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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

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## 35 **1 Introduction: crowdsourcing in image classification**

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

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

- 44 1) **How to identify good workers in the crowd and difficult tasks?** When multiple answers  
 45 are given to a single task, looking for who to trust for which type of task becomes necessary  
 46 to estimate the labels or later train a model with as few noise sources as possible. The module  
 47 `identify` uses different scoring metrics to create a worker and/or task evaluation. This is  
 48 particularly relevant considering the gamification of crowdsourcing experiments (Servajean et  
 49 al. 2016)
- 50 2) **How to aggregate multiple labels into a single label from crowdsourced tasks?** This  
 51 occurs for example when dealing with a single dataset that has been labeled by multiple  
 52 workers with disagreements. This is also encountered with other scoring issues such as polls,  
 53 reviews, peer-grading, etc. In our framework this is treated with the `aggregate` command,  
 54 which given multiple labels, infers a label. From aggregated labels, a classifier can then be  
 55 trained using the `train` command.
- 56 3) **How to learn a classifier from crowdsourced datasets?** Where the second question is  
 57 bound by aggregating multiple labels into a single one, this considers the case where we do  
 58 not need a single label to train on, but instead train a classifier on the crowdsourced data,  
 59 with the motivation to perform well on a testing set. This end-to-end vision is common in  
 60 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 that runs strategies where the aggregation has been transformed into a deep learning optimization problem.

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 network 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.

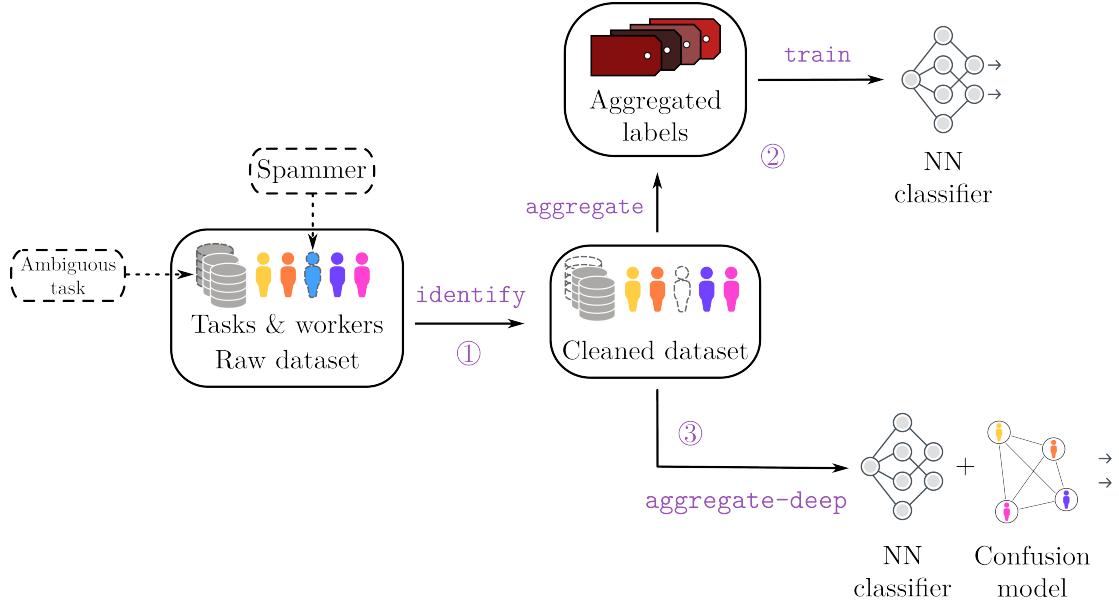


Figure 1: From crowdsourced labels to training a classifier neural network, the learning pipeline using the `peerannot` library. An optional preprocessing step using the `identify` command allows us to remove the worst-performing workers or images that can not be classified correctly (very bad quality 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  $\mathcal{D} = \{(x_i, y_i^*)\}_{i=1}^{n_{\text{task}}}$  is composed of  $n_{\text{task}}$  tasks  $x_i \in \mathcal{X}$  (the feature space) with (unknown) true label  $y_i^* \in [K] = \{1, \dots, K\}$  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 particular, given a classifier  $\mathcal{C}$  with logits outputs,  $\sigma(\mathcal{C}(x_i))_{[1]}$  represents the largest probability and we can sort the probabilities as  $\sigma(\mathcal{C}(x_i))_{[1]} \geq \sigma(\mathcal{C}(x_i))_{[2]} \geq \dots \geq \sigma(\mathcal{C}(x_i))_{[K]}$ . 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.

82 With crowdsourced data the true label of a task  $x_i$ , denoted  $y_i^*$  is unknown, and there is no single  
 83 label that can be trusted as in standard supervised learning (even on the train set!). Instead, there is a  
 84 crowd of  $n_{\text{worker}}$  workers from which multiple workers  $(w_j)_j$  propose a label  $(y_i^{(j)})_j$ . These proposed  
 85 labels are used to estimate a true label. The set of workers answering the task  $x_i$  is denoted by

$$\mathcal{A}(x_i) = \{j \in [n_{\text{worker}}] : w_j \text{ answered } x_i\}. \quad (1)$$

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

$$\mathcal{T}(w_j) = \{i \in [n_{\text{task}}] : w_j \text{ answered } x_i\}. \quad (2)$$

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

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

90 In this article, we do not address the setting where workers report their self-confidence (Yasmin et al.  
 91 2022), nor settings where workers are presented a trapping set – *i.e* a subset of tasks where the true  
 92 label is known to evaluate them with known labels (Khattak 2017).

## 93 2.2 Storing crowdsourced datasets in peerannot

94 Crowdsourced datasets come in various forms. To store [crowdsourcing datasets](#) efficiently and in a  
 95 standardized way, peerannot proposes the following structure, where each dataset corresponds to a  
 96 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
        ...
        data as imagename-<key>.png
        ...
    val
    test
    metadata.json
    answers.json
```

---

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

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

The figure shows two parts. On the left, a JSON object with three entries for smiley faces. Each entry contains a face icon and a dictionary of worker IDs and their answers. On the right, a 3x5 grid representing data collected from four workers. The grid has a legend at the top:  $K = 2$ , 0: not smiling, 1: smiling. The grid rows represent the three entries from the JSON object. The columns represent the four workers. The icons in the grid correspond to the answers in the JSON object.

$K = 2$	0: not smiling	1: smiling	Worker 1	Worker 2	Worker 3	Worker 4
Smiley Face	1	0	1	1		
Frowny Face	1	X	0	0		
Smiley Face	X	1	X	1		

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)

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

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

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

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

114 For both CIFAR-10H and LabelMe, the dataset was originally released in classical supervised learning  
 115 form (without crowdsourcing). These labels are used as true labels in evaluations and visualizations.  
 116 However, we emphasize that crowdsourcing strategies do not rely on the true labels (only on the  
 117 workers' answers). Examples of CIFAR-10H images are available in Figure 16, and LabelMe examples  
 118 in Figure 17 in Appendix. Crowdsourcing votes however bring information about possible confusions  
 119 (see Figure 3 for an example with CIFAR-10H and Figure 4 with LabelMe).

