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Peerannot: classification for crowdsourced image datasets with Python

Tanguy Lefort [1] IMAG, Univ Montpellier, CNRS, Inria, LIRMM
Benjamin Charlier IMAG, Univ Montpellier, CNRS
Alexis Joly Inria, LIRMM, Univ Montpellier, CNRS
Joseph Salmon IMAG, Univ Montpellier, CNRS, IUF

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Abstract

Crowdsourcing is a quick and easy way to collect labels for large datasets, involving many workers. However, workers often disagree with each other. Sources of error can arise from the workers' skills, but also from the intrinsic difficulty of the task. We present `peerannot`: a `Python` library for managing and learning from crowdsourced labels for classification. Our library allows users to aggregate labels from common noise models or train a deep learning-based classifier directly from crowdsourced labels. In addition, we provide an identification module to easily explore the task difficulty of datasets and worker capabilities.

Keywords: crowdsourcing, label noise, task difficulty, worker ability, classification

Contents

[1]Corresponding author: tanguy.lefort@umontpellier.fr

1 Introduction: crowdsourcing in image classification

Image datasets widely use crowdsourcing to collect labels, involving many workers that can annotate images for a small cost (or even free for instance in citizen science) and faster than using expert labeling. Many classical datasets considered in machine learning have been created with human intervention to create labels, such as CIFAR-10, (Krizhevsky and Hinton 2009), ImageNet (Deng et al. 2009) or Pl@ntnet (Garcin et al. 2021) in image classification, but also COCO (Lin et al. 2014), solar photovoltaic arrays (Kasmi et al. 2023) or even macro litter (Chagneux et al. 2023) in image segmentation and object counting.

Crowdsourced datasets induce at least three major challenges to which we contribute with `peerannot`:

1) **How to identify good workers in the crowd?** When multiple answers are given to a single task, looking for who to trust for which type of task becomes necessary to estimate the ground truth or later train a model with as few noise sources as possible. The module `identify` uses different scoring metrics to create a worker and/or task evaluation. This is particularly relevant considering the gamification of crowdsourcing experiments (Servajean et al. 2016)
2) **How to aggregate multiple labels into a single label from crowdsourced tasks?** This occurs for example when dealing with a single dataset that has been labeled by multiple workers with disagreements. This is also encountered with other scoring issues such as polls, reviews, peer-grading, *etc.* In our framework this is treated with the `aggregate` command, that given multiple labels, infers a ground truth label. From aggregated labels, a classifier can then be trained using the `train` command.
3) **How to learn a classifier from crowdsourced datasets?** Where the first question is bound by aggregating multiple labels into a single one, this considers the case where we do not need a single label to train on, but instead train a classifier on the crowdsourced data, with the motivation to perform well on a testing set. This end-to-end vision, is common in machine learning, however, it requires the actual tasks (the images, texts, videos, *etc.*) to train on – and in crowdsourced datasets publicly available, they are not always available. This is treated with the `aggregate-deep` command.

The library `peerannot` addresses these practical questions within a reproducible setting. Indeed, the complexity of experiments often leads to a lack of transparency and reproducible results for simulations and real datasets. We propose standard simulation settings with explicit implementation

parameters that can be shared. For real datasets, `peerannot` is compatible with standard neural networks architectures from the `Torchvision` (Marcel and Rodriguez 2010) library and `Pytorch` (Paszke et al. 2019), allowing a flexible framework with easy-to-share scripts to reproduce experiments.

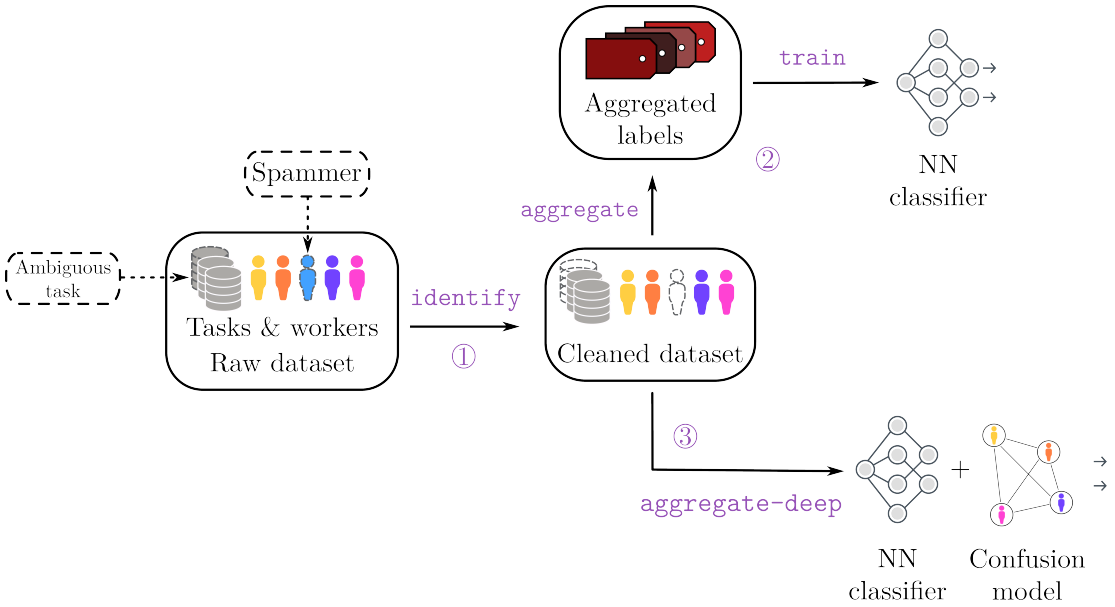


Figure 1: From crowdsourced labels to training a classifier neural network, the learning pipeline using the `peerannot` library. An optional preprocessing step using the `identify` command allows us to remove worse performing workers or images that can not be classified correctly (very bad quality for example). Then, from the cleaned dataset, the `aggregate` command may generate a single label per task from a prescribed strategy. From the aggregated labels we can train a neural network classifier with the `train` command. Otherwise, we can directly train a neural network classifier that takes into account the crowdsourcing setting in its architecture using `aggregate-deep`.

2 Notation and package structure

2.1 Crowdsourcing notation

Let us consider the classical supervised learning classification framework. A training set $\mathscr{D} = \{(x_i, y_i^\star)\}_{i=1}^{n_{\text{task}}}$ is composed of n_{task} tasks $x_i \in \mathscr{X}$ (the feature space) with (unobserved) ground truth label $y_i^\star \in [K] = \{1, \dots, K\}$ one of the K possible classes. In the following, the tasks considered are generally RGB images. We use the notation $\sigma(\cdot)$ for the softmax function. In praticular, given a classifier $\mathscr{C}$ with logits outputs, $\sigma(\mathscr{C}(x_i))_{[1]}$ represents the largest probability and we can sort the probabilities as $\sigma(\mathscr{C}(x_i))_{[1]} \geq \sigma(\mathscr{C}(x_i))_{[2]} \geq \cdots \geq \sigma(\mathscr{C}(x_i))_{[K]}$. The indicator function is denoted $\mathbf{1}(\cdot)$. We use the i index notation to range over the different tasks and the j index notation for the workers in the crowdsourcing experiment. Note that indices start at position 1 in the equation to follow mathematical standard notation such as $[K] = \{1, \dots, K\}$ but it should be noted that, as this is a `Python` library, in the code indices start at the 0 position.

With crowdsourced data the ground truth of a task x_i, denoted $y_i^\star$ is unknown, and there is no single label that can be trusted as in standard supervised learning (even on the train set!). Instead, there is a crowd of n_{worker} workers from which multiple workers $(w_j)_j$ propose a label $(y_i^{(j)})_j$. The set of workers answering the task x_i is denoted by

$$\mathscr{A}(x_i) = \left\{ j \in [n_{\text{worker}}] \,:\, w_j \text{ answered } x_i \right\}. \tag{1}$$

The cardinal $|\mathscr{A}(x_i)|$ is called the feedback effort on the task x_i. Note that the feedback effort can not exceed the total number of workers n_{worker}. Similarly, one can adopt a worker point of view: the set of tasks answered by a worker w_j is denoted

$$\mathscr{T}(w_j) = \left\{ i \in [n_{\text{task}}] \ : \ w_j \text{ answered } x_i \right\}. \tag{2}$$

The cardinal $|\mathscr{T}(w_j)|$ is called the workerload of w_j. The final dataset can then be decomposed as:

$$\mathscr{D}_{\text{train}} := \bigcup_{i \in [n_{\text{task}}]} \left\{ (x_i, (y_i^{(j)})) \text{ for } j \in \mathscr{A}(x_i) \right\} = \bigcup_{j \in [n_{\text{worker}}]} \left\{ (x_i, (y_i^{(j)})) \text{ for } i \in \mathscr{T}(w_j) \right\} .$$

In this article, we do not address the setting where workers report their self-confidence (Yasmin et al. 2022), nor settings where workers are presented a trapping set – *i.e* a subset of tasks where the ground truth is known to evaluate them with known labels (Khattak 2017).

2.2 Storing crowdsourced datasets in `peerannot`

Crowdsourced datasets come in various forms. To store crowdsourcing datasets efficiently and in a standardized way, `peerannot` proposes the following structure, where each dataset corresponds to a folder. Let us set up a toy dataset example to understand the data structure and how to store it.

Listing 1 Dataset storage tree structure.

```
datasetname
        train
             class1
                  imagename-<key>.png
                  ...
                  anotherimagename-<anotherkey>.png
             ...
             classK
        val
        test
        metadata.json
        answers.json
```

The `answers.json` file stores the different votes for each task as described in Figure 2. Thus, for example for an image named `smiley_face-1`, the associated labels are stored in the `answers.json` at the key numbered `1`. This key identification system allows us to track directly from the filename the crowdsourced labels without having to rely on multiple indexing files as can be traditionally proposed. Furthermore, storing labels in a dictionary is more memory-friendly than having an array of size `(n_task,n_worker)` and writing $y_i^{(j)} = -1$ when the worker w_j did not see the task x_i and $y_i^{(j)} \in [K]$ otherwise.

