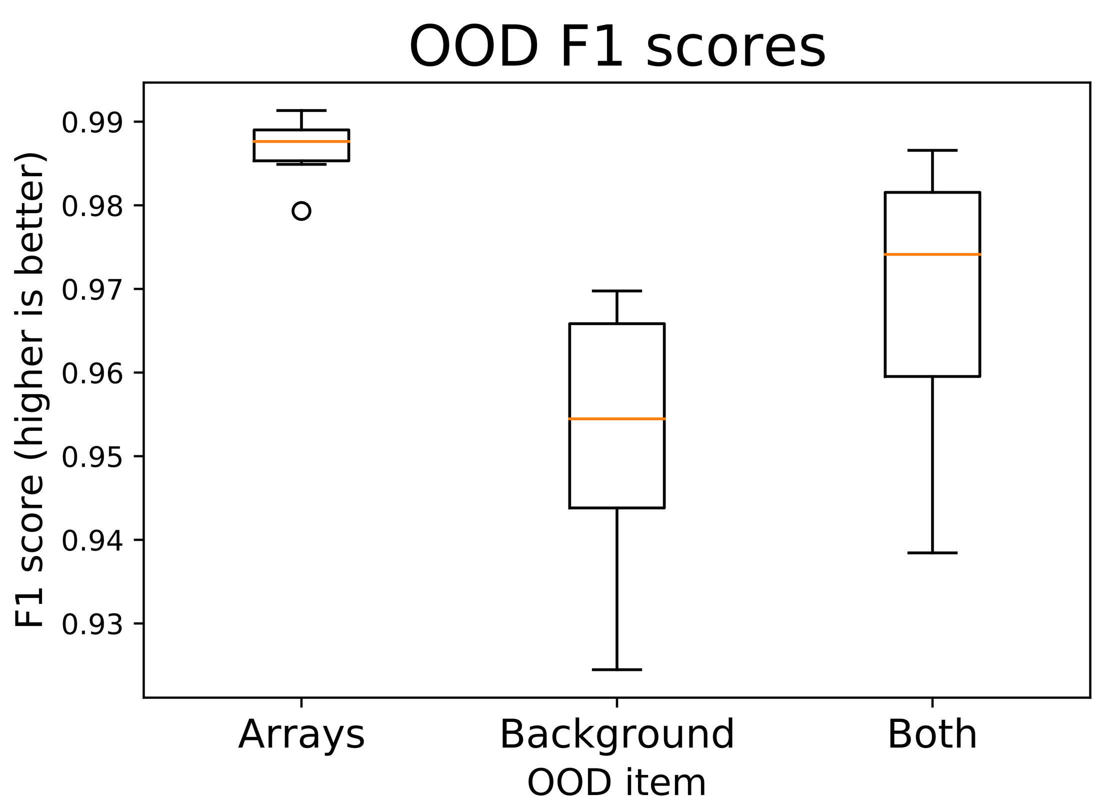

Figure 2: F1 scores on the OOD datasets

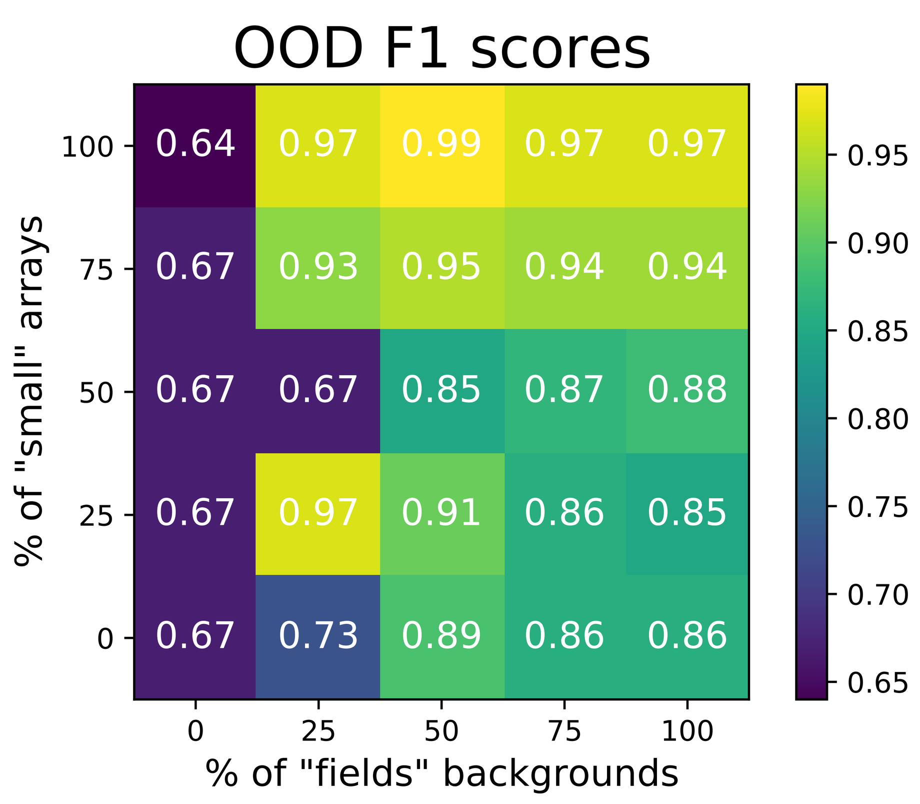

Figure 3: OOD F1 scores for different (background,instance) combinations

1. Decomposition of the OOD error For a fixed distribution of solar array types and backgrounds in the training dataset, the OOD performance (righmost box plot of figure 2) is mainly affected by the fact that the background changes (middle box plot).

→ *The drop in OOD performance is mostly driven by the fact that the background changes.*

2. Heterogeneous effects When controlling the proportion of background types and array types in the training data, we can significantly alter the model's performance.
The impact of altering the distribution of backgrounds types is larger than the impact of changing the distribution of solar array types.

→ *The type of background and solar array in the source dataset impacts OOD performance, with a larger effect for the background compared to the array type.*

3. Dimensionality estimates The estimated dimensionality for the concepts "background" and "solar array" does not vary with the type of background or solar array that we consider.

→ *Our method does not allow to quantify which background or solar array types are better for OOD generalization.*

5. Future work

- Incorporate additional factors (e.g. ground sampling distance) and study their interplay with the other factors in a more realistic synthetic dataset.
- Investigate further whether it is possible to find a link between how concepts are encoded in the latent representation and OOD performance.

References and supplementary material

[1] Md Amirul Islam, Matthew Kowal, Patrick Esser, Sen Jia, Bjorn Ommer, Konstantinos G Derpanis, and Neil Bruce. Shape or texture: Understanding discriminative features in cnns. *arXiv preprint arXiv:2101.11604*, 2021.

[2] Vaishnavh Nagarajan, Anders Andreassen, and Behnam Neyshabur. Understanding the failure modes of out-of-distribution generalization. *arXiv preprint arXiv:2010.15775*, 2020.

https://github.com/gabrielkasmi/ood_instances_sophia