```
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_5()
```

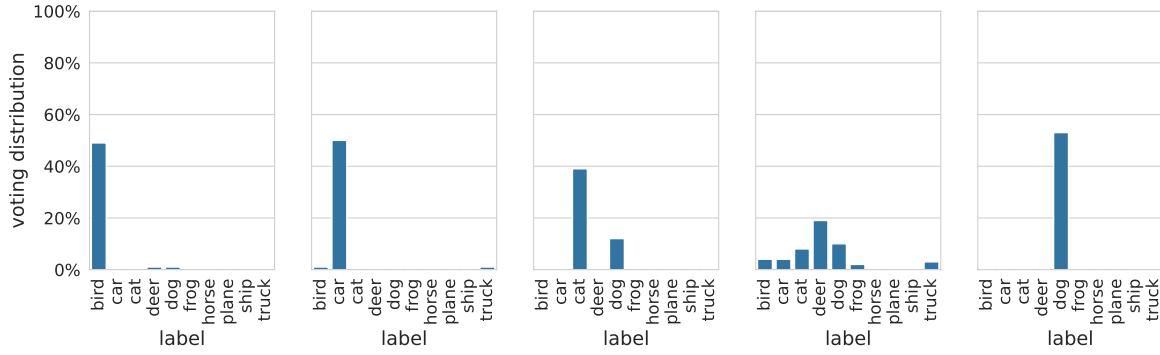


Figure 3: Example of crowdsourced images from CIFAR-10H. Each task has been labeled by multiple workers. We display the associated voting distribution over the possible classes.

```
utx.figure_5_labelmeversion()
```

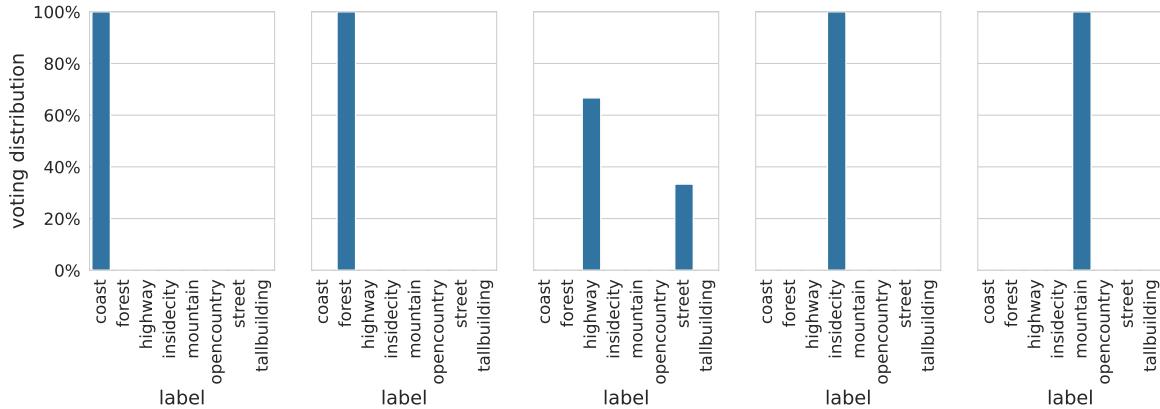


Figure 4: Example of crowdsourced images from LabelMe. Each task has been labeled by multiple workers. We display the associated voting distribution over the possible classes.

### 120 3 Aggregation strategies in crowdsourcing

121 The first question we address with peerannot is: *How to aggregate multiple labels into a single label*  
 122 *from crowdsourced tasks?* The aggregation step can lead to two types of learnable labels  $\hat{y}_i \in \Delta_K$

(where  $\Delta_K$  is the simplex of dimension  $K - 1$ :  $\Delta_K = \{p \in \mathbb{R}^K : \sum_{k=1}^K p_k = 1, p_k \geq 0\}$ ) 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 of belonging 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 releasing 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  $\pi_{k,\ell}^{(j)} = \mathbb{P}(y_i^{(j)} = \ell | y_i^* = k)$ . These quantities are not obtained using the true labels as they are unknown. In practice, the confusion matrices of each worker is estimated via an aggregation strategy like Dawid and Skene's (Dawid and Skene 1979) presented hereafter.