In Figure 2, there are three tasks, $n_{\text{worker}} = 4$ workers and $K = 2$ classes. Any available task should be stored in a single file whose name follows the convention described in Listing 1. These files are spread into a `train`, `val` and `test` subdir as in `ImageFolder` datasets from `torchvision`

Finally, a `metadata.json` file includes relevant information related to the crowdsourcing experiment such as the number of workers, the number of tasks, *etc.* For example, a minimal `metadata.json` file for the toy dataset presented in Figure 2 is:

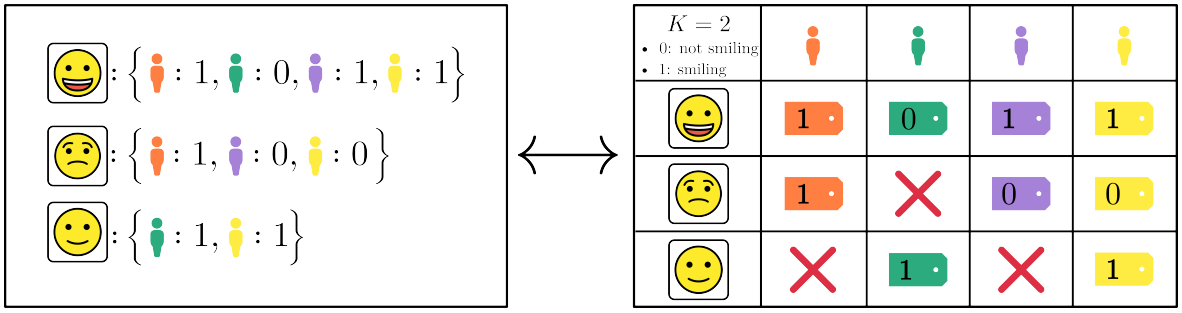


Figure 2: Data storage for the `toy-data` crowdsourced dataset, a binary classification problem ($K = 2$, smiling/not smiling) on recognizing smiling faces. (left: how data is stored in `peerannot` in a file `answers.json`, right: data collected)

```
{
    "name": "toy-data",
    "n_classes": 2,
    "n_workers": 4,
    "n_tasks": 3
}
```

The `toy-data` example dataset is available as an example in the `peerannot` repository. Classical datasets in crowdsourcing such as `CIFAR-10H` (Peterson et al. 2019) and `LabelMe` (Rodrigues, Pereira, and Ribeiro 2014) can be installed directly using `peerannot`. To install them, run the `install` command from `peerannot`:

```
! peerannot install ./datasets/labelme/labelme.py
! peerannot install ./datasets/cifar10H/cifar10h.py
```

For both `CIFAR-10H` and `LabelMe`, the dataset was originally released in classical supervised learning form (without crowdsourcing). These labels are used as ground truth in evaluations and visualizations. However, we emphasize that crowdsourcing strategies do not rely on the ground truth (only on the workers' answers).

```
import torch
import seaborn as sns
import matplotlib.pyplot as plt
from PIL import Image
import numpy as np
from pathlib import Path
import json
import matplotlib.ticker as mtick
import pandas as pd
sns.set_style("whitegrid")
import utils as utx

utx.figure_3()
```

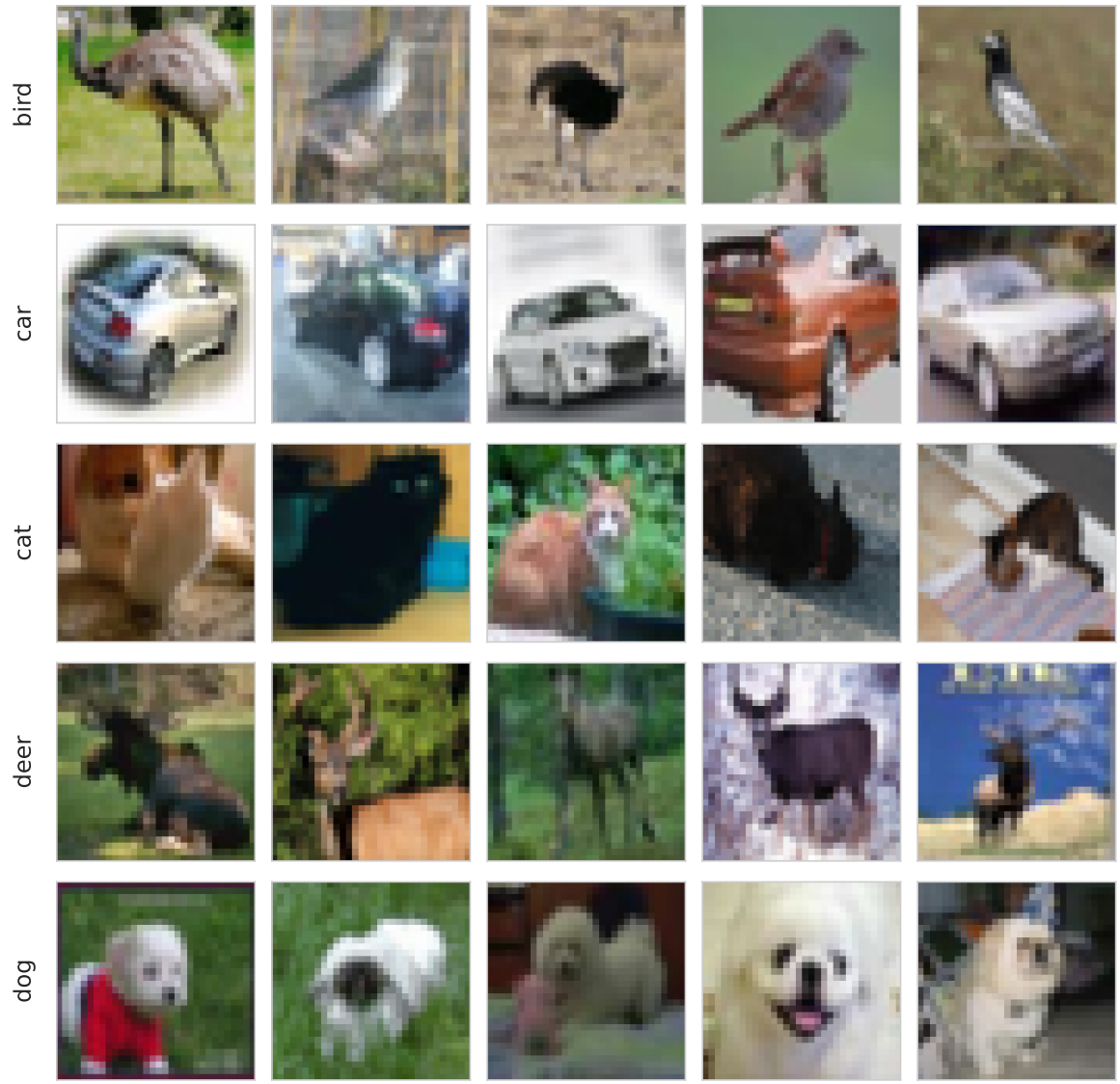


Figure 3: Example of images from CIFAR-10H. We display images rowise according to the ground truth label given initially in CIFAR-10.

Examples of `CIFAR-10H` images are available in Figure 3, and `LabelMe` examples in Figure 4 here below.

```
utx.figure_4()
```

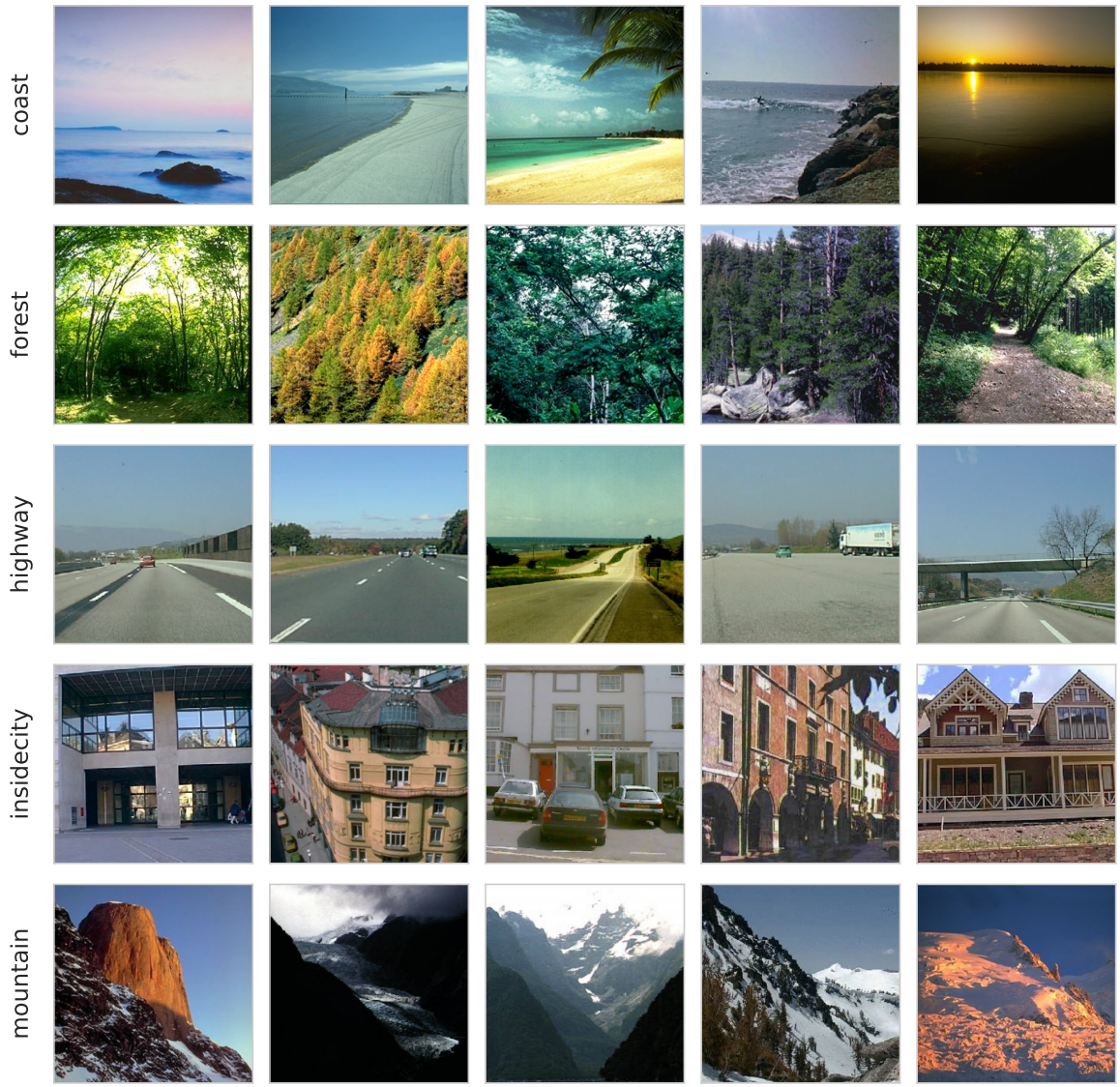


Figure 4: Example of images from LabelMe. We display images rowise according to the ground truth label given with the crowdsourced data.

Each of these tasks has been assigned a ground truth label by the dataset's authors. Crowdsourcing votes however bring additional information about possible confusions (see Figure 5).

```
utx.figure_5()
```

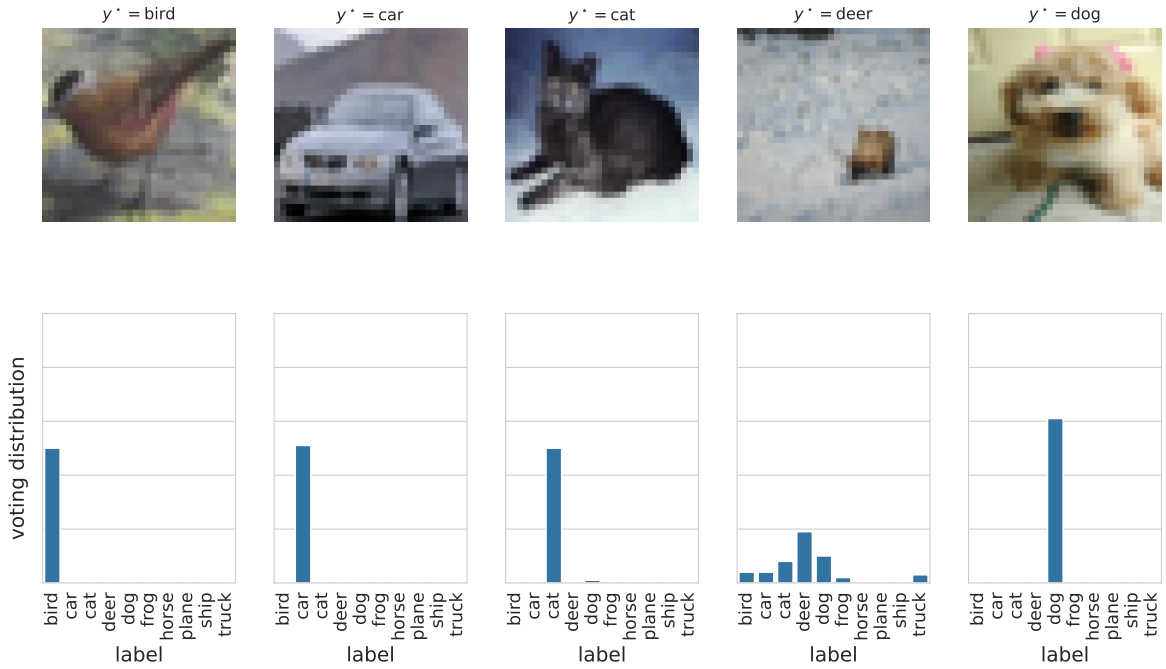


Figure 5: Example of crowdsourced images from CIFAR-10H. Each task has been labelled by multiple workers. We display the associated voting distribution over the possible classes. In addition, a ground truth label is provided using the original CIFAR-10 dataset. This ground truth is only used for performance evaluation.

