Pollinators: estimating Nature's services

Key words: image classification - imbalanced classes - transfer learning - real data - pollinators - agro-ecology

Context:

Animal pollination, the processes by which an animal facilitates the transfer of pollen from the anthers of one flower to the stigma of another, is **essential for the reproduction of** 87.5% **of all flowering plants**. In agriculture, the crop pollination service is valued at 195-387 billion US dollars annually, with direct implications for food security. Among animal pollinators, insects such as Hymenoptera (bees and wasps), Diptera (flies), Coleoptera (beetles) and Lepidoptera (butterflies and moths) play a critical role in agriculture. However, the current decline of these insect pollinators raises alarm for crop pollination and food security, due to **increasing evidence of pollination deficits** (i.e. the loss of crop yield related to the lack of animal pollination). **Estimating this pollination deficit** is therefore a current priority, as well as **clarifying which insects provide this pollination service** in order to develop adapted pollinator-friendly schemes in agricultural landscapes practices.

The use of camera traps on crop flowers over periods of 24 hours is a technique that could record pollinator visits during day and night, and thus determine crop pollinators to conserve. For a quantitative estimate of the pollination service however, one needs an automated processing of the recordings.

Available Data:

Concretely, **hundreds of hours were recorded** in the infra-red band (allowing for nightly video recording) for 5 types of flowering plants (*strawberry plant, raspberry plant, sunflower plant, apple tree, cacao tree*). Experts classified some of these recordings, **indicating when pollinators are visible and which is their morphogroup** (≈ species): *honey bee (Apis mellifera), bumble bee (Bombus sp.), wild bee, hoverfly (Syrphidae), other fly (Diptera), wasp (Vespidae), ant (Formicidae), beetle (Coleoptera) and spider (Araneae)*. This means we have 9 pollinator classes, plus the class "no pollinator", which is by far the majority class. For *strawberries, apples and cacao*, 50% of the recordings have been labelled. For *raspberries and sunflowers*, nothing has been labelled yet.

Internship goal:

The project can be split in two stages. The first is to classify **whether a pollinator is present or not** (binary or one-class classification). The second is to **classify the pollinators in the** 9 **classes**, when present (a priori more difficult task).

Proposed approach:

The first task will be to assess what has been done in the literature. Some works are somehow related to this original research project, such as [SGH+21, ABM+22, SSW+23, WGCM23, BAD+23, KK23].

For simplicity, the proposed approach for this M1 internship is to **ignore the temporal aspect** of the data and consider it as a collection of frames, and **apply conventional image classification** techniques (CNNs, Vision Transformers, etc). The drastic imbalance between classes means that under-sampling should be considered, while the correlation between frames implies a careful train/validation/test split procedure.

Before going into Deep methods, one should **assess the accuracy of simple baselines** (such as color histograms for the central pixels). This simple baseline may help to sample the majority examples that are harder to distinguish from the minority ones, to then train deeper networks efficiently.

In terms of **architecture, various strategies can be used**, from handcrafting a CNN from scratch, or training classic architectures from scratch, to fine-tuning foundation models. We may also consider self-supervised learning on the abundant majority class data.

An other outcome of the internship will be to select the images that might most benefit from the human oracle's classification (**active learning**).

In any case, the final result of the internship may be used as is but will also serve as a **baseline for an ML challenge**, to be crafted and published with the help of the **codalab team**. Indeed, the ideal model would be one that transfers well to new plants (flowers) and new pollinators, *i.e.* the task is not to classify a few pollinators for one plant, but rather to have a meta model that adapts well to various combinations of plants and pollinators: we have a meta-task.

References

[ABM+22] Darlin Apasrawirote, Pharinya Boonchai, Paisarn Muneesawang, Wannacha Nakhonkam, and Nophawan Bunchu. Assessment of deep convolutional neural network models for species identification of forensically-important fly maggots based on images of posterior spiracles. *Scientific Reports*, 12(1):4753, March 2022.

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[KK23] Vladimir A. Kulyukin and Aleksey V. Kulyukin. Accuracy vs. Energy: An Assessment of Bee Object Inference in Videos from On-Hive Video Loggers with YOLOv3, YOLOv4-Tiny, and YOLOv7-Tiny. *Sensors*, 23(15):6791, July 2023.

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[SSW+23] Thomas Stark, Valentin Stefan, Michael Wurm, Robin Spanier, Hannes Taubenbock, and Tiffany M. Knight. YOLO object detection models can locate and classify broad groups of flower-visiting arthropods in images. *Scientific Reports*, 13(1):16364, 2023.

[WGCM23] Chaoxin Wang, Ivan Grijalva, Doina Caragea, and Brian McCornack. Detecting common coccinellids found in sorghum using deep learning models. *Scientific Reports*, 13(1):9748, June 2023.

Expected abilities:

- Good python skills, some knowledge of pyTorch
- Basic theoretical knowledge of CNNs, and of Machine Learning in general

Learned Skills:

- Learning about pollinators
- Understand, develop and deploy CNNs, developped pyTorch practice.
- Using a job scheduler (slurm) on a computer cluster (a GPU farm).

Duration: The preferred duration would be of about 4 months.

Labs: (Co-supervision between 2 labs)
LISN, Université Paris-Saclay ; IDEEV, Université Paris-Saclay

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