```
!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)
```

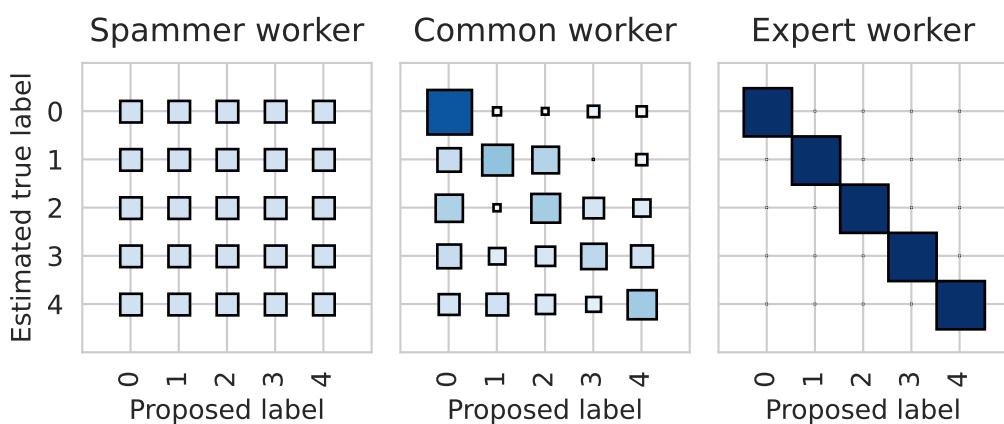


Figure 5: Three types of profiles of worker confusion matrices. The spammer answers independently from the true label. Expert workers identify classes without mistakes. In practice common workers are good for some classes but might confuse two (or more) labels. All workers are simulated using the `peerannot simulate` command presented in Section 3.2.

142 In Figure 5, we illustrate multiple profiles of workers. In particular, one type of worker that can hurt  
143 data quality is the spammer. Raykar and Yu (2011) defined a spammer as a worker that answers  
144 randomly:

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

145 Each row of the confusion matrix represents the label's probability distribution given an estimated  
146 true label, the spammer has a confusion matrix with near-identical rows. Apart from the spammer,  
147 common mistakes often involve workers mingling up one or several classes. Expert workers have a  
148 confusion matrix near the identity matrix.

### 149 3.1 Classical models

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

#### 151 3.1.1 Majority vote (MV)

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

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

#### 156 3.1.2 Naive soft (NS)

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

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

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

#### 163 3.1.3 Dawid and Skene (DS)

164 Refining the aggregation, researchers have proposed a noise model to take into account the workers'  
165 abilities. The **Dawid and Skene**'s (DS) model (Dawid and Skene 1979) is one of the most studied  
166 (Gao and Zhou 2013) and applied (Servajean et al. 2017; Rodrigues and Pereira 2018). These types of  
167 models are most often optimized using EM-based procedures. Assuming the workers are answering  
168 tasks independently, this model boils down to model pairwise confusions between each possible  
169 class. Each worker  $w_j$  is assigned a confusion matrix  $\pi^{(j)} \in \mathbb{R}^{K \times K}$  as described in Section 3. The  
170 model assumes that for a task  $x_i$ , conditionally on the true label  $y_i^* = k$  the label distribution of the  
171 worker's answer follows a multinomial distribution with probabilities  $\pi_{k,:}^{(j)}$  for each worker. Each  
172 class has a prevalence  $\rho_k = \mathbb{P}(y_i^* = k)$  to appear in the dataset. Using the independence between  
173 workers, we obtain the following likelihood to maximize (with latent variables  $\rho$ ,  $\pi = \{\pi^{(j)}\}_j$  and

174 unobserved variables  $(y_i^{(j)})_{i,j}$ :

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

175 When the true labels are not available, the data comes from a mixture of categorical distributions. To  
 176 retrieve ground truth labels and be able to estimate these parameters, Dawid and Skene (1979) have  
 177 proposed to consider the true labels as missing parameters. In this case, denoting  $T_{i,k} = \mathbf{1}_{\{y_i^* = k\}}$  the  
 178 vectors of label class indicators for each task, the likelihood with known true labels is:

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

179 This framework allows to estimate  $\rho, \pi, T$  with an EM algorithm as follows:

- 180 • With the MV strategy, get an initial estimate of the true labels  $T$ .  
 181 • Estimate  $\rho$  and  $\pi$  knowing  $T$  using maximum likelihood estimators.  
 182 • Update  $T$  knowing  $\rho$  and  $\pi$  using Bayes formula.  
 183 • Repeat until convergence of the likelihood.

184 The final aggregated soft label is  $\hat{y}_i^{\text{DS}} = T_{i,:}$ .

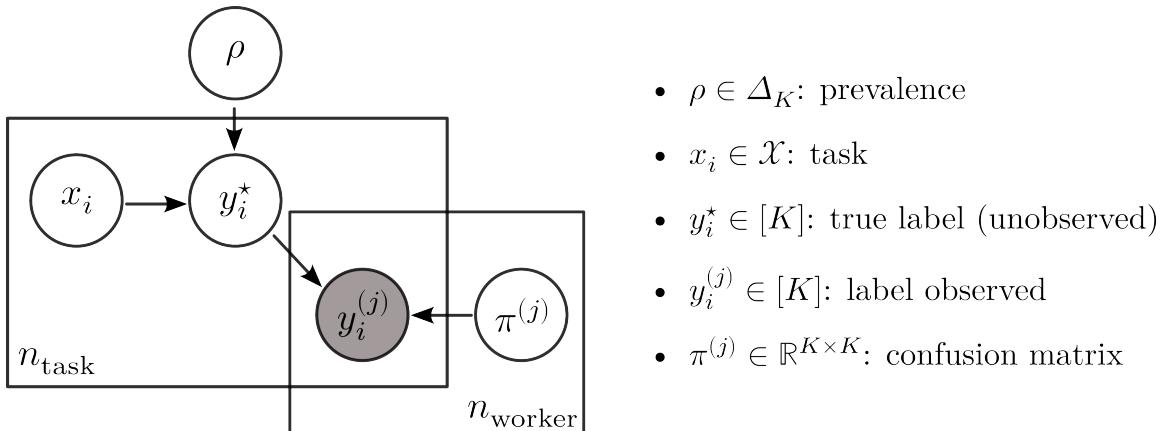


Figure 6: Bayesian plate notation for the DS model

### 185 3.1.4 Variations around the DS model

186 Many variants of the DS model have been proposed in the literature, using Dirichlet priors on the  
 187 confusion matrices (Passonneau and Carpenter 2014), using  $1 \leq L \leq n_{\text{worker}}$  clusters of workers  
 188 (Imamura, Sato, and Sugiyama 2018) (DSWC) or even faster implementation that produces only hard  
 189 labels (Sinha, Rao, and Balasubramanian 2018).

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

196 **3.1.5 Generative model of Labels, Abilities, and Difficulties (GLAD)**

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

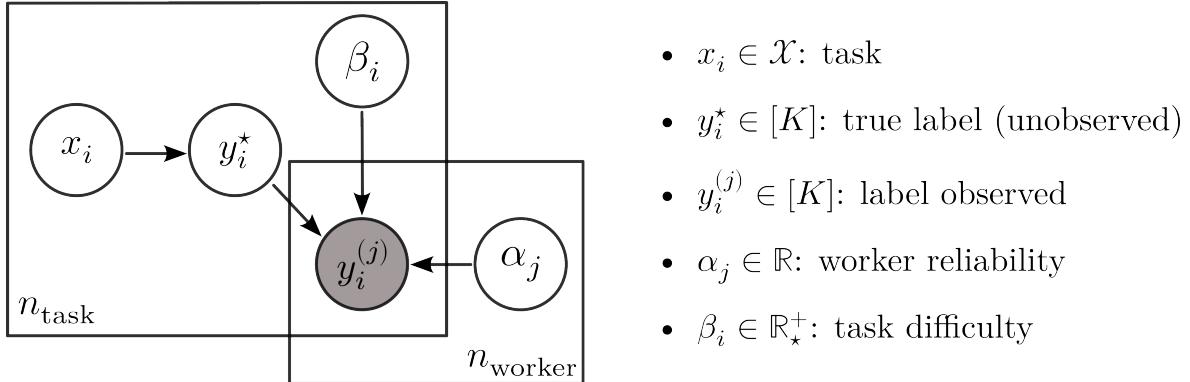


Figure 7: Bayesian [plate notation](#) for the GLAD model

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

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

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

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

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

204 **3.1.6 Aggregation strategies in peerannot**

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

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

211 **3.2 Experiments and evaluation of label aggregation strategies**

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

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

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

- 218 • the AccTrain metric does not consider the ambiguity of the soft label, only the most probable  
 219 class, whereas in some contexts ambiguity can be informative,  
 220 • in supervised learning one objective is to identify difficult or mislabeled tasks (Pleiss et al.  
 221 2020; Lefort et al. 2022), pruning those tasks can easily artificially improve the AccTrain, but  
 222 there is no guarantee over the predictive performance of a model based on the newly pruned  
 223 dataset,  
 224 • in practice, true labels are unknown, thus this metric would not be computable.

225 We first consider classical simulation settings in the literature that can easily be created and repro-  
 226 duced using peerannot. For each dataset, we present the distribution of the number of workers per  
 227 task ( $|\mathcal{A}(x_i)|_{i=1,\dots,n_{\text{task}}}$  Equation 1 on the right and the distribution of the number of tasks per worker  
 228 ( $|\mathcal{T}(w_j)|_{j=1,\dots,n_{\text{worker}}}$  Equation 2 on the left).

### 229 3.2.1 Simulated independent mistakes

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

238 We simulate  $n_{\text{task}} = 200$  tasks and  $n_{\text{worker}} = 30$  workers with  $K = 5$  possible classes. Each task  $x_i$   
 239 receives  $|\mathcal{A}(x_i)| = 10$  labels. With 200 tasks and 30 workers, asking for 10 leads to around  $\frac{200 \times 10}{30} \approx 67$   
 240 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)
workload = working_load(votes_path, metadata_path)
feedback = feedback_effort(votes_path)
utx.figure_simulations(workload, feedback)
plt.show()
```

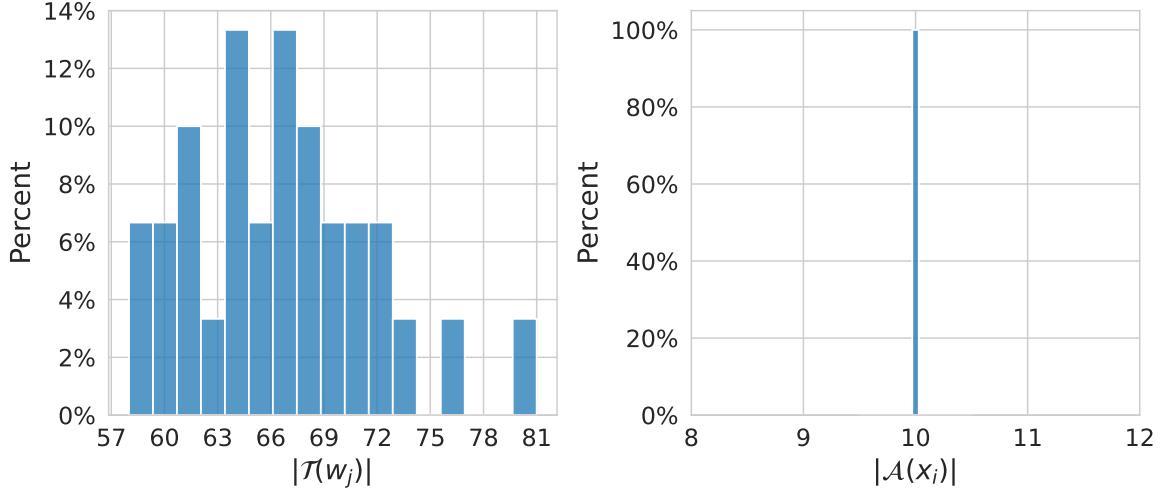


Figure 8: Distribution of number of tasks given per worker (left) and number of labels per task (right) in the independent mistakes setting.