3 Aggregation strategies in crowdsourcing

The first question we address with `peerannot` is: *How to aggregate multiple labels into a single label from crowdsourced tasks?* The aggregation step can lead to two types of learnable labels $\hat{y}_i \in \Delta_K$ (where Δ_K is the simplex of dimension $K-1$: $\Delta_K = \{p \in [K] : \sum_{k=1}^{K} p_k = 1, p_k \geq 0\}$) depending on the use case for each task $x_i, i = 1, \dots, n_{\text{task}}$:

- a **hard** label: $\hat{y}_i$ is a Dirac distribution, this can be encoded as a classical label in $[K]$,
- a **soft** label: $\hat{y}_i \in \Delta_K$ can represent any probability distribution on $[K]$. In that case, each coordinate of the $K-$ dimensional vector $\hat{y}_i$ represents the probability to belong to the given class.

Learning from soft labels has been shown to improve learning performance and make the classifier learn the task ambiguity (Zhang et al. 2018; Peterson et al. 2019; Park and Caragea 2022). However, crowdsourcing is often used as a stepping stone to create a new dataset. We usually expect a classification dataset to associate a task x_i to a single label and not a full probability distribution. In this case, we recommend to release the anonymous answered labels and the aggregation strategy used to reach a consensus on a single label. With `peerannot`, both soft and hard labels can be produced.

Note that when a strategy produces a soft label, a hard label can be easily induced by taking the mode, *i.e.*, the class achieving the maximum probability.

Moreover, the concept of confusion matrices has been commonly used to represent worker abilities. A confusion matrix $\pi^{(j)} \in \mathbb{R}^{K \times K}$ of a worker w_j is defined such that $\pi^{(j)}_{k,\ell} = \mathbb{P}(y_i^{(j)} = \ell | y_i^\star = k)$.

```
!peerannot simulate --n-worker=10 --n-task=100 --n-classes=5 \
  --strategy hammer-spammer --feedback=5 --seed=0 \
```

```
  --folder ./simus/hammer_spammer
!peerannot simulate --n-worker=10 --n-task=100 --n-classes=5 \
  --strategy independent-confusion --feedback=5 --seed=0 \
  --folder ./simus/hammer_spammer/confusion
```

```
mats = np.load("./simus/hammer_spammer/matrices.npy")
mats_confu = np.load("./simus/hammer_spammer/confusion/matrices.npy")

utx.figure_6(mats, mats_confu)
```

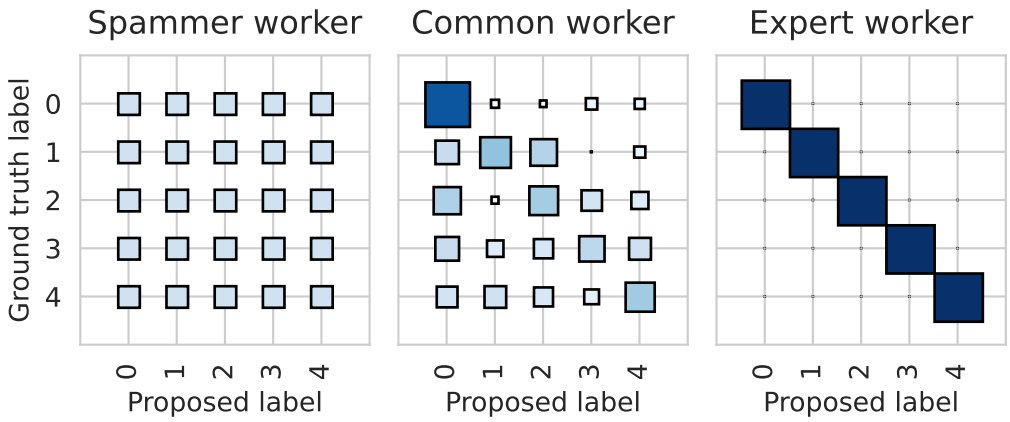


Figure 6: Three types of profiles of worker confusion matrices. The spammer answers independent from the ground truth label. Expert workers identify classes without mistakes. In practice common workers are good for some classes but might confuse two (ore more) labels. All workers are simulated using the `peerannot simulate` command presented in Section 3.2.

In Figure 6, we illustrate multiple profiles of workers. In particular, one type of worker that can hurt data quality is the spammer. Raykar and Yu (2011) defined a spammer as a worker that answers randomly as:

$$\forall k \in [K],\ \mathbb{P}(y_i^{(j)} = k | y_i^\star) = \mathbb{P}(y_i^{(j)} = k)\ . \tag{3}$$

As the probability distribution by row represent the confusion given a ground truth label, the spammer has a confusion matrix with near-identical rows. Apart from the spammer, common mistakes often involve workers ming-up one or several classes. Expert workers have a confusion matrix near the identity matrix.

3.1 Classical models

We list below the most classical aggregation strategies used in crowdsourcing.

3.1.1 Majority vote (MV)

The most intuitive way to create a label from multiple answers for any type of crowdsourced task is to take the majority vote (MV). Yet, this strategy has many shortcomings (James 1998) – there is no noise model, no worker reliability estimated, no task difficulty involved and especially no way to remove poorly performing workers. This standard choice can be expressed as:

$$\hat{y}_i^{\text{MV}} = \underset{k \in [K]}{\text{argmax}} \sum_{j \in \mathscr{A}(x_i)} \mathbf{1}_{\{y_i^{(j)} = k\}}\ .$$

3.1.2 Naive soft (NS)

One pitfall with MV is that the label produced is hard, hence the ambiguity is discarded by construction. A simple remedy consists in using the Naive Soft (NS) labeling, *i.e.* output the empirical distribution as the task label:

$$\hat{y}_i^{\mathrm{NS}} = \left(\frac{1}{|\mathscr{A}(x_i)|} \sum_{j \in \mathscr{A}(x_i)} \mathbf{1}_{\{y_i^{(j)}=k\}} \right)_{j \in [K]} .$$

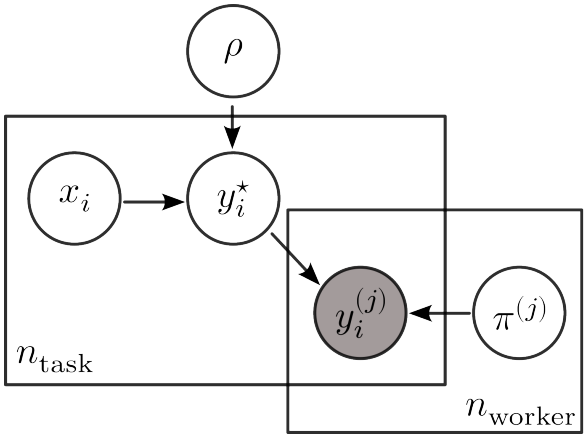
With the NS label, we keep the ambiguity, but all workers and all tasks are put on the same level. In practice, it is known that each worker comes with their abilities, thus modeling this knowledge can produce better results.

3.1.3 Dawid and Skene (DS)

Refining the aggregation, researchers have proposed a noise model to take into account the workers' abilities. The Dawid and Skene's (DS) model (Dawid and Skene 1979) is one of the must studied (Gao and Zhou 2013) and applied (Servajean et al. 2017; Rodrigues and Pereira 2018). These types of models are most often optimized using EM-based procedures. Assuming the workers are answering tasks independently, this model boils down to model pairwise confusions between each possible class. Each worker w_j is assigned a confusion matrix $\pi^{(j)} \in \mathbb{R}^{K \times K}$ as described in Section 3. The model assumes that for a task x_i, conditionally on the true label $y_i^\star = k$ the label distribution of the worker's answer follows a multinomial distribution with probabilities $\pi_{k,\cdot}^{(j)}$ for each worker. Each class has a prevalence $\rho_k = \mathbb{P}(y_i^\star = k)$ to appear in the dataset. Using the independence between workers, we obtain the following likelihood to maximize (with latent variables ρ, $\pi = \{\pi^{(j)}\}_j$ and $T = \{T_{i,k}\}_{i,k}$ and observed variables $\{y_i^{(j)}\}_{i,j}$):

$$\arg\max_{\rho,\pi,T} \prod_{i \in [n_{\mathtt{task}}]} \prod_{k \in [K]} \left[\rho_k \prod_{j \in [n_{\mathtt{worker}}]} \prod_{\ell \in [K]} \left(\pi_{k,\ell}^{(j)}\right)^{\mathbf{1}_{\{y_i^{(j)}=\ell\}}} \right]^{T_{i,k}},$$

with $T_{i,k} = \mathbf{1}_{\{y_i^\star = k\}}$. The final aggregated soft label is $\hat{y}_i^{\mathrm{DS}} = T_{i,\cdot}$.



- $\rho \in \Delta_K$: prevalence
- $x_i \in \mathcal{X}$: task
- $y_i^\star \in [K]$: true label (unobserved)
- $y_i^{(j)} \in [K]$: label observed
- $\pi^{(j)} \in \mathbb{R}^{K \times K}$: confusion matrix

Figure 7: Bayesian plate notation for the DS model

3.1.4 Variations around the DS model

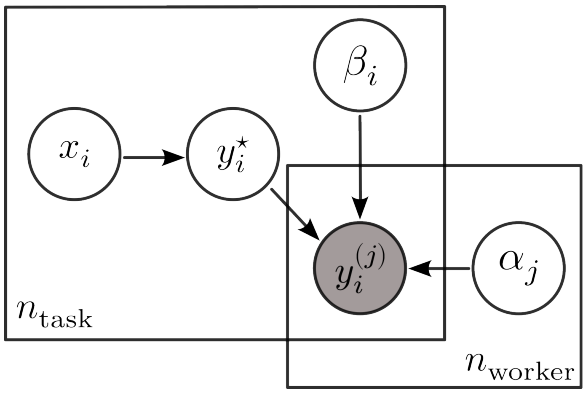
Many variants of the DS model have been proposed in the literature, using Dirichlet priors on the confusion matrices (Passonneau and Carpenter 2014), using $1 \leq L \leq n_{\mathrm{worker}}$ clusters of workers

(Imamura, Sato, and Sugiyama 2018) (DSWC) or even faster implementation that produces only hard labels (Sinha, Rao, and Balasubramanian 2018).

In particular, the DSWC strategy (Dawid and Skene with Worker Clustering) highly reduces the dimension of the parameters in the DS model. In the original model, there are $K^2 \times n_{\text{worker}}$ parameters to be estimated for the confusion matrices only. The DSWC model reduces them to $K^2 \times L + L$ parameters. Indeed, there are L confusion matrices $\Lambda = \{\Lambda_1, \dots, \Lambda_L\}$ and the confusion matrix of a cluster is assumed drawn from a multinomial distribution with weights $(\tau_1, \dots, \tau_L) \in \Delta_L$ over Λ, such that $\mathbb{P}(\pi^{(j)} = \Lambda_\ell) = \tau_\ell$.

3.1.5 Generative model of Labels, Abilities, and Difficulties (GLAD)

Finally, we present the GLAD model (Whitehill et al. 2009) that not only takes into account the worker's ability, but also the task difficulty in the noise model. The likelihood is optimized using an EM algorithm to recover the soft label $\hat{y}_i^{\text{GLAD}}$.



- $x_i \in \mathcal{X}$: task
- $y_i^\star \in [K]$: true label (unobserved)
- $y_i^{(j)} \in [K]$: label observed
- $\alpha_j \in \mathbb{R}$: worker reliability
- $\beta_i \in \mathbb{R}_\star^+$: task difficulty

Figure 8: Bayesian plate notation for the GLAD model

Denoting $\alpha_j \in \mathbb{R}$ the worker ability (the higher the better) and $\beta_i \in \mathbb{R}_\star^+$ the task's difficulty (the higher the easier), the model noise is:

$$\mathbb{P}(y_i^{(j)} = y_i^\star | \alpha_j, \beta_i) = \frac{1}{1 + \exp(-\alpha_j \beta_i)} \ .$$

GLAD's model also assumes that the errors are uniform across wrong labels, thus:

$$\forall k \in [K],\ \mathbb{P}(y_i^{(j)} = k | y_i^\star \neq k, \alpha_j, \beta_i) = \frac{1}{K-1}\left(1 - \frac{1}{1 + \exp(-\alpha_j \beta_i)}\right) \ .$$

This results in estimating $n_{\text{worker}} + n_{\text{task}}$ parameters.

3.1.6 Aggregation strategies in `peerannot`

All of these aggregation strategies – and more – are available in the `peerannot` library from the `peerannot.models` module. Each model is a class object in its own `Python` file. It inherits from the `CrowdModel` template class and is defined with at least two methods:

- `run`: includes the optimization procedure to obtain needed weights (*e.g.* the EM algorithm for the DS model),
- `get_probas`: returns the soft labels output for each task.

3.2 Experiments and evaluation of label aggregation strategies

One way to evaluate the label aggregation strategies is to measure their accuracy. This means that the underlying ground truth must be known – at least for a representative subset. As the set of n_{task} can be seen as a training set for a future classifier, we denote this metric AccTrain on a dataset $\mathscr{D}$ for some given aggregated label $(\hat{y}_i)_i$ as:

$$\text{AccTrain}(\mathscr{D}) = \frac{1}{|\mathscr{D}|} \sum_{i=1}^{|\mathscr{D}|} \mathbf{1}_{\{y_i^\star = \text{argmax}_{k \in [K]} (\hat{y}_i)_k\}} \ .$$

In the following, we write AccTrain for $\text{AccTrain}(\mathscr{D}_{\text{train}})$ as we only consider the full training set so there is no ambiguity. While this metric is useful, in practice there are a few arguable issues:

- the AccTrain metric does not consider the ambiguity of the soft label, only the most probable class, whereas in some contexts ambiguity can be informative,
- in supervised learning one objective is to identify difficult or mislabeled tasks (Pleiss et al. 2020; Lefort et al. 2022), pruning those tasks can easily artificially improve the AccTrain, but there is no guarantee over the predictive performance of a model based on the newly pruned dataset,
- in practice, ground truth labels are unknown, thus this metric would not be computable.

We first consider classical simulation settings in the literature that can easily be created and reproduced using `peerannot`. For each dataset, we present the distribution of the number of workers per task $(|\mathscr{A}(x_i)|)_i$ Equation 1 on the right and the distribution of the number of tasks per worker $(|\mathscr{T}(w_j)|)_j$ Equation 2 on the left.

3.2.1 Simulated independent mistakes

The independent mistakes setting considers that each worker w_j answers follows a multinomial distribution with weights given at the row $y_i^\star$ of their confusion matrix $\pi^{(j)} \in \mathbb{R}^{K \times K}$. Each confusion row in the confusion matrix is generated uniformly in the simplex. Then, we make the matrix diagonally dominant (to represent non-adversarial workers) by switching the diagonal term with the maximum value by row. Answers are independent of one another as each matrix is generated independently and each worker answers independently of other workers. In this setting, the DS model is expected to perform better with enough data as we are simulating data from its assumed noise model.

We simulate $n_{\text{task}} = 200$ tasks and $n_{\text{worker}} = 30$ workers with $K = 5$ possible classes. Each task x_i receives $|\mathscr{A}(x_i)| = 10$ labels. With 200 tasks and 30 workers, asking for 10 leads to around $\frac{200 \times 10}{30} \simeq 67$ tasks per worker (with variations due to randomness in the affectations).

```
! peerannot simulate --n-worker=30 --n-task=200  --n-classes=5 \
                     --strategy independent-confusion \
                     --feedback=10 --seed 0 \
                     --folder ./simus/independent
```

```
from peerannot.helpers.helpers_visu import feedback_effort, working_load
import matplotlib.pyplot as plt
from matplotlib.ticker import MaxNLocator
from pathlib import Path

votes_path = Path.cwd() / "simus" / "independent" / "answers.json"
metadata_path = Path.cwd() / "simus" / "independent" / "metadata.json"
```

```
efforts = feedback_effort(votes_path)
workerload = working_load(votes_path, metadata_path)
feedback = feedback_effort(votes_path)
utx.figure_simulations(workerload, feedback)
plt.show()
```

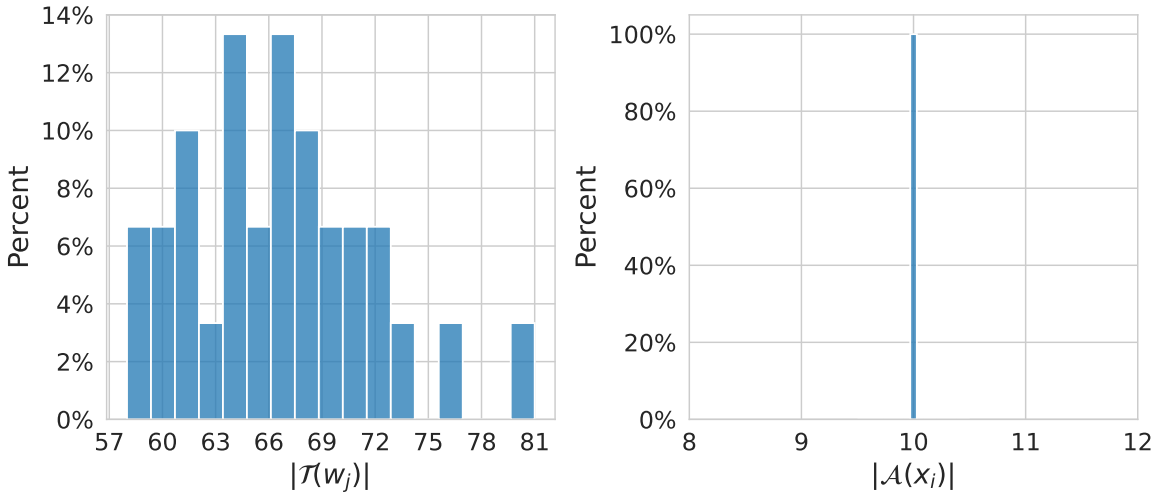


Figure 9: Distribution of number of tasks given per worker (left) and number of labels per task (right) in the independent mistakes setting.

With the obtained answers, we can look at the aforementioned aggregation strategies performance:

```
for strat in ["MV", "NaiveSoft", "DS", "GLAD", "DSWC[L=5]", "DSWC[L=10]"]:
  ! peerannot aggregate ./simus/independent/ -s {strat}
```

```
import pandas as pd
import numpy as np
from IPython.display import display
simu_indep = Path.cwd() / 'simus' / "independent"
results = {
  "mv": [], "naivesoft": [], "glad": [],
  "ds": [], "dswc[l=5]": [], "dswc[l=10]": []
  }
for strategy in results.keys():
  path_labels = simu_indep / "labels" / f"labels_independent-confusion_{strategy}.npy"
  ground_truth = np.load(simu_indep / "ground_truth.npy")
  labels = np.load(path_labels)
  acc = (
          np.mean(labels == ground_truth)
          if labels.ndim == 1
          else np.mean(
              np.argmax(labels, axis=1)
              == ground_truth
          )
        )
  results[strategy].append(acc)
results["NS"] = results["naivesoft"]
```

Table 1: AccTrain metric on simulated independent mistakes considering classical feature-blind label aggregation strategies

Table 2

	MV	GLAD	DS	DSWC[L=5]	DSWC[L=10]	NS
AccTrain	0.740	0.775	0.890	0.775	0.770	0.760

```
results.pop("naivesoft")
results = pd.DataFrame(results, index=['AccTrain'])
results.columns = map(str.upper, results.columns)
results = results.style.set_table_styles(
  [dict(selector='th', props=[('text-align', 'center')])]
  )
results.set_properties(**{'text-align': 'center'})
results = results.format(precision=3)
display(results)
```

As expected by the simulation framework, Table 1 fits the DS model, thus leading to better accuracy to retrieve the simulated labels for the DS strategy. The MV and NS aggregations do not consider any worker-ability scoring or the task's difficulty and performs the worse.

Remark. `peerannot` can also simulate datasets with an imbalanced number of votes chosen uniformly at random between 1 and the number of workers available). For example:

```
! peerannot simulate --n-worker=30 --n-task=200  --n-classes=5 \
                     --strategy independent-confusion \
                     --imbalance-votes \
                     --seed 0 \
                     --folder ./simus/independent-imbalanced/
```

```
sns.set_style("whitegrid")

votes_path = Path.cwd() / "simus" / "independent-imbalanced" / "answers.json"
metadata_path = Path.cwd() / "simus" / "independent-imbalanced" / "metadata.json"
efforts = feedback_effort(votes_path)
workerload = working_load(votes_path, metadata_path)
feedback = feedback_effort(votes_path)
utx.figure_simulations(workerload, feedback)
plt.show()
```

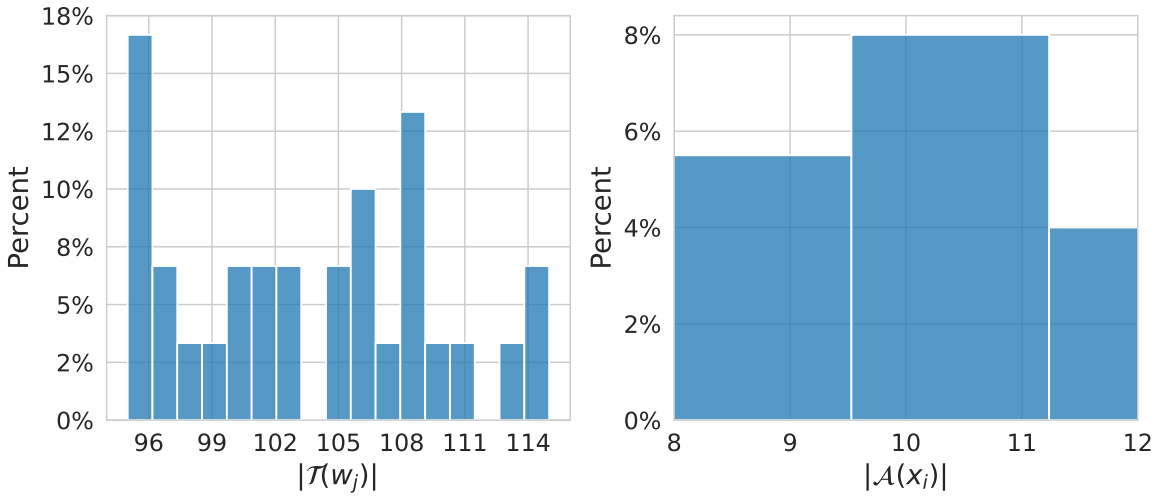


Figure 10: Distribution of number of tasks given per worker (left) and number of labels per task (right) in the independent mistakes setting with voting imbalance enabled.