241 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"]
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)

```

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

Table 1

	MV	GLAD	DS	DSWC[L=5]	DSWC[L=10]	NS
AccTrain	0.755	0.775	0.890	0.775	0.770	0.760

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

245 **Remark:** peerannot can also simulate datasets with an imbalanced number of votes chosen uniformly  
 246 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)
workload = working_load(votes_path, metadata_path)
feedback = feedback_effort(votes_path)
utx.figure_simulations(workload, feedback)
plt.show()

```

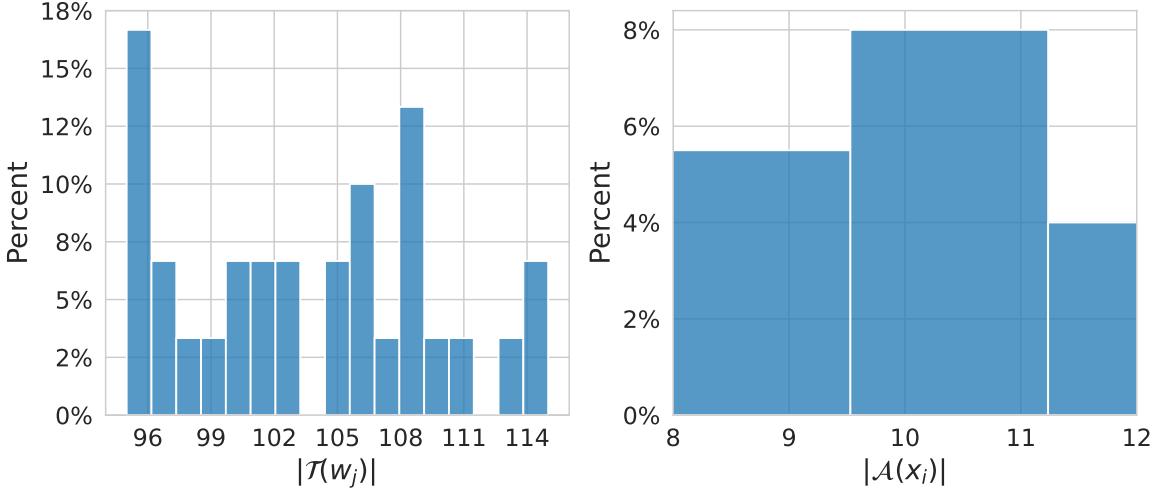


Figure 9: Distribution of the number of tasks given per worker (left) and of the number of labels per task (right) in the independent mistakes setting with voting imbalance enabled.

<sup>247</sup> 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)

```

```
display(results)
```

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

Table 2

	MV	GLAD	DS	DSWC[L=5]	DSWC[L=10]	NS
AccTrain	0.780	0.810	0.895	0.845	0.840	0.830

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

250 **3.2.2 Simulated correlated mistakes**

251 The correlated mistakes are also known as the student-teacher or junior-expert setting (Cao et al.  
 252 (2019)). Consider that the crowd of workers is divided into two categories: teachers and students  
 253 (with  $n_{\text{teacher}} + n_{\text{student}} = n_{\text{worker}}$ ). Each student is randomly assigned to one teacher at the beginning  
 254 of the experiment. We generate the (diagonally dominant as in Section 3.2.1) confusion matrices of  
 255 each teacher and the students share the same confusion matrix as their associated teacher. Hence,  
 256 clustering strategies are expected to perform best in this context. Then, they all answer independently,  
 257 following a multinomial distribution with weights given at the row  $y_i^*$  of their confusion matrix  
 258  $\pi^{(j)} \in \mathbb{R}^{K \times K}$ .

259 We simulate  $n_{\text{task}} = 200$  tasks and  $n_{\text{worker}} = 30$  with 80% of students in the crowd. There are  $K = 5$   
 260 possible classes. Each task receives  $|\mathcal{A}(x_i)| = 10$  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)
workload = working_load(votes_path, metadata_path)
feedback = feedback_effort(votes_path)
utx.figure_simulations(workload, feedback)
plt.show()
```

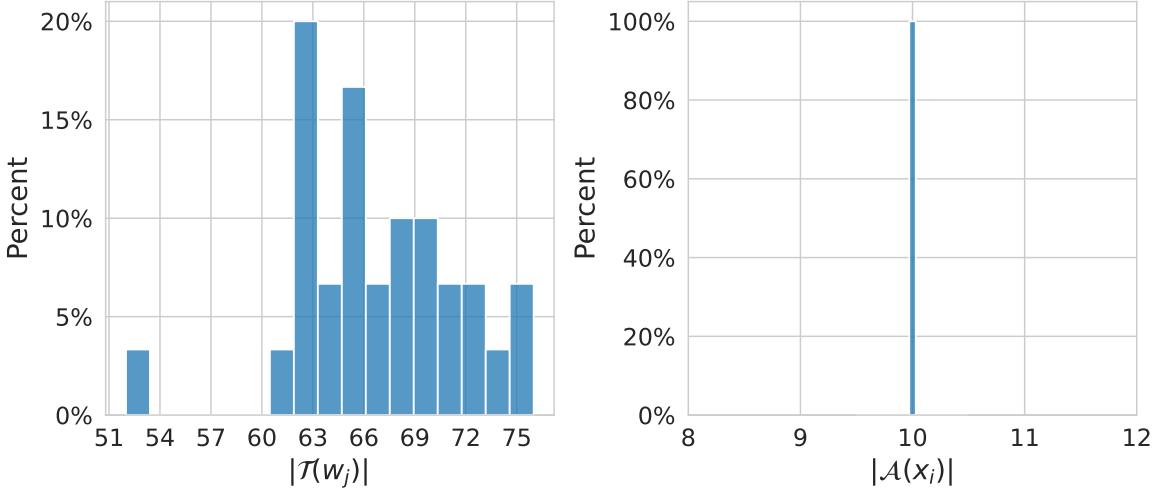


Figure 10: Distribution of number of tasks given per worker (left) and number of labels per task (right) in the correlated mistakes setting.

261 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)": [], "dswc[l=10)": []}
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)

```

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

Table 3

	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

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. The best-performing method here estimates only 10 confusion matrices (instead of 30 for the vanilla DS model).

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  $\mathcal{C}$  be  $z_i = \mathcal{C}(x_i)$ . 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  $\mathcal{L}_{CE}^{\text{CrowdLayer}}$  and computed as:

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

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

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.

291 **4.1.2 CoNAL**

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

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

$$\mathcal{L}_{CE}^{\text{CoNAL}}(x_i) = \sum_{j \in \mathcal{A}(x_i)} \text{CE}(h_i^{(j)}, y_i^{(j)}) ,$$

with  $h_i^{(j)} = \sigma((\omega_i^{(j)} \pi^g + (1 - \omega_i^{(j)}) \pi^{(j)}) z_i)$  .

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

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

305 **4.2 Prediction error when learning from crowdsourced tasks**

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

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

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

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

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

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

324 **4.3 Use case with peerannot on real datasets**

325 Few real crowdsourcing experiments have been released publicly. Among the available ones,  
326 CIFAR-10H (Peterson et al. 2019) is one of the largest with 10000 tasks labeled by workers (the  
327 testing set of CIFAR-10). The main limitation of CIFAR-10H is that there are few disagreements  
328 between workers and a simple majority voting already leads to a near-perfect AccTrain error. Hence,  
329 comparing the impact of aggregation and end-to-end strategies might not be relevant (Peterson et al.  
330 2019; Aitchison 2021), it is however a good benchmark for task difficulty identification and worker  
331 evaluation scoring.

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

334 Let us use peerannot to train a VGG-16 with two dense layers on the LabelMe dataset. Note that  
335 this modification was introduced to reach state-of-the-art performance in (Chu, Ma, and Wang 2021).  
336 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("_")
```

```

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)

```

Table 4: 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 4

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

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

## 341 5 Identifying tasks difficulty and worker abilities

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

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

347 sometimes voluntarily (e.g. the worker is a spammer).