With the obtained answers, we can look at the aforementioned aggregation strategies performance:

```
for strat in ["MV", "NaiveSoft", "DS", "GLAD", "DSWC[L=5]", "DSWC[L=10]"]:
  ! peerannot aggregate ./simus/independent-imbalanced/ -s {strat}
```

```
import pandas as pd
import numpy as np
from IPython.display import display
simu_indep = Path.cwd() / 'simus' / "independent-imbalanced"
results = {
  "mv": [], "naivesoft": [], "glad": [],
  "ds": [], "dswc[l=5]": [], "dswc[l=10]": []
  }
for strategy in results.keys():
  path_labels = simu_indep / "labels" / f"labels_independent-confusion_{strategy}.npy"
  ground_truth = np.load(simu_indep / "ground_truth.npy")
  labels = np.load(path_labels)
  acc = (
          np.mean(labels == ground_truth)
          if labels.ndim == 1
          else np.mean(
              np.argmax(labels, axis=1)
              == ground_truth
          )
        )
  results[strategy].append(acc)
results["NS"] = results["naivesoft"]
results.pop("naivesoft")
results = pd.DataFrame(results, index=['AccTrain'])
results.columns = map(str.upper, results.columns)
results = results.style.set_table_styles([dict(selector='th', props=[('text-align', 'center')])])
results.set_properties(**{'text-align': 'center'})
results = results.format(precision=3)
```

Table 2: AccTrain metric on simulated independent mistakes with an imbalanced number of votes per task considering classical feature-blind label aggregation strategies

Table 3

	MV	GLAD	DS	DSWC[L=5]	DSWC[L=10]	NS
AccTrain	0.815	0.810	0.895	0.845	0.840	0.830

```
display(results)
```

While more realistic, working with an imbalanced number of votes per task can lead to disrupting orders of performance for some strategies (here GLAD is downgraded with respect to other strategies).

3.2.2 Simulated correlated mistakes

The correlated mistakes are also known as the student-teacher or junior-expert setting (Cao et al. (2019)). Consider that the crowd of workers is divided into two categories: teachers and students (with $n_{\text{teacher}} + n_{\text{student}} = n_{\text{worker}}$). Each student is randomly assigned to one teacher at the beginning of the experiment. We generate the (diagonally dominant as in Section 3.2.1) confusion matrices of each teacher and the student share the same confusion matrix as their associated teacher. Hence, clustering strategies are expected to perform best in this context. Then, they all answer independently, following a multinomial distribution with weights given at the row $y_i^\star$ of their confusion matrix $\pi^{(j)} \in \mathbb{R}^{K \times K}$.

We simulate $n_{\text{task}} = 200$ tasks and $n_{\text{worker}} = 30$ with 80% of students in the crowd. There are $K = 5$ possible classes. Each task receives $|\mathscr{A}(x_i)| = 10$ labels.

```
! peerannot simulate --n-worker=30 --n-task=200  --n-classes=5 \
                     --strategy student-teacher \
                     --ratio 0.8 \
                     --feedback=10 --seed 0 \
                     --folder ./simus/student_teacher
```

```
votes_path = Path.cwd() / "simus" / "student_teacher" / "answers.json"
metadata_path = Path.cwd() / "simus" / "student_teacher" / "metadata.json"
efforts = feedback_effort(votes_path)
workerload = working_load(votes_path, metadata_path)
feedback = feedback_effort(votes_path)
utx.figure_simulations(workerload, feedback)
plt.show()
```

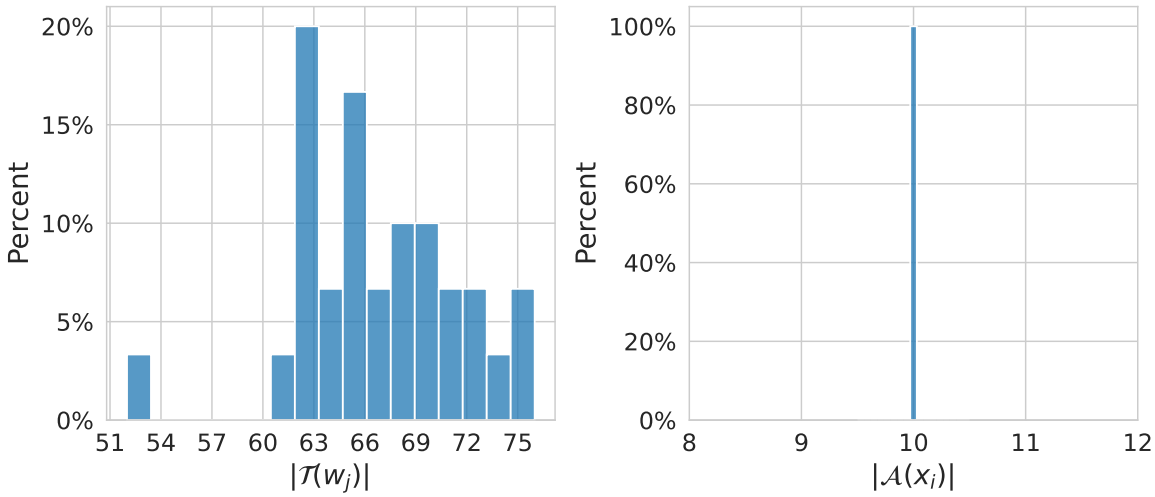


Figure 11: Distribution of number of tasks given per worker (left) and number of labels per task (right) in the correlated mistakes setting.

With the obtained answers, we can look at the aforementioned aggregation strategies performance:

```
for strat in ["MV", "NaiveSoft", "DS", "GLAD", "DSWC[L=5]", "DSWC[L=6]", "DSWC[L=10]"]:
  ! peerannot aggregate ./simus/student_teacher/ -s {strat}
```

```
simu_corr = Path.cwd() / 'simus' / "student_teacher"
results = {"mv": [], "naivesoft": [], "glad": [], "ds": [], "dswc[l=5]": [], "dswc[l=6]": [], "dsw
for strategy in results.keys():
  path_labels = simu_corr / "labels" / f"labels_student-teacher_{strategy}.npy"
  ground_truth = np.load(simu_corr / "ground_truth.npy")
  labels = np.load(path_labels)
  acc = (
          np.mean(labels == ground_truth)
          if labels.ndim == 1
          else np.mean(
              np.argmax(labels, axis=1)
              == ground_truth
          )
        )
  results[strategy].append(acc)
results["NS"] = results["naivesoft"]
results.pop("naivesoft")
results = pd.DataFrame(results, index=['AccTrain'])
results.columns = map(str.upper, results.columns)
results = results.style.set_table_styles([dict(selector='th', props=[('text-align', 'center')])])
results.set_properties(**{'text-align': 'center'})
results = results.format(precision=3)
display(results)
```

With Table 3, we see that with correlated data (24 students and 6 teachers), using 5 confusion matrices with DSWC[L=5] outperforms the vanilla DS strategy that does not consider the correlations. And the best-performing method here estimates only 10 confusion matrices (instead of 30 for the vanilla DS model).

Table 3: AccTrain metric on simulated correlated mistakes considering classical feature-blind label aggregation strategies

Table 4

	MV	GLAD	DS	DSWC[L=5]	DSWC[L=6]	DSWC[L=10]	NS
AccTrain	0.715	0.645	0.755	0.795	0.780	0.815	0.690

3.2.3 Simulated mistakes with discrete difficulty levels on tasks

For the final simulation setting, we consider the so called discrete difficulty presented in Whitehill et al. (2009). Contrary to other simulations, we here consider that workers belong to two levels of abilities: `good` or `bad`, and tasks have two levels of difficulty: `easy` or `hard`. The keyword `ratio-diff` indicates the prevalence of each level of difficulty, it is defined as the ratio of `easy` tasks over `hard` tasks:

$$\texttt{ratio-diff} = \frac{\mathbb{P}(\texttt{easy})}{\mathbb{P}(\texttt{hard})} \text{ with } \mathbb{P}(\texttt{easy}) + \mathbb{P}(\texttt{hard}) = 1 \ .$$

Difficulties are then drawn at random. Tasks that are `easy` are answered correctly by every worker. Tasks that are `hard` are answered following the confusion matrix assigned to each worker (as in Section 3.2.1). Each worker then answers independently to the presented tasks.

We simulate $n_{\text{task}} = 500$ tasks and $n_{\text{worker}} = 100$ with 35% of good workers in the crowd and 50% of easy tasks. There are $K = 5$ possible classes. Each task receives $|\mathscr{A}(x_i)| = 10$ labels.

```
! peerannot simulate --n-worker=100 --n-task=200  --n-classes=5 \
                     --strategy discrete-difficulty \
                     --ratio 0.35 --ratio-diff 1 \
                     --feedback 10 --seed 0 \
                     --folder ./simus/discrete_difficulty
```

```
votes_path = Path.cwd() / "simus" / "discrete_difficulty" / "answers.json"
metadata_path = Path.cwd() / "simus" / "discrete_difficulty" / "metadata.json"
efforts = feedback_effort(votes_path)
workerload = working_load(votes_path, metadata_path)
feedback = feedback_effort(votes_path)
utx.figure_simulations(workerload, feedback)
plt.show()
```

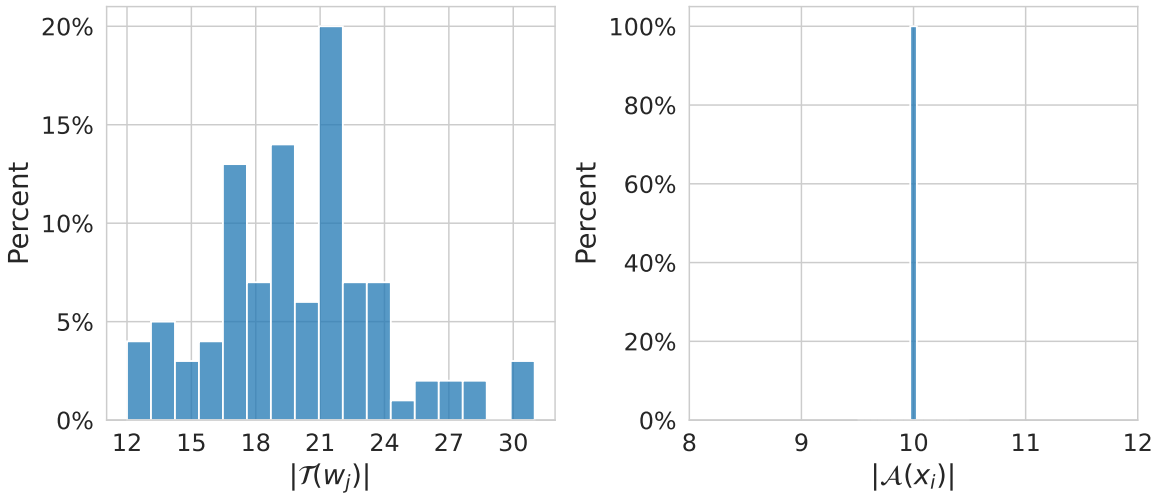


Figure 12: Distribution of number of tasks given per worker (left) and number of labels per task (right) in the setting with simulated discrete difficulty levels.