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

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

## 356 5.1 Exploring tasks' difficulty

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

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

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

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

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

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

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

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

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

381 **5.1.1 CIFAR-10H dataset**

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

```
! peerannot identify ./datasets/cifar10H -s entropy -K 10 --labels ./datasets/cifar10H/answers.json
! 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)

384 Unable to display output for mime type(s): text/html

385 Most difficult tasks identified depending on the strategy used (entropy, GLAD or WAUM) using a
386 Resnet34. Classes displayed are from the MV aggregation.

387 Unable to display output for mime type(s): text/html

388

389 The entropy, GLAD's difficulty, and WAUM's difficulty each show different images as exhibited in
390 the interactive Figure. While the entropy and GLAD output similar tasks, in this case, the WAUM
391 often differs. We can also observe an ambiguity induced by the labels in the truck category, with the
392 presence of a trailer that is technically a mixup between a car and a truck.
```

393 **5.1.2 LabelMe dataset**

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

397 Now, let us compare the tasks' difficulty distribution depending on the strategy considered using  
398 `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

399 Unable to display output for mime type(s): text/html

400 Most difficult tasks identified depending on the strategy used (entropy, GLAD or WAUM) using a
401 VGG-16 with two dense layers. Classes displayed are from the MV aggregation.
```

402

403 Note that in this experiment, because the number of labels given per task is in {1, 2, 3}, the entropy  
404 only takes four values. In particular, tasks with only one label all have a null entropy, so not just  
405 consensual tasks. The MV is also not suited in this case because of the low number of votes per task.  
406 The underlying difficulty of these tasks mainly comes from the overlap in possible labels. For example,  
407 tallbuildings are most often found insidecities, and so are streets. In the opencountry we  
408 find forests, river-coasts and mountains.

## 409 **5.2 Identification of worker reliability and task difficulty**

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

- 413 • The trace of the confusion matrix: the closer to  $K$  the better the worker.
- 414 • The closeness to spammer metric (Raykar and Yu 2011) (also called spammer score) that is the  
415 Frobenius norm between the estimated confusion matrix  $\hat{\pi}^{(j)}$  and the closest rank-1 matrix.  
416 The further to zero the better the worker. On the contrary, the closer to zero, the more likely it  
417 is for the worker to be a spammer. This score separates spammers from common workers and  
418 experts (with profiles as in Figure 5).

419 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 12 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 11 and Figure 12 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 the 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()
```

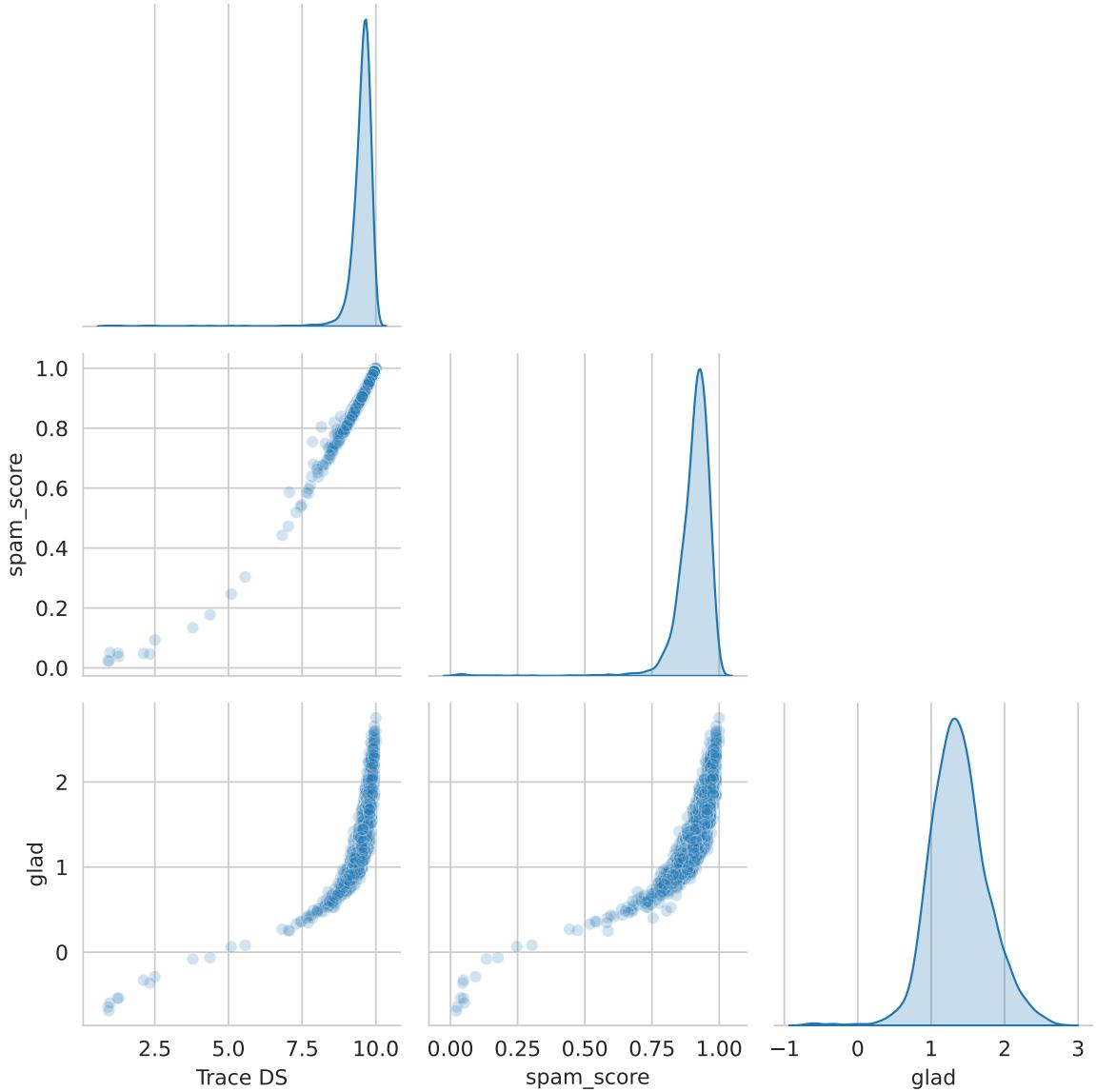


Figure 11: Comparison of ability scores by workers for the CIFAR-10H dataset. All metrics computed identify the same poorly performing workers. A mass of good and expert workers can be seen as the dataset presents few disagreements, thus few data to discriminate expert workers from the others.

433 From Figure 11, we can see that in this dataset, different methods easily separate the worst workers  
 434 from the rest of the crowd (workers in the left tail of the distribution).

#### 435 5.2.2 LabelMe

436 Finally, let us evaluate workers for the LabelMe dataset. Because of the lack of data (up to 3 labels  
 437 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()

```

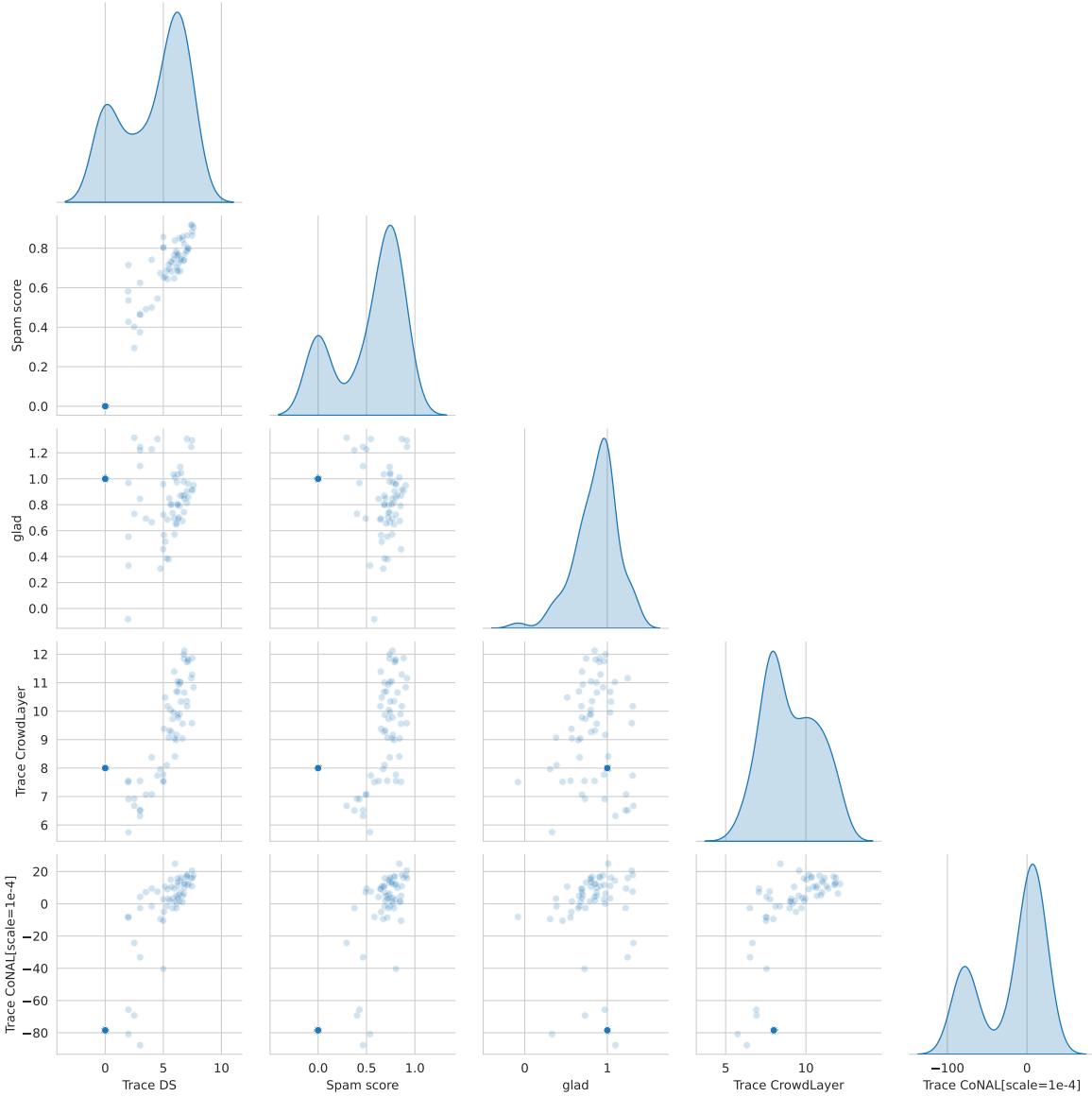


Figure 12: Comparison of ability scores by workers for the LabelMe dataset. With few labels per task, workers are more difficult to rank. It is more difficult to separate workers with their abilities in this crowd. Hence the importance of investigating the generalization performance of the methods presented in the previous section.

We can see in Figure 12 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 lets 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 the 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,

449 but also remove answers from spammers to improve the data quality as shown in Figure 1. The easy  
 450 access to the different strategies allows the user to decide if, for their collected dataset, there is a  
 451 need for more recent deep-learning-based strategies to improve the results. This is the case for the  
 452 LabelMe dataset. Otherwise, the user can decide that standard aggregation-based crowdsourcing  
 453 strategies are sufficient and for example, if there are plenty of votes per task like in CIFAR-10H, that  
 454 the entropy of the vote distribution is a criterion that identified enough ambiguous tasks for their  
 455 case. As often, not a single strategy works best for all datasets, hence the need to perform easy  
 456 comparisons with peerannot.

## 457 6 Conclusion

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

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

## 470 7 Appendix

### 471 7.1 Supplementary simulation: Simulated mistakes with discrete difficulty levels 472 on tasks

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

$$478 \text{ratio-diff} = \frac{P(\text{easy})}{P(\text{hard})} \text{ with } P(\text{easy}) + P(\text{hard}) = 1 .$$

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

481 We simulate  $n_{\text{task}} = 500$  tasks and  $n_{\text{worker}} = 100$  with 35% of good workers in the crowd and 50% of  
 482 easy tasks. There are  $K = 5$  possible classes. Each task receives  $|\mathcal{A}(x_i)| = 10$  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)
workload = working_load(votes_path, metadata_path)
feedback = feedback_effort(votes_path)
utx.figure_simulations(workload, feedback)
plt.show()

```

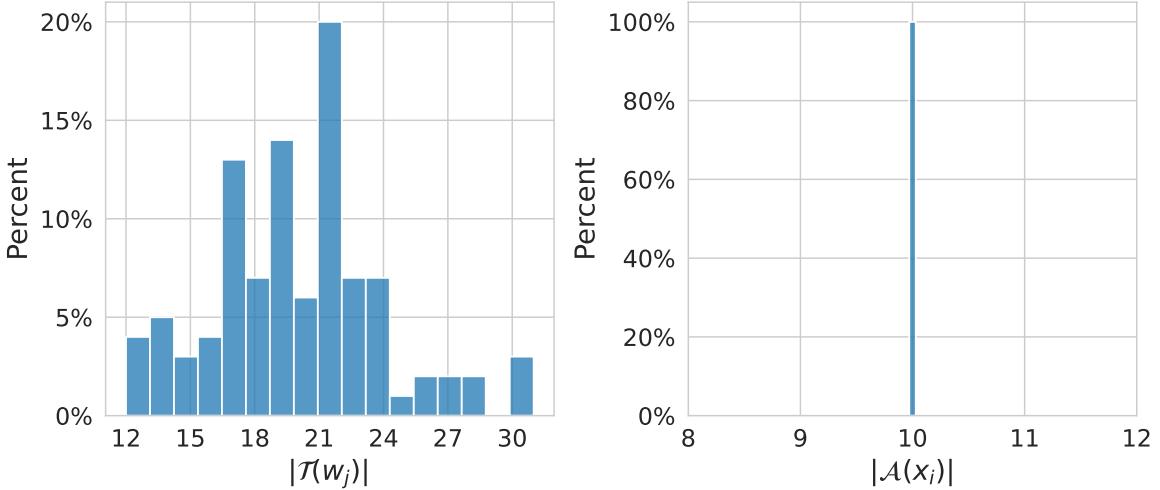


Figure 13: Distribution of the number of tasks given per worker (left) and of the number of labels per task (right) in the setting with simulated discrete difficulty levels.