With the obtained answers, we can look at the aforementioned aggregation strategies performance:

```
for strat in ["MV", "NaiveSoft", "DS", "GLAD", "DSWC[L=2]", "DSWC[L=5]"]:
  ! peerannot aggregate ./simus/discrete_difficulty/ -s {strat}
```

```
simu_corr = Path.cwd() / 'simus' / "discrete_difficulty"
results = {
  "mv": [], "naivesoft": [], "glad": [],
  "ds": [], "dswc[l=2]": [], "dswc[l=5]": []
  }
for strategy in results.keys():
  path_labels = simu_corr / "labels" / f"labels_discrete-difficulty_{strategy}.npy"
  ground_truth = np.load(simu_corr / "ground_truth.npy")
  labels = np.load(path_labels)
  acc = (
          np.mean(labels == ground_truth)
          if labels.ndim == 1
          else np.mean(
              np.argmax(labels, axis=1)
              == ground_truth
          )
        )
  results[strategy].append(acc)
results["NS"] = results["naivesoft"]
results.pop("naivesoft")
results = pd.DataFrame(results, index=['AccTrain'])
results.columns = map(str.upper, results.columns)
results = results.style.set_table_styles([dict(selector='th', props=[('text-align', 'center')])])
results.set_properties(**{'text-align': 'center'})
results = results.format(precision=3)
display(results)
```

Finally, in this setting involving task difficulty coefficients, the only strategy that involves a latent

Table 4: AccTrain metric on simulated mistakes when tasks are associated a difficulty level considering classical feature-blind label aggregation strategies

Table 5

	MV	GLAD	DS	DSWC[L=2]	DSWC[L=5]	NS
AccTrain	0.815	0.845	0.810	0.600	0.660	0.790

variable for the task difficulty, knowing GLAD, outperforms the other strategies (see Table 4). Note that in this case, creating clusters of answers leads to worse decisions than an MV aggregation.

To summarize our simulations, we see that depending on workers answering strategies, different latent variable models perform best. However, these are unknown outside of a simulation framework, thus if we want to obtain labels from multiple responses, we need to investigate multiple models. This can be done easily with `peerannot` as we demonstrated using the `aggregate` module. However, one might not want to generate a label, simply learn a classifier to predict labels on unseen data. This leads us to another module part of `peerannot`.

4 Learning from crowdsourced tasks

Commonly, tasks are crowdsourced to create a large annotated training set as modern machine learning models require more and more data. The aggregation step then simply becomes the first step in the complete learning pipeline. However, instead of aggregating labels, modern neural networks are directly trained end-to-end from multiple noisy labels.

4.1 Popular models

In recent years, directly learning a classifier from noisy labels was introduced. Two of the most used models: CrowdLayer (Rodrigues and Pereira 2018) and CoNAL (Chu, Ma, and Wang 2021), are directly available in `peerannot`. These two learning strategies directly incorporate a DS-inspired noise model in the neural network's architecture.

4.1.1 CrowdLayer

CrowdLayer trains a classifier with noisy labels as follows. Let the scores (logits) output by a given classifier neural network $\mathscr{C}$ be $z_i = \mathscr{C}(x_i)$. Then CrowdLayer adds as a last layer $\pi \in \mathbb{R}^{n_{\text{worker}} \times K \times K}$, the tensor of all $\pi^{(j)}$'s such that the crossentropy loss (CE) is adapted to the crowdsourcing setting into $\mathscr{L}_{CE}^{\text{CrowdLayer}}$ and computed as:

$$\mathscr{L}_{CE}^{\text{CrowdLayer}}(x_i) = \sum_{j \in \mathscr{A}(x_i)} \text{CE}\left(\sigma\left(\pi^{(j)}\sigma(z_i)\right), y_i^{(j)}\right) \ ,$$

where the crossentropy loss for two distribution $u, v \in \Delta_K$ is defined as $\text{CE}(u, v) = \sum_{k \in [K]} u_k \log(v_k)$.

The confusion matrices of DS are taken into the network architecture as a new layer of weights to transform the output probabilities. The backbone classifier predicts a distribution that is then corrupted through the added layer to learn the worker-specific confusion.

4.1.2 CoNAL

For some datasets, it was noticed that global confusion occurs between the proposed classes. It is the case for example in the `LabelMe` dataset (Rodrigues et al. 2017) where classes overlap. In this case, Chu, Ma, and Wang (2021) proposed to extend the CrowdLayer model by adding global confusion matrix $\pi^g \in \mathbb{R}^{K\times K}$ to the model on top of each worker's confusion.

Given the output $z_i = \mathscr{C}(x_i) \in \mathbb{R}^K$ of a given classifier and task, CoNAL interpolates between the prediction corrected by local confusions $\pi^{(j)} z_i$ and the prediction corrected by a global confusion $\pi^g z_i$. The loss function is computed as follows:

$$\mathscr{L}_{CE}^{\text{CoNAL}}(x_i) = \sum_{j\in\mathscr{A}(x_i)} \text{CE}(h_i^{(j)}, y_i^{(j)}) \ ,$$
$$\text{with } h_i^{(j)} = \sigma\Big(\big(\omega_i^{(j)}\pi^g + (1-\omega_i^{(j)})\pi^{(j)}\big) z_i\Big) \ .$$

The interpolation weight $\omega_i^{(j)}$ is unobservable in practice. So, to compute $h_i^{(j)}$, the weight is obtained through an auxiliary network. This network takes as input the image and worker information and outputs a task-related vector v_i and a worker-related vector u_j of the same dimension. Finally, $w_i^{(j)} = (1 + \exp(-u_j^\top v_i))^{-1}$.

Both CrowdLayer and CoNAL model worker confusions directly in the classifier's weights to learn from the noisy collected labels and are available in `peerannot` as we will see in the following.

4.2 Prediction error when learning from crowdsourced tasks

The AccTrain metric presented in Section 3.2 might no longer be of interest when training a classifier. Classical error measurements involve a test dataset to estimate the generalization error. To do so, we present hereafter two error metrics. Assuming we trained our classifier $\mathscr{C}$ on a training set and that there is a test set available with known ground truths:

- the test accuracy is computed as $\frac{1}{n_{\text{test}}}\sum_{i=1}^{n_{\text{test}}} \mathbf{1}_{\{y_i^\star = \hat{y}_i\}}$.
- the expected calibration error (Guo et al. 2017) over M equally spaced bins $I_1, \dots, I_M$ partitionning the interval $[0,1]$, is computed as:

$$\text{ECE} = \sum_{m=1}^{M} \frac{|B_m|}{n_{\text{task}}} |\text{acc}(B_m) - \text{conf}(B_m)| \ ,$$

  with $B_m = \{x_i | \mathscr{C}(x_i)_{[1]} \in I_m\}$ the tasks with predicted probability in the m-th bin, $\text{acc}(B_m)$ the accuracy of the network for the samples in B_m and $\text{conf}(B_m)$ the associated empirical confidence. More precisely:

$$\text{acc}(B_m) = \frac{1}{|B_m|}\sum_{i\in B_m} \mathbf{1}(\hat{y}_i = y_i^\star) \quad \text{and} \quad \text{conf}(B_m) = \frac{1}{|B_m|}\sum_{i\in B_m} \sigma(\mathscr{C}(x_i))_{[1]} \ .$$

The accuracy represents how well the classifier generalizes, and the expected calibration error (ECE) quantifies the deviation between the accuracy and the confidence of the classifier. Modern neural networks are known to often be overconfident in their predictions (Guo et al. 2017). However, it has also been remarked that training on crowdsourced data, depending on the strategy, mitigates this confidence issue. That is why we propose to compare them both in our coming experiments. Note that the ECE error estimator is known to be biased (Gruber and Buettner 2022). Smaller training sets are known to have a higher ECE estimation error. And in the crowdsourcing setting, openly available datasets are often quite small.

4.3 Use case with `peerannot` on real datasets

Few real crowdsourcing experiments have been released publicly. Among the available ones, `CIFAR-10H` (Peterson et al. 2019) is one of the largest with 10000 tasks labeled by workers (the testing set of CIFAR-10). The main limitation of `CIFAR-10H` is that there are few disagreements between workers and a simple majority voting already leads to a near-perfect AccTrain error. Hence, comparing the impact of aggregation and end-to-end strategies might not be relevant (Peterson et al. 2019; Aitchison 2021), it is however a good benchmark for task difficulty identification and worker evaluation scoring.

The `LabelMe` dataset was extracted from crowdsourcing segmentation experiments and a subset of $K = 8$ classes was released in Rodrigues et al. (2017).

Let us use `peerannot` to train a VGG-16 with two dense layers on the `LabelMe` dataset. Note that this modification was introduced to reach state-of-the-art performance in (Chu, Ma, and Wang 2021). Other models from the `torchvision` library can be used, such as Resnets, Alexnet *etc.*

```
for strat in ["MV", "NaiveSoft", "DS", "GLAD"]:
  ! peerannot aggregate ./labelme/ -s {strat}
  ! peerannot train ./labelme -o labelme_${strat} \
    -K 8 --labels=./labelme/labels/labels_labelme_${strat}.npy \
    --model modellabelme --n-epochs 500 -m 50 -m 150 -m 250 \
    --scheduler=multistep --lr=0.01 --num-workers=8 \
    --pretrained --data-augmentation --optimizer=adam \
    --batch-size=32 --img-size=224 --seed=1
for strat in ["CrowdLayer", "CoNAL[scale=0]", "CoNAL[scale=1e-4]"]:
  ! peerannot aggregate-deep ./labelme -o labelme_${strat} \
    --answers ./labelme/answers.json -s ${strat} --model modellabelme \
    --img-size=224 --pretrained --n-classes=8 --n-epochs=500 --lr=0.001 \
    -m 300 -m 400 --scheduler=multistep --batch-size=228 --optimizer=adam \
    --num-workers=8 --data-augmentation --seed=1
```

```
# command to save separately a specific part of conal model (memory intensive otherwise)
path_ = Path.cwd() / "datasets" / "labelme"
best_conal = torch.load(path_ / "best_models" / "labelme_conal[scale=1e-4].pth",
map_location="cpu")
torch.save(best_conal["noise_adaptation"]["local_confusion_matrices"],
path_ / "best_models"/ "labelme_conal[scale=1e-4]_local_confusion.pth")
```

```
def highlight_max(s, props=''):
    return np.where(s == np.nanmax(s.values), props, '')

def highlight_min(s, props=''):
    return np.where(s == np.nanmin(s.values), props, '')

import json
dir_results = Path().cwd() / 'datasets' / "labelme" / "results"
meth, accuracy, ece = [], [], []
for res in dir_results.glob("modellabelme/*"):
  filename = res.stem
  _, mm = filename.split("_")
```

Table 5: Generalization performance on LabelMe dataset depending on the learning strategy from the crowdsourced labels. The network used is a VGG-16 with two dense layers for all methods.