483 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)

```

Table 5: AccTrain metric on simulated mistakes made when tasks are associated with a difficulty level considering classical feature-blind label aggregation strategies.

Table 5

	MV	GLAD	DS	DSWC[L=2]	DSWC[L=5]	NS
AccTrain	0.830	0.845	0.810	0.600	0.660	0.790

Finally, in this setting involving task difficulty coefficients, the only strategy that involves a latent variable for the task difficulty, knowing GLAD, outperforms the other strategies (see Table 5). Note that in this case, creating clusters of answers leads to worse decisions than an MV aggregation.

## 7.2 Comparison with other libraries

In this section, we provide several comparisons with the Ustalov, Pavlichenko, and Tseitlin (2023) library.

- Framework: `peerannot` focuses on image classification problems with categorical answers. `crowd-kit` also considers textual responses and image segmentation with three aggregation strategies for each field.
- Data storage: `peerannot` introduces this `.json` storage that can handle large datasets. `crowd-kit` stores the collected data in a `.csv` file with columns `task`, `worker`, `label`.
- Identification module: one of the major differences between the two libraries resides in the `identification` module of `peerannot`. This module allows us to explore the dataset and detect poorly performing workers / difficult tasks easily. `crowd-kit` only allows us to explore workers with the `accuracy_on_aggregation` metric that computes the accuracy of a worker given aggregated hard labels. `peerannot`, as demonstrated in Section 5, proposes several metrics such as the spam score, GLAD's worker ability coefficient and the trace of the confusion matrices. As for the task side, `peerannot` proposes the different popular metrics in `crowd-kit` accompanied with the WAUM (and also the AUMC) metrics from Lefort et al. (2022) and GLAD's difficulty coefficients.
- Training: `peerannot` lets users directly train a neural network architecture from the aggregated labels. This feature is not proposed by `crowd-kit`.
- Simulation: `peerannot` created a `simulate` module to check strategies on. This feature is also not in the `crowd-kit` library.

Finally, to compare different strategies across libraries, we implemented a [crowdsourcing benchmark](#) in the `Benchopt` (Moreau et al. (2022)) library. The `Benchopt` library allows users to easily compare and reproduce optimization problem benchmarks between multiple frameworks. After running each strategy, we measure the cumulated time taken to reach the optimum during the optimization steps. The metric measured on the y-axis is the AccTrain. Each strategy is run 5 times until convergence. The differences in results across iterations for the MV strategy come from the randomness in the choice in case of equalities. We provide a clone of the crowdsourcing benchmark and the results are obtained by running the following command:

```
benchopt run ./benchmark_crowdsourcing
```

516 First, let us see the performances on the **Bluebirds** dataset, a small dataset with 39 workers, 108 tasks  
 517 and  $K = 2$  classes.

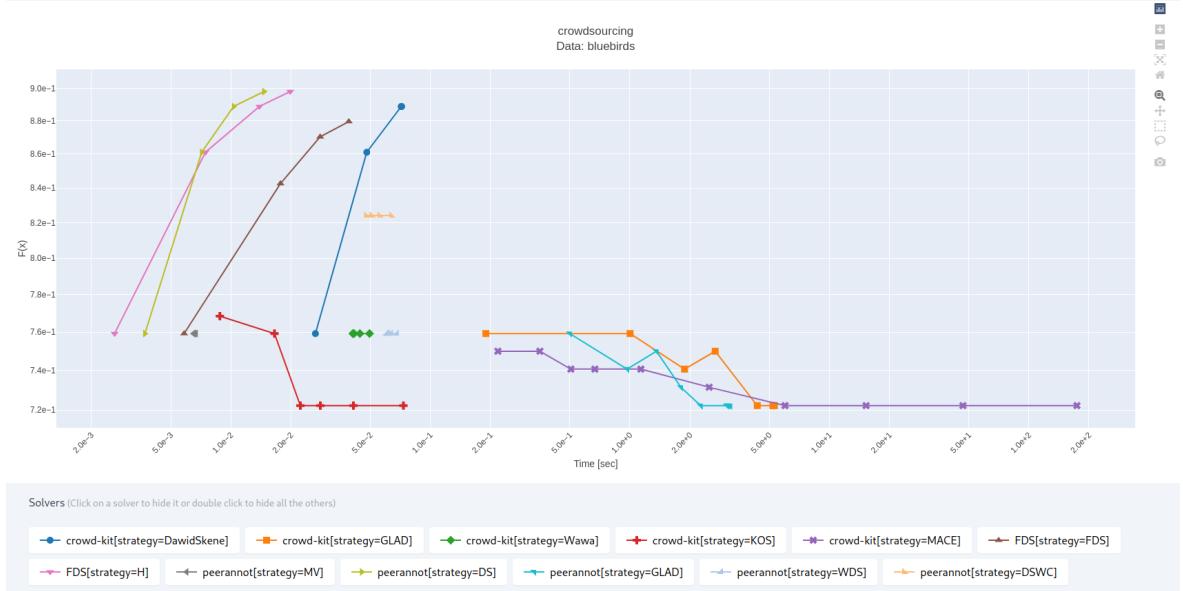


Figure 14: Aggregation strategies computational time during optimization procedure for the BlueBirds dataset with  $K=2$ .

518 We see in Figure 14 that the DS strategy from peerannot is the first to reach the optimum, followed  
 519 by the **Fast-DS strategy** and then crowd-kit DS. Other strategies do not lead to better accuracy on  
 520 this dataset and DS seems to be the best fitting strategy.

521 For the LabelMe dataset, DS strategy is also the best aggregation strategy, faster for crowd-kit. The  
 522 sensitivity of GLAD's method to the priors on  $\alpha$  and  $\beta$  parameters can lead to large performance  
 523 differences for real datasets as we see in Figure 15. Note that crowd-kit's KOS strategy is not  
 524 available for this dataset as it is only made for binary classification datasets.

### 525 7.3 Examples of images in CIFAR-10H and Labelme

526 In this section, we provide examples of images from the CIFAR-10H and LabelMe datasets. Both of  
 527 these datasets came with known true labels. For CIFAR-10H, the true labels were from the original  
 528 CIFAR-10 dataset. For LabelMe, the true labels were determined by the authors at release.

```
utx.figure_3()
```

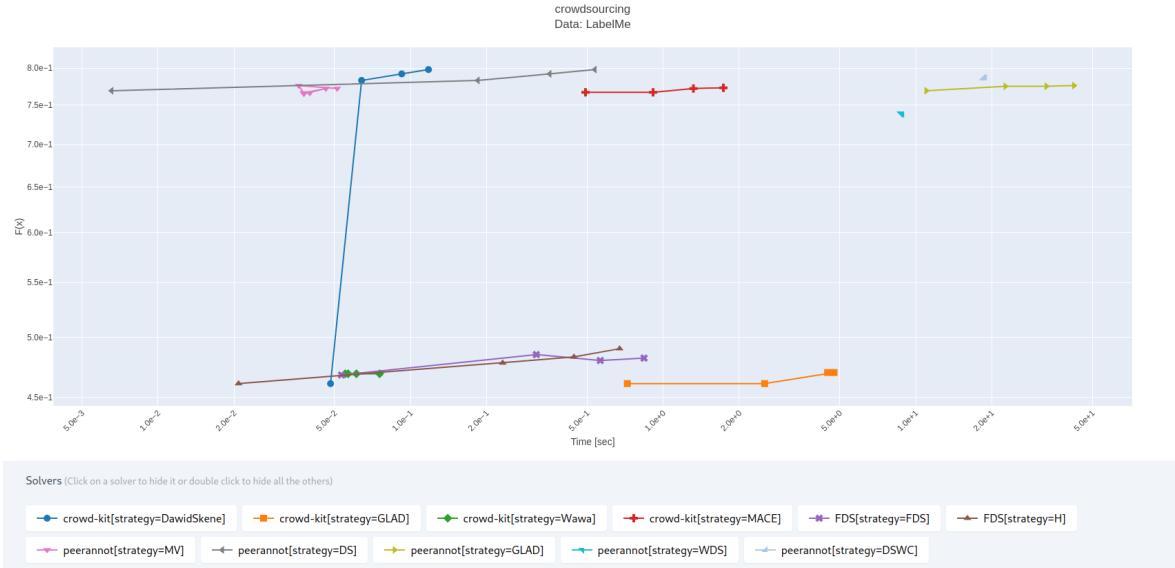


Figure 15: Aggregation strategies computational time during optimization procedure for the LabelMe dataset with  $K=8$

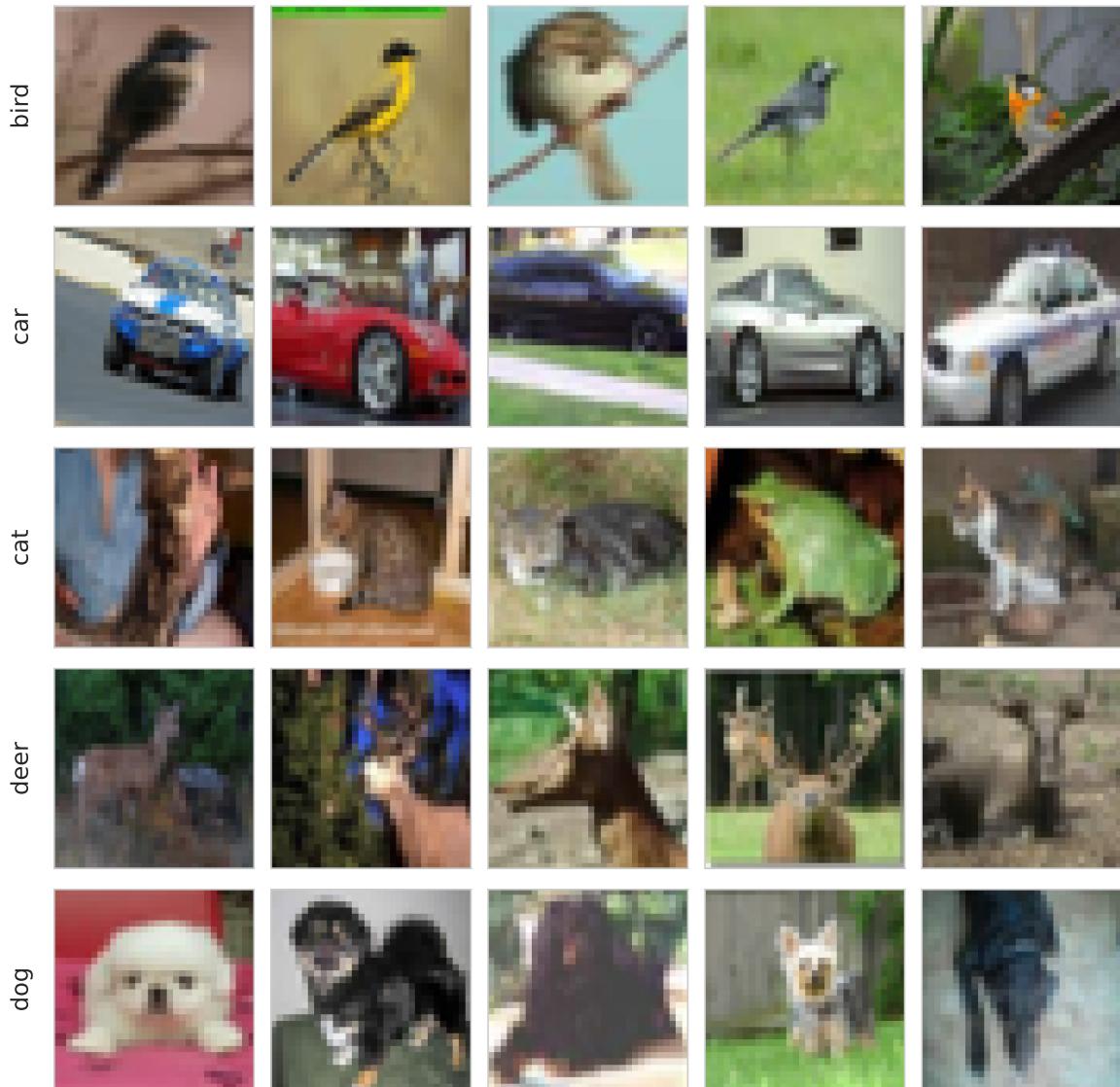


Figure 16: Example of images from CIFAR-10H. We display images row-wise according to the true label given initially in CIFAR-10.

utx.figure\_4()

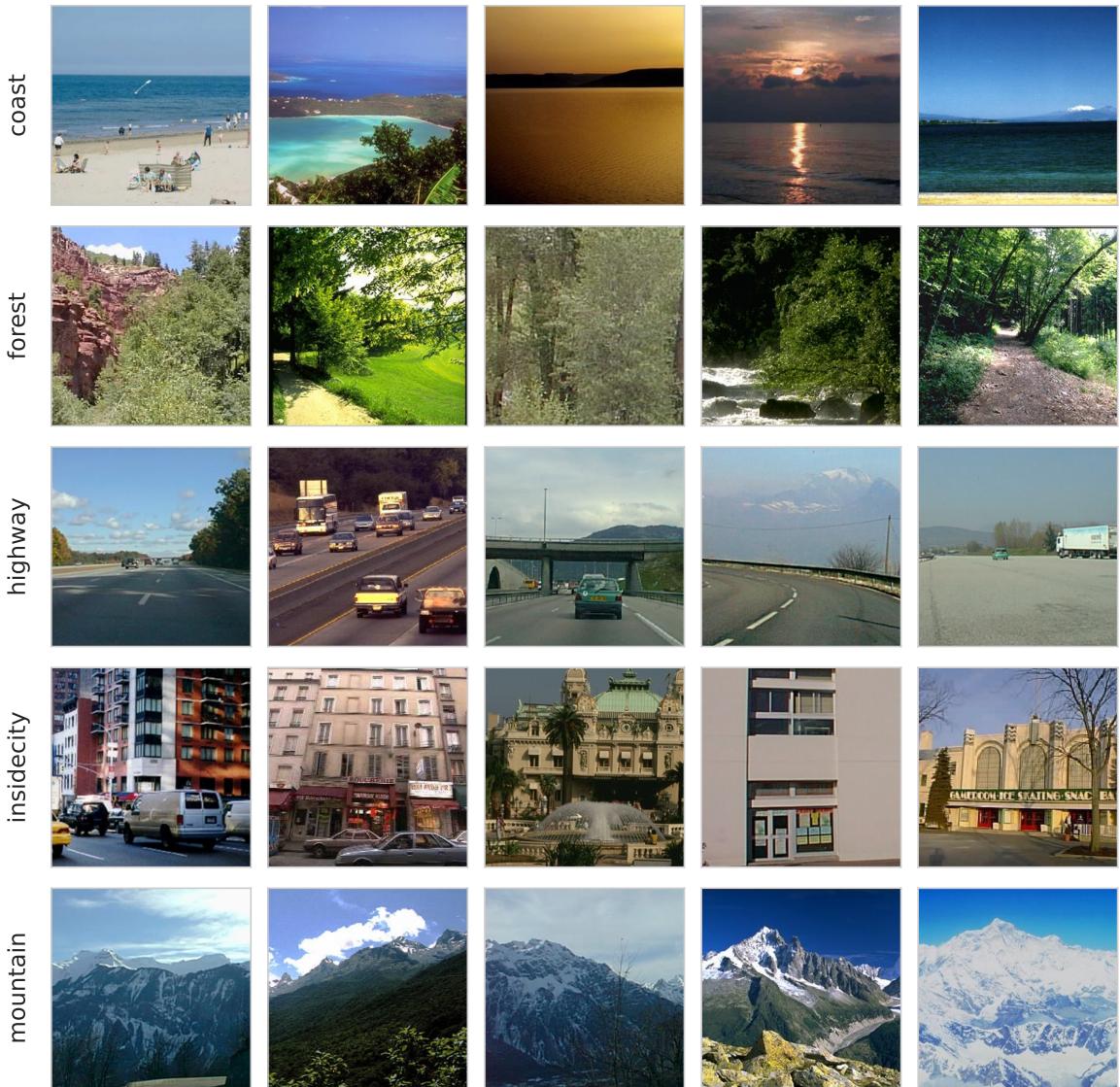


Figure 17: Example of images from LabelMe. We display images row-wise according to the true label given with the crowdsourced data.

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