Table 6

	method	AccTest	ECE
0	NS	81.061	0.189
1	DS	85.606	0.143
2	MV	86.448	0.136
3	CoNAL[scale=0]	87.205	0.117
4	CrowdLayer	87.542	0.124
5	GLAD	88.468	0.115
6	CoNAL[scale=1e-4]	88.889	0.112

```
  meth.append(mm)
  with open(res, "r") as f:
    dd = json.load(f)
    accuracy.append(dd["test_accuracy"])
    ece.append(dd["test_ece"])
results = pd.DataFrame(list(zip(meth, accuracy, ece)),
                       columns=["method", "AccTest", "ECE"])
results["method"] = [
  "NS", "CoNAL[scale=0]", "CrowdLayer", "CoNAL[scale=1e-4]", "MV", "DS", "GLAD"
  ]
results = results.sort_values(by="AccTest", ascending=True)
results.reset_index(drop=True, inplace=True)
results = results.style.set_table_styles([dict(selector='th', props=[
  ('text-align', 'center')])]
  )
results.set_properties(**{'text-align': 'center'})
results = results.format(precision=3)
results.apply(highlight_max, props='background-color:#e6ffe6;',
              axis=0, subset=["AccTest"])
results.apply(highlight_min, props='background-color:#e6ffe6;',
              axis=0, subset=["ECE"])
display(results)
```

As we can see, CoNAL strategy performs best. In this case, it is expected behavior as CoNAL was created for the `LabelMe` dataset. However, using `peerannot` we can look into **why modeling common confusion returns better results with this dataset**. To do so, we can explore the datasets from two points of view: worker-wise or task-wise in Section 5.

5 Exploring crowdsourced datasets

If a dataset requires crowdsourcing to be labeled, it is because expert knowledge is long and costly to obtain. In the era of big data, where datasets are built using web scraping (or using a platform like Amazon Mechanical Turk), citizen science is popular as it is an easy way to produce many labels.

However, mistakes and confusions happen during these experiments. Sometimes involuntarily (*e.g.* because the task is too hard or the worker is unable to differentiate between two classes) and sometimes voluntarily (*e.g.* the worker is a spammer).

Underlying all the learning models and aggregation strategies, the cornerstone of crowdsourcing is evaluating the trust we put in each worker depending on the presented task. And with the gamification of crowdsourcing (Servajean et al. 2016; Tinati et al. 2017), it has become essential to find scoring metrics both for workers and tasks to keep citizens in the loop so to speak. This is the purpose of the identification module in `peerannot`.

Our test cases are both the `CIFAR-10H` dataset and the `LabelMe` dataset to compare the worker and task evaluation depending on the number of votes collected. Indeed, the `LabelMe` dataset has only up to three votes per task whereas `CIFAR-10H` accounts for nearly fifty votes per task.

5.1 Exploring tasks' difficulty

To explore the tasks' intrinsic difficulty, we propose to compare three scoring metrics:

- the entropy of the NS distribution: the entropy measures the inherent uncertainty of the distribution to the possible outcomes. It is reliable with a big enough and not adversarial crowd. More formally:

$$\forall i \in [n_{\text{task}}],\ \text{Entropy}(\hat{y}_i^{NS}) = -\sum_{k\in[K]} (y_i^{NS})_k \log\left((y_i^{NS})_k\right) \quad .$$

- GLAD's scoring: by construction, Whitehill et al. (2009) introduced a scalar coefficient to score the difficulty of a task.
- the Weighted Area Under the Margins (WAUM): introduced by Lefort et al. (2022), this weighted area under the margins indicates how difficult it is for a classifier $\mathscr{C}$ to learn a task's label. This procedure is done with a budget of $T > 0$ epochs. Given the crowdsourced labels and the trust we have in each worker denoted $s^{(j)}(x_i) > 0$, the WAUM of a given task $x_i \in \mathscr{X}$ and a set of crowdsourced labels $\{y_i^{(j)}\}_j \in [K]^{|\mathscr{A}(x_i)|}$ is defined as:

$$\text{WAUM}(x_i) := \frac{1}{|\mathscr{A}(x_i)|} \sum_{j\in\mathscr{A}(x_i)} s^{(j)}(x_i) \left\{ \frac{1}{T}\sum_{t=1}^{T} \sigma(\mathscr{C}(x_i))_{y_i^{(j)}} - \sigma(\mathscr{C}(x_i))_{[2]} \right\} \quad .$$

  The weights $s^{(j)}(x_i)$ are computed à-la Servajean et al. (2017):

$$\forall j \in [n_{\texttt{worker}}] \forall i \in [n_{\text{task}}],\ s^{(j)}(x_i) = \left\langle \sigma(\mathscr{C}(x_i)), \text{diag}(\pi^{(j)}) \right\rangle \quad .$$

  The WAUM is a generalization of the AUM by Pleiss et al. (2020) to the crowdsourcing setting. A high WAUM indicates a high trust in the task classification by the network given the crowd labels. A low WAUM indicates a difficulty for the network to classify the task into the given classes (taking into consideration the trust we have in each worker for the task considered). Where other methods only consider the labels and not directly the tasks, the WAUM directly considers the learning trajectories to identify ambiguous tasks. One pitfall of the WAUM is that it is dependent of the architecture used.

Note that each of these statistics is useful in its context. The entropy can not be used in a setting with small $|\mathscr{A}(x_i)|$ (few labels per task), in particular for the `LabelMe` dataset it is uninformative. The WAUM can handle any number of labels, but the larger the better. However, as it uses a deep learning classifier, the WAUM needs the tasks $(x_i)_i$ in addition to the proposed labels while the other strategies are feature-blind.

5.1.1 CIFAR-10H dataset

First, let us consider a dataset with a large number of tasks, annotations and workers: the `CIFAR-10H` dataset by Peterson et al. (2019).

```
! peerannot identify ./datasets/cifar10H -s entropy -K 10 --labels ./datasets/cifar10H/answers.jso
! peerannot aggregate ./datasets/cifar10H/ -s GLAD
! peerannot identify ./datasets/cifar10H/ -K 10 --method WAUM \
            --labels ./datasets/cifar10H/answers.json --model resnet34 \
            --n-epochs 100 --lr=0.01 --img-size=32 --maxiter-DS=50 \
            --pretrained
```

```
import plotly.graph_objects as go
from plotly.subplots import make_subplots
from PIL import Image
import itertools

classes = (
    "plane",
    "car",
    "bird",
    "cat",
    "deer",
    "dog",
    "frog",
    "horse",
    "ship",
    "truck",
)

n_classes = 10
all_images = utx.load_data("cifar10H", n_classes, classes)
utx.generate_plot(n_classes, all_images, classes)
```

```
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```

Most difficult tasks identified depending on the strategy used (entropy, GLAD or WAUM) using a Resnet34.

```
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```

The entropy, GLAD's difficulty, and WAUM's difficulty each show different images as exhibited in the interactive Figure. We highlight that for the `cat` label, each strategy retrieves images that are mislabeled in the ground truth labeling. Indeed, the frog, dog and fox images are labeled as `cat` in `CIFAR-10`. And while the entropy and GLAD output similar tasks, in this case the WAUM often differs. We can also observe an ambiguity induced by the labels in the `truck` category, with the presence of a trailer that is technically a mixup between a `car` and a `truck`.

5.1.2 LabelMe dataset

As for the `LabelMe` dataset, one difficulty in evaluating tasks' intrinsic difficulty is that there a limited amount of votes available per task. Hence, the entropy in the distribution of the votes is no longer a reliable metric, and we need to rely on other models.

Now, let us compare the tasks' difficulty distribution depending on the strategy considered using `peerannot`.

```
! peerannot identify ./datasets/labelme -s entropy -K 8 \
  --labels ./datasets/labelme/answers.json
! peerannot aggregate ./datasets/labelme/ -s GLAD
! peerannot identify ./datasets/labelme/ -K 8 --method WAUM \
  --labels ./datasets/labelme/answers.json --model modellabelme --lr=0.01 \
  --n-epochs 100 --maxiter-DS=100 --alpha=0.01 --pretrained --optimizer=sgd
```

```
classes = {
    0: "coast",
    1: "forest",
    2: "highway",
    3: "insidecity",
    4: "mountain",
    5: "opencountry",
    6: "street",
    7: "tallbuilding",
}
classes = list(classes.values())
n_classes = len(classes)
all_images = utx.load_data("labelme", n_classes, classes)
utx.generate_plot(n_classes, all_images, classes) # create interactive plot
```

```
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```

Most difficult tasks identified depending on the strategy used (entropy, GLAD or WAUM) using a VGG-16 with two dense layers.

Note that in this experiment, because the number of labels given per task is in $\{1, 2, 3\}$, the entropy only takes four values. In particular, tasks with only one label all have a null entropy, so not just consensual tasks.

The underlying difficulty of these tasks mainly comes from the overlap in possible labels. For example, `tallbuildings` are most often found `insidecities`, and so are `streets`. In the `opencountry` we find `forests`, river-`coasts` and `mountains`.

5.2 Exploring workers' reliability

From the labels we can explore different worker evaluation scores. GLAD's strategy estimates a reliability scalar coefficient α_j per worker. With strategies looking to estimate confusion matrices, we investigate two scoring rules for workers:

- The trace of the confusion matrix: the closer to K the better the worker.
- The closeness to spammer metric (Raykar and Yu 2011) (also called spammer score) that is the Frobenius norm between the estimated confusion matrix $\hat{\pi}^{(j)}$ and the closest rank-1 matrix. The further to zero the better the worker. On the contrary, the closer to zero, the more likely it is the worker to be a spammer. This score separates spammers from common workers and experts (with profiles as in Figure 6).

When the tasks are available, confusion-matrix-based deep learning models can also be used. We thus add to the comparison the trace of the confusion matrices with CrowdLayer and CoNAL on the `LabelMe` datasets. For CoNAL, we only consider the trace of the confusion matrix $\pi^{(j)}$ in the

pairwise comparison. Moreover, for CrowdLayer and CoNAL we show in Figure 14 the weights learned without the softmax operation by row to keep the comparison as simple as possible with the actual outputs of the model.

Comparisons in Figure 13 and Figure 14 are plotted pairwise between the evaluated metrics. Each point represents a worker. Each off-diagonal plot shows the joint distribution between the scores of the y-axis row and x-axis column. They allow us to visualize the relationship between these two variables. The main diagonal represents the (smoothed) marginal distribution of the score of the considered column.

5.2.1 CIFAR-10H

The `CIFAR-10H` dataset has few disagreements among workers. However, these strategies disagree on the ranking of good against best workers as they do not measure the same properties.

```
! peerannot aggregate ./datasets/cifar10H/ -s GLAD
for method in ["trace_confusion", "spam_score"]:
  ! peerannot identify ./datasets/cifar10H/ --n-classes=10 \
                       -s {method} --labels ./datasets/cifar10H/answers.json
```

```
path_ = Path.cwd() / "datasets" / "cifar10H"
results_identif = {"Trace DS": [], "spam_score": [], "glad": []}
results_identif["Trace DS"].extend(np.load(path_ / 'identification' / "traces_confusion.npy"))
results_identif["spam_score"].extend(np.load(path_ / 'identification' / "spam_score.npy"))
results_identif["glad"].extend(np.load(path_ / 'identification' / "glad" / "abilities.npy")[:, 1])
results_identif = pd.DataFrame(results_identif)
g = sns.pairplot(results_identif, corner=True, diag_kind="kde", plot_kws={'alpha':0.2})
plt.tight_layout()
plt.show()
```

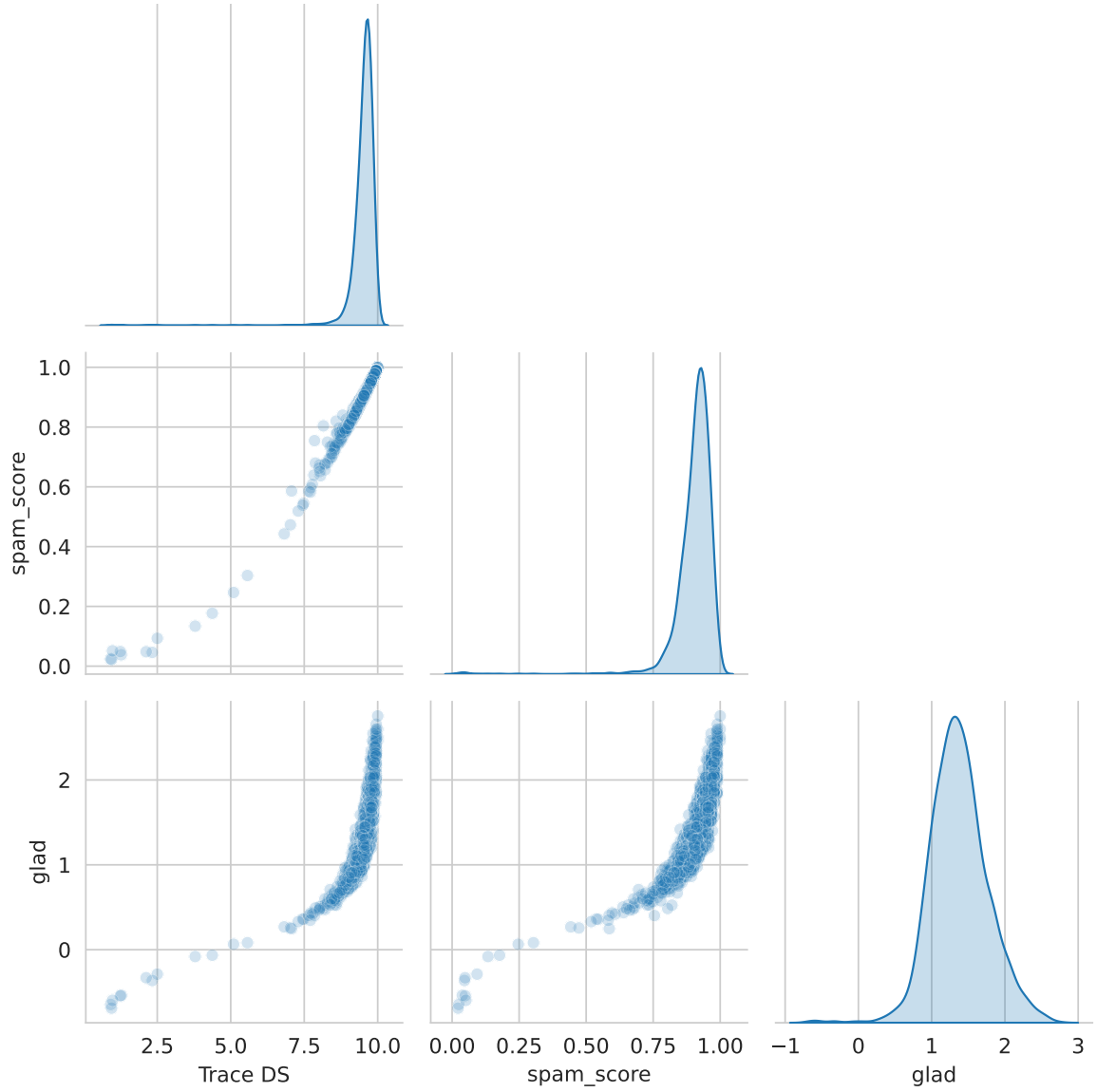

Figure 13: Comparison of ability scores by workers for the CIFAR-10H dataset. All metrics computed identify the same poorly performing workers. A mass of good and expert workers can be seen as the dataset presents few disagreements, thus few data to seperate good from best workers.

From Figure 13, we can see that in this dataset, different methods easily separate the worse workers from the rest of the crowd (workers in the left tail of the distribution).

5.2.2 LabelMe

Finally, let us evaluate workers for the `LabelMe` dataset. Because of the lack of data (up to 3 labels per task), ranking workers is more difficult than in the `CIFAR-10H` dataset.

```
! peerannot aggregate ./datasets/labelme/ -s GLAD
for method in ["trace_confusion", "spam_score"]:
  ! peerannot identify ./datasets/labelme/ --n-classes=8 \
                       -s {method} --labels ./datasets/labelme/answers.json
# CoNAL and CrowdLayer were run in section 4
```

```
path_ = Path.cwd() / "datasets" / "labelme"
results_identif = {
    "Trace DS": [],
    "Spam score": [],
    "glad": [],
    "Trace CrowdLayer": [],
    "Trace CoNAL[scale=1e-4]": [],
}
best_cl = torch.load(
    path_ / "best_models" / "labelme_crowdlayer.pth", map_location="cpu"
)
best_conal = torch.load(
    path_ / "best_models" / "labelme_conal[scale=1e-4]_local_confusion.pth",
    map_location="cpu",
)
pi_conal = best_conal
results_identif["Trace CoNAL[scale=1e-4]"].extend(
    [torch.trace(pi_conal[i]).item() for i in range(pi_conal.shape[0])]
)
results_identif["Trace CrowdLayer"].extend(
    [
        torch.trace(best_cl["confusion"][i]).item()
        for i in range(best_cl["confusion"].shape[0])
    ]
)
results_identif["Trace DS"].extend(
    np.load(path_ / "identification" / "traces_confusion.npy")
)
results_identif["Spam score"].extend(
    np.load(path_ / "identification" / "spam_score.npy")
)
results_identif["glad"].extend(
    np.load(path_ / "identification" / "glad" / "abilities.npy")[:, 1]
)
results_identif = pd.DataFrame(results_identif)
g = sns.pairplot(
    results_identif, corner=True, diag_kind="kde", plot_kws={"alpha": 0.2}
)
plt.tight_layout()
plt.show()
```

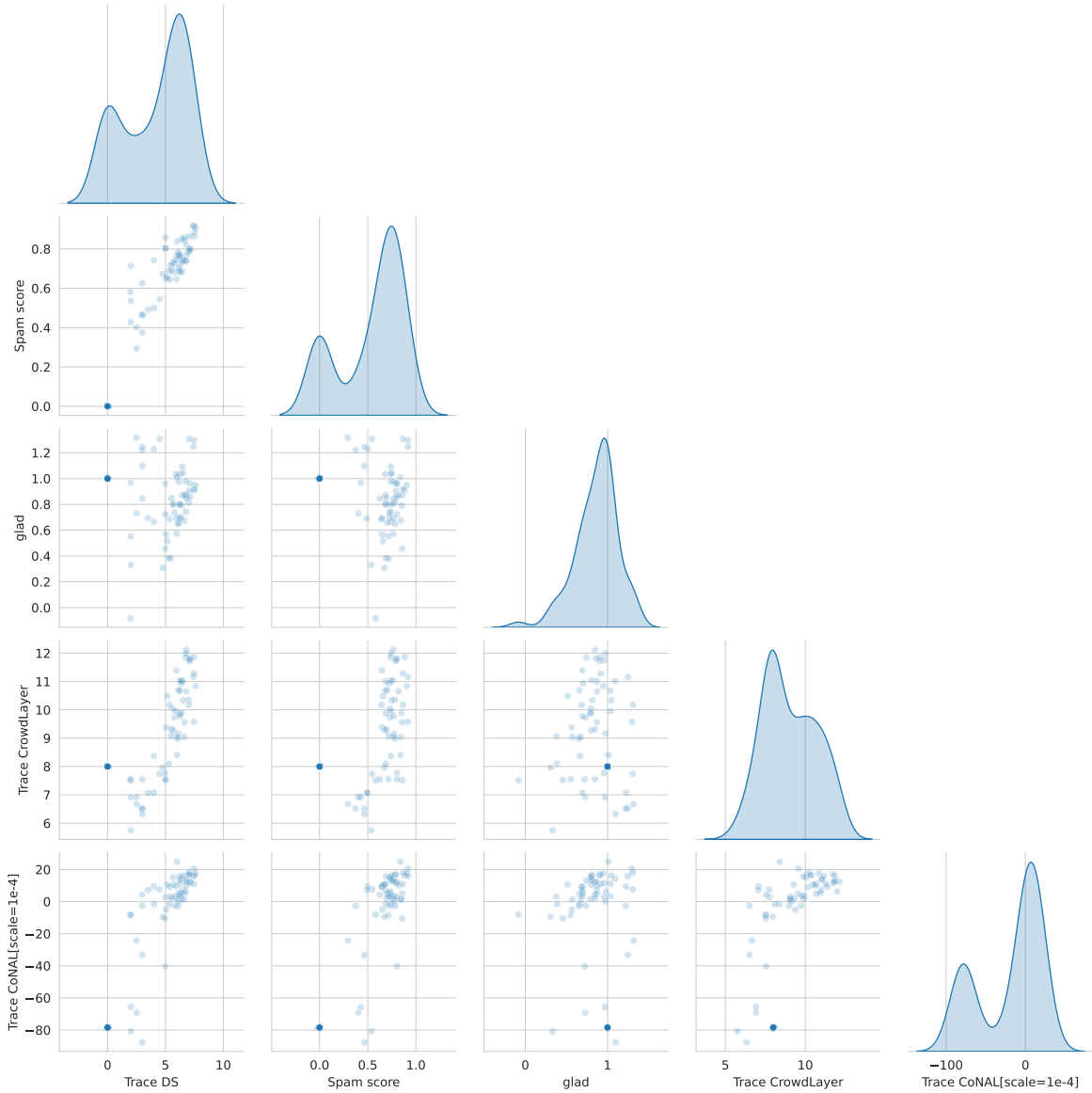

Figure 14: Comparison of ability scores by workers for the labelme dataset. With few labels per task, workers are more difficult to rank. It is more difficult to separate workers with their abilities in this crowd. Hence the importance of investigating the generalization performance of the methods presented in the previous section.

We can see in Figure 14 that the number of labels available by task highly impacts the worker evaluation scores. The spam score, DS model and CoNAL all show similar results in the distribution shape (bimodal distribution) whereas GLAD and CrowdLayer are more concentrated. However, this does not account for the ranking of a given worker by the methods considered. The exploration of the dataset let us look at different scores, but generalization performance presented in Section 4.3 should also be considered in crowdsourcing. This difference in worker evaluation scores indeed further highlights the importance of using multiple test metrics to compare model's prediction performance in crowdsourcing. We have seen that the library `peerannot` allows users to explore the datasets, both in terms of tasks and workers, and easily compare predictive performance in this setting.

In practice, the data exploration step can be used to detect possible ambiguities in the dataset's tasks, but also remove answers from spammers to improve the data quality as shown in Figure 1. The easy

access to the different strategies allows the user to decide if, for their collected dataset, there is a need for more recent deep-learning based strategies to improve the results. This is the case for the `LabelMe` dataset. Otherwise, the user can decide that standard aggregation-based crowdsourcing strategies are sufficient and for example, if there are plenty of votes per tasks like in `CIFAR-10H`, that the entropy in the votes distribution is a criterion that identified enough ambiguous tasks for their case. As often, not a single strategy works best for all datasets, hence the need to perform easy comparisons with `peerannot`.

6 Conclusion

We introduced `peerannot`, a library to handle crowdsourced datasets. This library enables both easy label aggregation and direct training strategies with classical state-of-the-art classifiers. The identification module of the library allows exploring the collected data from both the tasks and the workers' point of view for better scorings and data cleaning procedures. Our library also comes with templated datasets to better share crowdsourced datasets. Going beyond templating, it helps the crowdsourcing community to have openly accessible strategies to test, compare and improve in order to develop common strategies to analyse more and more common crowdsourced datasets.

We hope that this library helps reproducibility in the crowdsourcing community and also standardizes training from crowdsourced datasets. New strategies can easily be incorporated into the open-source code available on github. Finally, as `peerannot` is mostly directed to handle classification datasets, one of our future works would be to consider other `peerannot` modules to handle crowdsourcing for object detection, segmentation and even worker evaluation in other contexts like peer-grading.

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